Metaphor Detection with Cross-Lingual Model Transfer (Tsvetkov et al.)
Presentation Structure

• Contributions
• Problems with finding metaphors
• Methodology
• Experiments
• Conclusion/discussion
Contributions

• Discriminate whether a syntactic construction is meant literally or metaphorically
• Identify metaphoric expressions in other languages without language specific training data

→ Metaphors are conceptual, rather than lexical, in nature
How To Define A Metaphor?

• Metaphor is a type of "conceptual mapping" (Lakoff and Johnson, 1980)
• The proportion of words used metaphorically ranges from 5% to 20% (Steen et al.)
• A choice of metaphors affects decision making (Thibodeau and Boroditsky, 2013)
Problems With Finding Metaphors

1. Subjective component
2. Domain- and context-dependent
Methodology

Task: Define features that distinguish between metaphoric and literal uses for the constructs:

**AN (adjective-noun):**
- broken promise → *(metaphor)* ← my car drinks gasoline
- broken car → *(literal)* ← i drink water
Conceptual Features

coarse-grained conceptual features 🌟
fine-grained lexical features 😞

The vector will consist of the concatenation of the **conceptual features**:

1. Abstractness and imageability
2. Supersenses
3. Vector space word representations
1. Abstractness And Imageability

Abstractness and imageability are not a redundant, Examples:

**Vengeance** (Vergeltung) -> calls up an emotional image, Img. - ,Con. -

**Torture** (Folter) -> calls up emotions and even visual images, Img.533,Con.437

**Acrobat** --- Score: -- Imageability: **583** -- Concreteness: **566**

**Alacrity** (Bereitwilligkeit) --- Score: -- Imageability: **189** -- Concreteness: **269**

**Coif** (Haube) --- Score: -- Imageability: **202** -- Concreteness: **421**

→ train two separate classifiers for abstractness and imageability on a seed set of words from the MRC database
2. Supersenses

Example:

“drinks gasoline” \(<\text{verb.consumption, noun.substance}\>\)

“drinks juice” \(<\text{verb.consumption, noun.food}\>\)

the word head participates in 33 synsets, three of which are related to the supersense noun.body

\(\rightarrow\) supersense is \(3/33 \approx 0,09\)
3. Vector Space Word Representations

• designed to capture lexical semantic properties
• there is a strong similarity between the vector spaces across languages

→ vector space models can also be seen as vectors of (latent) semantic concepts, that preserve their “meaning” across languages
WordNet supersenses example:

The Russian word голова (golova) is translated as head and brain

→ We select all the synsets of the nouns *head* and *brain*

→ There are 38 such synsets (33 for head and 5 for brain)

→ Four of these synsets are associated with the supersense noun.body

→ Therefore, the value of the feature noun.body is $4/38 \approx 0.11$
Training:
For SVO \(\rightarrow\) TroFi (Trope Finder) dataset
For AN \(\rightarrow\) Created their own training set

<table>
<thead>
<tr>
<th></th>
<th>SVO</th>
<th>AN</th>
</tr>
</thead>
<tbody>
<tr>
<td>EN</td>
<td>222</td>
<td>200</td>
</tr>
<tr>
<td>RU</td>
<td>240</td>
<td>200</td>
</tr>
<tr>
<td>ES</td>
<td>220</td>
<td>120</td>
</tr>
<tr>
<td>FA</td>
<td>44</td>
<td>320</td>
</tr>
</tbody>
</table>

Testing:
We compile eight test datasets in four languages, four for SVO relations, and four for AN relations
## Experiments

**10-Fold Cross Validation In English**

<table>
<thead>
<tr>
<th></th>
<th>SVO</th>
<th></th>
<th>AN</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># FEAT</td>
<td>ACC</td>
<td># FEAT</td>
<td>ACC</td>
</tr>
<tr>
<td>AbsImg</td>
<td>20</td>
<td>0.73*</td>
<td>16</td>
<td>0.76*</td>
</tr>
<tr>
<td>Supersense</td>
<td>67</td>
<td>0.77*</td>
<td>116</td>
<td>0.79*</td>
</tr>
<tr>
<td>AbsImg+Sup.</td>
<td>87</td>
<td>0.78*</td>
<td>132</td>
<td>0.80*</td>
</tr>
<tr>
<td>VSM</td>
<td>192</td>
<td>0.81</td>
<td>228</td>
<td>0.84*</td>
</tr>
<tr>
<td>All</td>
<td>279</td>
<td><strong>0.82</strong></td>
<td>360</td>
<td><strong>0.86</strong></td>
</tr>
</tbody>
</table>
Experiments On Out-Of-Domain Data In English

(b) AN

(a) SVO
## Experiments
Comparing To Tsvetkov et al. / Turney et al.

<table>
<thead>
<tr>
<th></th>
<th>EN</th>
<th>RU</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SVO-baseline</strong></td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>This work</strong></td>
<td>0.86</td>
<td>0.85</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>AN-baseline</th>
<th>This work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Judge 1</td>
<td>0.73</td>
<td>0.75</td>
</tr>
<tr>
<td>Judge 2</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td>Judge 3</td>
<td>0.84</td>
<td>0.88</td>
</tr>
<tr>
<td>Judge 4</td>
<td>0.79</td>
<td>0.81</td>
</tr>
<tr>
<td>Judge 5</td>
<td>0.78</td>
<td>0.77</td>
</tr>
<tr>
<td><strong>average</strong></td>
<td>0.79</td>
<td>0.81</td>
</tr>
</tbody>
</table>
Experiments – Cross Lingual

<table>
<thead>
<tr>
<th>Language</th>
<th>SVO</th>
<th>AN</th>
</tr>
</thead>
<tbody>
<tr>
<td>EN</td>
<td>0.79</td>
<td>0.85</td>
</tr>
<tr>
<td>RU</td>
<td>0.84</td>
<td>0.77</td>
</tr>
<tr>
<td>ES</td>
<td>0.76</td>
<td>0.72</td>
</tr>
<tr>
<td>FA</td>
<td>0.75</td>
<td>0.74</td>
</tr>
</tbody>
</table>
Other Metaphor Examples

- “Travel is no more than a sorcerer's cauldron full of emeralds”
- **Implied Metaphors**: “Hanging out with her was worse than my date with Frankie”
- **In Georgian**: “bedniereba agaprens” which means in English --- happy is up and “ubedureba dzirs daganarcxebs” which means -- sad is down
  In English: “I'm feeling up/down”
- “Vep'his tqaosani” → “The one with the Wepchi(tiger or panther) fur”, a metaphor for a man wrapped in passions
Experiments support their hypothesis
Using all Feature Classes leads to best results
VSM has the biggest impact
they put a lot of effort into the experiments
Pros and Cons

Pros:
- Detection of metaphors in different languages with a training set in only one language (less annotation work)!
- Experiments showed good performance
  ➔ Could confirm their hypothesis that metaphors are conceptual

Cons:
- Cultural metaphors can not (are less likely to) be detected
- Only AN and SVO constructs
- Average when having multiple translations could be improved
Thank you for your attention
Discussion
Quellen

• *Automatic Identification of Conceptual Metaphors with Limited Knowledge*, by Gandy et al.
• *Metaphors in Different Cultures*, by Maggie Mandaria, Grigol Robakidze University
• *Metaphor Detection with Cross-Lingual Model Transfer*, by Tsvetkov et al., 2014
• *Cross-lingual metaphor detection using common semantic features*, by Tsvetkov et al., 2013
• https://examples.yourdictionary.com/types-of-metaphors.html
• http://websites.psychology.uwa.edu.au/school/MRCDaDataBase/uwa_mrc.html
• https://www.aclweb.org/anthology/W03-1022