BOOSTING

COMBINE WEAK LEARNERS THAT WERE TRAINED SEQUENTIALLY AND PREDICTS BASED ON THE WEIGHTS OF EACH MODEL (WEIGHT CALCULATED BASED ON MODEL PERFORMANCE).

GRADIENT BOOSTING

dY(0) = Y − MEAN(Y)

for k = 1 : (# OF TREES / # OF ITERATIONS) :

    LEARNER(k) = TRAIN_REGRESSOR(X, dY(k−1))
    dY(k) = dY(k−1) − α(k) * PREDICT(LEARNER(k), X)

"TRAIN OVER THE RESIDUAL"

BAGGING

* GENERATE N DIFFERENT BOOTSTRAP TRAINING SAMPLE WITH REPLACEMENT
* TRAIN ALGORITHM ON EACH BOOTSTRAPPED SAMPLE
* COMBINE THEM ALL USING MAJORITY VOTE / MEAN

RELATIVE VARIABLE IMPORTANCE

THE MEASURE IS MADE BASED ON # TIMES A VARIABLE IS SELECTED FOR SPLITTING AND WEIGHTED BY THE IMPROVEMENT TO THE MODEL AS A RESULT OF EACH SPLIT, THEN AVERAGED OVER ALL TREES.

CONFUSION MATRIX

POSITIVE CLASS = 0

PREDICT \ OBSERVED	P	N
P	TP	FP
N	FN	TN

SENSITIVITY = $\frac{TP}{TP+FN}$ = RECALL

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

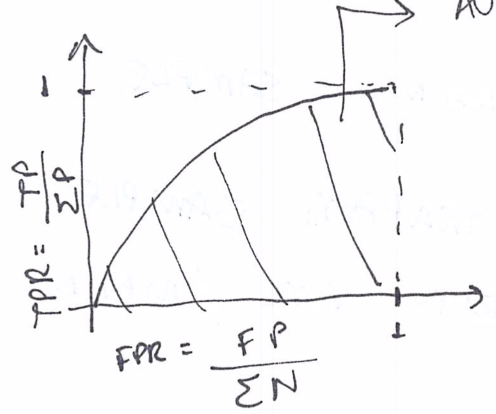
PRECISION = $\frac{TP}{TP+FP}$

F1 SCORE = $2 \cdot \frac{\text{PRECISION} * \text{RECALL}}{\text{PRECISION} + \text{RECALL}} = \frac{2}{\frac{1}{\text{PRECISION}} + \frac{1}{\text{RECALL}}}$ "HARMONIC MEAN"

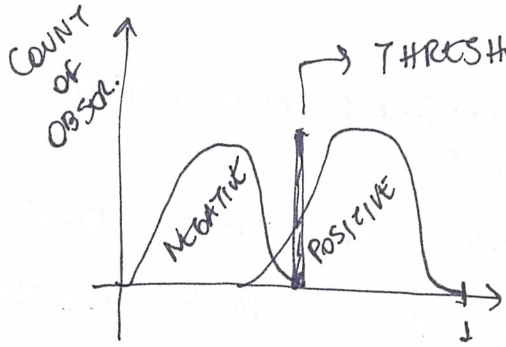
ACCURACY = $\frac{TP+TN}{P+N}$

ROC CURVE

AUC (AREA UNDER THE CURVE)



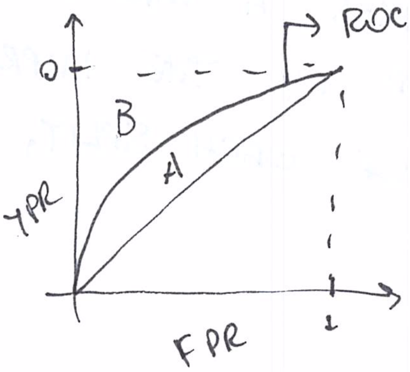
THRESHOLD FOR ROC



PROBABILITY OF EVENT

GINI COEFFICIENT (INEQUALITY COEFFICIENT)

ROC CURE



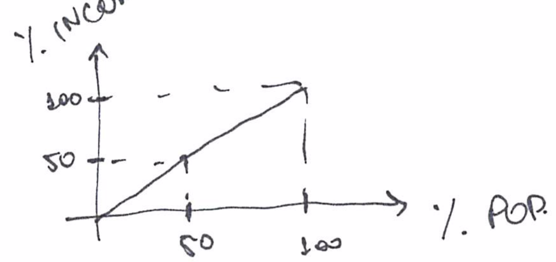
GINI = $\frac{A}{A+B}$

HIGHER A => BETTER MODEL

HIGHER INEQUALITY

REAL-WORLD EXAMPLE:

"PERFECT DISTRIBUTION OF MONEY OVER POPULATION"

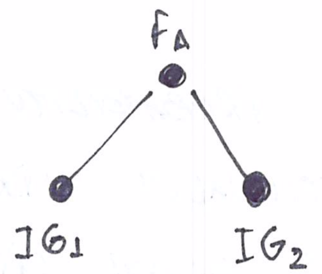


CLASSIFICATION TREES

FOR ALL FEATURES TESTS INFORMATION GAIN USING ENTROPY:

$$IG = -\sum_{i=1}^{J} P_i \cdot \log_2 P_i$$

P_i = PROPORTION OF CLASS i ON NODE



$$IG_T = IG_1 + IG_2$$

(FOR FEATURE A THE INFORMATION GAIN WILL BE THE SUM OF $IG_1 + IG_2$)

REGRESSION TREES

AT EACH ITERATION FOR EACH FEATURE x_k FIND OPTIMAL s:

$$\min_s \left[MSE(y \mid x_k < s) + MSE(y \mid x_k \geq s) \right]$$

(*s IS THE CUT OFF)

* FOR BOTH METHODS: VARIABLE IMPORTANCE GENERALLY BE COMPUTED BASED ON CORRESPONDING REDUCTION OF PREDICTIVE ACCURACY WHEN THE PREDICTOR OF INTEREST IS REMOVED OR SOME MEASURE OF DECREASE OF NODE IMPURITY.

LINEAR REGRESSION

LINEAR APPROACH TO MODELLING RELATIONSHIP BETWEEN SCALAR RESPONSE TO EXPLANATORY VARIABLES

"ORDINARY LEAST SQUARES"

$$\boxed{Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n \cdot X_n}$$

LOGISTIC REGRESSION

LOG-ODDS OF PROBABILITY OF AN EVENT IS A LINEAR COMBINATION OF EXPLANATORY VARIABLES

"MAXIMUM LIKELIHOOD ESTIMATION"

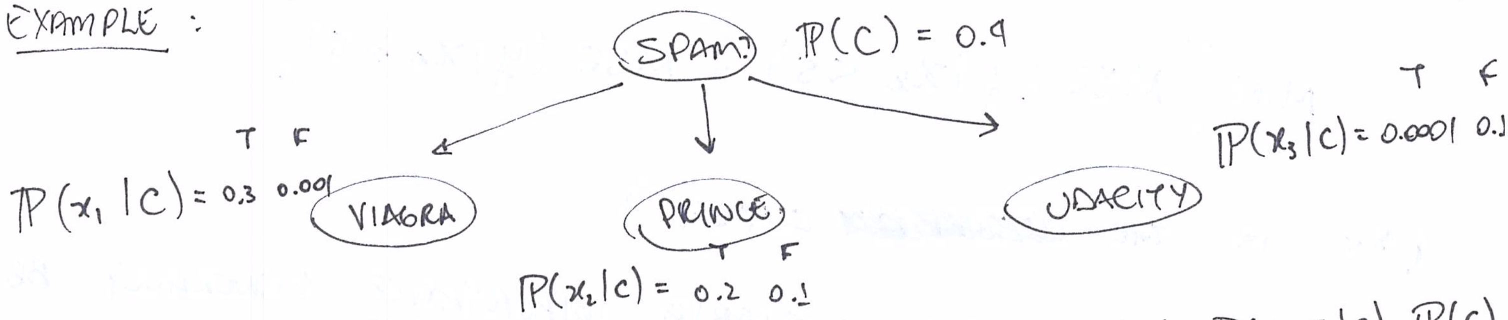
$$\boxed{\mathbb{P}(Y=1) = \frac{1}{1+e^{-x}}}$$

* VARIABLE IMPORTANCE FOR REGRESSION CAN BE SET BASED ON THE COEFFICIENTS ONLY. IF THE FEATURES ARE NORMALIZED (CONTINUOUS) OR THEY ARE DISCRETE.

NAIVE BAYES CLASSIFICATION

BASED ON BAYES THEOREM WITH CONDITIONAL PROBABILITY OF EVENT TO PREDICT. ASSUMES x_i CONDITIONALLY INDEPENDENT OF EVERY OTHER FEATURE x_j $(i \neq j)$ GIVEN CATEGORY C_k => $\boxed{\mathbb{P}(C_k \mid x_1, \dots, x_n) \propto \mathbb{P}(C_k) \cdot \prod_{i=1}^{n} \mathbb{P}(x_i \mid C_k)}$

EXAMPLE :



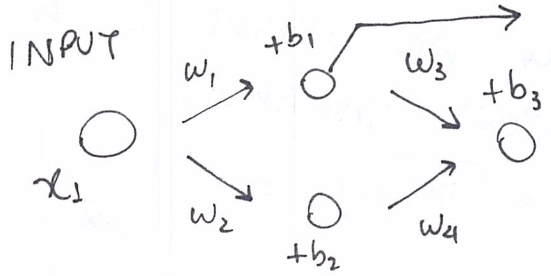
$$\mathbb{P}(C \mid x_1 = T, x_2 = F, x_3 = F) \propto \mathbb{P}(x_1 = T \mid C) \cdot \mathbb{P}(x_2 = F \mid C) \cdot \mathbb{P}(x_3 = F \mid C) \cdot \mathbb{P}(C)$$

RANDOM FOREST

SELECTING BAGGING SAMPLES FOR EACH TREE CHOOSE RANDOM FEATURES $(\sqrt{D})$.

* REDUCES VARIANCE BUT RANGE (AS ALL TREE MODELS) IS LIMITED.

NEURAL NETWORKS (ARTIFICIAL NEURAL NETWORKS)



$\sigma(z = w_1 \cdot x_1 + b_1)$

$\sigma(z) :=$ SIGMOID, TANH, RELU,

SIGMOID := $\sigma(z) = \dfrac{1}{1+e^{-z}}$; $\sigma(z) \in (0,1)$

TANH := $\sigma(z) = \dfrac{e^{z} - e^{-z}}{e^{z} + e^{-z}} = \tanh(z)$; $\sigma(z) \in (-1,1)$

RELU := $\sigma(z) = \max(0, z)$; $\sigma(z) \in [0, \infty)$.

SOFTMAX := $\sigma_i(\vec{z}) = \dfrac{e^{z_i}}{\sum_{j=1}^{J} e^{z_j}}$, $i = 1, \dots, J$; $\sigma(\vec{z}) \in (0,1)$

K-NN (K - NEAREST NEIGHBORS)

REGRESSION OR CLASSIFICATION OF K NEAREST NEIGHBORS BASED ON DISTANCE FUNCTIONS:

EUCLIDEAN : $\sqrt{\sum_{i=1}^{k} (x_i - y_i)^2}$

MANHATTAN : $\sum_{i=1}^{k} |x_i - y_i|$

MINKOWSKI : $\left(\sum_{i=1}^{k} (|x_i - y_i|)^q \right)^{1/q}$

K-MEANS

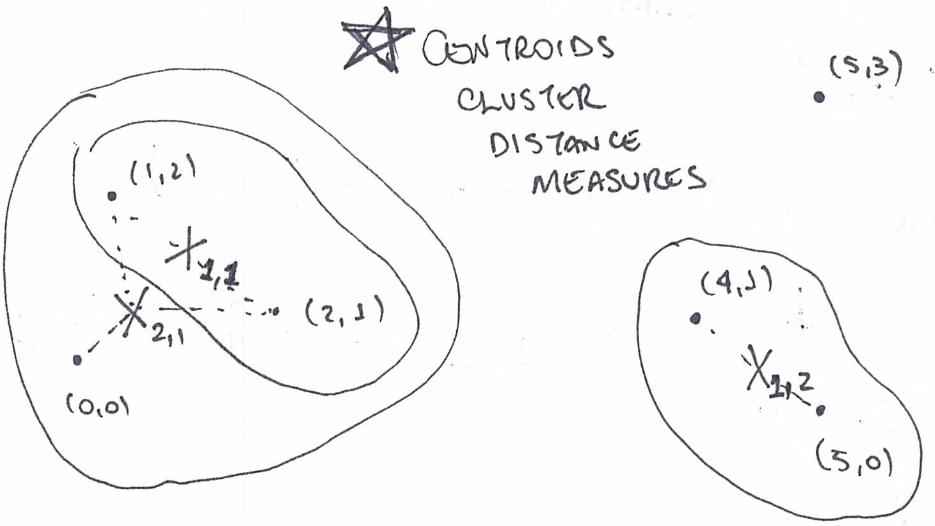
0. PLACE CENTROIDS AT RANDOM LOCATIONS (K CENTROIDS)
1. FIND NEAREST CENTROID TO EACH OBSERVATION
2. ASSIGN OBSERVATION TO CLOSER CLUSTER
3. CALCULATE NEW CENTROID

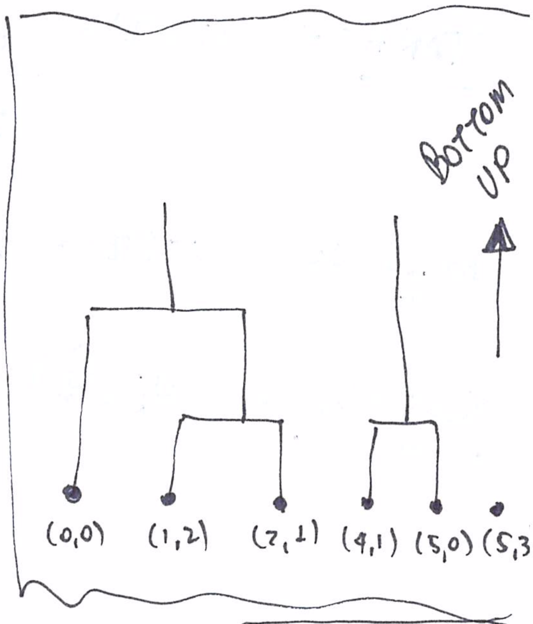
K

* REPEAT UNTILL DIFF. FROM PREVIOUS CENTROID IS MINIMUM (DIFFERENCE FROM DISTANCES)

→ K-MEANS ONLY USES EUCLIDEAN DISTANCE

HIERARCHICAL CLUSTERING





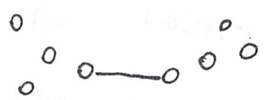
DISTANCES TO BE USED:

EUCLIDEAN, MANHATTAN, MINKOWSKI, MAHALANOBIS $:= \sqrt{(a-b)^T S^{-1} (a-b)}$

* S IS THE COVARIANCE MATRIX

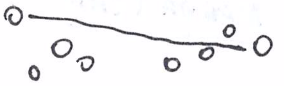
→ SINGLE LINKS: $D(c_1, c_2) = \min D(x_1, x_2)$

DISTANCE BETWEEN CLOSEST ELEMENTS IN CLUSTERS



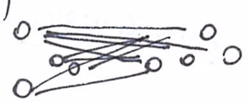
→ COMPLETE LINKS: $D(c_1, c_2) = \max D(x_1, x_2)$

DISTANCE BETWEEN FARTHEST ELEMENTS IN CLUSTERS



→ AVERAGE LINKS: $D(c_1, c_2) = \frac{1}{|c_1|} \frac{1}{|c_2|} \sum_{x_1} \sum_{x_2} D(x_1, x_2)$

AVERAGE OF ALL PAIRWISE DISTANCES

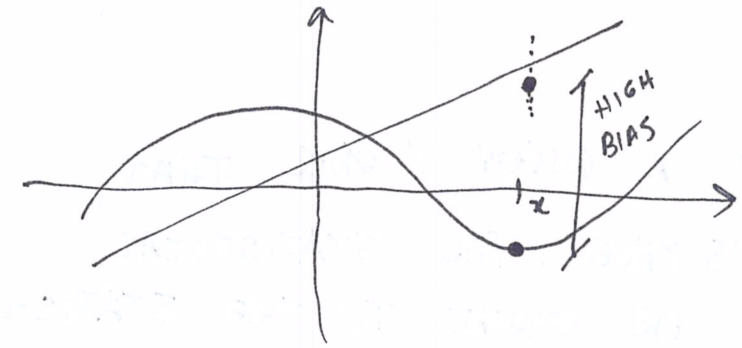


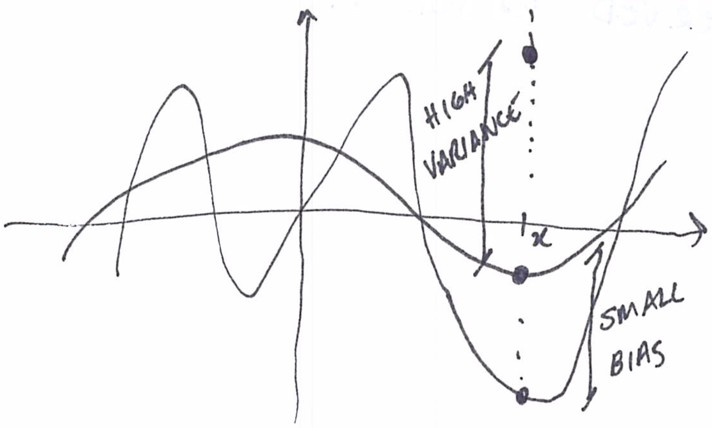
→ CONTROIDS: $D(c_1, c_2) = D\left[\left(\frac{1}{|c_1|} \sum_{x_1} \vec{x}\right), \left(\frac{1}{|c_2|} \sum_{x_2} \vec{x}\right)\right]$

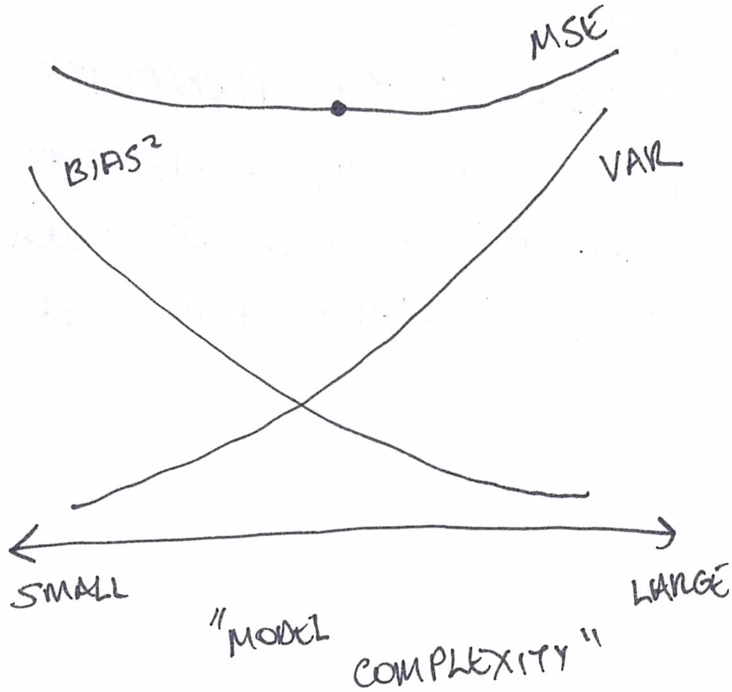
★ DISTANCE BETWEEN CONTROIDS (MEANS) OF TWO CLUSTERS

BIAS - VARIANCE DECOMPOSITION

- BIAS IS THE ERROR FROM ERRONEOUS ASSUMPTIONS IN THE MODEL
- VARIANCE IS THE ERROR FROM SENSITIVITY TO SMALL FLUTUATIONS IN THE TRAINING SET.







$$MSE(\hat{\theta}) = BIAS^2(\hat{\theta}) + VAR(\hat{\theta})$$

$$\begin{cases} BIAS \uparrow = \text{UNDERFITTING} \\ VAR \uparrow = \text{OVERFITTING} \end{cases}$$

CROSS- VALIDATION

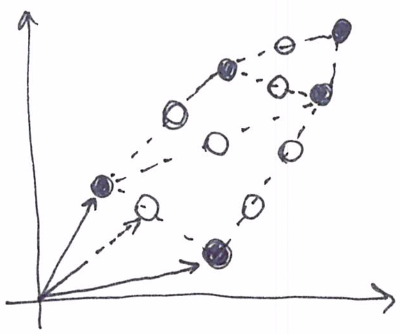
PREVENTS OVER FITTING BECAUSE MODEL THAT FITS RANDOM NOISE ON TRAINING DATA WON'T PERFORM GOOD ON VALIDATION DATASET.

K-FOLD : SEPARATES DATA ON K FOLDS, TRAINING WILL BE K-1 FOLDS AND VALIDATION WILL BE 1

LOOCV : LEAVE-ONE-OUT CROSS-VALIDATION IS THE SAME AS K-FOLD BUT K = N.

SMOTE (SYNTHETIC MINORITY OVER-SAMPLING TECHNIQUE)

→ CREATES NEW "SYNTHETIC" OBSERVATIONS



- IDENTIFY FEATURE VECTOR AND NEAREST NEIGH.
- TAKE THE DIFF. BETWEEN TWO
- MULTIPLY DIFF. BY RANDOM BETWEEN 0 AND 1
- IDENTIFY NEW POINT ON LINE ~~SEGMENT~~ SEGMENT BY ADDING RANDOM NUMBER TO FEATURE VECTOR
- REPEAT @

P- VALUE

P-VALUE IS THE PROBABILITY FOR A GIVEN MODEL THAT, WHEN THE NULL HYPHOTHESIS IS TRUE, THE STATISTICAL SUMMARY WOULD BE GREATER OR EQUAL TO THE STATISTICAL SUMMARY FOR THE OBSERVED RESULTS.

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P- VALUE IS THE PROBABILITY FOR A GIVEN MODEL THAT, WHEN THE NULL HYPHOTESIS IS TRUE, THE STATISTICAL SUMMARY WOULD BE GREATER OR EQUAL TO THE STATISTICAL SUMMARY FOR THE OBSERVED RESULTS.

REGULARIZATION

: REDUCE VARIANCE AT THE COST OF INTRODUCING SOME BIAS

(↑ BIAS ⇒ UNDERFITTING
↑ VAR ⇒ OVERFITTING)

$\boxed{\text{LINEAR REGRESSION MODEL}}$ $Y = X\beta + \varepsilon \, , \; \varepsilon \sim N(0, \sigma^2)$

ORDINARY LEAST SQUARES (OLS) ⇒ ESTIMATE $\hat{\beta}$ SUCH A WAY THAT SUM OF SQUARES OF RESIDUALS IS AS SMALL AS POSSIBLE

$$\min L_{OLS}(\hat{\beta}) = \min \sum_{i=1}^{n} (y_i - x_i^T \hat{\beta})^2 = \min \| y - X\hat{\beta} \|^2$$

IN ORDER TO OBTAIN $\hat{\beta}_{OLS} = (X^T X)^{-1} (X^T Y)$

- **RIDGE REGRESSION** (L2 PENALTY) OLS LOSS FUNCTION IS AUGMENTED IN A WAY WE PENALIZE THE SIZE OF PARAMETER ESTIMATES:

$$\boxed{L_{RIDGE}(\hat{\beta}) = \sum_{i=1}^{n} (y_i - x_i^T \hat{\beta})^2 + \lambda \sum_{j=1}^{m} \hat{\beta}_j^2 = \| y - X\hat{\beta} \|^2 + \lambda \| \hat{\beta} \|^2}$$

* ALSO CALLED AS L2 PENALTY

- LASSO REGRESSION (L1 PENALTY)

SIMILAR TO RIDGE REGRESSION BUT LOSS FUNCTION IS:

$$\boxed{L_{LASSO}(\hat{\beta}) = \sum_{i=1}^{n} (y_i - x_i^T \hat{\beta})^2 + \lambda \sum_{j=1}^{m} |\hat{\beta}_j|}$$

* ALSO CALLED L1 PENALTY

- ELASTIC NET

A COMBINATION OF BOTH RIDGE REGRESSION AND LASSO REGRESSION, LOSS FUNCTION IS:

$$\boxed{L_{ENET}(\hat{\beta}) = \frac{\sum_{i=1}^{n} (y_i - x_i^T \hat{\beta})^2}{2n} + \lambda \left(\frac{1-\alpha}{2} \sum_{j=1}^{m} \hat{\beta}_j^2 + \alpha \sum_{j=1}^{m} |\hat{\beta}_j| \right)}$$

WHERE α IS THE MIXING PARAMETER BETWEEN RIDGE ($\alpha=0$) AND LASSO ($\alpha=1$).

GRID - SEARCH

GRID-SEARCH IS USED TO FIND THE OPTIMAL HYPERPARAMETERS OF A MODEL WHICH RESULTS IN THE MOST 'ACCURATE' PREDICTIONS.

IT CAN BE CHOOSE THE FOLLOWING PARAMETERS:

- PENALTY : L1, L2, ELASTIC NET
- LEARNING RATE
- METRIC : ACCURACY, RECALL, PRECISION, F1-SCORE

* DISCUSSIONS ABOUT RANDOM - SEARCH IS BETTER (AND FASTER) THAN GRID - SEARCH. SAME CONCEPT BUT INSTEAD OF SETTING SOME VALUES/INPUTS THEY ARE RANDOMLY CHOSEN.

(PROBABILITY / ODDS / LOG ODDS)

PROBABILITY OF $\boxed{80\%}$ OF RAIN TODAY

ODDS RATIO IS 80% OF CHANCE OF RAIN DIVIDED BY 20% OF CHANCE OF NOT RAIN => 80%/20% = $\boxed{4}$

LOG ODDS IS THE LOGARITHM OF ODDS => $\boxed{LN(4)}$

* ODDS RATIO $= \frac{\mathbb{P}(A)}{\mathbb{P}(-A)} = \frac{\mathbb{P}(A)}{1-\mathbb{P}(A)}$ $\therefore$ LOG ODDS $= LN\left(\frac{P}{1-P}\right)$

AND LOG ODDS $= LN\left(\frac{P}{1-P}\right) = \beta_0 + \sum_{i=1}^{m} \beta_i x_i$