

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

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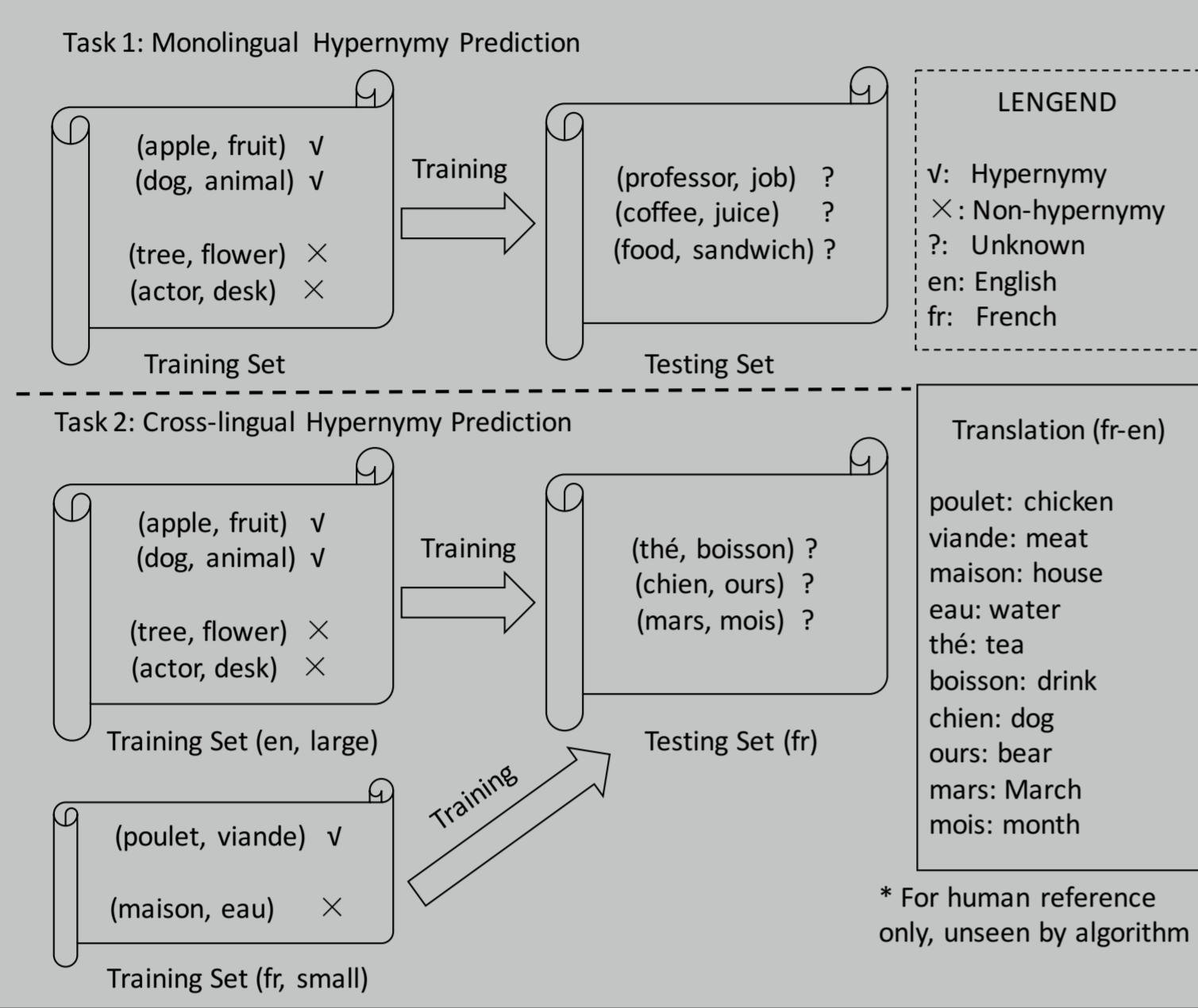
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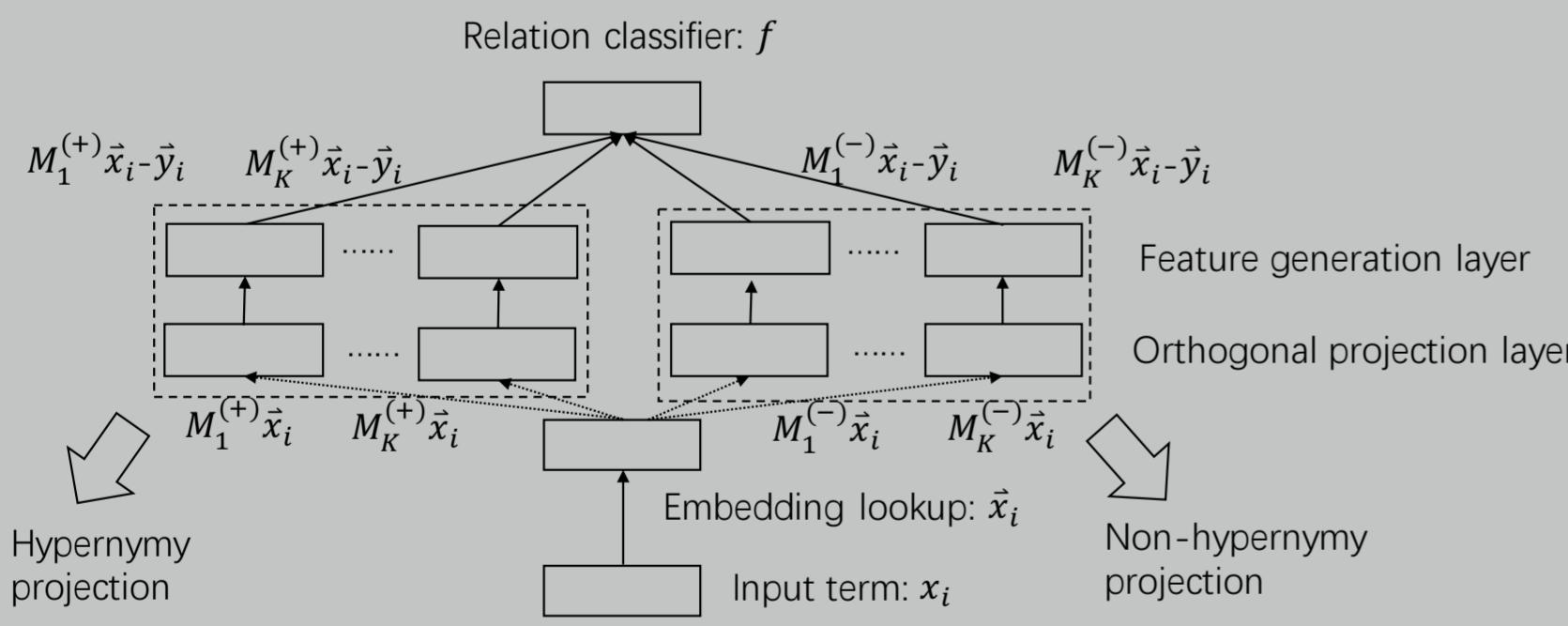
## Introduction

- Learning hypernymy relations is essential for taxonomy construction, fine-grained entity categorization, knowledge base population, etc.
- Previous monolingual distributional models may suffer from “lexical memorization”. The sizes of training sets for lower-resourced languages are usually small. Hence, cross-lingual models are necessary for these languages.
- We introduce a family of fuzzy orthogonal projection models for monolingual and cross-lingual hypernymy prediction.



## Monolingual Hypernymy Prediction Model: MWP

- Hypernymy fuzzy orthogonal projections ( $\mathcal{M}^{(+)} = \{\mathbf{M}_1^{(+)}, \dots, \mathbf{M}_K^{(+)}\}$ )
  - Input: a hypernymy relation set  $D^{(+)} = \{(x_i, y_i^{(+)})\}$
  - Learning objective ( $a_{i,j}^{(+)}$ : weight of  $(x_i, y_i^{(+)})$  w.r.t.  $j$ th cluster)
- $$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{1}{2} \sum_{j=1}^K \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2 \text{ s. t. } \mathbf{M}_j^{(+)\top} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D^{(+)}|} a_{i,j}^{(+)} = 1$$
- Non-hypernymy fuzzy orthogonal projections ( $\mathcal{M}^{(-)} = \{\mathbf{M}_1^{(-)}, \dots, \mathbf{M}_K^{(-)}\}$ )
  - Input: a non-hypernymy relation set  $D^{(-)} = \{(x_i, y_i^{(-)})\}$
  - Learning objective ( $a_{i,j}^{(-)}$ : weight of  $(x_i, y_i^{(-)})$  w.r.t.  $j$ th cluster)
- $$\min \tilde{J}(\mathcal{M}^{(-)}) = \frac{1}{2} \sum_{j=1}^K \sum_{i=1}^{|D^{(-)}|} a_{i,j}^{(-)} \|\mathbf{M}_j^{(-)} \vec{x}_i - \vec{y}_i^{(-)}\|^2 \text{ s. t. } \mathbf{M}_j^{(-)\top} \mathbf{M}_j^{(-)} = \mathbf{I}, \sum_{i=1}^{|D^{(-)}|} a_{i,j}^{(-)} = 1$$
- Training neural network-based hypernymy classifier



## Cross-lingual Hypernymy Prediction Models: TMWP and ITMWP

- Task input
    - Hypernymy sets of source and target languages ( $D_S^{(+)}$  and  $D_T^{(+)}$ )
    - Non-hypernymy sets of source and target languages ( $D_S^{(-)}$  and  $D_T^{(-)}$ )
    - Unlabeled relations  $U_T = \{(x_i, y_i)\}$  of the target language
  - Transfer MWP Model (TMWP)
    - Learning fuzzy orthogonal projections for hypernymy relations
    - $\beta$ : balance factor of two languages,  $\mathbf{S}$ : translation matrix (via bilingual lexicon induction),  $\gamma_i^{(+)}$ : additional weight of  $(x_i, y_i^{(+)}) \in D_S^{(+)} \cup D_T^{(+)}$
- $$\min \tilde{J}(\mathcal{M}^{(+)}) = \frac{\beta}{2} \sum_{j=1}^K \sum_{i=1}^{|D_S^{(+)}|} a_{i,j}^{(+)} \gamma_i^{(+)} \|\mathbf{M}_j^{(+)} \mathbf{S} \vec{x}_i - \mathbf{S} \vec{y}_i^{(+)}\|^2 + \frac{1-\beta}{2} \sum_{j=1}^K \sum_{i=1}^{|D_T^{(+)}|} a_{i,j}^{(+)} \|\mathbf{M}_j^{(+)} \vec{x}_i - \vec{y}_i^{(+)}\|^2 \text{ s. t. } \mathbf{M}_j^{(+)\top} \mathbf{M}_j^{(+)} = \mathbf{I}, \sum_{i=1}^{|D_S^{(+)}|} a_{i,j}^{(+)} \gamma_i^{(+)} = 1, \sum_{i=1}^{|D_T^{(+)}|} a_{i,j}^{(+)} = 1$$

## Cross-lingual Hypernymy Prediction Models: TMWP and ITMWP

- Transfer MWP Model (TMWP)
    - Learning fuzzy orthogonal projections for non-hypernymy relations
    - $\gamma_i^{(-)}$ : additional weight of  $(x_i, y_i^{(-)}) \in D_S^{(-)} \cup D_T^{(-)}$
- $$\min \tilde{J}(\mathcal{M}^{(-)}) = \frac{\beta}{2} \sum_{j=1}^K \sum_{i=1}^{|D_S^{(-)}|} a_{i,j}^{(-)} \gamma_i^{(-)} \|\mathbf{M}_j^{(-)} \mathbf{S} \vec{x}_i - \mathbf{S} \vec{y}_i^{(-)}\|^2 + \frac{1-\beta}{2} \sum_{j=1}^K \sum_{i=1}^{|D_T^{(-)}|} a_{i,j}^{(-)} \|\mathbf{M}_j^{(-)} \vec{x}_i - \vec{y}_i^{(-)}\|^2 \text{ s. t. } \mathbf{M}_j^{(-)\top} \mathbf{M}_j^{(-)} = \mathbf{I}, \sum_{i=1}^{|D_S^{(-)}|} a_{i,j}^{(-)} \gamma_i^{(-)} = 1, \sum_{i=1}^{|D_T^{(-)}|} a_{i,j}^{(-)} = 1$$
- Training neural network-based hypernymy classifier
- Iterative Transfer MWP Model (ITMWP)
  - Employing semi-supervised training data augmentation techniques over the TMWP model to improve the performance

## Monolingual Experiments

- Task 1: Supervised Hypernymy Detection
  - BLESS and ENTAILMENT: General-domain datasets
  - ANIMAL, PLANT and VEHICLE: Domain-specific datasets

Method	BLESS	ENTAILMENT	ANIMAL	PLANT	VEHICLE
Mikolov et al. (2013)	0.84	0.83	0.80	0.81	0.82
Yu et al. (2015)	0.90	0.87	0.67	0.65	0.70
Tuan et al. (2016)	0.93	0.91	0.89	0.92	0.89
Nguyen et al. (2017)	0.94	0.91	0.83	0.91	0.83
MWP (Non-orthogonal)	0.95	0.90	0.90	0.92	0.87
MWP	0.97	0.92	0.92	0.94	0.90

- Task 2: Unsupervised Hypernymy Relation Classification
  - The unsupervised measure:  $\tilde{s}(x_i, y_i) = \|\mathcal{F}^{(-)}(\vec{x}_i, \vec{y}_i)\|_2 - \|\mathcal{F}^{(+)}(\vec{x}_i, \vec{y}_i)\|_2$
  - BLESS: Hypernymy vs. Reverse-hypernymy
  - WBLESS: Hypernymy vs. Other relations

Method	BLESS	WBLESS
Santus et al. (2014)	0.87	-
Weeds et al. (2014)	-	0.75
Kiela et al. (2015)	0.88	0.75
Nguyen et al. (2017)	0.92	0.87
Roller et al. (2018)	0.96	0.87
MWP (Non-orthogonal)	0.95	0.89
MWP	0.97	0.92

## Cross-lingual Experiments

- Experimental Settings
  - Source language: 17,394 hypernymy relations and 67,930 non-hypernymy relations in English
  - Target languages: labeled word pairs of seven languages derived from the Open Multilingual Wordnet project
  - Learning settings: “few-shot learning” for target languages

### Experimental Results

Method	French	Chinese	Japanese	Italian	Thai	Finnish	Greek
Task: cross-lingual hypernymy direction classification							
Santus et al. (2014)	0.65	0.65	0.68	0.61	0.63	0.70	0.62
Weeds et al. (2014)	0.76	0.71	0.77	0.76	0.72	0.77	0.70
Kiela et al. (2015)	0.67	0.65	0.71	0.68	0.65	0.70	0.62
Shwartz et al. (2016)	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
Task: cross-lingual hypernymy detection							
Santus et al. (2014)	0.67	0.63	0.67	0.62	0.64	0.62	0.64
Weeds et al. (2014)	0.74	0.66	0.68	0.71	0.62	0.68	0.69
Kiela et al. (2015)	0.70	0.61	0.65	0.68	0.57	0.61	0.67
Shwartz et al. (2016)	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