Abstract

Fine grained sentiment analysis of text reviews has recently gained a lot of attention in the natural language processing community. Most work done earlier focuses on creating efficient feature representations of text reviews for classification. The methods generally ignore other common attributes like user identity, product identity and helpfulness rating during fine-grained sentiment classification. A major problem in current classification models is noise due to the presence of user bias in review ratings. We propose two simple statistical methods to remove such noise and improve fine-grained sentiment classification. We apply our methods on the SNAP published Amazon Fine Food Reviews data-set and on two major categories (Electronics and Movies and TV) of the e-Commerce Reviews data-set. After removing user bias, we get improved fine-grained sentiment classification with three commonly used feature representations.

1 Introduction

This section explains the problem of user bias in rating reviews and our core idea of rectifying it to improve classification using simple statistics.

1.1 User Bias Problem

Different users generally do not rate food or e-commerce products on the same scale. Every user has his/her own preferred scale of rating a product. Some users are generous and mostly rate only 4,5 (out of 1,2,3,4,5), thus introducing a positive bias in review scores. At the other extreme, some users mostly give only 1,2, thus introducing a negative bias in the scores. These preferred rating choices of particular users introduce a bias in scores. This makes it difficult to learn a general model for fine grained sentiment classification.

1.2 User Bias Removal

We remove user bias in scores corresponding to each user ($u_i$) by learning a statistical mapping from a user specific scale to a general scale common to all users. We propose two methods to remove user-bias.

1.2.1 User Bias Removal-I (UBR-I)

We develop a user specific statistical mapping for user bias removal, by normalizing each review score with respect to the mean and standard deviation of all products rated by that user. During prediction we use the same user specific mean and standard deviation (statistical mapping) to jump back to the original scale.

Let $R(u_i, p_j)$ represent the review score of user $u_i$ for product $p_j$. We calculate the normalized score $NR(u_i, p_j)$ for training, and predict score $PR(u_i, p_j)$ during prediction as follows:-

1. For each user, calculate and store the mean
$R_{\mu}(u_i)$ of all scores given by user $u_i$.

$$R_{\mu}(u_i) = \frac{1}{N_{u_i}} \sum_{j=1}^{N_{u_i}} R(u_i, p_j)$$

Here, $N_{u_i}$ represents the number of products reviewed by user $u_i$.

2. Similarly, for every user calculate and store standard deviation $R_{\sigma}(u_i)$ of all the scores given by the user $u_i$.

$$R_{\sigma}(u_i) = \sqrt{\frac{1}{N_{u_i}} \sum_{j=1}^{N_{u_i}} (R(u_i, p_j) - R_{\mu}(u_i))^2}$$

3. For every review score, calculate the Normalised user bias removed score $NR(u_i, p_j)$ as follows :

$$NR(u_i, p_j) = \frac{1}{R_{\sigma}(u_i)} (R(u_i, p_j) - R_{\mu}(u_i))$$

Here, $NR(u_i, p_j)$ represents the normalised score (after user bias removal) for user $u_i$ and product $p_j$. In the trivial case when $R_{\sigma}(u_i)$ is zero (i.e. all reviews have the same ratings) we set $NR(u_i, p_j)$ equal to zero.

4. We use this normalised $NR(u_i, p_j)$ as a label and train an ordinary least square linear regressor (Galton, 1886). This regressor is used to predict a normalised review rating $PNR(u_i, p_j)$ for a given user $u_i$ and product $p_j$.

5. During prediction we can recover the original user biased score by the equation:

$$PR(u_i, p_j) = PNR(u_i, p_j)*R_{\sigma}(u_i)+R_{\mu}(u_i)$$

Here, $PR(u_i, p_j)$ and $PNR(u_i, p_j)$ are the predicted score and predicted normalised score (user bias removed) respectively for user $u_i$ and product $p_j$. We can floor or cap the $PR(u_i, p_j)$ to the nearest integer in 1, 2, 3, 4, 5 to get the final prediction rating. This will be used for final error calculation.

Our method looks similar to zero mean normalization but a major difference is that instead of normalising over all reviews, we do user specific normalization.

Figure 2: User Bias Removal-I (UBR-I)

1.2.2 User Bias Removal-II (UBR-II)

A product has ratings given by multiple users. Given that a product has many ratings, we assume the average rating for the product is unbiased. Then the differences from the average rating can be considered the user bias. These individual biases averaged over all products gives us the net bias for a user. This bias can then be used in a manner similar to that in Method I. The details are as follows:

1. For each product calculate the mean $R_{\mu}(p_i)$ of the scores given by all the users.

$$R_{\mu}(p_i) = \frac{1}{N_{p_i}} \sum_{j=1}^{N_{p_i}} R(u_j, p_i)$$

Here, $N_{p_i}$ is the number of reviews for product $p_i$.

2. For a user $u_j$ and product $p_i$, $R(u_j, p_i) - R_{\mu}(p_i)$ is the bias of that user for product $p_i$. Now calculate the net bias of that user.

$$B(u_j) = \frac{1}{N_{u_j}} \sum_{i=1}^{N_{u_j}} R(u_j, p_i) - R_{\mu}(p_i)$$

Here, $N_{u_j}$ is the number of products reviewed by user $u_j$.

3. For each review score, calculate the user bias removed score $NR(u_j, p_i)$ as follows :

$$NR(u_j, p_i) = R(u_j, p_i) - B(u_j)$$

Here, $NR(u_j, p_i)$ represents the normalised score (after user bias removal) for user $u_j$ and product $p_i$.

4. We used this Normalised $NR(u_j, p_i)$ score and train an ordinary least square linear regressor (Galton, 1886). We use this regressor model to predict normalised review rating $PNR(u_j, p_i)$ for user $u_j$ and product $p_i$. 


5. During prediction we can recover the original user biased score by the equation:

\[ PR(u_j, p_i) = PNR(u_j, p_i) + B(u_j) \]

Here, \( PR(u_j, p_i) \) and \( PNR(u_j, p_i) \) are the predicted score and predicted normalised score (user bias removed) respectively for user \( u_j \) and product \( p_i \). We can floor or cap \( PR(u_j, p_i) \) to nearest integer in 1, 2, 3, 4, 5 to get the final prediction score. This will be used to calculate the final error.

Note that, instead of normalising over all reviews, we do product specific zero mean normalization and thus consider only review scores of a product.

![Figure 3: User Bias Removal-II (UBR-II)](https://warahul.github.io/UBR/)

Both methods would be able to predict score only for those users which are already seen in training data which is a reasonable and practical assumption. Code for both methods is at github.

2 Dataset Description

We use the Amazon Food Review Dataset (McAuley and Leskovec, 2013) consisting of 568,454 food reviews by Amazon users up to October 2012. Dataset is publicly available for download from the kaggle site (www.kaggle.com) as Amazon fine Food Reviews (Kag, 2012). Each review has a ReviewId, UserId, Text and a brief Summary of the review.

We also experiment on two major categories, Electronics and Movies and TV reviews, in the Amazon e-commerce dataset. These are described in detail in (McAuley and Leskovec, 2013) and (McAuley et al., 2015). The datasets are randomly divided into subsets of sizes 80% and 20% for forming the training and testing sets. We identify each user for removal of user bias using the UserId provided in the dataset. Similarly, each product is identified by the ProductId field.

3 Evaluation Metric

We use standard root mean square error (rmse) for evaluation as described below:

- Root Mean Square Error (RMSE)

\[ RMSE = \sqrt{\frac{\sum (P_{est} - P_{true})^2}{N}} \]

Here, \( P_{true} \) and \( P_{est} \) are the true and predicted value respectively for a sample data item and \( N \) is the total number of samples used in the test set.

4 Baselines

We compare our methods to six baseline methods as described below:

- Majority Voting: Predict score for a review as the mode of all reviews.
- User Mean: Predict score for a review by user \( u_i \) as the mean of all review scores of the user \( u_i \).
- User Mode: Predict score for a review by user \( u_i \) as the mode of all review scores of the user \( u_i \).
- Product Mean: Predict score for a review of product \( p_j \) as the mean of all review scores of the product \( p_j \).
- Product Mode: Predict score for a review of product \( p_j \) as the mode of all review scores of the product \( p_j \).
- Direct: Train a multi-class classifier (Linear SVM one-vs-rest) with text features from text+summary field to predict scores (class) for a given review.

Majority voting method is independent of specific product or specific user. The first five baseline methods are independent of extracted features.

5 Observations and Results

We compare the baselines with both our methods i.e. User Bias Removal-I (UBR-I) and User Bias Removal-II (UBR-II). We evaluate our approach with three feature formation techniques tf-idf (Salton and McGill, 1986) (25K Vocabulary), LDA (Blei et al., 2003) (ntopics = 100) and
Doc2Vec (PV-DBOW) (Le and Mikolov, 2014) to check effect of the feature formation technique. In tf-idf we compare our approach on both unigram (25K Vocabulary) and bi-grams (25K Vocabulary). All the hyper-parameters are tuned and the performance reported is the best performance.

| Methods       | tf-idf | LDA   | PV-DBOW |
|---------------|--------|-------|---------|
| Majority Voting | 1.535  | 1.535 | 1.535   |
| User Mean     | 0.599  | 0.599 | 0.599   |
| User Mode     | 2.557  | 2.557 | 2.557   |
| Product Mean  | 1.140  | 1.140 | 1.140   |
| Product Mode  | 1.746  | 1.746 | 1.746   |
| Direct        | 0.888  | 1.494 | 1.06    |
| Direct (bigram) | 0.737  | NA    | NA      |
| UBR-I         | 0.546  | 0.597 | 0.56    |
| UBR-I (bigram) | 0.529  | NA    | NA      |
| UBR-II        | 0.669  | 0.778 | 0.71    |
| UBR-II (bigram) | 0.642  | NA    | NA      |

Table 1: RMSE results for Amazon food dataset

| Methods       | tf-idf | LDA   | PV-DBOW |
|---------------|--------|-------|---------|
| Majority Voting | 1.494  | 1.494 | 1.494   |
| User Mean     | 1.005  | 1.005 | 1.005   |
| User Mode     | 1.258  | 1.258 | 1.258   |
| Product Mean  | 1.066  | 1.066 | 1.066   |
| Product Mode  | 1.347  | 1.347 | 1.347   |
| Direct        | 0.936  | 1.273 | 1.08    |
| Direct (bigram) | 0.853  | NA    | NA      |
| UBR-I         | 0.818  | 0.959 | 0.87    |
| UBR-I (bigram) | 0.783  | NA    | NA      |
| UBR-II        | 0.814  | 0.982 | 0.87    |
| UBR-II (bigram) | 0.775  | NA    | NA      |

Table 2: RMSE results for Amazon e-Commerce Electronic dataset

Table 1 shows results for Amazon Fine Food Reviews. It is clear from Table 1 that UBR-I and UBR-II generally outperform all six baselines for all feature formation techniques (tf-idf, LDA and Doc2Vec). Tf-idf with bigram features outperforms tf-idf with unigram possibly because of automatic handling of negation bigrams in the text. We also experiment with Amazon e-Commerce electronics and movies & TV data-sets. The corresponding results are shown in Table 2 and Table 3 respectively. Again, UBR-I and UBR-II generally outperform all six baselines for all feature formation techniques (tf-idf, LDA and Doc2Vec).

### 6 Related Work

Fine grained sentiment analysis is modelled as an ordinal regression problem in ((Pang and Lee, 2005); (Snyder and Barzilay, 2007)). The authors simply use a bag of words model. But their methods do not handle negation phrases explicitly. (Baccianella et al., 2009) use n-grams having certain PoS structure but their method suffers from feature sparsity for large $n$. The use of sentiment lexicons is also quite common. (Esuli and Sebastiani, 2007; (Kim and Hovy, 2004)) build domain-independent sentiment lexicons. However, their methods only do binary polarity classification and do not capture fine-grained sentiment. Several studies show that authorship is important in fine grained sentiment analysis (Pang and Lee, 2005). They train a user-specific classifier but they suffer from problems because the number of reviews for a user are usually small. (Li et al., 2011) propose a tensor based method to represent the relationship among reviewers, products and text features. However, their method is only applicable for binary polarity classification.

### 7 Conclusion

We consider the problem of user bias in fine grained sentiment analysis and suggest two simple statistical approaches to rectify and reduce prediction error (RMSE) that accounts for such bias. We did experiments on three frequently used feature vector representations tfidf, LDA and doc2vec on the Amazon fine food review dataset and on two datasets.
major categories of the Amazon e-commerce dataset (Electronics and Movies and TV) and showed improvement as compared to direct classification and other simple baseline approaches. Our experiments show that user-bias removal is a legitimate problem and needs to be handled in fine grained review analysis. Our proposed methods work well for all commonly used text feature representation techniques.

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