Reference:

https://papers.nips.cc/paper/5071-translating-embeddings-for-modeling-multi-relational-data.pdf

**Analysis and summary of “Translating Embeddings for Modeling Multi-relational Data”**

This paper examines an approach in embedding entities and relationships of multi-relational data into low-dimensional vector spaces. Multi-relational data is represented by graph, where a node is an entity and an edge is a relationship. For example, (*head, label, tail*): *head* has relationship *label* with *tail*. This paper tries to break the current mold of adapting single-relational approaches to multi-relational data. Previous models trades broader expressive capacity for higher model complexity and thus tend to overfit or underfit excessively.

**What is TransE?** TransE is an energy based model for learning low-dimensional embeddings of entities. It is similar to the idea presented in OG paper. That is to say, if (*head, label, tail*) then embedding of *tail* should be close to the embedding of (*head* + vector *label*). The exact formula and algorithm can be found in Section 2 of the paper. This algorithm is used to generate two different projection matrices, one for each node, with the idea that the relationship could be asymmetric. Each matrix is generated by minimizing a margin based ranking criterion over the training set and optimized using stochastic gradient descent.

**Note: I am not 100% sure on how this model is generated.**

TransE takes less time to train, but yield betters results despite being a “simpler,” less expressive model.

**CORPUS:** 1M entities, 25k relationships, 17M training samples. **Wordnet** and **Freebase**, removing things like repeated relationships.

The testing removes the head and tries to find the best ranked entity in the dictionary and averages the top 10 results. It does a similar thing with the tail. Very extensive testing, exploring not only the different possible configurations of relationships (1-to-1, etc. ) but also new relationships.

**What does expressive mean in this context?**

**RELATED WORK:**

1. Bordes, J. Weston, R. Collobert, and Y. Bengio. Learning structured embeddings of knowledge bases. In Proceedings of the 25th Annual Conference on Artificial Intelligence (AAAI), 2011.

R. Socher, D. Chen, C. D. Manning, and A. Y. Ng. Learning new facts from knowledge bases with neural tensor networks and semantic word vectors. In Advances in Neural Information Processing Systems (NIPS 26), 2013.

A. Bordes, X. Glorot, J. Weston, and Y. Bengio. A semantic matching energy function for learning with multi-relational data. Machine Learning, 2013

C. Kemp, J. B. Tenenbaum, T. L. Griffiths, T. Yamada, and N. Ueda. Learning systems of concepts with an infinite relational model. In Proceedings of the 21st Annual Conference on Artificial Intelligence (AAAI), 2006.