Towards Understanding

Christopher Manning
Stanford University
1980s Natural Language Processing

\[ VP \rightarrow \{ V (NP: (↑ OBJ) = \downarrow (NP: (↑ OBJ2) = \downarrow )) \) \)
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How does a project get to be a year late? ... One day at a time.

\[
P(\text{late}|a, \text{year}) = 0.0087 \\
P(\text{NN}|\text{DT}, a, \text{project}) = 0.9
\]
The traditional word representation

motel

\[[0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0 \ 0] \]

Dimensionality: 50K (small domain – speech/PTB) – 13M (web – Google 1T)

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0
Through corpus linguistics, large chunks the study of language and linguistics. The field of linguistics is concerned Written like a linguistics text book
Phonology is the branch of linguistics that

$$\text{linguistics} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \\ 0.487 \end{pmatrix}$$

[Bengio et al. 2003, Collobert & Weston 2008, Turian 2010, Mikolov 2013, etc.]
## Encoding meaning in vector differences

[Pennington et al., to appear 2014]

**Crucial insight:** Ratios of co-occurrence probabilities can encode meaning components

<table>
<thead>
<tr>
<th></th>
<th>(x = \text{solid})</th>
<th>(x = \text{gas})</th>
<th>(x = \text{water})</th>
<th>(x = \text{random})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P(x</td>
<td>\text{ice}))</td>
<td>large</td>
<td>small</td>
<td>large</td>
</tr>
<tr>
<td>(P(x</td>
<td>\text{steam}))</td>
<td>small</td>
<td>large</td>
<td>large</td>
</tr>
<tr>
<td>(\frac{P(x</td>
<td>\text{ice})}{P(x</td>
<td>\text{steam})})</td>
<td>large</td>
<td>small</td>
</tr>
</tbody>
</table>
Encoding meaning in vector differences

[Pennington et al., to appear 2014]

Crucial insight: Ratios of co-occurrence probabilities can encode meaning components

<table>
<thead>
<tr>
<th></th>
<th>$x = \text{solid}$</th>
<th>$x = \text{gas}$</th>
<th>$x = \text{water}$</th>
<th>$x = \text{fashion}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P(x</td>
<td>\text{ice})$</td>
<td>$1.9 \times 10^{-4}$</td>
<td>$6.6 \times 10^{-5}$</td>
<td>$3.0 \times 10^{-3}$</td>
</tr>
<tr>
<td>$P(x</td>
<td>\text{steam})$</td>
<td>$2.2 \times 10^{-5}$</td>
<td>$7.8 \times 10^{-4}$</td>
<td>$2.2 \times 10^{-3}$</td>
</tr>
<tr>
<td>$\frac{P(x</td>
<td>\text{ice})}{P(x</td>
<td>\text{steam})}$</td>
<td>$8.9$</td>
<td>$8.5 \times 10^{-2}$</td>
</tr>
</tbody>
</table>
GloVe: A new model for learning word representations  [Pennington et al., to appear 2014]

\[ w_i \cdot w_j = \log P(i|j) \]

\[ w_x \cdot (w_a - w_b) = \log \frac{P(x|a)}{P(x|b)} \]

\[ J = \frac{1}{2} \sum_{ij} f(P_{ij})(w_i \cdot \tilde{w}_j - \log P_{ij})^2 \]
Word similarities

Nearest words to frog:
1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus
## Word analogy task [Mikolov, Yih & Zweig 2013a]

<table>
<thead>
<tr>
<th>Model</th>
<th>Dimensions</th>
<th>Corpus size</th>
<th>Performance (Syn + Sem)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBOW (Mikolov et al. 2013b)</td>
<td>300</td>
<td>1.6 billion</td>
<td>36.1</td>
</tr>
</tbody>
</table>
Machine translation with bilingual neural language models

[Devlin et al., ACL 2014]

\[
S: \text{我 就 取 钱 给 了 她们}
\]

\[
T: \text{will get the money to them}
\]

\[
P(\text{the | get, will, i, 钱, 取, 给, 就, 了})
\]
Machine translation with bilingual neural language models  

[Devlin et al., ACL 2014]

### NIST 2012 Open MT Arabic Results

<table>
<thead>
<tr>
<th>Place</th>
<th>Arabic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Place</td>
<td>49.5</td>
</tr>
<tr>
<td>(BBN)</td>
<td></td>
</tr>
<tr>
<td>2nd Place</td>
<td>47.5</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>9th Place</td>
<td>44.0</td>
</tr>
<tr>
<td>10th Place</td>
<td>41.2</td>
</tr>
</tbody>
</table>

### NNJM on best system

<table>
<thead>
<tr>
<th>Arabic</th>
<th>Arabic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous best BBN system + NNJM</td>
<td>52.8</td>
</tr>
</tbody>
</table>

### NNJM on “Baseline”

<table>
<thead>
<tr>
<th>Arabic</th>
<th>Arabic</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Baseline Hiero” + NNJM</td>
<td>49.7</td>
</tr>
</tbody>
</table>

+ 3.0 BLEU
+ 6.3 BLEU

“Baseline Hiero” Features: (1) Rule probs, (2) lexical smoothing, (3) KN LM, (4) word penalty, (5) concat penalty
Sentence structure: Dependency parsing

ROOT He has good control .
PRP VBZ JJ NN .
Universal Stanford Dependencies
[de Marneffe et al., LREC 2014]

Sentence structure: Dependency parsing

ROOT He has good control .
PRP VBZ JJ NN .

root
nsubj
dobj
punct
amod
Deep Learning Dependency Parser
[Chen & Manning, forthcoming 2014]

Softmax layer:
\[ p = \text{softmax}(W_2 h) \]

Hidden layer:
\[ h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3 \]

Input layer: \([x^w, x^t, x^l]\)

Configuration

Stack

ROOT has VBZ good JJ

Buffer

control NN ...

He PRP

words

POS tags

arc labels

nsubj
### Deep Learning Dependency Parser

[Chen & Manning, forthcoming 2014]

<table>
<thead>
<tr>
<th>Parser type</th>
<th>Parser</th>
<th>LAS (Label &amp; Attach)</th>
<th>Sentences / sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition-based</td>
<td>MaltParser (stackproj)</td>
<td>86.9</td>
<td>469</td>
</tr>
<tr>
<td>Graph-based</td>
<td>MSTParser</td>
<td>87.6</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>TurboParser (full)</td>
<td>89.7</td>
<td>8</td>
</tr>
</tbody>
</table>
Grounding language meaning with images
[Socher, Karpathy, Le, Manning & Ng, TACL 2014]

<table>
<thead>
<tr>
<th>Compositional Sentence Vectors</th>
<th>Multi-Modal Representations</th>
<th>Image Vector Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A small child sits on a cement wall near white flower.</td>
<td><img src="image" alt="Multi-modal representations" /></td>
<td><img src="image" alt="Image 1" /> <img src="image" alt="Image 2" /></td>
</tr>
<tr>
<td>A man wearing a helmet jumps on his bike near a beach.</td>
<td><img src="image" alt="Multi-modal representations" /></td>
<td><img src="image" alt="Image 1" /> <img src="image" alt="Image 2" /></td>
</tr>
<tr>
<td>A man jumping his downhill bike.</td>
<td><img src="image" alt="Multi-modal representations" /></td>
<td><img src="image" alt="Image 1" /> <img src="image" alt="Image 2" /></td>
</tr>
<tr>
<td>Two airplanes parked in an airport.</td>
<td><img src="image" alt="Multi-modal representations" /></td>
<td><img src="image" alt="Image 1" /> <img src="image" alt="Image 2" /></td>
</tr>
</tbody>
</table>
Example dependency tree and image

$$h_i = f \left( \frac{1}{\ell(i)} \left( W_v x_i + \sum_{j \in C(i)} \ell(j) W_{\text{dep}(i,j)} h_j \right) \right)$$

A man wearing a helmet jumps on his bike near a beach
Recursive computation of dependency tree

\[ h_i = f \left( \frac{1}{\ell(i)} \left( W_{v} x_i + \sum_{j \in C(i)} \ell(j) W_{\text{dep}(i,j)} h_j \right) \right) \]
Evaluation

Data of [Rashtchian, Young, Hodosh & Hockenmaier 2010]

1. A woman and her dog watch the cameraman in their living with wooden floors.
2. A woman sitting on the couch while a black faced dog runs across the floor.
3. A woman wearing a backpack sits on a couch while a small dog runs on the hardwood floor next to her.
4. A women sitting on a sofa while a small Jack Russell walks towards the camera.
5. White and black small dog walks toward the camera while woman sits on couch, desk and computer seen in the background as well as a pillow, teddy bear and moggie toy on the wood floor.

A gray convertible sports car is parked in front of the trees. ✓
A close-up view of the headlights of a blue old-fashioned car. ❌
Black shiny sports car parked on concrete driveway. ✓
Five cows grazing on a patch of grass between two roadways. ❌

A jockey rides a brown and white horse in a dirt corral. ✓
A young woman is riding a Bay hose in a dirt riding-ring. ❌
A white bird pushes a miniature teal shopping cart. ❌
A person rides a brown horse. ✓

1000 images, 5 descriptions each; used as 800 train, 100 dev, 100 test
## Results for image search

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>52.1</td>
</tr>
<tr>
<td>Recurrent NN</td>
<td>19.2</td>
</tr>
<tr>
<td>Constituency Tree Recursive NN</td>
<td>16.1</td>
</tr>
<tr>
<td>kCCA</td>
<td>15.9</td>
</tr>
<tr>
<td>Bag of Words</td>
<td>14.6</td>
</tr>
<tr>
<td><strong>Dependency Tree Recursive NN</strong></td>
<td><strong>12.5</strong></td>
</tr>
</tbody>
</table>

Lower is better!
How to represent the meaning of texts

[Le and Mikolov, ICML 2014, Paragraph Vector]
Political Ideology Detection Using Recursive Neural Networks

[Iyyer, Enns, Boyd-Graber & Resnik 2014]
Extracting Semantic Relationships
[Socher, Huval, Manning & Ng, EMNLP 2012]

My $[\text{apartment}]_{e1}$ has a pretty large $[\text{kitchen}]_{e2}$
$\rightarrow$ component-whole relationship $(e2,e1)$
Save the planet and return your name badge before you leave (on Tuesday)
Image credits and permissions


Slide 3 From a paper of the author (Manning 1992, Romance is so complex) http://nlp.stanford.edu/manning/papers/romance.pdf

Slides 4: PR2 robot reading CC BY-SA 3.0 by Troy Straszheim from http://commons.wikimedia.org/wiki/File:PR2_Robot_reads_the_Mythical_Man-Month_2.jpg
Image credits and permissions

Slide 10 images from Wikipedia (i) Public domain
http://en.wikipedia.org/wiki/Litoria#mediaviewer/File:Caerulea_cropped(2).jpg
(ii) Brian Gratwick
http://en.wikipedia.org/wiki/Pristimantis_cruentus#mediaviewer/File:Pristimantis_cruentus_studio.jpg
(iii) Grand-Duc, Niabot
(iv) Public domain

Slides 19, 20, 21, 25 Images from the PASCAL Visual Object Challenge 2008 data set
http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2008/
## Results on Gao et al. (2014) Dataset

<table>
<thead>
<tr>
<th>Subtask</th>
<th>CW08</th>
<th>RNN</th>
<th>CBOB</th>
<th>GloVe</th>
<th>GloVe (840B)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>dim=50</td>
<td>dim=640</td>
<td>dim=1600</td>
<td>dim=100</td>
<td>dim=300</td>
</tr>
<tr>
<td>All capital cities</td>
<td>0.62%</td>
<td>1.23%</td>
<td>1.81%</td>
<td>6.62%</td>
<td>11.28%</td>
</tr>
<tr>
<td>Currency</td>
<td>0.25%</td>
<td>0.66%</td>
<td>0.87%</td>
<td>3.13%</td>
<td>4.32%</td>
</tr>
<tr>
<td>City-in-state</td>
<td>0.67%</td>
<td>3.14%</td>
<td>3.38%</td>
<td>1.55%</td>
<td>2.25%</td>
</tr>
<tr>
<td>Man-Woman</td>
<td>4.83%</td>
<td>18.46%</td>
<td>20.82%</td>
<td>25.89%</td>
<td>28.60%</td>
</tr>
<tr>
<td>Adjective to adverb</td>
<td>1.40%</td>
<td>1.17%</td>
<td>2.01%</td>
<td>3.45%</td>
<td>3.23%</td>
</tr>
<tr>
<td>Comparative</td>
<td>1.55%</td>
<td>34.92%</td>
<td>40.28%</td>
<td>33.41%</td>
<td>42.53%</td>
</tr>
<tr>
<td>Superlative</td>
<td>1.94%</td>
<td>25.33%</td>
<td>26.21%</td>
<td>23.56%</td>
<td>29.07%</td>
</tr>
<tr>
<td>Present participle</td>
<td>1.53%</td>
<td>20.03%</td>
<td>23.26%</td>
<td>8.20%</td>
<td>11.75%</td>
</tr>
<tr>
<td>Nationality adjective</td>
<td>3.07%</td>
<td>3.15%</td>
<td>3.76%</td>
<td>23.66%</td>
<td>47.44%</td>
</tr>
<tr>
<td>Past tense</td>
<td>1.84%</td>
<td>19.51%</td>
<td>22.77%</td>
<td>15.51%</td>
<td>24.15%</td>
</tr>
<tr>
<td>Plural nouns</td>
<td>3.21%</td>
<td>14.42%</td>
<td>18.28%</td>
<td>23.95%</td>
<td>38.82%</td>
</tr>
<tr>
<td>Plural verbs</td>
<td>2.44%</td>
<td>22.41%</td>
<td>26.62%</td>
<td>17.28%</td>
<td>31.82%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>2.36%</strong></td>
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<td><strong>17.85%</strong></td>
<td><strong>16.70%</strong></td>
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## Results on Gao et al. (2014) Dataset

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<th>CBOW</th>
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