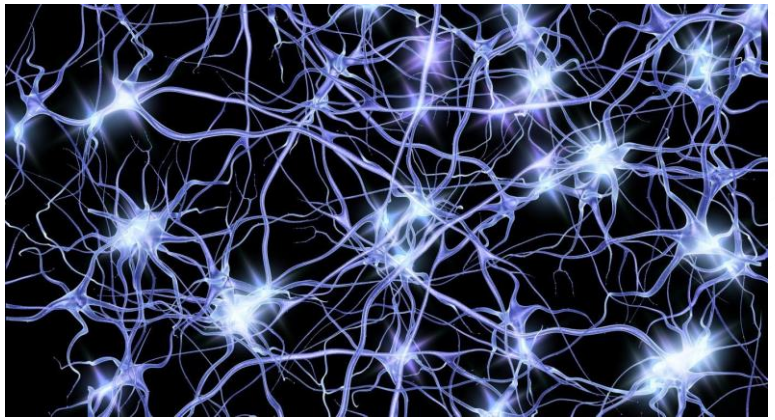
NEURAL NETWORK

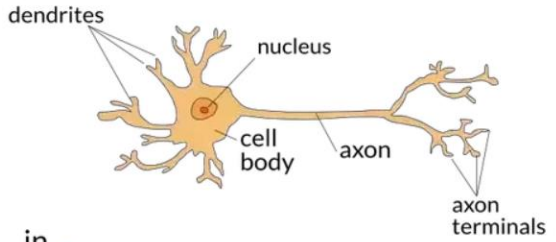
RESMI SURESH

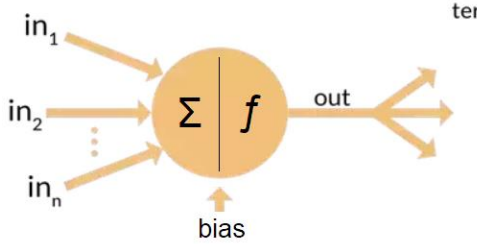
ASSISTANT PROFESSOR, IIT GUWAHATI

NEURAL NETWORK STRUCTURES



- Neural networks are modeled based on the structure of human brain
  - Have the possibility of capturing the human cognitive processes in future
  - Basic notion
    - All cognitive processes occur in brain
    - If one were able to understand the structure of the brain and then map functions to these structures, then one could have an in-silico system that will be able to perform cognitive tasks
    - Brain structure
      - Most fundamental unit – neurons
      - Neurons are connected to each other so that information in terms of electrical and chemical signals can be exchanged for collective decision making





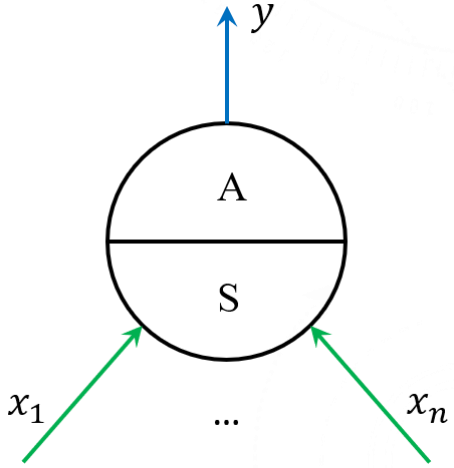
- These structures are quite useful in data science and ML even viewed purely as a nonlinear model form
- We would be discussing the engineering viewpoint
- Computational neural networks model the fundamental component and the interconnections through mathematical equations

NEURAL NETWORK STRUCTURES

- A neuron in a neural network receives multiple inputs from other neurons and/or exogenous inputs $(x_1, \ldots, x_n)$ and generates an output (y)
- Each node/neuron is partitioned into two components/functions (S and A)
  - S acting on $(x_1, \ldots, x_n)$ to provide an intermediate output o
  - Activation function A acting on o to give the final output y
  - S is generally a summation function

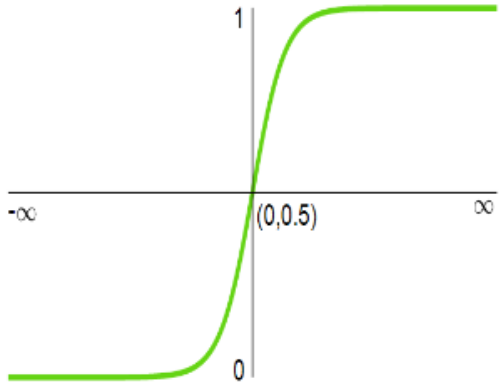
$$y = A(o);$$

$$o = S(x_1, x_2, \ldots, x_n) = \sum x_i$$



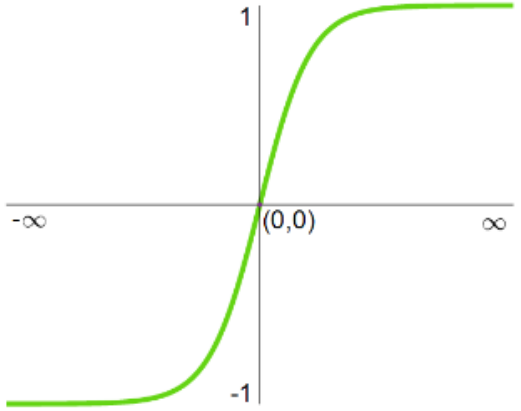
NEURAL NETWORK STRUCTURES ACTIVATION FUNCTIONS

- Some of the popular activation functions used in neural networks



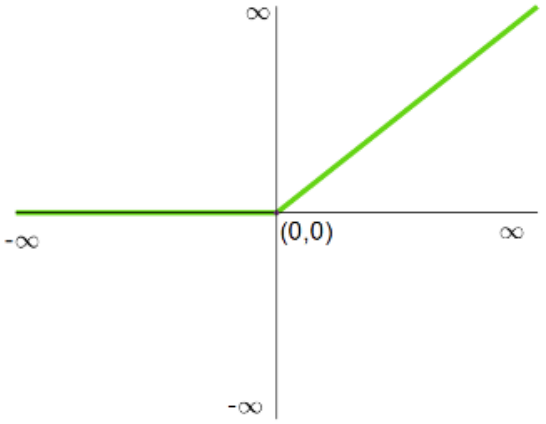
(a) Sigmoid function

$$A(o) = \frac{1}{1 + e^{-o}}$$



(b) tanh function

$$A(o) = \frac{e^{-o} - e^{o}}{e^{-o} + e^{o}}$$



(c) Relu function

$$A(o) = \begin{cases} o & \forall\ o \geq 0 \\ 0 & \forall\ o < 0 \end{cases}$$

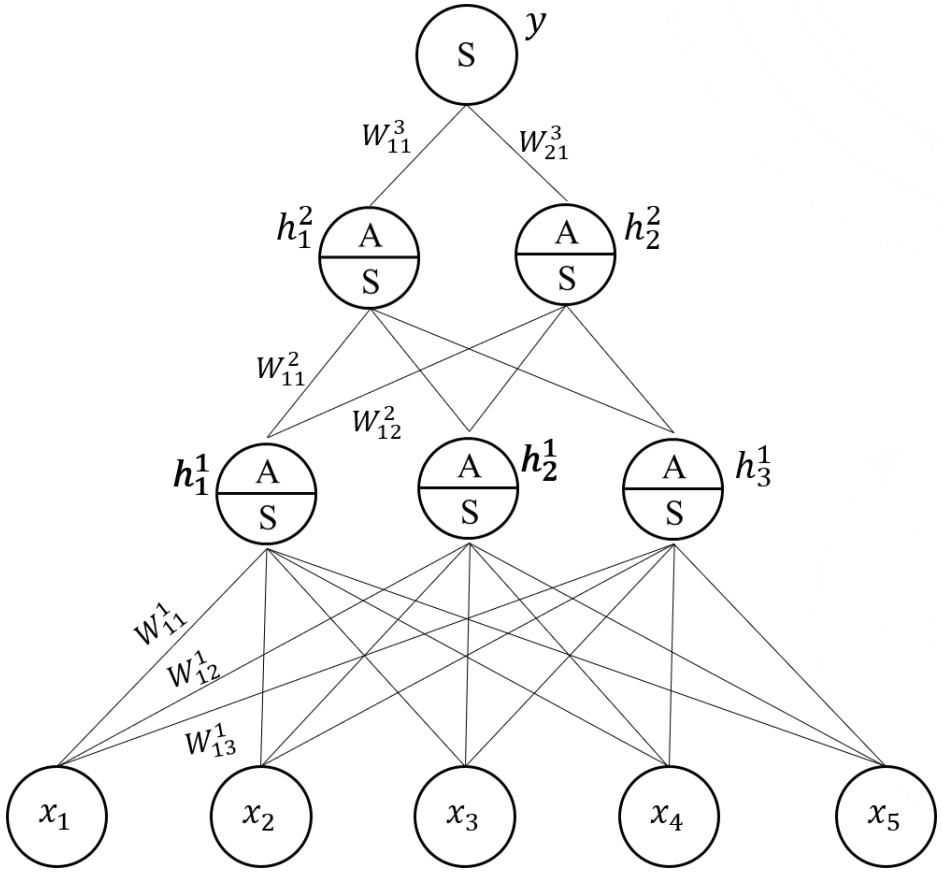
FULLY CONNECTED NEURAL NETWORK STRUCTURE

- Bottom most layer – input layer with input nodes (representing input variables)
  - Output of an input node is the value of the input variable
- Top most layer – output layer with output node (representing output variable)
- Layers in between – hidden layers
- Each node in a hidden layer will be connected to all the nodes in the previous layer
- The strength of each connection is represented by weights
- The output of jth node in the kth layer is calculated using

$$h_{k,j} = A(o_{k,j})$$

$$o_{k,j} = S(h_{k-1,1}, \dots, h_{k-1,r_{k-1}}) = \sum_{i=1}^{l=r_{k-1}} w_{k,lj}\, h_{k-1,l}$$

where r_{k-1} is the number of nodes in the (k-1)th layer



FULLY CONNECTED NEURAL NETWORK STRUCTURE

- If we have an m layer network (excluding input layer) and a single output y, then the predicted value of output from the given neural network is

$$\hat{y} = h_{m,1}$$

- Given a neural network structure, all the weights (W) and values of input variables, output can be calculated – forward calculation or propagation
  - Example: If sigmoid activation function is used and the inputs are $x_1 = -3.2$, $x_2 = 4.1$ and $x_3 = 0.163$,

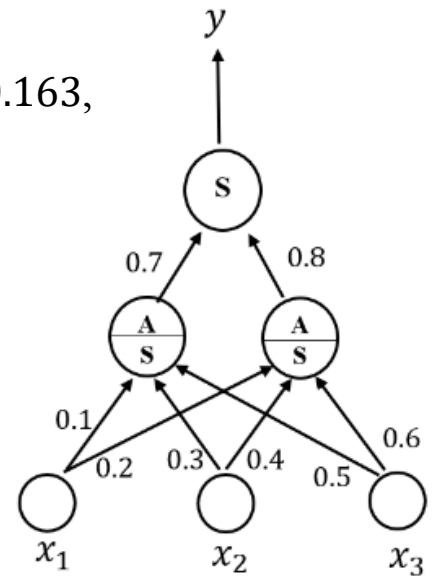
$$O_{1,1} = 0.1x_1 + 0.3x_2 + 0.5x_3 = 0.9915$$

$$O_{1,2} = 0.2x_1 + 0.4x_2 + 0.6x_3 = 1.0978$$

$$h_{1,1} = A(O_{1,1}) == \frac{1}{1 + e^{-1.0015}} = 0.7294$$

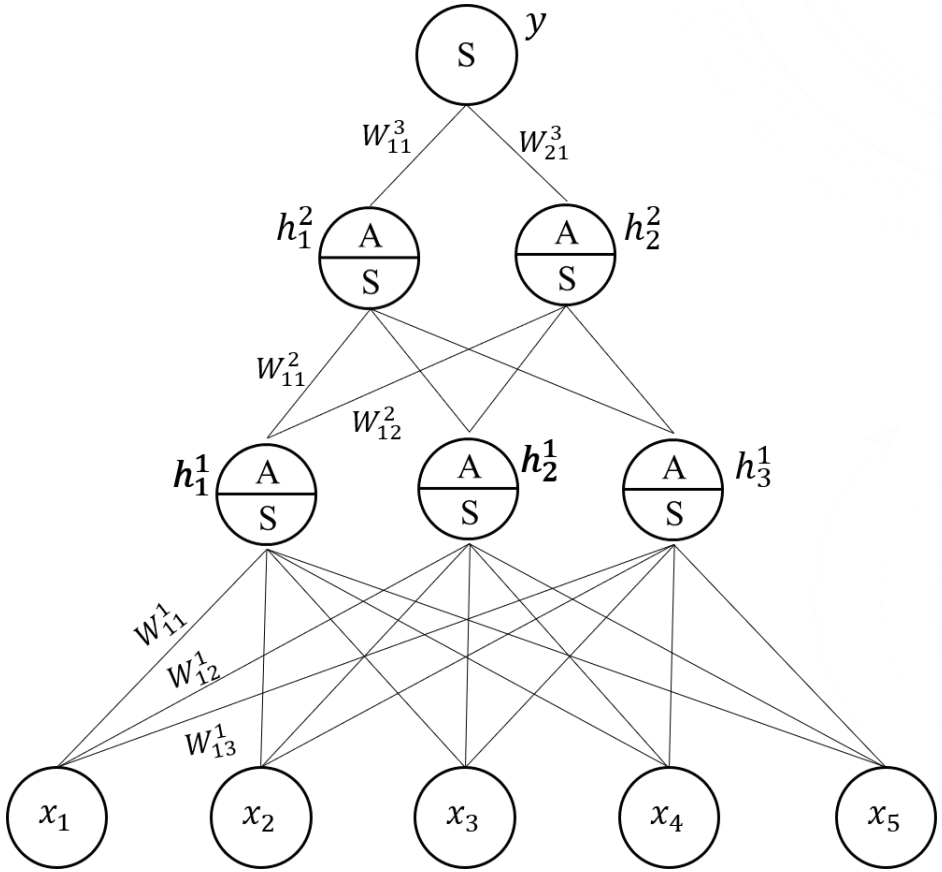
$$h_{1,2} = A(O_{1,2}) == \frac{1}{1 + e^{-1.1178}} = 0.7498$$

$$y = 0.7h_{1,1} + 0.8h_{1,2} = 1.1104$$



FULLY CONNECTED NEURAL NETWORK STRUCTURE

- Can be extended to multiple outputs
- Neural network is a non-linear model for the function approximation problem
- Though an explicit model form can be written, it is more convenient to refer to the model as a weights structure, W
- Use of a NN require
  - A choice for the structure
    - No. of hidden layers, choice of activation function and no of nodes in each hidden layer
  - Choice of weights given structure
- How do we decide the neural network structure and weights?



TRAINING OF NEURAL NETWORKS

- The neural network structure is usually decided based on prior knowledge or by trial-and-error
- Training a network implies the evaluation of optimal weights for the given network structure for the data available
- Optimization problem

$$\underset{W}{Min} \sum_{s=1}^{m} (\hat{y}^s(W) - y^s)^2$$

  - s – sample number; W – weight matrix (decision variable)
  - Predicted output will be a complex function of W
  - Objective – minimization of prediction error
  - Can we solve this using any of the methods we learned in optimization?
    - Non-linear programming problem
    - Any solution strategy to solve unconstrained NLP like steepest descent algorithm can be used

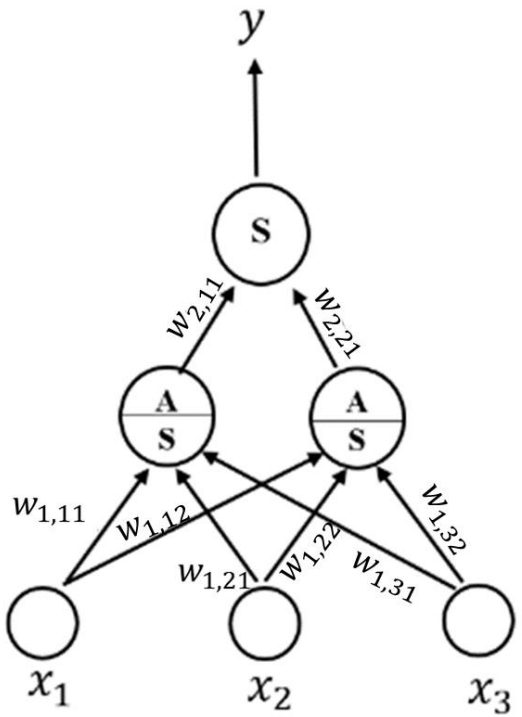
TRAINING OF NEURAL NETWORKS STEEPEST DESCENT

- Example: Given sample: $x_1 = -3.2, x_2 = 4.1, x_3 = 0.163$ and $y = 2$
- Decision variables: 8 weights ($w_{k,lj}$)
- Objective function: $min_w \quad f = (\hat{y}(w) - \quad y)^2$
- Steepest descent update rule:

$$w_{k,lj}^{[q+1]} = w_{k,lj}^{[q]} - \alpha \left(\frac{\partial f}{\partial w_{k,lj}} \right)_{w^{[q]}}$$

- Evaluating gradient

$$\frac{\partial f}{\partial w_{k,lj}} = 2(\hat{y} - y) \frac{\partial \hat{y}}{\partial w_{k,lj}}$$



TRAINING OF NEURAL NETWORKS BACKPROPAGATION

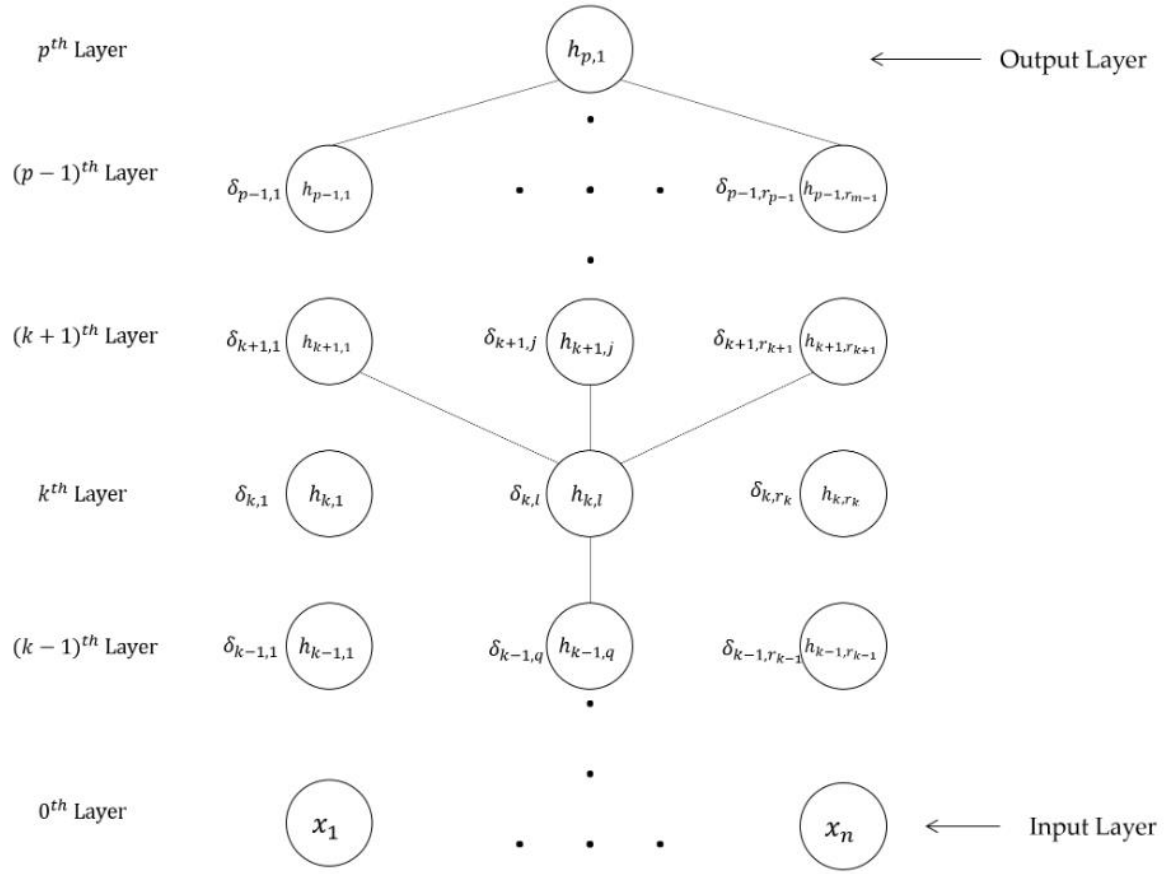
- Backpropagation – steepest descent with the gradient computed using chain rule of differentiation
- It efficiently computes one layer at a time, unlike a native direct computation
- Start with an initial guess of weights
- Each iteration has
  - Forward propagation (Given the weights, we calculate predicted output for the given input and error)
  - Backward propagation – Gradient calculation and updation of weights
- We will describe how the algorithm will work for one sample point; including all the points or a batch of points will only manifest as summation terms in the algorithm

TRAINING OF NEURAL NETWORKS BACKPROPAGATION

- Consider a p-layer neural network (0^{th} layer input, p^{th} layer output, p-1 hidden layers)
- Let the final output of the l^{th} node in k^{th} layer be $h_{k,l}$ and the intermediate output before the application of activation function be $o_{k,l}$
- r_k represents number of nodes in k^{rh} layer
- Predicted output $\hat{y} = h_{p,1}$
- Prediction error due to sample I

$$E^i = 0.5\left(y^i - \hat{y}^i\right)^2$$

- Total prediction error: $E = \sum E^i$



TRAINING OF NEURAL NETWORKS BACKPROPAGATION

- For every node, we define a new variable, $\delta_{k,l}$
  - For the l[th] node in the k[th] layer

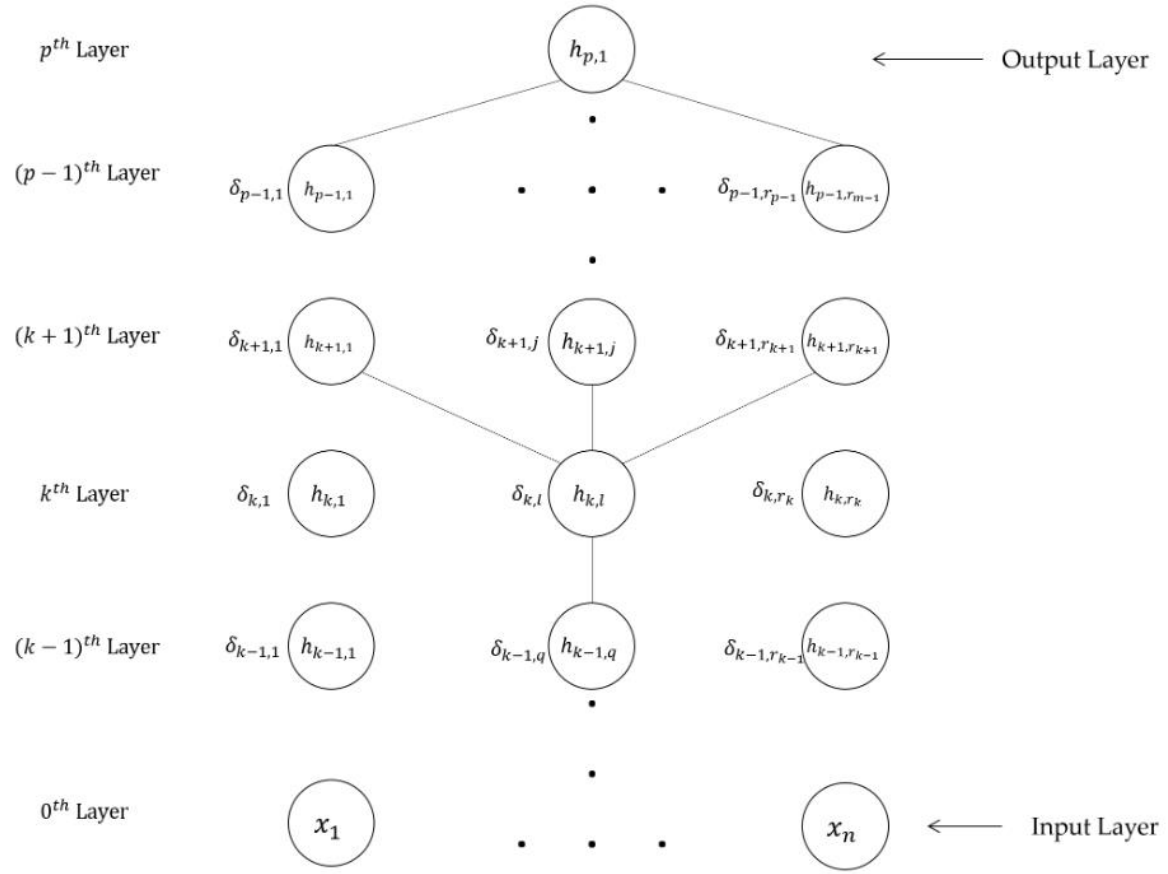
$$\delta_{k,l} = \frac{\partial E}{\partial o_{k,l}}$$

$$\delta^i_{k,l} = \frac{\partial E^i}{\partial o^i_{k,l}}$$

- Let the weight between l[th] node in the k[th] layer and j[th] node in the (k+1)[th] layer be $w_{k+1,ij}$
- Then,

$$h^i_{k,l} = A(o^i_{k,l}); \qquad h^i_{k+1,j} = A(o^i_{k+1,j})$$

$$o^i_{k+1,j} = \sum_{l=1}^{r_k} w_{k+1,lj} h^i_{k,l} = \sum_{l=1}^{r_k} w_{k+1,lj} A(o^i_{k,l})$$



TRAINING OF NEURAL NETWORKS BACKPROPAGATION

- To find $\delta^i_{k,l}$, we need to find $\frac{\partial E^i}{\partial o^i_{k,l}}$
- Changes in $o^i_{k,l}$ would affect $o^i_{k+1,j}$ which in turn affects E^i

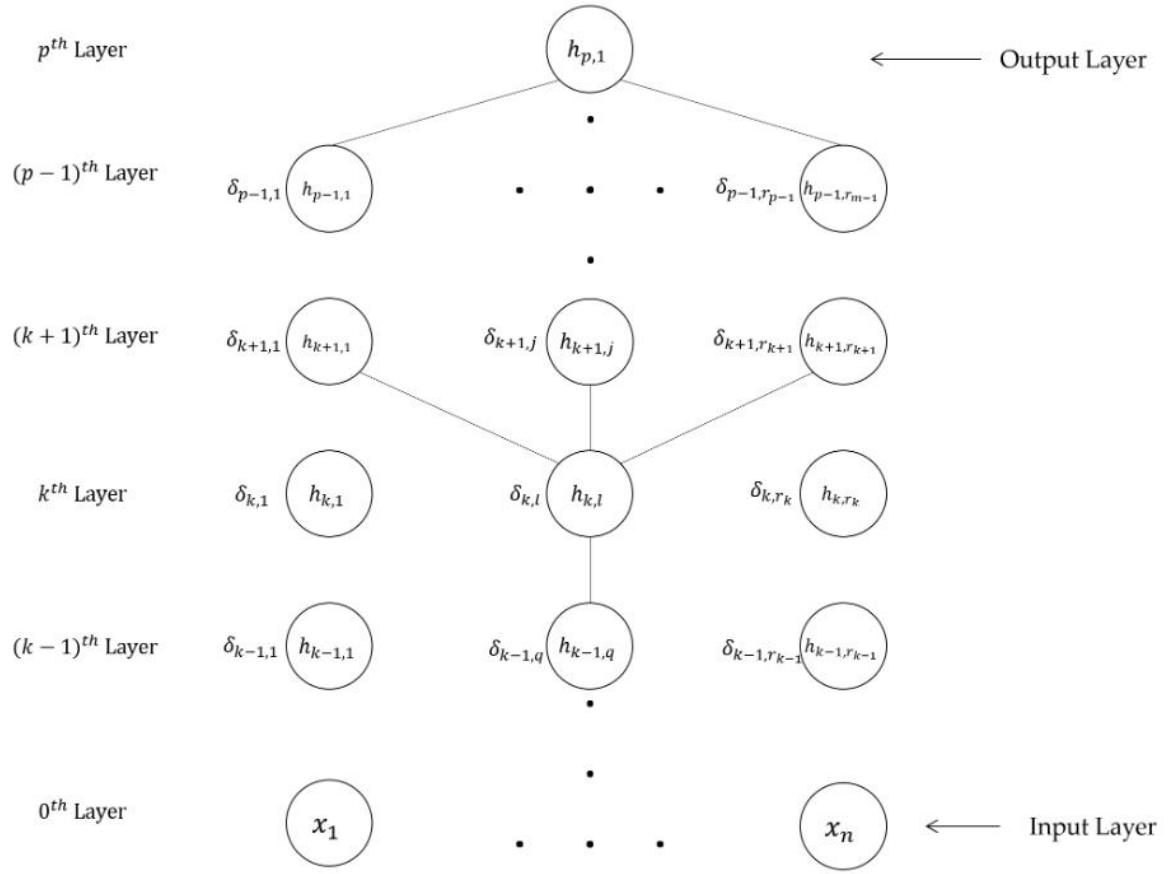
$$E^i = E^i\left(o^i_{k+1,j}\right)$$

- Using chain rule of differentiation,

$$\delta^i_{k,l} = \sum_{j=1}^{r_{k+1}} \frac{\partial E^i}{\partial o^i_{k+1,j}} \frac{\partial o^i_{k+1,j}}{\partial o^i_{k,l}} = \sum_{j=1}^{r_{k+1}} \delta^i_{k+1,j} \frac{\partial o^i_{k+1,j}}{\partial o^i_{k,l}}$$

- Since $\frac{\partial o^i_{k+1,j}}{\partial o^i_{k,l}} = w_{k+1,lj} A'(o^i_{k,l})$

$$\delta^i_{k,l} = \sum_{j=1}^{r_{k+1}} \delta^i_{k+1,j} w_{k+1,lj} A'(o^i_{k,l}) = A'(o^i_{k,l}) \sum_{j=1}^{r_{k+1}} w_{k+1,lj} \delta^i_{k+1,j}$$



BACKPROPAGATION (m SAMPLES)

- For m samples (m could be entire samples or a batch),

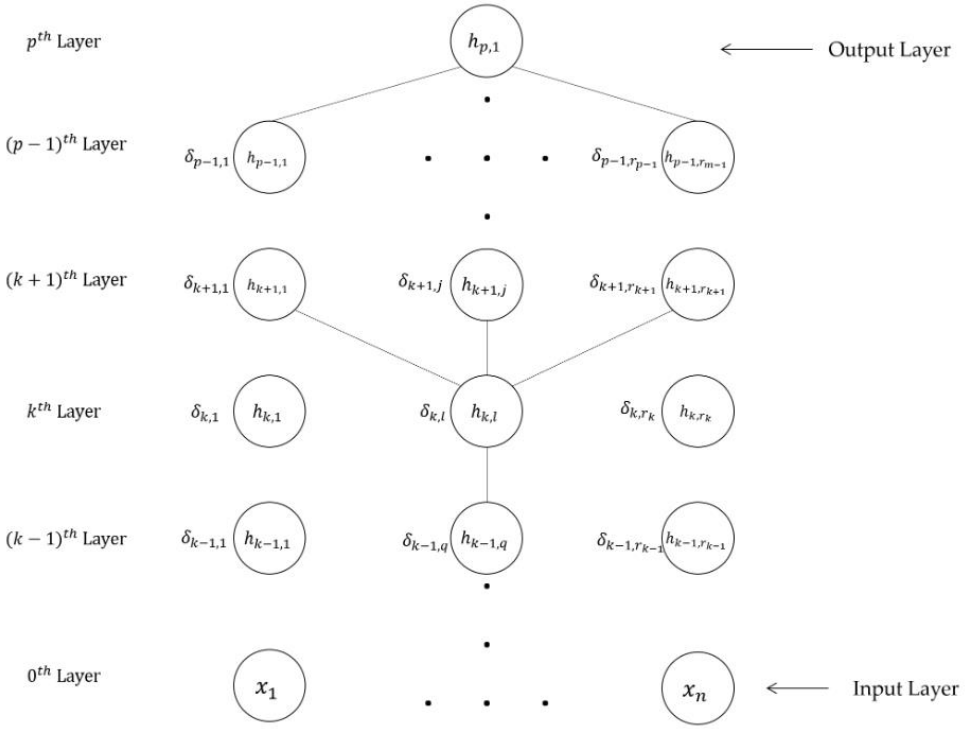
$$\delta_{k,l} = \frac{\partial E}{\partial o_{k,l}} = \sum_{i=1}^{m} \frac{\partial E^i}{\partial o_{k,l}^i} = \sum_{i=1}^{m} \delta_{k,l}^i = \sum_{i=1}^{m} \left(A'\left(o_{k,l}^i\right) \left(\sum_{j=1}^{r_{k+1}} w_{k+1,lj} \delta_{k+1,j}^i \right) \right)$$

$$\delta_{p,1} = \sum_{i=1}^{m} \delta_{p,1}^i = -\sum_{i=1}^{m} \left(y^i - h_{p,1}^i\right) A'\left(o_{p,1}^i\right)$$

- We first evaluate δ for the output node, then for all nodes in the (p-1)th layer, (p-2)th layer, and so on until the first layer
- Since we start at the output node and come all the way down to the input node, this scheme is referred to as back-propagation scheme

$$w_{k+1,lj}^n = w_{k+1,lj} + \eta \sum_{i=1}^{m} \left(\frac{-\partial E^i}{\partial w_{k+1,lj}} \right) = w_{k+1,lj} + \eta \sum_{i=1}^{m} \left(\frac{-\partial E^i}{\partial o_{k+1,j}} \right) \left(\frac{\partial o_{k+1,j}}{\partial w_{k+1,lj}} \right)$$

$$\implies w_{k+1,lj}^n = w_{k+1,lj} - \eta \sum_{i=1}^{m} \delta_{k+1,j}^i h_{k,l}^i \text{ (From 1.21)}$$

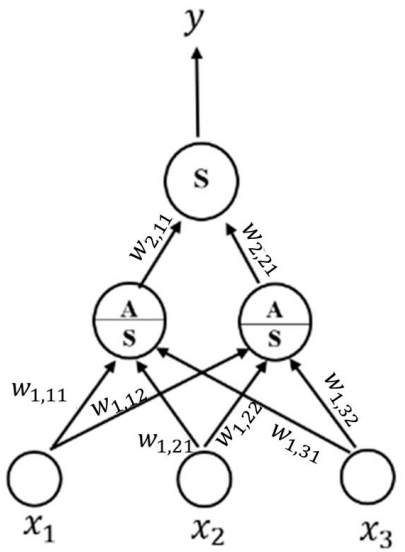


EXAMPLE

- Example: Given sample: $x_1 = -3.2, x_2 = 4.1, x_3 = 0.163$ and $y = 2$
- Decision variables: 8 weights ($w_{k,lj}$)
- Objective function: $min_w \quad f = (\hat{y}(w) - \quad y)^2$
- Steepest descent update rule with back-propagation

$$w_{k+1,lj}^{q+1} = w_{k+1,lj}^{[q]} - \eta \, \delta_{k+1,j}^{[q]} h_{k,l}^{[q]}$$

Decision Variable	*Initial Guess*	*Iteration 1*
$w_{1,11}$	*0.1*	*0.0633*
$w_{1,21}$	*0.3*	*0.347*
$w_{1,31}$	*0.5*	*0.5019*
$w_{1,12}$	*0.2*	*0.1602*
$w_{1,22}$	*0.4*	*0.4510*
$w_{1,32}$	*0.6*	*0.602*
$w_{2,11}$	*0.7*	*0.7605*
$w_{2,21}$	*0.8*	*0.8622*
Error	0.8851	0.7059




operation == "MIRROR_X":
irror_mod.use_x = True
irror_mod.use_y = False
irror_mod.use_z = False
operation == "MIRROR_Y":
irror_mod.use_x = False
irror_mod.use_y = True
irror_mod.use_z = False
operation == "MIRROR_Z":
irror_mod.use_x = False
irror_mod.use_y = False
irror_mod.use_z = True
selection at the end -add
_ob.select= 1
er_ob.select=1
ntext.scene.objects.acti
("Selected" + str(modifier
irror_ob.select = 0
bpy.context.selected_ob
ata.objects[one.name].se
int("please select exact

THANK YOU

k-NN, DECISION TREES, AND RANDOM FOREST FOR REGRESSION AND CLASSIFICATION

RESMI SURESH

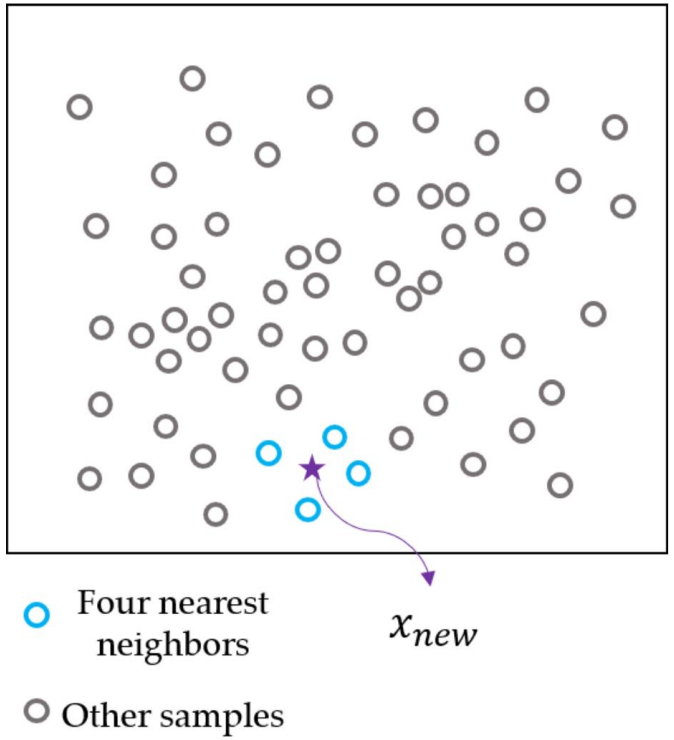
ASSISTANT PROFESSOR, IIT GUWAHATI

k-NEAREST NEIGHBORS

REGRESSION

FUNCTIONAL APPROXIMATION USING k-NEAREST NEIGHBOUR

- k-NN is a non-parametric supervised learning method
- Philosophy: If you want to know someone, understand the neighbors
- It is also called 'Lazy algorithm' as there's no training phase, just holding on to x,y data. – No model is built during training phase
- A distance metric (usually Euclidean) is needed to identify the nearest neighbours
- A tunable parameter 'k' is chosen to get the best performance
- For a new point x_{new}, the k-NN algorithm finds the k nearest neighbours and predicts the output $\hat{y} = \bar{y}$, where the average is done over the identified k neighbours
- While k-NN method is super-easy to implement, it can be susceptible to noise, as each & every distance need to be calculated



PRACTICE EXAMPLE OF k-NN

Example: Consider the following dataset.

Height (h)	1.5	1.7	1.6	1.5	1.4	1.6	1.4	1.9	2	1.4	1.8	1.5
Weight (w)	71.1	103.3	26.4	27.8	21.8	94.9	90	98.3	108.1	91.9	61.5	90.2
BMI ($y = w/h^2$)	31.6	35.74	10.31	12.36	11.12	37.07	45.92	27.23	27.23	46.89	18.98	40.09

If we use K-NN for predicting BMI from height and weight assuming the true model ($y = w/h^2$) is unknown, find BMI for a person with height 1.3m and weight 32kg. Use K-NN with 4 neighbours and Euclidean distance as the metric for choosing neighbours.

PRACTICE EXAMPLE OF k-NN

- Euclidian distance of point (1.3,32) from all points are-
- d = [39.1, 71.3, 5.61, 4.2, 10.2, 62.9, 58, 66.3, 76.1, 59.9, 29.5, 58.2]
- The 4 neighbours would be samples 4,3,5 and 11
- Now the predicted BMI for the given test sample would be the average BMI of the 4 neighbours
- i.e. $\hat{y}$ = 13.1924
- True BMI = 18.94
- Squared error prediction = 33.035

OPTIMAL VALUE OF K

- No structured way to find best k
  - Trial and error approach
  - Compare the models based on cross-validation performance
- Small value of k – noise will have high impact on the predictions, high SSE
- High value of k – Computationally more expensive
- A general practice: choose $k = \sqrt{n}$ where n is the number of samples in the training set

DISTANCE METRICS

- Continuous variables
  - Euclidean distance: $\sqrt{\sum(x^i - x_{test})^2}$
  - Manhattan distance: $\sum|x^i - x_{test}|$
- Strings of equal length
  - Hamming distance: Number of positions in which two strings differ. Example: Hamming distance between 'A23D' and 'A13E' is 2
- Strings of unequal length (eg: categories like lion, dog, cheetah etc.)
  - Reformulate features using
    - Integer encoding

      Each category is given a number, like lion – 1, dog -2, cheetah – 3 etc.
    - One-hot encoding

      The concerned feature is converted into multiple binary features

      For the above example, if we keep a separate binary variable for lion, dog, and cheetah

k-NEAREST NEIGHBORS

CLASSIFICATION

CLASSIFICATION USING *k*-NN

- The procedure of Classification using k-NN is quite similar to Functional Approximation using k-NN
- However, to predict an output for X(new) a majority vote of k neighbours is used
- It is useful for binary and multiclass classification problems
- As the number of data points are increased, using k-NN becomes computationally hard
- Odd numbers preferred for k in case of binary classification

EXAMPLE

- **Question:** Find the species for a new sample with (x1,x2,x3,x4) = (6.3,2.5,4.9,1.5)
- Let $k = 3$
- Nearest neighbors based on Euclidean distance

Sl No.	Nearest training data samples	Distance	Class Label
1	(6.8,2.8,4.8,1.4)	0.6	1
2	(5.7,2.8,4.5,1.3)	0.806	1
3	(5.6,3,4.5,1.5)	0.95	1

- Predicted class: 1

Dataset

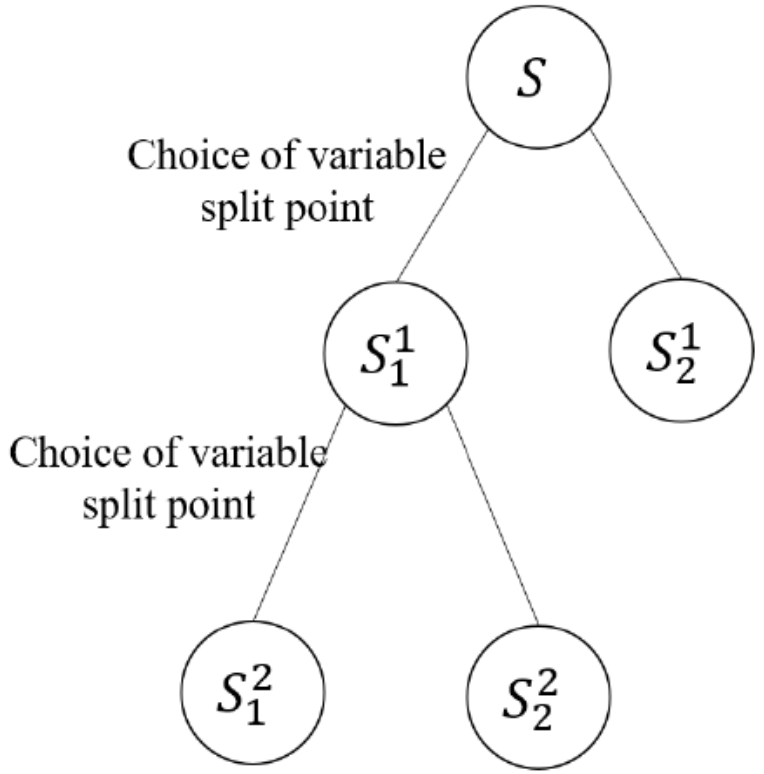
Sepal length (x1)	Sepal width (x2)	Petal length (x3)	Petal width (x4)	Species Class (y)
7.4	2.8	6.1	3	2
5.5	2.4	3.8	1.9	1
5.6	3	4.5	1.5	1
4.8	3	1.4	0.1	0
5	3.4	1.5	0.2	0
6.2	3.4	5.4	2.3	2
7.9	3.8	6.4	2	2
6.4	2.8	5.6	2.2	2
5.4	3.9	1.7	0.4	0
4.9	3.6	1.4	0.1	0
5.7	2.8	4.5	1.3	1
5.1	3.5	1.4	0.3	0
6.5	3	5.8	2.2	2
6.8	2.8	4.8	1.4	1
5.5	4.2	1.4	0.2	0
5.8	2.7	5.1	1.9	2
4.8	3	1.4	0.3	0

DECISION TREES

REGRESSION

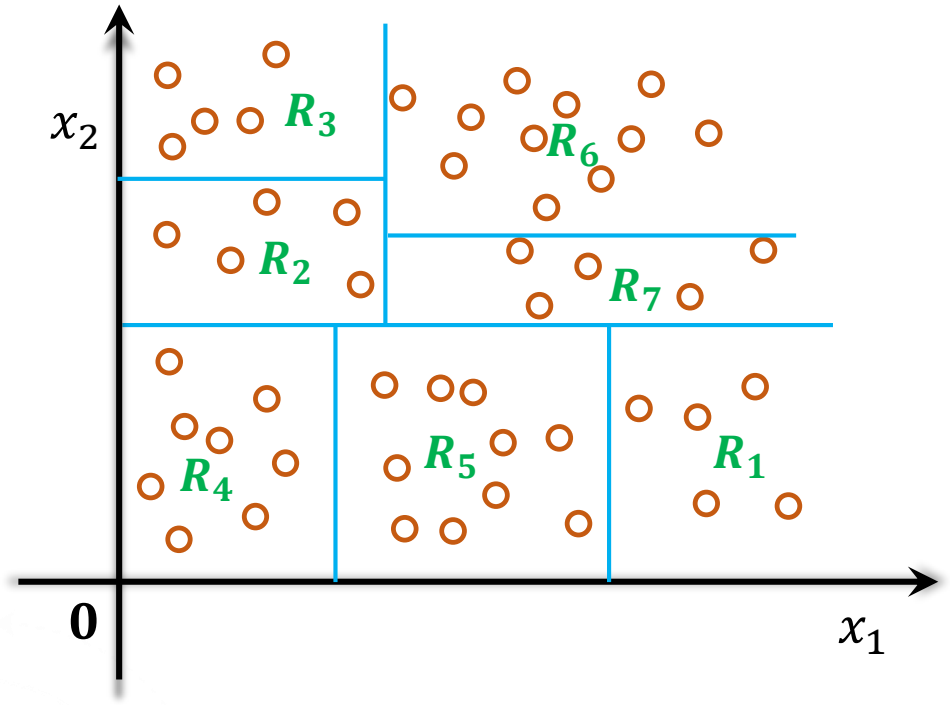
DECISION TREES

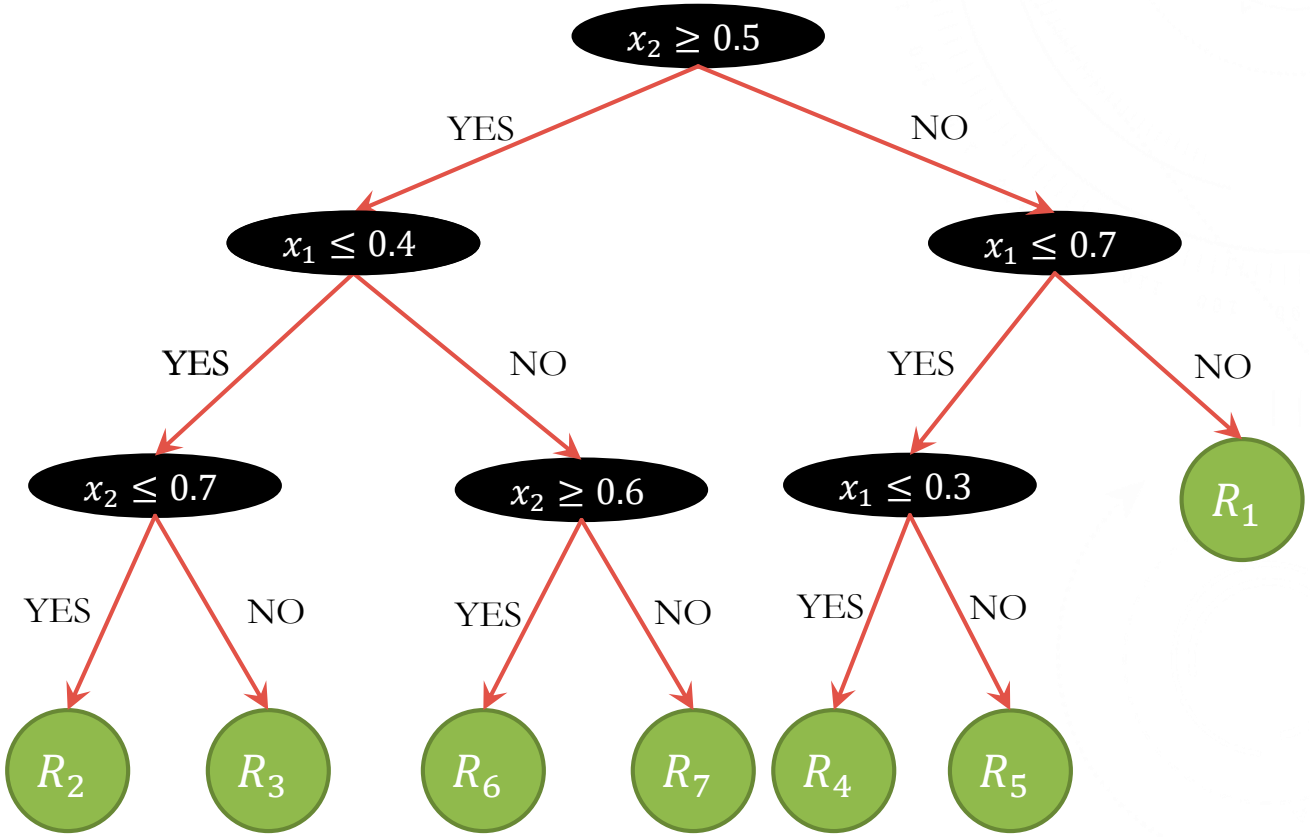
- Mimic the manner in which decisions are made by most of us
- Every decision point is represented as a node
- At each node, one variable is chosen from all the input variables and a decision is made based on the value of the variable
- Can be used for function approximation and classification
- Choice of variable and splitting value at each node have to be chosen based on our objective function:
  - Minimum prediction error for function approximation
  - Minimum classification error for classification



DECISION TREES

Input features: x_1 and x_2
Output feature: y





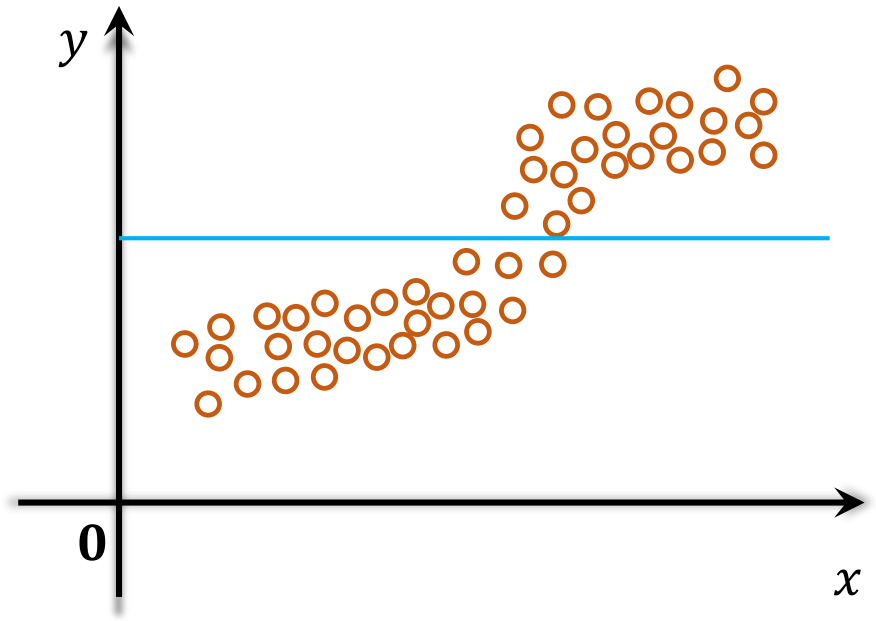
DECISION TREES

- Each end-node has a subset of samples – given data is split into multiple subsets
- Partitions happen only in the input space
- Outputs are used in computing the predicted value for each of the regions that is generated
- Output for a new test sample depends on the end-node to which the new point would fall
- One can keep growing the tree to a large number of nodes
  - Although performance on training set improves, may result in over-fitting
  - Size of tree might become computationally unwieldy
- Make choices that limit tree complexity
  - Tree depth
  - Number of end-nodes
  - Minimum size of each node (cardinality)
- Growing a tree is continued until a certain accuracy requirement is met and/or until the complexity becomes too much

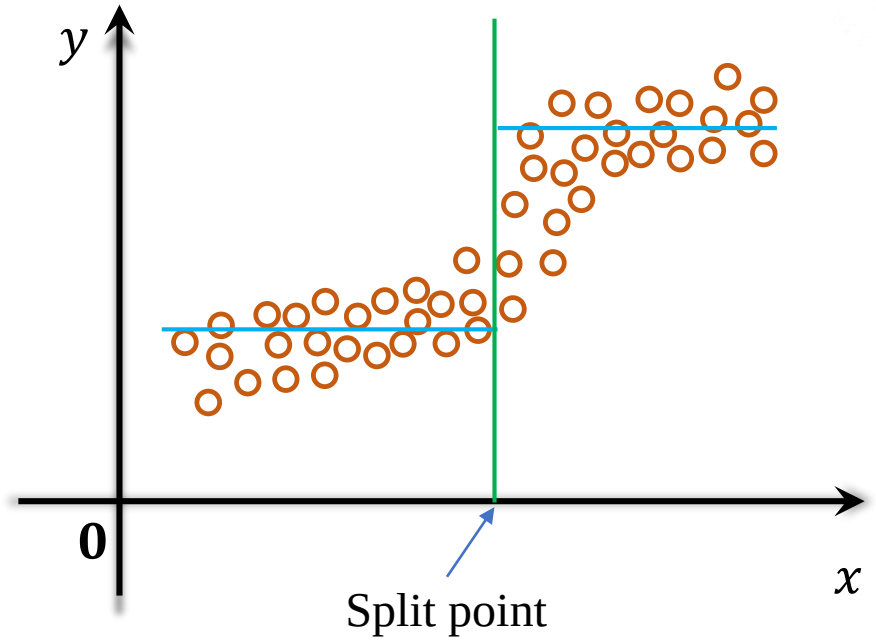
DECISION TREES FOR REGRESSION

ONE INPUT FEATURE

Without decision tree



With decision tree (one node)



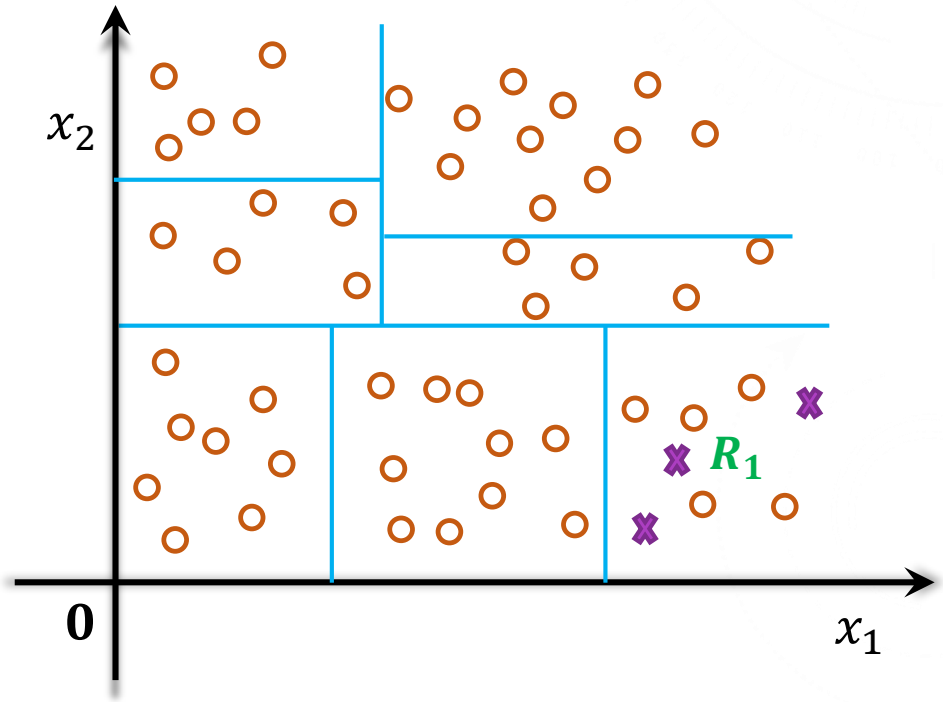
DECISION TREES FOR REGRESSION

GENERAL CASE

- For regression, to predict the output for a new test sample 'x_{new}',
  - identify the set (or rectangle) R_j corresponding to sample x_{new} and
  - $\hat{y}_{new}$ would be the average of the output values of all samples in set R_j
- Example: consider the new point marked by '✖'

$$\hat{y}_{new} = \text{mean}\left(y(x^i)\right) \text{ such that } x^i \in R_1$$

  - Same prediction for any point within the rectangle R_1
- How do we find the optimal split point?
  - Based on minimum squared error, $\sum(y^i - \hat{y}^i)^2$



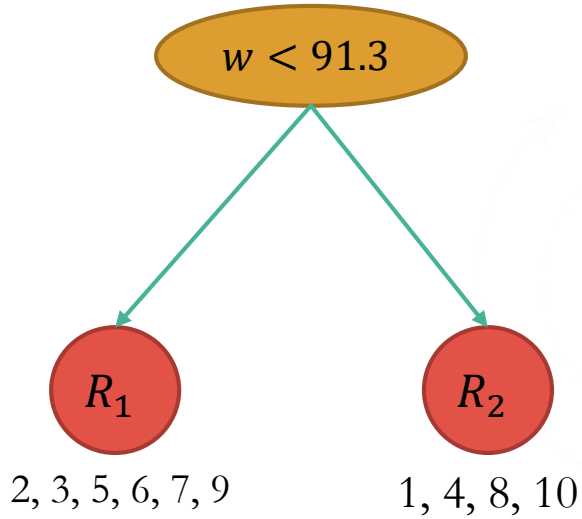
DECISION TREES FOR REGRESSION

- Consider the data relating weight to BMI
- If a single node decision tree is used, let us see how to find the best split point
- If 's' is split point, let the decision be $w < s$.

Sample No	1	2	3	4	5	6	7	8	9	10
Weight (w)	91.3	67.6	71.1	103.3	26.4	27.8	21.8	94.9	90	98.3
BMI (y)	40.58	23.39	27.77	45.91	13.47	10.86	11.12	26.29	22.5	50.15

Split point (w)	Samples in R_1	Samples in R_2	$\bar{y}_{R_1}$	$\bar{y}_{R_2}$	SSE
91.3	2,3,5,6,7,9	1,4,8,10	18.185	40.7325	587.49
67.6	5,6,7	1,2,3,4,8,9,10	11.8167	33.7986	792.9
71.1	2,5,6,7	1,3,4,8,9,10	14.71	35.5333	766.96
103.3	1,2,3,5,6,7,8,9,10	4	25.1256	45.91	1418.83
26.4	7	1,2,3,4,5,6,8,9,10	11.12	28.9911	1520.18
27.8	5,7	1,2,3,4,6,8,9,10	12.295	30.9313	1251.9
21.8	-	1,2,3,4,5,6,7,8,9,10	-	27.204	1807.6
94.9	1,2,3,5,6,7,9	4,8,10	21.3843	40.7833	1017.3
90	2,3,5,6,7	1,4,8,9,10	17.322	37.086	831.0856
98.3	1,2,3,5,6,7,8,9	4,10	21.9975	48.03	723.3192

Best split point



DECISION TREES

CLASSIFICATION

DECISION TREES FOR CLASSIFICATION

- Similar to function approximation, except for
  - how we find the best choice of split variable and split point
    - Minimization of error for function approximation while other metrics like maximization of Gini split index for classification
  - how we make predictions
    - Average of output values for function approximation while majority voting for classification
- Consider j^{th} node at the k^{th} level of the tree. Let the set of points in the node be $\{S_j^k\}$. Assume that n samples are present in set $\{S_j^k\}$. Let there be p classes in the data.
- $f_i(j,k)$ – fraction of data points in $\{S_j^k\}$ that belong to class i
- Gini impurity

$$GI(j,k) = 1 - \sum_{i=1}^{p} f_i(j,k)^2$$

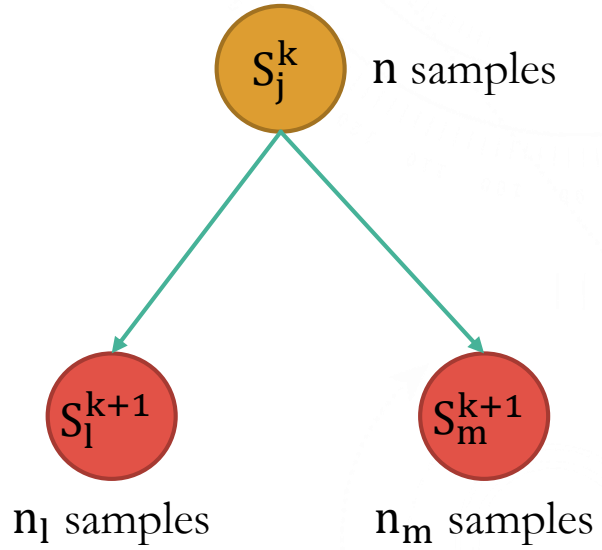
- When a node has data from only one class, $GI = 0 \rightarrow$ pure node

DECISION TREES FOR CLASSIFICATION

- When choosing the variable to branch on and split point, aim is to get pure or close to pure child nodes
- Let child nodes be S_l^{k+1} (with n_l samples) and S_m^{k+1} (with n_m samples)
- Gini split index

$$GSI = GI(j,k) - \frac{n_l}{n} GI(l,k+1) - \frac{n_m}{n} GI(m,k+1)$$

- If both child nodes are pure, $GSI = GI(j,k)$
- For any other split, GSI would be less than $GI(j,k)$
- Since the best case scenario is to get pure nodes on splitting, variable and split point that maximizes GSI is selected



$$n = n_l + n_m$$

DECISION TREES FOR CLASSIFICATION

- Consider the data relating hours studied to result

Sample No.	1	2	3	4	5	6	7	8
Hours studied	10.5	2.5	14	8.2	10.4	5	6.7	14.7
Pass (1)/Fail(0)	1	0	1	1	1	0	0	1

- If a single node decision tree is used, let us see how to find the best split point
- Gini impurity (GI) for the given data:

$$\mathrm{GI} = 1 - f_0^2 - f_1^2 = 1 - \left(\frac{3}{8}\right)^2 - \left(\frac{5}{8}\right)^2 = 0.4688$$

DECISION TREES FOR CLASSIFICATION

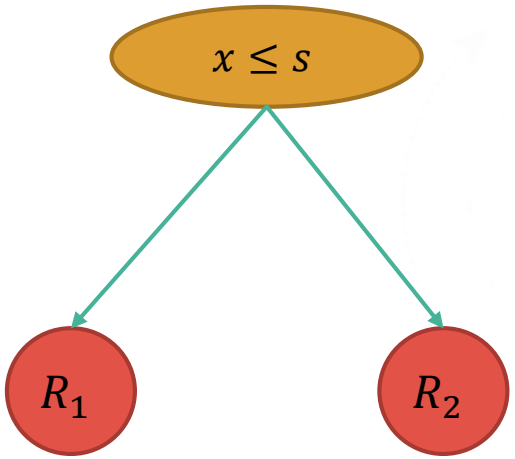
Sample No.	1	2	3	4	5	6	7	8
Hours studied	10.5	2.5	14	8.2	10.4	5	6.7	14.7
Pass (1)/Fail(0)	1	0	1	1	1	0	0	1

- Let 's' be a split point such that set R_1 contains all points such that $x \leq s$ and set R_2 contains all points such that $x > s$
- Let $x = 10.4$ be the split point, then R_1 contains samples {2, 4, 5, 6, 7}, and R_2 contains samples {1, 3, 8}
- Since 3 out of 5 samples in R_1 have label 0 and the remaining 2 have label 1.

$$f_0 \text{ for } R_1 = 0.6$$

$$f_1 \text{ for } R_1 = 0.4$$

$$GI \text{ for } R_1 = 1 - 0.6^2 - 0.4^2 = 0.48$$

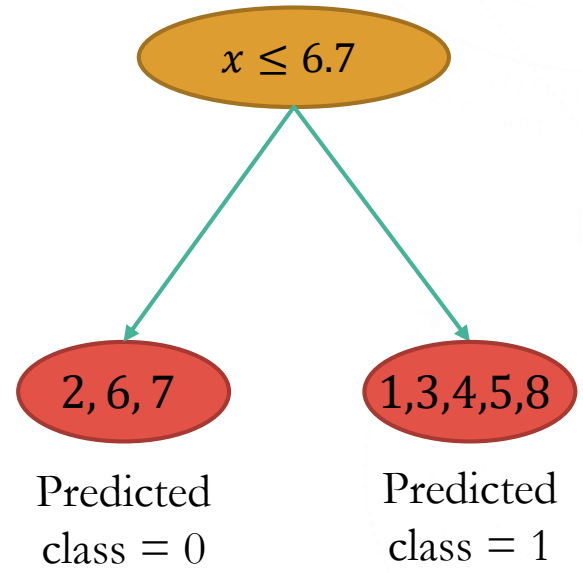


- R_2 is a pure node, implies GI = 0 for R_2
- GSI for split point $10.4 = 0.4688 - \left(\frac{5}{8}\right) 0.48 - 0 = 0.1688$

DECISION TREES FOR CLASSIFICATION

Sample No.	1	2	3	4	5	6	7	8
Hours studied	10.5	2.5	14	8.2	10.4	5	6.7	14.7
Pass (1)/Fail(0)	1	0	1	1	1	0	0	1

Split point (s)	Samples in R1	Samples in R2	GI for R1	GI for R2	GSI
10.5	1,2,4,5,6,7	3,8	0.5	0	0.094
2.5	2	1,3,4,5,6,7,8	0	0.408	0.112
14	1,2,3,4,5,6,7	8	0.49	0	0.04
8.2	2,4,6,7	1,3,5,8	0.375	0	0.28
10.4	2,4,5,6,7	1,3,8	0.48	0	0.169
5	2,6	1,3,4,5,7,8	0	0.28	0.26
Best split point 6.7	2,6,7	1,3,4,5,8	0	0	0.469
14.7	1,2,3,4,5,6,7,8	-	0.469	-	0

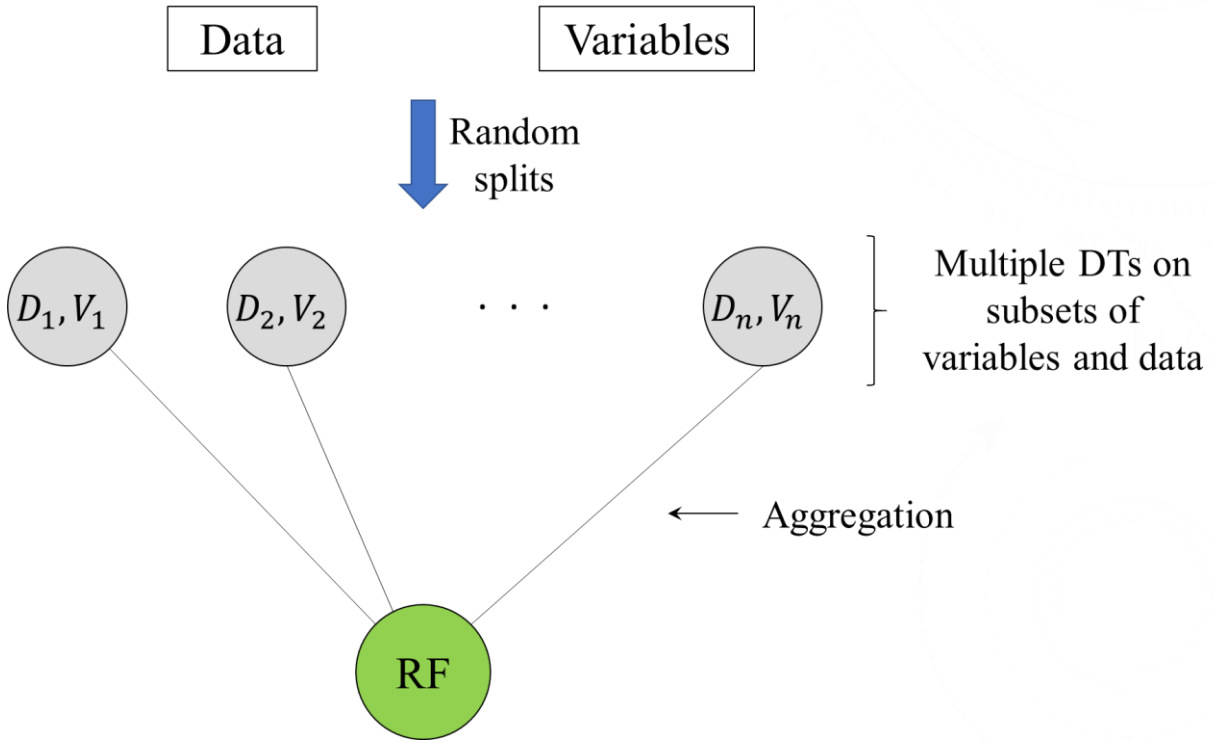


RANDOM FOREST

REGRESSION AND CLASSIFICATION

RANDOM FORESTS

- Simple extension of decision trees
- Forest comprise of many trees; equivalently, random forests consists of many decision trees
- Decision tree may give considerably different results for minor changes in the data or construction procedure
- Random forests help to avoid this by building multiple trees
- Each tree is realized by choosing a subset of datapoints or variables and building a decision for each sub-selected data matrix



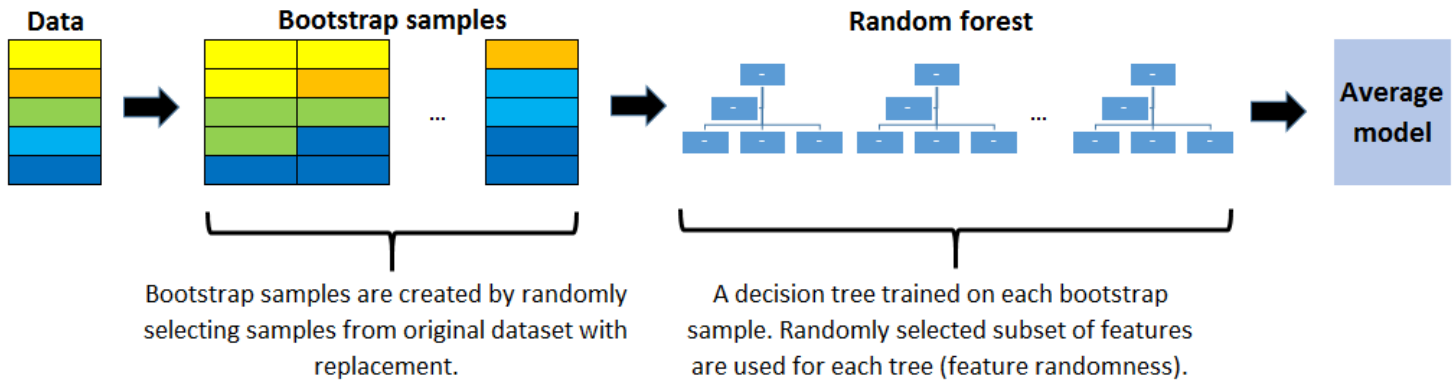
RANDOM FORESTS

- Predictions
  - Average of predictions from multiple trees for function approximation
  - Majority voting (or other metrics) for classification

- Advantages of random forest

  Stochasticity is included in various forms

  - Splitting on the basis of random subsets of samples
  - Splitting on the basis of random features
  - Bagging (Bootstrap aggregating) decision trees – random samples with replacement

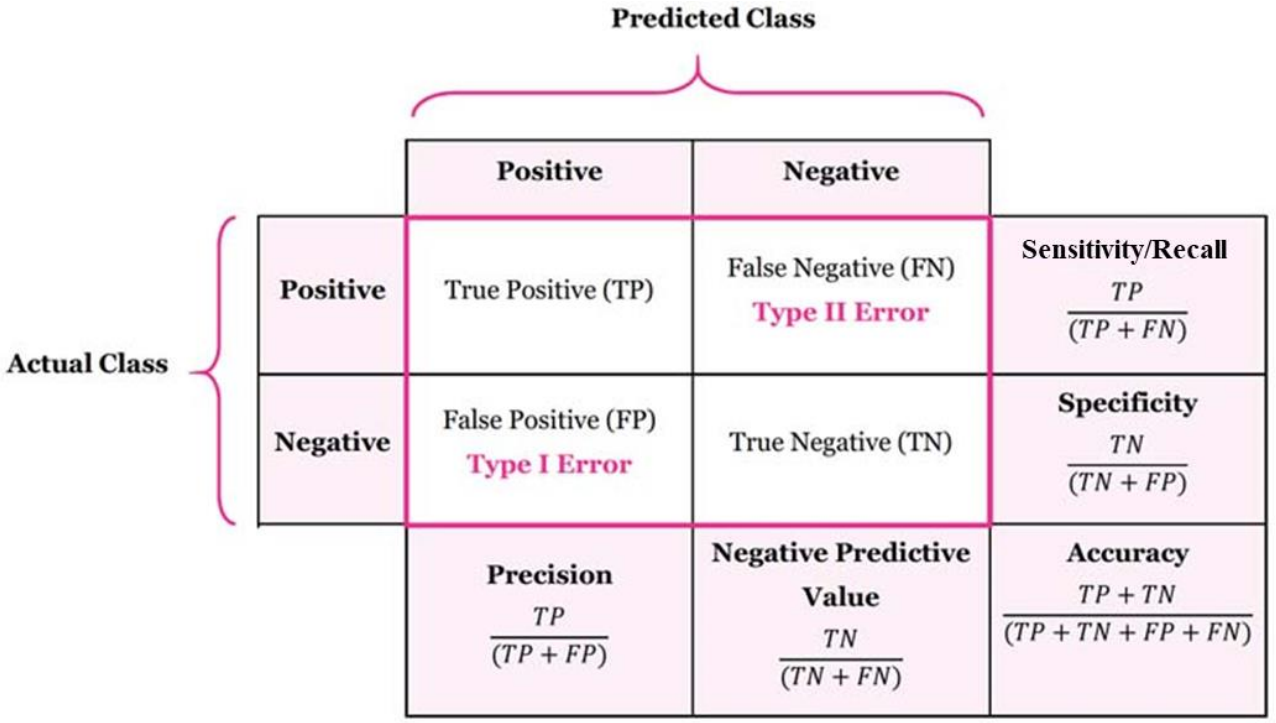


Other approaches for introducing stochasticity: Boosting decision trees – trees added sequentially

*https://towardsdatascience.com/gradient-boosted-decision-trees-explained-9259bd8205af

PERFORMANCE MEASURES FOR CLASSIFICATION

CONFUSION MATRIX



- TP – Correct identification of positive labels
- TN – Correct identification of negative labels
- FP – Incorrect identification of positive labels
- FN – Incorrect identification of negative labels

- Accuracy: Overall effectiveness of a classifier
- Total number of actual positive samples – TP+FN
- Total number of actual negative samples – TN+FP
- Sensitivity/Recall – Effectiveness of a classifier to identify positive labels

$$S_e = \frac{TP}{TP + FN}$$

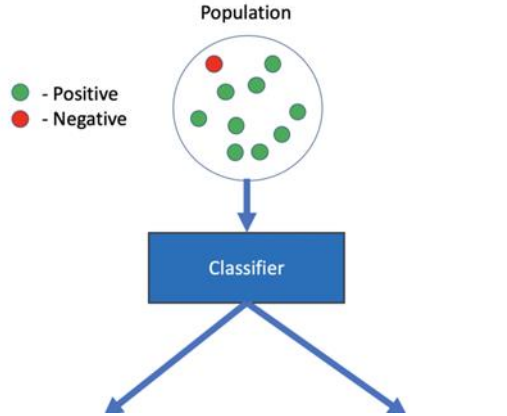
- Specificity – Effectiveness of a classifier to identify negative labels

$$S_p = \frac{TN}{FP + TN}$$

- Accuracy, specificity and sensitivity – maximum value is 1
- Balanced accuracy = 0.5(Specificity+Sensitivity)
- Maximizing recall may adversely affect precision and vice versa
- F1-score $\mathrm{F1-score} = \frac{2(\mathrm{Precision} \times \mathrm{Recall})}{\mathrm{Precision} + \mathrm{Recall}}$

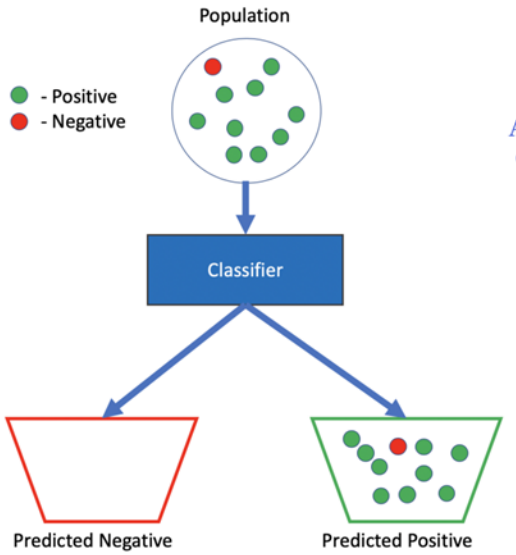
PERFORMANCE MEASURES

Actual Class \ Predicted Class	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity/Recall $\frac{TP}{(TP+FN)}$
Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$



Many possibilities depending on the classifier

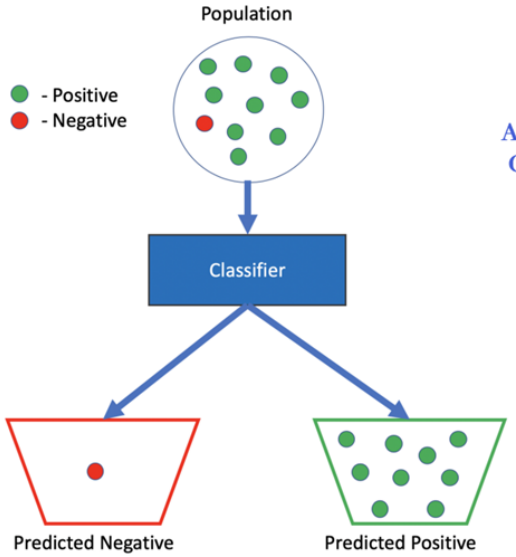
High precision and recall, low specificity



Actual Class \ Predicted Class	Positive	Negative
Positive	9	0
Negative	1	0

$$precision = \frac{tp}{tp+fp} = \frac{9}{10} = 90\%$$
$$recall = \frac{tp}{tp+fn} = \frac{9}{9} = 100\%$$
$$specificity = \frac{tn}{tn+fp} = \frac{0}{1} = 0\%$$
$$sensitivity = recall = 100\%$$

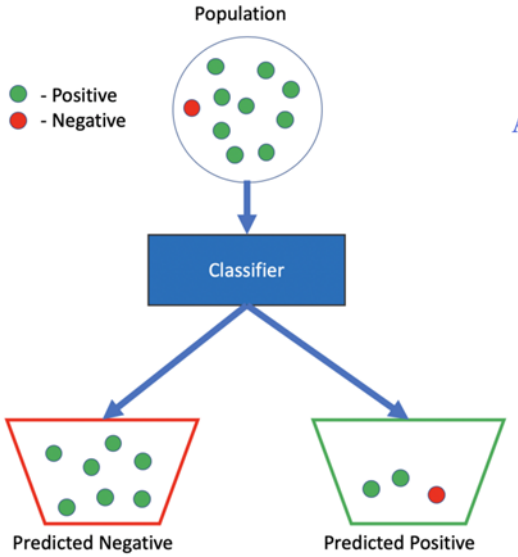
Best case scenario



Actual Class \ Predicted Class	Positive	Negative
Positive	9	0
Negative	0	1

$$precision = \frac{tp}{tp+fp} = \frac{9}{9} = 100\%$$
$$recall = \frac{tp}{tp+fn} = \frac{9}{9} = 100\%$$
$$specificity = \frac{tn}{tn+fp} = \frac{1}{1} = 100\%$$
$$sensitivity = recall = 100\%$$

High precision, low recall and specificity



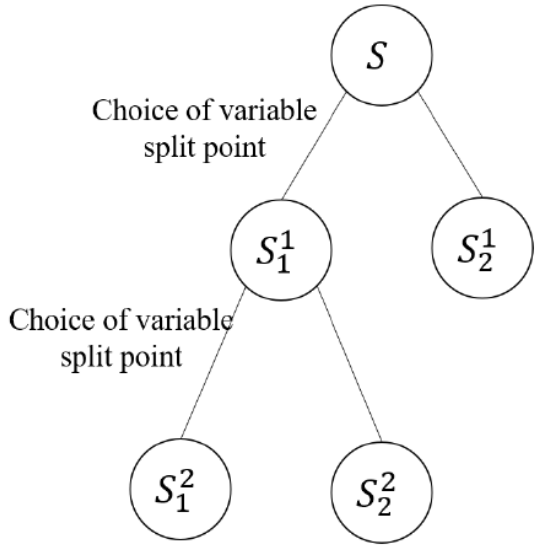
Actual Class \ Predicted Class	Positive	Negative
Positive	2	7
Negative	1	0

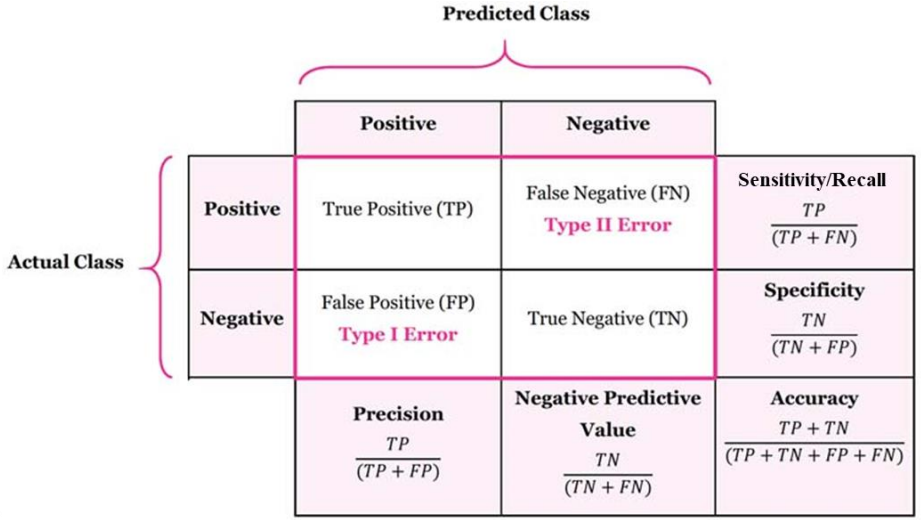
$$precision = \frac{tp}{tp+fp} = \frac{2}{3} = 66\%$$
$$recall = \frac{tp}{tp+fn} = \frac{2}{9} = 22\%$$
$$specificity = \frac{tn}{tn+fp} = \frac{0}{1} = 0\%$$
$$sensitivity = recall = 22\%$$

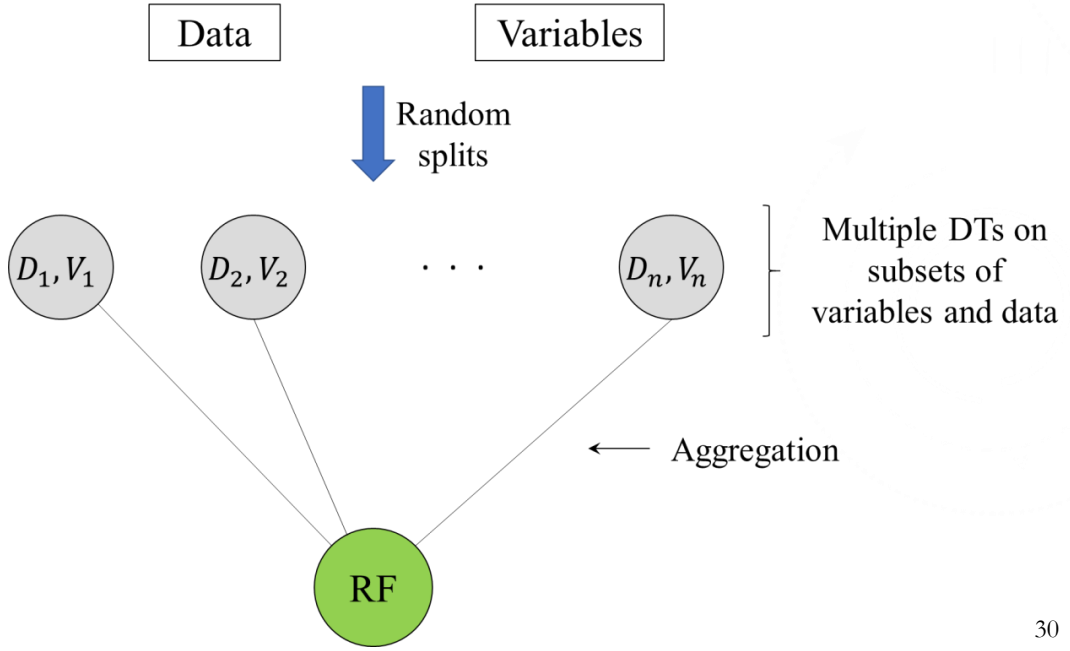
*https://towardsdatascience.com/should-i-look-at-precision-recall-or-specificity-sensitivity-3946158aace1

CONCLUSIONS

- Decision trees for both function approximation and classification
- Random forests for both function approximation and classification
- Performance measures for classification (using any algorithm)





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irror_mod.use_y = False
irror_mod.use_z = False
operation == "MIRROR_Y":
irror_mod.use_x = False
irror_mod.use_y = True
irror_mod.use_z = False
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irror_mod.use_x = False
irror_mod.use_y = False
irror_mod.use_z = True
selection at the end -add
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er_ob.select=1
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irror_ob.select = 0
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ata.objects[one.name].se
int("please select exact

THANK YOU