```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

from pandas import read_csv
from matplotlib import pyplot
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
from sklearn.svm import LinearSVC
from sklearn.preprocessing import StandardScaler


import seaborn as sns
```

Data Loading

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
data = pd.read_csv('/content/drive/Shareddrives/ML_Project/kickstarter_data_full.csv')
print(data.shape)
data.head()
```

```
(20632, 68)
<ipython-input-3-a618e42e4195>:1: DtypeWarning: Columns (29,30,31,32) have mixed types.
  data = pd.read_csv('/content/drive/Shareddrives/ML_Project/kickstarter_data_full.csv')
```

	Unnamed: 0	id	photo	name	blurb	goal
0	0	1454391034	{"small":"https://ksr-ugc.imgix.net/assets/011...	Auntie Di's Music Time Sign ASL for Hearing an...	MTS ASL Curriculum Workbook is a reproducible ...	1500.0
1	1	1655206086	{"small":"https://ksr-ugc.imgix.net/assets/012...	Jump Start Kindergarten Toolkit	This kit teaches how to print, correct an ugly...	500.0
2	2	311581827	{"small":"https://ksr-ugc.imgix.net/assets/012...	Ojukwu Balewa Awolowo (O.B.A.) Public Library ...	Establishing a free, world-class, public libra...	100000.0
3	3	859724515	{"small":"https://ksr-ugc.imgix.net/assets/011...	MASTIZE - [mas-TAHYZ, MAS-tahyz] - to spread	Goal: Introducing a new word into the English ...	5000.0
4	4	1613604977	{"small":"https://ksr-ugc.imgix.net/assets/012...	Synopse der EU-DSGVO - Artikel, Erwägungsgründ...	Zu den Artikeln der DSGVO sind die korrespondi...	3222.0

5 rows × 68 columns

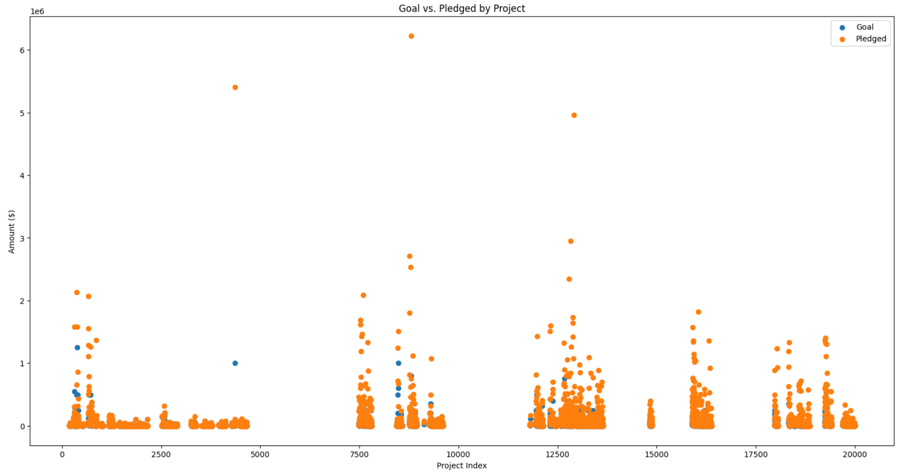
EDA

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20632 entries, 0 to 20631
Data columns (total 68 columns):
 #   Column                      Non-Null Count  Dtype
```

```
 ---  ------                    --------------  -----
 0    Unnamed: 0                20632 non-null  int64
 1    id                        20632 non-null  int64
 2    photo                     20632 non-null  object
 3    name                      20632 non-null  object
 4    blurb                     20627 non-null  object
 5    goal                      20632 non-null  float64
 6    pledged                   20632 non-null  float64
 7    state                     20632 non-null  object
 8    slug                      20632 non-null  object
 9    disable_communication     20632 non-null  bool
 10   country                   20632 non-null  object
 11   currency                  20632 non-null  object
 12   currency_symbol           20632 non-null  object
 13   currency_trailing_code    20632 non-null  bool
 14   deadline                  20632 non-null  object
 15   state_changed_at          20632 non-null  object
 16   created_at                20632 non-null  object
 17   launched_at               20632 non-null  object
 18   staff_pick                20632 non-null  bool
 19   backers_count             20632 non-null  int64
 20   static_usd_rate           20632 non-null  float64
 21   usd_pledged               20632 non-null  float64
 22   creator                   20632 non-null  object
 23   location                  20587 non-null  object
 24   category                  18743 non-null  object
 25   profile                   20632 non-null  object
 26   spotlight                 20632 non-null  bool
 27   urls                      20632 non-null  object
 28   source_url                20632 non-null  object
 29   friends                   60 non-null     object
 30   is_starred                60 non-null     object
 31   is_backing                60 non-null     object
 32   permissions               60 non-null     object
 33   name_len                  20627 non-null  float64
 34   name_len_clean            20627 non-null  float64
 35   blurb_len                 20627 non-null  float64
 36   blurb_len_clean           20627 non-null  float64
 37   deadline_weekday          20632 non-null  object
 38   state_changed_at_weekday  20632 non-null  object
 39   created_at_weekday        20632 non-null  object
 40   launched_at_weekday       20632 non-null  object
 41   deadline_month            20632 non-null  int64
 42   deadline_day              20632 non-null  int64
 43   deadline_yr               20632 non-null  int64
 44   deadline_hr               20632 non-null  int64
 45   state_changed_at_month    20632 non-null  int64
 46   state_changed_at_day      20632 non-null  int64
 47   state_changed_at_yr       20632 non-null  int64
 48   state_changed_at_hr       20632 non-null  int64
 49   created_at_month          20632 non-null  int64
 50   created_at_day            20632 non-null  int64
 51   created_at_yr             20632 non-null  int64
 52   created_at_hr             20632 non-null  int64
```

```python
import pandas as pd
import matplotlib.pyplot as plt

df = data[data['state'] == 'successful']

# Create the scatter plot
fig = plt.figure(figsize=(20, 10))
plt.scatter(df.index, df['goal'], label='Goal')
plt.scatter(df.index, df['pledged'], label='Pledged')
plt.title('Goal vs. Pledged by Project')
plt.xlabel('Project Index')
plt.ylabel('Amount ($)')
plt.legend()
plt.show()
```




```
# list of columns to drop
# There is very less data for the above features so we decided to drop these columns

cols_to_drop = ['Unnamed: 0', 'friends', 'is_starred', 'is_backing',
                'permissions']

# drop the columns
data = data.drop(cols_to_drop, axis=1)
```

```
columns = data.columns.tolist()
```

```
data.shape
```

```
(20632, 63)
```

```
data.isna().sum()
```

```
id                  0
photo               0
name                0
blurb               5
goal                0
                   ..
SuccessfulBool      0
USorGB              0
TOPCOUNTRY          0
LaunchedTuesday     0
DeadlineWeekend     0
Length: 63, dtype: int64
```

```
# get the list of integer columns
int_cols = data.select_dtypes(include=['int','float']).columns.tolist()

# fill missing values in integer columns with mean
for col in int_cols:
    mean = data[col].mean()
    data[col].fillna(mean, inplace=True)
```

```
# Replace missing values in categorical columns with mode
cat_cols = data.select_dtypes(include=['object']).columns.tolist()
for col in cat_cols:
    data[col].fillna(data[col].mode()[0], inplace=True)
```

```
#Checking unique values in categorical columns
for col in data.columns:
  if(data[col].dtype=='object'):
       print(col, ':---', len(data[col].unique()), 'labels')
```

```
photo :--- 20632 labels
name :--- 20610 labels
blurb :--- 20458 labels
state :--- 5 labels
slug :--- 20632 labels
country :--- 21 labels
currency :--- 13 labels
currency_symbol :--- 5 labels
deadline :--- 20213 labels
state_changed_at :--- 20238 labels
created_at :--- 20483 labels
launched_at :--- 20448 labels
creator :--- 20522 labels
location :--- 5178 labels
category :--- 24 labels
profile :--- 20632 labels
urls :--- 20632 labels
source_url :--- 33 labels
deadline_weekday :--- 7 labels
state_changed_at_weekday :--- 7 labels
created_at_weekday :--- 7 labels
launched_at_weekday :--- 7 labels
create_to_launch :--- 20553 labels
launch_to_deadline :--- 4987 labels
launch_to_state_change :--- 7544 labels
```

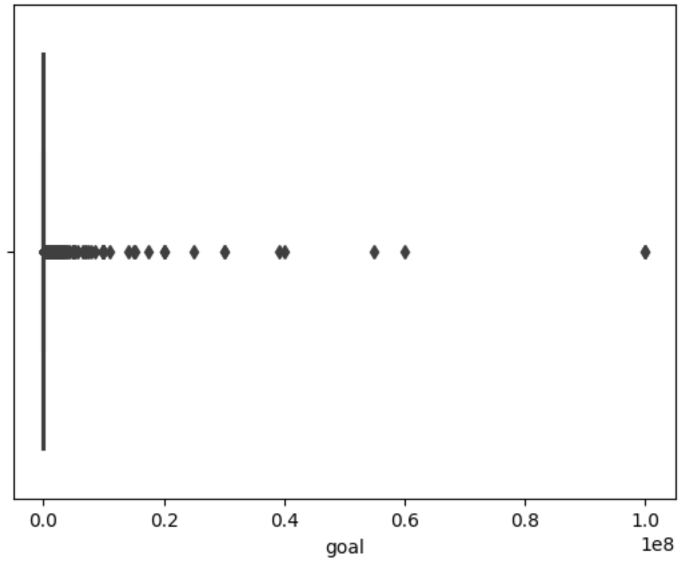
```
print(data.isna().sum())
```

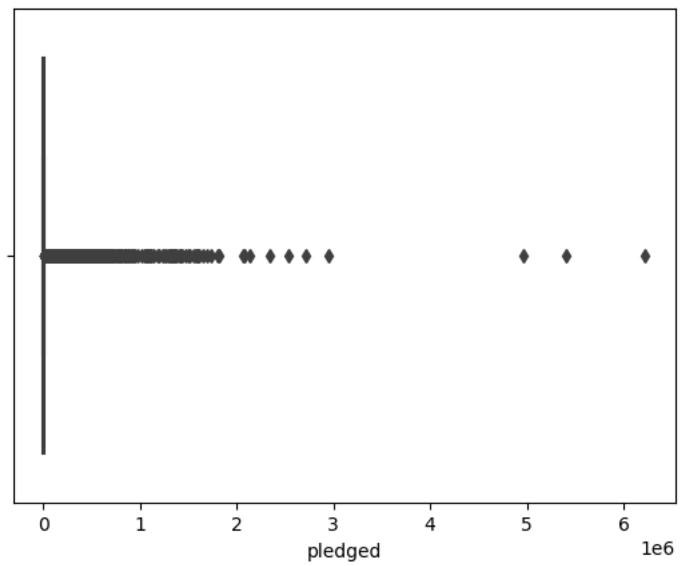
```
id                 0
photo              0
name               0
blurb              0
goal               0
                  ..
SuccessfulBool     0
USorGB             0
TOPCOUNTRY         0
LaunchedTuesday    0
DeadlineWeekend    0
Length: 63, dtype: int64
```

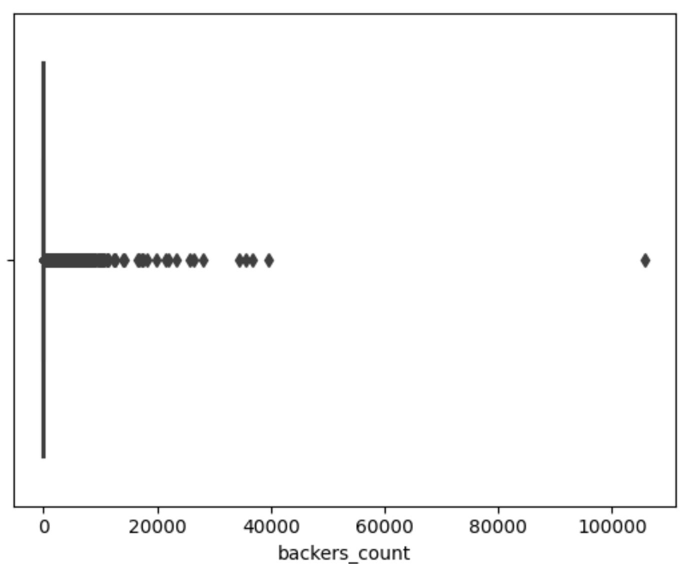
```
# Dropping the columns which have many unique values

data=data.drop(['photo','blurb','id','name','slug','creator','profile','urls','create_to_launch','location','launch_to_deadline','launch_to_s
```

```
data=data.drop(['source_url','deadline_weekday','state_changed_at_weekday','created_at_weekday','launched_at_weekday','currency_symbol','dead
```

```
# Visualize outliers using boxplot after handling the outliers

numerical_cols = data.select_dtypes(include=[np.number]).columns.tolist()
# Create a box plot for each column in the DataFrame
for column in numerical_cols:
    sns.boxplot(x=data[column])
    plt.show()
```


0.0
0.2
0.4
0.6
0.8
1.0
goal
1e8


0
1
2
3
4
5
6
pledged
1e6


0
20000
40000
60000
80000
100000
backers_count

```
#handling the outliers
import numpy as np

def handle_outliers(df, cols, threshold=3):
    for col in cols:
        if np.issubdtype(df[col].dtype, np.number):
            z = np.abs((df[col] - df[col].mean()) / df[col].std())
            df[col][z > threshold] = df[col].median()
    return df
```

static usd rate

```
import warnings
warnings.filterwarnings('ignore')

data = handle_outliers(data, numerical_cols)
```

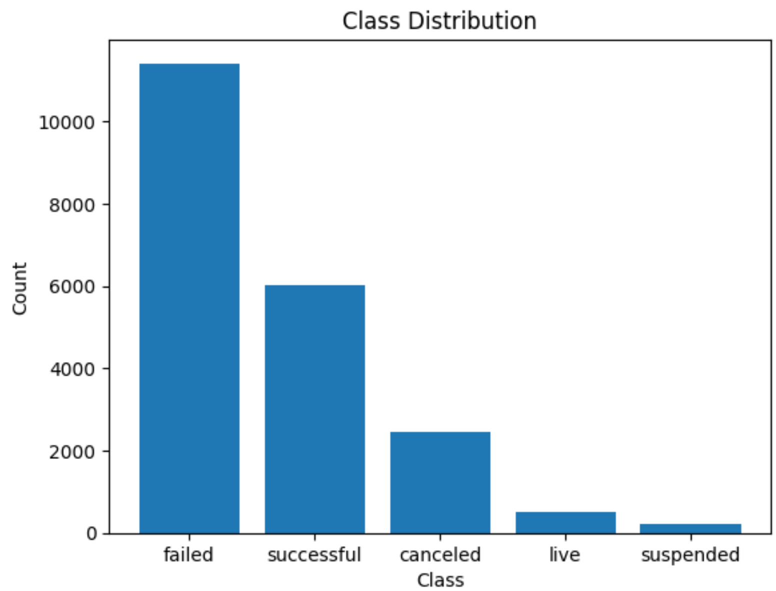
```
data.info()
```

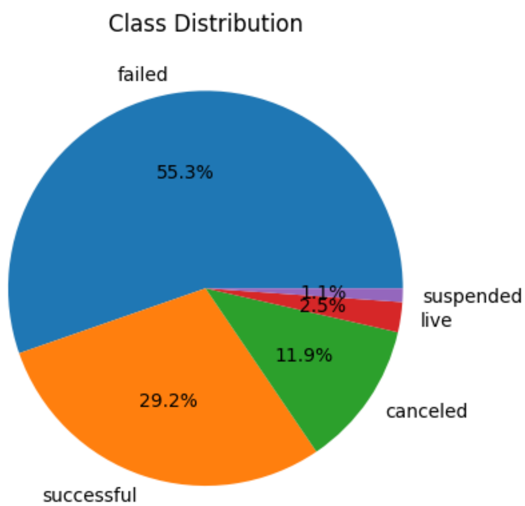
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20632 entries, 0 to 20631
Data columns (total 41 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   goal                        20632 non-null  float64
 1   pledged                     20632 non-null  float64
 2   state                       20632 non-null  object 
 3   disable_communication       20632 non-null  bool   
 4   country                     20632 non-null  object 
 5   currency                    20632 non-null  object 
 6   currency_trailing_code      20632 non-null  bool   
 7   staff_pick                  20632 non-null  bool   
 8   backers_count               20632 non-null  int64  
 9   static_usd_rate             20632 non-null  float64
 10  usd_pledged                 20632 non-null  float64
 11  category                    20632 non-null  object 
 12  spotlight                   20632 non-null  bool   
 13  name_len                    20632 non-null  float64
 14  name_len_clean              20632 non-null  float64
 15  blurb_len                   20632 non-null  float64
 16  blurb_len_clean             20632 non-null  float64
 17  deadline_month              20632 non-null  int64  
 18  deadline_day                20632 non-null  int64  
 19  deadline_yr                 20632 non-null  int64  
 20  deadline_hr                 20632 non-null  int64  
 21  state_changed_at_month      20632 non-null  int64  
 22  state_changed_at_day        20632 non-null  int64  
 23  state_changed_at_yr         20632 non-null  int64  
 24  state_changed_at_hr         20632 non-null  int64  
 25  created_at_month            20632 non-null  int64  
 26  created_at_day              20632 non-null  int64  
 27  created_at_yr               20632 non-null  int64  
 28  created_at_hr               20632 non-null  int64  
 29  launched_at_month           20632 non-null  int64  
 30  launched_at_day             20632 non-null  int64  
 31  launched_at_yr              20632 non-null  int64  
 32  launched_at_hr              20632 non-null  int64  
 33  create_to_launch_days       20632 non-null  int64  
 34  launch_to_deadline_days     20632 non-null  int64  
 35  launch_to_state_change_days 20632 non-null  int64  
 36  SuccessfulBool              20632 non-null  int64  
 37  USorGB                      20632 non-null  int64  
 38  TOPCOUNTRY                  20632 non-null  int64  
 39  LaunchedTuesday             20632 non-null  int64  
 40  DeadlineWeekend             20632 non-null  int64  
dtypes: bool(4), float64(8), int64(25), object(4)
memory usage: 5.9+ MB
```

```
for col in data.columns:
  if(data[col].dtype=='object'):
      print(col, ':---', len(data[col].unique()), 'labels')
```

```
state :--- 5 labels
country :--- 21 labels
currency :--- 13 labels
category :--- 24 labels
```

```
import pandas as pd
import matplotlib.pyplot as plt


# Count the number of instances for each class
class_counts = data["state"].value_counts()

# Plot the class distribution using a bar plot
fig, ax = plt.subplots()
ax.bar(class_counts.index.astype(str), class_counts.values)
ax.set_xlabel("Class")
ax.set_ylabel("Count")
ax.set_title("Class Distribution")
plt.show()

# Plot the class distribution using a pie chart
fig, ax = plt.subplots()
ax.pie(class_counts.values, labels=class_counts.index, autopct="%1.1f%%")
ax.set_title("Class Distribution")
plt.show()
```






```
# data_live = data[data["state"] == "live"]
# data_live.info()
```

```
# data= data[data["state"] != "live"]
```

```
data.shape
```

```
(20632, 41)
```

```
# Encoding state column

# Define a dictionary to map each value to a specific value
value_map = {
    "successful":1,
    "failed": 0,
    "suspended":0,
    "canceled":0,
    "live":0
}

# Encode the values in the "label" column using the dictionary
data["state"] = data["state"].replace(value_map)

# Check the encoded values
print(data["state"].unique())
```

```
[0 1]
```

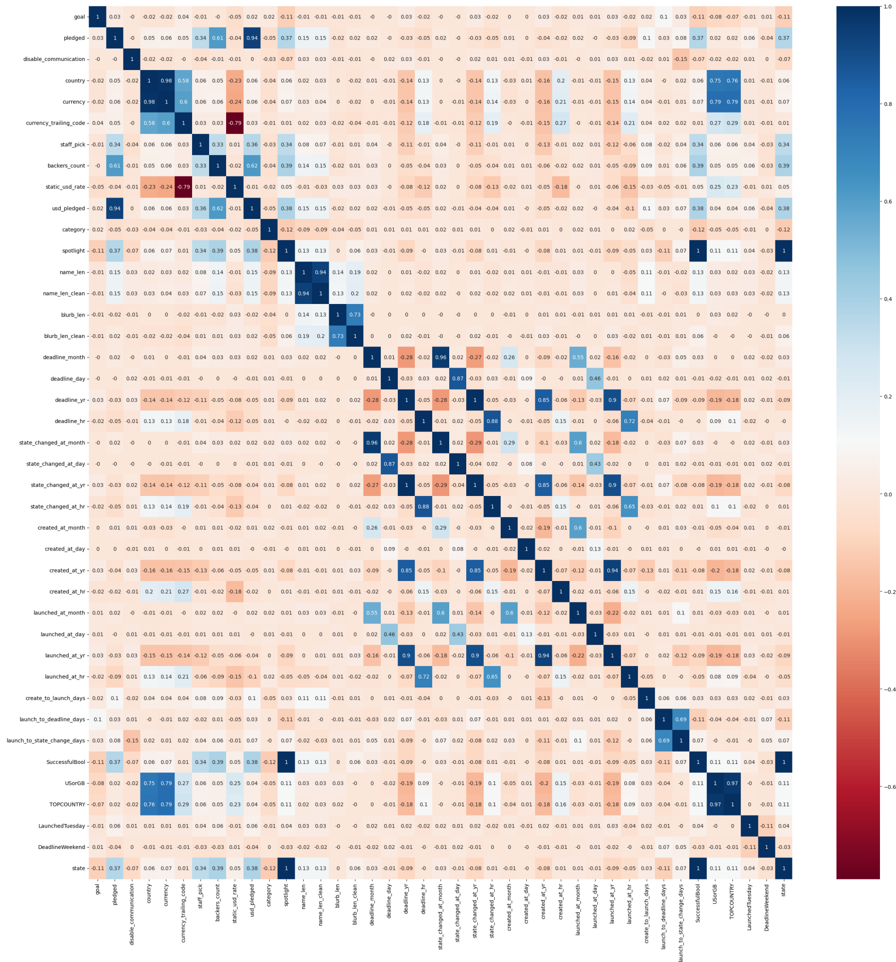
```
from sklearn.preprocessing import LabelEncoder
import pandas as pd

# Specify the columns to be encoded
cols_to_encode = ["country","currency","category"]

# Initialize the Label Encoder
le = LabelEncoder()

# Apply Label Encoding to the columns
for col in cols_to_encode:
    data[col] = le.fit_transform(data[col])
```

```
X=data.drop(['state'],axis=1)
y=data["state"]

y=pd.DataFrame(y)
```

```
X_cols=X.columns.tolist()
y_cols=y.columns.tolist()
```

```
data=pd.concat([X,y],axis=1)
```

```
# calculate the correlation matrix
corr_matrix = data.corr().round(2)

# create the heatmap
fig, ax = plt.subplots(figsize=(30, 30))
sns.heatmap(corr_matrix, annot=True, cmap='RdBu', ax=ax)

# show the plot
plt.show()
```



```
import pandas as pd

# Create a correlation matrix
corr_matrix = data.corr()

# Set the threshold for correlation coefficients
threshold = 0.7

# Find columns that have a correlation coefficient greater than the threshold
correlated_columns = set()
for i in range(len(corr_matrix.columns)):
```

```
    for j in range(i):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            colname = corr_matrix.columns[i]
            correlated_columns.add(colname)

# Convert the set of correlated columns to a list
correlated_columns = list(correlated_columns)

# Filter the original DataFrame to only include the non-correlated columns
non_correlated_data = data.drop(columns=correlated_columns)
non_correlated_data.shape
non_correlated_data.columns
```

```
Index(['goal', 'pledged', 'disable_communication', 'country',
       'currency_trailing_code', 'staff_pick', 'backers_count', 'category',
       'spotlight', 'name_len', 'blurb_len', 'deadline_month', 'deadline_day',
       'deadline_yr', 'deadline_hr', 'created_at_month', 'created_at_day',
       'created_at_hr', 'launched_at_month', 'launched_at_day',
       'create_to_launch_days', 'launch_to_deadline_days',
       'launch_to_state_change_days', 'LaunchedTuesday', 'DeadlineWeekend'],
      dtype='object')
```

```
data=pd.concat([non_correlated_data,y],axis=1)
data=data.drop(['spotlight'],axis=1)
data.shape
```

```
(20632, 25)
```

```
X=data.drop(["state"],axis=1)
y=data["state"]
y=pd.DataFrame(y)
```

```
X_cols=X.columns.tolist()
y_cols=y.columns.tolist()
```

```
data.hist(bins=20,figsize=(20,20))
plt.show()
```

Handling Imbalance Using Upsampling & Downsampling

```
# UNDER SAMPLING
from imblearn.under_sampling import RandomUnderSampler
undersample = RandomUnderSampler(sampling_strategy='majority')
X_under, y_under = undersample.fit_resample(X, y)
```

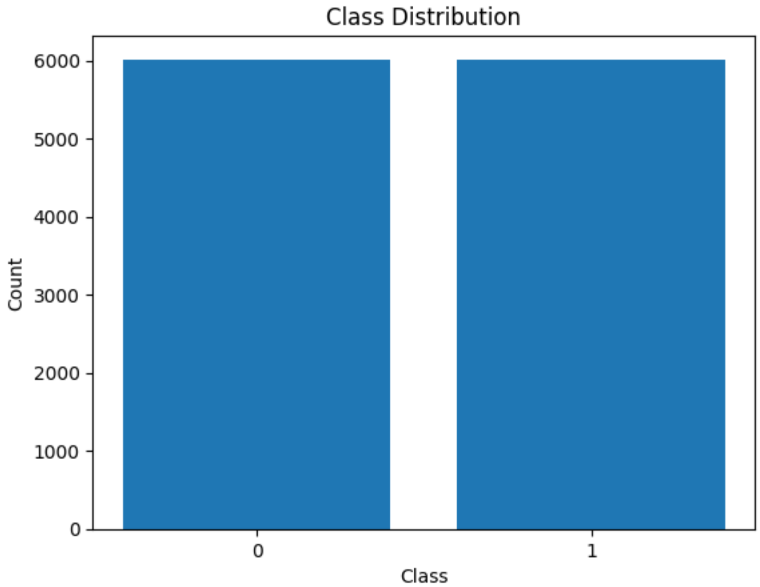
```
X_under.shape,y_under.shape
```

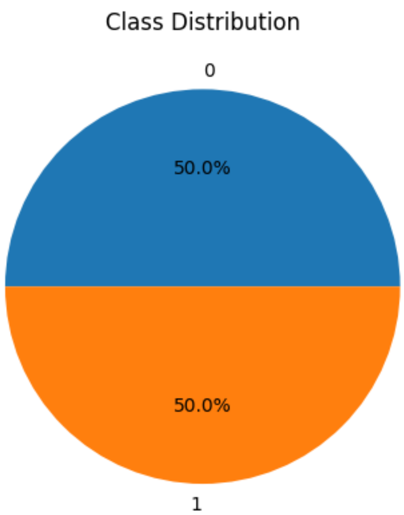
```
((12036, 24), (12036, 1))
```

```
y_under=pd.DataFrame(y_under,columns=["state"])
```

```
data_under = pd.concat([X_under, y_under], axis=1)
```

```
import pandas as pd
import matplotlib.pyplot as plt


# Count the number of instances for each class
class_counts = y_under["state"].value_counts()

# Plot the class distribution using a bar plot
fig, ax = plt.subplots()
ax.bar(class_counts.index.astype(str), class_counts.values)
ax.set_xlabel("Class")
ax.set_ylabel("Count")
ax.set_title("Class Distribution")
plt.show()

# Plot the class distribution using a pie chart
fig, ax = plt.subplots()
ax.pie(class_counts.values, labels=class_counts.index, autopct="%1.1f%%")
ax.set_title("Class Distribution")
plt.show()
```






```
data_under.hist(bins=20,figsize=(20,20))
plt.show()
```

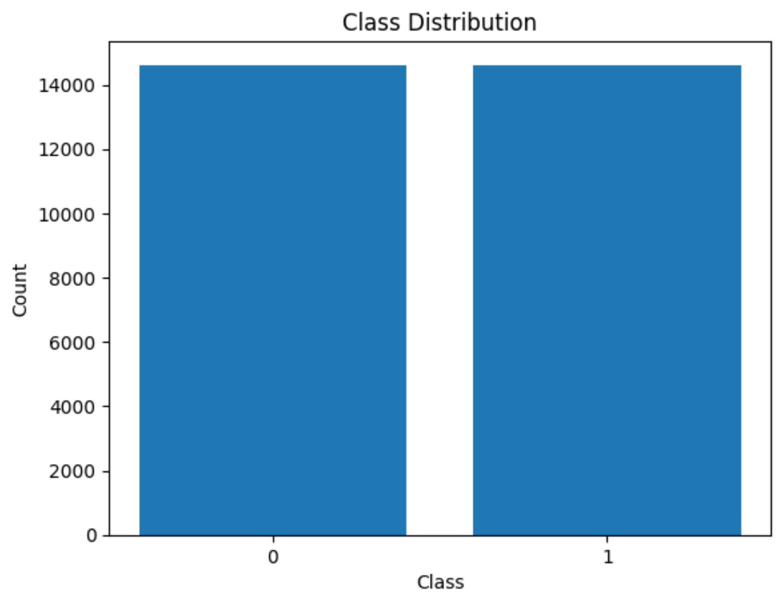

```
from imblearn.over_sampling import RandomOverSampler

oversample = RandomOverSampler(sampling_strategy='minority')
X_over, y_over = oversample.fit_resample(X, y)
X_over.shape, y_over.shape
```

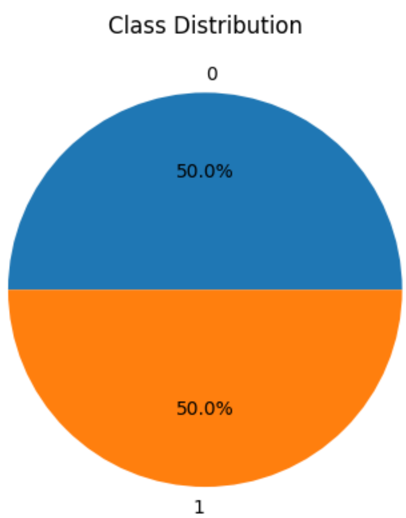
```
((29228, 24), (29228, 1))
```

```
y_over=pd.DataFrame(y_over,columns=["state"])
```

```
import pandas as pd
import matplotlib.pyplot as plt


# Count the number of instances for each class
class_counts = y_over["state"].value_counts()

# Plot the class distribution using a bar plot
fig, ax = plt.subplots()
ax.bar(class_counts.index.astype(str), class_counts.values)
ax.set_xlabel("Class")
ax.set_ylabel("Count")
ax.set_title("Class Distribution")
plt.show()

# Plot the class distribution using a pie chart
fig, ax = plt.subplots()
ax.pie(class_counts.values, labels=class_counts.index, autopct="%1.1f%%")
```

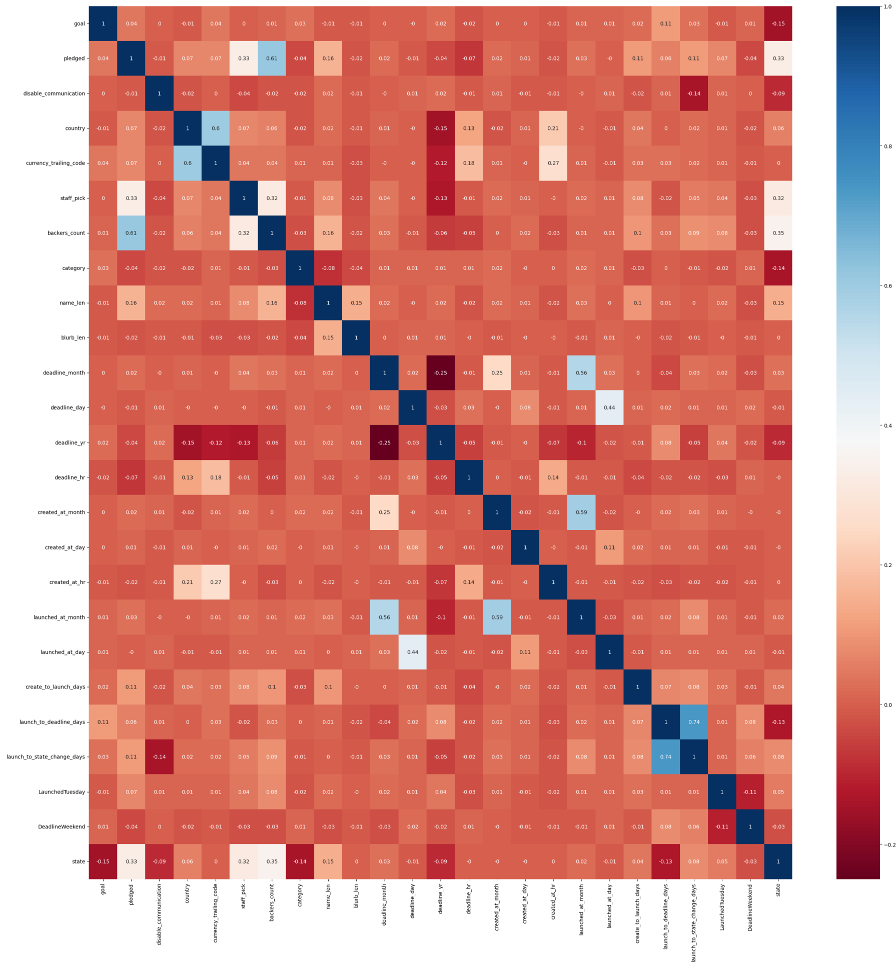
```
ax.set_title("Class Distribution")
plt.show()
```






```
X_over_final=pd.concat([X_over, y_over], axis=1)
```

```
# calculate the correlation matrix
corr_matrix = X_over_final.corr().round(2)

# create the heatmap
fig, ax = plt.subplots(figsize=(30, 30))
sns.heatmap(corr_matrix, annot=True, cmap='RdBu', ax=ax)

# show the plot
plt.show()
```



```
data_over = pd.concat([X_over, y_over], axis=1)
```

```
data_over.hist(bins=20,figsize=(20,20))
plt.show()
```

Scaling of over sampled data

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
X_over_scaled= scaler.fit_transform(X_over)
y_over_scaled=scaler.fit_transform(y_over)
```

```
X_over_scaled=pd.DataFrame(X_over_scaled,columns=X_cols)

y_over_scaled=pd.DataFrame(y_over_scaled,columns=y_cols)
```

```
X_scaled_over_final=pd.concat([X_over_scaled, y_over_scaled], axis=1)
```

```
X_scaled_over_final.describe()
```

	goal	pledged	disable_communication	country	currency_trailin
count	2.922800e+04	2.922800e+04	2.922800e+04	2.922800e+04	2.9228(
mean	2.722759e-17	5.445517e-17	-2.333793e-17	-1.312759e-16	1.2592
std	1.000017e+00	1.000017e+00	1.000017e+00	1.000017e+00	1.0000
min	-2.819720e-01	-4.065119e-01	-8.905943e-02	-2.609990e+00	-1.9696
25%	-2.626169e-01	-4.039479e-01	-8.905943e-02	-1.158163e+00	5.0770
50%	-2.174400e-01	-3.649649e-01	-8.905943e-02	6.162917e-01	5.0770
75%	-5.609378e-02	-1.574543e-01	-8.905943e-02	6.162917e-01	5.0770
max	2.553341e+01	7.769516e+00	1.122846e+01	6.162917e-01	5.0770

8 rows × 25 columns

Scaling of Under sampled data

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
X_under_scaled= scaler.fit_transform(X_under)
y_under_scaled=scaler.fit_transform(y_under)
```

```
X_under_scaled=pd.DataFrame(X_under_scaled,columns=X_cols)
y_under_scaled=pd.DataFrame(y_under_scaled,columns=y_cols)
```

```
X_scaled_under_final=pd.concat([X_under_scaled, y_under_scaled], axis=1)
```

```
X_scaled_under_final.describe()
```

	goal	pledged	disable_communication	country	currency_trailin
count	12036.000000	12036.000000	1.203600e+04	1.203600e+04	1.2036
mean	0.000000	0.000000	1.889113e-17	-2.361392e-17	9.917
std	1.000042	1.000042	1.000042e+00	1.000042e+00	1.0000
min	-0.279976	-0.405227	-9.013675e-02	-2.617631e+00	-1.9949
25%	-0.261116	-0.402653	-9.013675e-02	-1.165007e+00	5.0127
50%	-0.217093	-0.362354	-9.013675e-02	6.104229e-01	5.0127
75%	-0.059868	-0.153235	-9.013675e-02	6.104229e-01	5.0127
max	24.875974	7.803910	1.109425e+01	6.104229e-01	5.0127

8 rows × 25 columns

```
X_scaled_over_final.head()
```

	goal	pledged	disable_communication	country	currency_trailing_code	staff_p
0	-0.272298	-0.406512	-0.089059	0.616292	0.507708	-0.424
1	-0.278752	-0.406512	-0.089059	0.616292	0.507708	-0.424
2	0.363406	-0.403948	-0.089059	0.616292	0.507708	-0.424
3	-0.249709	-0.406512	-0.089059	0.616292	0.507708	-0.424

Scaling of Unbalanced data

[ ] ↳ *5 cells hidden*

PCA of oversampled data

[ ] ↳ *4 cells hidden*

PCA of Unbalanced data

[ ] ↳ *3 cells hidden*

MODELS

Logistic Regression

Applying logistic model on imbalanced data

```
models_im=[]
models_up=[]
models_down=[]
models_im1=[]
```

```
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# X= X_imbalance.drop(["state"],axis=1)
# y=X_imbalance["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Initialize the logistic regression model
logreg_im = LogisticRegression(max_iter=1000, solver='saga')

# Fit the model to the training data
logreg_im.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = logreg_im.predict(X_test)

# Evaluate the model performance using accuracy score
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Make predictions on the training data
y_pred = logreg_im.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)
print("train Accuracy:", accuracy)
```

```
models_im.append(logreg_im)
```

```
Accuracy: 0.8807850739035619
train Accuracy: 0.8807850739035619
```

```
models_im1.append(("Log_reg", logreg_im))
```

Logistic Reg on Under Sampled

```
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Split the dataset into X (features) and y (target)
X = X_scaled_under_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_under_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the logistic regression model
logreg = LogisticRegression(max_iter=1000, solver='saga')

# Fit the model to the training data
logreg.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = logreg.predict(X_test)

# Evaluate the model performance using accuracy score
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Make predictions on the training data
y_pred = logreg.predict(X_train)

# Evaluate the model performance using accuracy score
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_train, y_pred)
print("train Accuracy:", accuracy)
```

```
Accuracy: 0.8874584717607974
train Accuracy: 0.8800373909430826
```

Applying logistic model on up balanced data

```
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Split the dataset into X (features) and y (target)
X = X_scaled_over_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_over_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the logistic regression model
logreg_b_u = LogisticRegression(max_iter=1000, solver='saga')


# Fit the model to the training data
logreg_b_u.fit(X_train, y_train)

# Make predictions on the testing data
y_pred = logreg_b_u.predict(X_test)

# Evaluate the model performance using accuracy score
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
# Make predictions on the training data
y_pred = logreg_b_u.predict(X_train)

# Evaluate the model performance using accuracy score
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_train, y_pred)
print("train Accuracy:", accuracy)


models_up.append(("Log_reg", logreg_b_u))
```

```
Accuracy: 0.8963393773520356
train Accuracy: 0.8920964844752374
```

```
X_scaled.shape
```

```
(20632, 24)
```

RFE with Logistic Regression on Unbalanced scaled data

```
from sklearn.feature_selection import RFE
# Determiniation of dominant features , Method one Recursive Model Elimination,
# very similar idea to foreward selection but done recurssively. This method is gready
# which means it tries one feature at the time
NUM_FEATURES = 3 # this is kind of arbitrary but you should get an idea by observing the scatter plots and correlation.
model = LogisticRegression(multi_class='ovr')
#rfe = RFE(model, NUM_FEATURES)
rfe = RFE(model, n_features_to_select = NUM_FEATURES)

X=X_imbalance.drop(['state'],axis=1)
y=X_imbalance['state']

fit = rfe.fit(X,y)
print("Num Features:", fit.n_features_)
print("Selected Features:", fit.support_)
print("Feature Ranking:", fit.ranking_)
# calculate the score for the selected features
score = rfe.score(X,y)
print("Model Score with selected features is: ", score)
```

```
Num Features: 3
Selected Features: [ True False False False False False False False False False False False
 False False False False False False False False  True  True False False]
Feature Ranking: [ 1  4  3  8  9  5  2  6  7 21 13 17 11 15 16 19 14 12 20 10  1  1 18 22]
Model Score with selected features is:  0.7076870880186119
```

```
from sklearn.feature_selection import RFE
# Determiniation of dominant features , Method one Recursive Model Elimination,
# very similar idea to foreward selection but done recurssively. This method is gready
# which means it tries one feature at the time
NUM_FEATURES = 4 # this is kind of arbitrary but you should get an idea by observing the scatter plots and correlation.
model = LogisticRegression(multi_class='ovr')
#rfe = RFE(model, NUM_FEATURES)
rfe = RFE(model, n_features_to_select = NUM_FEATURES)
fit = rfe.fit(X, y)
print("Num Features:", fit.n_features_)
print("Selected Features:", fit.support_)
print("Feature Ranking:", fit.ranking_)
# calculate the score for the selected features
score = rfe.score(X,y)
print("Model Score with selected features is: ", score)
```

```
Num Features: 4
Selected Features: [ True False False False False False  True False False False False False
 False False False False False False False False  True  True False False]
Feature Ranking: [ 1  3  2  7  8  4  1  5  6 20 12 16 10 14 15 18 13 11 19  9  1  1 17 21]
Model Score with selected features is:  0.8460643660333462
```

Decision tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.tree import export_graphviz
import graphviz

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Define the decision tree classifier
dt = DecisionTreeClassifier()

# Define the hyperparameters to tune
parameters = {'criterion': ['gini', 'entropy'],
              'max_depth': [3, 5, 10, 20, None],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

# Perform a grid search over the hyperparameters
clf_im = GridSearchCV(dt, parameters, cv=5)
clf_im.fit(X_train, y_train)

# Print the best parameters found
print('Best parameters found:')
print(clf_im.best_params_)

# Make predictions on the test set
y_pred = clf_im.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)


# Visualize the decision tree
dot_data = export_graphviz(clf_im.best_estimator_,
                           out_file=None,
                           feature_names=X_train.columns,
                           class_names = np.unique(y_train.values.astype(str)),
                           filled=True,
                           rounded=True,
                           special_characters=True)
graph = graphviz.Source(dot_data)
graph.render('decision_tree', format='png')
graph

models_im.append(clf_im)
```

```
Best parameters found:
{'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2}
Accuracy: 0.9852192876181245
```

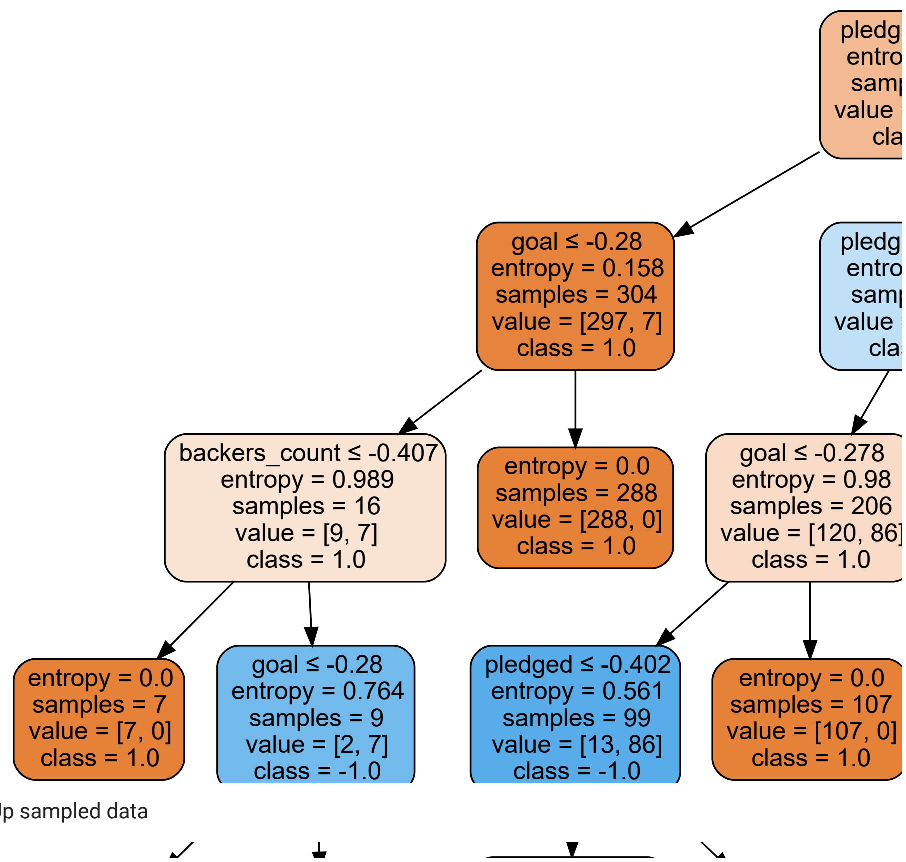
```
models_im1.append(("Decision tree", clf_im))
```

On Under sampled

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.tree import export_graphviz
import graphviz

# Split the dataset into X (features) and y (target)
X = X_scaled_under_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_under_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the decision tree classifier
dt = DecisionTreeClassifier()

# Define the hyperparameters to tune
```

```
parameters = {'criterion': ['gini', 'entropy'],
              'max_depth': [3, 5, 10, 20, None],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

# Perform a grid search over the hyperparameters
clf = GridSearchCV(dt, parameters, cv=5)
clf.fit(X_train, y_train)

# Print the best parameters found
print('Best parameters found:')
print(clf.best_params_)

# Make predictions on the test set
y_pred = clf.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)

# Visualize the decision tree
dot_data = export_graphviz(clf.best_estimator_,
                           out_file=None,
                           feature_names=X_train.columns,
                           class_names=y_train.unique().astype(str),
                           filled=True,
                           rounded=True,
                           special_characters=True)
graph = graphviz.Source(dot_data)
graph.render('decision_tree', format='png')
graph
```

```
Best parameters found:
{'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 5]
Accuracy: 0.9858803986710963
```



On Up sampled data

```
# Define the decision tree classifier
dt = DecisionTreeClassifier()


# Split the dataset into X (features) and y (target)
X = X_scaled_over_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_over_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the hyperparameters to tune
parameters = {'criterion': ['gini', 'entropy'],
              'max_depth': [3, 5, 10, 20, None],
              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 2, 4]}

# Perform a grid search over the hyperparameters
clf_d_up = GridSearchCV(dt, parameters, cv=5)
clf_d_up.fit(X_train, y_train)

# Print the best parameters found
print('Best parameters found:')
```

```
print(clf_d_up.best_params_)

# Make predictions on the test set
y_pred = clf_d_up.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)

# Visualize the decision tree
dot_data = export_graphviz(clf_d_up.best_estimator_,
                           out_file=None,
                           feature_names=X_train.columns,
                           class_names=y_train.unique().astype(str),
                           filled=True,
                           rounded=True,
                           special_characters=True)
graph = graphviz.Source(dot_data)
graph.render('decision_tree', format='png')
graph

models_up.append(("Decision tree", clf_d_up))
```

```
Best parameters found:
{'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2}
Accuracy: 0.9950393431406089
```

Random Forest

On unbalanced

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

X=X_imbalance.drop(['state'],axis=1)
y=X_imbalance['state']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the model
rfc_im = RandomForestClassifier()

# Define the parameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Define the GridSearchCV object
grid_search = GridSearchCV(estimator=rfc_im, param_grid=param_grid, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best parameters and best score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)

# Make predictions on the test set using the best model
y_pred = grid_search.predict(X_test)

# Evaluate the performance of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

models_im.append(rfc_im)
```

```
Best parameters:  {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Best score:  0.9735231747955165
Accuracy: 0.9769808577659317
```

```
models_im1.append(("RF", rfc_im))
```

On up sampled

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Split the dataset into X (features) and y (target)
X = X_scaled_over_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_over_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Define the model
rfc = RandomForestClassifier()

# Define the parameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Define the GridSearchCV object
grid_search = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best parameters and best score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)

# Make predictions on the test set using the best model
y_pred = grid_search.predict(X_test)

# Evaluate the performance of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)


models_up.append(("Random forest", grid_search))
```

```
Best parameters:  {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 200}
Best score:  0.9807116363808625
Accuracy: 0.9823811152925077
```

On down sampled

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Split the dataset into X (features) and y (target)
X = X_scaled_under_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_under_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the model
rfc = RandomForestClassifier()

# Define the parameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 5, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

```
# Define the GridSearchCV object
grid_search = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best parameters and best score
print("Best parameters: ", grid_search.best_params_)
print("Best score: ", grid_search.best_score_)

# Make predictions on the test set using the best model
y_pred = grid_search.predict(X_test)

# Evaluate the performance of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Best parameters:  {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 200}
Best score:  0.965101482110828
Accuracy: 0.965531561461794
```

Support Vector Machine

On unbalanced

```
# Import necessary libraries
from sklearn import svm, datasets
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

X=X_imbalance.drop(['state'],axis=1)
y=X_imbalance['state']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=0)

# Set the parameters for GridSearchCV
parameters = {'kernel': ('linear', 'rbf'), 'C': [0.1, 1, 10], 'gamma': [0.1, 1, 'scale', 'auto']}

# Initialize the SVM classifier
svc = svm.SVC()

# Set up GridSearchCV with 5-fold cross-validation
clf = GridSearchCV(svc, parameters, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
clf.fit(X_train, y_train)

# Print the best parameters and the corresponding score
print("Best parameters: ", clf.best_params_)
print("Best score: ", clf.best_score_)

# Make predictions on the testing set using the best estimator found by GridSearchCV
y_pred = clf.best_estimator_.predict(X_test)

# Print classification report and accuracy score
print(classification_report(y_test, y_pred))
print("Accuracy score: ", clf.best_estimator_.score(X_test, y_test))
```

```
Best parameters:  {'C': 10, 'gamma': 'auto', 'kernel': 'rbf'}
Best score:  0.8813181913629787
              precision    recall  f1-score   support

           0       0.90      0.95      0.93      4397
           1       0.86      0.75      0.80      1793

    accuracy                           0.89      6190
   macro avg       0.88      0.85      0.86      6190
weighted avg       0.89      0.89      0.89      6190

Accuracy score:  0.892730210016155
```

```
models_im1.append(("SVM", svc))
```

On Up sampled

```
# Import necessary libraries
from sklearn import svm, datasets
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

# Split the dataset into X (features) and y (target)
X = X_scaled_over_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_over_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Set the parameters for GridSearchCV
parameters = {'kernel': ('linear', 'rbf'), 'C': [0.1, 1, 10], 'gamma': [0.1, 1, 'scale', 'auto']}

# Initialize the SVM classifier
svc = svm.SVC()

# Set up GridSearchCV with 5-fold cross-validation
clf = GridSearchCV(svc, parameters, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
clf.fit(X_train, y_train)

# Print the best parameters and the corresponding score
print("Best parameters: ", clf.best_params_)
print("Best score: ", clf.best_score_)

# Make predictions on the testing set using the best estimator found by GridSearchCV
y_pred = clf.best_estimator_.predict(X_test)

# Print classification report and accuracy score
print(classification_report(y_test, y_pred))
print("Accuracy score: ", clf.best_estimator_.score(X_test, y_test))

models_up.append(("SVM", svc))
```

```
Best parameters:  {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}
Best score:  0.9187836093596735
              precision    recall  f1-score   support

        -1.0       0.95      0.90      0.92      2909
         1.0       0.90      0.95      0.93      2937

    accuracy                           0.92      5846
   macro avg       0.93      0.92      0.92      5846
weighted avg       0.93      0.92      0.92      5846

Accuracy score:  0.9247348614437222
```

On down sampled

```
# Import necessary libraries
from sklearn import svm, datasets
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

# Split the dataset into X (features) and y (target)
X = X_scaled_under_final.drop("state", axis=1)  # Drop the target column from the features
y = X_scaled_under_final["state"]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Set the parameters for GridSearchCV
parameters = {'kernel': ('linear', 'rbf'), 'C': [0.1, 1, 10], 'gamma': [0.1, 1, 'scale', 'auto']}

# Initialize the SVM classifier
```

```
svc = svm.SVC()

# Set up GridSearchCV with 5-fold cross-validation
clf = GridSearchCV(svc, parameters, cv=5, n_jobs=-1)

# Fit the GridSearchCV object to the data
clf.fit(X_train, y_train)

# Print the best parameters and the corresponding score
print("Best parameters: ", clf.best_params_)
print("Best score: ", clf.best_score_)

# Make predictions on the testing set using the best estimator found by GridSearchCV
y_pred = clf.best_estimator_.predict(X_test)

# Print classification report and accuracy score
print(classification_report(y_test, y_pred))
print("Accuracy score: ", clf.best_estimator_.score(X_test, y_test))
```

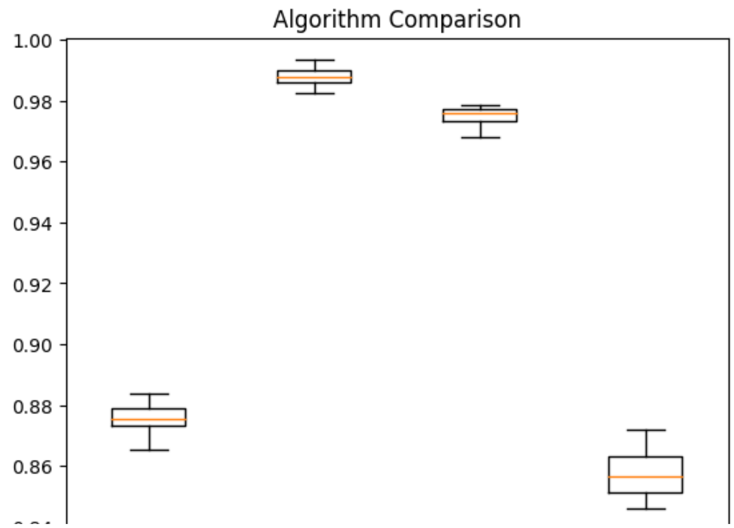
```
Best parameters:  {'C': 10, 'gamma': 0.1, 'kernel': 'linear'}
Best score:  0.8950977869482543
              precision    recall  f1-score   support

        -1.0       0.92      0.89      0.90      1238
         1.0       0.89      0.91      0.90      1170

    accuracy                           0.90      2408
   macro avg       0.90      0.90      0.90      2408
weighted avg       0.90      0.90      0.90      2408

Accuracy score:  0.9028239202657807
```

```
# import matplotlib.pyplot as plt

# # Define the models and their corresponding accuracy scores
# models = ['Linear SVC', 'RBF SVC', 'Random Forest(d=2)', 'AdaBoost']

# # Create a bar plot
# plt.bar(models, acc_scores, color='blue')

# # Set the title and labels
# plt.title('Accuracy Scores for Different Models')
# plt.xlabel('Model')
# plt.ylabel('Accuracy')

# # Show the plot
# plt.show()
```

```
from sklearn.model_selection import KFold, cross_val_score

results = []
names = []

X=X_imbalance.drop(['state'],axis=1)
y=X_imbalance['state']

for name,model in models_im1:
    kfold = KFold(n_splits=10, random_state=42, shuffle=True)
    cv_results = cross_val_score(model, X, y, cv=kfold, scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    print(name, " - Accuracy: ", cv_results.mean(), " (", cv_results.std(), ")")
```

```
Log_reg  - Accuracy:  0.8753871976537517  ( 0.0055404090775467325 )
Decision tree  - Accuracy:  0.9876402056161154  ( 0.003014429452062157 )
RF  - Accuracy:  0.9746992507336725  ( 0.0033794372662044013 )
SVM  - Accuracy:  0.857938291680288  ( 0.007953236174697651 )
```

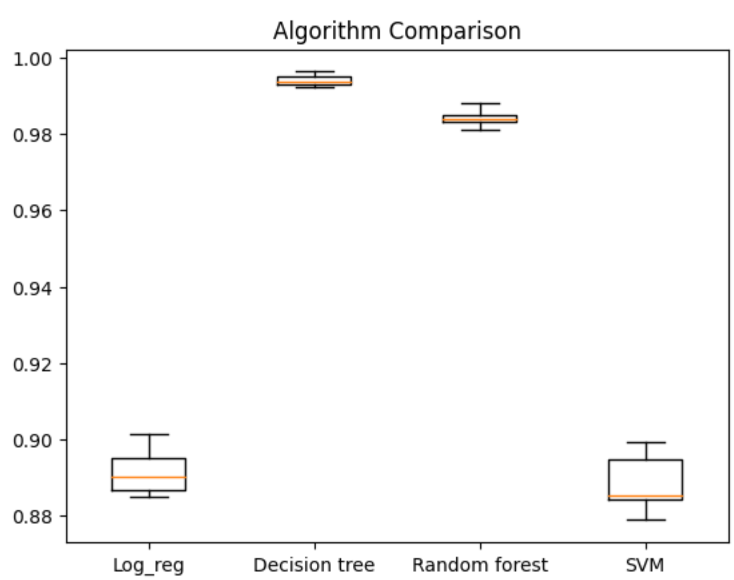
```
# Compare the results of all models using boxplots
plt.boxplot(results, labels=names)
plt.title("Algorithm Comparison")
plt.show()
```




```
from sklearn.model_selection import KFold, cross_val_score

results_up = []
names_up = []

for name,model in models_up:
    kfold = KFold(n_splits=10, random_state=42, shuffle=True)
    cv_results = cross_val_score(model, X_over_scaled, y_over_scaled, cv=kfold, scoring='accuracy')
    results_up.append(cv_results)
    names_up.append(name)
    print(name, " - Accuracy: ", cv_results.mean(), " (", cv_results.std(), ")")
```

```
Log_reg  - Accuracy:  0.891234252733226  ( 0.005152594898801572 )
Decision tree  - Accuracy:  0.9938757448478552  ( 0.0014389443452886169 )
Random forest  - Accuracy:  0.9841590206118574  ( 0.001867987466605648 )
SVM  - Accuracy:  0.8886681147396456  ( 0.006802838770751357 )
```

```
# Compare the results of all models using boxplots
plt.boxplot(results_up, labels=names_up)
plt.title("Algorithm Comparison")
plt.show()
```



Double-click (or enter) to edit

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