Summary of Research & Future Directions

Nisansa de Silva
Department of Computer Science & Engineering,
University of Moratuwa

Summary of Research & Future Directions

- Dissertation:

  “Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language”

- SigmaLaw Project
- Sinhala NLP
- Future Directions

Summary of Research & Future Directions

- **Dissertation:**

  "Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language"

- SigmaLaw Project
- Sinhala NLP
- Future Directions

Dissertation Question

"Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language"

How can we convert the linguistic concept of semantic oppositeness to the computing domain?

Semantic Oppositeness

versus

Synonyms & Antonyms

- Boolean relationship

- Expand is a synonym of increase: True
- Expand is an antonym of increase: False

- Decrease is a synonym of increase: False
- Decrease is an antonym of increase: True

- Change is a synonym of increase: False
- Change is an antonym of increase: False

Similarity & Oppositeness

- Numerical relationship

- Similarity of expand and increase: 0.80
- Oppositeness of expand and increase: ??

- Similarity of decrease and increase: 0.75
- Oppositeness of decrease and increase: ??

- Similarity of change and increase: 0.46
- Oppositeness of change and increase: ??

[1] Mettinger, A.: Aspects of Semantic Opposition in English. Oxford University Press, New York (1994)
[2] Schimmack, U.: Pleasure, displeasure, and mixed feelings: are semantic opposites mutually exclusive? Cogn. Emotion 15(1), 881–97 (2001)

Minimal Difference with Maximal Similarity Principle

"Shared commonalities magnify the impact or the degree of oppositeness which exists between words."

- Caesar: { Casssius, Casca, Brutus }
- Increase: { Expand, Change, Decrease }

[3] Clark, E. V.: On the child's acquisition of antonyms in two semantic fields. Journal of Verbal Learning and Verbal Behavior **11**(6), 750–758 (1972)
[4] Cruse, D. A.: Lexical Semantics, Cambridge University Press (1986)
[5] Lyons, J.: Semantics. 1, Cambridge University Press (1987)
[6] Murphy, M. L.: Semantic relations and the lexicon: Antonymy, synonymy and other paradigms, Cambridge University Press (2003)
[7] Jones, S.: Antonymy: A Corpus-Based Perspective. Routledge (2003)

Irrelevancy Principle

"Only a subset of words which exist in the vocabulary will feature on the oppositeness scale of a given word. The rest of the words are deemed irrelevant."

- *Does not reduce oppositeness to antonymy.*
- Increase: { Expand, Change, Decrease, Cat }

[6] Murphy, M. L.: Semantic relations and the lexicon: Antonymy, synonymy and other paradigms, Cambridge University Press (2003)
[8] Murphy, M. L., Jones, S. & Koskela, A.: Signals of contrastiveness: But, oppositeness, and formal similarity in parallel coontexts, Journal of English Linguistics, **43**(3), 227–249 (2015)
[9] Jones, S., Murphy, M. L., Paradis, C. & Willners, C.: Antonyms in English: Construals, Constructions and Canonicity. Cambriidge University Press (2012)
[10] Lobanova, G. V.: The anatomy of antonymy: A corpus-driven approach. University of Groningen The Netherlands (2012)
[11] Charles, W. G. & Miller, G. A.: Contexts of Antonymous Adjectives. Applied Psycholinguistics, 10 (3), 357–375 (1989)

Semantic Oppositeness Measure

- Example words

increase

cat

expand

change

decrease

[12] de Silva, N., Dou, D. & Huang, J.: Discovering Inconsistencies in PubMed Abstracts through Ontology-Based Information Extraction. In. Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics, 2017, pp. 362–371
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- Example words

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Semantic Oppositeness Measure

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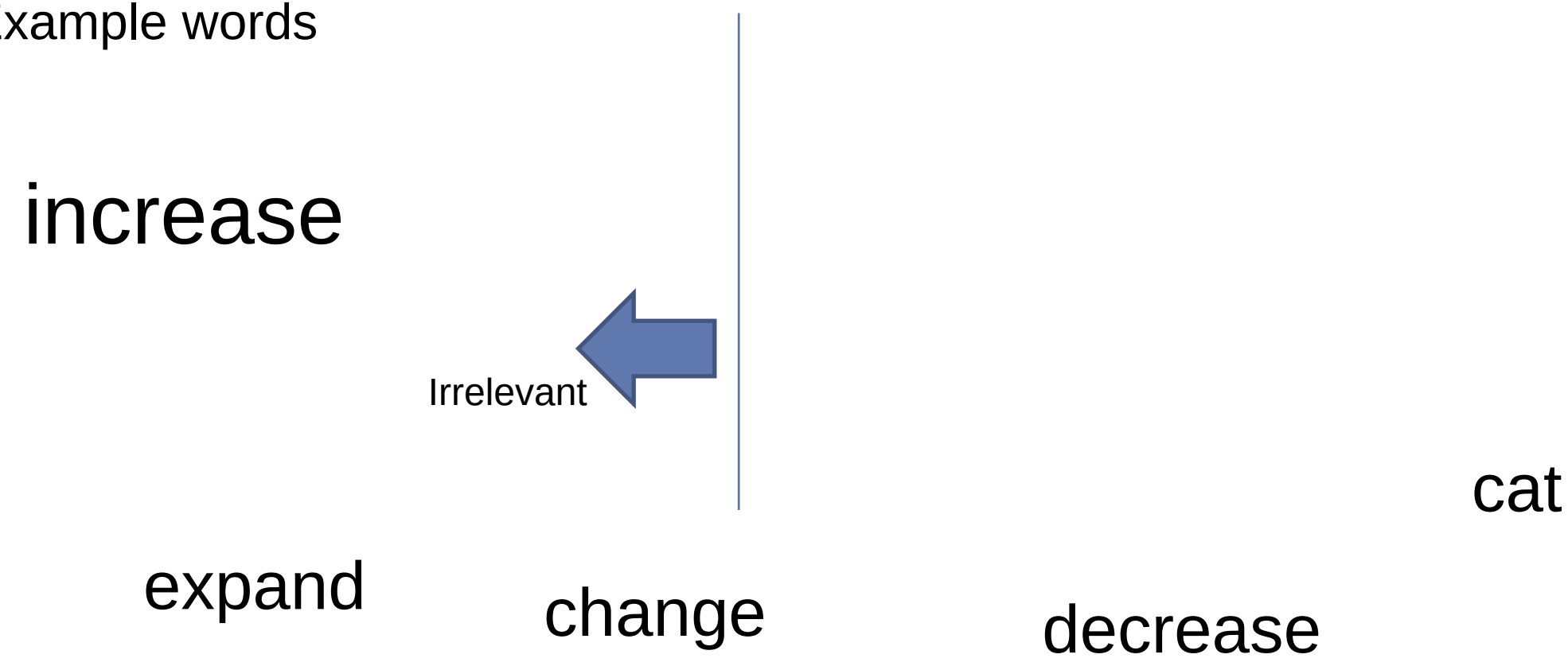

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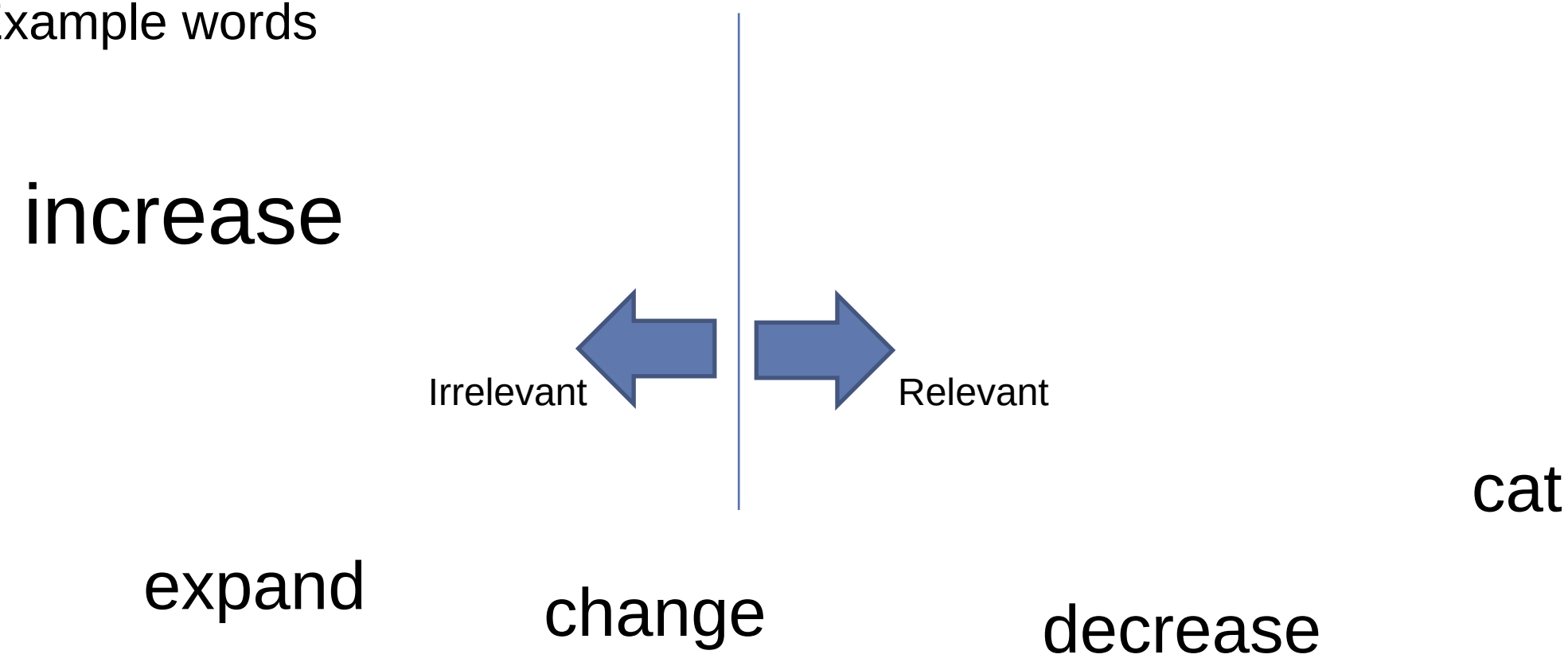

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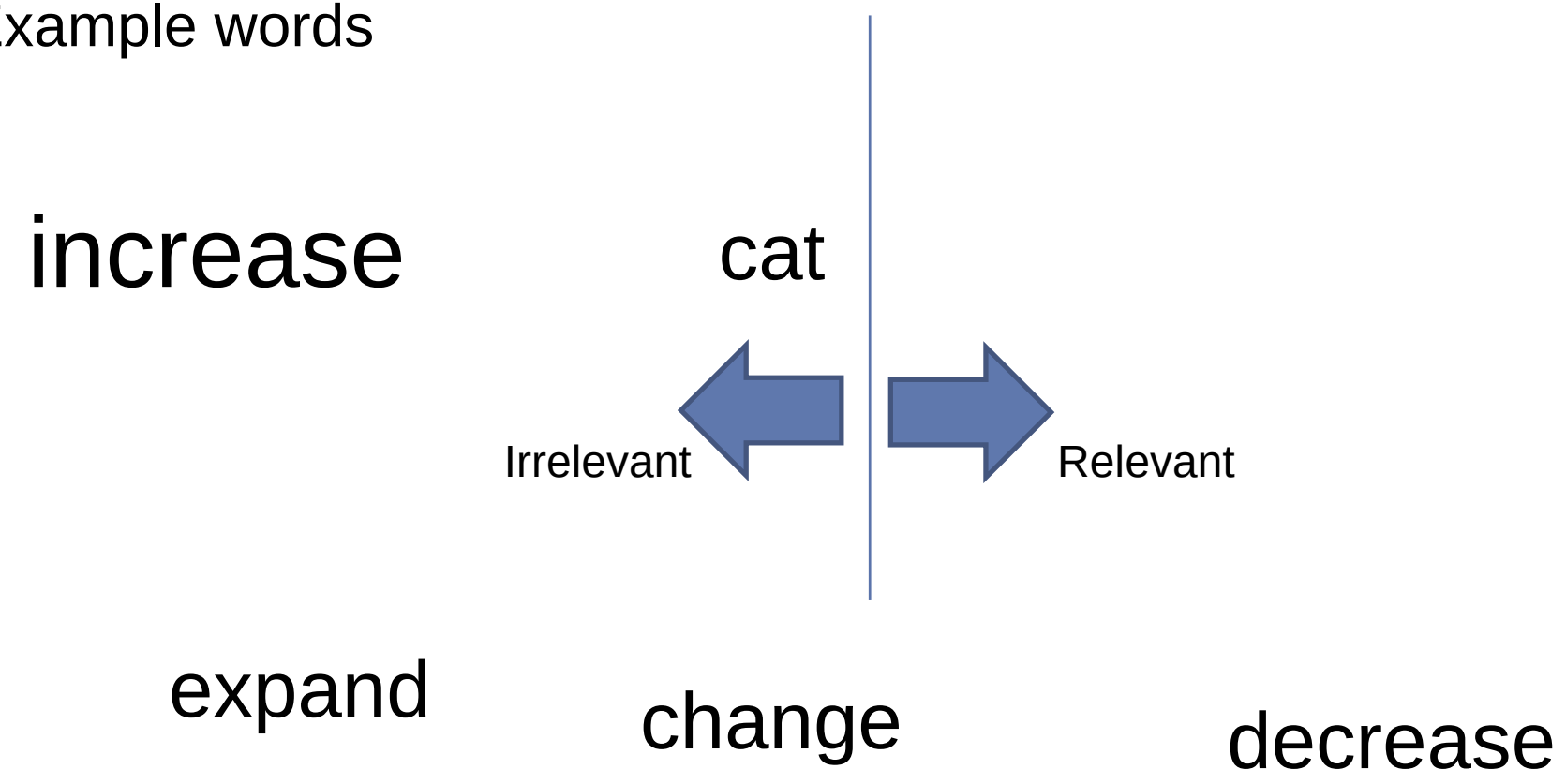

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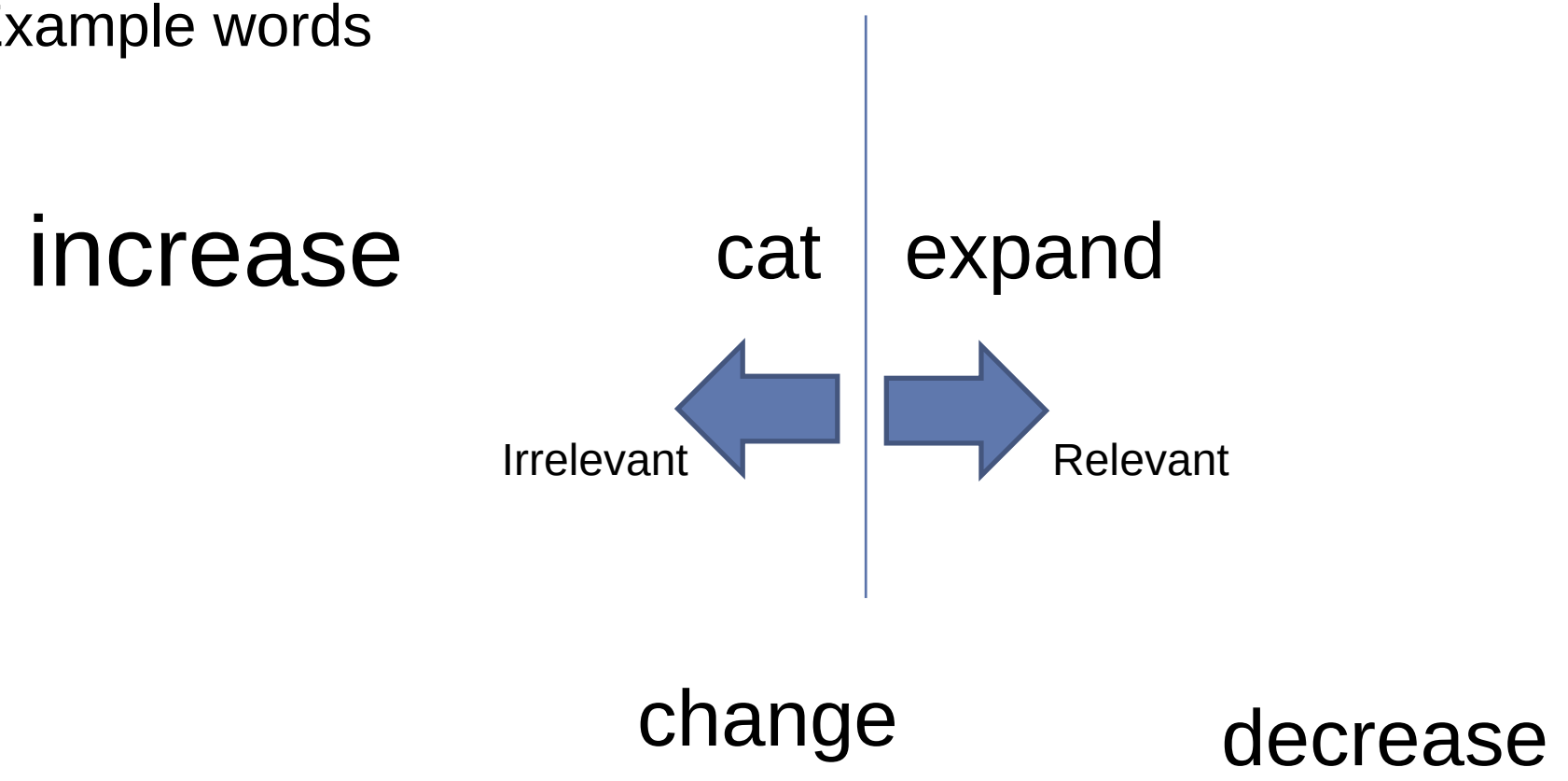

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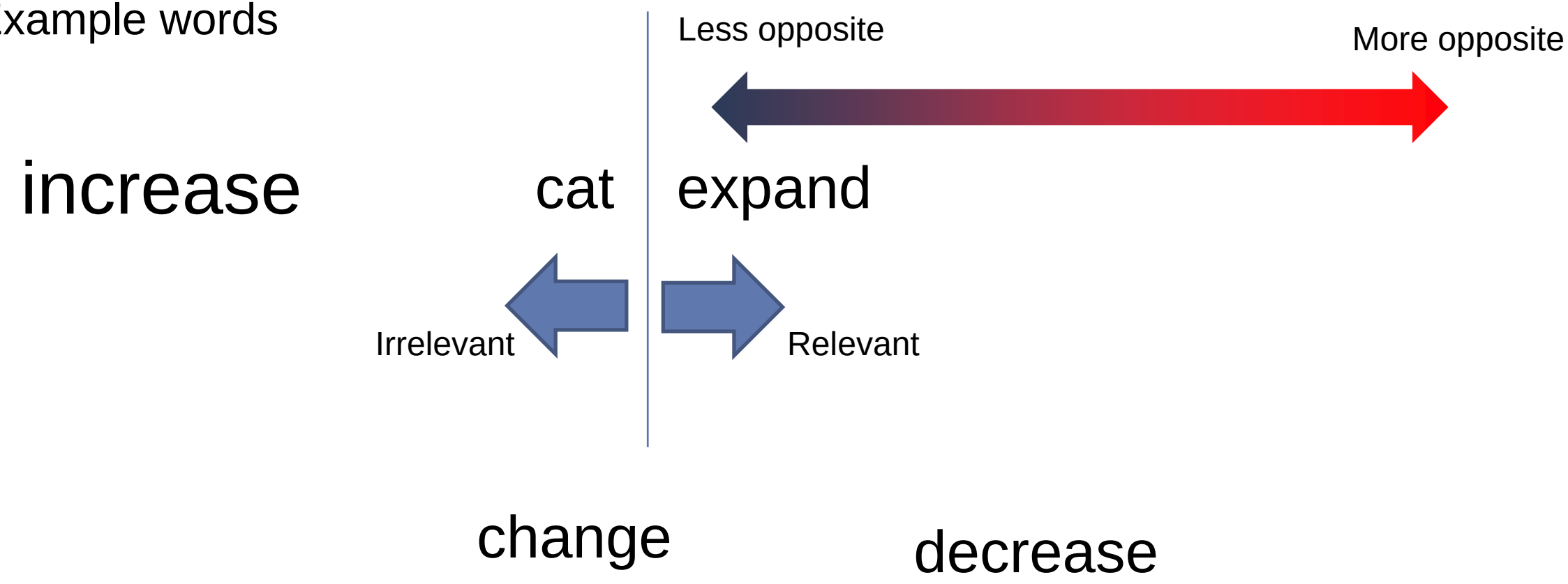

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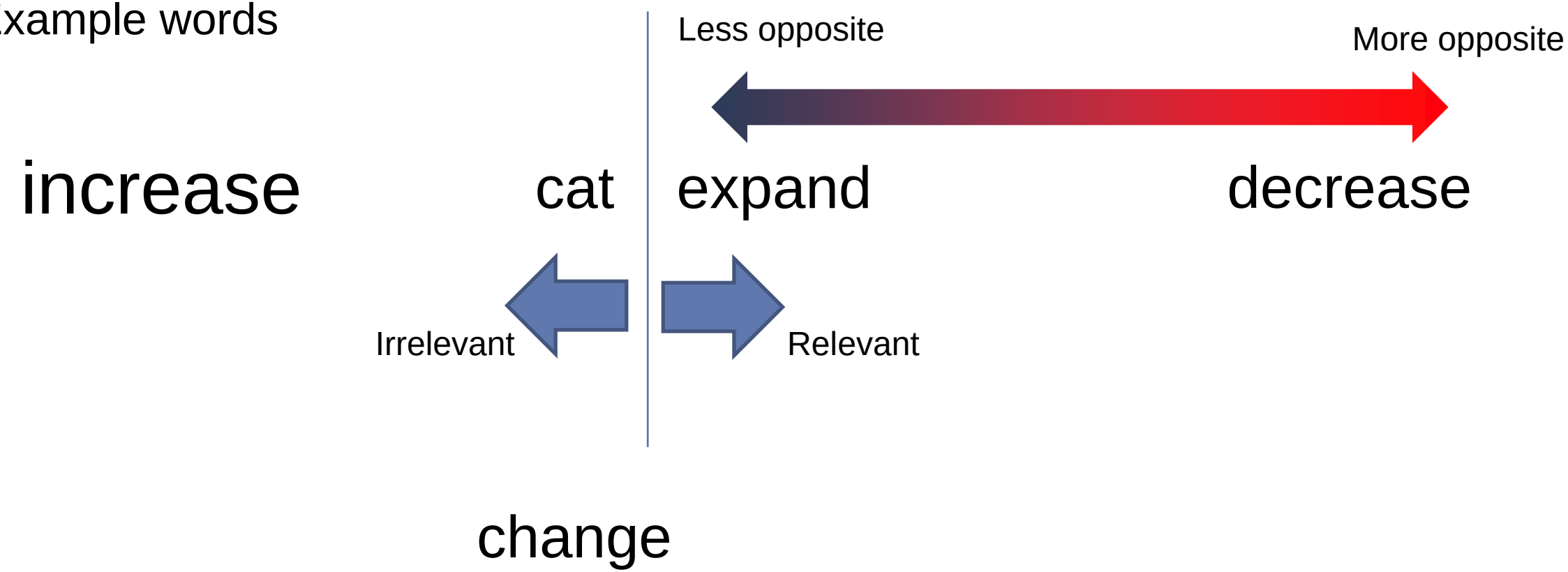

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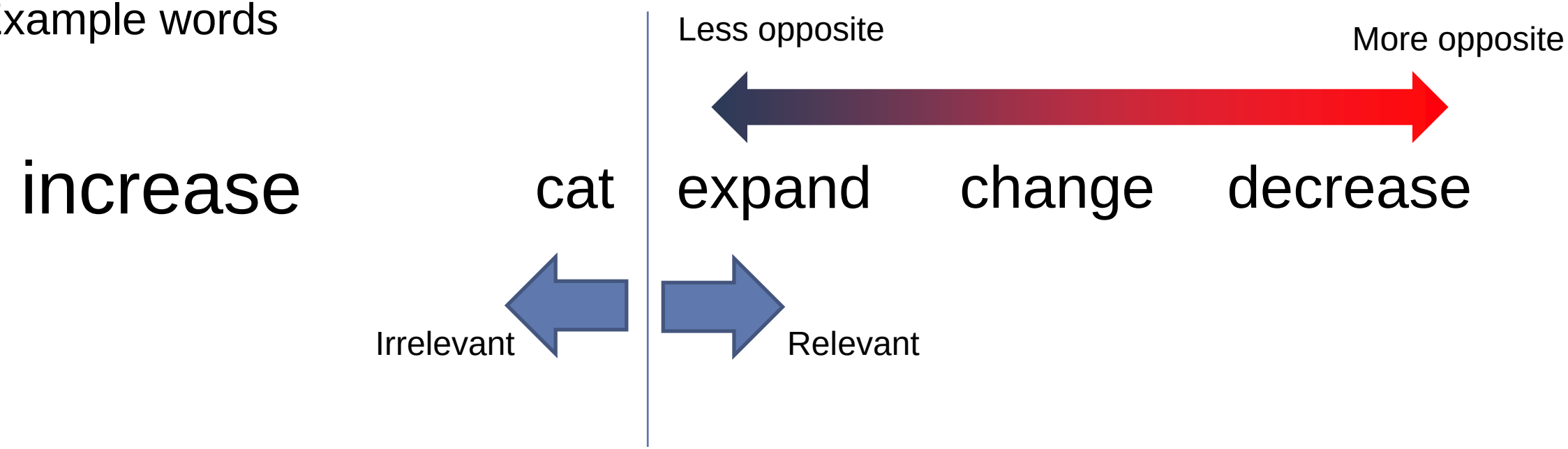

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Semantic Oppositeness Measure

$$reldif_{w_1,w_2} = \underset{(i,j)\epsilon P}{\text{avg}} \left[\underset{a_k \epsilon A_i}{\text{argmax}} \left(sim\left(L_j, a_k\right) \right) \right]$$

$$oppo\_ori_{w_1,w_2} = reldif_T^{\left(K * sim_{w_1,w_2} + 1\right)}$$

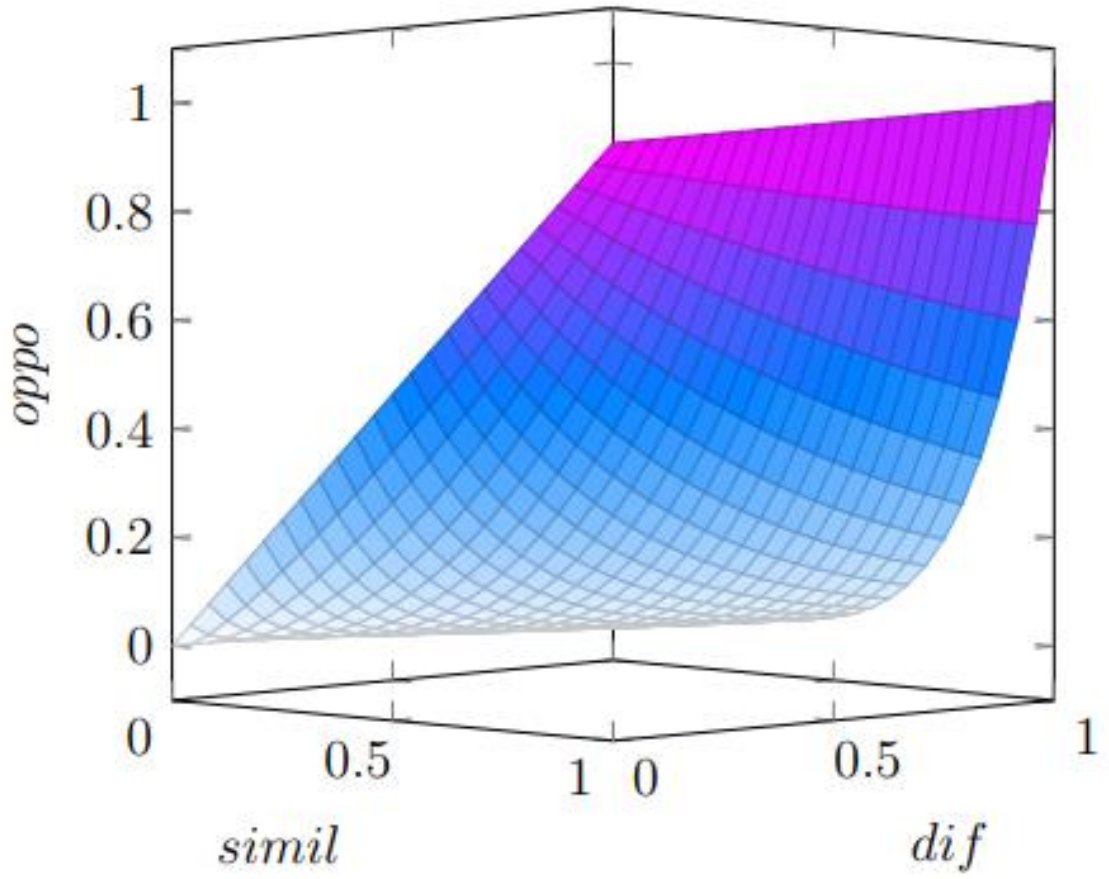
$$oppo\_nai_{w_1,w_2} = \left(1 - sim_{w_1,w_2}\right)$$

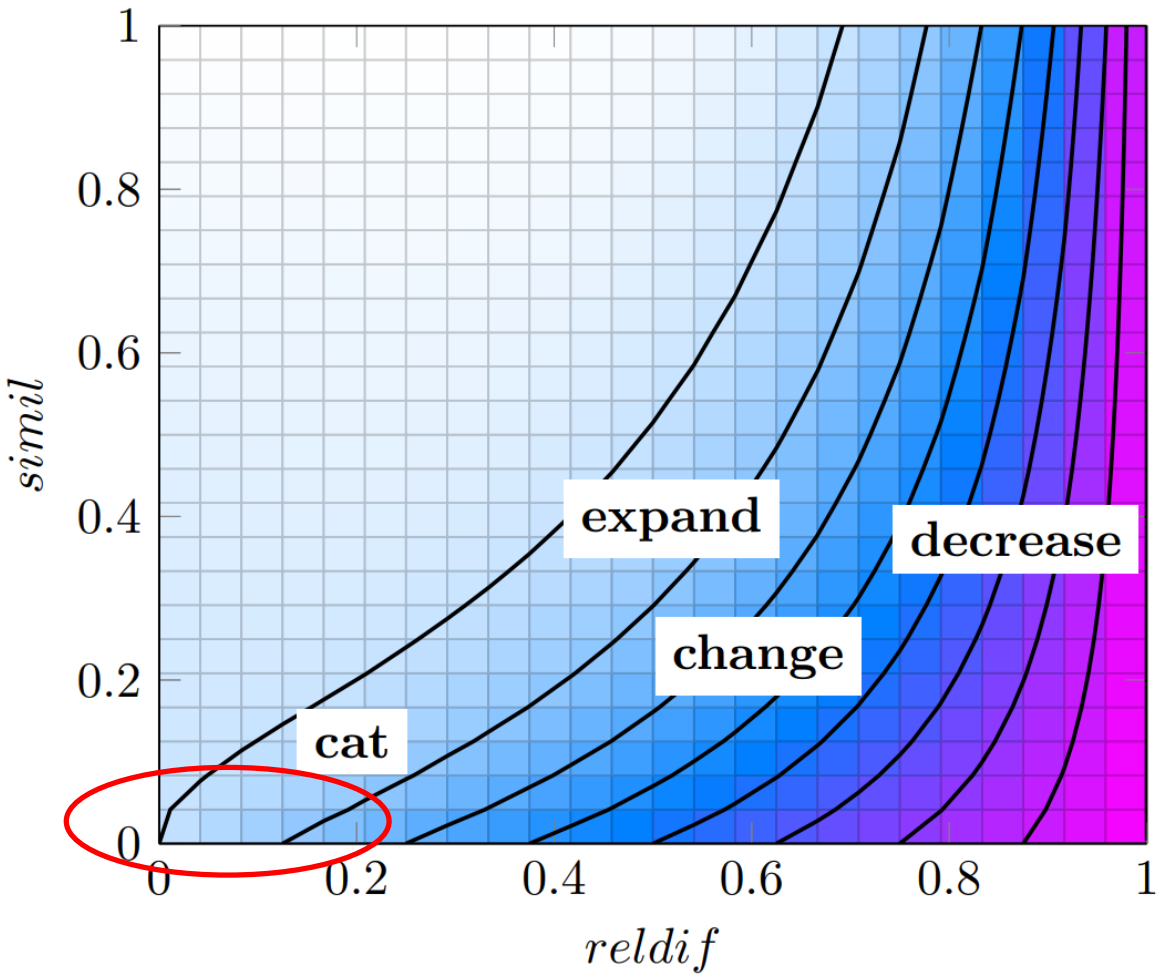
$$oppo_{w_1,w_2} = \alpha * oppo\_ori_{w_1,w_2} + (1 - \alpha)\left(1 - reldif_{w_1,w_2}\right) * oppo\_nai_{w_1,w_2}$$

$$I_{w_1} = \underset{simil_{w_1,w_i}, w_i \in W}{\arg\max} \left(oppo(w_1, w_i) \right)$$

[14] de Silva, N. & Dou, D.: Semantic Oppositeness Embedding Using an Autoencoder-based Learning Model. 30th International Conference on Database and Expert Systems Applications, pp. 159–174 (2019)

Semantic Oppositeness Measure





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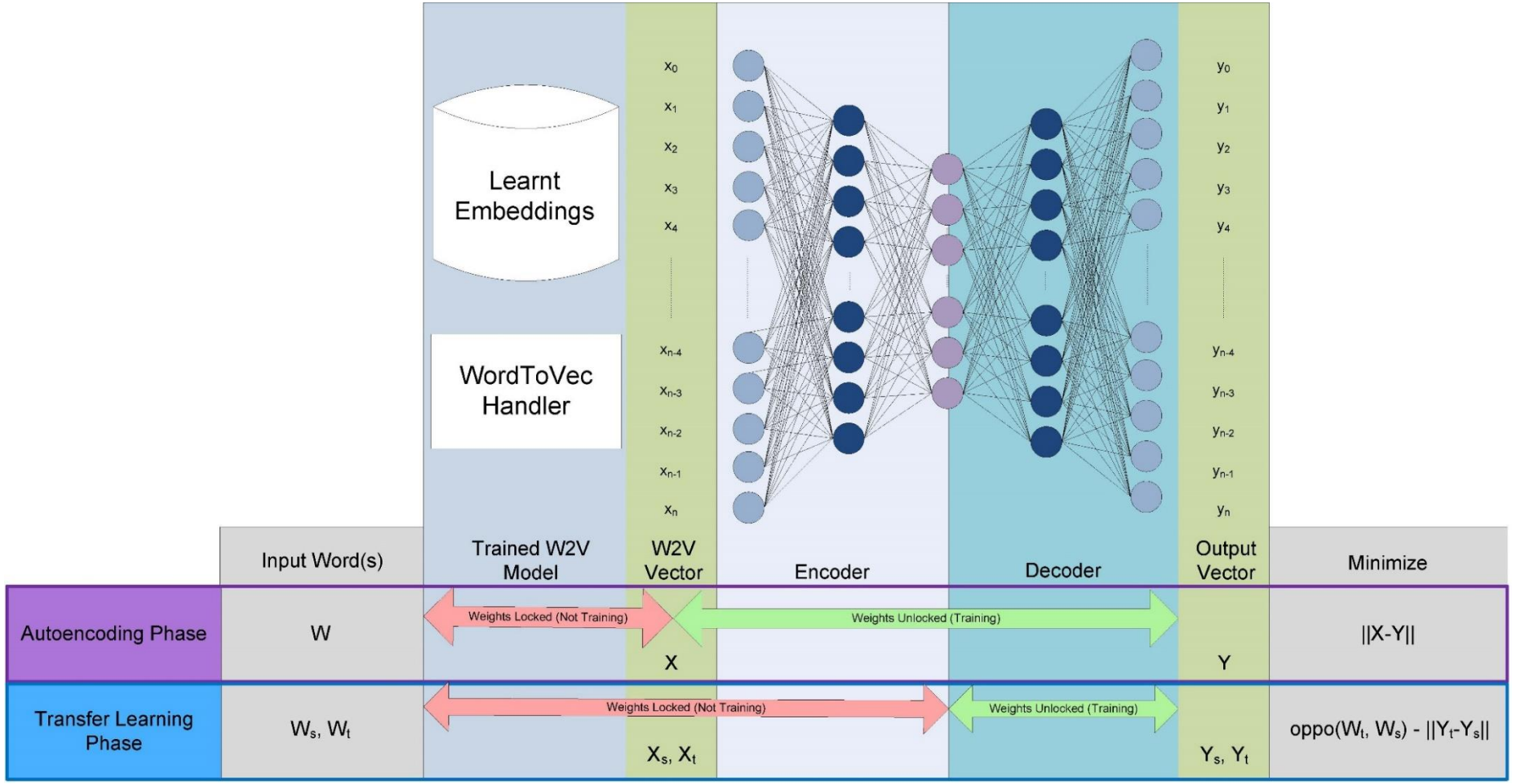
Embedding Semantic Oppositeness : Autoencoder-Based Learning



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Dissertation Question

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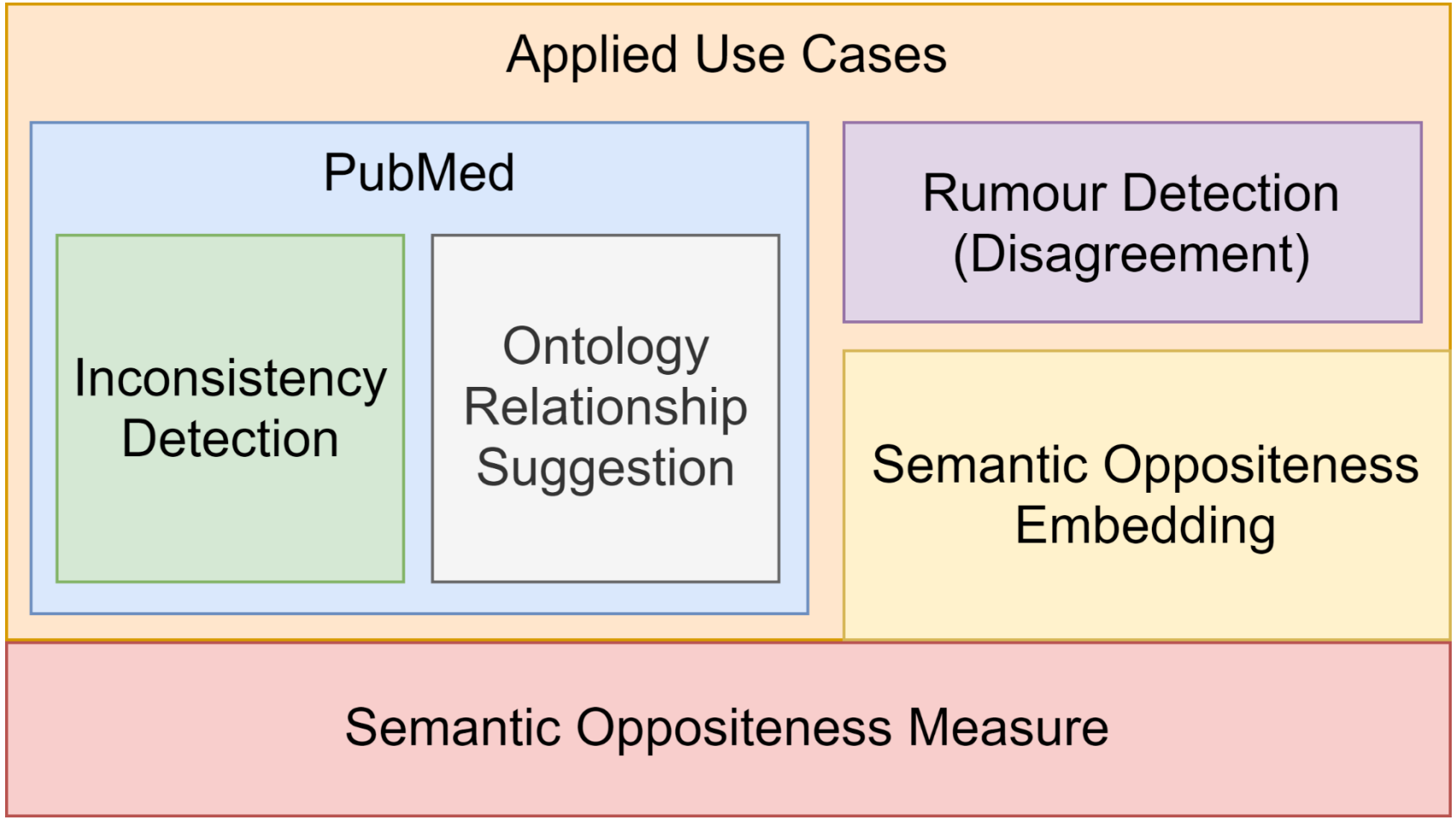
How can we convert the linguistic concept of semantic oppositeness to the computing domain?

Overall Structure



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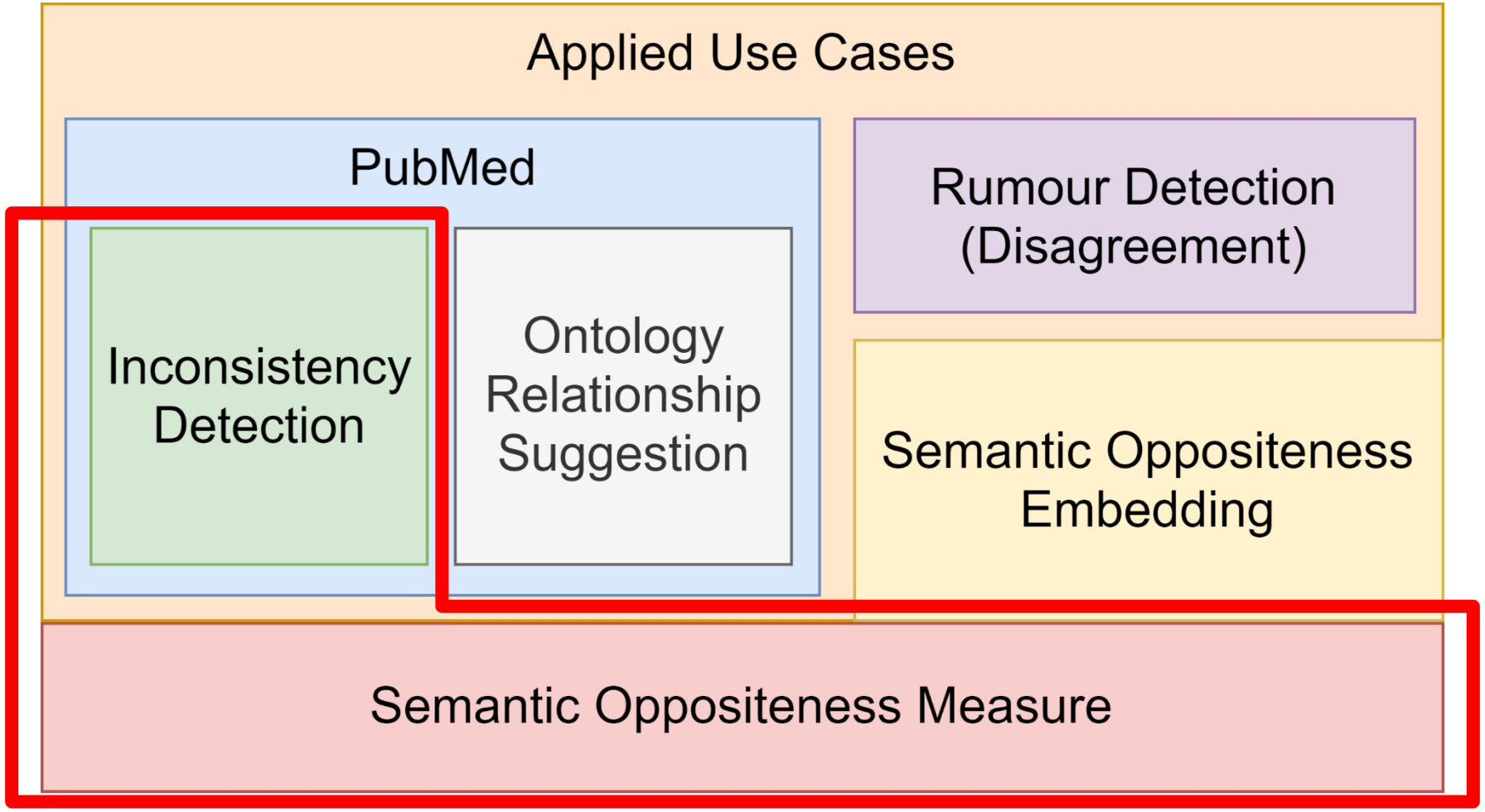

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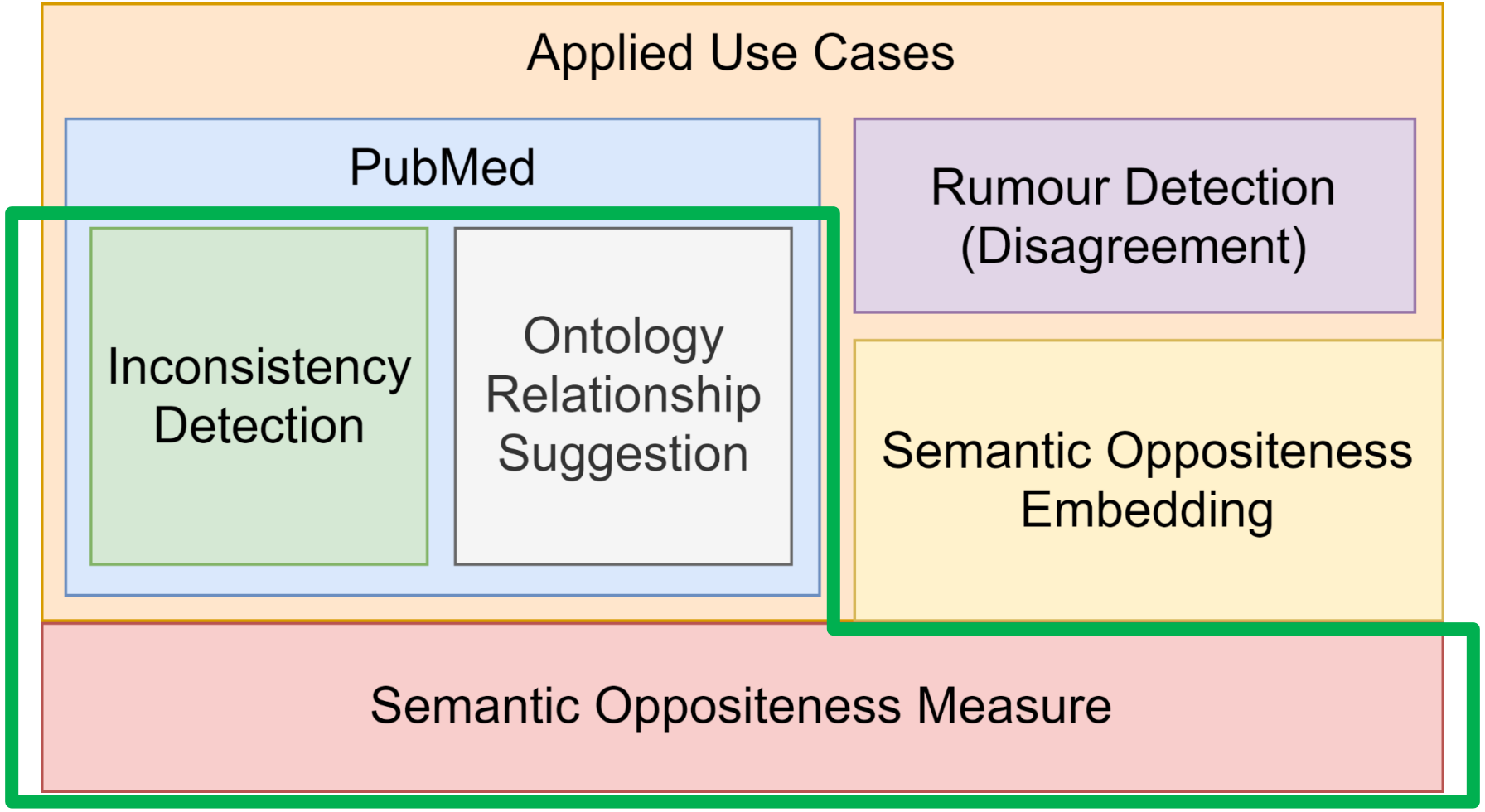

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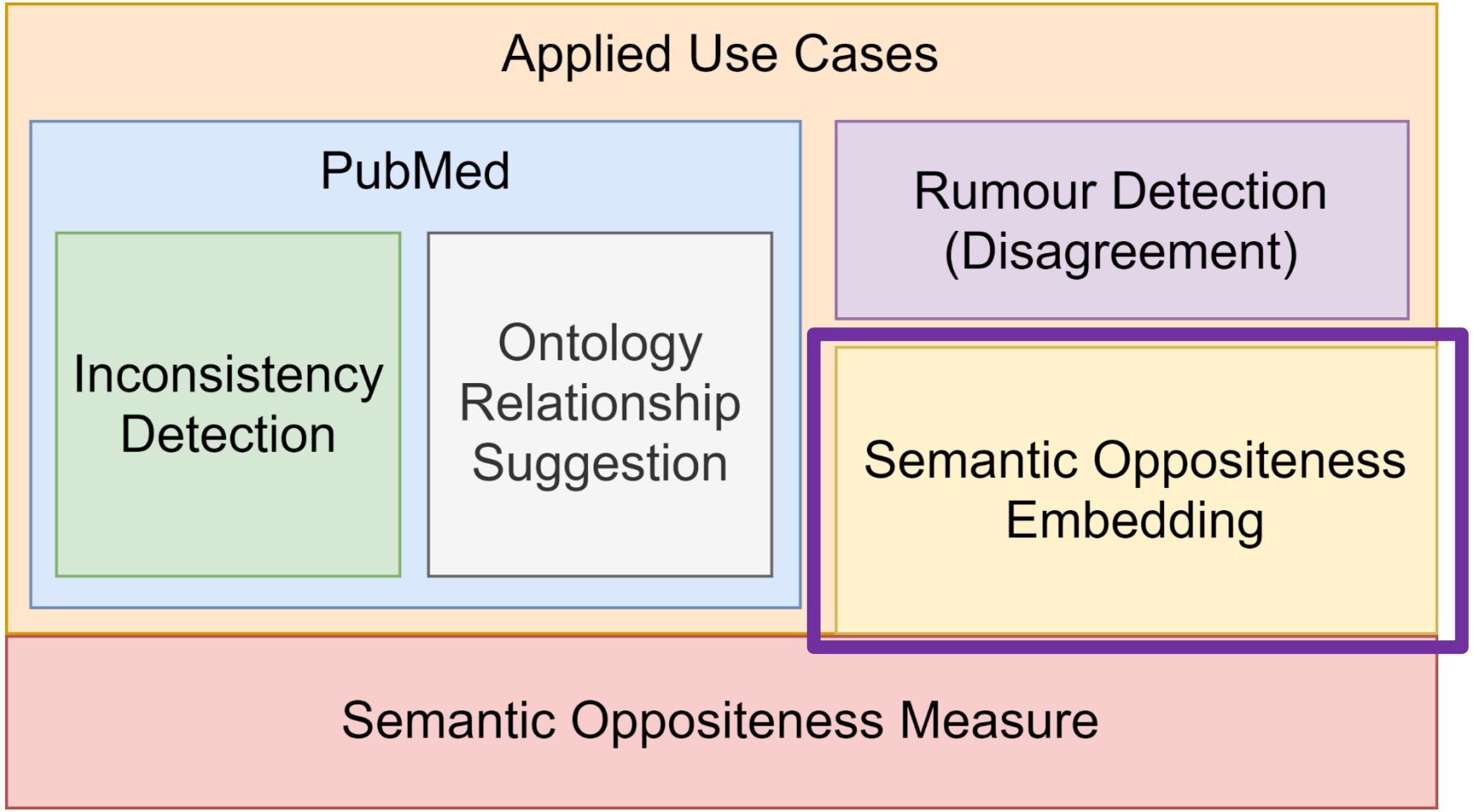

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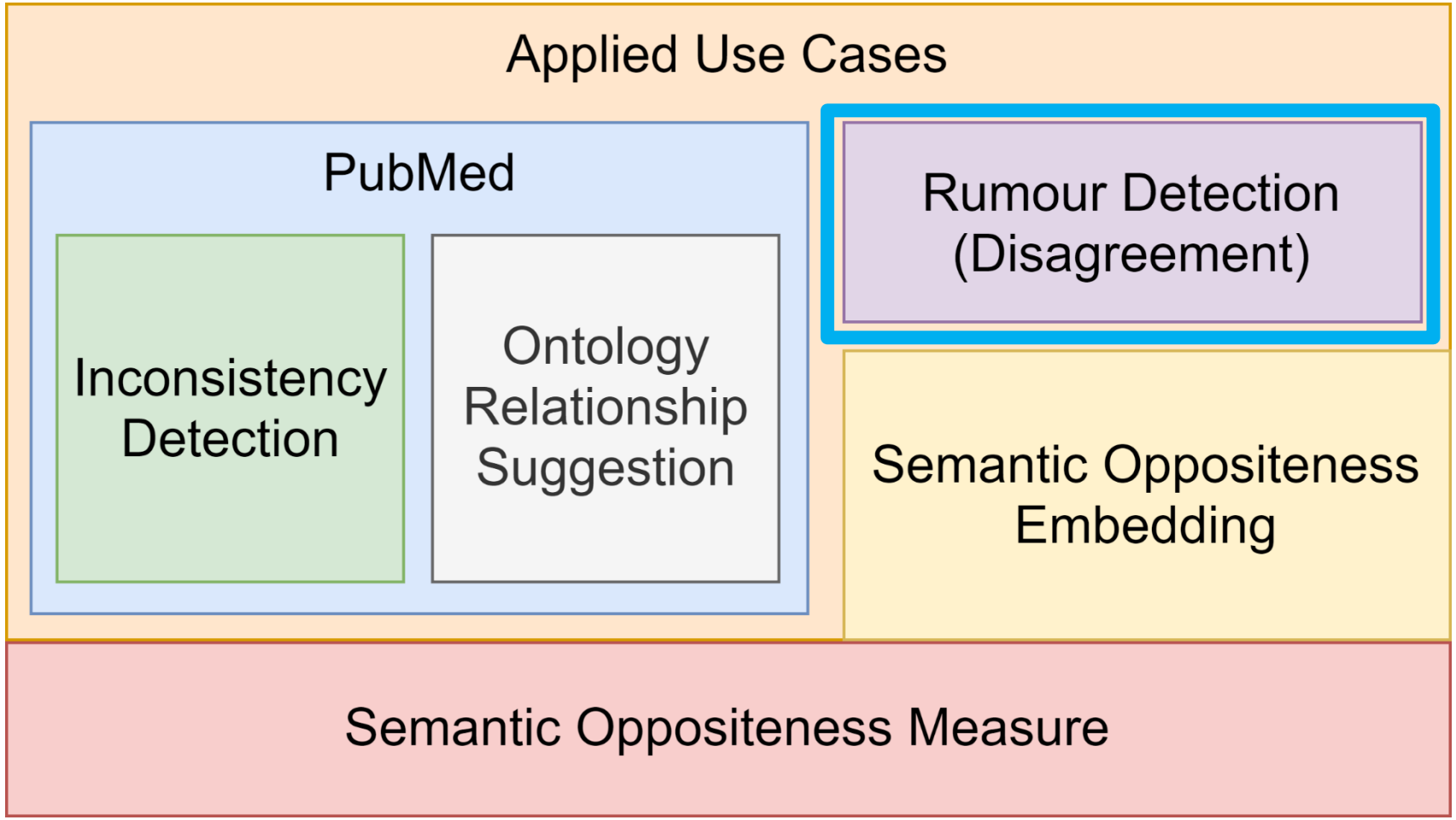

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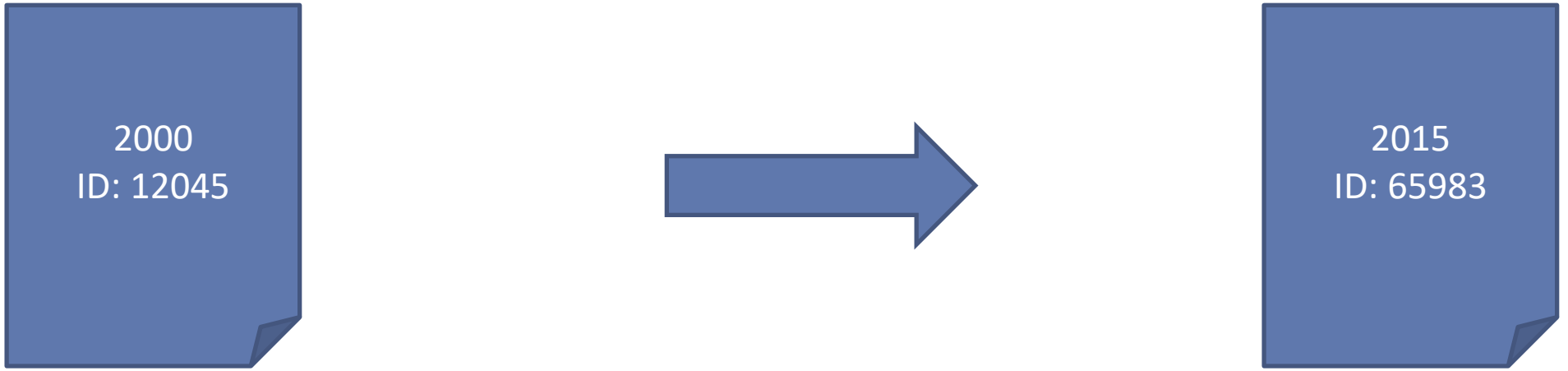
How Does Scientific Progress Happen?



We found that miR-125b promotes myeloid and B-cell neoplasm by inducing tumorigenesis in hematopoietic progenitor cells.

Despite past claims, we found no proof that miR-125b promotes B-cell neoplasm.

(miR-125b ; promotes ; B-cell neoplasm)

(miR-125b ; not promote ; B-cell neoplasm)

65983 contradicts 12045

Results for Inconsistency Use Case

- The PubMedID extraction step extracted 39,149 relevant abstract IDs.
- 36,877 were processed and downloaded (94.2%).
- 67,481 unique subject-object pairings.

Inconsistency Finding	Relationship Finding
▪ 503 total contradictions – Involved 224 out of the 36,877 downloaded abstracts. (0.61%) ▪ 102 miRNA contradictions – 89 deemed reasonable by human. (87.25% Precision) – Only 20.28% of the 503 total contradictions. – Involved 95 out of the 36,877 downloaded abstracts. (0.26%)	• 4443 subject-object pairs – 6.58% of the total 67,481 yielded potential relationships • 636 miRNA relationships – 36.82% of the suggested 4443 potential relationships – 2.42% of the total 67,481 • 1.87 blocks per subject-object pair

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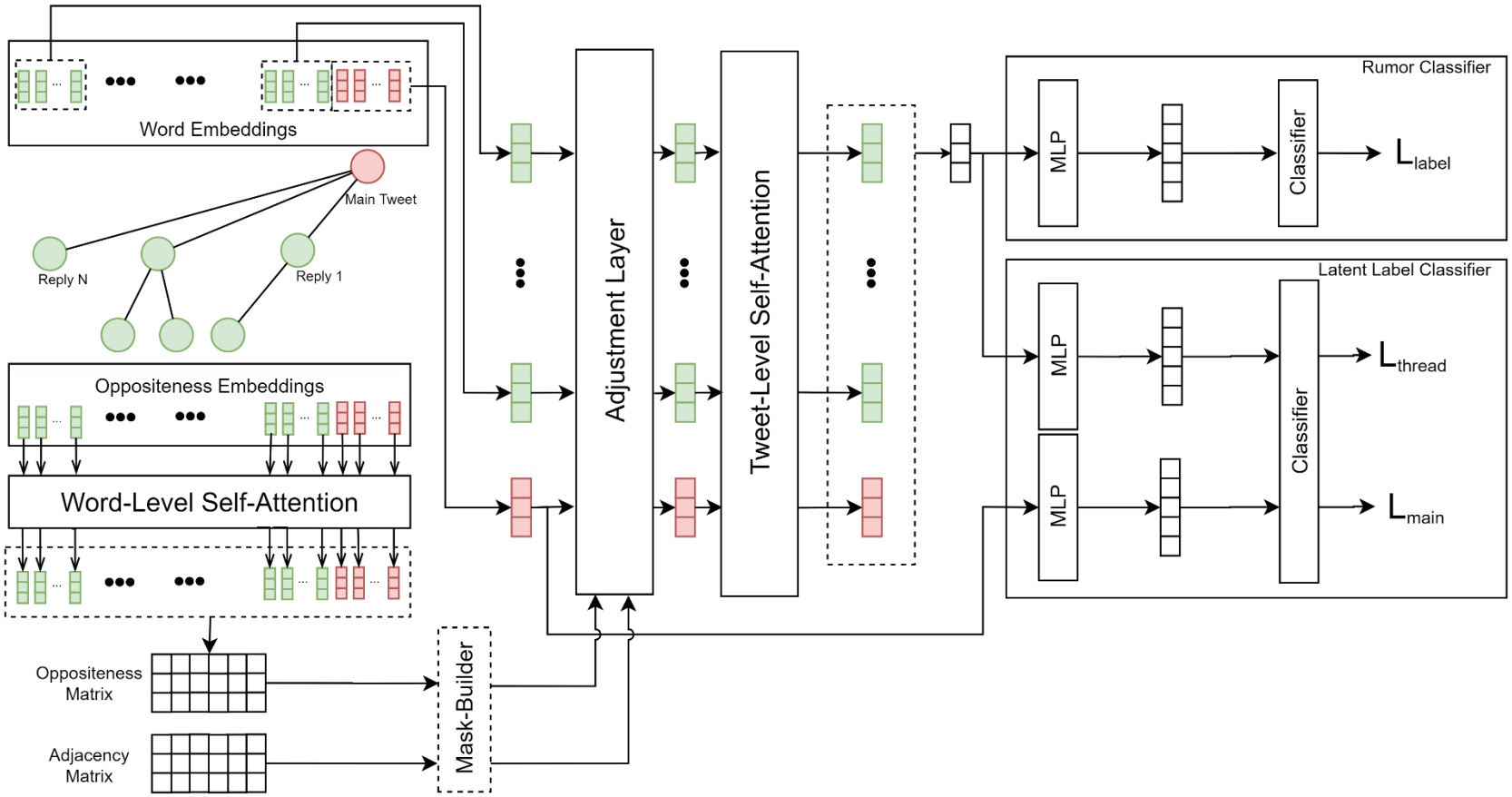
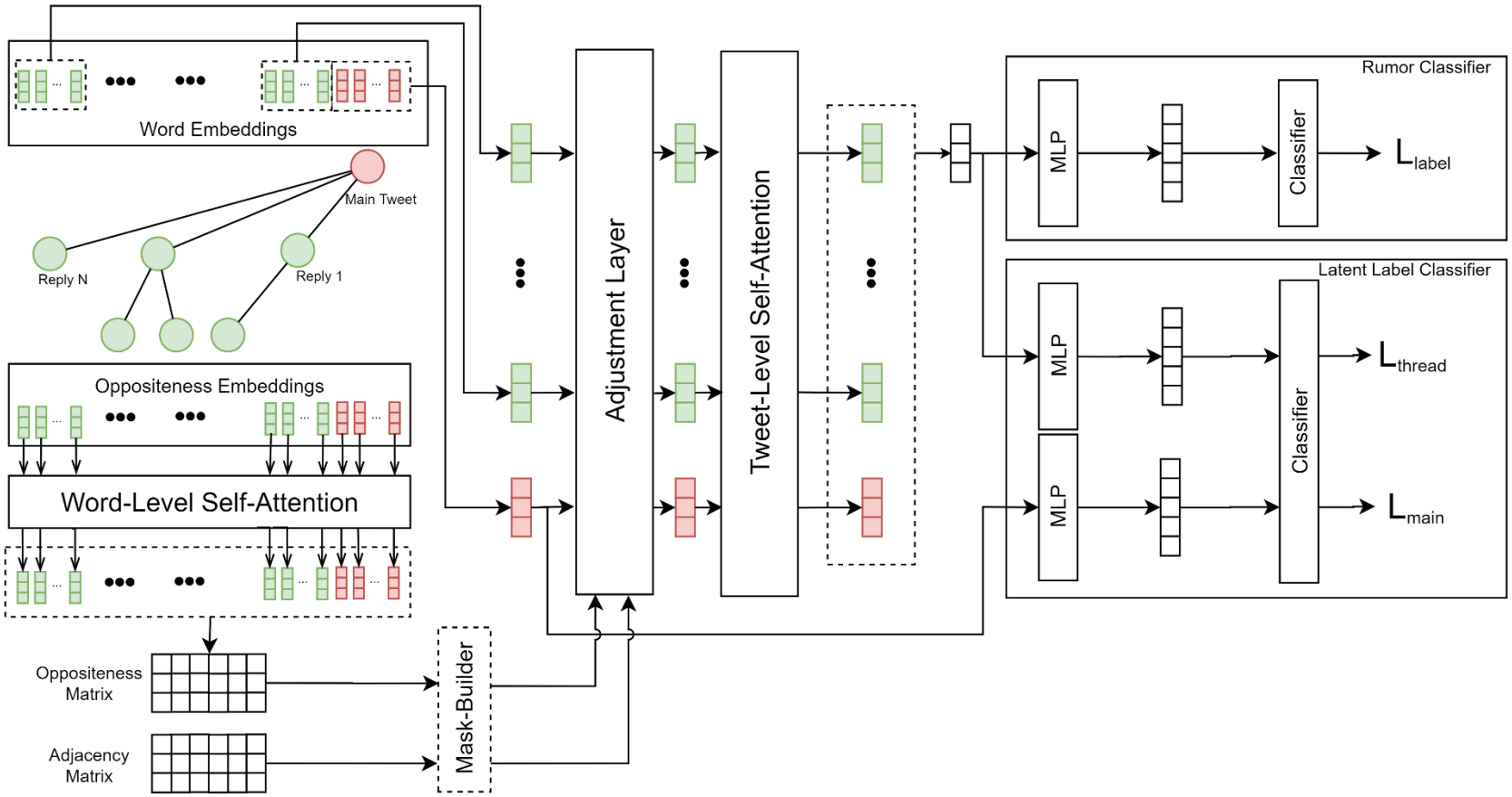
Automatic Rumour Detection in Social Networks



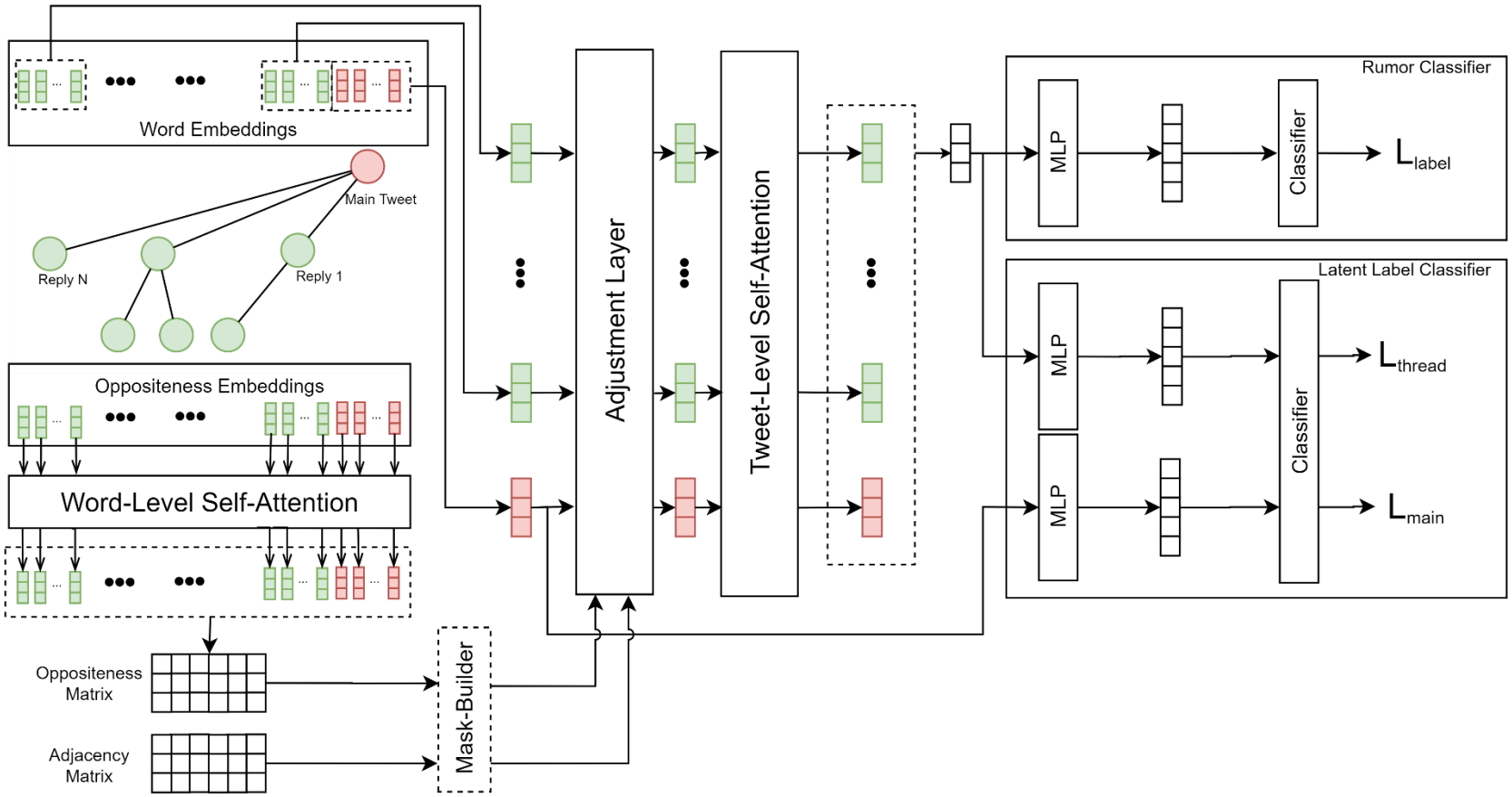
Automatic Rumour Detection in Social Networks

$$k_i' = W_k * o_i + b_k$$
$$q_i' = W_q * o_i + b_q$$



Automatic Rumour Detection in Social Networks

$$k_i' = W_k * o_i + b_k$$
$$q_i' = W_q * o_i + b_q$$
$$op_{i_x,j_y} = d\left(k'_{i_x,}, q'_{j_y}\right)$$



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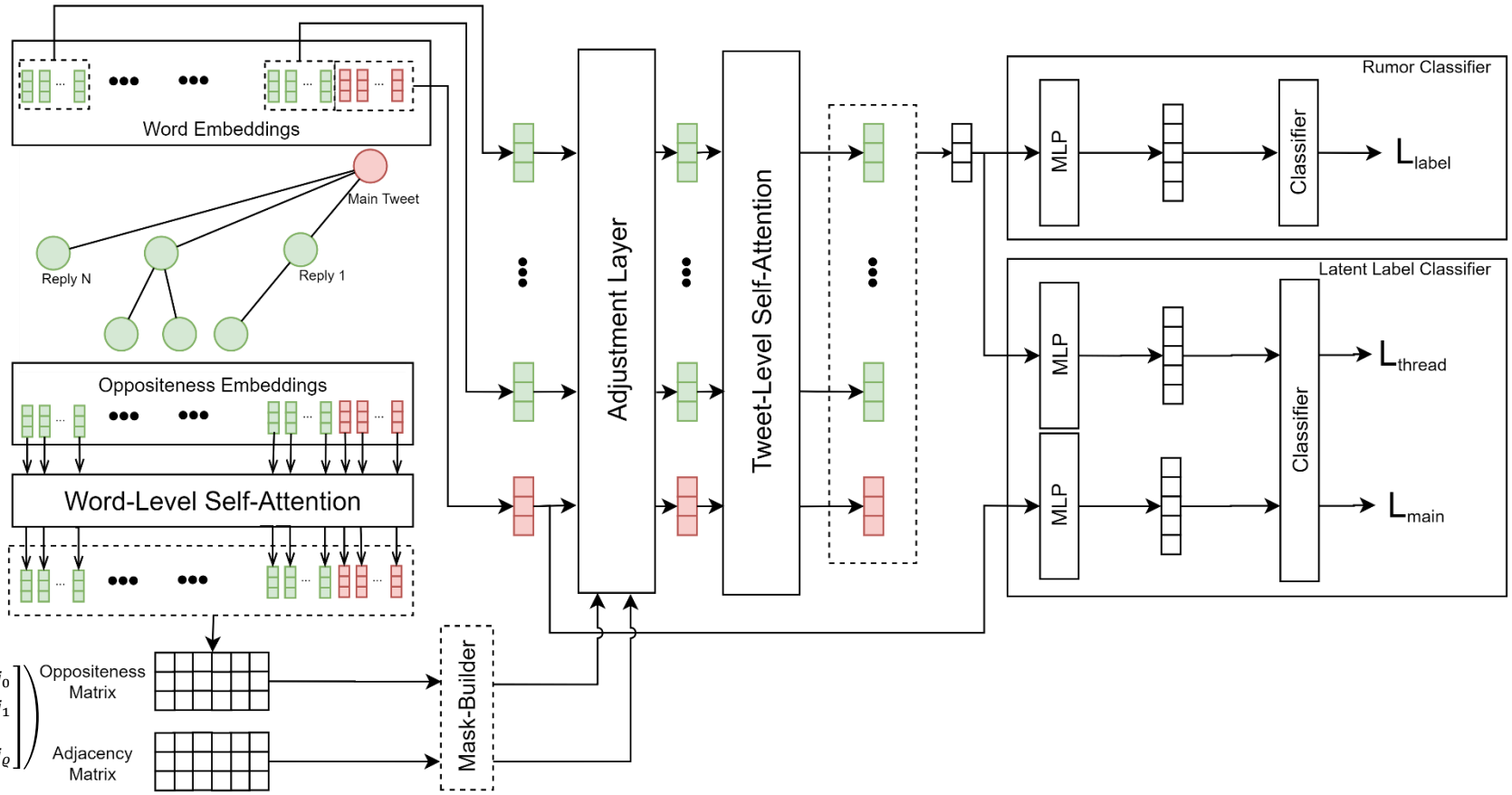
$$op_{i_x,j_y} = d\left(k'_{i_x,}, q'_{j_y}\right)$$
$$o''_{i,j} = EA\left(\begin{bmatrix} op_{i_0,j_0} & op_{i_1,j_0} & \dots & op_{i_\delta,j_0} \\ op_{i_0,j_1} & op_{i_1,j_1} & \dots & op_{i_\delta,j_1} \\ \dots & \dots & \dots & \dots \\ op_{i_0,j_\varrho} & op_{i_1,j_\varrho} & \dots & op_{i_\delta,j_\varrho} \end{bmatrix}\right)$$



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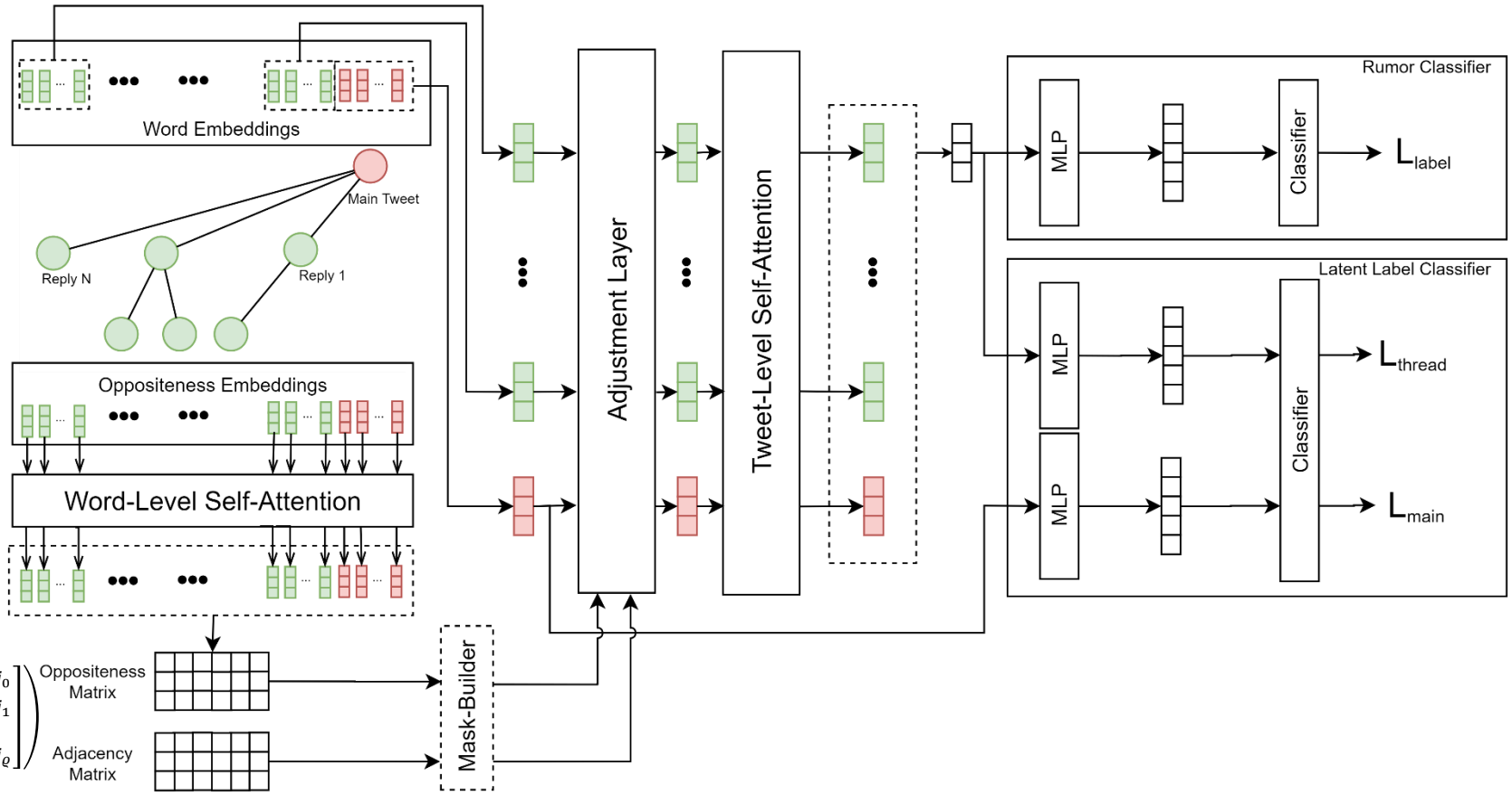
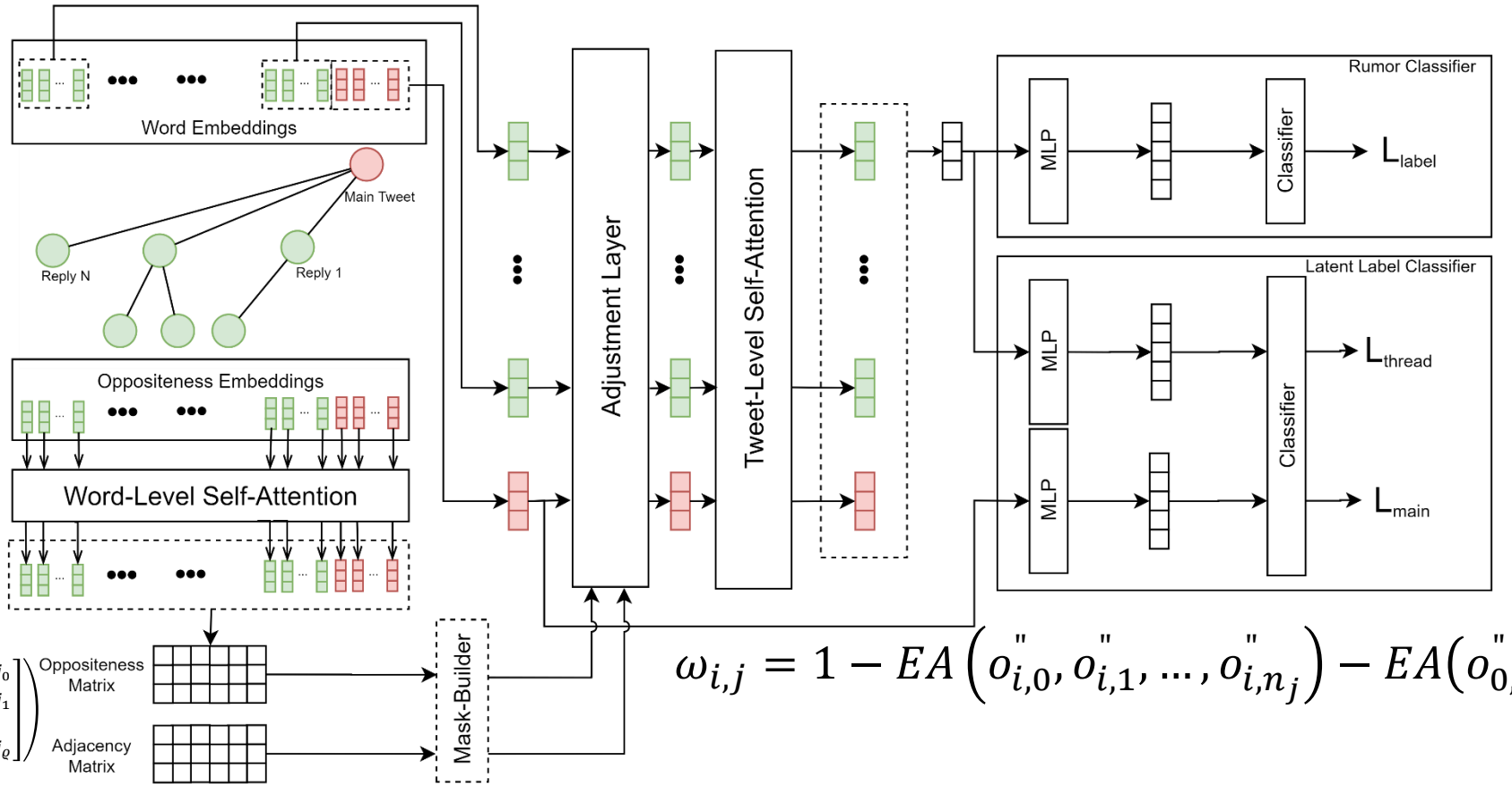


Automatic Rumour Detection in Social Networks

$$k'_i = W_k * o_i + b_k$$
$$q'_i = W_q * o_i + b_q$$
$$op_{i_x,j_y} = d\left(k'_{i_x,}, q'_{j_y}\right)$$



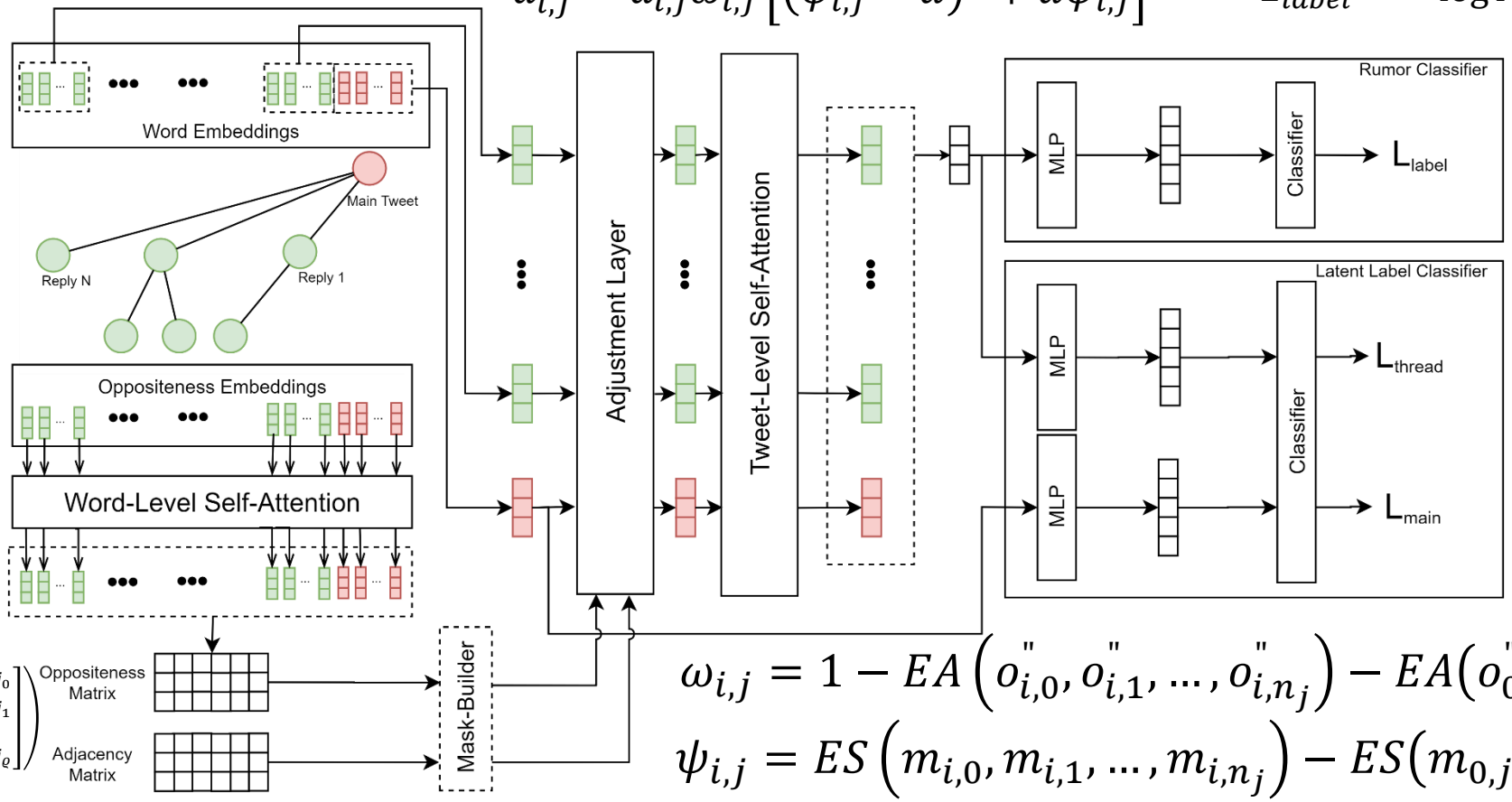
$$o''_{i,j} = EA\left(\begin{bmatrix} op_{i_0,j_0} & op_{i_1,j_0} & \dots & op_{i_\delta,j_0} \\ op_{i_0,j_1} & op_{i_1,j_1} & \dots & op_{i_\delta,j_1} \\ \dots & \dots & \dots & \dots \\ op_{i_0,j_\varrho} & op_{i_1,j_\varrho} & \dots & op_{i_\delta,j_\varrho} \end{bmatrix}\right)$$

$$\omega_{i,j} = 1 - EA\left(o''_{i,0}, o''_{i,1}, \dots, o''_{i,n_j}\right) - EA\left(o''_{0,j}, o''_{1,j}, \dots, o''_{n_i,j}\right)$$

Automatic Rumour Detection in Social Networks

$$a'_{i,j} = a_{i,j}\omega_{i,j}\left[(\psi_{i,j} - \alpha)^2 + \alpha\psi_{i,j}\right]$$

$$L_{label} = -\log P(y^*|R_0, R_1, R_2, \ldots, R_T; \Theta)$$



$$k'_i = W_k * o_i + b_k$$

$$q'_i = W_q * o_i + b_q$$

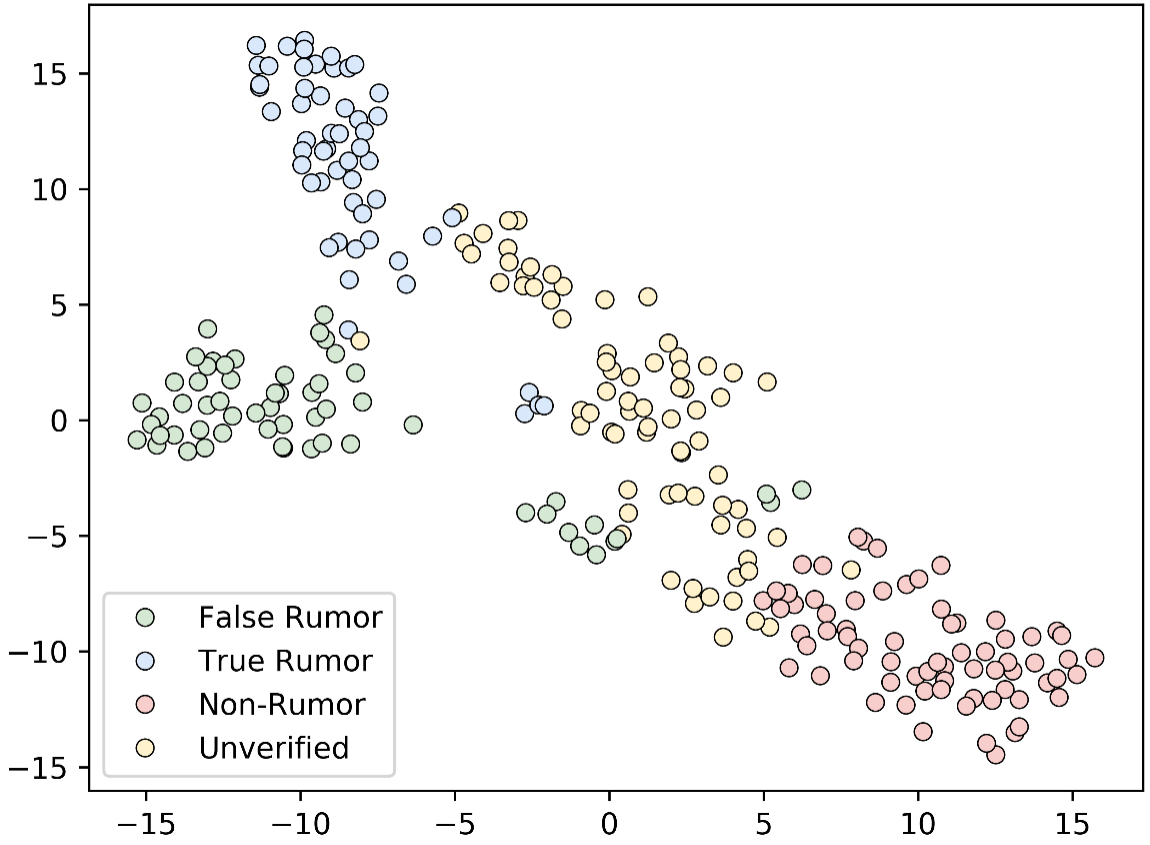
$$op_{i_x,j_y} = d\left(k'_{i_x}, q'_{j_y}\right)$$

$$o''_{i,j} = EA\left(\begin{bmatrix} op_{i_0,j_0} & op_{i_1,j_0} & \cdots & op_{i_\delta,j_0} \\ op_{i_0,j_1} & op_{i_1,j_1} & \cdots & op_{i_\delta,j_1} \\ \cdots & \cdots & \cdots & \cdots \\ op_{i_0,j_\varrho} & op_{i_1,j_\varrho} & \cdots & op_{i_\delta,j_\varrho} \end{bmatrix}\right)$$

$$\omega_{i,j} = 1 - EA\left(o''_{i,0}, o''_{i,1}, \ldots, o''_{i,n_j}\right) - EA\left(o''_{0,j}, o''_{1,j}, \ldots, o''_{n_i,j}\right)$$

$$\psi_{i,j} = ES\left(m_{i,0}, m_{i,1}, \ldots, m_{i,n_j}\right) - ES\left(m_{0,j}, m_{1,j}, \ldots, m_{n_i,j}\right)$$

Results of Disagreement Use Case



Without the Oppositeness Component

With the Oppositeness Component

Summary of Research & Future Directions

- Dissertation:

  “Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language”

- SigmaLaw Project
- Sinhala NLP
- Future Directions

SigmaLaw Project

- Started in 2017 with Dr. Shehan Perera.
- Initial objective: Information Extraction/Retrieval for the Legal Domain.
- Now it is a stack of NLP tools and research.
- So far, five FYPs and one Masters student.
- We have published 15 papers so far:
  - 11 Conference papers (10 published, 1 accepted)
  - 2 Journal papers (both by invitation)
  - 2 Workshop papers
- In the pipeline:
  - 3 Conference papers (1 submitted, 1 very early draft)
  - 2 Journal papers (1 by invitation and under review)

Word Vector Embeddings and Domain Specific Semantic based Semi-Supervised Ontology Instance Population

Semi-Supervised Instance Population of an Ontology using Word Vector Embedding

Deriving a Representative Vector for Ontology Classes with Instance Word Vector Embeddings

Legal Document Retrieval using Document Vector Embeddings and Deep Learning

Party-based Sentiment Analysis Pipeline for the Legal Domain

Sigmalaw PBSA - A Deep Learning Model for Aspect-Based Sentiment Analysis for the Legal Domain

Effective Approach to Develop a Sentiment Annotator For Legal Domain in a Low Resource Setting

Context Sensitive Verb Similarity for Legal Information Extraction

Party-Based Sentiment Analysis of Legal Opinion Texts using a Linguistics Rule-Based Model

Identifying Legal party Members from Legal Opinion Text using Natural Language Processing

Classifying Sentences in Court Case Transcripts using Discourse and Argumentative Properties

Fast Approach to Build an Automatic Sentiment Annotator for Legal Domain using Transfer Learning

Rule-Based Approach for Party-Based Sentiment Analysis in Legal Opinion Texts

Party Identification of Legal Documents using Co-reference Resolution and Named Entity Recognition

Identifying Relationships Among Sentences in Court Case Transcripts Using Discourse Relations

Shift-of-Perspective Identification Within Legal Cases

SigmaLaw-ABSA: Dataset for Aspect-Based Sentiment Analysis in Legal Opinion Texts

Legal Party Extraction from Legal Opinion Text with Sequence to Sequence Learning

Synergistic Union of Word2Vec and Lexicon for Domain Specific Semantic Similarity

Summary of Research & Future Directions

- Dissertation:

  “Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language”

- SigmaLaw Project
- Sinhala NLP
- Future Directions

Sinhala NLP

- Sinhala Text Classification: Observations from the Perspective of a Resource Poor Language
- Survey on Publicly Available Sinhala Natural Language Processing Tools and Research

- Collaborations with LIRNEasia
  - Natural Language Processing for Government: Problems and Potential
  - Sinhala Language Corpora and Stopwords from a Decade of Sri Lankan Facebook
  - Seeking Sinhala Sentiment: Predicting Facebook Reactions of Sinhala Posts (under review)

- Quality at a Glance: An Audit of Web-Crawled Multilingual Datasets

Summary of Research & Future Directions

- Dissertation:

  “Semantic Oppositeness for Inconsistency and Disagreement Detection in Natural Language”

- SigmaLaw Project
- Sinhala NLP
- Future Directions

Future Directions

- SigmaLaw Project
  - Extract relevant arguments from retrieved case documents depending on the client party role
  - Legal document summarization
  - Statement/argument synthesis from prompts
- Sinhala NLP
  - Multilingual Embedding Alignment
  - Oppositeness for Sinhala
  - Hate Speech Detection

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Q&A

Email: NisansaDdS@cse.mrt.ac.lk

Web: nisansads.staff.uom.lk