Towards Improved Model Design for Authorship Identification: A Survey on Writing Style Understanding

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Abstract

Authorship identification tasks, which rely heavily on linguistic styles, have always been an important part of Natural Language Understanding (NLU) research. While other tasks based on linguistic style understanding benefit from deep learning methods, these methods have not behaved as well as traditional machine learning methods in many authorship-based tasks. With these tasks becoming more and more challenging, however, traditional machine learning methods based on handcrafted feature sets are already approaching their performance limits. Thus, in order to inspire future applications of deep learning methods in authorship-based tasks in ways that benefit the extraction of stylistic features, we survey authorship-based tasks and other tasks related to writing style understanding. We first describe our survey results on the current state of research in both sets of tasks and summarize existing achievements and problems in authorship-related tasks. We then describe outstanding methods in style-related tasks in general and analyze how they are used in combination in the top-performing models. We are optimistic about the applicability of these models to authorship-based tasks and hope our survey will help advance research in this field.

1 Introduction

Writing style understanding is a key topic in Natural Language Processing (NLP) research. While the content varies strongly across documents written by the same author, stylistic features, as defined by Herrmann et al. (2015), remain constant and are the cause of a wide range of phenomena, e.g. text genre, metaphor, and irony. An important application of stylistic features is the identification of authorship. Because of the importance of stylistic features in NLP tasks related to authorship and other stylistic phenomena (Kestemont et al., 2016), useful model architectures and feature sets are likely to be shared. This motivates us to survey recent research achievements in style-related tasks to find possible ways of advancing the research on authorship-based tasks¹.

Our paper consists of three main parts. We first introduce the NLU tasks included in our survey. While we cannot cover all possible tasks depending on writing style understanding, we take into account the five most-studied authorship-based tasks and nine other prevalent tasks related to writing style understanding. Second, we provide a summary of linguistic features and neural network architectures that appear frequently in related papers. While existing reviews have examined various solutions to these tasks, our survey emphasizes newly-emerged neural network architectures. For example, Stammatatos (2009) lists 21 linguistic features in five categories which are prevalent in authorship identification tasks and Zhang et al. (2018a) introduce three neural network architectures widely used in sentiment-related tasks. We not only include these methods, but we also provide detailed analysis of techniques such as Capsule Networks (CapsNets) and Transformer networks. In the last part, we list the models that achieve outstanding performance in authorship-based tasks and analyze their feature engineering and model designs. Finally, to inspire the development of effective model design for authorship-based tasks, we analyze top-performing models in other style-based tasks.

The main contributions of this paper are:

- By expanding the scope of our review to a wider range of NLU tasks related to writing styles, we bridge the authorship-based tasks and other style-related tasks and enable knowledge transfer of feature engineer-

¹Our survey covers NLU tasks only.
ing and model designs to authorship-based tasks.

- By including the most up-to-date neural network architectures in our survey, we demonstrate the strong possibility of applying these architectures to authorship-based tasks.

- By examining the detailed usage of models and/or linguistic features for extracting stylistic features, we provide guidance for future model design in authorship-based tasks.

2 Tasks and Datasets

Our survey covers a wide range of style-related tasks besides authorship-related tasks. We provide definitions of these tasks and regularly-used standard evaluation datasets in this section. To be consistent, in all the task definitions we use \( d = \{w_1, w_2, ..., w_n\} \) to represent a document with \( n \) words and \( L \) to denote task-specific label sets.

2.1 Authorship-related Tasks

**Authorship Attribution (AA)** Given a document \( d \) and \( k \) groups of documents \( D_i = \{d_1^{(i)}, d_2^{(i)}, ..., d_j^{(i)}\} \) each authored by one of \( k \) authors, the goal of AA (Juola, 2006) is to decide whether \( d \) belongs to any \( D_i \) for all \( 0 < i \leq k \).

AA benchmark datasets include the CCAT10 and CCAT50 (Stamatatos, 2008), IMDB62 (Seroussi et al., 2010), Blogs10 and Blogs50 (Schler et al., 2006), and Novel9 (Feng and Hirst, 2013) datasets. Recently Preot˘iuc-Pietro and Devlin Marier (2019) also released a Twitter-based AA dataset. PAN shared tasks provide additional datasets for AA. The most up-to-date in-domain AA dataset is released in PAN-12 challenges and cross-domain AA dataset in PAN-19 shared tasks.

**Authorship Verification (AV)** With two documents \( d_1 \) and \( d_2 \), the AV task aims at predicting whether they are written by the same author. The Webis Authorship Verification dataset (Bevendorff et al., 2019) is benchmarked for AV. PAN shared tasks provide other AV datasets in PAN-13, PAN-14, and PAN-15 challenges as well.

**Authorship Profiling (AP)** Given a document \( d \), the AP task classifies \( d \) into author groups.

There can be multiple different label sets for AP, e.g. \( L = \{\text{male, female}\} \) in PAN-18 AP task and \( L = \{\text{bot, human\_male, human\_female}\} \) in PAN-19 AP challenge. Celebrity Profiling (CP) is similar to AP, with the documents coming from celebrity Twitter accounts.

PAN has been hosting AP challenges from 2013, and CP since 2019. Evaluation datasets can be found in PAN shared tasks.

**Style Change Detection (SCD)** In a document with \( k \) paragraphs \( d = \{p_1, p_2, ..., p_k\} \), the goal of SCD is to detect whether any pair of adjacent paragraphs \( p_i \) and \( p_{i+1} \) are written by the same author or not. SCD datasets are available in PAN challenges since the year of 2017.

2.2 Other Style-Related Tasks

**Sentiment Analysis (SA)** Given a document \( d \), the aim of SA (Pang et al., 2002) is to predict the sentiment class or sentiment polarity associated with \( d \). SA labels can be either from a discrete label set \( L = \{\text{Negative, Neutral, Positive}\} \) or a sentiment polarity score in \( L = [-1, 1] \).

Stanford Sentiment Treebank (Socher et al., 2013) is a standard evaluation bed for SA. The RT dataset (Pang and Lee, 2005) is constructed from Internet movie reviews and it provides two types of sentiment labels. Yelp\(^3\) also provides a large-scale SA dataset based on business reviews.

**Aspect-Based Sentiment Analysis (ABSA)** Different from SA, ABSA (Pang and Lee, 2008) evaluates the sentiment of \( d \) on each aspect \( a \) in \( d \). Each aspect \( a = \{w_1^a, w_2^a, ..., w_K^a\} \) can be either a substring in \( d \) or an aspect type (e.g. restaurant). There can be multiple aspects in \( d \) and the sentiment polarity on each aspect does not have to be towards the same direction (Saedi et al., 2016). The International Workshop on Semantic Evaluation (SemEval) provides multiple ABSA evaluation datasets (Pontiki et al., 2014; Cortis et al., 2017; Pontiki et al., 2015, 2016). Dong et al. (2014) also release an ABSA dataset based on Twitter posts.

**Stance Detection (SD)** SD (Thomas et al., 2006; Hasan and Ng, 2013) takes two inputs, a document \( d \) and a target \( c \). \( c \) can be either an entity (e.g. a person) or a claim. The goal is to classify the stance of \( d \) towards \( c \) into the label set \( L = \{\text{Agree, Disagree, Discuss, Unrelated}\} \).

\(^2\)https://pan.webis.de/shared-tasks.html

\(^3\)https://www.yelp.com/dataset
c does not have to physically appear in d. The number of c per d is not limited either.

One benchmark dataset for SD is from SemEval-2016 Task 6 (Mohammad et al., 2016b). The Brexit Blog Corpus (Simaki et al., 2017), US Election Tweets Corpus (Mohammad et al., 2016a), and Moral Foundations Twitter Corpus (Hoover et al., 2019) have also received much attention recently. Siddiqua et al. (2019) publish an SD dataset where each document contains two targets and two stance labels. Some other related datasets are provided in the review by Kıcıçık and Can (2020).

**Emotion Recognition (ER)** ER is closely related to SA, but with more fine-grained labels and better expressiveness (Zhou et al., 2018). ER classifies d into L containing pre-defined emotion types or draws intensity scores of d over the emotion types in L. The most common ER label set contains eight basic emotion types, i.e. L = {Joy, Sadness, Anger, Anticipation, Surprise, Love, Disgust, Neutral} (Ekman, 1992).

The standard evaluation datasets of uni-modal ER consist of the EmoBank (Buechel and Hahn, 2017) and MELD (Portia et al., 2019) datasets. Benchmark datasets on multi-modal ER include the IEMOCAP (Busso et al., 2008), MOUD (Pérez-Rosas et al., 2013), ICT-MMMO (Wöllmer et al., 2013), MOSI (Zadeh et al., 2016) and MOSEI (Bagher Zadeh et al., 2018) datasets.

**Metaphor Detection (MD)** A word or phrase is metaphorical if it bears different meaning from its literal semantic meaning in a context. MD is designed to detect whether d or any word group $w_i, ..., w_{i+m}$ in d is metaphorical. Benchmark datasets on MD include MOH (Mohammad et al., 2016c) and its subset MOH-X, TSV (Tsvetkov et al., 2014), TroFi (Birke and Sarkar, 2006), VUA (Steen et al., 2010), and LCC (Mohler et al., 2016).

**Other Tasks** The Irony Detection (ID), Offense Detection (OD), Formality Classification (FC), and Humor Detection (HD) tasks are all document-level classification tasks. ID detects whether the contextual meaning of d is opposite to its literal meaning. SARC (Khodak et al., 2018) is a common evaluation dataset on ID. Castro et al. (2019) also release a multi-modal ID dataset named MUSTARD. OD classifies d into $L = \{\text{Offensive}, \text{Non-offensive}\}$. Subtasks of OD include the detection of hate speech, cyber-bulling and cyber-aggression (Zampieri et al., 2019). Zampieri et al. (2019) and Ousidhoum et al. (2019) provide two benchmarked OD datasets. FC evaluates whether d is formal or informal and HD identifies humorous writing styles from d. Rao and Tetreault (2018) provide a large-scale dataset for formality transfer, while its labels fit the FC task perfectly. Weller and Seppi (2019) label a HD dataset based on data from Reddit, Kaggle, and Pun of the Day. Zhang et al. (2019b) make HD more fine-grained by introducing eight humor categories and five humor levels to the annotations.

### 3 Methods

In this section, we summarize useful features and common neural network architectures in style-related tasks. We also display the various feature engineering methods and model designs to inspire future research on writing style understanding.

#### 3.1 Linguistic Features

**Language Model Features** N-Gram features on both word and character levels are among the most frequently used language model features in representing writing styles. The most common choices of n-gram features are word-level 1-, 2-, and 3-gram and character-level 3-, 4-, and 5-gram features. Muttenzhaler et al. (2019) additionally show the importance of punctuation marks in the AA task using an n-gram model with everything except for punctuation marks masked by asterisk symbols (*). Markov et al. (2017) claim that digits and named entities are also key identifiers of writing styles. Sapkota et al. (2015) attribute the advantage of using character-level n-gram features to the high priority of subword features (e.g. suffixes and prefixes) in authorship-related tasks. Zhao et al. (2019) loosen the constraint of n-gram features and consider the co-occurrence of word pairs instead. Statistical features, e.g. TF-IDF scores, are regularly used in combination to the language-model-based features to avoid overemphasizing stop words (Vu et al., 2018). As text representations generated from n-gram features tend to be high-dimensional and sparse, Niu et al. (2017) apply Principal Component Analysis to compress them into low-dimensional vectors. Zhou et al. (2018) achieve the similar goal using topic models (e.g., Latent Dirichlet Allocation). Recently,
many researchers have turned to neural language models (e.g. Skip-gram model, Mikolov et al. (2013)) for text representations (Zhang and Singh, 2018; Kumar et al., 2017; Rei et al., 2017). Word vectors from neural language models can be compared, clustered, and used in any statistical method to form document representations (Preot˘iu-Pietro and Devlin Marier, 2019; Aragón et al., 2019).

**Syntactic Features** Part-of-Speech (POS) tags and dependency relations are two main sets of syntactic features used in style-related tasks. The coexistence of a set of POS forms syntactic patterns that can be used to recognize stylistic phenomena, e.g. complaints (Preoțiuc-Pietro et al., 2019). Flekova et al. (2016) also argue that the pattern of using each POS in a document is related to the formality of the text. Dependency parsing is in most cases used in combination to POS tagging to help extract meaningful syntactic patterns. Basile et al. (2019) claim that pure POS tags are simplistic and are only able to model shallow syntactic features, while dependency parsing provides richer authorship information. Their experiments suggest that jointly using POS and dependency features results in the best performance. The reason why syntactic features are important in style-based tasks is clear: writing styles are usually specific to the choice and arrangement of words in a document, so the inter-relationship among words is crucial.

**Lexical Features** When addressing stylistic phenomena including sentiments and emotions, specifically-designed lexicons provide solid help, especially to short and simple documents. Preoțiu-Pietro et al. (2019), for example, approach the SA task with the help of MPQA (Wiebe et al., 2005) lexicon for sentiment, and the NRC (Mohammad and Turney, 2010, 2013) and Volkova & Bachrach (Volkova and Bachrach, 2016) lexicons for sentiment and emotion. The function of lexicons, however, is limited as stylistic phenomena are often caused by linguistic expressions in a long span of text. According to Preoţiu-Pietro et al. (2019), the best-performing lexicon in their experiments produces worse results than a simple bag-of-words model. The semantic relatedness between words is beneficial to style-related tasks as well. WordNet (Miller, 1998) is the most heavily used lexical database of semantic relation information among words, according to our survey. Mao et al. (2018) use hypernyms and synonyms of words from WordNet to disambiguate them when discovering nuanced metaphors from text. Since different authors tend to express different attitudes towards specific events, lexical features can help solve simple cases in authorship-related tasks with high accuracy and thus reduce noise when training complex models.

**Other Features** In our survey, we came across some linguistic features that are used for specific tasks. We group these features here since we think they can be potentially help detect authorship information. Downgraders and politeness are used by Preoțiu-Pietro et al. (2019) to identify complaints and Mihalcea and Strapparava (2005) introduce alliterations, slangs, and rhyming to the HD task. These features are all author-specific language-use features and qualify for coarse-grained authorship identification. Hashtags, URLs, retweets, tweet popularity, elongated words, hapax legomena, and superlatives are valuable features for AA (Preoțiu-Pietro and Devlin Marier, 2019), and they well fit all the authorship-based tasks in the social media domain, e.g. the CP task.

### 3.2 Neural Network Architectures

**Convolutional Neural Networks (CNNs)** CNNs (LeCun et al., 1999) extract local dependency features from positionally nearby tokens, which act similarly to n-gram models with n bounded by the sizes of convolution kernels. Benefited from parameter sharing, the training process of CNNs is easy and time-efficient. Xue and Li (2018) combine the features extracted by multiple one-layer CNNs, each with different kernel sizes, into document representations. While CNN-based models on style-related tasks generally share the same architecture, their inputs and external resources usually vary. Zhang et al. (2018b) apply CNNs on text embeddings explicitly enriched by n-gram and syntactic features. They show by experiments that these additional features help their model achieve better performance than vanilla CNNs. Ruder et al. (2016) argue that character-level CNNs are superior in capturing stylistic features. This attributes to the ability of character-level CNNs in modeling sub-word features, e.g. prefixes, which are important style markers. Similarly, Ferracane et al. (2017)
convert documents into character-level bigram embeddings and apply CNN feature extractors on these feature maps. Lexical features can also be used in conjunction with CNNs. For example, Dong and de Melo (2018) keep pre-trained sentiment embeddings of words from multiple domains in a memory module and inject the lexical information into CNN encodings of documents by appending normal word vectors attended by the sentiment embeddings to the end of the CNN output.

**Graph Neural Networks (GNNs)** GNNs have recently attracted a lot of research attentions in the NLP community. Popular graph models on style-related tasks include Graph Convolutional Networks (GCNs) (Kipf and Welling, 2017) and Graph Attention Networks (GATs) (Velickovic et al., 2018). While GCNs are similar to CNNs, they convolve on graphs, treating nodes connected by edges as neighbors regardless of the absolute positions of words. In addition to connectivity, GATs generate the representation of each node by applying self-attention mechanism on all its neighbor nodes. These characteristics make GNNs appropriate for encoding dependency information. Researchers have been using multi-layer GCNs (Sun et al., 2019; Zhang et al., 2019a) and multi-layer GATs (Huang and Carley, 2019) to encode documents after syntactic parsing for the ABSA task, for example. In these scenes, GCNs and GATs are usually used jointly with other feature extractors (e.g. a Long-Short-Term Memory (LSTM) model) since syntactic features solely are not enough for style-related tasks. From this perspective, GCNs and GATs are valuable model architectures in authorship-related tasks where syntactic information is crucial. As Ghosal et al. (2019) additionally use GCN to capture high-level features across dialogue utterances, we can foresee the application of GNNs in SCD tasks by viewing the paragraphs as dialogue utterances.

**Recurrent Neural Networks (RNNs)** The use of RNNs is widespread in NLP tasks since RNNs are designed to encode sequential data, and because they are able to preserve long-term dependency information. LSTM and Gated Recurrent Units (GRU) are the two most prevalent model architectures in the family of RNNs. Biswas et al. (2015) show an example of approaching the SA task with a one-layer uni-directional GRU model. Similar to CNNs, RNN-based models are also used to extract character-level dependency features in style-related tasks (Bagnall, 2015). Multiple RNN-based model architectures have been invented to improve their encoding ability. Hierarchical RNNs (Hihi and Bengio, 1995) are designed to extract features at different abstraction levels. Chen et al. (2016) break documents down to word- and sentence-level pieces and use two LSTM models to generate sentence- and document-level encodings, respectively. Stacked RNNs are relatively rare in our survey. Akhtar et al. (2017) examine two-layer LSTM and GRU models on the SA task and their performances are very closed to a single-layer CNN model. Rather, bidirectional RNNs (BiRNNs, Schuster and Paliwal (1997)) or stacked BiRNNs are popular for their ability to use information flows from both directions of the input sequence, which helps with a lot of style-related tasks (Qian et al., 2017; Xu et al., 2018; Hu, 2019; Chen et al., 2017). Attention mechanism (Bahdanau et al., 2015) is applicable to all the RNN architectures we describe above. In pure RNN models, each token contributes to the output embeddings equally, while some words are in fact more important to the predictions than the rest. Impaired verbs and objects in a sentence are strong signs of metaphors, for example. Attention mechanism teaches the RNN-based models to dynamically weigh the token embeddings and thus improves their performances (Felbo et al., 2017; Gao et al., 2018; Yang et al., 2017). In recent research, RNNs are frequently used in combination to CNNs as well. There are two main forms of assembling CNNs and RNNs, one of which is separately encoding the document with CNN and CNN models and concatenating the output vectors together (Rouvier, 2017) or combining the predictions made by both models through majority voting (Cliche, 2017). The second form is to stack the CNN and RNN models together and have the CNN model extracting local dependency features on the output of the RNN model or the other way around (Li et al., 2018).

**Memory Networks (MemNNs)** MemNNs (Weston et al., 2015) encode sequences with the help of external memories storing global information and preceding states. Initialization, read, and update are three basic operations to the memory cells in MemNNs, the latter two of
which are usually implemented using attention mechanism. Multi-hop memories are used dominantly in style-related tasks as they preserve features from multiple different abstraction levels (LeCun et al., 2015). Tang et al. (2016) apply MemNNs in an ABSA task. Their model stacks embeddings of context words to initialize external memory and queries the memory with embeddings of the aspect terms. In recent research, MemNNs are usually used in parallel with other neural networks, e.g. RNNs and CNNs, to keep richer contextual information in the memories. Hazarika et al. (2018b) initialize and update the memories both with the help of GRU, while in Hazarika et al. (2018a) the memory cells are initialized by an ensemble CNN-GRU feature extractor. Memory cells in a MemNN model can save author-specific information so we are especially optimistic about its use in AA and AP tasks.

Capsule Networks (CapsNets) CapsNets (Sabour et al., 2017) feature spatial relation modeling and the dynamic routing mechanism. CapsNets internally cluster the encodings of similar entities (e.g. words with the same sentiment labels) together in a capsule and adjust the encodings’ attributes (e.g. sentiment polarity) with affine operations. The dynamic routing mechanism enables CapsNets to reduce the effect of noise words on the representation of the entire text. These features make CapsNets sensitive to writing styles and robust to irrelevant information. Chen and Qian (2019) use dynamic routing to select appropriate n-gram groups for predictions in the ABSA task. Jiang et al. (2019) show by experiments that even with simple dynamic routing strategy (e.g. using averaged embeddings of sentiment words), CapsNets are able to boost the performance of complex-enough models (e.g. BERT (Devlin et al., 2019), a pre-trained Transformer-based model). Xia et al. (2018) utilize CapsNets to address zero-shot learning problem. All the above examples show that CapsNets are efficient in extracting and clustering style markers, and making predictions accordingly. So the use of CapsNets solely or combined with other neural networks on authorship-based tasks is promising and deserves more research attention.

Transformer Networks Transformer Networks (Vaswani et al., 2017) is a newly-emerged family of neural networks, the core of which are self-attention and positional encoding. Models based on Transformer Networks are usually deep, with giant amounts of parameters. In most cases, Transformer-based models are pre-trained on large unlabeled corpora and fine-tuned on task-specific datasets, e.g. BERT. Benefited from their large sizes of parameters and training data, Pre-trained Transformer-based models have been refreshing the records on style-related tasks since their emergence. For example, Weller and Seppi (2019) use BERT to encode text for the HD task and their model achieves results comparable to human annotators without feature engineering or model restructuring. Zhong et al. (2019) use external knowledge from ConceptNet (Speer et al., 2017) and the NRC-VAD lexicon (Mohammad, 2018) to augment word embeddings with emotion information, and they introduce dialogue structure information to the self-attention mechanism in Transformer networks. This shows the advantage of combining Transformer-based models with handcrafted feature sets or other neural network architectures, providing possibilities of improving the performance of Transformer networks in authorship-based tasks where handcrafted feature sets are extensively researched.

4 Discussions

In this section, we first explain in more details the feature engineering methods and model designs that achieve good results in extracting authorship information. We also analyze the causes that some methods do not behave as well as expected. Next, we do similar analysis for the SA, ABSA, and ER tasks to infer if any specific model design can be transferred to authorship-based tasks. These three tasks are among the most well-developed style-based tasks and the models we discuss are also top-performing models in these tasks.

We show the best-performing models with different classifier architectures on four AA datasets in Table 1 to discuss current research on the AA task. We choose PAN-12 instead of PAN-19 since the PAN-12 AA task is under in-domain settings, similar to other tasks we list. According to the PAN official reports (Kestemont et al., 2019; Juola, 2012), existing systems are based on similar feature sets and classifiers so the task choice does not affect our analysis. From the table we can see the importance of character-level n-gram
features for the AA task. Syntactic features additionally show great potentials in this task, according to our observations. As for the choice of model architectures, a shallow neural model (e.g. FastText) does not beat SVM classifiers with similar feature sets, while CNNs show superior encoding ability on the AA task. The combination of CNNs and RNNs with POS features also outperform the SVM model on the PAN-12 Task I, achieving 100% accuracy on the test set. The task, however, is too constrained in data size, with 28 training examples and 14 test examples (Juola, 2012). As a result, models with handcrafted features and probabilistic models also perform well. Evaluations of the model by Jafariakinabad et al. (2020) on more complex AA tasks should be performed to show its strength and robustness. Existing models on the PAN AV challenges almost entirely rely on handcrafted features sets. Character-level n-gram features are again the most favored linguistic features. Bevendorff et al. (2019) construct character trigram vectors for the documents and evaluate the differences between each pair of documents as features using seven distance measures. Bagnall (2015) uses an RNN-based model on character level to verify authorship and achieves higher scores than Bevendorff et al. (2019) on PAN-15 AV task, proving the power of deep neural networks on authorship-based tasks.

Table 2 lists the performances of six systems, each with different model architectures, on the PAN-19 AP shared task (Pardo and Rosso, 2019). It is worth noting that deep neural models perform substantially worse than the Random Forest and Logistic Regression models. This is most likely due to the limited training data size (2,060 records for bot/user specification and 2,060 for gender prediction subtasks). The BERT-based model (Joo and Hwang, 2019) generates better results than the RNN- or CNN-based models probably because it has been pre-trained on a large corpus. In the AP task, word- and character-level n-gram features are still among the top choices and are used in all the models listed in Table 2. For example, Johansson (2019) bases their predictions on the TF-IDF scores of 300 most frequent word unigrams in the training set. On the other hand, since the corpus is made up of tweets, almost all the systems consider tweet-specific linguistic features including the counts of URLs, retweets, mentions, emojis, wrongly-spelled words, hashtags, etc. Valencia et al. (2019) and Petrík and Chudá (2019) replace emojis with their respective descriptive phrases at the preprocessing stage to provide the models with enriched stylistic information. All the knowledge learned from the AP tasks well apply to the PAN-19 CP challenge (Wiegmann et al.,

**Table 1: Model architectures and accuracy scores on four mainstream AA datasets. CN-gram refers to character-level n-gram. PAN-12 displays accuracy scores on task I of the 2012 PAN Authorship Attribution shared task. The best score on each dataset is in bold.**

| Models                      | Datasets |
|-----------------------------|----------|
| Markov et al. (2017)        | CCAT10   |
|                             | CCAT50   |
|                             | IMDB62   |
|                             | PAN-12   |
| Sari et al. (2017)          | 79.60    |
|                             | 74.80    |
|                             | 94.80    |
| Zhang et al. (2018b)        | 88.20    |
|                             | 81.00    |
| Jafariakinabad et al. (2020)| 100.00   |
| Akiva (2012)                | 85.71    |

**Table 2: Accuracy scores on PAN-19 AP challenge. Bot refers to the Bot/user detection subtask and Gender is the author gender prediction subtask of the challenge.**

| Models                      | Subtasks |
|-----------------------------|----------|
| Johansson (2019)            | 95.95    |
| Random Forest               | 83.79    |
| Valencia et al. (2019)      | 90.61    |
| Logistic Regression         | 84.32    |
| Joo and Hwang (2019)        | 93.33    |
| Transformer                 | 83.60    |
| Bolonyai et al. (2019)      | 91.36    |
| CNN+RNN                     | 79.73    |
| Petrík and Chudá (2019)     | 90.08    |
| CNN+RNN                     | 77.58    |
Table 3: Evaluation results on the SA, ABSA, and ER tasks. SST-2 and SST-5 refer to the binary and fine-grained Stanford Sentiment Treebank datasets, respectively; Laptop14 and Rest14 are the laptop and restaurant datasets from SemEval 2014 Task 4; Rest16 is from SemEval 2016 Task 5. Accuracy scores are evaluated for SST-2, SST-5, RT, and Yelp challenge datasets and F-1 scores for the rest tasks.

| Models            | Datasets          | SA  | SST-2 | SST-5 | RT  | Yelp |
|-------------------|-------------------|-----|-------|-------|-----|------|
| Xu et al. (2019)  |                   | CNN | 81.60 | 41.99 | 76.12 | 61.18 |
|                   |                   | RNN | 81.58 | 41.67 | 76.22 | 61.86 |
|                   |                   | Transformer | 93.03 | 55.38 | 88.68 | 67.85 |
| Jiang et al. (2019)| ABSA              | CapsNets+Transformer | - | - | 85.93 | - |
| Sun et al. (2019) | ABSA              | RNN+GCN | 73.66 | 72.99 | 74.02 | 69.93 |
| Tang et al. (2019)| ABSA              | RNN+CNN+Attention | 77.72 | 73.84 | 72.90 | - |
| Huang and Carley (2019)| ER             | RNN+Transformer+GAT | - | 80.10 | 83.00 | - |
|                   | ER                | CNN+RNN+MemNN | 63.50 | - | - | - |
| Hazarika et al. (2018a) | IEMOCAP       | Transformer | 59.56 | 58.18 | - | - |

2019) where the number of instances in each class is very imbalanced, e.g., Martinc et al. (2019) show that directly using BERT or other deep neural networks is not as competitive as statistical or probabilistic methods.

The design of neural models has been the major topic in a wide range of style-based tasks, while neural networks are mostly used in the simplest way in authorship-related tasks. To better fit deep neural networks to authorship-related tasks, we also review the usage of neural models in other style-related tasks. Table 3 displays current top-ranking results and their model architectures on SA, ABSA, and ER tasks. Directly applying pre-trained Transformer-based models on the text generates good results except when the utterances are short and transitions between them are frequent (Zhong et al., 2019). This suggests that Transformer Networks can potentially be applied to AA and AV tasks without much modification, if the training instances in each class are enough to fine-tune a Transformer-based model. Using Transformer-based models in the SCD task is also promising since they are stronger than RNNs and CNNs in encoding long text pieces, e.g. paragraphs, in an article. CapsNets are effective extractors for stylistic features that can probably be used to solve authorship-based tasks since their dynamic routing mechanism benefits the identification of style markers. Jiang et al. (2019) demonstrate the power of CapsNets by the combined use of CapsNets and Transformer networks in an ABSA task. Xu et al. (2019) additionally introduce adversarial training (Goodfellow et al., 2014) to train a robust classifier. Similar methods can be used in authorship-based tasks, e.g. the AP and CP tasks, to compensate for the lack of training data in small classes, relieving the problem of data imbalance.

It is also noteworthy that attention mechanism is widely used in the style-related tasks we surveyed, while participants in the authorship identification tasks seldom take advantage of attentions. The attention mechanism weighs each token in the text differently according to their interrelationships, in order not to confuse the classifier with unimportant tokens. This can be implanted to authorship-related tasks as well since style markers are sparse compared to other words, and as useful information for classification can often be located easily even using handcrafted features only. The combined use of CNNs and RNNs or MemNNs also show strong ability in style-related tasks, as is consistent with results shown in Table 1. Besides hard-coding POS or dependency relationship information into the inputs of CNNs, GNNs used in combination with dependency features show strong ability on the ABSA and ER tasks, implying the importance of syntactic features. These light-weight neural network architectures, though not beating the performances of Transformer-based models on many tasks, are probably more suitable for
authorship-related shared tasks in PAN since they require much less data to train. They can also be used in combination to the handcrafted feature sets easily, without the need for restructuring the models and retraining the weights.

5 Conclusion

The identification of authorship is a foundational task in NLP research. In this paper, we analyzed linguistic features and model architectures in recent authorship-based research. Our survey indicates that though feature engineering has been studied extensively for this task, research on the use of neural network models is not as up-to-date as in other style-related tasks. As authorship-based tasks are becoming increasingly complex, the sole use of traditional machine learning models with handcrafted feature sets will be less competitive. To better take advantage of the power of deep neural networks, we examined the model design in various writing style understanding tasks which we hope will inspire future research on authorship-based tasks.

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