
CUSP UCSL Summer 2016: Probabilities and Probability distributions.

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@fedhere

Material related to this lecture
can be found at

[https://github.com/fedhere/
UInotebooks/tree/master/UCSL2016](https://github.com/fedhere/UInotebooks/tree/master/UCSL2016)

why do we bother with probabilities?

IF WE COULD SAMPLE THE ENTIRE *POPULATION* WE WOULD NOT NEED STATISTICS. Statistics allows us to say something about the entire population from what we know about a subsample.

- Outlier detection: e.g. is this event rare?
(Hurricane Sandy, Meeting a Dinosaur in the streets of NYC)
- Prediction: based on current knowledge and current state, what is the probability that an event will occur?
(can you predict a disease epidemic?)
- Average and typical: what is the average asthma in a certain area of the city? is it the same as in a different area, where traffic is lower, or where there are fewer construction sites?
(better allocation of resources, connecting causes and effect)

Classical Discrete distributions

Classical Discrete distributions:

$$Bin(X = k \mid n, p) = \frac{n!}{(n - k)!k!} p^k (1 - p)^{n - k}$$


$$Poi(X = k \mid \lambda) = e^{-\lambda} \frac{\lambda^k}{k!}$$

Classical Discrete distributions

Classical Discrete distributions:

$$P(\text{1 head in 1 toss}) = \text{Bin}(1, 0.5) = 0.5$$

$$P(\text{1 tail in 1 tail}) = \text{Bin}(1, 0.5) = 0.5$$

$$\text{Bin}(X = k \mid n, p) = \frac{n!}{(n - k)!k!} p^k (1 - p)^{n - k}$$



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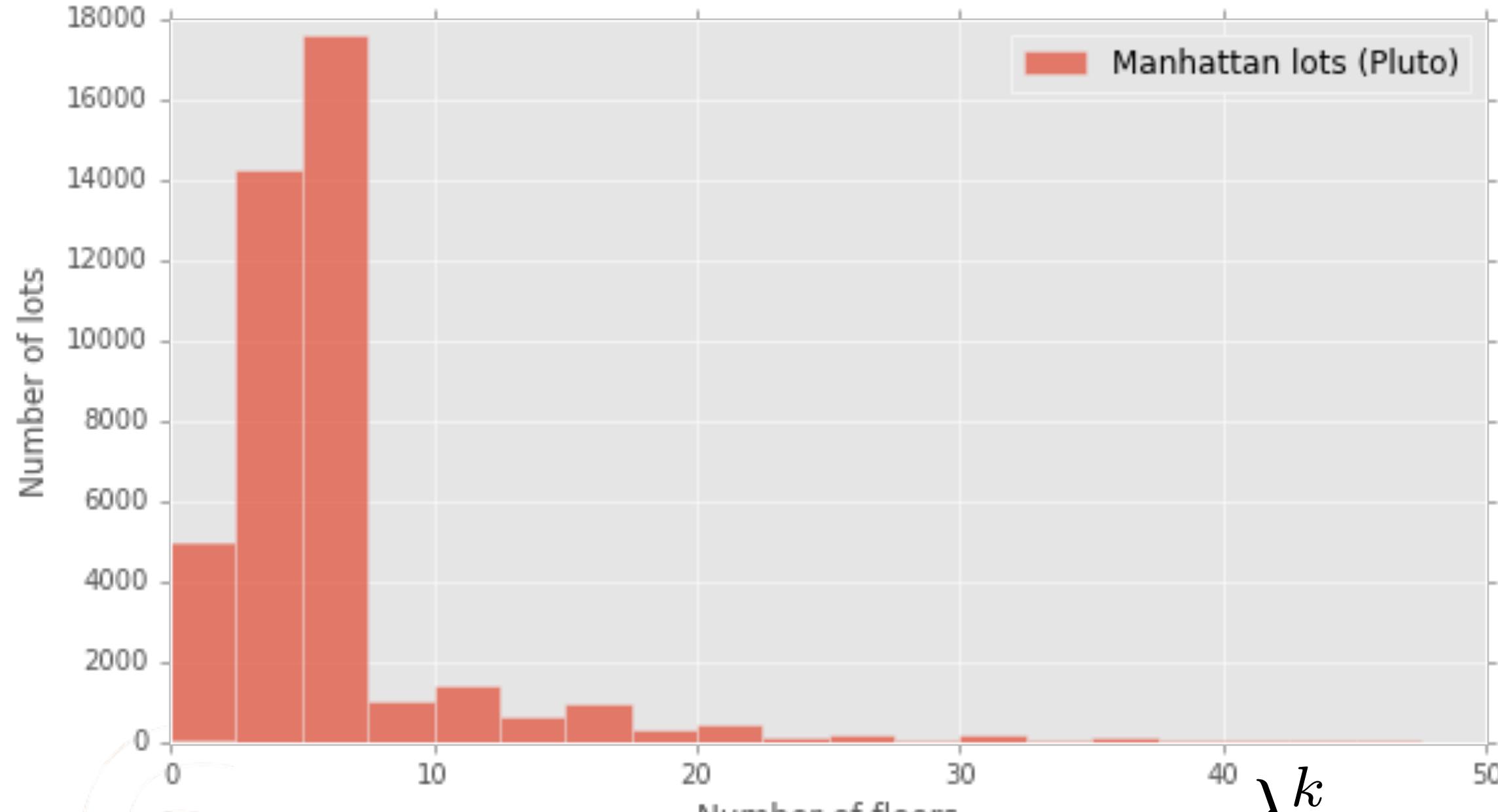
“Count statistics”:

the poisson distribution describes the probability of *number of occurrences non-negative integer values*

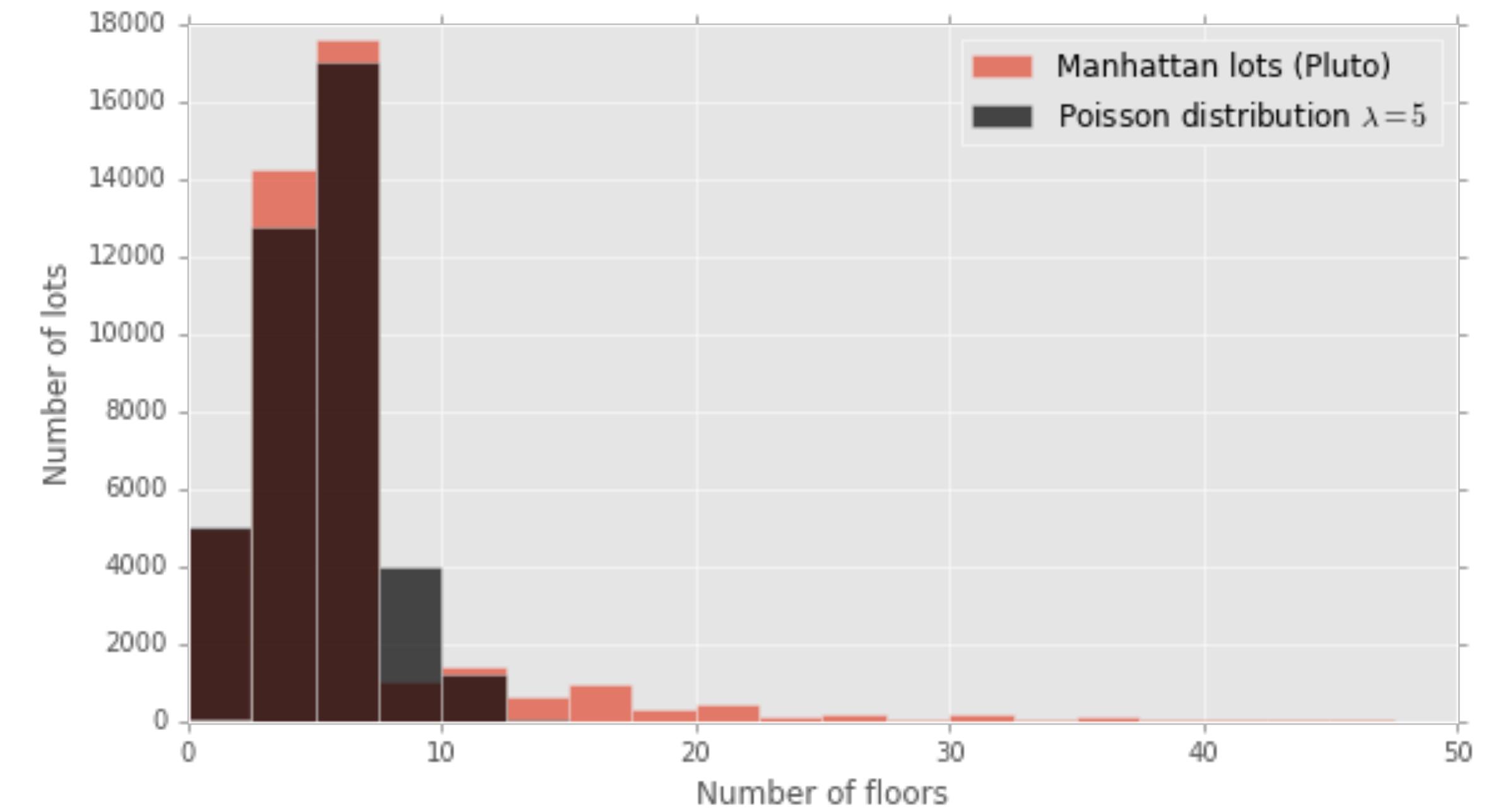
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Classical Continuous distributions:

Classical Discrete distributions:

$$Bin(X = k \mid n, p) = \frac{n!}{(n - k)!k!} p^k (1 - p)^{n - k}$$

$$P(X=2 \mid 2) = 0.27,$$

$$Poi(X = k \mid \lambda) = e^{-\lambda} \frac{\lambda^k}{k!}$$

$$P(X=7 \mid 2) = 0.003$$

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~~$$P(X \neq 0.2 \mid 2)$$~~

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$$5! = 5 \times 4 \times 3 \times 2 \times 1 = 120$$

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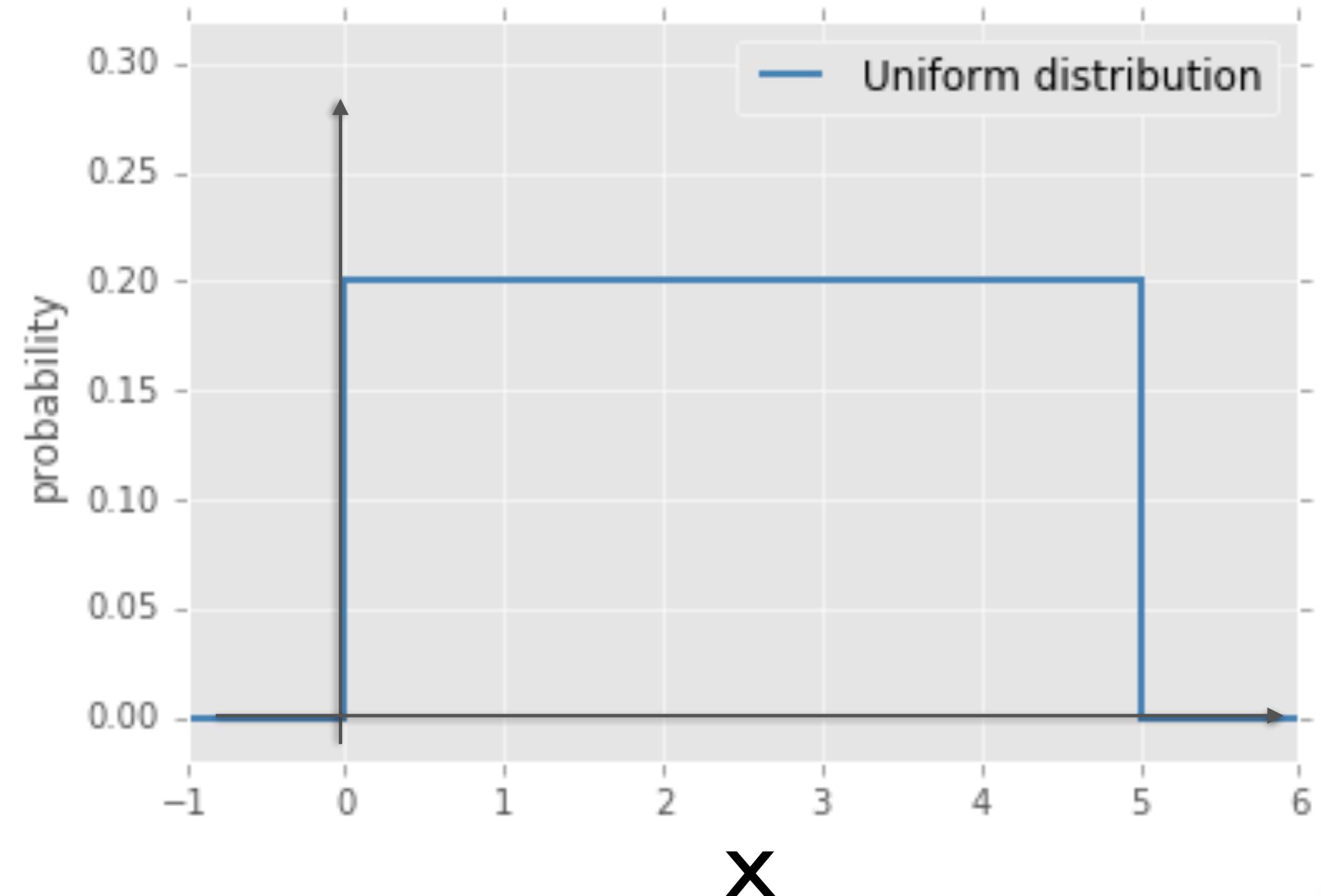
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Classical Continuous distributions

Classical Continuous distributions:

$$P(x) = \begin{cases} c & 0 \leq x \leq 5 \\ 0 & \text{elsewhere} \end{cases}$$

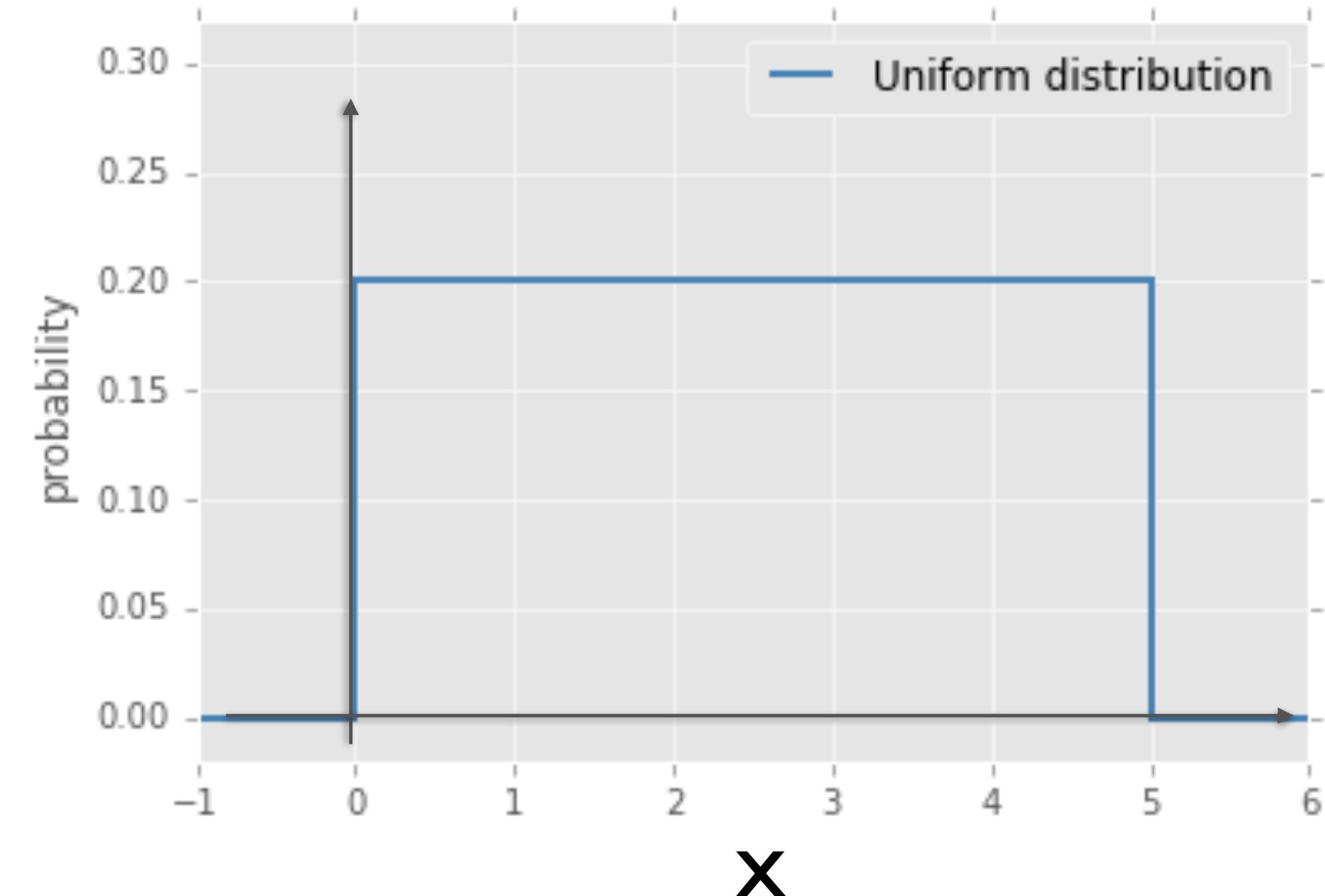


Classical Continuous distributions

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$$P(x) = \begin{cases} c & 0 \leq x \leq 5 \\ 0 & \text{elsewhere} \end{cases}$$

$P(X = \text{any value}) = 1$ by definition



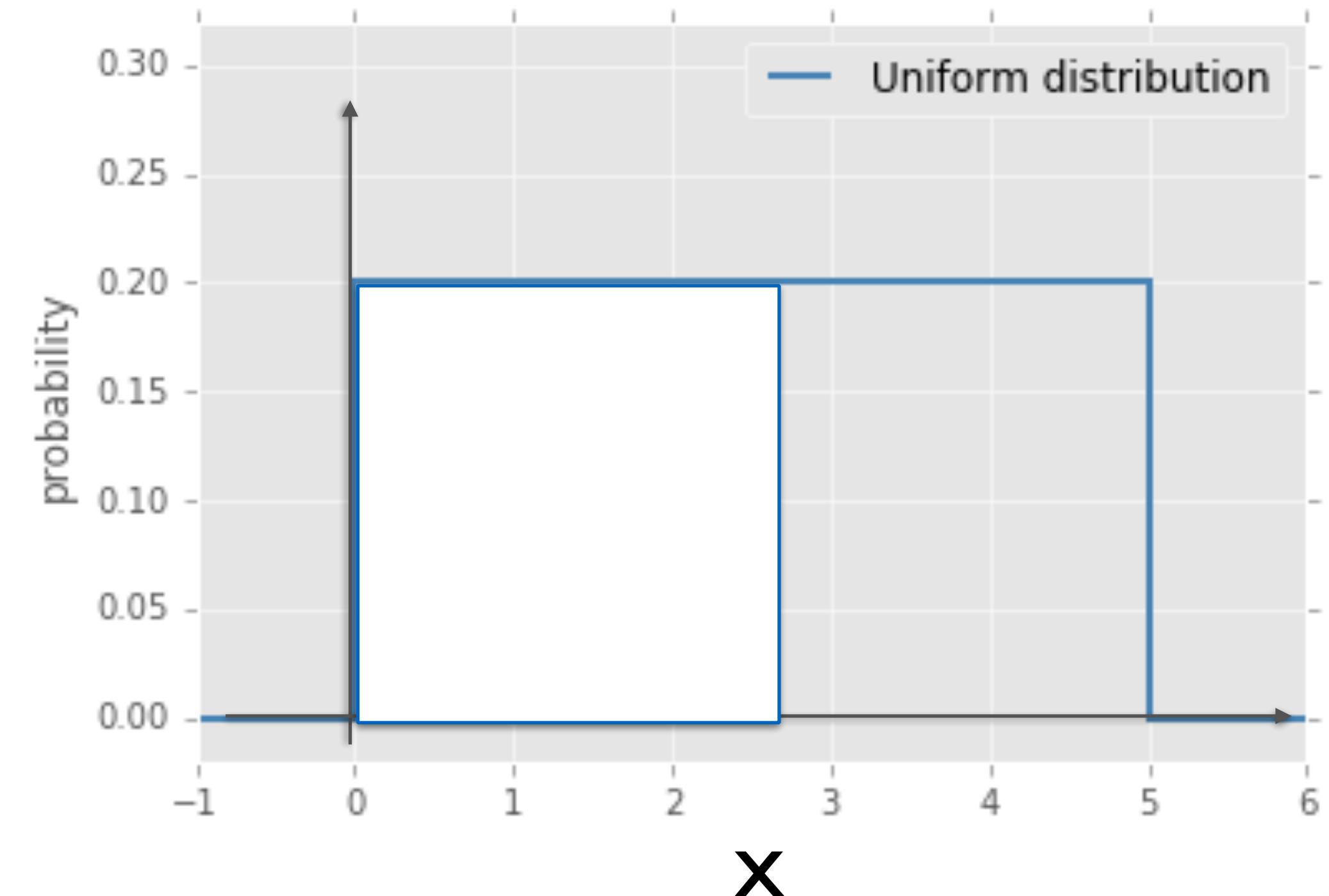
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$$P(0 < X = < 2.5) = 1/2 = 0.5$$



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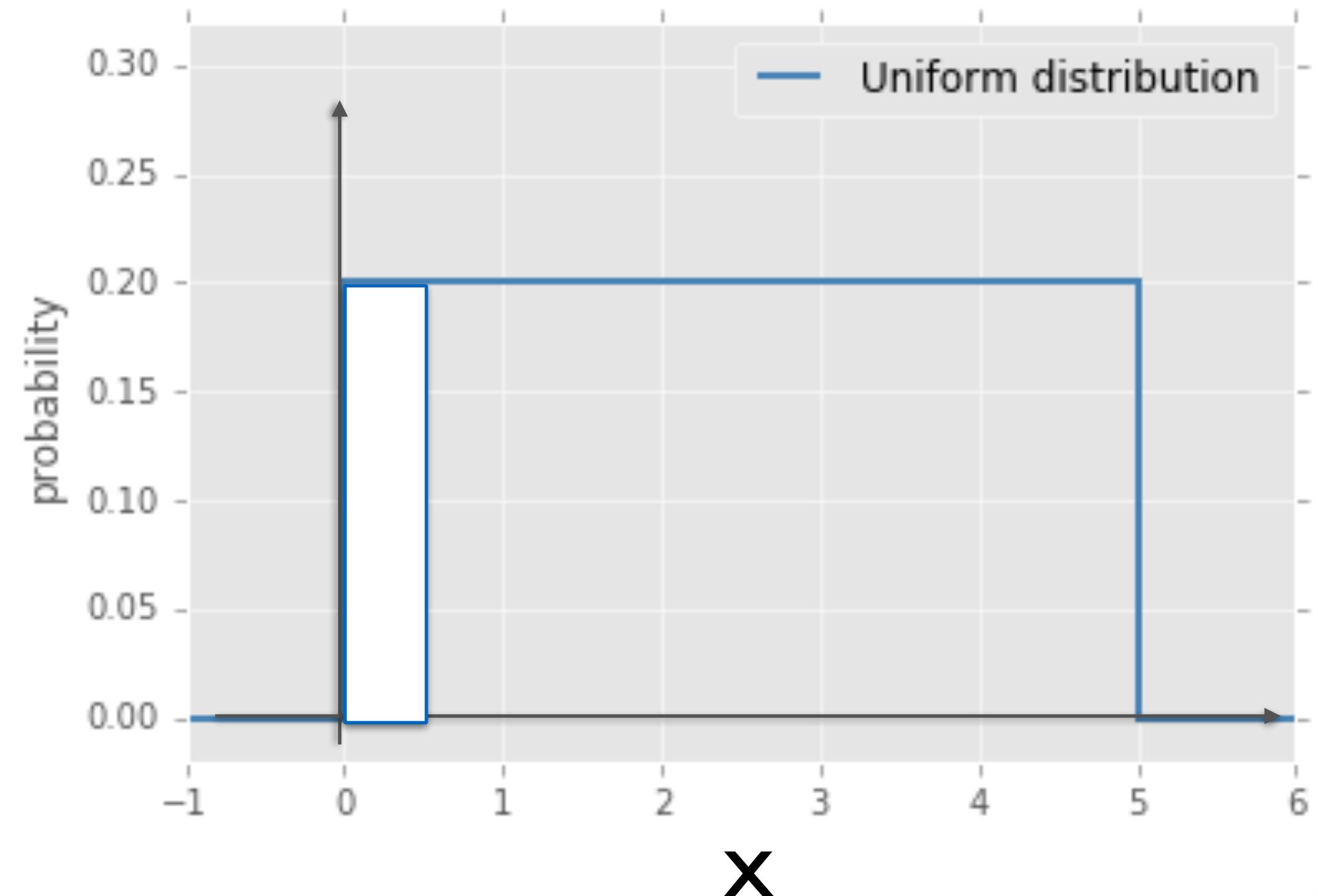
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$$P(0 < X = < 2.5) = 1/2 = 0.2 \times 2.5 = 0.5$$

$$P(0 < X = < 0.5) = 1/10 = 0.2 \times 0.5 = 0.1$$



Classical Continuous distributions

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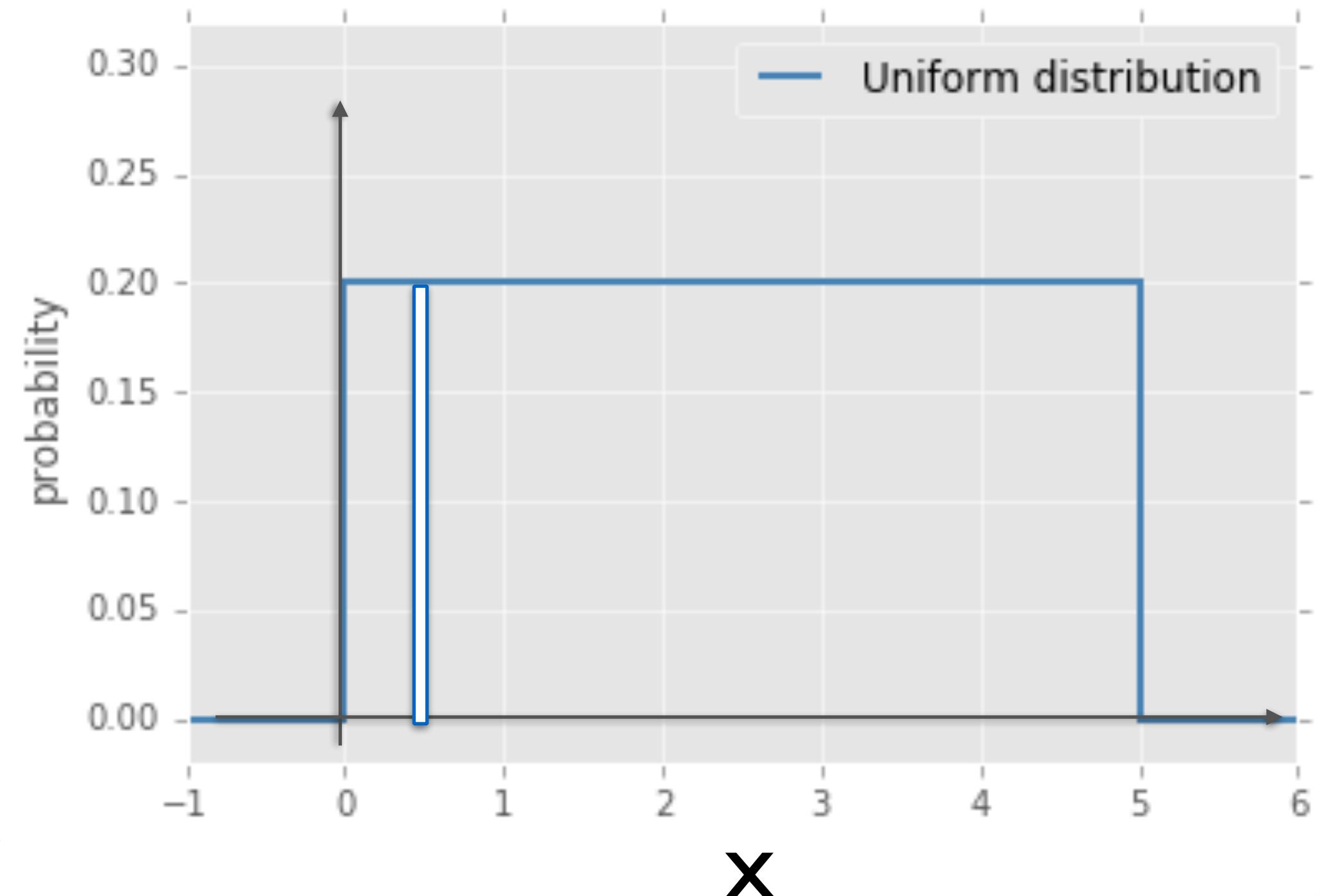
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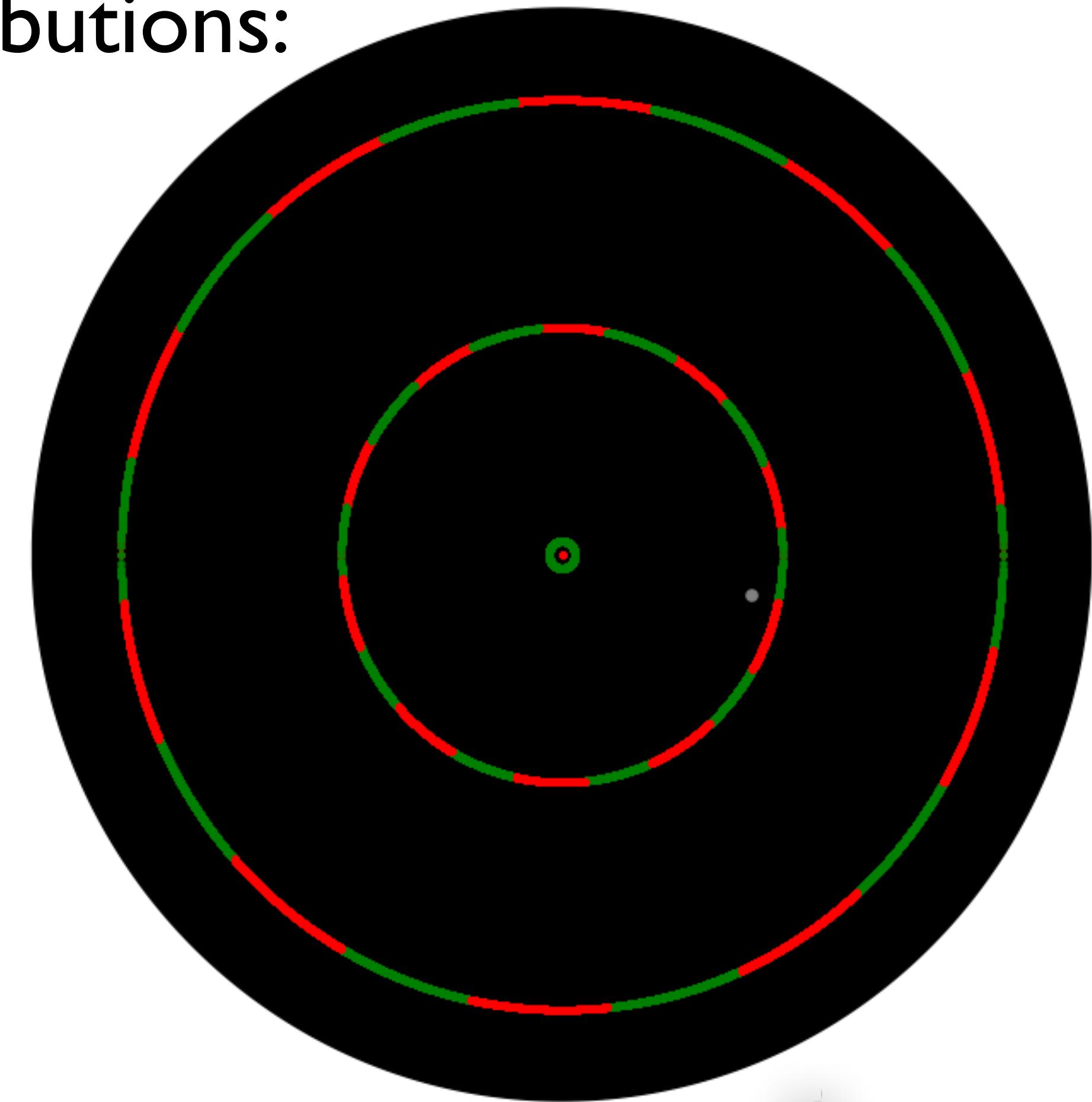
$$P(0 < X = < 0.5) = 1/10 = 0.2 \times 0.5 = 0.1$$

$$P(0.45 < X = < 0.5) = 1/100 = 0.2 \times 0.05 = 0.01$$



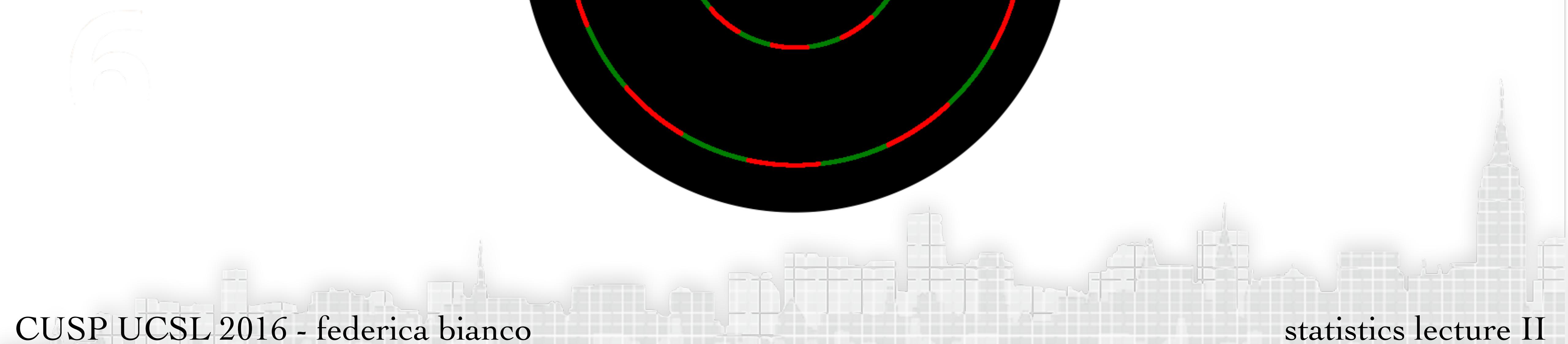
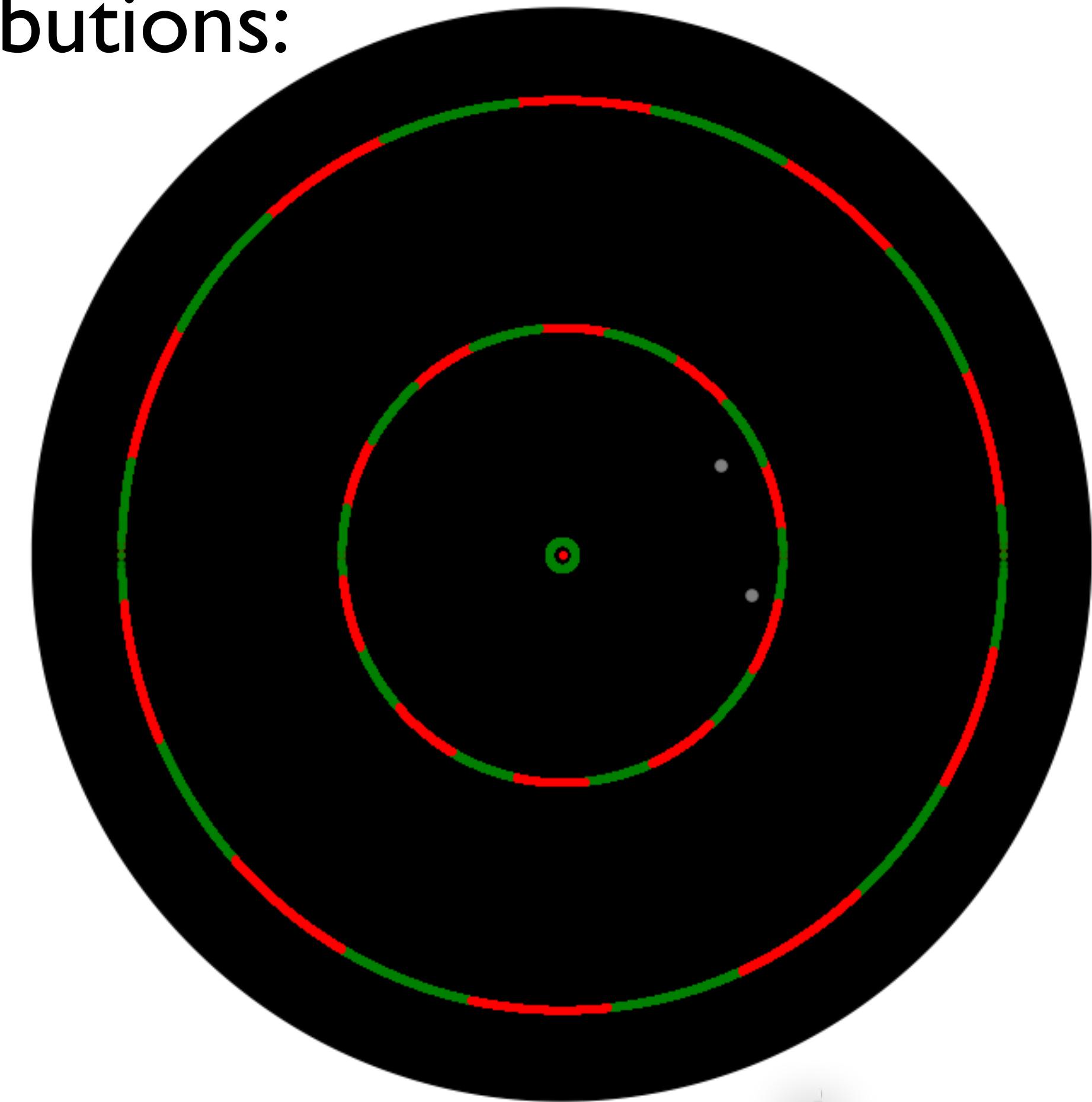
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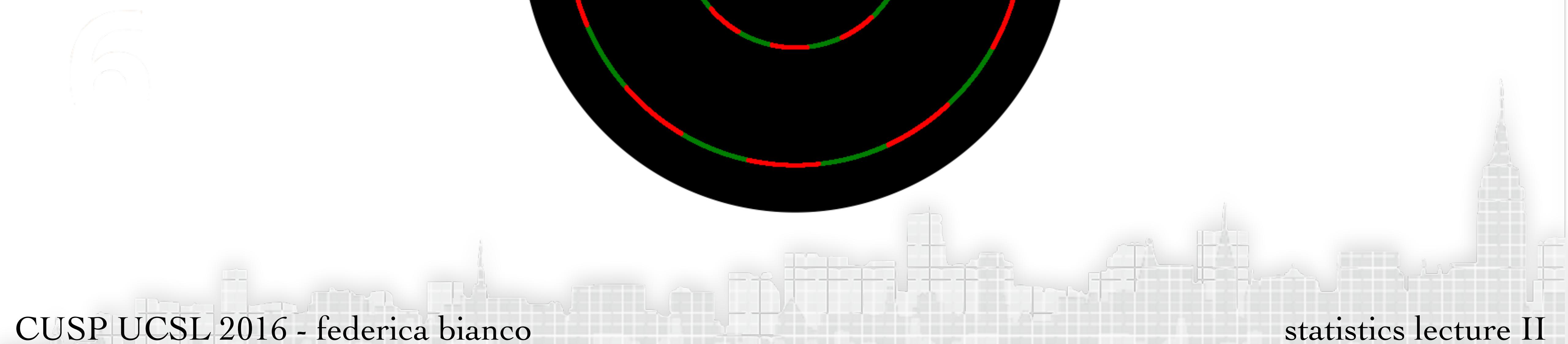
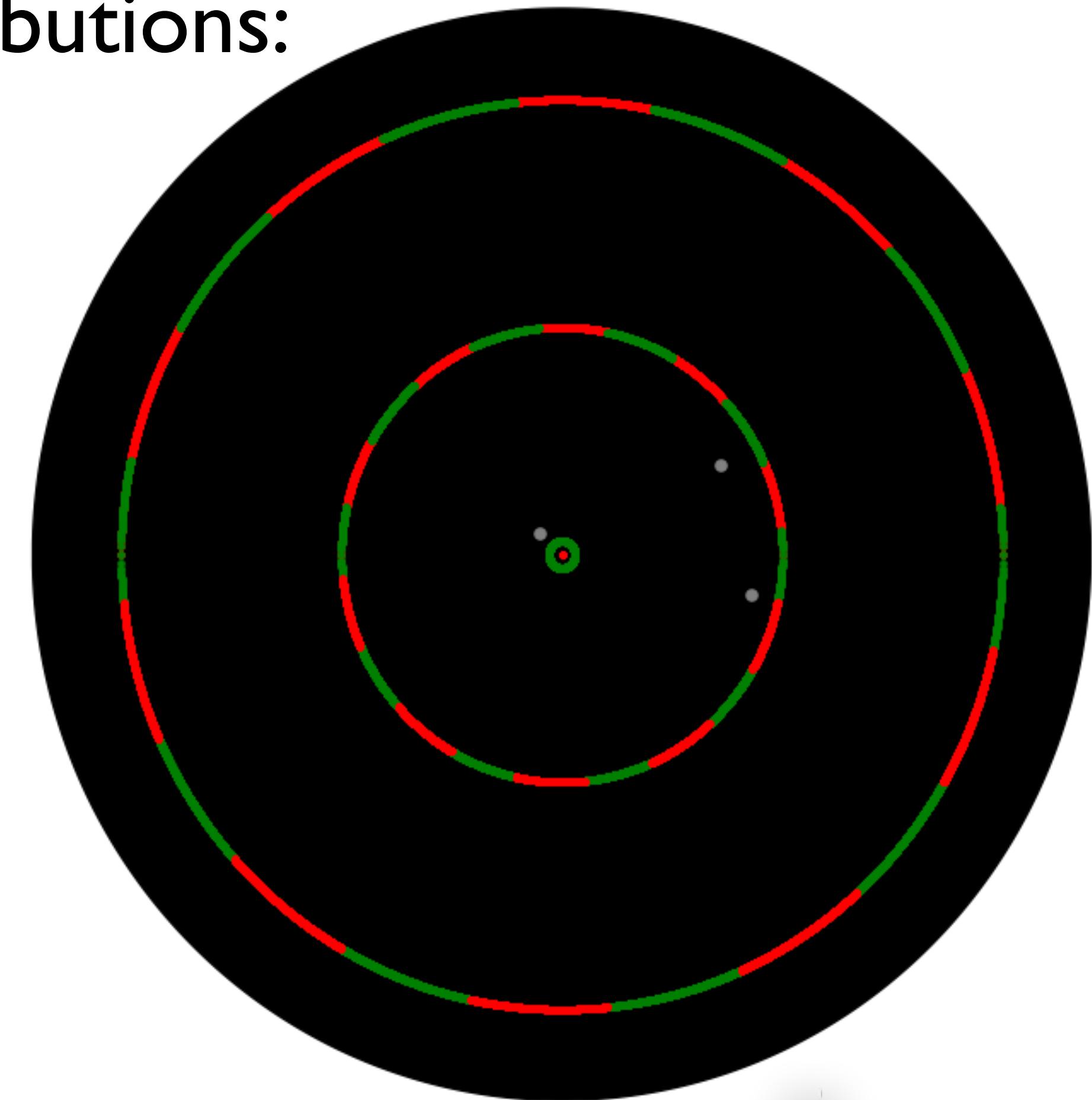
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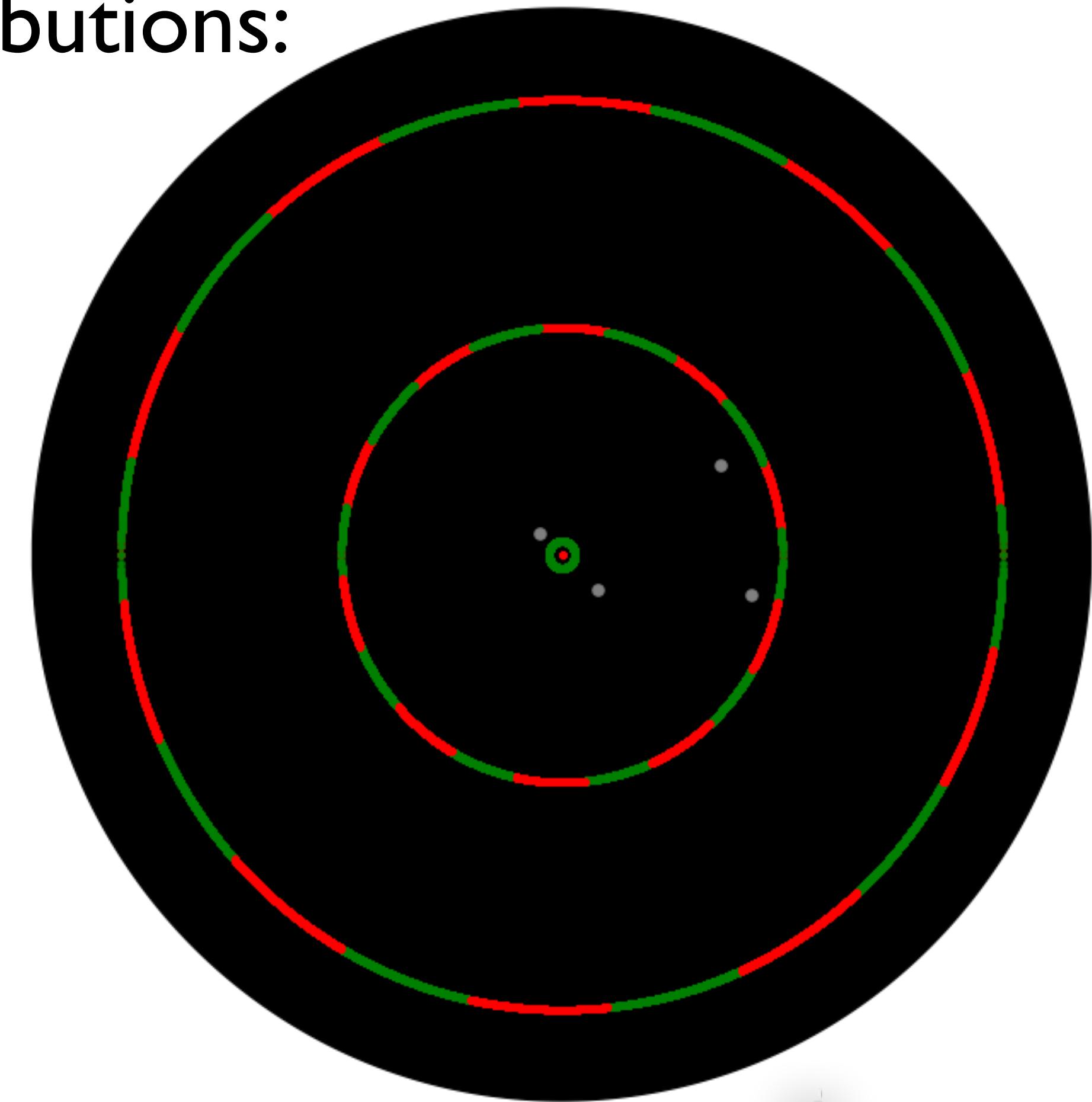
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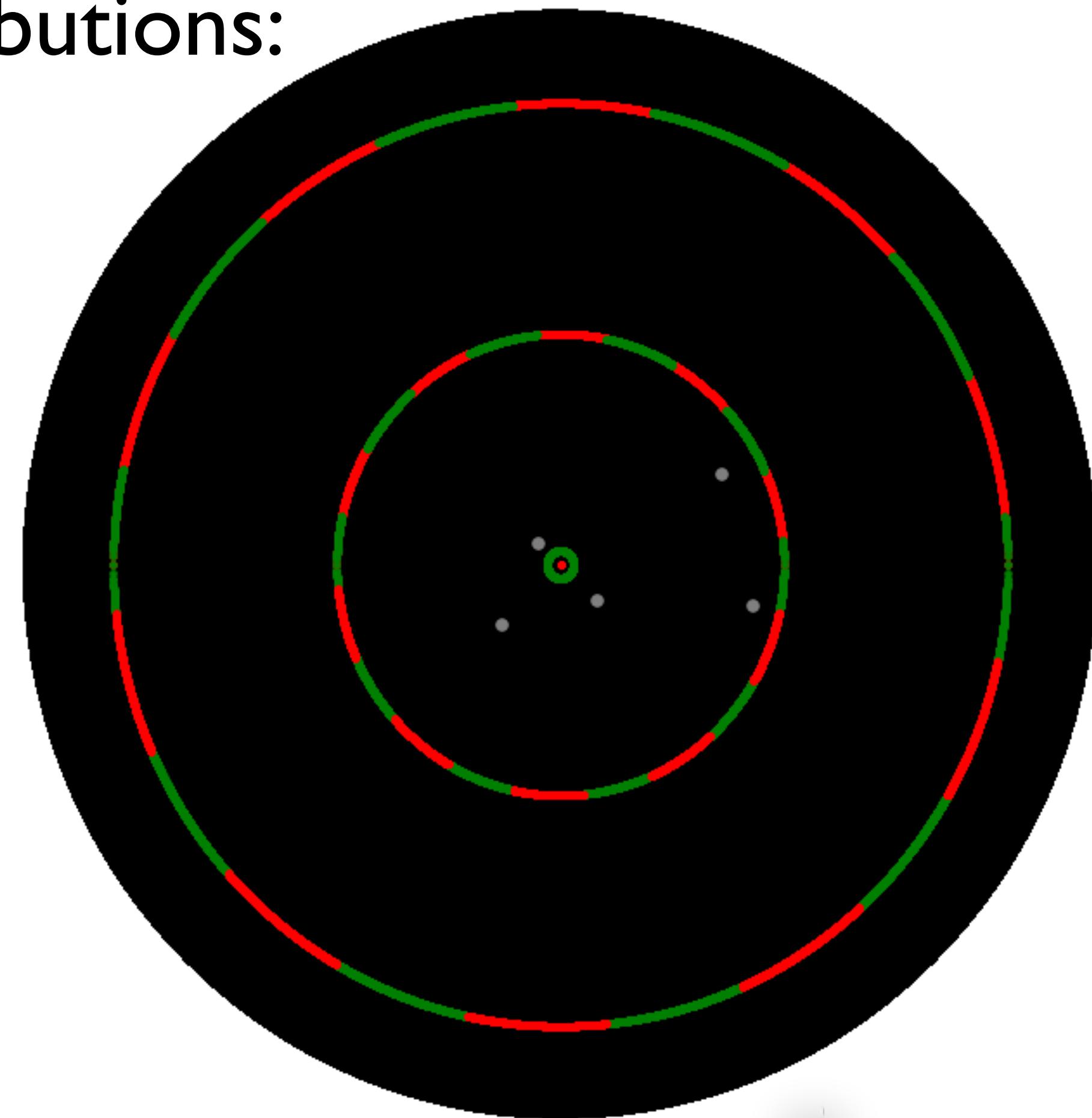
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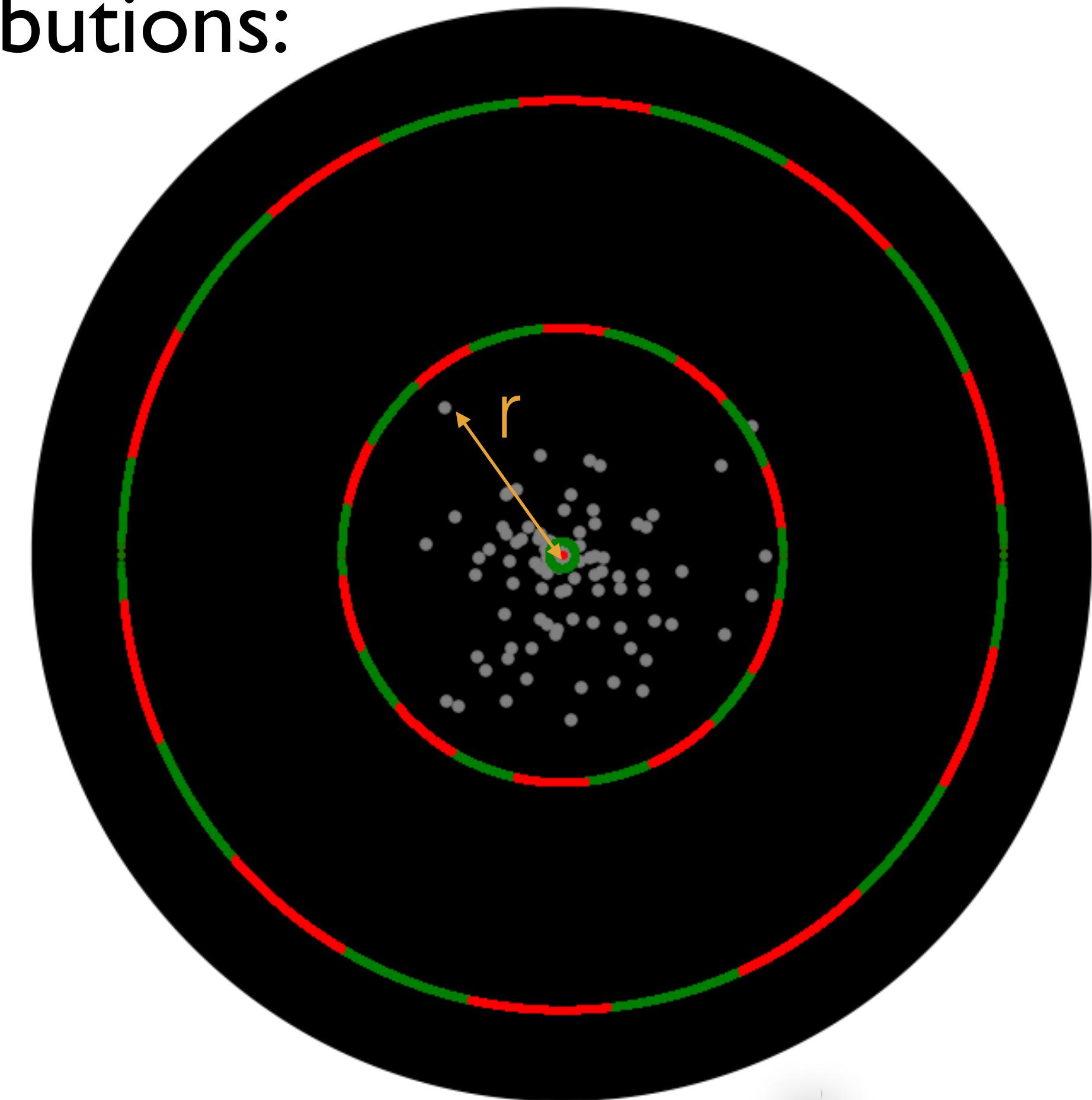
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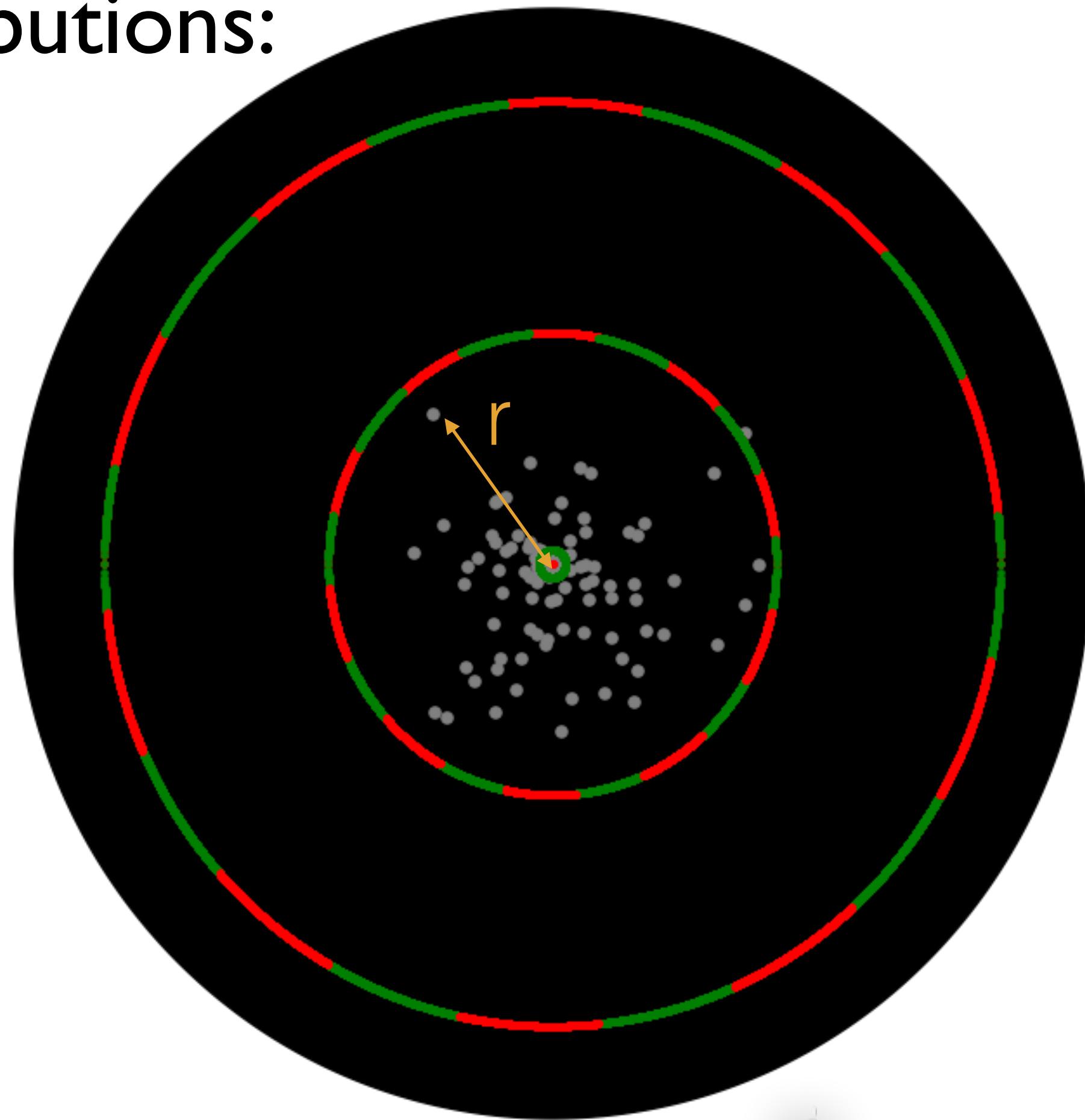
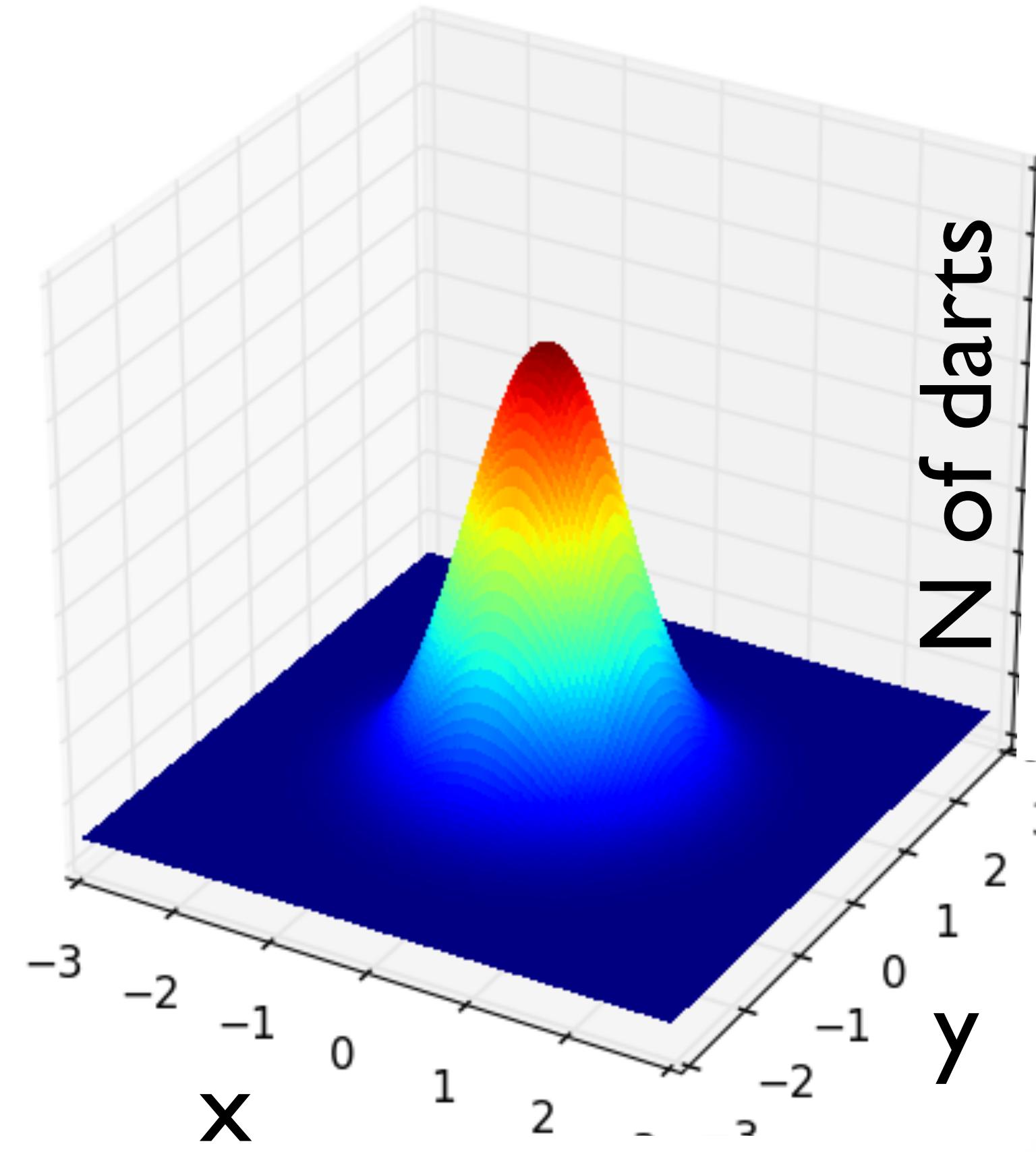
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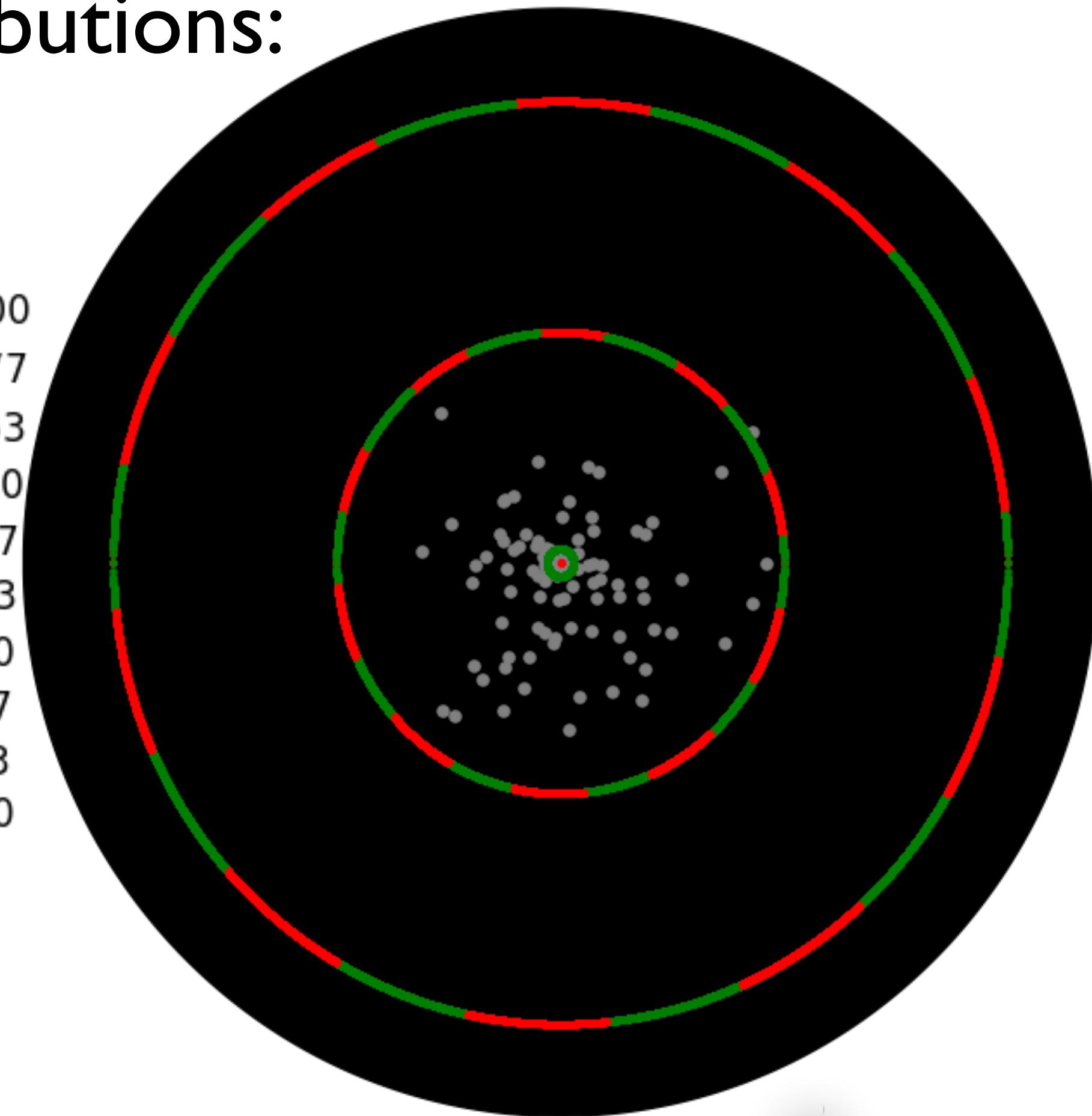
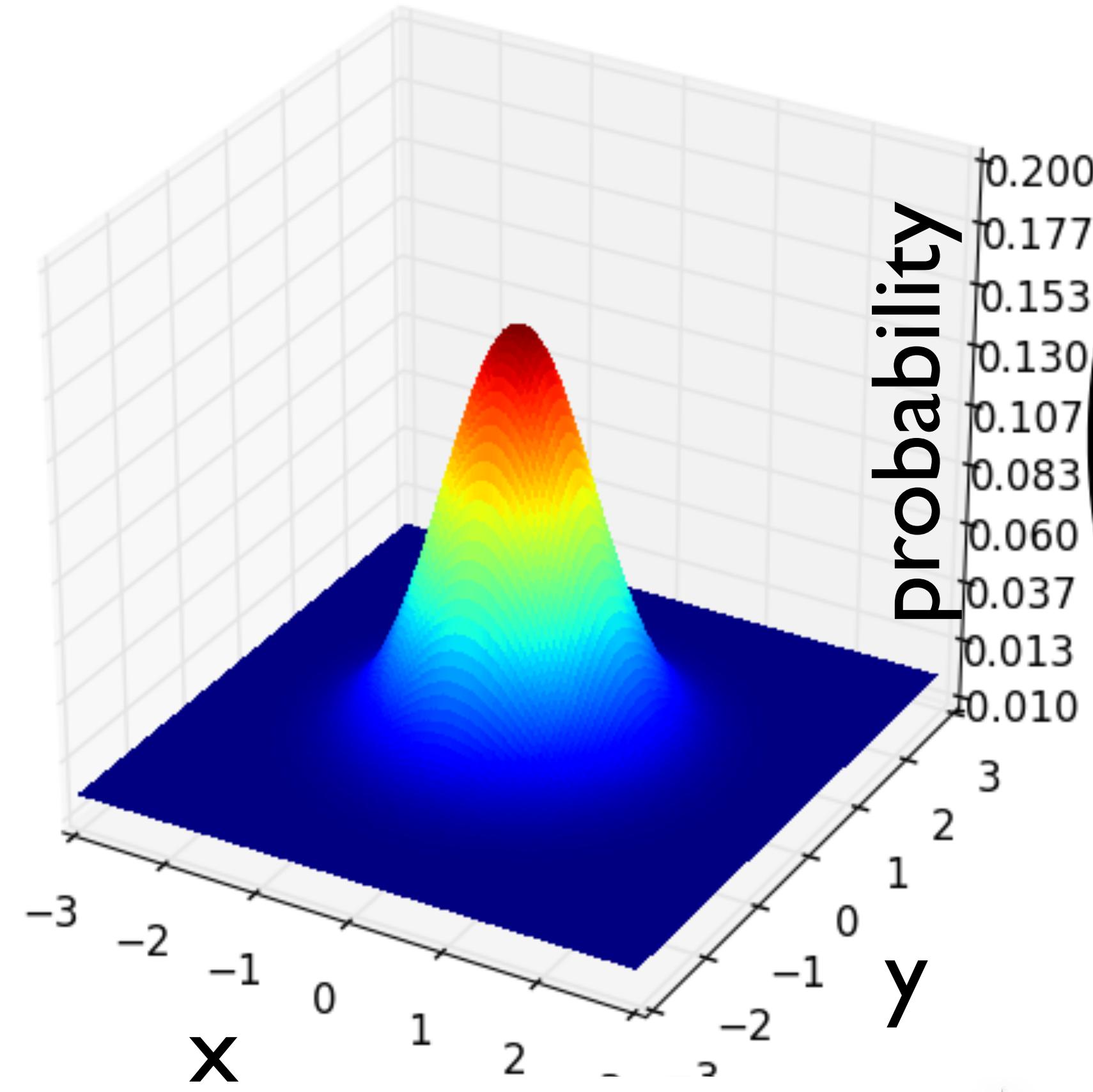
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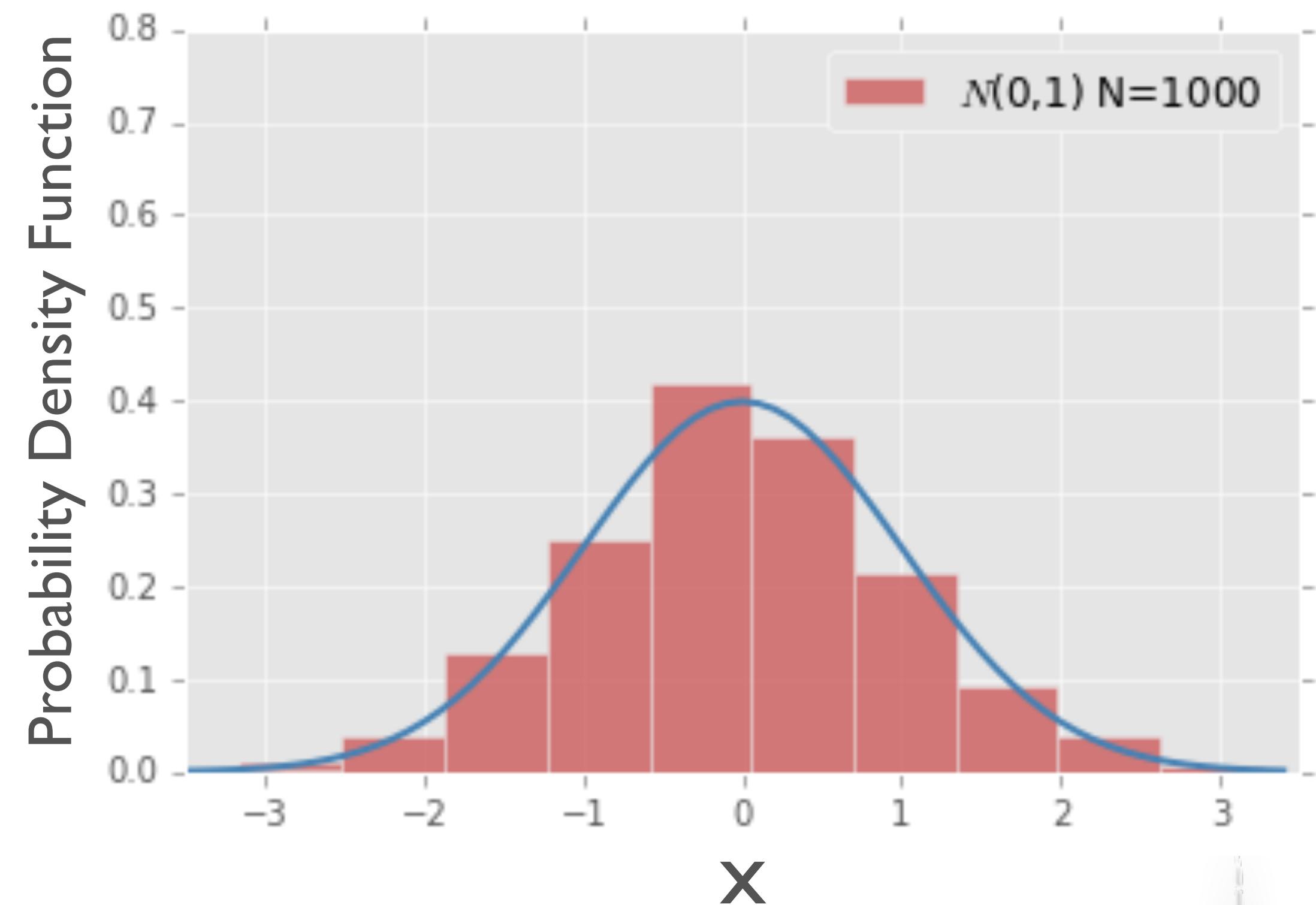
Classical Continuous distributions:

Gaussian (or Normal) distribution

$$N(x | \mu, \sigma) = \frac{1.0}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{\sigma^2}}$$

μ : mean

σ : standard deviation



Classical Continuous distributions:

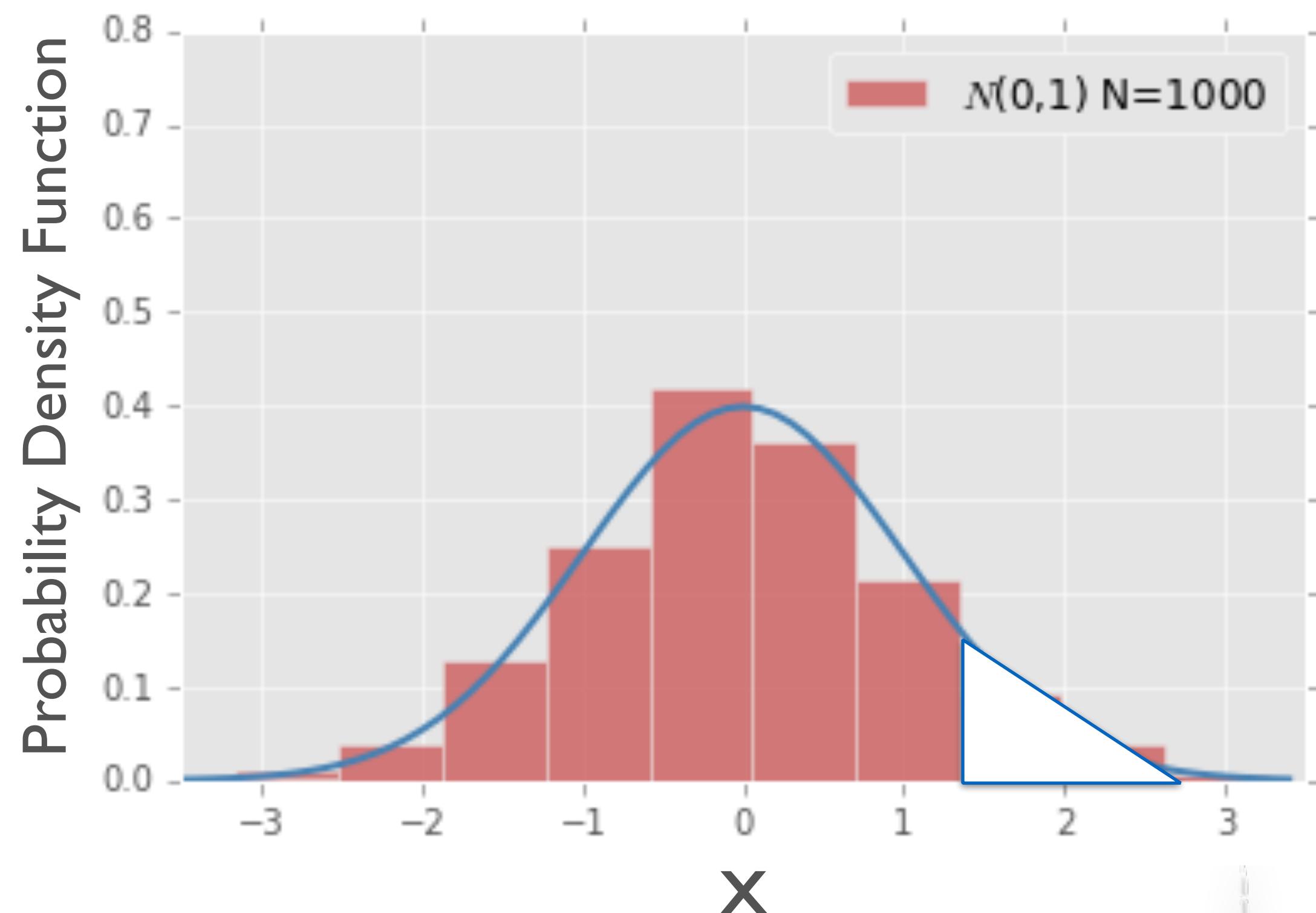
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$P(X = \text{any } x) = 0$ by definition

$$x \in [-\infty, \infty]$$

$$P(X > x) = \int_x^{\infty} N(x | \mu, \sigma)$$



Classical Continuous distributions:

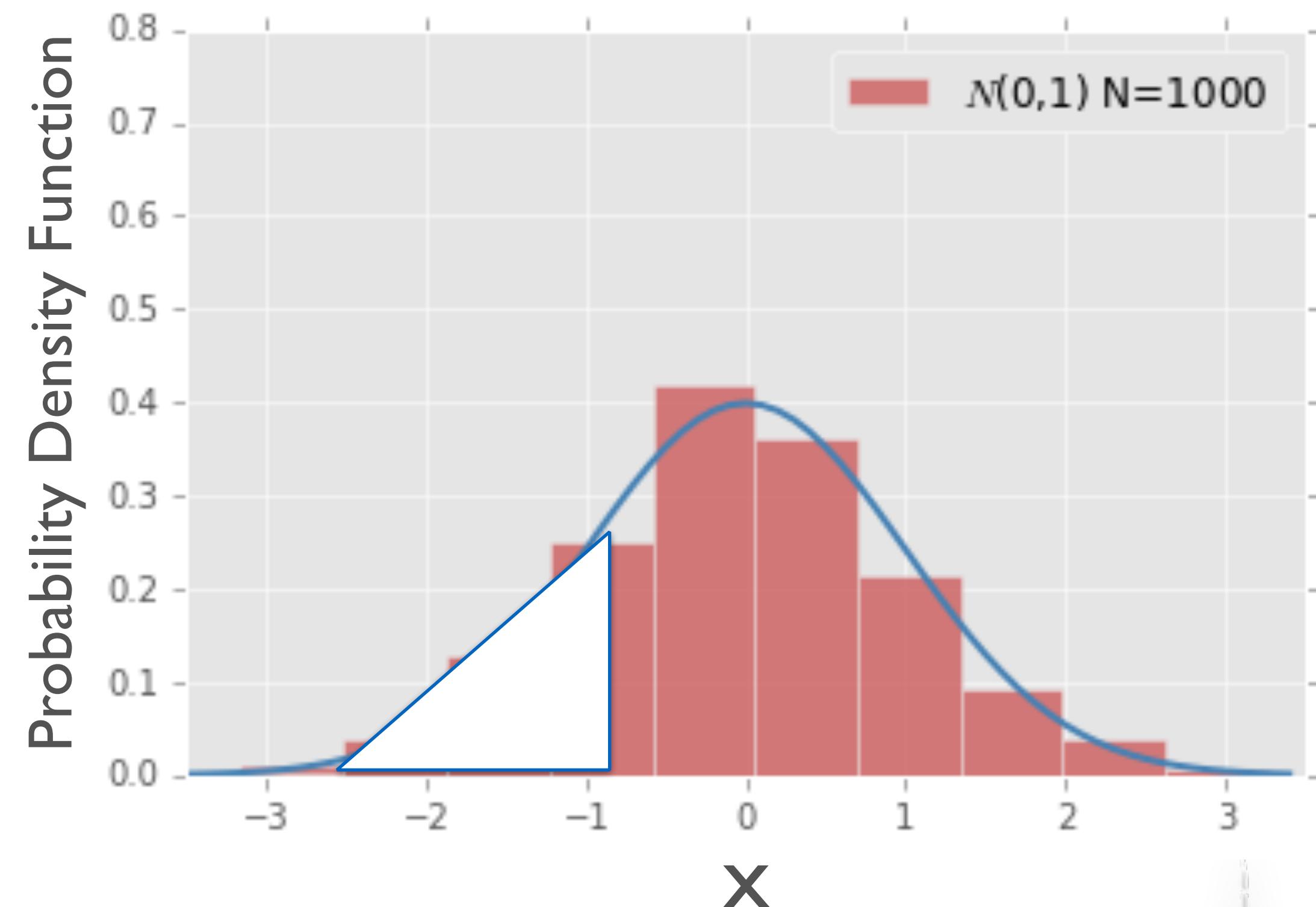
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$P(X < \text{some value})$

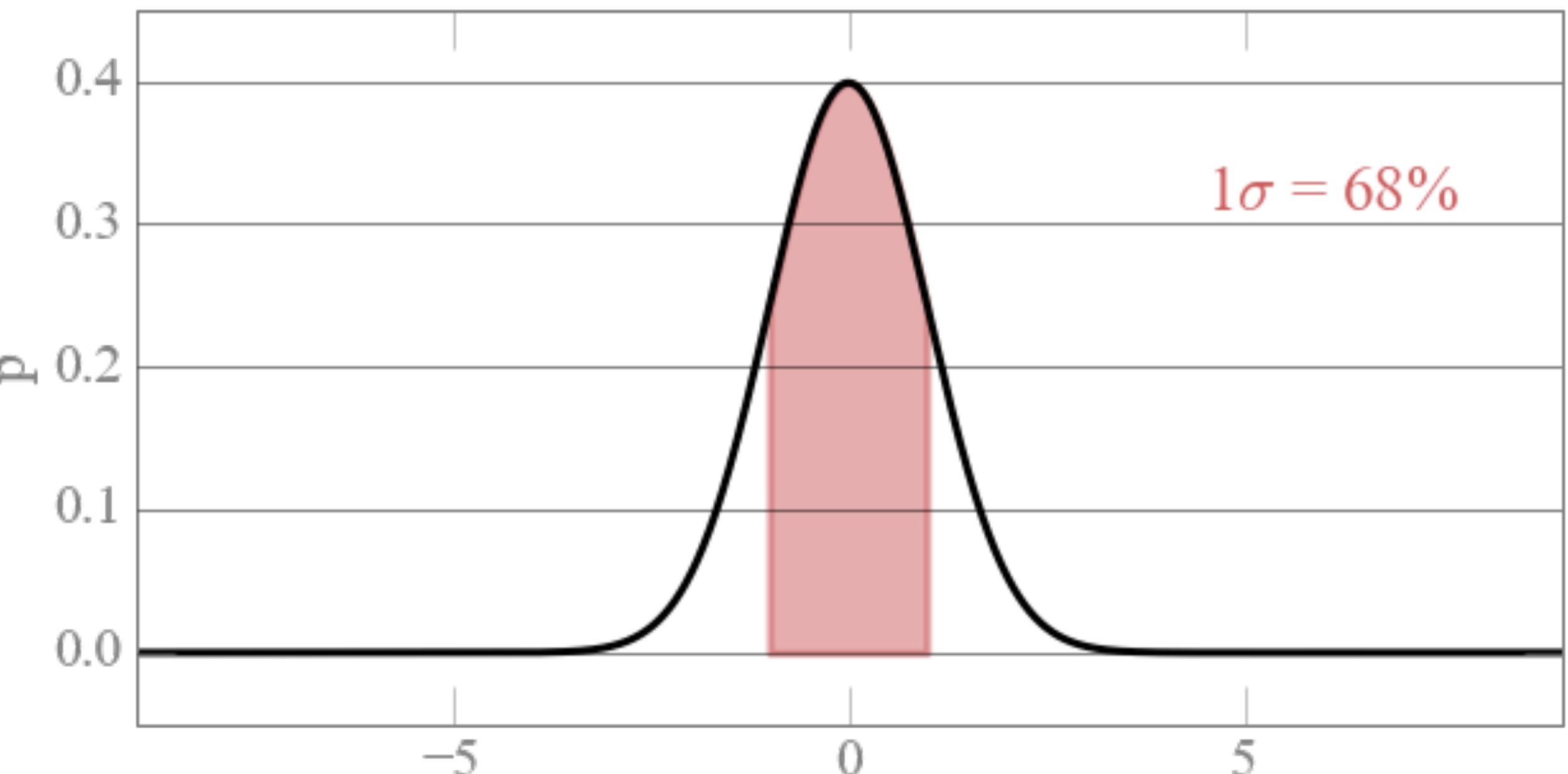


Normal Distribution

Classical *Continuous* distributions:

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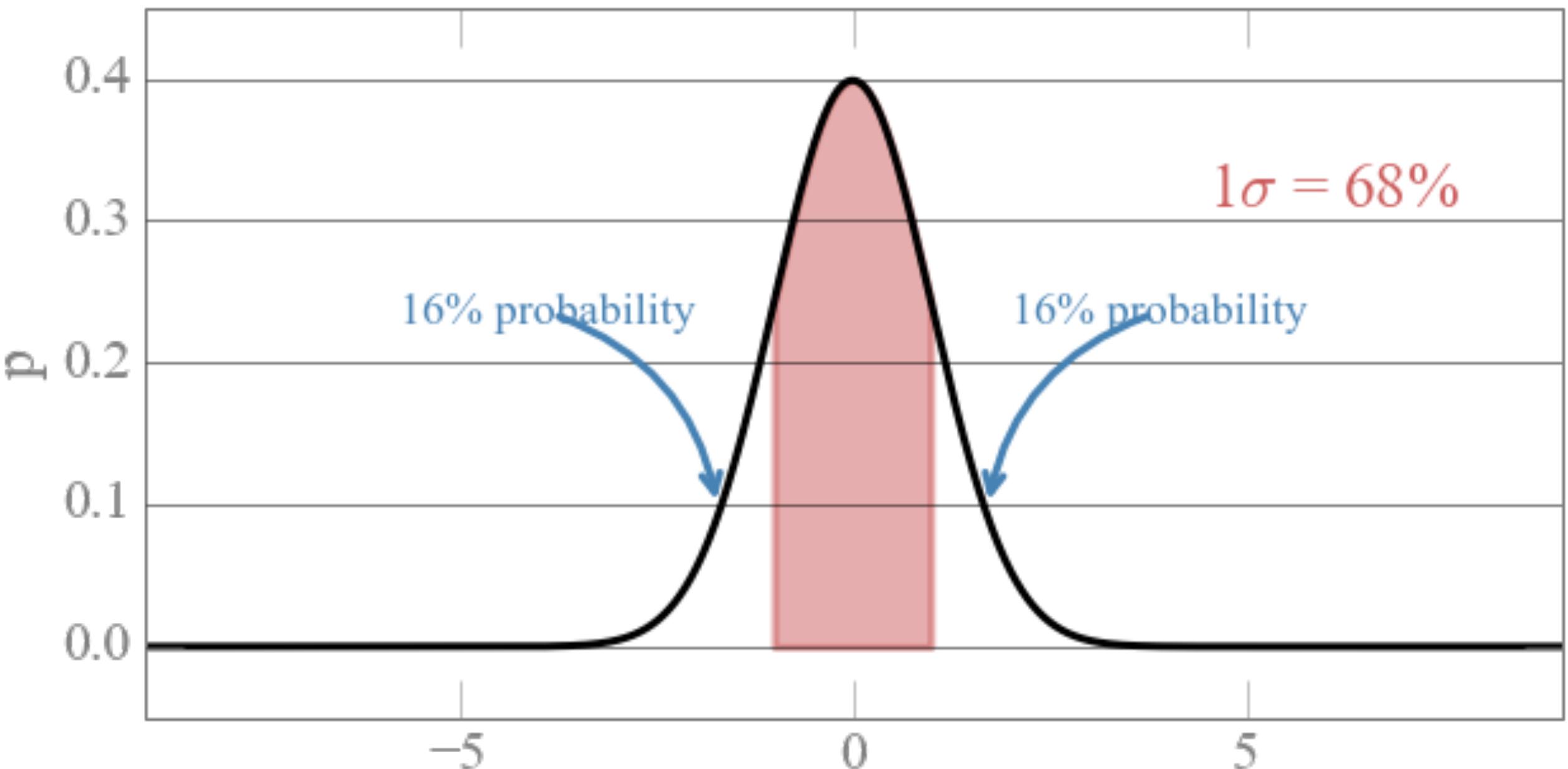


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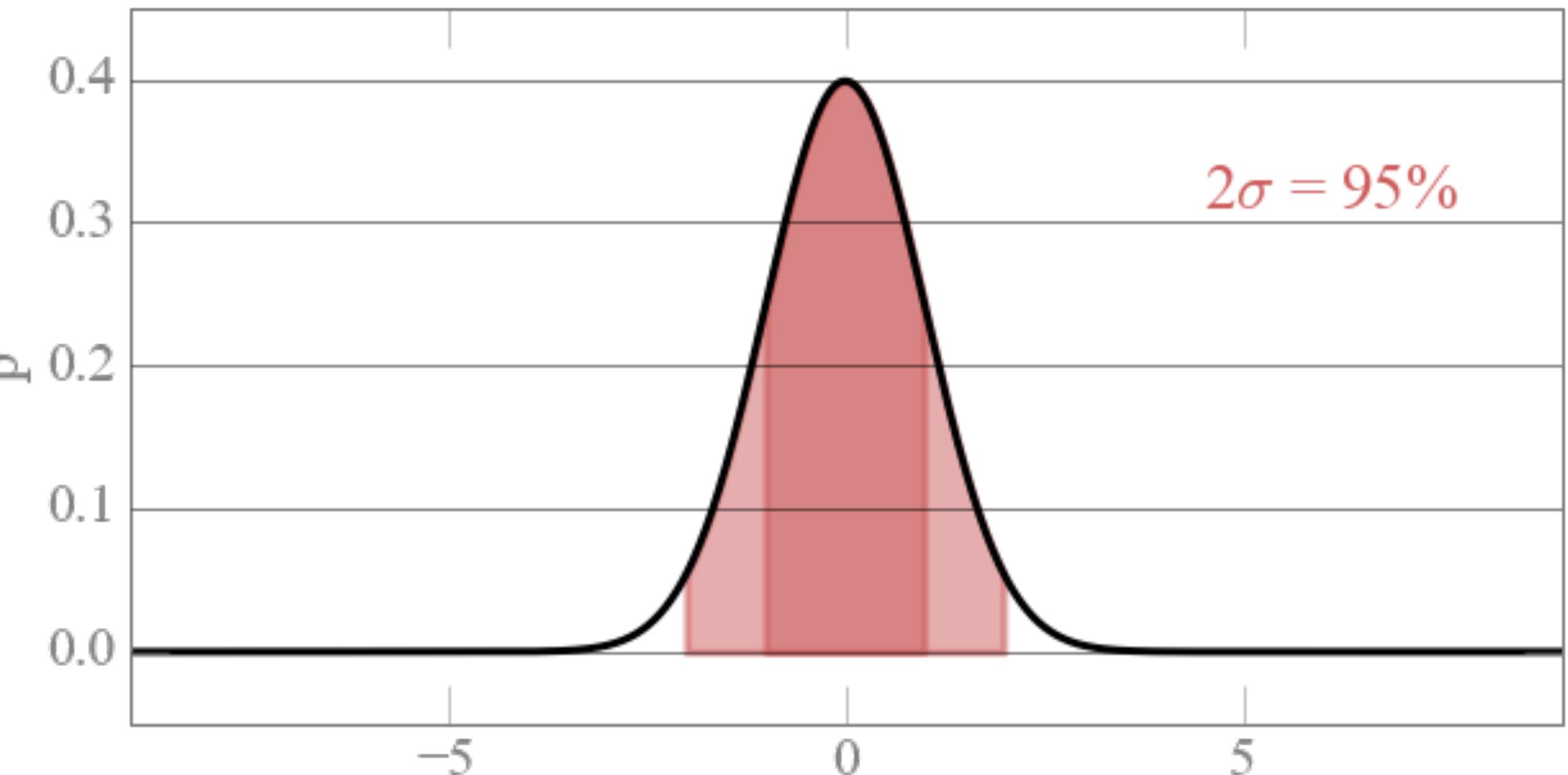


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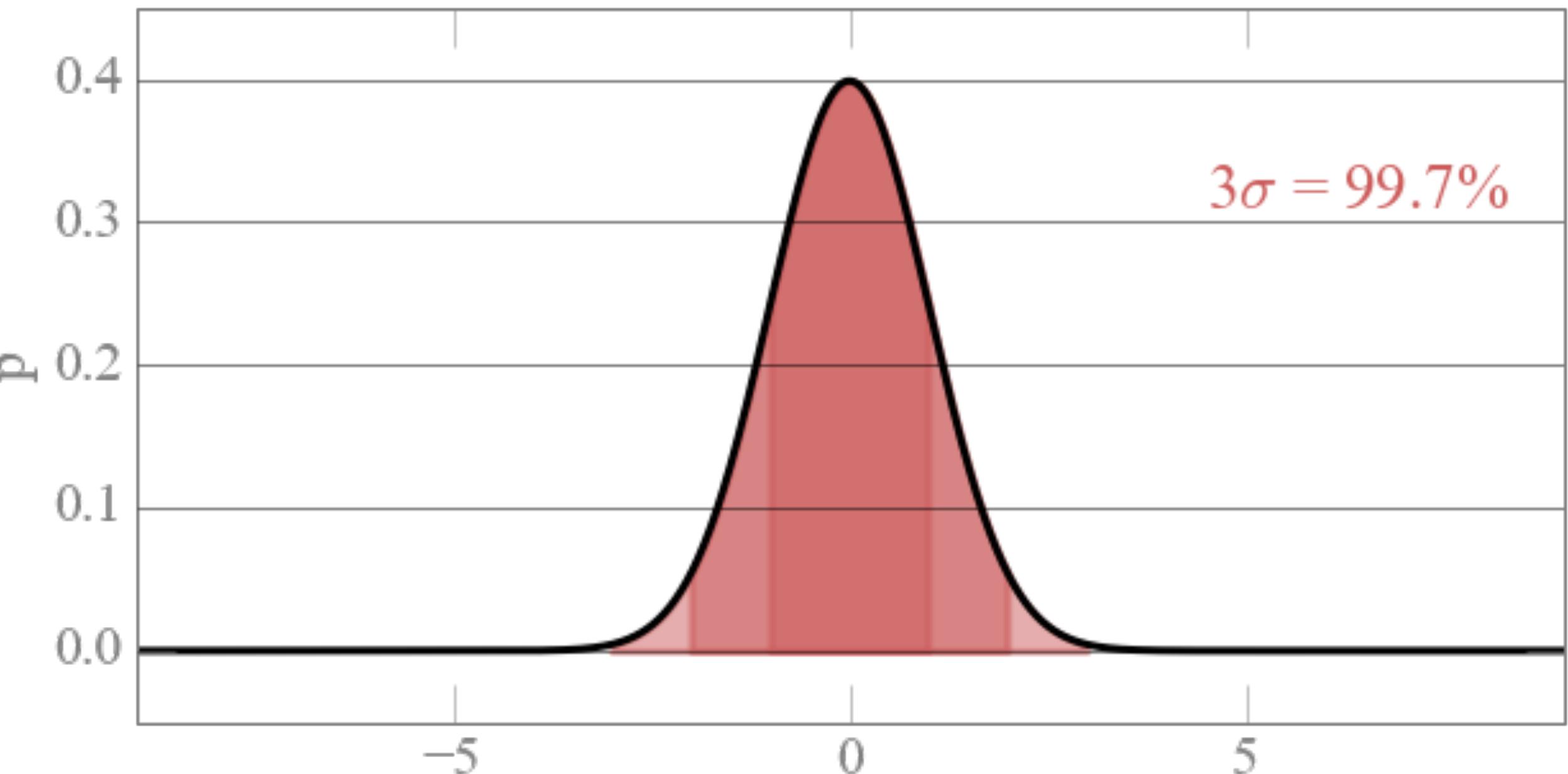


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we will encounter this over and over again
when we talk about *p*-values and *hypothesis testing*

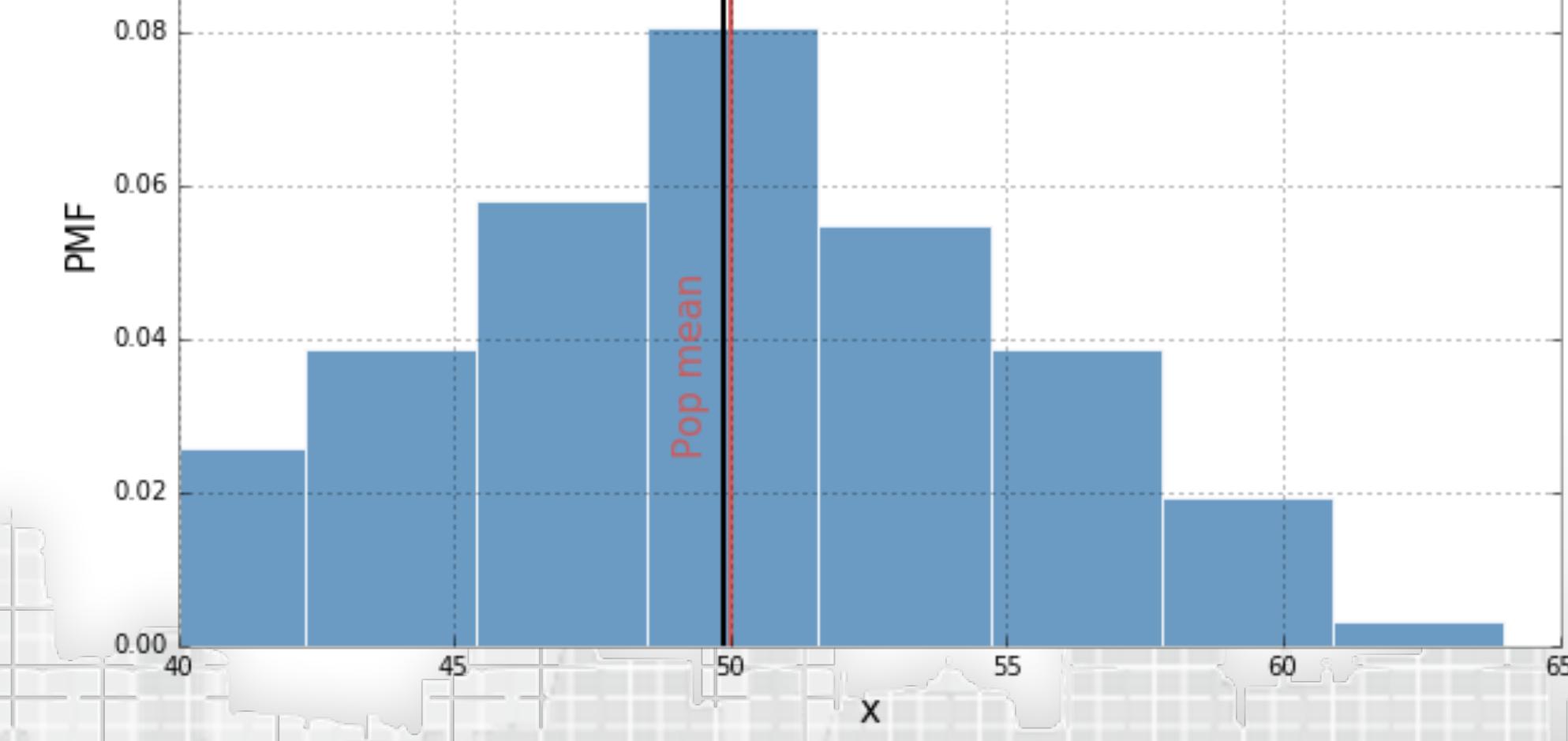
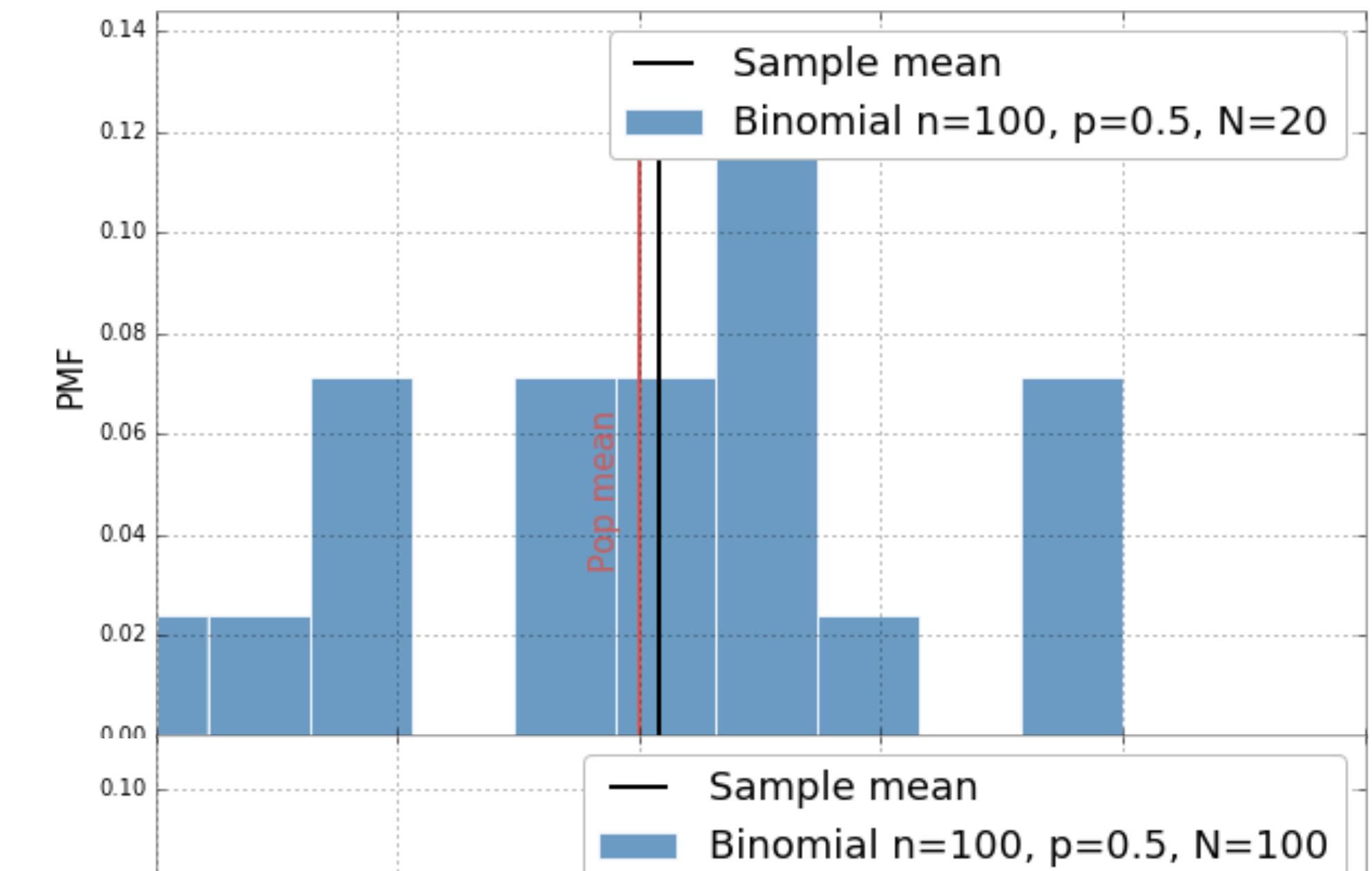
Central Limit Theorem

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for ANY distribution, as the sample size increases, the *distribution of sample means* converges to the *population mean*

AND

the distribution of the means is Gaussian



Central Limit Theorem

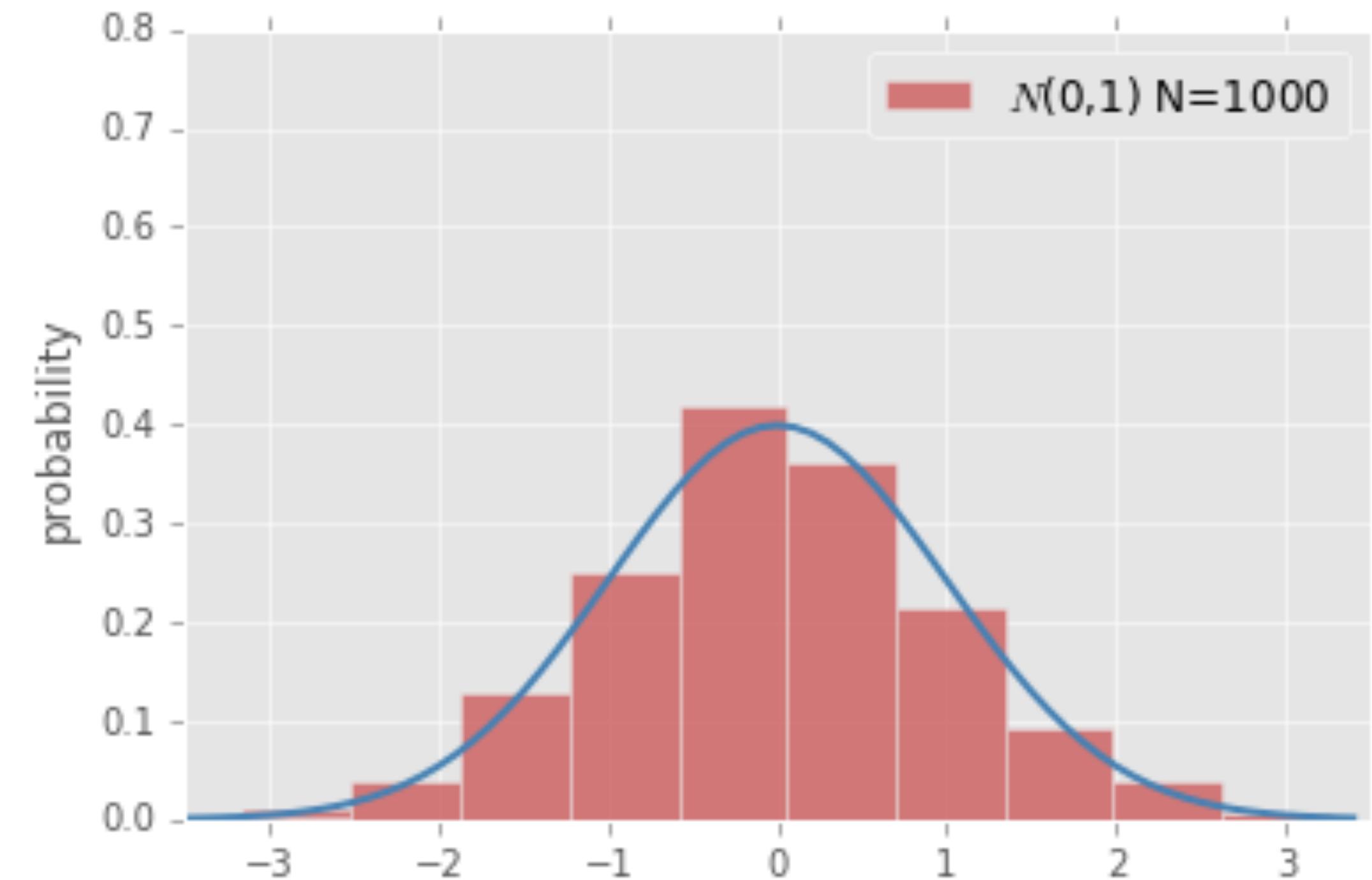
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AND

the distribution of the means is Gaussian

Pois(λ) \longrightarrow $N(\lambda, \sqrt{\lambda})$ for $\lambda \rightarrow \infty$:

The Poisson Pois(λ) distribution converges to a *Gaussian distribution $N(\lambda, \sqrt{\lambda})$* for large λ



<https://github.com/fedhere/UInotebooks/blob/master/UCSL2016/UCSL2016%20continuous%20distributions%20demo.ipynb>

Key Points

- Statistics allows us to make inference about the world, even if we cannot observe all of the world: inference on the population from a sample.
- Some statistical distributions describe any phenomena well: the Poisson distribution, which is a discrete distribution, and the Gaussian distribution, which is a continuous distribution.
- If the samples are large enough, the Poisson, Binomial, and a few other distribution start looking like a Gaussian. So in many cases we can make the assumption that the phenomena we study are Gaussian in nature.
- If we have many samples (patients in many clinical trials for example) the means of the samples is itself going to be Gaussian-distributed (*Central limit theorem & Law of large numbers*).