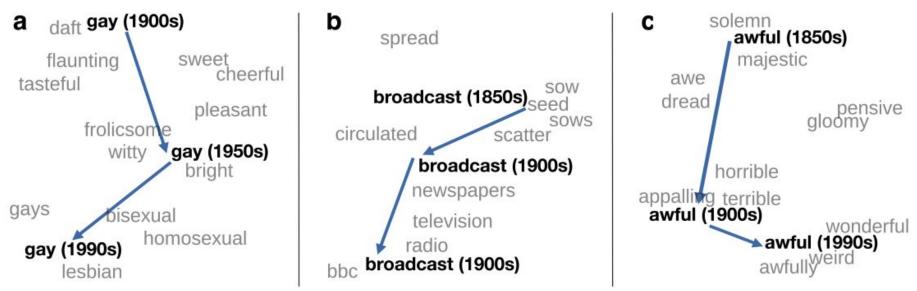
A Semantic Distance Metric Learning approach for Lexical Semantic Change Detection

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Background: Semantic Change Detection (SCD)

- Words can have different meanings overtime
- Manual detection is laborious

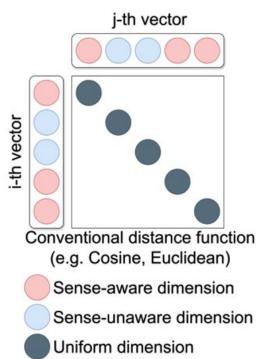
→ Automatic detection (e.g. vector space)



[Hamilton+16] Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change

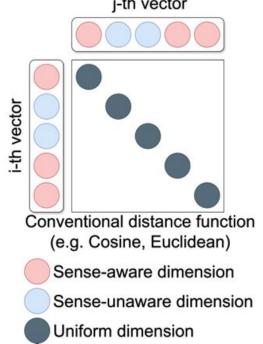
- Representational challenge

- Measurement challenge



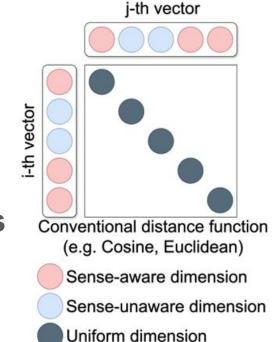
- Representational challenge

- word can take different meanings in different contexts within the same corpus
- should we consider time or sense information?
 →time << sense [Cassotti+23]
- Measurement challenge



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 →time << sense [Cassotti+23]
- Measurement challenge
 - SCD is an unsupervised task
 →comparing vector sets using
 parameter-free distance functions
 (Cosine, Euclidean)
 - considers sense-aware/unaware dimensions uniformly

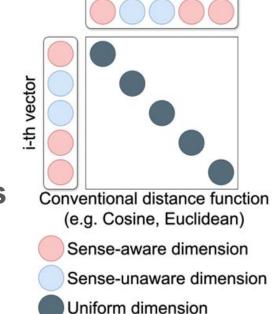


How to overcome the measurement challenge?

→<u>time << sense</u> [Cassotti+23]

- Measurement challenge

- SCD is an unsupervised task
 →comparing vector sets using
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Proposal: Semantic Distance Metric Learning (SDML)

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- SDML = sense-aware supervision
 - + metric learning
 - We use Mahalanobis distance

$$h(\boldsymbol{w}_i, \boldsymbol{w}_j; \mathbf{A}) = (\boldsymbol{w}_i - \boldsymbol{w}_j)^\top \mathbf{A} (\boldsymbol{w}_i - \boldsymbol{w}_j)$$

- Mahalanobis matrix A is optimised for sense-aware supervision using metric learning
 - sense-aware supervision: Word-in-Context (WiC)
 - **metric learning**: Information Theoretic Metric Learning (ITML)

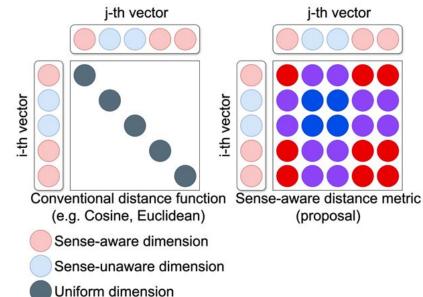
$$\min_{\mathbf{A}} \quad \mathrm{KL}(p(\boldsymbol{w};\mathbf{A}_0)||p(\boldsymbol{w};\mathbf{A}))$$

subject to
$$h(\boldsymbol{w}_1, \boldsymbol{w}_2) \leq u \quad y = 1,$$

 $h(\boldsymbol{w}_1, \boldsymbol{w}_2) \geq \ell \quad y = 0.$

Proposal: Semantic Distance Metric Learning (SDML)

- SDML vs measurement challenge
 - considers sense-aware/unaware dimensions
 (diagonal elements of Mahalanobis matrix A)
 - accounts for cross-dimensional information
 - (off-diagonal elements of Mahalanobis matrix A)



Experiment: Settings

- Task 1: WiC (binary classification)

- "They stopped at an open <u>space</u>(()) in the jungle"
- "The astronauts walked in outer $\underline{space}(\mathscr{D})$ without a tether"
- word "*space*" takes the same meaning?: <u>False</u>

- Task 2: SCD (ranking)

- "If a *plane*() be parallel to the horizontal…"
 "The sun is in the same *plane*) as the picture…"
- "The President's <u>plane</u>() landed at Goose Bay..."
 "The <u>plane</u>) kept climbing and climbing..."
- the meaning of "*plane*" is changed?: <u>True (degree: 0.7)</u>

Experiment: WiC (binary classification)

- SDML significantly enhances performance in multiple languages

Method	En	De	Fr	It	Ru
XLM-RoBERTa [Conneau+20]	86.6	84.0	76.2	72.3	80.9
+Sense-aware Fine-tuning [Cassotti+23]	78.0	78.3	73.2	67.1	78.2
+SDML [ours]	90.3	84.9	78.7	75.3	87.6

Experiment: SCD (ranking)

- SDML improves performance by 2~5%
- A(diag) < A(full): cross-dimensional</p>

information is also important

Method	En	De	Sv	La	Ru
Sense-aware Fine-tuning [Cassotti+23]	0.757	0.877	0.754	0.056	0.775
+SDML (<i>diag</i>) [ours]	0.750	0.902	0.642	0.083	0.804
+SDML (full) [ours]	0.774	0.902	0.656	0.124	0.805

Ablation: Correlation analysis

- Calculate correlations with
 - gold labels (Gold)
 - number of senses (#Synsets)
 - frequency (Freq. C1/C2)

Method	Gold	WordNet #Synsets	Freq. C1	Freq. C2
Sense-aware Fine-tuning [Cassotti+23]	0.757	0.427	-0.182	-0.062
+SDML (<i>diag</i>) [ours]	0.750	0.355	-0.205	-0.121
+SDML (full) [ours]	0.774	0.404	-0.122	-0.037

Ablation: Correlation analysis

- Higher correlation with polysemy

contributes to the performance improvement

Consistent with the law of innovation [Hamilton+16]
 "polysemous words tend to change their meanings"

Method	Gold	WordNet #Synsets	Freq. C1	Freq. C2
Sense-aware Fine-tuning [Cassotti+23]	0.757	0.427	-0.182	-0.062
+SDML (<i>diag</i>) [ours]	0.750	0.355	-0.205	-0.121
+SDML (full) [ours]	0.774	0.404	-0.122	-0.037

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Ablation: Correlation analysis

- Lower correlation with frequency contribute to the performance improvement
 - Differ from the law of conformity [Hamilton+16]
 "frequent words tend to be stable"

Method	Gold	WordNet #Synsets	Freq. C1	Freq. C2
Sense-aware Fine-tuning [Cassotti+23]	0.757	0.427	-0.182	-0.062
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Conclusion

- SCD task has two challenges
 - Representational challgenge
 - Measurement challenge
- To overcome the measurement challenge, we propose SDML
 - SDML = sense-aware supervision + metric learning
- Experimental results show that
 - **SDML enhances performance** in WiC and SCD tasks
 - Considering **cross-dimensional** information is also important

Future directions

- Considering **time + sense** information
 - **time**: Time Masking [Rosin+22a], Temporal Attention [Rosin+22b] ...
 - LLMs are not temporally grounded [Qiu+24]
 - sense: Sense-aware fine-tuning [Cassotti+23] / distance metric [Ours] ...
 - time + sense = ? (e.g. TempoWiC [Loureiro+22])
- Beyond the **degree** of semantic change
 - semantic change types [Cassotti+24, Periti+24]
 - find **new sense** [Mariia+24]
 - more ...?