



(Image Source: Garfield)

# Importance of Data & Controllability in Neural Text Simplification

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# Today's Talk — Automatic Text Simplification

- **Controllable Text Generation**

- Neural semi-Markov CRF for Monolingual Word Alignment (Lan\*, Jiang\* & Xu, ACL 2021)

Also useful for natural language understanding, etc.

- Controllable Text Simplification with Explicit Paraphrasing (Maddela, Alva-Manchego & Xu, NAACL 2021)

How to incorporate linguistic rules with neural networks?

- **High-quality Training Data**

- Neural CRF Model for Sentence Alignment in Text Simplification (Jiang, Maddela, Lan, Zhong & Xu, ACL 2020)

Performance gains from better data are huge!

# **Text Simplification**

Rewrite complex text into simpler language while retain its original meaning.

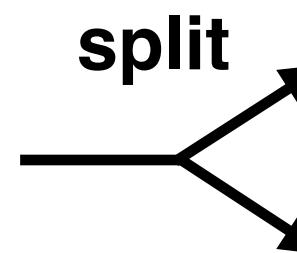
The layers of calcified plaque entomb the bacteria that also live in our mouths -- turning them into small fossils even when we are alive.

And when we die, these dense, calcified micro-fossils remain intact, even as most of the rest of us decomposes.

# Text Simplification

Rewrite complex text into simpler language while retain its original meaning.

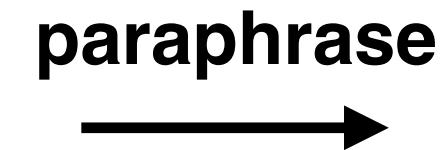
The ~~layers of calcified~~ plaque ~~entomb~~ the bacteria that also ~~live~~ in our mouths -- turning them into ~~small~~ fossils ~~even when we are alive~~.



The **buildup** of plaque **can trap** the bacteria that live in our mouths.

**It** turns them into **tiny** fossils.

And when we die, these ~~dense, calcified~~ micro-fossils ~~remain intact~~, even as most of the rest of us decomposes.

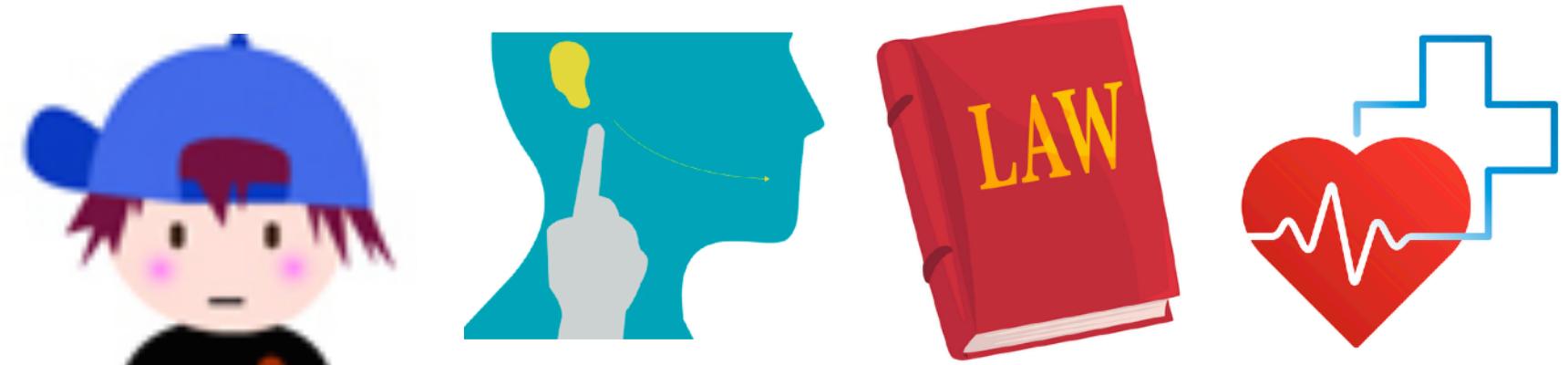


Even after death, these micro-fossils **don't break down**.

# Why Text Simplification?

It can help a lot of people!

- Children (Leonardo et al., 2018) ← research on education using Newsela data
  - Second language learners (Housel et al., 2020) ←
  - Deaf and hard-of-hearing students (Alonzo et al., 2020) ← using our EMNLP 2018 work on lexical simplification
  - People with dyslexia (Rello at al., 2013)
  - People with autism spectrum disorder (González-Navarro et al., 2014)
- 
- and many others ... e.g., to read medical & legal documents, etc.



# Human Text Simplification

Professional editors rewrite news articles into 4 different readability levels for grade 3-12 students.

**NEWSLEA**

WAR & PEACE SCIENCE KIDS MONEY HEALTH

SCIENCE 1738 SHARE

**Archaeologist may have found remains of ancient Egyptian Queen Nefertiti**

By Robert Gebelhoff, Washington Post.  
08.17.15



The 3,330-year-old bust of Nefertiti sits in an exhibition in the Kulturforum in Berlin, Germany, March 1, 2005.  
Photo: AP/Herbert Knosowski

Nefertiti — she's an ancient Egyptian queen and the source of a fantastic mystery regarding the iconic remnants of long-lost royalty.

For decades, archaeologists have speculated on the location of the queen's remains, the last royal mummy missing from the dynasty of the famous King Tutankhamun, better known as King Tut. But now, an archaeologist claims that he has found her

MAX  
1140L  
960L  
720L  
420L  
 WRITE  
 QUIZ

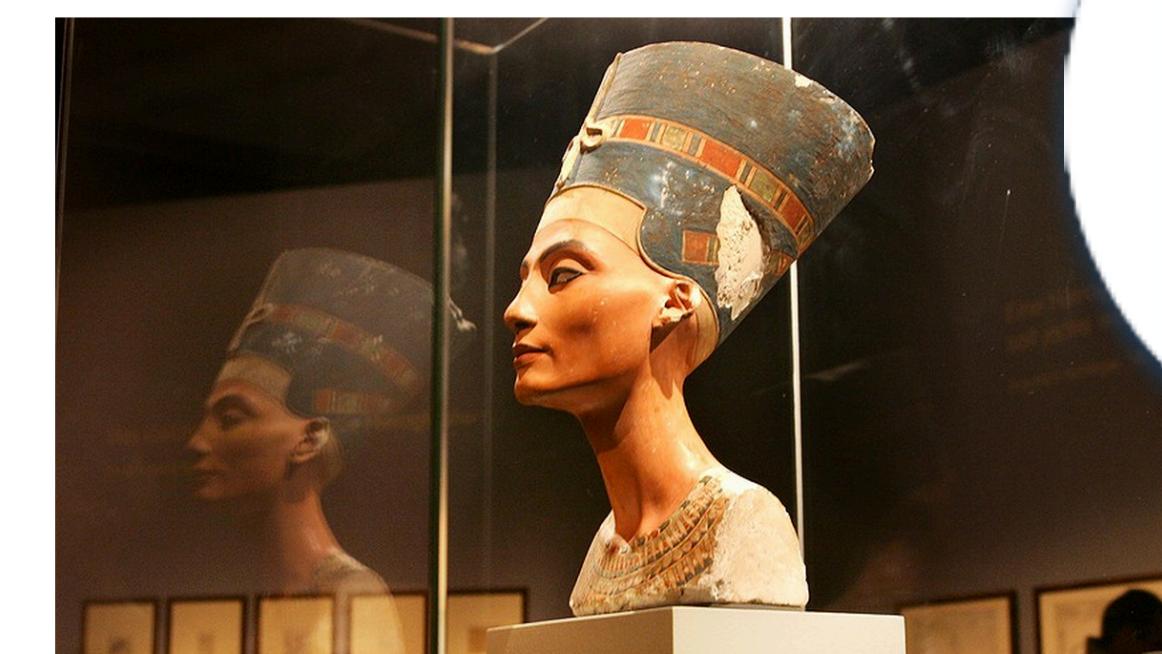
**NEWSLEA**

WAR & PEACE SCIENCE KIDS MONEY LAW HEALTH

SCIENCE 1738 SHARE

**Mystery of ancient Egypt solved? Tomb of queen may be hidden near King Tut'**

By Washington Post, adapted by Newsela staff  
08.17.15



The 3,330-year-old bust of Nefertiti sits in an exhibition in the Kulturforum in Berlin, Germany, March 1, 2005.  
Photo: AP/Herbert Knosowski

The ancient Egyptian Queen Nefertiti has long been at the center of a mystery.

For years, archaeologists have wondered where her tomb might be hidden. Nefertiti belonged to the family line of the famous King Tutankhamun, better known as King Tut. Indeed, some believe she was Tut's mother. While the other royals in her line are

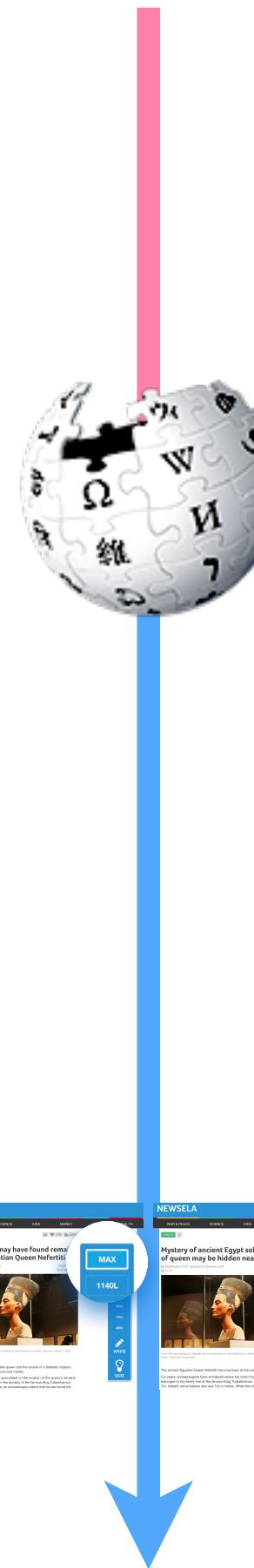
1140L  
960L  
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 QUIZ

# Automatic Text Simplification

A brief history ...

## rule-based methods

Simple English  
WIKIPEDIA



## statistical machine translation

newsela®

- |             |   |
|-------------|---|
| 1997        | Chandrasekar & Srinivas   |
| 1999        | Dras (PhD thesis)   |
| 2000        | Carroll, Minnen, Pearce, Canning, Devlin  |
| 2002        | Canning (PhD thesis)  |
| 2004        | Siddharthan (PhD thesis)  |
| <b>2010</b> | <b>Zhu, Bernhard, Gurevych</b>  |
| 2011        | Woodsend & Lapata   |
| 2011        | Coster & Kauchak  |
| 2012        | Wubben, van den Bosch, Krahmer  |
| 2014        | Narayan & Gardent   |
| 2014        | Siddharthan (Survey)  |
| 2014        | Angrosh, Nomoto, Siddharthan  |
| 2014        | Narayan (PhD thesis)  |
| <b>2015</b> | <b>Xu, Callison-Burch, Napoles</b>  |
|             | “Problems in Current Text Simplification Research: New Data Can Help” (TACL 2015) |
| <b>2016</b> | <b>Xu, Napoles, Pavlick, Chen, Callison-Burch</b>                                 |
|             | “Optimizing Statistical Machine Translation for Simplification” (TACL 2016)       |

# Automatic Text Simplification

Now, primarily addressed by sequence-to-sequence neural network models.

## Input sentence:

Since 2010, project researchers have uncovered documents in Portugal that have revealed who owned the ship



## Generated Output:

Scientists have found documents in Portugal.  
They have also found out who owned the ship.

- **Some early works:**

- LSTM model (Nisioi et al. 2017)
- Transformer model (Zhao et al. 2018)

# Automatic Text Simplification

However, SOTA neural generation models perform mostly deletion.

## Input sentence:

According to Ledford, Northrop executives said they would build substantial parts of the bomber in Palmdale, creating about 1,500 jobs.

## Generated output:

---

Programmer-interpreter  
(Dong et al., 2019)

ledford **is a big group** of bomber in palmdale.

---

Rerank  
(Kriz et al., 2019)

ledford **is** northrop.

---

Reinforcement Learning  
(Zhang & Lapata, 2017)

, said they would build **palmdale** parts of **the substantial** in **creating**.

# Automatic Text Simplification

However, SOTA neural generation models perform mostly deletion.

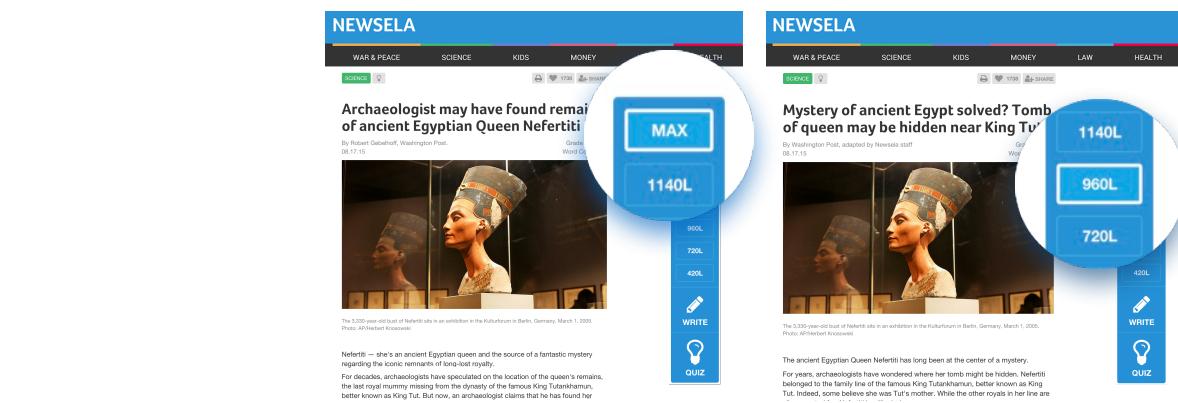
Avg. length of input sentences is 20.7 tokens.



	<b>Output-Length</b>	<b>New-Words</b>	<b>Identical-to-Input</b>	<b>Sentence-Split</b>
Programmer-interpreter (Dong et al., 2019)	10.9	8.4%	4.6%	0%
Rerank (Kriz et al., 2019)	10.8	11.2%	1.2%	0%
Reinforcement Learning (Zhang & Lapata, 2017)	13.8	8.1%	16.8%	0%
Professional Editors	17.9	29.0%	0.0%	30.0%

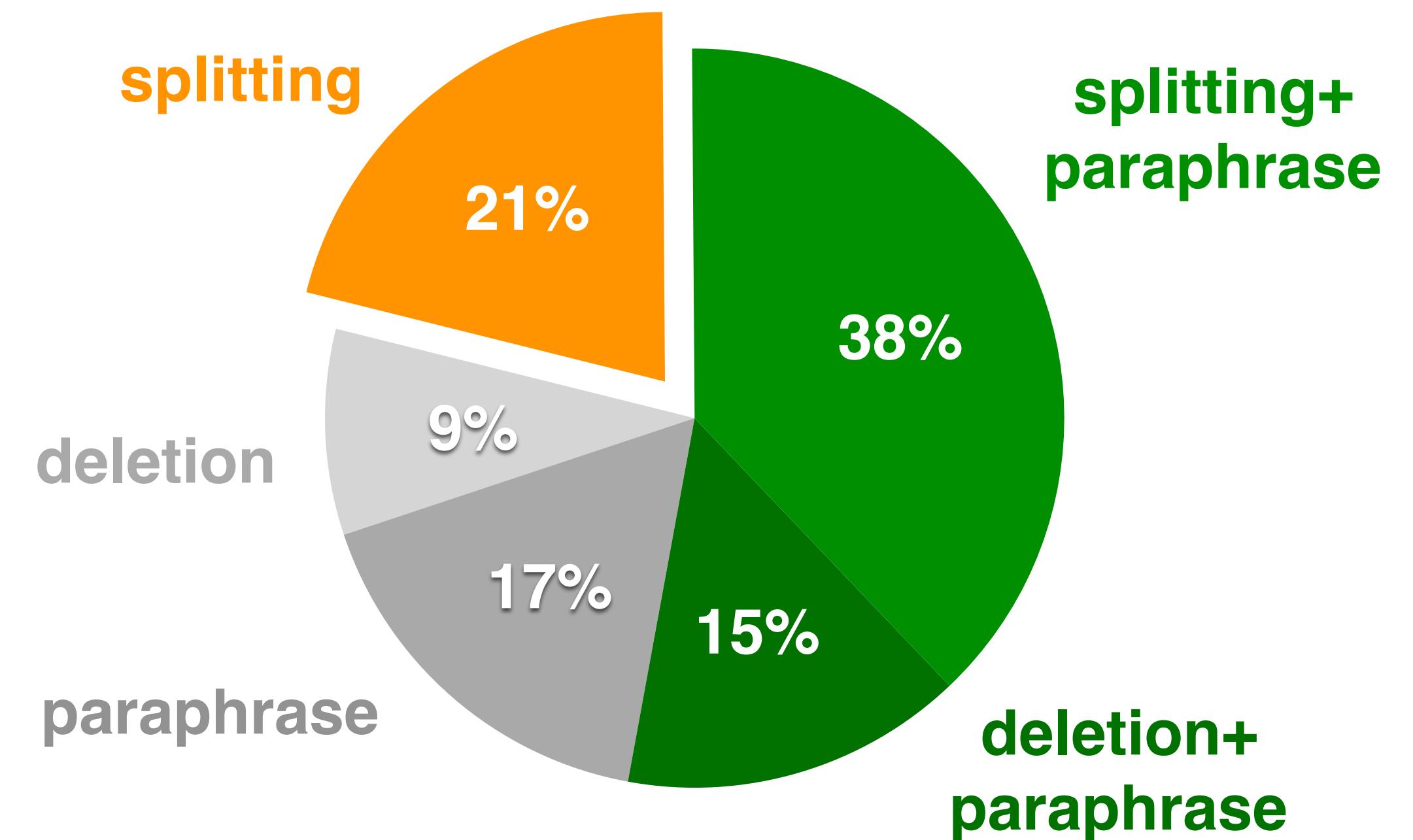
# Text Simplification Data

Professional editors use a sophisticated combination of rephrasing, splitting, and deletion.



1882 news articles x 4 readability levels

Sentence Alignment →

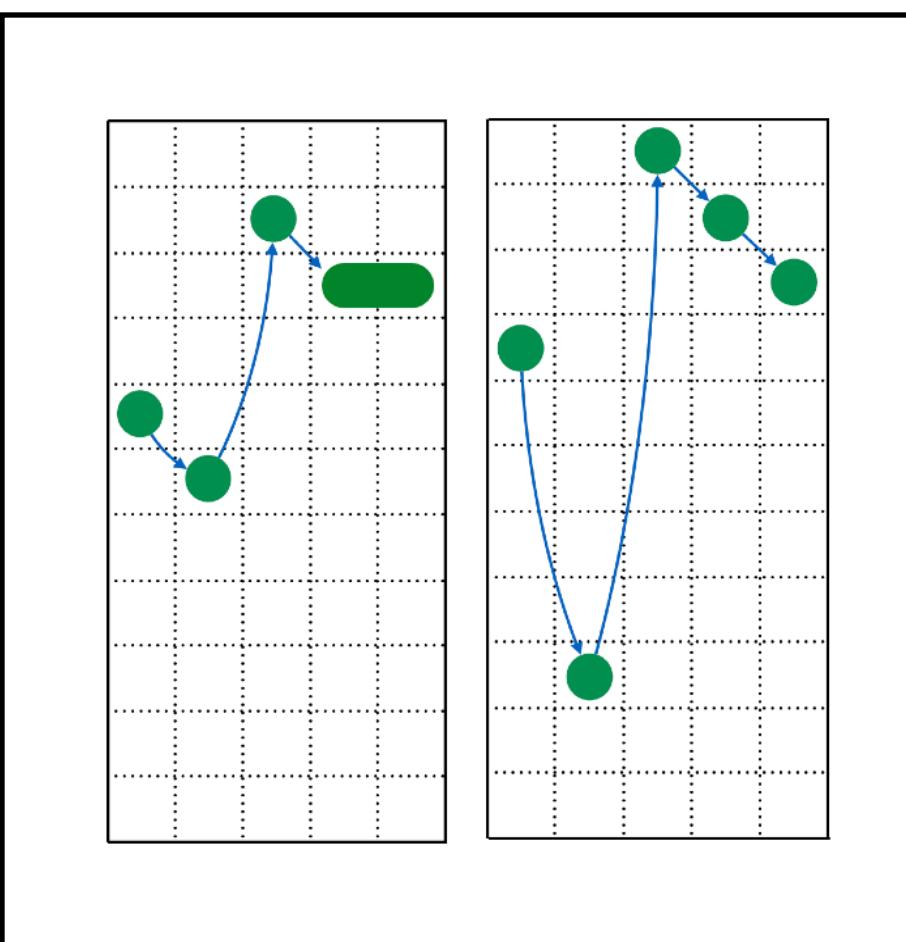


**Newsela-Auto Corpus (Jiang et al. 2020)**

666k sentence pairs

+ **Wiki-Auto Corpus** 488k sentence pairs

# Part 0 — Monolingual Word Alignment



## Neural semi-Markov CRF for Monolingual Word Alignment

Wuwei Lan\*, Chao Jiang\*, Wei Xu (ACL 2021)



# Monolingual Word Alignment

Can support not only text-to-text generation tasks, but also natural language understanding tasks.

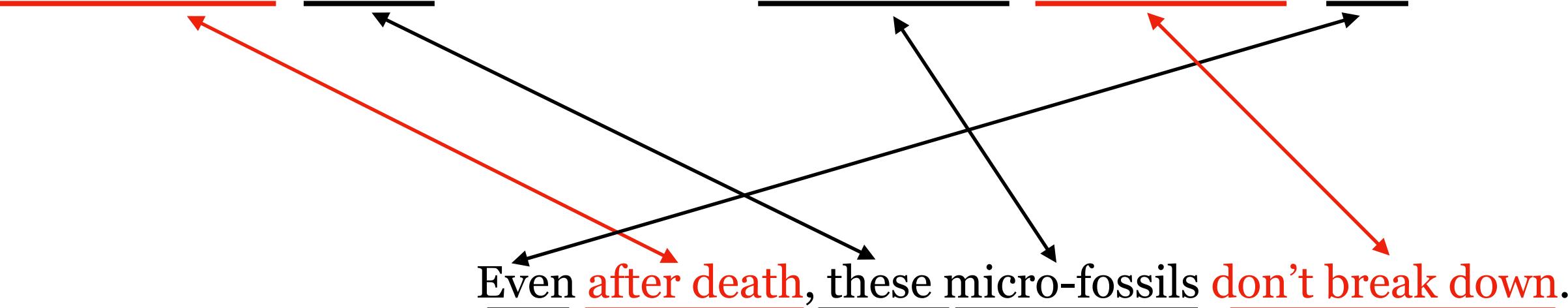
**Rephrase**

**Keep**

**Delete**

And when we die, these dense, calcified micro-fossils remain intact, even as most of the rest of us decomposes.

Even after death, these micro-fossils don't break down.



# ~~Span~~ Monolingual Word Alignment

Can support not only text-to-text generation tasks, but also natural language understanding tasks.

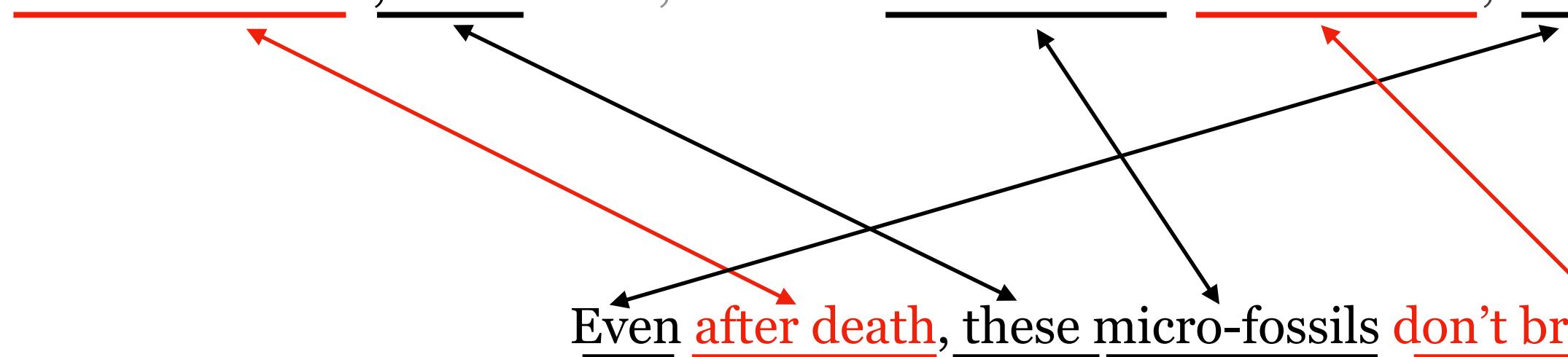
## Rephrase

And when we die, these dense, calcified micro-fossils remain intact, even as most of the rest of us decomposes.

## Keep

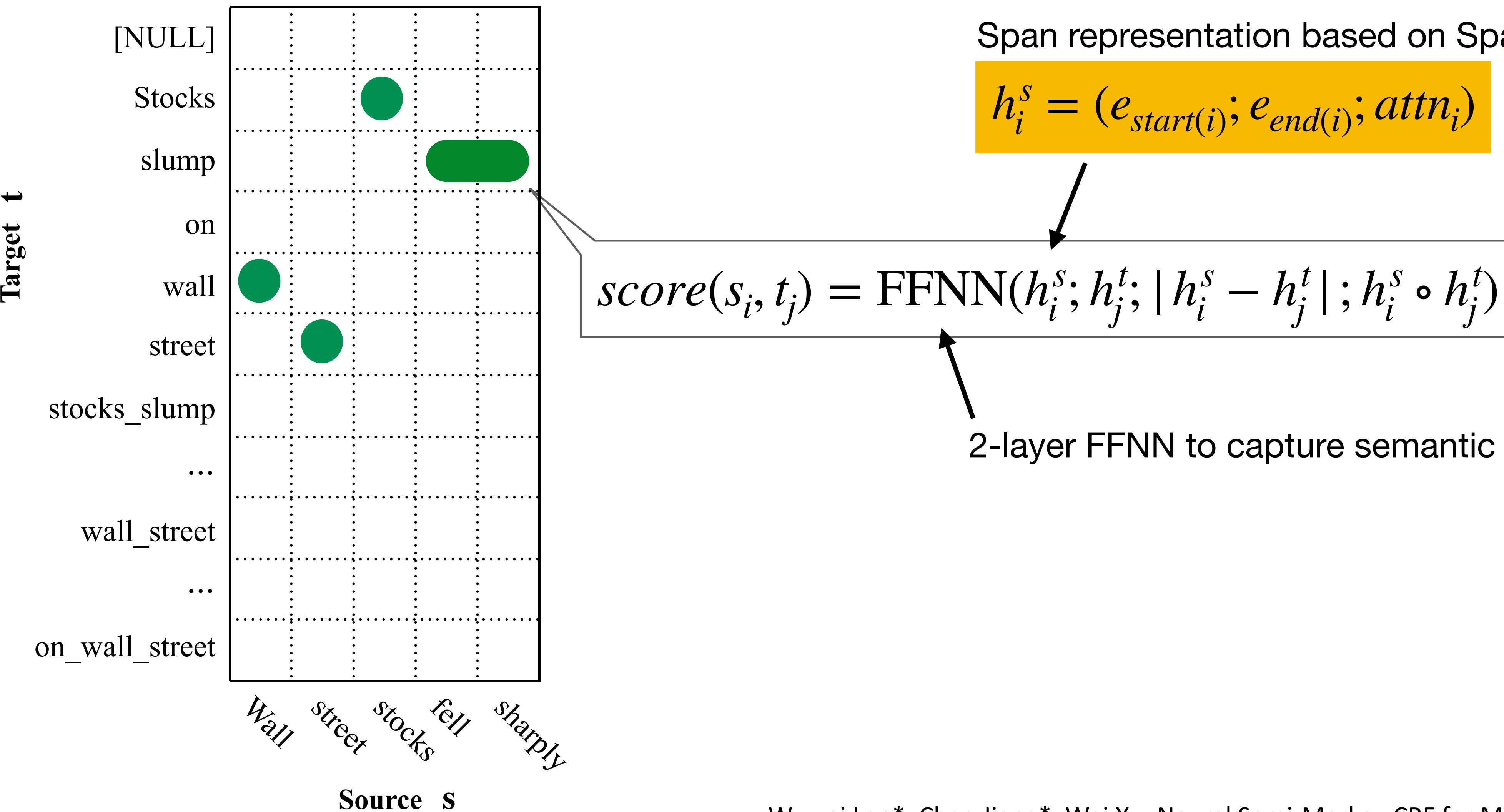
Even after death, these micro-fossils don't break down.

## Delete



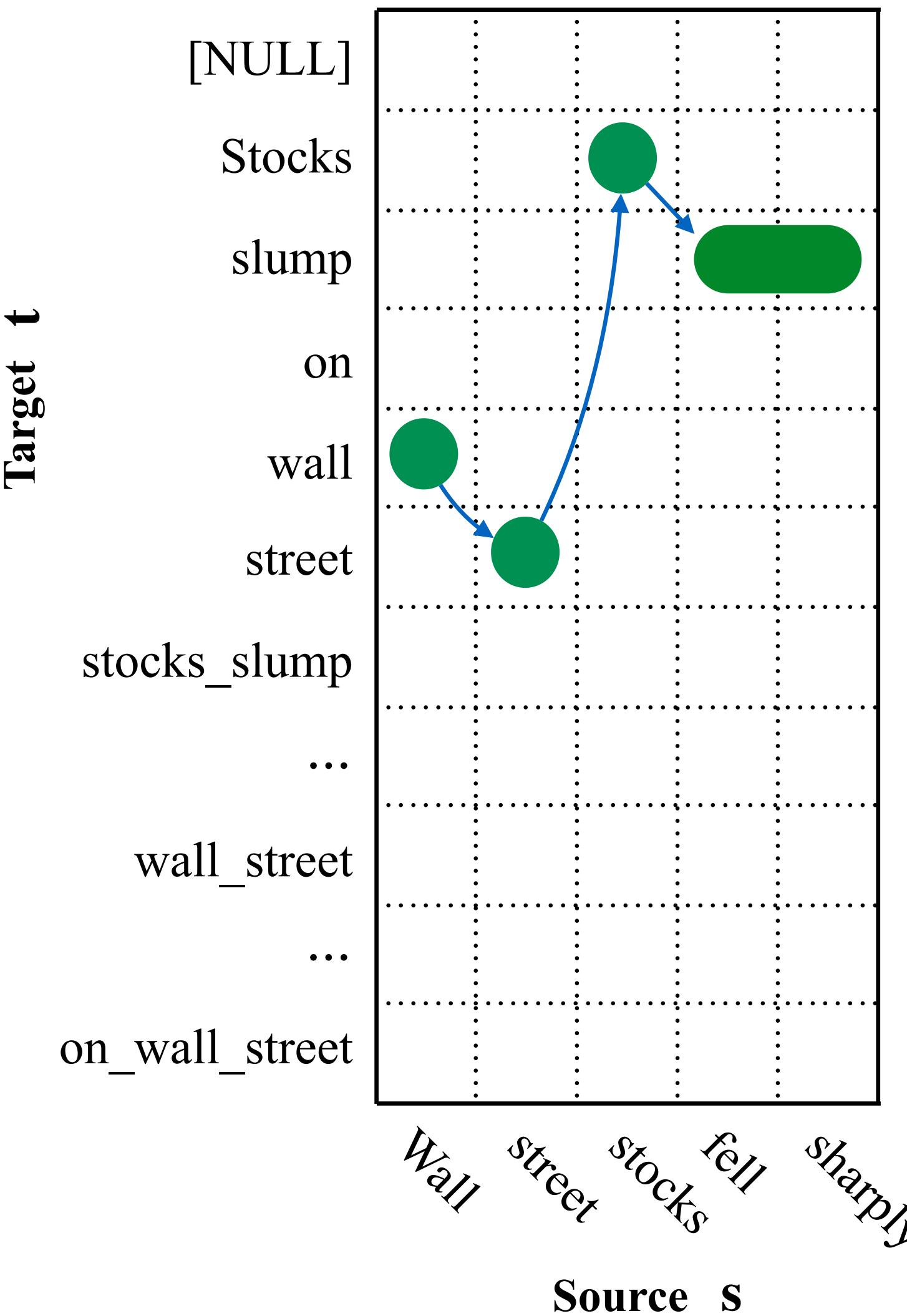
# Semi-CRF Word Alignment Model

## Span Interaction Matrix



# Semi-CRF Word Alignment Model

## Alignment Label Transition



semi-Markov Conditional Random Fields for span alignment

$$\Psi(\mathbf{a}, \mathbf{s}, \mathbf{t}) = \sum_i score(s_i, t_{a_i}) + T(a_{i-1}, a_i) + cost(\mathbf{a}, \mathbf{a}^*)$$

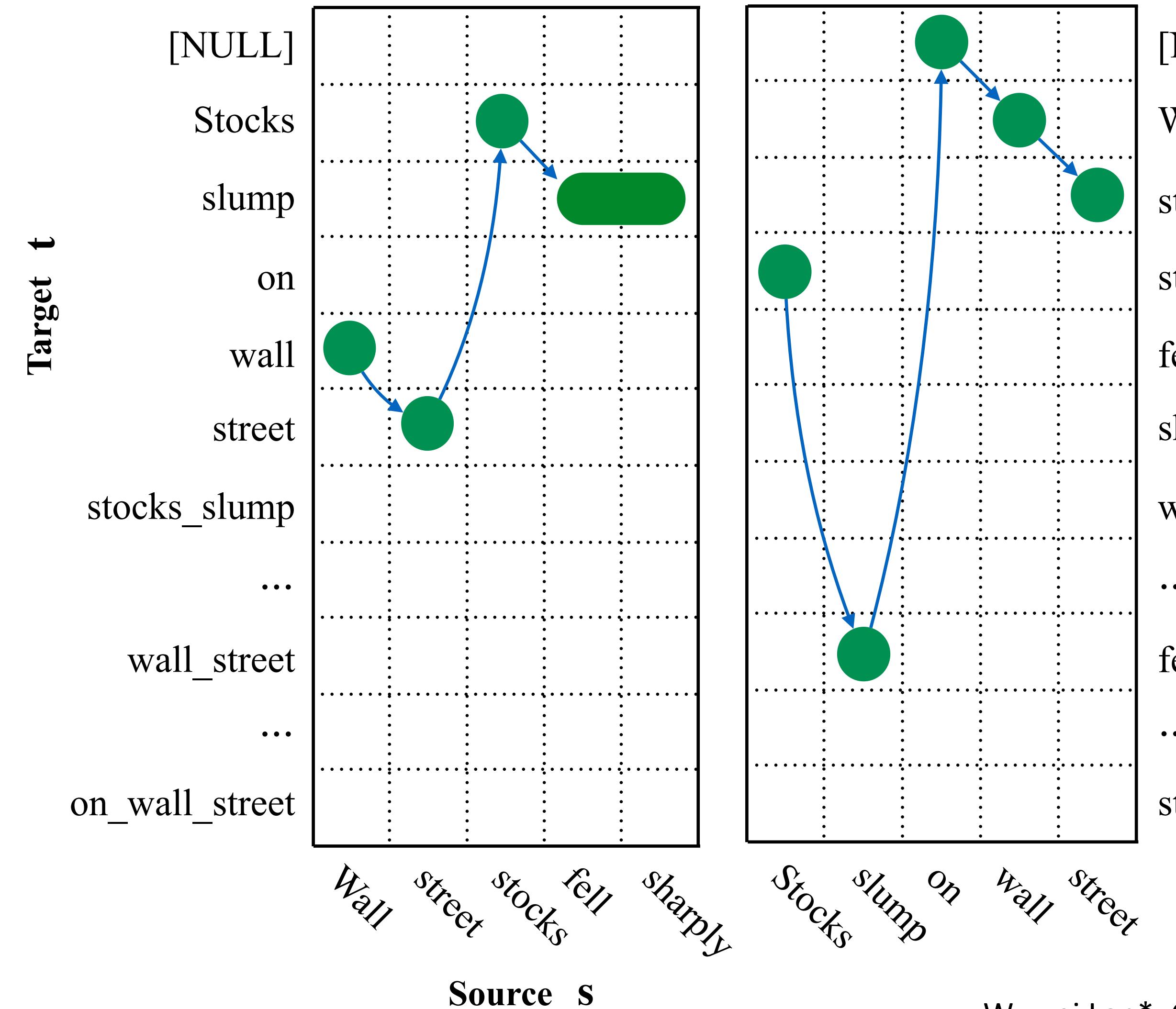
Negative Log-likelihood Loss      Hamming Loss

$$P(\mathbf{a} | \mathbf{s}, \mathbf{t}) = \frac{\exp (\Psi(\mathbf{a}, \mathbf{s}, \mathbf{t}))}{\sum_{\mathbf{a} \in A} \exp (\Psi(\mathbf{a}, \mathbf{s}, \mathbf{t}))}$$

all possible alignments over variable length spans

# Semi-CRF Word Alignment Model

## Bi-directional Training / Decoding



Training objective:

$$\sum_{s,t,a} -\log P(a_{s2t} | s, t) - \log P(a_{t2s} | t, s)$$

Source-to-target

Target-to-source

Decoding:

Viterbi-like Algorithm + Intersect + Expand

# Experiments on MultiMWA Benchmark

We annotate a Multi-Genre Monolingual Word Alignment dataset that covers four different text genres.

	In-domain	Out-of-domain		
		MTReference	Newsela	arXiv
JacanaToken (Yao et al. 2013a)	76.2	79.8	95.8	95.8
JacanaPhrase (Yao et al. 2013b)	75.8	79.4	93.7	94.9
PipelineAligner (Sultan et al. 2014)	74.8	80.3	96.5	97.1
Our Neural CRF aligner	90.8	86.6	95.7	97.0
Our Neural semi-CRF aligner	92.4	87.2	97.3	97.4

🚀 16.2 F1

🚀 6.9 F1

🚀 0.8 F1

🚀 0.3 F1

# Part 1 — Controllable Generation Model



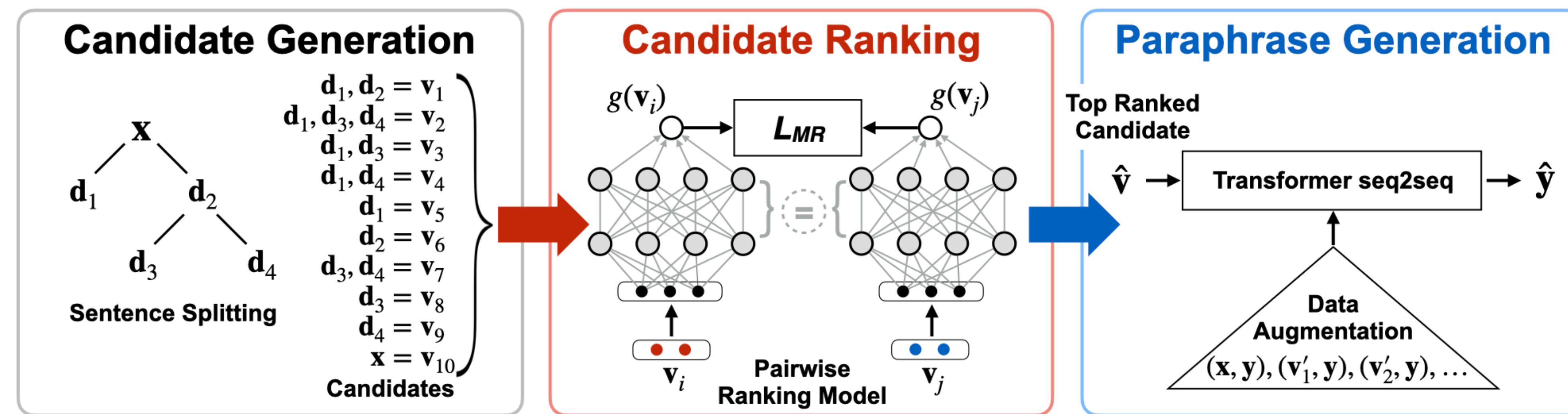
## Controllable Text Simplification with Explicit Paraphrasing

Mounica Maddela, Fernando Alva-Manchego, Wei Xu (NAACL 2021)



# Controllable Text Generation

- Control over 3 edit operations - deletion, splitting and paraphrasing.
- Incorporate linguistic rules with neural generation models.
- New setup to evaluate generation models's capability over these edit operations.

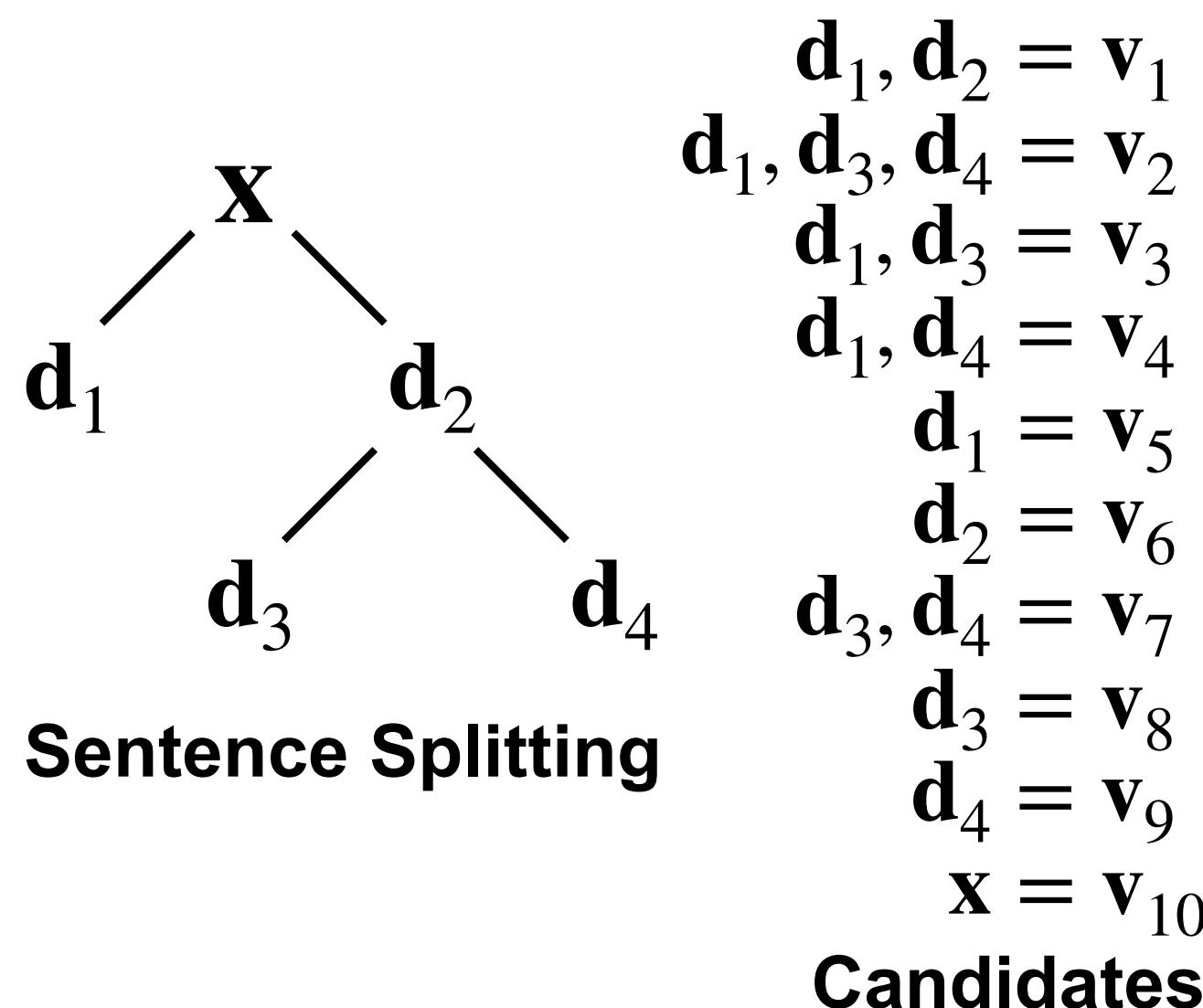


# Step 1 —

We use a rule-based method (Niklaus et al., 2019) + a seq2seq model for splitting and deletion.

- 35 hand-crafted grammar rules for English based on Stanford's parser (Socher et al., 2013).
- successfully split 92% of sentences with  $\geq 20$  words and make only 6.8% errors.

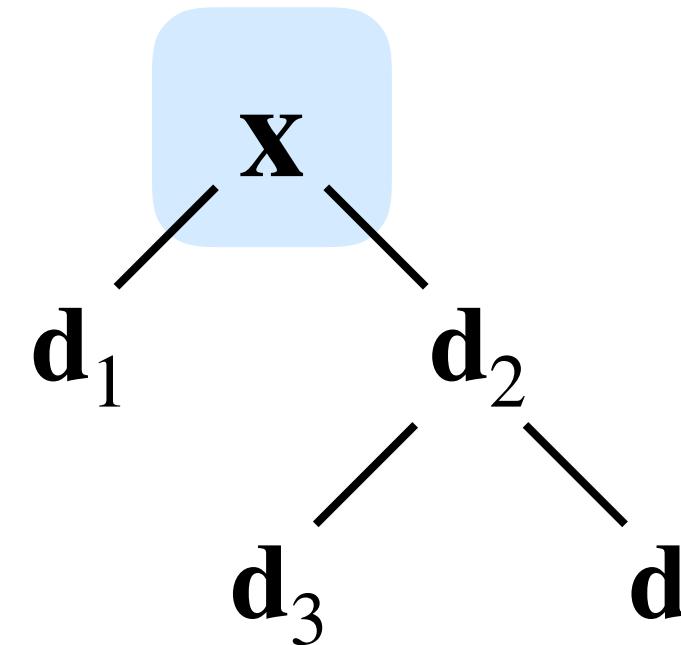
## Candidate Generation



# Step 1 —

We use a rule-based method (Niklaus et al., 2019) + a seq2seq model for splitting and deletion.

## Candidate Generation



## Sentence Splitting

- $d_1, d_2 = v_1$
- $d_1, d_3, d_4 = v_2$
- $d_1, d_3 = v_3$
- $d_1, d_4 = v_4$
- $d_1 = v_5$
- $d_2 = v_6$
- $d_3, d_4 = v_7$
- $d_3 = v_8$
- $d_4 = v_9$
- $x = v_{10}$

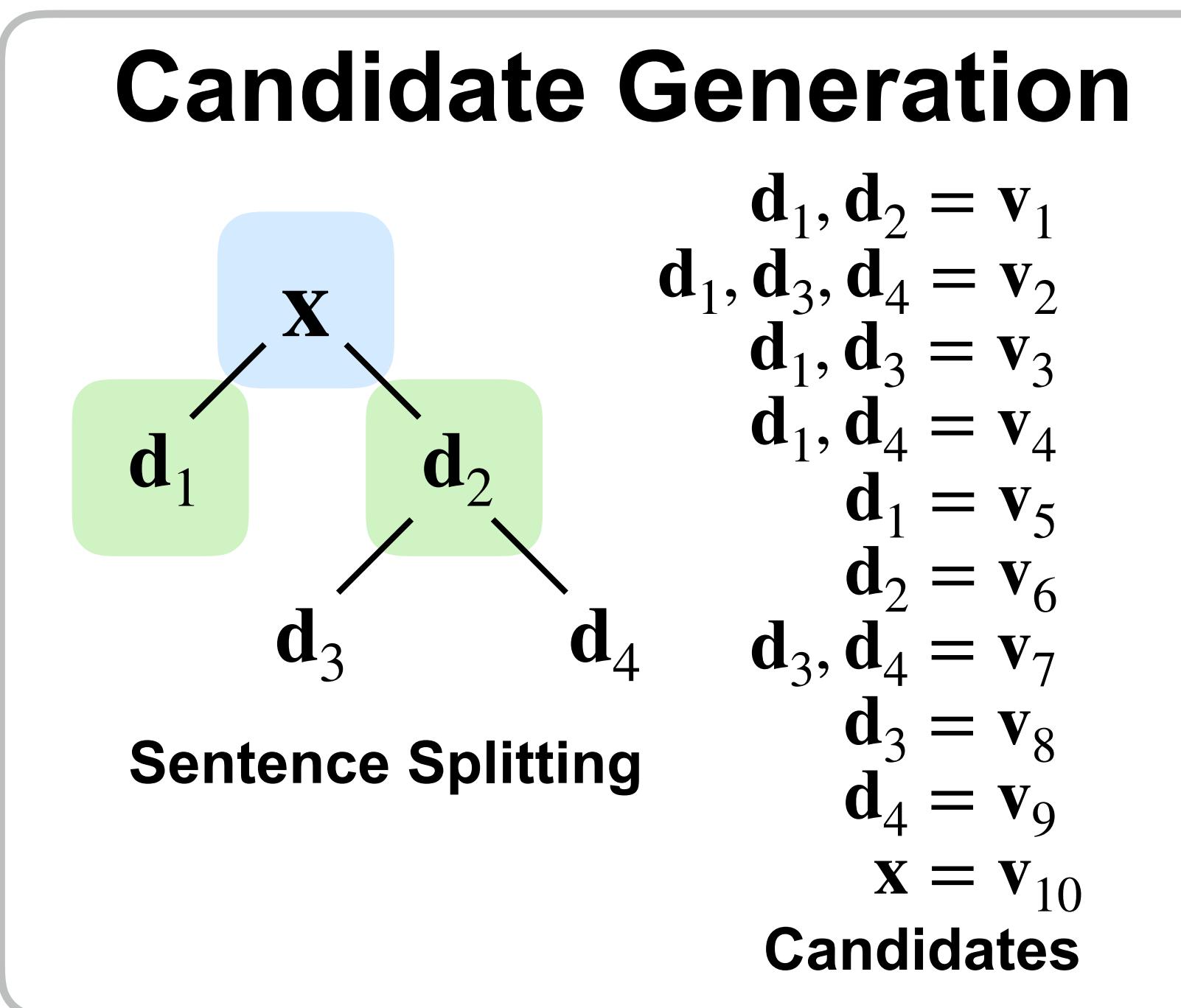
## Candidates

## Input sentence:

The exhibition, which opened Oct. 8 and runs through Jan. 3, features 27 self-portraits.

# Step 1 —

We use a rule-based method (Niklaus et al., 2019) + a seq2seq model for splitting and deletion.



**Input sentence:**

The exhibition, which opened Oct. 8 and runs through Jan. 3, features 27 self-portraits.

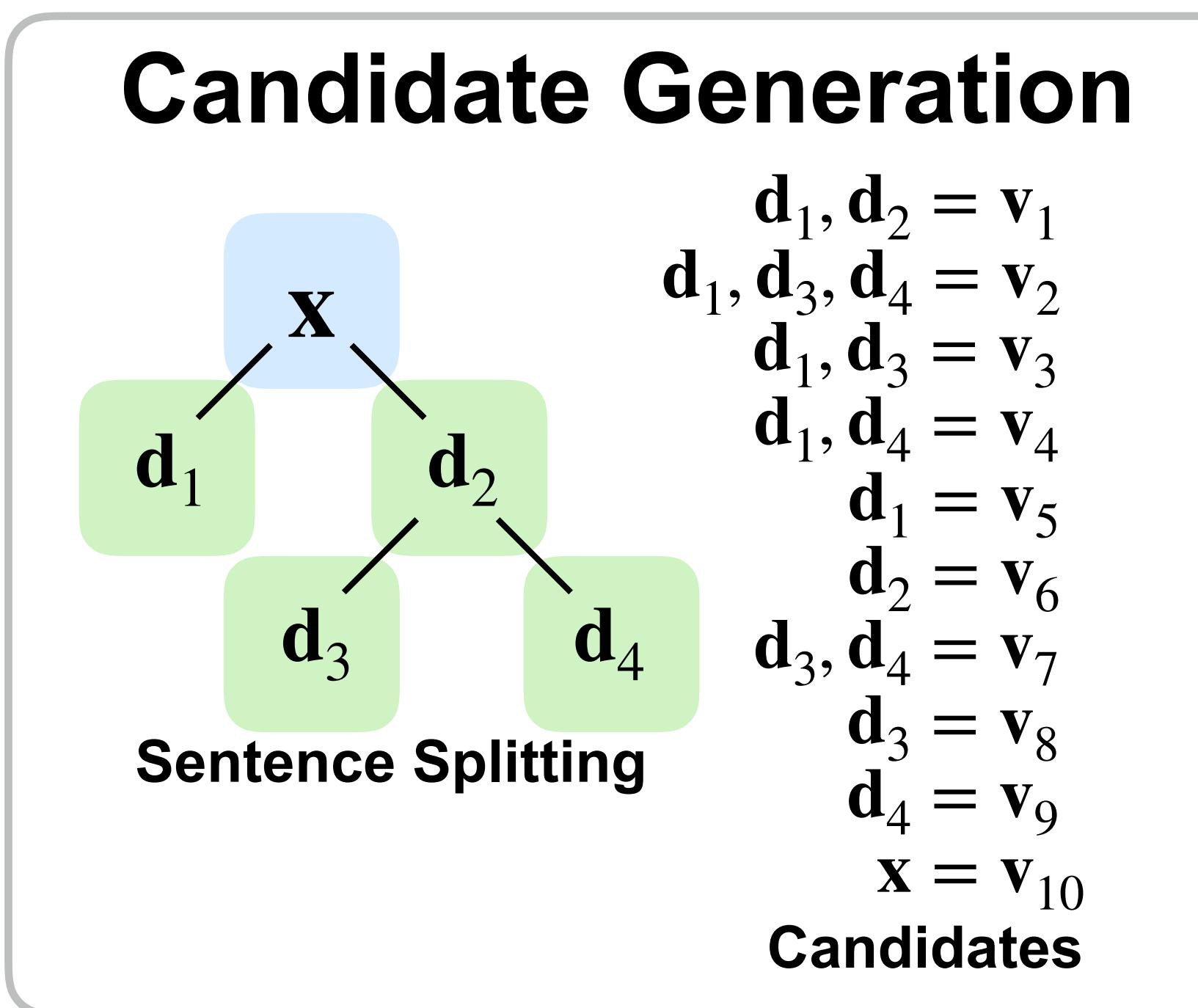
**Split sentences:**

The exhibition features 27 portraits.

The exhibition opened Oct. 8 and runs through Jan. 3.

# Step 1 —

We use a rule-based method (Niklaus et al., 2019) + a seq2seq model for splitting and deletion.



**Input sentence:**

The exhibition, which opened Oct. 8 and runs through Jan. 3, features 27 self-portraits.

**Split sentences:**

The exhibition features 27 portraits.

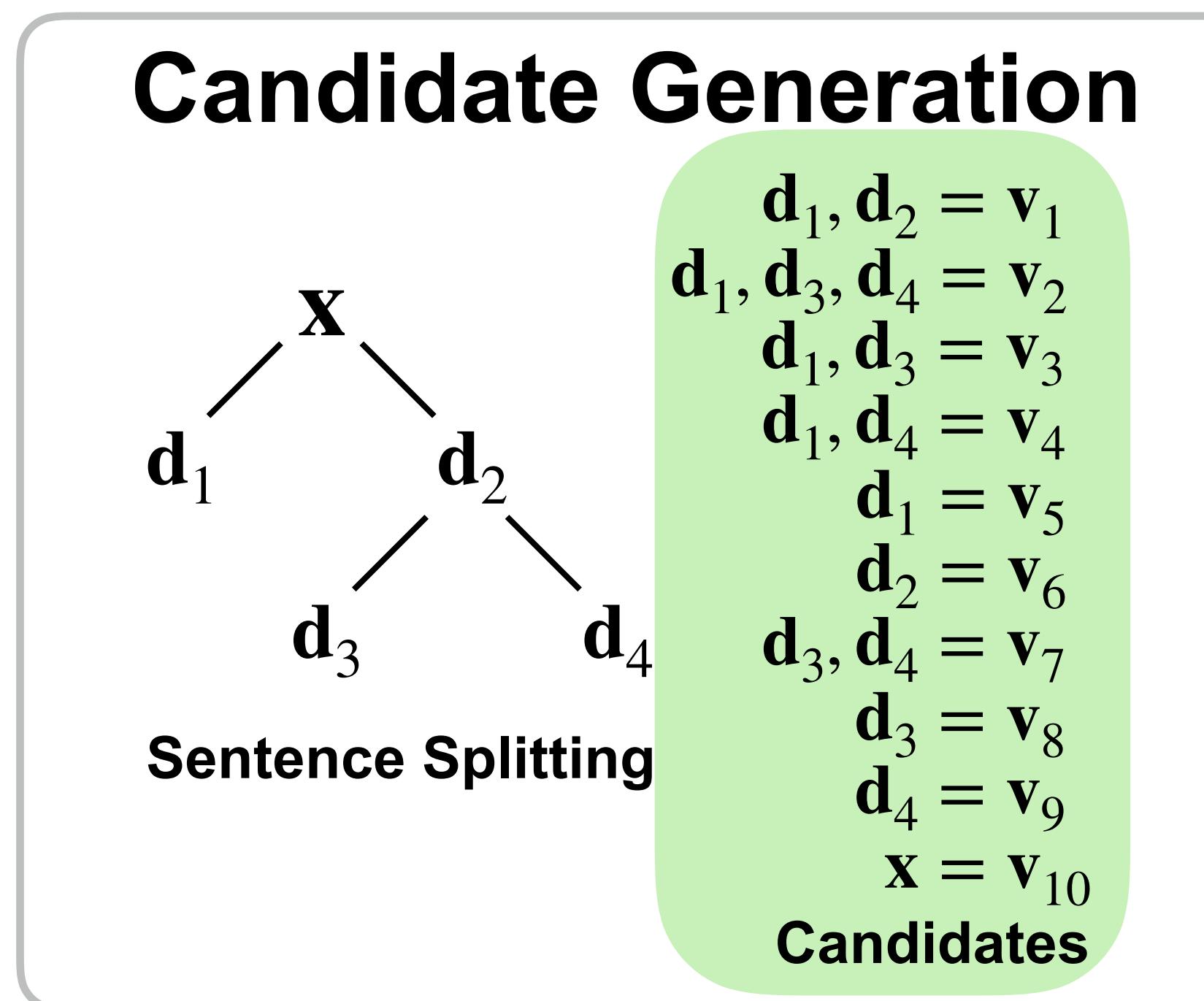
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The exhibition opened Oct. 8.

The exhibition runs through Jan. 3.

# Step 1 —

We use a rule-based method (Niklaus et al., 2019) + a seq2seq model for splitting and deletion.



## Candidates:

The exhibition features 27 portraits. The exhibition opened Oct. 8 and runs through Jan. 3.

The exhibition opened Oct. 8 and runs through Jan. 3.

The exhibition features 27 portraits.

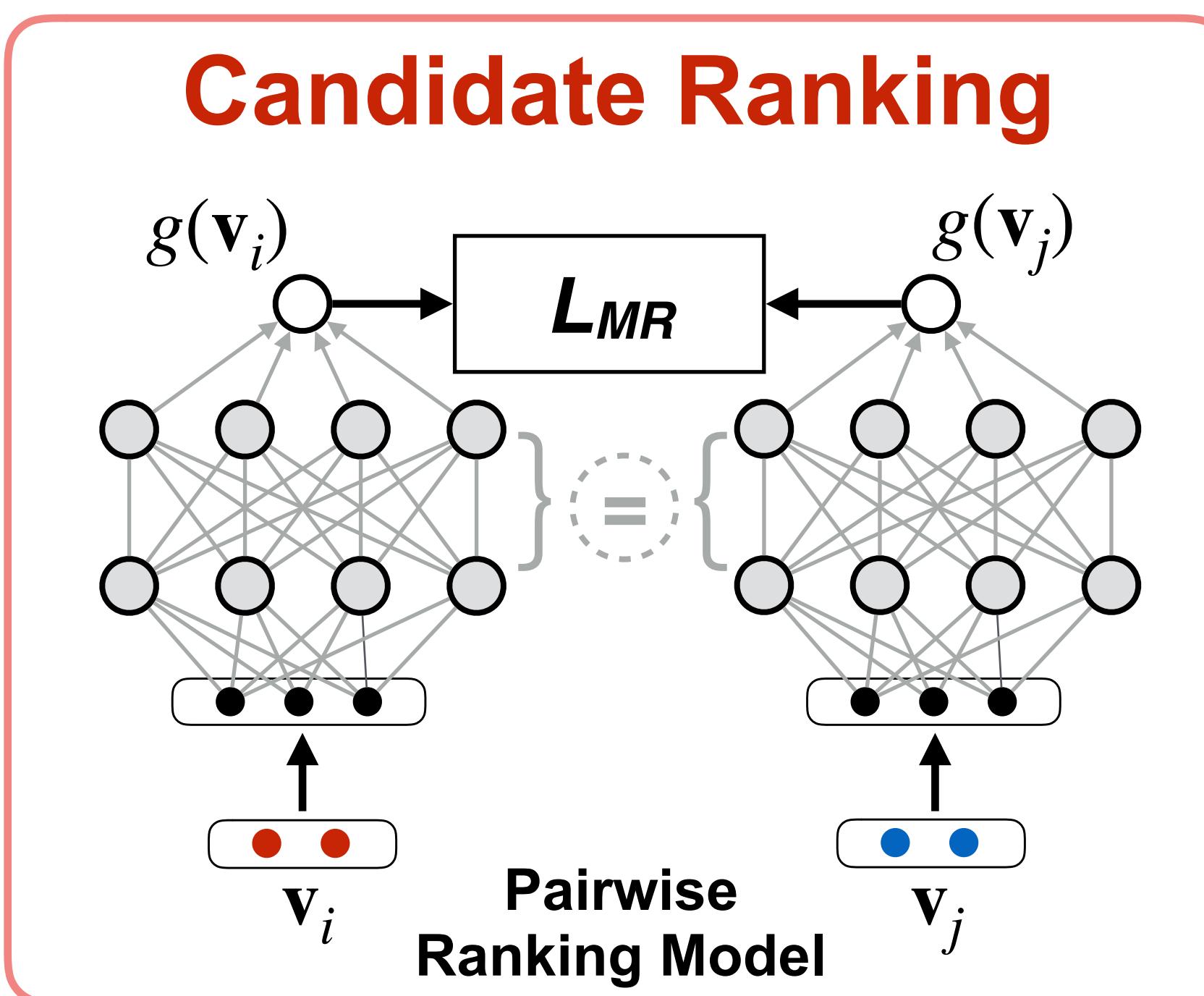
The exhibition opened Oct. 8. The exhibition runs through Jan. 3.

The exhibition features 27 portraits. The exhibition opened Oct. 8.

... (and more)

# Step 2 —

Then, we rank all the intermediate outputs (after splitting & deletion).



### Candidates:

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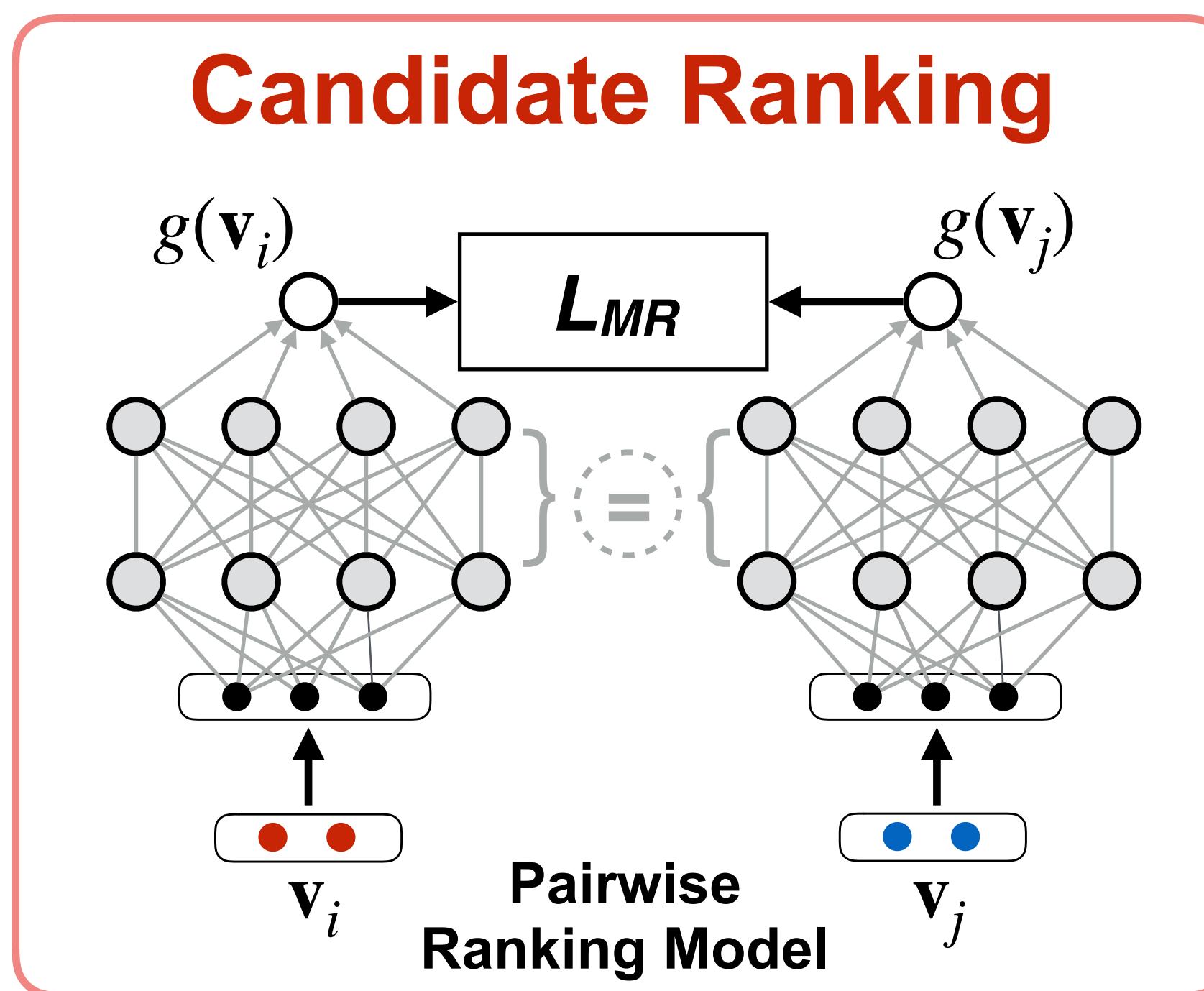
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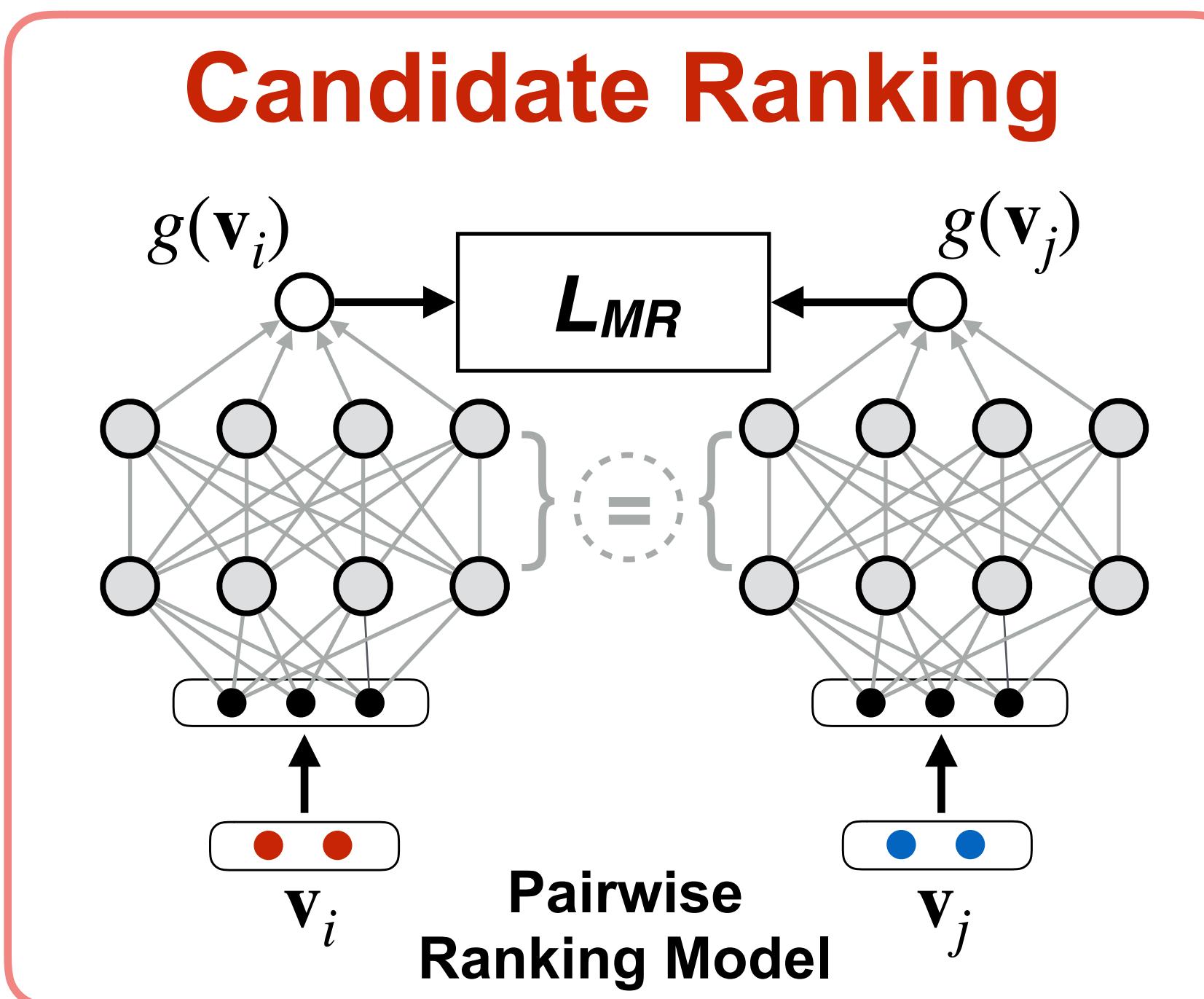
... (and more)

### Human reference:

The show started Oct. 8. It ends. Jan 3.

## Step 2 —

During training, we access each candidate using BERTScore (Zhang et al. 2019) with length penalty.



**Scoring function:**

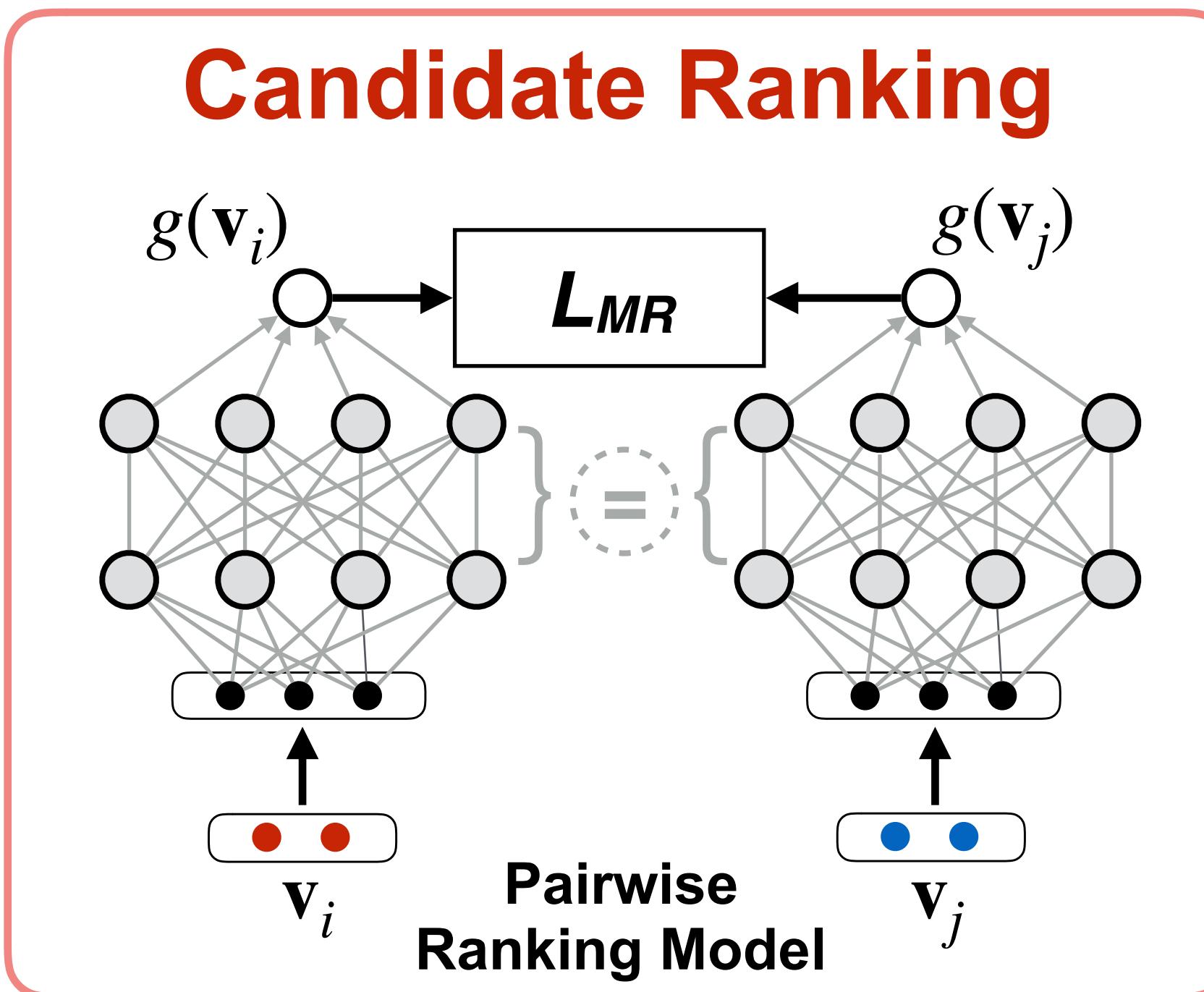
$$g^*(\mathbf{v}_i, \mathbf{y}) = e^{-\lambda \|\phi_{\mathbf{v}_i} - \phi_{\mathbf{y}}\|} \times BERTScore(\mathbf{v}_i, \mathbf{y})$$

target compression ratio

candidate reference

## Step 2 —

During training, we access each candidate using BERTScore (Zhang et al. 2019) with length penalty.



**Loss function:**

$$L_{MR} = \frac{1}{m} \sum_{k=1}^m \frac{1}{n_k^2} \sum_{i=1}^{n_k} \sum_{j=1, i \neq j}^{n_k} \max(0, 1 - l_{ij}^k d_{ij}^k)$$

$$d_{ij}^k = g(\mathbf{v}_i^k) - g(\mathbf{v}_j^k)$$

$$l_{ij}^k = \text{sign} \left( g^*(\mathbf{v}_i^k, \mathbf{y}^k) - g^*(\mathbf{v}_j^k, \mathbf{y}^k) \right)$$

Length-penalized BERTScore

Features: number of words in  $v_i$  and  $x$ , compression ratio of  $v_i$  with respect to  $x$ , Jaccard similarity between  $v_i$  and  $x$ , the rules applied on  $x$  to obtain  $v_i$ , and the number of rule applications.

# Step 3 —

Finally, we have a paraphrase generation model trained with augmented training data.  
(some selected candidates, in addition to the original input, are paired with the human reference)

## Paraphrase Generation

Top Ranked Candidate

$$\hat{v} \rightarrow \text{Transformer seq2seq} \rightarrow \hat{y}$$

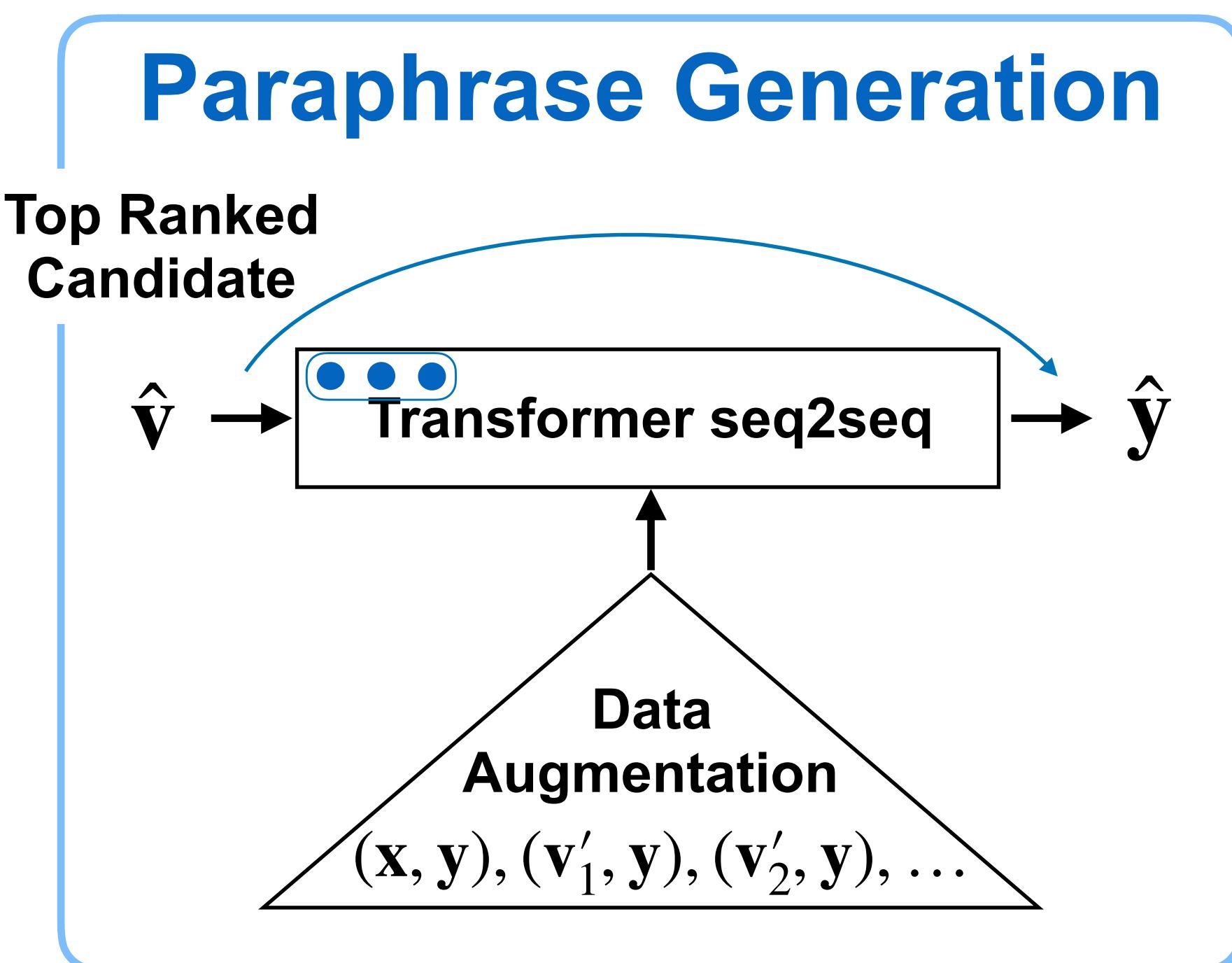
Data  
Augmentation

$$(x, y), (v'_1, y), (v'_2, y), \dots$$

Training a specific generation model that focuses on generating more diverse paraphrases.

# Step 3 —

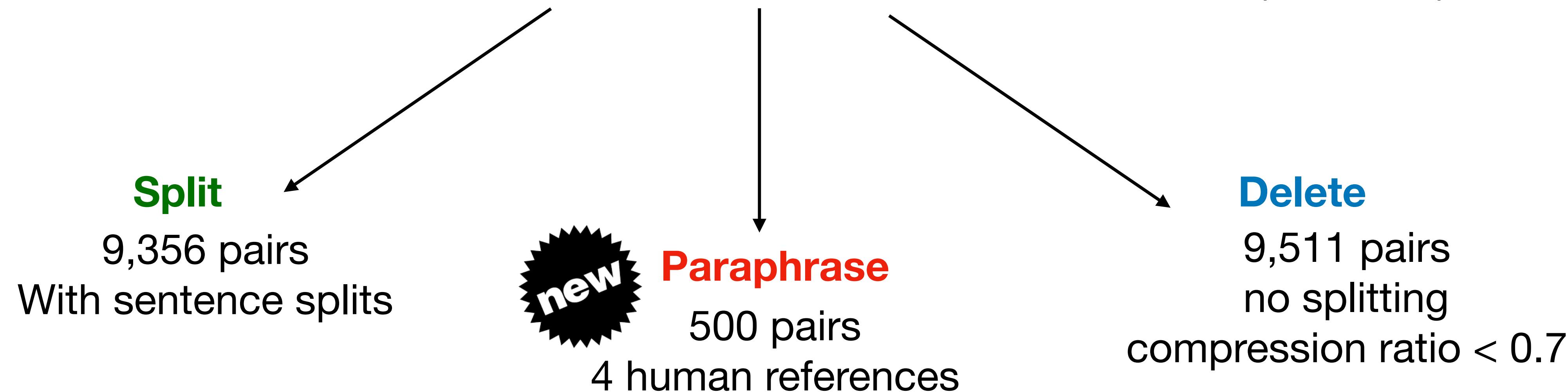
Finally, we have a paraphrase generation model trained with augmented training data.  
(some selected candidates, in addition to the original input, are paired with the human reference)



- Additional control over the degree of paraphrasing:**
- A copy-control token as soft constraint.
  - An auxiliary task (whether a word should be copied) using a **monolingual word aligner** to derive noisy training labels.

# Experiments on Text Simplification

- Evaluation setup
  - Standard Evaluation on **Newsela-Auto** and **Wikipedia-Auto** (Jiang et al. 2020).
  - Edit-focused Evaluation on different sections of test set (Our work).



# Controllable Text Generation

We can control the degree of sentence splitting, deletion, and paraphrasing.

**Input:** Experts say China's air pollution exacts a tremendous toll on human health.

**Reference:** China's air pollution is very unhealthy.

Our Model  
( $cp = 0.6$ )

experts say china's air pollution **is a big problem for** human health.

Our Model  
( $cp = 0.7$ )

experts say china's air pollution **can cause a lot of damage on** human health.

Our Model  
( $cp = 0.8$ )

experts say china's air pollution **is a huge** toll on human health.

Hybrid-NG

experts say **government's** air pollution exacts a tremendous toll on human health.

LSTM

experts say china's air pollution exacts a tremendous toll on human health.

Transformer

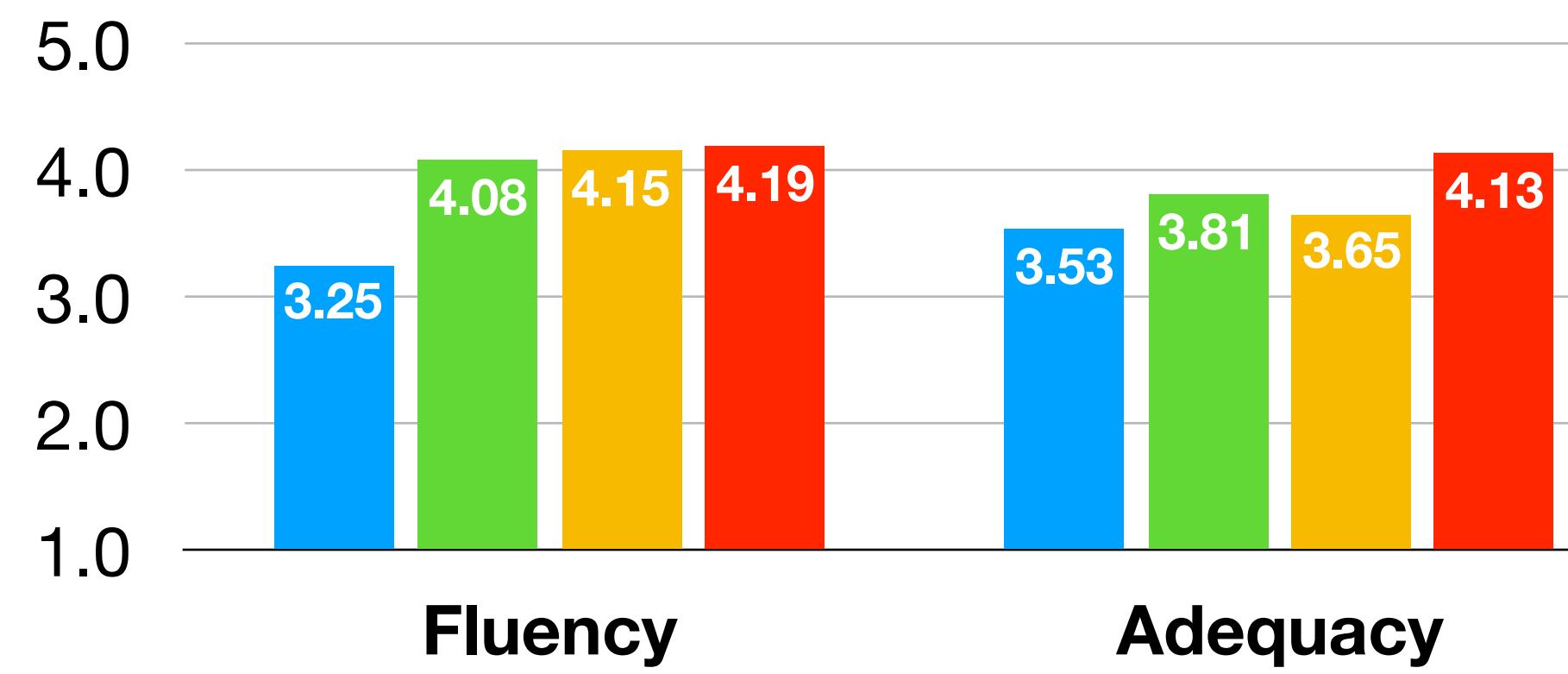
experts say china's air pollution exacts a tremendous **effect** on human health.

EditNTS

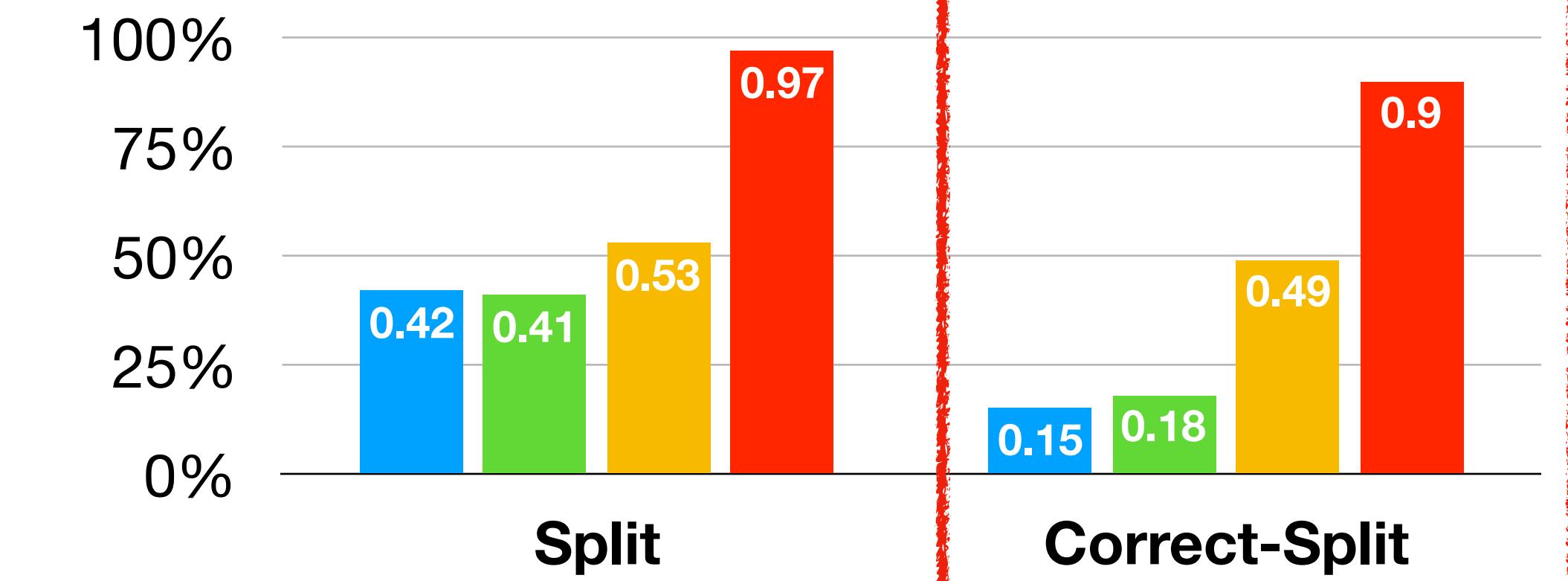
experts say china's air pollution **can cause** human health.

# More Syntactic Transformations

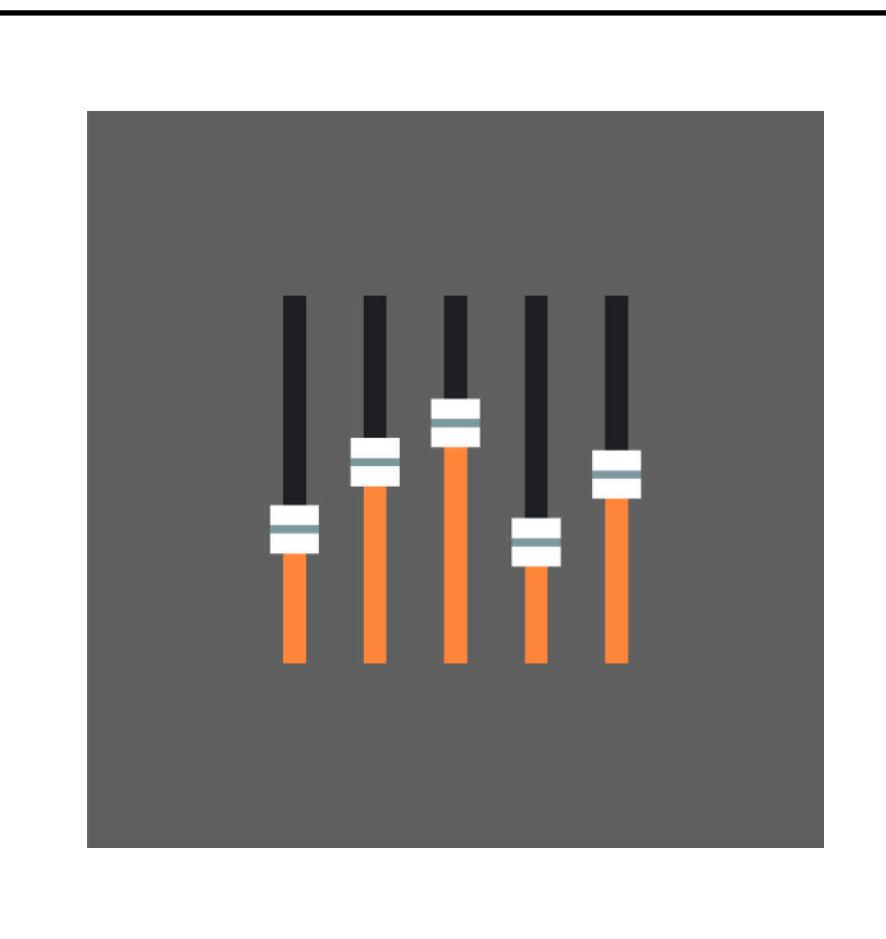
Human evaluation (1-5 Likert scale) on sentences where simplification involves splitting.



- Hybrid (Narayan & Gardent, 2014)
- Programmer-Interpreter (Dong et al., 2019)
- Transformer (Jiang et al., 2020 — also our work)
- ControllableTS (this work)



# Controllable Generation & Evaluation



Models	SARI	add	keep	del	FK	SLen	OLen	CR	%split	s-BL	%new	%eq
Complex (input)	22.3	0.0	67.0	0.0	12.8	23.3	23.5	1.0	0.0	100.0	0.0	100.0
Simple (reference)	62.3	44.8	68.3	73.9	11.1	23.8	23.5	1.01	0.0	48.5	24.1	0.0
Hybrid-NG	38.2	2.8	57.0	54.8	10.7	21.6	23.1	0.98	7.0	57.2	9.1	1.4
Transformer <sub>bert</sub>	36.0	3.3	54.9	49.8	8.9	16.1	20.2	0.87	23.0	58.7	13.3	7.6
EditNTS	36.4	1.1	59.1	48.9	9.9	17.5	20.6	0.88	17.0	70.6	5.2	3.2
Our Model	38.1	<b>3.9</b>	55.1	55.5	8.8	16.6	20.2	0.86	19.6	<b>50.4</b>	15.7	<b>0.0</b>
Our Model (no split; $cp = 0.6$ )	39.0	3.8	57.7	55.6	<b>11.2</b>	22.1	22.9	0.98	0.2	55.9	<b>18.0</b>	1.0
Our Model (no split; $cp = 0.7$ )	<b>41.0</b>	3.4	63.1	<b>56.6</b>	11.5	22.2	22.9	0.98	<b>0.0</b>	69.4	10.4	4.7
Our Model (no split; $cp = 0.8$ )	40.6	2.9	<b>65.0</b>	54.0	11.8	<b>22.4</b>	<b>23.0</b>	<b>0.99</b>	<b>0.0</b>			

paraphrasing

Table 2: Automatic evaluation results on NEWSEA-TURK that focuses on paraphrasing (500 complex sentences with 4 human written paraphrases). We control the extent of paraphrasing of our models by specifying the percentage of words to be copied ( $cp$ ) from the input as a soft constraint.

Models	SARI	add	keep	del	FK	SLen	OLen	CR	%split	s-BL	%new	%eq
Complex (input)	17.0	0.0	51.1	0.0	14.6	30.0	30.2	1.0	0.0	100.0	0.0	100.0
Simple (reference)	93.0	89.9	91.6	97.5	7.0	13.4	28.6	0.98	100.0	36.8	29.7	0.0
Hybrid-NG	37.1	2.2	44.9	64.1	11.6	25.5	<b>30.1</b>	<b>1.0</b>	17.3	57.7	8.7	1.6
Transformer <sub>bert</sub>	39.5	4.2	47.3	67.0	8.8	17.1	25.3	0.85	39.7	57.7	11.9	5.2
EditNTS	38.5	1.1	48.3	66.1	9.6	18.3	24.7	0.83	32.8	67.7	3.7	1.5
Our Model	39.4	4.0	46.6	67.6	8.7	17.5	25.5	0.85	40.6	<b>48.3</b>	<b>15.6</b>	<b>0.1</b>
Our Model (w/ split)	<b>42.1</b>	<b>5.6</b>	<b>50.6</b>	<b>70.1</b>	<b>8.1</b>	<b>15.3</b>	30.3	1.02	<b>93.5</b>	60.7	12.4	

splitting

Table 3: Automatic evaluation results on a subset of NEWSEA-AUTO test set that focuses on splitting (9,356 complex-simple sentence pairs with splitting). Our model chooses only candidate simplifications that have undergone splitting during the ranking step of the pipeline.

Models	SARI	add	keep	del	FK	SLen	OLen	CR	%split	s-BL	%new	%eq
Complex (input)	9.6	0.0	28.8	0.0	12.9	25.8	26.0	1.0	0.0	100.0	0.0	100.0
Simple (reference)	85.7	82.7	76.0	98.6	6.7	12.6	12.6	0.5	0.0	19.6	32.6	0.0
Hybrid-NG	35.8	1.4	27.0	79.1	10.6	22.7	25.9	1.0	13.3	58.9	8.7	3.6
Transformer <sub>bert</sub>	36.8	2.2	29.6	78.7	8.4	<b>16.2</b>	21.7	0.85	27.7	57.9	12.3	8.2
EditNTS	37.4	0.9	<b>29.8</b>	81.5	9.2	17.5	22.0	0.86	24.1	68.9	4.6	2.5
Our Model	<b>39.2</b>	<b>2.4</b>	<b>29.8</b>	<b>85.3</b>	<b>8.2</b>	16.4	21.9	0.85	29.1	48.8	<b>15.6</b>	0.4
Our Model (no split; CR<0.7)	38.2	2.0	28.5	84.1	8.6	16.8	<b>17.5</b>	<b>0.68</b>	<b>0.1</b>	<b>42.0</b>	12.5	

deletion

Table 4: Automatic evaluation results on a subset of NEWSEA-AUTO test set that focuses on deletion (9,511 complex-simple sentence pairs with compression ratio  $< 0.7$  and no sentence splits). Our model selects only candidates with similar compression ratio and no splits during ranking.

# Part 1.5 — Automatic Evaluation Metric



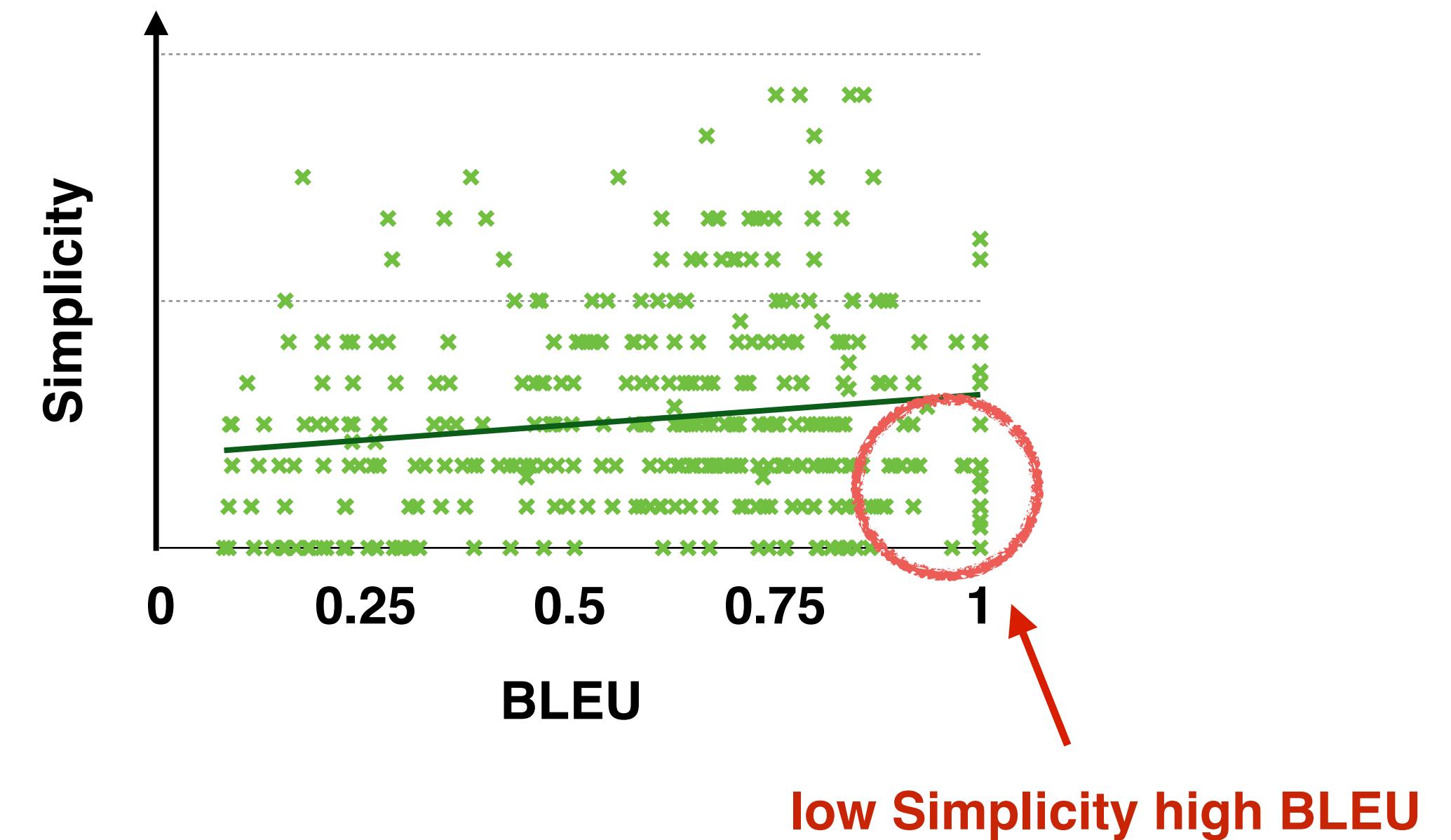
**Optimizing Statistical Machine Translation for Simplification**  
Xu et al. (TACL 2016)

# BLEU is not for Simplification

If a text generation model simply output the input unchanged, it gets perfect grammar, perfect meaning preservation, and very high BLEU score.

## Human Evaluation (1-5 Likert scale)

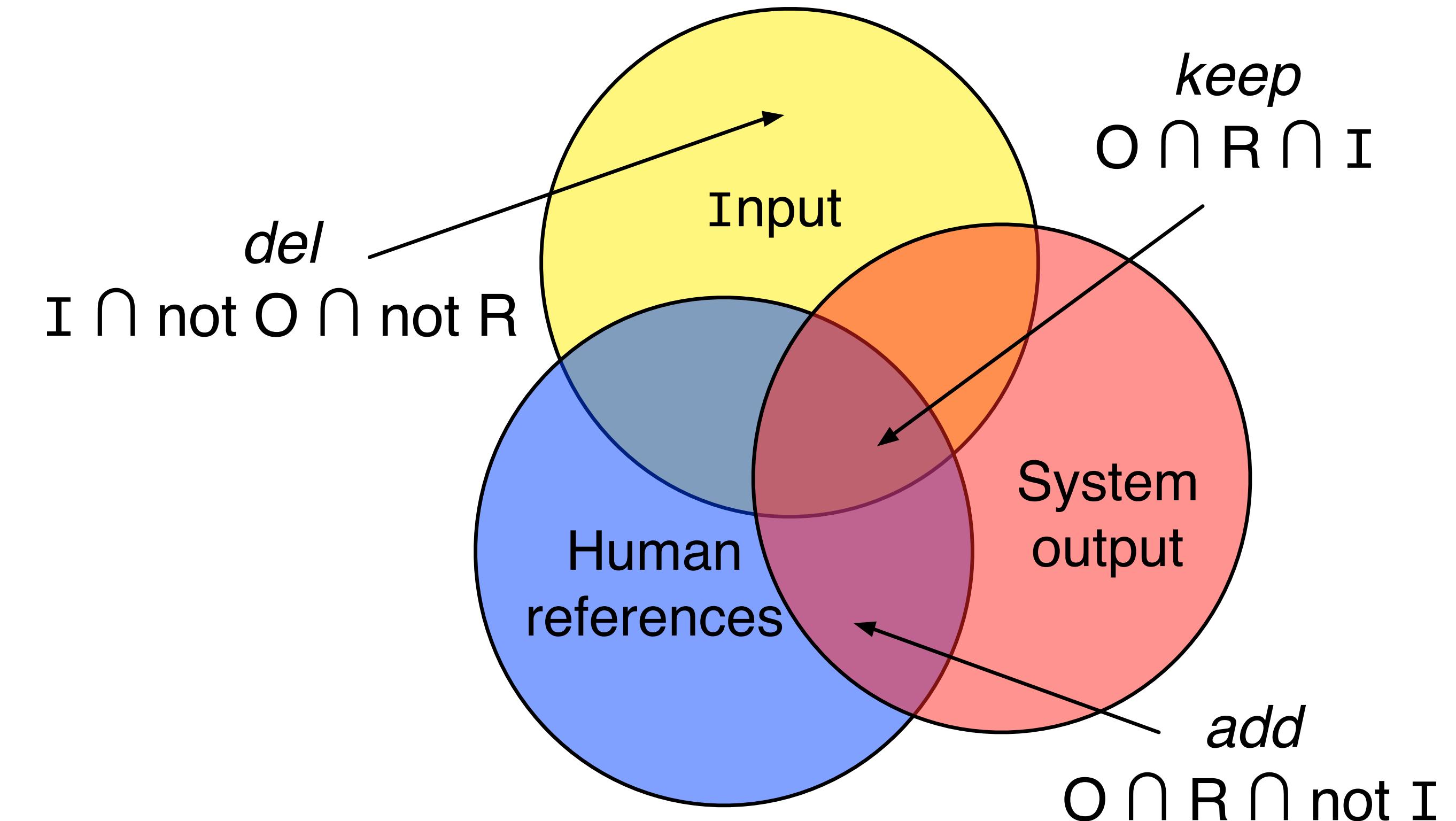
- Grammaticality / Fluency
- Meaning preservation / Adequacy
- Simplicity





# SARI Metric

It compares **system output** against **references** and against the **input sentence**.



$$p_{add}(n) = \frac{\sum_{g \in O} \min(\#_g(O \cap \bar{I}), \#_g(R))}{\sum_{g \in O} \#_g(O \cap \bar{I})}$$

$$r_{add}(n) = \frac{\sum_{g \in O} \min(\#_g(O \cap \bar{I}), \#_g(R))}{\sum_{g \in O} \#_g(R \cap \bar{I})}$$

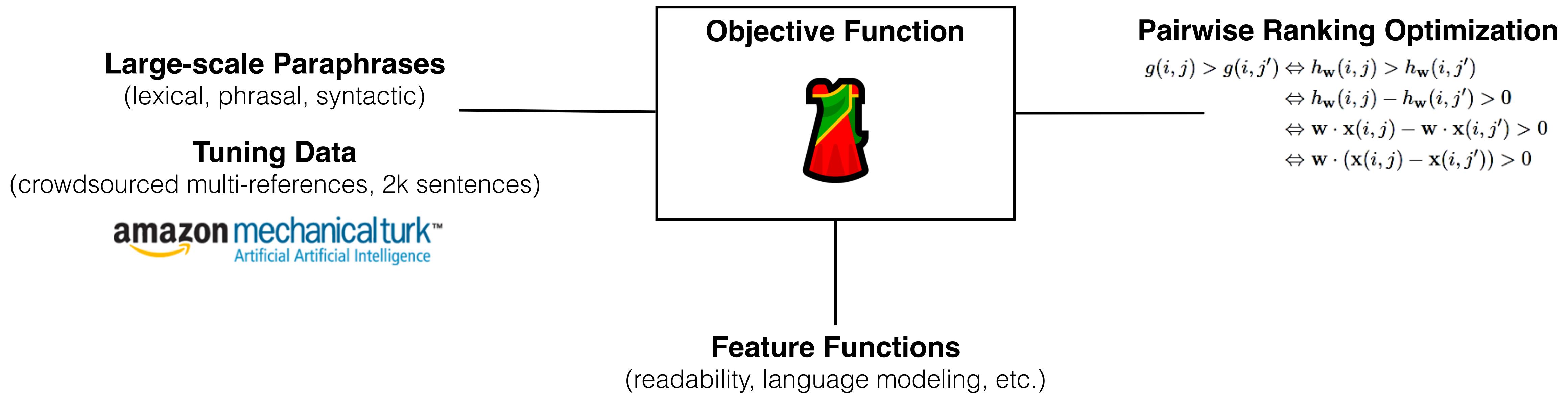
$$\text{SARI} = d_1 F_{add} + d_2 F_{keep} + d_3 P_{del}$$

$$d_1 = d_2 = d_3 = 1/3$$



# SARI Metric + Turk Corpus

SARI can also be used as (part of) the training objective/reward function.



 tensorflow / tensor2tensor

Watch 458

<> Code Issues Pull requests Actions Security Insights

 master ▾ tensor2tensor / tensor2tensor / utils / sari\_hook.py / <> Jump to ▾

 afrozenator Remove unknown flag from t2t\_trainer. ... ✓

Latest commit

5 contributors 

252 lines (210 sloc) | 9.69 KB

```
1 # coding=utf-8
2 # Copyright 2020 The Tensor2Tensor Authors.
3 #
4 # Licensed under the Apache License, Version 2.0 (the "License");
5 # you may not use this file except in compliance with the License.
6 # You may obtain a copy of the License at
7 #
8 #     http://www.apache.org/licenses/LICENSE-2.0
9 #
10 # Unless required by applicable law or agreed to in writing, software
11 # distributed under the License is distributed on an "AS IS" BASIS,
12 # WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
13 # See the License for the specific language governing permissions and
14 # limitations under the License.
15
16 """SARI score for evaluating paraphrasing and other text generation models.
17
18 The score is introduced in the following paper:
19
20 Optimizing Statistical Machine Translation for Text Simplification
21 Wei Xu, Courtney Napoles, Ellie Pavlick, Quanze Chen and Chris Callison-Burch
22 In Transactions of the Association for Computational Linguistics (TACL) 2015
23 http://cs.jhu.edu/~napoles/res/tacl2016-optimizing.pdf
24
25 This implementation has two differences with the GitHub [1] implementation:
26 (1) Define 0/0=1 instead of 0 to give higher scores for predictions that match
27 a target exactly.
```

# SARI is added to TensorFlow by Google AI group in Feb 2019.



## Now, also in



HUGGING FACE



# SARI Metric

It compares **system output** against **references** and against the **input sentence**.

## Beyond text simplification ...

“Leveraging Pre-trained Checkpoints for Sequence Generation Tasks”

[Sascha Rothe, Shashi Narayan, Aliaksei Severyn - TACL 2020]

← using SARI for sentence splitting and fusion

“Decontextualization: Making Sentences Stand-Alone”

[Eunsol Choi, Jennimaria Palomaki, Matthew Lamm, Tom Kwiatkowski, Dipanjan Das, Michael Collins - TACL 2021]

← using SARI for sentence decontextualization:  
taking a sentence together with its context and  
rewriting it to be interpretable out of context,  
while preserving its meaning

“Evidence-based Factual Error Correction”

[James Thorne, Andreas Vlachos - ACL 2021]

← using SARI for revising claims based on facts  
correlates well with human judgements!

# Part 2 — High-quality Training Data



*Simple English  
WIKIPEDIA*

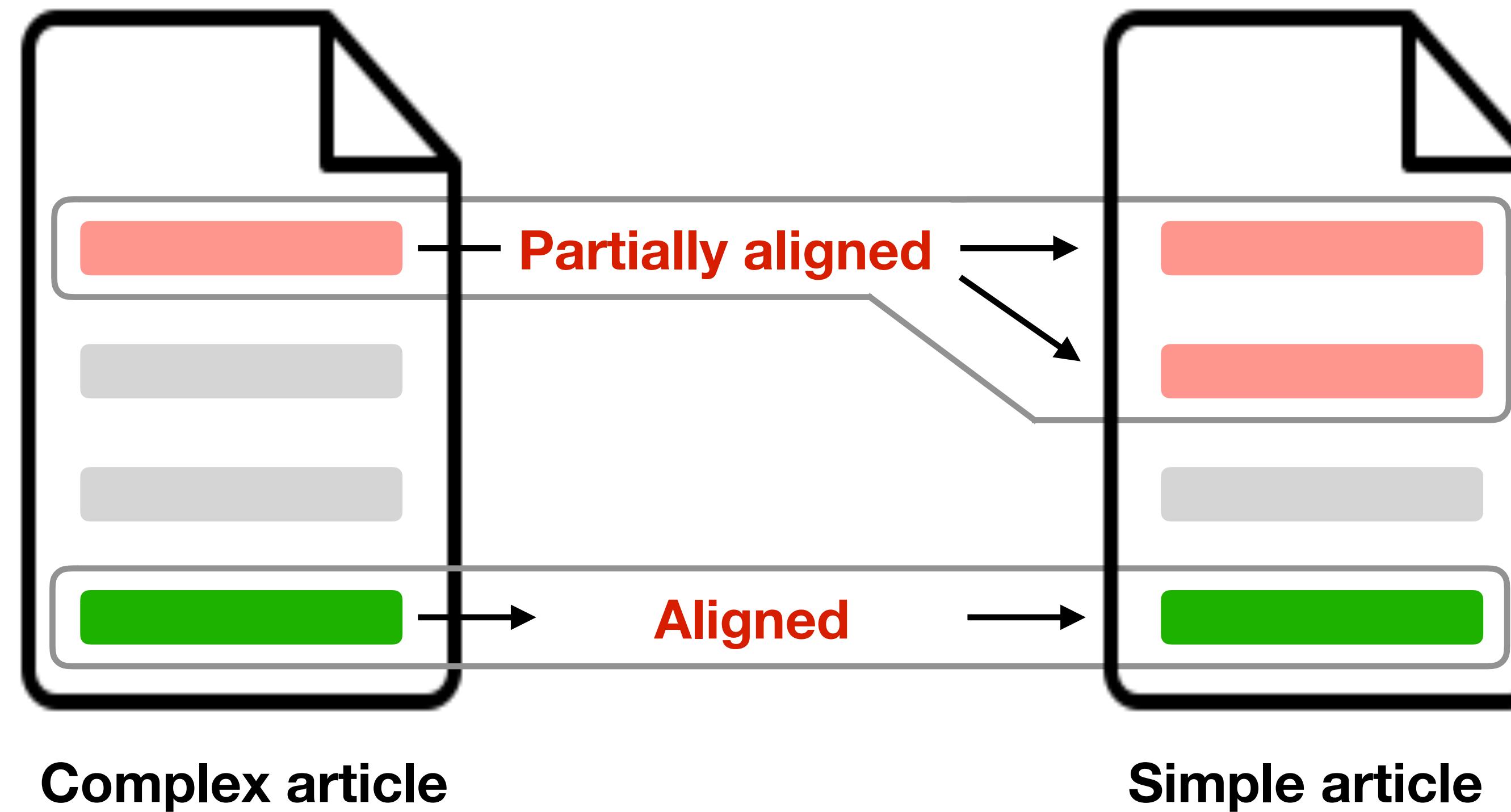
## Neural CRF Model for Sentence Alignment in Text Simplification

Chao Jiang, Mounica Maddela, Wuwei Lan, Yang Zhong, Wei Xu (ACL 2020)



# Automatic Text Simplification

- Primarily addressed by sequence-to-sequence models.
- Training corpus are complex-simple sentence pairs extracted by **aligning parallel articles**.



**WIKIPEDIA**  
The Free Encyclopedia

**newsela**  
(Original article)

*Simple English*  
**WIKIPEDIA**  
**newsela**  
(Simplified article)

# Our Solution for Sentence Alignment

- Two high-quality manually annotated sentence alignment datasets (20k / 10k sentence pairs).
- Structure prediction +  $\text{BERT}_{\text{finetune}}$  → A neural CRF alignment model.

		aligned + partial vs. others*		
		Precision	Recall	F1
Greedy	JaccardAlign (Xu et al., 2015)	98.66	67.58	80.22
Dynamic Programming	MASSAlign (Paetzold et al., 2017)	95.49	82.27	88.39
Greedy	CATS (Štajner et al., 2018)	88.56	91.31	89.92
Threshold	$\text{BERT}_{\text{finetune}}$	94.99	89.62	92.22
Threshold	$\text{BERT}_{\text{finetune}} + \text{paragraph alignment}$	98.05	88.63	93.10
CRF	Our CRF aligner	97.86	91.31	95.59

\* Results are on the manually annotated Newsela dataset.

# Our Work

Two manually annotated  
**sentence alignment** datasets  
( 20k / 10k sentence pairs )

↓  
train / evaluate

Neural CRF **alignment model**

SOTA

Seq2Seq generation models  
for **text simplification**

SOTA

↑  
train / evaluate

Two **text simplification** datasets  
Newsela-Auto and Wiki-Auto  
( 666k / 488k sentence pairs )

Apply the trained alignment model to the entire  
Newsela and Wikipedia corpora to generate

# Crowdsourcing Annotation Interface

## Sentence A

Since 2010, project researchers have uncovered documents in Portugal that have revealed who owned the ship

## Sentence B

Since 2020, experts have been figuring out who owned the ship.

### What's the relationship between Sentence A and Sentence B ?

A and B are equivalent

- A and B are equivalent (convey the same meaning, though one sentence can be much shorter or simpler than the other sentence)

A , B are partially overlapped

- A and B are partially overlap (share information in common, while some important information differs/missing).

A and B are mismatched

- The two sentences are completely dissimilar in meaning.

### Comments (Optional)

If you have any comment about this HIT, please type it here

# Neural CRF Alignment Model

## Step 1: Paragraph alignment algorithm

- Based on sentence similarity and vicinity information.
- Significantly improve alignment accuracy (+3 points in precision)

## Step 2: Sentence alignment model

---

### Algorithm 1: Pairwise Paragraph Similarity

---

```
Initialize: simP ∈ ℝ2×k×l to 02×k×l
for i ← 1 to k do
    for j ← 1 to l do
        simP[1, i, j] = avg ( maxsp ∈ Si simSent(sp, cq) )
        simP[2, i, j] = maxsp ∈ Si, cq ∈ Cj simSent(sp, cq)
    end
end
return simP
```

---

### Algorithm 2: Paragraph Alignment Algorithm

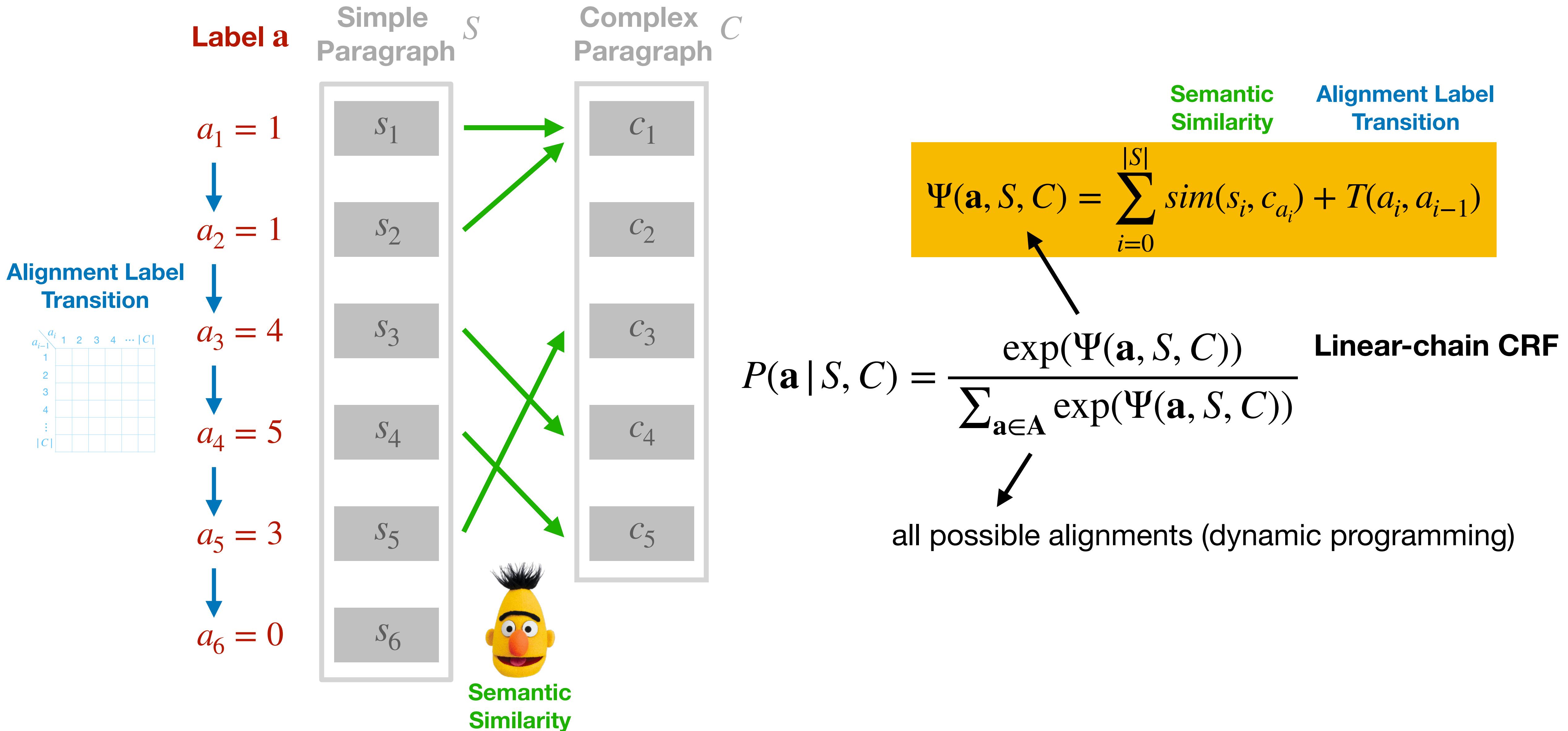
---

```
Input: simP ∈ ℝ2×k×l
Initialize: alignP ∈ ℤk×l to 0k×l
for i ← 1 to k do
    jmax = argmaxj simP[1, i, j]
    if simP[1, i, jmax] > τ1 and d(i, jmax) < τ2 then
        | alignP[i, jmax] = 1
    end
    for j ← 1 to l do
        if simP[2, i, j] > τ3 then
            | alignP[i, j] = 1
        end
        if j > 1 & simP[2, i, j] > τ4 &
           simP[2, i, j - 1] > τ4 & d(i, j) < τ5 &
           d(i, j - 1) < τ5 then
            | alignP[i, j] = 1
            | alignP[i, j - 1] = 1
        end
    end
end
return alignP
```

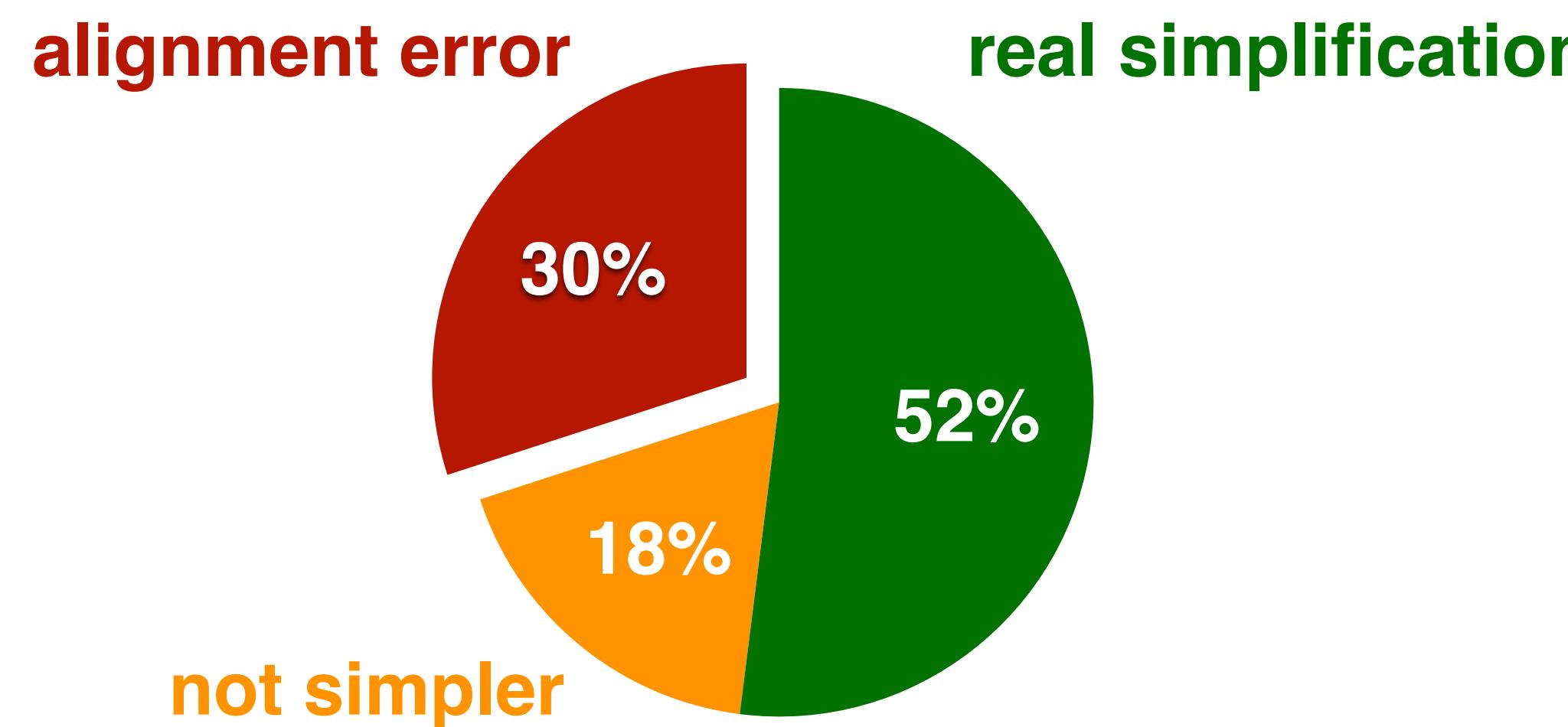
---

Screenshots of paragraph alignment algorithm

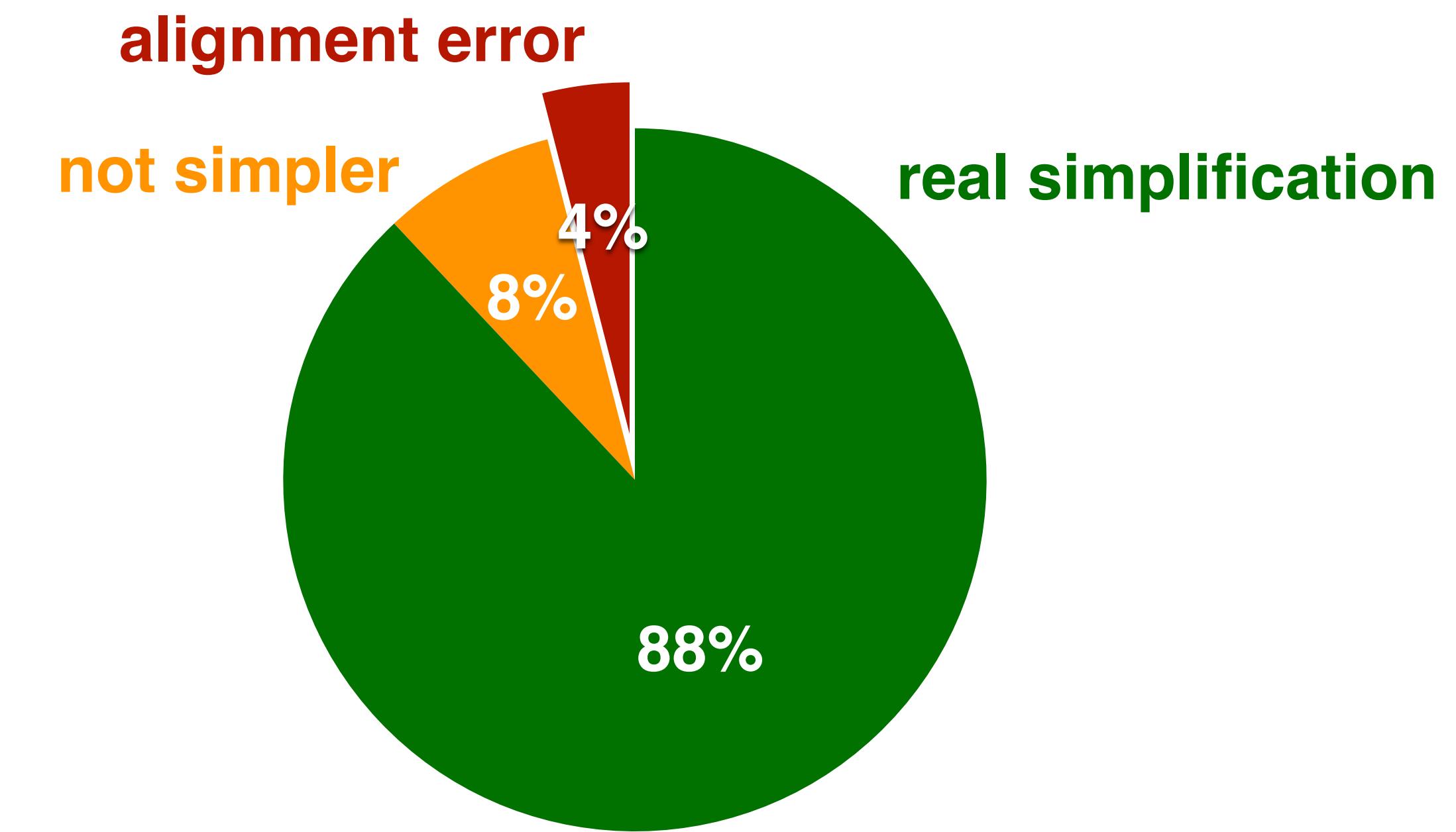
# Neural CRF Alignment Model



# New Corpora Contain Way Fewer Errors\*



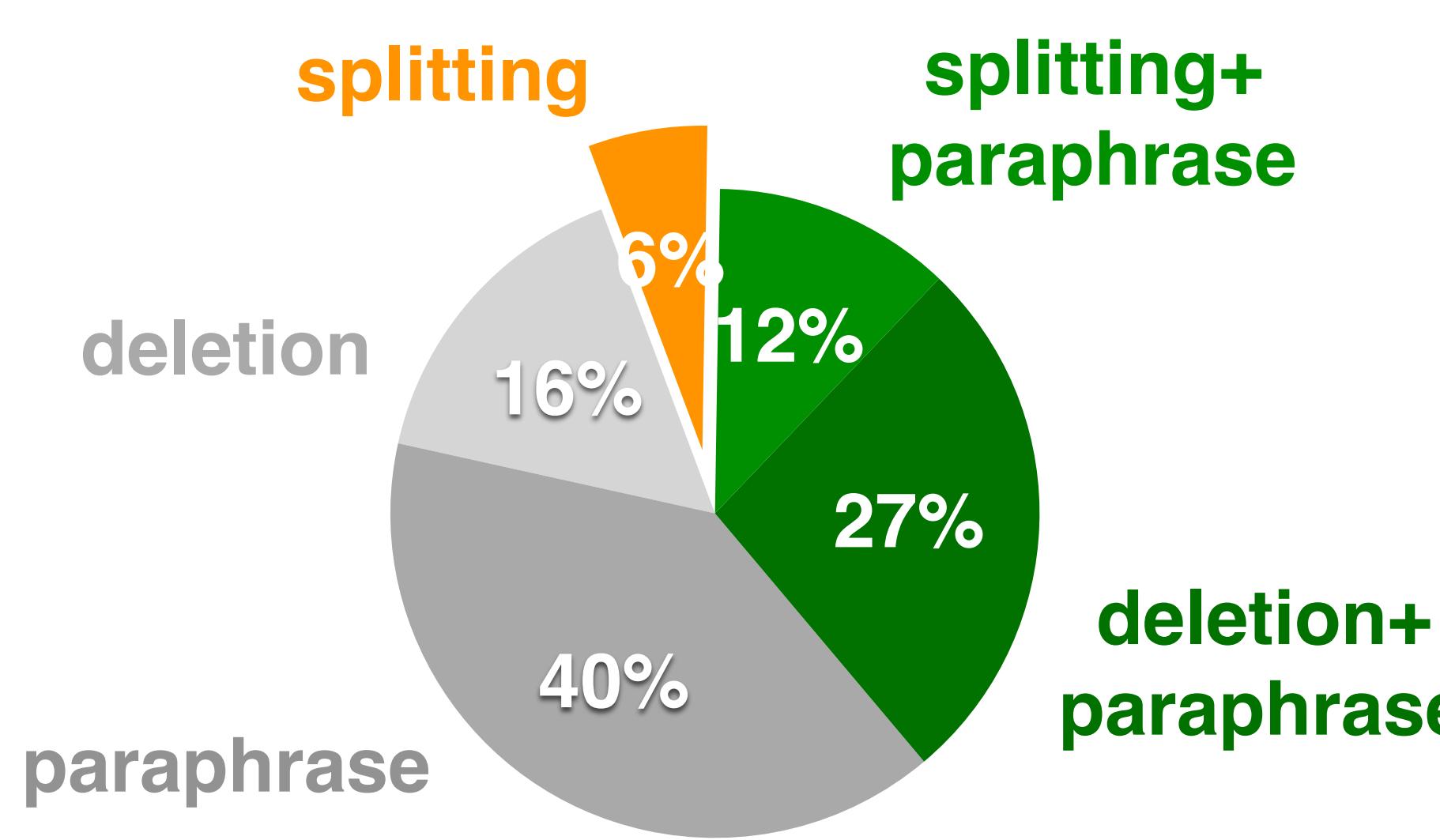
**Wiki-Large**  
(Zhang and Lapata, 2017)



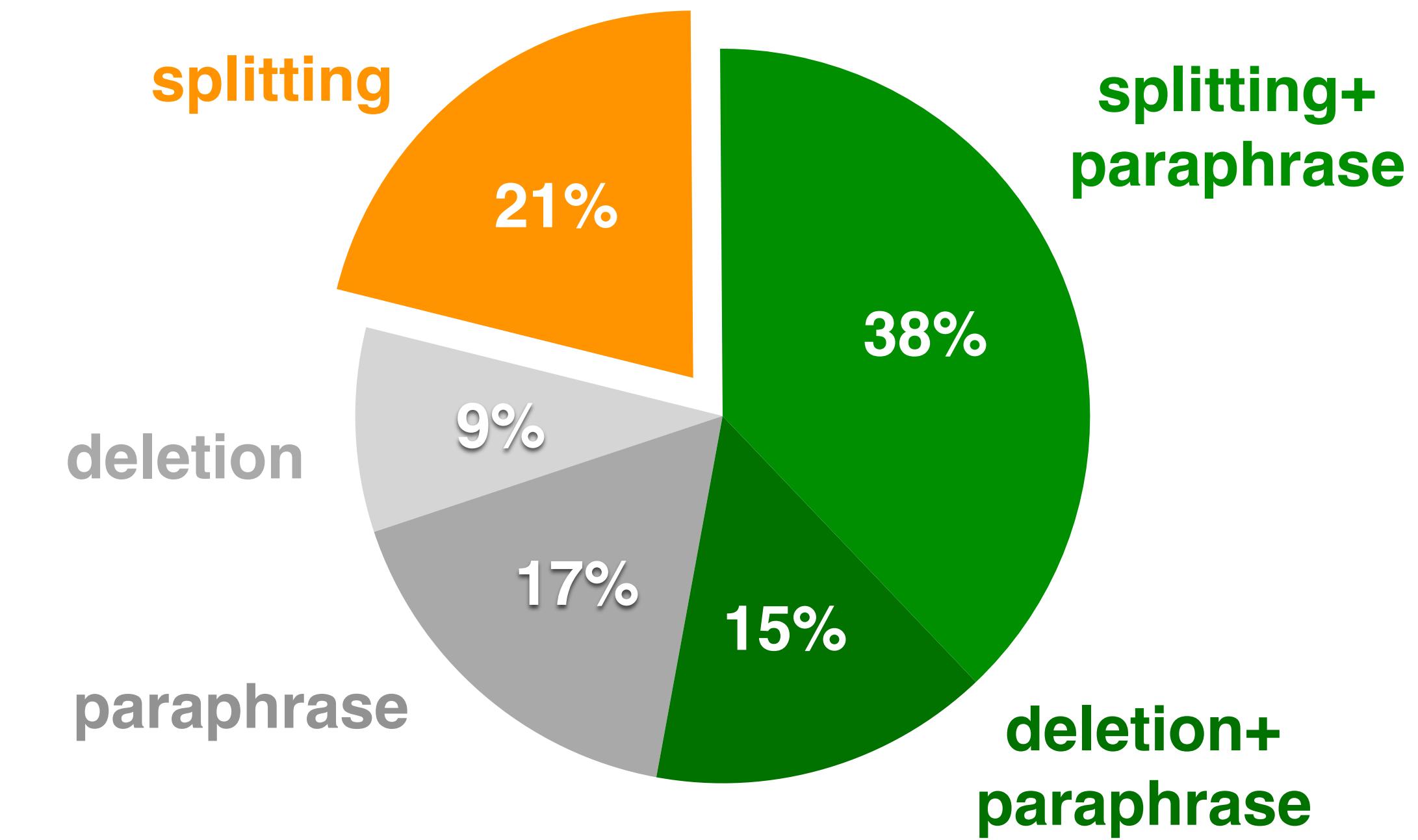
**Wiki-Auto (our work)**  
1.6 times larger — 488k sentence pairs

Wiki-Auto has 75% less defective pairs (alignment error + not simpler).

# New Corpora Contain More High-quality Simplification\*



**Newsela**  
(Xu et al., 2015)



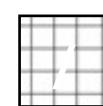
**Newsela-Auto (this work)**  
4.7 times larger — 666k sentence pairs

Newsela-Auto has much more splitting and complex re-writes.

# Experiments on Text Simplification

- Transformer<sub>BERT</sub> (Rothe, Narayan, Severyn, 2020)
- Baseline models
  - LSTM
  - EditNTS (Dong et al., 2019)
  - Rerank (Kriz et al., 2019)
- Datasets
  - This work: **Newsela-Auto** and **Wiki-Auto**
  - Previously existing datasets: Newsela (Xu et al., 2015) and Wiki-Large (Zhang & Lapata, 2017)

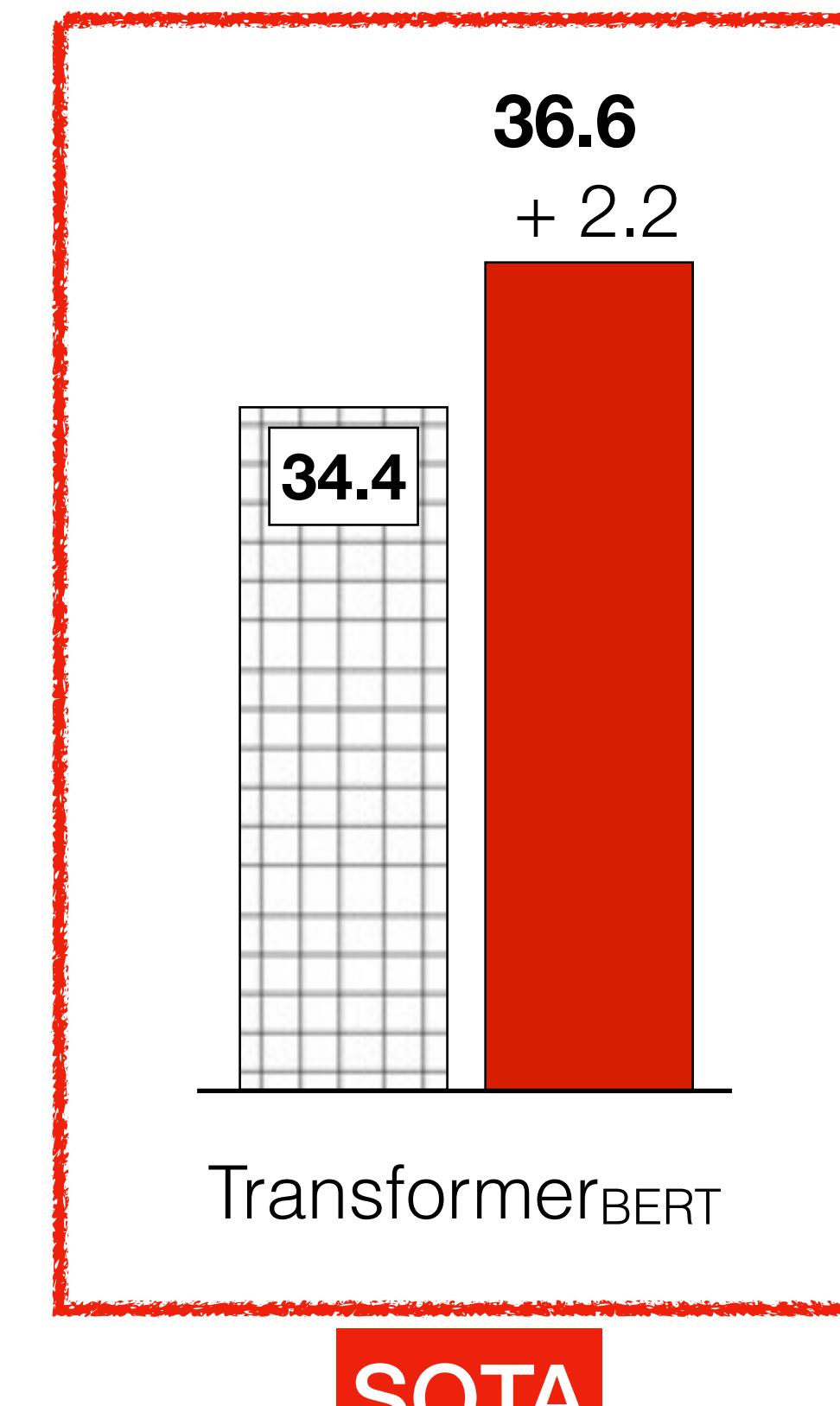
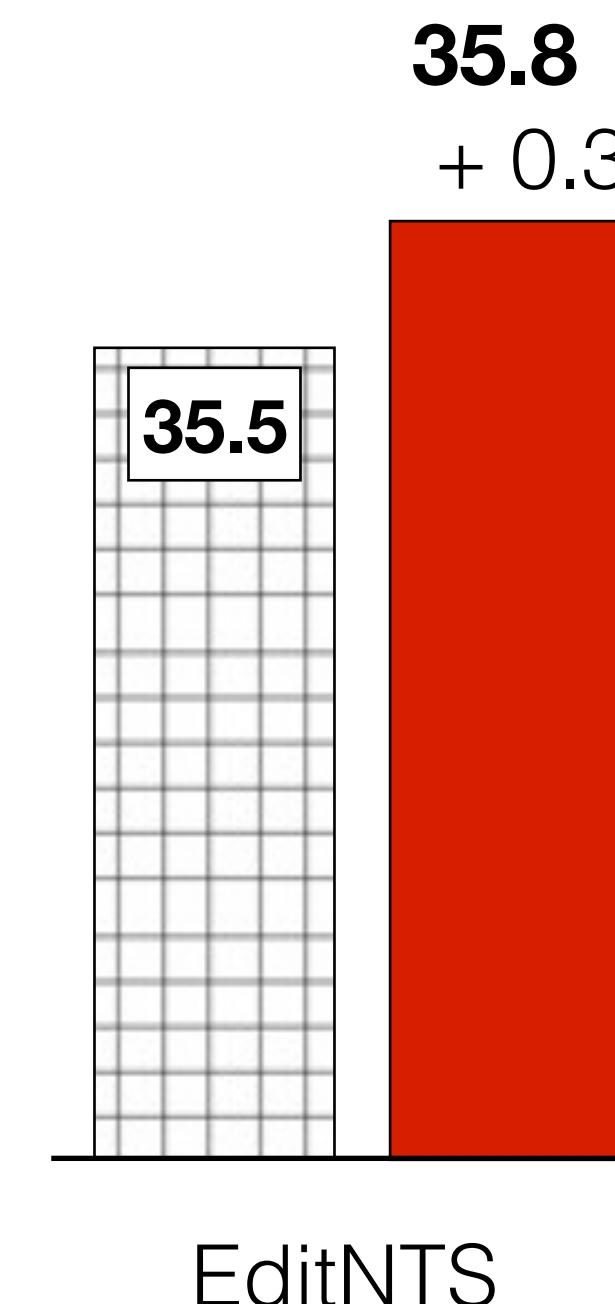
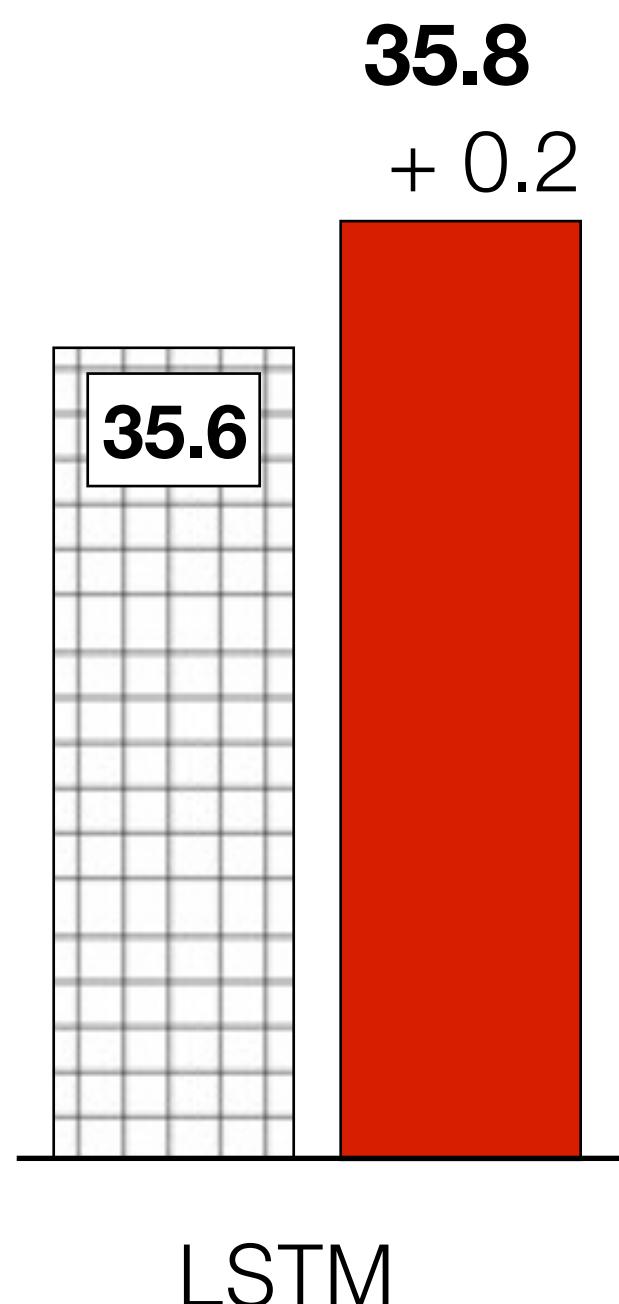
# Automatic Evaluation on Text Simplification\*



Trained on old Newsela (Xu et al., 2015)



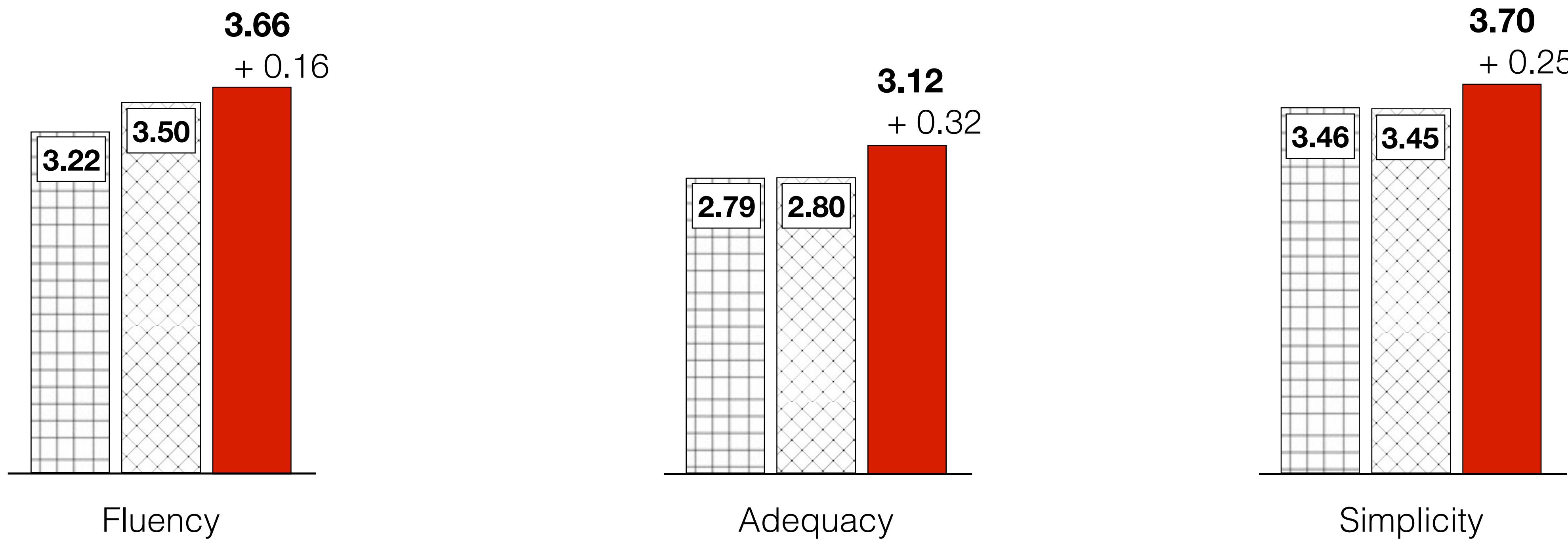
Trained on Newsela-Auto (our work)



\* Evaluate on the Newsela-Auto (this work) test set.

# Human Evaluation on Text Simplification\*

>EditNTS (Dong et al., 2019) Rerank (Kriz et al., 2019) Transformer<sub>BERT</sub> (our work)



1-5 Likert Scale

# Open Source

Code and data are available at - <https://github.com/chaojiang06/wiki-auto>



## Neural CRF Model for Sentence Alignment in Text Simplification

Chao Jiang, Mounica Maddela, Wuwei Lan, Yang Zhong, Wei Xu (ACL 2020)



# Take Aways

- **Controllable Generation Model**

- Neural semi-Markov CRF for Monolingual Word Alignment (Lan\*, Jiang\* & Xu, ACL 2021)

Also useful for semantics and natural language understanding.

- Controllable Text Simplification with Explicit Paraphrasing (Maddela, Alva-Manchego & Xu, NAACL 2021)

How to incorporate linguistic rules with neural networks?

- **High-quality Training Data**

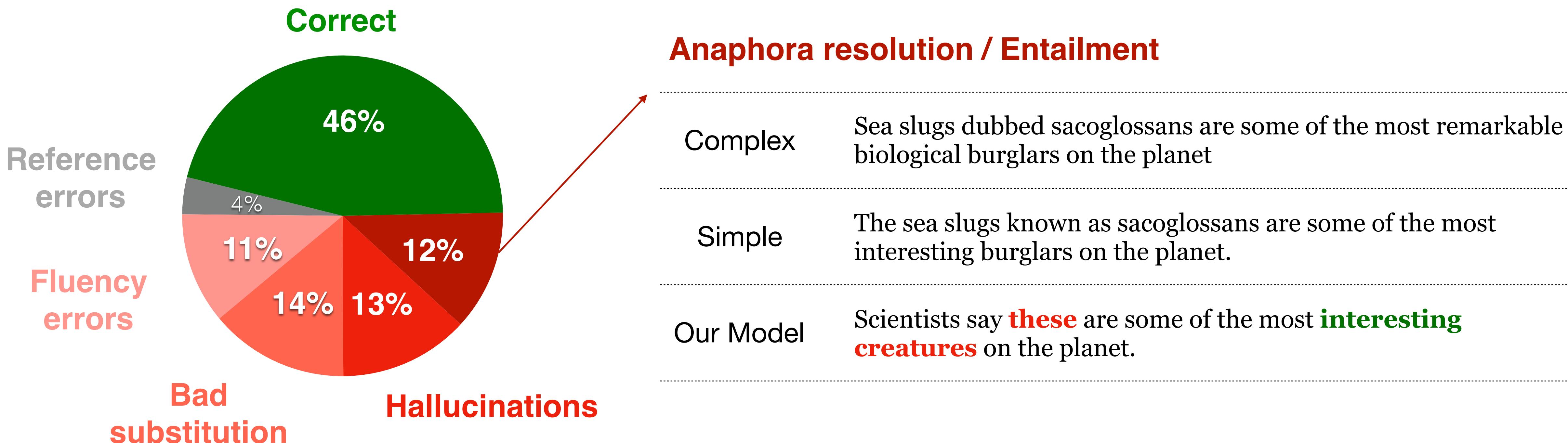
- Neural CRF Model for Sentence Alignment in Text Simplification (Jiang, Maddela, Lan, Zhong & Xu, ACL 2020)

Performance gains from better data are huge!

- Discourse Level Factors for Sentence Deletion in Text Simplification (Zhong, Jiang, Xu & Li, AAAI 2020)
- A Neural Readability Ranking Model and A Word-Complexity Lexicon for Lexical Simplification (Maddela & Xu, EMNLP 2018)
- Optimizing Statistical Machine Translation for Text Simplification (Xu et al., TACL 2016)
- Problems in Current Text Simplification Research: New Data Can Help (Xu et al., TACL 2015)

# What lie in the future? Here is an error analysis.

Manually inspected 100 simplifications by our model from the **Newsela-Auto** test set.



# Thank you!

<https://cocoxu.github.io/>

thank you

gramercies

thnx

say thanks

thx

tyvm

thanku

gratitude

thanks

thank u 4 ur time

I am grateful

appreciate it

thanks a lot

3x

thank you very much

thanks a ton

wawwww thankkkkkkkkkkk you alottttttttttt!

I can no other answer make but thanks, and thanks, and ever thanks.

