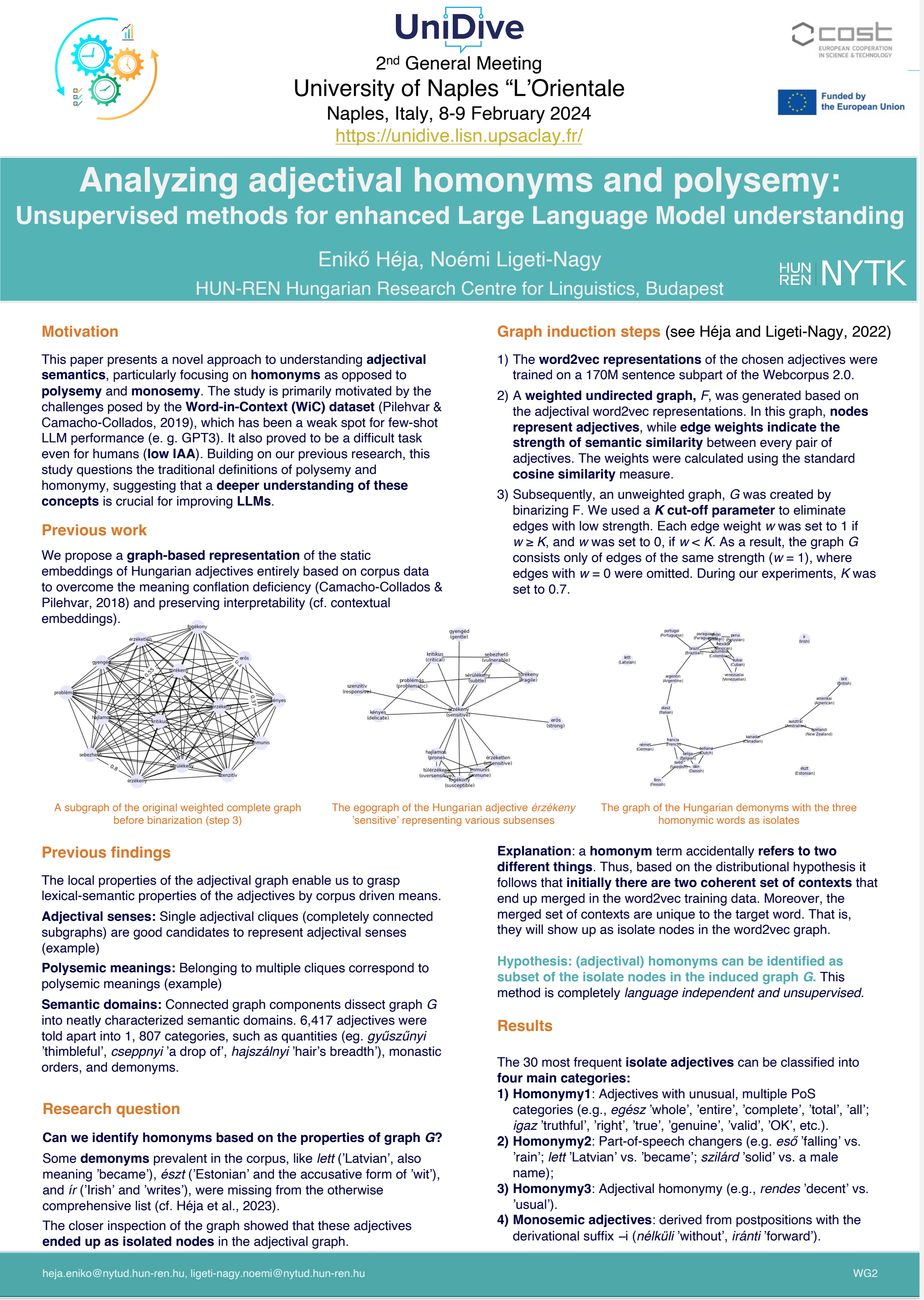
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Analyzing adjectival homonyms and polysemy:
Unsupervised methods for enhanced Large Language Model understanding

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Motivation

This paper presents a novel approach to understanding **adjectival semantics**, particularly focusing on **homonyms** as opposed to **polysemy** and **monosemy**. The study is primarily motivated by the challenges posed by the **Word-in-Context (WiC) dataset** (Pilehvar & Camacho-Collados, 2019), which has been a weak spot for few-shot LLM performance (e. g. GPT3). It also proved to be a difficult task even for humans (**low IAA**). Building on our previous research, this study questions the traditional definitions of polysemy and homonymy, suggesting that a **deeper understanding of these concepts** is crucial for improving **LLMs**.

Previous work

We propose a **graph-based representation** of the static embeddings of Hungarian adjectives entirely based on corpus data to overcome the meaning conflation deficiency (Camacho-Collados & Pilehvar, 2018) and preserving interpretability (cf. contextual embeddings).

Graph induction steps (see Héja and Ligeti-Nagy, 2022)

1) The **word2vec representations** of the chosen adjectives were trained on a 170M sentence subpart of the Webcorpus 2.0.
2) A **weighted undirected graph**, *F*, was generated based on the adjectival word2vec representations. In this graph, **nodes represent adjectives**, while **edge weights indicate the strength of semantic similarity** between every pair of adjectives. The weights were calculated using the standard **cosine similarity** measure.
3) Subsequently, an unweighted graph, *G* was created by binarizing F. We used a ***K* cut-off parameter** to eliminate edges with low strength. Each edge weight *w* was set to 1 if $w \geq K$, and *w* was set to 0, if $w < K$. As a result, the graph *G* consists only of edges of the same strength ($w = 1$), where edges with $w = 0$ were omitted. During our experiments, *K* was set to 0.7.

A subgraph of the original weighted complete graph before binarization (step 3)

The egograph of the Hungarian adjective *érzékeny* 'sensitive' representing various subsenses

The graph of the Hungarian demonyms with the three homonymic words as isolates

Previous findings

The local properties of the adjectival graph enable us to grasp lexical-semantic properties of the adjectives by corpus driven means.

Adjectival senses: Single adjectival cliques (completely connected subgraphs) are good candidates to represent adjectival senses (example)

Polysemic meanings: Belonging to multiple cliques correspond to polysemic meanings (example)

Semantic domains: Connected graph components dissect graph *G* into neatly characterized semantic domains. 6,417 adjectives were told apart into 1, 807 categories, such as quantities (eg. *gyűszűnyi* 'thimbleful', *cseppnyi* 'a drop of', *hajszálnyi* 'hair's breadth'), monastic orders, and demonyms.

Research question

Can we identify homonyms based on the properties of graph *G*?

Some **demonyms** prevalent in the corpus, like *lett* ('Latvian', also meaning 'became'), *észt* ('Estonian' and the accusative form of 'wit'), and *ír* ('Irish' and 'writes'), were missing from the otherwise comprehensive list (cf. Héja et al., 2023).

The closer inspection of the graph showed that these adjectives **ended up as isolated nodes** in the adjectival graph.

Explanation: a **homonym** term accidentally **refers to two different things**. Thus, based on the distributional hypothesis it follows that **initially there are two coherent set of contexts** that end up merged in the word2vec training data. Moreover, the merged set of contexts are unique to the target word. That is, they will show up as isolate nodes in the word2vec graph.

Hypothesis: (adjectival) homonyms can be identified as subset of the isolate nodes in the induced graph *G*. This method is completely *language independent and unsupervised.*

Results

The 30 most frequent **isolate adjectives** can be classified into **four main categories:**

1) **Homonymy1**: Adjectives with unusual, multiple PoS categories (e.g., *egész* 'whole', 'entire', 'complete', 'total', 'all'; *igaz* 'truthful', 'right', 'true', 'genuine', 'valid', 'OK', etc.).
2) **Homonymy2**: Part-of-speech changers (e.g. *eső* 'falling' vs. 'rain'; *lett* 'Latvian' vs. 'became'; *szilárd* 'solid' vs. a male name);
3) **Homonymy3**: Adjectival homonymy (e.g., *rendes* 'decent' vs. 'usual').
4) **Monosemic adjectives**: derived from postpositions with the derivational suffix –i (*nélküli* 'without', *iránti* 'forward').

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WG2

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- **Unsupervised graph-based** method
- **Adjectival** semantics: homonymy (previous study: polysemy)
- **Homonyms** appear as isolate nodes in the graph; 4 distinct categories
- **Language-independent**