# Semantic Structural Evaluation for Text Simplification

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NAACL HLT 2018



# **Text Simplification**

Last year I read the book John authored → John wrote a book. I read the book.

Original sentence

One or several simpler sentences

## Text Simplification

Last year I read the book John authored → John wrote a

Original sentence One or sev

John wrote a book. I read the book.
One or several simpler sentences

- **Multiple motivations**
- Preprocessing for Natural Language Processing tasks e.g., machine translation, relation extraction, parsing
- Reading aids, Language Comprehension

  e.g., people with aphasia, dyslexia, second language learners

# Two types of Simplification

Last year I read the book John authored → John wrote a book. I read the book.

Original sentence One or several simpler sentences

Lexical operations

e.g., word substitution

Structural operations

e.g., sentence splitting, deletion

All the previous evaluation approaches targeted lexical simplification.

Here: the first automatic evaluation measure for structural simplification.

#### Overview

- 1. Current Text Simplification Evaluation
- 2. A New Measure for Structural Simplification

**SAMSA** (Simplification Automatic Measure through Semantic Annotation)

- 2.1. SAMSA properties
- 2.2 The semantic structures
- 2.3 SAMSA computation
- 3. Human Evaluation Benchmark
- 4. Correlation Analysis with Human Evaluation
- 5. Conclusion

## **Current Text Simplification Evaluation**

#### Main automatic metrics

BLEU, Panineni et al., 2002 SARI, Xu et al., 2016

Reference-based

The output is compared to one or multiple references

Focus on lexical aspects

Do not take into account structural aspects

### A New Measure for Structural Simplification

#### SAMSA

Simplification Automatic evaluation Measure through Semantic Annotation

## SAMSA Properties

- Measures the preservation of the sentence-level semantics
- Measures structural simplicity
- No reference simplifications
- Fully automatic
- Semantic parsing only on the source side

## **SAMSA** Properties

#### Example:

John arrived home and gave Mary a call. (input)

John arrived home. John called Mary. (output)



#### **Assumption:**

In an ideal simplification each event is placed in a different sentence.

Fits with existing practices in Text Simplification.

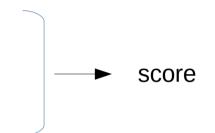
(Glavaš and Štajner, 2013; Narayan and Gardent, 2014)

## SAMSA Properties

#### Example:

John arrived home and gave Mary a call. (input)

John arrived home. John called Mary. (output)

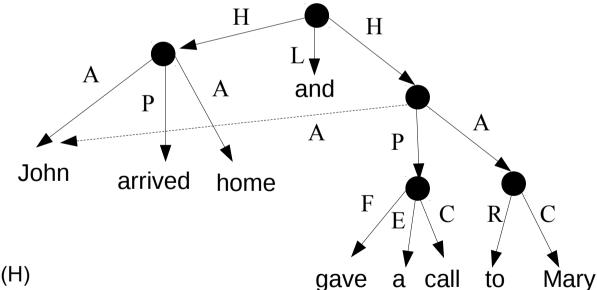


SAMSA focuses on the core semantic components of the sentence, and is tolerant to the deletion of other units.

#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- Based on typological and cognitive theories

(Dixon, 2010, 2012; Langacker, 2008)



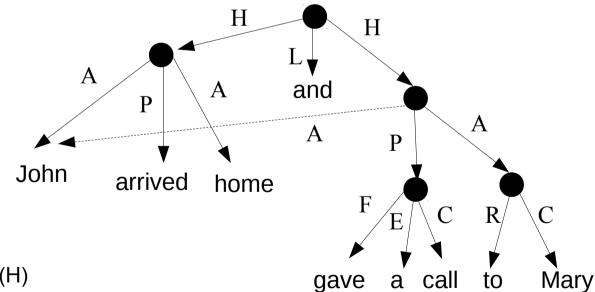
Process (P) Function (F)

Participant (A) Parallel Scene (H)

Center (C) Linker (L)

#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- Stable across translations (Sulem, Abend and Rappoport, 2015)
- Used for the evaluation of MT and GEC (Birch et al., 2016; Choshen and Abend, 2018)



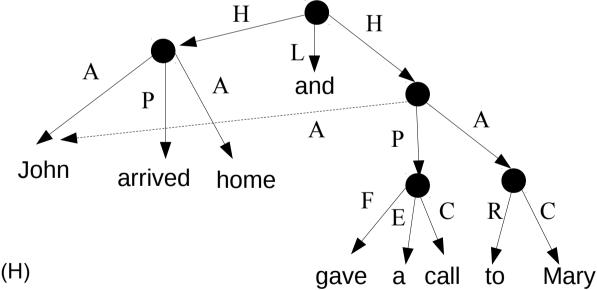
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#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- Explicitly annotates semantic distinctions, abstracting away from syntax (like AMR; Banarescu et al., 2013)
- Unlike AMR, semantic units are directly anchored in the text.



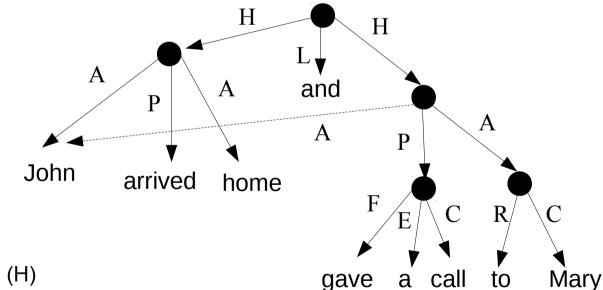
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#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- UCCA parsing (Hershcovich et al., 2017, 2018)
- Shared Task in Sem-Eval 2019!



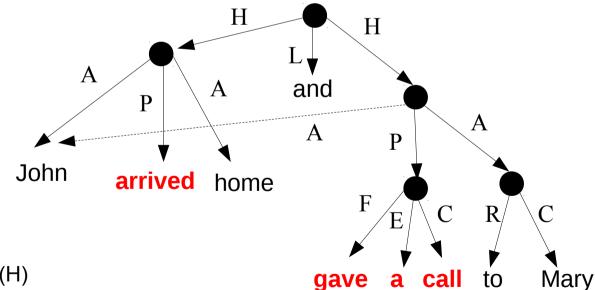
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#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- Scenes evoked by a Main Relation (Process or State).



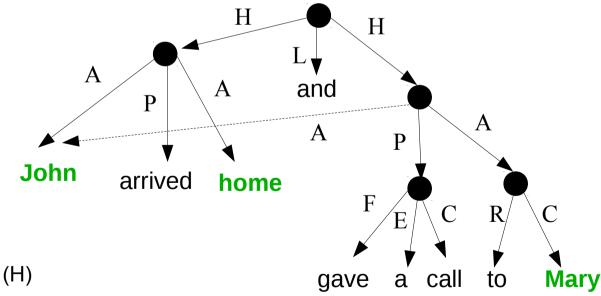
Process (P) Function (F)

Participant (A) Parallel Scene (H)

Center (C) Linker (L)

#### Semantic Annotation: UCCA (Abend and Rappoport, 2013)

- A Scene may contain one or several **Participants**.



Process (P) Function (F)

Participant (A) Parallel Scene (H)

Center (C) Linker (L)

#### Example:

John arrived home John gave Mary a call (input Scenes)



John arrived home. John called Mary. (output sentences)

- 1. Match each Scene to a sentence.
- 2. Give a score to each Scene assessing its meaning preservation in the aligned sentence.
  - Evaluated through the preservation of its main semantic components.
- 3. Average the scores and penalize non-splitting.

#### Scene to Sentence Matching:

- A word alignment tool is used (Sultan et al., 2014) for aligning a Scene to the candidate sentences.
  - → Each word is aligned to 1 or 0 words in the candidate sentence.
- To each Scene we match the sentence for which the highest number of word alignments is obtained.
- If there are more sentences than Scenes, a score of zero is assigned.

John arrived home John gave Mary a call (input Scenes)



John arrived home. John called Mary. (output sentences)

Word alignment

**UCCA** annotation

Scene John gave Mary a call



Sentence John called Mary

Suppose the Scene *Sc* is matched to the sentence *Sen*:

$$Score_{Sen}(Sc) = \frac{1}{2}(Score_{Sen}(MR) + \frac{1}{K} \sum_{i=1}^{K} Score_{Sen}(Par_k))$$

MR - Minimal center of the Main Relation (Process / State)

 $Par_k$  - Minimal center of the  $k^{\text{th}}$  Participant

$$Score_{Sen}(u) = \begin{cases} 1 & u \text{ is aligned to a word in } Sen \\ 0 & \text{otherwise} \end{cases}$$

Average over the input Scenes

• Non-splitting penalty:  $\frac{n_{out}}{n_{inp}}$  Number of output sentences Number of input Scenes

We also experiment with SAMSA<sub>abl</sub>, without non-splitting penalty.

#### **Human Evaluation Benchmark**

- **5** annotators
- **100** source sentences (PWKP test set)
- 6 Simplification systems + Simple corpus
- 4 Questions for each input-output pair (1 to 3 scale):
  - Oa Is the output grammatical?
  - Qb Does the output add information, compared to the input?
  - Oc Does the output remove important information, compared to the input?
  - Od Is the output simpler than the input, ignoring the complexity of the words?
- Parameters: -Grammaticality (G)
  - -Meaning Preservation (P)
  - -Structural Simplicity (S)

#### **Human Evaluation Benchmark**

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  - Qa Is the output grammatical?
  - Qb Does the output add information, compared to the input?
  - Oc Does the output remove important information, compared to the input?
  - Qd Is the output simpler than the input, ignoring the complexity of the words?

AvgHuman = 
$$\frac{1}{3}$$
 (G+P+S)

	Reference-less				Reference-based		
	SAMSA Semi-Aut.	SAMSA Aut.	SAMSA <sub>abl</sub> Semi-Aut.	SAMSA <sub>abl</sub> Aut.	BLEU	SARI	Sent. with Splits
G	0.54	0.37	0.14	0.14	0.09	-0.77	0.09
P	-0.09	-0.37	0.54	0.54	0.37	-0.14	-0.49
S	0.54	0.71	-0.71	-0.71	-0.60	-0.43	0.83
AvgHuman	0.58	0.35	0.09	0.09	0.06	-0.81	0.14

Spearman's correlation at the system level of the metric scores with the human evaluation scores, considering the output of the 6 simplification systems

**G** – Grammaticality, **P** – Meaning Preservation, **S** – Strucutral Simplicity

- → SAMSA obtained the best correlation for AvgHuman.
- SAMSA<sub>abl</sub> obtained the best correlation for Meaning Preservation.

	Reference-less				Reference-based		
	SAMSA Semi-Aut.	SAMSA Aut.	SAMSA <sub>abl</sub> Semi-Aut.	SAMSA <sub>abl</sub> Aut.	BLEU	SARI	Sent. with Splits
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P	-0.09	-0.37	0.54	0.54	0.37	-0.14	-0.49
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**G** – Grammaticality, **P** – Meaning Preservation, **S** – Strucutral Simplicity

- SAMSA is ranked second and third for Simplicity.
- When resctricted to multi-Scene sentences, SAMSA Semi-Aut. has a correlation of 0.89 (p=0.009). For Sent. with Splits, it is 0.77 (p=0.04).

	Reference-less				Reference-based		
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**G** – Grammaticality, **P** – Meaning Preservation, **S** – Strucutral Simplicity

→ High similarity between the **Semi-Automatic** and **the Automatic** implementations. For **SAMSA**<sub>abl</sub>, the ranking is the same.

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**G** – Grammaticality, **P** – Meaning Preservation, **S** – Strucutral Simplicity

Low and negative correlations for BLEU and SARI.

## Correlation with Existing Benchmark

QATS task (Štajner et al., 2016)

Pearson Correlation with the Overall Human Score:

- Semi-automatic and automatic SAMSA rank 3<sup>rd</sup> and 4<sup>th</sup> (0.32 and 0.28), out of 15 measures.
- Surpassed by the best performing systems by a small margin (0.33 and 0.34).

Although: - We did **not use training data** (human scores)

- SAMSA focuses on **structural simplicity**.

#### Conclusion

- We proposed SAMSA, the first structure-aware measure for Text Simplification.
- SAMSA explicitly targets the structural component of Text Simplification.
- SAMSA gets substantial correlations with human evaluation.
- Existing measures fail to correlate with human judgments when structural simplification is performed.

#### **Future Work**

- SAMSA can be used for **tuning** Text Simplification systems.
- Semantic decomposition with UCCA can be used for improving Text Simplification (Sulem, Abend and Rappoport, ACL 2018).
- SAMSA can be extended to **other Text-to-Text generation tasks** as paraphrasing, sentence compression, or fusion.

## Thank you

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Code and Data: https://github.com/eliorsulem/SAMSA

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