Statistical Foundations of Data Science

# Statistical Foundations of Data Science Continuous Distributions

University of the Witwatersrand

2025

### Review Question

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• A five card poker hand is drawn. What's the probability that all five cards are the same suit.

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- Review Question
- Continuous distributions

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- Preview of the normal and t-distributions

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- $\bullet \ \ \tfrac{12}{51} \times \tfrac{11}{50} \times \tfrac{10}{49} \times \tfrac{9}{48} = 0.00198079231$

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- f(x) is called a "density function"

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- Variance formulas hold.
- We're also interested in  $F(c) = \mathbb{P}(X \le c) = \int_{-\infty}^{c} f(x) dx$

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- $c = \frac{1}{2}$

# Example

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$$\mathbb{E}[X] = \int_0^2 x f(x) dx = \int_0^2 \frac{x^2}{2} dx = \frac{x^3}{6} |_0^2 = \frac{4}{3}$$

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• 
$$V(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2 = 2 - \frac{4^2}{3} = \frac{2}{9}$$

# (Continuous) Uniform distribution

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$$V(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2 = \frac{a^2 + ab + b^b}{3} - (\frac{a+b}{2})^2$$

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• 
$$V(X) = \frac{(b-a)^2}{12}$$

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## Exponential distribution

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- $\mathbb{E}[X] = \int_0^\infty x \lambda e^{-\lambda x} dx$
- Let  $y = \lambda x$  so  $\frac{dy}{dx} = \lambda$  and  $\mathbb{E}[X] = \int_0^\infty y e^{-y} \frac{dy}{\lambda} = \frac{1}{\lambda}$

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- $V(X) = \mathbb{E}[X^2] (\mathbb{E}[X])^2 = \frac{1}{\lambda^2}$

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- $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$  is a scaling factor.
- It's also the continuous analog of the choose function.

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Lastly let's show that that is the right scaling factor!

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$$B(x,y) = \int_0^1 t^{x-1} (1-t)^{y-1} dt, \quad \text{for } x,y > 0.$$
 (1)

• Our goal is to show that:

$$B(x,y) = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)} \tag{2}$$

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- Consider the product of two Gamma functions:

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Statistical Foundations of Data Science Our goal is to show that:

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• The Jacobian is given by:

$$J = \begin{vmatrix} \frac{\partial u}{\partial s} & \frac{\partial v}{\partial s} \\ \frac{\partial u}{\partial t} & \frac{\partial v}{\partial t} \end{vmatrix} = \begin{vmatrix} t & s \\ 1 - t & -s \end{vmatrix} = s. \tag{5}$$

• This gives us:

$$\Gamma(x)\Gamma(y) = \int_0^\infty s^{x+y-1} e^{-s} ds \int_0^1 t^{x-1} (1-t)^{y-1} dt.$$
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Showing that

$$B(x,y) = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)}. (7)$$

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   Which roughly says that if we add some i.i.d random variables together that the sample mean will be approximately distributed normally.

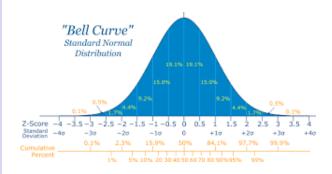
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- Cavaets exist here. We need finite moments and how good the approximation is will depend on how many X<sub>i</sub> we're adding.

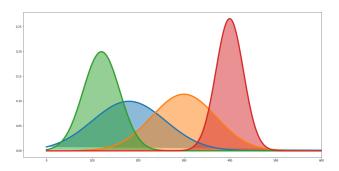
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- $f(x) = \frac{1}{\sqrt{2\sigma\pi}} e^{\left(\frac{x-\mu}{\sigma}\right)^2}$

- Two parameter family (mean and variance).
- $f(x) = \frac{1}{\sqrt{2\sigma\pi}} e^{(\frac{x-\mu}{\sigma})^2}$
- F(X) doesn't have a nice closed form. We'll use a table to look up values.





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- We'll talk about how/why next lecture.

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- f(X) is really ugly, and in practice we'll use a table.

## Student T-distribution

