# The Concordia NLG Surface Realizer at SR'19

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### **Objective**

We participated in the SR'19 [1] shallow track only. The model takes as input an unordered and lemmatized list of words, and finds the correct word order and inflected words.

#### **Dataset**

#	Training set	Number of Sentences
1	en_ewt-ud-train	12,543
2	en_gum-ud-train	2,914
3	en_lines-ud-train	2,738
4	en_partut-ud-train	1,781

Table 1: Training data which are taken from Universal Dependency (UD) datasets [2]

## Methodology

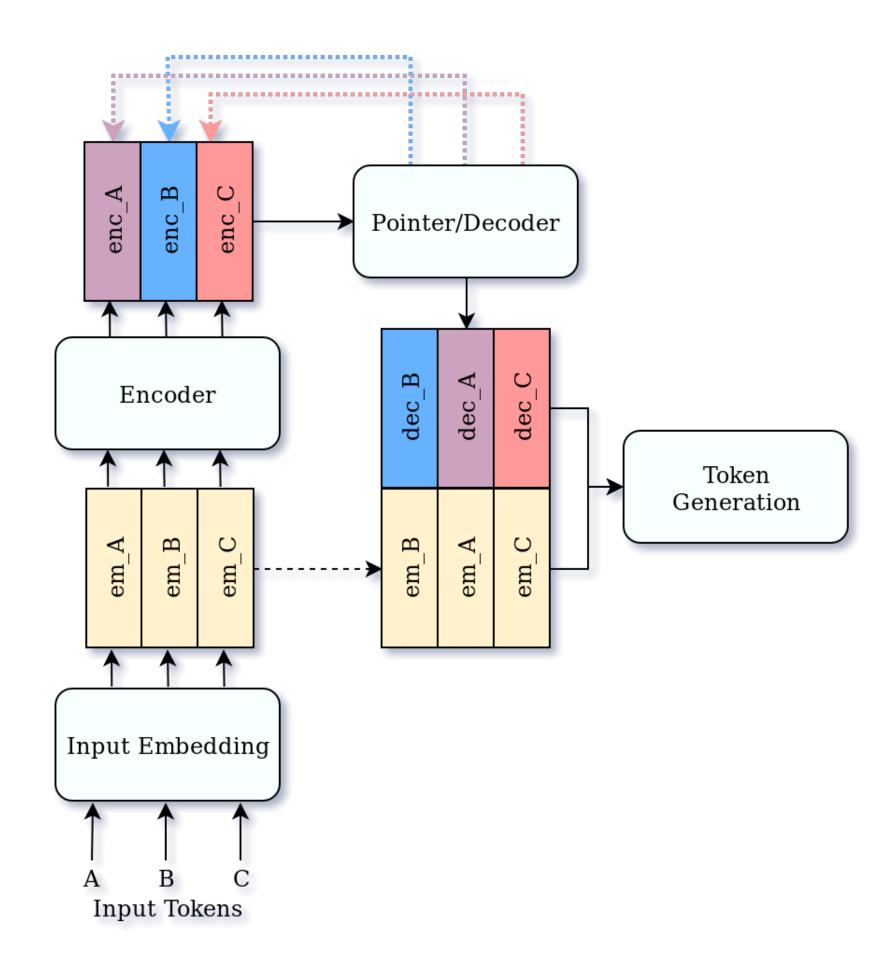


Figure 1: The model architecture used for the shallow track at SR'19

Our model (Figure 1) consists of five main sub-modules.

- Input Embedding: embeds each token X alongside its features to an embedded token  $(em_X)$
- Encoder: encodes each embedded token (enc\_X) <sup>1</sup>
- **Decoder:** generates the query for the Pointer  $(dec_X)$  given previously selected tokens and encoded tokens from the Encoder <sup>1</sup>
- Pointer: is an attention mechanism that attends over the encoded tokens and uses  $dec_X$  as its query [4]
- Token Generation: generates the inflected form of tokens using the concatenation of embedded token  $(em_X)$  and decoded token  $(dec_X)$

#### Results and Analysis

Our model achieved the average scores of 48.1 and 60.9 for the Readability/Quality and Meaning Similarity on the English datasets. Both the automatic and the human evaluations show that our system performance was below the median.

#		Test sets	<b>BLEU</b>
1	In-domain	en_ewt-ud-test	22.08
2		en_gum-ud-test	15.32
3		en_lines-ud-test	15.30
4		en_partut-ud-test	10.07
5	Out-of-domain	en_pud-ud-test	12.36
6	Predicted	en_ewt-Pred-HIT-edit	21.21
7		en pud-Pred-LATTICE	12.89

Table 2: BLEU Scores of our submission in SR'19

b) Meaning Similarity

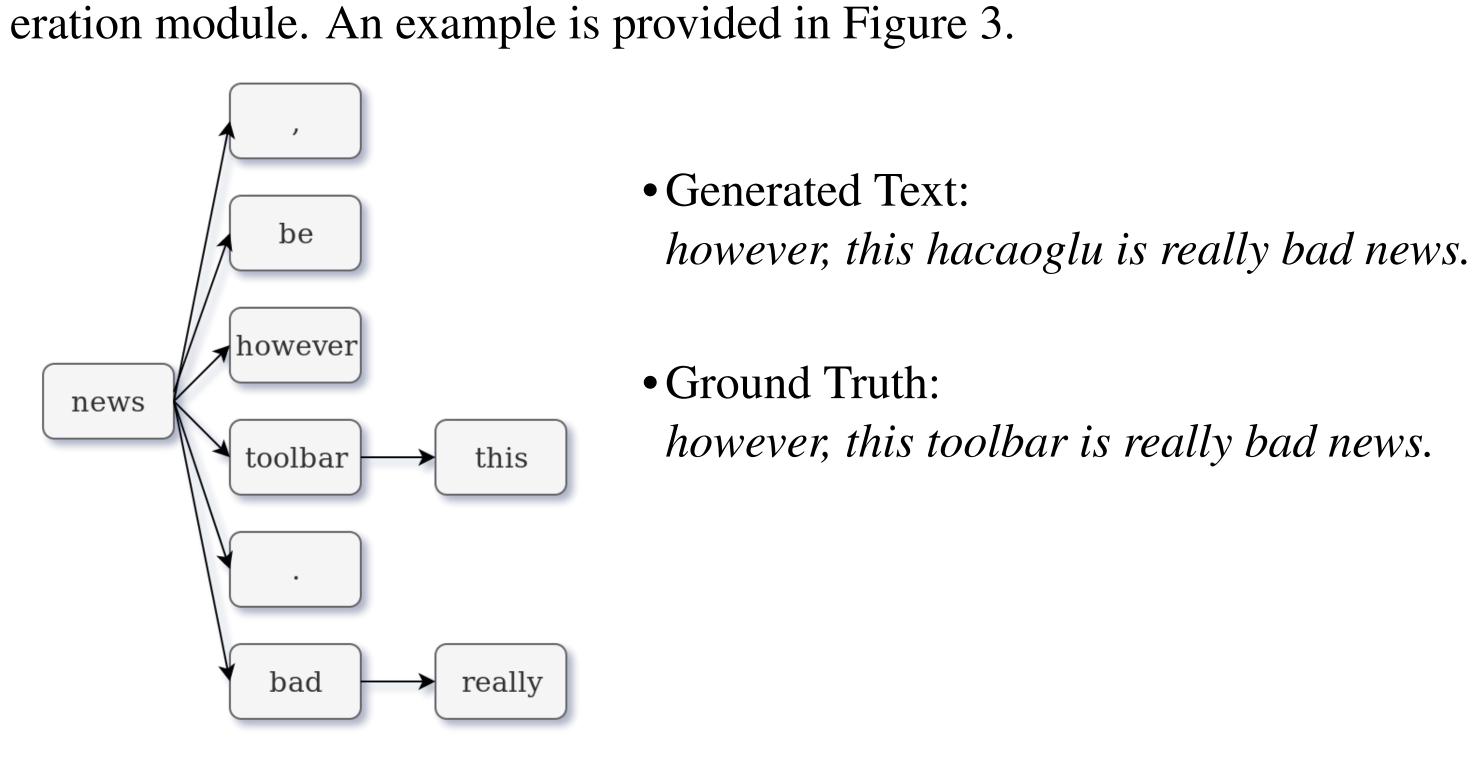


Figure 3: Example of a generated text

## **Future Work**

The proposed system is composed of a pointer network where its encoder and decoder modules borrowed from transformer, aim to reconstruct the tokens' order and inflection.

For the future work, it would be interesting to

a) Readability/Quality

- Investigate the model sensitivity to the training size
- Utilize more features provided by the universal dependency structure
- The possibility of using pretrained language models

#### **Contact**

For further information please visit: https://github.com/farhoodf/SR19



## References

- [1] Simon Mille, Anja Belz, Bernd Bohnet, Yvette Graham, and Leo Wanner. The Second Multilingual Surface Realisation Shared Task (SR'19): Overview and Evaluation Results. In *Proceedings of the 2nd Workshop on Multilingual Surface Realisation (MSR), 2019 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Hong Kong, China, 2019.
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- [3] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30 (NIPS 2017)*, pages 5998–6008. Curran Associates, Inc., 2017.
- [4] Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. Pointer Networks. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28 (NIPS 2015)*, pages 2692–2700. Curran Associates, Inc., 2015.

Figure 2: Human evaluation results compared to all participants at SR'19

Analysis: An analysis of a few generated outputs of our model showed that the low performance is mainly due to the poor performance of the Token gen-

We employed transformer encoder and decoder [3]