# Probability Distributions: Continuous

Introduction to Data Science Algorithms
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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

## Why Bayesian

- 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.

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

## Conjugacy

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

$$p(\theta|\alpha,\vec{w}) \propto p(\vec{w}|\theta)p(\theta|\alpha) \tag{3}$$
$$\propto \prod_k \theta^{n_k} \prod_k \theta^{\alpha_k - 1} \tag{4}$$
$$\propto \prod_k \theta^{\alpha_k + n_k - 1} \tag{5}$$

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

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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?

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

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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