

# **Machine Learning**

Lesson 4—Math Refresher









# **Learning Objectives**



- Explain the concepts of Linear Algebra
- Oescribe eigenvalues, eigenvectors, and eigendecomposition
- Oefine differential and integral calculus
- Explain the concepts of probability and statistics

# Math Refresher Topic 1—Concepts of Linear Algebra



# **Introduction to Linear Algebra**



Linear algebra is a branch of mathematics that deals with the study of vectors and linear functions and equations.



# **Linear Equations**

The main purpose of linear algebra is to find systematic methods for solving systems of linear equations.

A linear equation of n variables is of the form:

$$a_1x_1 + a_2x_2 + ... + a_nx_n = b$$

where  $x_1, x_2, ..., x_n$  are the unknown quantities to be found,  $a_1, \dots, a_n$  are the coefficients (given numbers), and b is the constant term.



A linear equation does not involve any products, inverses, or roots of variables. All variables occur only to the first power and not as arguments for trigonometric, logarithmic, or exponential functions.

# **System of Linear Equations**

A system of linear equations is a finite collection of linear equations.

A linear system of m equations in n variables has the form:

$$a_{11}x_1 + a_{12}x_2 + ... + a_{1n}x_n = b_1$$
  
 $a_{21}x_1 + a_{22}x_2 + ... + a_{2n}x_n = b_2$   
 $a_{m1}x_1 + a_{m2}x_2 + ... + a_{mn}x_n = b_m$ 

In the case of a single linear equation, a linear system can have infinitely many solutions, one solution, or no solutions at all.



A linear system that has a solution is called consistent, and the one with no solution is termed inconsistent.

# **Solving Linear Systems of Equations**



Solving a linear system of equations is a long and tedious process.

The concept of **matrix** was introduced to simplify the computations involved in this process.

A matrix contains the essential information of a linear system in a rectangular array.

# Matrix

A matrix of size m × n is a rectangular array of the form:

where the  $a_{ij}$ 's are the entries of the matrix, n represents the number of columns, and m represents the number of rows.

# **Forms of Matrix**

- If n = m, that is, the number of columns and rows are equal, the matrix is called a square matrix.
- An entry of the form  $a_{ii}$  is said to be on the main diagonal.
- A is called a diagonal matrix if a<sub>ij</sub> = 0, where i ≠ j.

### **ADDITION**

Consider the following two matrices:

The corresponding elements in the rows are added.



Two matrices can be added only if they have the same number of rows and columns. Also, during addition, A + B = B + A

### **SUBTRACTION**

Now consider the same matrices again:

The corresponding elements in the rows are subtracted.



Two matrices can be subtracted only if they have the same number of rows and columns. Also, during subtraction, A - B ≠ B - A

Consider the same matrices again:

Let AB = C. To compute the value of every element in the 2 x 2 matrix C, use the formula  $C_{ik} = \sum_i A_{ii} B_{ik}$ 

Dot

$$A.B =$$

$$(22 \times 13) + (32 \times 13)$$

$$(22 \times 8) + (32 \times 16)$$

$$(11 \times 13) + (16 \times 13)$$

$$(11 \times 8) + (16 \times 16)$$

product

(22 x 13) + (32 x 13)
(22 x 8) + (32 x 16)

The 1<sup>st</sup> and 2<sup>nd</sup> rows of A are multiplied with the 1<sup>st</sup> and 2<sup>nd</sup> columns of B and added.



The matrix product AB is defined only when the number of columns in A is equal to the number of rows in B. BA is defined only when the number of columns in B is equal to the number of rows in A. AB is not always equal to BA.

### **TRANSPOSE**

A transpose is a matrix formed by turning all the rows of a given matrix into columns and vice versa. The transpose of matrix A is denoted as  $A^T$ 

From the previous examples:

### **ANALOGY TO DIVISION**



Now that you know about matrix addition, subtraction, and multiplication, is division of matrices possible?

There is no matrix division, but there is a similar analogy called inverse.

### **INVERSE**

An n-by-n square matrix A is called invertible (also nonsingular or nondegenerate) if there exists an n-by-n square matrix B such that

$$AB = BA = I_n$$

where  $I_n$  denotes the n-by-n **identity matrix** and the multiplication used is ordinary matrix multiplication.

When the matrix B is uniquely determined by A, it is called the inverse of A, denoted by A<sup>-1</sup>

# **Special Matrix Types**

- Diagonal Matrix: a matrix **D** is diagonal only if  $D_{i,j} = 0$  for all  $i \neq j$
- Symmetric Matrix: a matrix A for which  $\mathbf{A} = \mathbf{A}^{\mathsf{T}}$
- Identity matrix: denoted as  $I_n$  such that  $I_n A = A$

$$\left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array}\right]$$

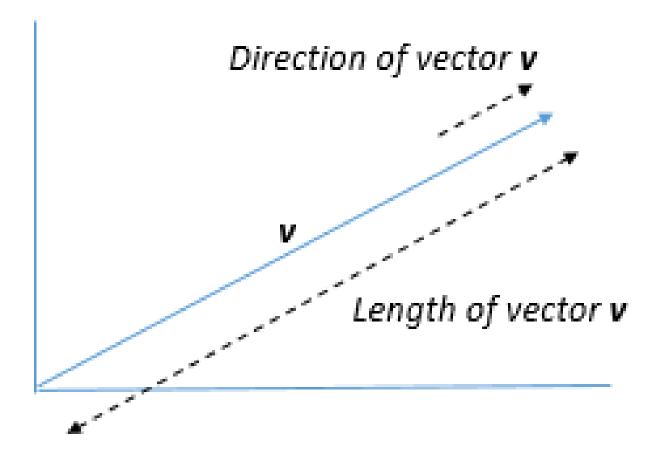


An array with more than two axes is called a tensor. Example: A tensor might have 3 dimensions, so the value at coordinates (i, j, k) is  $A_{i,j,k}$ 

# What Is a Vector?

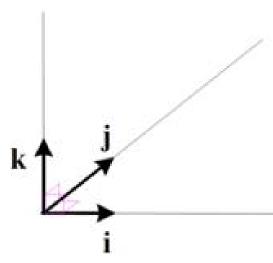
A vector (v) is an object with both magnitude (length) and direction.

It starts from origin (0,0), and its length is denoted by ||v||



# **Properties of Vectors**

- A unit vector is a vector with unit norm (unit length)  $| | x | |_2 = 1$
- A vector x and a vector y are orthogonal to each other if  $x^Ty = 0$ . This also means that both vectors are at a 90 degree angle to each other.
- An orthogonal vector that has a unit norm is called an orthonormal vector.



Here, vector i and k are orthogonal (orthonormal if they are assumed to be of unit norm).

Vectors k and j are not orthogonal. Vectors j and i and not orthogonal.

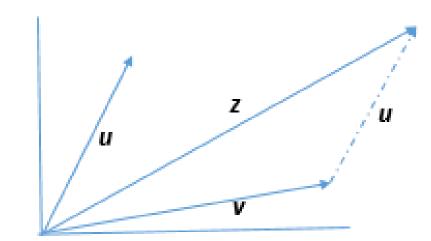


An orthogonal matrix is a square matrix whose rows are mutually orthonormal and whose columns are mutually orthonormal. In this case  $A^TA = AA^T = I$ . Also, for an orthogonal matrix,  $A^{-1} = A^T$ 

### ADDITION AND SUBTRACTION

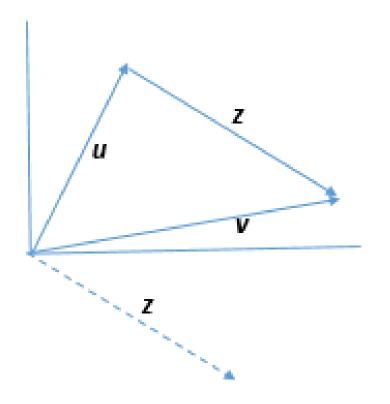
The operation of adding two or more vectors together into a vector sum is referred to as vector addition. For two vectors u and v, the vector sum is:

$$u + v = z$$



Vector subtraction is the process of subtracting two or more vectors to get a vector difference. For two vectors u and v, the vector difference is:

$$u - v = z$$



### **MULTIPLICATION**

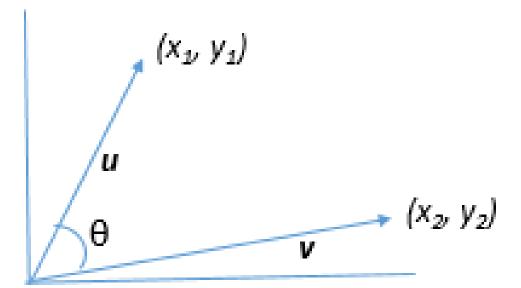
Vector multiplication refers to a technique for the multiplication of two (or more) vectors with themselves

$$u*v = z$$

$$u*v = (x_1x_2 + y_1y_2) = \sum (x_iy_i)$$

This can be shown to equal:

$$u*v = ||x|| ||y|| \cos \theta$$



### **NORM**

In machine learning, the size of a vector is called a norm. On an intuitive level, the norm of a vector x measures the distance from the origin to the point x.

Example: a vector with  $L^p$  norm where  $p \ge 1$ .

 $L^p$  norm

$$||\boldsymbol{x}||_p = \left(\sum_i |x_i|^p\right)^{\frac{1}{p}}$$

### **NORM: FEATURES**

- The most popular norm is the  $L^2$  norm with p = 2, also called the **Euclidean norm**.
- It is simply the Euclidean distance from the origin to the point identified by x.
- The 2 in the  $L^2$  norm is frequently omitted, that is,  $||x||_2$  is just written as ||x||
- Size of vector is often measured as squared  $L^2$  norm and equals  $x^Tx$ . This is better as its differential only depends on x.
- $L^1$  norm is commonly used when the difference between zero and non-zero elements is very important. This is due to the fact that  $L^1$  norm increases slowly in all directions from the origin.

L1 norm, 
$$p=1$$
:  $||x||_1 = \sum_i |x_i|$ 

- Every time an element of x moves away from 0 by  $\epsilon$ , the  $L^1$  norm increases by  $\epsilon$ .
- Max norm, infinite  $p: ||x||_{\infty} = \max_{i} |x_{i}|.$



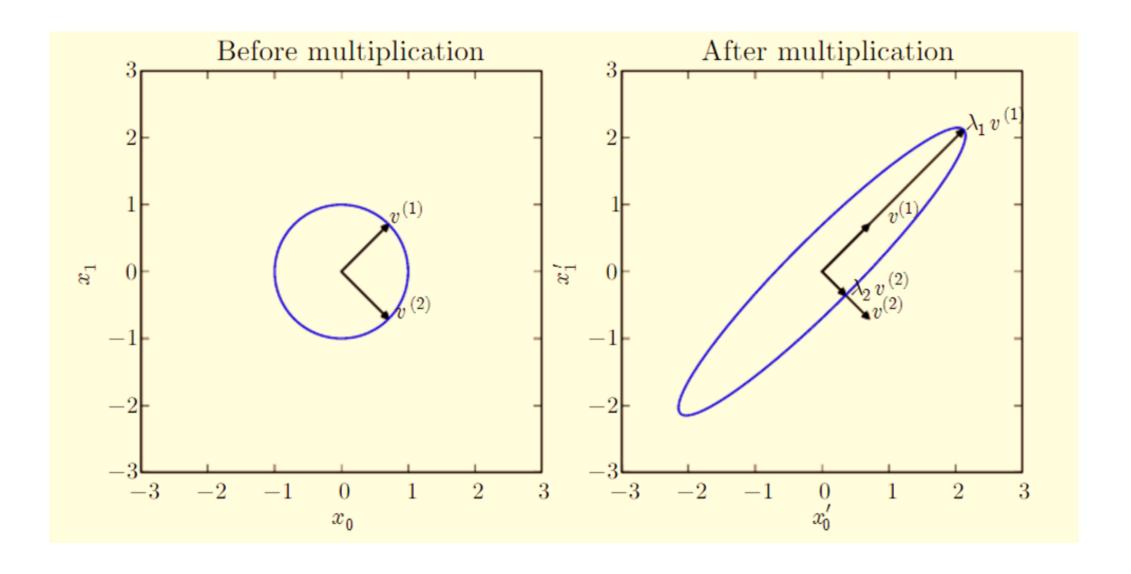
# **Eigenvector and Eigenvalue**

An eigenvector of a square matrix A is a non-zero vector such that multiplication by A alters only the scale of v.

$$Av = \lambda v$$

where  $\lambda$  is eigenvalue corresponding to this eigenvector.

# **Effect of Eigenvectors and Eigenvalues**



Here, matrix A has two orthonormal eigenvectors,  $v^{(1)}$  with eigenvalue  $\lambda_1$  and  $v^{(2)}$  with eigenvalue  $\lambda_2$ . (*left*). Plot the set of all unit vectors  $u \in \mathbb{R}^2$  as a unit circle. (*Right*) Plot the set of all points *Au*. By observing the way A distorts the unit circle, you can see that it scales space in the direction  $v^{(i)}$  by  $\lambda_i$ 

# Eigendecomposition

Integers can be broken into their prime factors to understand them, example:  $12 = 2 \times 2 \times 3$ . From this, useful properties can be derived, for example, the number is not divisible by 5 and is divisible by 2 and 3.

Similarly, matrices can be decomposed. This will help you discover information about the matrix.

If A has a set of eigenvectors  $v_1$ ,  $v_2$ ,... represented by matrix V, and the corresponding eigenvalues  $\lambda_1$ ,  $\lambda_2$ ,... represented by vector  $\lambda$ , then eigendecomposition of A is given by:

 $A = V \operatorname{diag}(\lambda) V^{-1}$ 

# **Math Refresher Topic 3—Introduction to Calculus**

OSimplifearn. All rights reserved.

## What Is Calculus?



Calculus is the study of change. It provides a framework for modelling systems in which there is change and ways to make predictions of such models.



# **Differential Calculus**

Differential calculus is a part of calculus that deals with the study of the rates at which quantities change.

Let x and y be two real numbers such that y is a function of x, that is, y = f(x).

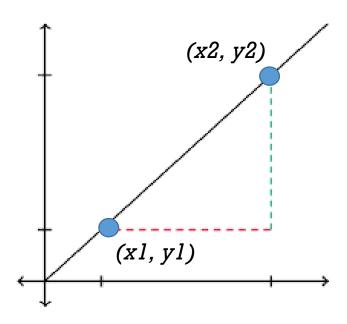
If f(x) is the equation of a straight line (linear equation), then the equation is represented as y = mx + b.

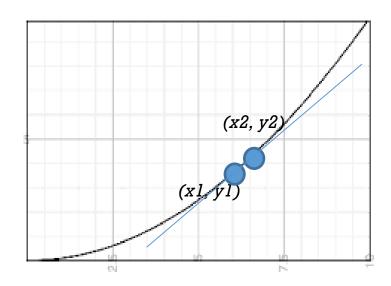
Where m is the slope determined by the following equation:

$$m = rac{ ext{change in } y}{ ext{change in } x} = rac{\Delta y}{\Delta x}$$

 $\Delta y/\Delta x$  or dy/dx is the derivative of y with respect to x and is also the rate of change of y per unit change in x.

Slope of a curvature changes at various points of the graph. It represents slope of an imaginary straight line drawn through that small graph segment.



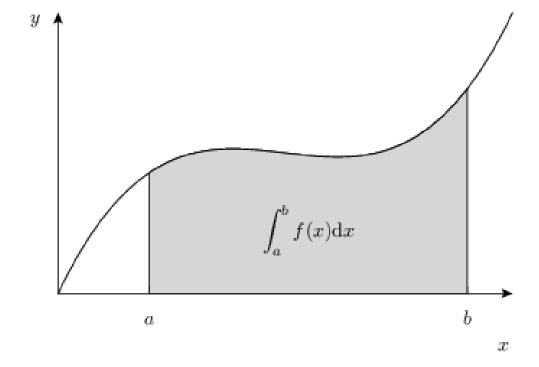


# **Integral Calculus**

Integral Calculus assigns numbers to functions to describe displacement, area, volume, and other concepts that arise by combining infinitesimal data.

Given a function f of a real variable x and an interval [a, b] of the real line, the definite integral is defined informally as the signed area of the region in the xy-plane that is bounded by the graph of f, the x-axis, and the vertical lines x = a and x = b.

$$\int_a^b f(x) \, dx$$





An integral is the inverse of a differential and vice versa.

# Math Refresher Topic 4—Probability and Statistics

CSimplifearn. All rights reserved.

# **Probability Theory**

Probability is the measure of the likelihood of an event's occurrence.

Example: The chances of getting heads on a coin toss is ½ or 50%



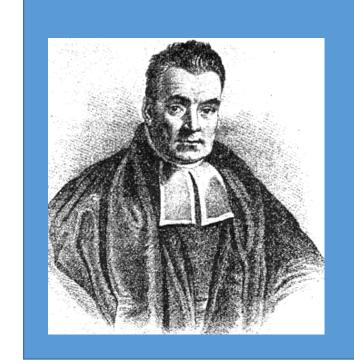


Probability of any specific event is between 0 and 1 (inclusive). The sum of total probabilities of an event cannot exceed 1, that is,  $0 \le p(x) \le 1$ . This implies that  $p(x) \le 1$  (integral of p for a distribution over x)

# **Conditional Probability**

Conditional probability of y=y given x=x is:

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



This is also called **Bayesian probability**.

# **Conditional Probability**

### **BAYES MODEL EXAMPLE**

Bayes model defines the probability of event A occurring, given event B has occurred.

P(A) = probability of event A

P(B) = probability of event B

 $P(A \mid B) = probability of both events happening$ 

Consider the coin example:

$$P(Coin1-H) = 2/4$$

$$P(Coin2-H) = 2/4$$

P(Coin1-H 
$$\square$$
 Coin2-H) =  $\frac{1}{4}$ 

P(Coin1-H | Coin2-H) = 
$$(1/4)/(2/4) = \frac{1}{2} = 50\%$$
 (probability of Coin1-H, given Coin2-H)

Two Coin Flip	
Coin 1	Coin 2
Н	Т
Т	Н
Н	Н
Т	Т

$$P(A|B) = rac{P(A \cap B)}{P(B)} \implies P(A \cap B) = P(A|B)P(B)$$

# **Conditional Probability**

### **SIMPLIFYING THE BAYES EQUATION**

Events A and B are statistically independent if:

$$P(A \cap B) = P(A|B)P(B)$$

$$\Rightarrow P(A \cap B) = P(A)P(B)$$

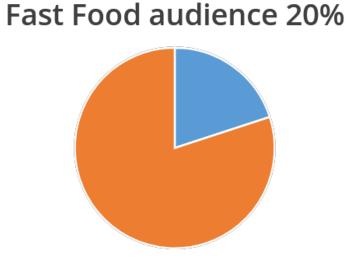
$$P(A|B) = P(A)$$
 assumes P(B) is not zero

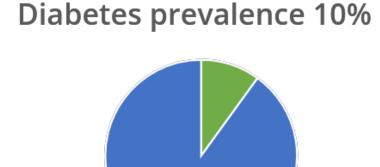
$$P(B|A) = P(B)$$
 assumes P(A) is not zero

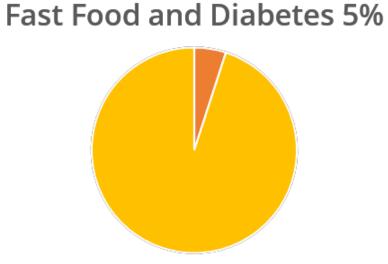
# Al with Bayes Model: Example

Calculating the chance of developing diabetes given the incidence of fast food.

Observed Data







Chances of Diabetes, given fast food: (conditional probability)

$$\Rightarrow$$
 (D and F)/F = 5%/20% =  $\frac{1}{4}$  = 25%

Analysis: If you eat fast food, you have 25% chance of developing Diabetes.

# **Chain Rule of Probability**

Joint probability distribution over many random variables may be decomposed into conditional distributions over only one variable. It can be represented as:

$$P(\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}) = P(\mathbf{x}^{(1)}) \prod_{i=2}^{n} P(\mathbf{x}^{(i)} \mid \mathbf{x}^{(i)}, \dots, \mathbf{x}^{(i-1)})$$

For example: P(a, b, c) = P(a | b, c) \* P(b | c) \* P(c)

### **Standard Deviation**

Standard deviation is a quantity that expresses the value by which the members of a group differ from the mean value for the group.

- Its symbol is  $\sigma$  (the Greek letter sigma). If the data points are further from the mean, there is higher deviation within the data set.
- For example, a volatile stock has a high standard deviation, while the deviation of a stable blue-chip stock is usually rather low.

### **FORMULA**

If X is a random variable with mean value (or expected value)  $\mu$  such that:  $\mathbf{E}[X] = \mu$ 

Then standard deviation : 
$$\sigma = \sqrt{\mathbf{E}[(X-\mu)^2]}$$



Standard deviation is used more often than variance because the unit in which it is measured is the same as that of mean, a measure of central tendency.

## **Variance**

Variance ( $\sigma^2$ ) refers to the spread of the data set, for example, how far the numbers are in relation to the mean.

- Variance is particularly useful when calculating the probability of future events or performance.
- Example: India has high variation in environmental temperature, from very hot to very cold weather. That is, India has high variance of weather conditions.

### **FORMULA**

If X is a random variable with mean value (or expected value)  $\mu$  such that:  $\mathbf{E}[X] = \mu$ 

Then variance: 
$$\mathrm{Var}(X) = \mathrm{E} ig[ (X - \mu)^2 ig]$$



Notice that variance is just the square of standard deviation.

## Covariance

Covariance is the measure of how two random variables change together. It is used to calculate the correlation between variables.

- A positive covariance indicates that both variables from the prior line tend to move upward and downward in value at the same time. An inverse or negative covariance means that variables move counter to each other: when one rises, the other falls
- Example: Purchasing stock with a negative covariance is a great way to minimize risk in a portfolio (diverse portfolio)

### **FORMULA**

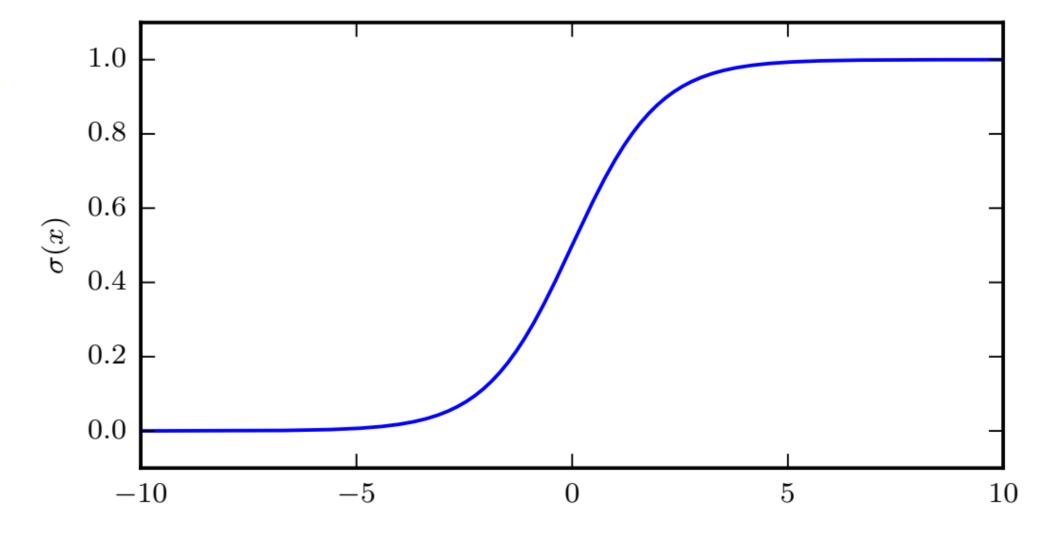
If X is a random variable with mean value (or expected value)  $\mu$  such that:  $\mathbf{E}[X] = \mu$ 

Then covariance: 
$$\operatorname{cov}(X,Y) = \operatorname{E}\left[(X - \operatorname{E}[X])(Y - \operatorname{E}[Y])\right]$$

# **Logistic Sigmoid**

The Logistic Sigmoid is a useful function that follows the S curve. It saturates when input is very large or very small.

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

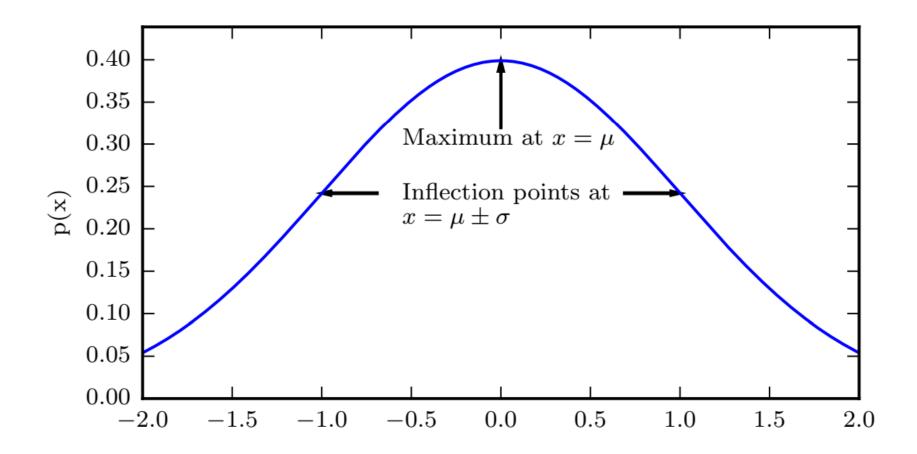


### **Gaussian Distribution**

#### **DEFINITION**

Data can be distributed in various ways.

The distribution where the data tends to be around a central value with lack of bias or minimal bias toward the left or right is called Gaussian distribution, also known as normal distribution.



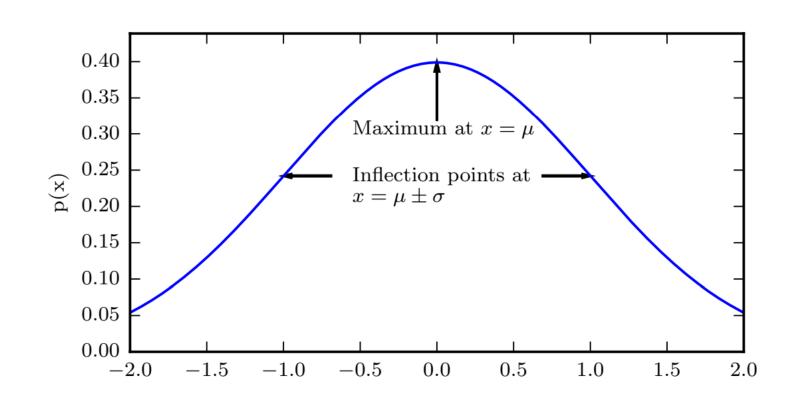
In absence of prior knowledge, normal distribution is often a good assumption in machine learning.

### **Gaussian Distribution**

### **EQUATION**

$$\mathcal{N}(x; \mu, \sigma^2) = \sqrt{\frac{1}{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)$$

$$\mathcal{N}(x; \mu, \beta^{-1}) = \sqrt{\frac{\beta}{2\pi}} \exp\left(-\frac{1}{2}\beta(x - \mu)^2\right)$$

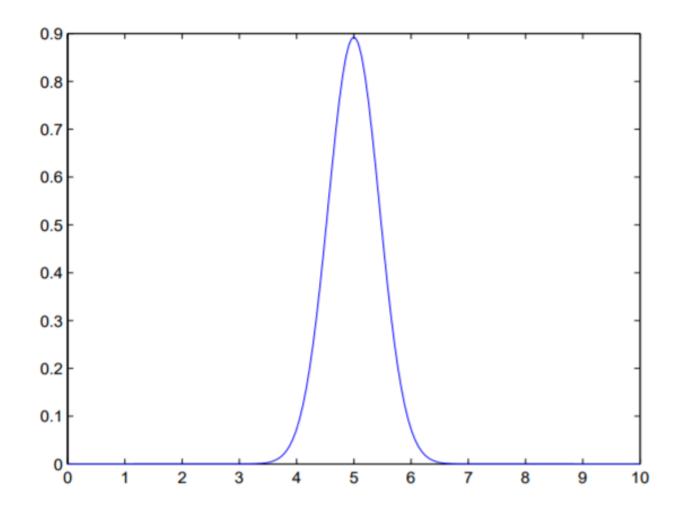


- $\mu$  = mean or peak value, which also means  $E[x] = \mu$
- $\sigma$  = standard deviation and  $\sigma^2$  = variance
- A "standard normal distribution" has  $\mu = 0$  and  $\sigma = 1$
- For efficient handling, invert  $\sigma$  and use precision  $\beta$  (inverse variance) instead

# **Types of Gaussian Distribution**

#### **UNIVARIATE**

Univariate Gaussian distribution refers to the distribution over a single variable.

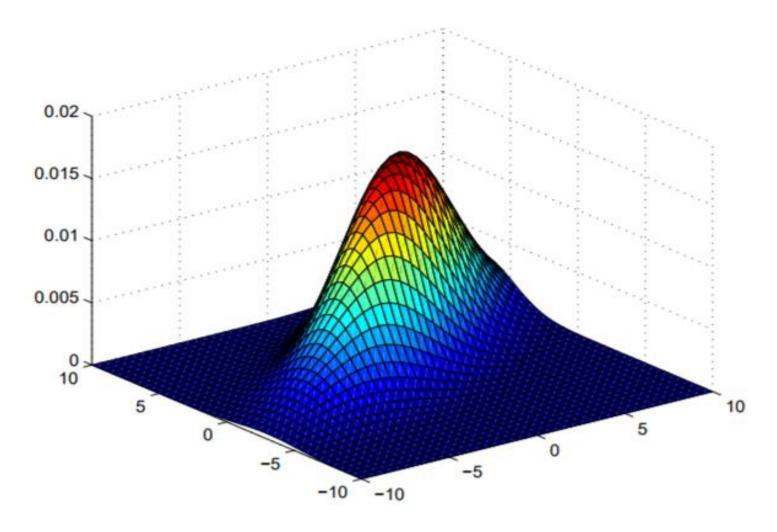


Univariate Gaussian distribution over single variable x

# **Types of Gaussian Distribution**

#### **MULTIVARIATE**

Multivariate normal distribution is the generalization of the univariate normal distribution to multiple variables.



Multivariate Gaussian distribution over two variables  $x_1$  and  $x_2$ 

# **Key Takeaways**



- Linear algebra is a branch of mathematics that deals with the study of vectors and linear functions and equations.
- $\bigcirc$  A matrix of size m  $\times$  n is a rectangular array.
- A vector (v) is an object with both magnitude (length) and direction. It is represented by an arrow on a graph.
- Eigenvector of a matrix A is a vector v that only changes the scale of the vector v when multiplied by A.
- Differential Calculus is the incremental rate of change of dependent variable y with respect to x. Integral Calculus is summation of a function f(x) over x.
- Probability is the chance of something happening.
- Standard deviation and variance indicate the spread of a data distribution around its mean.



simpl<sub>i</sub>learn



1

### Matrix Multiplication of two matrices A and B involves:

- a. multiplying rows of both matrices
- b. multiplying columns of both matrices
- c. multiplying both matrices diagonally
- d. None of the above



1

### Matrix Multiplication of two matrices A and B involves:

- a. multiplying rows of both matrices
- b. multiplying columns of both matrices
- c. multiplying both matrices diagonally
- d. None of the above



### The correct answer is d. None of the above

Matrix Multiplication of two matrices A and B involves the 1<sup>st</sup> and 2<sup>nd</sup> rows of A multiplied with the 1<sup>st</sup> and 2<sup>nd</sup> columns of B and added.

2

### When are two vectors $v_1$ and $v_2$ considered orthogonal?

- a. When both are at 90 degrees to each other
- b. When both are at 180 degrees to each other
- c. When both are pointing in the same direction
- d. When both are pointing in the opposite direction



2

When are two vectors  $v_1$  and  $v_2$  considered orthogonal?

- a. When both are at 90 degrees to each other
- b. When both are at 180 degrees to each other
- c. When both are pointing in the same direction
- d. When both are pointing in the opposite direction



The correct answer is **a. When both are at 90 degrees to each other** 

Two vectors  $v_1$  and  $v_2$  are considered orthogonal when both are at 90 degrees to each other.

