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Abstract

People's writing style is affected by many factors, including topics, sentiment, and individual personality. In this paper we show that writing tasks that impose constraints on the writer result in the author adopting a different writing style compared to tasks that do not. As a case study, we experiment with a recently published machine reading task: the story cloze task (Mostafazadeh et al., 2016). In this task, annotators were asked to generate two sentences: one which makes sense given a previous paragraph and another which doesn't. We show that a linear classifier, which applies only simple style features, such as sentence length and character n-grams, obtains state-of-the-art results on the task, substantially higher than sophisticated deep learning models. Importantly, our model doesn't even look at the previous paragraph, just the two candidate sentences, which, out of context, differ only in the constraint put on the authors. Our results indicate that such constraints dramatically affect the way people write. They also suggest that careful attention to the instructions given to the authors needs to taken when designing new NLP tasks.

1 Introduction

Writing style is defined as the the author's choice of words, spelling, grammar and punctuation.[1] It is often affected by inter-writer factors such as age (Schler et al., 2006), gender (Argamon et al., 2003), native language (Koppel et al., 2005), or mere personality (Stamatatos, 2009), but also by other parameters such as the sentiment of the text (Davidov et al., 2010) and its level of sarcasm (Tsur et al., 2010). In this paper we study to what extent is writing style affected by more intricate factors, such as the type of constraints put on the author.

Type	Example
Original story	My mother loves clocks that chime. Her house is full of them. She sets them each a little different so she can hear them chime. It sounds like a bell tower during a wedding in her house all day. When I visit I stop them or I'd never be able to sleep at night.
Correct story	Kathy went shopping. She found a pair of great shoes. The shoes were $300. She bought the shoes. She felt buyer's remorse after the purchase.
Wrong story	I Kathy went shopping. She found a pair of great shoes. The shoes were $300. She bought the shoes. Kathy hated buying shoes. Kathy hated buying shoes.

Table 1:
Examples of stories from the story cloze task. The first row shows an original story written by one author. The second and third row show two endings of the same story: a *correct* ending and a *wrong* one.

As a testbed, we experiment with the story cloze task (Mostafazadeh et al., 2016). In this task, authors were asked to write five-sentence self-contained stories. Following, the stories were given to another group of authors, who were shown only the first four sentences of each story, and were asked to write two one-sentence endings for it: a *correct* ending, and a *wrong* ending. The goal of the task is to determine which of the endings is the correct one. Table 1 shows an example of an original story, a *correct* story and a *wrong* story.

Interestingly, although originally intended to be a machine reading task, the compilation of this task raises several research questions which seem

[1] https://en.wikipedia.org/wiki/Writing_style

to differ from the original intent of the designers. First, do authors use different style when asked to write a *correct* sentence, compared to a *wrong* sentence? Second, do authors use different style when writing the ending as part of their own five sentence story, compared to reading four sentences, and then writing a standalone (*correct*) ending?

Our experiments indicate that the answer to both questions is positive. We train a linear classifier, using simple stylistic features, such as sentence length, character n-grams and PoS counts. First, we show that on a balanced dataset (random guess is 50%) our classifier distinguishes between *correct* and *wrong* sentences in 64.5% of the cases. Importantly, the classifier is trained **only** on the last sentences, and does not consider the four input sentences. Second, when trained to distinguish between original endings and new (*correct*) endings, the classifier obtains 70.9% accuracy.

In order to estimate the quality of our results, we turn back to the story cloze task. Using our classifier, we are able to obtain 71.5% accuracy on the task, a 11.6% improvement compared to the published state-of-the-art results (Salle et al., 2016).[2] An ablation study shows that the style differences are realized in syntactic features (such as the over/under use of coordination words like "and" and "but"), but that sentiment also plays an important role in the writing style differences. For instance, one of the key features for distinguishing between correct and wrong sentences is the over-representation of the word "hate" in the latter.

Our results may have a wide impact on a range of fields. First, they have the potential to shed light on cognitive processes that take place in the brain during writing. Second, our results might have a more practical value in an era when fake news are becoming prominent, as they suggest that these might have different style compared to real news. Third, the results presented here also provide valuable lessons for designing new NLP tasks, both in terms of the potential impact of even the smallest details, and the need to carefully run baseline models.

Finally, one interesting question that remains open is whether state-of-the-art machine reading tools, for which this task was designed, capture in fact the same stylistic features as our linear classifier. We show that this is not the case. We train a neural language model on the original five sentence training corpus, and then compute the language probability of each of the candidates answers. We add the numbers as features in our linear classifier, and get an additional 3.6% improvement (75.1%).

the reminder of this paper is organized as follows. In Section 2 we introduce the cloze story task. We present our model and our experiments at sections 3 and 4 respectively. Sections 5 and 6 present an ablation study and a discussion, while Section 7 surveys related work. We conclude at Section 8.

2 The Cloze Story Task

Developed as an effort to simplify the representation and learning of commonsense knowledge, the *Cloze Story Task* (Mostafazadeh et al., 2016) has become the Shared Task for the LSDSem workshop. The task provides two types of datasets: the *ROC Stories* and the *Story Cloze test sets*.

ROC Stories consist of 98,163 five-sentence commonsense stories, collected on AMT. Workers were instructed to write a coherent story where something happens, and with a clear beginning and end. To collect a broad spectrum of commonsense knowledge, there was no imposed subject for the stories.

Story Cloze test sets were created on AMT, using a subset of ROC Stories. Presented with the first four sentences of a story, workers were asked to write a "right" and a "wrong" ending. Both endings had to complete the story using a character in it, and when read out of context, had to be "realistic and sensible" (Mostafazadeh et al., 2016).

The resulting stories were then individually rated for coherence and meaningfulness by AMT workers. Only stories with a coherent and meaningful "right" ending and a neutral "wrong" ending were selected for the test, yielding 3,744 test stories.

3 Model

The goal of this paper is to determine to what extent does constraining authors in their writing assignments lead to them adopting different writing styles. In order to answer these questions, we use

[2] Recently, a shared task for the story cloze task has been published (https://competitions.codalab.org/competitions/15333). At the time of submission, the leading results is 71.1%, which is much closer to our results, although still inferior. No details about the methods used to generate this result are available.

simple, classic NLP tools, which have been shown to be very effective for recognizing style (see Section 7). We describe our model below.

We train a linear SVM classifier to distinguish between different endings. Each feature vector is computed using the words in one ending, without considering earlier parts of the story. We use the following style features.

- Length The number of words in the sentence.
- Word n-grams We use sequences of 1-5 words. Following (Tsur et al., 2010; Schwartz et al., 2013), we distinguish between high frequency and low frequency words. Specifically, we replace content words with their part-of-speech tags (Nouns, Verbs, Adjectives and Adverbs).
- Character n-grams Character n-grams are one of the most useful features in identifying author style (Stamatatos, 2009). We used character 5-grams.

4 Experiments

We design two experiments to answer our research questions. The first is an attempt to distinguish between *correct* and *wrong* endings. The second attempts to distinguish between original endings and new *correct* endings. We describe both experiments below.

Experiment 1: Correct/Wrong Endings. The goal of this experiment is to measure to what extent style features capture differences between *correct* and *wrong* endings. As the cloze story task doesn't have a training corpus for the *correct* and *wrong* endings, we use the development set as our training set. We split it (90/10) into our training and development set. We keep the story cloze test set as is. The final size of our training/development/test sizes are 3366/374/3742, respectively.

We take *correct* endings as positive samples and *wrong* endings as our negative examples. By ignoring the coupling between *correct*/*wrong* pairs, we are able make a more general claim about the style used when writing each of the tasks.

We add a special START symbol at the beginning of each sentence. For computing our features, we keep n-gram (character or word) features that occur at least five times in the training set.[3] For the PoS features, we tag each sentence with the Spacy PoS tagger.[4] We use sklearn's LinearSVC SVM implementation[5] with L2 loss. We grid search the regularization parameter on our development set.

Experiment 2: Original/New Endings. Here the goal is to measure whether writing the ending as part of a story imposes different style compared to writing a (*correct*) ending to an existing story. We use the endings of the original ROC stories as our *original* training samples and *correct* endings from the ROC stories development set as *new* training samples. As there are far more *original* samples than *new* ones, we randomly select N *original* samples, where N is the number of *new* samples, such that we have balanced labels in our training, validation and test sets. We apply the same experimental decisions as in Experiment 1, and repeat this process 5 times while reporting the average.

Results. Figure 1 shows our results. Results show that for Experiment 1, our model obtains results well above a random baseline – 64.5% classification accuracy. For Experiment 2, we get even higher results – 70.9%. These numbers indicate that these different writing tasks clearly impose a different writing style on authors.

As a complementary experiment, we measured whether these style differences are additive. That is, whether the style differences between *correct* endings and *wrong* ones are different from the differences between *correct* and *original* endings. We repeated Experiment 2, this time comparing between *original* and *wrong* sentences. Our hypothesis is that differences would be even clearer. Our results (Figure 1) show that this is indeed the case: the classifier's accuracy jumps to 78%.

Story Cloze. Results of Experiment 1 indicate that *correct* and *wrong* endings are characterized by different styles. In order to estimate the quality of our classification results, we tackle the story cloze task using our classifier. This classification task is much more constrained than Experiment 1, as here the task is given two endings, which one is *correct* and which is *wrong*. In order to solve

[3] Virtually all sentences end with a period, so no need for an END token

[4] spacy.io/

[5] scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html

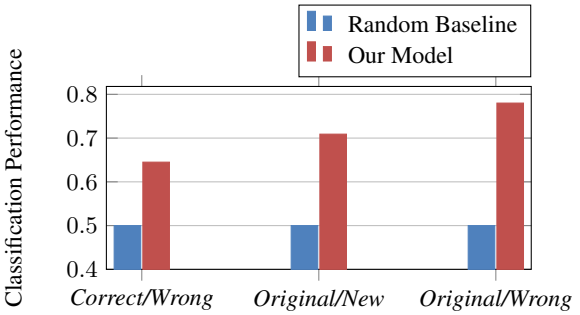

Figure 1: Results of experiments 1 and 2 (left two charts). Rightmost experiment shows a control experiment which classifies *original* endings vs ***wrong*** endings.

the task, we use the output of our trained classifier. For each pair of endings e_1, e_2, if both endings have different classification labels, we keep these labels. If they share the same label, we use the classifier confidence level as a deciding factor: the label of the one with the lower confidence is reversed.

Table 2 shows our results on the story cloze test set. Our classifier obtains 71.5% accuracy, which is 11.6% better than the published state-of-the-art result on the task. Importantly, unlike previous approaches, our classifier does not require the story corpus training data, and in fact doesn't even look at the first four sentences of the story in question. These numbers indicate that the styles between *correct* and *wrong* are indeed very different.

Other than the published works that tackled this task, a few recent works published their results in the LSDSem shared task website.[6] As to the time of submission, our results are still state-of-the-art (though by a much smaller margin). No other information other than the name of the group and their results is available.

5 Ablation Study

Most Discriminative Feature Types. A natural question that follows this study is which features are most helpful in making predictions about writing style. To answer this question, we re-ran Experiment 1 with different sub-groups of features. Table 3 shows our results. Results clearly show that character n-grams are the most effective style predictors, reaching within less than 2% of the full model. These findings are in line with previous works that used character n-grams along with other types of features to predict writing style (Schwartz et al., 2013).

[6] https://competitions.codalab.org/competitions/15333

Model	Results
DSSM (Mostafazadeh et al., 2016)	0.585
LexVec (Salle et al., 2016)	0.599
RNN	0.677
Our Model	**0.715**
Combined (Our model, RNN)	**0.751**
tbmihaylov (shared task)	0.711
Niko (shared task)	0.7
Human judgment	1

Table 2:
Results on the test set of the cloze story task. Upper part are published results (Lexvec results are taken from (Speer et al., 2016)). Bottom part are taken from the cloze task shared task webpage.

Feature Type	Result
Word n-grams	0.646
Char n-grams	0.699
Word n-grams, length, char n-grams (Full Model)	0.715

Table 3:
Results on Experiment 1 with different types of features.

Most Salient Features. In order to understand which features were most salient, we repeated Experiment 1, this time running SVM with L1 norm, such that it generates a sparse separating hyperplane. This came at a minor cost of less than 2% in performance compared to our L2 results (0.697 compared to 0.715). Table 4 shows the 5 features with the highest positive and negative weights in the hyperplane. These correspond to the 5 most salient features for *correct* and *wrong* endings, respectively.

The table shows a few interesting trends. First, some syntactic features play become salient when authors are asked to write *wrong* vs. *correct* endings. For instance, *correct* endings are more likely to the coordinator "but", while *wrong* ones would prefer to use "and".

More interestingly, *correct* endings are likely to use positive words (e.g., " bett", which in all cases stands for " bet**ter**"), while *wrong* endings would use negative words (e.g., " hate"). The idea that sentiment would play a role in this task was suggested in the original story cloze paper, where two sentiment-based baselines were evaluated. However, these baselines measured the relative sentiment between the ending and the previous sen-

Positive	Negative
‘ time’	‘ed of’
‘ bett’	‘and d’
‘found’	‘threw’
‘but’	‘ever ’
‘ally ’	‘ hate’

Table 4:
The top 5 most discriminative features for predicting *correct* (Positive) and *wrong* (Negative) endings.

tences, and did not test whether there is a general tendency of the *wrong* endings to have a negative sentiment, and the *correct* one to have a positive sentiment. Indeed, the performance of both these baselines was roughly chance-level.

Neural Language Model. We trained a simple RNN Language model (Mikolov et al., 2010) using a single-layer LSTM (Hochreiter and Schmidhuber, 1997) of hidden dimension $h = 512$. We used the ROC Stories for training, setting aside 10% for validation of the language model. We replaced all words occuring less than 3 times by a special out-of-vocabulary character, yielding a vocabulary size of $|V| = 21,582$. Only during training, we applied a dropout rate of 60% while running the LSTM over all 5 sentences of the stories. Using AdamOptimizer (Kingma and Ba, 2014) and a learning rate of $\eta = .001$, we trained with backpropagation on cross-entropy.

To construct features for the Story Cloze task, we scored each of the two endings using our neural language model. We computed the probability of each ending given the first four sentences $p_\theta(ending|story)$, as well as the probability of the endings out of context $p_\theta(ending)$. We also included the likelihood ratio $\frac{p_\theta(ending|story)}{p_\theta(ending)}$ into our classifier.

6 Discussion

7 Related Work

- Different style application (as in introduction). Also include deception works (Yejin has 1-2 papers on it).
- Machine reading papers?
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8 Conclusion

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