MachLe - Résumé Olivier D'Ancona

Evaluation Metrics

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$
$$Precision = \frac{TP}{TP+FP}$$
$$Recall = \frac{TP}{TP+FN}$$
$$Specificity = \frac{TP}{TN+FP}$$
$$Fscore = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$
$$error\ rate = 1 - accuracy$$
$$macro\ average = \frac{1}{n}\sum_{i=1}^{n} avg_i$$

Activation Functions

Sigmoid : $\sigma(x) = \frac{1}{1+e^{-x}}$

Hyperbolic tangent : $\frac{e^x - e^{-x}}{e^x + e^{-x}}$

Relu : $\begin{cases} 0 & \text{si } x < 0 \\ x & \text{si } x \geq 0 \end{cases}$

Gaussian : e^{-x^2}

Softmax : $\frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$

Neural Network

Structure

Biais : b, An extra weight that can be learned using a learning algorithm. The purpose is to replace threshold.
Input : I, Input vector
Weights : W, Vector of weights

Learning algorithm

1. Randomly initialize weights
2. Compute the neuron's output for a fiven input vector X
3. Update weights : $W_j(t+1) = W_j(t) + \eta\,(\hat{y_i} - y)\,x$ with η the learning rate and $\hat{y_i}$ the desired output.
4. Repeat steps 2 and 3 for the number of epochs you need or until the error is smaller than a threshold.

KNN

Hyperparameters :

- Number of neighbours k
- Distance metric
- normalization type
- strategy if no majority

Big k :
(+) More confidence, probabilistic (-) No locality, heavier

Bayes

Théorème de Bayes :

$$P(C_k|x) = \frac{P(x|C_k) \cdot P(C_k)}{P(x)}$$

où

- C_k : Classe ciblée
- x : Évidence
- $P(C_k)$: Probabilité a priori de la classe C_k
- $P(x|C_k)$: probability of observing x given class j
- $P(C_k|x)$: Probabilité a posteriori de la classe C_k après observation de x
- $P(x)$: Probabilité de l'évidence x

avec

$$P(x) = \sum_{\text{toutes classes } C_k} P(x|C_k) \cdot P(C_k)$$

Exemple Classificateur Fille/Garçon :

- $P(C_f) = \frac{4}{70}, P(C_g) = \frac{66}{70}$
- $p(x|C_g) = 0.8, p(x|C_f) = 0.2$
- Calcul de $p(x)$:

$$p(x) = 0.2 \times \frac{4}{70} + 0.8 \times \frac{66}{70}$$

- Calcul de $P(C_f|x)$ et $P(C_g|x)$:

$$P(C_f|x) = \frac{0.2 \times \frac{4}{70}}{p(x)}, \quad P(C_g|x) = \frac{0.8}{p(}$$

(+)Can deal with imbalanced dataset, prior can be changed

Linear Regression

Soit un tableau de données :
x = Surface(g) , y = Price(cm) , $x \cdot y$, x^2

$$X = [1, Surface]$$
$$X^T X = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix} = \begin{bmatrix} 7 & 38.5 \\ 38.5 & 218.95 \end{bmatrix}$$
$$X^T y = \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix} = \begin{bmatrix} 348 \\ 1975 \end{bmatrix}$$
$$\hat{\theta} = (X^T X)^{-1} X^T y = \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix} = \begin{bmatrix} -2.67 \\ 9.51 \end{bmatrix}$$
$$\hat{y} = \theta_0 + \theta_1 x$$

Inverse d'une matrice 2x2 :

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Logistic Regression

$$P(Y = 1|X) = \sigma(x\theta^T)$$

- $P(Y = 1|X)$: Probability of $Y = 1$ given X
- θ : model's parameters
- X : input vector

Goal : Find the θ that maximizes the likelihood of the data.
Loss :

$$J(\beta) = -\frac{1}{n}\sum_{i=1}^{n} y_i \log(P(y_i|X_i)) + (1 - y_i)\log(1 - P(y_i|X_i))$$

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Normalization

Normalization

Min-max [0,1] : $x' = \frac{(x - x_{min})}{(x_{max} - x_{min})}$
Min-max [-1,1] : $x' = 2 \cdot min\_max(x) - 1$
min-max doesn't handle outliers.
Z-norm : $x' = \frac{(x - \mu)}{\sigma}$

transformations

log : $x' = log(x)$

SVM

Clustering

Decision Trees

Convolutional Neural Networks

Recurrent Neural Networks

Dimensionality Reduction

Reinforcement Learning

Computational Complexity of ML Algorithms

Algorithm	**Assumption**	**Train Time/Space**	**Inference Time/Space**
KNN (Brute Force)	Similar things exist in close proximity	$O(knd)$ / $O(nd)$	$O(knd)$ / $O(nd)$
KNN (KD Tree)	Similar things exist in close proximity	$O(nd\log(n))$ / $O(nd)$	$O(k\log(n)d)$ / $O(nd)$
Naive Bayes	Features are conditionally independent	$O(ndc)$ / $O(dc)$	$O(dc)$ / $O(dc)$
Logistic Regression	Classes are linearly separable	$O(nd)$ / $O(nd)$	$O(d)$ / $O(d)$
Linear Regression	Linear relationship between variables	$O(nd)$ / $O(nd)$	$O(d)$ / $O(d)$
SVM	Classes are linearly separable	$O(n^2d^2)$ / $O(nd)$	$O(kd)$ / $O(kd)$
Decision Tree	Feature selection by information gain	$O(n\log(n)d)$ / $O(\text{nodes})$	$O(\log(n))$ / $O(\text{nodes})$
Random Forest	Low bias and variance trees	$O(kn\log(n)d)$ / $O(\text{nodes}\times k)$	$O(k\log(n))$ / $O(\text{nodes}\times k)$
GBDT	High bias, low variance trees	$O(Mn\log(n)d)$ / $O(\text{nodes}\times M+\gamma_m)$	$O(M\log(n))$ / $O(\text{nodes}\times M+\gamma_m)$