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# **Relation Extraction Using Liberalism love and beloved**

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## **Acknowledgements**

### **Eidesstattliche Erklärung**

Hiermit erkläre ich, dass ich die vorliegende Arbeit selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe.

### **Declaration**

I hereby confirm that the thesis presented here is my own work, with all assistance acknowledged.

Saarbrücken, 4th December 2013

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## **Abstract**

**Keywords:** Blah, Blah



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# 1 Introduction

Nowadays searching through Internet is the first step we take if we want to get answer to our question. We convert our questions to sequences of keywords and search engines are trying to lead us to web pages where might contain the answer to our questions, they return us a set of related documents which are sorted by their popularity and similarity of their text to our query. In this way, users themselves are responsible to find the desired knowledge from documents. The next generation search engines should go further than current approaches in understanding the meaning of a query and the underlying semantics of documents on the web. The next natural improvement is to return a piece of information which directly approaches to answer the user question. For this reason, the elements of a query, concepts or entities and their relations should be identified and documents ( which might have the answer) should be mapped to the same space of entities and relations in order to find the the desired information in the question.

Relation Extraction is the task of detecting and classifying semantic relationship between named entities (NE). The goal of this task is to find a triple of binary relations and their arguments [2]. For instance, we want to induce a relation like *bornIn* with its arguments which could be for example like this: ( *bornIn*, *Beata Nyari*, *Budapest* ). Applications of such task is numerous in natural language processing; Question/Answering, machine translation and text summarization are systems that benefit from relation extraction [2].

In this task, we are trying to have a model to find paraphrases which means that we are interested to have all the similar semantically similar relations under one umbrella. So it is desired to have all different surface realizations of one relation like *isGivenBirth*, *isBorn*, *isFrom* in a same set, namely *bornIn*.

From a classic method, DIRT [19], to very famous frameworks , TextRunner[4] or distant supervision[22], and more recent works e.g. PATTY[25], all are examples of several

different family of approaches. These methods could be categorized from different perspectives (1) amount of annotated data they need (2) if they can only handle a predefined enumeration of entities and relations or are open to any number of relations (3) organization of semantic interpretation and (4) underlying family of methods they use.

In this proposal, we suggest a new method which learns informative features from data using deep learning methods and then use the learnt features to develop a relation extraction system in two schema (1) Weakly supervised and (2) Unsupervised.

In next chapters we review recent or influential related works and finally we will describe our new model as an improvement to current approaches.

## **2 Machine Learning**

Bye [16]



### 3 Representation Learning

In this chapter, we will define and justify the task of *Representation Learning* and we will see different families of methods for inducing word representation and its application in NLP.

In machine learning specially in industry, most of the labor is dedicated to *Feature Engineering*. Extracting informative features is the crucial part of most supervised methods and it is done mostly manually. While many different applications share common learning models and classifiers, the difference in performance of competing methods mostly goes to the data representation and hand-crafted features that they use. This observation reveals an important weakness in current models, namely their inability to extract and organize discriminative features from data. Representation learning is an umbrella term for a family of unsupervised methods to learn features from data. Most of recent works on the application of this idea in NLP focus on inducing word representations. *Word representation* is a mathematical object, usually a vector, which each dimension in this vector represents a grammatical or semantical feature to identify this word and is induced automatically from data [35]. Recently, it has been shown in [35] and [13] that using induced features can be helpful to improve state-of-the-art methods in different NLP tasks. It seems that relation extraction can also benefit from such features since similar tasks like semantic role labeling has been shown to benefit from induced word representations. In section ?? we will describe one possible way of incorporating this idea in to our task. In the next two sections, two major families of representations will be shortly reviewed.

#### 3.1 Distributional Representation

In distributional semantics, the meaning of a word is expressed by the context that it appears in it [15]. Features that are used to represent the meaning of a word are other

words in its neighborhood as it is so called the context. In some approaches like LDA and latent semantic analysis (LSA), the context is defined in the scope of a document rather than a window around a word. To represent word meanings in via distributional approach, one should start from count matrix (or zero-one co-occurrence matrix) which each row represents a word and each column is a context. The representation can be limited to raw usage of the very same matrix or some transforms like *tf-idf* will be applied first. A further analysis over this matrix to extract more meaningful features is applying dimensionality reduction methods or clustering models to induce latent distributional representations. A similar clustering method to k-means is used in [18] to represent phrase and word meanings and brown clustering algorithm [11] has been shown to have impact on near to state-of-the-art NLP tasks [35].

### 3.2 Distributed Representation

Distributed representation has been introduced in the literature for the first time in [5] where Bengio et al. introduced a first language model based on deep learning methods[6]. Deep learning is learning through several layers of neural networks which each layer is responsible to learn a different concept and each concept is built over other more abstract concepts. In the deep learning society, any word representation that is induced with a neural network is called *Word Embedding*. In contrast to raw count matrix in distributional representations, word embeddings are low-dimensional, dense and real-valued vectors. The term, ‘**Distributed**’, in this context refers to the fact that exponential number of objects (clusters) can be modeled by word embeddings. Here we will see two famous models to induce for such representations. One family will use n-grams to learn word representation jointly with a language model and the other family learns the embedding from structured resources.

### 3.3 Representation Learning of Knowledge Bases

#### 3.3.1 Distributed Representation Learning of Knowledge Bases

Bordes et al. in [9] and [8] have attempted to use deep learning to induce word representations from lexical resources such as WordNet and knowledge bases (KB) like Freebase. In Freebase for example, each named entity is related to another entity by an instance of

a specific type of relation. In [9], each entity is represented as a vector and each relation is decomposed to two matrices. Each of these matrices transform left and right-hand-side entities to a semantic space. Similarity of transformed entities indicates that the relation holds between the entities. A prediction task is defined to evaluate the embeddings. Given a relation and one of the entities, the task is to predict the missing entity. The high accuracy (99.2%) of the model on prediction of training data shows that learnt representation highly captures attributes of the entities and relations in Freebase.

Two major models are proposed in [Bordes2011] and [Bordes2012] to learn features in continuous vector space from a Knowledge Bases(KB) which information is usually represented in form of triples of  $(e_i, r_k, e_j)$  where  $e_i$  and  $e_j$  are  $i_{th}$  and  $j_{th}$  entities related by a binary relation of type  $r_k$ . The purpose of the models is to induce a vector space and associate each entity or relation to an embedding vector or a matrix. The dimensions of such an embedding vector are supposed to reflect a set of informative features of entities and relations.

In the first model, **structured embeddings(SE)**, entities are modeled as  $d$ -dimensional vectors. An associated vector to the  $i_{th}$  entity,  $e_i$ , is  $E_i \in \mathbb{R}^d$ . Each relation  $r_k$  is decomposed to two operators each represented as  $d \times d$  matrix,  $R_k = (R_k^{left}, R_k^{right})$ . These operators transform the left and right entities to a new space induced by each relation and by using a  $p$ -norm measure (L1 norm in this work) they associate a similarity value or a score to each triple. This similarity value is being calculated by Equation (3.1).

$$Sim(E_i, E_j, R) = ||R_k^{left} E_i - R_k^{right} E_j||_1 \quad (3.1)$$

The similarity between transformed entities works as a score to measure the strength of a relation holds between two entities.

Using the idea of contrastive learning, the model will be trained to increase similarity of embeddings for a positive triple (a triple which exists in the KB) or lowering its rank among other training samples and decrease the similarity of embeddings when the relation doesn't hold (negative triple) or raising its rank. For each positive triple, two negative triples will be generated by randomly alternating the right entity or left entity with other entities. Inspired from large margin methods a constraint is introduced on the model that forces negative triples to have lower associated similarity value than correspondent positive triples by a large margin.

The second model, **Semantic Matching Energy using Bilinear layers(SME-Bil)**, is using a different representation for relations, weighted bilinear transformation of embeddings and dot product similarity function instead of L1 norm. In this model, each relation is represented by a  $d$ -dimensional vector  $R_k$  same as entities. For triple  $(e_i, r_k, e_j)$ , the model combines the weighted transformation of each entity embedding with the weighted embedding of relation using element-wise vector product. as it is shown in Equation (3.2).

$$E'_{left} = (W_i E_i) \odot (W_k R_k) + b_{left} \quad (3.2)$$

$W_i$  and  $W_k$  are  $d \times d$  weight matrices and  $b_{left}$  is a  $d$ -dimensional bias vector. The same equation holds for transforming the right entity embeddings to  $E'_{right}$ . Finally, the associated score for the triple can be calculated by dot product of  $E'_{left}$  and  $E'_{right}$  which is shown in Equation 3.3.

$$Sim(E_i, E_j, R_k) = -E'_{left} E'_{right} \quad (3.3)$$

Similar constraints to the first model are also applied to this model and both models can be trained by stochastic gradient descent (SGD) (??)



## 4 Word Embeddings

### 4.1 Neural Language Models

In [12], Weston and Collobert use a non-probabilistic and discriminative model to jointly learn word embeddings and a language model that can separate plausible n-grams from noisy ones. For each word in a n-gram, they combine the word embeddings and use it as positive example. They put noise in the n-gram to make negative examples and then train a neural network to learn to classify positive labels from negative ones. The parameters of neural network (neural language model) and word embedding values will be learned jointly by an optimization method called *Stochastic Gradient Descent* [10].

A hierarchical distributed language model (HLBL) proposed by Mnih and Hinton in [23] is another influential work on word embeddings. In this model a probabilistic linear neural network (LBL) will be trained to combine word embeddings in first  $n - 1$  words of a n-gram to predict the  $n_{th}$  word.

Weston-Collobert model and HLBL by Mnih and Hinton are evaluated in [35] in two NLP tasks: chunking and named entity recognition. With using word embeddings from these models combined with hand-crafted features, the performance of both tasks are shown to be improved.

### 4.2 Learning Word Embeddings from Lexical Resources



## 5 Relation Discovery

### 5.1 Distant Supervision

Labeling data with entity-relation annotation is tedious, specially in large scale domains such as web. Mintz et al. [22] used the idea of *distant supervision* and combined it with a large knowledge base, Freebase, to extract relations from text. They assumed that for each pair of entity related to each other in Freebase, any piece of text contained both of the entities is most probably expressing the same relation. Therefore, they started to make an automatically annotated dataset of relations. From around 1.2 million Wikipedia, they collected contexts that a pair of related entities have been mentioned in them. This dataset of 1.8 million instances of 102 relation type is considered as positive labels. To learn a classifier, they also needed negative labels which were created with random sampling of entities that don't happened to be related in Freebase. The number of negative examples should be at least twice a number of positive examples. After this phase, a multi-class logistic regression classifier was trained to extract relation (separate sentences which express a relation from those which do not).

A variety of features were extracted to make the dataset and each type of features is shown to have different impact in final performance of the model. For example it is mentioned in [22] that the method is benefiting a lot from syntactic features specially in ambiguous relations or where the entities are near in the dependency tree but far in the sentences. Word representations which we will be covered in chapter ??, are capable of abstracting and learning both semantic and syntactic features from various resources. This will suggest us to use word embeddings combined with authors' hand-crafted features with the hope of improving their results. This idea will be elaborated more in section ??.

## 5.2 Unsupervised Relation Extraction

In this chapter we will review four major works on unsupervised relation discovery. We will discuss their formulation of the task, their models and the features they incorporate, the model constraints and finally we will take a look at how good a model is performing.

### 5.2.1 DIRT

Lin and Pantel in [19] proposed an unsupervised method for finding paraphrases from text which proved to be very influential and their method, **DIRT**, has become a classic work in literature. In addition to this paper we will also review two major improvements to DIRT proposed in [7] and [27]. DIRT tries to cluster semantically equivalent relations based on the similarity of their arguments. Relations (or inference rules) that DIRT can discover are mostly limited to paraphrases which are a subset of possible types of inference rules.

In this section, first, the key idea of DIRT will be elaborated more and then we will review the algorithm and analyze the observations. Based on these observations, two other methods, ISP [27] and LEDIR [7], which try to address a subset of DIRT's problems, will be discussed.

### 5.2.2 Extended Distributional Hypothesis

Synonymy of words and other semantic relations in word level have been studied very well in literature. For example Pereira et al. in [28] cluster similar words which convey a similar meaning. The key assumption in this work and related ones is so called **Distributional Hypothesis** [15]. It tells that words which usually occur in similar context have similar meaning. This idea can be generalized to phrases or predicates-arguments. A set of relations or phrases that appear in a similar context are semantically equivalent. Lin and Pantel have extended this idea with giving a slightly different notion of context. The context that they define in their work is the dependency path between a predicate of relation and its arguments. As the Extended Distributional Hypothesis states: If two paths tend to occur in similar contexts, the meaning of the path tend to be similar

In this sense, the task of finding paraphrases or semantically equivalent relations can be formulated as *finding paths with similar meaning*. An algorithm to find such a similar path is a topic of the next part.

### 5.2.3 Model Description

DIRT starts with dependency parsing of sentences and continues with pruning of these dependency trees. It amounts to several conditions on dependency path such as that only nouns will be kept as arguments. Additionally, all the function words will be filtered to have the dependency relations that only connect two content words. Dependency relations with less than a certain number of occurrence will be removed to make the task feasible. After the pruning phase, a set of binary relations with a list of nouns associated to each of their slots is generated. The similarity of relations can be expressed based on similarity of associated list of slot words. Lin and Pantel have used *pointwise mutual information (pmi)* two measure similarity of slots. It measures the independency of two random variables or the amount of information they contain for each other. The similarity function for relations is a geometric average of similarity of correspondent slots.

Instead of clustering of relations which seems to be a natural next phase, they maintain a databases of triples (relation and its slots). For each relation queried they measure the similarity of relations which share at least one common slot word and then report top-40 of them.

#### 5.2.3.1 Evaluation and Analysis

Based on what Lin and Pantel have reported in [19] they extracted 231,000 unique paths from a newspaper corpus. They have used a manually generated paraphrases to evaluate their method. For six questions from TREC-8 they have generated top-40 paraphrases and then evaluate them manually to report percentage of correctly found paraphrases. This approach has a very obvious flaw which is that number of returned paraphrases is fixed. Clustering has this advantage that each cluster of relations can have arbitrary number of paraphrases. Average accuracy for these six questions is 50.3% and no paraphrases have been found for one of the questions. The recall can't be measured easily since many correctly found paraphrases by DIRT are not discovered by humans.

Beside the problem of having fixed number of returned paraphrases, there are three other major problems after observing the results of DIRT which two of them will be addressed by Pantel et al. and will be discussed in the next parts. These problems are:

1. Antonymy of relations can not be captured with DIRT and antonym relations will be returned as similar relations. After more than a decade, it is still an open problem
2. DIRT results are very noisy in a sense that it doesn't induce the type of arguments.
3. DIRT results or paraphrases are always considered as bi-directional. Relation *A* implies relation *B* and vice versa. This assumption doesn't hold for many instances and needs to be regarded in the model.

In the next two sections ISP and LEDIR methods will be covered as proposed improvements to DIRT to filter erroneous relations.

### 5.2.3.2 Inference Selectional Preferences

Selectional preference of a predicate is the constraint that it puts over the class of words can be used as its arguments. For example: *x drives y* has a selectional preference on the second argument for motorized vehicles with more than two wheels and *x rides y* has a preference for vehicles or animals which rider is positioned astride [21] .

In order to model this type of constraint on discovery of paraphrases, Pantel et al. [27] have proposed that relations which are similar but are not sharing a same class of arguments should be filtered out. For each relation, they compute a distribution of possible semantic classes for its arguments. For two equivalent relations, they will be kept if this distribution is similar for both. Yao et al. [36] also incorporate selectional preferences to their model and which we will see in detailed in the last section.

Two models are proposed to compute this distribution. The first one, the distribution is computed jointly for both of arguments and the second one two different distributions are computed for each argument. The computation is just a simple count.

The question that naturally arises is that how one can obtain these semantic classes? The answer is that they are obtainable from lexical resources such as WordNet or they can be induced by clustering words. The authors have used both methods. As the first approach, they have used top level nodes in WordNet and all their successors together as semantic classes. They have also used CBC clustering algorithm [26] to induce semantic classes. In [11] and [18] a similar approach but with different clustering algorithms has been chosen and the later is the current state-of-the-art method.

After computing selectional preferences for each relation, those relations which don't have similar selectional preference distribution will be considered as nonequivalent. The plausibility of an inference rule which contains two relations is discussed in detailed in [7] and [17] .

Inducing word clusters and using independent selectional preferences distributions has been shown to outperform other models and have the highest increase of accuracy compare to DIRT.

### 5.2.3.3 Direction of Inference Rules

So far all the similar relations are considered to be paraphrases and they have bi-directional semantic equivalency relation.

Since this assumption doesn't hold for all the inference rules that are discovered by DIRT, Pantel et al. pushed their model another step further to find the direction of implications among relations, in addition to just find equivalent relations.

They have used the results from DIRT and ISP to find out which direction holds for an implication over two relations. having  $relation_i \iff relation_j$  they want to examine if it holds or either of  $relation_i \implies relation_j$  or  $relation_j \implies relation_i$  is the correct rule.

the key assumption in [7] is that the direction is most likely from a specific relation to a more general relation. By specific relation they mean a relation that has a narrow set of semantic classes and selectional preferences and a general relation is a relation with broader semantic classes. Number of acceptable semantic classes for each relation is a good measure for such purpose. If this number is greater for the antecedent then the direction is right otherwise it should be flipped. A similar approach has been used in [17] which additionally confirm the results of this work.

In the next section we will review a method which operates in web-scale and extract relations with bootstrapping.

### 5.2.4 TextRunner

TextRunner is the first system that addresses open domain relation extraction in web-scale [37]. In this section we will describe the architecture of TextRunner and then we

will review two main elements of this system, *Learner* and *Extractor*, in more details and shortly we will comment on the third element *Assessor*.

#### 5.2.4.1 TextRunner Architecture

Original TextRunner paper proposed four elements for its architecture:

- Learner
- Extractor
- Assessor
- Query Processor

The last sub-system has no major role in relation extraction so we put our focus on the first three elements.

#### 5.2.4.2 Model Description

TextRunner avoids using parsing for large-scale and inhomogeneous corpus like web. *Learner* sub-system is responsible for providing a substitution or an approximation for syntactic parsing which, called as extractor by the authors. The approach that they follow in [37] is that they use a small corpus to train a relation classifier and this classifier will be applied to a much bigger web corpus. After parsing the small corpus, authors have used a set of predefined heuristics just based on POS tags and syntactic role of words to generate positive and negative relation examples. The heuristics were designed as prototypes of syntactic behavior of general relations and they are not dependent on any certain type of relation. For example:  $E_1$  *Verb*  $E_2$  as template of  $X$  *created*  $Y$  or  $E_1$  *NP Prep*  $E_2$  for  $X$  *is birthplace of*  $Y$  are such heuristics.

A Naive Bayes classifier is self-trained on this small dataset, it starts with small seed of relations for training then it labels more instances in the corpus. This classifier will be used as *Extractor* in the next phase. This classifier is not relying on any lexical or relation-specific features, hence it can operate in open domain like web [3]. In the extraction phase,



a maximum-entropy classifier was used to find entities and then by using the extractor learned from the previous phase, they recognize explicit relations among named entities.

These extracted relations and named entities contain many redundant or equivalent relations. The role of *Assessor* is to find equivalent relations. It starts with normalization of relations and entities and then based on string-similarity and shared relational attributes it finds explicitly equivalent relations, it should be mentioned that this approach differs from DIRT which finds semantically equivalent relations.

### **5.2.4.3 Evaluation**

TextRunner is evaluated against a manually tagged dataset of 500 sentences. While the precision is in the accepted level, 86.6%, recall is low (23.2%). The recall has been improved by using a *Conditional Random Field* [3] as classifier instead of Naive Bayes. The model precision is slightly improved by using a CRF for about 2% but we see a tremendous increase in recall which levels to 45.2% .

TextRunner suffers from using very shallow features. Its ability to find relations is limited to explicitly mentioned relations and it can only find them if they occur in a sentence. In the next part we will review a model which does not suffer from these disadvantages due to its deeper semantic analysis.

### **5.2.5 USP**

In this section we will review the first unsupervised semantic parsing method which proposed by Poon and Domingos [30], we will first define what is semantic parsing and after describing the method in [30] we show its application for relation extraction. In the evaluation subsection we will compare this model to its related models and analyze its advantages and disadvantages.

#### **5.2.5.1 Semantic Parsing**

Semantic parsing is mapping a sentence to its formal meaning representation [30] The aim is to represent a natural language text with first-order logic. One can derive a semantic parse of a sentence by starting from a lexicon of atomic formulas and combining

each fragment to build a composition of formulas combined with quantifiers and logical connectives. In [30] the lexicon will be induced from a raw corpus. It is in contrast to traditional means of semantic parsing with manually produced lexicons.

The main challenge in unsupervised semantic parsing is that for a single semantic representation there could be several syntactic realizations or even harder, different surface representations. For example, all of the sentences below has a same semantic representation:

- Microsoft buys Skype
- Microsoft acquires the VoIP company Skype
- Skype is acquired by Microsoft Corporation
- The Redmond software giant buys Skype
- Microsoft's purchase of Skype,...

A simple lexicon to represent all of the examples above is:

$$\begin{aligned}
 &BUY(n_1) \\
 &\lambda x_2.BUYER(n_1, x_2) \quad \lambda x_3.BOUGHT(n_1, x_3) \\
 &MICROSOFT(n_2) \quad SKYPE(n_3)
 \end{aligned}$$

Having a corpus of sentences in natural language, USP [30] will induce such a lexicon and will also extract a formal representation for each sentence. In the next subsection we will review the necessary steps toward this goal.

### 5.2.5.2 Model Description

In this section we will first identify the three key ideas that the model is built upon them and then we will describe the necessary steps toward unsupervised semantic parsing.

Three observations are made by the authors which is crucial to understand the model assumptions:

1. Different syntactic variations of predicates and constants can be clustered together to express a same meaning. This can be learned from a raw corpus, in contrast to supervised methods which use meaning annotation of text.
2. Not only fixed elements in a relation can be clustered together but also arbitrary forms with same sub-forms to co-occurred forms can be put in a cluster. In this way the meaning composition will be learned through clustering of the forms.
3. Learning syntax and semantics jointly is a complex problem. Authors have shown that translating a syntactic analysis to semantic parse has superior performance over joint learning of syntax and semantics. In this way, a model can be built on the shoulder of state-of-the-art syntactic parsers.

Based on these assumptions, they propose a method to model joint probability of the dependency tree and its meaning representation. Markov Logic Networks (MLN) [31] is used to represent the meaning of a sentence. For each sentence we will have an undirected graphical model (Markov network) which each nodes corresponds to atoms and cliques correspond to first-order clauses. The best meaning representation is the one which maximizes the probability of the observed dependency [34]. These are the major steps of the USP system:

### **Dependency Parsing**

the authors believe that dependency parsing is a better starting point than phrase-structure parsing, since it expresses the relation-argument structure at the lexical level. They have used Minipar [20] to make the results more comparable with previous methods, e.g. DIRT.

### **Converting Dependency Trees into Quasi-Logical Forms**

Extracting lambda forms and atoms (lexical entries) is done by a deterministic procedure. Arguments of a dependency path will be converted to atoms, their predicate consists of the lemma and their part-of-speech tags. Each edge from the head to arguments will be a predicate labeled as type of the dependency path. This predicate together with two lambda function for each argument form a QLF. In this QLF, only one constant can be presented.

### **Clustering Lambda-Forms**

It starts from atom levels and cluster them based on their relation, then it recursively

clusters larger formula based on their subformula lambda forms. The composition of meaning of any formula can be obtained by applying *lambda reduction* and substituting constants with lambda variables. At the end we will have a clustering of lambda forms which each cluster contains a set of semantically equivalent lambda forms. this solves the problem of having different syntactic realizations with a same meaning.

### Creating a Markov Logic Network

Each atom can be modeled as a node and each first-order clause can be modeled as a feature. This is still not a complete Markov Logical Network since this model needs a weighting for features. Thus, the weight of feature is defined as a weight of its correspondent clause. A log-linear distribution ??? is used to model the probability of each clique (configuration of nodes and features).  $Z$  is a normalization factor which its computation is infeasible.  $w_i$  is the weight of  $i$ th formula.  $n_i$  is number of satisfied atoms and formulas that appeared in the sentence.

### Learning the weights of MLN

Given the dependency parse and QLF forms, weights can be learned from data such as the log-likelihood of having QLFs given the dependency trees will be maximized. The form of likelihood is:

$$L_{\theta}(QLF) = \log \sum_L P_{\theta}(QLF, L)$$

where  $L$  is a semantic parse.

Since the summation of all possible semantic parses is infeasible, a set of additional constraints on the form of clauses and also a prior over weights are added to model to make the learning feasible. Their algorithm merges any possible two clusters to form a bigger cluster or create a new cluster if either increases the likelihood.

### Finding the Best Semantic Parse

A semantic parse is a partition of atoms of a QLF, assignment of its head and argument form to a cluster. This can be seen as a structure prediction problem. Given the described MLN and its parameters, inference can be done by finding a Maximum A Posterior solution. An exact solution needs a summing over all possible syntactic realizations and possible dependency parses, therefore a greedy algorithm to search for a good solution is proposed by the authors.

### 5.2.5.3 Evaluation

Since USP is the first system for unsupervised semantic parsing, it is compared against other models in a Question/Answering task. GENIA is an Q/A annotated dataset in medical domain and USP has been shown to find the answers with 88% precision which is about 10% higher than TextRunner and more than 30% better than DIRT. It is worthwhile to mention that GENIA is a rather small dataset.

There are two major problems observed by the authors themselves and others for USP.

- Same as the other models that we have already seen, it doesn't address the separation of antonym relations
- It is mentioned in [36] and [34] that USP suffers from using a large memory and therefore low ability to scale to bigger dataset.

Two modifications for USP runtime is proposed in [29] and [34]. In [34] it is proposed to use directed graphical models instead of undirected graphs(MLN) to increase the learning and inference speed. The result is slightly worse than the original model but it performs faster than USP. In [29] a new representation of the model is given in the framework of deep learning which yields the same performance but with faster learning algorithm.

In the next section we will see another model which shows improvement to DIRT, TextRunner and USP and is much more scalable than the former.

### 5.2.6 Rel-LDA & Type-LDA

In this section we will review the method proposed for relation discovery by Yao et. al. [32] The method they proposed is an unsupervised method using generative models which is based on modification of well-known model, Latent Dirichlet Allocation. They have invented three similar models which we will go through them in following. We elaborate on input of the three models and then we describe their generative story and at the end we will finish this part by discussing about model evaluation.

### 5.2.6.1 Input format and preprocessing

Authors have chosen a subset of New York Times articles from year 2000 to 2007 which some of its parts with abnormal style of writing like obituary content are filtered out. They have done several preprocessing steps:

1. Tokenization
2. Sentence split
3. POS tagging
4. Named entity tagging
5. Dependency parsing

Among all dependency paths they are just interested in those which link two named entities. Authors assume that realization of one relation is available in this path most likely as a verb which relates two mentioned named entities. These types of paths are collected and based on some conditions that we have already discussed in Section ??, non-important links are filtered out. Finally in this phase, 2.5 million dependency paths were collected which will serve as an input to the models that we describe in the next subsection.

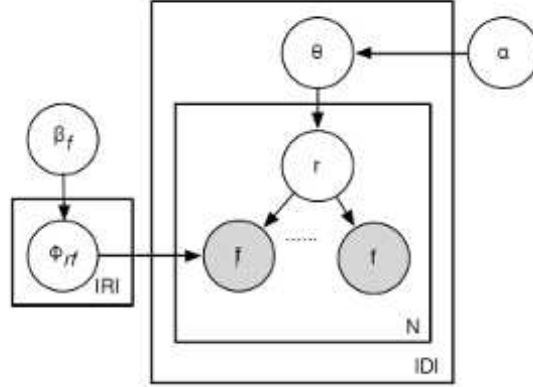
### 5.2.6.2 Model Description

All the three models in this work are generative models. Generative models are jointly modeling hidden variables and observable variables and are in contrast to discriminative models. For more information on generative models please see [24].

**Rel-LDA** is the first model proposed in [32]. In this model, features,  $f$ , are generated from a distribution,  $\Phi_{r,f}$ . Each type of relation is represented with a binary indicator variable,  $r$ . Each document is a mixture of few relations and relations are generated from a multinomial distribution  $\Theta_{doc}$ .  $\Theta_{doc}$  is a distribution of relations for a specific document and can be shown as  $P(r|doc)$ . By choosing a right prior distribution for  $\Theta$  and  $\Phi$  we can impose an assumption that any document contains a few number of relation types. Another advantage of having prior is that it helps to avoid overfitting. Dirichlet prior with

small parameter  $\alpha$  is chosen for this purpose in the paper. For more on the role of priors and specially Dirichlet prior please read [33] and [14] . Rel-LDA is described with a graphical model in Figure 5.1 .

Figure 5.1: Rel-LDA



Shaded circles are showing the observable variables and other circles are hidden variables except the priors which are set by ourselves. The direction of arrow shows the dependency in this sense that destination node (variable) is dependent on source node.

Features or observable variables in Rel-LDA are:

- The dependency path
- Source of the path (the first named entity)
- Destination of the path (the second named entity)

An exact sampling method called *variational inference* is used by authors to compute the posterior distribution of the model,  $P(r|f)$ . After learning, we will have clusters of relation types which each instance of a specific cluster is a relation that is supposed to be semantically equivalent to the other members of this cluster.

In the second model, **Rel-LDA1**, The only difference is that more features are used in the learning procedure. The idea is that using more features could be useful as tie-breakers and also discriminators between instances to make new clusters. With direct reference

to the paper, the authors believe that more features lead to better refinement of clusters. We will see later that this assumption holds in practice. The new features that they have introduced in this new model are:

- Trigger: Any word in a dependency path except than stop words.
- Part of speech sequence: The sequence of POS tags of a dependency path.
- Named entity pair: The type of source and destination named entity.
- Syntactic pair: The type of dependency edges connecting source and destination to the head.

Among all the newly introduced features, NE pair is the most interesting one which leads to a significant observation that the third model will try to address that. Authors observed that Rel-LDA will put these three relations in one cluster because the second argument of all of them is location:

1. *X was born in Y*
2. *X lives in Y*
3. *X, a company in Y*

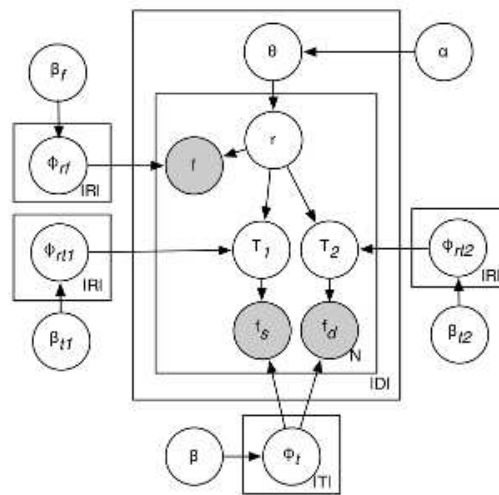
While the first argument in the first two relations refers to a PER, the first argument of the third relation is an instance of ORG type. By using NER pairs as feature we can split this cluster to two clusters with respect to basic types of NE in relations arguments. This observation leads us to invest more on type identification of arguments to have more pure clusters and is the main focus of the third model, **Type-LDA**.

Selectional preferences of a relation are constraint over possible arguments for the relation. Basically, any relation only accepts a few number of entity types and this could be an important constraint for inducing relations. Relations of each cluster should have similar selectional preferences and accept same entity types. Type-LDA is proposed for this reason, it will induce entity types and relation clusters jointly to benefit more from selectional preferences of relations. As we have already mentioned in Section ??, this idea have been used in [27] .



The generative model is modified in a way that features of arguments (source and destination) will be generated from two new distributions,  $T_1$  &  $T_2$  which are modeling entity types. The graphical model is shown in Figure 5.2. This model not only clusters relations

Figure 5.2: Type-LDA



but also clusters entities to entity clusters.

For their experiments on all three models they have set the number of relation clusters to 100 and for Type-LDA they used 50 entity clusters. Choosing other numbers of relation clusters in the range of 50 to 200 is shown to be not very significant.

### 5.2.6.3 Evaluation

They have used human judgments to measure their models precision. Humans are asked to label 50 instances in each relation cluster and in order to measure the recall, induced relations are compared against Freebase. Rel-LDA1 and Type-LDA which are using selectional preferences features are performing better than Rel-LDA. Rel-LDA1 is shown to have the best precision among other models. Rel-LDA and Type-LDA have been also compared against USP and have been shown to have superior performance both in scalability and F-measure.

Like most of the other models, antonymy is not handled in their model and therefor for example they have *X was born in Y* and *X die in Y* in one cluster.

Entity clusters also sometimes suffer from high-frequency or low-frequency words and for example, ‘New York’ , is in the same cluster as other publications like ‘New York Times’, ‘Vanity Fair’ and ...

Yao et al. have shown that they have induced relations in different granularity from Freebase and reported some relations which are not mentioned in Freebase but positively hold. For example, Freebase relation *worksFor* is subsumed with more relations each indicates a different role of employment relation. *leaderOf* and *editorOf* are such examples. This will boost the idea of inducing hierarchical relations which will be discussed more in the last chapter. A similar approach which tries to induce hierarchical structures is [1] .

### 5.3 Problem Identification

Based on what we have seen in recent works, we can now give a list of vital attributes that a state-of-the-art model for extracting relations from open text should be able to carry out. The author will use these facts to suggest a list of possible improvements in the next section. Modeling all of these factors in a joint model is the necessary step to push forward the previous works.

#### **The number of relations and entities is an unknown parameter.**

The model can not be confined to a limited set of relations or entities. Being able to extract relations in open domain text is the first and (most likely) a trivial attribute of the model. More non-trivial feature of the model should be its ability to extract as many relations as there are in text. Giving this freedom about the model complexity to have no assumption about the exact number of entities and relations is suggested by the applicant to be beneficial and is also supported in the literature. [22] [37]

#### **Relations may not be expressed explicitly in text.**

Relation extraction task is definitely more than finding paraphrases. The model should be able to handle long-distance relations among entities as well as hidden semantic indications of a relation. [30]

#### **Relations and entities have their inner organization and types.**

It is shown by several recent works that relations of relations play a substantial role in identifying relations. Relations and entities belong to a hierarchy of types and

therefore the constraints they put on each other should be learned as well.[36] [1]  
[25]

**Using KB is necessary but not enough.**

There are more relations among entities than what is collected in Knowledge Bases e.g. Freebase. At the same time, it is statistically shown that a supervision from such resources strongly contributes to convergence of any model to a better objective configurations.[36] [22]

**Relations and entities are sharing information within each other.**

Relations and entities should be learned jointly since they share same explanatory factors (hidden variables) . Meaning of an entity can be learned from its relation to other entities and same argument holds among relations. Basically, the model should be able to carry out multi-task learning. [36]



## 6 Experimental Setup

### 6.1 Entity Linking Among Lexical Resources

#### 6.1.1 Creating of Dataset

In this part of paper we describe the methodology we followed to encode available information in two different lexical resources, WordNet and GermaNet, that makes it possible to link entities of the two different resources and learn bi-lingual embeddings of word senses in German and English. The main idea is to relate two senses from two different resources using cross-lingual sense alignments. This is an additional information which can play a role of bridge between two different tasks, learning German embeddings and English embeddings, and can help to transfer knowledge from one to the another. Using this new feature we make our WordNet-GermaNet dataset which contains three type of relations (1) WordNet relations (2) GermaNet relations (3) Cross-lingual sense alignments between WordNet and GermaNet

First two types of relations are directly extracted from WordNet and GermaNet and for the cross-lingual relations we used Interlingual Index mappings between WordNet and GermaNet.

Example of relations:

WN-sense-A	WN-rel-1	WN-sense-B
GN-sense-C	GN-rel-2	GN-sense-D
WN-sense-A	ILI-rel-1-2	WN-sense-B

Left and right entities are WordNet and GermaNet senses and relations are current semantical relations in each of lexicons such as: meronymy, holonymy and . . . .

We have created four different dataset, each divided to train, test and validation separated subsets. Our four datasets are:

1. Only WordNet triples (WN)
2. Only GermaNet triples (GN)
3. WordNet-GermaNet triples with one-direction cross-lingual alignments (WN-GN)
4. WordNet-GermaNet with double-direction cross-lingual alignments (WN-GN DD)

Dataset 3 includes both relations extracted from WordNet and GermaNet and also the mapping between senses. Dataset 4 is same as dataset 3 but since the models we will use are assuming all the relations are assymetric we will try to encode the symmetry of cross-lingual alignments by reversing each of them and include the reverse in the dataset. Datasets 3 and 4 contains two different variants: the first variants contains only WordNet relations (test on WN) in the held-out test dataset and the second variant contains only GermaNet triples (test on GN). In this way we can observe the direction of possibly transferring information from English to German or vice versa.

For reducing the sparsity of data and boosting the learning runtime we filtered out all the entities that appeared less than 3 times in our datasets.

(version of wordnet, germanet, ILI and role of uby should be described here)

### **6.1.2 Evaluation**

To show the effectiveness of joint learning of features from multiple knowledge bases we suggest two experiment setups. In the first schema we follow Bordes et al. ranking task. The goal of this task is to show how well the information in knowledge bases can be preserved by the learned features. On the other hand, the second setup is investigating on this question that if the learned word embeddings from multiple resources are able to improve the performance of monolingual embeddings in a standard NLP task, here word-pair similarity or not. In this setup we will look to contribution of the learned features in predicting similarity of words.

### 6.1.2.1 Intrinsic Evaluation

Bordes et al. (Bordes2011) proposed a ranking task that for each triple  $(e_i, r_k, e_j)$  in the data set, all the entities will be ranked as a candidate for being right entity of the triple given the relation and the left entity. Depends on which one of the models is used, SE or SME-Bil, all the entities will be sorted based on their score regarding Equation (3.1) or Equation 3.3 previously introduced in section ???. By keeping the statistics of difference between the predicted rank of  $e_j$  and its true rank and also repeat the same process for left entities, we will be able to report the mean and median predicted rank of entities per relation and in total. Bordes et al. proposed to schema for calculating the average rank, micro averaging which emphasis on more frequent relations by weighted averaging with frequency of relations as weights and macro averaging which consider all the relations equally, either frequent or infrequent ones. The third statistic that we report following their work,  $r@100$ , is the ratio of number of times that an entity is correctly among top 100 entities ranked and predicted for a triple to the number of occurrences of this entity in the dataset. We applied SE and SME-Bil models on our created datasets and the ranking performance on each of them is presented in Table 6.1.

### 6.1.2.2 Extrinsic Evaluation

We are interested to further analyze the effectiveness of learned embeddings to capture semantic features of words, therefor we compare the embeddings learned a single resource or from multiple resources against human judgments. Five datasets of word-pair similarity are used to compare the correlation of predicted similarity of pair of words against human judgments. [rubensteinGoodenough], [yangPowers], [millerCharles],[Szumlanski] and [finkelstein] are English datasets that we used to measure the correlation of similarities predicted by our embeddings and embeddings induced by the other methods to human judgments. For German, we use [this and that]. The other embeddings which are used in our comparison are (Turian et al., HLBL and Klementiev et al.). To measure the similarity between any given wordpair  $(w_1, w_2)$  we find all vectors associated to different senses of the given words in our embedding dictionary and pick the pair of embeddings that maximize cosine similarity between two words. We can motivate this by saying that for each word pair any of words works as a context for disambiguating the sense of the other word.

Both Pearson and Spearman correlation of predicted and gold similarities are calculated

and is reported in table 6.3 for English and 6.4 for German.

For English, we can see that . . . .

On the other hand in German . . . .

As we see in the table 6.3 in two datasets the performance of learned embeddings from bi-lingual resources are slightly worse but comparable to the mono-lingual embeddings and in the other two datasets one can observe a significant increase of performance of bi-lingual resources over monolingual resources.

More analysis on why some dataset is good and some is not good.



Table 6.1: Intrinsic Evaluation (Ranking Score Performance)

Dataset	#relations	#entities		Micro	Macro
GN SE	16	64025	lhs	84.42	72.59
			rhs	84.04	72.38
			mean	1003.59	3739.85
			median	5.0	2213.37
			global	84.23	72.49
GN SME-BIL	16	64025	lhs	79.06	58.58
			rhs	83.30	81.11
			mean	407.90	308.01
			median	10.0	54.18
			global	81.18	69.85
WN SE	23	148976	lhs	91.90	89.47
			rhs	92.30	90.25
			mean	148.72	623.10
			median	5.0	4.69
			global	92.10	89.86
WN SME-BIL	23	148976	lhs	83.08	72.21
			rhs	85.2	77.92
			mean	128.82	511.21
			median	10.0	26.63
			global	84.14	75.57
WN-GN SE (WN held out)	32	213002	lhs	90.82	89.14
			rhs	91.56	88.76
			mean	293.16	1356.30
			median	5.0	5.10
			global	91.19	88.95
WN-GN SME-BIL(WN held out)	32	213002	lhs	82.42	73.65
			rhs	83.40	73.44
			mean	124.85	331.82
			median	11.0	33.86
			global	82.91	73.55
WN-GN SE (GN held out)	32	213002	lhs	81.82	70.56
			rhs	79.92	70.06
			mean	3031.44	15470.56
			median	7.0	10080.5
			global	80.87	70.313
WN-GN SME-BIL(GN held out)	32	213002	lhs	63.54	41.64
			rhs	64.78	70.32
			mean	984.79	1021.37
			median	40.0	428.90
			global	64.16	55.98
WordNet-GermaNet-DD (GN held out)	32 33	213002	lhs	57.72	38.063
			rhs	60.72	63.617
			mean	932.49	719.47
			median	56.0	175.56
			global	59.22	50.84
WordNet-GermaNet-DD (WN held out)	32	213002	lhs	69.66	59.54
			rhs	66.60	58.95
			mean	166.18	18.0
			median	466.91	55.41
			global	68.13	59.25

Table 6.2: Ranking Performance for Mapped Relations

Dataset	#dimension	#relations	#entities		Micro(%)	Macro(%)
GermaNet	25	10	64025	lhs	82.60	68.18
				rhs	81.90	68.84
				global	82.25	68.51
WordNet	25	19	148976	lhs	83.50	83.17
				rhs	84.22	83.64
				global	83.86	83.40
WordNet-GermaNet (WN)	25	24	213002	lhs	78.70	82.60
				rhs	79.56	83.06
				global	79.13	82.83
WordNet-GermaNet (GN)	25	24	213002	lhs	69.66	59.54
				rhs	66.60	58.95
				global	68.13	59.25

Table 6.3: Word-pair Similarity Performance for English

Dataset		WN-SE	WN-GN-SE	WN-SME-BIL	WN-GN-SME-BIL	WN-GN-SME-BIL-DD	H
RubensteinGoodenough65	P	0.682	0.666	0.540	0.508	0.611	-0
	S	0.769	0.741	0.447	0.478	0.552	-
MillerCharles30	P	0.611	0.644	0.592	0.555	0.541	-0
	S	0.720	0.648	0.564	0.561	0.468	-
Finkelstein353	P	0.179	0.206	0.272	0.208	0.193	0
	S	0.087	0.146	0.240	0.196	0.162	0
Szumlanski122	P	-0.145	0.032	0.010	0.043	0.048	-0
	S	-0.159	0.034	0.035	0.037	0.041	-0
YangPowers130	P	0.729	0.682	0.597	0.767	0.819	0
	S	0.829	0.853	0.483	0.793	0.836	0

Table 6.4: Word-pair Similarity Performance for German

Dataset		GN-SE	WN-GN-SE	GN-SME-BIL	WN-GN-SME-BIL	WN-GN-SME-BIL-DD	Klementiev*
wortpaare222	P	-0.022	0.112	0.058	0.103	0.203	0.118
	S	-0.100	0.225	0.230	0.091	0.195	0.153
wortpaare30	P	0.865	0.984	-0.443	0.671	0.656	-0.887
	S	1.0	1.0	-0.500	0.682	0.686	-1.0
wortpaare350	P	-0.089	0.045	0.163	0.300	0.256	0.168
	S	-0.158	-0.017	0.135	0.295	0.231	0.117
wortpaare65	P	0.800	0.558	-0.572	0.607	0.480	0.233
	S	0.800	0.800	-0.8	0.588	0.439	0.200



## **7 Future Work**



## **8 Conclusion**





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