Guiding Graph Embeddings using Path-Ranking Methods for Error Detection in noisy Knowledge Graphs

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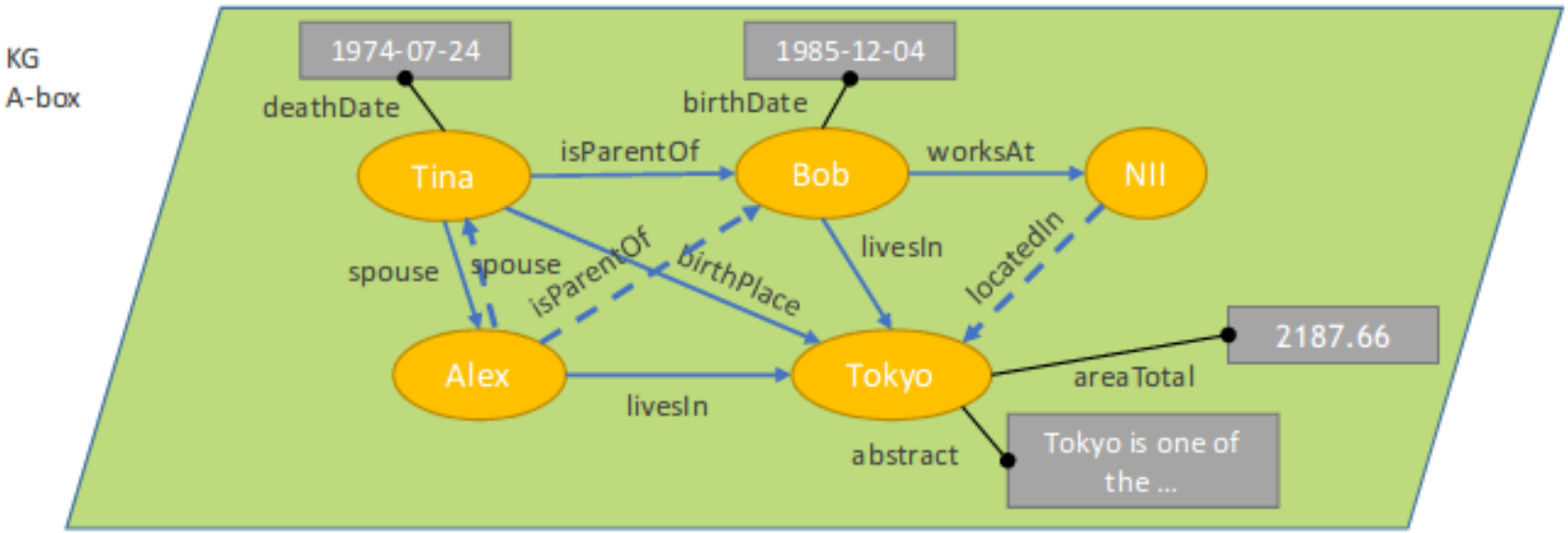
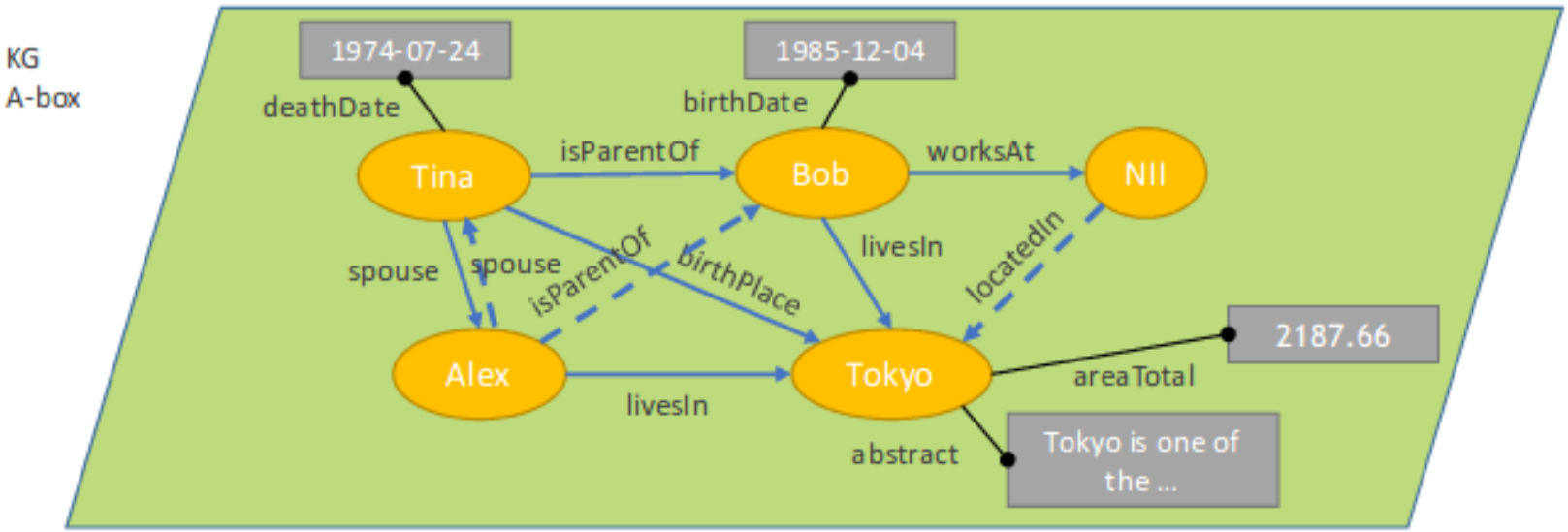
Knowledge Graphs



- **Knowledge Graph**: A heterogeneous graph with *context*
- Information is depicted in triples (s, r, o), where:
  1. s : subject
  2. o : object
  3. r : relation

The need for error detection



- KG construction mainly relied on manual annotation.
- Nowadays knowledge graphs are automatically constructed.
- Noise and errors are automatically introduced!

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Path Ranking Algorithm (PRA)

Original Implementation (first proposed in 2010 by Lao et al.)

- *Key Idea*: Explicitly use paths that connect two entities as features.
- *Path*: A sequence of relations $<r1, r2, ..., r_\lambda>$ that link two entities.
- 1. *Feature extraction*: Extract paths of **bounded** length.
  2. *Main computation*: Given an entity pair (s, o), and a path p, estimate probability $p(o|p, s)$ (mostly **random walks**).
  3. *Prediction*: Train individual classifier for each relation:

$$Score_r(s, o) = \sum_{p \in P} p(o|p, s)\theta_{pr}$$

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PRA Extensions

- Incorporating a text corpus as additional evidence during inference + relaxing main computation (Gardner et al.).
- PaTyBRED: Paths and Types with Binary Relevance for Error Detection (Andre Melo, 2017).

PaTyBRED

$$
\begin{array}{l}
 & \overbrace{(TREATS, IS\_A)}^{} \quad \overbrace{\text{feature paths}}^{} \\
(s, IS\_A, o) \\
\text{positives} \\
\\
\\
\\
\text{negatives} \\
\\
\\
\end{array}
\begin{bmatrix}
0 & 1 & 1 & \dots & 0 & 0 \\
1 & 0 & 1 & \dots & 0 & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
1 & 0 & 0 & \dots & 1 & 1 \\
\hdashline
0 & 0 & 0 & \dots & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 1 & \dots & 0 & 0
\end{bmatrix}
\begin{array}{c}
\overbrace{\text{labels}}^{} \\
\\
\\
\\
\\
\\
\\
\end{array}
\begin{bmatrix}
1 \\
1 \\
\vdots \\
1 \\
\hdashline
0 \\
\vdots \\
0
\end{bmatrix}
=
\begin{array}{c}
\overbrace{\text{confidence}}^{} \\
\\
\\
\\
\\
\\
\\
\end{array}
\begin{bmatrix}
0.8 \\
1.0 \\
\vdots \\
0.6 \\
\hdashline
0.3 \\
\vdots \\
0.0
\end{bmatrix}
$$

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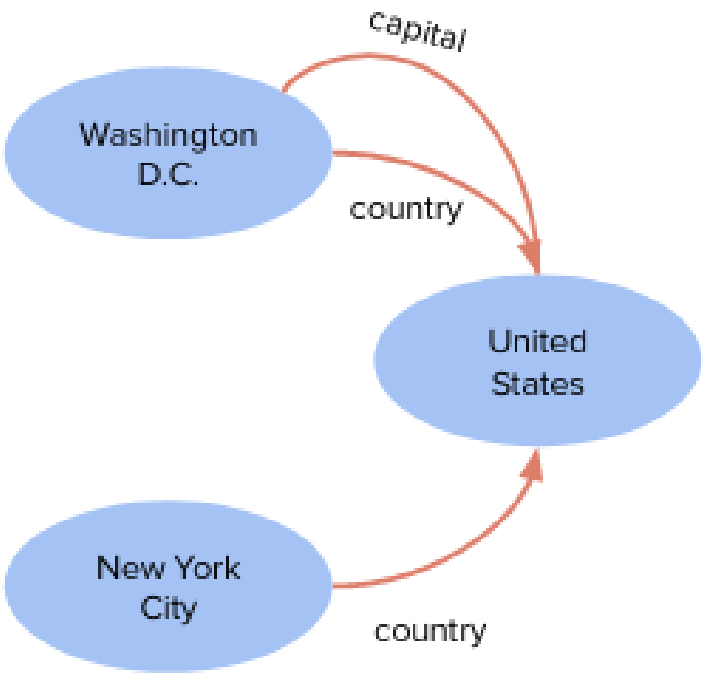
Graph Embeddings



Embedding

Washington D.C.	New York City	United States	country	capital
1	1	5	1	2
2	2	6	2	2
4	5	4	4	5
5	4	4	1	1
6	7	8	4	5
7	7	7	5	5

- Embedding methods generate representations of the elements of the knowledge graph that are embedded in a vector space.
- These representations encode latent properties of the graph.
- ...e.g. similar entities tend to be described with similar vectors.

Main KG Graph Embedding approaches

Translational approaches

- Often based on learning translations from the subject to the object.
- Have the advantages of having a concise definition and getting good performances while being scalable at the same time.
- *Most representative model*: **TransE**:

$$E(s, r, o) = ||s + r - o||_2$$

based on the idea that $s + r = o$.

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BiLinear approaches

- High expressive power due to the use of a full rank matrix for each relationship.
- At the same time, the full rank matrix is prone to overfitting (constraints have been suggested)
- *Most representative model*: **RESCAL**: $E(s, r, o) = sW_r o$.

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Path Guided Embeddings

Utilize paths that connect an (s, o) tuple to train embeddings of triples:

PTransE

- Path : $p = r_1 + r_2 + ... + r_l$
- $Loss = \sum_{(s,r,o) \in S} L(s, r, o) + \frac{1}{Z} * \sum_{p \in P(s,o)} R(p|s, o) * L(p, r)$
- $L(s, r, o) = \sum_{(s',r,o') \in S'} max(0, \gamma + E(s, r, o) - E(s', r, o'))$
- $L(p, r) = \sum_{(s,r',o) \in S'} max(0, \gamma + ||p - r|| - ||p - r'||)$

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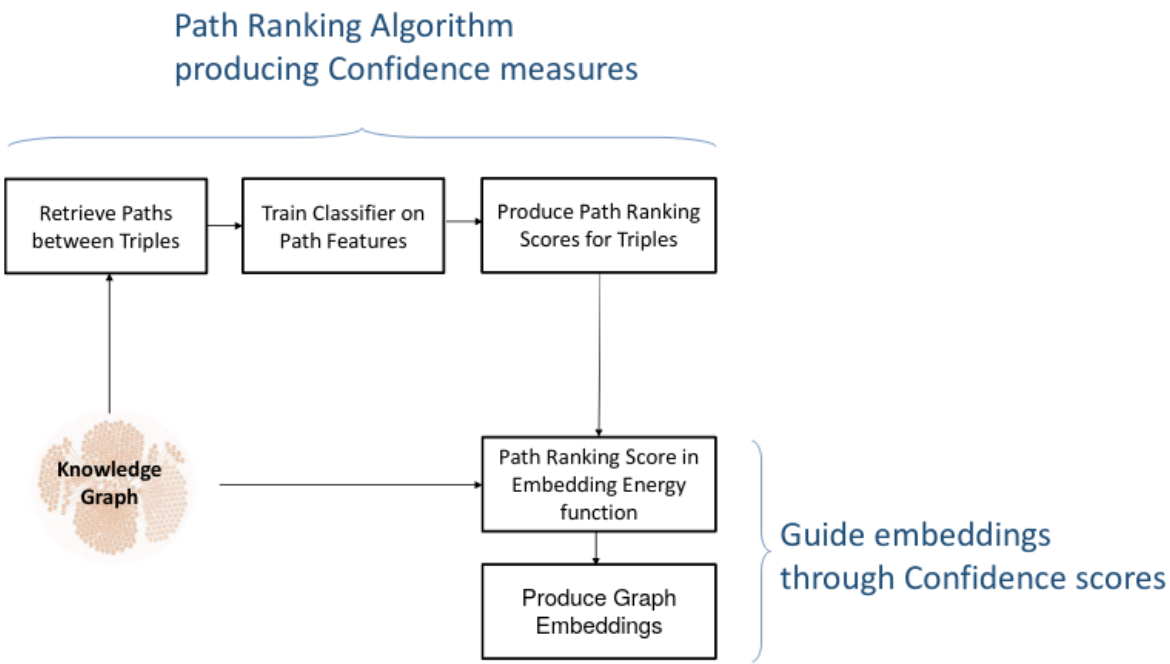
- $L(p, r) = \sum_{(s,r',o) \in S'} max(0, \gamma + ||p - r|| - ||p - r'||)$

CKRL

- $Loss = \sum_{(s,r,o) \in S} L(s, r, o) * C(s, r, o)$
- $C(s, r, o) = \lambda_1 LT(s, r, o) + \lambda_2 PP(s, r, o) + \lambda_3 AP(s, r, o)$

PRGE



PRGE

- Instead of competing end-to-end, make something more modular.
- An embedding-based loss scaled with a Path Ranking Score:

$$L = \sum_{T \in S} \sum_{T \in S'} max(0, \gamma + E(s, r, o) - E(s', r, o')) \cdot P(s, r, o)^{\lambda}$$

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Experiments

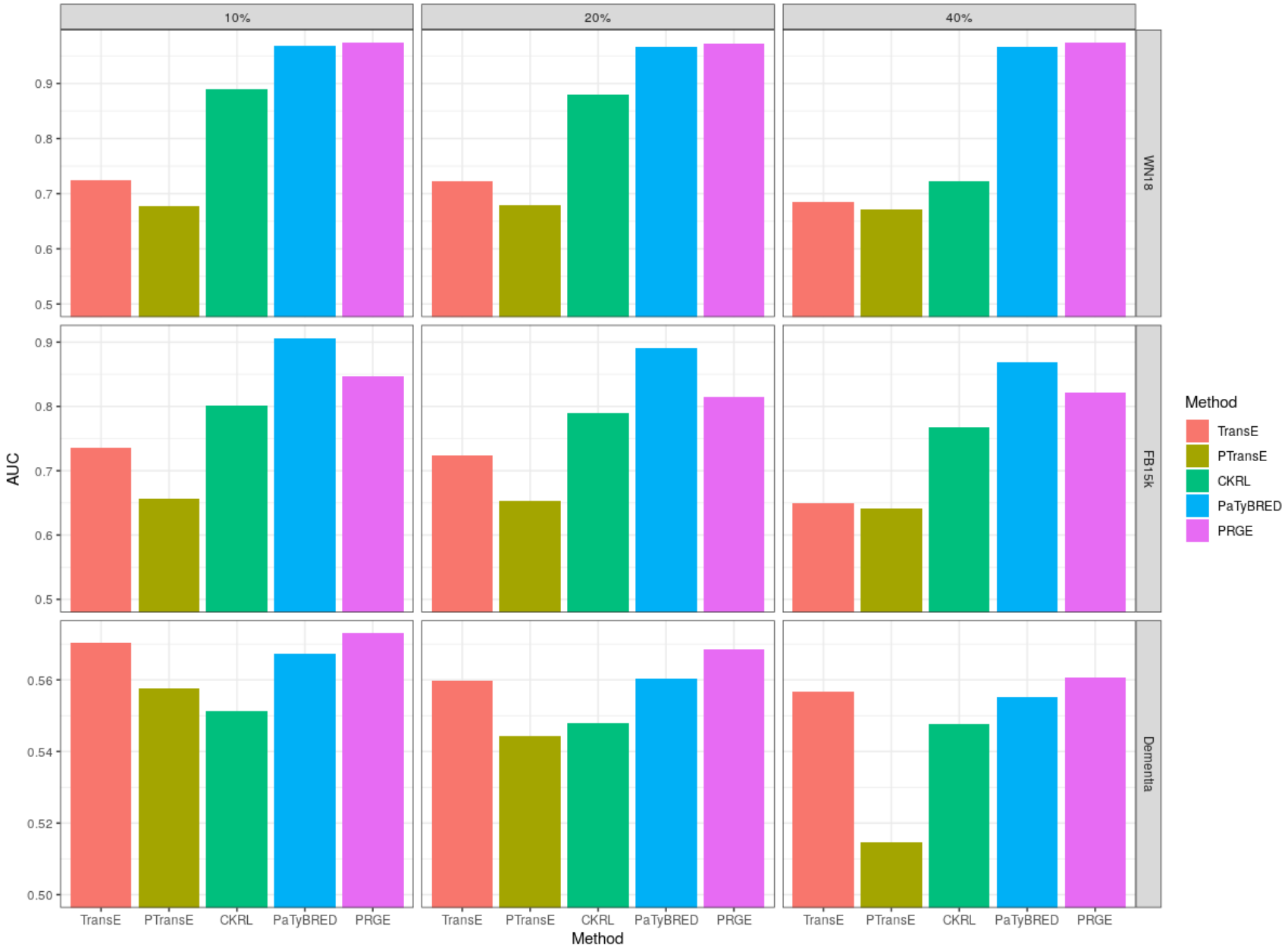
Datasets: Two benchmark datasets and one in-house dataset (Dementia from IASIS) were used for evaluation purposes:

Dataset	#Rel	#Ent	#Triples
WN18	18	40,943	141,442
FB15k	1345	14,951	483,142
Dementia	64	48,008	135,000

Evaluation Metrics:

- Ranking-based ones (Mean Rank, Mean Reciprocal Rank)
- Classification based ones (AUC)

Results


10%
20%
40%
WN18
FB15k
Dementia
AUC
0.9
0.8
0.7
0.6
0.5
0.56
0.54
0.52
0.50
TransE
PTransE
CKRL
PaTyBRED
PRGE
Method
Method
TransE
PTransE
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PaTyBRED
PRGE

Downstream Tasks

Advantages of the method:

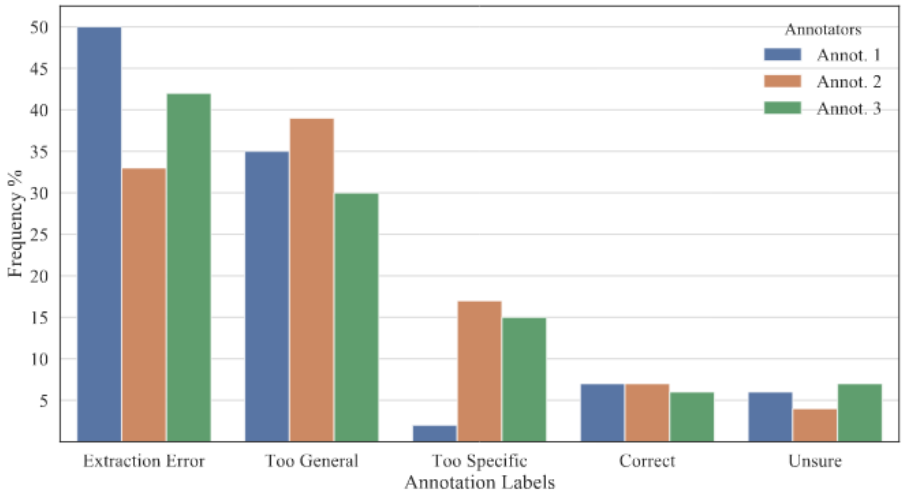
- *Modularity*: Any Embedding method can be used (Translational/Bilinear), and any PRA can be used.
- Other Triple confidence scores can be used from other sources (Text Similarity/Rule-based scores (Probabilistic soft Logic)).
- *Creation of Embeddings*: A result of this process is the creation of embeddings that can be used in other downstream tasks

TRIPLE CLASSIFICATION

Method	FB15K-10%	FB15K-20%	FB15K-40%
TransE	**0.717**	0.703	0.671
PTransE	0.686	0.678	0.67
CKRL	0.639	0.709	0.691
PRGE	0.715	**0.712**	**0.702**

Qualitative results

Applying PRGE to the IASIS Dementia dataset:



Erroneous triple (s - r - o)	Type	Supporting text
acetonitrile - AUGMENTS - 80%	ER	... The **acetonitrile** concentration was increased to 80% in 5 min and then held in **80%** acetonitrile for an additional 5 min ...
Denmark - PART_OF - Neurons	ER	... **Neurons** transfected with **DA**-GFP were found to have dendritic spines that had significantly lengthened necks compared to ...
Cells - PART_OF - Medial geniculate body	TG	... Dendritic spines of the polyhedral and elongated **cells** of the **medial geniculate bodies** were decreased in number ...
Entire thumb - PART_OF - Patients	TG	... The **patient** is asked to hold the ruler with his **thumb** and forefinger and to release the ruler while the investigator continues to ...
DDMS - PART_OF - Homo sapiens	TS	... HT-22 hippocampal cells and confirms observations using brain extracts from monkey, mouse, rat and **human DDM** ...
Brain - LOCATION_OF - Decreased plasmalogens	TS	... data suggest that long-term alterations in plasmalogen synthesis degradation result in **decreased brain plasmalogen** levels, a hallmark feature of AD ...

Conclusions/Future Work

Conclusions:

- The proposed PRGE method combines the path ranking score of a triple with the graph embedding framework, creating embeddings robust towards noise present in the graph
- The proposed PRGE method is agnostic of the underlying energy function and triple-scoring mechanism, as such, other path-ranking scores and energy function could work even better.
- Overall, we have proposed a generic framework to generate embeddings resilient to noise and we proved that they can also be used in multiple downstream tasks enhancing performance in the presence of noise.

Future Work:

- More experimentation and a thorough comparison with other state-of-the-art methods.
- An extended study with different combination of methodologies is needed (Different Path ranking algorithms/prior scores, different embedding approaches).