GUC
German University in Cairo

CSEN 1022: Machine Learning

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Winter 2019

CSEN 1022 – Machine Learning

- Instructor
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  - TAs: Mohamed Abdelfattah and Mai Gamal

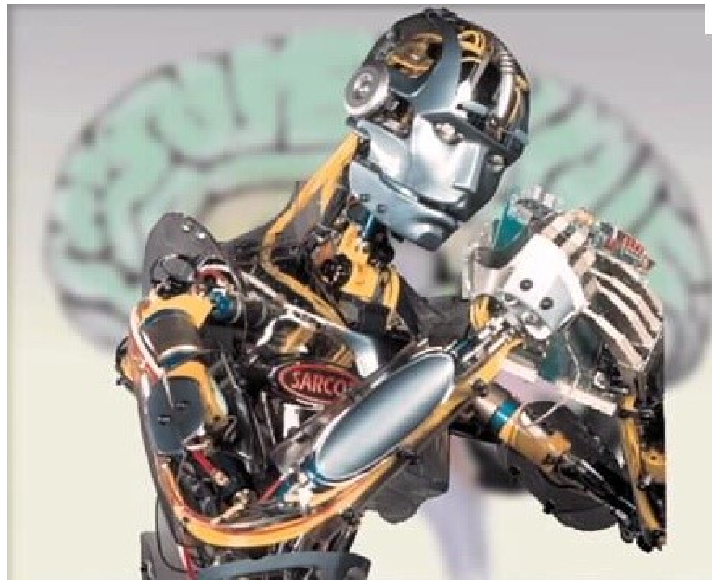
- Office Hours
  - Sundays – 2:00pm to 3pm (Office: C7-210)

- Textbook
  - Pattern Recognition and Machine Learning, Christopher M. Bishop, Springer, 2006
  - Machine Learning, Tom Mitchell, McGraw Hill, 1997
  - Research papers

CSEN 1022 – Machine Learning

- Course Evaluation
  - 3 Assignments (using Python): 35%
  - Quizzes: 10%
  - Mid-term exam: 15%
  - Final exam: 40%

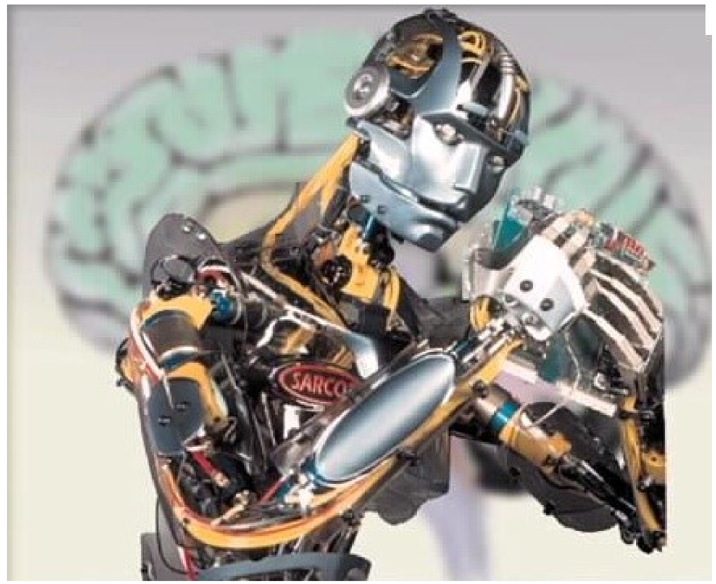
Machine Learning?



Informal definition (Wikipedia):

Designing and developing algorithms that allow computers to evolve behaviors based on empirical data

Machine Learning?

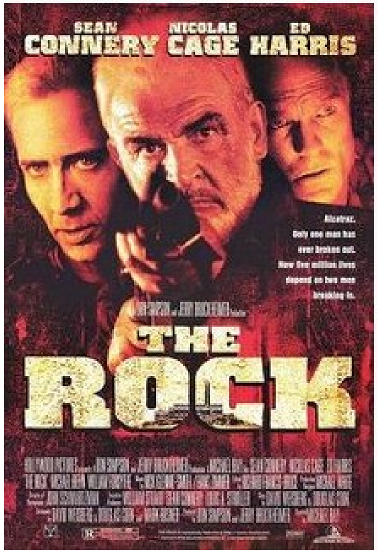


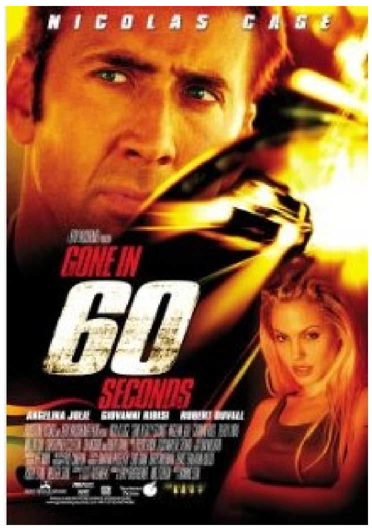
Formal definition:

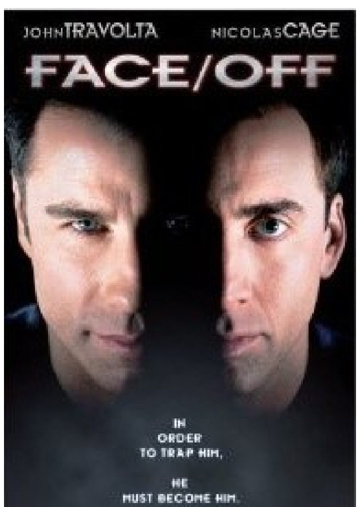
> *A computer program is said to learn from experience* ***E*** *with respect to some class of tasks* ***T*** *and performance measure* ***P*** *if its performance at tasks in* ***T****, as measured by* ***P****, improves with experience* ***E***

Examples: Movie Recommendation System

Watch History (Experience E)







Recommendation

(Task T)

Examples:

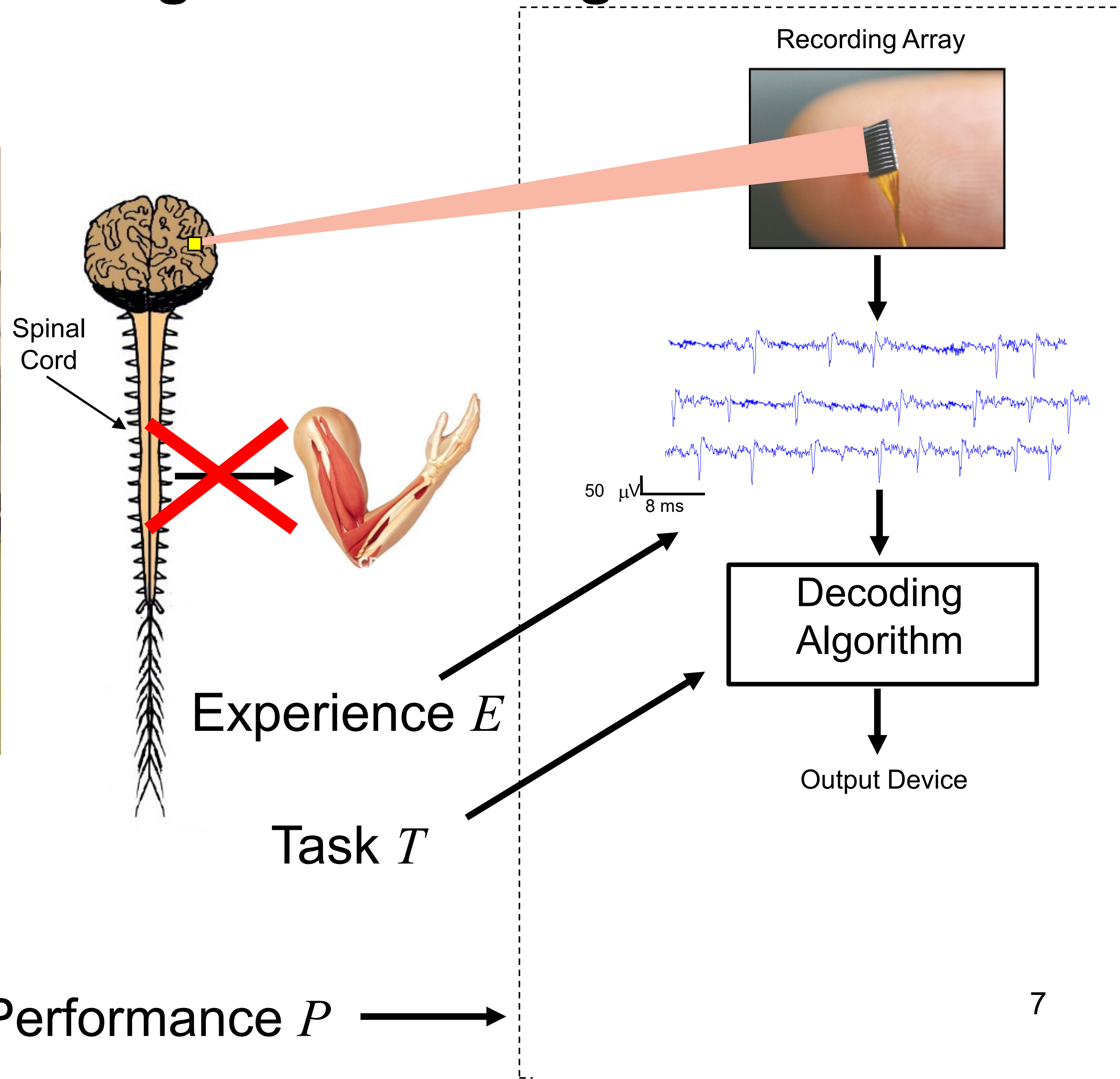
- Netflix
- Veoh.com
- Youtube.com

Does it match the user's preference?

(Performance P)

Examples: Brain Signals Decoding

(Hochberg et al., 2006)

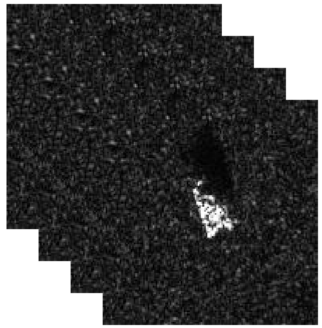


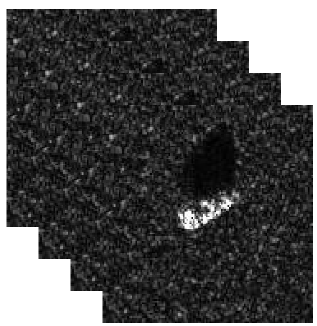
Examples: Brain Signals Decoding

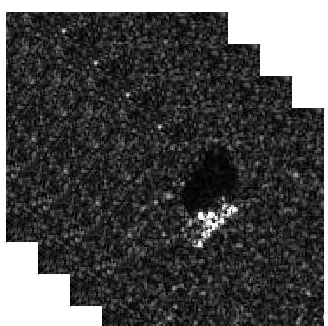
(Hochberg et al., 2012)

Examples: Automatic Target Recognition (ATR)

Training Dataset
(Experience E)

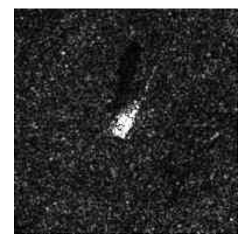







Which target is it?

(Task T)

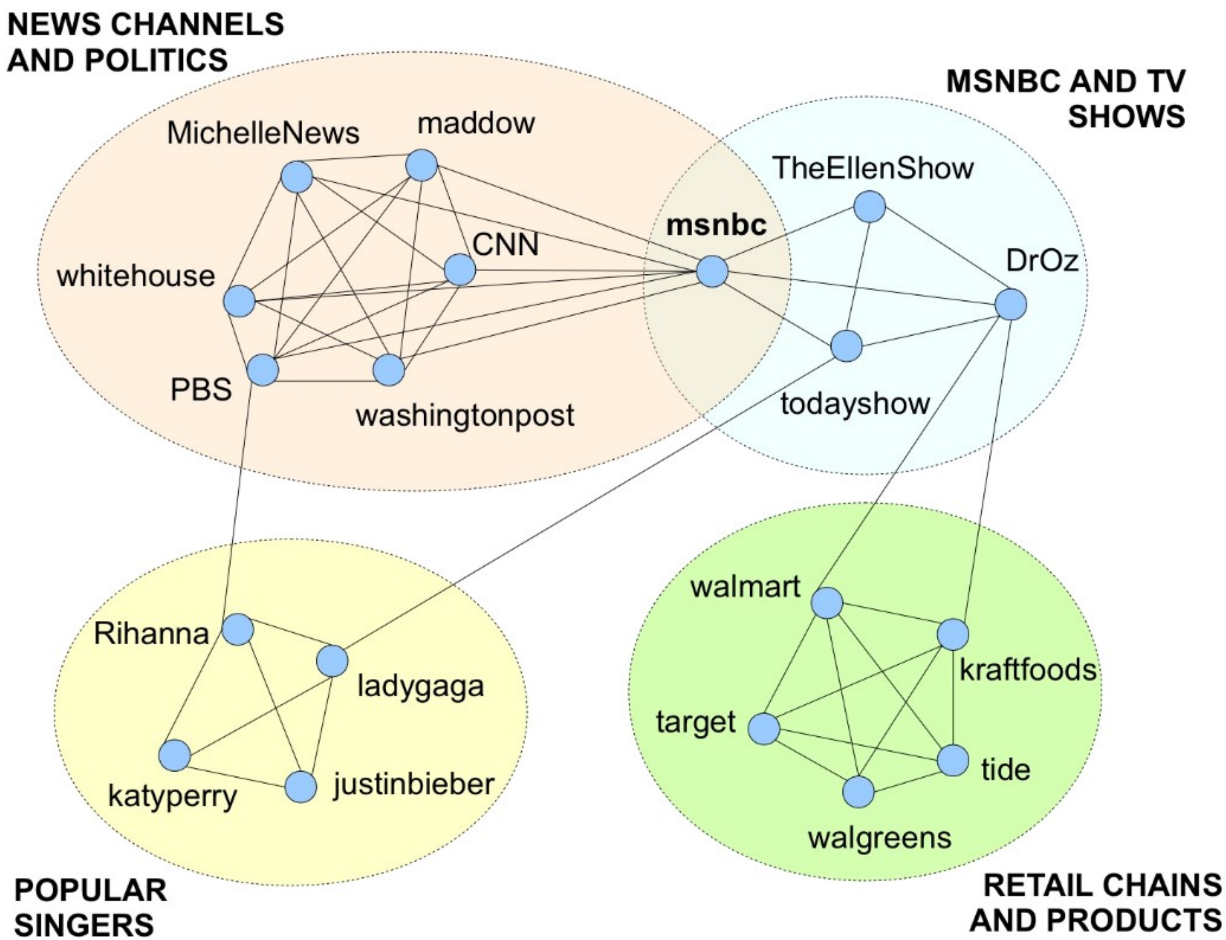


How many targets are classified correctly?

(Performance P)

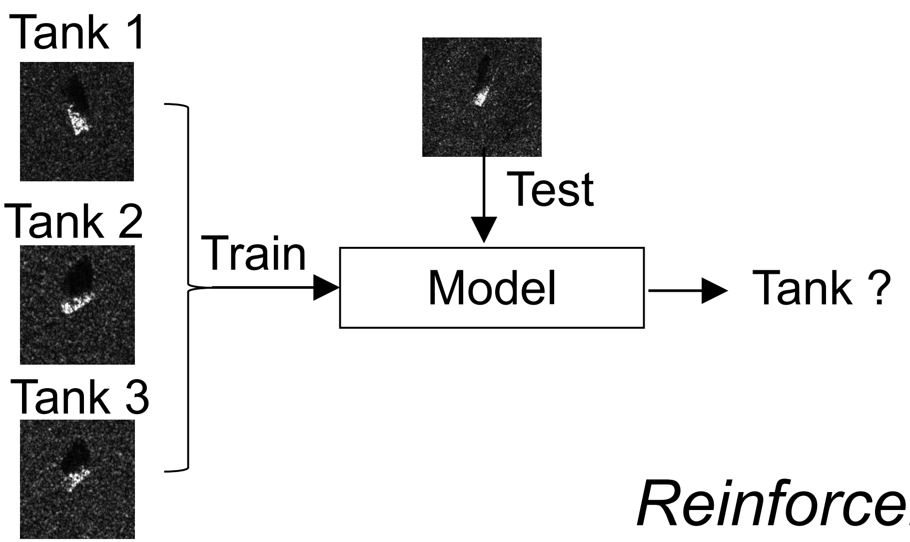
Examples: Social Network Analysis

- Grouping communities together

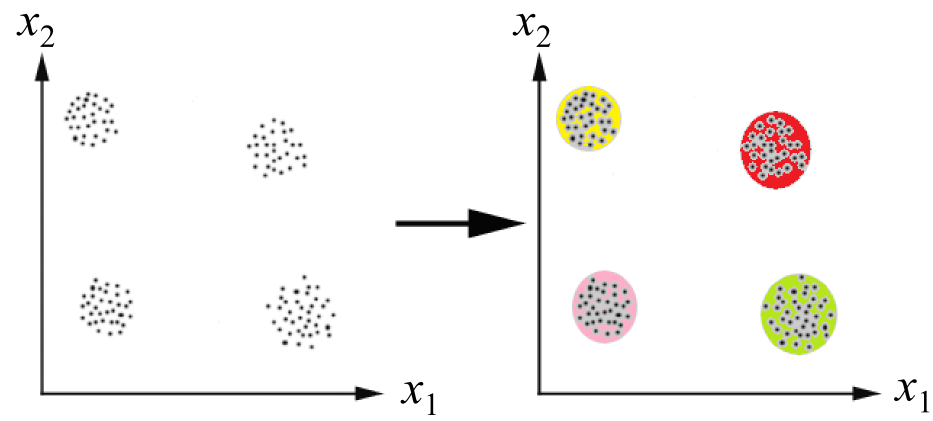


Machine Learning Algorithms

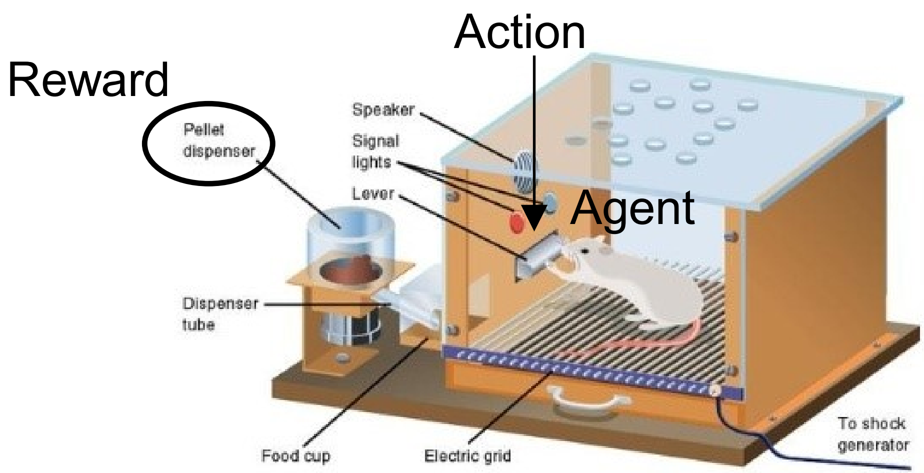
Supervised Learning



Unsupervised Learning



Reinforcement Learning



Course Outline

- **Linear Algebra and Probability Theory Review**
- **Linear Classification:**
  - Discriminant Functions:
    - Discriminant Functions Properties
    - Least Squares Classifier
    - Fisher’s Linear Discriminant
    - Perceptron
  - Probabilistic Generative Models:
    - Gaussian Generative Model
    - Naïve Bayes Classifier
- **Non-linear Classification:**
    - K-nearest Neighbor Classifier
    - Weighted K-nearest Neighbor
    - Support Vector Machines
- **Clustering Techniques:**
  - K-means Clustering
  - Clustering Validity Indices
  - Fuzzy C-means Clustering
  - Gaussian Mixture Model
  - Hierarchical Clustering
  - Spectral Clustering
- **Dimensionality Reduction and Feature Extraction:**
  - Principal Component Analysis
  - Independent Component Analysis
- **Introduction to Reinforcement Learning:**
  - Markov Decision Process
  - Q-learning
  - Non-deterministic Rewards

Linear Algebra Review: Matrices

- Matrix: A set of elements organized in rows and columns

$$\begin{array}{c c} & \begin{array}{cc} \text{Col 1} & \text{Col 2} \end{array} \\ \begin{array}{c} \text{Row 1} \\ \text{Row 2} \end{array} & \begin{bmatrix} a & b \\ c & d \end{bmatrix} \end{array}$$

- Matrix Dimensions: (# of Rows) x (# of Columns)
- Matrix Addition and Subtraction

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \pm \begin{bmatrix} e & f \\ g & h \end{bmatrix} = \begin{bmatrix} a \pm e & b \pm f \\ c \pm g & d \pm h \end{bmatrix}$$

Linear Algebra Review: Matrices

- Matrices Multiplication

$$\begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix} \times \begin{bmatrix} x & z & k \\ y & g & l \end{bmatrix} = \begin{bmatrix} ax+by & az+bg & ak+bl \\ cx+dy & cz+dg & ck+dl \\ ex+fy & ez+fg & ek+fl \end{bmatrix}$$

(3 x 2) x (2 x 3) = (3x3)

- Multiplying an (n x m) matrix by (m x k) matrix results in (n x k) matrix

- Matrix Transpose

$$\mathbf{M} = \begin{bmatrix} a & b \\ c & d \\ e & f \end{bmatrix} \qquad \mathbf{M}^T = \begin{bmatrix} a & c & e \\ b & d & f \end{bmatrix}$$

(3 x 2) (2 x 3)

Linear Algebra Review: Matrices

- Inverse of matrix $\mathbf{A}$ denoted by $\mathbf{A}^{-1}$

$$\mathbf{A}^{-1}\mathbf{A} = \mathbf{I} \qquad \text{where} \qquad \mathbf{I} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Identity matrix if $\mathbf{A}$ is (3 x 3)

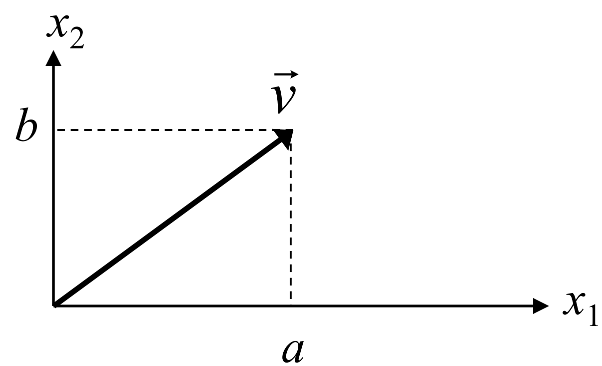
- For a (2 x 2) matrix

$$\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \qquad \det(\mathbf{A}) = ad - bc \qquad \mathbf{A}^{-1} = \frac{1}{ad-bc}\begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

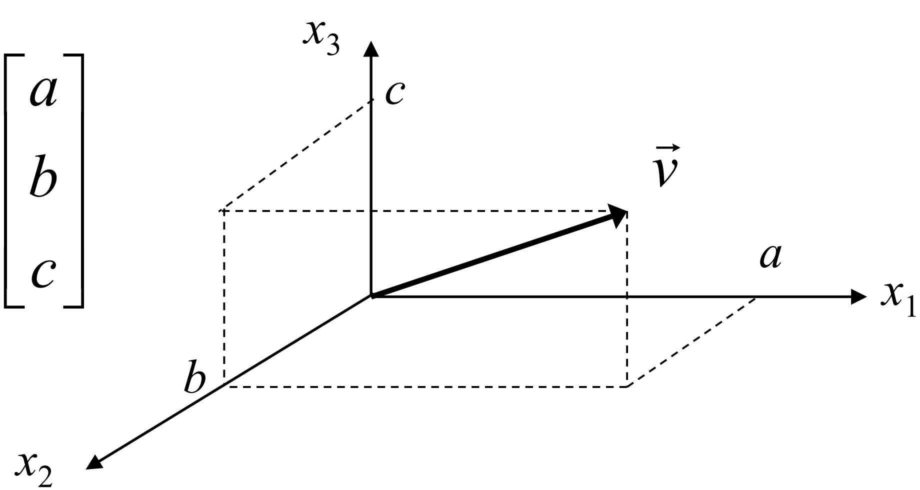
Linear Algebra Review: Vectors

- Vector = n x 1 matrix
- Represents a straight line in n-dimensional space

$$\vec{v} = \begin{bmatrix} a \\ b \end{bmatrix}$$



$$\vec{v} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

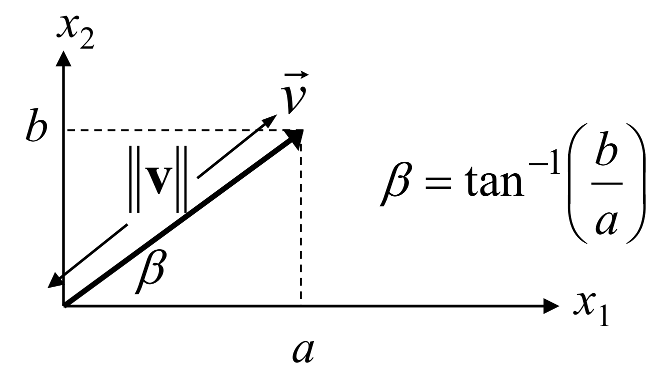


- A vector is denoted as $\vec{v}$ or $\mathbf{v}$

Linear Algebra Review: Vectors

- Vector Magnitude (Norm): Gives the length of a vector

$$\mathbf{v} = \begin{bmatrix} a \\ b \end{bmatrix} \qquad \|\mathbf{v}\| = \sqrt{a^2 + b^2}$$



- Unit Vector: Vector with norm = 1
- For an n-dimensional vector

$$\mathbf{v} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \qquad \|\mathbf{v}\| = \sqrt{\sum_{i=1}^{n} a_i^2}$$

- The norm of the vector squared is equivalent to

$$\|\mathbf{v}\|^2 = \mathbf{v}^T \mathbf{v} = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = a_1^2 + a_2^2 + \ldots + a_n^2 = \sum_{i=1}^{n} a_i^2$$

(1 x n) (n x 1) (1 x 1)

Linear Algebra Review: Vectors

- Vectors Dot Product

$$\mathbf{v} = \begin{bmatrix} a \\ b \end{bmatrix} \qquad \mathbf{u} = \begin{bmatrix} c \\ d \end{bmatrix}$$

$$\mathbf{v} \cdot \mathbf{u} = \mathbf{v}^T \mathbf{u} = \mathbf{u}^T \mathbf{v} = \begin{bmatrix} a & b \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = ac + bd$$

(Always (1 x 1))

- For an n-dimensional vector

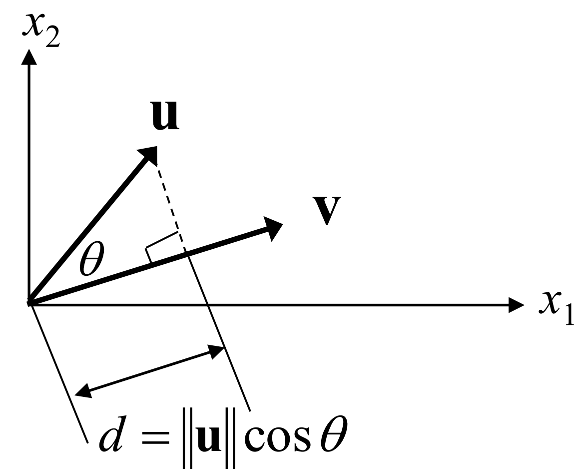
$$\mathbf{v} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \qquad \mathbf{u} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

$$\mathbf{v} \cdot \mathbf{u} = \mathbf{v}^T \mathbf{u} = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} = \sum_{i=1}^{n} a_i b_i$$

Linear Algebra Review: Vectors

- Dot product can be expressed as

$$\mathbf{v} \cdot \mathbf{u} = \|\mathbf{v}\| . \|\mathbf{u}\| \cos \theta$$



- $\|\mathbf{u}\| \cos \theta$ is the projection of the vector $\mathbf{u}$ on the vector $\mathbf{v}$

- If $\mathbf{v}$ is a unit vector, then the dot product is equivalent to the projection of the vector $\mathbf{u}$ on the vector $\mathbf{v}$

- If both vectors are unit vectors, the dot product will be maximum if both vectors are perfectly aligned

- If two vectors are orthogonal, the dot product will equal 0

Linear Algebra Review

- Matrix Calculus

$$\frac{\partial(\mathbf{a}^T\mathbf{x})}{\partial \mathbf{x}} = \frac{\partial(\mathbf{x}^T\mathbf{a})}{\partial \mathbf{x}} = \mathbf{a}$$

$$\frac{\partial(\mathbf{x}^T\mathbf{A}\mathbf{x})}{\partial \mathbf{x}} = (\mathbf{A} + \mathbf{A}^T)\mathbf{x} \longrightarrow \frac{\partial \mathbf{x}^T\mathbf{x}}{\partial \mathbf{x}} = 2\mathbf{x}$$

$$\frac{\partial(\mathbf{a}^T\mathbf{X}\mathbf{b})}{\partial \mathbf{X}} = \mathbf{a}\mathbf{b}^T$$

Function Optimization

- To find the minimum (maximum) of a function, take the derivative and equate with zero

$$\min f(x) = f(x^*) \quad \text{where} \quad \frac{df(x)}{dx}\Big|_{x^*} = 0$$

- Example

$$f(x) = (x-2)^2$$

$$f'(x) = 2(x-2) = 2x - 4 = 0$$

$$x^* = 2$$

$$f(x^*) = 0$$