WUST at NTCIR-11 RITE-VAL System Validation Task

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ABSTRACT
This paper describes our work in NTCIR-11 on RITE-VAL System Validation task in Simplified Chinese including Binary-class (BC) subtask and Multi-class (MC) subtask. We construct the classification model based on support vector machine to recognize semantic inference in Chinese text pair. In our system, we use multiple features including statistical features, lexical features and syntactic features. Particularly, for contradiction recognition, we put forward the Chinese textual contradiction approach using linguistic phenomena.

Categories and Subject Descriptors
I.2.7 [Artificial Intelligence]: Natural Language Processing - text analysis.

I.3.1 [Information Storage and Retrieval]: Content Analysis and Indexing - linguistic processing.

General Terms
Experimentation.

Keywords
Textual Entailment, Textual Contradiction, Linguistic Phenomena, Semantic Rules

- WUST
- RITEVAL – System Validation – CS – BC
- RITEVAL – System Validation – CS – MC

1. Introduction
In NTCIR-11, RITE-VAL is an evaluation task to recognize entailment, paraphrase, and contradiction between texts, which is a common problem shared widely among researchers of natural language processing and information access. We focus on Binary Class (BC) and Multiple Class (MC) subtasks in RITE-VAL System Validation (SV) task.

BC subtask means that given a text pair (T, H), a system can automatically identify whether text T entails or infers hypothesis text H or not. Text T entailing text H means that T has the same meaning with H while T also has more meaning than H. In other words, the events described in H can be inferred from T. If the events described in T can be true, the events in H are always true. The following text pair (T1, H1) is a textual entailment example.

T1: 干物女是来自于日本的流行语。
H1: 干物女来自于日本。

MC subtask is a 4-way labeling task to automatically detect there is one of the four semantic relations including **Forward(F)**, **Bi-direction(B)**, **Contradiction(C)** and **Independence(I)**, in a given text pair.

Forward entailment means that T entails H and H does not entail T and it is a one-way entailment. If it is the case that T entails H and H entails T, then T and H are true in exactly the same conditions, and are thus equivalent or paraphrase. In other words, equivalence or paraphrase is the bidirectional entailment and we also call it **Bi-direction**.

The text pair (T1, H1) mentioned above is also an example of **Forward** entailment and the text pair of T2 and H2 is an example of **Bi-directional** entailment.

T2: 手语主要使用者是失聪者。
H2: 手语主要使用者是有听觉障碍的失聪者。

In MC subtask, non-entailment contains **Contradiction** and **Independence**. **Contradiction** means that T and H contradicts, or cannot be true at the same time. Independence means that if the text pair (T, H) cannot be put into any of the three-way entailment, we put it into the **Independence** class. For instance, the relation between T3 and H3 is contradiction, the relation between T4 and H4 is **Independence**.

T3: 约瑟夫•傅立叶是十九世纪法国数学家、物理学家。
H3: 约瑟夫•傅立叶是法国数学家、生物学家。

T4: 铅笔的原型可以追溯至古罗马时代。
H4: 罗马人发明铅笔。

Recognizing textual entailment is essentially a classification problem which can be implemented by machine learning methods. In this paper, we use SVM based classification method and multiple textual features to solve the entailment problem. For Chinese textual contradiction recognition, an approach based on linguistic phenomena has been proposed in this paper.

2. System Description
Our system includes five main modules, including data preprocessing, SVM feature extraction, classification, linguistic phenomena analysis and contradiction recognition. Figure 1 illustrates our system architecture in detail.

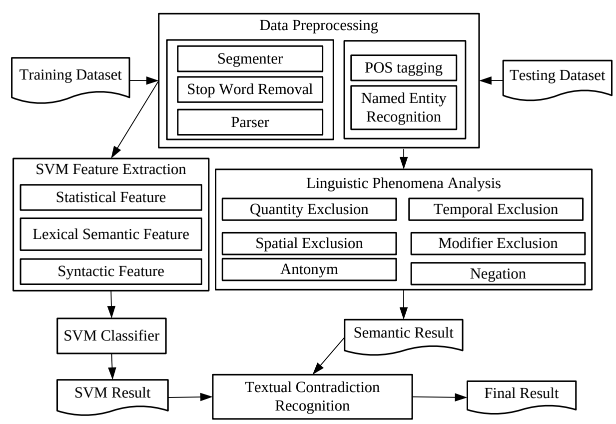

Figure 1. System Architecture

2.1 Data preprocessing

In this phrase, the main work of the system is to segment the Chinese words, remove the stop words and parse the text pairs. For testing dataset, tagging and named entity recognition is also needed besides the above steps, which is prepared for the extraction of contradiction related information. We choose Stanford Chinese word segmenter with PKU standard as the tool to segment the Chinese word.

2.2 Feature extraction

In this subsection, we mainly focus on three kinds of features, including statistical feature, lexical semantic feature, and syntactic feature. We almost use the same features as in the system of RITE1 and RITE2, which are described in detail in our former reports.

Statistical features are relevant to seven features in our system, including word overlap, length difference, Manhattan distance, Euclidean distance, cosine similarity, Jaro-Winkler distance, LCS similarity in shorter text. Statistical features refer to unstructured features including word set features and vector features. Word set features are extracted based on word set of the two texts after data preprocessing. Vector features are extracted in the vectorized texts.

Lexical semantic features are extracted based on semantic resources such as antonyms table, negation table, HowNet, TongyiCilin. The antonym feature and negation feature are calculated to recognize contradiction relation.

Syntactic features are extracted from grammatical structure of syntax trees of text T and text H. In the text pair (T, H), we suppose that the syntactic structures of text T and text H has higher similarity, text T and text H mostly have higher probability to express the similar meaning.

2.3 SVM classifier

We choose LIBSVM as the classifier. LIBSVM is a library for support vector classification and regression. After preparing and scaling data set in LIBSVM form, our system chooses the RBF kernel function to do the cross-validation.

The SVM based classification model is constructed to determine which class the Chinese text pairs belong to. The features of the training dataset will be used to train the optimal parameters for the SVM classifier and the features of the testing dataset will be used to predict the class of the testing text pairs.

2.4 Contradictory Linguistic Phenomena and Semantic Rules

In order to detect Chinese textual contradiction successfully, it is necessary to have a deep analysis on the linguistic phenomena behind contradictory text pairs. In this paper, we provide six categories of linguistic phenomena related to textual contradiction and design corresponding semantic rules based on the linguistic phenomena, which is brand new in this task compared with RITE1 and RITE2.

(1) Quantity Exclusion

Quantity exclusion is defined as a numeric mismatch between T and H. The following text pairs illustrate various kinds of numeric mismatches which cause textual contradictions between T and H. The four types of numeric mismatches in the following text pairs can obviously lead to textual contradictions.

T5: 艾弗森职业生涯最高单场得分 60 分。
H5: 艾弗森的最高得分纪录为 65 分。

T6: 阿诺尔特大花直径最多达 3 米。
H6: 阿诺尔特大花直径能够到达 3 千米。

T7: 平均一天睡 10 个多小时的人最长寿。
H7: 每晚平均睡近 10 小时的人，寿命最长。

T8: 大卫像高 4.342 公尺。
H8: 大卫像高 2.5 米。

The text pair (T5, H5) shows a value mismatch and the value of number in text T5 is “60” while that in H5 is “65”. As in the text pair (T6, H6), the numbers share the same value “3” while hold different units “米” and “千米” respectively. Another kind of numeric mismatch is range mismatch as in text pair (T7, H7) and the words “多” and “近”, meaning more than and less than, determine opposite ranges of the same number “10”. In text pair (T8, H8), there exists a value mismatch and a unit mismatch. After unit conversion from “4.342 公尺” in text T8 to “4.342 米”, it is also not equal to “2.5 米” in text H8.

T9: 熊猫体长约 180 厘米。
H9: 熊猫身长能达到 1.8 米。

T10: 北极熊平均年龄 30 岁左右。
H10: 北极熊平均年纪三十岁左右。

However, not every kind of numeric mismatch would lead to a textual contradiction. In text pair (T9, H9), although “180 厘米” differs from “1.8 米”, they are equal to each other after unit conversion. In text pair (T10, H10), as the same number “thirty” can be expressed as “30” and “三十” in Chinese and Arabic ways, the text pair will not be considered as a contradictory one. The two types of linguistic phenomena in the two text pairs mentioned above cannot lead to textual contradiction because there are different forms of expressions for the same number in Chinese texts, for example, “四万”, “40000” and “4 万” all refer to the same number.

Before textual contradiction judgment, the numbers should be normalized and presented as a triple (value, unit, range) by using Stanford POS tagger. We normalize a number as the Arabic one and the units of measurement should also be standardized. The ranges of number can be determined by some signal words such as “大于 (More than)”, “小于 (Less than)”, “超过 (Over)” or “不足 (Within)”. The numeric mismatch, including value mismatch, unit mismatch and range mismatch, could conclude the textual contradiction if T and H have high similarity. According to the linguistic phenomena of quantity exclusion, the corresponding rules have been designed as follows.

Quantity Rule 1: For a given text pair (T, H), which holds high similarity, if the two numbers in T and H have the same unit and range but different values, it can be justified as textual contradiction.

Quantity Rule 2: For a given text pair (T, H), which has high similarity, if the two numbers in T and H have the same value and range but different units, it can be justified as textual contradiction.

Quantity Rule 3: For a given text pair (T, H) which has high similarity, if the two numbers in T and H have the same value and unit but different ranges, it can be justified as textual contradiction.

Quantity Rule 4: For a given text pair (T, H) which has high similarity, if the two numbers in T and H have the same range but different values and units and they aren't equal to each other after unit conversion, it can be justified as textual contradiction.

(2) Temporal Exclusion

Temporal exclusion means a time or date mismatch which could conclude the textual contradiction between T and H. The following text pairs show temporal exclusion.

T11: 撒切尔于 1992 年被册封为终身贵族。
H11: 1991 年撒切尔得到终身贵族的头衔。

T12: 京都议定书为 1997 年 12 月在气候变化纲要第三次缔约国大会中通过。
H12: 一九九七年十二月第三次缔约国会议中通过"京都议定书"。

T13: 2005 年 7 月 7 日的清晨 8 点 50 分伦敦多处地铁站爆炸。
H13: 2005 年 7 月 7 日的伦敦地铁爆炸发生于早上 8 点 50 分。

In the text pairs above, the temporal exclusion could occur via the year, month, day or format mismatch. The text pair (T11, H11) is contradictory because the year information, "1992 年" and "1991 年", is different which is a typical temporal exclusion. However temporal expression mismatch may not conclude a contradiction sometimes because the date or time could be represented in various formats in Chinese. As in text pair (T12, H12), "1997 年 12 月" and "一九九七年十二月" refer to the same temporal information. In text pair (T13, H13), "清晨" and "早上" are different descriptions of "morning".

As a result of diverse expressions of date and time, they should be normalized before contradiction identification. For example, "1990/02/21", "19900221" and "1990 年 2 月 21 日" will not be considered as temporal mismatch. The Stanford POS tagger is used to extract time or date information in the text pairs according to the labels "/T" and "/NT". A temporal mismatch could lead to a contradiction of a text pair if the structural similarity of two texts is high. The following rule is designed based on temporal exclusion.

Temporal Rule: For a given text pair (T, H) which has high similarity, if the date or time in T and H has a mismatch after normalization, it can be justified as textual contradiction.

(3) Spatial Exclusion

Spatial exclusion is also crucial for the textual contradiction in the case of the spatial information referring to the same event. In text pair (T14, H14), the textual contradiction results from different locations, "中国" and "日本", which are both involved in the same event "原产". Another situation is that the same location information in different events may also conclude textual contradiction. In text pair (T15, H15), the same location information "江西德安" is involved in two different events, "祖籍" and "出生". The spatial information is extracted by Stanford NER (Named Entity Recognizer) according to the label "/GPE".

T14: 土豆原产于中国。
H14: 土豆原产于日本。

T15: 袁隆平祖籍是江西德安。
H15: 袁隆平出生于江西德安。

According to this linguistic phenomenon, the spatial rules, listed as follows, are used to recognize the spatial contradictory text pairs.

Spatial Rule 1: For a given text pair (T, H) which has high similarity, if the different location information in T and H denoted the same event occurring, it can be justified as textual contradiction.

Spatial Rule 2: For a given text pair (T, H) which has high similarity, if the same location information in T and H involved in different events, it can be justified as textual contradiction.

(4) Modifier Exclusion

The different modifiers for the same thing may create textual contradictions sometimes. The different modifiers "唯一" and "次要" make texts T16 and H16 conflict with each other. However, if the different modifiers are synonym, hypernym or hyponym ones, the modifier exclusion is not sufficient to indicate a textual contradiction. Taking text pair (T17, H17) for example, it is the bidirectional entailed text pair instead of contradictory one because "丰富" and "大量" are synonyms. Similarly, the text pair (T18, H18) is the forward entailed one as the "葱科植物" is the hyponym of the "草本植物". The following semantic rules illustrate the linguistic phenomena mentioned above.

T16: 海底地震造成地层大幅度陷落抬升是引发大海啸的唯一原因。
H16: 海底地震造成地层大幅度陷落抬升是引发大海啸的次要原因。

T17: 草莓含有丰富维生素 C。
H17: 草莓含有大量维生素 C。

T18: 韭菜，属多年生葱科植物。
H18: 韭菜，属多年生草本植物。

Modifier Rule 1: For a given text pair (T, H) which has high similarity, if there exists a modifier mismatch which is not a synonym pair, it can be justified as textual contradiction.

Modifier Rule 2: For a given text pair (T, H) which has high similarity, if there exists a modifier mismatch which is not a hypernym or hyponym pair, it can be justified as textual contradiction.

(5) Antonym

The antonym is a very useful cue for textual contradiction as the antonym pairs usually convey oppositional information. The antonym pair "富裕" and "清贫" can lead to the textual contradiction between texts T19 and H19. To calculate the pair number of the antonym in text pair (T, H), one antonym table should be created first.

T19: 柏拉图出生于较为富裕的家庭。
H19: 柏拉图诞生于清贫家庭。

Antonym Rule: For a given text pair (T, H) which has high similarity, if there exists a pair of antonyms between T and H, it can be justified as textual contradiction.

(6) Negation

The negation is also a good indicator for textual contradiction. The negation "不" in the following text pair (T20, H20) makes the polarity of T20 and H20 opposite. To calculate the number of negative words in each text, one negation table has been generated. The numbers of the negative words in texts T and H are calculated respectively. If the difference between two numbers is an odd, which indicates the opposite polarity between two texts, the conclusion can be drawn that the text pair is the contradictory one. Negation Rule is created for negative contradiction.

T20: 草莓不适合运输储存。

H20: 草莓容易运输储存。

Negation Rule: For a given text pair (T, H) which has high similarity, if the difference of the negation numbers of T and H is an odd number, it can be justified as textual contradiction.

3. Experiments

There are two main tasks of RITE-VAL including fact validation and system validation. We participated in BC and MC subtasks of simplified Chinese in system validation task. We submitted one run of BC and three runs of MC to NTCIR-11. The official evaluation results of performance are listed in the Table 1.

Table 1. Official results of WUST formal run experiment

Run	Subtask	MacroF1	Accuracy
WUST-CS-SVBC-01	BC	0.391	0.523
WUST-CS-SVMC-01	MC	0.444	0.518
WUST-CS-SVMC-02	MC	0.442	0.517
WUST-CS-SVMC-03	MC	0.438	0.515

3.1 BC subtask

For the simplified Chinese BC subtask, we submit only one run: WUST-CS-SVBC-01. The experiment results of the BC subtask are shown in the following Table 2, where Y and N denote entailment and non-entailment respectively.

Table 2. Experiment results of WUST-CS- SVMC-01

Label	Precision	Recall	F1-Measure
Y	0.512	0.987	0.674
N	0.814	0.058	0.109

In BC subtask, statistical features, lexical features and syntactic features of Chinese are extracted to train and predict the training dataset and testing dataset. According to Table 2, we find the accuracy of “Y” is much better than that of “N”.

In the BC subtask, we only use statistical features, lexical features and syntactic features. The contradiction linguistic phenomena have not been analyzed in this subtask. As the three kinds of features such as word overlap, Manhattan distance, cosine similarity, LCS similarity, HowNet similarity, TongyiCilin similarity and dependency tree similarity most focus on textual similarity, it is hard to recognize contradictory and independence text pairs which have high similarity literally. Contradictory and independence text pairs are classified as non-entailment relation and there is a high percentage of contradiction and independence in both training dataset and test dataset, which may cause the poor performance of the recognition of N label. In BC subtask, we use the same features with MC subtask. However the characteristics of the BC and MC subtasks should be different, which may cause the dissatisfaction of BC result.

3.2 MC subtask

For the simplified MC subtask, we submit three runs: WUST-CS-SVMC-01, WUST-CS-SVMC-02 and WUST-CS-SVMC-03. Since our aim in this subtask is to estimate the impact of the contradiction linguistic phenomenon and semantic rules to the contradiction recognition, the experiments are set up as follows: the three runs have the same steps before contradiction modification. First, the three experiment systems employ the same features mentioned in section 2.2 including statistical features, lexical features and syntactic features for SVM classifier. After that, contradiction features including quantity, temporal, spatial, modifier, antonym and negation are extracted. Then corresponding semantic rules based on linguistic phenomenon are generated. The three experiment systems vary on contradiction modification. The first system WUST-CS- SVMC-01 uses the semantic rules to modify the contradictory text pairs which have been recognized as bidirectional relation by SVM classifier. The second system WUST-CS- SVMC-02 uses the semantic rules to modify the contradictory text pairs which have been recognized as forward and bidirectional relations by SVM classifier. The third system uses two-stage classifier. In the first stage, we choose LIBSVM, a library for support vector classification and regression, to train and predict the RITE training dataset and testing dataset with statistical features, lexical features and syntactic features. In the second stage, we choose BP Neural Networks classifier to judge contradiction relation based on linguistic phenomena and semantic rules. As most contradictory text pairs are judged incorrectly as forward and bidirectional by the first classifier SVM, we utilize the second classifier to modify the result of contradictory recognition according to contradiction semantic features including quantity, temporal, spatial, modifier, antonym and negation.

The experiment results of the three runs of MC subtask are shown in the following Table 3, Table 4 and Table 5, where F denotes forward entailment relation, B bidirectional relation, C contradiction relation and I independence relation.

Table 3. Experiment results of the WUST-CS- SVMC-01

Label	Precision	Recall	F1-Measure
B	45.77	86.67	59.91
F	50.86	68.67	58.44
C	68.72	52.00	59.20
I	0.00	0.00	0.00

Table 4. Experiment results of WUST-CS- SVMC-02

Label	Precision	Recall	F1-Maesure
B	45.77	86.67	59.91
F	50.12	69.33	58.18
C	70.05	50.67	58.80
I	0.00	0.00	0.00

Table 5. Experiment results of WUST-CS- SVMC-03

Label	Precision	Recall	F1-Maesure
B	45.22	93.00	60.85
F	49.52	68.67	57.54
C	79.64	44.33	56.96
I	0.00	0.00	0.00

According to Table 3, Table 4 and Table 5, we can find that the three runs have almost little differences in forward entailment, bidirectional entailment and contradiction recognition. Contradiction recognition can be attributed to contradiction linguistic phenomena and semantic rules. Particularly, in the third run which uses two-stage classifier, the precision of contradiction is higher than the other two runs. WUST-CS-SVMC-01 and WUST-CS- SVMC-02 use semantic rules based on contradiction linguistic phenomena to modify the contradictory text pairs manually while WUST-CS-SVMC-03 use the second stage classifier BP Neural Networks classifier to make secondary judgment on contradiction relation.

However independence relation recognition is not optimistic in the three systems. Independent text pairs have not been recognized at all. In order to explore the reason leading to the bad performance of independence relation recognition, we have a deep analysis on the result of SVM classifier. In SVM classification stage, contradiction semantic features have not been introduced. We focus on text similarity features such as statistical feature, lexical feature and syntactic feature. These features are benefit for entailment recognition when the text pairs have high similarity literally. In our dataset including training data and testing data in MC task, independence text pairs have high similarity as entailment text pairs, our system have little features to distinguish entailed text pairs with independent ones.

As a result the independence text pairs are recognized as entailed text pairs. We should add corresponding features to improve independence recognition and make a deep analysis of independence linguistic phenomena to optimize independence result. We should recognize the four relations not literally but semantically.

4. Conclusions

In this paper, we construct the classification model based on support vector machine to recognize semantic inference in Chinese text pair using multiple features, including statistical, syntactic and lexical semantic ones. In order to recognize contradiction relations, we put forward a Chinese textual contradiction recognition approach based on linguistic phenomena and semantic rules.

From the experiment results, we find that using multiple features to recognize textual entailment in Chinese text pairs is workable and effective. The experiment results demonstrate the effectiveness and feasibility of textual contradiction recognition. After further analysis, we find that the result of BC task is not satisfactory. We use the same features in BC task as in MC task, but the characteristics of the BC and MC subtasks should be different. Moreover contradiction recognition based on linguistic phenomena and semantic rules is not applied to BC task, which may cause the dissatisfaction of BC result.

In the MC subtask, as we have used contradiction recognition approach, the accuracy of contradiction relation is improved significantly. However independence text pairs haven’t been recognized at all, which may be because most features we use all focus on text similarity and the independence text pairs with high similarity are recognized as entailed ones literally.

In our system, we mostly consider statistical features, but similarity is not entailment. If we add some corresponding features and semantic rules according to independence relation as which has been used in contradiction recognition, the accuracy of independence and the whole system may be significantly improved.

ACKNOWLEDGMENTS

The work presented in this paper is supported by the National Nat ural Science Foundation of China (No. 61100133 and 61173062), the Major Projects of National Social Science Foundation of Chin a (No. 11&ZD189).

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