From *Partial* to *Strictly* Incremental Constituent Parsing

Ana Ezquerro   Carlos Gómez-Rodríguez   David Vilares

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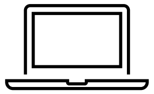
How do SoTA parsers work?

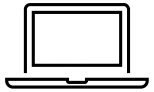


State-of-the-art System

How do SoTA parsers work?

I have a flight to Malta

Full sentence



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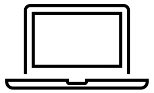

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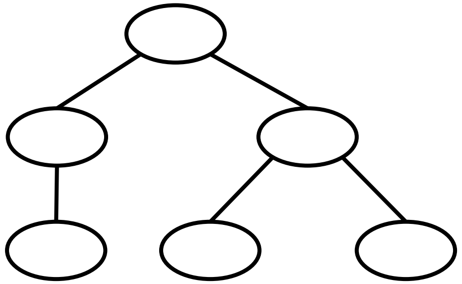

Full syntactic tree

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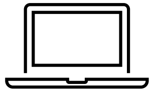

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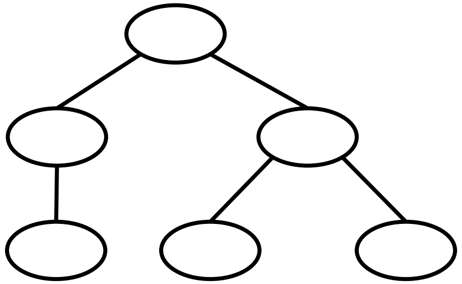

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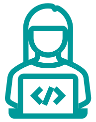
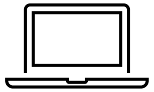


- Non incremental.
- Simultaneous access to all elements of the sentence.
- No reference of the information provided by each word to build the tree.

Human-like Incremental Parsing

I have a flight to Malta

Full sentence



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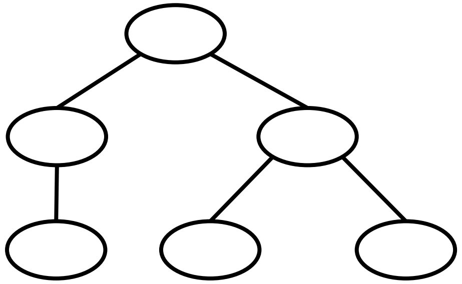

Full syntactic tree

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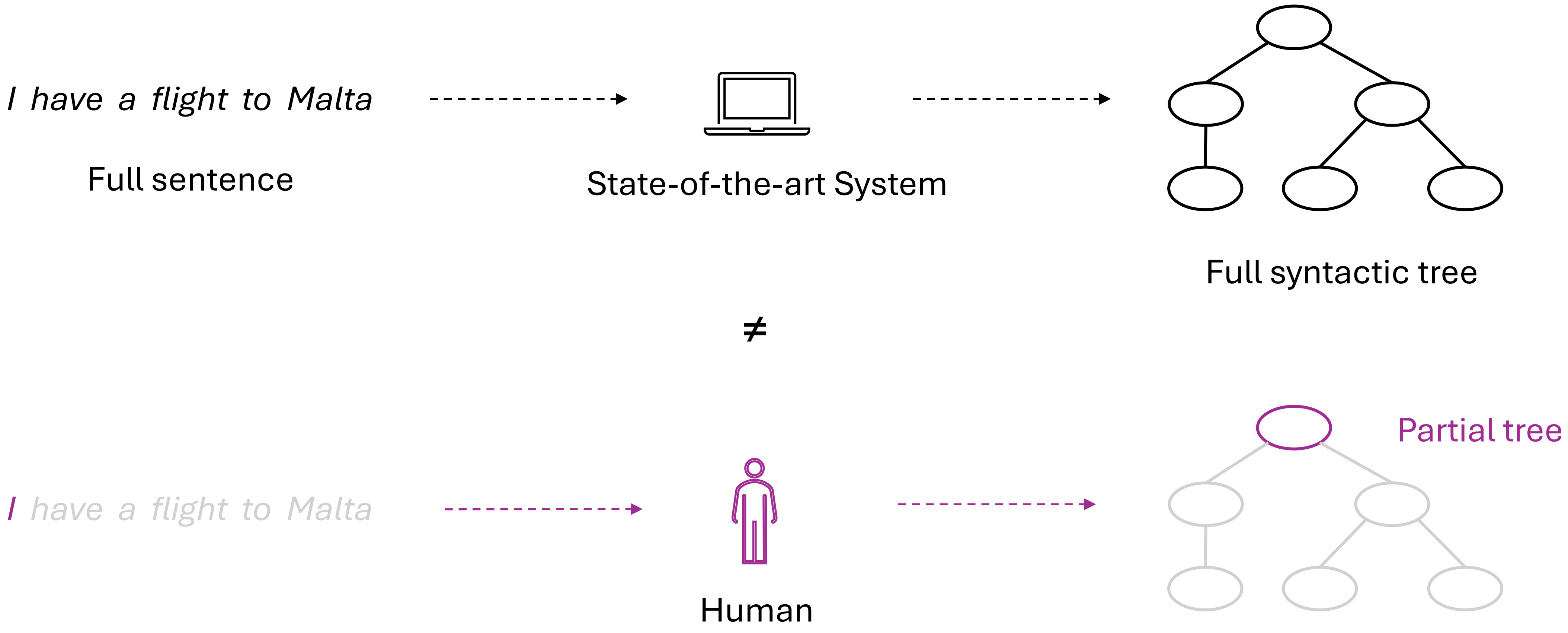
?

Human

Human-like Incremental Parsing



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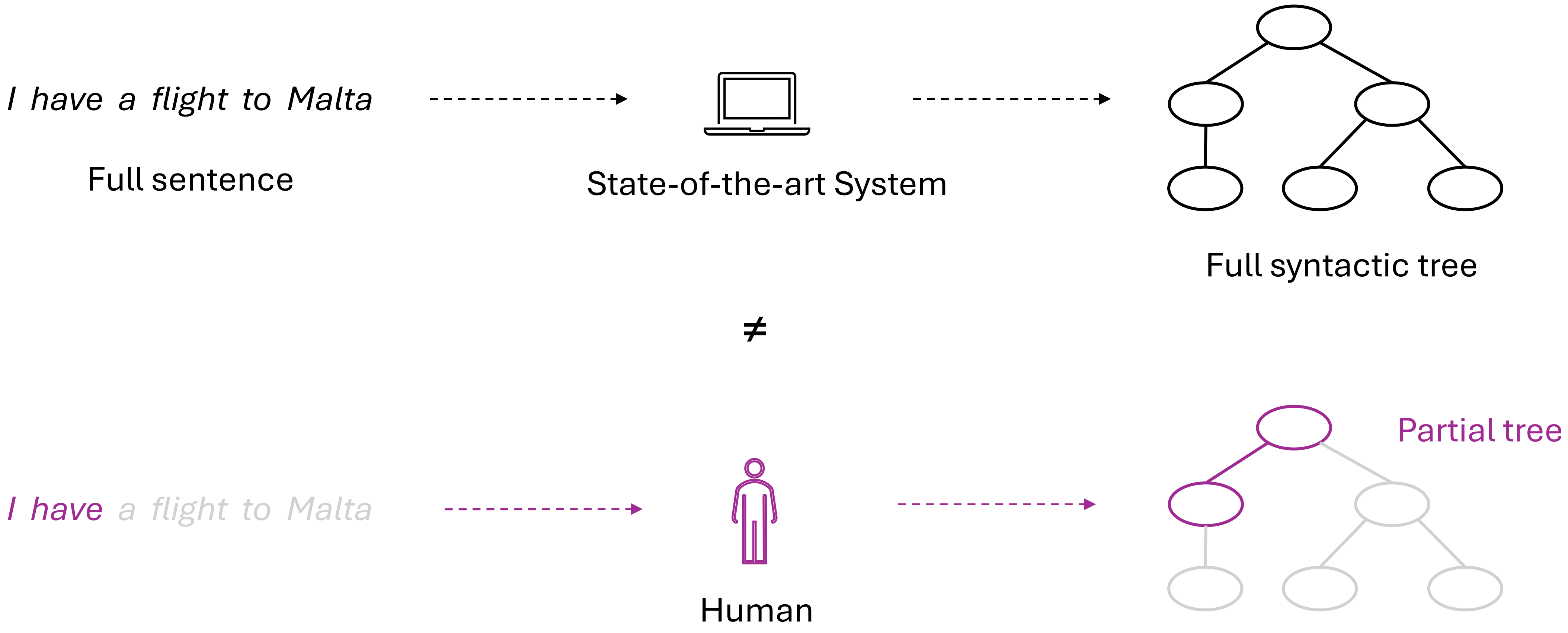

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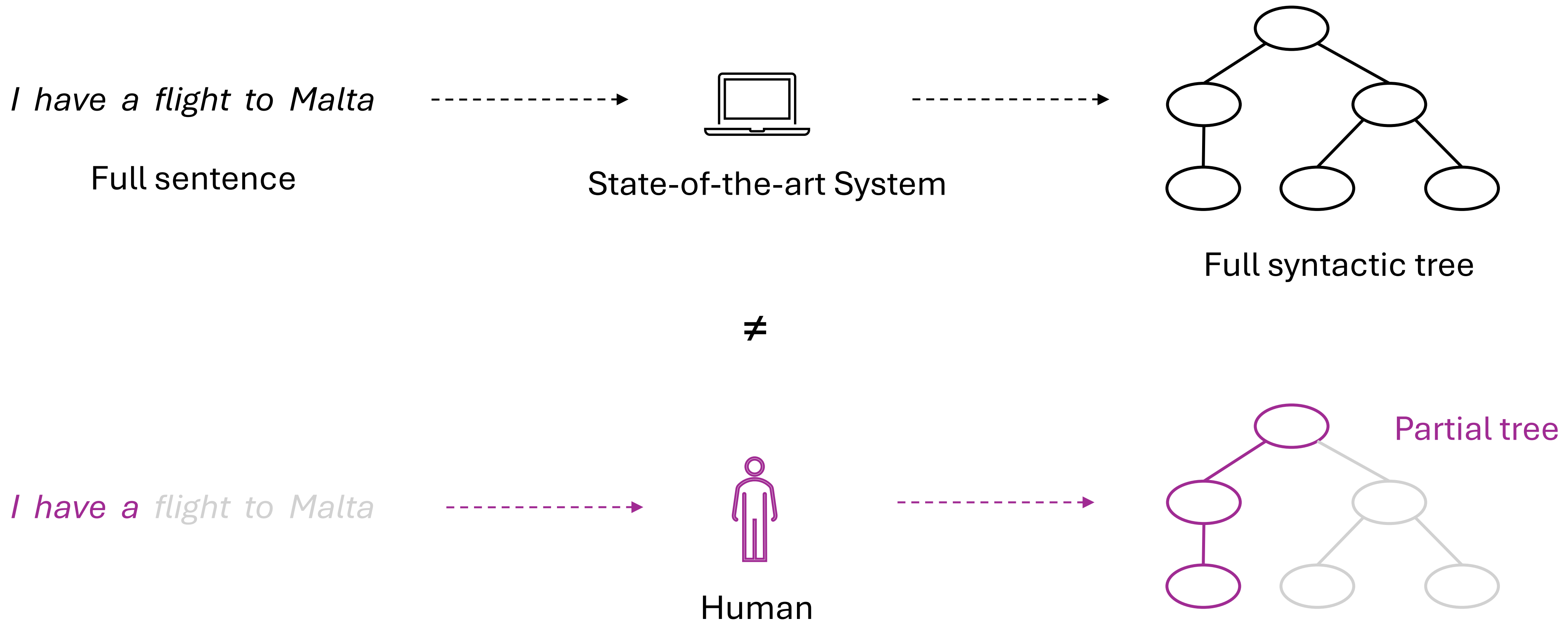

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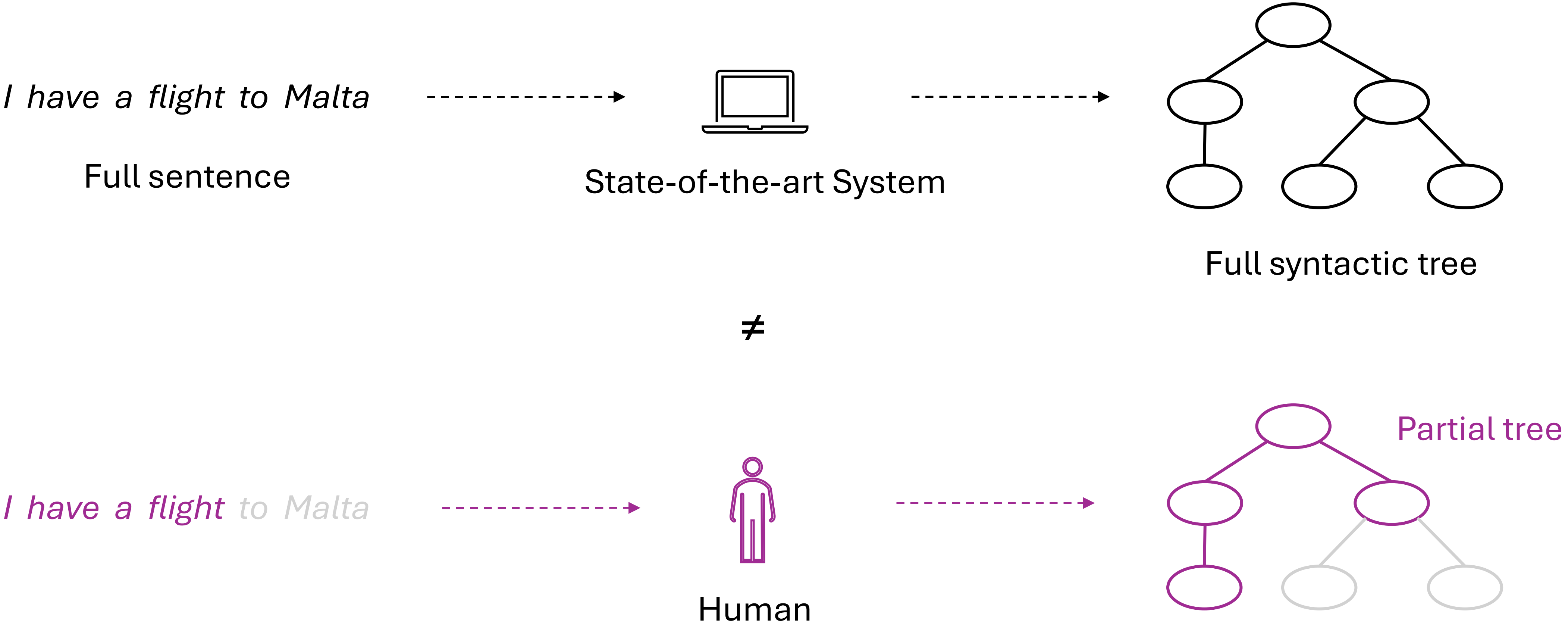

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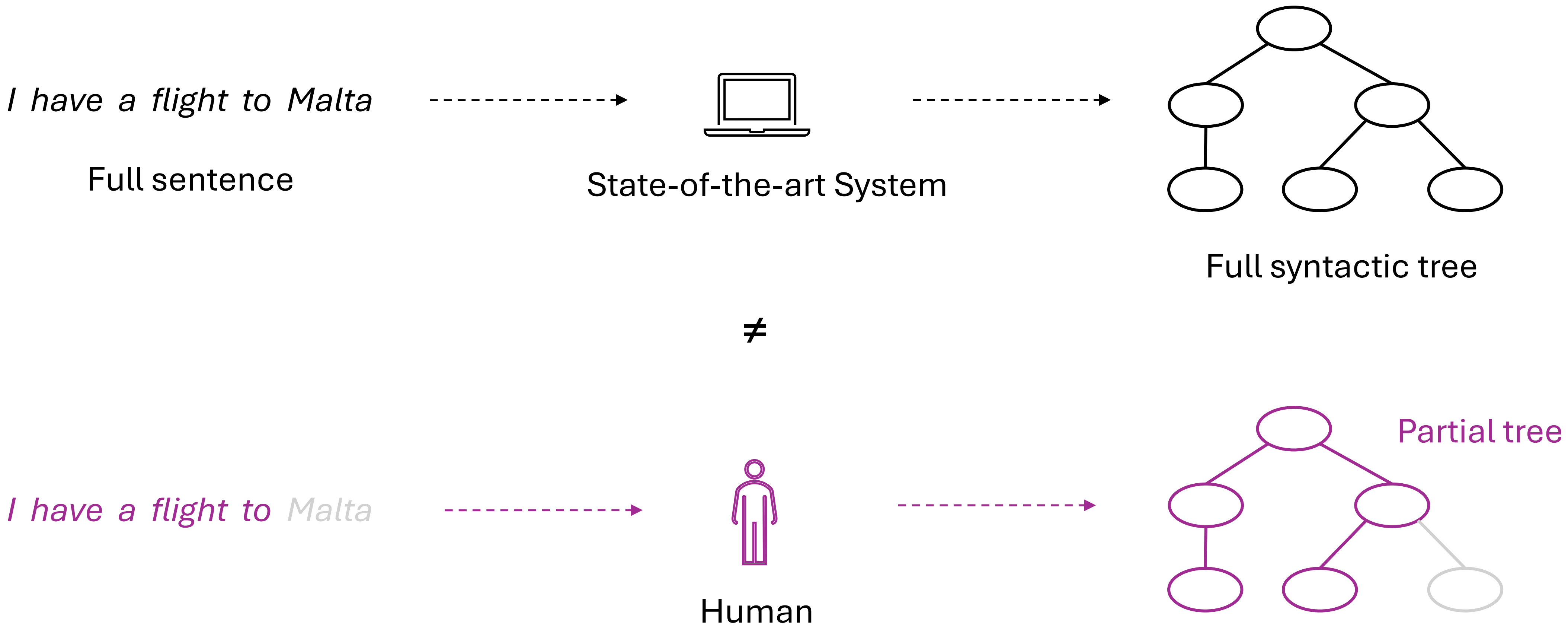

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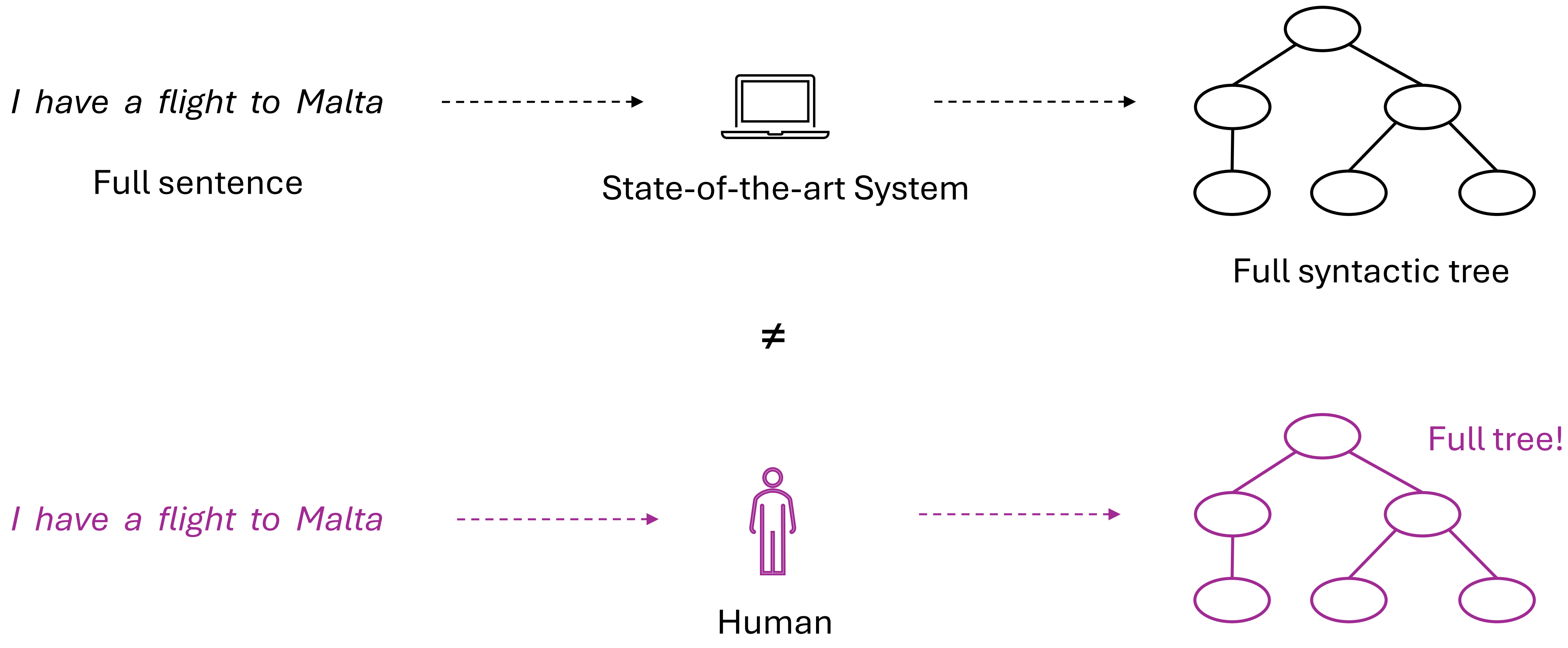

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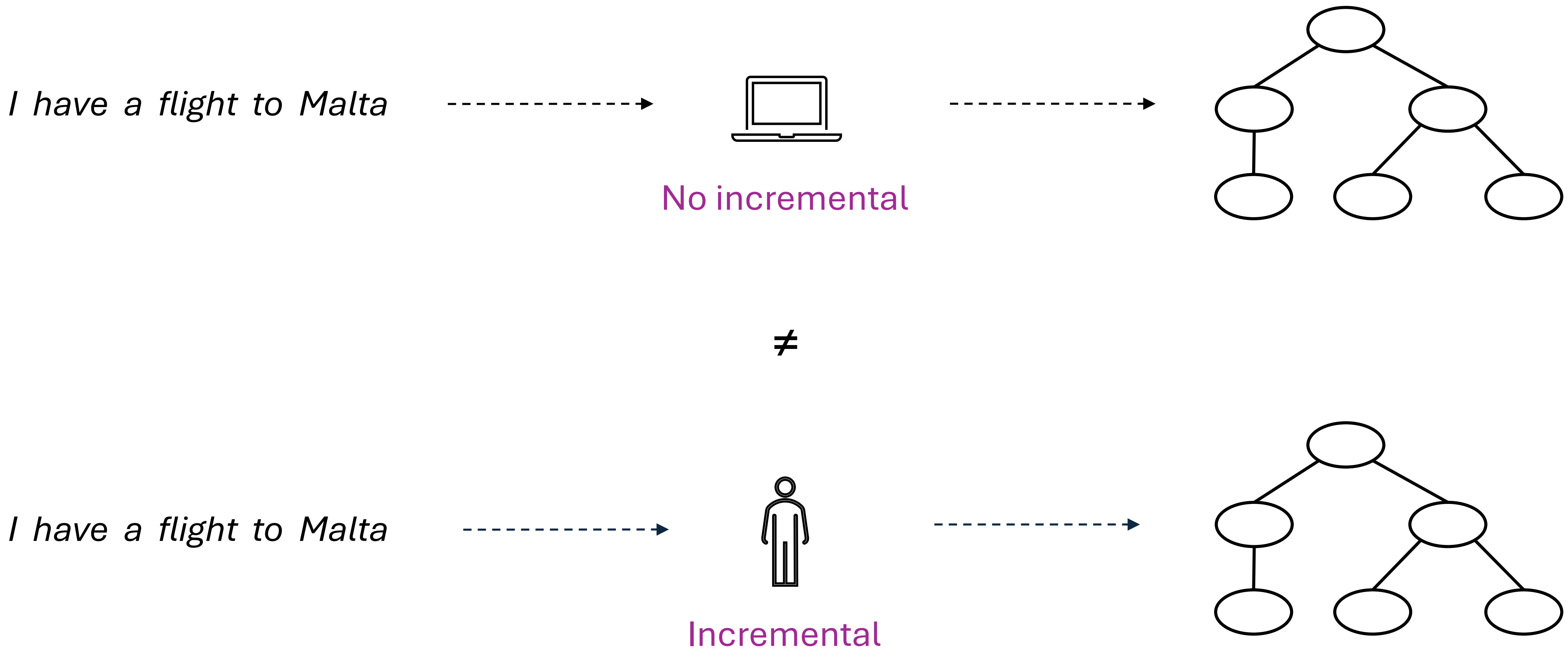
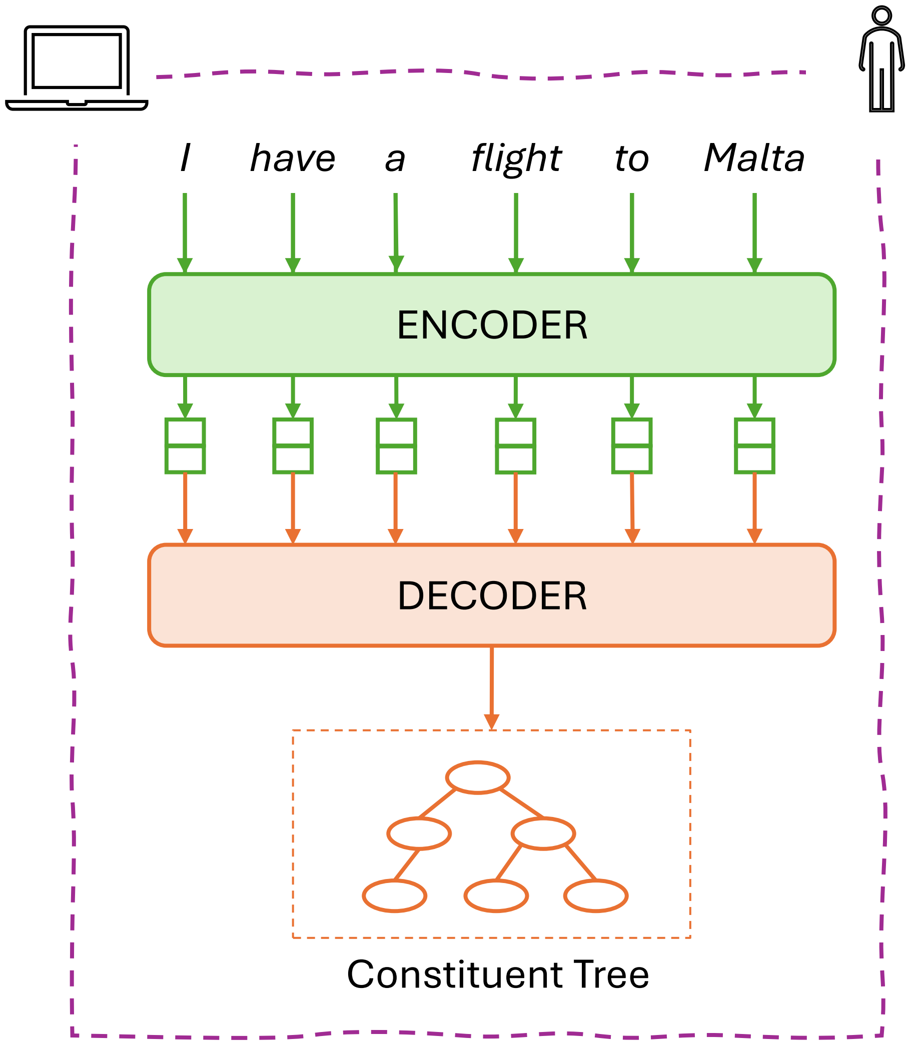


Incremental *Constituent* Parsing

State-of-the-Art System

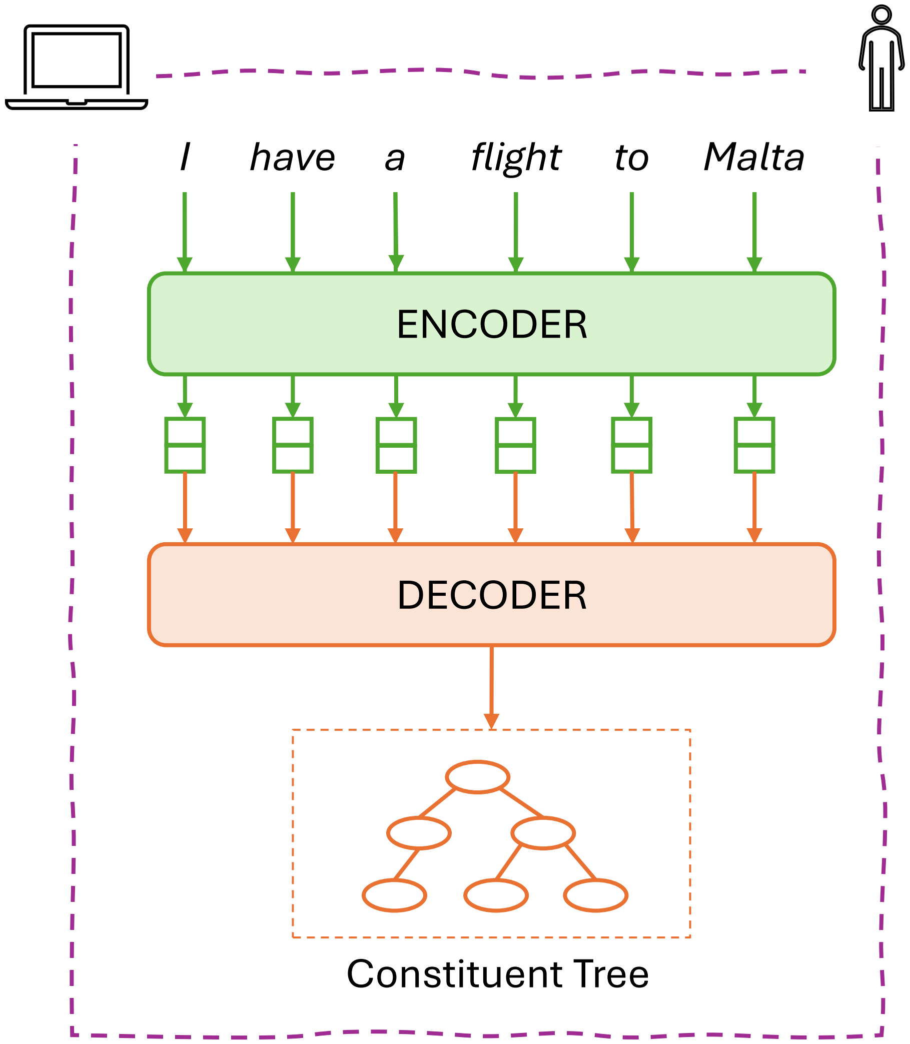
- Bidirectional encoder:
  - BERT & ELMo.
- Non-incremental decoder.
  - Kitaev & Klein (2018).



Incremental System

- Unidirectional encoder:
  - GPT & LSTMs.
- Incremental decoder.
  - Transition-based.
  - Sequence labeling.

From Partial to Strictly Incremental *Constituent* Parsing



Incremental decoder

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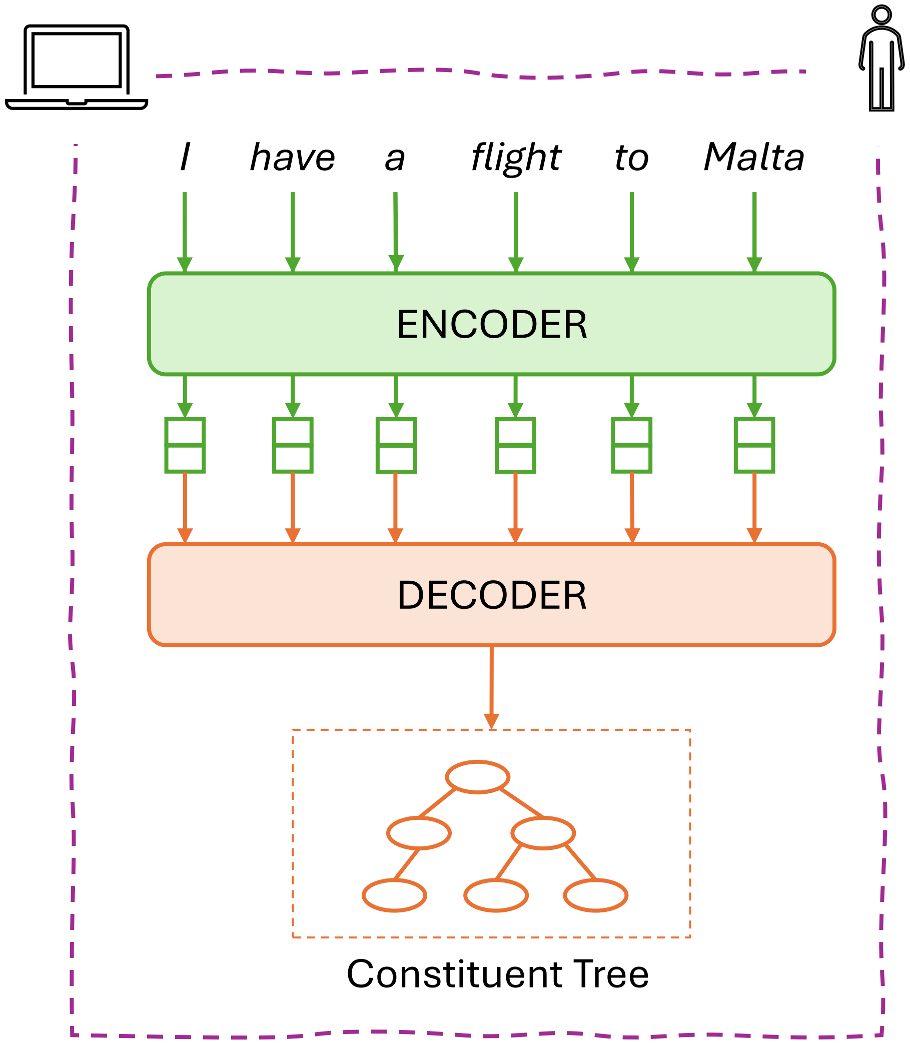

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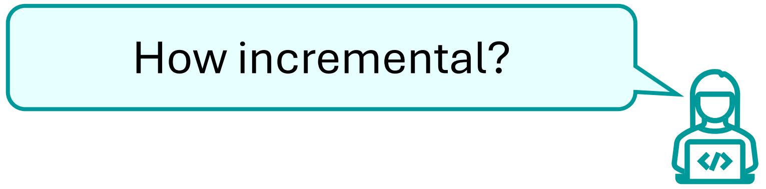

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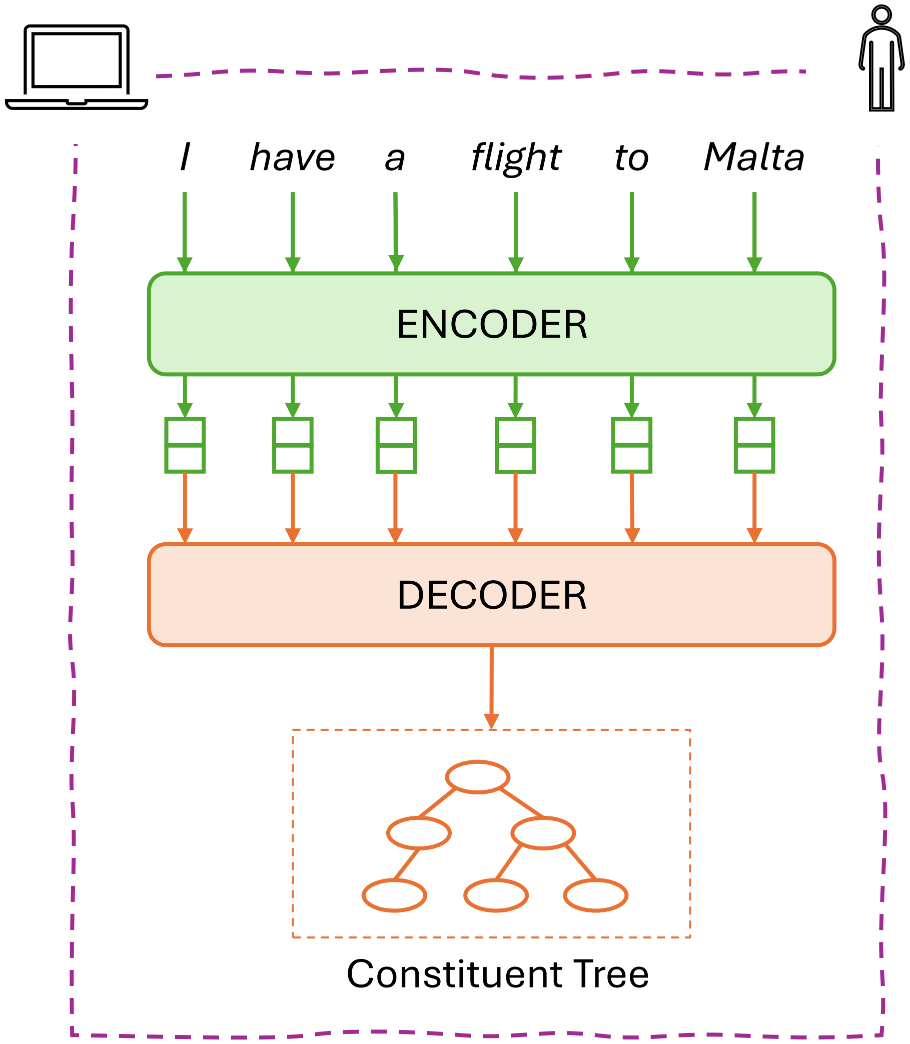

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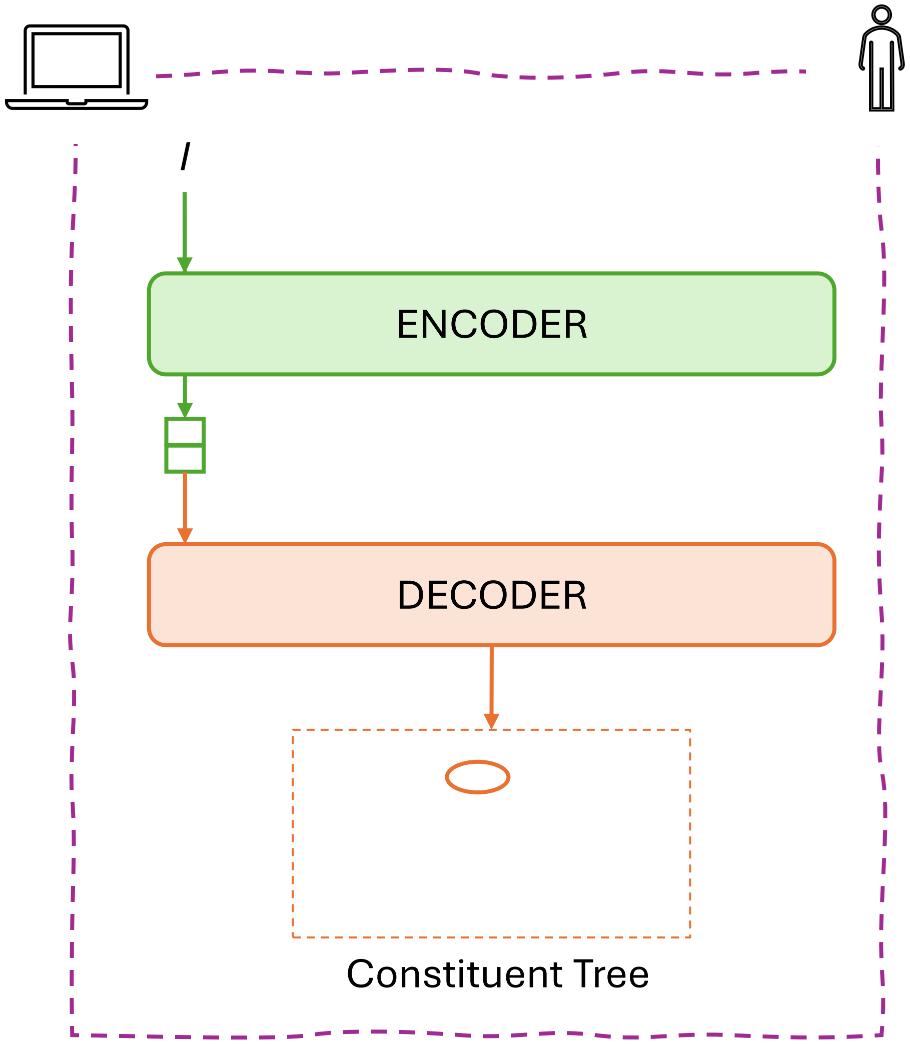

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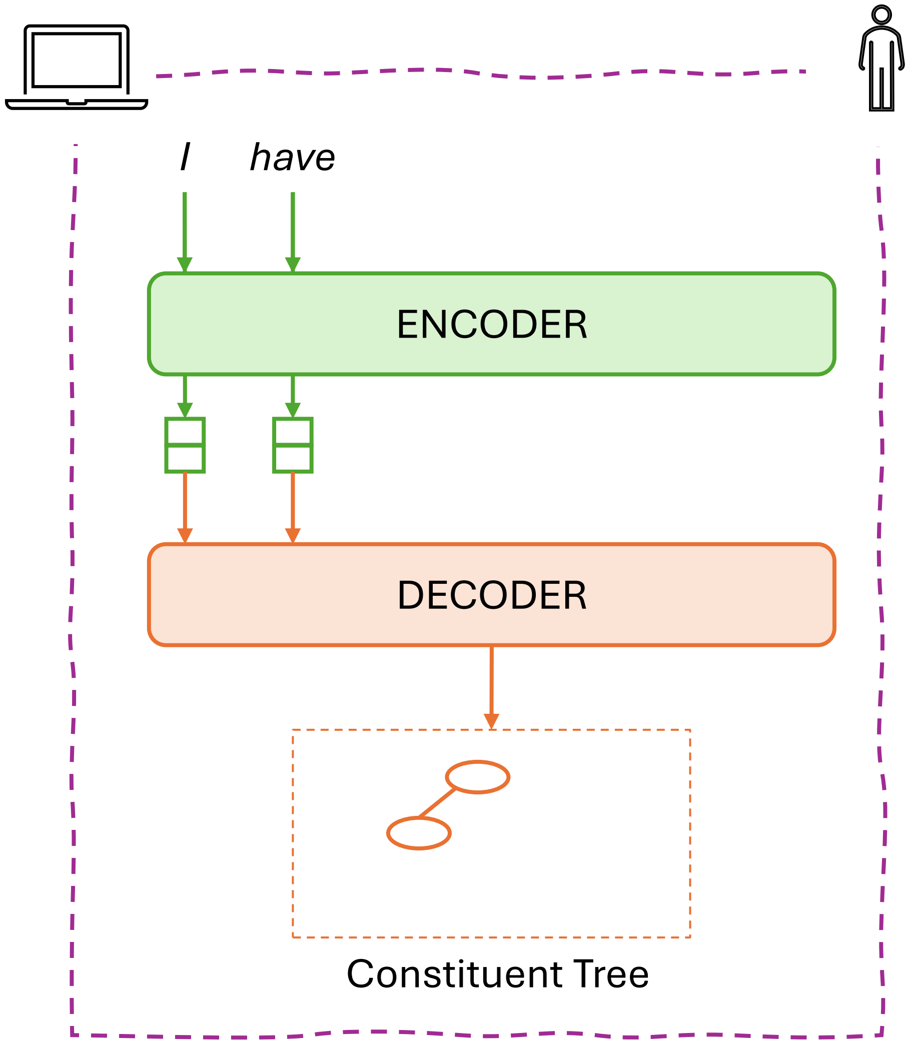

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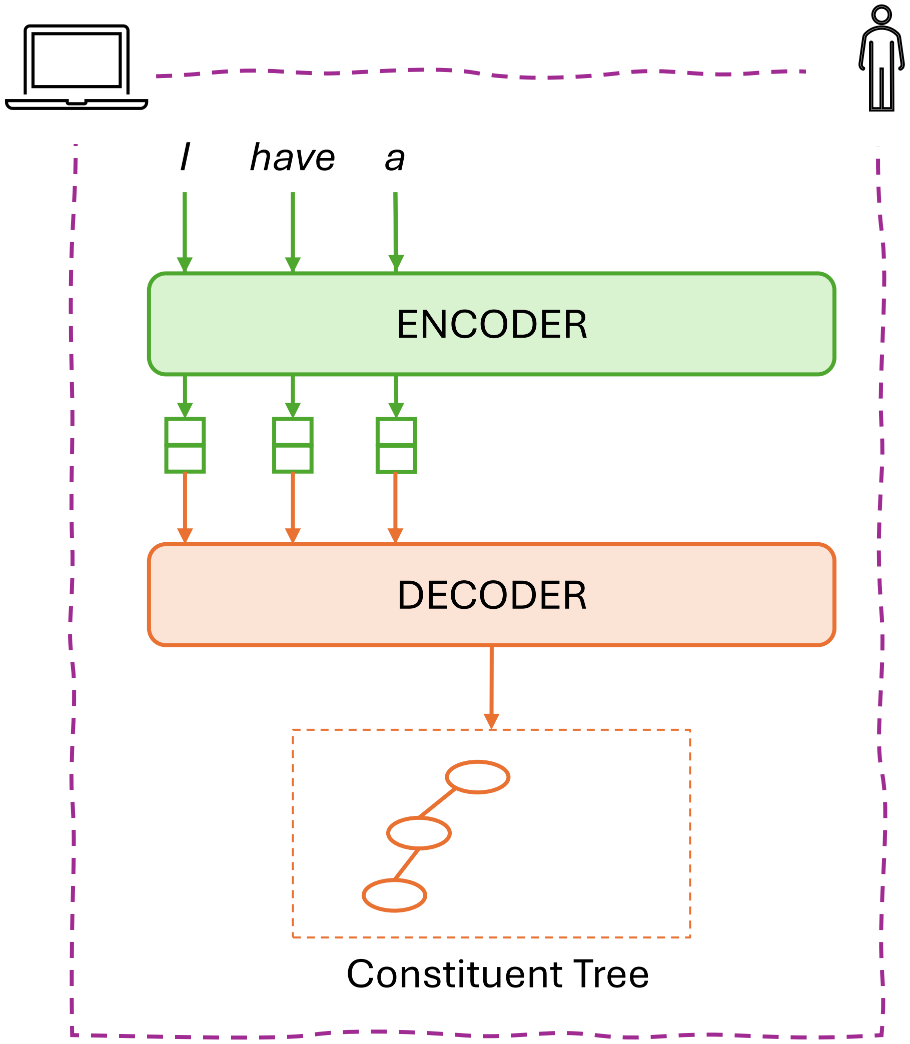

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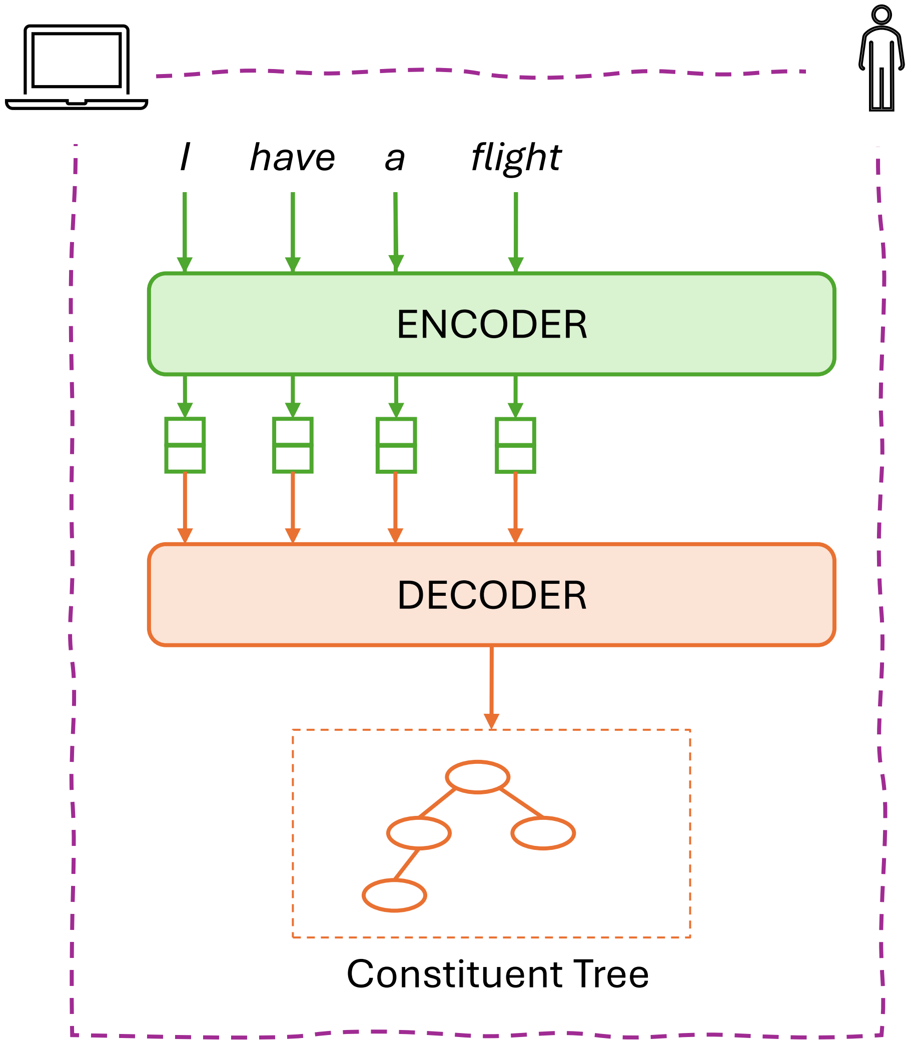

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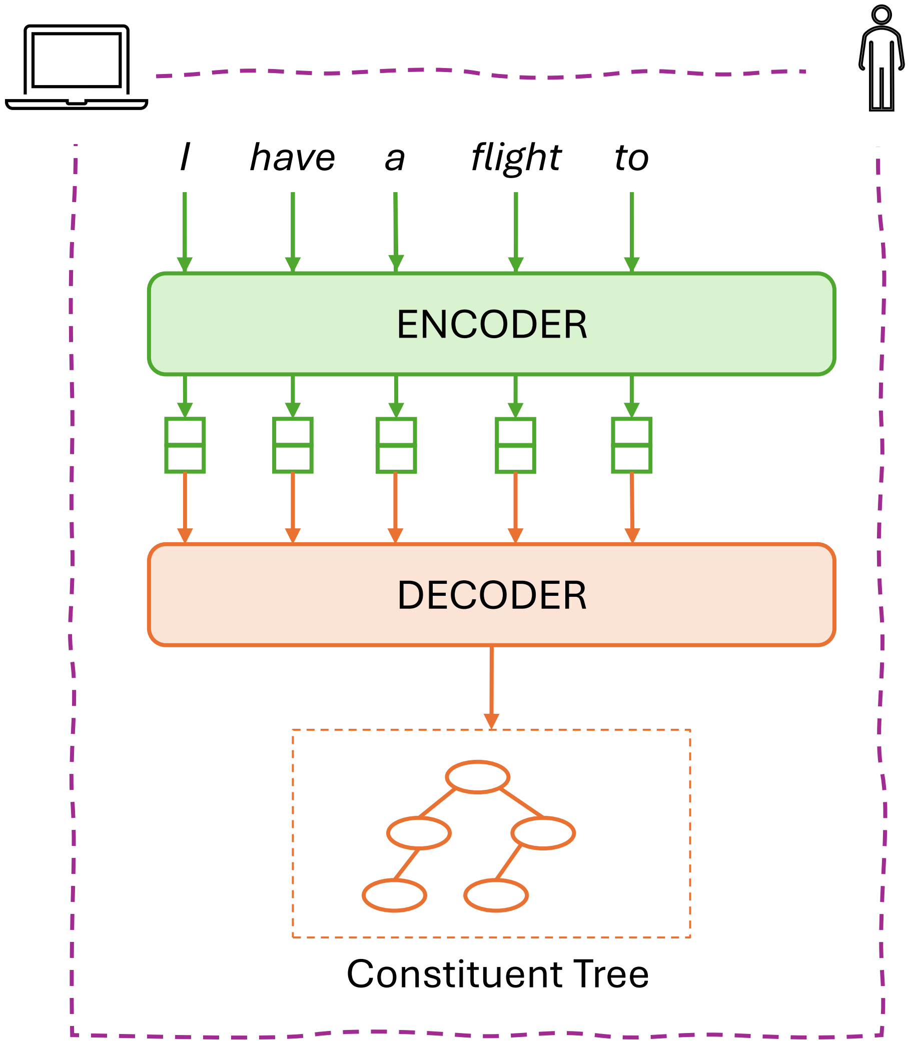

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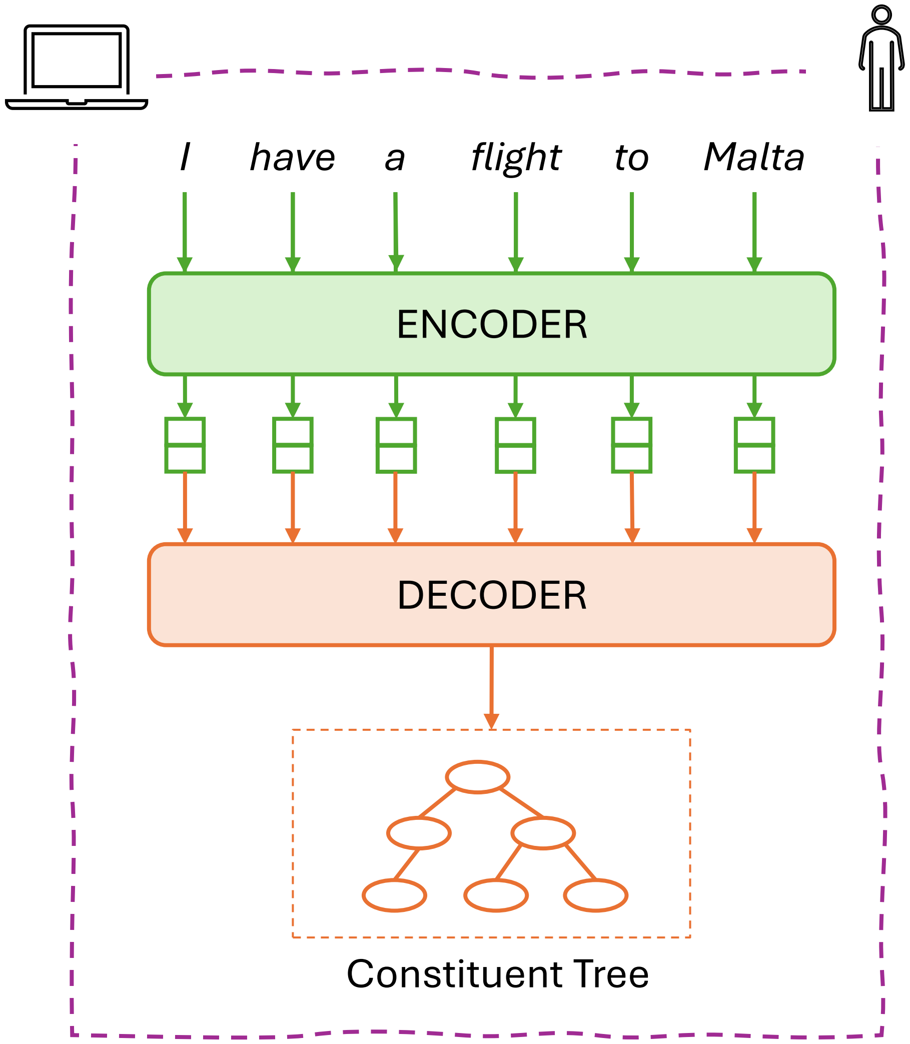

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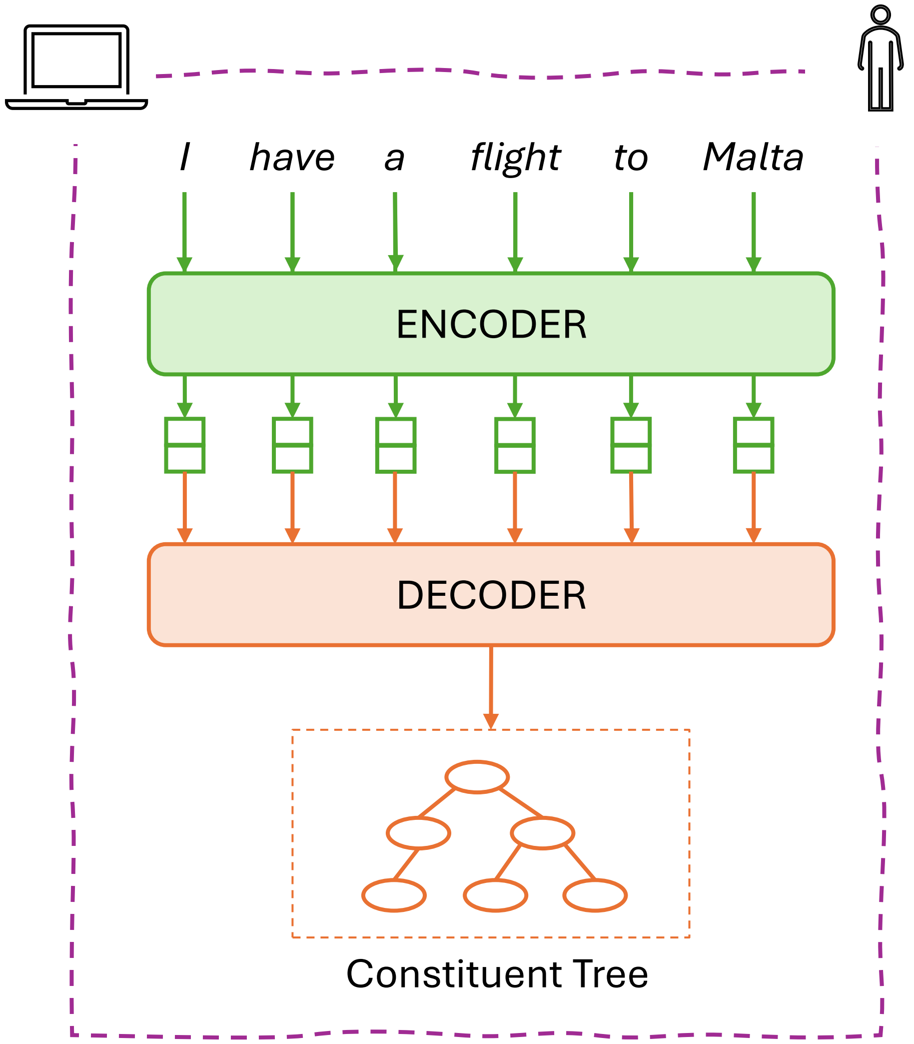

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Delayed incremental processing

- Parameter k (by default, $k = 0$) .
- *Incrementally* encode each word w_i with $w_1, \ldots, w_{i+k}$.
- In practice: $\Phi_{\mathrm{k}}(\mathbf{h}_i \cdots \mathbf{h}_{i+k})$ where Φ is a feed-forward network.

What happens if delay $k > 0$?

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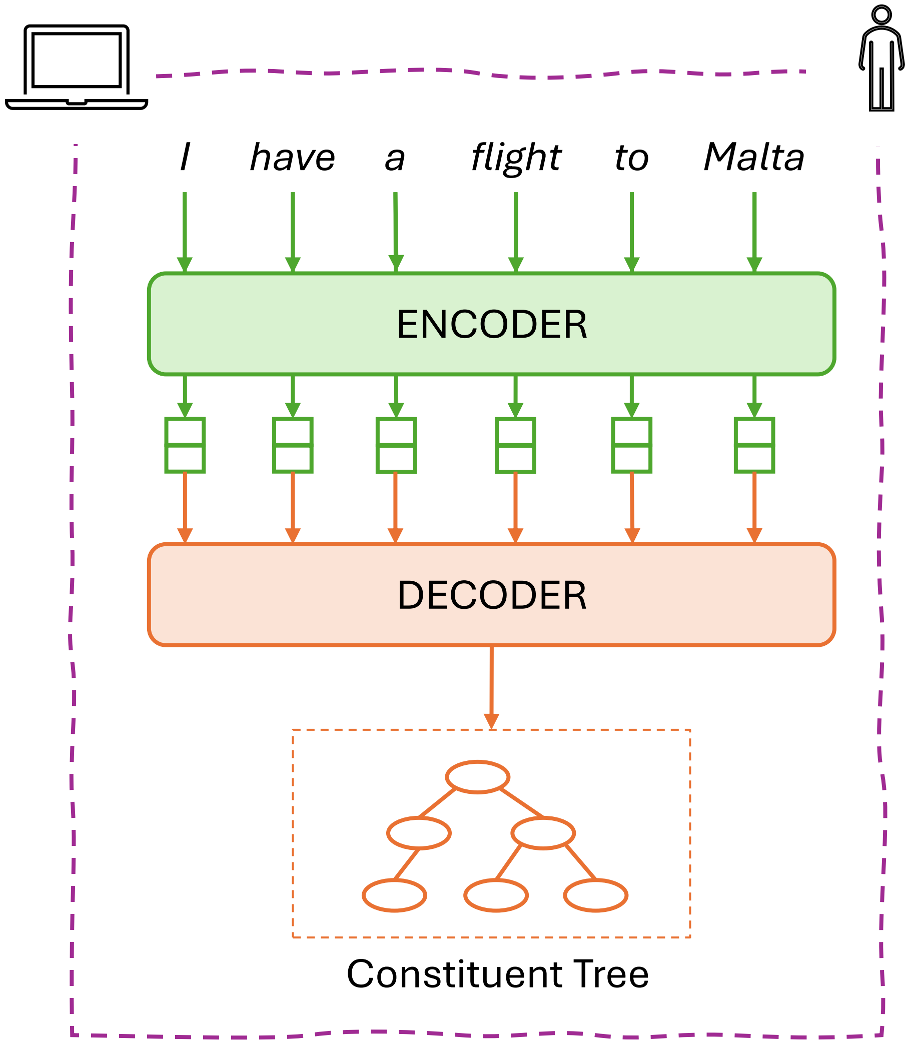

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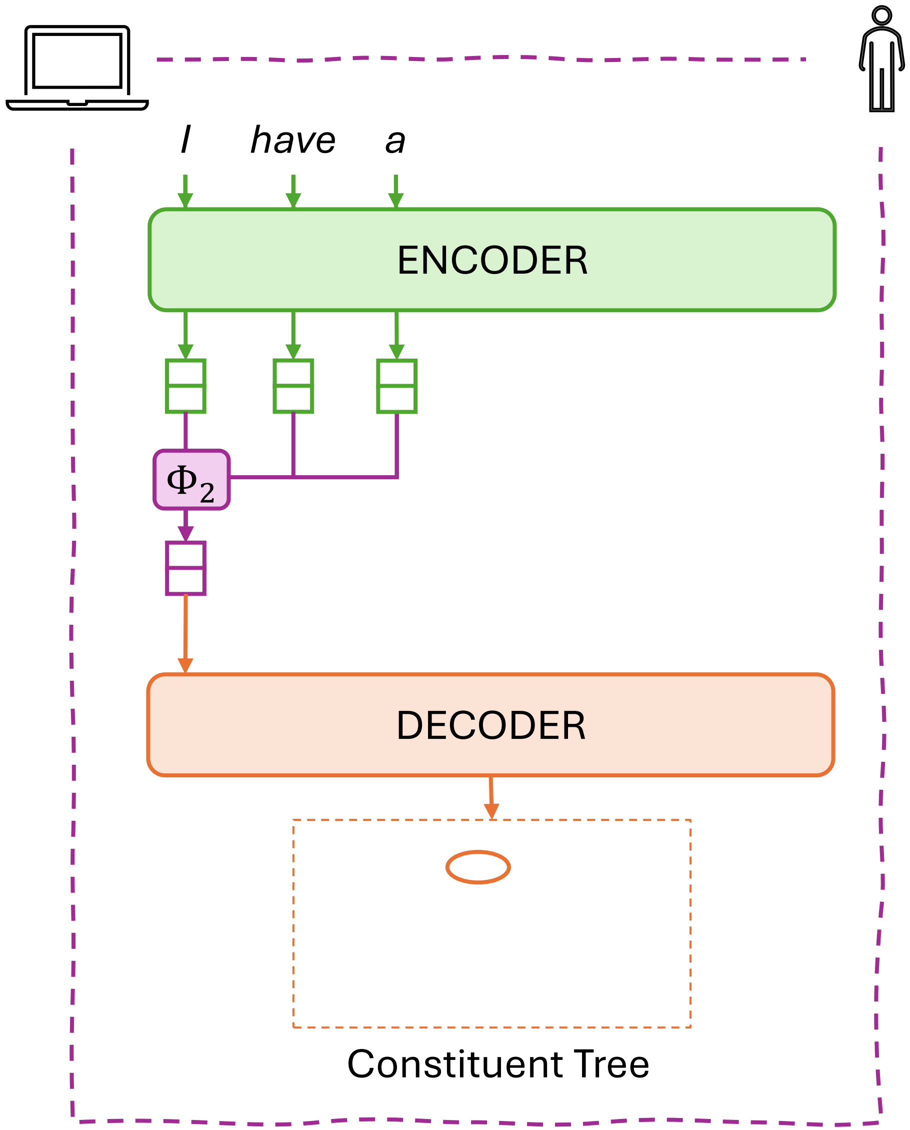

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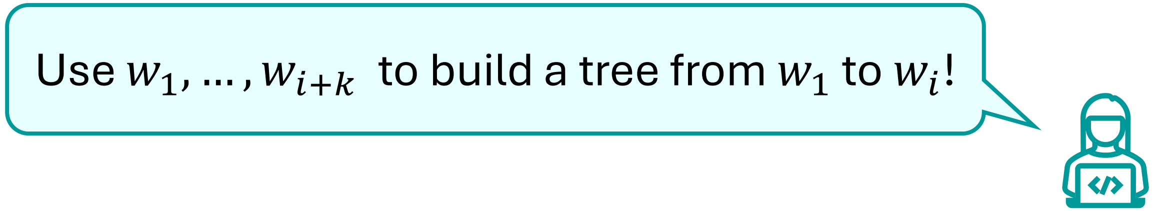

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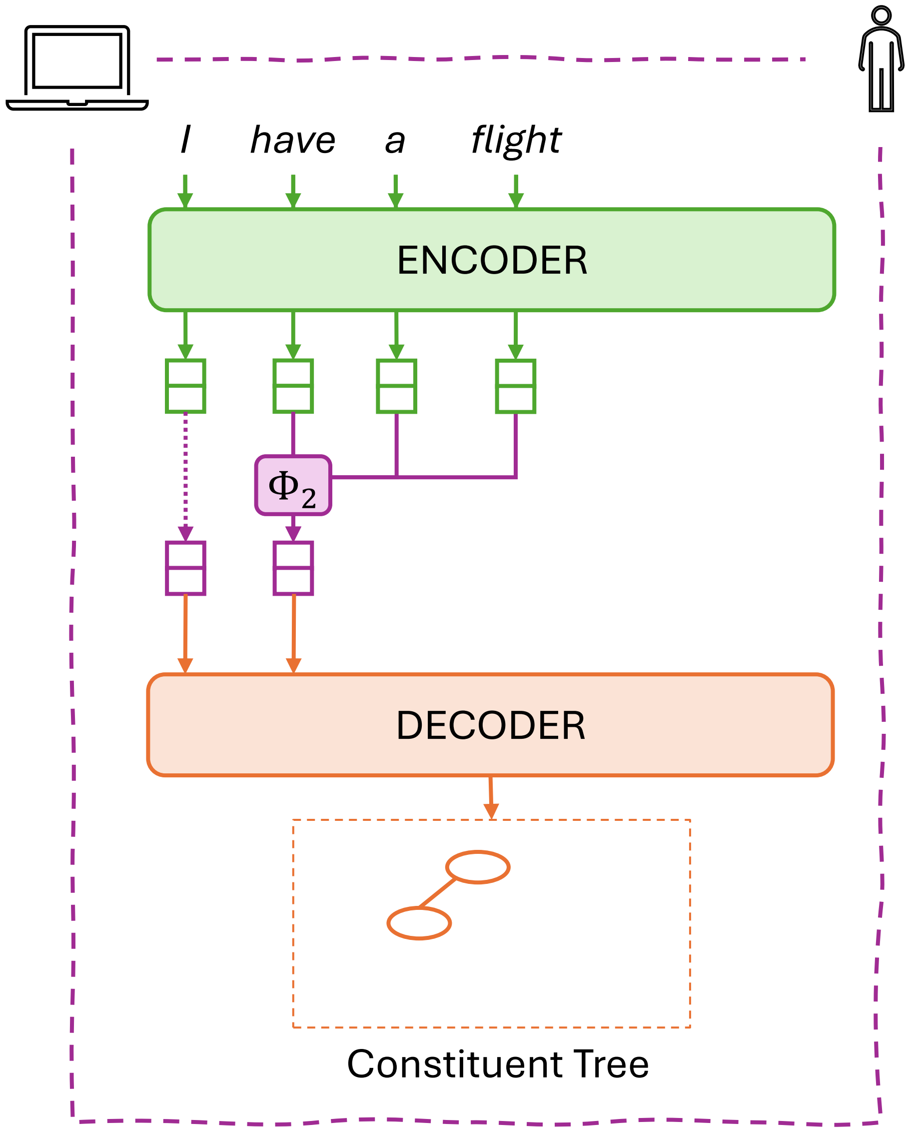

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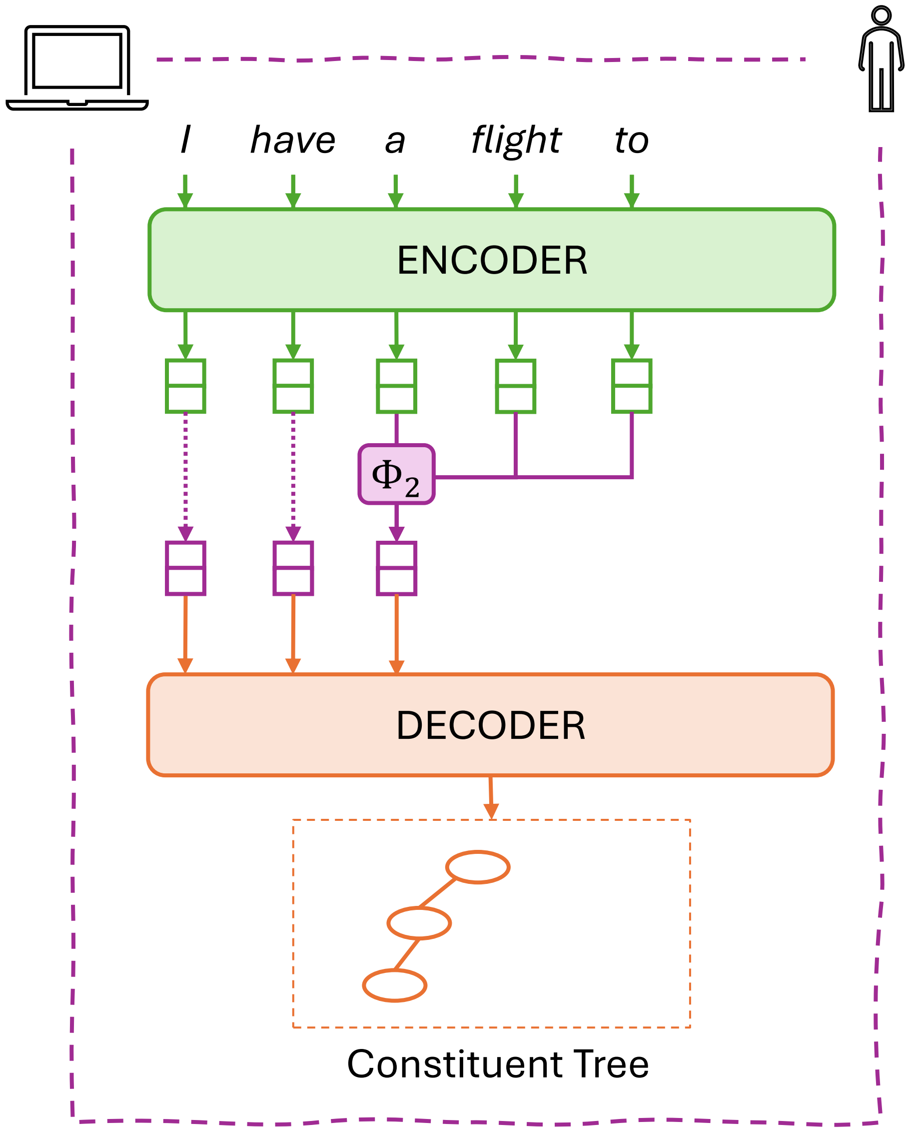

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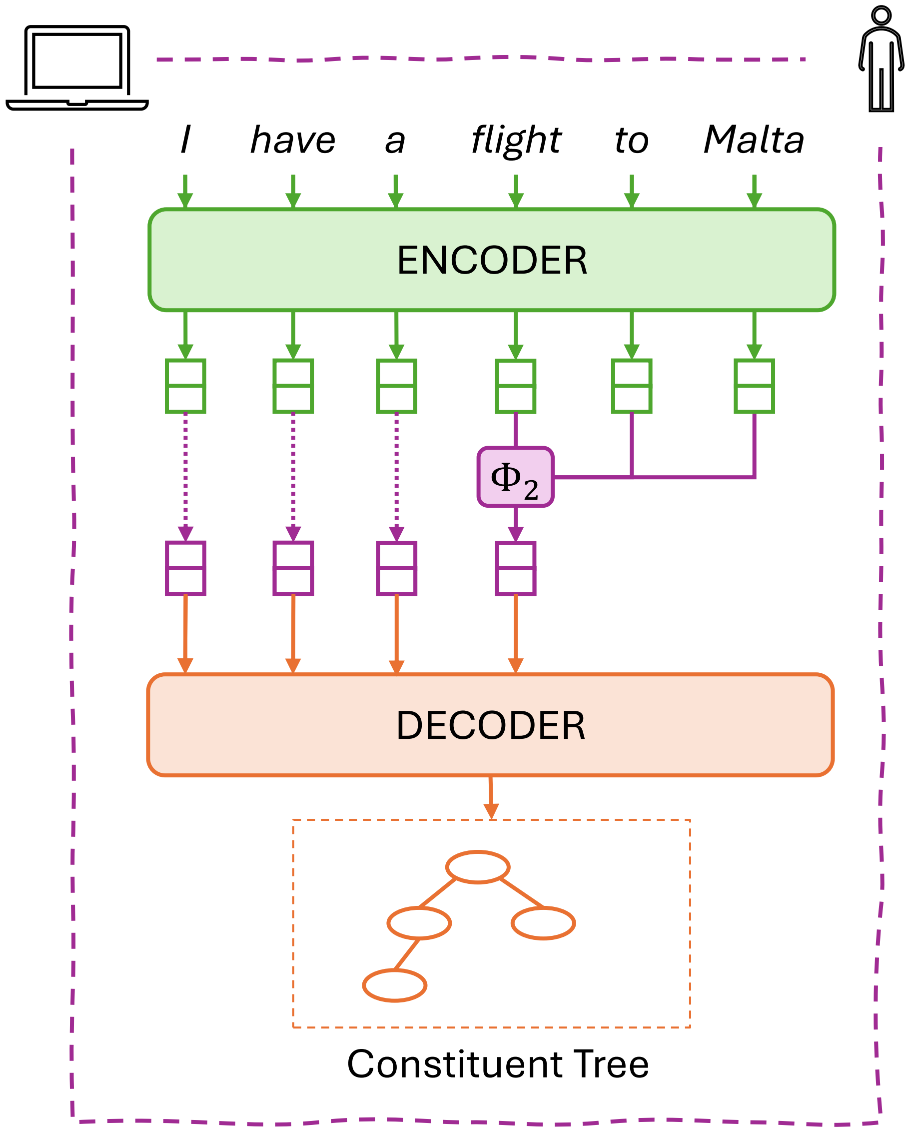

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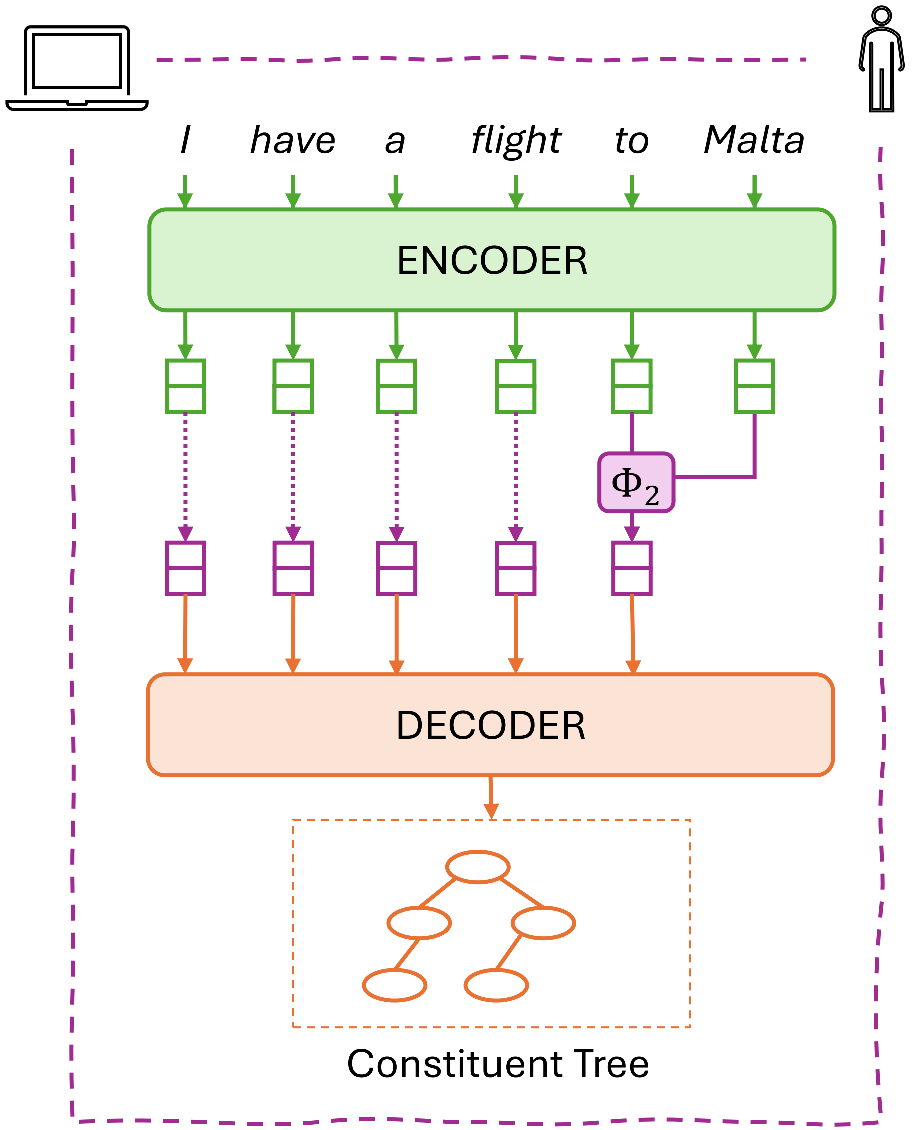

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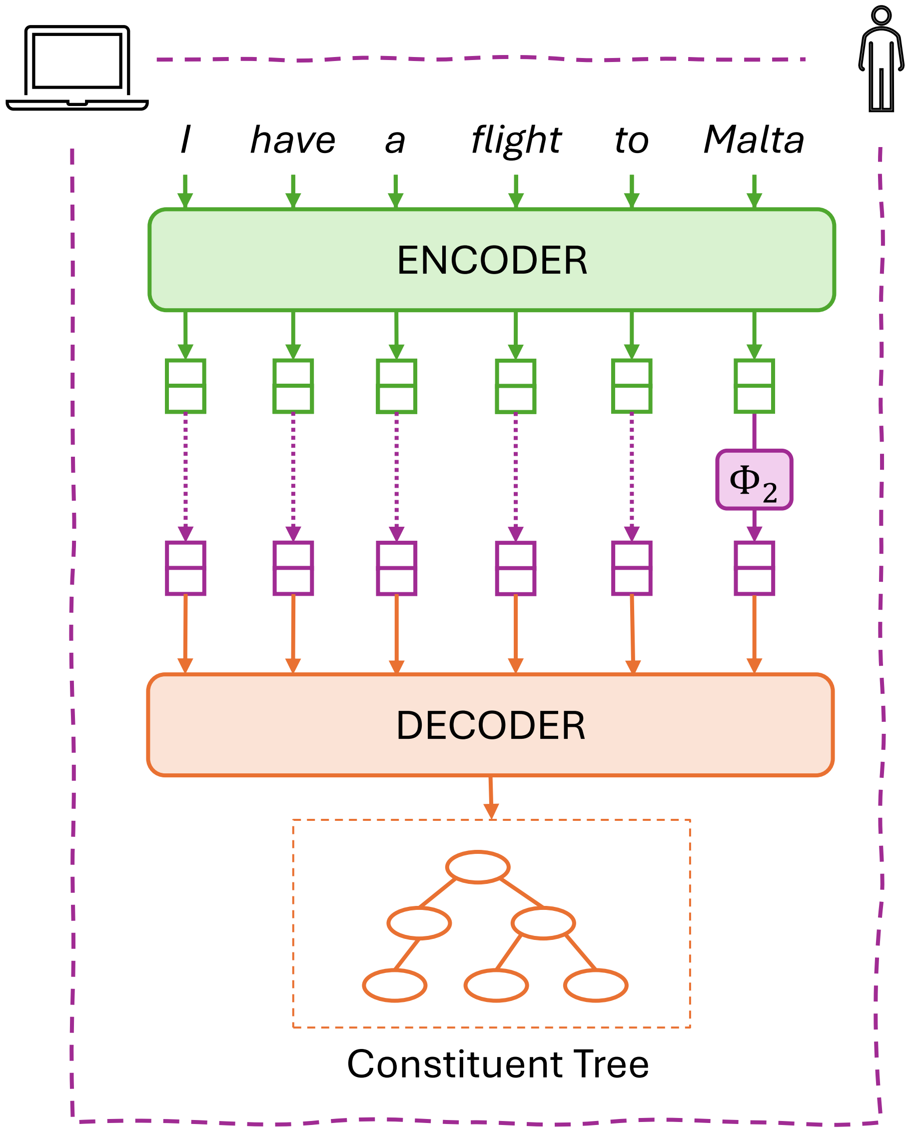

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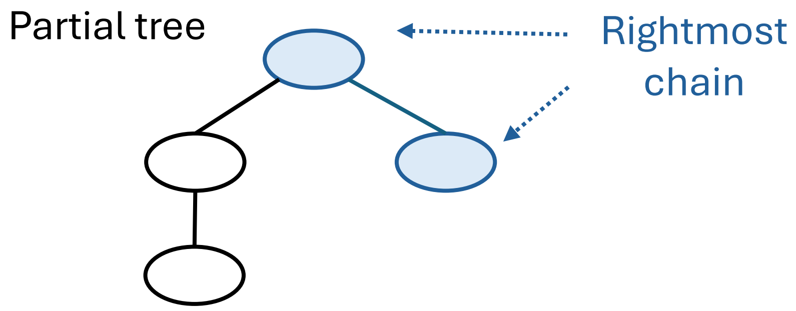
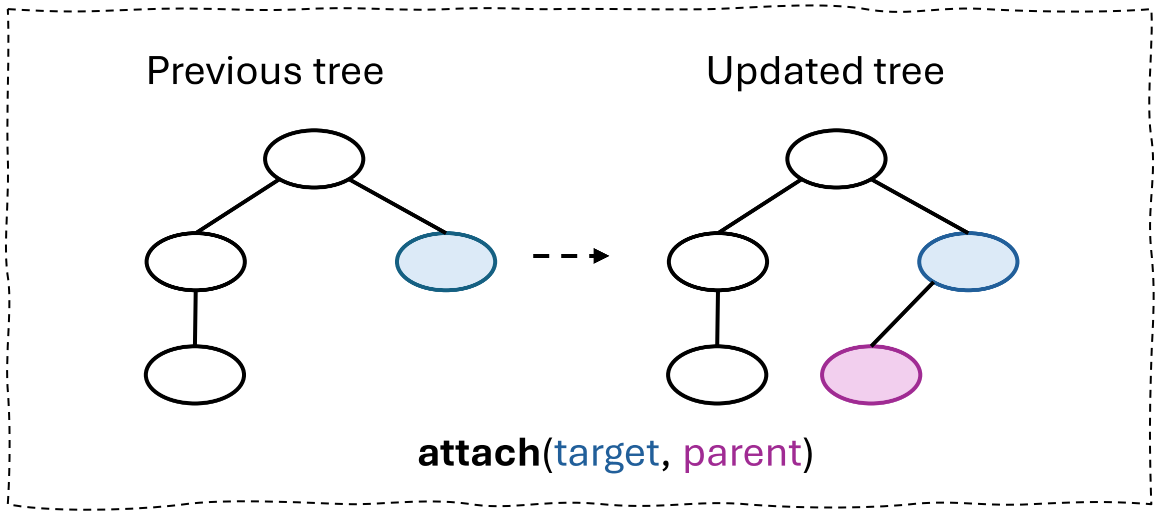
Attach-Juxtapose (Yang & Deng, 2020)

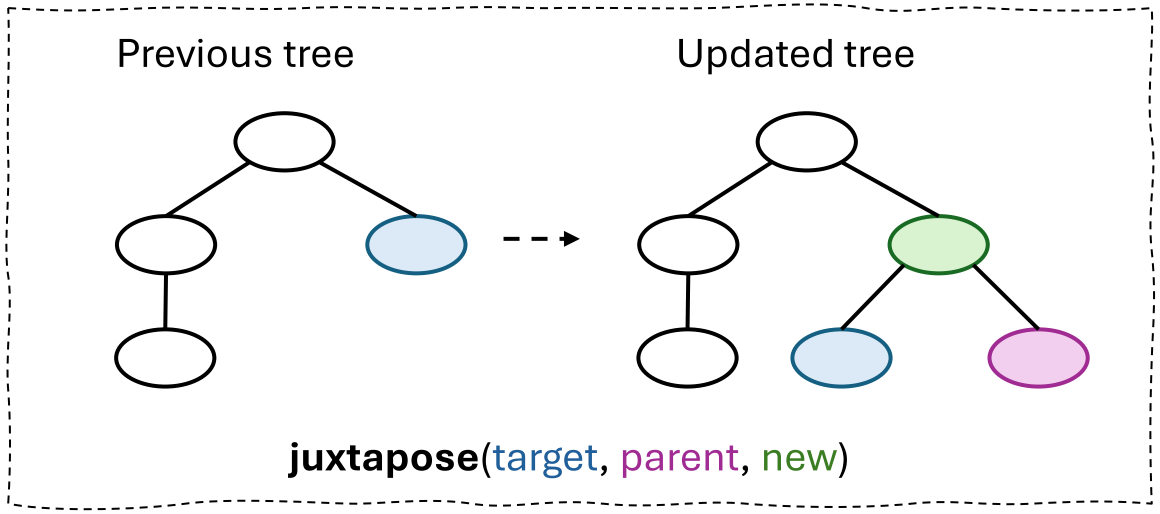
- Transition-based system.
- Two actions: **attach** & **juxtapose**.
- Sentence of n words to n transitions.

$$w_1, \dots, w_n \rightarrow t_1, \dots, t_n$$

- Graph Convolutional Network (GCN).
- Append subtrees to the rightmost chain.







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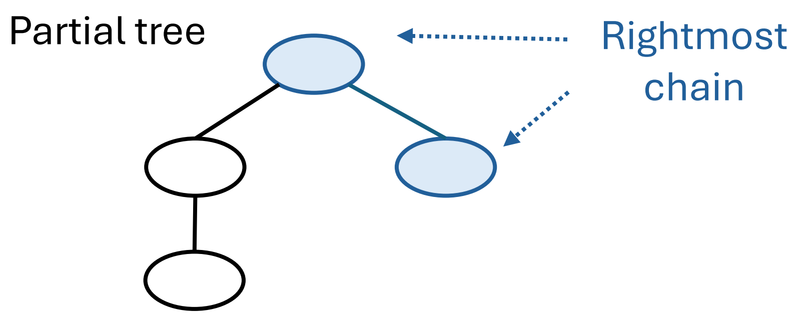

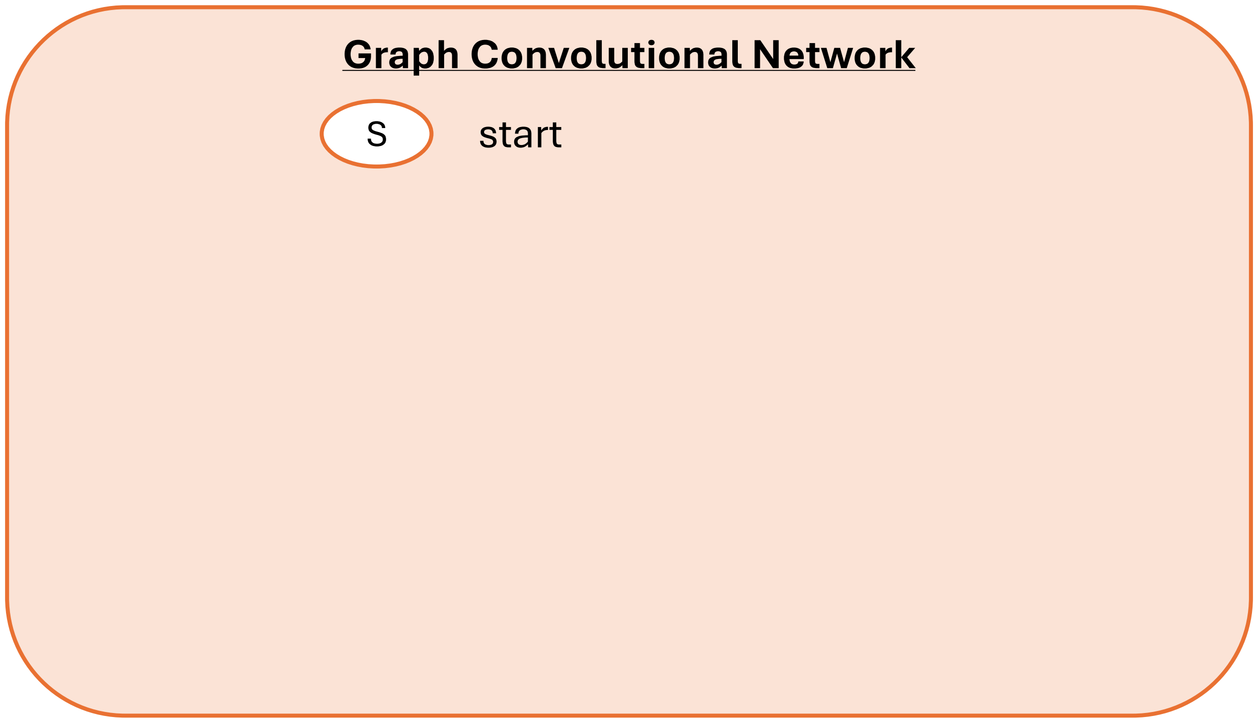

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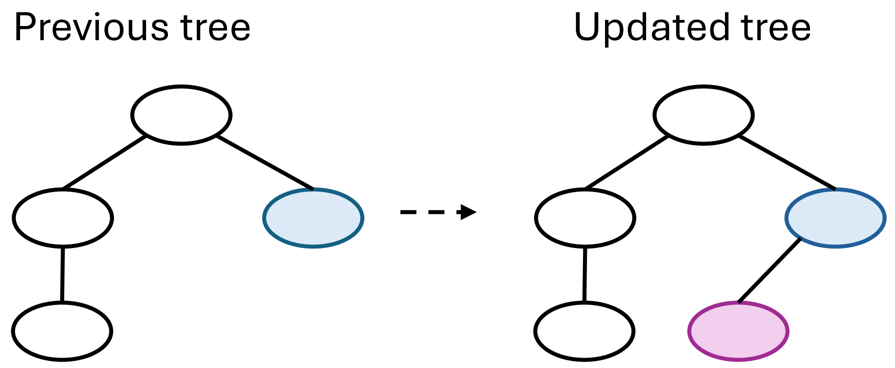
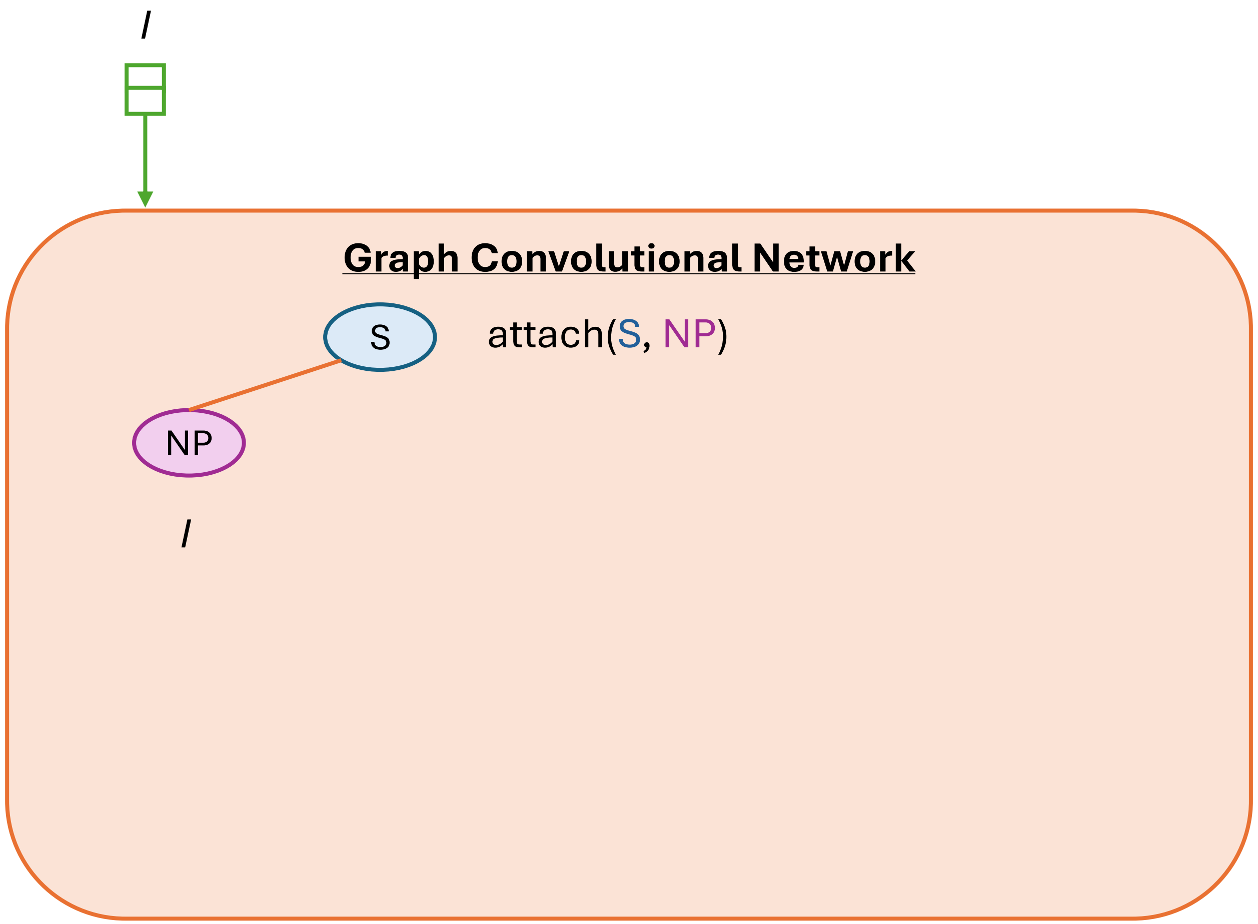


attach(target, parent)



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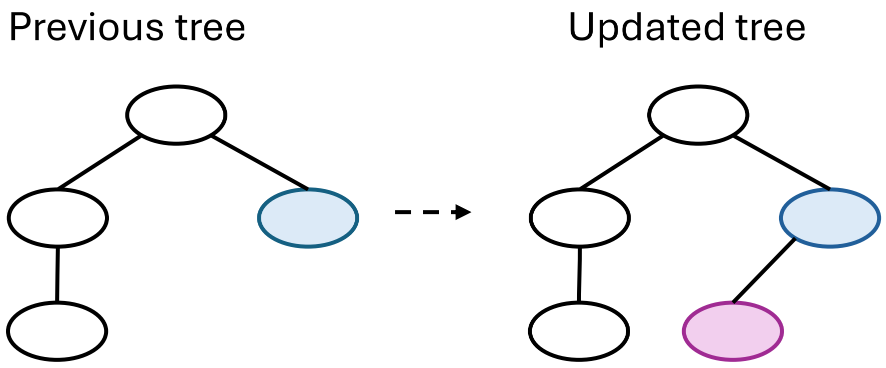

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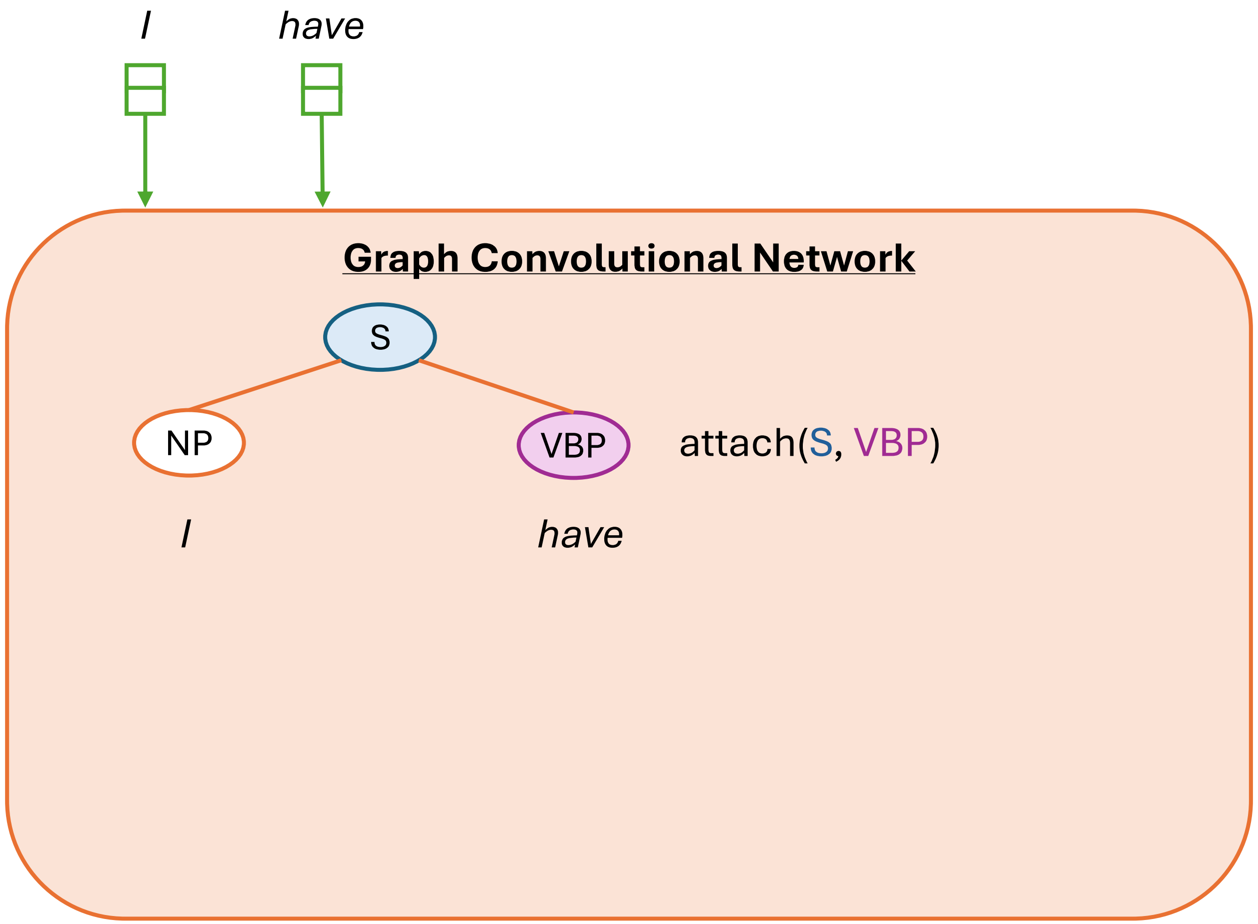

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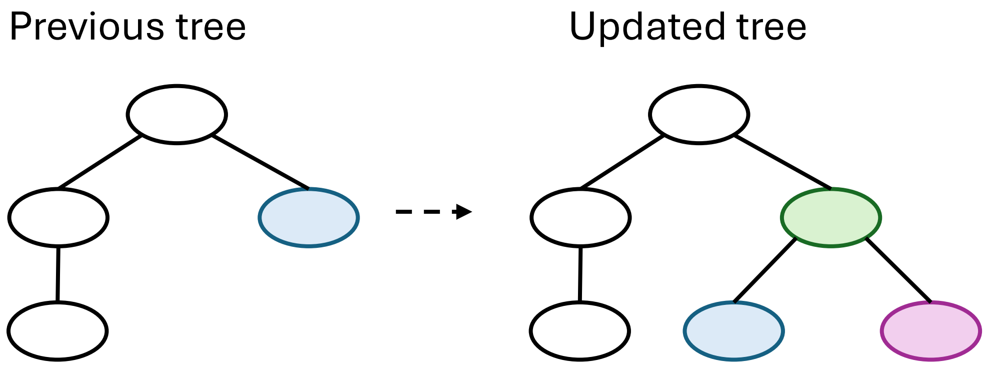
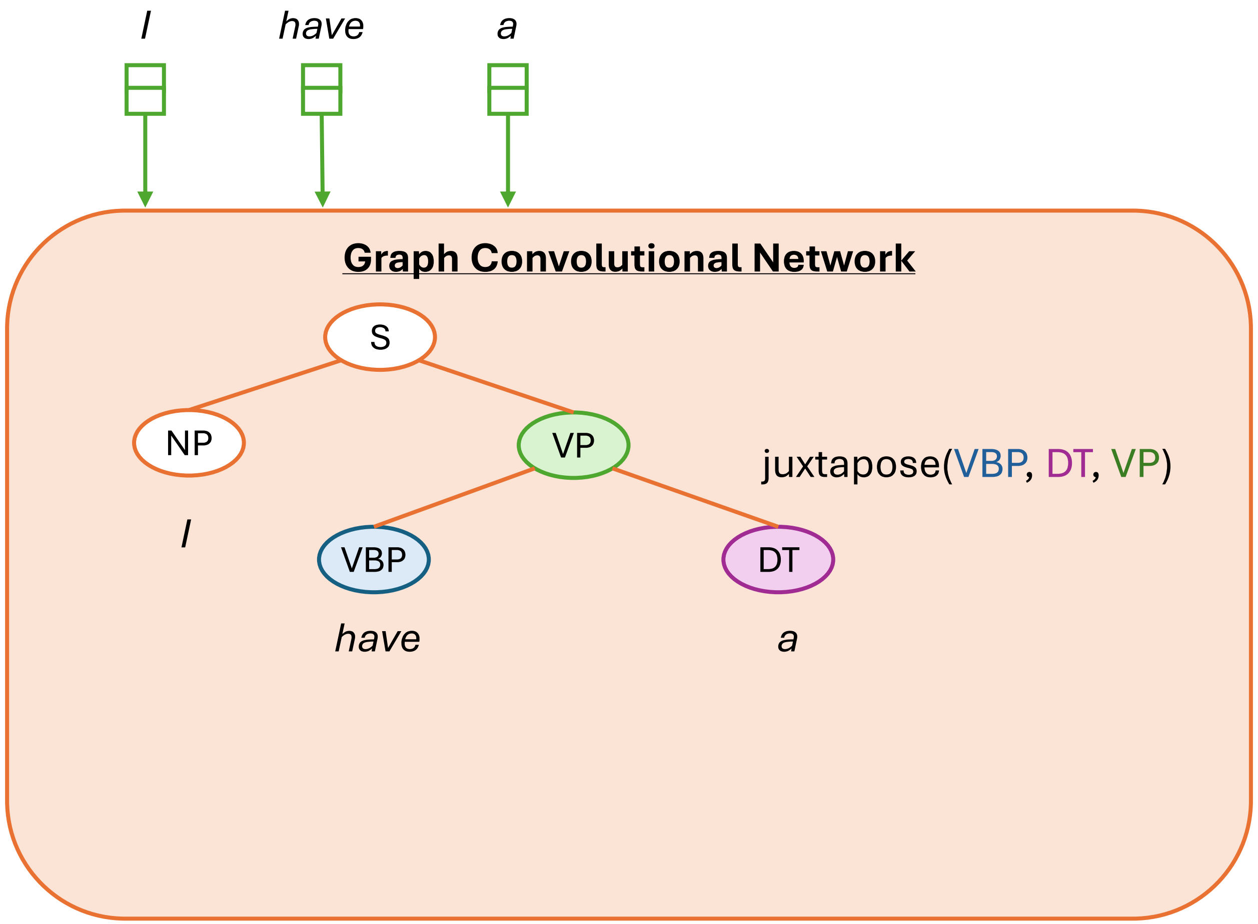


juxtapose(target, parent, new)



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- Two actions: **attach** & **juxtapose**.
- Sentence of n words to n transitions.

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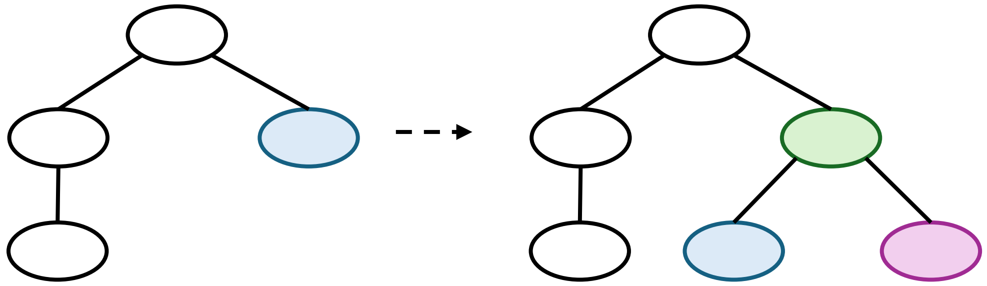
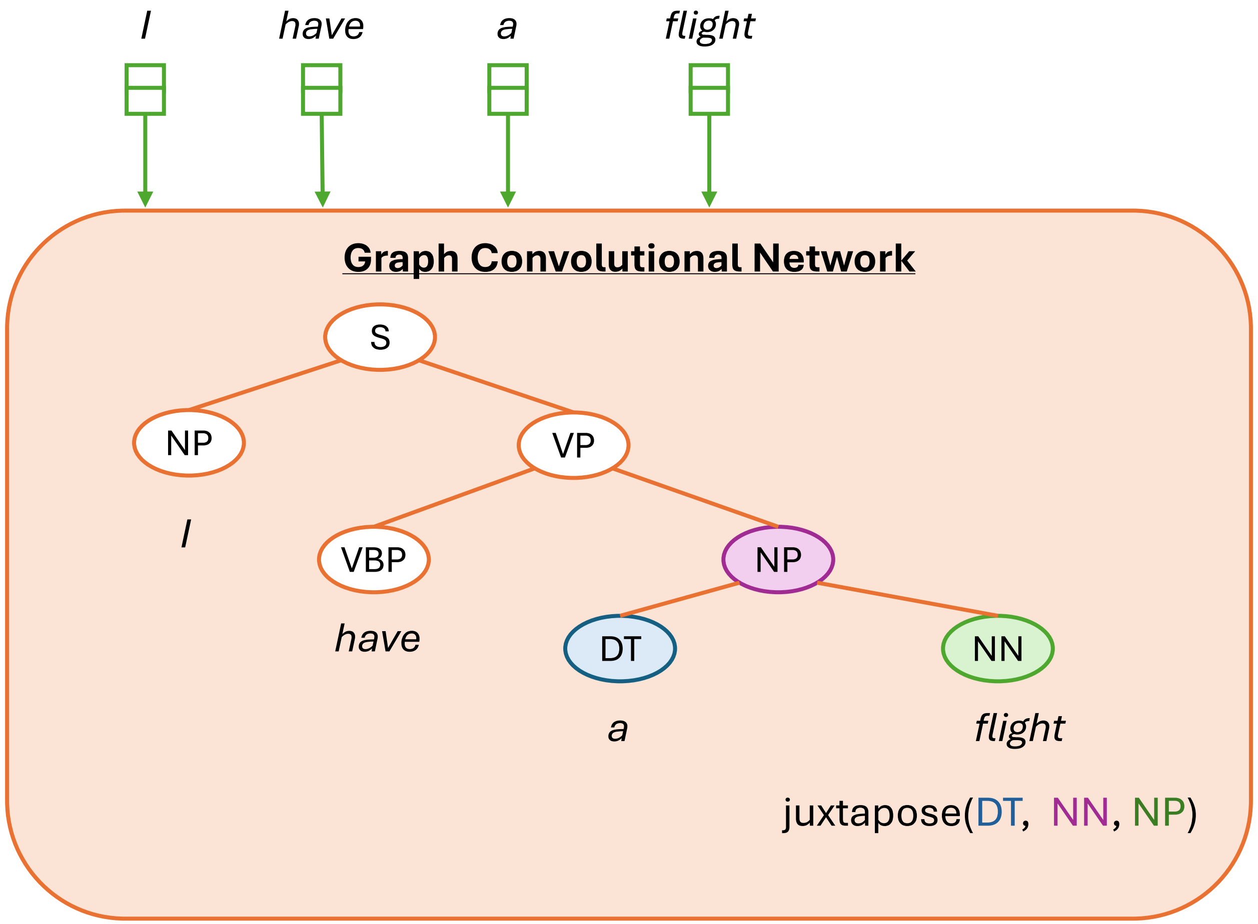
- Graph Convolutional Network (GCN).
- Append subtrees to the rightmost chain.

Previous tree   Updated tree



juxtapose(target, parent, new)



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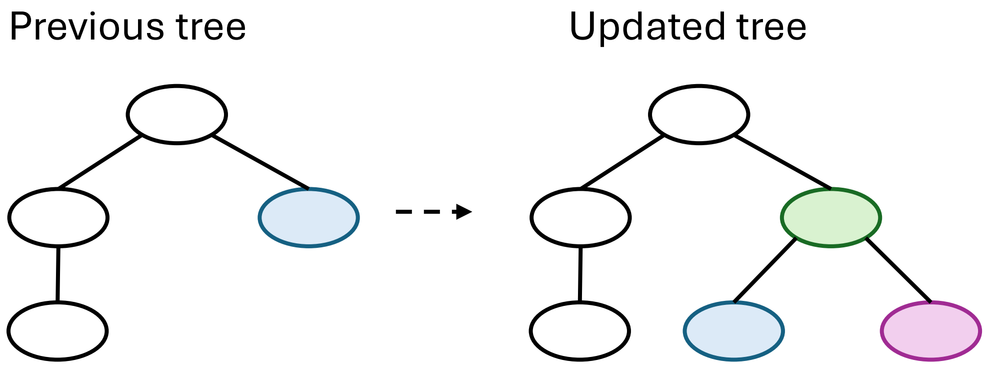

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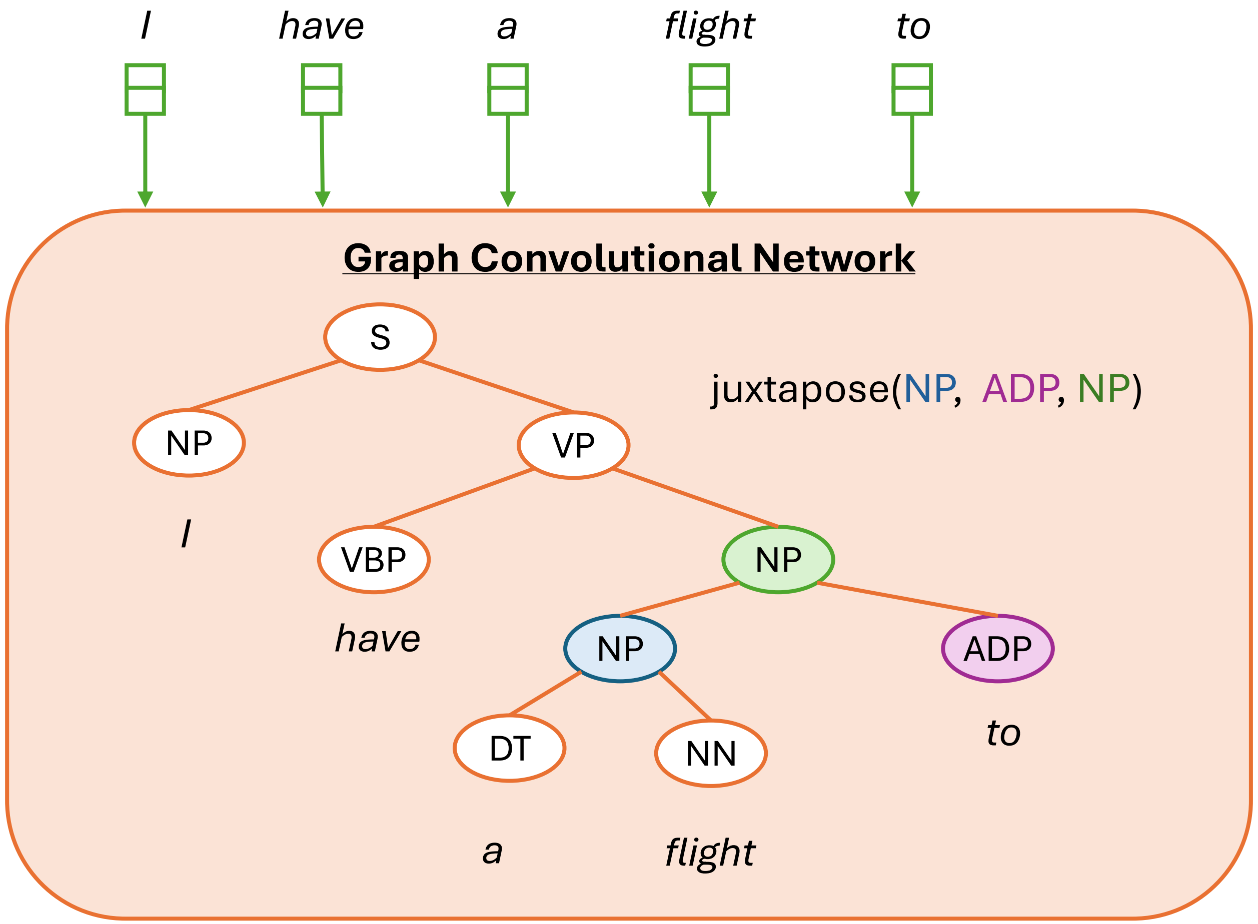

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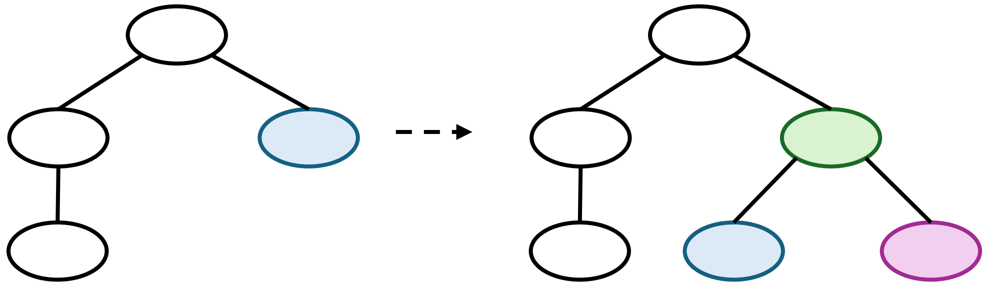

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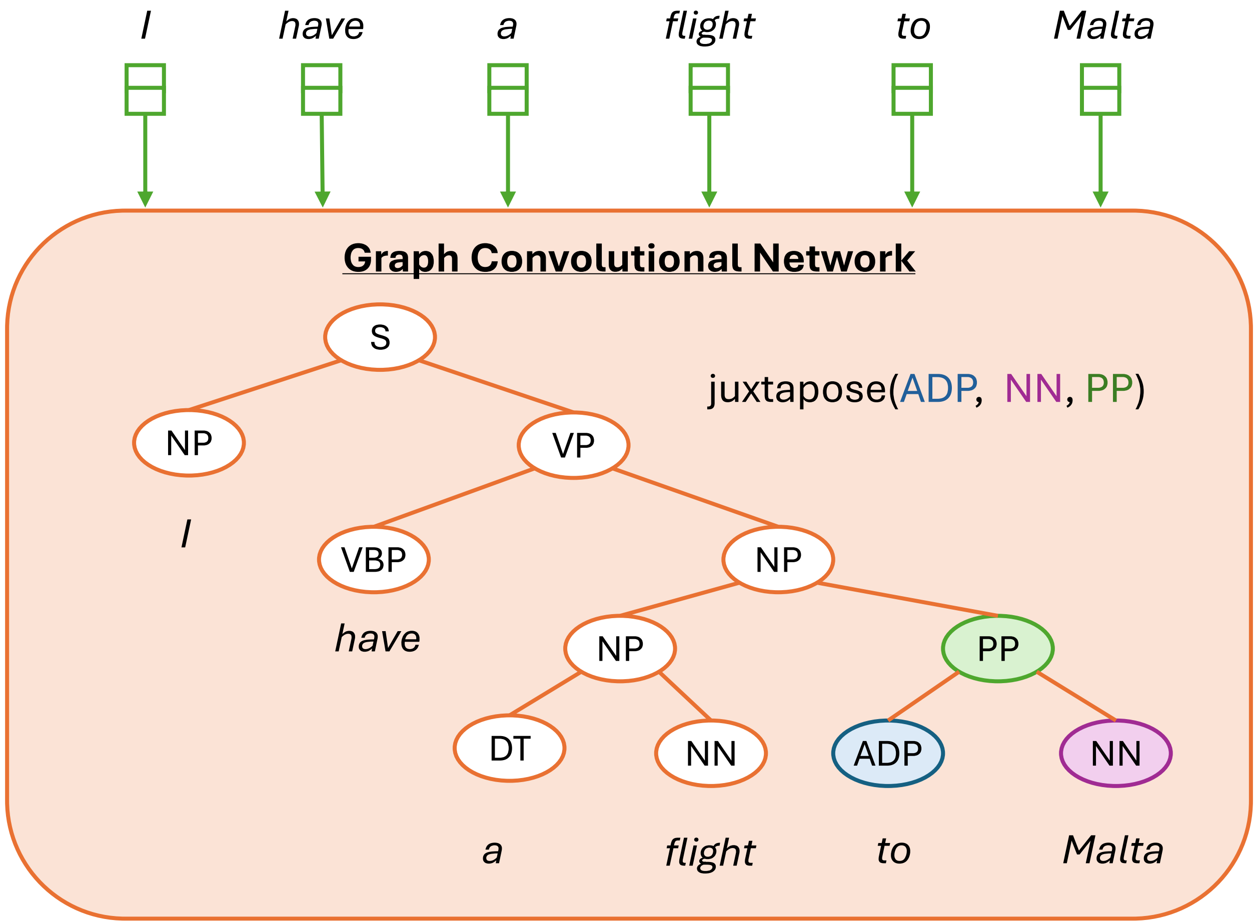

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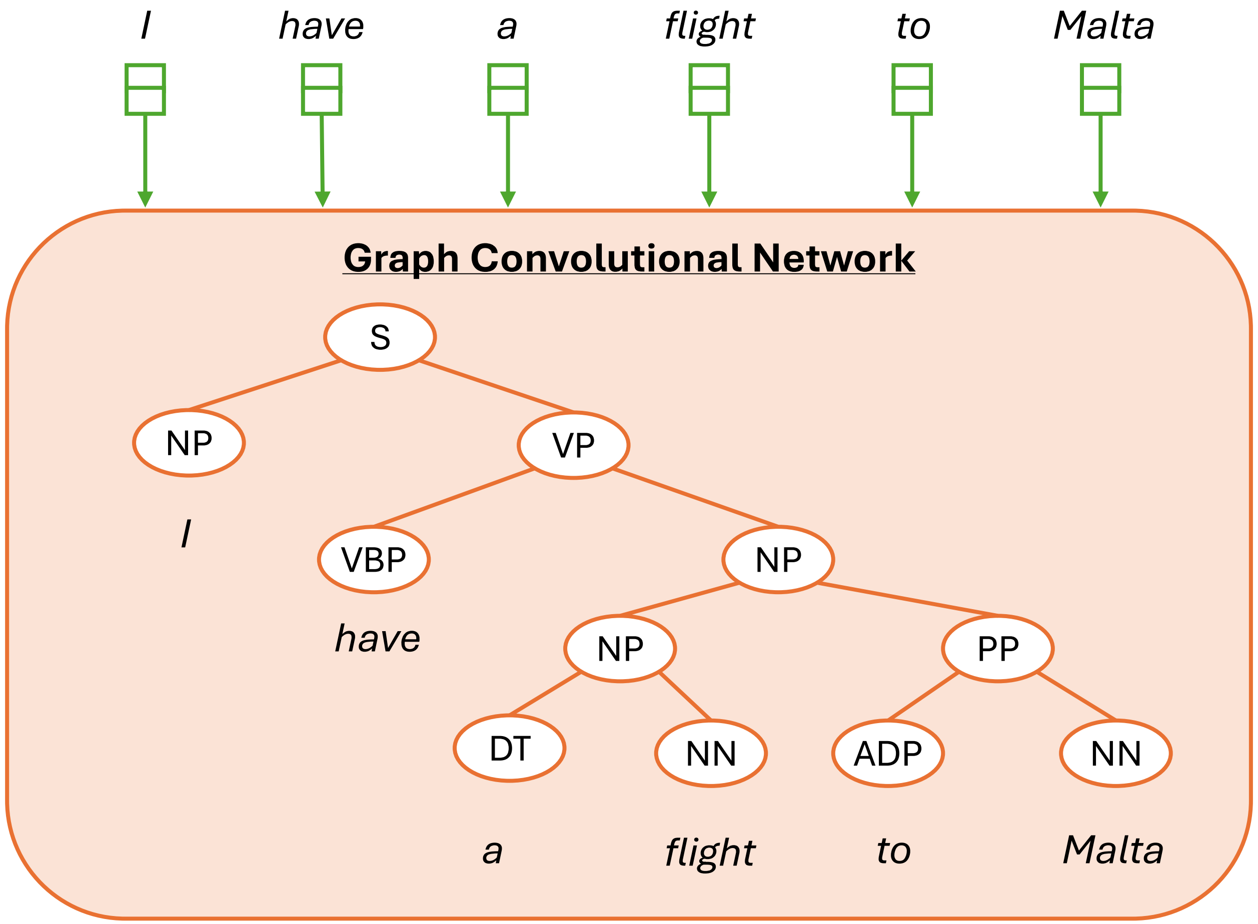

Full constituent tree!

Absolute & Relative Indexing (Gómez-Rodríguez & Vilares, 2018)

- Sequence labeling method.
- Sentence of n words to n labels.

$$w_1, \dots, w_n \to \ell_1, \dots, \ell_n$$

- Each label has 2 components: $\ell_i = (d_i, c_i)$.
    - l_i: # common constituents of w_i and w_{i+1}.
    - Absolute: $d_i = l_i$.
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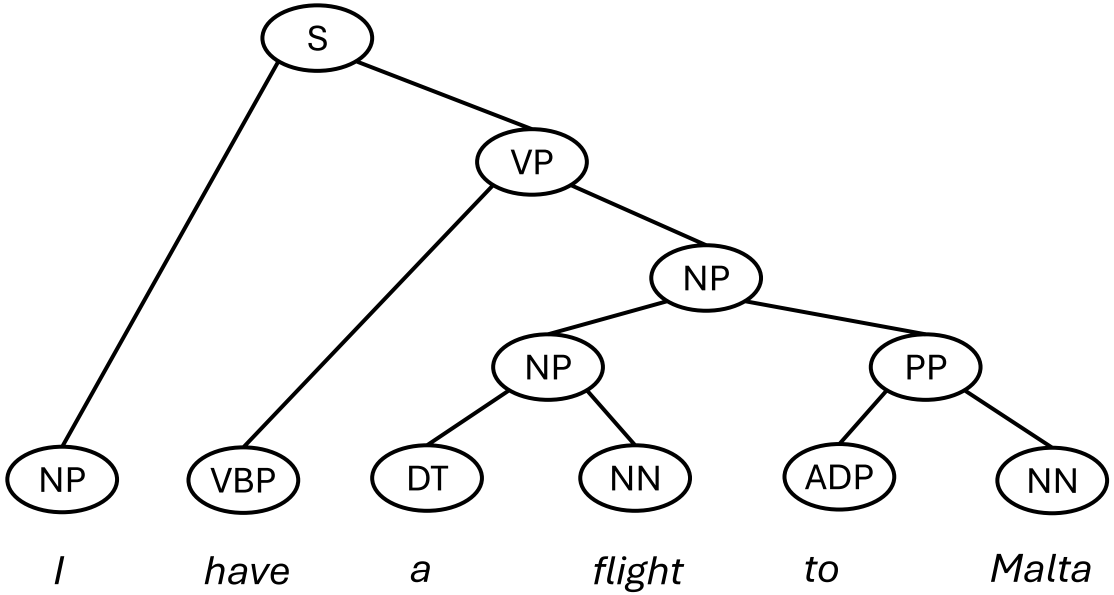
- Two feed forward networks (d_i, c_i).



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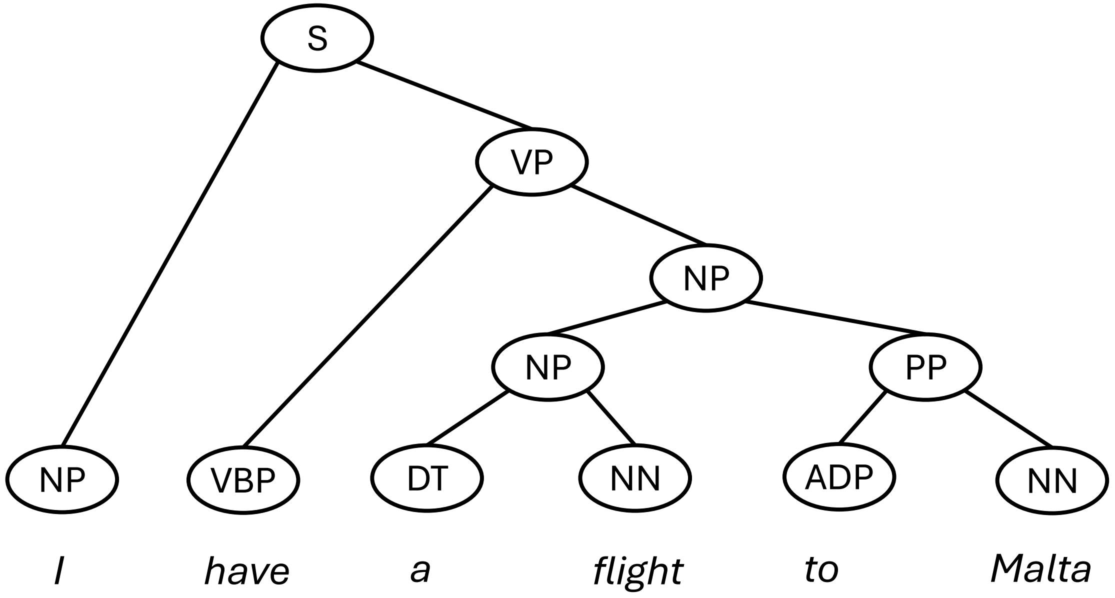

How to encode?

Absolute & Relative Indexing (Gómez-Rodríguez & Vilares, 2018)

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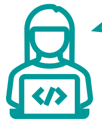
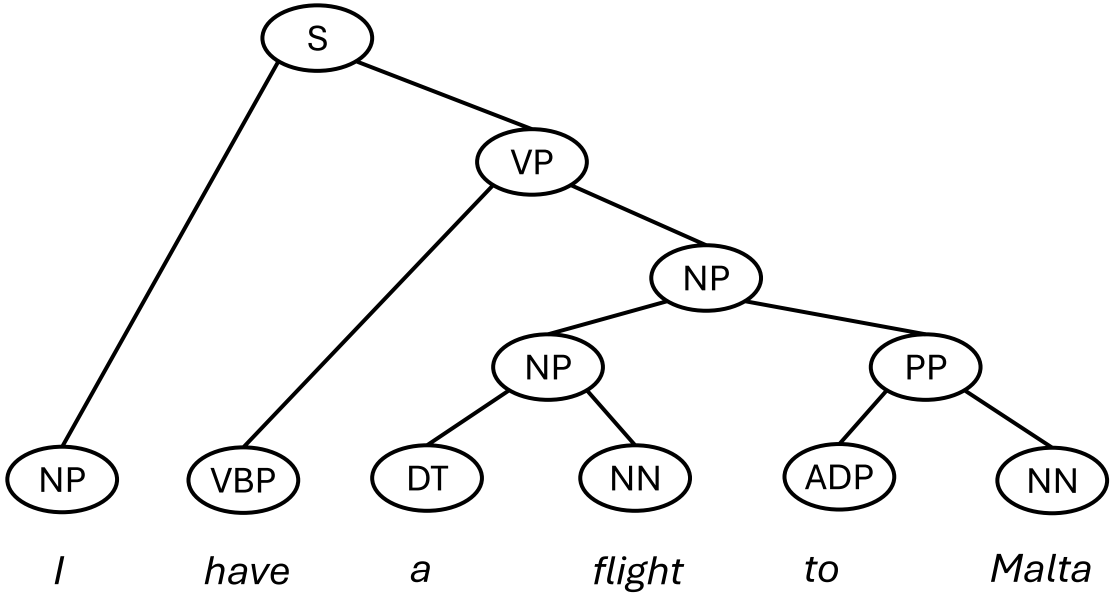


Incrementally obtain ℓ_i and append right nodes.



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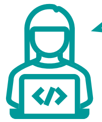

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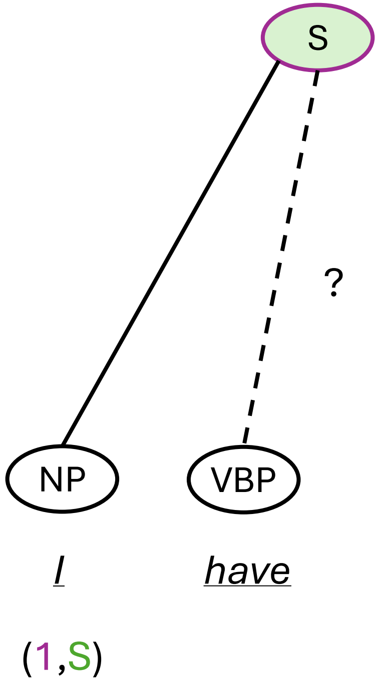

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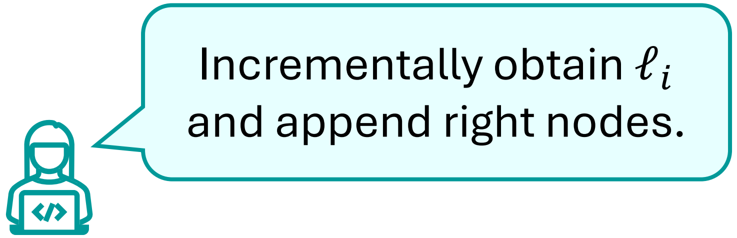

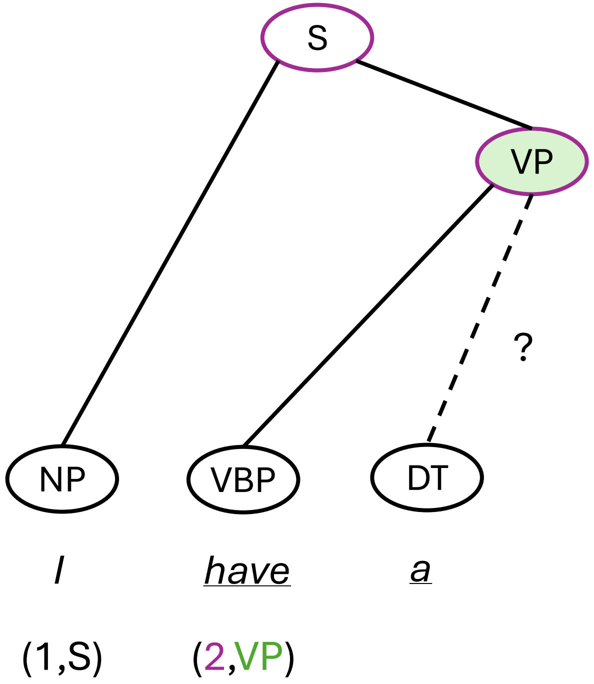

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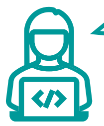

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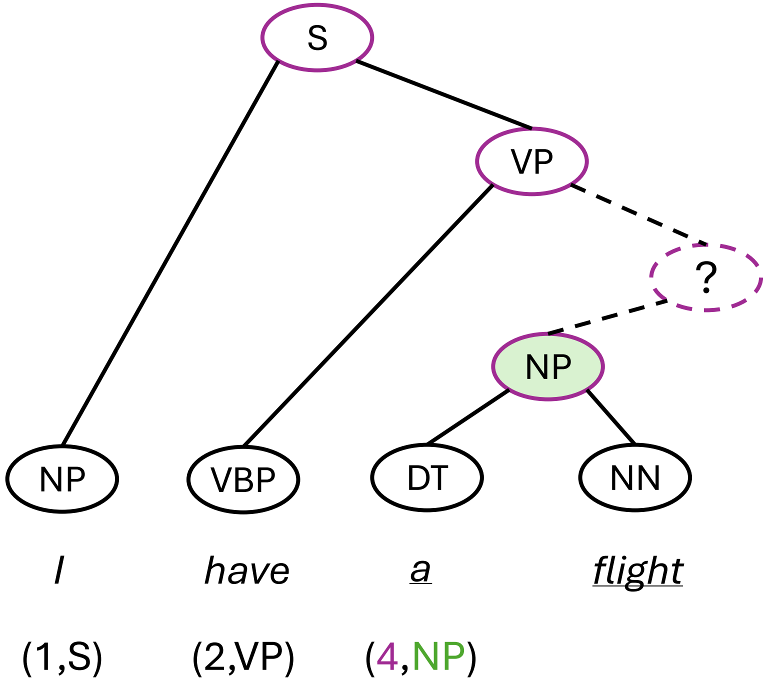

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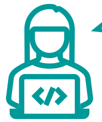

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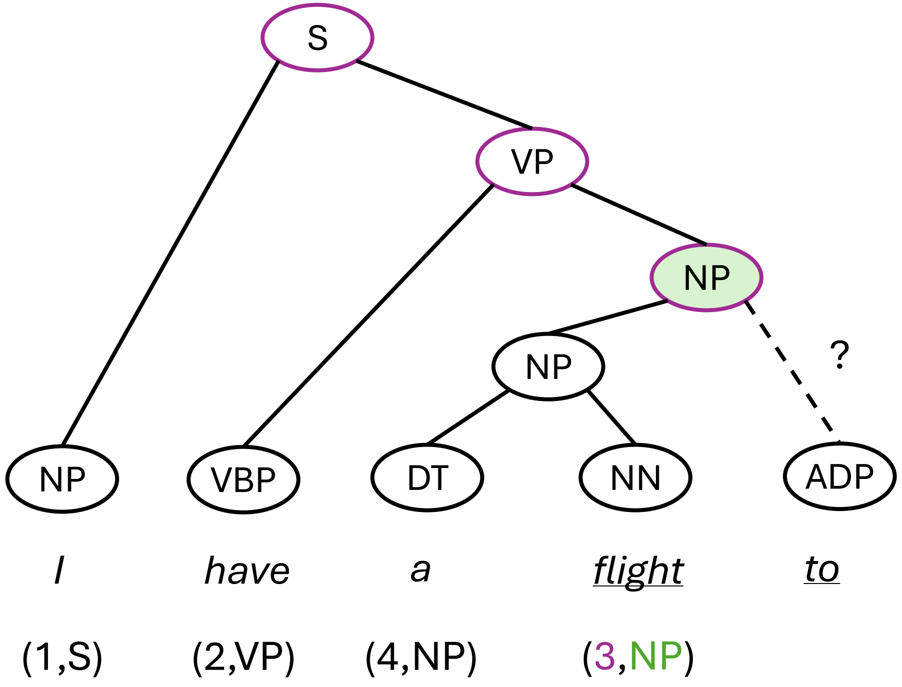

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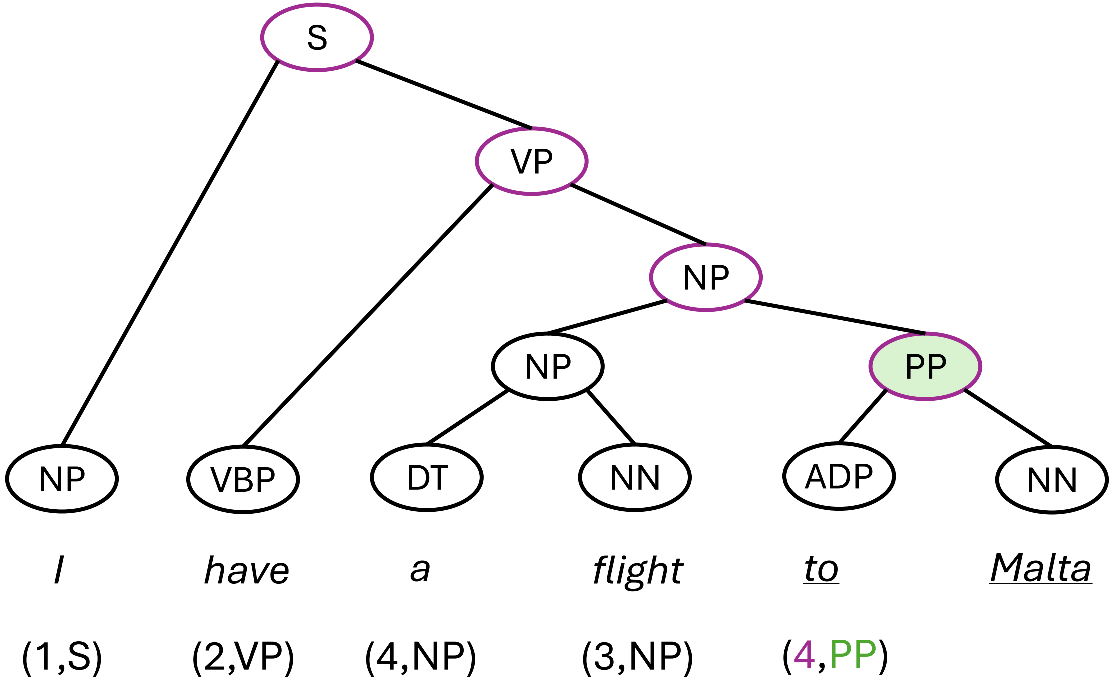

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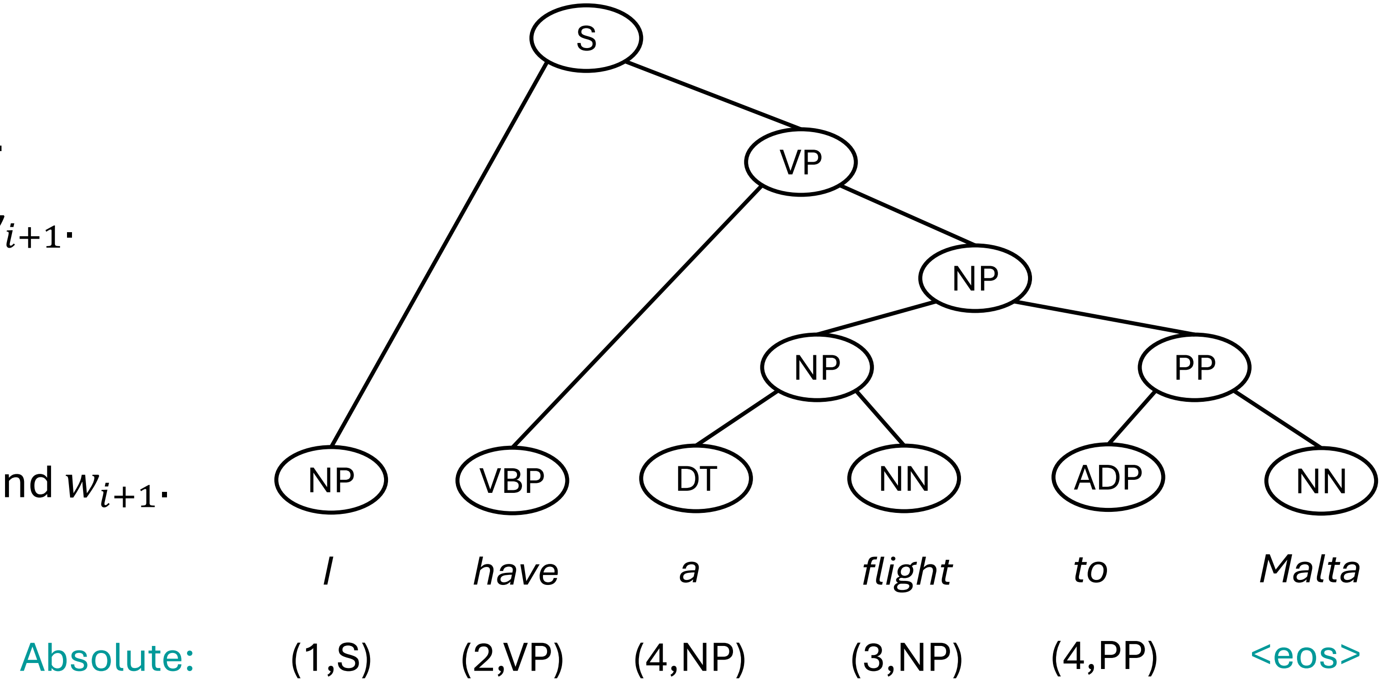

Absolute encoding!

Absolute & Relative Indexing (Gómez-Rodríguez & Vilares, 2018)

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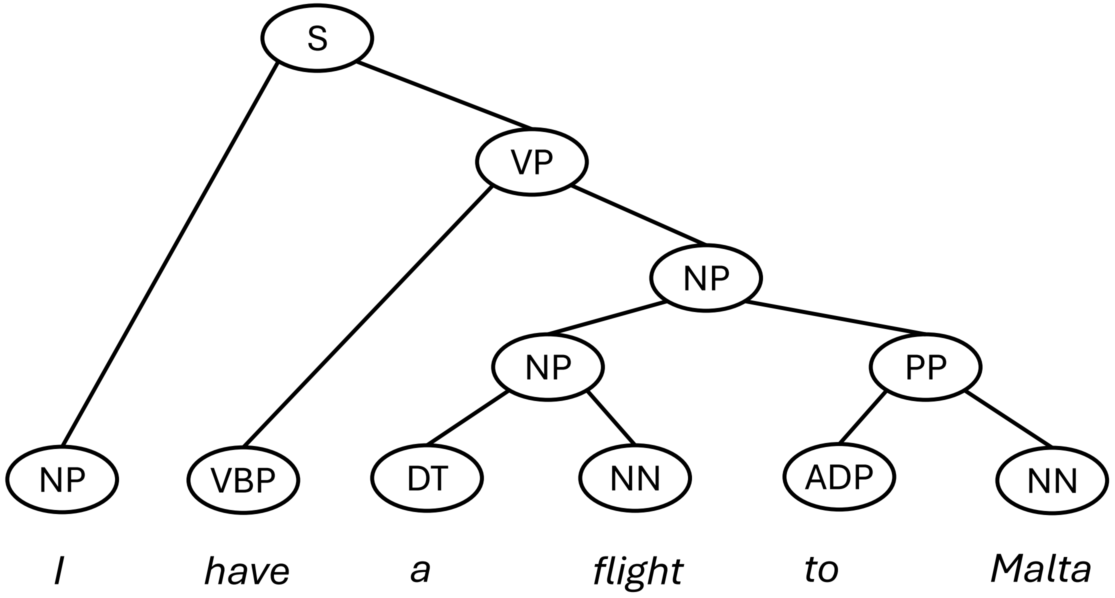


Absolute:	(1,S)	(2,VP)	(4,NP)	(3,NP)	(4,PP)	<eos>
Relative:	(1,S)	(1,VP)	(2,NP)	(-1,NP)	(1,PP)	<eos>

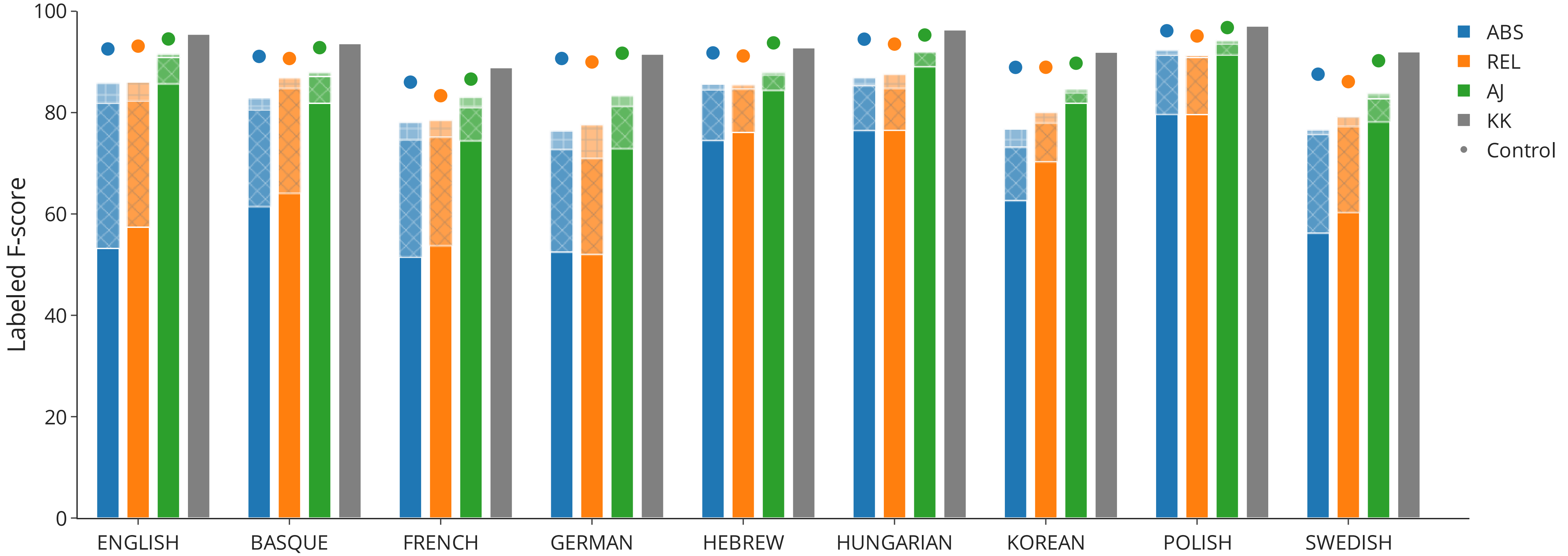
Relative: $d_i = l_i - l_{i-1}$

Experiments

- **Multilingual benchmark:** PTB + SPMRL (wo. Arabic).
- **Baseline:** Kitaev & Klein (2018).
    - Bidirectional encoder: XLM-RoBERTa.
    - Non-incremental decoder: span-based.
- **Encoders**:
    - Bidirectional: 4-BiLSTM, XLM-RoBERTa.
    - Unidirectional: 4-LSTM, BLOOM-560M, mGPT.
- **Delay experiments:** $k = 0, 1, 2$.

Results

- **Incremental** (mGPT): absolute (■), relative (■) and attach-juxtapose (■).
- **Control** (XLM): absolute (●), relative (●) and attach-juxtapose (●).
- **Non-incremental** (XLM): Kitaev & Klein, 2018 (■).
- **Delay 1** (⊠, ⊠, ⊠) and **Delay 2** (⊞, ⊞, ⊞).



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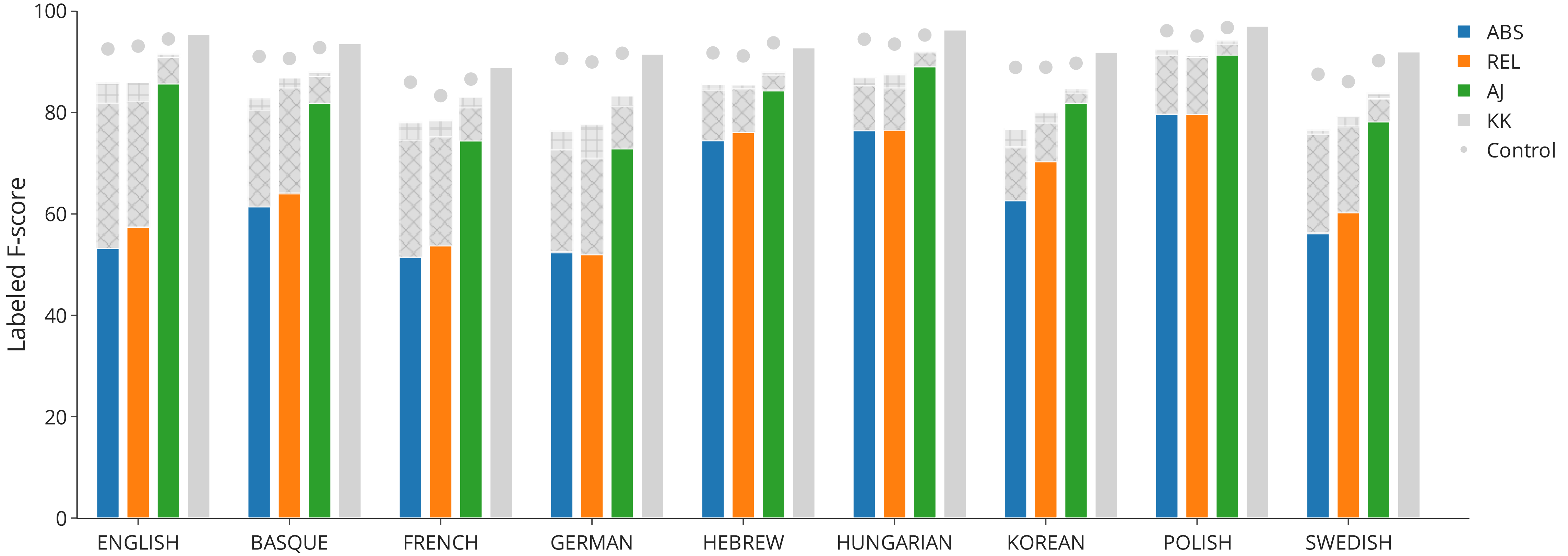

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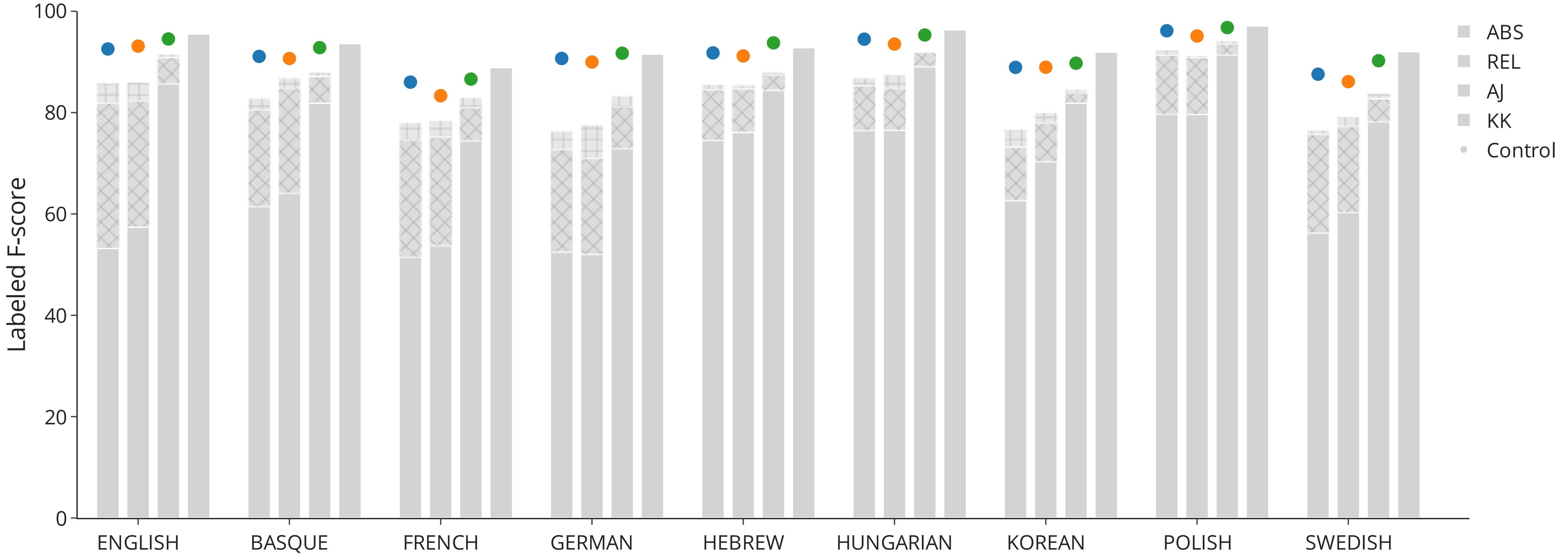

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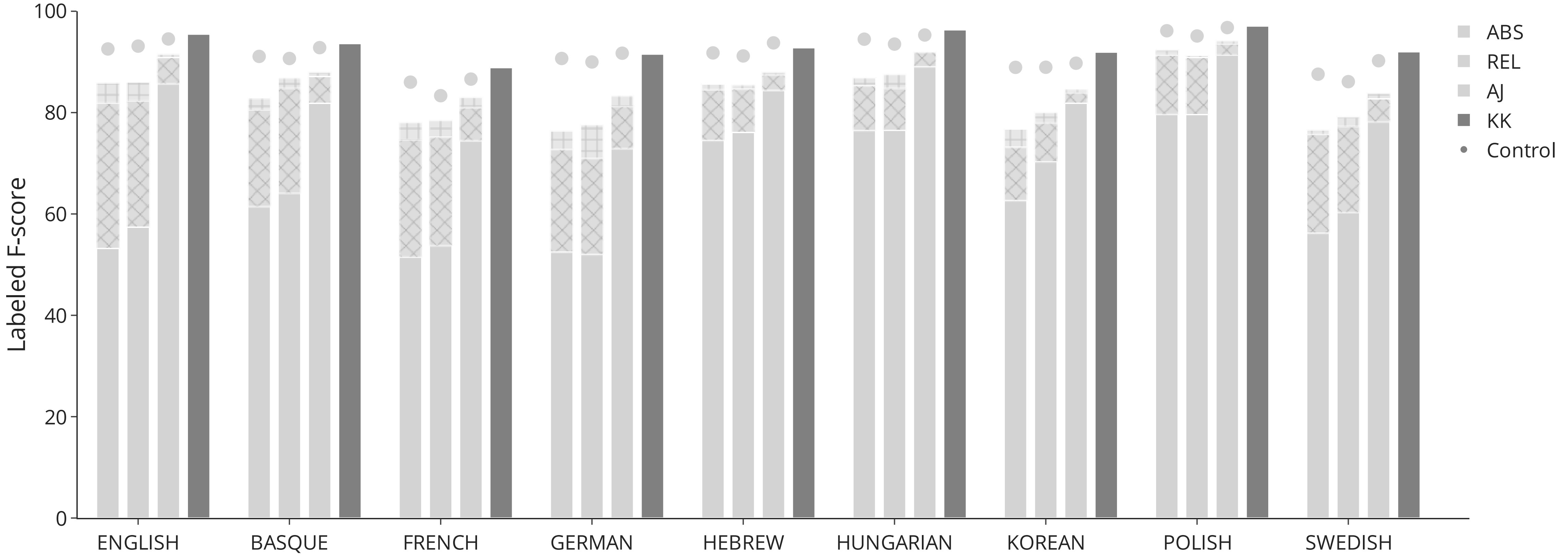

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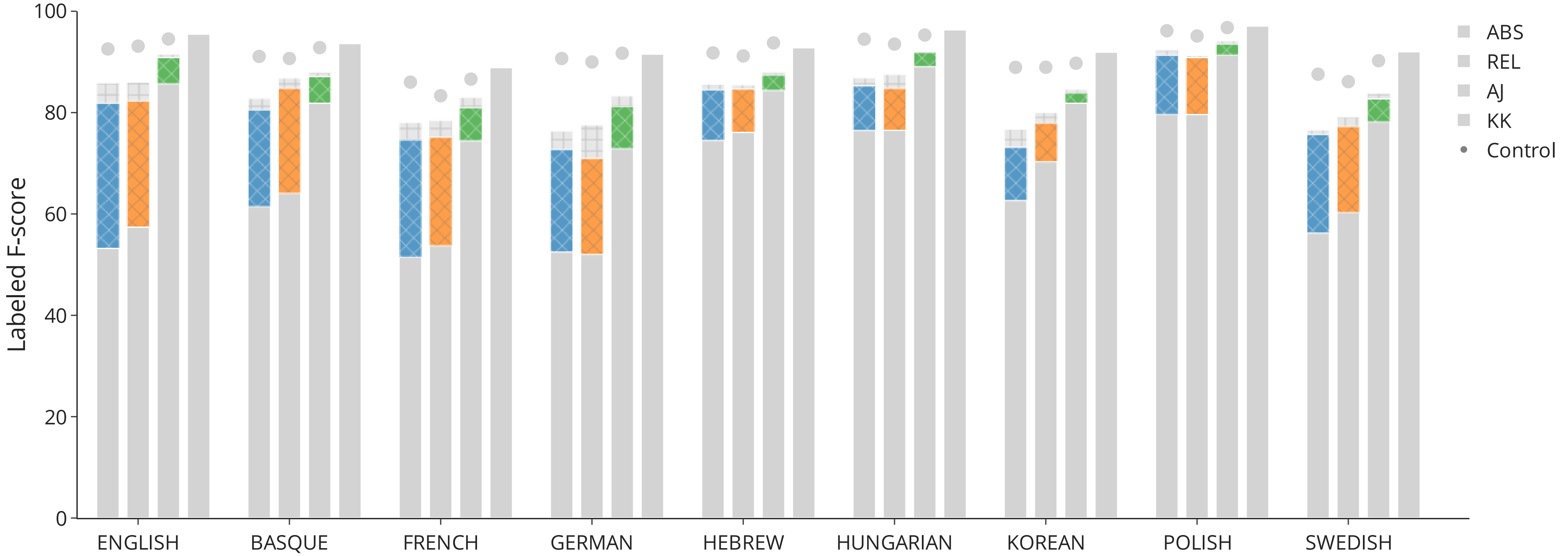

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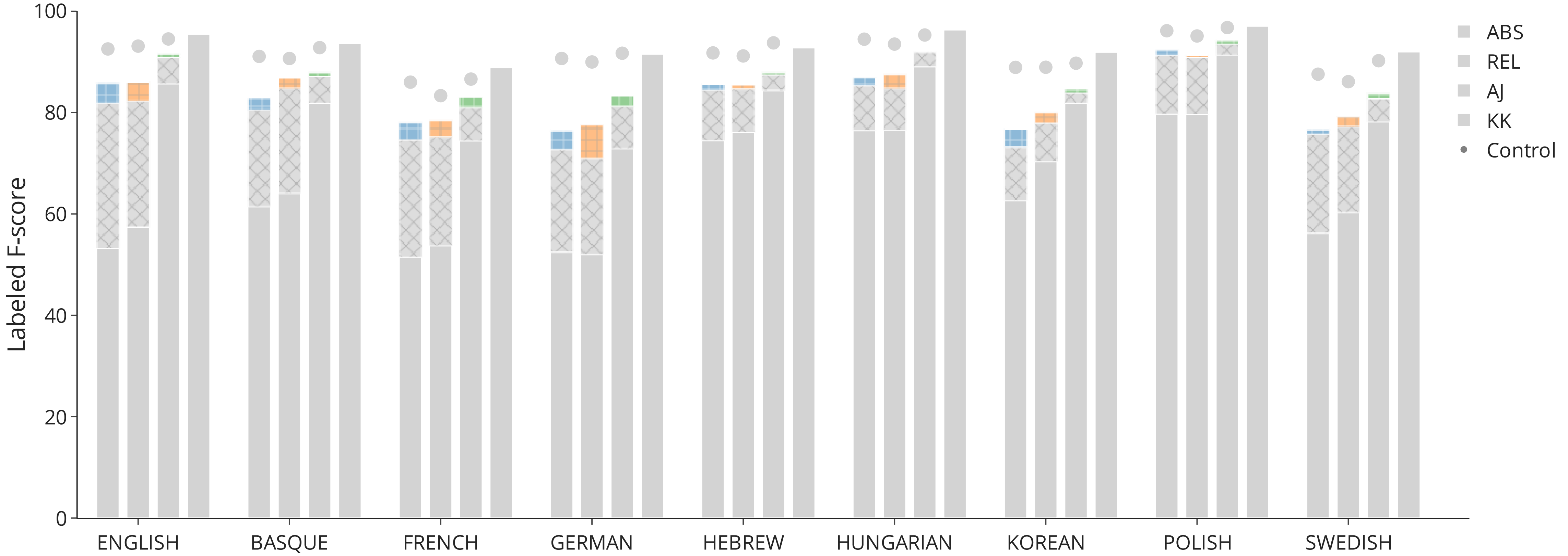

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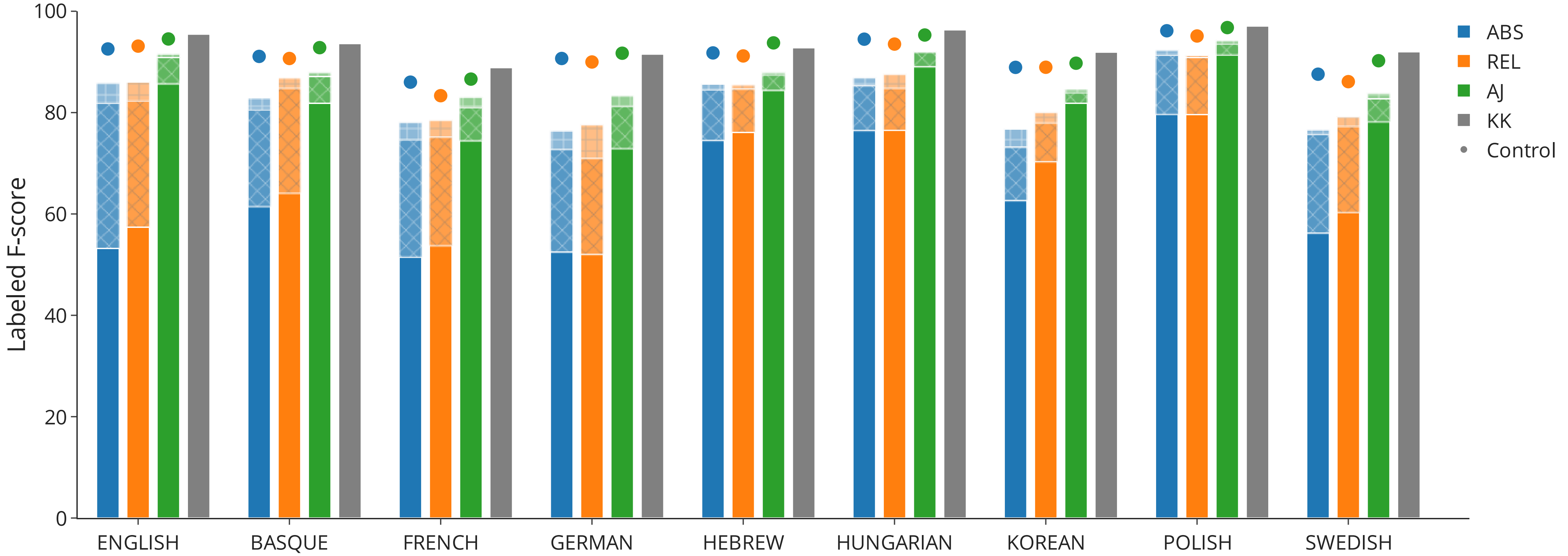
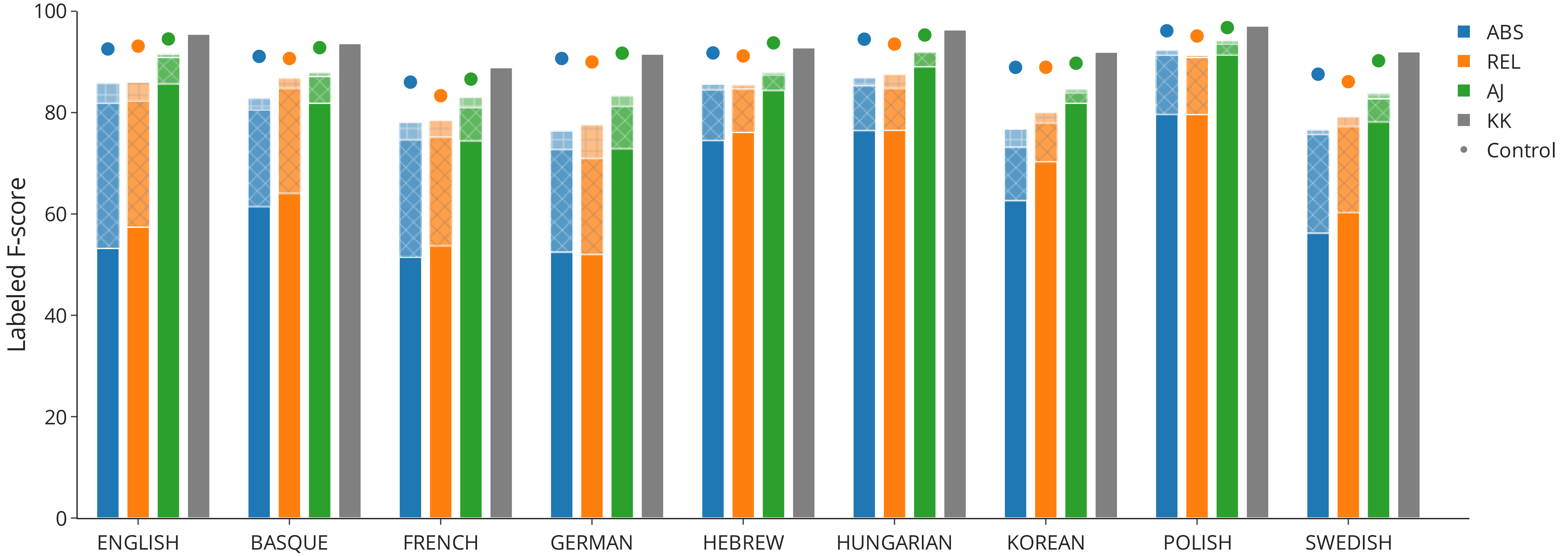
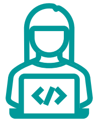


Conclusions

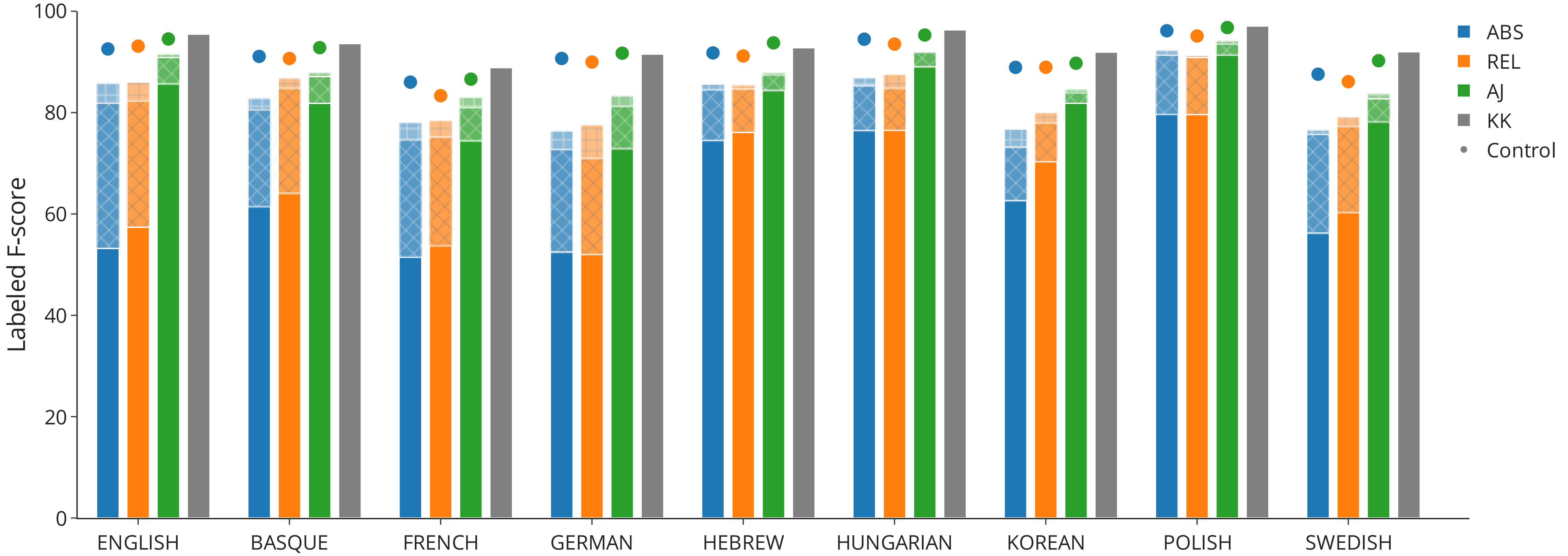
1. Control parsers (● ● ●) ≈ Kitaev & Klein, 2018 (■).
   - Meaning? State-of-the-art relies on a bidirectional encoder.
2. Incremental parsers (■ ■ ■) considerably worse than Control (● ● ●) and KK (■).
   - But introducing delay (☒, ☒, ☒) significantly improves the performance.



Conclusions



3. Sequence Labeling performance (■ ■) lags behind Attach-Juxtapose (■).
   - Attach-Juxtapose (■) relies on a powerful neural decoder (GCN).
   - Considering a larger decoder will improve the incremental results?
   - ABS (■) and REL (■) are more benefited of delayed processing than AJ (■).



Thanks for listening!

Ana Ezquerro Carlos Gómez-Rodríguez David Vilares

Acknowledgements:

This work has received funding by the European Research Council (ERC), under the Horizon Europe research and innovation programme (SALSA, grant agreement No 101100615), ERDF/MICINN-AEI (SCANNER-UDC, PID2020-113230RB-C21), Xunta de Galicia (ED431C 2020/11), Grant GAP (PID2022-139308OA-I00) funded by MCIN/AEI/10.13039/501100011033/ and by ERDF 'A way of making Europe', and Centro de Investigación de Galicia 'CITIC', funded by the Xunta de Galicia through the collaboration agreement between the Consellería de Cultura, Educación, Formación Profesional e Universidades and the Galician universities for the reinforcement of the research centers of the Galician University System (CIGUS).