# Document Oriented Gap Filling of Definite Null Instantiation in FrameNet

Ning Wang[1], Ru Li[1,2], Zhangzhang Lei[1], Zhiqiang Wang[1], and Jingpan Jin[3]

[1] School of Computer & Information Technology
[2] Key Laboratory of Ministry of Education for Computation Intelligence & Chinese Information Processing, Shanxi University, Taiyuan 030006, China
[3] School of Computer, Beijing Institute of Technology, Beijing 100081, China
{Wanganning.com,Leizhangzhang77777,zhiq.wang, jinjingpan}@163.com, liru@sxu.edu.cn

**Abstract.** Null instantiation has attracted much attention recently. In this paper, we focus on gap filling of definite null instantiation, namely, finding an antecedent for a given definite null instantiation from context. Most of the approaches for solving this problem use syntactic features, and only few consider semantic features. Moreover, these approaches only take the noun, noun phrase and pronoun as candidate words, so the coverage of antecedent is narrow. In this paper, we use new features of words and frame except traditional features, and create a rule to build candidate words set. At last, we choose the best candidate words set and feature template based on employing standard annotated corpus, then use them to deal with corpus of NIs only in task SemEval-10 Task 10. According to the experimental results, our approach achieves a better performance than existing approaches.

**Keywords:** Definite Null Instantiation, Gap Filling, Semantic Features, Candidate Words Set.

## 1 Introduction

FrameNet [1] is a computational lexicography project, which based on the theory of Frame Semantics and concerned with networks of meaning in which words participate. The primary units of lexical analysis in FrameNet are the frame and the lexical unit. Null instantiation is the core frame element which is neither expressed as a dependent of the predicator nor can it be found through gap filling in FrameNet [2]. We can divide null instantiation into two categories: definite null instantiation (DNI) and indefinite null instantiation (INI). Cases of indefinite null instantiation are the missing objects of verbs like eat, sew, bake, and drink, etc. where the nature or semantic type of the missing element can be understood, and there is no need to retrieve or construct a specific discourse referent, as core frame element FOOD in the following 1. Definite null instantiation are those in which the missing element must be something that is already understood in the linguistic or discourse context, as the following example in 2. The target word difficult evokes the difficulty frame, which has two core frame

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elements, only one of which is filled locally, namely ACTIVITY, which is realized by business. However, another argument, EXPERIENCER, is filled by the I in preceding sentence.

1. [Sue INGESTOR]had eaten already.[INI FOOD]
2. I think that I shall be in a position to make the situation rather more clearly to you before long. It has been an [exceedingly DEGREE] difficult and most complicated [business ACTIVITY].[DNI EXPERIENCER]

Gap filling identifies the overt antecedents of null instantiation in controlled structures, as INIs do not need to be accessible within a context, the task of resolving NIs is restricted to DNIs. As the example 2, gap filling of DNI aims to find the overt expression "I" to fill the omitted frame element "EXPERIENCER". Because DNI is not overt argument in sentence, it is difficult to find some information to describe it, which causes the gap filling of DNI becomes a challenging problem in discourse processing.

Given a DNI, we think that gap filling of DNI can be seen as a classified problem to judge whether a candidate could be taken as filler of a DNI, so we use classification method to solve the problem. In this task, an important step is to determine the scope of candidate words set and features for classification. In this paper, we design a rule to select candidate words set, combine features in a diversified portfolio, and finally use the maximum entropy model to classify candidate words.

The remainder of this paper is structured as follows. In section 2, we briefly summarize the related work on gap filling of DNI. Section 3 introduces the way to build select rule of candidate words set, features description and the maximum entropy model in DNI gap filling. Section 4 reports the results of experiments. Finally, Section 5 concludes this paper.

## 2 Related Work

There is a growing interest in developing algorithms for resolving null instantiations. Null instantiations were the focus of the SemEval-10 Task 10, which showed two mission modes, namely full task (semantic role recognition and labeling + NI linking) and NIs only task, i.e. the identification of null instantiations and their referents given a test set with gold standard local semantic argument structure[3]. This paper focus on NIs only task to realize gap filling of DNI.

There are two teams participate in NIs only task. Tonelli and Delmonte[4] developed a knowledge-based system called VENSES++, different resolution strategies are employed for verbal and nominal predicates. For verbal predicates, the system finds a comparable PAS in previous sentences, and then looks for the best head available in that PAS as a referent for the DNI in the current sentence by semantic matching with the FE label. For nominal predicates, NIs are resolved by making use of a common sense reasoning module that builds on ConceptNet[5]. Because it relies on large-scale corpus to train the feature templates, ultimately they obtained precision and recall rate was 4.62% and 0.86%. The second SemEval system[6] modeled the problem as the same way of semantic role labeling. They consider nouns, pronouns, and noun phrases from the previous three sentences as candidate DNI referents. When evaluating potential filler, the system checks whether it fills the null instantiated role overtly in one of the FrameNet sentences at first, if not, they calculates the distributional similarity between filler and role. But, these semantic features have virtually no effect on performance possibly due to data sparseness.

Philip and Josef[7] developed a weakly supervised approach that investigates and combines a number of linguistically motivated strategies. Silberer and Frank[8] view NI resolution as a coreference resolution (CR) task, employing an entity-mention model, combining features of SRL and CR, and achieving F-score is 7.1% at last. Gerber and Chai[9,10] present a study of implicit arguments for a group of nominal predicates. They also use an entity mention approach and model the problem as a classical supervised task, implementing a number of syntactic, semantic, and discourse features. Because Gerber and Chai's corpus cover 10 nominal predicates from the commerce domain, with on average 120 annotated instances per predicate, so their results are noticeably higher than those obtained for the SemEval data.

# 3 Model for Gap Filling of DNI

It is critical to determine search space and POS of candidate fillers for DNI in gap filling of DNI, as well as features for classification. Search space is the number of sentences that candidate fillers away from target, the choice of search space could affect the cover probability of antecedent and the result of DNI gap filling. A good candidate words set (includes search space and POS of words) could reduce the complexity of the system and improve the efficiency of the experiment. In this section, we focus on the selection of candidate words set and features.

## 3.1 Selection of Candidate Words Set

Candidate words are those which may be used as explicit referents of implicit argument. The accuracy of search space and POS for candidate words would influence the result of gap filling. Because the distribution of explicit referents for DNI is chaotic, and their part-of-speech is diverse, it is difficult to create an appropriate candidate words set which could maximum cover the entire antecedent and has a minimum size. In order to solve this problem, we count the distribution of DNI referents in training data of NIs only task.

**Table 1.** The distribution of DNI referents in training data

| Distance of sentences | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| number | 95 | 63 | 19 | 6 | 4 | 5 | 4 | 2 | 2 |

Table 1 shows the main distribution of DNI referents in training data. We can see that the distribution of DNI referents mainly concentrates in the same sentence, previous one sentence and two sentences, and other sentences are relatively less. The data listed in table 1 account for only 65.79 percent of the total number of DNI referents. In training data, there are 58 DNIs have no referent, 6 appear in six sentences before, 28 appear at least 25 sentence prior. Observe the above data, we can draw that the coverage probability has obvious growth trend from one sentence to three sentences, when we choose four sentences or five sentences as search space, there are only 1 percent increase than others. Based on the above data, we list several methods in table 2 to choose the best candidate words set.

**Table 2.** The search space of candidate words set (%)

| Num | Search space | coverage probability | description |
|---|---|---|---|
| H1 | n≤2&&n≠0 | 46.05 | Words in previous two sentences |
| H2 | n≤2&&n=0 | 77.30 | Words in this and previous two sentences |
| H3 | n≤3&&n≠0 | 48.03 | Words in previous three sentences |
| H4 | n≤3&&n=0 | 79.28 | Words in this and previous three sentences |
| H5 | n≤4&&n≠0 | 49.34 | Words in previous four sentences |
| H6 | n≤4&&n=0 | 80.59 | Words in this and previous four sentences |
| H7 | n≤5&&n≠0 | 50.99 | Words in previous five sentences |
| H8 | n≤5&&n=0 | 82.24 | Words in this and previous five sentences |

In corpus, some words in search space are impossible to act as frame element fillers, such as VB, VBP and VBZ. These words would increase the complexity of the system and impact the efficiency of the experiment, therefore we should remove them from candidate words set. In the following, we analyze the part-of-speech distribution of DNI referents in training data to choose suitable candidate words.

**Table 3.** Part-of-speech distribution of DNI referents in training data (%)

| POS of antecedent | NPB | PRP | NNP | NP | S | PRP$ | VP | NN | VBN | SBAR | SG |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Num | 91 | 77 | 15 | 13 | 12 | 9 | 7 | 3 | 1 | 1 | 1 |
| Probability | 39.57 | 33.48 | 6.52 | 5.65 | 5.22 | 3.91 | 3.04 | 1.30 | 0.43 | 0.43 | 0.43 |

As shown in table 3, the words which POS are NPB (noun phrase) and PRP (pronoun) account for 73.05% in total, as a result we take them as basic POS of candidate words for DNI, and the following rules are devised for building candidate words set based on the data in table 3:

1. Given the current DNI frame element, looking for the same frame elements in the train data.
2. If the same frame elements are found, counting the POS of their fillers, choosing the largest one as C, and taking NPB, PRP, and C as candidate words for DNI in search space.
3. Otherwise, only taking noun phrases and pronoun as candidate words for DNI in search space.

### 3.2 Features Description

Feature selection is important in classification problems and the performance of classification largely depends on feature selection, which is also a key issue in gap filling of DNI. For definite null instantiations, their conceptually-relevant content is left unexpressed or is not explicitly linked to the frame via linguistic conventions, so it is difficult to get some information from discourse to describe them. Only can we take as features for gap filling of DNI are information of candidate words and DNI frame element.

In discourse, head words are frequently used as role filler. The closer head word away from the target, the more likely it becomes DNI explicit expression. Hence, we take information of head word as features for gap filling of DNI. In a frame, the NI type of the same frame element would be different for the lexical varies, and different roles would be having different NI type under the same lexical as well. In the case of frame element GOAL and SOURCE, some verbs allow its omission under indefinite null instantiation (1, 4), others allow its omission under definite null instantiation (2, 3).

1. Adam **left** Paris [INI Goal].
2. Smithers **arrived** [DNI Goal].
3. Sue **left** [DNI Source].
4. Sue **arrived** in Rome [INI Source].

**Table 4.** Features description

| | Num | Features Name | Features description |
|---|---|---|---|
| C1 | T1 | DistantSen | The number of sentences between candidate and target |
| | T2 | WordContent | Candidate word |
| | T3 | WordCat | Cat of candidate word |
| | T4 | WordLength | Length of candidate word |
| C2 | T5 | headWord | Head word of candidate word |
| | T6 | headWordLemma | The lemma of head word |
| | T7 | HeadWordPos | The pos of head word |
| C3 | T8 | frame | The frame that target evokes |
| | T9 | FENI | DNI argument |
| | T10 | target | target |
| | T11 | targetLemma | The lemma of target |
| | T12 | targetPos | The pos of target |

In conclusion, we also take account of frame information when gap filling of DNI. In table 4, we describe all of the features that may be useful in gap filling for DNI.

### 3.3 Maximum Entropy Models

Maximum entropy model which is based on the maximum entropy principles is set up for all known facts without any other influence of factors. We can add any useful feature for the final classification without considering the interaction between each other. Maximum entropy model, as a kind of statistical method, has been widely used to aspects of natural language processing (such as part-of-speech, chinese word segmentation and machine translation) in the late.

In the experiment, it will involve a variety of factors when predicting whether a candidate is DNI filler. Supposed X is a vector of these factors, y represents whether potential filler is DNI referent or not. p(y | X) is a probability that a candidate is predicted as filler of DNI. Maximum entropy model ask for p(y | X) to make the entropy defined below largest under certain restrict conditions.

$$\mathrm{H}(p) = -\sum_{X,y} p(y \mid X) \log p(y \mid X)$$

The restrict conditions refers to all known facts actually, the final output of the probability is:

$$p(y \mid X) = \frac{1}{Z(X)} \exp\left( \sum_{i}^{\mathrm{n}} \lambda_i f_i(X, y) \right),$$

$$Z(X) = \sum_{y} \exp\left( \sum_{i}^{n} \lambda_i f_i(X, y) \right)$$

fi (X, y) is features of maximum entropy model, n is the number of features, and the features describe the relationship between X and y. λi is the weight of each feature.

In this paper, we use the maximum entropy toolkit of Dr. Zhang Le for classification[11].

## 4 System Output and Evaluation

In gap filling of DNI, search space of candidate words set and feature selection are two key steps in the experiment. In this section, we use corpus which has annotated NI type to get the best feature template firstly, and then choose the best candidate words set with the best feature template in the same corpus. At last we apply them to NIs only task data and compare the result with previous works.

### 4.1 Corpus

In our experiment, we used the corpus distributed for SemEval-2010 Task 10 on "Linking Events and Their Participants in Discourse". The data set consists of the SemEval-2007 data plus annotated data in the fiction domain: parts of two Sherlock Holmes stories by Arthur Conan Doyle. The training set has about 7800 words in 438 sentences; it has 317 frame types, including 1370 annotated frame instances. The test set consists of two chapters, which has about 9000 words, 525 sentences, 452 frame types and 1703 frames. All data released for the 2010 task include part-of-speech tags, lemmas, and phrase-structure trees from a parser, with head annotations for constituents. Table 5 shows the statistics about this data set.

**Table 5.** Statistics for NIs only task corpus

| Data Set | sentences | frame inst. | frame types | DNIs |
|---|---|---|---|---|
| train | 438 | 1370 | 317 | 304 |
| test | 525 | 1703 | 452 | 349 |

### 4.2 Evaluation Measures

The correct gap filling of DNI refers to the content and boundary of antecedent correct, as well as NI type, we use precision, recall, and F-score to evaluate the performance of this system. Assume that Cp is the DNI number predicted by system, Cc is the DNI number which is predicted correct and DNI number in the answer of test set for Co, and then we define precision, recall and F-score as following formulas.

$$\mathrm{P} = \frac{C_c}{C_p} \qquad R = \frac{C_c}{C_o} \qquad F = \frac{2PR}{P+R}$$

We evaluate the performance of experiments based on their average value of chapter 13 and chapter 14.

### 4.3 Result in Gold Standard Annotated Corpus

In this section, we use the corpus which has annotated information about null instantiation, i.e., the NI type (DNI vs. INI), assuming that NIs have been identified and correctly classified as DNI or INI, we only focus on the DNI. For each DNI, the experiment chooses candidate words in context based on the rules defined in 3.1, and then takes their features as input for training and predicting on the maximum entropy model. We think a DNI has no referents, when no word in candidate words set of this DNI is judged as its antecedent. In order to get the best feature template, we choose H3 in table 1 as search space for DNI candidate set according to Chen et al. The results are listed in table 6.

**Table 6.** The results of different characteristics combination under gold standard annotation(%)

| character | Chapter13 | | | Chapter 14 | | |
|---|---|---|---|---|---|---|
| | Prec. | Rec. | F | Prec. | Rec. | F |
| C1 | 22.93 | 22.78 | 22.86 | 28.04 | 27.75 | 27.89 |
| C2 | 22.93 | 22.78 | 22.86 | 28.04 | 27.75 | 27.89 |
| C3 | 16.98 | 22.78 | 19.46 | 24.32 | 28.27 | 26.15 |
| C1+C2 | 22.93 | 22.78 | 22.86 | 28.04 | 27.75 | 27.89 |
| C1+C3 | 23.27 | 23.42 | 23.34 | 27.55 | 28.27 | 27.91 |
| C2+C3 | 18.09 | 22.78 | 20.17 | 24.76 | 27.23 | 25.94 |
| C1+C2+C3 | 23.27 | 23.42 | 23.34 | 27.69 | 28.27 | 27.98 |

Based on the data shown in table 6, we can get that combination of C1, C2 and C3 has better performance than others. This means that combining all features to build feature template could provide more information to the system. In addition, table 6 also shows that the results of chapter 13 were lower than chapter 14, which may be caused by several reasons. Firstly, in test data, chapter 13 contains 97 DNI frame elements which are same with train data, while chapter 14 has 130. So it is obvious that candidate words set in chapter 14 can cover more DNI referents than chapter 13 based on the first candidate words select rule. Secondly, the experiment consider words in previous three sentences as candidate DNI referents, but there are 14 percent of antecedent out of it in chapter 13, and 5 percent in chapter 14. A case in chapter 13 is given as follows:

```
<fe id="s42_f2b_e1" name="Judge">
  <fenode idref="s33_8" />
  <flag name="Definite_Interpretation" />
</fe>
```

Finally, it is exists that DNI referents is composed of multiple phrases rather than one word, which is not taken into account in the system. This situation in chapter 13 has 8, and in chapter 14 has 7. For example:

```
<fe id="s33_f6_e2" name="Action">
  <fenode idref="s33_7" />
  <fenode idref="s33_13" />
  <fenode idref="s33_12" />
  <fenode idref="s33_11" />
  <fenode idref="s33_9" />
  <fenode idref="s33_8" />
  <flag name="Definite_Interpretation" />
</fe>
```

Because combining all features to build feature template could improve the performance of the system, so we choose C1+C2+C3 in table 6 as features to study the influence of candidate words set in different search space, aiming to choose the best one which could get optimal performance. The results are showed in table 7.

When choose H2、H4、H6 or H8 as search space of candidate words set, we can get more information to train than others. It leads to the number of classification results and correctly predicted more than choose H1、H3、H5 or H7. As a result, the precision of the former ones is lower than the latter ones, but have higher recall. We can conclude that the F-score of system is highest when candidate set is H3 via comparison.

**Table 7.** The results of DNI gap filling in different candidate words sets (%)

| Num | Prec. | Rec. | F |
|---|---|---|---|
| H1 | 25.24 | 25.53 | 25.38 |
| H2 | 24.21 | 27.06 | 25.55 |
| H3 | 25.48 | 25.84 | 25.66 |
| H4 | 23.40 | 26.74 | 24.95 |
| H5 | 25.31 | 25.53 | 25.42 |
| H6 | 23.23 | 26.42 | 24.72 |
| H7 | 25.31 | 25.53 | 25.42 |
| H8 | 22.72 | 26.79 | 24.57 |

### 4.4 Result in NIs only Task Test Data

We have systematically evaluated our model on the corpus distributed for NIs only task of SemEval-10's Task-10, as described in Section 4.1. Besides, in order to focus on gap filling of DNI automatically and compare with related work, all the experiments are carried out on gold-standard semantic role labeling. The complete task can be modeled as a pipeline consisting of three sub-tasks: (a) identifying potential NIs by taking into account information about core arguments, (b) automatically distinguishing between DNIs and INIs via maximum entropy model, and (c) resolving NIs classified as DNI to a suitable referent in the text. We identify NI types based on FrameNet and use maximum entropy model to classify Nis[12]. The result of DNI identification is shown in table 8. The number of our predicted DNI is more than VENSES++, which is a big reason why our result of DNI gap filling is better than them. But we can also see from the table, our result is far from the gold standard number. Because task (c) is on the basis of task (a) and (b), so it is a limit to the result of DNI gap filling.

**Table 8.** Result of NI identification

| | Chapter 13 | | Chapter 14 | |
|---|---|---|---|---|
| | DNIs | INIs | DNIs | INIs |
| Gold | 158 | 116 | 191 | 245 |
| VENSES++ | 35 | 16 | 30 | 20 |
| Predicted | 144 | 85 | 158 | 144 |

As concluded in section 4.3, the system achieved the best performance when the model was H3+C1+C2+C3, so we use it to build feature template for gap filling of DNIs which are predicted by our system.

**Table 9.** Compare the results in corpus of gold standard annotated and NIs only task (%)

| corpus | gold standard annotated corpus | | | NIs only task corpus | | |
|---|---|---|---|---|---|---|
| | Prec. | Rec. | F | Prec. | Rec. | F |
| Chapter 13 | 23.27 | 23.42 | 23.34 | 13.89 | 12.67 | 13.25 |
| Chapter 14 | 27.69 | 28.27 | 27.98 | 17.72 | 14.66 | 16.05 |
| Average | 25.48 | 25.85 | 25.66 | 15.81 | 13.66 | 14.65 |

Table 9 shows the average result of gap filling of DNI in gold-standard annotated corpus and NIs only corpus. We can see from the table that precision of the former is nearly 10 percent higher than the latter, as well as recall and F-score, the majority reason is that the result of third step in NIs only corpus is greatly influenced by the former two steps. According to our statistics, the number of DNI predicted by the system accounts for 66.76 percent of the answer, and the number that predicted correctly is only 42.41 percent, which could cause that the input of DNI gap filling in NIs only task is little than it in gold-standard annotated corpus, which would largely influence on the result of the classification.

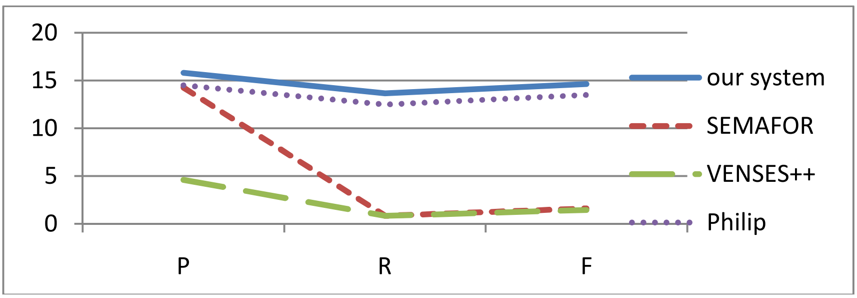


**Fig. 1.** Comparison with previous works

We compare our results with precious work to illustrate the effectiveness of our model. The comparison is showed in figure 1, the horizontal axis display precision, recall and F-score of every system, and the ordinate said percentage. We can see from the figure that our system is better than other ones, the reason of which may boil down to the following:

1. SEMAFOR and VENSES++ combine classification of NI and DNI resolution, they look for an antecedent for an omitted role, if find it, they label the role as DNI, otherwise, it is labeled as INI. While in our system, we decompose the problem into two independent steps. Our system identifies null instantiation at first, and then resolves the DNIs, which entails finding referents in the context. By the way, we can take the DNIs which have no referent into account, so the recall of our system is higher than others.
2. SEMAFOR system consider nouns, pronouns, and noun phrases from the previous three sentences as candidate DNI referents, so 26.65 percent of gold DNI referents haven't be considered according to table 1 and table 2. In addition, the semantic features they choose received negligible weight and had virtually no effect on performance because of data sparseness.
3. VENSES++ system requires large corpus to get information of PAS and AHDS, but the corpus of NIs only task is too small to cover all the information.
4. Philip and others only make use of minimal supervision for modeling the role linking task, which make their result lower than ours.

Compared with the three models, there are two advantages of our proposed model. One is the rule for selecting candidate words in this paper could maximum cover all the DNI referents. And the other one is adding information of head word and frame to traditional features could get the best feature template.

## 5 Conclusion and Further Work

In this paper, we have presented a new approach to find the antecedents for definite null instantiations which are widely used in many fields of natural language processing. By adding new features such as the information of head word and frame to traditional features, we proposed a candidate selection rule which can be used to choose the best candidate words set and combination of features. Experiments show that the proposed model can get a better result than existing ones. It is our wish that this study provides new views and thoughts in natural language processing.

Identification and classification of null instantiation is the cornerstone of DNI gap filling, so it is significant to improve the performance of NI classification for DNI gap filling. Besides, there are a lot of relations between frames in FrameNet. If the relationship of two frames is inheritance, their frame element fillers also have some special connection. Therefore, we will focus on the research of applying frame relations to gap filling of DNI in the future.

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