THE GEORGE WASHINGTON UNIVERSITY
WASHINGTON, DC

Data Mining for Entity Relationship Associations

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

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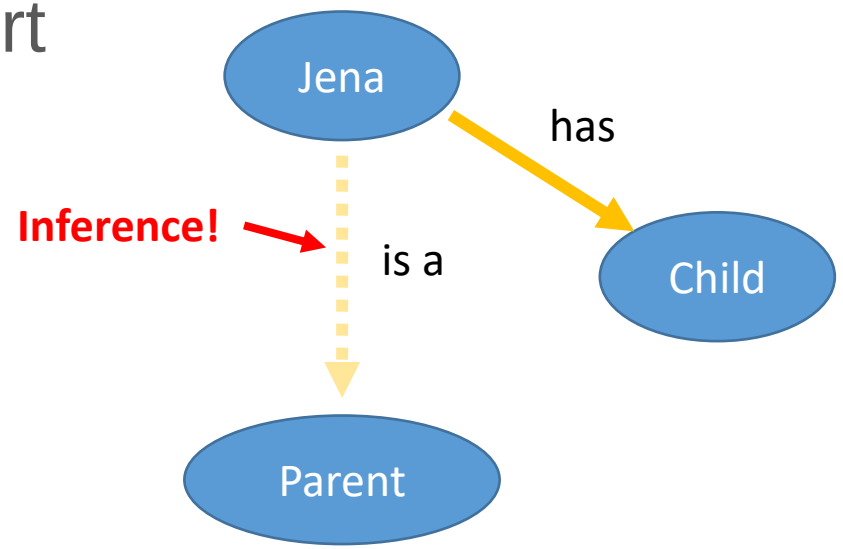
Problem Definition

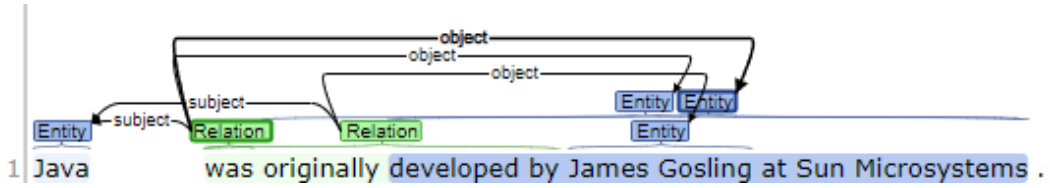
- Many chatbots are a combination of expert systems and machine learning.
- A knowledge base is often used as the “brain” of the chatbot due to its ability to perform inference.
- Traditionally knowledge bases perform inference based on inference rules, which are brittle and don’t scale well.



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

Problem Definition Continued

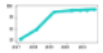
- Unsupervised learning of entity relationships is difficult and supervised learning datasets are costly to create.
- Performance is subjective and language dependent.
- State-of-the-art NLP algorithms struggle to perform Relationship Extraction (RE) with the precision and recall of a person.



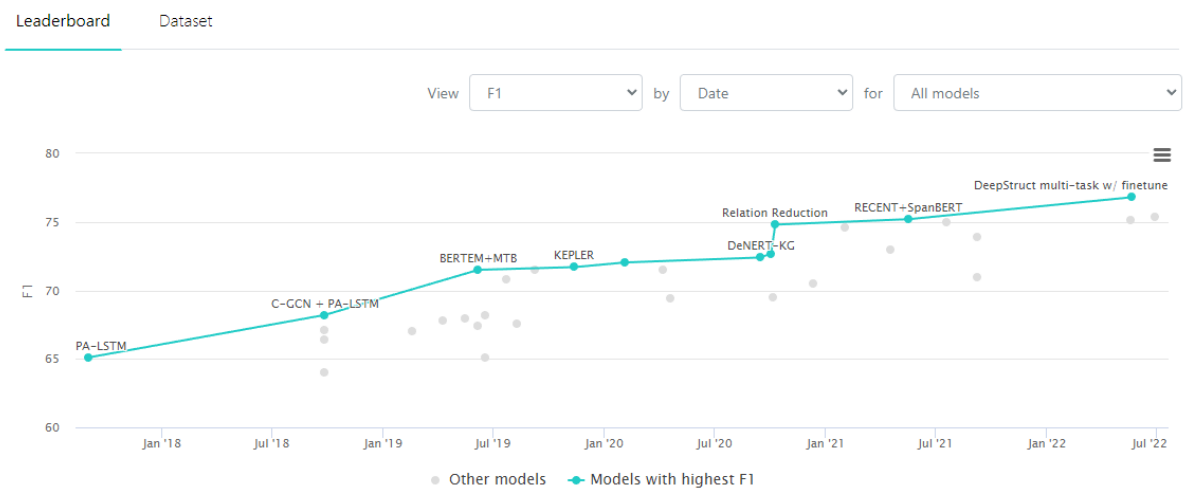
https://corenlp.run/

Related Work

- Datasets (not all are free):
  - https://paperswithcode.com/datasets?task=relation-extraction
- Papers:
  - https://paperswithcode.com/task/relation-extraction#papers-list
- Notable Algorithms Types:
  - Open Information Extraction (OpenIE)
  - Convolutional Neural Network (CNN)
  - Sequence based networks (RNN, LSTM, GRU, Transformers)

Trend	Dataset	Best Model	Paper	Code	Compare
	DocRED	KD-Rb-l			See all
	TACRED	DeepStruct multi-task w/ finetune			See all
	ACE 2005	PL-Marker			See all
	NYT	DeepStruct multi-task			See all

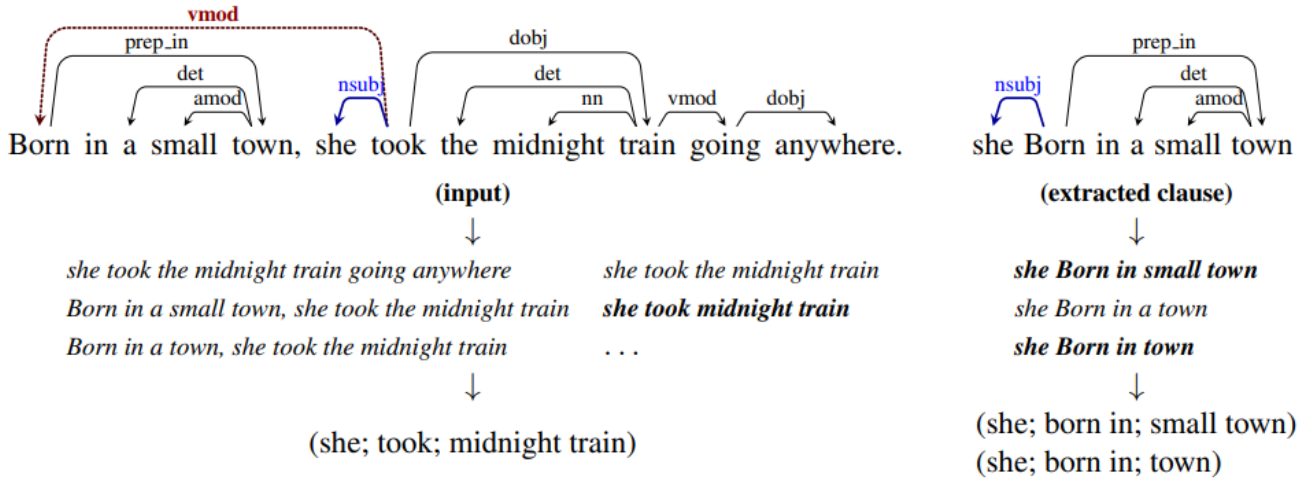
Relation Extraction on TACRED



https://paperswithcode.com/task/relation-extraction

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

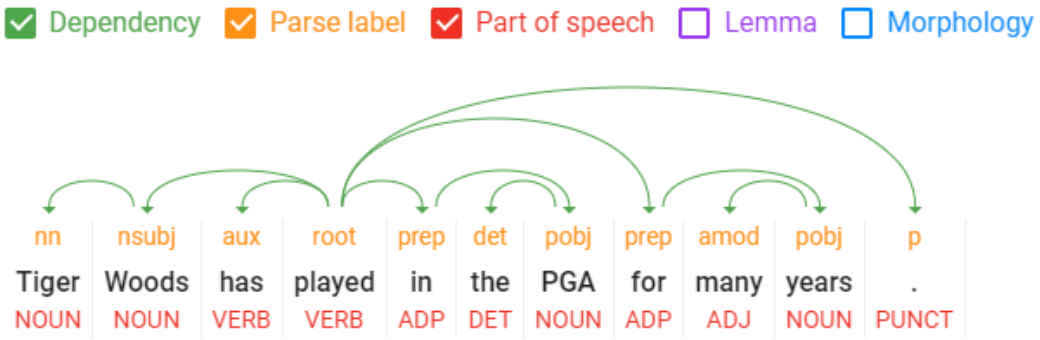
Related Work Continued

- Methods of doing RE:
  - Named Entity Extraction (NER) + Classification of relations between entities using neural networks
    - Text and/or Part of Speech (POS) tags are input features along with entities
  - Graph Convolutional Neural Networks (GCN)
    - Create graph from dependencies
    - GCN learns features and structures in graph that are associated to training data

⟨Tiger Woods⟩$_1$ has played in the ⟨PGA⟩$_2$ for many years.

NER Example

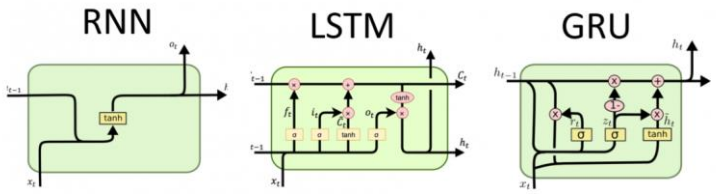
https://cloud.google.com/natural-language



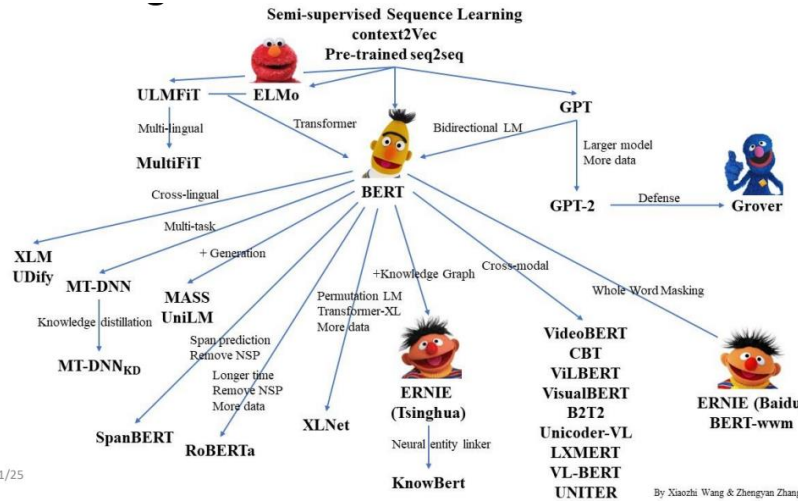
https://cloud.google.com/natural-language

Related Work Continued

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



http://dprogrammer.org/rnn-lstm-gru



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

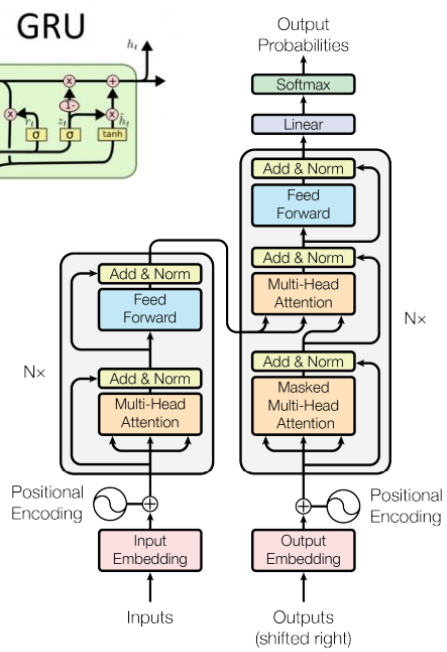
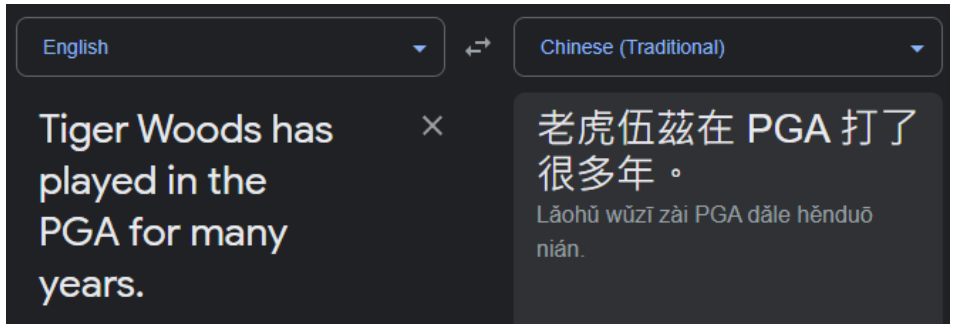
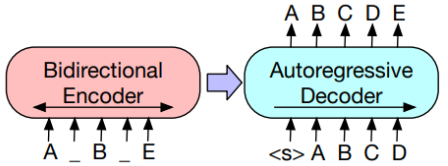


Figure 1: The Transformer - model architecture.

https://arxiv.org/pdf/1706.03762.pdf



https://translate.google.com/



BART

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)

Evaluation Criteria	Apriori	FP Growth	Eclat
1. Techniques	Breadth first search	Divide and Conquer	Depth first search and intersection of transaction id.
2. Database Scan	Database is scanned each time a candidate item set is generated	Database Id scanned two times only.	Database is scanned few times.
3. Advantages	-Easy to implement. -Use large item set property.	Database scanned two times only.	No need to scan database each time.
4. Disadvantages	-Require large memory space. -Too many candidate item set	FP tree is expensive to build consumes more memory.	It requires virtual memory to perform the transaction.
5. Data format	Horizontal	Horizontal	Vertical
6. Storage Format	Array	Tree (FP tree)	Array
7. Time	More execution time	Less time as compared to Apriori algorithm	Execution time is less than Apriori algorithm.

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

Proposed Approach

- Text already mined and transforming to JSON files

Text Dataset

- Zipped text moved to AWS cloud environment
- This allows servers to access as needed with higher download speeds

Amazon Simple Storage Service (Amazon S3)

- Download data
- Unzip
- Split into manageable data message sizes
- Publish text to queue

Amazon Elastic Compute Cloud (Amazon EC2)

- High performance queue
- Allows consuming service to be parallel by ensuring only one consumer gets each message

Amazon Simple Queue Service (Amazon SQS)

- Perform Relation Extraction (RE) to convert unstructured data to structured data
- Write to DB

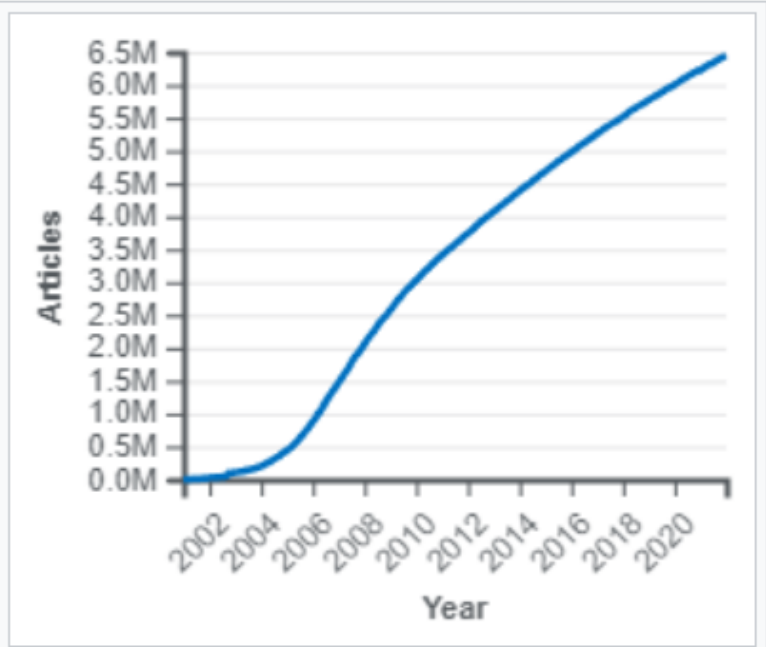
Amazon Elastic Compute Cloud (Amazon EC2)

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

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



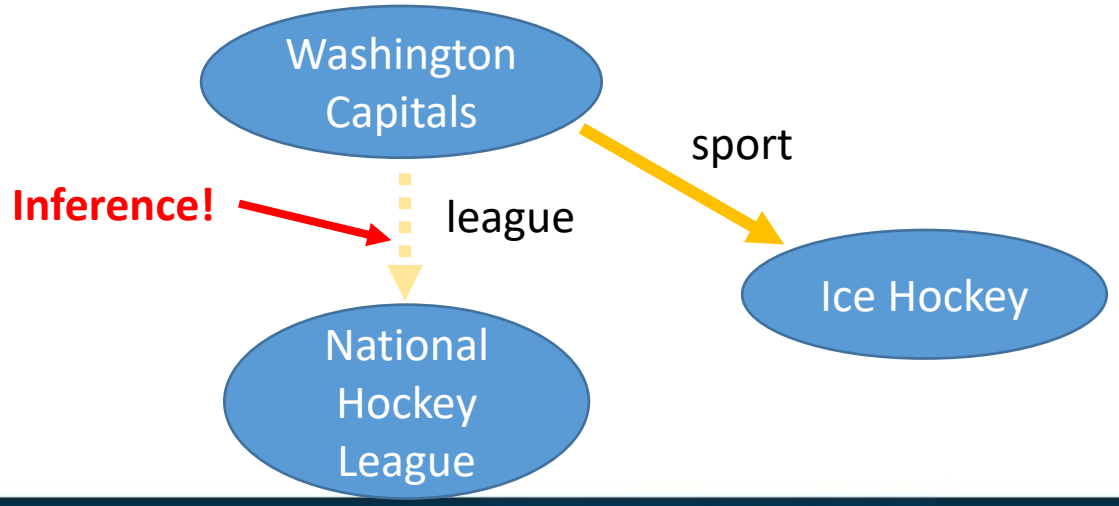
Number of English Wikipedia articles[5]

https://en.wikipedia.org/wiki/Wikipedia:Size_of_Wikipedia

Current Progress

Some early associations

support	itemsets
0.002395	(league Southern Conference, member of SEC)
0.002395	(sport ice hockey, league National Hockey League)



Date: October 2022

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Estimated Total $13.50

Name	Type	Created	Messages available
Articles.fifo	FIFO	10/20/2022, 17:04:48 EDT	100158

Name	Instance ID	Instance state	Instance type
Article Queue Worker	i-091ebaa6da955fdaa	Terminated	t2.large
Relation Extraction Worker	i-0ab1850889ef24422	Running	c5.xlarge
Relation Extraction Worker	i-0af5a562cb22ab67e	Running	c5.xlarge
Relation Extraction Worker	i-0d9e48489f40dcf72	Running	c5.xlarge
Relation Extraction Worker	i-0bf6d65705a462b48	Running	c5.xlarge
Relation Extraction Worker	i-0915356135ede0d01	Running	c5.xlarge
Relation Extraction Worker	i-0ca912cea7d0f9f5b	Running	c5.xlarge
Relation Extraction Worker	i-0f543502e49154966	Running	c5.xlarge
Relation Extraction Worker	i-06771b02375ff6f29	Running	c5.xlarge
Relation Extraction Worker	i-0ca674c2d2d2d77f6	Running	c5.xlarge
Relation Extraction Worker	i-09daf15fce53d4b36	Running	c5.xlarge

a. (John_E_Blaha birthDate 1942_08_26) (John_E_Blaha birthPlace San_Antonio) (John_E_Blaha occupation Fighter_pilot)

b. *John E Blaha, born in San Antonio on 1942-08-26, worked as a fighter pilot*

https://webnlg-challenge.loria.fr/

Future Work

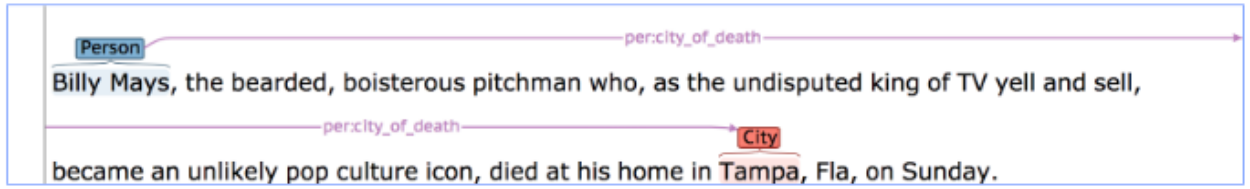
- Generate a new set of training data
- Start with generated triples by determining how often entities and verbs/predicates appear in the same sentence
- Use transformer to generate sentences from generated triple
- This would give the algorithm a more direct triple to sentence training

dbp:yearpro	• 1996 (xsd:integer)

https://dbpedia.org/page/Tiger_Woods

Woods turned professional in 1996

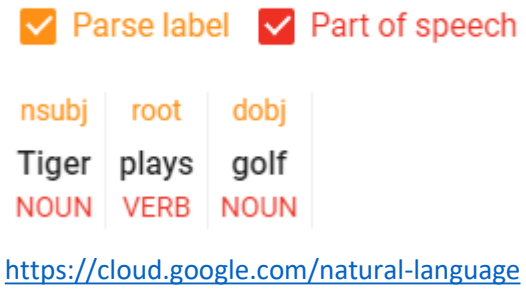
https://en.wikipedia.org/wiki/Tiger_Woods



https://nlp.stanford.edu/projects/tacred/

Future Work Continued

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



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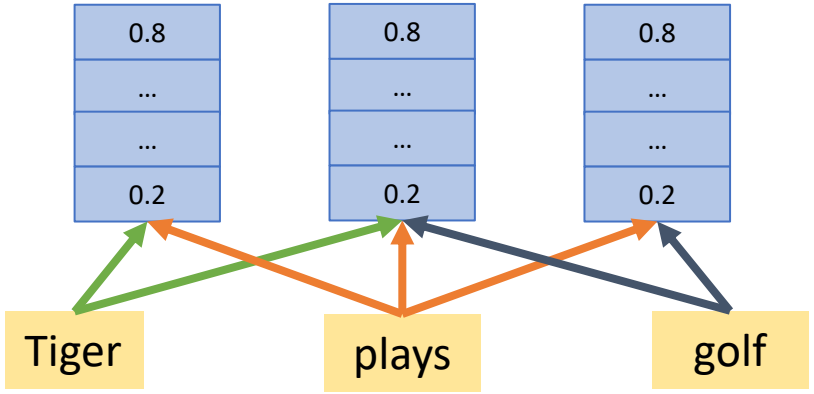
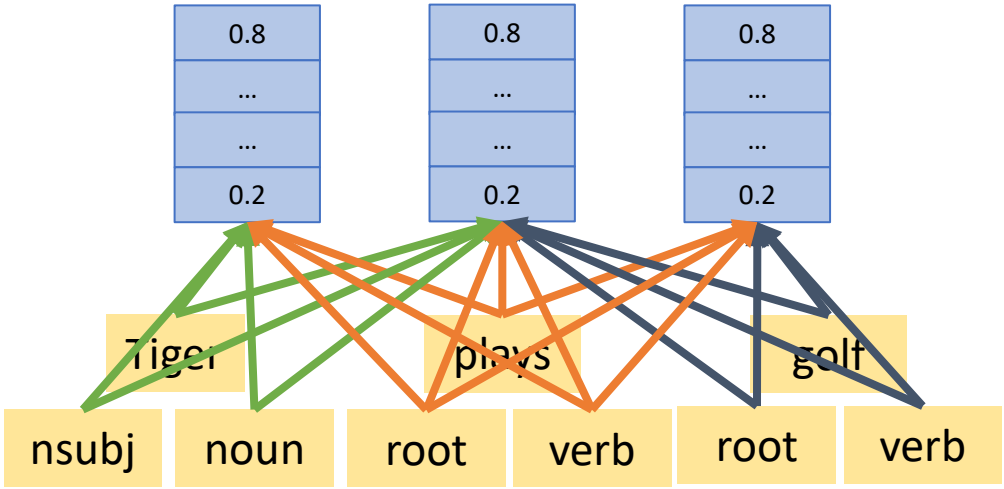


Typical text encoding



Can we do this?

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