# Metaphors Shutova 2010

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# Metaphor or not?

### Metaphor

To understand one concept in terms of another.

- I killed the program
- 2 Please don't hold back your ideas
- 3 The presentation stirred some excitement
- **4** He attacked my arguments
- **5** For I have neither wit, nor words, nor worth, Action or utt' range, nor the power of speech, *To stir men's blood*



Make clear the distinction conventional vs. creative metaphors Difficulty in assessing metaphoricality

## Anatomy of Metaphors

I killed the program.

Theories: Comparison, Interaction, Conceptual, Selectional Restriction Violation

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Metaphors

-Introduction

—Anatomy of Metaphors

Anatomy of Metaphors

I killed the program.

Living Entity → Computer Program Source → Target Vehicle → Tenor

Theories: Comparison, Interaction, Conceptual, Selectional Restriction Violation

Introduce key notions Explain each theory shortly, 1 sentence or so What about Salience Imbalance?

## Selectional Preference Violation



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## Selectional Preference Violation

# My car *drinks* gasoline.



Image: A match a ma



Metaphors

Selectional Preference Violation

Selectional Preference Violation

My car drinks gasoline.



Quickly illustrate the concept of selectional preference violation And how it can be used to detect metaphors Mention issues with SelPrefs here or later? Currently it's at the end

## Computational Approaches

- Metaphor Recognition: met\* (Fass 1991), CorMet (Mason 2004)
- Metaphor Interpretation: MIDAS (Martin 1990), KARMA (Narayanan 1997), Shutova (2010)

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#### Metaphors

Introduction

-Computational Approaches

Computational Approaches

Metaphor Recognition: met\* (Fass 1991), CorMet (Mason 2004)

 Metaphor Interpretation: MIDAS (Martin 1990), KARMA (Narayanan 1997), Shutova (2010)

Two tasks

Exemplary approaches: Knowledge-rich (met\*, MIDAS, KARMA) vs. Knowledge-poor (CorMet, Shutova) Theories they depend on: MIDAS (Conceptual metaphors, rich

dependencies between metaphors) vs. met\*, Shutova, CorMet

(SelPrefViolation) - not sure about KARMA

# Metaphor Knowledge

- Master Metaphor List
- MetaBank
- Hamburg Metaphor Database
- Automatic: TalkingPoints-Slipnet (Veale/Hao 2007)



Some relevant resources - say a few words - most of them are based on the conceptual metaphor theory

TP/Slipnet is listed under "Interpretation" by Shutova 2010, but IMHO

it's rather a resource for Interpretation than an actual approach

# Metaphor Annotation in Corpora

- .. is hard (see beginning)!
- Binary annotation vs. source-target tags
- Search for source + target vocabulary
- Search for linguistic markers ("metaphorically speaking")
- Manual search: Metaphor Interpretation Procedure (MIP)



Metaphors

-Introduction

Metaphor Annotation in Corpora

Metaphor Annotation in Corpora - ...is hard (as bigining)! - Binay mentation vis correct tappt tags - Sach for invest + struct viscolarly - Sach for inguist: making ("metaphorizity speaking") - Minaui asach: Relative Integration Proceeding (MPP)

Refer to the slide with example metaphors from the beginning MIP especially relevant, it is used by Shutova to tag their corpus

### Shutova 2010: Automatic Metaphor Interpretation <sup>as a</sup> Paraphrasing Task

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### The Ingredients:

Parsed corpus, annotated metaphorical verbs plus direct object or subject -

- the new idea stirred excitementobject
- the report<sub>subject</sub> leaked to the media

### The Recipe:

- Find other verbs in same context
- 2 Rank by likelihood
- 3 Throw out junk verbs

—Put aside as BASELINE———

- 4 Re-rank by selectional association
- 6 Choose top rank



Make clear that they were concerned with conventional metaphors Will say more about concrete data set later  $% \left( {\left[ {{{\rm{A}}} \right]_{{\rm{A}}}} \right)_{{\rm{A}}} \right)$ 

 $\ldots$  and SelAssociation ranking completely ignores likelihood ranking - is like a second approach

#### 1. Find other verbs in same context

provoked excitement created excitement made excitement demand excitement

### 2. Rank by likelihood

P(verb) \* P((context - word, syntactic - rel)|verb)
(P given by relative frequencies in corpus)

| LogLh  | Paraphrase |
|--------|------------|
| -14.28 | create     |
| -14.84 | provoke    |
| -15.53 | make       |
| -15.82 | demand     |

#### 3. Throw out junk verbs

Requirement: New verb and metaphorical verb have common hypernym in WordNet (maximum 3 levels)

| LogLh             | Paraphrase |
|-------------------|------------|
| -14.28            | create     |
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| -14.28            | create Baseline! |
| -14.84            | provoke          |
| -15.53            | make             |
| <del>-15.82</del> | demand           |

### 4. Re-rank by selectional association

v = the verb.

 $\mathsf{c}=\mathsf{one}$  of 200 noun classes given by a noun clustering algorithm:

$$A_R'(v,c) = P(c|v) * \log rac{P(c|v)}{P(c)}$$
  $A_R(v,c) = rac{A_R'(v,c)}{\sum_{c'} A_R'(v,c')}$ 

| $A_R(v,c)$ | Paraphrase |
|------------|------------|
| 0.069      | provoke    |
| 0.003      | create     |
| 0.000      | make       |



Introduction

Example: ... stirred excitement-biect v = the verb. c = one of 200 noun classes given by a noun clustering algorithm  $A'_R(v, c) = P(c|v) * log \frac{P(c|v)}{D(c)}$  $A_R(v, c) = \frac{A'_R(v, c)}{\sum_{c'} A_n(v, c')}$ A<sub>R</sub>(v, c) Paraphrase 0.003 create 0.000 make

How much to say about the noun clustering?

#### 5. Choose top rank

This is the literal interpretation of the metaphor.

| $\mathbf{A}_{\mathbf{R}}(\mathbf{v},\mathbf{c})$ | Paraphrase |
|--|------------|
| <u>0.069</u>                                     | provoke    |
| 0.003  | create     |
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#### 5. Choose top rank

This is the literal interpretation of the metaphor.

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| 0.000  | make       |
|  |            |

Next: stir well and evaluate!

## Evaluation

- Annotators tagged verb occurrences in subset of BNC as +/metaphorical
- Filter out noisy cases (named entities and pronouns at subject/object position etc.)
- 62 metaphorical expressions in total
- Find paraphrases for all of them

**First question:** How good are top paraphrases chosen by system ("Precision")? **Second question:** How good and exhaustive is overall ranking ("Recall")?

## Evaluation

**First question:** How good are top paraphrases chosen by system (Precision)?

Second question: How good and exhaustive is overall ranking ("Recall")?

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Evaluation
First question: How good are top paraphrases chosen by system
(Precision)?

(Precision)? Second question: How good and exhaustive is overall ranking ("Recall")?

Actual recall hard to determine, since gold standard not exhaustive

## Evaluation - First question

### How good are top paraphrases chosen by system?

Answered by human annotators. E.g.

Is "provoke excitement" a good literal paraphrase for "stir excitement"?

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## Evaluation - First question

### How good are top paraphrases chosen by system?

Answered by human annotators. E.g.

Is "provoke excitement" a good literal paraphrase for "stir excitement"?

81% accuracy for system vs. 55% for baseline.

## Evaluation - Second question

### How good and exhaustive is ranking?

- Gold standard: For each metaphorical expression, human annotators give paraphrases
- For each paraphrase ranking given by system: Calculate Reciprocal Rank
- Calculate Mean Reciprocal Rank over all metaphorical expressions

## Evaluation - Second question

### How good and exhaustive is ranking?

### Mean Reciprocal Rank (MRR)

For each paraphrase ranking: R = rank of first gold paraphrase

$$RR = egin{cases} R^{-1} & R \leq 5 \ 0 & \textit{else} \end{cases}$$
 $MRR = ext{Mean over } RR ext{ of all expressions}$ 

### Selectional Association Ranking for stir excitement

 $A_R$ Paraphrase0.069provoke0.003create:  $RR = \frac{1}{2}$ 0.000make

## Evaluation - Second question

### How good and exhaustive is ranking?

 $0.63~\mbox{MRR}$  vs. baseline MRR of 0.55

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-Evaluation - Second question

Evaluation - Second question

How good and exhaustive is ranking 0.63 MRR vs. baseline MRR of 0.55

#### Strange: Why is Baseline MRR = Baseline Accuracy? Coincidence?

## Conclusion

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- Most theories to metaphor w/o enough formal strictness
- Selectional Preference Violations not unproblematic, but at least helpful for computational approaches:
  - SPV  $\neq$  Metaphor: Metonymies, Anomalies, metaphors which don't violate SelPref..
  - Very general verbs, like "improve"
  - Frequent conventional metaphors
- Metaphors are still a unsolved problem for NLP.



-Metaphors + CoLi in general



Maybe give intermediate conclusion after first part! Problem with other theories? Are all rather vague and hard to formalize Might be too much, need to summarize

- Unlike previous approaches, Shutova 2010 works without predefined knowledge (apart from WN)
- Interpretation result directly usable as input to other NLP modules
- But: Very restricted wrt kind of metaphor
- Issues with Selectional Preference Violation apply as well
- Evaluation: Only 62 metaphorical expressions, which seem to be (judging by the examples) rather strongly lexicalized (in other words, is it really necessary to paraphrase them?)

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Shutova 2010

- Unlike previous approaches, Shutova 2010 works without predefined knowledge (apart from WN)
- · Interpretation result directly usable as input to other NLP modules
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- Evaluation: Only 62 metaphorical expressions, which seem to be (judging by the examples) rather strongly lexicalized (in other words, is it really necessary to paraphrase them?)

Why no WordNet baseline (Replacing metaphorical senses by other verbs in Synset, or the hypernym)? Actually, the three examples in her paper are all contained in WN



### [Shutova, 2010a] E. Shutova.

Automatic Metaphor Interpretation as a Paraphrasing Task Proceedings of NAACL 2010, 2010.

[Shutova, 2010] E. Shutova. Models of Metaphor in NLP Proceedings of ACL 2010, 2010.

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