Coping with Uncertainty:
Modelling Personality when Collaborating on Noisy Problems

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Abstract

Collaboration is an essential aspect of human interaction. Despite being mutually beneficial to everyone involved, it often fails due to behaviour differences as individuals process information, form opinions, and interact with each other, especially when their task contains uncertainty. Thus, to understand collaboration on noisy problems effectively, it is necessary to consider the psychology of the individuals involved. We propose an agent-based model of collaboration that incorporates human psychology. We abstract the shared goal as a shared optimisation task, and model personality differences as strategies for moving within, interpreting and sharing information about the solution space. Although used to explore a specific hypothesis here, the model is psychology theory-agnostic and problem-independent and can also be used to investigate other tasks and different psychology theories.

Introduction

Humans are social animals. We spend most of our lives collaborating with other people at work and at play. Collaboration makes our activities more effective, especially complex innovative work where uncertainties are common. As a result, organisations seek to create a collaborative environment where members of a team work together to achieve shared goals.

The need for good collaborative environments is increasing as choice of work is today influenced by job satisfaction (e.g., shared vision, doing meaningful work, having good relationships with immediate manager and teammates) (Buckingham & Coffman, 2014). There is also an increase of self-employment and new working arrangements in the "gig economy", where parties convene quickly to meet urgent needs. In response to these changing needs, rather than forcing employees to cooperate, organisations are moving towards creating collaborative environments where employees work together to achieve shared goals.

Despite the importance of collaboration, it has received comparatively little attention compared to its close cousin – cooperation. Cooperation is a process whereby individuals with *competing* goals work together for mutual benefit instead of competing with each other (Axelrod & Hamilton, 1981). Agent-based modelling researchers over the years have been fascinated by the conditions in which cooperation develops when each individual is incentivised to be selfish (Axelrod & Hamilton, 1981; Rand et al., 2009), usually not by choice but by some rational calculation of current and future benefit.

Collaboration is not the same as cooperation. During a collaboration, individuals with the *same* goal work together to achieve their common goal. Each collaborating individual gains from collaborating. For example, a criminal may choose to *cooperate* with a police officer even though they have competing goals; multiple police officers *collaborate* with each other because they have a shared goal.

If, like studies of cooperation, we assume rationality of all individuals, then every collaboration should always be successful. In practice, it is clear that the true behaviour of collaborating individuals can be irrational. Real problems and goals contain uncertainties, which may be handled differently by members of teams. Misunderstandings and conflicts are common. Parties sometimes disband before shared goals are achieved, and in the worst case, they choose never to work together again despite it being mutually beneficial. Psychological research suggest that individual differences can emerge as predictors of behaviours as individuals process information, form opinions, and interact with each other (Anastasi, 1937; Cronin & Weingart, 2007). Thus, to understand collaboration effectively, it is necessary to consider the psychology of the individuals involved (Anastasi, 1937).

In this work, we develop an agent-based model that incorporates human psychology, in order to understand what helps and hinders collaboration, specifically in terms of tolerance to uncertainty. We abstract the shared goal as a shared optimisation task, add uncertainty to the task by varying the degrees of noise perceived by agents, and model personality differences as strategies for moving within, interpreting and sharing information about the solution space.

The motivation behind this work is to address some of the significant issues in psychological research today. Human experimentation can create ethical issues and has been increasingly difficult to conduct, making it more difficult to progress our understanding in the area. Our model creates a realistic laboratory for which to conduct such experiments. Our model is agnostic of any specific psychology theory, and indeed could be used to compare and assess competing theories. We anticipate that by introducing rigorous computational modelling to this sometimes contentious area, it will help strengthen the field of psychology.

Background

Individual Differences Research

Individual differences research is a field in psychology that investigates differences in individuals and groups in terms of personality, ability, self-perception, motivation, interests, and values (Anastasi, 1937; Eysenck & Eysenck, 1987). It is based on the observation that individuals have different perceptions and thought processes, leading to different behaviours under the same circumstances. Such differences inadvertently influence collaboration (Furnham, 1992).

Personality psychology is one of the main areas of research in individual differences. There are several existing theories of personality. In trait theory, personality is made up of a number of broad traits (i.e., habitual patterns of feelings, thoughts and behaviour) and each individual possesses all the traits at different levels on a continuum. Some of the best-known research in trait theory include the five-factor model (FFM) (Goldberg, 1990) where an individual is characterised on five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. In type theory, personalities are classified into distinct types (e.g., introverted or extraverted) rather than measured on a continuum (e.g., the level of extraversion). Some of the best-known work in type theory include Jung's Type Theory (Jung, 1923), and the Myers-Briggs Type Indicator (MBTI), which was built on Jung's work (Myers, 1962) (described in the next section).

Agent-based Models of Personality

Agent-based modelling has a long history of success in many related fields from economics and cooperative behaviours, to social conflict, civil violence and revolution. However, its use remains very limited in studies of how human interaction is affected by individual personality.

Salvit and Sklar (2012) used the Myers-Briggs Type Indicator (MBTI) to model termites gathering food. In their model, Thinking agents set straight for their targeted food, while Feeling agents avoid food that their neighbours are targeting. Sensing agents focus on food that is close by and return to the place they last saw food if they cannot see food, while Intuitive agents prefer bigger clusters of food and explore new areas when they cannot see food. They found that agents with different personality types performed differently in the same environment.

Campos et al. (2009) simulated a firefighting scenario where a building is on fire and a person is in danger. A firefighter agent can either put a safety-net in place and wait for the person to jump on it or enter the building and bring the person out. They simulated agents' MBTI personality types and found that Sensing agents prefer to use the safety-net and Intuitive agents prefer to enter the building.

Ahrndt et al. (2015) used the five-factor model (FFM) to model ants in a colony working together to collect food and defend themselves from other ant colonies and bugs. In their model, variations on agreeableness and extraversion influence an agent's preference to commit to selfish or altruistic goals, and variations on conscientiousness influence an agent's preference to change their intentions.

Finally, Durupinar (2011) extended an existing crowd simulation system using the FFM. They provided each agent with personalities that are associated with an existing behaviour in the system and found that specifying an agent's personality leads to an automation of low-level parameter tuning. In their model, people with low conscientiousness and agreeableness cause congestion and neurotic people display panic behaviour.

All of these works demonstrated that using psychology theory to model agent behaviours can increase our understanding of human interaction and collaboration. However, as many these models were early prototypes, the interpretations of the personalities only loosely match the actual psychology theory they are modelling. In addition, the personality models are context dependent: personality is modelled specific to the environment in which agents are simulated and the tasks that agents are addressing (Salvit & Sklar, 2012). A more general, problem-independent computational model would improve our understanding of the effects of personality, and also to help analyse and compare different psychology theories.

Modelling Psychology Theory

As many different personality theories exists in psychology research, it is necessary to choose one so that it can be investigated in our model. Here we use Jung's Type Theory (Jung, 1923); future work will examine the five-factor model (FFM) (Goldberg, 1990).

Jung's Type Theory

Jung's pioneering theory of psychological type is based upon the recognition that what appears to be random behaviour is actually the result of differences in the way people prefer to use their mental capacities (Jung, 1923). Specifically, according to Jung, there exist distinctions with respect to the sources from which information is derived, the ways in which information is perceived, and the ways in which information is dealt with in reaching conclusions.

A person's general attitude determines the sources from which they prefer to derive information. According to Jung (1923) there are two opposing attitudes:

- **Extraversion.** Directs perception and judgment on outer world of people and things.
- **Introversion.** Directs perception and judgment on inner world of concepts and ideas.

With these two fundamental attitudes, each person performs cognitive functions along two dimensions: judging and perception. According to Jung (1923), there are two opposing ways of judging:

- **Thinking**. Impersonal assessment, comes to conclusions based on a logical process, aimed at an impersonal finding (facts and ideas), analyses and determines the truth or falseness of information in an impersonal fashion.
- **Feeling**. Person-centred assessment, comes to conclusions based on a process of appreciation, giving things a personal, subjective value.

According to Jung (1923), there are two opposing ways of perceiving:

- **Sensing**. Concrete perception, finds interest in actualities (made aware directly through the senses), prefers not to go beyond the objective, empirical world of facts. Relies on concrete, actual information.
- **Intuition**. Abstract perception, finds interest in connecting concepts and drawing parallels (made aware indirectly by way of the unconscious). Relies upon their conception about things based on their own understanding.

Each general attitude (extraversion and introversion) is used as a source of information for each function (Thinking, Feeling, Sensing, Intuition), resulting in Jung's eight psychological types: extraverted Thinking (Te), introverted Thinking (Ti), extraverted Feeling (Fe), introverted Feeling (Fi), extraverted Sensing (Se), introverted Sensing (Si), extraverted iNtuition (Ne), introverted iNtuition (Ni). These types do not exist in isolation in a person. Jung observed that most people have a most developed function (referred to as "dominant") supported by a lesser developed function (referred to as "auxiliary").

Myers-Briggs Type Indicator (MBTI)

The Myers-Briggs Type Indicator (MBTI) is a formalisation of Jung's work (Myers, 1962). Since Jung did not provide a method to determine the personality type of a person, Myers and Briggs developed a questionnaire to assess a person's type preferences on four opposing dichotomies: Extraversion (E) – Introversion (I), Sensing (S) – Intuition (N), Thinking (T) – Feeling (F), and Judging (J) – Perceiving (P) (Myers, 1962). J–P is not specifically recognised as a separate dimension in Jung's theory. It defines the person's preferred manner (either S–N or T–F) of dealing with the outer world and was proposed as a fourth dichotomy in the MBTI as a way of determining the dominant and auxiliary functions. This results in a total of 16 personality types as seen in Table 1.

Type	**ISTJ**	**ISFJ**	**INFJ**	**INTJ**
Dominant	Si	Si	Ni	Ni
Auxiliary	Te	Fe	Fe	Te
Type	**ISTP**	**ISFP**	**INFP**	**INTP**
Dominant	Ti	Fi	Fi	Ti
Auxiliary	Se	Se	Ne	Ne
Type	**ESTP**	**ESFP**	**ENFP**	**ENTP**
Dominant	Se	Se	Ne	Ne
Auxiliary	Ti	Fi	Fi	Ti
Type	**ESTJ**	**ESFJ**	**ENFJ**	**ENTJ**
Dominant	Te	Fe	Fe	Te
Auxiliary	Si	Si	Ni	Ni

Table 1: Myers-Briggs Type Table showing the 16 personality types, with dominant and auxiliary functions (Myers, 1962).

MBTI is the most widely used measure of Jungian psychological type in industry (Chen & Lin, 2004). Although it is criticised for its use of scales to identify binary preferences (scales are conventionally used to measure intensity over a continuum) (Pittenger, 2005), millions of people take the test every year, and the results are used for team building and management development (Chen & Lin, 2004). Eighty-nine of the Fortune 100 companies use MBTI (Gladwell, 2004) and it is widely used within education (Schroeder, 1993).

The Personality Agent-based Model

In this work, we propose a psychology theory-agnostic and problem-independent model of human collaboration, which may be used to investigate any psychology theory or collaborative task. We achieve this through the following key abstractions:

- **Problem**. We abstract the shared goal of all agents as the shared task to optimise a function (i.e., find the values of $\mathbf{x}$ such that $f(\mathbf{x})$ is maximised).
- **Agent psychology**. Inspired by swarming algorithms, we model the current mental state of each agent by giving it a position in the solution space (denoting the solution its mind has found so far), a velocity vector (denoting the direction and speed of its thought process), and acceleration vectors (representing the force of ideas and influences that modify the direction and speed of thought), the latter determined by its personality.
- **Agent communication**. We model the distribution of information between agents as they each try to solve the same problem. The exact type of information perceived by each agent and its use is determined by its personality.
- **Agent intuition**. The Jungian intuitive functions (Ne and Ni) includes the notion of intuiting solutions, i.e., from sparse data they interpolate missing information, sometimes resulting in remarkable predictions (and sometimes not). We model intuition through a Gaussian process regression function (Williams & Rasmussen, 1996) which builds, from the data available to the agent, an internal imaginary view of the solution space for that agent. The agent then samples its imaginary space and is attracted to the area that it "believes" is a maximum.

Figure 1 shows the algorithm of the model, and the following sections describe each component in detail.

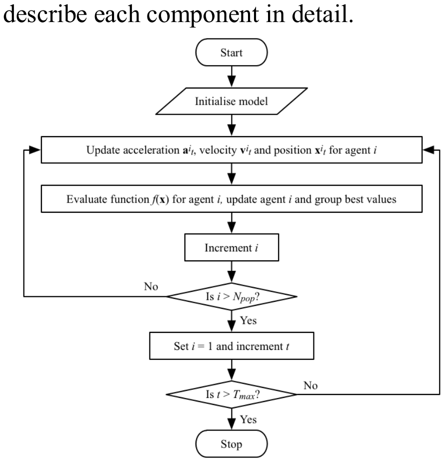

Figure 1: Algorithm of the model.

Initialise

The model is initialised with:

- a problem space $\mathbf{D} \in \mathbb{R}^n$
- an objective function $f(\mathbf{x})$
- the number of timesteps T_{max} to run the model
- a population of agents N_{pop}, each agent $i \in \{1, \ldots, N_{pop}\}$ is initialised with:

⇒ a personality type $\mathbf{P}^i$ (one of the 16 in Table 1)
⇒ a random position $\mathbf{x}^i{}_0 \in \mathbf{D}: \mathbf{x}_{min} \leq \mathbf{x}^i{}_0 \leq \mathbf{x}_{max}$
⇒ a random velocity $\mathbf{v}^i{}_0 \in \mathbb{R}^n: -\mathbf{v}_{init} \leq \mathbf{v}^i{}_0 \leq \mathbf{v}_{init}$
⇒ personal best $f^i{}_{best} = f(\mathbf{x}^i{}_0)$ and personal best position $\mathbf{x}^i{}_{best} = \mathbf{x}^i{}_0$

- group best $f^g{}_{best}$ is the best $f^i{}_{best}$, and group best position $\mathbf{x}^g{}_{best}$ is the corresponding $\mathbf{x}^i{}_{best}$

Update

For each timestep $t \in \{1, \ldots, T_{max}\}$, each agent i's position $\mathbf{x}^i{}_t$ is updated using equation (1):

$$\mathbf{x}^i{}_t = \mathbf{x}^i{}_{t-1} + \mathbf{v}^i{}_t \tag{1}$$

with the velocity $\mathbf{v}^i{}_t$ calculated using equation (2):

$$\mathbf{v}^i{}_t = \mathbf{v}^i{}_{t-1} + \mathbf{a}^i{}_t \tag{2}$$

If $|\mathbf{v}^i{}_t| > \mathbf{v}_{max}$, it is scaled to equal $\mathbf{v}_{max}$, in order to prevent excessive speed (an individual with high velocity would literally become too "set in their ways" and would find it impossible to change its direction of thought into a useful direction).

Acceleration $\mathbf{a}^i{}_t$ is used to change the direction of thought, as determined by the interpretation of the psychology theory – in this work, the 16 MBTI personality types. The interpretation provided here is designed to enable each separate personality to have an equally good chance of finding the solution. Interpretations were created in order to represent MBTI personality types appropriately and were not tuned in order to achieve any specific result in later experiments.

Each MBTI personality type has a dominant and auxiliary Jungian function (Table 1). $\mathbf{a}^i{}_t$ is calculated in equation (3):

$$\mathbf{a}^i{}_t = \mathbf{a}_J{}^i{}_t + \mathbf{a}_P{}^i{}_t \tag{3}$$

where $\mathbf{a}_J{}^i{}_t$ is the judging acceleration is calculated using Table 2 and $\mathbf{a}_P{}^i{}_t$ is the perceiving acceleration calculated using equation (4):

$$\mathbf{a}_P{}^i{}_t = \sum_{j=1}^{3} r_j(\mathbf{c}_j - \mathbf{x}^i{}_{t-1}) \tag{4}$$

where $r_1 = 0.5$, $r_2 = 0.3$, and $r_3 = 0.2$, and $\mathbf{c}_1$, $\mathbf{c}_2$ and $\mathbf{c}_3$ are the top 3 candidates derived using Table 3 with $f(\mathbf{c}_1) \geq f(\mathbf{c}_2) \geq f(\mathbf{c}_3)$. In both tables, agent i's neighbours are defined as the five nearest agents to agent i measured by Euclidean distance, i.e., the peer group of each agent comprises those who share similar ideas to the agent. To ensure that the auxiliary component plays a lesser role compared to the dominant component, $\mathbf{a}_J{}^i{}_t$ is scaled down such that $\left|\mathbf{a}_J{}^i{}_t\right|^2 = \frac{|\mathbf{a}_P{}^i{}_t|^2}{2}$ if $\left|\mathbf{a}_J{}^i{}_t\right|^2 > \frac{|\mathbf{a}_P{}^i{}_t|^2}{2}$ (if $\mathbf{P}^i$ has dominant perception and auxiliary judgment, otherwise vice versa).

Evaluate

Agent i's fitness at timestep t is evaluated as $f^i{}_t = f(\mathbf{x}^i{}_t)$. Finally, the agent's personal best $f^i{}_{best}$, the agent's personal best position $\mathbf{x}^i{}_{best}$, group best $f^g{}_{best}$ and group best position $\mathbf{x}^g{}_{best}$ are updated.

Experiment

Given the formalisation of Jung's Type Theory in the current model, it is possible to explore the validity of the hypothesis: *tolerance of uncertainty depends on personality type*, i.e., some personalities are better able to cope with a situation in which something is not known, or uncertain. Here we investigate the

Function	Interpretation	Implementation
Te: According to MBTI, Te is externally focused, applying rational thought to the outside world. Te makes decisions being influenced by external facts.	The agent is influenced by its neighbours' best personal best. It accelerates towards its neighbours' best personal best from the previous timestep.	$\mathbf{a}_{Te}{}^i{}_t = \mathbf{x}_n{}^i{}_{best_{t-1}} - \mathbf{x}^i{}_{t-1}$ (5) where $\mathbf{x}_n{}^i{}_{best_{t-1}}$ is agent i's neighbours' personal best position in the previous timestep that results in the highest $f(\mathbf{x})$, and $\mathbf{x}^i{}_{t-1}$ is the agent's position in the previous timestep.
Ti: According to MBTI, Ti is internally focused, applying rational thought to an inner world of values. Ti loves to explore internally.	The agent focusses on its own personal best (the outcome of its own thoughts). It accelerates towards its own personal best, with randomness added to enable exploration.	$\mathbf{a}_{Ti}{}^i{}_t = (\mathbf{x}^i{}_{best_{t-1}} - \mathbf{x}^i{}_{t-1}) + \varphi$ (6) where $\mathbf{x}^i{}_{best_{t-1}}$ is agent i's personal best position in the previous timestep, $\mathbf{x}^i{}_{t-1}$ is the agent's position in the previous timestep, and φ is a random float in the interval $[-2.0, 2.0]$.
Fe: According to MBTI, Fe identifies with and is affected by other people's feelings, seeks harmony in interpersonal relationships.	The agent "identifies with other agent's feelings" and "seeks harmony" by matching its neighbours' average velocity (direction of thought) from the previous timestep and to a lesser extent accelerates towards its neighbours' best personal best from the previous timestep.	$\mathbf{a}_{Fe}{}^i{}_t = \omega_1 \cdot \bar{\mathbf{v}}_N{}^i{}_{t-1} + \omega_2 \cdot \mathbf{a}_{Te}{}^i{}_t$ (7) where weights $\omega_1 = 0.8$, $\omega_2 = 0.2$, $\bar{\mathbf{v}}_N{}^i{}_{t-1}$ is agent i's neighbours' average velocity in the previous timestep, and $\mathbf{a}_{Te}{}^i{}_t$ is calculated using equation (5).
Fi: According to MBTI, Fi has high empathy for others, yet cares about its own feelings, seeks harmony between its actions, thoughts, and personal or inner values.	The agent "empathises with" its neighbours' ideas by accelerating towards its neighbours' average position from the previous timestep. It also cares about its own personal thoughts, so accelerates towards its own best position.	$\mathbf{a}_{Fi}{}^i{}_t = \omega_1 \cdot (\mathbf{C}_n{}^i{}_{t-1} - \mathbf{x}^i{}_{t-1}) + \omega_2 \cdot (\mathbf{x}^i{}_{best_{t-1}} - \mathbf{x}^i{}_{t-1})$ (8) where weights $\omega_1 = 0.8$, $\omega_2 = 0.2$, $\mathbf{C}_n{}^i{}_{t-1}$ is the centroid (arithmetic mean position) of agent i's neighbours' positions in the previous timestep.

Table 2: Jungian judging functions and how they are used to calculate judging acceleration, $\mathbf{a}_J{}^i{}_t$.

Function	Interpretation	Implementation
Se: According to MBTI, Se is attuned to concrete events that are happening around, including trends, fashions, and styles, made aware directly through the senses.	The agent sees its neighbours' positions and their quality. Candidates are the positions of the agent's nearest neighbours in the previous timestep.	$\mathbb{C}_{Se}{}^{i}{}_{t} = \{\mathbf{x}^{i}{}_{n1_{t-1}}, \dots, \mathbf{x}^{i}{}_{n5_{t-1}}\}$ (9) where $\mathbf{x}^{i}{}_{n1_{t-1}}$ is agent i's first neighbour's position in the previous timestep, and $\mathbf{x}^{i}{}_{n5_{t-1}}$ is agent i's fifth neighbour's position in the previous timestep. The candidates for current and previous timestep $\mathbb{C}_{Se}{}^{i}{}_{t}$ and $\mathbb{C}_{Se}{}^{i}{}_{t-1}$ are then sorted in the order of decreasing $f(\mathbf{x})$.
Si: According to MBTI, Si is attuned to immediate inner sensations such as muscle tension, pain, hunger, thirst, numbness. It remembers what it has experienced and preserves past ways of doing things.	The agent remembers all its own previous positions and a few nearby points and their quality. Candidates are the agent's previous path and new points near to their position.	$\mathbb{C}_{Si}{}^{i}{}_{t} = \{\mathbf{x}^{i}{}_{0}, \dots, \mathbf{x}^{i}{}_{t-1}\} \cup \boldsymbol{P}$ (10) where $\boldsymbol{P}$ is the set of points near to $\mathbf{x}^{i}{}_{t-1}$. Given $\mathbf{x}^{i}{}_{t-1} = (x_1, x_2, \dots, x_n)$, $\boldsymbol{P} = \{(x_1+\delta, x_2, \dots, x_n), (x_1-\delta, x_2, \dots, x_n), (x, x_2+\delta, \dots, x_n), (x_1, x_2-\delta, \dots, x_n), \dots, (x_1, x_2, \dots, x_n+\delta), (x_1, x_2, \dots, x_n-\delta)\}$ where δ is a random number from a normal distribution $N(\mu, \sigma)$ with $\mu = 1$ and $\sigma = 0.01$. The candidates for current and previous timestep $\mathbb{C}_{Si}{}^{i}{}_{t}$ and $\mathbb{C}_{Si}{}^{i}{}_{t-1}$ are then sorted in the order of decreasing $f(\mathbf{x})$.
Ne: According to MBTI, Ne connects concepts and draw parallels using tangible data found in the environment. It trusts bursts of the unconscious or following a "gut feeling".	The agent sees its neighbours' positions and uses them to create an "imaginary solution space". Candidates produced from Se (data from the environment) are used as input to train the Gaussian process regression function. Candidates are then the best quality solutions resulting from sampling this imaginary space.	$f^* = \mathcal{GP}: train(\mathbb{C}_{Se}, f(\mathbb{C}_{Se}));\ predict(\mathbb{C}_{Ne}{}^{i}{}_{t})$ where $\mathcal{GP}$ is the Gaussian process regression function, training on $\mathbb{C}_{Se}$ *and* $f(\mathbb{C}_{Se})$, and $\mathbb{C}_{Ne}{}^{i}{}_{t}$ is a vector of all discrete points in $\mathbf{D}$. The candidates for current and previous timestep $\mathbb{C}_{Ne}{}^{i}{}_{t}$ and $\mathbb{C}_{Ne}{}^{i}{}_{t-1}$ are then sorted in the order of decreasing f^*.
Ni: According to MBTI, Ni connects concepts and draw parallels using data from their internal framework of perspectives and values. It trusts bursts of the unconscious or following a "gut feeling".	The agent sees its own previous positions and a few nearby points and uses them to create an "imaginary solution space". Candidates produced from Si (internal data) are used as input to train the Gaussian process regression function. Candidates are then the best quality solutions resulting from sampling this imaginary space.	$f^* = \mathcal{GP}: train(\mathbb{C}_{Si}, f(\mathbb{C}_{Si}));\ predict(\mathbb{C}_{Ni}{}^{i}{}_{t})$ where $\mathcal{GP}$ is the Gaussian process regression function, training on $\mathbb{C}_{Si}$ and $f(\mathbb{C}_{Si})$, and $\mathbb{C}_{Ni}{}^{i}{}_{t}$ is a vector of all discrete points in $\mathbf{D}$. The candidates for current and previous timestep $\mathbb{C}_{Ni}{}^{i}{}_{t}$ and $\mathbb{C}_{Ni}{}^{i}{}_{t-1}$ are then sorted in the order of decreasing f^*.

Table 3: Jungian perceiving functions and how they are used to get candidates. The first 3 candidates are returned as c_1, c_2 and c_3.

relative performance of groups of individuals with different personality types, as they collaboratively solve a problem with varying noise. If the hypothesis is true, then some teams will not perform as well compared to others, as noise increases.

We created teams with opposing MBTI dichotomy: Extraverts vs. Introverts, Sensors vs. Intuitives, Thinkers vs. Feelers, and Judgers vs. Perceivers. Each team has 8 agents with personality described in Table 4.

Team	Agent Personality							
Extraverts	**E**STP	**E**SFP	**E**NFP	**E**NTP	**E**STJ	**E**SFJ	**E**NFJ	**E**NTJ
Introverts	**I**STP	**I**SFP	**I**NFP	**I**NTP	**I**STJ	**I**SFJ	**I**NFJ	**I**NTJ
Sensors	I**S**TJ	I**S**FJ	I**S**TP	I**S**FP	E**S**TP	E**S**FP	E**S**TJ	E**S**FJ
Intuitives	I**N**FJ	I**N**TJ	I**N**FP	I**N**TP	E**N**FP	E**N**TP	E**N**FJ	E**N**TJ
Thinkers	IS**T**J	IN**T**J	IS**T**P	IN**T**P	ES**T**P	EN**T**P	ES**T**J	EN**T**J
Feelers	IS**F**J	IN**F**J	IS**F**P	IN**F**P	ES**F**P	EN**F**P	ES**F**J	EN**F**J
Judgers	IST**J**	ISF**J**	INF**J**	INT**J**	EST**J**	ESF**J**	ENF**J**	ENT**J**
Perceivers	IST**P**	ISF**P**	INF**P**	INT**P**	EST**P**	ESF**P**	ENF**P**	ENT**P**

Table 4: Teams and agent personality.

The model was initialised with constant settings in Table 5 and an objective function $f(\mathbf{x})$ as described in equation (11):

$$f(x, y) = -\sqrt{x^2 + y^2} \tag{11}$$

The function was normalised such that $f(\mathbf{x}) \in [0,1]$: $\forall\, x \in [\mathbf{x}_{min}, \mathbf{x}_{max}]$. Figure 2 shows the heatmap and surface plot. The function represents a simple problem with a clear gradient.

Constants	T_{max}	N_{pop}	$\mathbf{v}_{max}$	$\mathbf{x}_{min}$	$\mathbf{x}_{max}$	$\mathbf{v}_{init}$
Values	50	8	5.0	(-100,-100)	(100, 100)	(1.0, 1.0)

Table 5: Constants settings for the model.

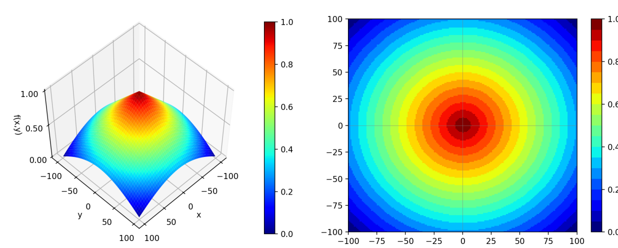

Figure 2: Surface plot (left) and heatmap (right) for normalised equation (11) with a maximum in (0, 0). Colour ranges from blue (minimum) to red (maximum).

To evaluate the effect of uncertainty on the performance of different teams, we added a 5%, 10% and 20% uniform noise to the fitness perceived by each agent. Each experiment was repeated 100 times. The group best at the end of each run was recorded and team performance was measured by their average group best, which is the total group best for all runs divided by total number of runs. *t*-test is used to assess whether the differences between average group best for the pairs is significant. We also measured the average group best over time, which is the total group best for all runs at each timestep divided by the total number of runs. Following the experiments, the findings were assessed to see whether the predictions made by the model were supported by literature.

Results

Figure 3 shows the average group best for each pair of teams and Figure 4 shows their average group best over time. In general, noise causes all teams to deteriorate in performance. However, the extent it affects performance differs based on the personalities of the individuals that form the team. When there is no noise, Introverts perform equally well compared to Extraverts with no significant differences (p=.681). With increasing noise, Introverts performed increasingly worse compared to Extraverts with significant differences in average group best ($p < .001$). This is consistent with literature. For example, Berenbaum et al. (2008) surveyed more than 200 university students and found that introverts are less tolerant of uncertainty compared to extraverts. In studying adult language learning styles, Ehrman and Oxford (1990) found that introverts dislike surprises and want to know what is coming next. They also found that when uncertain, extraverts employ social strategies such as asking peers and teachers, while introverts reported learning best alone. This behaviour can be seen in our model and causes the Introverts team to perform worse with increasing noise as they do not corroborate their findings with one another (Figure 5).

When there is no noise and 5% noise, Sensors perform better than Intuitives with significant differences in average group best ($p < .001$), see Figure 3. As the noise level increases, Intuitives start to outperform Sensors with average group best higher than Sensors at 10% noise (although the difference is not significant at p=.358 as this is the point it starts to change), and average group best higher than Sensors at 20% noise (the difference is significant at $p < .001$). From 10% to 20% noise, Sensors deteriorate hugely in their performance, while Intuitives maintain a relatively similar performance as they converge to the solution (Figure 3). Since Intuitives use a Gaussian process regression function, it is possible to visualise their changing imaginary view of the problem over time. Figure 6 shows how each agent in an Intuitives team see the problem space in one run with no noise and with 20% noise. Although noise makes the agents more confused, many are still able to visualise the problem space with a maximum around (0, 0), helping them to remain tolerant to noise. These findings are consistent with the literature. For example, Ehrman and Oxford (1990) found that sensing learners dislike guessing and have a low tolerance for ambiguity, while intuitive learners search for the "big picture", relied heavily on guessing from context and do not require complete comprehension of texts to make progress. Francis and Jones (1999) surveyed more than 300 church-goers using the MBTI questionnaire and found that participants who prefer intuition rather than sensing are more tolerant of religious uncertainty. The average group best over time (Figure 4) shows that Sensors take longer than Intuitives to reach a stable good fitness. When noise is 20%, they did not manage to reach a stable good fitness in the given time (Figure 4). Although there is literature indicating that sensing learners are disadvantaged on timed aptitude measures compared to

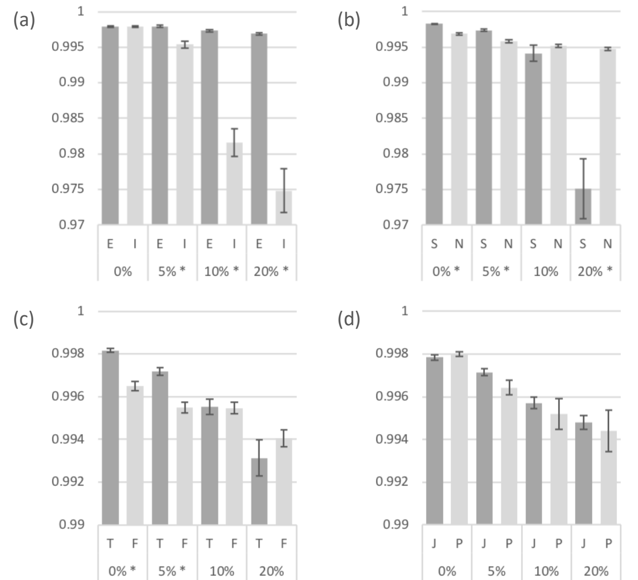

Figure 3. Average group best when noise=0%, 5%, 10%, 20% for (a) Extraverts vs. Introverts, (b) Sensors vs. Intuitives, (c) Thinkers vs. Feelers, and (d) Judgers vs. Perceivers where y-axis is average group best and x-axis is noise and team. Error bars represent one standard error. * indicates that the t-test results show a significant difference between the average group best for the pair of teams at $p < .001$.

intuitive learners (e.g., they take longer reading exam questions, often going over them several times) (Schroeder, 1993), there is also literature stating that intuitive personalities take longer in specific tasks. For example, Vaassen et al. (1993) studied the cognitive styles of experienced auditors in the Netherlands and found that sensing people take significantly less time than intuitive people to perform an auditing task.

Thinkers also perform better than Feelers with significant differences when there is no noise and 5% noise ($p < .001$). At 10% and 20% noise, Feelers start to outperform Thinkers, however the difference is not significant (p=.886 and p=.319). In our model, when noise is high, Thinkers (and Sensors), who rely on factual information, cannot see the gradient of the solution space and struggle to converge on the correct solution (Figure 5). This is corroborated by the literature. Vaassen et al. (1993) found that thinking types have a lower tolerance for ambiguity compared to feeling types (i.e., they are less willing to accept a state of affairs which may have alternate interpretations or outcomes) and the difference is significant. They also found that thinking types access significantly more information (almost twice the number of pages) in the auditing task compared to feeling types. They also take significantly longer to complete their task. This can be seen in our model (Figure 4) where Feelers reach their stable good fitness faster than Thinkers in both 0% and 20% noise.

Finally, Judgers perform worse than Perceivers when there is no noise, and better than Perceivers when there is noise (Figure 3), although the differences are not significant (p=.361, p=.060, p=.507, and p=.704). In Figure 4, Judgers are quicker to arrive at their stable good fitness than Perceivers when noise is 0%; this is less noticeable when noise is 20%. The literature

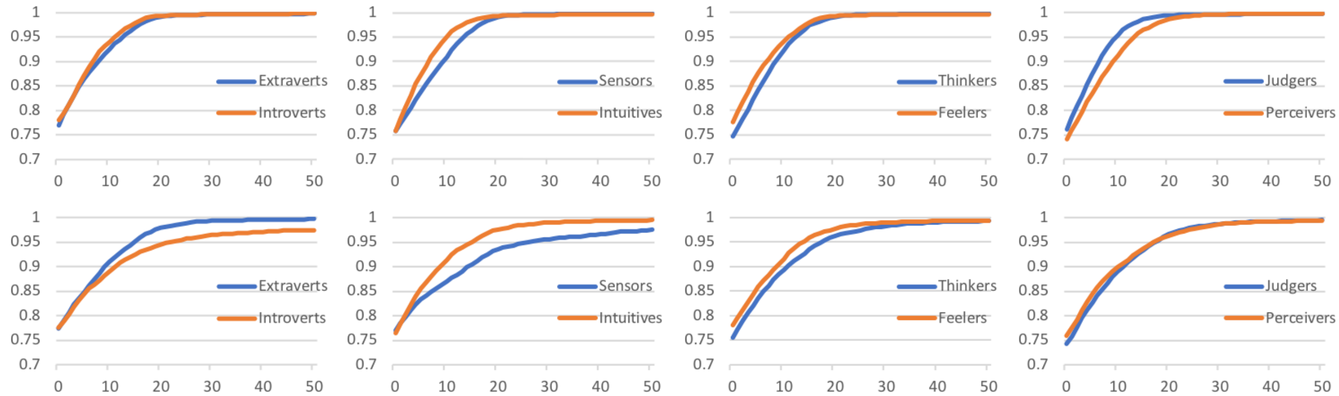

Figure 4. Average group best over time for Extraverts vs. Introverts, Sensors vs. Intuitives, Thinkers vs. Feelers, and Judgers vs. Perceivers for noise=0% (top row) and noise=20% (bottom row) where *y*-axis is average group best and *x*-axis is timestep.

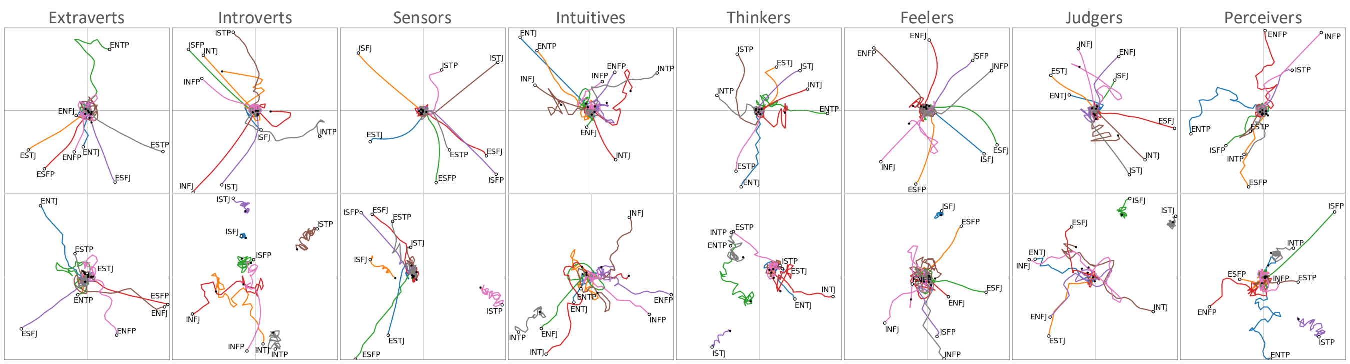

Figure 5. Representative runs showing each agent's path as they navigate the solution space to find the optimal solution for noise=0% (top row) and noise=20% (bottom row). Black circle indicates their position at t=0 and black dot indicates their position at t=50. The maximum is located at the centre of each image.

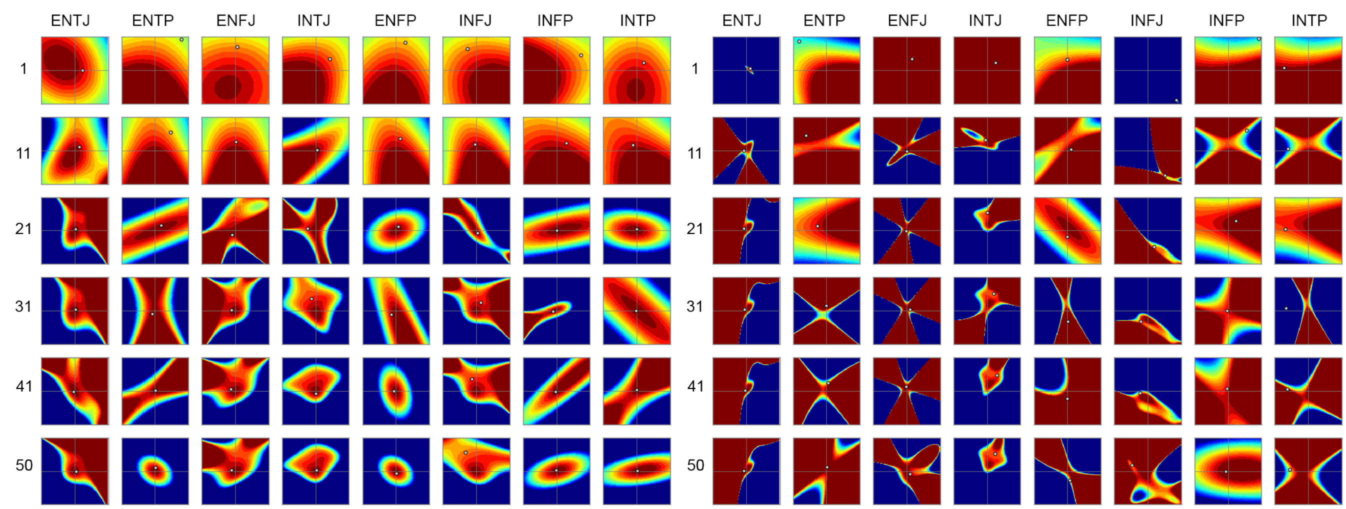

Figure 6. Solution space as perceived by each agent in the Intuitives team for noise=0% (left) and noise=20% (right) sampled every 10 timesteps. Black circle denotes the agent's position for that timestep. Each image uses the same scale and colour range as the heatmap shown in Figure 2 with the maximum in the centre.

comparing judging and perception in terms of uncertainty is weaker, which appears consistent with the model as the differences are not significant. Ehrman and Oxford (1990) suggest that judging types may be uncomfortable with ambiguity but in our model they do better than perceiving types, although the differences are not significant. Trevino et al. (1990) studied 91 employed graduate business school students with an average of eight years' work experience and found that uncertainty had no significant effect on the behaviour of judging types compared to perceiving types.

Conclusion

It is no easy task to understand the effects of human personalities on our interactions with each other, as decades of sometimes controversial psychology research illustrates. Today, for ethical reasons, it is often not possible to run experiments with humans as test subjects. In this work, we argue that computational modelling may provide a useful new investigative tool in this domain. Agent-based models have already elucidated diverse areas of human behaviour from economics to crowd movement. Here we presented a problem-independent and psychology theory-agnostic model of collaboration that enables human psychology to be incorporated. We abstract a shared goal as a shared optimisation task, and model differences of personality as different strategies for moving within, interpreting and sharing information about the solution space.

To test the effectiveness of this modelling approach we investigated the hypothesis: *tolerance of uncertainty depends on personality type*, investigating the relative abilities of groups of individuals with contrasting personality types, as they collaboratively solve a problem with varying degrees of noise. The model predicted that significant differences occur between personality types when faced with uncertainty. In particular, Sensors perform significantly better than Intuitives when there are low levels of noise and they perform significantly worse compared to Intuitives in high levels of noise. Introverts and Extraverts perform equally well when there is no noise, but Introverts perform significantly worse when there is noise. Thinkers perform significantly better than Feelers when there is no noise or little noise and when noise is high there is no significant differences in their performance. These predictions were then corroborated by experimental psychology literature.

The potential for such computational models is considerable. We anticipate that this approach could be used with existing psychology theories to investigate other hypotheses relating to collaborative working, for example, to help determine the optimal group composition and size for various problem types, or help predict which personality types might benefit from which type of management. We also anticipate that the approach can be used to compare different psychology theories, or even derive new models of personality from data representative of human behaviours.

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