Simple and Effective Text Simplification Using Semantic and Neural Methods

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The Hebrew University of Jerusalem

ISCOL 2018

האוניברסיטה העברית בירושלים
THE HEBREW UNIVERSITY OF JERUSALEM

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Based on a paper published in ACL 2018.

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Proc. of ACL 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 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, 2nd 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

Multiple operations

- Word or phrase substitution — Lexical
- Sentence splitting
- Deletion

Sentence splitting and Deletion — Structural

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:

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

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.

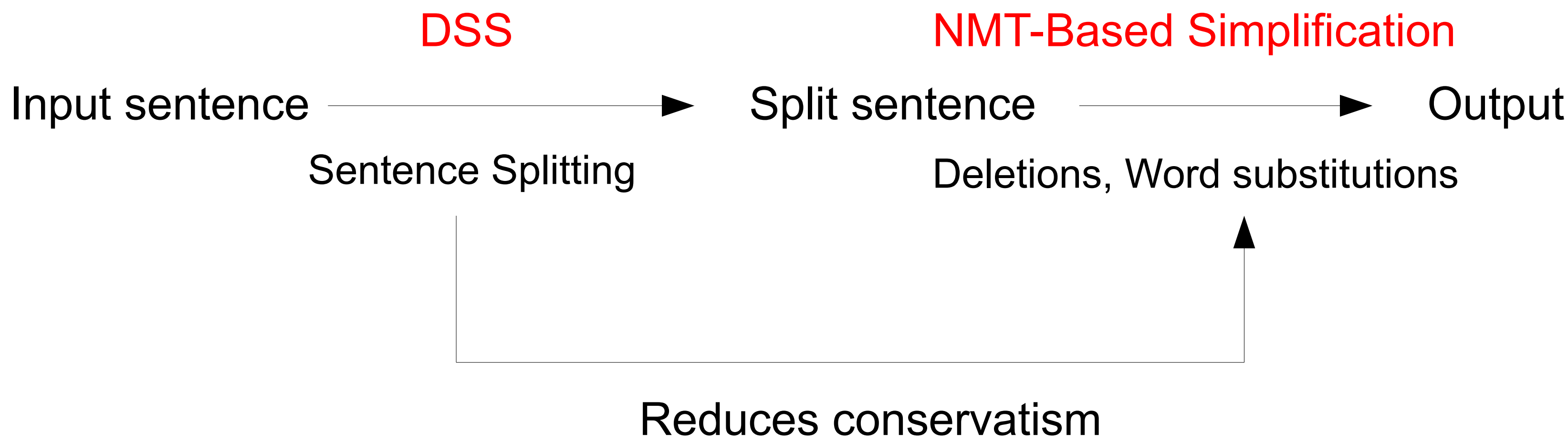
- Depends on the proportion of splittings in the training corpus.

→ 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.

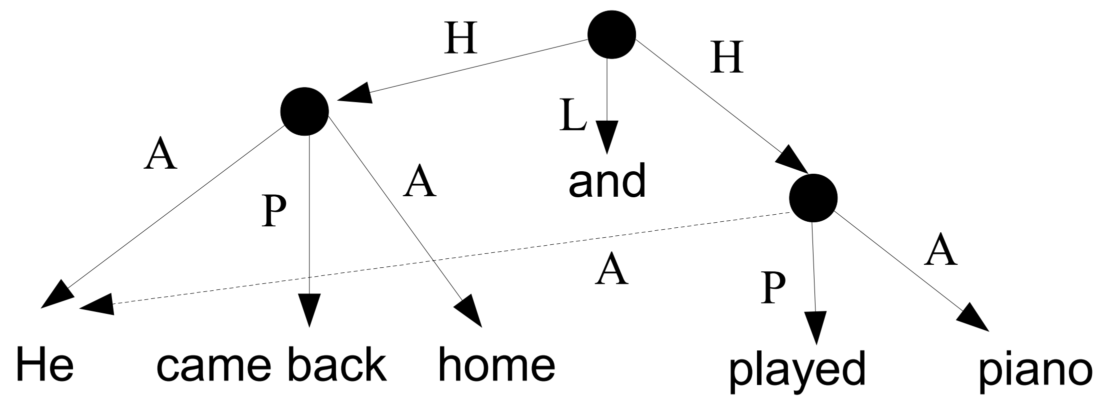


The Semantic Structures

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

- Based on typological and cognitive theories

(Dixon, 2010, 2012; Langacker, 2008)



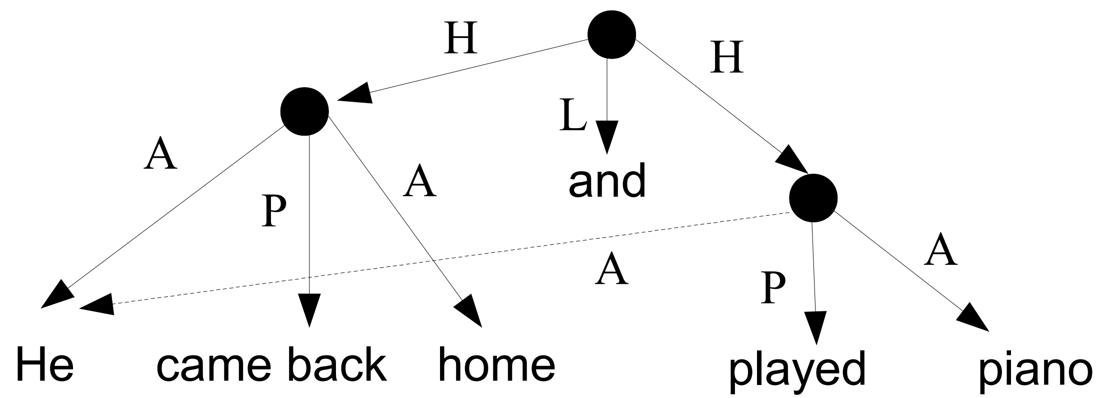
Parallel Scene (H) Linker (L)

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)

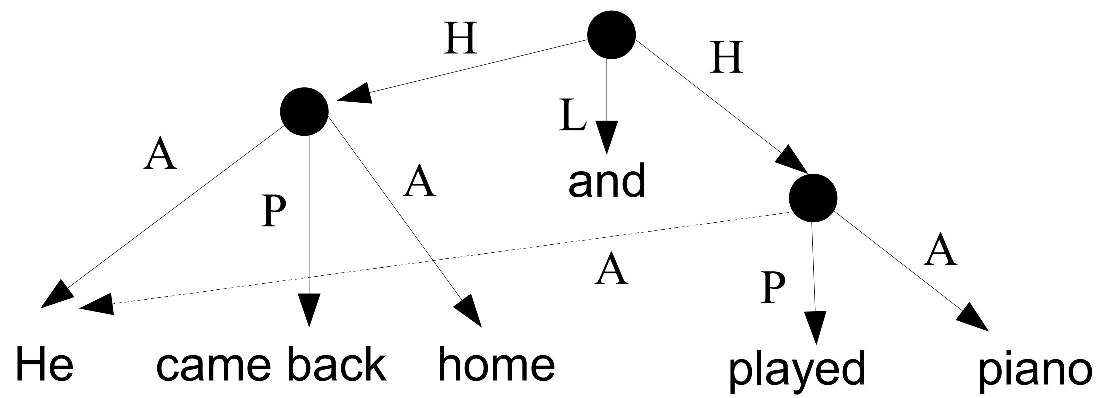
Participant (A)   Process (P)

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)

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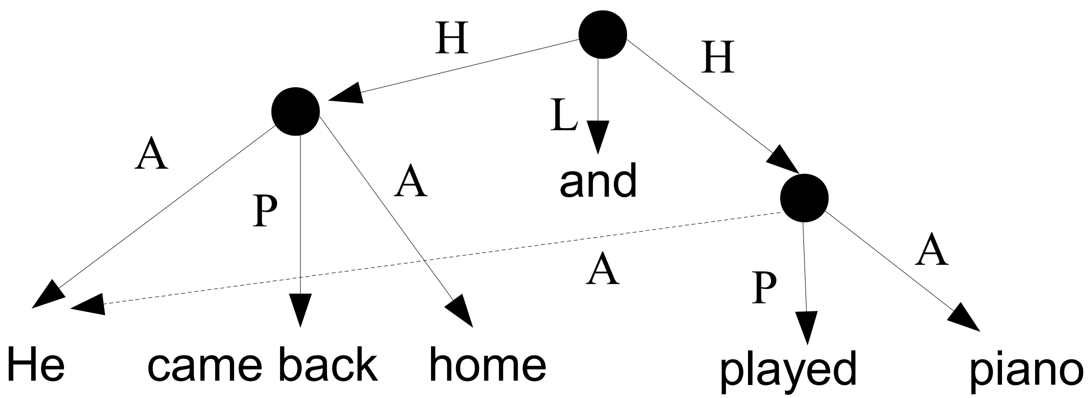
The Semantic Structures

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.



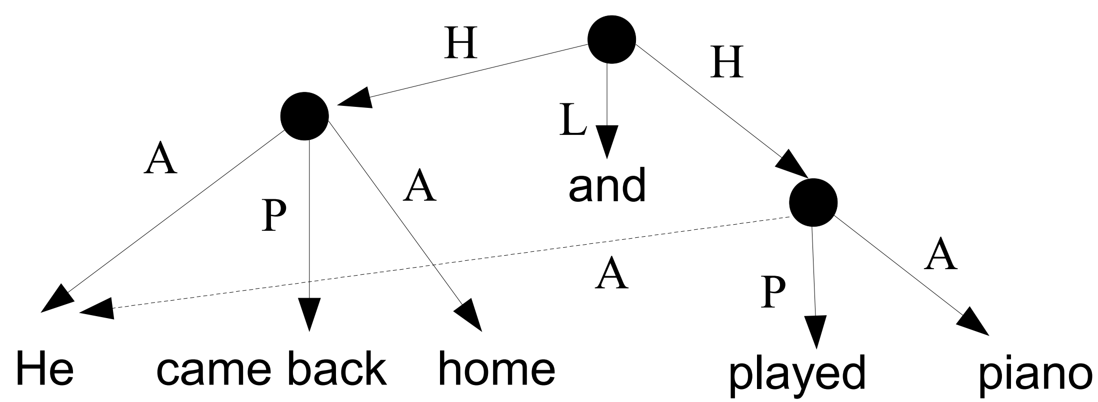
Parallel Scene (H)   Linker (L)

Participant (A)   Process (P)

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!



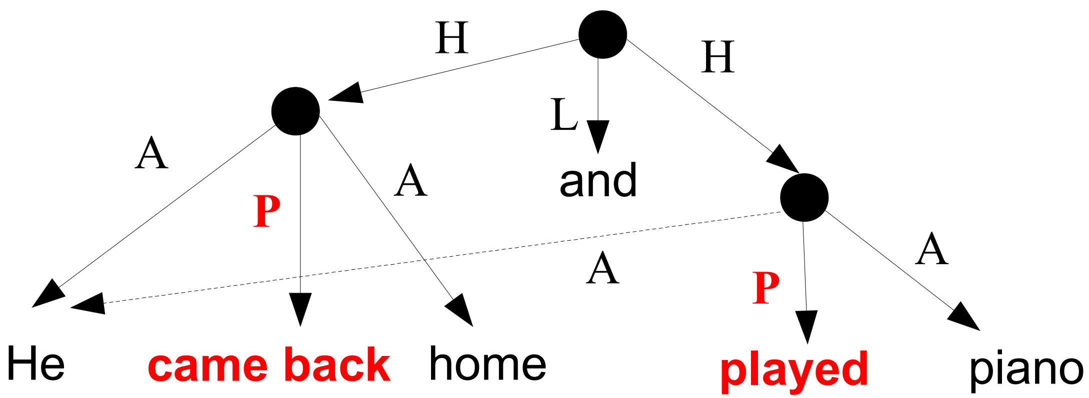
Parallel Scene (H) Linker (L)

Participant (A) Process (P)

The Semantic Structures

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

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



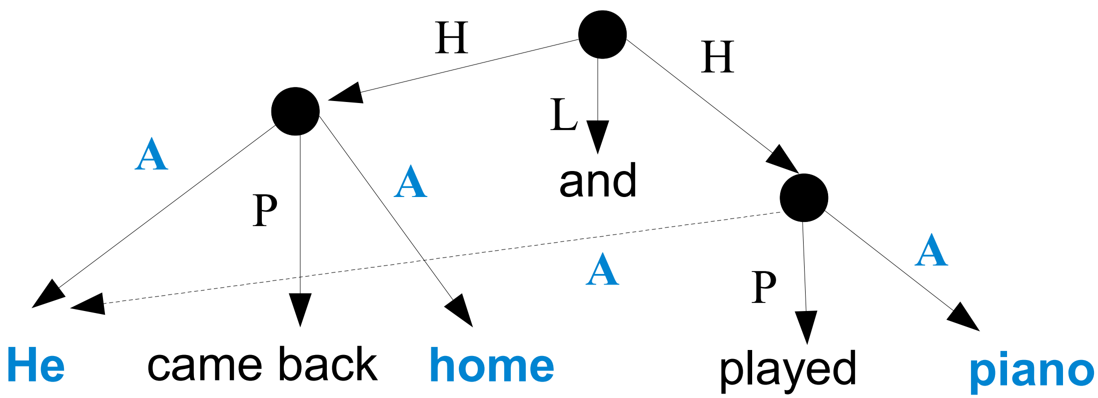
Parallel Scene (H)   Linker (L)

Participant (A)   Process (P)

The Semantic Structures

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

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



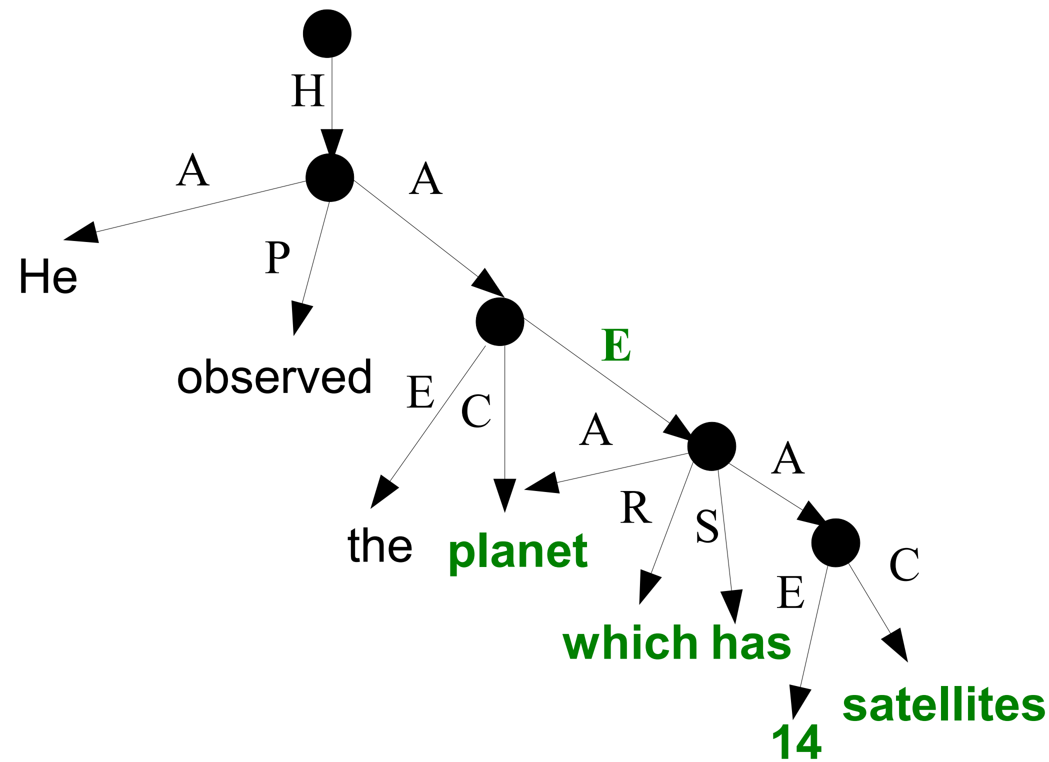
Parallel Scene (H)   Linker (L)

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)

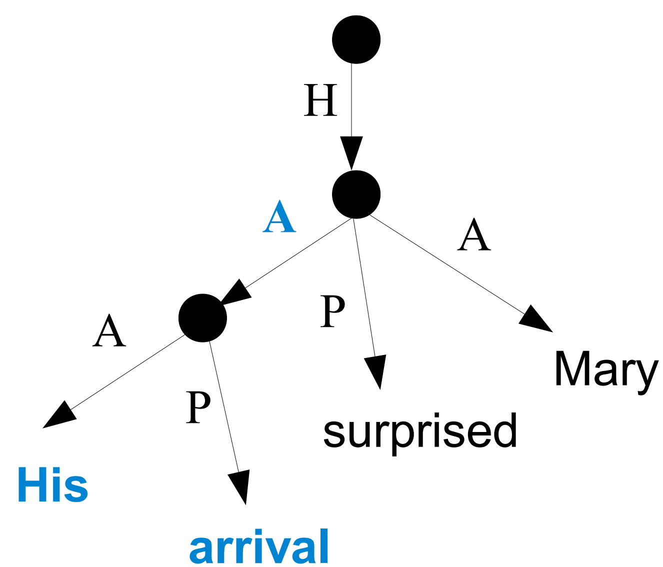
Center (C) Elaborator (E) Relator (R)

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)

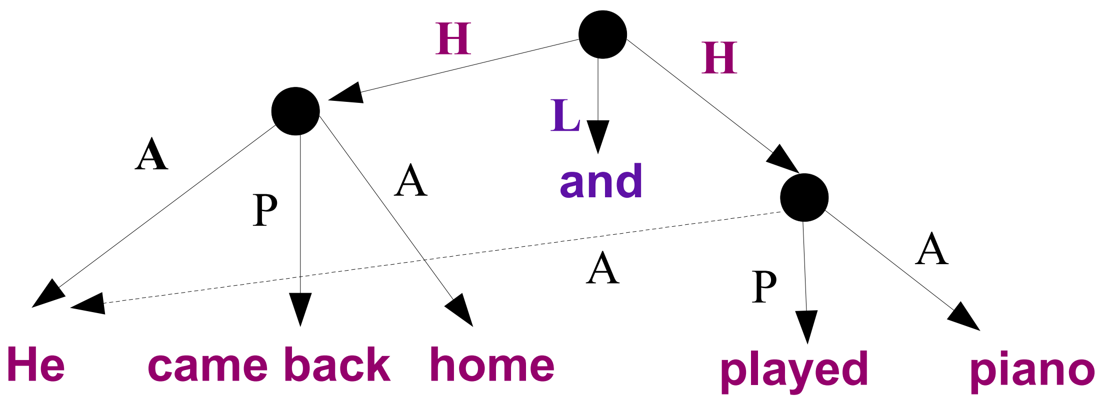
Participant (A) Process (P)

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.

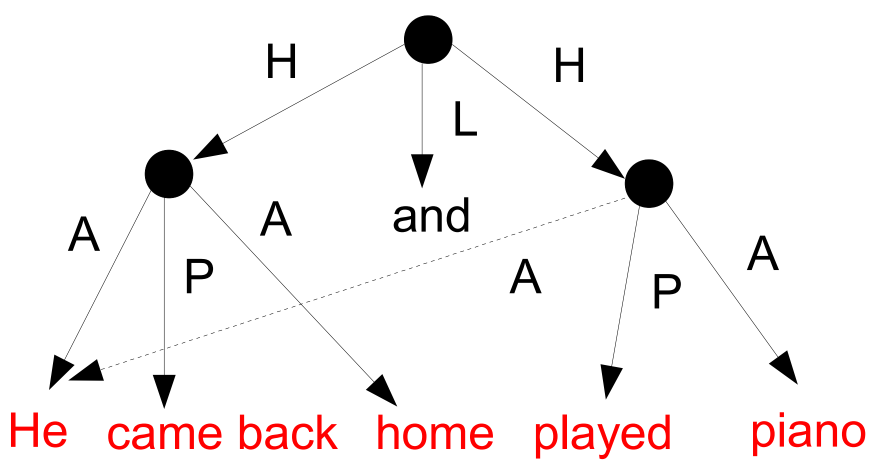
- It was also investigated in the context of Text Simplification evaluation:

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

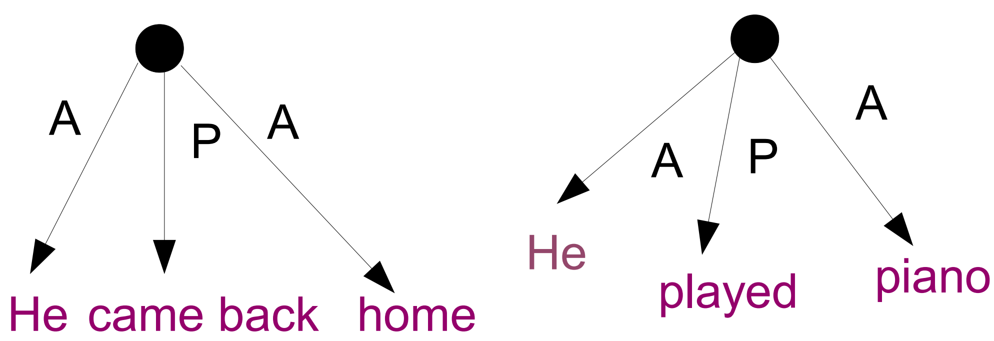
Rule 1:

The Semantic Rules

Parallel Scenes



He came back home and played piano.

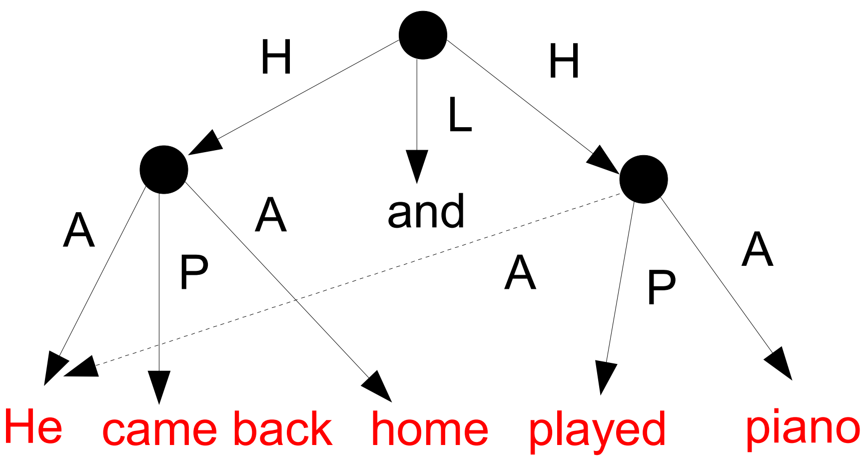


He came back home. He played piano.

Rule 1:

The Semantic Rules

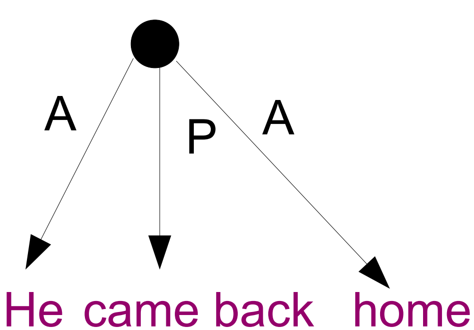
Parallel Scenes

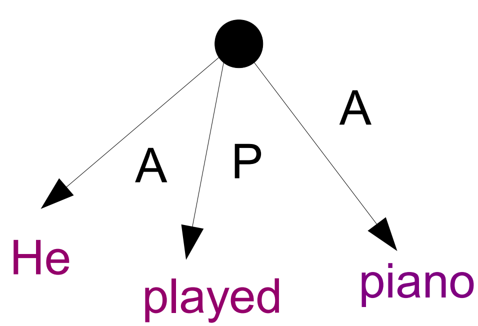


$$S \rightarrow Sc_1 | Sc_2 | \ldots | Sc_n$$

Input sentence

Input Scenes

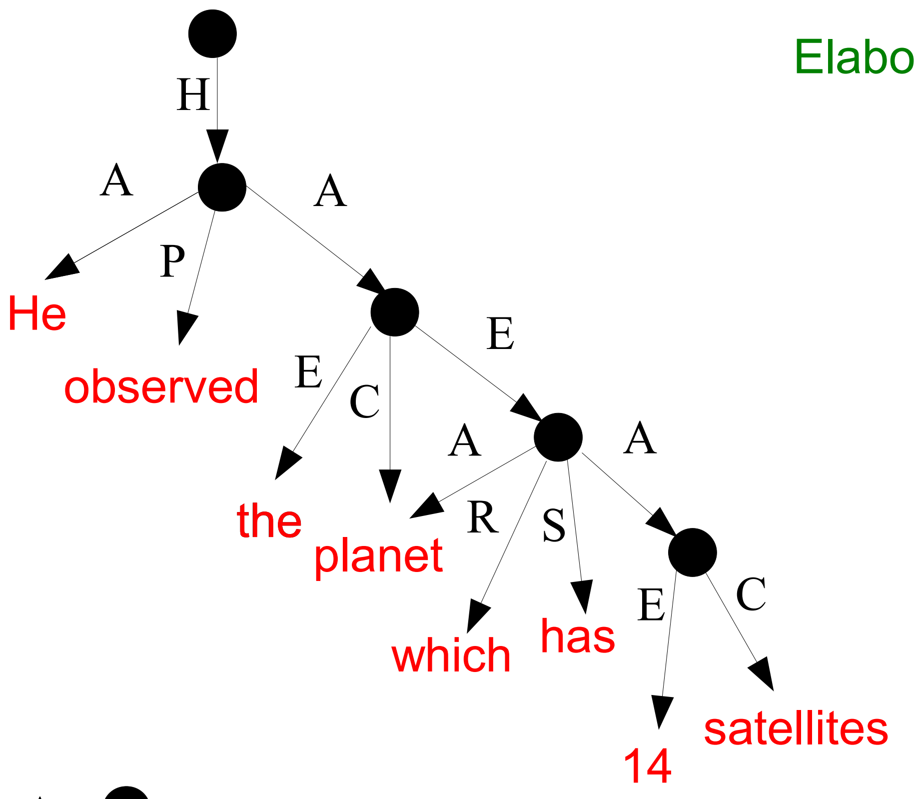




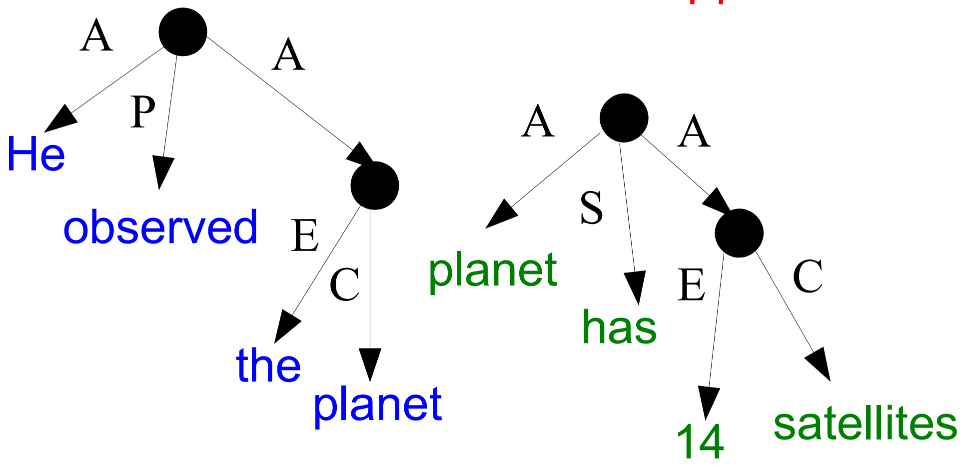
The Semantic Rules

Rule 2:

Elaborator Scenes



He observed the planet which has 14 satellites.

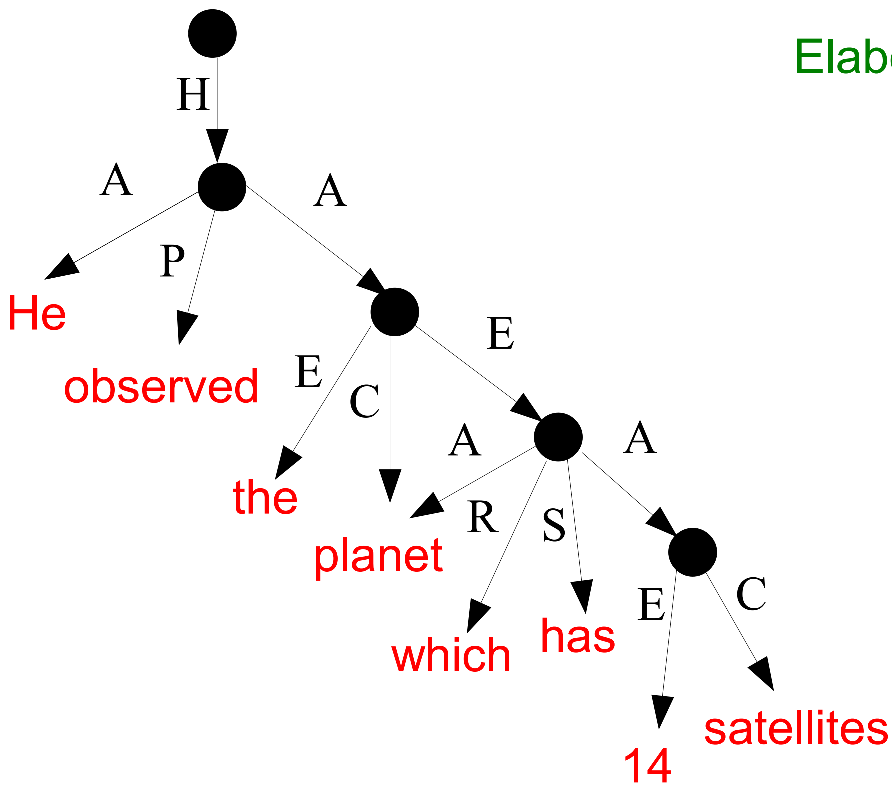


He observed the planet. Planet has 14 satellites.

The Semantic Rules

Rule 2:

Elaborator Scenes

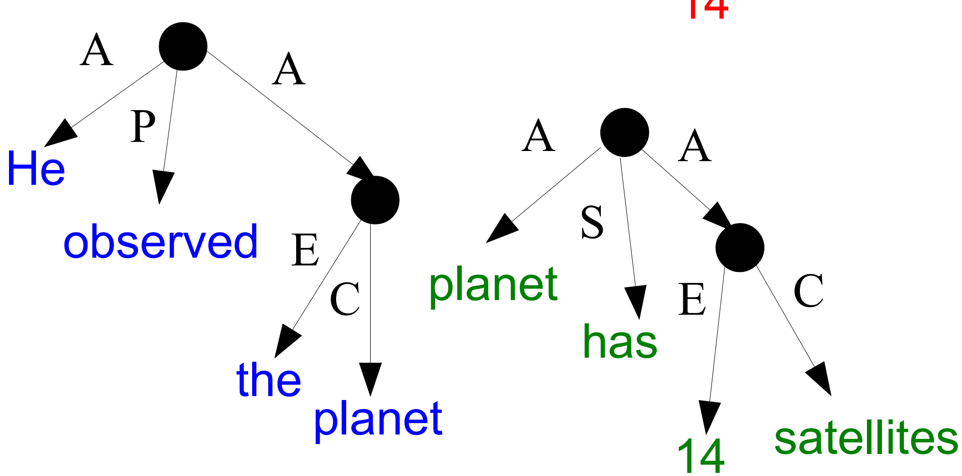


$$S \rightarrow S - \cup \left(Sc_i - C_i \right) \big| Sc_1 \big| \ldots \big| Sc_n$$

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

<u>Automatic evaluation:</u> **BLEU**, **SARI**

<u>Human evaluation</u> (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	**58.94**	30.27	**3.98**	**3.33**	**0.68**	**0.63**
SENTS-h4	57.71	**31.90**	3.54	2.98	0.50	0.36

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

Human evaluation (first 70 sentences):

G – Grammaticality: 1 to 5 scale

P – Meaning Preservation: 1 to 5 scale

S – Simplicity: -2 to +2 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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