

# Target-based Sentiment Annotation in Chinese Financial News

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## Abstract

This paper presents the design and construction of a large-scale target-based sentiment annotation corpus on Chinese financial news text. Different from the most existing paragraph/document-based annotation corpus, in this study, target-based fine-grained sentiment annotation is performed. The companies, brands and other financial entities are regarded as the targets. The clause reflecting the profitability, loss or other business status of financial entities is regarded as the sentiment expression for determining the polarity. Based on high quality annotation guideline and effective quality control strategy, a corpus with 8,314 target-level sentiment annotation is constructed on 6,336 paragraphs from Chinese financial news text. Based on this corpus, several state-of-the-art sentiment analysis models are evaluated.

**Keywords:** Target-based Sentiment, Annotation, Chinese Financial Text

## 1. Introduction

With the rapid development of the Internet, it becomes easier to collect a large scale of public textual data. Identifying the sentiment corresponding to the financial entities such as companies from the financial text is crucial to financial investment and decision making. Thus, sentiment analysis techniques on financial text attracted much research interest in the recent years.

Sentiment analysis (SA) is a hot research topic in natural language processing. It has gained increasing popularity due to the its widely applications (Pang et al., 2008). (Kim, 2014; Li et al., 2015; Zhou et al., 2016; Yang et al., 2016; Chen et al., 2017; Li et al., 2015) focused on classifying the given text as positive, negative, neutral at document level and sentence level. However, the accuracy of sentiment classification on multiple opinion aspects/targets level is unsatisfactory. Especially, such kind of fine-grained sentiment analysis is essential to many practical applications. Hence aspect-based sentiment analysis (ABSA) (Pontiki et al., 2014; Pontiki et al., 2016; Poria et al., 2016), target-based sentiment analysis (TBSA) (Tang et al., 2016a; Tang et al., 2016b; Dong et al., 2014; Wang et al., 2017) and targeted aspect-based sentiment analysis (TABSA) (Liang et al., 2019; Ma et al., 2018) had been proposed to tackle the subtler sentiment in term of different aspects/targets in a sentence. For TBSA, it aims to identify the sentiment expression and determine the polarities of different target entities. Take the following Ex.1, as an example, there are three entities in this paragraph, 乐融致新(*LeMall*), 乐视网(*LETV*) and 乐视控股(*LeEco*). 乐融致新(*LeMall*) and 乐视网(*LETV*) appear more than once and their corresponding sentiment polarities are negative, while for 乐视控股(*LeEco*), the polarity is neutral.

**Ex.1** 虽然乐融致新增资获得通过，但记者从乐视网人事处了解到，今年至今，无论是乐融致新还是乐视网，业务发展的颓势仍没有出现明显的好转。而对于这种情况的持续，外界以及乐视网都将部分原因归结于乐视控股等关联方应收款项的难以收回。

*Although capital increase in LeMall is approved, our journalist has learned from personnel department of LETV that in this year, neither LeMall nor LETV has gained significant improvement in their business development. With the continuation of this situation, the outside world and LETV partly attribute it to the difficulty in recovering their receivables of related parties such as LeEco.*

There are three major difficulties in this study of target-based sentiment analysis in financial text. Firstly, up to now, existing ABSA/TBSA corpora are mainly sub-domain of commodity comment text, e.g. (Pontiki et al., 2014; Pontiki et al., 2016). And except for FiQA<sup>1</sup>, there are few large open dataset available for financial TBSA. As a result, TBSA in financial text has been hindered by the data scarcity. Secondly, most existing ABSA/TBSA corpora annotated aspect/target based sentiment information on each sentence, but lost the context. The third is that corpus annotation and quality control is always complicated and difficult. To address these problems, in the paper, we design and construct a large-scale target-based sentiment annotation corpus on Chinese financial news text. This TBSA corpus is quite different from most existing sentiment analysis corpora, because in the financial news text, most expressions are objective and declarative statements. Furthermore, for the subjective expression, the targets and corresponding sentiment expression are often dense. Ex.1 shows a example for TBSA in financial domain. 乐视网(*LETV*) appears for three times with one sentiment expression, and 乐融致新(*LeMall*) appears for twice with one sentiment expression. The fact that multiple entities may appear in one paragraph and each entity may appear more than once,

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<sup>1</sup><https://sites.google.com/view/fiqa/home>

makes TBSA in financial domain a more challenging problem comparing to the traditional TBSA.

In this study, we designed clear annotation scheme and detailed annotation guidelines. Besides, we develop an annotation system to construct this corpus efficiently. Finally, we constructed a large corpus on financial news text with target annotation and target-based sentiment annotation. Using this corpus as a benchmark, some state-of-the-art TBSA algorithms are evaluated.

To sum up, the contributions of this paper are three folds:

- We designed a target-based sentiment analysis corpus with clear definition and efficient annotations for TBSA task.
- We proposed a detailed annotation guideline and annotation quality control scheme for constructing this corpus.
- We presented a large Chinese Financial Target-based Sentiment Analysis corpus (FiTSA). The multiple financial entities, sentiment targets and corresponding polarities are annotated in paragraphs from Chinese financial news text.
- A corpus with 8,314 target-level sentiment annotation is constructed on 6,336 paragraphs. It is the known largest target-based sentiment annotated corpus on Chinese financial text.
- Using this corpus as a benchmark, some state-of-the-art TBSA algorithms are evaluated which is helpful to promote the relevant research.

The rest of this paper is organized as follows. Section 2 briefly reviews the related work. Section 3 presents the corpus design issues including annotation scheme, annotation guideline and annotation tool. Section 4 gives the detail of corpus construction including data preparation, annotation process and quality control. The statistics of FiTSA is given in Section 5. The evaluations on FiTSA are presented in Section 6 and finally Section 7 concludes.

## 2. Related Work

There are a few available ABSA/TBSA dataset in which most of them are for English. Currently, the widely used ABSA/TBSA dataset, SemEval 2014 and SemEval 2015, are on user product reviews. Moreover, because of expensive annotation cost for fine-grained sentiment annotation, most of these dataset is at sentence-level with short text length. Finally, the scale of these dataset are small.

For English dataset, SemEval 2014 subtask 4 (Pontiki et al., 2014) and SemEval 2015 subtask 12 (Pontiki et al., 2015) aimed at detecting sentiment polarity given a target or an aspect. The sentiment expressions are annotated on user product reviews about restaurants and laptops. Both of them annotated targets and aspects in sentence-level. Twitter (Dong et al., 2014) is also a widely used ABSA dataset. It collected data from tweets concentrating on celebrities, products, and companies. Twitter dataset made balanced sentiment polarity proportion for 25% negative, 50% neutral, and 25% positive.

SentiHood (Saeidi et al., 2016) focused on locations and neighborhoods. Different from previous dataset, SentiHood replaced all targets with specific terms using Location\_1 or Location\_2.

There exist few Chinese ABSA dataset. SemEval 2016 subtask 5 (Pontiki et al., 2016) released two domain-specific dataset for consumer electronics including mobile phones and digital cameras.

For financial ABSA dataset, (Gaillat et al., 2018) constructed the SSIX corpora on stock market related micro-blog text which aimed at annotating continuous sentiment scores. FiQA 2018 challenge subtask1 constructed a financial ABSA dataset on micro-blogs and headlines. Different from traditional ABSA task, FiQA aimed at predicting aspects in a given snippet and its corresponding sentiment score at the same time.

## 3. Corpus Design

To construct a high quality target-based sentiment annotation corpus, firstly we design a detailed annotation scheme and guidelines. To enhance the annotation efficiency, we developed an annotation tool.

### 3.1. Annotation Scheme and Guideline

There are two essential objects which should be annotated for our target-based sentiment annotation corpus, namely target entities and sentiment polarity of each target entity. For assisting annotators in better understanding sentiment and annotation checking, we need also annotate the sentiment expression clauses.

#### Target entity annotation

Enterprises are the subject in economic activities. Thus, the entities corresponding to enterprises are candidates of the sentiment targets. In the corpus design, the first step is to determine how to annotate these entities. Based on the observation on the financial text, the candidate entities is decided to include name of the company, brand name (normally it is the abbreviation of a company name) and other financial entity. Some examples and corresponding discussions are given below:

1. **company name + region name or region name + company name:** taking 奔驰中国(Mercedes-Benz China) as an example, the company name is 奔驰(Mercedes-Benz) and region name is 中国(China). We should annotate them together as one entity.  
*Example:* 德国戴姆勒与奔驰中国达成一系列商业协议(Germany's Daimler and Mercedes-Benz China reach a series of commercial agreements)
2. **enterprise attribute + company name:** Sometimes, there are some description words appearing before the name of company which indicate the attribute of the company. For these cases, the attribute words are not regarded as part of target entity. In the following example, we do not annotate 俄罗斯风投基金(Russian venture capital fund) as a part of the entity Apoletto.  
*Example:* 除此之外, 俄罗斯风投基金Apoletto与中金公司也跟投此轮融资(Besides, Russian venture capital fund Apoletto and CICC also invested in this round of financing)

3. **company name + professional title:** For these cases, the professional title is not regarded as the part of enterprise entity. For the following example, CFO is a professional title and it is not regarded as entity.

**Example:** 天府国际公司董事长宣布与阿里巴巴CFO完成会面，达成相关商业协议(*The chairman of Tianfu International Corporation announced the completion of the meeting with the Alibaba CFO and reached a relevant business agreement*)

4. **company abbreviation and stock code:** The abbreviation of a company name or the corresponding stock code are regarded as the alternative expression of company name. Thus, they are also annotated as the targets. For the following example, we annotate 阿里巴巴网络技术有限公司(*Alibaba Group*), "BABA.NYSE" and 阿里(*Ali*).

**Example:** 已入股小鹏汽车的阿里巴巴网络技术有限公司 (BABA.NYSE, 以下简称阿里), 也是此轮融资的联合领投资方(*Alibaba Group (BABA.NYSE, hereinafter referred to as Ali), which has already invested in Xiaopeng Motors, is also the joint lead investor of this round of financing*)

5. **brand name:** The general brand name is regarded the abbreviation of a company. However, when the brand name is used to define specific product, it is not regarded as enterprise entity. In the following example, 荣耀6 PLUS(*Honor 6PLUS*) and 荣耀V8(*Honor V8*) are specific products and thus they are not annotated while the bold brand name 荣耀(*Honor*) is annotated as candidate entity.

**Example:** 2014年12月发布的荣耀6PLUS, 曾是双摄技术开拓者。此后, 荣耀又在荣耀V8上率先应用VR技术(*Honor 6PLUS, released in December 2014, was a pioneer in dual-camera technology. Since then, Honor is the first to apply VR technology on Honor V8*)

**Sentiment expression clause annotation.** For the purpose of improving annotation quality in the following sentiment polarity annotation, the annotators should also annotate those critical statements which can clearly express a sentiment. These clauses should reflect sentiment polarity of a financial entity. In this paper, clause means the comma-separated sentences. For example, In Ex.1, the sentiment expression clause for 乐融致新(*LeMall*) and 乐视网(*LETV*) is "业务发展的颓势仍没有出现明显的好转(*Neither LeMall nor LETV has gained significant improvement in business development*)".

**Sentiment polarity annotation.** We develop the following principles for determining the sentiment polarity. As mentioned before, SA in financial domain is different from SA in commodity/restaurant comments. Here the sentiment is determined by words that can reflect profitability, losses or other business status of those financial entities. There are three categories for annotator to choose, namely positive, negative and neutral. The examples are given below:

1. **Positive:** If a sentiment expression clause conveys the information that the target company benefits from a

policy or it made profits, such clause should be annotated as positive. The following example shows that the business of 水井坊(*Shuijingfang*) is getting better recently, thus the sentiment polarity is positive.

**Example:** 伴随着近年来白酒行业复苏, 水井坊业绩也水涨船高(*With the recovery of the liquor industry in recent years, the performance of Shuijingfang has also risen*)

2. **Neutral:** It means that a clause is relevant to the company business, but we can not determine the influence of it. In other words, we cannot judge whether it is profitable or it suffers from losses. In the following example, we cannot find an obvious emotional tendency for 华为(*Huawei*), so the corresponding sentiment polarity is annotated as neutral.

**Example:** 电商是未来发展的方向, 所有的企业都在发力, 华为也不例外, 但目前来看, 这一动作的成效需要检验(*E-commerce is the direction of future development. All enterprises are making efforts. Huawei is no exception. But the effectiveness remain to be discussed*)

3. **Negative:** If a sentiment expression clause indicates the poor business or bad trend of a company, the sentiment polarity should be annotated as negative. In the following example, we can figure out the 腾讯(*Tencent*) seems to be unpromising because of poor market. The sentiment polarity should be negative.

**Example:** 由于游戏收入下滑, 热门游戏进入周期末尾, 近期市场对腾讯的评估本来就不太乐观(*textitAs the game revenue decline and the popular game step into the end of the cycle, recent market assessment of Tencent are already less optimistic*)

## 3.2. Annotation Tool

To speed up the annotation process, we developed a user-friendly interactive online annotation system.<sup>2</sup> This tool has three main advantages: (1) It is flexible for an annotator to choose labels for each entity; (2) convenient for an annotator to change previous annotations based on his new observation; and (3) it contains some mistake avoidance checking to reduce missing annotation and incorrect annotation. As a result, the annotators efficiently annotated all of the entities and sentiment polarity with good accuracy and consistency.

## 4. Corpus Annotation

### 4.1. Data Collection

Financial experts and investors usually pay much interests in financial news containing much information about companies and markets, which helps them analyze financial status and make an investment decision. Thus, we crawled the news text from financial news websites, such as National Business Daily<sup>3</sup> and Caixin Media<sup>4</sup> in period from 2015 to 2019, using Python framework scrapy.<sup>5</sup> For

<sup>2</sup><http://label.dadastudio.top/>

<sup>3</sup><http://www.nbd.com.cn>

<sup>4</sup><https://www.caixin.com>

<sup>5</sup><https://github.com/scrapy/scrapy>

the obtained 17,600 raw articles, the following three pre-processing methods were applied to eliminate no-desirable articles.

- Remove irrelevant contents such as JavaScript/HTML code and URL in websites because no useful information for classifying the polarity of target entity is contained.
- Delete documents with less than 20 words for the reason that we aim to construct a paragraph-level target-based sentiment corpus.
- Filter some special characters, such as emoji and Greek alphabets.

#### 4.2. Annotation Process

Considering the characteristic of news text, the data sparseness is obvious in our corpus. There are a large number of texts without any sentiment. To tackle this problem for better annotation, we propose a filter principle: Each paragraph has at least one keyword which is relevant to business status.

We construct a financial sentiment dictionary to filter those texts with sentiment. This dictionary contains the keywords that are relevant to company business status. For example, "大幅下降(textifdramatically drop) tends to be "non-profit" for a company, which is negative.

Using these filters, we obtained 12,052 paragraphs for next step annotation. Each paragraph has at least one financial entity and at least one sentiment keyword. By applying the annotation guidelines discussed in Section 3, we construct the target-based sentiment corpus in the following steps. The first step is to identify and annotate the target entities. In the second step, the financial target sentiment are determined. To achieve better inter-agreement between annotators, the annotators are required to identify the sentiment expression clauses for post-checking. Each paragraph is annotated by two different annotators independently during the annotation process.

JSON format is used to store the annotated dataset. The following information has been stored:

- The annotated financial target entity. Normally, it is a company or a brand name.
- The location of financial target entity in the text. We should record the starting position and the length of the financial target entity for avoiding the ambiguities caused the multiple appearances of the target entity.
- The paragraph sentiment for the target entity. Positive polarity will be annotated as 1, negative as -1 and neutral as 0.
- The sentiment expression clauses.

#### 4.3. Difficult Cases

Sometimes, the sentiment polarity conflict of the target entity makes difficult to identify the ground truth. In the following example, there are multiple target entities with multiple sentiment polarities.

**Ex.2** 近几年来攀钢的财务状况一直不容乐观。与此同时，虽然重庆钢铁在去年也亏损严重，今年一季度，却实现了大幅扭亏为盈，这也是重庆钢铁自2011年以来首次实现扭亏为盈。

*The financial situation of PANGANG GROUP is getting worse in recent years. Meanwhile, although Chongqing Iron & Steel suffered a great loss last year, it realized a substantial turnaround in losses In the first quarter of this year, This is also the first time that Chongqing Iron & Steel has turned losses into profits since 2011.*

From the first clause, the sentiment polarity for 攀钢(PANGANG GROUP) is determined as negative. But it is hard to determine the sentiment polarity of 重庆钢铁(Chongqing Iron & Steel). In the second clause, the sentiment polarity for the company is negative because it lost a lot in last year. While in the forth clause and the fifth clause, the sentiment is positive because of the company achieving a profit turnaround in the first quarter of this year. They are both typical sentiment expressions, whereas we pay more attention to the current status of the target entity in the paragraph. As a whole, the sentiment polarity for 重庆钢铁(Chongqing Iron & Steel)is positive.

Furthermore, the conjunctions always play an important role in distinguishing sentiment polarity conflict situations because people normally emphasizes the part behind the adversative conjunction. As a result, we determine the sentiment polarity according to the emphasized part.

#### 4.4. Quality Assurance

Five highly educated native speakers are organized to annotate the dataset individually. The whole raw dataset is divided into several parts. Two annotators duplicate annotated each part. After the first pass annotation, the comparison are performed. For the cases that different sentiment polarities on a same target entity or different target entities are provided by the two annotators, the third annotator will discuss with the others until they obtain the agreement.

### 5. Corpus Statistics

The statistics information of FiTSA is summarized in Table 1. There are 8,314 sentiment instances corresponding to target entity are annotated from 6,336 paragraphs of Chinese financial news text. On the average, each paragraph contains 1.314 target entity types. And each entity type appears 1.583 times in a paragraph.

Table 1: Statistics of FiTSA corpus

Paragraph number	6,336
Instance number	8,314
clause number	67,736
Character number	647,648

It is observed that totally FiTSA has 3,908 negative, 1,598 positive and 2,858 neutral instances. The proportion of three different polarities is relative balanced. An interest thing is that financial news prefers to publish negative reports more than positive ones.

To estimate the inter-annotator agreement of the annotated corpus, we compute Cohen's Kappa (Cohen, 1960) and

Fleiss' Kappa (Fleiss and others, 1971). We reach Fleiss' Kappa value of 0.6686 which indicates substantial agreement. The Cohen's Kappa value reaches 0.7210, which confirms that the annotator could reliably identify the target entity sentiment for a given text. During Cohen's kappa computing, we find that the annotators can easily discriminate polarity between positive and negative, but for neutral sentiment polarity, annotators may be confused. The reason is that some situations are arduous for people to judge whether they affect the company's profitability.

## 6. Evaluation

Using FiTSA as the benchmark data, several state-of-the-art target-based sentiment analysis method are evaluated. The goal is to classify sentiment polarity for each given financial target entity. Here, we use precision, recall, and Micro-F1 as the evaluation metrics.

For the total 8,314 instances in annotated corpus, we use 5,820 instances as training data (70%) and the remaining 2,494 instances as testing data (30%). The distribution of training and testing data is shown in Table 2.

Table 2: The Training and testing data

Polarity	Train	Test
Negative	2,705	1,203
Positive	1,099	449
Neutral	2,016	842
Total	5,820	2,494

For FiTSA corpus, it is different from the traditional aspect/target-based sentiment analysis task. As we mentioned above, it is multiple target and multiple sentiment annotation corpus. Each entity appears 1.58 times on average in a paragraph, while for SemiEval ABSA corpus, it is much shorter than FiTSA and each target entity only appears once. Thus, some state-of-the-art methods can not be applied to this corpus straight forward.

In the evaluation, we developed several ABSA/TBSA classifier including traditional machine learning baselines and the newest deep neural network models. For the deep neural network based models, pre-trained word embeddings from (Song et al., 2018) is used as the input for RNN based models:

- **LR:** TF-IDF and some target entity attributes such as entity positions and appearing times in the text are used as features. Logistic Regression is applied as the classifier.
- **SVM:** Using the features in LR and Support Vector Machine as the classifier.
- **XGBoost:** Using the features in LR and Extreme Gradient Boosting method as the classifier.
- **LSTM-ATT:** LSTM is applied for feature extraction. Attention mechanism is adopted to learn target entity related representations and MLP is adopted as the classifier.

- **TD-LSTM:** The model from (Tang et al., 2016a) is used to learn the representation of target entity features for classifying.
- **BERT:** Treat this task as a sequence pair classification in (Devlin et al., 2018). We consider the whole paragraph as text A and target entity as text B. Then use [CLS] embedding for classification. More details can be found in the original paper.

We conduct several experiments with these models. The obtained performances are illustrated in Table 3.

Table 3: The evaluation performance on FiTSA

Method	Precision	Recall	F1
LR	0.7296	0.6655	0.6826
SVM	0.7268	0.6905	0.7039
XGBoost	0.7185	0.6910	0.7031
LSTM-ATT	0.7354	0.6999	0.7122
TD-LSTM	0.7419	0.7096	0.7214
BERT	0.7963	0.8017	0.7984

## 7. Conclusion

In this paper, we present the design and construction of FiTSA, a large-scale target-based sentiment annotation corpus on Chinese Financial news text. In this corpus, the entities for enterprises including company name, brand name and other financial entities are regarded as the targets. The corresponding sentiment expressions and polarities are then annotated. Finally, we constructed a large annotated corpus with multiple targets and multiple sentiments. It will be a helpful resource to relevant aspect-based/target-based sentiment analysis research. Additionally, we conduct experiments based on machine learning and neural network methods to estimate their performance on FiTSA. The code is available on Github<sup>6</sup>.

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<sup>6</sup><https://github.com/bbruceyuan/FiTSA>

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