



UnFound

ELMo Embeddings

Exploring the power of **context**.

Session flow

- Characterization Problem at hand
- Existing solutions and how they work
- Drawbacks of these solutions
- In comes ELMO
- How does it solve the problem
- Testing on our results
- Applications of ELMO



Artificial Intelligence meets News

We want to change the way news is consumed today.

www.unfound.news



Summarization

Question
Answer
Generation

Quotes
Generation

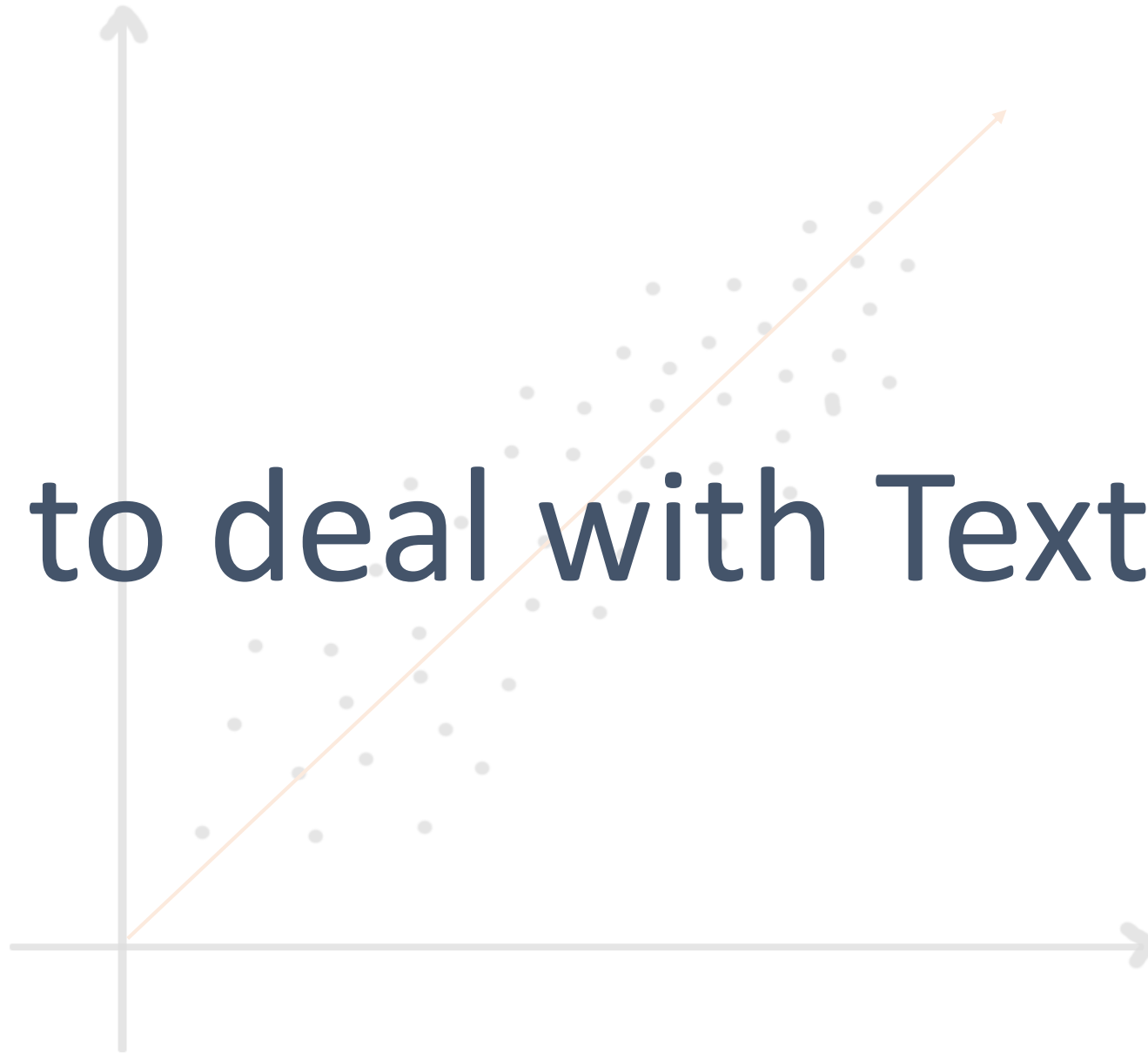
AI behind UnFound

News Ranking

Timeline
Detection

Stance
Detection

How to deal with Text data ?



Word Embeddings!

One-hot encoding

What if the **size of vocabulary** increases
to a million words ?

Do the words **ants** and **toxic**
have any resemblance ?

The	0	1	0	0	0	0
ants	0	0	1	0	0	0
in	0	0	0	0	0	0
USA	0	0	0	1	0	0
are	0	0	0	0	1	0
toxic	0	0	0	0	0	1

Word Embeddings

Hello \longrightarrow [0.3 0.6 0.1 0.9]

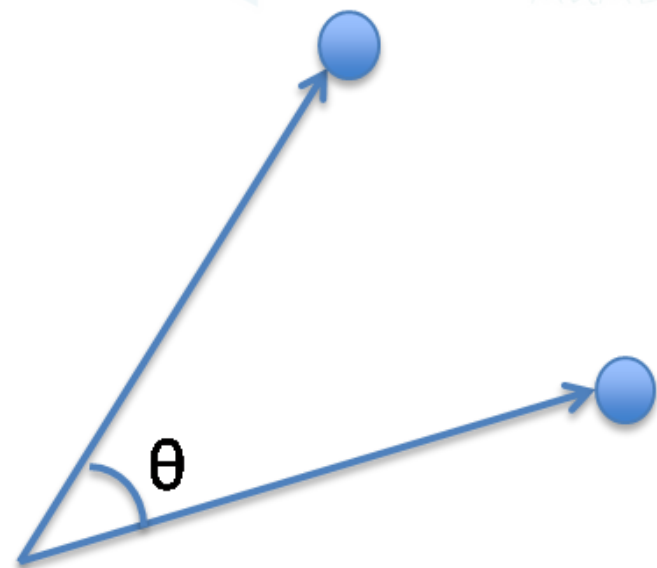
Word embeddings are distributed representations in vector space.

Understanding Embeddings

King → [0.1 0.2 0.7]
Queen → [0.2 0.3 0.5] → 0.80

King → [0.1 0.2 0.7]
Apple → [0.9 0.5 0.6] → 0.20

$$\text{sim}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$



Task- News Clustering

1. The **king** of Africa had planted this tree.
2. The **queen** of England is set to land in Africa this year .
3. This year we received a good quality of **apples**.

Popular Embedding models

- Word2Vec
- GloVe
- Doc2Vec
- fastText
- Gensim

A simple Skip-gram model

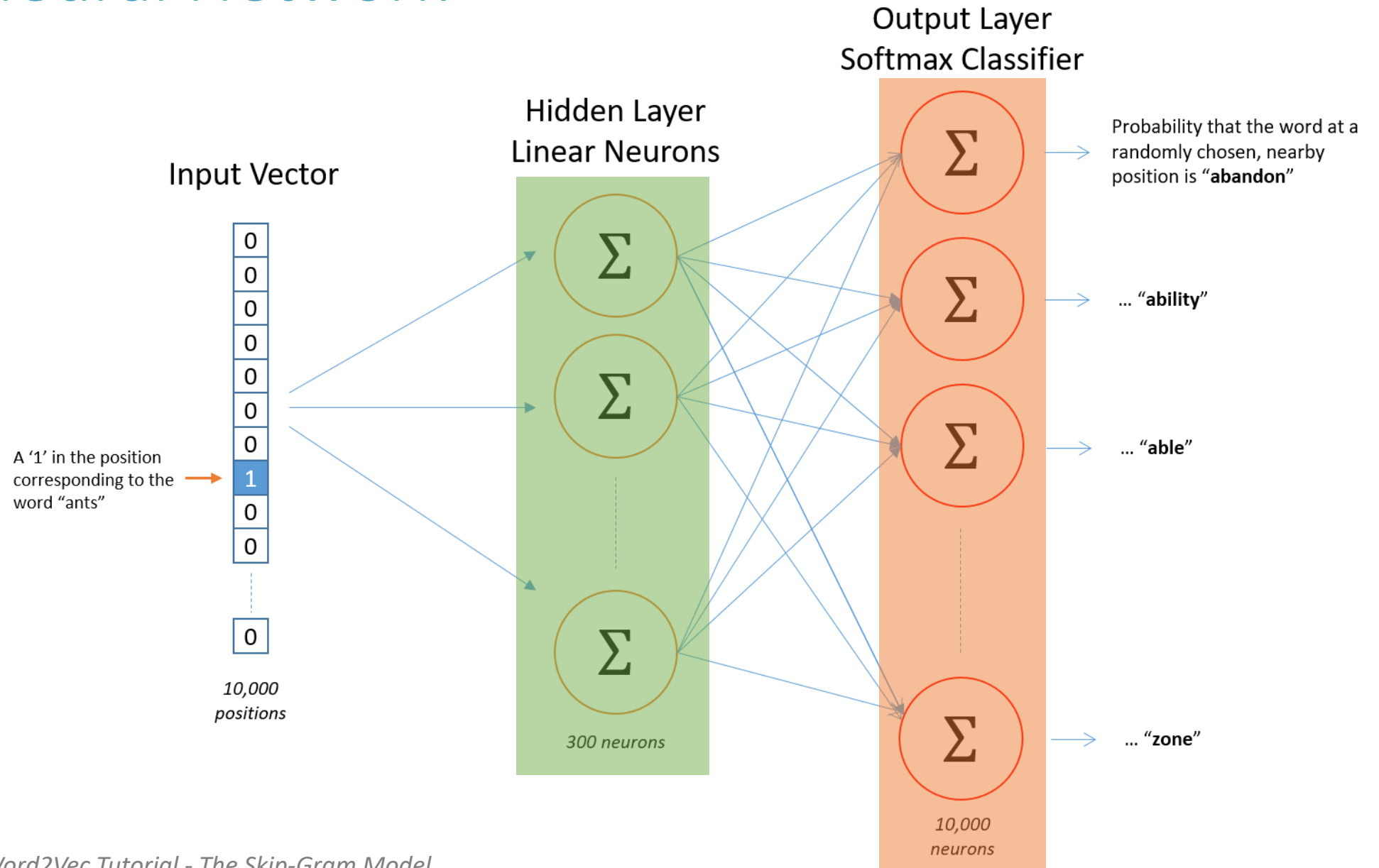
Source Text	Training Samples					
<table><tr><td>The</td><td>quick</td><td>brown</td></tr></table> fox jumps over the lazy dog. ➡	The	quick	brown	(the, quick) (the, brown)		
The	quick	brown				
The <table><tr><td>quick</td><td>brown</td><td>fox</td></tr></table> jumps over the lazy dog. ➡	quick	brown	fox	(quick, the) (quick, brown) (quick, fox)		
quick	brown	fox				
The quick <table><tr><td>brown</td><td>fox</td><td>jumps</td></tr></table> over the lazy dog. ➡	brown	fox	jumps	(brown, the) (brown, quick) (brown, fox) (brown, jumps)		
brown	fox	jumps				
The <table><tr><td>quick</td><td>brown</td><td>fox</td><td>jumps</td><td>over</td></tr></table> the lazy dog. ➡	quick	brown	fox	jumps	over	(fox, quick) (fox, brown) (fox, jumps) (fox, over)
quick	brown	fox	jumps	over		

The quick **brown fox** jumps over the **lazy dog**. The **lazy dog** was sleeping when the **brown fox** arrived. The **brown fox** found no other way to get on the other side. Jumping over the **lazy dog** was the only option that the **brown fox** had.

brown —————→ **fox**

lazy —————→ **dog**

A Shallow Neural Network



Drawbacks of current approaches ...

The **play** performed by the artists was very funny.

All work and no **play** makes everyone dull.

Polysemy

ELMo: To the Rescue!

- “Deep Contextualized Word Embeddings”
- The Paper was presented at this year’s NAACL, in June.
- Developed by AllenNLP team at the University of Washington
- Detailed info at <https://allennlp.org/elmo>

Elmo representations are...

1. Contextual

The representation for each word depends on the entire **context** in which it is used.

The **play** performed by the artists was very funny.

All work and no **play** makes everyone dull.

Elmo representations are...

2. Deep

The word representations combine all layers of a deep **pre-trained** neural network.

Elmo representations are...

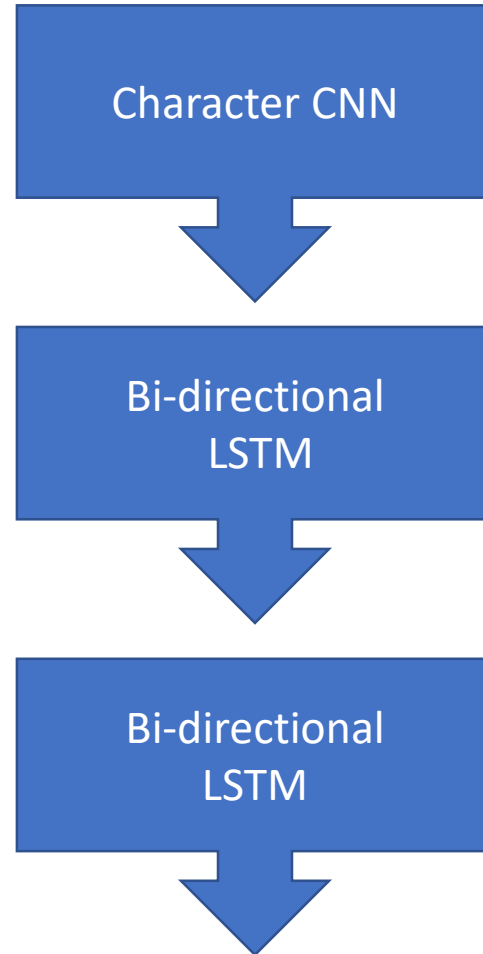
3. Character Based

ELMo representations are purely character based, allowing the network to use morphological clues to form robust representations for **out-of-vocabulary tokens** unseen in training.

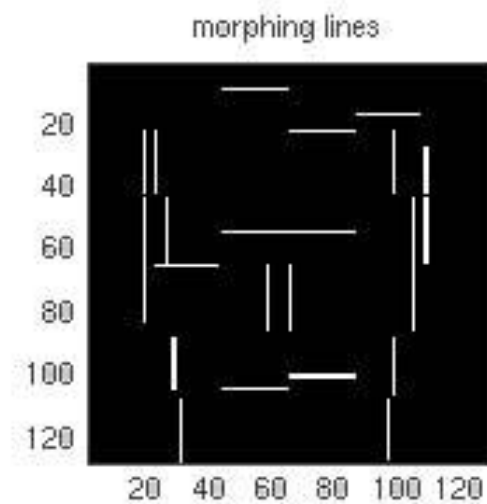
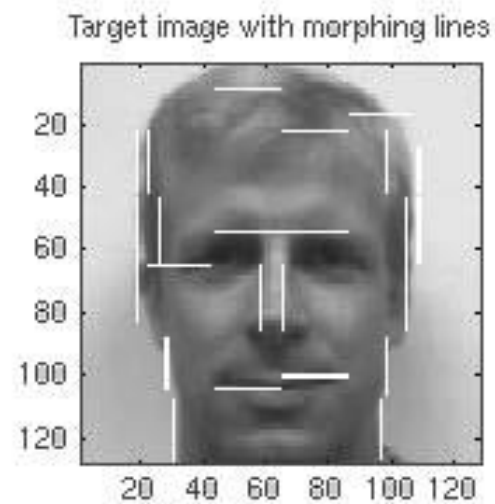
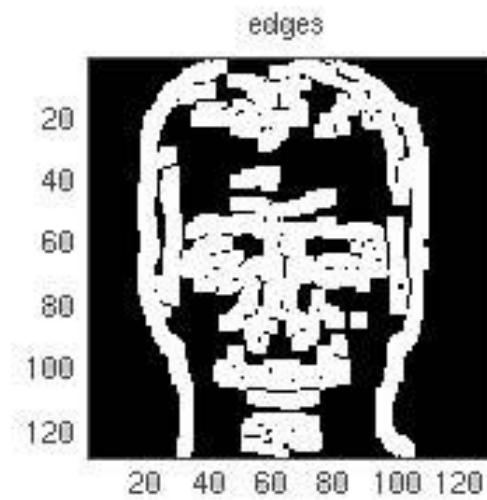
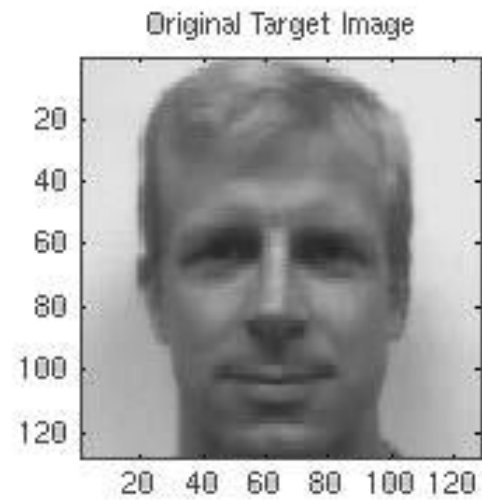
US → us

A sneak-peak into ELMo architecture..

- Consists of 3 Layers –



CNN Layer



CNN Layer

a p p l e



a p p l e

a p p l e

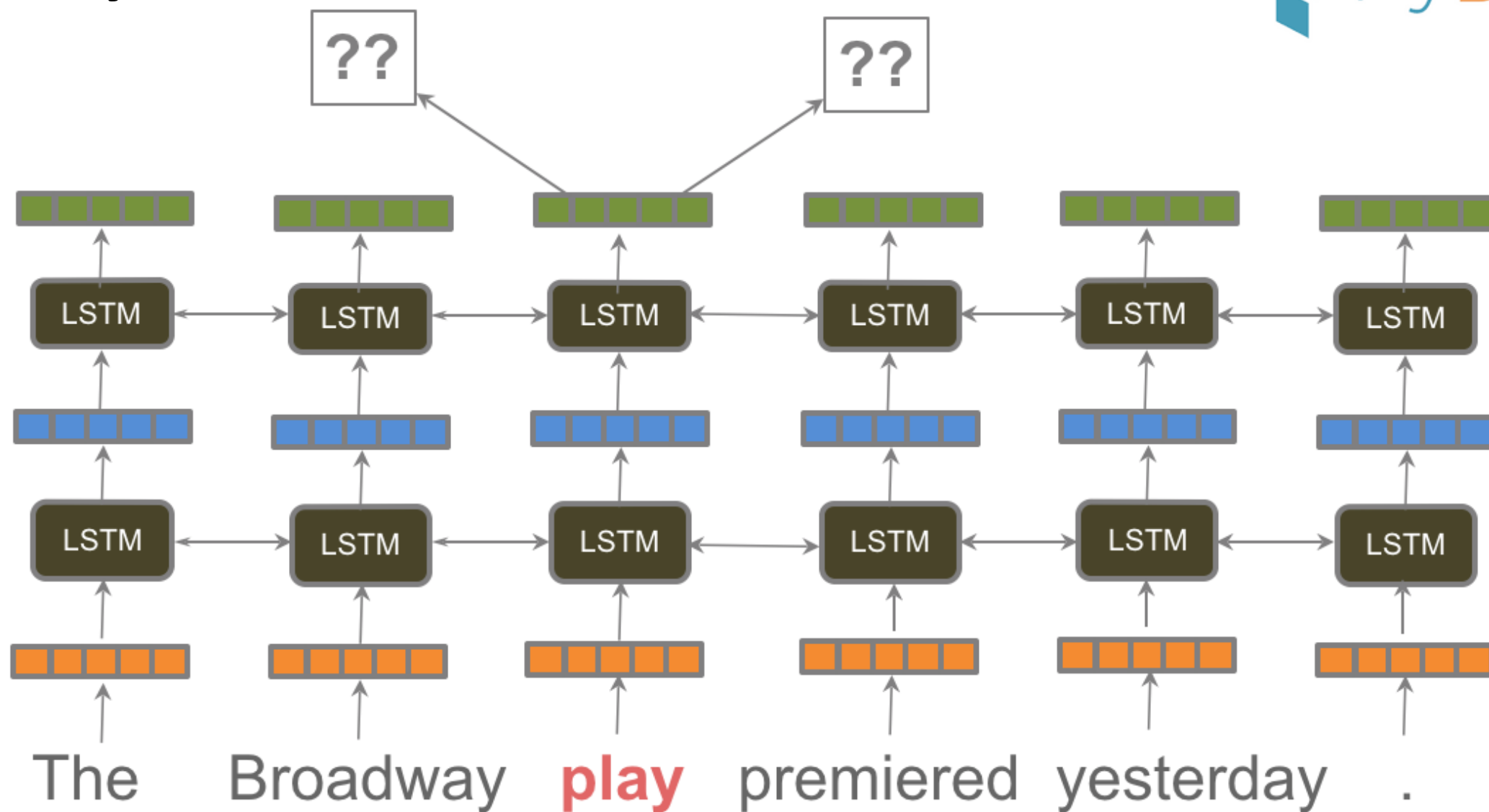
a p p l e

a p p l e



0 0 ... 2048 ... 1 0

LSTM layers



Global benchmarks achieved

Task	Previous SOTA		Our baseline	ELMo + Baseline	Increase (Absolute/Relative)
SQuAD	SAN	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al (2017)	88.6	88.0	88.7 +/- 0.17	0.7 / 5.8%
SRL	He et al (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al (2017)	91.93 +/- 0.19	90.15	92.22 +/- 0.10	2.06 / 21%
Sentiment (5-class)	McCann et al (2017)	53.7	51.4	54.7 +/- 0.5	3.3 / 6.8%

Our Results and Observations

1. The **play** performed by the artists was very funny.
2. All work and no **play** makes everyone dull.
3. We must **play** everyday to be fit and fine.

1. The **play** performed by the artists was very funny.

Noun

2. All work and no **play** makes everyone dull.

Verb

Similarity = 0.79

2. All work and no **play** makes everyone dull.

Verb

3. We must **play** everyday to be fit and fine.

Verb

Similarity = 0.87

Conclusion

Similarity (Verb-Verb) > Similarity (Verb-Noun)

0.87 0.79

Our Results and Observations

1. The **cat** sat on the mat.
2. **Dog** came on the **cricket** field.
3. The **football** World Cup is held in Russia.

The **cat** sat on the mat.

A **Dog** came on the cricket field.

Similarity = 0.49

A Dog came on the **cricket** field.

The **football** World Cup is held in Russia.

Similarity = 0.68

Conclusion

The model gives decent similarity between words that are different but used in **similar context.**

Applications of ELMo

Feature	Current Model	Future Model
Summarization	GloVe	ELMo
Question Generation	GloVe	ELMo
Answer Generation	GloVe	ELMo
Stance Detection	GloVe	ELMo (Implemented)
Document Retriever	Concept Net	ELMo

Questions!