

# Neural Metaphor Detection in Context

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# Metaphors Are Pervasive

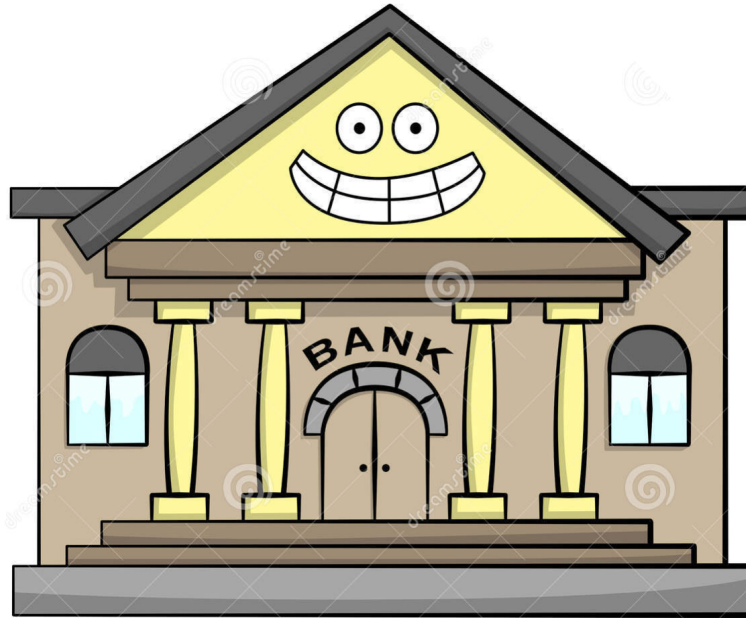
# Metaphors Are Pervasive

The bank pumped \$108 bn into the economy.



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- Some statistics (based on our study on benchmark corpus)
  - Sentence-level: 28%
  - Token-level: 11%

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- Some statistics (based on our study on benchmark corpus)
  - Sentence-level: 28%
  - Token-level: 11%
- Potential application of metaphor processing
  - Machine Translation (Mao et al., 2018)
  - Sentiment Analysis (Mohammad et al., 2016)
  - Educational Applications (Kordoni, 2018 )
  - Relation Extraction
  - .....

# Task

# Task

## 1. Classification Task

✓

The bank pumped \$108 bn into the economy .

## 2. Sequence Labeling Task

X ✓ ✓ X X X X X X

The bank pumped \$108 bn into the economy .



# Related Works

## **Feature-based approach**

concreteness, abstractness,  
imaginability, feature norms,  
sensory features, bag-of-words  
features, WordNet features

Rei et al., 2017, Köper and im Walde, 2017, Bulat et al.,  
2017, Shutova et al., 2016, Tekiroglu et al., 2015,  
Tsvetkov et al., 2014, Broadwell et al., 2013, Strzalkowski  
et al., 2013, Hovy et al., 2013, Turney et al., 2011

# Related Works

Limited Context

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# Context is Important

Limited Context

[bank, pump, money]

Full Context

The bank pumped \$108 bn into the economy.

# Context is Important

Limited Context

[bank, pump, money]

[experts, examine, country]

Full Context

The bank pumped \$108 bn into the economy.

The experts started examining the Soviet Union with a microscope to study perceived changes.

# Related Works

Limited Context

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Full Context

## Context-aware model

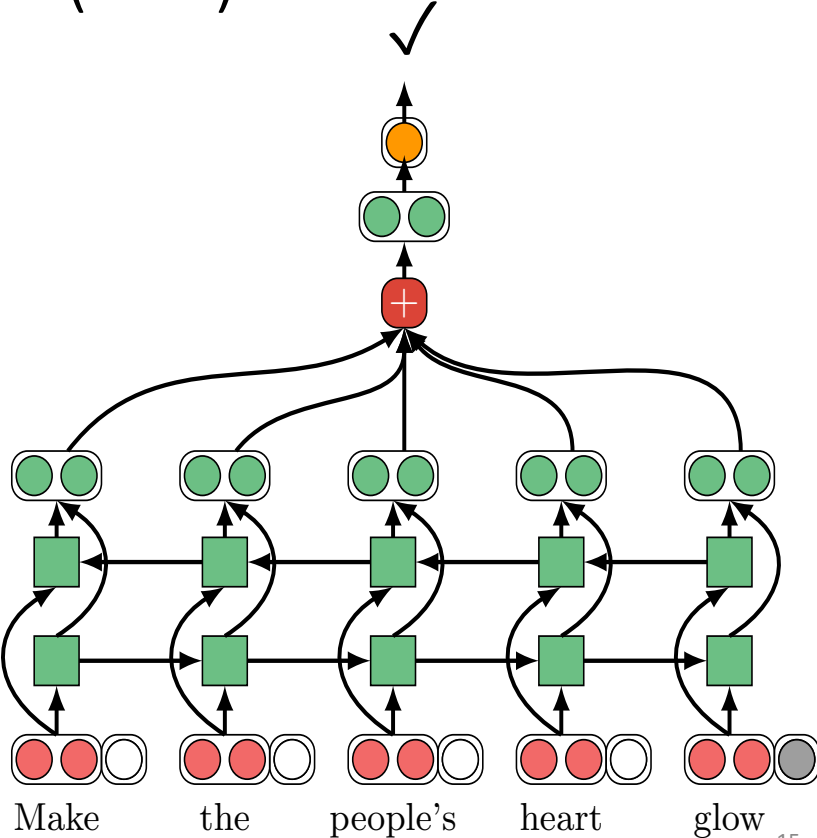
LSTM-based models and CRFs  
augmented by linguistic features:  
WordNet, POS tags, concreteness  
score, unigrams, lemmas, verb clusters

Swarnkar and Singh, 2018; Pramanick et al., 2018; Mosolova et al., 2018; Bizzoni and Ghanimifard, 2018; Wu et al., 2018

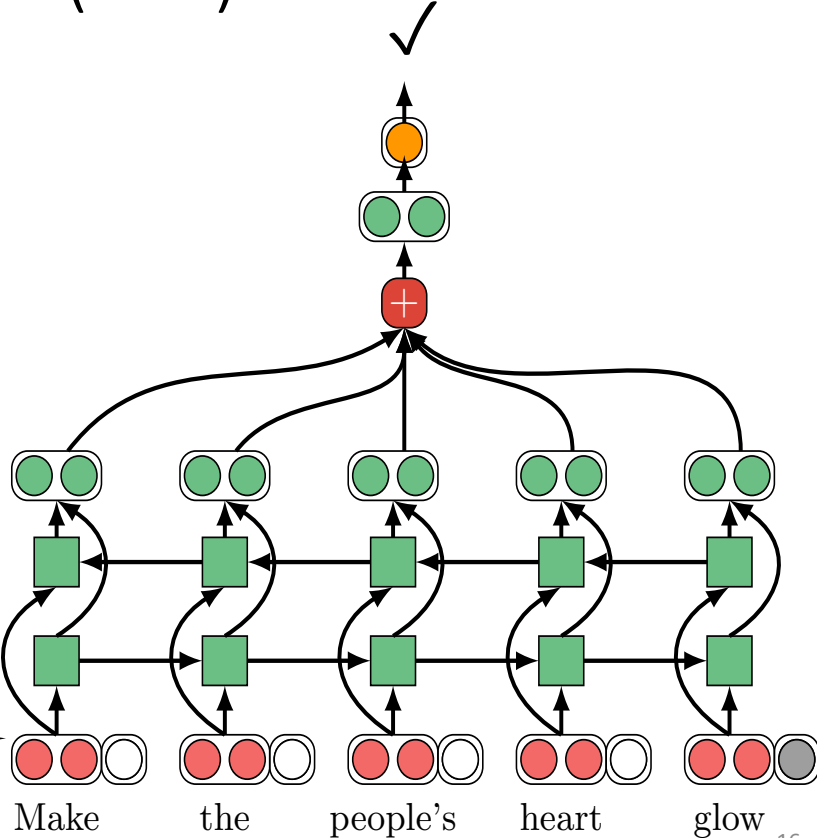
# This Work

- Predicting the metaphoricity of all words in context
- BiLSTM models + contextualized word representation (ELMo)
- New state-of-the-arts on benchmark!

# Our Classification Model (CLS)



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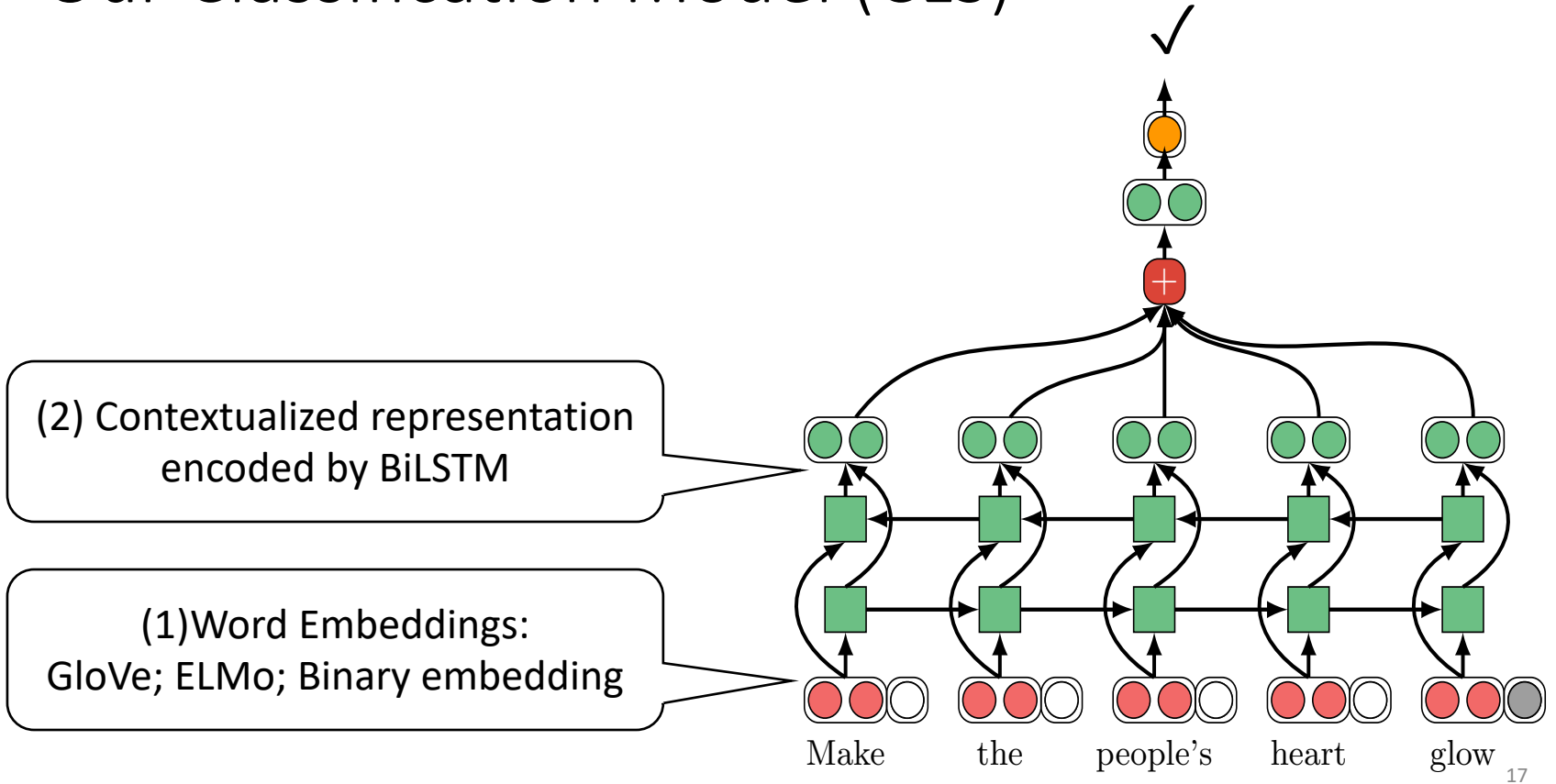


(1) Word Embeddings:  
GloVe; ELMo; Binary embedding

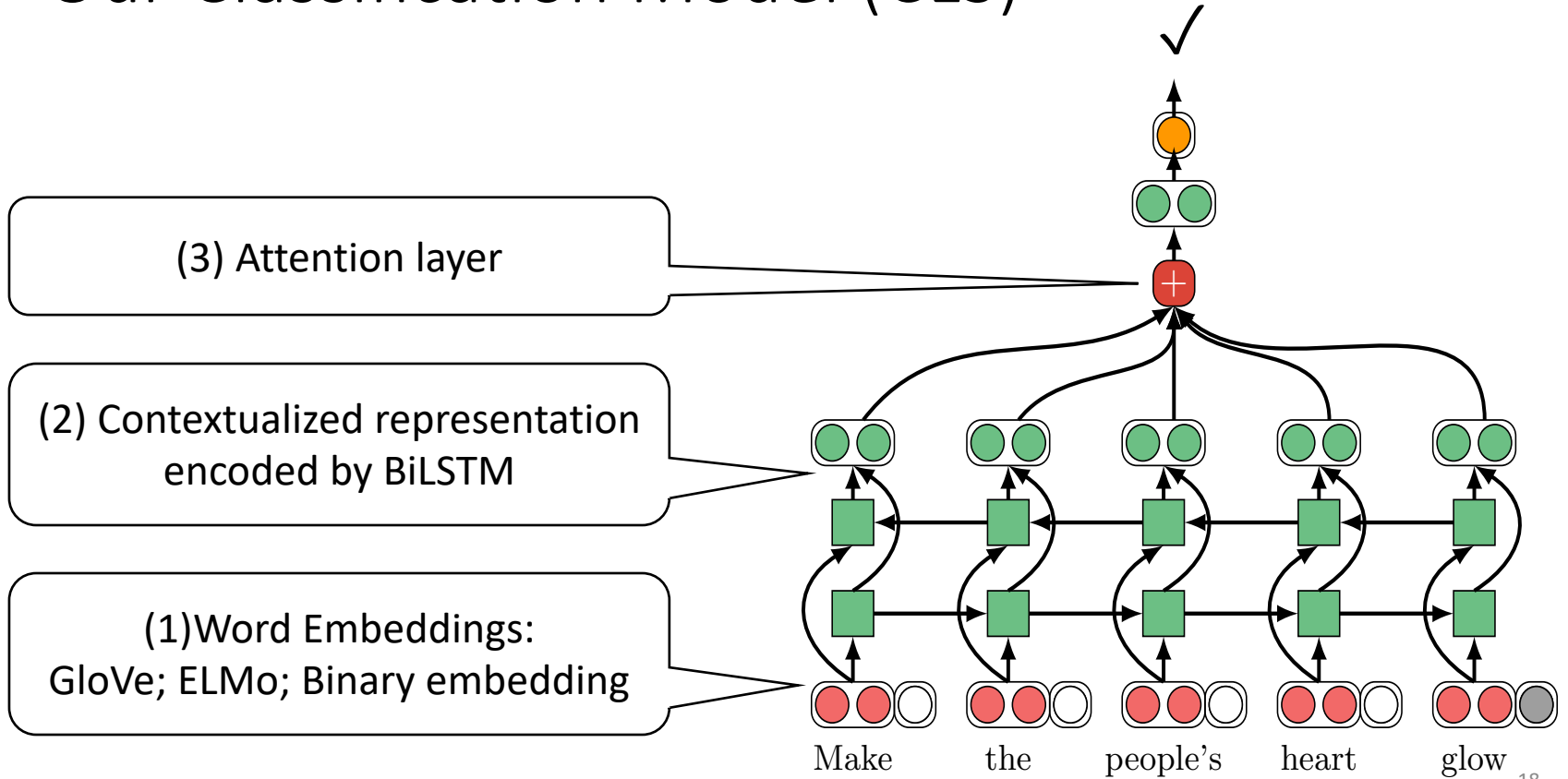
GloVe: Pennington et al., (2014)  
ELMo: Peters et al. (2018)



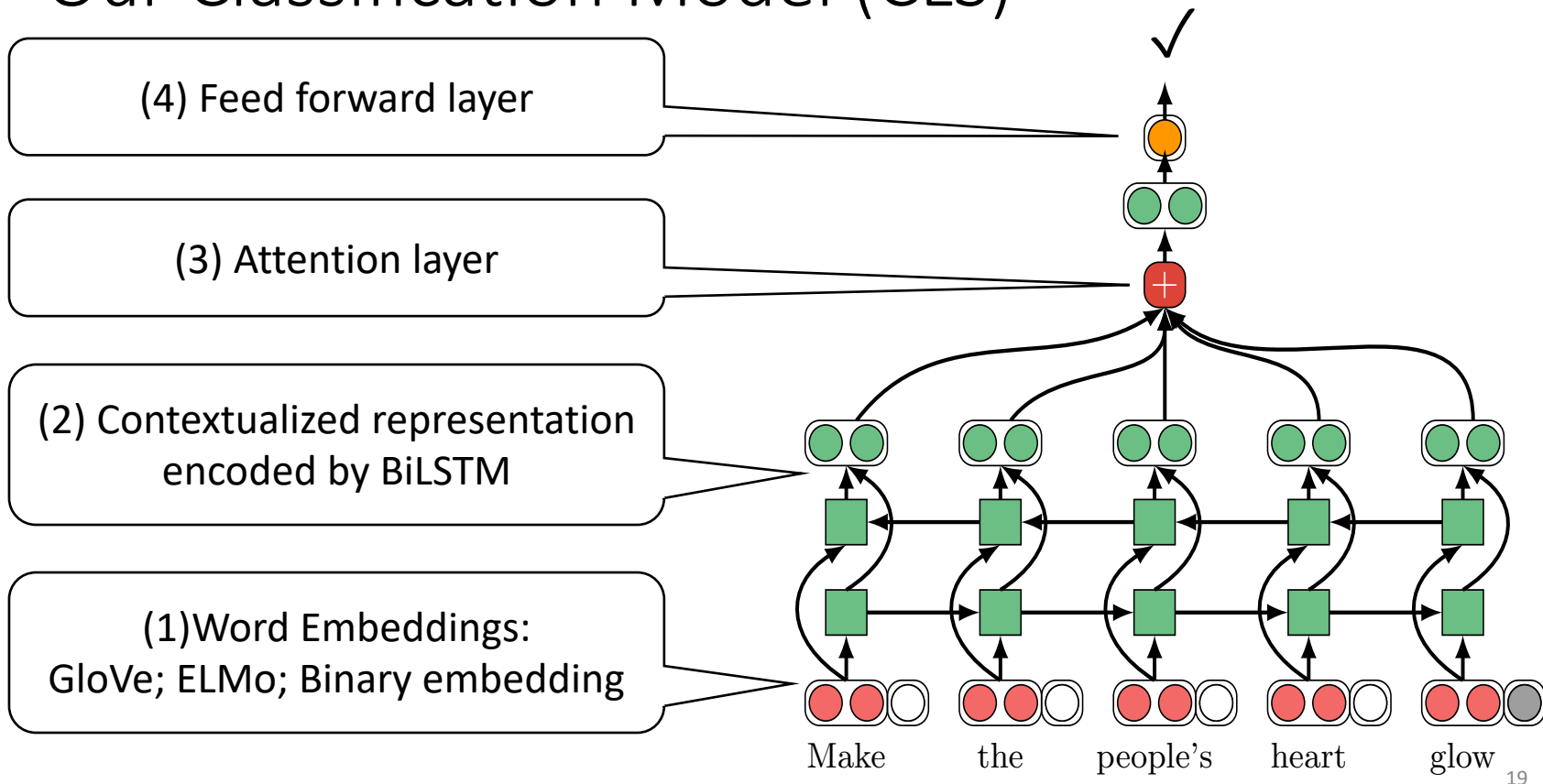
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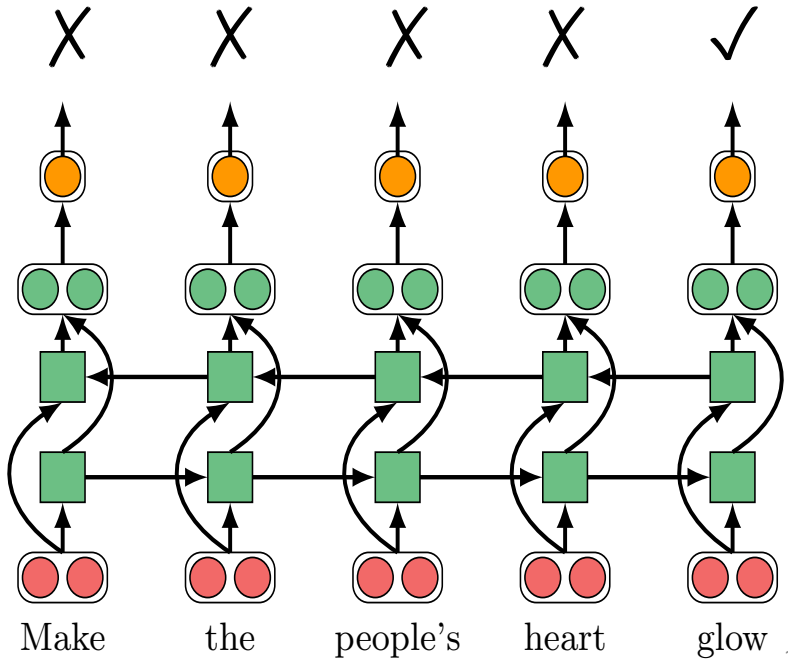
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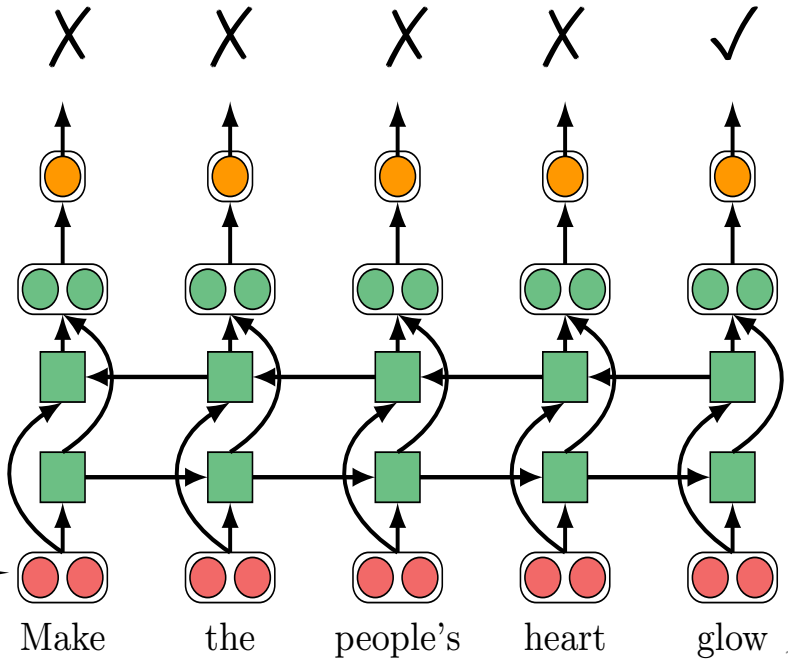


# Our Sequence Labeling Model (SEQ)

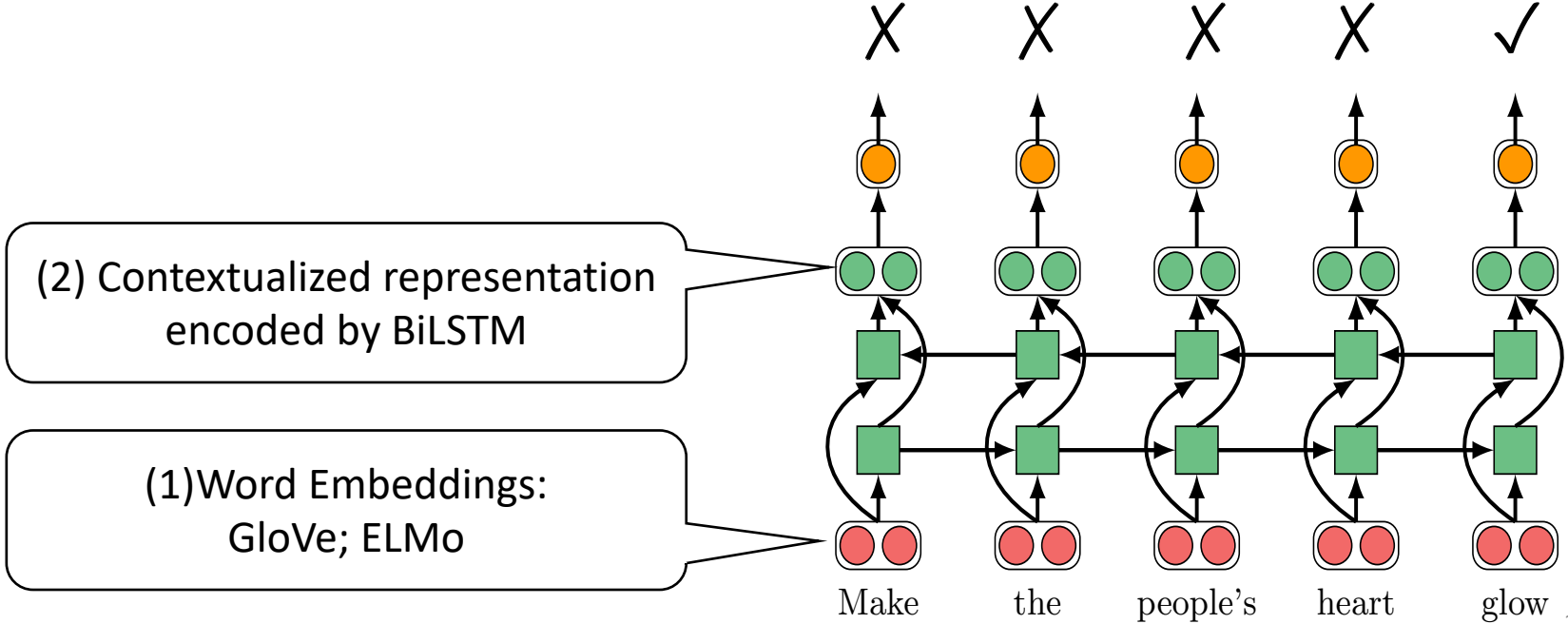


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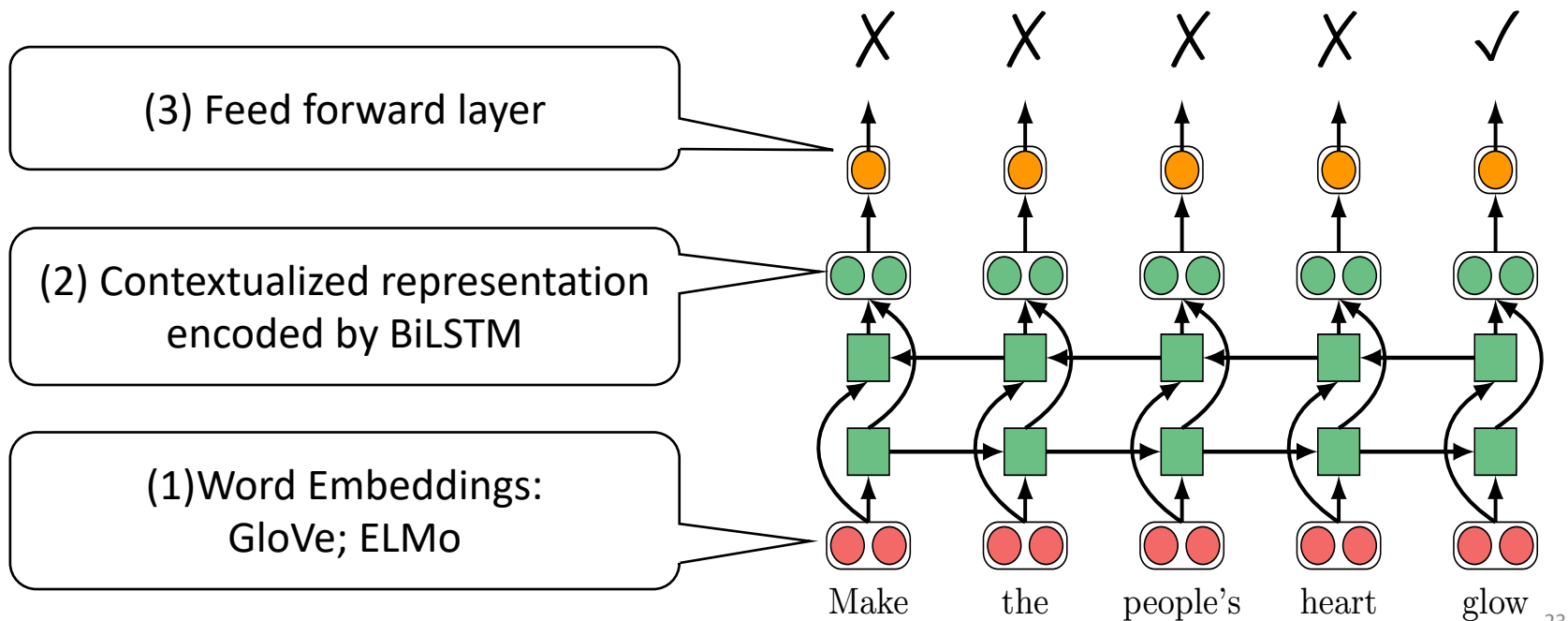
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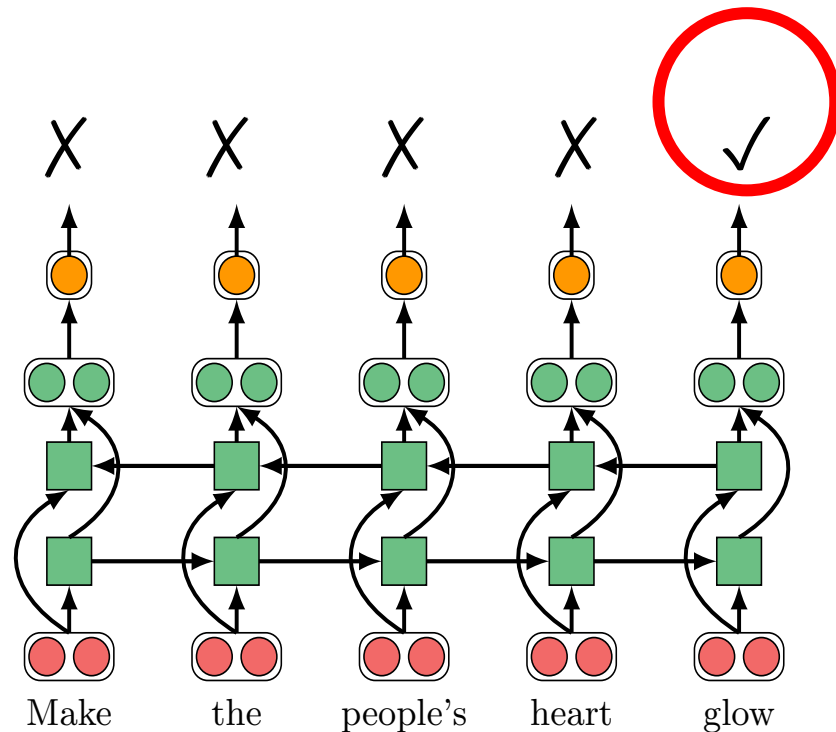
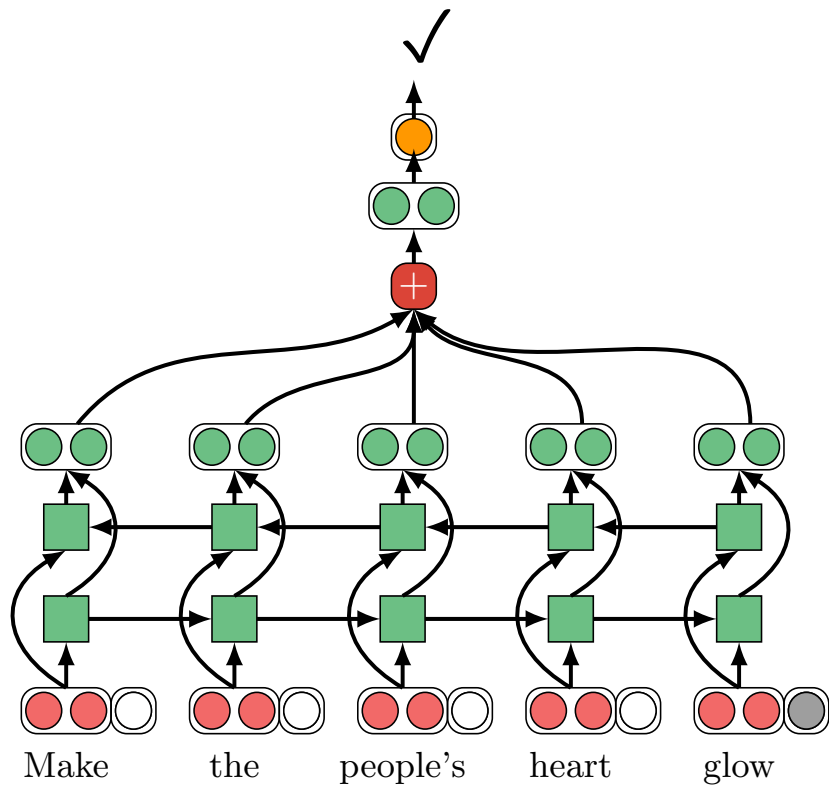
# Dataset: Verb Classification

**# Examples    % Metaphor    # Uniq. Verb    Avg Sent. Len**

|  |               |            |             |             |
|--|---------------|------------|-------------|-------------|
| <b>MOH-X</b><br>Mohammad et al., 2016  | <b>647</b>    | <b>49%</b> | <b>214</b>  | <b>8.0</b>  |
| <b>TroFi</b><br>Birke and Sarkar, 2006 | <b>3,737</b>  | <b>43%</b> | <b>50</b>   | <b>28.3</b> |
| <b>VUA</b><br>Steen et al., 2010       | <b>23,113</b> | <b>28%</b> | <b>2047</b> | <b>24.5</b> |



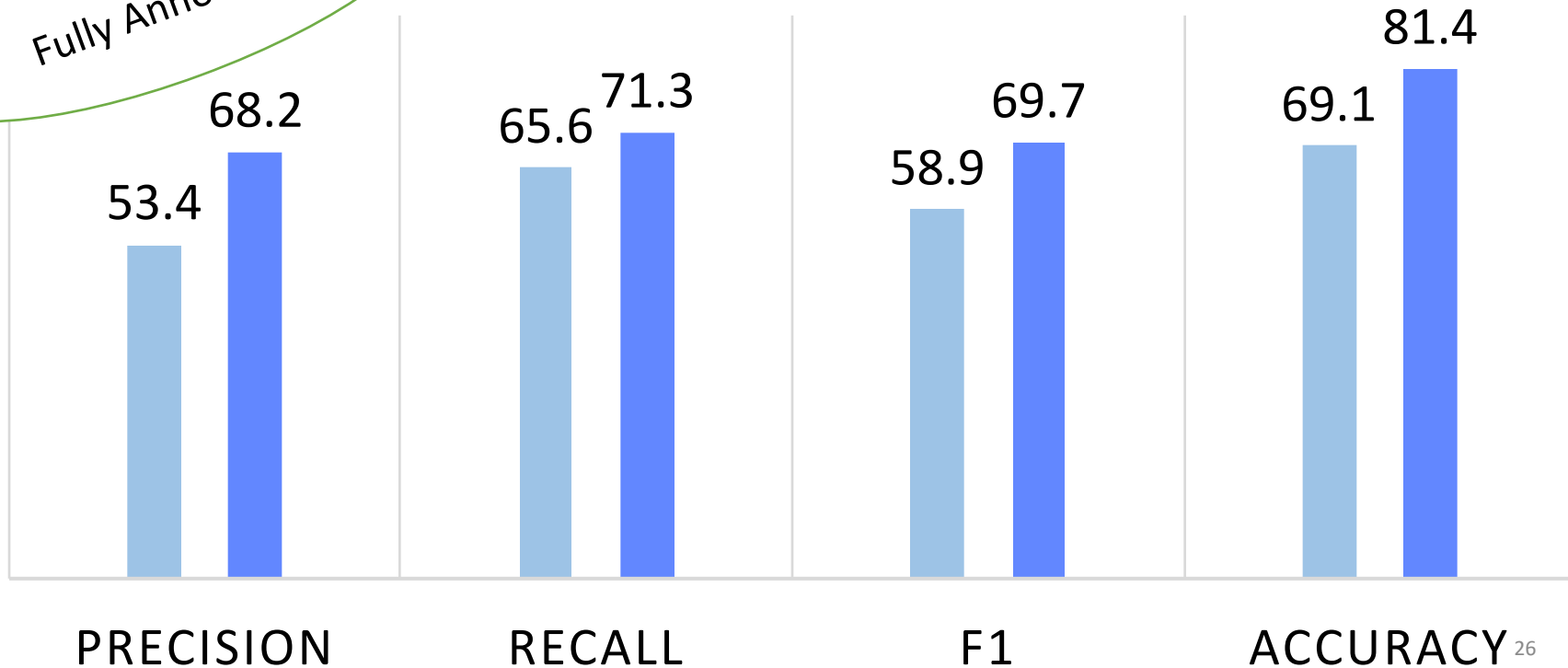
# Direct Comparison



# Performance: Verb Classification (VUA-verb)

■ CLS ■ SEQ

Fully Annotated!



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■ CLS ■ SEQ

Fully Annotated!

81.4

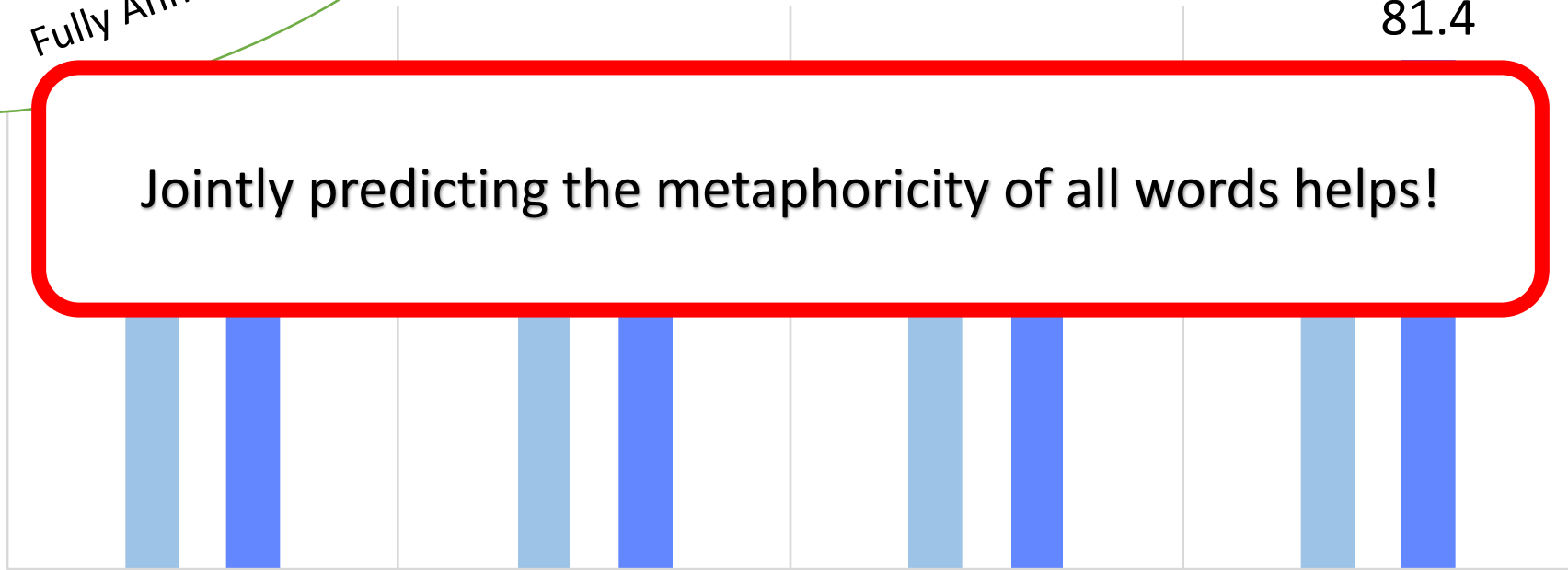
Jointly predicting the metaphoricity of all words helps!

PRECISION

RECALL

F1

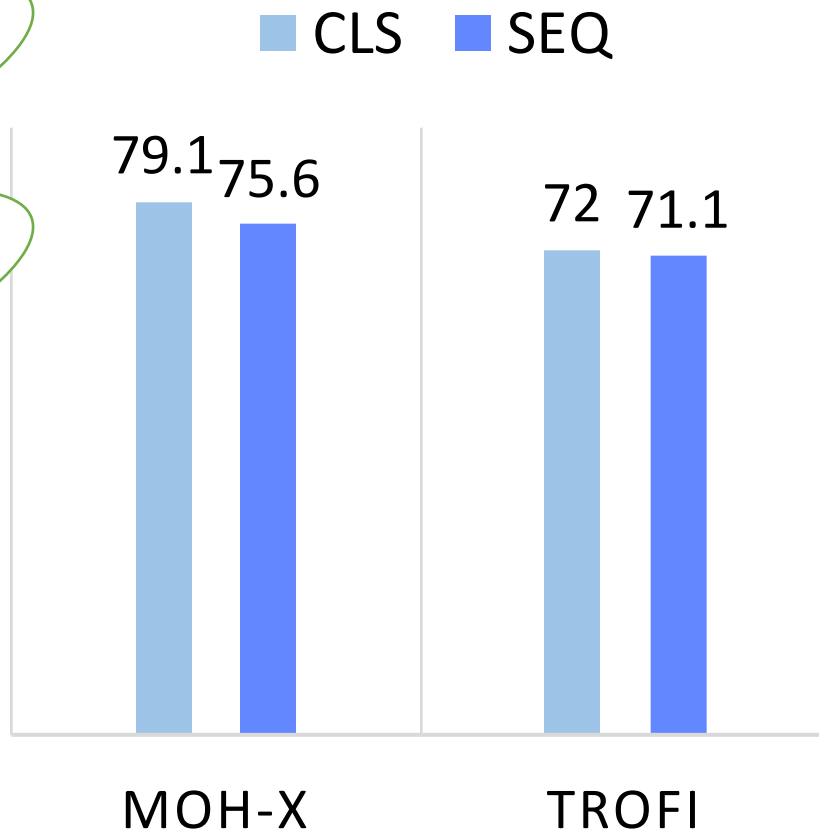
ACCURACY<sup>27</sup>



# Performance: Verb Classification (MOH, TroFi)

Partially Annotated!

Unannotated: literal



# Performance: Verb Classification (MOH, TroFi)

■ CLS ■ SEQ

F1

79.1 75.6

Jointly predicting the metaphoricity is limited on partially-annotated dataset!

MOH-X

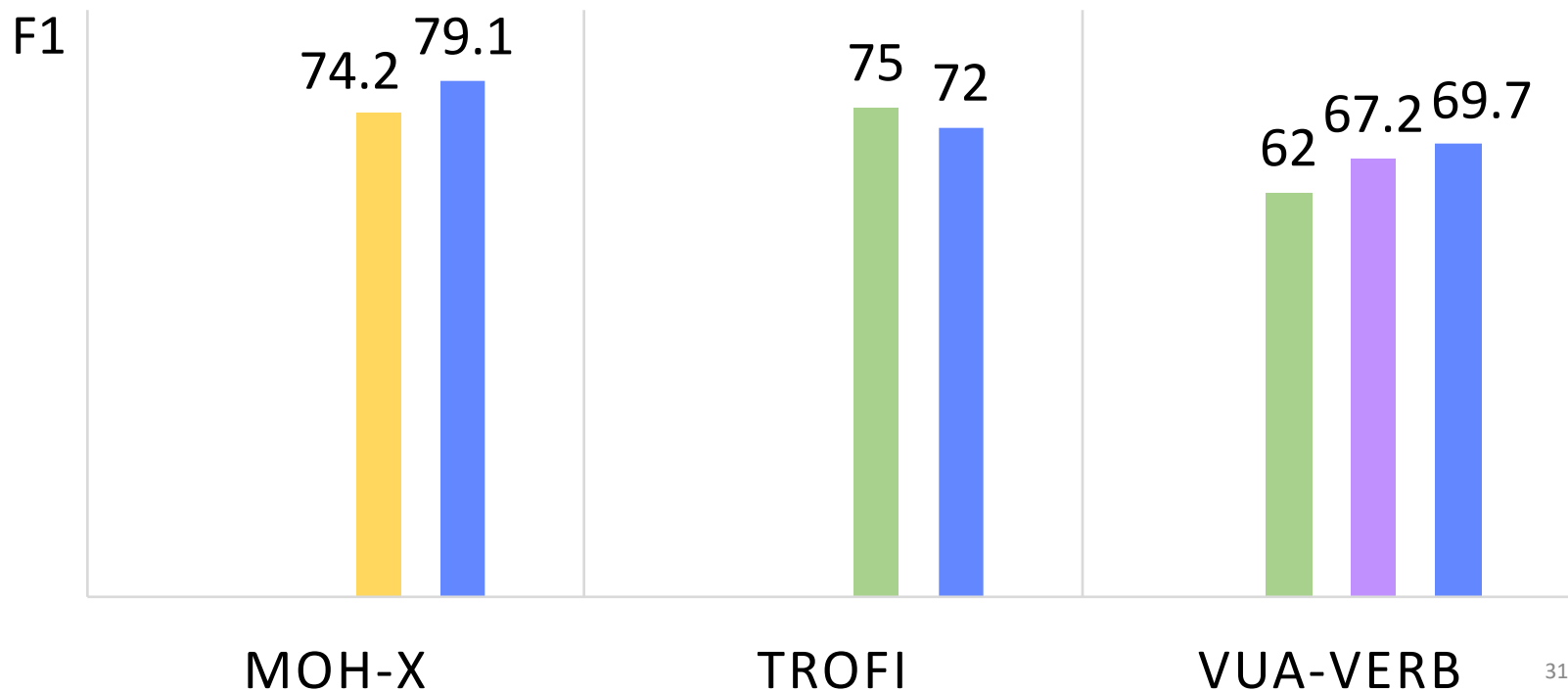
TROFI

# Comparison System

- Wu et al. (2018) Ensemble
  - a CNN-LSTM ensemble model with weighted-softmax classifier
  - pre-trained word2vec + POS tags + word cluster features
- Rei et al. (2017)
  - a neural similarity network on verb-noun pairs
  - pre-trained skip-gram word embeddings
- Köper et al. (2017)
  - a balanced logistic regression classifier
  - target verb lemma + 7 features based on abstractness rating

# Performance: Verb Classification

■ Rei(2017) ■ Köper (2017) ■ Wu (2018) ensemble ■ Our Best Model



# Performance: Verb Classification

■ Rei(2017) ■ Köper (2017) ■ Wu (2018) ensemble ■ Our Best Model

F1

79.1

75

Strong performance across verb classification datasets!

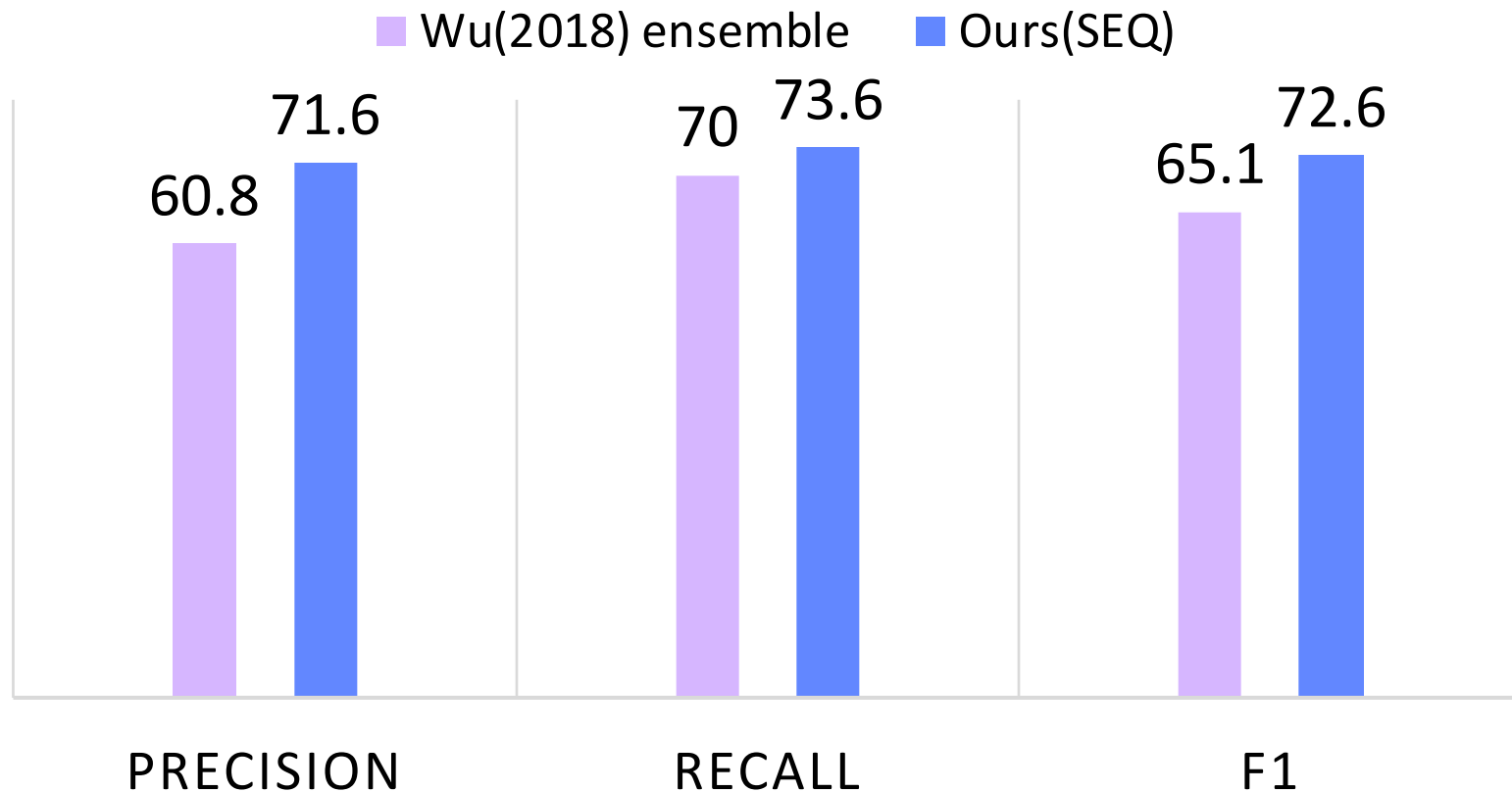
MOH-X

TROFI

VUA-VERB



# Performance: Sequence Labeling (VUA)



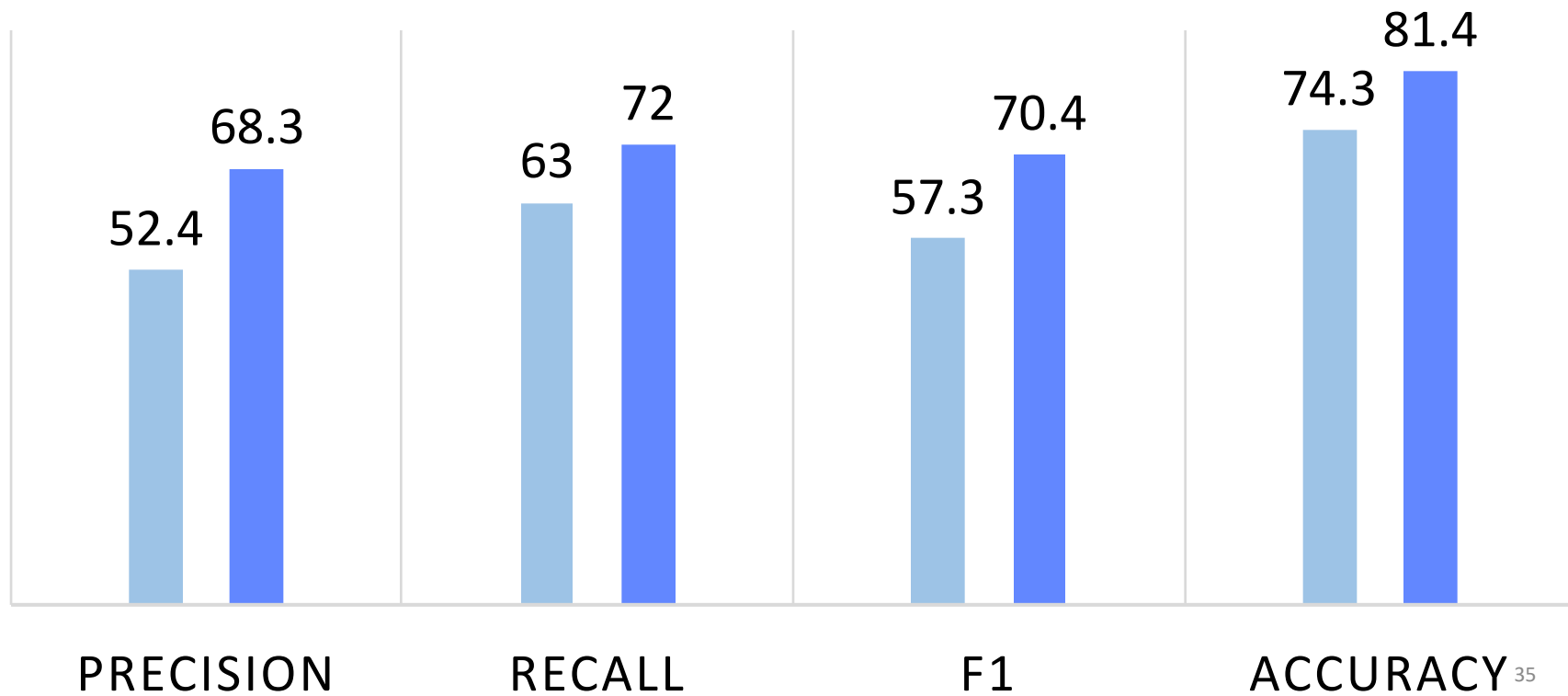
# Analysis

1. How helpful is the contextualized word representation?
2. How well does the model perform on non-verbal POS tags?
3. When does the sequence labeling model outperforms the classification model in general?
4. What kind of errors does the sequence labeling model make on verb classification?

.....

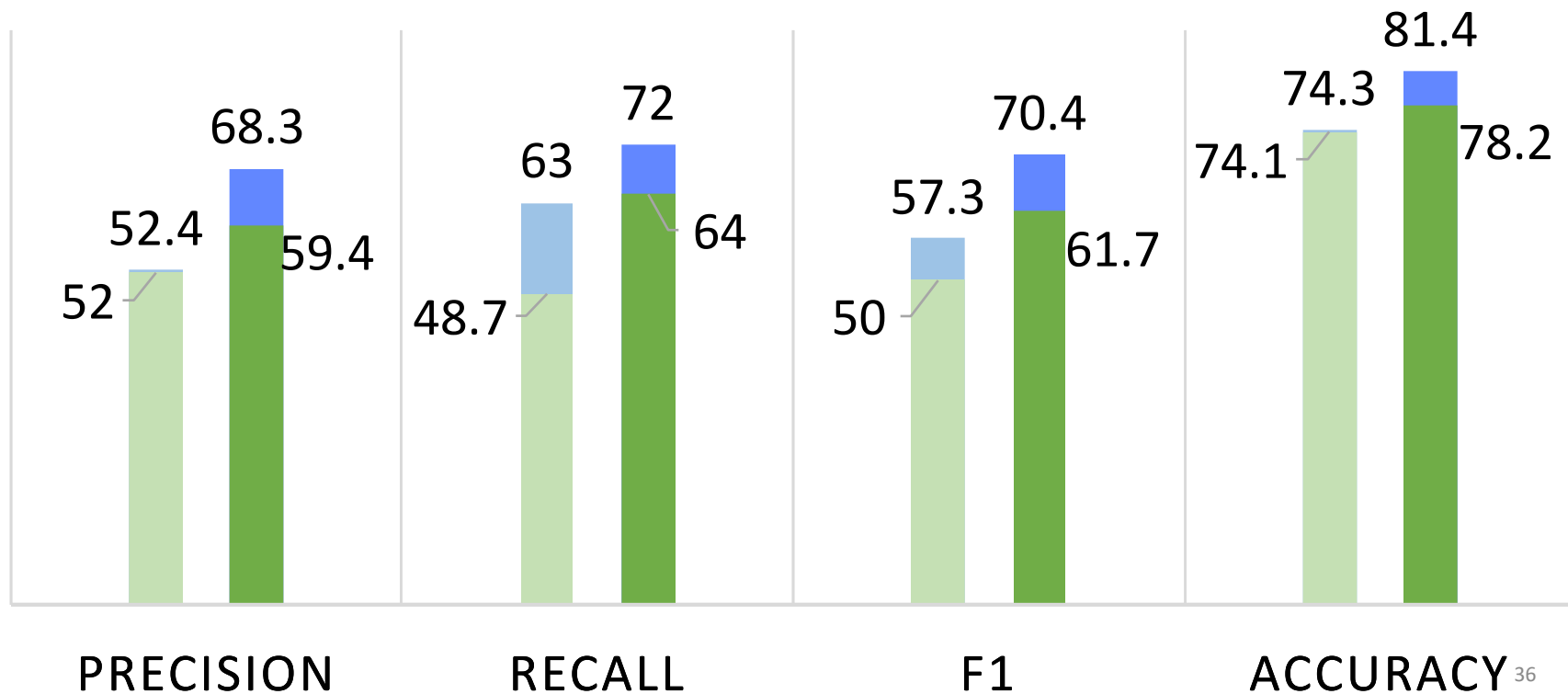
# Ablation Study: Verb Classification (VUA dev)

■ CLS ■ SEQ



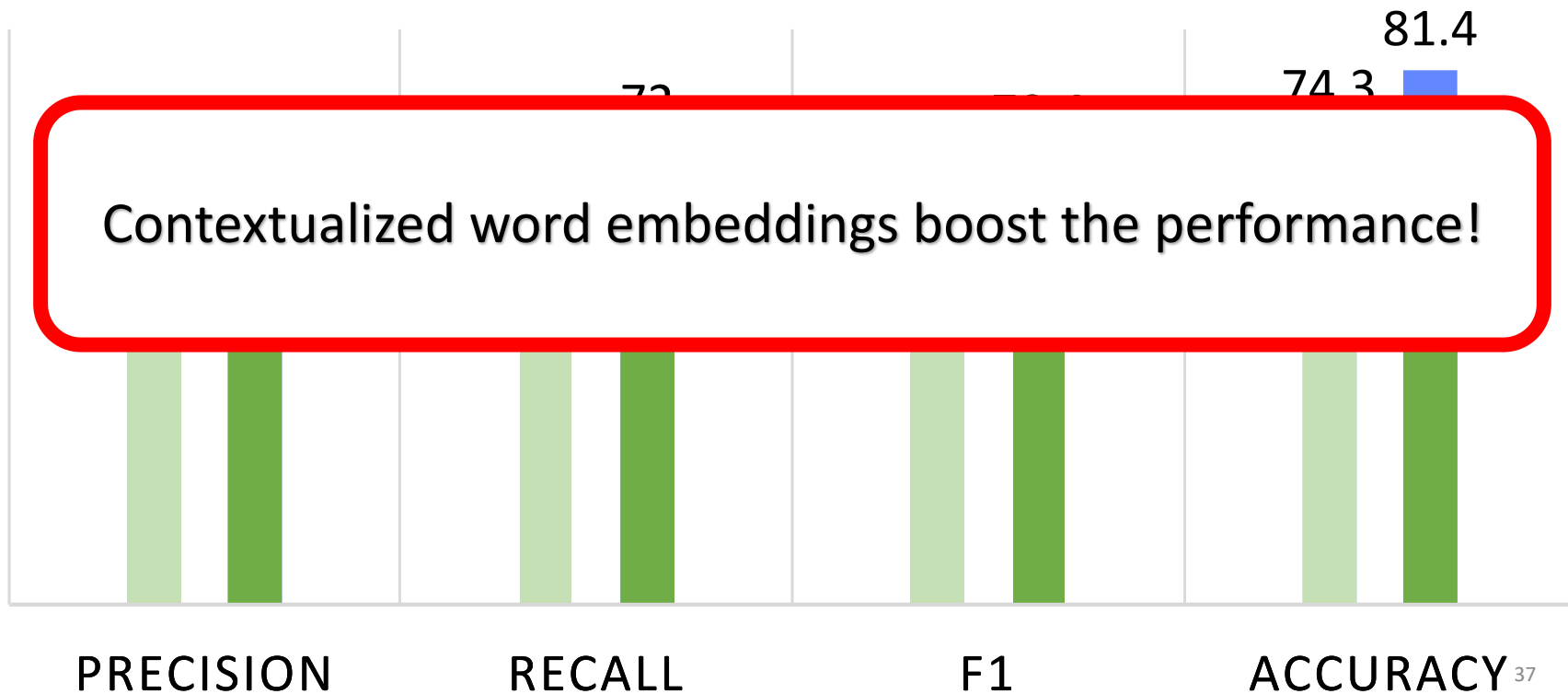
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■ CLS ■ SEQ ■ CLS-ELMo ■ SEQ-ELMo



# Ablation Study: Verb Classification (VUA dev)

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Contextualized word embeddings boost the performance!

PRECISION

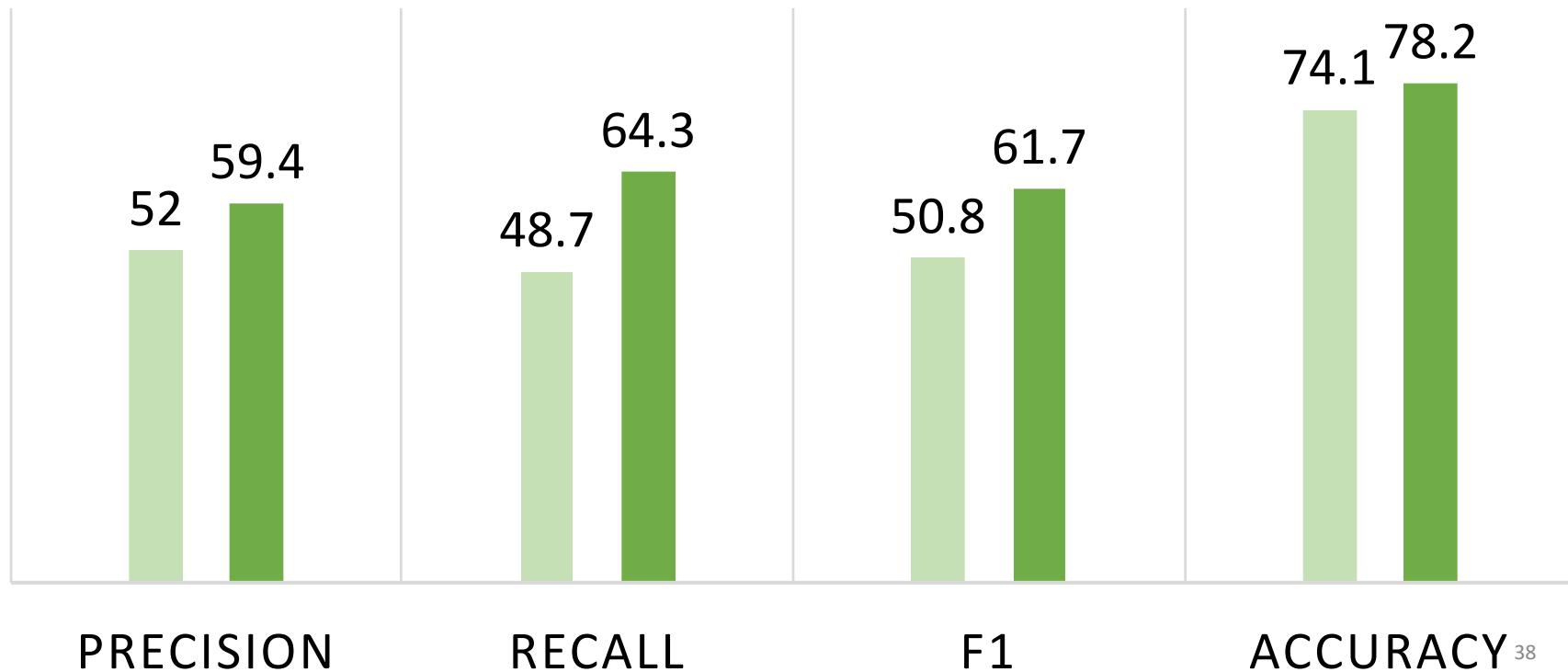
RECALL

F1

ACCURACY<sup>37</sup>

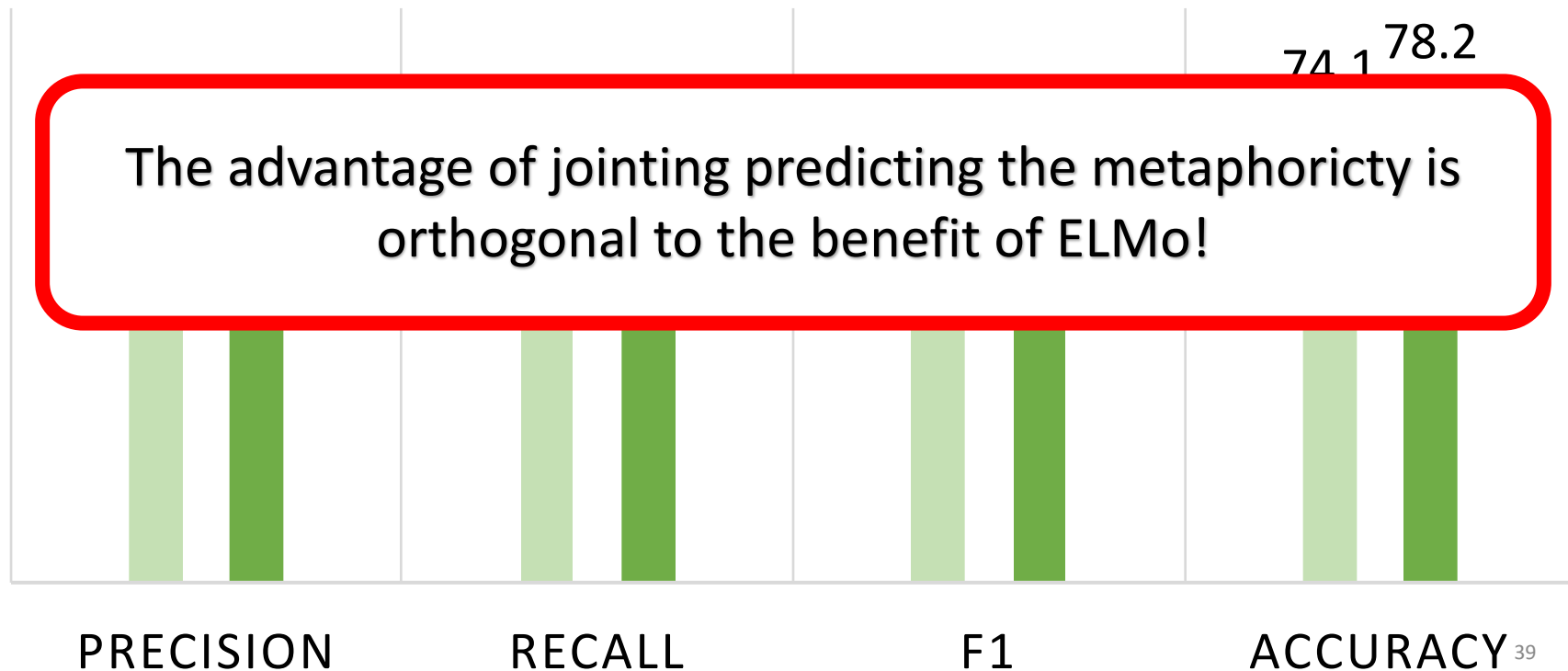
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- Verbs, nouns and adpositions are relatively easier to classify
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  - Higher percentage of metaphors
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- Metaphorical particles are challenging to identify
  - Multiple meanings
  - Often associated with multi-word expressions
  - Examples: put  **down** the disturbance

# Summary

- Jointly predicting the metaphoricity of all words in a sentence can enhance the classification performance.
- Standard BiLSTM models augmented with contextualized word representation perform strongly across various datasets.

Thank you!

Questions?