AI Personification: Estimating the Personality of Language Models

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Technology for open-ended language generation, a key application of artificial intelligence, has advanced to a great extent in recent years. Large-scale language models, which are trained on large corpora of text, are being used in a wide range of applications everywhere, from virtual assistants to conversational bots. While these language models output fluent text, existing research shows that these models can and do capture human biases. Many of these biases, especially those that could potentially cause harm, are being well investigated. On the other hand, studies that infer and change personality traits inherited by these models have been scarce or non-existent. In this work, we explore the personality traits of several large-scale language models designed for open-ended text generation and the datasets used for training them. Our work builds on the popular Big Five factors and develops robust methods that quantify the personality traits of these models and their underlying datasets. In particular, we trigger the models with a questionnaire designed for personality assessment and subsequently classify the text responses into quantifiable traits using a Zero-shot classifier. Our classification sheds light on an important anthropomorphic element found in such AI models and can help stakeholders decide how they should be applied and how society could perceive them. We augment our analysis by studying approaches that can alter these personalities.

Key words: Language models, Personality, Zero-shot learning

1. Introduction

With advancements in methodologies and increasing availability of computational resources for training deep neural networks in recent years, Natural Language Processing (NLP) research has seen substantial progress on a variety of tasks such as language modeling...
and Lapata 2018), question answering (Soares and Parreiras 2020), and machine translation (Zong and Hong 2018) to name a few. In particular, Natural Language Generation (NLG) models that enable the generation of human-readable language have become the central building blocks of modern artificial intelligence (AI) applications, such as virtual assistants, chatbots, automatic translators, and text summarizers.

Consumer demand for personality in the aforementioned AI applications has recently garnered interest, prompting research directions such as in (Dibitonto et al. 2018, Spencer et al. 2018). Personality refers to a set of behaviors and emotional, motivational thought patterns that derive from both biological and environmental factors. The ability to detect one’s personality traits automatically has many important practical applications such as job screening, forensics, and political forecasting. Numerous studies, such as the Myers Briggs Type Indicator (Miles and Hempel 2004), the Five-Factor Model (Digman 1990) and others, attempt to turn personality traits into quantifiable data. Building on this informal definition of personality in humans, *personality traits of AI models (such as language models studied in this paper) can be thought of as the presence of these human-like characteristics.* Since these language models are commonly trained on human-generated text from sources across the Internet, they indirectly incorporate personalities and other human tendencies (as reflected in written text) without any deliberate intention or knowledge of their creators. The general phenomena of human biases becoming an integral part of language models have been recently investigated in multiple works such as (Bordia and Bowman 2019, Sheng et al. 2019). In many ways, language models will naturally inherit predominant human personality traits reflected in the training data unless elaborate care is taken in pre-processing them. It is imperative then to be able to measure and modify these imbued personality traits as necessitated by the application at hand. In this direction, our paper
is one of the first to empirically validate and quantify these models’ personalities, and we also explore ways to modify the personalities given exogenous requirements.

With the widespread adoption of language models across numerous applications, studying personality in these models will become increasingly important for creating a user experience that is functional and enjoyable. While many users find the responses that these models provide today acceptable, it is conceivable that users may likely miss the human touch when interacting much more with such AI systems in the future. With an explicit understanding and control of the personalities of AI systems, we can potentially have the best of both worlds. One direct approach to designing the personality of language generation models, in particular, would be to take inspiration from human psychological research (Keh et al. 2019). Broadly, one could train/fine-tune the language models on personality annotated text data to orient their personalities. While how to achieve precise control while changing personality in such a way is yet to be answered, if we do succeed in setting quantifiable personality traits that can influence the algorithm’s behavior in response to different circumstances, it can be beneficial in many applications (Lu et al. 2020). We can also aim to design learning systems such that the language models can slowly alter their personality traits over time in response to changing environmental factors. This would result in dynamic AI systems that are responsive and possibly more engaging to users over a long time frame.

Investigating personality traits of language models, which is an initial step in this direction, is not completely straightforward. This is primarily due to the outputs of the models being stochastic and the need for a suitable auxiliary verification model to elicit traits from the text responses (for example, manual human verification may not be feasible). In this paper, we investigate the personality traits of popular language models in open-ended text
generation and the datasets used in training them, while addressing the aforementioned challenges. To the best of our knowledge, we are one of the first to explore personality traits of language models in general, complementing the literature that studies biases. To recapitulate, the prime contributions of this work are as follows:

- We explore the *five-factor method* (Digman 1990) to quantify the personality traits of datasets and language models.
- We evaluate the personality traits of datasets using a novel method designed using *Zero-shot learning* (Xian et al. 2018). Using this approach, we trigger the language models with a questionnaire widely used for personality assessment and subsequently classify the text responses into quantifiable traits.
- Finally, we explore approaches to alter the personalities of these models by finetuning as well as using a pretrained auxiliary personality classification model.
- Extensive experiments on the language models and their underlying training corpora show promising results and validate the effectiveness of our proposed methodology.

The rest of the paper is structured as follows. In Section 2, we discuss closely related work. In Section 3, we introduce the Big Five traits, the Zero-shot classifier, and the pretrained language models. In Section 4, we propose the methods to evaluate the personality traits of datasets and language models, followed by a discussion on approaches to alter these traits. In Section 5, we discuss the experimental setup and extensively document the traits of datasets and the corresponding language models. In addition, we also provide preliminary results for altering these personalities. We conclude with some comments on future work in Section 6.

2. Related Work

Our work builds on research that: (a) measures personality traits, (b) designs personality detection methodologies, and (c) studies societal biases in open-ended text generation. We briefly discuss some of the works below.
2.1. Personality Measures

Researchers in the past have used various schemes for personality modeling such as 16PF (Schuerger 2000), EPQ-R (Miles and Hempel 2004), Myers–Briggs Type Indicator (MBTI) (Miles and Hempel 2004), and three trait personality models/PEN (Eysenck 2012) among others. For instance, MBTI is one of the most widely adopted personality measures. It relies on the theory that random variation in human behavior is quite orderly and consistent due to certain basic differences in the way people prefer to use perception and judgment. The MBTI personality measure categorizes people into two categories in each of the four dimensions: introversion versus extroversion; sensing versus intuiting; thinking versus feeling; and judging versus perceiving. Another popular measure used in the literature on automated personality detection is the Big Five personality traits measure (Digman 1990) given by: Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness. In this work, we estimate the Big Five personality traits of language models and their underlying datasets using a novel methodology described in Section 4.

2.2. Methods for Automatic Personality Detection

Automatic detection of personality traits from text has gained significant attention in Natural Language Processing research due to its applicability in various fields. (Pennebaker and King 1999) compiled a dataset of anonymous essays tagged with the authors’ personalities based on the Big Five traits. The authors used the so-called Linguistic Inquiry and Word Count (LIWC) features to determine the correlation between the essays and personality. (Liu et al. 2016) used deep learning-based models in combination with the atomic features of text, i.e., the characters, to predict personality traits of individuals using hierarchical and vectorized word and sentence representations. (Akrami et al. 2019) developed a model that can extract Big Five personality traits from text using machine learning
techniques. (Jeremy et al. 2019) performed experiments to automatically predict a user’s personality based on Big Five personality traits on Twitter. (Ribeiro et al. 2020) proposed an evaluation methodology and discussed the accompanying tool for comprehensive behavioral testing of NLP models. (Mehta et al. 2020) provides an overview of state-of-the-art machine learning models for automatic personality detection with a specific focus on multimodal approaches. Recently (Derekmracek 2020) used Zero-shot learning (ZSL) to classify text responses from a self-report questionnaire in terms of the Big Five personality traits. Through their experiments, the authors show that a strong positive relationship (e.g., correlation) exists between the ZSL scores and the scores on the self-report questionnaire for each specific trait. Building upon their work, we quantify the traits of our models by using the ZSL framework (see Section 4). Our novel approach overcomes the drawbacks of the previous work by exploring all the possible scenarios for defining the personality trait labels, and thus robustly adapts the ZSL framework to language models.

2.3. Study of Biases in Language Generation

Recent works have explored multiple biases that are learned by language models, which may sometimes be at odds with the prevailing societal values. (Bolukbasi et al. 2016) quantitatively demonstrate that word-embeddings contain biases in their geometry that reflect gender stereotypes present in the broader society. (Sheng et al. 2019) perform experiments to analyze different textual contexts where biases can occur for different demographics in NLG systems. (Bordia and Bowman 2019) evaluate the magnitude of gender bias in word-level language models that are trained on a text corpus. The authors (Nadeem et al. 2020) evaluate popular models like BERT (Devlin et al. 2018), GPT2 (Radford et al. 2019), and XLNET (Yang et al. 2019) using a large scale dataset and show that these models exhibit strong stereotypical biases in four domains: gender, profession, race, and religion.
Our work is complementary to all these studies in the following sense: While we aim to understand human tendencies captured by language models similar to these prior studies, our narrow but well-defined focus on characterizing the learned personality traits and potentially altering them is different and novel, as well as a first of its kind.

3. Preliminaries

In this section, we discuss the Big Five personality traits and our hypothesis for quantifying traits of language models and their corresponding training datasets. We further elaborate on the Zero-shot classifier (ZSC) and the language models analyzed in our study.

3.1. Big Five personality traits

Our study quantifies personality traits using the Big Five Model, also known as the five-factor model \cite{Digman1990}. Under this model, personality can be reduced to the following five core factors:

- **Extraversion**: sociable and energetic versus reserved and solitary.
- **Neuroticism**: sensitive and nervous versus secure and confident.
- **Agreeableness**: trustworthy, straightforward, generous, and modest versus unreliable, complicated, meager, and boastful.
- **Conscientiousness**: efficient and organized versus sloppy and careless.
- **Openness**: inventive and curious versus dogmatic and cautious.

The Neuroticism factor has a negative connotation in contrast to the other four factors. Therefore, we estimate Emotional stability instead to be consistent with other factors in the rest of the paper.

Assessment of these personality traits typically makes use of two types of data sources: self-reports and peer reports (e.g., friends, colleagues, etc.). Among the two, the more popular approach is via self-reports, in which people describe how they see themselves
while responding to a personality assessment questionnaire. For example, a participant is expected to respond to statements such as “I am someone who is outgoing, sociable” on a Likert-type scale (e.g., from 1 = strongly disagree to 5 = strongly agree). Self-reports tap people’s explicit self-concepts about their traits, which are parts of their identities. On the other hand, peer reports help understand how an individual is perceived by his/her neighboring people. Unlike personality recognition using self-reports, the main target of perceived personality analysis is the personality attributed to them by their interaction with the neighboring people. These people fill a similar personality assessment questionnaire on the individual, which then determines the perceived personality of that individual.

In this study, Our approach to measuring personality traits is analogous to self-reports. Besides, peer reports require users to fill out a questionnaire on how they perceive the language models, which, while feasible, is not in the scope of our work. We hypothesize that the language models generate text responses that carry the personality traits of the datasets they were trained upon when prompted. Subsequently, we process the text responses generated by language models using auxiliary prediction models (which can be quite sophisticated themselves) to quantify their personalities. In addition, we also quantify the personality traits of datasets used to train these language models as a way to partially validate our hypothesis.

3.2. Zero-shot classifier

ZSC proposed by (Yin et al. 2019) effectively predicts the class label without any prior training data pertaining to that label. Compared to traditional supervised learning approaches, which rely on a large number of examples for each class, the critical idea of ZSC is based on the semantic transfer of information from observed labels to newly seen labels. ZSC uses a Natural Language Inference (NLI) model, which is a pre-trained sequence-pair
transformer/classifier that uses both a premise and a hypothesis input to predict whether the hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given the premise. For instance, Bart-large model is a NLI model that is trained on the MultiNLI (MNLI) dataset (Williams et al. 2017), which is a collection of 433-thousand multi-genre spoken and written sentence pairs annotated with textual entailment information. While this model is publicly available, performing inference on this model requires extensive computational resources. Hence, we use a distilled version of Bart-large-mnli (Suraj 2019) created using the No Teacher Distillation idea to speed up the inference process without sacrificing much performance. Our work comprehensively explores different ways to set up ZSC for accurately assessing personality traits from a given text response.

3.3. Language Models in Open Ended Text Generation

We study multiple pretrained language models that differ in their training strategy and corpora. All these models make use of auto-regressive language generation, which is based on the assumption that the probability distribution of a word sequence can be decomposed into the product of conditional next word distributions:

\[ P(w_{1:T}|W_0) = \prod_{t=1}^{T} P(w_t|w_{1:t-1},W_0), \]  

where \( w_{1:0} := \emptyset \) and \( W_0 \) is the initial context word sequence. The length \( T \) of the word sequence is usually determined on-the-fly and corresponds to timestep \( t \) when a special token called the EOS (end of sentence) token is generated from \( P(w_t|w_{1:t-1},W_0) \). Below we briefly discuss the language models studied in the paper.

3.3.1. GPT-2: GPT-2 is a transformer-based language model that is trained with a causal language modeling objective: predicting the next word given a sequence of previous words (Radford et al. 2019). GPT-2 was pretrained on the WebText dataset that was collected by scraping and filtering web pages from sources such as Reddit (a popular social networking website).
3.3.2. **GPT-3:** GPT-3 is the 3rd version release and is an upgraded version of GPT-2. GPT-3 model is trained with 175 billion parameters \cite{brown2020language} which is over 10x the size of its predecessor, GPT-2. With its superior performance, GPT-3 can generate text that human evaluators typically have a higher difficulty distinguishing from those written by humans. GPT-3 was pretrained on an open-source dataset called *Common Crawl*, and other text corpora from sources such as Wikipedia (a popular online encyclopedia).

3.3.3. **TransformerXL:** TransformerXL is a transformer-based language model capable of learning dependencies beyond a fixed-length without disrupting temporal coherence \cite{dai2019transformer}. The model’s architecture enables a segment-level recurrence mechanism and a novel positional encoding scheme that captures longer-term dependency better and resolves the so-called context fragmentation problem. TransformerXL was pretrained on the WikiText language modeling dataset, a collection of over 100 million tokens extracted from the set of verified *good* and *featured* articles on Wikipedia.

3.3.4. **XLNET:** XLNET is an extension of the TransformerXL model \cite{yang2019xlnet}. The model learns bidirectional contexts by maximizing the expected likelihood over all permutations of the input sequence factorization orders. The auto-regressive objective provides a natural way to use the product rule for factorizing the joint probability of the predicted tokens, eliminating a specific independence assumption that was made in BERT \cite{devlin2018bert}. This model was trained on BooksCorpus \cite{zhu2015aligning} and English Wikipedia datasets in a self-supervised fashion.

4. **Methods for Estimating and Altering Personalities**

In this section, we explore various approaches for evaluating the personality traits of datasets. Building on this, we design a robust approach to evaluate the traits of language models. Finally, we present methods for alter the personality traits of language models.
4.1. Evaluating Personalities of Datasets

Extracting quantifiable personality traits from datasets requires defining suitable labels for ZSC, followed by a scoring scheme based on the ZSC outputs. As discussed earlier in Section 3, ZSC takes a premise and a hypothesis as input and predicts whether the hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given the premise. So the first step in dealing with ZSC as an entailment problem is to convert the desired trait labels into hypotheses. In this work, we use the following hypothesis input while evaluating the ZSC: *This response is characterized by* \{label\}. , where the placeholder \{label\} is replaced by trait-specific keywords.

We investigate different approaches to finalize our model setup and extract personality trait scores in terms of the Big Five factors.

**Approach 1:** We assume that the premise and the hypothesis can either be positively related or negatively related in this approach. Accordingly, We set up the ZSC to quantify the five personality traits independently using five labels: openness, conscientiousness, extraversion, agreeableness, and neuroticism, to generate the hypothesis for feeding into a ZSC. We transform the output probabilities obtained for each label to Big Five factor scores using a linear fit on a scale from 1 to 5.

**Approach 2:** We assume that the premise and hypothesis can either be positively related or unrelated in this approach. Under this assumption, we measure the personality scores using labels for the two extreme ends of each trait independently. Then, the output probabilities for both extremes are passed through a softmax function and interpolated to obtain the final scores for each Big Five factor. The labels for extreme ends of each trait are provided in Table 1.

**Approach 3:** In this approach, we consider all three scenarios where the premise and hypothesis can either be positively related, negatively related, or unrelated. This is because,
under assumptions made in the previous two approaches, measuring the five personality traits independently using ZSC might lead to incorrect results. The reason for this is because ZSC classifies a non-synonymic or antithetical hypothesis with low probability for a given premise. Therefore, one cannot guarantee if the lower score for a particular label is due to negative relation or no relation between the hypothesis and premise. Hence in this third approach, we set up one ZSC for each trait to measure the two extreme ends in a dependent manner. Under the hood, the ZSC will calculate a single probability score using only the NLI model’s (DistilBart-MNLI) entailment scores of the two extreme ends of a trait. We then use a one-dimensional linear interpolation step to match the probabilities with values from 0 to 1 to the Big Five personality test scores ranging from 1 to 5. We use the same labels for extreme ends of each trait as discussed in Approach 2.

Discussion: Our first approach works well whenever the hypothesis and premise entail or contradict each other. However, when ZSC is prompted with unrelated premises and hypotheses, output label probabilities are low, which leads to the inability of measuring the personality traits accurately. The second approach also has its limitations. ZSC uses the NLI model’s entailment and contradiction scores behind-the-screens to calculate the probability of the output label. We cannot conclude that a low score means the hypothesis
and the premise are neutral to each other since ZSC does not use the neutral score of the NLI model. Our third approach overcomes these pitfalls of the first two approaches discussed above, and enables a more precise assessment of personality traits of datasets.

4.2. Evaluating Personalities of Language Models

We adopt an assessment questionnaire that measures personality traits using the Big Five factor markers. The questionnaire is a list of fifty statements, each referring to different characteristics of an individual. Accordingly, each statement is designed to elicit a specific Big Five factor behavior. In general, individuals respond to every statement in the questionnaire by opting for one of the following choices: (a) very inaccurate, (b) moderately inaccurate, (c) neither inaccurate nor accurate, (d) moderately accurate, and (e) very accurate. The response to every statement is scored against a predetermined Big Five factor on a scale of 1 to 5 as shown in Table 2. There are ten statements evaluated for the Extraversion factor, ten questions for Agreeableness, and so forth. Finally, the aggregated scores against each of the Big Five factors are averaged to obtain the quantifiable trait scores.

| Response                            | Score |
|-------------------------------------|-------|
| Very Inaccurate                     | 1     |
| Moderately Inaccurate               | 2     |
| Neither Inaccurate nor Accurate      | 3     |
| Moderately Accurate                 | 4     |
| Very Accurate                       | 5     |

Table 2  Scoring scheme to determine the traits based on text output

Acquiring the responses in the format discussed above is not feasible in open-ended text generation since the language model output is a sequence of words. Instead, we start
by setting the statements from the questionnaire as prompts to the language model and generate text responses as shown in Figure 1. To account for the stochastic nature of the responses, we trigger the model $N \in \mathbb{Z}_+$ times using the same prompt to observe $N$ different text completions for every statement in the questionnaire. Moreover, we prompt the language models with each statement independently. So the order in which statements are fed as input to the model does not affect the final results.

Each of the generated text responses is passed independently as an input premise to the ZSC setup as discussed in Approach 3. The resulting outputs are the independent probabilities for the responses to be characterized according to the five factors. We obtain $N$ such probabilities for each input prompt. We then use a one-dimensional linear interpolation to match the probabilities to scores ranging from 1 to 5. Finally, we compute the median of the scores aggregated for all the respective statements, which represent the personality of the concerned language model.

4.3. Modifying Personalities of Language Models

Pretrained language models possess varied personality traits due to their training on diverse datasets and due to differences in their model definitions and training approaches. We
propose the following two methods aimed at altering the personality traits of language models.

4.3.1. **Method 1:** Modifying the personalities of the language models in a desired fashion can be implicitly equated to updating the model’s parameters such that it generates modified text responses that are closer to the desired personality traits. One way to achieve this partially is by finetuning the language models using suitably chosen personality annotated text data. In particular, since the training of these language models from scratch requires a substantial computational overhead and large datasets, we instead finetune the language models using a personality annotated dataset. Finetuning allows the language model to partially adapt to the new data corpus and change the traits of the generated text without expending much computational overhead. Accordingly, when we trigger the fine-tuned language model with a prompt from our questionnaire, we expect that the generated response reflects the altered personality.

For finetuning, we leverage a personality annotated text dataset made available as part of a machine learning competition [SIOP (2019)]. The dataset includes text responses to open-ended situational judgment items (SJIs) designed to elicit trait-relevant behaviors and aggregate trait scores based on the Big Five personality traits. To modify the personality of a language model with respect to a specific trait, we train the model on the filtered textual responses corresponding to that factor. Note that under this approach, precise control towards changing the personality traits to a specific desired set of values while maintaining language generation quality is generally non-trivial.

4.3.2. **Method 2:** In this closely related approach to the above, we start by finetuning a pre-trained model on personality annotated text data but focus on a specific auxiliary classification task instead of the original text generation objective. In particular, using
the text annotated with a specific Big Five factor, we finetune the model on a binary classification task. For example, our classification task is to classify text responses as having either the extrovert or the introvert trait. Once we finetune the model via the auxiliary task, we use the same model weights for text generation.

Irrespective of the approach, we evaluate the resultant model using the process discussed in Section 4.2 above and report the altered trait measurements if any.

5. Experiments

In this section, we present the experimental setup and the results obtained from evaluating the personality traits of the language models and datasets. We also compare the personalities of language models and their underlying datasets. Finally, we discuss how our approaches to altering the personality traits of language models fare.

5.1. Traits of Datasets

5.1.1. Setup: We explore the personality traits of datasets used in training the language models discussed in Section 3 namely: BOOKCORPUS, ENGLISH WIKIPEDIA, WIKITEXT103, and WEBTEXT TEST SET.

- **BookCorpus** *(Zhu et al. 2015)* is a large collection of free novel books written by unpublished authors, which contains 11,038 books of 16 different sub-genres and is used to train XLNET.

- **English Wikipedia** contains cleaned articles that are built from the Wikipedia dump and used to train XLNET and GPT-3. However, the exact versions of the dataset used to develop those models are publicly unknown. We obtain a version of this data that was available on May 1st, 2020.

- **Wikitext103** *(Merity 2016)* contains more than 100 million tokens retrieved from the arrangement of (verified) good and featured articles on Wikipedia and is used to train TransformerXL.
| Dataset                | Size    | Percent uses for inference | Models              |
|------------------------|---------|---------------------------|---------------------|
| Wikitext103            | 0.70 GB | 100%                      | TransfoXL           |
| Bookcorpus             | 5.75 GB | 10%                       | XLNET               |
| English Wikipedia      | 34.88 GB| 2%                        | GPT-3, XLNET        |
| Webtext Test Set       | 1.28 GB | 20%                       | GPT2                |

Table 3 Summary statistics of the datasets

- **WebText Test Set** ([Gokaslan et al. 2019](#)) is provided by the firm OpenAI. The training dataset was used to train GPT-2 and has not been publicly released. Hence, we use the test set for our experiments.

Evaluating each of the datasets discussed above requires extensive computational resources due to their size. To overcome this issue, we infer the personality traits using random sub-samples of the datasets as indicated in Table 3. These samples of datasets can be evaluated at different levels of granularity, from sentence level, paragraph level, to document level. In the experiments, We notice that when a long document containing many paragraphs and sentences is passed as a standalone input, our ZSC that estimates personality traits doesn’t perform well, predicting a score close to 3 (which is neutral) for most samples. The reason is that these paragraphs and sentences may exhibit multiple conflicting traits or have multiple trait-less sentences (e.g., facts). Therefore, we process the data so that all samples are at the sentence or small paragraph level. The processed datasets are passed as an input independently to ZSCs’ using Approach 3 discussed in Section 4. The resulting outputs are collated to obtain the personality trait distributions.

5.1.2. **Results:** Figure 2 depicts the personality trait distributions across the datasets. In particular, we observe that the distributions for all five traits are skewed to the right of the neutral 3.0 score, reflecting a positive sense of personality. The medians of different traits from the box plots gives us the scores of the traits on average, which we use
Figure 2  Personality trait distributions of datasets

to compare the prominence of the traits. The lengths of the boxes can be used to determine the spreads or variances of the traits. The most prominent trait for Wikitext103 is Extraversion, and the least prominent trait is Conscientiousness. Agreeableness scores spread the widest compared to other traits, followed by openness. The most prominent traits in the BookCorpus dataset are Extraversion and Agreeableness, followed by Openness, Emotional stability, and conscientiousness. Again, Agreeableness scores have the highest variance compared to other trait scores, followed by Openness. The trait scores for the English Wikipedia dataset have smaller spreads compared to other datasets.
The most prominent trait is Agreeableness, followed by Extraversion, Emotional stability, Openness, and Conscientiousness. Finally, the Webtext Test Set dataset’s prominent traits are Agreeableness and Extraversion, followed by Emotional stability, Openness, and Conscientiousness. The spreads of Agreeableness and Openness are wider than the other traits in the dataset.

Our findings suggest that we can achieve the desired personalities in language models by training them using datasets with high median score and low spread for the corresponding trait.

5.2. Traits of Models

5.2.1. Setup: To quantify the personality traits of language models, we trigger them using the Big Five questionnaire and classify the generated text responses using the ZSC framework discussed in Approach 3.

In our experiments, we selected a fixed set of hyper-parameters for text generation using language models. For GPT-3 evaluation, we use the programmatic API from OpenAI [Brown et al. (2020)] made publicly available to users for research and commercial purposes. We use the setting of open-ended text generation with hyper-parameters maxseqlength set to 256, temperature, and top-p set to 1. For the rest of the language models, namely GPT-2, TransformerXL, and XLNET, we use text generation pipeline from Hugging Face’s transformer package [Wolf et al. 2019]. We set the parameters temperature to 1, top-k to 40, top-p to 1, and maxseqlength to 256 respectively.

5.2.2. Results: Table 4 shows a few examples of generated text responses and the corresponding input prompts to GPT-2. These responses generated in an auto-regressive manner inherit the traits learned during model training. Consequently, we observe noticeable variations in trait distributions across language models due to differences in their
I don’t talk a lot.  
I’m more of an introvert so I’m less than happy to take time to talk.  
I prefer to be able to take control over how I work and make sure I be able to talk a lot.

I’m relaxed most of the time  
In all my experiences I did not notice a single problem about myself or others I dealt with, because I was focused on my personal well being and that was all.

I feel comfortable around people.  
I get a lot done and it’s nice working out or just enjoying myself and being around people.  
A lot of that comes with me.

I am full of ideas  
I am also a very creative person, so it is important to me to develop my own ideas.  
I have a lot of inspiration and a lot of love for the world.

### Table 4  Examples of text responses generated using GPT-2

| Prompt                                | Generated Response                                                                 |
|---------------------------------------|-----------------------------------------------------------------------------------|
| I don’t talk a lot.                   | I’m more of an introvert so I’m less than happy to take time to talk.               |
|                                       | I prefer to be able to take control over how I work and make sure I be able to talk a lot. |
| I’m relaxed most of the time          | In all my experiences I did not notice a single problem about myself or others I dealt with, because I was focused on my personal well being and that was all. |
| I feel comfortable around people.     | I get a lot done and it’s nice working out or just enjoying myself and being around people. |
|                                       | A lot of that comes with me.                                                       |
| I am full of ideas                    | I am also a very creative person, so it is important to me to develop my own ideas. |
|                                       | I have a lot of inspiration and a lot of love for the world.                        |

### Table 5  Personality scores with their uncertainties of Language Models

| Trait         | GPT2      | GPT3      | Transformer-XL | XLNET     |
|---------------|-----------|-----------|----------------|-----------|
| Agreeableness | 3.41 (0.73) | 4.19 (1.14) | 3.86 (0.66) | 3.64 (0.87) |
| Conscientiousness | 3.18 (0.39) | 3.66 (0.77) | 3.96 (0.78) | 3.73 (0.64) |
| Extraversion  | 3.07 (0.60) | 3.94 (1.10) | 3.43 (0.69) | 3.63 (0.91) |
| Emotional stability | 3.15 (0.46) | 2.79 (1.11) | 3.36 (0.74) | 3.01 (0.70) |
| Openness      | 2.97 (0.47) | 3.78 (1.06) | 4.02 (0.83) | 3.55 (0.71) |

Furthermore, Table 5 shows the median five factor scores evaluated for all language models. Based on these, we can make a few observations. Firstly, we observe that the Agreeableness scores are higher for GPT-3, suggesting the generated text reflects a more generous and empathetic personality. Secondly, Conscientiousness scores are higher for TransformerXL. On the other hand, GPT-3 has a higher median Extraversion score, implying that the response generated emulate extroverted personalities as opposed to introverted personalities. Finally, TransformerXL has the highest Emotional stability score reflecting a more emotionally stable personality compared to the other language models.
Scoring Modes: As discussed earlier, the datasets are composed of text at different levels of granularity. Similarly, the text responses generated using these language models can be multiple sentences long. As a result, personality trait distributions may vary depending on whether we evaluate individual sentences or the complete responses. To address this issue, we generate personality trait scores using different output modes as discussed below.

- **Mode 1**: Trait score of the entire generated response.
- **Mode 2**: Trait score of the first sentence in the generated response.
- **Mode 3**: Median of the trait scores of all sentences present in the generated response.
Figure 4 shows the trait distributions for all the language models obtained using the modes listed above. The distributions remain the same for GPT-3, XLNET and TransformerXL. This is because all the responses generated using these models were single sentences. However, distribution spread varies for GPT-2 across different modes of evaluation, implying that the structure of the output influences the personality score estimation.

5.3. Traits of Datasets vs Models

To validate our hypothesis on whether the language models inherit personality traits of datasets during their training, we compare the trait distributions of the language models and their underlying corpora. Specifically, we evaluate the traits of WebText Test dataset and text responses generated using GPT-2. We observe that trait distributions of WebText Test dataset and randomly generated texts using the GPT-2 without considering any input prompts are very similar, as shown in the Figure 5, implying that traits of datasets are entirely inherited by GPT-2 during the training phase. On the other hand, there is a noticeable difference in trait distribution of WebText Test dataset in comparison to GPT-2 when the Big Five questionnaire is passed as an input. This phenomenon is probably due to the GPT-2 trying to capture personality from both input prompts and the dataset. Overall, we can conclude that datasets and input prompt together influence the inferred personality traits of the language models.

5.4. Altering the Traits of Models

5.4.1. Setup: To investigate the methods for altering traits, We restrict ourselves to working with GPT-2 due to limitations of computational resources.

To evaluate Method 1 discussed in the Section 4.3, we filter the SIOP (2019) dataset by retaining text responses labeled with Big Five factor scores greater than 4 for the individual traits. We finetune the GPT-2 model on the filtered dataset corresponding to each trait
Figure 4 Personality trait distributions of language models obtained from different modes of evaluation
and subsequently evaluate the generated text responses. For finetuning, we set the batch size to 16 and the number of epochs to 20 with warmup proportion set to 0, learning rate set to $1e^{-5}$, and weight decay set to 0.01.

Similar to Method 1, we analyze Method 2 using the same filtered dataset [SIOP (2019)] according to the following criteria. Since the personality trait scores in the annotated dataset are continuous values from 1 to 5, we filter the dataset at different thresholds from the set {2.5, 3, 3.5, 4, 4.5} to obtain labels suitable for defining a binary classification problem. We finetune the original model using this classification task. In particular, we use the standard cross-entropy loss and the ADAM optimizer [Kingma and Ba (2014)]. We set the learning rate to $5e^{-5}$ and the number of epochs to 10 while finetuning.

### 5.4.2. Results:

Table 6 summarizes the results from using Method 1 for finetuning GPT-2. We observe a notable improvement in the personality scores for Agreeableness, Conscientiousness, Emotional Stability and Openness once the language model is finetuned using the respective filtered datasets. These changes are also reflected in the personality trait distributions of finetuned language models shown in Figure 5. We can conclude that the derived language models learn from the new data corpus during finetuning, thus allowing one to alter their personality traits in an open loop setting. However, we also notice that

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**Figure 5**  Distributions of different traits in (a) Wikitext103, and (b) GPT-2.
| Trait         | Before finetuning | Agreeableness | Conscientiousness | Extraversion | Emotional stability | Openness |
|--------------|------------------|---------------|-------------------|--------------|---------------------|----------|
| Agreeableness| 3.41 (0.73)      | 3.33 (0.43)   | 3.30 (0.21)       | 3.27 (0.36)  | 3.09 (0.27)         | 3.33 (0.37) |
| Conscientiousness | 3.18 (0.39)   | 3.41 (0.39)   | **3.26 (0.25)**   | 3.15 (0.22)  | 3.13 (0.34)         | 3.50 (0.38) |
| Extraversion  | 3.07 (0.60)      | 3.27 (0.26)   | 3.39 (0.30)       | **3.39 (0.32)** | 3.15 (0.24)       | 3.63 (0.44) |
| Emotional stability | 3.15 (0.50)   | 3.35 (0.38)   | 3.26 (0.29)       | 3.27 (0.28)  | **3.23 (0.37)**    | 3.42 (0.36) |
| Openness     | 2.97 (0.47)      | 3.42 (0.36)   | 3.37 (0.29)       | 3.31 (0.31)  | 3.27 (0.38)         | **3.47 (0.39)** |

Table 6  Personality scores with their uncertainties of the finetuned language models

Finetuning changes the personality scores of other traits in addition to the focal trait (represented by the filtered dataset). This phenomenon is not desirable as we lose precise control over improving a specific trait during finetuning. Addressing this aspect is left for future work.

![Figure 6](image_url)  Personality trait distributions of finetuned language models
Table 7 summarizes the results from using Method 2 to finetune the GPT-2 model using *Extraversion* labeled data. We observe that some *Extraversion* scores have improved compared to the GPT-2 before its finetuning. However, there are noticeable variations in the scores of other factors, which is not desirable (similar to Method 1). We observe similar changes in personality trait scores when the model is finetuned using other personality annotated datasets, and these results are summarized in Appendix 7.

Overall, the results demonstrate that our methodology to alter traits is a promising first step in attempt to alter the personality traits of language models. Further work in this direction would be a fruitful endeavour.

### 6. Conclusion

In this paper, we proposed methods to quantify the personality traits of datasets and language models designed for open-ended text generation. We presented a principled approach for evaluating the personality traits of datasets using a pre-trained zero shot classifier. We further extended our work to estimate personality profiles of language models using the prompts from the Big Five personality test questionnaire. Our experiments found that language models possess varied personality traits reflecting the datasets that were used in their training, and this influences the generated outputs. Furthermore, we proposed...
straightforward approaches to alter the personality traits of language models by finetuning them on personality-annotated datasets. Overall, our work provides a key starting point for assessing and understanding the personality traits of language models.

In the future, we aim to design robust approaches that precisely alter the personality traits of language modes. We also aim to investigate other commonly used assessments like the Myer Briggs Type indicator to validate the personality traits of language models and contrast them with the results obtained in this work.

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7. Appendix

Tables 8, 9, 10 and 11 shows detailed results of finetuning GPT-2 model using Method 2 on personality annotated data.

| Trait          | Before finetuning | After finetuning at threshold (2.5) | After finetuning at threshold (3.0) | After finetuning at threshold (3.5) | After finetuning at threshold (4.0) | After finetuning at threshold (4.5) |
|----------------|-------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| Agreeableness  | 3.41 (0.73)       | 3.51 (0.51)                         | 3.19 (0.30)                         | 3.19 (0.44)                         | 3.10 (0.68)                         | 3.04 (0.45)                         |
| Conscientiousness | 3.18 (0.39)     | 3.29 (0.53)                         | 3.17 (0.41)                         | 3.13 (0.34)                         | 2.96 (0.57)                         | 2.96 (0.47)                         |
| Extraversion   | 3.07 (0.60)       | 3.24 (0.55)                         | 3.13 (0.29)                         | 3.20 (0.27)                         | 3.00 (0.63)                         | 3.04 (0.42)                         |
| Emotional stability | 3.15 (0.46)   | 3.42 (0.53)                         | 3.15 (0.37)                         | 3.11 (0.42)                         | 3.09 (0.70)                         | 2.94 (0.34)                         |
| Openness       | 2.97 (0.47)       | 3.33 (0.56)                         | 3.23 (0.36)                         | 3.26 (0.38)                         | 3.03 (0.50)                         | 3.11 (0.45)                         |

**Table 8**  Personality scores before and after finetuning the GPT-2 using Conscientiousness labeled data at different thresholds using the Method 2

| Trait          | Before finetuning | After finetuning at threshold (2.5) | After finetuning at threshold (3.0) | After finetuning at threshold (3.5) | After finetuning at threshold (4.0) | After finetuning at threshold (4.5) |
|----------------|-------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| Agreeableness  | 3.41 (0.73)       | 3.05 (0.45)                         | 3.22 (0.34)                         | 2.83 (0.49)                         | 2.99 (0.71)                         | 3.06 (0.13)                         |
| Conscientiousness | 3.18 (0.39)     | 3.08 (0.38)                         | 3.28 (0.49)                         | 2.93 (0.49)                         | 3.12 (0.72)                         | 3.09 (0.11)                         |
| Extraversion   | 3.07 (0.60)       | 3.03 (0.41)                         | 3.30 (0.46)                         | 2.90 (0.47)                         | 3.11 (0.71)                         | 3.08 (0.10)                         |
| Emotional stability | 3.15 (0.50)   | 3.09 (0.37)                         | 3.17 (0.41)                         | 2.93 (0.45)                         | 3.09 (0.60)                         | 3.08 (0.14)                         |
| Openness       | 2.97 (0.47)       | 3.08 (0.38)                         | 3.22 (0.44)                         | 2.87 (0.32)                         | 3.04 (0.78)                         | 3.09 (0.12)                         |

**Table 9**  Personality scores before and after finetuning the GPT-2 using Openness labeled data at different thresholds using the Method 2
| Trait          | Before finetuning | After finetuning at threshold (2.5) | After finetuning at threshold (3.0) | After finetuning at threshold (3.5) | After finetuning at threshold (4.0) | After finetuning at threshold (4.5) |
|----------------|-------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| Agreeableness  | 3.41 (0.73)       | 3.83 (0.55)                         | 3.05 (0.49)                         | 2.89 (0.18)                         | 2.93 (0.73)                         | 3.04 (0.69)                         |
| Conscientiousness | 3.18 (0.39)     | 3.31 (0.55)                         | 2.98 (0.42)                         | 2.90 (0.15)                         | 3.02 (0.80)                         | 3.05 (0.80)                         |
| Extraversion   | 3.07 (0.60)       | 3.38 (0.77)                         | 3.06 (0.47)                         | 2.90 (0.13)                         | 2.99 (0.76)                         | 3.20 (0.58)                         |
| Emotional stability | 3.15 (0.50) | 3.12 (0.52)                         | 3.01 (0.55)                         | 2.97 (0.12)                         | 3.04 (0.75)                         | 3.22 (0.71)                         |
| Openness       | 2.97 (0.47)       | 3.15 (0.59)                         | 3.19 (0.51)                         | 2.91 (0.17)                         | 3.19 (0.76)                         | 3.07 (0.83)                         |

Table 10  Personality scores before and after finetuning the GPT-2 using Emotional stability labeled data at different thresholds using the Method 2

| Trait          | Before finetuning | After finetuning at threshold (2.5) | After finetuning at threshold (3.0) | After finetuning at threshold (3.5) | After finetuning at threshold (4.0) | After finetuning at threshold (4.5) |
|----------------|-------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| Agreeableness  | 3.41 (0.73)       | 3.29 (0.73)                         | 3.07 (0.63)                         | 3.05 (0.51)                         | 2.99 (0.23)                         | 3.05 (0.36)                         |
| Conscientiousness | 3.18 (0.39)     | 3.10 (0.80)                         | 2.88 (0.57)                         | 3.03 (0.70)                         | 3.06 (0.31)                         | 3.04 (0.24)                         |
| Extraversion   | 3.07 (0.60)       | 3.06 (0.66)                         | 2.98 (0.61)                         | 3.01 (0.40)                         | 3.05 (0.24)                         | 3.08 (0.38)                         |
| Emotional stability | 3.15 (0.50) | 3.08 (0.66)                         | 3.00 (0.65)                         | 3.04 (0.40)                         | 3.03 (0.19)                         | 3.03 (0.25)                         |
| Openness       | 2.97 (0.47)       | 3.28 (0.66)                         | 2.91 (0.62)                         | 3.16 (0.32)                         | 3.04 (0.13)                         | 3.06 (0.22)                         |

Table 11  Personality scores before and after finetuning the GPT-2 using Agreeableness labeled data at different thresholds using the Method 2
| I am the life of the party. | I have little to say. |
|----------------------------|----------------------|
| I feel little concern for others. | I have a soft heart. |
| I am always prepared. | I often forget to put things back in their proper place. |
| I get stressed out easily. | I get upset easily. |
| I have a rich vocabulary. | I do not have a good imagination. |
| I don’t talk a lot. | I talk to a lot of different people at parties. |
| I am interested in people. | I am not really interested in others. |
| I leave my belongings around. | I like order. |
| I am relaxed most of the time. | I change my mood a lot. |
| I have difficulty understanding abstract ideas. | I am quick to understand things. |
| I feel comfortable around people. | I don’t like to draw attention to myself. |
| I insult people. | I take time out for others. |
| I pay attention to details. | I shirk my duties. |
| I worry about things. | I have frequent mood swings. |
| I have a vivid imagination. | I use difficult words. |
| I keep in the background. | I don’t mind being the center of attention. |
| I sympathize with others’ feelings. | I feel others’ emotions. |
| I make a mess of things. | I follow a schedule. |
| I seldom feel blue. | I get irritated easily. |
| I am not interested in abstract ideas. | I spend time reflecting on things. |
| I start conversations. | I am quiet around strangers. |
| I am not interested in other people’s problems. | I make people feel at ease. |
| I get chores done right away. | I am exacting in my work. |
| I am easily disturbed. | I often feel blue. |
| I have excellent ideas. | I am full of ideas. |

**Table 12  Questions from the Big Five questionnaire**