



Detecting novel metaphor using selectional preference information

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Outline

1. Types of metaphor
2. Selectional preference violation
3. Approach & implementation
4. Evaluation & results
5. Analysis & discussion



A definition of metaphor

A lexical unit is metaphorical if it has a more basic contemporary meaning in other contexts than in the current context



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- › Wide range of metaphor:
 1. ‘Do the Greeks **have** a word for it?’
 2. ‘only little scientific evidence **supports** the link’



Degrees of metaphoricity

1. None

Literal meaning, most basic, in lexicon

2. Conventional

Metaphorical meaning, non-basic, in lexicon

3. Novel

Metaphorical meaning, non-basic, not in lexicon



Examples

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‘You wanted to **eat** up my sadness.’

eat#? (take away/cure/remove)



Metaphor processing and WSD

- › Problem: which is the meaning of this ambiguous word/phrase in this specific context?
- › WSD and metaphor processing overlap on conventional metaphors
- › Novel metaphor outside of scope WSD
- › Improved handling of metaphor can benefit WSD



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Selectional preference violation

- › Selectional preferences capture intuitive knowledge about what fits in a certain domain
- › Metaphor combines a source and target domain
- › Violation of selectional preferences as an indicator of two distinct domains, metaphor



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‘The scientists **eat** their sandwiches.’

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‘You wanted to **eat** up my sadness.’

eat#? (take away/cure/remove)



Novel metaphor

- › Automatically acquired selectional preferences capture frequency, not basicness
- › Conventional metaphor sometimes more frequent than literal
e.g. ‘uncover a treasure’ vs. ‘uncover a secret’
- › Assumption: novel metaphors are always infrequent



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Approach

- › Gather verb-subject and verb-object pairs from a large, parsed English corpus
- › Extract selectional preference metrics
- › Generalize over co-occurrence counts
- › Use as features in a logistic regression classifier to detect metaphors in the VUAMC



Selectional preference information

- › Word-level verb metaphor detection
- › Parse Wikipedia dump (1.6B words), extract and count verb-noun pairs
- › Calculate conditional probability (CP), log probability (LP), selectional association (SA) and selectional preference strength (SPS)
- › CP, LP, SA represent likelihood of verb-noun pair
- › SPS represents selectivity of verb



Generalization

- › Generalization helps going from word-word pairs to domain-domain pairs
- › Three approaches
 1. Pre-trained Brown clusters, from Derczynski et al. (2015), 80-5120 clusters
 2. K-means clustered GloVe embeddings (300D/840B), 400k vocabulary, 80-5120 clusters
 3. Neural net predictor of LP, based on embeddings, single hidden layer, 600 units, ADAM, Dropout



Training data

| Verb | Subj. | Obj. | CP-s | LP-s | SPS-s | SA-s | ... | Label |
|----------|--------|-------|-------|-------|-------|------|-----|-------|
| maintain | couple | link | 0.005 | -7.51 | 0.93 | 6.20 | | 1 |
| need | we | pilot | 0.05 | -2.98 | 0.73 | 0.17 | | 0 |



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Evaluation data

- › VU Amsterdam Metaphor Corpus (VUAMC), parsed
- › Extract all verbs
 - Verb-subject-object: 5,539
 - Verb-subject: 13,466
 - Verb-object: 3,913
- › Downside: broad definition of metaphor, highly conventionalized metaphors dominate
- › Manual inspection of metaphor type



Classifier

- › Logistic regression with L2 regularization
- › 10-fold cross-validation
- › Separate classifier per dataset
- › Back-off to majority class (non-metaphor)



Re-weighting

- › Re-weighting of examples to counter class imbalance
 - Subject-verb: 13.0%
 - Verb-object: 34.7%
 - Subject-verb-object: 36.4%
- › Assign more weight to minority class examples



Results (1)

Without re-weighting of training data

| Data | BL | CP | LP | Pred-LP | SPS | SA | All |
|---------|-------------|-----|------|---------|-----|-----|------|
| Subject | 23,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 1,3 |
| Object | 50,8 | 0,0 | 3,2 | 1,4 | 0,0 | 0,0 | 2,4 |
| Both | 53,4 | 0,0 | 18,1 | 0,7 | 0,0 | 2,3 | 32,1 |



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With re-weighting of training data

| Data | BL | CP | LP | Pred-LP | SPS | SA | All |
|---------|------|-------------|------|---------|------|------|-------------|
| Subject | 23,0 | 24,5 | 24,5 | 23,2 | 20,9 | 26,4 | 33,6 |
| Object | 50,8 | 53,4 | 45,6 | 49,2 | 49,0 | 51,2 | 47,6 |
| Both | 53,4 | 54,2 | 44,3 | 50,0 | 50,5 | 63,8 | 57,8 |



Results (2)

With Brown clustering

| Data | BL | 80 | 160 | 320 | 640 | 1280 | 2560 | 5120 |
|---------|-------------|------|-------------|------|------|------|------|-------------|
| Subject | 23,0 | 26,3 | 28,8 | 27,9 | 25,9 | 26,3 | 26,6 | 25,3 |
| Object | 50,8 | 48,7 | 47,7 | 45,3 | 46,9 | 44,7 | 44,6 | 46,2 |
| Both | 53,4 | 52,7 | 52,8 | 53,7 | 54,3 | 53,5 | 54,3 | 54,5 |

With k-means clustering

| Data | BL | 80 | 160 | 320 | 640 | 1280 | 2560 | 5120 |
|---------|-------------|------|------|-------------|------|------|------|------|
| Subject | 23,0 | 24,2 | 23,5 | 30,7 | 28,6 | 24,4 | 23,6 | 22,9 |
| Object | 50,8 | 40,4 | 44,8 | 45,8 | 44,2 | 48,9 | 48,8 | 49,8 |
| Both | 53,4 | 49,8 | 48,2 | 50,4 | 49,2 | 47,6 | 50,4 | 49,5 |



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Generalization

- › In the current set-up, generalization does not work
 - Brown \approx k-means \approx prediction
 - No clear effect of cluster size
- › Information loss outweighs generalization gain
- › Clusters do not form coherent domains



Error analysis

- › Large number of (unresolved) pronouns
- › True positives contain many light verbs (*take, have, make, put*).
- › Logistic regression exploits corpus distribution
- › One example of novel metaphor:
 - [...] Adam might have **escaped** the file memories for years, [...]



Conclusion

- › *Is selectional preference information useful for detecting novel metaphors?*
- › Better evaluation data is needed
 - Annotate novel/OOV senses in VUAMC
 - Annotate metaphor on a scale, not binary
 - Use selectional preference violation to discover novel metaphors