NLP Project Presentation

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Unsupervised Multilingual Word Embeddings (Chen and Cardie, 2018)

Overview

- Proposes a framework to learn Multilingual Word Embeddings (MWEs)
- Exploits relations between all language pairs
- Performs in $O(N)$ time, where N is the number of languages

Related Work

- Most use cross-lingual supervision, some sort of parallel corpora
- pivot-BWEs: mapping all languages individually into a target language space (training Bilingual Word Embeddings, N times)
    - Does not capture relations between all language pairs
- BWE-Direct: training embeddings for all language pairs.
    - Computational Complexity: $O(N^2)$

Solution

- Maps all monolingual embeddings into a shared space via a two-step algorithm:
  - Multilingual Adversary Training (MAT)
  - Multilingual Pseudo-Supervised Refinement (MPSR)
- Outperforms both pivot-BWE and BWE-Direct
- $O(N)$ complexity

Definitions for the Architecture

For each language $l \in L$ (where L is the set of languages considered), we take the embedding E_l that is in the embedding space S_l

- The models learn:
  - Encoder M_l into target space T s.t. $M_l : S_l \rightarrow T$
  - Decoder M_l^{-1}, so $M_l^{-1} : T \rightarrow S_l$

Encoders M_l are all orthogonal linear matrices

Definitions for the Architecture (cont.)

Language classifiers D_l: a binary classifier with a sigmoid layer on top, trained to identify how likely it is a vector is from space S_l

Multilingual Adversary Training

Overview

- Setup an adversarial relation between D_l and M_l
- Stimulates M_l to learn a shared multilingual embedding space
  - So that D_l cannot predict if the vector is genuine or converted from another language

Multilingual Adversary Training (cont.)

Language Discriminators

- For random pair (l_i, l_j) convert vector from S_i to S_j (using M_{l_i}, $M_{l_j}^{-1}$ and via T)
- Objective: confuse D_j
- Formal definitions: TODO

Multilingual Adversary Training (cont.)

Other improvements and optimizations

- l_i and l_j can be the same language (adversarial autoencoder is formed, shown to be beneficial)
- Instead of random sampling throughout, the external iteration loops through all languages to ensure updation of all language discriminators at least once

Multilingual Pseudo-Supervised Refinement

Overview

- MAT gives reasonable quality embeddings, but not SOTA
- May be due to noisy training signals from D
- Improvement: Induce a dictionary of *highly confident word pairs* for each language pair, and use this