

决策树分裂过程详解

1 决策树分裂过程数学推导

1.1 核心公式

设节点 D 中共有 N 个样本，类别数为 K ，第 k 类的比例为 p_k 。

- 基尼指数 (Gini)

$$Gini(D) = 1 - \sum_{k=1}^K p_k^2$$

- 熵 (Entropy)

$$H(D) = - \sum_{k=1}^K p_k \log_2 p_k$$

- 分裂后的加权不纯度

$$Impurity_{after} = \frac{N_L}{N} \cdot impurity(D_L) + \frac{N_R}{N} \cdot impurity(D_R)$$

- 不纯度下降

$$\Delta = impurity(D) - Impurity_{after}$$

1.2 算法伪代码

Algorithm 1 决策树节点分裂算法

```

1: best_gain  $\leftarrow -\infty$ 
2: best_feature  $\leftarrow \text{None}$ 
3: best_threshold  $\leftarrow \text{None}$ 
4: for each feature  $A$  do
5:   values  $\leftarrow \text{sorted}(\text{unique values of } A \text{ in node})$ 
6:   for  $j \leftarrow 1$  to  $\text{len}(\text{values})-1$  do
7:      $t \leftarrow (\text{values}[j] + \text{values}[j+1])/2$ 
8:     split  $D$  into  $D_{\text{left}}$  ( $A \leq t$ ) and  $D_{\text{right}}$  ( $A > t$ )
9:     compute  $\text{impurity}(D_{\text{left}}), \text{impurity}(D_{\text{right}})$ 
10:    weighted_after  $\leftarrow \frac{|D_{\text{left}}|}{|D|} \cdot \text{imp}(D_{\text{left}}) + \frac{|D_{\text{right}}|}{|D|} \cdot \text{imp}(D_{\text{right}})$ 
11:    gain  $\leftarrow \text{imp}(D) - \text{weighted\_after}$ 
12:    if gain > best_gain then
13:      best_gain  $\leftarrow$  gain
14:      best_feature, best_threshold  $\leftarrow A, t$ 
15:    end if
16:  end for
17: end for
18: choose (best_feature, best_threshold) to split this node

```

1.3 数值计算示例

以Iris数据集的分裂点petal length ≤ 2.45 为例:

- 父节点Gini:

$$Gini_{\text{parent}} = 1 - \left(\frac{1^2}{3} + \frac{1^2}{3} + \frac{1^2}{3} \right) = \frac{2}{3}$$

- 左节点 (50个setosa):

$$Gini_L = 1 - 1^2 = 0$$

- 右节点 (50 versicolor + 50 virginica):

$$Gini_R = 1 - \left(\frac{1^2}{2} + \frac{1^2}{2} \right) = \frac{1}{2}$$

- 加权不纯度:

$$Weighted = \frac{1}{3} \cdot 0 + \frac{2}{3} \cdot \frac{1}{2} = \frac{1}{3}$$

- 基尼下降:

$$\Delta = \frac{2}{3} - \frac{1}{3} = \frac{1}{3} \approx 0.3333$$

2 代码解析

```
data = load_iris()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['Species'] = data.target

target = np.unique(data.target)          # [0,1,2]
target_names = np.unique(data.target_names) # ['setosa','versicolor','virginica']
targets = dict(zip(target, target_names))  # {0:'setosa',1:'versicolor',2:'virginica'}
df['Species'] = df['Species'].replace(targets)

X = df.drop(columns="Species")
y = df["Species"]
feature_names = X.columns
labels = y.unique()

X_train, test_x, y_train, test_lab = train_test_split(
X, y, test_size=0.4, random_state=42)
```

- `df.shape`: (150, 5) (4个特征+1个标签)
- 训练集/测试集划分:
 - 训练集: 90样本 (60%)
 - 测试集: 60样本 (40%)
- `random_state=42`保证可复现性

3 参数说明

决策树关键参数:

- `criterion`: 'gini'或'entropy'
- `max_depth`: 控制树深度
- `min_samples_split`: 节点最小分裂样本数
- `min_samples_leaf`: 叶节点最小样本数