LexSemTM: A Semantic Dataset Based on All-words Unsupervised Sense Distribution Learning

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Unsupervised Sense Distribution Learning

- Task is to automatically learn relative frequencies of word senses, from unlabelled text

- Learning is type-level (one sense distribution per lemma type)

- Shown to be useful in WSD, particularly in domain adaptation, plus other applications (Lau et al., 2014)

Example

Example uses of word

“The crane flew north over the marsh”

“The crane is a graceful bird”

“A crane is a type of tall wading birds”

“The crane lifted the beam to the top of the building”

“Before they could construct the building, they needed a new crane”

Sense glosses from dictionary

crane -- (large long-necked wading bird of marshes and plains in many parts of the world)

crane -- (lifts and moves heavy objects; lifting tackle is suspended from a pivoted boom that rotates around a vertical axis)

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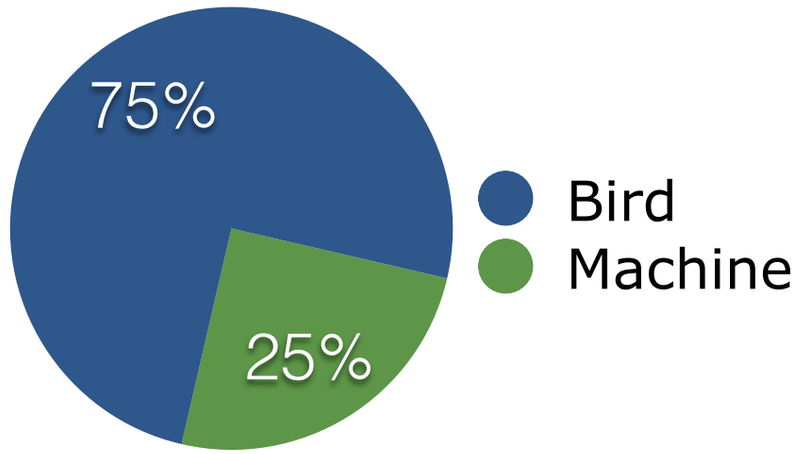

Existing Sense Frequency Datasets

- Most comprehensive English language sense frequency resource is *SemCor*
- *SemCor* contains major gaps / inconsistencies
- Resources for other languages similarly limited

Our Goals

1. Apply unsupervised sense distribution learning to create resource to replace or supplement *SemCor*

2. Refine existing unsupervised sense distribution learning methodology to facilitate this

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Lau et al., (2014)

HDP-WSI

- Existing state-of-the-art method for unsupervised sense distribution learning
- Main computational component is HDP topic modelling (Teh et al., 2006)
  - HDP is a non-parametric generalisation of LDA (automatically learns “right” number of topics)
- Process performed separately for each lemma

Lau et al., (2014)

HDP-WSI

1. **Run HDP on usages to obtain topics**
2. Assignment of each usage to single topic
3. Soft alignment of each topic to all senses

Example uses of word

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Topic Distributions (bags of words)

t_1

crane flew north marsh crane is graceful bird crane is type of tall wading bird of tall before they they crane

t_2

the over the the a a a the crane lift the beam to the top the building could construct the building need a new

Lau et al., (2014)

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$$P(t_2) = 0.4$$

Lau et al., (2014)

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Sense Gloss Distributions (bags of words)

s_1

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lift and move heavy object lift tackle is suspend from a pivoted boom that rotate around a vertical axis

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JSD = Jensen-Shannon Divergence between corresponding bags-of-words distributions

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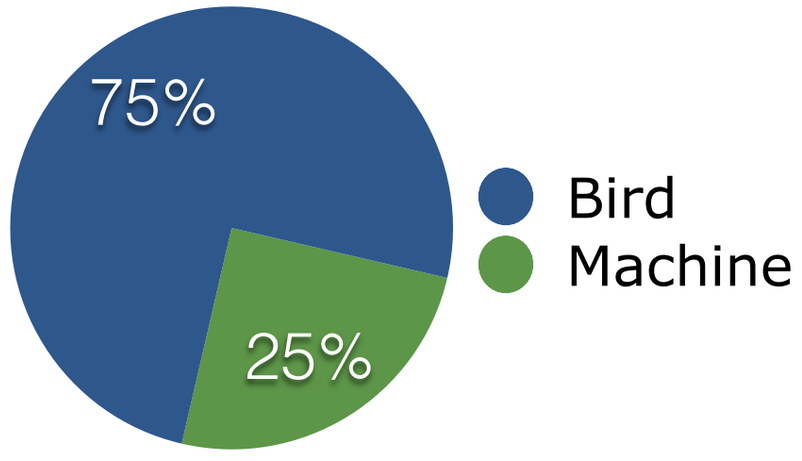


Normalised prevalence scores

$$prev(s_i) = \sum_{j=1}^{T} P(t_j)(1 - JSD(s_i, t_j))$$

JSD = Jensen-Shannon Divergence between corresponding bags-of-words distributions

Why not Use HDP-WSI?

- Too slow!

- ~1 hour per word, doesn't scale well to language-wide computation

Our Method: HCA-WSI

- Follows same procedure as HDP-WSI, except HDP is replaced by HCA (Buntine and Mishra, 2014)

- Differences between HCA and HDP:

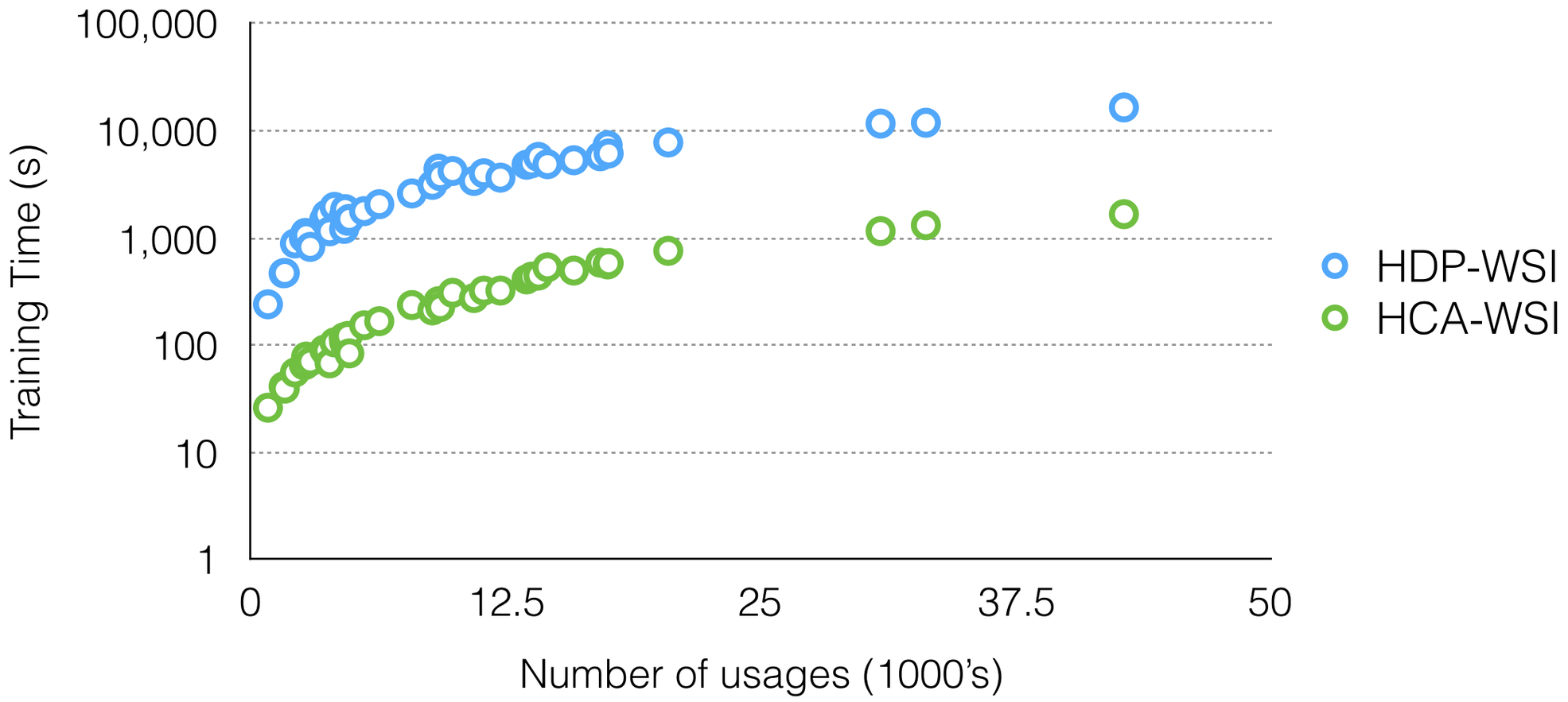
1. **HCA uses more efficient Gibbs sampling inference algorithm than HDP**

2. HCA based on Pitman-Yor processes rather than Dirichlet processes

3. HCA models document-level burstiness

4. HCA requires setting fixed number of topics

HCA-WSI vs HDP-WSI



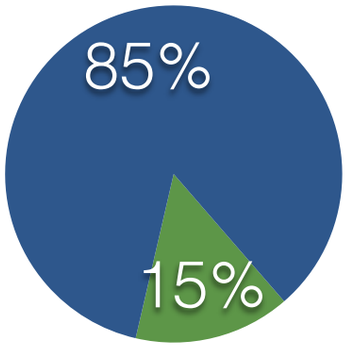
- Impact on sense distribution quality of HCA-WSI versus HDP-WSI not statistically significant ($p > 0.05$)

Lau et al., (2014)

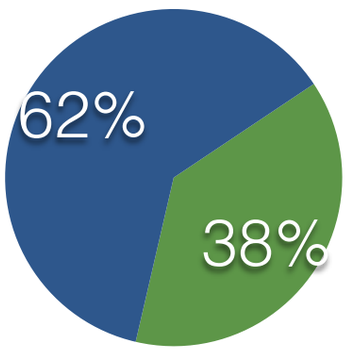
Sense Distribution Quality Metric: JSD

Gold-Standard

Candidate 1



Candidate 2



Lau et al., (2014)

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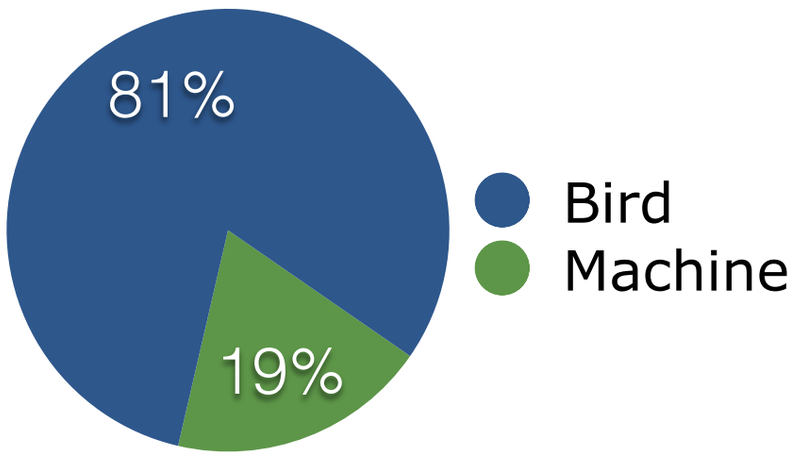

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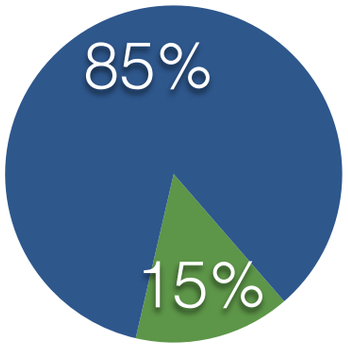
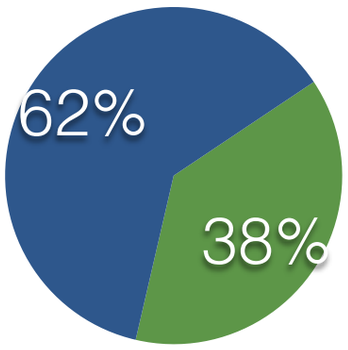


$JSD = 0.0020$

Candidate 2



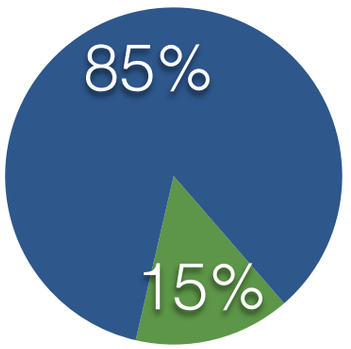
$JSD = 0.0324$

Lau et al., (2014)

Sense Distribution Quality Metric: JSD

Gold-Standard

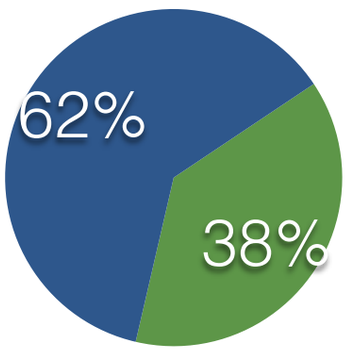
Candidate 1



$JSD = 0.0020$

(lower is better)

Candidate 2



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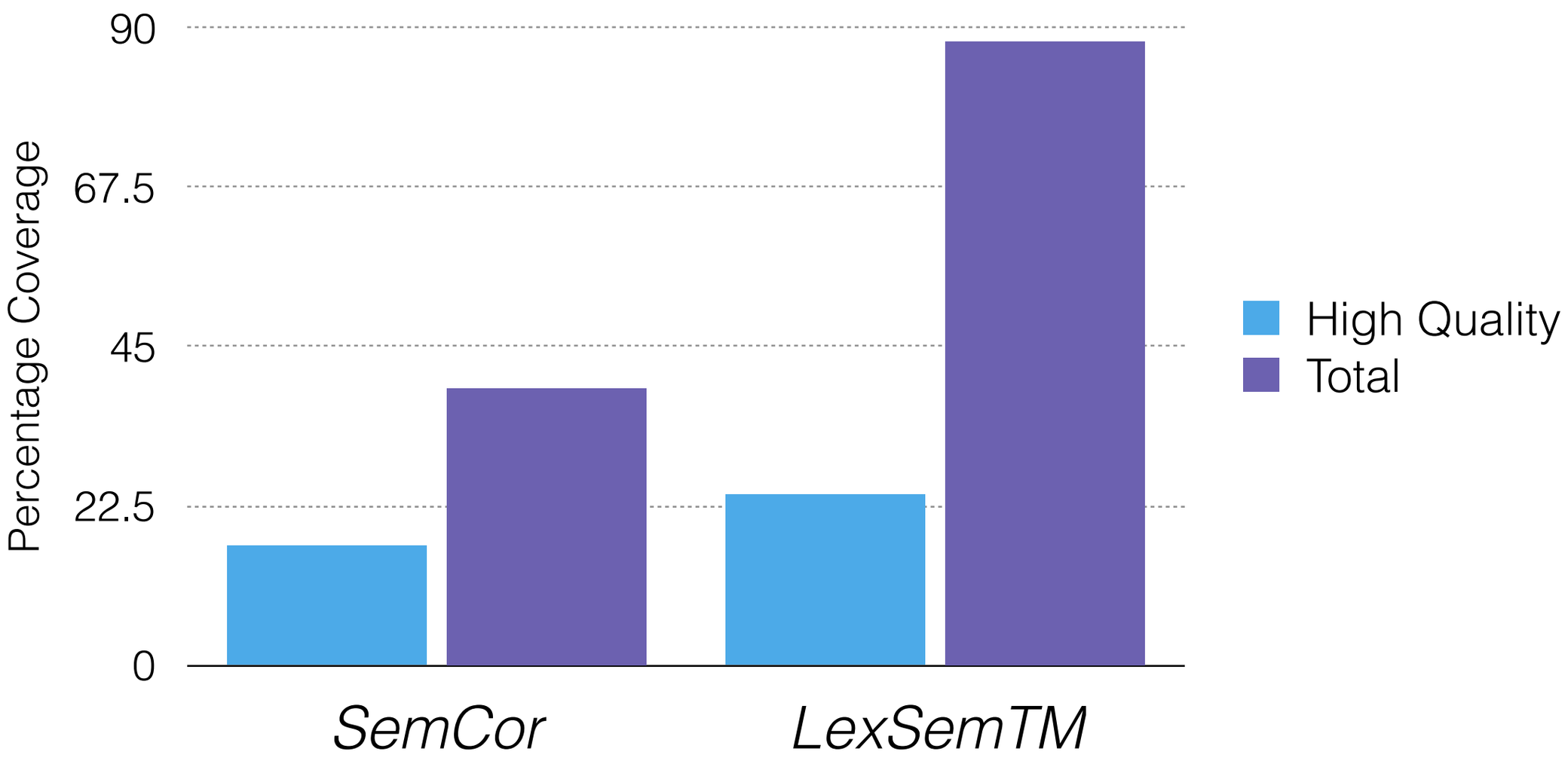
LexSemTM Dataset

- Created by applying HCA-WSI to usages sampled from English Wikipedia, for all *WordNet* lemmas with at least 20 usages

- Also contains topic HCA topic modelling output for all lemmas (can be realigned to other sense inventories)

Coverage of Polysemous *WordNet* Lemmas



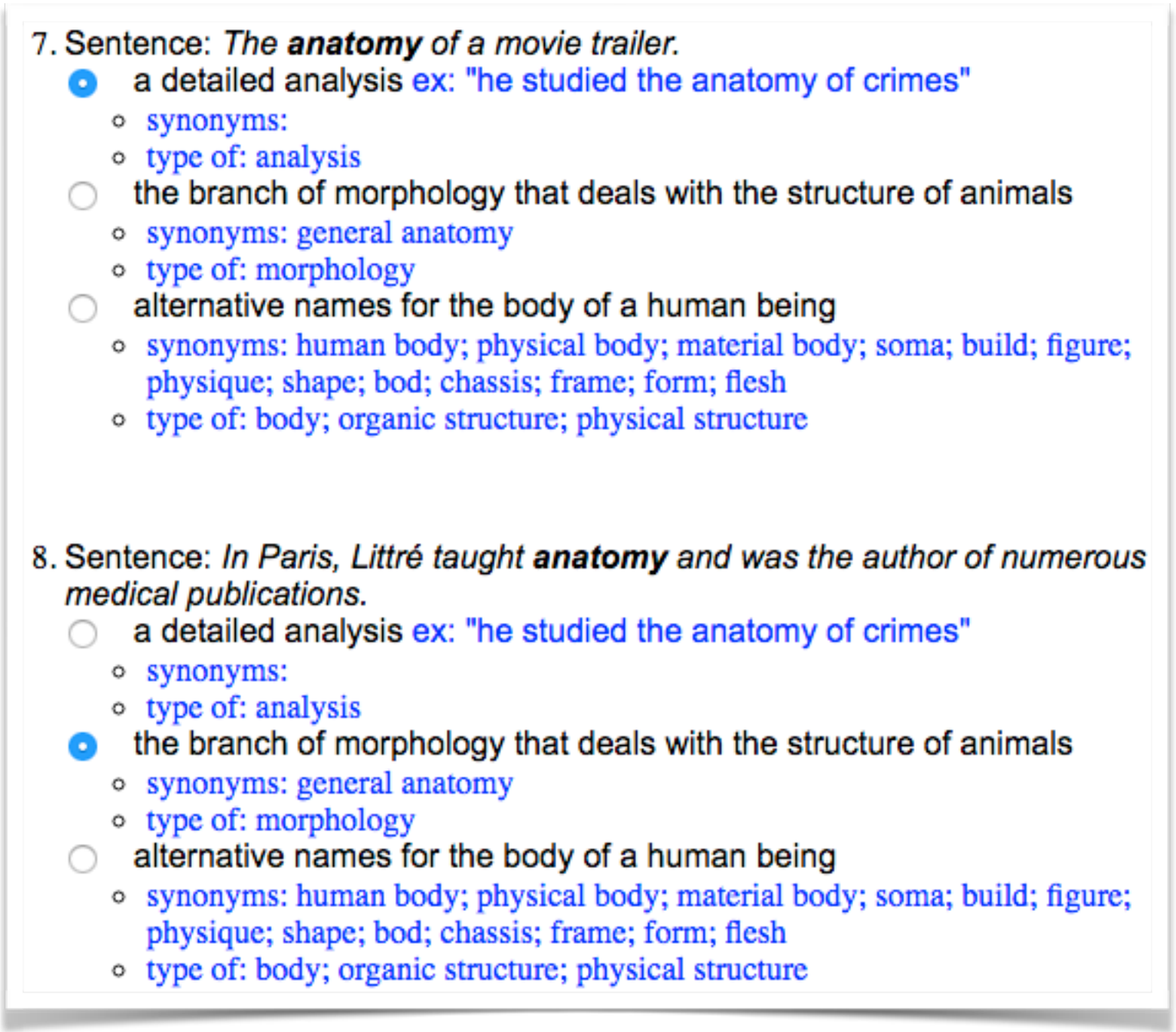
Evaluation

- Evaluating how *LexSemTM* and *SemCor* compare in quality, as a function of *SemCor* frequency

- Want to decide for which lemmas *LexSemTM* can replace/supplement *SemCor*

- Evaluation performed on set of 50 nouns covering wide range of *SemCor* frequencies

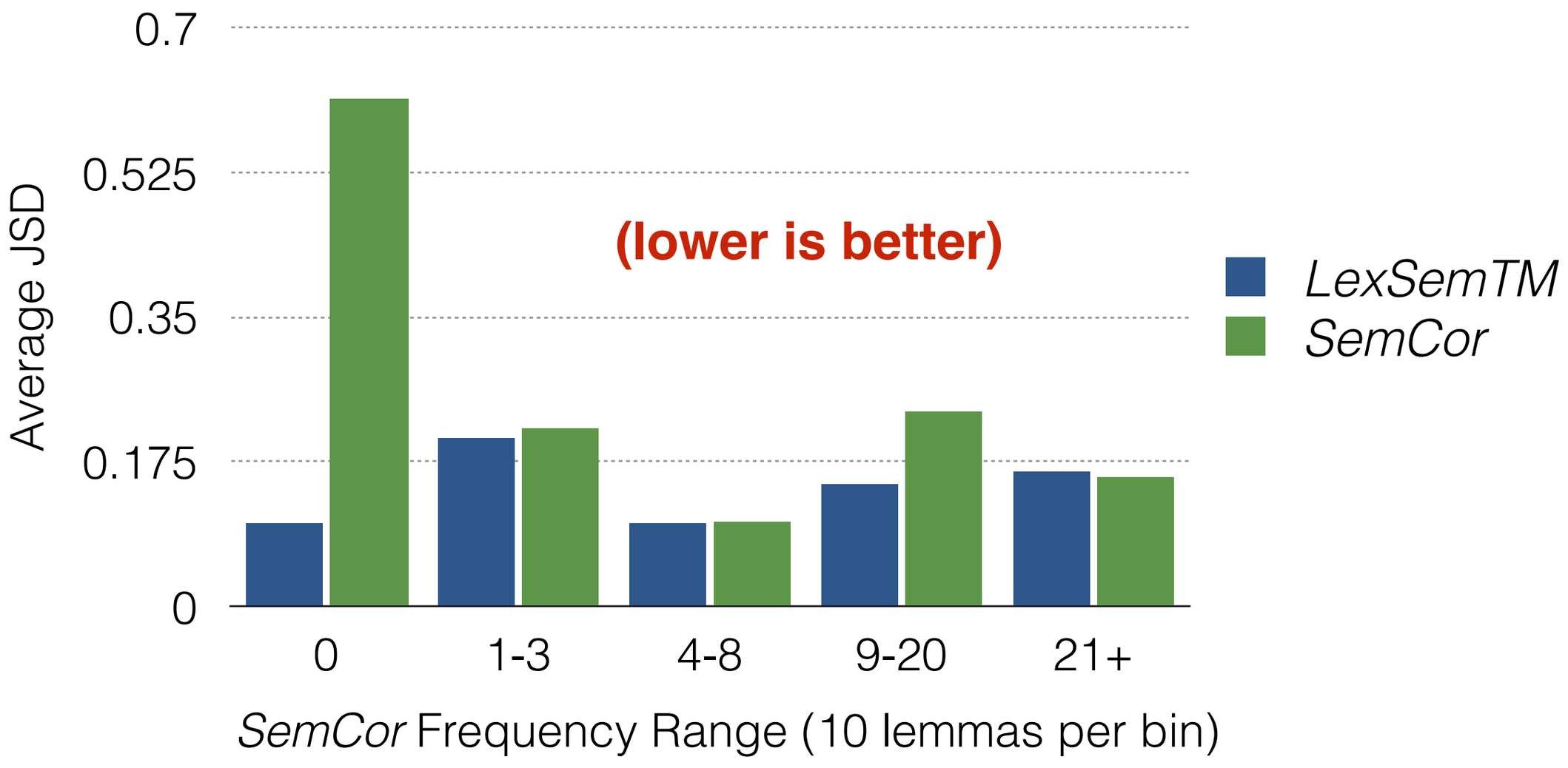
Gold-Standard Annotation



Annotation Interface

- For each of 50 lemmas, 100 sentences randomly sampled to be sense-annotated
- Annotation done using Amazon Mechanical Turk
- Annotation results processed and normalised to give gold-standard distributions

Evaluation Results



Summary

- HCA-WSI is on par with previous state-of-the-art in terms of sense distribution quality, and 10-20 times faster

- *LexSemTM* provides substantially greater coverage of polysemous *WordNet* lemmas than *SemCor*, and appears to be at least as accurate

- *LexSemTM* also contains topic model output that can be re-aligned to other sense inventories

Questions?

References

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