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Course

Unit 4 Unsupervised Learning (2 weeks)

Lecture 15. Generative Models

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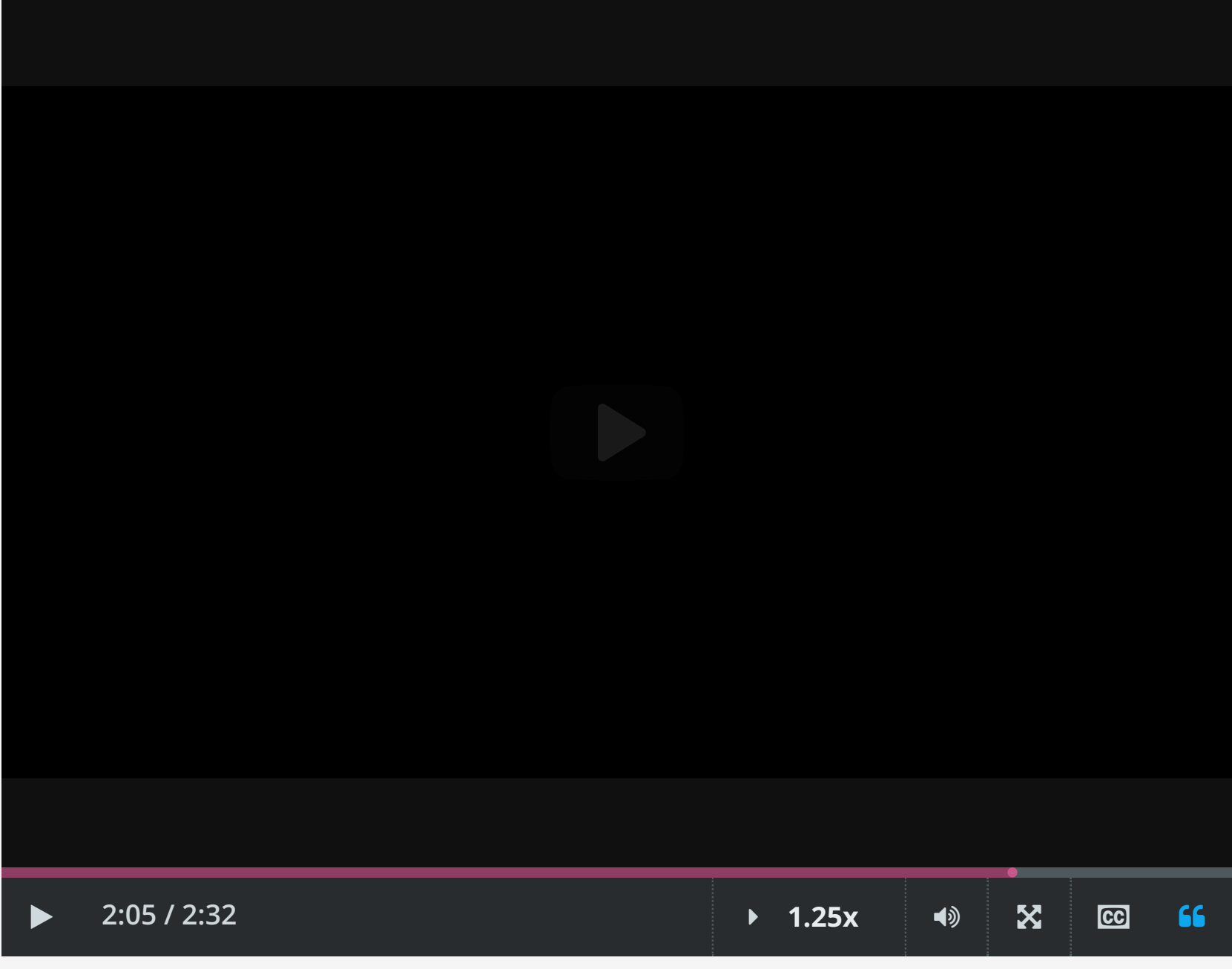
## 6. MLE for Multinomial Distribution

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Exercises due Nov 17, 2020 18:59 EST 

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### Maximum Likelihood Estimate



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to find a multinomial which fits the data the best.  
And again, at this point, what we were discussing,  
I just told you all the time that we have a single document.  
In reality, you can assume that even if you have a collection of documents, the whole story is exactly the same because whenever we're making our assumption that we are generating the words, these words are generated independently. So pretty much, you can do exactly the same formula by concatenating many of your documents into a single document and then repeating the same story.  
So now we're done with the discussion of estimation for multinomial.  
And with that, we are ready to start

### Deriving MLE for a General Multinomial Model: Likelihood

1/1 point (graded)

In the following problems, we will derive the maximum likelihood estimates for a multinomial model with more than 2 parameters. We will employ the method of lagrange multipliers for the optimization problem.

Let the document  $D$  be a sequence of words  $w_1, \dots, w_n$  from a collection  $W$  consisting of  $N$  words. For simplicity, we assume that  $w_i$ 's are independent, and that the probability of a word  $w$  is given by the parameter  $\theta_w$ , and denote by  $\theta = \{\theta_w\}_{w \in W}$ .

Let  $P(D|\theta)$  be the probability of  $D$  being generated by the simple model described above.

Find  $P(D|\theta)$ .

- ☐  $P(D|\theta) = \sum_{w \in W} \theta_w^{\text{count}(w)}$
- ☒  $P(D|\theta) = \prod_{w \in W} \theta_w^{\text{count}(w)}$
- ☐  $P(D|\theta) = \prod_{w \in W} \text{count}(w)^{\theta_w}$
- ☐  $P(D|\theta) = \prod_{w \in W} \theta_w + \text{count}(w)$



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### Constraints on the Parameters

1/1 point (graded)

What are the constraints on the parameters  $\theta_w$  in the model described in the previous problem?

- ☒  $\theta_w \geq 0, \sum_{w \in W} \theta_w = 1$
- ☐  $\theta_w \geq 0, \sum_{w \in W} \theta_w < 1$
- ☐  $\theta_w < 0, \sum_{w \in W} \theta_w > -1$
- ☐  $\theta_w \geq 0, \sum_{w \in W} \theta_w \geq 1$



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### Stationary Points of the Lagrange Function

2/2 points (graded)

The maximum likelihood estimate of  $\theta$  is the value of  $\theta$  that maximizes the likelihood function:

$$P(D|\theta) = \prod_{w \in W} (\theta_w)^{\text{count}(w)}.$$

Maximizing  $P(D|\theta)$  is equivalent to maximizing  $\log P(D|\theta)$ , so we take the natural logarithm on both sides of the equation above to bring down the exponents:

$$\log P(D|\theta) = \sum_{w \in W} \text{count}(w) \log \theta_w.$$

Recall that  $\theta$  is subject to the following constraint:

$$\sum_{w \in W} \theta_w = 1.$$

To maximize  $\log P(D|\theta)$  subject to the constraint  $\sum_{w \in W} \theta_w = 1$ , we use the Lagrange multiplier method.

**Method of Lagrange Multipliers** [Show](#)

Define the Lagrange function:

$$L = \log P(D|\theta) + \lambda \left( \sum_{w \in W} \theta_w - 1 \right)$$

where  $\lambda$  is a constant scalar.

Then, find the stationary points of  $L$  by solving the equation  $\nabla_{\theta} L = 0$ . The components of this equation are

$$\frac{\partial}{\partial \theta_w} \left( \log P(D|\theta) + \lambda \left( \sum_{w \in W} \theta_w - 1 \right) \right) = 0 \quad \text{for all } w \in W.$$

Solve for  $\theta_w$  from the above equation. Choose the right answer for  $\theta_w$  from options below.

- ☐  $\theta_w = \frac{-\lambda}{\text{count}(w)}$
- ☐  $\theta_w = \lambda \text{count}(w)$
- ☐  $\theta_w = -\lambda \text{count}(w)$
- ☒  $\theta_w = \frac{-\text{count}(w)}{\lambda}$



Now, apply the constraint that  $\sum_{w \in W} \theta_w = 1$  to the answer above to obtain  $\lambda$ .

$\lambda =$

- ☒  $\lambda = - \sum_{w \in W} \text{count}(w)$
- ☐  $\lambda = \sum_{w \in W} \text{count}(w)$
- ☐  $\lambda = - \sum_{w \in W} (\theta_w \text{count}(w))$
- ☐  $\lambda = \sum_{w \in W} (\theta_w \text{count}(w))$



Find  $\theta_w$  that maximizes  $\log P(D|\theta)$  subject to  $\sum_{w \in W} \theta_w = 1$ .

(There is no answer box for this final question.)

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| <div><div><div>Stationary Points of the Lagrange Function</div><div>How is the differentiation of the summation operator of theta_w, 1? Shouldn't we be left with summation(1) after differentiating it w.r.t theta_w ?</div></div><div>3</div></div> |                    |

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