

# APS1070

Foundations of Data Analytics and  
Machine Learning

Winter 2021

## **Week 4:**

- *Probability Theory*
- *Summary Statistics*
- *Gaussian Distribution*
- *Performance Metrics*

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# Slide Attribution

These slides contain materials from various sources. Special thanks to the following authors:

- William Fleshman
- Scott Sanner
- Ali Hadi Zadeh
- Jason Riordon

# Last Time

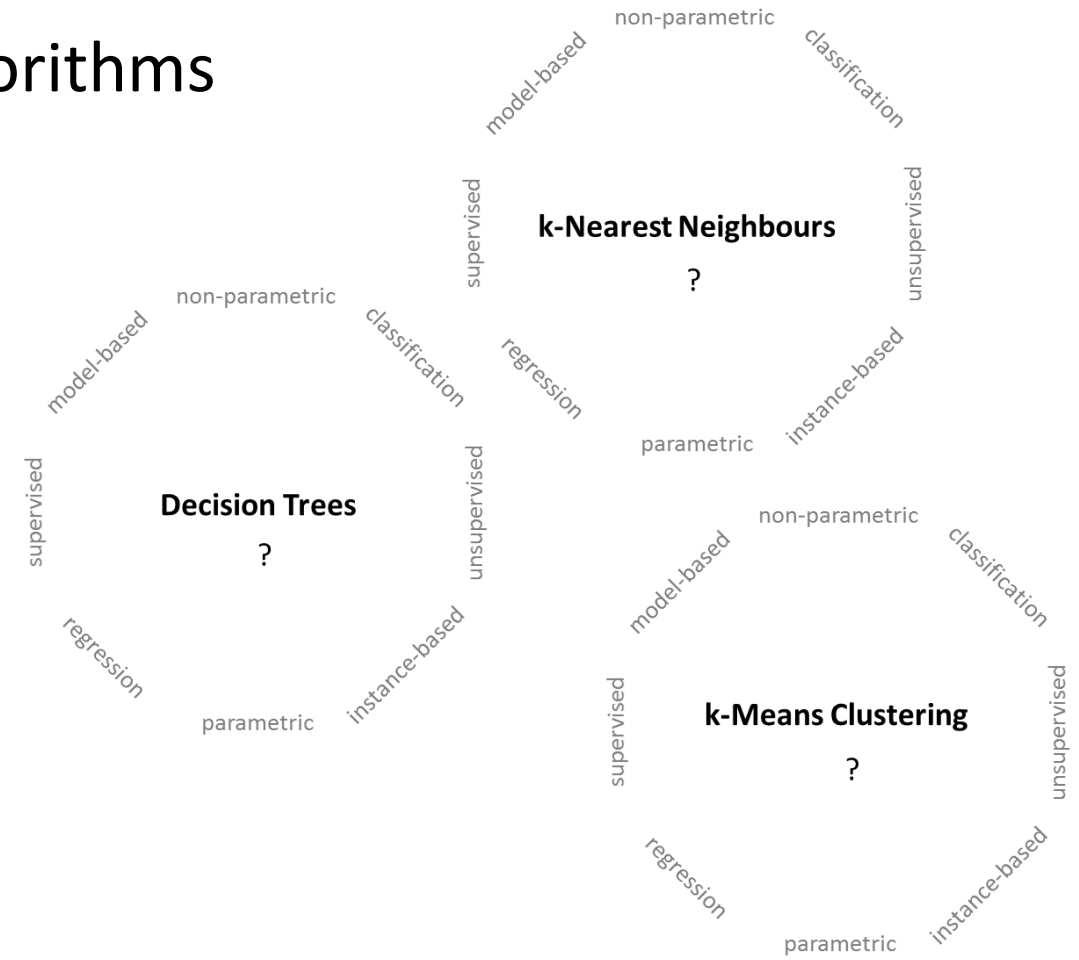
- Compared several machine learning algorithms

- Supervised Learning

- k-Nearest Neighbours and Decision Trees

- Unsupervised Learning

- k-Means



- Q: How did we measure performance?

# Measuring Uncertainty

- In machine learning it is important to understand how confident we can be about the decisions (or predictions) being made by our models/algorithms.
- Q: A model/algorithm is tested on two new samples and classifies both correctly. What is the accuracy and how confident are you with that result?

# Agenda

- Probability Theory
  - Examples
  - Summary Statistics
  - Gaussians
- Mixture of Gaussians
  - Anomaly Detection
- Performance Metrics
  - Precision and Recall
  - Confusion Matrix
  - ROC and AUC



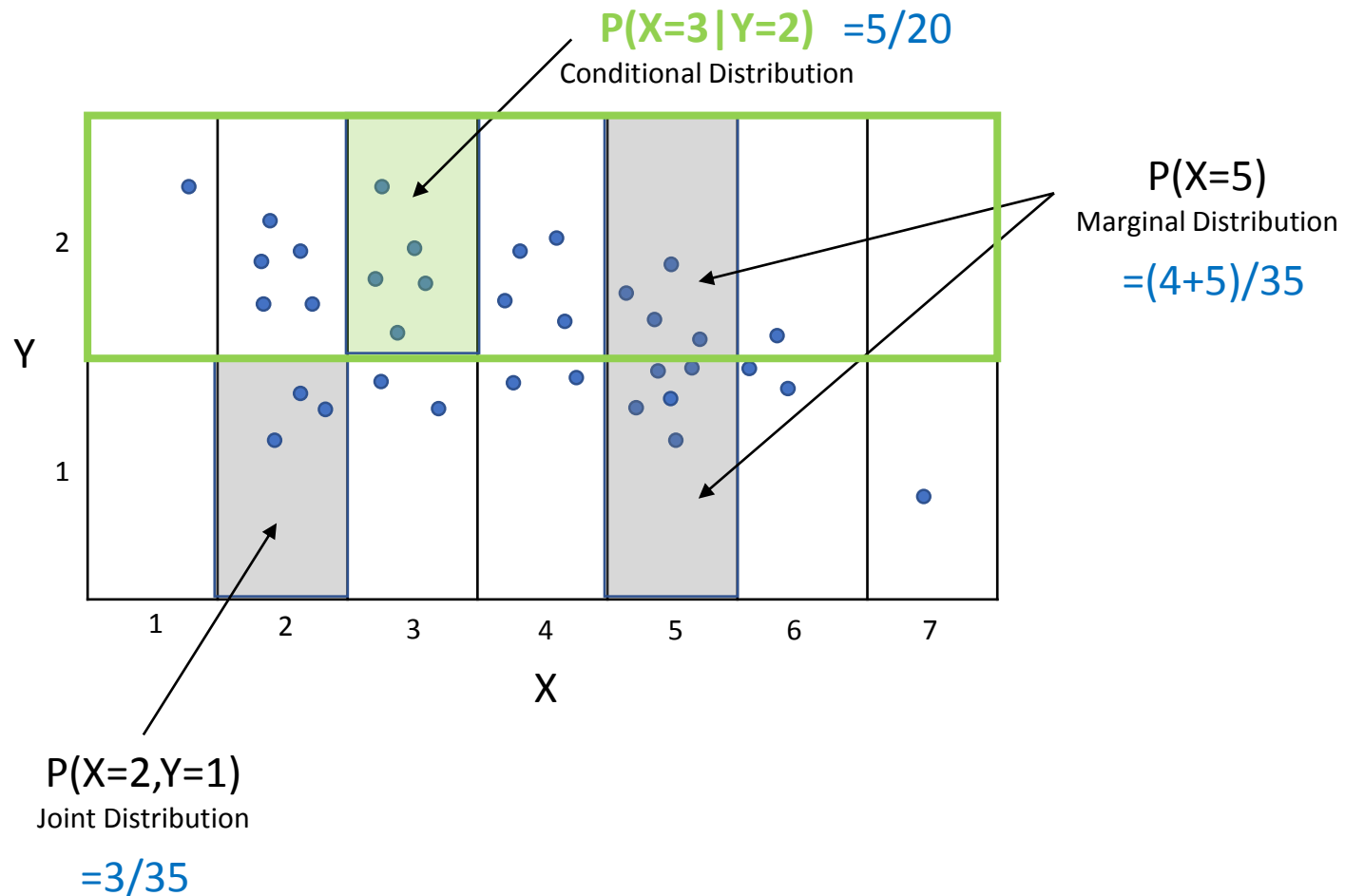
Theme:  
**Measuring Uncertainty**

# Probability Theory

**Readings:**

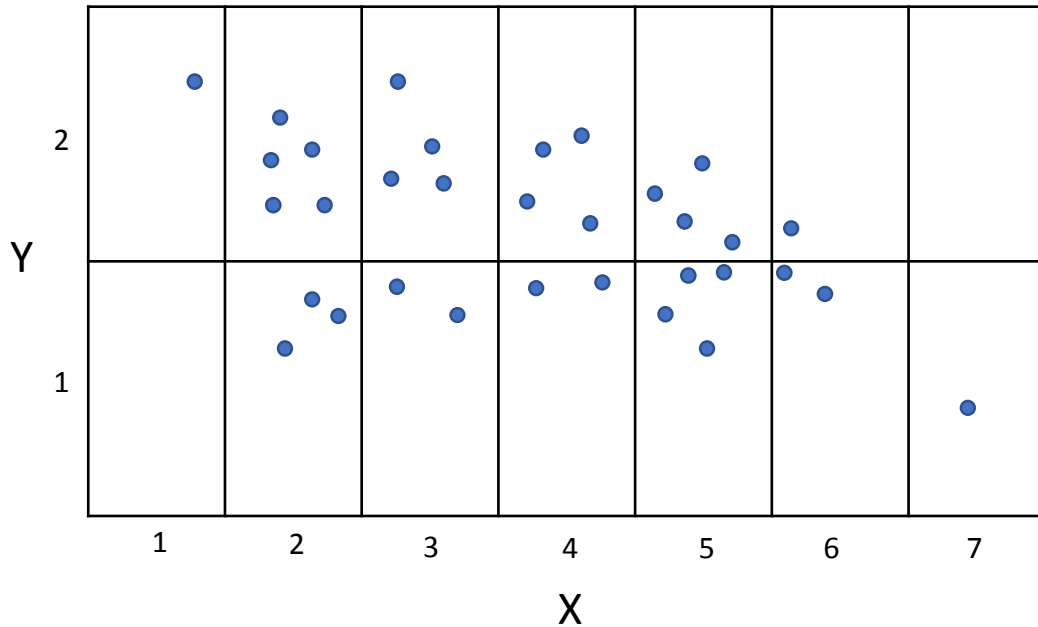
- **Chapter 6.1-5 MML Textbook**

# Example: Random Variables

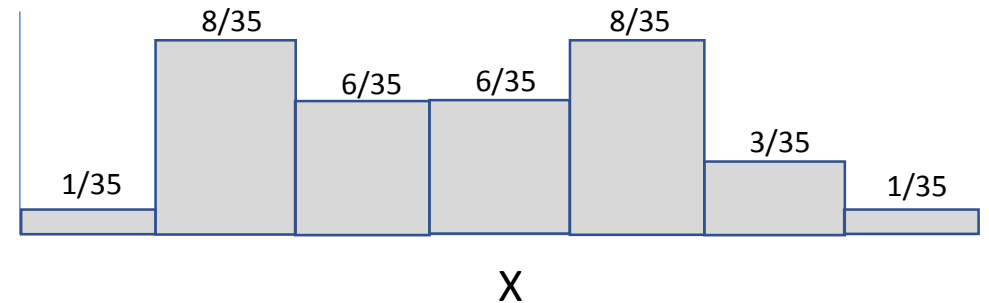
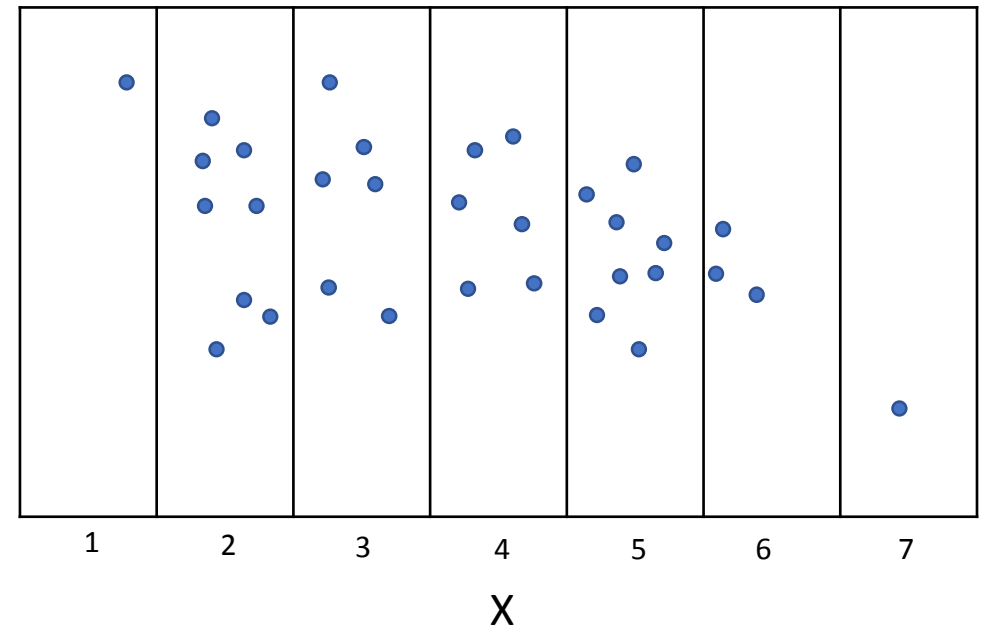


# Example: Marginal Distribution of X

$P(X,Y)$  – Joint Distribution



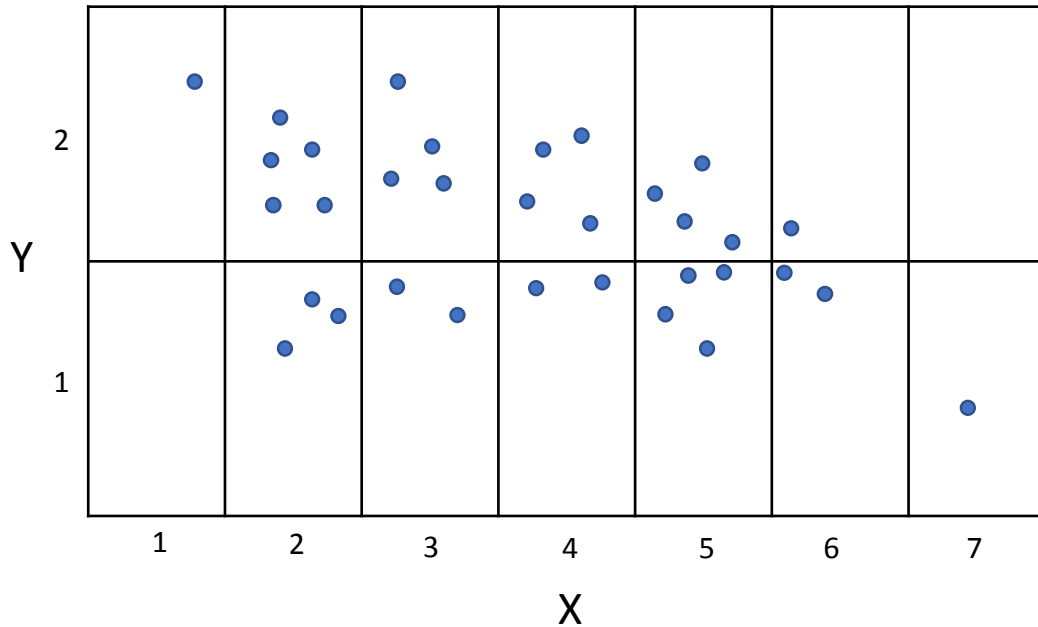
$P(X)$  – Marginal Distribution



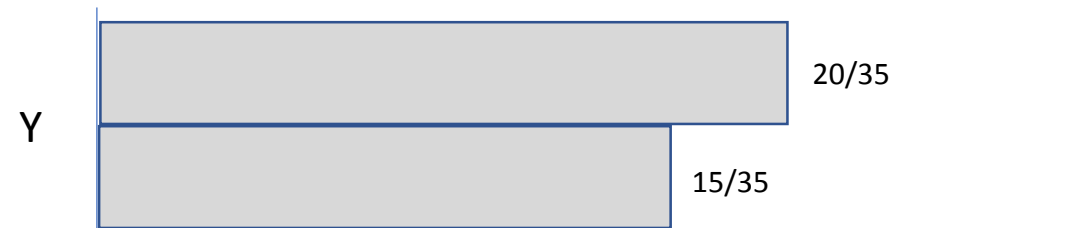
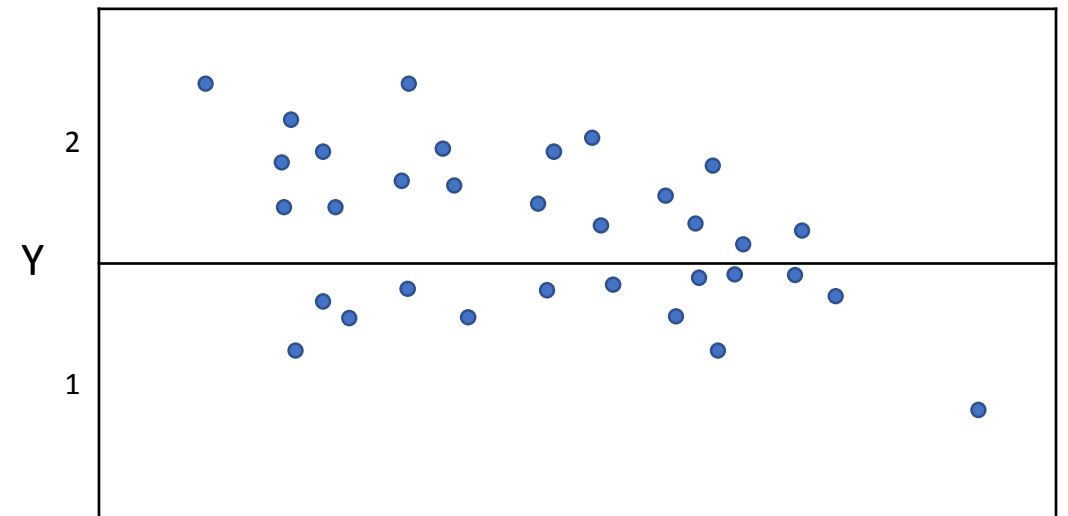


# Example: Marginal Distribution of Y

$P(X,Y)$  – Joint Distribution

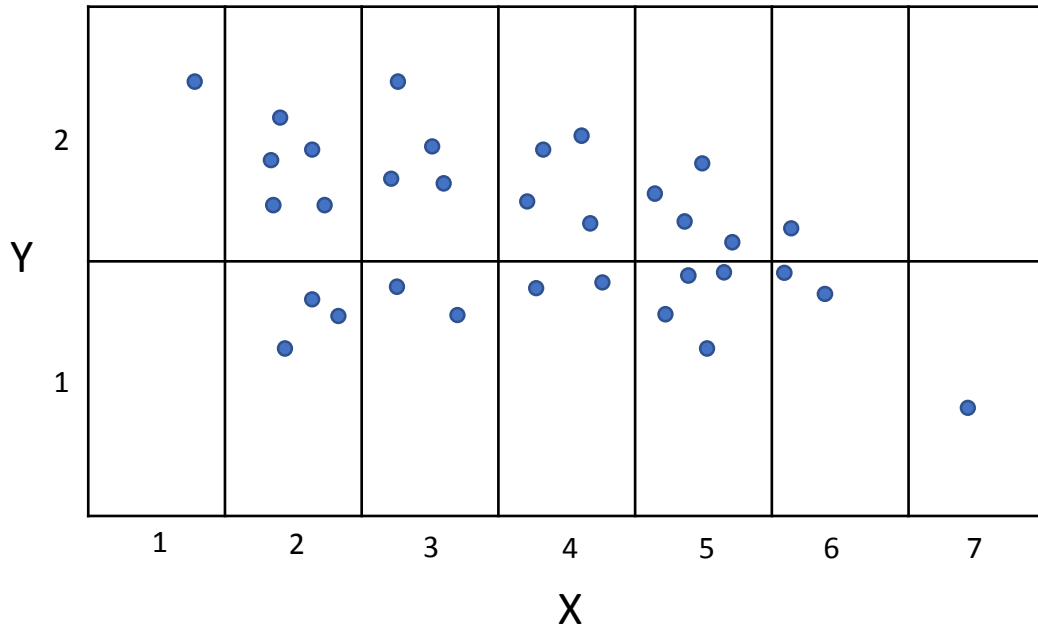


$P(Y)$  – Marginal Distribution

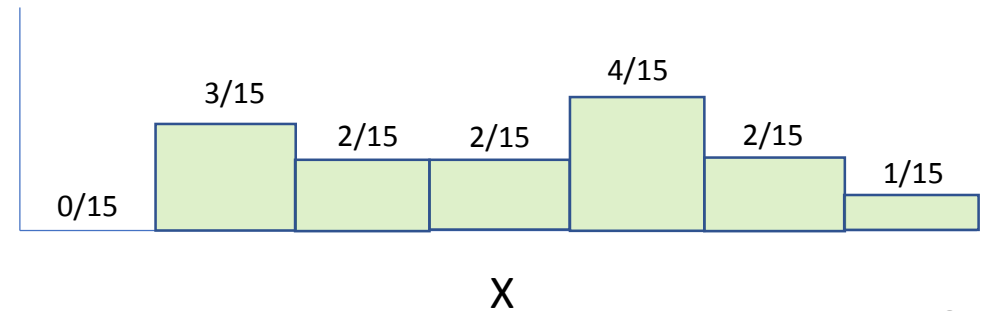
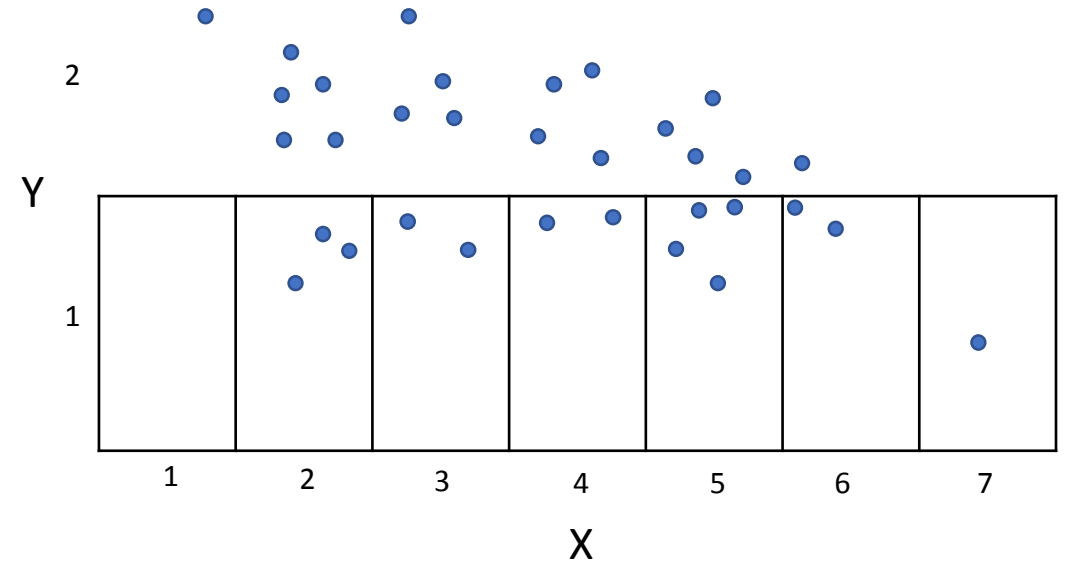


# Example: Conditional Distribution $X|Y$

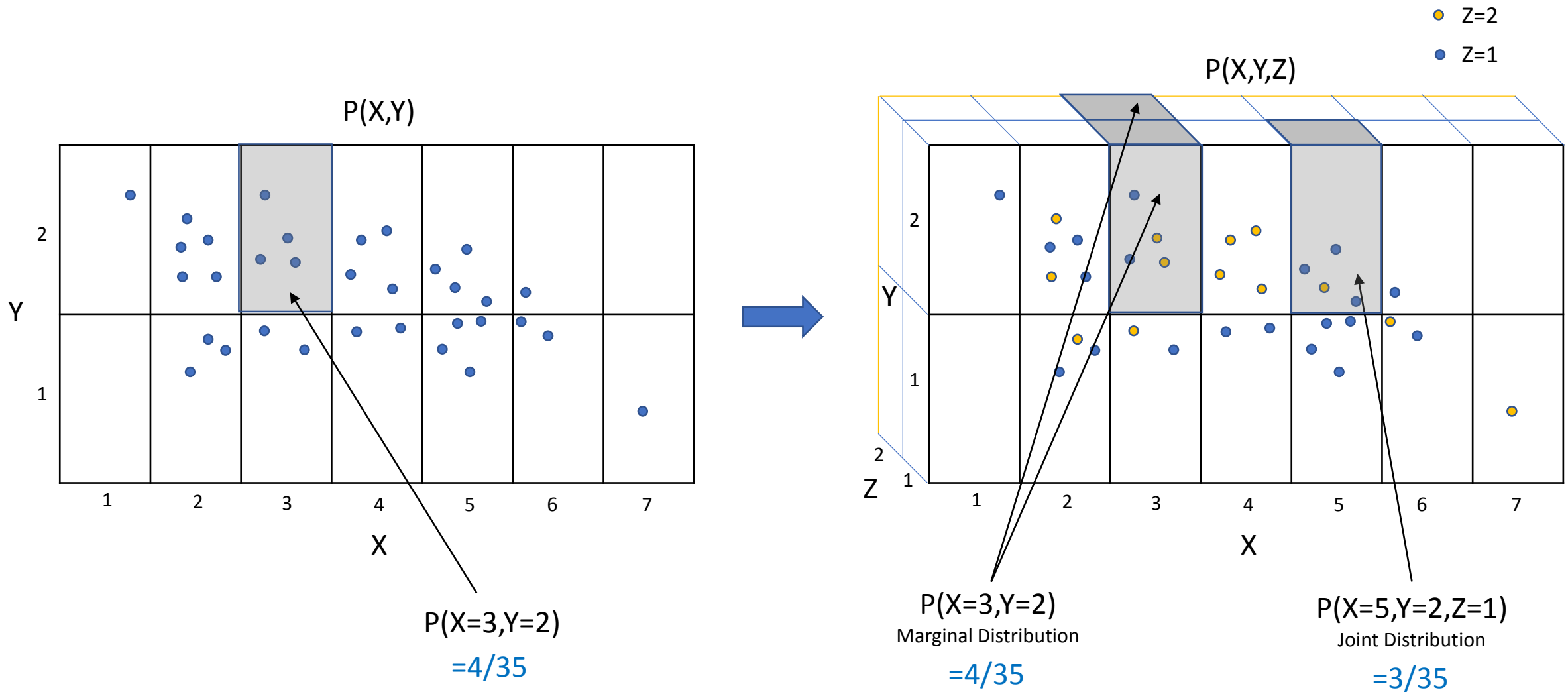
$P(X,Y)$  – Joint Distribution



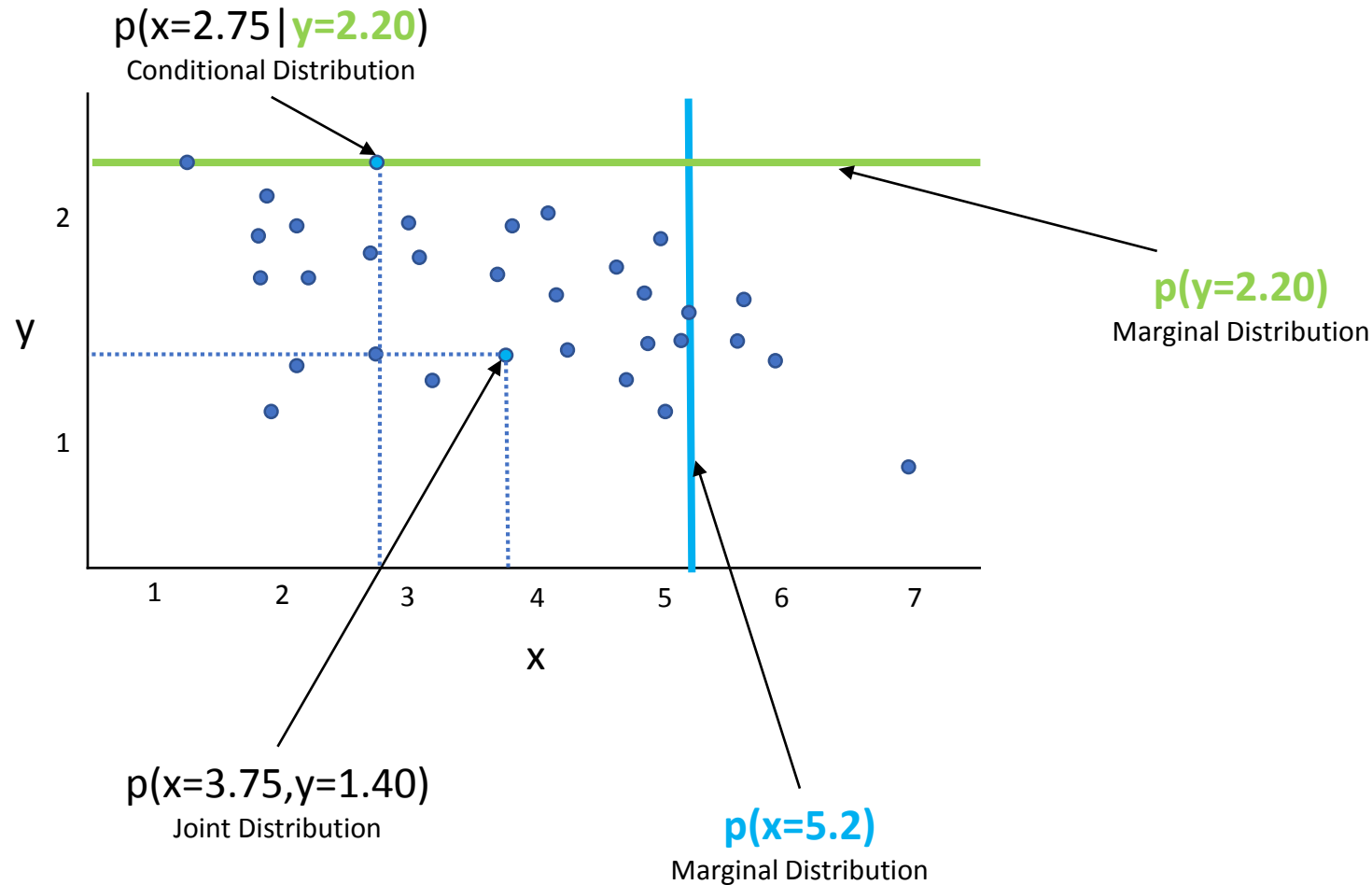
$P(X|Y=1)$  – Conditional Distribution



# Example: From 2 to 3 Random Variables



# Example: Continuous Distributions



- Probability at a point is meaningless
- Needs to add up to 1
- Consider areas

# Probability with Real Data

```
pd.crosstab(df['Pclass'], df['Sex'])
```

Counts

Class	Sex		
	0	1	All
1	80	136	216
2	97	87	184
3	372	119	491
All	549	342	891



Probabilities

Class	Sex		
	0	1	All
1	0.090	0.153	0.242
2	0.109	0.098	0.207
3	0.418	0.134	0.551
All	0.616	0.384	1.000

```
pd.crosstab(df['Pclass'], df['Sex']) / 891
```

# Probability with Real Data

Q: What is the probability of a first-class male passenger surviving?

Q: What is the probability of there being a first-class male passenger that survived?

Probabilities

		Sex		
		0	1	All
Class	1	0.090	0.153	0.242
	2	0.109	0.098	0.207
	3	0.418	0.134	0.551
	All	0.616	0.384	1.000

# Example: Permutations and Combinations

## Permutation

- arrangement of items in which **order matters**

## Combination

- selection of items in which **order does not matter**

Order Matters	Repetition Allowed	Formula
Yes (Permutation)	Yes	$P(n, r) = n^r$
Yes (Permutation)	No	$P(n, r) = \frac{n!}{(n - r)!}$
No (Combination)	No	$C(n, r) = \frac{n!}{r!(n - r)!}$
No (Combination)	Yes	$C(n + r - 1, r) = \frac{(n + r - 1)!}{r!(n - 1)!}$

$n$  – number of items in a set

$r$  – number of items selected from the set

# Example: Combinations

Q: (Lottery Game) A player chooses 6 numbers 1 to 55. If all numbers match the 6 winning numbers, **regardless of order**, the player wins. What is the probability that the winning numbers are 4, 15, 30, 55, 10, 1

$$C(n + r - 1, r) = \frac{(n + r - 1)!}{r!(n - 1)!}$$

Q: Same problem as above, but now **each number can be chosen only once**. How does the probability change?

$$C(n, r) = \frac{n!}{r!(n - r)!}$$



# Example: Permutations

Q: (Lottery Game) A player chooses 6 numbers 1 to 55. If all numbers match the 6 winning numbers **and in the correct order**, the player wins. What is the probability that the winning numbers are 4, 15, 30, 55, 10, 1

$$P(n, r) = n^r$$

Q: Same problem as above, but now **each number can be chosen only once**. How does the probability change?

$$P(n, r) = \frac{n!}{(n - r)!}$$

Let us Summarize...

# Why Probability?

- Probability theory is a **mathematical framework for quantifying our uncertainty** about the world.
  - It allows us (and our software) to reason effectively in situations where being certain is impossible.
- Probability theory is at the foundation of many machine learning algorithms.

# Perspectives on Probability

- **Objectivist perspective:** randomness is fundamental to the universe.
  - They would say that the probability of a fair coin coming up heads is 0.5, because that's the nature of fair coins.
- **Subjectivist perspective:** probabilities represent our degree of belief that an event will occur.
  - If we knew the initial position of the coin and how the force was applied, then we could determine with certainty if it would come up heads or tails.
  - Under this perspective, probability is a measure of our ignorance (like not knowing how the force is applied to the coin).

# Frequentists

- **Frequentist's position:** estimations come from experiments and experiments only.
  - e.g., if we want to estimate how likely a six-sided die is to roll a 4, we should roll the die many times and observe how frequently 4 appears.
    - This method works well when we have a large amount of data, but with fewer examples we can't be confident in our estimates.
    - If we haven't seen a 4 after five rolls, does that mean a 4 is impossible?
    - The other issue is that we **can't inject any of our prior knowledge about dice into our estimates**. If we knew the die was fair, not seeing a 4 in the first five rolls is completely understandable.
- **Bayesian perspective** allows us to combine our prior beliefs with our observations

# Bayesian vs Frequentist

- For example: Imagine that a coin we believe to be fair is flipped three times and results in three heads.
- **Frequentist calculation** would suggest the coin is loaded (although with low confidence)
- **Bayesian** our prior knowledge that the coin is fair allows us to maintain some degree of belief that a tails is still possible.
  - The actual mechanics of how we combine our prior belief relies on something called Bayes' rule, which will be covered later.

# Mathematical Framework

- Probability theory is a mathematical framework.
- As with any mathematical framework there is some vocabulary and important rules needed to fully leverage the theory as a tool for machine learning.

# Probability Spaces

- Probability is all about the possibility of various outcomes. The set of all possible outcomes is called the sample space.
  - e.g., sample space for coin flip is {heads, tails}.
  - e.g., the sample space for the temperature of water is all values between the freezing and boiling point.
- Only one outcome in the sample space is possible at a time, and the sample space must contain all possible values.



# Random Variables

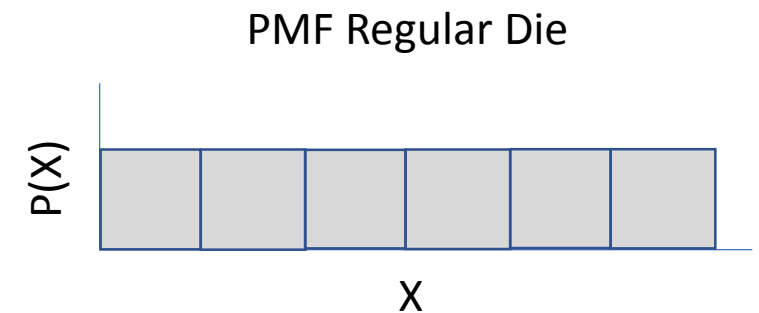
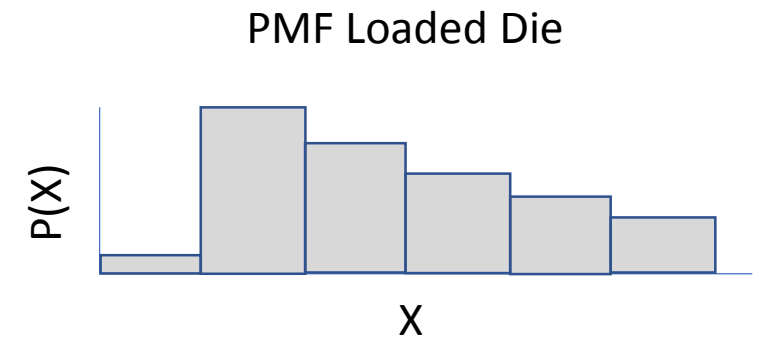
- Are variables which randomly takes on values (discrete or continuous) from a sample space.
- Probability of any event has to be between 0 (impossible) and 1 (certain), and the sum of the probabilities of all events should be 1.

$$0 \leq p(x) \leq 1$$

$$\sum_x p(x) = 1$$

# Discrete Probabilities

- Discrete random variables are described with a **probability mass function (PMF)**.
- PMF maps each value in the variable's sample space to a probability.
  - e.g., PMF for a loaded die and how does it compare with a normal die



# Bernoulli Distribution

- Common discrete distribution is the **Bernoulli**.
  - A Bernoulli distribution specifies the probability for a random variable which can take on one of two values.
    - e.g., heads or tails
  - We can specify the entire distribution with a single parameter  $p$ , the probability of the positive outcome.
    - e.g., for a fair coin we have  $p = 0.5$ ,
    - e.g., given the probability of rain is  $p = 0.2$ , we can infer the probability of no rain is 0.8.
- Other common discrete distributions are the **binomial** (e.g., handles multiple tosses of a coin) and **multinomial** distributions (e.g., rolling a die), and **Poisson** (events occurring in fixed interval of time).

# Types of Probabilities

## ➤ Joint Probability

- a joint distribution over two random variables  $x, y$  specifies the probability of any setting of the random variables.

$$P(x, y)$$

## ➤ Marginal Probability

- called the marginal probability distribution, since we've “marginalized” away the random variable  $y$  (uses the **sum rule**).

$$P(x) = \sum_y P(x, y)$$

## ➤ Conditional Probability

- the probability of an event given that another event has already been observed.

$$P(x|y) = \frac{P(x, y)}{P(y)}$$

# Bayes' Theorem

➤ Product Rule:

$$P(x, y) = P(x|y) \cdot P(y).$$

➤ We can write the product rule for two variables in two equivalent ways:

$$P(x, y) = P(y|x) \cdot P(x)$$

➤ By setting both equations equal and divide by  $P(y)$ , we get **Bayes' rule**:

$$P(x|y) = \frac{P(y|x) \cdot P(x)}{P(y)}$$

Note

Bayes's rule is crucially important to much of statistics and machine learning. Driving force behind Bayesian statistics (Bayesian perspective).

This simple rule allows us to update our beliefs about quantities as we gather more observations from data.

# Independence

- Two variables  $x$  and  $y$  are said to be independent if

$$P(x, y) = P(x) \cdot P(y)$$

Q: Can you think of an example where this would happen?

# Conditional Independence

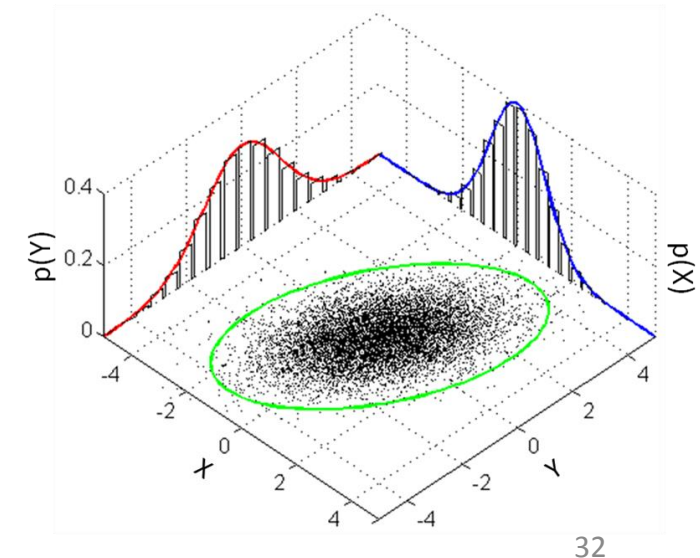
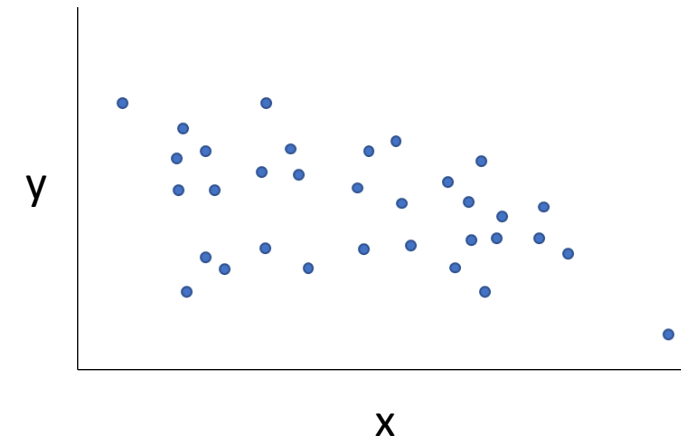
- Two variables  $x$  and  $y$  are called conditionally independent given another variable  $z$  if

$$P(x, y | z) = P(x | z) \cdot P(y | z)$$

- Q: Can you think of an example where this would happen?

# Continuous Probabilities

- Continuous random variables are described by **probability density functions (PDF)** which can be a bit more difficult to understand.
  - PDFs map an infinite sample space to relative likelihood values.
  - To understand this, let's look at an example with one of the most famous continuous distributions, the Gaussian (aka Normal) distribution.

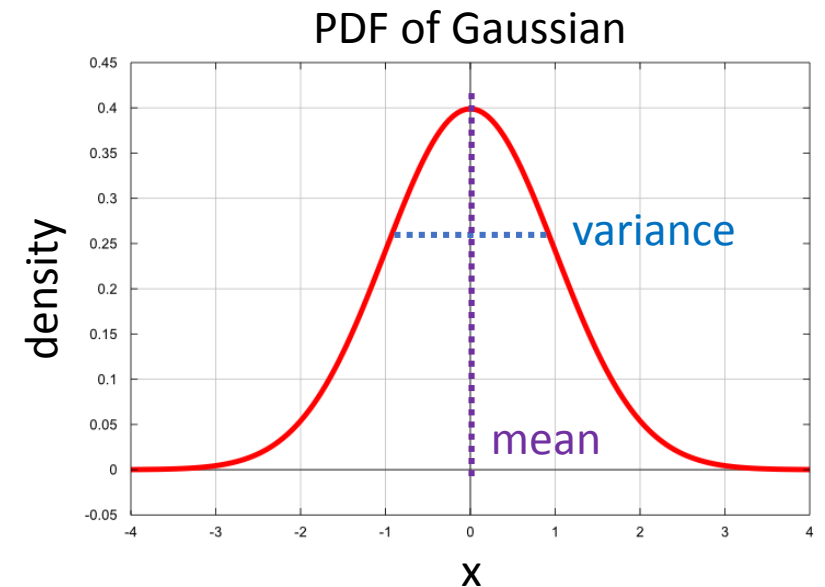




# Gaussian Distribution

- The Gaussian distribution is parameterized by two values: the mean  $\mu$  (mu) and variance  $\sigma^2$  (sigma squared).
- The **mean specifies the center** of the distribution, and the **variance specifies the width** of the distribution.
- You may have also heard about the standard deviation  $\sigma$ , which is just the square root of the variance.

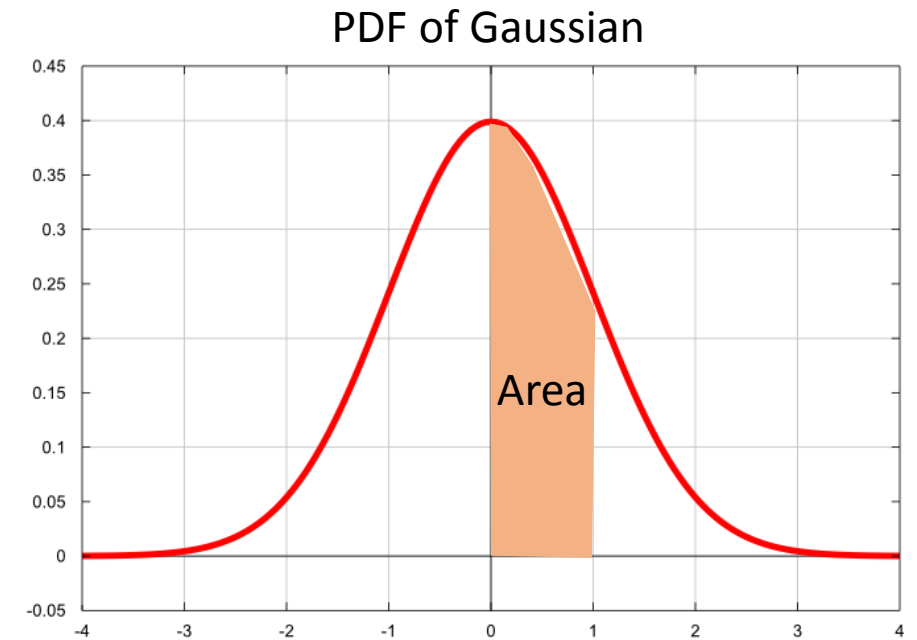
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



# Relative Likelihood

- The value of the PDF is not the actual probability of  $x$ .
- Remember, the **total probability for every possible value needs to sum to 1**.
- Q: How can we sum over infinite number of values?
- A: Need to calculate the area under the PDF to obtain the probability

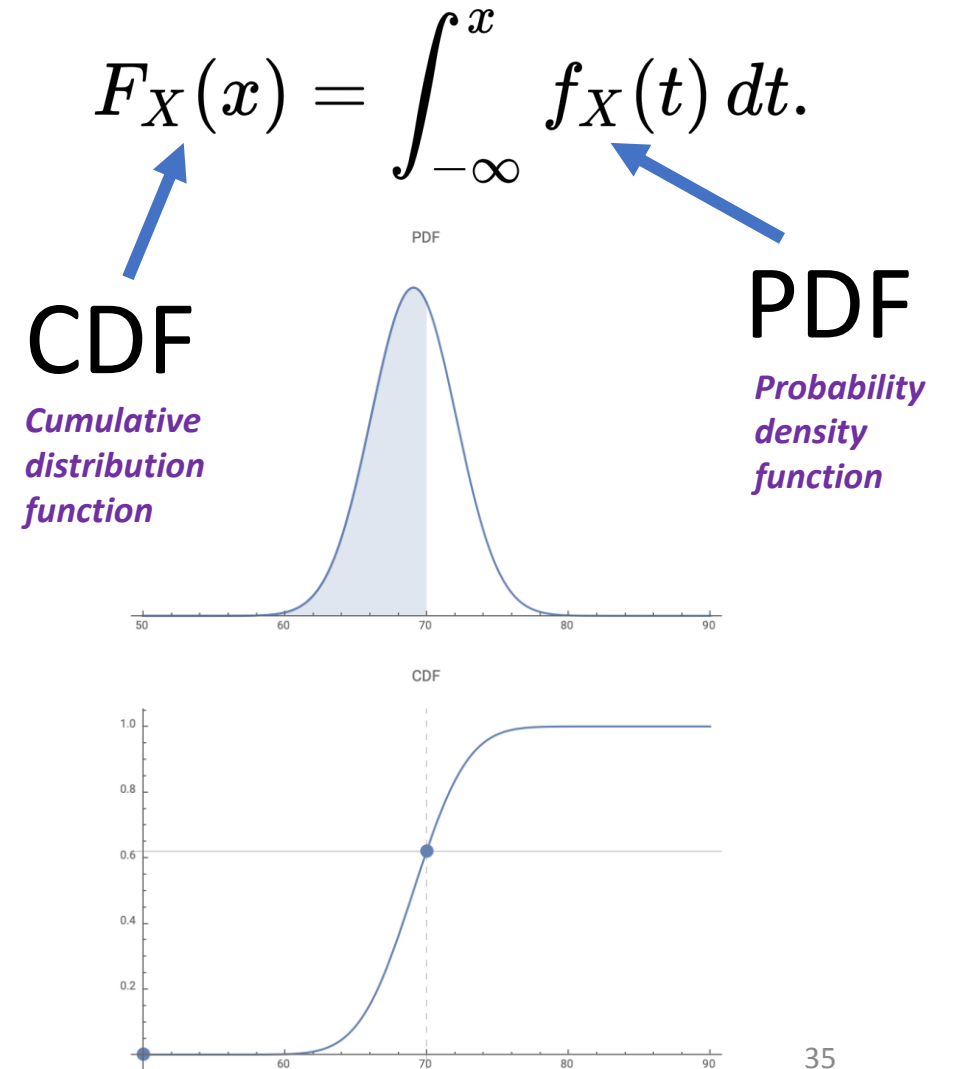
Since we are interested in the area, it is often more useful to work with a continuous random variable's cumulative density function (CDF).



$$p(0 < x < 1) = \int_0^1 f(x) dx$$

# Relative Likelihood Con't

- We just determined that the area corresponds to the probability, so  $F(x)$  gives us  $P(X \leq x)$ .
- Use the CDF to determine the **probability of any given range**  $[a, b]$  using  $P(a \leq X \leq b) = F(b) - F(a)$ .
- Note that asking for  $P(X=x)$  is equivalent to asking  $P(x \leq X \leq x) = F(x) - F(x) = 0$



# Functions of Random Variables

- Often useful to create functions which take random variables as input.
- e.g., it costs \$2 to play the game, “guess a number between 1 and 10”. Correct guess = \$10, Incorrect guess = \$0, but it costs \$2 to play. Let  $x$  be a random variable indicating whether you guessed correctly. We can write a function:

$$h(x) = \{\$8 \text{ if } x = 1, \text{ and } -\$2 \text{ if } x = 0\}$$

- **You may be interested in knowing in advance what the expected outcome will be.**

# Expectation

- The expected value, or expectation, of a function  $h(x)$  on a random variable  $x \sim P(x)$  is the average value of  $h(x)$  weighted by  $P(x)$ . For a discrete  $x$ , we write this as:

$$\mathbb{E}[h(x)] = \sum_x P(x) \cdot h(x)$$

If  $x$  had been continuous, we would replace the summation with an integral

- The expectation acts as a weighted average over  $h(x)$ , where the weights are the probabilities of each  $x$ .

$$\begin{aligned} \text{e.g., } \mathbb{E}[h(x)] &= P(\text{winning}) \cdot h(\text{winning}) + P(\text{loosing}) \cdot h(\text{loosing}) \\ &= (1/10) \cdot \$8 + (9/10) \cdot (-\$2) = \$0.80 + (-\$1.80) \\ &= -\$1 \end{aligned}$$

On average, we'll lose \$1 every time we play!

# Expectation

- A nice property of expectations is that they're linear.
- Let's assume  $h$  and  $g$  are functions of  $x$ , and  $\alpha$  and  $\beta$  are constants. Then we have:

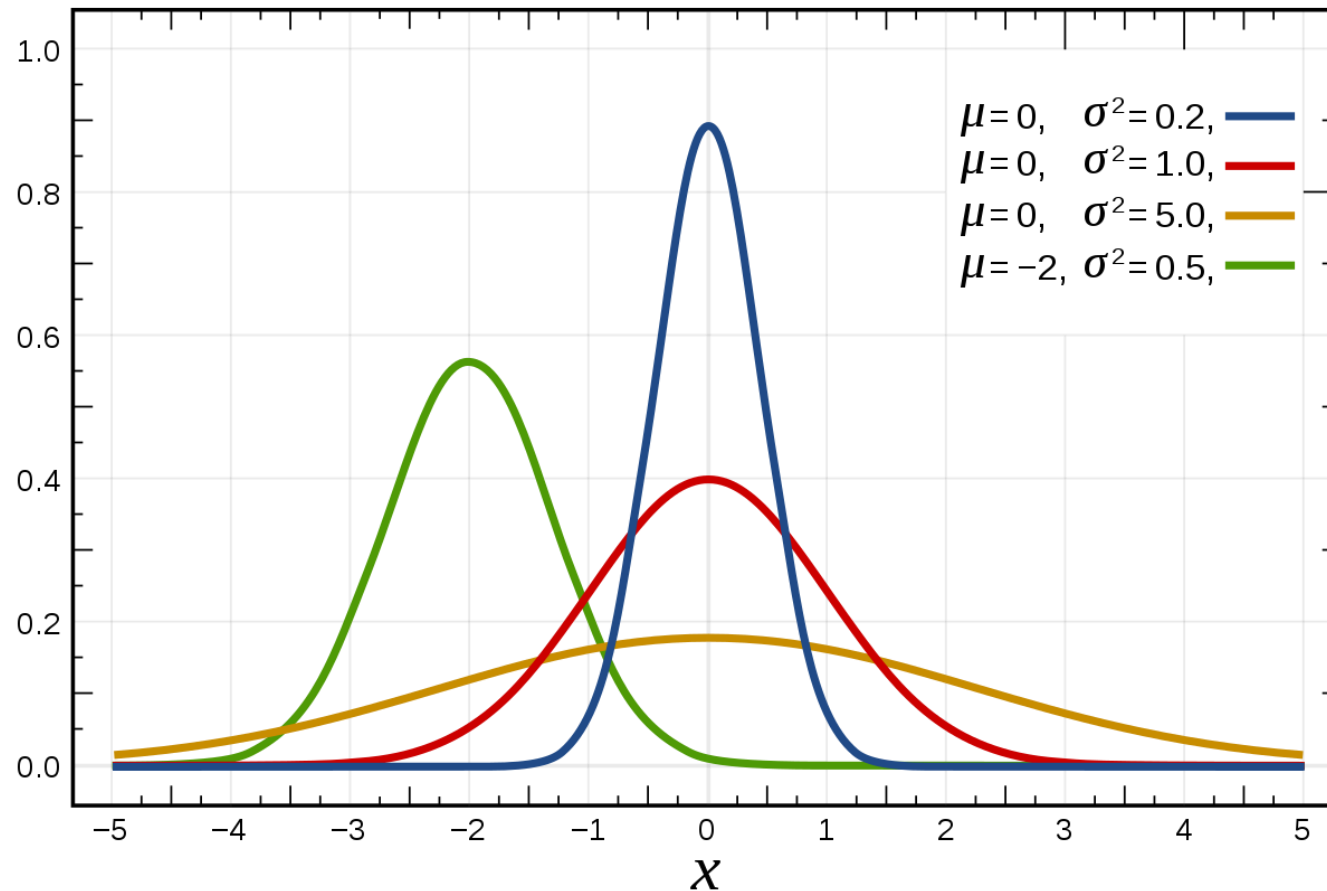
$$\mathbb{E}[\alpha h(x) + \beta g(x)] = \alpha \mathbb{E}[h(x)] + \beta \mathbb{E}[g(x)]$$

# Variance

- We saw variance with respect to a Gaussian distribution when we were talking about continuous random variables. In general, **variance is a measure of how much random values vary from their mean.**
- Similarly, for functions of random variables, the variance is a measure of the **variability of the function's output from its expected value.**

$$\text{Var}(h(x)) = \mathbb{E}[(h(x) - \mathbb{E}[h(x)])^2]$$

# Describing a Gaussian Distribution





# Multivariate Data

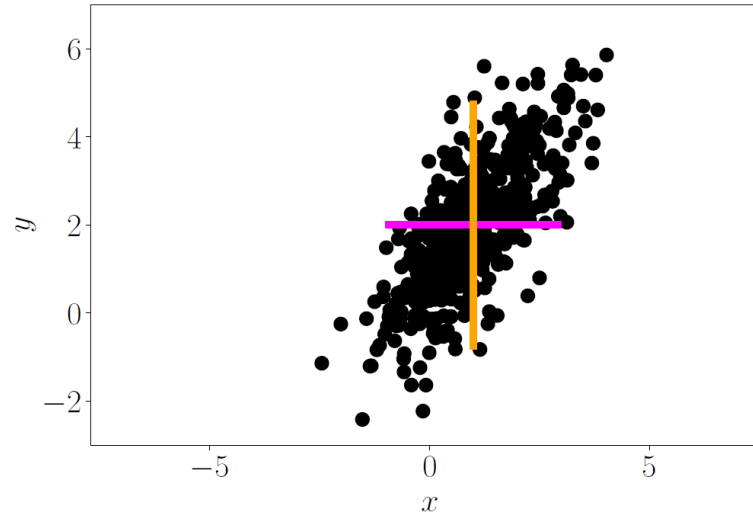
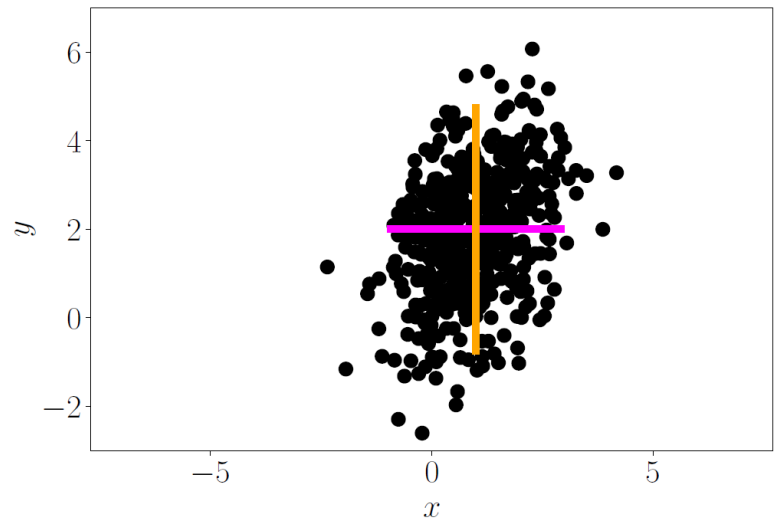
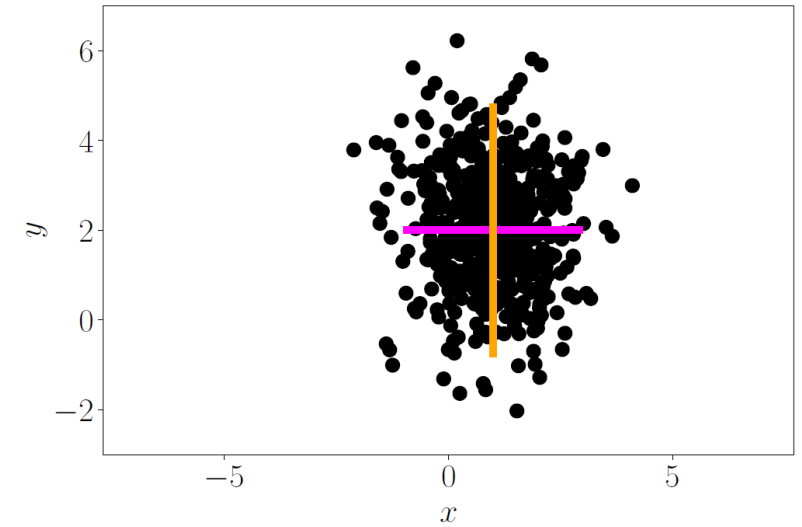
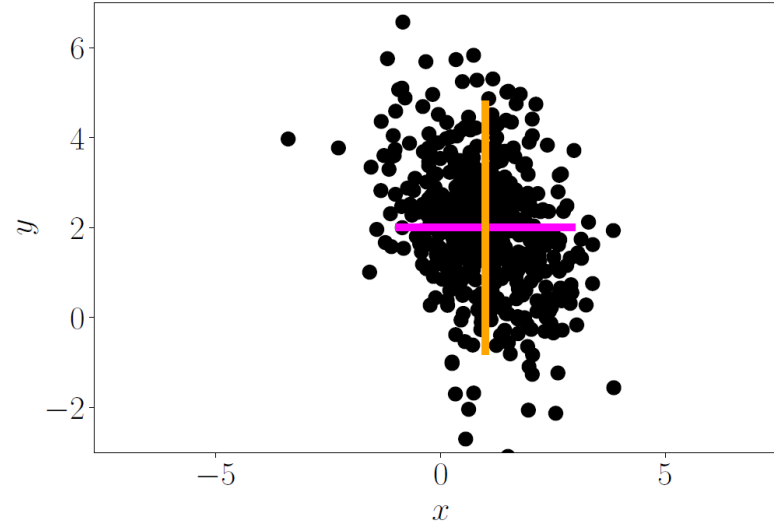
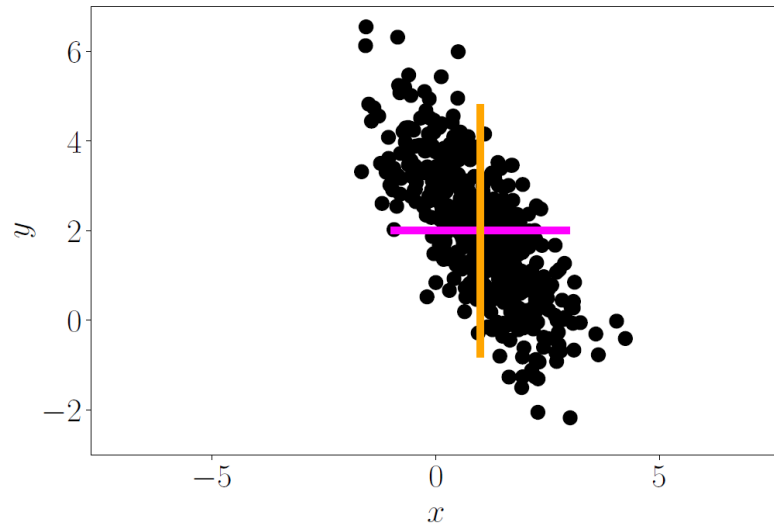
- Multiple measurements (e.g., different sensors)
- $d$  features/attributes (e.g., number of sensors)
- $N$  instances/observations/examples

$$\mathbf{X} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \dots & x_d^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{(N)} & x_2^{(N)} & \dots & x_d^{(N)} \end{bmatrix}$$

rows  $\Rightarrow$  instances

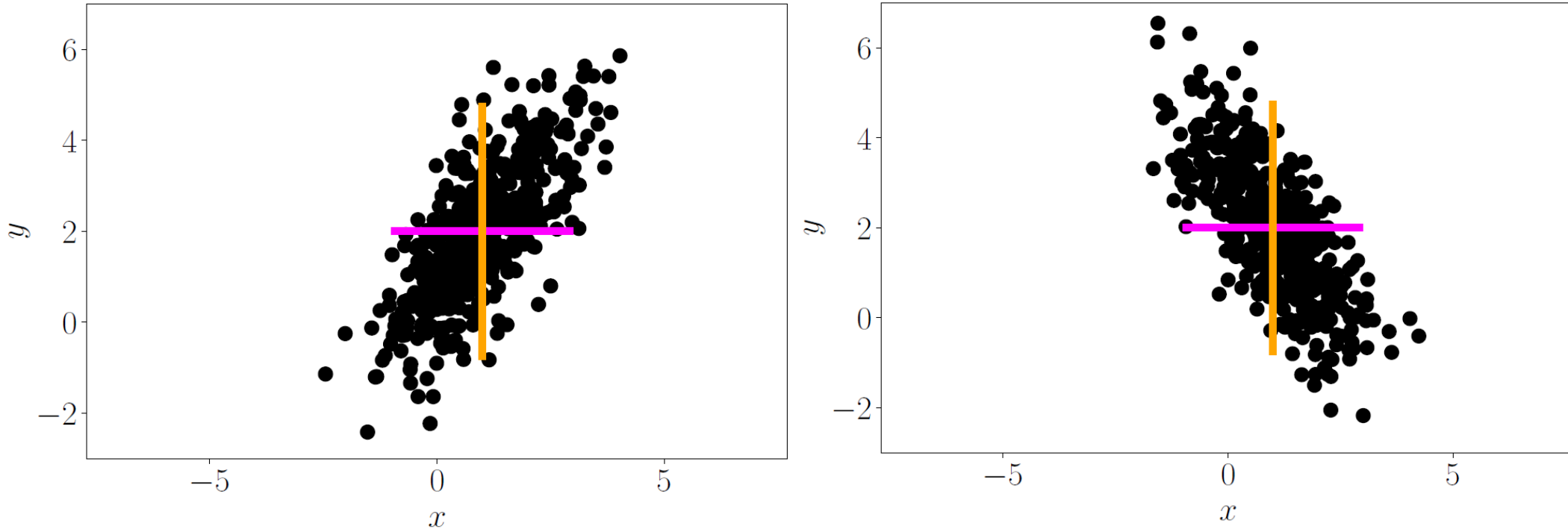
columns  $\Rightarrow$  features for a single instance

# Describing Multivariate Datasets



➤ What do all these graphs have in common?

# Covariance



- Variances along each axis remain constant, but properties of the dataset change
- Variances insufficient to characterize the relationship/correlation of two random variables -> **we need cross-variance!**

# Covariance Matrix

- **Expectation (mean):** centre of the dataset

$$\mathbb{E}[\mathbf{x}] = [\mu_1, \dots, \mu_d]^T$$

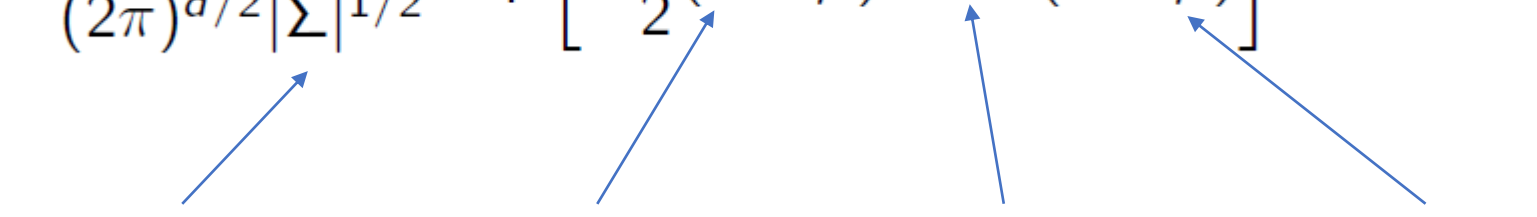
- **Covariance:** “variance” of a d-dimensional random variable is given by a covariance matrix.

$$\Sigma = \text{Cov}(\mathbf{x}) = \mathbb{E}[(\mathbf{x} - \mu)^T (\mathbf{x} - \mu)] = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1d} \\ \sigma_{12} & \sigma_2^2 & \cdots & \sigma_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{d1} & \sigma_{d2} & \cdots & \sigma_d^2 \end{bmatrix}$$



$$\text{cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

# Multivariate Gaussian Distribution

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[ -\frac{1}{2} (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu) \right]$$


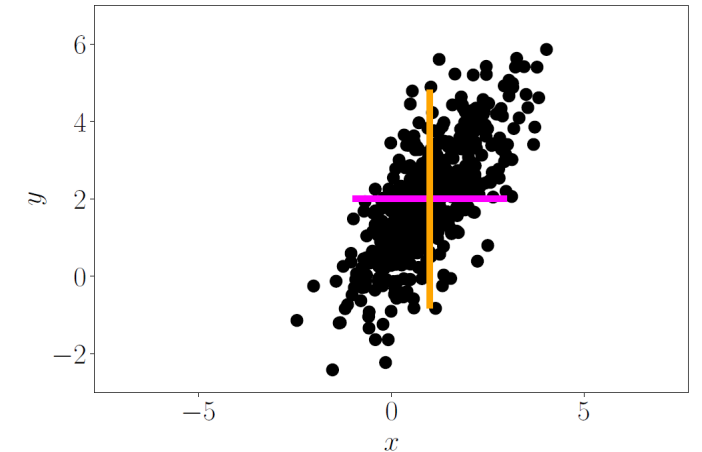
The diagram illustrates the components of the Multivariate Gaussian distribution formula. Four blue arrows point from labels below to specific parts of the equation:

- Determinant of Covariance Matrix**: Points to the term  $|\Sigma|^{1/2}$  in the denominator.
- Multivariate Sample**: Points to the term  $\mathbf{x}$  in the exponent.
- Covariance Matrix**: Points to the term  $\Sigma^{-1}$  in the exponent.
- Multivariate Mean**: Points to the term  $\mu$  in the exponent.

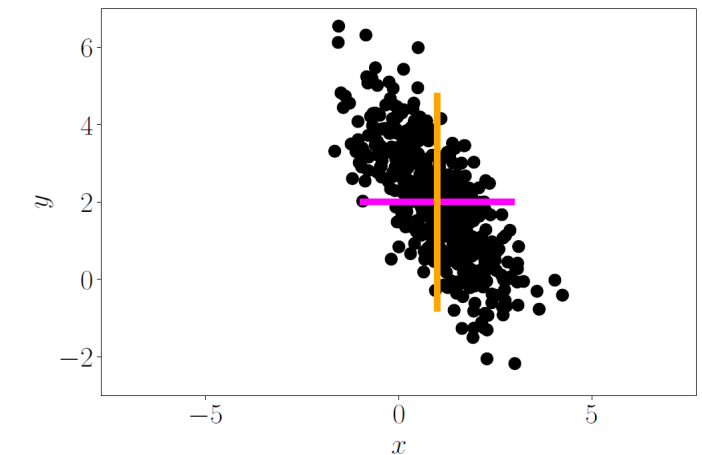
# Covariance

- When the **absolute value of covariance is high**, the two variables tend to vary far from their means at the same time.
- When the **sign of the covariance is positive**, the two functions map to higher values together.
- When the **sign of the covariance is negative**, the one function maps to higher values, the other maps to lower values (or vice versa)

Positive Covariance



Negative Covariance



# Bivariate Normal

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$\Sigma = 0.5 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$\Sigma = 2 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

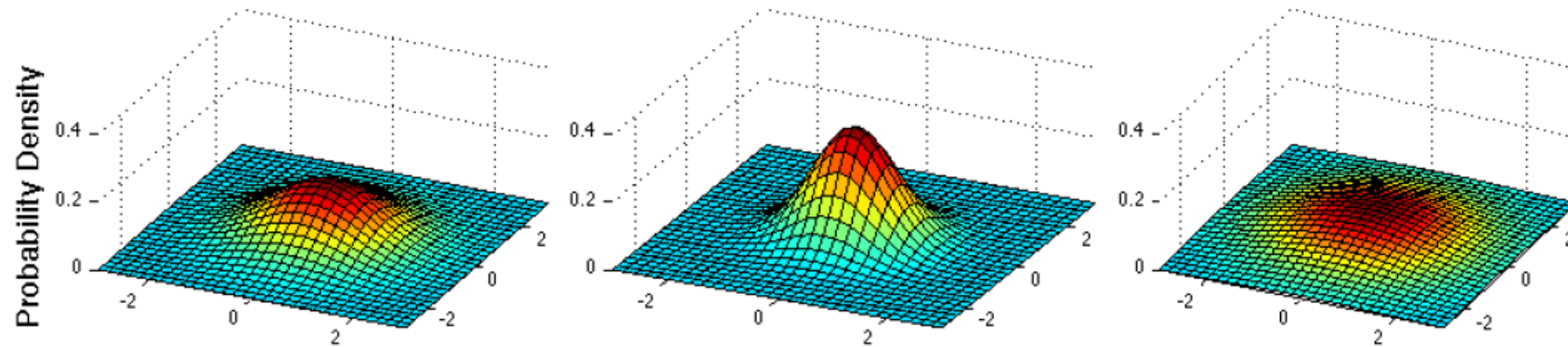


Figure: Probability density function

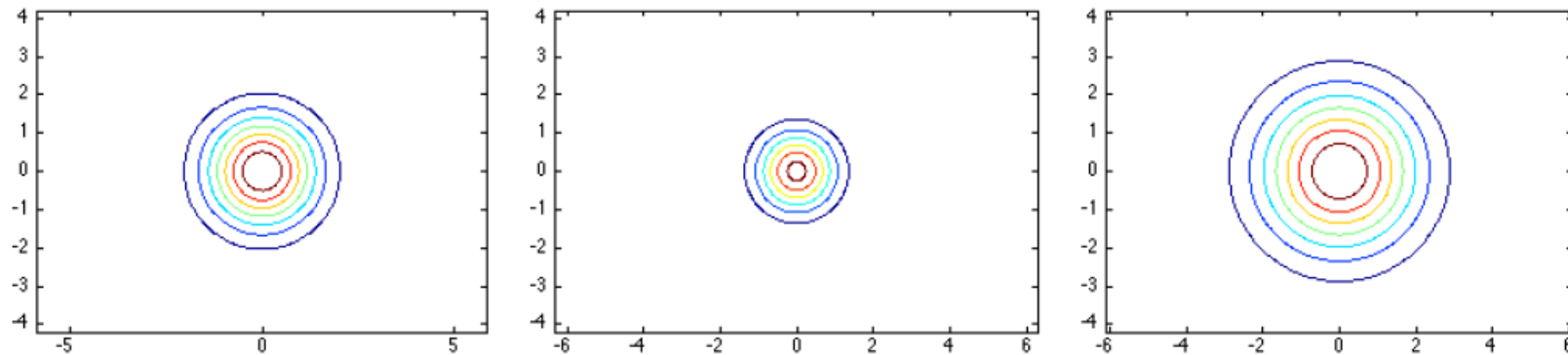


Figure: Contour plot of the pdf

# Bivariate Normal

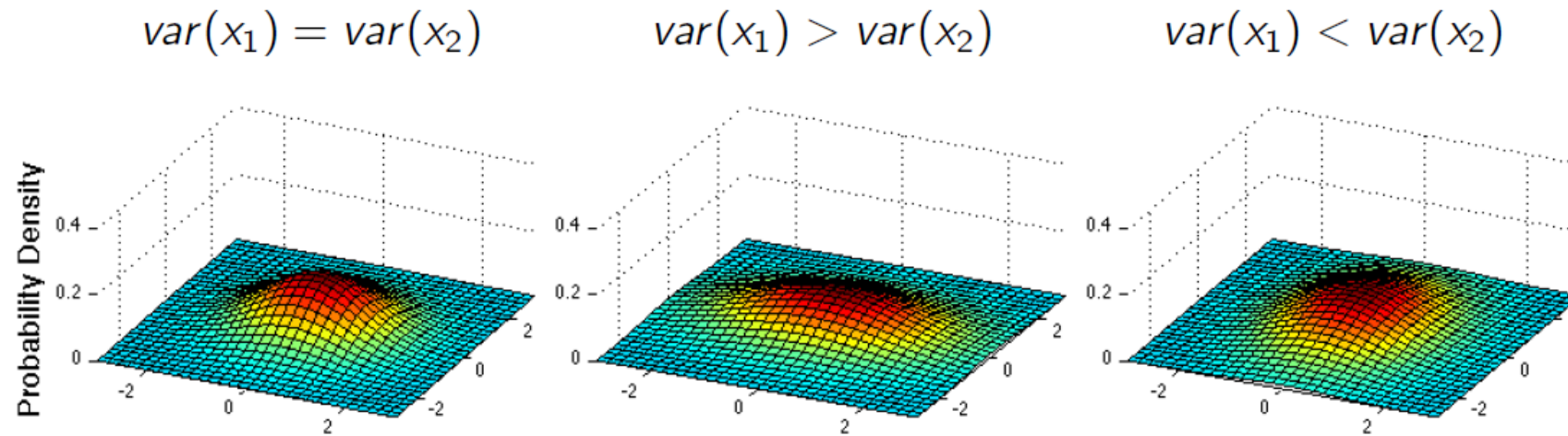


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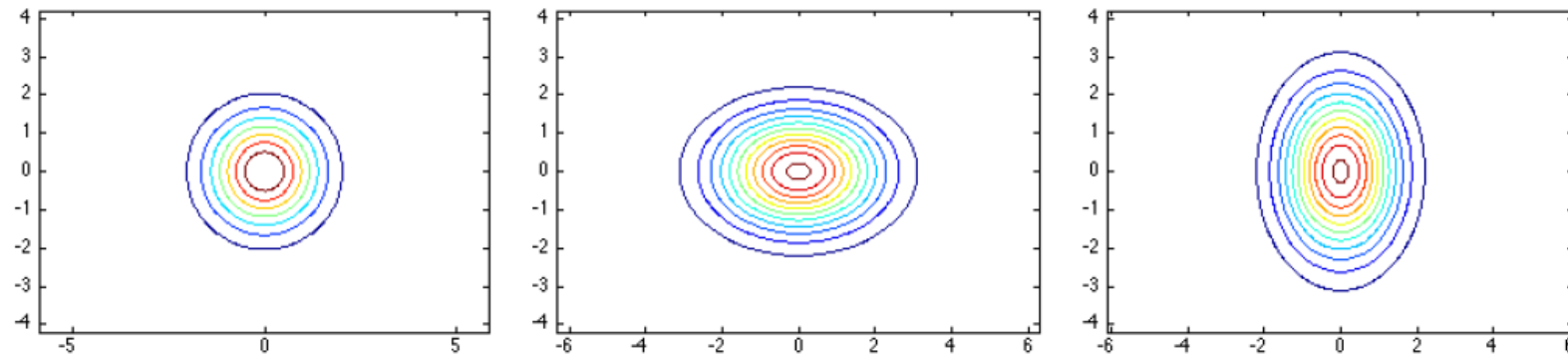
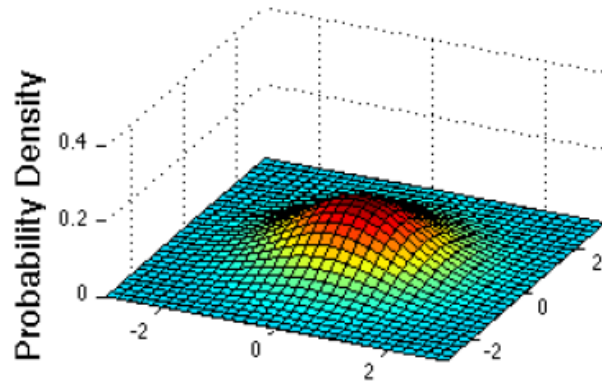


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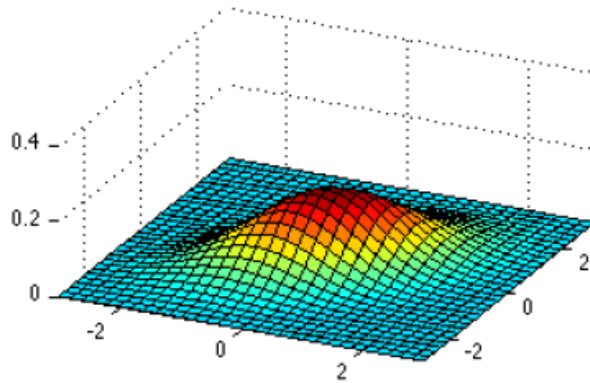


# Bivariate Normal

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$



$$\Sigma = \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix}$$



$$\Sigma = \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}$$

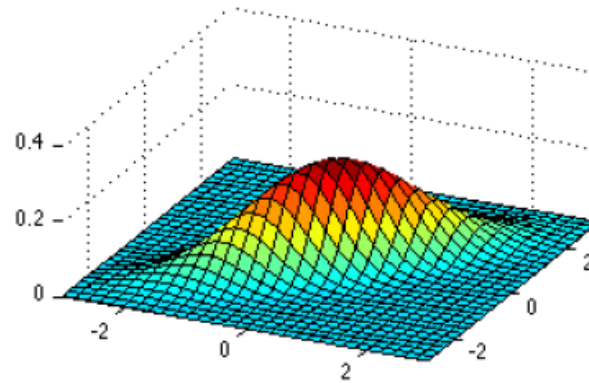


Figure: Probability density function

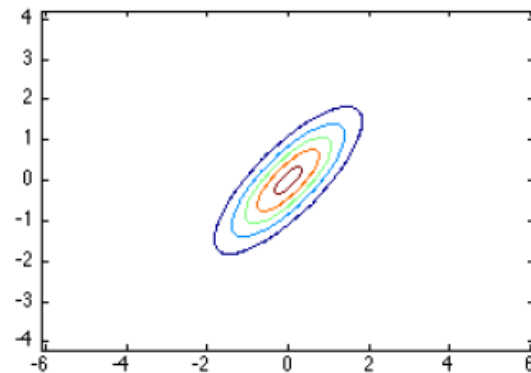
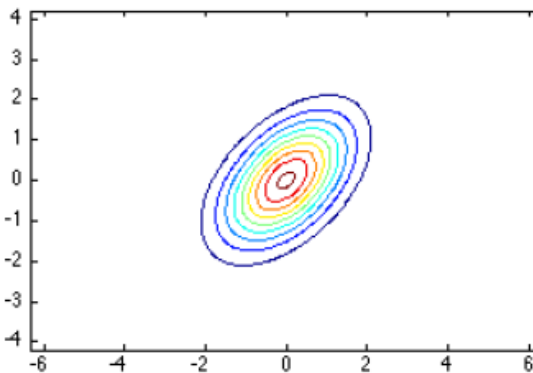
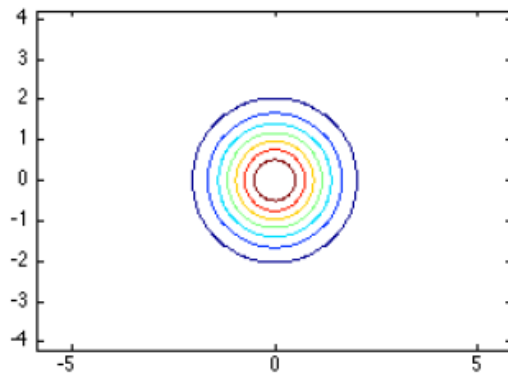


Figure: Contour plot of the pdf

# Bivariate Normal

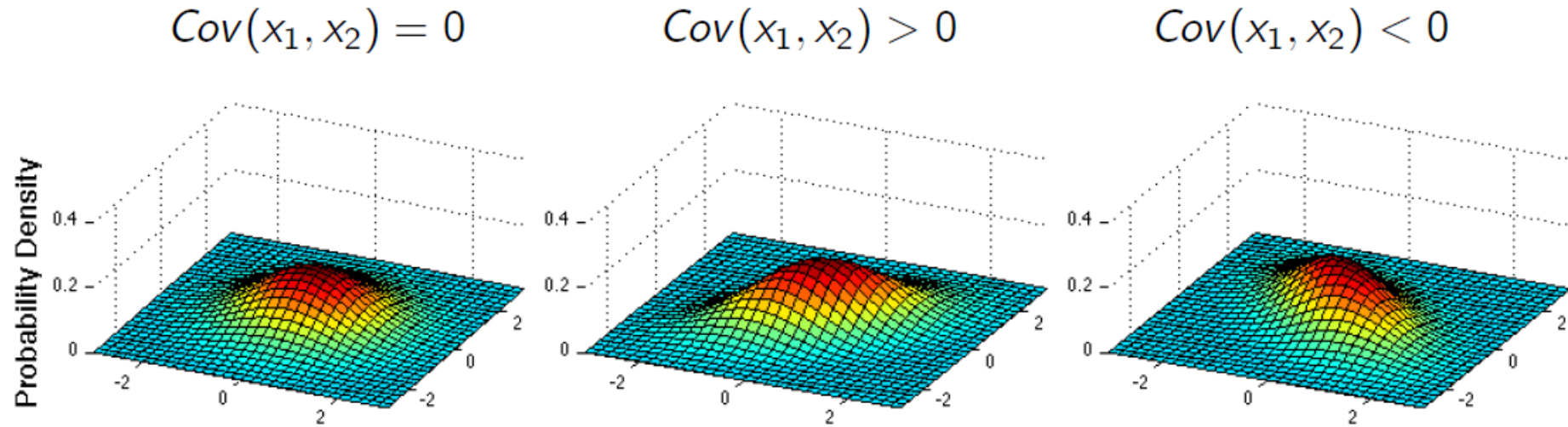


Figure: Probability density function

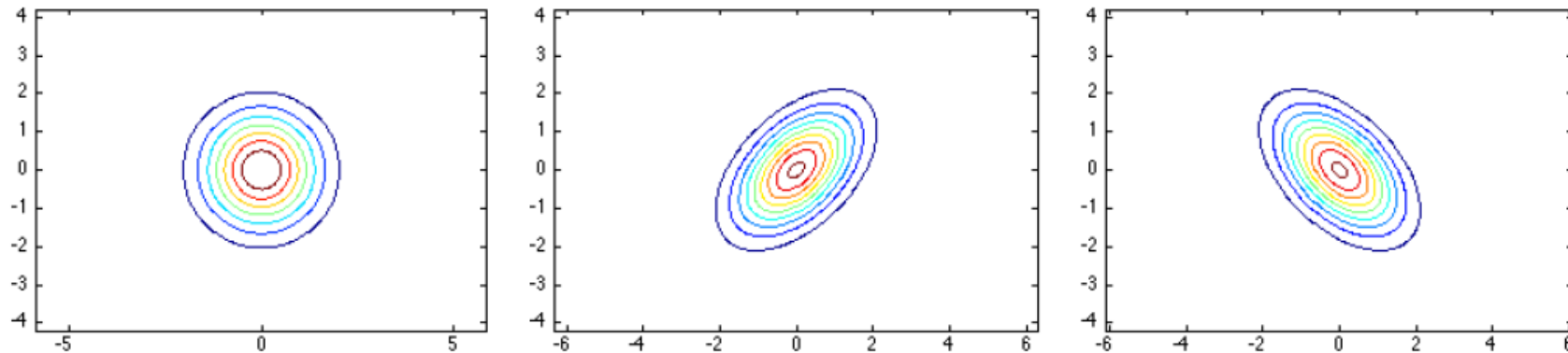
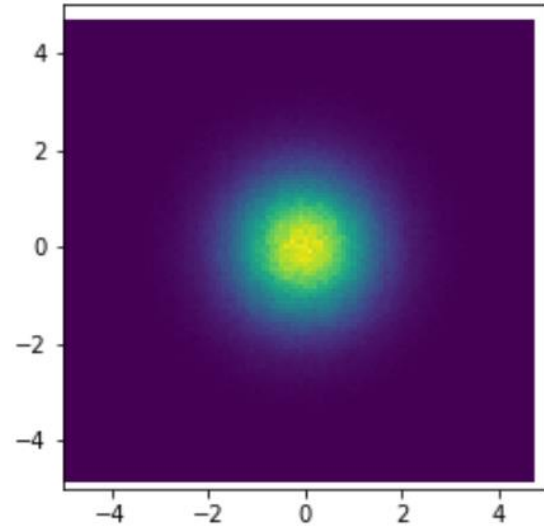
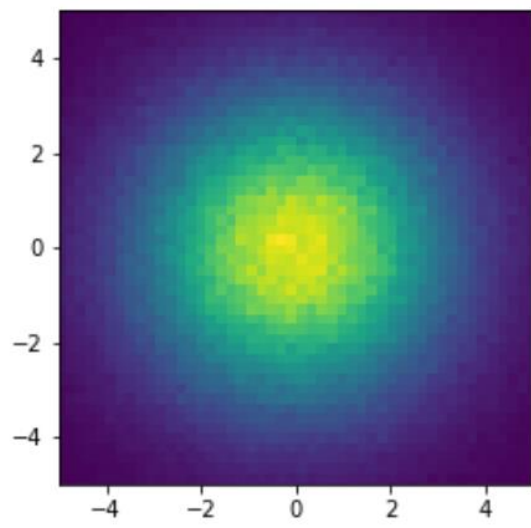


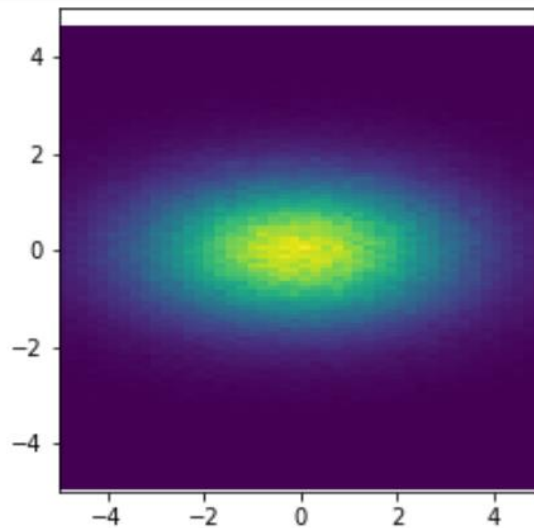
Figure: Contour plot of the pdf



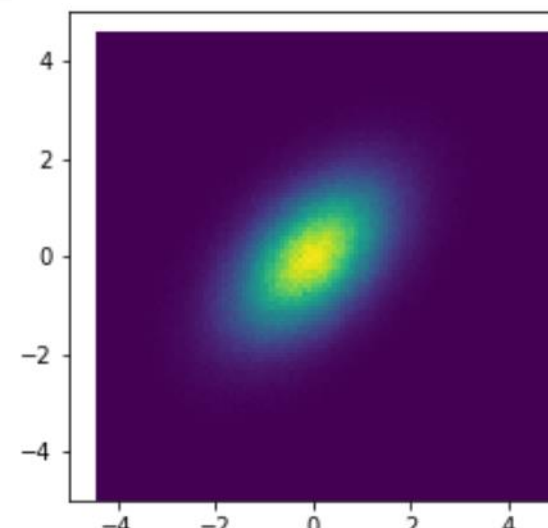
[[1 0]  
[0 1]]  
0.0



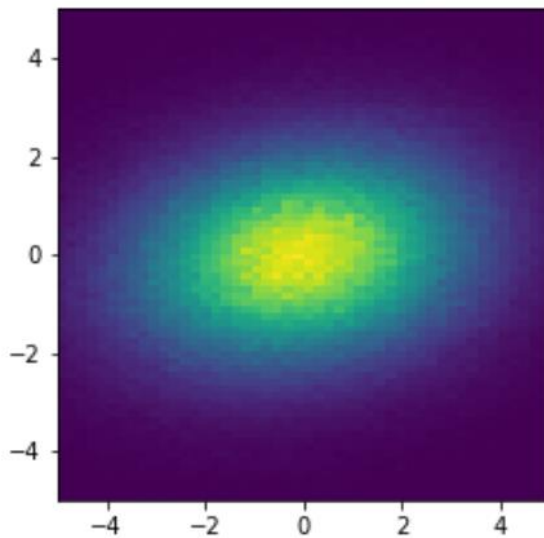
[[5 0]  
[0 5]]  
0.0



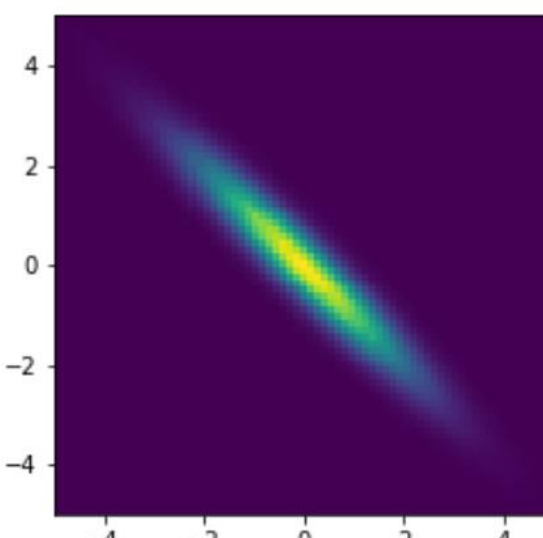
[[5 0]  
[0 1]]  
0.0



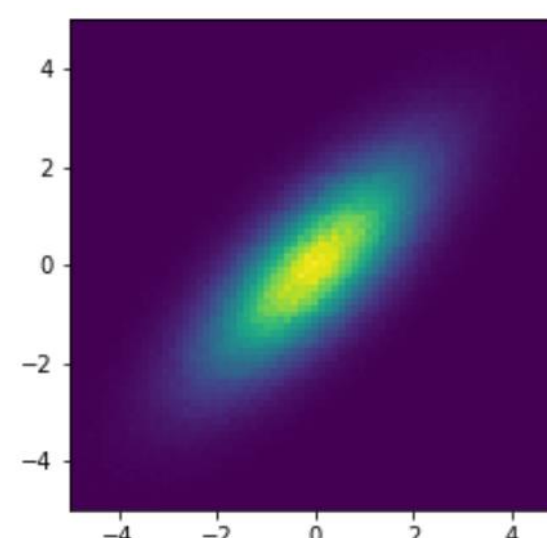
[[1. 0.5]  
[0.5 1. ]]  
0.5



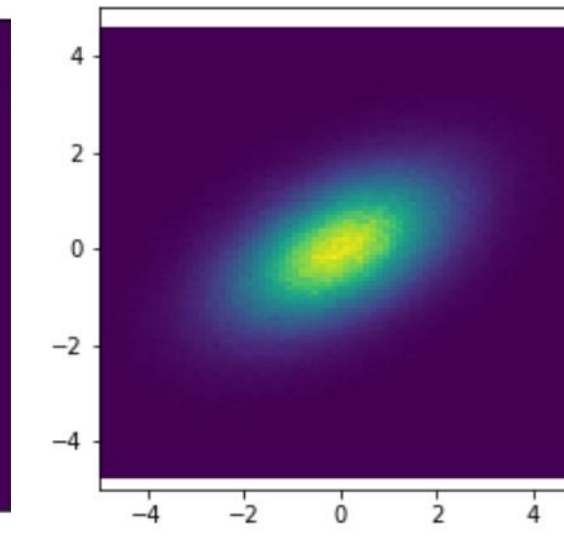
[[5. 0.5]  
[0.5 2. ]]  
0.15811388300841897



[[ 2. -1.9]  
[-1.9 2. ]]  
-0.9499999999999997



[[2. 1.5]  
[1.5 2. ]]  
0.7499999999999999



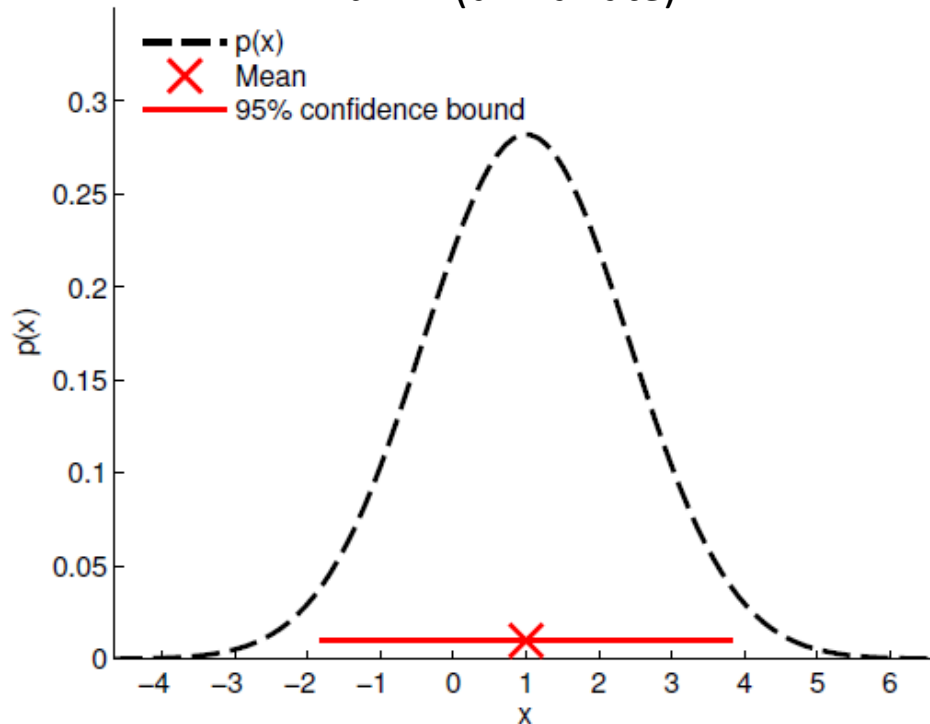
[[2. 0.7]  
[0.7 1. ]]  
0.4949747468305832

# Confidence Intervals

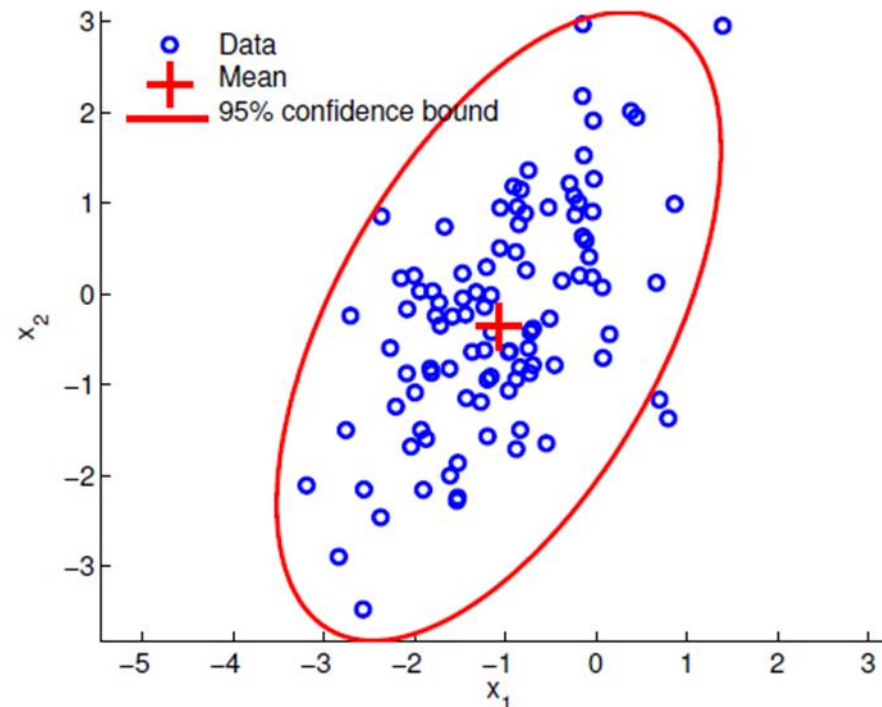
$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[ -\frac{1}{2} (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu) \right]$$

- ▶ Mean vector  $\mu$  ► Average of the data
- ▶ Covariance matrix  $\Sigma$  ► Spread of the data

$d = 1$  (univariate)



$d = 2$  (bivariate)



# Example: Calculate the Covariance Matrix

Joint Probability $P(X_1, X_2)$		$X_2$		$P(X_1)$
		0	1	
$X_1$	-1	0.24	0.06	0.3
	0	0.16	0.14	0.3
	1	0.40	0	0.4
$P(X_2)$		0.8	0.2	1

compute the mean

$$\vec{\Sigma} = \begin{bmatrix} E_x(X_1 - \mu_1)^2 & E_x(X_1 - \mu_1)(X_2 - \mu_2) \\ E_x(X_2 - \mu_2)(X_1 - \mu_1) & E_x(X_2 - \mu_2)^2 \end{bmatrix}$$

$$\mu_1 = E_x(X_1) = \sum_{all X_1} x_1 p_1(x_1)$$

$$(-1)(0.3) + (0)(0.3) + (1)(0.4) = \mathbf{0.1}$$

$$\mu_2 = E_x(X_2) = \sum_{all X_2} x_2 p_2(x_2)$$

$$(0)(0.8) + (1)(0.2) = \mathbf{0.2}$$

# Example: Calculate the Covariance Matrix

Joint Probability $P(X_1, X_2)$		$X_2$		$P(X_1)$
		0	1	
$X_1$	-1	0.24	0.06	0.3
	0	0.16	0.14	0.3
	1	0.40	0	0.4
$P(X_2)$		0.8	0.2	1

compute the covariance

$$\vec{\Sigma} = \begin{bmatrix} E_x(X_1 - \mu_1)^2 & E_x(X_1 - \mu_1)(X_2 - \mu_2) \\ E_x(X_2 - \mu_2)(X_1 - \mu_1) & E_x(X_2 - \mu_2)^2 \end{bmatrix}$$

$$\sigma_{11} = E_x(X_1 - \mu_1)^2 = \sum_{all\ X_1} (X_1 - 0.1)^2 p_1(X_1)$$

$$(-1-0.1)^2(0.3) + (0-0.1)^2(0.3) + (1-0.1)^2(0.4) = \mathbf{0.69}$$

$$\sigma_{22} = E_x(X_2 - \mu_2)^2 = \sum_{all\ X_2} (X_2 - 0.2)^2 p_2(X_2)$$

$$(0-0.2)^2(0.8) + (1-0.2)^2(0.2) = \mathbf{0.16}$$

$$\sigma_{12} = E_x(X_1 - \mu_1)(X_2 - \mu_2)$$

$$= \sum_{all\ pairs} (X_1 - 0.1)(X_2 - 0.2)p_{12}(X_1, X_2)$$

$$(-1-0.1)(0-0.2)(0.24) + (-1-0.1)(1-0.2)(0.06) + (0-0.1)(0-0.2)(0.16)$$

$$+ (0-0.1)(1-0.2)(0.14) + (1-0.1)(0-0.2)(0.40) + (1-0.1)(1-0.2)(0) = \mathbf{-0.08}$$

# Example: Calculate the Covariance Matrix

Joint Probability $P(X_1, X_2)$		$X_2$		$P(X_1)$
		0	1	
$X_1$	-1	0.24	0.06	0.3
	0	0.16	0.14	0.3
	1	0.40	0	0.4
$P(X_2)$		0.8	0.2	1

$$\vec{\Sigma} = \begin{bmatrix} E_x(X_1 - \mu_1)^2 & E_x(X_1 - \mu_1)(X_2 - \mu_2) \\ E_x(X_2 - \mu_2)(X_1 - \mu_1) & E_x(X_2 - \mu_2)^2 \end{bmatrix}$$

putting it all together

$$\vec{\Sigma} = \begin{bmatrix} 0.69 & -0.08 \\ -0.08 & 0.16 \end{bmatrix}$$

**Covariance matrix**

# Example: Calculate the Covariance Matrix

Joint Probability $P(X_1, X_2)$		$X_2$		$P(X_1)$
		0	1	
$X_1$	-1	0.24	0.06	0.3
	0	0.16	0.14	0.3
	1	0.40	0	0.4
$P(X_2)$		0.8	0.2	1

$$\vec{\Sigma} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} = \begin{bmatrix} 0.69 & -0.08 \\ -0.08 & 0.16 \end{bmatrix}$$

Covariance matrix



$$\rho_{ik} = \frac{\sigma_{ik}}{\sqrt{\sigma_{ii}}\sqrt{\sigma_{kk}}}$$

$$\rho_{12} = \frac{\sigma_{12}}{\sqrt{\sigma_{11}}\sqrt{\sigma_{22}}} = -0.24$$

Population correlation coefficient

➤ **Normalizing the covariance matrix** will give you the population correlation coefficient, a measure of how correlated two variables are.



# Example: Visualization

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[ -\frac{1}{2} (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu) \right]$$

Determinant of  
Covariance Matrix

Multivariate  
Sample

Covariance Matrix

Multivariate  
Mean

$$\vec{\mu} = \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$\vec{\Sigma} = \begin{bmatrix} 0.69 & -0.08 \\ -0.08 & 0.16 \end{bmatrix}$$

$$|\Sigma| = 0.104$$

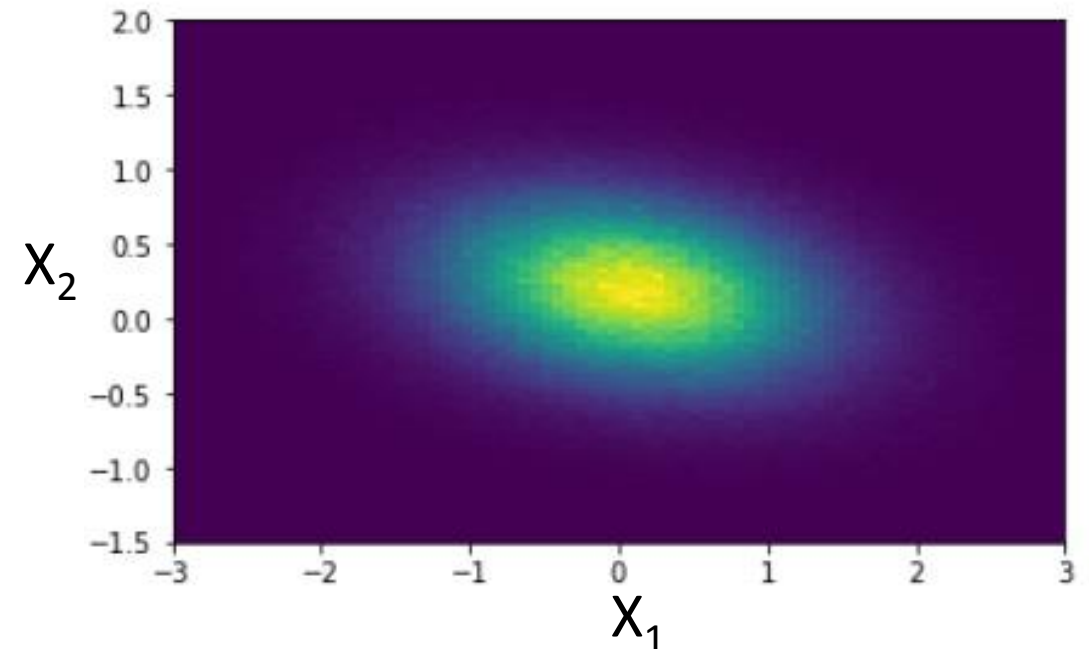
Determinant Calculation  
(bivariate example)

$$\vec{\Sigma} = \begin{bmatrix} 0.69 & -0.08 \\ -0.08 & 0.16 \end{bmatrix}$$

$$(0.69 * 0.16) - (-0.08 * -0.08)$$

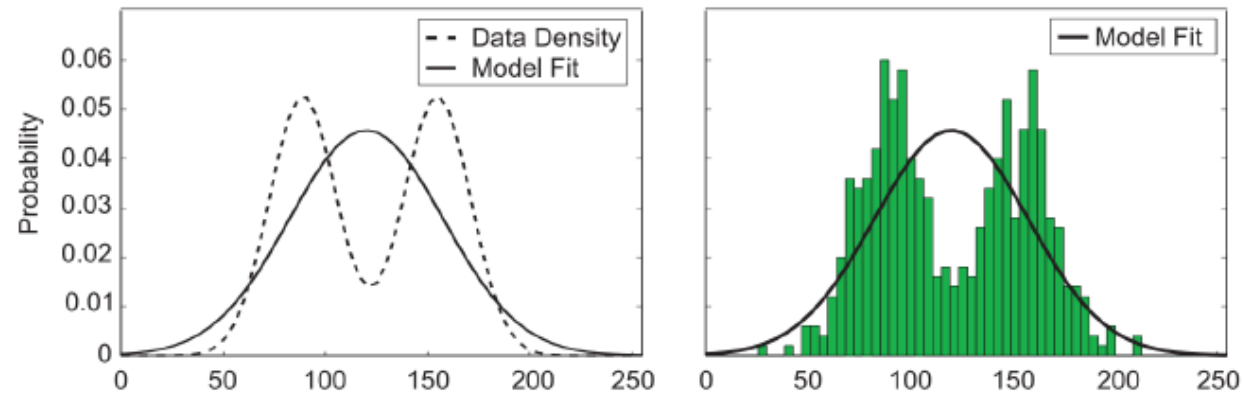
Determinant will be covered in week 7

**Bivariate Gaussian Example** (See Sample Code)

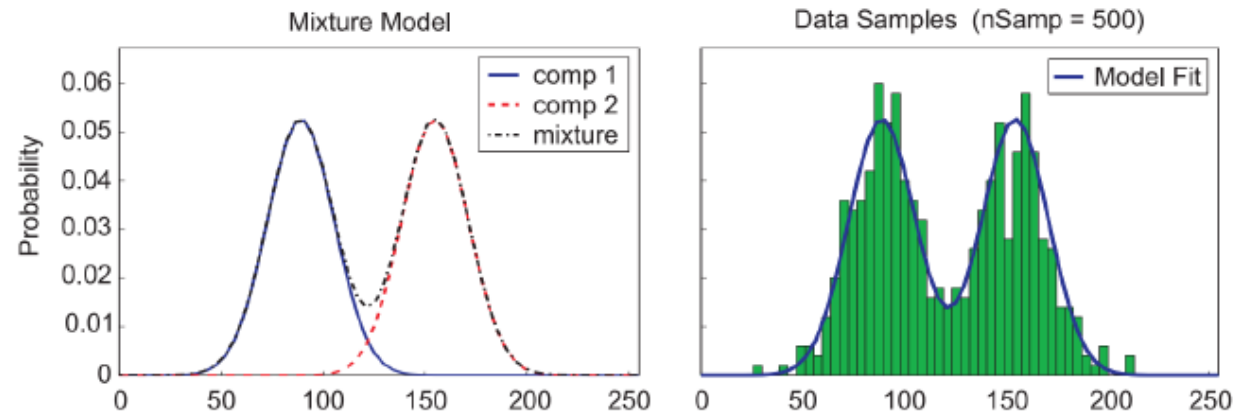


# Gaussian Mixture Models (GMM)

- If you fit a Gaussian to data:

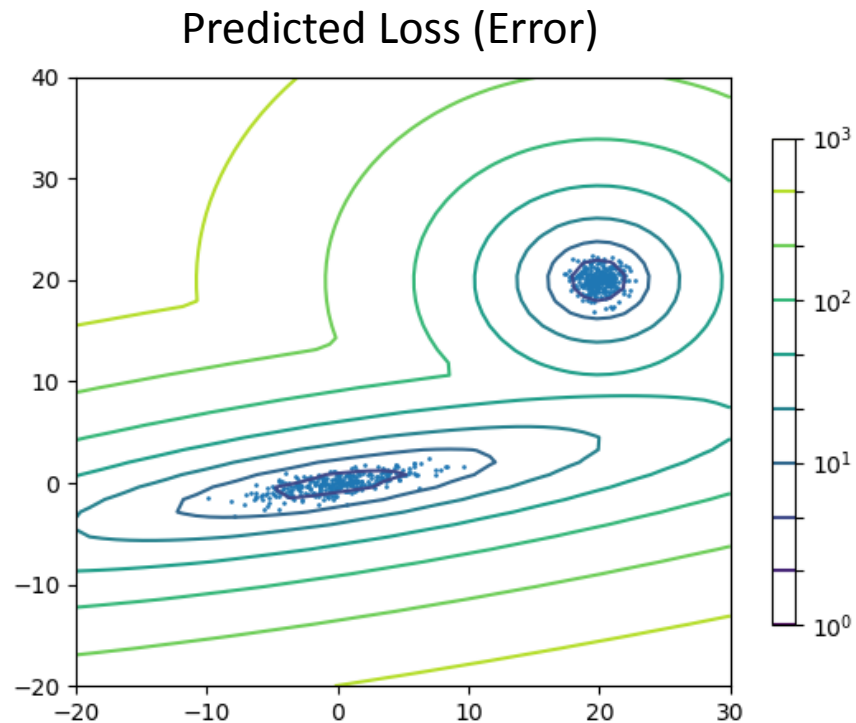


- Now, we are trying to fit a GMM (with  $K = 2$  in this example):



[Slide credit: K. Kutulakos]

# Gaussian Mixture Models (GMM)



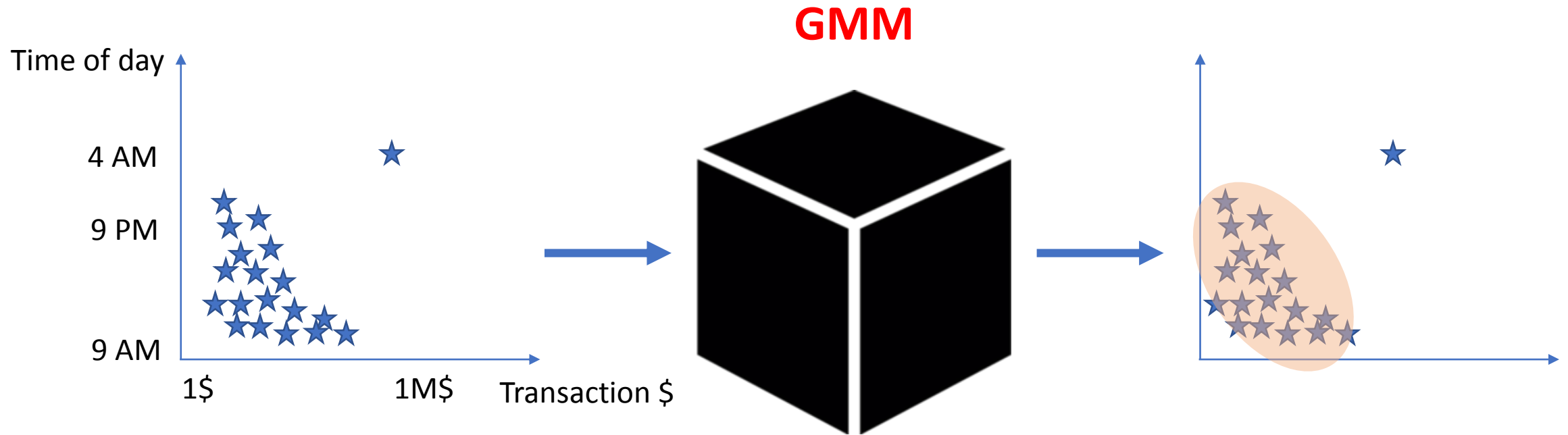
Source: [Scikit-learn](https://scikit-learn.org/)

- Can be extended to multivariate data (e.g., bivariate GMM)

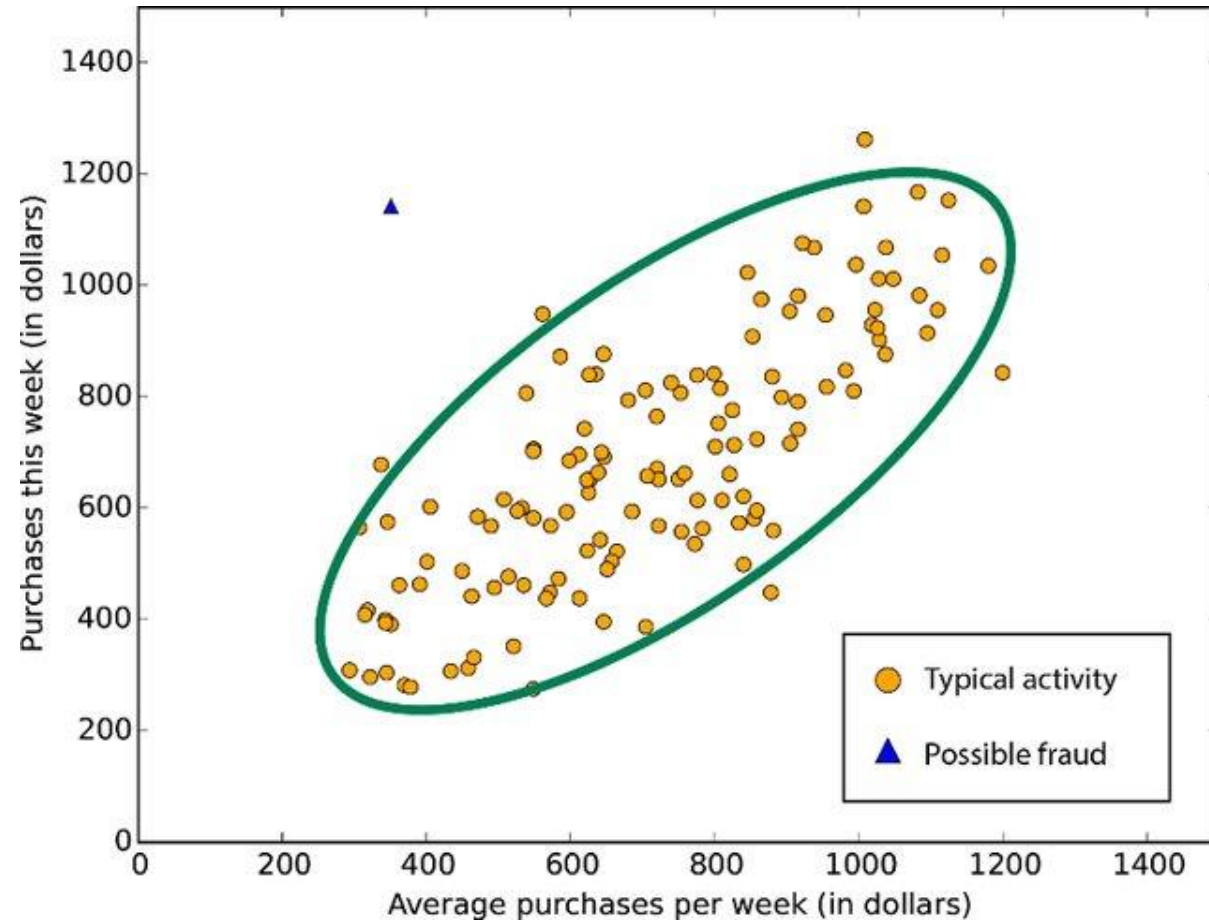
# Google Colab (Code Example)

# Anomaly Detection (Semi-Supervised)

# What is the goal?



# Outlier



# Performance Metrics



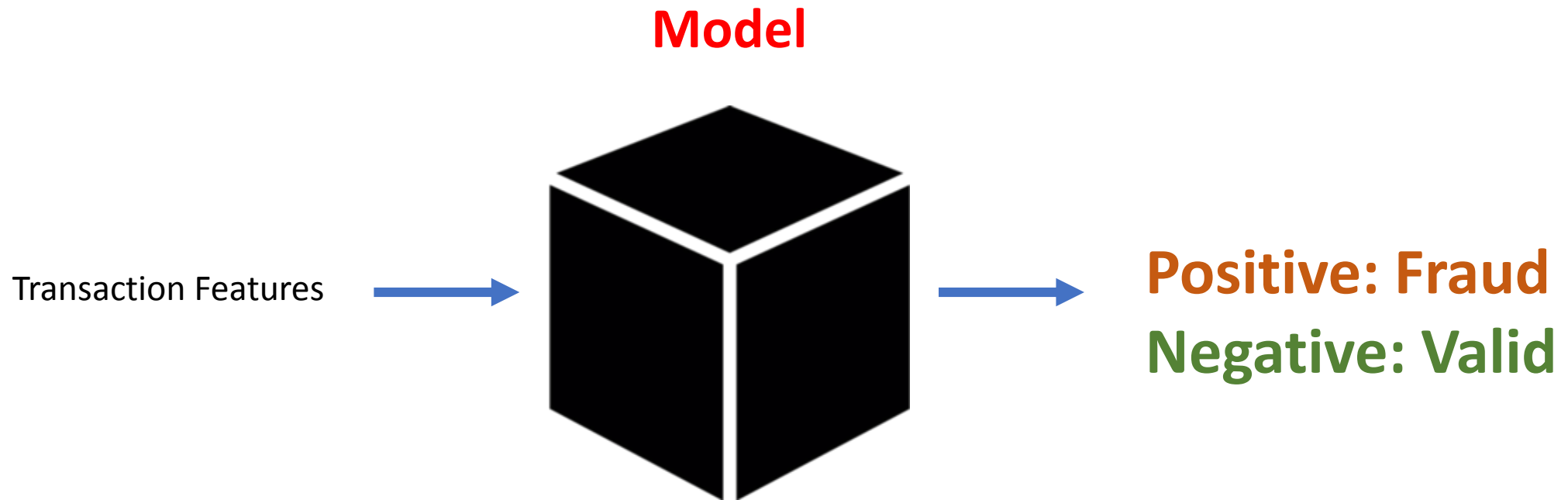
# Why Performance?

- Q: Why do we care about performance?
- Identifying how well our models are doing is not trivial. Easy to fall into the trap of believing (or wanting to believe) our models are working based on weak assessment.

# How to measure the performance of a model?

- Assume a case where we want to detect outliers and we know:
  - Dataset has 100 points
  - 98 are non-outlier
  - 2 are outliers
- If we detect all the points as non-outliers:
  - $98 \text{ True predictions} / 100 = \mathbf{98\% \text{ accuracy}}$  for a model that is not working
- Q: How can we improve our performance measurements?

# Fraud Detection System



# Fraud Detection System

(Positive = **Fraud**)


- If transaction is **Valid**:
  - Prediction : **Valid** (True Negative) 😊
  - Prediction : **Fraud** (False Positive) ☹️
- If transaction is **Fraud**:
  - Prediction : **Fraud** (True Positive) 😊
  - Prediction : **Valid** (False Negative) ☹️

# Precision and Recall

- If transaction is **Valid**:
  - Prediction : **Valid** (True Negative) **OK!**
  - Prediction : **Fraud** (False Positive) **Not that bad!**
- If transaction is **Fraud**:
  - Prediction : **Fraud** (True Positive) **GOOD!**
  - Prediction : **Valid** (False Negative) **Super BAD!**


How many selected items are relevant?

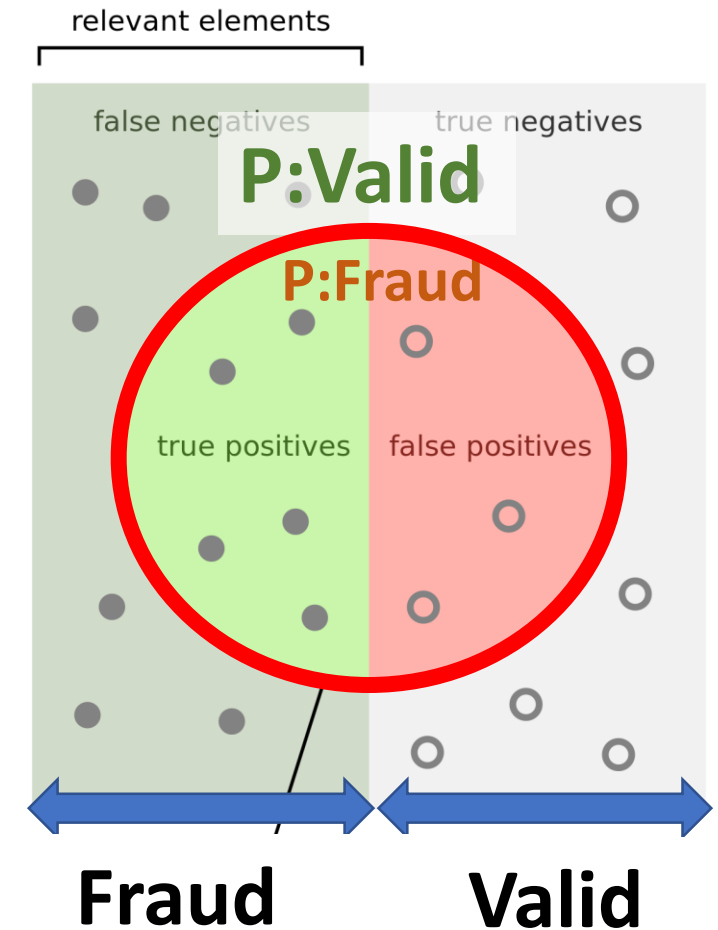
(MISTAKE) Precision =  $\frac{\text{TP}}{\text{TP} + \text{FP}}$



How many relevant items are selected?

Recall =  $\frac{\text{TP}}{\text{TP} + \text{FN}}$  (MISS)





# Confusion Matrix

		Actual Value (as confirmed by experiments)	
		positives	negatives
Predicted Value (predicted by the test)	positives	<b>TP</b> True Positive	<b>FP</b> False Positive
	negatives	<b>FN</b> False Negative	<b>TN</b> True Negative

- Table used to describe prediction performance on a set of test data

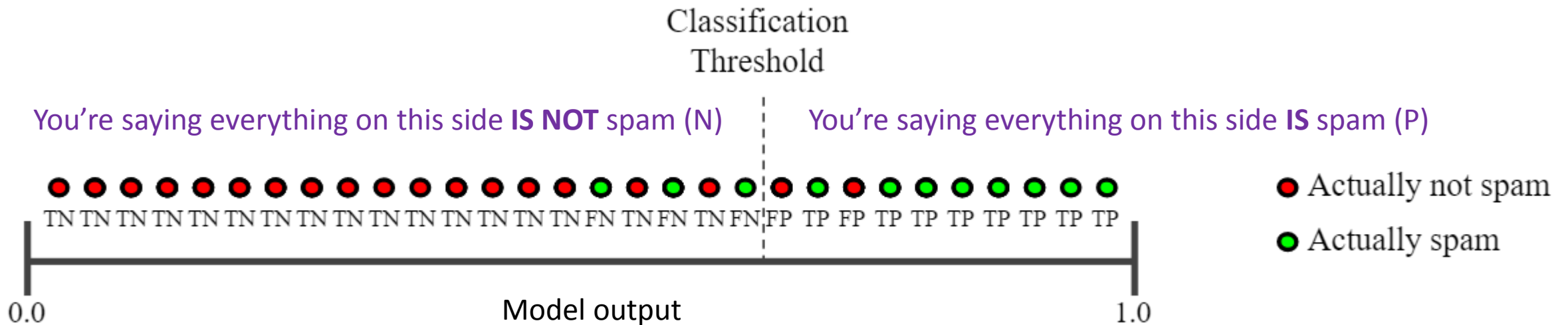
# F<sub>1</sub> score

$$F_1 = 2 * \frac{\textit{precision} * \textit{recall}}{\textit{precision} + \textit{recall}}$$

- A balanced measure of accuracy giving equal importance to recall and precision
- The highest possible value of F<sub>1</sub> is 1, and lowest possible value is 0

# Precision and Recall – tug of war

- Application – spam detection
- Improving precision usually reduces recall, vice-versa



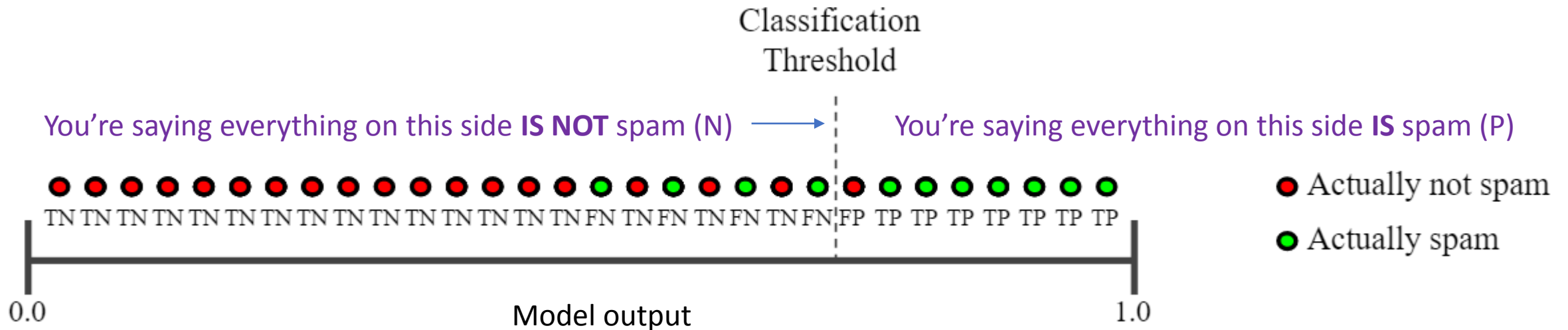
What is the **precision** (emails flagged as spam)?  $tp/(tp+fp) = 8/(8+2) = 0.8$

What is the **recall** (actual spam correctly classified)?  $tp/(tp+fn) = 8/(8+3) = 0.73$



# Precision and Recall – tug of war

- Application – spam detection
- Improving precision usually reduces recall, vice-versa

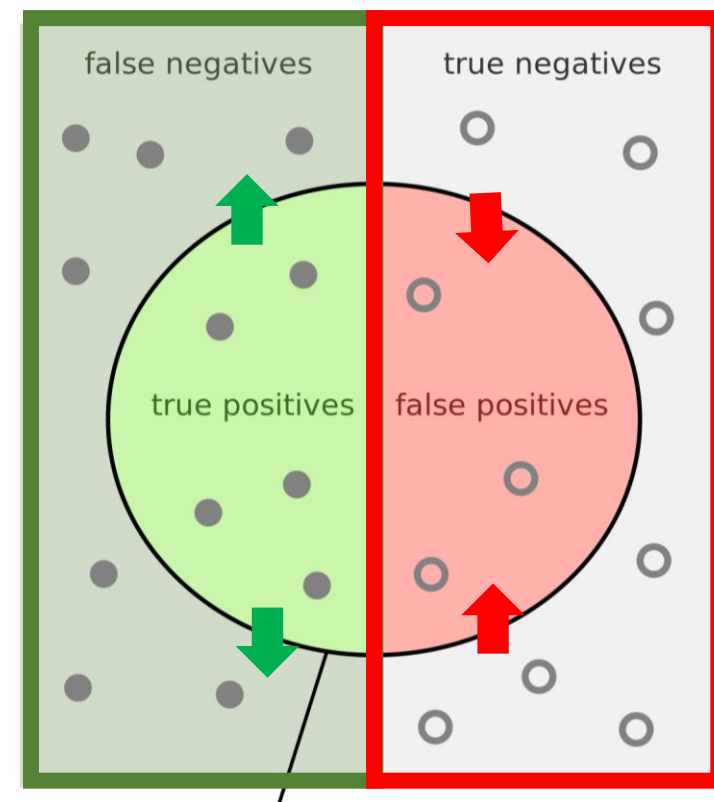
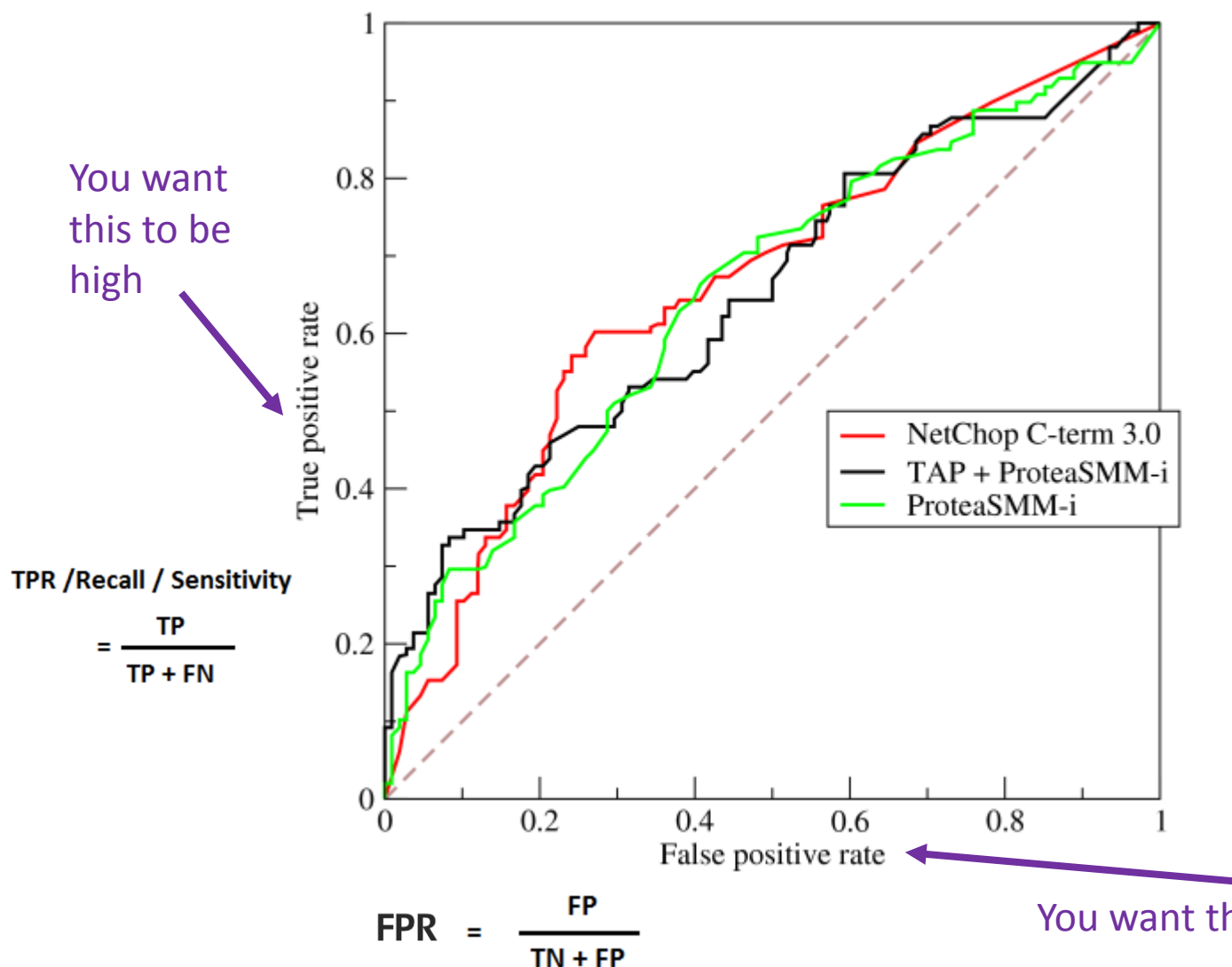


What is the **precision** (emails flagged as spam)?  $tp/(tp+fp) = 7/(7+1) = 0.88$

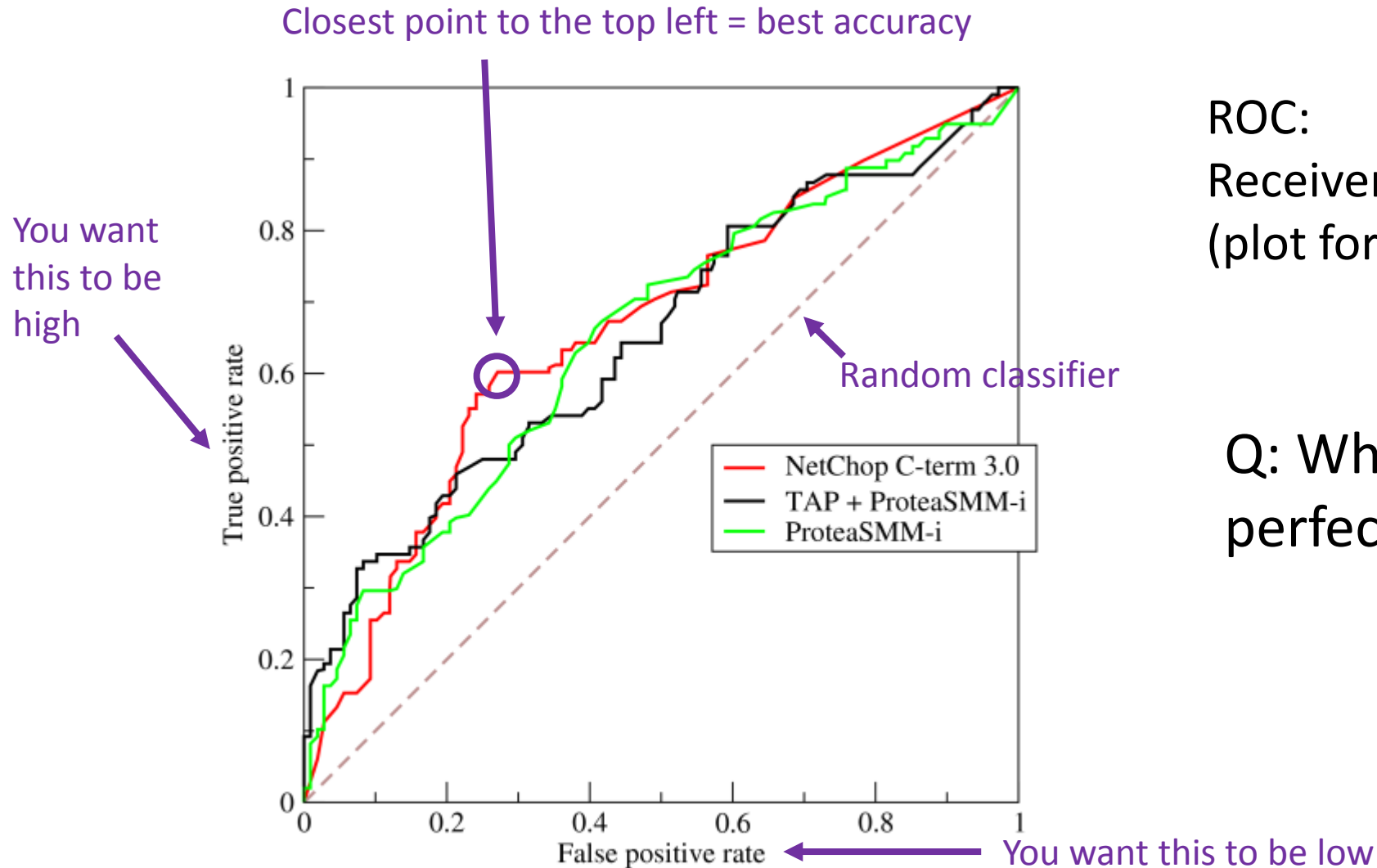
What is the **recall** (actual spam correctly classified)?  $tp/(tp+fn) = 7/(7+4) = 0.64$

how do we  
choose a  
threshold?

# ROC (Receiver Operating Characteristic) Curve



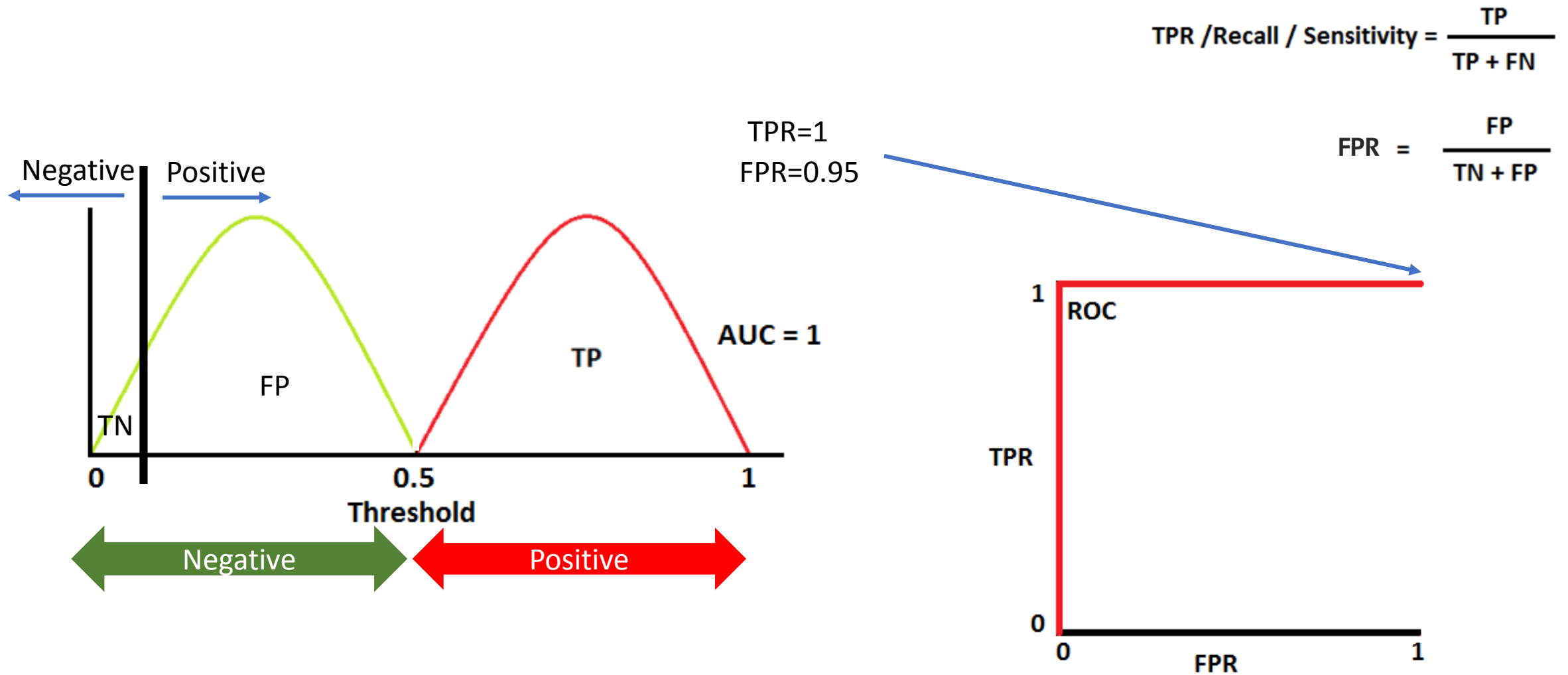
# ROC Curve



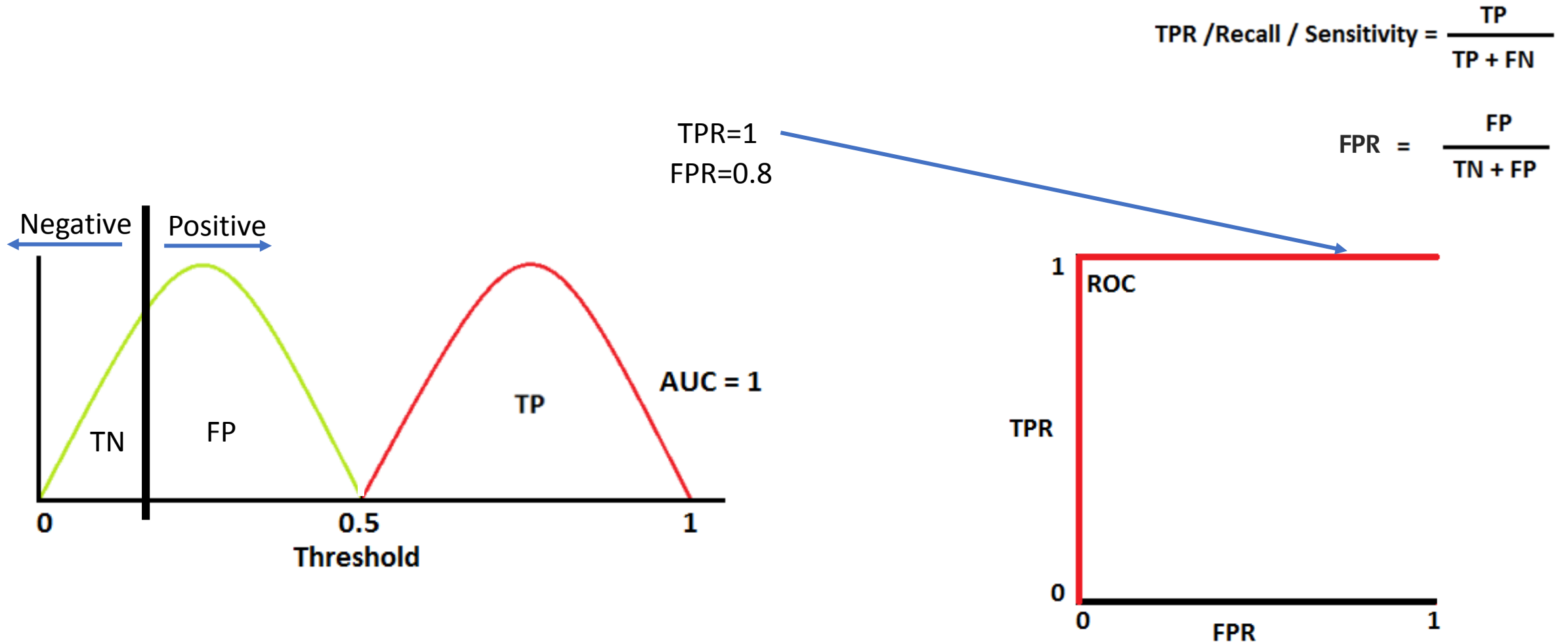
ROC:  
Receiver Operating Characteristic  
(plot for binary classifiers)

Q: What would be a  
perfect classifier?

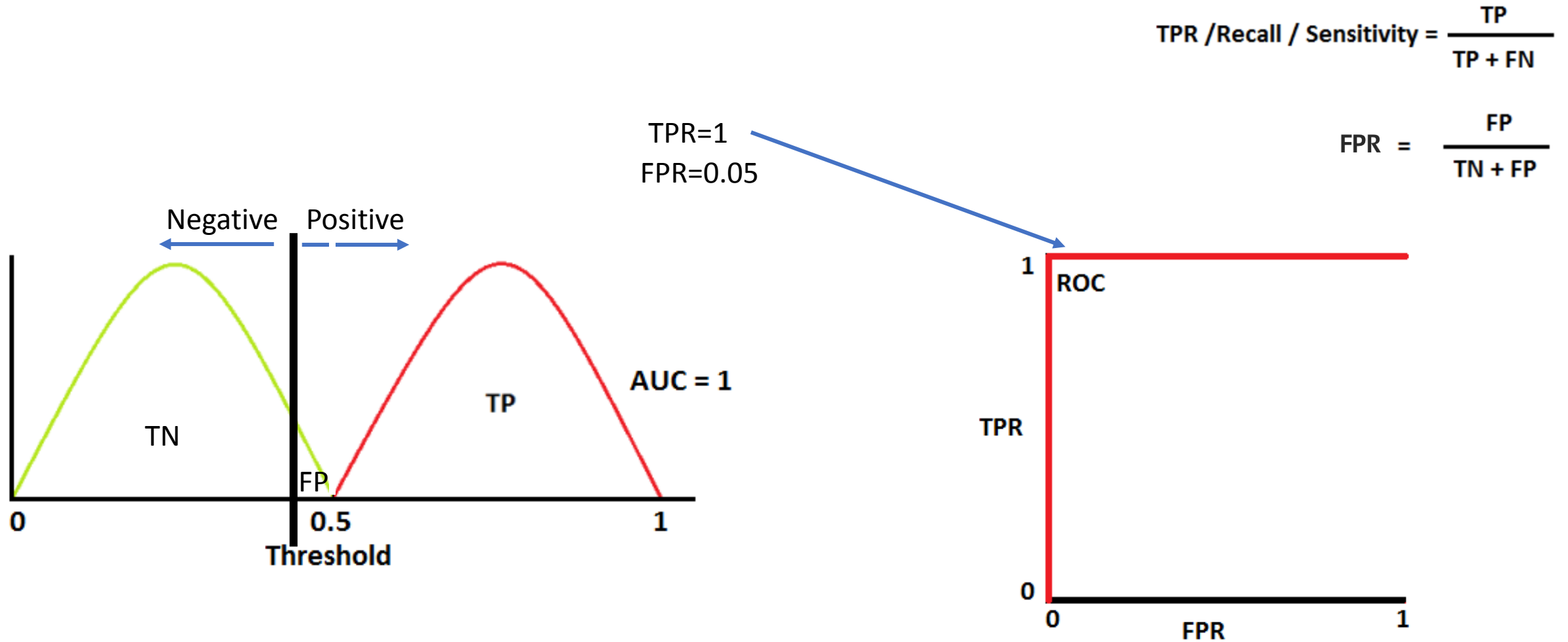
# ROC Curve



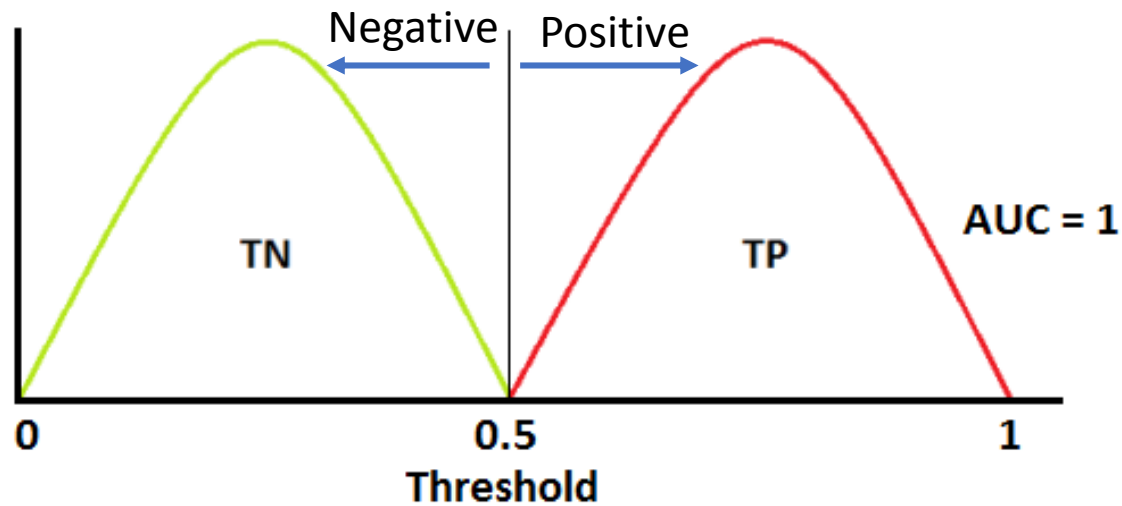
# ROC Curve



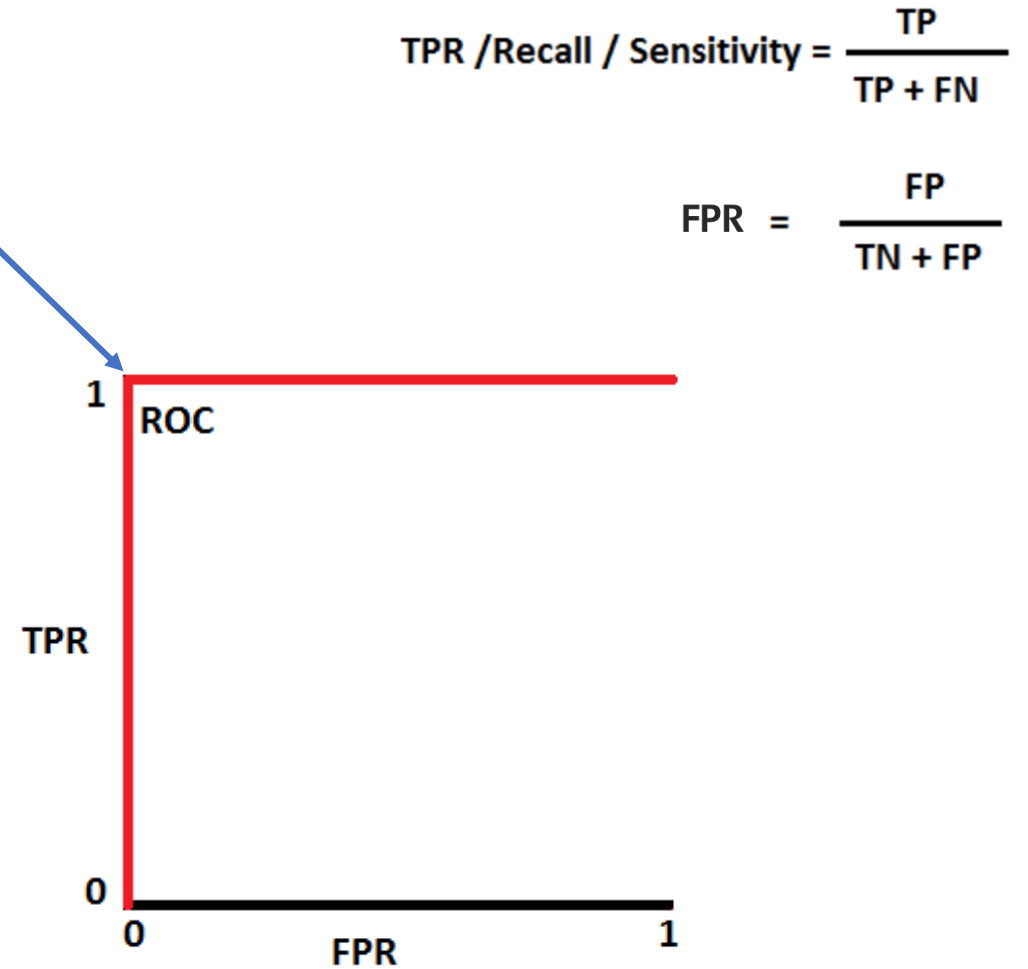
# ROC Curve



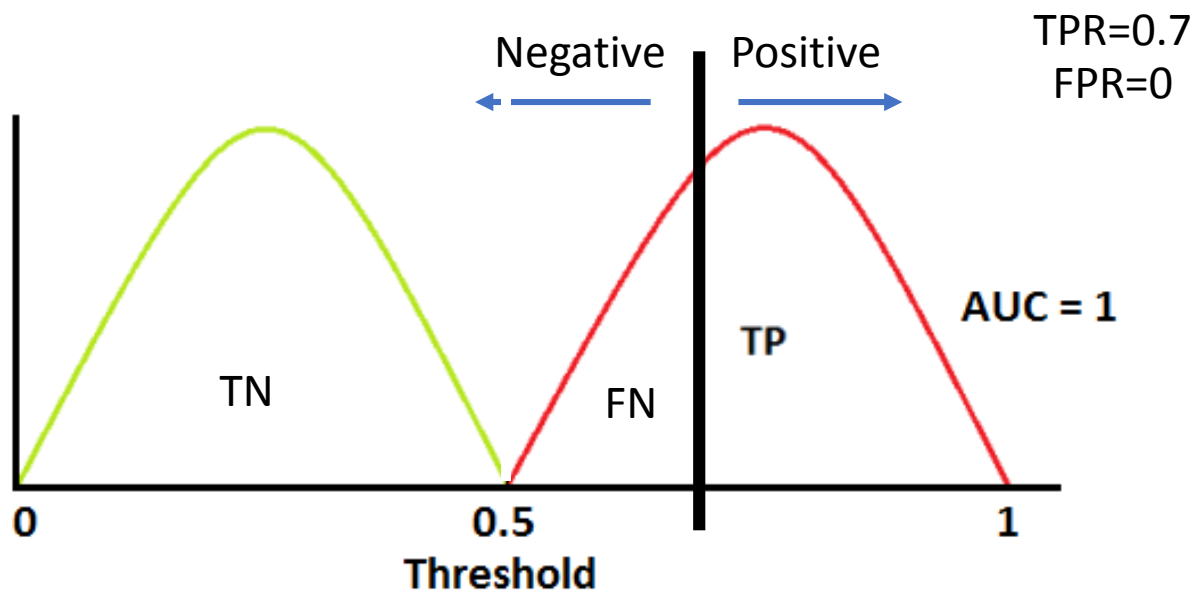
# ROC Curve



TPR=1  
FPR=0

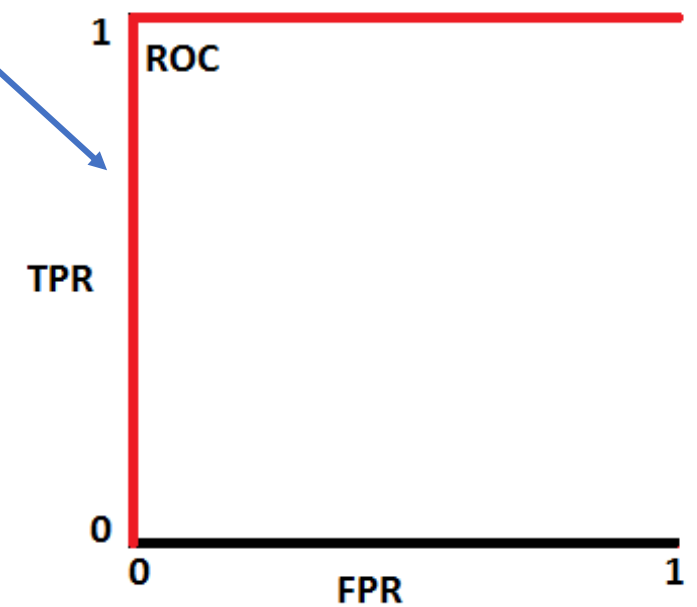


# ROC Curve



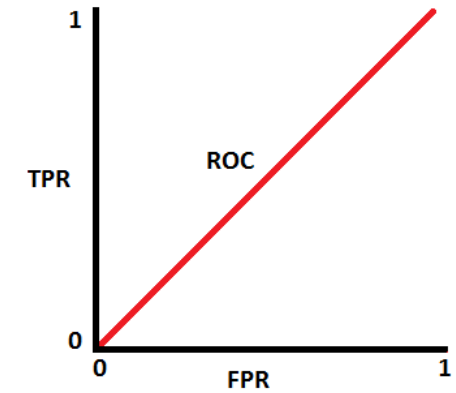
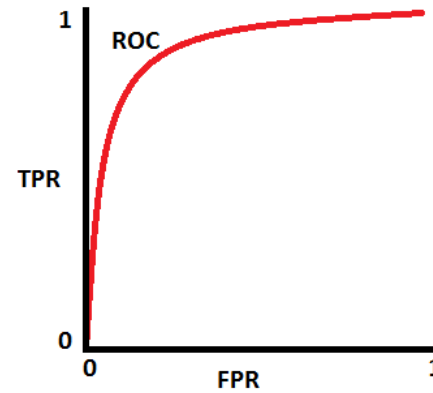
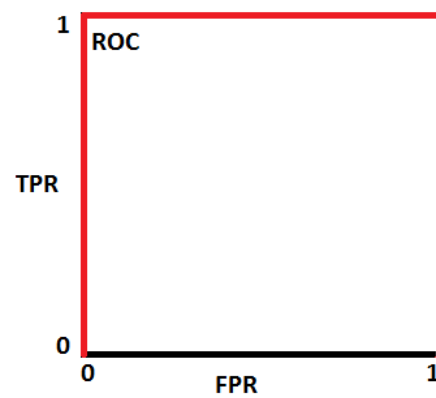
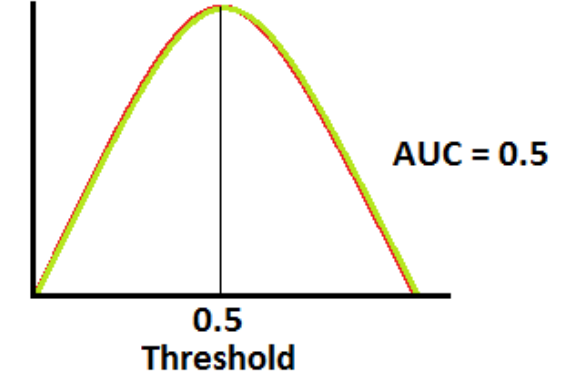
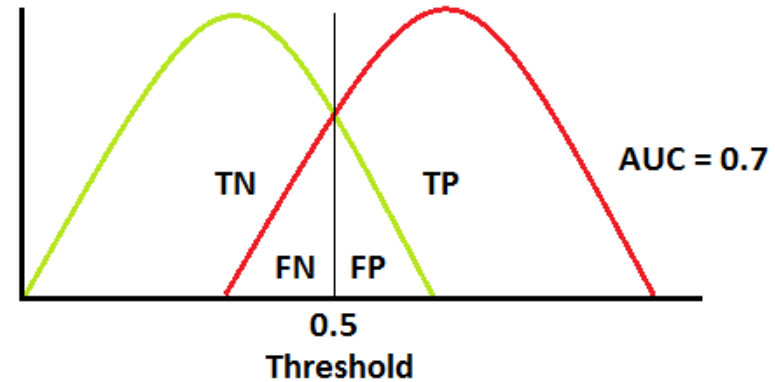
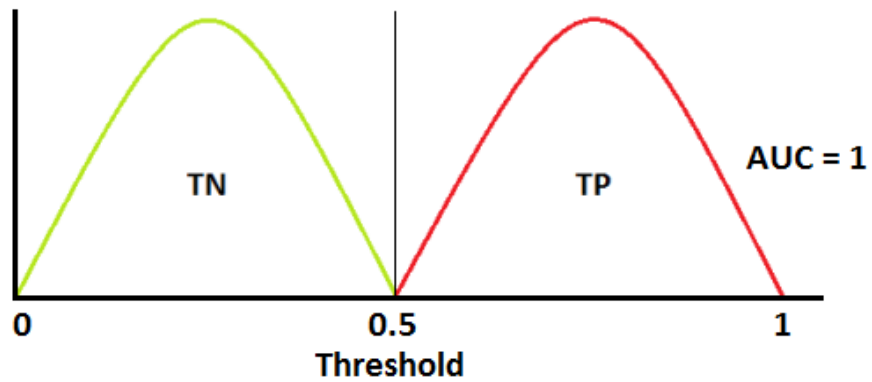
$$\text{TPR / Recall / Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}}$$





# AUC (Area Under the Curve)

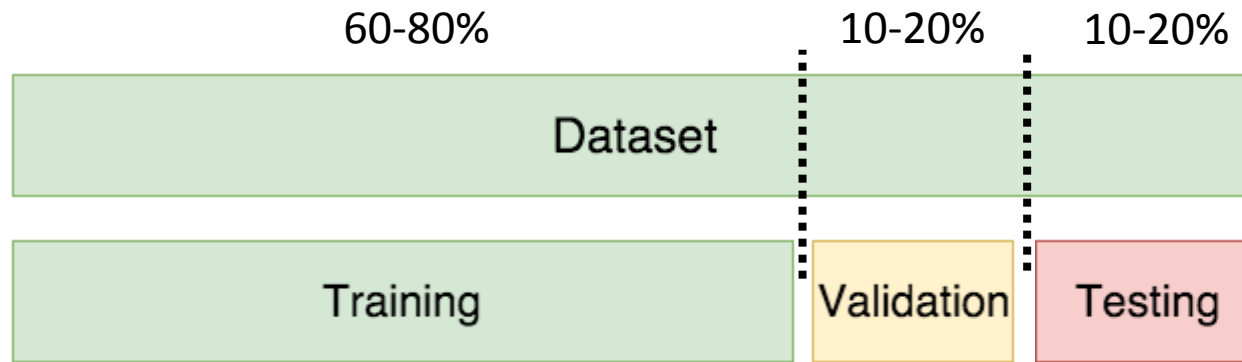


# Data Selection

- How we select our data is another aspect that is often overlooked.
- Can have serious effects on the prediction's performance.
- Q: What are some issues with arbitrary data selection?

# Splitting the Dataset

## ➤ Training, Validation and Testing



- More training data => better model
- More testing data => more confidence in assessment
- **Cross-Validation is an attempt to have both...**

# Independent and Identically Distributed

- It is important that the generative process of data is the same for all data and the process has no memory of past generated samples.
- Sampling of data needs to be independent

# Limited Data

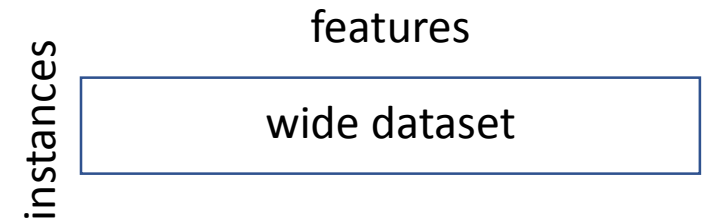
- There are often situations where it is difficult to obtain sufficient data to train a machine learning algorithm.
- For example: A common practice with medical data is to **increase the sample size by obtaining multiple samples from the same patient.**
- Q: What are some concerns resulting from this?

# Generalization

- We have seen previously that correctly predicting on new data is what we're interested in.
- **Golden Rule:** No model selection decisions should come from the test data!

# Wide and Short Data

- Another challenge that can come up is that there are **many more features** (wide dataset) **than samples** (short dataset).
- We know that as the feature size increases, we have to account for it by increasing the model complexity/capacity,
  - which in-turn increases the number of parameters,
  - which require more training samples
  - which can be difficult and expensive to obtain...
- Q: What can be done in these situations?



Data Processing  
to the Rescue!

# Next Time

- Week 4 Q/A Support Session
  - Project Questions
- Week 5 Lecture - Data Processing
  - Linear Algebra
  - Analytical Geometry
  - Data Augmentation