

Turkish synonym identification from multiple resources: monolingual corpus, mono/bilingual online dictionaries, and WordNet

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Abstract: In this study, a model is proposed to determine synonymy by incorporating several resources. The model extracts the features from monolingual online dictionaries, a bilingual online dictionary, WordNet, and a monolingual Turkish corpus. Once it has built a candidate list, it determines the synonymy for a given word by means of those features. All these resources and the approaches are evaluated. Taking all features into account and applying machine learning algorithms, the model shows good performance of F-measure with 81.4%. The study contributes to the literature by integrating several resources and attempting the first corpus-driven synonym detection system for Turkish.

Key words: Synonym, dependency relations, corpus-based statistics

1. Introduction

As one of the most well-known semantic relations, synonymy has been subject to numerous studies. Synonym is defined as expressions with the same meaning being synonymous [1]. The identification of synonym relations automatically helps to address various natural language processing (NLP) applications, such as information retrieval and question answering [2,3], automatic thesaurus construction [4,5], automatic text summarization [6], language generation [7], and lexical entailment acquisition [8].

A variety of methods have been proposed to automatically or semiautomatically detect synonyms from a text source, dictionaries, Wikipedia, and search engines. Among them, distributional similarity is the most popular method. It is based on the distributional hypothesis [9], which assumes that semantically similar words share similar contexts. There have been many studies [5,10,11] that used distributional similarity in the automatic extraction of semantically related words from large corpora. Distributional approaches are applied to monolingual corpora [5,12], monolingual parallel corpora [13,14], bilingual corpora [13,15], multilingual parallel corpora [16], monolingual dictionaries [17,18], and bilingual dictionaries [19]. Some of the studies [20–24] relied on multiple-choice synonym questions such as those of the Scholastic Aptitude Test (SAT) or the Test of English as a Foreign Language (TOEFL).

Although distributional similarity is the most popular method for extracting synonymy, this methodology itself can be ambiguous and insufficient. This is because it can cover other semantically related words and might not distinguish between synonyms and other semantic relations. Hence, recent studies have used different

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strategies such as integrating 2 independent approaches such as distributional similarity and pattern-based approaches, utilizing external features or the ensemble method, which uses multiple learning algorithms to obtain more accuracy. One study [8] integrated the pattern-based and distributional similarity methods to acquire lexical entailment. Another study [25] investigated the impact of contextual information selection for automatic synonym acquisition by extracting 3 kinds of contextual information, dependency, sentence cooccurrence, and proximity, from 3 different corpora. The authors proposed that while dependency relations and proximity perform relatively well by themselves, the combination of two or more kinds of contextual information gives more stable results. In another study [26], a synonym extraction method was proposed using supervised learning based on distributional and/or pattern-based features. Yet another study [27] used 3 vector-based models to detect semantically related nouns in Dutch and analyzed the impact of 3 linguistic properties of the nouns. The authors compared the results from a dependency-based model with context features with first and second order bag-of-words model. They examined the effect of the nouns' frequency, semantic specificity, and semantic class. In one of the recent studies [28], the authors introduced synonym discovery as a graded relevance ranking problem in which synonym candidates of a target term are ranked by their quality. The method used linear regression with 3 contextual features and one string similarity feature. The method was compared with 2 different methods [21,25]. The proposed method outperformed the existing ones.

For Turkish, a WordNet for Turkish was proposed as a part of the BalkaNet project, which is a multilingual lexical database comprising individual WordNets for the Balkan languages [29]. Dictionary entries were parsed and patterns such as the following were used: hw: $w_1, w_2 \dots w_n$ and hw: $(w_i)^*$, w, where hw is a head word and w_i is a single word. In these cases, the authors harvested synonyms from the dictionary definitions that consist of a list of synonyms and that are separated by commas. A total of 11K and 10.8K sets of potential synonyms were extracted. Recent studies for Turkish [30,31] were based on dictionary definitions from the Turkish Language Association (Turkish abbreviation: TDK) Comprehensive Turkish Dictionary and VikiSözlük (Turkish Wiktionary - Wiki) to find specific semantic relations. As a first step, the researchers defined some phrasal patterns that were observed in dictionary definitions to represent specific semantic relations. Reliable patterns were then applied to the dictionary to find the semantic relations. In a study [30], the researchers extracted 24.8K relations with an 86.85% accuracy rate on average. The same process and the same patterns were applied to the TDK dictionary and also to Wiki [31]. Only 206 out of 66K synonymy relations were taken into consideration with an 88% success rate.

As another attempt to detect synonyms in Turkish [32], a corpus-driven distributional similarity model was proposed based on only features, i.e. dependency relations and semantic features obtained by syntactic patterns and lexicosyntactic patterns (LSPs), respectively. The linear regression algorithm was applied to all acquired features and it showed promising results with an 80.3% success rate.

In the current study, the overall objective was to determine synonym nouns from a monolingual Turkish corpus. For each target word, the model automatically proposes the closest K candidate words that are built by means of dependency relations, which refer to certain kinds of grammatical relations between words and phrases such as subjects and objects of verbs and modifications of nouns. The similarities between the target and each candidate were computed using many different features ranging from dictionary definitions to corpus-based statistics. The class labels of the pairs were obtained from monolingual online synonym dictionaries. Finally, linear regression was successfully applied to the data including all these extracted features. The proposed model and the extracted features are presented in the Figure. This study also incorporated semantic relations such as hypernymy and meronymy gathered from a corpus by LSPs, which are string matching patterns based

on tokens in the text and syntactic structure and used dependency relations for the problem of synonymy detection. The main difference and motivation of this framework is that it is the first major attempt for Turkish synonym identification based on a corpus-driven distributional similarity approach using multiple resources such as monolingual online dictionaries, a bilingual online dictionary, and WordNet.

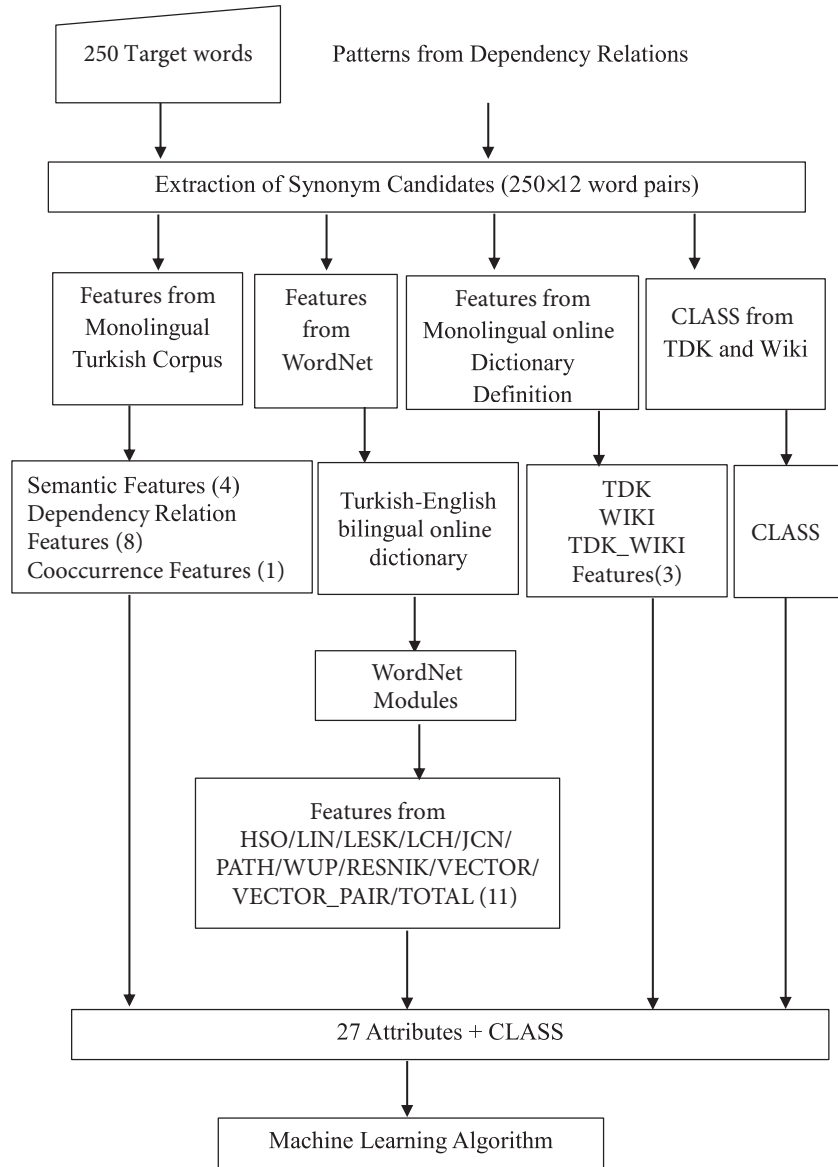


Figure. Process of the model for synonym detection.

2. Methodology

2.1. Resources

The methodology employed here is to identify the synonym pairs with the aid of a monolingual Turkish corpus of 500M words. A finite-state implementation of a morphological parser and an averaged perceptron-based morphological disambiguator were also used [33]. The parser is based on a two-level morphology with accuracy

of 98%. The corpus contains four subcorpora; three of them are from major Turkish news portals and another corpus is a general sampling of web pages in the Turkish language.

In addition, 2 monolingual online dictionaries (TDK and Wiki), a bilingual online dictionary (Tureng, <http://tureng.com/en/turkish-english>), and WordNet were utilized to build features.

2.2. Features

In this study, the target/candidate words are represented by a set of features that are compatible with machine learning algorithms. Features are extracted from different resources: a monolingual Turkish corpus, 2 monolingual online dictionaries, a bilingual online dictionary, and WordNet. For class labels, monolingual online synonym dictionaries are used to tag a given synonym pair. All the processes and features are shown in the Figure.

2.2.1. Features from a monolingual Turkish corpus

Our corpus-based feature extraction methodology relies on the assumption that synonym pairs mostly show similar dependency and semantic characteristics in a monolingual corpus. In terms of semantic relations, if words share the same meronym/holonym and hyponym/hypernym relations, they are more likely to be synonymous. With a similar approach, they can have the same particular list of governing verbs and a similar adjective modification profile. Thirteen different features are extracted from the corpus: cooccurrence, 4 semantic relations based on LSPs, and 8 dependency relations based on syntactic patterns.

Cooccurrence: The first feature is the cooccurrence of word pairs within a broad context where window size is 8 from left and right. Synonym pairs are not likely to cooccur together in same discourse. Thus, a simple cooccurrence measure might not be used for synonymy but for nonsynonymy. We experimentally selected the dice metric to measure the cooccurring feature.

Meronym/holonym: The meronymy/holonymy relation is used to detect a synonymy relation. For meronym relation extraction, some LSPs are categorized into 3 forms for the Turkish corpus: general patterns, dictionary-based patterns, and bootstrapped patterns, as proposed in a previous work [34]. All the details and examples of pattern specifications can be found in [34]. After applying these LSPs, some elimination assumptions and measurement metrics such as χ^2 or Pmi are utilized to acquire the meronym/holonym relation. A big matrix in which rows depict whole candidates and columns depict partial candidates is derived. Each cell in the matrix represents the cooccurrence of the corresponding whole and part. Cosine similarity is used to measure the meronym/holonym profile of 2 given words by applying it to the rows/columns in the matrix.

Hyponym/hypernym: The same procedure used for meronymy acquisition is applicable for the hyponym/hypernym relation. Likewise, a big matrix in which rows depict hyponym candidates and columns depict hypernym candidates is derived by the hyponymy and hypernymy patterns that were explained in detail in [35].

Dependency relations: The dependency relation profile of the nouns can be utilized for the synonymy detection problem. For example, verb/direct object and modifying adjective/noun relations are easily captured by syntactic patterns. In the phrases “driving car” and “driving auto”, car and auto share the same governing verb, drive. Other verbs such as design, produce, or manufacture might also take place in the same relation with these two nouns and they can be easily captured by the patterns. Such cases are simply and technically recognized by regular expressions. The more two given nouns are governed by the same verb and modified by the same adjective, the more likely it is that they are synonyms. The dependency relation profiles of all nouns are built in advance from the corpus, and then the similarity between any given two nouns is computed over these profiles. The other technical details of dependency relation features are shown in Table 1.

Table 1. Dependency features (F: features, adj: adjectives, #ofP: number of patterns).

F	Dependency relations	#ofP	Examples in English and Turkish
G1	Direct object of verb	13	I drive a car/araba sürüyorum
G2	Subject of verb	3	Waiting car/bekleyen araba
G3	Direct object/subject of verb	3	-
G4	Modified by adj+(with/without)	2	Car with gasoline/benzinli araba
G5	Modified by infinitive	1	Swimming pool/yüzme havuzu
G6	Modified by noun	1	Toy car/oyuncak araba
G7	Modified by adj	1	Red car/kırmızı araba
G8	Modified by location	2	The car at park/parktaki araba

Candidate selection for synonymy: We randomly selected 250 target words from the corpus to test the model. To harvest the candidates for a given target word, the system only incorporates dependency relations because of its production capacity and simplicity. We looked at the dependency relation features, which are strong indicators or predictors of semantic relations. For this purpose, the first K, which was chosen to be 6 after a number of tests, and the nearest neighboring words to a given 250 target words were selected in terms of dependency relation features. Four semantic relations were considered for each target word and its nearest 6 words: hypernym/hyponym, meronym/holonym, synonym and cohyponym. The objective is to find which dependency relation features are the most informative and have a tendency to indicate a synonym relation. The model uses them to produce candidate synonyms. For example, the G8 dependency feature proposed nearest words of car as vehicle, automobile, jeep, engine, etc. These words are tagged as hypernym, synonym, cohyponym, and meronym, respectively. All the nearest words are detected and manually evaluated for each target word. According to our results, features G1 and G7 are the most productive for the meronym/holonym relations with a performance of 49.3%. Feature G3 has the highest tendency for a hypernym/hyponym relation with a 21.6% success rate. While features G2 and G5 have tendencies for a cohyponym with a performance of 31.4% and 29.8%, features G4 and G7 are the most successful dependency relations for synonym detection with 25.0% and 30.3% success rates. Thus, for each target word, only the candidates proposed by features G4 and G7 were taken into consideration. The output of this process gives us up to 12 candidates for 250 target words.

2.2.2. Features from monolingual online dictionaries

Dictionaries are the most popular source for acquiring a synonymy relation. In our study, dictionary definitions of target/candidate words are incorporated to compute the similarity of words. All the definitions of target/candidate words are accessed through the TDK dictionary and Wiki. If the target word and its potential synonym mutually appear in their definitions in the TDK dictionary and Wiki, they are labeled as true, and otherwise as false, as a Boolean value.

2.2.3. Features from WordNet

This phase is divided into 2 steps: the translation of each pair from Turkish to English using a bilingual online dictionary and the features extracted from WordNet::Similarity modules for each target/candidate word pair.

Bilingual online dictionary: Using bilingual dictionaries is another method for extracting semantic relations, especially for extracting the synonymy relations. We also utilized a bilingual online dictionary, Tureng. Each target and candidate synonym was translated from Turkish to English to exploit the modules in WordNet resources.

WordNet Corporation: WordNet::Similarity [36] is a freely available software package that contains a variety of semantic similarity and relatedness measures based on WordNet. It supports the measures of Hirst-St. Onge (HSO), Jiang-Conrath (JCN), Leacock-Chodorow (LCH), Lin (LIN), Banerjee-Pedersen (LESK), Patwardhan-Pedersen (PATH), Resnik (RES), Wu-Palmer (WUP), Vector, and Vector Pair. While some similarity measures are based on path lengths between concepts, some are based on information content or vector modules. Translated target/candidate pairs are given to all modules. Their similarities are computed and normalized to be between 0 and 1. The sum of all normalized scores is also kept as an additional potential feature, namely TOTAL.

2.2.4. Synonym classification

The target class is labeled as SYN/NONSYN by using monolingual online synonym dictionaries (TDK and Wiki). Synonymy of all pairs is mutually checked and tagged. While most of the attributes contain real values between 0 and 1, a few of them contain Boolean data. Linear regression is an excellent and simple approach for such a classification.

3. Results and discussion

The similarities between the target and each candidate are computed by 27 different features. The evaluation of attributes can be simply done by looking at their information gain (IG) scores in Table 2. All attributes but cooccurrence provide a positive indicator to detect synonymy. At first glance, the WordNet and dictionary-based similarities seem to show good performance. The most successful algorithms of WordNet are LCH and WUP. They are based on depth and shortest-path approaches. All attributes regarding corpus-based similarities are provided at the end of the list in Table 2. Among corpus-based attributes, the most important dependency relations are G4 and G7. Among the semantic relations, the meronym and holonym relations have better performance than the others. The cooccurrence measure shows a very slight indicator capacity. Error analysis is based on some observations and simple statistics. We applied univariate analysis, the simplest form of statistical analysis, where each individual feature is evaluated within the entire training set. This analysis gives

Table 2. Information gain (IG) of each feature.

IG	Features	Types	IG	Features	Types
0.29	TOTAL	WordNet	0.09	G7	Corpus
0.28	LCH	WordNet	0.07	G4	Corpus
0.28	WUP	WordNet	0.07	Meronym	Corpus
0.27	LIN	WordNet	0.06	Holonym	Corpus
0.27	PATH	WordNet	0.05	G8	Corpus
0.27	VECTOR	WordNet	0.04	G1	Corpus
0.27	HSO	WordNet	0.02	G2	Corpus
0.25	TDK/WIKI	Dictionary	0.008	Co-occur	Corpus
0.23	RES	WordNet	0	G6	Corpus
0.23	TDK	Dictionary	0	G5	Corpus
0.22	VECTOR_PAIR	WordNet	0	G3	Corpus
0.22	LES	WordNet	0	Hypernym	Corpus
0.21	JCN	WordNet	0	Hyponym	Corpus
0.11	WIKI	Dictionary			

a chance to explore the characteristics of the variables. For example, as a result of this analysis, we found that some semantic relations such as hypernymy suffer from sparse data and lack of corpus evidence for words.

Taking all the attributes as a features set of training data, the success rate is 95.2% and the F-measure for synonym is 81.4%, where the false positive rate is 24% and the false negative rate is 1.6%, as shown in Table 3. When running the model only with WordNet similarity scores, the linear regression algorithm has an F-measure score of 68.2%, as given in Table 3. Although WordNet has a good performance, it is 2 times more expensive than other dictionary-based approaches. This is because the words need to be translated into English, and afterwards their similarities are measured through WordNet packages. The second weakest point is the selection of the translation of the first sense of the given word. The other translations and senses are ignored. WordNet needs to be used due to the incompleteness of Turkish WordNet [29]. That lack makes the model more expensive. Likewise, the success of the dictionary-based approach is 94% and the F-measure is 74.4%, as shown in Table 3. It is the most naïve approach; the definitions of 2 words are automatically retrieved from the dictionary and their mutual presence is utilized. However, the approach can be considered costly due its nature, unless we dump the whole content of the dictionaries. As expected, the corpus-based model has a weak performance with an F-measure of 41.7%. Table 3 covers all the performance measurements for the corpus-based model. The main reason for the failure is that some word pairs cannot be represented in a corpus-based framework. For example, the production capacity of the hypernym /hyponymy relation is limited due to the fact that not every pair is matched by LSPs designed for hypernymy. The same argument holds true for other semantic and dependency relations. In terms of time-cost, the proper features are corpus-based ones. Dependency relations are easily extracted from the corpus by syntactic patterns as shown in Table 1. Among the semantic relations, meronym/holonym and hyponym/hypernym have high time complexity. The candidate selection phase exploits only the dependency relation, since these relations are easily captured by the system. Other corpus-based features are discarded for several reasons. The most important one is the production capacity of those relations. The hypernymy or meronymy relations do not guarantee returning a corresponding result for any given word. We applied a variety of dependency relations. The most effective relations found are G4 and G7. Surprisingly, both relations are the alternations of adjective-modifier patterns. We can conclude that the patterns of adjective modification are very useful to disclose important characteristics of words. There are no corpus-based synonym detection studies but dictionary-based ones for the Turkish language to compare our results. One study [30] achieved an 86.85% accuracy rate on average with 24.8K relations. In [31], only 206 out of 66K synonym relations were taken into consideration with an 88% success rate. In our previous

Table 3. Precision, recall and F-measure of only features from different sources.

Sources		Precision	Recall	F-measure
WordNet	NONSYN	93.7	97.7	95.7
	SYN	80.6	59.1	68.2
	Weighted avg.	91.9	92.4	91.9
Dict. Def.	NONSYN	94.4	98.8	96.6
	SYN	89.6	63.6	74.4
	Weighted avg.	93.8	94.0	93.5
Corpus	NONSYN	89.7	97.7	93.5
	SYN	67.9	30.1	41.7
	Weighted avg.	86.7	88.4	86.4
All	NONSYN	96.2	98.4	97.3
	SYN	88.1	75.6	81.4
	Weighted avg.	95.1	95.2	95.1

study [32], the F-measure was 80.3%. In the current study, we used a variety of features obtained from multiple sources and the success rate was 95.2%. The F-measure for synonymy was increased to 81.4%. In future work, we are planning to extract antonym relations as a filter to improve the performance of synonym identification.

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