

You Are What You Talk About: Inducing Evaluative Topics for Personality Analysis

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Abstract

Expressing attitude or stance toward entities and concepts is an integral part of human behavior and personality. Recently, evaluative language data has become more accessible with social media's rapid growth, enabling large-scale opinion analysis. However, surprisingly little research examines the relationship between personality and evaluative language. To bridge this gap, we introduce the notion of evaluative topics, obtained by applying topic models to pre-filtered evaluative text from social media. We then link evaluative topics to individual text authors to build their evaluative profiles. We apply evaluative profiling to Reddit comments labeled with personality scores and conduct an exploratory study on the relationship between evaluative topics and Big Five personality facets, aiming for a more interpretable, facet-level analysis. Finally, we validate our approach by observing correlations consistent with prior research in personality psychology.

1 Introduction

Sharing opinions has always been rooted in people's daily habits, but nowadays, it has scaled up with a plethora of user-generated texts on social media (Lee and Ma, 2012). Opinions, as dispositions toward specific entities, can be the key to understanding human behavior. Oftentimes, there is a need to predict sentiment or stance toward a particular target of interest, making opinion analysis useful in marketing research, social and political sciences, and recommender systems, to name a few. Moreover, analyzing how we express our opinions, i.e., the linguistic aspect and the psychological disposition of the opinion holder, is crucial for various downstream tasks, such as personality analysis and mental health prediction.

In public communication, among other situations, people use linguistic resources known as *evaluative language* (Hunston, 2010) to express their attitudes. Thompson and Hunston (2000) define

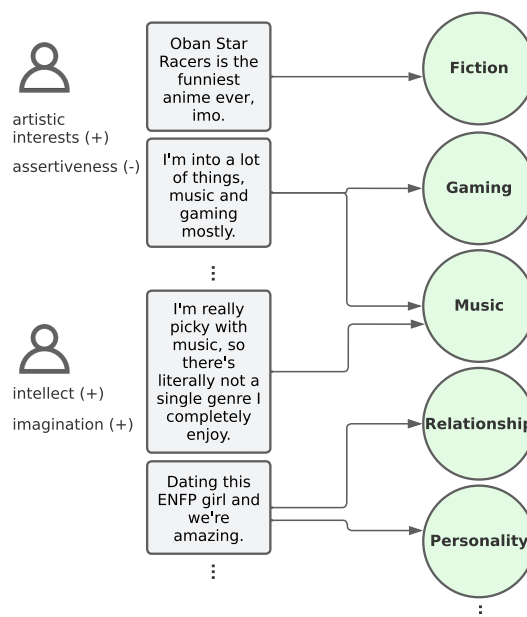


Figure 1: An illustrative example of mapping user statements to *evaluative topics*, i.e., topics induced from evaluative texts. Based on the prevalence of such topics, we construct an *evaluative profile* of each author. We then measure the correlation between each author profile and personality facets, such as artistic interests, assertiveness, intellect, and imagination.

evaluation as a cover term for unified phenomena of certainty and goodness/desirability, and evaluative language includes every expression of the speaker or writer's attitude or stance towards, or feelings about the entities or propositions. As evaluation is associated with psychological disposition (Malrieu, 1999), evaluative language can help uncover people's distinguishing qualities, i.e., recurrent behavioral, cognitive, or affective tendencies. Such behavioral differences resulting from interaction with the environment fall within the purview of *personality psychology*, where they are typically examined as *personality traits* – sets of characteristic patterns of behavior, cognition, and feelings stable over time and across situations (Funder, 2012).

Moreover, personality traits have been shown to correlate with occupational preferences, political or religious tendencies, intelligence, personal interests, and opinions (Larson et al., 2002; Ackerman and Heggestad, 1997; Hyman, 1957).

To the best of our knowledge, evaluative language has not yet been studied in the context of personality analysis on social media. This can perhaps be attributed to methodological challenges. One of the difficulties in analyzing evaluative language is separating the signal from the noise. Although evaluation in text is pervasive, it remains a challenge to automatically distinguish evaluative from non-evaluative text. Evaluative expressions come in all sort of flavors, with varying amounts of explicit lexical stance markers. Another difficulty is choosing the right level of abstraction both for personality and evaluative language. If the evaluation targets are too specific, it is difficult to relate them to personality. Nevertheless, we can choose the appropriate operationalization of the personality in terms of its breadth, thus aligning it with the abstraction level of the evaluative targets.

In this paper, we study how evaluative language on social media can be used for personality analysis. More specifically, our study aims to explore how the topics people talk about are related to their personality, as illustrated in Figure 1. To this end, we introduce the notion of an *evaluative topic*, which is a topic constructed from evaluative text. To address the signal-noise problem in detecting evaluative text, we develop an iterative filtering technique based on detecting evaluative expressions and paraphrase mining. We then leverage topic models to induce evaluative topics from prefiltered evaluative text. Aiming to maximize coherence and diversity, we test several topic model families, including probabilistic, decompositional, and neural topic models. Finally, we link evaluative topics to individual text authors to construct authors' *evaluative profiles*.

In the experimental part, we investigate the relationship between evaluation and personality. Our focus is on the *Big Five* model of personality (Goldberg, 1981), which includes broad personality traits and their more specific (and arguably more interpretable) aspects called *facets*. We present a correlation study of evaluative topics and Big Five facets on comments from Reddit, one of the most popular discussion websites, which covers an astoundingly diverse range of topics while preserving

user anonymity. We find correlations between evaluation and personality that are consistent with prior research in personality psychology. Finally, we provide empirical evidence that evaluative statements have a stronger association with personality than non-evaluative expressions.

In summary, our contribution is threefold: we (1) develop an approach for evaluative author profiling based on topic models with evaluative filtering, (2) apply evaluative profiling on Reddit comments, and (3) study how evaluative author profiles of Reddit users correlate with Big Five personality facets.

The rest of the paper is structured as follows. Section 2 lays out the background and related work. We describe our technique for filtering evaluative text along with topic modeling in Section 3. We conclude the section by presenting the idea of evaluative author profiles. We describe our experiments and results in Section 4. Finally, Section 5 overlays the main conclusions and takeaways of the paper.

2 Background and Related Work

Evaluative language. In linguistics, studies of evaluative language are embedded in functional approaches to language that aim to understand and explain linguistic structures in terms of the semantic and communicative functions of language and which assume that its primary function is to be a vehicle for social interaction (Allan, 2007). Most research in evaluative language covers only a particular niche of evaluation, such as subjectivity (Wiebe et al., 2004) and stance (Kiesling et al., 2018). For instance, Biber and Finegan (1989) describe lexical and grammatical markers of stance, i.e., categorizations along the continuum of epistemic and attitudinal meanings, developing groups of markers for people's attitude, affect, and assessment. More recently, Pavalanathan et al. (2017) compiled a lexicon of stance markers on Reddit data. On the other hand, because sentiment analysis is ubiquitous in NLP, evaluative language has been viewed through the prism of sentiment (Benamara et al., 2017; Pang and Lee, 2008). In our work, we attempt to combine several aspects of evaluative language, namely sentiment, stance, and opinion markers.

Target awareness. Given the nature of expressing opinions, evaluation is directed toward a particular target. Among others, sentiment-based approaches to evaluation have been prevalent, which led to the establishment of aspect-based sentiment

analysis (ABSA), an NLP task that combines aspect extraction with sentiment classification (Pontiki et al., 2014). Recent research in ABSA has evolved from traditional perspectives, e.g., using conditional random fields for aspect extraction as a sequence labeling task (Toh and Wang, 2014), to neural-based approaches (He et al., 2017; Luo et al., 2019; Hoang et al., 2019; Tulkens and van Cranenburgh, 2020). However, ABSA systems are better suited for smaller domains. Besides ABSA, there have been target-based approaches in stance classification (Du et al., 2017) and topic-dependent argument classification (Reimers et al., 2019), among others. As we are trying to cover diverse domains, we opt for a topic-level approach to targets.

NLP and personality. NLP has been used extensively for personality analysis, starting with essay analysis (Pennebaker and King, 2000) and followed by social network research (Park et al., 2014; Schwartz et al., 2013). The more recent studies were mainly conducted with Facebook data. For example, Kulkarni et al. (2018) used trait-level factor analysis for the Big 5 personality system on Facebook. However, as far as we know, there is no research that leverages NLP to analyze personality in the context of evaluative language. Moreover, there is little research in NLP that covers facet-level personality analysis.

3 Methodology

We propose a three-step process from raw text to evaluative profiles. We start with evaluative filtering to extract evaluative text and then construct topics from the filtered dataset. Finally, we use the developed evaluative topics to create the corresponding evaluative profiles.

3.1 Dataset

We used PANDORA, a dataset with personality scores for Reddit users, extracted from self-reported personality questionnaire results (Gjurković et al., 2021). In total, there are 1,608 users with self-reported Big Five scores. These users have written a total of 1.3M comments, consisting of 14.3M sentences. Additionally, 127 users self-reported their questionnaire scores for the NEO PI-R facets.¹ NEO PI-R provides information on six facets of each Big Five personality trait. A facet is a specific and unique aspect of a broader

personality trait. For example, *anxiety* and *depression* are facets of *neuroticism*, while *friendliness* and *gregariousness* are extraversion facets. After we applied preprocessing, which included segmenting the comments into sentences, we ended up with 6.5M sentences. We filtered out non-English comments since we used models pre-trained on English texts. We attach more details on the preprocessing step in Appendix A.1.

3.2 Evaluative filtering

Although social media abounds with evaluative language, it is challenging to automatically distinguish evaluative from non-evaluative text. To filter out non-evaluative expressions, we collected comments with evaluative markers – lexical or grammatical language forms that express the act of evaluation. We combined off-the-shelf sentiment analysis tools with opinion and stance lexicons to cover different aspects of evaluative language. On top of that, we searched for sentences that contain *evaluative patterns*, i.e., phrases that express opinions.

To extract sentiment-laden sentences, we used VADER (Hutto and Gilbert, 2014), where we summed the positive and negative VADER scores to determine the overall sentiment score. We used the opinion lexicon devised by Hu and Liu (2004) and the lexicon of stance markers Pavalanathan et al. (2017). Inspired by Hunston and Thompson (2000), we compiled a list of evaluative patterns in the form of regular expressions that we matched across the dataset. These include phrases such as *I like/hate/believe/support, personally, in my (honest) opinion*, etc. Along with variations of the aforementioned phrases, we extended the regular expressions to support negations and modifiers, as well as the vernacular language used in the online community (e.g., *IMO – in my opinion, FMPOV – from my point of view*). To collect matched sentences, we set a constraint that a given match must exceed the thresholds for sentiment, opinion, and stance scores. We took the intersection of matched sentences in the 50th percentile for each category except sentiment, for which we set an upper bound. This is because we found that sentences with extreme sentiment scores often do not have an explicit target, and the target cannot be induced without additional context.²

²We decided not to use sentences above the 90th percentile in sentiment, which typically indicates sentences expressing emotions with highly implicit targets (e.g., a sentence with many emojis).

¹https://ipip.ori.org/newNEO_FacetsTable.htm

After applying evaluative filtering on PANDORA, we obtained 29k sentences, focusing on precision as we used strict pattern matching with high evaluative scores. To improve recall, we developed quasi-snowballing (QSB), a simple paraphrase mining technique.³ QSB is an iterative procedure that starts with a seed set of evaluative expressions and extends it with similar statements. We employed sentence transformers⁴ (Reimers and Gurevych, 2019) to compute contextualized representations and use these representations to detect paraphrases. We initialized QSB with the filtered evaluative sentences as the seed set. Afterward, we used cosine similarity as a criterion to extract similar sentences according to the similarity threshold t_{sim} , which is adjusted at each step by the similarity growth factor γ . Inspired by simulated annealing, the factor γ increases the threshold exponentially to achieve easier convergence as the whole set of sentences grows with each iteration. At the end of each iteration, we augmented the old seed set with the newly obtained matches. The process stops when there are no more candidates. Using QSB, we obtained 310k sentences with evaluative markers (details in Appendix A.2).

QSB mines expressions that can differ in target, polarity, or intensity. Since we use a high similarity threshold, in most cases only one of the above three components will be different in a paraphrase match. Multiple iterations of paraphrase mining can evolve the original sentence, resulting in more lenient matches overall, as shown in Table 1.

3.3 Evaluative topics

In the second step, we applied topic modeling to the pre-filtered evaluative comments to obtain evaluative topics. We adopted the definition of a topic as a distribution over a fixed vocabulary of terms (Blei and Lafferty, 2009), and further defined an *evaluative topic* as a topic built from target-specific opinions derived from evaluative language. To produce evaluative topics, we experimented with traditional probabilistic models as well as neural-based architectures. Furthermore, since we are dealing with Reddit comments, which tend to be short, we considered several topic modeling approaches for short texts.

³The code for quasi-snowballing is available at the link: <https://github.com/josipjukic/quasi-snowballing>

⁴We chose *all-mpnet-base-v2* from <https://www.sbert.net/>

LDA. From the family of traditional topic models, we opted for the latent Dirichlet allocation (LDA), a well-established probabilistic topic model (Blei et al., 2003), which also serves as a strong baseline. Considering that LDA deals poorly with short texts due to the data sparsity problem (Hong and Davison, 2010), following Zuo et al. (2016), we grouped comments into larger documents. For each author, we created pseudo-documents grouped by subreddit, i.e., a forum dedicated to a particular topic on Reddit.

BTM. We tested the biterm topic model (BTM), which is primarily designed for short texts (Cheng et al., 2014). We fed the model with comment-level text, where we filtered out non-evaluative sentences from the comment.

ABAE. We tried out a neural-based architecture in *Attention-based Aspect Extraction* (ABAE), an autoencoder proposed by He et al. (2017). We include this model as it is designed specifically for aspect clustering, which we expect to align well with our objective of building evaluative topics. ABAE exploits word embeddings to improve coherence and attempts to group together words that appear in similar contexts. Furthermore, ABAE uses the attention mechanism to reduce the relative importance of irrelevant words during training. We adopted ABAE but made a few changes to the training procedure. First, we trained custom Word2Vec embeddings (Mikolov et al., 2013) on PANDORA. We also modified the reconstruction loss function from the ordinary dot product to match cosine similarity with values in the $[-1, 1]$ interval, which improved the learning stability. We fed the model with segmented evaluative sentences to learn the topics.

CTM. Finally, we experimented with the combined topic model (CTM) from (Bianchi et al., 2021), which has been shown to increase coherence compared to other topic models. CTM is a blend of a variational autoencoder and embeddings from a sentence transformer.⁵

Topic models are usually evaluated by means of topic coherence. However, this method suffers from a validation gap, i.e., automated coherence is not validated by human experimentation (Hoyle et al., 2021). To mitigate this problem, we count

⁵We used *paraphrase-distilroberta-base-v2* to produce contextual embeddings.

Original hit	Paraphrase match	Similarity
Age is inexcusable to lie about IMO .	I'm not a fan of lying about age.	.86
I support the death penalty, but I would never label myself as pro-life.	I'm pro-life in the sense that I would rather not have people abort later term when it could be reasonably considered a person...	.77
I'm torn on this one, because I support trans folks 100% and I believe that a trans woman is a woman, end of story, and same for a man.	I'm supportive of transgender people transitioning and being legally treated as someone of the opposite sex.	.78

Table 1: Examples of QSB paraphrase matching. The first column represents the comments that are matched to regular expressions with matched text shown in bold. The second column lists matched paraphrases.

	NPMI	IRBO	#topics
LDA	-.1413	.9905	20
BTM	-.2159	.8241	30
ABAE	-.0521	.9833	20
CTM	.0628	.9981	20

Table 2: Topic modeling evaluation results. NPMI is a coherence score in $[-1, 1]$ range, with -1 indicating that the topic representative terms occurred together, 0 indicating that the term occurrences were independent of each other, and 1 indicating that the terms co-occurred perfectly with each other. IRBO measures topic diversity with 1 for completely different and 0 for identical topics. We repeated each experiment 10 times with different seeds. Shown in bold is the score that is significantly better than the scores for the rest of the models (independent Wilcoxon test for each model pair with $p < .01$, adjusted for family-wise error rate with the Holm-Bonferroni method).

token co-occurrences on the whole dataset and not only on the training data, which has been shown to have a stronger association with human judgment (Ding et al., 2018). Specifically, we used the normalized pointwise mutual information (NPMI) to evaluate the coherence of the induced topics. For evaluating diversity, we adopted the metric proposed by Bianchi et al. (2021), defined as the reciprocal of the standard RBO (Terragni et al., 2021).⁶ We used NPMI and IRBO as two criteria of a multi-objective optimization procedure. We determined the Pareto front of the trained models, i.e., the set of non-dominated models, from which we chose the model with the smallest number of topics (Table 2).

3.4 Evaluative author profiles

In the third step, we leverage evaluative topics to produce evaluative author profiles. Specifically, we describe each user in terms of topic preva-

⁶RBO uses a weighted ranking to estimate the disjointedness between the top 10 words for each topic.

lence, where user text is distributed as a sentiment-weighted mixture of topics across different targets. Each user is thus assigned the average topic prevalence. We compute the average topic distributions for the entire collection of user sentences, where a given sentence contributes with a value from the $[0, 1]$ interval for each topic.

To formalize our procedure, we begin by defining a topic distribution for a specific document $\mathbf{d} = [c_1 c_2 \dots c_K]^T$, where \mathbf{d} represents a document (e.g., sentence, comment), and c_k is the corresponding mixture component for the k -th topic. We aggregate the values of the user’s evaluative sentences to compute the n -th user’s components for each topic and concatenate the aggregations into the vector $\mathbf{u}^{(n)}$:

$$\mathbf{u}^{(n)} = \frac{1}{N_n} \sum_{i=1}^{N_n} \mathbf{d}^{(n,i)},$$

where N_n is the number of the n -th user’s documents and $\mathbf{d}^{(n,i)}$ is the i -th document of the n -th user. Moreover, we incorporate the sentiment intensity information to obtain a sentiment-enhanced representation $\mathbf{v}^{(n)}$:

$$\mathbf{v}^{(n)} = \frac{1}{N_n} \sum_{i=1}^{N_n} s^{(n,i)} \mathbf{d}^{(n,i)},$$

where $s^{(n,i)}$ is the sentiment intensity for the i -th document of the n -th user calculated as the sum of the positive and negative VADER scores.

The use of sentiment intensity in lieu of polarity deserves further explanation. When considering sentiment polarity, we can discern two types: the user’s sentiment polarity for a given statement and the implicit polarity (Russo et al., 2015) of the topic itself. This gives rise to a number of different ways in which sentiment information can be incorporated into evaluative representations. However, the inclusion of sentiment polarity makes it

difficult to distinguish whether the topic sentiment is driven primarily by implicit or explicit polarity. We sought parsimony, primarily to facilitate explainability, and thus chose to use only sentiment intensity. Future work may look into combining both types of sentiment.

4 Experiments

Our investigation of the association between evaluative language and personality proceeded in two steps. We first built evaluative author profiles from Reddit comments from PANDORA, as described in the previous section. To build evaluative topics, we used the CTM model on the filtered evaluative sentences, as CTM yielded the best result in terms of coherence and diversity scores. We induced 20 evaluative topics, as per the results of the optimization process. Table 3 shows a sample of the topics alongside manually assigned labels.

In the next step, we carried out a correlation study on the relationship of Big Five personality facets and evaluative topics. We adopted the Revised NEO Personality Inventory (NEO PI-R), designed to measure the Big Five personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Costa Jr and McCrae, 1995). In the first part of the analysis, we examined individual correlations between particular topics and facets. In the second part, we used canonical correlation analysis (CCA) to explore common associations between the entire set of topics on the one side and the set of all Big Five facets on the other. We chose to focus on personality facets rather than personality traits, hypothesizing that the abstraction level of facets aligns better with the granularity of induced topics. In that sense, the choice of facets supports the Brunswik symmetry principle, which stipulates that analyzed constructs (in our case, personality and topics) must have similar levels of generality (Wittmann, 2012).

4.1 Pairwise correlations

We calculated partial pairwise correlations between evaluative author profiles and Big Five facets with control for gender as a possible confounder. For gender, we used the values provided with the PANDORA dataset, which surpassed the F_1 score of .90 (Gjurković et al., 2021).⁷ Figure 2 shows sig-

⁷The gender prediction model of Gjurković et al. (2021) is a binary classifier trained only on a subset of users that

nificant correlations corrected for false discovery rate with the Benjamini-Hochberg method. We observe numerous small correlations and even moderate correlations ($> .4$) for some topic-facet pairs (Bosco et al., 2015). This is surprising, given that the average correlation in questionnaire-based studies of individual differences is .19 (Gignac and Szodorai, 2016) and that text data are noisier than questionnaire data.

To assess the validity of our results, we looked into personality psychology literature for reference. According to psychological research, facets of openness to experience are expected to correlate positively with *curiosity*, *food/drinks*, *fiction*, *music*, *gaming*, *political*, *personality*, *debate*, and *occult* topics, while they correlate negatively with the *religion* topic (Stewart et al., 2022; Ozer and Benet-Martinez, 2006; Soto, 2019; Intiful et al., 2019; Skimina et al., 2021; Church et al., 2008; Marshall et al., 2015; Chauvin and Mullet, 2021). As Figure 2 shows, the majority of our results are consistent with mentioned prior research. Three listed associations that we do not significantly support are positive correlations with *debate* (hypothesized direction, but not significant), *gaming* (hypothesized direction, but not significant), and *occult* (opposite sign). However, we note that in most of the referenced psychological literature, effects were analyzed at the trait level rather than the facet level.

4.2 Canonical correlation analysis

As facets are inherently intertwined, we can gain deeper insight from analyzing the facets jointly with respect to the set of evaluative topics. To this end, we employed canonical correlation analysis (CCA). The goal of CCA is to find a linear combination of evaluative profiles on the one side and facets on the other, with the goal of maximizing the correlation between the newly created canonical variables. CCA assumes that both variable sets have multivariate normal distributions, which we confirmed with the Henze-Zirkler test (Henze and Zirkler, 1990).⁸ We computed 20 canonical dimensions and sorted them in descending order

self-reported one of the two binary gender categories. Consequently, its predictions will be incorrect for users with non-binary gender. However, we presume that this, along with the fact that even for binary cases, predictions will not always be correct, has only a limited effect on correlation estimates partialled out for gender.

⁸Normality was not rejected in both cases, where $p = .62$ and $p = .51$ for evaluative and personality variables, respectively.

Label	Representants
open	people, lot, free, good, permit, time, going, open, big, trying
food/drinks	taste, meat, smell, beer, texture, flavour, savory, drink, palate, sweet
religion	testimony, believe, truth, god, witness, primordial, bible, church, jesus, earth
demeaning	shit, tell, talking, strangers, rude, stupid, bitch, upset, weird, shitty
investing/finance	recommend, pack, vouch, opt, buying, invest, fund, ticket, stock, dealt
fiction	watch, character, read, movies, story, books, thought, cool, new, anime
music	songs, album, pop, favourite, music, voice, listen, lyrics, track, sound
gaming	play, game, level, team, damage, skill, hit, gear, combat, dungeons
social issues	society, human, religion, culture, rights, moral, white, argument, victimhood, black
hatred	despise, hate, passion, stand, fucking, goddamn, nerd, mad, smug, ads
day-to-day	day, work, hours, week, spend, food, money, sleep, home, eat
relationships	relationship, woman, dating, child, partner, man, sex, ex, gay, alimony
argument	opinion, salt, grain, sanctimonious, worthless, controversial, assessment, disclaimer, 180, nuanced
political	government, party, vote, trump, support, country, state, speaker, system, tax
sexual/looks	hot, hair, sexy, gross, facial, body, attractive, wear, porn, dimorphism
personality	type, personality, mbti, emotions, test, cognitive, learning, ideas, brain, jung
debate	understand, discussion, post, saying, person, wrong, think, point, internet, debate
maltreatment	despised, hated, school, dropped, sucked, harass, refuses, skipped, hood, beaten
occult	fate, chime, cat, spirits, guides, luck, desperately, talisman, invite, mirror

Table 3: Evaluative topics produced by the CTM. The topic labels shown in first column were manually assigned as the most frequent label among five annotators. The second columns shows the top 10 words for each topic.

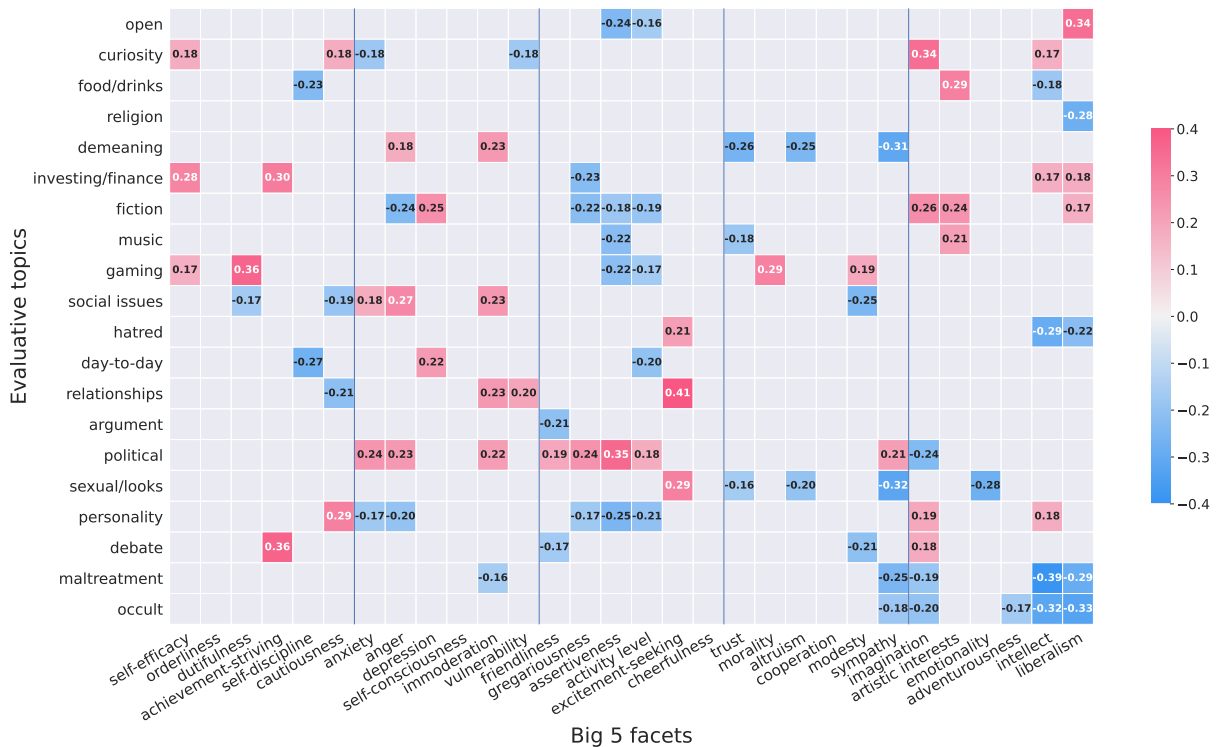


Figure 2: Pairwise partial correlations between Big 5 facets (x-axis) and evaluative topics (y-axis) with control for gender. We show only significant correlations ($p < .01$), determined using Fisher's z-transformation of correlations and corrected for false discovery rate with the Benjamini-Hochberg method.

of correlation magnitude.⁹ We found statistically significant correlations for the first three pairs of canonical variates with Wilks' lambda test.¹⁰

⁹In general, the number of canonical dimensions is equal to the number of variables in the set with fewer variables.

¹⁰We observed significant correlation ($p < .01$) for the following ranges: 1–20, 2–20, and 3–20.

An additional question we wanted to answer is whether personality analysis benefits from evaluative topics (constructed from pre-filtered evaluative text) as opposed to ordinary topics (constructed from all text). To this end, we applied CCA to three different data subsets: (1) unfiltered text, (2) text obtained with evaluative filtering, and (3) non-

evaluative text, obtained as the difference between the first and the second set. In addition, we ran CCA on (4) evaluative text with sentiment intensity in order to investigate whether evaluative profiles benefit from sentiment information. Figure 3 shows the canonical correlations of the first three canonical pairs on the four data subsets. Higher correlations computed by CCA indicate stronger associations between the two sets of variables. Thus, under the assumption that evaluative profiles and personality are associated, obtaining higher correlations supports construct validity of evaluative profiles as construed by our model. Construct validity, in this case, concerns the extent to which an evaluative topic accurately assesses what it is designed for. With this in mind, two main observations emerge from the results: (1) evaluative pre-filtering seems to be more apt than using unfiltered data for establishing an association with Big 5 personality and (2) sentiment information amplifies the correlations.

To further investigate the relationship between facets and evaluative topics as well as their individual importance, we computed canonical loadings, i.e., canonical structure correlations, by projecting both sets of original variables onto the first and second canonical dimensions (Figure 4). Canonical loadings reflect the shared variance of the observed variable and the canonical variate. We followed the common practice in psychometrics (ter Braak, 1990) and computed the intra-set variable-to-variate correlation for the instrument variable (evaluative topic), and the inter-set correlation for the goal variable (facet). We identified three distinct clusters of facets and topics. The first one is at the bottom right corner of Figure 4 (*music, fiction; artistic-interests, imagination*) and it indicates the openness aspect of openness to experiences. The bottom-left cluster (*maltreatment, demeaning; vulnerability, immoderation, and excitement-seeking*) roughly corresponds to unpleasantly emotionally charged cluster. Finally, the top left cluster (*political, social issues; activity level, assertiveness*) can be interpreted as social engagement. We further validate the CCA results by showing the dispersion of facets in the first and second canonical dimensions (Figures 5 and 6 in the Appendix). We find that facets from the same domain are grouped but that there are also associations between facets from different domains, which is expected based on prior research (Schwaba et al., 2020).

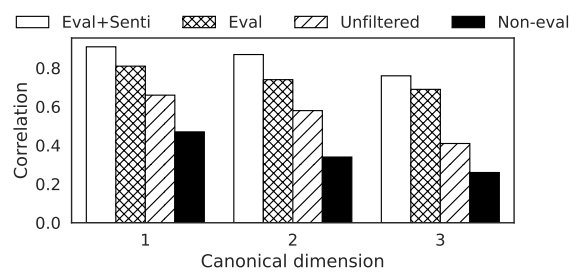


Figure 3: Canonical correlations of the first three canonical pairs ($p < .01$) estimated on four data subsets: original text (*Unfiltered*), text obtained with evaluative filtering (*Eval*), Eval with sentiment information included when calculating the evaluative profiles (*Eval+Senti*), and non-evaluative text (*Non-eval*) obtained as the set difference between *Non-filtered* and *Eval* sets.

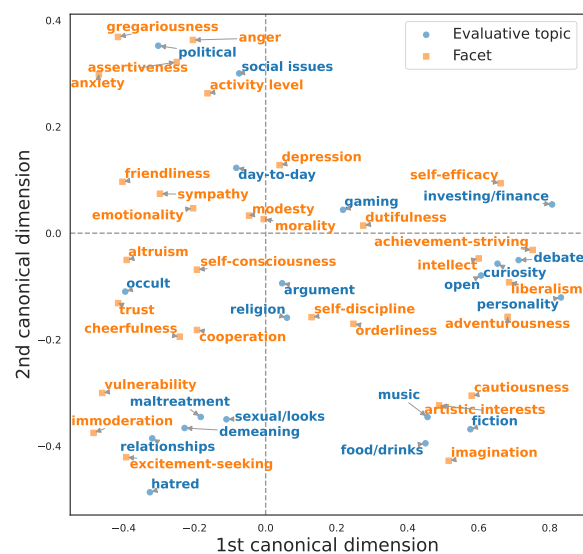


Figure 4: Canonical loadings of the first two dimensions for facets and evaluative topics. The proximity of individual points indicates the strength of association between two data points. Specifically, when two points, regardless of their type (topic or facet), have similar angles with respect to the origin and similar magnitudes, this hints that the two points contribute similarly to the canonical variate and have stronger associations.

5 Conclusion

The relationship between evaluative language and personality has been understudied in NLP research. We aim to fill this gap by proposing evaluative author profiling – linking text of authors to topics obtained from text filtered for evaluative language. We applied evaluative profiling on a dataset of Reddit comments with self-reported Big 5 personality facet scores. Using canonical correlation analysis, we showed that the facets within the same trait have stronger associations in the canonical space. We

found that evaluative topics have moderate correlations with Big 5 facets. Moreover, we corroborate the hypothesis that evaluative expressions hold greater informational value for personality analysis than unfiltered texts. Additionally, we showed that non-evaluative text has a much weaker association with Big 5 facets compared to evaluative text. Finally, we observed correlations consistent with previous research in personality psychology. We believe that our study can contribute to a better understanding of evaluative language on social media and how it relates to personality traits.

Ethical considerations

Our research has been approved by an academic IRB.

Potential harm. Our study is an exploratory study, hence one cannot generalize based on the correlations we obtained. Otherwise, that could lead to unsupported generalization, which may discriminate against certain groups of people.

Collecting data from users. According to the American Psychological Association's Ethical Principles,¹¹ researchers may waive informed consent when analysing archival data (i.e., data collected before the study began) if disclosure of responses would not expose participants to risk of criminal or civil liability or harm. In our case, we use Reddit data, where Reddit users agree via Reddit User Agreement that they will not disclose any sensitive information of others and they are informed that their comments are publicly available. As users may opt out and delete their data, we removed deleted user accounts and comments. We also present our results at the group level rather than the individual level to further protect users' identities.

Misuse potential. In principle, evaluative profiling could be used for making decisions at the individual level based on their social media textual data, e.g., in micro-targeting. We strongly advocate against the use of our methods for these or other ethically questionable applications.

Biases. We note that we used self-reported data from Reddit. As such, this data may not be perfectly accurate and may include various biases, notably the acquisition bias. The dataset we use may not be representative of Reddit population, and it

is certainly not representative of any wider populations of users.

Limitations

Although our evaluative filtering technique resulted with evaluative topics that have stronger correlations with Big 5 facets than non-evaluative text, filtering cannot be validated in isolation without additional annotation. Additionally, incorporating additional information such as sentiment polarity can hurt interpretability of the results. A possible solution to circumvent this problem is to use structural topic models (Roberts et al., 2014), which can model additional information such as user demographics as covariates. Since we use topic modeling and try to optimize topic diversity and coherence, which has been criticized as of late (Hoyle et al., 2021), it can be hard to choose appropriate representants for the topic and there are no guarantees that a certain topic will be coherent enough to translate to a meaningful concept. From the psychology point of view, we conduct only an exploratory study where we observe correlation, so we cannot make any confirmation of the results from personality psychology, but only support it with associations. Moreover, since we conduct a facet-level study and take only the scores from the same questionnaire to mitigate the noise from different tests, the number of reports of facet scores is relatively small ($n = 127$) compared to the total number of users with reported traits scores ($n = 1,608$).

Our study was limited to English texts. A potential transfer to other languages would require additional resources, namely adequate lexicons and sentiment classifier to enable evaluative filtering, making the transfer non-trivial. Finally, we would need to retrain the topic models on texts in the target languages.

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¹¹<https://www.apa.org/ethics/code>

References

- Phillip L Ackerman and Eric D Heggstad. 1997. Intelligence, personality, and interests: evidence for overlapping traits. *Psychological bulletin*, 121(2):219.
- Keith Allan. 2007. *The western classical tradition in linguistics*. Equinox London.
- Farah Benamara, Maite Taboada, and Yannick Mathieu. 2017. [Evaluative language beyond bags of words: Linguistic insights and computational applications](#). *Computational Linguistics*, 43(1):201–264.
- Federico Bianchi, Silvia Terragni, and Dirk Hovy. 2021. [Pre-training is a hot topic: Contextualized document embeddings improve topic coherence](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 759–766, Online. Association for Computational Linguistics.
- Douglas Biber and Edward Finegan. 1989. [Styles of stance in english: Lexical and grammatical marking of evidentiality and affect](#). *Text - Interdisciplinary Journal for the Study of Discourse*, 9(1):93–124.
- David M Blei and John D Lafferty. 2009. Topic models. In *Text mining*, pages 101–124. Chapman and Hall/CRC.
- David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent dirichlet allocation. *J. Mach. Learn. Res.*, 3:993–1022.
- Frank Bosco, Kulraj Singh, James Field, and Charles Pierce. 2015. [Correlational effect size benchmarks](#). *Journal of Applied Psychology*, 100:431–449.
- Bruno Chauvin and Etienne Mullet. 2021. Individual differences in paranormal beliefs: The differential role of personality aspects. *Current psychology*, 40(3):1218–1227.
- Xueqi Cheng, Xiaohui Yan, Yanyan Lan, and Jiafeng Guo. 2014. [Btm: Topic modeling over short texts](#). *IEEE Transactions on Knowledge and Data Engineering*, 26(12):2928–2941.
- A Timothy Church, Marcia S Katigbak, Jose Alberto S Reyes, Maria Guadalupe C Salanga, Lilia A Miramontes, and Nerissa B Adams. 2008. Prediction and cross-situational consistency of daily behavior across cultures: Testing trait and cultural psychology perspectives. *Journal of Research in Personality*, 42(5):1199–1215.
- Paul T Costa Jr and Robert R McCrae. 1995. Domains and facets: Hierarchical personality assessment using the revised neo personality inventory. *Journal of personality assessment*, 64(1):21–50.
- Ran Ding, Ramesh Nallapati, and Bing Xiang. 2018. [Coherence-aware neural topic modeling](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 830–836, Brussels, Belgium. Association for Computational Linguistics.
- Jiachen Du, Ruifeng Xu, Yulan He, and Lin Gui. 2017. [Stance classification with target-specific neural attention](#). In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17*, pages 3988–3994.
- David C Funder. 2012. Accurate personality judgment. *Current Directions in Psychological Science*, 21(3):177–182.
- Gilles E Gignac and Eva T Szodorai. 2016. Effect size guidelines for individual differences researchers. *Personality and individual differences*, 102:74–78.
- Matej Gjurković, Mladen Karan, Iva Vukojević, Mhaela Bošnjak, and Jan Šnajder. 2021. [PANDORA talks: Personality and demographics on Reddit](#). In *Proceedings of the Ninth International Workshop on Natural Language Processing for Social Media*, pages 138–152, Online. Association for Computational Linguistics.
- Lewis R Goldberg. 1981. Language and individual differences: The search for universals in personality lexicons. *Review of personality and social psychology*, 2(1):141–165.
- Ruidan He, Wee Sun Lee, Hwee Tou Ng, and Daniel Dahlmeier. 2017. [An unsupervised neural attention model for aspect extraction](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 388–397, Vancouver, Canada. Association for Computational Linguistics.
- Norbert Henze and Bernd Zirkler. 1990. A class of invariant consistent tests for multivariate normality. *Communications in Statistics-theory and Methods*, 19:3595–3617.
- Mickel Hoang, Oskar Alija Bihorac, and Jacobo Rouces. 2019. [Aspect-based sentiment analysis using BERT](#). In *Proceedings of the 22nd Nordic Conference on Computational Linguistics*, pages 187–196, Turku, Finland. Linköping University Electronic Press.
- Liangjie Hong and Brian D Davison. 2010. Empirical study of topic modeling in twitter. In *Proceedings of the first workshop on social media analytics*, pages 80–88.
- Alexander Hoyle, Pranav Goel, Andrew Hian-Cheong, Denis Peskov, Jordan Boyd-Graber, and Philip Resnik. 2021. [Is automated topic model evaluation broken? the incoherence of coherence](#). In *Advances in Neural Information Processing Systems*, volume 34, pages 2018–2033. Curran Associates, Inc.
- Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 168–177.

- Susan Hunston. 2010. *Corpus approaches to evaluation: Phraseology and evaluative language*, volume 13. Routledge.
- Susan Hunston and Geoffrey Thompson. 2000. *Evaluation in text: Authorial stance and the construction of discourse: Authorial stance and the construction of discourse*. Oxford University Press, UK.
- Clayton Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 8.
- Herbert H Hyman. 1957. An exploration into opinions and personality. *World Politics*, 10(1):144–153.
- Freda Dzifa Intiful, Emeffa Gifty Oddam, Irene Kretchy, and Joana Quampah. 2019. Exploring the relationship between the big five personality characteristics and dietary habits among students in a Ghanaian university. *BMC psychology*, 7(1):1–7.
- Scott F. Kiesling, Umashanthi Pavalanathan, Jim Fitzpatrick, Xiaochuang Han, and Jacob Eisenstein. 2018. [Interactional stancetaking in online forums](#). *Computational Linguistics*, 44(4):683–718.
- Vivek Kulkarni, Margaret L. Kern, David Stillwell, Michal Kosinski, Sandra Matz, Lyle Ungar, Steven Skiena, and H. Andrew Schwartz. 2018. [Latent human traits in the language of social media: An open-vocabulary approach](#). *PLOS ONE*, 13(11):1–18.
- Lisa M. Larson, Patrick J. Rottinghaus, and Fred H. Borgen. 2002. [Meta-analyses of big six interests and big five personality factors](#). *Journal of Vocational Behavior*, 61(2):217–239.
- Chei Sian Lee and Long Ma. 2012. News sharing in social media: The effect of gratifications and prior experience. *Computers in human behavior*, 28(2):331–339.
- Ling Luo, Xiang Ao, Yan Song, Jinyao Li, Xiaopeng Yang, Qing He, and Dong Yu. 2019. [Unsupervised neural aspect extraction with sememes](#). In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 5123–5129. International Joint Conferences on Artificial Intelligence Organization.
- Jean Pierre Malrieu. 1999. *Evaluative semantics: Language, cognition, and ideology*. Psychology Press.
- Tara C Marshall, Katharina Lefringhausen, and Nelli Ferenczi. 2015. The big five, self-esteem, and narcissism as predictors of the topics people write about in facebook status updates. *Personality and Individual Differences*, 85:35–40.
- Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.
- Daniel J Ozer and Veronica Benet-Martinez. 2006. Personality and the prediction of consequential outcomes. *Annual review of psychology*, 57:401.
- Bo Pang and Lillian Lee. 2008. [Opinion mining and sentiment analysis](#). *Found. Trends Inf. Retr.*, 2(1–2):1–135.
- Gregory Park, H. Schwartz, Johannes Eichstaedt, Margaret Kern, Michal Kosinski, David Stillwell, Lyle Ungar, and Martin Seligman. 2014. [Automatic personality assessment through social media language](#). *Journal of personality and social psychology*, 108.
- Umashanthi Pavalanathan, Jim Fitzpatrick, Scott Kiesling, and Jacob Eisenstein. 2017. [A multidimensional lexicon for interpersonal stancetaking](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 884–895, Vancouver, Canada. Association for Computational Linguistics.
- James Pennebaker and Laura King. 2000. [Linguistic styles: Language use as an individual difference](#). *Journal of personality and social psychology*, 77:1296–312.
- Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. 2014. [SemEval-2014 task 4: Aspect based sentiment analysis](#). In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 27–35, Dublin, Ireland. Association for Computational Linguistics.
- Nils Reimers and Iryna Gurevych. 2019. [Sentence-BERT: Sentence embeddings using Siamese BERT-networks](#). In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.
- Nils Reimers, Benjamin Schiller, Tilman Beck, Johannes Daxenberger, Christian Stab, and Iryna Gurevych. 2019. [Classification and clustering of arguments with contextualized word embeddings](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 567–578, Florence, Italy. Association for Computational Linguistics.
- Margaret E Roberts, Brandon M Stewart, Edoardo M Airoidi, K Benoit, D Blei, P Brandt, and A Spirling. 2014. Structural topic models. *Retrieved May*, 30:2014.
- Irene Russo, Tommaso Caselli, and Carlo Strapparava. 2015. [SemEval-2015 task 9: CLIPeval implicit polarity of events](#). In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pages 443–450, Denver, Colorado. Association for Computational Linguistics.

- Ted Schwaba, Mijke Rhemtulla, Christopher J Hopwood, and Wiebke Bleidorn. 2020. A facet atlas: Visualizing networks that describe the blends, cores, and peripheries of personality structure. *PLoS one*, 15(7):e0236893.
- H. Andrew Schwartz, Johannes C. Eichstaedt, Margaret L. Kern, Lukasz Dziurzynski, Stephanie M. Ramones, Megha Agrawal, Achal Shah, Michal Kosinski, David Stillwell, Martin E. P. Seligman, and Lyle H. Ungar. 2013. [Personality, gender, and age in the language of social media: The open-vocabulary approach](#). *PLOS ONE*, 8(9):1–16.
- Ewa Skimina, Jan Ciecuch, and Włodzimierz Strus. 2021. Traits and values as predictors of the frequency of everyday behavior: Comparison between models and levels. *Current Psychology*, 40(1):133–153.
- Christopher J Soto. 2019. How replicable are links between personality traits and consequential life outcomes? the life outcomes of personality replication project. *Psychological Science*, 30(5):711–727.
- Ross David Stewart, René Möttus, Anne Seeboth, Christopher John Soto, and Wendy Johnson. 2022. The finer details? the predictability of life outcomes from big five domains, facets, and nuances. *Journal of personality*, 90(2):167–182.
- Cajo ter Braak. 1990. [Interpreting canonical correlation analysis through biplots of structure correlations and weights](#). *Psychometrika*, 55:519–531.
- Silvia Terragni, Elisabetta Fersini, and Enza Messina. 2021. [Word embedding-based topic similarity measures](#). In *Natural Language Processing and Information Systems: 26th International Conference on Applications of Natural Language to Information Systems, NLDB 2021, Saarbrücken, Germany, June 23–25, 2021, Proceedings*, page 33–45, Berlin, Heidelberg, Springer-Verlag.
- Geoffrey Thompson and Susan Hunston. 2000. Evaluation: an introduction. In *Evaluation in text: Authorial stance and the construction of discourse*. Oxford University Press.
- Zhiqiang Toh and Wenting Wang. 2014. [DLIREC: Aspect term extraction and term polarity classification system](#). In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pages 235–240, Dublin, Ireland. Association for Computational Linguistics.
- Stéphan Tulkens and Andreas van Cranenburgh. 2020. [Embarrassingly simple unsupervised aspect extraction](#). In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3182–3187, Online. Association for Computational Linguistics.
- Janyce Wiebe, Theresa Wilson, Rebecca Bruce, Matthew Bell, and Melanie Martin. 2004. [Learning subjective language](#). *Computational Linguistics*, 30(3):277–308.
- Werner W Wittmann. 2012. Principles of symmetry in evaluation research with implications for offender treatment. *Antisocial behavior and crime. Contributions of developmental and evaluation research to prevention and intervention*, (2011):357–368.
- Yuan Zuo, Junjie Wu, Hui Zhang, Hao Lin, Fei Wang, Ke Xu, and Hui Xiong. 2016. [Topic modeling of short texts: A pseudo-document view](#). In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16*, page 2105–2114, New York, NY, USA. Association for Computing Machinery.

A Technical details

A.1 Dataset

We selected the comments from users with Big Five self-reports on PANDORA. We kept only the comments in English and removed unlikely candidates for evaluative expressions, including comments that were too short – those with fewer than five words – and noisy comments – those consisting of 50% or more non-alphanumeric characters. We segmented the comments into sentences using spaCy’s English pipeline *en_core_web_lg*¹² to proceed at a finer level. Once again, we discarded texts that were too short, but this time the sentences with fewer than three words.

A.2 Evaluative filtering

When we employed QSB to mine paraphrases of the initial set of evaluative expressions, we aimed for a tenfold increase in size of the seed set (29k sentences), so we tuned the values of t_{sim} and γ . We used grid search with the parameter range $t_{sim} \in [0.50, 0.90]$ with step 0.05 and $\gamma \in [0.90, 1.10]$ with a step of 0.05 in both cases, which led us to $t_{sim} = 0.7$ and $\gamma = 1.05$. QSB yielded 310k sentences with evaluative markers.

A.3 Topic modeling

We used *scikit-learn* implementation of LDA.¹³ We adapt the code from the original papers for BTM (Cheng et al., 2014), ABAE (He et al., 2017), and CTM (Bianchi et al., 2021). The neural-based architectures in ABAE and CTM have 100,020 and 19,794,280, respectively. We trained ABAE for 5 epochs and CTM for 20 epochs, with average running times of 71.4 and 590.8 minutes over 10 different runs.

We used the same preprocessing for all topic models that we experimented with. Specifically, we removed punctuation and lowercased the text. We also eliminated stop words, URLs, emails, digits, and currency symbols, after which we lemmatized the tokens. We repeated each experiment 10 times with different seeds. We conducted a grid search with the number of topics as a hyperparameter in the $[5, 100]$ range with step 5. For the rest of the hyperparameters, we used default values.

A.4 Computing infrastructure

We conducted our experiments on $2 \times$ AMD Ryzen Threadripper 3970X 32-Core Processors and $2 \times$ NVIDIA GeForce RTX 3090 GPU’s with 24GB of RAM. We used *PyTorch* version 1.9.0 and CUDA 11.4.

B Additional analysis

In Figure 2, there are cases where certain evaluative topics show significant correlation with several facets from the same trait. For instance, the topic *social issues* correlates positively and significantly with *anger*, *immoderation*, and *anxiety* facets from the *neuroticism* trait. On the other hand, there are a number of cases where the correlation between facets from the same trait and a topic is of a different sign. This corroborates our hypothesis that topics align better with facets than with traits.

¹²https://spacy.io/models/en#en_core_web_lg

¹³<https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.LatentDirichletAllocation.html>



Figure 5: Facet projection onto the first canonical variate. The values on the y-axis represent the canonical loadings of facets in the first canonical dimension.



Figure 6: Facet projection onto the second canonical variate. The second dimension provides a perfect separation of conscientiousness and neuroticism, with a mixture of facets from the remaining traits.