Mining Health-related Cause–Effect Statements with High Precision at Large Scale

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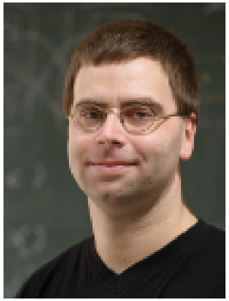
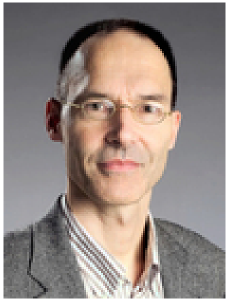

Matthias Hagen*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“The weak strength of Mars causes blood infections, high/low BP, obstruction in physical growth, muscle cramps, . . . ”

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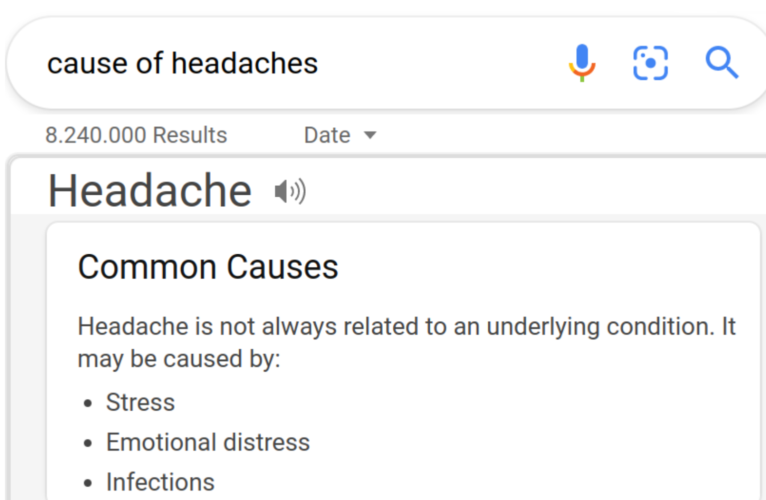

Cause–Effect Statement Extraction

State of the Art

CauseNet is a graph of more than 11M causal relations extracted from the ClueWeb12 web crawl [Heindorf et al., CIKM'20]

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- "*Cardiac arrhythmia* may **lead to** *death*."
- "The *tsunami* **was caused** by an *earthquake*."
- "The *tsunami* **resulted in** *death* and *destruction*."

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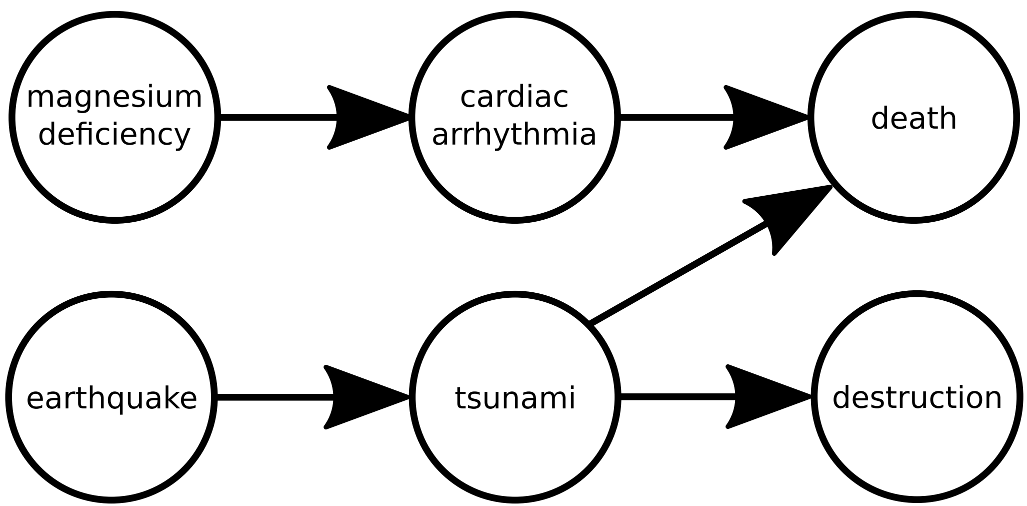

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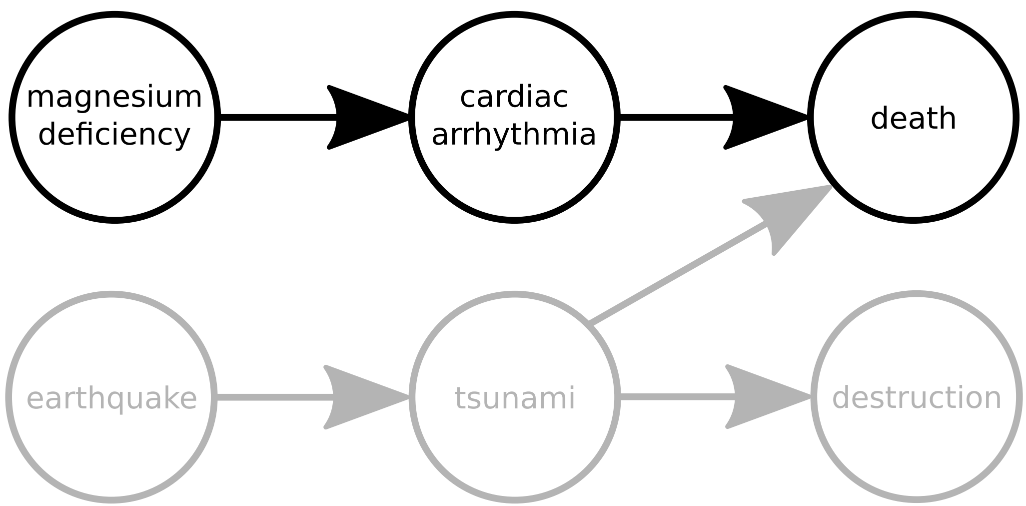

Phrase Health Relatedness Assessment

Termhood Scores

Task: Classify whether a phrase is health-related

- “Her death was a result of cancer.”
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Termhood scores determine the degree to which a phrase is specific for a domain

Phrase	Health-related Corpus (PubMed)	Contrastive Corpus (Wikipedia)
actor	5,590	**539,180**
carcinoma	**987,164**	7,410
diagnosis	**1,851,514**	34,218
study	**10,630,098**	508,740
the	**200,926,211**	196,374,618
ward	47,099	**186,811**

Termhood Scores

Specifically three scores were considered in this work

1. Contrastive Weight [Basili et al., TIA'01]
2. Term Domain Specificity [Park et al., INTERSPEECH'08]
3. Discriminative Weight [Wong et al., AusDM'07]

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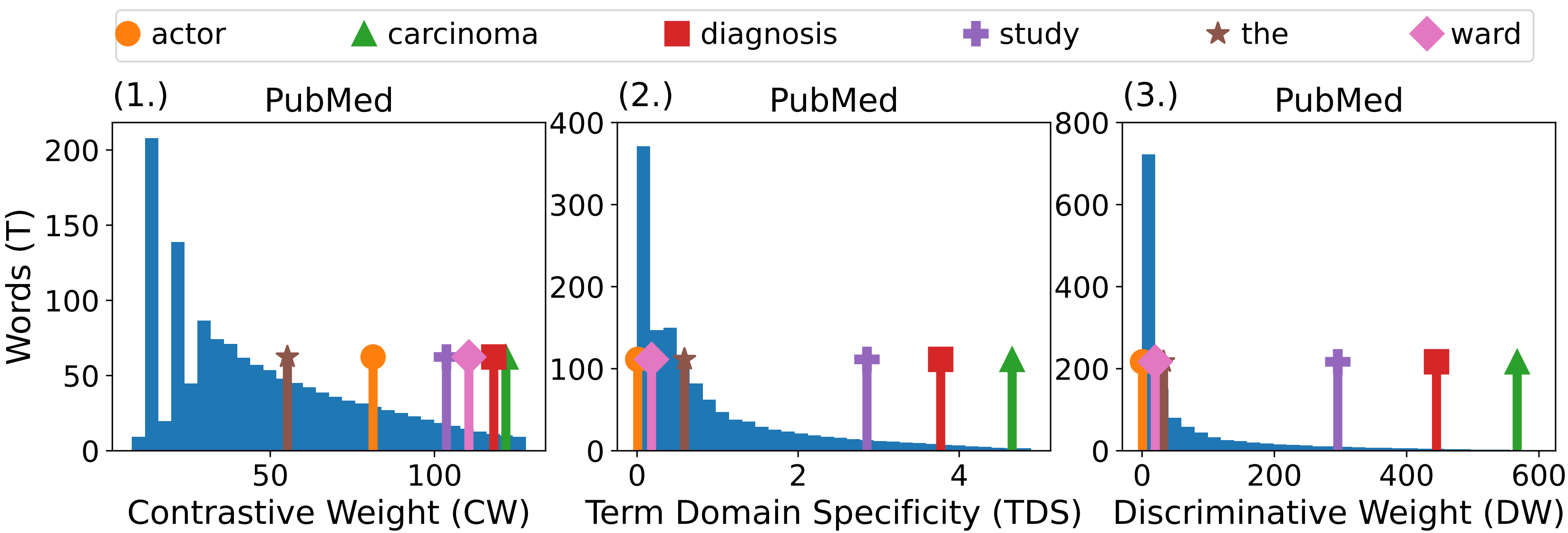

Evaluation

Annotated Datasets

We evaluate our termhood scores on two manually labelled subsets of CauseNet

Dataset	Type	Train Size	Test Size
CauseNet-P-Phrase	High Precision	800	200
CauseNet-F-Phrase	Full	800	200

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Comparison Approaches

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and compare them to four medical entity linkers

1. cTakes [Savova et al., Journal of the American Medical Informatics Association (2010)]
2. MetaMap [Aronson et al., AMIA'01]
3. QuickUMLS [Soldaini et al., MedIR'16]
4. SciSpacy [Neumann et al., BioNLP@ACL'19]

as well as three fine-tuned BERT models

1. Base BERT [Devlin et al., NAACL'19]
2. SciBERT [Beltagy et al., BioNLP@ACL'19]
3. PubMedBERT [Gu et al., ACM Transactions on Computing for Healthcare (2022)]

Evaluation

Effectiveness Results

Optimizing for precision (>0.9) or Matthews correlation coefficient

Main Takeaways

	Approach	R	M
P-Phr.	Entity Linker	–	0.52 †
	BERT	**0.89**	**0.83**
	Termhood	**0.89**	0.79
F-Phr.	Entity Linker	0.05 †	0.54 †
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2. BERT best effectiveness in all scenarios

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Webis Health CauseNet 2022

Using the termhood scores, we create a resource of health-related cause–effect statements extracted from the web

https://github.com/webis-de/COLING-22

Subset	Statements	Sentences	P	R
Precision (P)	103,273	1,259,339	0.93	0.89
Precision (MCC)	112,707	1,340,873	0.89	0.93
Full (P)	2,201,071	5,680,635	1.00	0.74
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Important to note: it contains *claimed* statements

- ‘stress’ ➜ ‘insomnia’
- ‘incorrect placement of jupiter’ ➜ ‘diabetes’

Summary

Contributions

Generalized termhood-based method to effectively and efficiently assess the health-relatedness of phrases

- Performs as good or not significantly worse than BERT
- Substantially faster than BERT, making application at web scale possible

Creation and release of Webis Health CauseNet 2022

- 7.8M health-related cause–effect sentences
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Thank you!

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Runtime Results

Runtime comparison classifying the phrase datasets

Main Takeaways

1. Termhood scores substantially faster than all other approaches
2. Large variance in entity linkers and comparably slow

Approach	**ms**	$\times$
cTakes	119.68	0.5
MetaMap	49.64	1.2
QuickUMLS	7.23	8.3
ScispaCy	16.38	3.7
PubMedBERT	60.19	1.0
Termhood	**0.56**	**107.5**