Makeup reputation engine based on Social Network

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I. Problem Overview

IN the proposal, we state the problem into product name entity recognition(NER) problem. To narrow down the problem, we decide to study makeup market. Makeup market is a highly competitive market. Product lifecycle is comparatively short. In order to extract product name from a discussion on Twitter. After an evaluation from raw text from a different data source, Amazon, Sephira. E-commerce platform is a better source to collect product name.

Therefore, we set two new goals: (A)Build reviewer reputation score. Provide each review with different weights (B)Summarize Pros and Cons of social media. We assume customer want to know more than score, but the reason why the product isn't a decent option.

II. Data

In order to evaluate the result. We need to collect rating and review from online stores. We collect data from Sephora and Amazon. Both of them have structured data.

The biggest problem with Amazon is fake suppliers. 1 shows a really common situation. The "L'Oreal Paris" is the real supplier. "L'Oreal" is a highly possible fake seller. We can guess by the number of products, however, it doesn't work every time. Some of the real suppliers might not have enough products items. It's no ground truth to set the threshold to eliminate fake supplier. It brings in the score under those fake supplier might affect the actual product ranking. Another problem comes from different supplier might use different title structure. It's common to see combo for promoting.

Sephora is mature makeup online store which focuses more on beauty field. They select a high quality make-up product. It provides limited but reliable data. Both brand and product name are easy to analyze.

Twitter data is the final goal for this project. We assume the bias of comments is less than shop platform. It also needs more treatment of raw data. We collect data by simulating the ordinary user scroll the mouse since the free Twitter API doesn't allow to track 7 days before. We extract the product name form previous two resources. Search all tweets contain exact phrase of a product name. Also, most of the people like to share their feeling on social media like twitter when they use the latest product rather than on E-commerce platform mall, therefore twitter data can help us to predict potential hottest makeup.

III. Method & Evaluation

One of goal in the previous proposal targets the latest popular product. One assumption we make here: Review number is strong correlate the sales number. Since we don't have actual sales number for each product. Then, we collect 67

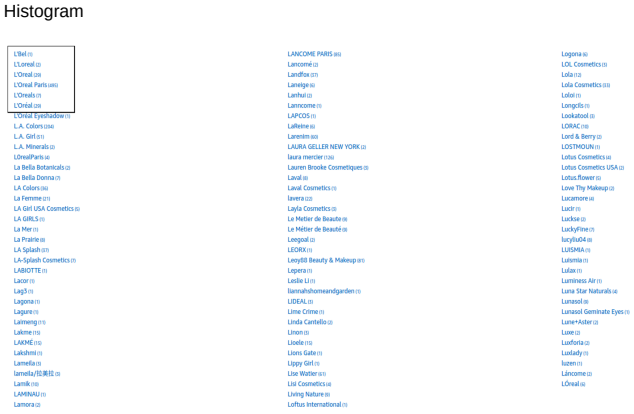

Fig. 1. Amazon contains many fake brand

TABLE I
Data source summery

	Pons	Cons
Twiiter	Provide almost every product reviews	No product Catogooy
Amazon	Structured Score system	(1)Fake product (2)Combo set for selling. Can't rate for single product.
sephora	Structured Score system	Total product coverage is compare less

TABLE II
Number of collection

	# of Product(Eye Shadow)
Twiiter	Unknown
Amazon	∼800
sephora	67

eyeshadow product names form Sephora. Calculate correlation between the tweeter number in one year and review numbers in Sephora. We get correlation 0.23. We conclude tweets number can't be a good signal to determine the popular product.

There 2 possible reasons :(a)Some product name are very common using in a non-relevant tweet. One example is "Eye Gloss", it is a category in eyeshadow, also one product name. Therefore the tweets number can't direct mean specific product discussion. (b) There are only 67 items in the analysis, only few items can affect the correlation result.

IV. Who does what

YiChen is responsible for collecting Amazon and Sephora product information into MongoDB. ChiHung is responsible for collecting Twitter data from each makeup product and analyze the correlation between Twitter review and Sephora rating.

V. Timeline

The next step is designing automatically product rating system. We would implement three steps. First, we identifiy product feature mining based on product review. Second, we obtain the optimal feature weight in each review and compute the final score in all reviews. Regarding evaluation method, we use correlation with rating to check our result. We use bag of words analysis as baseline, compare feature-based method with chi-square analysis.

We hope these two method performance is good enough for us to implement on unknown Twitter data.

TABLE III
Timeline

3/19∼3/25	Extract product feature from reviews
3/26∼4/1	Weight each feature for each review
4/2∼4/8	Compare bag of word method and chi-square method
4/9∼4/15	Use feature-based method in twitter review
4/16∼4/18	code review and report review

VI. Related Work

Compared to our projects, [1] uses the same data source to lower the influence of spammer in a social network. The similarity is they use Twitters official policy of suspending accounts to check is it a spammer or not. Also, they examined url posted by users using URL shortening services and checked whether these URLs are the presence of blacklisted URLs or not. The difference is we would more focus on a sponsored post, which is not real makeup review. We would classify this kind of poster as a spammer.

We would use the method of extracting important aspects of a product from [5]. The goal of [5] is to automatically identify important product aspects from online consumer reviews. There is three step to achieve their goal. Doing aspect identification first by using Stanford parser and extracting the phrases to identify aspects of the candidates. Then they utilized these aspects to train SVM sentiment classifier and select sentiment terms. Finally, they use alternating optimization technique and compute the score for each aspect by integrating all the reviews. The difference is we would focus more on the reviews having a lower rating. Since most of the people would not like to give a too low rating, otherwise they would have a really bad experience with that product.

Based on data mining method, we would use NLTK package, and the concept is similar to [4]. The goal of [4] is solving product feature problem when parsing reviews. They introduce the concept of phrase dependency parsing and propose an approach to construct it.

[3] also provide a new framework for score news and web via a network. The role for determine news can be replaced by make-up product. Web score can be replaced as Twitter users. The difficult to apply the framework for 2 reasons: (A)We need initial good and bad users group. In the [3], they provide the reliable web by empirical method, bad webs from web certificate service. (B)Build network. Unlike citing web, cite the product can have so many different ways. Abbreviation, the nickname isn't easy to track. This two reason we might need to solve before we applying the same framework.

Based on twitter/Sephora reviews and time slot, we can do trend analysis to predict potential hottest makeup. The method is similar to [2]. The goal is using moving average convergence-divergence to predict the trends of the topic on Twitter. They also take three main factor into account, key users, key words and topic interaction, which utilize chi-square to examine.

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