SphereRE: Distinguishing Lexical Relations with Hyperspherical Relation Embeddings

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Outline

- Introduction
- The SphereRE Model
  - Learning Objective
  - Relation-aware Semantic Projection
  - Relation Representation Learning
  - Lexical Relation Classification
- Experiments
- Conclusion
Introduction (1)

- **Lexical Relation Classification**
  - Task: Classifying a word pair into a finite set of relation types (e.g., synonymy, antonymy)

<table>
<thead>
<tr>
<th>Relation</th>
<th>Tag</th>
<th>Template</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synonymy</td>
<td>SYN</td>
<td>W2 can be used with the same meaning as W1</td>
<td>candy-sweet, apartment-flat</td>
</tr>
<tr>
<td></td>
<td></td>
<td>W2 can be used as the opposite of W1</td>
<td>clean-dirty, add-take</td>
</tr>
<tr>
<td>Antonymy</td>
<td>ANT</td>
<td>W1 is a kind of W2</td>
<td>cannabis-plant, actress-human</td>
</tr>
<tr>
<td>Hypernymy</td>
<td>HYPER</td>
<td>W1 is a kind of W2</td>
<td>calf-leg, aisle-store</td>
</tr>
<tr>
<td>Part-whole meronymy</td>
<td>PART_OF</td>
<td>W1 is a part of W2</td>
<td></td>
</tr>
<tr>
<td>Random word</td>
<td>RANDOM</td>
<td>None of the above relations apply</td>
<td>accident-fish, actor-mild</td>
</tr>
</tbody>
</table>

Examples taken from the CogALex-V shared task
**Existing Approaches**

- **Path-based approaches**: use dependency paths connecting two terms to infer lexical relations
  - “Low coverage” problem

- **Distributional approaches**: consider the global contexts of terms to predict lexical relations using word embeddings
  - “Lexical memorization” problem
Introduction (3)

- **Our Idea**
  - Learning relation embeddings for term pairs (in the hyperspherical embedding space)
  - Term pairs with similar lexical relation types share similar embeddings
# SphereRE: Learning Objective (1)

## Basic Notations
- Training data (term pairs): \((x_i, y_i) \in D\)
- Testing data (term pairs): \((x_i, y_i) \in U\)
- Lexical relation types (e.g., synonymy, antonymy): \(r_i \in R\)

## Learning Objective in the Word Embedding Space
- \(f_m(\vec{x}_i)\): maps the relation subject \(x_i\) to the relation object \(y_i\) in the embedding space, where \(x_i\) and \(y_i\) have the lexical relation type \(r_m \in R\)
- Objective function:
\[
J_f = \sum_{i=1}^{|D|} \sum_{r_m \in R} I(r_i = r_m) \|f_m(\vec{x}_i) - \vec{y}_i\|^2
\]
SphereRE: Learning Objective (2)

• Learning Objective in the Hyperspherical Relation Space

\[
J_g = \sum_{i,j}^{D \cup U} \delta(r_i, r_j) g( f_i(\vec{x}_i) - \vec{x}_i, f_j(\vec{x}_j) - \vec{x}_j )
\]

\[
\delta(r_i, r_j) = \begin{cases} 
1, (x_i, y_i), (x_j, y_j) \text{ have the same relation type} \\
-1, (x_i, y_i), (x_j, y_j) \text{ have different relation types}
\end{cases}
\]

• General Learning Objective of SphereRE

\[
J(\Theta) = J_f + \lambda_1 J_g + \lambda_2 \|\Theta\|^2
\]
SphereRE: Relation-aware Semantic Projection

• **Learning $J_f$**
  - For each lexical relation type $r_m \in R$
    $$J_m = \sum_{i=1}^{\lvert D \rvert} I(r_i = r_m) \| M_m \vec{x}_i - \vec{y}_i \|^2 + \mu \| M_m \|^2_F$$
  - Closed-form solution
    $$\begin{array}{l}
    M_m^* = \arg \min_{M_m} J_m = (X_m^T X_m + \mu E)^{-1} X_m^T Y_m
    \end{array}$$

• **Approximating the probabilistic distribution over all lexical relation types $R$ w.r.t. $(x_i, y_i) \in U$**
  - Train a logistic regression classifier using the feature set
    $$\mathcal{F}(x_i, y_i) = (M_1 \vec{x}_i - \vec{y}_i) \oplus \cdots \oplus (M_{\lvert R \rvert} \vec{x}_i - \vec{y}_i)$$
SphereRE: Relation Representation Learning (1)

- Approximating $J_g$
  - Learning a SphereRE vector $\vec{r}_i$ for each $(x_i, y_i) \in D \cup U$

  - Re-writing $J_g$ via negative log likelihood

  $$J'_g = - \sum_{(x_i, y_i) \in D \cup U} \sum_{(x_j, y_j) \in Nb(x_i, y_i)} \log Pr((x_j, y_j) | \vec{r}_i)$$

  Similar to node2vec!
SphereRE: Relation Representation Learning (2)

- Minimizing $J'_g$ by random walk based sampling
  - Sampling probability

\[
\Pr((x_j, y_j)|(x_i, y_i)) = \frac{w_{i,j}}{\sum_{(x'_j, y'_j) \in D_{\text{mini}}} w_{i,j'}}
\]

<table>
<thead>
<tr>
<th>Condition</th>
<th>Value of $w_{i,j}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(x_i, y_i) \in D, (x_j, y_j) \in D, r_i = r_j$</td>
<td>1</td>
</tr>
<tr>
<td>$(x_i, y_i) \in D, (x_j, y_j) \in D, r_i \neq r_j$</td>
<td>0</td>
</tr>
<tr>
<td>$(x_i, y_i) \in D, (x_j, y_j) \in U, r_i = r_m$</td>
<td>$\frac{1}{2} p_{j,m} (\cos(M_m x_i - \bar{x}_i, M_m x_j - \bar{x}_j) + 1)$</td>
</tr>
<tr>
<td>$(x_i, y_i) \in U, (x_j, y_j) \in D, r_j = r_m$</td>
<td>$\frac{1}{2} p_{i,m} (\cos(M_m x_i - \bar{x}_i, M_m x_j - \bar{x}_j) + 1)$</td>
</tr>
<tr>
<td>$(x_i, y_i) \in U, (x_j, y_j) \in U$</td>
<td>$\frac{1}{2} \sum_{r_m \in R} p_{i,m} p_{j,m} \cdot (\cos(M_m x_i - \bar{x}_i, M_m x_j - \bar{x}_j) + 1)$</td>
</tr>
</tbody>
</table>
SphereRE: Relation Representation Learning (3)

• Overall Procedure of Learning SphereRE Vectors

Algorithm 1 SphereRE Learning

1: for each \((x_i, y_i) \in D \cup U\) do
2:     Randomly initialize SphereRE vector \(\vec{r}_i\);
3: end for
4: for \(i = 1\) to max iteration do
5:     Sample a sequence based on Eq. (3):
       \[ S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_{|S|}, y_{|S|})\}; \]
6:     Update all SphereRE vectors \(\vec{r}_i\) by minimizing
       \[ -\sum_{(x_i, y_i) \in S} \sum_{j=i-l(j \neq i)}^{i+l} \log \Pr((x_j, y_j)|\vec{r}_i); \]
7: end for
SphereRE: Lexical Relation Classification

- Train a feed-forward neural network over all the features to predict lexical relations

![Diagram of a neural network with input layers, a hidden layer, and an output layer. The bottom layer represents projection-based features with respect to |R| lexical relation types, and the SphereRE Vector.]
Experiments (1)

- **Datasets and Experimental Settings**
  - Word embeddings: fastText embeddings, $d = 300$
  - Default parameters settings:
    - $\mu = 0.001$, $d_r = 300$, $|D_{mini}| = 20$, $|S| = 100$, $\gamma = 2$, $l = 3$
  - Five datasets:

<table>
<thead>
<tr>
<th>Relation</th>
<th>K&amp;H+N</th>
<th>BLESS</th>
<th>ROOT09</th>
<th>EVALution</th>
<th>CogALex</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antonym</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1,600</td>
<td>601</td>
</tr>
<tr>
<td>Attribute</td>
<td>-</td>
<td>2,731</td>
<td>-</td>
<td>1,297</td>
<td>-</td>
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<tr>
<td>Co-hyponym</td>
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<td>3,565</td>
<td>3,200</td>
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<td>-</td>
</tr>
<tr>
<td>Event</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Holonym</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>544</td>
<td>-</td>
</tr>
<tr>
<td>Hypernym</td>
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<td>1,337</td>
<td>3,190</td>
<td>1,880</td>
<td>637</td>
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<td>Meronym</td>
<td>1,043</td>
<td>2,943</td>
<td>-</td>
<td>654</td>
<td>387</td>
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<td>Random</td>
<td>26,378</td>
<td>12,146</td>
<td>6,372</td>
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<td>5,287</td>
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<td>Substance meronym</td>
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<td>-</td>
<td>-</td>
<td>317</td>
<td>-</td>
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<tr>
<td>Synonym</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1,086</td>
<td>402</td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>57,509</td>
<td>26,546</td>
<td>12,762</td>
<td>7,378</td>
<td>7,314</td>
</tr>
</tbody>
</table>
Experiments (2)

- **General Performance over Four Public Datasets**
  - SphereRE outperforms all the baselines in terms of F1 scores.

<table>
<thead>
<tr>
<th>Method</th>
<th>Dataset →</th>
<th>K&amp;H+N Pre</th>
<th>Rec</th>
<th>F1</th>
<th>BLESS Pre</th>
<th>Rec</th>
<th>F1</th>
<th>ROOT09 Pre</th>
<th>Rec</th>
<th>F1</th>
<th>EVALution Pre</th>
<th>Rec</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concat</td>
<td></td>
<td>0.909</td>
<td>0.906</td>
<td>0.904</td>
<td>0.811</td>
<td>0.812</td>
<td>0.811</td>
<td>0.636</td>
<td>0.675</td>
<td>0.646</td>
<td>0.531</td>
<td>0.544</td>
<td>0.525</td>
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<tr>
<td>CONCAT</td>
<td>h</td>
<td>0.983</td>
<td>0.984</td>
<td>0.983</td>
<td>0.891</td>
<td>0.889</td>
<td>0.889</td>
<td>0.712</td>
<td>0.721</td>
<td>0.716</td>
<td>0.57</td>
<td>0.573</td>
<td>0.571</td>
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<tr>
<td>Diff</td>
<td></td>
<td>0.888</td>
<td>0.886</td>
<td>0.885</td>
<td>0.801</td>
<td>0.803</td>
<td>0.802</td>
<td>0.627</td>
<td>0.655</td>
<td>0.638</td>
<td>0.521</td>
<td>0.531</td>
<td>0.528</td>
</tr>
<tr>
<td>DIFF</td>
<td>h</td>
<td>0.941</td>
<td>0.942</td>
<td>0.941</td>
<td>0.861</td>
<td>0.859</td>
<td>0.860</td>
<td>0.683</td>
<td>0.692</td>
<td>0.686</td>
<td>0.536</td>
<td>0.54</td>
<td>0.539</td>
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<tr>
<td>NPB</td>
<td></td>
<td>0.713</td>
<td>0.604</td>
<td>0.55</td>
<td>0.759</td>
<td>0.756</td>
<td>0.755</td>
<td>0.788</td>
<td>0.789</td>
<td>0.788</td>
<td>0.53</td>
<td>0.537</td>
<td>0.503</td>
</tr>
<tr>
<td>LexNET</td>
<td></td>
<td>0.985</td>
<td>0.986</td>
<td>0.985</td>
<td>0.894</td>
<td>0.893</td>
<td>0.893</td>
<td>0.813</td>
<td>0.814</td>
<td>0.813</td>
<td>0.601</td>
<td>0.607</td>
<td>0.6</td>
</tr>
<tr>
<td>LexNET h</td>
<td></td>
<td>0.984</td>
<td>0.985</td>
<td>0.984</td>
<td>0.895</td>
<td>0.892</td>
<td>0.893</td>
<td>0.812</td>
<td>0.816</td>
<td>0.814</td>
<td>0.589</td>
<td>0.587</td>
<td>0.583</td>
</tr>
<tr>
<td>NPB+Aug</td>
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<td>-</td>
<td>-</td>
<td>0.897</td>
<td>-</td>
<td>-</td>
<td>0.842</td>
<td>-</td>
<td>-</td>
<td>0.778</td>
<td>-</td>
<td>-</td>
<td>0.489</td>
</tr>
<tr>
<td>LexNET+Aug</td>
<td></td>
<td>-</td>
<td>-</td>
<td>0.970</td>
<td>-</td>
<td>-</td>
<td>0.927</td>
<td>-</td>
<td>-</td>
<td>0.806</td>
<td>-</td>
<td>-</td>
<td>0.545</td>
</tr>
<tr>
<td>SphereRE</td>
<td></td>
<td>0.990</td>
<td>0.989</td>
<td>0.990</td>
<td>0.938</td>
<td>0.938</td>
<td>0.938</td>
<td>0.860</td>
<td>0.862</td>
<td>0.861</td>
<td>0.62</td>
<td>0.621</td>
<td>0.62</td>
</tr>
<tr>
<td>Improvement</td>
<td></td>
<td>-</td>
<td>-</td>
<td>0.5%↑</td>
<td>-</td>
<td>-</td>
<td>1.1%↑</td>
<td>-</td>
<td>-</td>
<td>4.7%↑</td>
<td>-</td>
<td>-</td>
<td>2.0%↑</td>
</tr>
</tbody>
</table>
Experiments (3)

- Detailed analysis of SphereRE
  - Network structure analysis
    - Varying #hidden layers
    - Varying #nodes
  - MC sampling analysis

```
Algorithm 1 SphereRE Learning
1: for each $(x_i, y_i) \in D \cup U$ do
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6:       $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_{|S|}, y_{|S|})\}$;
7:    Update all SphereRE vectors $\vec{r}_i$ by minimizing
8:       $-\sum_{(x_i, y_i) \in S} \sum_{j=i-1}^{i+1} \text{Pr}((x_j, y_j)|\vec{r}_i)$;
9: end for
```
Experiments (4)

- Experiments over the CogALex-V Shared Task (Subtask 2)
  - Consider random relations as noise, discarding it from the averaged F1 score.
  - Enforce the lexical spilt of the training and testing sets.
  - SphereRE outperforms previous systems in the shared task.

<table>
<thead>
<tr>
<th>Method</th>
<th>Relation</th>
<th>SYN</th>
<th>ANT</th>
<th>HYP</th>
<th>MER</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attia et al. (2016)</td>
<td></td>
<td>0.204</td>
<td>0.448</td>
<td>0.491</td>
<td>0.497</td>
<td>0.423</td>
</tr>
<tr>
<td>Shwartz and Dagan (2016)</td>
<td></td>
<td>0.297</td>
<td>0.425</td>
<td>0.526</td>
<td>0.493</td>
<td>0.445</td>
</tr>
<tr>
<td>Glavas and Vulic (2018)</td>
<td></td>
<td>0.221</td>
<td>0.504</td>
<td>0.498</td>
<td>0.504</td>
<td>0.453</td>
</tr>
<tr>
<td>SphereRE</td>
<td></td>
<td>0.286</td>
<td>0.479</td>
<td>0.538</td>
<td>0.539</td>
<td>0.471</td>
</tr>
</tbody>
</table>
Experiments (5)

• Visualization of SphereRE Vectors

(a) ROOT09 (Training)  (b) ROOT09 (Testing)  (c) EVALution (Training)  (d) EVALution (Testing)
Conclusion

• **Model**
  - SphereRE: A distributional model for lexical relation classification based on hyperspherical relation embeddings

• **Result**
  - Outperforming previous baselines on four public datasets and the CogALex-V shared task

• **Future Work**
  - Dealing with datasets containing a relatively large number of lexical relation types and random term pairs
  - Improving the mapping technique used for relation-aware semantic projection
Thank You!

Questions & Answers