Recent Work on Deep Learning at Fudan NLP Group

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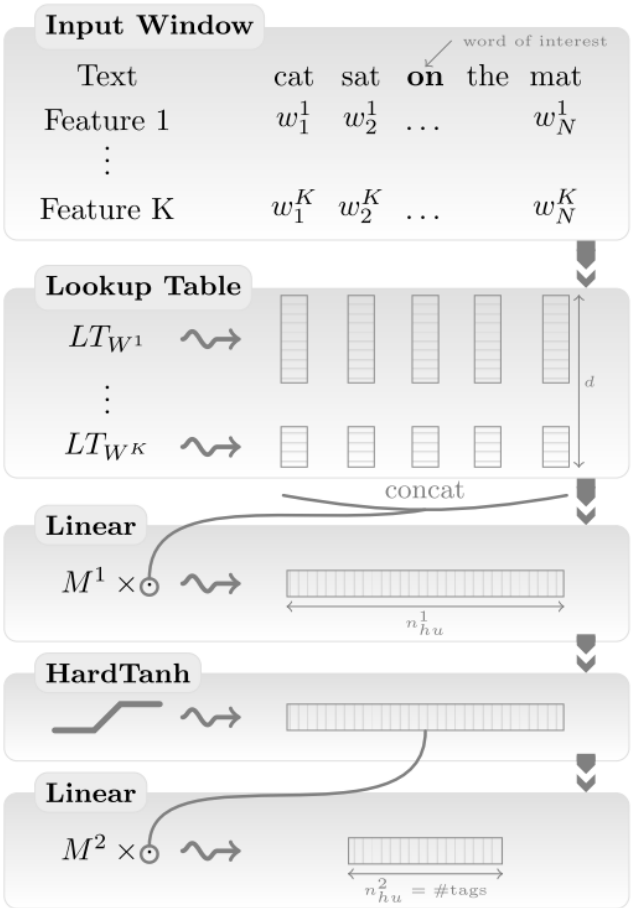
Outline

General Neural Architectures for NLP



1. represent the words/features with dense vectors (embeddings) by lookup table;
2. concatenate the vectors;
3. classify/match/rank with multi-layer neural networks.

from [Collobert et al., 2011]

Distributed Representation for Three Levels

- **Word Level**
  - NNLM
  - C&W
  - CBOW & Skip-Gram
- **Sentence Level**
  - **NBOW**
  - **Sequence Models**: Recurrent NN (LSTM and GRU), Paragraph Vector
  - **Topological Models**: Recursive NN,
  - **Convolutional Models**: DCNN
- **Document Level**
  - **NBOW**
  - **Hierachical Models** two-level CNN
  - **Sequence Models** LSTM, Paragraph Vector

Quite Simple Feature Composition

Given two embeddings **a** and **b**,

1. how to calculate their similarity/relevence/relation?
   1. Concatenation
   $$\mathbf{a} \oplus \mathbf{b} \rightarrow \text{ANN} \rightarrow \text{output}$$
   2. Bilinear
   $$\mathbf{a}^T \mathbf{M} \mathbf{b} \rightarrow \text{output}$$
2. how to use them in classification task?
   1. Concatenation
   $$\mathbf{a} \oplus \mathbf{b} \rightarrow \text{ANN} \rightarrow \text{output}$$
   2. Sum/Average
   $$\mathbf{a} + \mathbf{b} \rightarrow \text{ANN} \rightarrow \text{output}$$

Focused Problem 1: Dense Feature Composition

Not "Really" Deep Learning in NLP

- Most of the neural models is very shallow in NLP.
- The major benefit is introducing dense representation.
- The feature composition is also quite simple.
  - Concatenation
  - Sum/Average
  - Bilinear model

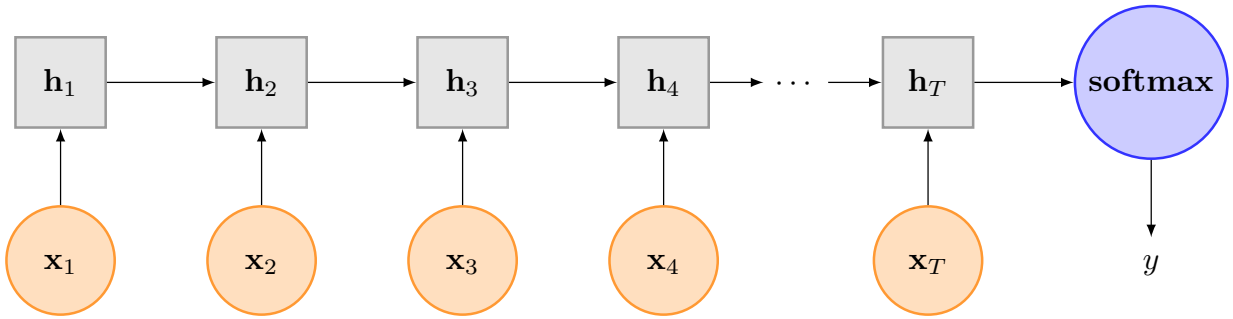
Focused Problem 1: Dense Feature Composition

Many previous works (half a year ago) have shown that increasing the network depth cannot improve the performances of many NLP tasks.

Our Motivation:

How to enhance the neural model by modeling compositions of the dense features?

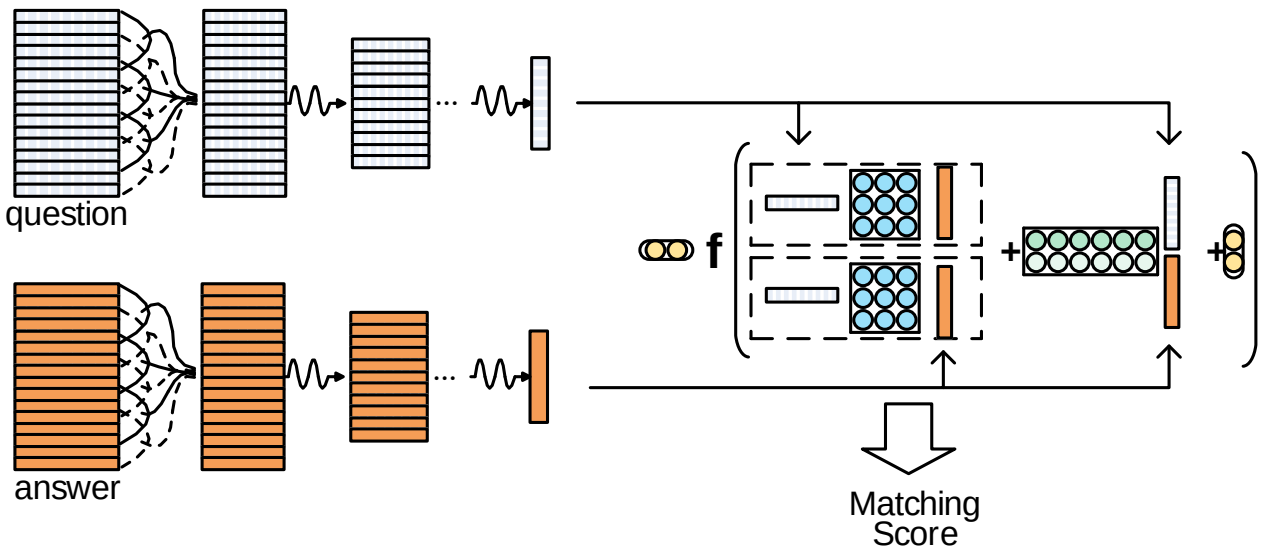
Focused Problem 2: Long Distance Dependence for LSTM



Unfolded LSTM for Text Classification

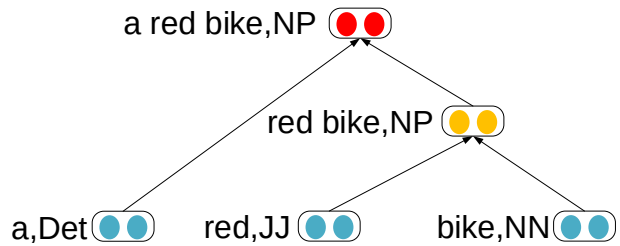
Drawback: long-term dependencies need to be transmitted one-by-one along the sequence.

Convolutional Neural Tensor Network for Text Matching [Qiu and Huang, 2015]



Architecture of Convolutional Neural Tensor Network

Recursive Neural Network (RecNN) [Socher et al., 2013]



Topological models compose the sentence representation following a given topological structure over the words.

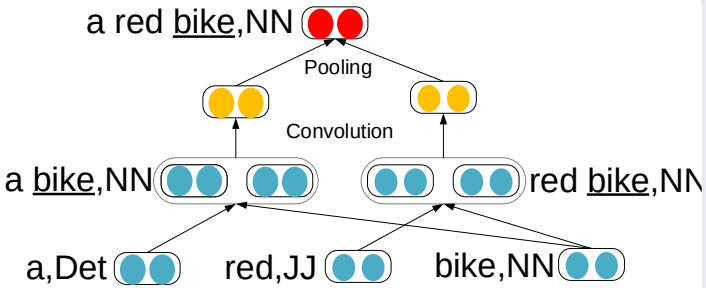
Given a labeled binary parse tree, $((p_2 \rightarrow ap_1), (p_1 \rightarrow bc))$, the node representations are computed by

$$\mathbf{p}_1 = f(\mathbf{W} \begin{bmatrix} \mathbf{b} \\ \mathbf{c} \end{bmatrix}),$$

$$\mathbf{p}_2 = f(\mathbf{W} \begin{bmatrix} \mathbf{a} \\ \mathbf{p}_1 \end{bmatrix}).$$

A variant of RecNN: Recursive Convolutional Neural Network [Zhu et al., 2015]

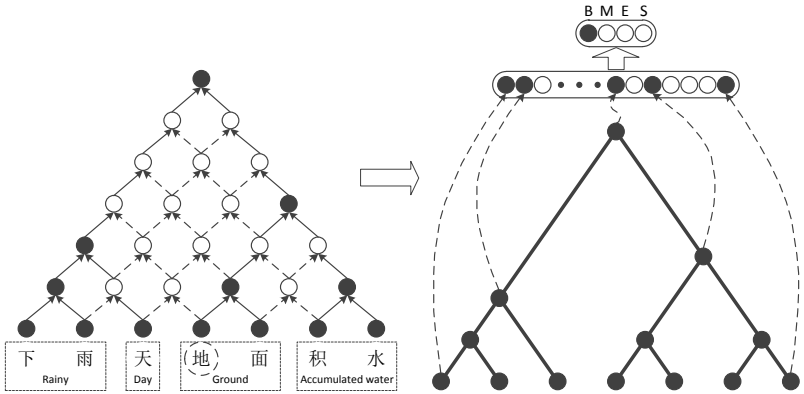
Recursive neural network can only process the binary combination and is not suitable for dependency parsing.



Recursive Convolutional Neural Network

- introducing the convolution and pooling layers;
- modeling the complicated interactions of the head word and its children.

Gated Recursive Neural Network [Chen et al., 2015a]



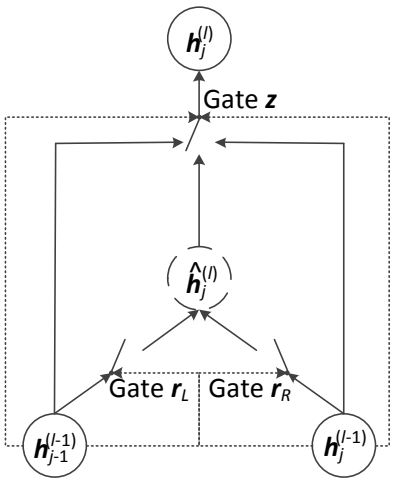
- DAG based Recursive Neural Network
- Gating mechanism

An relative complicated solution

GRNN models the complicated combinations of the features, which selects and preserves the useful combinations via reset and update gates.

A similar model: AdaSent [Zhao et al., 2015]

GRNN Unit

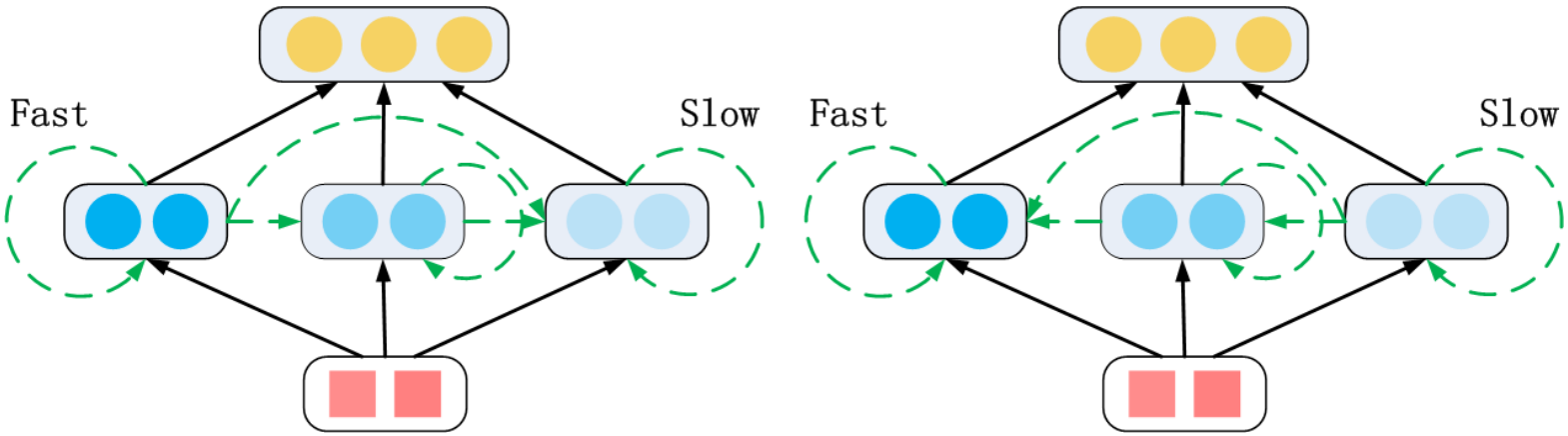


Two Gates

- reset gate
- update gate

- Chinese Word Segmentation [Chen et al., 2015a]
- Dependency Parsing [Chen et al., 2015c]
- Sentence Modeling [Chen et al., 2015b]

Multi-Timescale LSTM

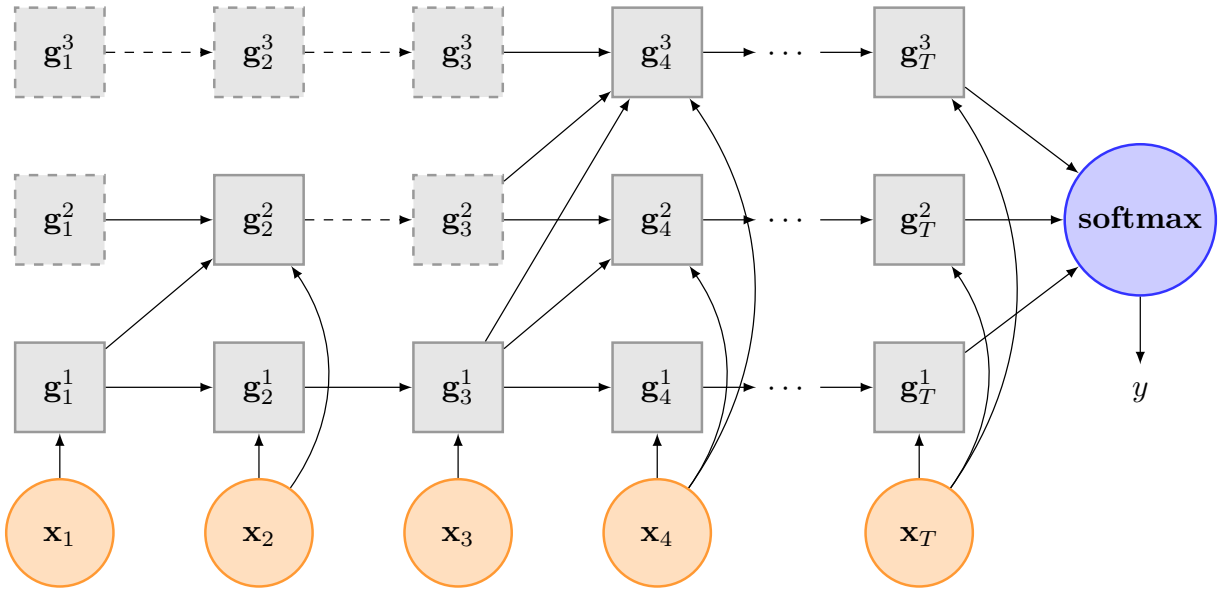


(a) Fast-to-Slow Strategy (b) Slow-to-Fast Strategy

Figure: Two feedback strategies of our model. The dashed line shows the feedback connection, and the solid link shows the connection at current time.

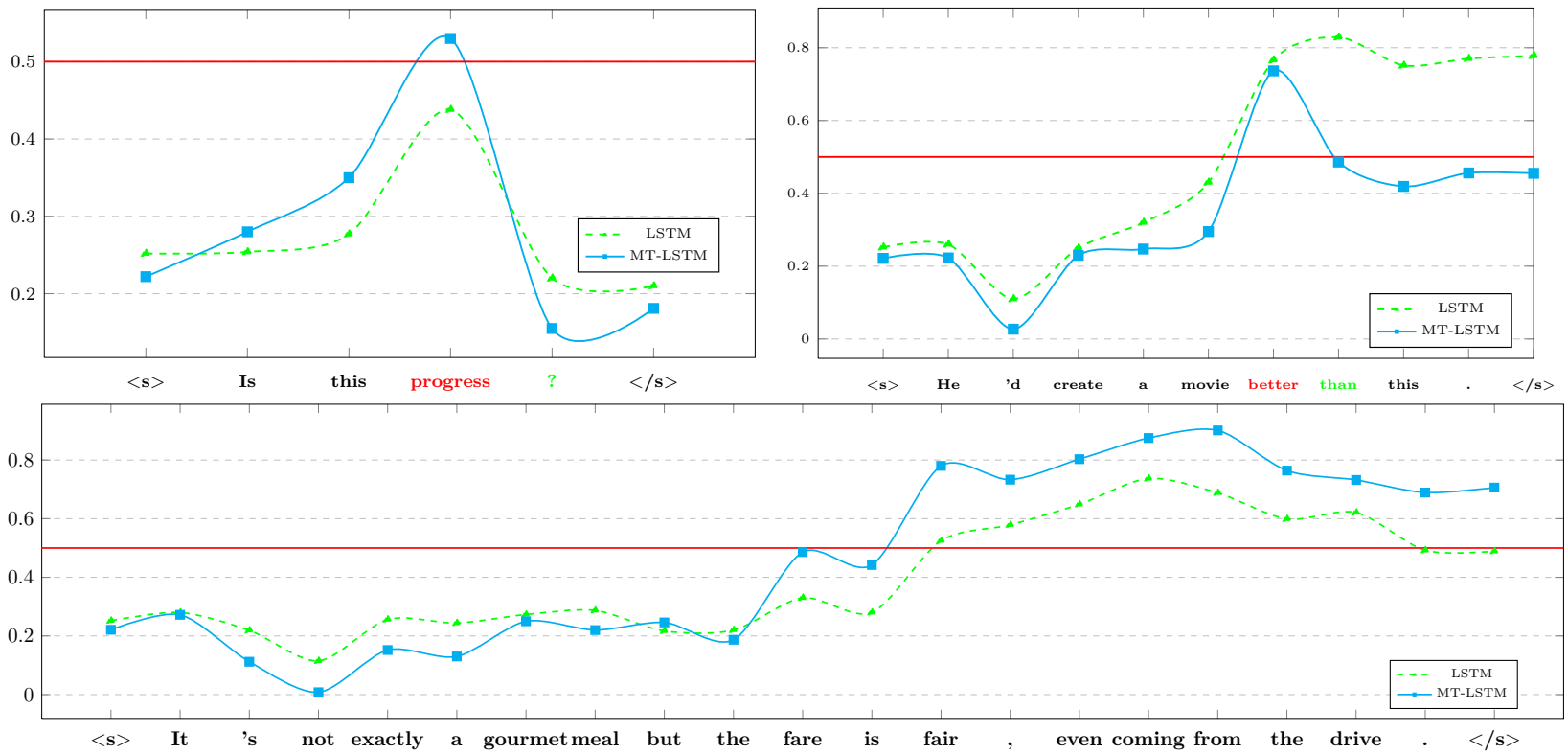
from [Liu et al., 2015]

Unfolded Multi-Timescale LSTM with Fast-to-Slow Feedback Strategy



from [Liu et al., 2015]

LSTM for Sentiment Analysis



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