Learning High-Order Word Representations

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Motivation

Distributional Compositional Semantics

Idea: structure-preserving map $\mathcal{F}$

$$\mathcal{F} : \mathcal{G} \to \textbf{\textit{FdVect}}$$

- Atomic types translated to vectors (order-one tensors)
- Complex types translated to (multi-)linear maps (higher order tensors)

Example

Word Type	$\mathcal{G}$ Type	$\mathcal{F}$ Translation
Noun	NP	$\mathbb{R}^{NP}$
Adjective	$NP \backslash NP$	$\mathbb{R}^{NP \times NP} \equiv \mathbb{R}^{NP} \to \mathbb{R}^{NP}$

$$\begin{aligned} \textit{cat} &\in \mathbb{R}^{NP} \\ \textit{black},\ \textit{stray} &\in \mathbb{R}^{NP \times NP} \\ \textit{black stray cat} &\in \mathbb{R}^{NP} \end{aligned}$$

Why Compositionality?

- Bridging of formal & distributional semantics
- Syntax-informed meaning derivations
- Modeling of functional words
- Formal treatment of ambiguous derivations
- Contextual Disambiguation
- Richer representations

$\vdots$

Why Not Compositionality?

- ✓ Great properties
- ? How to obtain word representations?

Possible options:

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- **?** How to obtain word representations?

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1. Co-occurrence statistics

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1. Co-occurrence statistics ✗
2. Unsupervised techniques (*a la word2vec*)

Why Not Compositionality?

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- **?** How to obtain word representations?

Possible options:

1. Co-occurrence statistics ✗
2. Unsupervised techniques (*a la word2vec*) ✗
3. Supervised learning **?**

Problem Statement

Examine whether supervised learning can be used to find higher-order word representations (transitive verbs)

Supervised Learning

Overview

- Search over set of functions $A \to B$ parameterized over P
- Find optimal approximation $\hat{f}_P$ to $f : A \to B$
- Use samples $(a, f(a)) \in A \times B$ to update P

Supervised Learning

Dataset

Finding Data

Sample space must be:

- labeled
- constrained
- of large size
- of high quality

Paraphrase Database

Raw text paraphrase pairs

Example pair

proposed by the president $\sim$ *suggested by the chairman*

- labeled ✓
- constrained ✗ *(different syntactic types)*
- of large size ✓
- of high quality **?**

Dataset: Preprocessing

1. **Parse and filter by type** (transitive verb case)

- labeled ✓
- constrained ✓
- of large size ✗ *(>95% loss)*
- of high quality ✗ *(parser-induced errors)*

Dataset: Preprocessing

2. **Back-translation**

- Labeled ✓
- constrained ✓
- of large size ✓
- of high quality ✗ *(translation-induced errors)*

Dataset: Preprocessing

3. **Filter by co-occurrence / mutual information**

   - Labeled ✓
   - constrained ✓
   - of large size ✓
   - of high quality **?**

Dataset: End Result

Verb / object dictionaries:

$$\mathcal{V} : \{v_1 : 1, v_2 : 2, ..., v_N : N\}$$
$$\mathcal{O} : \{o_1 : 1, o_2 : 2, ..., o_M : M\}$$

Paraphrase relation:

$$\mathcal{P} : \mathbb{N} \times \mathbb{N} \times \mathbb{N} \times \mathbb{N} \to \{0, 1\} \qquad \text{(binary classification)}$$

$$\mathcal{P}(i, j, k, l) = \mathcal{P}(k, l, i, j) = \begin{cases} 1 & v_i o_j \sim v_k o_l \\ 0 & \text{otherwise} \end{cases}$$

Supervised Learning

Formulating the Network

Training Objective

Our semantic interpretations are:

- Actions: $\lceil a \rceil = \mathbb{R}^A$
- Objects: $\lceil np \rceil = \mathbb{R}^{NP}$
- Transitive Verbs: $\lceil a/np \rceil = \mathbb{R}^{A \times NP}$

And our objective is to learn a verb embedding function ε_{verb}:

$$\varepsilon_{verb} : \mathbb{N} \rightarrow \mathbb{R}^{A \times NP}$$

But instead we have samples from some $f : \mathbb{N}^4 \rightarrow \{0, 1\}$

Intermediate Representations

Solution

Formulate f_P to incorporate ε_{verb}.

$$f_p = f_1 \circ f_2 \circ \cdots \circ \varepsilon_{verb} \circ \ldots$$

Intermediate Representations

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Simplification (1)

Assume pre-trained object embedding function ε_{object}.

$$\varepsilon_{object} : \mathbb{N} \rightarrow \mathbb{R}^{300}$$

Filling the missing blocks

$i \in \mathbb{N}$ $j \in \mathbb{N}$ $k \in \mathbb{N}$ $l \in \mathbb{N}$

$\hat{y} \in \mathbb{R}$

Filling the missing blocks

$$
\begin{array}{cccc}
i \in \mathbb{N} & j \in \mathbb{N} & k \in \mathbb{N} & l \in \mathbb{N} \\
 & \Big\downarrow \varepsilon_{object} & & \Big\downarrow \varepsilon_{object} \\
 & \boldsymbol{j} \in \mathbb{R}^{300} & & \boldsymbol{l} \in \mathbb{R}^{300}
\end{array}
$$

$$\hat{y} \in \mathbb{R}$$

Filling the missing blocks

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\begin{array}{cccc}
i \in \mathbb{N} & j \in \mathbb{N} & k \in \mathbb{N} & l \in \mathbb{N} \\
\Big\downarrow \varepsilon_{verb} & \Big\downarrow \varepsilon_{object} & \Big\downarrow \varepsilon_{verb} & \Big\downarrow \varepsilon_{object} \\
\mathcal{I} \in \mathbb{R}^{100\times 300} & \boldsymbol{j} \in \mathbb{R}^{300} & \mathcal{K} \in \mathbb{R}^{100\times 300} & \boldsymbol{l} \in \mathbb{R}^{300}
\end{array}
$$

$$\hat{y} \in \mathbb{R}$$

Filling the missing blocks

$$
\begin{tikzcd}
i \in \mathbb{N} \arrow[d, "\varepsilon_{verb}"] & & j \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] & k \in \mathbb{N} \arrow[d, "\varepsilon_{verb}"] & & l \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] \\
\boldsymbol{\mathcal{I}} \in \mathbb{R}^{100\times300} \arrow[rr, bend left, dash] \arrow[dr, bend right] & & \boldsymbol{j} \in \mathbb{R}^{300} & \boldsymbol{\mathcal{K}} \in \mathbb{R}^{100\times300} \arrow[rr, bend left, dash] \arrow[dr, bend right] & & \boldsymbol{l} \in \mathbb{R}^{300} \\
& \boldsymbol{\mathcal{I}}(\boldsymbol{j}) \in \mathbb{R}^{100} & & & \boldsymbol{\mathcal{K}}(\boldsymbol{l}) \in \mathbb{R}^{100} & \\
& & \hat{y} \in \mathbb{R} & & &
\end{tikzcd}
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\boldsymbol{\mathcal{I}} \in \mathbb{R}^{100\times300} \arrow[r, bend left, no head] \arrow[d] & \boldsymbol{j} \in \mathbb{R}^{300} & \boldsymbol{\mathcal{K}} \in \mathbb{R}^{100\times300} \arrow[r, bend left, no head] \arrow[d] & \boldsymbol{l} \in \mathbb{R}^{300} \\
\boldsymbol{\mathcal{I}}(\boldsymbol{j}) \in \mathbb{R}^{100} \arrow[dr, "cosine"] & & \boldsymbol{\mathcal{K}}(\boldsymbol{l}) \in \mathbb{R}^{100} \arrow[dl] & \\
& \hat{y} \in \mathbb{R} & &
\end{tikzcd}
$$

Sanity Check

Objective Function

$$cos(\mathbf{V}_i(\mathbf{j}), \mathbf{V}_k(\mathbf{l})) \rightsquigarrow \mathcal{P}(i, j, k, l) \quad \forall\ (i, j, k, l) \in \mathcal{V} \times \mathcal{O} \times \mathcal{V} \times \mathcal{O}$$

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Considerations:

1. Network Size
   - 1.000 verbs
   - $100 \times 300 = 30.000$ parameters per verb

   $\Rightarrow$ 30.000.000 parameters for ε_{verb} to learn

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2. Quantifying over two spaces ...

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2. Quantifying over two spaces ...
3. ... both of which are non-convex

… A ”beast” to train ☹

Supervised Learning

Transferring Knowledge

Finding an Oracle

Dataception: use our labeled dataset to create a new dataset

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Simplification (2)

Assume another pre-trained verb embedding function ε'_{verb}.

$$\varepsilon'_{verb} : \mathbb{N} \rightarrow \mathbb{R}^{300}$$

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Simplification (2)

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Oracle

We can now train a paraphrase embedding function ε_{par}.

$$\varepsilon_{par} : \mathbb{R}^{300} \times \mathbb{R}^{300} \to \mathbb{R}^{100}$$

Oracle Flow

$i \in \mathbb{N}$ $j \in \mathbb{N}$ $k \in \mathbb{N}$ $l \in \mathbb{N}$

$\hat{y} \in \mathbb{R}$

Oracle Flow

$$
\begin{array}{cccc}
i \in \mathbb{N} & j \in \mathbb{N} & k \in \mathbb{N} & l \in \mathbb{N} \\
 & \downarrow \varepsilon_{object} & & \downarrow \varepsilon_{object} \\
 & \boldsymbol{j} \in \mathbb{R}^{300} & & \boldsymbol{l} \in \mathbb{R}^{300}
\end{array}
$$

$$\hat{y} \in \mathbb{R}$$

Oracle Flow

$$
\begin{tikzcd}
i \in \mathbb{N} \arrow[d, "\varepsilon'_{verb}"] & j \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] & k \in \mathbb{N} \arrow[d, "\varepsilon'_{verb}"] & l \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] \\
\boldsymbol{i} \in \mathbb{R}^{300} & \boldsymbol{j} \in \mathbb{R}^{300} & \boldsymbol{k} \in \mathbb{R}^{300} & \boldsymbol{l} \in \mathbb{R}^{300}
\end{tikzcd}
$$

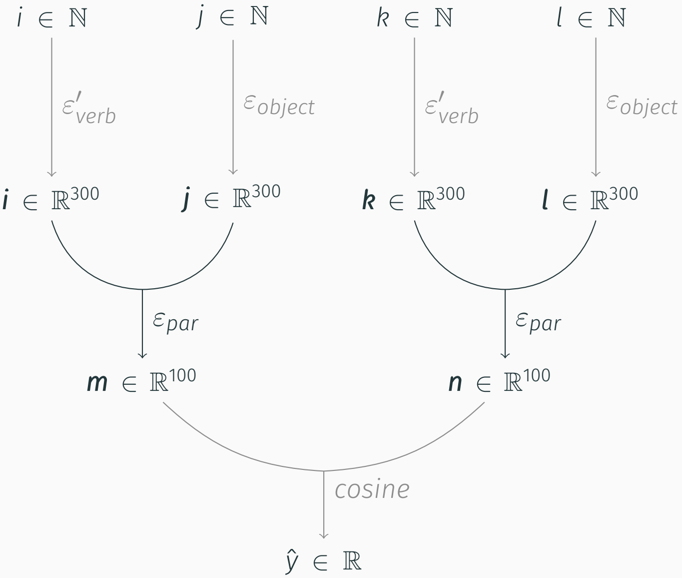
$$\hat{y} \in \mathbb{R}$$

Oracle Flow

$$\begin{tikzcd}
i \in \mathbb{N} \arrow[d, "\varepsilon'_{verb}"] & & j \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] & & k \in \mathbb{N} \arrow[d, "\varepsilon'_{verb}"] & & l \in \mathbb{N} \arrow[d, "\varepsilon_{object}"] \\
\boldsymbol{i} \in \mathbb{R}^{300} \arrow[dr, no head] & & \boldsymbol{j} \in \mathbb{R}^{300} \arrow[dl, no head] & & \boldsymbol{k} \in \mathbb{R}^{300} \arrow[dr, no head] & & \boldsymbol{l} \in \mathbb{R}^{300} \arrow[dl, no head] \\
& \cdot \arrow[d, "\varepsilon_{par}"] & & & & \cdot \arrow[d, "\varepsilon_{par}"] & \\
& \boldsymbol{m} \in \mathbb{R}^{100} & & & & \boldsymbol{n} \in \mathbb{R}^{100} &
\end{tikzcd}$$

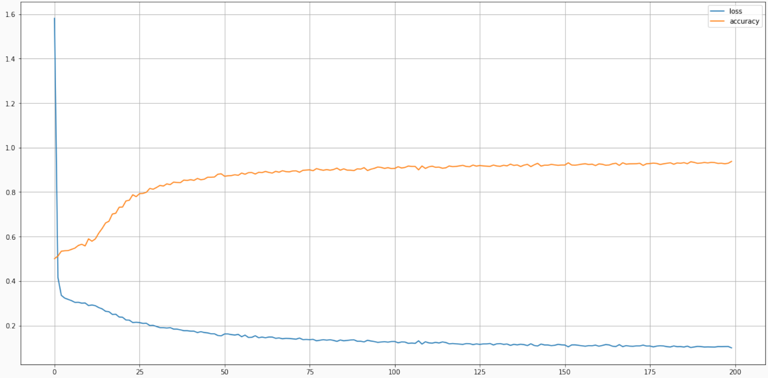
$$\hat{y} \in \mathbb{R}$$

Oracle Flow


$i \in \mathbb{N}$
$j \in \mathbb{N}$
$k \in \mathbb{N}$
$l \in \mathbb{N}$
ε'_{verb}
ε_{object}
ε'_{verb}
ε_{object}
$\boldsymbol{i} \in \mathbb{R}^{300}$
$\boldsymbol{j} \in \mathbb{R}^{300}$
$\boldsymbol{k} \in \mathbb{R}^{300}$
$\boldsymbol{l} \in \mathbb{R}^{300}$
ε_{par}
ε_{par}
$\boldsymbol{m} \in \mathbb{R}^{100}$
$\boldsymbol{n} \in \mathbb{R}^{100}$
cosine
$\hat{y} \in \mathbb{R}$

Training the Oracle

ε_{par}: recurrent autoencoder ($\approx$ 700.000 parameters)



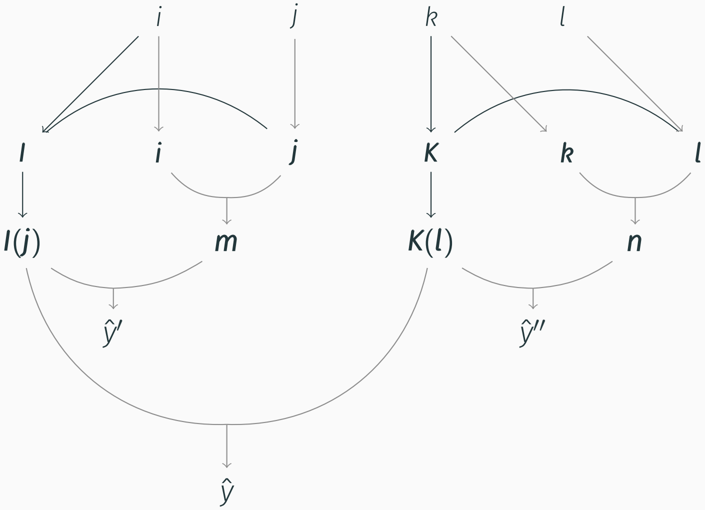
Utilizing the Oracle

New Objective Function

$$cos(\boldsymbol{V}_i(\boldsymbol{j}), \varepsilon_{par}(\boldsymbol{v}_i, \boldsymbol{j})) \rightsquigarrow 1 \quad \forall\ (i, j) \in \mathcal{V} \times \mathcal{O}$$

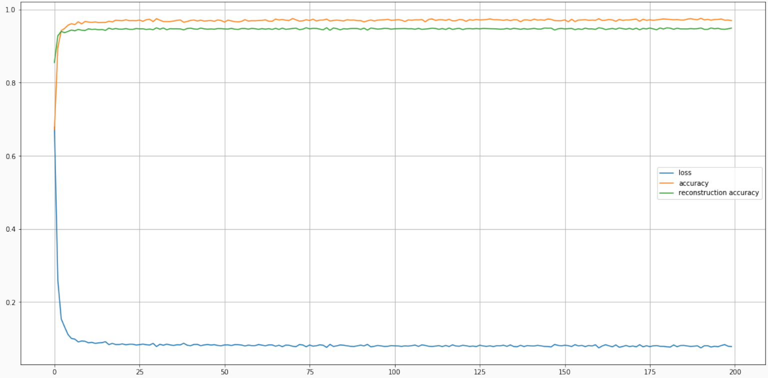
- ε_{par} gives us paraphrase embeddings '*for free*'
- We can use them to facilitate training
- Much smaller problem space

Composing Networks



Training the Original

ε_{verb}: tanh activated dense layer ($\approx$ 30.000.000 parameters)



The beast has been tamed! ☺

Evaluation

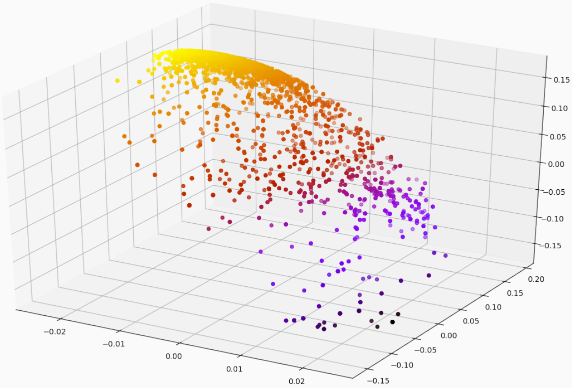
Microstructure

Task-specific performance relates to the small-scale structure of the learned space:

Ground Truth \ Prediction	Oracle $\top$	Oracle $\bot$	Final $\top$	Final $\bot$
$\top$	0.92	0.08	0.88	0.02
$\bot$	0.08	0.92	0.12	0.98

Macrostructure

3D PCA on paraphrase embeddings



Conclusion

Critique

1. Metric reliability
2. Uninformative error signal
3. Over-parameterization
   a) Linearity constraint
   b) Chasing after an oracle
   c) Bad scaling

Next Steps

1. Directly evaluate verb matrices
2. More structural constraints (activity regularization)
3. Iterative learning
4. Other data formats:
    - Different syntactic types
    - Different labels / samples altogether
5. Different oracle architectures
6. Different embedder architectures (encoder/decoder)

Bag of Tricks

Negative Sampling

Let $L : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ be the *loss function*.

Objective translates to:

$$\min_{P} \; L \left[\mathcal{P} \left(i, j, k, l \right), \; \hat{y}_P \right] \quad \forall (i, j, k, l) \qquad \text{(Intractable)}$$

Randomly generate and select negative samples (different every epoch).

Curriculum Learning

”Two phrases are not similar unless they are”

- Class imbalance $\Rightarrow$ bad predictions
- Treat negative samples as noise
- Learn positive examples then increase noise

Loss Mixing

Cross-entropy vs. MSE vs. Categorical Hinge

- Different assumptions, none correct.
- Many falsities $\Rightarrow$ Truth **?**