Detection of Latent Writing Style in Online Reviews

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Abstract

Every writing has a voice. In almost any forms of writing, from a formal literature to a casual blog, the personality of the writer is conveyed through their writings. In this research, I aim to detect such subtle stylistic decisions in Yelp reviews and discover correlations between the type of business or users, answering questions such as 'do more pricey restaurants tend to get more sophisticated reviews?'

1 Research Context

The style detection in natural language has been done in many forms, usually in a context of machine translation and style transfer. Some previous studies show successful translations from English to German while preserving the level of politeness, or translating Shakespeare to more colloquial language without breaking the semantics. Those researches usually have constraints of not having 'ground-truth' labels and require meticulous labeling by human hands or a large-scale survey. In the Yelp review, however, we are able to validate the accuracy of models by constructing a classifier for the matching problems (ex, given review A, find the review written by the same author). For this purpose, Seq2Seq model (bidirectional LSTMs) seems very promising. Furthermore, this simulation is very rigid against the missing values in Yelp as we can build matching problems as long as we have 2 or more writing samples from the same user.

2 Data / Design

While we are training models to extract writing styles, we use Yelp dataset in the context of supervised learning. This means we will train the model using the reviews written by a single user, and test if the model can find the reviews by this user amongst other random choices. In this case, we need to make sure the model is accurate even with the reviews in different semantics so that the prediction is made purely by writing styles not by the topics. (ex, train with positive reviews and test with negative reviews, train with restaurant reviews and test with hotel reviews etc). Once we succeed in extracting writing styles, we can further expand the usage of Yelp dataset by observing the correlations between latent values in writing styles and user or business trend. For example, I would like to see if the users tend to like reviews with similar styles from theirs. I am also curious to study what type of business or price range will get more sophisticated writings, whether or not writing styles change over time or it is something more inherent. The objective of this research is not to discover the new algorithm, but more so, to apply and modify the algorithm in machine translation to detect writing styles and draw statistical inferences about social cues, business trend and user's characteristics.

3 Methods

We are going to use the state-of-the-art machine translation algorithm, specifically Seq2Seq to train the models. This complex model will able to learn the sequential information about the word choice. The challenge is if this complex model can learn subtle writing styles in significantly different topics of reviews. Therefore, it is more natural to implement an ensemble method between the word embedding, text ordering as well as more conventional machine learning metrics such as bag of words, verb adjective ratio. As I conduct the initial analysis with 2 sample users, some metrics showed promising distributions. In this experiment, I selected 2 users from top 10 users

Figure 1: Pronouns Ratio to the Text Length

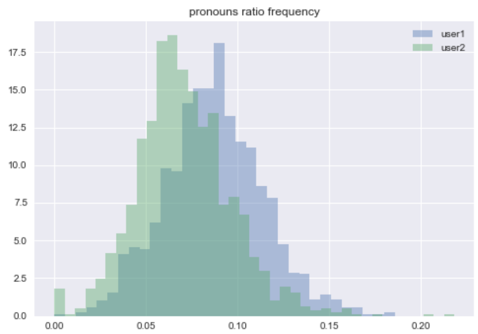

Figure 2: Verb/Adjective Ratio

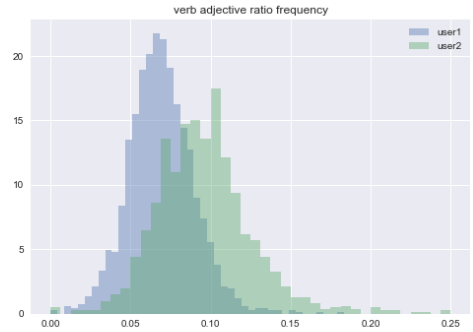

Table 1: Top 10 Words with tf-idf Values

Top 10 tf-idf values			
User1	tf-idf	User2	tf-idf
good	0.397	good	0.286
time	0.179	like	0.217
got	0.174	food	0.183
place	0.165	service	0.179
like	0.141	chicken	0.148
menu	0.131	little	0.134
ordered	0.130	sauce	0.127
just	0.128	time	0.126
small	0.124	friendly	0.125
came	0.117	nice	0.124

with most reviews and selected 2 based on similarity user status. As we can see in Figure1, the user 1 tends to use more pronouns in one review and user 2 tends to use more verbs than adjective. I also observed the 2 users' diction or word choice by calculating tf-idf values. Some notable words are 'got', 'ordered' and 'came' from User1 and 'service', 'friendly' from User2. In fact, if we read the reviews by User1, we can tell this person tends to write a review based on his experience while user2 uses more descriptive sentences to write the services in general. For example, User1 writes review in a following manner:

> I tried Settebello for the first time last night. I had read the reviews of my Yelp friends and likes the sound of the Rafael pizza which was on their special of the day and it sounded good. When I talked to the young man at the podium and told him I wanted to place a To Go order, I told him about the pizza and the reviews.

While User2 wrote a following review:

> Tried the kung pao soy chicken to go. The lunch special comes with a scoop of rice, and small portion of salad. The outstanding feature is the flavorful sauce which complements the soy chicken and veggies very well. The veggies and chicken themselves are prepared very well. The veggies are not too hard or soft, and the chicken is tender.

As we see, there is a distinct difference between the 2 users' writing style. We are hoping that there is a computational method to extract these differences.

4 Significance

There have been many studies in machine translation but not in a context with Yelp dataset in the past. I believe that the subtle writing cues represent not only about the stylistic decisions but also about the characteristics of users as well. Through this research, we could potentially give a new user similarity metrics, which will open up the new possibilities in recommendation systems. For example, if people tend to read more from the authors with similar writing styles, we might be able to suggest 'next reading' based on their business preferences as well as their writing style in order to maximize the user engagement. If one's writing style changes over time, we could potentially use it as an additional feature to the elite user detection. If it is inherent to the user, however, we could potentially learn about ones cultural, economical or educational backgrounds. The study on one's writing style gives a unique perspective to our Yelp research that has not been explored. I believe that this topic is also able to ignite further studies in the field.

References

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