

Data Mining for Entity Relationship Associations

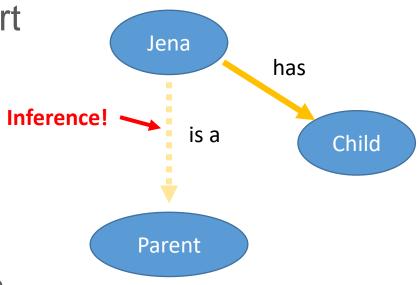
School of Engineering and Applied Science
Department of Computer Science CSCI 6443— Data Mining

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Problem Definition

- Many chatbots are a combination of expert systems and machine learning.
- A knowledge base is often used as the "brain" of the chatbot due to its ability to perform inference.
- Traditionally knowledge bases perform inference based on inference rules, which are brittle and don't scale well.



IF <subject> has Child THEN <subject> is a Parent



Problem Definition Continued

- Unsupervised learning of entity relationships is difficult and supervised learning datasets are costly to create.
- Performance is subjective and language dependent.
- State-of-the-art NLP algorithms struggle to perform Relationship Extraction (RE) with the precision and recall of a person.

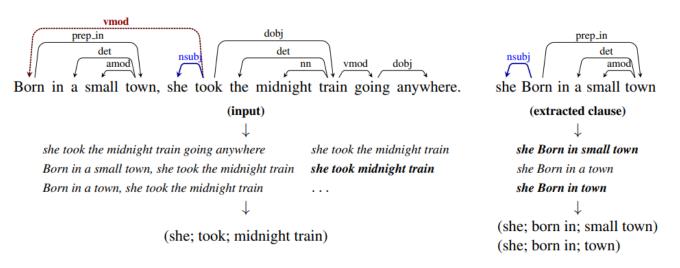
Java was originally developed by James Gosling at Sun Microsystems

https://corenlp.run/



Related Work Continued

- Methods of doing RE :
 - OpenIE
 - Greedy search on dependency tree
 - Goal is to reduce sentence to utterance, and keep reducing until triple is all that is remaining



https://nlp.stanford.edu/pubs/2015angeli-openie.pdf



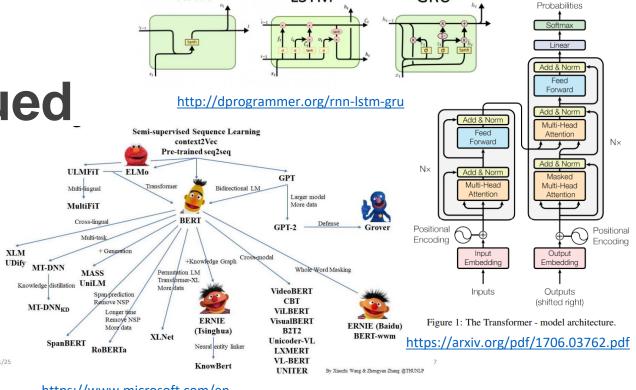
Related Work Continued

- Methods of doing RE :
 - Applying language generation/translation techniques
 - RNN, LSTM, GRU, Transformers (Seq2Seq (BERT, ERNIE, GPT, BART))



https://translate.google.com/





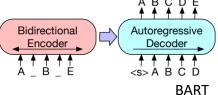
LSTM

GRU

Output

https://www.microsoft.com/enus/research/uploads/prod/2021/06/Pre-training-Models-Xu-Tan.pdf

RNN



 $\underline{https://arxiv.org/pdf/1906.07510v8.pdf}$



Related Work Continued

- After RE, associations between relations occurs.
- Leading association algorithms are:
 - Apriori (Low Mem, Slow Speed)
 - Eclat (Medium Mem, Medium Speed)
 - FP Growth (High Mem, Fast Speed)

	FP Growth	Eclat
Breadth first search	Divide and Conquer	Depth first search
		and intersection of
		transaction id.
Database is scanned	Database Id scanned	Database is scanned
each time a	two times only.	few times.
candidate item set is		
generated		
-Easy to implement.	Database scanned	No need to scan
	two times only.	database each time.
-Use large item set		
property.		
-Require large	FP tree is expensive	It requires virtual
memory space.	to build consumes	memory to perform
	more memory.	the transaction.
-Too many		
candidate item set		
Horizontal	Horizontal	Vertical
Array	Tree (FP tree)	Array
More execution	Less time as	Execution time is
time	compared to Apriori	less than Apriori
	Database is scanned each time a candidate item set is generated -Easy to implement. -Use large item set property. -Require large memory space. -Too many candidate item set Horizontal Array More execution	Database is scanned each time a two times only. candidate item set is generated -Easy to implement. -Use large item set property. -Require large memory space. Too many candidate item set Horizontal Horizontal Array Tree (FP tree) Database scanned two times only. FP tree is expensive to build consumes more memory. Tree (FP tree)

Evaluation Criteria

https://www.semanticscholar.org/paper/Market-basket-analysis-for-improving-the-of-and-FP-Khan-Solaiman/99115afbb9202eba44c7522dccdf71fec8fd6b21



Approach

- Text already mined and transforming to JSON files
- Zipped text moved to AWS cloud environment
- This allows servers to access as needed with higher download speeds
- · Download data
- Unzip
- Split into manageable data message sizes
- Publish text to queue

- High performance queue
- Allows consuming service to be parallel by ensuring only one consumer gets each message
- Perform Relation Extraction (RE) to convert unstructured data to structured data
- Write to DB

- Clean, Transform, and Filter Structured Data
- DB Scans and Queries
- Apply FP Growth







Amazon Simple Storage Service (Amazon S3)



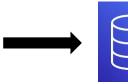
Amazon Elastic Compute Cloud (Amazon EC2)



Amazon Simple Queue Service (Amazon SQS)



Amazon Elastic Compute Cloud (Amazon EC2)

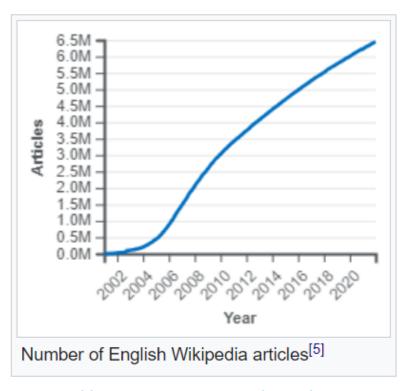


Amazon Neptune



Selected Dataset

- Wikipedia
- 6.5M+ English articles as of 2022
- 10TB of data as of 2015
 - https://dumps.wikimedia.org/enwiki/latest/
 - https://www.kaggle.com/datasets/ltcmdrdata/plain-text-wikipedia-202011
 - https://github.com/daveshap/PlainTextWikipedia

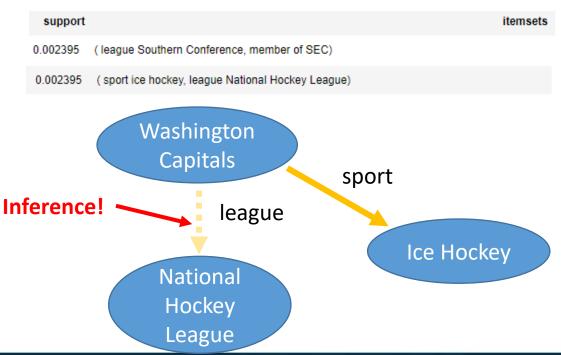


https://en.wikipedia.org/wiki/WikipediaSize of Wikipedia



Results

Some early associations



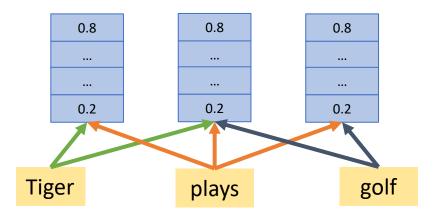
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country United States', 'country United States of America
league NFL', 'sport American football'
position held President', 'residence White House'
member of NATO', 'continent Europe'
diplomatic relation United States', 'member of NATO'
conflict World War I', 'conflict First World War'
league National League', 'league Major League Baseball
shares border with Pennsylvania', 'instance of state', 'country U
part of Central America', 'part of North America'
instance of color', 'instance of colour'
headquarters location London', 'location London'
sport football', 'sport soccer'
country US', 'country United States', 'country American'
country US', 'country USA', 'country United States'
author Shakespeare', 'author William Shakespeare'
league Segunda División', 'country Spain'
league National Hockey League', 'sport ice hockey'
located in or next to body of water Persian Gulf', ' part of Middle East'
shares border with France', 'participant in World Cup'
member of NFL', 'member of National Football League', 'sport American foot
```



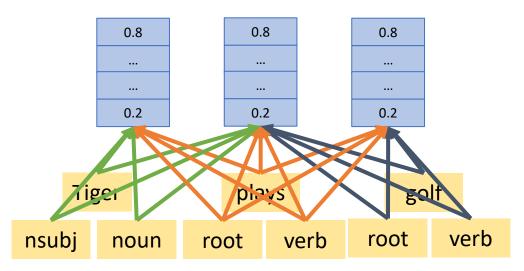
Future Work

- Investigate methods of factoring in POS tags and parse labels
 - Helps to generalize
 - Due to generalization could reduce training size needed





Typical text encoding



Can we do this?



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