# CS540 Introduction to Artificial Intelligence Lecture 7

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Based on lecture slides by Jerry Zhu, Yingyu Liang, and Charles Dyer

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## Exam Date

#### Admin



- July 26 AND 27 (in person and or online) from 1 : 00 to 2 : 30.
- July 27 (online only, with the other section) from 5 : 30 to 8 : 30.
- A: I will be available on July 26 AND 27 from 1:00 to 2:30.
- ullet B:I will be available on July 27 from 5:30 to 8:30.
- C: I am not available on both dates (email me).

## Midterm Details

- July 26 AND July 27 from 1:00 to 2:30:
- Complete the exam online at home and join by Zoom for announcements.
- Complete the exam online in person here, bring your laptop.
- Request a paper copy of the exam and submit the answer sheet (I need to know the number of exams to print).

## Midterm Coverage

• More midterm-related details next Monday:

- $\sim 10$  questions from M2 to M7 (same question different randomization).
- $\sim$  10 questions from relavent questions on X1, X2, X3, and in-class quizzes Q1 to  $Q6_{12}$
- $\circ$  ~ 10 new questions.
  - All questions have the format: enter a number, vector, matrix or select multiple options.

#### Coordination Game

Quiz



- You are not allowed to discuss anything about this question in chat. There will be around 10 new questions on the midterm exam. I will post n of them before the exam (this weekend):
- A: n = 0.





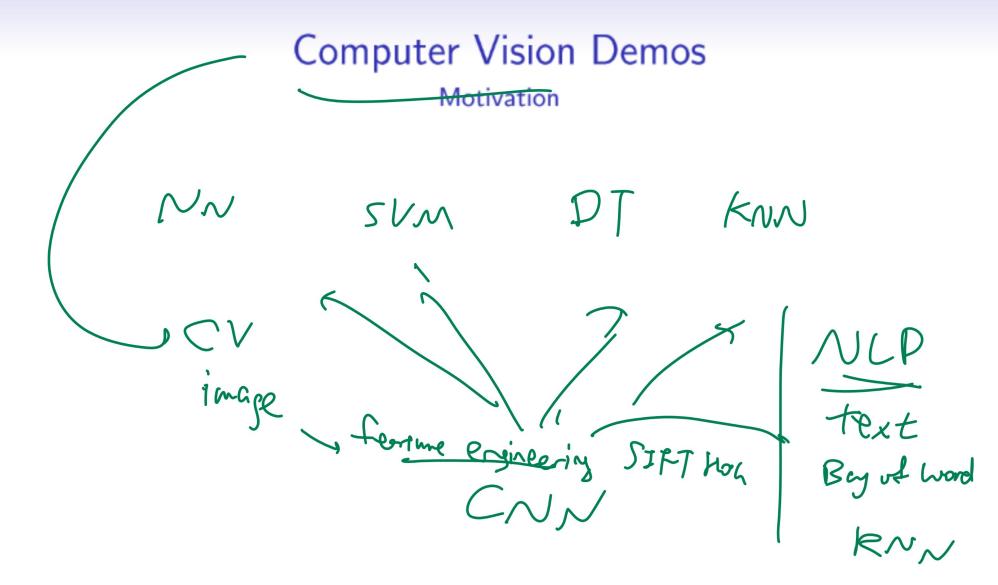
• C: n=2 if more than 75 percent of you choose C.



• D:n=3 if more than 95 percent of you choose D.

- E: n = 0.
- I will repeat this question a second time. If you fail to coordinate both times, I will not post any of the new questions.





#### **Tokenization**

#### Motivation

- When processing language, documents (called corpus) need to be turned into a sequence of tokens.
- Split the string by space and punctuations.
- Remove stopwords such as "the", "of", "a", "with" ...
- Lower case all characters.
- Stemming or lemmatization words: make "looks", "looked", "looking" to "look".

## Vocabulary

#### Motivation

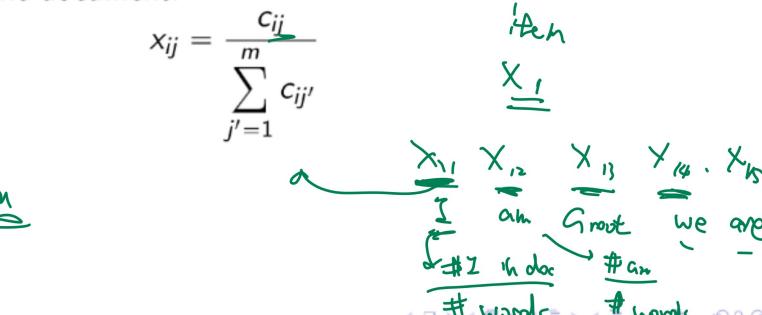
- Word token is an occurrence of a word.
- Word type is a unique token as a dictionary entry.
- Vocabulary is the set of word types.
- Characters can be used in place of words as tokens. In this case, the types are "a", "b", ..., "z", " ", and vocabulary is the alphabet.



### Bag of Words Features

Definition

- Given a document i and vocabulary with size m, let  $c_{ij}$  be the count of the word j in the document i for j = 1, 2, ..., m.
- Bag of words representation of a document has features that are the count of each word divided by the total number of words in the document.



### Bag of Words Features Example

#### Motivation

Given a training set, the set of documents is called a corpus.
 Suppose the set is "I am Groot", "I am Groot", ... (9 times),
 "We are Groot". The vocabulary is "I" "am" "Groot" "we"
 "are", then the bag of words features will have the following training set.

X	$\chi_{r}$	\ \tag{\chi}		
3	$\frac{1}{3}$	1	0	0
1 3	3 1 3	3 1 3	0	0
$\frac{1}{3}$	$\frac{1}{3}$	$\begin{array}{c c} 1\\\hline 3\\\hline 1\\\hline 3\end{array}$	0	0
0	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
7	0			

we go

#### TF IDF Features

#### Definition

Another feature representation is called tf-idf, which stands

for normalized term frequency, inverse document frequency. 
$$\mathsf{tf}_{ij} = \frac{c_{ij}}{\max\limits_{j'}}, \ \mathsf{idf}_{j} = \log\frac{n}{\sum\limits_{i=1}^{n}\mathbb{1}_{\left\{c_{ij}>0\right\}}}$$
 
$$x_{ij} = \mathsf{tf}_{ij} \ \mathsf{idf}_{j}$$

• n is the total number of documents and  $\sum_{i=1}^n \mathbb{1}_{\left\{c_{ij}>0\right\}}$  is the number of documents containing word j.

## Unigram Model s



Definition Simple not realistic

Unigram models assume independence.

$$\mathbb{P}\left\{\underline{z_1, z_2, ..., z_d}\right\} = \prod_{t=1}^d \mathbb{P}\left\{z_t\right\}$$

• In general, two events A and B are independent if:

$$\mathbb{P}\left\{A|B\right\} = \mathbb{P}\left\{A\right\} \text{ or } \underbrace{\mathbb{P}\left\{A,B\right\}} = \mathbb{P}\left\{A\right\}\mathbb{P}\left\{B\right\}$$

For a sequence of words, independence means:

$$\mathbb{P}\left\{z_{t} | z_{t-1}, z_{t-2}, ..., z_{1}\right\} = \underline{\mathbb{P}\left\{z_{t}\right\}}$$

#### Maximum Likelihood Estimation

#### Definition

•  $\mathbb{P}\{z_t\}$  can be estimated by the count of the word  $z_t$ .

$$\hat{\mathbb{P}}\{z_t\} = \underbrace{\sum_{m}^{C_{Z_t}} c_z}_{z=1} + Grave$$

 This is called the maximum likelihood estimator because it maximizes the probability of observing the sentences in the training set.

Bigram models assume Markov property.

$$\mathbb{P}\{z_1, z_2, ..., z_d\} = \mathbb{P}\{z_1\} \prod_{t=2}^d \mathbb{P}\{z_t | z_{t-1}\}$$

 Markov property means the distribution of an element in the sequence only depends on the previous element.

$$\mathbb{P}\left\{z_{t} | z_{t-1} | z_{t-2}, ..., z_{1}\right\} = \mathbb{P}\left\{z_{t} | z_{t-1}\right\}$$

#### Markov Chain Demo

Motivation

### Conditional Probability

#### Definition

 In general, the conditional probability of an event A given another event B is the probability of A and B occurring at the same time divided by the probability of event B.

$$\mathbb{P}\left\{A|B\right\} = \frac{\mathbb{P}\left\{AB\right\}}{\mathbb{P}\left\{B\right\}}$$

 For a sequence of words, the conditional probability of observing z<sub>t</sub> given z<sub>t-1</sub> is observed is the probability of observing both divided by the probability of observing z<sub>t-1</sub> first.

$$\frac{\mathbb{P}\left\{z_{t}|z_{t-1}\right\}}{\mathbb{P}\left\{z_{t-1},z_{t}\right\}} = \frac{\mathbb{P}\left\{z_{t-1},z_{t}\right\}}{\mathbb{P}\left\{z_{t-1}\right\}}$$
So of

### **Bigram Model Estimation**

Definition

• Using the conditional probability formula,  $\mathbb{P}\{z_t|z_{t-1}\}$ , called transition probabilities, can be estimated by counting all bigrams and unigrams.

$$\hat{\mathbb{P}}\left\{z_{t}|z_{t-1}\right\} = \underbrace{\frac{c_{z_{t-1},z_{t}}}{c_{z_{t-1}}}}_{C_{z_{t-1}}}$$

## Unigram MLE Probability

Quiz

Dr 5 Gm [ ] = Pr 5 7 Gm]
Pr 57 F

 Given the training data 'Lam Groot am I', with the unigram model, what is the probability of observing a new sentence "I am I"?

Uni Pr[] am 2] = Pr[] Pr[an]. Pr[]

MLE

2

5

5

125

bigram Pr[I am Groof Signam Pr[I]. Pr[an]

MLE

2

5

125

ALE

2

125

ALE

2

125

ALE

2

125

ALE

2

125

## Bigram MLE Probability

Quiz

 Given the training data "I am Groot am I", with the bigram model, what is the probability of observing a new sentence "I am I" given the first word is "I"?

## Unigram MLE Probability

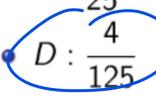
Quiz

- Given the training data "I am Groot am I", with the unigram model, what is the probability of observing a new sentence "I am Groot"?
- A: I am Groot (translation: I don't understand).

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• 
$$B: \frac{2}{25}$$

•  $C: \frac{4}{25}$ 



•  $E: \frac{8}{125}$ 

mi Prszl Prams. Prschoot]



### Bigram MLE Probability

Quiz

- Given the training data "I am Groot am I", with the bigram model, what is the probability of observing a new sentence "I am Groot" given the first word is "I"?
- A: I am Groot (translation: I don't understand).
- B: <sup>1</sup>/<sub>4</sub>
- $C: \frac{1}{5}$
- $D: \frac{1}{10}$
- $E: \frac{4}{25}$

#### Transition Matrix

#### Definition

• These probabilities can be stored in a matrix called transition matrix of a Markov Chain. The number on row j column j' is the estimated probability  $\hat{\mathbb{P}}\{j'|j\}$ . If there are 3 tokens  $\{1,2,3\}$ , the transition matrix is the following.

 Given the initial distribution of tokens, the distribution of the next token can be found by multiplying it by the transition probabilities.

### **Estimating Transition Matrix**

Definition

Suppose the vocabulary is "I", "am", "Groot", "we", "are", and the training set contains 9 "I am Groot" then 1 "We are Groot". Then the transition matrix is:

	_	I	am	Groot	we	are
		0	1	7 0	0	0
/	am _	0	0	1	0	0
	Groot	8   9	0	0	$\frac{1}{9}$	0
	we	0	0	0	0	1
\	are	0	0	.1	0	0

### Trigram Model

#### Definition

Sampling

 The same formula can be applied to trigram: sequences of three tokens.

$$\hat{\mathbb{P}}\left\{z_{t}|z_{t-1},z_{t-2}\right\} = \frac{c_{z_{t-2},z_{t-1},z_{t}}}{c_{z_{t-2},z_{t-1}}}$$

 In a document, likely, these longer sequences of tokens never appear. In those cases, the probabilities are Because of this, Laplace smoothing adds 1 to all counts.

$$\hat{\mathbb{P}}\left\{z_{t}|z_{t-1},z_{t-2}\right\} = \frac{c_{z_{t-2},z_{t-1},z_{t}}+1}{c_{z_{t-2},z_{t-1}}+m}$$

$$\text{regular Ration}$$

### Laplace Smoothing

#### Definition

 Laplace smoothing should be used for bigram and unigram models too.

$$\hat{\mathbb{P}} \{ z_t | z_{t-1} \} = \frac{c_{z_{t-1}, z_t} + 1}{c_{z_{t-1}} + m}$$

$$\hat{\mathbb{P}} \{ z_t \} = \frac{c_{z_t} + 1}{\sum_{z=1}^{m} c_z + m}$$

 Aside: Laplace smoothing can also be used in decision tree training to compute entropy.

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# Smoothing Example Quiz

• Given a vocabulary of  $10^6$ , a document with  $10^{12}$  tokens with  $c_{\text{Groot}} = 3$ . What is the MLE estimation of  $\mathbb{P}\{\text{ Groot }\}$  with and without Laplace smoothing?

# Smoothing Example 2

- Given the training instance with 9 "I am Groot" followed by 1
  "We are Groot", what is the MLE estimation of ₱ { Groot }
  with Laplace smoothing?
- A: I am Groot (translation: I don't understand).

$$\begin{array}{c}
B : \frac{11}{35} \\
1
\end{array}$$

•  $C: \frac{1}{3}$ 

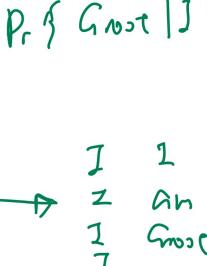
•  $D: \frac{11}{31}$ 

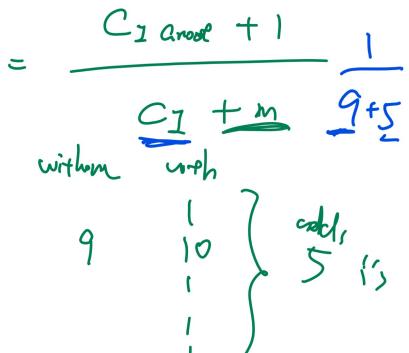
•  $E:\frac{1}{4}$ 

## Smoothing Example 3

Quiz

- Given the training instance with 9 (1 am Groot) followed by 1 We are Groot', what is the MLE estimation of  $\mathbb{P}$  { Groot  $| \mathsf{I} \rangle$  Appeared in Section 1.1. with Laplace smoothing?
- am Groot (translation: I don't understand).



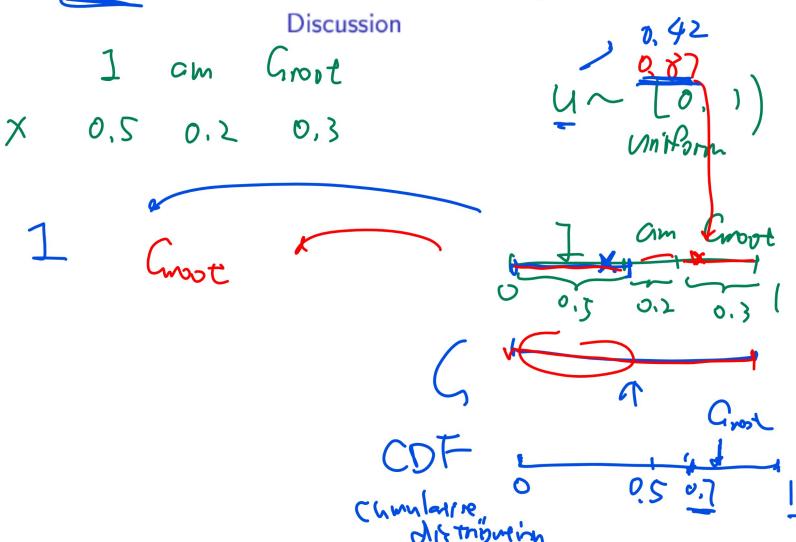


### Sampling from Discrete Distribution

Discussion

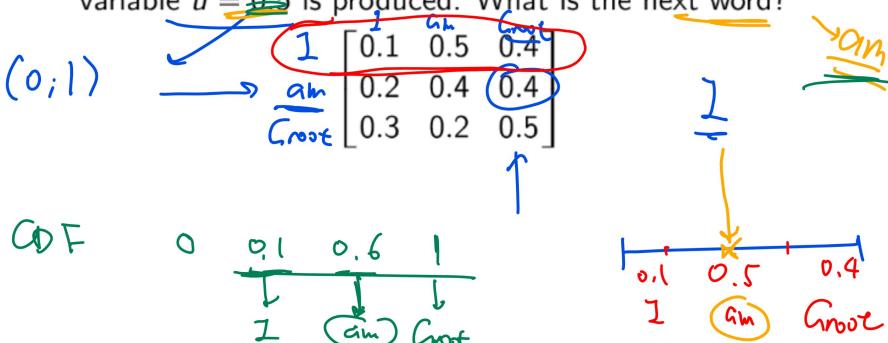
- To generate new sentences given an N gram model, random realizations need to be generated given the conditional probability distribution.
- Given the first N-1 words,  $z_1, z_2, ..., z_{N-1}$ , the distribution of next word is approximated by  $p_x = \hat{\mathbb{P}}\{z_N = x | z_{N-1}, z_{N-2}, ..., z_1\}$ . This process then can be repeated for on  $z_2, z_3, ..., z_{N-1}, z_N$  and so on.

## CDF Inversion Method Diagram



# Generating New Words 1 Quiz

 Given the transition matrix for words "I" "am" "Groot", starting a sentence with the "I" and a uniform random variable u = 0.5 is produced. What is the next word?



## Generating New Words 2

QZ

• Given the transition matrix for words "I" "am" "Groot", starting a sentence with the  $\sqrt{am'}$  and a uniform random variable u = 0.75 is produced. What is the next word?

$$7 \begin{bmatrix} 0.1 & 0.5 & 0.4 \\ 0.2 & 0.4 & 0.4 \\ 0.3 & 0.2 & 0.5 \end{bmatrix}$$

0 0,2 0,6 0,6

• A: I, B: am, C: Groot, D: I don't understand

p3 - don4 use gackage