pn-coupons

December 10, 2021

[1]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

# import os
# for dirname, _, filenames in os.walk('/kaggle/input'):
#     for filename in filenames:
#         print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

[2]:
```
from tqdm.auto import tqdm
from sklearn.naive_bayes import BernoulliNB, GaussianNB
from sklearn.decomposition import PCA, FastICA
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
import seaborn as sns
from matplotlib import pyplot as plt
import statsmodels.api as sm

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.manifold import TSNE
```

```
import time
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score, f1_score
```

[3]:
```
train = pd.read_csv('data/train.csv')
```

[4]:
```
train.describe()
```

[4]:
```
                 id      Decision   Temperature      Children           Bar  \
count  10184.000000  10184.000000  10184.000000  10184.000000  10091.000000
mean    5092.500000      0.569914     63.361155      0.414277      1.038846
std     2940.011905      0.495112     19.137079      0.492621      1.095480
min        1.000000      0.000000     30.000000      0.000000      0.000000
25%     2546.750000      0.000000     55.000000      0.000000      0.000000
50%     5092.500000      1.000000     80.000000      0.000000      1.000000
75%     7638.250000      1.000000     80.000000      1.000000      2.000000
max    10184.000000      1.000000     80.000000      1.000000      4.000000

        Coffeehouse     Carryaway  Restaurantlessthan20  Restaurant20to50  \
count  10002.000000  10059.000000          10079.000000      10033.000000
mean       1.574285      2.416741              2.283064          1.269909
std        1.238135      0.929992              0.919968          0.882393
min        0.000000      0.000000              0.000000          0.000000
25%        1.000000      2.000000              2.000000          1.000000
50%        1.000000      2.000000              2.000000          1.000000
75%        2.000000      3.000000              3.000000          2.000000
max        4.000000      4.000000              4.000000          4.000000

       Direction_same      Distance
count    10184.000000  10184.000000
mean         0.211115      1.684309
std          0.408120      0.675322
min          0.000000      1.000000
25%          0.000000      1.000000
50%          0.000000      2.000000
75%          0.000000      2.000000
max          1.000000      3.000000
```

[5]:
```
def find_unique(frame):
    unique_values = []
    for column_name in frame.columns:
        column = frame[column_name]
        unique_values.append((column_name, column.unique().shape[0], column.
↪dtype))
    return pd.DataFrame(unique_values, columns=['column', 'count', 'dtype'])

find_unique(train)
```

[5]:

	column	count	dtype
0	id	10184	int64
1	Decision	2	int64
2	Driving_to	3	object
3	Passanger	4	object
4	Weather	3	object
5	Temperature	3	int64
6	Time	5	object
7	Coupon	5	object
8	Coupon_validity	2	object
9	Gender	2	object
10	Age	8	object
11	Maritalstatus	5	object
12	Children	2	int64
13	Education	6	object
14	Occupation	25	object
15	Income	9	object
16	Bar	6	float64
17	Coffeehouse	6	float64
18	Carryaway	6	float64
19	Restaurantlessthan20	6	float64
20	Restaurant20to50	6	float64
21	Direction_same	2	int64
22	Distance	3	int64

https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html

[6]:

```
x_train, y_train, ids = (
    train[train.columns[~np.isin(train.columns, ('Decision', 'id'))]],
    train['Decision'], train['id']
)
```

[7]:

```
x_train_dummies, filled = pd.get_dummies(x_train), {}
x_train_not_na = x_train_dummies.dropna()

for col in tqdm(x_train_dummies.columns):
    x_train_minus_col = x_train_not_na[
        x_train_not_na.columns[x_train_not_na.columns != col]]
    bnb = BernoulliNB()
    bnb.fit(x_train_minus_col,
            x_train_not_na.loc[x_train_minus_col.index, col])
    pred = bnb.predict(x_train_dummies[x_train_minus_col.columns]
                       .fillna(method='ffill'))
    filled[col] = pred

x_train_imputed = x_train_dummies.fillna(pd.DataFrame(filled))
```

```
scaler = MinMaxScaler()
x_train_scaled = pd.DataFrame(scaler.fit_transform(x_train_imputed),
                              index=x_train_imputed.index,
                              columns=x_train_imputed.columns)
```

```
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```

[8]:
```
# tsne = TSNE()
# x2d = tsne.fit_transform(x_train_scaled)
```

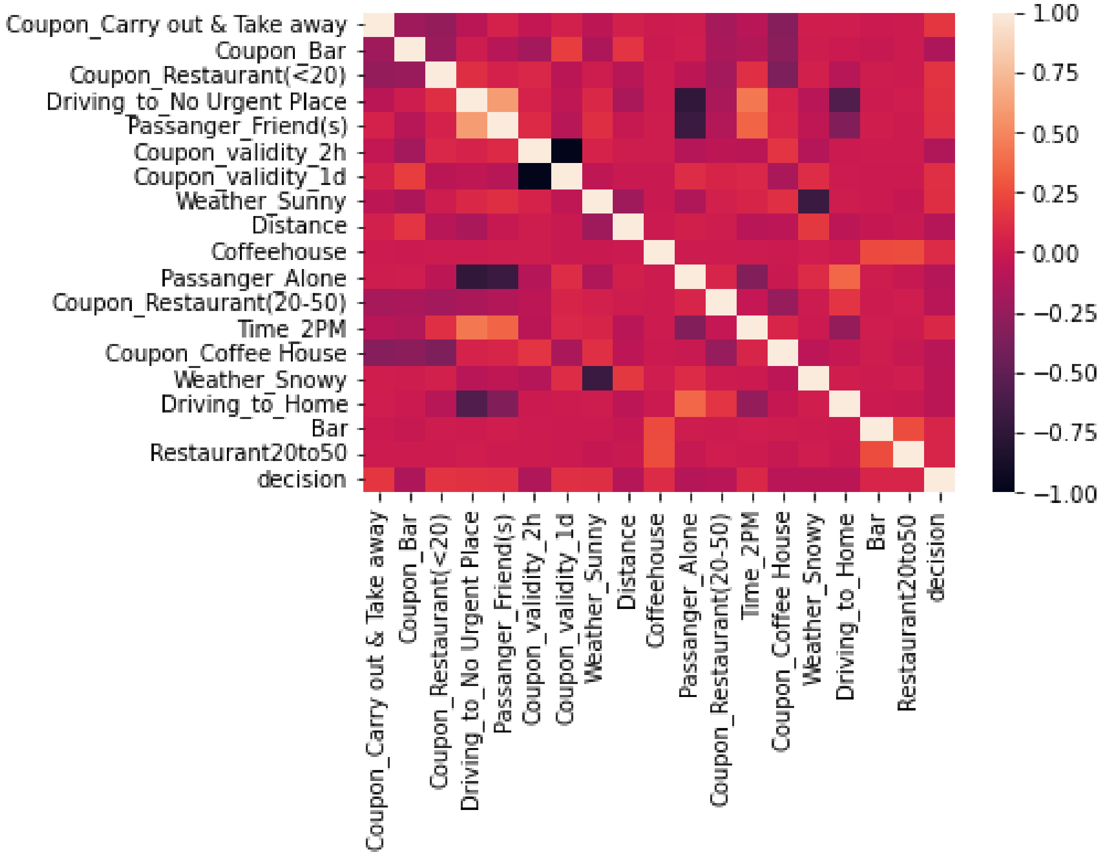
[9]:
```
# fig, ax = plt.subplots()
# ax.scatter(x2d[:, 0], x2d[:, 1], s=3)
# ax.set_title('t-SNE reduction')
# plt.show()
```

[10]:
```
corrs = x_train_imputed.assign(decision=y_train).corr()['decision'].abs().
 ↪drop('decision').sort_values(ascending=False)
corrs
```

[10]:
```
Coupon_Carry out & Take away                        0.162444
Coupon_Bar                                          0.146025
Coupon_Restaurant(<20)                              0.144975
Driving_to_No Urgent Place                          0.133277
Passanger_Friend(s)                                 0.130095
                                                      …
Occupation_Installation Maintenance & Repair        0.001325
Occupation_Farming Fishing & Forestry               0.001296
Maritalstatus_Unmarried partner                     0.000723
Occupation_Food Preparation & Serving Related       0.000105
Occupation_Sales & Related                          0.000032
Name: decision, Length: 86, dtype: float64
```

[11]:
```
fig, ax = plt.subplots()
sns.heatmap(x_train_imputed
            .assign(decision=y_train)
            .loc[:, corrs.index[corrs > 0.075].append(pd.Index(['decision']))]
            .corr())
```

[11]:
```
<AxesSubplot:>
```



1 Model 1: Bernoulli Naive Bayes with ICA

[12]:
```
fast_ica = FastICA(24, max_iter=3000, tol=0.001)
x_train_ica = fast_ica.fit_transform(x_train_scaled)
X_train_ica, X_test_ica, Y_train_ica, Y_test_ica = train_test_split(
    x_train_ica, y_train, train_size=0.6
)

gnb = GaussianNB()
gnb.fit(X_train_ica, Y_train_ica)
gnb.score(X_test_ica, Y_test_ica)
```

```
/home/nimkar/miniconda3/envs/police/lib/python3.9/site-
packages/sklearn/decomposition/_fastica.py:116: ConvergenceWarning: FastICA did
not converge. Consider increasing tolerance or the maximum number of iterations.
  warnings.warn(
```

[12]: 0.6512027491408935

[13]:
```
gnb_pred, gnb_proba = gnb.predict(X_test_ica), gnb.predict_proba(X_test_ica)[:,␣
↪1]
print('roc auc score:', roc_auc_score(Y_test_ica, gnb_proba))
print('f1 score:', f1_score(Y_test_ica, gnb_pred))
```

```
roc auc score: 0.6927067013300584
f1 score: 0.7179996030958522
```

2 Model 2: Logistic Regression with PCA

First we shall show the performance of a simple logistic regression model. The performance of more advanced linear classification models such as Ridge classifier were in the similar range as the simple logistic regression in this case

[14]:
```
X_train, X_test, Y_train, Y_test = train_test_split(
    x_train_scaled, y_train, train_size=0.6, random_state=1)
```

[14]:
```
lr = LogisticRegression()
lr.fit(X_train.to_numpy(), Y_train.to_numpy())
lr.score(X_test, Y_test)
```

We see a significant improvement after applying PCA

[15]:
```
pca = PCA(0.99)
x_train_pca = pca.fit_transform(x_train_scaled)
X_train_pca, X_test_pca, Y_train_pca, Y_test_pca = train_test_split(
    x_train_pca, y_train, train_size=0.6)

lr_pca = LogisticRegression(C=1)
lr_pca.fit(X_train_pca, Y_train_pca)
lr_pca.score(X_test_pca, Y_test_pca)
```

[15]:
```
0.6779577810505646
```

[16]:
```
lr_pca_pred, lr_pca_proba = lr_pca.predict(X_test_pca), lr_pca.
↪predict_proba(X_test_pca)[:, 1]
print('roc auc score:', roc_auc_score(Y_test_pca, lr_pca_proba))
print('f1 score:', f1_score(Y_test_pca, lr_pca_pred))
```

```
roc auc score: 0.7327057493593443
f1 score: 0.7290375877736472
```

3 Restoring the original X_train

[17]:
```
X_train, X_test, Y_train, Y_test = train_test_split(
    x_train_scaled, y_train, train_size=0.6, random_state=1)
```

4 Deriving sample weights

[18]:
```
knn = KNeighborsClassifier()
knn.fit(X_train, Y_train)
Y_pred_knn = knn.predict(X_train)
print((Y_train != Y_pred_knn).mean())

Sample_weight = np.where(Y_train != Y_pred_knn, 2, 1)
Sample_weight = Sample_weight / Sample_weight.sum()
```

```
/home/nimkar/miniconda3/envs/police/lib/python3.9/site-
packages/sklearn/base.py:441: UserWarning: X does not have valid feature names,
but KNeighborsClassifier was fitted with feature names
  warnings.warn(
```

```
0.19574468085106383
```

5 Model 3: Random forest classifier

[19]:
```
n_estimator_score = []
for md in tqdm((256, 128, 64, 32, 16, 8, 4, 2)):
    for ne in tqdm((30, 54, 100, 180, 300, 540)):
        forest = RandomForestClassifier(
            n_estimators=ne, random_state=2, min_samples_split=3,
            max_depth=md
        )
        forest.fit(X_train, Y_train, sample_weight=Sample_weight)
        score = forest.score(X_test, Y_test)
        n_estimator_score.append((ne, md, score))
```

```
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  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]

  0%|          | 0/6 [00:00<?, ?it/s]
```

```
0%|          | 0/6 [00:00<?, ?it/s]
```

[20]:
```
nescore = pd.DataFrame(n_estimator_score, columns=['n_estimator', 'max_depth',␣
↪'score'])
```

[21]:
```
print(nescore
      .groupby(['n_estimator', 'max_depth'])
      .agg({'score': 'mean'})
      .unstack()
      .droplevel(0, axis=1)
      .to_latex())
```

```
\begin{tabular}{lrrrrrrrr}
\toprule
max\_depth &       2   &       4   &       8   &       16  &       32  &
64  &       128 &       256 \\
n\_estimator &           &           &           &           &           &
&           &           \\
\midrule
30          &  0.608493 &  0.674767 &  0.704222 &  0.723368 &  0.725331 &
0.728522 &  0.728522 &  0.728522 \\
54          &  0.620275 &  0.679431 &  0.710604 &  0.733922 &  0.734659 &
0.734413 &  0.734413 &  0.734413 \\
100         &  0.623466 &  0.684094 &  0.716249 &  0.735641 &  0.737850 &
0.738832 &  0.738832 &  0.738832 \\
180         &  0.619784 &  0.683358 &  0.720668 &  0.735886 &  0.740304 &
0.742268 &  0.742268 &  0.742268 \\
300         &  0.616593 &  0.681640 &  0.719440 &  0.737850 &  0.741532 &
0.742023 &  0.742023 &  0.742023 \\
540         &  0.617329 &  0.680167 &  0.720668 &  0.739813 &  0.739323 &
0.739323 &  0.739323 &  0.739323 \\
\bottomrule
\end{tabular}
```

[22]:
```
big_forest = RandomForestClassifier(
    n_estimators=3000, max_depth=128, min_samples_split=3)
big_forest.fit(X_train, Y_train)
big_forest.score(X_test, Y_test)
```

[22]: 0.7417771232204222

[23]:
```
big_forest_pred, big_forest_proba = (
    big_forest.predict(X_test), big_forest.predict_proba(X_test)[:, 1])
print('roc auc score:', roc_auc_score(Y_test, big_forest_proba))
print('f1 score:', f1_score(Y_test, big_forest_pred))
```

```
roc auc score: 0.8087146542777136
```

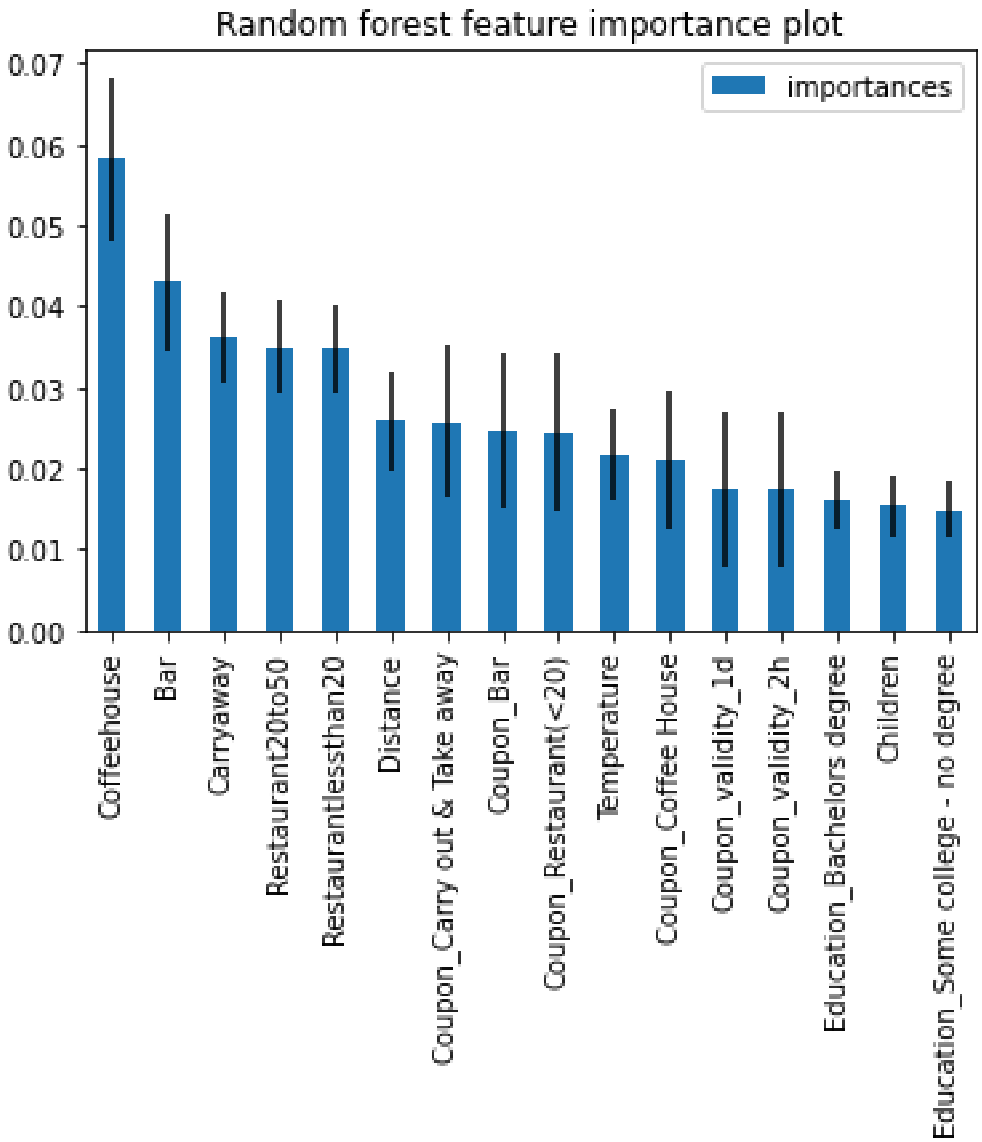
```
f1 score: 0.786178861788618
```

[24]:

```
importances = big_forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in big_forest.estimators_],␣
 ↪axis=0)
importance_frame = (
    pd.DataFrame({'importances': importances, 'yerr': std},
                 index=x_train_scaled.columns)
    .sort_values('importances', ascending=False)
)
```

[25]:

```
fig, ax = plt.subplots()
importance_frame.head(16).plot.bar(yerr='yerr', ax=ax)
ax.set_title('Random forest feature importance plot')
plt.show()
```



6 Model 4: Gradient boosting classifier

Unfortunately, I deleted the cell where I searched for the optimal parameters using GridSearchCV. However, I had saved the output of the cell in an image which is attached in the project write-up.

[26]:
```
gbcf = GradientBoostingClassifier(
    max_depth=None, min_samples_split=8, learning_rate=0.018,
    n_estimators=400, random_state=2, subsample=0.3
)
gbcf.fit(X_train, Y_train, sample_weight=Sample_weight)
gbcf.score(X_test, Y_test)
```

[26]: 0.7538046146293569

[27]:
```
gbcf_pred, gbcf_proba = (
    gbcf.predict(X_test), gbcf.predict_proba(X_test)[:, 1])
print('roc auc score:', roc_auc_score(Y_test, gbcf_proba))
print('f1 score:', f1_score(Y_test, gbcf_pred))
```

```
roc auc score: 0.8239727955431101
f1 score: 0.7915194346289751
```

7 Loading and preparing the test data

[29]:
```
test = pd.read_csv('data/test.csv')

x_test = test[test.columns[test.columns != 'id']]
test_id = test['id']

x_test_dummies, filled = pd.get_dummies(x_test), {}
x_test_not_na = x_test_dummies.dropna()

for col in tqdm(x_test_dummies.columns):
    x_test_minus_col = x_test_not_na[
        x_test_not_na.columns[x_test_not_na.columns != col]]
    bnb = BernoulliNB()
    bnb.fit(x_test_minus_col,
            x_test_not_na.loc[x_test_minus_col.index, col])
    pred = bnb.predict(x_test_dummies[x_test_minus_col.columns]
                       .fillna(method='ffill'))
    filled[col] = pred

x_test_imputed = x_test_dummies.fillna(pd.DataFrame(filled))
x_test_scaled = pd.DataFrame(scaler.transform(x_test_imputed),
                             index=x_test_imputed.index,
                             columns=x_test_imputed.columns)

x_test_scaled = x_test_scaled.loc[:, x_train_scaled.columns]
```

```
  0%|          | 0/86 [00:00<?, ?it/s]
```

8 Training the final classifier on the complete training data

We are using the parameters obtained earlier directly to train the new classifier

[30]:
```
knn = KNeighborsClassifier()
knn.fit(x_train_scaled, y_train)
y_pred_knn = knn.predict(x_train_scaled)
```

```
print((y_train != y_pred_knn).mean())

sample_weight = np.where(y_train != y_pred_knn, 2, 1)
sample_weight = sample_weight / sample_weight.sum()
```

```
/home/nimkar/miniconda3/envs/police/lib/python3.9/site-
packages/sklearn/base.py:441: UserWarning: X does not have valid feature names,
but KNeighborsClassifier was fitted with feature names
  warnings.warn(
```

```
0.1923605655930872
```

[31]:
```
start = time.time()
gbcf_final = GradientBoostingClassifier(
    max_depth=None, min_samples_split=3, learning_rate=0.018,
    n_estimators=250, random_state=2, subsample=0.3
)
gbcf_final.fit(x_train_scaled, y_train, sample_weight=sample_weight)
elapsed = time.time() - start
print(f'trained in {elapsed} seconds')
```

```
trained in 21.044183492660522 seconds
```

[32]:
```
start = time.time()
final_big_forest = RandomForestClassifier(
    n_estimators=3000, max_depth=128, min_samples_split=3)
final_big_forest.fit(x_train_scaled, y_train, sample_weight=sample_weight)
elapsed = time.time() - start
print(f'trained in {elapsed} seconds')
```

```
trained in 31.831401348114014 seconds
```

9 Obtaining the prediction on test data

[33]:
```
preds = gbcf_final.predict(x_test_scaled)
pd.DataFrame({'id': test_id, 'Decision': preds}).set_index('id').to_csv('output.
↪csv')
```

[ ]:
```
```