

# Contextualizing Trending Entities in News Stories

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Engineering

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# Introduction

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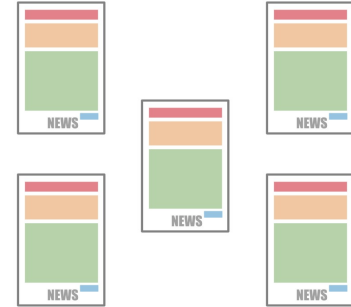
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# Introduction

- ▷ Every day an overwhelming amount of data is produced
  - Millions of news stories, web pages, and social media posts
- ▷ Important to provide automatic tools for:
  - Identify the **most relevant information**
  - Understand **why** a particular piece of information was selected
- ▷ **Trends** distill units (e.g., keywords, phrases, or names) meaningful for characterizing the news stories content
  - Units allow readers to **discover** and stay **focused** on **relevant information**



# Introduction

- ▷ Bloomberg Terminal functionality:

News Reader Activity		News Sentiment		Twitter Sentiment		News Volume		Twitter Volume		Social Velocity	
Largest Increase			Largest Total								
Security	Pub.	↓ GN	Δ Price	Δ AVAT	News Summary						
1) Alibaba Group Holdin...	190	↗	0.00%	+9.83%	Alibaba Group Founder Jack Ma First Appearance						
2) FactSet Research Sys...	112	↗	0.00%	+18.50%	FactSet : 144 01/14/2021						
3) LG Electronics Inc	56	↗	0.00%	+153.32%	17:12 LG Electronics May Exit Smartphone Business						
4) MediaTek Inc	56	↗	+0.23%	+40.94%	Like Qualcomm and Apple, MediaTek Designs Chips						
5) BASF SE	55	↗	+1.24%	+52.13%	BASF Sees FY Adj. Ebit EU3.56 Billion						
6) Tesla Inc	54	↗	0.00%	-34.58%	Tesla Breaking Into India After China Success						
7) Burberry Group PLC	53	↗	+4.43%	+887.53%	Burberry Sales Fall						
8) Taiwan Semiconducto...	53	↗	+0.47%	+67.62%	ASML Beats Grapples With Chip Supply Shortage						
9) Alphabet Inc	50	↗	0.00%	+32.49%	Trump Pardons Former Google Car Engineer						
10) Microsoft Corp	48	↗	0.00%	-3.99%	Microsoft GM Cars						

- ▷ Can we do one step further and contextualize the trending entities?

# Introduction

- ▷ Can we do one step further and **contextualize** the **trending entities**?

*What do we mean for contextualization?*

- Given a **trending entity**, we want to **retrieve** and **rank contextual entities**
- **Contextual entity** is an entity that helps explaining why the **trending entity** is actually trending

- ▷ Result of such contextualization can have different **applications**
  - Entity-centric **summary** driven by trending and contextual entities
  - **Recommend** related entities or news stories
  - **Query expansion**
  - *And many others!*



# Our Contributions



New **research problem!**



**Unsupervised** and **supervised solutions** based on:

1. Personalized PageRank and entity embeddings
2. Feature engineering and learning to rank

with **improvements** ranging from 7% to 12% in terms of Precision@1



Creation and release of a **test collection**  
built with **crowdsourcing**. Available at

 <https://doi.org/10.5281/zenodo.4422044>

# Problem Formulation

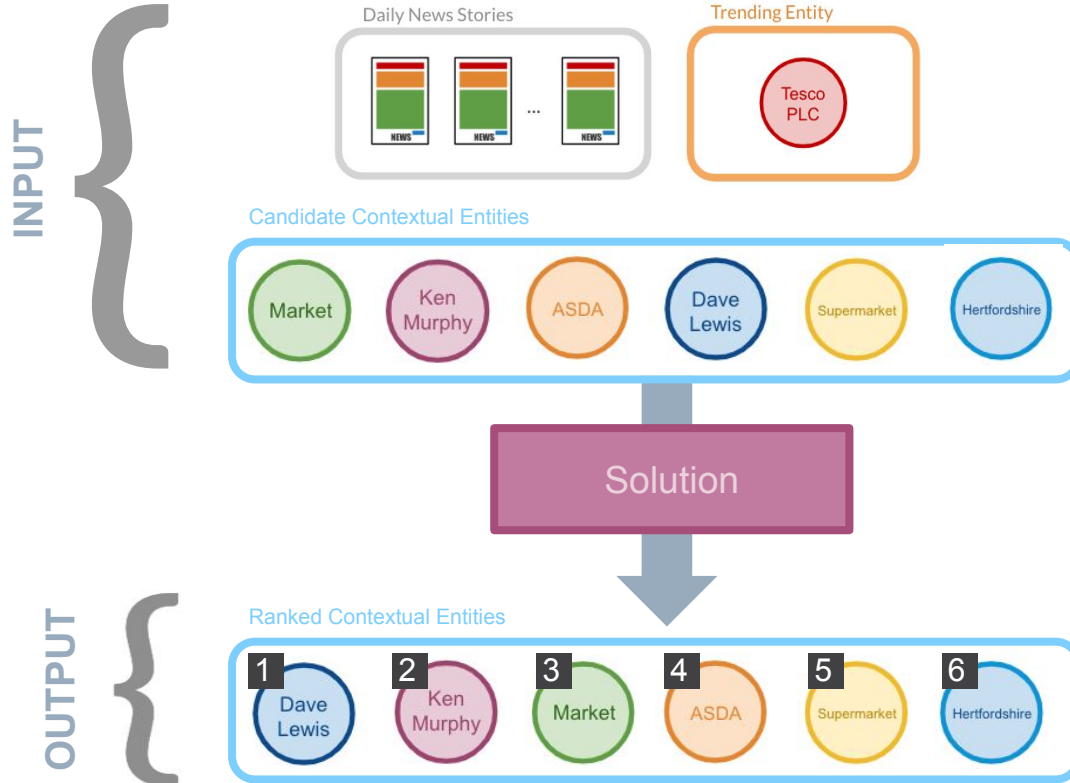
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# Contextualization as a Ranking Problem



The CEO of **Tesco** **Dave Lewis** resigned and **Ken Murphy** is supposed to become the new CEO.



# Solutions

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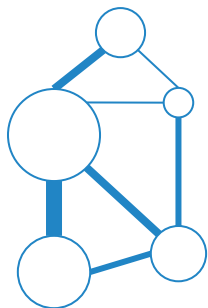
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# Two Main Solutions

Unsupervised vs. Supervised



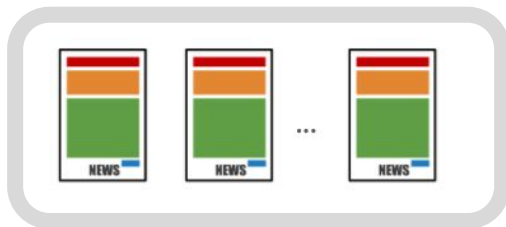
*Unsupervised* Solution based on Personalized PageRank, Saliency, and Embeddings



*Supervised* Solution based on Feature Engineering and Learn to Rank

# Unsupervised Solution

Daily News Stories



Trending Entity



Contextual Entities



# Unsupervised Solution

**Schema:** All contextual entities linked to the trending entity

1

**Intuition:** Graph pivoted around the trending entity

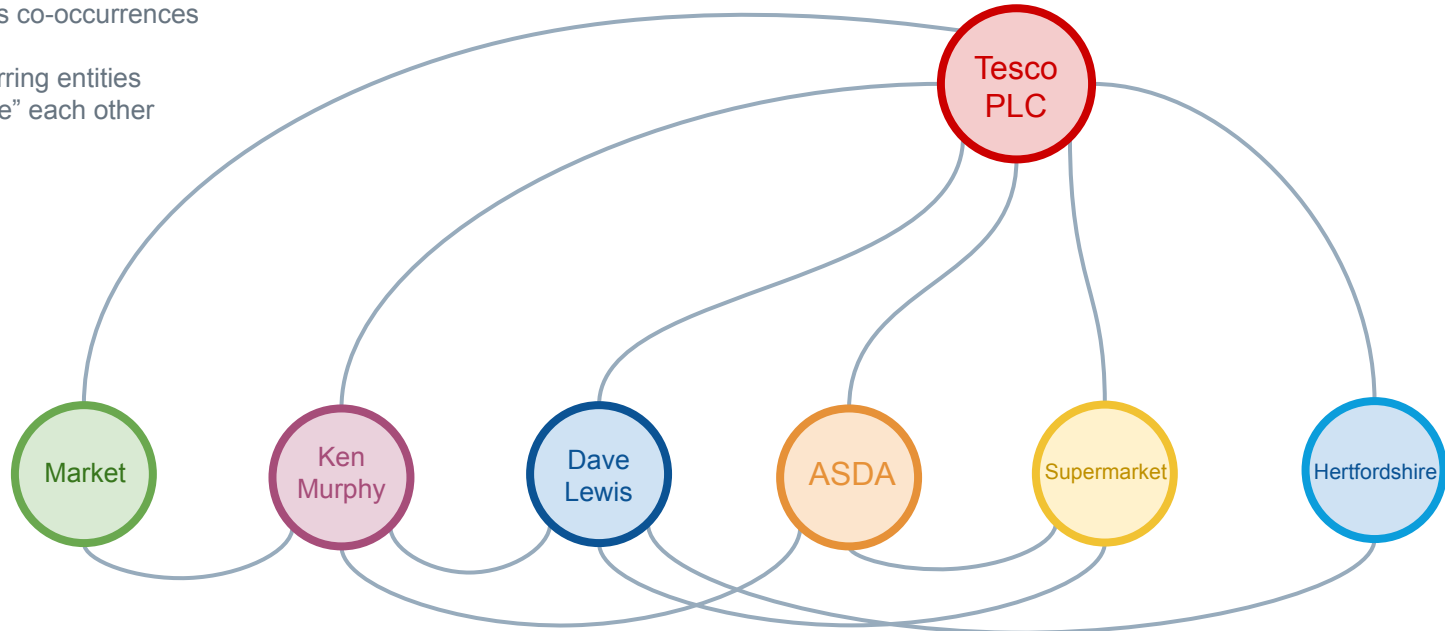


# Unsupervised Solution

**Schema:** Edges connections draw by stories co-occurrences

2

**Intuition:** Co-occurring entities will "vote" each other

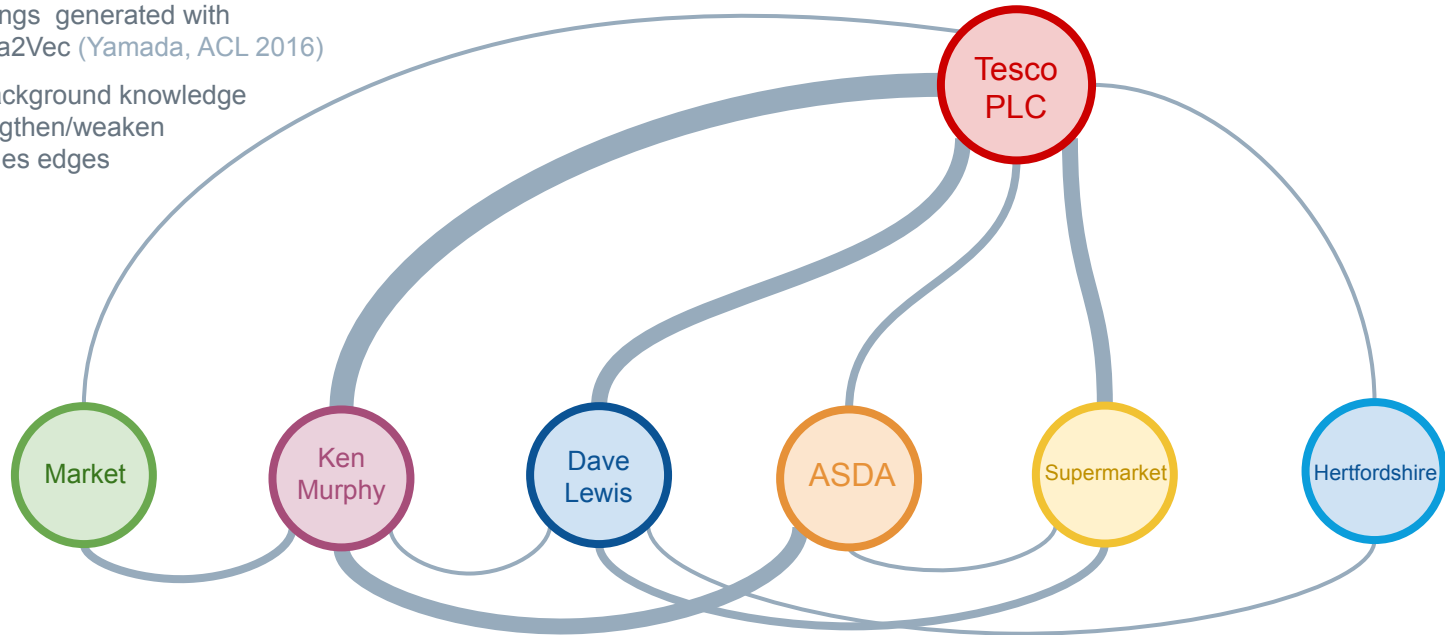


# Unsupervised Solution

**Schema:** Edges weighted via cosine embeddings generated with Wikipedia2Vec (Yamada, ACL 2016)

3

**Intuition:** Using background knowledge for strengthen/weaken the entities edges



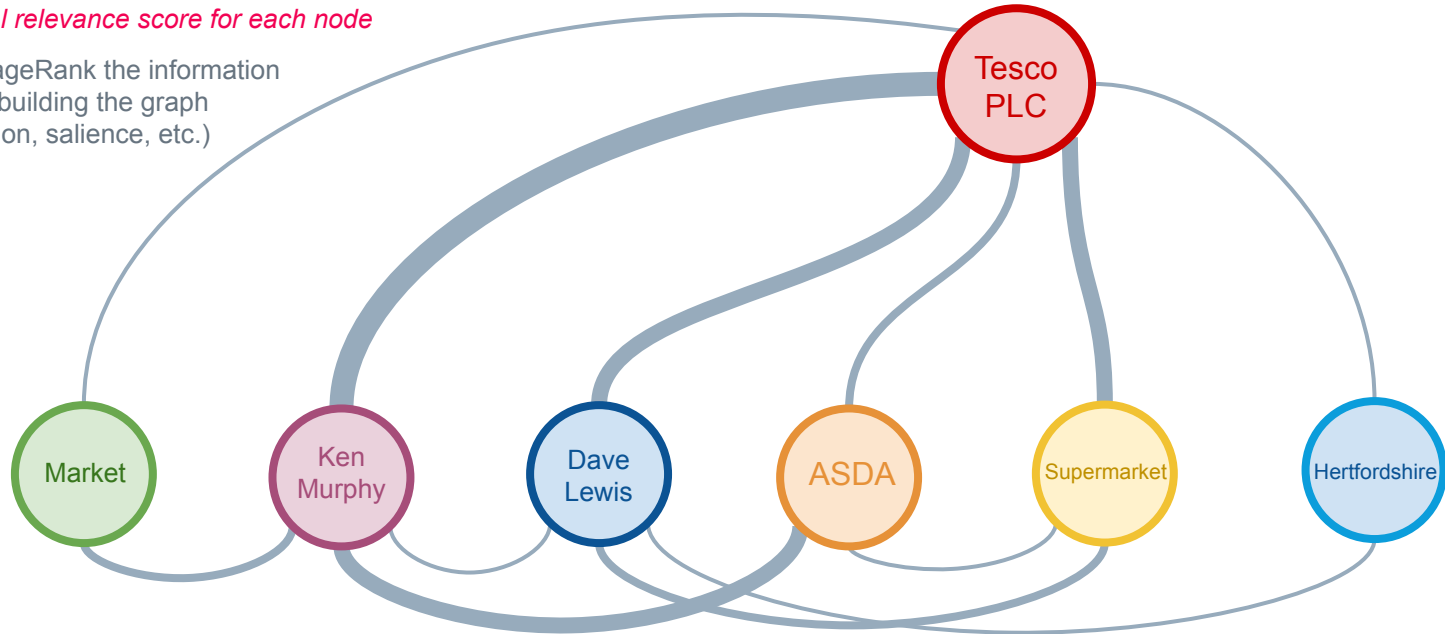


# Unsupervised Solution

Node Ranking Problem! We can use *Personalized PageRank*!

*Teleport Vector: Initial relevance score for each node*

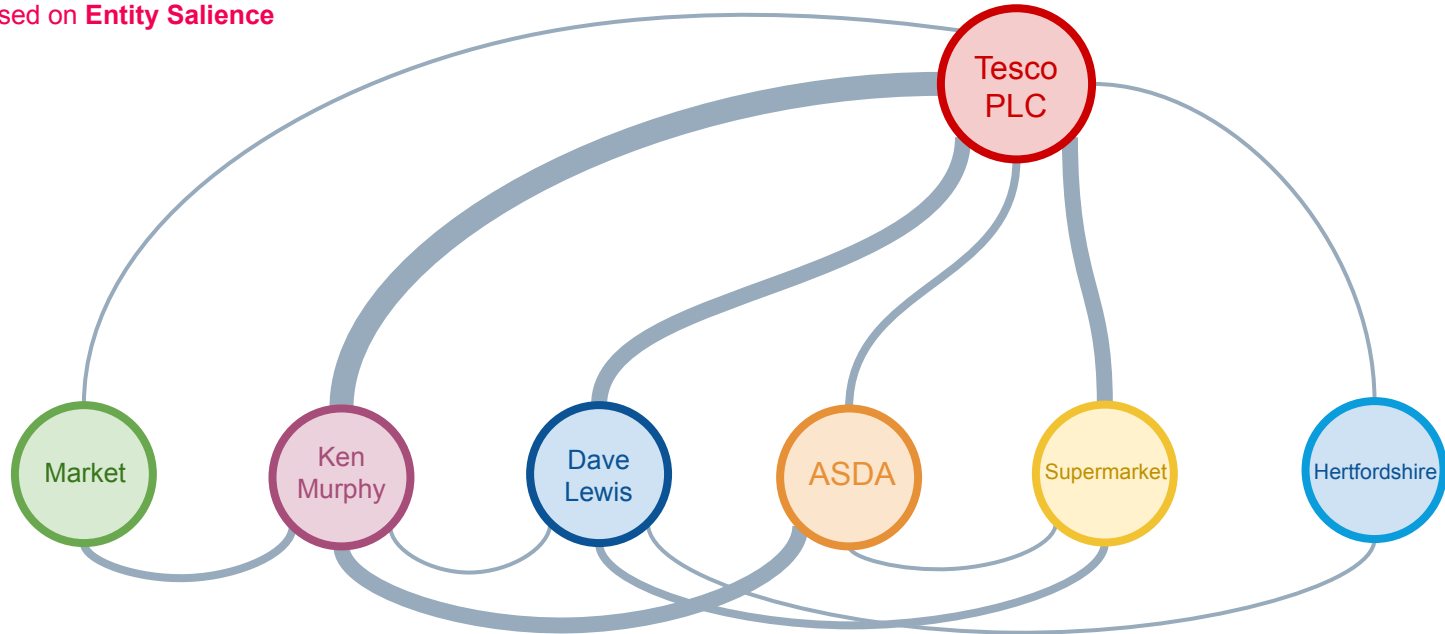
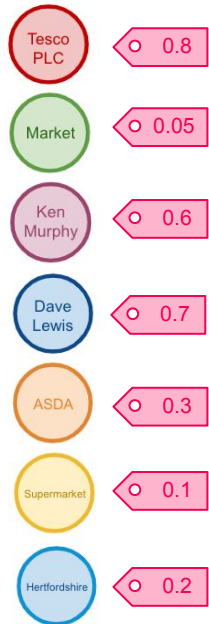
**Intuition:** Inject in PageRank the information we lost by building the graph (e.g., position, salience, etc.)



# Unsupervised Solution

Node Ranking Problem! We can use *Personalized PageRank*!

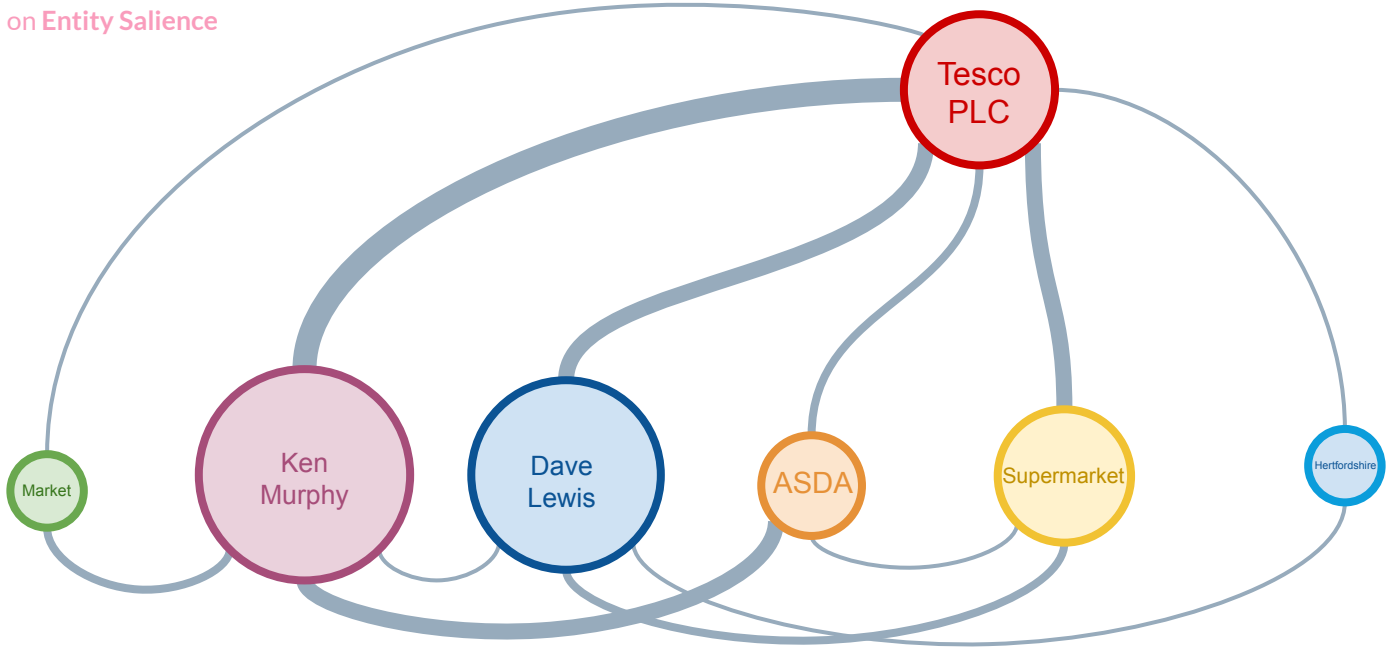
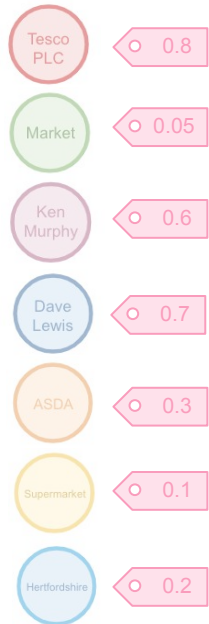
Teleport Vector based on **Entity Salience**



# Unsupervised Solution

Node Ranking Problem! We can use *Personalized PageRank*!

Teleport Vector based on **Entity Saliency**



# Experimental Results

- ▷ Dataset built via crowdsourcing
- ▷ 149 trends ~120K contextual entities (~800 per trend)

Publicly available at <https://doi.org/10.5281/zenodo.4422044>

# Experimental Results

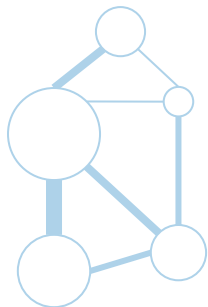
Method	“Relevant” & “Somewhat Relevant” as Gold Labels						“Relevant” as Gold Label					
	MAP	P@1	P@3	NDCG@5	NDCG@10	MRR	MAP	P@1	P@3	NDCG@5	NDCG@10	MRR
Frequency	0.098	0.262	0.224	0.168	0.233	0.448	0.097	0.208	0.177	0.179	0.242	0.382
Position	0.237	0.195	0.152	0.237	0.319	0.354	0.247	0.114	0.105	0.249	0.331	0.274
Co-Occurrence	0.359	0.477	0.295	0.441	0.479	0.604	0.441	0.416	0.221	0.486	0.515	0.528
PMI	0.147	0.161	0.15	0.186	0.209	0.324	0.173	0.107	0.105	0.195	0.219	0.252
Milnc&Witten	0.177	0.141	0.136	0.179	0.242	0.311	0.177	0.094	0.087	0.174	0.24	0.23
Jaccard	0.214	0.248	0.183	0.234	0.276	0.394	0.229	0.174	0.116	0.240	0.282	0.299
Stories' Embeddings	0.210	0.208	0.161	0.238	0.287	0.373	0.237	0.148	0.110	0.253	0.299	0.295
Wikipedia Embeddings	0.206	0.221	0.154	0.214	0.274	0.372	0.213	0.154	0.096	0.210	0.276	0.276
Reciprocal Rank	0.418	0.523	0.291	0.460	0.508	0.630	0.488	0.430	0.219	0.501	0.542	0.541
Saliency	0.497	0.570	<b>0.394</b>	0.556	0.612	0.727	0.555	0.456	<b>0.286</b>	0.593	0.640	0.622
PPR	<b>0.519</b>	<b>0.644</b>	0.391	<b>0.586</b>	<b>0.637</b>	0.773 <sup>Δ</sup>	0.605 <sup>Δ</sup>	0.564 <sup>Δ</sup>	0.282	0.639 <sup>Δ</sup>	0.678 <sup>Δ</sup>	0.686 <sup>Δ</sup>

Average improvements around +3/10% wrt Saliency

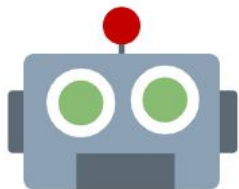
- PPR better for detection of **Highly Relevant Entities**
- Qualitative better ranking for top ranked entities

# Two Main Solutions

## Unsupervised vs. Supervised



*Unsupervised* Solution based on Personalized PageRank, Saliency, and Embeddings

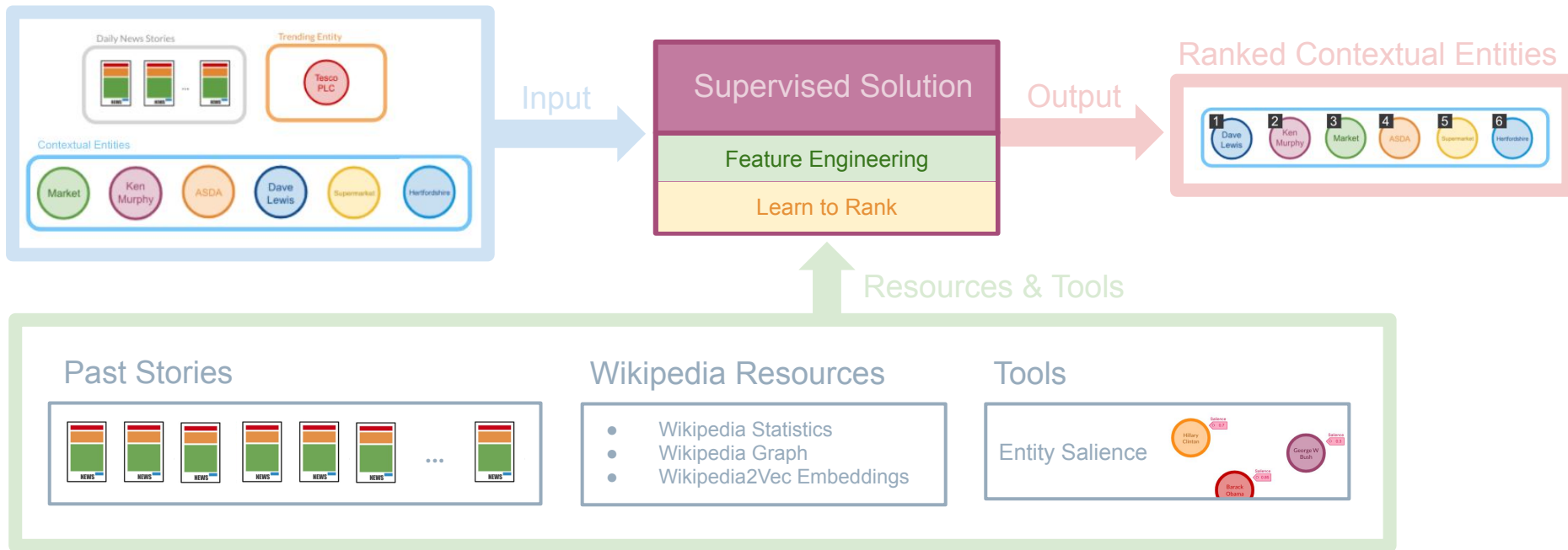


*Supervised* Solution based on Feature Engineering and Learn to Rank



# Supervised Solution

Trend in Question



# Supervised Solution

## Feature Engineering

### FREQUENCY

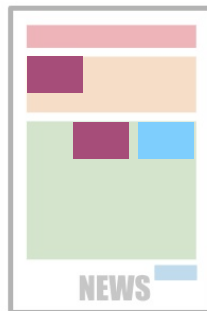
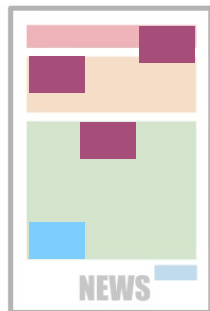


Provide a sense on how often an entity is **mentioned** across the news stories

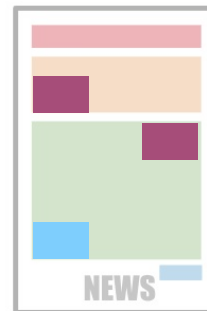
Ken  
Murphy

vs.

Hertfordshire



...



# Supervised Solution

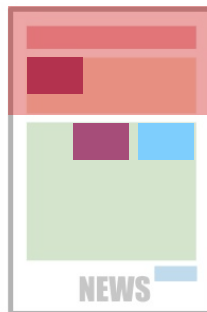
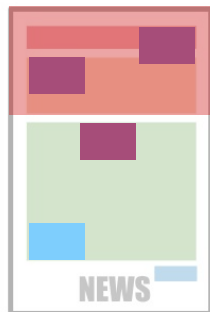
## Feature Engineering

### POSITION

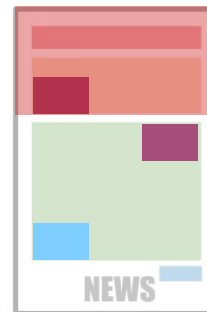
Provide a sense on where an entity is *mentioned* across the news stories



vs.



...



# Supervised Solution

## Feature Engineering

### POPULARITY



Provide a sense on general popularity of an entity from background knowledge

Ken  
Murphy

vs.

Market



Wikipedia



# Supervised Solution

## Feature Engineering

### POPULARITY



Provide a sense on general popularity of an entity from background knowledge



vs.



[en.wikipedia.org/wiki/Ken\\_Murphy](https://en.wikipedia.org/wiki/Ken_Murphy)

[en.wikipedia.org/wiki/Simon\\_Roberts](https://en.wikipedia.org/wiki/Simon_Roberts)

[en.wikipedia.org/wiki/Dave\\_Lewis](https://en.wikipedia.org/wiki/Dave_Lewis)

[en.wikipedia.org/wiki/Market \(economics\)](https://en.wikipedia.org/wiki/Market_(economics))

[en.wikipedia.org/wiki/Financial\\_Market](https://en.wikipedia.org/wiki/Financial_Market)

[en.wikipedia.org/wiki/Economy\\_of\\_the\\_UK](https://en.wikipedia.org/wiki/Economy_of_the_UK)

[en.wikipedia.org/wiki/Wall\\_Street](https://en.wikipedia.org/wiki/Wall_Street)

[en.wikipedia.org/wiki/NASDAQ](https://en.wikipedia.org/wiki/NASDAQ)

# Supervised Solution

## Feature Engineering

# POPULARITY

Provide a sense on general popularity of an entity from background knowledge



vs.



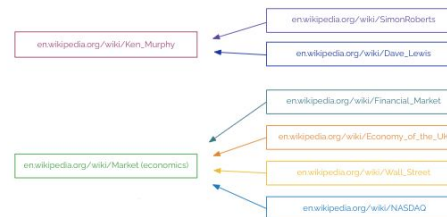
12



648



vs.





# Supervised Solution

## Feature Engineering

# TEXT COHERENCE



Provide a sense of coherence in the texts of the news stories

Ken  
Murphy

*Murphy* new *Tesco* CEO

Will *Ken Murphy* succeed after *Lewis*?

Tesco  
PLC

$$P(\text{Ken Murphy} \mid \text{Murphy}) = 0.4$$

$$P(\text{Tesco PLC} \mid \text{Tesco}) = 0.95$$

Dave  
Lewis

$$P(\text{Ken Murphy} \mid \text{Ken Murphy}) = 0.9$$

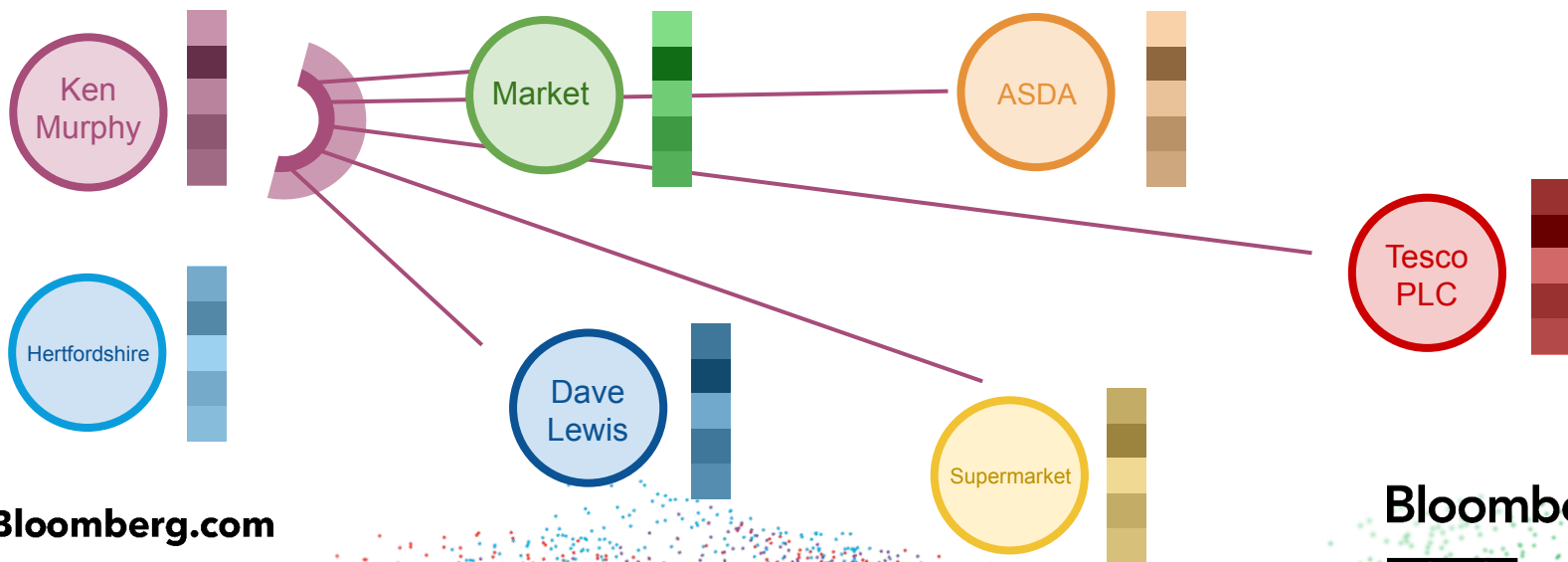
$$P(\text{Dave Lewis} \mid \text{Lewis}) = 0.7$$

# Supervised Solution

## Feature Engineering

# NEURAL COHERENCE

Provide a sense of coherence of an entity with the other entities

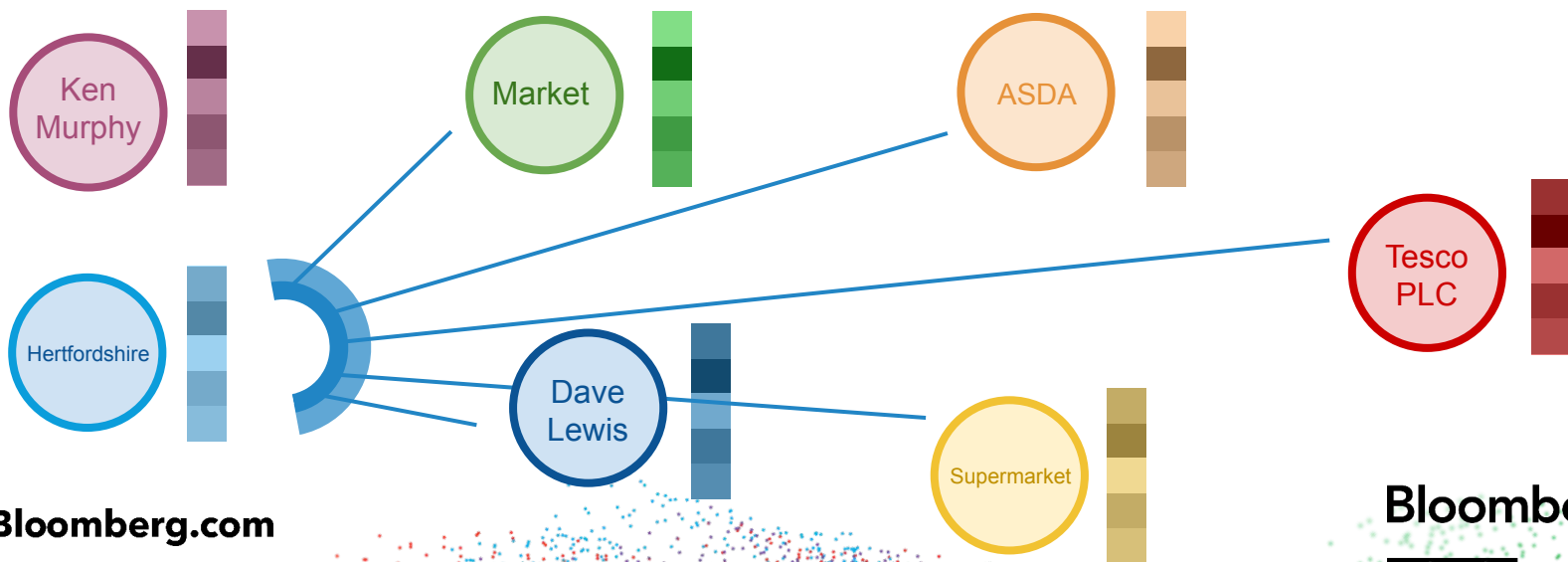


# Supervised Solution

## Feature Engineering

# NEURAL COHERENCE

Provide a sense of coherence of an entity with the other entities



# Supervised Solution

## Feature Engineering

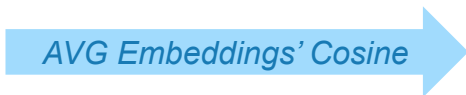
### NEURAL COHERENCE



Provide a sense of coherence of an entity with the other entities



0.57



0.12

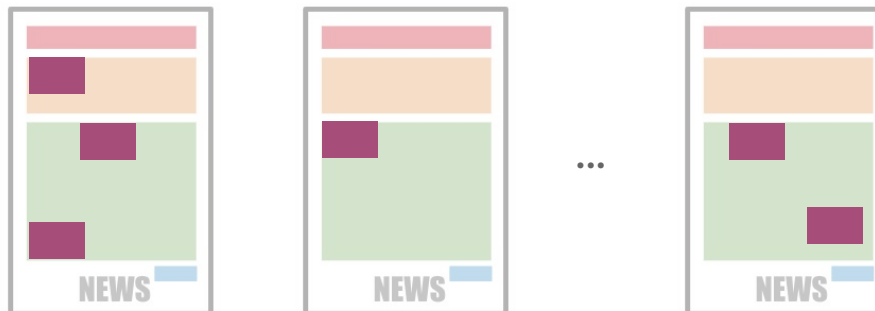


# Supervised Solution

## Feature Engineering

# SALIENCE

Provide a sense on stories' importance on an entity



# Supervised Solution

## Feature Engineering

### SALIENCE

Provide a sense on stories' importance on an entity



Cosine

$$\left( \begin{array}{cccc} 0.7 & 0.4 & \dots & 0.5 \\ 0.9 & 0.5 & \dots & 0.6 \end{array} \right) = 0.73$$

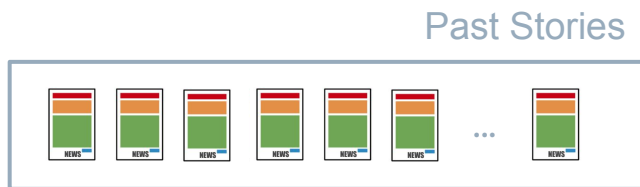


# Supervised Solution

## Feature Engineering

# SALIENCE

Provide a sense on stories' importance on an entity



Trend in Question



Contextual Entities



Story Frequency where



and have

saliency score  $\geq \tau$  ( $= 0.3$ )

Ken  
Murphy

# Supervised Solution

## Feature Engineering



Ken Murphy

Cosine  $\left( \begin{matrix} 0.7 & 0.4 & \dots & 0.5 \\ 0.9 & 0.5 & \dots & 0.6 \end{matrix} \right) = 0.73$

The diagram shows a cosine similarity matrix for 'Ken Murphy'. The matrix is a 2x4 grid of values: 0.7, 0.4, ..., 0.5 in the first row, and 0.9, 0.5, ..., 0.6 in the second row. The result of the cosine similarity calculation is 0.73.



## Learn to Rank



(Guolin et alii., NeurIPS 2017)

# Experimental Results

- ▷ Dataset split into training / validation / test sets
- ▷ Model tuned on training / validation sets
- ▷ Results of the methods reported on the test set

# Experimental Results

Method	“Relevant” & “Somewhat Relevant” as Gold Labels						“Relevant” as Gold Label					
	MAP	P@1	P@3	NDCG@5	NDCG@10	MRR	MAP	P@1	P@3	NDCG@5	NDCG@10	MRR
Saliency	0.474	0.569	0.364	0.526	0.584	0.714	0.534	0.462	0.251	0.566	0.616	0.604
PPR	0.495	0.646	0.364	0.565	0.617	0.767	0.591	0.554	0.256	0.622	0.659	0.665
LTR	<b>0.574<sup>◆▲</sup></b>	<b>0.708</b>	<b>0.472<sup>◆▲</sup></b>	<b>0.629<sup>▲</sup></b>	<b>0.682<sup>◆▲</sup></b>	<b>0.815<sup>▲</sup></b>	<b>0.609</b>	<b>0.569</b>	<b>0.308<sup>◆▲</sup></b>	<b>0.654<sup>▲</sup></b>	<b>0.696<sup>▲</sup></b>	<b>0.710<sup>▲</sup></b>

Average improvement around +6/9% wrt PPR

- Qualitative better ranking in the head+tail
- Able to detect partially relevant entities

# Conclusion

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# Take-Home Messages

- ▷ We introduced the **problem** of **ranking contextual entities** for a trend
- ▷ We experimented with two methods:
  - **Unsupervised**, based on **Personalized PageRank**.
  - **Supervised**, based on **feature engineering** and **learning to rank**.
- ▷ The **Supervised** method generally works **better** than **unsupervised** ones
  - With **improvements** between +10% in terms of P@3
  - **Feature analysis** show most important features are based on **salience** and **text coherence**

# Thank you!

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