Hearst Patterns Revisited:

Automatic Hypernym Detection from Large Text Corpora

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Hypernymy

- Hierarchical relations play a central role in knowledge representation (Miller, 1995)

cat is a feline is a mammal is an animal

All animals are living things -> cats are living things

- Automatic hypernymy detection approaches:
  - **Pattern based:** high-precision lexico-syntactic patterns (Hearst, 1992)
  - **Distributional Inclusion**: unconstrained word co-occurrences (Zhitomirsky-Geffet and Dagan, 2005)

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/[NP] such as [NP] (and [NP])?/
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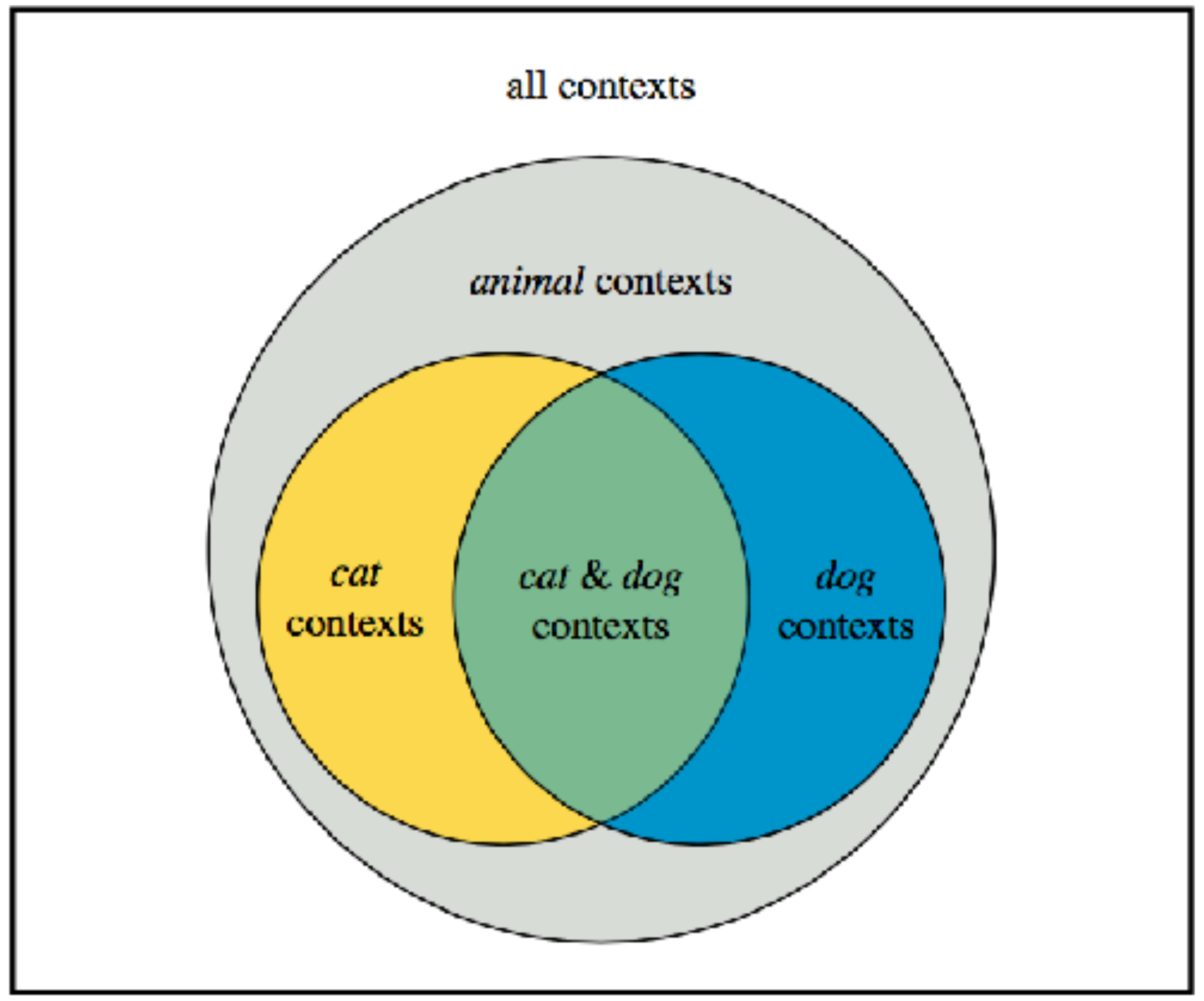
animals such as cats and dogs

animals including cats and dogs

cats, dogs, and other animals



Objectives

- Are Hearst patterns more valuable than distributional information?
  - Do we learn more from using **general semantic contexts**, or exploiting **highly targeted ones**?
  - Are differences robust across multiple evaluation settings?

- Can we remedy some of Hearst patterns' weaknesses?
  - Scaling up data and extraction is cheaper and easier today
  - Do embedding methods help alleviate sparsity?

Tasks

10% Validation, 90% Test

Detection

- Distinguish hypernymy pairs from other relations
- Average Precision (AP) across 5 datasets (Shwartz et al., 2017)

Direction

- Identify the direction of entailment (X⇒Y or Y⇒X?)
- Accuracy across 3 datasets (Kiela et al., 2015)
- 2 also contain non-entailments (X⇎Y)

Graded Entailment

- Predict the *degree* of entailment
- Spearman's rho on 1 dataset (Vulić et al., 2017)

Detection

- BLESS (Baroni and Lenci, 2011)
- EVAL (Santus et al., 2015)
- LEDS (Baroni et al., 2012)
- Shwartz (Shwartz et al., 2016)
- WBLESS (Weeds et al., 2014)

Direction

- BLESS (Baroni and Lenci, 2011)
- WBLESS (Weeds et al., 2014)
- BiBless (Kiela et al., 2015)

Graded Entailment

- Hyperlex (Vulić et al., 2017)

Hearst Pattern Extraction

Preprocessing

- 10 Hearst patterns
- Gigaword + Wikipedia
  - Lemmatized, POS tagged
- Matches were aggregated and filtered:
  - Pair must match 2 distinct patterns
- 431K distinct pairs covering 243K unique types

Pattern
X which is a (example|class|kind|...) of Y
X (and|or) (any|some) other Y
X which is called Y
X is JJS (most)? Y
X a special case of Y
X is an Y that
X is a !(member|part|given) Y
!(features|properties) Y such as X_1, X_2, ...
(Unlike|like) (most|all|any|other) Y, X
Y including X_1, X_2, ...

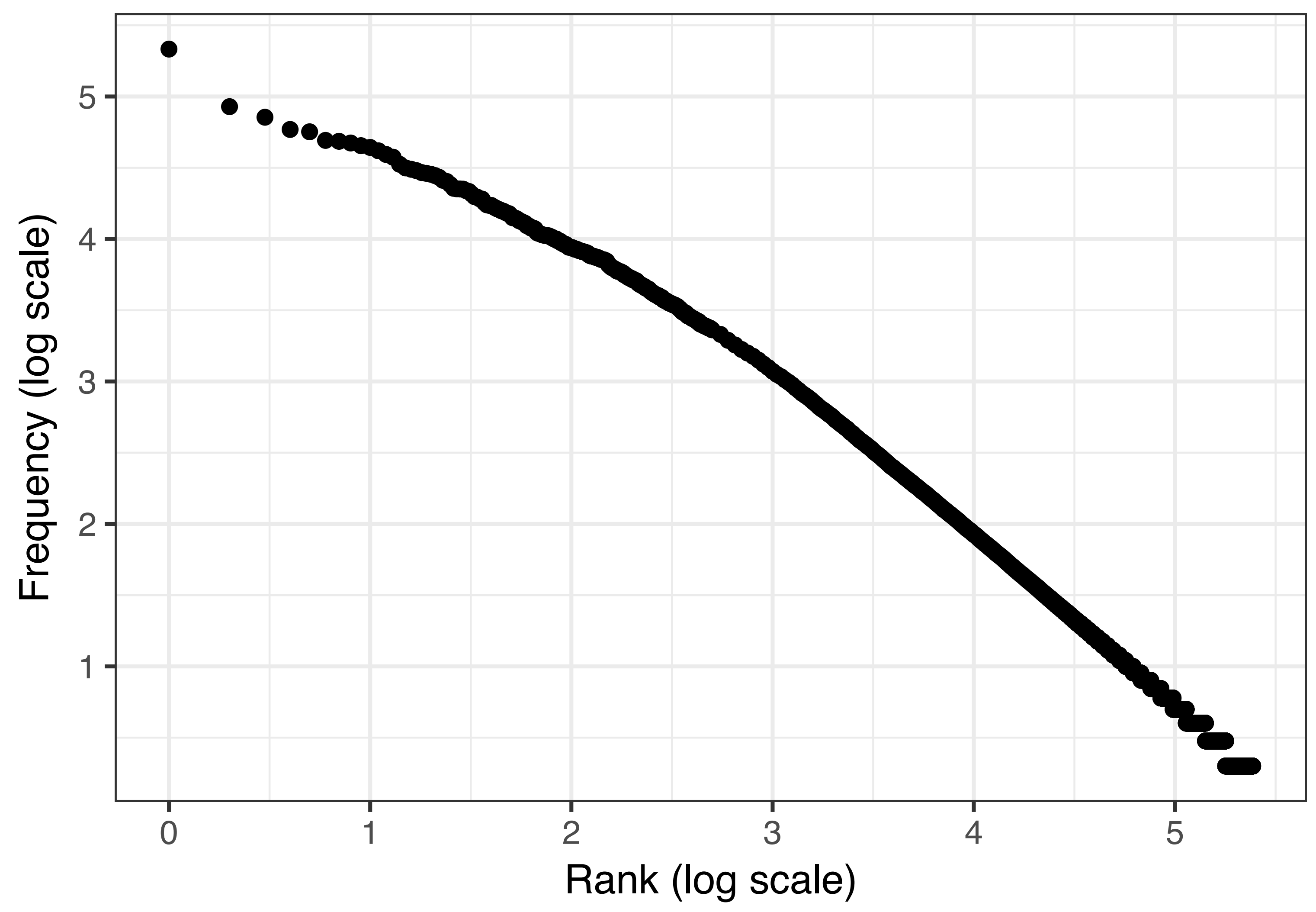
Hearst Pattern Models

Count transformation

- **PPMI**(x, y): transform counts using Positive Pointwise Mutual Information

Simple embedding (Truncated SVD)

- **SPMI**(x, y): apply truncated SVD to PPMI counts
- Select *k* using validation set
- Related to Cederberg and Widdows (2003)



$$\mathrm{ppmi}(x, y) = \max\left(0, \log \frac{p(x, y)}{p^-(x)p^+(y)}\right)$$

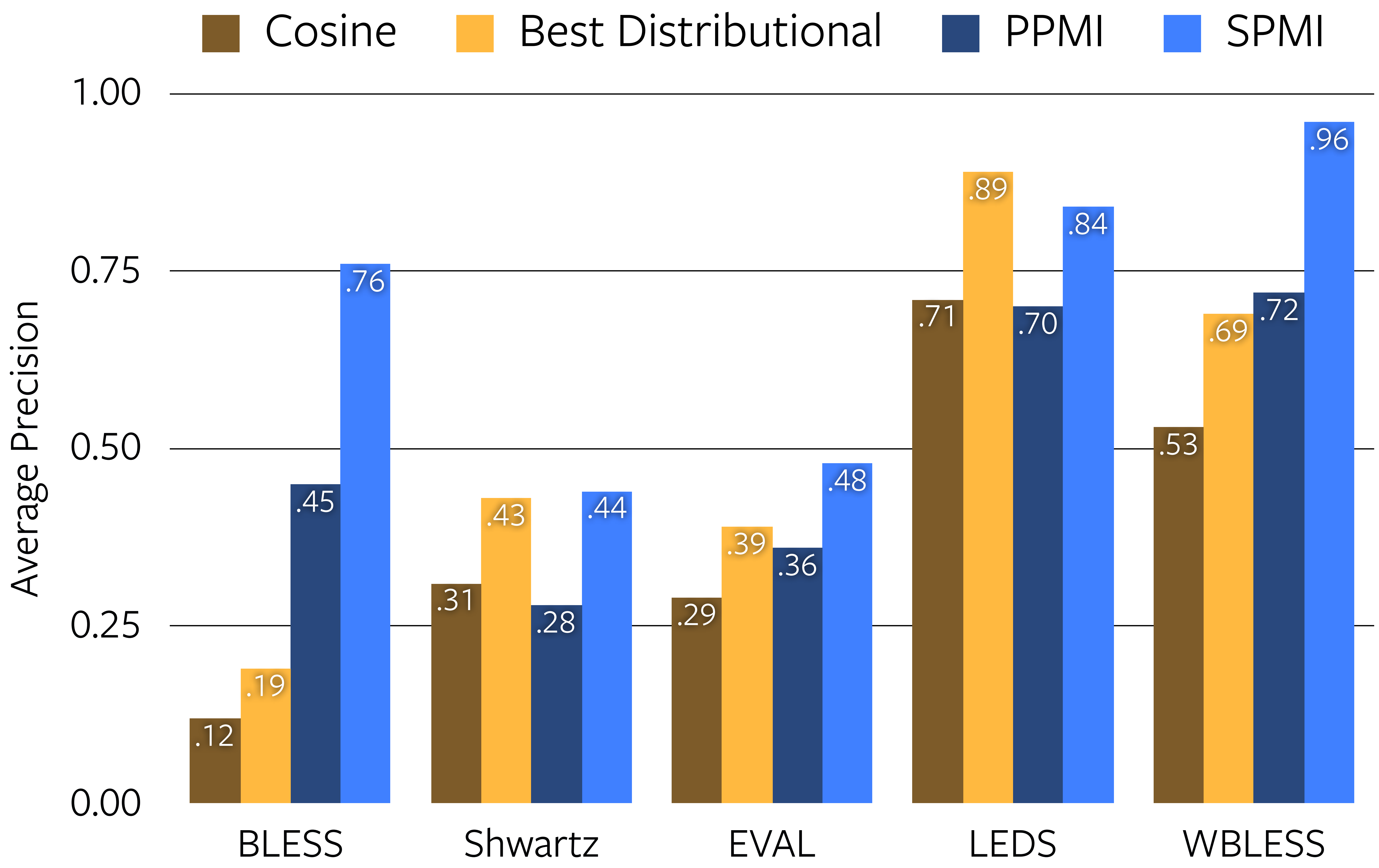
$$\mathrm{spmi}(x, y) = \mathbf{u}_x^\top \Sigma_r \mathbf{v}_y$$

Distributional Methods

- Cosine baseline
- Selected 3 high performing, unsupervised methods based on Shwartz et al. (2017)
  - WeedsPrec (Weeds et al., 2004); invCL (Lenci and Benotto, 2012); SLQS (Santus et al., 2014)
- Use strong distributional space from Shwartz et al. (2017)
  - Wikipedia + UkWaC
  - POS tagged and lemmatized
  - Dependency contexts (Pado and Lapata, 2007; Levy and Goldberg, 2014)
- Tune hyperparameters on validation

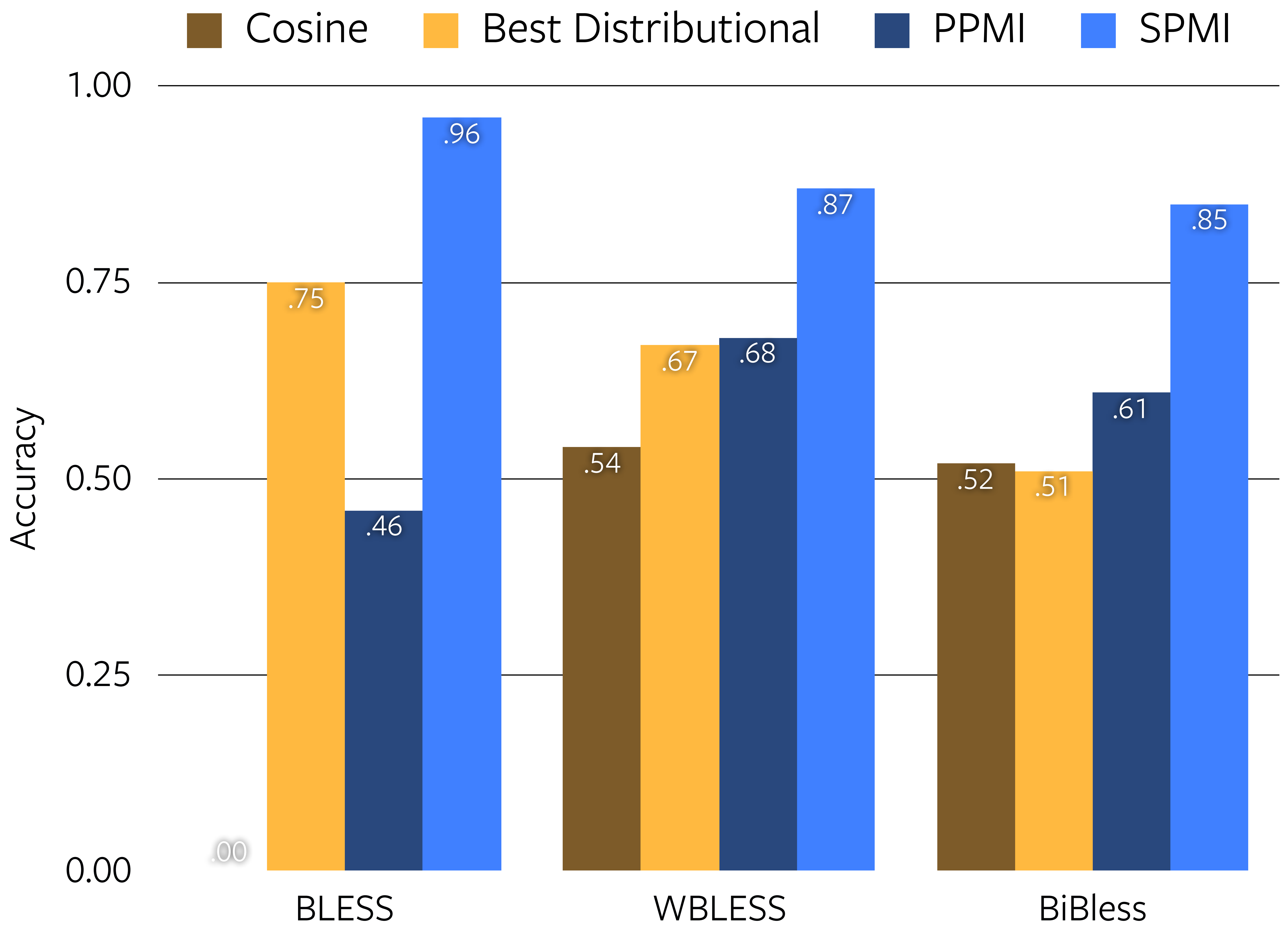
Detection

- Distr. methods have trouble with global calibration (AP)
- Pattern has mixed performance
- SPMI model best on 4/5 datasets.
- Embedding Hearst patterns helps overcome sparsity
  - Fills in gaps
  - Downweights outliers



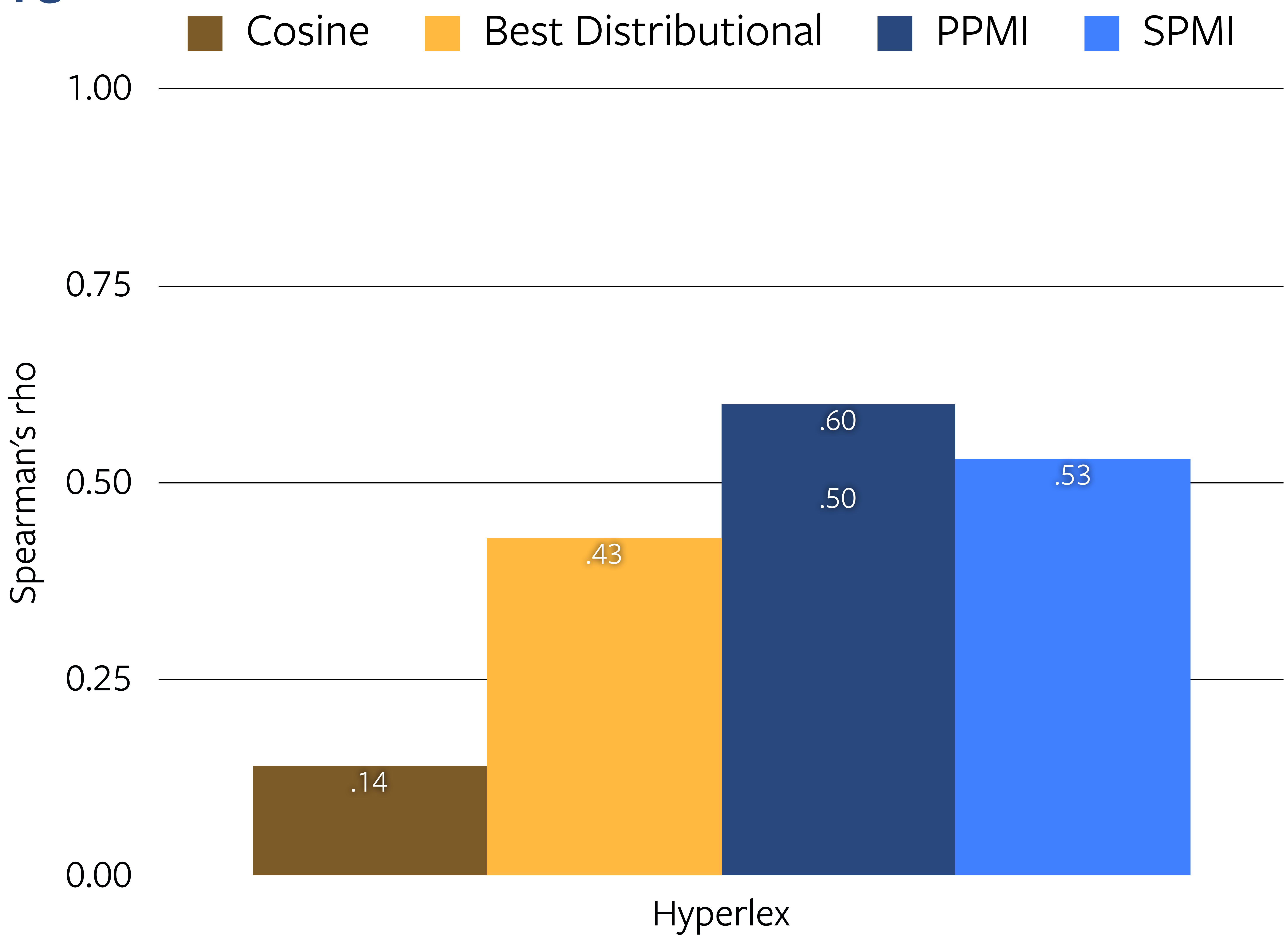
Direction

- Detection + Direction difficult for distributional methods
- Patterns outperform distr. methods on 2/3
  - BLESS pathologically difficult for cosine and PPMI
- SPMI significantly better
- Embedding patterns overcomes sparsity



Graded Entailment

- Pattern based methods outperform distr.
- Embedding hurts...
  - Spearman's rho doesn't punish ties (many 0s)
  - Add small noise (10^{-6}) to PPMI model to break ties randomly
  - SPMI best after adjustment



Conclusions

- Pattern-based approaches outperform distributional methods
  - Targeted Hearst contexts are more valuable than semantic similarity gains
- Embedding Hearst patterns works well
  - Helps substantially with sparsity issues
- We open source our experiments and evaluation framework:
  https://github.com/facebookresearch/hypernymysuite

Thank you!
Questions?