The Impact of Artificial Intelligence on Decision-Making in Venture Capital Firms

Christina Schmidt

Dissertation written under the supervision of Gonçalo Saraiva

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Abstract

Title: The Impact of Artificial Intelligence on Decision-Making in Venture Capital Firms.
Author: Christina Schmidt
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This exploratory study examines the opportunity of Artificial Intelligence in the decision-making process of Venture Capitals. Investors have to take decisions under uncertainty, time pressure and suffer from bias. This study investigates the potential of Artificial Intelligence to overcome these challenges and improve the process. The results are based on a qualitative analysis based on 12 interviews with Venture Capitals, AI Experts, and companies offering solutions for Venture Capitals as well as secondary data in form of academic articles and online magazines. The findings reveal that Artificial Intelligence is currently mostly implemented at the beginning of the decision-making process. The usage of Artificial Intelligence improves the process of making decisions by lowering uncertainty, bias and increasing productivity and efficiency. The interviews show that that AI can be implemented in every step in the decision-making process and presents the specific use cases. Furthermore, implementation challenges and implications for practice are outlined. By applying AI, Venture Capitals improve their decision-making process, which ultimately could have a positive impact on the return of their portfolio.

Resumo

Título:	O impacto da Inteligência Artificial no processo de tomada de decisão em empresas de capital de risco.
Autor:	Christina Schmidt
Palavras-chave:	Inteligência Artificial, Indústria de Capital de Risco, Processo Decisório, Tecnologia

Este estudo exploratório examina a oportunidade da Inteligência Artificial no processo de tomada de decisão das Capitais de Venture. Os investidores têm que tomar decisões sob incerteza, pressão de tempo e sofrer de parcialidade. Este estudo investiga o potencial da Inteligência Artificial para superar esses desafios e melhorar o processo. Os resultados são baseados em uma análise qualitativa baseada em 12 entrevistas com Venture Capitals, AI Experts e empresas oferecendo soluções para Venture Capitals, bem como dados secundários em forma de artigos acadêmicos e revistas on-line. Os resultados revelam que a Inteligência Artificial atualmente é implementada principalmente no início do processo de tomada de decisão. O uso da Inteligência Artificial melhora o processo de tomada de decisões, diminuindo a incerteza, o viés e aumentando a produtividade e a eficiência. As entrevistas mostram que a IA pode ser implementada em todas as etapas do processo de tomada de decisão e apresenta os casos de uso específicos. Além disso, desafios de implementação e implicações para a prática são delineados. Ao aplicar a inteligência artificial, as empresas de capital de risco melhoram seu processo de tomada de decisão, o que, em última instância, pode ter um impacto positivo no retorno de sua carteira.

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Glossary

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
VC	Venture Capital
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
RRL	Recurrent Reinforcement Learning
SVM	Support Vector Machines
LSTM	Long Short-Term Memory
SDK	Software Development Kit
NLP	Natural Language Processing

Chapter 1: Introduction

1.1. Background and Problem Statement

Research on decision-making in VCs has primarily attempted to explain what criteria investors use to evaluate companies (Hall and Hofer, 1993; Hisrich & Jankowicz 1990; MacMillan et. al, 1987; MacMillan et. al, 1985), and how they take decisions (Petty and Gruber, 2011; Fried and Hisrich, 1994; Tyebjee and Bruno, 1984). Due to the absence of databases on VC investments, researchers relied on subjective instead of quantitative criteria. Although a high amount of research has been conducted to identify the challenges in the process (Franke et al., 2006; Shepherd et al., 2003; Zacharakis and Shepherd, 2001; Zacharakis and Meyer, 1998), only few researchers have investigated solutions that would support investors in their decision-making (Czazar et al., 2006; Shepherd and Zacharakis, 2002; Zacharakis and Meyer, 2000; Khan, 1987).

The underlying research focuses on Artificial Intelligence (AI) and its potential in the VC industry. Improving decision-making was named the third biggest benefit provided by AI (Briggs et. al, 2018). AI is currently on the top of the list of technologies in which companies plan to invest in (Briggs and Buchholz, 2018). Among the technology's potential to redesign systems, processes, and business strategies (Briggs and Buchholz, 2018) its main goal is the establishment of organizations in which humans and machines work together to obtain data-driven insights. AI could help companies to increase productivity, and to gain insights from large data sets.

Applications of AI in the financial industry have been widely discussed (Butaru et. al, 2016; Harris, 1992). Identifying the high need for a more data-driven approach to investing, several researchers have focused on developing quantitative approaches for the evaluation of companies. Bhat and Zaelit (2011) applied random forest algorithms to predict private company exists from qualitative data. Dixon and Chong (2014), developed a Bayesian approach for ranking companies using a set of Support Vector Machines (SVM) models trained on several feature pairs. Although the methods developed in these studies could be highly beneficial for VCs, their impact on the decision-making process of VCs has not been studied yet. Therefore, the underlying research fills this gap in the academic literature by analyzing the opportunity of AI capabilities in the VC industry from a business perspective.

1.2. Aim and Scope

The aim of the underlying research is to broaden the current knowledge about the opportunity of AI in the decision-making process of VCs. In order to achieve this, the VC industry, the process to make investment decisions as well as AI will be analyzed in depth. First, the various steps of the decision-making process in VCs and their main challenges will be investigated. Second, the current state of AI capabilities and their ability to impact the decision-making process are evaluated. Lastly, the main challenges in the implementation of AI in the process will be discussed and several solutions offered.

Throughout the research, the following questions will be addressed:

Problem Statement: What is the business opportunity of AI in the decision-making process in VCs?

RQ1: How is the decision-making process in VCs structured?

RQ2: What are the key challenges in the process?

RQ3: What are the AI capabilities currently available?

RQ4: How can AI help to solve the challenges and impact performance in the process?

RQ5: What difficulties come up in the implementation of AI on the decision-making process? How can they be solved?

1.3. Research Method

In order to answer the research questions, exploratory research using both primary and secondary data was conducted. Secondary data in the form of academic articles was used in the literature review to answer RQ1 – RQ3 and to establish a theoretical background. Primary data was collected in the form of 12 semi-structured interviews conducted between March and May 2019 to generate in-depth knowledge about the current use cases of AI in the decision-making process in VCs. This data – complemented with secondary data in the form of newspaper articles, as well as academic literature – was used to support RQ2, and to answer RQ4 and RQ5.

1.4. Relevance

The well-known problems in VCs, namely high uncertainty, time pressure and overload of information as well as the increased competition in the industry resulting from the availability of more money, but fewer deals, emphasizes the high relevance of the underlying study. Although these challenges are well discussed in academic literature, investors themselves have difficulties to introspect their own decision-making process. This study outlines the main opportunities and challenges related to the implementation of AI in the decision-making process in VCs and will support VCs in identifying which AI capabilities could be valuable for their own process. Thereby, it is not only highly relevant for VC investors, but also for entrepreneurs seeking funding.

1.5. Dissertation Outline

The following chapter will give an overview of the literature available about decision-making in VCs. Decision-making theory, the VC industry as well as decision-making in VCs are discussed. The literature review finishes by providing an overview of the AI capabilities available, and the research conducted in combination of AI and the VC decision-making process so far. The third chapter describes the methodology, whereas the fourth chapter presents the results of the underlying research. The dissertation ends with conclusions, in which recommendations for further research as well as limitations of the study will be discussed.

Chapter 2: Literature Review

2.1. The Decision-Making Process

There have been numerous studies to investigate the decision-making process. Before developing his widely recognized framework of the decision-making process, Simon (1997) identified three factors influencing choice: 1) the identification of all the possible alternatives, 2) the determination of all the possible consequences of these alternatives and 3) the evaluation of all these alternatives and their connection with behavior alternatives. These factors built the foundation for his framework of the decision-making process (Simon, 1997, 1955), as described in Figure 1.

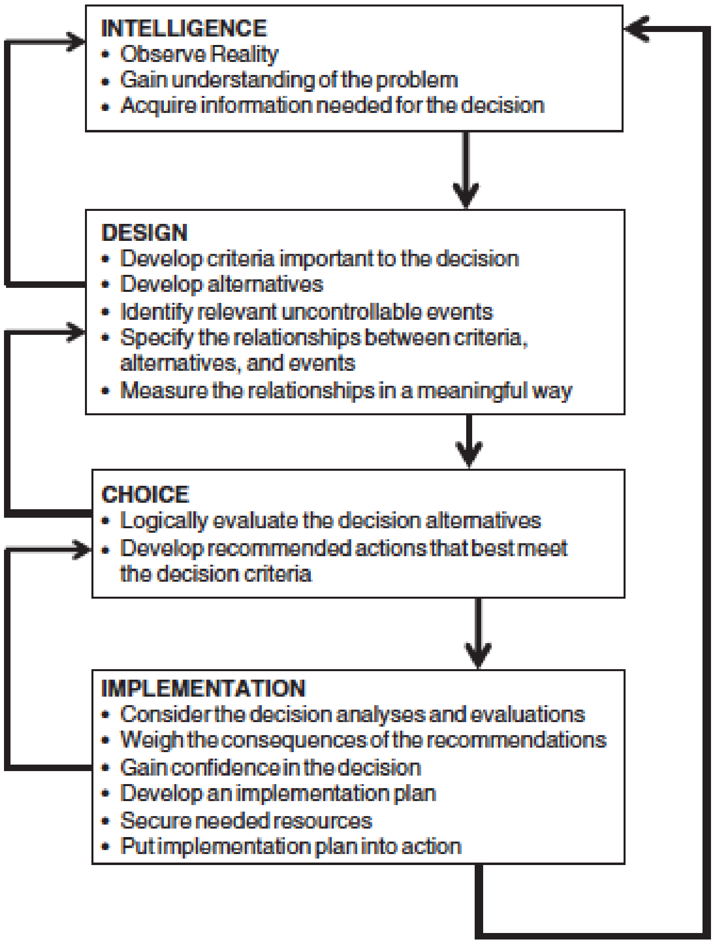

Figure 1: Description of Simon's Model of the Decision-Making Process (Doumpos and Grigoroudis, 2013)

The first phase – intelligence – consists of the understanding of the problem and the acquisition of relevant information. The second phase – design – is used for the development of alternatives and criteria important for the decision. This phase is followed by choice, the third phase, in which the alternatives are evaluated and a decision that best fits the decision criteria is selected. In the last phase, implementation, the consequences of the decision are elaborated and an implementation plan is developed.

However, it is well established in the literature that people don't take perfectly rational, but boundedly rational decisions (Kahneman, 2003; Camerer, 1998; Simon, 1955). Instead of maximizing utility in this decision-making process, decision makers act according to a satisficing utility model, resulting from a lack of information and ability (Simon, 1955). Conrath (1967) identifies four major areas decision makers are lacking information about: 1) the environmental conditions, 2) the probability distribution, 3) the alternative options available and 4) the value of these different options. In order to minimize the need to estimate probabilities and forecast the values of the different options, decision makers rely on heuristics. Although these heuristics can be useful, they can lead to cognitive biases (Tversky and Kahneman, 1974), followed by errors like sunk cost, anchoring or status quo (Gilovich et al., 2002; Kahneman and Tversky, 1982; Hogarth and Makridakis, 1981; Tversky and Kahneman, 1974).

Besides the problem of biases in decision making, decisions are taken as a response to uncertainty (Berkley and Humphreys, 1982). Although individuals struggle to take decisions under those circumstances, uncertainty is typical especially for high-velocity environments (George, 1980). Such environments are characterized by the need to take fast, high-quality decisions (Eisenhardt and Bourgeois, 1988), limited access to information, high cost of mistakes and difficulties to recover from missteps (Eisenhardt and Bourgeois, 1989). However, rapid decision making is essential for effective performance (Eisenhardt and Bourgeois, 1988), emphasizing the need to constantly optimize decision-making tactics.

In order to overcome the challenges described above, technology is already used as an essential part of organizational decision-making (Phillips-Wren et al., 2009). Technology not only serves as a rational basis to compare available alternatives and therefore supports the elimination of human cognitive biases (Doumpos and Grigoroudis, 2013) but also assists the decision maker by selecting relevant input and data and supports him in the interpretation of outcomes from the decision model (Phillips-Wren, 2012). As the VC industry is characterized as a high-velocity, high-pressure environment (Zacharakis and Shepherd, 2001) that leads investors to depend on using their intuition when making decisions (Hisrich and Jankowicz, 1990), the underlying research is going to investigate the main challenges of the decision-making process in this industry and examines how AI could be applied to solve those challenges.

2.2. The Venture Capital Industry

2.2.1. Overview

VCs professionally administer a pool of capital (Sahlman, 1990) and provide private ventures with financing, often in combination with managerial knowledge (Amit et al., 1998). They act as financial intermediaries (Jeng and Wells, 2000) by connecting investors with financial capacities that are looking for opportunities to invest in, with entrepreneurs with promising ideas (Kaplan and Lerner, 2010).

VCs are an important contributor to economic growth (Jeng and Wells, 2000). Many of the largest, most successful companies like Google or Apple have been backed by VCs (Kaplan and Lerner, 2010). As new ventures require a high amount of money to accelerate their growth, debt-based finance provided by banks is unsuitable from a cash management perspective. VCs emerged to fill this gap in startup financing (Jeng and Wells, 2000), representing for many new ventures the only possible source of capital (Fried and Hisrich, 1994).

There are several differences between VCs and other financial intermediaries (Amit et al., 1998; Tyebjee and Bruno, 1984). The environment VCs operate in is characterized by a high level of information asymmetry (Amit et al., 1998; Sahlman, 1990) and uncertainty about the payoffs (Sahlman, 1990), resulting from a lack of historical data to measure the performance of a new venture (Jeng and Wells, 2000; Tyebjee and Bruno, 1984). The nature of the relationship between the investor and the investee requires a higher level of direct involvement compared to other intermediaries (Tyebjee and Bruno, 1984). In order to decrease the risk associated with information asymmetry and ameliorate the likelihood of success, VCs get actively involved in their ventures' activities (Sahlman, 1990).

VCs differ in strategies, goals, resources, geographic scope, organizational forms (Timmons and Bygrave, 1986) and in the industries and stages of investment they focus on (Sahlman, 1990). The three stages of development of a new venture represent the different types of investing. The first two, seed and startup investments, are referred to as early-stage investments. The third type, expansion, is also known as a later-stage investment (Jeng and Wells, 2000). In order to get a better understanding of the challenges associated with these different types of investing, the current key trends of the industry will be analyzed.

2.2.2. Trends

In 2018, over $254 billion of Venture Capital were invested in 15000+ transactions worldwide, representing the highest sum of the decade (Lavender et. al, 2018). The capital available for VCs has grown massively, however, the number of deals available has not increased at the same rate, resulting in increased competition. Throughout 2018, the number of deals declined (Lavender et. al, 2018) and seed-stage deal share continued to fall, as later-stage deals received more funding (MoneyTree Report, 2018). In 2019, VCs are expected to keep preferring investments in safe bets and late-stage ventures. This trend represents one of the key issues in the VC industry which could result in pipeline issues in the future (Lavender et. al, 2018). The trends mentioned emphasize the high relevance of the underlying research, especially for early-stage VCs. In the next section, the decision-making process used to derive investment decisions and its challenges will be investigated.

2.2.3. Decision-Making in the Venture Capital Industry

As the investment decision is part of the function that determines the performance of a VC, improving the investment decision can improve the firm's success (Zacharakis and Meyer, 1998).

Decision making in VCs takes place in the rapid environment of a new venture, characterized by intense time pressure (Zacharakis and Shepherd, 2001) and a high amount of information available (Zacharakis and Meyer, 1998). Although the information used by VCs is deeply quantified (Hisrich and Jankowicz, 1990), they combine this "hard information" (Huang, 2018) with own personal beliefs and subjective evaluations (Huang, 2018; Hisrich and Jankowicz, 1990).

VCs often examine the "chemistry" between themselves and the founder (Zacharakis and Meyer, 1998) and refer to their intuition when making a decision (Hisrich and Jankowicz, 1990). This referral to their "gut-feel", is a developed narrative that supports the investors in decision-making by seeing past the risk associated with a deal (Huang, 2018). This usage of subjective information adds complexity to the decision-making process and leads to biased decisions. VCs suffer from availability bias (Zacharakis and Meyer, 1998), similarity bias (Franke et al., 2006), overconfidence bias (Zacharakis and Shepherd, 2001) and information overload (Shepherd et al., 2003; Zacharakis and Meyer, 1998), often leading to the reliance on rules of thumb and mental shortcuts, after reaching a specific amount of experience (Shepherd et al., 2003).

Besides taking biased decisions, the allocation of time and resources represent another challenge. On average, it takes 97.1 days for new ventures to receive funding (Fried and Hisrich, 1994). Only 1% of all viewed deals make it to the portfolio, 10% are considered as "dead" after a significant amount of time and resources have already been invested in the evaluation (Petty and Gruber, 2011). In addition, 55% of the evaluations of business plans are conducted by only one person (Franke et al., 2006), often resulting in rejection of a venture before it can even be discussed in the weekly deal flow meeting (Shepherd et al., 2003).

Several studies about the criteria used in the decision-making process (MacMillan et al., 1985; MacMillan et al., 1987; Tyebjee and Bruno, 1984; Fried and Hisrich, 1994) emphasize the need to rethink decision-making in VCs. The literature assumes that VCs are able to introspect their own criteria. However, as they rely on post-hoc methodologies such as interviews and surveys, they are likely to suffer from recall and post-hoc rationalization bias (Zacharakis and Meyer, 1998). Most of the criteria identified in these post-hoc studies are actually used in the decision-making process, however, they miss important criteria (Petty and Gruber, 2011), suggesting that VCs have difficulties understanding their own decision process (Zacharakis and Meyer, 1998).

The process to derive decisions in VCs is complex. The steps of this process will be described in the following section.

2.2.4. Steps in the Decision-Making Process

VCs use a multistage decision-making process (Hall and Hofer, 1993), allowing them to reduce the risk of adverse selection (Fried and Hisrich, 1994). Although several authors developed a model for the decision-making process in VCs, there is no clear definition of the distinct steps in the process (Fried and Hisrich, 1994; Hall and Hofer, 1993; Silver, 1985; Tyebjee and Bruno, 1983). As Fried and Hisrich (1994) present the newest and most widely accepted model, it will be used in this research, complemented with additional information from further studies. As shown in Figure 2, the decision-making process developed by Fried and Hisrich (1994), consists of six steps: 1) Origination, 2) VC firm-specific screen, 3) Generic screen, 4) First-phase evaluation, 5) Second-phase evaluation and 6) Closing. In the next section, the main characteristics of the steps of the decision-making process will be identified.

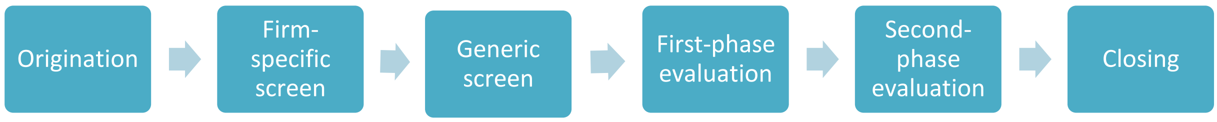

Figure 2: Overview of the Steps in the VC Decision-Making Process

Origination

VCs use three different sources to identify new potential deals (Fried and Hisrich, 1994; Tyebjee and Bruno, 1983). First, they rely on referrals. Referrers can be friends or family, or the management team of the VCs' portfolio firms (Fried and Hisrich, 1994) and provide the VCs with information that is not yet publicly available (Shane and Cable, 2002). Second, they receive potential deals 'cold', but these deals rarely receive funding (Fried and Hisrich, 1994). Third, a minority of VCs actively source deals. They scan the environment by attending relevant events and by using their network (Tyebjee and Bruno, 1983).

VC firm-specific screen

After originating a high amount of deals, the VCs reduce this number by applying firm-specific criteria (Fried and Hisrich, 1994). In a short period of time, deals that don't fit the firm's criteria for investment size, geographic location, industries, and technology or the stage of funding, are rejected (Fried and Hisrich, 1994; Tyebjee and Bruno, 1983).

Generic screen

VCs tend to limit their investments to areas they have experience in (Tyebjee and Bruno, 1983). In this stage of the decision-making process, they screen the business plan of the new venture using the relevant knowledge they already gained in the respective area (Fried and Hisrich, 1994).

First-phase evaluation

In the first step of the evaluation process, VCs evaluate the business plan by comparing it with the information provided by the new venture as well as outside resources (Fried and Hisrich, 1994). The market attractiveness, competitive advantage, environmental threat resistance, managerial capabilities, and the cash-out potential are analyzed by conducting several activities (Tyebjee and Bruno, 1983). First, the investors meet with the founder to increase their understanding of the business and the industry they plan to invest in. Second, they check references to obtain information about management capabilities. Third, existing and potential customers are contacted and technical studies of the product are conducted. Fourth, VCs and portfolio companies in related industries are consulted (Fried and Hisrich, 1994).

Second-phase evaluation

After evaluating the VC's interest in the first-phase evaluation, the second-phase examines the potential hurdles of a potential investment. VCs prefer to have a basic understanding of the structure of the deal before entering this stage (Fried and Hisrich, 1994).

Closing

In the last stage of the decision-making process, the structure of the VC investment agreement is negotiated (Fried and Hisrich, 1994; Tyebjee and Bruno, 1983). Although companies reaching this stage passed the evaluation, 20% don't receive funding after this stage (Fried and Hisrich, 1994).

The literature agrees that VCs have to improve their understanding of the decision-making process (Shepherd et al., 2003) and offers several solutions. VCs should get better insights into the process (Zacharakis and Meyer, 1998), recruit a heterogeneous staff that evaluates the business plans (Franke et al., 2006), implement counterfactual thinking, push themselves out of their comfort zone (Shepherd et al., 2003) and develop decision aids (Shepherd and Zacharakis, 1999; Zacharakis and Meyer, 1998). As the underlying research analyzes the opportunity of AI in the decision-making process, the following section will provide an overview of the technology.

2.3. Artificial Intelligence

2.3.1. Concept and History

Although the term Artificial Intelligence was introduced more than 60 years ago (Pan, 2016), a widely accepted definition has not been established in the literature. In 1956, John McCarthy, together with other scholars, defined the term (Russel and Norvig, 2010; Crevier, 1993) as "the ability of machines to understand, think, and learn in a similar way to human beings, indicating the possibility of using computers to simulate human intelligence" (Pan, 2016). More recently published literature expands this definition by the capability to learn from experience, to adapt to new data (Duan et al., 2019) and refers to algorithms as the core of Artificial Intelligence (Burgess, 2018).

Artificial Intelligence overcame several 'winters' over the last 60 years (Pan, 2016). Due to the advancements in Big Data, like cheap and improved storage and fast-speed data processing capabilities (Duan et al., 2019; Burgess, 2018), the high amount of mergers and acquisitions in this field and the increased demand outside of academic curiosity resulting from new goals of companies like intelligent cities or smart products that require AI, the adoption of AI is accelerated (Pan, 2016).

A high amount of companies is focusing on AI research. According to a survey of 3000 business executives by MIT Sloan Management Review and the BCG, 2017, 90% of the surveyed companies already developed AI strategies (Ransbotham et. al, 2017). Two surveys conducted by Deloitte, 2019, name AI as the top technology CIOs plan to invest in, emphasizing its fast acceleration (Briggs et. al, 2018). Along the main benefits of this new technology, namely the enhancement of current products and the optimization of internal operations, making better decisions is named third by a survey conducted by Deloitte, 2018. It is considered the biggest benefit by Burgess (2018), confirming the high relevance of this research.

2.3.2. AI Capabilities

In order to get a clear understanding of the capabilities of AI, its related technologies will be defined first. Figure 3 provides an overview of the main terminologies related to AI, the most relevant associated technologies for the underlying research will be presented in the following section.

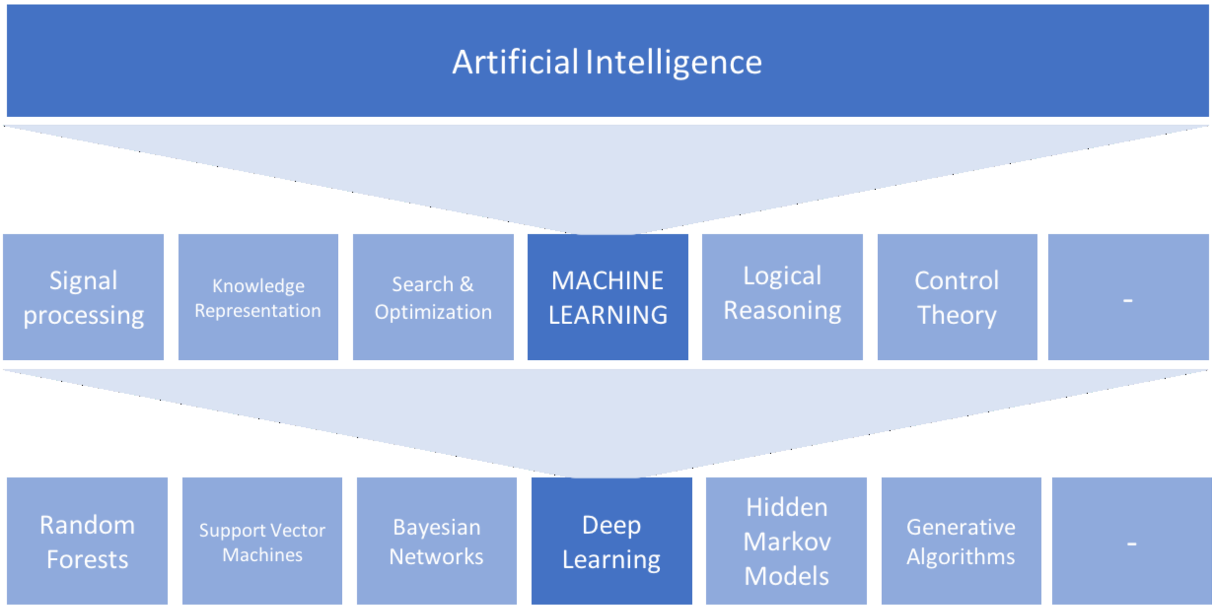

Figure 3: Overview of AI Technologies (adapted from BCG, 2018)

Machine learning (ML), is a sub-category of AI, that enables machines to learn while executing tasks. If a response y should be found to a specific input data x, this problem can be presented as the function y = f(x). The process of finding the best approximation to f is called ML (Ghatak, 2017). ML can be divided into three types of learning: 1) supervised learning, 2) unsupervised learning, and 3) reinforcement learning (Skansi, 2018; Marsland, 2011).

Supervised learning provides its algorithms with a training dataset, that contains the correct responses (labeled target data) (Skansi, 2018; Marsland, 2011). After the training phase, the algorithm is able to predict, which label to give to unlabeled data (Skansi, 2018). Supervised learning can be divided into two groups:

1. *Regression*: the algorithm receives input, and predicts the value of the output

2. *Classification*: the algorithm receives input and decides to which of *n* classes the input belongs to (Marsland, 2011).

Unsupervised learning is a learning approach without correct answers, meaning without labelled data. Instead, the algorithm tries to identify the underlying structure of data by inspection (Graves, 2008), and generates interesting “summaries”. An example of unsupervised learning is the division of a dataset into clusters of similar data points – this approach is called *clustering* (Ghatak, 2017).

In *Reinforcement learning*, the algorithm is only provided with positive or negative reward values for training (Graves, 2008). The algorithm obtains the information when a specific answer is wrong, however, it has to explore and try different possibilities by itself (Marsland, 2011).

Although the differentiation between the three types of learning is helpful for structuring ML, in current research they overlap. For example, semi-supervised learning uses unlabeled data to complement labeled data (Jordan and Mitchell, 2015).

Deep learning (DL) covers all three types of learning (Skansi, 2018). By exposing multilayered neural networks to big amounts of data, DL provides a larger viable space and thereby represents a scalable version of ML (Ghatak, 2017). Applications of DL are for example natural language translation or collaborative filtering (Jordan and Mitchell, 2015).

As the analysis part of the underlying research will often refer to the term **Natural Language Processing** (NLP), a short definition will be given in this chapter. NLP includes many different techniques for interpreting human language, ranging from ML to DL. Ideally, an NLP system would be able to analyze large amounts of text, understand them, and would be able to answer questions or discuss with human beings. Applications of NLP include contextual extractions or speech-to-text and text-to-speech conversions (Nugues, 2006).

Now that a basic understanding of AI has been given, the next section will address the current state of research on the usage of AI capabilities in the decision-making process of VCs.

2.3.3. AI in Decision-Making and the Venture Capital Industry

Despite the high interest in AI in decision making in VCs in online magazines and forums, it is not an established topic in academic literature. A high amount of companies keep information about the usage of AI in their processes proprietary, in order to preserve the competitive advantage that it bestows (Burgess, 2018).

Although AI in the financial industry is highly discussed in academic literature, and was one of the main areas of technology development in 2018 (Lavender et. al, 2018), only a limited amount of VCs announced publicly their usage of AI . The impact of AI on the decision-making process in VCs presents a gap in academic literature. However, several researchers have developed AI based methods for the evaluation of companies. Bhat and Zaelit (2011), applied random forests algorithms to predict the exits of private companies using data from several industry sectors. Beside ranking which features are most predictive for late stage investment decision making, they also incorporate the strength of the investors' network into their analysis. Dixon and Chong (2014), used a different approach to the evaluation of companies. They developed a four step predictive model to rank companies within one industry. After extracting and selecting features from the data which are indicative for investors, they trained SVM classifiers over combinations of feature-pairs. Using the results of these classifiers, a non-parametric Bayesian model gives each company a score.

Although these studies offer great insights on how to build a predictive model for the evaluation of companies, they analyze the usage of AI in the Private Equity / VC industry from a technical perspective. Therefore, the underlying research will fill this gap in academic research and investigate the potential of AI in the VC industry through a business lens.

Chapter 3: Methodology

3.1. Research Approach and Settings

Following the example of various researchers investigating decision-making in VCs (Petty and Gruber, 2011; Zacharakis and Shepherd, 2001; Hisrich and Jankowicz, 1990), the underlying study used an exploratory research design. It focuses on investigating the emerging opportunity by using AI in the decision-making process as well as the challenges that arise with it. Therefore, a qualitative method was the best strategy to answer the research questions. Qualitative research is most appropriate for obtaining an in-depth description of how something occurs within a specific matter (Denzin & Lincoln, 2008) and represents an optimal choice for a topic not yet discussed in academic literature.

3.1.1. Research Setting, Participants, and Data Sources

For the present study, a total of 12 interviews was conducted between March 2019 and May 2019. The sample was composed of VCs using AI or another data-driven approach to investing, companies offering solutions to improve the decision-making process in VCs, and AI Experts. An article published in Forbes, 2019, by Francesco Corea, as well as extensive online research were used to identify relevant participants. The potential candidates were contacted via email to request their participation in the underlying study. An overview of the participants can be found in Table 1.

Participant	Name	Company	Headquarter	Position
Participant 1	Thomas Gieselmann	e.ventures	San Francisco	Founder & CEO
Participant 2	Anton Ask Åström	EQT Ventures	Stockholm, London	Analyst
Participant 3	Andrey Shirben	Follow[the]Seed	Sydney	Partner
Participant 4	Carles Guillem	Nauta Capital	London	Software Engineer & Data Scientist
Participant 5	David Lambert	Right Side Capital Management	San Francisco	Founder & Managing Director
Participant 6	Amr Shady	Aingel.ai	San Jose	Co-founder and CEO
Participant 7	Dominik Vacikar	Crunchdex	Amsterdam	Founder & CEO
Participant 8	Chris Hjelm	Connetic Ventures	Covington	Principal
Participant 9	Ben Wilde	Georgian Partners	Toronto	Vice President Marketing
Participant 10	Mark Rowan	Swiss Re	Zurich	Vice President, Cognitive Data

				Scientist
Participant 11	Yannik Zuehlke	/	Munich	/
Participant 12	Francesco Corea	/	Barcelona	Tech investor & AI technologist

Table 1: Overview of Interview Participants

3.1.2. Data Collection

Primary Data collection

As a primary method of data collection, 12 semi-structured interviews were conducted to gather narrative data and encourage the participants to talk in depth about their experiences (Cook, 2008). The interviews lasted between 25 and 40 minutes, taking into account the limited availability of the participants (Rowley, 2012), and were held via the interviewee's preferred method to call. As proposed by Johnson and Rowlands (2012), the interview guide was divided into three parts. After a brief set of introductory questions that served as icebreakers and mainly collected information about the company of the participant, two transition questions about the current state of the industry in general followed. This part was pursued by the key questions, focusing entirely on gathering in-depth descriptions about the steps in the decision-making process, the challenges and their approach to solving them as well as potential implementation barriers. To encourage story-telling, grand tour questions such as "Could you walk me through" were posed (Spradley, 1979) and the participants were encouraged to share their personal opinions and experiences, in order to make the interview more interesting (Rowley, 2012). Throughout the period of the data collection, the interview guide was adapted to include emerging topics (Spradley, 1979) and one of the questions was eliminated, as it hindered the natural flow of the interview.

Secondary data

37 potential interview partners were identified. Out of those, 10 (37%) were willing to participate in the underlying research. In order to be able to include data about other VCs using AI, the data obtained through the conducted interviews was complemented by secondary data in form of articles published in online magazines. Furthermore, the findings obtained in the interviews were constantly combined with academic literature to get a clear picture of the topic. Figure 4 gives an overview of the methodology of the underlying research.

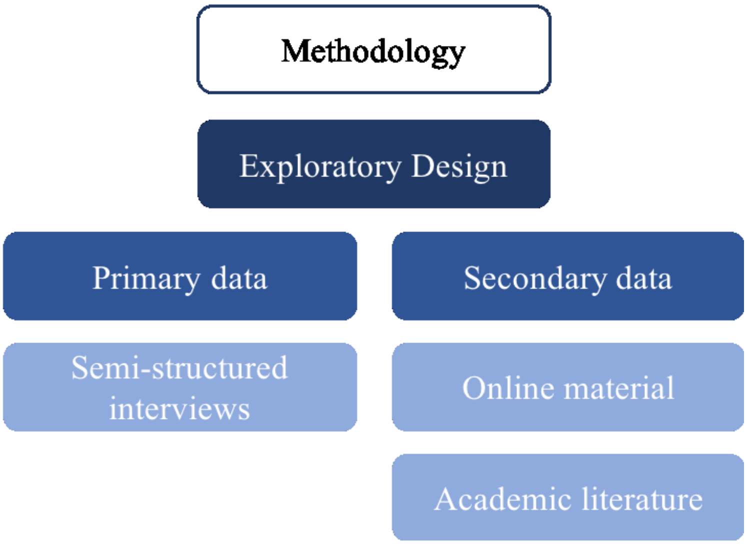

Figure 4: Methodology Overview

3.1.3. Data Analysis

The interview data was analyzed following recommended practices for thematic analysis (Silverman, 2011). After reading the transcripts to get familiar with the dataset, first codes on key, essential, or repeated information were taken. These codes were applied to the whole dataset and collated into themes. A document was used (see appendix 3) to create a clear overview of the interview data. In the last step, the relationships and associations between the themes were considered.

In this research, the interview data is looked at through a business lens, in order to identify differences and similarities between the interviewees' statements and perceptions. The emerging themes were constantly combined with secondary data to get a clear picture of the topic. By carefully reading through the interview transcripts, eight initial categories were created to structure the data:

1. Industry challenges
2. Internal challenges
3. Decision-making challenges
4. Usage of data in the process
5. Improvements
6. Implementation challenges
7. Reasons for reluctance
8. The Future of VC

These eight initial groups were combined and the main topics of the analysis chapter created (Table 2). Industry challenges, internal challenges, as well as decision-making challenges are discussed in chapter 4.1. and support RQ2, namely the challenges in the decision-making process of VCs. Usage of data in the process and improvements are presented in chapter 4.2. and provide an answer to RQ4, how AI can help to solve the challenges in the process. Implementation challenges, reasons for reluctance, and the future of VC are combined in chapter 4.3. and provide insights on the main implementation challenges and give a suggestion on how to overcome them, thereby addressing RQ5.

<table>
<tr><th>Initial topics</th><th>Chapter evolved</th><th>RQ adressed</th></tr>
<tr><td>Industry challenges</td><td rowspan="3">4.1. Challenges in the decision-making process</td><td rowspan="3">RQ2</td></tr>
<tr><td>Internal challenges</td></tr>
<tr><td>Decision-making challenges</td></tr>
<tr><td>Usage of data in the process</td><td rowspan="2">4.2. The potential of AI in the decision-making process of VCs</td><td rowspan="2">RQ4</td></tr>
<tr><td>Improvements</td></tr>
<tr><td>Implementation challenges</td><td rowspan="3">4.3. Implementation challenges and plan</td><td rowspan="3">RQ5</td></tr>
<tr><td>Reasons for reluctance</td></tr>
<tr><td>The Future of VC</td></tr>
</table>

Table 2: Overview of Coding Grouping

Chapter 4: Results and Discussion

This chapter presents and analyzes the empirical data from a business perspective. First, the main challenges in the industry and the decision-making process are identified. Second, an overview of the main players in the market using AI in their decision-making process is given. Third, the information obtained in the interviews with VCs using AI is analyzed in terms of commonalities. Fourth, by mainly relying on information obtained by AI experts, secondary data as well as information from the interviews with VCs using AI, the potential use cases of AI in the process are discussed. Fifth, implementation challenges are identified and an implementation plan is presented to help VCs implement AI in their processes.

4.1. Challenges in the Decision-Making Process

In order to understand the main reasons behind the adoption of a data-driven approach to investing and the problems to be solved, the interviewees were asked about the main industry and decision-making challenges they are facing.

According to the interviewees, the VC market is currently overcapitalized. More players in the market, resulting for example from the high growth of corporate VC arms, lead to an overload of money chasing too few deals. This overload leads to high valuations of startups and increased competition among the VCs. In order to get into promising deals, VCs have to have a special value proposition, pay up (Interview 2) or have a well-known brand in the market (Interview 7). Interviewee 7 stated that some funds raising 80 - 150 million struggle eight to nine months to close one deal. These external challenges directly impact the decision-making process in VCs. Due to the highly competitive environment, VCs are facing an increased time pressure to find interesting opportunities to invest in, before anyone else does.

Beside the externally created challenges, VCs are confronted with general challenges that arise from the nature of the decision-making process. First, VCs operate under high uncertainty. Under imperfect information, and high time pressure to find the available information (Interview 1), investors have to select investment opportunities that will convert into big companies (Interview 4). However, there is no standardized way to value startup companies (Interview 8). Although an investment opportunity looks promising in the beginning, investors are faced with high uncertainty about the outcome of the investment (Interview 4). Second, VCs are network driven, representing not only a challenge for the investors but also for the founders looking for funding. In order to „get into the wheel of a VC, you need a lot of connections. If you don't have connections, it's hard to build a business“ (Interview 2). This tendency leads to the third challenge in investor's decision-making: VCs suffer from similarity, location and availability bias. Most of the funds tend to „judge the envelope, instead of judging the inside“, making it easier for white men living in hotspots that studied at a Top Tier university to raise money, than for e.g. women or minorities (Interview 3). Furthermore, investors strongly believe in serial entrepreneurs – if someone was a successful founder before, he will do it again. However, as currently there is a high amount of male CEOs of European descent, this way of thinking will favor particular demographics and create a feedback loop that states that European males tend to be better founders than others (Interview 9).

The challenges identified in the interviews are similar to the ones discussed in the literature review. In line with the findings of Zacharakis and Shepherd (2001), the interviewees stated that they have to take decisions under time pressure. They need to act fast and find interesting investment opportunities before anyone else does. This environment, namely a high-velocity environment, is combined with high uncertainty (George, 1980), in the underlying study related to the outcome of the investments. Furthermore, investors suffer from biases like similarity bias and availability bias, congruent with the findings of Franke et. al (2006), and Zacharakis and Meyer (1998). These challenges emphasize the need to optimize the decision-making process of VCs. In the following section, the potential of AI to solve the just named challenges will be investigated.

4.2. The Potential of AI in the Decision-Making Process of VCs

This chapter addresses RQ4, namely how AI can be applied to solve the challenges in the decision-making process and improve performance. Therefore, an overview of the VCs currently using AI is given. The main use cases currently applied by VCs are presented and complemented with additional use cases. Lastly, the improvements obtained through the usage of AI in the process are analyzed and evaluated in regard to their ability to solve the challenges.

4.2.1. Status Quo: Company Examples using AI

In order to obtain a clear understanding of the VCs currently using AI, the following section gives an overview of the interviewees that are using AI in their investment approach, as well as other top players that are known for using AI, but that were not available for an interview. The information about the founding date, headquarters, as well as capital under management, was obtained from Crunchbase.

EQT Ventures

EQT Ventures, founded in 2015 and with 566 million EUR under management, operates as the venture arm of the private equity firm EQT. They are headquartered in Stockholm and usually participate in late Series A until Series C rounds for European companies. EQT Ventures built their own proprietary platform called ‚Motherbrain‘. Motherbrain uses Convolutional Neural Networks (CNNs) to analyze the time series of the performance of companies and based on those defines if a company is attractive. Motherbrain is an interface that is used throughout the whole decision-making process: first for prioritizing which companies to look at first, but also e.g. for investor analysis and competitive mapping back at the term-sheet stage.

Nauta Capital

Nauta Capital, founded in 2014, has 300 million EUR under management. They typically invest in Series A. Nauta Capital hired a software engineer and data scientist in 2017. Their engine is divided into two parts. The first part collects information from several data sources, the second part are the ML models they run over the data platform. When they have a set of companies, they start analyzing various features like the funding round, characteristics of the founder, the round size and create models that give them a scoring or success rate for each company (for each characteristic). The engine is a web interface that can be used by all employees to get information about e.g. investors and competitors of a company.

Georgian Partners

Georgian Partners, founded in 2008, is a growth fund and has raised $1.1 billion across four funds. They use AI / ML early on, for identifying companies and – although not related to decision-making – for reaching out to firms. They look at a universe of about 30k companies, coming from various data inputs and combined with their own operational environment (e.g. feedback from Salesforce). For downselecting the potential companies, Georgian Partners has its own R&D team. Once they identified interesting companies, they get handed over to the sales team and operate like a sales force.

e.ventures

e.ventures, founded in 1998, has more than $1 billion under management and is based in San Francisco. They use AI for a unique way of deal sourcing, using large amounts of data on user streams, startup growth rates, and viral attention on the Internet. On the one side, they use ML to source deals, on the other side they automate the work normally an analyst does and evaluate companies by building bottom-up financial models.

Connetic.Ventures

Connetic.Ventures was founded in 2015 and has $25 million under management. They invest in companies in the US that have a less than $10 million pre-money valuation. Their decision-making process is completely automated up to due diligence. Companies that are interested in obtaining funding apply to Wendal, their own data platform, and have to complete six different models. Each model is pass / fail – only companies that pass all six stages are moved into due diligence. In addition, they use algorithms for deal sourcing, and are „pretty good at understanding when a company is going to be raising money that fits our criteria".

Hone Capital

Hone Capital was founded in 2015 and invests in early-stage companies in Silicon Valley and selectively in growth stage investments. They have $50 million under management. By partnering with AngelList to build their proprietary ML platform, they doubled their weekly deal flow. Their ML model was created from a database of more than 30,000 deals and analyzed the characteristics which are significant for receiving Series-A rounds. Based on this analysis, they identified 20 characteristics that are predictive for success. Using this data, their model generates an investment recommendation for each deal they look into. Veronica Wu, Managing Partner at Hone Capital, states, that the portfolio best performs – 3.5 times above the industry average – by combining it with recommendations from humans (McKinsey, 2017).

InReach Ventures

InReach Ventures was founded in 2015. They invest in early-stage startups across Europe and have raised $53 million. They combine data and ML to identify interesting investment opportunities based on e.g. the additions to their teams, their products, and their website traffic. According to Mr. Bonanzinga, co-founder at InReach Ventures, building the platform cost them 2 years and an investment of $5 million and helped them to become 10 times more productive as well as discover companies that they would have otherwise not found (Palmer, 2017).

Signalfire

Signalfire was founded in 2013, invest in seed stage and breakout companies, and have raised $154.6 million across two funds. They built their own „Mini-Google“ that tracks 8 million startups around the world. Interesting companies are flagged up on a dashboard, therefore, the platform helps to identify companies that they would have otherwise not found (Palmer, 2017).

Besides the five VCs mentioned, there are several other VCs that are working on a data-driven approach to investing. Fly Ventures, Correlation Ventures, Kleiner Perkins, Social Capital, Google Ventures, are other VCs that use data in their decision-making.

4.2.2. Degree of Automation

As discussed in Chapter 2, the decision-making process can be divided into six steps: 1) Sourcing, 2) Firm-specific screen, 3) Generic screen, 4) 1st-phase evaluation, 5) 2nd-phase evaluation and 6) Closing (Fried and Hisrich, 1994). Figure 5 gives an overview of the degree of automation of the VCs using AI that were interviewed. Each VC was rated for each step of the decision-making process on a scale from 1-5, based on the perceived degree of automation. Although the VCs automate the steps of the decision-making process to a different level, one commonality can be identified. All of the interviewed VCs using AI built their own database and automated part of their 1) Sourcing, 2) Firm-specific screen, and 3) Generic screen. However, the investment decision is still made by humans.

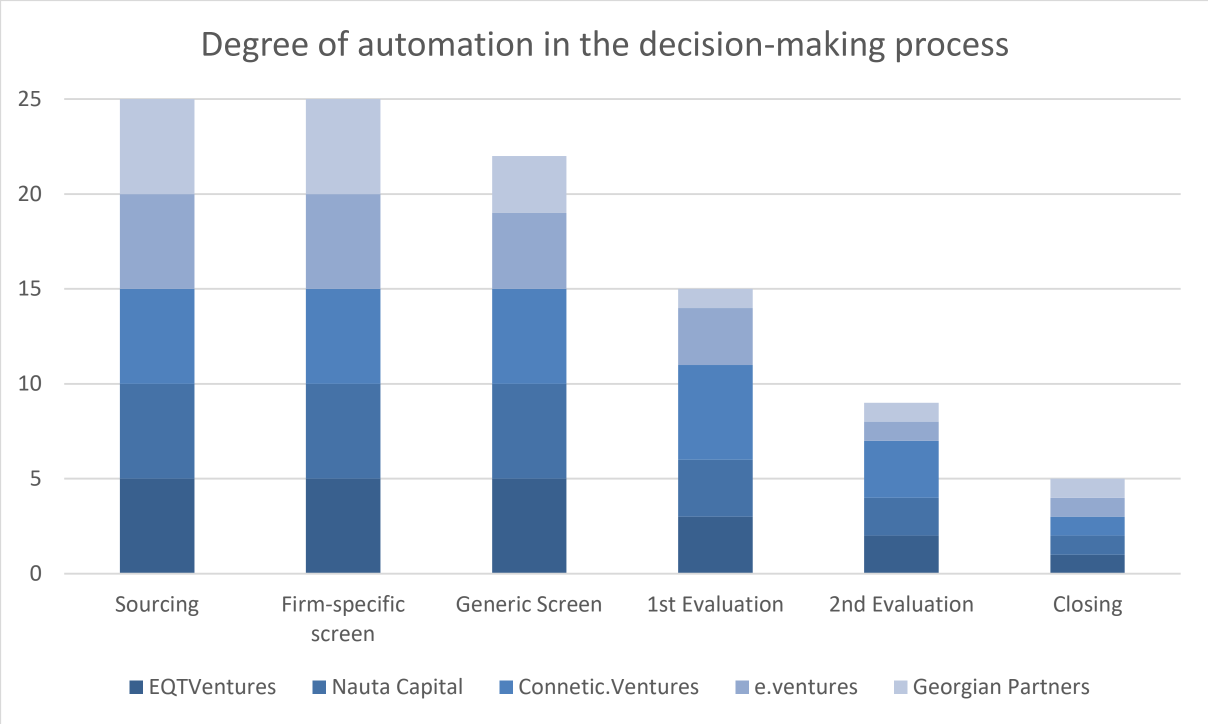

Figure 5: Degree of Automation in the Decision-Making Process of VCs

As shown in Figure 5, the degree of automation in the decision-making process peaks at the beginning of the process, and continuously decreases until the deal is closed. Even though Interviewee 2 and Interviewee 4 use their database as an interface throughout the whole process e.g. for investor or competitor analysis, humans are involved in these steps. As the automation of deal sourcing and deal screening is the main field of application of AI in the VC industry right now, Figure 6 was developed to give an overview of the steps that are required to build an ML model automating these steps.

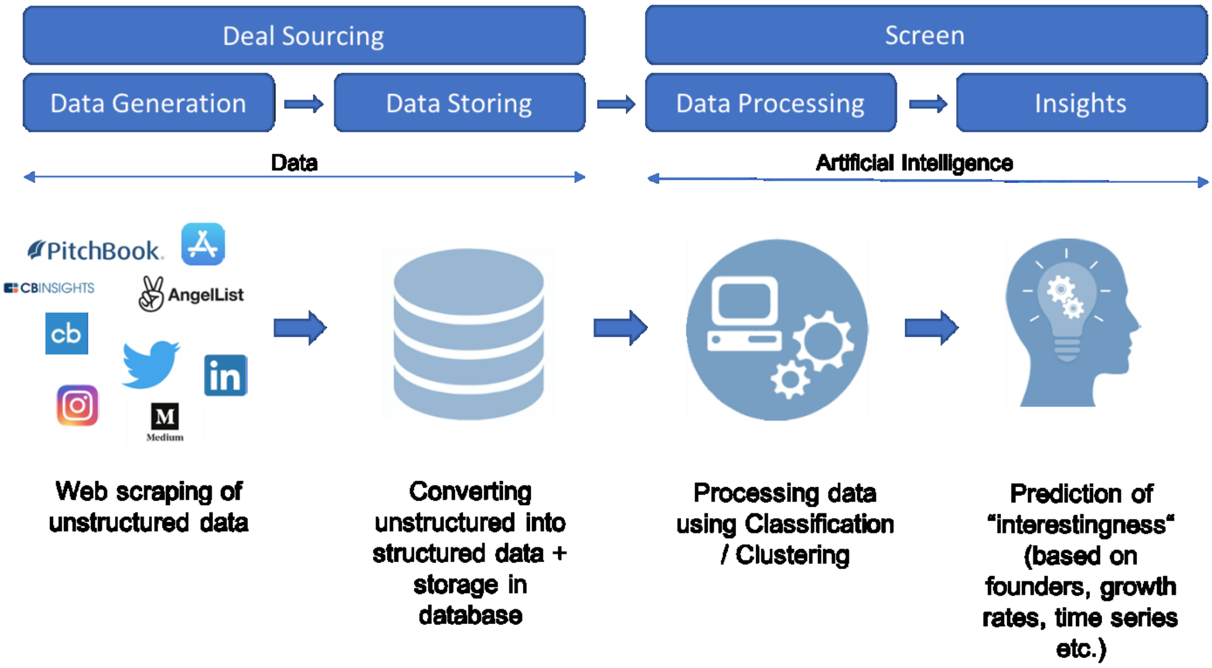

Figure 6: Process Overview on how to build a ML Model

The first step of building an ML model is to obtain relevant data. In order to source and screen deals automatically, a set of crawlers is applied to collect information from multiple sources. Among the sources mentioned in the interviews were VC databases like Pitchbook, CBInsights, and AngelList, Social Media platforms like LinkedIn, Instagram or Twitter, as well as online news platforms like Medium. Then, the collected data is converted from unstructured data to structured data and stored in the database. In order to obtain more information, this database can be connected with the operational environment of a company e.g. Salesforce (Interview 9). This database is then used to build algorithms on.

After collecting and storing the data, it has to be processed to build a high-quality training set. By using supervised learning, labels can be created according to the VC's investment thesis. These classifiers can be used to teach the ML model to e.g. classify companies into specific categories (Biotech, 3D Printing, IoT) or divide them according to their investment stage or geographic location.

In order to be able to predict a startup's interestingness or likelihood to succeed, features have to be selected that are indicative for the company's success. ML can be used to look at past success stories and analyze the history of these companies. After having built the training set and having trained the algorithm, the algorithm should be tested on a validation set to evaluate how well it has learned (Marsland, 2011).

As the VCs usually use the same data sources to build their databases, this step doesn't contribute to their competitive advantage. Although VCs can incorporate untraditional data sets, like university projects, they are going to source the same companies in the end. However, they can obtain an advantage by assessing these companies in a more efficient and effective way, e.g. by creating scoring or assessment systems that give information about the likelihood of success of a company (Interview 12). The approaches of the interviewees differ in how they assess the potential success of a company, namely which features they select for building their classifiers. According to Interview 7, 8 and 9, the success of a company cannot be predicted. The ‚interestingness' of a startup can be predicted based on the analysis of several features of the company (e.g. founders, markets, funding rounds) that correlate positively with success (Interview 4), time series of performance data (Interview 2), growth rates (Interview 7), the founding teams (Interview 6), or the employees they hire, products they develop, and the traffic they get on their website (Palmer, 2017). Hone Capital states that they analyze companies based on whether they obtained Series A - funding and identified 20 characteristics of seed deals that are most predictive for future success (McKinsey, 2017). Based on this data, the model generates an investment recommendation – or a score representing the interestingness of a company.

Besides the use case presented in this chapter, there are several other use cases of AI that could support the decision-making process of VCs. These use cases are presented in the following section.

4.2.3. Further Use Cases for AI

A selection of use cases of AI in the decision-making process of VCs that were identified through interviews with AI experts as well as secondary data are presented in the following section. Although the use cases that are presented could be beneficial for the decision-making process of VCs, it is important to mention that their benefits haven't been validated yet. Table 3 provides an overview of the application of the use cases in the several steps of the decision-making process. In order to provide a more complete overview of the potential of AI in the process, the company examples (using AI) were added to the table.

		Deal Sourcing	1st screen	2nd screen	1st evaluation	2nd evaluation	Closing
Use Cases	Network Analysis	x	x	x	x	x	
	Market Analysis	x	x		x		
	Competitor Analysis				x		
	Matching					x	x
	Pitch Deck Analysis		x	x	x		
	Team Analysis				x		
	Pricing					x	x
	Conversation Analysis				x	x	
	Reserve Planner		x			x	x
Company Cases	EQT Ventures	x	x	x	x	x	
	Nauta Capital	x	x	x	x	x	
	Georgian Partners	x	x	x			
	e.ventures	x	x	x	x	x	
	Connetic.Ventures	x	x	x	x	x	

Table 3: Overview Use and Company Cases divided by Decision-Making Steps

Network Analysis:

According to interviewee 11, AI is not enough to draw conclusions about the interestingness of startups, domain expertise is highly relevant as well. In order to build a network analysis tool, a similar approach as described in chapter 4.2.2. has to be followed. Crawlers automatically collect a high amount of news, university information or patents which are then stored in a database and analyzed by applying Natural Language Processing (NLP) and semantic analysis. Afterwards, the relevance and weight of the information obtained is classified and combined with a specific startup (Interview 11), and the strength of connections in a specific network is analyzed (Interview 10). These steps result in a network in which several types of objects are associated with each other. An example on how to use this network is to analyze the quality of a startup based on its investor. The network could provide information about the type of investors that invested in a startup. If a deep tech startup has five investors, and four of them invested mainly in e-commerce before, one can conclude that the investors can not provide a network in this area (Interview 11). This tool could help VCs to analyze startups in a more complex way. Instead of relying only on static data, this approach takes into account the whole ecosystem of a startup (Interview 11, Interview 12).

Market Analysis

AI can support market analysis in two ways. First, ML and NLP can be used to analyze consumer behavior and market trends by performing sentiment analysis on social media, public posts, and newspapers (Interview 10). Second, AI can spot general trends and identify market gaps by analyzing the abstract from academic articles by using NLP techniques to extract specific keywords and cluster them into groups. This analysis offers a basic perception of where the research is going, which is usually an indicator of the development of market trends. By obtaining an overview of a specific research field, missing areas can be identified. Missing areas can be an indicator of future growth of startups in this space. Therefore this tool could give VCs an advance in preparing their investment thesis (Interview 12).

Competitor Analysis

By combining descriptive text and data, similarity metrics can be established. Based on the content of the text, clusters of startups that are dealing in certain industries can be built (Interview 10). Guo et. al (2017) developed a fully automated big data competitor analysis system using ML algorithms and NLP. Their system divides direct competitors from indirect ones, identifies top performers within an industry, assesses competitive market structures, and predicts future moves of competitors. Such a system would be highly beneficial for VCs to evaluate and keep track of the competitors of a specific investment opportunity.

Matching

Some VCs already use AI to match their deals with talent or co-investors. Once a startup has found an investor, other VCs that can complement the round have to be found. Usually, VCs refer to a list of investors they already know and have worked with before. However, as there could be a better partner for a specific deal, this way of finding co-investors is not efficient. Furthermore, VCs like EQT Ventures or Signalfire offer post-investment support to their startups by matching them with talent (Interview 12).

Pitch Deck Analysis

The potential success of a startup can be predicted based on its pitch deck by applying long short-term memory (LSTM) networks, which are variants of artificial Recurrent Neural Networks (RNNs) that are used in DL. Deep neural networks can be used for text understanding and building classifiers based on the features of success. After processing the document and training the models, features can be identified that correlate most with success (Interview 10). Furthermore, this tool could give VCs the following insights:

1) As structures of pitch decks are usually common, it could give an indication about how much it aligns with industry standards.
2) Slides with too many words could be an indicator that the startup is not able to explain its problem and solution in a concise way.
3) A limited amount of competitors could show that the founders haven't done excessive research on their market. (Interview 12)

Team analysis

Videos or transcripts combined with NLP could be used to analyze meetings with founders or pitches. This tool could help to analyze if specific words were used that are inflated, whether questions were answered in a precise way or if the founders mumbled (Interview 12). Furthermore, it could give information about who was less or more engaged in the conversation (Interview 10).

Pricing

VCs struggle to give meaningful values or prices to startups, especially at the early stage. In the past, instruments like convertibles were used to avoid giving valuations without having access to the required information and postpone this decision. In order to support this step in the decision-making process, ML could be used to extract patterns based on past valuations, and offer a solution to find prices in a more consistent way (Interview 12).

Conversation Analysis

Investment decisions in VCs involve meetings with multiple parties. In addition, it is common in VCs to have a weekly deal flow meeting. However, recording and tracking all the information discussed in these meetings can be difficult. By installing an NLP engine, or virtual facilitator in meeting rooms, discussions can be automatically analyzed. By developing a set of information extraction algorithms and labeling decision elements from a dataset with alternatives and criteria, a training set can be developed to train supervised classifiers to extract decision elements. Furthermore, sentiment analysis can be applied to identify the sentiments toward the elements (IBM Research, 2018). The implementation of such a technology would not only provide investors with a clear overview of the discussed investment options but also identify topics that require additional research. In addition, startups that are rejected for funding could be provided with a clear overview of the reasons for rejection that have been raised during the discussion.

Reserve planner

In order to support their portfolio companies, VCs have to carefully plan their available resources for follow-on investments. By using a supervised learning approach, VCs can analyze past reserves data and predict when these investments will occur. This information can help them to decide how much money they have to save for these follow-on rounds (Interview 4).

As stated before, the majority of the use cases presented are not validated. As VCs are rather restrictive about the information they publish about their usage of AI, the information presented in this chapter is mainly based on what was heard or stated by the interviewees. The overview of the use cases provided in Table 3 indicates that AI capabilities can be applied in every step of the decision-making process. Depending on the goal VCs want to achieve and the data available, several AI applications can be developed (Interview 10, Interview 12). However, the data obtained through the interviews indicate that AI offers most value to early-stage investors. Investors at later stages usually invest in companies that provide a higher amount of information that they can use for evaluating the company (Interview 12). Furthermore, according to interviewee 9, compared to early-stage funds that have to look at a high amount of deals, funds at a later stage have more time for tasks like getting to know the team. The later the funding stage, meaning the more data available about an investment opportunity, the less the value added by applying the use cases presented in the decision-making process.

Although AI can be beneficial in every step of the decision-making process, there are other data-driven, non-AI solutions that can be applied to the process. Follow[the]Seed has developed a Software Development Kit (SDK) that companies that want to apply for funding have to download from their website and plug into their product. After three weeks, they receive a RavingFans score that decides if they contact them (Interview 3). Right Side Capital Management uses a quantitative scorecard system and assesses different criteria, depending on the business model of a company, by gathering a large number of quantitative data points about a company, and then come to a quick decision (Interview 5).

In the following section, the main improvements obtained through the usage of a more data-driven approach to investing will be examined.

4.2.4. Main Improvements by the Usage of a Data-Driven Approach to Investing

In order to assess the value of AI in the decision-making process of VCs and answer RQ 4, namely, how AI can solve the above-named challenges of the decision-making process and improve the outcome, an analytical hierarchy process (AHP) (Saaty, 1990) was followed. The frameworks established by Philips-Wren et. al (2009), and Forgionne (1999), were reduced and adapted to reflect criteria that measure the value of AI in decision-making based on the research presented (Figure 7).

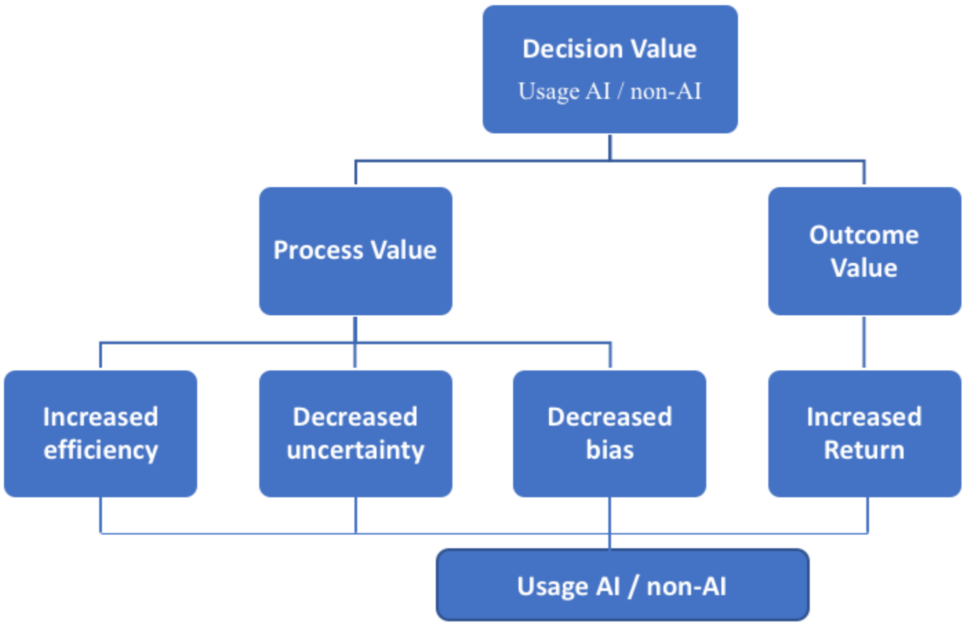

Figure 7: Overview of the Evaluation Criteria Usage AI vs. Non-Usage AI

The decision value represents the top of the hierarchy and is determined by the process and the outcome of the decision. The outcome describes the ability of the system to achieve the decision objective. In the context of the underlying research, the decision objective can be defined as an increased return of the portfolio of the VCs. Although the outcome of the decision-making process may seem most important for VCs, enhanced outcomes are the result of an improved process. The literature suggests that improvements in the process should be measured by the enhanced ability to perform the phases of the decision-making process, increased productivity and increased efficiency (Philips-Wren et. al, 2009; Forgionne, 1999). However, due to the objective of the underlying research, these measurements are adapted and extended to reflect the potential of the system to solve the challenges of the decision-making process, as discussed in chapter 4.1.. Therefore, the value of the process is evaluated based on its potential to increase efficiency and productivity, to decrease bias as well as lower uncertainty.

Having established the evaluation criteria, the performance of the alternatives – usage of AI and non-usage of AI in the decision-making process – is compared based on the information obtained in the interviews as well as additional secondary data. A detailed overview of the evaluation can be found in Appendix 4. As soon as more than 20% of the analyzed VCs stated that one of the criteria improved by using data, the weight associated with the alternative was increased by 0.1.

The usage of a data-driven approach to investing increases productivity as well as efficiency in the process. VCs using data show higher productivity by finding a greater amount of alternatives, that would not have been found otherwise. According to Interviewee 8, their deal flow increased by factor 12 by using data, Interviewee 2 states to screen 5k-6k companies per year. By predicting the ‚interestingness‘ of a company, promising investment opportunities can be prioritized. Due to the high amount of information in the database, VCs can get a picture of the company more quickly, save time by not having to search for information manually, and therefore faster screen companies. Efficiency is increased by identifying interesting opportunities before anyone else does (Interview 2) and excluding uninteresting ones (Interview 8). Quantitative measurements of the improvement have been given by Interviewee 8, stating to automatically pass 93% of startups and by Interviewee 3, describing the improvement in efficiency by a time saving of 99%, that would have otherwise been spent „by looking into deals we shouldn't even look at“. Hone Capital states that they doubled their deal flow (McKinsey, 2017), and InReach Ventures claims to became ten times more productive (Palmer, 2017). The usage of data clearly improves the process in terms of efficiency and productivity, therefore the weights associated with usage AI / non-usage AI are 1.00 / 0.00.

As presented in the challenges of the decision-making process in VCs as well as in the literature review, investors suffer from biases. Using data in the process leads to a more objective evaluation of companies (Interview 4) and democratizes the access to capital by identifying investment opportunities in territories, verticals, and geographies, the investors wouldn't have looked at otherwise (Interview 7). Although the majority of interviewees stated to meet the team before making an investment decision, Interviewee 8 implemented an online personality test to completely remove the human bias from the equation. Their portfolio consists of 42% of investments in women or minority founders, compared to the US average of 6%. Interviewee 4 states to analyze companies in a more objective way, Interviewee 7 claims that data democratizes access to capital, and Signalfire stated in an interview with the Financial Times (2017), that passed on some well-connected founders and went with several first-time founders. The weights associated with usage AI / non-usage AI are 0.6 / 0.4.

Although uncertainty, more specifically imperfect information, and the lack of knowledge about the outcome of an investment opportunity, was mentioned as one of the challenges in the decision-making process, none of the interviewees directly pointed out the decrease of uncertainty as one of the improvements of the decision-making process. However, it was remarked that by combining several data sources, the investors can obtain a more complete database (Interview 2), and conduct analysis, like competitor and investor analysis. In addition, by using AI several characteristics can be rated with a score (Interview 4) and Interviewee 1 agreed that his company now takes decisions with greater confidence. Therefore, the weights associated with usage AI / non-usage AI are 0.6 / 0.4.

As the majority of the interviewees, as well as other VCs like Signalfire and InReach Ventures (Palmer, 2017), implemented their data-driven approach only in the last years, there is not enough data to analyze the impact on the return of the portfolio. According to Interviewee 4, it takes 5-6 years to obtain results. However, Interviewee 2 stated that they sourced four investment opportunities purely through their platform. Although these companies were more scrutinized than others, they are currently among the top performing companies in their portfolio. Hone Capital claimed that by combining the ML model and human recommendations, follow-on rounds of their deals increase 3.5 times above the industry average (McKinsey, 2017). As the data about the impact on returns is limited and currently only information about the performance of the portfolio companies, however, not about their final outcome can be made, the weights associated with usage AI / non-usage AI are 0.5 / 0.5.

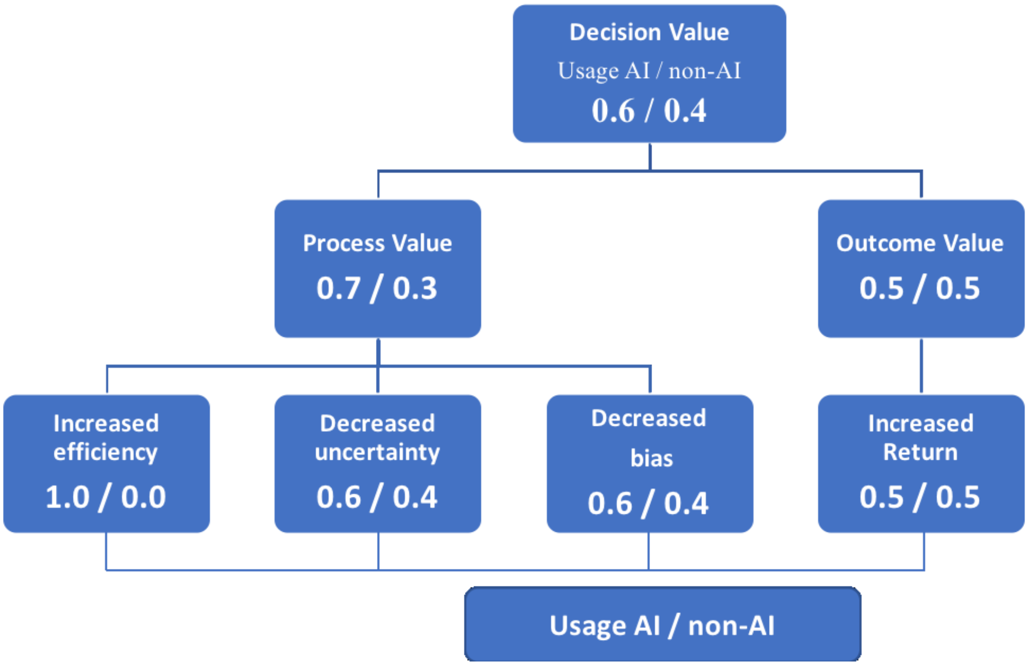

Figure 8: Evaluation of Usage AI vs. Non-Usage AI

A summary of the evaluation of usage AI vs. non-usage AI can be seen in Figure 8. The overall decision value of VCs increases by using a data-driven approach to investing (0.60 vs. 0.40), indicating that the use of data improves decision-making. The usage of data primarily improves the decision-making process (0.7 vs. 0.3), more specifically the efficiency and productivity in the process (1.00 vs. 0.00). Thereby, data supports the VCs mainly in facing the challenge to act fast and find deals before anyone else does, representing the main challenge arising from the external environment of the VCs. However, the usage of data also slightly decreases the bias as well as uncertainty in decision-making (0.6 vs. 0.4). Nevertheless, the data obtained in the underlying research is not sufficient to provide insights about the impact of data on organizational performance (both 0.5 vs. 0.5). In order to be able to measure the latter, the return of the portfolios has to be compared in 5-6 years, when the data in the decision-making process is more established.

4.3. Implementation Challenges & Plan

According to the interviewees, the implementation of AI in the decision-making process faces several challenges. These challenges, as well as suggestions on what steps to take when implementing AI, are presented in the following section.

4.3.1. Implementation Challenges

As the data collected regarding the implementation challenges and the reasons for the reluctance of some VCs to adopt a data-driven approach to investing are related, the insights obtained are summarized in this chapter. VCs are faced with three main challenges when implementing AI into their decision-making process: 1) technical, specifically data availability challenges, 2) financial challenges, and 3) organizational culture challenges.

The well-established literature about data and machine learning characterizes data based on several dimensions. These dimensions include the variety, velocity, volume, veracity (L'heureux et. al, 2017), complexity, and value of data (Katal et. al, 2013). According to the results obtained in the interviews as well as secondary data, the velocity of data, more specifically the availability of data, represents the main challenge in the development of ML models for the decision-making process in VCs. Due to the time frame in VCs, data, especially on early-stage investments, is scarce (Interview 1, Interview 9). VCs make a limited number of decisions per year, leading to the generation of a low amount of data points. However, to apply supervised ML algorithms, realistic training data (Interview 1), meaning data that shows signals and can be labeled (Interview 9), is essential. The feedback cycle in VC takes several years (Interview 1). In order to obtain realistic data, Interviewees mentioned VCs have to commit to almost a decade-long project (Interview 1, Interview 9, Signalfire in Financial Times, 2017).

The need for high-quality data to train the algorithms leads to financial challenges. As data sources like Pitchbook or CBInsights cost money, VCs are facing financial struggles to build their tech stack (Interview 8). Acquiring these data sources is expensive especially for smaller funds, in order to build the platform and keep it running a big budget is required (Interview 9). In an interview with the Financial Times, 2017, Signalfire stated to spend at least $10 million per year on maintaining the platform, InReach Ventures planned – at the time of the interview – to spend at least $1 million.

Even if VCs overcome the technical and financial challenges associated with the usage of AI in their processes, the organizational culture remains a challenge to be solved. Especially if VCs are successful by applying their conventional methods (Interview 9), "it will take a lot of guts to say, now we're gonna change the way we are working" (Interview 2). Furthermore, investment professionals have to be convinced to approach investing in a different way. In order to implement AI, organizational behaviors have to be changed slowly (Interview 1). However, the more often investment professionals are outperformed by the algorithm, the more the trust in the algorithm increases (Interview 2).

As in all industries, VCs differ in their willingness and speed to adopt a data-driven approach to investing (Interview 4). By analyzing the background of the VCs that implemented such an approach, several commonalities can be identified. The majority of the interviewed VCs as well as other VCs using a data-driven approach, have a combination of, or at least one of the following characteristics: 1) technical background, 2) implementation of data right at the beginning of the fund or several years ago, or 3) no previous experience in the VC industry. According to interviewee 8 who states that his team is formed of former traders, financial analysts, or analytical professionals, “this just makes sense”. Interviewee 9 explains that their company is founded by people with a software-driven mindset. Interviewee 1, 2, 4, 8, 9 as well as Signalfire, InReach Ventures, and Hone Capital used data either from the beginning of their fund or implemented a data-driven approach several years ago. Interviewee 8 and 9 have no previous experience in the VC industry. According to Interviewee 8, investors that have worked in VC several years pride themselves with making decisions and picking unicorns. He believes, if his team has worked in VC before for five to ten years, adapting to a data-driven approach to investing would now be a big issue.

All in all, to be able to successfully implement AI in the decision-making process, it has to be in the core DNA of the fund (Interview 7). Several factors have to be considered, therefore, the next chapter suggests an implementation plan for VCs planning to use a more data-driven approach to investing.

4.3.2. Implementation Plan

The number of VCs building their own data-driven approach is increasing (Interview 7). Due to the high amount of competition in the industry, VCs “will not be able to rely on their brand and network forever” (Interview 2). In order to improve their work (Interview 4), and “don’t miss the train” (Interview 7), VCs have to start using a data-driven approach to investing. As discussed above, the usage of AI can enhance the decision-making process of VCs, however, developing the right implementation plan (Interview 8) as well as a strategy with data at its core (Interview 7) is crucial. Therefore, the technology implementation models developed by Chang (2006), and by Arvidsson et. al (2014), were studied and adapted to the underlying research. The following implementation plan (Figure 9) represents a simplified suggestion for VCs on how to implement AI in their decision-making process.

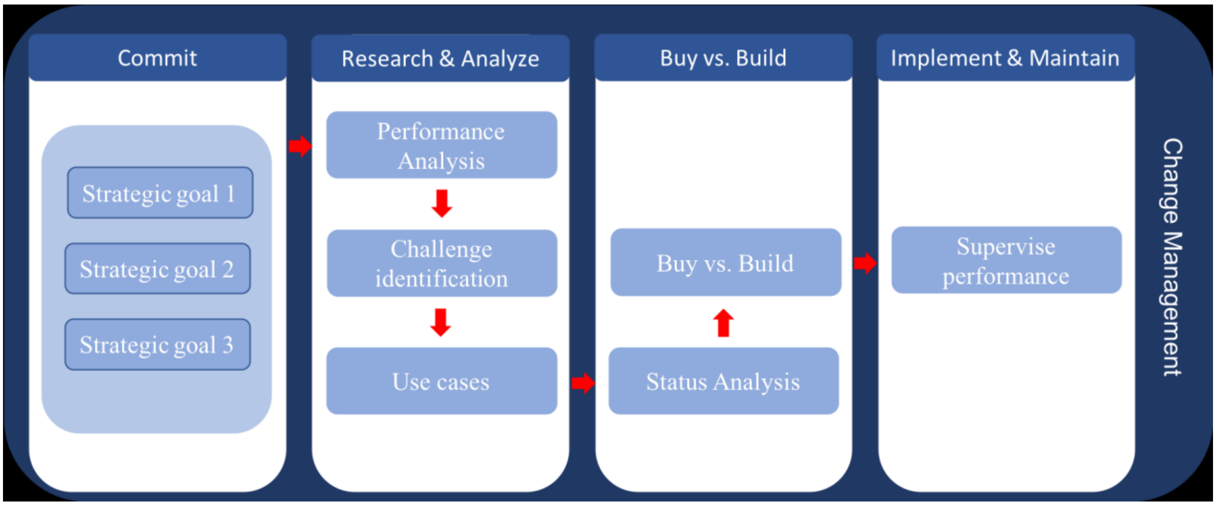

Figure 9: Implementation Plan

Commit: The commitment phase consists of two steps. First, in order to implement AI successfully in the decision-making process, it is essential that the organization adopts the idea of implementing data in the process. The resistance of the organization to accept business changes is often the reason the implementation of new technologies fails at the end (Chang, 2006). Investors are used to making decisions by relying on their gut. Especially if they were successful by applying this method, they are reluctant to change their behavior (Interview 9). However, investors have to be slowly prepared to adapt to the new investment approach (Interview 1). Second, the VC should tie the usage of AI in the decision with strategic goals, that use the decision-making process as a key enabler (Arvidsson et. al, 2014; Chang, 2006). An example would be to double deal flow or to increase productivity by factor 10.

Research & Analysis: In order to prepare the VC for change, a leader within the company should be identified. This leader should ideally be an investor who is open to adopting AI in the decision-making process, has obtained influence over the rest of the company and can convince his colleagues of the usage of a data-driven approach to investing (Arvidsson et. al, 2014; Chang, 2006). This investor should also be able to understand the uses and limitations of AI and be able to communicate with data scientists. In addition, this step serves to collect information about the current decision-making process. In order to measure the improvements obtained through the implementation of AI, the actual performance has to be analyzed. Furthermore, all levels of the company should discuss the main challenges in the process (Mittal et. al, 2019). These challenges serve as a basis for identifying the main use cases of AI in the process.

Build or Buy: Once a VC determined the use cases of AI in its decision-making process, it can analyze its existing technology, in-house talent, as well as its budget available (Mittal et. al, 2019). Based on this analysis, VCs should discuss the advantages of building proprietary vs. buying solutions. As AI experts and data scientists are the hardest talents to attract, VCs wanting to implement AI in their processes should consider applying off-the-shelf solutions. Interviewee 6 and 7 offer solutions for deal sourcing and deal screening, the solution of interviewee 7 can also be implemented as a third party data source. The usage of outside solutions can lead to quicker results, as well as lower initial investment, representing a low-cost opportunity for VCs to test a data-driven approach to investing.

Implement & Maintain: After building or buying a solution, it has to be implemented and tested. If VCs decided to build their own data platform, in order to benefit from the implementation of AI in the process and gain a competitive advantage, the platform should be continuously improved. Furthermore, VCs should constantly measure the performance of their decision-making process with AI, to compare it to the process performance without AI.

Chapter 5: Conclusions and Limitations

The purpose of this research study is to assess the opportunity of AI in the decision-making process of VCs. The underlying research reported the results of semi-structured interviews with VCs, AI Experts as well as companies offering solutions to VCs. In line with the findings presented by Zacharakis and Shepherd (2001), George (1980), Franke et. al (2006), and Zacharakis and Meyer (1998), VCs reported to face challenges in form of high time pressure, high uncertainty about the outcome of investments, as well as biases like similarity and availability bias. In order to solve these challenges, VCs apply AI in their decision-making process. Although VCs automate the decision-making steps up to a different level, the results of the interviews show one commonality. The VCs using AI built their own databases, and automate deal sourcing and deal screening. However, as the data sources VCs use to build their databases are similar, the main competitive advantage is not obtained through deal sourcing, but by building scoring systems that give information about the likelihood of success of a company and thereby assess companies in a more efficient and effective way. These models are built based on different criteria, e.g. criteria about the founders, markets, or growth rates of a company. By evaluating the impact of the usage of AI on the process and the outcome of the decision, the underlying study shows that the usage of AI improves the process. However, the impact on the outcome cannot be measured due to the lack of long-term data on the usage of AI in VCs. Usage of AI improves the process by increasing productivity and efficiency and decreasing uncertainty and biases.

The present study also allowed to gain insights on further use cases of AI in the decision-making process. Although the majority of these use cases hasn't been validated yet, they show that when having access to data and a clear objective, AI applications can be developed that support investors in every step of the decision-making process. As in the early stage, less data is available about investment opportunities, the use cases add more value to early-stage VCs than to late-stage VCs. However, the results of the interviews also indicate that VCs face technical, financial, and cultural challenges when implementing AI into their decision-making. In order to obtain the maximum value of the implementation of AI, technology has to be in the core DNA of the fund. Therefore, a detailed implementation plan should be followed.

As with any empirical study, the underlying analysis and results come with several limitations. First, due to the limited time frame of the study, the sample size of VCs interviewed is too small to generalize the findings across the whole industry. Second, due to the research design, namely interviews, the results are likely to suffer from recall and post-hoc rationalization bias. According to a study conducted by Zacharakis and Meyer (1998), VCs have difficulties to introspect their own decision-making process. Nevertheless, this research method was valuable in obtaining insights about how AI capabilities can be used in the several steps of the decision-making process. Although VCs are restrictive about the information they share about their usage of AI in the process, the research provided a clearer understanding of the current state of the implementation of the technology in the process, the advantages obtained as well as challenges arising with its implementation. However, in order to measure the advantage of the usage of AI compared to the traditional way of decision-making in VCs, a more quantitative analysis has to be conducted.

Although the present study identified that the usage of AI can improve the process of making decisions, it is undefined if it is worth it as a VC to invest in AI. Decreasing uncertainty, biases, as well as increasing productivity and efficiency, are useful advantages. However, the underlying research didn't generate insights about the impact of the usage of AI on the return. Therefore clear conclusions about the advantage of AI cannot be made. As more and more VCs follow the example of the interviewed VCs, it is important to study the impact of AI on returns as quickly as possible. Compagni et. al (2015) conducted a study to assess how early implementations of a technology impact later adoptions on the example of robotic surgery. Their findings showed that central actors adopt new technologies and share success stories to show their mastery in a specific field. These stories lead to imitations of further players, although the technological advantages are unclear. Simply the media pressure as well as the fear to be left behind result in the adoption of the technology – technological advantages still remaining unclear. This effect could be present in the underlying study. Although the impact of AI on the outcome, namely the return, of the decision is still unclear, and the use cases presented in the present research have not been validated, more and more VCs are planning to adopt the new technology, in order to not "miss the train".

Research on AI in VCs can follow many directions in the next years. First, as the number of VCs participating in the underlying study is small, the findings have to be validated on a larger sample. By analyzing more VCs, insights about the value of AI in regard to the investment stage of VCs should be generated. Second, researchers should conduct a quantitative study in 5-6 years, when data about the returns of the portfolios is available. More empirical research should explore in what situations the costs of implementing AI in the process are justified by comparing the costs to the outcome. Third, each of the use cases presented in this study should be validated. Fourth, the reasons for VCs for implementation of

AI in their process, as well as the effect of this shift to data-driven investing on entrepreneurs seeking funding, could be investigated.

In summary, the underlying study makes a unique contribution to the academic literature by examining the previously unexplored opportunity of AI in the decision-making process of VC and offers some indications for future research. AI is going to play an important role in the VC industry within the next years. Further studies will show if the insights generated in the underlying study are part of a short-term trend, or if AI will be able to provide sustainable advantages to VCs in the future.

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Annex

Appendix 1: Interview Guide

Part I: Introduction

1. Please describe the position of your company in the Venture Capital market.
2. What are your firms' criteria for investment size, geographic location, industries and technology, and stage of funding?

Part II: VC Industry

1. What main challenges does the Venture Capital industry face today?
2. What internal challenges is your company facing?

Part III: Key questions

1. Could you walk me through the decision-making process of your company?
2. What are the main challenges your company is facing in taking decisions? Please be precise about the stages of the decision-making process in which they occur.
3. How are you using AI capabilities to solve those challenges?
4. Please indicate from 1 to 5 (strongly disagree - strongly agree):
    a. My team needs less time to reach a decision.
    b. My team considers a greater amount of alternatives when making decisions.
    c. The usage of AI in decision making increased the performance of my company.
    d. My team takes decisions now with greater confidence.
5. Are you using AI to replace humans or to augment your capabilities?
6. Could you describe how you developed this technology (in-house – outsourcing)?
7. What problems did you encounter when implementing technology in the decision-making process

Appendix 2: Interview Transcripts

EQT Ventures

What is the position of your company in the venture capital market?

We are a fairly new, large fund, with 566m euros. We are headquartered in Stockholm and London, but we have offices in Amsterdam, Berlin, San Francisco, Luxembourg and on our way in Paris.

What are your firms' criteria for investment size, geographic location, industries and technology, and stage of funding?

Since we are a large and multi-stage fund, we don't do that much early investing, meaning seed stage investment. We have participated in a couple of seed rounds, but our sweet spot is late Series A until Series C. Our smallest check is one million euros and we can do up until 75 million euros in one check. The companies we invest in are mainly in Europe, or in the US if there's a clear focus on that company going to Europe. So that's like our value proposition because we have lots of expertise in Europe. We are an operative fund, a lot of people here have been working for example for Booking, Spotify. Some of them have founded companies themselves, so that is another value proposition that we have. We are all founders, that means we are here to help. We are quite hands-on, we are very hands-on compared to others.

What main challenges does the Venture Capital industry face today?

I think the Venture Capital industry has been growing. There are more and more funds. To win deals, you have to have a special value prop or you have to pay up. A lot of companies get a very high valuation today. Another challenge that I think – for the venture capital industry or the entrepreneurial landscape – is that in order to get into the wheel of the venture capitalist, meaning to get funding, you need a lot of connections. If you don't have the connections, it's hard to build a business, so it needs to be much more democratized. And one way we do it is to use AI to get in touch.

What internal challenges is your company facing?

It's linked to the other question, right? The more funds, the more the prices go up, the more expensive it gets.

Did you use motherbrain right from the beginning?

I started at EQT Ventures two years ago, and EQT Ventures was founded three years ago. When I started there was a platform, but as you know we are developing the platform all the time so it is getting better and better. There is still so much stuff we can do. From as far as I know there was already a platform from the very beginning or maybe after the first couple of months.

Could you walk me through the decision-making process of your company?

There is no one single process, the process is always different, especially for a young fund. We start with some way of sourcing deals, where the network is one part, and motherbrain is another. Then there is initial screening, initial analysis, where you meet companies, but where you first do some type of research. Meet companies. Decide if this investment opportunity is attractive or relevant enough for this fund to take the deal to the full team. Then we take it to the full team, there is a party meeting, like the company meets the partners and the rest of the fund, or they present the whole team to the whole fund and then from there, we go on taking a decision on the term sheet or not. After the term sheet, we have some due diligence, which is more legal, financial due diligence and then there is closing. But basically, the decision to invest or not is taken when the term sheet is signed.

In which of the steps you just described are you using motherbrain?

So motherbrain is our investment tool, but it is not just used for giving us companies. It is giving us companies it thinks we should look at first, and it is prioritizing companies for us. So as an Analyst I could have a queue of 30 companies to screen and the screen takes a while. It could take 2 seconds, but it could also take 30 minutes. So motherbrain can help us prioritize, which company it thinks we should look at first. That's one way, that's part of the first thing let's say, or the screening. Motherbrain has also a complex platform, meaning we have a lot of data sources, that we match. This is part of the secret sources called motherbrain, something that I don't think anybody else does. There is no startup database or data sources, but if you look at a single one of them, they are quite scared for the data, so the data is not very complete. But if you merge them… I think you will never have a pretty complete data source, but you will have a much much much more complete data source. That's one of the things that we continuously develop. So when I do my first analysis, I can get a picture of the company much quicker, than otherwise. And then not just AI but you can also do certain analysis, you can do match applications of investors, for example. One thing, that we have – I can give you 15 examples for that one. You get like an objective ranking… Otherwise, we fall back into the trap that there are some investors that are better than others, but it's hard enough to factor that. One way that we do this analysis automatically and we have that. So motherbrain is a platform but it is also a huge database, what we then build our algorithms on, so it's also an interface that we use throughout the whole process. So also in the back when we work towards a term sheet we still do for example competitive mapping. We have algorithms that give us similarities between companies and then we can teach the algorithm to give us more companies like this, we call it similar search. So we can, for example, if I pack 10 companies or competitors in a map, then I can get companies that are similar to those 10. So then I get a new one, and I can say: What is this, does it look like the other 10? Do I want it in my competitor mapping or not? And if I say no it will learn from that and it gives me another one, and I can teach that live in the platform.

How does the platform know which companies to prioritize? How does the platform know which companies you should look at?

The epic thing is that we have all this data, which is from all the databases. So I guess, if we should go a little bit more technical, we use kind of the same methodology that you use when you do image classification. But we use it for time series. So instead of me looking at 20 different time periods or – I don't know how many I could look at – maybe I could only take a look at five in my mind when I analyze the company. And then try to see if this is an attractive company based on those time series. We see all time series of all companies every day and we have an objective measure if the company is successful or not and if it is a successful company we train the algorithm based on that. So we also train the algorithm to try to keep up what we like as individuals and as a team, because for example we don't look at biotech companies or we might look at a biotech company if it is super attractive, but otherwise that should not be prioritized. Like if it's a company doing medicine, we will probably not invest, because that is out of scope for our fund. So the algorithm should learn all those small rules, that we have when we look at companies, so it learns from us. And it also learns – because when we analyze the company, I can on certain dimensions, let's say I like that of the company but I don't like that. And from that it can learn that for example, I like the timing of this company, like right now was the right timing, it can learn from the… for example like round data, and at one point it will weigh that in and try and find similar companies in the future. So there are different dimensions, it is not trained objectively, it is trained on what companies we like or not, it is also trained on different dimensions, so what exactly is it that we like with this company. It is quite advanced at this point.

How much do you rely on it? How many of the investments that you made came from this platform?

It is difficult to say. On every deal that we work on, we use the platform. Every investment professional at EQT Ventures uses the platform. We have so far four companies that are sourced through the platform. The number of companies that we sourced through the platform are now 20%, but the work that we do, so for example, every time I have to do something for the company, like competitive mapping, I do it through the platform. That's just an example but, I don't google the company, I look it up on the platform. Because that is where I know I get all the analysis that I do on a daily basis. Where someone else would have to google, do a spreadsheet, putting in some numbers and do all the analysis, I have it at hand everywhere on my phone or on my computer. So every company or every deal you ever work on, you use the platform. So if I should say, me personally, I spend probably 80% of my time as an investor on Motherbrain, or you know, with Motherbrain. But deal source: 4 of our 40.

What about startups that don't have any data in the databases?

I think – so far – we have not found a round that we wanted to see that did not have any data at all, especially because we are not doing the absolute first round. Because it could be that companies are very self, you know, really really hiding, but many times there are, you know, we have that screen data, for example, you have – data you know where these numbers have been before. For example, if an entrepreneur has previously started a couple of startups and they are successful, that signals itself. Of course, there are companies that are buried under the radar. We always do this analysis when a round happened that we did not see, we try, on a data perspective, how can we get to a level where we acquire this data. One app we have with motherbrain that I guess other venture capitals in the industry do not have is, that we have the backing of a very very big private equity fund, that has a big budget to spend on something like this because they believe that this could also disrupt the private equity industry. So we can deal with this platform for them to profit from it but also for … but also to acquire data sources that would be otherwise quite expensive for smaller funds.

What problems did you encounter when implementing technology in the decision making process? What are the main concerns raised by investors using the technology?

Yeah I mean, of course, there is … I think to AI in general, wherever it is, there will be reluctance in terms of it has to be proven before anybody believes in it, because it's a black box, right? So that is gonna happen in whatever industry you take. It doesn't have to be AI, just someone telling you to use this because it is statistically much better. So, of course, there are people and still… You know I'm trying to give an example: if a good friend of mine came to me and said, this is a good company, I look it up on the platform and it says that this is not a good company. I have to be proven wrong a couple of times before I trust it. So far the platform is learning from everything and it's getting better and when investment professionals see it thinks better, you start to trust it more and more. When for example a company was hiding itself and we missed the deal, and if it shows that if we used the algorithms we could have found it, the more and more people will start to trust it. We are quite far but sure, it is always a problem to trust an algorithm. Myself with engineering and data science background I also needed it to be proven before I trust an algorithm, right? And especially when I can't to it myself.

Do you already know how you compare to other venture capital firms not using AI?

The investments that we sourced purely through motherbrain probably have been even more scrutinized than other investments. They are the ones that are maybe performing among the top of our portfolio. So to use AI and get that outside view , of course, you can not see everything on an outside view, you know, at leat not yet. I believe that we can see … It's not a clear cut then in the sense that it screens the startup and .. but it's one of the best performing companies that we have sourced by motherbrain and we found it before everyone else. It's hard to say right now, and in the future, time will help, but one thing that we can see already is that we are able to faster screen more companies. We already screen 5k – 6k a year now, maybe even higher right now actually. I think you can compare that number to a lot of other venture funds and I don't think that there are that many venture funds that screen that many companies. And that is also when we do a slightly deeper screening if you want to count the number of companies that we actually run our algorithms on that is 8 million. We track 8 million companies globally. And obviously, that would be then a big difference. A normal venture fund gets 1000 or 2000 inbound companies each year.

What are in your opinion the main reasons some venture capital firms are not using AI?

I mean it is difficult, right. It is difficult to build that platform but it's also difficult to start building that database and matching companies. The matching companies part is very difficult actually. I think also because, venture capital, like the industry, is a network-driven industry. So you are a Tier 1 and you have been able to live with that for some time it will take a lot of guts to say now we're gonna change the way we are working. But it's also amazing that investors that are investing in companies that are going to disrupt big industries, don't think enough on that maybe our industry is gonna be disrupted as well. And I think that is happening right now and I truly believe that is what's going to happen. You are not able to 100% rely on your brand, your name, and your network forever. Maybe for a little longer but not forever. But I also think we see more and more funds starting to think about how they can use more data in their own day to day work.

How do you think the future of AI and Venture Capital is going to look like? Are normal investors going to be needed anymore?

I think in the end it is always a team that will do the work in the companies we invest in. And as I said, one of our value propositions is to help that team, so I think there will always be a need for people.

Is it going to be in the end about who has the best platform and the best data?

In a perfect world, yeah. So then what would happen to the industry? I think that is what also happened to hedge funds. You still need a lot of people at hedge funds proving new algorithms, finding new data. I don't think we will ever get to the stage where AI completely takes over. I think you will always need people taking care of it, the algorithms, new data and all that. But I do believe that you will have to have a bigger people understanding, like understanding of the platform, like as you can see with for example hedge funds. If you go tens of years back it was very fundamental analysis heavy and now it is very algorithm driven. So a lot of artificial work at hedge funds and have final measures. And maybe a similar shift will come to the venture capital industry. And it leaves people more time over to actually begin instead of doing a lot of manual work, and that's what's going to happen in a lot of other industries as well.

Georgian Partners

Throughout the process, we are making decisions to down select until we get to roughly about 5-6 deals a year. So we use ML and AI early on, in particular for identifying companies of interest. And we also use it for assisting – this is not related to decision-making – but we use it for assisting with reaching out to firms. So how do we discover relationships with firms and things like that. So there's a whole bunch of stuff that we do, that's some of it's in-house, like the algorithms for identifying companies is in-house developed, and relationship discovery, machine learning products, that one, in particular, that is a third party one. but then right through to the investment decision process itself, like, you know, this stages we treat. So our whole process is really like a sales process. So I'm not sure of your background, if you've ever worked in a software company or a technology company, where you, you know, like, leads, and then you have sales accepted leads, you know, sales qualified leads, and you have so on. So we treat… we behave like a technology company. And it seems we progress things through our pipeline. as it gets later, In the process, even though we're very data-driven, we're not using automation or AI at the end. So in the end, it's still a human decision as to, to invest or not. You can think of it as the amount of innovation and ML is quite high at the beginning. And then it actually decreases as we get closer to making a decision. That might not always be the case. But the bottleneck for us, or the end for many firms is finding companies. And it's often where you'll see a lot of venture capital firms starting on sourcing using AI and ml for sourcing. And then probably with the other end, we are looking at some techniques for looking at heuristics and things around decision making. will also trying to, I think the first step is for any firm and so particularly as to just to continue to be more data-driven decision even to human making a decision, because that allows you to consider what am I doing later? So at the moment, I would say. So our qualitative inputs are going to the last decision-making process around the team, for example, around the team that you're investing in. But also we have a lot of because we invest in growth-stage companies, that means typically, companies that have more than $5 million in revenue, there are also a lot of data metrics that we use as well. But we don't yet we haven't yet taken the step of automating that it's more augmenting that decision making with data science is probably a more accurate statement.

How is your decision-making process structured?

Well, it's a, it's sure. So it's, it starts off by looking at a universe of about 30,000 companies. And then it quickly is filtered. Basically, we're using the in-house machine learning platform. Because we have an r&d team, which is a little bit different from other funds. So we actually have an r&d team of 1000 researchers and engineers, and that, that helps us down select to those companies that are in mandate, meaning overall revenue, the North American are growing quickly, etc. And we use various data inputs for that. And the usual stuff like pitch book and social media data, and also, it's hooked up to our operational environment. So it gets all the feedback from Salesforce and stuff like that. So that's, that's how we do it in the in. That's my team is responsible for that we reach out to those companies that are most interested etc. So it's very similar to a regular VC process. It's just that we use very high levels of automation and have a much lower number of people that are required involved with it. Once we identifying qualified companies, it's just like any sales forces, they didn't get handed over to the sales , team management team, and, and it works its way through.

Do you predict success?

yeah, we're not trying to predict success. At this point. We're trying to make ourselves more efficient in identifying potentially interesting companies and excluding uninteresting companies. Predicting actual business success, you may need a quantum computer for that.

For the other steps, you still need investors?

Yeah, we're not, we're not trying to automate getting to know the team or anything like that. Okay, we are using a lot of data in that process. But it's still a very human-driven process. And because the number like I think, if you talk to early-stage funds are trying to look at, you know, that may be trying to write hundred thousand up to a half a million dollar check, you might find that they the volume of deals they look at is so high that maybe they're starting to do more automation of filtering and selection of companies, once they were interacting with the companies I've even seen a few years ago, they found those funds, they don't do it anymore, but they used to keep using it into all your data on their website, and then try and tell you whether they would fund you or not, it was a very mechanical process. We don't do anything like that. And we don't need to because we look at a lot of companies, but we, we don't look at so many that we can't take the time to get to know people. But certainly, we are always looking at how we improve and how we use AI to improve. We just invested in a company called chorus, the AI that actually can be used to monitor conversations and tell you if you're selling talking to a match or you know, if the person you're talking to is not engaged, or this was not using it right now, by the way. But that sort of stuff is of interest to us as well. So how can we be more efficient? But fundamentally, we… Yeah, it does for us is it has a whole bunch of speech to text and the natural language processing capabilities. That's one of our areas of interest is NLP, we have one NLP, deep learning researcher on staff, we have another computational linguist as well. So it's kind of one of the best things is around that. And yeah, we're definitely looking at how we use that in our processes, as well to be more efficient. But, you know, so we've, we've experimented with generating outreach emails, for example. But in the end, we don't want to make outreach or anything like that, we think that you've always got to take the time to get to know entrepreneurs. So I personally don't think growth equity will be an automated process for a long time. It may get the one. I mean, surely once businesses are more, like, more quantifiable, but businesses are still there's a lot of qualitative inputs into understanding of business, though.

You are using this since 2008?

Yeah. But people would now call it ML / AI. And certainly, our technology has evolved over time, but I would say the last in their 60s 70s. We've been developing this for a long time. But the first couple of years, we certainly were more focused on just more manual processes for identifying companies.

Did you have implementation problems?

Well, most of us are from a technology background, like our companies founded by software people. So we're a little different, right? That we're not, we weren't VCs before this, this is our first go at being venture capitalists. So we came with a very software driven mindset. So that's why pretty early on, we started experimenting with this. But yeah, I think they will continue to be some hesitation around. Like, I think that's why at the decision-making process at the end because it makes a decision with input from the team with the data with tools that support the decision-making process. But for now, we're not going to have a computer, make a decision to write a check for 20 or $40 million. So I think, I think is a lot of acceptance of automation in the process. But as you get further closer to the decision, the level of automation for us at least decreases. Okay, to stay that way for a while.

What do you think are the reasons some VCs still use the traditional approach?

Probably, I mean, I can't speak for other people. But I would say probably habit. And especially if they've been successful. And they already have plenty of IPOs. And, you know, lots of successful companies, and they can probably get away with doing what they're doing. If you're a new fund like us, where you don't like we've made a conscious decision to invest a lot of our resources into helping companies be successful after we invest. So that's why we have this Georgian impact team. So that's the you know, the the doesn't also in software, researchers and engineers. Now, when we invest in that, that makes me kind of invest in, people elsewhere. So our people investment is very oriented towards helping companies. And so almost by necessity, we've had to come up with ways to automate other parts of the business. And that's why we are very data-driven on sourcing. So it's some of its necessity because we've made a strategic decision to focus our resources elsewhere. So it's like, Okay, well, I mean, if you look at a company, like I did this, the other day, I looked at insight venture partners are big. And, you know, multiple billions of dollars under management. And I counted up about 47 people on the team that was like, you don't have that, you know, venture capital, you have analysts, and Associates and senior associates and vice presidents, and in principles, and then partners. And so they had 47 or so on LinkedIn, vice presidents, or below who all of whom would be involved in some capacity, and source. And maybe 13. Also, that were full time on sourcing, I estimated about 20, to 25. But the majority of their time was on reaching out to companies finding companies. And we have a fraction of that sort of resource on their problem. So we are, you know, very interested in continuing to innovate around data and automation because it makes us more efficient. It also, interestingly, helps us learn about I mean, those are the sorts of companies we're investing in any way like we're at, for the whole life of the firm, one of our investment thesis, theses has been around analytics, data science, machine learning, and AI. So it would kind of be a bit off, right? If we didn't understand that, so So one of the ways that we stay close to the industry that we're investing in, is using the technologies that our portfolio, other companies will say us and makes it really, it's a good experiment for us as well as being a great productivity tool.

What advantages do you have compared to other VCs?

It's hard to prove because, you know, it's how do you AB test it? So and by the way, I believe we may be more efficient in some areas. But like I was, I can't prove that because I don't have access to the data. But I think at least one of the other ways that being more data-driven helps is probably in helping with coverage and being able to get across more opportunities in a systematic way. And, if you take a primarily a network-based approach, where you just get access to the deals that people introduce you to for your network, and you're not, you're not using the data-driven sourcing approach, and you're probably missing, you probably hear about a lot of opportunities in particular markets, but you don't necessarily hear about opportunities in all markets. So I think that's the model that has led to a lot of focus on Silicon Valley in New York and Boston. And then maybe, maybe fans of the more data-driven look for opportunities. in more places, like we've just done an investment in Columbus, Ohio, right? It's a great company is based in Columbus, it's possibly least likely that you would come across opportunities like that if you would just focus on your personal network, because that's the alternative, right? The source, in particular, is a very strong reliance in DC on just to personal networks, we still that's very important to us. That's a really key part of how we find deals as well. But it's not the only way that we find deals.

How many deals come from network, how many from the platform?

it's pretty balanced. There's a lot of I mean, we get a lot of inbound from, I mean, in venture, once you start working with other people, we get a lot of good recommendations. So that's pretty, it's a pretty strong source for us.

You already said you think about other areas you could improve. And you also mentioned NLP. Do you have any ideas or example where that could help in the future in the process?

one possibility is to monitor customer sentiment. So sentiment analysis during the deal process, or the selling process? And so once you identify the company using technologies like chorus, or others to monitor like a is, is this going well? Or is this going badly, and it's another opportunity, analysis of the company, potentially, by the content that puts out. So potentially analyzing the quality of the thinking of the company through its output, stuff like that. But that's still early days because NLP isn't really natural language understanding. So there's a bit of work to do there. And it's also quite subjective as well. But stuff like that. And then I did mention heuristics. So potentially codifying how decisions are made. So if you can, over time see commonality and how decisions are made, and you can find data inputs for it, or, you know, some part of the decision-making process is, is clearly data-driven. And the decision was made in a consistent way by human with those inputs, then you can automate that, to some extent, right. And focus the humans time on relationship building. So you can get that time back to spend on getting to know the company. I think the I think I think there are more opportunities, I just think that it's probably a slow process. we're pretty conservative bunch, I would say I think this is just my personal view, the more data driven we become in the decision-making process, the more equitable will be, because there is bound to be inherent, but there are inherent biases and assumptions around venture, for example, it is one strongly held belief is that entrepreneurs who have done it before will do it again. And that tends to favor particular demographics because currently, there's a lot more say, males of European descent that are CEOs, right. So if part of your decision-making processes, previous found that is a good founder, then you're sort of creating a feedback loop that says, European males, the Europeans have seen our be the founders, then others. So I think the more data we can get into the process, the better. And I think that that'll be part of increasing the diversity of investment over time. But it's a long, it's a long and tough process because you've got to find enough data and signal that can be used to make good decisions. And I think you'll, it'll honestly, Christina be like a 10 to 20-year project. Because we there's so few data points, one of the problems in venture is you don't make that many decisions. So if you're, if you're trying to build a medical center, right, and using email, to do it, you get a lot of data points, a lot of things happen every minute, every hour. But in VC, and in another field, like farming, like decisions around farming and putting crops and you only make a decision once a year. for farming, it's even worse than venture capital. So it's very hard to apply machine learning and things to these problems where there isn't a lot of labeled data. So and you said you're not technical, but basically labeling is just the price of categorizing a piece of decision or a piece of data or So you can use it as to train an algorithm. And VC if you're only making five or six, and this year, it's quite hard to get enough data, right?

Nauta Capital

Can you give me some basic info about your company?

300m under management, based in London, Barcelona, and Munich. Typically invest in Series A and were founded in 2014. I'm a software engineer and data scientist since 2017 at Nauta.

What are in your opinion the main challenges the Venture Capital industry is facing today?

The first challenge is to detect interesting opportunities to invest in, and then select the good ones, the ones that will convert into big companies.

Could you walk me through your decision-making process?

We discover some company or some founders come to us and explain what they do. If it matches with our investment thesis. Because depending on the VC, some VCs are more specialized in software or I don't know, healthcare or whatever. So if the company matches with our investment thesis then we make a deep dive, analyzing all the different aspects of the company, the founders, the market. And after that, if everything goes well, then we propose a term sheet with all the clauses for the investment round, and if they agree, then we sign the contract and we invest the money and after that, we help the company to grow. Usually, one of our investment managers or partners is on the board of the company and helps them to make the company grow and doing well.

What are the main challenges in the process you just described?

Sometimes a company looks great and is amazing, the founding team is good, but we are not completely sure if this company will succeed or not. These are the main difficulties that we face because we believe all the times – we invest in a company because we believe that this company will succeed and sometimes it doesn't.

Can you describe what the Dealflow Engine is, and how are you using it to improve your decision-making process?

That is a software that automatically collects information from potential investment opportunities so it is a set of crawlers that collects information from multiple sources and saves it in a structured way. So we can dig into it, and use it appropriately. And this engine helps us to find companies that we would not have found otherwise. And it is faster because it is a software and it processes a lot of information easily. The most important thing is that we are curating a big knowledge database that allows us to build predictive models that help us to enhance our decision-making process. So what we are looking is with this big database, we try to identify attributes of the founders, the companies or the markets or the different aspects that are related to a company that correlate positively with the probability of success of a company. So it is a big database, we also have a website the investment teams can connect with it and make queries and can retrieve information from this database easily. It's not only for web guys, we also have a web interface so all people at Nauta have access to it and can do queries and get information.

How does it exactly work?

We try to collect all the information that we can and after that we process it and if … for the companies that match with our investment thesis then we try to get more information. So for example, if we get all the companies from an acquisition, and then maybe some of them are not good for us, and then we just leave the information in the database, that's all. Some of these companies could be an investment opportunity, then we try to find more information about the founders, or the market if it is a market that we are not familiar with, the social media that we can get…

How are you using Artificial Intelligence?

Intelligence goes after we have the information. So we have the engine divided into two parts. One is the collection information part, where we try to get information from all the different sources that we can. And after that, we do a study and analysis over this information that we have. So the Artifical Intelligence is the models that we run over this information. So when we have a set of companies, we start analyzing their funding round, characteristics of the founders, the size of the market, and with all these features, we create models that give us like a scoring or success rate for each company. And with this information, the investment team manually analyzes these companies. So all the machine learning models are over the platform, the data platform.

Since when are you using this data-driven approach to investing?

When I arrived I started creating the platform, the crawlers, the database. But Nauta has always been working with data. Maybe not on this level, but the culture of the firm is always analyze as much data as they can, so it is a natural way that we are following. Before my position, they collected manually all this information of all type of the companies, founders, and markets and they tried to do it manually.

What did improve in the decision-making process since you arrived, and since you have this platform you just described?

It improved in two ways. One is that with this platform we are able to discover companies that we were not been able to discover otherwise. Because it searches in blog, in news, in social media so it's always searching for new companies. And when it discovers something interesting, we will see its power. So first it helps us to discover new companies, and then, on the other side, it helps us to analyze the company in a more objective way. Because it gives us different scores for the different characteristics of the company. And then, maybe in some case, one company would be discarded because of the size of the market, but then the tool says that the market is bigger than we thought, for example. So it helps us to find companies but also to improve our decision-making process.

How did the process improve in terms of time?

Of course, because all the information – all the time that we had to spend searching for information, this is already done, so all the information that is related to the company and the founders is already in the database. So it easier to look at it because on one side, we have all the information of all the different sources where you can get the information from. So for the investment team, it's easy to look into the company because it just one page, they have the company information, the information from other founders, information from investors that have already invested in this company, the information about the market, the information about the competitors. This is very important because we also have all the companies related with their competitors so we know easily if a small company has a very big competitor, for example.

Can you already give any statement about your performance since you use the platform? Are you investing in better startups?

No, it takes 5-6 years.

How many people are working on this platform?

Directly on the platform, we are two people. But all the investment teams collaborate with ideas, so the things that we do to our platform is because of our users. So in the end, we are only two techies, but all the company helps us to improve the platform.

Did you encounter any problems when implementing the platform in the decision-making process?

The investors are very happy with the platform. The idea of the platform is not mine, so it was their idea, to help them, to do their jobs better. They decided to create this platform and then they hired me. So it's your request, not mine. They are very very interested in data, that's why they are always thinking about new things, helping me, help to improve it. Because I'm not an investor, I'm a computer engineer. They are very happy with that.

What do you think are the main reasons some Venture Capitals are not using a data-driven approach yet?

I think it's the same in all the industries. So some companies are more willing to use technology to improve their work and some companies are slower. I know that most of the important VCs are using this data-driven approach, and I think it will be more common in the coming years. Because by using this type of tools they are improving their job, so their work.

Connetic.Ventures

Basic info about company

For an initial check, we do not invest in companies that are more than $10 million pre-money valuation. And right now we're US only even though this week we just started looking at six different countries and sourcing deals from there. For the US, we will do any state except for California and New York and Massachusetts. And then that's just a valuation-driven decision. Founded in 2015. I'm in our office, Pittsburgh Office, Cincinnati, or Covington as our office.

Main challenges the industry is facing

So the main challenges at least in the areas that we invest in our investors have no way to source and evaluate deals in multiple cities. most venture funds are established in one city and only source deals and evaluate deals from that city. So Chicago, I work with a lot of funds here, 80% only invest in Chicago companies. And we don't believe that any city outside of the major cities in America has enough deals are really ideas to be fundable and create a successful venture fund long term. Generally, any people struggle with standardizing anything. And I think ventures, it's easy to make excuses about kind of going with your gut and ignore kind of standardization or any sort of data. We just see lots of people making exceptions. So a lot of times we get pushback on valuation. And most people don't think there's really an effective way to use financial modeling the most experienced level to create a valuation for companies. But I think one of the biggest issues is you have no way to standardize, valuing startup companies.

What are the main internal challenges that you are facing?

Resources. So we go do everything in-house. And so we faced some financial struggles with… there are a lot of different things, but building our data, and technology stack as well as finding deals. So we have APIs with a bunch of different companies like Pitchbook, where we source deals from based on certain criteria, and each one of those pools cost us money. I think the biggest thing is getting enough deal flow, given certain financial restraints. And then yes, it has taken us probably almost two years to build what we have standing today because we've learned a lot about the venture ecosystem, we've learned a lot about collecting. Everything in venture happens so slowly, and it takes a long time learning curve is very steep. So just learning enough to where you can structure an application process with the right variables has been really tough.

Could you walk me through the decision-making process of your company?

So we write three different checks generally into companies. So I'll just talk, just talk about our first check. The company applies to Wendal, which is our data platform, there are six different modules in Wendal. Each module is a pass / fail. And so for us to move a company into due diligence, they need to pass all six stages. And those are financial companies past those stages, then we move into diligence, which involves a number of things, but the main thing is we're a part of it as our valuation calculator. So once we identify the company, and they are at the right stage and the team has got the right team, we need to make sure that the deal makes sense financially. generally, between six to 7%, companies that apply past those stages, so we're automatically screening out 93% of companies. And for them, they receive an auto-generated email that we're not interested, we're building a feedback loop. So they can actually, you know, learn something through a process. They're giving us the data, we want to give them something in return. But right now, our decision-making process is completely automated up to the due diligence point, and then it's passed to a Principal, which would be myself and the Midwest, or one of my colleagues. And then we collect documents and go through the financials. So the last step of due diligence is to human review mainly of inputs through the process.

How are you using AI in the process?

every data point collected, which, depending on the responses between 160 180 variables on Microsoft Azure as machine learning platform, and we built a process to automatically recalculate that every so often, we don't share how often we do it. But

so in our, in our database, we have thousands of companies, 160 variables each and dependent on the success of those companies that we track regularly. All of our everything is auto related. And a lot of the inputs are actually changed by - I guess, there is discussion about what AI actually is - but everything is changed and made smarter over time, based on this automated process.

What advantages do you have compared to others by using this process?

Based on that, automatically, we are not only collecting data from but passing on 93% of investments, we see 12 times more companies or have 12 times the capacity for deal flow than any other. We remove human bias from the equation because our initial interaction with the company is on a phone call or an interview, which generally go better. You're the same gender or ethnicity 42% of our investments have been women or minority founders, compared to the US venture average of 6%. I'm still using this process removes as much human bias from it, I think, as you can get, save a lot of time, you know, we don't even meet US companies before making an investment. And then just being able to measure yourself, I don't personally interact with any ventures on that collects structured data, and is able to accurately tells anyone why they made an investment. And so when a company fails or succeeds in the future, no one, you know, like, they can go back with like, Oh, yeah, we, I know, there isn't a direct data point or series of decisions that they can point to like, okay, that's where we went wrong, or, you know, we can learn from that. So, actually, having structured data allows you to learn from successes or failures.

How are you sourcing companies?

Yeah, so it's 70% automated sourcing. So we have algorithms we've built depending on the source. So Pitchbook, we've got an algorithm that brings us an account last funding round, a number of employees – we don't like to share exactly what goes into it. But we're pretty good at understanding when a company is going to be raising money that fits our criteria. We also scrape LinkedIn and lots of other websites for keywords that we can source deals from that we know are actively raising. So I think it's about 70%, automated from various channels. 20% is probably the human network. So know, myself going to conferences or just being in cities. And then 10% is referral. So other venture funds know our model, they know, we like to see a lot of deals and can write a check quickly. 10% comes just from brand recognition and referrals.

And then they have to go through the process?

Before we just.. we found ourselves – and we actually measured this – we were taking calls from all our referrals and they tended to be mostly white male founders because a lot of the venture funds are run by white males. And so we think or we decided that will never take a phone call unless they go through that process first, so we won't be clouded by judgment.

Did you encounter any problems when implementing it?

And I know we have not had any of that. But we're also all of the partners – and there are three partners in our fund. Were all either former traders, financial analysts or analytical professionals. So for us, like this just makes sense. And we also had never, and we didn't kind of grow up through venture capital, which I think a lot of people do. And people pride themselves on making investment decisions and having companies they picked became unicorns. And so I think there's a lot of ego that we didn't have from the beginning because we're so new to this. I guarantee you, if we did all work in venture capital for five to 10 years before we started doing this, they would have been a big issue.

Can you think of any other reasons why some VCs are still using the traditional approach?

I think it's the time frame associated with Venture Capital, on an average .. 8,6 years from now, seed stage funding, like to have the discipline and structure to be able to measure that and like.. to do this, I think you're committing to a decade long project, which for a lot of people is really overwhelming. most people grow up through different industries, and no one in venture capital has ever used data to make decisions. just purely based on your research, funds doing it more people are kind of penetrating venture capital that is this and other industries. And that'll continue to change. But unlike being an equity trader trading stocks, you can backtest models, publicly available data and you can build models off of and you can actually test it without having to trade with real money. And so PhDs and university can create financial models, get hired as a trader. In private markets, there just isn't a publicly available data that you can build models off of and also say whether it works or not. So the really smart people that are good at this don't have access to the tools and data they need to create …. There are so many issues with using us and venture that. I mean, that's Yeah, that's obvious why people aren't doing it. And I think it makes the process really fun. But that's also there's so many … given, macro trends, founding teams, I'm not 100% confident that this will ever be proven. I think it'll be proven to be better than gut. But how much better it will work…

Crunchindex

Basic Info

Um, yeah, so we did only launching in March, I've been sort of working on this in the background for about four or five years. So it took a while to figure it out, basically, how to track other companies, and how to track metrics, which actually, not only for VC but also for private equity investors. And currently, we also work with a lot of corporates who are looking for acquisition targets. So long story short, I've been working on this for like, four or five years, until I felt, it's ready. So we launched in March, then we have to be able to partner with a lot of different VCs, so right now we have, for example, index ventures, one of the biggest venture capitals. We also work with the biggest PE fund in Sweden, and we work with some VCs in Canada in the US. It's going really fast, but it isn't going like it's not, it will be kind of overnight. Again, it was some it was something that I was making for the last few years. And what we basically do is basically explain so we basically try to find out which are the fastest growing companies in the world. That's the mission, so the only differentiator that we have for the client is basically that they don't need to filter through the noise. So they don't need to go through like a lot of companies we already give them like the 1%. And the second thing is they can tell us basically which categories in which industries and geographies and features they're interested in. And we make sure that our, our engine and algorithms only feed them companies which are very useful.

How does it exactly work?

So we have 60 or 70 different sources. Just imagine like the typical Linkedin, Twitter, and general sites like Crunchbase and so on, And we bump it up with like data, for instance, from 10 million websites, we also top it up with some data from 125,000 hosting companies, so whenever there is like a new, new like domain, or like a new website, we already know about it. And then what we basically do every single day, we scrape and we gather data. So what that means is that we look at how many employees do they have, how many new backlinks are being added, has anybody on Medium written about them, And how many Twitter followers do they have, do they go on Instagram. Are people are viewing the app on the App Store, are they getting reviews, it can be like a lot of different things, depending on how we trim it down. And that's how we find out which ones …

What criteria are relevant for success? Are you just looking at growth rates?

Yes, and there's a simple reason for it. Because I don't believe in like in between, I don't believe you should look backward. And I don't think you can look, you can look forward. two explanations there. So I don't think you can look backward, because the valuations of companies are changing rapidly, going in different ways and much faster than the US. And also the accessibility of capital, right? I mean, like, even now companies like from our country, you're from Ukraine, or Slovakia can get can get some VC money. So it's totally different than how it used to be. And then looking forward, again, you would have to use the backward in order to be able to predict what's going to happen. And I simply don't believe in that. I think in VC you should only look to the left and to the right. And find out which company is ahead of us… big horses. I don't think looking backward and forward works for anyone. I don't think any single VC would be successful in doing that.

Main challenges in the industry

Too much money, too much capital. Which causes a big issue. The deals you want to get into are extremely competitive. Even my, like not top deals but mid deals, so B players or C players, when it comes to VCs, it's almost impossible to get into good deals at a normal valuation. So I think I think that's an overload of capital is driving the valuations on up too much. And secondly, I think it's very difficult to get it into deals, for many VCs, especially the brand is not too strong. I think it's, it's difficult. So I think we're kind of realizing it, and I think they're trying to be earlier than they used to be, maybe to go a little bit downstream. But I don't think it's working super well for many of them. So like .. I think funds, which have raised by like 80 – 150 million. And when they struggle for like, you know, eight, nine months to get a single deal in the fund. It's not just like tiny funds, it's easy, a lot of funds struggle with it. And I think that's something that it's going to sort out like naturally, but it's definitely one of the major obstacles for VCs to succeed.

What are your experiences with implementing your technology? How do investors react?

I think it has to be in the core DNA of the fund. I mean, like it has to be one of the major activities. So I used to do this for two years in Hummingbird ventures, which is a mid-size VC fund, and I felt for 2 years that it was not in their core DNA. So that's why I left and I said, okay, I don't want to do it. And you can imagine how it is at other smaller funds, I think in general, it's two things. One, VC was never supposed to be able to data, I think every like super senior partner who is invested is 60 now, so it is going to be like network and relationship driven. And they are going to be referred the best entrepreneurs. And then they're going to apply their pattern recognition and realize that the founder is the next Mark Zuckerberg and then they cannot speak about it. But they will Realize that the game is getting so competitive, but they need to do something about it. So now every single VC, who reaches out to us is telling me Hey we are just building our own data approach. And I was thinking about a simple question, Why now? And we're like, Yeah, well, we see, like, people around us, you know, EQT, Nauta Capital, Correlation, we see WR Hambrecht, we see all these people. And we see that if we don't do it, now we're going to miss a train in so I'm happy to do it for them. But I already know that this is not going to become a core part of their DNA, it's … which is going to fail anyway.

Advantages inhouse vs. outsourcing

Like one part of it is like even like somebody like Index, which are building their own tool, which is honestly the best in the market right now, compared to all the other competitors. And they just need another data source, which is different from the others. So we are not going to date with both and I cannot disclose this, like what exact data points like they need from us. But it's basically like a combination. So I think, even if, even if you have somebody like EQT, they still gets a lot of data from third parties, I used to work for a company, which gave a lot of data to them, I don’t think it’s necessarily like a or b, I think it is going to go into this together, which is perfectly fine. And whatever benefits or whatever disadvantages, like I think, again, like I'm going to repeat myself, we just, we just spent like four or 5 million euros on this on a yearly *Basic Info*

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How's the future of VC going to look like

I think like given the competition, even how many companies are launched on a daily basis., there's no way you can do this business without data. Absolutely no way you can do this without data nowadays. So I think is going to become more digitalized. And I think second thing is that, like, nowadays, enough money to basically make it into into like a new private market. So I think what's going to happen over the next five to 10 years, and I think it's already slightly happening in the US is that all the companies, which are private now will try to share a lot more about themselves. And I think it's going to basically increase the visibility. So I think right now what I'm missing in order to make it algorithmic and what all the other VCs are missing is the hard data, right? So we are missing profits, we're missing revenue, margins, and we're missing all this data of companies. And I think as long as or as soon as, like companies start sharing it to some platform, which can be like the new private market ,? or some version of that. And then I think we are going to move to a completely different era where the VC as you know it nowadays is not going to even be able to exist, going to happen in the future. *Not sure, like a fun one. And now it's going to be ugly, and so on. But like if I was supposed to bet*, what's going to happen, I bet it's going to be this.

Main improvements of data to the decision-making process

It can be defined as inverse pyramid, right? So every every single company on the planet, including like all the corporates, … The issue is that you have like too many partners, and too little Junior people, but the decision power is basically happening on the top without too much of an interference with the junior people. So I think can become extremely frustrating. So coming back to combining this question with the data part, I think data helps you to to democratize it a little bit, because then you have to look at the objectives of the company , so let's say more numbers and the market, and the market sizing, and so on. So I think data helps to democratize it internally, but I think it also helps to democratize it externally, so many VCs have this bias, that they are only going ot invest in their network and the areas that they know, right. So maybe they only want to invest in like Western Europe, because the companies are nice and shiny, and like the markets are big enough, and so on, and they know the markets, and they can imagine how it going to grow. But I think with data it also pushes you to territories, verticals and geographies where like maybe you wouldn't have looked otherwise. So there were some use cases at Hummingbird, where we looked at African companies, when we look at companies from like Columbia, where we looked at companies from like South-East Asia, which we normally probably wouldn't have, like heard about, or noticed otherwise, and with data we found them and I think we even backed a few of them. So I think it opens up your eyes, I think both internally and externally. And I think it's a good tool, especially for the junior people to get to get some deals going in, to get maybe a bit to the top let's say.

Follow the Seed

Could you describe your company in terms of investment size, geographic focus and investment stage?

We became best at the post-seed stage. So once the company has a product, and actually some, some users, that they use its product. We invest both in the consumer and in the enterprise space. We are headquartered in Australia, but we invest globally, so we have four partners in the fund. We have one partner in Tel Aviv, one partner in the Silicon Valley, one partner in Beijing, and I'm typically based in Sydney. So we pretty much invest worldwide, but the fund is headquartered in Australia, so we have a bit more investments in Australia itself. In terms of the verticals, we are pretty much kind of sector agnostic, and we invest almost across the board. We sometimes invest less, but 0.5 – 2m would be the average investment size.

What are in your opinion the main challenges the venture capital industry is facing today?

There are a lot of challenges. The main challenge is that the industry that is in charge of investing in innovation, disruptive technology and kind of the cutting edge, itself as an industry is actually very much backwards faced. It didn't really change in the last 40 years and if you look at the way people were raising venture capital or how venture capital was invested back in the 70s, it's pretty much the same today. It's more about who you know, rather than who you are. And this basically causes significant disparity in terms of where the capital invested. So obviously if you are the white man living in the Silicon Valley that studied at Stanford, so the chances that you are raising capital are probably 100 times higher than if you're a woman living kind of – not even third world countries but you know, outside of the obvious hot spots. And maybe English is not your first language, so your chances are significantly lower. And again, I'm not necessarly talking about someone in Africa, but even someone in Europe or even in the US itself, you know if you are living in North Dakota, good luck raising venture capital there. Noone invests there. So that are the main challenges we see, most of the funds are basically relying on judging the envelope, instead of judging the inside. And that is what we are trying to face now with our approach, which is very much data driven. And looking more into the company itself and into it's execution and it's products, so we analyze the way people interact with the products that the company has built, and based on this – so we are making an initial screening, and most of the process is basically based on that, rather than whether the founders were first asked by someone we know or whether they studied in a good university or not. So that's our approach.

Could you walk me through your decision-making process? How are you using technology to improve it?

In our case, all decisions are still made by humans. The technology doesn't make the investment decision, so the investment decision is managed by the partners, the four of us have a vertical distribution of deals, not geographical. So simply of the way the experience of the partners. Our… partner is much more experienced in enterprise, while the .. partner is much more experienced in consumer, and the Chinese guy is much more into gaming, sports entertainment and stuff like this. And I'm much more of a generalist, I can say pretty much all of it, so I'm kind of filling the gaps. And basically one of the partners picks up the deal, kind of brings it to another partner to validate his thinking. If both of them are on the same page, then they put it on the partnership table. But obviously, beforehand we have the whole technology part, which is applicable in our case mostly to the consumer internet investments, which is the area where we see the most noise coming from. So we see less noise coming from the enterprise space, it's much easier for us to filter it. But when you talk about companies that are creating various apps, or games, or services, that are aiming at the general consumer market, there are way more companies than we can process. So instead of just filing all of them to one big file that no one looks at, we manage to automate the process. And today, companies that pitch to us, they don't even need to talk to us at this stage, all they need to do is to go to the website, download our SDK, plug it into their product, and within something like three weeks, we'll have enough data to analyze. And the algorithm will give them a RavingFans score, and if this score is above a certain threshold, we will basically contact them. So we are saving them all day the calls, preparing pitch deck, driving or flying around. So we are saving ourselves a lot of time as well, but we basically don't waste their time, if they are not a good fit for us. So their entire dealing with us could be limited to 5-10 minutes, that takes them to go online, download the SDK, integrate it into their product, it's basically as easy as putting a Google Analytics script on your webpage.

So if the startup wants investment from you, they just need to plug in the SDK to get feedback?

We are very transparent in terms of what data we collect, so we don't collect any PII (personal identifiable information), that's any information that can identify the user, so if you heard about the GDPR and all of this, so basically all the privacy stuff, we don't collect any of this, so we don't collect IP addresses, don't put any cookies, we don't correlate the data with any other data set. So our SDK basically creates a unique ID per device, which again, is completely random and anonymous, we don't correlate it with anything else. And then, the only other thing we get is every time a user starts a session and ends the session, we get a signal from the SDK. And that's it. So we don't look into what happened in the session, we don't care whether there was a transaction, whether there was a purchase or anything else. So we completely ignore the content of the session, we only get the information about when the session started, and when the session ended. That's it. So these two pieces of information are the only thing that we collect. So basically in terms of the privacy or you know, data security, there is absolutely no concern, because we actually don't even collect anything else. Because some companies do collect some more sensitive information, and then they kind of process, aggregate and drop the raw data, we don't even collect. So basically, the fact that some random device started a session and finishes it, there is absolutely nothing sensitive in it. And that's the only thing that is being stored in our database. So it's very straightforward, everyone who implements it can have a look at this, and they can basically understand what it does.

How does the usage of this technology improve your decision-making process compared to other VCs?

So the main point is that it saves us about 99.9% of our time, that would we otherwise spend in looking into deals that we shouldn't even look at. As a person that has been in this space between entrepreneurship and VC for more than 22 years now, and in recent years I was spending more and more of my time meeting with companies that I shouldn't even meet. Simply because they weren't relevant to my kind of investment criteria. And that's basically what our algorithm is saving, and it basically does online due diligence for us, which is pretty much impossible to say. So when it does flag a particular product that acts interesting, that shows some very interesting characteristics, then the entire process, is compressed into potentially only a couple of weeks. So we can move much much faster. And again at the same time, obviously, we care most about saving time to ourselves. Time is always the most scarce resource that we have, you know you can always raise money. But we also save a lot of time and distraction to the startups themselves. I started more than 20 companies myself and I met countless investors, I know how time-consuming the fundraising process is. So basically if someone, the only thing they asked me is to give access to my user data, again I know exactly what I share with them, and in return, there is basically a promise not to waste my time. And it's a good thing that the timeframe to get investments is significantly shorter, it's a great thing. Obviously, not everyone shares the same opinion, you know there are a lot of companies that have concerns about doing that. But that itself is an important signal for us because companies that are not willing to give access to their data in the way we require it, for us, it means that they are not relevant to be considered an investment.

Did you develop this technology in-house?

Yes

Did you encounter any problems when implementing this technology?

Absolutely not, because we built the whole technology stack from the ground up to serve a particular purpose. And it was built by people that really understand the investment process, and also the kind of way companies approach us. And we are looking at it as a very very meaningful indicator or a very meaningful part of our due diligence. So in a similar way, where you know, other investors, before making an investment decision, there was at the very least asked for usage, data, the Google Analytics report, or whatever analytics system is being used by a particular company. So for us, everything is done by our own tools. So I don't even need access to their analytics, because it's irrelevant. A typical analytics platform has a problem where they aggregate the data and hence it becomes way less useful. In our case, we are analyzing consumer behavior when looking at individual consumers. Now, of course, we don't know who the particular person is, and we don't actually care, but we do look at their behavior.

What are in your opinion the main reasons VCs are not using a data-driven approach?

The first one is that it is actually not that trivial to come up with the right implementation in order to be of real value for the investor. That's number one. I think there is a secondary consideration, maybe some fund managers are somewhat concerned using technology will eventually make them redundant. I mean we completely disagree with that. Basically, as I mentioned, the decision itself is made by the partner, by humans. The technology is there to assist, so to facilitate, to screen. And provide us important information throughout the due diligence process. And because it is not trivial to built what we have built, because in our case it is based on a very significant research that one of our partners did for many many years, so we actually built our technology in a way that it can be relevant for other investors as well. So we don't just sit on top of our technology stack, and then use it for our own benefit, we also license it to other funds. Because we think this is a much more correct approach, that helps both fund managers to make better decisions, and it enables better companies to get funded. And more important, it democratizes access, as I mentioned before. Instead of only being able to invest around the block where you are located, this technology enables you to invest anywhere in the world. So as long as you are open to invest outside of your immediate geography it could be a substantial assistance to do it. It is obviously much more difficult to do due diligence on a company when it is based in a different country or it speaks a different language than to do it just right around the corner from where your office is.

Right Side Capital Management

What are in your opinion the biggest challenges the VC industry is facing today?

I'd say some of the biggest ones is that the venture capital industry, particularly at the later stages, I think, is overcapitalized. So there's too much money chasing too few deals. There's a number of reasons why that's the case, you know, at the very late stages, you just got to not have the sources of money coming into the system, whether it's, you know, hedge funds, sovereign wealth funds, a lot of even publicly traded mutual funds that are starting to try to play capitals, sort of in that, you know, unicorn stage. And then as you get earlier than that, you just got the traditional late-stage VCs raised big loads of capital. And then I think that's exacerbated by the fact that almost every major corporation these days now has a venture arm, in 2010, almost no corporate, very few corporations have venture capital arm. And now it seems like everyone does, and they've all launched in the last five or six years, and they all sort of focused on Series B and later. So I think, in the venture world as a whole, you know, there's a lot of challenges at that space. I think, you know, we don't invest in that, that space. And none of that affects us a lot. I think what that's done, though, is increased round sizes. At these later stages, which has sort of worked backward a bit to increase ground sizes at the earlier stages and valuations as well. You also have the fact that you know, the stage that we invest in, which is sort of the, you know, very early pre-seed investors, and we're sort of a round or two earlier than even most VC firms that market themselves as pre-seed investors, or seed investors, but as he goes around later than us, and you get sort of into the general micro VC world, it's also an incredibly crowded space, you know, and it's mostly phenomenon in the last five to six years, you know, if you went back to 2010, or 12, there were, you know, handful dozens of micro VC firms. And now there's, you know, one to 2000 in the US. And they all have very similar investment theses, they all tend to focus on, you know, overweight, investing in major markets, you know, San Francisco Bay Area, New York, Boston. And it's just, that's also true for that valuations and deal size and round sizes and stuff like that, in those areas. So I think the whole ecosystem sort of trying to absorb it, figure out how to handle all this, this new cash rising valuations, raising round sizes, and everything is, is one of the biggest things in the industry to impact the last few years.

What internal challenges are you facing?

They are actually totally unrelated to any of that. Ours are very unique to us. So what we find is that the market we focus on is largely almost completely ignored by professional investors in the US, because we tend to write check sizes that are just smaller than what any, even a micro VC can ever deploy, you know, our tradition, our average check size is $100,000. You know, and I would say that math, unit economics don't work out for a traditional fund, even micro VC funds generally. So our challenges tend to be on the other spectrum, like, we tend to find that we don't have any real professional competition. But even just the US market is so large, it's harder for us to just get all even all the coverage we want. So we primarily invest outside of the Bay Area and outside of New York City. But the US is so large, and there's such a thriving, you know, entrepreneurial market, Renaissance going on at these really early stages, that it's hard for us to get sort of access and coverage across all the secondary markets, you know. And then that's, that's one area. And then the second one is just, we're often capital constraint. So what we do and how we invest, even though we have very healthy returns that constantly outperform, the overall market, we do that by breaking about half of the proceeds best practices of the venture capital industry. So that makes it challenging for us to fundraise. From a lot of the traditional sources, so, you know, our, our challenges tend to be more on fundraising side and issues with us sort of breaking a lot of perceived best practices. And then because we tend to be undercapitalized, we sort of have the opposite of most funds. So like finding deals to invest in is not our biggest challenge. Usually, it's, then once we found all these deciding which ones were investing in, because we often have more attractive deals, than capital to deploy.

Could you walk me through the decision-making process of your company?

Yes, I mean, our decision-making process, either the best way to describe it, you know, in simple terms, is we're somewhat of an automated scorecard system. So we, you know, evaluate startups, primarily by gathering up a large number of quantitative data points about a company, and then coming to a pretty quick yes or no decision, you know, based on those data points as to whether or not that's an attractive investment at a certain valuation. And I would say, the, you know, an example of that, you know, to just pick one area, let's say, we're going to look at a team of a startup, the way a traditional venture capital investor would evaluate a team would be to invite the CEO or maybe founders into their office or go meet them have sort of an unstructured interview with them. And at the end of the day, come to some conclusion as to whether or not that was a good team. And ultimately, we think what people are really doing when they do that is, you know, they tend to like that team if there like them? And they tend to not like them as much if they're not like them. Whereas the said, we'll just quantify that. So we'll say what makes up a good team. And we make a sort of list, it's, you know, hey, that they've got previous startup experience, they've founded startups, before they've raised capital, they've gotten a start up towards generating revenue, they've got technical skills, they've managed people and budgets, they've got domain expertise. And all these things are either sort of yes or no have a yes or no answer to them. Or you can sort of graded on the skills, you know, whether it's one, two, or three, or one to five. And so if we want to look at a team and say, Is this a good team or not? You know, just by looking at their LinkedIn profiles, or by asking that team questions over a 60 minute period, I can use our rubric and come up, and sort of put that team into an average team better than average team or worse than average team, that, you know, part of that is my personal assessment of whether I liked them or not. So that's sort of an example. And we sort of take that and apply that to all aspects of the startup. So we're basically taking startups and reducing them to profiles that are largely independent of the what it is a specific idea of what they do. So we're looking at defining a startup by, you know, is it a B2C or B2B company? You know, is it transactional? Or a SAS business model? How much capital has the company raised to date? How much cash is it burning right now? How many founders does it have, you know, quality of the team, you know, price point of the product can it support a sales force all of these things? And, you know, almost nothing about what we look at is, what is the idea? What is the company doing? And do we like the idea? Do we think it has a large growing market, you know, sort of, we remove all that subjective analysis out of it. And I would say that's the most challenging part of our, of our investment process is, is to remove the sort of subjective judgment and emotion out of it, you actually have to systematically do that. Because otherwise, it's always creeps in, it's really hard to find the company that's doing something that might sort of subjectively seemed crazy to the average person. Unless you don't allow yourself to take what they're doing into account in basing your yes or no decision.

So you have a list of criteria on which you base your decision?

We have an ideal profile, but there are lots of profiles. What we are basically doing… maybe the best way to say it is the fundamental difference between how we operate and how a traditional venture firm or traditional angel investor, or me personally, when I was an active angel investor, look at companies is that you know, most investors look at a specific company, and they're actually trying to predict whether that company will succeed or fail that specific company. And our fundamental beliefs. You know, there's two major overriding sort of beliefs that make that not rational to do. The first is, we believe there are too many variables of uncertainty to predict almost anything about the future of a startup at this early stage, you know, human brains like to think you can, but ultimately, you know, you just like you can't predict the weather very far out, or economies, you just can't predict startups very far out the future. The second part is that we already know just based on that, the outcome at our stage is that the most likely outcome of every investment we make is that it's going to fail and go to zero. So we sort of look at this is the most likely outcome of this specific company is that we're going to lose all our money. So we predicted the future, what else can we know? And instead, what we're doing is really saying, All right, this specific company is likely going to go to zero. But how would a pool of 100 companies, all of them have a similar profile? You know, how would that pool perform if we invested them all at this specific valuation. And if you think of it like that, the world and your decision-making process suddenly becomes very different. In our view. to give you an example of sort of how this comes into play in the real world, maybe what I could do is I'll take an actual company, of our portfolio, and I'll describe that company how a normal angel investor, venture capitalists would describe it to their partners, and then I'll describe it, how we would describe it to my partners. Okay, so let me come up with one here and how it looked at the time that we invested. Okay, so you know, I'm going to take a company, it's from, you know, a company in San Diego. And so, normally what I do, as a traditional venture capital investor, and go to my partners, they have come across a new company, that's very interesting. It's a SAS product in the veterinary space. And their product, you know, allows that, to interact with their customers, both through SMS text messaging to confirm appointments, instead of mailing out postcards, it also allows our customers to have a mobile app to access, you know, create cancel appointments, and to communicate with the vet and to see sort of their pets history. This space is, you know, there's relatively little competition in this space. And it's pretty recession-proof, because that still got a business in a recession, I think this is a huge growing market, you know, in the US, people tend to be spending more and more on their pets each year. And so I think the market size will be substantially larger than it is, you know, in five years than it is now. You know, blah, blah, blah, blah. And, and almost everything about that description is sort of what the company does, and why I think this idea is a good idea and will have good market acceptance market. So, capital, I would describe this company as follows I go to my partners, by just talking to with them, and I would say have found an interesting company that we should look at, is a b2b SAS company. Down in San Diego, it's got a SAS product that, you know, that sells in sort of a vertical, you know, a niche vertical. The price point of the product is 350 $400 a month supply enough to support a sales force. The company currently has 35 K, MRR, they've gotten to that point, having only raised you know, a couple hundred to $200,000. The founding is a three-person founding team, one of the founders, his previous startup expertise to them have technical experience. And one has significant domain expertise. A company's only burning through $15,000 a month in cash right now, they're looking to raise $500,000 at a $3 million valuation. That's, that's a simple, simplistic, there'll be more things we'd look at. I just sort of give you a profile of a company and my description internally. In RSC, I never even said what the company did. I didn't mention that it was that they sold to that. So I didn't mention what the product did all that it's just, it's a b2b SAS product, with a certain price point that is high enough to support a sales force, they've got this traction level, you know, they've got this, blah, blah, blah, blah, you know, as we dive in, and we'd look at some of the unit economics of what their Kak Telly TV ratios are, and things like that. But ultimately, we wouldn't care what they do to try and predict the market forward. And so when I described that to other investors a lot, I'll sometimes use an example like that for some random company. And, you know, usually the response, I'll get back as well, yeah, that's a great investment. But you can't find deals like that. You know, I'd invest in that too. But you can't find deals that attack but that that valuation, and you know, my answer back to them is usually well, to start with, you'd never invest in that company because I didn't tell you what they did. And then investors usually will pause and think you're like, Oh, yeah, you didn't. Our philosophy, our belief to those deals are out there all over, they're just not in the main markets. Where everyone is chasing the same deals.

So you are using kind of a checklist and then manually search for all the data you need?

So we define ahead of time what criteria we think are important. And then it is not like there is a single ideal profile we are looking for. We are looking for different criteria that also are more or less important, depending on the business model that a company is doing. So it's not like it's one size fits all. And all metrics just work for all business models. So if you got a B2B business model, there are different things, we care about than if you have a B2C business model. But ultimately, in looking at and evaluating a company, you know, we know, it's sort of a combination of this sort of quantitative scorecard system, and a bunch of knowledge and data that we've accumulated on the market. So we know already, what deals are getting done at what valuations and at what traction levels in the market across the US, because we've been doing this since 2012, we've made over and invested in over 900, companies that been looked at thousands and thousands or 10s of thousands of companies and see what's going on. So we know that in the marketplace, a company with this level of traction doing this is generally getting funded at this valuation. So we also know that, you know, the market as a whole sort of has this average return here. And so we can, you know, keep multiple things we can say here are things that, you know, instead of trying to beat the market, by out picking, you know, which ideas will you know, having a higher success rate, you know, we can beat the market, by very quickly assessing what profiles are, you know, are, are attractive at better valuations than what the markets funding that you're basically putting together, you know, that you could have a profile that's very attractive. And we might say, this is a very attractive profile at a $2 million valuation, but it's actually quite unattractive at a $3 billion valuation. So, you know, for us, there's no, there's not just a simple… it's not just a simple yes or no. And now let's figure out what valuation we can get it that everything's evaluation and all the other characteristics that we're looking at are intertwined with each other.

What do you think are the main reasons some VCs are still using the traditional approach of investing?

Well, I think, a few reasons. One, it goes against all the core principles of venture capital, the belief of venture capital is that the partners that run a firm are these luminaries who have this ability to predict the future and see which business models will succeed or fail, which companies will succeed or fail, what markets are growing or not. And so, you know, our, our, our investment thesis is sort of based on sort of this fundamental belief that that's not true at all. That's really predictable. So that's, that, that makes it difficult. And psychologically, it's also just really difficult to execute. Like, we're, you know, we're three people to whom come from sort of a quantitative engineering background. And, and we've systematically designed a process that doesn't allow you sort of take into account a lot of the, the fuzzy, subjective data points that most people use, and it's still even, it's still hard for us. You know, I've talked to two firms that have said, they've tried to do something similar, they've tried to create a process where they make very quick decisions. But what ends up happening is they end up spending just as much time internally discussing and doing diligence on a $200,000 investment as they do on a $2 million investment. It's just human brains, I think, are wired for this. So it's very difficult. You want to, you know, every aspect of life, the human brain takes in the data around it, and weaves a story around that, to try and make that data make sense. And to try and, you know, convince yourself that you can take that and tell a story that actually helps you predict, and an account for the future. Because that's what we do in life. That's what you need to do to survive, you know, evolutionarily. So that's what people do, I think, in the startup world, so you people really, brains trick ourselves into, into believing that there are recognizable patterns that can be used to predict the future and, you know, with high confidence level.. It's all psychology.

How do you deal with the problems just described? If you have a bad feeling, do you still invest?

It's not like a bad feeling, it's more of a feeling like, This is crazy. Why am I investing in this. I can't believe that there would be an opportunity here or something, but you know, it's just more reminding ourselves that, hey, this checks all the boxes, you know, this company, they've got a live product, it's generating revenue, you've got some customers that are paying a pretty high price point for this, you've got a team with a lot of domain expertise, that could be making much higher salaries somewhere else. And they're choosing to give up that opportunity costs to build out this product, and they've got a lot more domain expertise than we know about this. So who are we to say this is crazy? So we do have to remind ourselves with that, occasionally. And I would say that universally what we found, because, you know, both in our history of sort of being active investors in the years leading up to before we launched, you know, sort of the two to three years beforehand, when we interviewed and talk with a lot of very active investors. You know, the common thread that we found, for most of you, almost any investor that we met, that it made sort of 100 or more investments. You know, the common thread was that the ones there's largest winners almost always came from the investments that they thought were complete flyers. And where were, they were the least confident about and they invested the smallest amount in. And inevitably, the ones that they were the most confident about when they invested whenever they're huge winners. So I think it's just very hard at these very early stages to the revolutionary and the ridiculous look almost the same thing. When you try and filter out the ridiculous, you actually end up filtering out almost all of the revolutionary because they look almost always ridiculous.

Aingel.Ai

Basic info about your company

The company was founded in 2016 as a spinoff from research at NYU on using artificial intelligence to scale early stage investing, and predict startup success as early as possible. We currently have around 50 people, five zero, working with us. We are based in San Francisco, we have teams in are based in the Bay Area, actually San Jose and Silicon Valley. And we have teams in San Francisco, San Jose, New York. And a large chunk of our team is also in Cairo, Egypt. So all the data processing and data teams is happening there some development there, we also have a small team in Belarus and one or two people in London and New. And so it's kind of a distributed team. Most of the data science takes happens in Silicon Valley. And then most of the other services that we have are happening outside. So business development and data science is happening in Silicon Valley. And then also the other functions are happening outside.

How many firms are already using your technology?

Well, we have a little bit over 150 registered users. Activity level is different. There are some that are using the interface. Some are using API's. And, yeah, and the usage is quite varied. I mean, obviously API usage as much higher, much higher volume of usage, versus kind of checking in kind of using the web interface.

What main challenges do you see in the Venture Capital industry today?

I mean, it's a broad question, what is if you're talking about, irrespective of data, or the use of data, I think the problems, venture capital problems are quite diverse. I mean, there are, depending on the tier of the VC, each one looks at their problems differently. And there's also kind of macro challenges with, with the whole VC community, in my opinion, so I'm not sure which ones you want to answer. But you know, for example, tier to tier two, tier two VCs in general, are very, you know, hungry for looking at deals, analyzing a large number of deals, they don't necessarily have all the resources, this is where the use of data can become handy. So how can you analyze a larger number of companies and try to find, find these startups early VCs also talk about the challenge of getting into some of the good deals. So some VC, there is this kind of mentality as well within the VC community with where, you know, most of us are going up, most of the good deals are already taken, or most of the good deals are very hard to get into, you really need to buy your way into the good deals. I guess the overall, we're just seeing how in the current environment, especially in Silicon Valley, we're seeing more and more. The data shows that there's fewer number of deals, closing year on year, but there's more VC money, which kind of means that VCs are piling more money on a fewer number of startups, I think there is that level of, you know, just looking for outside confirmations and outside signals. If I see that other VCs are getting into this deal, then I'll jump on this deal and they want to be part of it, you will find a fewer number of VCs that are, that will go against, you know, go against the grain or go against the tide and invest in companies that that others might not necessarily be, you know, so excited about, we get some of the top tier VCs were there, people are looking for confirmation, where if this VC has invested in this company, you get all these other VCs, you know, how was telling telling this investor? How come you're investing in this company? These guys are, you know, they're, they're bold, or they're, you know, there is this or this. So, there is that kind of confirmation. And people looking for kind of these confirmations and very few VCs are, are going against that type. I think it's just becoming a prize. And there are a few very interesting articles about the challenges with early-stage investing these days, and how the current partners that are in VC firms are very different from the partners that were there that founded some of these big companies, and how that decision making process has has changed how the risk appetite has changed, and our decision-making process has changed. So there are a few good articles about this. I can't remember the name of which we see us talking about it.

What are the main challenges in the decision-making process of VCs?

The biggest challenge for the VC community is from my, from my, from our, you know, 2 year experience with working with them so far, I would say is, so we're seeing two types of VCs, we're seeing ones that recognize that data can play a big role in, in, in their decision-making process and others that are basically they you know, they don't, they feel like data cannot contribute to, to my success. I've been doing really well just using my gut. And I'm going to continue using my own kind of formula, my gut to to make to make these judgment calls. And we're seeing over the past few years, but overall, we've just been seeing more and more VCs start hiring data scientists, it could be part of a trend, it could be something in Vogue, it could be something that LPs are interested to see. LPs I've heard that LPs are now you know, they want to see a process they want to see something repeatable, they don't necessarily want specially for kind of the emerging managers, they don't necessarily want to see this kind of dependent on a star they want to see. Sure you you're doing this, but there is a process around that. And you can start seeing you see this, but some of these funds that are emerging, that our data driven, like signal fire, correlation has been around for some time, but there are more and more that are coming out. And you know, Andreessen Horowitz, you know, they started hiring their data scientists back in 2016. And we are seeing more and more VCs that now are having this automation, some of them actually call them partners, like an AI partner, like city light capital, for example. They have one of the partners listed on their website is called the machine. So in terms of challenges, I guess, the challenge, though, When, when, when it comes to so that's kind of in general decision-making challenges, I think the problem has been the data, what kind of data can we bring in and use? And can we find the signal and all of this. And the earlier you are in the life cycle of a startup, the more challenging it is. And as you know, from research, research that's done by, you know, Stanford and Harvard Business School and Chicago Booth. And they talk about how early stage investing is really dependent on the team is kind of one of the strongest signals early on. And, and this, this is where we come in, we've been focusing our our data efforts in our data science, especially at NYU on trying to quantify what does a strong team look like trying to generate kind of a predictive signal from the quality of the team. And so our research has been quite, quite focused on this. results have been very promising we to kind of confirm that the team is important. We also show how there is diversity in the types of teams. There are diversities and types of personalities of founders. There's diversity and types of backgrounds of founders, and the ones that are successful are not necessecarily on kind of the same ?. We do show, for example, that there are some there are stereotypes of successful founders. But there's also other types of founders that are not necessarily they don't come they don't appear that there is not kind of the typical cut of a successful founder. Right. So so we thought we show how there is diversity in in success. And that's, that's been kind of our focus. So our focus has been kind of making sure we understand their bias, understand their selection bias and understand that there are other data points that take us to look at look at founding teams as well as they're making a decision.

Are you only focusing your product on the team?

That's part of the product. That's what we that's what we focused on initially, which was, which was the the team, the founding team, we started to look at other things. So we worked with VCs on. We noticed kind of other challenges. They want to look at compare comparables, look at who else's, you know, compared to the startup, so we started looking at what other startups was the quality of their teams? How do you compare two startups to each other, you cannot use kind of the categorization that are existing today in like crunchbase, or any other platforms. So what do you do so we do a lot of analysis on. So we created our own clusters cluster together, you know, and train their own 800. And train based on 850,000 organizations and created kind of our own clusters. We created distances between all of these companies. And look at the amount of funding that the companies have received when they were founded, who invested? Where are they located, and we created these kind of funding scores. We created these VC scores. So it kind of it took, it took a different life form, beyond just the founders, but all of these are there to support dif different types of questions. So next question is, well, this team is already kind of a seed stage. And not isn't seed stage. I'm doing series A or follow ons. So I want to understand what does the landscape look like? What other startups are in the same space? What does the quality of the team look like? And also look at? Well, I want to, you know, if I'm doing even later, later, like Series B, or C, I want the ability to filter for ones that have, you know, what the? What kind of funding, whether it's high or low, whatever it is, and what else? And what kind of investors that are on board. So.

So you are not only using your platform for deal evaluation? I can also use it for deal sourcing?

We have the sourcing, we're not offering it to all VCs. But yes, there is a sourcing.

basis, just on salaries and acquiring data, and so on and didn't end it didn't result in anything new, I think we should be really careful with like how we build it. And I think for them, it's much safer to just try it out with somebody, it's going to cost them much much less. And when they can see if it's something that the people in the fund are going to spend time on. So I would say we provide them with a way to test it out without spending all the resources and all the time and all the money, whatever else.

How's the future of VC going to look like

I think like given the competition, even how many companies are launched on a daily basis., there's no way you can do this business without data. Absolutely no way you can do this without data nowadays. So I think is going to become more digitalized. And I think the second thing is that, like, nowadays, enough money to basically make it into like a new private market. So I think what's going to happen over the next five to 10 years, and I think it's already slightly happening in the US is that all the companies, which are private now will try to share a lot more about themselves. And I think it's going to basically increase the visibility. So I think right now what I'm missing in order to make it algorithmic and what all the other VCs are missing is the hard data, right? So we are missing profits, we're missing revenue, margins, and we're missing all this data of companies. And I think as long as or as soon as, like companies start sharing it to some platform, which can be like the new private market. And then I think we are going to move to a completely different era where the VC as you know it nowadays is not going to even be able to exist, going to happen in the future. *Not sure, like a fun one. And now it's going to be ugly, and so on. But like if I was supposed to bet*, what's going to happen, I bet it's going to be this.

Main improvements of data to the decision-making process

It can be defined as an inverse pyramid, right? So every single company on the planet, including like all the corporates, … The issue is that you have like too many partners and too little Junior people, but the decision power is basically happening on the top without too much of an interference with the junior people. So I think can become extremely frustrating. So coming back to combining this question with the data part, I think data helps you to democratize it a little bit because then you have to look at the objectives of the company, so let's say more numbers and the market, and the market sizing, and so on. So I think data helps to democratize it internally, but I think it also helps to democratize it externally, so many VCs have this bias, that they are only going to invest in their network and the areas that they know, right. So maybe they only want to invest in like Western Europe, because the companies are nice and shiny, and like the markets are big enough, and so on, and they know the markets, and they can imagine how it going to grow. But I think with data it also pushes you to territories, verticals and geographies where like maybe you wouldn't have looked otherwise. So there were some use cases at Hummingbird, where we looked at African companies, when we look at companies from like Columbia, where we looked at companies from like South-East Asia, which we normally probably wouldn't have, like heard about, or noticed otherwise, and with data we found them and I think we even backed a few of them. So I think it opens up your eyes, I think both internally and externally. And I think it's a good tool, especially for the junior people to get some deals going in, to get maybe a bit to the top let's say.

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Could you describe your company in terms of investment size, geographic focus, and investment stage?

We became best at the post-seed stage. So once the company has a product, and actually some, some users, that they use its product. We invest both in the consumer and in the enterprise space. We are headquartered in Australia, but we invest globally, so we have four partners in the fund. We have one partner in Tel Aviv, one partner in the Silicon Valley, one partner in Beijing, and I'm typically based in Sydney. So we pretty much invest worldwide, but the fund is headquartered in Australia, so we have a bit more investments in Australia itself. In terms of the verticals, we are pretty much kind of sector agnostic, and we invest almost across the board. We sometimes invest less, but 0.5 – 2m would be the average investment size.

What are in your opinion the main challenges the venture capital industry is facing today?

There are a lot of challenges. The main challenge is that the industry that is in charge of investing in innovation, disruptive technology and kind of the cutting edge, itself as an industry is actually very much backwards faced. It didn't really change in the last 40 years and if you look at the way people were raising venture capital or how venture capital was invested back in the 70s, it's pretty much the same today. It's more about who you know, rather than who you are. And this basically causes significant disparity in terms of where the capital invested. So obviously if you are the white man living in the Silicon Valley that studied at Stanford, so the chances that you are raising capital are probably 100 times higher than if you're a woman living kind of – not even third world countries but you know, outside of the obvious hot spots. And maybe English is not your first language, so your chances are significantly lower. And again, I'm not necessarily talking about someone in Africa, but even someone in Europe or even in the US itself, you know if you are living in North Dakota, good luck raising venture capital there. Noone invests there. So that are the main challenges we see, most of the funds are basically relying on judging the envelope, instead of judging the inside. And that is what we are trying to face now with our approach, which is very much data driven. And looking more into the company itself and into it's execution and it's products, so we analyze the way people interact with the products that the company has built, and based on this – so we are making an initial screening, and most of the process is basically based on that, rather than whether the founders were first asked by someone we know, or wether they studied in a good university or not. So that's our approach.

Could you walk me through your decision making process? How are you using technology to improve it?

In our case, all decisions are still made by humans. The technology doesn't make the investment decision, so the investment decision is managed by the partners, the four of us have a vertical distribution of deals, not geographical. So simply of the way the experience of the partners. Our… partner is much more experienced in enterprise, while the .. partner is much more experienced in consumer, and the chinese guy is muc more into gaming, sports entertainment and stuff like this. And I'm much more of a generalist, I can say pretty much all of it, so I'm kind of filling the gaps. And basically one of the partners picks up the deal, kind of brings it to another partner to validate his thinking. If both of them are on the same page, then they put it on the partnership table. But obviously beforehand we have the whole technology part, which is applicable in our case mostly to the consumer internet investments, which is the area where we see the most noice coming from. So we see less noise coming from the enterprise space, it's much easier for us to filter it. But when you talk about companies that are creating various apps, or games, or services, that are aiming at the general consumer market, there are way more companies than we can process. So instead of just filing all of them to one big file that no one looks at, we manage to automate the process. And today, companies that pitch to us, they don't even need to talk to us at this stage, all they need to do is to go to the website, download our SDK, plug it into their product, and within something like three weeks, we'll have enough data to analyze. And the algorithm will give them a RavingFans score, and if this score is above a certain threshold, we will basically contact them. So we are saving them all day the calls, preparing pitch deck, driving or flying around. So we are saving ourselves a lot of time as well, but we basically don't waste their time, if they are not a good fit for us. So their entire dealing with us could be limited to 5-10 minutes, that takes them to go online, download the SDK, integrate it into their product, it's basically as easy as putting a Google Analytics script on your webpage.

So if the startup wants investment from you, they just need to plug in the SDK to get feedback?

We are very transparent in terms of what data we collect, so we don't collect any PII (personal identifyable information), that's any information that can identify the user, so if you heard about the GDPR and all of this, so basically all the privacy stuff, we don't collect any of this, so we don't collect IP addresses, don't put any cookies, we don't correlate the data with any other data set. So our SDK basically creates a unique ID per device, which again, is completely random and anonymous, we don't correlate it with anything else. And then, the only other thing we get, is every time a user starts a session, and ends the session, we get a signal from the SDK. And that's it. So we don't look into what happened in the session, we don't care whether there was a transaction, whether there was a purchase or anything else. So we completely ignore the content of the session, we only get the information about when the session started, and when the session ended. That's it. So these two pieces of information are the only thing that we collect. So basically in terms of the privacy or you know, data security, there is absolutely no concern, because we actually don't even collect anything else. Because some companies do collect some more sensitive information, and then they kind of process, aggregate and drop the raw data, we don't even collect. So basically, the fact that some random device started a session and finishes it, there is absolutely nothing sensitive in it. And that's the only thing that is being stored in our database. So it's very straightforward, everyone who implements it can have a look at this,and they can basically understand what it does.

How does the usage of this technology improve your decision making process compared to other VCs?

So the main point is that it saves us about 99.9% of our time, that would we otherwise spend in looking into deals that we shouldn't even look at. As a person that has been in this space between entrepreneurship and VC for more than 22 years now, and in recent years I was spending more and more of my time meeting with companies that I shouldn't even meet. Simply because they weren't relevant to my kind of investment criteria. And that's basically what our algorithm is saving, and it basically does an online due diligence for us, which is pretty much impossible to say. So when it does flag a particular product that acts interesting, that shows some very interesting characteristics, than the entire process is compressed into potentially only a couple of weeks. So we can move much much faster. And again at the same time, obviously, we care mostly about saving time to ourselves. Time is always the most scarce resource that we have, you know you can always raise money. But we also save a lot of time and distraction to the startups themselves. I started more than 20 companies myself and I met countless investors, I know how time consuming the fundraising process is. So basically if someone, the only thing they asked me is to give access to my user data, again I know exactly what I share with them, and in return there is basically a promise not to waste my time. And it's a good thing that the timeframe to get investmetns is significant shorter, it's a great thing, great deal. Obviously not everyone shares the same opinion, you know there are a lot of companies that have concerns about doing that. But that itself is an important signal for us, because companies that are not willing to give access to their data in the way we require it, for us it means that they are not relevant to be considered an investment.

Did you develop this technology in-house?

Yes

Did you encounter any problems when implementing this technology?

Absolutely not, because we built the whole technology stack from the ground up to serve a particular purpose. And it was built by people that really understand the investment process, and also the kind of way companies approache us. And we are looking at it as a very very meaningful indicator, or a very meaningful part of our due diligence. So in a similar way, where you know, other investors, before making an investment decision, there was at the very least asked for usage, data, the Google Analytics report, or whatever analytics system is being used by a particular company. So for us, everything is done by our own tools. So I don't even need access to their analytics, because it's irrelevant. A typical analytics platform has a problem where they aggregate the data and hence it becomes way less useful. In our case, we are analyzing the consumer behavior when looking at individual consumers. Now , of course, we don't know who the particular person is, and we don't actually care, but we do look at their behavior.

What are in your opinion the main reasons VCs are not using a data driven approach?

The first one is that it is actually not that trival to come up with the right implementation in order to be of real value for the investor. That's number one. I think there is a secondary consideration, maybe some fund managers are somewhat concerned using technology will eventually make them redudant. I mean we completely disagree with that. Basically as I metnioned, the decision itself is made by the partner, by humans. The technology is there to assist, so to facilitate, to screen. And provide us important information throughout the due diligence process.

And because it is not trival to built what we have built, because in our case it is based on a very significant research that one of our partners did for many many years, so we actually built our technology in a way that it can be relevant for other investors as well. So we don't just sit on top of our technology stack, and then use it for our own benefit, we also license it to other funds. Because we think this is a much more correct approach, that helps both fund managers to make better decisions, and it enables better companies to get funded. And more important, it democratizes access, as I mentioned before. Instead of only being able to invest around the block where you are located, this technology enables you to invest anywhere in the world. So as long as you are open to invest outside of your immediate geography it could be a substantial assistance to do it. It is obviously much more difficult to do due diligence on a company when it is based in a different country or it speaks a different language than to do it just right around the corner from where your office is.

Right Side Capital Management

What are in your opinion the biggest challenges the VC industry is facing today?

I'd say some of the biggest ones is that the venture capital industry, particularly at the later stages, I think, is over capitalized. So there's too much money chasing too few deals. There's a number of reasons why that's the case, you know, at the at the very late stages, you just got to not have the sources of money coming into the system, whether it's, you know, hedge funds, sovereign wealth funds, a lot of even publicly traded mutual funds that are starting to try to play capitals, sort of in that, you know, unicorn stage. And then as you get earlier than that, you just got the traditional late stage VCs raised big loads of capital. And then I think that's exacerbated by the fact that almost every major corporation these days now has a venture arm, in 2010, almost no corporate, very few corporations have venture capital arm. And now it seems like everyone does, and they've all launched in the last five or six years, and they all sort of focused on Series B and later. So I think, in the venture world as a whole, you know, there's a lot of challenges at that space. I think, you know, we don't invest in that, that space. And none of that affects us a lot. I think what that's done, though, is increased round sizes. At this later stages, which has sort of worked backwards a bit to increase ground sizes at the earlier stages and valuations as well. You also have the fact that, you know, the stage that we invest in, which is sort of the, you know, very early pre seed investors, and we're sort of a round or two earlier than even most VC firms that market themselves as pre seed investors, or seed investors, but as he goes around later than us, and you get sort of into the general micro VC world, it's also an incredibly crowded space, you know, and it's mostly phenomenon in the last five to six years, you know, if you went back to 2010, or 12, there were, you know, handful dozens of micro VC firms. And now there's, you know, one to 2000 in the US. And they all have very similar investment theses, they all tend to focus on, you know, overweight, investing in major markets, you know, San Francisco Bay Area, New York, Boston. And it's just, that's also true for that valuations and deal size and round sizes and stuff like that, in those areas. So I think the whole ecosystem sort of trying to absorb it, figure out how to handle all this, this new cash rising valuations, raising round sizes, and everything is, is one of the biggest things in the industry to impact the last few years.

What internal challenges are you facing?

They are actually totally unrelated to any of that. Ours are very unique to us. So what we find is that the are or market we focus on is largely almost completely ignored by professional investors in the US, because we tend to write check sizes that are just smaller than what any, even a micro VC can ever deploy, you know, our tradition, our average check size is $100,000. You know, and I would say that math, unit economics don't work out for a traditional funds, even micro VC funds generally. So our challenges tend to be on the other spectrum, like, we tend to find that we don't have any real professional competition. But even just the US market is so large, it's harder for us to just get all even all the coverage we want. So we primarily invest outside of the Bay Area and outside of New York City. But the US is so large, and there's such a thriving, you know, entrepreneurial market, Renaissance going on at these really early stages, that it's hard for us to get sort of access and coverage across all the secondary markets, you know. And then that's, that's one area. And then the second one is just, we're often capital constraint. So what we do and how we invest, even though we have very healthy returns that constantly outperform, the overall market, we do that by breaking about half of the proceeds best practices of the venture capital industry. So that makes it challenging for us to fundraise. From a lot of the traditional sources, so, you know, our, our challenges tend to be more on fundraising side and issues with us sort of breaking a lot of perceived best practices. And then because we tend to be undercapitalized, we sort of have the opposite of most funds. So like finding deals to invest in is not our biggest challenge. Usually, it's, then once we found all these deciding which ones were investing in, because we often have more attractive deals, than capital to deploy.

Could you walk me through the decision making process of your company?

Yes, I mean, our decision making process, either the best way to describe it, you know, in simple terms, is we're somewhat of an automated of an automated scorecard system. So we, you know, evaluate startups, primarily by gathering up a large number of quantitative data points about a company, and then coming to a pretty quick yes or no decision, you know, based on those data points as to whether or not that's an attractive investment at a certain valuation. And I would say, the, you know, an example of that, you know, to just pick one area, let's say, we're going to look at a team of a startup, the way a traditional venture capital investor would evaluate a team would be to invite the CEO or maybe founders into their office or go meet them have sort of an unstructured interview with them. And at the end of the day, come to some conclusion as to whether or not that was a good team. And ultimately, we think what people are really doing when they do that is, you know, they tend to like that team if there like them? And they tend to not like them as much if they're not like them. Whereas the said, we'll just quantify that. So we'll say what makes up a good team. And we make a sort of list, it's, you know, hey, that they've got previous startup experience, they've founded startups, before they've raised capital, they've gotten a start up towards generating revenue, they've got technical skills, they've managed people and budgets, they've got domain expertise. And all these things are either sort of yes or no have a yes or no answer to them. Or you can sort of graded on the skills, you know, whether it's one, two, or three, or one to five. And so if we want to look at a team and say, Is this a good team or not? You know, just by looking at their LinkedIn profiles, or by asking that team questions over 60 minute period, I can use our rubric and come up, and sort of put that team into a average team better than average team or worse than average team, that, you know, part of that is my personal assessment of whether I liked them or not. So that's sort of an example. And we sort of take that and apply that to all aspects of the startup. So we're basically taking startups and reducing them to profiles that are largely independent of the what it is a specific idea of what they do. So we're looking at defining a startup by, you know, is it a b2c or or b2b company? You know, is it a transactional? Or a SAS business model? How much capital has the company raised to date? How much cash is a burning right now? How many founders does it have, you know, quality of the team, you know, price point of the product can it support a sales force all of these things? And, you know, almost nothing about what we look at is, what is the idea? What is the company doing?

And do we like the idea? Do we think it has a large growing market, you know, sort of, we remove all that subjective analysis out of it. And I would say that's the most challenging part of our, of our investment process is, is to remove the sort of subjective judgment and emotion out of it, you actually have to systematically do that. Because otherwise, it's always creeps in, it's really hard to find the company that's doing something that might sort of subjectively seemed crazy to the average person. Unless you don't allow yourself to take what they're doing into account in basing your yes or no decision.

So you have a list of criteria on which you base your decision?

We have an ideal profile, but there are lots of profiles. What we are basically doing… maybe the best way to say it is the fundamental difference between how we operate and how a traditional venture firm or traditional angel investor, or me personally, when I was an active angel investor, looks at companies is that, you know, most investors look at a specific company, and they're actually trying to predict whether that company will succeed or fail that specific company. And our fundamental beliefs. You know, there's two major overriding sort of beliefs that make that not rational to do. The first is, we believe there are too many variables of uncertainty to predict almost anything about the future of a startup at this early stage, you know, human brains like to think you can, but ultimately, you know, you just like you can't predict the weather very far out, or economies, you just can't predict startups very far out the future. The second part is that we already know just based on that, the outcome at our stage is that the most likely outcome of every investment we make is that it's going to fail and go to zero. So we sort of look at this is the most likely outcome of this specific company is that we're going to lose all our money. So we predicted the future, what else can we know? And instead, what we're doing is really saying, All right, this specific company is likely going to go to zero. But how would a pool of 100 companies, all of them had the similar profile? You know, how would that pool perform if we invested them all at this specific valuation. And if you think of it like that, the world and your decision making process suddenly becomes very different. In our view. to give you an example of sort of how this comes into play in the real world, maybe what I could do is I'll take a actual company, of our portfolio, and I'll describe that company how a normal angel investor, venture capitalists would describe it to their partners, and then I'll describe it, how we would describe it to my partners. Okay, so let me come up with one here and how it looked at the time that we invested. Okay, so you know, I'm going to take a company, it's from, you know, a company in San Diego. And so, normally what I do, as a traditional venture capital investor, and go to my partners, they have come across a new company, that's very interesting. It's a SAS product in the veterinary space. And their product, you know, allows that, to interact with their customers, both through SMS text messaging to confirm appointments, instead of mailing out postcards, it also allows our customers to have a mobile app to access, you know, create cancel appointments, and to communicate with the vet and to see sort of their pets history. This space is, you know, there's relatively little competition in this space. And it's pretty recession proof, because that still got a business in a recession, I think this is a huge growing market, you know, in the US, people tend to be spending more and more on their pets each year. And so I think the market size will be substantially larger than it is, you know, in five years than it is now. You know, blah, blah, blah, blah. And, and almost everything about that description, is sort of what the company does, and why I think this idea is a good idea and will have good market acceptance market. So, capital, I would describe this company as follows I go to my partners, by just talking to with them, and I would say have found an interesting companies that we should look at, is a b2b SAS company. Down in San Diego, it's got a SAS product that, you know, that sells in sort of a vertical, you know, a niche vertical. The price point of the product is 350 $400 a month supply enough to support a sales force. The company currently has 35 K, MRR, they've gotten to that point, having only raised you know, a couple hundred to $200,000. The founding is a three person founding team, one of the founders, his previous startup expertise to them have technical experience. And one has domain that significant domain expertise. A company's only burning through $15,000 a month in cash right now, they're looking to raise $500,000 at a $3 million valuation. That's, that's a simple, simplistic, there'll be more things we'd look at. I just sort of give you a profile of a company and my description internally. In RSC, I never even said what the company did. I didn't mention that it was that they sold to that. So I didn't mention what the product did all that it's just, it's a b2b SAS product, with a certain price point that is high enough to support a sales force, they've got this traction level, you know, they've got this, blah, blah, blah, blah, you know, as we dive in, and we'd look at some of the unit economics of what their Kak Telly TV ratios are, and things like that. But ultimately, we wouldn't care what they do to try and predict the market forward. And so when I described that to other investors a lot, I'll sometimes use an example like that for some random company. And, you know, usually the response, I'll get back as well, yeah, that's a great investment. But you can't find deals like that. You know, I'd invest in that too. But you can't find deals that attack but that that valuation, and you know, my answer back to them is usually well, to start with, you'd never invest in that company, because I didn't tell you what they did. And then investors usually will pause and think you're like, Oh, yeah, you didn't. Our philosophy, our belief to those deals are out there all over, they're just not in the main markets. Where everyone is chasing the same deals.

So you are using kind of a checklist and then manually search for all the data you need?

So we define ahead of time what criteria we think are important. And then it is not like there is a single ideal profile we are looking for. We are looking for different criteria that also are more or less important, depending on the business model that a company is doing. So it's not like it's one size fits all. And all metrics just work for all business models. So if you got a B2B business model, there are different things, we care about than if you have a B2C business model. But ultimately, in looking at and evaluating a company, you know, we know, it's sort of a combination of this sort of quantitative scorecard system, and a bunch of knowledge and data that we've accumulated on the market. So we know already, what deals are getting done at what valuations and at what traction levels in the market across the US, because we've been doing this since 2012, we've made over and invested in over 900, companies that been looked at thousands and thousands or 10s of thousands of companies and see what's going on. So we know that in the marketplace, a company with this level of traction doing this is generally getting funded at this valuation. So we also know that, you know, the market as a whole sort of has this average return here. And so we can, you know, keep multiple things we can say here are things that, you know, instead of trying to beat the market, by out picking, you know, which ideas will you know, having a higher success rate, you know, we can beat the market, by very quickly assessing what profiles are, you know, are, are attractive at better valuations than what the markets funding that you're basically putting together, you know, that you could have a profile that's very attractive. And we might say, this is a very attractive profile at a $2 million valuation, but it's actually quite unattractive at a $3 billion valuation. So, you know, for us, there's no, there's not just a simple… it's not just a simple yes or no. And now let's figure out what valuation we can get it that everything's evaluation, and all the other characteristics that we're looking at are intertwined with each other.

What do you think are the main reasons some VCs are still using the traditional approach of investing?

Well, I think, a few reasons. One, it goes against all the core principles of venture capital, the belief of venture capital is that the partners that run a firm are these luminaries who have this ability to predict the future and see which business models will succeed or fail, which companies will succeed or fail, what markets are growing or not. And so, you know, our, our, our investment thesis is sort of based on sort of this fundamental belief that that's not true at all. That's really predictable. So that's, that, that makes it difficult. And psychologically, it's also just really difficult to execute. Like, we're, you know, we're three people to whom come from sort of a quantitative engineering background. And, and we've systematically designed a process that doesn't allow you sort of take into account a lot of the, the fuzzy, subjective data points that most people use, and it's still even, it's still hard for us. You know, I've talked to two firms that have said, they've tried to do something similar, they've tried to create a process where they make very quick decisions. But what ends up happening is they end up spending just as much time internally discussing and doing diligence on a $200,000 investment as they do on a $2 million investment. It's just human brains, I think, are wired for this. So it's very difficult. You want to, you know, every aspect of life, the human brain takes in the data around it, and weaves a story around that, to try and make that data make sense. And to try and, you know, convince yourself that you can take that and tell a story that actually helps you predict, and an account for the future. Because that's what we do in life. That's what you need to do to survive, you know, evolutionarily. So that's what people do, I think, in the startup world, so you people really, brains trick ourselves into, into believing that there's recognizable patterns that can be used to predict the future and, you know, with high confidence level.. It's all psychology.

How do you deal with the problems just described? If you have a bad feeling, do you still invest?
It's not like a bad feeling, it's more of a feeling like, This is crazy. Why am I investing in this. I can't believe that there would be an opportunity here or something, but you know, it's just more reminding ourselves that, hey, this checks all the boxes, you know, this company, they've got a live product, it's generating revenue, you've got some customers that are paying a pretty high price point for this, you've got a team with a lot of domain expertise, that could be making much higher salaries somewhere else. And they're choosing to give up that opportunity costs to build out this product, and they've got a lot more domain expertise than we know about this. So who are we to say this is crazy? So we do have to remind ourselves with that, occasionally. And I would say that universally what we found, because, you know, both in our history of sort of being active investors in the years leading up to before we launched, you know, sort of the two to three years beforehand, when we interviewed and talk with a lot of very active investors. You know, the common thread that we found, for most of you, almost any investor that we met, that it made sort of 100 or more investments. You know, the common thread was that the ones there's largest winners almost always came from the investments that they thought were complete flyers. And where were, they were the least confident about and they invested smallest amount in. And inevitably, the ones that they were the most confident about when they invested whenever they're huge winners. So I think it's just very hard at these very early stages to the revolutionary and the ridiculous look almost the same thing. When you try and filter out the ridiculous, you actually end up filtering out almost all of the revolutionary because they look almost always ridiculous.

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Basic info about your company

The company was founded in 2016 as a spinoff from research at NYU on using artificial intelligence to scale early stage investing, and predict startup success as early as possible. We currently have around 50 people, five zero, working with us. We are based in San Francisco, we have teams in are based in the Bay Area, actually San Jose and Silicon Valley. And we have teams in San Francisco, San Jose, New York. And a large chunk of our team is also in Cairo, Egypt. So all the data processing and data teams is happening there some development there, we also have a small team in Belarus, and one or two people in London and New. And so it's kind of a distributed team. Most of the data science takes happens in Silicon Valley. And then most of the other services that we have are happening outside. So business development, and data science is happening in Silicon Valley. And then also the other functions are happening outside.

How many firms are already using your technology?

Well, we have a little bit over 150 registered users. Activity level is different. There are some that are using the interface. Some are using API's. And, yeah, and the usage is quite varied. I mean, obviously API usage as much higher, much higher volume of usage, versus kind of checking in kind of using the web interface.

What main challenges do you see in the Venture Capital industry today?

I mean, it's a broad question, what is if you're talking about, irrespective of data, or the use of data, I think the problems, venture capital problems are quite diverse. I mean, there are, depending on the tier of the VC, each one looks at their problems differently. And there's also kind of macro challenges with, with the whole VC community, in my opinion, so I'm not sure which ones you want to answer. But you know, for example, tier to tier two, tier two VCs in general, are very, you know, hungry for looking at deals, analyzing a large number of deals, they don't necessarily have all the resources, this is where the use of data can become handy. So how can you analyze a larger number of companies and try to find, find these startups early VCs also talk about the challenge of getting into some of the good deals. So some VC, there is this kind of mentality as well within the VC community with where, you know, most of us are going up, most of the good deals are already taken, or most of the good deals are very hard to get into, you really need to buy your way into the good deals. I guess the overall, we're just seeing how in the current environment, especially in Silicon Valley, we're seeing more and more. The data shows that there's fewer number of deals, closing year on year, but there's more VC money, which kind of means that VCs are piling more money on a fewer number of startups, I think there is that level of, you know, just looking for outside confirmations and outside signals. If I see that other VCs are getting into this deal, then I'll jump on this deal and they want to be part of it, you will find a fewer number of VCs that are, that will go against, you know, go against the grain or go against the tide and invest in companies that that others might not necessarily be, you know, so excited about, we get some of the top tier VCs were there, people are looking for confirmation, where if this VC has invested in this company, you get all these other VCs, you know, how was telling telling this investor? How come you're investing in this company? These guys are ex You know, they're, they're bold, or they're, you know, there is this or this. So, there is that kind of confirmation. And people looking for kind of these confirmations and very few VCs are, are going against that type. I think it's just becoming a prize. And there are a few very interesting articles about the challenges with with early stage investing these days, and how the current partners that are in VC firms are very different from the partners that were there that founded some of these big companies, and how that decision making process has has changed how the risk appetite has changed, and our decision making process has changed. So there are a few a few good articles about this. I can't remember the name of which we see us talking about it.

What are the main challenges in the decision-making process of VCs?

The biggest challenge for the VC community is from my, from my, from our, you know, 2 year experience with working with them so far, I would say is, so we're seeing two types of VCs, we're seeing ones that recognize that data can play a big role in, in, in their decision making process and others that are basically they you know, they don't, they feel like data cannot contribute to, to my success. I've been doing really well just using my gut. And I'm going to continue using my own kind of formula, my gut to make these judgment calls. And we're seeing over the past few years, but overall, we've just been seeing more and more VCs start hiring data scientists, it could be part of a trend, it could be something in Vogue, it could be something that LPs are interested to see. LPs I've heard that LPs are now you know, they want to see a process they want to see something repeatable, they don't necessarily want especially for kind of the emerging managers, they don't necessarily want to see this kind of dependent on a star they want to see. So you’re doing this, but there is a process around that. And you can start seeing you see this, but some of these funds that are emerging, that our data-driven, like Signalfire, Correlation has been around for some time, but there are more and more that are coming out. And you know, Andreessen Horowitz, you know, they started hiring their data scientists back in 2016. And we are seeing more and more VCs that now are having this automation, some of them actually call them partners, like an AI partner, like city light capital, for example. They have one of the partners listed on their website is called the machine. So in terms of challenges, I guess, the challenge, though, When, when, when it comes to so that's kind of in general decision making challenges, I think the problem has been the data, what kind of data can we bring in and use? And can we find the signal and all of this. And the earlier you are in the life cycle of a startup, the more challenging it is. And as you know, from research, research that's done by, you know, Stanford and Harvard Business School and Chicago Booth. And they talk about how early-stage investing is really dependent on the team is kind of one of the strongest signals early on. And, and this, this is where we come in, we've been focusing our data efforts in our data science, especially at NYU on trying to quantify what does a strong team look like trying to generate kind of a predictive signal from the quality of the team. And so our research has been quite, quite focused on this. results have been very promising we to kind of confirm that the team is important. We also show how there is diversity in the types of teams. There are diversities and types of personalities of founders. There's diversity and types of backgrounds of founders, and the ones that are successful are not necessarily on kind of the same. We do show, for example, that there are some there are stereotypes of successful founders. But there are also other types of founders that are not necessarily they don't come they don't appear that there is not kind of the typical cut of a successful founder. Right. So so we thought we show how there is diversity in success. And that's, that's been kind of our focus. So our focus has been kind of making sure we understand their bias, understand their selection bias and understand that there are other data points that take us to look at founding teams as well as they're making a decision.

Are you only focusing your product on the team?

That's part of the product. That's what we focused on initially, which was, which was the team, the founding team, we started to look at other things. So we worked with VCs on. We noticed kind of other challenges. They want to look at compare comparables, look at who else's, you know, compared to the startup, so we started looking at what other startups was the quality of their teams? How do you compare two startups to each other, you cannot use kind of the categorization that is existing today in like Crunchbase, or any other platforms. So what do you do so we do a lot of analysis on. So we created our own clusters cluster together, you know, and train their own 800. And train based on 850,000 organizations and created kind of our own clusters. We created distances between all of these companies. And look at the amount of funding that the companies have received when they were founded, who invested? Where are they located, and we created these kinds of funding scores. We created these VC scores. So it kind of it took, it took a different life form, beyond just the founders, but all of these are there to support dif different types of questions. So next question is, well, this team is already kind of a seed stage. And not isn't seed stage. I'm doing series A or follow ons. So I want to understand what does the landscape look like? What other startups are in the same space? What does the quality of the team look like? And also look at? Well, I want to, you know, if I'm doing even later, later, like Series B, or C, I want the ability to filter for ones that have, you know, what the? What kind of funding, whether it's high or low, whatever it is, and what else? And what kind of investors that are on board. So.

So you are not only using your platform for deal evaluation? I can also use it for deal sourcing?

We have the sourcing, we're not offering it to all VCs. But yes, there is sourcing.

Appendix 3: Overview Main Findings

Basic Information		
Industry challenges	Internal challenges	DM-Process Structure
- Detect interesting opportunities to invest in - Define which opportunities are the "good" ones - Highly competitive environment, more funds -> you have to have a special value prop or pay up; hard to get into the good deals - Overcapitalized market: too much money chasing too few deals -> overload of capital is driving the valuations up too much - For entrepreneurs: high need for connections to get funding (backward focused) - Biased: difficult to raise money if you are not a white male living in a hot spot; every major corporation has now a venture arm - High valuations and bigger round sizes - It is very difficult to get into deals if your brand is not strong	- The more funds, the more the prices go up, the more expensive it gets	- No single process, the process is always different, especially for a young fund - Different depending on VC, size of the company etc.; but all have the same: - 1. Sourcing - Some kind of screening / evaluation - Discussion with the full team, meet founders - Term sheet, due diligence, closing
Challenges in the DM-Process	Degree of reliance	Improvements
- High uncertainty: you can not be completely sure if a company will succeed or not - Making investment decisions with imperfect information - Rare / Never have answers to all the questions that they have - Try to get as much info as possible in a relatively short time - Some investors prefer to rely on their gut rather than on data - What kind of data can we bring and use; identify signals in the data	- Use it for every step in the decision-making process - 4 companies are sourced via the platform - All decisions are still made by humans	- Consider a greater amount of alternatives; able to discover companies that would not have been discovered otherwise - Higher performance - Take decisions with greater confidence - Evaluation of companies in a more objective way - Save time: all the information you need is in the database, you don't have to search for it anymore - See companies related to competitors - Prioritize which companies you should look at first -> makes you more efficient - Get a more complete overview of the data available; if you look only at one data source, data is often scarce - Get a picture of a company much quicker

		than otherwise - Investments that were sourced only through the platform were more scrutinized, but perform better (EQT) - Faster screen more companies: screen 5k – 6k per year - Track 8 million companies globally (EQT) - Leaves people more time to begin instead of doing a lot of manual work
Implementation Challenges	Main reasons for reluctance	Future of VC
- Cultural change: convince a team of professional investors to change their behavior -> force them, slowly change behavior - Data: very sparse on early-stage investment side, feedback cycle takes some years; takes time to get realistic training data, train not for ultimate success, but proxy; still have to apply human measurement; incredible noisy data -> general main problems in ML: data sourcing, cleaning, normalization - It has to be proven before anyone believes in it: when investment professionals see that it thinks better than themselves, they start to trust it more and more	- It is difficult to build the platform and start building the database and matching companies - It takes a lot of guts to say now we're going to change the way we are working - It's the same in all industries: some companies are more willing to use tech to improve their work, some companies are slower - Usage of data goes against the core principles of VCs: partners are able to predict the future and see which business models and markets will succeed / grow - Difficulty for the human brain to rely on data on not on gut feeling - Not trivial to come up with the right implementation in order to be valuable for the investor - Some investors are concerned that using technology will make them redundant	- Data-driven investing will be more common in the next years; this type of tools are improving their job, so their work - Most of the important VCs are already using a data-driven approach - You cannot rely on your brand and your network forever; more and more funds will start to use data - Don't think we will ever get to the stage where AI completely takes over; you will always need people to take care of it, the algorithms, the new data

Appendix 4: Evaluation Usage AI vs. Non-Usage AI

VC	Uncertainty	Bias	Productivity / Efficiency	Return
EQT Ventures			- get a picture of the company much quicker than otherwise - prioritize which companies to look at first	- investments sourced via platform are among top performing
Nauta Capital	- gives us scores for the different characteristics of a company - more info: e.g. overview of competitors	- analyze companies in a more objective way	- help us find companies that we would not have found otherwise - faster, because it processes a lot of info easily	
Georgian Partners			- trying to make us more efficient	
Connetic.Ventures		- removes human bias from the equation	- 12 times more dealflow - Automatically passing 93% of investments	
e.ventures	- more confidence in taking decisions		- Greater amount of alternatives	
Follow[the]Seed		- Democratizes access	- Saves us 99% of the time we would otherwise spend looking into uninteresting deals - We can move much faster	
RSCM			- Improve process	
Hone Capital			- Doubled weekly dealflow	- Success defined by

				follow-on round: combination of ML + humans -> 3.5 times industry average
Signalfire		- Broader geographic scope - Passed on some very well-connected founders and went with some first-time founders	- Detect companies they would otherwise not have seen before	
InReach Ventures			- 10 times more productive - Find deals before anyone else does	
Summary	**2/10**	**4/10**	**10/10**	**0/10**
Calculation	**0.1**	**0.2**	**0.5**	**0.0**