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# Improving word mover's distance by leveraging self-attention matrix

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EMNLP 2023 Findings

# Housekeeping

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## Materials:

- Paper: <https://arxiv.org/abs/2211.06229>
- Code: <https://github.com/ymgw55/WSMD>
- Slides: <https://ymgw55.github.io/publication/wsmd/slides.pdf>
- Poster: <https://ymgw55.github.io/publication/wsmd/poster.pdf>

Paper



Code



Slides



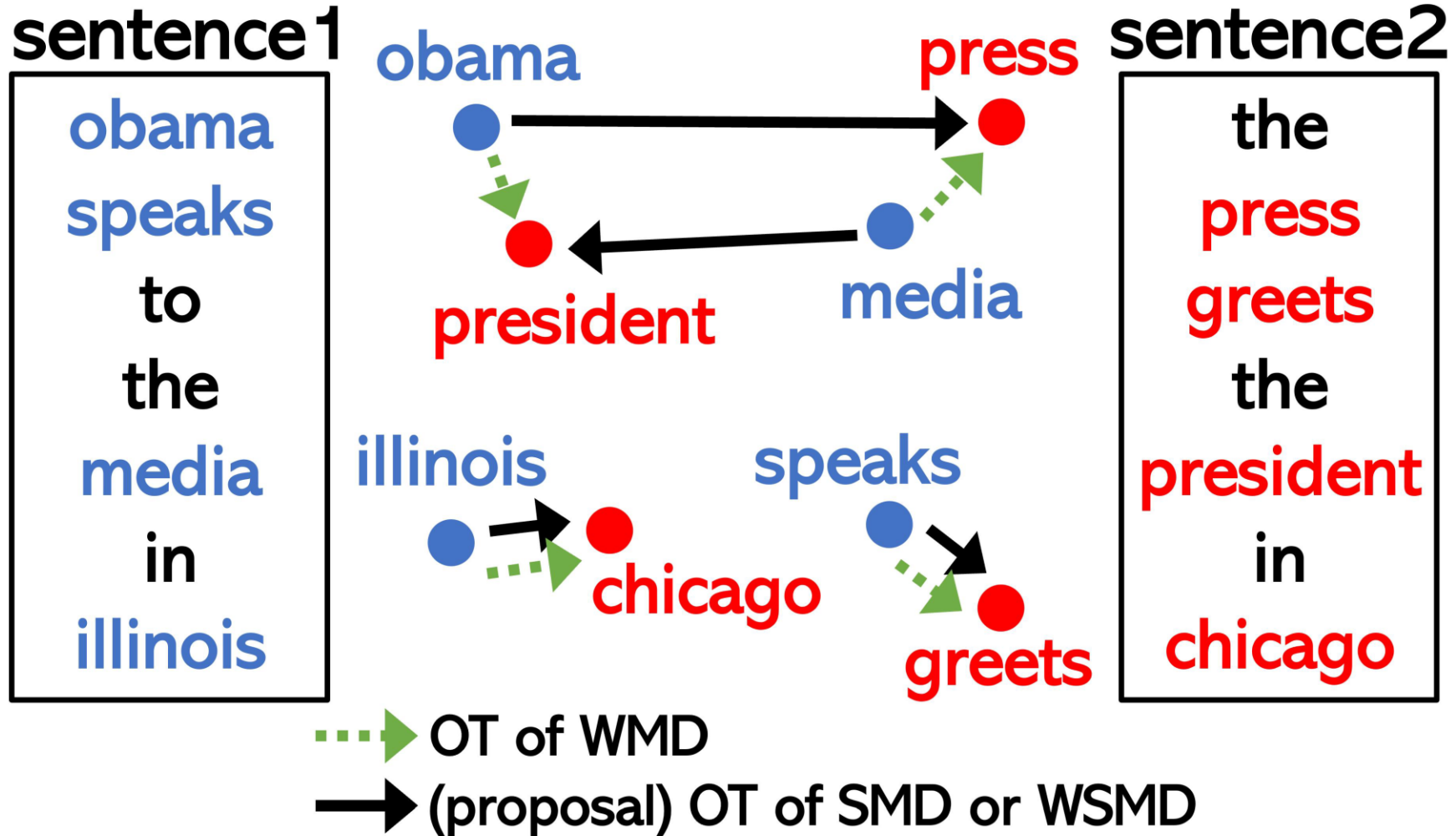
Poster



# Summary

- **Word Mover's Distance (WMD)** [1] uses the **Wasserstein distance** to measure semantic textual similarity.
- **WMD cannot deal with the order of words** within a sentence.
- We propose the **Word and sentence Structure Mover's Distance (WSMD)** that **can** address this limitation.

# WMD vs. WSMD

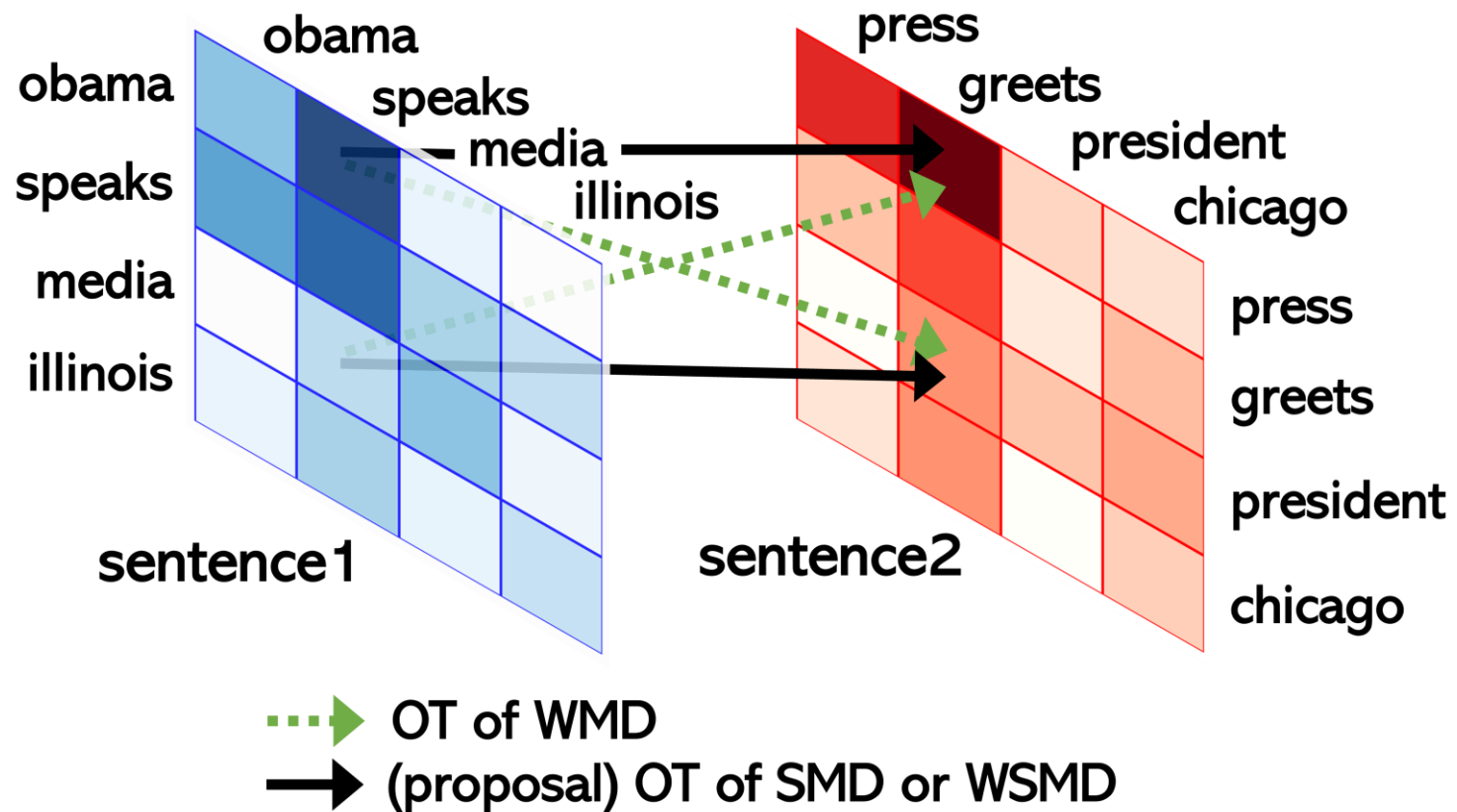


# Approach

- Use the **Self-Attention Matrix (SAM)** from BERT-based models as **structure information**.
- Combine **WMD** and **SAM** using the **Fused Gromov-Wasserstein distance** [2].

# Self-Attention Matrix

- Both pairs, (obama, speaks) and (press, greets), show a high attention weight.



# Proposed Method

- Let  $A$  and  $A'$  be the **SAMs** for sentences  $s$  and  $s'$ .
- Define the **Word and sentence Structure Mover's Distance (WSMD)** as follows:

$$\text{WSMD}((s, A), (s', A')) = \min_{P \in \Pi(u, u')} \sum_{i, j, i', j'} \left\{ (1 - \lambda) C_{ij} + \lambda k |A_{ii'} - A'_{jj'}|^2 \right\} P_{ij} P_{i'j'}$$

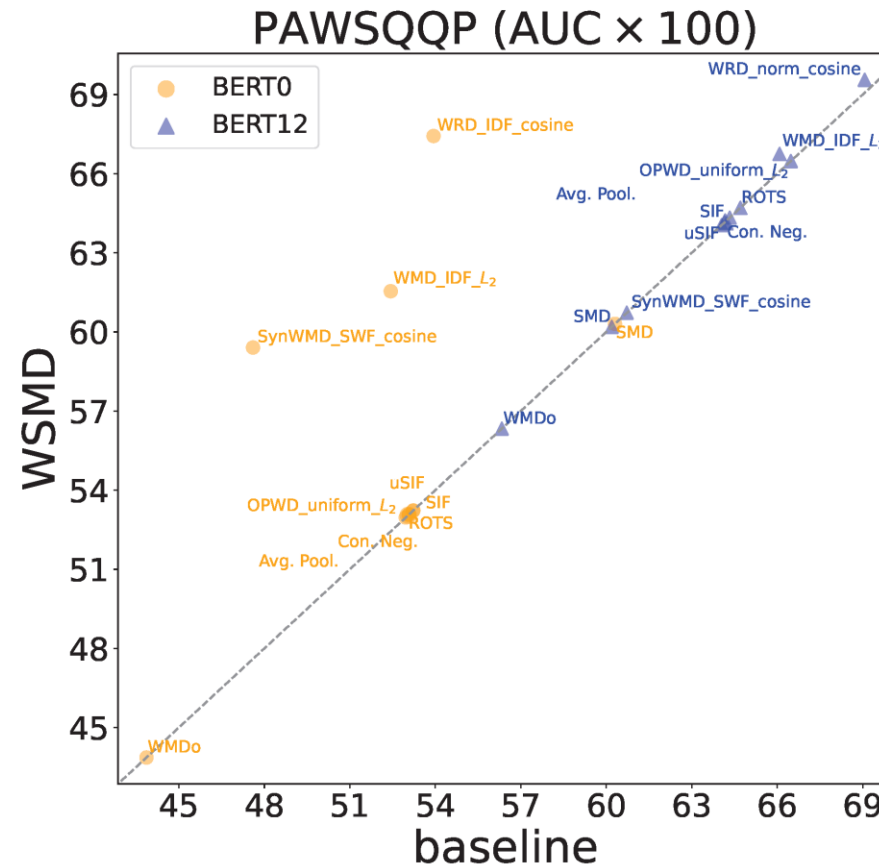
**Normalization parameter**

**Wasserstein**      **Gromov-Wasserstein**

**Fused Gromov-Wasserstein**

# Results

- We used the PAWS [3] dataset for paraphrase identification.
- **WSMD** was effective for **WMD-like** methods such as **WMD**, **WRD**, and **SynWMD**.



The values above the diagonal line show the performance improvement by WSMD.



# References

1. Matt J. Kusner, Yu Sun, Nicholas I. Kolkin, and Kilian Q. Weinberger. 2015. *From word embeddings to document distances*. ICML.
2. Titouan Vayer, Nicolas Courty, Romain Tavenard, Laetitia Chapel, and Rémi Flamary. 2019. *Optimal transport for structured data with application on graphs*. PMLR.
3. Yuan Zhang, Jason Baldridge, and Luheng He. 2019. *PAWS: Paraphrase adversaries from word scrambling*. NAACL.