Modulating Agent Behavior using Human Personality Type

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Abstract. A prototype model is presented that demonstrates the idea of modulating agent behavior using human personality type. The psychological theory of personality type known as the Myers-Briggs Type Indicator (MBTI) is applied here. The MBTI theory defines four dichotomies to explain how individual humans differ in the ways that they perceive their environment, interact with others, and make decisions based on these traits. MBTI is integrated into a simple agent architecture and the resulting variations in behaviors are demonstrated in a simplified multiagent simulation environment. Experimental results illustrate that each personality type produces very different outcomes, distinct for and characteristic of its MBTI classification.

Keywords: behavior modeling, multiagent simulation, artificial life, BDI

1 Introduction

In the field of human-agent modeling, often agents are used to model the outcome of human behaviors. For example, Learning from Demonstration (LfD) is an approach that builds agent behaviors based on the actions of a human teacher [1]. Our work takes a different viewpoint. Humans are all very different and approach the world differently; thus, individual humans, when faced with the same situation, will react differently. Psychologists often explain these differences using the heading of "personality type". For example, when approached by a contrary co-worker, a person who is aggressive would confront the individual, whereas a person who is passive would walk away. Our long term goal is to model the common spectrum of human-like behaviors in a population of agents, as a means to emulate the natural variations in humans' reactions and to predict the likely distribution of outcomes. The reasons for doing this are two-fold. First, in designing interactive systems for a general market, having a systematic way to model the full range of characteristic human behaviors can help focus development efforts within more popular sub-sections of the complete interaction landscape. Second, in designing simulations of human-centric processes, having a systematic way to label behavior characteristics can help guide data-mining activities to produce results that are clearly connected to well-understood models of human behavior. The work we present here is a prototype model that demonstrates our idea. We take the psychological model of personality type known as MBTI and apply it to a simple multiagent environment discussed frequently in the Artificial Life community.

The *Myers-Briggs Type Indicator (MBTI)* is a well-known psychological theory of human personality developed in the mid 1900's by Katharine Myers and Isabel Briggs Myers [2], and based on an earlier theory developed by Carl Jung [3]. We explore the use of the MBTI as the basis for defining a guideline for complex agent behaviors. The reason MBTI is a good fit for agent modeling is because it has clearly defined traits for each personality preference. Additionally, every preference contains an opposite, which makes it easy to compare experimental results.

Jung's theory states that human mental activity essentially involves receiving information and processing that information to make decisions. The input of information (*perceiving*, according to Jung) can be handled in one of two ways, either by overtly *sensing* or by using *intuition*. This process is analogous to setting an agent's beliefs. The process of *making decisions* can be driven by logical *thinking* or by emotional *feelings*. This process is analogous to defining a set of desires and intentions [3]. Jung also explained that some people derive their energy[3] for these processes from the influences of the external world around them (*extroversion*), while others rely on internal mechanisms such as thoughts or memories (*introversion*).

Briggs Myers and Myers expanded on these three dichotomies by adding a fourth "lifestyle" axis which distinguishes between people whose personalities revolve around either *perceiving* (e.g., exploring new intentions) or *judging* (e.g., exploiting previous intentions). This function helps define how committed an agent is to an intention and how it sets a plan and follows through [2].

Typical results of MBTI tests label individuals using one-character abbreviations for each pole on each axis, as follows:

- *Extroversion* (E) versus *Introversion* (I)
- *Sensing* (S) versus *iNtuition* (N)
- *Thinking* (T) versus *Feeling* (F)
- *Judging* (J) versus *Perceiving* (P)

So, for example, an individual whose personality is labeled ENTJ is someone who gets their energy from interacting with others, who makes decisions based

[3] The term *energy* in this context refers to mental energy, such as motivation, and how action (mental, physical, or emotional) is tempered by a person's energy level. This should not be confused with "energy" as often employed in multiagent systems to refer to how much (e.g.) fuel an agent has to complete a task. The latter usage implies that the energy level can be increased by consuming more resources (e.g., petrol or food), whereas the former usage intends that the energy level is influenced by less tangible interactions, such as with other agents in the environment.

on abstract observations of their environment, who solves problems using logical reasoning, and is organized and methodical about what they do. An ENTJ individual makes a commitment to complete a certain task in a certain way and sticks with their plan until the task is complete. In contrast, an individual whose personality is labeled ISFP is someone who gets their energy from inside, who learns from experience and focuses on facts, and lets empathy influence their decision-making. An ISFP individual commits to an intention, but constantly re-evaluates its commitments to decide if there is a better way to complete the task or a better task to address.

It is important to note that MBTI labels people with these four letters, because the theory states that everyone has a natural preference for only one side of the spectrum or the other. As humans, we have the ability to train ourselves and learn how to use other functions, but inherently we only have one preference. An example that is often brought up in the MBTI literature is someone's preference for left-handedness or right-handedness [4]. Humans generally use one hand as their dominant hand, but with practice it is possible for someone to learn how to use their less dominant hand as well as their dominant hand. Would you still label that person as their original dominant handedness? MBTI does. In this work, we assume that agents only have one dominant function in each dichotomy that does not change throughout their artificial life.

The Meyers-Briggs hypothesis is that all combinations of $2^4 = 16$ personality types exist in humans, and knowledge of which personality type corresponds to an individual can help that individual make life and career decisions. Certain personality types tend to be well-suited to particular types of jobs; certain pairings of personality types tend to work better than others for business or life partnerships. The same reasoning could be applied to design and evaluation of multiagent-systems. We integrate MBTI into an agent architecture by creating each of the four MBTI dichotomies and then combining them to reflect the sixteen distinct MBTI personality types. Experimental results illustrate that each personality type produces very different outcomes, distinct for and characteristic of its MBTI classification. Our observation is that some agent personality types are better suited to particular tasks—the same observation that psychologists make about humans. The implication in the agent modeling and agent-based simulation communities is that the success or failure of an experiment could be affected by agents' inherent personality types, because personality type influences perception and interpretation of inputs, mode of interaction with others, generation of outputs, and decision-making processes.

The remainder of this paper is organized as follows. Section 2 details the theory behind our implementation, embedding personality type into each component of the BDI framework. Sections 3 and 4 present our experimental environment and results, showing the differences between each personality type. A review of related work is contained in Section 5. Lastly, we finish off in Section 6 with a summary and description of future work.

	E-I	S-N	T-F	J-P
sense environment and update *beliefs*	×	×		
update *desires* and *intentions*	×		×	
update *plan* and select *actions*	×			×

Table 1. MBTI influences in BDI process

2 Modeling Agents with MBTI

In order to model the agents, we embed the four MBTI dichotomies into a BDI architecture. The inherent structure of both MBTI and BDI leverage functions that help define beliefs, functions that help establish desires and also formulate intentions. We represent an agent as a sequence of states, where each state is a set of variables:

- ϕ: the set of personality preferences the agent has, which do not change throughout the agent's lifetime;
- σ: a set of sensor values that the agent has read from the environment;
- β, δ and ι: the agent's sets of beliefs, desires and intentions, respectively;
- γ: the agent's goals;
- ψ: the current plan that the agent has chosen; and
- α: the action that the agent is currently executing.

In a BDI architecture, an agent uses a *perception function*, a method for sensing its environment ($\mathcal{E}$) and interpreting what the sensor input means, to define its beliefs. In our implementation, the perception function uses σ and ϕ, applying personality to the agent's beliefs as they are formed. Specifically, the second dichotomy (S-N) plays the largest role in influencing the agent's beliefs. The agent then assesses its beliefs (β), goals(γ) and personality type preferences (ϕ) when establishing a set of desires. Here ϕ applies mainly to the third dichotomy (T-F) because this is where the decision-making process plays the largest role. Once a set of desires have been defined, the agent formulates its intentions as a function of its desires (δ), goals(γ) and personality type preferences (ϕ). Similar to δ, the third dichotomy (T-F) plays the largest role. This is because the set of desires represents a wide array of possible goals to achieve and the agent needs to use its decision-making process to select an immediate set of desires and convert them to intentions. After defining the set of intentions, the agent selects a plan, ψ, and follows through with it. The planning function takes into account the agent's intentions, (ι), and personality type,(ϕ). In this step, the fourth, "lifestyle" dichotomy (J-P) plays the largest role because it dictates whether an agent will tend to exploit a proven plan or explore a new one. This includes an agent's assessment of its commitment to its short-and long-term desires—whether it should abandon the most recent desire in favor of another that seems somehow more promising. Finally, the agent's behavior model contains an *action-selection function* in which the agent decides what action to take, given its plan (ψ), its personality type (ϕ) and the set of possible actions it could perform.

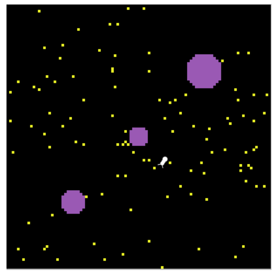


Fig. 1. Sample screen shot of "Termite World"

The first dichotomy (E-I) plays a role in each of the BDI functions. This is because an extroverted agent's energy is derived from other agents and so its focus is on other agents. This means that an extrovert will try to interact with other agents, help other agents and collaborate with them; and all their decisions will be biased towards their outer world. An introvert's biases will be the opposite. It prefers to work alone and pays attention to its own inner thoughts and personal goals. The decision about when to update an agent's internal state also lies within personality type. The fourth dichotomy (J-P) dictates an agent's commitment to its beliefs, desires, intentions and plans. Table 1 summarizes the influence of each personality type dichotomy on each phase of the BDI process.

3 Experimental Setup

This section introduces a simulated environment for experimentation and describes how we implemented an example $MBTI$ multiagent system. We consider the specific implementation of each personality type within the context of our simulated environment. Rather than separate our code into sixteen separate rule sets, one for each of the sixteen personality types (i.e., ESFJ, ISFJ, ESFP, etc.), we invoke the appropriate dichotomy(ies) at the appropriate point within the typical BDI program structure.

Our experimental environment is based on an existing model from the artificial life community that simulates termites gathering food [5]. We constructed a prototype of this environment using NetLogo [6]. The termites' task is to gather food particles and place them in piles. We modified the standard termite model by using pre-determined locations (instead of allowing the number and locations of piles to emerge as the simulation runs) in order to help illustrate the distinguishing characteristics of the different agent personality types. The environment is represented as a two-dimensional grid, where each (x, y) location in the grid is referred to as a "patch". The differences between the personalities are revealed quantitatively in terms of several metrics: the number of different patches visited, the number of food particles gathered and delivered to piles, and the time interval between gathering a food particle and delivering it to a pile. A view of the simulation environment with a single agent is shown in Figure 1.

At each timestep in the simulation, an agent senses its environment, defines its beliefs, desires, intentions and then acts. They can sense the following properties: their own locations, whether they are holding food, the location of food within their range of sight, and the locations of other agents within their range of sight. They can also sense what other agents within their range of sight are targeting. Agents actions are selected from the following set: move forward, turn, pick up food, drop off food, and wiggle (turn randomly and moving forward). Agents' behaviors are affected by their personality type as follows:

- E vs I: An introvert gets its energy from within and an extrovert gets its energy from interacting with others. We give each agent an energy level that increases or decreases based on others around them. Introverts lose energy when they are around other agents and gain energy when they are alone. Extroverts follow the opposite rules.
- S vs N: Two attributes that explain the sensing and intuitive preferences are concrete and abstract, respectively. These attributes can be used as a lens, modulating what each agents sees and what it is looking for. Concrete, sensing agents are focused on food that is close by. When they cannot see food, they go back to the last place they saw food, hoping something is still there. Abstract, intuitive agents look for food that is clustered together, prioritizing larger clusters over smaller ones. When intuitive agents cannot see food, they try to explore new areas.
- T vs F: The third dichotomy helps agents make decisions about their desires and intentions. Thinking types are logical and detached, so we implemented the thinking agents to set a straight line for their preferred food. Feeling types are empathetic in their decision process. Therefore, our feeling agents take into account the food that their neighbors are targeting, and they ignore those cells.
- J vs P: This dichotomy manifests itself in the choice between exploration versus exploitation. Judging agents make a decision, set a plan and act to exploit what they see immediately. This type of agent will find food and set a plan to pick it up; it will remain committed to the plan until completed (or failed) and will not sense the world again until reaching its destination and picking up food, or failing to pick up food because the food has been picked up by another agent. Perceiving agents want to research the world, explore as much as possible, and only act when required. At every timestep, this type of agent senses the world and re-assesses its beliefs, desires and intentions, continually modifying its plans accordingly.

4 Experimental Results

In this section, we present experimental results to prove our hypothesis and demonstrate that various personality types produce different outcomes, and the MBTI layer provides a structure for explaining those differences. Each experiment was run across 9 different scenarios for a fixed duration to ensure that our results were not random. Each scenario differs by two factors: where the agents

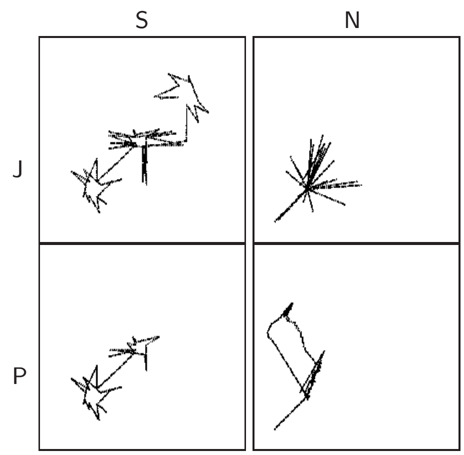


Fig. 2. Sample paths of different personalities.

and the food particles are placed in the environment at the beginning of the run. In addition to running each experiment with 9 different starting conditions, we also ran each experiment with 6 different population sizes: 1, 5, 10, 20, 30 or 50 agents. To help focus our explanations of the results, this paper only includes the results from experiments with a population size of 20 agents (with one exception, as explained below).

The results we present highlight differences across the following metrics: the number of different patches visited, the number of food particles gathered and delivered to piles, the time interval between gathering a food particle and delivering it to a pile, and the effects of considering other agents when making decisions about actions.

4.1 Path taken

We start by showing how each personality's path differs and illustrating graphically why they take different numbers of steps. Figure 2 shows the typical paths of four different agent types (ISFJ, INTJ, ISFP and INTP). In order to keep the illustrations uncluttered, we show paths from one set of 1-agent runs. To ensure that the differences cannot be traced to the energy function, we chose four introverted agents, since they continue to move at full speed in a solitary environment. The agents' actions create straight or squiggly lines, depending on their approach and commitment. This figure illustrates where each agent's focus lies. For both sensing agents, ISFJ and ISFP, Figure 2b and 2c, respectively, their paths are short and they do not stray far from their starting point. The graphs illustrate how the focus of sensing types is based on proximity and that they prefer to concentrate on the details in front of them. On the other hand, intuitive types tend to focus on the bigger picture and try to look for patterns or clusters. Their paths are typically longer because they are willing to travel

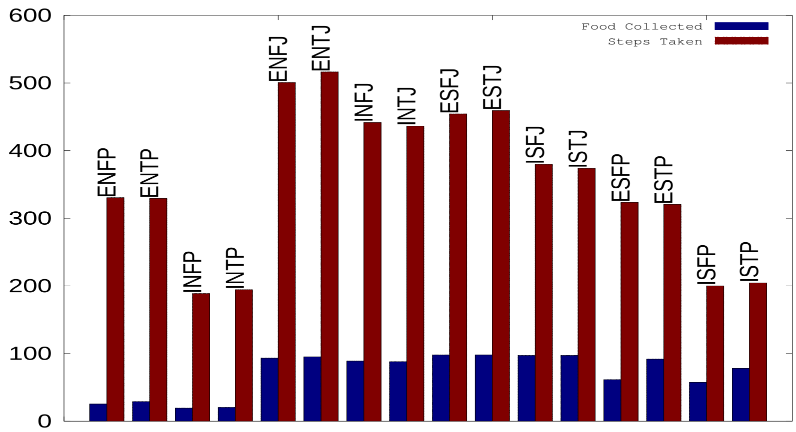


Fig. 3. Total food particles collected and number of moves taken.

farther to find the largest cluster of food. Notice how both the INTJ and the INTP do not stay near their starting points for long. They are quickly pulled towards the largest pile. This again illustrates how the Ns focus is not defined by proximity, but cluster size.

Looking at both the INTJs and INTPs paths side-by-side, and the ISFJs and ISFPs paths side-by- side, it is also clear that aside from the length of their paths, there are other differences between the types. The other differences can be attributed to the judging and perceiving function. As explained in Section 3, judging types prefer to make a decision and commit to it. Perceiving types prefer to continue researching and are not committed to their decisions. Looking at the INTJs and INTPs paths, we can see that the INTJs paths taken are all straight, whereas the INTPs paths are mixed with both straight and wiggly lines. This shows how the INTJ senses for food, is able to find the largest cluster of food within its line of sight and makes a decision of where to go. The agent continues in a straight line till arriving at its destination. On the other hand, the INTP re-evaluates its path at every step. Since moving forward may bring new information about the largest cluster, the old decision is no longer valid. The re-evaluation and continuous research is illustrated by the wiggly path. This also confirms our earlier understanding of why the perceiving types take fewer steps than judging types.

4.2 Amount of food gathered and delivered

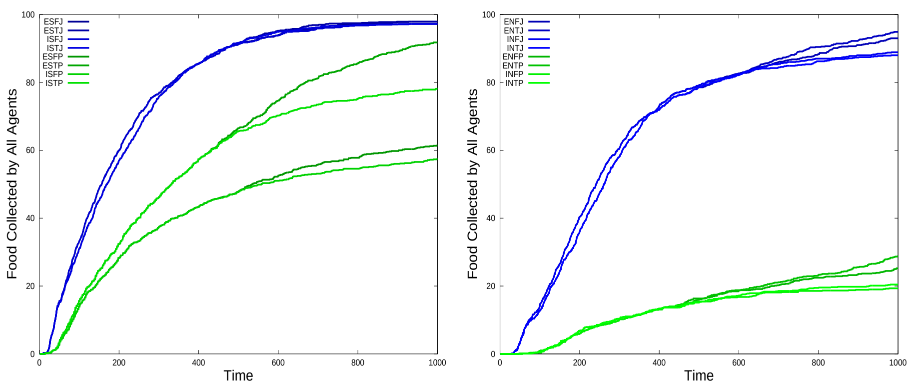
To help illustrate the different productivity levels of each agent type, we look at how much food each agent type collected. Table 2 shows the results averaged over all the 20-agent runs. The grid format of the results is meant to help see patterns in the results, pointing out which personality preferences are impacting the results. Notice that six out of the eight J types collect around the same

		Sensing		*Intuitive*	
		Thinking	*Feeling*	*Thinking*	*Feeling*
Introvert	*Judging*	**97.2 (7.8)**	**97.2 (7.8)**	88.0 (4.9)	88.9 (6.0)
	Perceiving	78.1 (4.5)	57.4 (17.0)	20.4 (6.1)	19.3 (4.7)
Extrovert	*Judging*	**97.9 (7.6)**	**97.9 (7.5)**	**95.1 (7.3)**	**93.2 (6.5)**
	Perceiving	91.8 (6.2)	61.4 (19.7)	29.0 (5.9)	25.3 (6.1)

Table 2. Number of food particles collected (mean and standard deviation).

amount of food. All four of the I**J types perform the worst, collecting 75% less food than the top gatherers. Figure 3 shows the same results as a bar graph, highlighting the differences across all 16 types.

This figure also includes a bar for the number of steps each agent type took during each run. Notice how the 8 Perceiving types all took many fewer steps than the Judging types. As explained in Section 3, this is because the perceiving types continually re-assess their plans, whereas the judging types do not re-evaluate until their plan is complete.



(a) Sensing (b) iNtuitive

Fig. 4. Graph showing the progress made by Sensing vs Intuitive agents.

In addition to their paths and moves, we can easily see how the judging and perceiving types differ by looking at the two graphs in Figure 4, illustrating how much food each agent type collects as a function of time. Figure 4a displays the results of all Sensing types. Figure 4b displays the result of all iNntuitive types. It is very easy to see how the Judging types (blue lines) collect more food early on and have a steep slope, whereas, the Perceiving types (green lines) collect food gradually over time, producing a straighter line.

4.3 Task efficiency

As we saw above, in a single-agent environment the intuitive agents took more steps and traveled more than their sensing counterparts. In order to put our understanding in terms of a concrete metric, Figure 5 shows the overall *task efficiency* of each agent type in a 20-agent environment. We define task efficiency as the amount of food collected divided by the number of steps taken. The graph is sorted with all intuitive types on the left and all Sensing agent types on the right. This shows that the iNtuitive agents are less efficient than the Sensing agents, and that the *N*P agents are the least efficient of all.

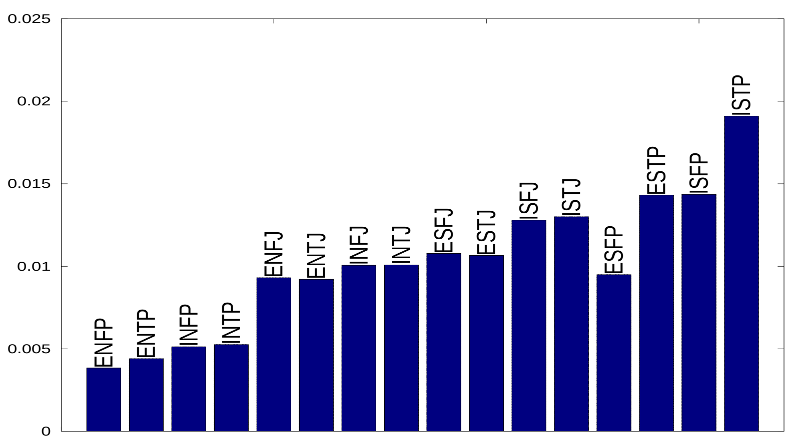


Fig. 5. Task efficiency (amount of food collected divided by time).

Figure 6 clarifies the differences between the Introverts and Extroverts. The graph illustrates each agent type's performance as a function of their energy level. This highlights the divergent paths the Is and Es take. The Is start losing energy from the beginning and use their reserve energy up completely before coming to a halt, no longer being productive. On the other hand, the Es gain energy with every time-step and remain productive throughout the entire run. The varying energy levels have to do with how the agents traveled. Certain types traveled together, in packs and either boosted their energy (Es) or drained their energy (Is). Other types traveled separately and that produced the opposite result.

4.4 Consideration of others

Until this point, all of the experiments we have shown were run with only one agent type in the environment at a time. In order to best illustrate the differences between agents with Thinking and Feeling preferences, we ran a set of experiments with four different agent types in the environment at the same time.

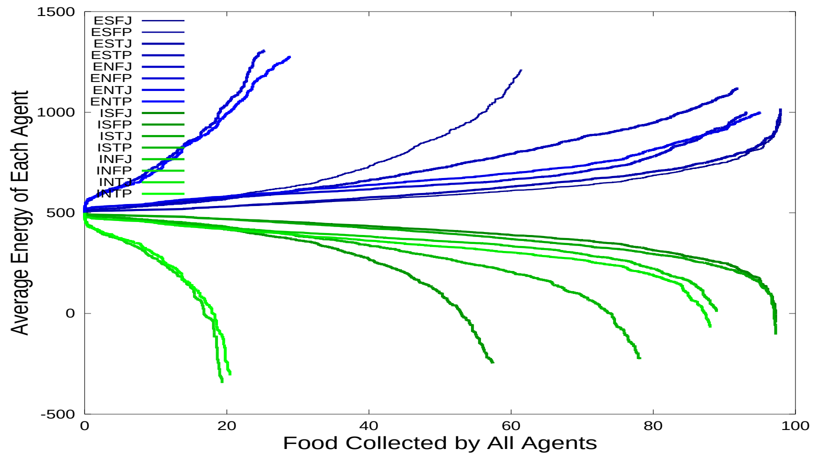


Fig. 6. The amount of food collected, as a function of energy level.

To keep the agent populations analogous with each of the experiments shown above, these experiments have a total of 20 agents in the environment at a time. We ran four different experiments. In the first experiment, we placed 5 ESFJ's, ISFJ's, ESTJ's and ISTJ's in the environment. The second experiment included all *S*P's, the third included all *N*J's and the last included all *N*P's. We specifically chose so we could attribute the differences in behavior to either the first (E-I) or third (T-F) dichotomies.

In Figure 7, we show the differences between the steps taken by the Feeling agents compared with their Thinking counterparts. Each bar in the graph represents the number of steps taken by **T* agents subtracted from the number of steps taken by **F* agents. For example, the first bar in the graph shows that the ESTJ traveled 5% more steps than the ESFJ did. On the left side of the graph, we see that both the ESFJ and ENFJ travel less than the ESTJ and the ENTJ. This makes sense since the Feeling agents avoid competition by targeting pieces of food that no other agents are targeting, meaning that it is less likely for ESFJ's to arrive at a target and find the food was already taken by another agent. Whereas, the ESTJ's are in a state of constant competition with other ESTJ's, often finding themselves at their target without anything to pick up. As we can see in the graph, the impact of the Feeling function starts to have a negative effect on the Perceiving agents. This also makes sense, because both the Feeling and Thinking agents are constantly re-evaluating their environment and are driven to constantly empathize with new agents, shifting their direction and targeted food regularly.

Interestingly, although we explained that the Feeling and Judging agents would have an advantage and walk less than than their counterparts, we see that the INFJ walked greater than 60 steps more than the INTJ. The reason for this can be explained due to the varying energy levels of the introverts and the impact energy has on step length. In the four right-most bars we see that Introverted Feeling agents' empathy took them to solitary spaces, where they were not competing with other agents, keeping them energized and productive longer.

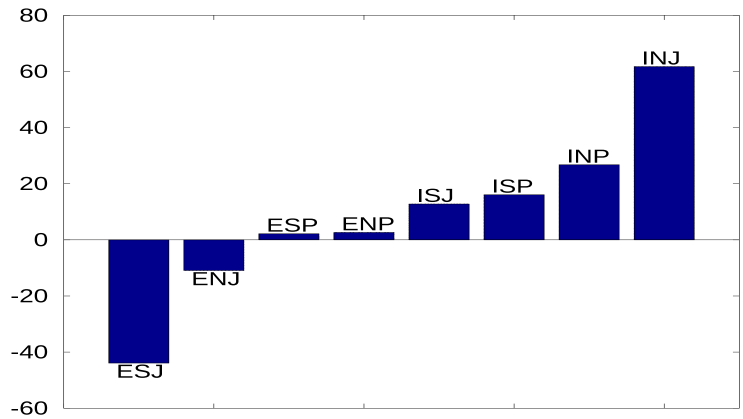


Fig. 7. The number of steps taken by Thinking agents subtracted from the number of steps taken by Feeling agents.

Overall, these experiments show that each personality type performs differently, but in a predictable way, one that follows the MBTI personality types.

5 Related Work

This section reviews related work that explores the use of personality types in agent-based systems. Most approaches that embed personality type into agent modeling focus in one of two directions. The first, more prevalent, focus is on creating personalities for agents that interact with human users in social environments. In these cases, the research involves encoding personality type or temperament to increase social acceptance. Dryer [7] explains that personality types can be used to enhance human-machine interaction. Lin and McLeod [8] introduce personality into their work, but instead of incorporating type as the part of the mechanism underlying agents' actions, they train their engine to recognize temperaments and information associated with each temperament. They use this training to filter results more effectively and provide better recommendations. Allbeck and Badler [9] use the "Big Five" theory to embody personality traits and make the actions of each agent flow more realistically and believably.

Lisetti [10] defines a taxonomy for socially intelligent agents, stressing *emotion* as a strong component of personality. She describes state machines that illustrate how an agent can shift from one emotion, such as "happy", to another emotion, such as "concerned". These shifts can occur for different reasons in agents with different personality types. For example, a "determined" agent that is "frustrated" may shift into an "angry" state and use that anger to work itself back into a "happy" state; whereas a "meek" agent may shift from "frustrated" to "discouraged" and never return to "happy".

The second focus is on modeling complex interactions between agents and their environment and describing variations in agent behaviors as personalities. Castelfranchi *et al.* [11] present a simulation framework called *GOLEM* in which agents of different personality traits are modeled. GOLEM provides an experimental framework for exploring the effect of personality traits on social actions, such as delegation. Agents develop models of each other, labeled as personality traits, and use these models to motivate their interactions. Talman *et al.* [12] model personality along two axes: "cooperation" and "reliability". These different traits are implemented in a logical framework where agents play a game and reason about each others' "helpfulness", or lack thereof. Agents can recognize different personality types and respond effectively, customizing their actions appropriately for different personalities.

Both of these last two examples use the notion of personality as a means for agents to model each other and make decisions about how to effect (or not) co-operative activity with others. Another approach is given by Parunak *et al.* [13], where personality is closely tied to emotion, as with the first type of focus listed above. In this work, agents' internal decision-making processes are guided by personality types. Agents are deployed in a simulated military combat scenario in which factors such as "cowardice" and "irritability" are modeled and act as motivators for certain types of actions. For example, an agent labeled as cowardly may be driven by fear and run away from threats when attacked; whereas an agent driven by anger might move forward and face the enemy. Others [14–16] also explore the space of embedding personality and emotion into simulated agents. In André *et al.'s* [14, 15], lifelike characters are built and tested in three separate spaces. One is for interacting with children and is static in its approach, limiting the personality and responses to a specific set. The second is a market place with different personalities for buyers and sellers. In this scenario, they limit the personality to only two attributes, again illustrating the differences. Lastly, their most promising application is their Presence system. The system is based on an "Affective Reasoning Engine", one that interprets emotion and personality and affects the input and decision making process. While their work describes a novel approach to agent modeling, it is hard to discern if the impact they describe is due to the emotional model or the personality type.

Drupinar *et al.* [17] employ the *OCEAN (openness, conscientiousness, extroversion, agreeableness and neurotic-ism)* personality model [18] to an agent-based visualization of crowds. They employ a crowd simulation system and assign individuals in the crowd personality traits that correspond to the OCEAN model. They associate particular behavioral characteristics, such as willingness to wait or walking speed, with specific personality traits, e.g., agreeableness or extroversion, respectively. Their results show that different proportions of individuals with different personality traits lead to different types of group behavior in the simulated crowd, such as congestion or panic.

Canuto *et al.* [19] starts with a similar assumption and hypothesis as we do; that individuals performing the same role with different personalities will affect different results. They develop a simulation environment and scenario called SimOrg and integrate a personality type developed by Theodore Millon. They show, as we do in this work, that an agent behavior model for personality type is impactful.

All of the work discussed above is highly context dependent: personality traits are designed in tandem with the environment in which agents are simulated and the tasks that agents are addressing. Egges *et al.* [16, 20] create a generic model for personality and emotion, but they abstract the concept and therefore interpret the attributes of personality type differently than we do. For example, their description of an interaction with an introvert versus an extrovert effectively illustrates that each type will behave differently, but their example assumes introverts are confrontational when their inner space is invaded.

The advantage of the MBTI model is that it is generic and can, in theory, be adapted to any environment and task. In addition, each dichotomy has a clear set of attributes that define it, providing a clear set of guidelines for implementation. While the instantiation details of agents' personalities will necessarily be tailored to a particular environment, the abstract definition of the personality traits themselves is not specific.

Campos *et al.* [21] employ the MBTI model to leverage personality type and test agent performance in one environment with different personalities. Similar to our work, the authors model axes; they restrict to S/N and T/F. However, their interpretation of the functions differs from ours. They implement the S/N dichotomy as a mechanism for developing a plan, and they implement a hybrid between the S/N and J/P dichotomies for plan selection. We feel that this makes it harder to distinguish between the different types.

Overall, our literature review showed much research including personality type into simulations and systems, but each work has different reasons for using personality type and therefore their implementations and interpretations are very different. These differences make it clear that there is a need for a unifying model of personality type for agent behavior, paving the way for the work presented here.

6 Summary

The motivation of the work described here was driven by our exposure to MBTI and our experiences dealing with a range of human personalities in our professional and personal lives. For example, we frequently observe groups of students in a lab, all faced with accomplishing the same exercise, but they address the task with different problem-solving strategies, time-management approaches, and interpersonal skills. With this in mind, the purpose of this work is to demonstrate that the MBTI theory can be applied to an agent architecture and produce agents that perform differently within the same task environment. As we showed in the experimental results, each agent's performance was different and characteristic to their respective behavior models and personality types.

Although the work presented here is for a simplified environment, we hope that our method of interpreting the MBTI theory within an agent-based context can ultimately generalize to other domains. One of our next steps is to expand this work into other domains that show more complex (human) behaviors, such as domains requiring agents to have both individual and shared group goals. An example is a basketball team, where individual players within a team compete to be one of the 5 players on the court, while the team as a whole collaborates in order to be competitive against other teams. Without a personality model to guide the implementation of agents acting in complex spaces like this, it could be very difficult to predict and validate the behaviors and interactions between humans and agents in a structured and systematic way.

We understand that the goal of most research is not to find the right agent for a task, but rather to solve larger problems. We believe that when designing an environment and developing the solution to a larger problem, it can be beneficial to select the behavior characteristics necessary to solve the problem, i.e., in terms of identifying which classes of behaviors will produce the overall outcomes sought. For example, a designer might want to implement agents whose behaviors are impervious to the actions of others, or agents who are overly empathetic to others. With personality type as an underlying design criteria, a developer can select certain behavioral traits to implement.

Therefore, it is our belief that having a systematic way to model human behaviors in agents, founded on a theory of personality type, has the potential to impact many areas within agent modeling and multiagent systems.

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