# How do Transformer-Architecture Models Address Polysemy of Korean Adverbial Postpositions?



Seongmin Mun<sup>1</sup> & Guillaume Desagulier<sup>2</sup> Ajou University<sup>1</sup>, Paris VIII University & UMR 7114, MoDyCo<sup>2</sup>





# Introduction

- A Korean postposition normally involves many-to-many associations between form and function. As such a postposition is polysemous. For example, an adverbial postposition -(u)lo (-ulo after a consonant) is interpreted as six major functions: criterion (CRT), direction (DIR), effector (EFF), final state (FNS), instrument (INS), and location (LOC) (Shin, 2008). For instance, the following sentence involving the postposition -(u)lo as a marker of INS (instrument) as in (1).
  - (1) -(u)lo as INS (instrument)

na-nun kamca-lul khal-lo ssel-ess-ta.

I-TOP potato-ACC knife-INS cut-PST-DECL

'I cut a potato with a knife.'

- Contextualized word-embedding model: The model considers neighborhood information about a polysemous word on the basis of sequences of words around the target word.
- Background: Several studies have used transformerarchitecture models to address the word-level polysemy of Korean adverbial postpositions (e.g., Bae et al., 2020). Notably, the particular reason for the transformer architecture's superior performance over the others is somewhat unclear.
- Question: How do Transformer-Architecture Models Address Polysemy of Korean Adverbial Postpositions?

### Methods

• **Input:** A portion of Sejong corpus (Shin, 2008), with semantic annotations of postpositions *-ey, -eyes,* and *-(u)lo* crossverified by three native speakers of Korean ( $\kappa = 0.948$  (*-eys*), 0.928 (*-eyse*), and 0.947 (*-(u)lo*)).

| -ey      |           | -eyse    |           | -(u)lo   |           |
|----------|-----------|----------|-----------|----------|-----------|
| Function | Frequency | Function | Frequency | Function | Frequency |
| LOC      | 1,780     | LOC      | 4,206     | FNS      | 1,681     |
| CRT      | 1,516     | SRC      | 647       | DIR      | 1,449     |
| THM      | 448       |          |           | INS      | 739       |
| GOL      | 441       |          |           | CRT      | 593       |
| FNS      | 216       |          |           | LOC      | 158       |
| EFF      | 198       |          |           | EFF      | 88        |
| INS      | 69        |          |           |          |           |
| AGT      | 47        |          |           |          |           |
| Total    | 4,715     | Total    | 4,853     | Total    | 4,708     |

- Classification models: We devised a classification model by employing Bidirectional Encoder Representations from Transformer (BERT; Devlin et al., 2018) and Generative Pre-Training 2 (GPT-2; Radford et al., 2018)
- Visualization system: In order to better understand how BERT and GPT-2 recognize the word-level polysemy, we developed a visualization system by using the test set under the two-dimensional distribution (i.e., t-distributed Stochastic Neighbor Embedding; Maaten and Hinton, 2008).

# Methods

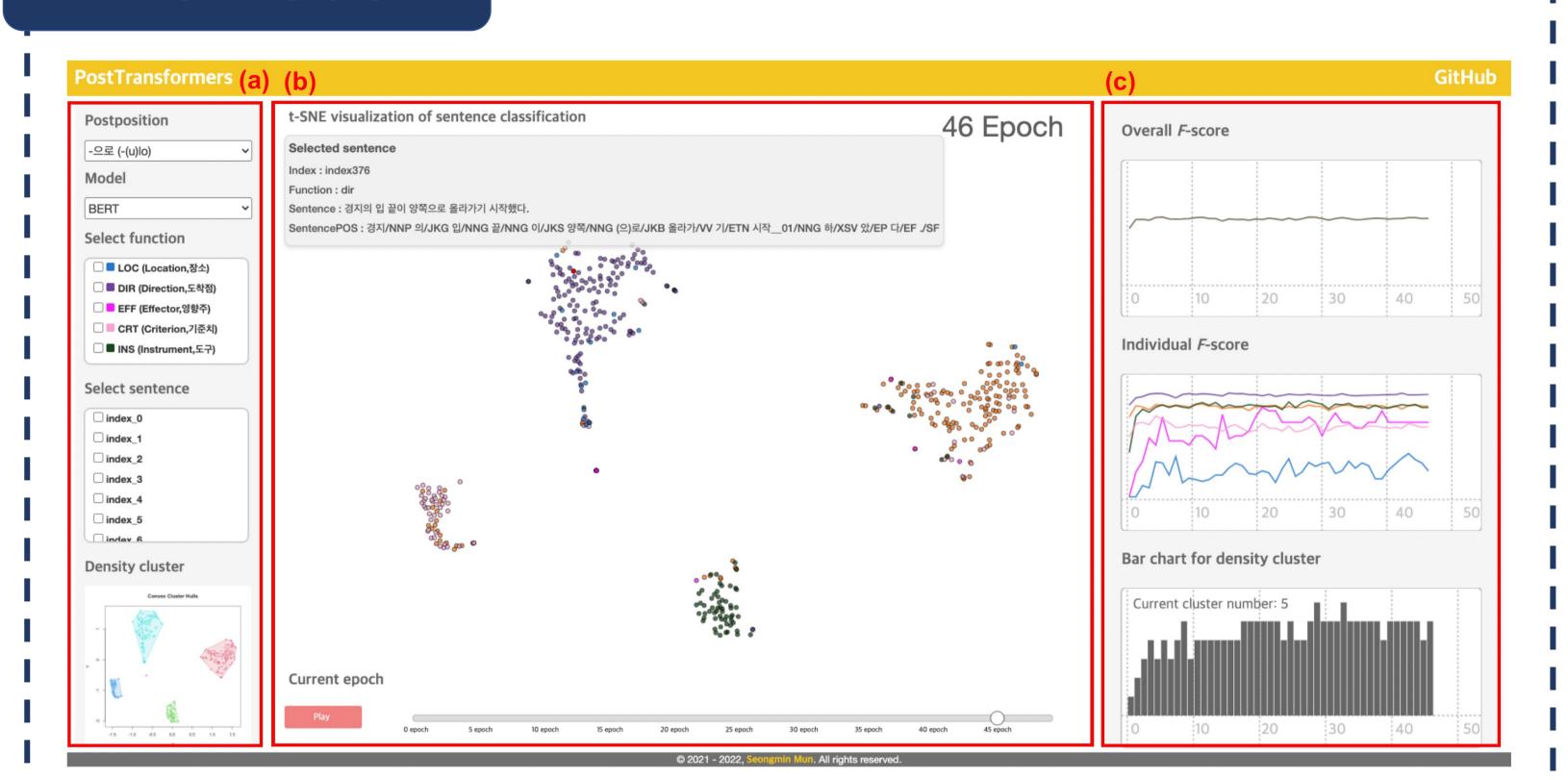


Figure 1: The overview interface of the visualization system (available at: <a href="https://seongmin-mun.github.io/Visualization/2022/PostTransformers/index.html">https://seongmin-mun.github.io/Visualization/2022/PostTransformers/index.html</a>)

## Results

- Findings
  - ✓ First, BERT performed better than GPT-2 in revealing the polysemy of Korean postpositions (BERT: 0.744 for -ey, 0.875 for -eyse, 0.795 for -(u)lo; GPT-2: 0.68 for -ey, 0.844 for -eyse, 0.676 for -(u)lo).
  - ✓ Second, there was an inverse relation between the classification performance and the number of functions of each postposition.
  - ✓ Third, the model was affected by the corpus size of each function.
  - ✓ Fourth, the model was able to identify the intended functions of a postposition as the epoch progressed (see Figure 2).
  - ✓ Fifth, these models were affected by the rarely occurring input and/or semantic closeness between the items, limiting the performance of two models in the given task to some extent.

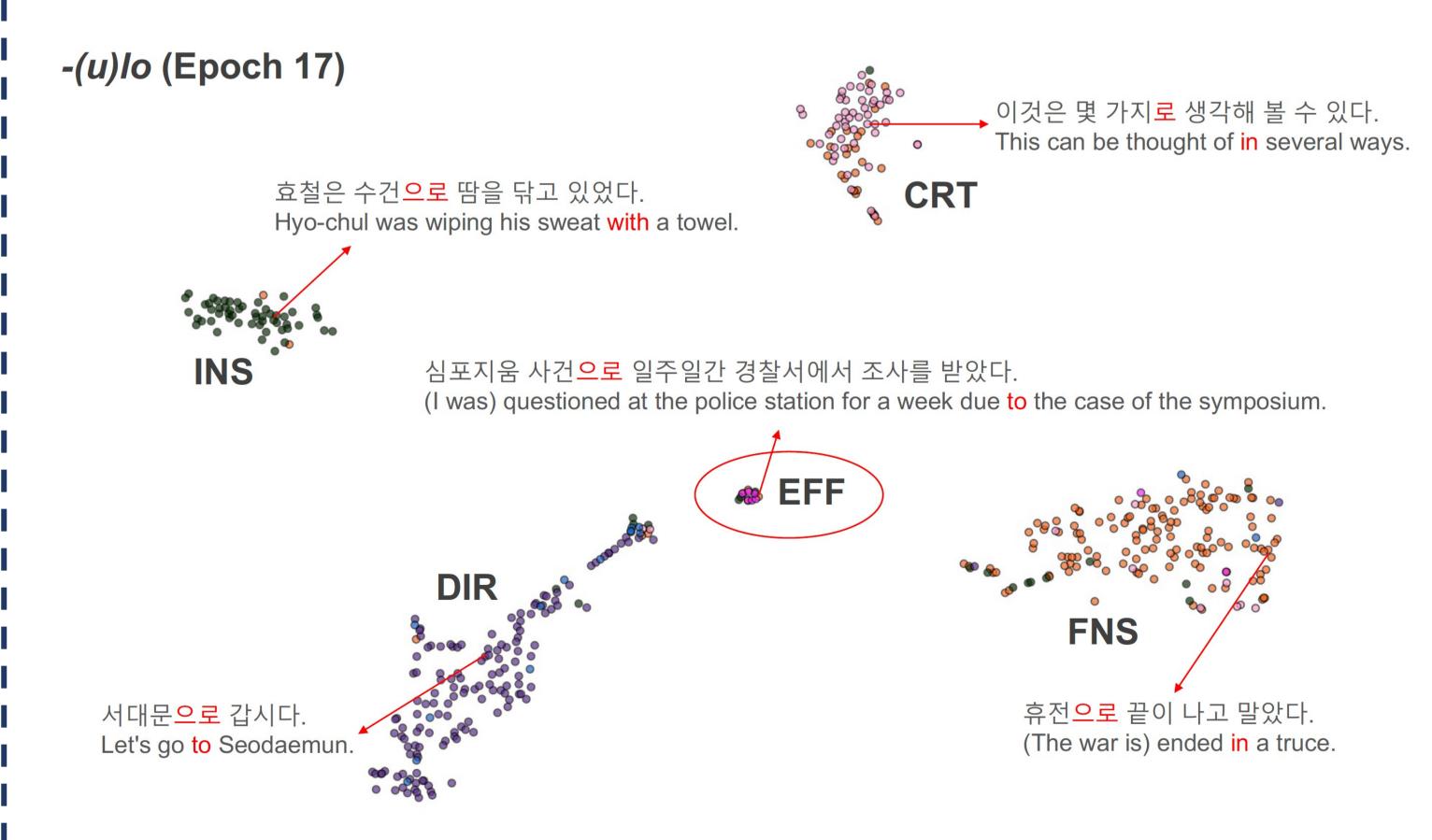


Figure 2: The t-SNE outcome of BERT model for -(u)lo in Epoch 17

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