Introduction to Decesion trees

Notes of class

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0.1 Decision trees

Powerful algorithm, based in measures of homogenity in this notes we discuss and construct over the concept of gain information and entropy.

Data: Empty tree ;
while *features to split* **do**
  Select the variable to split data ;
  repeat the before steps again until reach a stopping criteria;
end

0.2 Entropy

Derived from Information theory, we can measure the homogenity of a set, $E = 1$ at maximun disorder, and $E = 0$ when.

We also, can take in mind that the construction is recursive implementation.

Write pseudocode.

```
while stopping criteria is false:
    select the better variable:
        update data:
            select the better variable
```

1 Overfitting

Hint: A big gap in validation error with training error are a strong signal about over fitting.

We can select the better depth $\min E_{validation} - E_{training}$ select

The are some ways of avoid overfiting, however note that this is not a solution to the generalization.

The depth of three reduce training error, therefore decision boundaries are more complex.

1.1 Early stopping

Before of construc the tree: **limit the depth of tree**: We can uses cross validation:

1.2 Prunning

If we select a tree based in $R(T)$ that is resubstitution rate is the rate of responses predicted well with training dataset.

select α we need uses cross validation to select the parameter

1.3 Feature importance

How we can establish, what is the degree of importance of the variables?

hint: if you have two tress that have the same validation error pick always the simplest model.

Algorithm 1: Cross validation

```
Result: Write here the result
initialization;
while While condition do
    instructions;
    if condition then
        instructions1;
        instructions2;
    else
        instructions3;
    end
end
```

Algorithm 2: Cross validation

```
for i ← 2 to l do
    test data i
end
```

Algorithm 3: Simple algorithm

```
for i to 4 do
    print in screen i ;
    if i > 4 then
        print this number is major 4;
        if i = 3 then
            three
        end
    else
        print is lesser ;
    end
end
```

1.4 K fold cross validation

K means samples of K size, therefore we could have $\frac{N}{k}$, where N is the total amount of instances or observations.

$MSE = \frac{1}{k}\sum_{i=1}^{k} Accuracy_i$.

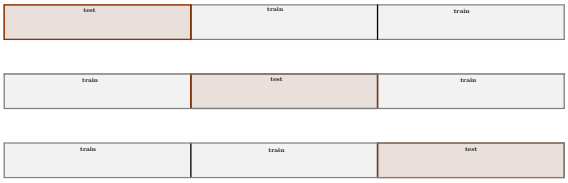
with cross validation we search optimize the parameter max_depth in librarie sickit-learn.

Algorithm 4: K fold: Cross validation algorithm

```
Data: N observations
Split the data in k groups ;
for i in k do
    Test the model in i and train in the rest data ;
    Measure the accuracy in each iteration ;
end
```

Note that could split the data.

1.5 sklearn KFold




```
import numpy as np
e = np.array(('a','b','c','d','e','o','p'))
Kfold = KFold(n_splits=3)
for itrain, itest in Kfold.split(e):
    print('train index', itrain)
    print('test index', itest)
    print('--')
# This return the indices we can attach to the index the X and the Y
  X.iloc[itrain]
  X.iloc[itest]
```

```
from sklearn import DecisionTreeClassifier
model = DecisionTreeClassifier(
criterion='entropy' # by default is gini.
max_depth=None #by default.
)
model.fit(X,y)
```

1.6 Methods

```
predict(X) #  Return the predicted class
predict_proba(X) # Return classes probabilities
score(X,y) where y is the true labels.
```

2 Prunning

2.1 Post pruning

2.1.1 Reduce error pruning

let the tree growth and after chop off,
reduce error pruning.

2.2 Cost complexity pruning

2.3 Weakest link pruning

3 AUC in decision tree

$D(n)$ number of leafs.

Total cost = Measure of fit + Measure of complexity = classification error + number of leaf

4 Search

Greedy algorithms suffer of horizon effect.

4.1 Assess the precision

5 Preprocessing DATA

```
sklearn.preprocessing.OrdinalEncoder # to encode X
sklearn.preprocessing.LabelEcoder() # to label y
```

6 Pruning Uppen

A node t and t_L and t_R left and right child nodes respectively. T represent all nodes, $\tilde{T}$ all leafs. a split is denoted by s the set of all splits S.

7 Impurity function

$|a|$ means the number or 'cardinal' elements that belong to the set a. (We can write with a indicator function).

8 HyperParamter

8.1 Gridsearch

8.2 Example one

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
df =datasets.load_iris(as_frame=True)
df = df['frame']
X = df.iloc[:,:-1]
y = df.iloc[:,[-1]]
y = y.astype('int')
clf = DecisionTreeClassifier()
fitM = clf.fit(X,y)
clf.score(X,y)
scores =[]
from sklearn.model_selection import KFold
kfolds = KFold(n_splits=5, shuffle=True)
for itrain, itest in kfolds.split(X):
    Xtrain, Xtest = X.iloc[itrain], X.iloc[itest]
    ytrain, ytest = y.iloc[itrain], y.iloc[itest]
    model = clf.fit(Xtrain,ytrain)
    score = accuracy_score(ytest,model.predict(Xtest))
    scores.append(score)
mean = np.mean(scores)
```

```
sd = np.std(scores)
print(mean, sd)
```

9 Confusion Matrix

9.1 Sensitivity and specificity

9.2 Multinomial distribution

Before we need specify the multinomial coefficient that is, $\binom{N}{n_1 \ldots n_k}$ where $n_1 + .. + n_k = N$, note also that $\binom{N}{n_1 \ldots n_k} = \frac{N!}{n_1! n_2! \ldots n_k!}$. Thus we need select n_1 objects from N, select n_2 from $N - n_1$, select n_3 from $(N - n_1 - n_2)$ and thus in the k selection then we have n_k from $(N - n_1 - n_2 - n_3 - ... - n_{k-1})$.

10 Minimal cost complexity

Prunning based in minimal cost complexity and weakest link. The problem reduced to minimize the following expression:

$$C_\alpha(T) = R(T) + \alpha|T| \tag{1}$$

where $R(T)$ is miss classification rate in training data and $|T|$ is the number of leaves in the tree. Note that if $\alpha = 0$ then the tree assign to each node a observation. Then we need find the optimize value of α.

Recursively you can uses minimal cost beginning with the last leaves and ascending evaluating (1).

Remember that is a trade off between complexity and accuracy.

for each α we need find the $T_\alpha \subset T_0$ that minimize the expression of cost complexity.

the value of *alpha*

---

for α **to** N **do**
  find $T \subset T_0$ that $\min C_\alpha(T)$;
  Split data in k folds
  for k *in* **do**
    make;

$$\arg\max_{x \in R} f(x) \tag{2}$$

in python or sklearn this effective alpha: https://www.programmersought.com/article/16766848143/ to select alpha among all

---

```
def alphaZ(Xtrain,ytrain,Xtest,ytest):
    clf = DecisionTreeClassifier(random_state=0)
    path = clf.cost_complexity_pruning_path(Xtrain, ytrain)
    ccp_alphas, impurities = path.ccp_alphas, path.impurities
    clfs = []
    for ccp_alpha in ccp_alphas:
        clf = DecisionTreeClassifier(random_state=0, ccp_alpha=ccp_alpha)
        clf.fit(X_train, y_train)
        clfs.append(clf)
    train_scores = [clf.score(Xtrain, ytrain) for clf in clfs]
    test_scores = [clf.score(Xtest, ytest) for clf in clfs]
    alpha , tscore = ccp_alphas[test_scores.index(max(test_scores))], max(test_scores)
    return alpha, tscore
```

10.1 Questions

How interpret machine learning models a category instead a numerical value?

how we can encode without order.

11 OneHotEncoding

how we can encode categorical variables? this is used to created dummy variables.

```
var1 = ['A','B','C','A','B','A']
var2 = ['real','bot','bot','bot','real','real']
df = pd.DataFrame({"var1":var1, "var2":var2})
for var in df.columns:
    if df[var].dtype=='object':
        df = pd.get_dummies(df,prefix=[var], columns = [var], drop_first=True)
```

12 LabelEncoder

According to the documentation this must be used to the outcome or y variable. due rank the input ant could alter the results.

12.1 Theil index

$$H(x) = p(x) \tag{3}$$

```
import numpy as np
import pandas as pd
pd.read_excel(df)
```

```
print('hello world')
```