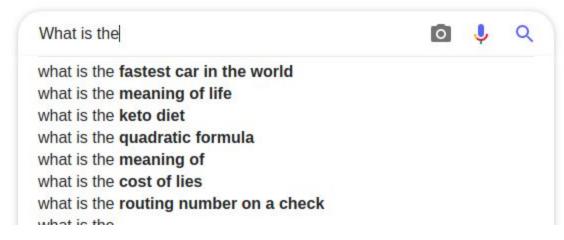
#### Language Modeling



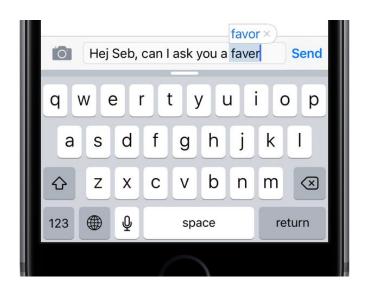






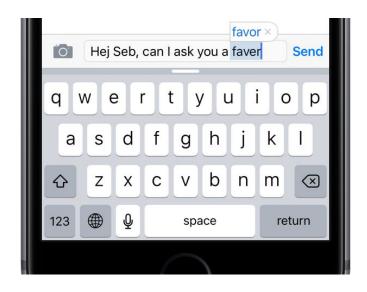




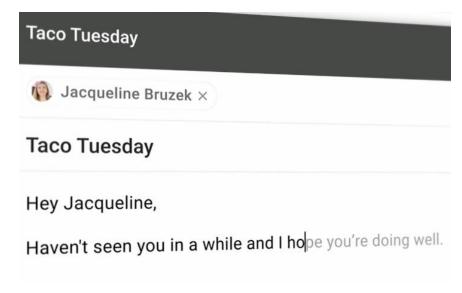


**Auto-Correct** 





**Auto-Correct** 



**Email Completion** 



my alarm	Code circle shute clock	soil raid risk visit did	rout hot riot not must
----------	-------------------------	--------------------------------------	------------------------------------

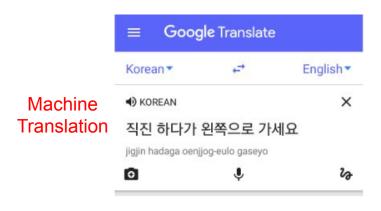
Handwriting Recognition

wake me up this moving taxis having this running tier morning loving

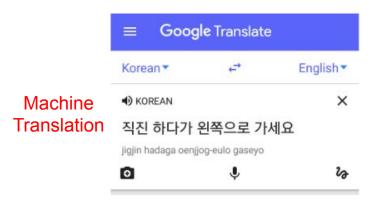
my alarm code circle soil raid rout hot riot shute risk clock visit not must did up this morning Wake me wake me up thai moving 4 taxis having this running morning loving tier

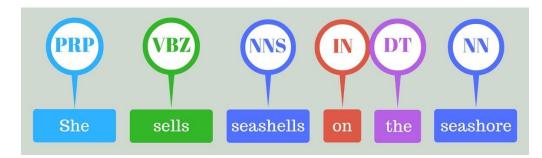
Handwriting

Recognition



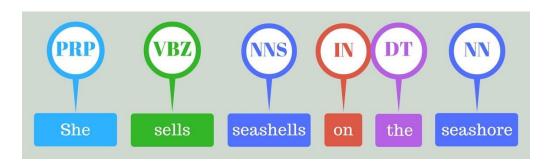
my alarm code soil circle raid rout hot riot shute risk clock visit not must Handwriting did Recognition Wake me up this morning wake me thai moving d taxis having this running morning loving tier





my alarm code soil circle raid rout hot riot shute risk not clock visit must Handwriting did Recognition Wake me up this morning wake me thai moving d taxis having this running morning loving tier







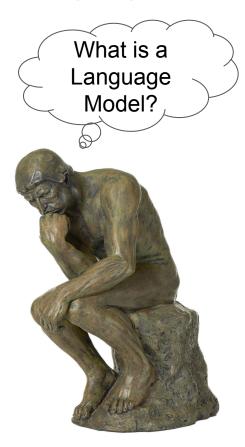
**POS Tags** 

#### Module Topics

- What is a Language Model in NLP?
- N-gram Language Model
- Implementing an N-gram Language Model
- Neural Language Model
- Implementing a Neural Language Model









A language model learns to predict the probability of a sequence of words.



A language model learns to predict the probability of a sequence of words.

the students opened their\_\_\_\_\_

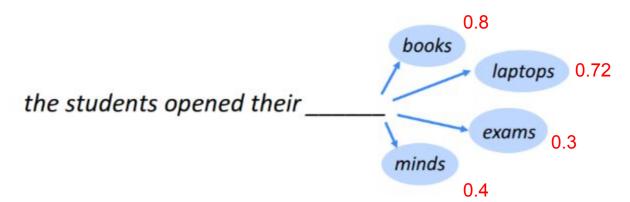


A language model learns to predict the probability of a sequence of words.





A language model learns to predict the probability of a sequence of words.





A language model learns to predict the probability of a sequence of words.

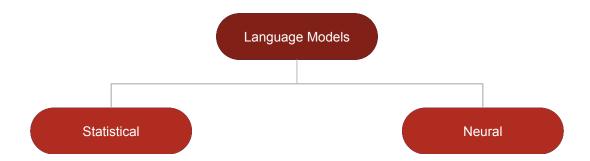
#### Why?

- P(I saw a van) > P(eyes awe of an) → Speech Recognition
- P(high winds tonite) > P(large winds tonite) → Machine Translation
- P(about fifteen **minutes** from) > P(about fifteen **minuets** from) → Spell Correction
- And many more..

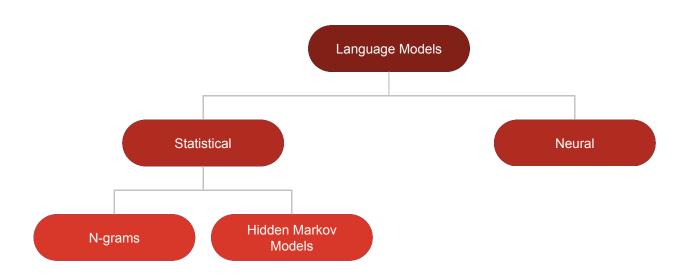


Language Models

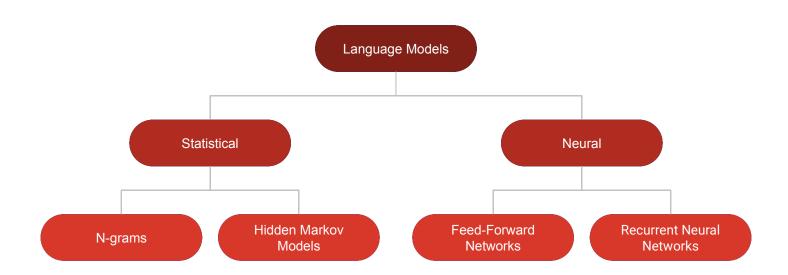




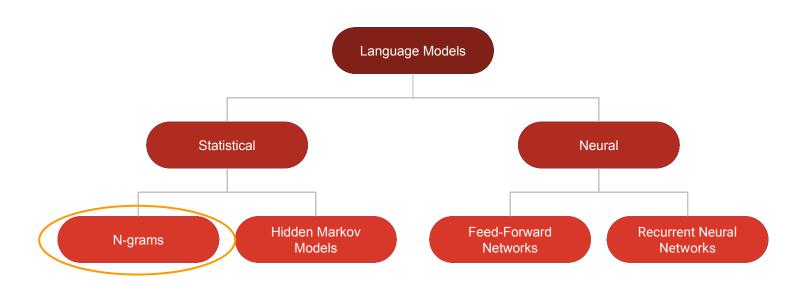




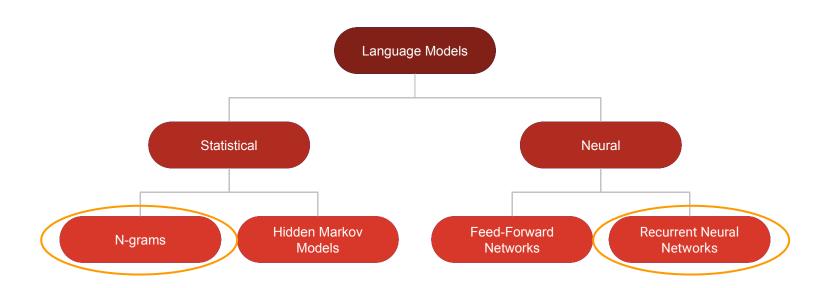






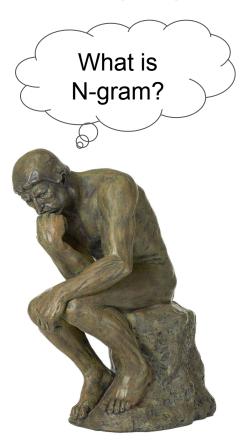














I love reading blogs about data science on Analytics Vidhya.



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An N-gram is a sequence of N tokens (or words).



I love reading blogs about data science on Analytics Vidhya.

• An N-gram is a sequence of N tokens (or words).

N=1 [I, love, reading, blogs, about, data, science, on, Analytics, Vidhya]



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N=1 [I, love, reading, blogs, about, data, science, on, Analytics, Vidhya]

N=2 [I love, love reading, reading blogs, blogs about...]



I love reading blogs about data science on Analytics Vidhya.

• An N-gram is a sequence of N tokens (or words).

```
N=1 [I, love, reading, blogs, about, data, science, on, Analytics, Vidhya]
```

N=2 [I love, love reading, reading blogs, blogs about...]

N=3 [I love reading, love reading blogs, reading blogs about...]



I love reading blogs about data science on Analytics Vidhya.

An N-gram is a sequence of N tokens (or words).

```
    N=1 [I, love, reading, blogs, about, data, science, on, Analytics, Unigrams Vidhya]
    N=2 [I love, love reading, reading blogs, blogs about...]
    N=3 [I love reading, love reading blogs, reading blogs about...]
```



# Can you please come

History







## 







We need:



#### We need:

P(here | can, you , please, come)



#### We need:

• P(here | can, you, please, come) =  $P(w_n | w_1, w_2, ..., w_{n-1})$ 



#### We need:

- P(here | can, you, please, come) = P(w<sub>n</sub> | w<sub>1</sub>, w<sub>2</sub>,..., w<sub>n-1</sub>)
- $P(w_n \mid w_1, w_2, ..., w_{n-1}) \approx P(w_n \mid w_{n-1})$  (markov assumption)



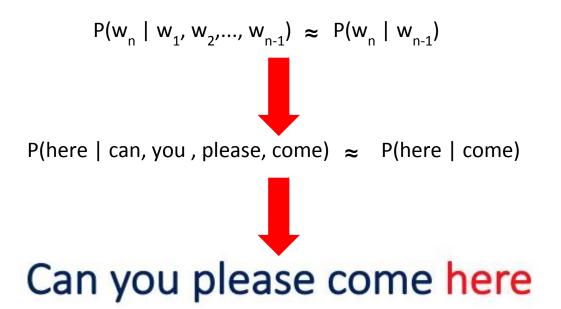
$$P(W_n \mid W_1, W_2, ..., W_{n-1}) \approx P(W_n \mid W_{n-1})$$



$$P(w_n \mid w_1, w_2, ..., w_{n-1}) \approx P(w_n \mid w_{n-1})$$

$$P(here \mid can, you, please, come) \approx P(here \mid come)$$







```
P(w_n | w_1, w_2, ..., w_{n-1}) \approx P(w_n | w_{n-1}) "unigram"
```

$$P(w_n | w_1, w_2, ..., w_{n-1}) \approx P(w_n | w_{n-1}, w_{n-2})$$
 "bigram"



## Implementing an N-gram Language Model

<JUPYTER NOTEBOOK>



Limitations of N-grams approach:



# Limitations of N-grams approach:

• Requires large amounts of compute





# Limitations of N-grams approach:

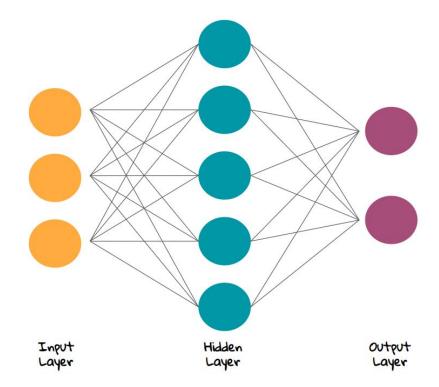
- Requires large amounts of compute
- N-grams are a sparse representation of language.

	i	want	to	eat	chinese	food
i	0.002	0.33	0	0.0036	0	0
want	0.0022	0	0.66	0.0011	0.0065	0.0065
to	0.00083	0	0.0017	0.28	0.00083	0
eat	0	0	0.0027	0	0.021	0.0027
chinese	0.0063	0	0	0	0	0.52
food	0.014	0	0.014	0	0.00092	0.0037
lunch	0.0059	0	0	0	0	0.0029
spend	0.0036	0	0.0036	0	0	0

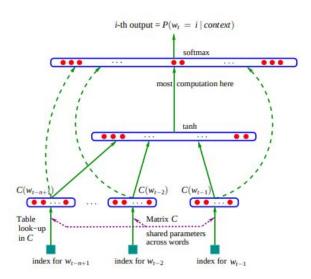


#### **Neural Language Modeling:**

- Outperformed all previous approaches
- Better ability to generalize
- Multiple approaches:
  - Feed Forward NN
  - o CNN
  - RNN etc.

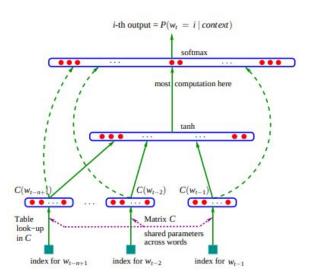




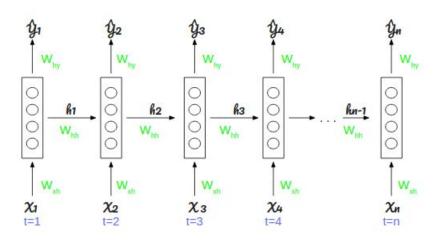


Feed Forward NN





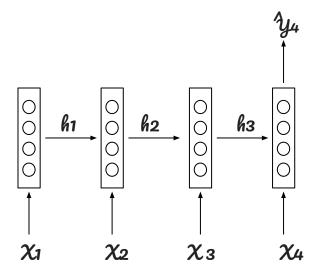
Feed Forward NN



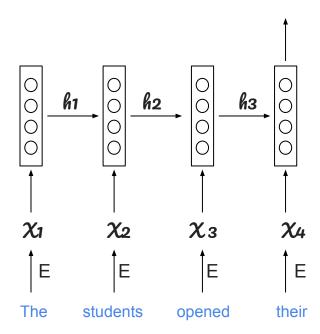
Recurrent NN



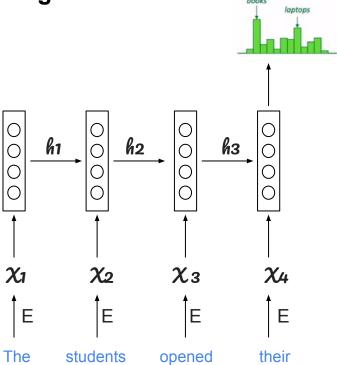






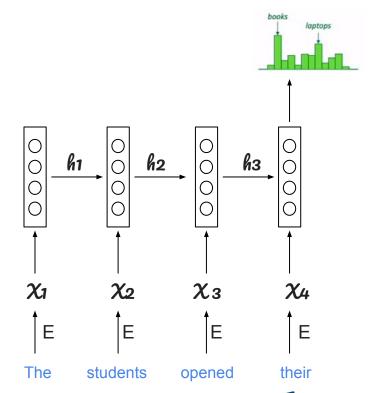








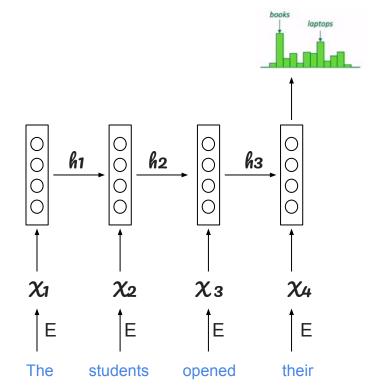
# Advantages of RNN for Language Modeling:





# Advantages of RNN for Language Modeling:

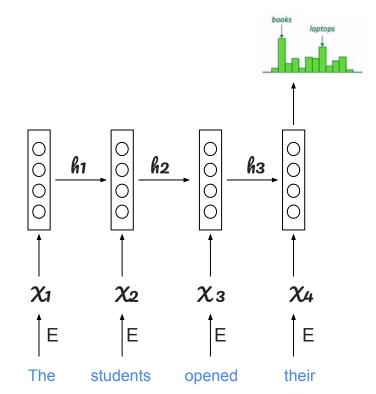
Variable length input sequences





# Advantages of RNN for Language Modeling:

- Variable length input sequences
- Combined context
- Fixed computation/model size



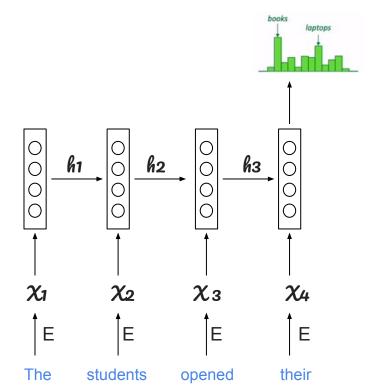


# Advantages of RNN for Language Modeling:

- Variable length input sequences
- Combined context
- Fixed computation/model size

The cat,.., which already ate,..., was full

Cats,..., which already ate,..., were full





### Implementing a Neural Language Model

<JUPYTER NOTEBOOK>

