# Machine Learning for Data Science (CS4786) Lecture 17

Latent Dirichlet Allocation & Intro to Graphical Models

Course Webpage:

http://www.cs.cornell.edu/Courses/cs4786/2016sp/

#### ANNOUNCEMENTS

- Assignment A2 is out.
- Due date: April 15th, 11:59pm
- Consists of two simple problems
- Group size: 1-4, groups not transferred from last time
- Competition I will begin soon and you will have 3 weeks.

#### PROBABILISTIC MODELS

- Set  $\Theta$  consists of parameters s.t.  $P_{\Theta}$  is the distribution over the random variables by each  $\Theta \in \Theta$
- Data is generated by one of the  $\theta \in \Theta$
- Learning: Estimate value or distribution for  $\theta^* \in \Theta$  given data (we saw MLE and talked about MAP)

# MAXIMUM LIKELIHOOD PRINCIPAL

$$\theta_{MLE} = \operatorname{argmax}_{\theta \in \Theta} \log P_{\theta}(x_1, \dots, x_n)$$

$$\theta_{MAP} = \operatorname{argmax}_{\theta \in \Theta} \log P(x_1, \dots, x_n | \theta) + \log P(\theta)$$

### EM ALGORITHM

(E step) For every t, define distribution  $Q_t$  over the latent variable  $c_t$  as:

$$Q_t^{(i)}(c_t) = P(c_t|x_t, \theta^{(i-1)})$$

(M step)

$$\theta^{(i)} = \operatorname{argmax}_{\theta \in \Theta} \sum_{t=1}^{n} \sum_{c_t} Q_t^{(i)}(c_t) \log P(x_t, c_t | \theta)$$

•  $x_t$  observation,  $c_t$  latent variable.

## MIXTURE OF MULTINOMIALS

- Eg. Model purchases of each customer
- *K*-types of customers, each designated with distribution over the *d* items to buy
- Generative model:
  - $\pi$  is mixture distribution over the K-types of buyers
  - $p_1, \ldots, p_K$  are the K distributions over the d items, one for each customer type
  - Generative process, each round draw customer type  $c_t \sim \pi$
  - Next given  $c_t$  draw list of purchases as  $x_t \sim \text{multinomial}(p_{c_t})$

## MIXTURE OF MULTINOMIALS

#### What is missing in this story?

- Every customer could be a bit of every type, or at least a few types
- Another example is modeling documents based on words contained in them.
- A document could belong to multiple topics (unline clustering)

# LATENT DIRICHLET ALLOCATION

- Each document has a mixture of topics
- Every word in each document is assigned a specific topic

• How do we model this?

n. # of documents d. size of lexicon

m. # of words in each document

k. # of topics

## DIRICHLET DISTRIBUTION

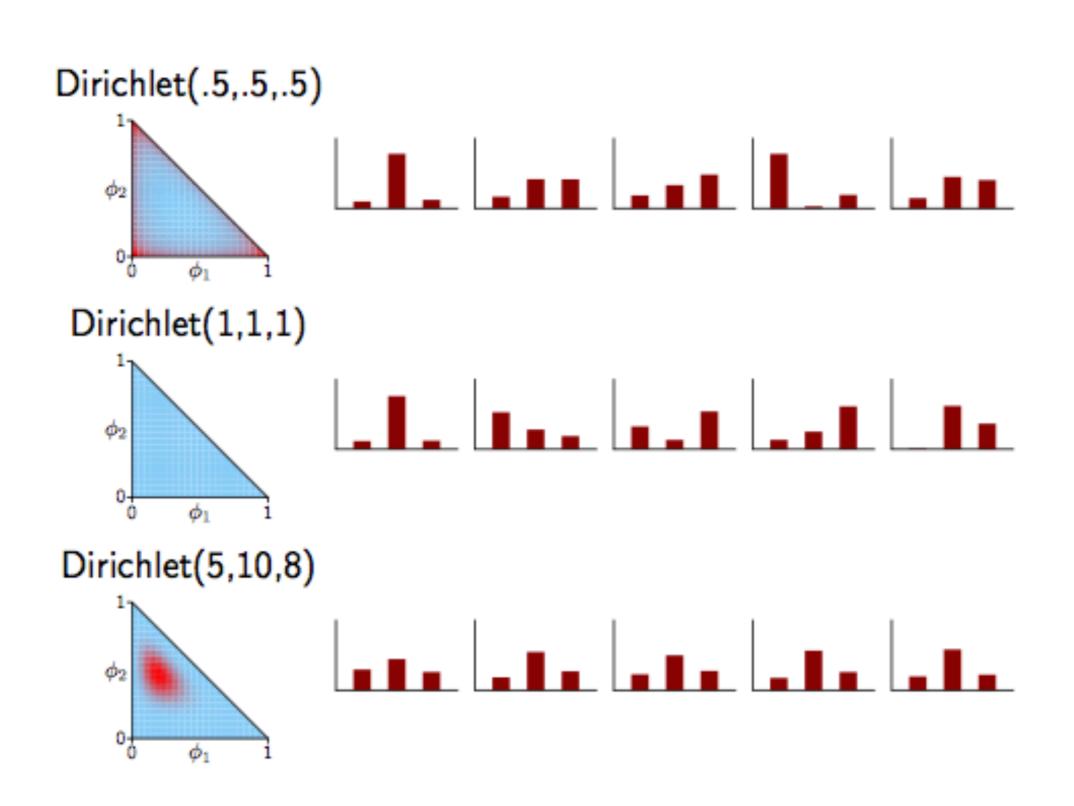
- Its a distribution over distributions!
- Parameters  $\alpha_1, \ldots, \alpha_K$  s.t.  $\alpha_k > 0$
- The density function is given as

$$p(\pi; \alpha) = \frac{1}{B(\alpha)} \prod_{k=1}^{K} \pi_k^{\alpha_k}$$

where 
$$B(\alpha) = \prod_{k=1}^{K} \Gamma(\alpha_k) / \Gamma(\sum_{k=1}^{K} \alpha_k)$$

- K = 2 its called  $\beta$  distribution
- For each document we draw  $\pi$  from a Dirchlet distribution (each customer is a mixture of the various types)

# DIRICHLET DISTRIBUTION



# LATENT DIRICHLET ALLOCATION

Generative story:

```
For t = 1 to n

For each customer draw mixture of types \pi_t \sim \text{Dirchlet}(\alpha)

For i = 1 to m

For each item to purchase, first draw type c_t[i] \sim \pi_t

Next, given the type draw x_t[i] \sim p_{c_t[i]}

End For

End For
```

• Parameters,  $\alpha$  for the Dirichlet distribution and  $p_1, \ldots, p_K$  the distributions for each time over the d items.

# LATENT DIRICHLET ALLOCATION

