Exploratory Neural Relation Classification for Domain Knowledge Acquisition

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Outline

- **Introduction**
- Related Work
- Proposed Approach
- Experiments
- Conclusion

Relation Extraction

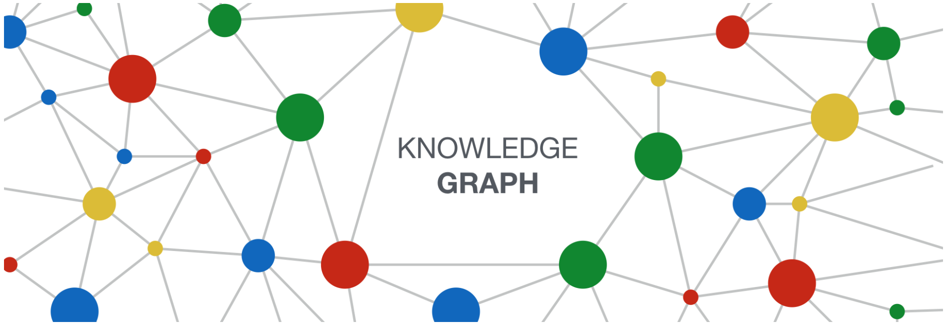
- Relation extraction
  - Structures the information from the Web by annotating the plain text with entities and their relations
    - E.g., "**Inception** is directed by **Christopher Nolan**."

      entity$_1$ relation entity$_2$

- Relation classification
  - Formulates relation extraction as a classification problem
    - E.g., (**Inception**, **Christopher Nolan**) should be classified as the relation "directed by", instead of "played by".

Domain Knowledge Acquisition

- Knowledge graph
  - Relation extraction is a key technique in constructing knowledge graphs.



- Challenges for domain knowledge graph
  - **Long-tail domain entities**: Most domain entities which follow long-tail distribution, leading to the context sparsity problem for pattern-based methods.
  - **Incomplete predefined relations**: Since predefined relations are limited, unlabeled entity pairs may be wrongly forced into existing relation labels.

Dynamic Structured Neural Network for Exploratory Relation Classification

- Goal
  1. Classifies entity pairs into a finite pre-defined relations
  2. Discovers new relations and instances from plain texts with high confidence
- Method
  - **Context sparsity problem:** A distributional embedding layer is introduced to encode corpus-level semantic features of domain entities.
  - **Limited label assignment:** A clustering method is proposed to generate new relations from unlabeled data which can not be classified to be any existing relations.

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Relation Classification Approaches

- Traditional approaches
  - Feature-based: applies textual analysis
    - N-grams, POS tagging, NER, dependency parsing
  - Kernel-based: similarity metric in higher dimensional space
    - Kernel functions are applied to strings, word sequences, parsing trees
  - Requires empirical features or well-designed kernel functions
- Deep learning models
  - Distributional representation: word embeddings
  - Neural network models:
    - CNN: extracts features with local information
    - RNN: captures long-term dependency on the sequence
  - Automatically extracts features

Relation Discovery Approaches

- Open relation extraction
  - automatically discovers relations from large-scale corpus with limited seed instances or patterns without predefined types
  - Representative systems: TextRunner, ReVerb, OLLIE
  - Inapplicable to domain knowledge due to data sparsity problem
- Clustering-based approaches
  - Predefined K: Standard KMeans
  - Automatically learned K: Non-parametric Bayesian models
    - Chinese restaurant process (CRP), distance dependent CRP (ddCRP)

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Task Definition

- Notations
  - Labeled entity pair set $X^l = \{(e_1, e_2)\}$ and their labels Y^l
  - Unlabeled entity pair set $X^u = \{(e_1, e_2)\}$
- Exploratory relation classification (ERC)
  - Trains a model to predict the relations for entity pairs in X^u with $K + n$ output labels, where K denotes the number of pre-defined relations in Y^l, and n is the number of newly discovered relations.

General Framework

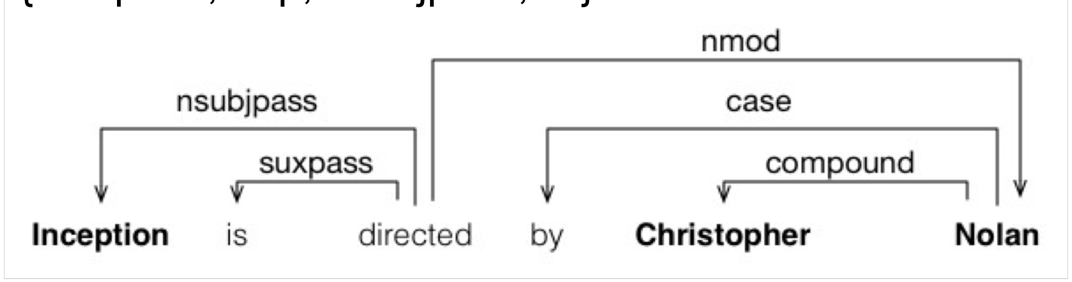
Algorithm 1 ERC Training Process

Input: Labeled data X^l and Y^l, unlabeled data X^u
Output: Expanded relation set R_{new}

while no new relations can be discovered **do**
    // Base neural network training
    Train base neural network N_t with X^l and Y^l
    // Relation discovery
    Generate candidate clusters $\{C_1, \ldots, C_m\}$ for X^u
    Pick the best cluster C^* from $\{C_1, \ldots, C_m\}$
    Update relation set $R_{new} = R_{new} \cup \{C^*\}$
    // Relation prediction
    Predict confident labels for unlabeled data X^u on R_{new}
end while
return R_{new}

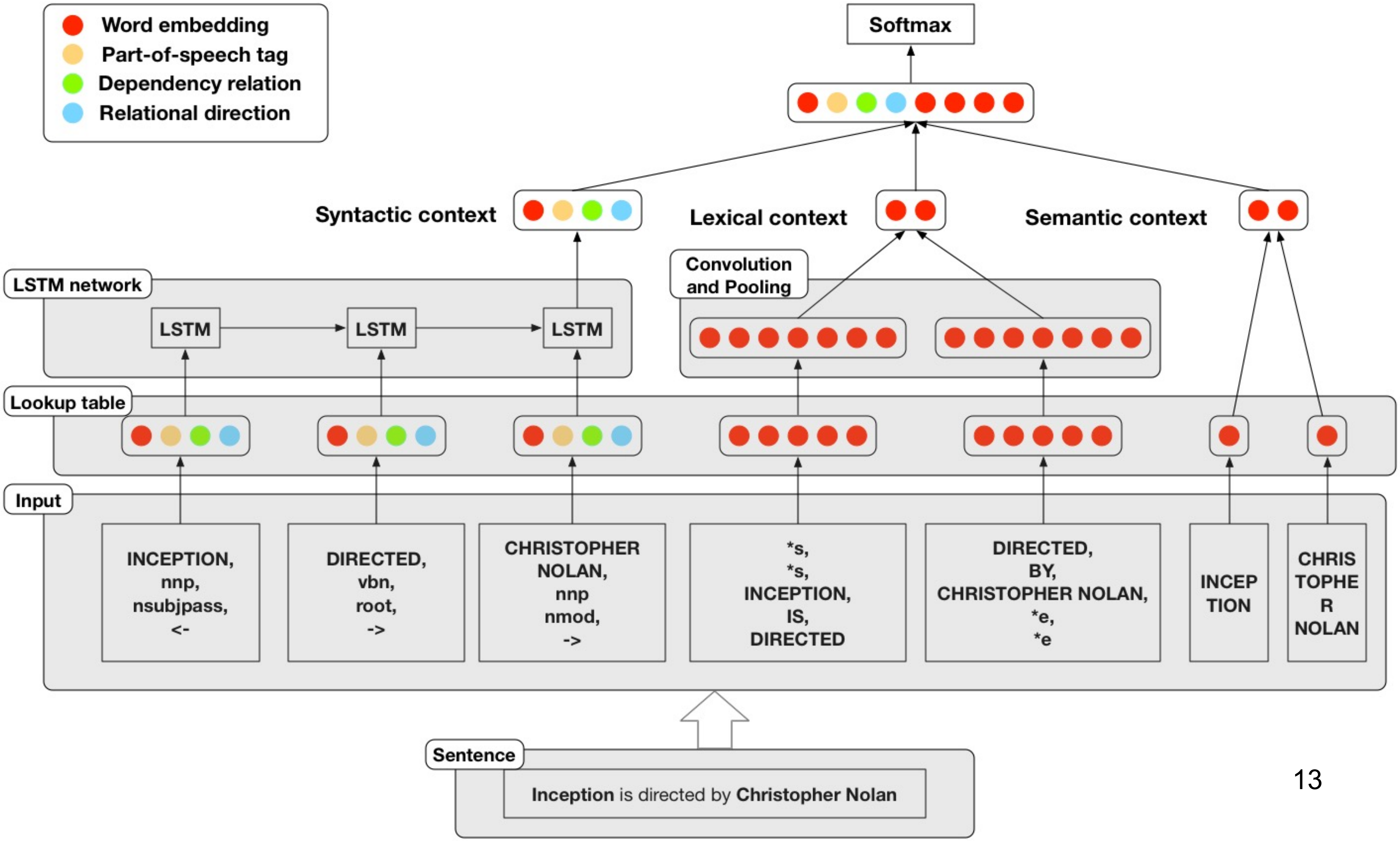
Base Neural Network Training

- Syntactic contexts via LSTM
  - Nodes on the root augmented dependency path (RADP)
    - E.g. [Inception, directed, Christopher Nolan]
  - Node representation
    - {word embedding, POS tag, dependency relation, relational direction}
    - E.g. {Inception, nnp, nsubjpass, <-}



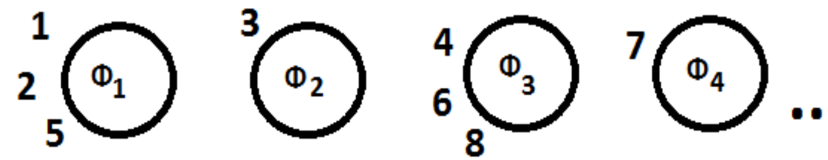
- Lexical contexts via CNN
  - Word embeddings of sliding window of n-grams around entities
- Semantic contexts
  - Word embeddings of two tagged entities

Base Neural Network Architecture



Chinese Restaurant Process (CRP)

- Goal
  - Groups customers into random tables where they sit



- Distribution over table assignment

$$\Pr(z_i = p \mid \vec{z}_{-i}, \alpha) \propto \begin{cases} N_p & \text{if } p \leq K \\ \alpha & \text{if } p = K + 1 \end{cases}$$

  - N_p: number of customers sitting at table p
  - z_i: index of the table where the i-th customer sits
  - $\overrightarrow{z_{-i}}$: indices of tables for customers except for the i-th customer
  - α: scaling parameter for a new table
  - K: number of occupied tables

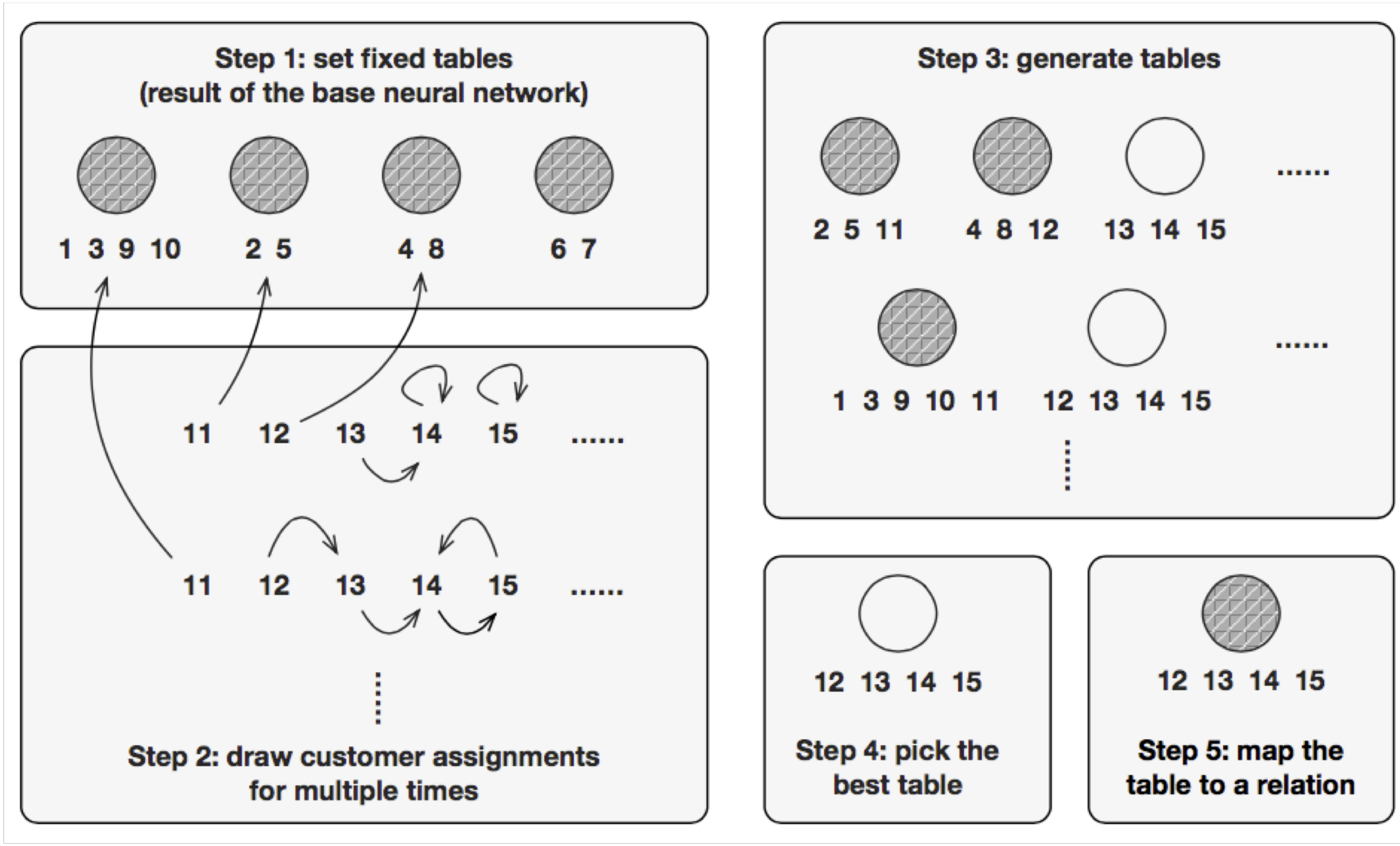
Similarity Sensitive Chinese Restaurant Process (ssCRP)

- Idea
  - Exploits similarities between customers
  - Turns the problem to customer assignment
- Distribution over customer assignment

$$\Pr(c_i = j \mid \eta) \propto \begin{cases} \alpha & \text{if } j \text{ is customer } i \text{ itself} \\ g(s_{ij}) & \text{if } j \text{ is an upcoming customer} \\ g(s_{ij})(1 + \beta \lg N_p) & \text{if } j \text{ is averaged from table } p \end{cases}$$

  - s_{ij}: similarity score between the i-th and j-th customer
  - $g(x)$: similarity function to magnify input differences
  - β: the parameter balancing the weight of table size
  - $\eta = \{S, N_p, \alpha, \beta\}$: set of hyperparameters

Illustration of ssCRP



Relation Prediction

- Idea
  - Populates small clusters generated via ssCRP
  - Enriches existing relations with more instances
- Prediction criteria
  - Distribution over $K + l$ relations for entity pair (e_1, e_2):
    $$[\Pr(r_1|e_1, e_2), \dots, \Pr(r_{K+l}|e_1, e_2)]$$
  - "Max-secondMax" value for "near uniform" criteria:

$$\mathrm{conf}(e_1, e_2) = \frac{\max([\Pr(r_1|e_1, e_2), \dots, \Pr(r_{K+l}|e_1, e_2)])}{\mathrm{secondMax}([\Pr(r_1|e_1, e_2), \dots, \Pr(r_{K+l}|e_1, e_2)])}$$

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Experimental Data

- Text corpus
  - Text contents from 37,746 pages of entertainment domain in Chinese Wikipedia
- Statistics
  - Training & Validation & Testing:
    - 3480 instances on 4 predefined relations from (Fan et al., 2017)
  - Unlabeled:
    - 3161 entity pairs which share joint occurrence in the sentences

Predefined relations	Directing	Singing	Starring	Spouse
# Instances	633	648	1609	590

Evaluation of Relation Classification

- Comparative study
  - We compare our method to CNN-based and RNN-based models, and experiment with different feature sets to verify their significance.

Classifier	Feature set	F1 (%)
logistic regression/ SVM	entity pairs (add)	77.3/ 77.4
	entity pairs (sub)	75.9/ 80.8
	entity pairs (concat)	89.0/ 87.5
	syntactic units, entity pairs (concat)	84.9/ 82.5
	context words, entity pairs (concat)	87.6/ 86.6
	syntactic units, context words	89.2/ 87.8
	syntactic units, context words, entity pairs (concat)	89.9/ 88.0
Shwartz et al. (Shwartz et al., 2016)	shortest dependency path, entity pairs	65.3
Zeng et al. (Zeng et al., 2014)	context words, entity pairs	81.5
RNN+E	syntactic units, entity pairs (concat)	66.8
CNN+E	context words, entity pairs (concat)	91.4
Full implementation	syntactic units, context words, entity pairs (concat)	**92.2**

Evaluation of Relation Discovery

- Pairwise experiment
  - We manually construct a testing set by sampling pairs of instances (x_i, x_j) from unlabeled data where $x = (e_1, e_2)$.

$$\text{Precison} = \frac{\left|\left\{\left(x_i, x_j\right) \in D \middle| v_{i,j} = 1 \wedge v_{i,j}{}' = 1\right\}\right|}{\left|\left\{\left(x_i, x_j\right) \in D \middle| v_{i,j}{}' = 1\right\}\right|}$$

$$\text{Recall} = \frac{\left|\left\{\left(x_i, x_j\right) \in D \middle| v_{i,j} = 1 \wedge v_{i,j}{}' = 1\right\}\right|}{\left|\left\{\left(x_i, x_j\right) \in D \middle| v_{i,j} = 1\right\}\right|}$$

  - $v_{i,j} \in \{1,0\}$ for the ground truth, $v_{i,j}{}' \in \{1,0\}$ for the clustering result

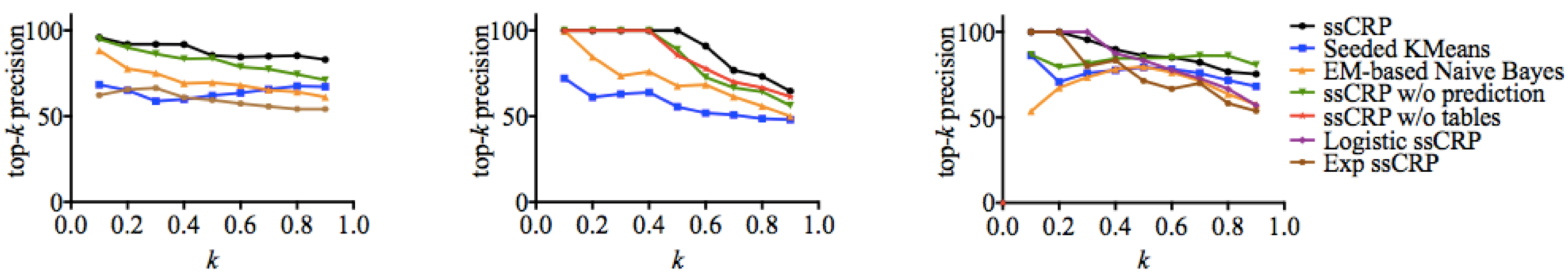
Algorithm	# Instances	Precision (%)	Recall (%)	F1 (%)
Fit ssCRP	3161	31.0	35.7	33.2
Exploratory EM-based Naive Bayes	3161	70.7	40.2	52.8
Exploratory seeded KMeans	3161	80.5	53.0	63.9
ssCRP w/o tables	593	66.6	60.4	63.3
ssCRP w/o prediction	903	83.7	61.0	70.6
Exp ssCRP	3161	77.9	66.7	71.9
Logistic ssCRP	3161	81.4	66.9	73.0
Full implementation of ssCRP	3048	**83.1**	**68.4**	**75.0**

Evaluation of Relation Discovery

- Newly discovered relations
  - 6 new relations are generated, covering 96.4% unlabeled data

Relation name	# Instances	Relation name	# Instances
Group members	1328	Belong to the country	956
Family members	355	Series works	247
Employed by	144	Produced by	18

- Top-k precision
  - We heuristically choose $k = 0.4$ because the precision drops relatively faster when k is larger than this setting.



(a) Series works (b) Produced by (c) Employed by

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Conclusion

- Exploratory relation classification
  - Problem: assign labels for unlabeled entity pairs to both pre-defined and unknown relations
  - Iterative process:
    - an integrated base neural network for relation classification
    - a similarity-based clustering algorithm ssCRP to generate new relations
    - constrained relation prediction process to populate new relations
  - Experiments: on Chinese Wikipedia entertainment domain, with base neural network achieving 0.92 F1-score, and 6 new relations generated with 0.75 F1-score.

Thanks!