Contextual and Position-Aware Factorization Machines for Sentiment Classification

Shuai Wang  
University of Illinois at Chicago  
shuaiwanghk@gmail.com

Mianwei Zhou  
Yahoo! Research  
mianwei@yahoo-inc.com

Geli Fei  
University of Illinois at Chicago  
gfei2@uic.edu

Yi Chang  
Huawei Research America  
yichang@acm.org

Bing Liu  
University of Illinois at Chicago  
liub@cs.uic.edu

Abstract

While existing machine learning models have achieved great success for sentiment classification, they typically do not explicitly capture sentiment-oriented word interaction, which can lead to poor results for fine-grained analysis at the snippet level (a phrase or sentence). Factorization Machine provides a possible approach to learning element-wise interaction for recommender systems, but they are not directly applicable to our task due to the inability to model contexts and word sequences. In this work, we develop two Position-aware Factorization Machines which consider word interaction, context and position information. Such information is jointly encoded in a set of sentiment-oriented word interaction vectors. Compared to traditional word embeddings, SWI vectors explicitly capture sentiment-oriented word interaction and simplify the parameter learning. Experimental results show that while they have comparable performance with state-of-the-art methods for document-level classification, they benefit the snippet/sentence-level sentiment analysis.

1 Introduction

Although machine learning-based methods have achieved great success for sentiment classification (Liu, 2012), they have some limitations in explicitly capturing or presenting sentiment-oriented word interactions. Here the sentiment-oriented (SO) word interaction means that when two (or more) individual words function together as a sentiment expression (in a review snippet), the effect of word-wise interaction determines the sentiment orientation of that snippet. For example, in an online review snippet “this button is hard to push”, besides the sentiment polarity of every single word, the word interaction between “hard” and “push” indicates a negative signal for this snippet. Although some of the existing models consider such SO word interaction, it is coarsely modeled or implicitly captured, which we will detail in section 2.

The lack of SO word interaction may not be critical for coarse sentiment classification at the document level (a full review), but the involvement of such SO interaction can play a crucial role in finer-grained analysis at the snippet level (a phrase or short sentence). The reasons are: (1) while a long document contains rich content, only limited text information is available in a short snippet, and (2) some salient opinion words (e.g., “good” and “amazing”) can dominate document classification but these words may not always appear in short expressions classification.

Specifically, the sentiment expression in a review snippet may consist of multiple words. Let us take a further look at the aforementioned example “the button is hard to push”. We can see the “hard” and “push” are used to deliver a negative opinion from a customer. However, “hard” or “push” independently indicate no clear sentiment. Notice that there are also other snippets like “this is a hard (cellphone) case” where “hard” and “case” together assign a positive sentiment. In the above examples, an individual word like “hard”, “case” or “push” is not able to determine the whole sentiment polarity of a snippet. Instead, the word interactions play more important roles in identifying sentiment in such snippets, e.g., “hard” and “push” together indicate a negative opinion while “hard” and “case” interactively specify a positive opinion.

This paper proposes a solution that can capture such interaction explicitly by exploiting Factorization Machine (Rendle, 2010). Factorization Machine (FM), which is widely used in recommender systems, is a general approach that can break the independence of interaction variables. It suggests a possible way to realize our goal, i.e., to capture
the SO interaction. However, direct application
of FM is not suitable due to two main reasons.
First, while FM aims at learning the global inter-
atraction between all elements, it neglects the impor-
tance of modeling (local) context in text. Different
from recommender systems, contextual informa-
tion plays a key part in sentiment analysis. Sec-
ond, while the position/ordering of different fea-
tures/fields in recommender systems may not be
sensitive, the position information of words is an
indicative signal in text data.

To address them, we first propose Contextual
Factorization Machine (CFM) which models con-
text by capturing the focused interactions for a
specific sentiment expression. After that we pro-
pose Position-aware Factorization Machine (PFM)
to further encode position information. In these
two models, the word interaction, context and
position information are jointly learned by a set
of vectors termed sentiment-oriented Word Inter-
action (SWI) vectors. Compared to word em-
beddings that are widely used in neural models
for sentiment classification, SWI vectors explic-
tly capture SO word interaction and simplify the
parameter learning. Experimental results show
that while they give comparable performance with
state-of-the-art methods for document-level clas-
sification, they effectively benefit the snippet-level
analysis.

This paper makes the following contributions:
1. It proposes a new solution to explicitly model
sentiment-oriented word interaction for fine-
grained sentiment analysis.
2. It proposes two new models called CFM and
PFM to learn a set of Sentiment-sensitive
Word Interaction (SWI) vectors. Such vec-
tors jointly capture SO word interaction and simplify the
parameter learning. Experimental results show
that while they give comparable performance with
state-of-the-art methods for document-level clas-
sification, they effectively benefit the snippet-level
analysis.

This paper makes the following contributions:
1. It proposes a new solution to explicitly model
sentiment-oriented word interaction for fine-
grained sentiment analysis.
2. It proposes two new models called CFM and
PFM to learn a set of Sentiment-sensitive
Word Interaction (SWI) vectors. Such vec-
tors jointly capture SO word interaction, context
and position information and also simplify the
parameter learning.
3. Comprehensive experiments are conducted
on three real-world review datasets at
document and snippet/sentence level. By
comparison with state-of-the-art models,
experimental result shows the effectiveness
of our approaches.

2 Sentiment-Oriented Word Interaction
In this section, we review some state-of-the-art
machine learning methods for sentiment classi-
fication and analyze their limitations in model-
ing sentiment-oriented (SO) word interaction. Al-
though some of them consider SO word interac-
tion; however, it is coarsely modeled or implicit-
ly captured. Based on the fashion of word repre-
sentation, they are generally grouped into Bag-of-
Words (BoW) and Word Embedding (WE) based
methods. We illustrate them as follows and related
notations are shown in Table 1.

2.1 Bag-of-Words (BoW) based Methods
In the Bag-of-Words model, words are indexed
and text documents are converted to vectors. The
values in such vectors can be word occurrence,
word counts or TF-IDF. In this case, sentiment in-
formation is learned by corresponding model pa-
rameters. Specifically, in linear models like Log-
istic Regression (LR) in Equation 1 or non-linear
models like SVM with feature projections (or ker-
nels) in Equation 2, we can see \( w \) is the parameter
capturing sentiment information under supervised
learning. For simplicity of illustration, bias terms
are excluded here but they will still be used in our
experiments.

\[
LR : y = \sigma(w \cdot x) \tag{1}
\]
\[
SVM : y = \langle w, \phi(x) \rangle \tag{2}
\]

When BoW is used in linear models like LR,
the sentiment information captured by \( w \) is inter-
pretable but we cannot measure the direct inter-
action between words. For example, a learned
parameter of the word “good” (i.e., \( w_{\text{good}} \)) can
make a text snippet containing “good” more likely
to be predicted as positive (when \( w_{\text{good}} > 0 \)),
which is straightforward. However, it has prob-
lems when predicting sentiment for snippets con-
taining “hard” and “push” or “hard” and “case”.
Ideally, their word-wise interaction should be con-
sidered but here the sentiment polarity is deter-
mined by \( w_{\text{hard}}, w_{\text{push}}, w_{\text{case}} \) which are indepen-
dent variables. On the other hand, when BoW
is used with non-linear projection like SVM with
non-linear kernels, it may help solve the problem
but it is harder to track the SO word interaction
due to the non-linear feature projections.

SVM with Polynomial Projection (SVM-Poly)
Using BoW with a \( m \)-degree polynomial feature
projection (or \( m \)-poly kernel) is an exception, for
example, the 2-poly kernel. Its feature mapping
and prediction function are shown in Equation 3
and 4. Note that the bias and linear terms are ex-
cluded for simplicity in Equation 4. One can see
this approach is capable of capturing word interactions, for instance, the direct interaction of “hard” and “case” can be parameterized as $w_{\text{hard, case}}$. However, this is still problematic as all such interaction parameters are independent. That is, we can learn $w_{\text{hard, case}}$ and $w_{\text{hard, push}}$ but they are two isolated parameters, regardless of the fact that they share the word “hard”. In addition, this approach suffers from data sparsity and we need $N^m$ parameters and $O(N^m)$ time complexity, especially when the keys words for interaction are distant, like “hard” and “case” in “the case I bought is really hard”. Finally, it is worth noting that the problems of $m$-gram BoW model ($m > 1$) are very similar to the ones of SVM-Poly by shifting the encoding of word-pairs from $w_{\text{hard, case}}$ to $x_{\text{hard, case}}$. For consistency, we will use SVM-Poly as a general case for the following discussion.

$$\phi_{\text{poly2}}(x) = (1, \sqrt{2}x_1, ... , \sqrt{2}x_n, x_1^2, ... , x_1^n, \sqrt{2}x_1x_2, ... , \sqrt{2}x_2x_3, ... , \sqrt{2}x_{n-1}x_n)$$

$$y = \langle w, \phi_{\text{poly2}}(x) \rangle$$

$$y = \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_{i,j}x_ix_j$$

2.2 Word Embedding (WE) based Methods

Recently word embeddings become widely used in many machine learning models. Generally speaking, the embeddings for words are mainly learned by maximizing the likelihood of correct prediction of contextual information, e.g., the skip-gram model (Mikolov et al., 2013a). Consequently, words that are semantically similar have similar representations, e.g., “cost” and “price”. However, such word embeddings do not directly carry sentiment information, e.g., “good” and “bad” are also neighbors\(^1\) in word vector space but they actually hold opposite sentiment polarities.

A natural way to learning sentiment information with WE is following the manner of BoW, i.e., to train a classifier like LR/SVM. Certainly, deep learning models like convolutional neural network (CNN) can be more suitable to employ word embeddings as input with their particular architecture designs. Recently some advanced models jointly encode semantic and sentiment information in word vector space (Kim, 2014; Tang et al., 2014). However, they still do not explicitly reflect SO word interaction.

The reason is, while most of the neural network models are based on full sentence/document modeling, they are coarse-grained in nature and not good at capturing fine-grained information at the word/snippet level (He and Lin, 2016). Specifically, let us first investigate the convolution operation in Equation 5. Note that a word is now denoted by a vector $v_i \in \mathbb{R}^k$. The learning parameter $w$ is applied to a window of $h$ words to generate a convolutional feature $c_i$. A feature map $c$ is then obtained by processing a sequence of words. After that, a max pooling operation is applied to take the maximum value (Collobert et al., 2011) for each such feature map.

Although here $w$ can capture the interaction between different words, it is not used in a word-wise manner, i.e., the SO word interaction is modeled implicitly, as is is hard to measure the direct interaction between two particular words, say “hard” and “case”. However, they can be explicitly encoded in $w_{\text{hard, case}}$ in SVM-Poly. Also, due to the non-linear function $f$ and pooling operation in CNN, the specific word interaction between two words becomes harder to track.

$$c_i = f(w \cdot v_{i:i+h-1} + b)$$

$$c = [c_1, c_2, ..., c_{n-h+1}]$$

3 Proposed Factorization Machines

As discussed above, some related models coarsely consider SO word interaction and they have limi-
tations. For example, CNN considers the contextual relationship between words and encodes all interactions in a general parameter \( w \) but the specific word-wise interaction is implicitly modeled and hard to track. SVM-Poly encodes SO word interaction in parameters like \( w_{i,j} \) but it requires \( O(N^m) \) such parameters and those parameters are all independent.

It will be a promising direction if we can adopt their advantages while overcome their shortcomings in a joint modeling process. Motivated by this, Factorization Machine (FM) is exploited by us. However, notice that FM is originally used in recommender system and does not directly applicable for fine-grained sentiment analysis. Therefore, we propose two new models CFM and PFM.

In this section, we first introduce the basis of FM. We then illustrate how to exploit it and point out its problems in fine-grained sentiment analysis. After that, we represent our new models, the optimization approach, and the analysis of complexity.

### 3.1 Factorization Machine Basis

Factorization Machine (FM) (Rendle, 2010) was proposed as a generic framework to learn the dependency of interaction variables by factorizing them into latent factors. A factor can be generally understood as a vector. So in this paper we will use the term factor and vector interchangeably. The model equation of 2-degree factorization machine is presented in Equation 6. Here \( v_i \) is called a factor/vector for element \( x_i \) \((v_i \in \mathbb{R}^k)\) and \((v_i, v_j)\) denotes the dot product operation of \( v_i \) and \( v_j \). Similarly, its linear and bias terms are not included here but will be used in experiments.

\[
y = \sum_{i=1}^{n} \sum_{j=i+1}^{n} (v_i, v_j) x_i x_j \quad (6)
\]

### 3.2 Exploiting FM for Sentiment Analysis

This is for test. We exploit FM for sentiment analysis in the following manner: while \( x_i \) is used as word features like LR/SVM for the word at position \( i \), the factor \( v_i \) can be viewed as its word vector. However, different from the traditional word embedding, the word vector here carries word-wise interaction information and is sentiment-sensitive. We refer it as sentiment-sensitive Word Interaction (SWI) vector. In this setting, the SO interaction between two words is determined by the dot product of their SWI vectors, for example, the interaction between “hard” and “case” is denoted by \((v_{hard}, v_{case})\).

Let us compare FM (Equation 6) and SVM-Poly (Equation 4) for a better understanding. By comparison, one can see that instead of using an independent interaction parameter \( w_{i,j} \), here the SO interaction effect of two words is jointly determined by two SWI vectors \( v_i \) and \( v_j \). Recall that \( w_{hard,case} \) and \( w_{hard,push} \) are two isolated parameters in SVM-Poly, but in our case, \((v_{hard}, v_{case})\) and \((v_{hard}, v_{push})\) can reflect that they share the same word “hard”, because they both contain the SWI vector \( v_{hard} \). Meanwhile, note that their resulting sentiment polarities are different, when \( v_{hard} \) interacting with \( v_{push} \) is probe to the negative class (e.g., \((v_{hard}, v_{push}) \approx 0\), where 0 indicate a negative sentiment class) and \( v_{hard} \) interacting with \( v_{case} \) is close to positive class (e.g., \((v_{hard}, v_{case}) \approx 1\)). The SWI vectors such as \((v_{hard}, v_{case})\) and \((v_{hard}, v_{push})\) are jointly learned under the supervision of sentiment labels.

However, this direct application of FMs is not suitable for fine-grained analysis at the snippet level due to two main reasons: (1) they lack the modeling of contextual information; (2) they do not consider the position/ordering of words. But they are two important signals to connect aspect and opinion information for sentiment reasoning at the snippet level. To address them, two new models are proposed and introduced below.

### 3.3 Contextual Factorization Machine

We first propose Contextual Factorization Machine (CFM). Different from other existing FMs, CFM models contextual information in text. Note that in fine-grained analysis, we aim at detecting sentiment for an aspect-specific opinion expression, for example, a snippet the screen is very clear from a full review “I made this purchase two days ago ... the screen is very clear ... ”. We observe that to generally determine the sentiment of that snippet, there is no need to catch fully pairwise word interactions. Concretely, the sentiment interaction between word “screen” to the first/last few words in the original full review could be less informative. Those words may even not be related to “screen” but another aspect (e.g., “purchase”). As a result, their word interactions can be harmful if they are involved in learning. So an intuitive solution is to focus on the interactions constructed by nearest contextual words. In other words, by cap-
turing the most significant word dependency, CFM can learn fine-grained SO interaction more accurately. Its model equation is shown in Equation 7. The idea is to impose a constraint $t$ so that word interactions will be learned within a certain distance, which is inspired by the neural skip-gram model. However, here it is designed for better alignment of aspect and opinion information but not for word prediction.

$$y = \sum_{i=1}^{n} \sum_{j=i+1}^{\min(i+t,N_d)} \langle v_i, v_j \rangle x_i x_j$$

$$= \frac{1}{2} \sum_{t=1}^{k} \left( \sum_{i=1}^{n} \sum_{j=\max(1,i-t)}^{\min(i+t,N_d)} v_i, v_j, x_i x_j \right)$$

$$- \sum_{i=1}^{n} v_i, v_{i,l}, x_i x_j$$

(7)

3.4 Position-aware Factorization Machine

One shortcoming of CFM is that it considers the same words with different word positions identical in SO interaction, which is not always true. In fact, word positions may be helpful to distinguish different sentiment polarities in some cases. To incorporate this indicative signal, we create a more comprehensive model named Position-aware Factorization Machine (PFM), where the SO word interaction, context and position information are jointly learned by the SWI vectors. Equation 8 shows its model equation. Compared to CFM, $ds(i,j)$ is newly-designed to denote the distance between two words. Take the snippet “the case is very hard” again as an example and we will have $\text{ds}(\text{case, hard}) = 3$, i.e., the distance between “case” and “hard” is 3, and now their SO word interaction is depicted as $\langle v_{\text{case,3}}, v_{\text{hard,3}} \rangle$.

$$y = \sum_{i=1}^{n} \sum_{j=i+1}^{\min(i+t,N_d)} \langle v_{i,ds(i,j)}, v_{j,ds(i,j)} \rangle x_i x_j$$

$$= \frac{1}{2} \sum_{t=1}^{k} \left( \sum_{i=1}^{n} \sum_{j=\max(1,i-t)}^{\min(i+t,N_d)} v_{i,ds(i,j),l}, v_{j,ds(i,j),l}, x_i x_j \right)$$

$$- \sum_{i=1}^{n} v_{i,ds(i,j),l}, v_{i,ds(i,j),l}, x_i x_j$$

(8)

3.5 Optimization

In terms of learning, we formulate our task as an optimization problem. Since the sentiment information needs to be learned by supervision from document labels (positive/negative), we use logistic loss to optimize. In addition, we impose L2 regularization parameterized by $\lambda$. Following (Jahrer et al., 2012), mini-batch based stochastic gradient descent (SGD) is used. We also implement the adaptive learning-rate schedule (Zeiler, 2012) to boost our learning process. Particularly, AdaGrad (Duchi et al., 2011) is adopted. We show the gradient of the factor $v_i$ in CFM below and the gradient for PFM can be derived similarly. $\lambda$ is the regularization term and $\eta$ is the learning rate.

$$g_{i,t} \leftarrow \sum_{j=\max(1,i-t), j \neq i}^{\min(i+t,N_d)} v_{j,ds(i,j),l} x_i x_j + \lambda v_{i,l}$$

$$G_{i,t} \leftarrow G_{i,t} + g_{i,t}^2$$

$$v_{i,t} \leftarrow v_{i,t} - \frac{\eta}{\sqrt{G_{i,t}}} g_{i,t}$$

(9)

3.6 Complexity and Analysis

We report the number of parameters and complexity for learning in Table 2. $n$ is the average length of one document. $t$ is the distance indicator and $k$ is the vector dimension. CNN-S means the CNN model using static word embeddings as input and CNN-J means the CNN model jointly learning word embeddings. The meaning of other symbols can be found in Table 1. We have the following observations: (1) both CFM and PFM are linear in $n$ for the growth of variables and complexity. (2) CFM and PFM are faster than FM because FM calculates all pairwise interactions while they do not need to. (3) CFM and PFM are both less complicated than SVM-Poly. While $O(N^2)$ parameters are required to learn all pairwise word interactions in SVM-Poly, only $O(Nk)$ ones are needed for FMs. (4) Compared to CNNs, CFM and PFM simplify the learning process. That is because while word embeddings are used in the input layer and CNN learns the sentiment information by other deep layers, the SWI vectors used in CFM and PFM jointly encode all related information.

4 Experiments

Our evaluation is two-step. First, we conducted sentiment classification at the document level using full online reviews. Second, we used the models built from full reviews to classify review snippets (phrases or sentences). Specifically, a set of review snippets with human labels (positive/negative) was used as our prediction targets.
while we still utilized the same set of full documents for training. The intuition is that, as discussed in section 1, the SO word interaction may have limited impact at the document level, but it plays a crucial role for fine-grained analysis at the snippet level, because a short text usually contains limited information or has less strong salient opinion words (e.g., “excellent”). In this case, when all candidate models are trained on a same set of full documents, a model better capturing explicit SO word interaction should be able to identify the sentiment of a short snippet more accurately.

### 4.1 Datasets

We use three real-word review datasets. The label for a full review can be directly obtained because a rating score is often provided, but the label for a text snippet requires human labeling. We thus download the human-labeled snippets from the UCI dataset as our test sets in our second step. They are word phrases or short sentences (snippets from full reviews) about movie from IMDB, cellphone from Amazon and restaurant from Yelp. Each set contains 1000 snippets (500 positive/negative). For full reviews, we use the movie review dataset from Pang and Lee (2004) which contains 1000 positive and 1000 negative movie reviews, cellphone reviews from McAuley et al. (2015), and restaurant reviews from Yelp. For consistency, 1000 positive and 1000 negative reviews are sampled from cellphone and restaurant. Reviews with rating scores 5 and 4 are treated as positive and scores 2 and 1 are treated as negative like (Chen et al., 2015; Johnson and Zhang, 2014). For the first task, the document-level sentiment classification, we conduct 5-folds cross validation using only full reviews. We split the data to 70%, 10%, 20% for training, validation, and testing for each data set. For the second task, we use the classifiers trained by all full reviews to classify review snippets. Notice that we have kept the same parameter settings for the classifiers used in both tasks. The average document/snippet length of each data set is reported in Table 3.

### 4.2 Candidate Models for Comparison

| Model      | Parameters | Time Complexity |
|------------|------------|-----------------|
| LR/SVM     | n          | O(n)            |
| FM         | nk         | O(nk)           |
| CFM        | nk         | O(nk)           |
| PFM        | nkt        | O(nk)           |
| SVM-Poly   | n^2        | O(n^2)          |
| CNN-S      | nk + lhkg  | O(lhkg)         |
| CNN-J      | nk + lhkg  | O(nk + lhkg)    |

**Table 2**: Comparison of the number of parameters and computing complexity with related models

| Data            | Training (docs) | Testing (snippets) |
|-----------------|-----------------|--------------------|
| Dataset         | Source          | Average Length    | Average Length    |
| Cellphone       | Amazon          | 90                 | 10                 |
| Restaurant      | Yelp            | 70                 | 11                 |
| Movie           | IMDB            | 668                | 15                 |

**Table 3**: Data Information

7% https://archive.ics.uci.edu/ml/machine-learning-databases/00331/
8% http://www.yelp.com/dataset_challenge
9% https://code.google.com/archive/p/word2vec/
4.3 Parameter Settings

For CFM and PFM, we set the context size \( t \) to 5 following related vector learning approaches (Mikolov et al., 2013b; Mnih and Kavukcuoglu, 2013) and the dimension of word vector \( k \) to 10. We did pilot experiments and found a bigger vector length does not have significant influence, which indicates that to learn SWI vectors a small vector length is enough. We maintain the same setting for training skip-gram vectors, which are used in SVM-WE, LR-WE, CNN-S and CNN-J. We learn vectors with a small vector length and simplified parameters from Mikolov et al. (2013b) for CNN-S(+) and CNN-J(+). The learning rate \( \eta \) is empirically set to 0.01 for CFM and PFM. The regularization term \( \lambda \) is set to 1 for CFM and PFM for all data sets, which works consistently well. Bias and L2 regularization terms are also used in SVM-BoW, LR-BoW, SVM-WE and LR-WE for consistency. We follow the parameter settings from Kim (2014) for CNNs.

### 4.4 Experimental Results and Analysis

The experimental results are given in Table 4, 5 and 6. In every table, the left hand side shows the accuracy and F1-Score for document-level sentiment classification and the right hand side shows the snippet-level ones. A table consists of two parts, where the lower part belongs to FM models (FMs) and the upper part presents the baseline models. The highest scores are marked in bold for both parts.

First, we have the following observations at the document level (from first two columns in tables):

1. Most models have competitive performance (except LR-WE, SVM-WE, CNN-S and CNN-J), which implies that when rich information is available in a full review, simply summarizing its overall sentiment orientation can alleviate the problem of lacking SO word interaction.
2. Our proposed models CFM and PFM are comparable to state-of-the-art baselines. While a small vector length and simplified parameters are used in CFM and PFM for learning, their performance is close to CNN-S/J(+), which is encouraging.
3. CFM and PFM outperform FM in all data sets, which shows their superiority and rationality in sentiment analysis.

Second, we have the following observations at the snippet level (from last two columns in tables):

1. Our proposed models CFM and PFM dramatically outperform other baselines significantly in this fine-grained setting. In addition, they can consistently achieve good results on three data sets.
2. Compared to CNN-S/J(+), CFM and PFM have better performance, even when these CNNs use...
bigger size vectors (length 300). It is worth noting that these two CNNs actually achieve very good results at the document level (see the left two columns) and their parameters are well fit; however, they do not perform well at the snippet level as ours, which indicates the effectiveness of capturing SO word interaction.

3. FM preforms very poorly and we can see the significant improvement gain from CFM and PFM which demonstrates their effectiveness for fine-grained sentiment analysis.

Third, we have the following further observations:

1. Considering the performances on both two settings, we can see the robustness of PFM and also CFM, where they can achieve consistently stable results.

2. We also tried SVM with different kernels including SVM-Poly, but the linear SVM achieves the best results consistently. It has also been reported by researchers that the linear kernel performs the best for binary text classification. (Joachims, 1998; Colas and Brazdil, 2006; Fei and Liu, 2015).

5 Related Work

In machine learning context, Bag-of-Words models were first used for building classifiers (Pang et al., 2002) for sentiment classification. Later, dense low-dimensional word vector becomes a better alternative (Blei et al., 2003) for word representation. Recently word embeddings like skip-gram model (Mikolov et al., 2013a) have shown their superiority in many NLP tasks (Turian et al., 2010). (Maas et al., 2011) first introduced a topic model variant to jointly encode sentiment and semantic information; later with the development of CNN (Collobert et al., 2011) in text mining, joint CNN models (Kim, 2014; Tang et al., 2014) achieve better and state-of-the-art results. But they did not conduct fine-grained analysis at the snippet level. (Tang et al., 2016; Li et al., 2017) performed aspect-level sentiment classification using aspect labels for training and testing, which is essentially different from our task. None of the above work explicitly captures SO word interaction.

Another related work is from He and Lin (2016) who considered the word interaction problem but aimed at mapping similar word interactions across different sentences. Johnson and Zhang (2014) inspected position information but it is not for modeling word interactions.

The concept of SO word interaction is related to sentiment negation/shifter theory (Polanyi and Zaenen, 2006), contextual polarity (Wilson et al., 2009) and sentiment composition related works (Choi and Cardie, 2008; Moilanen and Pulman, 2007; Neviarouskaya et al., 2009). However, they do not target at learning a joint model with information encoded in SWI vectors like us. Also, we do not use external resources like NLP parser (Socher et al., 2013; Naseem et al., 2010) to help infer sentiment information.

Factorization Machine (Rendle, 2010) is a general approach that learns feature conjunctions. It is widely used for recommender system (Jaher et al., 2012; Petroni et al., 2015; Juan et al., 2016) but existing FMs are not suitable for sentiment analysis. we also compared the classical FM in our experiments.

6 Conclusion

This paper introduced a framework that can explicitly capture sentiment-oriented word interaction by learning a set of sentiment-sensitive Word Interaction (SWI) vectors. Specifically, two new models were developed, namely, Contextual Factorization Machine (CFM) and Position-aware Factorization Machine (PFM). They benefit fine-grained analysis at the snippet level and also simplify the parameter learning. Extensive experimental results show their effectiveness.

References

David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. Journal of machine Learning research, 3(Jan):993–1022.

Zhiyuan Chen, Nianzu Ma, and Bing Liu. 2015. Lifelong learning for sentiment classification. In ACL (2), pages 750–756.

Yejin Choi and Claire Cardie. 2008. Learning with compositional semantics as structural inference for subentential sentiment analysis. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, pages 793–801. Association for Computational Linguistics.

Fabrice Colas and Pavel Brazdil. 2006. Comparison of svm and some older classification algorithms in text
classification tasks. In *IFIP International Conference on Artificial Intelligence in Theory and Practice*, pages 169–178. Springer.

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12(Aug):2493–2537.

Xiao Ding, Ting Liu, Junwen Duan, and Jian-Yun Nie. 2015. Mining user consumption intention from social media using domain adaptive convolutional neural network. In *AAAI*, volume 15, pages 2389–2395.

John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12(Jul):2121–2159.

Geli Fei and Bing Liu. 2015. Social media text classification under negative covariate shift. In *EMNLP*, pages 2347–2356.

Hua He and Jimmy Lin. 2016. Pairwise word interaction modeling with deep neural networks for semantic similarity measurement. In *Proceedings of NAACL-HLT*, pages 937–948.

Michael Jähner, Andreas Töscher, Jeong-Yoon Lee, J Deng, Hang Zhang, and Jacob Spoelstra. 2012. Ensemble of collaborative filtering and feature engineered models for click through rate prediction. In *KDD Cup Workshop*.

Thorsten Joachims. 1998. Text categorization with support vector machines: Learning with many relevant features. In *European conference on machine learning*, pages 137–142. Springer.

Rie Johnson and Tong Zhang. 2014. Effective use of word order for text categorization with convolutional neural networks. *arXiv preprint arXiv:1412.1058*.

Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. 2016. Field-aware factorization machines for ctr prediction. In *Proceedings of the 10th ACM Conference on Recommender Systems*, pages 43–50. ACM.

Nal Kalchbrenner, Edward Grefenstette, and Phil Blunsom. 2014. A convolutional neural network for modelling sentences. *arXiv preprint arXiv:1404.2188*.

Yoon Kim. 2014. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*.

Dimitrios Kotzias, Misha Denil, Nando De Freitas, and Padhraic Smyth. 2015. From group to individual labels using deep features. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 597–606. ACM.

Cheng Li, Xiaoxiao Guo, and Qiaozhu Mei. 2017. Deep memory networks for attitude identification. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pages 671–680. ACM.

Bing Liu. 2012. Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, 5(1):1–167.

Andrew L. Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*, pages 142–150. Association for Computational Linguistics.

Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton van den Hengel. 2015. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 43–52. ACM.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013b. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119.

Andriy Mnih and Koray Kavukcuoglu. 2013. Learning word embeddings efficiently with noise-contrastive estimation. In *Advances in neural information processing systems*, pages 2265–2273.

Karo Moilanen and Stephen Pulman. 2007. Sentiment composition. In *Proceedings of RANLP*, volume 7, pages 378–382.

Tahira Naseem, Harr Chen, Regina Barzilay, and Mark Johnson. 2010. Using universal linguistic knowledge to guide grammar induction. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, pages 1234–1244. Association for Computational Linguistics.

Alena Neviarouskaya, Helmut Prendinger, and Mitsuru Ishizuka. 2009. Compositionality principle in recognition of fine-grained emotions from text. In *ICWSM*.

Bo Pang and Lillian Lee. 2004. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In *Proceedings of the 42nd annual meeting on Association for Computational Linguistics*, page 271. Association for Computational Linguistics.
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up?: sentiment classification using machine learning techniques. In Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10, pages 79–86. Association for Computational Linguistics.

Fabio Petroni, Luciano del Corro, and Rainer Gemulla. 2015. Core: Context-aware open relation extraction with factorization machines. Assoc. for Computational Linguistics.

Livia Polanyi and Annie Zaenen. 2006. Contextual valence shifters. In Computing attitude and affect in text: Theory and applications, pages 1–10. Springer.

Steffen Rendle. 2010. Factorization machines. In 2010 IEEE International Conference on Data Mining, pages 995–1000. IEEE.

Richard Socher, Alex Perelygin, Jean Y Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, Christopher Potts, et al. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the conference on empirical methods in natural language processing (EMNLP), volume 1631, page 1642. Citeseer.

Duyu Tang, Bing Qin, and Ting Liu. 2016. Aspect level sentiment classification with deep memory network. arXiv preprint arXiv:1605.08900.

Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, and Bing Qin. 2014. Learning sentiment-specific word embedding for twitter sentiment classification. In ACL (1), pages 1555–1565.

Joseph Turian, Lev Ratinov, and Yoshua Bengio. 2010. Word representations: a simple and general method for semi-supervised learning. In Proceedings of the 48th annual meeting of the association for computational linguistics, pages 384–394. Association for Computational Linguistics.

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. 2009. Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis. Computational linguistics, 35(3):399–433.

Matthew D Zeiler. 2012. Adadelta: an adaptive learning rate method. arXiv preprint arXiv:1212.5701.