

Entity Type Prediction in Knowledge Graphs using Embeddings

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Motivation

What are the types of the following entities?

Violin



Instrument

Lisbon



City

Yellow billed duck



Bird

Motivation

What are the types of the following entities?

Violin

Lisbon

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The image shows three screenshots of the DBpedia 'About' page for different entities. Each screenshot has a red circle around the text 'An Entity of Type : [entity type], from Named Graph : ht...'. Below each screenshot is a label for the entity type.

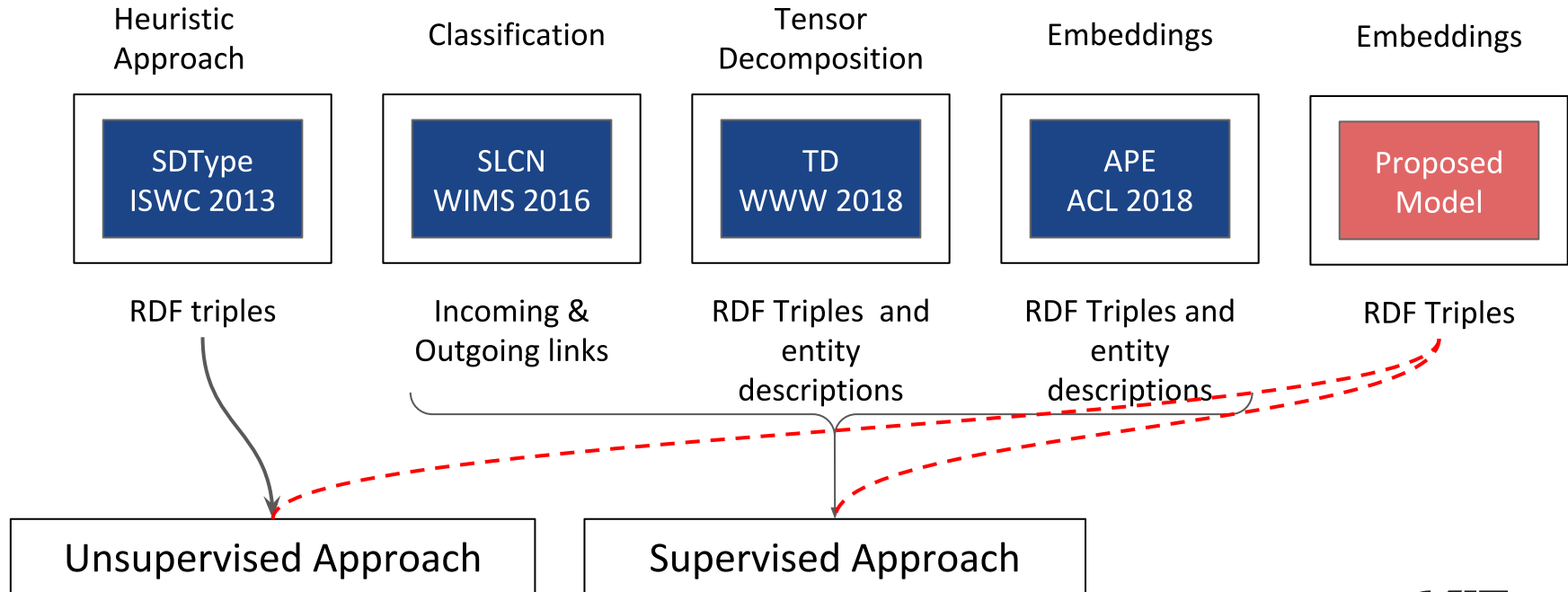
| Entity | Entity Type |
|--------------------|-------------|
| Violin | Instrument |
| Lisbon | City |
| Yellow billed duck | Bird |

Motivation

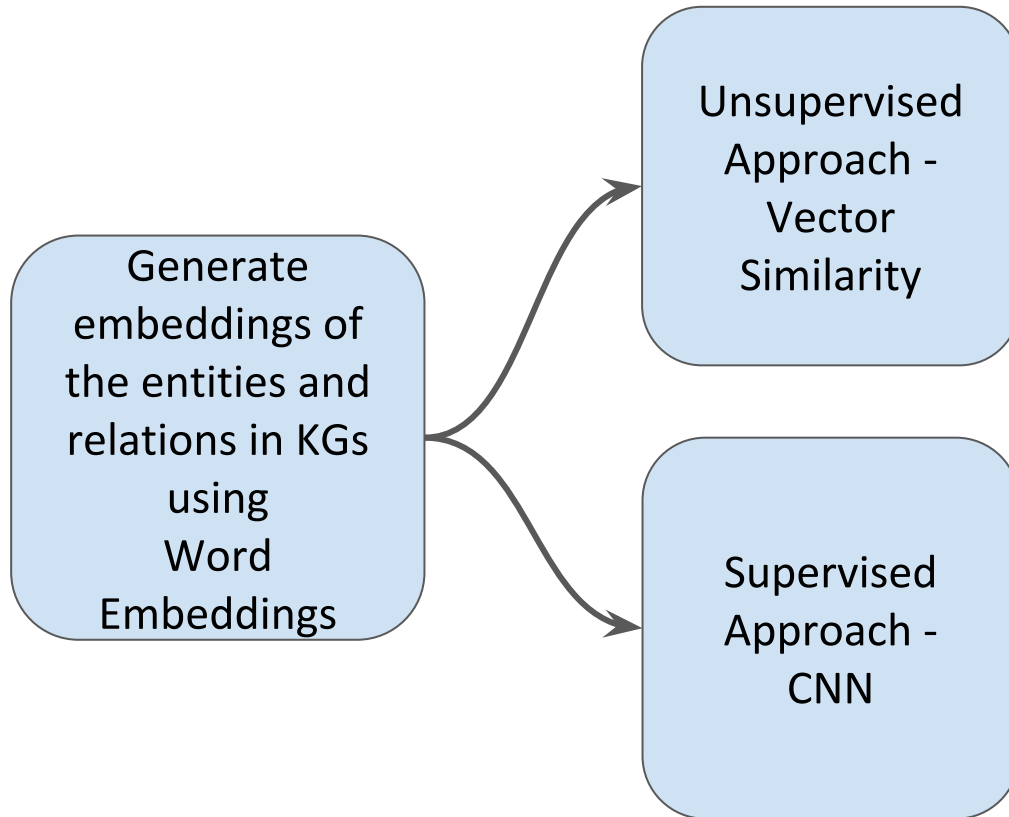
Coarse grained Type information in DBpedia at a glance

| Classes | #Total entities | Percentage of entities with more fine grained type |
|----------------|-----------------|--|
| dbo:Person | 1,818,072 | 36.6% |
| dbo:Scientist | 25,760 | 3.5% |
| dbo:Settlement | 581,293 | 68.3% |
| dbo:Company | 109,629 | 13.9% |

Related Work



Proposed Approach



- Three different word embedding models are used to model the KGs
 - Word2Vec
 - FastText
 - GloVe
- Entity Typing is done based on these 3 word embedding models separately and are compared against each other.

Embeddings

Input: <dbr:Albert_Einstein, dbo:birthPlace, dbr:Ulm>.
<dbr:Albert_Einstein, dbo:field, dbr:Physics>.

} **Sentences**

words

Embedding models are trained on triples with **Object Properties**

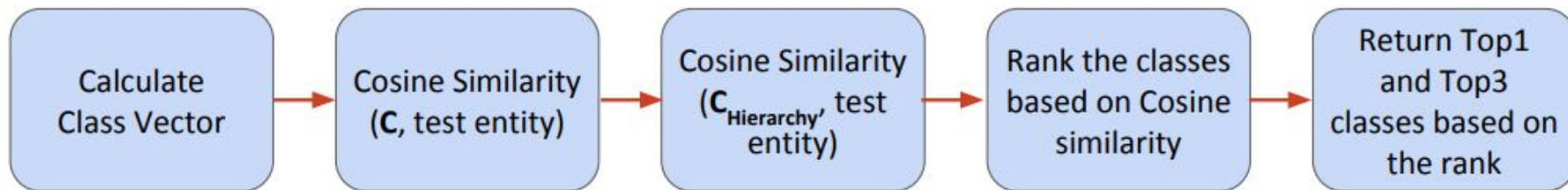
Word2Vec:
Continuous Bag
of Words
(CBOW)
approach is used.

FastText:
Continuous Bag
of Words
(CBOW)
approach is used.

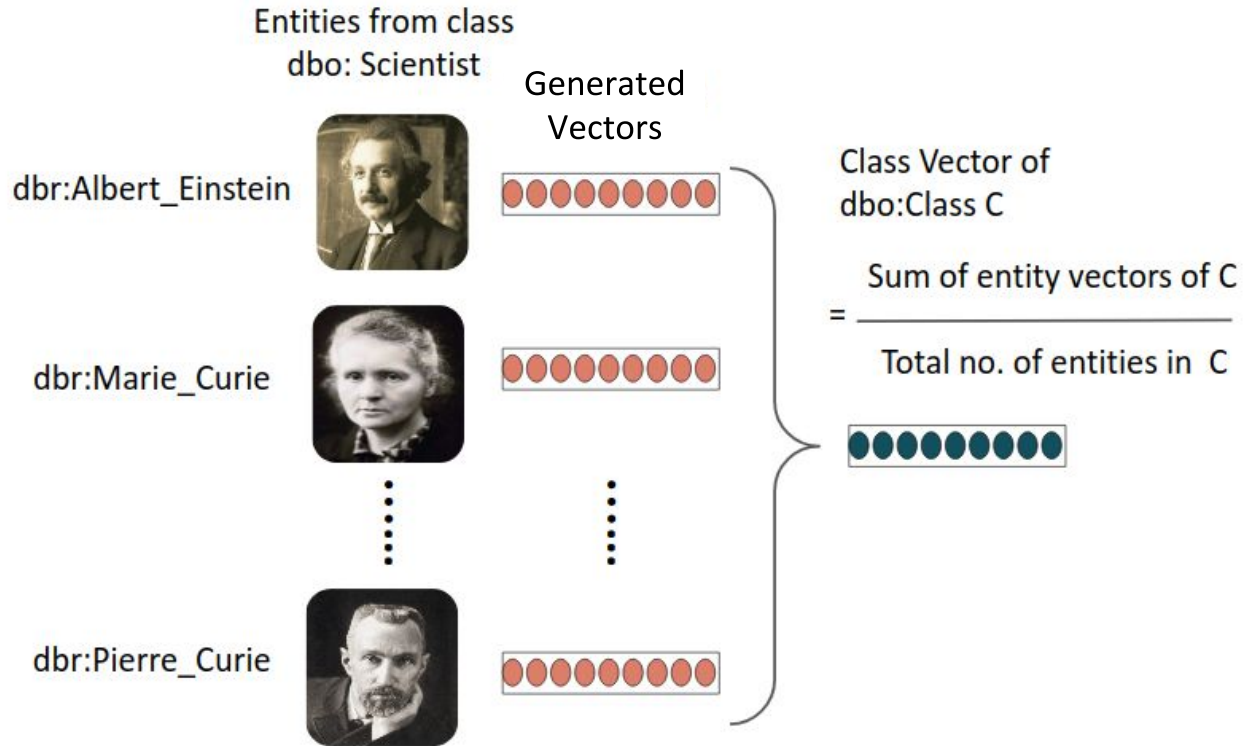
GloVe:
Word
co-occurrence
matrix is used to
learn the model.

Pipeline of the Unsupervised Approach

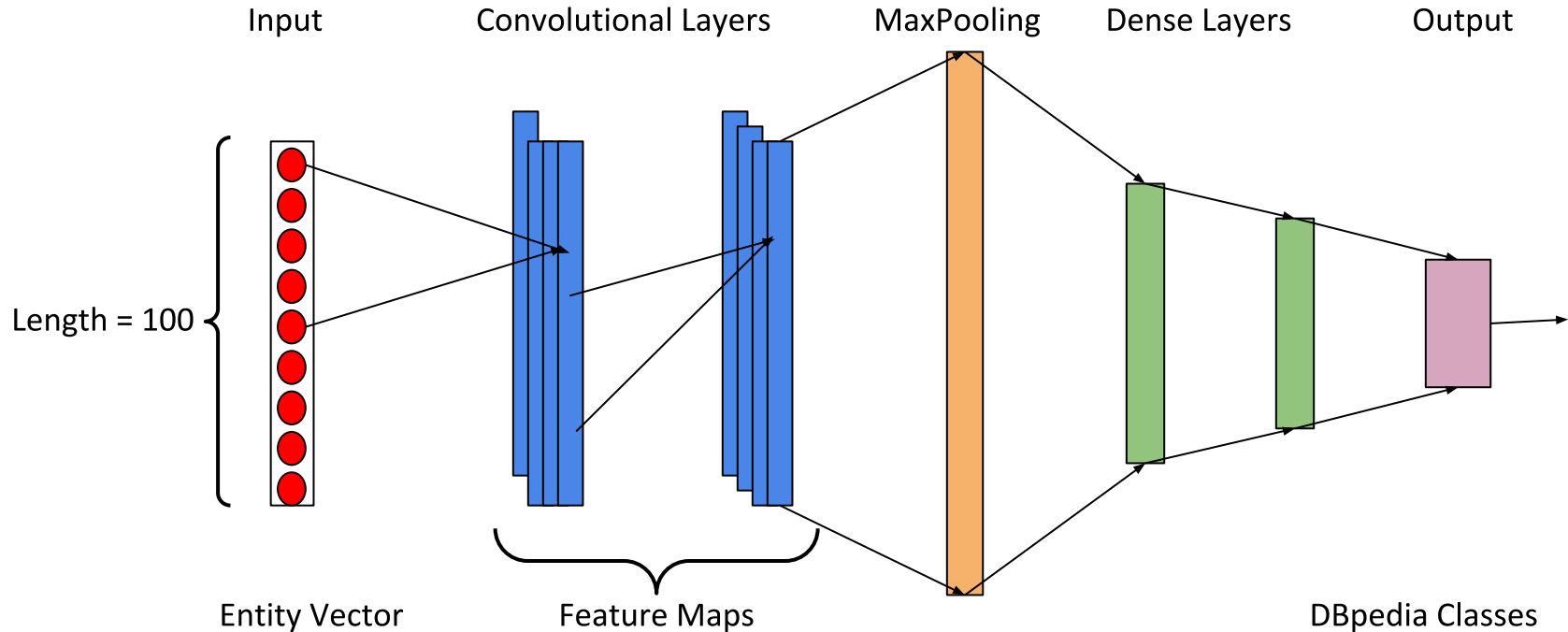
Unsupervised approach is based on the vector similarity between the class vector and entity vector



Generation of Class Vectors



Supervised Approach - 1D CNN



Datasets

1. **Dataset 1:**
 - a. **59** less popular classes with the following characteristics:
 - i. **15 classes** that have less than **500 entities per class**,
 - ii. **20 classes** that have entities between **500 and 1000 entities per class**,
 - iii. **24 classes** have more than **1000 entities per class**,
 - iv. **Max.** no. of entities per class in this dataset is **500**, and
 - v. **Min.** no. of entities per class in this dataset is **276**.
2. **Dataset 2: 86** classes with **2k entities per class**.
3. **Dataset 3: 81** classes with **4k entities per class**.

Results

| Datasets | Models (Results in Percentage Accuracy) | | | | | | | | |
|-----------|---|--------|-------------|-------------------|--------|-----|-------------------|--------|------|
| | Word2Vec | | | FastText | | | GloVe | | |
| | Vector Similarity | | CNN | Vector Similarity | | CNN | Vector Similarity | | CNN |
| | Hits@3 | Hits@1 | | Hits@3 | Hits@1 | | Hits@3 | Hits@1 | |
| Dataset 1 | 47.83 | 28.46 | 56 | 29.81 | 17.44 | 54 | 7.07 | 3.54 | 53.7 |
| Dataset 2 | 58 | 39.4 | 58.4 | 43.81 | 31.16 | 56 | 15.9 | 8.2 | 55 |
| Dataset 3 | 58 | 39.7 | 62 | 44.3 | 31.4 | 59 | 16.2 | 8.4 | 55.8 |

Results - Comparison with SDType

Test Dataset: The common entities between our dataset and the entities for which SDType model[1] predicts a change are considered.

| Datasets | #Test Entities | SDType | Vector Similarity (Accuracy in Percentage) | | | | | |
|-----------|----------------|--------|--|--------|----------|--------|--------|--------|
| | | | Word2Vec | | FastText | | GloVe | |
| | | | Hits@1 | Hits@3 | Hits@1 | Hits@3 | Hits@1 | Hits@3 |
| Dataset 1 | 7425 | 83.35 | 32 | 63.78 | 12.58 | 25.87 | 2.8 | 11.04 |
| Dataset 2 | 57467 | 80.43 | 46.94 | 69.53 | 38 | 61.8 | 16.37 | 30.4 |
| Dataset 3 | 109948 | 81.22 | 48.21 | 71.6 | 39.54 | 64.14 | 17.07 | 31.58 |

<http://wiki.dbpedia.org/services-resources/documentation/datasets#InstanceTypesSdtypedDb>

Russa Biswas et al. Entity Type Prediction in KGs using Embeddings. DL4KG Workshop @ ESWC 2020.

Conclusion and Future Work

- **Word embeddings** when applied on the Knowledge Graphs can be efficiently used for the task of Entity Type Prediction.
- **Word2Vec proves** to be the **best word embedding approach** out of the three word embedding approaches used **in KGs**.
- Supervised approach, **1D CNN works better than the unsupervised approach** for the task
- In Future Work, more information from the DBpedia such as **Datatype properties** are to be explored for the type prediction task.

References

Literature:

1. Melo A, Paulheim H, Völker J. Type prediction in RDF knowledge bases using hierarchical multilabel classification. In Proceedings of the 6th International Conference on Web Intelligence, Mining and Semantics 2016 Jun 13 (p. 14). ACM.
2. Jin H, Hou L, Li J, Dong T. Attributed and Predictive Entity Embedding for Fine-Grained Entity Typing in Knowledge Bases. In Proceedings of the 27th International Conference on Computational Linguistics 2018 Aug (pp. 282-292).
3. Paulheim H, Bizer C. Type inference on noisy rdf data. In International semantic web conference 2013 Oct 21 (pp. 510-525). Springer, Berlin, Heidelberg.
4. Moniruzzaman AB, Nayak R, Tang M, Balasubramaniam T. Fine-grained Type Inference in Knowledge Graphs via Probabilistic and Tensor Factorization Methods. In The World Wide Web Conference 2019 May 13 (pp. 3093-3100). ACM.
5. Pirrò G. Explaining and suggesting relatedness in knowledge graphs. In International Semantic Web Conference 2015 Oct 11 (pp. 622-639). Springer, Cham.

Images:

https://en.wikipedia.org/wiki/Lisbon#/media/File:Montagem_de_Lisboa.png

https://en.wikipedia.org/wiki/Violin#/media/File:Violin_VL100.png

https://en.wikipedia.org/wiki/Yellow-billed_duck#/media/File:Yellow-billed_Duck_Plettenbergbay_RWD.jpg

Thank you

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