



# Probability Distributions: Continuous

Introduction to Data Science Algorithms Jordan Boyd-Graber and Michael Paul

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## **Combining Discrete and Continuous Distributions**

- We can chain together two distributions
- E.g., imagine your multinomial distribution came from a Dirichlet
- Often called "Bayesian Data Analysis"
- This why explain why "add one" Laplace smoothing isn't crazy

• Imagine you have vector of counts  $\vec{n}$  that come from multinomial  $\vec{\theta}$ . This multinomial comes from a Dirichlet with parameter  $\vec{\alpha}$ . (Chain rule)

$$p(\vec{n}) = p(\vec{n} \mid \theta) p(\vec{\theta} \mid \vec{\alpha}) \tag{1}$$

• Now let's assume that you see some counts  $\vec{n}$ . You want to know what the multinomial distribution parameter looks like.

$$p(\vec{\theta} \mid \vec{n}, \vec{\alpha}) \tag{2}$$

• If  $\vec{\theta} \sim \text{Dir}(()\alpha)$ ,  $\vec{w} \sim \text{Mult}(()\theta)$ , and  $n_k = |\{w_i : w_i = k\}|$  then

$$p(\theta|\alpha, \vec{w}) \propto p(\vec{w}|\theta)p(\theta|\alpha)$$
 (3)

$$\propto \prod_{k} \theta^{n_k} \prod_{k} \theta^{\alpha_k - 1}$$
 (4)

$$\propto \prod_{k} \theta^{\alpha_k + n_k - 1}$$
 (5)

- Conjugacy: this posterior has the same form as the prior
- In fact, it looks like you're just adding counts!

• If  $\vec{\theta} \sim \text{Dir}((\alpha), \vec{w} \sim \text{Mult}((\theta), \text{ and } n_k = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then } \vec{\theta} = |\{w_i : w_i = k\}| \text{ then$ 

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# Why add one?

- The count that we add is equivalent to the Dirichlet parameter
- What does this mean in the case of Dirichlet distribution?

$$f(\theta) = \frac{\prod_{k=1}^{K} \Gamma(\alpha_k)}{\Gamma(\sum_{k=1}^{K} \alpha_i)} \prod_{k=1}^{K} \theta_k^{\alpha_k - 1}$$

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• Uniform distribution! Doesn't matter what x is.

#### **Next time**

- Drawing from and plotting various distributions
- Be sure to bring laptops