# Investigating Conformity by Personality Type

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## Abstract

When someone goes against their own ideas and instead follows the ideas of others, they conform. In this work, we investigate the tendency of different personality types to conform. We use an agent-based model to simulate interactions between people with different personalities and goals. We look at how likely agents are to retain their original goal when they interact with other agents that have different goals. We found there are significant differences in tendency to conform between different personality types.

## Introduction

For teams in organizations, striking a balance between conformity at the one end and diversity of opinion at the other end is an everyday challenge (Schweiger et al., 1986). Understanding factors that impact the levels of conformity in team-interactions is necessary to manage this balance. Avoiding groupthink or agreement on suboptimal decisions (Janis, 1972) is just as important as avoiding paralysis due to irresolvable disagreements. Therefore, investigating the factors that contribute to levels of conformity in teams is essential.

What makes these investigations challenging is that humans do not always act as perfectly rational decision-makers. In the real world, complex dynamics emerge in interactions between individuals. One of the factors influencing the degree of conformity of team members could be personality types of individuals. Research in this area is sparse and conflicting. Recent work indicates there is a correlation between personality and conformity (Chen and Palmer, 2018); other work found no correlation (Endler, 1961).

In previous work, an agent-based model was developed to investigate the effect of personality differences in teamwork (Lim and Bentley, 2018). It is one of the first agent-based models that incorporates human psychology (Lim and Bentley, 2018). The model is inspired by particle swarm optimisation. It abstracts a shared team goal as a shared optimisation task, and models the personality differences in team members as strategies for moving within, interpreting and sharing information about the solution space. The model has been used to investigate different levels of task uncertainty (Lim and Bentley, 2018), different types of tasks and changing goals (Lim and Bentley, 2019a) and diversity in team background (Lim and Bentley, 2019b). However, previous models only investigated scenarios in which every team member shares the same goal.

In this paper, we further develop the model to enable agents to work towards different goals. When an agent appears to work towards the goal of other agents and not towards its own goal, we interpret this as the agent conforming. We investigate if personality type has an effect on conformity and if the proportion of agents with differing goals has an effect on conformity.

## Model

We use the agent-based model that is explained in detail in (Lim and Bentley, 2018). The algorithm used to model interactions between agents has the following structure.

### Initialise

The model is initialised with:

- a problem space $D = [-100, 100] \times [-100, 100]$
- two objective functions $f_A, f_B \colon D \to \mathbb{R}$
- the number of timesteps $T_{\text{max}}$
- a population of $N$ agents, each agent $i \in \{1, \dots, N\}$ has:
  - a personality type defined in Table 1 and implemented as described in Table 2
  - an assignment to either optimise for $f_A$ or $f_B$
  - a random position vector $\mathbf{x}_0^i \in D$, with corresponding initial personal best position, and random velocity vector $\mathbf{v}_0^i \in \mathbb{R}^2$ such that $(-1, -1) \leq \mathbf{v}_0^i \leq (1, 1)$

### Personality Framework

In this paper, we use the Myers-Briggs Type Indicator (MBTI) as the personality framework for our model. MBTI consists of 16 personality types based on assessing a person's preferences on four opposing dichotomies: Introversion (I) – Extraversion (E), Sensing (S) – Intuition (N), Thinking (T) – Feeling (F), and Judging (J) – Perceiving (P) (Myers, 1962).

Each MBTI personality type is determined by a dominant Jungian function and an auxiliary Jungian functions (Table 1). There are eight Jungian functions: extraverted Thinking (Te), introverted Thinking (Ti), extraverted Feeling (Fe), introverted Feeling (Fi), extraverted Sensing (Se), introverted Sensing (Si), extraverted iNtuition (Ne), introverted iNtuition (Ni). Table 2 describes how each function is implemented in the model.

| 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: For each MBTI type we list its corresponding dominant and auxiliary Jungian functions.

| Function | Implementation |
|---|---|
| Te: The agent is influenced by its neighbours' best personal best. It accelerates towards its neighbours' best personal best from the previous timestep. | $\mathbf{a}_{\text{Te}}{}_t^i := \mathbf{x}_{\text{neig}_{\text{best}_{t-1}}^i} - \mathbf{x}_{t-1}^i$ where $\mathbf{x}_{\text{neig}_{\text{best}_{t-1}}^i}$ is agent $i$'s neighbours' personal best position in the previous timestep that results in the highest $f(\mathbf{x})$, and $\mathbf{x}_{t-1}^i$ is the agent's position in the previous timestep. |
| Ti: 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. | $\mathbf{a}_{\text{Ti}}{}_t^i := \mathbf{x}_{\text{best}}{}_{t-1}^i - \mathbf{x}_{t-1}^i + \varphi$ where $\mathbf{x}_{\text{best}_{t-1}}^i$ is agent $i$'s personal best position in the previous timestep, $\mathbf{x}_{t-1}^i$ is the agent's position in the previous timestep, and $\varphi$ is a random float in the interval $[-2.0, 2.0]$. |
| Fe: 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. | $\mathbf{a}_{\text{Fe}}{}_t^i := \omega_1 \cdot \bar{\mathbf{v}}_{\text{neig}_{t-1}^i} + \omega_2 \cdot \mathbf{a}_{\text{Te}}{}_t^i$ where weights $\omega_1 = 0.8$, $\omega_2 = 0.2$, $\bar{\mathbf{v}}_{\text{neig}_{t-1}^i}$ is agents $i$'s neighbours' average velocity in the previous timestep, and $\mathbf{a}_{\text{Te}}{}_t^i$ is calculated using Te's equation. |
| Fi: 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. | $\mathbf{a}_{\text{Fi}}{}_t^i := \omega_1 \cdot (C_{\text{neig}}{}_{t-1}^i - \mathbf{x}_{t-1}^i) + \omega_2 \cdot (\mathbf{x}_{\text{best}_{t-1}}^i - \mathbf{x}_{t-1}^i)$ where weights $\omega_1 = 0.8$, $\omega_2 = 0.2$, and $C_{\text{neig}}{}_{t-1}^i$ is the centroid of agent $i$'s neighbours' positions in the previous timestep. |
| Se: The agent sees its neighbours' positions and their quality. Candidates are the positions of the agent's nearest neighbours in the previous timestep. | $\mathbb{C}_{\text{Se}}{}_t^i := \{\mathbf{x}_{\text{neig}_1}{}_{t-1}^i, \ldots, \mathbf{x}_{\text{neig}_5}{}_{t-1}^i\}$ where $\mathbf{x}_{\text{neig}_j}{}_{t-1}^i$ is agent $i$'s $j$-th neighbour in timestep $t-1$. The candidates for the current timestep $\mathbb{C}_{\text{Se}}{}_t^i$ and previous timestep $\mathbb{C}_{\text{Se}}{}_{t-1}^i$ are sorted in order of decreasing $f(\mathbf{x})$. |
| Si: 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. | $\mathbb{C}_{\text{Si}}{}_t^i := \{\mathbf{x}_0^i, \ldots, \mathbf{x}_{t-1}^i\} \bigcup P$ where $P := \{(x+\delta, y), (x-\delta, y), (x, y+\delta), (x, y-\delta)\}$ and $\mathbb{C}_{\text{Si}}{}_t^i$ and $\mathbb{C}_{\text{Si}}{}_{t-1}^i$ are sorted in order of decreasing $f(\mathbf{x})$. |
| Ne: 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. | The Gaussian process regression function $\mathcal{GP}$ is used. The process is trained on pairs $(\mathbf{x}, f(\mathbf{x}))$ with $\mathbf{x} \in \mathbb{C}_{\text{Se}}$. The process predicts what $f$ values correspond to points in $D$ and sorts these in decreasing order. |
| Ni: 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. | The Gaussian process regression function $\mathcal{GP}$ is used. The process is trained on pairs $(\mathbf{x}, f(\mathbf{x}))$ with $\mathbf{x} \in \mathbb{C}_{\text{Si}}$. The process predicts what $f$ values correspond to points in $D$ and sorts these in decreasing order. |

Table 2: Interpretation of Jungian types (Lim and Bentley, 2018).

### Update

In each timestep $t \in \{1, \ldots, T_{\text{max}}\}$, each agent $i$'s position $\mathbf{x}_t^i$ and velocity $\mathbf{v}_t^i$ are updated using the equations

$$\mathbf{x}_t^i := \mathbf{x}_{t-1}^i + \mathbf{v}_t^i \text{ and } \mathbf{v}_t^i := \mathbf{v}_{t-1}^i + \mathbf{a}_t^i.$$

The acceleration vector is calculated using the equation

$$\mathbf{a}_t^i := \mathbf{a}_{\text{Judge}}{}_t^i + \mathbf{a}_{\text{Perceive}}{}_t^i,$$

where $\mathbf{a}_{\text{Judge}}{}_t^i$ is calculated using one of the four Judging functions in Table 2 (Te, Ti, Fe, Fi) and $\mathbf{a}_{\text{Perceive}}{}_t^i$ is calculated using the top 3 candidates $c_1$, $c_2$ and $c_3$ derived using one of the four Perceiving functions in Table 2 (Se, Si, Ne, Ni) and the equation $\mathbf{a}_{\text{Perceive}}{}_t^i := 0.5 \cdot (c_1 - \mathbf{x}_{t-1}^i) + 0.3 \cdot (c_2 - \mathbf{x}_{t-1}^i) + 0.2 \cdot (c_3 - \mathbf{x}_{t-1}^i)$.

Each personality type has a dominant and auxiliary function. If an agent has dominant perception, then $\mathbf{a}_{\text{Judge}}{}_t^i$ is scaled down such that

$$(\mathbf{a}_{\text{Judge}}{}_t^i)^2 := \frac{(\mathbf{a}_{\text{Perceive}}{}_t^i)^2}{2} \text{ if } (\mathbf{a}_{\text{Judge}}{}_t^i)^2 > \frac{(\mathbf{a}_{\text{Perceive}}{}_t^i)^2}{2}.$$

If an agent has dominant judging, then $\mathbf{a}_{\text{Perceive}}{}_t^i$ is scaled down such that

$$(\mathbf{a}_{\text{Perceive}}{}_t^i)^2 := \frac{(\mathbf{a}_{\text{Judge}}{}_t^i)^2}{2} \text{ if } (\mathbf{a}_{\text{Perceive}}{}_t^i)^2 > \frac{(\mathbf{a}_{\text{Judge}}{}_t^i)^2}{2}.$$

### Evaluate

Every timestep the personal best performance and the personal best position $\mathbf{x}_{\text{best}}$ are updated for each agent. (Unlike a conventional PSO, group best is not evaluated here.) Each agent maximizes either $f_A$ or $f_B$. If the agent optimizes for $f_A$, then its performance is evaluated as

$$f_A(x, y) = \frac{-((x - 75)^2 + y^2) + 2 \times 100^2}{2 \times 100^2}.$$

If the agent optimizes for $f_B$, then its performance is evaluated as

$$f_B(x, y) = \frac{-((x + 75)^2 + y^2) + 2 \times 100^2}{2 \times 100^2}.$$

Note that $f_A(x, y), f_B(x, y) \in [-1.04, 1]$ for all $(x, y) \in [-100, 100] \times [-100, 100]$. Figure 1 shows the heatmaps for both functions.

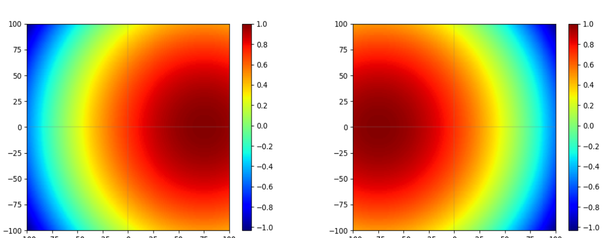

Figure 1: Heatmaps for $f_A$ (left) and $f_B$ (right).

We chose simple functions that have a unique optimum and clear gradient. The optima of the two functions are far apart, which makes it clear which goal an agent is working towards.

## Experiment

We seek to test the hypothesis that there is a significant difference in tendency to conform between different personality types. To do so, we investigate how well agents with goal $A$ optimize for goal $A$ when we introduce agents with goal $B$ into the system. We also vary the number of agents optimizing for each goal in order to investigate its effect on conformity. The number of agents optimizing $f_A$ is $k$ and the number of agents optimizing $f_B$ is $6 - k$, where $k \in \{1, 2, 3, 4, 5, 6\}$.

In the model each agent chooses its position based on its personality and information available. In this setting where some agents are solving one problem and others are solving a different problem, some may converge to one optimum and some may converge on the other. When an agent appears to work towards a solution that other agents regard as optimal, but that this agent regards as suboptimal, we can interpret this as conformity: this agent has been negatively influenced by others - it has conformed. When an agent converges to its own optimum regardless of the behaviour of others then it is not influenced - it has not conformed.

We conduct an experiment for each $k \in \{1, 2, 3, 4, 5, 6\}$. First, we initialise six agents with randomly selected personality types, of which $k$ agents optimise function $f_A$ and $6-k$ agents optimise function $f_B$. Then, we record the value of $k$ and the average performance per personality type at each timestep for all of the $k$ agents that optimize function $f_A$. Each experiment was repeated 500 times.

In our analysis, we compare agents by their MBTI dichotomies (I vs. E, S vs. N, T vs. F, and J vs. P). We also compare agents by their dominant Jungian functions (Te, Ti, Fe, Fi, Se, Si, Ne, Ni). We use *t*-tests to assess whether the differences between the dichotomies are significant. We use ANOVA to assess whether the differences between Jungian functions are significant. For the statistically significant ANOVA tests, post hoc analyses are also conducted, to compare all possible pairwise contrasts.

## Results

We found significant differences in tendency to conform between different personality types. As expected, agents are more inclined to conform to the other goal when there are more agents optimizing for the other goal, and they are more inclined to stick to their own goal when there are more agents optimizing for the same goal. However, the level of inclination varies greatly depending on the personality type. The rest of this section describes the results in detail.

Figure 2 illustrates the average performance per timestep on function $A$ of all agents with goal $A$. We see that agents' average performance converges after around 30 timesteps indicating that they tend to choose their solution in the first 30 timesteps and then stick to it.

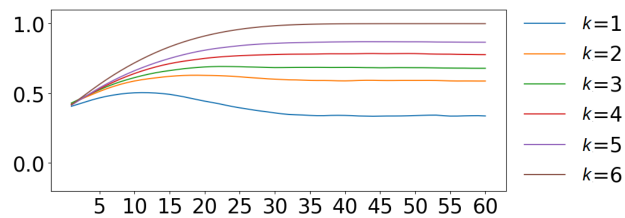


Figure 2: Agents' average performance for goal $A$ (y-axis) per timestep (x-axis).

Figure 3 shows the agents' average performance at timestep 30. The more agents with goal $A$, the better their average performance, with smaller standard deviation. It also shows that overall, regardless of personality, when there are fewer agents with goal $A$, their performance on goal $B$ is better (i.e., they are more inclined to conform to other agents' goals), and when there are more agents with goal $A$, their performance for goal $B$ is worse (i.e., they are less inclined to conform to other agents' goals).

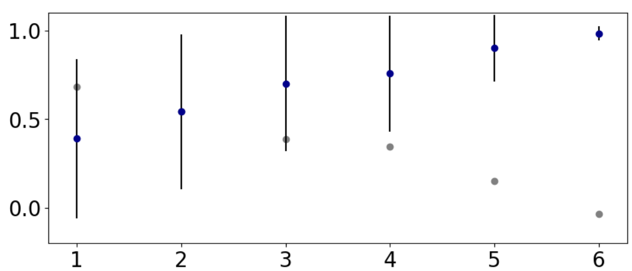


Figure 3: Average performance at timestep 30 (y-axis) as $k$ (x-axis) increases. Dark blue dots indicate agents' average performance on $f_A$, error bars indicate the standard deviation of agents' performance, and gray dots indicate the average performance on $f_B$ for agents with goal $A$.

Figure 4 compares each Jungian function as $k$ is increased. As expected, the more agents with the same goal, the better the performance. Some Jungian functions, such as Si and Ni, are not affected by the number of agents with goal $A$. Their average performance remains consistent regardless of the number of agents. Some Jungian functions are more conforming than others. For example, Se, Ne, Te, Fe perform badly on their own goal when there are only 1 or 2 agents with goal $A$, and are optimizing very well for the other agents' goals (grey dots almost at 1).

There was a statistically significant difference between the average performances for all values of $k$ as determined

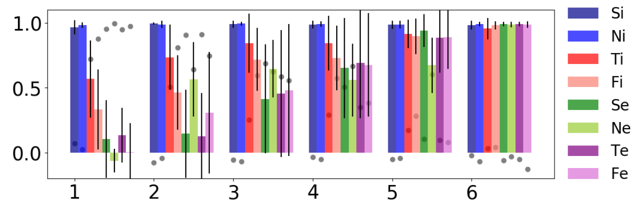


Figure 4: Average performance at timestep 30 (y-axis) for each Jungian function as $k$ (x-axis) increases. Error bars represent the standard deviation. The gray dots indicate the average performance on $f_B$ for agents with goal $A$.

by ANOVA, and Table 3 shows the significance for the post hoc analyses between all possible pairwise contrasts.

| | Ni | Ti | Fi | Se | Ne | Te | Fe |
|---|---|---|---|---|---|---|---|
| $k$ | 1 2 3 4 5 6 | 1 2 3 4 5 6 | 1 2 3 4 5 6 | 1 2 3 4 5 6 | 1 2 3 4 5 6 | 1 2 3 4 5 6 | 1 2 3 4 5 6 |
| Si | - - - * * - | * * * * * * | * * * * * - | * * * * * - | * * * * * * | * * * * * - | * * * * * - |
| Ni | | * * * * * * | * * * * * - | * * * * * - | * * * * * - | * * * * * - | * * * * * - |
| Ti | | | * * * - - * | * * * - - * | * * * - - * | * * * - * * | * * * * - * |
| Fi | | | | * * - - - - | * * - - * * | * * - * - - | * * * - - - |
| Se | | | | | - * - - * - | - - - - * - | - - - - - - |
| Ne | | | | | | - * - - * - | - * - - * - |
| Te | | | | | | | - - - * - - |

Table 3: Significance of difference between means for Jungian functions. Each cell in the table shows the significance for $k = 1$ to 6. We denote significance by * and non-significance by -.

Figure 5 compares the performances between dichotomies and Table 4 shows whether the differences are significant. We again see that all personality types perform worse when there are fewer agents with goal $A$.

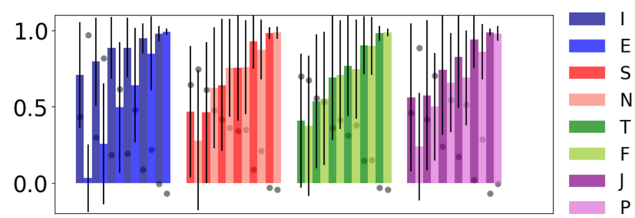


Figure 5: Average performance at timestep 30 (y-axis)for each MBTI dichotomy as $k$ (x-axis) increases. Error bars represent the standard deviation. The gray dots indicate the average performance on $f_B$ for agents with goal $A$.

In Figure 5 we see that introverted agents are significantly (Table 4) less conforming compared to extraverted agents. Moreover, we observe that introverted agents are affected less by the number of agents with goal $A$ than extraverted agents. In the study by (Kilmann and Thomas, 1976), one of the strongest and most consistent correlations was that extraverted individuals are more cooperative (attempting to satisfy the other person's concerns), which is consistent with the finding of the model. The study also found that extraverted individuals are more assertive (attempting to satisfy one's own concerns).

Judging agents are significantly less conforming than perceiving agents for all values of $k$. The big five conscientiousness personality trait is positively correlated with judging in the MBTI framework (Furnham, 1996). Conscientious types hold more rigid beliefs (Chen and Palmer, 2018). This is consistent with our observation that judging agents conform less.

We see that thinking agents are affected less than feeling agents. The differences between thinking and feeling agents are significant for all $k$, apart from $k = 4$. People high on agreeableness are more cooperative (Kilmann and Thomas, 1976). Agreeableness as big five personality trait is positively correlated with feeling in the MBTI framework (Furnham, 1996). Based on this we would expect feeling agents to more readily conform. This supports our finding that feeling is more conforming than thinking.

The results for sensors versus intuitives are less clear cut. At $k = 1, 2, 3$, sensing agents are affected more by the number of agents with goal $A$ than intuitive agents (although only $k = 2$ is significant). At $k = 4$ and $k = 5$, intuitive agents are affected more and it is significant.

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| I-E | * | * | * | * | * | * |
| S-N | - | * | - | * | * | - |
| T-F | * | * | * | - | * | * |
| J-P | * | * | * | * | * | * |

Table 4: Significance (*) and non-significance (-) of difference between means for each dichotomy for $k = 1$ to 6.

Figure 6 shows the paths in representative runs from start to finish. For $k = 1$ we see ENTJ with goal $A$ conforming with its neighbours and moving towards goal $B$. The plot at $k = 2$ shows agent INFP with goal $B$ ending up in the middle and agent ENTJ with goal $B$ conforming to goal $A$. At $k = 3$ we see ESTJ and ESFJ with goal $A$ moving towards the optimum of $f_B$. We also see INFJ with goal $A$ move towards goal $A$ by itself. For $k = 4$ we see agents with goal $A$ not quite reaching their goal, but moving in the right direction, and INTP with goal $B$ moving towards its goal but also not reaching it. The plot at $k = 5$ shows ENFP going off on its own and INFJ with goal $B$ going straight towards its goal.

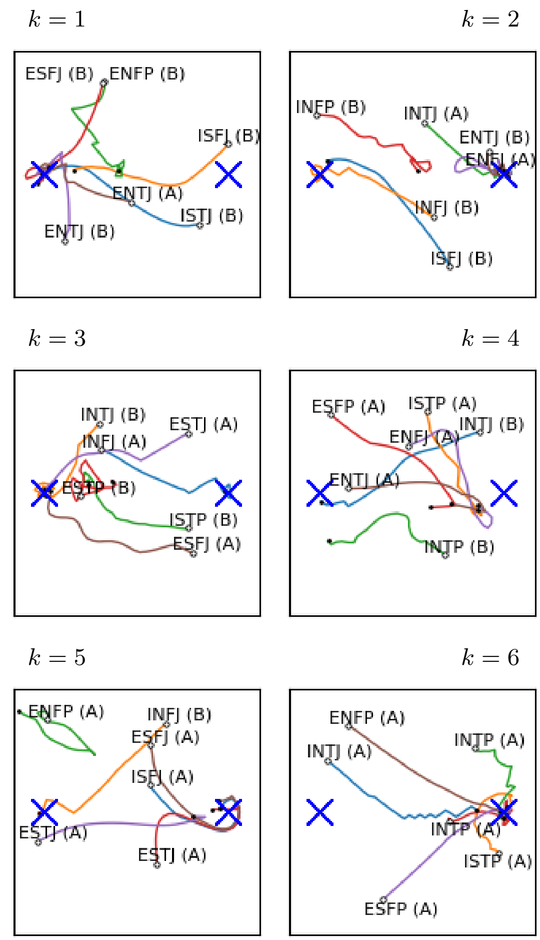


Figure 6: Representative runs (for $k = 1$ to 6) showing each agent's path as they navigate the solution space to find the optimal solution. The start of an agent's path is indicated with its dominant Jungian function and goal. The right cross indicates the optimum of $f_A$ and the left cross indicates the optimum of $f_B$.

## Analysis

**Si and Ni** are both quite non-conforming. In Figure 4 we see that their average performance is much higher than the average performance of agents with different dominant Jungian functions (at $k = 1, 2, 3, 4$ and 5). This can be explained by the fact that the model of Si considers points the agent has already been in and points with fixed distance around the current location of the agent. To choose a new location the Ni model applies a function (independent of neighbours) to the points that Si considers. These are very individual process and other agents have no influence over it, so it comes as no surprise that these agents perform as well regardless of what goal neighbouring agents optimize for.

**Ti** chooses a new location independently of neighbours, so the fact that agents with dominant Ti function seem to be influenced by neighbours' goals could be explained by agents' auxiliary functions. In Figure 4 we see that Ti performs worse than Si and Ni, but better than all other types (at $k = 1, 2, 3, 4$).

**Fi** agents are moderately conforming. In Figure 4 we see that Fi is less conforming than half of the types and more conforming than the other half. Agents with dominant Fi function accelerate towards a weighted average of their neighbours' average position from the previous timestep and their own best position.

**Se, Te and Fe** agents are highly conforming and perform poorly when there are many other agents with a different goal. In Figure 4 we see that agents with Se, Te or Fe dominant function, perform much worse than average when $k = 1, 2$ or 3. Agents with dominant function Se consider points that are the positions of agent's nearest neighbours in the previous timestep. Te accelerates towards its neighbours' best personal best location from the previous timestep. If other agents have the same goal then these are good strategies, otherwise they are not. Fe dominant agents match their neighbours' average velocity and to a lesser extent accelerate towards their neighbours' best personal best from the previous timestep, making them highly conforming.

**Ne** is moderately conforming and shows interesting behaviour. In Figure 4 we observe that Ne performs similarly for $k = 2, 3, 4$ and 5. In Figure 7 we see that even after many timesteps Ne's solution space does not converge to a peak at the maximum of $f_A$ when there are 5 agents with goal $A$ (or at the maximum of $f_B$ when there are 2 agents with goal $A$), which does happen when all agents optimize for goal $A$. Ne does not get pushed more towards goal $A$ when there are many agents with goal $A$, as long as there are some agents with goal $B$.

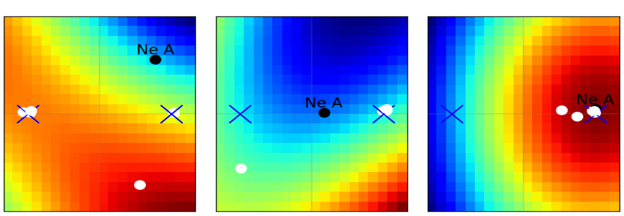


Figure 7: An example of the solution space of Ne (black) at 30 timesteps for $k = 2$, $k = 5$ and $k = 6$ (from left to right) with other agents as white dots, when Ne has goal $A$. The right cross indicates the optimum of $f_A$ and the left cross indicates the optimum of $f_B$.

## Conclusion

We found personality type to have a significant effect on conformity. For example, we found that our model of extraverted agents is significantly more influenced by other agents with different goals than introverted agents. We also found that the proportion of agents has a significant effect on conformity for some personality types. For instance, agents with dominant Jungian function extraverted sensing, extraverted thinking or extraverted feeling are all highly conforming when there are many agents sharing a different goal, and not conforming when very few agents share a different goal.

Findings from this work should be corroborated by collecting data from real teams. In turn this work can serve to guide future psychology research on the relationship between conformity and other personality traits.

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