Assume a knowledge graph: 

\[ D \rightarrow \text{target} \rightarrow \text{prot1} \rightarrow \text{drug1} \rightarrow \text{prot1} \rightarrow \text{drug2} \]

And an embedding mapping entities and relations:

\[ \mathbb{R}^n \]

In EmbedS, we model entities as points, classes as sets of points (an \( n \)-sphere, with a central vector and a radius), and properties as sets of pairs of points (modeled analogously).

These models represent relations as a translational vector. Learning is achieved by minimizing the cost:

\[
\mathcal{L} = \sum_{(s,p,o)} \left[ \| \vec{s} + \vec{p} - \vec{o} \| - \| \vec{s}' + \vec{p} - \vec{o}' \| + \gamma \right] +
\]

This model, TransE [1], was inspired by word2vec. The cost per triple is:

\[
\mathcal{L}_{(s,p,o)} = \| \vec{s} + \vec{p} - \vec{o} \|
\]

EmbedS: Scalable and Semantic-Aware Knowledge Graph Embeddings

Performance: Initial experimental evaluation on a benchmark dataset and an ad hoc dataset show competitive performance.

\[
\text{wn18 dataset:} \\
\text{hits@10: 94.9\%, MRR: 0.560 (HMR: 1.79)}
\]

\[
P = 84.2\% \text{ and a Recall } = 83.9\%, f-measure: 84.0\% \\
(\text{optimizing the geometrical interpretation})
\]

\[
\text{dbpedia_v2 dataset:} \\
\text{EmbedS: hits@10: 22.7\%, MRR: 0.133 (HMR: 18.52)}
\]

\[
\text{TransE: hits@10: 11.6\%, MRR: 0.054 (HMR: 18.52)}
\]

References:
