#### **Al Bootcamp**

## Advanced NLP Techniques: Topic Modeling and RNN

Module 20 Day 3

- 1 Apply NLP preprocessing to large corpora of text.
- **2** Demonstrate how to classify text into topics using unsupervised learning.
- 3 Understand and demonstrate how to use LSTM RNN to generate text.



## Instructor **Demonstration**

Topic Modeling with Latent Dirichlet Allocation (LDA)

**Topic modeling** is used to identify and extract meaningful topics or themes from the large volumes of text, without prior knowledge of the topics.

Latent Dirichlet (dee-rish-lay) allocation (LDA)— (an unsupervised learning algorithm)— is used to identify topics within a collection of documents, where each topic is a distribution over words in the documents after the text has been preprocessed.



## Topic Modeling with LDA

LDA assumes that documents are mixtures of topics and that topics are mixtures of words. It starts with a fixed number of topics, which the user defines, and aims to find two probability distributions:



#### **Document-topic distribution**:

For each document, what is the probability of it belonging to each topic?



#### **Topic-word distribution**:

For each topic, what is the probability of each word being associated with that topic?

## **An Example of Documents**

- Document 0: Cleveland Browns quarterback Deshaun Watson to undergo season-ending surgery for shoulder injury.
- Document 1: Plane turns back to JFK after horse escapes on board.
- Document 2: Pizza Hut selling snake pizza in Hong Kong.
- Document 3: Inside the remarkably intricate planning for Biden's meeting with Xi.
- Document 4: Eight-year-old boy becomes youngest person to climb California's El Capitan
- Document 5: US retail sales fell in October for the first time in seven months.
- Document 6: From soups to cheese: what seaweed can bring to the dinner table.
- Document 7: Escape the crowds at these affordable alternatives to travel hot spots.
- Document 8: House passes stopgap bill to avert government shutdown.
- Document 9: Walmart, Costco and other companies rethink self-checkout.

## **Preparing Text Data: Cleaning the Text**

Clean the text by removing punctuation and numbers.

```
# Convert each document to a unicode string.
def clean_text(text):
    # Remove non-alphabetic characters
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    # Convert to lowercase
    return text.lower()

# Get the cleaned documents
cleaned_documents = [clean_text(doc) for doc in documents]
```

#### **Cleaned Documents**

```
['Cleveland browns quarterback deshaun watson to undergo season-ending surgery for shoulder injury',
'plane turns back to JFK after horse escapes on board',
'pizza hut selling snake pizza in hong kong',
'inside the remarkably intricate planning for bidens meeting with 'Xi',
'eightyearold boy becomes youngest person to climb californias el capitan',
'us retail sales fell in october for the first time in seven months',
'from soups to cheese what seaweed can bring to the dinner table',
'escape the crowds at these affordable alternatives to travel hot spots',
'house passes stopgap bill to avert government shutdown',
'walmart costco and other companies rethink selfcheckout']
```

## **Preparing Text Data: Tokenization and DTM**

- 1 Tokenize the text to words and remove stopwords to create a vocabulary.
- Process all the documents—each headline or summary—into a document term matrix (DTM) that has the frequency of the words that occur in each document. Where every row is a document and every column is the tokens or the words.

```
from sklearn.feature_extraction.text import CountVectorizer
# Use CountVectorizer to tokenize the text
vectorizer = CountVectorizer(stop_words='english')
# Use fit_transform to create the DTM
dtm = vectorizer.fit_transform(cleaned_documents)
```

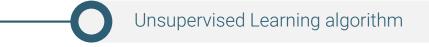
## **A DTM after Processing**

If a word from the vocabulary appears in the document the value is a "1," otherwise it's "0."

	affordable	alternatives	avert	bidens	board	boy	bring	browns	californias	capitan		surgery	table	time	travel	turns	undergo	walmart	watson
0	0	0	0	0	0	0	0	1	0	0		1	0	0	0	0	1	0	1
1	0	0	0	0	1	0	0	0	0	0		0	0	0	0	1	0	0	0
2	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
3	0	0	0	1	0	0	0	0	0	0		0	0	0	0	0	0	0	0
4	0	0	0	0	0	1	0	0	1	1		0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0		0	0	1	0	0	0	0	0
6	0	0	0	0	0	0	1	0	0	0	•••	0	1	0	0	0	0	0	0
7	1	1	0	0	0	0	0	0	0	0		0	0	0	1	0	0	0	0
8	0	0	1	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	1	0

10 rows × 68 columns

## **Non-negative Matrix Factorization (NMF)**



It simultaneously performs dimensionality reduction and clustering-like PCA.

Unlike LDA, you can use it with TF-IDF to model topics across documents.



In this activity, you will use LDA to determine the topic for BBC News summaries. After you have determined the label for each topic, you will add two new columns to the DataFrame that assigns each news summary a topic number and topic label.



**Suggested Time:** 

20 Minutes



## Time's up! Let's review



## **Questions?**



## Instructor **Demonstration**

Topic Modeling with Non-negative Matrix Factorization

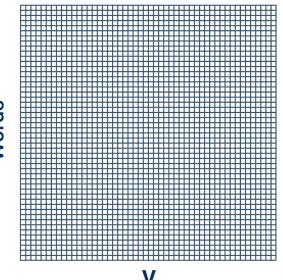
## **Topic Modeling with NMF**

Using TfidfVectorizer we get a matrix, we will call "M," that has rows and columns, where the rows represent documents, and columns represent unique terms, or words in your document collection.



**Vector (V)** = Documents x Terms

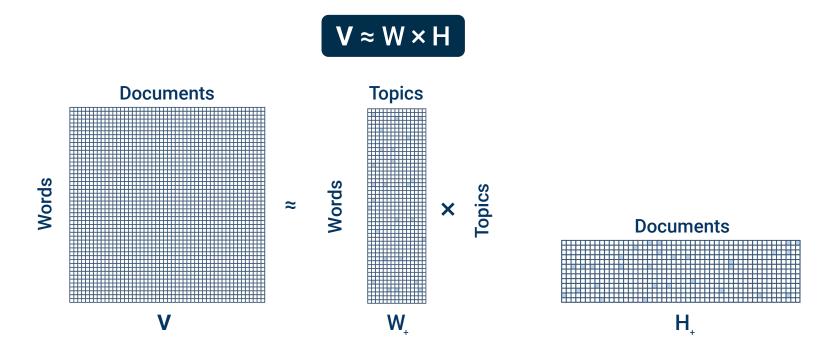




## **Topic Modeling with NMF**

When we apply topic modeling we use the matrix, M, from the TfidfVectorizer, which will be split into two non-negative matrices, "H" for height and "W" for width, where "H" is a document-topic matrix and "W" is a topic-word matrix.





## **A DTM after Processing**

The matrix that is created from transforming the documents consists of:

each index

A tuple, where the first number represents the row for each document, and the second number represents the index of the word in the vocabulary created by **fit\_transform**.

0

The last number is the value of the TF-IDF score for that word in the vocabulary.

(0,	29)	0.31622776601683794
(0,	52)	0.31622776601683794
(0,	58)	0.31622776601683794
(0,	47)	0.31622776601683794
	63)	0.31622776601683794
	65)	0.31622776601683794
	16)	0.31622776601683794
	42)	0.31622776601683794
(0,		0.31622776601683794
	11)	0.31622776601683794
(1,		0.408248290463863
	21)	0.408248290463863
	25)	0.408248290463863
	32)	0.408248290463863
	62)	0.408248290463863
- 5	40)	0.408248290463863
	33)	0.3333333333333333
	24)	0.3333333333333333
	54)	0.3333333333333333
	50)	0.3333333333333333
	28)	0.3333333333333333
	39)	0.666666666666666
	66)	0.3779644730092272
	34)	0.3779644730092272
(3,		0.3779644730092272
	41)	0.3779644730092272
	31)	0.3779644730092272
	43)	0.3779644730092272
(3,	30)	0.3779644730092272



In this activity, you will code along with the instructor using NMF to determine the topic for BBC News summaries.



Suggested Time:

20 Minutes



## Time's up! Let's review



## **Questions?**



# **Break**15 mins

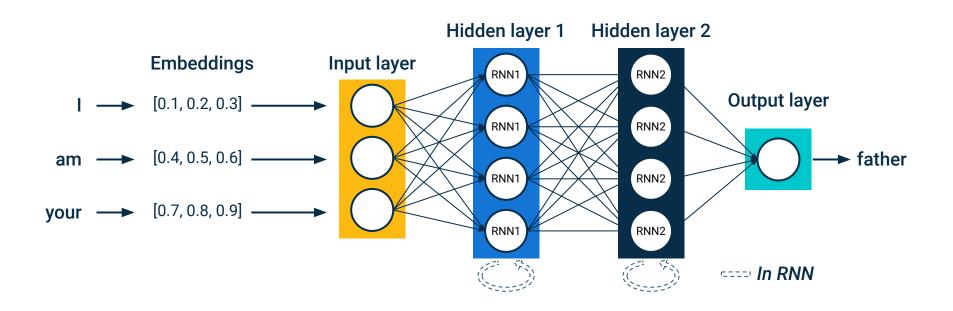


## Instructor **Demonstration**

Introduction to RNNs and LSTMs

## **Recurrent Neural Networks (RNNs)**

RNNs are able to remember the past. Their decisions are influenced by what they have learned in the past. Imagine we trained a simple RNN model on the text "I am your father". When we feed the trained model with "I am your," it will predict "father" as the output based on the word embeddings.





# What are recurrent neural networks used for?



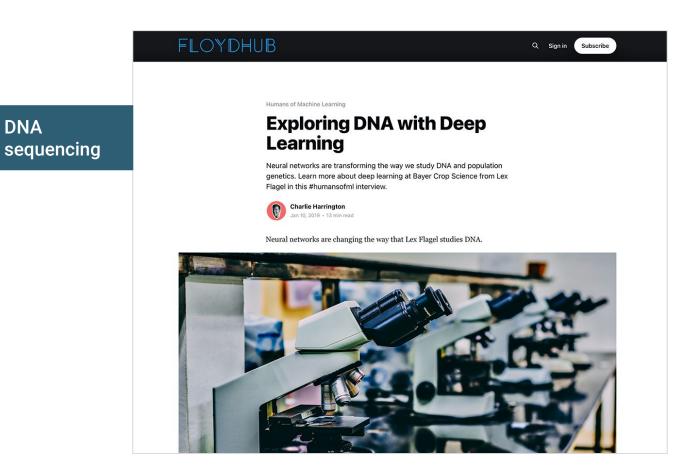




Send \$50 to Allison to be delivered today from my check account

I understand, Tom. I'd be happy to help you with that



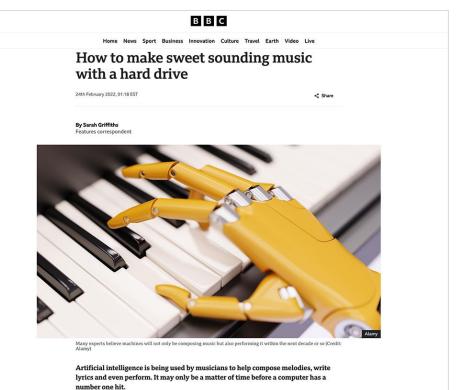


DNA

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data

Music composition



Asked how The Beatles approached songwriting, John Lennon <u>quipped</u> "on the M1 (motorway) - turn right, past London." His songwriting partner, Paul McCartney described the process as more of a <u>long and winding road</u>, in which the pair looked for chord shapes and then worked out a melody as if they were "doing a crossword

puzzle".

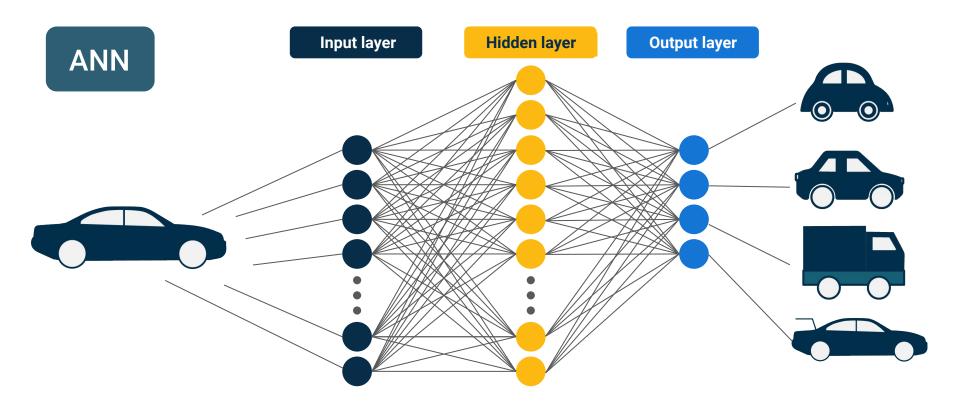


# Artificial neural networks (ANNs) vs.

Recurrent Neural Networks (RNNs)

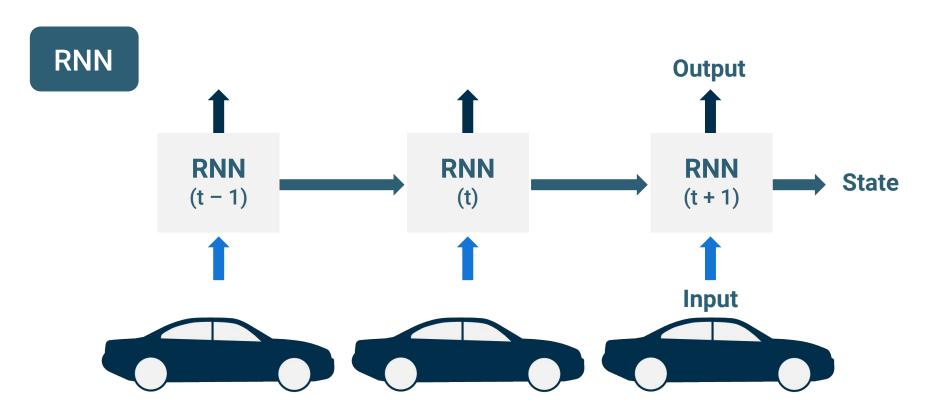
#### **ANNs vs. RNNs**

We can use **ANNs** to identify the type of car from a still image. But can we predict the direction of a car in movement?



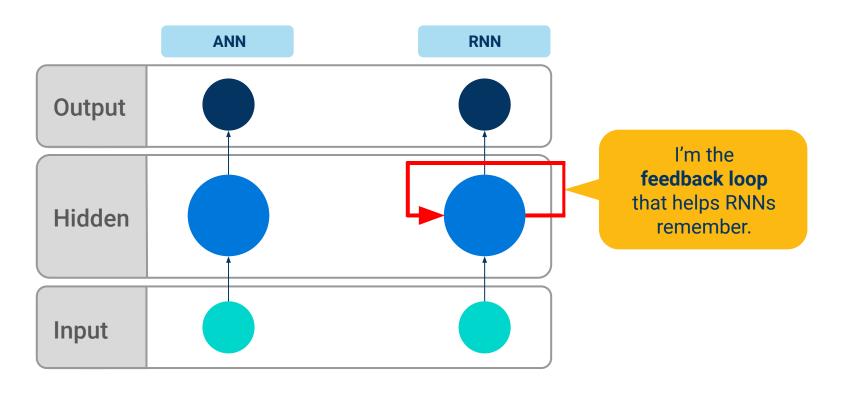
#### **ANNs vs. RNNs**

**RNNs** are good at modeling sequence data because of their **sequential memory**. Using RNNs, we can predict that the car is moving to the right, where t = time.



### **ANNs vs. RNNs**

RNNs are good at modeling sequence data because of their **sequential memory**. Using RNNs, we can predict that the car is moving to the right.





## How do **RNNs** work?

## How do RNNs work?

When you read this sentence, your

## brain



is able to decode and understand it . . .

... because our

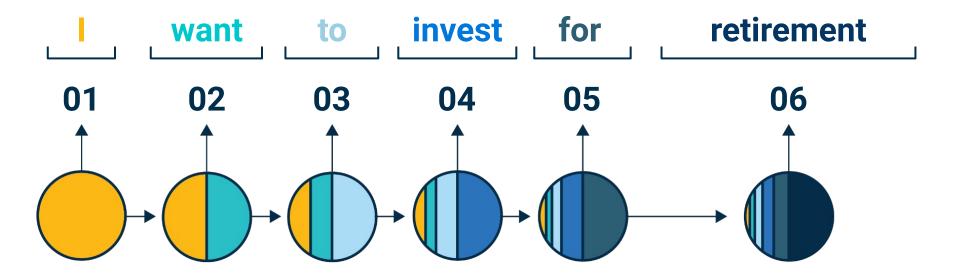
## neurons



have memory, like RNNs.

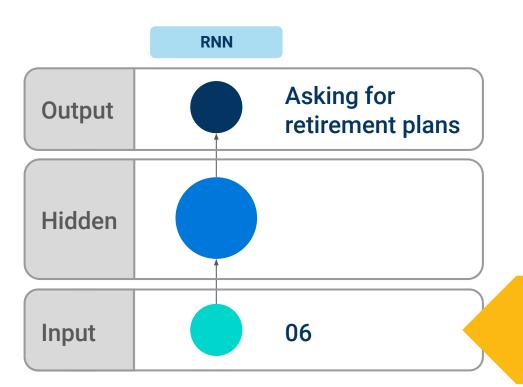
### How do RNNs work?

The sentence is split into individual words. RNNs work sequentially, so we feed it one word at a time. By the final step, the RNN has encoded information from all the words in previous steps.



#### How do RNNs work?

RNNs are good at modeling sequence data because of their **sequential memory**. Using RNNs, we can predict that the car is moving to the right.

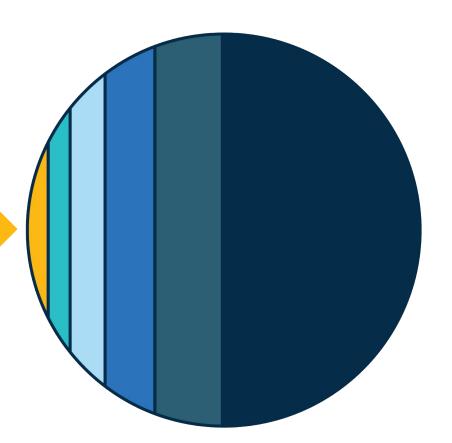


The final output was created from the rest of the sequence. To predict what the phrase means, we take the input and pass it to the feed-forward layer of the RNN to classify the intent.

## **RNNs** are forgetful

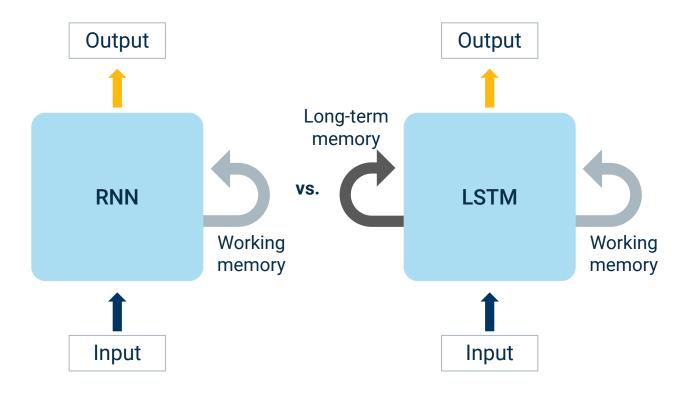
RNNs only "remember" the most recent few steps.

The vanishing gradient in the hidden states illustrates an issue with RNNs: **short-term memory**.



#### RNNs vs. LSTMs

RNNs use their internal state (memory) to process sequences of inputs. Long short-term memory (LSTM) networks are a type of RNN, with additional long-term memory to remember past data.

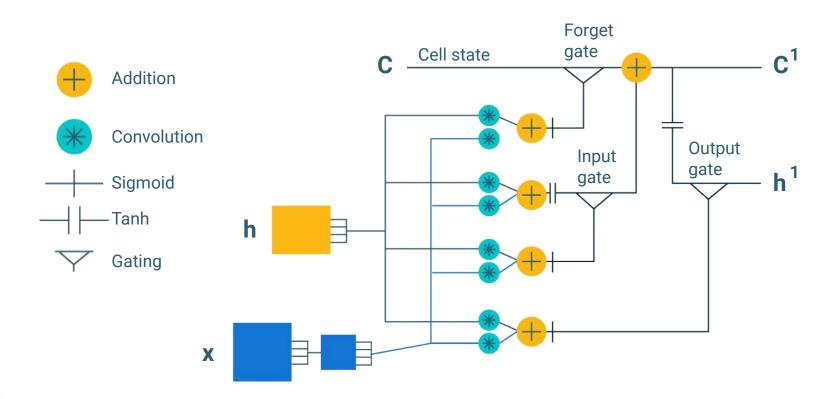




## Long Short-Term Memory (LSTM)

## LSTMs to the rescue

LSTM RNNs are one solution for longer time windows. An LSTM RNN works like an original RNN, but it selects which types of longer-term events are worth remembering and which are okay to forget.



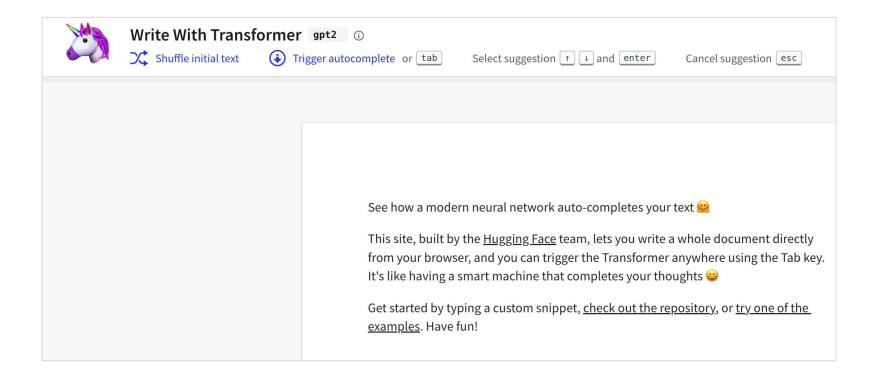


## Instructor **Demonstration**

**Automatic Text Generation with RNNs** 

## **Automatic text generation with RNNs**

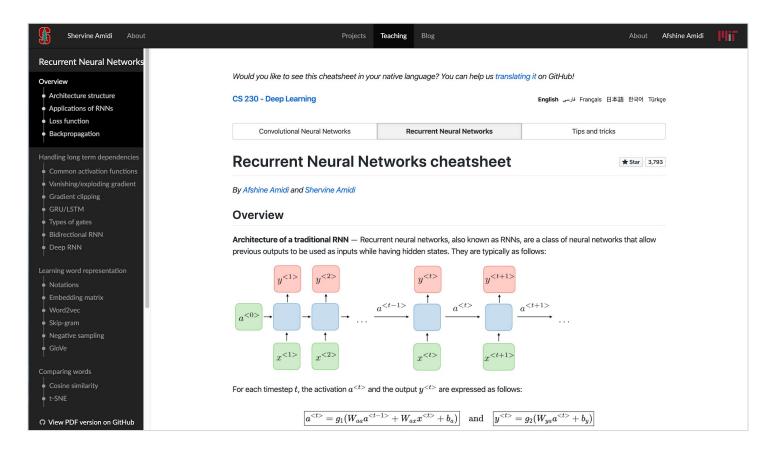
In this demo, we will explore how an RNN can be used to automatically generate text.





# Want to learn more about **RNNs**?

#### Take a look at this RNNs cheat sheet





## Instructor **Demonstration**

**Text Generation with LSTMs** 



In this activity, you will clean and tokenize a Sherlock Holmes short story, "A Case of Identity," then create and train a LSTM using the tokenized text. After the model has been trained you will provide the model with 25 words from the short novel as a seed text, then the model will return the next 25 words from the short story.



**Suggested Time:** 

20 Minutes



# Time's up! Let's review



# **Questions?**



Let's recap

- 1 Apply NLP preprocessing to large corpora of text.
- 2 Demonstrate how to classify text into topics using unsupervised learning.
- **3** Understand and demonstrate how to use LSTM RNN to generate text.



# **Questions?**

