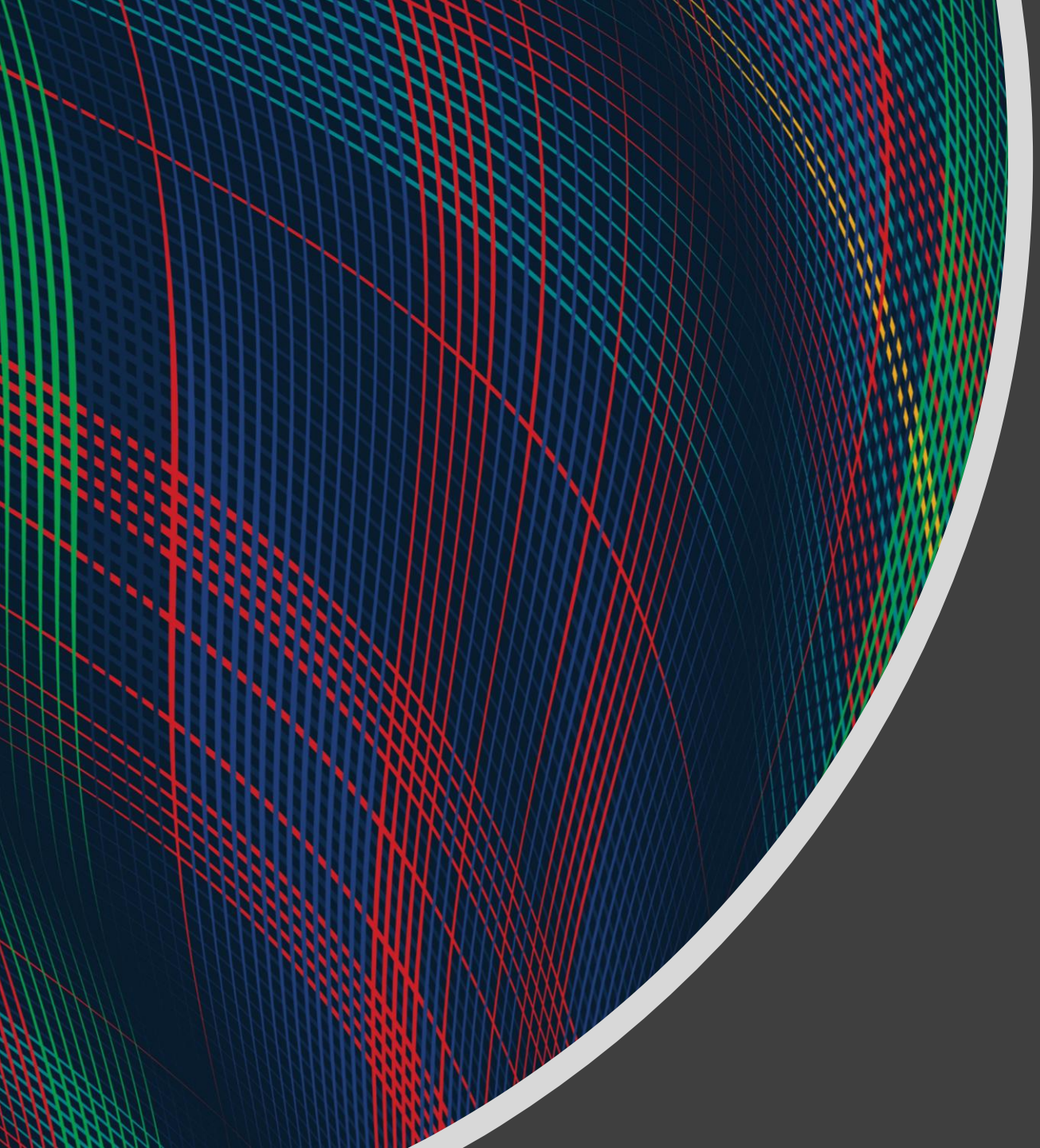


10-315 Introduction to ML

MLE and Probabilistic Formulation of Machine Learning

Instructor: Pat Virtue

Logistics

Exam

- Wed in class, see Piazza for details

Coming this week

- Probability Primer
- MAP Pre-reading
- Mini project info

Today

- Wrap-up regularization (for now)
- MLE
  - Maximum likelihood estimation
  - Probabilistic formulation of linear and logistic regression

Poll 1

Course feedback link on Piazza

Are you finished with the course feedback form?

A. Yes
B. No
C. Still working on it

Exercises

Calculate the probability of these event sequences happening

1. Coin
   a) Fair:
      {H, H, T, H}
   b) Biased, $\phi = 3/4$ heads
      {H, H, T, H}

2. 4-sided die with sides: A, B, C, D
   a) Fair:
      {A, B, D, D, A}
   b) Weighted, $[\phi_A, \phi_B, \phi_C, \phi_D] = [1/10,\ 2/10,\ 3/10,\ 4/10]$
      {A, B, D, D, A}

Exercises

Calculate the probability of these event sequences happening

1. Coin
   a) Fair:
      {H, H, T, H}

      $\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{16}$

   b) Biased, $\phi = 3/4$ heads
      {H, H, T, H}

      $\phi \cdot \phi \cdot (1-\phi) \cdot \phi = \frac{3}{4} \cdot \frac{3}{4} \cdot \frac{1}{4} \cdot \frac{3}{4} = \frac{27}{256}$

2. 4-sided die with sides: A, B, C, D
   a) Fair:
      {A, B, D, D, A}

      $\frac{1}{6} \cdot \frac{1}{6} \cdot \frac{1}{6} \cdot \frac{1}{6} \cdot \frac{1}{6}$

   b) Weighted, $[\phi_A, \phi_B, \phi_C, \phi_D] = [1/10,\ 2/10,\ 3/10,\ 4/10]$
      {A, B, D, D, A}

      $\phi_A \cdot \phi_B \cdot \phi_D \cdot \phi_D \cdot \phi_A = \frac{1}{10} \cdot \frac{2}{10} \cdot \frac{4}{10} \cdot \frac{4}{10} \cdot \frac{1}{10}$

Poll 2

Implement a function in Python for the pdf of a Gaussian distribution.

Python numpy or math packages are fine, no scipy, etc.

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

```
def gaussian(x, mu, sigmaSq):
```

What is `gaussian(3.3, 2.2, 1.1)`?

Poll 3

0.0000023
→ 0.0000401

Assume that exam scores are drawn independently from the same Gaussian (Normal) distribution.

Given three exam scores {75, 80, 90}, which pair of parameters is a better fit (a higher likelihood)?

A) Mean 80, standard deviation 3 ← $p(75|80,3)\,p(80|80,3)\,p(90|80,3)$

B) Mean 85, standard deviation 7 $p(75|85,7)\;\;p(80|85,7)\,p(90|85,7)$

C) I don't know

Use a calculator/computer.

Gaussian PDF: $p(y \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$

Poll 4

Trick coin: comes up heads only 1/3 of the time

1 flip: H probability: $\frac{1}{3}$

2 flips: H,H probability: $\frac{1}{3} \cdot \frac{1}{3}$

3 flips: H,H,T probability: $\frac{1}{3} \cdot \frac{1}{3} \cdot \left(1 - \frac{1}{3}\right)$

But what property allows us to just multiply these? indepe.

Poll 5

$\mathcal{D} = \{y^{(1)}, y^{(2)}, y^{(3)}\}$

$Y \sim Bern(\phi)$

Which of these is the correct labeling of these properties?

$$p(\mathcal{D} \mid \theta) = p(Y_1 = y^{(1)}, Y_2 = y^{(2)}, Y_3 = y^{(3)} \mid \phi_1, \phi_2, \phi_3)$$

ident. distr.

$$= p(Y_1 = y^{(1)}, Y_2 = y^{(2)}, Y_3 = y^{(3)} \mid \phi)$$

product rule

$$= p(Y_1 \mid \phi)\, p(Y_2 \mid Y_1, \phi)\, p(Y_3 \mid Y_1, Y_2, \phi)$$

indep.

$$= p(Y = y^{(1)} \mid \phi)\, p(Y = y^{(2)} \mid \phi)\, p(Y = y^{(3)} \mid \phi)$$

$$= \prod_{i=1}^{N} p(Y = y^{(i)} \mid \phi)$$

Likelihood

Pre-reading

Likelihood

Likelihood: The probability (or density) of random variable Y taking on value y given the distribution parameters, $\boldsymbol{\theta}$.

Likelihood

Likelihood: The probability (or density) of random variable Y taking on value y given the distribution parameters, $\boldsymbol{\theta}$.

Grades

$\mathcal{D} = \{y^{(1)} \quad y^{(2)} \quad y^{(3)}\}$

$= \{80 \quad 70 \quad 85\}$

$p(\mathcal{D} \mid \mu \; \sigma^2)$

Gaussian PDF: $p(y \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$

Likelihood

$\phi = \frac{1}{3}$

Trick coin: comes up heads only 1/3 of the time

1 flip: H probability: $\frac{1}{3}$

2 flips: H,H probability: $\frac{1}{3} \cdot \frac{1}{3}$

3 flips: H,H,T probability: $\frac{1}{3} \cdot \frac{1}{3} \cdot \left(1 - \frac{1}{3}\right)$

But why can we just multiply these?

Likelihood and i.i.d

Likelihood: The probability (or density) of random variable Y taking on value y given the distribution parameters, $\boldsymbol{\theta}$.

i.i.d.: Independent and identically distributed

$$p(D \mid \theta)$$

$$p(Y_1 = y^{(1)}, Y_2 = y^{(2)}, Y_3 = y^{(3)} \mid \phi_1, \phi_2, \phi_3)$$

indeNT

$$p(Y = y^{(1)}, Y = y^{(2)}, Y = y^{(3)} \mid \phi)$$

indep.

$$p(Y = y^{(1)} \mid \phi)\, p(Y = y^{(2)} \mid \phi)\, p(Y = y^{(3)} \mid \phi)$$

$$\prod_{i=1}^{N} p(Y = y^{(i)} \mid \phi)$$

Bernoulli Likelihood

Bernoulli distribution:

$$Y \sim Bern(\phi) \qquad p(y \mid \phi) = \begin{cases} \phi, & y = 1 \\ 1 - \phi, & y = 0 \end{cases}$$

What is the likelihood for three i.i.d. samples, given parameter ϕ:

$$\mathcal{D} = \{y^{(1)} = 1, y^{(2)} = 1, y^{(3)} = 0\}$$

$$\prod_{i=1}^{N} p(Y = y^{(i)} \mid \phi)$$

$$= \phi \cdot \phi \cdot (1 - \phi)$$

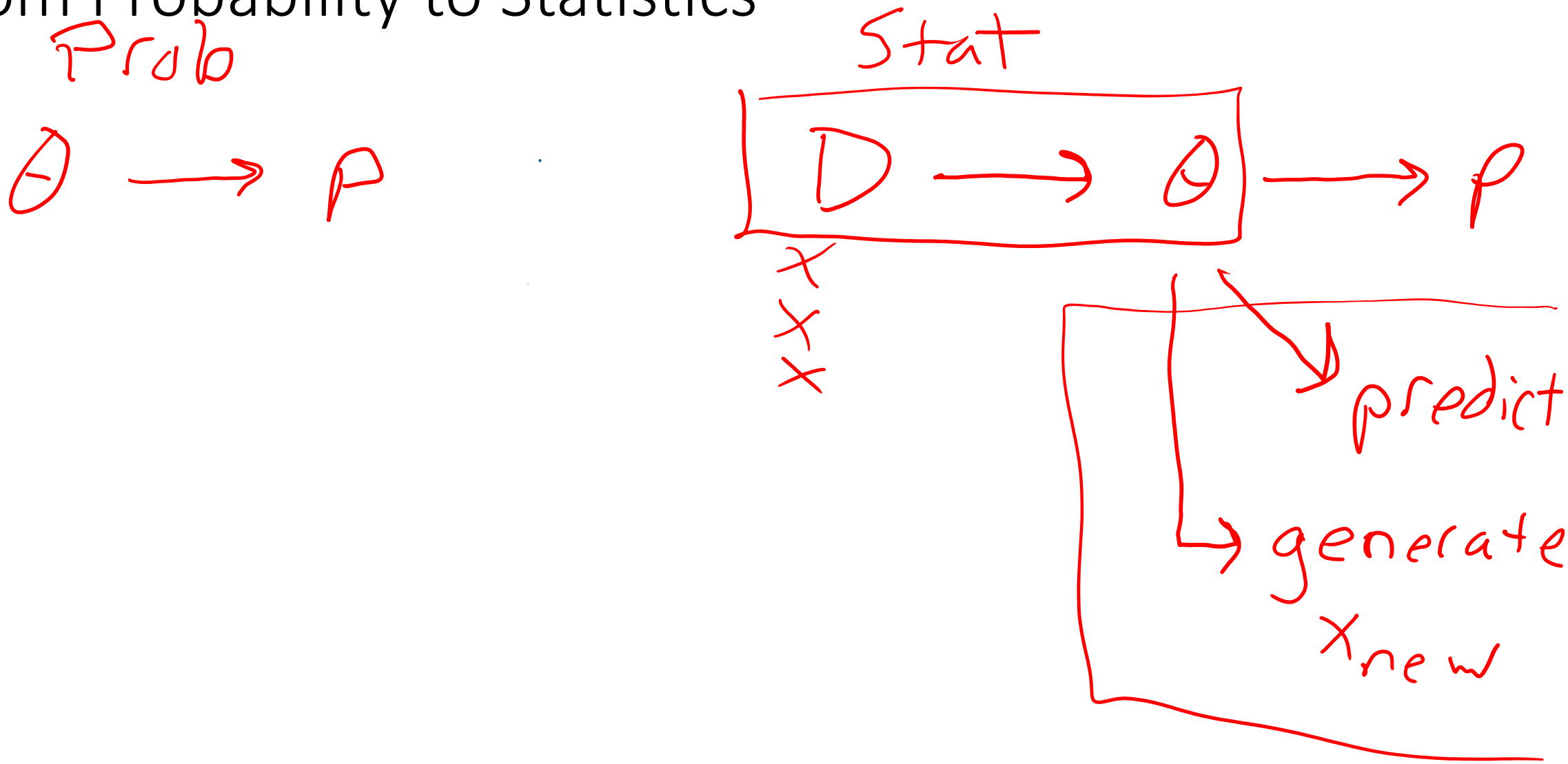
$$\mathbb{1}(y^{(i)} = 1) \qquad \mathbb{1}(y^{(i)} = 0)$$

$$\phi^1(1-\phi)^0 \cdot \phi^1(1-\phi)^0 \; \phi^0(1-\phi)^1$$

MLE

Maximum likelihood estimation

From Probability to Statistics



Estimating Parameters with Likelihood

We model the outcome of a single mysterious weighted-coin flip as a Bernoulli random variable:

$$Y \sim Bern(\phi)$$

$$p(y \mid \phi) = \begin{cases} \phi, & y = 1 \ (heads) \\ 1 - \phi, & y = 0 \ (tails) \end{cases}$$

Given the ordered sequence of coin flip outcomes:

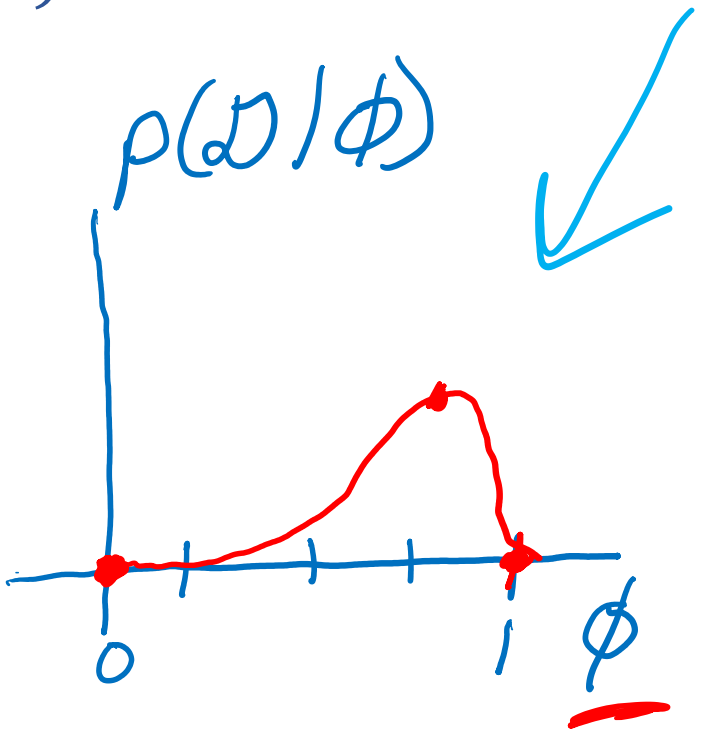
$$[1, 0, 1, 1]$$

What is the estimate of parameter $\hat{\phi}$?

$$p(D \mid \phi) = \phi \cdot \phi \cdot (1 - \phi) \cdot \phi$$

$$= \phi^3 (1 - \phi)^1$$

3/4



https://www.desmos.com/calculator/kr7m2m6cf7

Likelihood and Maximum Likelihood Estimation

Likelihood: The probability (or density) of random variable Y taking on value y given the distribution parameters, $\boldsymbol{\theta}$.

$$p(D|\theta) = \prod_{i=1}^{N} p(x^{(i)}|\theta)$$

Likelihood function: The value of likelihood as we change theta

(same as likelihood, but conceptually we are considering many different values of the parameters)

$$\mathcal{L}(\theta; D) = p(D|\theta)$$

Maximum Likelihood Estimation (MLE): Find the parameter value that maximizes the likelihood.

$$\hat{\theta}_{MLE} = \arg\max_{\theta} \mathcal{L}(\theta)$$

MLE as Data Increases

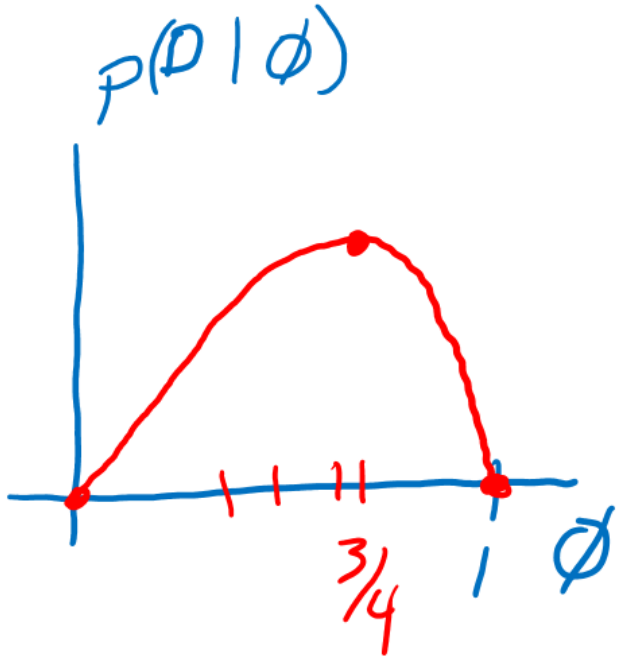
Given the ordered sequence of coin flip outcomes:

$$[1, 0, 1, 1]$$

$$\mathrm{p}(\mathcal{D} \mid \phi) = \prod_{i}^{N} p\left(y^{(i)} \mid \phi\right) = \phi^{N_{y=1}}(1-\phi)^{N_{y=0}}$$

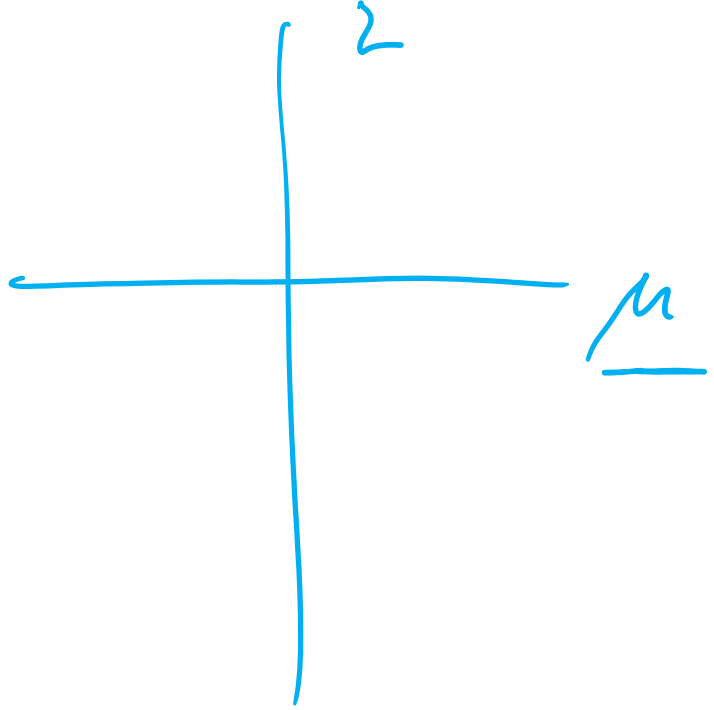
What happens as we flip more coins?

better MLE with more data



https://www.desmos.com/calculator/kr7m2m6cf7

MLE for Gaussian



Gaussian distribution:

$$Y \sim \mathcal{N}(\mu, \sigma^2)$$

$$p(y \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

$$\mathcal{D} = \{y^{(1)} = 65, y^{(2)} = 95, y^{(3)} = 85\}$$

Formulate the likelihood for three i.i.d. samples, given parameters μ, σ^2?

$$L(\mu, \sigma^2) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y^{(i)}-\mu)^2}{2\sigma^2}}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(65-\mu)^2/2\sigma^2} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(95-\mu)^2/2\sigma^2} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(85-\mu)/2\sigma^2}$$

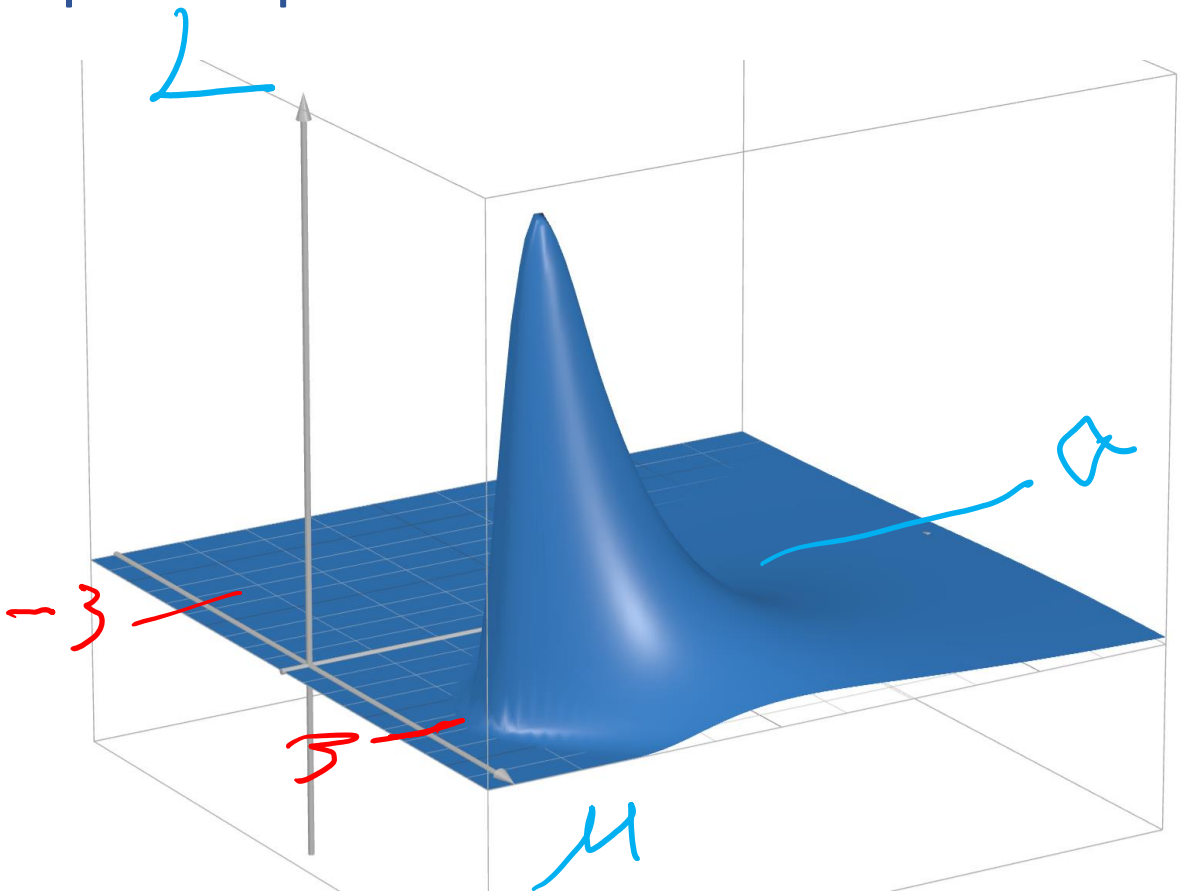
$$\hat{\theta}_{MLE} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i}^{N} p(y^{(i)} \mid \boldsymbol{\theta})$$

MLE for Gaussian

Assume that exam scores are drawn independently from the same Gaussian (Normal) distribution.

Given three exam scores 2, 3, 4, which pair of parameters is the best fit (the highest likelihood)?

$$p(\mathcal{D}|\mu,\sigma^2) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y^{(i)}-\mu)^2}{2\sigma^2}}$$



https://www.desmos.com/3d/988327bd26

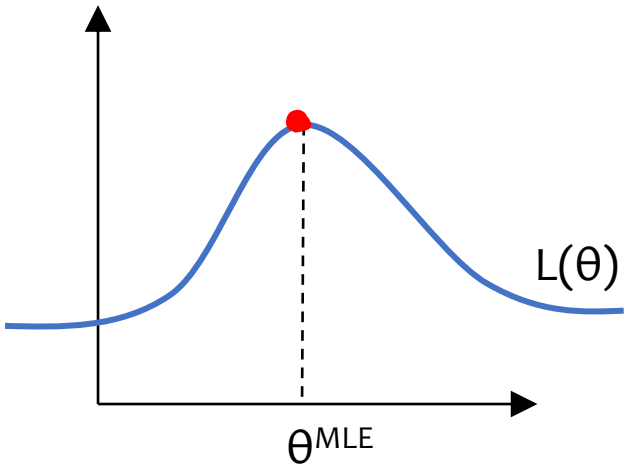
MLE

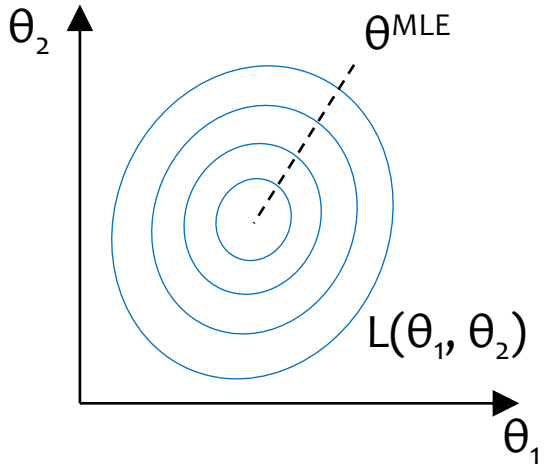
Suppose we have data $\mathcal{D} = \{x^{(i)}\}_{i=1}^{N}$

Principle of Maximum Likelihood Estimation:
Choose the parameters that maximize the likelihood of the data.

$$\boldsymbol{\theta}^{\text{MLE}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i=1}^{N} p(\mathbf{x}^{(i)}|\boldsymbol{\theta})$$

Maximum Likelihood Estimate (MLE)





Slide credit: CMU MLD Matt Gormley

Likelihood and Log Likelihood

$\log mn = \log m + \log n$

Likelihood: The probability (or density) of random variable Y taking on value y given the distribution parameters, θ.

$$\mathrm{p}(\mathcal{D} \mid \theta) = \prod_{i=1}^{N} p\left(y^{(i)} \mid \theta\right)$$

Likelihood function: The value of likelihood as we change theta

(same as likelihood, but conceptually we are considering many different values of the parameters)

$$\mathcal{L}(\theta; \mathcal{D}) = \prod p(y^{(i)} \mid \theta)$$

$$\ell(\theta; \mathcal{D}) = \log \mathcal{L}(\theta; \mathcal{D}) = \sum_{i=1}^{N} \log p(y^{(i)} \mid \theta)$$

MLE Objective

Updating our objective: Minimize neg. log likelihood

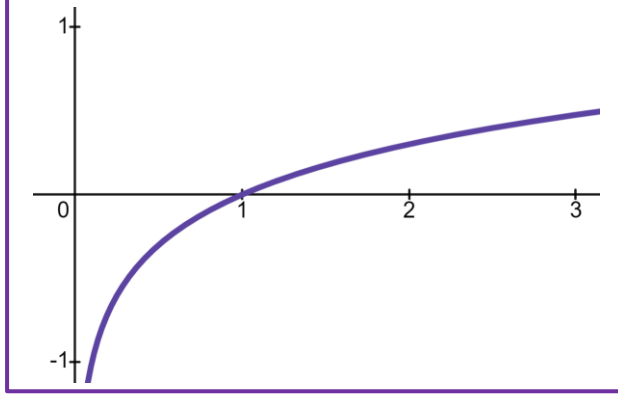
$$\hat{\theta}_{MLE} = \underset{\theta}{\text{argmax}} \prod_{i=1}^{N} p\left(y^{(i)} \mid \theta\right)$$

$$= \underset{\theta}{\text{argmax}} \sum_{i=1}^{N} \log p\left(y^{(i)} \mid \theta\right)$$

$$= \underset{\theta}{\text{argmin}} -\sum_{i=1}^{N} \log p\left(y^{(i)} \mid \theta\right)$$

Minimize $J(\theta) = -\log \mathcal{L}(\theta; \mathcal{D}) = -\sum_{i=1}^{N} \log p\left(y^{(i)} \mid \theta\right)$

Log is monotonic:
If $a < b$
then $\log a < \log b$



Benefits of log

- Easier math
  - $\prod \rightarrow \sum$
  - $e^z \rightarrow z$
  - calculus
- Numerical stability

MLE for Gaussian

$p(75 \mid 80, 3)\ p(80 \mid 80, 3)\ p(90 \mid 80, 3)$

$0.033 \times 0.133 \times 0.0005 = 0.0000023$

$\log \rightarrow -3.4 - 2.0 - 7.6 = -13.0$

Gaussian distribution:

$$Y \sim \mathcal{N}(\mu, \sigma^2)$$

$$p(y \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

What is the log likelihood for three i.i.d. samples, given parameters μ, σ^2?

$$\mathcal{D} = \{y^{(1)} = 75, y^{(2)} = 80, y^{(3)} = 90\}$$

$$L(\mu, \sigma^2) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y^{(i)}-\mu)^2}{2\sigma^2}}$$

$$\ell(\mu, \sigma^2) = \sum_{i=1}^{N} -\log\sqrt{2\pi\sigma^2} - \frac{(y^{(i)} - \mu)^2}{2\sigma^2}$$

$$\hat{\theta}_{MLE} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i}^{N} p(y^{(i)} \mid \boldsymbol{\theta})$$

$$\hat{\theta}_{MLE} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \sum_{i}^{N} \log p(y^{(i)} \mid \boldsymbol{\theta})$$

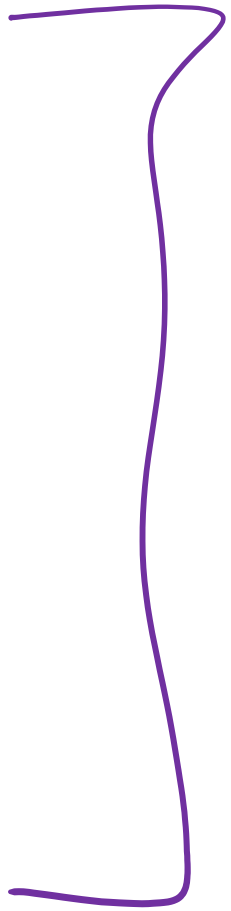
Recipe for Estimation

MLE

1. Formulate the likelihood, $p(\mathcal{D} \mid \theta)$
2. Set objective $J(\theta)$ equal to negative log of likelihood

   $$\mathrm{J}(\theta) = -\log p(\mathcal{D} \mid \theta)$$

3. Compute derivative of objective, $\partial J / \partial \theta$
4. Find $\hat{\theta}$, either
   a. Set derivate equal to zero and solve for θ
   b. Use (stochastic) gradient descent to step towards better θ



Probabilistic Formulation for ML

MLE for Linear and Logistic Regression

Using Statistics for Machine Learning

$D = \{x^i, y^i\}$

Likelihood vs conditional likelihood

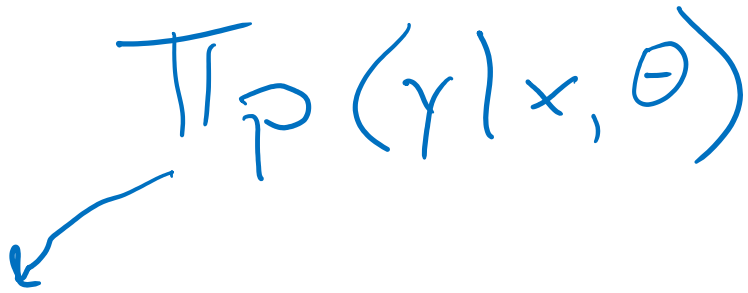
(conditional) likelihood

$$\prod p(y^i | x^i, \theta)$$

likelihood $p(D|\theta)$

$$= \prod_{i=1}^{N} p(x^i, y^i | \theta)$$

Recipe for Estimation



MLE

1. Formulate the likelihood, $p(\mathcal{D} \mid \theta)$
2. Set objective $J(\theta)$ equal to negative log of likelihood

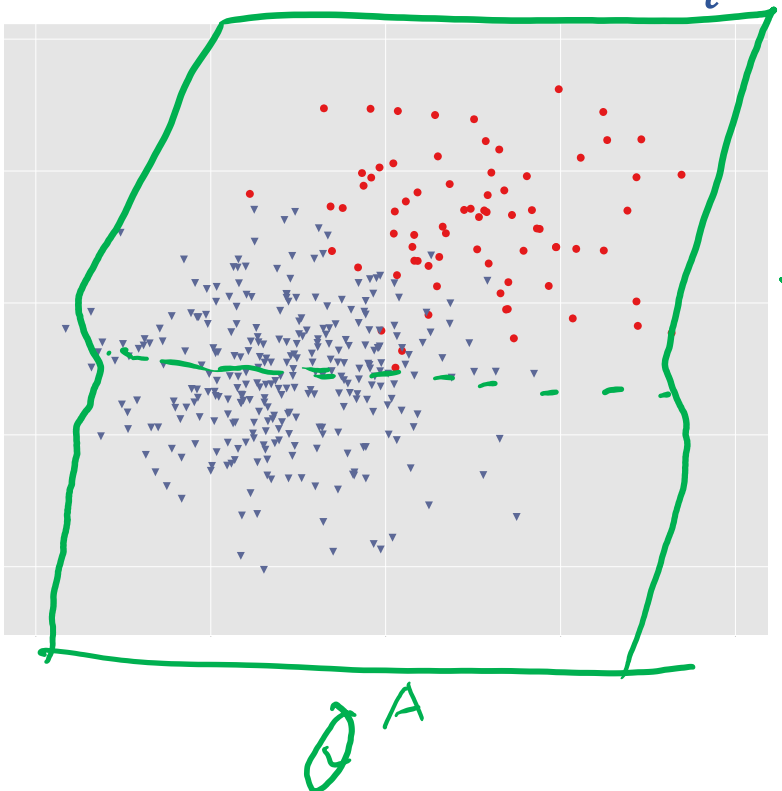
$$\mathrm{J}(\theta) = -\log p(\mathcal{D} \mid \theta)$$

3. Compute derivative of objective, $\partial J / \partial \theta$
4. Find $\hat{\theta}$, either
   a. Set derivate equal to zero and solve for θ
   b. Use (stochastic) gradient descent to step towards better θ

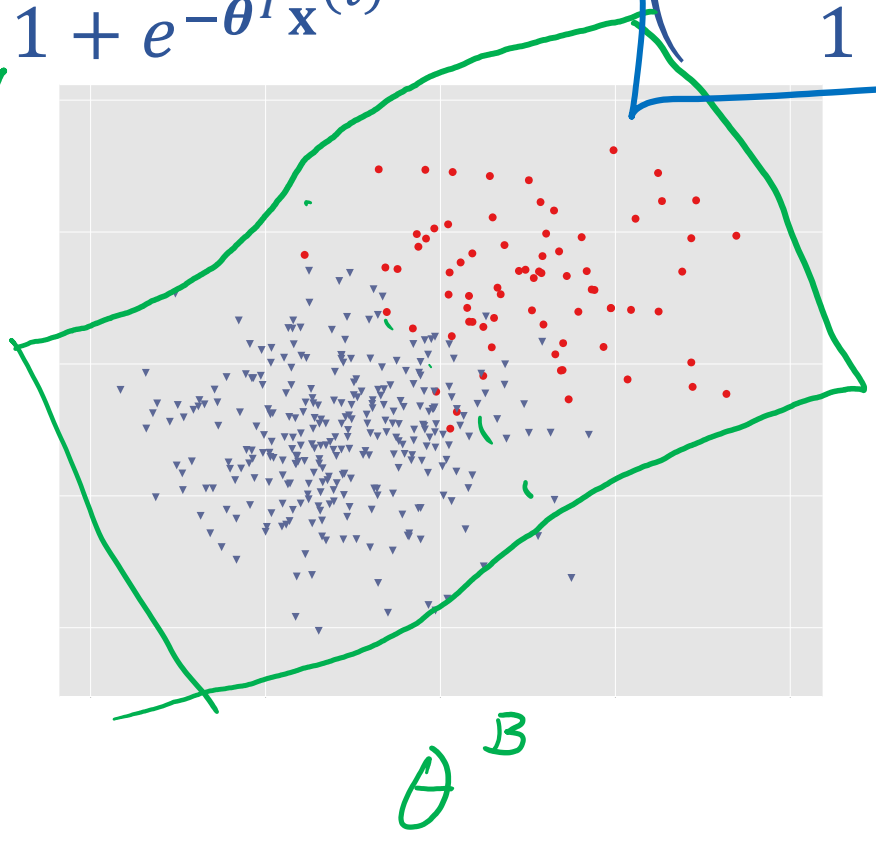
M(C)LE for Logistic Regression

Learn to predict if a patient has cancer ($Y = 1$) or not ($Y = 0$) given the input of just one test results, X_A and X_B

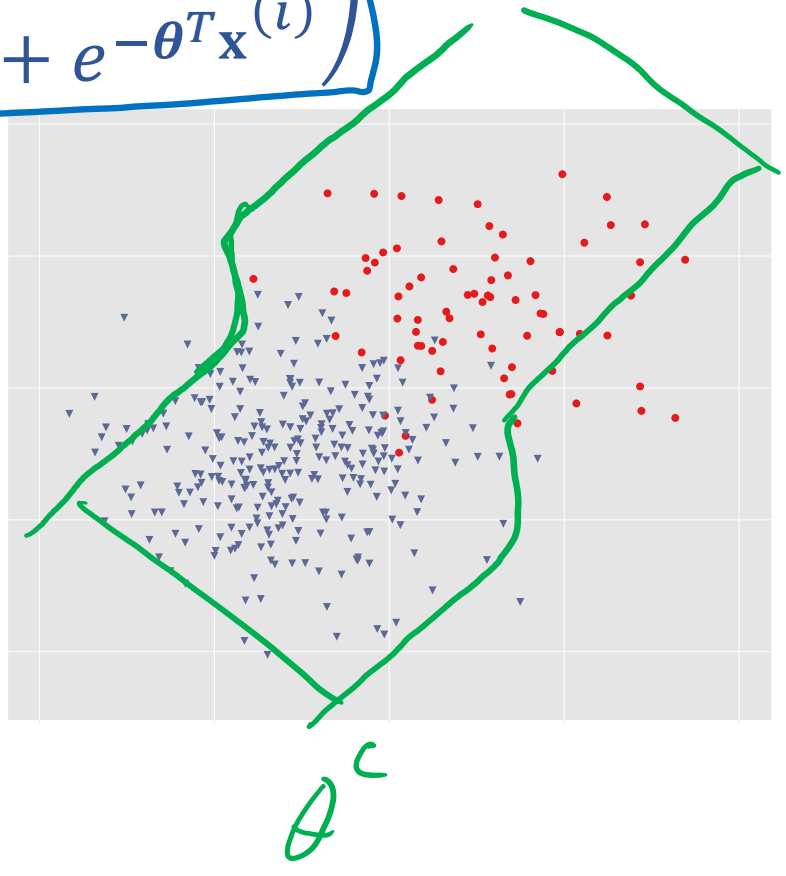
$$\hat{\theta}_{MLE} = \underset{\theta}{\operatorname{argmax}} \prod_{i}^{N} \frac{1}{1 + e^{-\theta^T \mathbf{x}^{(i)}}}^{\mathbb{I}(y^{(i)}=1)} \left(1 - \frac{1}{1 + e^{-\theta^T \mathbf{x}^{(i)}}}\right)^{\mathbb{I}(y^{(i)}=0)}$$



θ^A



θ^B

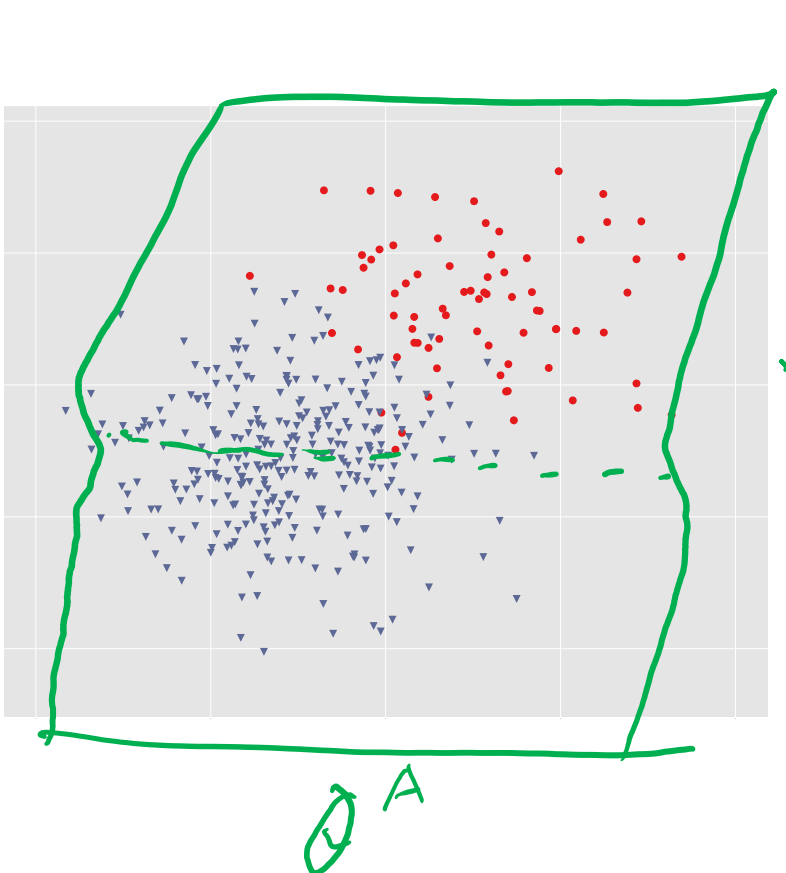


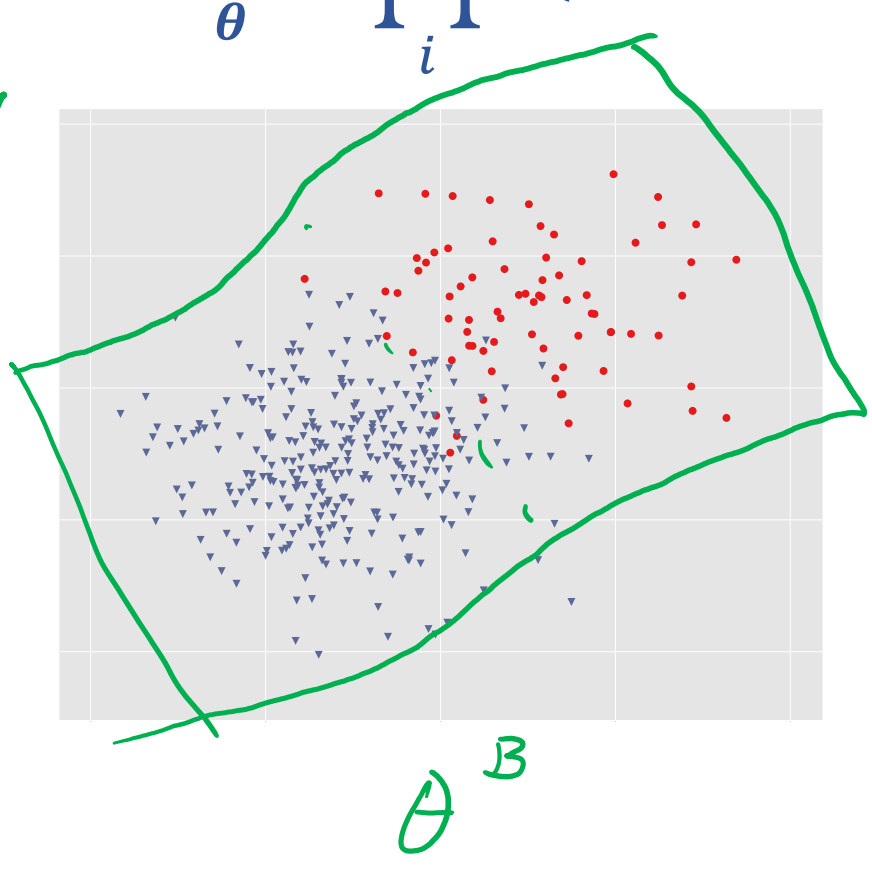
θ^C

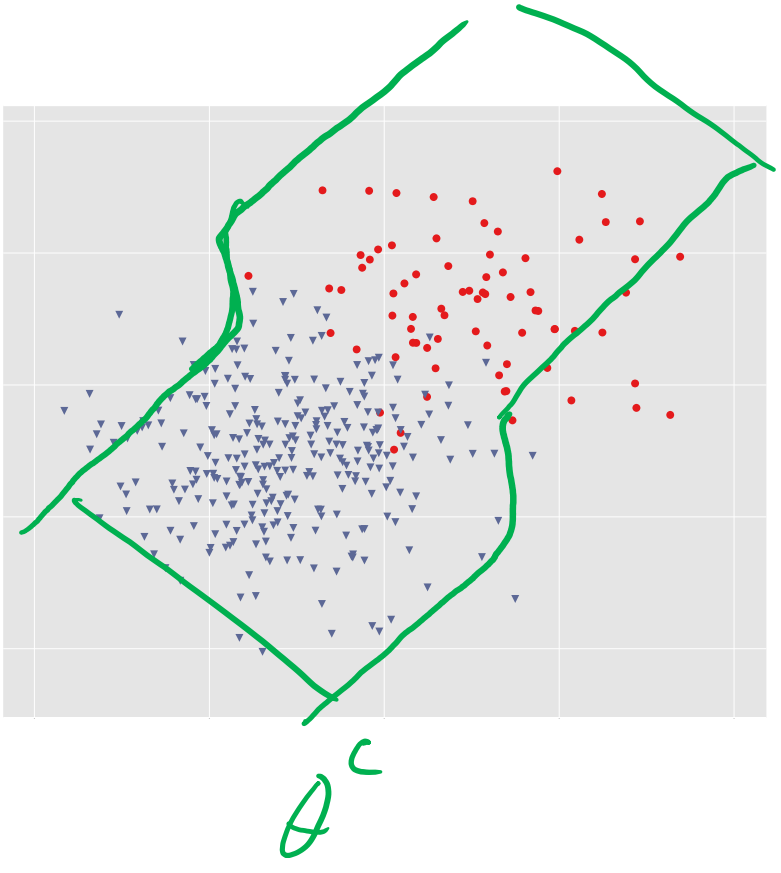
M(C)LE for Logistic Regression

Learn to predict if a patient has cancer ($Y = 1$) or not ($Y = 0$) given the input of just one test results, X_A and X_B

$$\hat{\theta}_{MLE} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i}^{N} p\left(y^{(i)} \mid \mathbf{x}^{(i)}, \boldsymbol{\theta} \right)$$







M(C)LE for Multi-class Logistic Regression

Learn to predict if probability of output belonging to class k, Y_k , given input X, $P(Y_k = 1 \mid X, \boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_K)$

$$\widehat{\Theta}_{MLE} = \underset{\boldsymbol{\Theta}}{\operatorname{argmax}} \prod_i \prod_k \frac{e^{\boldsymbol{\theta}_k^T \mathbf{x}^{(i)}}}{\sum_{l=1}^{K} e^{\boldsymbol{\theta}_l^T \mathbf{x}^{(i)}}}^{\mathbb{I}\left(y_k^{(i)}=1\right)}$$

M(C)LE for Multi-class Logistic Regression

Learn to predict if probability of output belonging to class k, Y_k , given input X, $P(Y_k = 1 \mid X, \boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_K)$

$$\mathcal{L}(\Theta; \mathcal{D}) = \prod_i^N \prod_k^K \frac{e^{\boldsymbol{\theta}_k^T \mathbf{x}^{(i)}}}{\sum_{l=1}^K e^{\boldsymbol{\theta}_l^T \mathbf{x}^{(i)}}}^{\mathbb{I}\left(y_k^{(i)}=1\right)}$$

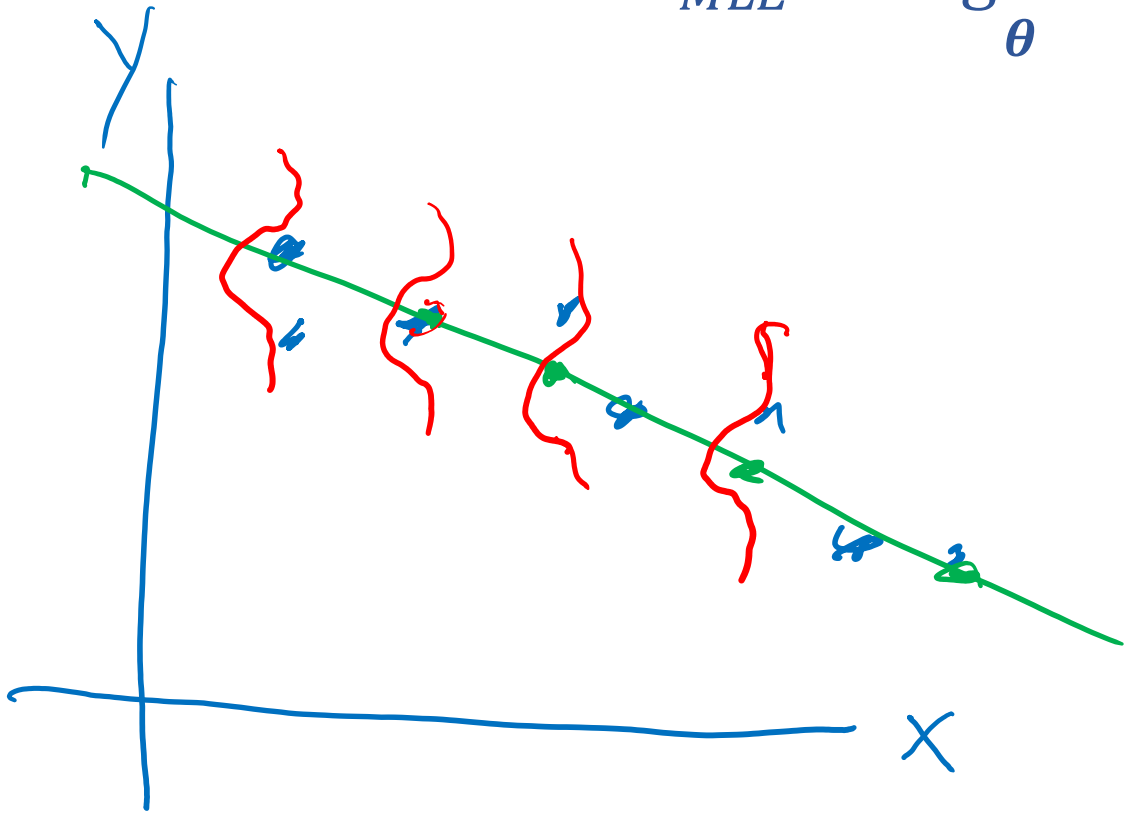
$$J(\theta) = -\log L(\theta; D)$$

M(C)LE for Linear Regression

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

Probabilistic interpretation of linear regression

$$\hat{\theta}_{MLE} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i}^{N} p\left(y^{(i)} \mid \mathbf{x}^{(i)}, \boldsymbol{\theta}\right)$$



$$y = w^T x + b + \epsilon$$

$$\epsilon \sim \mathcal{N}(0, a^2)$$

$$y \sim \mathcal{N}(w^T x + b,\ a^2)$$

$$\theta^T \vec{x}$$

M(C)LE for Linear Regression

$y \sim \mathcal{N}(\theta^T x, \sigma^2)$

$y^{(i)}$

$\theta^T x$

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

Probabilistic interpretation of linear regression

$$\mathcal{L}(\theta; \mathcal{D}) = \prod_i^N p\left(y^{(i)} \mid \mathbf{x}^{(i)}, \boldsymbol{\theta}\right)$$

$$\prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(z^{(i)}-\mu\right)^2}{2\sigma^2}}$$

$\mu = \theta^T x$

$$= \prod_i \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(y^{(i)} - \theta^T x^{(i)}\right)^2 / 2\sigma^2}$$

$$\sum_{i=1}^{N} -\log\sqrt{2\pi\sigma^2} - \frac{\left(z^{(i)} - \mu\right)^2}{2\sigma^2}$$

$$\ell(\theta; D) = \sum_i -\log\sqrt{2\pi\sigma^2} - \frac{\left(y^{(i)} - \theta^T x^{(i)}\right)^2}{2\sigma^2}$$

$$J(\theta; D) = -\ell(\theta; D) \propto \sum_{i=1}^{N} \left(y^{(i)} - \theta^T x^{(i)}\right)^2$$

Just like MSE!

Additional Slides

Probability Primer

Probability Vocab

Outcomes

Sample space

Events

Probability

Random variable

Discrete random variable

Continuous random variable

Probability mass function

Probability density function

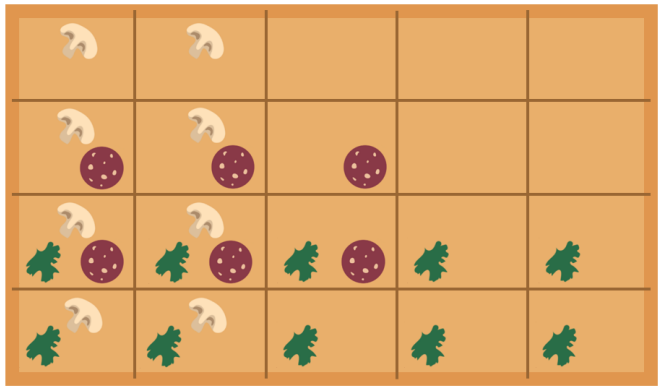
Parameters

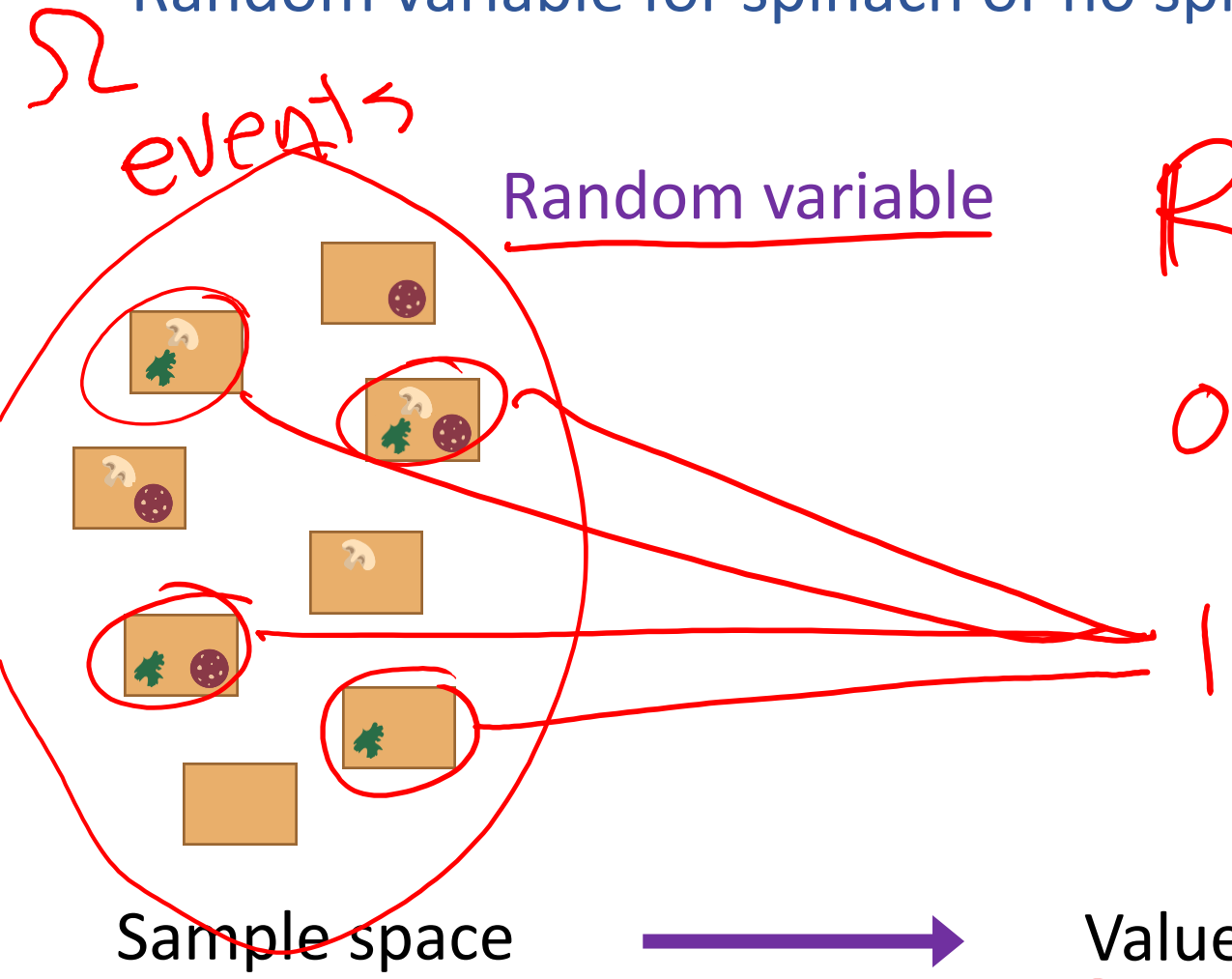
Example

$S \in \{0, 1\}$

$S: \Omega \to \{0, 1\}$

Random variable for spinach or no spinach





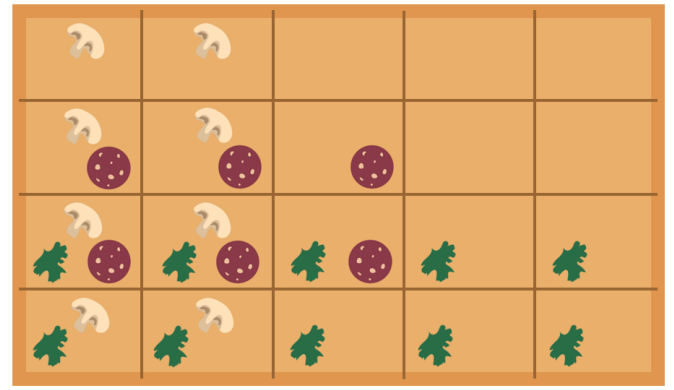
Distribution

Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Example

Random variable for spinach or no spinach



true

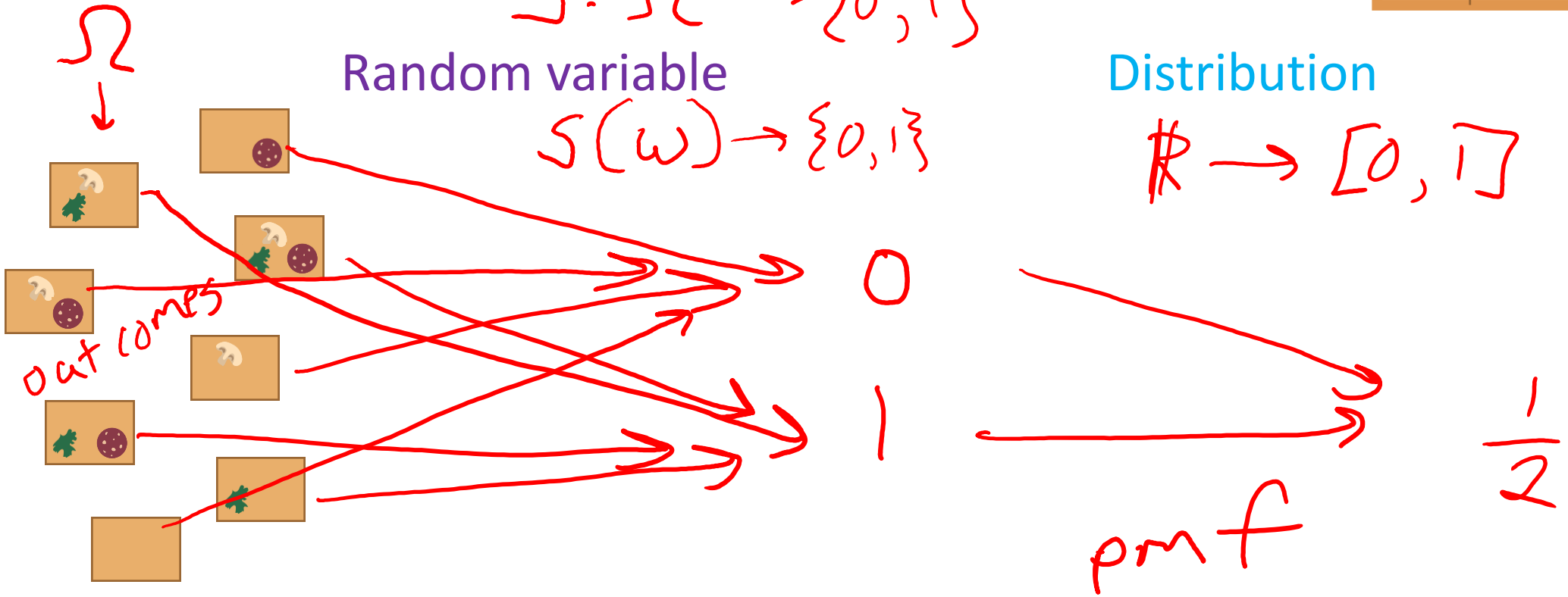
$S : \Omega \to \{0, 1\}$

Random variable

$S(\omega) \to \{0, 1\}$

Distribution

$\# \to [0, 1]$ pmf



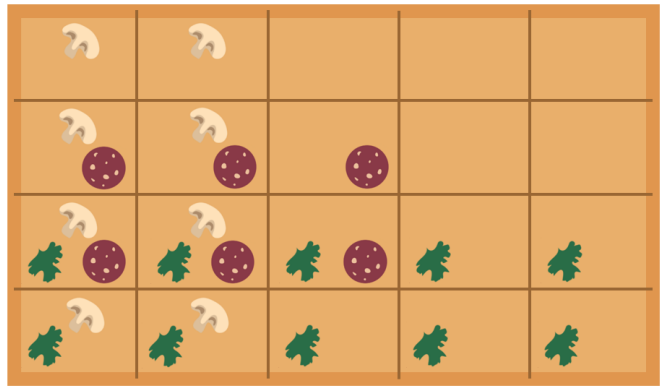
Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

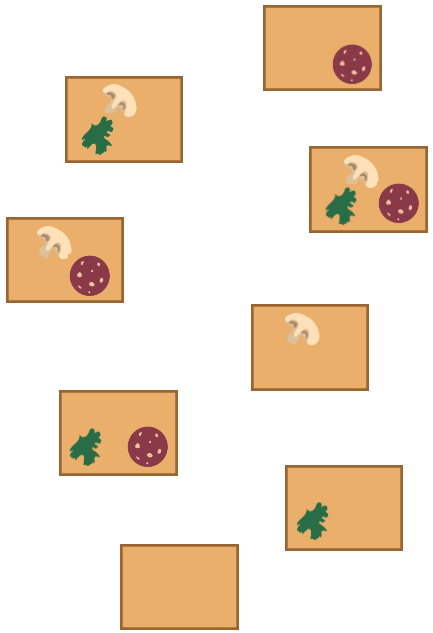
Example

Random variable for topping type with three categories: none, non-meat, meat

true



Random variable



Distribution

1

2

3

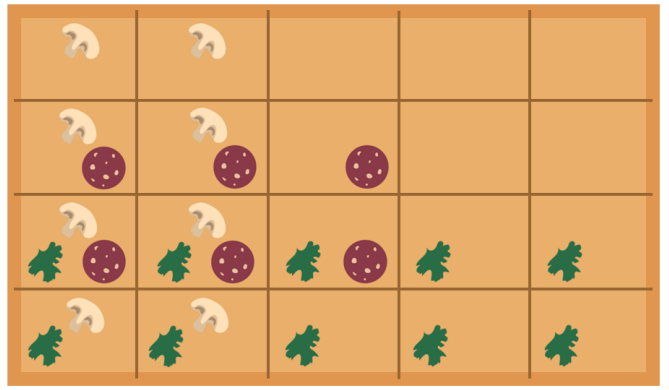
pmf

Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

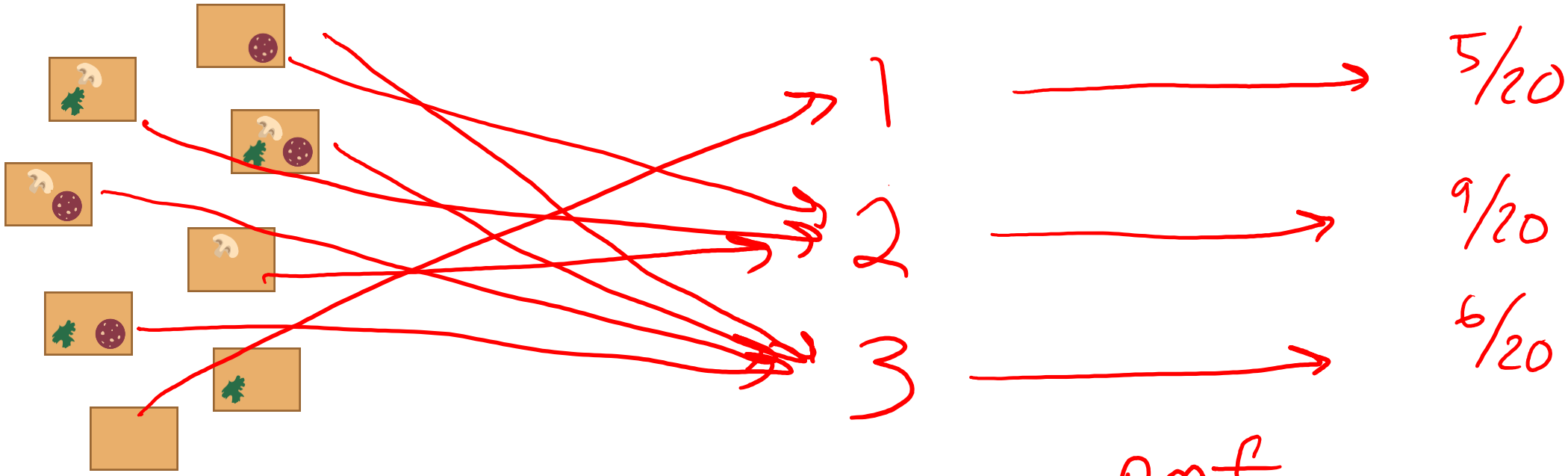
Example

Random variable for topping type with three categories: none, non-meat, meat



Random variable

Distribution



Sample space → Values → Probabilities or Densities

pmf

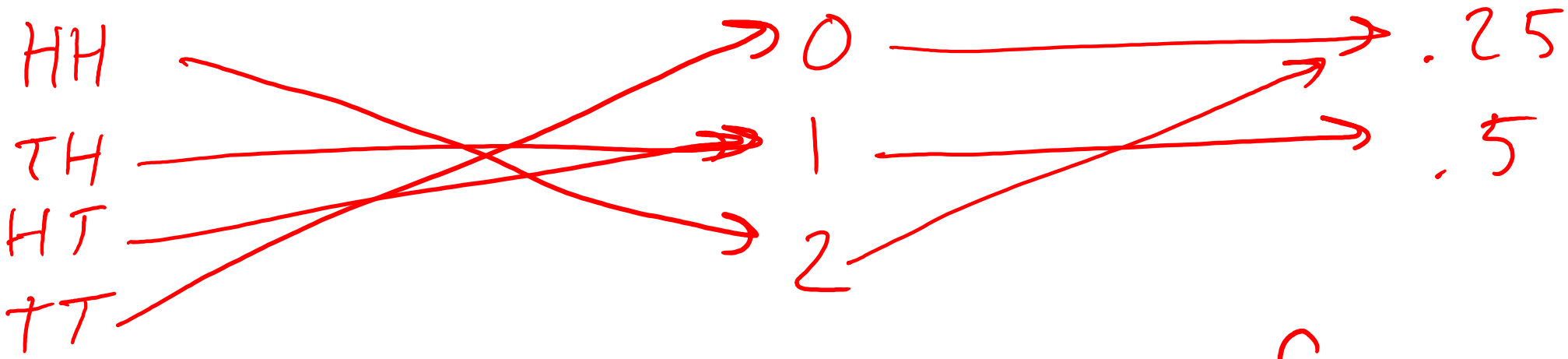
Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Example

Random variable for number of heads after two flips of a fair coin

Random variable

Distribution



pmf

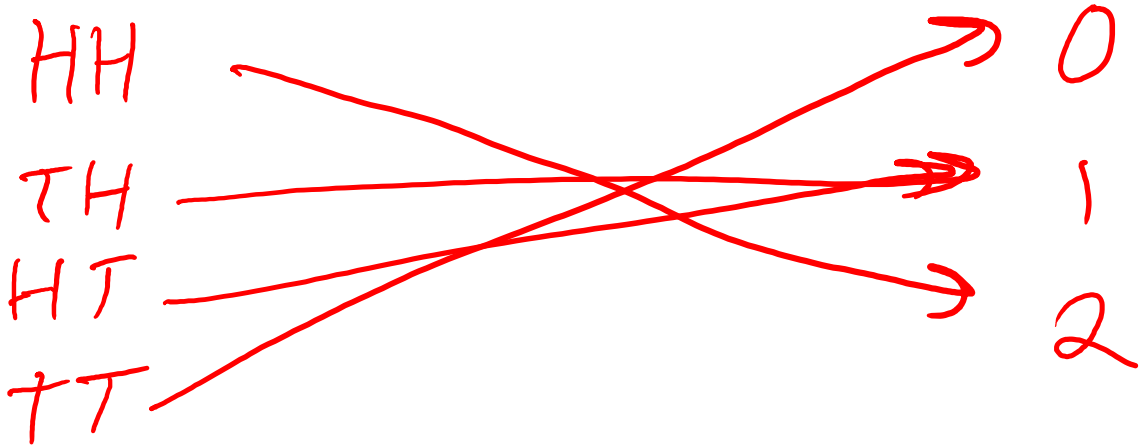
Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Example

Random variable for number of heads after two flips of a *biased* coin that lands heads 75%

Random variable



Distribution

$$\frac{1}{4}\cdot\frac{1}{4}$$

$$\frac{1}{4}\cdot\frac{3}{4}+\frac{3}{4}\frac{1}{4}$$

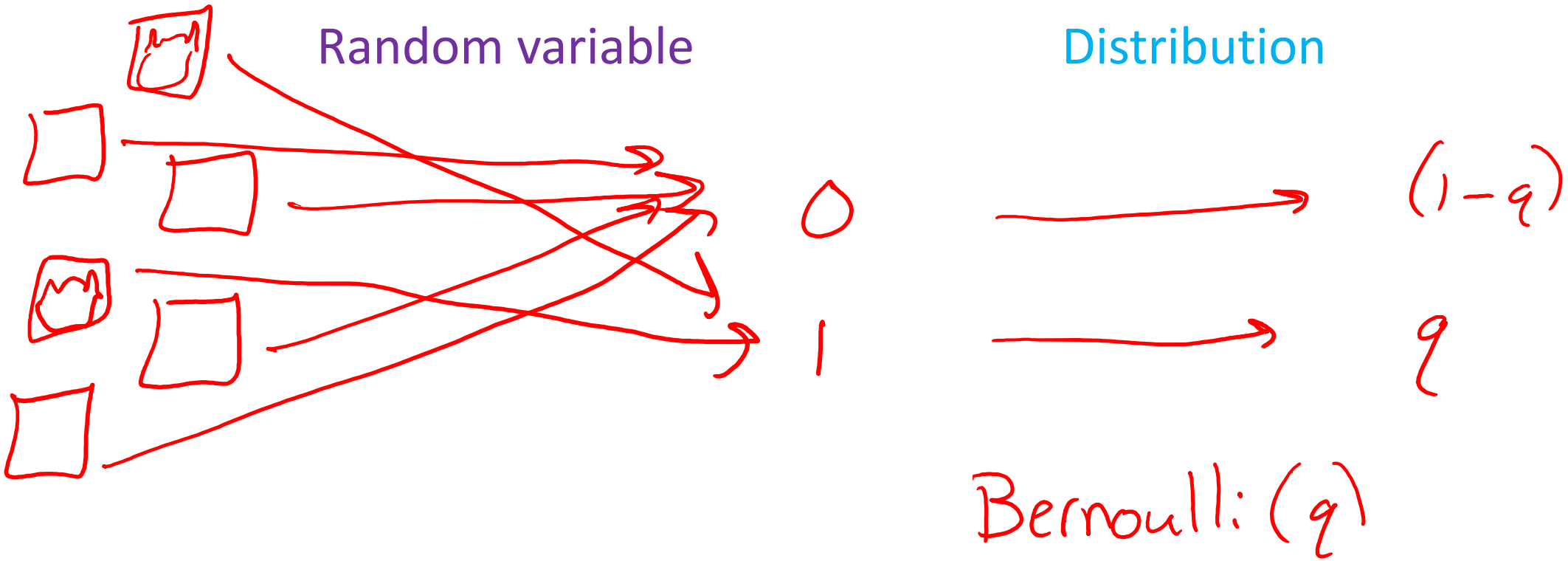
$$\frac{3}{4}\frac{3}{4}$$

Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Example

Random variable for cat in picture or not



Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

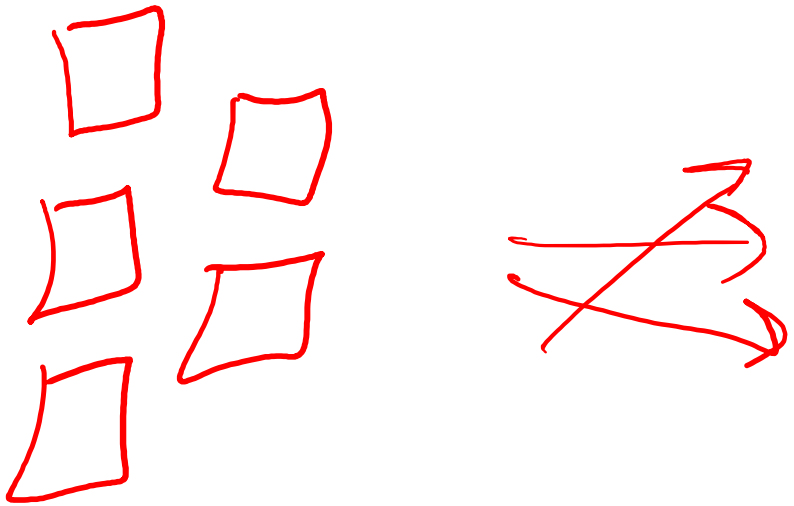
Example

Random variable for animal species in picture assuming one animal picture and available species: dog, cat, pig

$$\sum_{i=1}^{3} q_i = 1$$

Random variable

Distribution



1

2

3

q_1

q_2

$q_3 = (1 - q_1 - q_2)$

Categorical $(q_1\ q_2\ q_3)$

Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Example

Random variable for height of student

$H(\omega) \to \mathbb{R}$ Continuos $f(x) \to \mathbb{R}^+$

Random variable

Distribution

R

Gaussian

$N(\mu, \sigma^2)$

$f(x; \mu, \sigma^2)$

parameters

pdf

Sample space → Values → Probabilities or Densities

Icons: CC, https://openclipart.org/detail/296791/pizza-slice

Probability Vocab

Outcomes

Sample space

Events

Probability

Random variable

Discrete random variable

Continuous random variable

Probability mass function

Probability density function

Parameters

Pr[event]

P(event)

p(value)

P(Y = 1)

P(x) = P(X = x)

f(x) p(x)

CDF

F(x) = P(X ≤ x)

Example Discrete Distributions

Bern Binom.
Categorial Multinom

Bernoulli

$P(Y=1) = \phi$

$Y \in \{0,1\}$ $P(Y=0) = 1-\phi$

Categorical

$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_k \end{bmatrix}$ $Y_k \in \{0,1\}$

$\begin{bmatrix} P(Y_1=1) = \phi_1 \\ P(Y_2=1) = \phi_2 \\ \vdots \\ P(Y_k=1) = \phi_k \end{bmatrix}$ $1 = \sum_{k=1}^{K} \phi_k$

- Binomial
- Multinomial
- Uniform

Example Continuous Distributions

Gaussian

$$p(y;\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(y-\mu)^2}{2\sigma^2}}$$

Beta

Laplace

Probability Vocab

Marginal $p(x) = \sum_y p(x, y)$ Marginalizing

Joint $p(x, y)$ $p(x, y, z, w)$

Conditional $p(x \mid y)$ $p(x, w \mid z, y)$

Notation

Dataset

Parameters, generically θ

$p(\mathcal{D} \mid \theta), p(\mathcal{D}\,;\,\theta)$

Random variables

Capital

$P(Y=y)$

Values

lower case

Random variable: function that maps events to values

Y is rand variable that maps the event of a coin toss being heads to value one and the event of a coin toss being tails to zero

$P(Y = 1 \mid \phi) = 3/4$, where $\phi = 3/4$

$P(Y = 1) = 3/4$

Sometimes even

$P(Y = heads) = 3/4$

Probability Toolbox

- Algebra
- Three axioms of probability
- Theorem of total probability
- Definition of conditional probability
- Product rule
- Bayes' theorem
- Chain rule
- Independence
- Conditional independence

Probability Tools Summary

Adding to the toolbox

1. Definition of conditional probability

$$P(A|B) = \frac{P(A,B)}{P(B)}$$

2. Chain Rule Product rule

$$P(A,B) = P(A \mid B)P(B)$$

3. Bayes' theorem

$$P(B|A) = \frac{P(A \mid B)P(B)}{P(A)}$$

4. Chain Rule…

$$P(A_1, \ldots A_N) = P(A_1) \sum_{i=2}^{N} P(A_i \mid A_{i-1})$$