1. Classification
    (a) K-Nearest Neighbor
    (b) Adaboost
    (c) Iterative Dichotomiser 3
    (d) C4.5
    (e) Naive Bayes
    (f) Bagging
2. Neural Networks
    (a) Perceptron
    (b) Back-Propagation
    (c) Learning Vector Quantization
    (d) Self Organizing Map
3. Clustering Algorithms
    (a) Hierarchial Agglomerative Clustering
    (b) Hierarchial Division Clustering
4. Regression Algorithms
    (a) Lasso Regression
5. Deep Learning Algorithms
    (a) Deep Q-Learning
6. Other Methods
    (a) Gradient Descent

Algorithm 1 k-Nearest Neighbor [Tay et al., 2014] link:36

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 Random forest [Bernstein, 2016]

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 5 Iterative Dichotomiser 3 [., 2015]

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 6 Perceptron [Brownlee, 2015d]

Input: $ProblemSize, InputPatterns, iterations_max, learn_rate$
Output: $Weights$

for $i = 1$ to $iterations_{max}$ **do**
  $Pattern_i \leftarrow SelectInputPattern(InputPatterns)$
  $Activation_i \leftarrow ActivateNetwork(Pattern_i, Weights)$
  $Output_i \leftarrow TransferActivation(Activation_i)$
  $UpdateWeights(Pattern_i, Output_i, learn_{rate})$
end for
Return $Weights$

Algorithm 7 Back-propagation [Brownlee, 2015a]

Input: $ProblemSize, InputPatterns, iterations_max, learn_rate$
Output: $Network$

$Network \leftarrow ConstructNetworkLayers()$
$Network_weights \leftarrow InitializeWeights(Network, ProblemSize)$
for $i = 1$ to $iterations_{max}$ **do**
  $Pattern_i \leftarrow SelectInputPattern(InputPatterns)$
  $Output_i \leftarrow ForwardPropagate(Pattern_i, Network)$
  $BackwardPropagateError(Pattern_i, Output_i, Network)$
  $UpdateWeights(Pattern_i, Output_i, Network, learn_{rate})$
end for
Return $Network$

Algorithm 8 Learning Vector Quantization [Brownlee, 2015c]

Input: $ProblemSize, InputPatterns, iterations_{max}, CodebookVectors_{num}, learn_{rate}$
Output: $CodebookVectors$

$CodebookVectors \leftarrow InitializeCodebookVectors(CodebookVectors_{num}, ProblemSize)$
for $i = 1$ to $iterations_{max}$ **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 9 Self Organizing Map [Brownlee, 2015b]

Input: $InputPatterns, iterations_{max}, learn_{rate}, Grid_width, Grid_height$
Output: $CodebookVectors$

$CodebookVectors \leftarrow InitializeCodebookVectors(Grid_{width}, Grid_{height}, InputPatterns)$
for $i = 1$ to $iterations_{max}$ **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 10 Hierarchial Agglomerative Algorithm [Stein, 2016a]

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

$C = \{\{v \mid v \in V\}\}$ ▷ 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 11 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 12 C4.5 [Dai and Ji, 2014]

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 13 Gradient Descent

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 14 Naive Bayes

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 15 Lasso Regression

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 16 Bagging

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 $d(X_i, x)$
  $h_i \leftarrow \text{apply}L\text{to}examples_i$
  Return $h_1, h_2, ...h_B$
end function

Algorithm 17 Deep Q-Learning with Experience Replay [Mnih et al., 2013]

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 18 PageRank

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

```
1: function PageRank(G, iteration)
2:     d ← 0.85                                   ▷ damping factor: 0.85
3:     oh ← G                                     ▷ get outlink hash from G
4:     ih ← G                                     ▷ get inlink hash from G
5:     N ← G                                      ▷ get number of pages from G
6:     for all p in the graph do
7:         opg[p] ← 1/N
8:     end for
9:     while iteration > 0 do
10:        dp ← 0
11:        for all p that has no out-links do
12:            dp ← dp + d * opg[p]/N
13:        end for
14:        for all p in the graph do
15:            npg[p] ← dp + [1−d]/N
16:            for all ip in ih[p] do
17:                npg[p] ← dp + d*opg[ip]/oh[ip]
18:            end for
19:        end for
20:        opg ← npg
21:        iteration ← iteration − 1
22:    end while
23: end function
```

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Algorithm 19 DBSCAN link:42

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

Output: Clustered Data

```
1: function DBSCAN(D, ε, minPts)
2:     C = 0
3:     for each point P in dataset D do
4:         if P is visited then
5:             continue next point
6:         end if
7:         mark P as visited
8:         NeighborPts = regionQuery(P, ε)
9:         if sizeof(NeighborPts) < MinPts then
10:            mark P as NOISE
11:        else
12:            C = next cluster
13:            expandCluster(P, NeighborPts, C, ε, MinPts)
14:    end if
15: end for
16: end function
17: function expandCluster(P, NeighborPts, C, ε, MinPts)
18: add P to Cluster C
19: for each point P'in NeighborPts do
20:    if P' is not visited then
21:        mark P' as visited
22:        NeighborPts' = regionQuery(P', eps)
23:        if sizeof(NeighborPts) >= MinPts then
24:            NeighborPts = NeighborPts joined with NeighborPts'
25:        end if
26:    end if
27:    if P' is not yet member of any cluster then
28:        add P' to cluster C
29:    end if
30: end for
31: end function
32: function regionQuery(P, ε)
33: return all points within P's ε neighborhood
34: end function
```