CatBoost Algorithm

CatBoost is a state-of-the-art open-source gradient boosting on decision trees library. It's simple and easy to use. And is now regularly one of the top algorithms used in data science competitions as it produces very good results without extensive data clean-up or feature engineering.

```
# !pip install catboost
In [1]:
        # import libraries
In [2]:
         import pandas as pd
         import numpy as np
        import matplotlib.pyplot as plt
         import seaborn as sns
         from catboost import CatBoostClassifier
         from sklearn.model selection import train test split
         from sklearn.metrics import accuracy score, confusion matrix, classification report
        # data import titanic
In [3]:
         df = sns.load_dataset('titanic')
         df.head()
Out[3]:
            survived pclass
                               sex age sibsp parch
                                                          fare embarked
                                                                         class
                                                                                  who adult male deck embark town
                                                                                                                       alive alone
         0
                              male 22.0
                                                       7.2500
                                                                       S Third
                                                                                                          Southampton
                                                                                  man
                                                                                              True
                                                                                                   NaN
                                                                                                                          no
                                                                                                                              False
         1
                  1
                         1 female 38.0
                                                    0 71.2833
                                                                                                      C
                                                                          First woman
                                                                                              False
                                                                                                             Cherbourg
                                                                                                                         yes
                                                                                                                              False
         2
                  1
                                             0
                                                       7.9250
                         3 female 26.0
                                                                         Third
                                                                                woman
                                                                                                    NaN
                                                                                                          Southampton
                                                                                              False
                                                                                                                         yes
                                                                                                                               Tru
         3
                         1 female 35.0
                                                    0 53.1000
                                                                          First woman
                                                                                              False
                                                                                                          Southampton
                                                                                                                              False
                                                                                                                         yes
         4
                              male 35.0
                                             0
                                                       8.0500
                                                                         Third
                                                                                              True NaN
                                                                                                          Southampton
                                                                                                                               Tru
                                                                                  man
                                                                                                                          no
```

pre-processing

```
In [4]: df.isnull().sum().sort_values(ascending=False)
Out[4]: deck
                        688
                        177
         age
         embarked
                         2
                         2
        embark_town
        survived
                         0
         pclass
         sex
                         0
         sibsp
                         0
         parch
        fare
         class
        who
         adult_male
         alive
         alone
        dtype: int64
In [5]: # impute missing values using knn imputers in age
        from sklearn.impute import KNNImputer
        imputer = KNNImputer(n_neighbors=5)
        df['age'] = imputer.fit_transform(df[['age']])
        # impute embarked missing values using pandas
        df['embarked'] = df['embarked'].fillna(df['embarked'].mode()[0])
        df['embark_town'] = df['embark_town'].fillna(df['embark_town'].mode()[0])
        # drop deck column
        df.drop('deck', axis=1, inplace=True)
        # df missing values
        df.isnull().sum().sort_values(ascending=False)
```

```
Out[5]:
        survived
                        0
         pclass
                        0
         sex
                        0
         age
                        0
         sibsp
                        0
         parch
                        0
         fare
                        0
         embarked
         class
                        0
         who
                        0
         adult male
                        0
         embark_town
         alive
                        0
         alone
                        0
         dtype: int64
In [6]:
        df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 891 entries, 0 to 890
       Data columns (total 14 columns):
                         Non-Null Count Dtype
            Column
            _____
            survived
                         891 non-null
                                          int64
                                          int64
        1
            pclass
                         891 non-null
        2
                         891 non-null
                                          object
            sex
        3
                         891 non-null
                                          float64
            age
            sibsp
                         891 non-null
                                          int64
        5
            parch
                         891 non-null
                                          int64
            fare
                         891 non-null
                                          float64
            embarked
                         891 non-null
                                          object
        8
            class
                         891 non-null
                                          category
        9
            who
                         891 non-null
                                          object
            adult male 891 non-null
                                          bool
        11 embark town 891 non-null
                                          object
        12 alive
                         891 non-null
                                          object
                                          bool
        13 alone
                         891 non-null
       dtypes: bool(2), category(1), float64(2), int64(4), object(5)
       memory usage: 79.4+ KB
In [7]: # convert each category column to category
        categorical_cols = df.select_dtypes(include=['object', 'category']).columns
```

```
# add this as a new column in the dataframe
        df[categorical_cols] = df[categorical_cols].astype('category')
In [8]: # split data into X and y
        X = df.drop('survived', axis=1)
        y = df['survived']
        # split data into train and test
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
In [9]: # run the catboost classifier
        model = CatBoostClassifier(iterations=100,
                                   learning_rate=0.1,
                                    depth=3,
                                    loss function='Logloss',
                                    eval_metric='Accuracy',
                                    random_seed=42,
                                    verbose=False)
        # train the model
        model.fit(X_train, y_train, cat_features=categorical_cols.tolist())
        # predictions
        y_pred = model.predict(X_test)
        # evaluate the model
        print(f'Accuracy Score: {accuracy_score(y_test, y_pred)}')
        print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred)}')
        print(f'Classification Report: \n {classification_report(y_test, y_pred)}')
```

Accuracy Score: 1.0 Confusion Matrix: [[105 0]

[0 74]]

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	105
1	1.00	1.00	1.00	74
accuracy			1.00	179
macro avg	1.00	1.00	1.00	179
weighted avg	1.00	1.00	1.00	179

In []: