Abstract

Modeling personality is a challenging problem with applications spanning computer games, virtual assistants, online shopping and education. Many techniques have been tried, ranging from neural networks to computational cognitive architectures. However, most approaches rely on examples with hand-crafted features and scenarios. Here, we approach learning a personality by training agents using a Deep Q-Network (DQN) model on rewards based on psychoanalysis, against hand-coded AI in the game of Pong. As a result, we obtain 4 agents, each with its own personality. Then, we define happiness of an agent, which can be seen as a measure of alignment with agent’s objective function, and study it when agents play both against hand-coded AI, and against each other. We find that the agents that achieve higher happiness during testing against hand-coded AI, have lower happiness when competing against each other. This suggests that higher happiness in testing is a sign of overfitting in learning to interact with hand-coded AI, and leads to worse performance against agents with different personalities.

1 Introduction

Personality is defined in [19] as the “unique, relatively enduring internal and external aspects of a person’s character that influence behavior in different situations.” Theories of personality strive to explain and describe different types of personalities among people. Freud [4, 3] was the first to develop a modern theory of personality based mostly on clinical observations. In [19], Freudian structure of personality is described as composing of three elements: id, ego, and superego. Id is concentrated on following basic instincts. It is interested in instant gratification, knows no morality and is selfish. On the opposite side, superego constitutes the moral aspect of personality. It wants to act according to parental and societal values and standards. Ego is the rational element of the Freudian model. Its role is to resolve the conflicts between the demands of id and the moralizing superego by using defense mechanisms such as denial or repression. Many alternative approaches describing personality have been proposed since (e.g., see [19]). Moreover, computational models of personality have also been implemented (see section 2). Most of them concentrate on intrapersonal aspects of personality and work with hand-crafted features, in relatively simple settings.

In the last few years, the advances in Deep Learning (DL) [7, 18] and the development of Deep Q-Networks (DQN) [9] have made it possible to work with increasingly more complex environments, e.g. Atari 2600 games [2], using only pixels as input.

In this work, we explore the applicability of DQN to computational psychology on the intrapersonal level. We concentrate on id and superego components of personality. The key idea is to employ DQN to learn a Freudian-inspired personality model from raw input in the game of Pong and use the resulting agents with different personalities to study their performance both in training and in a society of bots. Firstly, to achieve agents with different personalities, we formulate and train a DQN-based model using Freudian-inspired reward functions (section 3). We let one DQN learn
from a reward signal strengthening selfish behavior - in Pong this can be reflected by scoring a point against an opponent - which is a typical characteristic of id \[19\]. Another DQN learns superego - based on rewards corresponding to morality, cooperation. In the game, this can be represented by trying to win, but without getting ahead of our opponent by more than one point. Secondly, we define a “happiness” measure of a resulting id/superego agent based on its performance in relation to its objective function (section 3). Finally, when the trained id and superego agents play against each other, we find that the agents that are less happy after the training session - or less aligned with their intended reward objective - are more happy when they compete against each other (section 4). This suggests that less overfitting during training, leads to a more successful, resilient behavior of an agent in a society.

2 Related work

To our knowledge, the first attempt to computationally describe the psychoanalytic theory of mind was \[11\] (cf. \[10\]), and used basic probability. We did not find any extensions of the model to computer simulations. A computational model of personality using some of the traits of the Big Five theory of personality (the Five Factor Model, FFM; cf. \[19\]) and neural networks was presented in \[15\]. Other studies using neural networks to learn a personality include \[13, 14\]. Another probabilistic approach was given by \[6\], which used a Bayesian Belief Network with the FFM to build a multilayer personality model in a chat application. The fact that you can replicate many of the previous experiments used in computational models of personality, e.g. \[15, 14\], within a CLARION cognitive architecture was demonstrated in \[20\]. As far as other cognitive architectures are concerned, \[5\] used one trait of the FFM in the ACT-R architecture and demonstrate the behavior of their model, PIACT, in a soccer simulation environment. The BDI architecture was used to simulate personality in \[12\], and more recently with the FFM in \[1\]. The biggest difference in our approach to modeling personality is that it only involves specifying new reward signals for the id or superego components of the personality model to achieve complex behavior in a challenging environment.

3 Problem description

Motivated by the Freudian theory of personality \[4,3\], we formulate two types of rewards and agents corresponding to the id and superego elements of personality.

**Definition 1.** ID reward \((r_{ID})\) is a predefined, scalar reward signal sent to the agent at each time step, encouraging selfish behavior.

**Definition 2.** SE reward \((r_{SE})\) is a predefined, scalar reward signal sent to the agent at each time step, encouraging social behavior.

**Definition 3.** Cumulative ID reward \((R_{ID})\) is a total reward achieved by an agent in a Markov Chain of length \(n\), ending with a terminus event \(e\):

\[
R_{ID} = r_{ID1} + ... + r_{IDn}
\]
Figure 2: Training \( ID_L \) and \( SE_R \) agents against hand-coded AI for 10 million frames.

Figure 3: Lower happiness score during testing leads to higher happiness in a society.

**Definition 4.** Cumulative SE reward \((R_{SE})\) is a total reward achieved by an agent in a Markov Chain of length \( n \), ending with a terminus event \( e \):

\[
R_{SE} = r_{SE1} + ... + r_{SEn}
\]  

(2)

**Definition 5.** ID is an agent with an objective of maximizing \( R_{ID} \).

**Definition 6.** SUPEREGO (SE) is an agent with an objective of maximizing \( R_{SE} \).

Happiness of people can be measured through surveys, e.g. [8], and captured as a scalar value on a scale. More recently, it has been described mathematically in computational neuroscience as a relation between certain rewards, expected values of given gambles, and the difference between expected and actual rewards in individual [17], and more broadly in social context [16]. Our definition of happiness is for artificial agents and takes into account maximum, and minimum values they can obtain in an environment, and is independent of the happiness of other agents.

**Definition 7.** Happiness of Agent X \((H_X)\) is defined as the quotient:

\[
H_X = \frac{(R_X - R_X^*)}{(R_X^* - R_X)}
\]

(3)

where the cumulative reward obtained by agent X in a Markov Chain, ending with a terminus event \( e \) is denoted as \( R_X \), and its potential maximum and minimum values as \( R_X^* \) and \( R_X^* \), respectively.

Using the above definitions, we train ID and SE agents in the game of Pong. We study their happiness both when training against hand-coded AI, and when they play against each other in a society of bots.

### 4 Experiment set-up and results

In order to demonstrate ID and SE agents in practice, we modified a simple Pong game. The game has 2 players, each controlling one of the paddles on either side of the screen. The goal of the game is to bounce the ball in such a way, so that it goes past the opponent’s paddle - for which the player is awarded 1 point. The game ends with one of the players scoring 11 points.

In terms of the terminology from section 3, scoring 11 points is the terminus event \( e \), after which a new match begins. A subjective reward \((r_{ID})\) used to train ID relates to the id component of the Freudian theory of personality that is selfish. Here, we set \( r_{ID} \) to +1, if the ball goes past the opponent (ID scores a point), -1 if it goes past ID (ID loses a point), and 0 otherwise. As a result, the minimum value of \( R_{ID} \) (i.e. \( R_{ID}^* \)), in one match is -11 (losing every single point), and the maximum is +11 (\( R_{ID}^* \)). On the other hand, \( r_{SE} \) captures the social aspect of the environment, in line with the superego component of personality. Here, the rules for getting the reward are more involved. In short, the goal of \( SE \) is still winning, ideally 11:10, and taking turns in scoring the points with the opponent^1. Hence, \( R_{SE}^* \) is -6, and \( R_{SE}^* \) is 10.5. Fig. 1 shows possible values of \( R_{ID} \) and \( R_{SE} \) that an agent can obtain at the end of each match (for clarity, the values of \( R_{SE} \) are rounded).

To see the full code and the videos showing the performance of agents, go to https://git.io/vbT1v.

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In this paper we describe the computational model of personality based on Freudian psychoanalysis and DQN, and define “happiness” of an agent. Through the experiments, we show that the agents that are less aligned with their intended objective after the training period, exhibit more alignment when interacting with other agents. Here, we acknowledge the weaknesses of this work and mention possible further improvements. Firstly, due to the nature of the DQN algorithm, it is impossible to compare our work with other computational models of personality as was done in [20]. Secondly, this study relies on the psychoanalytic theory of personality. However, it appears that extending this work to the FFM could further improve the ability of the model to capture human personality. Lastly, in order to calculate the happiness, one needs to know the minimum and maximum values of $R_{SE}$ and $R_{ID}$, which may be impossible in more complex environments.

5 Conclusions

In this paper we describe the computational model of personality based on Freudian psychoanalysis and DQN, and define “happiness” of an agent. Through the experiments, we show that the agents that are less aligned with their intended objective after the training period, exhibit more alignment when interacting with other agents. Here, we acknowledge the weaknesses of this work and mention possible further improvements. Firstly, due to the nature of the DQN algorithm, it is impossible to compare our work with other computational models of personality as was done in [20]. Secondly, this study relies on the psychoanalytic theory of personality. However, it appears that extending this work to the FFM could further improve the ability of the model to capture human personality. Lastly, in order to calculate the happiness, one needs to know the minimum and maximum values of $R_{SE}$ and $R_{ID}$, which may be impossible in more complex environments.
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