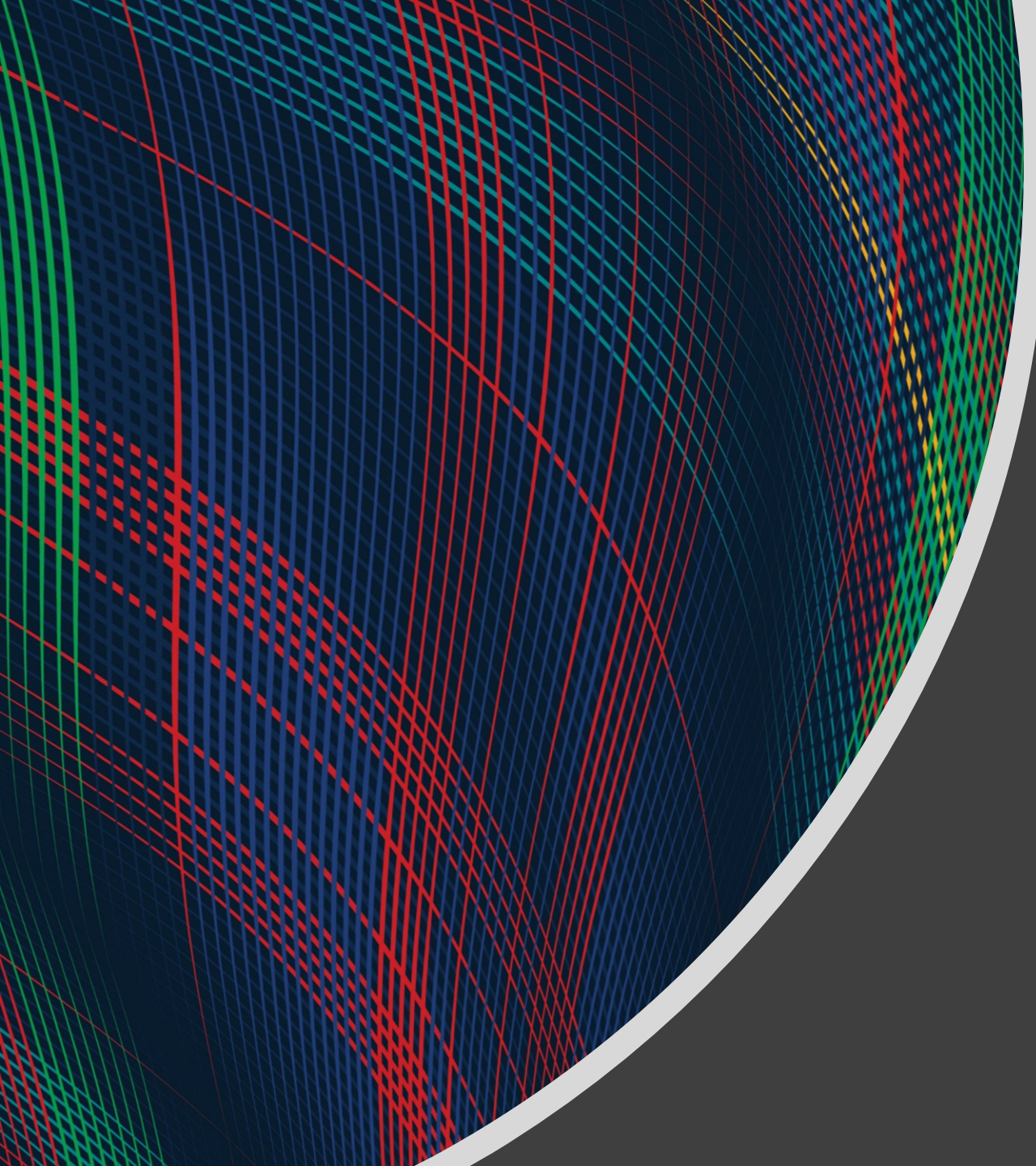


An abstract graphic on the left side of the slide, featuring a sphere-like shape composed of a dense grid of intersecting red, green, and blue lines. The lines are curved and follow the contour of the sphere, creating a complex, woven pattern. The sphere is set against a dark gray background.

07-280
AI & ML I

Natural Language
Processing (NLP):
N-gram Language Models

Instructors:
Pat Virtue & Nihar Shah

Natural Language Processing (NLP)

Quick NLP Intro

Tokenization

N-grams

Language Models (LMs)

LM Sampling

Natural Language Processing (NLP)

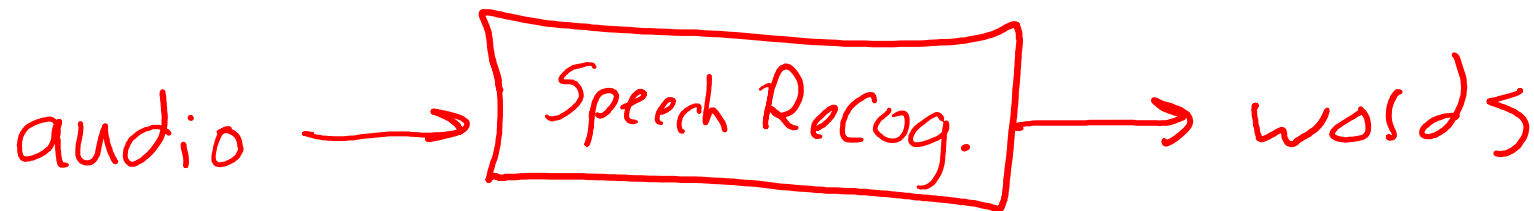
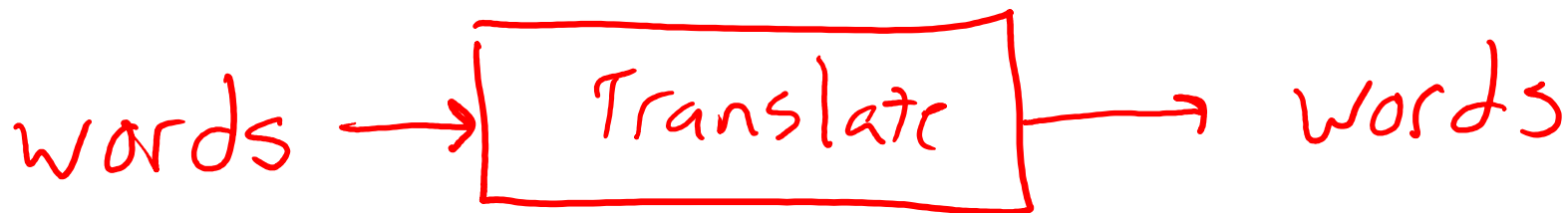
Language is Hard

Emphasis can drastically change meaning

I didn't eat your dog

NLP Tasks Examples

How many different NLP Input/Output agents can you think of?



NLP Task: Sentiment Analysis

Sentiment analysis demo

<https://text2data.com/Demo>

“I recommend that you find something better to do with your time”

I **recommend** that you find something **better** to do with your time

This document is: **positive (+0.60)**



Vocab

Corpus

Tokenization/Tokens

Vocabulary

Context

Corpus:

The dog ran.
The dog ate.
The dog ran the zoo.
The cat ate the dog!
The cat ran the zoo.

Tokenizer

(Simple) Tokenized Corpus:

['the', 'dog', 'ran', '.', 'the',
'dog', 'ate', '.', 'the', 'dog',
'ran', 'the', 'zoo', '.', 'the',
'cat', 'ate', 'the', 'dog', '!',
'the', 'cat', 'ran', 'the',
'zoo', '.']

Vocabulary:

['!',
'.',
'ate',
'cat',
'dog',
'ran',
'the',
'zoo']

NLP Vocab

Corpus, Tokenizer

Corpus:

The dog ran.
The dog ate.
The dog ran the zoo.
The cat ate the dog!
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Tokenizer

(Simple) Tokenized Corpus:

['the', 'dog', 'ran', '.', 'the',
 'dog', 'ate', '.', 'the', 'dog',
 'ran', 'the', 'zoo', '.', 'the',
 'cat', 'ate', 'the', 'dog', '!',
 'the', 'cat', 'ran', 'the',
 'zoo', '.']

Vocabulary:

['!',
 '.',
 'ate',
 'cat',
 'dog',
 'ran',
 'the',
 'zoo']

Tokenization

Tokenization

Text encoding: token → index within vocabulary

What is our "vocabulary", i.e., what are our tokens?

- Characters
- Byte pair encoding
- Words and punctuation

Corpus

I am Sam. I am

Sam. Sam I am.

That Sam-I-am.

That Sam-I-am!

Tokenization

I am Sam. I am Sam. Sam I am.
That Sam-I-am. That Sam-I-am!

Text encoding: token → index within vocabulary

What is our "vocabulary", i.e., what are our tokens?

Character token
vocabulary

0: !
1: -
2: .
3: I
4: S
5: T
6: a
7: h
8: m
9: t
10: _ (space)

BPE token
vocabulary

0: !
1: -
2: .
3: I
4: S
5: T
6: a
7: h
8: m
9: t
10: _ (space)
11: Sam
12: Th
13: am
14: _Sam
15: _am

Word token
vocabulary

0: !
1: .
2: am
3: I
4: Sam
5: That
6: Sam-I-am

Tokenization

I am Sam. I am Sam. Sam I am.
That Sam-I-am. That Sam-I-am!

Text encoding: token → index within vocabulary

Byte pair encoding (BPE)

Current token vocabulary

(Initialize to characters in corpus)

!	h
-	m
.	t
I	— (space)
S	
T	
a	

Pair frequencies

Count frequencies of all pairs
of current tokens appearing
together in corpus

_a:	3
am:	10
_s:	4
Sa:	5
_I:	1
Th:	2
ha:	2
at:	2

New tokens

Add most frequent pair to tokens

!	h
-	m
.	t
I	— (space)
S	am
T	
a	

Tokenization

I am Sam. I am Sam. Sam I am.
That Sam-I-am. That Sam-I-am!

Text encoding: token → index within vocabulary

Byte pair encoding (BPE)

Current token vocabulary

(Initialize to characters in corpus)

!	h
-	m
.	t
I	_ (space)
S	am
T	
a	

Pair frequencies

Count frequencies of all pairs
of current tokens appearing
together in corpus

_S:	4
_I:	1
Th:	2
ha:	2
at:	2
_am:	3
Sam:	5

New tokens

Add most frequent pair to tokens

!	h
-	m
.	t
I	_ (space)
S	am
T	Sam
a	

Tokenization

I am Sam. I am Sam. Sam I am.
That Sam-I-am. That Sam-I-am!

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Word token
vocabulary

0: !
1: .
2: am
3: I
4: Sam
5: That
6: Sam-I-am

Language Models

Human Language Model



Wheel of Fortune

What is a language model (LM)?

LM Applications: Speech Recognition

Example: Speech Recognition

“artificial

Find most probable next word given “artificial” and the audio for second word.

LM Applications: Speech Recognition

Example: Speech Recognition

“artificial

Find most probable next word given “artificial” and the audio for second word.

Which second word gives the
highest probability?

Break down problem

n-gram probability * audio probability

$P(\text{limb} \mid \text{artificial}, \text{audio})$

$P(\text{limb} \mid \text{artificial}) * P(\text{audio} \mid \text{limb})$

$P(\text{intelligence} \mid \text{artificial}, \text{audio})$

$P(\text{intelligence} \mid \text{artificial}) * P(\text{audio} \mid \text{intelligence})$

$P(\text{flavoring} \mid \text{artificial}, \text{audio})$

$P(\text{flavoring} \mid \text{artificial}) * P(\text{audio} \mid \text{flavoring})$

LM Applications: Text Generation

Given a LM that can model the joint distribution any 10-token sequence in the vocabulary, $p(w_1, w_2, \dots, w_{10})$, how can we get the probability of a 6th token, given 5 previous tokens

Language Models

N-grams

N-gram Worksheet

[Worksheet linked on website](#)

N-gram Worksheet

Corpus:	(Simple) Tokenized Corpus:	Vocabulary:
The dog ran. The dog ate. The dog ran the zoo. The cat ate the dog! The cat ran the zoo.	['the', 'dog', 'ran', '.', 'the', 'dog', 'ate', '.', 'the', 'dog', 'ran', 'the', 'zoo', '.', 'the', 'cat', 'ate', 'the', 'dog', '!', 'the', 'cat', 'ran', 'the', 'zoo', '.']	['!', '.', 'ate', 'cat', 'dog', 'ran', 'the', 'zoo']

Compute the unigram probabilities given the tokenized corpus above

x_t	!	.	ate	cat	dog	ran	the	zoo
$p(x_t)$								

Compute the bigram probabilities given the tokenized corpus above

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	!
	.	!
	ate	!
	cat	!
	dog	!
	ran	!
	the	!
	zoo	!

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	.
	.	.
	ate	.
	cat	.
	dog	.
	ran	.
	the	.
	zoo	.

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	ate
	.	ate
	ate	ate
	cat	ate
	dog	ate
	ran	ate
	the	ate
	zoo	ate

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	cat
	.	cat
	ate	cat
	cat	cat
	dog	cat
	ran	cat
	the	cat
	zoo	cat

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	dog
	.	dog
	ate	dog
	cat	dog
	dog	dog
	ran	dog
	the	dog
	zoo	dog

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	ran
	.	ran
	ate	ran
	cat	ran
	dog	ran
	ran	ran
	the	ran
	zoo	ran

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	the
	.	the
	ate	the
	cat	the
	dog	the
	ran	the
	the	the
	zoo	the

$p(x_{t+1} x_t)$	x_{t+1}	x_t
	!	zoo
	.	zoo
	ate	zoo
	cat	zoo
	dog	zoo
	ran	zoo
	the	zoo
	zoo	zoo