

# Simple and Effective Text Simplification Using Semantic and Neural Methods

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The Hebrew University of Jerusalem

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האוניברסיטה העברית בירושלים  
THE HEBREW UNIVERSITY OF JERUSALEM



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# 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

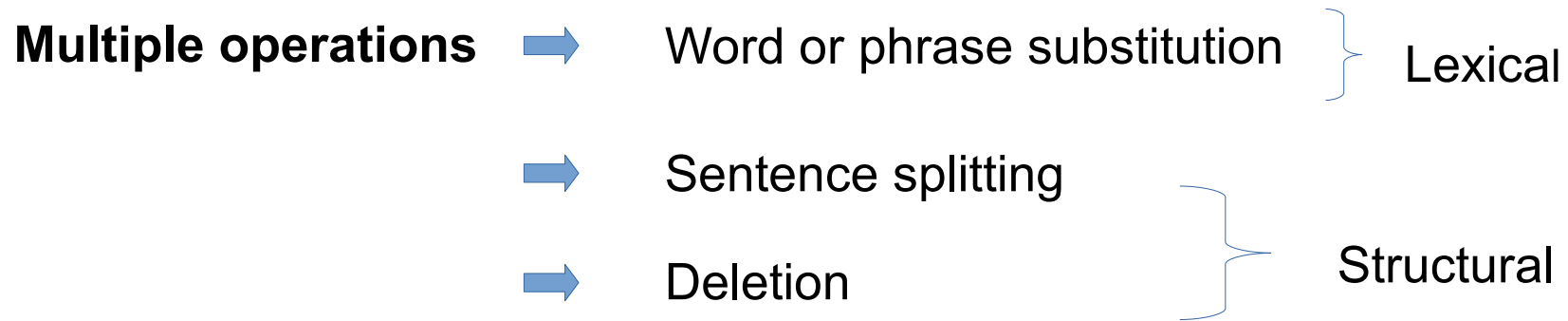
# Text Simplification

Last year I read the book John authored —→ John wrote a book. I read the book.  
Original sentence 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, 2<sup>nd</sup> language learners

# 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



# In this talk

- Both **structural** and **lexical** simplification.
- The first simplification system combining structural transformations, using **semantic structures**, and **neural machine translation**.
- **Compares favorably to the state-of-the-art** in combined structural and lexical simplification.
- **Alleviates the over-conseratism** of MT-based systems.

# Overview

1. Current approaches and challenges
  - 1.1 Conservatism in MT-Based Simplification
  - 1.2 Sentence splitting in Text Simplification
2. Direct Semantic Splitting (DSS)
  - 2.1. The semantic structures
  - 2.2. The semantic rules
3. Combining DSS with Neural Text Simplification
4. Experiments
5. Results
6. Human Evaluation Benchmark
7. Conclusion

# Current Approaches and Challenges

## MT-Based Simplification

Sentence simplification as monolingual machine translation

### Models

- Phrase-Based SMT (Specia, 2010; Coster and Kauchak, 2011; Wubben et al, 2012; Štajner et al., 2015)
- Syntax-Based SMT (Xu et al., 2016)
- Neural Machine Translation (Nisioi et al., 2017; Zhang et al., 2017; Zhang and Lapata, 2017)



# Current Approaches and Challenges

## MT-Based Simplification

Sentence simplification as monolingual machine translation

### Corpora

- English / Simple Wikipedia (Zhu et al., 2010; Coster and Kauchak., 2011; Hwang et al., 2015)
- Newsela (Xu et al., 2015)

# Conservatism in MT-Based Simplification

- In both SMT and NMT Text Simplification, **a large proportion of the input sentences are not modified**. (Alva-Manchego et al., 2017; on the Newsela corpus).
- **It is confirmed in the present work** (experiments on Wikipedia):

For the **NTS system** (Nisioi et al., 2017) / **Moses** (Koehn et al., 2007)

- **66%** / **80%** of the input sentences remain unchanged.
- None of the references are identical to the source.
- According to automatic and human evaluation, the references are indeed simpler.



Conservatism in MT-Based simplification is excessive

# Sentence Splitting in Text Simplification

## Splitting in NMT-Based Simplification

- Sentence splitting is not addressed.
- Rareness of splittings in the simplification training corpora.  
(Narayan and Gardent, 2014; Xu et al., 2015).
- Recently, corpus focusing on sentence splitting for the Split-and-Rephrase task  
(Narayan et al., 2017) where the other operations are not addressed.

# Sentence Splitting in Text Simplification

## Directly modeling sentence splitting

### 1. Hand-crafted syntactic rules:

- Compilation and validation can be laborious (Shardlow, 2014)
- **Many rules** are often involved (e.g., 111 rules in Siddharthan and Angrosh, 2014) for relative clauses, appositions, subordination and coordination).
- Usually **language specific**.

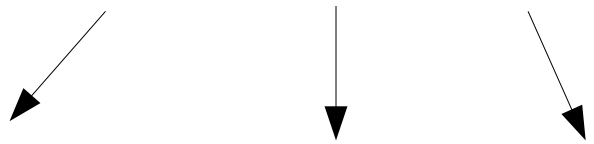
# Sentence Splitting in Text Simplification

Directly modeling sentence splitting

1. Hand-crafted syntactic rules:

Example:

$$V W_{NP}^x X [RC_n RELPR^{\#x} Y] Z. \longrightarrow \{(a) V W X Z (b) W Y\}$$

  
Noun phrase    Relative clause    Relative Pronoun

One of the two rules for relative clauses in Siddharthan, 2004.

# Sentence Splitting in Text Simplification

## Directly modeling sentence splitting

### 2. Using semantics for determining potential splitting points

Narayan and Gardent (2014) - HYBRID

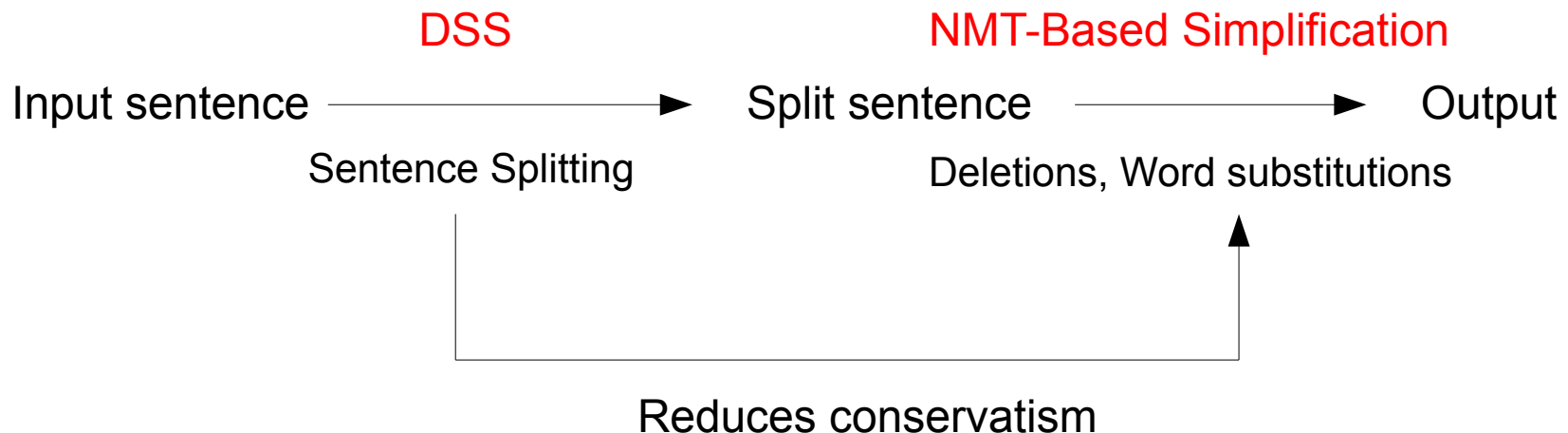
- Discourse Semantic Representation (DRS) structures for splitting and deletion.
- Depends on the proportion of splittings in the training corpus.

→ We here use an intermediate way:

Simple algorithm to directly decompose the sentence into its semantic constituents.

# Direct Semantic Splitting (DSS)

- A simple algorithm that directly decomposes the sentence into its semantic components, using **2 splitting rules**.
- The splitting is directed by **semantic parsing**.
- The semantic annotation directly captures **shared arguments**.
- It can be used as a preprocessing step for **other simplification operations**.

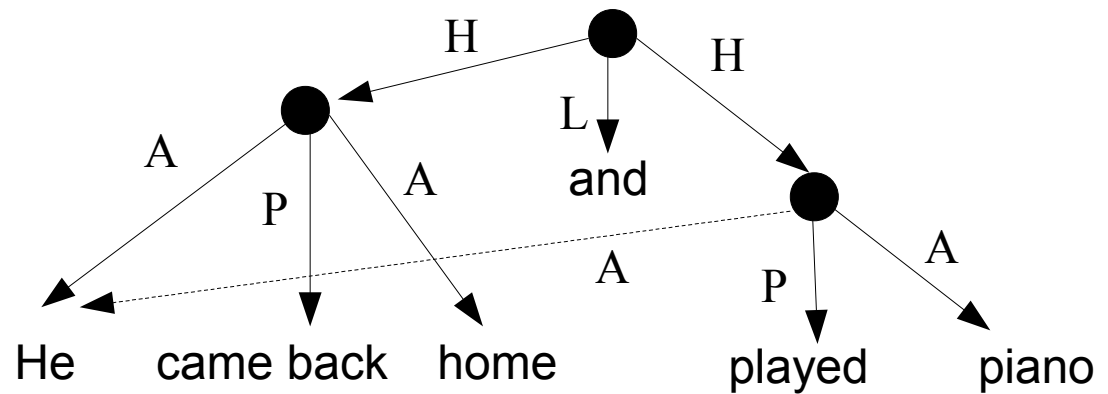


# The Semantic Structures

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

- Based on typological and cognitive theories

(Dixon, 2010, 2012; Langacker, 2008)



Parallel Scene (H)    Linker (L)

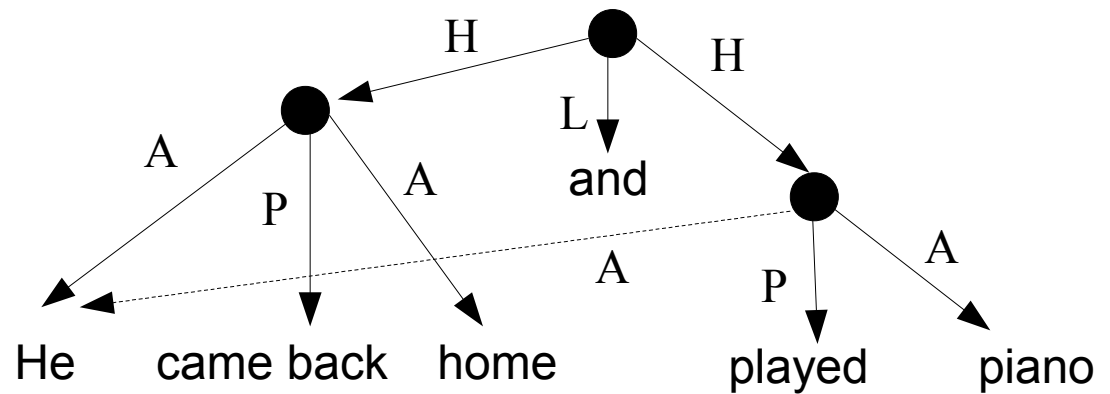
Participant (A)      Process (P)



# The Semantic Structures

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

- Stable across translations (Sulem, Abend and Rappoport, 2015)



Parallel Scene (H)    Linker (L)

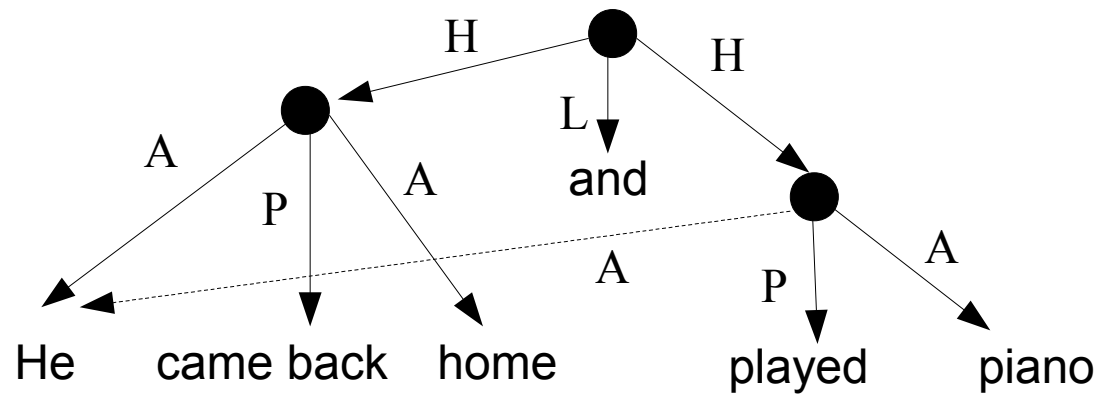
Participant (A)      Process (P)

# The Semantic Structures

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

- Used for the evaluation of MT, GEC and Text Simplification

(Birch et al., 2016; Choshen and Abend, 2018; Sulem et al., 2018)



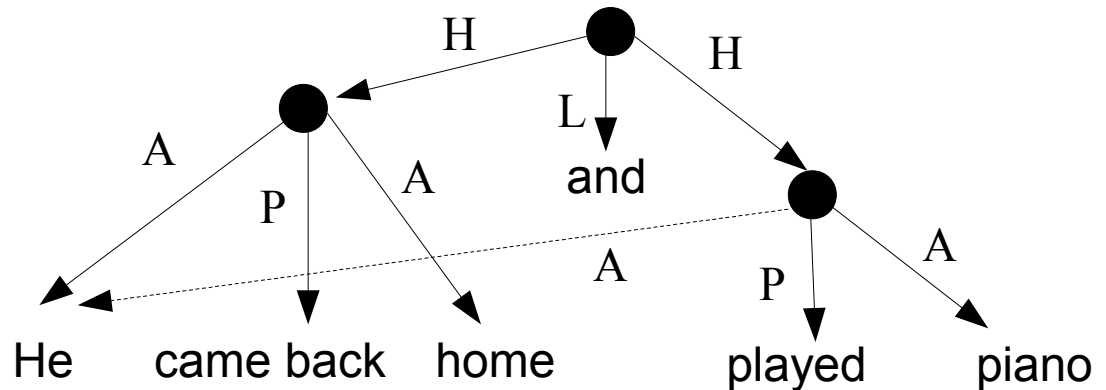
Parallel Scene (H)    Linker (L)

Participant (A)      Process (P)

# The Semantic Structures

## 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.



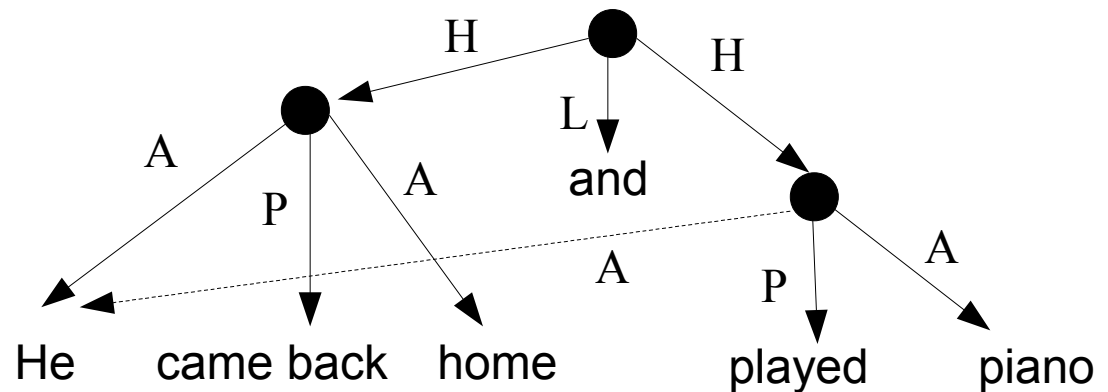
Parallel Scene (H)    Linker (L)

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# The Semantic Structures

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

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



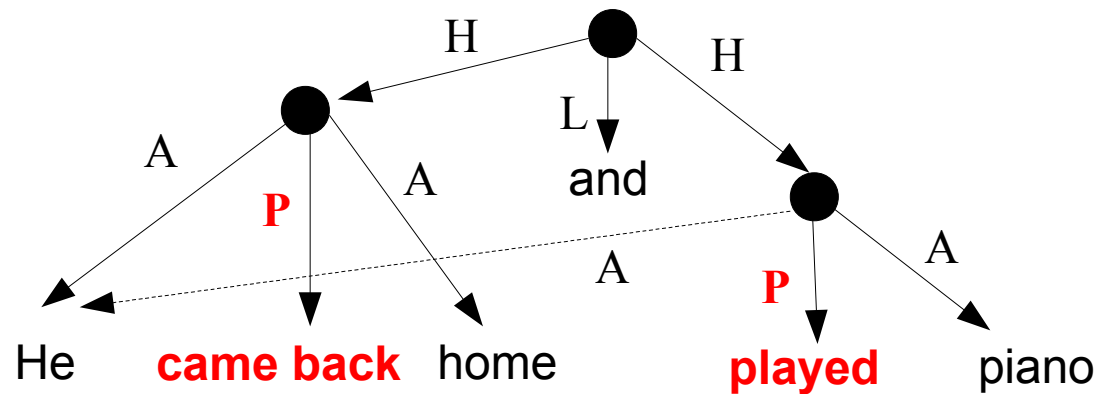
Parallel Scene (H)    Linker (L)

Participant (A)      Process (P)

# The Semantic Structures

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

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



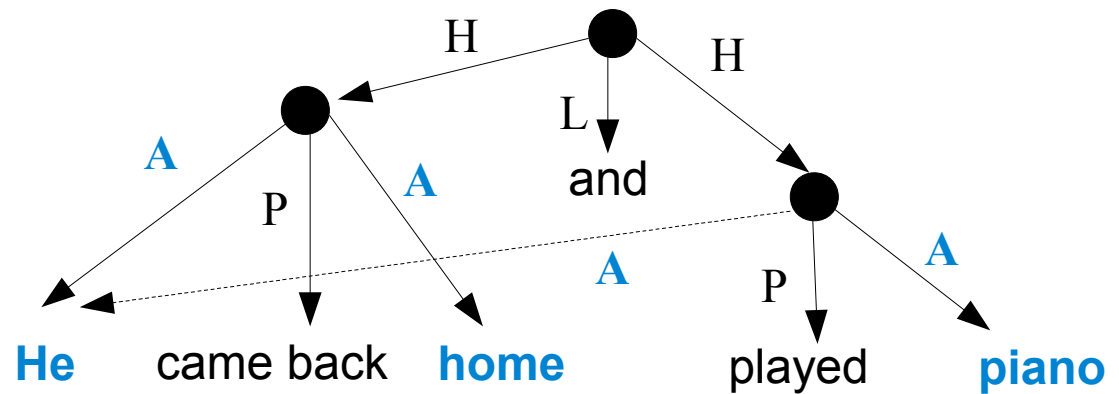
Parallel Scene (H) Linker (L)

Participant (A) Process (P)

# The Semantic Structures

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

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



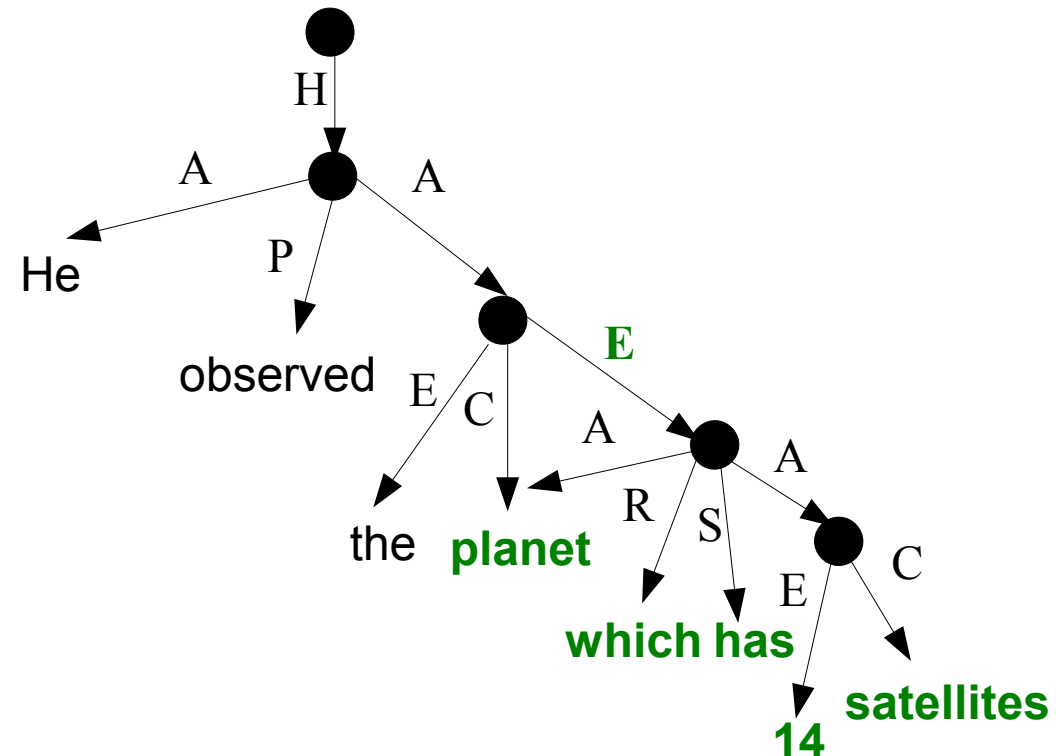
Parallel Scene (H)    Linker (L)

Participant (A)      Process (P)

# The Semantic Structures

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

- A Scene can provide additional information on an established entity:  
it is then an **Elaborator Scene**.



Parallel Scene (H)

Participant (A)    Process (P)    State (S)

Center (C)    Elaborator (E)    Relator (R)

# The Semantic Structures

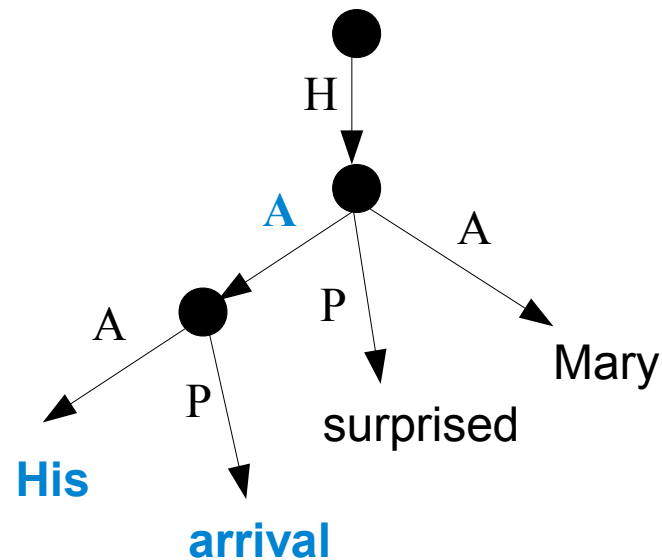
**Semantic Annotation: UCCA** (Abend and Rappoport, 2013)

- A Scene may also be a Participant in another Scene:

It is then a **Participant Scene**.

Parallel Scene (H) Linker (L)

Participant (A) Process (P)



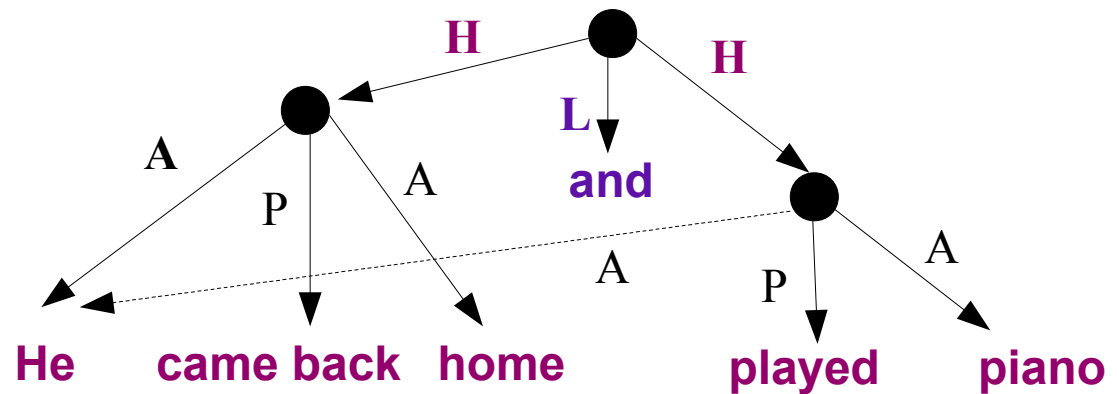


# The Semantic Structures

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

- In the other cases, Scenes are annotated as **Parallel Scenes**.

A **Linker** may be included.



Parallel Scene (H)    Linker (L)

Participant (A)      Process (P)

# The Semantic Rules

## **Main idea:**

*Placing each Scene in a different sentence.*

- Fits with event-wise simplification (Glavaš and Štajner, 2013)

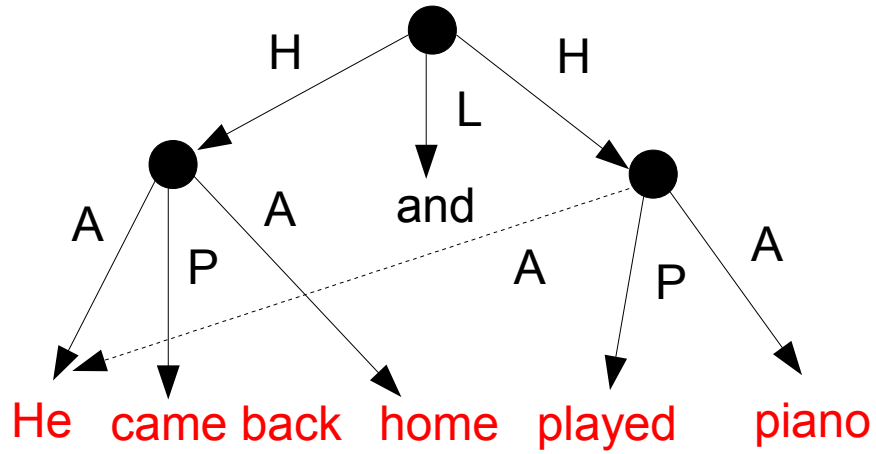
Here we only use semantic criteria.

- It was also investigated in the context of Text Simplification evaluation:

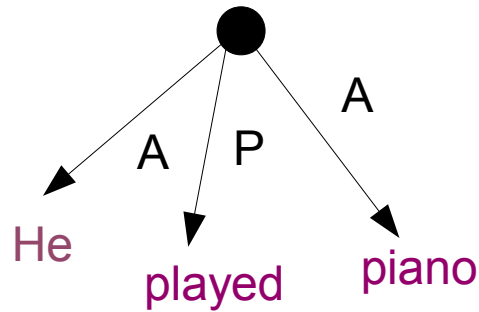
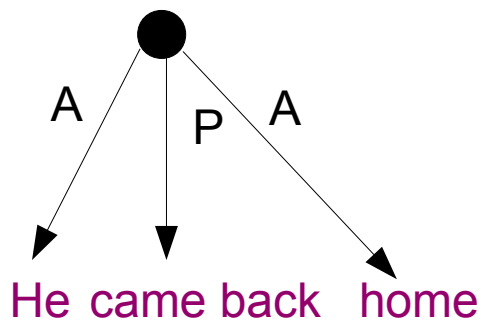
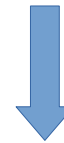
SAMSA measure (Sulem, Abend and Rappoport, NAACL 2018)

# Rule 1: The Semantic Rules

Parallel Scenes



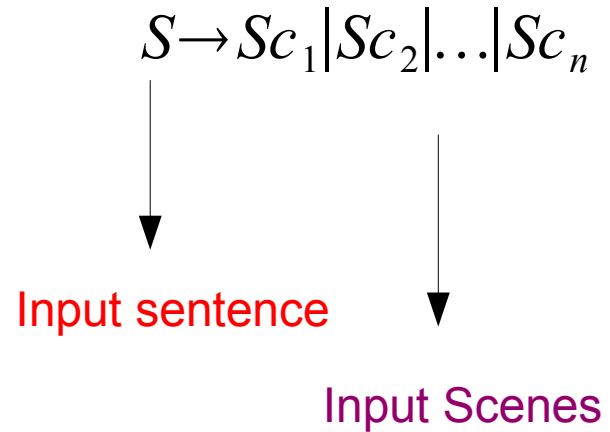
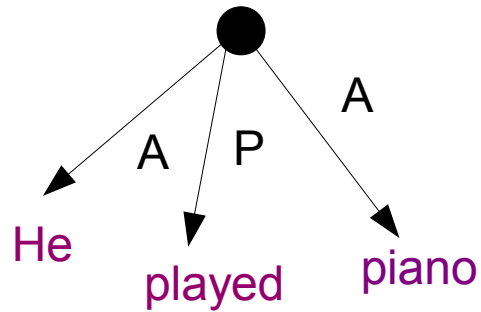
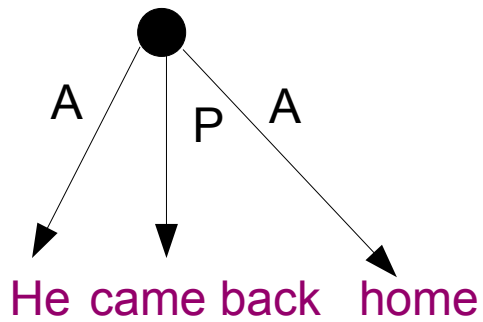
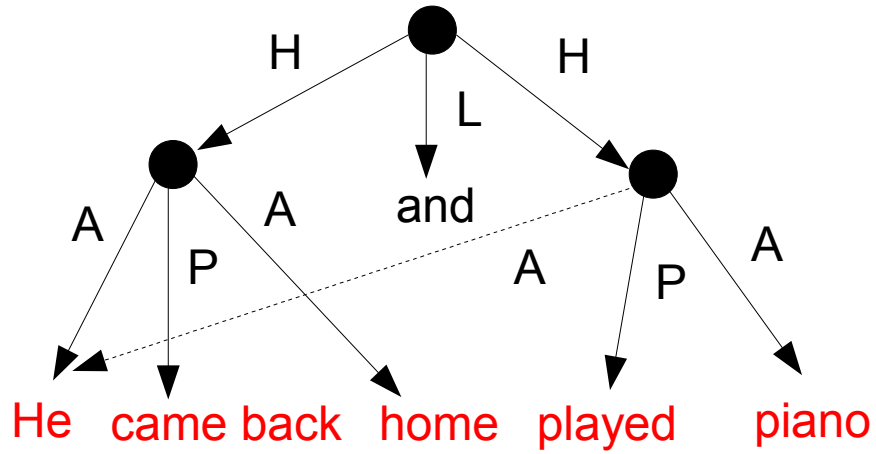
He came back home and played piano.



He came back home. He played piano.

# Rule 1: The Semantic Rules

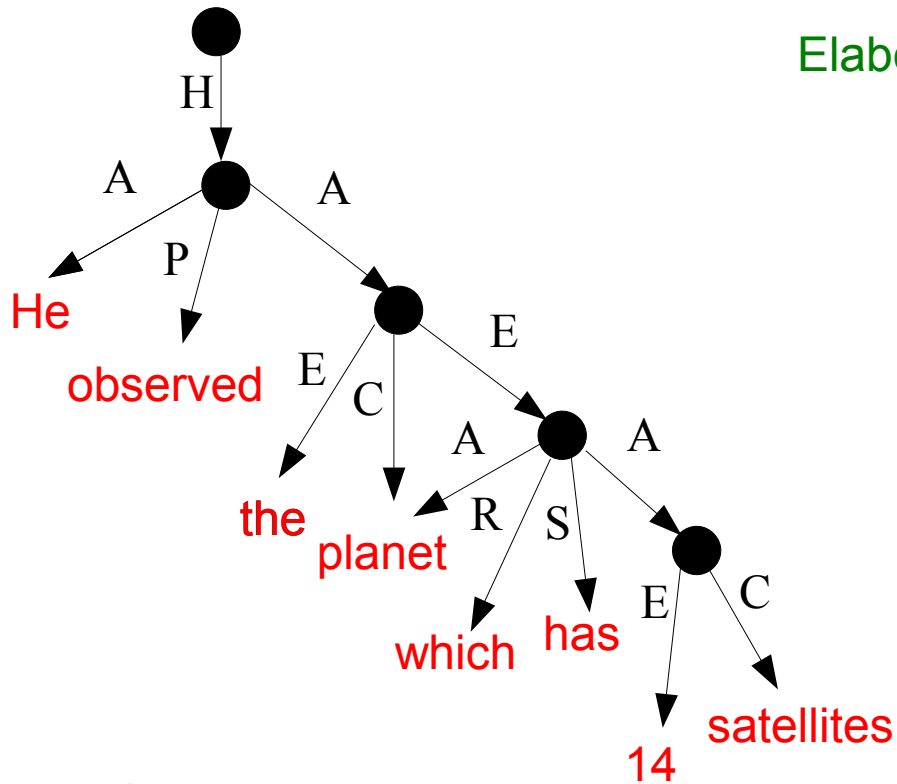
## Parallel Scenes



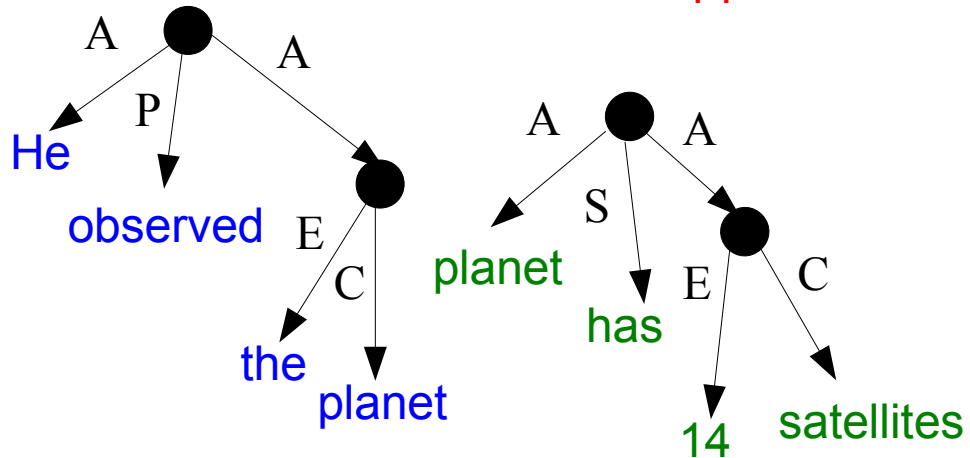
## Rule 2:

# The Semantic Rules

Elaborator Scenes



He observed the planet which has 14 satellites.

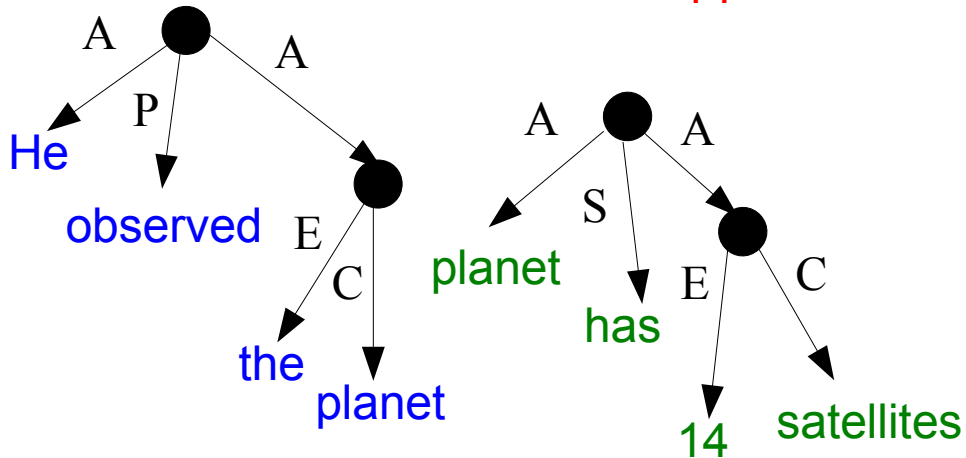
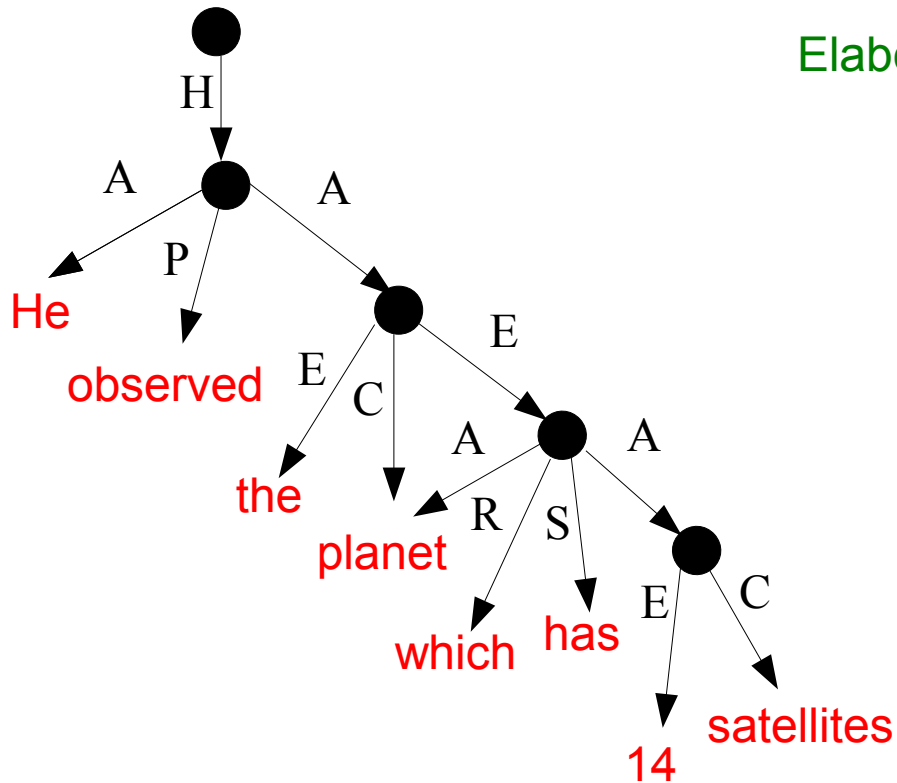


He observed the planet. Planet has 14 satellites.

## Rule 2:

# The Semantic Rules

Elaborator Scenes



$$S \rightarrow S - \cup (Sc_i - C_i) | Sc_1 | \dots | Sc_n$$

Input sentence

Elaborator Scenes

Input sentence  
without the Elaborator Scenes,  
preserving the Minimal Center

# The Semantic Rules

- No regeneration module
- Grammatical errors resulting from the split are not addressed by the rules. e.g., no article regeneration.
- The output is directly fed into the NMT component.

## Example:

He observed the planet which has 14 satellites



He observed the planet. Planet has 14 satellites.

# The Semantic Rules

- Participant Scenes are not separated here to avoid direct splitting in these cases:
  - Nominalizations:

His arrival surprised Mary.
  - Indirect speech:

He said John went to school.
- More transformations would be required for splitting in these cases.



# Combining DSS with Neural Text Simplification

- After **DSS**, the output is fed to an MT-based simplification system.
- We use a state-of-the-art NMT-Based TS system, **NTS** (Nisioi et al., 2017).
- The combined system is called **SENTS**.

# Combining DSS with Neural Text Simplification

- NTS was built using the **OpenNMT** (Klein et al., 2017) framework.
- We use the NTS-w2v provided model where **word2vec embeddings** are used for the initialization.
- Beam search is used during decoding. We explore both the highest (**h1**) and a lower ranked hypothesis (**h4**), which is less conservative.
- NTS model trained on the corpus of Hwang et al., 2015 (~280K sentence pairs).
- It was tuned on the corpus of Xu et al., 2016 (2000 sentences with 8 references).

# Experiments

## Corpus:

Test set of Xu et al., 2016: **359** sentences, each with **8 references**

## Automatic evaluation:

- BLEU (Panineni et al., 2002)
- SARI (Xu et al., 2016)

## Conservatism statistics:

e.g., percentage of sentences copied from the input (%Same)

# Experiments

## Human evaluation:

- First 70 sentences of the corpus
- 3 annotators – native English speakers
- 4 questions for each input-output pair

- Qa Is the output fluent and grammatical?
- Qb Does the output preserve the meaning of the input?
- Qc Is the output simpler than the input?
- Qd Is the output simpler than the input, ignoring the complexity of the words?

- 4 parameters: Grammaticality (**G**)  
Meaning Preservation (**P**)  
Simplicity (**S**)  
Structural Simplicity (**StS**)

# Results

	BLEU	SARI	G	M	S	StS
Identity	94.93	25.44	4.80	5.00	0.00	0.00
Simple Wikipedia	69.58	39.50	4.60	4.21	0.83	0.38

Automatic evaluation: **BLEU**, **SARI**

Human evaluation (first 70 sentences):

**G** – Grammaticality: 1 to 5 scale

**S** – Simplicity: -2 to +2 scale

**P** – Meaning Preservation: 1 to 5 scale

**StS** – Structural Simplicity: -2 to +2 scale

➔ Identity gets the highest BLEU score and the lowest SARI scores.

# Results

	BLEU	SARI	G	M	S	StS
HYBRID	52.82	27.40	2.96	2.46	0.43	0.43
SENTS-h1	<b>58.94</b>	30.27	<b>3.98</b>	<b>3.33</b>	<b>0.68</b>	<b>0.63</b>
SENTS-h4	57.71	<b>31.90</b>	3.54	2.98	0.50	0.36

Automatic evaluation: **BLEU**, **SARI**

Human evaluation (first 70 sentences):

**G** – Grammaticality: 1 to 5 scale

**S** – Simplicity: -2 to +2 scale

**P** – Meaning Preservation: 1 to 5 scale

**StS** – Structural Simplicity: -2 to +2 scale

➔ The two SENTS systems outperform HYBRID in terms of BLEU, SARI, G, M and S.

SENTS-h1 has the best StS score.

# Results

	%Same	SARI	G	M	S	StS
NTS-h1	66.02	28.73	4.56	4.48	0.22	0.15
NTS-h4	2.74	36.55	4.29	3.90	0.31	0.19
SENTS-h1	6.69	30.27	3.98	3.33	0.68	0.63
SENTS-h4	0.28	31.90	3.54	2.98	0.50	0.36

Automatic evaluation: %Same, SARI

Human evaluation (first 70 sentences):

**G** – Grammaticality: 1 to 5 scale

**S** – Simplicity: -2 to +2 scale

**P** – Meaning Preservation: 1 to 5 scale

**StS** – Structural Simplicity: -2 to +2 scale

➡ Compared to NTS, SENTS reduces conservatism and increases simplicity.

# Results

	%Same	SARI	G	M	S	StS
DSS	8.64	36.76	3.42	4.15	0.16	0.16
SENTS-h1	6.69	30.27	3.98	3.33	0.68	0.63
SENTS-h4	0.28	31.90	3.54	2.98	0.50	0.36

Automatic evaluation: %Same, SARI

Human evaluation (first 70 sentences):

**G** – Grammaticality: 1 to 5 scale

**S** – Simplicity: -2 to +2 scale

**P** – Meaning Preservation: 1 to 5 scale

**StS** – Structural Simplicity: -2 to +2 scale

➡ Compared to DSS, SENTS improves grammaticality and increases structural simplicity, since deletions are performed by the NTS component.



# Results

## Replacing NTS by Statistical MT

- Combination of DSS and Moses: **SEMoses**
- The behavior of SEMoses is similar to that of DSS, confirming the **over-conservatism of Moses** (Alva-Manchego et al., 2017) for simplification.
- All the splitting points from the DSS phase are preserved.

## Replacing the parser by manual annotation

- In the case of **SEMoses**, meaning preservation is improved. Simplicity degrades, possibly due to a larger number of annotated Scenes.
- In the case of **SENTS-h1**, high simplicity scores are obtained.

# Human Evaluation Benchmark

- **1960** sentence pairs
- **70** source sentences
- **28** systems
- **3** annotators
- **4** parameters

**Data:** <https://github.com/eliorsulem/simplification-acl2018>

# Conclusion (1)

- We presented here the first simplification system combining **semantic structures** and **neural machine translation**.
- Our system **compares favorably to the state-of-the-art** in combined structural and lexical simplification.
- This approach **addresses the conservatism** of MT-based systems.
- Sentence splitting is performed **without relying on a specialized corpus**.

# Conclusion (2)

- Sentence splitting is treated as the **decomposition of the sentence into its Scenes** (as in SAMSA evaluation measure; Sulem, Abend and Rappoport, NAACL 2018)
- Future work will leverage **UCCA's cross-linguistic applicability** to support multi-lingual text simplification and simplification pre-processing for MT.

# Thank you

Elior Sulem

**Data:** <https://github.com/eliorsulem/simplification-acl2018>

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[www.cs.huji.ac.il/~eliors](http://www.cs.huji.ac.il/~eliors)

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