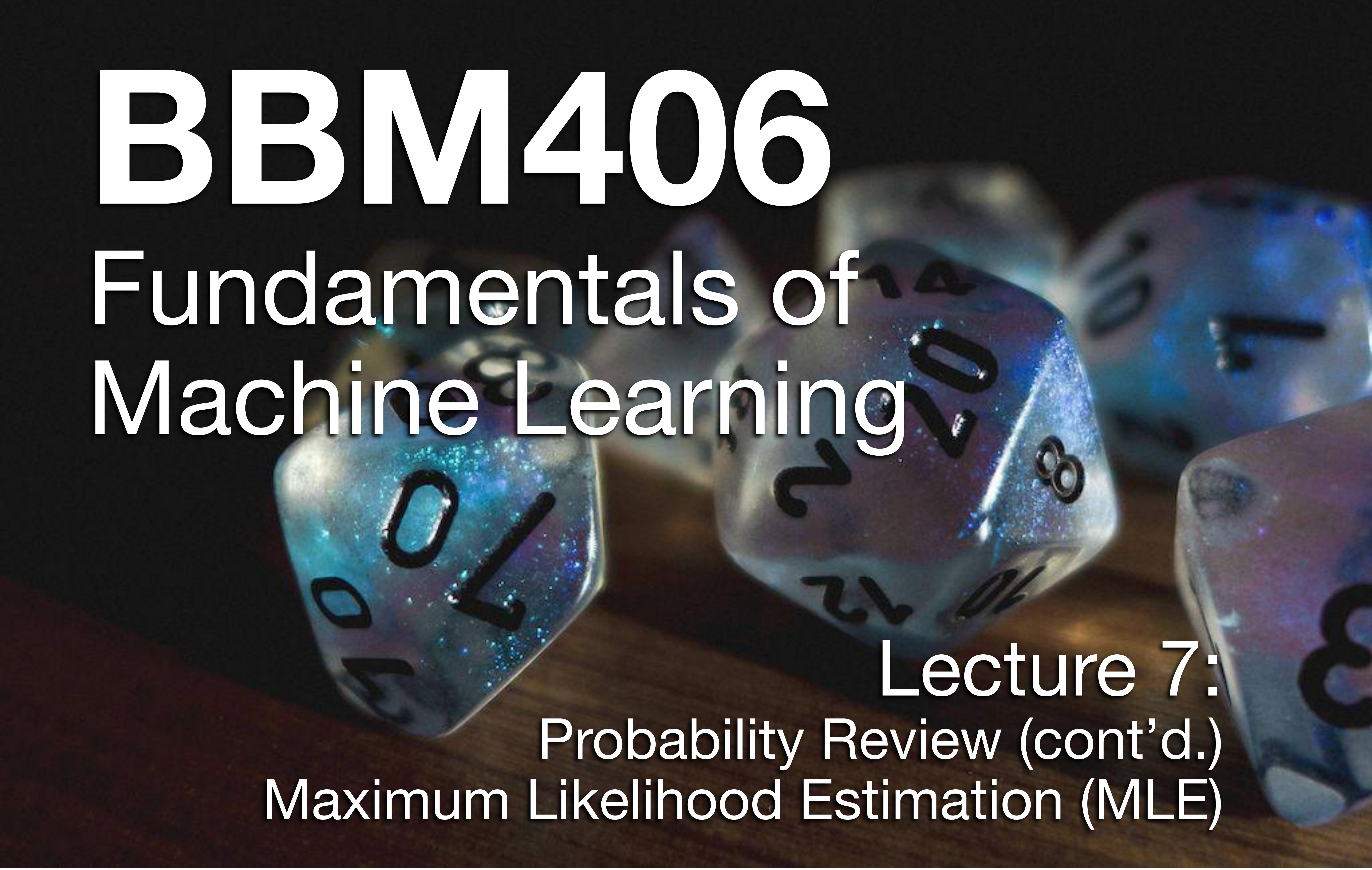
photo: Chessex Borealis™ Aquerple Polyhedral



BBM406

Fundamentals of Machine Learning

Lecture 7:

Probability Review (cont'd.)
Maximum Likelihood Estimation (MLE)

HACETTEPE UNIVERSITY COMPUTER VISION LAB

Aykut Erdem // Hacettepe University // Fall 2019

Administrative

- **Project proposal** due November 15
- A half page description
  - problem to be investigated,
  - why it is interesting,
  - what data you will use,
  - related work.


Deadlines in the syllabus are
closer than they appear

Today

- Probabilities
  - Dependence, Independence, Conditional Independence
- Parameter estimation
  - Maximum Likelihood Estimation (MLE)
  - Maximum a Posteriori (MAP)

Last time... **Sample space**

Def: A **sample space** Ω is the set of all possible outcomes of a (conceptual or physical) random experiment. (Ω can be finite or infinite.)

Examples:

- Ω may be the set of all possible outcomes of a dice roll (1,2,3,4,5,6)

- Pages of a book opened randomly. (1-157)
- Real numbers for temperature, location, time, etc

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Last time… **Events**

We will ask the question:
What is the probability of a particular event?

Def: Event A is a **subset** of the sample space Ω

Examples:
What is the probability of
- the book is open at an odd number
- rolling a dice the number <4
- a random person’s height X : a<X<b

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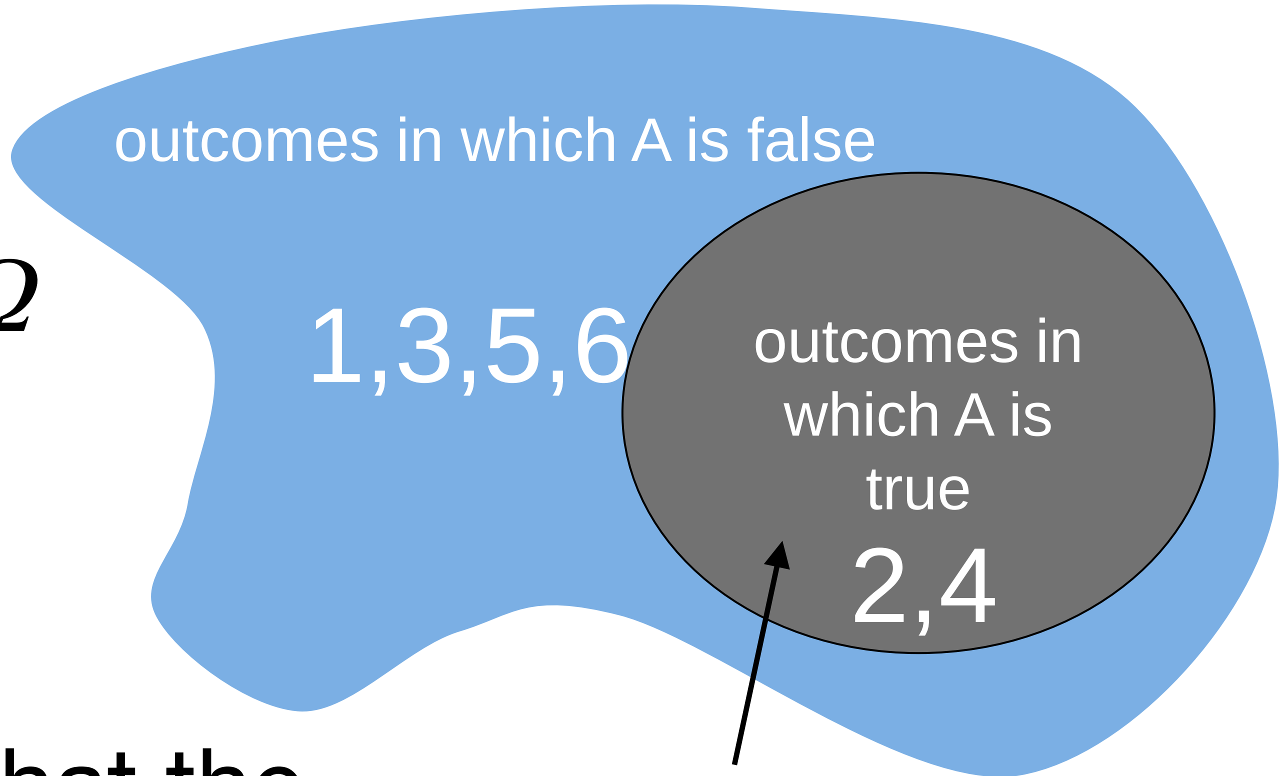
Last time… **Probability**

Def: *Probability P(A), the probability that event (subset) A happens*, is a function that maps the event A onto the interval [0, 1]. *P(A)* is also called the **probability measure** of A.

sample space Ω



P(A) is the volume of the area.

Example:

What is the probability that the number on the dice is 2 or 4?

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Last time... **Kolmogorov Axioms**

(i) Nonnegativity: $P(A) \geq 0$ for each A event.

(ii) $P(\Omega) = 1$.

(iii) σ-additivity: For disjoint sets (events) A_i, we have

$$P(\cup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P(A_i)$$

Consequences:

$P(\emptyset) = 0$.

$P(A \cup B) = P(A) + P(B) - P(A \cap B)$.

$P(A^c) = 1 - P(A)$.

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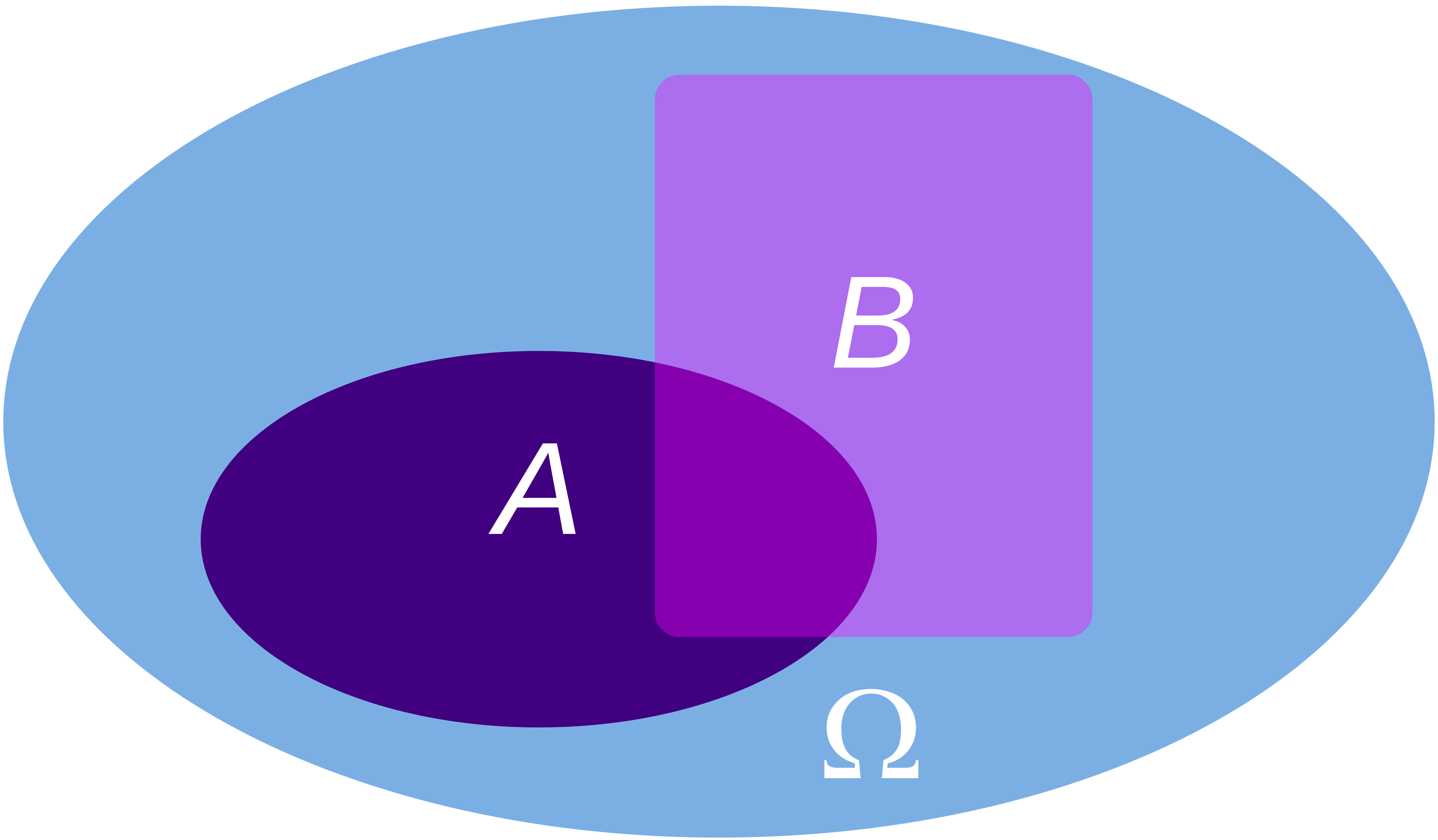
Last time… **Venn Diagram**



$P(A \cup B) = P(A) + P(B) - P(A \cap B)$

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Last time… **Random Variables**

Def: Real valued **random variable** is a function of the outcome of a randomized experiment

$$X : \Omega \to \mathbb{R}$$

$$P(a < X < b) \doteq P(\omega : a < X(\omega) < b)$$
$$P(X = a) \doteq P(\omega : X(\omega) = a)$$

Examples:

- **Discrete random variable examples (Ω is discrete):**
- X(ω) = True if a randomly drawn person (ω) from our class (Ω) is female
- X(ω) = The hometown X(ω) of a randomly drawn person (ω) from our class (Ω)

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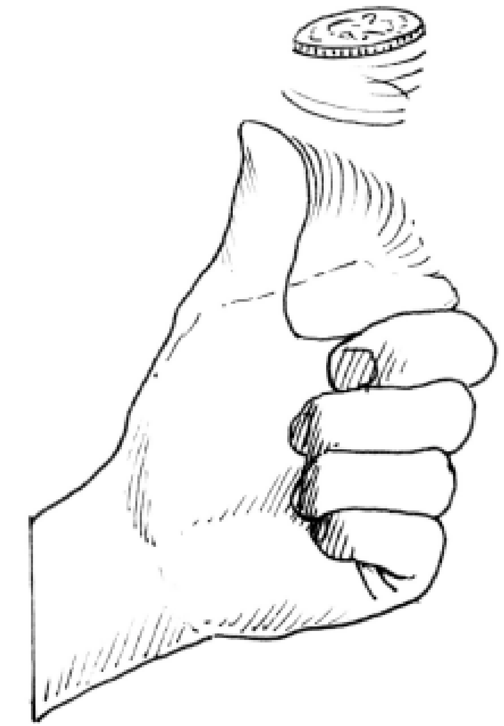
Last time… **Discrete Distributions**

- Bernoulli distribution: Ber(p)

$$\Omega = \{\text{head, tail}\} \;\; X(head) = 1, \; X(tail) = 0.$$



Last time... **Discrete Distributions**

- Bernoulli distribution: Ber(p)

$$\Omega = \{\text{head}, \text{tail}\} \quad X(head) = 1, \; X(tail) = 0.$$

$$P(X = a) = P(\omega : X(\omega) = a) = \begin{cases} p, & \text{for } a = 1 \\ 1 - p, & \text{for } a = 0 \end{cases}$$

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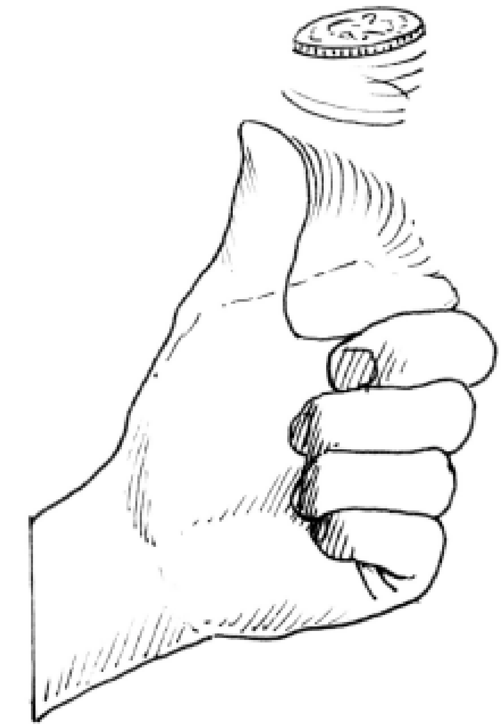

- Binomial distribution: Bin(n,p)

Suppose a coin with head prob. *p* is tossed *n* times. What is the probability of getting *k* heads and *n-k* tails?

$$\Omega = \{ \text{ possible } n \text{ long head/tail series}\}, \; |\Omega| = 2^n$$

$$K(\omega) = \text{number of heads in } \omega = (\omega_1, \ldots, \omega_n) \in \{\text{head}, \text{ tail}\}^n = \Omega$$

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Last time... **Discrete Distributions**

- Bernoulli distribution: Ber(p)

$\Omega = \{\text{head, tail}\}$ $X(head) = 1$, $X(tail) = 0$.

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$$P(K = k) = P(\omega : K(\omega) = k) = \sum_{\omega : K(\omega) = k} p^k (1-p)^{n-k} = \binom{n}{k} p^k (1-p)^{n-k}$$

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Last time... **Conditional Probability**

P(X|Y) = Fraction of worlds in which X event is true given Y event is true.

$$P(X|Y) = \frac{P(X,Y)}{P(Y)}$$

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Last time… **Conditional Probability**

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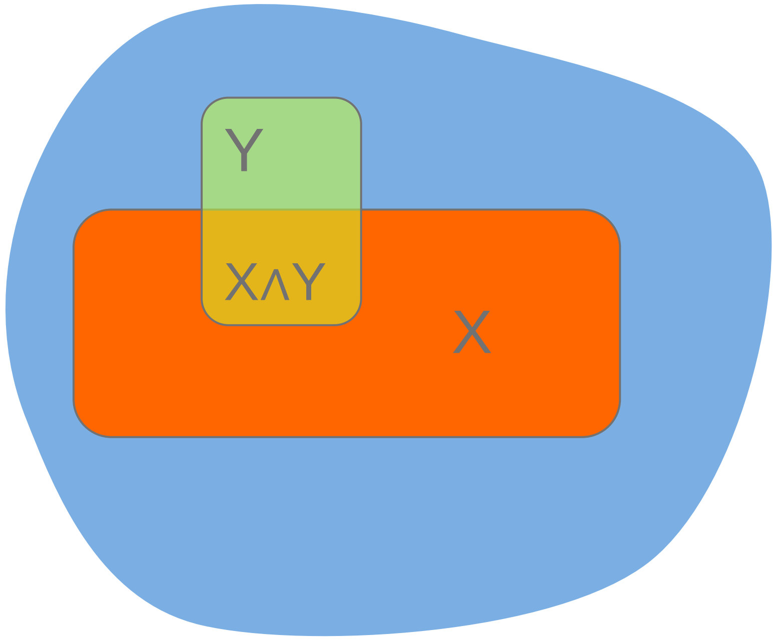
$$P(X|Y) = \frac{P(X,Y)}{P(Y)}$$

$$P(\text{flu}|\text{headache}) = \frac{P(\text{flu, headache})}{P(\text{headache})} = \frac{1/80}{1/80 + 7/80}$$

	Flu	No Flu
Headache	1/80	7/80
No Headache	1/80	71/80



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Independence

Independent random variables:

$$P(X, Y) = P(X)P(Y)$$

$$P(X|Y) = P(X)$$

Y and X don't contain information about each other.
Observing Y doesn't help predicting X.
Observing X doesn't help predicting Y.

Examples:

Independent: Winning on roulette this week and next week.
Dependent: Russian roulette

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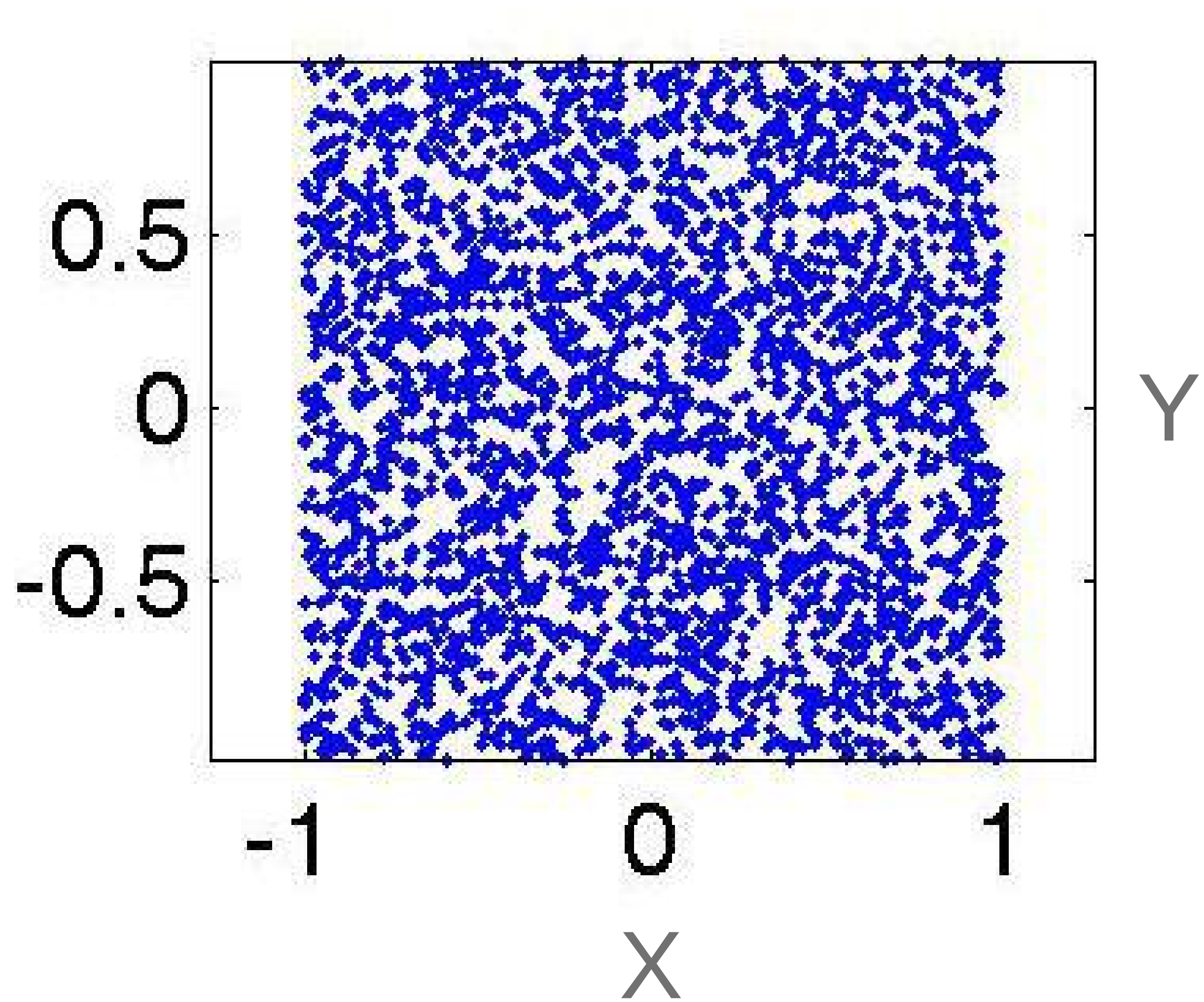
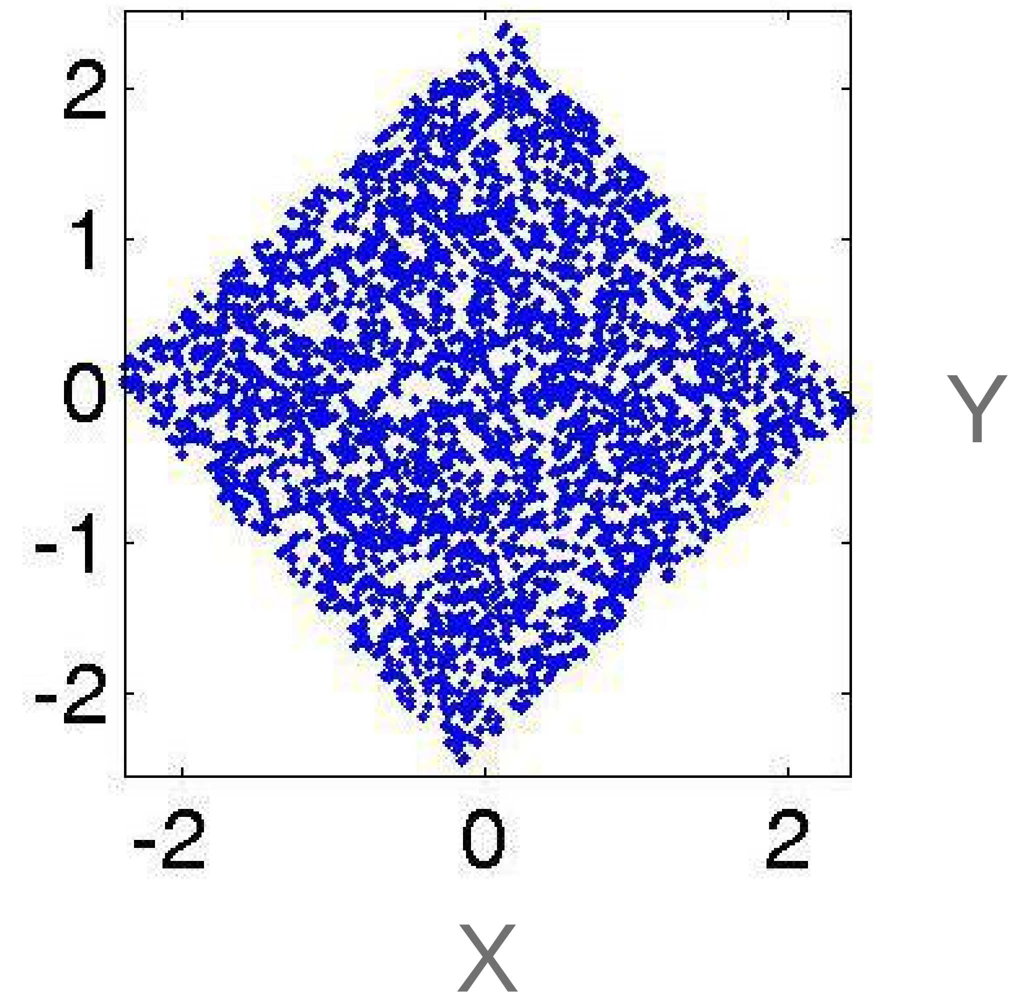
Dependent / Independent



Independent X,Y



Dependent X,Y

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Conditionally Independent

Conditionally independent:

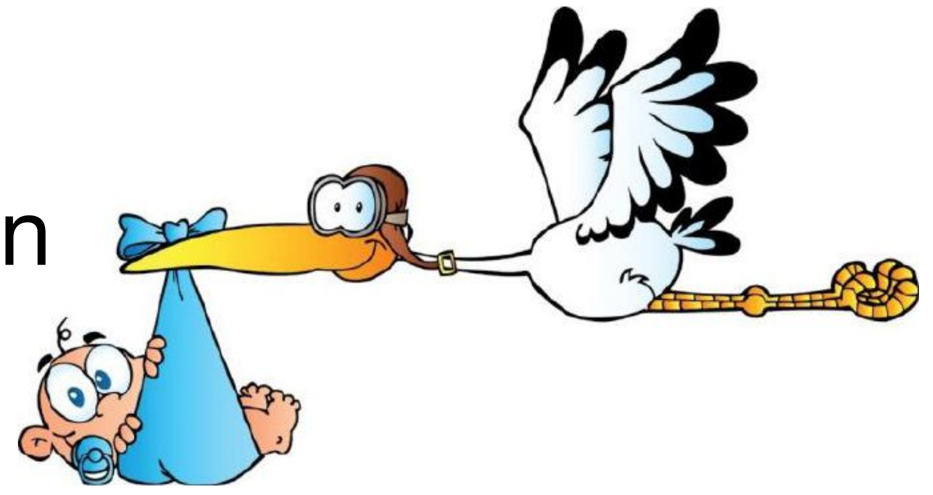
$$P(X,Y|Z) = P(X|Z)P(Y|Z)$$

Knowing Z makes X and Y independent

Examples:

Dependent: shoe size of children and reading skills
Conditionally independent: shoe size of children and reading skills given **age**

Stork deliver babies:
Highly statistically significant correlation exists between stork populations and human birth rates across Europe.



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Conditionally Independent

- **London taxi drivers:** A survey has pointed out a positive and significant correlation between the number of accidents and wearing coats. They concluded that coats could hinder movements of drivers and be the cause of accidents. A new law was prepared to prohibit drivers from wearing coats when driving.

Finally, another study pointed out that people wear coats when it rains…

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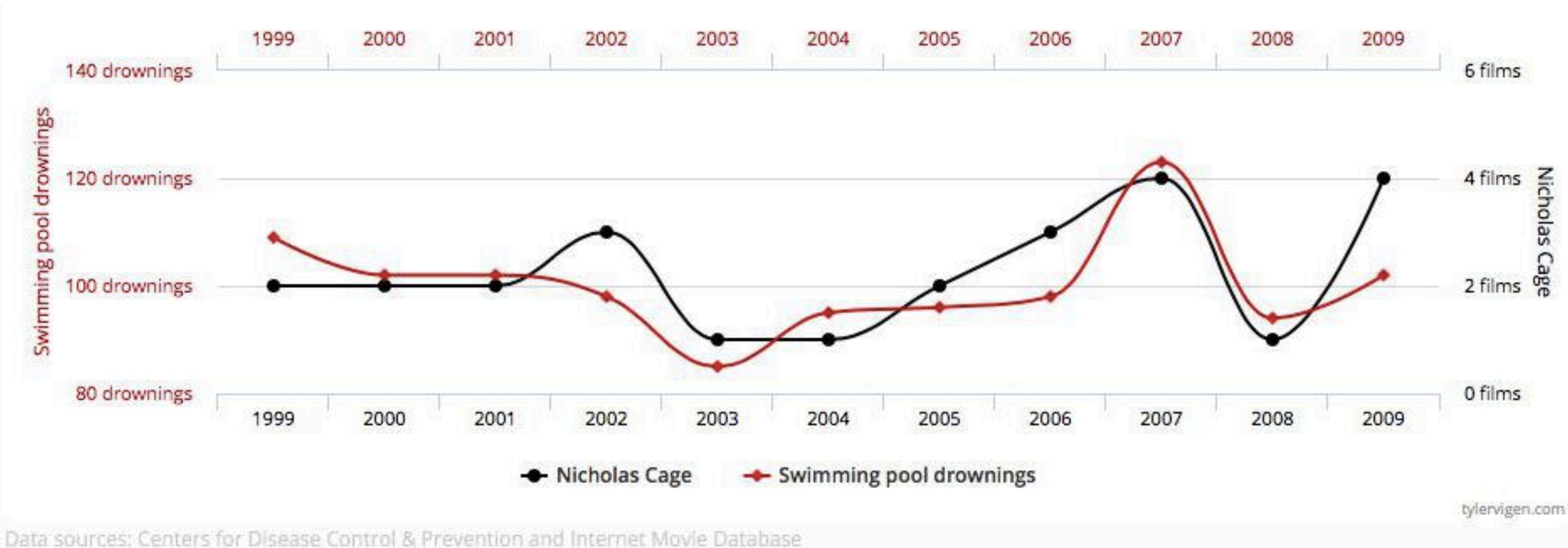
Correlation ≠ Causation

Number people who drowned by falling into a swimming-pool
correlates with
Number of films Nicolas Cage appeared in



Correlation: 0.666004

Conditional Independence

Formally: X is **conditionally independent** of Y given Z

$$P(X,Y|Z) = P(X|Z)P(Y|Z)$$

$$P(\text{Accidents}, \text{Coats} \,|\, \text{Rain}) = P(\text{Accidents} \,|\, \text{Rain}) P(\text{Coats} \,|\, \text{Rain})$$

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Equivalent to:

$$(\forall x, y, z)P(X = x|Y = y, Z = z) = P(X = x|Z = z)$$

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Equivalent to:

$$(\forall x, y, z)P(X = x|Y = y, Z = z) = P(X = x|Z = z)$$

$$P(Thunder|Rain, Lightning) = P(Thunder|Lightning)$$

Note: does NOT mean Thunder is independent of Rain
But given Lightning knowing Rain doesn't give more info about Thunder

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Parameter estimation: MLE, MAP

Estimating Probabilities

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Flipping a Coin

I have a coin, if I flip it, what's the probability that it will fall with the head up?

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Let us flip it a few times to estimate the probability:

The estimated probability is: **3/5** "Frequency of heads"

Flipping a Coin

The estimated probability is: **3/5** "Frequency of heads"

Questions:

(1) Why frequency of heads???

(2) How good is this estimation???

(3) Why is this a machine learning problem???

We are going to answer these questions

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Question (1)

Why frequency of heads???

- Frequency of heads is exactly the
  maximum likelihood estimator for this problem

- MLE has nice properties
  (interpretation, statistical guarantees, simple)

Maximum Likelihood Estimation

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MLE for Bernoulli distribution

Data, *D* =

$$D = \{X_i\}_{i=1}^n, \;\; X_i \in \{\mathrm{H}, \mathrm{T}\}$$

P(Heads) = θ*, P(Tails) = 1-*θ

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Flips are **i.i.d.**:

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Flips are **i.i.d.**:

- **Independent** events
  - **Identically distributed** according to Bernoulli distribution

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MLE: Choose θ that maximizes the probability of observed data

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Maximum Likelihood Estimation

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$$\widehat{\theta}_{MLE} = \arg\max_{\theta} P(D|\theta)$$

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$$= \arg\max_{\theta} \prod_{i=1}^{n} P(X_i|\theta)$$

independent draws

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$$\widehat{\theta}_{MLE} = \arg\max_{\theta} P(D|\theta)$$

$$= \arg\max_{\theta} \prod_{i=1}^{n} P(X_i|\theta)$$

independent draws

$$= \arg\max_{\theta} \prod_{i:X_i=H} \theta \prod_{i:X_i=T} (1-\theta)$$

identically distributed

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independent draws

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identically distributed

$$= \arg\max_{\theta} \theta^{\alpha_H} (1-\theta)^{\alpha_T}$$

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Maximum Likelihood Estimation

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independent draws

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identically distributed

$$= \arg\max_{\theta} \underbrace{\theta^{\alpha_H}(1-\theta)^{\alpha_T}}_{J(\theta)}$$

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Maximum Likelihood Estimation

MLE: Choose θ that maximizes the probability of observed data

$$\widehat{\theta}_{MLE} = \arg\max_{\theta} P(D|\theta)$$

$$= \arg\max_{\theta} \underbrace{\theta^{\alpha_H}(1-\theta)^{\alpha_T}}_{J(\theta)}$$

$$\frac{\partial J(\theta)}{\partial \theta} = \alpha_H \theta^{\alpha_H - 1}(1-\theta)^{\alpha_T} - \alpha_T \theta^{\alpha_H}(1-\theta)^{\alpha_T - 1}\Big|_{\theta=\hat{\theta}_{\mathrm{MLE}}} = 0$$

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Maximum Likelihood Estimation

MLE: Choose θ that maximizes the probability of observed data

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$$\alpha_H(1-\theta) - \alpha_T\theta \,\Big|_{\theta=\widehat{\theta}_{MLE}} = 0$$

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Question (2)

- How good is this MLE estimation???

$$\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$$

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How many flips do I need?

I flipped the coins 5 times: 3 heads, 2 tails

$$\widehat{\theta}_{MLE} = \frac{3}{5}$$

What if I flipped 30 heads and 20 tails?

$$\widehat{\theta}_{MLE} = \frac{30}{50}$$

- **Which estimator should we trust more?**
- **The more the merrier???**

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Let θ* be the true parameter.

For $n = \alpha_H + \alpha_T$, and $\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$

For any ε>0:

Hoeffding's inequality:

$$P(|\ \widehat{\theta} - \theta^*\ | \geq \epsilon) \ \leq \ 2e^{-2n\epsilon^2}$$

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Probably Approximate Correct (PAC) Learning

I want to know the coin parameter θ, within ε = 0.1 error with probability at least 1-δ = 0.95.

How many flips do I need?

$$P(|\,\hat{\theta} - \theta^*\,| \geq \epsilon) \;\; \leq \;\; 2e^{-2n\epsilon^2}$$

Sample complexity:

$$n \geq \frac{\ln(2/\delta)}{2\epsilon^2}$$

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Question (3)

Why is this a machine learning problem???

- improve their performance (accuracy of the predicted prob.)
- at some task (predicting the probability of heads)
- with experience (the more coins we flip the better we are)

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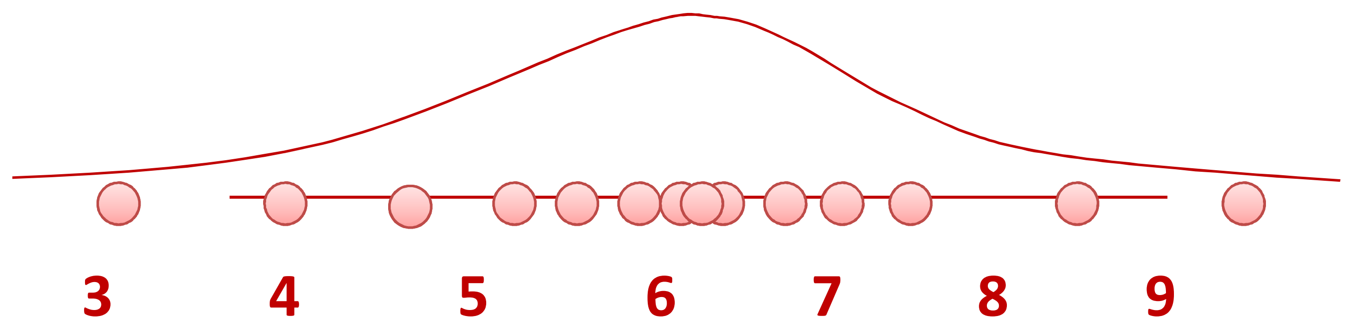
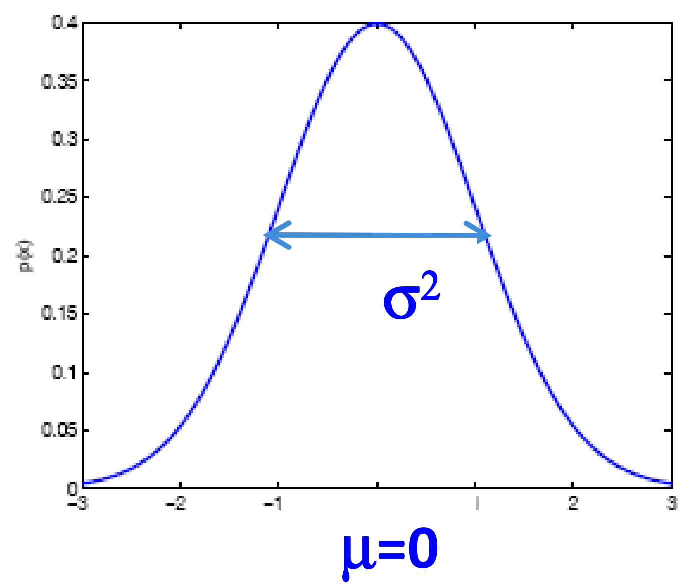
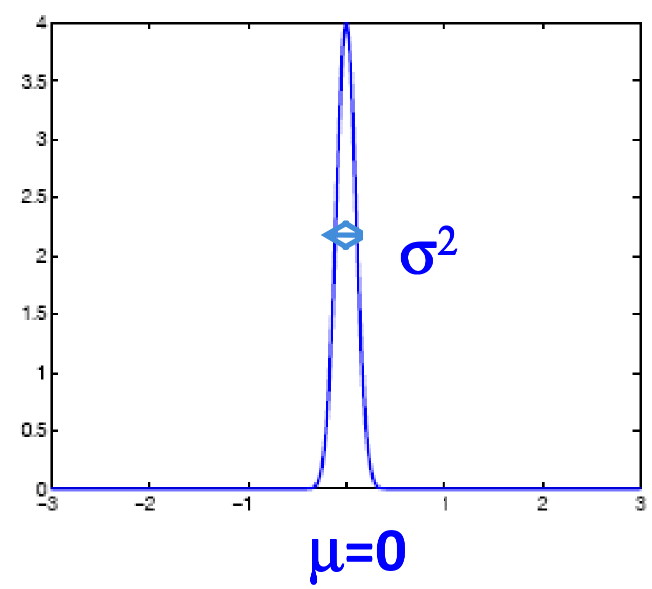
What about continuous features?



Let us try Gaussians...

$$p(x \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) = \mathcal{N}_x(\mu, \sigma)$$





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MLE for Gaussian mean and variance

Choose $\theta = (\mu, \sigma^2)$ that maximizes the probability of observed data

$$\widehat{\theta}_{MLE} = \arg\max_{\theta} \; P(D \mid \theta)$$

$$= \arg\max_{\theta} \prod_{i=1}^{n} P(X_i | \theta)$$

Independent draws

$$= \arg\max_{\theta} \prod_{i=1}^{n} \frac{1}{2\sigma^2} e^{-(X_i-\mu)^2/2\sigma^2}$$

Identically distributed

$$= \arg \max_{\theta=(\mu,\sigma^2)} \underbrace{\frac{1}{2\sigma^2} e^{-\sum_{i=1}^{n}(X_i-\mu)^2/2\sigma^2}}_{J(\theta)}$$

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MLE for Gaussian mean and variance

$$\widehat{\mu}_{MLE} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\widehat{\sigma}^2_{MLE} = \frac{1}{n}\sum_{i=1}^{n} (x_i - \widehat{\mu})^2$$

Note: MLE for the variance of a Gaussian is **biased**

[Expected result of estimation is not the true parameter!]

Unbiased variance estimator: $\widehat{\sigma}^2_{unbiased} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \widehat{\mu})^2$

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Next Class:

MAP estimation
Naïve Bayes Classifier