A Family of Fuzzy Orthogonal Projection Models for Monolingual and Cross-lingual Hypernymy Prediction

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Outline

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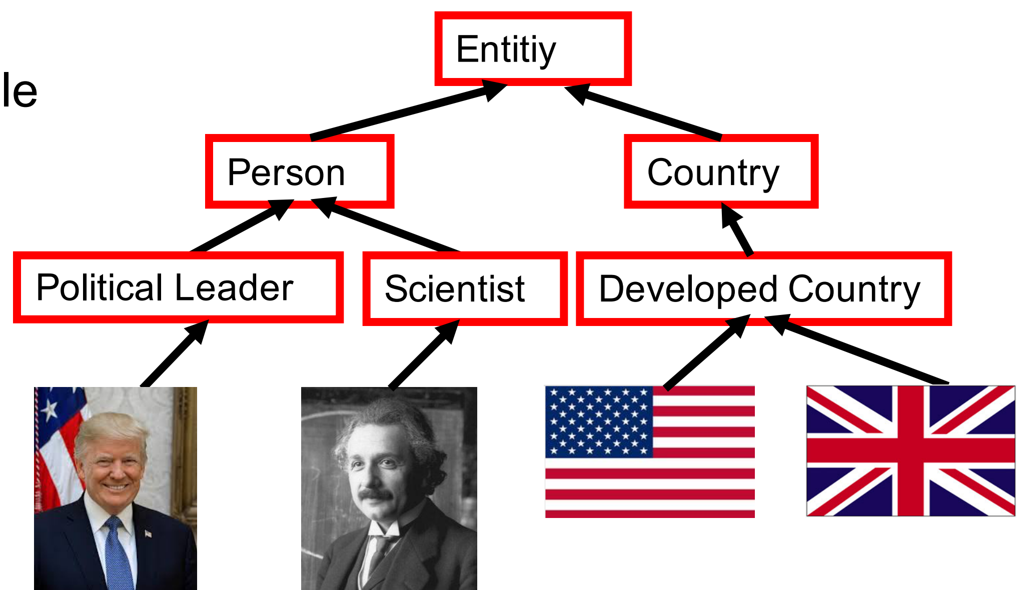
Introduction (1)

- Hypernymy ("is-a") relations are important for NLP and Web applications.
  - Semantic resource construction: semantic hierarchies, taxonomies, knowledge graphs, etc.
  - Web-based applications: query understanding, post-search navigation, personalized recommendation, etc.

A simple example of taxonomy



Introduction (2)

- Research challenges for predicting hypernymy relations between words:
  - Monolingual hypernymy prediction
    - Pattern-based approaches: have low recall
    - Distributional classifiers: suffer from the "lexical memorization" problem
  - Cross-lingual hypernymy prediction
    - The small size of training sets for lower-resourced languages
    - Not sufficient research in this area

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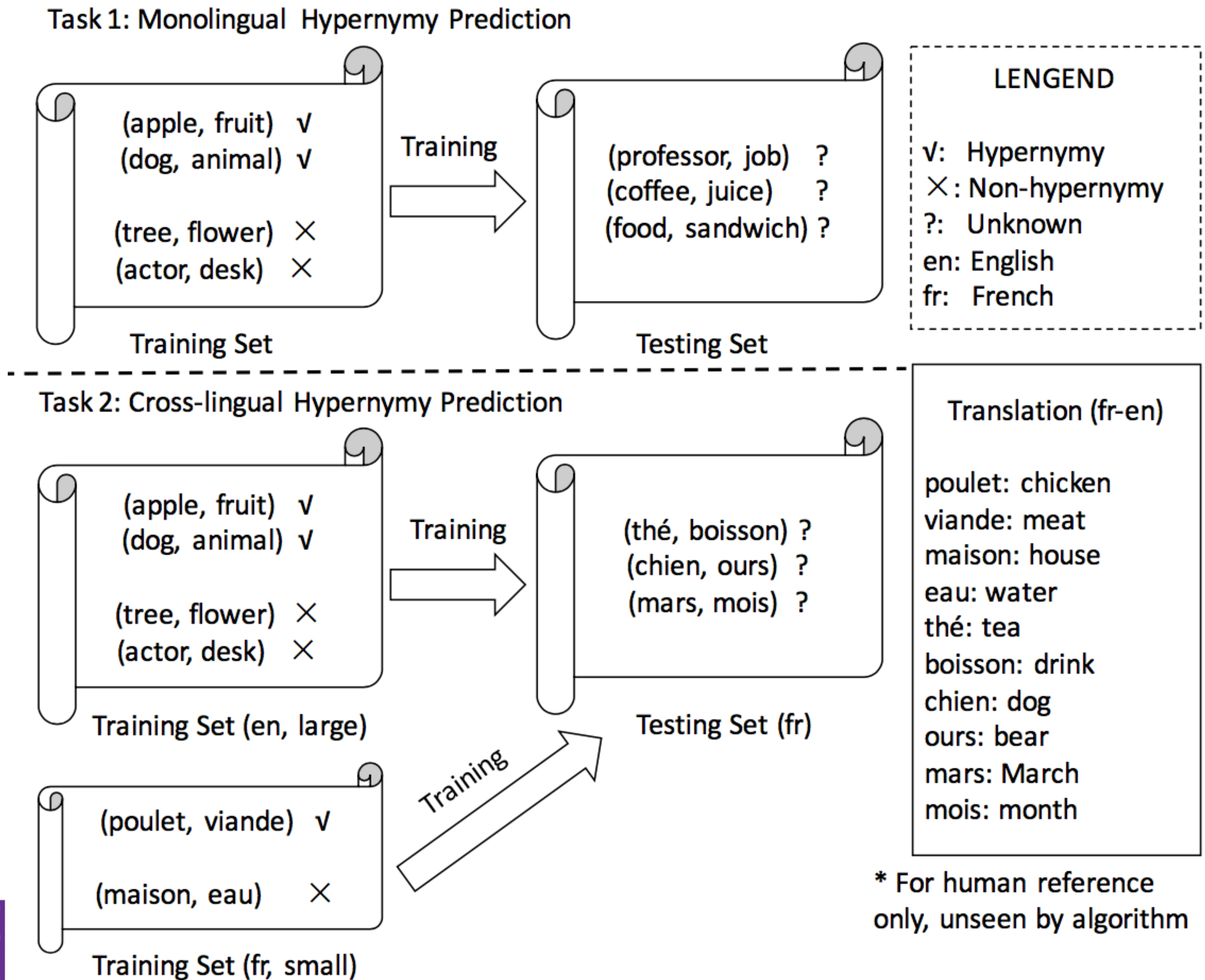
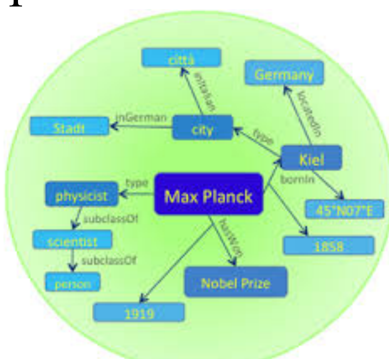

Task 1: Monolingual Hypernymy Prediction
(apple, fruit) √
(dog, animal) √
(tree, flower) ×
(actor, desk) ×
Training Set
Training
(professor, job) ?
(coffee, juice) ?
(food, sandwich) ?
Testing Set
LENGEND
√: Hypernymy
×: Non-hypernymy
?: Unknown
en: English
fr: French
Task 2: Cross-lingual Hypernymy Prediction
(apple, fruit) √
(dog, animal) √
(tree, flower) ×
(actor, desk) ×
Training Set (en, large)
Training
(thé, boisson) ?
(chien, ours) ?
(mars, mois) ?
Testing Set (fr)
Training
(poulet, viande) √
(maison, eau) ×
Training Set (fr, small)
Translation (fr-en)
poulet: chicken
viande: meat
maison: house
eau: water
thé: tea
boisson: drink
chien: dog
ours: bear
mars: March
mois: month
* For human reference only, unseen by algorithm

Related Work (1)

- Monolingual hypernymy prediction
  - Pattern based approaches:
    - Handcraft patterns: high accuracy, low coverage
      - Hearst Patterns: NP1 such as NP2
    - Automatic generated patterns: higher coverage, lower accuracy
    - High language dependency
  - Distributional approaches:
    - Unsupervised distributional measures: relatively low precision
    - Supervised distributional classifiers: suffer from the "lexical memorization" problem

Related Work (2)

- Cross-lingual hypernymy prediction
  - Learning multi-lingual taxonomies based on existing knowledge sources
    - YAGO3: Muti-lingual Wikipedia + WordNet
    - More precise but have limited scope constrained by sources



  - This task has not been extensively studied for lower-resourced languages.

Monolingual Model (1)

- Basic Notations
  - Hypernymy training set $D^{(+)} = \{(x_i, y_i^{(+)})\}$
  - Non-hypernymy training set $D^{(-)} = \{(x_i, y_i^{(-)})\}$
- Orthogonal Projection Model for Hypernymy Relations
  - Objective function

Normalized embeddings

$$\min \sum_{i=1}^{|D^{(+)}|} ||\mathbf{M}\vec{x}_i - \vec{y}_i^{(+)}||^2 \ \ \text{s. t.} \ \ \mathbf{M}^T\mathbf{M} = \mathbf{I}$$

Adding orthogonal constraints to guarantee normalization!

  - It does not consider the complicated linguistic regularities of hypernymy relations.

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Monolingual Model (2)

- Fuzzy Orthogonal Projection Model for Hypernymy Relations
  - Apply K-means to $D^{(+)}$ over the features $\vec{x}_i - \vec{y}_i^{(+)}$ with cluster centroids as $\vec{c}_1^{(+)}, \vec{c}_2^{(+)}, \cdots, \vec{c}_K^{(+)}$.
  - Compute the weight of $(x_i, y_i^{(+)})$ in $D^{(+)}$ w.r.t. the jth cluster.

$$a_{i,j}^{(+)} = \frac{\cos(\vec{x}_i - \vec{y}_i^{(+)}, \vec{c}_j^{(+)})}{\sum_{i'=1}^{|D^{(+)}|} \cos(\vec{x}_{i'} - \vec{y}_{i'}^{(+)}, \vec{c}_j^{(+)})}$$

  - Objective function

$$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{1}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \| \mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)} \|^2$$

Multi-Wahba Projection (MWP)

$$\text{s. t. } {\mathbf{M}_j^{(+)}}^T \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1, j = 1, \ldots, K$$

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Some Observations

- Objective Function

Multi-Wahba Projection (MWP)

$$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{1}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(+)T} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1, j = 1, \ldots, K$$

  - The optimization of different matrices is independent from each other!

Extended Wahba's Problem

$$\min J(\mathbf{M}_j^{(+)}) = \frac{1}{2} \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(+)T} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1$$

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Monolingual Model (3)

- Solving the MWP Problem
  - Consider the jth cluster only:

$$\min J(\mathbf{M}_j^{(+)}) = \frac{1}{2}\sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)}\vec{x}_i - \vec{y}_i^{(+)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(+)T}\mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1$$

  - An SVD-based closed-form solution:

(1) $\mathbf{B}_j = \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \vec{y}_i^{(+)} \vec{x}_i^T;$

(2) $SVD(\mathbf{B}_j) = \mathbf{U}_j \Sigma_j \mathbf{V}_j^T;$

(3) $\mathbf{R}_j = diag(\underbrace{1, \ldots, 1}_{d-1}, det(\mathbf{U}_j) det(\mathbf{V}_j));$

(4) $\mathbf{M}_j^{(+)} = \mathbf{U}_j \mathbf{R}_j \mathbf{V}_j^T;$

Refer to the paper for the proof of correctness.

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Monolingual Model (4)

- Overall Procedure
  - Learning hypernymy projections

$$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{1}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(+)T} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1, j = 1, \ldots, K$$

  - Learning non-hypernymy projections

$$\min \tilde{J}(\mathcal{M}^{(-)}) = \frac{1}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D^{(-)}|} a_{i,j}^{(-)} \|\mathbf{M}_j^{(-)} \vec{x}_i - \vec{y}_i^{(-)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(-)T} \mathbf{M}_j^{(-)} = \mathbf{I}, \sum_{i=1}^{|D^{(-)}|} a_{i,j}^{(-)} = 1, j = 1, \ldots, K$$

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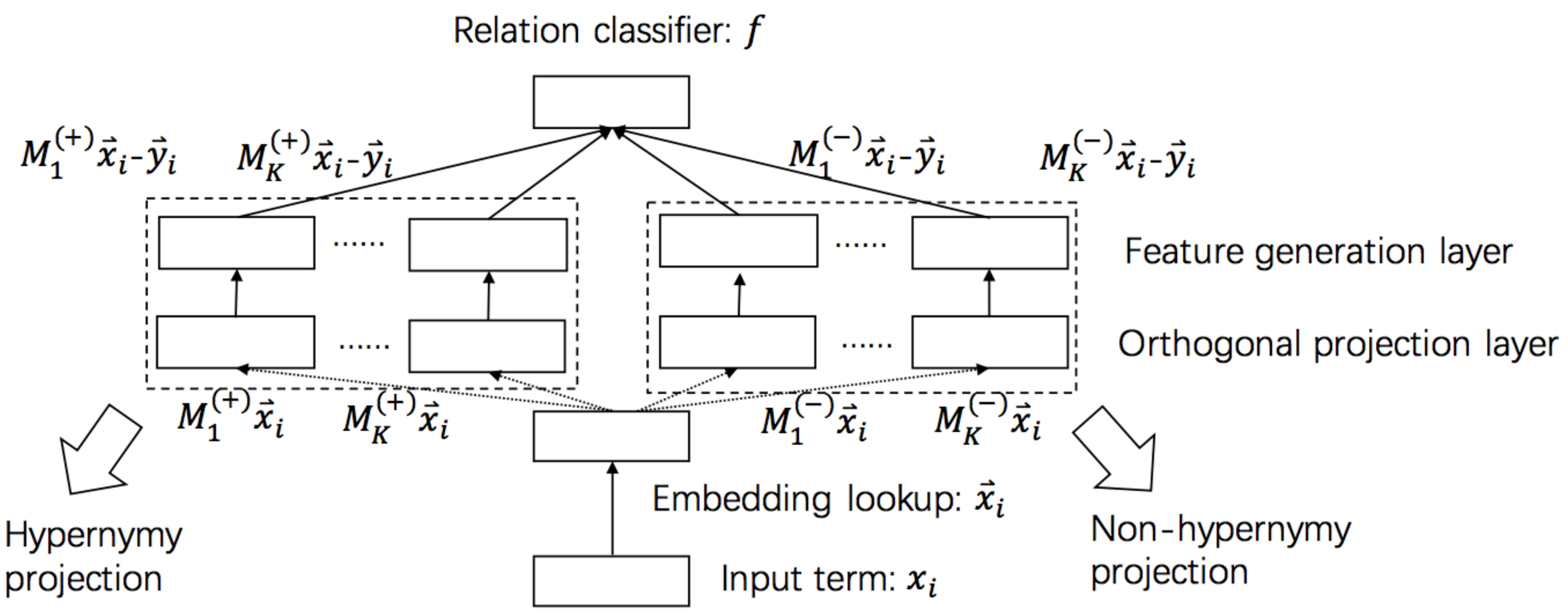
Monolingual Model (5)

- Overall Procedure
  - Training the projection-based neural network



Cross-lingual Models (1)

- Basic Notations
  - Hypernymy training sets
    - Source language: $D_S^{(+)}$
    - Target language: $D_T^{(+)}$

    $$\left|D_S^{(+)}\right| \gg \left|D_T^{(+)}\right|$$
  - Non-hypernymy training sets
    - Source language: $D_S^{(-)}$
    - Target language: $D_T^{(-)}$

    $$\left|D_S^{(-)}\right| \gg \left|D_T^{(-)}\right|$$
  - Unlabeled set of the target language: $U_T = \{(x_i, y_i)\}$

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Cross-lingual Models (2)

- Transfer MWP Model (TMWP)
  - Learning hypernymy projections

$$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{\beta}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D_S^{(+)}|} a_{i,j}^{(+)} \gamma_i^{(+)} \|\mathbf{M}_j^{(+)} \mathbf{S} \vec{x}_i - \mathbf{S} \vec{y}_i^{(+)}\|^2$$
$$+ \frac{1-\beta}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D_T^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2$$
$$\text{s. t. } \mathbf{M}_j^{(+)T} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D_S^{(+)}|} a_{i,j}^{(+)} \gamma_i^{(+)} = 1, \sum_{i=1}^{|D_T^{(+)}|} a_{i,j}^{(+)} = 1,$$
$$j = 1, \ldots, K$$

S: maps the embeddings of the source language to the target language by Bilingual Lexicon Induction

  - β: controls the importance of training sets of source and target languages.
  - $\gamma_i^{(+)}$: controls the individual weight of each training instance of the source language

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Cross-lingual Models (3)

- Transfer MWP Model (TMWP)
  - Hypernymy projections in TMWP can also be converted into a high-dimensional Wahba's problem.
  - The SVD-based closed form solution:

$$(1)\ \mathbf{B}_j = \beta \sum_{i=1}^{|D_S^{(+)}|} a_{i,j}^{(+)} \gamma_i^{(+)} \mathbf{S}\vec{y}_i^{(+)} (\mathbf{S}\vec{x}_i)^T + (1-\beta) \sum_{i=1}^{|D_T^{(+)}|} a_{i,j}^{(+)} \vec{y}_i^{(+)} \vec{x}_i^T;$$

$$(2)\ SVD(\mathbf{B}_j) = \mathbf{U}_j \Sigma_j \mathbf{V}_j^T;$$

$$(3)\ \mathbf{R}_j = diag(\underbrace{1, \ldots, 1}_{d-1}, det(\mathbf{U}_j) det(\mathbf{V}_j));$$

$$(4)\ \mathbf{M}_j^{(+)} = \mathbf{U}_j \mathbf{R}_j \mathbf{V}_j^T;$$

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Cross-lingual Models (4)

- Transfer MWP Model (TMWP)
  - Learning non-hypernymy projections

$$\min \tilde{J}(\mathcal{M}^{(-)}) = \frac{\beta}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D_S^{(-)}|} a_{i,j}^{(-)} \gamma_i^{(-)} \|\mathbf{M}_j^{(-)} \mathbf{S} \vec{x}_i - \mathbf{S} \vec{y}_i^{(-)}\|^2 + \frac{1-\beta}{2} \sum_{j=1}^{K} \sum_{i=1}^{|D_T^{(-)}|} a_{i,j}^{(-)} \|\mathbf{M}_j^{(-)} \vec{x}_i - \vec{y}_i^{(-)}\|^2$$

$$\text{s. t. } \mathbf{M}_j^{(-)T} \mathbf{M}_j^{(-)} = \mathbf{I}, \sum_{i=1}^{|D_S^{(-)}|} a_{i,j}^{(-)} \gamma_i^{(-)} = 1, \sum_{i=1}^{|D_T^{(-)}|} a_{i,j}^{(-)} = 1, \quad j = 1, \ldots, K$$

  - Training the projection-based neural network

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Cross-lingual Models (5)

- Iterative Transfer MWP Model (ITMWP)
  - Employ semi-supervised learning for training set augmentation

Algorithm 3 Cross-lingual Hypernymy Prediction (ITMWP)

Train TMWP over $D_S^{(+)}$, $D_S^{(-)}$, $D_T^{(+)}$ and $D_T^{(-)}$ by Algorithm 2;
while not converge **do**
    for each pair $(x_i, y_i) \in U_T$ **do**
        if $conf(x_i, y_i) > \tau$ **then**
            if $f(x_i, y_i) =$ HYPERNYMY **then**
                Update $D_T^{(+)} = D_T^{(+)} \cup \{(x_i, y_i)\}$;
            else
                Update $D_T^{(-)} = D_T^{(-)} \cup \{(x_i, y_i)\}$;
            end if
            Update $U_T = U_T \setminus \{(x_i, y_i)\}$
        end if
    end for
    Update TMWP over $D_S^{(+)}$, $D_S^{(-)}$, $D_T^{(+)}$ and $D_T^{(-)}$ by Algorithm 2;
end while

Monolingual Experiments (1)

- Task 1: Supervised hypernymy detection
  - MWP outperforms state-of-the-art over two benchmark datasets (BLESS and ENTAILMENT)

Method	BLESS	ENTAILMENT
Mikolov et al. [24]	0.84	0.83
Yu et al. [54]	0.90	0.87
Luu et al. [20]	0.93	0.91
Nguyen et al. [26]	0.94	0.91
MWP (Non-orthogonal)	**0.95**	0.90
MWP	**0.97**	**0.92**

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Monolingual Experiments (2)

- Task 1: Supervised hypernymy detection
  - MWP outperforms state-of-the-art over three domain-specific datasets derived from existing domain-specific taxonomies.

Method	**ANIMAL**	**PLANT**	**VEHICLE**
Mikolov et al. [24]	0.80	0.81	0.82
Yu et al. [54]	0.67	0.65	0.70
Luu et al. [20]	0.89	0.92	0.89
Nguyen et al. [26]*	0.83	0.91	0.83
MWP (Non-orthogonal)	**0.90**	**0.92**	0.87
MWP	**0.92**	**0.94**	**0.90**

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Monolingual Experiments (3)

- Task 2: Unsupervised hypernymy classification
  - Hypernymy measure: $\tilde{s}(x_i, y_i) = \left\|\mathcal{F}^{(-)}(\vec{x}_i, \vec{y}_i)\right\|_2 - \left\|\mathcal{F}^{(+)}(\vec{x}_i, \vec{y}_i)\right\|_2$

Hypernymy vs. Reverse-hypernymy

Hypernymy vs. Other relations

Measure	BLESS	WBLESS
Santus et al. [31]	0.87	-
Weeds et al. [49]	-	0.75
Kiela et al. [15]	0.88	0.75
Nguyen et al. [26]	0.92	0.87
Roller et al. [30]	0.96	0.87
MWP (Non-orthogonal)	0.95	**0.89**
MWP	**0.97**	**0.92**

Cross-lingual Experiments (1)

- Dataset Construction
  - English dataset: combining five human-labeled datasets (Training set)
    - 17,394 hypernymy relations
    - 67,930 non-hypernymy relations
  - Other languages: deriving from the Open Multilingual Wordnet project
    - 20% for training, 20% for development and 60% for testing

	French	Chinese	Japanese	Italian	Thai	Finnish	Greek
Relation↓ Language →	fr	zh	ja	it	th	fi	el
# Hypernymy relations	4,035	2,962	1,448	3,034	1,156	7,157	2,612
# Non-hypernymy relations	8,947	6,382	3,203	6,081	1,977	9,433	1,454

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Cross-lingual Experiments (2)

- Task 1: Cross-lingual hypernymy direction classification
  – hypernymy vs. reverse-hypernymy

Method	fr	zh	ja	it	th	fi	el
Task: cross-lingual hypernymy direction classification							
Santus et al. [31]	0.65	0.65	0.68	0.61	0.63	0.70	0.62
Weeds et al. [49]	0.76	0.71	0.77	0.76	0.72	0.77	0.70
Kiela et al. [15]	0.67	0.65	0.71	0.68	0.65	0.70	0.62
Shwartz et al. [34]	0.79	0.67	0.71	0.72	0.66	0.75	0.66
TMWP (N)	0.78	0.71	0.75	0.76	0.73	0.76	0.71
TMWP	0.80	0.72	0.76	0.78	0.75	0.78	0.73
ITMWP (N)	**0.82**	0.72	0.76	0.78	0.75	**0.81**	0.72
ITMWP	0.81	**0.74**	**0.78**	**0.81**	**0.78**	**0.81**	**0.75**

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Cross-lingual Experiments (3)

- Task 1: Cross-lingual hypernymy detection
  – hypernymy vs. non-hypernymy

Method	fr	zh	ja	it	th	fi	el
Task: cross-lingual hypernymy detection							
Santus et al. [31]	0.67	0.63	0.67	0.62	0.64	0.62	0.64
Weeds et al. [49]	0.74	0.66	0.68	0.71	0.62	0.68	0.69
Kiela et al. [15]	0.70	0.61	0.65	0.68	0.57	0.61	0.67
Shwartz et al. [34]	0.72	0.66	0.69	0.64	0.66	0.69	0.70
TMWP (N)	0.72	0.67	0.70	0.70	0.68	0.71	0.70
TMWP	0.75	0.71	0.76	0.72	0.69	0.72	0.71
ITMWP (N)	0.72	**0.74**	0.77	**0.74**	0.67	0.71	0.72
ITMWP	**0.76**	0.73	**0.78**	**0.74**	**0.72**	**0.73**	**0.73**

Conclusion

- Models
  - Monolingual hypernymy prediction: MWP
  - Cross-lingual hypernymy prediction: TMWP & ITMWP
- Results
  - State-of-the-art performance in monolingual experiments
  - Highly effective in cross-lingual experiments
- Future Works
  - Predicting multiple types of semantic relations over multiple languages
  - Improving improve cross-lingual hypernymy prediction via multi-lingual embeddings

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Thank You!

Questions & Answers