Frame-Based Continuous Lexical Semantics through Exponential Family Tensor Factorization and Semantic Proto-Roles

Understanding Participating in Actions
Word embeddings robustly capture word similarity & associativity. What does it mean for “the paper” to “reflect the truth?” And how do we represent it?

The paper reflected the truth.

Frame Semantics
Provide Structured Word Meaning
Understanding through defined and structured concepts (Minsky ’74; Fillmore ’76, ’82)
Examples: FrameNet and PropBank

Semantic Proto-Roles
Decompose Categorical Roles
Dowty ’91, Reisinger et al. ’15:
Describe semantic arguments as properties of participating in an action

Frame Embeddings from Tensor Factorization
Further generalize Cotterell et al. ’17’s 3-tensor factorization
\[ p(t_i, w_j, c_1, \ldots, c_K) \propto \exp(1^T (t_i \odot w_j \odot c_1 \odot \cdots \odot c_K)) \]

Evaluating Attributive Embeddings
QVEC: Correlate learned and oracle ontology vectors (Tsvetkov et al. ’15)
Use SPR annotations as ontology:
1. Properties & syntax are coordinates: 80 total
2. SPR Likert \(\rightarrow\) 0-5 rating
3. Sum & normalize over ratings

Extracting Frame Counts from Large Corpora
1. Record every word triggering \textit{frames}...
2. Each \textit{role}'s fillers...
3. \textit{Frames} and \textit{roles}...
4. And \textit{context}

Higher SPR Correlations in Learned Frame Trigger Embeddings
Frames give helpful extended context
Frames rival and outperform strong lexical models
Extended context and frames are complementary
Predict role fillers for higher correlation

Learning Paraphrases and Inflectional Relations
Under three newswire models, what triggers are most similar to \textit{anticipated}?

Conclusion
Semantic frames obtained from large, disparate corpora can be used to learn enriched word vectors resulting in higher semantic proto-role based correlations.