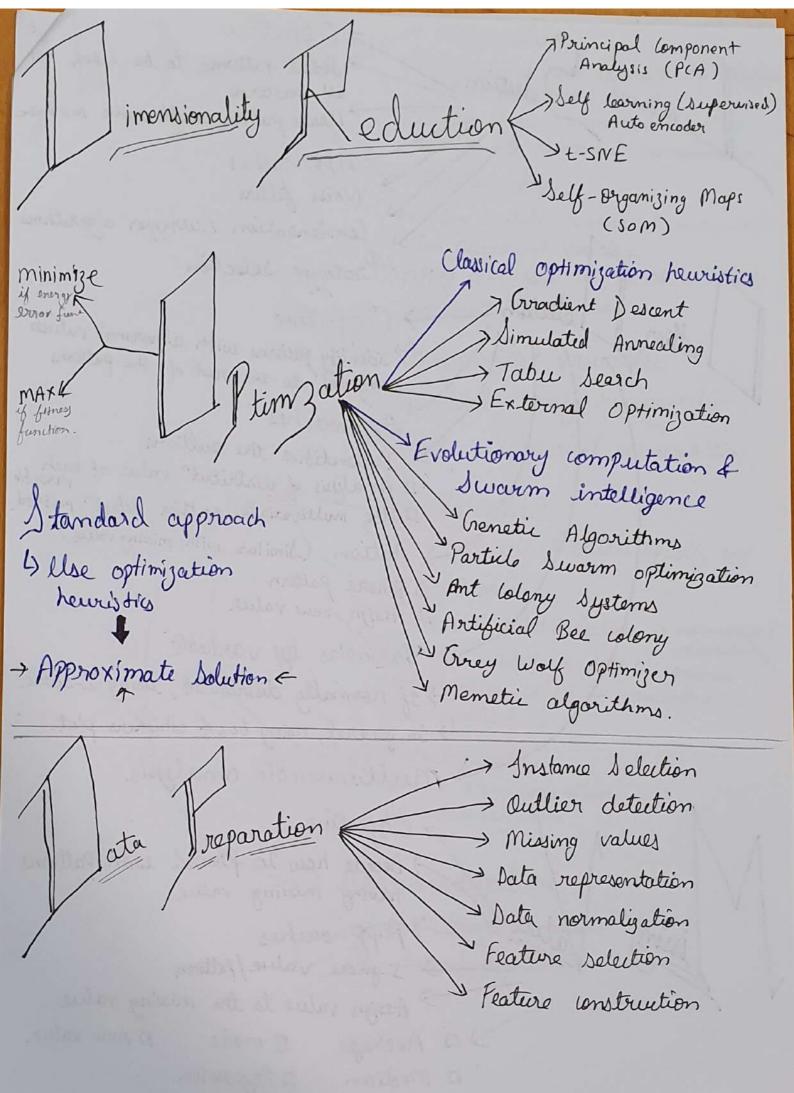
Data Solumns: Variables, feature, attribute 4 Input variable
☐ Input variable ← ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐ ☐
Rows: instances, patterns.
Variables / features:
Mumerical: integral, real
· Signed, unsigned
- Bounded, unbounded
> Categorical
· Sorted: Low, medium, Ligh
· Baby, toddler, Wild. · Unsorted: Color, Country, gender.
L Tentual
I Identification of Pattern (name, ID).
Il Free text: report, description.
Complex attributes
4) images, sound, time series.
Marian Comment of Comment of the Com

6) Encoding 1) Prediction I roblems > 7) Prototyping 2) Classification 8) Visualization 9) Familiarity 3) Clustering Dimensionality Reduction 10) feature Optimization. Multilinear (MLR) Regression n Non-linear dependencies Polynomial approximation > Highly dimensionality m>>1 Multilayer Newdy Network (NN) Linear classifiers 7 K-nearest meighbors Binary K > Multi-layer NN -> Support Vector Machine Non-Binary 4 Tree > Decision tree > Random forest x K-means find Partition belong to Agglomerative Hierachy (AHC) Similiar pattern < -) Donsity models Vector Quantization (VQ) Self-Organizing Mgps (som)



nstance Deletion Select patterns to be used, no our patterns
Desire pattern could seems too noise > Approaches Noise felters s Condensation / wrapper algorithms utlier detection Protogge selection > Objective (compared to the rest of the patterns Approaches I dentifies the outliers Analysis of distribut ralue of each variable Illse multivariate outlier detect method) Action (Similar with missing value) 1) ignore pattern
11 Assign new value > Variables by variable 4) If normally distributed, using Z-score. 4) In general, using box 4 whisters plot. > multivariable analysts. issing lalue 7 Objective I Decide how to proceed with patterns having missing value. Approaches I gnove Value/Pattern > Assign value to the missing value Il Average I mode prew value. 11 Median 11 Regression

ata Representation 7 Objective Algorithm need number, no categories or free text. Subtitute non-numerical value by appropriate numerical representation. > Approaches 4) Finding Suitable numerical representat for Categorical variables. -> Apply NLP tech. to free txt to identify relevant information. -> Categorical variables. > Unsorted : Unary representation Dorted: Numerical representation -> Objective -> make all features equally imp.) Approaches. 2 Each unrelated feature is normalized independently For each related var. sets a common normalization could be meaningful > Two method => J Normalization - linear transformation - De-normalization > D tandardization - linear transformation - De- standardization.

Teature Delection > Objective - leave only relevant variables. > Approaches > Removal of variables - Reductant - Unrelated to Objective of analysis - Low quality:- missing value, outliers, noisy > belection of variables - Identify the relevant var. Usually time consuming. Peature Construction -> Objective -- Add new synthetic var. which could facilists the analysis > Approaches - Build a new var. from existing one I linear or non-linear combination → Change of reference (e.g. from cartesian to Polar coordinate) Intitud work) weight (wij)

Threshold (or blas)

or hield of unit i

tim function -> Neuron or unit Processing Hyperbolic temgent Activation Sunction Heaviside (or threshold) Sign linear (Rectified linear unit (ReLU)) sigmoidal

I reduction

-> give the best prediction

to approximate date

-> multilinear regression (MLR) rearning (earning) Classification > K-nearest neighbors(KNN) William Regression (MLR) - Logistic regression, naive bayes. (based on Probabilities) -> Unidimensional output → Minimize quardratie error over training Patterns → Results ogistic Corression -> Statistical model for binary classifict from set of input data (continous/divis)

It is based on a legistic function. () It is based on a logistic function. Jo fit model (identity best co-efficient) we use

Maximum Likelihood Estimation (MLF)

Vaive lassifer > Algo. for classification based on Probabilities

L prior information. Newest Neighbory (KNN) => Dataset

Predict X, based on it's Knearest regalors in detaset

7 If applied to whole dataset valuation of Redictions STrey masure quality of fitting not the quality of Prediction > Solution D Division of dataset Totaining Set
- To fit f Validation Set Test set - To evaluate - To evaluate Parameters Bredictions -> (ross-Validation (multiple validation) -3-fold cross validation > Validation is resessary to avoid overfitting -> Production evaluation measures 1) Mean squared error mean absolute error 4> Relative absolute error.) I valuation of Prediction: Classification of evaluation measures. - Sensitivity - Spececificity - Fall - out - Precision (or Rand index) - Accuracy (or thread index) - Jaccard - FI score - ROC-curve -> Area under the curve (AUC)~ - Confusion matrix (or contingency table)

Application of gradient descent to nopogation the training set of a mer > Observations 4) gradient calculation (chain rule of derivolis) 4) It is needed a differentiable activation Lunction (Sigmoid, hyberbolic tangent, Relu) From Back-Propagation > Output - layer > Rest of the layer (in backwards order)) Amount of weights 4 throsholds update Includes Shearning nate of Momentum & Derivative of activation function >> Sigmoid -> ReLU > (omparison Batched back-Propagation → Correct gradient descent → Too Slow Online back - Propogation 4) Stochastic gradient descent 4) Fast but with fluctuations Partial batched back- Propagation 4) Intermediate blu online & batched 4) fast & stable -> Efficient use of hardware.

Hilayer Neural Network. > Architecture -input layer - Output layer - One or more hidden layers Feed forward Propogation Prediction Problem Training - find weight 4 Hereshold of multibuyer PN short minimize quardrate error over the training patterns - Minimize Problem + E has too many local minima PTIMIZATION BY -> Cannot be solve by dorivates =0 Gradient Decent Start in random Position - Try to move down in small step Formalization (minus the gradient - VE) > Update weights & threshold to steepest descent. I To ensure small step, learning rate of is used. -) To avoid oscillation, include INERTIA to the movement. - Movementum term.

Linear Dupport Vector Machine (SVM) Linearly separated Data >> Best separation -Maximize marigin

Support vectors

Separating hyperplane > Auxilliary hyperplane) margin. -) Optimization Objective Duardratic programing problem with linear inequality constraints (1) Optimization with Lagrange multipliers & Karush-Kuhn-Tucker (KKT) conditions Primal lagrangian -> Dual Lagrangian => Subjected to KKT Condition for KKT

All patterns correctly classified. Only support vector (SV) contribute to result I separating hyperlane only depends on sv > Solving the quardrate programing problem with linear inequality constraints

it is a convex problem of can be solved in polynomial

Home - Interior point method many algorithms exists - conjugate gradient method.
- Augumented Lagrangian method. - Active set method

Pinear Support Vector Machine (SVM) I What if data is non-linearly separable!

4 Due to non-linear separation => Non-linear SVM Linear SVM with slack variables -> A Slack variables (F" 20) account for error in classificat > Optimization objective Primal lagrangian Dual lagrangian Deparating hyperlane 4) Prediction 7 Kernel trick Von-Linear SVM -) Make non-linear transf. of deta & apply Lovm. > Dual lagrangian Separating hyperlane How to find non-linear framsformation I? Prediction -) Observation [Dot. Product] -) Kernel truck - Insted of I(M), choose Kernel K(a,y) -) Dual lagrangion with Kernel A Polynomial (momo + inhomogenous) Prediction 7 Craussian / Radial Basis Sunction (RBF) Sigmoidal - Kernel -> Linear) common kornel -> 2 nd poly. 3nd polynomial

Insupervised Learning Approaches) imensionality Reduction

Visualization

Clustering

Prototy ping > Encoding > Leature mapping. imensionality Reduction Visualization > Methods Principal Component Analysis + distributed Stochastic Network Embedding (t-SNE) Hebbian learning -> Self-supervised learning / Autoencodors > Seff-organizing maps (som) -> Methods -> Centroid-bosed clustering -> K-mean, K-median, K-mediad, fuzzy (-means. -> Connectivity - based clustering -> Agglomerative Kierarchical clustering (AHC) > Density-based dustering Oustribution-based clustering > Craussian Mixture model > Competitive clustering (SOM) > Vector Quantisation (VQ), Self-Organizing Maps

7 it define a clustering { C. ... (,) of the original data. notoyping > Some clustering algo, ore based on Protoyping > Methods 4) Controid - based clustering 4) K-means, K-means, K-medoids, fuggy (mean 4) Competitive clustering > Vector Quantization (VQ), Self-organ--izing maps (som) > find lower-dimensional Protogpes & the encoding 4 decoding function (with loss function)) Methods () Combination of dimensionality reduction 4
Prototyping algorithms Teature Mapping: Jind Prologping that Preserve a certain geometric arrangment >) methods 4) Self-organizing-Maps (SOM) 7 Dimensionality Reduction lassical /odels < -> Principal Component Analogus (PCA) t-distributed Stochastic Network Embedding (t-SNE) > Clustering > K-means Agglomerative Hierarchical Clustering (AMC)

nsupervised learning with Jewal Jetwork Lebbian Clarning
Lebo dimensionality reduction 4 visualization Self-Supervised learning / Autoencoder Sor dimensionality reduction & visualization Competitive learning / 4 Vector Quantization (VQ) - for clustering 4 Protyping. 4) Self-organizing maps (som) Adaptive Competitive learning - learning vector Quantization (LVQ) ARTMAP