

CS461 – RECITATION 01

MACHINE LEARNING PRINCIPLES

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CONTACT

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 - Not Yet

BACKGROUND

- First-year PhD
- Deep Learning
- Neural Network Efficiency
- High Performance Computation

TODAY'S CONTENT

Recap what you have learned before

- Common Distributions
 - Continuous
 - Discrete
- Hypothesis Testing
 - P-values
 - χ^2 Test

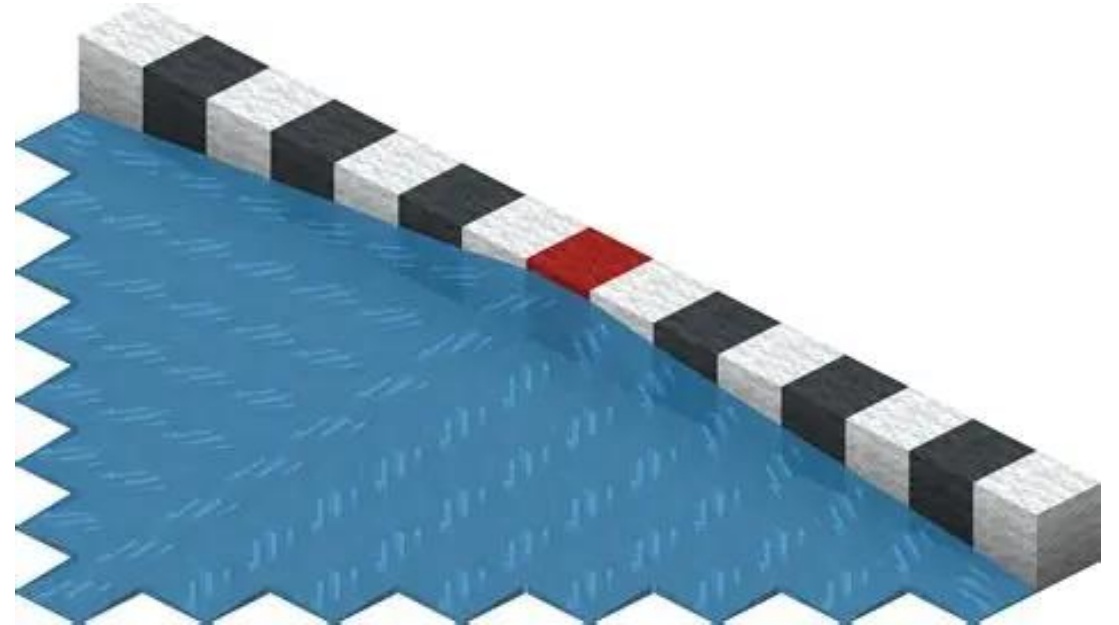
NOISE

- $Y = \beta_0 + \beta_1 x + \epsilon_i$
- Data points are noised
- How to model it?

DISTRIBUTIONS



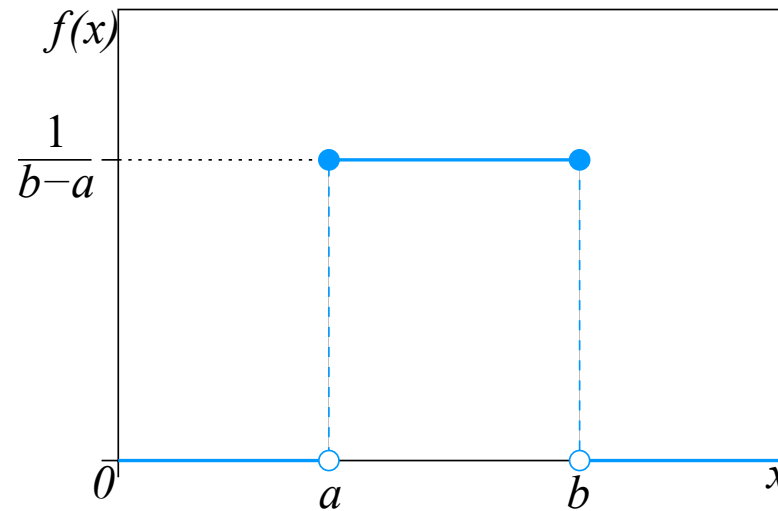
Continuous



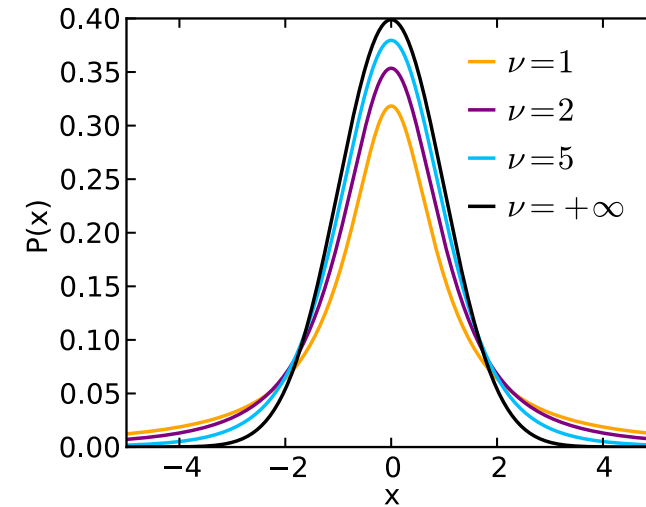
Discrete

CONTINUOUS DISTRIBUTIONS

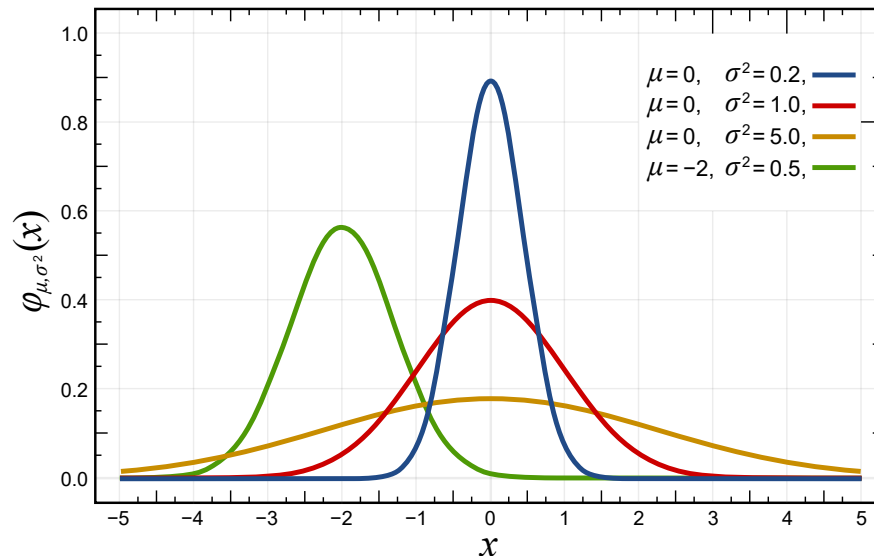
Uniform



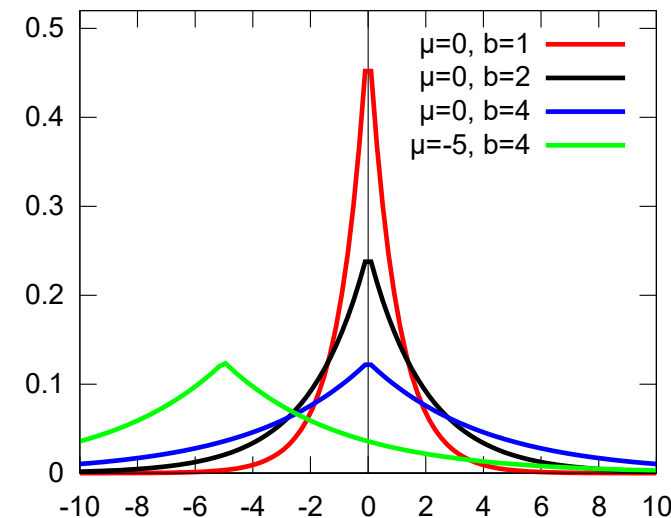
Student's t



Gaussian



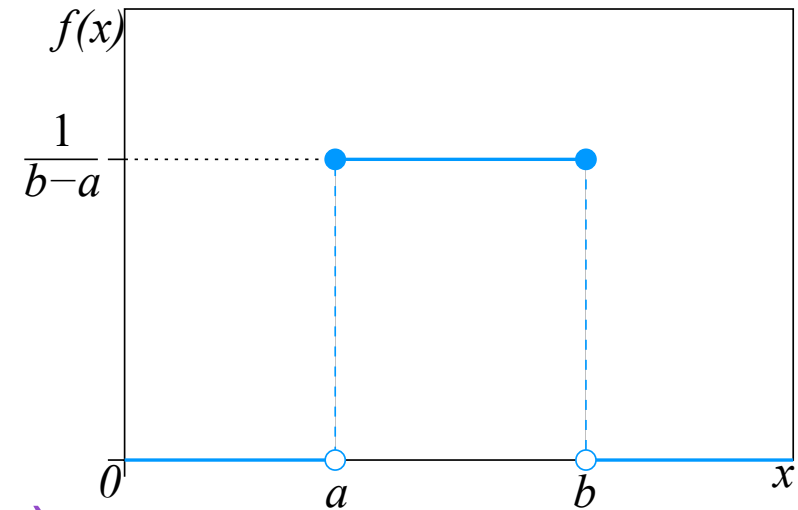
Laplace



UNIFORM DISTRIBUTION

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{for } x < a \text{ or } x > b. \end{cases}$$

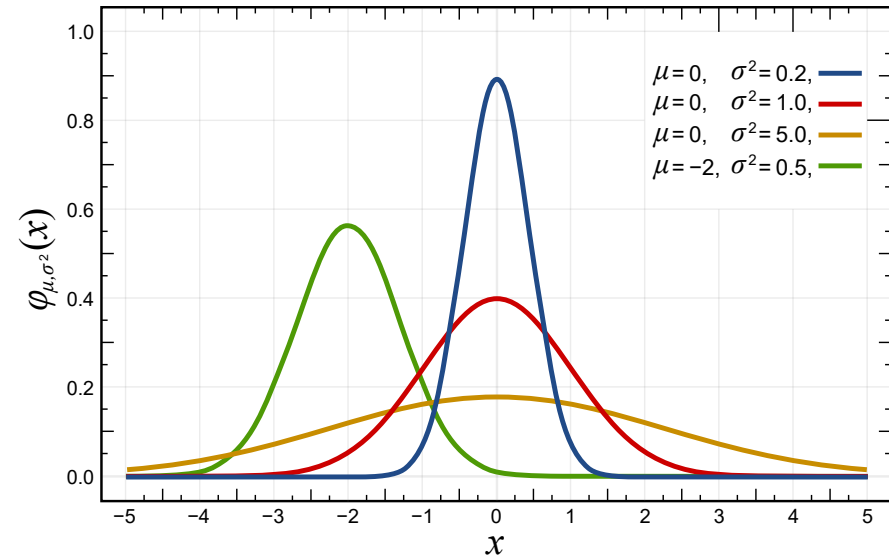
- Perfectly smooth tabletop
- `numpy.random.uniform(low, high)`



GAUSSIAN DISTRIBUTION

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

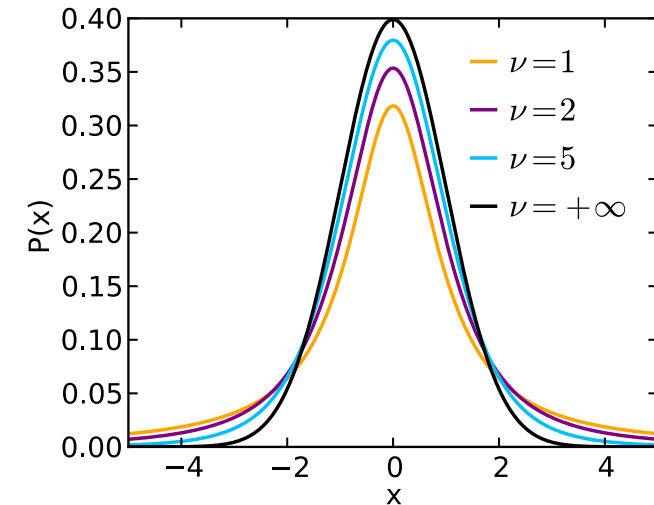
- Exam scores
- Heights and weights
- `numpy.random.normal(mu, sigma)`



STUDENT'S T DISTRIBUTION

$$f(t) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi\nu}\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{t^2}{\nu}\right)^{-(\nu+1)/2},$$

- Gaussian distribution w/ fatter tails
- Financial modeling (asset returns)
- `numpy.random.student_t(nu)`



$f(t) \rightarrow N(0,1)$ as $\nu \rightarrow \infty$

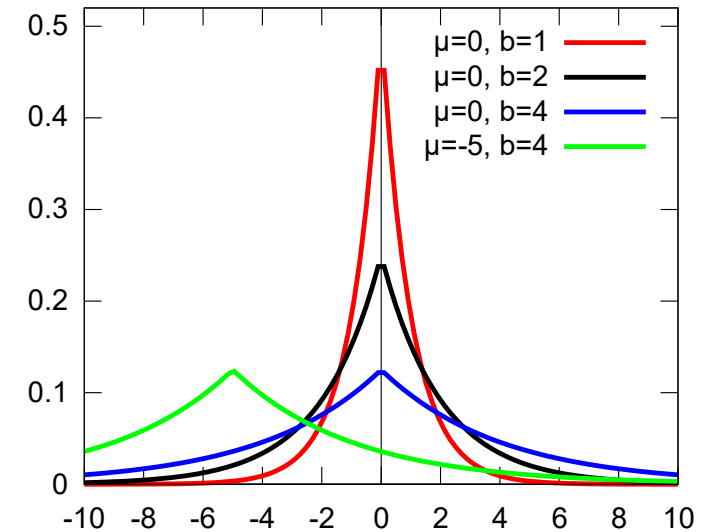
ν : degrees of freedom

Number of data points left after
estimating parameters

LAPLACE DISTRIBUTION

$$f(x \mid \mu, b) = \frac{1}{2b} \exp\left(-\frac{|x - \mu|}{b}\right),$$

- Sharper peak at the center
- Heavier tails
- Signal processing (spiky noise)
- `numpy.random.laplace(mu, b)`



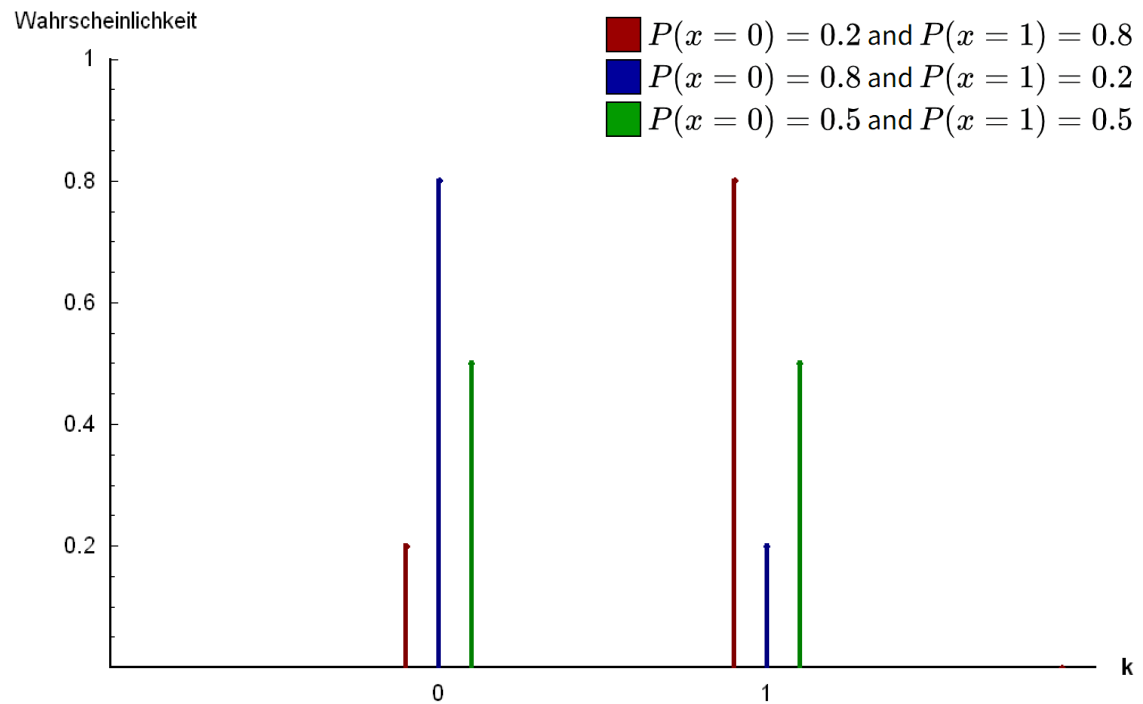
COIN TOSS

- Head=1, Tail=0
- Not all randomness is continuous
- How to measure?

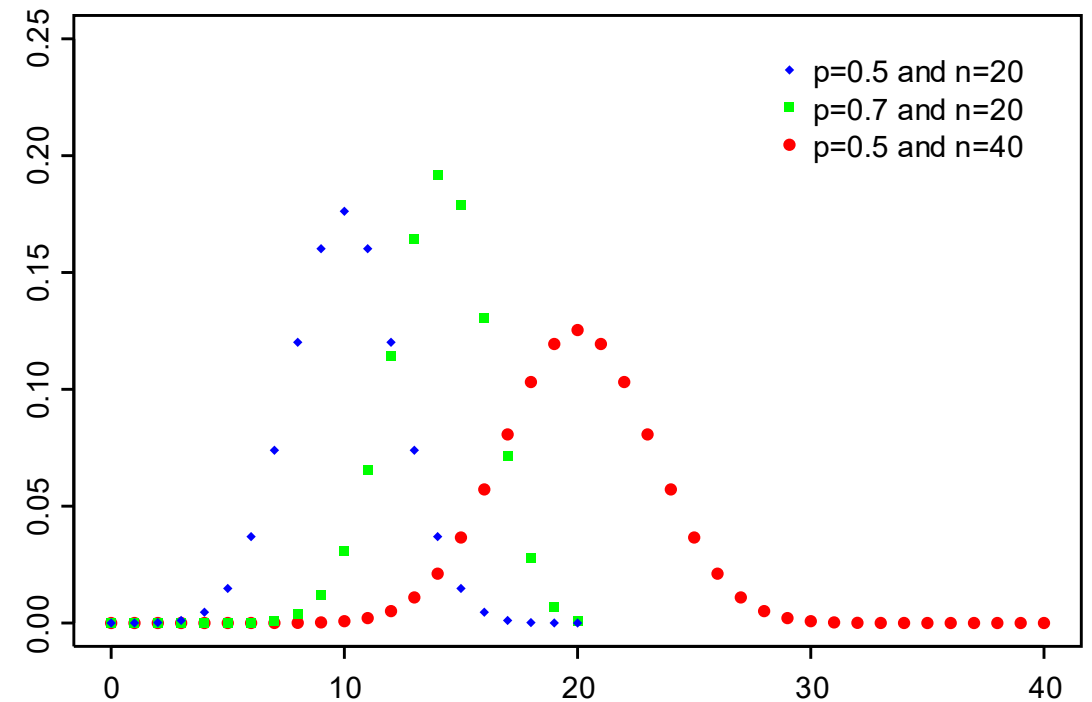


DISCRETE DISTRIBUTIONS

Bernoulli



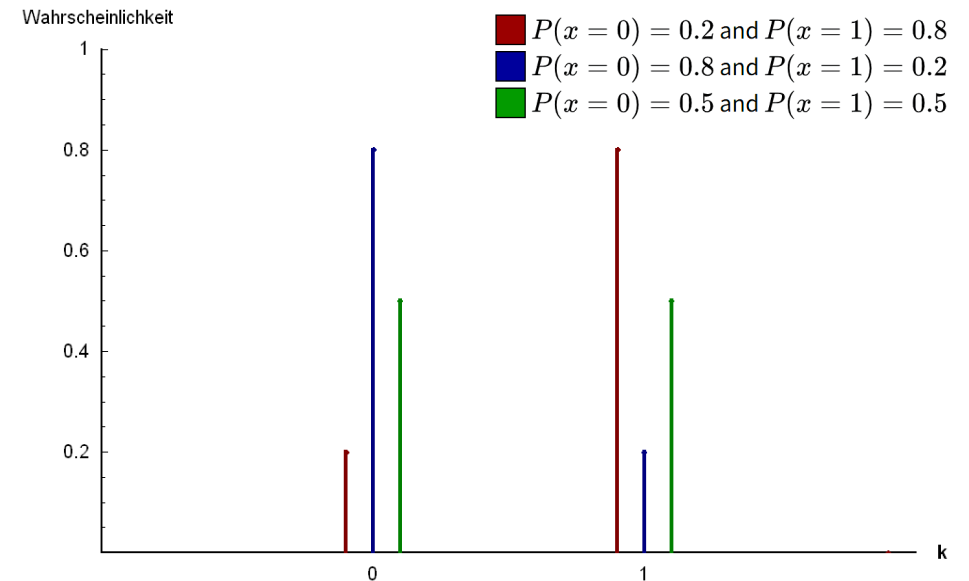
Binomial



BERNOULLI DISTRIBUTION

$$f(k; p) = \begin{cases} p & \text{if } k = 1, \\ q = 1 - p & \text{if } k = 0. \end{cases}$$

- Tossing a coin → heads/tails
- Light bulb test → work/fail
- `numpy.random.binomial(n=1, p)`

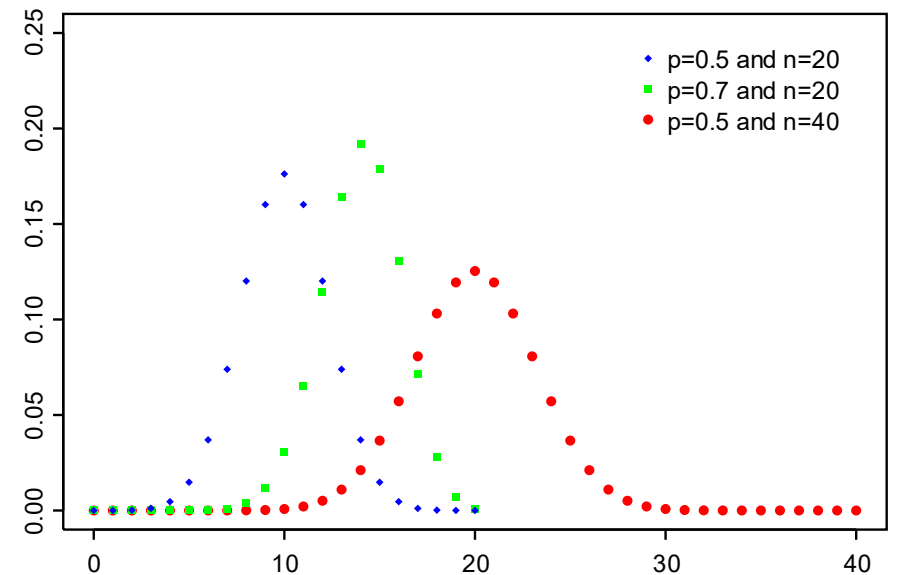


BINOMIAL DISTRIBUTION

$$f(k, n, p) = \Pr(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

- Combination of Bernoulli
- Number of heads in 20 tosses
- `numpy.random.binomial(n, p)`



SO FAR

- Modeling continuous noise — how much
 - Uniform (all values equally likely)
 - Gaussian (bell curve)
 - Student's t (bell curve with heavy tails)
 - Laplace (sharp peak, heavy tails)
- Modeling discrete noise — how many
 - Bernouli (single trial)
 - Binomial (number of successes in n trials)

HYPOTHESIS TESTING



How to verify the significance/goodness of our model?

- Question:
 - Is this coin fair?
- Hypothesis:
 - $H_0: p = 0.5$
 - $H_1: p \neq 0.5$
- Data:
 - Head=1, Tail=0
 - 010111010110010101 (eight 0s, ten 1s)



P-VALUES

- The probability of observing data at least as extreme as what we saw, under the **null hypothesis H_0**
- $p = P(\text{Test statistic} \geq \text{observed value} \mid H_0)$
 - Small $p \rightarrow$ evidence against H_0
 - Large $p \rightarrow$ evidence consistent with H_0
- Decide whether observed results are “too extreme” under H_0

P-VALUES



- $H_0: p = 0.5$
- $X: 010111010110010101$ (eight 0s, ten 1s)
 - $X \sim \text{Binomial}(n=18, p=0.5)$
- $p = P(X \geq 10 \text{ or } X \leq 8 \mid H_0)$
 $= 1 - P(X = 9 \mid H_0)$
 $= 1 - \binom{18}{9} 0.5^{18}$
 $\approx 1 - 0.1854$
 $= 0.8146$



P-VALUES

- Common conventions
 - $p > 0.1$: Data are very consistent with H_0
 - $0.05 < p < 0.1$: Borderline case
 - $0.01 < p < 0.05$: Moderate evidence against H_0
 - $p < 0.01$: Strong evidence against H_0 .
- By convention, people use 0.05 as a threshold
- $p = 0.8146 > 0.05 \rightarrow$ significant

χ^2 TEST

(Chi-Square)



- Whether observed data frequencies match the expected frequencies predicted under the **null hypothesis** H_0
- $\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i}$
 - Observed counts: O_1, O_2, \dots, O_k
 - Expected counts: E_1, E_2, \dots, E_k
 - Small $\chi^2 \rightarrow$ good fit under H_0
 - Large $\chi^2 \rightarrow$ bad fit under H_0
- Degree of freedom: $df = k - 1 - r$
 - Number of classes
 - Number of estimated parameters
e.g. μ, σ

χ^2 TEST



- $H_0: p = 0.5$
- $X: 010111010110010101$ (eight 0s, ten 1s)
 - Observed: $O_1 = 8, O_2 = 10$
 - Expected: $E_1 = 9, E_2 = 9$

$$\begin{aligned}\chi^2 &= \sum_{i=1}^2 \frac{(O_i - E_i)^2}{E_i} \\ &= \frac{(8 - 9)^2}{9} + \frac{(10 - 9)^2}{9} \\ &= \frac{2}{9}\end{aligned}$$

$$\approx 0.2222$$

$$df = 2 - 1 - 0 = 1$$



χ^2 TEST

- Reference values for χ^2 with $df = 1$

Significance level (α)	Critical value (χ^2 cutoff)
0.10	2.71
0.05	3.84
0.01	6.63

- By convention, people use 0.05 as a threshold
- $\chi^2 = 0.2222$ (df=1) < 3.84
- Very significant



χ^2 TEST

Chi Square Table & Chi Square Calculator

	P										
DF	0.995	0.975	0.20	0.10	0.05	0.025	0.02	0.01	0.005	0.002	0.001
1	0.0000393	0.000982	1.642	2.706	3.841	5.024	5.412	6.635	7.879	9.550	10.828
2	0.0100	0.0506	3.219	4.605	5.991	7.378	7.824	9.210	10.597	12.429	13.816
3	0.0717	0.216	4.642	6.251	7.815	9.348	9.837	11.345	12.838	14.796	16.266
4	0.207	0.484	5.989	7.779	9.488	11.143	11.668	13.277	14.860	16.924	18.467
5	0.412	0.831	7.289	9.236	11.070	12.833	13.388	15.086	16.750	18.907	20.515
6	0.676	1.237	8.558	10.645	12.592	14.449	15.033	16.812	18.548	20.791	22.458
7	0.989	1.690	9.803	12.017	14.067	16.013	16.622	18.475	20.278	22.601	24.322
8	1.344	2.180	11.030	13.362	15.507	17.535	18.168	20.090	21.955	24.352	26.124
9	1.735	2.700	12.242	14.684	16.919	19.023	19.679	21.666	23.589	26.056	27.877
10	2.156	3.247	13.442	15.987	18.307	20.483	21.161	23.209	25.188	27.722	29.588

SO FAR

- P-values
 - Are the results extreme under H_0 ?
 - Bigger is better
- χ^2 Test
 - Do observed results match expected ones?
 - Smaller is better

Q&A