Extracurricular Materials

High-Order Inference for Dep Parsing, SRL, IE

Conditional Random Fields (CRF)

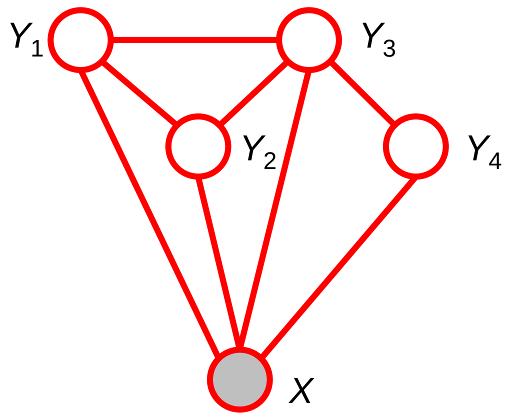
- An extension of MRF where everything is conditioned on an input

$$P(\mathrm{y}|x) = \frac{1}{Z(x)} \prod_{C} \psi_C(\mathrm{y}_C, x)$$

where $\psi_C(y_C, x)$ is the potential over clique C and

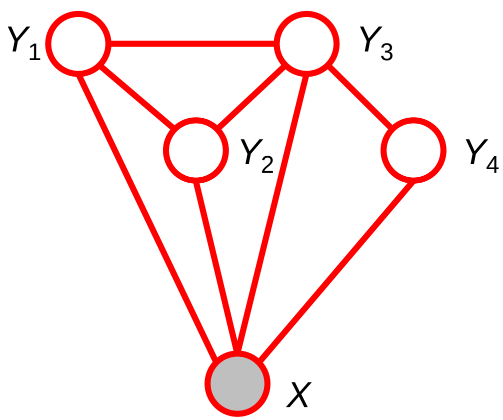
$$Z(x) = \sum_{\mathrm{y}} \prod_{C} \psi_C(\mathrm{y}_C, x)$$

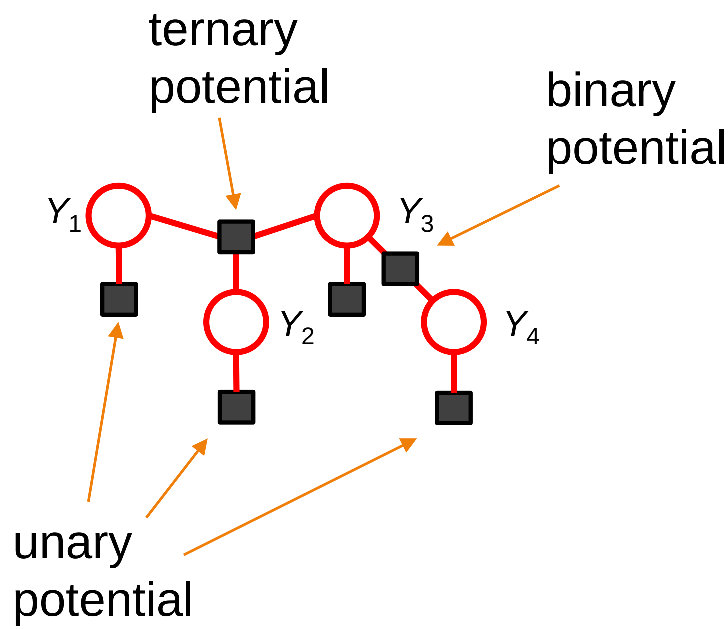
is the normalization coefficient.



Factor Graph

- A factor graph explicitly shows the potential functions (aka factors) in an CRF





Factor Graph

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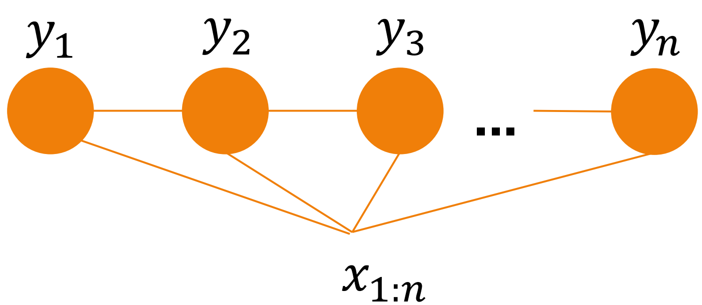
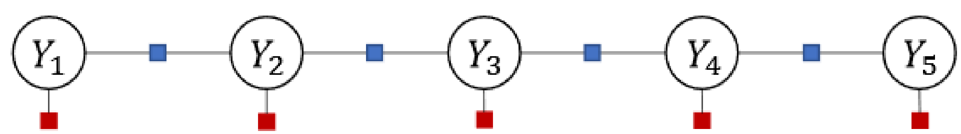




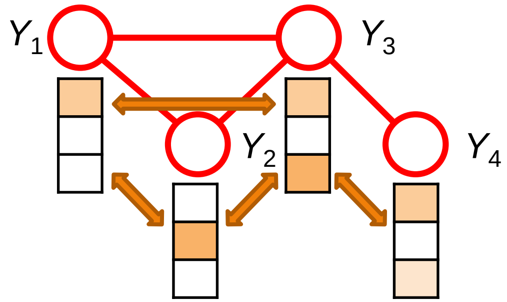
Inference over CRF

- Inference
  - Find the assignment to all the variables with the highest probability: $\arg\max_{\mathrm{y}} P(\mathrm{y}|x)$
  - Ex: find the most likely label sequence, parse tree, etc.

- Exact inference is hard or even intractable in many cases
- Iterative algorithms for approximate inference
  - Mean-field Variational Inference
  - Loopy Belief Propagation
  - …

Inference over CRF

- Iterative algorithms for approximate inference
- At each iteration:
  - Compute an intermediate vector (e.g., a discrete distribution) for each random variable…
  - …based on the vectors from the previous iteration
  - …following a fixed graph structure
  - …using fixed model parameters
  - …in a fully differentiable way



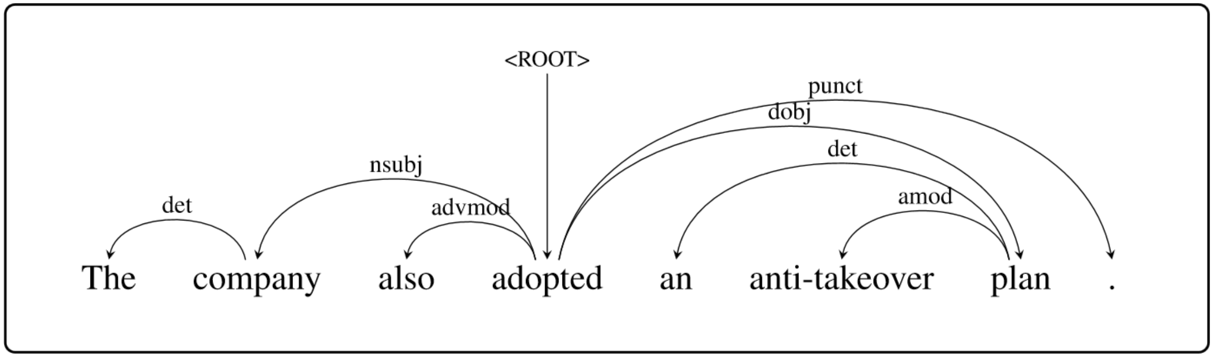
This is similar to a Graph Neural Network!

Papers

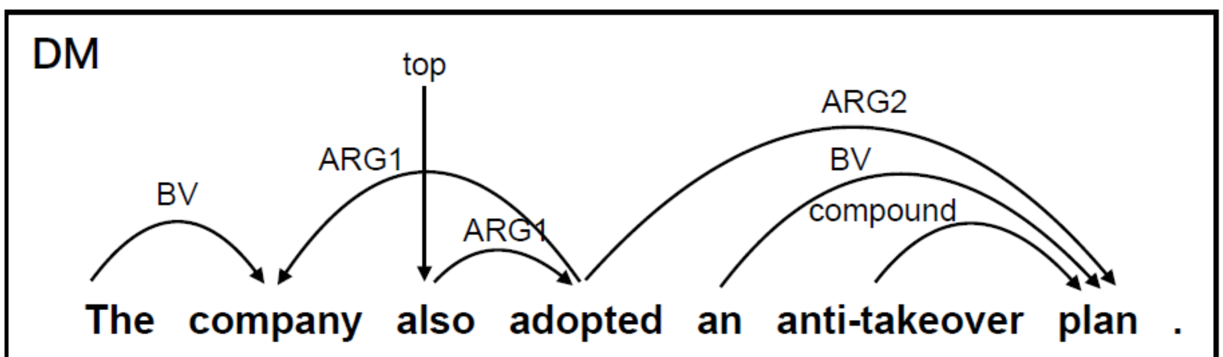
- Xinyu Wang, Jingxian Huang, and Kewei Tu, "Second-Order Semantic Dependency Parsing with End-To-End Neural Networks", ACL 2019.
- Xinyu Wang and Kewei Tu, "Second-Order Neural Dependency Parsing with Message Passing and End-to-End Training", AACL-IJCNLP 2020.
- Zixia Jia, Zhaohui Yan, Haoyi Wu, and Kewei Tu, "Span-based Semantic Role Labeling with Argument Pruning and Second-Order Inference". AAAI 2022.
- Zixia Jia, Zhaohui Yan, Wenjuan Han, Zilong Zheng, Kewei Tu, "Joint Information Extraction with Cross-Task and Cross-Instance High-Order Modeling", arXiv 2022.

(Semantic) Dependency Parsing

- Dependency parse

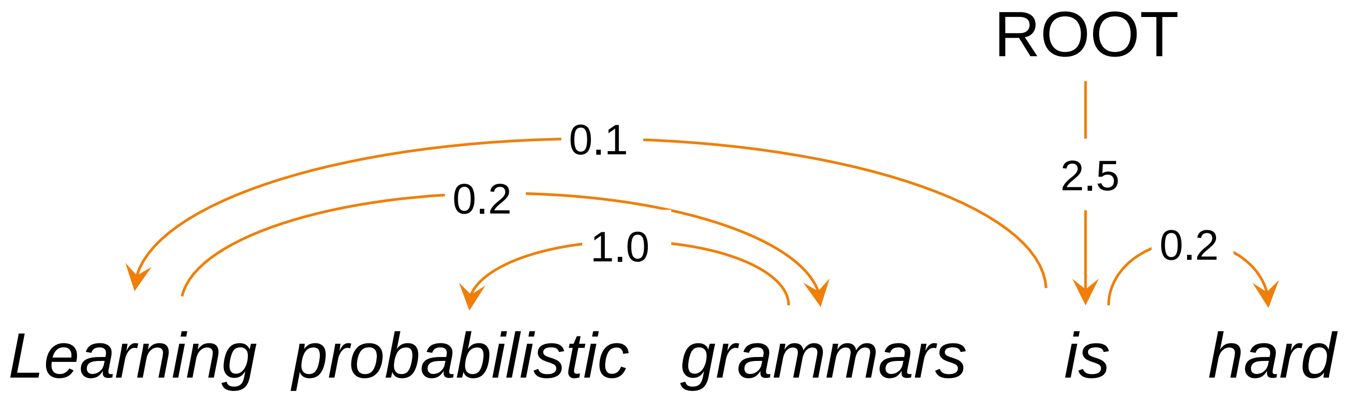


- Semantic dependency parse (SDP)



First-order graph-based dependency parsing

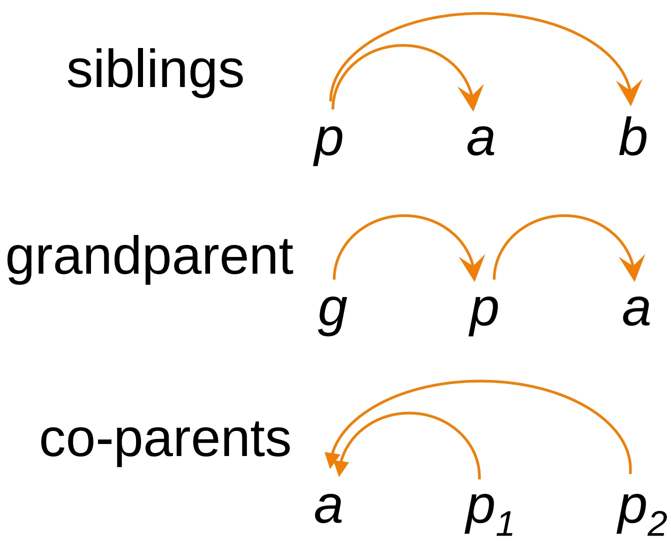
- Parse tree scoring
  - Each arc has a score. The tree score is the sum of arc scores.



- Parsing: finding the highest-scored parse tree/graph
  - Eisner, Chu-Liu-Edmonds

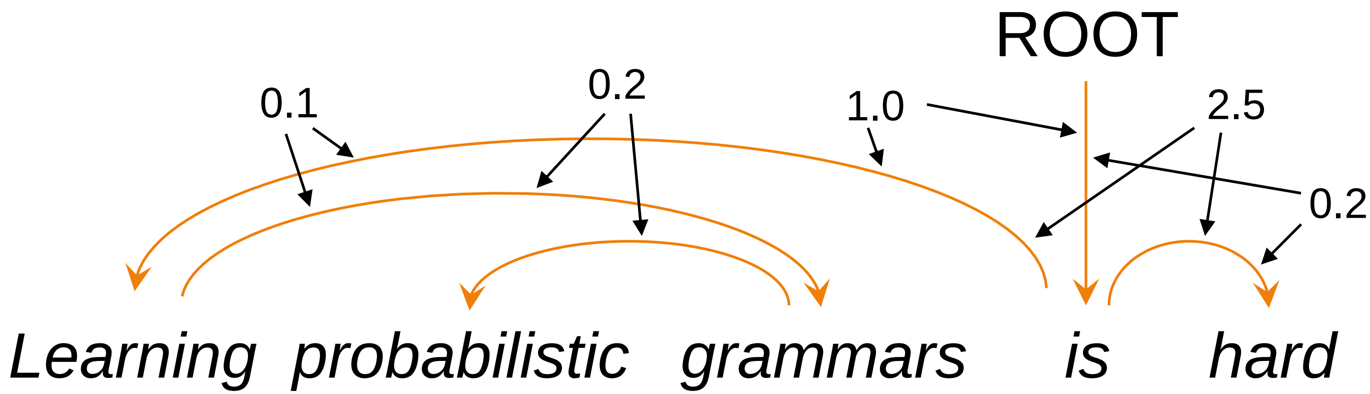
Second-order graph-based dependency parsing

- Parse tree scoring
  - Also assign a score to each pair of connected dependency arcs



Second-order graph-based dependency parsing

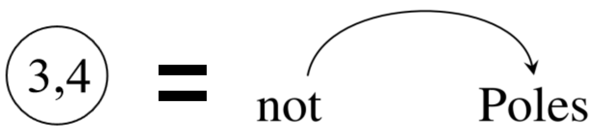
- Parse tree scoring
  - Also assign a score to each pair of connected dependency arcs



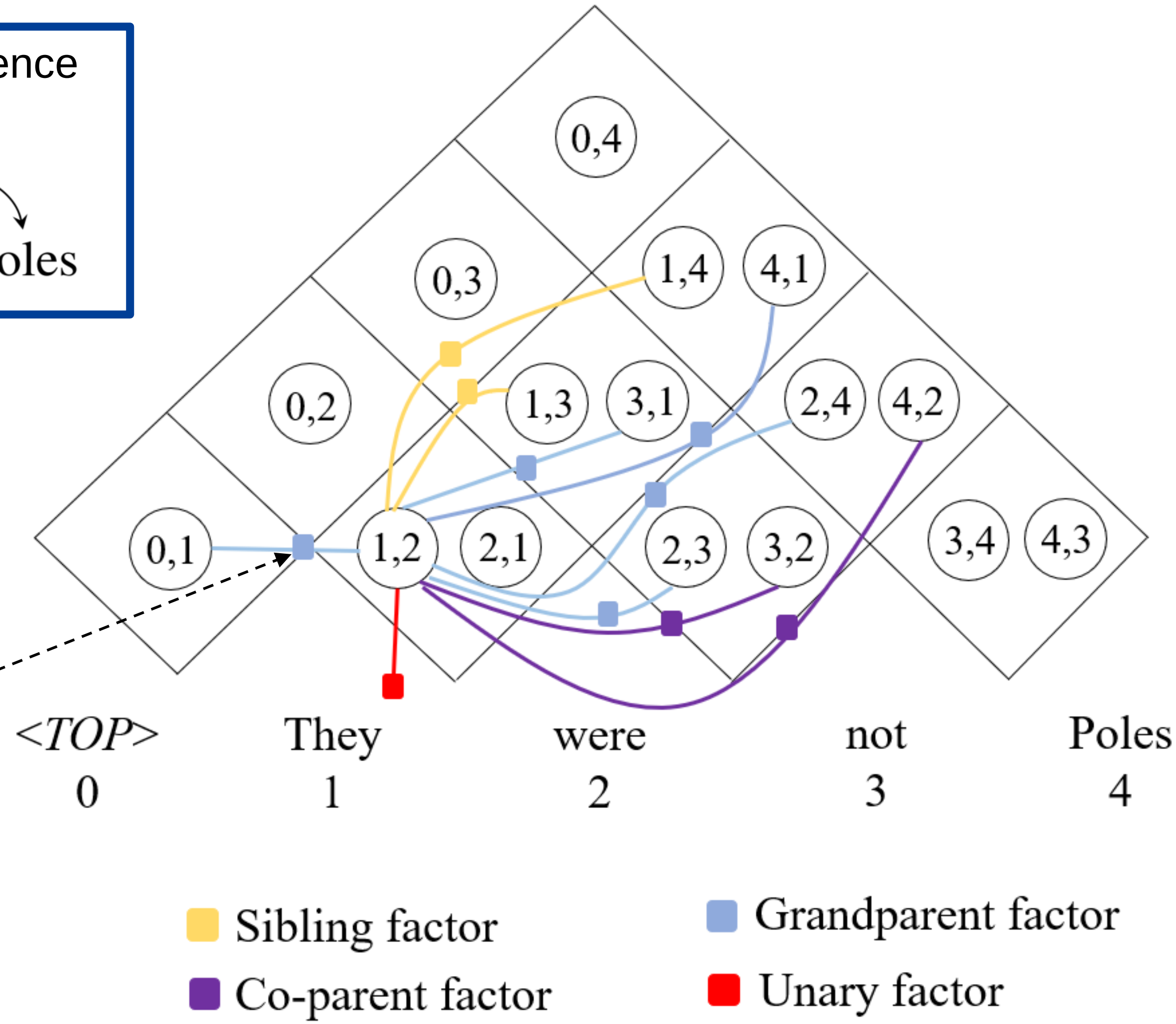
- Parsing: finding the highest-scored parse tree/graph
  - Intractable for non-projective tree and graph parsing

Parsing as MAP Inference on CRF

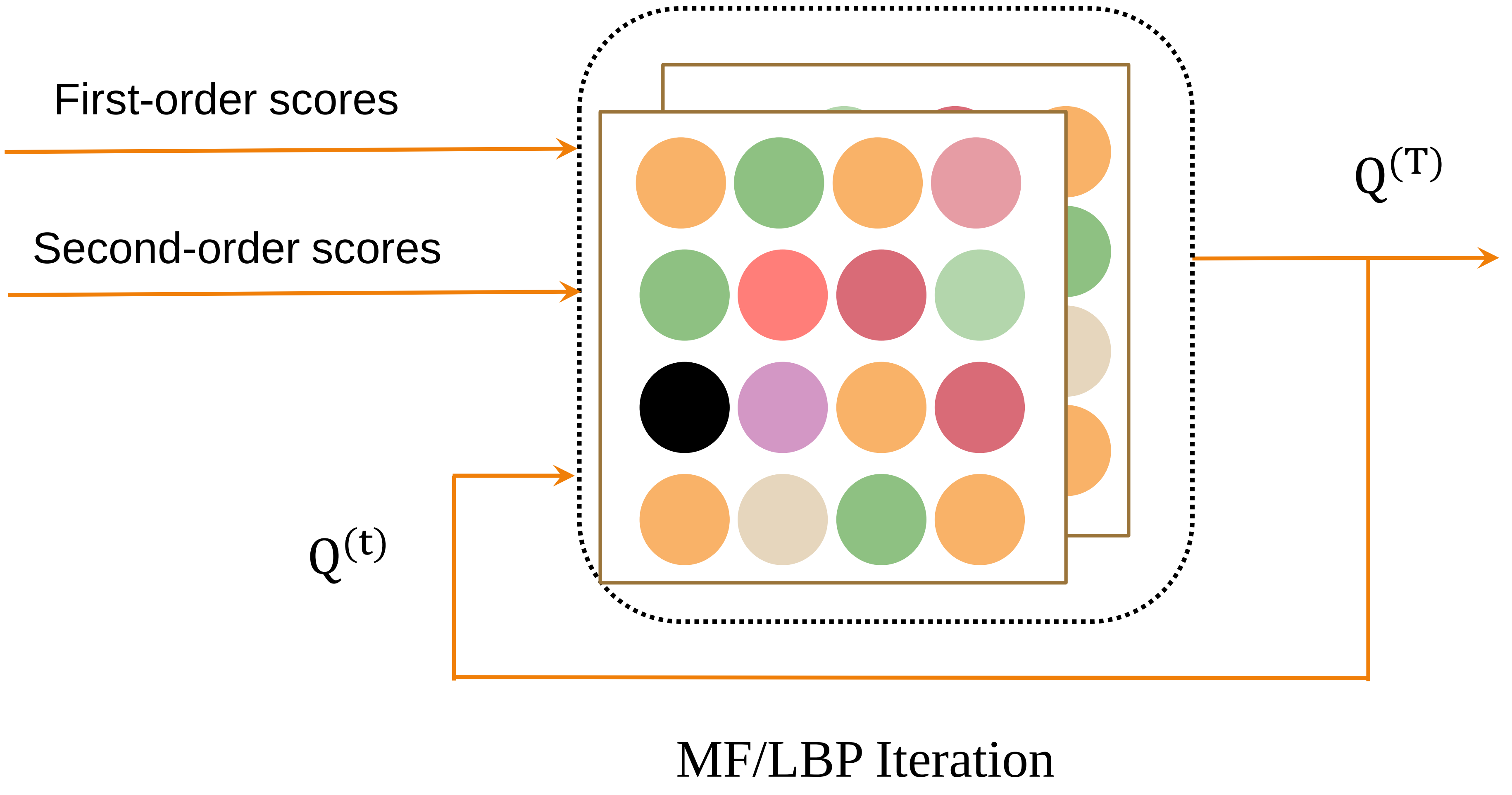
Boolean Variable: Edge existence between two words



(0,1)	(1,2)	
T	T	$\exp\left(s_{01,12}^{(gp)}\right)$
T	F	1
F	T	1
F	F	1

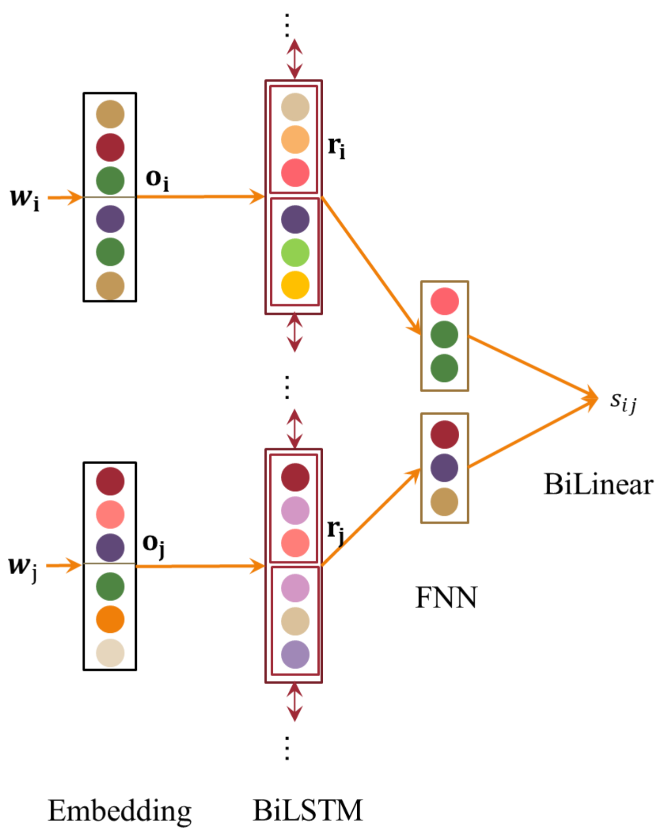


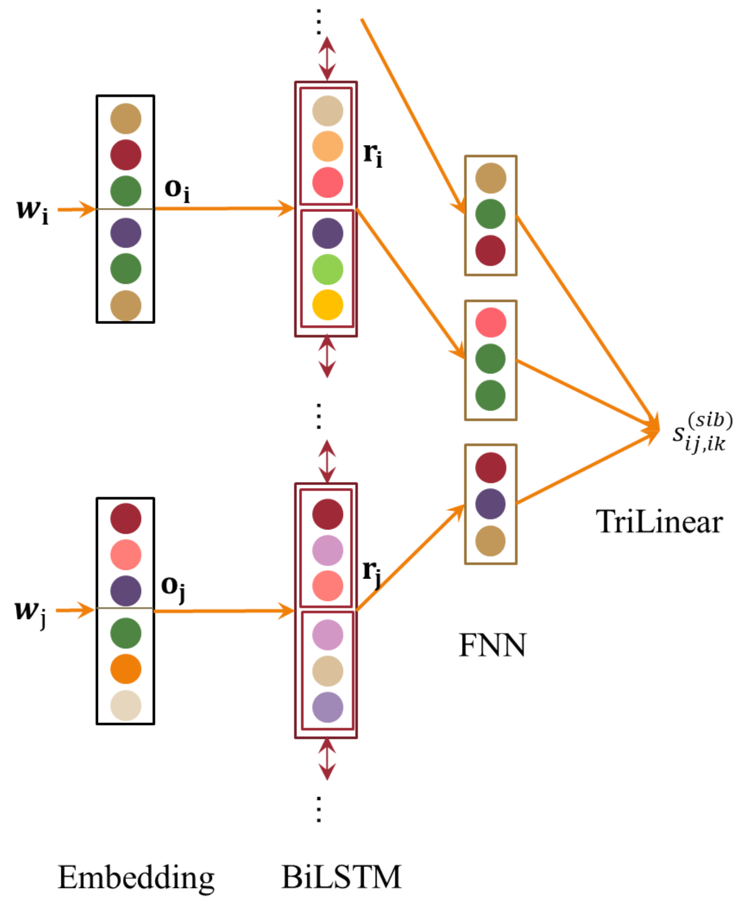
MF/LBP as GNN


First-order scores
Second-order scores
$Q^{(t)}$
$Q^{(T)}$
MF/LBP Iteration

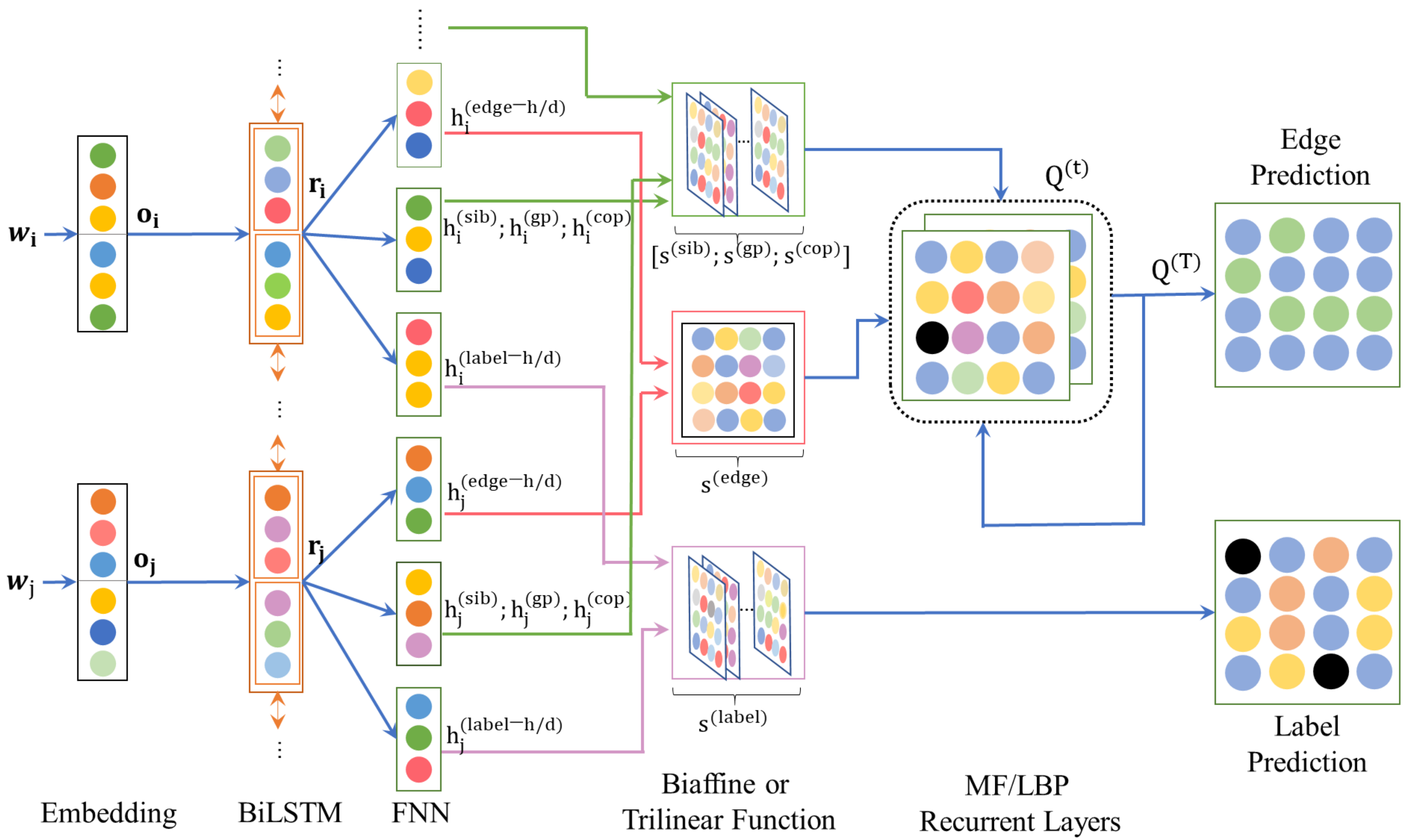
Neural Scoring

- Compute dependency scores using neural networks





End-to-End Neural Network



Semantic Role Labeling (SRL)

- SRL identifies predicate-argument structures in a sentence
  - Predicate: typically a single word
  - Argument: a span consisting of one or more words

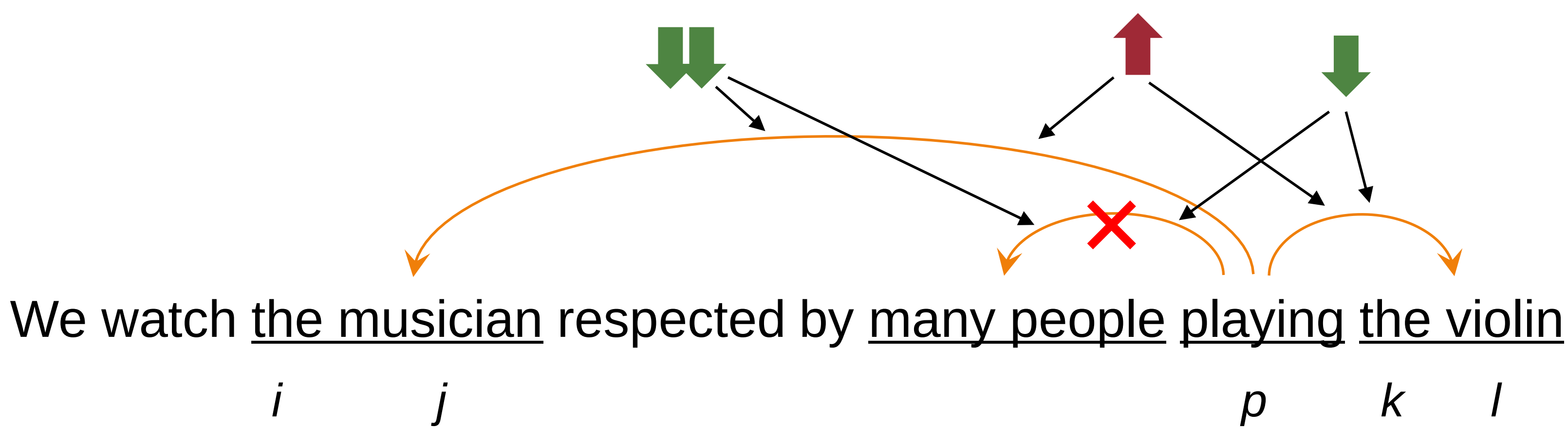
Who **did what** **to whom** **at where?**

The police officer detained the suspect at the scene of the crime

Agent Predicate Theme Location

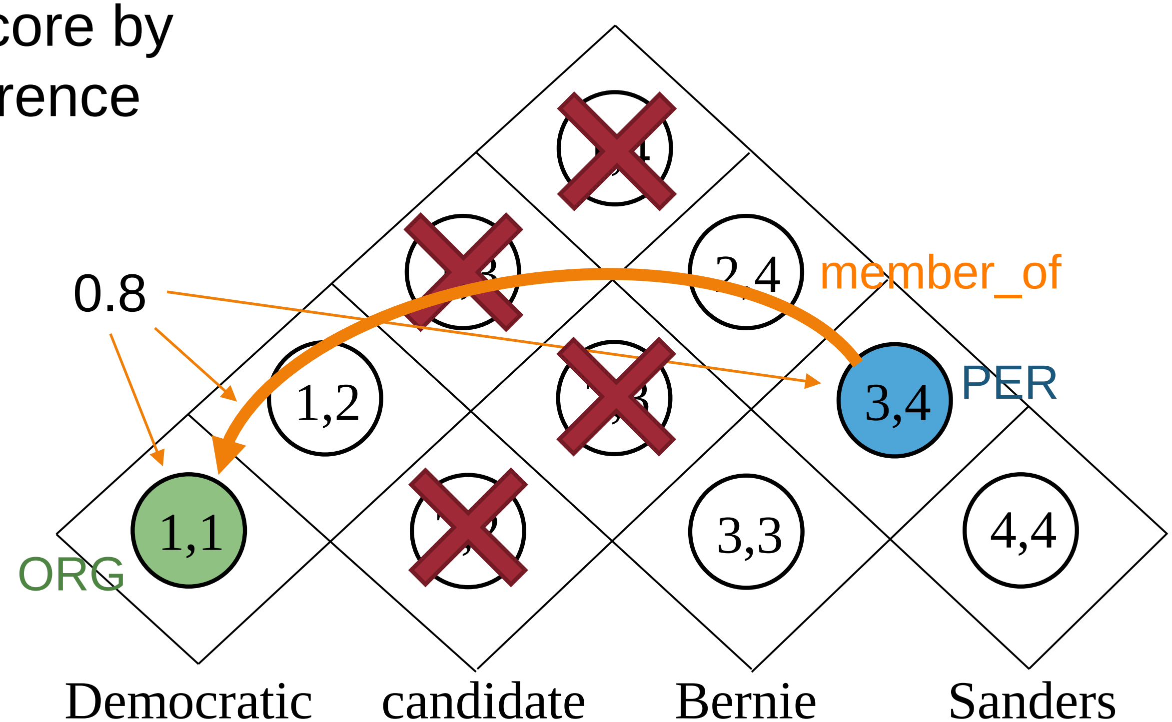
CRF for SRL

- Random variable $Y_{p,ij}$
  - Whether w_p is a predicate and $w_{i:j}$ is one of its arguments
- Unary potential $\phi_u\left(Y_{p,ij}\right) = \exp(score_{p,ij}^{edge})$
  - How likely $Y_{p,ij}$ is true
- Binary potential $\phi_b\left(Y_{p,ij}, Y_{p,kl}\right) = \exp(score_{p,ij,kl}^{sib})$
  - How likely $Y_{p,ij}, Y_{p,kl}$ are both true (sibling structure)

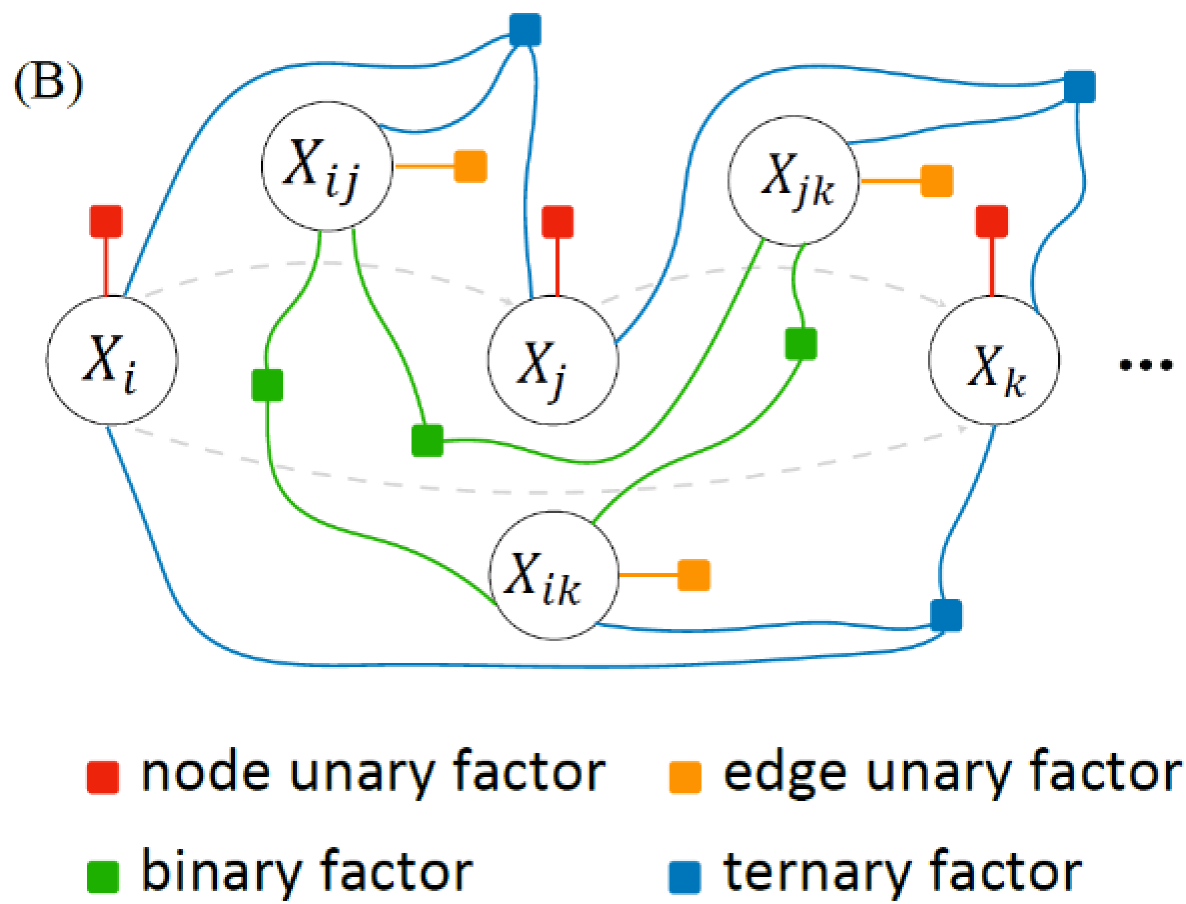


Joint Entity & Relation Extraction

- Method 1
  - Score every labeled triple containing two entities and one relation (including <u>null</u> labels)
    - Entity pruning needed to reduce time complexity
  - Maximize total score by approximate inference



CRF for Joint Entity & Relation Extraction



Summary

- High-order inference on CRF unfolded as GNNs
  - Dependency parsing
  - Semantic role labeling
  - Joint entity & relation extraction

Neuralizing Regular Expressions

Papers

- Chengyue Jiang, Yinggong Zhao, Shanbo Chu, Libin Shen, and Kewei Tu, "Cold-start and Interpretability: Turning Regular Expressions into Trainable Recurrent Neural Networks", EMNLP 2020.
- Chengyue Jiang, Zijian Jin, and Kewei Tu, "Neuralizing Regular Expressions for Slot Filling", EMNLP 2021.

Regular Expressions (RE)

- One of the most representative and useful forms of symbolic rules
- Widely used in practice: word tokenization, text classification, slot filling, etc.

Label	[*distance*]
RE	*$*(how (far | long) | distance) $**
Matched Text	⟨BOS⟩ tell me **how far** is oakland airport from downtown ⟨EOS⟩

Regular Expressions (RE)

- Pros
  - Highly interpretable
  - Support fine-grained diagnosis and manipulation
    - Easy to add/delete/revise rules to quickly adapt to changes in task specification
  - No need for training
    - Hence no need for data annotation, less computational cost
    - Good for cold-start scenarios
- Cons
  - Rely on human experts to write
  - Often: high precision but low recall
  - Cannot evolve by training on labeled data when available
    - Underperform neural approaches in rich-resource scenarios

Our Idea

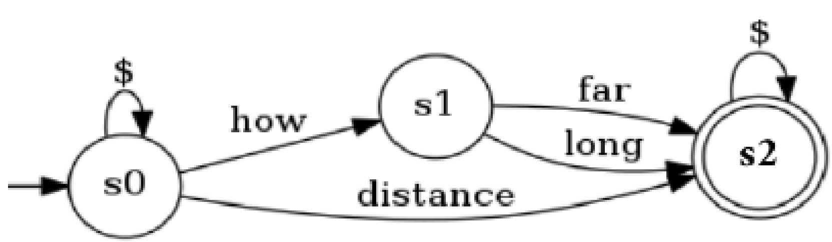
- Convert a RE to a new form of recurrent neural networks
  - Roughly equivalent to RE
    - ✓ Can still be used in cold-start scenarios
  - Trainable on labeled data
    - ✓ Can outperform REs and compete with neural approaches in rich-resource scenarios
  - Can be converted back to RE
    - ✓ Possibility of fine-grained manipulation

Step 1. RE to Finite Automaton (FA)

- Any RE can be converted into a FA that expresses the same language

Label	[*distance*]
RE	*\$*(how (far | long) | distance) \$**

FA



FA parameters

- Binary transition tensor:

$$T \in \mathbb{R}^{V\times K\times K}$$

- Binary start vector:

$$\alpha_0 \in \mathbb{R}^{K}$$

- Binary final vector:

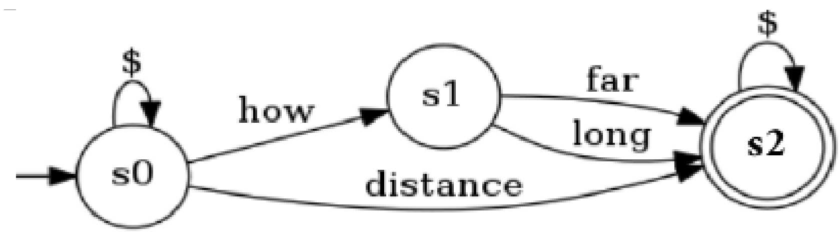
$$\alpha_\infty \in \mathbb{R}^{K}$$

V: vocabulary size

K: state number

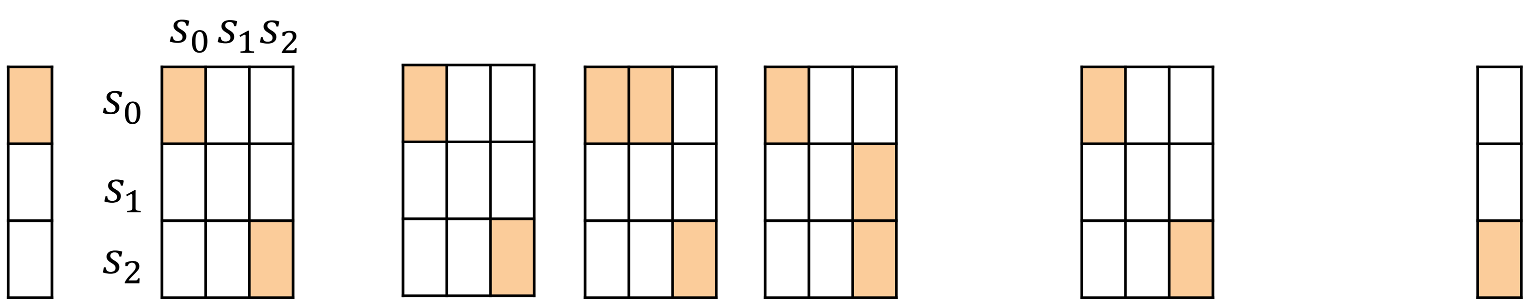
Step 2. FA as Recurrent Neural Network (RNN)

- Score of a FA accepting a sentence can be calculated using the forward algorithm



Forward score:

$$\boldsymbol{\alpha}_0^T \cdot \left(\prod_{i=1}^{N} \boldsymbol{T}[x_i] \right) \cdot \boldsymbol{\alpha}_\infty$$



α_0 $T[x_1]$ $T[x_2], T[x_3]$ $T[x_4]$ $T[x_5]$ $T[x_6], \ldots, T[x_9]$ α_∞

<BOS> Tell me **how** **far** is Oakland airport <EOS>

Step 2. FA as Recurrent Neural Network (RNN)

- The computation can be rewritten into a recurrent form

$$\boldsymbol{\alpha}_0^T \cdot \left(\prod_{i=1}^{N} \boldsymbol{T}[x_i] \right) \cdot \boldsymbol{\alpha}_\infty$$

$$\Downarrow$$

$$\begin{aligned} \boldsymbol{h}_{\mathbf{0}} &= \boldsymbol{\alpha}_0^T \\ \boldsymbol{h}_t &= \boldsymbol{h}_{t-1} \cdot \boldsymbol{T}[x_t],\ 1 \leq t \leq N \quad \text{(recurrent step)} \\ \mathcal{B}_{\text{forward}}(\mathcal{A}, \boldsymbol{x}) &= \boldsymbol{h}_N \cdot \boldsymbol{\alpha}_\infty \end{aligned}$$

Step 3. Decomposing the Parameter Tensor

- Goal: reduce the computational complexity to match that of traditional RNN

Tensor Rank Decomposition

$$\boldsymbol{T} \in \mathbb{R}^{V \times K \times K} \Rightarrow \boldsymbol{E}_{\mathcal{R}} \in \mathbb{R}^{V \times r}, \boldsymbol{D}_1 \in \mathbb{R}^{K \times r}, \boldsymbol{D}_2 \in \mathbb{R}^{K \times r}$$

(word embedding) (state embeddings)

- Now the recurrent step becomes:

$$\boldsymbol{h}_t = \boldsymbol{h}_{t-1} \cdot \boldsymbol{T}[x_t] \Rightarrow \begin{aligned} \boldsymbol{v}_t &= \boldsymbol{E}_{\mathcal{R}}(x_t) \\ \boldsymbol{a} &= (\boldsymbol{h}_{t-1} \cdot \boldsymbol{D}_1) \circ \boldsymbol{v}_t \\ \boldsymbol{h}_t &= \boldsymbol{a} \cdot \boldsymbol{D}_2^T \end{aligned}$$

Step 4. Integrating Pretrained Word Embedding

- Goal: bringing external lexical knowledge into our model
- Method:
  - Approximate $\boldsymbol{E}_{\mathcal{R}}$ with $\boldsymbol{E}_w\boldsymbol{G}$

    initialized with $\boldsymbol{E}_w^{\dagger}\boldsymbol{E}_{\mathcal{R}}$

    $\boldsymbol{E}_w^{\dagger}$ is the pseudo-inverse of $\boldsymbol{E}_w$

    external word embedding
  - Interpolate $\boldsymbol{E}_{\mathcal{R}}$ and $\boldsymbol{E}_w\boldsymbol{G}$
  - The recurrent step becomes:

$$
\begin{aligned}
\boldsymbol{v}_t &= \boldsymbol{E}_{\mathcal{R}}(x_t) \\
\boldsymbol{a} &= (\boldsymbol{h}_{t-1} \cdot \boldsymbol{D}_1) \circ \boldsymbol{v}_t \\
\boldsymbol{h}_t &= \boldsymbol{a} \cdot \boldsymbol{D}_2^T
\end{aligned}
$$

$$
\boxed{
\begin{aligned}
\boldsymbol{v}_t &= \boldsymbol{E}_{\mathcal{R}}(x_t) \quad \boldsymbol{u}_t = \boldsymbol{E}_w(x_t) \\
\boldsymbol{z}_t &= \beta \boldsymbol{v}_t + (1-\beta)\boldsymbol{u}_t \boldsymbol{G} \\
\boldsymbol{a} &= (\boldsymbol{h}_{t-1} \cdot \boldsymbol{D}_1) \circ \boldsymbol{z}_t \\
\boldsymbol{h}_t &= \boldsymbol{a} \cdot \boldsymbol{D}_2^T
\end{aligned}
}
$$

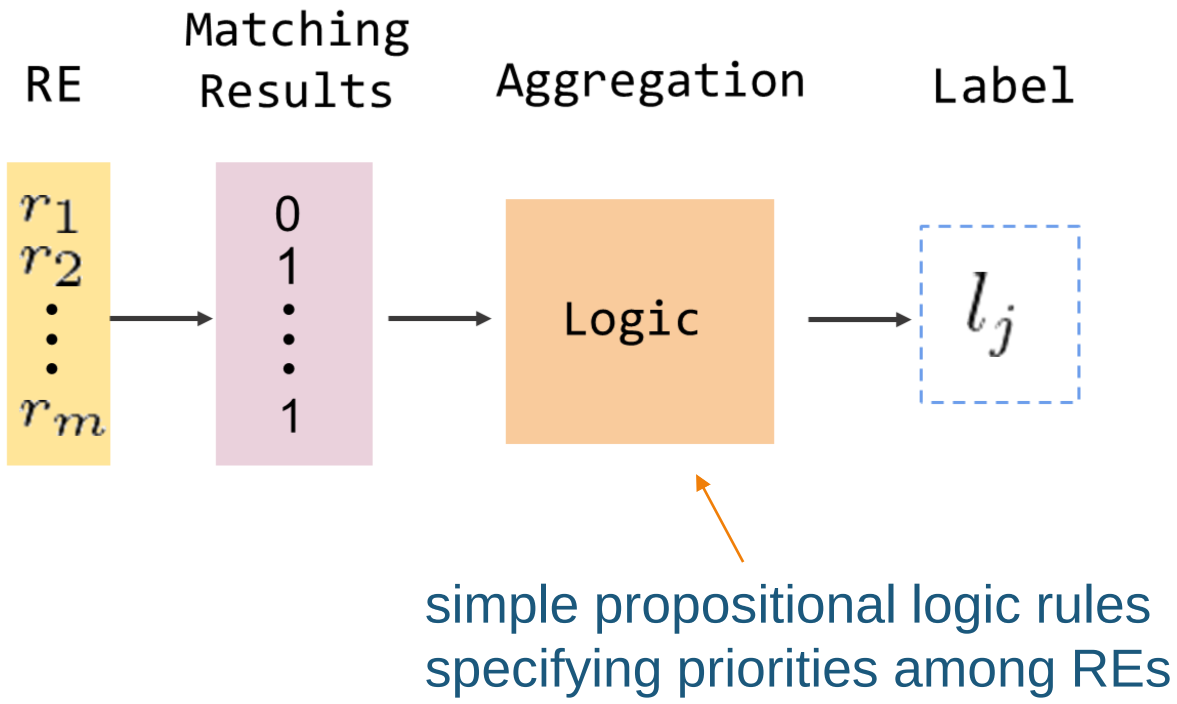
FA-RNN

FA-RNN Extensions

- Gated extension
  - Add forget gate and reset gate like in GRU
  - Initialize parameters to make the gates inactive initially
- Combine two FA-RNNs of opposite directions
  - Create a left-to-right FA-RNN from the RE
  - Create a right-to-left FA-RNN from the reversed RE
  - Output the average score of the two FA-RNNs

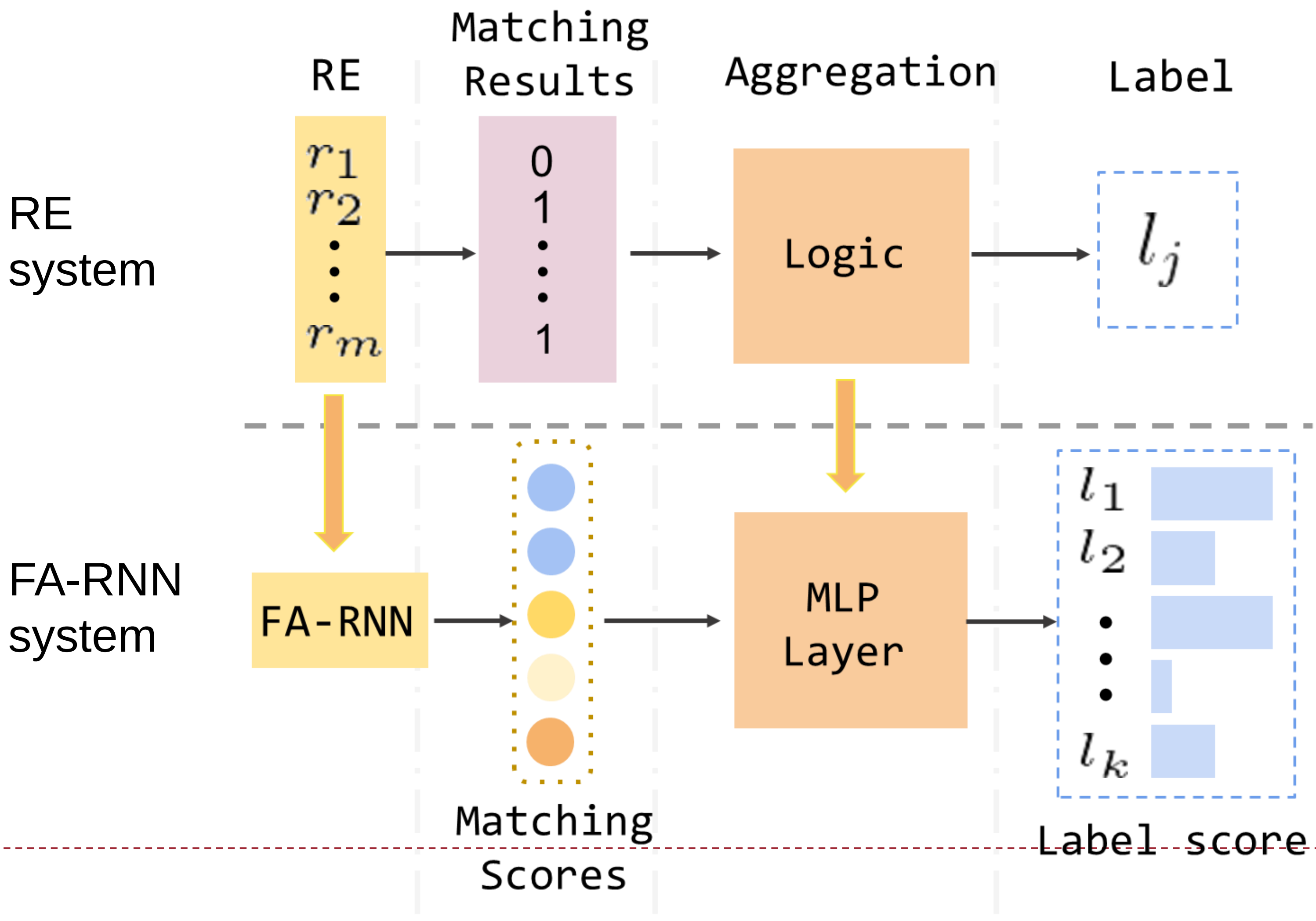
Text classification

- An RE system for text classification:
  - Aggregating results from multiple REs to form a prediction



Text classification

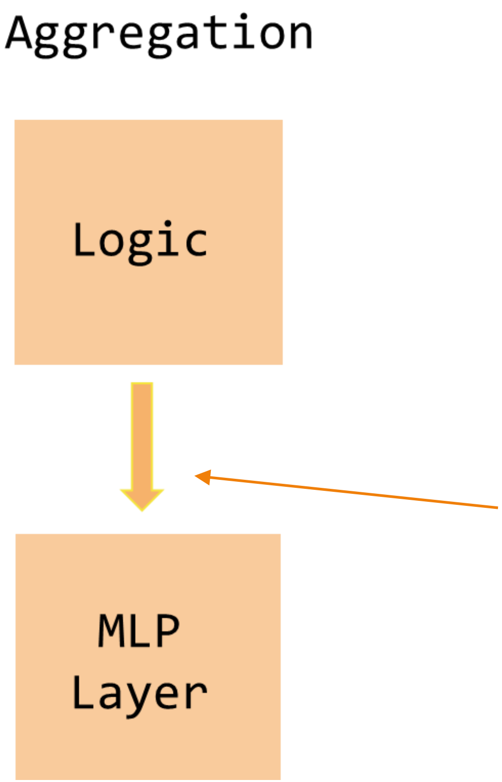
- From a RE system to a FA-RNN system



Text classification

- From a RE system to a FA-RNN system

RE system

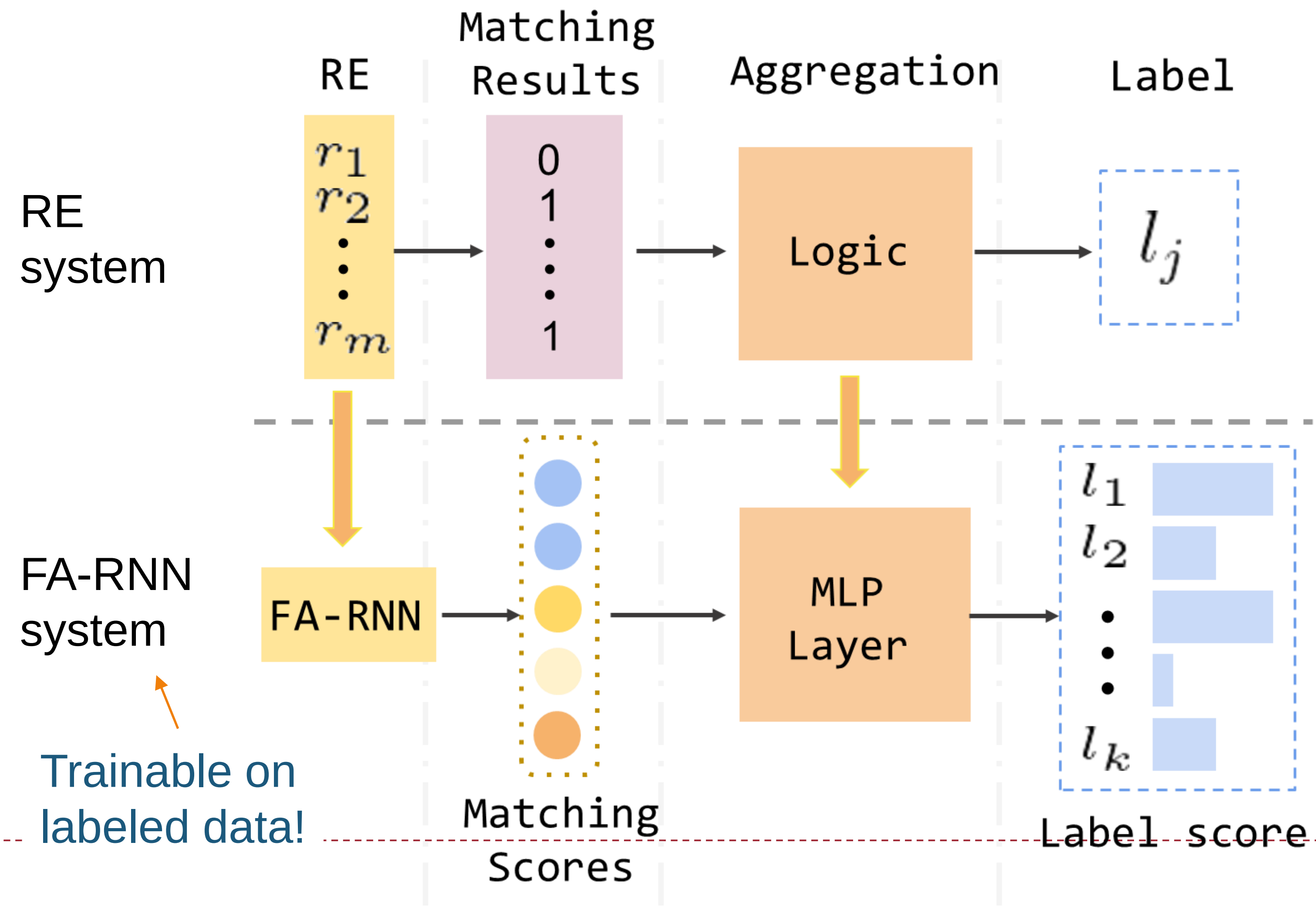


FA-RNN system

Logic	Soft Logic
$\neg A$	$1 - a$
$A \vee B$	$\min(1, a + b)$
$A \wedge B$	$\max(0, a + b - 1)$

Text classification

- From a RE system to a FA-RNN system



Experiments

- Three intent classification datasets:
  - ATIS, QC (TREC-6), SMS
- Baselines
  - Bi-RNN/GRU/LSTM, CNN, DAN
  - RE-enhanced NN (+i, +o, +io) [Luo et al., 2016]
  - Knowledge Distillation (+kd, +pr) [Hinton et al,.2015; Hu et al,. 2016]

Experiments – Zero-Shot

	ATIS	QC	SMS
RE system	87.01	64.40	93.20
FA-RNN	86.53	61.95	93.00
FA-GRU	86.81	62.90	93.20
BiFA-RNN	88.10	62.90	93.00
BiFA-GRU	88.63	62.90	93.20
BiGRU+*i*	1.34	18.75	11.90
BiGRU+*o*	30.74	27.50	30.40
BiGRU+*io*	38.69	25.70	73.25
BiGRU+*pr*	9.94	17.70	53.00
BiGRU+*kd*	9.94	17.70	53.00

Experiments – Low-Resource and Full Training

	ATIS (26-class)			QC (6-class)			SMS (2-class)		
	1%	10%	100%	1%	10%	100%	1%	10%	100%
FA-RNN	90.43	90.79	96.52	**67.75**	79.6	91.3	93.1	96.75	98.8
FA-GRU	88.94	**90.85**	96.61	66.2	80.7	91.85	**94.25**	**96.8**	**99.2**
BiFA-RNN	89.31	**90.85**	96.72	57.65	81.5	91.55	91.7	96.7	99
BiFA-GRU	**90.62**	90.26	96.64	64.15	**82.8**	**92.4**	93.9	96.75	98.8
CNN	71.61	86.09	94.74	50.9	74.9	89.25	89.85	95.9	98.8
DAN	71.02	83.68	90.4	47.25	65.4	77.8	89.9	93.7	98.6
RNN	70.91	75.17	91.55	22.4	67.9	85	85.1	89.85	97.75
LSTM	69.37	78.14	95.72	40.45	75.75	90	86.2	95.75	97.85
GRU	70.72	88.52	96.3	42.35	79.75	91.2	86.15	95.55	98.05
BiRNN	70.72	79.98	93.39	49.35	75.95	87.35	86.75	94.9	97.8
BiLSTM	70.77	87.12	96.25	55.95	76.75	90.95	92.15	95.8	97.7
BiGRU	70.69	88.35	96.75	62.7	80.05	91.5	89.6	95.95	98.4
BiGRU +i	82.84	90.01	96.56	66.3	80.25	92	90.95	96.75	98.55
BiGRU +o	80.21	89.22	96.33	60.15	80.2	91.7	90.6	95.95	98.4
BiGRU +io	82.61	89.95	95.46	65.05	79.65	90.7	93.85	96.75	98.25
BiGRU +pr	72.4	88.89	96.5	61.6	80.45	91.85	90.9	96.05	98.45
BiGRU +kd	73.38	88.86	**96.75**	62.65	80.3	91.25	87.65	96	98.55

Summary

- Turning symbolic systems (RegExp) to neural networks
  - Combining strengths of symbolic rules and neural networks
  - Excels in zero-shot and low-resource scenarios
  - Competitive in rich-resource scenarios