

# The Nature of Novelty Detection\*

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## Abstract

Sentence level novelty detection aims at reducing redundant sentences from a sentence list. In the task, sentences appearing later in the list with no new meanings are eliminated. Aiming at a better accuracy for detecting redundancy, this paper reveals the nature of the novelty detection task currently overlooked by the Novelty community – Novelty as a combination of the partial overlap (PO, two sentences sharing common facts) and complete overlap (CO, the first sentence covers all the facts of the second sentence) relations. By formalizing novelty detection as a combination of the two relations between sentences, new viewpoints toward techniques dealing with Novelty are proposed. Among the methods discussed, the similarity, overlap, pool and language modeling approaches are commonly used. Furthermore, a novel approach, selected pool method is provided, which is immediate following the nature of the task. Experimental results obtained on

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all the three currently available novelty datasets showed that selected pool is significantly better or no worse than the current methods. Knowledge about the nature of the task also affects the evaluation methodologies. We propose new evaluation measures for Novelty according to the nature of the task, as well as possible directions for future study.

**Keywords:** Novelty detection, overlap relations, meanings, TREC

## 1 Introduction

From 2002 to 2004 (Harman, 2003; Soboroff and Harman, 2004; Soboroff, 2005), there were three Novelty tracks held by the Text REtrieval Conference (TREC). The focus was on sentence level query-specific (intra-topic) novelty detection. In the tracks, first, sentences relevant to a given topic (a query) are retrieved; secondly, according to the chronological ordering of sentences, latter sentences which provide no new meanings should be removed. Since the novelty task is becoming increasingly important as information distribution and users' needs for novel information from multiple sources increase, it is drawing more and more attention from IR researchers all over the world. In the many previous works, (Gabrilovich et al., 2004) provided a vivid scenario showing the importance of novelty detection. The novelty task can have applications in filtering (Zhang et al., 2002), question and answering (QA) or any other retrieval tasks that may return redundancies to users.

Unlike many other natural language processing (NLP) tasks such as retrieval, summarization, machine translation or QA, which mainly deals with the relevance between documents and queries, or the syntax or meanings of documents or sentences, novelty detection is a task that deals with relations between sentences. Whether a sentence's meanings are covered by another sentence or other sentences is its major concern, while the meanings

of sentences themselves are indirectly involved.

In Novelty (by Novelty, we refer to the novelty detection task, and so is for the rest of the paper), sentences whose entire information content has already been returned by earlier retrieved sentences should be eliminated; only novel sentences remain. In this paper, the novelty or redundancy is Boolean valued; a sentence is either redundant because of previous sentences or novel (same as in the TREC Novelty tracks).

Most previous works (Zhang et al., 2002; Allan et al., 2003; Zhang et al., 2003; Gabrilovich et al., 2004; Zhang et al., 2004) concentrated on the retrieval aspect of the novelty detection task which treated Novelty as a single process of retrieving novel sentences from a sentence list with possible redundancies, and thus, inevitably overlooked the characteristics of the novelty task we here propose. In this work, we review the task from an “overlap” perspective. The overlap method is one typical novelty measure introduced by (Zhang et al., 2003). Later on, the reader will see that overlap is not only a method, but also one nature of Novelty. Note, the focus of this paper is on novelty detection – eliminating redundant sentences while preserving all sentences that contain new information; whenever we refer to “Novelty” or “the Novelty track” in this paper, we are referring to this step (namely, the “task 2” of the TREC 2003 and 2004 Novelty tracks). In “task 1” of the TREC Novelty tracks, the participants first tried to retrieve the relevant sentences from a collection of sentences, then to reduce the redundancies of the retrieved sentences, while in task 2, the relevant sentences were already given, and only redundancy reductions were to be performed. The experimental results of this paper were obtained on the Novelty 2003, 2004 task 2 datasets and Yi Zhang’s novelty collection, in which redundancy reductions were performed on the sets of all the relevant and only the relevant sentences (documents). The collections are consisted of about 50 topics, and of course with each topic a different set of relevant sentences (documents). Though

the units of novelty processing in Yi Zhang’s collection were documents, different from TREC’s sentences, our selected pool method was also proved effective on this collection, which showed that our method generalizes well for different units of processing. The qualities of the available datasets could be another reason why researchers have not noticed the nature of Novelty we here propose, there was only a short time after all the three collections were established; more importantly, in natural language processing tasks, theoretical evidence from semantic theories though could provide a solid basis for discussion, experiments done on more collections make people more confident about the empirical validity of a proposed framework: in this paper, the PO-CO relation formalization of the novelty task.

In Yi Zhang’s pioneering work on Novelty (Zhang et al., 2002), several questions were raised regarding the redundancy measure and the novelty detection procedure: symmetric or asymmetric redundancy measure, sentence-to-sentence or sentence-to-multiple-sentences comparison model. We hope that this study has found satisfying answers to the questions both theoretically and empirically. Problems such as novelty depending on the user (what’s novel for the user) are not the focus. Actually various forms of background information can be brought into the novelty task. For example, logic can be used to derive more meanings given a fixed set of sentences. Physics, geographical information or even personal knowledge of a user can also be adopted. Though only the original meanings were considered in this study, we can still incorporate into our framework further information or rules other than the original lexical meanings, with certain modifications.

An outline for the rest of the paper is as follows: Section 2 starting from the similarity method, summarizes the widely used overlap methods and some current difficulties in novelty computation. Section 3 is the heart of the paper, in which the nature of the novelty detection task is provided as a combination of the PO-CO relations. Though our formalization can be seen as a direct

derivation from the semantic theories of natural language, this formalization is actually independent of the representations of sentences or documents (as sets of meanings, as sets of terms, or as language models). Some implications toward techniques dealing with Novelty suggested by this nature will also be discussed in this section, such as the use of language modeling and clustering techniques in Novelty. In section 4, we try to address the current difficulties in novelty computation empirically, with the help of its nature, which leads to the selected pool method. We provide, in section 5, the corresponding experimental results on the three novelty detection datasets, which reveals the comparative advantage of selected pool to the overlap and pool methods. Furthermore, in section 6, following the experiments in the previous sections, we discuss the evaluation methodologies for Novelty from two distinct views, and propose a more reasonable measure. Section 7 concludes the paper and provides possible directions for novelty detection.

Here, we apologize in advance for the dispersed experimental results among the sections: section 2 (which contains an introduction to the three novelty datasets and experiments for overlap and similarity method), section 5 (which contains the comparisons between selected pool and other methods on the three collections; these comparisons are essential in supporting the main thesis of the paper), and section 6 (which evaluates the results between similarity and overlap in section 2 with a different measure: SPSM). The experiments were distributed to the corresponding sections to maintain a continuity of discussion in this paper.

In the course of our investigation, meanings of sentences are inevitably involved. Our mathematical treatment of meanings is from a unique viewpoint, different from any previous semantic theories; we studied the relations between sentences in their meanings. Although these treatments are far from complete, they do work for Novelty at least. Nevertheless, novelty detection remains a difficult task which is determined by the complexities and

arbitrariness of natural language. The purpose of our study was to identify exactly where the difficulties lie, and divide the difficulties into as many small pieces as possible. The field of novelty detection must still face problems that cannot be easily solved, relating to natural language understanding.

## 2 The overlap method

In the previous works, there were always two standard themes of novelty detection techniques. In one theme, to judge the current sentence, first, redundancy comparisons between the current sentence and each of the previous sentences were performed. Next, the maximum of the redundancy scores obtained from the first step was compared against a threshold ( $\alpha$ ) to finally decide whether the current sentence is redundant; if the maximum redundancy score exceeded  $\alpha$ , the current sentence would be classified as redundant. Simple similarity method (Zhang et al., 2002) and overlap method (Zhang et al., 2003) both adopted this one-to-one comparison paradigm. In the other theme, the redundancy score between the current sentence and the pool of all the previous sentences together was used against threshold  $\alpha$  to make the redundancy decision. The simple pool (Zhang et al., 2003) and the interpolated aggregate smoothing Language model (Allan et al., 2003) applied this paradigm.

The two themes were adopted because of the conception of the novelty detection task that in judging a current sentence, all previous sentences should be used. Next, we will show that this conception is generally wrong, because novelty judgment is not what we used to think a single inseparable judgment process.

We introduce three implementations of the above two themes related to this investigation: the similarity method, simple term overlap method and simple pool method. Improvements of our method over the methods will

shown in the experiments section.

## 2.1 From similarity to overlap

There are two notions essential in Novelty: the *differentiation of meanings* and the *chronological ordering* of acquisition of knowledge; if a new sentence contains meanings that are *different* from any other *previously* known meanings (facts), it is novel. (For example, “Tom is five” is different from “Tom has a sister” even though Tom appears in both.) Consequently, if humans were unable to differentiate the meanings of sentences, the novelty task would no longer exist.

From the *differentiation of meanings* we know that if the meaning of a sentence is the same as some known fact, the sentence is redundant. So a symmetric similarity measure between *sentences* can be used to estimate the symmetric “same” relation between *meanings*. A sentence sufficiently similar to a previous one is considered redundant. Taking a first look at the novelty task, anyone would probably come up with a similarity measure. The differentiation of meanings is probably the only reasonable explanation for the use of symmetric methods in Novelty, which depends on identifying meaning (fact) with sentence; one sentence could only contain one fact.

Although similarity has been proven to be effective experimentally (Zhang et al., 2002), (Zhang et al., 2004), if we think twice, when one sentence’s meanings are covered by another, this relation is not necessarily symmetric, because sentences may contain multiple meanings. An asymmetric overlap measure should be used eventually ((Zhang et al., 2002) and (Zhang et al., 2003) mentioned such belief). The overlap method in (Zhang et al., 2003) was proved to be stable among different data collections (Zhang et al., 2003, 2004, 2005). The similarity and overlap methods presented in this paper were defined as

in (Zhang et al., 2003, 2004):

$$\begin{aligned} Sim(A, B) &= \frac{|A \cap B|}{|A \cup B|} = \frac{\sum_{i \in A \cap B} \min(A_i, B_i)}{\sum_{i \in A \cup B} \max(A_i, B_i)} \\ OverlapB_A &= \frac{|A \cap B|}{|B|} = \frac{\sum_{i \in A \cap B} \min(A_i, B_i)}{\sum_{i \in B} B_i} \end{aligned} \quad (1)$$

$OverlapB_A$  is the overlap of sentence B by a previous sentence A.  $A_i$  is the TFIDF weight of term i in A (Salton and Buckley, 1988). In experiments, thresholds were set to judge whether two sentences are sufficiently similar, or whether a large enough portion of one sentence is overlapped by another.

Surprisingly, despite the theoretical advantage of overlap, similarity is empirically better than asymmetric methods like the overlap method, as experimental results from (Zhang et al., 2002) and (Zhang et al., 2003) indicated.

Before we present the experimental results, let us first introduce the three datasets of novelty detection.

In Zhang Yi's pioneering work on large scale empirical study of the novelty detection problem (Zhang et al., 2002), a document level novelty detection dataset (nyyiz) was constructed on the archive of news articles from Associated Press (AP) year 1988 to 1990 and Wall Street Journal (WSJ) 1988 to 1990. This collection has totally 50 topics, but 5 of them lacks human redundancy assessments which were excluded from the experiments in this paper. In (Zhang et al., 2002), two notions of redundancy were used in the assessments: absolutely redundant and somewhat redundant. In the experiments below, we are concerned only with the notion of absolute redundancy which is the same as from the TREC Novelty collections.

In TREC 2003 and 2004, two datasets TREC Novelty 2003 (nv03) and 2004 (nv04) were constructed, also on newswire articles. Both consist of 50 topics, but use sentences as units of processing instead of documents (sentences from 25 relevant articles for each topic were used to construct

Table 1: Similarity and the overlap method

<b>nv04</b> 5 docs	#ret	Av.P	Av.R	Av.F	#novel
s0.4	986	0.688	0.977	0.790	627
o0.7	974	0.694	0.964	0.786	634
<b>nv04</b> 25docs	#ret	Av.P	Av.R	Av.F	#novel
s0.4	7008	0.463	0.957	0.610	3282
o0.7	6965	0.462	0.950	0.608	3255
<b>nv03</b>	#ret	Av.P	Av.R	Av.F	#novel
s0.4	13495	0.719	0.978	0.817	9962
o0.7	13303	0.719	0.972	0.815	9836
<b>nvyiz</b>	#ret	Av.P	Av.R	Av.F	#novel
s0.4	9082	0.919	0.977	0.946	8313
o0.8	9349	0.909	0.988	0.945	8452

nv03 and nv04).

Experiments in this paper were performed on these three collections, the only public text collections currently available for novelty detection research.

Table 1 provides for each run: #ret - the total number of sentences for the 50 topics returned by a run (judged to be novel by a run), Av.P - precision of the true novel sentences in the returned averaged over 50 topics, Av.R - average recall of novel sentences, Av.F - average F-measure (F-measure trades off between precision and recall), and #novel - number of novel sentences returned. In all the tables, we used the following abbreviations: “s  $\alpha$ ” for similarity with threshold  $\alpha$ , “o  $\alpha$ ” for overlap with threshold  $\alpha$ , and “p  $\alpha$ ” for pool. In Table 1, “o0.7” is the overlap method with threshold  $\alpha = 0.7$ ; “s0.4” is the similarity method with  $\alpha = 0.4$ . (both overlap and similarity thresholds were chosen to optimal on the test collection.)

From the table, we can see that in F-measure, similarity was uniformly

better than overlap on the three collections: nv03 (0.817 vs. 0.815, significant at  $p=0.04$  by a paired t-test), nv04 (for all the 25 documents, 0.610 vs. 0.607 but not significant by paired t-test, for the first 5 documents, 0.790 vs. 0.786, not significant; we keep the results from the first 5 documents for nv04 due to reasons that will be given in section 6), and nvyiz (0.946 vs. 0.945, similarity is better, but not significant). The F-measure difference was small because overlap and similarity differ slightly.

## 2.2 The pool method

In the above subsection, only sentence to sentence comparison is considered. But for general novelty detection, since all “old” sentences should be used to judge the current sentence, a possible method would be to compare the current sentence with all previous sentences. A pool method would be an obvious choice, in which overlap between the pool of terms from all previous sentences and the set of terms from the current sentence is computed, with a fixed threshold  $\alpha$  for redundancy judgment like in overlap.

But features like TFIDF weighted terms, being only surface features of sentences not the exact meanings, make this pool consisting of all previous sentences too noisy to perform well. Section 5 compares the performance of overlap and pool method on 2003, 2004 Novelty datasets and Yi Zhang’s novelty collection; in Table 3, an overall comparison is given. On one hand, overlap returned about 30% redundant sentences (in table 1, average precision is about 70%), which suggests to remove more sentences, on the other hand, the pool method which removes more sentences is too “noisy”, we resolve this difficulty by looking deeper into the task.

## 3 The two relations

By “relation” we mean the mathematical relation; a relation  $R$  between the elements of a set  $A$  is a subset  $C$  of the Cartesian product  $A \times A$ . Any  $a \in A$  and  $b \in A$ ,  $aRb$ , if  $(a, b) \in C$ . In this paper,  $A$  is a set of sentences, and we deal with relations between sentences.

In which follows, mathematics will help us clarify the conception about Novelty. In the novelty task, one relation requires much attention: the relation whether a sentence is overlapped by another or some others. But the definition of this relation is never clearly stated in any previous work about Novelty, because this relation is not exactly one relation! Previous literature, such as (Zhang et al., 2002; Gabrilovich et al., 2004; Zhang et al., 2003, 2004) have mixed the following two relations with very different properties in forming this “one relation” in Novelty. ((Collins-Thompson et al., 2003) only considered the  $>_{co}$  relation between two sentences.)

### 3.1 The two relations

First, the partial order relation  $>_{co}$ , we called the *complete overlap relation*. One sentence  $A >_{co} B$ , if  $A$  contains all the meanings of sentence  $B$ . This relation is a partial order relation. It is transitive and antisymmetric. For sentences  $A$ ,  $B$  and  $C$ :

1.  $A >_{co} A$  (Reflexivity).
2. If  $A >_{co} B$  and  $B >_{co} A$ , then  $A = B$  in meaning (Antisymmetry).
3. If  $A >_{co} B$  and  $B >_{co} C$ , then  $A >_{co} C$  (Transitivity).

In Yi’s work (Zhang et al., 2002), only the third property is presented explicitly as an assumption. The above three properties together characterize the complete overlap (CO) relation.

Second, the symmetric relation  $>_{po}$ , we called *partial overlap relation*.  $A >_{po} B$ , if A and B have meanings in common. Note that having common meanings does not require A to completely overlap B, though complete overlap is sufficient for partial overlap. This relation is non-transitive and symmetric. For sentences A, B and C:

1.  $A >_{po} A$  (Reflexivity).
2. If  $A >_{po} B$  then  $B >_{po} A$  (Symmetry).
3. If  $A >_{po} B$  and  $B >_{po} C$ , A and C need not have the  $>_{po}$  relation. (E.g.,  $A = \{a\}$ ,  $B = \{a, b\}$ ,  $C = \{b\}$ . Here,  $A >_{po} B$  and  $B >_{po} C$ , but  $A >_{po} C$  do not have this PO relation. No transitivity here).
4. If  $A >_{po} B$  then  $\exists C \neq \emptyset$  such that  $A >_{co} C$  and  $B >_{co} C$  (*Separation of meanings*). Here, C is a separated sentence containing common meanings of A and B, but need not contain all the common meanings of A and B.
5. If  $A >_{co} B$ ,  $B \neq \emptyset$  then  $A >_{po} B$  (Complete overlapping is sufficient for partial overlapping).
6. If  $A >_{co} B$  and  $B >_{po} C$ , then  $A >_{po} C$ . Here, A is called a CO expansion of B, and this property states that CO expansions preserve PO relations.
7. If  $A >_{po} B$  and  $B >_{co} C$ , A and C need not have the  $>_{po}$  relation.
8. If  $A >_{po} B$  then  $\exists C = A \cap B, C \neq \emptyset$  (*The intersection definition*). Here, C contains all the common meanings.

As the PO relation is symmetric, we called the sentences that are PO related to one sentence its PO relatives. (e.g., for sentence A in  $\{A\}$ :  $A >_{po} B$

and  $A >_{po} C\}$ , B and C are called A's PO relatives, and similarly A is also B's and C's PO relative.)

In the above properties, (1, 2, 3, 5, 6 and 7) are the basic properties of the PO relation as they can be derived from having common-meaning definition, or from property (4) – separation of meanings alone, or property (8) alone. Property (4) is sufficiently strong for the PO relation, but may not be necessary. Property (8) is even sufficient for (4).

In the case of multiple sentences (e.g., A, B and C) overlapping one single sentence (say D), the PO relation conforms to reality, because to have an overlap relation, A, B and C must all be D's PO relative (not necessarily  $>_{co}$  D each), and together  $A \cup B \cup C >_{co} D$ .

Note that for sentences we assume there are also operations and relation like in set theory:  $\cup \cap$  and  $\subset$ , but they need not be exactly the same as in set theory. In the introduction, we said we can adopt background information and rules such as geographical information and logic rules. The only difference it will make is that there should be corresponding modifications to the operations of the sentences. For example,  $A \cup B$  will be  $A \cup B \cup \{\text{the facts derived from } A, B \text{ and background information (if there is any)}\}$  according to the rules}.

In PO relations which are actually symmetric, we still use the “ $>$ ” sign usually used to denote asymmetric relations. The reason for this is that even though the PO relation itself is symmetric, in the novelty task, where sentences are aligned along a time line and only previous sentences can overlap a subsequent one, thus, an asymmetry is imposed onto the PO relation. If  $A >_{po} B$  and  $B >_{po} A$ , then A and B must appear at the same time, which means A and B must be the same sentence. Hence we could see clearly that the asymmetry of the PO relation is external; it should not be mixed up with other properties of the PO relation (unfortunately there was already a paper that did make the mistake).

Note that the relations defined above are completely different from the “partially redundant” and “absolutely redundant” in (Zhang et al., 2002), where the redundancy is more subjective, as being judged by assessors. The two relations we here defined are more objective; they are Boolean valued, and the CO relation must be either completely redundant or novel, which is closer to the notion of “absolutely redundant”, thus only the “absolutely redundant” judgments in Yi Zhang’s collection were used for the experiments of this paper.

### 3.2 Sets of facts

In this subsection, we provide an explanation of the PO-CO framework with semantic theories of language. Facts (which can be represented as logical expressions) are meanings of the statements that can be asserted as either true or false. In Novelty, only sentences that tell clear and complete facts are considered. Even though Tom appears in both “Tom is five” and “Tom has a sister”, the two statements are about two distinct facts, and therefore, there are no common meanings between the two. Throughout the paper, we are talking about “meanings” of sentences, to be exact, it is actually the senses of sentences; we distinguish reference and sense from the ambiguous word “meaning” like Gamut (1991) did. Novelty requires senses, not references, because it is intensional in its nature rather than extensional, since it asks the question: ”Is the sentence novel?” rather than ”Is it true?”. Actually, the above relational structure and properties of the relations arise from the discrepancy between the units of novelty processing (i.e. sentences) and the units of novelty definition (i.e. sense – what is novel is actually individual senses, not sentences; sentence is a much larger unit).

From the discussions of the previous sections, it may seem that meanings of sentences are actually treated as sets of facts, or similar to sets. We have

even used sets in the examples. The set of facts assumption for meanings is strong enough to provide all previous properties listed. Since the set assumption is very strong (which may even be the finest we can attain), we can use sets to provide counter examples, as in the PO relation property (3). But using sets introduces a problem; the set definition is too strong, and has a narrower range of application. We should generalize it little by little to the weakest assumptions we can possibly achieve.

When we define the PO relation, there are actually three different definitions. For *the first*:  $(A \ B)$  is a PO pair if there is common meaning between them. This definition is precise in the sense that there are no assumptions about what meanings of sentences would be like. In this definition, the properties (1, 2, 3, 5, 6 and 7) of the PO relation can be derived. In spite of its simplicity, this PO definition is too ambiguous and should be formalized to bring the PO relation into the PO-CO framework. This can be achieved by *the second definition*, which defines the PO relation using the three properties of the CO relation and the *separation of meanings* ( $A >_{po} B$  if  $\exists C \neq \emptyset$  such that  $A >_{co} C$  and  $B >_{co} C$ ). Separation of meanings is stronger than the first definition, because it says if there are common meanings, some common meanings can be separated (from A and B to a sentence C). *The third definition* is the intersection definition, which requires that for  $A >_{po} B$ , there exists a maximum sentence  $C = A \cap B$ . Here, maximum means for any sentence S, if  $A >_{co} S$  and  $B >_{co} S$  then  $C >_{co} S$ . This definition is stronger than the separation of meanings definition, since the separation of meanings can be derived from it. None of the three definitions require meanings to be treated as sets. The set assumption is even stronger than the intersection definition. That is to say, in our definitions of CO and PO relations, meanings of sentences need not be exact sets of facts.

Every assumption here has its exceptions, of course. But at least it's likely that in most cases the weak assumptions are not far from the reality

or from the users' needs if we just focus our interest on the novelty detection in news stories where only simple facts and events are involved. (Cases such as abnormal state detection in industrial plant monitoring or novelty detection in robot navigation (Saunders and Gero, 2001) apparently seem quite different from the text novelty task we are considering here; even natural language is not involved. For these applications, usually a deviancy measure for a new event to the current probabilistic model alone is enough. But there can be similar improvements like those we have brought into sentence level novelty detection: introducing a PO relation and locating the PO relatives before using deviancy measure. This means, the PO-CO framework is a true nature of novelty detection, and exists in every novelty detection task, not necessarily text novelty detection.) What definition we shall choose at a specific occasion depends on what properties we need in processing, but if we adopt stronger and finer properties like separation of meanings or intersection property or even set assumption, we must be aware that the results we attain can only be applied to more limited cases.

Here are some examples. A: "Tom has a sister; she is reading a book", B: "Tom's sister is reading a book".

Sentence A contains more meaning than B because A states that Tom has a sister (if we take only lexical information into account, implications or presumptions of sentences are not considered). A consists of two facts, but B only one. So  $A >_{co} B$ . This example can still be explained under sets of facts assumption, but is surely less obvious than in "Tom is five, and Tom goes to school"  $>_{po}$  "Tom is a five-year-old boy" where the common meaning can be separated as "Tom is five". The following will be even more obscure.

C: "I frightened the cat, and it ran away", D: "I frightened the cat, so it ran away".

C contains only two facts, but D contains two facts the same as C, and also a belief that the cat ran away because I frightened it. So  $D >_{co} C$ . If

sentences become more complicated, even for the most sophisticated minds, it will be a difficult task to count the facts in them. This is especially true when we consider more background information or implications of meanings, because not only can sentences have generated meanings but also there may be contradictions derived from original sentences or the meanings implied by them. Even if the assumptions do not fail, it is still difficult to program a computer to solve them.

If, for example, we take emotional facts implied by sentences into account, it will be difficult for the separation of meanings assumption to hold: E: “You savagely killed the cat”, F: “You murdered the cat”. The separation of the emotional subtleties between E and F seems difficult. As we consider more facets of the natural language, since the emotional suggestions of the terms like “murder” or “savagely” are hardly exact and clear, probabilistic models or fuzzy models may be of use.

Here in defining CO and PO relations, we only set up assumptions about relations between sentences, since this is the least the novelty task requires. The meanings of a sentence, whether behaving like a set or not, are not necessarily concerned. At least, we are very fortunate, as whatever definition among the three we adopt, we can always have the several basic properties of the PO relation.

Interestingly, there is also a correspondence (Opitz et al., 1999) of the PO and CO relations in the human brain during novelty processing to the “*retrieval of related semantic concepts*” at the right prefrontal cortex (which usually actively maintains context information during performance of working memory tasks) and “*registration of deviancy*” at the superior temporal gyrus (the language and music processing center), which strongly supports the discussions here. No matter how a PO relation is defined or what the meanings of sentences may look like, there should be a procedure that corresponds to the *retrieval of related semantic concepts*. This correspondence is

the best evidence that the PO relation actually widely exists, and thus should not be neglected in novelty processing. But as we saw in the above examples, if we are to practically use these relations, there are many factors to be defined and specified (such as what background information or rule to use, whether implications or presumptions of sentences are considered and setting up rules to resolve contradictions in the data, etc.), to resolve uncertainties and rule out difficult cases in the natural language.

### 3.3 Some direct results from the relations

After clarifying the nature of the novelty task, we can have some nontrivial examples (applications) explained under the framework of PO-CO relations.

A first example to see will be a method for Novelty that uses clustering techniques (Zhang et al., 2004) (the Subtopic III method: sentences are clustered into several classes and only sentences within one class can have an overlap relation; overlaps between clusters are not considered). As we know from the properties of the PO relation, PO relations actually differ in one point from equivalent relations: transitivity. PO relations are not transitive, thus there can be no equivalent classes. The usage of the clustering methods in the novelty task has an intrinsic difficulty - the sentences need not necessarily form classes. So introducing clustering techniques without taking this fact into account can be harmful. In TREC 2003, the Subtopic III method was shown to be ineffective. (The work (Yang et al., 2002) is different from the intra-topic clustering discussed here. In (Yang et al., 2002), inter-topic clustering of documents were performed, which is not our concern.)

A second example is the uses of language models (LM) in novelty detection. There can be two usages of LM. In the first, like in retrieval (Ponte and Croft, 1998), a generation probability of the current sentence on the basis of previous sentences can be used to estimate redundancy. Take

for example, the task of ranking new documents according to novelty given a known set of seed documents (Gabrilovich et al., 2004). According to the PO-CO framework, each different newly appearing document, the LM for the previous sentences should be constructed on the PO relatives of the new document. The document sets used to construct the models could be different for different new documents; thus, the comparison of generation probability of the two new sentences using two respective LMs is not mathematically justified. This is clearer under the measure theoretic view of probability. The two different models impose two distinct measures onto the event space. In ranking documents in generation probability, what we are doing is measuring two objects (the two new documents) using two different rulers (the two models). This explains the intuition that if two facts (A and B) are different and both are novel, it is impossible to judge whether A is more novel than B or not. Since Novelty requires only the differentiation of meanings, the ranking of documents here must have been imposed by attributes other than novelty (such as the amount of new information or the number of new meanings). In practice ((Zhang et al., 2002; Gabrilovich et al., 2004; Allan et al., 2003)), another usage of LM is common; for a current document, two LMs are constructed for previous documents and the current document respectively, and the KL-divergence between the two models is used to approximate the degree of novelty. This use of LM, unlike generation probability, is mathematically justified. However, there is no step of finding PO relatives; all previous documents are used. Because of this, it can be easily adopted into the PO-CO framework by constructing the LM on the PO relatives.

Next, there is an important and direct implementation that benefits from the successful distinguishing of the above PO-CO relations.

### 3.4 Novelty – a complex task

Now, we return to the novelty task itself. Once we are clear about the two relations discussed above, we can see immediately that the novelty task we used to refer to as one single task can be considered as actually consisting of two independent subtasks.

The first step is to find out the pairs of sentences that share common meanings. (For a current sentence, this step is just locating the previous sentences having PO relation with the current one.) In this subtask, the *separation of meanings* definition can be useful, as in determining whether a pair has PO relation, we only need to separate some common meaning. This subtask can have its own judgment and evaluation method. One apparent suggestion would be the error rate of the PO pairs (with false alarms and misses as errors).

The next step is to judge whether a current sentence is completely overlapped by previous PO relatives, with all the known PO pairs. We may need to separate all common meanings between two PO sentences in this subtask. And combining all the common meanings of the previous sentences with respect to the current one, we will finally be able to judge whether all meanings of the current sentence are covered by the previous sentences.

In practice, if all the sentences are short, containing only one simple fact, there is no need to use the PO relation; one CO step would serve the purpose well, and there will be almost no difference between the asymmetric overlap and the symmetric similarity measure. The longer the sentences are, the more likely multiple facts exist in a single sentence, and the more likely methods that adopt the PO-CO framework will work better than the methods that treat the complex Novelty as one single task. In the real world data, informative articles always try to include several facts in one single sentence (usually, with the aid of clauses), which justifies applying the PO-CO framework to real world data.

But the two subtasks are still difficult in the sense that they have to deal with complicated cases, outliers of the simplified assumptions we proposed. Even within the scope of the assumptions, a computational solution to manipulate facts in the novelty task is still not apparent. But since we have broken down the novelty task into two subtasks where problems and difficulties are fewer than the complex task that takes Novelty as a whole, it is expectable that novelty research will move a step forward.

We are now able to see that the problems mentioned in the introduction (symmetric or asymmetric novelty measure, one-to-one or multiple-to-one comparison) arose because of an unclear perception of the novelty task, and these questions are gone once we take the view from the nature of the novelty task. But this viewpoint still cannot explain how these questions arose empirically. And our study of novelty, described below, tried to investigate the empirical facet of the questions.

## 4 The selected pool method

Following the previous section, the final and best unit for processing novelty would seem to be facts (i.e. logical forms formalized from sentences). Unfortunately, without proper formalizations, computers do not know what a fact is. And the task of changing natural language sentences into logical forms is still too difficult. When we do novelty detection, we have to use units such as documents or sentences to base our novelty computation on. Therefore, the two classification steps (PO: the step of classifying whether two sentences are PO related, and CO: classification of whether PO relatives of a sentence  $>_{co}$  the current sentence) always exist. Here we use the word classification in the sense as in Pattern Classification, by Duda et al. (2000).

From the stance of the PO-CO framework, it is clear that the previous overlap and pool methods came about because of the ambiguous conception

of the novelty task that when making *the novelty judgment* of the current sentence, we could and should use all the previous sentences in the list, while as a matter of fact, all the previous sentences should be used in the PO judgment, not necessarily the CO step. Accordingly, we propose a selected pool method, in which only sentences that are related to the current sentence are included in the pool (the PO step), followed by a pool-sentence overlap judgment (the CO step). In the experiments, if the TFIDF overlap score of the current sentence by a previous sentence exceeded the selection threshold  $\beta$ , that previous sentence was considered to be PO related to the current sentence. By setting the threshold  $\beta$  to be 0, we include all previous sentences in the pool - the selected pool turns back into the simple pool method. Setting  $\beta$  to be the threshold for pool-sentence overlap judgment  $\alpha$ , the selected pool becomes the simple overlap method. Table 2 shows the change in the performance of selected pool as  $\beta$  changes. A comparison between selected pool, and overlap and pool methods, with automatically learned parameters  $\alpha$  and  $\beta$  using cross validation will be provided in the next section, which is summarized as Table 3. What we must point out is that the overlap score as a feature for making PO and CO decisions is very coarse and certainly not perfect, which suggests possible further improvements.

## 5 Experiments and analyses

We provide experiments comparing selected pool and the baseline methods (overlap and simple pool) on Novelty 2003 (nv03), 2004 (nv04) and Yi Zhang’s novelty collection (nvyiz). Analyses concerning the different characteristics of the three collections and the differences in the performance of the different methods will be also be stated here.

In Table 2, “spa s $\beta$ ” is an abbreviation for selected pool method with overlap threshold  $\alpha$  and selection threshold  $\beta$ . To avoid confusion between

Table 2: The relationship between overlap, pool and selected pool methods with a changing parameter:  $\beta$

<b>nv04</b>	#ret	Av.P	Av.R	Av.F	Difference
p0.7	5713	0.495	0.864	0.615	192 novel in 492 extra
sp0.7s2.0	6205	0.487	0.911	0.620	
sp0.7s2.0	6205	0.487	0.911	0.620	80 novel in 347 extra
sp0.7s3.0	6552	0.475	0.929	0.615	
sp0.7s3.0	6552	0.475	0.929	0.615	56 novel in 266 extra
sp0.7s4.0	6818	0.466	0.942	0.609	
sp0.7s4.0	6818	0.466	0.942	0.609	15 novel in 75 extra
sp0.7s5.0	6893	0.464	0.945	0.608	
sp0.7s5.0	6893	0.464	0.945	0.608	22 novel in 72 extra
o0.7	6965	0.462	0.950	0.608	
<b>nv03</b>	#ret	Av.P	Av.R	Av.F	Difference
p0.7	9127	0.755	0.762	0.744	2763 novel 4123 extra
sp0.7s5.0	13250	0.720	0.969	0.815	
sp0.7s5.0	13250	0.720	0.969	0.815	25 novel 53 extra
o0.7	13303	0.719	0.972	0.815	
<b>nvyiz</b>	#ret	Av.P	Av.R	Av.F	Difference
sp0.8s5.0	9199	0.914	0.978	0.943	70 novel 97 extra
sp0.8s6.0	9296	0.911	0.985	0.946	
sp0.8s6.0	9296	0.911	0.985	0.946	19 novel 53 extra
o0.8	9349	0.909	0.988	0.945	

the two thresholds, the selection threshold was defined to be 8 times the actual one-to-one overlap threshold, so  $o0.7 = sp0.7s5.6$ , with selection threshold  $5.6/8=0.7$ . As the parameter for selection changes, the method changes gradually from pool to overlap. The selected pool with a higher selection threshold will include fewer sentences in the pool, and thus will return more sentences than with a lower selection threshold. The last column of the table (“Difference”) is the number of additional returned novel sentences in the totality of the extra sentences returned. In F-measure s2.0 is better than p0.7, and s5.0 is almost the same as o0.7. But for the additional returned sentences, only a small part (about 1/3 to 1/4) of the additional returned sentences were novel. Simple derivation showed that to increase the F-measure of a set of results, additionally returning a set with precision higher than  $P \div (P+R)$  is sufficient, where P and R are the precision and recall of the original result set. For example, if  $P=0.5$  and  $R=0.9$ , including a set with precision greater than 0.36 already increases F-measure. This strange property of the F-measure can be misleading when comparing different Novelty methods only using the F-measure (e.g. similarity and overlap in Table 1).

## 5.1 Within-collection analyses

On nv04 collection, the F-measure for sp0.7s2.0 (the best performing selected pool) was significantly better than that for o0.7 (the baseline overlap method of the best selected pool) by a paired t-test (0.620 vs. 0.608, significant at  $p = 0.000006$ ; of all the 50 topics, 40 increased, 9 decreased, 1 remained the same); if we consider #errors made in novelty judgments, the change from sp0.7s2.0 to o0.7 is more conspicuous (44 topics decreased in #errors – improved, 3 increased – degraded, 3 remained unchanged, with an average improvement of 8.5%). On the nvyiz collection, sp0.8s6.0 was slightly better than o0.8 in average F-measure (0.946 vs. 0.945,  $p=0.30$ , not significant

by a t-test. But in #errors, 15 topics improved, 7 degraded, 23 did not change, sp0.8s6.0 was significantly better than o0.8 at p=0.037). On the nv03 collection, sp0.7s5.0 was not significantly better than o0.7, and was also no worse. These experiments on the three collections suggested that multiple-to-one comparison is no worse and sometimes better than one-to-one comparison if we use a proper method like selected pool.

Now we are able to answer the question mentioned in the introduction: one-to-one or multiple-to-one comparison. In (Zhang et al., 2002), the multiple-to-one comparison was actually an all-to-one comparison, like in the simple pool method, and simple pool was significantly worse than overlap on nvyiz and nv03 (0.744 vs. 0.815, significant at p=0.0000000001) collections, but was significantly better than overlap on nv04 (0.615 vs. 0.608, significant at p=0.05), which suggests that the pool method is unstable among datasets. The multiple-to-one comparison in (Zhang et al., 2002) was worse than one-to-one because the authors of that paper were not clear about the PO-CO framework we here propose and thus were unable to find an adequate way of using the multiple-to-one comparison theme, whereas novelty computation should use a multiple-to-one theme rather than one-to-one comparison.

For the nv04 collection, the best performance of the selected pool (sp0.7s2.0) was observed around the top runs submitted to TREC 2004 task 2 (Best run: City U. Dublin average F-measure: 0.622, second: Meiji F: 0.619), among all runs with language modeling approaches, cosine similarity measure, information gain and named entity recognition (Soboroff, 2005). Even the worst (simple overlap) could be ranked as high as 7<sup>th</sup>. Thus, the overall performance of the selected pool method as a technique that adopts the PO-CO framework is encouraging.

## 5.2 Inter-collection experiments and analyses

Above are analyses within collections; inter-collection comparisons of the collections themselves and of the performance differences of the methods on different collections are provided below:

Although nv03 and nv04 are datasets selected from the same set of topics and from the same newswire data collection, the redundancy rate by human assessments in nv03 is 34.1% while in nv04 53.7%. This difference was surprising but unexplained by (Soboroff, 2005). We believe that this difference in human assessed redundancy rate is the cause for the difference in performance of selected pool on the nv03 and nv04 collections. Selected pool is better on nv04 than nv03 probably because of the possible different characteristics in the Novelty 2003 and 2004 human assessments - 04 contains more multiple-to-one overlapping cases while one-to-one dominates in 03. There is no direct evidence for this conjecture (human assessments are somewhat incomplete for nv03 and nv04 collections), but it seems to be the most probable explanation for the different behaviors of selected pool. It is possible that with a much shorter list of relevant sentences for each topic, (the rate of relevant sentences is almost less than half that of nv03, this allows assessors to consider multiple-to-one overlap cases more easily) when they were constructing the nv04 dataset, the assessors paid more attention to the multiple-to-one overlapping cases. This also is a feasible explanation for the higher redundancy percentage in nv04 than that of nv03.

Compared to the nv03 and nv04 collections, nvyiz has a more complete structure (for each redundant document, the human assessments also include all the previous documents that actually make this document redundant). Therefore we can have direct evidence from the human assessments showing that nvyiz has a per topic redundancy rate of 10.8%, multiple-to-one cases occupy about 34.7% of the 10.8% redundancies. Because of the existence of those multiple-to-one cases, the selected pool performed better than simple

overlap on nvyiz collection.

One last thing about the comparison between overlap and selected pool is how to choose the parameters  $\alpha$  and  $\beta$ . As selected pool has one degree more freedom than overlap – parameter  $\beta$ , does selected pool tend to overfit because of its superior learning ability? To answer this question, we did Leave-One-Out (LOO) estimations to estimate the expected F-measure and expected #errors of overlap and selected pool. In these experiments, for each topic, the other 49 topics were used for training, the one topic left out was used for validation. Because the parameters were few, the entire parameter space was searched at the training step. Paired t-tests on F-measures of the 50 (45 for nvyiz) test topics showed that on nvyiz selected pool was better than overlap in F-measure (0.946 vs. 0.945, but not significant,  $p = 0.30$ ); on nv04 selected pool was significantly better than overlap (0.620 vs. 0.614, significant at  $p=0.036$ ); on nv03 selected pool and overlap performed almost the same (0.815 vs. 0.815, overlap was slightly better, but not significant). The important thing here is that the LOO estimate of selected pool performed almost the same as the selected pool with the best parameter setting, which means selected pool is stable in spite of its greater learning ability.

The performance of selected pool and simple pool compared to overlap on the three (nv03 nv04 and nvyiz) collections are summarized in table 3. In the table, “–” stands for significantly worse than overlap on the corresponding collection; “++” stands for significantly better under both F-measure and #errors than the overlap method; “+” stands for not significant improvement in average F, but significant improvement under #errors; “0” stands for almost no difference.

In the next section about evaluation, we delve into further measuring of novelty techniques and propose measures suggested by the PO-CO framework. In Yi’s work (Zhang et al., 2002), precision and recall for redundancy and number of mistakes in novelty judgments were used. Based on the frame-

Table 3: Performance compared to overlap

Collections:	<b>nv03</b>	<b>nv04</b>	<b>navyiz</b>
Simple pool	--	++	--
Selected pool	0	++	+

work of PO-CO relations, the measures we investigated were finer and could reveal richer contents.

## 6 Evaluation methodologies

There can be two different viewpoints to the novelty task.

### a. Novelty task as retrieval of novel sentences

A set of novel sentences is to be retrieved from a stream of sentences that may contain redundancies, and in the novelty judgment for a current sentence, all previous sentences (they are the acquired knowledge) can be used. This viewpoint is taken by the TREC Novelty tracks (Harman, 2003), and is seemingly intuitive, because this is just what the novelty task aims at. In this study, the measure for evaluating results from this viewpoint was designated as the Standard Novelty Measure (SNM), which is the F-measure for the novel sentences:

$$SNM = \frac{2 \times P \times R}{P + R} \quad (2)$$

P is the precision of the novel sentences returned, and R is recall. As we will see later, some things are missed when only the SNM is used for judging the results.

### b. Novelty task – a closer look

When asked why one sentence is redundant, one must be able to point out the exact previous sentences that make the current sentence redundant (its PO relatives). So for PO-CO based methods there should be a finer

evaluation method that involves a closer look, which does not only take into account the number of correctly retrieved novel sentences but also the previous sentences covering the redundant sentences. Even if a judgment for the novelty of the current sentence is correct, if the previous sentences that cover this current sentence are not correctly judged, this chance output of the system certainly cannot be called correct. We must construct a new kind of judgment that can prevent the above fallacy.

In our method, we treat the novelty task as a classification of overlapping sentence pairs. Measuring from a classification viewpoint is what the previous TREC Novelty tracks lacked. In our evaluation method, the error rate of the classification is used, as in the following Pairwise Sentence Measure (PSM):

$$PSM = 1 - \frac{\#\text{misclassified pairs(system output)}}{\#\text{total pairs(judgment)}}$$

(3)

where,  $\#\text{misclassified pairs}$

$$= \#\text{missed pairs} + \#\text{false overlapping pairs.}$$

Here, by “#” we mean “the number of”. In the second formula, the missed pairs and the false overlapping pairs are usually called misses and false alarms in the classification terminology (face detection for example), whereas the task here is to detect the overlapping pairs. We define the PSM more clearly; for a run A, suppose  $A_R$  is the set of redundant sentences judged by A, and  $A_N$  the novel sentences judged by run A (the sentences finally returned by A). Immediately,  $A_R \coprod A_N = C$  (disjoint union), where  $C$  is the collection of all sentences.  $i$  is a sentence,  $\mathfrak{R}$  is the set of redundant sentences by judgment (true redundant sentences),  $PO_i$  is the set of true PO relatives of sentence  $i$ , and  $SPO_i$  is the set of sentences run A judges as the PO relatives of  $i$ . For any X set of sentences, suppose,  $|X|$  is the usual measure of  $X$  (the number of elements in  $X$ ),  $|X|_R$  is the redundancy measure of  $X$  (the number of redundant ones in  $X$ ), and  $|X|_N$  is the novelty measure of  $X$  (the number of novel ones in  $X$ ). Here, we have  $|X|_N + |X|_R = |X|$ ,

$$|X|_R = |X \cap \mathfrak{R}|.$$

#misclassified pairs and #total pairs are further defined in equation (4):

$$\begin{aligned} \text{\#misclassified} &= \sum_{i \in A_R - \mathfrak{R}} |SPO_i| + \sum_{i \in \mathfrak{R} - A_R} |PO_i| \\ &\quad + \sum_{i \in A_R \cap \mathfrak{R}} |(SPO_i - PO_i) \cup (PO_i - SPO_i)| \\ \text{\#total pairs} &= \sum_{i \in \mathfrak{R}} |PO_i| \end{aligned} \quad (4)$$

With more correct pairs judged, the PSM will be larger, just as the SNM increases when more novel sentences are found. Even better, the PSM is a finer measure compared to the SNM. The SNM does not correspond to the number of correctly classified pairs, but, if the correct pairs are known, the precision and recall for the novel (or redundant) sentences can be derived from them directly. If the human assessments for PSM are known, we should restrict the use of SNM and adopt this better choice.

In the experiments, unfortunately, as we were unable to determine all the correct pairs for PSM evaluation for all the 50 topics; there are thousands of sentences and tens of thousands of sentence pairs in the Novelty datasets (quite a tremendous task for the limited labor force available). Also, not all methods can return the PO relatives of a sentence, so we adopted an alternative that only made use of the human assessments currently available.

*Simplified PSM (SPSM):* since the  $PO$  and  $SPO$  are unknown, we define  $|PO_i|$  and  $|SPO_i|$  to behave like indicator functions, i.e.

$$\begin{aligned} \sum_{i \in A_R - \mathfrak{R}} |SPO_i| &= |A_R - \mathfrak{R}|, \quad \sum_{i \in A_R - \mathfrak{R}} |PO_i| = 0 \\ \sum_{i \in \mathfrak{R} - A_R} |PO_i| &= |\mathfrak{R} - A_R|, \quad \sum_{i \in \mathfrak{R} - A_R} |SPO_i| = 0 \end{aligned}$$

Then, for a run A,

$$\begin{aligned}
SPSM(A) &= (|\mathfrak{R}| - |A_R - \mathfrak{R}| - |\mathfrak{R} - A_R|)/|\mathfrak{R}| \\
&= (-|A_R| + |A_R \cap \mathfrak{R}| + |A_R \cap \mathfrak{R}|)/|\mathfrak{R}| \\
&= (|A_N| - |C| + 2|A_R|_R)/|\mathfrak{R}| \\
&\quad (\text{since } |A_R|_R = |\mathfrak{R}| - |A_N|_R = |\mathfrak{R}| - |A_N| + |A_N|_N) \\
&= (2|\mathfrak{R}| - |A_N| + 2|A_N|_N - |C|)/|\mathfrak{R}| \\
&= (|A_N|_N - |A_N|_R - (|C| - 2|\mathfrak{R}|))/|\mathfrak{R}|
\end{aligned}$$

This simplification is intuitively proper; SPSM increases as more novel sentences are returned, and decreases with more redundancies returned. Also, the SPSM is linearly related to the Redundancy-Mistake measure in (Zhang et al., 2002) - an increase in SPSM always corresponds to a decrease in the Redundancy-Mistake, if for one topic (for an average over all the topics, SPSM does not always equal to Redundancy-Mistakes, because  $|\mathfrak{R}|$  could be different for different topics). If a run A returns more novel sentences on the basis of B (i.e.  $A_N \supset B_N$ ),  $|A_N|_N - |B_N|_N = |A_N - B_N|_N$ , then

$$SPSM(A) - SPSM(B) = (|A_N - B_N|_N - |A_N - B_N|_R)/|\mathfrak{R}|$$

#novel in  $A_N - B_N$  (number of novel sentences in the additional returned sentences) corresponds to the decrease in #false alarms, and #redundant in  $A_N - B_N$  corresponds to the increase in #misses. This is shown in the last column of Table 2. Under SPSM, in Table 2, selected pool (sp0.7s5.0) on nv03 dataset is slightly better than overlap, and simple pool is far worse than both selected pool and overlap. For nv04 the improvement of selected pool is consistent under both SNM and SPSM. For nvyiz under SPSM, none of the differences between similarity, overlap and selected pool is significant.

Here, in Table 4 we compare the similarity method with the overlap method for nv04 nv03 and nvyiz datasets under SPSM. The results indicate that under SPSM, the overlap method is comparable to the similarity

Table 4: Comparisons between similarity and overlap under different measures

<b>nv04</b> 5 docs	SNM	Mistake%	SPSM
s0.4	0.790	29.5%	0.1094
o0.7	0.786	30.2%	0.1196
<b>nv04</b> all 25 docs	SNM	Mistake%	SPSM
s0.4	0.610	47.8%	0.1607
o0.7	0.608	47.9%	0.1561
<b>nv03</b> 5 docs	SNM	Mistake%	SPSM
s0.4	0.872	19.9%	0.2105
o0.7	0.872	19.5%	0.1970
<b>nv03</b> all 25 docs	SNM	Mistake%	SPSM
s0.4	0.817	26.4%	0.2645
o0.7	0.815	26.7%	0.2320
<b>nvyiz</b>	SNM	Mistake%	SPSM
s0.4	0.946	9.74%	0.0773
o0.8	0.945	10.02%	0.0236

method. Similarity is not always better than overlap; overlap is better on the collections of the first 5 documents of nv04; the differences between SPSMs of similarity and overlap are all insignificant by paired t-tests, even though the change in SPSM on the nvyiz collection is relatively large: 0.0237 vs. 0.0773. That is to say, similarity is better than overlap on all the three datasets under SNM because of the use of SNM. (The asymmetric novelty methods in (Zhang et al., 2002) were far less effective than similarity, and those asymmetric methods were less effective than both the similarity and the overlap method in this study.) The reason we keep the results from the first 5 documents of the nv03 and nv04 collections is that, with increasing number of documents, the possibility of multiple-to-one overlap cases will also increase, which could affect the evaluation of simple overlap and similarity methods which only consider one-to-one overlapping cases. The better performance of similarity on nv03 and nvyiz datasets suggests that these two collections possibly contain more near duplicates, while nv04 contains more overlapping cases (not just simple duplicates) between sentences. Till this point we have both theoretically and empirically answered the questions proposed by (Zhang et al., 2002): symmetric or asymmetric measure, one-to-one or multiple-to-one comparison.

As an alternative to PSM, the Simplified PSM is economical; it is close to PSM, while requiring only information about the novel sentences. Unlike PSM, we do not have to reassess the TREC Novelty datasets before computing the SPSM.

## 7 Conclusions and future work

The PO-CO framework and related discussions (such as the *differentiation of meanings* and the classification viewpoint) as the characteristics of novelty detection is important because they provide new insights into Novelty

theoretically and empirically.

Knowing these properties of the novelty task, we can have two possible and reasonable directions to deal with the task.

The first possibility, as indicated in section 3.4, is to divide novelty into two subtasks: the symmetric procedure of identifying PO pairs and the asymmetric procedure of CO judgment. To improve the novelty detection performance, this direction would seem to be the most probable and feasible one, with separate measures (such as error rates of PO pair and CO relation detection) for the separate subtasks, or with PSM as a final measure.

If the complexity for evaluating the two separate subtasks is intolerable, the second possible direction is to treat the novelty task as a whole, but we should try to find new techniques that improve only one relation of the two, and use SPSM, SNM and even precision recall to measure the improvements. One method that affects both relations can be difficult to evaluate.

Although the experiments in our study were on query-specific novelty detection datasets, many of the conclusions obtained in this paper can have a larger generalization to non query-specific cases. For the novelty task itself, there is still much work to do following this direction, but we hope this paper as a summary for one major aspect of the three years' work on Novelty can be a starting point for those who would like to continue the quest for efficient novelty detection. For the study of semantics, the novelty task also provides us a new insight into the characteristics of meanings: the overlapping relations between meanings of sentences. In our treatment, unlike previous theories which consider meanings themselves, we studied meanings of sentences with the relations between them. We hope this can inspire new methods and insights to applications dealing with complicated objects such as the meanings of natural language.

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