Predicting Semantic Relations using Global Graph Properties

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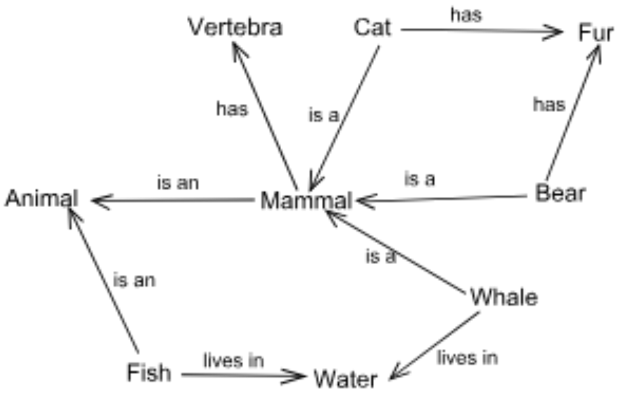
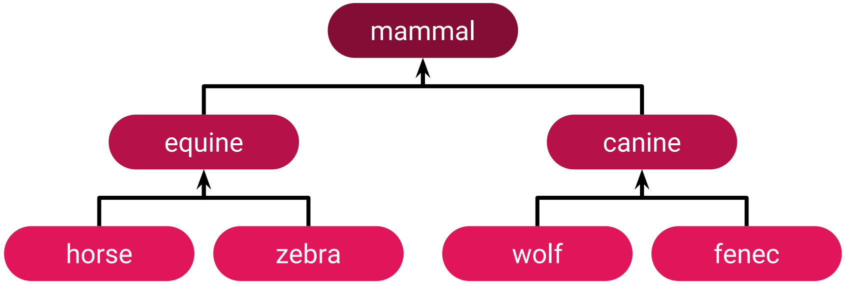
Semantic Graphs

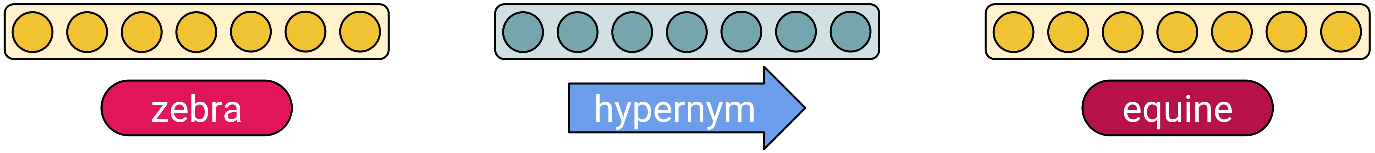
- **WordNet**-like resources are curated to describe relations between word senses
- The graph is **directed**
  - Edges have form <S, r, T>: <*zebra*, is-a, *equine*>
  - Still, some relations are symmetric
- Relation types include:
  - Hypernym (is-a) <*zebra*, r, *equine*>
  - Meronym (is-part-of) <*tree*, r, *forest*>
  - Is-instance-of <*rome*, r, *capital*>
  - Derivational Relatedness <*nice*, r, *nicely*>





Semantic Graphs - Relation Prediction

- The task of predicting relations (*zebra* is a *<BLANK>*)
- **Local** models use embeddings-based composition for scoring edges



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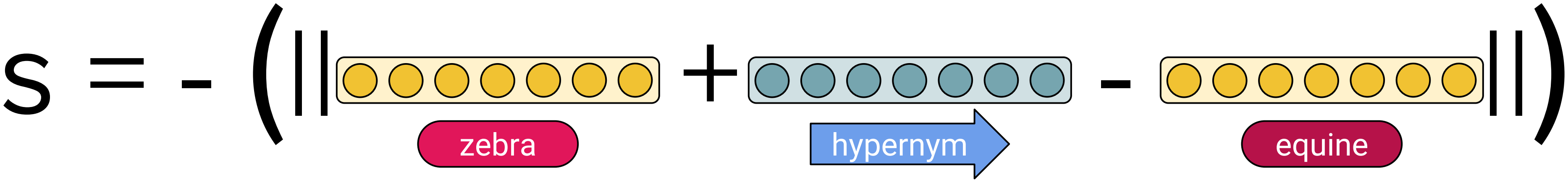

Translational Embeddings (transE) [Bordes et al. 2013]

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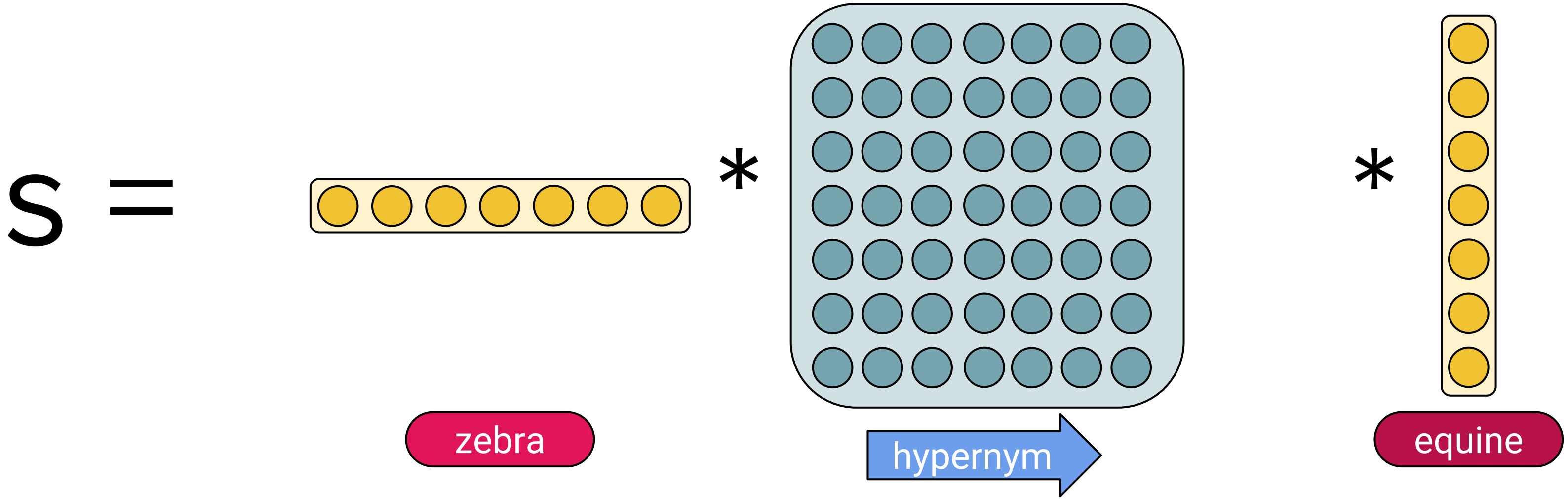

Full-Bilinear (Bilin) [Nickel et al. 2011]

Semantic Graphs - Relation Prediction

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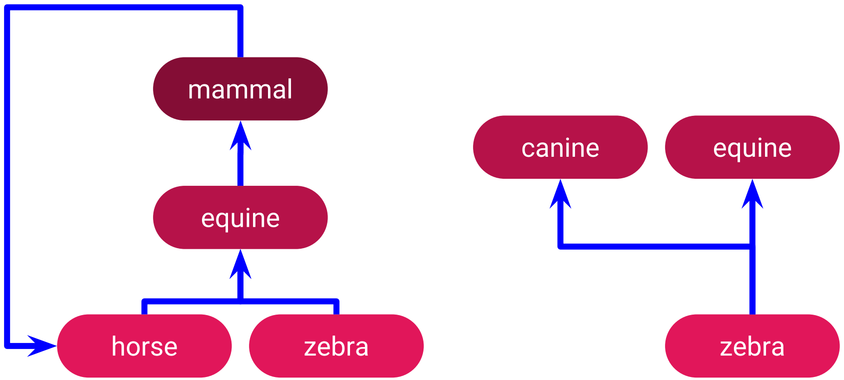
- **Local** models use embeddings-based composition for scoring edges
- Problem: task-driven method can learn unreasonable graphs



Incorporating a Global View

- We want to avoid unreasonable graphs
- Imposing hard constraints isn’t flexible enough
  - Only takes care of **impossible graphs**
  - Requires domain knowledge
- We still want the local signal to matter - it’s very strong.

Incorporating a Global View

- We want to avoid unreasonable graphs
- Imposing hard constraints isn't flexible enough
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- We still want the local signal to matter - it's very strong.
- Our solution: an additive, learnable **global graph score**

$$\text{Score}(\langle \textit{zebra}, \text{hypernym}, \textit{equine} \rangle \mid \textbf{WordNet}) =$$

$$s_{local}(\text{edge}) + \Delta\left(s_{global}(\text{WN} + \text{edge}),\ s_{global}(\text{WN})\right)$$

Global Graph Score

- Based on a framework called Exponential Random Graph Model (**ERGM**)
- The score $s_{global}(WN)$ is derived from a log-linear distribution across possible graphs that have a fixed number *n* of nodes

$$p_{ERGM}(WN) \propto \exp(\boldsymbol{\theta}^{T} \cdot \boldsymbol{\Phi}(WN))$$

Weights vector

Graph features

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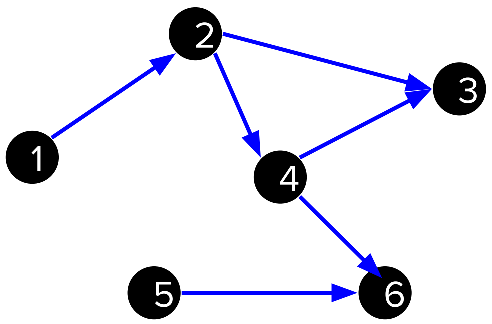
- OK. What are the **features**?

Graph Features (*Motifs*)

- #edges: 6
- #targets: 4
- #3-cycles: 0
- #2-paths: 4
- Transitivity: ¼ = 0.25



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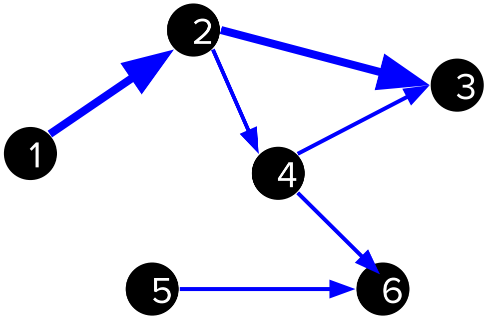

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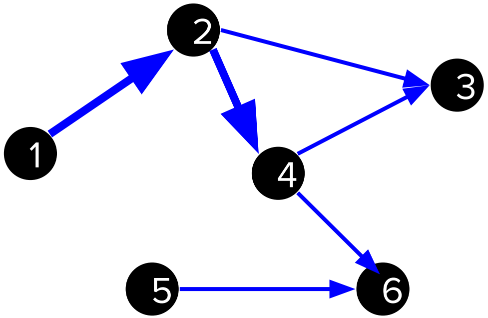

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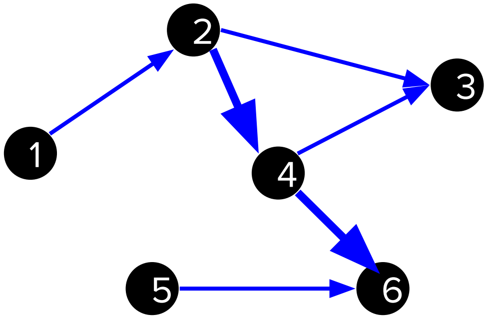

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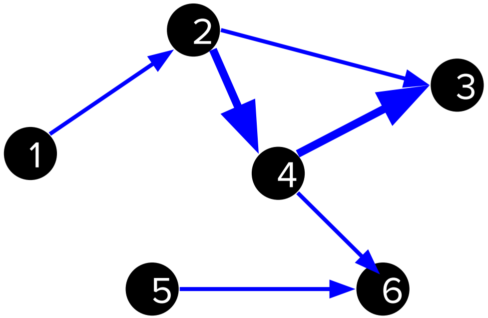

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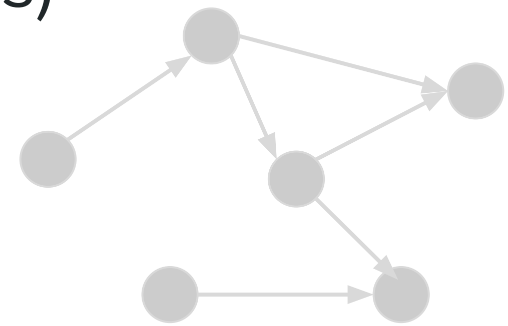

(some) joint blue/orange motifs:

- #edges {b, o}: 9
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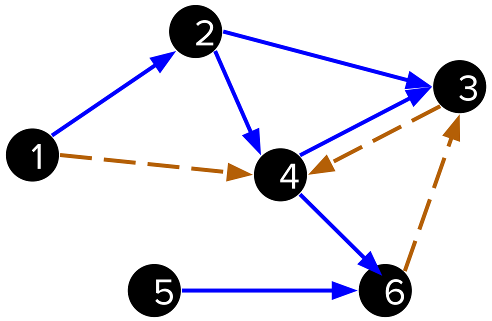

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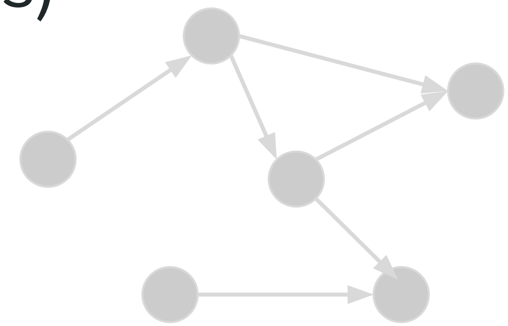

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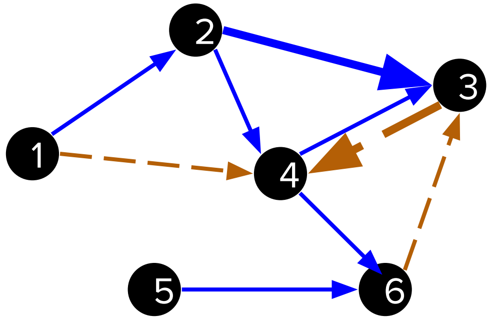

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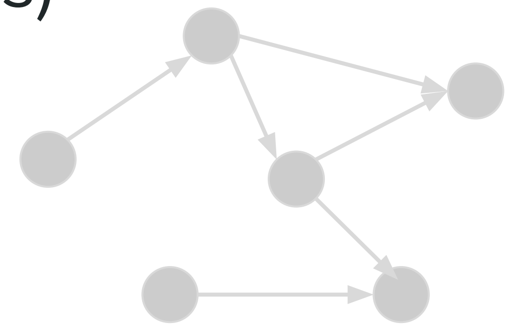

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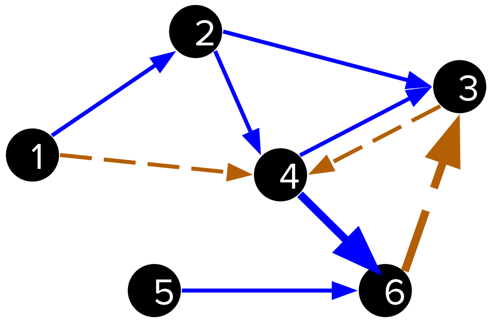

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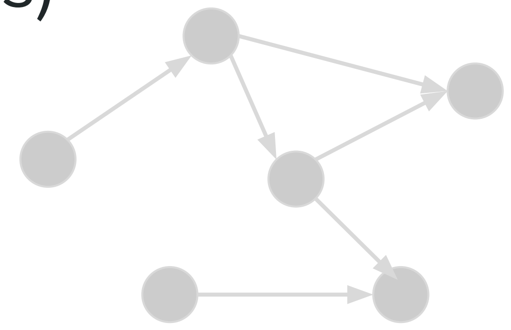

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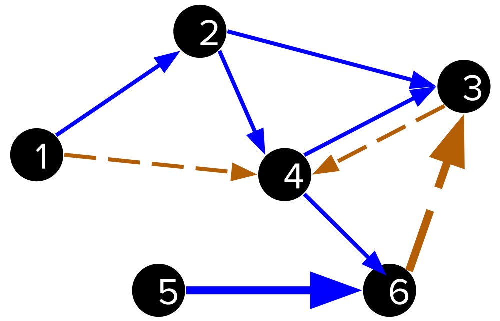

ERGM Training

- Estimating the scores for all possible graphs to obtain a probability distribution is **implausible**
  - Number of possible directed graphs with **n** nodes: $\mathbf{O(exp(n^2))}$
  - **n** nodes, **R** relations: $\mathbf{O(exp(R*n^2))}$
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<u>What can we do?</u>

- Decompose score over dyads (node pairs) in graph
- Draw and score negative sample graphs

Max-Margin Markov Graph Model (M3GM)

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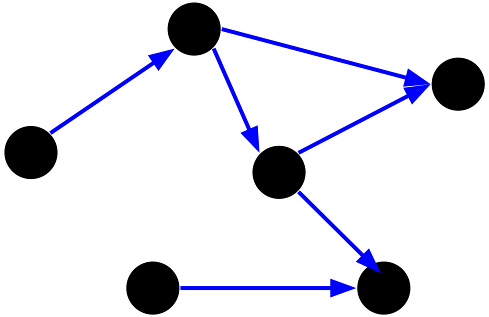

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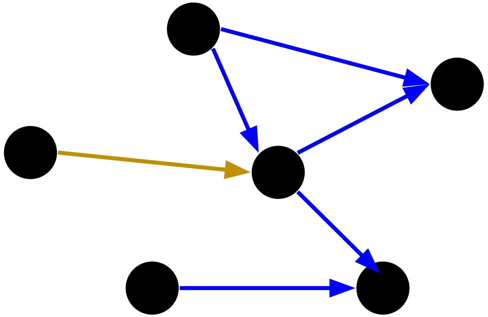

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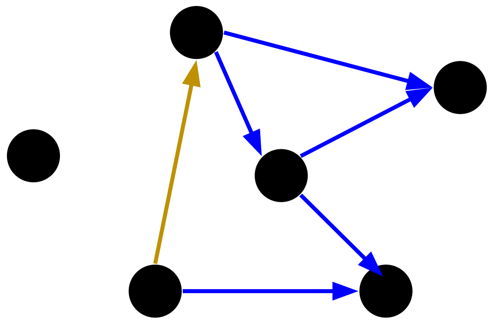

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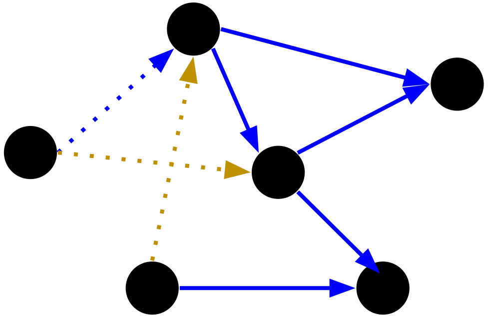
- Loss = Max $\{0, 1 + \text{score(negative sample)} - \text{score(WN)}\}$



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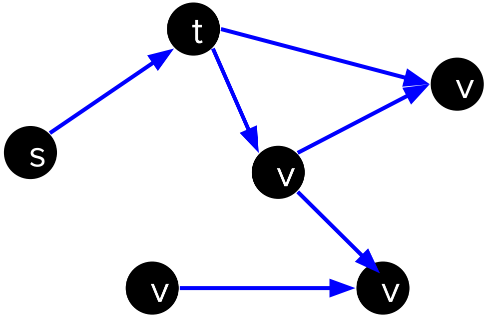

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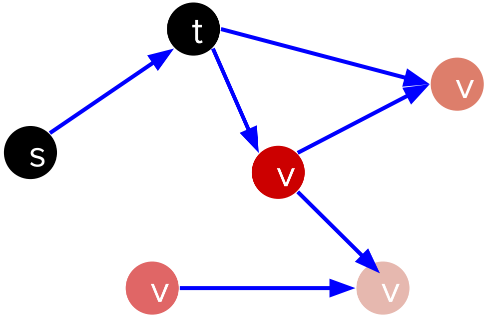
- We want to make things **hard** for the scorer



$$Q(v|s, r) \propto s_{local}(\langle s, r, v \rangle)$$

Evaluation

- Dataset - WN18RR
  - No reciprocal relations (hypernym ⇔ hyponym)
  - **Still includes symmetric relations**
- Metrics - MRR, H@10

- Rule baseline - take symmetric if exists in train
  - Used in all models as default for symmetric relations
- Local models
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- M3GM (re-rank top 100 from local)
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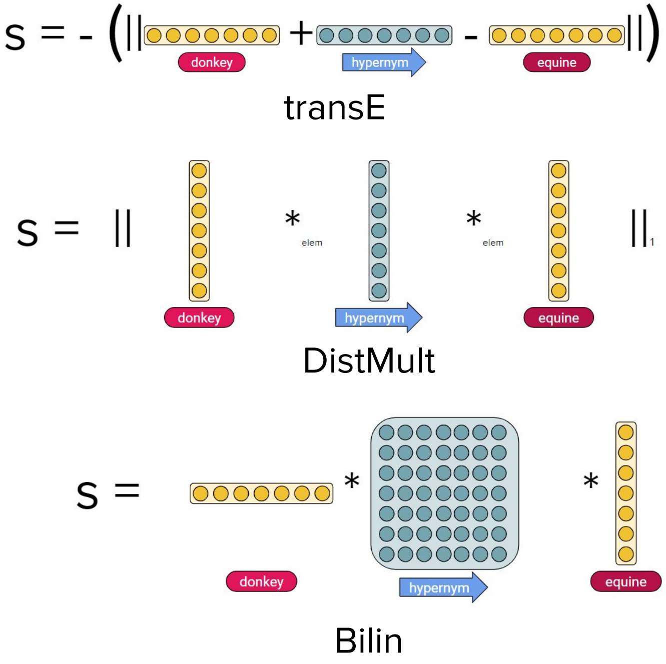

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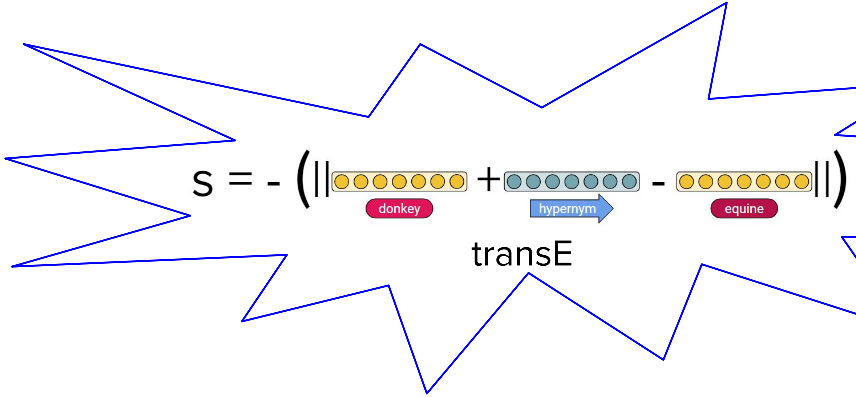

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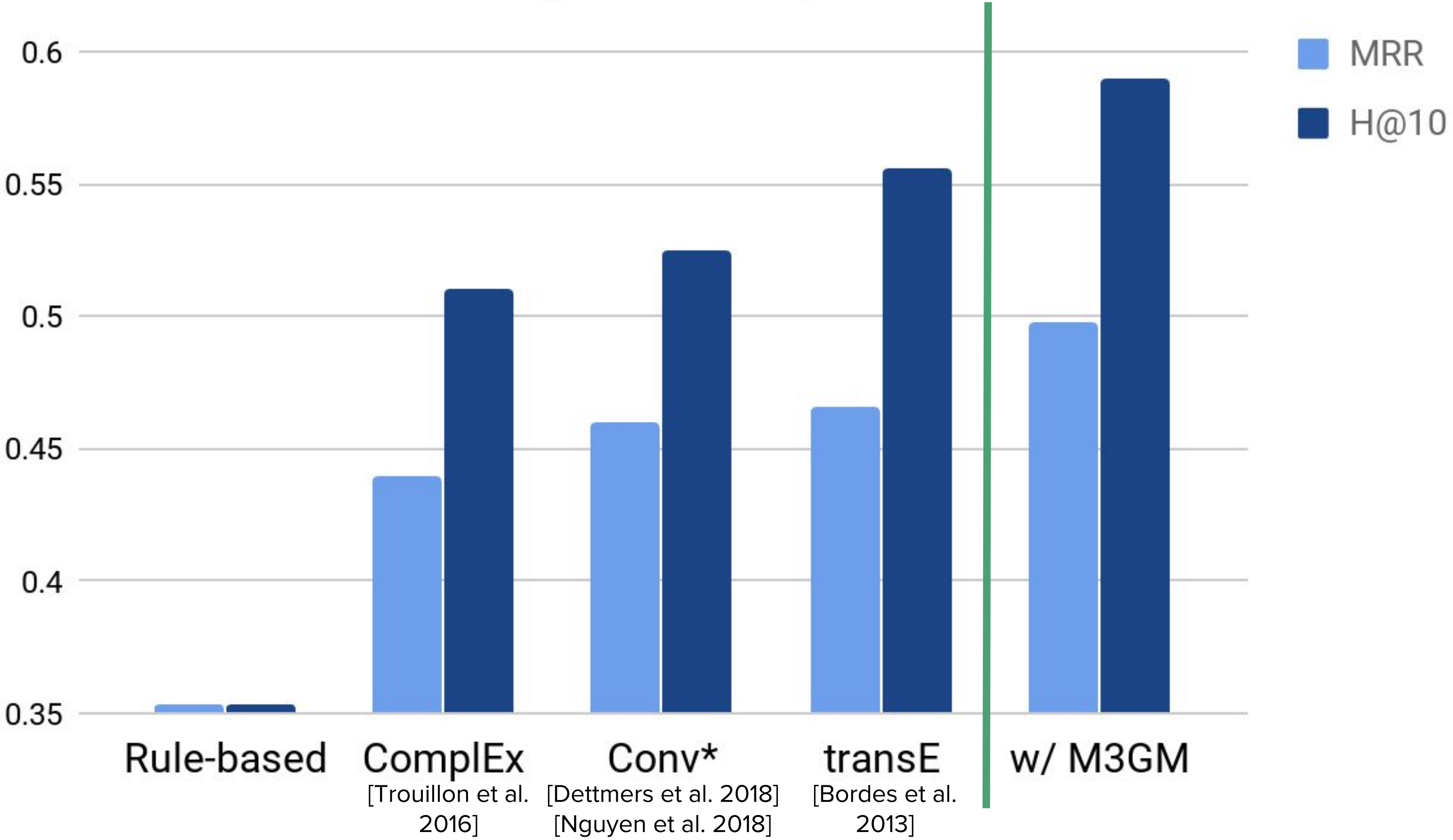
Relation Prediction (WN18RR)



Feature Analysis

- Motifs with heavy positive weights:
    - Targets of *has_part*
    - Two-paths *hypernym* ➔ *derivationally_related_form*
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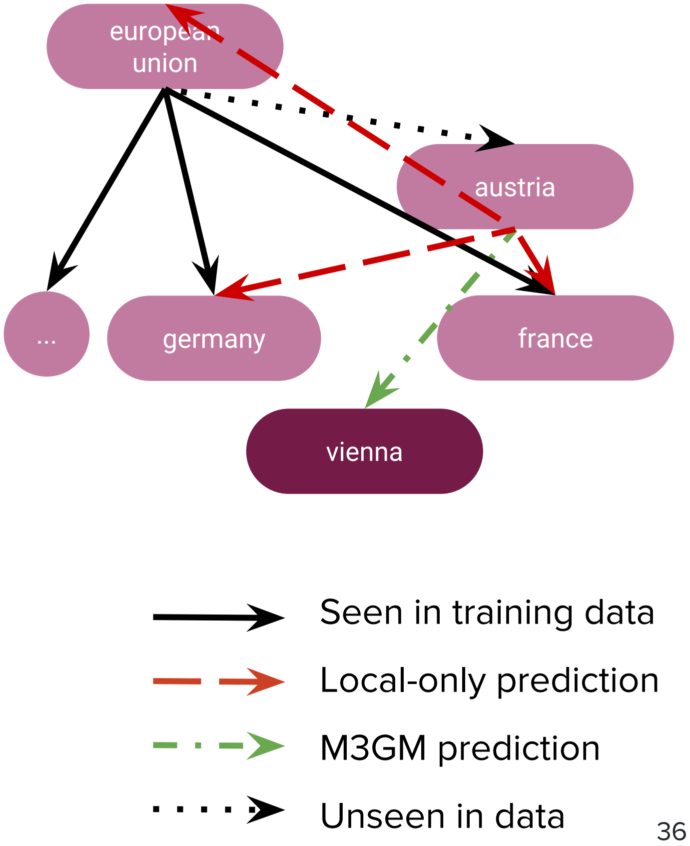

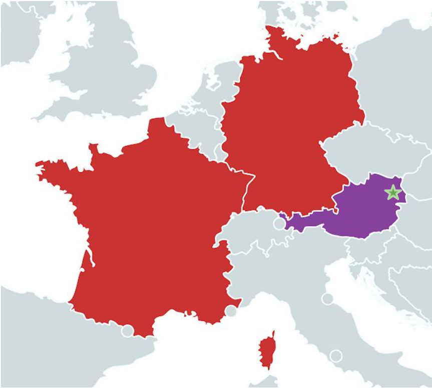

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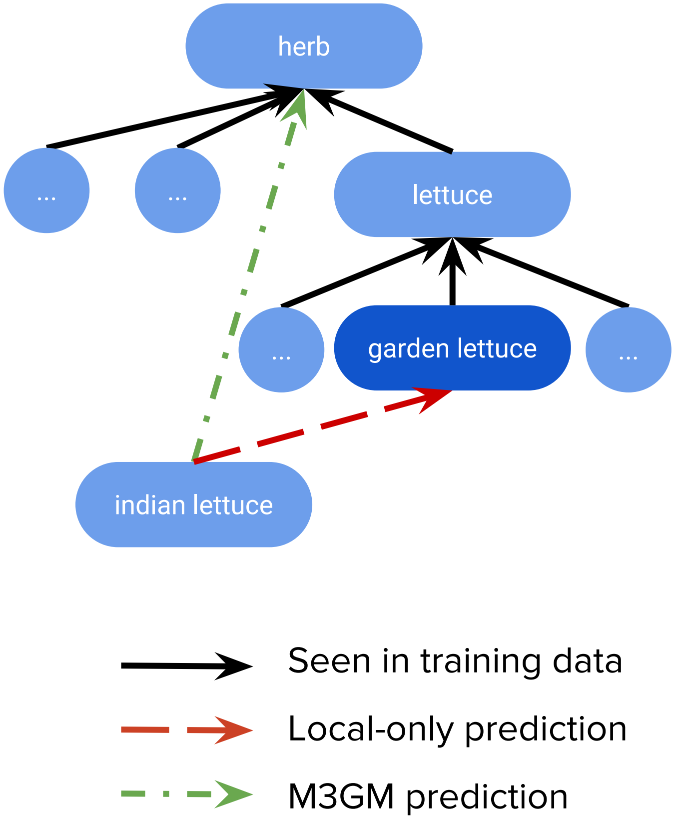

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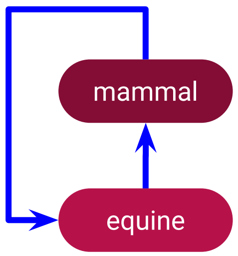

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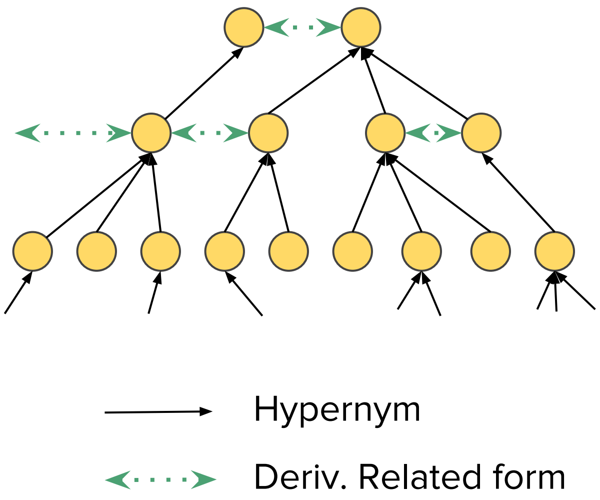
"Derivations occur in the abstract parts of the graph"

(*bodega* / *canteen* vs. *shop*)



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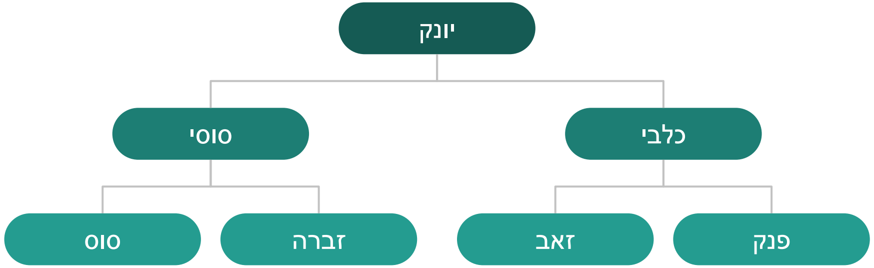
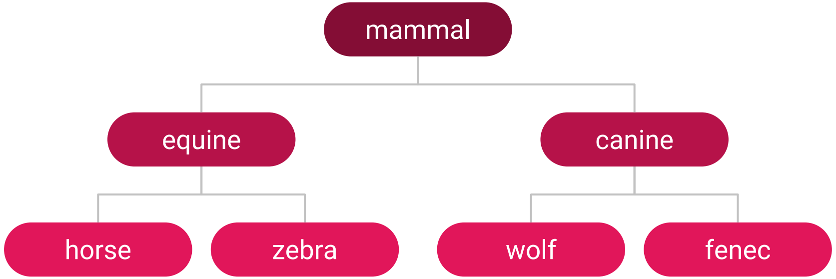
Nouns **Verbs**

Future Work

- Multilingual transfers of semantic graphs





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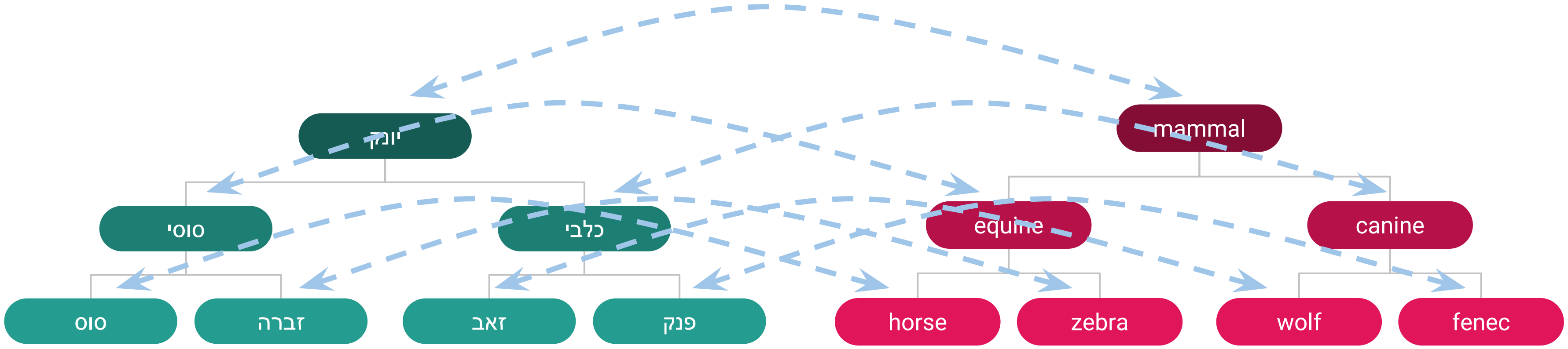

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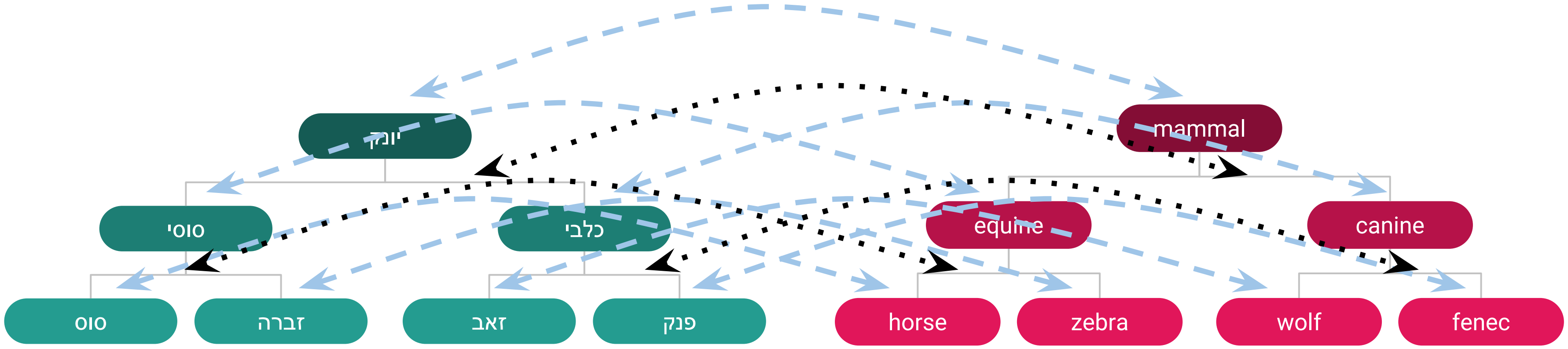
- Can we introduce global features to help?



Conclusion

- Global reasoning of graph features is beneficial for relation prediction
- Works well on top of strong local models
- Applicable to large graphs with dozens of relation types ← **M3GM**
- Orthogonal of word / synset embedding techniques
- Finds a wide variety of linguistic patterns in semantic graphs

Thanks

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