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

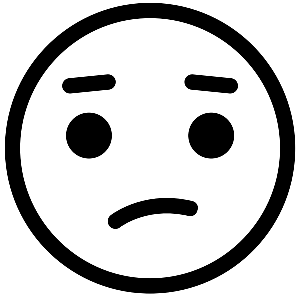
→ Metaphors are conceptual, rather than lexical, in nature

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

SVO (subject-verb-object):

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

1	person	7	cognition	13	attribute	19	quantity	25	plant
2	communication	8	possession	14	object	20	motive	26	relation
3	artifact	9	location	15	process	21	animal		
4	act	10	substance	16	Tops	22	body		
5	group	11	state	17	phenomenon	23	feeling		
6	food	12	time	18	event	24	shape		

Example:

“drinks gasoline” <verb.consumption, noun.substance>

“drinks juice” <verb.consumption, noun.food>

≠

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

→ supersense is 3/33 ≈ 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

Cross Lingual

WordNet supersenses **example**:

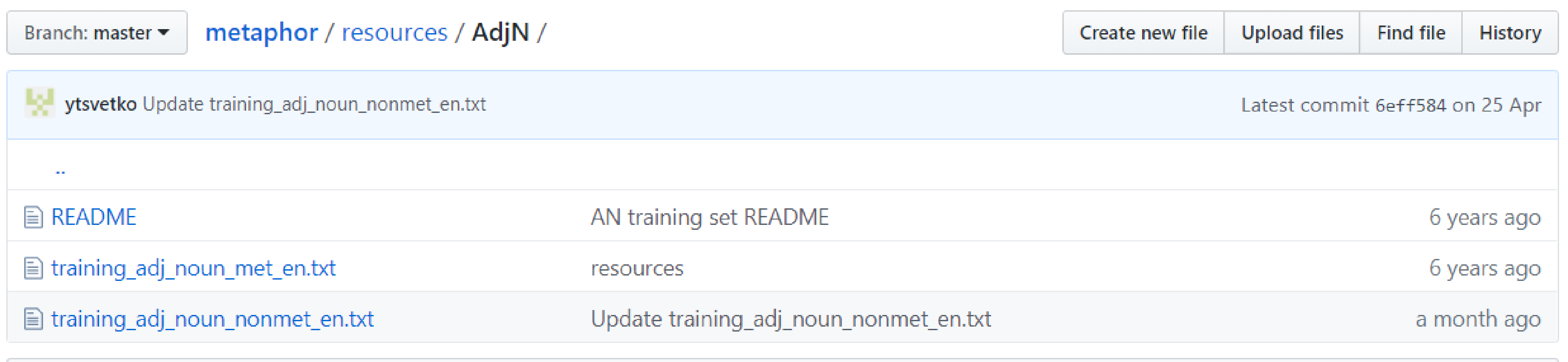
The Russian word голова(golova) is translated as head and brain

→ 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 → TroFi (Trope Finder) dataset

For AN → Created their own training set

Testing:

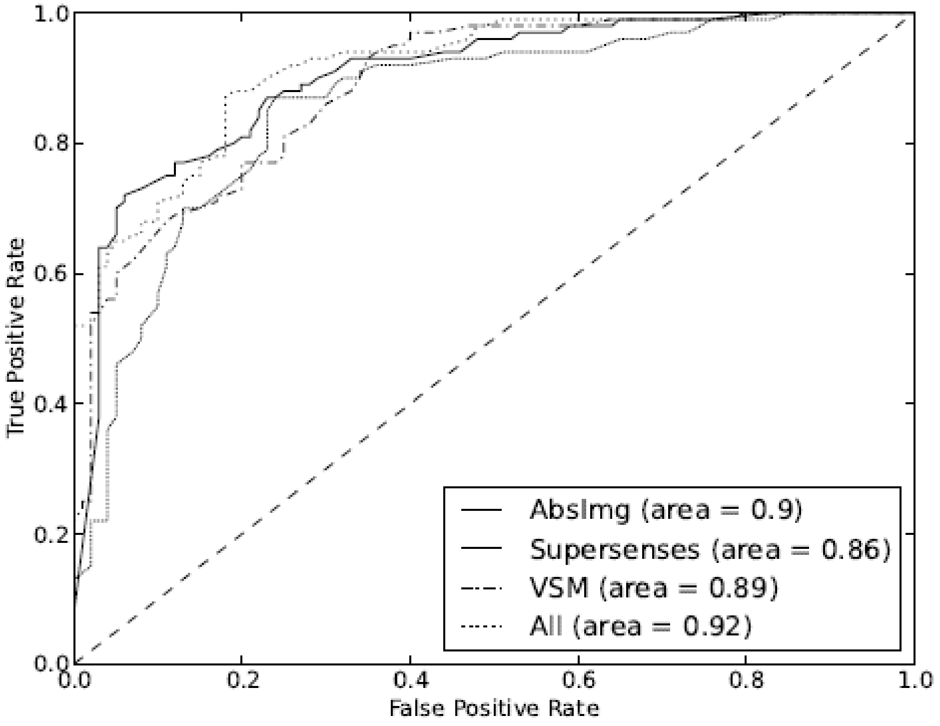
We compile eight test datasets in four languages, four for SVO relations, and four for AN relations

	SVO	AN
EN	222	200
RU	240	200
ES	220	120
FA	44	320

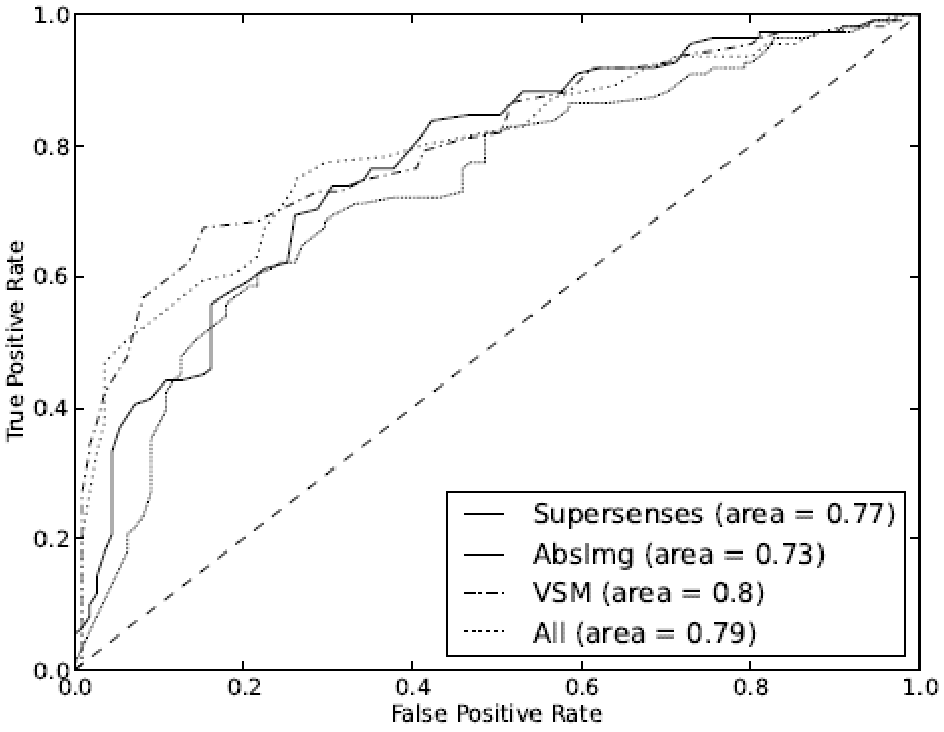
Experiments
10-Fold Cross Validation In English

	SVO		AN	
	# FEAT	ACC	# FEAT	ACC
AbsImg	20	0.73*	16	0.76*
Supersense	67	0.77*	116	0.79*
AbsImg+Sup.	87	0.78*	132	0.80*
VSM	192	0.81	228	0.84*
All	279	**0.82**	360	**0.86**

Experiments
On Out-Of-Domain Data In English



(b) **AN**



(a) **SVO**

Experiments
Comparing To Tsvetkov et al. / Turney et al.

Tsvetkov et al.

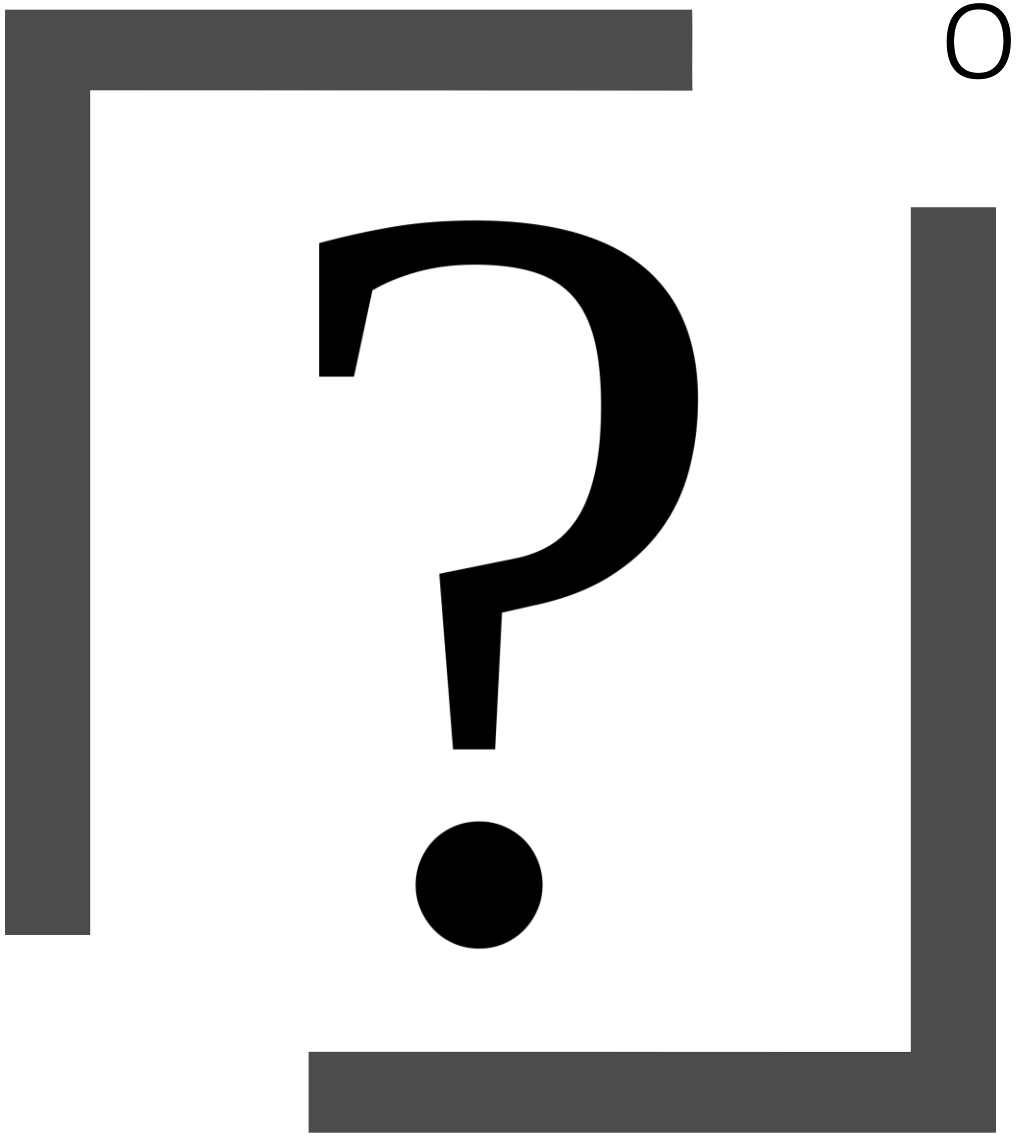
	EN	RU
SVO-baseline	0.78	0.76
This work	0.86	0.85

Turney et al.

	AN-baseline	This work
Judge 1	0.73	0.75
Judge 2	0.81	0.84
Judge 3	0.84	0.88
Judge 4	0.79	0.81
Judge 5	0.78	0.77
average	0.79	0.81

Experiments – Cross Lingual

	SVO	AN
EN	0.79	0.85
RU	0.84	0.77
ES	0.76	0.72
FA	0.75	0.74



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

Conclusion

→ 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
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- http://websites.psychology.uwa.edu.au/school/MRCDataBase/uwa_mrc.htm
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