Linear Dimensionality Reduction and Affect

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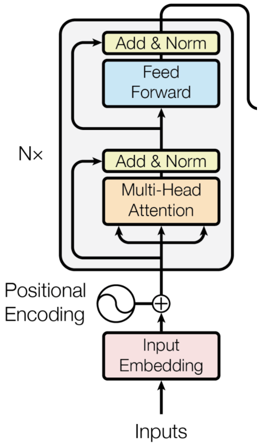
Word Embeddings as Features

- Words can be represented by semantic embeddings.
  - $$\left\{ \begin{array}{rcl} \textit{good} & : & \left[\begin{array}{rrrr} -0.3 & 0.9 & 0.2 & -0.8 \end{array}\right] \\ \textit{bad} & : & \left[\begin{array}{rrrr} -0.4 & -0.8 & 0.1 & -0.8 \end{array}\right] \\ \textit{terrorist} & : & \left[\begin{array}{rrrr} 0.1 & -0.7 & 0.5 & 0.0 \end{array}\right] \\ \textit{Tim} & : & \left[\begin{array}{rrrr} 0.9 & 0.6 & -0.4 & 0.7 \end{array}\right] \end{array} \right\}$$
- Words that appear in similar contexts have similar word embeddings, and a thus a higher cosine similarity.
  - This apple tastes *good*. This apple tastes *bad*. `CosSim(good, bad) = 0.74`
  - This apple tastes *good*. This apple tastes *terrorist*. `CosSim(good, terrorist) = 0.43`
- Embeddings can be created for words using different encoders: the most famous being Word2Vec, GloVE, ELMo, and BERT.
- These embeddings can be used as feature vectors for different downstream tasks.

BERT

- BERT is unique in that it uses transformers in determining the embedding of a word. This allows BERT to use context to give more contextually accurate word embeddings and disambiguate between homonyms.
- The success of BERT as an encoder has led to many variants: we are using a XLM-RoBERTa (XLMR) longformer.
  - RoBERTa (Robustly Optimized BERT Approach) is similar to BERT, but trained longer, on more data, and with a modified learning objective.
  - XLM-RoBERTa is a multilingual version of RoBERTa.
  - A longformer takes more input tokens.



Affect

- Words have three different affect dimensions:
  - Sentiment (Valence): goodness/badness
  - Agency (Arousal): activeness/passiveness
  - Power (Dominance): strength/weakness
- This gives us the ability to more finely distinguish between synonyms.
- Hypothesis: Derog can be defined to be a combination of different affect dimensions.

Dimension	Word	Score↑	Word	Score↓
valence	*love*	1.000	*toxic*	0.008
	happy	1.000	*nightmare*	0.005
	happily	1.000	*shit*	0.000
arousal	*abduction*	0.990	*mellow*	0.069
	exorcism	0.980	*siesta*	0.046
	homicide	0.973	*napping*	0.046
dominance	*powerful*	0.991	*empty*	0.081
	leadership	0.983	*frail*	0.069
	success	0.981	*weak*	0.045

Table 2: The terms with the highest (↑) and lowest (↓) valence (V), arousal (A), and dominance (D) scores in the VAD Lexicon.

Entity-Level Derog

- Architecture: input sentence $\rightarrow$ **BERT** $\rightarrow$ entity embedding(s) $\rightarrow$ **decoder** $\rightarrow$ affect scores
- Decoders: Field and Tsvetkov proposes two models for decoding:
  - Kernel Ridge Regression (KRR): similar to SVM, where a RBF kernel is used.
  - Affect Subspace Projection (ASP): uses extreme-valued words and linear decomposition to project scores.
- Why use ASP when KRR performs better?
  - Confounds are words that “trick” or “confuse” a model into learning incorrectly. For example, for agency, the KRR might learn to differentiate between animate and inanimate objects instead of high and low agency words.
  - ASP allows us to control for confounds, by selecting the most extreme-valued words, and “measuring” words of interest along the axis separating the two extremes.

ASP

- For each affect dimension:
  1. From the lexicon, find the embeddings for the $|\mathcal{H}|$ highest-valued words and $|\mathcal{L}|$ lowest-valued words.
  2. Use cosine similarity to find the N most similar pairs between $\mathcal{H}$ and $\mathcal{L}$.
  3. Subtract each embedding by the average of itself and its pair, and construct a matrix M out of all the embedding pairs.
  4. Linearly decompose the matrix into a subspace of one dimension with the highest variance.
  5. For each entity, project its embedding onto the subspace.

Linear Decomposition

- Currently, ASP is using the first principle of principle component analysis (PCA) as its method of linear decomposition.
- There may be more suitable methods of linear decomposition than PCA, like UMAP.
- Objective: determine if UMAP or any other decomposition technique is better suited for ASP than PCA.