1. Classification
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Algorithm 1 k-Nearest Neighbor [Tay et al., 2014] link:16,31

Input: X: training data, Y:Class labels of X, x: unknown sample
Output: Class label of unknown sample

function CLASSIFY(X, Y, x)
  for $i = 1$ to m **do**
    Compute distance $d(X_i, x)$
  end for
  Compute set I containing indices for the k smallest distances $d(X_i, x)$
  Return majority label $\{Y_i$ where $i \in I\}$
end function

Algorithm 2 Adaboost [Schapire, 2014]

Input:
Training data $\{(x_i, y_i)_{i=1}^N$ where $x_i \in \mathbb{R}^k$ and $y_i \in \{-1, 1\}\}$
Large number of classifiers denoted by $f_m(x) \in \{-1, 1\}$
0-1 loss function I defined as

$$I(f_m(x, y)) = \begin{cases} 0, & \text{if } f_m(x_i) = y_i \quad (1) \\ 1, & \text{if } f_m(x_i) \neq y_i \quad (2) \end{cases}$$

Output: The final classifier

for $i = 1$ to N **do**
  for $i = 1$ to M **do**
    Fit weak classifier m to minimize the objective function:
    $\epsilon_m = \frac{\sum_{i=1}^N w_i^m I(f_m(x_i)) \neq y_i}{x^2+2x+1}$
    where $I(f_m(x_i) \neq y_i) = 1$ if $f_m(x_i) \neq y_i$ and 0 otherwise
    $\alpha_m = \ln \frac{1-\epsilon_m}{\epsilon_m}$
  end for
  for all i **do**
    $w_i^{m+1} = w_i^{(m)} e^{\alpha_m I(f_m(x_i) \neq y_i)}$
  end for
end for

Algorithm 3 Adaboost [Hertzmann et al., 2015]

Input:
Training data $\{(x_i, y_i)_{i=1}^N$ where $x_i \in \mathbb{R}^k$ and $y_i \in \{-1, 1\}\}$
Output: Weighted sum that represents the final output of the boosted classifier

Given Training data $\{(x_i, y_i)$ where $y_i \in \{-1, 1\}\}$
initialize D_1 = uniform distribution on training examples
for $t = 1$ to T **do**
  Train weak classifier h_t on D_t
  choose $\alpha_t > 0$
  compute new distribution D_{t+1}:
  for all i **do**
    multiply $D_t(x)$ by

$$\begin{cases} e^{-\alpha_t}, & (< 1) \text{ if } y_i = h_t(x_i) \quad (3) \\ e^{\alpha_t}, & (> 1) \text{ if } y_i \neq h_t(x_i) \quad (4) \end{cases}$$

    renormalize
  end for
  output final classifier $H_{final(x)} = sign(\sum \alpha_t h_t(x))$
end for

Algorithm 4 Adaboost4 [Hertzmann et al., 2015] Link:23,35,93,95

Input:
Training data $\{(x_i, y_i)_{i=1}^N$ where $x_i \in \mathbb{R}^k$ and $y_i \in \{-1, 1\}\}$
Output: Weighted sum that represents the final output of the boosted classifier
Set uniform example weights.
for each base learner do **do**
    Train base learner with weighted sample.
    Test base learner on all data.
    Set learner weight with weighted error.
    Set example weights based on ensemble predictions.
end for

Algorithm 5 Random forest [Bernstein, 2016] Link:42

Input: S: training set, F:Features and number of trees in forest B
Output: Constructed tree
function RANDOMFOREST(S, F)
    $H \leftarrow \emptyset$
    for $i \in 1, ...B$ **do**
        $S^{(i)} \leftarrow$ A bootstrap sample from S
        $h_i \leftarrow RANDOMIZEDTREELEARN(S^i, F)$
        $H \leftarrow H \bigcup \{h_i\}$
    end for
    return H
end function
function RANDOMIZEDTREELEARN(S, F)
    At each node:
    $f \leftarrow$ a very small subset of F
    Split on best feature in f
    return The learned tree
end function

Algorithm 6 Iterative Dichotomiser 3 [., 2015a] Link:12,14,56,74,131,140

Input: D : Training Data, X : Set of Input Attributes
Output: A decision tree
function ID3(D, X)
    Let T be a new tree
    if all instances in D have the same class c **then**
        Label $(T) = c$; Return T
    end if
    if $X = \emptyset$ or no attribute has positive information gain **then**
        Label (T) = most common class in D; Return T
    end if
    $X \leftarrow$ attribute with highest information gain
    Label$(T) = X$
    for each value x of X **do**
        $D_x \leftarrow$ instances in D with $X = x$
        if D_x is empty **then**
            Let T_x be a new tree
            Label(T_x) = most common class in D
        else
            $T_x =$ ID3$(D_x, X - \{x\})$
    end if
    Add a branch from T to T_x labeled by x
end for
return T
end function

Algorithm 7 Perceptron [Brownlee, 2015d] Link:65

Input: ProblemSize,InputPatterns,Max number of iterations,Learning rate
Output: WeightsClassification of the entire training set)

1: **for** $i = 1$ to Max number of iterations **do**
2: $Pattern_i \leftarrow$ SelectInputPattern(InputPatterns)
3: $Activation_i \leftarrow$ ActivateNetwork($Pattern_i$,Weights)
4: $Output_i \leftarrow$ TransferActivation($Activation_i$)
5: UpdateWeights($Pattern_i, Output_i$,Learning rate)
6: **end for**
7: Return Weights

Algorithm 8 Perceptron [Amini, 2015] Link:65

Input:
Training set S = $((x_1, y_1),....(x_m, y_m))$
Learning rate $\eta > 0$
Maximum number of iterations T
Output: Parameters of the linear model $w^{(t)}$
Initialize weights $w^{(0)} = (\bar{w}^{(0)}, w_0^{(0)})$
$t \leftarrow 0$

1: **while** $t \leq T$ **do**
2: Choose an example at random $(x, y) \in S$
3: **if** $y \times (\langle \bar{w}^{(t)}, x \rangle + w_0^{(t)}) \leq 0$ **then**
4: $w_0^{(t+1)} \leftarrow w_0^{(t)} + \eta \times y$
5: $\bar{w}^{(t+1)} \leftarrow \bar{w}^{(t)} + \eta \times y \times x$
6: **else**
7: $w^{(t+1)} \leftarrow w^{(t)}$
8: **end if**
9: **end while**
10: t $\leftarrow$ t +1

Algorithm 9 Back-propagation [Brownlee, 2015a] Link:17,30,42

Input: ProblemSize,InputPatterns,Max number of iterations,Learning rate
Output: Network

1: Network $\leftarrow$ ConstructNetworkLayers()
2: $Network_{weights} \leftarrow$ InitializeWeights(Network,ProblemSize)
3: **for** $i = 1$ to Max number of iterations **do**
4: $Pattern_i \leftarrow$ SelectInputPattern(InputPatterns)
5: $Output_i \leftarrow$ ForwardPropagate($Pattern_i$,Network)
6: BackwardPropagateError($Pattern_i, Output_i$,Network)
7: UpdateWeights($Pattern_i, Output_i$,Network,Learning rate)
8: **end for**
9: Return Network

Algorithm 10 Back-propagation2 [Ng,]

Input:
Training Set $x^{(1)}, y^{(1)}, , ..., (x^{(m)}, y^{(m)})$
Output:
Gradient of the cost function
$\Delta_{ij}^{(l)} = 0$(for all l,i,j)
for $i = 1$ to m **do**
  Set $a^{(1)} = x^{(i)}$
  Perform forward propagation to compute $a^{(l)}$ for $l = 2, 3, ...L$
  Using $y^(i)$, compute $\delta^(L) = a^(L) - y^(i)$
  Compute $\delta^(L-1), \delta^(L-2), ...\delta^(2)$
  $\Delta_{ij}^{(l)} := \Delta_{ij}^{(l)} + a_j^{(l)} \delta_i^{(l+1)}$
end for
$D_{ij}^{(l)} := \frac{1}{m}\Delta_{ij} + \lambda\theta_{ij}^{(l)}$ if $j \neq 0$
$D_{ij}^{(l)} := \frac{1}{m}\Delta_{ij}$ if $j = 0$
$\frac{\partial}{\partial\theta_{ij}^{(l)}} J(\theta) = D_{ij}^(l)$

Algorithm 11 Learning Vector Quantization [Brownlee, 2015c] Link : 50 and 58

Input: ProblemSize,InputPatterns,Max number of iterations,$CodebookVectors_{num}$,Learning rate
Output: CodebookVectors
$CodebookVectors \leftarrow InitializeCodebookVectors(CodebookVectors_{num}, ProblemSize)$
for $i = 1$ to Max number of iterations **do**
  $Pattern_i \leftarrow$ SelectInputPattern(InputPatterns)
  $Bmu_i \leftarrow$ SelectBestMatchingUnit($Pattern_i$,CodebookVectors)
  for $Bmu_i^{attribute} \in Bmu_i$ **do**
    if $Bmu_i^{class} \equiv Pattern_i^{class}$ **then**
      $Bmu_i^{attribute} \leftarrow Bmu_i^{attribute} + learn_{rate} \times (Pattern_i^{attribute} - Bmu_i^{attribute})$
    else
      $Bmu_i^{attribute} \leftarrow Bmu_i^{attribute} - learn_{rate} \times (Pattern_i^{attribute} - Bmu_i^{attribute})$
  end if
end for
end for
Return CodebookVectors

Algorithm 12 Self Organizing Map [Brownlee, 2015b] Link:69

Input: InputPatterns,Max number of iterations,Learning rate,$Grid_{width}, Grid_{height}$
Output: CodebookVectors
$CodebookVectors \leftarrow InitializeCodebookVectors(Grid_{width}, Grid_{height}, InputPatterns)$
for $i = 1$ to Max number of iterations **do**
  $Learn_{rate}^i \leftarrow$ CalculateLearningRate($i, learn_{rate}^{init}$)
  $neighborhood_{size}^i \leftarrow$ CalculateNeighborhoodSize($i, neighborhood_{init}^{size}$)
  $Pattern_i \leftarrow$ SelectInputPattern(InputPatterns)
  $Bmu_i \leftarrow$ SelectBestMatchingUnit($Pattern_i$,CodebookVectors)
  Neighborhood $\leftarrow Bmu_i$
  Neighborhood $\leftarrow$ SelectNeighbors(Bmu_i,CodebookVectors,$neighborhood_{size}^i$)
  for $Vector_i \in$ Neighborhood **do**
    for $Vector_i^{attribute} \in Vector_i$ **do**
      $Vector_i^{attribute} \leftarrow Vector_i^{attribute} + learn_{rate} \times (Pattern_i^{attribute} - Vector_i^{attribute})$
    end for
  end for
end for
Return CodebookVectors

Algorithm 13 Self Organizing Map [., g] Link:69

Input:

Training data: Vectors of length n

$(x_{1,1}, x_{1,2}, ...x_{1,n})$

....

....

$(x_{p,1}, x_{p,2}, ...x_{p,n})$ ▷ p distinct training vectors

Output:

A vector Y of length m :$(y_1, y_2, ...y_m)$

▷ Sometimes $m < n$, sometimes $m > n$, sometimes $m = n$

Select output layer network topology ▷ Initialize current neighborhood distance,$D(0)$, to a positive value

Initialize weights from inputs to outputs to small random values

Let $t = 1$

while computational bounds are not exceeded **do**

Select an input sample i_l

Compute the square of the Euclidean distance of i_l

from weight vectors(w_j) associated with each output node

$$\sum_{k=1}^{n}((i_{l,k} - w_{j,k}(t)))^2$$

Select output node j^* that has weight vector with minimum value from step 2)

Update weights to all nodes within a topological distance given by $D(t)$ from j^* using the weight update rule: $w_j(t+1) = w_j(t) + \eta(t)(i_l - w_j(t))$

increment t

end while

Algorithm 14 Hierarchial Agglomerative Algorithm [Stein, 2016a] Link:24,54

Input:

$\langle V, E, w\rangle$.

d_c.Distance measure for two clusters

Output: $\langle V_T, E_T\rangle$.Cluster hierarchy or dendogram

$C = \{\{v \mid v \in V\}\}$ ▷ Initial Clustering

$V_t = \{v_C \mid C \in C\}, E_T = \emptyset$ ▷ Initial Dendogram

while $|C| > 1$ **do**

$update\_distance\_matrix(C, G, d_c)$

$\{C, C'\} = \underset{\{C_i,C_j\}\in C:C_i\neq C_j}{argmin} d_c(C_i, C_j)$

$C = (C \backslash \{C, C'\}) \cup \{C \cup C'\}$ ▷ Merging

$V_T = V_T \cup \{v_{C,C'}\}, E_T = E_T \cup \{\{v_{C,C'}, v_C\}, \{v_{C,C'}, v_C\}\}$ ▷ Dendogram

end while

Return T

Algorithm 15 Hierarchial Agglomerative Algorithm 2 [., 2015c] Link:28,54

Input:

N number of Data points

d_c.Distance measure for two clusters

Output: Cluster hierarchy or dendogram of size N

while More than one cluster remains **do**

Compute the proximity graph if necessary

repeat

Merge the closest two clusters.

Update the proximity matrix to reflect the proximity between the new cluster and the original clusters.

end while

Algorithm 16 Hierarchial Divisive Algorithm [Stein, 2016b]

Input:
$\langle V, E, w\rangle$.Weighted graph
d_c.Distance measure for two clusters
Output: $\langle V_T, E_T\rangle$.Cluster hierarchy or dendogram

$C = \{V\}$ ▷ Initial Clustering
$V_t = \{v_C \mid C \in C\}, E_T = \emptyset$ ▷ Initial Dendogram
while $\exists C_x : (C_x \in C \wedge |C| > 1)$ **do**
  $update\_distance\_matrix(C, G, d_c)$
  $\{C, C'\} = \underset{\{C_i,C_j\}:C_i\cup C_j=C_x \wedge\ C_i\cap C_j=\emptyset}{argmax} d_c(C_i, C_j)$
  $C = (C\backslash\{C, C'\}) \cup \{C \cup C'\}$ ▷ Merging
  $V_T = V_T \cup \{v_{C,C'}\}, E_T = E_T \cup \{\{v_{C,C'}, v_C\}, \{v_{C,C'}, v_C\}\}$ ▷ Dendogram
end while
Return T

Algorithm 17 Hierarchial Divisive Algorithm [Stein, 2016b]

Input:
$\langle V, E, w\rangle$.Weighted graph
d_c.Distance measure for two clusters
Output: $\langle V_T, E_T\rangle$.Cluster hierarchy or dendogram

while More than one cluster remains **do**
  Create a new cluster by breaking the link corresponding to the largest distance (smallest similarity).
end while

Algorithm 18 C4.5 [Dai and Ji, 2014] Link :22,55

Input:
T : Training dataset
S : Attributes
Output: decision tree $Tree$

function C4.5(T)
  if T is $NULL$ **then**
    return failure
  end if
  if S is $NULL$ **then**
    return $Tree$ as a single node with most frequent class label in T
  end if
  if $|S| = 1$ **then**
    return $Tree$ as a single node S
  end if
  set $Tree = \{\}$
  for $a \in S$ **do**
    set $Info(a, T) = 0$ and $SplitInfo(a, T) = 0$
    compute $Entropy(a)$
    for $v \in values(a, T)$ **do**
      set $T_{a,v}$as the subset of T with attribute $a = v$
      $Info(a, T) += \frac{|T_{a,v}|}{|T_a|} Entropy(a)$
      $SplitInfo(a, T) += -\frac{|T_{a,v}|}{|T_a|} \log \frac{|T_{a,v}|}{|T_a|}$
    end for
    $Gain(a, T) = Entropy(a) - Info(a, T)$
    $GainRatio(a, T) = \frac{Gain(a,T)}{SplitInfo(a,T)}$
  end for
  set $a_{best} = argmax\{GainRatio(a, T)\}$
  a_{best}into $Tree$
  for $v \in values(a_{best}, T)$ **do** call $C4.5(T_{a,v})$
  end for
  return $Tree$
end function

Algorithm 19 Gradient Descent [., 2015b] Link : 59

Input:
f
starting value x_1
termination tolerances
Output: $x_{maxIters}$

for $i = 1$ to $maxIters$ **do**
  Compute the search direction $d_t = -\delta f(x_t)$
  if $|d_T| < \epsilon_g$ **then**
    return "Converged to critical point", output x_t
    Find α_t so that $f(x_t + \alpha_t d_t) < f(x_t)$
  end if
  if $|\alpha_t d_T| < \epsilon_x$ **then**
    return "Converged in x", output x_t
    Find α_t so that $f(x_t + \alpha_t d_t) < f(x_t)$
  end if
  Let $x_{t+1} = x_t + \alpha_t d_t$
end for
Return "Max number of iterations reached", output $x_{maxIters}$

Algorithm 20 Naive Bayes [., e] Link: 9, 59

Input:
C : A fixed set of classes
D : Documents
Output: Category(Class) of the Documents

function TrainMultinomialNB(C, D)
  $V \leftarrow EXTRACTVOCABULARY(D)$
  $N \leftarrow COUNTDOCS(D)$
  for each $c \in C$ **do**
    $N_c \leftarrow COUNTDOCSINCLASS(D, c)$
    $prior|c| \leftarrow N_c/N$
    $text_c \leftarrow CONCATENATETEXTOFALLDOCSINCLASS(D, C)$
    for each $t \in V$ **do**
      $condprob|t||c| \leftarrow \frac{T_{ct}+1}{\sum_{t'}(T_{ct'}+1)}$
    end for
  end for
  return $V, prior, condprob$
end function
function ApplyMultinomialNB($C, D, prior, condprob, d$)
  $W \leftarrow EXTRACTTOKENSFROMDOC(V, d)$
  for each $c \in C$ **do**
    $score|c| \leftarrow \log\ prior|c|$
    for each $t \in W$ **do**
      $score|c| += \log condprob|t||c|$
    end for
  end for
  return $arg\ max_{c \in C} score|c|$
end function

Algorithm 21 Lasso Regression [Wang et al.,] Link:30,33,124

Input:
ipy : Inner product vector, $ipy_i =< y, X_{\cdot i} >$
ipx : Inner product matrix, $ipx_{ij} =< X_{\cdot i}, X_{\cdot j} >$
λ : Penalty parameter
N : Number of samples
Output: $beta$: Regression parameter vector

function FastLasso(ipy, ipx, λ, N)
    `stop_thr` ▷ Threshold for stopping iteration
    $p \leftarrow length(ipy)$
    $beta \leftarrow 0$ with length p
    $gc \leftarrow 0$ with length p
    while $difBeta_{max} \geq$ `stop_thr` **do**
        $difBeta_{max} \leftarrow 0$
        for $j = 1 \leftarrow p$ **do**
            $z \leftarrow (ipy|j| - gc|j|)/N + beta|j|$
            `beta_tmp` $\leftarrow max(0, z - \lambda) - max(0, -z - \lambda)$
            $difBeta \leftarrow$ `beta_tmp` $- beta|j|$
            $difabs \leftarrow abs(difBeta)$
            if $difabs > 0$ **then**
                $beta|j| \leftarrow$ `beta_tmp`
                $gc \leftarrow gc + ipx|j| \times difBeta$
                $difBeta_{max} = max(difBeta_{max}, difabs)$
            end if
        end for
    end while
end function

Algorithm 22 Bagging [., a] Link:57

Input:
B: the number of bags or base hypotheses
L: Base Learning Algorithm
Output: New Training Sets

function Bagging($examples, B, L$)
    for $i = 1$ to B **do**
        $examples_i \leftarrow$ a bootstrap sample of $examples$
    end for
    Compute set I containing indices for the k smallest distances $d(X_i, x)$
    $h_i \leftarrow$ apply L to $examples_i$
    Return $h_1, h_2, ...h_B$
end function

Algorithm 23 Deep Q-Learning with Experience Replay [Mnih et al., 2013] Link: 91

Input:
D: data set
Q: Action-Value Function
Output: New Training Sets

for $i = 1$ to M **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi = \phi(s_1)$
  for $i = 1$ to T **do**
    With probability ϵ select a random action a_t otherwise select $a_t = max_a Q * (\phi(s_t).a : \theta)$
    Execute action a_t in emulator and observe reward r and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Set $y_j =$

$$\begin{cases} r_j, & \text{for terminal } \phi_{j+1} \quad (5) \\ r_j + \gamma max_{a'} Q(\phi_{j+1,a';\theta}), & \text{for terminal } \phi_{j+1} \quad (6) \end{cases}$$

    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to the following equation

$$\Delta_\theta L_i(\theta_i) = \mathbb{E}_{s,a\sim\rho(.);s'\sim\epsilon[(r+\gamma max_{a'} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i))\Delta_{\theta_i} Q(s,a;\theta_i)]}$$

  end for
end for

Algorithm 24 PageRank [., f] Link:24,64,98,99

Input:
G: inlink file
iteration: Number of iteration
Output: PageRank

function PageRank($G, iteration$)
  $d \leftarrow 0.85$ ▷ damping factor: 0.85
  $oh \leftarrow G$ ▷ get outlink hash from G
  $ih \leftarrow G$ ▷ get inlink hash from G
  $N \leftarrow G$ ▷ get number of pages from G
  for all p in the graph **do**
    $opg[p] \leftarrow \frac{1}{N}$
  end for
  while $iteration > 0$ **do**
    $dp \leftarrow 0$
    for all p that has no out-links **do**
      $dp \leftarrow dp + d * \frac{opg[p]}{N}$
    end for
    for all p in the graph **do**
      $npg[p] \leftarrow dp + \frac{[1-d]}{N}$
      for all ip in $ih[p]$ **do**
        $npg[p] \leftarrow dp + \frac{d*opg[ip]}{oh[ip]}$
      end for
    end for
    $opg \leftarrow npg$
    $iteration \leftarrow iteration - 1$
  end while
end function

Algorithm 25 K means [., b] Link:25,29,40,104

Input:

$E = \{e_1, e_2, ...e_k\}$
k(number of clusters)
$MaxIters$(limit of iterations)

Output:

$C = \{c_1, c_2, ...c_k\}$
$L = \{l(e)|e = 1, 2, ...n\}$ (set of cluster labels of E)

for each $c_i \in C$ **do**
    $c_i \leftarrow e_j \in E$(e.g random selection)
end for
for each $e_i \in E$ **do**
    $l(e_i) \leftarrow argminDistance(e_i, c_j)j \in \{1..k\}$
end for
$changed \leftarrow false$
$iter \leftarrow 0$
while $changed = trueanditer <= MaxIters$ **do**
    for $c_i \in C$ **do**
        $UpdateCluster(c_i)$
    end for
    for $c_i \in E$ **do**
        $minDist \leftarrow argminDistance(e_i, e_j)j \in \{1..k\}$
        if $minDist \neq l(e_i)$ **then**
            $l(e_i) \leftarrow minDist$
            $changed \leftarrow true$
        end if
    end for
    $iter$++
end while

Algorithm 26 DBSCAN link:13,76,97 [Ram et al., 2010]

Input:
D: Data
ϵ:Threshold distance
$MinPts$: Minimum number of points required to form a cluster
Output: Clustered Data

function DBSCAN($D, \epsilon, minPts$)
  $C = 0$
  for each point Pin dataset$D$ **do**
    if P is visited **then**
      continue next point
    end if
    mark P as visited
    $NeighborPts = regionQuery(P, \epsilon)$
    if $sizeof(NeighborPts) < MinPts$ **then**
      mark P as NOISE
    else
      $C =$ next cluster
      $expandCluster(P, NeighborPts, C, \epsilon, MinPts)$
  end if
end for
end function
function EXPANDCLUSTER($P, NeighborPts, C, \epsilon, MinPts$)
add P to Cluster C
for each point $P'inNeighborPts$ **do**
  if P' is not visited **then**
    mark P' as visited
    $NeighborPts' = regionQuery(P', eps)$
    if $sizeof(NeighborPts) >= MinPts$ **then**
      $NeighborPts = NeighborPts$ joined with $NeighborPts'$
    end if
  end if
  if P' is not yet member of any cluster **then**
    add P' to cluster C
  end if
end for
end function
function REGIONQUERY(P, ϵ)
return all points within $P's$ ϵ $neighborhood$
end function

Algorithm 27 Principle Component Analysis [., 2014] Link:41,69,72

Input:
$x_1, ...x_n$d length vector k
Output: Transform matrix R

$X \leftarrow n \times d$ data matrix with x_i in each row
$x \leftarrow \frac{1}{n}\sum_{i=1}^{n} x_i$
$X \leftarrow$ subtract x from each row $x_i inX$
$COV \leftarrow \frac{1}{n-1}X^T \times X$Compute eigenvalue $e_1, ..., e_d$ of COV, and sort them
Compute matrix V which satisfy $V^{-1} \times COV \times V = D$, D is the diagonal matrix of eigenvalue of COV
$R \leftarrow$ the first k column of V

Algorithm 28 Logistic Regression [., d] link:66,67,71

Input:

Training data of the form $\{(x_1, 1), (x_2, 0), ..\}$

x: unknown sample

Output: The output is a probability that the given input point belongs to a certain class

1: $0 \leftarrow \beta$

2: Compute y by setting its elements to

$$y = \begin{cases} 1, & \text{if } g_i = 1 \quad (7) \\ 0, & \text{if } g_i = 2 \quad (8) \end{cases}$$

i = 1,2,..N

3: Compute p by setting its elements to

$$p(x_i, \beta) = \frac{e^{\beta^T x_i}}{1 + e^{\beta^T x_i}}$$

i = 1,2,..N

4: Compute the diagonal matrix W. The ith diagonal element is $p(x_i, \beta)(1 - p(x_i; \beta))$

5: $z \leftarrow X\beta + W^{-1}(y - p)$

6: $\beta \leftarrow (X^T W X)^{-1} X^T W z$

7: If the stopping criteria,stop;otherwise go back to step 3

Algorithm 29 Gaussian Process [., c] Link:78, 122

Input:

$X = \begin{bmatrix} x_1^T \\ \dots \\ x_n^T \end{bmatrix} \in \mathbb{R}^{n \times D}$, m training inputs

$y = \begin{bmatrix} y_1^T \\ .. \\ y_n^T \end{bmatrix} \in \mathbb{R}^n$

$k(.,.) : \mathbb{R}^{D \times D}$

x_*test input

σ^2noise level on the observations

$$[y(x) = f(x) + \epsilon, \epsilon \sim N(0, \sigma^2)]$$

Output:

f_*

$cov(f_*)$

1: $K \in \mathbb{R}^{n \times n}$Gram matrix.$K_{ij} = k(x_i, x_j)$

$$k(x_*) = k_* = k(X, x_*) = \begin{bmatrix} k(x_1, x_*) \\ \dots\dots\dots \\ k(x_n, x_*) \end{bmatrix} \in \mathbb{R}$$

2: $\alpha = (K + \sigma_2 \mathbb{I}_n)^{-1} y$

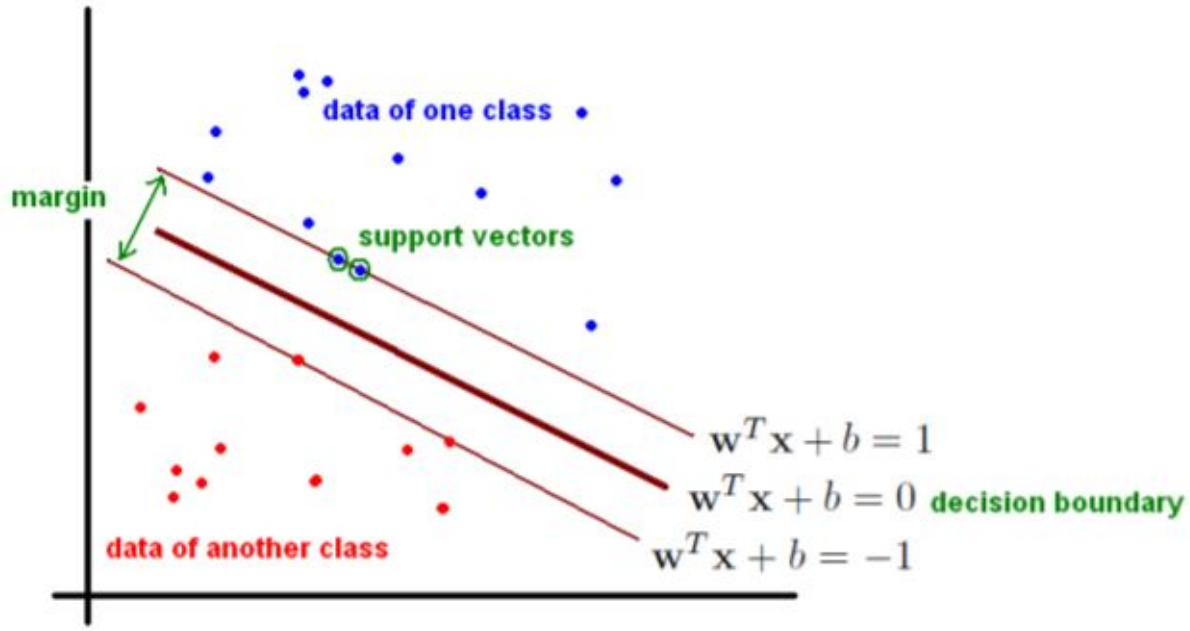
3: $f_* = k_*^T \alpha \in \mathbb{R}$

4: $cov(f_*) = k(x_*, x_*) - k_*^T [K + \sigma_2 \mathbb{I} n]^{-1} k_*$

Algorithm 30 Support Vector Machines [Gavrilov,] Link : 39,70

Input:

Set of N input-output pairs $\{x, y\}^{N_1}$ x: input vectors of the same dimension and y : set of output target labels $y_i = \{0, 1\}$



1 Simple case : linearly-separable data,binary classification

Goal:we want to find the hyperplane(i.e. decision boundary)linearly separating our classes. Our boundary will have the equation: $\mathbf{w^T x} + \mathbf{b} = 0$

Anything above the decision boundary should have label 1 i.e., $\mathbf{w^T x}_i + b > 0$ will have corresponding $y_i = 1$

Similarly, anything below the decision boundary should have label -1 i.e. $\mathbf{w^T x}_i + b < 0$ will have corresponding $y_i = -1$

The reason for this labeling scheme is that it lets us condense for the decision function to

$$f(x) = sign(\mathbf{w^T} + b)$$

since $f(x) = +1$ for all x above the boundary , and $f(x) = -1$ for all x below the boundary.

Thus, we can figure out if an instance has been classified properly by checking that $y(\mathbf{w^T} + b) \geq 1$ (which will be the case as long as either both $y, \mathbf{w^T} + b > 0$ or else $y, \mathbf{w^T} + b < 0$)

You'll notice that we will now have some space between our decision boundary and the nearest data points of either class. Thus,let's rescale the data such that anything on or above the boundary $\mathbf{w^T x} + b = 1$ is of one class(with label 1), and anything on or below the boundary $\mathbf{w^T x} + b = -1$ is of another class (with label -1)

What is the distance between these newly added boundaries?

First note that the two lines are parallel,and thus share their parameters w, b.Pick an arbitary point x_1 to lie on line $\mathbf{w^T x} + b = -1$. Then the closest point on line $\mathbf{w^T x} + b = 1$ is the point $\mathbf{x}_2 = \mathbf{x}_1 + \lambda\mathbf{w}$(since the closest point will always lie on the perpendicular;recall that the vector $\mathbf{w}$ is perpendicular to both lines). Using this formulation, $\lambda\mathbf{w}$ will be the line segment segment connecting $\mathbf{x}_1$ and $\mathbf{x}_2$, and thus, $\lambda \|\mathbf{w}\|$, the distance between $\mathbf{x}_1$ and $\mathbf{x}_2$ is the shortest distance between the two lines/boundaries.

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Algorithm 30 Support Vector Machines (continued)

Solving for λ : $\mathbf{w^T x}_2 + b = 1$ where $\mathbf{x}_2 = \mathbf{x}_1 + \lambda\mathbf{w}$
$\mathbf{w^T}(\mathbf{x}_1\lambda\mathbf{w}) + b = 1$ $\mathbf{w^T}(\mathbf{x}_1\lambda\mathbf{w}) + b = 1$
$\mathbf{w^T x}_1 + b + \lambda\mathbf{w^T w} = 1$ where $\mathbf{w^T x}_1 + b = -1$
$-1 + \lambda\mathbf{w^T w} = 1$
$\lambda\mathbf{w^T w} = 2$
$\lambda = \frac{2}{\mathbf{w^T w}} = \frac{2}{\|\mathbf{w}\|^2}$
And, so the distance $\lambda\|w\| is \frac{2}{\|\mathbf{w}\|^2}\|w\| = \frac{2}{\|w\|} = \frac{2}{\sqrt{\mathbf{w^T w}}}$

It's intuitive that we would want to maximize the distance between the two boundaries demarcating the classes(Why?We want to be as sure that we are not making classification mistakes and thus we want our data points from the two classes to lie as far away from each other as possible).This distance is called the margin,so went to obtain the maximal margin.

Thus, we want to maximize $\frac{2}{\sqrt{\mathbf{w^T w}}}$, which is equivalent to minimizing $\frac{\sqrt{\mathbf{w^T w}}}{2}$ which is in turn equivalent to minimizing $\frac{\mathbf{w^T w}}{2}$(since square root is a monotonic function)

This quadratic programming problem is expressed as :
$min_{w,b}\frac{\mathbf{w^T w}}{2}$
subject to : $y_i(\mathbf{w}^T\mathbf{x} + b) \geq 1(\forall$ data points $\mathbf{x}_i)$

2 Soft-margin extension

Consider the case that your data isn't linearly separable.For instance, maybe you aren't guaranteed that all your data points are correctly labelled, so you want to allow some data points of one class to appear on the other side of the boundary.

We can introduce *slackvariables*an $- \epsilon_i \geq 0$. Our quadratic programming problem becomes:
$min_{\mathbf{w},b,\epsilon}\frac{\mathbf{w^T w}}{2} + C\sum_i \epsilon_i$
subject to : $y_i(\mathbf{w^T x}_i + b) \geq 1 - \epsilon$

3 Nonlinear decision boundary

Mapping your data vectors, x_i,into a higher-dimension(even infinite) feature space may make them linearly separable in that space (whereas they may not be linearly separable in the original space). The formation of the quadratic programmatic problem is as above,but with all $\mathbf{x}_i$ replaced with $\phi(\mathbf{x}_i)$, where ϕprovides the higher-dimensional mapping.So we have the standard SVM formulation:
$min_{\mathbf{w},b,\epsilon}\frac{\mathbf{w}^T\mathbf{w}}{2}$
subject to : $y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \epsilon$and $\epsilon_i \geq 0(\forall$ data points $\mathbf{x}_i)$

4 Reformulating as a Lagrangian

We can introduce Lagrange multipliers to represent the condition:
$y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b))$ must be as close to 1 as possible. This condition is captured by: $max_{ai\geq 0}\alpha_i[1 - y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b))]$ This ensures that when $y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b)) \geq 1$, the expression above is maximal when $\alpha_i = 0$(since [1-$y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b)]$ ends up being negative). Otherwise, $y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b)) < 1$, so $[1 - y_i(\mathbf{w}^T\phi(\mathbf{x}_i + b))]$ is a positive value, and the expression is maximal when $a_i \to \infty$. This has the effect of penalizing any misclassified data points, while assigning 0 penalty to properly classified instances.

We thus have the following formulation:
$min_{w,b}[\frac{\mathbf{w}^T\mathbf{w}}{2} + \sum_i max_{\alpha\geq 0}\alpha_i[1 - \mathbf{w}^T\phi(\mathbf{x}_i + b)]]$
To allow for slack(soft-margin), preventing the α variables from going to ∞, we can impose constraints on the Lagrange multipliers to lie within: $0 \leq \alpha_i \leq C$. We can define the dual problem by interchanging the max and min as follows (i.e minimize after fixing alpha):
$max_{alpha\geq zero}[min_{w,b}J(\mathbf{w}, b; \alpha)]$where $= \frac{\mathbf{w}^T\mathbf{w}}{2} + \sum_i \alpha_i[1 - y_i(\mathbf{w}^T\phi(x_i) + b)]$

Algorithm 30 Support Vector Machines (continued)

Since, we're solving an optimization problem, we set $\frac{\partial J}{\partial \mathbf{w}} = 0$ and discover that the optimal setting of $\mathbf{w}$ is $\sum_i \alpha_i y_i \phi(x_i)$,while seeting $\frac{\partial J}{\partial \mathbf{b}} = 0$ yields the constraint $\sum_i \alpha_i y_i = 0$

Thus, after substituting and simplifying,we get:
$min_{w,b} J(\mathbf{w}, b, \alpha) = \sum_i \alpha_i \alpha_j y_i y_j \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ And thus our dual is:
$max_{\alpha \geq 0}[\sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_j y_i y_j \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)]$
Subject to: $\sum_i \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C$

5 Kernel trick

Because we're working in a higher-dimension space(and potentially even an infinite-dimensional space),calculating $\phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ may be intractable.However, it turns out there are special *kernel* functions that operate on the lower dimension vectors $\mathbf{x}_i$ and $\mathbf{x}_j$ to produce a value equivalent to the dot-product of the higher dimensional vectors. For instance, consider the function $\phi: \mathbb{R}^3 \longmapsto \mathbb{R}^{10}, where : \phi(x) = (1, \sqrt{2}x^{(1)}, \sqrt{2}x^{(2)}, \sqrt{2}x^{(3)}, [\mathbf{x}^{(1)}]^2, [\mathbf{x}^{(2)}]^2, [\mathbf{x}^{(3)}]^2, \sqrt{2}x^{(1)(2)}, \sqrt{2}x^{(1)(3)}, \sqrt{2}x^{(2)(3)})$ Instead, we have the the kernel trick, which tells us that $K(\mathbf{x}_i, \mathbf{x}_j) = (1 + \mathbf{x}_i^T \mathbf{x}_j)^2 = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ for the given ϕ. Thus, we can simplify our calculations. Re-writing the dual in terms of the kernel yields: $max_{\alpha \geq 0}[\sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j]$

6 Decision function

To classify a novel instance $\mathbf{x}$ once you've learned the optimal α_i parameters, all you have to do is calculate $f(\mathbf{x}) = sign(\mathbf{w}^T \mathbf{x} + b) = \sum_i \alpha_i y_i \phi(\mathbf{x}_i$ and using the kernel trick). Note that α_i is only non-zero for instances $\phi(\mathbf{x}_i)$ on or near the boundary-those are called the *supportvector* since they alone specify the decision boundary. We can toss out the other data points once training is complete. Thus, we only sum over the x_i which constitute the support vectors.

Algorithm 31 Stacking [Wolpert, 1992] link : 95,104

Input:
A training set
Output: the final output of the combined learners
1: Split the training set into two disjoint sets
2: Train several base learners on the first part
3: Test the base learners on the second part.
4: Using the predictions from 3) as the inputs, and the correct responses as the outputs, train a higher level learner.

Algorithm 32 Winnow [., 2017] Link :96,97,153

Input:
A training set
d : The Number of attributes
Output: Weights(Classification of the entire training set)
$\theta \leftarrow \frac{d}{2}$
$w \leftarrow (1, 1, ...1)$
for $i = 1, 2, ...$ **do**
  if $w^T x^{(i)} > \theta$ **then**
    $c_*(x^{(i)}) = 1$
  else
    $c_*(x^{(i)}) = 0$
  end if
  if $c_*(x^{(i)}) \neq c(x^{(i)})$ **then**
    $\forall : x_j^{(i)} = 1, w_j \leftarrow 2w_j$
  else
    $\forall : x_j^{(i)} = 1, w_j \leftarrow 0$
  end if
end for

Algorithm 33 Hidden Markov Models - The forward algorithm [Jurafsky and Martin, 2008] Link:27,28,89,90,91,98

Input:
observations of length T, state-graph of length N
Output: forward-probability
create a probability matrix $forward[N+2,T]$
for state s from 1 *to* N **do**
  $forward[s,1] \leftarrow a_{o,s} \times b_s(o_1)$
end for
for time step t from 2 *to* T **do**
  for state s from 1 *to* N **do**
    $forward[s,t] \leftarrow \sum_{s'=1}^{N} forward[s,1] \times a_{s',s} \times b_s(o_t)$
  end for
end for
$forward[q_F,T] \leftarrow \sum_{s=1}^{N} forward[s,t] \times a_{s,qF}$
return $forward[q_F,T]$

Algorithm 34 Hidden Markov Models - Viterbi algorithm [Jurafsky and Martin, 2008] Link:26,27,90,91,98

Input:
observations of length T, state-graph of length N
Output: best-path
create a path probability matrix $viterbi[N+2,T]$
create a path probability matrix $backpointer[N+2,T]$
for state s from 1 *to* N **do**
  $viterbi[s,1] \leftarrow a_{o,s} \times b_s(o_1)$
  $backpointer[s,1] \leftarrow 0$
end for
for time step t from 2 *to* T **do**
  for state s from 1 *to* N **do**
    $viterbi[s,t] \leftarrow max_{s'=1}^{N} viterbi[s',1] \times a_{s',s} \times b_s(o_t)$
    $backpointer[s,t] \leftarrow argmax_{s'=1}^{N}\ viterbi[s',1] \times a_{s',s}$
  end for
end for
$viterbi[q_F,T] \leftarrow max_{s=1}^{N} viterbi[s,t] \times a_{s,qF}$
$backpointer[q_F,T] \leftarrow argmax_{s=1}^{N}\ viterbi[s,1] \times a_{s,qF}$
return the backtrace path by following backpointers to states back in time from $backpointer[q_F,T]$

Algorithm 35 Hidden Markov Models - The Forward-Backward algorithm [Jurafsky and Martin, 2008] Link : 26

Input:
observations of len T
output vocabulary V
hidden state set Q
Output:
The forward and backward probabilities A and B
initialize A and B
iterate until convergence **E-step**
$\gamma_t(j) = \frac{\alpha_t(j)\beta_t(j)}{\alpha_t(q_F)}$ $\forall$ t and j
$\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\alpha_T(N)}$ $\forall$ t, i, and j **M-step**
$\overset{\wedge}{\alpha}_{ij} = \frac{\sum_{t=1}^{|T-1|}\xi_t(i,j)}{\sum_{t=1}^{|T-1|}\sum_{j=1}^{N}\epsilon_t(i,j)}$
$\overset{\wedge}{\beta}_j(v_k) = \frac{\sum_{t=1 s.t. O_t=v_k}^{|T|}\gamma_t(j)}{\sum_{t=1}^{T}\gamma_t(j)}$
return A,B