Incorporating Sample Filtering into Subject-based Ensemble Model for Cross-domain Sentiment Classification

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Abstract. Recently, cross-domain sentiment classification is becoming popular owing to its potential applications, such as marketing et al. It seeks to generalize a model, which is trained on a source domain and using it to label samples in the target domain. However, the source and target distributions differ substantially in many cases. To address this issue, we propose a comprehensive model, which takes sample filtering and labeling adaptation into account simultaneously, named joint Sample Filtering with Subject-based Ensemble Model (**SF-SE**). Firstly, a sentence level Latent Dirichlet Allocation (LDA) model, which incorporates topic and sentiment together (SS-LDA) is introduced. Under this model, a high-quality training dataset is constructed in an unsupervised way. Secondly, inspired by the distribution variance of domain-independent and domain-specific features related to the subject of a sentence, we introduce a Subject-based Ensemble model to efficiently improve the classification performance. Experimental results show that the proposed model is effective for cross-domain sentiment classification.

Keywords: Cross-Domain; SS-LDA; Sentiment Analysis

1 Introduction

Web 2.0 presents an online forum for people to express their feelings on anything freely. Under this situation, as a special task of text classification, sentiment classification (Pang, Lee, and Vaithyanathan 2002; Pang and Lee 2008) has become attractive because of its potential commercial applications (Liu, Huang, and An 2007; Yu, Liu, and Huang 2012). However, sentiment classification is domain-specific due to the divergent distributions. Traditional supervised classification methods usually perform poorly when the training and test data belong to completely different domains. This is largely because the sentiment polarities depend on the domain or the topic where they are expressed to a large degree. Some opinion words, which convey positive sentiment in one domain may express little or opposite meaning in another domain. For example, in book reviews, the high-frequency word "*superficial*" often indicates negative sentimental orientation. But it hardly appears in electronics reviews. Similarly, the word "*smoothly*" may be positive in electronics reviews, but it bears little semantic orientation when talking about books. Furthermore, with the rise of new areas, collecting annotated data is time-consuming and expensive. So, how to effectively transfer a classifier trained on source domain to the target domain is challenging and significant.

In this paper, we propose a two-stage model, which takes sample filtering and labeling adaptation in account for cross-domain sentiment classification. During experimental procedure, each training review (sample) is segmented into a sentence set. In the first stage, we introduce a novel topic model that incorporates topic and sentiment simultaneous on sentence level (SS-LDA) for constructing a reliable training dataset. In the second stage, considering the subject of a sentence, a view mining method combining heuristic rules and machine learning algorithm will be proposed to classify each sentence into corresponding views, namely personal and object view for distinguishing. The experimental results demonstrate that our method is effective for cross-domain sentiment classification.

Organization of the rest paper is as follows. Section 2 will introduce the related works of domain adaptation in sentiment classification. In section 3, we present SS-LDA model for sample filtering. Section 4 will discuss the Subject-based ensemble model for cross-domain sentiment classification. Then experimental results and analysis will be shown in section 5. At last, section 6 draws our conclusions and outlines directions for future work.

2 Related Work

Exiting works for domain adaptation in sentiment classification mostly belong to feature-based transfer methods (Blitzer, McDonald, and Pereira 2006; Blitzer, Dredze, and Pereira 2007; Pan, Ni, and Sun 2010; He, Lin, and Alani 2011; Duan andXu 2012), such as the Structural Corresponding Learning (SCL) (Blitzer, Dredze, and Pereira 2007), the Spectral Feature Alignment (SFA) (Pan, Ni, and Sun 2010) et al. The key idea of SCL is to detect a shared latent space by modeling the correlations between pivot features and non-pivot features for transfer learning. In SFA, spectral clustering algorithm is employed to co-cluster the domain-dependent and domain-independent features into a common latent space. In addition, Duan et al. (Duan andXu 2012) augment the heterogeneous features from the source and target domains by using two newly proposed feature mapping functions respectively. The representative example of instance-based transfer method is instance weighting for domain adaptation proposed by Jiang et al. (Jiang andZhai 2007).

There also exits some works belonging to parameter-based transfer method (Xia and Zong 2011; Samdani and Yih 2011; Gao, Fan and Jiang 2011; Yoshida, Hirao, and Iwata 2011), such as POS-based ensemble model introduced by Xia et al. (Xia and Zong 2011). In addition, Gao et al. (Gao, Fan and Jiang 2011) propose a locally weighted ensemble framework to combine multiple models for transfer learning. Our model also belongs to parameter-based transfer approaches, but different from above-mentioned works, we add a procedure for training sample filtering. During training sample filtering, we raise a topic model which incorporates topic and sentiment simultaneously based on sentence level. Distinguishing form Joint Sentiment/Topic model (*JST*) (Lin and He 2009) which adds a sentiment layer between the document and the topic, SS-LDA puts an additional sentiment layer between the topic and the word layer. Moreover, SS-LDA bases on sentence level while *JST* depends on document level.

The most closely related work to ours is Feature Ensemble plus Sample Selection model (**SS-FE**) (Xia and Zong 2013) proposed by Xia et al. But there are still several intrinsical differences between **SS-FE** and **SF-SE**. Firstly, **SF-SE** implements the sample filtering procedure on sentence level by topic model whereas **SS-FE** processes on document level relying on Principal Component Analysis (**PCA**). Secondly, the view division strategy of **SF-SE** is inspired by the distribution variance of domain-independent and domain-specific features related to the subject of a sentence. However, **SS-FE** considers that the features with different type of POS tags may have distinct change across domains. Overall, there are several limitations in **SS-FE**.

3 Methodology

3.1 SS-LDA

The Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) model is a well-known topic model based on the assumption that documents are mixture of topics. It has been widely used in the field of NLP (such as Lu, Ott, andCardie 2011). In order to mining the sentence sentiment polarities, we propose an expansion of LDA model, jointing sentiment with topic based on sentence level, named SS-LDA. The motivation is that sentiment polarities usually depend on topics. For example, in electronics reviews, the adjective “complex” may bear negative orientation while talking about cell phone operations. However, it also has positive orientation when describing the novel plot in books reviews. The SS-LDA model has four layers where a sentiment layer is added between the topic layer and the word layer, as shown in figure 1. In SS-LDA, the sentiment layer is associated with the topics while the words are associated with both the topic and sentiment layers. Figure 1 shows the framework of SS-LDA.

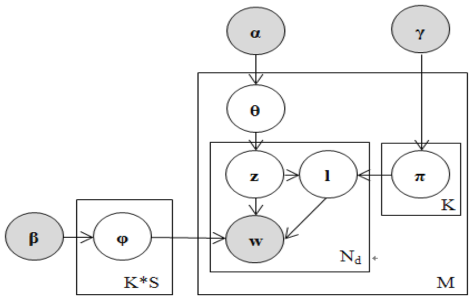


Fig.1 The framework of SS-LDA

Assume that there is a dataset with a collection of M review sentences, denoted by $C = \{d_1,d_2,...,d_m\}$. Each sentence is a sequence of N_d words denoted by $d = \{w_1, w_2,...,w_n\}$. And each word in sentence is an feature from a vocabulary index with V distinct terms denoted by $V = \{1,2,...V\}$. K refers the total number of topics and S is the number of sentiment labels. More detailed notations are presented in table 1.

Tab.1 The notations of SS-LDA

Notations	Meanings
M / K / S / N_d	the number of sentences / topics / sentiments / words
z	topic label
l	sentimental label：(positive / negative / neutral)
θ	multinomial distribution over topics
π	multinomial distribution over sentiments
φ	multinomial distribution over words
α / β / γ	the hyper parameters

In this paper, S is set to 3, that is to say, for a sentiment variable l, if $l = 1$, the corresponding sentiment is positive; “-1” indicates negative orientation; the value of “0” implies neutral sentiment. The formal definition of the generative process of SS-LDA model is as follows:

1. For each sentence d, choose a distribution θ from $Dir\ (\alpha)$
2. For each topic z, under sentence d, choose a distribution $\pi_{d,z}$ from $Dir\ (\gamma)$
3. For each word w_i in sentence d
   1) Choose a topic z_i from θ_d
   2) Choose a sentiment label l_i from π_{d,z_i}
   3) Choose a word w_i from the distribution over words defined by topic z_i and sentiment label l_i, $\varphi_{z_i l_i}$

In order to inference the algorithm, we utilize Gibbs Sampling for estimating the latent variable θ, φ, π. Firstly, conditional probability $P\ (z_i = z, l_i = l \mid z_{-i}, l_{-i}, w)$, where z_{-i} and l_{-i} are vectors of assignments of topics and sentiment for all the words in collection exception the considered word at position i in a given sentence should be calculated.

$$P(z_i = z, l_i = l \mid z_{-i}, l_{-i}, w) \propto \frac{\{n_m^{(z)}\}_{-i} + \alpha}{\{n_m\}_{-i} + K\alpha} * \frac{\{n_m^{(z,l)}\}_{-i} + \gamma_l}{\{n_m^{(z)}\}_{-i} + \sum_{l=1}^{S} \gamma_l} * \frac{\{n_{z,l}^{(t)}\}_{-i} + \beta}{\{n_{z,l}\}_{-i} + V\beta} \tag{1}$$

Where, n_m^z is the number of times words assigned to topic z in sentence m; n_m is the total number of words in sentence m; $n_m^{(z,l)}$ is the number of times words assigned to topic z and sentiment l in sentence m; $n_{(z,l)}^t$ is the number of times word i appeared in topic z with sentiment l; $n_{z,l}$ is the total number of times words assigned to topic z and sentiment l; the subscript $-i$ denotes a quantity that excludes data from the position i.

$$\theta_m^{(z)} = \frac{n_m^{(z)} + \alpha}{n_m + K\alpha} \tag{2}$$

The approximate probability of topic z for sentiment l in sentence m is:

$$\pi_m^{(z,l)} = \frac{n_m^{(z,l)} + \gamma_l}{n_m^{(z)} + \sum_{l=1}^{S} \gamma_l} \tag{3}$$

In addition, the approximated predictive distribution of word i for sentiment l and topic z is:

$$\varphi_{z,l}^{(t)} = \frac{n_{z,l}^{(t)} + \beta}{n_{z,l} + V\beta} \tag{4}$$

3.2 Sample Filtering

Due to varieties of topics, customers mostly express mixture sentiments in a product feedback review. The following provides two reviews in electronic domain. By observing the samples, the first one has overall positive sentimental orientation, while the second one bears negative orientation generally. Take the first review for example, the first three sentences are consistent with the overall sentiment polarity whereas the last sentence reveals opposite orientation on sentiment. Hence, assigning an accurate sentiment label to a given review may be uncertain when annotated. That is to say, the manual labeled training dataset may be unreliable actually. So how to construct a reliable training dataset for building a precise model is indispensable. Assuming that, a high quality training sample is supposed to be consistent for its included sentences on sentimental orientations.

Tab.2 Reviews with mixture sentiment

Reviews	Review sentences	Overall sentimental polarity
Case 1	The design for this headset is ingenious. The audio quality is pretty good. I'm also very satisfied with the reasonable price. *But the earpieces are uncomfortable for my ears*	positive
Case 2	*I bought this DVDs player eight months ago and was quite satisfied.* But it constantly gives "Bad Disc" errors and skips since the last week. I am really disappointed for its bad quality.	negative

Based on the above analysis, we propose a training sample filtering procedure on sentence level. In detail, we firstly split every sample into a sentence set. For a given training sample, we move the sentences whose sentiment orientations opposites to that of the sample. In order to mining the sentiment polarity of every sentence, SS-LDA is adapted for orientation prediction. Particularly, clustering is implemented for the sentence collection by SS-LDA. Furthermore, prior knowledge that obtained from sentiment lexicons is utilized during the initialization for Gibbs Sampling. After modeling the parameters, we can use the following equations to calculate the sentiment polarity for the sentence *m*.

$$p(s=l \mid d=m)=\sum_{z=1}^{K}\theta_m^{(z)} * \pi_m^{(z,l)} \tag{5}$$

$$y_m = \arg\max_l p(s=l \mid d=m) \tag{6}$$

Where the variable *y* denotes the sentiment label of sentence *m*. Given a training sample *r* that consists of *n* sentences denoted as $\{d_1,d_2,\ldots,d_n\}$, we assume that its manual annotated overall sentiment label refers as l_r. We will remove the sentence d_i which satisfies the following criteria:

$$d_i \in \{d_i \mid l_r = Oppo(y_{d_i}) \wedge p(s=y_{d_i} \mid d_i) > \delta \wedge i \in [1,n]\} \tag{7}$$

Where the function $Oppo(y_m)$ denotes the opposite sentiment label from y_m. And δ is a posteriori probability confidence threshold value. From the description above, we can see that only the sentence associated with strong opposite sentiment polarity to the belonging sample will be filtered. We regard the samples which consist of the remaining sentence as high quality training dataset. These training samples are expected to build a more precise classification model for the remaining works due to its purity on sentimental orientation.

3.3 Subject-based Ensemble Model

The task of sentiment classification is domain-specific. Classifiers trained on the source domain usually perform poorly in the target domain owing to the changing of feature distribution. So how to eliminate the differences between the source and target domain are significant for transfer learning.

The dataset is divided into two views based on the subject of the sentence, personal and object views in this paper. The intuition is that when domain changes, the vocabulary implying sentimental orientation in personal view usually changes slightly. In object view, however, it changes obviously. Based on this observation, we can conclude that the majority of words with semantic opinion orientation in personal view are domain-independent while domain-specific in object view. A motivating example will be shown in table 3:

Considering the reviews in table 3, we find that words in personal view, such as "*disappointed*" and "*recommend*", usually act domain-independent across domains. More specifically, they express similar sentimental orientation across domains. However, in object view, some opinion words like "*superficial*" and "*portable*" often behave domain-specific. In other words, they often appear in a particular domain. Apparently, the personal view changes rarely between domains. On the contrary, the object view varies sharply across domains. So, we infer that the performance of cross-domain sentiment classification might benefit more from personal view.

Tab. 3 An example on personal/object view

Domain	Personal view	Object view
Books	I *dislike* the cover style of this book.	The bestseller is really *informative.*
DVDs	My friends were *disappointed* to the sound.	It *broke down* several times in the past weeks.
Electronics	Do not *waste* your time and money	This flash disk is very *smart* and *portable*!
Kitchen appliances	Highly *recommend*.	Works *intermittently*.

Holding this belief, we observe the Jensen-Shannon divergence (***JSD***) (Lin 1991) between source and target domains. The Jensen-Shannon divergence is widely used to measure the variance between two probability distributions. It is asymmetry and smoothed version of the Kullback-Leibler (*KL*) divergence. More specifically, the ***JSD*** divergence between distribution *P* and *Q* can be measured as follows:

$$JSD(P \| Q) = \frac{1}{2} KL(P \| M) + \frac{1}{2} KL(Q \| M) \tag{8}$$

Where M = 1/2 (P + Q) and $KL(*\|*)$ is the Kullback-Leibler divergence between two distributions. So, the less ***JSD*** of two domains is, the more similar their distributions act. That indicates that people often express their opinions using similar vocabularies in these domain reviews. Intuitively, domain-independent words appear frequently in similar domains.

4 Experiments and Analysis

4.1 Dataset Description

Our experiments are carried out on the Multi-Domain Sentiment Dataset collected by Blitzer et al. It has been widely used in the field of cross-domain sentiment classification. The dataset consists of product reviews from four domains: books, DVDs, electronics and kitchen appliances, B, D, E and K for short in this paper. Each domain contains 1000 positive, 1000 negative reviews besides hundreds of unlabeled reviews. Table 4 shows the scale of dataset. We can see that the review in domain books and DVDs is relatively longer than that in domain electronics and kitchen appliances. After observation, we find that people often discuss the story of books and films in these domain reviews. Owing to this reason, the review is usually larger.

4.2 Experiment Setting

For each domain, we randomly sample 800 positive reviews and 800 negative reviews from labeled dataset as training instances while the remaining is used for testing. During sentiment classification, 5-fold validation is applied to evaluate the performance. Following majority of previous works, we use accuracy to evaluate the classification performance in this paper.

In the stage of data preprocessing, Stanford Core NLP Parser is applied to stemming and segment all the reviews into sentences. Sentence subject detection is also carried out by parsing for the sake of view division in the following stage. Following pervious work (Xia and Zong 2011), in order to reduce the dimensionality, we only use features including unigrams and bigrams that appear at least 4 times in a particular task. Additionally, we remove the stop words and punctuations for sake of less noisy. Further, feature weight is measured via standard tf-idf algorithm.

With respect to the training sample filtering procedure, we implement SS-LDA model based on JGibbs LDA package. The number of topics is set ranging from 20 to 60. In the latter section, we will discuss the effect of topic number on the experimental performance. During Gibbs Sampling, we set the number of iterations to 1000 times because the distributions have been relatively stable after 1000 iterations. Besides, in order to improving the sentiment detection, prior knowledge is incorporated during the initialization of Gibbs Sampling. The sentiment prior knowledge is mainly obtained from the sentiment lexicon MPQA. At last, we set the confidence threshold δ to 0.8.

In the stage of Subject-based ensemble, the sentences are divided into personal/object views respectively. Then base classifiers are built according to corresponding dataset. Furthermore, Stochastic Gradient Descent (*SGD*) that optimizes the Minimal Classification Error (*MCE*) is exploited to obtain the best parameter settings for combination. For simplicity, we use “X_Y” to denote the task transferring from domain X to Y for sentiment classification. In our experiment, support vector machine (SVM) is implemented as classification algorithm with the help of Lib-SVM tools. And linear kernel function is adopted besides default parameter setting.

Tab. 4 Scale of the dataset

Domain	Average number of sentences	Average length of review
books	8.5	175.6
DVDs	9.6	194.6
electronics	6.7	116.7
kitchen appliances	5.8	98.6

4.3 Baselines

For illustrating the effectiveness of our method **SF-SE**, we present several methods for comparison including some state-of-the-art cross-domain classification methods in this sub-section. All these algorithms are described as follows:

NoTrans: This baseline means that the classifier trained on all the source domain dataset only and applied to target domain samples for classification directly using SVM.

SF: SF (Sample Filtering) which refers the first stage of our model is similar to NoTrans. The only difference is that the classifier is trained on the high quality training data after SS-LDA filtering.

SCL: SCL, short for structural correspondence learning, is proposed by Blitzer et al. in 2006. We follow the details described in Blitzer's thesis to implement SCL.

SFA: SFA is well-known domain adaptation algorithm proposed by Pan et al (Pan, Ni, and Sun 2010). It can discover the shared latent space via fully exploiting the features relationship with the aid of spectral clustering algorithm.

SS-FE: SS-FE (Feature Ensemble plus Sample Selection) is the most closely related work to ours. The basic idea of SS-FE is utilizing features ensemble according to Part-of-Speech (POS) after training sample selection procedure by PCA.

4.4 Experimental Results and Analysis

Considering the complex expression, we firstly employ SS-LDA to cluster the training dataset for detecting sentimental orientation on sentence level. The motivation is that the sentences deriving from a specific review might belong to different topics. Hence, people might convey completely different sentimental orientations. In summary, filtering the sentences whose polarities opposite to the overall orientation is significant for constructing a high quality training set.

Figure 2 shows the performance of **SF** when topics ranging from 20 to 60. The symbol "X_*" refers the tasks transferring from domain X to other domains. Noting that, the performance of **SF** is sensitive to the number of topics. Generally speaking, best performance is obtained when the number of cluster topics is set to 40, whereas worst on 20 topics.

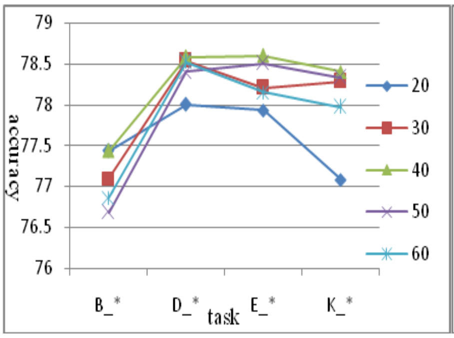


Fig.2 Performance of SF

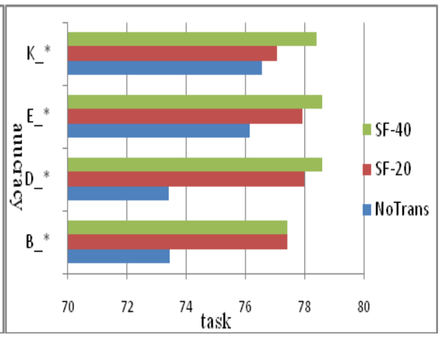


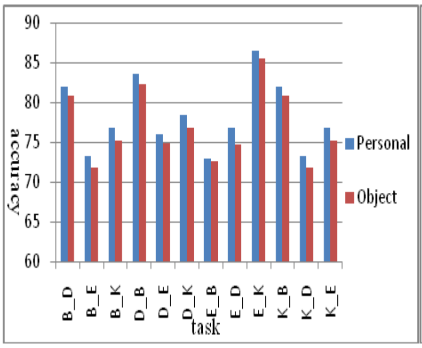
Fig. 3 Comparison between NoTrans and SF

Figure 3 reveals the comparison between **NoTrans** and **SF** when best and worst performances obtained. Simply, we use the symbol "SF-topicNum" denoting the classification accuracy when topic number is set to "topicNum".

Observing the result above, we can conclude that the performance of **SF** gets significant improvement compared with **NoTrans** which using all the sentences in source domain. Particularly, when the cluster topic is set to 40, it gets the best performance, approximately 3.4% improvement compared with **NoTrans** on average classification accuracy. As mentioned above, mixture sentimental polarities are usually conveyed owing to various topics talked in a review. This phenomenon leads to uncertainty when label the training samples. That is to say, the classification model might not accurate when applying these samples for training directly. By SS-LDA filtering, we move the sentences whose sentimental polarity strongly opposites the overall orientation. This procedure can enhance the reliability of the training set to a certain extent. Therefore the classification performance will be improved due to the more precise model built.

Figure 4 presents the classification performance of different base classifiers, where "personal" denotes the task using the personal view for training, the similar definition for "object" respectively. Note that the classifier based on personal view performs better than object classifier completely, 1.32% in average. In particular, the task "E_D" achieves the largest improvement by 2.05%. The experimental results are coincident with our assumption. More specifically, the personal view contributes more than object view in cross-domain sentiment classification because most domain-independent opinion words are from personal view.

To demonstrating the effectiveness of our model, we compare it with several state-of-the-art cross-domain classification methods mentioned in Baseline. Figure 5 shows these comparisons.



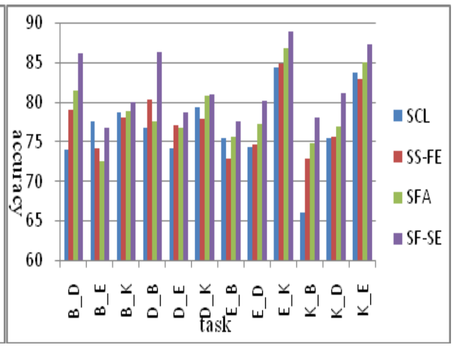


Fig. 4 Performance of personal/object view **Fig. 5** Performance of different algorithms

Compared with **SS-FE**, **SF-SE** shows its superiority in almost all the tasks, approximately 4.3% in average. This justifies the effectiveness of our model again. Firstly, different from **SS-FE** which conducting filtration on sample level, **SF-SE** only filters the sentences whose sentimental orientation opposite to that of the belonging sample. Obviously, we can fully exploit the training dataset. Furthermore, our subject-based view division strategy is more coincident with the distribution of domain-independent/domain-specific words compared with POS-based view division.

In detail, thousands of domain-independent opinion words such as “like”, “hate” are verbs. On the contrary, the subject-based model ignores the POS tags of vocabulary, mainly focusing on the distribution of domain-independent/domain-specific words. Still, compared with **SCL** and **SFA**, **SF-SE** gains relatively advantages by 5.2%, 3.2% in average accuracy.

5 Conclusions and Future Work

With the explosive expansion of online subjective data, cross-domain sentiment classification has attracted more attention in NLP and data mining field. In this paper, we propose a **SF-SE** model for cross-domain sentiment classification. During sample filtering, an extended LDA that incorporates sentiment on sentence level, named SS-LDA is adapted. Additionally, a Subject-based ensemble model is introduced, motivating that the opinion words in personal view are usually domain-independent while domain-specific in object view. Therefore, an efficient ensemble of them could leverage distinct strengths and improve the classification performance. Finally, experiments demonstrate that the proposed is effective for cross-domain sentiment classification.

In the future, subjectivity summarization strategy (Pang and Lee 2004) will be integrated to help reducing noisy objective sentences. Because objective sentences usually contains little semantic orientation. Moreover, we should improve our view mining algorithm for more accurate view division.

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