DOZEN: Cross-Domain Zero Shot Named Entity Recognition with Knowledge Graph

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ABSTRACT

With the new developments of natural language processing, increasing attention has been given to the task of Named Entity Recognition (NER). However, the vast majority of work focus on a small number of large-scale annotated datasets with a limited number of entities such as *person*, *location* and *organization*. While other datasets have been introduced with domain-specific entities, the smaller size of these largely limits the applicability of state-of-the-art deep models. Even if there are promising new approaches for performing zero-shot learning (ZSL), they are not designed for a cross-domain settings. We propose Cross Domain Zero Shot Named Entity Recognition with Knowledge Graph (DOZEN), which learns the relations between entities across different domains from an existing ontology of external knowledge and a set of analogies linking entities and domains. Experiments performed on both large scale and domain-specific datasets indicate that DOZEN is the most suitable option to extract unseen entities in a target dataset from a different domain.

CCS CONCEPTS

• **Computing methodologies** → **Natural language processing**;
Information extraction; *Knowledge representation and reasoning*;
Learning paradigms.

KEYWORDS

named entity recognition; zero-shot learning; natural language processing; knowledge graph; cross-domain machine learning

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1 INTRODUCTION

For Named Entity Recognition (NER), many approaches have recently been proposed to leverage the expressive power of language

models for extracting entities [16]. However, such solutions require large-scale annotated datasets, such as CoNLL-2003 [14] or Onto Notes 5.0 [4], which contain thousands of sentences with manually annotated entities such as *person*, *location* and *organization*. Such solutions generalize poorly in cross-domain scenarios, where: 1) the entities are domain-specific, such as *chemical element* or *artist* and 2) there is no large-scale annotated dataset. Recently, Liu et al. [8] released five cross-domain datasets for the domains of *Politics*, *Natural Science*, *Music*, *Literature* and *Artificial Intelligence*. However, even if some entities are shared across the five domains, the datasets also have a large number of domain-specific entities. Second, the cross-domain datasets are much smaller than the commonly used large-scale dataset, making the adoption of the most recent state-of-the-art supervised methods unsuitable.

To address the recognition of unseen entities, a common solution is Zero-Shot Learning (ZSL). Several works have been recently proposed to perform ZSL for NER [5, 6], mostly using some kind of metric learning to compare the sentence tokens with the entities [2]. However, the majority of these solutions assume that the training and evaluation set belong to the same domain, while in cross-domain NER, both source and target datasets differ in both the set of labels and the domain. For example, Jia et al. [6] use source-target combinations either from the same domain of biology [10], or from general-domain datasets such as CoNLL-2003 and Twitter [9], which differ only for entity *Miscellaneous*. The cross-domain settings has two main challenges. First, the unseen entities in the target domain are often semantically very different from the entities of the source domain. For example, the entity *enzyme* in the science domain is an extremely different concept from entities in the domain of music. Second, the entities that we expect to be recognized in an input sentence depend on the domain from which the sentence was sampled from. For example, given the sentence *Radium was discovered by Marie Curie for which she earned her Nobel Prize in 1911.*, *Marie Curie* can be in most cases annotated as *Person*, but in the domain of *Science*, the entity *Scientist* will instead be the most appropriate prediction. Standard methods for ZSL in NER don't address these two issue, resulting in low performance when performing inference on a target dataset from a different domain.

To address these limitations we propose Cross-Domain Zero Shot Named Entity Recognition with Knowledge Graph (DOZEN). The model learns the relations between entities across different domains from an existing ontology of external knowledge and a set of analogies linking entities and domains. By leveraging entities which are shared from source and target domain, the ontology acts as bridge between the two domains, as the entities are connected within each others in the graph. For example, we can consider the

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Figure 1: Example of knowledge graph: the nodes in blue and yellow are entities and domains respectively

following two sentences from the two domains of science and music respectively, and the knowledge graph in Figure 1:

- (1) Radium [chemical element] was discovered by Marie Curie [scientist] for which she earned her Nobel Prize [award] in 1911.
- (2) Donald Glover [artist] composed "This is America" [song] and was awarded the Grammy [award] in 2018.

From this figure we can see that the entity *Person* can link the two entities *scientist* and *artist* from the two different domains of *science* and *music*. A similar behaviour can be observed for shared entity *award* and the domain-specific entities *Nobel Prize* and *Grammy*. Thanks to these observations, even if DOZEN was never trained on the music domain, it can still recognize the entity *Grammy*. To learn rich graph embedding that capture these relations, DOZEN employs a Recurrent Graph Convolutional Neural Networks (RGCN) and regularizes the embedding with a novel auxiliary tasks of analogy classification, which captures the analogies of the entities across domains. In the example of Figure 1, such analogies are *science* : *scientist* :: *music* : *artist* and *science* : *Nobel prize* :: *music* : *Grammy*.

To the best of our knowledge, this is the first solution to address the task of cross-domain NER by performing ZSL on a knowledge graph. Experiments performed on public datasets illustrate that our solution not only better extracts unseen entities, but also have better performances on the seen entities in sentences from the target domain.

2 DOZEN-METHODOLOGY

In this section we describe the various components of DOZEN. The first input of the model is a sentence, represented as a sequence of tokens. We assume that each token has an embedding representation, which we indicate as $\mathbf{x}_i$, $i \in 1, \dots, K$, with K equals to the number of tokens in the input sentence. The second input is the source and target domain, which we use to sample the relevant knowledge graph. We use N to indicate the total number of entities, including both source and target domain.

The architecture of DOZEN is designed to learn rich token and entity representation as well as integrate the domain information in

the token embedding. The three main components of the model are: 1) a sentence network that learns domain-independent token features, 2) a graph network to learn entity representation for source and target domain and 3) a domain integration network that integrates the domain information into the token representation, generating domain-specific token features. We provide more details on each component in the rest of this section. The overall architecture is illustrated in Figure 2.

2.1 Domain Independent Token Features: Sentence Network

Inspired by the most recent works on NER, we adopt a network based on BERT [1] to obtain a contextualized representation of words and entities [16]. For this component, which we indicate as ϕ , we take inspiration from the LUKE architecture [16], since it is the current state-of-the-art of traditional NER. LUKE outputs contextualized representation for each word and entity. The LUKE model is trained on a set of downstream tasks, such as NER, Q&A, relation classification and entity typing. Since the LUKE network has no knowledge of what is the domain of the input sentence, we use the output representation as domain independent token features. We denote such vector as $\mathbf{h}_i = \phi(\mathbf{x}_i)$, where $i \in 1, \dots, K$. To facilitate learning, we use the pre-trained network provided by [16].

2.2 Entity Features: Graph Network

In order to take advantage of the knowledge incorporated in the ontology, we adopt a graph network to learn entity features that capture the proximity and relations between the graph nodes. The first step consists in sampling a subset ontology given the source and target domain. For this goal, we use the source and target entities as seed nodes and propagate one level in the ontology graph to retrieve all the neighbor nodes. We denote the sampled graph as $\mathcal{G}$, and use $\mathbf{g}_i$, $i \in 1, \dots, N$ to indicate the vector representation of the N entities. Given the recent advances in graph learning, we use a recurrent graph neural network (RGCN) [12] to learn the entity representations: $\mathbf{e}_i = \psi(\mathbf{g}_i)$, where $i \in 1, \dots, N$. We introduce a special entity vector $\mathbf{e}_0$ for the outside-entity tokens, which don't have any entity. Since we use RGCN, this node representation captures the patterns observable in the local neighborhoods, such as the relation between *musical artist* and *scientist* in Figure 1. Same as in [3], we pre-train the graph network on the task of link prediction for better performance.

2.3 Domain Integration Network

Since the input to the sentence network ϕ is only the input sentence, the output representation is domain independent. We compute the domain-specific features with a multi-head attention followed by a concatenation operator:

$$\mathbf{d}_i = \gamma(\mathbf{h}_i) = MHA(\mathbf{h}_i, \mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N, \mathbf{e}_0) \oplus \mathbf{h}_i \oplus \mathbf{g}^* \quad (1)$$

where $MHA(\mathbf{h}_i, \mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N, \mathbf{e}_0)$ is the result of multi-head attention [15]. $\mathbf{h}_i$ acts as the attention query and the label entity vectors $\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N, \mathbf{e}_0$ acts as the attention keys and values where $\oplus$ is the concatenation operator. The intuition is that most compatible

Figure 2: Architecture of DOZEN. We use yellow for the inputs and output, while we use white for the intermediate features in white and grey for the network components

label entity will generate highest attention values and its vector will contribute the highest weight in the domain-specific features.

In order to maintain the domain-independent information, h_i is concatenated to the result of multi-head attention, together with g^* , which is computed as:

$$g^* = \begin{cases} g_j & \text{if } i\text{-th token} \in \mathcal{G} \\ \text{zeros} & \text{if otherwise} \end{cases} \quad (2)$$

In other words, if the i -th token corresponds to a node in the domain-specific graph $\mathcal{G}$, then we concatenate the corresponding entity vector. With this approach we aim at facilitating the prediction of the correct entity by enriching the feature d_i with relevant information.

A fully connected layer FCN reduces the dimensionality of d_i to a more compact representation, before we finally compute the dot product of each token feature d_i with each of the entity features e_j . To annotate the i -th token with the final prediction, we then use:

$$y_i = \underset{j}{\operatorname{argmax}}(\operatorname{softmax}(x_i \cdot e_j)) \quad (3)$$

3 DOZEN-OPTIMIZATION

We optimize the parameters of DOZEN with a combination of multiple loss functions. We denote our source training dataset as $\mathcal{D} = \{(x^j, \hat{y}^j)\}$, where $x^j = [x_1, x_2, \dots, x_K]$. $\hat{y}^j = [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_K]$ is used to indicate the ground truth annotations. Following the standard approach for NER optimization, we employ the following cross entropy loss to minimize the error between the predicted tokens y^j and the labels $\hat{y}^j$:

$$\mathcal{L}_{main} = -\frac{1}{|\mathcal{D}|} \sum_{j,i} (\hat{y}_i^j \log y_i^j + (1 - \hat{y}_i^j) \log(1 - y_i^j)) \quad (4)$$

3.1 Analogy Classification

We designed the second loss terms from the intuition that entities of multiple domains are connected by analogies. For example, entity *scientist* in domain *science* correspond to entity *artist* in domain *music*. Analogy prediction has been formalized in the NLP literature

as the task of predicting what entity best suits an analogy of shape $a:b::c:d$ [7]. Our goal is to enforce that such analogies are reflected in the graph embedding that we learn during training. In order to enforce this behavior, we introduce a new loss term as follows.

Given a tuple (d_s, d_t, e_s, e_x) with the source domain d_s , a target domain d_t , two entities e_s and e_x , with $e_s \in d_s$, the task consists in predicting if $e_x \in d_t$. For example, given $(\text{music}, \text{science}, \text{artist}, \text{scientist})$, we expect the model to predict a positive outcome. For this task we use an auxiliary dataset $\mathcal{D}_{anlg} = \{(d_s, d_t, e_s, e_x, out)\}$, where out is the binary outcome.

Figure 3 illustrates the main intuition behind this task. We first retrieve the corresponding ontology vector for each entity or domain, as described in section 2.2. For tuple $(d_s, d_t, e_s, e_x, out)$, we obtain vectors $(d_s, d_t, e_s, e_x, out)$. We then compute the vector difference $d_s - e_s$ and sum it to d_t , obtaining the expected analogy vector e^* . The loss objective is computed as:

$$\mathcal{L}_{anlg} = -(out * \log(e^* \cdot e_x) + (1 - out) \log(1 - (e^* \cdot e_x))) \quad (5)$$

By minimising this term, we encourage the graph vectors for entities with positive outcome to follow the geometric rules of analogies, while at the same time the entities with negative outcomes will assume a more distant position.

The final expression of the loss is

$$\mathcal{L} = \mathcal{L}_{main} + \alpha \mathcal{L}_{anlg} \quad (6)$$

Figure 3: Geometric interpretation of the analogy classification: DOZEN either minimizes or maximises the distance between e^* and e_x , according to the out variable

4 EXPERIMENTS

4.1 Experiment Settings

For domain specific datasets we use the datasets by Liu et al. [8]. We choose the three domains of *science*, *literature* and *music*, since they have the largest number of entities. Each domain has a training, a development and a testing set. We re-arrange the original train-validation-test sets to increase the amount of training data. Among these three we perform multiple experiments, where one domain is fixed as source, and a second as target, for a total of six combinations. For the source dataset we use the annotation as labels $\hat{y}^j$, while for the target domain we assume there is no label available.

For the common-sense knowledge graph, we chose ConceptNet5.5 [13] as in [3]. Since the network contains more than 34 million edges contains, we sample a smaller ontology with a pre-fixed universe of the five domains in the dataset by [8]. We perform the sampling by extracting nouns and pronouns with a part-of-speech algorithm from all sentences in the dataset, then search for nodes in ConceptNet5.5 and selecting the adjacent nodes.

We compare DOZEN with two baselines. The first is based on the state-of-the-art NER model LUKE [16]. To extend it to ZSL, we learn feature for entities, then compute the dot product with these with the token hidden states after a fully connected layers. The second baseline is an ablated version of DOZEN without analogy loss, which we name as *DOZEN**. Source code is available at ¹.

We used the development set for tuning the parameters and for the stopping criteria.

4.2 Results

Table 1 shows our experiment results in terms of macro F1 score. Results in the table are organized for three different settings, where we consider unseen and seen target entities separately, and all the target entities together.

Unseen entities (ZSL): we observe that DOZEN improves from LUKE+ZSL in 5 out of 6 domain pairs on unseen data. The improvement margin in terms of F1 score is 0.04 on average, ranging from 0.148 in *science-to-literature* domain pair to -0.001 in *music-to-literature* domain pair. This confirms the importance of commonsense knowledge in ZSL.

Seen entities (Cross-domain): we can see that our model can achieve a higher F1 score across 5 in 6 domain pairs on unseen data, with average improvement margin of 0.036. This shows that the knowledge graph and analogies do not benefit the ZSL capability only, but also help with recognizing the same source entities in sentences from the target domain.

All entities: on all entities, DOZEN improves LUKE across 5 out of 6 domain pairs with average improvement margin of 0.039, indicating that DOZEN is the most suitable option for cross-domain NER. From the table we can see that in the *science-to-music*, all of the models fail to achieve ZSL, with F1 score close to 0. In order to explain this behaviour, we followed the approach by [11], where they used the KL divergence as a measure of how the target domain differ from the source domain in terms of the distribution of concepts. We found out that among all the six pairs of domain, the

		All Entities	Seen Entities	Unseen Entities
S:Science T:Literature	DOZEN	0.372	0.569	0.097
	DOZEN*	0.338	0.563	0.023
	LUKE+ZSL	0.344	0.545	0.063
S:Literature T:Science	DOZEN	0.327	0.536	0.180
	DOZEN*	0.316	0.502	0.187
	LUKE+ZSL	0.268	0.408	0.169
S:Music T:Literature	DOZEN	0.485	0.616	0.301
	DOZEN*	0.445	0.567	0.274
	LUKE+ZSL	0.495	0.633	0.302
S:Literature T:Music	DOZEN	0.415	0.592	0.264
	DOZEN*	0.355	0.576	0.098
	LUKE+ZSL	0.322	0.559	0.118
S:Music T:Science	DOZEN	0.265	0.438	0.116
	DOZEN*	0.253	0.435	0.104
	LUKE+ZSL	0.227	0.430	0.061
S:Science T:Music	DOZEN	0.284	0.527	0.000
	DOZEN*	0.288	0.525	0.010
	LUKE+ZSL	0.261	0.486	0.000

Table 1: Performance of DOZEN in terms of macro F1 score

KL diverge is the highest when the source is *science* and the target is *music*, suggesting that this combination is the hardest for ZSL.

*DOZEN**: first, we notice that in 2 out of 6 cases, *DOZEN** achieves a smaller F1 score than the baseline *LUKE + ZSL*, but *DOZEN* has the highest score. This indicate that the anomaly classification is a critical component of DOZEN. Second, we observe that the *DOZEN* has better results than the *DOZEN** variation, with the exception of 2 domain pairs, namely literature-science and science-music, confirming that overall the model benefits from the analogy learning. A possible explanation for these two combinations is that since we engineered the analogies dataset ourselves, these may be biased and fail to reflect the correct analogical relationships between labels of certain domain pairs. Future works shall seek to mitigate this engineering bias and propose more robust analogies.

5 CONCLUSION

Most of works that do zero shot learning are not designed for cross-domain settings, where the entities domain-specific and there is no large-scale annotated dataset. Our solution, which we name Cross Domain Zero Shot Named Entity Recognition with Knowledge Graph (DOZEN), bridges the gap between the multiple domains by leveraging an external knowledge and learning to correctly classify associations. Our experiments performed on six combination of three domain-specific datasets indicate that our solution not only better extracts unseen entities, but also have better performances on the seen entities in sentences from the target domain. In the future, we plan to reduce the engineering bias from the analogy dataset and to integrate domain adaptation in the model, to address the differences in the data and label distribution across multiple domains.

¹<https://github.com/GelliFrancesco/DOZEN>

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