Learning to Learn Sales Prediction with Social Media Sentiment

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Abstract

Social media sentiment has shown to be a useful resource for product sales forecast. However, research on modeling the correlation between sentiment index and sales is often limited by the scariness of quarterly sales data. In this paper, we propose to learn how to learn sentiment-sales correlation from different source products and transfer to sales prediction of another, target product. We evaluated our approach on sales data of seven different smartphones and showed that the knowledge transfer from six source products significantly reduced the sales prediction error for the target product, in a 7-fold cross-validation experiment.

1 Introduction

The sales forecast is crucial in the financial domain since it indicates the future trend of a product and thus, it allows investors to make better decisions. During the years, time-series models have been widely applied in sales prediction using historical seasonal sales data. However, they are often unreliable since historical sales ignore the importance of customers opinions (e.g., Social Media, News), which are critical for sales prediction [Ahn and Spangler, 2014]. On the other hand, user-generated content in social media acts as word of mouth contains a large number of customer opinions. Sentiment analysis of social media provides a good summary of customers’ feedback and allow companies to have a better intuition of how the market reacts to their products.

Several existing work use sentiment features to predict product sales, for instance for movie sales [Duan et al., 2008; Gaikar and Marakarkandy, 2015; Ahn and Spangler, 2014; Marshall et al., 2013; Asur and Huberman, 2010], e-commerce products [Davis and Khazanchi, 2008; Tuarob and Tucker, 2013] and car sales [Wijnhoven and Plant, 2017; Geva et al., 2017; Barreira et al., 2013]. These works show positive correlations between sentiments features and sales, and thus, the sentiment is a useful indicator to predict the outcome of future sales. However, most of them focus on correlation studies between features, but they have not explored the possibility to transfer information from different brands.

Moreover, the preferred models for the sales prediction task are usually linear (e.g., BIC, ARIMA) due to the particularly small datasets. Indeed, a well-known problem for deep learning models, and in general non-linear models, is that they require a large amount of data to work properly.

Differently from the previous work, in this paper, we study the sales of seven smartphones in China’s market such as Samsung, Gionee, Huawei, Oppo, Vivo, Meizu, and iPhone. We show the importance of sentiment features by incorporating sentiment information extracted from the biggest Chinese social media platform Weibo – for improving sales prediction. To extract reliable sentiment index from Weibo, we build an accurate sentiment analyzer by applying the state-of-the-art pre-trained model BERT: Bidirectional Encoder Representation from Transformer [Devlin et al., 2018]. Moreover, we report the sales prediction results of several statistical models and show the usefulness of sentiment features. Most importantly, we propose a viable way to alleviate the scariness of sales data by using meta-learning. This technique allows a non-parametric model such as neural networks to leverage historical sales of other brands, and use them as the prior knowledge. The intuition of applying meta-learning is that it optimizes the model for fast adaptability, allowing it to adapt to new prediction tasks.

The main contributions of this paper are: 1) Collecting and pre-processing a large scale dataset of user comments of seven different smartphone companies from a popular Chinese social media platform Weibo, and providing human la-
Table 1: The number of Weibo comments for smartphone brands.

| Brands | # Comments |
|--------|------------|
| Samsung | 288,081    |
| Gionee  | 302,866    |
| Huawei  | 524,468    |
| Oppo    | 633,406    |
| Vivo    | 670,408    |
| Meizu   | 945,312    |
| iPhone  | 994,155    |

beled sentiment annotations of 25K comments; 2) Training a state-of-the-art sentiment classifier to produce reliable sentiment features for the sales prediction; 3) Reporting consistent improvements in the sales prediction by using the extracted sentiments features, which confirms existing related previous works; 4) Proposing a deep learning-based solution that can compete, and improve, with very strong statistical models. By using meta-learning, our model is able to leverage other brands sales history for making a more accurate sales prediction. To the best of our knowledge, we are the first to report positive results in this setting.

In the following sections, we introduce 1) Corpus collection and annotation, and the historical sales dataset used in our experiments; 2) Sentiment analyzer and sales prediction models; 3) Experiments and results; 4) Related work; and 5) Conclusion.

2 Dataset Collection

2.1 Weibo Sentiment Dataset

We crawl around 5 million Weibo comments for seven different smartphones: Samsung, Gionee, Huawei, Oppo, Vivo, Meizu, and iPhone from their company official accounts from 2013 to 2018. In the data cleaning process, we remove all emojis, user mentions such as "@user", hashtags, and hyperlinks using regular expressions. Then, we group them by quarter, a period of four months. The statistics of the dataset for each brand is showed in Table 1.

We randomly sample 25,000 Weibo comments and manually annotated them with Positive, Negative, and Neutral labels via crowd-sourcing. The agreement is taken by majority vote. The annotation result shows that the percentage of Positive, Negative, and Neutral labels are 20%, 16%, and 64% respectively. We further take around 5,000 comments as our test set.

2.2 Smartphone Sales Dataset

We collect quarterly China sales data of seven smartphones: Samsung, Gionee, Huawei, Oppo, Vivo, Meizu, and iPhone from the first quarter of 2013 to the third quarter of 2018 released by IDC. In each brand, we reserve the last five quarters for testing, and we use the rest for training our models.

Figure 2: Sentiment Analyzer. The model accepts user comment tokens and generate a probability distribution over three classes. In the figure, green states for positive, red for negative, and gray for neutral.

3 Methodology

3.1 Sentiment Analysis

Building a reliable sentiment classifier is crucial to the final sales prediction. To alleviate the dependence of the human effort and build a robust sentiment classifier, we apply current state-of-the-art pre-trained language model BERT: Bidirectional Encoder Representations from Transformers [Devlin et al., 2018] to our task. It is a multi-layer bidirectional Transformer encoder pre-trained by using “masked language model” objective. In our proposed model, we adapt BERTBASE [Devlin et al., 2018] to generate the semantic representation of each comment to improve the sentiment prediction task. Following the same fine-tuning procedure of [Devlin et al., 2018], a special token [CLS] is added at the beginning of every input to obtain the fixed-dimensional representation of input sequence. As shown in Figure 1, we stack another linear layer with Softmax function on top of BERT to compute the probabilities of three sentiment classes. We keep all parameters trainable, and they are fine-tuned with the sentiment training data. Our sentiment analyzer achieves around 80% accuracy in the final test set.

Sentiment Features To incorporate sentiment information into the sales predictor, we quantify the sentiment score of each brand in the quarter. We calculate the score $x_t$ by the following [Lassen et al., 2014]:

$$x_t = \frac{p_t}{p_t + n_t} \quad (1)$$

where $p_t$ is the number of comments with positive sentiment in the quarter $t$, and $n_t$ is the number of comments with negative sentiment in the quarter $t$. The score is normalized to 0-1 range.

3.2 Sales Prediction

Let us define a vector $S = [s_0, \ldots, s_t, \ldots, s_N]$ as the sales at each quarter and vector $X = [x_0, \ldots, x_t, \ldots, x_N]$ as sentiment features at each quarter, where $N$ is the total number of quarters, $s_t$ is the sales value at quarter $t$, and $x_t$ is the sentiment of comments posted in one month time before in each quarter. For example, in the second quarter of a year from

\footnotesize
\begin{itemize}
  \item We used a PyTorch implementation from https://github.com/huggingface/pytorch-pretrained-BERT
\end{itemize}
In this work, we apply Model-Agnostic Meta-Learning (MAML) [Finn et al., 2017] to sales prediction task. The goal of MAML in our task is to find initial parameters \( \theta_0 \) of sales predictor model \( f_0 \) (MLP in our case) such that the model can make an accurate prediction on a new product after training on few historical sales samples.

In our meta-learning scenario, every product is considered as a different task. As we showed in the Figure 3, datasets \( D_i \) are constructed separately for each task. We take one product out as meta-test set \( D_{i, \text{test}} \) and other datasets as meta-training set \( D_{i, \text{train}} \). In meta-training setting of [Finn et al., 2017], for each dataset \( D_i \), they random sample some data points \( D_{i, \text{train}} \) for inner training and sample some other data points \( D_{i, \text{val}} \) for meta-update. Instead, we always fix the split \( D_{i, \text{train}} \) and \( D_{i, \text{val}} \), because we are only interested in forecasting sales given historical sales. During the meta training, the model keeps simulating learning process that minimizes the prediction error by utilizing the historical training samples. The prediction error is measured by MSE (Mean Square Error) defined by equation (5). We describe the learning procedure in Algorithm 1. After meta-learning, we train our model on historical sales data \( D_{i, \text{train}} \) from meta-training set \( D_{meta-\text{train}} \), and finally evaluate our model on \( D_{i, \text{test}} \) from \( D_{meta-\text{test}} \).

4 Experimental and Results

4.1 Settings

In our experiments, we compare the sales prediction performance of our models with and without using sentiment information, with and without using the meta-learning method in our smartphone sales dataset. We also compare our model with two baselines: linear regression and SVR (Support Vector Regression). As mentioned in the dataset section we use...
the last five quarters for testing and the previous for training. Hence, the model’s performance to predict the next quarter sales is evaluated using Mean Squared Error (MSE) of the test set.

Hyper-parameters SARIMAX model is identified by following hyper-parameters: order of difference (d), the order of seasonal difference (D), non-seasonal autoregressive order (p), seasonal autoregressive order (P), non-seasonal moving average order (q), seasonal moving average order (Q). All of them are identified by Autocorrelations function (ACF) and partial autocorrelations function (PACF) as we showed in Table 3. For our gradient base model, we use two layer MLP with hidden size 5 and Rectified Linear Units (ReLU) as the activation function. For meta-learning, we use SGD optimizer with learning rate 0.01 for both inner and outer optimization. we run 9 iterations for each inner update, and 10 epochs of meta update.

4.2 Results
Table 2 shows the results for each model and each brand in the term of Mean Squared Error (MSE). Two results stand out: Sentiments Features consistently improves the MSE for all the models, and the MLP with sentiment features trained using Meta-Learning can improve the average MSE among different brands.

Sentiment Features The features help in all the evaluated models, this confirms the usefulness of such a feature in sales prediction. Indeed, this shows that Weibo comments hold essential information that can be used to predict future sales. However, from Table 2 we can notice that the only case where sentiment features hurt the performance is on Meizu data. One possible reason could be the price of Meizu is much lower than other brands; hence the sentiment might not affect the sales of low price products that target a different market.

SARIMAX vs MLP Moreover, in Table 2 we can see that both SARIMAX and MLP using sentiment features have a very similar average MSE and they performs consistently better than SVR and Linear Regression. Especially, MLP works the best for Huawei and Samsung where instead for iPhone, Oppo and Meizu SARIMAX works the best.

Meta-learning The best MSE average is achieved by the meta-learned model, MLP+Sentiment+Meta in Table 2. This is due to the ability to transfer knowledge between different brands. Indeed, meta-learning is trained to find a set of parameters that are able to quickly adapt to a given task. In our instance, this means to learn a set of parameters that can quickly adapt to the sales behavior of a certain brand.

Moreover, in Figure 4 we plot the Gionee, Vivo, Samsung and iPhone sales traces and the prediction made by MLP by using with and without sentiment feature including meta-learning to describe our findings. For Vivo, Samsung and iPhone, we can note that by just using MLP the sales predictions are not aligned with the real sales. Instead by adding sentiment features we can achieve a very good fit in the two quarters, but a more substantial error when a trend inversion appears (i.e., 2017Q4 in iPhone). This is mostly solved by meta-learning training, in which the model achieves almost a perfect fit (0.822 MSE).

We can also notice that in some brands predictions are easier than the others. For instance, the iPhone has seasonal patterns where there are peaks between the third and fourth quarters in the last two years. In this case, our autoregressive model SARIMAX can capture this pattern better than MLP with meta-learning as we showed in Table 2. On the other hand, SARIMAX predicts very poorly on Gionee and Vivo which have less repeating sales patterns. Conversely to our meta-learning based model is more robust as it can accurately predict in sales trends with irregular changes.

5 Related work
5.1 Sales prediction with sentiment analysis
Sentiment and emotional analysis are important methods to quantify customers’ emotional engagement [Winata et al., 2019]. The importance and effectiveness of using social media opinion, a.k.a. Word-of-Mouth, for Sales Prediction is a well known topic [Hennig-Thurau et al., 2003; Hennig-Thurau et al., 2004; Ceron and d’Adda, 2016; Liu, 2012;
Figure 4: The sales prediction for Gionee, Vivo, Samsung and iPhone: Grey line represents the real sales, the blue line represents the prediction of MLP without sentiment information, the red line represents the prediction of MLP with sentiment information, and the green line represents the prediction of meta trained MLP with sentiment information.

Shi et al., 2016; Asur and Huberman, 2010]. Among the years, using sentiment analysis as an additional features for sales forecasting has been widely used in different domains. For instance, it has been used for predicting: movies sales [Duan et al., 2008; Gaikar and Marakarkandy, 2015; Ahn and Spangler, 2014; Marshall et al., 2013; Asur and Huberman, 2010], e-commerce products [Davis and Khazanchi, 2008; Tuarob and Tucker, 2013], car sales [Wijnhoven and Plant, 2017; Geva et al., 2017; Barreira et al., 2013]. To the best of our knowledge we are the first to report positive correlation between sentiment feature and smartphones quarter sales.

5.2 Meta-learning

Meta-learning [Thrun and Pratt, 1998; Schmidhuber, 1987; Schmidhuber, 1992; Naik and Mamone, 1992; Bengio et al., 1992] also known as Learning To Learn, is machine learning technique that tries to learn the algorithm itself. Recently, several meta-learning models has been proposed for solving few-shot image classification [Ravi and Larochelle, 2017; Vinyals et al., 2016; Finn et al., 2017; Mishra et al., 2017; Santoro et al., 2016], optimization [Andrychowicz et al., 2016], dialogue system [Lin et al., 2019] and reinforcement learning [Finn et al., 2017]. In our setting, we are applying Meta-learning for learning a set of parameter that can adapt to certain products, and have good performance in sales prediction.

6 Conclusion

In this paper, we explore four different sales prediction models SARIMAX, SVR, Linear Regression and MLP. The results of our experiments show that sentiment information improves the performance of these models which confirms the effectiveness of the sentiment index. Moreover, the proposed
meta-learning method help models transfer the knowledge of sentiment-sales correlation from different products, further reduce the sales prediction error.

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