Chapter

Best Practices in Accelerating the Data Science Process in Python

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Abstract

The number of data science and big data projects is growing, and current software development approaches are challenged to support and contribute to the success and frequency of these projects. Much has been researched on how data science algorithm is used and the benefits of big data, but very little has been written about what best practices can be leveraged to accelerate and effectively deliver data science and big data projects. Big data characteristics such as volume, variety, velocity, and veracity complicate these projects. The proliferation of open-source technologies available to data scientists can also complicate the landscape. With the increase in data science and big data projects, organizations are struggling to deliver successfully. This paper addresses the data science and big data project process, the gaps in the process, best practices, and how these best practices are being applied in Python, one of the common data science open-source programming languages.

Keywords: Python, big data, data science process, best practices, open source

1. Introduction

Organizations use insights derived from data to stay competitive. The big data phenomenon has made deriving insights more challenging due to the changing characteristics of the data landscape. The increased volume, variety, and velocity of big data challenge traditional information technology (IT) processes to scale and support big data analytics and data science. Big data is used by organizations as a resource in data science projects to develop new business value and insights. Big data examples include sensor data, images, text, audio, and video data. These data sources can provide new insight opportunities alone and when paired with existing data sources such as organizational data warehouses.

Data science is a competency that leverages data processing, algorithms, and math to develop insights from data. Data science is a core competency that organizations want to develop to stay competitive. While data science as a competency is growing, the practices to ensure these projects are successful have not kept up with the pace. One primary challenge is using existing software development methodologies to deliver data science projects. Applying traditional software methodologies, such as the waterfall approach, is problematic and has been identified as the one contributing factor for data science project failure; organizations are treating data science projects like other IT projects [1].

According to Saltz, current research in data science and big data has primarily focused on the use and application of algorithms and generating insights, but little to no research has occurred about tools, methodologies, or frameworks used to deliver data science projects [2]. Saltz outlined that existing tools, methodologies, and frameworks are not mature enough to effectively use in data science and big data projects [2]. This paper focuses on the changing data landscape, the data science process, and identifying best practices to accelerate the data science processing using Python. Python is an interpreter, object-oriented programming language and one of the most popular tools used in big data and data science projects.

2. The changing data landscape

The increased use of internet-connected smart devices has changed how organizations use information [3–5]. The Internet of Things (IoT) creates large amounts of data quickly from sensors embedded in devices, one of the contributing factors in creating the category of big data [5]. The rise of data science is primarily a result of big data, due to the need to analyze data, other than traditional structured data, such as text, machine-generated, and geospatial data [5]. Big data and data science go hand in hand; thus software development approaches used need to consider both [1, 4, 6]. Results of a data science project not only include insight, but also working software that needs to be deployed and supported. Analyzing the characteristics of big data highlights the challenges with traditional software development approaches.

2.1 Volume

The growth of data impacts the scope of data used in data science and software development. Scope increases project complexity where new technology is used to accommodate more data [3]. Large amounts of unstructured data cannot be easily ingested and processed using a traditional relational database for example.

2.2 Variety

Data variety becomes a concern for software development as the types of data sources to be used for development and analysis increase. The variety of data means increasingly complex forms of data such as structured and unstructured data [3–5]. Traditionally, structured data is created in rows and columns and easily understood; however, unstructured data comes in different forms, levels of details, and without clear metadata complicating the ability to understand and use [3–5].

Examples of data variety include images, IoT sensor data, clickstream, images, and event data. These data sources may be analyzed independently, but often analysis requires data to be integrated. Integrating multiple data sources with different structures increases the complexity of projects.

2.3 Velocity

The speed at which data is created is referred to as velocity. In 2014, Twitter averaged 1 billion tweets every few days [7]. Fresher data results in the ability to analyze new patterns and trends that were not possible before big data. With IoT applications, data that is 15 minutes may be too old for analysis [5]. Data acquisition becomes a challenge as traditional data acquisition focused on extract, transformation, and load (ETL) of data. Increased velocity changes the order where data is loaded first, then analyzed, otherwise known as extract, load, and then transformation (ELT) [3–5].

2.4 Veracity

Veracity refers to how accurate data is and how well the data is understood. Big data is not clearly analyzed prior to ingestion due to the volume and speed of creation, which results in data that may have credibility and reliability problems. Often metadata for big data sources do not exist. These challenges increase the complexity of deriving insights from big data sources [3–5].

Software development lifecycles have traditionally focused on requirements which drove the design, leveraging the design to develop software, testing, and then deploying the software. Projects using big data change the order in which these phases occur. Big data sources are ingested, stored, and explored first, and then requirements are determined which changes the traditional order of activities for project delivery. Using the traditional software development lifecycle for projects that include big data has failed further supporting that projects using big data need to adjust project approaches [1].

According to Mayer-Schönberger and Cukier, big data changes how the world interacts and means a disruption to what was considered normal. This disruption also means disruption to the software development processes that create the software that derives knowledge and value from data. Big data results in changes to IT processes, technologies, and people. One greater reliance observed is that data scientists need to address the complexity introduced with big data and help derive the knowledge from data [3, 4].

3. The data science process

According to Saltz, most data science processes focus on the tasks that need to be completed in data science such as the techniques to acquire and analyze data [2]. Saltz analyzed different data science approaches and found that most outlined the steps as data acquisition, cleansing, transformation, integration, modeling, analysis, and deployment [2]. The data science approaches are task-oriented, and no real evolution of the process had occurred since the cross-industry standard process for data mining (CRISP-DM) was introduced in the 1990s [2].

3.1 CRISP-DM

The most commonly used data mining process is CRISP-DM which is a process that conceptually described the stages used in data mining. Originally created to support data mining projects, it has been adapted by data scientists. There are six stages in the CRISP-DM process which are presented sequentially, but iteration is expected:

- Business understanding
- Data understanding
- Data preparation
- Modeling
- Evaluation
- Deployment

3.2 Business understanding

The start of the process, business understanding, focuses on the business value of the project. Once requirements and objectives are understood, the problem definition is created. Data science projects start with a problem to be addressed or a question to be explored. Tools to support identifying the problem include diagrams such as a decision model such as a fishbone diagram [8].

3.3 Data understanding

Once the problem to be addressed is identified, the next focus is on data source identification and collection. Data source identification includes identifying the sources, such as a transactional processing system, and the attributes needed to address the problem. Problems may involve several different data sources, which means data integration work is likely. After integration, data is profiled and statistically analyzed to determine quality, demographics, relationships between variables, and distribution. The outcome of data understanding is a definition of how the data can be used. The data understanding stage is often referred to as exploratory data analysis (EDA) [8].

3.4 Data preparation

The goal of data preparation is to create the data that is to be used in the modeling stage. Input from data understanding is used to determine the final set of attributes, often referred to as features that will be used in the model. Preparation includes integration, cleansing, and deriving of new attributes. Data preparation is iterative as the training and testing of the model may require new or changed data. The result of data preparation is the data set to be used as input into the modeling stage [8].

3.5 Modeling

As part of the modeling stage, different techniques and algorithms are used to determine the best model. Modeling goes through cycles of testing and training, where the data scientist adjusts parameters to produce the best outcomes. It may be necessary to return to data understanding and preparation stages if the model performance is not acceptable [8].

3.6 Evaluation

Model evaluation is determined based on the overall fit to the problem statement and business objectives. Evaluation is conducted by analyzing error rates, variance, and bias of the model. Often models using different techniques are compared to determine the best performing one. Once the best performing model is identified, a formal review is conducted to move to model deployment [8].

3.7 Deployment

The deployment stage is often overlooked and unplanned for but important as this is where business value is realized. Deployment focuses on a working software model that can be supported and executed on a regular frequency. Once deployed, models are monitored for performance as model accuracy will degrade because of organizational change and time. Models are often retrained once this occurs [8].

The description provided of CRISP-DM is a summary and does not highlight the granularity of effort needed for successful data science outcomes. Many organizations use CRISP-DM as a framework and add steps to each stage for software development teams to follow. There was an effort to create CRISP-DM 2.0 in 2007, but there is no new research or activity in this area [2].

4. The role of open source in data science projects

Landset et al. outlined that big data has caused IT departments to rethink how data is processed and the use of data science software [9]. Choosing the right processing framework and data science software can be challenging due to data science project requirements and that data complexity might require more than a single solution [9]. Additionally, tools available to conduct data science are many with partial functionality, limited ability to handle big data, and integrate into big data processing platforms, which contributes to the fragmentation and complexity of the data science and big data technology solutions.

Landset et al. called out that no single tool or framework covers all of the requirements of a data science project [9]. Data scientists and computer engineers need tools that support computing performance, usability, machine learning algorithm breadth, and portability. To support these needs, data scientists and computer engineers have turned to open-source tools to address the variety of requirements of data science projects. Open-source technology categories include data processing platforms and engines and machine learning tools. The Hadoop ecosystem is commonly used to address the data processing aspect of big data and data science [9]. The Hadoop ecosystem includes workflow, data collection, storage, and processing, for example. While there are many open-source machine learning tools, Python has become one of the leading programming languages used in data science as well as R and Mahout [9].

5. Challenges with big data and data science projects

To best understand what the best practices are in big data and data science projects, it is beneficial to highlight some of the challenges. Some of the challenges highlighted so far include lack of a detailed software development methodology and the characteristics of big data. Other challenges include that many data science projects are managed as a single project and the focus on reproducibility, collaboration, and communication is overlooked [10].

Andrejevic argued that big data changes how businesses and customers interact which disrupts normal business processes [11]. This disruption also means disruption to the software development processes used to create the data science models that derive data insights [11]. When organizations leverage big data, this results in changes to IT processes, technologies, and people [11]. One change observed is that data scientists are challenged to handle all activities related to the data science process including all the data wrangling activities which can consume most of the project timeline [3, 11]. Traditional IT projects normally have defined roles and activities involving several team members [3, 11].

Mayer-Schönberger and Cukier highlighted the impact of big data on organizations citing that the volume, variety, and velocity characteristics make data science and big data projects difficult to deliver using traditional IT project approaches [12]. Volume challenges how much data is ingested and consumed, variety highlights the need to support different data structures, and velocity outlines the need to ingest data as soon as it is created [12]. The need for nontraditional (non-relational databases and storage systems) data processing platforms and software that can handle big data is the reason why traditional IT processes are unsuited for data science and big data projects [12].

Some of the challenges in delivering data science and big data projects include having clear business objectives, dealing with volume, identifying what data to use, understanding opportunities to store and process data, and having clear privacy and security requirements [13]. Mousannif et al. proposed a framework for a big data project workflow that included planning, implementation, and post-implementation phases [13]. Mousannif et al. highlighted a need to focus on reproducibility of data ingestion, processing, and storage to expedite future big data projects [13].

Lowndes et al. proposed that data science and big data projects can be accelerated by focusing on reproducibility, transparency, and collaboration by implementing new processes leveraging open-source tools [10]. Lowndes et al. published the results of implementing new processes to accelerate data science for the Ocean Health Index (OHI) project which is repeated yearly to address the change in global ocean health [10]. New processes were implemented in the categories of reproducibility, communication, and collaboration and broken down further into specific tasks [10].

Lowndes et al. outlined that the following areas need to be addressed for reproducibility: data preparation, modeling, version control, and organization [10]. Data preparation includes creating and leveraging common coding routines to sort, cleanse, transform, and format data [10]. Modeling focused on standardizing to a common programming language to ensure all were using the same algorithm methods which resulted in reduced iterations on validating results [10]. Version control ensured that the team was treating the data science process as a software development process where code was tracked and change management was put in place to improve software reusability [10]. Organization was addressed through leveraging in-code documentation standards, file naming standards, and treating each data science project as a single set of common code by implementing the project function in the programming language [10].

Lowndes et al. proposed that collaboration be improved by having centralized coding repositories, common workflows for promoting code, and a centralized repository for communication [10]. Git, a widely used cloud-based version control system, was used as the common coding repository, and a Wiki was used for documenting projects [10]. Having a common project management approach was also highlighted as a benefit [10].

Lowndes et al. focused on improved team communication and effectiveness through sharing data and methods [10]. The focus was on not redoing work if the work was already completed [10]. Data sharing covered centralizing cleansed data sets for reuse and creating common data pipelines to be used for data science projects (like the OHI project) [10]. Since the OHI project is completed yearly, much of the software development work could be leveraged from the prior year in place of starting the project from scratch each time [10].

There are several gaps and lack of maturity in the data science process as outlined by the research of Landset et al., Mayer-Schönberger and Cukier, Mousannif et al., and Saltz. Based on these gaps, best practices will be proposed to accelerate the data science process leveraging Python. While other open-source programming languages could be used in the same manner as suggested in the next section, the choice of Python is not meant to recommend that Python is the only choice or best choice to use in data science projects. Python was chosen due to its popularity, performance, and portability capabilities in the data science and big data space.

6. Best practices to accelerate data science with Python

People, process, and technology are contributing factors to data science complexity. Data scientists are expected to multiskilled resources knowing statistics, big data platforms, pipeline development, and deep learning neural networks. The primary process leveraged for data science is CRISP-DM which has not really changed since it was introduced in the 1990s. Lastly, there is so much available technology to use in data science it boggles the mind. While these problems will take time to solve, there are some best practices that can be leveraged to make data science less complex and more scalable in organizations. Best practices will be addressed in general as well as with Python.

6.1 Team collaboration

Data science initiatives tend to be done as independent efforts or one-off projects. Data scientists often work as the project manager, data wrangler, software developer, data engineer, tester, and do the data science as well. Data scientists cannot be effective assuming all these roles. With data wrangling (cleansing, transformation, formatting, etc.) taking up more than half the project, the data engineer has emerged as a key role in supporting the data science process. Assign a data engineer to handle the data wrangling, and let the data scientist focus on data science. Additionally, data science initiatives are projects. Ensure the data science initiative has a lead who can remove barriers, deal with stakeholders and get the required subject matter experts to support the data science project. Collaboration is key in making progress and valuable data science results [10, 14].

6.2 Why Python?

Python is an interpreter, object-oriented programming language introduced in 1991 and has emerged as one of the leading open-source data science tools used by data scientists [15]. Python has become a leading data science tools for several reasons. As an open-source tool, Python is freely available and modifiable, keeping costs low and promoting rich features through the open-source community [6].

Python is easy to learn. Although it is a programming language, the syntax is easy to adopt, especially by programmers, and through studies, the learning cycle tends to be shorter than a comparable data science tool—R. R is another open-source programming environment specializing in statistical computing and graphics. Both tools are comparable in many areas; however, Python has emerged as being more scalable and portable [15].

Scalability and portability are important in the data science community. With big data characteristics such as volume, velocity, and variety, data science tools need to be robust. Scalability refers to the ability to handle growing computing requirements, and portability is the ability to easily run on multiple computing platforms. Python has libraries and packages that support fast computing, and it runs on the common operation systems such as Linux, Windows, Unix, and macOS [15]. While Python is discussed as a data science tool, it is also a programming language used in the development of applications.

Team collaboration was mentioned as a best practice in data science; however, collaboration is inherent within open-source communities. Python has a deep reach in the data science community with data scientists contributing to creating new libraries and code routines. In addition, the tech companies often choose Python to release new functionality first. Google, for example, released its deep learning package TensorFlow first in Python, setting a trend [14, 15]. The Python community provides an avenue for new data scientist or even seasoned ones to find solutions to data science problems. Communities often exchange questions and answers on websites such as Stack Overflow or share code on public repositories such as Git [14, 15].

Through the data science process, data scientists must visualize data relationships, and Python also supports robust visualization options [14]. Libraries exist to support multiple graphing options such as charts, graphs, and interactive plots [15]. Libraries are collections of methods and functions that data scientists can leverage without having to write new code.

The most significant factor supporting Python as the leading open-source data science tool is the number of libraries available for data scientists. These libraries, as mentioned, provide prepackaged methods and functions, and several libraries available in Python have enabled data scientists to leverage the latest machine learning algorithms (such as TensorFlow), manipulate data easily, and create data science models that perform and scale [15].

While there are several reasons why Python is popular with data scientists, other tools such as R, Scala, and Ruby are available that provide similar functionality as Python. The intent of the following section is to show how functionality in tools can accelerate the data science process. The scope of this research is not to compare Python to other languages, but to illustrate how to accelerate the process of data science.

6.3 Libraries in Python

Python has a plethora of libraries available for use, but there are a few that can accelerate the data science process and have become the set of tools that data scientists leverage. Libraries that are heavily used by the data science community include NumPy, SciPy, pandas, Matplotlib, and Scikit-learn. The "Py" at the end of Python libraries is pronounced "Pie" [15].

NumPy is a library created by Travis Oliphant that is leveraged by most of the other data science libraries. NumPy provides a large set of mathematical functions that operate on multidimensional array data structures. Arrays allow data to be stored in blocks across multiple dimensions which enable mathematical operations to be applied to matrices and vectors. Arrays support vectorization which allows fast math operations supporting scalability and performance which is valuable in solving data science problems [15].

SciPy is another library created by Oliphant, Peterson, and Jones. SciPy leverages NumPy functionality and includes additional algorithms, matrix processing, and image processing; SciPy and NumPy are often paired together in data science where NumPy provides enhanced performance and SciPy an extended library of mathematical functions and advanced processing on data types [15].

Pandas focuses on object data structures. Most working in data management default to thinking of data in rows and columns. Pandas handles processing of data tables with different data types (very similar to a relational database table) as well as time series. Pandas enables easy data manipulation without the constraints of a relational database. Slicing, dicing, dropping, and adding elements, reshaping, joining, and aggregating data is much easier, leveraging the object data structures called dataframes. Dataframes are commonly used in R as well [15].

Matplotlib is another library that leverages NumPy. Matplotlib is highly used for charting, graphing, and time series analysis, especially in the data understanding and preparation phases of the data science process [15].

Scikit-learn (also referred to as Sklearn) contains the core data science method and functions for Python [15]. Scikit-learn contains methods and functions that cover supervised and unsupervised algorithms, model selection, model validation, and final evaluation of performance. Several modules exist that data scientists should be aware of such as preprocessing and feature extraction that contribute to accelerating the data science project. Specific examples will be addressed as part of the data science process. The stages of CRISP-DM will be used to address when best practices get leveraged. Although CRISP-DM starts with business understanding, the application of Python typically starts in data understanding.

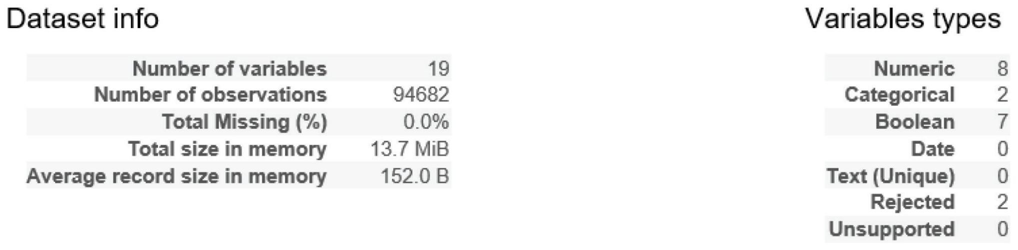
6.4 Data understanding

Data understanding focuses on the data collection and analysis of the data sources to be used in the data science project. In data understanding, the three areas that can help accelerate the data science process are data profiling, data visualization, and data preprocessing. Data profiling is the process of gathering statistics and demographics about data sets. Profiling provides the ability to assess data quality and understand how attributes are populated. Library pandas_profile can be leveraged to complete data profiling. Data profiling includes data set info, variable types, descriptive statistics, and correlations between numeric variables [15]. An example of the output is listed in **Figures 1** and **2**.

6.5 Data preparation

Data preprocessing focuses on scaling, normalization, binarization, and one hot encoding. Scaling is applied when the values of potential features have a large variance between random variables. Data normalization is used to adjust the values in a feature vector so that they can be measured on a common scale. Binarization is used to convert a numerical feature vector into a binary vector such as true or false. One hot encoding is a process by which categorical variables are converted into a form that could be provided enables better prediction by algorithms. One hot encoding determines feature frequency, identifies the total number of distinct values, and then uses a one-of-k scheme to encode the values [15, 16]. Preprocessing data accelerates the data science process by minimizing the number of iterations in the modeling stage. The Scikit-learn library has methods for scaling, normalization, binarization, and one hot encoding such as sklearn.preprocessing.

Automating feature selection is the process of reducing the number of input variables used by predictive models. Feature selection can be a time-consuming process for data scientist. Automatically selecting those features that are most useful or most relevant for use in the analytical problem accelerates the data science process. Scikit-learn has multiple methods that support overfitting, improve accuracy, and reduce the training time of models such as sklearn.feature_extraction [15, 16].



Dataset info

Number of variables	19
Number of observations	94682
Total Missing (%)	0.0%
Total size in memory	13.7 MiB
Average record size in memory	152.0 B

Variables types

Numeric	8
Categorical	2
Boolean	7
Date	0
Text (Unique)	0
Rejected	2
Unsupported	0

Figure 1.
The data set information and variables types can be created using the pandas_profile library.

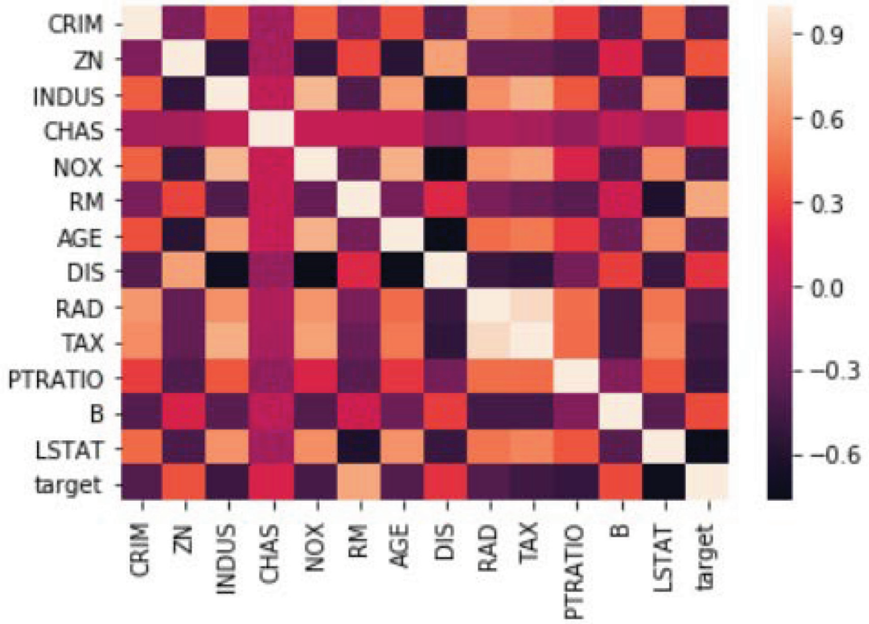


Figure 2.
Data visualization using the Matplotlib and Seaborn libraries is highly effective in the data understanding stage. Both libraries support multiple charts and graphs to visualize data relationships. Using the Matplotlib library, a correlation heat map can be created to demonstrate correlations within a data set.

6.6 Data pipelines

When data science is done as an independent effort, much of the work in the data understanding and preparation phase of a data science project is done without the end-state vision. Data understanding and preparation mimics many of the development activities that are used to develop data pipelines. The activities to develop the data pipeline include acquiring the data, exploring the data for deep understanding and value determining, integration, transformation and formatting to get the data ready to be consumed by the model. Why not develop the pipeline as part of the project? At the end of the data science project, the expectation is a working data science model. The model will have no value if the data pipeline to produce the input is not available and ready for production deployment.

With data understanding and preparation taking more than 50% of the project timeline, data scientists need to have access to the correct data in the correct format. Not only will developing the pipeline as part of the project prepare the data for production consumption, but it may also be leveraged for other data science projects.

Another area to review is existing ETL or pipelines in the data warehouse environment. Data science leverages all kinds of data, and often models use existing transactional data enriched with big data sources. Reusing existing ETL or pipelines promotes consistency and reduces the development work in the data science project. Pipelines in Python are an easy way to automate common and repeatable steps such as the preprocessing steps. One pipeline library that can be leveraged in Python is Luigi.

One of the challenges with data pipelines is pipelines contain components that need to be linked together for processing. Many of the components in a pipeline support long-running job, streaming of data, and running machine algorithms that may fail. Luigi, the pipeline library, can help link many of these pipeline components together or provide the workflow management so that the components can be run and managed as a single pipeline. Workflow management handles the dependencies between the components. As part of the Luigi library, templates are provided that provide support for long-running jobs in Python. Luigi also contains file system abstractions for the Hadoop File System (HDFS) which ensures the pipeline will not fail holding incomplete data. Luigi also includes a Visualizer page that provides a visual status of the pipeline and provides a visual graph of the pipeline [15].

6.7 Modeling and evaluation

Scikit-learn is the library that is leveraged for modeling and evaluation. The data scientist will choose the modeling approach or algorithm to be used for the data science problem; however, tuning the model and choosing the best performing model can be a challenge. Scikit-learn has several functions and methods that can be leveraged to expedite this stage of the data science process. One example is train_test_split which supports the random creation of training and test files [15].

Training and test files are used to "fit" the model, and through this process different settings or hyperparameters are tuned to improve the accuracy of the model. This causes overfitting where performance is no longer generalized in the model. The approach to avoid overfitting is called cross validation. A function in Scikit-learn can be leveraged called cross_validate where another data is held out, referred to as the validation data set. The cross_validate function can be used where the training is completed, but evaluation is completed on the validation set. Once appropriate accuracy is achieved, the test set is used for final evaluation [15].

Model and feature selection can also be time-consuming activities in the data science process. Scikit-learn can also be leveraged to evaluate an algorithm's performance as well as to select the best fit parameters using cross validation. Another method that can be used is GridSearchCV. GridSearchCV is used to wrap an estimator, where it selects parameters from training file to maximize the score; GridSearchCV can be used as part of a pipeline to combine several transform components and estimators to create a new estimator as well. Scikit-learn offers many options for data processing, model selection, and model validation. It also includes a complete set of methods to support many different modeling algorithms [15].

6.8 Deployment

Software engineering principles should be applied to both the data pipeline and the data science model. The likelihood of using big data where volume, velocity, and variety need to be addressed means that the data science project scope is not only to produce working software, but also software that has quality and can scale.

The characteristics of data science software quality specifically focus on supportability, reusability, reliability, portability, and scalability. Supportability focuses on the ability of IT operations to address maintenance and failure issues. Reusability is the ease with which software can be reused other data science projects. Reliability is the frequency and criticality of software failure, where failure is an unacceptable behavior occurring under permissible operating conditions. Portability is the ease with which software can be used on computer configurations other than its current one. Last, scalability is the ability to handle performance demand without having to re-architect the software. All these characteristics should be applied to data science pipelines and models [10].

Scalability tends to be the largest challenge with machine learning algorithms. The expectation with machine learning algorithms is that as data increases, the algorithm addresses the volumes in an efficient way where the run time increases linearly. Machine learning algorithms that do not scale increase running time exponentially or simply stop running. One way to address the scaling problem is to use out-of-core learning [15].

Out-of-core learning uses a set of algorithms where data that does not fit into memory can be stored in another location such as a repository or disk. Scikit-learn includes functionality that supports the streaming of data from storage and iterative learning [15].

6.9 Summary of Python libraries to accelerate data science

As mentioned prior, there are many tools available to data scientists, and the landscape is evolving daily [9]. For this research, Python was chosen due to popularity, and other open-source languages may have similar capabilities. Several different Python libraries were recommended that could accelerate the data science process. A summary of these libraries follows.

There are five core libraries available in Python that accelerate performance in the data science process. NumPy provides a large set of mathematical functions that operate on multidimensional array data structures. SciPy, which is often paired with NumPy, includes additional algorithms, matrix processing, and image processing functionality. Pandas enables the use of object data structures in rows and columns. Matplotlib is a visualization library which pairs well with NumPy. Scikit-learn contains many different machine learning algorithms.

While most of these core libraries will be used in the phases of data science, there are several packages in each library that help accelerate some of the challenges with the data science process. In the data understanding stage, both Matplotlib and Seaborn support many different types of visualizations. Pandas_profile, part of the Pandas library, quickly completed the profiling process exposing data set demographics.

Data preparation tends to make time which could be better spent on data science modeling. Leveraging the packages of preprocessing and feature_extraction as part of Scikit-learn helps reduce some of the work. Preprocessing quickly handles scaling, normalization, and binarization of variables. Feature_extraction evaluates different features for value to reduce training time. Focusing on building a reusable pipeline in the data preparation stage can accelerate the deployment stage. Luigi is a pipeline package that can automate code modules, create workflow, and help with support of data pipelines once in production.

As part of modeling and evaluation, packages from Scikit-learn are used to automate training and testing data set creation using train_test_split. Both the cross-validate and GridSearchCV can be used to evaluate models and compare models to get the final recommendation. Once the model is ready for deployment, the use of out-of-core learning can be used to maximize the use of computing resources in production as data science models tend to heavily use computing power.

7. Conclusion

Current research in data science and big data has primarily focused on the use and application of algorithms and generating insights, but little to no research has occurred about tools, methodologies, or frameworks used to deliver data science projects. Analyzing the characteristics (volume, variety, and velocity) of big data highlights the challenges with traditional software development approaches. Results of a data science project not only include insight, but also working software that needs to be deployed and supported; thus software engineering practices should not be avoided. Leveraging tools such as Python can help accelerate the data science process. Python has become a leading data science tool for several reasons, primarily due to the functionality that is created quickly to address the data science community needs.

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