Decision Tree Assignment - 1

March 5, 2024

[]: """Q1. Describe the decision tree classifier algorithm and how it works to make \Box \Box predictions.

Ans: A decision tree classifier algorithm is a supervised learning method $_{\sqcup}$ $_{\hookrightarrow}$ that creates a tree-like model to predict the target variable based on a set $_{\sqcup}$ $_{\hookrightarrow}$ of input features.

It works by recursively partitioning the data into subsets based on the feature that provides the most information gain, which maximizes the separation between classes.

The tree is built by splitting the data at each node based on the best \Box feature until the leaf nodes contain only samples from a single class. \Box \Box During prediction,

new data is classified by following the path down the tree based on \sqcup \hookrightarrow its feature values, ultimately reaching a leaf node with the predicted class \sqcup \hookrightarrow label.

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[]: """Q2. Provide a step-by-step explanation of the mathematical intuition behind \Box \Box decision tree classification.

Ans: The decision tree classification algorithm uses entropy and \Box \Rightarrow information gain to determine the best feature to split the data at each \Box \Rightarrow node.

Entropy measures the impurity of a node's class distribution, while \Box \Rightarrow information gain calculates the reduction in entropy achieved by splitting \Box \Rightarrow on a particular feature.

The algorithm iteratively selects the feature with the highest $_{\sqcup}$ $_{\hookrightarrow}$ information gain and splits the data accordingly until all leaf nodes are $_{\sqcup}$ $_{\hookrightarrow}$ pure.

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[]: """Q3. Explain how a decision tree classifier can be used to solve a binary_□ ⇔classification problem.

Ans: A decision tree classifier can be used to solve a binary $_{\sqcup}$ $_{\hookrightarrow}$ classification problem by recursively splitting the data into subsets based $_{\sqcup}$ $_{\hookrightarrow}$ on the feature that provides the

most information gain, until the leaf nodes contain only samples from $_{\!\!\!\perp}$ one class. The resulting tree can then be used to classify new input data as $_{\!\!\!\perp}$ $_{\!\!\!\perp}$ either one of the

two classes.

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[]: """Q4. Discuss the geometric intuition behind decision tree classification and \Box \rightarrow how it can be used to make predictions.

Ans: The geometric intuition behind decision tree classification is that it_{\sqcup} \Rightarrow partitions the input space into smaller regions using decision boundaries_{\sqcup} \Rightarrow that are aligned with

the coordinate axes. The resulting regions are labeled with the \Box \Box majority class of the training data within each region, and new input data \Box \Box can be classified by

identifying the region it falls into based on its feature values.

H/H/H

[]: """Q5. Define the confusion matrix and describe how it can be used to evaluate \Box \Box the performance of a classification model.

Ans: The confusion matrix is a table that summarizes the performance of a_{\sqcup} $\neg classification$ model by comparing its predicted class labels with the actual $\Box \neg class$ labels.

It includes metrics such as true positives, false positives, true_\u00ed \u00f3negatives, and false negatives, which can be used to calculate evaluation_\u00ed \u00e4metrics such as accuracy,

precision, recall, and F1 score.

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[]: """Q6. Provide an example of a confusion matrix and explain how precision, \Box \neg recall, and F1 score can be calculated from it.

Ans: Here is an example of a confusion matrix:

50 20

10 70

From this matrix, we can calculate precision, recall, and F1 score: Precision: the ratio of true positives to the total predicted \sqcup

 \Rightarrow positives. Precision = TP / (TP + FP) = 50 / (50 + 20) = 0.71

Recall: the ratio of true positives to the total actual \Box \Box positives. Recall = TP / (TP + FN) = 50 / (50 + 10) = 0.83

F1 score: the harmonic mean of precision and recall. F1 score = $2*(precision*recall) / (precision*recall) = <math>2*(0.71*0.83) / (0.71_{\square} + 0.83) = 0.76$

[]: """Q7. Discuss the importance of choosing an appropriate evaluation metric for \Box \Box a classification problem and explain how this can be done.

Ans: Choosing an appropriate evaluation metric is important for a \sqcup \neg classification problem because it provides a way to measure the performance \sqcup \neg of the model and compare it

with other models or benchmarks. The choice of metric should be based $_{\sqcup}$ $_{\hookrightarrow}$ on the specific goals of the problem, as different metrics prioritize $_{\sqcup}$ $_{\hookrightarrow}$ different aspects of

performance such as accuracy, precision, recall, or F1 score. To_ \neg choose an appropriate metric, it is important to consider factors such as_ \neg the class balance, \land

the cost of false positives or false negatives, and the desired $_{\sqcup}$ $_{\hookrightarrow}$ trade-off between different performance aspects.

[]: """Q8. Provide an example of a classification problem where precision is the smoot important metric, and explain why.

the cost of false positives (i.e., flagging a legitimate transaction \Box \Box as fraudulent) is low, but the cost of false negatives (i.e., missing a \Box \Box fraudulent transaction)

can be high. Therefore, it is more important to have a high precision $(i.e., low\ false\ positive\ rate)$ to minimize the number of legitimate $(i.e., low\ false\ positive\ rate)$ to minimize the number of legitimate $(i.e., low\ false\ positive\ rate)$

incorrectly flagged as fraudulent, even if this means sacrificing some \neg recall (i.e., potentially missing some fraudulent transactions).

[]: """Q9. Provide an example of a classification problem where recall is the most \hookrightarrow important metric, and explain why.

Ans: An example of a classification problem where recall is the most $_{\sqcup}$ $_{\hookrightarrow}$ important metric is medical diagnosis for a life-threatening disease such as $_{\sqcup}$ $_{\hookrightarrow}$ cancer.

In this case, the cost of false negatives (i.e., failing to diagnose a_{\sqcup} \Rightarrow patient who has the disease) is very high, while the cost of false positives

(i.e., diagnosing a patient who does not have the disease) is lower. \Box \Box Therefore, it is more important to have a high recall (i.e., low false \Box \Box negative rate)

to ensure that all patients who have the disease are correctly \neg diagnosed, even if this means sacrificing some precision (i.e., diagnosing \neg some patients who do not

have the disease).

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