DA5401 - Assignment 7

October 4, 2024

Name: Anirudh Rao

Roll No.: BE21B004

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

We import the training set of the IDA2016 Challenge.

[ ]:
```
df = pd.read_csv("aps_failure_training_set.csv")
```

[ ]:
```
len(df)
```

[ ]:
```
60000
```

[ ]:
```
df.head()
```

[ ]:
```
  class  aa_000 ab_000      ac_000 ad_000 ae_000 af_000 ag_000 ag_001 ag_002  \
0   neg   76698     na  2130706438    280      0      0      0      0      0
1   neg   33058     na           0     na      0      0      0      0      0
2   neg   41040     na         228    100      0      0      0      0      0
3   neg      12      0          70     66      0     10      0      0      0
4   neg   60874     na        1368    458      0      0      0      0      0

  …   ee_002  ee_003  ee_004  ee_005  ee_006  ee_007  ee_008 ee_009 ef_000  \
0 …  1240520  493384  721044  469792  339156  157956   73224      0      0
1 …   421400  178064  293306  245416  133654   81140   97576   1500      0
2 …   277378  159812  423992  409564  320746  158022   95128    514      0
3 …      240      46      58      44      10       0       0      0      4
4 …   622012  229790  405298  347188  286954  311560  433954   1218      0

  eg_000
0      0
1      0
2      0
3     32
```

```
4      0

[5 rows x 171 columns]
```

We check the class imbalance of this dataset.

[ ]:
```
df["class"].value_counts()
```

[ ]:
```
class
neg    59000
pos     1000
Name: count, dtype: int64
```

As mentioned in the question, there is an imbalance of 59:1 for neg:pos.

We also observe that there are many "na" values in the dataset. For ease of cleaning the data, we replace them with NumPy NaN values.

[ ]:
```
df.replace("na",np.nan,inplace=True)
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
class         0
aa_000        0
ab_000    46329
ac_000     3335
ad_000    14861
          …
ee_007      671
ee_008      671
ee_009      671
ef_000     2724
eg_000     2723
Length: 171, dtype: int64
```

We can see that many feature columns have NaN values. They will have to be cleaned. If the number of NaN values in a column is more than 1000, we will discard that column.

[ ]:
```
for column in df.columns:
  if df[column].isna().sum() > 1000:
    df.drop(column, axis=1, inplace=True)
```

[ ]:
```
df.isna().sum()
```

[ ]:
```
class       0
aa_000      0
ag_000    671
ag_001    671
ag_002    671
```

```
             …
ee_005     671
ee_006     671
ee_007     671
ee_008     671
ee_009     671
Length: 101, dtype: int64
```

There are still some datapoints with NaN values. We will drop all those datapoint that contain at least 1 NaN value.

[ ]:
```python
df = df.dropna(axis=0, how="any")
```

[ ]:
```python
df.isna().sum()
```

[ ]:
```
class      0
aa_000     0
ag_000     0
ag_001     0
ag_002     0
          ..
ee_005     0
ee_006     0
ee_007     0
ee_008     0
ee_009     0
Length: 101, dtype: int64
```

We have effectively cleaned the dataset and freed it from NaN values.

[ ]:
```python
len(df)
```

[ ]:
```
58127
```

[ ]:
```python
df["class"].value_counts()
```

[ ]:
```
class
neg    57198
pos      929
Name: count, dtype: int64
```

The number of datapoints has the same order of magnitude, as does the class imbalance.

1 Task 1

We divide the dataset into a training set and testing set.

[ ]:
```python
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(df.drop("class", axis=1),␣
↪df["class"], test_size=0.3, random_state=5401)
```

To ensure the support vector algorithm to efficiently learn from the data, we will perform standard scaling.

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

We construct the base models for the three classification algorithms - SVC, Logistic Regression, and Decision Trees. We will perform 5-fold cross-validation to find their best hyperparameters. They will be train on the imbalanced dataset.

```
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.model_selection import GridSearchCV
```

```
svc_params = {"kernel":["poly","rbf"],
              "gamma": ["scale", "auto"],
              "degree":[1, 2, 3]}
```

```
logreg_params = {"penalty": ["l1", "l2"],
                 "C": [0.01, 0.1, 1]}
```

```
tree_params = {"max_depth": [5, 10, None],
               "min_samples_leaf": [1, 2, 4]}
```

We run a grid search to find the best hyperparameters. This takes a while to run owing to the size of the dataset.

```
svc_grid = GridSearchCV(SVC(), svc_params, cv=5, scoring="f1_macro", verbose=2)
logreg_grid = GridSearchCV(LogisticRegression(solver="liblinear"),␣
↪logreg_params, cv=5, scoring="f1_macro", verbose=2)
tree_grid = GridSearchCV(DecisionTreeClassifier(), tree_params, cv=5,␣
↪scoring="f1_macro", verbose=2)

print("Fitting SVC")
svc_grid.fit(X_train, y_train)
print("\nFitting Logistic Regression")
logreg_grid.fit(X_train, y_train)
print("\nFitting Decision Tree")
tree_grid.fit(X_train, y_train)
```

```
baseline_svc = svc_grid.best_estimator_
baseline_logreg = logreg_grid.best_estimator_
baseline_tree = tree_grid.best_estimator_
```

```
Fitting SVC
Fitting 5 folds for each of 12 candidates, totalling 60 fits
[CV] END …degree=1, gamma=scale, kernel=poly; total time=   3.6s
[CV] END …degree=1, gamma=scale, kernel=poly; total time=   3.7s
[CV] END …degree=1, gamma=scale, kernel=poly; total time=   3.5s
[CV] END …degree=1, gamma=scale, kernel=poly; total time=   4.3s
[CV] END …degree=1, gamma=scale, kernel=poly; total time=   3.5s
[CV] END …degree=1, gamma=scale, kernel=rbf; total time=   7.7s
[CV] END …degree=1, gamma=scale, kernel=rbf; total time=   7.3s
[CV] END …degree=1, gamma=scale, kernel=rbf; total time=   7.7s
[CV] END …degree=1, gamma=scale, kernel=rbf; total time=   6.8s
[CV] END …degree=1, gamma=scale, kernel=rbf; total time=   7.9s
[CV] END …degree=1, gamma=auto, kernel=poly; total time=   3.3s
[CV] END …degree=1, gamma=auto, kernel=poly; total time=   3.7s
[CV] END …degree=1, gamma=auto, kernel=poly; total time=   5.4s
[CV] END …degree=1, gamma=auto, kernel=poly; total time=   4.6s
[CV] END …degree=1, gamma=auto, kernel=poly; total time=   4.9s
[CV] END …degree=1, gamma=auto, kernel=rbf; total time=   9.6s
[CV] END …degree=1, gamma=auto, kernel=rbf; total time=   9.1s
[CV] END …degree=1, gamma=auto, kernel=rbf; total time=   7.5s
[CV] END …degree=1, gamma=auto, kernel=rbf; total time=   8.8s
[CV] END …degree=1, gamma=auto, kernel=rbf; total time=   6.8s
[CV] END …degree=2, gamma=scale, kernel=poly; total time=   6.0s
[CV] END …degree=2, gamma=scale, kernel=poly; total time=   5.1s
[CV] END …degree=2, gamma=scale, kernel=poly; total time=   6.7s
[CV] END …degree=2, gamma=scale, kernel=poly; total time=   6.5s
[CV] END …degree=2, gamma=scale, kernel=poly; total time=   5.4s
[CV] END …degree=2, gamma=scale, kernel=rbf; total time=   7.7s
[CV] END …degree=2, gamma=scale, kernel=rbf; total time=   9.1s
[CV] END …degree=2, gamma=scale, kernel=rbf; total time=   6.9s
[CV] END …degree=2, gamma=scale, kernel=rbf; total time=   7.9s
[CV] END …degree=2, gamma=scale, kernel=rbf; total time=   6.9s
[CV] END …degree=2, gamma=auto, kernel=poly; total time=   6.0s
[CV] END …degree=2, gamma=auto, kernel=poly; total time=   5.6s
[CV] END …degree=2, gamma=auto, kernel=poly; total time=   5.0s
[CV] END …degree=2, gamma=auto, kernel=poly; total time=   7.1s
[CV] END …degree=2, gamma=auto, kernel=poly; total time=   5.5s
[CV] END …degree=2, gamma=auto, kernel=rbf; total time=   7.6s
[CV] END …degree=2, gamma=auto, kernel=rbf; total time=   7.3s
[CV] END …degree=2, gamma=auto, kernel=rbf; total time=   7.7s
[CV] END …degree=2, gamma=auto, kernel=rbf; total time=   7.9s
[CV] END …degree=2, gamma=auto, kernel=rbf; total time=   8.0s
```

```
[CV] END …degree=3, gamma=scale, kernel=poly; total time=  10.2s
[CV] END …degree=3, gamma=scale, kernel=poly; total time=  11.1s
[CV] END …degree=3, gamma=scale, kernel=poly; total time=  11.1s
[CV] END …degree=3, gamma=scale, kernel=poly; total time=   9.9s
[CV] END …degree=3, gamma=scale, kernel=poly; total time=  10.3s
[CV] END …degree=3, gamma=scale, kernel=rbf; total time=   7.3s
[CV] END …degree=3, gamma=scale, kernel=rbf; total time=   8.1s
[CV] END …degree=3, gamma=scale, kernel=rbf; total time=   7.4s
[CV] END …degree=3, gamma=scale, kernel=rbf; total time=   8.3s
[CV] END …degree=3, gamma=scale, kernel=rbf; total time=   6.6s
[CV] END …degree=3, gamma=auto, kernel=poly; total time=   9.0s
[CV] END …degree=3, gamma=auto, kernel=poly; total time=  10.9s
[CV] END …degree=3, gamma=auto, kernel=poly; total time=  10.1s
[CV] END …degree=3, gamma=auto, kernel=poly; total time=  10.3s
[CV] END …degree=3, gamma=auto, kernel=poly; total time=  10.0s
[CV] END …degree=3, gamma=auto, kernel=rbf; total time=   7.5s
[CV] END …degree=3, gamma=auto, kernel=rbf; total time=   7.4s
[CV] END …degree=3, gamma=auto, kernel=rbf; total time=   7.8s
[CV] END …degree=3, gamma=auto, kernel=rbf; total time=   7.5s
[CV] END …degree=3, gamma=auto, kernel=rbf; total time=   8.0s

Fitting Logistic Regression
Fitting 5 folds for each of 6 candidates, totalling 30 fits
[CV] END …C=0.01, penalty=l1; total time=   1.5s
[CV] END …C=0.01, penalty=l1; total time=   2.0s
[CV] END …C=0.01, penalty=l1; total time=   2.0s
[CV] END …C=0.01, penalty=l1; total time=   1.4s
[CV] END …C=0.01, penalty=l1; total time=   1.9s
[CV] END …C=0.01, penalty=l2; total time=   1.6s
[CV] END …C=0.01, penalty=l2; total time=   1.7s
[CV] END …C=0.01, penalty=l2; total time=   1.6s
[CV] END …C=0.01, penalty=l2; total time=   1.7s
[CV] END …C=0.01, penalty=l2; total time=   2.0s
[CV] END …C=0.1, penalty=l1; total time=   7.3s
[CV] END …C=0.1, penalty=l1; total time=   5.4s
[CV] END …C=0.1, penalty=l1; total time=   6.5s
[CV] END …C=0.1, penalty=l1; total time=   6.0s
[CV] END …C=0.1, penalty=l1; total time=  10.8s
[CV] END …C=0.1, penalty=l2; total time=   3.1s
[CV] END …C=0.1, penalty=l2; total time=   3.6s
[CV] END …C=0.1, penalty=l2; total time=   3.4s
[CV] END …C=0.1, penalty=l2; total time=   2.7s
[CV] END …C=0.1, penalty=l2; total time=   3.0s
[CV] END …C=1, penalty=l1; total time=  40.2s
[CV] END …C=1, penalty=l1; total time=  25.7s
[CV] END …C=1, penalty=l1; total time=  31.8s
[CV] END …C=1, penalty=l1; total time=  32.2s
[CV] END …C=1, penalty=l1; total time=  37.3s
```

```
[CV] END …C=1, penalty=l2; total time=   6.6s
[CV] END …C=1, penalty=l2; total time=   5.9s
[CV] END …C=1, penalty=l2; total time=   5.9s
[CV] END …C=1, penalty=l2; total time=   5.4s
[CV] END …C=1, penalty=l2; total time=   6.7s

Fitting Decision Tree
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV] END …max_depth=5, min_samples_leaf=1; total time=   2.2s
[CV] END …max_depth=5, min_samples_leaf=1; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=1; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=1; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=1; total time=   2.8s
[CV] END …max_depth=5, min_samples_leaf=2; total time=   2.3s
[CV] END …max_depth=5, min_samples_leaf=2; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=2; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=2; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=2; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=4; total time=   2.8s
[CV] END …max_depth=5, min_samples_leaf=4; total time=   2.4s
[CV] END …max_depth=5, min_samples_leaf=4; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=4; total time=   2.1s
[CV] END …max_depth=5, min_samples_leaf=4; total time=   2.1s
[CV] END …max_depth=10, min_samples_leaf=1; total time=   4.6s
[CV] END …max_depth=10, min_samples_leaf=1; total time=   4.3s
[CV] END …max_depth=10, min_samples_leaf=1; total time=   4.0s
[CV] END …max_depth=10, min_samples_leaf=1; total time=   4.4s
[CV] END …max_depth=10, min_samples_leaf=1; total time=   4.6s
[CV] END …max_depth=10, min_samples_leaf=2; total time=   4.1s
[CV] END …max_depth=10, min_samples_leaf=2; total time=   4.1s
[CV] END …max_depth=10, min_samples_leaf=2; total time=   4.8s
[CV] END …max_depth=10, min_samples_leaf=2; total time=   3.9s
[CV] END …max_depth=10, min_samples_leaf=2; total time=   4.0s
[CV] END …max_depth=10, min_samples_leaf=4; total time=   5.8s
[CV] END …max_depth=10, min_samples_leaf=4; total time=   4.5s
[CV] END …max_depth=10, min_samples_leaf=4; total time=   4.0s
[CV] END …max_depth=10, min_samples_leaf=4; total time=   4.5s
[CV] END …max_depth=10, min_samples_leaf=4; total time=   4.4s
[CV] END …max_depth=None, min_samples_leaf=1; total time=   8.3s
[CV] END …max_depth=None, min_samples_leaf=1; total time=   8.6s
[CV] END …max_depth=None, min_samples_leaf=1; total time=   8.8s
[CV] END …max_depth=None, min_samples_leaf=1; total time=   8.1s
[CV] END …max_depth=None, min_samples_leaf=1; total time=  10.9s
[CV] END …max_depth=None, min_samples_leaf=2; total time=   9.0s
[CV] END …max_depth=None, min_samples_leaf=2; total time=   7.6s
[CV] END …max_depth=None, min_samples_leaf=2; total time=   8.9s
[CV] END …max_depth=None, min_samples_leaf=2; total time=   9.2s
[CV] END …max_depth=None, min_samples_leaf=2; total time=  10.2s
```

```
[CV] END …max_depth=None, min_samples_leaf=4; total time=   9.1s
[CV] END …max_depth=None, min_samples_leaf=4; total time=   8.3s
[CV] END …max_depth=None, min_samples_leaf=4; total time=   8.0s
[CV] END …max_depth=None, min_samples_leaf=4; total time=   9.1s
[CV] END …max_depth=None, min_samples_leaf=4; total time=  10.9s
```

We obtain the optimized hyperparameters and compute the baseline performance on the imbalanced dataset using macro-averaged F1-score as the metric.

[ ]:
```python
baseline_svc_params = svc_grid.best_params_
baseline_logreg_params = logreg_grid.best_params_
baseline_tree_params = tree_grid.best_params_
```

[ ]:
```python
from sklearn.metrics import f1_score
```

[ ]:
```python
baseline_svc.fit(X_train, y_train)
baseline_logreg.fit(X_train, y_train)
baseline_tree.fit(X_train, y_train)

svc_train_score = f1_score(y_train, baseline_svc.predict(X_train),␣
 ↪average="macro")
logreg_train_score = f1_score(y_train, baseline_logreg.predict(X_train),␣
 ↪average="macro")
tree_train_score = f1_score(y_train, baseline_tree.predict(X_train),␣
 ↪average="macro")

svc_test_score = f1_score(y_test, baseline_svc.predict(X_test), average="macro")
logreg_test_score = f1_score(y_test, baseline_logreg.predict(X_test),␣
 ↪average="macro")
tree_test_score = f1_score(y_test, baseline_tree.predict(X_test),␣
 ↪average="macro")

print(f"SVC train score: {svc_train_score}")
print(f"SVC test score: {svc_test_score}")
print(f"Logistic Regression train score: {logreg_train_score}")
print(f"Logistic Regression test score: {logreg_test_score}")
print(f"Decision Tree train score: {tree_train_score}")
print(f"Decision Tree test score: {tree_test_score}")
```

```
SVC train score: 0.9487467078627851
SVC test score: 0.8667468233242389
Logistic Regression train score: 0.8684941626785421
Logistic Regression test score: 0.8408095081608062
Decision Tree train score: 0.9529418840132171
Decision Tree test score: 0.8495030592427718
```

The classifiers actually perform decently on the imbalanced data. We will now use some sampling strategies to overcome the imbalance and obtain better performance.

2 Task 2

To keep track of the class balance, we will use the `Counter` class from the `collections` library.

[ ]:
```
from collections import Counter
```

[ ]:
```
print(Counter(y_train))
```

```
Counter({'neg': 40036, 'pos': 652})
```

Undersampling the majority class

We will first undersample the majority class ('neg') to overcome the class imbalance. We can do so using the `RandomUnderSampler` class of the `imblearn` library.

[ ]:
```
from imblearn.under_sampling import RandomUnderSampler
```

[ ]:
```
undersampler = RandomUnderSampler(random_state=5401,␣
↪sampling_strategy="majority")
X_train_under, y_train_under = undersampler.fit_resample(X_train, y_train)
print(Counter(y_train_under))
```

```
Counter({'neg': 652, 'pos': 652})
```

The number of datapoints in the training set has been reduced due to the undersampling. We fit the 3 hyperparameter-optimized classification algorithms with this training data.

[ ]:
```
svc_undersampling = SVC(**baseline_svc_params)
logreg_undersampling = LogisticRegression(**baseline_logreg_params,␣
↪solver="liblinear")
tree_undersampling = DecisionTreeClassifier(**baseline_tree_params)
```

[ ]:
```
svc_undersampling.fit(X_train_under, y_train_under)
logreg_undersampling.fit(X_train_under, y_train_under)
tree_undersampling.fit(X_train_under, y_train_under)

svc_undersampling_train_score = f1_score(y_train_under, svc_undersampling.
↪predict(X_train_under), average="macro")
logreg_undersampling_train_score = f1_score(y_train_under, logreg_undersampling.
↪predict(X_train_under), average="macro")
tree_undersampling_train_score = f1_score(y_train_under, tree_undersampling.
↪predict(X_train_under), average="macro")

svc_undersampling_test_score = f1_score(y_test, svc_undersampling.
↪predict(X_test), average="macro")
logreg_undersampling_test_score = f1_score(y_test, logreg_undersampling.
↪predict(X_test), average="macro")
tree_undersampling_test_score = f1_score(y_test, tree_undersampling.
↪predict(X_test), average="macro")
```

```
print(f"Undersampling SVC train score: {svc_undersampling_train_score}")
print(f"Undersampling SVC test score: {svc_undersampling_test_score}")
print(f"Undersampling Logistic Regression train score: 
 ↪{logreg_undersampling_train_score}")
print(f"Undersampling Logistic Regression test score: 
 ↪{logreg_undersampling_test_score}")
print(f"Undersampling Decision Tree train score: 
 ↪{tree_undersampling_train_score}")
print(f"Undersampling Decision Tree test score: 
 ↪{tree_undersampling_test_score}")
```

```
Undersampling SVC train score: 0.9646872932183873
Undersampling SVC test score: 0.7290021995766903
Undersampling Logistic Regression train score: 0.9654849314198293
Undersampling Logistic Regression test score: 0.6942524457760246
Undersampling Decision Tree train score: 0.9930978307215931
Undersampling Decision Tree test score: 0.6414801858050804
```

We will compare all the sampling strategies at the end.

Oversampling the minority class

We then oversample the minority class (‘pos’) to overcome the class imbalance. We can do so using the `RandomOverSampler` class of the `imblearn` library.

[ ]:
```
from imblearn.over_sampling import RandomOverSampler
```

[ ]:
```
oversampler = RandomOverSampler(random_state=5401, sampling_strategy="minority")
X_train_over, y_train_over = oversampler.fit_resample(X_train, y_train)
print(Counter(y_train_over))
```

```
Counter({'neg': 40036, 'pos': 40036})
```

The number of datapoints in the training set has been increased due to the oversampling. We fit the 3 hyperparameter-optimized classification algorithms with this training data.

[ ]:
```
svc_oversampling = SVC(**baseline_svc_params)
logreg_oversampling = LogisticRegression(**baseline_logreg_params,
 ↪solver="liblinear")
tree_oversampling = DecisionTreeClassifier(**baseline_tree_params)
```

[ ]:
```
svc_oversampling.fit(X_train_over, y_train_over)
logreg_oversampling.fit(X_train_over, y_train_over)
tree_oversampling.fit(X_train_over, y_train_over)

svc_oversampling_train_score = f1_score(y_train_over, svc_oversampling.
 ↪predict(X_train_over), average="macro")
```

```
logreg_oversampling_train_score = f1_score(y_train_over, logreg_oversampling.
 ↪predict(X_train_over), average="macro")
tree_oversampling_train_score = f1_score(y_train_over, tree_oversampling.
 ↪predict(X_train_over), average="macro")

svc_oversampling_test_score = f1_score(y_test, svc_oversampling.
 ↪predict(X_test), average="macro")
logreg_oversampling_test_score = f1_score(y_test, logreg_oversampling.
 ↪predict(X_test), average="macro")
tree_oversampling_test_score = f1_score(y_test, tree_oversampling.
 ↪predict(X_test), average="macro")

print(f"Oversampling SVC train score: {svc_oversampling_train_score}")
print(f"Oversampling SVC test score: {svc_oversampling_test_score}")
print(f"Oversampling Logistic Regression train score:␣
 ↪{logreg_oversampling_train_score}")
print(f"Oversampling Logistic Regression test score:␣
 ↪{logreg_oversampling_test_score}")
print(f"Oversampling Decision Tree train score:␣
 ↪{tree_oversampling_train_score}")
print(f"Oversampling Decision Tree test score: {tree_oversampling_test_score}")
```

```
Oversampling SVC train score: 0.9797386348597599
Oversampling SVC test score: 0.8302525916192145
Oversampling Logistic Regression train score: 0.962001942189947
Oversampling Logistic Regression test score: 0.7669832029733352
Oversampling Decision Tree train score: 0.9843755155880201
Oversampling Decision Tree test score: 0.7434434443515703
```

Using `class_weight`

We then use the `class_weight` parameter of the 3 algorithms to deal with the class imbalance. Setting it to '`balanced`' allows the algorithms to better classify the minority class.

[ ]:
```
svc_class_weight = SVC(**baseline_svc_params, class_weight="balanced")
logreg_class_weight = LogisticRegression(**baseline_logreg_params,␣
 ↪solver="liblinear", class_weight="balanced")
tree_class_weight = DecisionTreeClassifier(**baseline_tree_params,␣
 ↪class_weight="balanced")
```

[ ]:
```
svc_class_weight.fit(X_train, y_train)
logreg_class_weight.fit(X_train, y_train)
tree_class_weight.fit(X_train, y_train)

svc_class_train_score = f1_score(y_train, svc_class_weight.predict(X_train),␣
 ↪average="macro")
```

```
logreg_class_train_score = f1_score(y_train, logreg_class_weight.
 ↪predict(X_train), average="macro")
tree_class_train_score = f1_score(y_train, tree_class_weight.predict(X_train),␣
 ↪average="macro")

svc_class_test_score = f1_score(y_test, svc_class_weight.predict(X_test),␣
 ↪average="macro")
logreg_class_test_score = f1_score(y_test, logreg_class_weight.predict(X_test),␣
 ↪average="macro")
tree_class_test_score = f1_score(y_test, tree_class_weight.predict(X_test),␣
 ↪average="macro")

print(f"Class Weight SVC train score: {svc_class_train_score}")
print(f"Class Weight SVC test score: {svc_class_test_score}")
print(f"Class Weight Logistic Regression train score:␣
 ↪{logreg_class_train_score}")
print(f"Class Weight Logistic Regression test score: {logreg_class_test_score}")
print(f"Class Weight Decision Tree train score: {tree_class_train_score}")
print(f"Class Weight Decision Tree test score: {tree_class_test_score}")
```

```
Class Weight SVC train score: 0.9039305766072113
Class Weight SVC test score: 0.829674868674819
Class Weight Logistic Regression train score: 0.7730223776731191
Class Weight Logistic Regression test score: 0.7682367938494301
Class Weight Decision Tree train score: 0.7905370485118826
Class Weight Decision Tree test score: 0.7463994007877692
```

Using `sample_weights`

The last method to deal with the imbalance is to attach more weight to the samples from the minority class. This can be done using `sklearn`'s `compute_sample_weight` function.

[ ]:
```
from sklearn.utils.class_weight import compute_sample_weight
```

[ ]:
```
sample_weights = compute_sample_weight("balanced", y_train)
```

[ ]:
```
svc_sample_weights = SVC(**baseline_svc_params)
logreg_sample_weights = LogisticRegression(**baseline_logreg_params,␣
 ↪solver="liblinear")
tree_sample_weights = DecisionTreeClassifier(**baseline_tree_params)
```

[ ]:
```
svc_sample_weights.fit(X_train, y_train, sample_weight=sample_weights)
logreg_sample_weights.fit(X_train, y_train, sample_weight=sample_weights)
tree_sample_weights.fit(X_train, y_train, sample_weight=sample_weights)

svc_sample_train_score = f1_score(y_train, svc_sample_weights.predict(X_train),␣
 ↪average="macro")
```

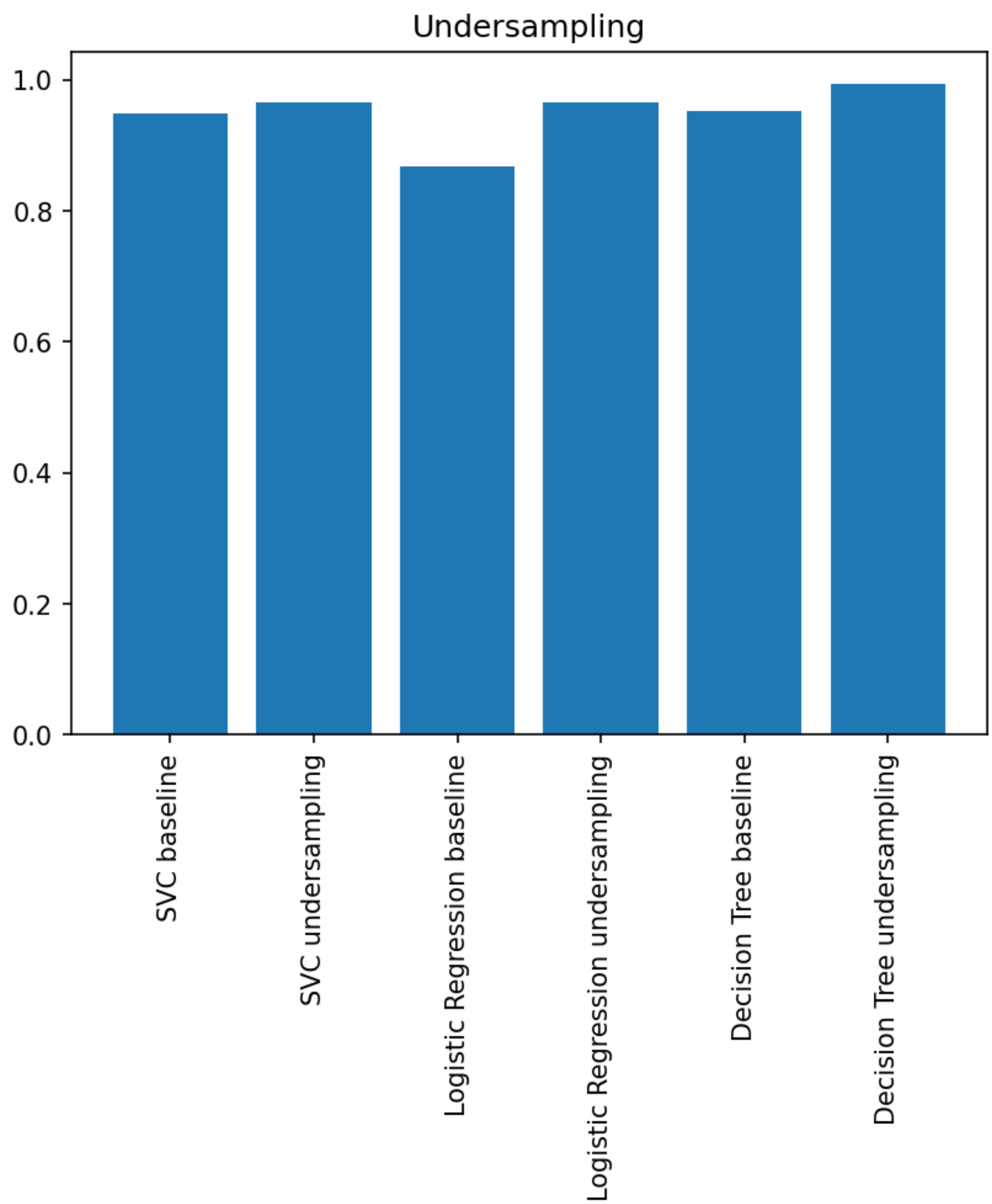
```
logreg_sample_train_score = f1_score(y_train, logreg_sample_weights.
 ↪predict(X_train), average="macro")
tree_sample_train_score = f1_score(y_train, tree_sample_weights.
 ↪predict(X_train), average="macro")

svc_sample_test_score = f1_score(y_test, svc_sample_weights.predict(X_test),␣
 ↪average="macro")
logreg_sample_test_score = f1_score(y_test, logreg_sample_weights.
 ↪predict(X_test), average="macro")
tree_sample_test_score = f1_score(y_test, tree_sample_weights.predict(X_test),␣
 ↪average="macro")

print(f"Sample Weights SVC train score: {svc_sample_train_score}")
print(f"Sample Weights SVC test score: {svc_sample_test_score}")
print(f"Sample Weights Logistic Regression train score:␣
 ↪{logreg_sample_train_score}")
print(f"Sample Weights Logistic Regression test score:␣
 ↪{logreg_sample_test_score}")
print(f"Sample Weights Decision Tree train score: {tree_sample_train_score}")
print(f"Sample Weights Decision Tree test score: {tree_sample_test_score}")
```

```
Sample Weights SVC train score: 0.9039305766072113
Sample Weights SVC test score: 0.829674868674819
Sample Weights Logistic Regression train score: 0.7730223776731191
Sample Weights Logistic Regression test score: 0.7672956265348699
Sample Weights Decision Tree train score: 0.7906794652380246
Sample Weights Decision Tree test score: 0.7469252148215904
```

Visualising the performance

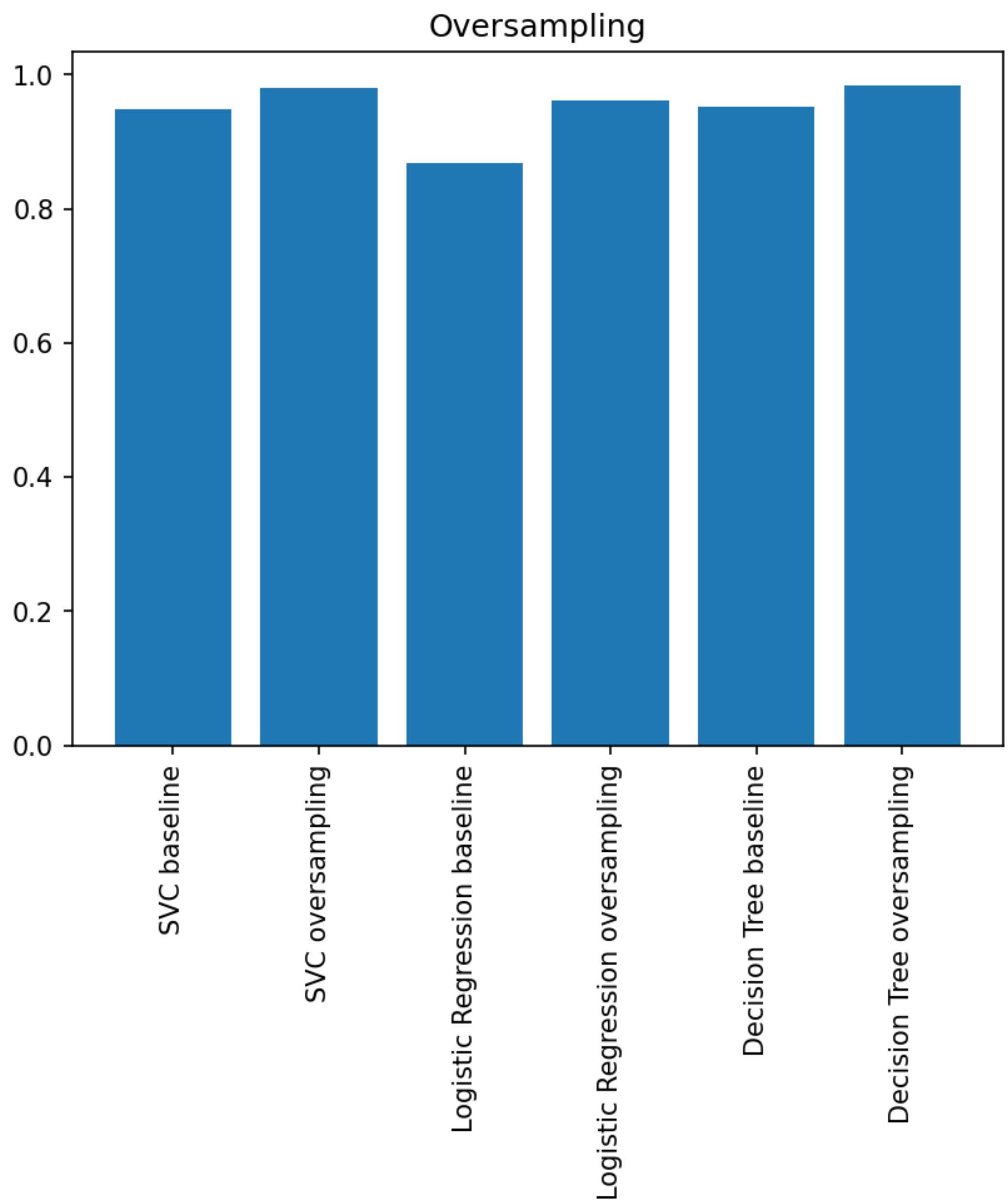
We then visualise the performance of all the sampling strategies using the training set.

[ ]:
```
plt.figure(dpi=150)
plt.title("Undersampling")
plt.bar(["SVC baseline","SVC undersampling","Logistic Regression␣
 ↪baseline","Logistic Regression undersampling","Decision Tree␣
 ↪baseline","Decision Tree undersampling"],
        [svc_train_score, svc_undersampling_train_score, logreg_train_score,␣
 ↪logreg_undersampling_train_score, tree_train_score,␣
 ↪tree_undersampling_train_score])
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```
plt.figure(dpi=150)
plt.title("Oversampling")
plt.bar(["SVC baseline","SVC oversampling","Logistic Regression␣
 ↪baseline","Logistic Regression oversampling","Decision Tree␣
 ↪baseline","Decision Tree oversampling"],
        [svc_train_score, svc_oversampling_train_score, logreg_train_score,␣
 ↪logreg_oversampling_train_score, tree_train_score,␣
 ↪tree_oversampling_train_score])
plt.xticks(rotation=90)
```

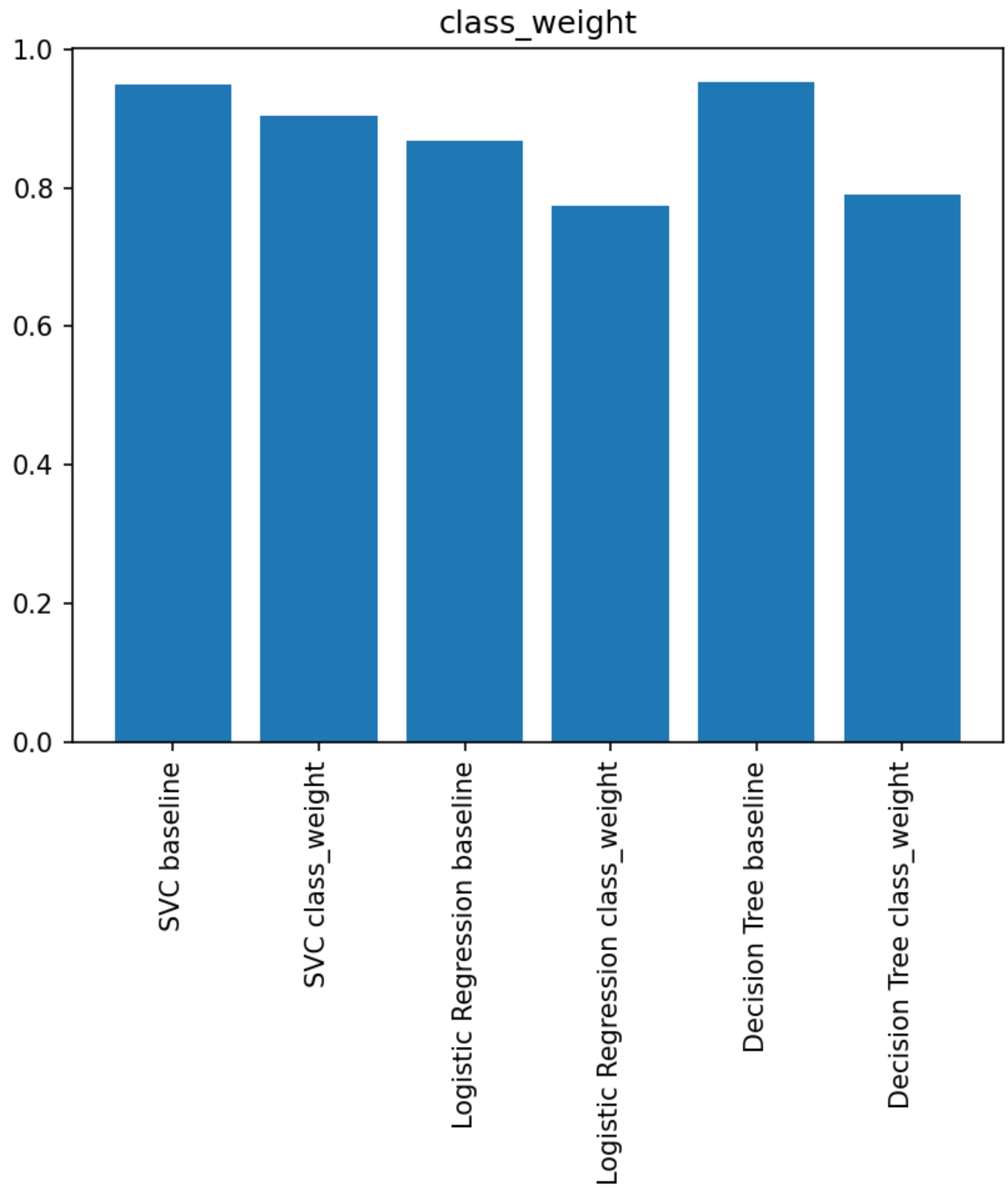
```
plt.show()
```



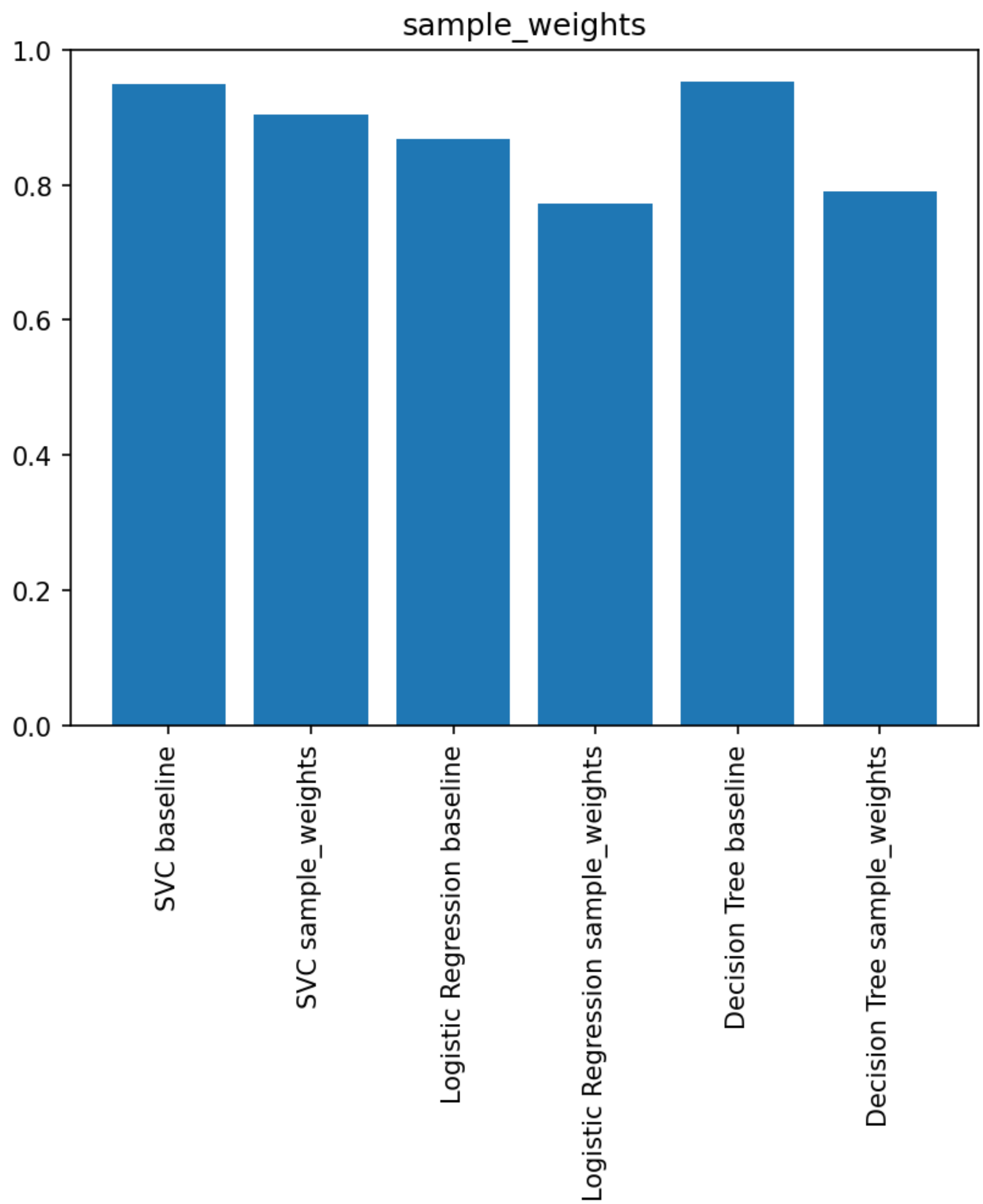
Both undersampling and oversampling achieve better training performance for all 3 algorithms than when the imbalanced dataset is used directly.

[ ]:
```
plt.figure(dpi=150)
plt.title("class_weight")
```

```
plt.bar(["SVC baseline","SVC class_weight","Logistic Regression␣
↪baseline","Logistic Regression class_weight","Decision Tree␣
↪baseline","Decision Tree class_weight"],
        [svc_train_score, svc_class_train_score, logreg_train_score,␣
↪logreg_class_train_score, tree_train_score, tree_class_train_score])
plt.xticks(rotation=90)
plt.show()
```



[ ]:
```
plt.figure(dpi=150)
plt.title("sample_weights")
plt.bar(["SVC baseline","SVC sample_weights","Logistic Regression␣
↪baseline","Logistic Regression sample_weights","Decision Tree␣
↪baseline","Decision Tree sample_weights"],
        [svc_train_score, svc_sample_train_score, logreg_train_score,␣
↪logreg_sample_train_score, tree_train_score, tree_sample_train_score])
plt.xticks(rotation=90)
plt.show()
```



Both class weights and sample weights achieve poorer training performance for all 3 algorithms than when the imbalanced dataset is used directly.

Thus, we can conclude that oversampling or undersampling are better strategies to deal with the class imbalance of the given dataset.