MACHINE LEARNING WITHOUT LEARNING

PREMANANDA INDIC, PH.D.

DEPARTMENT OF ELECTRICAL ENGINEERING

ORS Research Design & Data Analysis Lab

Office of Research and Scholarship

PREREQUISITE

➢NO KNOWLEDGE OF PROGRAMMING

➢NO KNOWLEDGE OF ANY QUANTITATIVE METHODS

http://clipart-library.com/clipart/2096816.htm

OUTLINE

➢ INTRODUCTION

➢ DIFFERENT MACHINE LEARNING APPROACHES

➢ EXAMPLES

ANALYSIS PLATFORM

MathWorks®

University of Texas at Tyler

Get Software | Learn MATLAB | Teach with MATLAB | What's New

MATLAB Access for Everyone at

University of Texas at Tyler

https://www.mathworks.com/academia/tah-portal/university-of-texas-at-tyler-1108545.html
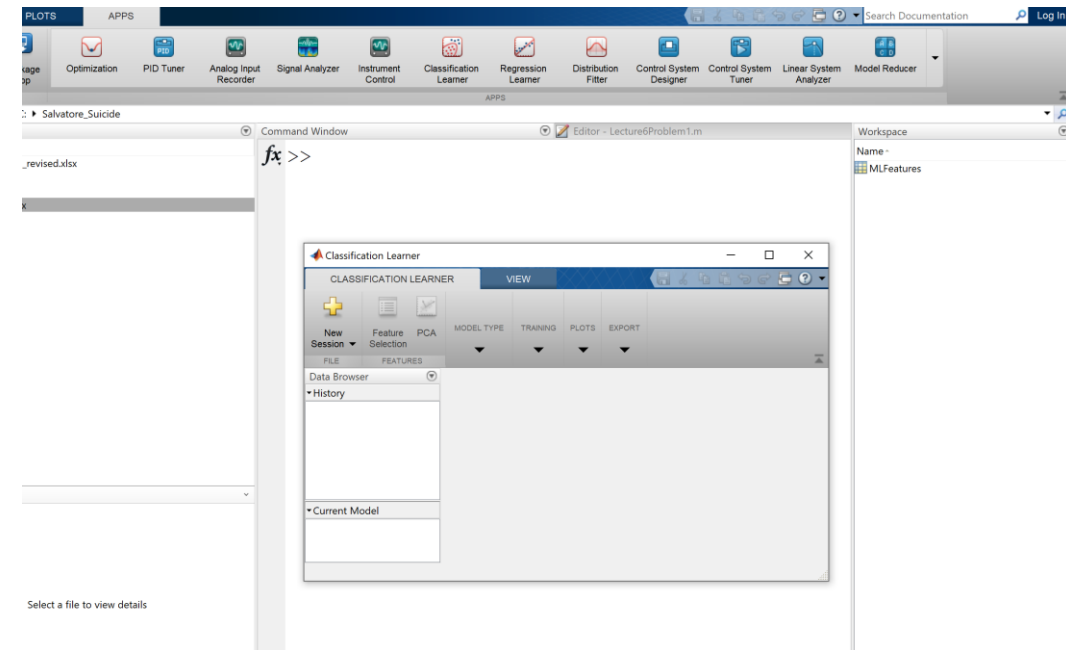
ANALYSIS PLATFORM

https://www.mathworks.com/academia/tah-portal/university-of-texas-at-tyler-1108545.html

OUTLINE

➢INTRODUCTION

➢DIFFERENT MACHINE LEARNING APPROACHES

➢EXAMPLES

INTRODUCTION

➤ What is Machine Learning ?

▪ Machine Learning is a field of study that gives computers the ability to "learn" without being explicitly programmed

- Prediction

- Classification

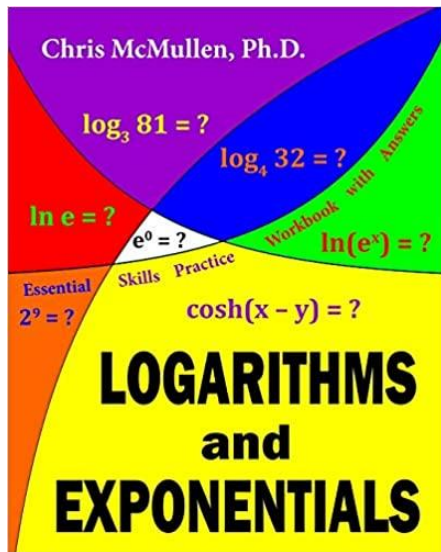*Samuel AL, IBM J. Research & Development, 1959, vol. 3 (3), 210-229*

INTRODUCTION

➢Too many books spoil the curiosity

▪ Start with Andrew Ng, Machine Learning, Stanford University available on YouTube

Some Statistics & Programming Knowledge Helps !

INTRODUCTION

Analytical Tools

Simple Calculator
(Boolean Algebra)

Scientific Calculator
(Series Expansion,
Boolean Algebra)

Computer
(Programming
Language, Assembly
Language, Series
Expansion, Boolean
Algebra)

Smart Devices
(ML Models,
Programming
Language, Assembly
Language, Series
Expansion, Boolean
Algebra)

INTRODUCTION

➢Always there is a mathematical foundation

Analytical Tools (Logarithm, Laplace Transform, Fourier Transform…….)

Computational Tools (Boolean Algebra, Taylor Series Expansion,……..)

Programming Languages (Basic, Fortran, C, C++, Java, …….)

Assembly Languages (depending upon the computer processors)

Machine Learning Models

Artificial Intelligence

INTRODUCTION

➢Examples of Smart Systems

      Voice Recognition

      Tumor Detection

      Weather Forecast

      Driverless Cars

WHAT IS NEEDED?

➢Training Data

➢Appropriate Model

➢Procedure to Train (Make a machine to "learn")

(Learning Algorithms, Online vs Batch Learning, Instance Based vs Model Based)

➢Test Data

OUTLINE

➢INTRODUCTION

➢DIFFERENT MACHINE LEARNING APPROACHES

➢EXAMPLES

APPROACHES

➢STANDARD MACHINE LEARNING

➢ADVANCED MACHINE LEARNING

Based on Artificial Neural Networks (Deep Learning)

APPROACHES

➢ SUPERVISED LEARNING

➢ UNSUPERVISED LEARNING

APPROACHES

➢SUPERVISED LEARNING

➢UNSUPERVISED LEARNING

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

Provide training set with features and solutions

APPROACHES

➤ SUPERVISED LEARNING (Classification / Prediction)
   Find the area of a rectangle

L	W	A	A1 (L+W)	A2 (L-W)	A3 (L*W)	A4 L/W
12.1	13.4	162.3	25.5	-1.3	162.14	0.90
8.6	9.7	83.4	18.3	-1.1	83.42	0.89
3.2	5.4	17.3	8.6	-2.2	17.28	0.59
6.1	10.2	62.25	16.3	-4.1	62.22	0.60
18.2	6.4	116.5	24.6	11.8	116.48	2.83
1.6	2.8	4.5	4.4	-1.2	4.48	0.57
7.7	0.6	4.7	8.3	7.1	4.62	12.83

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)
Find the area of a rectangle

L	W	A	E1 |A-A1|	E2 |A-A2|	E3 |A-A3|	E4 |A-A4|
12.1	13.4	162.3	136.8	163.6	0.16	161.40
8.6	9.7	83.4	65.1	84.5	0.02	82.51
3.2	5.4	17.3	8.7	19.5	0.02	16.71
6.1	10.2	62.25	45.95	66.35	0.03	61.65
18.2	6.4	116.5	91.90	104.70	0.02	113.66
1.6	2.8	4.5	0.1	5.7	0.02	3.93
7.7	0.6	4.7	3.6	2.4	0.08	8.13

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

- Logistic Regression

- Support Vector Machines

- k-Nearest Neighbors

- Decision Trees and Random Forests

- Neural Networks

APPROACHES

➤ SUPERVISED LEARNING (Classification / Prediction)

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APPROACHES

➢SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

Given m outcomes y^i where $i = 1,2,\ldots,m$ with each outcome depends on n features x_j where $j = 1,2,\ldots,n$. Find the best estimate of y^i as $\hat{y}^i$ using the n features with appropriate parameters θ_j such that $J = \left\langle \left(\hat{y}^i - y^i\right)^2 \right\rangle$

$$\hat{y}^i = \theta_0^i + \theta_1^i x_1^i + \theta_2^i x_2^i + \cdots \ldots \ldots + \theta_n^i x_n^i$$

APPROACHES

➤ SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

$$\hat{y}^i = \theta_0^i + \theta_1^i x_1^i + \theta_2^i x_2^i + \cdots \ldots \ldots . + \theta_n^i x_n^i$$

$$\hat{Y} = \theta . X = h_\theta(X)$$

Cost Function to Minimize

$$J = \left\langle \left(\hat{y}^i - y^i\right)^2 \right\rangle = (\hat{Y} - Y)^T (\hat{Y} - Y)$$

APPROACHES

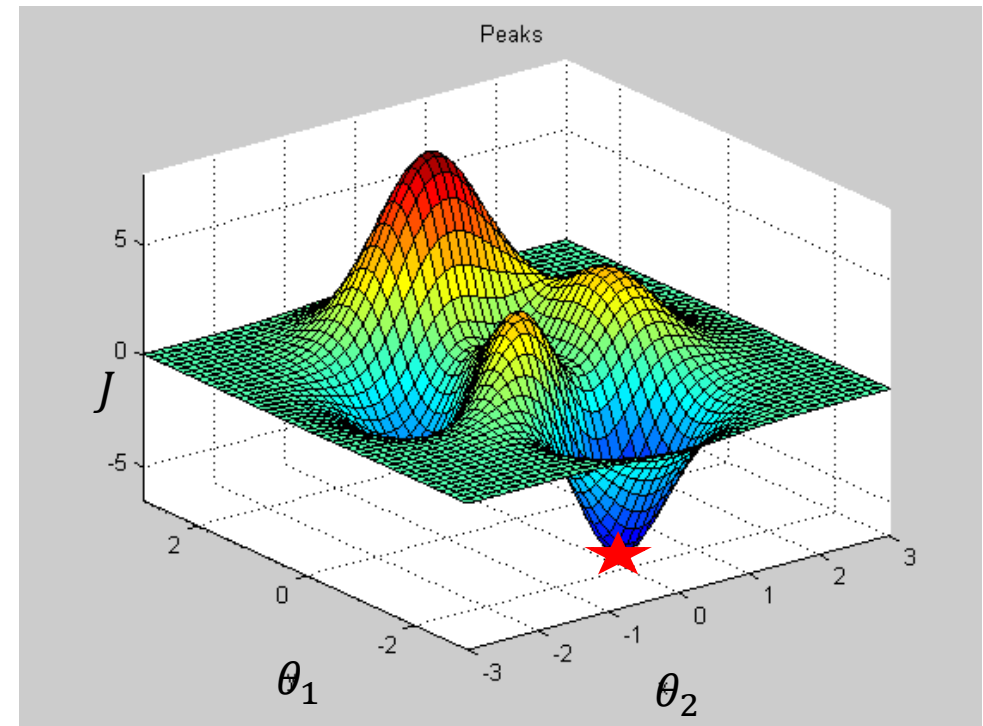➢ SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

$$\hat{y}^i = \theta_0^i + \theta_1^i x_1^i + \theta_2^i x_2^i + \cdots \ldots \ldots + \theta_n^i x_n^i$$

$$\hat{Y} = \theta . X = h_\theta(X)$$

- Gradient Descent by **Louis Augustin Cauchy** in 1847

Cost Function to Minimize

$$J = \left\langle (\hat{y}^i - y^i)^2 \right\rangle = (\hat{Y} - Y)^T (\hat{Y} - Y)$$

Peaks

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

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APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Logistic Regression

$$\hat{p} = f(\theta.X) = h_\theta(X);\quad f(\theta.X) = \frac{1}{1+e^{-\theta.X}}$$

$$\hat{y} = 1\ if\ \hat{p} < 0.5;\ \ \hat{y} = 0\ if\ \hat{p} \geq 0.5$$

Derive Cost Function to Minimize
J

APPROACHES

➢SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

  Mainly for regression (predicting an outcome)

- Logistic Regression

  Mainly for classification (0 or 1)

  High Risk vs. Low Risk
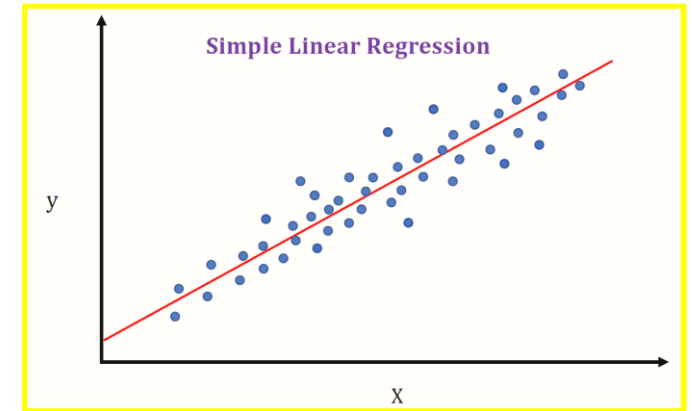
Simple Linear Regression

https://medium.datadriveninvestor.com/machine-learning-101-part-1-24835333d38a

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

- Logistic Regression

- Support Vector Machines

- k-Nearest Neighbors

- Decision Trees and Random Forests

- Neural Networks

APPROACHES
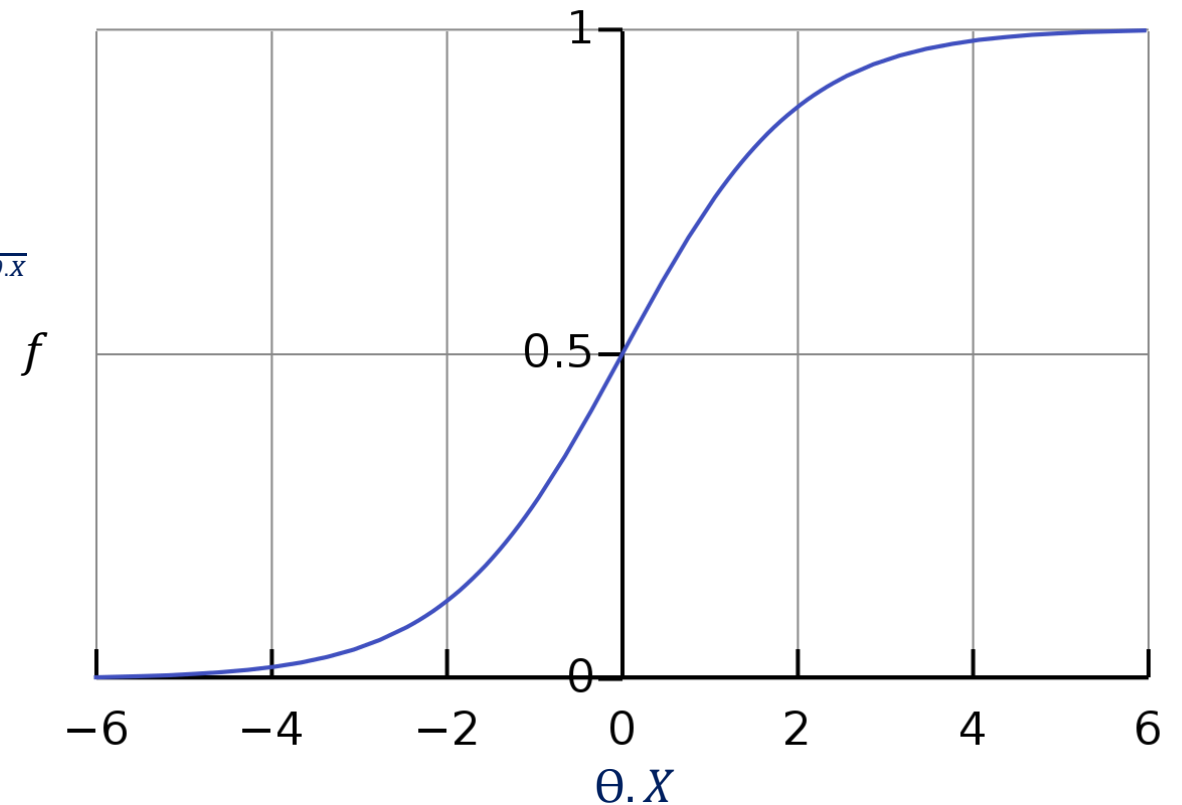
➢SUPERVISED LEARNING (Classification / Prediction)

- Support Vector Machine

Used for regression as well as classification

APPROACHES

➢SUPERVISED LEARNING (Classification / Prediction)

- Support Vector Machine (SVM)

Used for regression as well as classification

Linear vs. SVM Regression

APPROACHES

➢SUPERVISED LEARNING (Classification / Prediction)

• Support Vector Machine (SVM)

Used for regression as well as classification

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Support Vector Machine (SVM)

Used for regression as well as classification

x_2

x_1

https://www.mathworks.com/matlabcentral/fileexchange/62061-multi-class-svm

APPROACHES

➤ SUPERVISED LEARNING (Classification / Prediction)

- Linear Regression

- Logistic Regression

- Support Vector Machines

- k-Nearest Neighbors

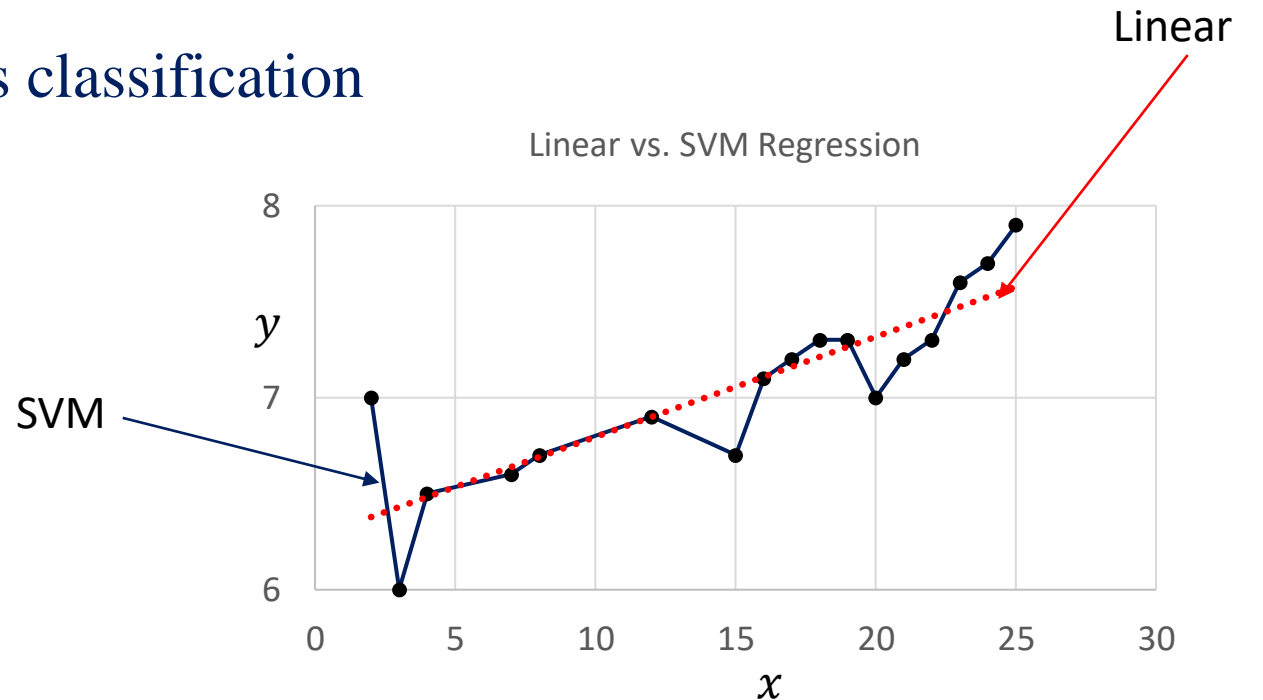- Decision Trees and Random Forests

- Neural Networks

APPROACHES

➢ SUPERVISED LEARNING

➢ UNSUPERVISED LEARNING

APPROACHES

➢Unsupervised Learning

Clustering

- Principal Component Analysis

- Independent Component Analysis

- Singular Value Decomposition

- …….

- ………

APPROACHES

➤ Machine Learning with MATLAB

Machine Learning Driving School

MathWorks®

Get MATLAB

ouette(meas,cidxCos,'cos');
(silh3) mean(silhCos)]

cidxCos==i);
ust,1),meas

Machine Learning with MATLAB

Read ebook
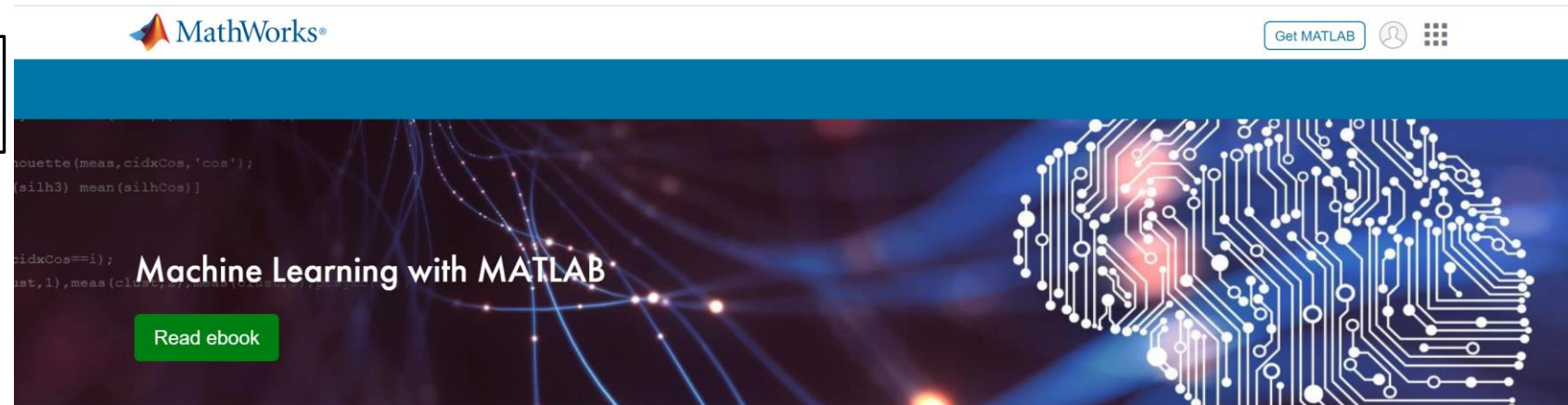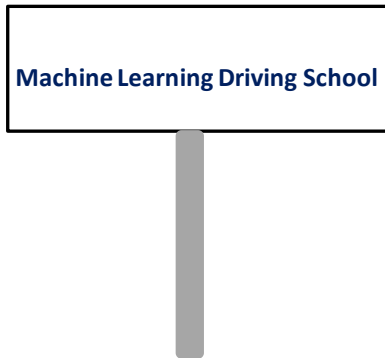
You have a complex problem involving a large amount of data and lots of variables. You know that machine learning would be the best approach—but you've never used it before. How do you deal with data that's messy, incomplete, or in a variety of formats? How do you choose the right model for the data?

Sounds daunting? Don't be discouraged. A systematic workflow will help you get off to a smooth start.

Mastering Machine Learning: A Step-by-Step Guide with MATLAB

Read ebook

https://commons.wikimedia.org/wiki/File:Man_Driving_Car_Cartoon_Vector.svg

http://clipart-library.com/mechanic-cliparts.html

OUTLINE

➢ INTRODUCTION

➢ DIFFERENT MACHINE LEARNING APPROACHES

➢ EXAMPLES

Example 1

➤ Prediction of House Price (housing.csv) Regression Problem

longitude

latitude

housing_median_age

total_rooms

total_bedrooms

population

households median_income

median_house_value

ocean_proximity

https://www.kaggle.com/camnugent/california-housing-prices/metadata

Example 1

➢Prediction of House Price: Regression Problem

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	median_house_value
-122.23	37.88	41	880	129	322	126	8.3252	NEAR BAY	452600
-122.22	37.86	21	7099	1106	2401	1138	8.3014	NEAR BAY	358500
-122.24	37.85	52	1467	190	496	177	7.2574	NEAR BAY	352100
-122.25	37.85	52	1274	235	558	219	5.6431	NEAR BAY	341300
-122.25	37.85	52	1627	280	565	259	3.8462	NEAR BAY	342200
-122.25	37.85	52	919	213	413	193	4.0368	NEAR BAY	269700
-122.25	37.84	52	2535	489	1094	514	3.6591	NEAR BAY	299200
-122.26	37.84	42	2555	665	1206	595	2.0804	NEAR BAY	226700
-122.25	37.84	52	3549	707	1551	714	3.6912	NEAR BAY	261100
-122.26	37.85	52	2202	434	910	402	3.2031	NEAR BAY	281500
-122.26	37.85	52	3503	752	1504	734	3.2705	NEAR BAY	241800
-122.26	37.85	52	2491	474	1098	468	3.075	NEAR BAY	213500
-122.26	37.84	52	696	191	345	174	3.6736	NEAR BAY	191300

Example 1

➤Prediction of House Price: Regression Problem

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	median_house_value
-122.23	37.88	41	880	129	322	126	8.3252	NEAR BAY	452600
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-122.26	37.85	52	3503	752	1504	734	3.2705	NEAR BAY	241800
-122.26	37.85	52	2491	474	1098	468	3.075	NEAR BAY	213500
-122.26	37.84	52	696	191	345	174	3.6736	NEAR BAY	191300

Demo

Example 2

➢ Prediction of House Price (housing_classification.csv) Classification Problem

longitude

latitude

housing_median_age

total_rooms

total_bedrooms

population

households median_income

median_house_value (High/Low) Threshold= Average Price ($206875)

ocean_proximity

Example 2

➢Prediction of House Price: Classification Problem

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	class
-122.23	37.88	41	880	129	322	126	8.3252	NEAR BAY	1
-122.22	37.86	21	7099	1106	2401	1138	8.3014	NEAR BAY	1
-122.24	37.85	52	1467	190	496	177	7.2574	NEAR BAY	1
-122.25	37.85	52	1274	235	558	219	5.6431	NEAR BAY	1
-122.25	37.85	52	1627	280	565	259	3.8462	NEAR BAY	1
-122.25	37.85	52	919	213	413	193	4.0368	NEAR BAY	1
-122.25	37.84	52	2535	489	1094	514	3.6591	NEAR BAY	1
-122.26	37.84	42	2555	665	1206	595	2.0804	NEAR BAY	1
-122.25	37.84	52	3549	707	1551	714	3.6912	NEAR BAY	1
-122.26	37.85	52	2202	434	910	402	3.2031	NEAR BAY	1
-122.26	37.85	52	3503	752	1504	734	3.2705	NEAR BAY	1
-122.26	37.85	52	2491	474	1098	468	3.075	NEAR BAY	1
-122.26	37.84	52	696	191	345	174	2.6736	NEAR BAY	0
-122.26	37.85	52	2643	626	1212	620	1.9167	NEAR BAY	0
-122.26	37.85	50	1120	283	697	264	2.125	NEAR BAY	0
-122.27	37.85	52	1966	347	793	331	2.775	NEAR BAY	0

Example 2

➢Prediction of House Price: Classification Problem

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	class
-122.23	37.88	41	880	129	322	126	8.3252	NEAR BAY	1
-122.22	37.86	21	7099	1106	2401	1138	8.3014	NEAR BAY	1
-122.24	37.85	52	1467	190	496	177	7.2574	NEAR BAY	1
-122.25	37.85	52	1274	235	558	219	5.6431	NEAR BAY	1
-122.25	37.85	52	1627	280	565	259	3.8462	NEAR BAY	1
-122.25	37.85	52	919	213	413	193	4.0368	NEAR BAY	1
-122.25	37.84	52	2535	489	1094	514	3.6591	NEAR BAY	1
-122.26	37.84	42	2555	665	1206	595	2.0804	NEAR BAY	1
-122.25	37.84	52	3549	707	1551	714	3.6912	NEAR BAY	1
-122.26	37.85	52	2202	434	910	402	3.2031	NEAR BAY	1
-122.26	37.85	52	3503	752	1504	734	3.2705	NEAR BAY	1
-122.26	37.85	52	2491	474	1098	468	3.075	NEAR BAY	1
-122.26	37.84	52	696	191	345	174	2.6736	NEAR BAY	0
-122.26	37.85	52	2643	626	1212	620	1.9167	NEAR BAY	0
-122.26	37.85	50	1120	283	697	264	2.125	NEAR BAY	0
-122.27	37.85	52	1966	347	793	331	3.775	NEAR BAY	0

Demo

Example 2

➢Prediction of House Price (housing_classification.csv) Classification Problem

Confusion Matrix

True Class

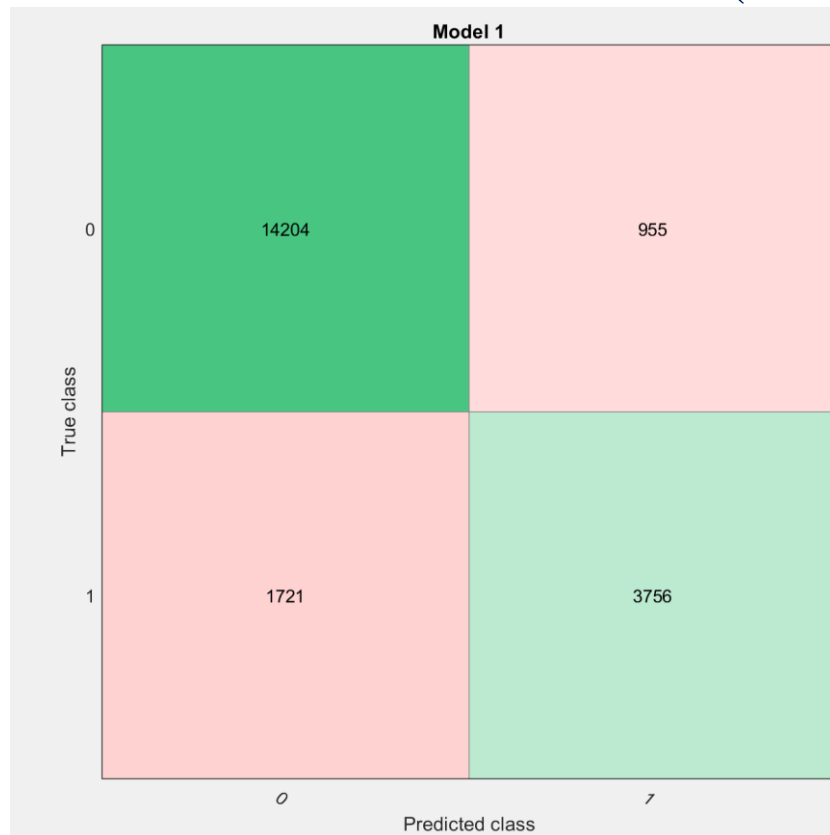|		
P	True Positive	False Negative
N	False Positive	True Negative

$\widehat{P}$ $\widehat{N}$

Predicted Class

True Positive Rate = True Positive / P

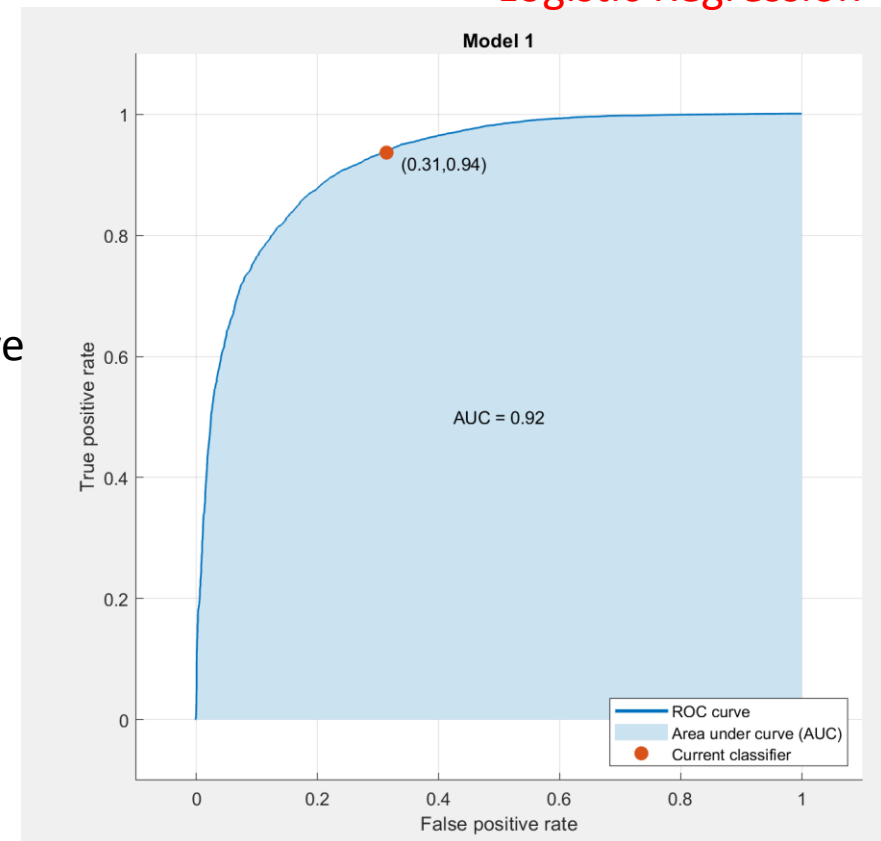True Negative Rate = True Negative / N= 1 – False Positive Rate (FP/N)

Example 2

➢Prediction of House Price (housing.csv) Classification Problem Logistic Regression

0: below average

1: average or above

Testing of the Models

longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	median_house_value	Prediction	Classification
-122.25	37.84	52	3104	687	1157	647	3.12	NEAR BAY	241400	256052	High
-119.55	36.71	32	1963	508	2052	518	1.9076	INLAND	55800	56741	Low
-124.17	40.8	52	1557	344	758	319	1.8529	NEAR OCEAN	62500	164720	Low
-123.76	41.03	24	2386	565	1058	414	2.0644	<1H OCEAN	79800	132235	Low

THANK YOU

Research Design & Data Analysis Lab
Office of Research, Scholarship, and Sponsored Programs

SBIR: RAE (Realize, Analyze, Engage) - A digital biomarker based detection and intervention system for stress and carvings during recovery from substance abuse disorders.
PIs: M. Reinhardt, S. Carreiro, P. Indic

STARs Award

The University of Texas System
P. Indic (PI, UT Tyler)

Design of a wearable sensor system and associated algorithm to track suicidal ideation from movement variability and develop a novel objective marker of suicidal ideation and behavior risk in veterans.
Clinical Science Research and Development Grant (approved for funding),
P. Indic (site PI, UT-Tyler)
E.G. Smith (Project PI, VA)
P. Salvatore (Investigator, Harvard University)

Pre-Vent

National Institute Of Health Grant
P. Indic (Analytical Core PI, UT-Tyler)
N. Ambal (PI, Univ. of Alabama, Birmingham)

ViSiON

National Institute Of Health Grant
P. Indic (Co-Investigator & site PI , UT-Tyler)
P. Ramanand (Co-Investigator, UT-Tyler)
N. Ambal (PI, Univ. of Alabama, Birmingham)

UT Tyler Center for Health Informatics & Analytics

QUESTIONS