Imperial College London

June 9 2021

Novelty Detection in Scientific Research Papers

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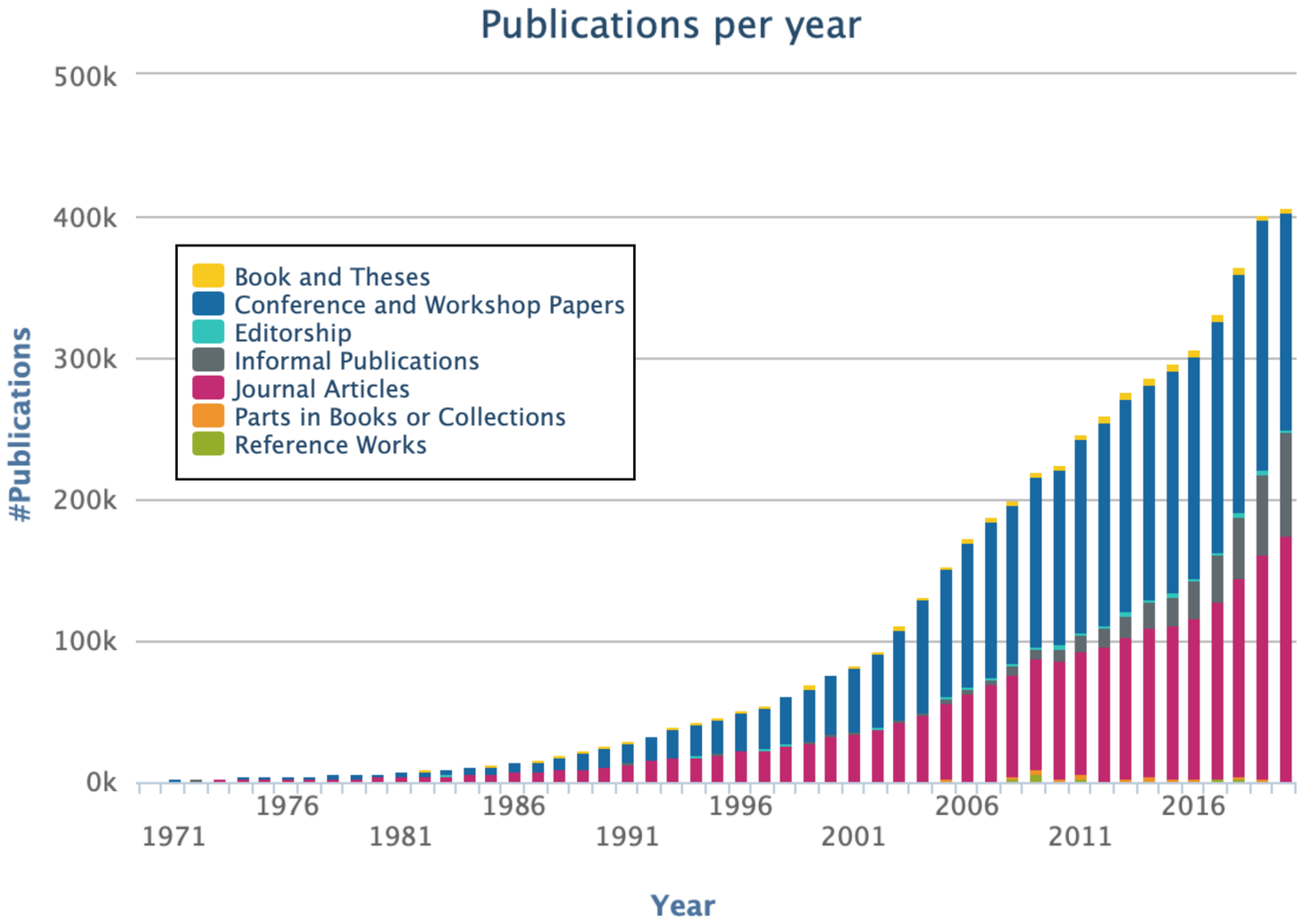
Contents

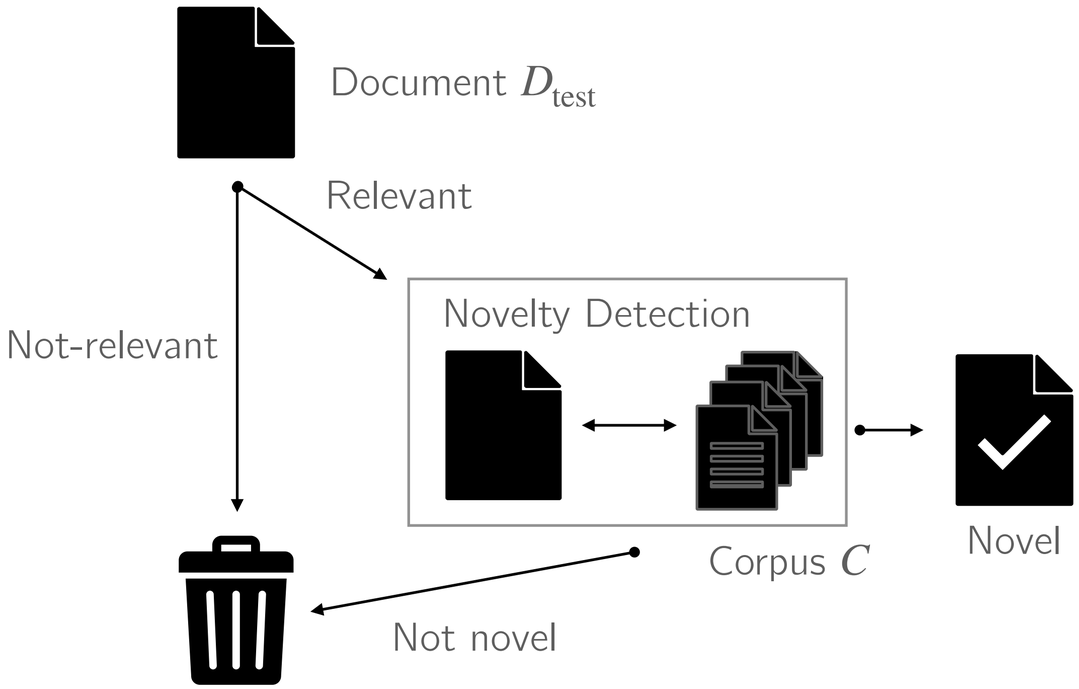
Problem Definition



[1] *Publications per year.* Digital Bibliography and Library project. Link: dblp.org/statistics/publicationsperyear.html

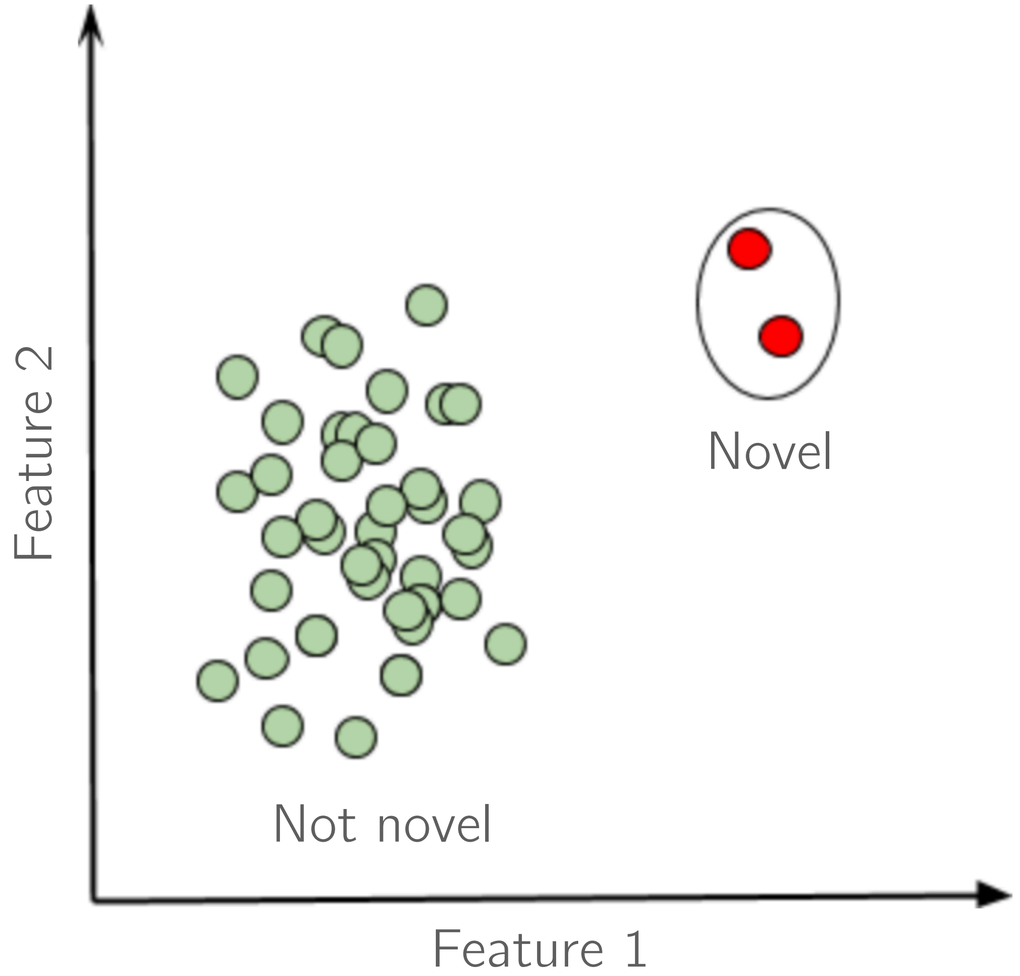
Problem Definition

- Need for tools that distinguish novel subject matter from redundant content
- **Novelty:** dissimilarity provided that a document is relevant
- Needs deep semantic representation of documents



Problem Definition

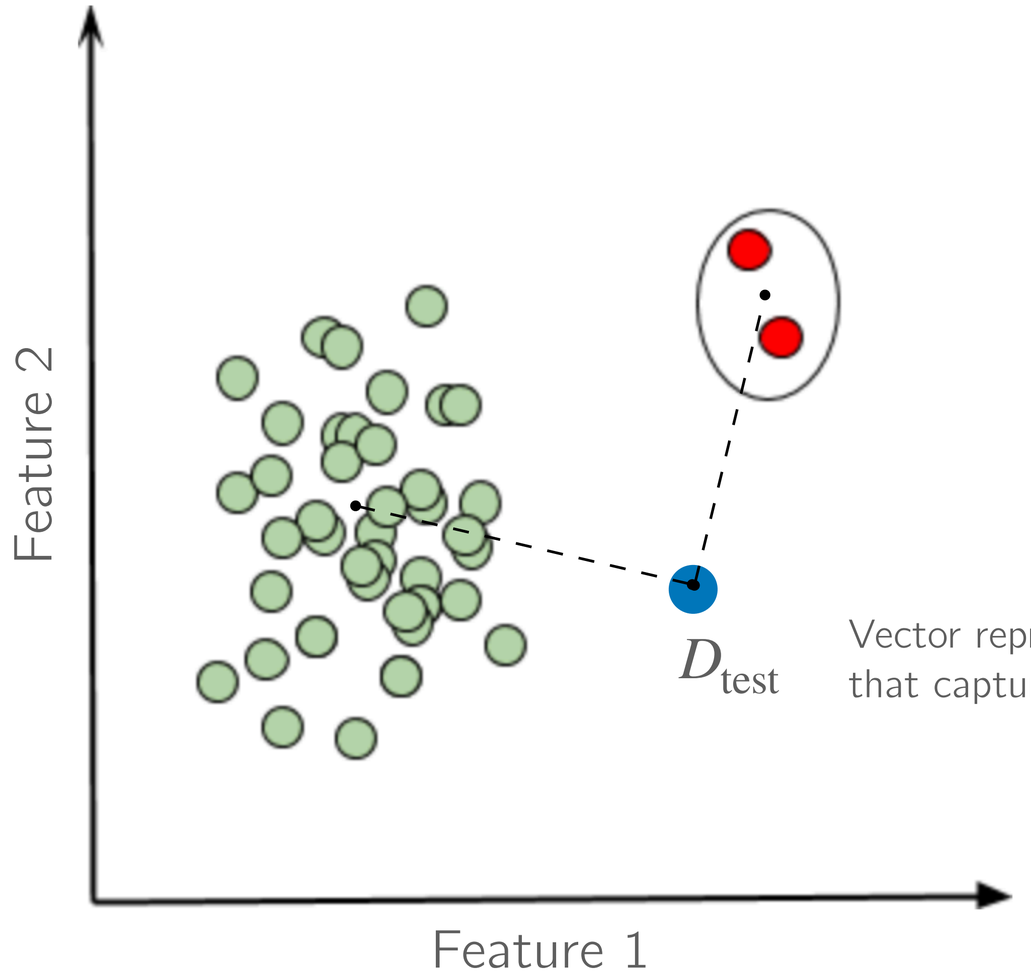
Novelty
Dissimilarity provided that a document is relevant



[2] *Introduction to Anomaly Detection.* FloydHub. Link: blog.floydhub.com/introduction-to-anomaly-detection-in-python/

Problem Definition

Novelty
Dissimilarity provided that a document is relevant

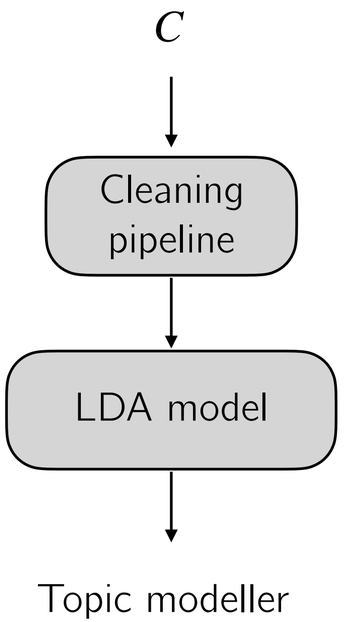


Vector representation of a document that captures it's semantic meaning

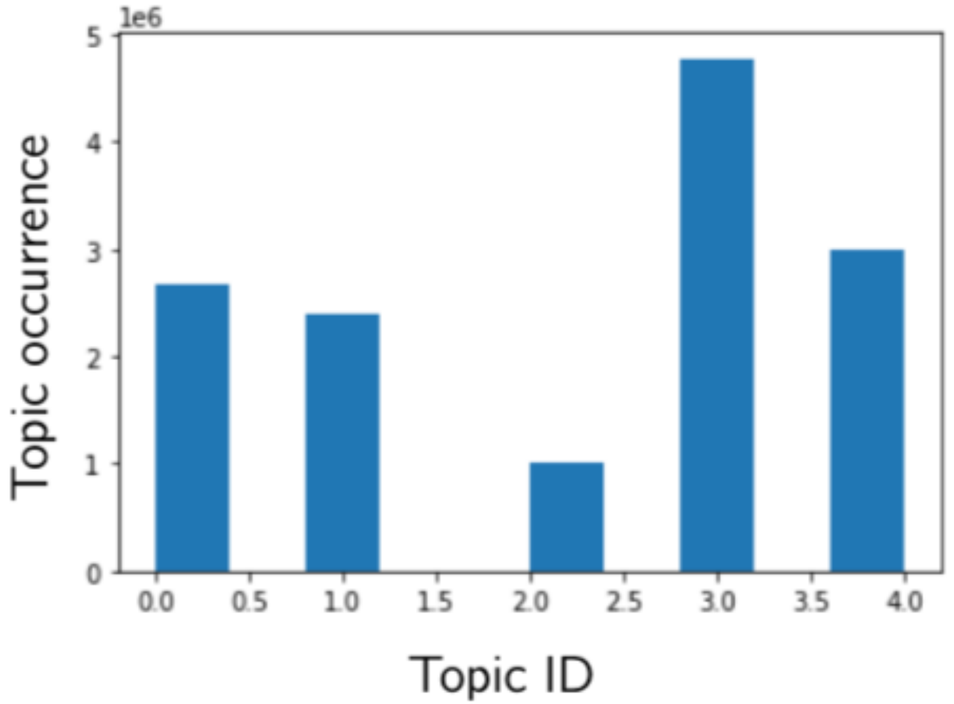
[2] *Introduction to Anomaly Detection.* FloydHub. Link: blog.floydhub.com/introduction-to-anomaly-detection-in-python/

Exploratory Data Analysis

- Statistical model known as Latent Dirichlet Allocation (LDA)
- Learns the topic distribution of documents
- Effectively finds the probability that a word w_i belongs to any of m topics selected by user



Exploratory Data Analysis




```
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*"figure" + 0.008*"show" + 0.008*"wall" + 0.008*"surface" + 0.007*"result"'),
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wer" + 0.010*"pressure" + 0.010*"design" + 0.009*"high" + 0.008*"figure" + 0.008*"perf
ormance"')]
```
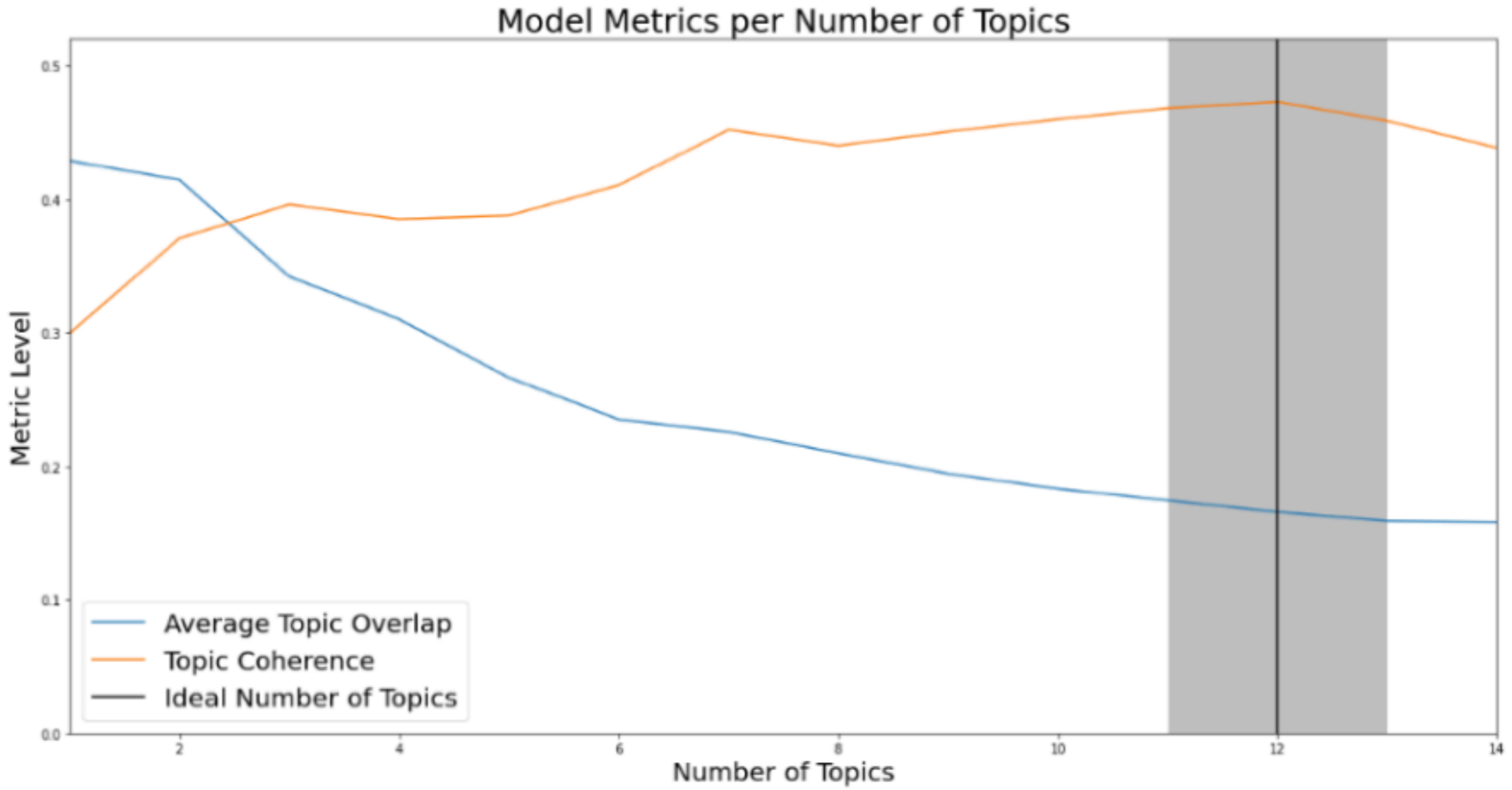

Exploratory Data Analysis



Jaccard score

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Coherence

Measures the semantic similarity

Text as vectors

Bag-of-words and TF-IDF

- Consider $C = \{ "My\ name\ is\ Yousef",\ "NLP\ is\ awesome" \}$
- Represented by matrix $V_{ij} \in \mathbb{R}^{N \times L}$ where N is # of documents, L vocab size
- Does not capture deep semantic information!

	My	$name$	is	$Yousef$	NLP	$awesome$
$My\ name\ is\ Yousef$	1	1	1	1	0	0
$NLP\ is\ awesome$	0	0	1	0	1	1

	My	$name$	is	$Yousef$	NLP	$awesome$
$My\ name\ is\ Yousef$	0.5	0.5	**0.25**	0.5	0	0
$NLP\ is\ awesome$	0	0	**0.33**	0	0.67	0.67

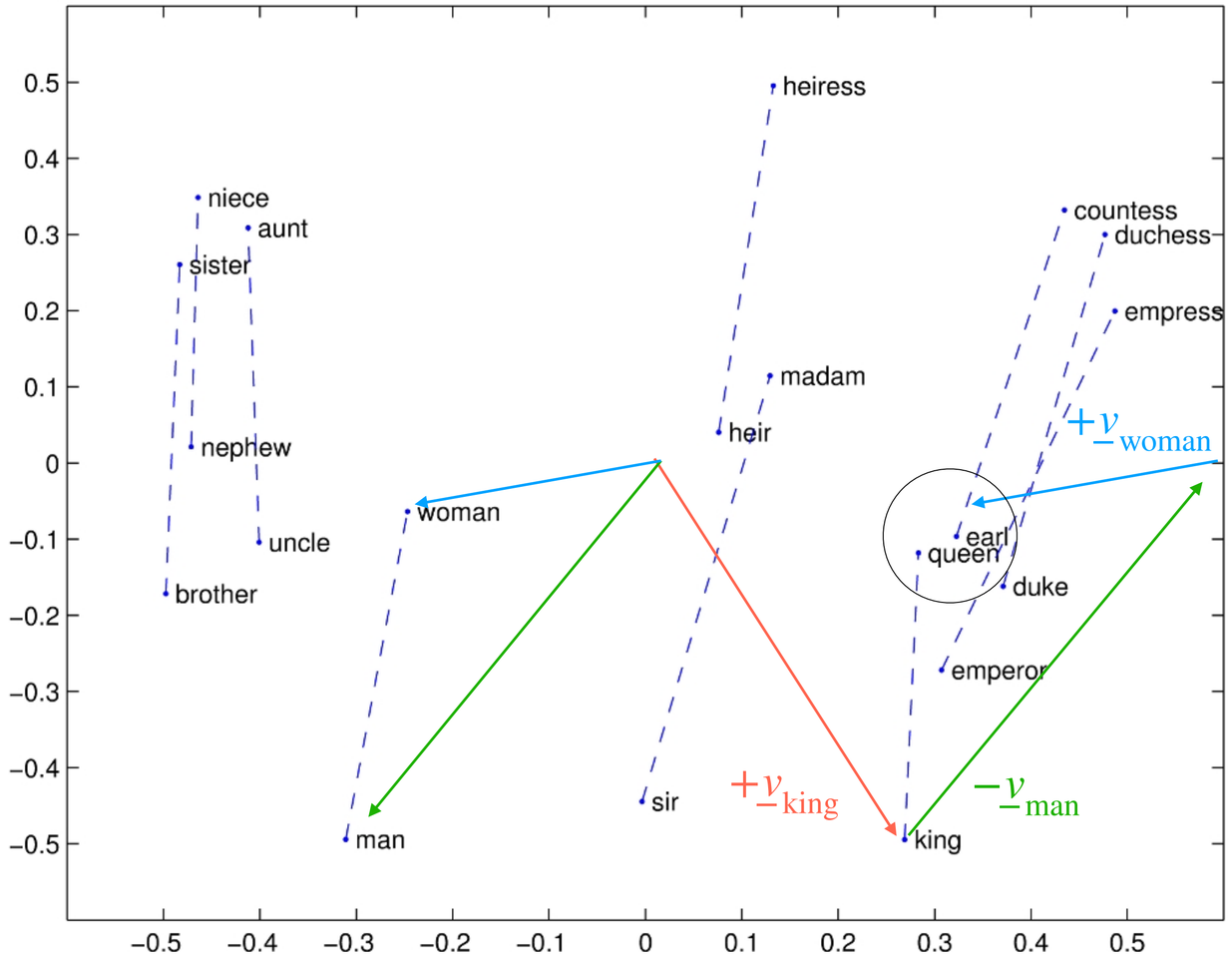
Text as vectors

GloVe

- Represent each word w_i as a vector $\underline{v} \in \mathbb{R}^l$, where l is an **embedding length**
- Typically, $l \in [50, 300]$
- Word vectors carry semantic meaning
- They are linear and additive, but also contain spatial information

Text as vectors

GloVe



Additive meaning

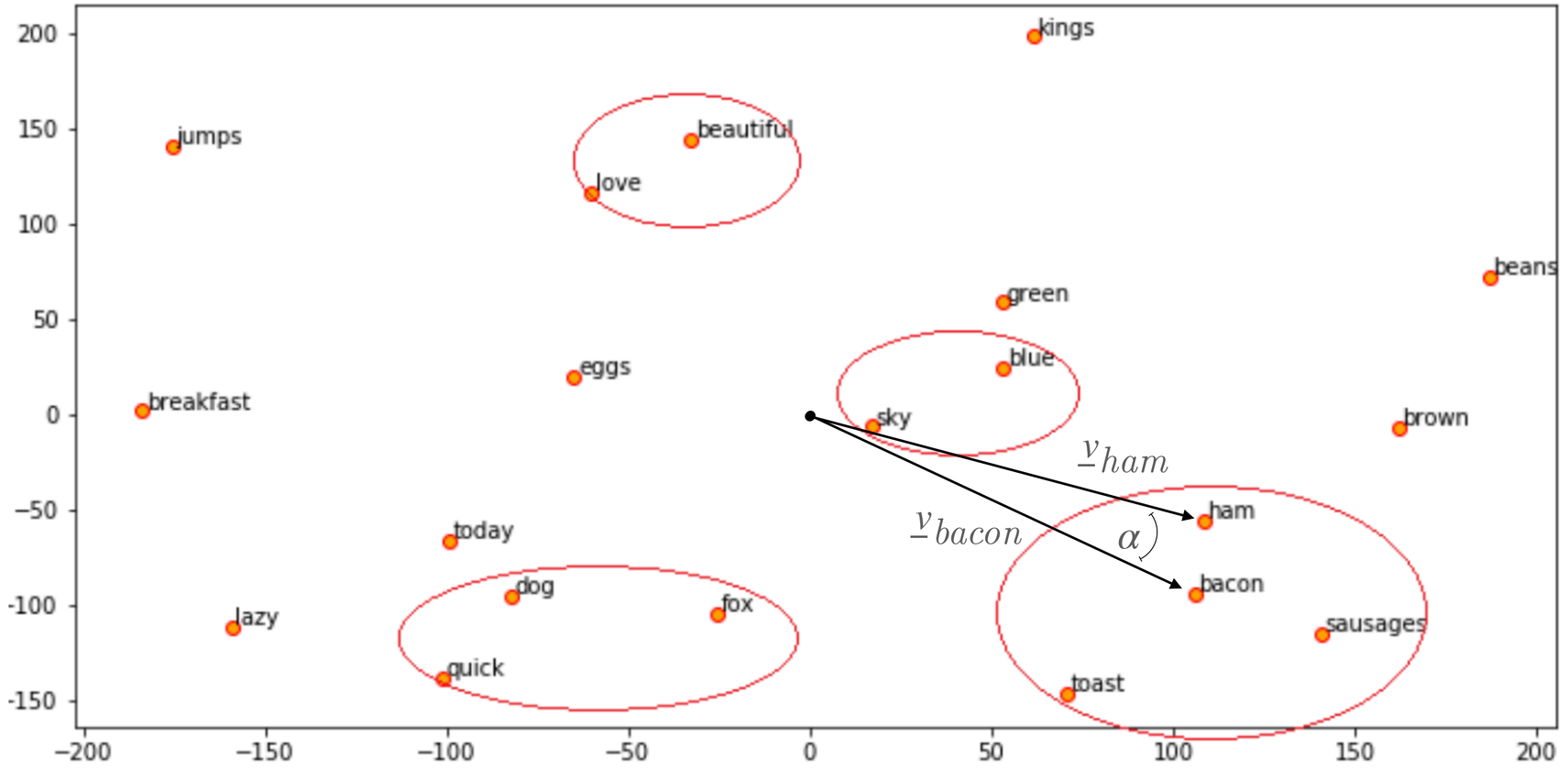
Vectors can add to each other, mimicking real relationships

$$\underline{v}_{king} - \underline{v}_{man} + \underline{v}_{woman} \approx \underline{v}_{queen}$$

[3] *GloVe: Global Vectors for Word Representation.* Pennington et al. Link: nlp.stanford.edu/projects/glove/

Text as vectors

GloVe



Spatial closeness

clusters indicate semantic family

$C = \{"quick",\ "dog",\ "fox"\} \approx "animal"$

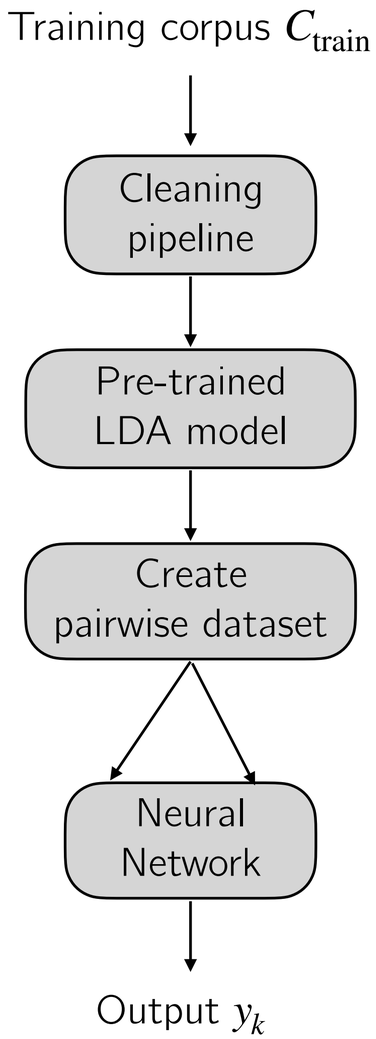
$$\cos\alpha = \underline{v}_{ham} \cdot \underline{v}_{bacon} \approx 1$$

[4] *Hands on approach to Deep Learning methods for text data.* Dipanjan Sarkar. Link: towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa

Pseudo-Supervised Model

Training process

- Assigns a topic to each sentence
- Pairs all sentences together
- Trains a neural network to predict the probability that a pair belongs in the same class
- Model based on pairwise network by Qin et al. [6]



[6] *Text Classification with novelty detection.* Qin Q, Hu W, Liu B. Link: https://arxiv.org/abs/2009.11119

Pseudo-Supervised Model

Pairwise data

	Topic ID
My name is Yousef	0
NLP is awesome	1
Deep Learning	1

Topic ID	Meaning
0	People
1	Artificial Intelligence

Sentence pair

Sent 1	Sent 2	Topic ID 1	Topic ID 2	Same topic?
My name is Yousef	*NLP is awesome*	0	1	0
My name is Yousef	*Deep Learning*	0	1	0
NLP is awesome	*Deep Learning*	1	1	1

Pseudo-Supervised Model

Testing process

- Topic 0: People
- Topic 1: Artificial Intelligence

Test sentence	Sentences from corpus	Probability	Mean by topic
Machine learning is very broad	*My name is Yousef*	0.1	0.1
Machine learning is very broad	*NLP is awesome*	0.7	**0.75**
Machine learning is very broad	*Deep Learning*	0.8	

Not-novel

Test sentence	Sentences from corpus	Probability	Mean by topic
A turbine is a Turbomachine	*My name is Yousef*	0.1	0.1
A turbine is a Turbomachine	*NLP is awesome*	0.3	0.25
A turbine is a Turbomachine	*Deep Learning*	0.2	

Novel

Unsupervised Model

- Document representation found using mean GloVe word vectors

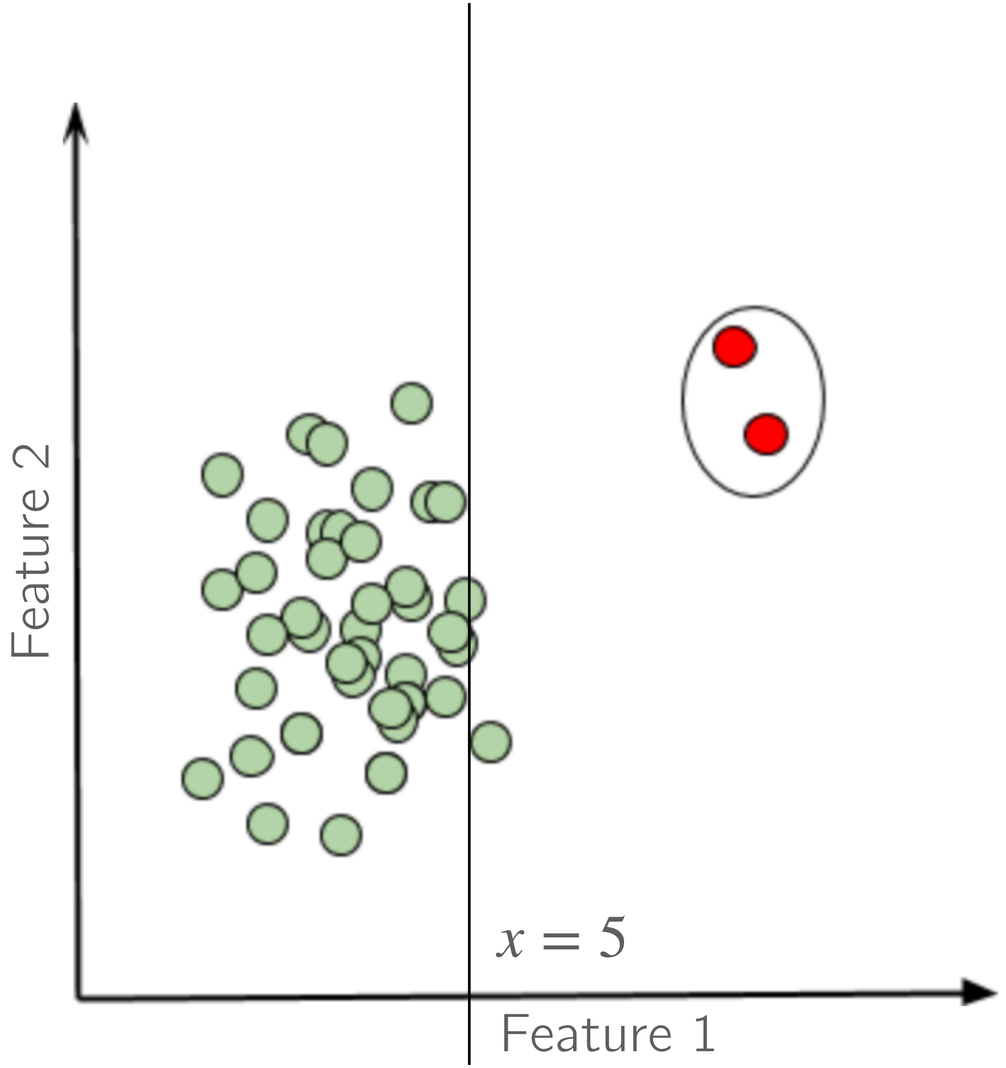
$$\bar{v} = \frac{\sum_i^N v_i}{N}$$

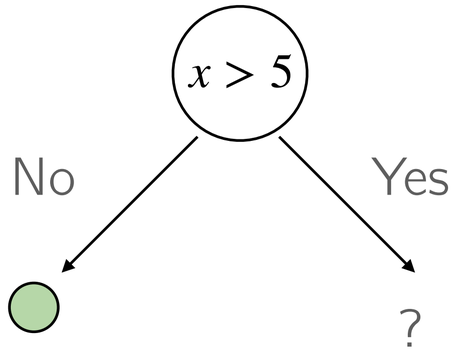
N is the # of words per document

v_i is the word vector for word i

- IsolationForest algorithm was used to determine anomalies
- Results compared with TF-IDF embedded documents

Unsupervised Model





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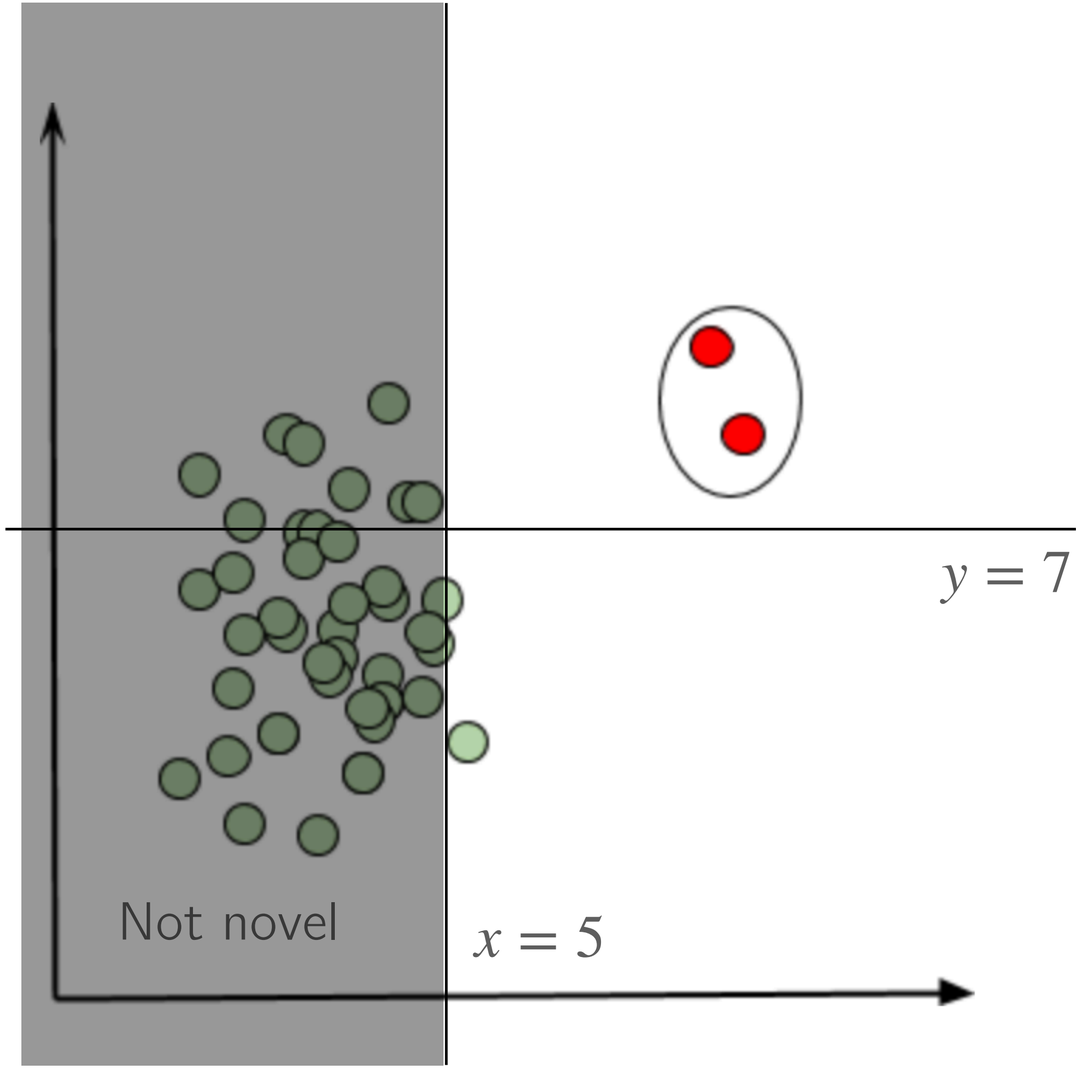

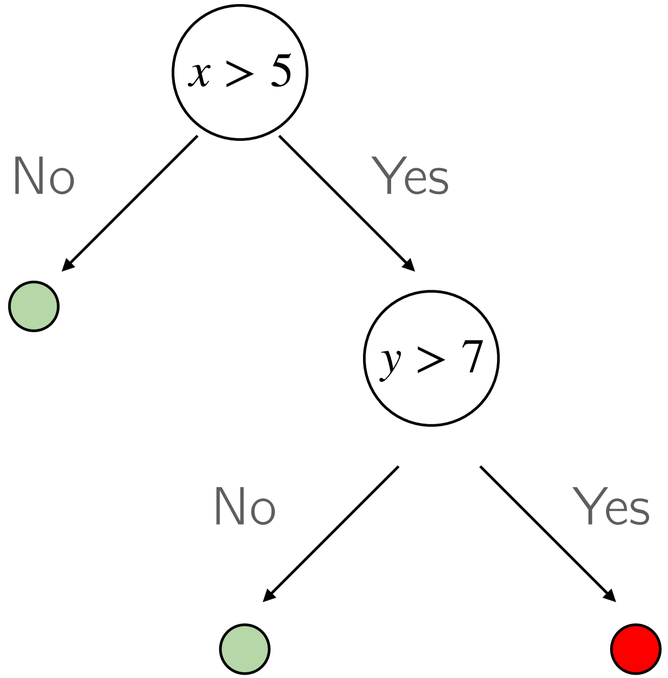

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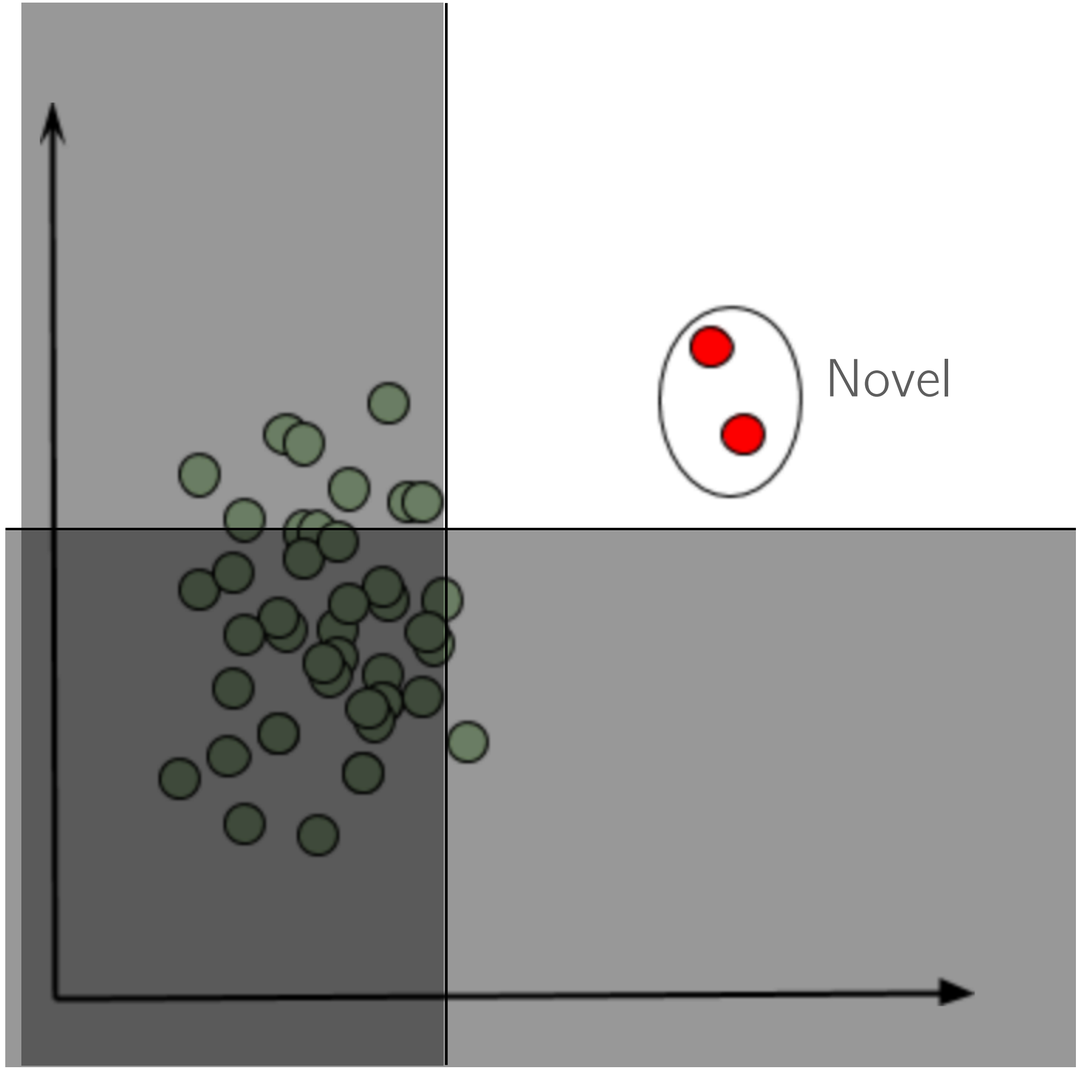

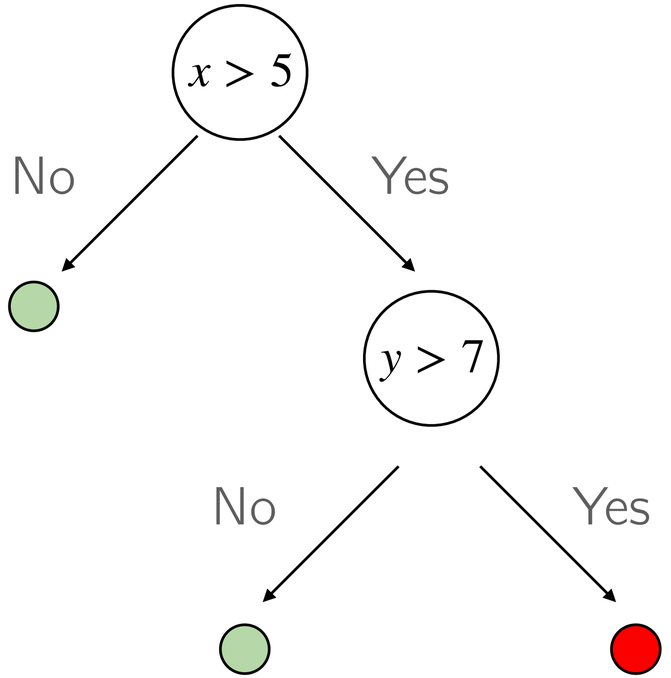

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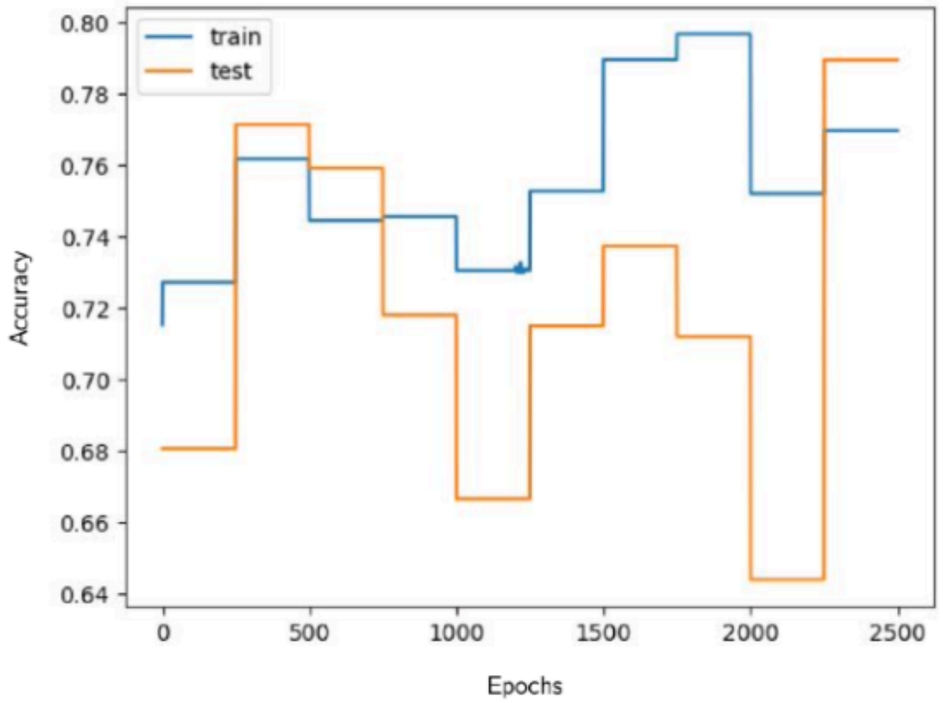
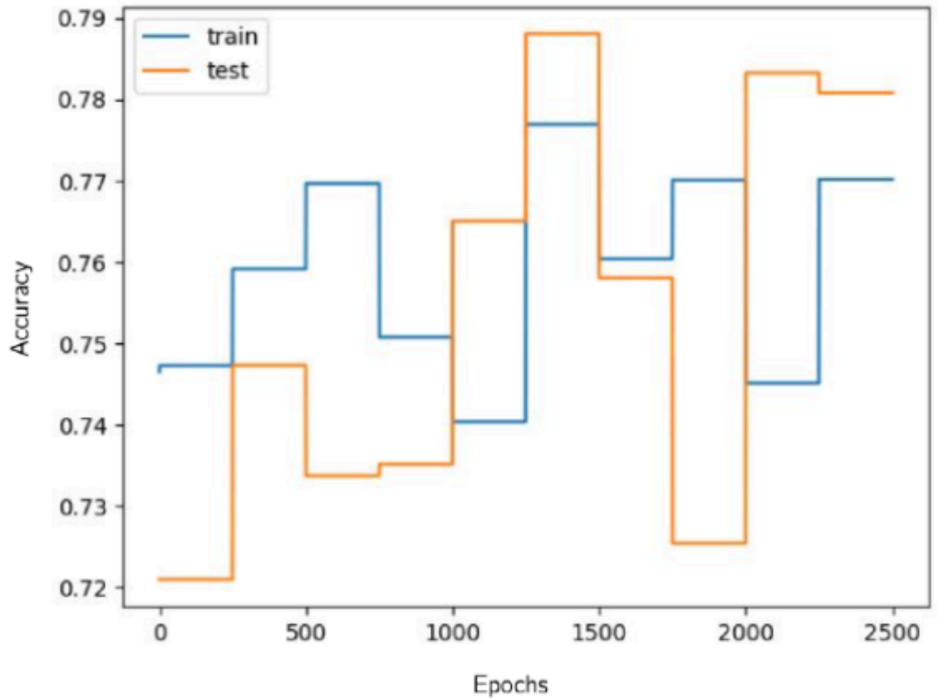
Project Outcomes and Discussion

Pseudo-Supervised Model



$n = 200$ sentences

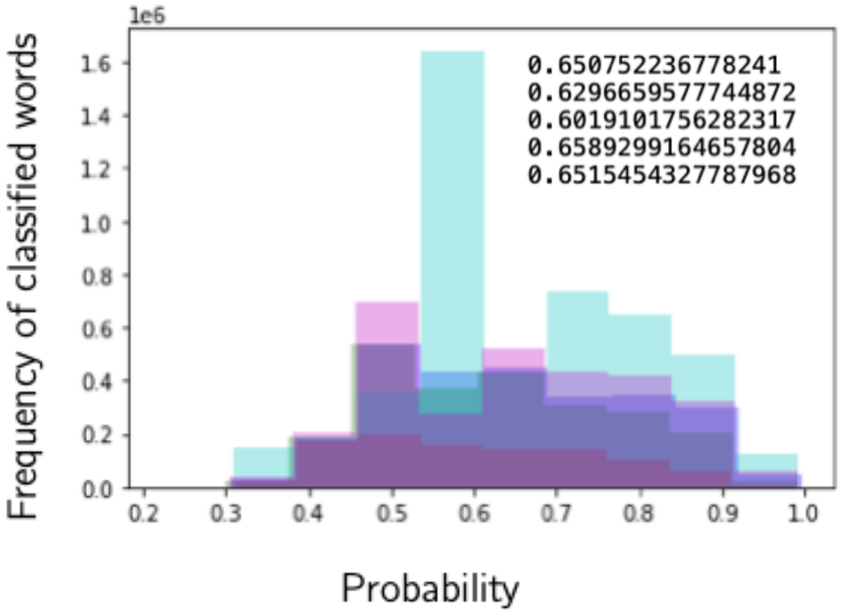


$n = 1000$ sentences

Project Outcomes and Discussion

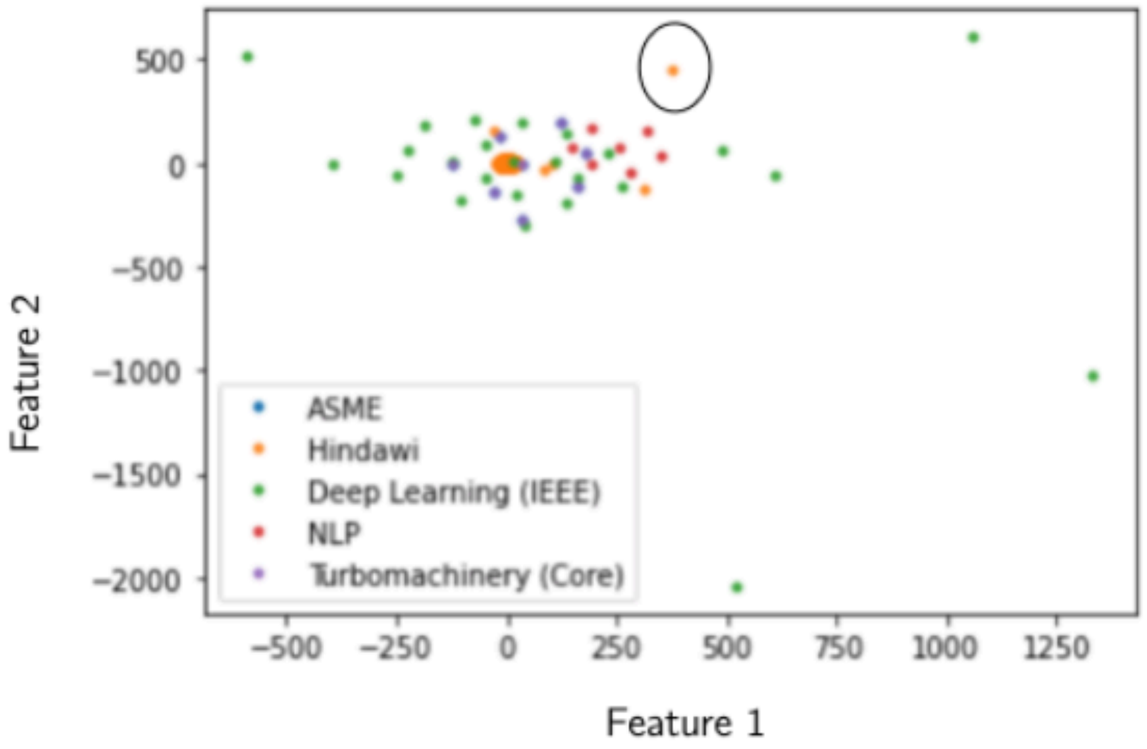
Pseudo-Supervised Model

- Pseudo-supervised nature of the model not rigorously analysed
- Assumed that the LDA model can generate topics both at corpus (macro) and sentence (micro) level
- Degree of prediction confidence not considered
- Should set a threshold (e.g. 0.8)
- Would decrease computational cost



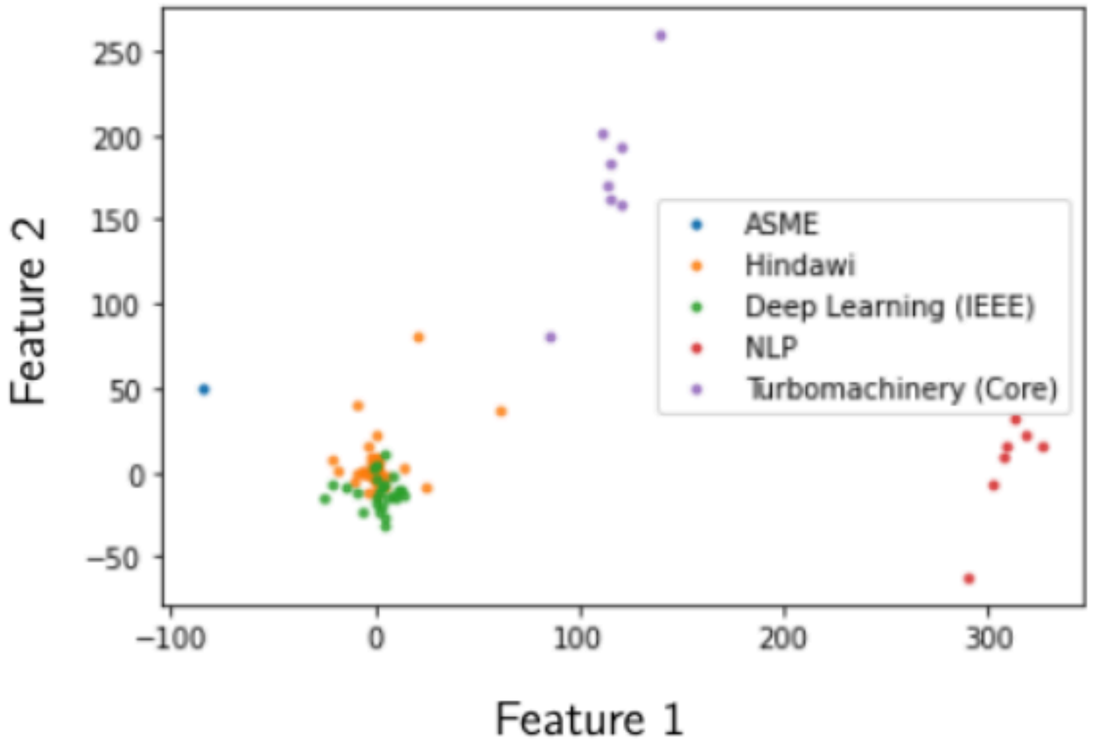
Project Outcomes and Discussion

Unsupervised Model



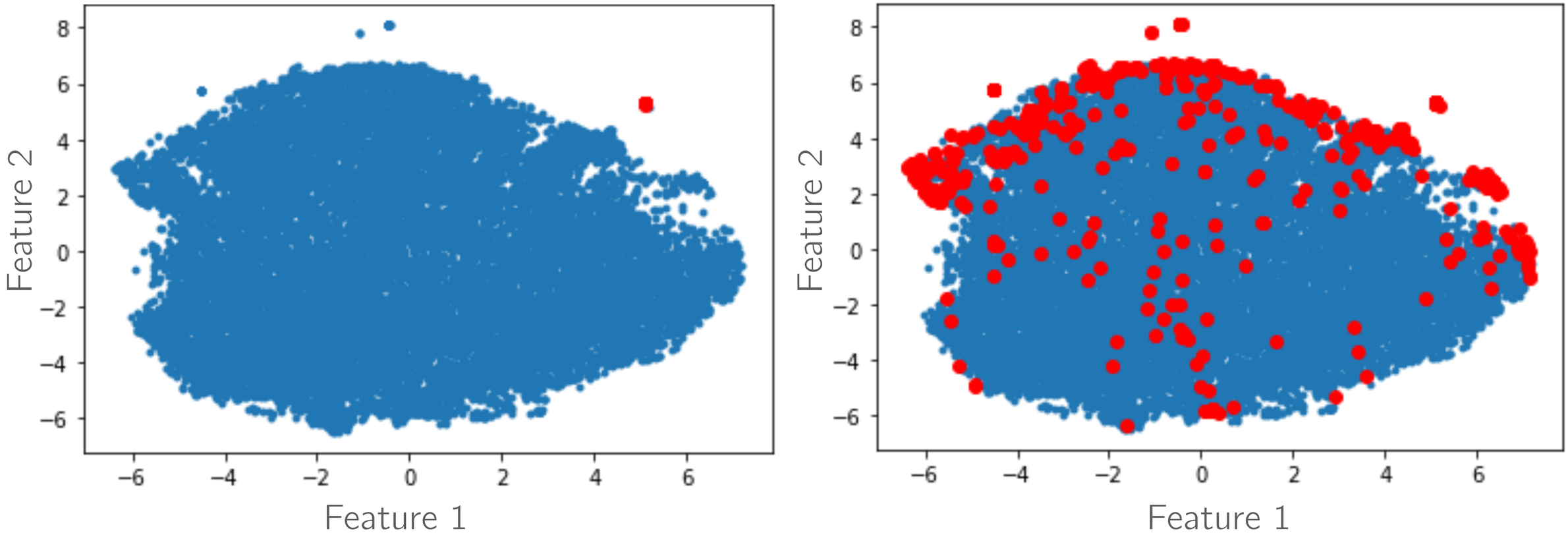
$l = 300$ length document vectors projected in 2D plane

$l = L$ length document vectors projected in 2D plane where L is the unique number of words in corpus



Project Outcomes and Discussion

Unsupervised Model



$l = 300$ length document vectors projected in 2D plane

Project Outcomes and Discussion

Data Quality

- ASME corpus data is not great

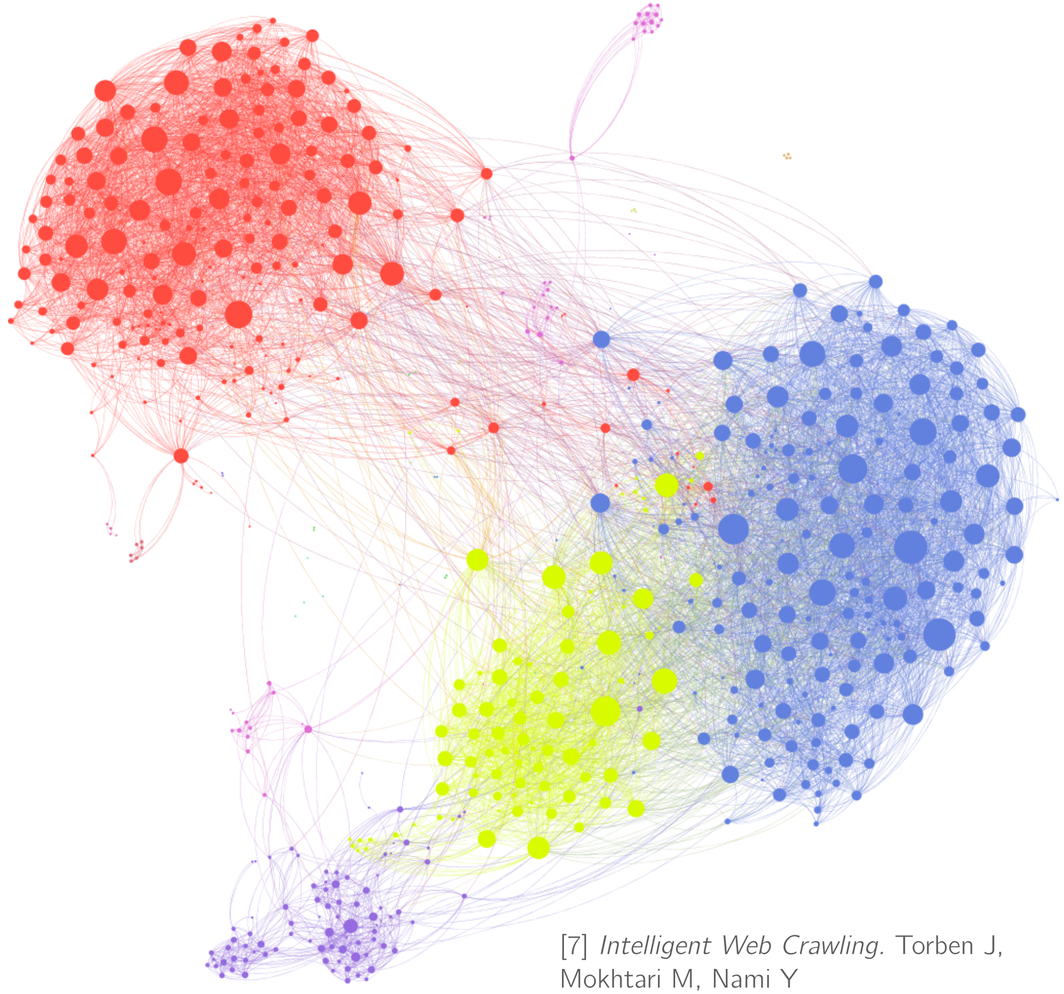
Type	Actual word	Unrecognized word
Spelling mistakes	capturing	capaturing
Incorrectly read characters	copyright	capyright
Foreign words		brennkammersystem
Maths symbols	$b \sin y$	bsiny
Phrases captured without whitespace	burner loudspeaker setup	burnerloudspeakersetup
Named entities that weren't removed		mohammadpour
Technical terms		eulerian

Conclusion

- Two models: 1 pseudo-supervised, 1 unsupervised
- Pseudo-supervised model: highly computationally expensive, best left for pre-labelled and small sized documents
- Unsupervised model: Performance predictable, not consistent at detecting novelty
- Document representations not informative enough due to low quality data and choice of embeddings (GloVe, TF-IDF)
- TF-IDF is useful for detecting relevance, but not novelty

Future Work

- **Redefining novelty:** considering graphical representations of documents for extracting information
- A novel research trend could be a branch that leads to another branch from a different cluster
- Can also examine novelty in graphical structures



[7] *Intelligent Web Crawling.* Torben J, Mokhtari M, Nami Y

Future Work

- **Data enhancement:** use of TF-IDF as filtration step for noise removal, spell checking
- **Improved document representations:** use of state-of-the-art document representation techniques, including document encoder-decoder models
- **Computational considerations:** use of `tensorflow`'s `tf.Dataset` for better GPU acceleration
- **References:** using citations as extra features for training

Imperial College London

June 9 2021

Thank you for your attention

Any Questions

Reference List

[1] Digital Bibliography and Library project. *Publications per year.* Available from: dblp.org/statistics/publicationsperyear.html [Accessed 5th June 2021]

[2] FloydHub. *Introduction to Anomaly Detection.* Available from: blog.floydhub.com/introduction-to-anomaly-detection-in-python/ [Accessed 5th June 2021]

[3] Pennington J, Socher R, Manning CD. Global Vectors for Word Representation. Available from: nlp.stanford.edu/projects/glove/ [Accessed 5th June 2021]

[4] Sarkar D. Hands on Approach to Deep learning methods for text data. Available from: towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa [Accessed 5th June 2021]

[5] Hui J. *Word Embedding and GloVe.* Available from: https://jonathan-hui.medium.com/nlp-word-embedding-glove-5e7f523999f6 [Accessed 5th June 2021]

[6] Qin Q, Hu W, Liu B. Text Classification with Novelty Detection. Arxiv [Preprint] 2020. Available from: https://arxiv.org/abs/2009.11119 [Accessed 5th June 2021]

[7] Torben J, Mokhtari R, Nami Y. *Intelligent Web Crawling* [Accessed 6th June 2021]