Relation Schema Induction using Tensor Factorization with Side Information

Madhav Nimishakavi
MALL Lab, CDS
Indian Institute of Science
Bangalore, India
madhav@csa.iisc.ernet.in

Uday Singh Saini
MALL Lab
Indian Institute of Science
Bangalore, India
uday7.2008@gmail.com

Partha Talukdar
MALL Lab, CDS
Indian Institute of Science
Bangalore, India
ppt@serc.iisc.in

Abstract

Given a set of documents from a specific domain (e.g., medical research journals), how do we automatically identify the schema of relations, i.e., type signature of arguments of relations (e.g., *undergo(Patient, Surgery)*) – a necessary first step towards building a Knowledge Graph (KG) out of the given set of documents? We refer to this problem as *Relation Schema Induction (RSI)*. While Open Information Extraction (OIE) techniques aim at extracting surface-level text triples of the form *(John, underwent, Angioplasty)*, they don't induce the yet unknown schema of the relations themselves. Tensors provide a natural representation for such triples, and factorization of such tensors provide a plausible solution for the RSI problem. To the best of our knowledge, tensor factorization methods have not been used for the RSI problem. We fill this gap and propose Coupled Non-Negative Tensor Factorization (CNTF), a tensor factorization method which is able to incorporate additional side information in a principled way for more effective Relation Schema Induction. We report our findings on multiple real-world datasets and demonstrate CNTF's effectiveness over state-of-the-art baselines both in terms of accuracy and speed. We hope to make all datasets and code publicly available upon publication of the paper.

1 Introduction

Over the last few years, several techniques to build Knowledge Graphs (KGs) from large unstructured text corpus have been proposed, examples include NELL (Mitchell et al., 2015) and Google Knowledge Vault (Dong et al., 2014). Such KGs consist of millions of entities (e.g., *Oslo, Norway*, etc.), their types (e.g., *isA(Oslo, City)*, *isA(Norway, Country)*), and relationships among them (e.g., *cityLocatedInCountry(Oslo, Norway)*). These KG construction techniques are called ontology-guided as they require as input list of relations, their schemas (i.e., their type signatures, e.g., *cityLocatedInCountry(City, Country)*), and seed instances of each such relation. Listing of such relations and their schemas are usually prepared by human domain experts.

The reliance on domain expertise poses significant challenges when such ontology-guided KG construction techniques are applied to domains where domain experts are either not available or are too expensive to employ. Even when such a domain expert may be available for a limited time, she may be able to provide only a partial listing of relations and their schemas relevant to that particular domain. Moreover, this expert-mediated model is not scalable when new data in the domain becomes available, bringing with it potential new relations of interest. In order to overcome these challenges, we need automatic techniques which can discover relations and their schemas from unstructured text data itself, without requiring extensive human input. We refer to this problem as *Relation Schema Induction (RSI)*.

In contrast to ontology-guided KG construction techniques mentioned above, Open Information

	Interpretable latent factors?	Target task	Can induce relation schema?	Can use NP side info?	Can use relation side info?
Typed RESCAL (Chang et al., 2014a)	No	Embedding	No	Yes	No
Universal Schema (Singh et al., 2015)	No	Link Prediction	No	No	No
KB-LDA (Movshovitz-Attias and Cohen, 2015)	Yes	Ontology Induction	Yes	Yes	No
CNTF (this paper)	Yes	Schema Induction	Yes	Yes	Yes

Table 1: Comparison among CNTF (this paper) and other related methods. KB-LDA (Movshovitz-Attias and Cohen, 2015) is the most related prior method which is extensively compared against CNTF in Section 4.

Extraction (OIE) techniques (Etzioni et al., 2011) aim to extract surface-level triples from unstructured text. Such OIE triples may provide a suitable starting point for the RSI problem. In fact, KB-LDA, a topic modeling-based method for inducing an ontology from OIE triples was recently proposed in (Movshovitz-Attias and Cohen, 2015). We note that ontology induction (Velardi et al., 2013) is a more general problem than RSI, as we are primarily interested in identifying categories and relations from a domain corpus, and not necessarily any hierarchy over them. Nonetheless, KB-LDA maybe used for the RSI problem and we use it as a representative of the state-of-the-art of this area.

Instead of a topic modeling approach, we take a tensor factorization-based approach for RSI in this paper. Tensors are a higher order generalization of matrices and they provide a natural way to represent OIE triples. Applying tensor factorization methods over OIE triples to identify relation schemas is a natural approach, but one that has not been explored so far. Also, a tensor factorization-based approach presents a flexible and principled way to incorporate various types of side information. Moreover, as we shall see in Section 4, compared to state-of-the-art baselines such as KB-LDA, tensor factorization-based approach results in better and faster solution for the RSI problem. In this paper, we make the following contributions:

- We present Coupled Non-Negative Tensor Factorization (CNTF), an unsupervised tensor factorization method which is able to incorporate various types of additional side information in a principled way for more effective Relation Schema Induction (RSI).

- We compare CNTF against multiple state-of-the-art baselines on various real-world datasets. We observe that CNTF is not only significantly more accurate than such baselines, but also much faster. For example, CNTF achieves 11.8x speedup over KB-LDA (Movshovitz-Attias and Cohen, 2015).

- We hope to make all the datasets and code publicly available upon publication of the paper.

2 Related Work

Properties of CNTF and other related methods are summarized in Table 1. A method for inducing (binary) relations and the categories they connect was proposed by (Mohamed et al., 2011). However, in that work, categories and their instances were known a-priori. In contrast, in case of RSI, both categories and relations are to be induced.

A method for canonicalizing noun and relation phrases in OIE triples was recently proposed in (Galárraga et al., 2014). The main focus of this approach is to cluster lexical variants of a *single* entity or relation. This is not directly relevant for RSI, as we are interested in grouping *multiple* entities of the same type into one cluster, and use that to induce relation schema.

A method for event schema induction, the task of learning high-level representations of complex events and their entity roles from unlabeled text, was proposed in (Chambers, 2013). This approach is heavily dependent on Named Entity Recognition (NER) and hence may not be scalable for every domain. Our focus in this paper is on unsupervised tensor factorization methods for RSI without requiring such heavy supervision. (Chen et al., 2013) and (Chen et al., 2015) deal with the problem of finding semantic slots for unsupervised spoken language understanding, but we are interested in finding schemas of relations relevant for a given domain.

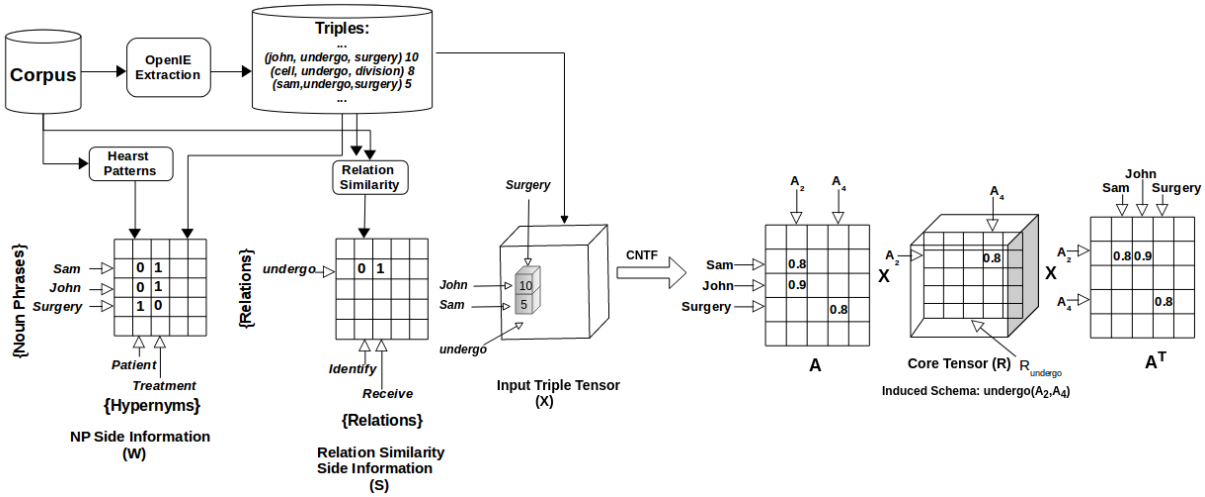


Figure 1: Relation Schema Induction (RSI) by CNTF, the proposed method. First, a tensor (X) is constructed to represent OpenIE triples extracted form a domain corpus. Noun phrase side information in the form of (noun phrase, hypernym), and relation-relation similarity side information are separately calculated and stored in two separate matrices (W and S, respectively). CNTF then performs coupled factorization of the tensor and the two side information matrices to identify relation schemas which are stored in the core tensor (R) in the output. Please see Section 3 for details.

Due to their flexibility of representation and effectiveness, tensor factorization methods have seen increased application in Knowledge Graph (KG) related problems over the last few years. Methods for decomposing ontological KGs such as YAGO (Suchanek et al., 2007) were proposed in (Nickel et al., 2012; Chang et al., 2014b; Chang et al., 2014a). In these cases, relation schemas are known in advance, while we are interested in inducing such relation schemas from unstructured text. A PARAFAC (Harshman, 1970) based method for jointly factorizing a matrix and tensor for data fusion was proposed in (Acar et al., 2013). In such cases, the matrix is used to provide auxiliary information (Narita et al., 2012; Erdos and Miettinen, 2013). Similar PARAFAC-based ideas are explored in Rubik (Wang et al., 2015) to factorize structured electronic health records. In contrast to such structured data sources, CNTF aims at inducing relation schemas from unstructured text data. As we shall see in Section 4, PARAFAC-based methods are not quite effective for the RSI problem. Propstore, a tensor-based model for distributional semantics, a problem different from RSI, was presented in (Goyal et al., 2013). Even though coupled factorization of tensor and matrices constructed out of unstructured text corpus provide a natural and plausible approach for the RSI problem, they have not yet been explored – we fill this gap in this paper.

Methods for link prediction in the Universal Schema setting using matrix and a combination of matrix and tensor factorization are proposed in (Riedel et al., 2013) and (Singh et al., 2015), respectively. Instead of link prediction where relation schemas are assumed to be given, CNTF focuses on discovering such relation schemas. Moreover, in contrast to such methods which assume access to existing KGs, the setting in this paper is unsupervised.

Relation Schema Induction can be considered a sub problem of Ontology Induction (Velardi et al., 2013). Instead of building a full-fledged hierarchy over categories and relations as in ontology induction, we are particularly interested in finding relations and their schemas from unstructured text corpus. We consider KB-LDA[1] (Movshovitz-Attias and Cohen, 2015), a topic-modeling based approach for ontology induction, as a representative of this area. Among all prior work, KB-LDA is most related to CNTF. While both KB-LDA and CNTF make use of noun phrase side information, CNTF is also able to exploit relational side information in a principled manner. In Section 4, through experiments on multiple real-world

[1]In this paper, whenever we refer to KB-LDA, we only refer to the part of it that learns relations from unstructured data.

datasets, we observe that CNTF is not only more accurate than KB-LDA but also significantly faster with a speedup of 11.8x.

3 Our Approach: Coupled Non-Negative Tensor Factorization (CNTF)

3.1 Overview

CNTF poses the RSI problem as a coupled factorization of a tensor along with matrices containing relevant side information. Overall architecture of the CNTF system is presented in Figure 1. First, a tensor $X \in \mathbb{R}_+^{n \times m \times n}$ is constructed to store OpenIE (OIE) triples and their scores extracted from the text corpus[2]. Here, n and m represent the number of NPs and relation phrases, respectively. Following (Movshovitz-Attias and Cohen, 2015), CNTF makes use of noun phrase (NP) side information in the form of (noun phrase, hypernym). Additionally, CNTF also exploits relation-relation similarity side information. These two side information are stored in matrices $W \in \{0,1\}^{n \times h}$ and $S \in \{0,1\}^{m \times m}$, where h is the number of hypernyms extracted from the corpus. CNTF then performs collective non-negative factorization over X, W, and S to output matrix $A \in \mathbb{R}_+^{n \times c}$ and the core tensor $R \in \mathbb{R}_+^{c \times m \times c}$. Each row in A corresponds to an NP, while each column corresponds to an induced category (latent factor). For brevity, we shall refer to the induced category corresponding to the q^{th} column of A as A_q. Each entry A_{pq} in the output matrix provides a membership score for NP p in induced category A_q. Please note that each induced category is represented using the NPs participating in it, with the NPs ranked by their membership scores in the induced category. In Figure 1, $A_2 = [(John, 0.9), (Sam, 0.8), \ldots]$ is an induced category.

Each slice of the core tensor R is a matrix which corresponds to a specific relation, e.g., the matrix $R_{undergo}$ highlighted in Figure 1 corresponds to the relation *undergo*. Each cell in this matrix corresponds to an induced schema connecting two induced categories (two columns of the A matrix), with the cell value representing model's score of the induced schema. For example, in Figure 1, *undergo(A_2, A_4)* is an induced relation schema with score 0.8 involving relation *undergo* and induced categories A_2 and A_4.

In Section 3.2, we present details of the side information used by CNTF, and then in Section 3.3 present details of the novel optimization problem solved by CNTF.

[2] $\mathbb{R}_+$ is the set of non-negative reals.

MEDLINE
(hypertension, disease), (hypertension, state), (hypertension, disorder) , (neutrophil, blood element), (neutrophil, effector cell), (neutrophil, cell type)
StackOverflow
(image, resource), (image, content), (image, file), (perl, language), (perl, script), (perl, programs)

Table 2: Noun Phrase (NP) side information in the form of (Noun Phrase, Hypernym) pairs extracted using Hearst patterns from two different datasets. Please see Section 3.2 for details.

MEDLINE	StackOverflow
(evaluate, analyze), (evaluate, examine), (indicate, confirm), (indicate, suggest)	(provides, confirms), (provides, offers), (allows, lets), (allows, enables)

Table 3: Examples of relation similarity side information in the form of automatically identified similar relation pairs. Please see Section 3.2 for details.

3.2 Side Information

- **Noun Phrase Side Information**: Through this type of side information, we would like to capture type information of as many noun phrases (NPs) as possible. We apply Hearst patterns (Hearst, 1992), e.g., *"<Hypernym> such as <NP>"*, over the corpus to extract such *(NP, Hypernym)* pairs. Please note that neither hypernyms nor NPs are pre-specified, and they are all extracted from the data by the patterns. Examples of a few such pairs extracted from two different datasets are shown in Table 2. These extracted tuples are stored in a matrix $W_{n \times h}$ whose rows correspond to NPs and columns correspond to extracted hypernyms. We define,

$$W_{ij} = \begin{cases} 1, & \text{if NP}_\text{i} \text{ belongs to Hypernym}_\text{j} \\ 0, & \text{otherwise} \end{cases}.$$

  Please note that we don't expect W to be a fully specified matrix, i.e., we don't assume that we know all possible hypernyms for a given NP.

- **Relation Side Information**: In addition to the side information involving NPs, we would also like to take prior knowledge about textual relations into account during factorization. For example, if we know two relations to be similar to one another, then we also expect their schemas to be similar

as well. Consider the following sentences *"Mary purchased a stuffed animal toy."* and *"Janet bought a toy car for her son."*. From these we can say that both relations *purchase* and *buy* have the schema i.e., (Person, Item). Even if one of these relations is more abundant than the other in the corpus, we still want to learn similar schemata for both the relations. As mentioned before, $S \in \mathbb{R}_{+}^{m \times m}$ is the relation similarity matrix, where m is the number of textual relations. We define,

$$S_{ij} = \begin{cases} 1, & \text{if Similarity(Rel}_\text{i}\text{, Rel}_\text{j}\text{)} \geq \gamma \\ 0, & \text{otherwise} \end{cases}$$

where γ is a threshold[3]. For the experiments in this paper, we use cosine similarity over word2vec (Mikolov et al., 2013) vector representations of the relational phrases. Examples of a few similar relation pairs are shown in Table 3.

3.3 CNTF Model Details

CNTF performs coupled non-negative factorization of the input triple tensor $X_{n \times m \times n}$ along with the two side information matrices $W_{n \times h}$ and $S_{m \times m}$ by solving the following novel optimization problem presented below.

$$\min_{A,V,R} \sum_{k=1}^{m} f(X_k, A, R_k) + f_{np}(W, A, V) + f_{rel}(S, R)$$

where,

$$f(X_k, A, R_k) = \| X_{:,k,:} - AR_{:,k,:}A^T \|_F^2 + \lambda_R \| R_{:,k,:} \|_F^2$$

$$f_{np}(W, A, V) = \lambda_{np} \| W - AV \|_F^2 + \lambda_A \| A \|_F^2 + \lambda_V \| V \|_F^2$$

$$f_{rel}(S, R) = \lambda_{rel} \sum_{i=1}^{m} \sum_{j=1}^{m} S_{ij} \| R_{:,i,:} - R_{:,j,:} \|_F^2$$

$$A_{i,j} \geq 0, V_{j,k} \geq 0, R_{r,j,k} \geq 0$$
$$\forall\, 1 \leq i \leq n, 1 \leq j, k \leq c, 1 \leq r \leq m$$

In the objective above, the first term $f(X_k, A, R_k)$ minimizes reconstruction error for the k^{th} relation, with additional regularization on the $R_{:,k,:}$ matrix[4]. The second term, $f_{np}(W, A, V)$, factorizes the NP side information matrix $W_{n \times h}$ into two matrices $A_{n \times c}$ and $V_{c \times h}$, where c is the number of induced categories. We also enforce A to be non-negative. Typically, we require $c \ll h$ to get a lower dimensional embedding of each NP (rows of A). Finally, the third term $f_{rel}(S, R)$ enforces the requirement that two similar relations as given by the matrix S should have similar signatures (given by the corresponding R matrix). In this objective, λ_R, λ_{np}, λ_A, λ_V, and λ_{rel} are all hyper-parameters.

We derive the following non-negative multiplicative updates using (Lee and Seung, 2000) algorithm, to solve for the CNTF objective above.

$$A \leftarrow A * \frac{\sum_k (X_k A R_k^T + X_k^T A R_k) + \lambda_{np} W V^T}{A(\tilde{B} + \lambda_A I + \lambda_{np} V V^T)}$$

$$\tilde{B} = \sum_k (R_k A^T A R_k^T + R_k^T A^T A R_k)$$

$$R_k \leftarrow R_k * \frac{A^T X_k A + 2\,\lambda_{rel} \sum_{j=1}^{m} R_j S_{kj}}{A^T A R_k A^T A + \tilde{D}}$$

$$\tilde{D} = 2\,\lambda_{rel}\, R_k \sum_{j=1}^{m} S_{kj} + \lambda_R R_k$$

$$V \leftarrow V * \frac{\lambda_{np} A^T W}{\lambda_{np} A^T A V + \lambda_V V}$$

In the equations above, $*$ is the Hadamard or elementwise product[5]. Even though these iterative updates don't have any formal converge guarantees, we found them to converge in about 15-20 iterations in all our experiments.

Dataset	# Docs	# Triples
MEDLINE	50,216	13,308
StackOverflow	5.5m	37,439

Table 4: Datasets used in the experiments.

4 Experiments

In this section we evaluate performances of different methods on the Relation Schema Induction (RSI) task. Specifically, we address the following questions.

- Which method is most effective on the RSI task? (Section 4.3.1)
- What is the importance of non-negativity in RSI with tensor factorization? (Section 4.3.2)
- How important are the additional side information for RSI? (Section 4.3.3)

We start by briefly discussing the methods that we experimented with.

[3]For the experiments in this paper, we set $\gamma = 0.7$, a relatively high value, to focus on highly similar relations and thereby justifying the the binary S matrix.

[4]For brevity, we also refer to $R_{:,k,:}$ as R_k, and similarly $X_{:,k,:}$ as X_k

[5]$(A * B)_{i,j} = A_{i,j} \times B_{i,j}$

- **PARAFAC**: PARAFAC (or CANDECOMP) (Harshman, 1970) decomposes the tensor $\mathcal{X} \in \mathbb{R}^{n \times m \times n}$ into a sum of component rank-one tensors: $\mathcal{X} \approx \sum_{i=1}^{K} a_i \circ b_i \circ c_i$, where $\circ$ is the outer product, K is a positive integer and $a_i \in \mathbb{R}^n$, $b_i \in \mathbb{R}^m$ and $c_i \in \mathbb{R}^n$ for $i = 1, ..., K$. We used MATLAB Tensor Toolbox Version 2.6 (Bader et al., 2015) for computing the PARAFAC decomposition.

- **NN-PARAFAC**: The objective of Non-Negative PARAFAC (NN-PARAFAC) (Bro and De Jong, 1997) is same as that of PARAFAC, with additional non-negativity constraints. We used MATLAB Tensor Toolbox Version 2.6 (Bader et al., 2015) for computing the factorization.

- **RESCAL**: RESCAL (Nickel et al., 2011) can be thought of as an ablated version of CNTF. RESCAL's objective function can be obtained by dropping the non-negativity constraints on A and $\mathcal{R}$ and by setting $\lambda_{np} = \lambda_V = \lambda_{rel} = 0$ in the CNTF objective (Equation 3.3). We used the RESCAL implementation provided by the authors of (Nickel et al., 2011).[6]

- **NN-RESCAL**: Non-Negative Rescal (Krompaß et al., 2013) implements non-negative tensor decompositions based on RESCAL by optimizing the same objective function, but employing multiplicative update rules for A and $\mathcal{R}$ as given in (Krompaß et al., 2013). Since no implementation of NN-RESCAL was publicly available, we implemented it ourselves.

- **KB-LDA** (Movshovitz-Attias and Cohen, 2015): As discussed in Section 2, KB-LDA is a topic-modeling based ontology induction method which is the most related prior method to CNTF. Since the KB-LDA implementation was not available, we implemented it ourselves, and ran experiments with the same hyperparameters as used in the original KB-LDA paper[7].

- **CNTF** (Section 3): This is our proposed method.

[6] https://github.com/mnick/rescal.py

[7] Obtained through personal communication with the authors of (Movshovitz-Attias and Cohen, 2015)

4.1 Experimental Setup

Datasets: We used two datasets for the experiments in this paper which are summarized in Table 4. We obtained the StackOverflow triples directly from the authors of (Movshovitz-Attias and Cohen, 2015). Since these were already pre-processed, the triple set was used as-is to facilitate direct comparison with the KB-LDA method of (Movshovitz-Attias and Cohen, 2015). For details about the triple extraction and filtering steps for the MEDLINE dataset, please see Appendix A in the supplementary material.

Following (Movshovitz-Attias and Cohen, 2015), we use frequency of the triples in case of StackOverflow data while constructing the tensor. Comparatively, we observed higher sparsity and lower quality triples in case of the MEDLINE dataset. To address these issues, we used a triple scoring scheme for the MEDLINE triples, please see Appendix B for details.

Hyperparameters were set using grid search and reconstruction fit criteria. We set $\lambda_{np} = \lambda_{rel} = 100$ for StackOverflow, and $\lambda_{np} = 150$ and $\lambda_{rel} = 50$ for Medline and we use $c = 50$ for our experiments.

Side Information: Seven Hearst patterns such as *"<hypernym> such as <NP>", "<NP> or other <hypernym>"* etc., were used to extract NP side information from the MEDLINE documents[8]. NP side information for the StackOverflow dataset was obtained from the authors of (Movshovitz-Attias and Cohen, 2015).

As described in Section 3, word2vec embeddings of the relation phrases were used to extract relation-similarity based side-information. This was done for both datasets. Cosine similarity threshold of $\gamma = 0.7$ was used for the experiments in the paper.

Samples of side information used in the experiments are shown in Table 2 and Table 3. A total of 2067 unique NP-hypernym pairs were extracted from MEDLINE data and 16,639 were from StackOverflow data. 9 unique pairs of relation phrases out of 100 were found to be similar in MEDLINE data, whereas 280 unique pairs of relation phrases out of approximately 3200 were found similar in StackOverflow data.

Relation Schema	Top 3 NPs in Induced Categories which were presented to annotators	Annotator Judgment
StackOveflow		
clicks(A_0, A_1)	A_0: *users, client, person* A_1: *link, image, item*	valid
refreshes(A_{19}, A_{13})	A_{19}: *browser, window, tab* A_{13}: *page, activity, app*	valid
can_parse(A_{41}, A_{17})	A_{41}: *access, permission, ability* A_{17}: *image file, header file, zip file*	invalid
MEDLINE		
receive(A_1, A_{18})	A_1: *patient, NUM patients, one patient* A_{18}: *flecainide, aerosolized pentamidine, prophylaxis*	valid
undergo(A_1, A_3)	A_1: *patient, NUM patients, one patient* A_3: *surgery, abdominal surgery, open heart surgery*	valid
fail_to(A_{32}, A_{36})	A_{32}: *chest pain, bacteriologic failure, unresectable disease* A_{36}: *nodular disease, valvular disease, Crohn disease*	invalid

Table 5: Examples of relation schemas induced by CNTF from the StackOverflow and MEDLINE datasets. Top NPs from each of the induced categories, along with human judgment of the induced schema are also shown. See Section 4.3.1 for more details.

4.2 Evaluation Protocol

In this section, we shall describe how the induced schemas are presented to the human annotators and how final accuracies are calculated. In factorizations produced by CNTF and other RESCAL-based methods, we first select a few top relations with best reconstruction score. The schemas induced for each selected relation k is represented by the matrix slice R_k of the core tensor obtained after factorization (see Section 3). From each such matrix, we identify the indices (i, j) with highest values. The indices i and j select columns of the matrix A. A few top ranking NPs from the columns A_i and A_j along with the relation k are presented to the human annotator, who then evaluates whether the tuple $\text{Relation}_k(A_i, A_j)$ constitutes a valid schema for relation k. Examples of a few relation schemas induced by CNTF are presented in Table 5. A human annotator would see the first and second columns of this table and then offer judgment as indicated in the third column of the table. All such judgments across all top-reconstructed relations are aggregated to get the final accuracy score. This evaluation protocol was also used in (Movshovitz-Attias and Cohen, 2015) to measure learned relation accuracy.

We follow a similar evaluation protocol in case of PARAFAC-based methods. For the experiments in this paper, we considered top 100 StackOverflow and top 50 MEDLINE relations, and top 3 induced schemas per relation during evaluation. All evaluations were blind, i.e., the annotators were not aware of the method that generated the output they were evaluating. Though recall is a desirable statistic to have, it is very challenging to calculate due to the non-availability of relation schema annotated text on large scale.

4.3 Results

4.3.1 Effectiveness of CNTF

Experimental results comparing performances of various methods on the RSI task in the two datasets are presented in Figure 2(a). RSI accuracy is calculated based on the evaluation protocol described in Section 4.2. Performance number of KB-LDA for StackOveflow dataset is taken directly from the (Movshovitz-Attias and Cohen, 2015) paper, we used our implementation of KB-LDA for the MEDLINE dataset. Annotation accuracies from two annotators were averaged to get the final accuracy. From Figure 2(a), we observe that CNTF outperforms all other methods, including KB-LDA, on the RSI task. This is the main result of the paper.

Using a CorConDia-based analysis (Bro and Kiers, 2003), we also observed that PARAFAC is able to induce only a small number of relation schemas[9]. PARAFAC's ineffectiveness at factorizing highly correlated data, such as the ones used in the paper, have also been previously recognized in (Nickel et al., 2011). In comparison, CNTF is able to induce more and better relation schemas.

Runtime comparison: Runtimes of CNTF and KB-LDA over both datasets are compared in Figure 2(b). From this figure, we find that CNTF is able to achieve a 11.8x speedup on average over KB-LDA[10]. In other words, CNTF is not only able to induce better relation schemas, but also do so at a significantly faster speed.

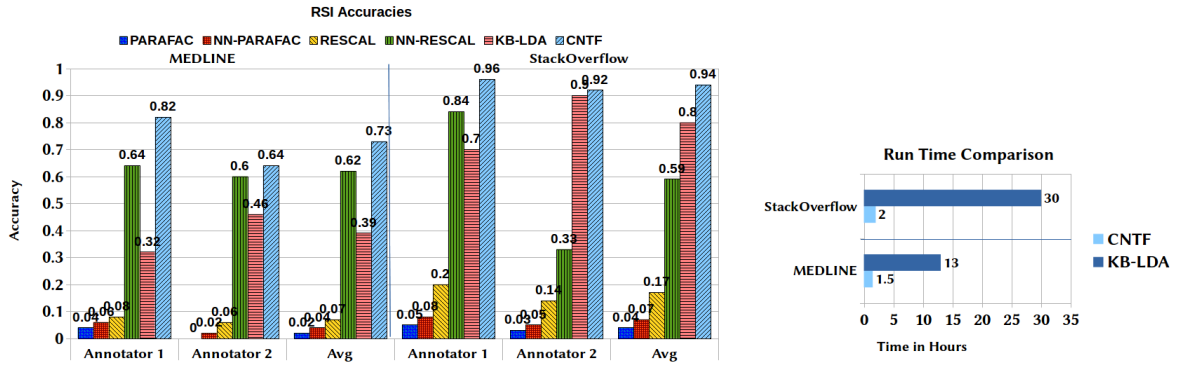
4.3.2 Importance of Non-Negativity on Relation Schema Induction

From Figure 2(a), we observe that non-negativity constraints over the A matrix and core tensor R re-

[8]Complete list of Heart Patterns used are available in Appendix C

[9]We hope to include details of this analysis in a longer version of the paper.

[10]Runtime of KB-LDA over the StackOverflow dataset was obtained from the authors of (Movshovitz-Attias and Cohen, 2015) through personal communication. Our own implementation of KB-LDA also resulted in similar runtime over this dataset.



(a) (b)

Figure 2: (a) Relation Schema Induction (RSI) accuracies of different methods on the two datasets. CNTF, our proposed method, significantly outperforms all other methods (right most bar corresponds to CNTF in each group). This is the main result of the paper. Results for KB-LDA on StackOveflow are directly taken from the paper. Please see Section 4.3.1 for details. (b) Runtime comparison between KB-LDA and CNTF. We observe that CNTF results in 11.8x speedup over KB-LDA. Please see Section 4.3.1 (Runtime Comparison) for details.

Ablation	MEDLINE			StackOverflow		
	A1	A2	Avg	A1	A2	Avg
CNTF ($\lambda_{rel} = 0$)	0.68	0.54	0.61	0.83	0.70	0.77
CNTF ($\lambda_{np} = 0$)	0.68	0.56	0.62	0.89	0.90	0.90
CNTF	0.82	0.64	**0.73**	0.96	0.92	**0.94**

Table 6: Performance comparison of CNTF with its ablated versions when no relation side information is used ($\lambda_{rel} = 0$) and when no NP side information is used ($\lambda_{np} = 0$). From this, we observe that additional side information improves performance, validating one of the central thesis of this paper. Please see Section 4.3.3 for details.

sult in improved performance, e.g., NN-RESCAL vs RESCAL. We note that CNTF also imposes non-negativity constraints. The reason for this improved performance may be explained by the fact that absence of non-negativity constraint results in an under constrained factorization problem where the model often overgenerates incorrect triples, and then compensates for this overgeneration by using negative latent factor weights. In contrast, imposition of non-negativity constraints restricts the model further forcing it to commit to specific semantics of the latent factors in A. This improved interpretability also results in better RSI accuracy as we have seen above. Similar benefits of non-negativity on interpretability have also been observed in matrix factorization (Murphy et al., 2012).

4.3.3 Importance of Side Information

One of the central hypothesis of our approach is that coupled factorization through additional side information should result in better relation schema induction. In order to evaluate this thesis further, we compare performances of CNTF with its ablated versions, CNTF ($\lambda_{rel} = 0$), which corresponds to the setting when no relation side information is used with CNTF and CNTF ($\lambda_{np} = 0$), which corresponds to the setting when no noun phrases side information is used with CNTF. Results are presented in Table 6. From this, we observe that additional coupling through the side information significantly helps improve CNTF performance. This further validates the central thesis of our paper.

5 Conclusion

Relation Schema Induction (RSI) is an important first step towards building a Knowledge Graph (KG) out of text corpus from a given domain. While human domain experts have traditionally prepared listing of relations and their schemas, this expert-mediated model poses significant challenges in terms of scalability and coverage. In order to overcome these challenges, in this paper, we present CNTF, a novel non-negative coupled tensor matrix factorization method for relation schema induction. CNTF is flexible enough to incorporate various types of side information

during factorization. Through extensive experiments on real-world datasets, we find that CNTF is not only more accurate but also significantly faster (about 11.8x speedup) compared to state-of-the-art baselines. As part of future work, we hope to analyze CNTF and its optimization further, assign labels to induced categories, and also apply the model to more domains. We hope to make all code and datasets used in the paper publicly available upon publication of the paper.

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Appendix

A. Triplet Extraction and Filtering

We describe below the triple extraction and filtering steps for the MEDLINE dataset.

Open IE Triple Extraction:Open IE v4.0[11] was used to extract triples from the MEDLINE abstracts. Following processing steps were carried out during and after triple extraction.

- Stanford CoreNLP was used for coreference resolution. This was performed to make sure there were no pronouns in triple arguments.
- Justeson and Katz filter was applied over triple arguments to extract base NPs from arguments with extraneous tokens.
- Duplicate triples were removed, and verb phrases in the triples were lemmatized. All the numbers in triple arguments were normalized with a keyword $<NUM>$.
- Triples in which neither of the noun phrases has a hypernym in the Hearst patterns extracted were filtered out.

B. Triplet Scoring

The following scoring scheme is used for MEDLINE triples.

$$\mathcal{X}_{a_1,r,a_2} = \Gamma - \log(\#(a_1) \times \#(a_2)) - \textsc{len}(a_1) - \textsc{len}(a_2)$$

where a_1 and a_2 are the first and second arguments of the triple, $\#(a_i)$ is frequency of a_i in the triple set, $\textsc{len}(a_i)$ is the number of tokens of a_i, and Γ is a positive offset added to make the score positive. This scoring scheme is intended to discount triples with very common arguments. Moreover, it doesn't prefer triples with very long arguments, a common signal of segmentation errors in OpenIE systems. Triples having these properties are deemed to be less informative from the tensor factorization perspective and hence given lower importance by the score.

[11] Open IE v4.0: `http://knowitall.github.io/openie/`

C. Hearst Patterns

The following are the seven hearst patterns that we used for our work.

1. NP_0 *such as* $\{NP_1, NP_2, ..., (and|or)\}NP_n$
2. *such* NP *as* $\{NP,\}^*\{(or|and)\}NP$
3. $NP\{,NP\}^*\{,\}$ *or other* NP
4. $NP\{,NP\}^*\{,\}$ *and other* NP
5. $NP\{,\}$ *including* $\{NP,\}^*\{(or|and)\}NP$
6. $NP\{,\}$ *especially* $\{NP,\}^*\{(or|and)\}NP$
7. $NP\{,\}$ *except* $\{NP,\}^*\{(or|and)\}NP$