TraSE: Towards Tackling Authorial Style from a Cognitive Science Perspective

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Abstract
Stylistic analysis of text is a key task in research areas ranging from authorship attribution to forensic analysis and personality profiling. The existing approaches for stylistic analysis are plagued by issues like topic influence, lack of discriminability for large number of authors and the requirement for large amounts of diverse data. In this paper, the source of these issues are identified along with the necessity for a cognitive perspective on authorial style in addressing them. A novel feature representation, called Trajectory-based Style Estimation (TraSE), is introduced to support this purpose. Authorship attribution experiments with over 27,000 authors and 1.4 million samples in a cross-domain scenario resulted in 90% attribution accuracy suggesting that the feature representation is immune to such negative influences and an excellent candidate for stylistic analysis. Finally, a qualitative analysis is performed on TraSE using physical human characteristics, like age, to validate its claim on capturing cognitive traits.

1 Introduction
A key attribute that makes a literary work unique is its writing style. Writing style controls how a concept is portrayed in the text. This can transform an interesting idea into a literary masterpiece. The active role played by the author’s thought processes in the composition of text makes it a great candidate for understanding cognitive processes and its development. Existence of evaluation measures, like readability scores and lexical richness measures, that quantify education proficiency levels from text as a stand-in proxy for latent cognitive development are testament to this fact (Kincaid et al., 1975; Ferrer-i Cancho and Elvevåg, 2010; Yule, 1939; Zipf, 1937).

Cognitive science places focus on language acquisition. Although authorial style is not directly studied, insights towards understanding its behaviour can be borrowed from existing research. For instance, it was suggested that acquisition of linguistic syntax saturated around 18 years of age (Hartshorne et al., 2018). Similarly, it was also observed that linguistic creativity reached peak potential at around 25 years and continued to grow throughout the lifetime for people actively involved in professions requiring linguistic creativity (Simonton, 1988). These observations suggest that writing style is dependent on the author’s life experiences and degree of exposure to language. Consequently, authorial style was defined as the author’s conscious response to the requirements of genre and context as well as the result of his or her unconscious and habituated choices of the grammatical elements acquired through the long-term experiential process of writing (McMenamin, 2010; Coulthard, 2012). Some life experiences can be shared but, when holistically evaluated, they will be unique for the individual. This makes writing style a great candidate for identifying the author and profiling them -both physically in terms of gender and age, or psychologically in terms of their personality traits (Yang and Chow, 2014; Rangel et al., 2013; Rangel Pardo et al., 2015).

Computational linguistics provided several empirical approaches to capture authorial style. Initially, Rudman (1997) suggested over a 1000 features to assess style. Some of these features have gained prominence in recent years as the to-go features for tasks involving stylistic analysis. One of these features is the n-grams. There are several types of n-gram in use at different language levels: character, word and syntactic or parts-of-speech (POS) n-grams (Kešelj et al., 2003; Stamatatos, 2012; Kestemont et al., 2018). Character-level methods include SVM char-2-gram and SVM char-3-gram (Kestemont et al., 2019). Examples of word-level methods are CNN+GloVe (Ruder et al., 2016).
et al., 2016) and BertAA (Fabien et al., 2020). Simple frequency-based features such as counts of punctuation and function words were also used (Argamon and Levitan, 2005; Kestemont, 2014; Segarra et al., 2013; Neal et al., 2018). Recently, deep learning architectures such as recurrent neural nets, convolutional neural nets and transformers are rising in popularity (Gupta et al., 2019; Shrestha et al., 2017; Hu et al., 2020; Fabien et al., 2020). Similarly, complex approaches utilizing a combination of features like eBOW+SVM (Wilson et al., 2021) or using committee of classifiers combining several of these features were also tested with good success in works such as Style-HAN (Jafariakinabad and Hua, 2021), Amann (2019), Bacciu et al. (2019) and Rahgouy et al. (2019). While these approaches reported state-of-the-art performance for their target data, they universally demonstrated significant reduction in attribution performance with change in topic, genre and domain (Sundararajan et al., 2018; Sapkota et al., 2014, 2015; Stamatas, 2013; Bischoff et al., 2020). Furthermore, the performance was also conditioned on the number of authors in the attribution experiment i.e., more authors meant less performance (Luyckx and Daelemans, 2008, 2011; Neal et al., 2018). These issues limited their viability for any real-world usage and led some researchers, like Fobbe (2020), to question their validity: does frequency-based analysis of literary components in a text sample actually capture authorial style? Ideally, authorial style should be readily distinguishable under any circumstance and immune to the influence of any text characteristics.

The source of these issues stem from a fundamental misunderstanding in the computational interpretation of authorial style. This misunderstanding can be condensed into two key observations.

- Existing approaches in computational linguistics does not discriminate between conscious choice and unconscious habits of the author. Conscious choices like topic, genre and domain change between documents. However, unconscious habits stay consistent for a longer period.

- Computational linguistics focuses on discriminating between authors. Understanding their psycho-linguistic behaviour is often foregone. For instance, consider a simple n-gram. Conventional wisdom regarding n-grams suggest that a particular n-gram of high variance is not a good predictor of the author’s style. A good predictor of style demonstrates low variance across the author’s samples. However, it can be argued that the high variance of that particular n-gram describes the author’s psycho-linguistic behaviour. This consistency in the author’s behaviour is also a good stylometric marker.

To address this misunderstanding and provide a stable cognitive style signature for identifying the author, a novel feature representation, called Trajectory-based Style Estimation (TraSE), is introduced. Section 2 expands on the methodology used in the paper beginning with the introduction of the feature representation followed by the corpus description and, finally, a comprehensive quantitative evaluation to support the claims in the paper in Section 3. Sections 4 and 5 explains the reasoning behind the performance displayed by TraSE followed by a corroborati on with well-studied qualitative aspects of language to assert its utility as a cognitive marker. Finally, the work is concluded in Section 6.

2 Methodology

 Initially, the feature representation is introduced. The workflow for obtaining the TraSE feature representation, model development and its evaluation is shown in Figure 1. A large collection of corpora from diverse genre, topic and domain, listed in Section 2.3, are utilized to comprehensively evaluate the performance of the feature representation in Section 3.

2.1 Feature Representation

The feature representation is motivated by two observations: the tendency of n-gram based feature representation to overfit text samples and the analogous nature of a word embedded in an embedding space to that of a elementary particle in physics. N-grams are the most common feature representations used in stylistic analysis. However, they are overly fine-tuned to the word occurrences in text. For instance, an author may prefer to polish a manuscript by looking up a dictionary to improve the sophistication of the vocabulary usage in the manuscript. These sophisticated words would occur at a very low frequency in the text. Further-
more, it is an accepted practice to limit n-gram comparisons to the most common 1000 n-grams in the corpus. In such scenarios, these words would be considered outliers and eliminated from comparison. However, such behaviour should be considered a stylistic trend or cognitive preference of the author. To offset this limitation, a contextual embedding is required. Contextual embedding assigns similar representations for words used in similar contexts.

Contextual embedding is not sufficient in itself for stylistic analysis. The requirement is to extract unique patterns in the author’s style unaffected by topic, genre and domain. The second motivation comes into play at this point. Contextual embedding condenses a words into a point in an $n$-dimensional space. Consequently, a sentence can be decomposed into a series of points with each point representing a word in the sentence in the $n$-dimensional embedding space. The path connecting each point in the embedding space can be considered analogous with the trajectory travelled by a particle from the first word to the last word in the sentence. Parts of the trajectory that the particle tend to visit often can be considered an inherent behaviour associated with the particle. In other words, such behaviour can be translated into a stylistic signature for the author. This feature representation is called Trajectory-based Style Estimation (TraSE).

Sentences have varying length and the information conveyed by the sentence is also dependent on the topic, genre and domain. Consequently, assessing similarity between trajectories of two different sentences in a $n$-dimensional embedding space requires the definition of reference points in the sentences. The optimal solution to this problem would be topic words in the sentence. Topic words represent the content aspect of the sentence and likely play a minor role in the style of the author. This is supported by observations in several studies that have achieve higher authorship attribution performance by masking topic words in the sample. However, extraction of topic words is a tedious process and requires the execution of approaches like the Latent Dirichlet Allocation (LDA) on the target corpus. A simpler proxy can be used to replace topic words. It was suggested in literature that most topic words are NOUNS and masking them can reduce topic influence to a great extent (Sundararajan and Woodard, 2018; Martin and Johnson, 2015; Halvani and Graner, 2021; Markov et al., 2017). Similarly, the requirement for topic words can be substituted with the most frequently occurring NOUNS in the text sample. Topic words act like anchors for the particle’s trajectory and the behaviour of the particle in between these anchor points are captured to form the feature representation. Anchor points, being subjective, are excluded from the representation.

To analyze and capture the behaviour of the particle between the topic words, vector algebra is utilized. The embedded representations of two consecutive words in the sentence is used to form a vector going from the first word to the second word. The evolution of the vector with respect to each subsequent word encountered in the sentence is recorded. The evolution of the vector is quantified by the angle formed in between the initial vector at the beginning of the sentence and the resultant vector obtained with the addition of each subsequent vectors. The algorithm for obtaining the feature vector, called recursive resultant evolution, is defined in Algorithm 1. The resultant vector is always compared to the initial vector to maintain a common frame of reference for com-
A changing frame of reference would result in invalid comparisons. The algorithm lists the steps involved in obtaining a feature representation for the word sequence between two consecutive topic words in the sentence. The accumulator in the algorithm is updated for every pair of consecutive topic words in the sentence and for all the sentences in the text sample. Finally, the accumulator is normalized by sum to unity. This forms a 180-dimensional (the cosine inverse in the algorithm is limited to two quadrants of the coordinate system) feature representation for each text sample in the target corpus.

**Algorithm 1** Recursive resultant evolution for word_sequence in between topic words $t_1$ and $t_2$

| Line | Description |
|------|-------------|
| 1:   | **Input** word_sequence |
| 2:   | accumulator ← array of dimension 180 |
| 3:   | init_vec ← embed(word[1]) - embed(word[0]) |
| 4:   | Initialize $i ← 2$ |
| 5:   | **while** $i < \text{length(word_sequence)}$ **do** |
| 6:   | cur_word ← embed(word_sequence[i]) |
| 7:   | prev_word ← embed(word_sequence[i-1]) |
| 8:   | cur_vec ← cur_word - prev_word |
| 9:   | $\theta ← \cos^{-1}(1 - \text{cosine_distance(resultant, cur_vec)})$ |
| 10:  | resultant ← cur_vec + init_vec |
| 11:  | $\theta ← \text{round}(\theta)$ |
| 12:  | accumulator[$\theta$] ← accumulator[$\theta$] + 1 |
| 13:  | $i ← i + 1$ |
| 14:  | **end while** |

2.2 Model Development and Evaluation

Transforming the features representation into a usable form for stylistic analysis requires the development of a latent language model. Kessler et al. (1997) suggested that a text sample is composed of two components: content and structure. The content aspect of the text sample was suppressed, to an extent, by the removal of topic words in the feature generation process. However, suppression of the structure aspect requires the generation of the latent language model (LLM). Once content and structure are filtered out from the feature representation, a refined representation of the author’s stylistic signature should remain. TraSE feature vectors when averaged for a large number of authors (typically between 20-50) converges to a Gaussian distribution. The LLM, parameterized by the mean and standard deviation of this Gaussian distribution, is consistent for any text data.

The feature vectors are processed using Algorithm 2 before they are fed to a classifier. The algorithm requires an author profile model (APM). The APM is computed by averaging the TraSE feature vectors extracted from Algorithm 1 for all training text samples of an author. The algorithm performs two important tasks. First, it makes the feature vector dense for the author. When a text sample for the author is too short, the extracted feature vector from Algorithm 1 will be sparse i.e. certain positions in the feature vector will be zero. This does not mean that the author does not use those specific positions. The algorithm offsets this issue by replacing positions with zero value with the corresponding mean value from the APM. Finally, the algorithm suppresses the structural contributions present in the feature vector by subtracting the LLM from the feature vector. Now, the feature vectors can be fed into a classifier for training. In the testing phase, only the LLM is used in Algorithm 2. Providing APM to Algorithm 2 during testing generates an identity claim, thereby, transforming the workflow from authorship attribution to verification.

2.3 Corpus Description

The corpora assembled in this section represents the common corpora used in authorship attribution research. They have varying number of authors, topics, genre, domain, sample count/length and sample quality. The diversity in the corpora characteristics will serve to effectively benchmark the feature representation. The author selection process for each corpus ensures that there are at least four samples for each candidate author. Table 1 describes the statistics for the resultant corpora used for this paper.

**Blogs Authorship Corpus** (Schler et al., 2006): This corpus originally consisted of 678,161 blog

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1 Performance remains unchanged in both cases (Table 3)
Table 1: Corpus statistics for all corpora used in this work

| Corpus (→) | BAC | IMDB1M | PAN18-Twitter | FICSIT | Enron | Guardian10 |
|------------|-----|--------|---------------|--------|-------|------------|
| Statistics (↓) / Source of data (→) | Blogs | Movie reviews | Twitter | Forum posts | Emails | News articles |
| Number of authors | 14,650 | 6,090 | 4,900 | 1,237 | 149 | 14 |
| Total samples | 667,118 | 142,456 | 423,611 | 188,077 | 12,762 | 444 |
| Avg. samples per author | 45 | 23 | 88 | 152 | 85 | 34 |
| Avg. characters per sample | 1,597 | 723 | 78 | 2,331 | 254 | 6,234 |
| Avg. words per sample | 335 | 148 | 16 | 416 | 49 | 1,202 |
| Avg. sentences per sample | 19 | 9 | 1 | 17 | 2 | 52 |

posts written by 19,320 bloggers.

**FICSIT (Wilson et al., 2021):** FICS Inter Topic corpus is controlled specifically for cross-topic samples from StackExchange and contains text samples from over 308 topics.

**Guardian10 (Stamatatos, 2012):** This cross-domain corpus consists of two genres: opinion articles and book reviews on four topics: politics, UK, world and society.

**IMDB1M (Seroussi et al., 2011):** This corpus originally consisted of 66,816 reviews and 204,809 posts written by 22,116 International Movie Database (IMDB) users.

**Enron Email Corpus**: This corpus contains over 500,000 emails generated by 151 senior management of the Enron Corporation. Apart from the qualification criteria, the corpus was constrained to at most 100 samples for each author.

**PAN18 Twitter Corpus (Rangel et al., 2018):** This corpus was introduced as a part of PANCLEF 2018’s Author Profiling task and extracted from Twitter. Out of the three languages available, this paper uses English language text corpus. Apart from the qualification criteria, this corpus was constrained to a minimum of five words per text sample after pre-processing the samples to remove all non-ASCII characters and emojis.

Some of the corpora are not considered cross-topic. However, they are not guaranteed to be devoid of topic influence. Consequently, topic dissimilarity for each corpus was assessed. PAN18-Twitter was precluded from the study due to its ultra-short text samples. LDA topic models, with the number of latent topics limited to 20, are trained on samples of each author belonging to a specific corpus. Cosine distance is then used to compare the vectors obtained for each author’s samples from the trained LDA model against each other. Finally, the topic dissimilarity distribution for each corpus was obtained. The results are plotted in Figure 2. This suggests that most of the corpora display topic diversity despite not being explicitly labelled as cross-topic corpora.

### 3 Quantitative Traits of Style

Stamatatos (2016) outlined the protocol for comprehensive evaluation of attribution algorithms in a recent work. Following the outline, the influence of author count on attribution performance is evaluated first. A successful evaluation would entail a state-of-the-art performance in comparison to existing approaches in literature with no correlation on author counts. Next, auxiliary experiments are conducted to assess the influence of sample statistics, sample quality and topic diversity. If successful, the attribution performance will saturate with a limited number of text samples. Further, no significant drop in performance will be observed when attribution is performed over samples with high topic diversity.

To facilitate performance evaluation, the attribution accuracy from recent state-of-the-art approaches were populated from the source works. The chosen approaches, introduced in Section 1, are representative of existing literature. These approaches provide a good benchmark for comparison against TraSE. The collated performance mea-
Table 2: Matching performance (in %) of several authorship attribution algorithms on the chosen corpora. These values were collated from the source works. The number of authors used in the source work is highlighted in parenthesis. “-” indicates that the source work was not evaluated on that corpus. The bold value indicates the performance using TraSE for the corresponding data.

| Type | Corpus (→) Method (\() | Guardian10 | BAC | Enron | IMDB1M | FICSIT |
|------|-------------------------|------------|-----|-------|--------|--------|
| N-grams | SVM char-2-gram | 75/95(13) | 88/92(1,863) | - | 48/79(2,426) | 26/97(1,237) |
| | SVM char-3-gram | 83/95(13) | 94/92(1,863) | - | 58/79(2,426) | 37/97(1,237) |
| | eBoW+SVM | 34/95(13) | 10/92(1,863) | - | 19/79(2,426) | 5/97(1,237) |
| Ensemble | Bacciu et al. (2019) | 94/95(13) | 91/92(1,863) | - | 56/79(2,426) | 44/97(1,237) |
| | Amann (2019) | 46/95(13) | 75/92(1,863) | - | 40/79(2,426) | 17/97(1,237) |
| | Rahgouy et al. (2019) | 55/95(13) | 88/92(1,863) | - | 55/79(2,426) | 30/97(1,237) |
| Deep Neural Networks | CNN+GloVe | 22/95(13) | 19/92(1,863) | - | 22/79(2,426) | 3/97(1,237) |
| | BertAA | - | 59/99(100) | 97/99(100) | 86/99(100) | - |
| | Style-HAN | - | 61/99(50) | - | - | - |
| | CNN-char | - | 48/99(50) | 88/99(50) | 92/99(62) | - |
| | Syntax-CNN | - | 57/99(50) | 96/99(62) | - | - |

There are two critical observations that can be drawn from Tables 2 and 3. First, TraSE provides state-of-the-art performance in most cases. There are some instances where the performance is slightly lower than the state-of-the-art performance for the corpus. However, in those cases, TraSE works with a larger number of authors in comparison. Secondly, the attribution performance is not dependent on the number of authors in the attribution experiments. For instance, the standalone performance for IMDB1M is around 76.75% with 6,090 authors while the all inclusive performance reached 89.26% with 27,037 authors at a 0.7 train-test ratio. These observations suggest that TraSE satisfies the success requirement for the raw attribution performance part of the ex-

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3 bert-base-uncased from https://huggingface.co/models
4 Link: https://scikit-learn.org
Table 3: Comprehensive attribution performance evaluation using TraSE. Accuracy values and their corresponding weighted F-measure (in bold) are recorded. Overall performance is only applicable to all inclusive criteria. Individual corpus performance metrics for the all inclusive criteria was obtained by isolating samples belonging to the particular corpus.

| Sample count | Author count | Evaluation criteria | Corpus/Train split | All inclusive | Standalone |
|--------------|--------------|---------------------|--------------------|---------------|------------|
|              |              |                     | 0.3                | 0.5           | 0.7        |
| 667,118      | 14,650       | BAC                 | 0.74/0.76          | 0.82/0.83     | 0.86/0.86  |
| 188,077      | 1,237        | FICSIT              | 0.91/0.93          | 0.94/0.96     | 0.96/0.97  |
| 142,456      | 6,090        | IMDB1M              | 0.55/0.60          | 0.66/0.70     | 0.71/0.74  |
| 12,762       | 149          | Enron               | 0.92/0.95          | 0.96/0.98     | 0.97/0.98  |
| 432,611      | 4,900        | PAN18 Twitter       | 0.91/0.93          | 0.95/0.96     | 0.97/0.97  |
| 444          | 13           | Guardian10          | 0.55/0.67          | 0.67/0.77     | 0.70/0.77  |
| 1,443,471    | 27,041       | Overall performance | 0.81/0.80          | 0.86/0.86     | 0.90/0.89  |

Figure 3: Correlation between topic diversity and attribution accuracy (all correlations have p-value < 0.01). Pearson correlation close to zero indicates no correlation.

Figure 4: Correlation between attribution accuracy with increasing amounts of training data. Attribution performance turns independent of data quantity with more data (all correlations have p-value < 0.01).

3.1 Impact of topic influence

The LDA-based experiments performed in Section 2.3 highlighted the topic diversity present in the corpora. With literature suggesting the negative influence of cross-topic samples on attribution performance, assessing the robustness of TraSE against topic influence is necessitated. To facilitate this task, the mean cosine distance for each author was extracted using the LDA topic models developed in Section 2.3. Next, the mean cosine distance for each author is correlated against the attribution accuracy for the same author using Pearson correlation in a target corpus. If TraSE obtains a refined representation of authorial style, no correlation will be observed between topic dissimilarity and attribution performance. The result of this experiment, shown in Figure 3, suggests very little to no correlation. Consequently, it can be reasoned that TraSE is not affected by topic diversity in text samples.

3.2 Influence of sample statistics

It is a well known fact that more data makes the models more robust. Consequently, research literature recommends adding more text data for a robust representation of authorial style. But, the cognitive definition of authorial style suggests that it is unique and present in every text sample written by the author. So, it can be asserted that the authorial style can be extracted from a limited number of text samples. An ideal feature representation for extracting authorial style would satisfy this assertion. To this end, an auxiliary experiment was designed. For each corpus, the amount of training data was adjusted from 30% to 90% with increments of 10% and rest of the data was reserved for testing. The attribution accuracy for each au-
Table 4: Pearson correlation between sample quality (represented by SQSE) and word count in training data with attribution accuracy (all correlations have $p$-value $< 0.01$).

| Corpus       | Sample Quality | Word Count |
|--------------|----------------|------------|
| BAC          | 0.44           | 0.25       |
| FICSIT       | 0.89           | 0.29       |
| IMDB1M       | 0.39           | 0.13       |
| Enron        | 0.58           | 0.29       |
| PAN18 Twitter| 0.75           | 0.22       |
| Guardian10   | 0.99           | -0.07      |

Figure 5: Convergent nature of TraSE style profiles

4 Understanding and Interpreting Style

To fully grasp the potential of TraSE, an explainable and interpretable understanding of the feature representation is necessary. Authorial style is reflected through unconscious habituated choices of the author in manipulating the grammatical elements of the language. This behaviour of the author is captured through TraSE and can be demonstrated using a simple experiment. Using the TraSE workflow, all text samples for an author are processed. They are incrementally added to an array and the corresponding covariance matrix is calculated. The covariance indicate the preference of the author in adhering to certain co-occurring patterns to compose their text. The change in the covariance matrix for the addition of each text sample to the array is computed using the sum of absolute differences ($l_1$-norm) between the two matrices. The mean change for authors in each corpus is shown in Figure 5. The convergent nature of the trend indicate that these are habituated choices of the author. This also explains the trend in Figure 4 where the addition of more text samples did not improve attribution performance. Capturing authorial style requires a finite amount of text data.

To further breakdown the workings of TraSE, the psycho-linguistic profile of an author captured by an existing feature representation and TraSE needs to be compared. Considering the evaluations in Table 2 and the community consensus on a good stylometric feature representation, the character n-gram was chosen as the basis of comparison. Since the unique n-gram counts are often limited to the top-N most frequently occurring unique n-grams in literature, “N” was also added as a hyper-parameter to this experiment. Likewise, the top-N unique n-grams belonging to the corpus are extracted. Essentially, each dimension in TraSE, represented by an angle between 0 and $\pi$, assess
Figure 6: Correlation between standard deviation of each dimension in TraSE with the divergence between character n-gram representation of each dimension to the overall character n-gram profile (all correlations have \(p\)-value <0.01).

the likelihood of occurrence of a particular pattern (see Algorithm 1 step 9). The angle is generated after the algorithm moves from one word to the next one. The angle and the character n-grams for the corresponding two words are recorded. The character n-grams from the two words are populated into a feature vector with the top-N n-grams as basis. This process is repeated for all the text samples of an author yielding a character n-gram feature vector for each angle in the TraSE feature representation. The character n-gram feature vector for all the text samples of the author, called the overall character n-gram representation, is also calculated. Next, the divergence between the character n-gram representation for each angle and the overall character n-gram representation (both normalized by sum to unity) for the author is calculated using Jensen-Shannon divergence (JSD). Further, the standard deviation for each angle in the TraSE feature representation for all the text samples of the author is also calculated. This is followed by assessing the correlation of the divergence value with the standard deviation for each angle using Pearson correlation. The experiment is repeated for all authors in the chosen corpora with n-gram lengths of two and three. The results are shown in Figure 6. Limiting the comparisons to at least the top-1000 or 2000 unique n-grams tends to produce better discriminating n-gram feature representation as discovered in existing literature. The intention of this experiment is to show that dimensions with higher standard deviation in TraSE capture discriminating stylistic information that are essential for developing the author’s psycho-linguistic profile. Most of the information captured by the n-grams are of the low standard deviation nature. Further, the experiment also suggests that individual character n-grams are fuzzy in nature. Being part of different words, the individual character n-grams that helps discriminate also increase similarity between authors in different situations -rendering them inadequate for authorship attribution.

Next, using the same protocol, the experiment was extended to study discriminability between authors. For any two chosen authors from the corpora, the JSD between the character n-gram representations for every angle in the TraSE representation is calculated. Also, the JSD between the overall character n-gram representation between the authors is calculated. This is considered to be the baseline discriminability provided by character n-grams for those two authors. For any angle in the TraSE feature representation, the probability of finding a JSD below the baseline discriminability provided by the overall character n-gram representation is less than 0.05. This result was empirically calculated from comparison between every possible pair of authors in the chosen corpora. This held true for all n-gram lengths, unique n-gram counts in every chosen corpora, suggesting that TraSE is more discriminating than character n-grams. Consequently, the state-of-the-art performance displayed by TraSE can be attributed to capturing the psycho-linguistic behavior of the authors through their unconscious habituated preferences for certain linguistic elements.

5 Qualitative Traits of Style

Comprehensive quantitative analysis and an interpretable feature space supports TraSE. However, a qualitative support is necessary to cement its utility as a cognitive signature. This is demonstrated through the authorial style’s influence on age and neural language models.

5.1 Influence of Age

TraSE identifies authorial style through analysis of unconscious habituated patterns in the author’s
Figure 7: Density of habituated choices with age.

Figure 8: Discriminating between human and machine generated text using style.

psycho-linguistic profile. This bias can be cast as a cognitive trait and corroborated with existing research in cognitive science on language acquisition. An individual acquires most of the grammatical components of a language by 18 years of age. Up to 18 years of age, language education will expose the author to various grammatical elements forming a holistic representation of the language. This is the reason empirical studies on adolescents around 18 years of age show poor attribution (Koppel et al., 2009; Pascucci et al., 2019). Around 18 to 25 years of age, linguistic creativity peaks and the author’s linguistic behavior evolves. They tend to become stable over time with habit formation. The covariance matrix obtained from the TraSE feature representation of all the author’s samples can capture this behavior. The ratio of sum of off-diagonal elements to the sum of the covariance matrix, also called relative density, quantifies this behavior. Higher relative density correlates with stronger habituated choices. The mean trend computed using BAC and PAN13 author profiling corpus (Rangel et al., 2013) (labeled with author’s age), shown in Figure 7, agrees with this observation. TraSE complies with age-based cognitive models for language acquisition.

5.2 Neural Language Models and Style

Neural language models learn language from exemplary text data. There are no constraints on the authorship of these text samples. Consequently, its highly likely that the information learned pertains more to linguistic syntax and vocabulary usage over nuanced authorial style components. Good machine learning models generalize to overall structure in the data and avoid overfitting outlier attributes. If TraSE understands the notion of authorial style, it will be able to accurately identify human generated text over machine generated text. An experiment centered around the work done by Uchendu et al. (2020), using various neural language models like CTRL, GPT, GPT-2, GROVER, XLM, XLNET, PPLM and FAIR with their exemplary generated data, was designed. Data generated using GPT-35 (Brown et al., 2020) was fetched separately. The experiment was done in two phases. First, the language models were considered as individual authors and the performance evaluated using the TraSE workflow (SVM@0.7 train-test split) to baseline each model in terms of style. Next, human authored data from the chosen corpora were added and the experiment was repeated. The overall F1-score, shown in Figure 8, for the human samples and individual neural language models were recorded. The samples sourced from the language models mismatched with each other indicating their lack of affinity towards authorial style. Interestingly, some neural language models, especially GPT-3, exhibited some affinity towards authorial style. Moreover, human-authored text samples were identified with an F1-score of 0.98 suggesting that TraSE captures cognitive markers from text samples.

6 Conclusion

Authorial style is an artifact of cognitive processes. Yet, the cognitive aspect of it was overlooked in existing literature leading to several critical issues. TraSE is the first feature representation that combines insights from computational linguistics with cognitive sciences to provide an interpretable feature space with state-of-the-art attribution performance at scale. It also provides a pathway for applications that operate on cognitive markers extracted from natural language text facilitating more inter-community collaboration.

5Link: https://github.com/openai/gpt-3
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