MACHINE LEARNING WITHOUT LEARNING

PREMANANDA INDIC, PH.D.

DEPARTMENT OF ELECTRICAL ENGINEERING

The University of Texas at TYLER Center for Health Informatics & Analytics

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

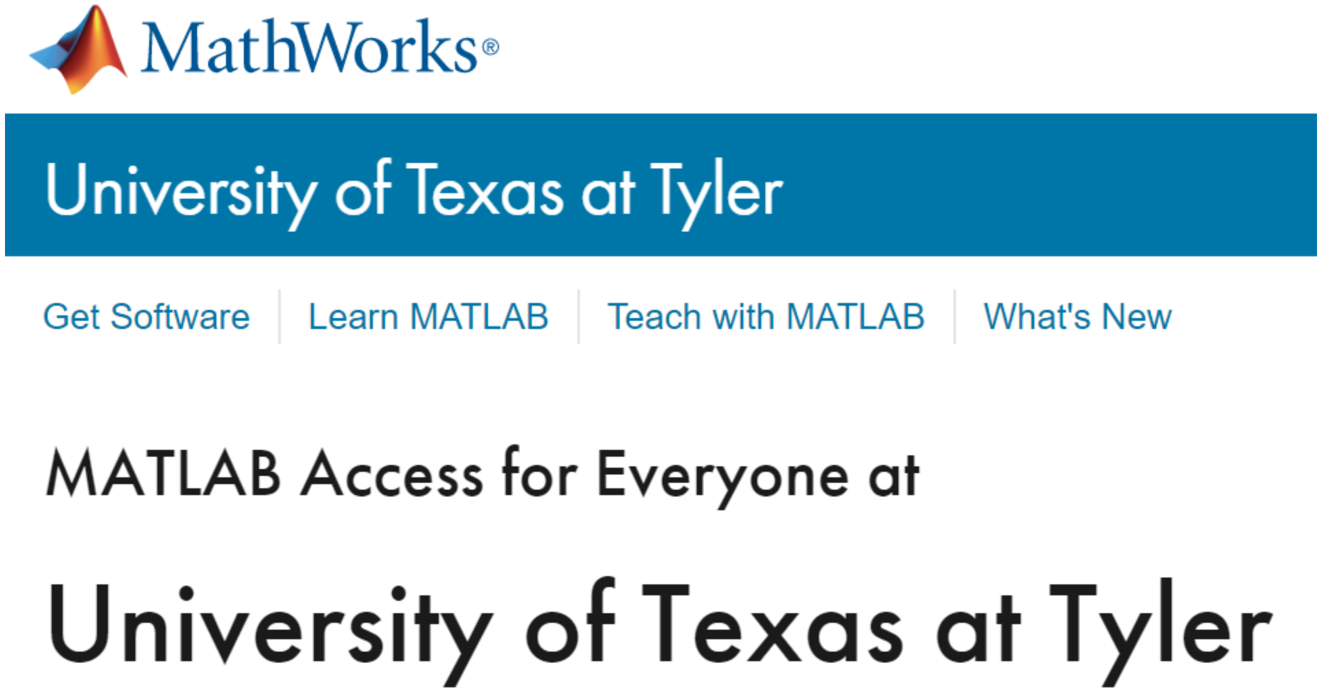
Get Software | Learn MATLAB | Teach with MATLAB | What's New

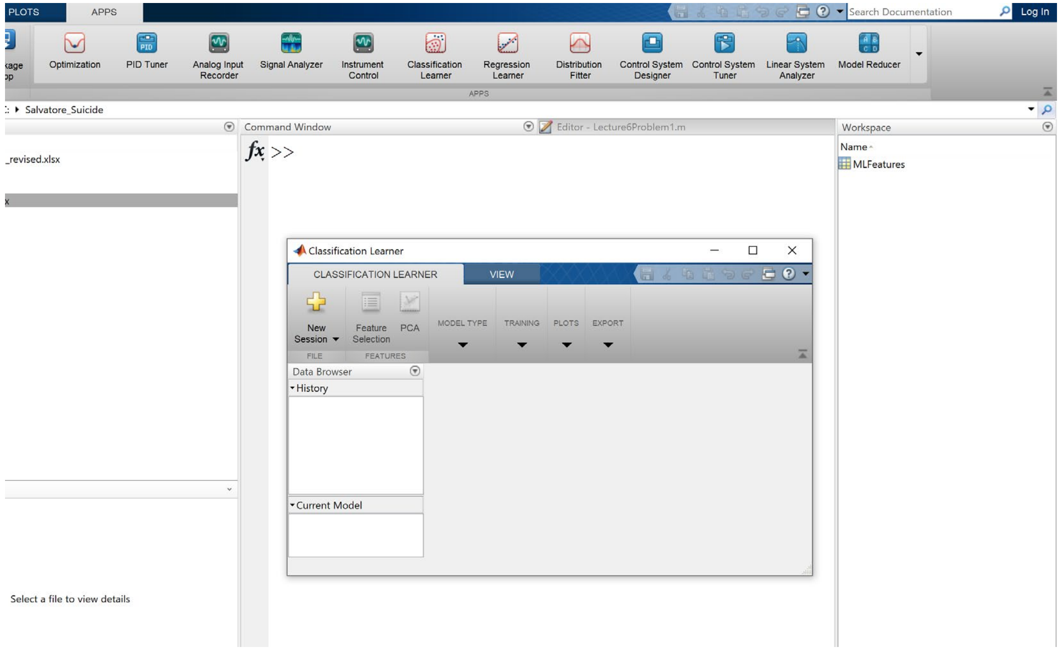
MATLAB Access for Everyone at

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

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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

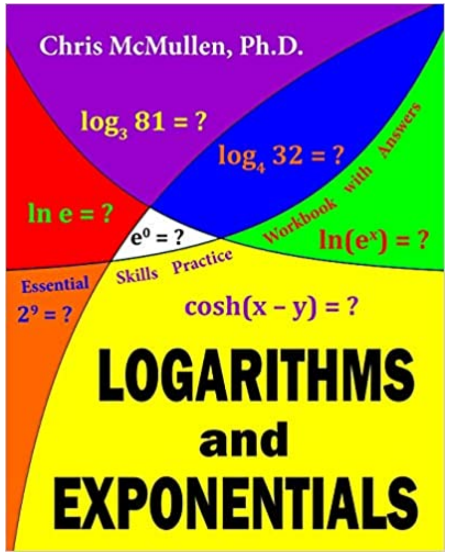
INTRODUCTION

- Too many books spoil the curiosity

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

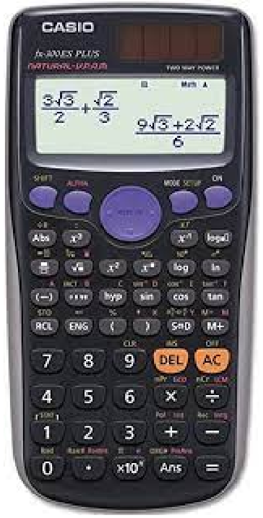
Some Statistics & Programming Knowledge Helps !

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

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

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

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

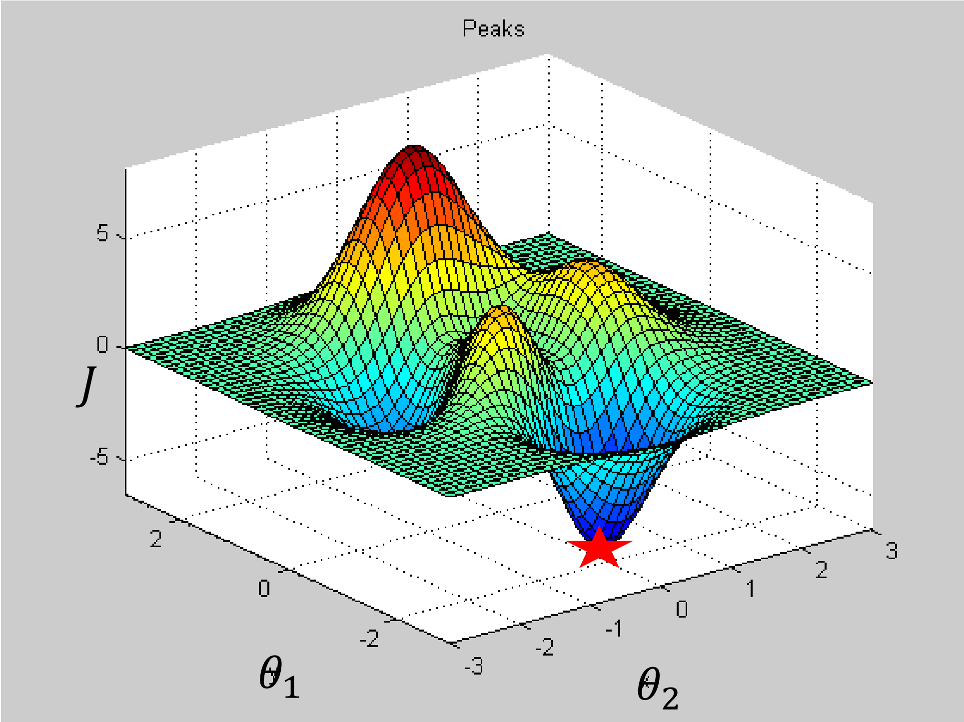
$$\hat{y}^i = \theta_0^i + \theta_1^i x_1^i + \theta_2^i x_2^i + \cdots \ldots \ldots . + \theta_n^i x_n^i$$

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

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

Cost Function to Minimize

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



APPROACHES

- SUPERVISED LEARNING (Classification / Prediction)
  - Linear Regression
  - Logistic Regression
  - Support Vector Machines
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  - Decision Trees and Random Forests
  - Neural Networks

APPROACHES

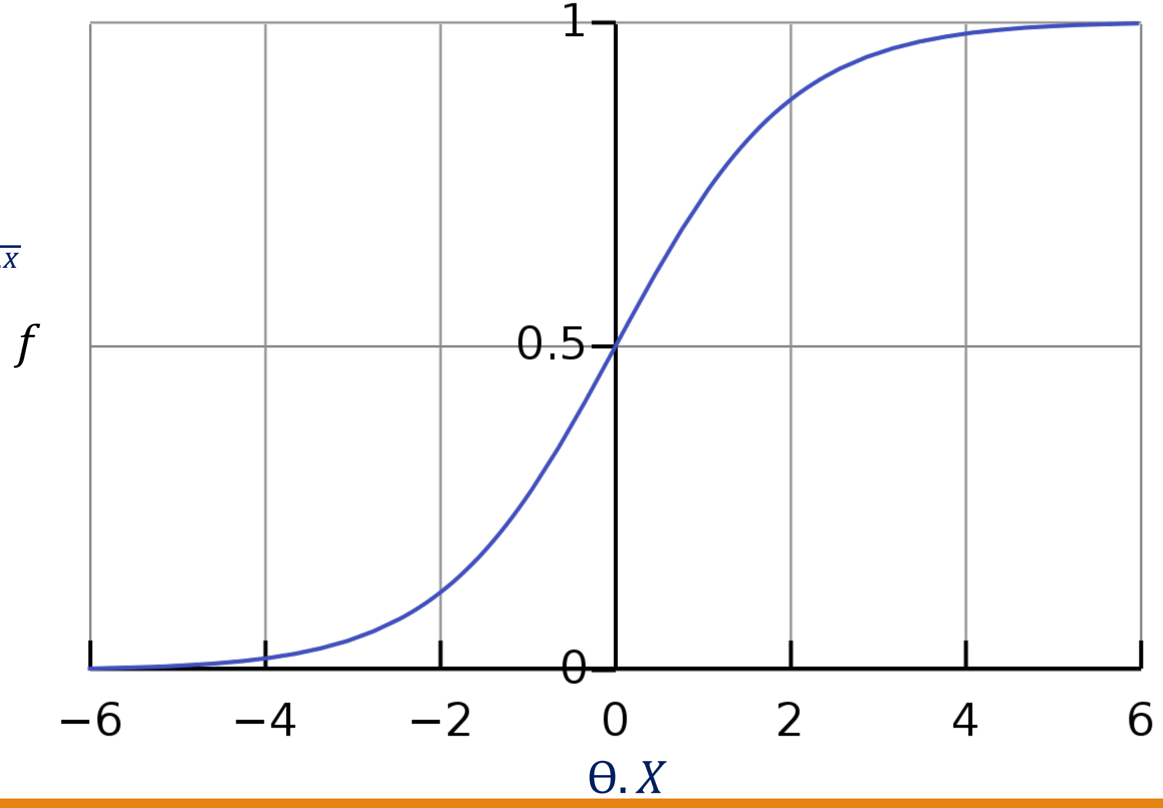
- SUPERVISED LEARNING (Classification / Prediction)
  - Logistic Regression

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

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

Derive Cost Function to Minimize

J



APPROACHES

➤ SUPERVISED LEARNING (Classification / Prediction)

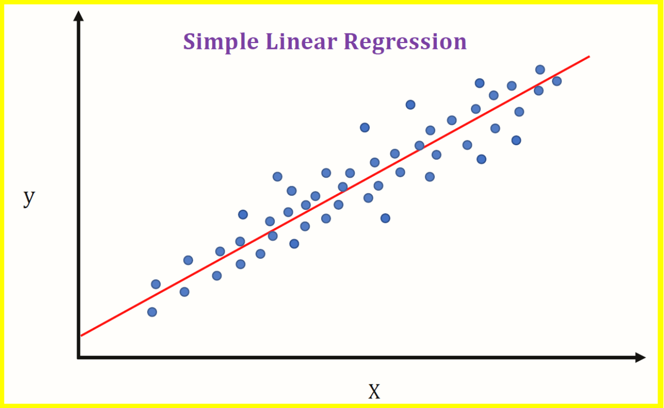
- Linear Regression

Mainly for regression (predicting an outcome)

- Logistic Regression

Mainly for classification (0 or 1)

High Risk vs. Low Risk



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
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  - Neural Networks

APPROACHES

- SUPERVISED LEARNING (Classification / Prediction)
  - Support Vector Machine

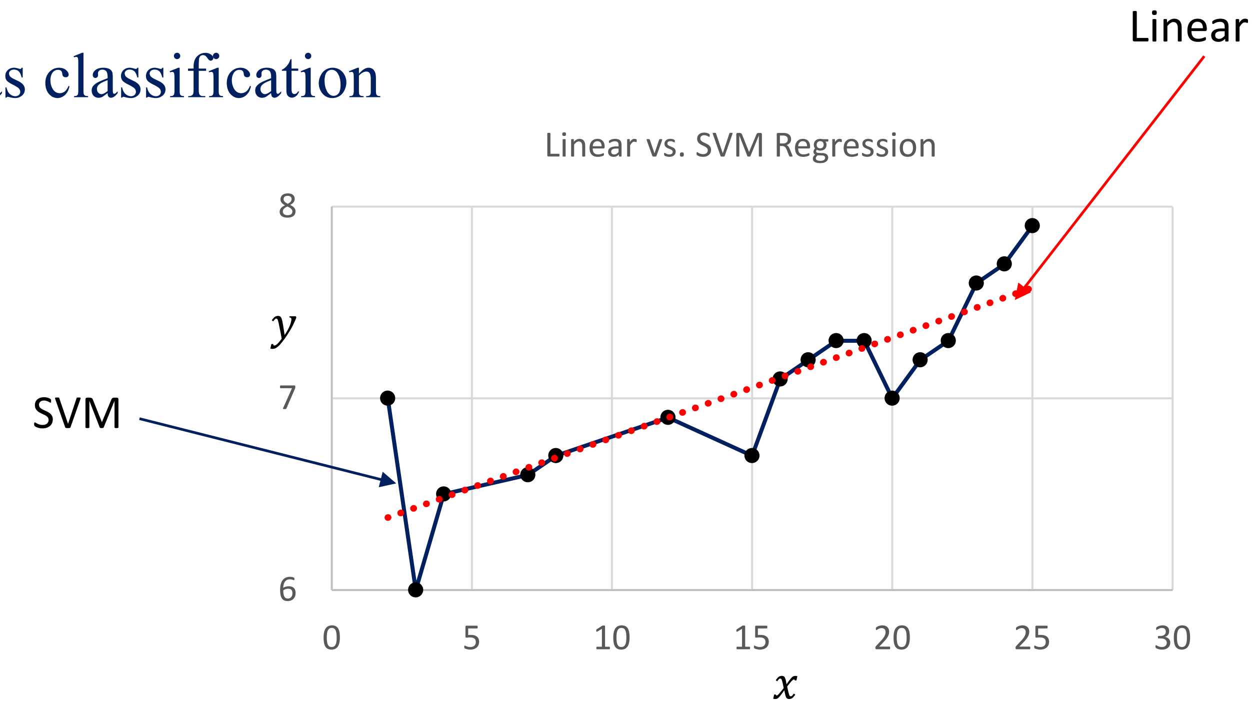
Used for regression as well as classification

APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Support Vector Machine (SVM)

Used for regression as well as classification

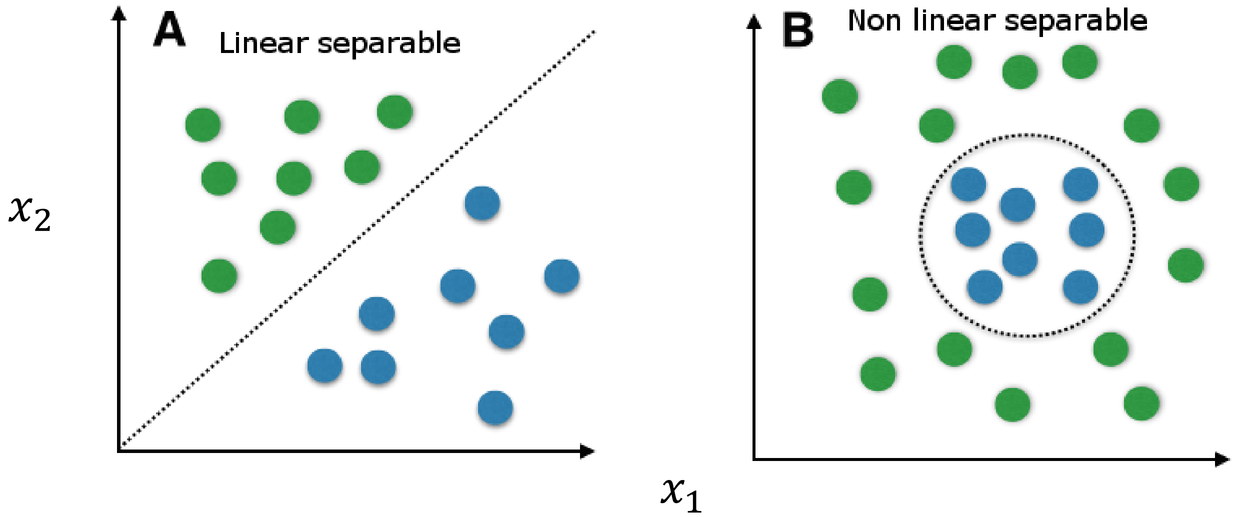


APPROACHES

➢ SUPERVISED LEARNING (Classification / Prediction)

- Support Vector Machine (SVM)

Used for regression as well as classification

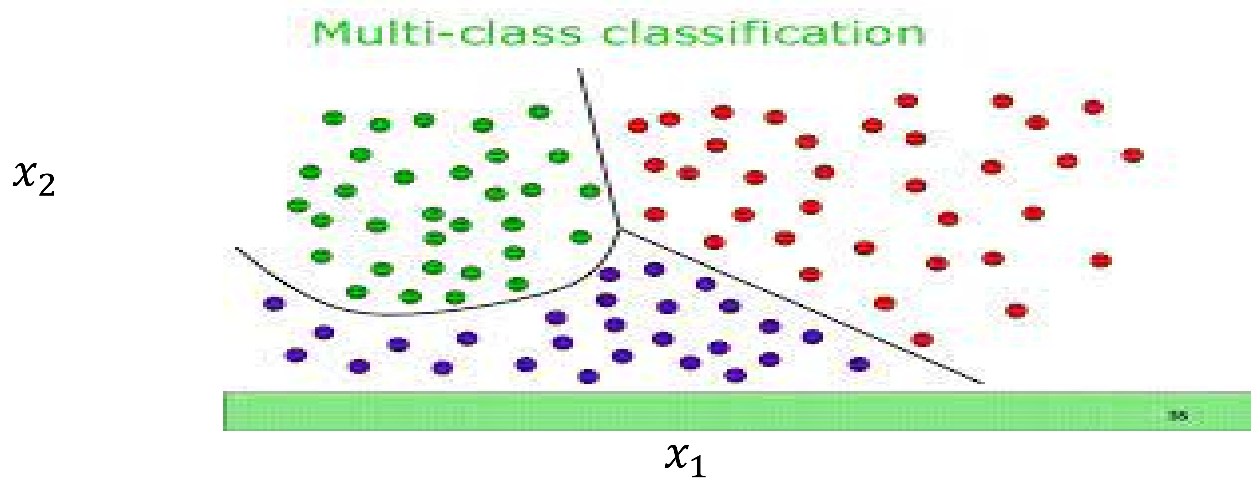


https://medium.com/@LSchultebraucks/introduction-to support-vector-machines-9f8161ae2fcb

APPROACHES

- SUPERVISED LEARNING (Classification / Prediction)
  - Support Vector Machine (SVM)

Used for regression as well as classification



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

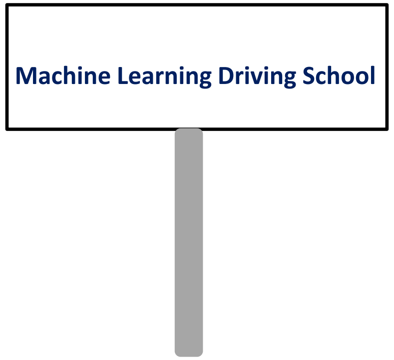
- Unsupervised Learning

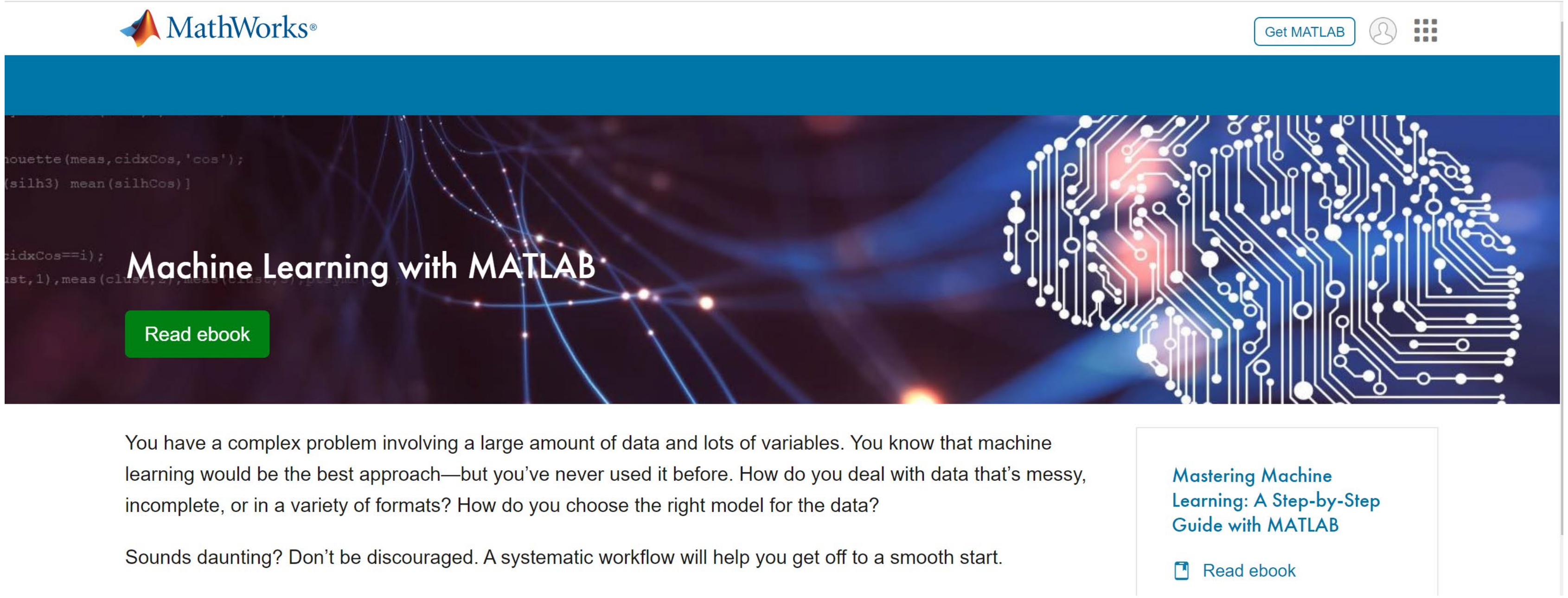
  Clustering

  - Principal Component Analysis
  - Independent Component Analysis
  - Singular Value Decomposition
  - …….
  - ………

APPROACHES

- Machine Learning with MATLAB





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

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

OUTLINE

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- 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

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
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-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

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

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

Demo

Example 2

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

Confusion Matrix

True Class		$\hat{P}$	$\hat{N}$
	P	True Positive	False Negative
	N	False Positive	True Negative

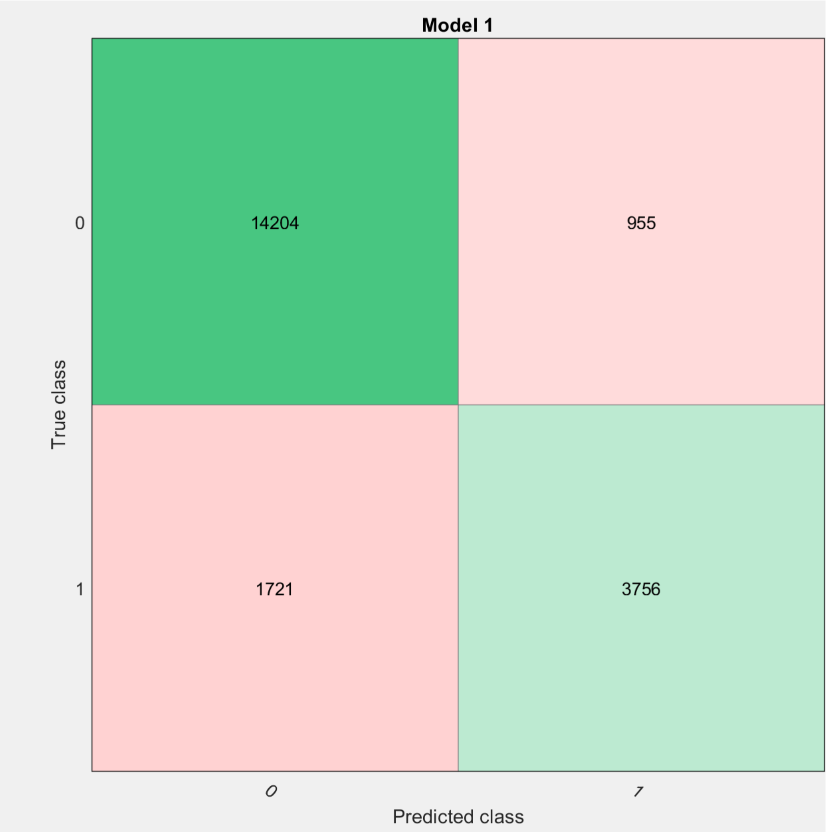
Predicted Class

True Positive Rate = True Positive / P

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

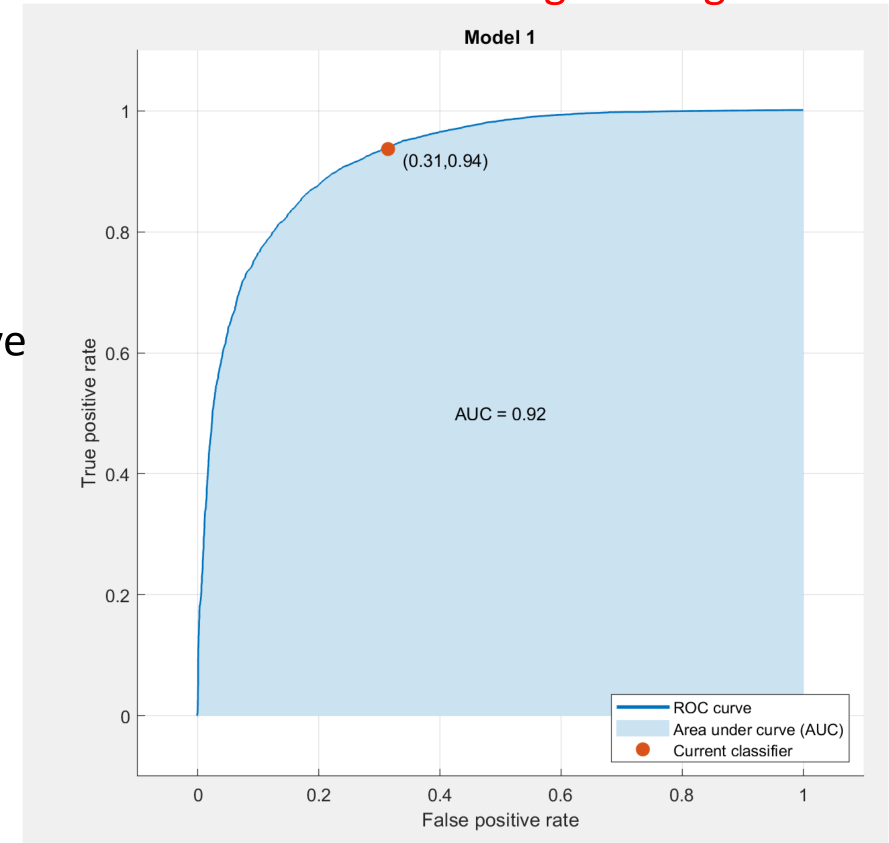
Example 2

- 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	220630	High
-119.55	36.71	32	1963	508	2052	518	1.9076	INLAND	55800	52440	Low
-124.17	40.8	52	1557	344	758	319	1.8529	NEAR OCEAN	62500	79030	Low
-123.76	41.03	24	2386	565	1058	414	2.0644	<1H OCEAN	79800	92500	Low

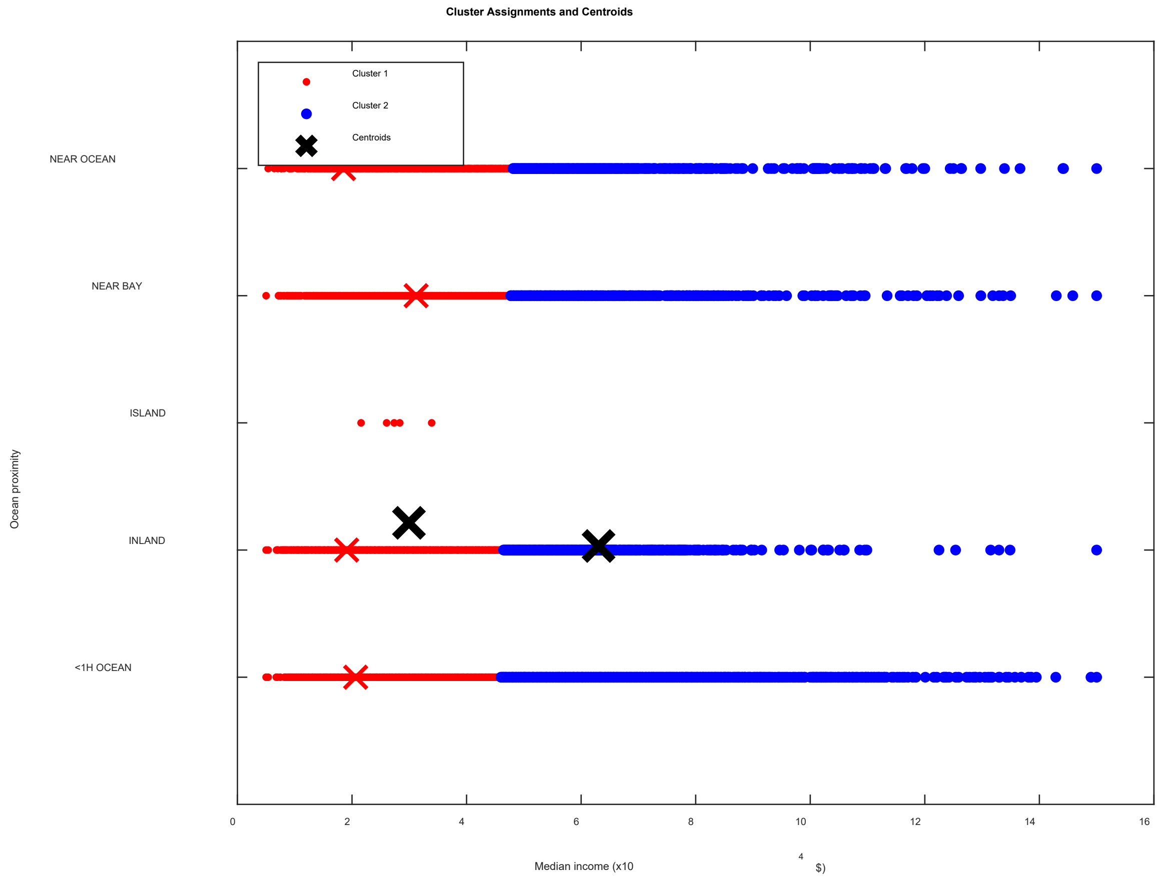
Example 3

- Unsupervised Learning (Clustering)

longitude
latitude
housing_median_age
total_rooms
total_bedrooms
population
households median_income
median_house_value
ocean_proximity

Example 3

- Unsupervised Learning (Clustering)



THANK YOU

ORS Research Design & Data Analysis Lab
Office of Research and Scholarship

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)

Department of Veterans Affairs

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)

Design of a wearable biosensor sensor system with wireless network for the remote detection of life threatening events in neonates.

National Science Foundation Smart & Connected Health Grant
P. Indic (Lead PI, UT-Tyler)
D. Paydarfar (Co PI, UT-Austin)
H. Wang (Co PI, UMass Dartmouth)
Y. Kim (Co PI, UMass Dartmouth)

Pre-Vent

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

ViSiOn
P. Indic (site PI, UT-Tyler)
P. Ramanand (Co-I, UT Tyler
N. Ambal, (PI, Univ. of Alabama, Birmingham)

QUESTIONS