Template for Kaggle InClass Competition Report

CompSci 671
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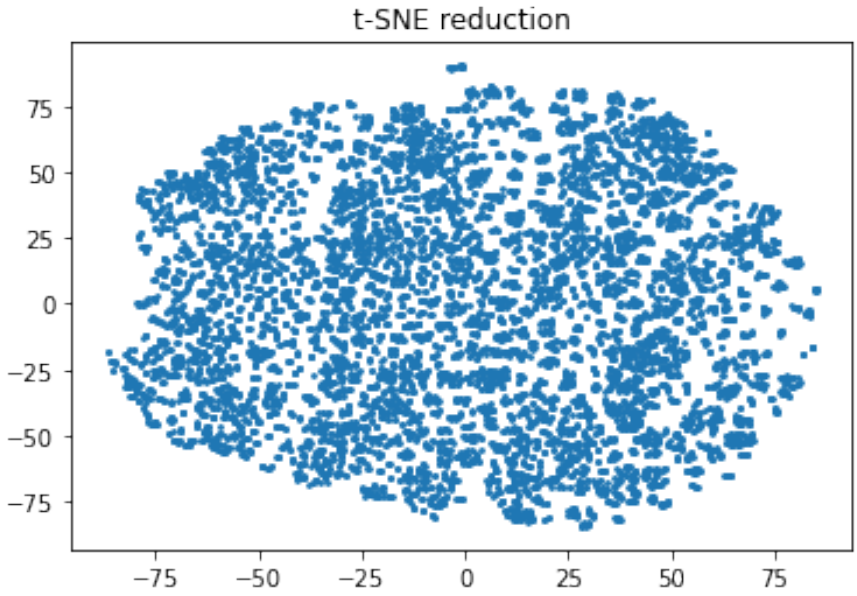
1 Introduction

This report is a part of final project towards for CS671 class. The data used for this project was originally presented by [Wang et al., 2017] as a survey conducted via Amazon Mechanical Turks. The survey describes different driving scenarios including the destination, current time, weather, passenger, etc., and then ask the person whether he will accept the coupon if he is the driver.

2 Exploratory Analysis

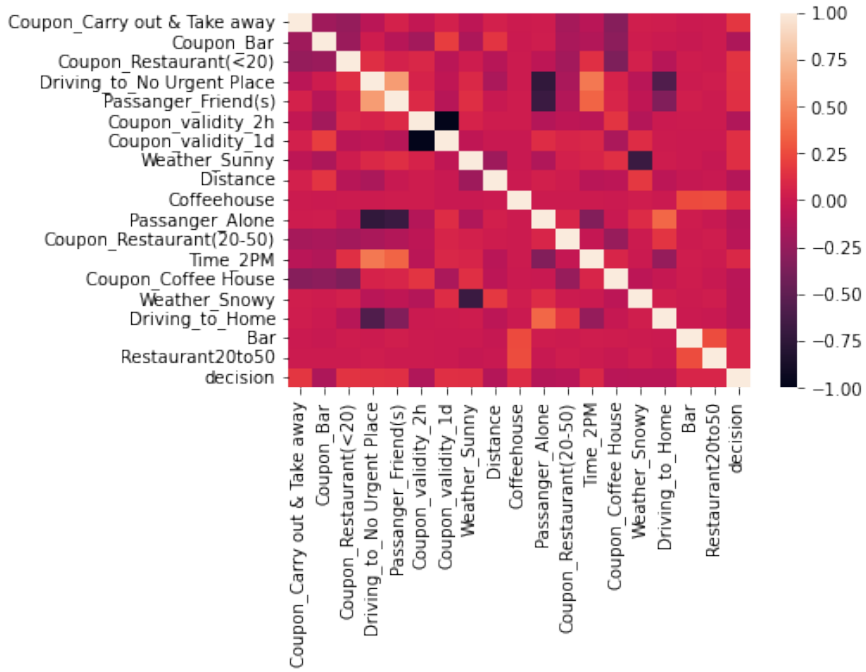
2.1 Nature of the data

The coupon recommendation dataset provided for this competition only contains categorical features. After transforming the categorical features to dummy variables. To better understand the structure of the data, I tried to visualize it using t-SNE (I had considered using the PacMAP algorithm [Wang et al., 2021] but there were troubles related to the version of other libraries required. So I switched back to using t-SNE.). The following figure shows the results:



We don't see many high-level patterns here. But, we can notice that the data is segregated into numerous groups that potentially represent various scenarios.

Next, I plotted the correlation plot of all the features which show correlation of more than 0.075 with our target variable. The columns in the heatmap below are ordered by the absolute value of their correlation with the target variable.



2.2 Transformations applied

As mentioned in the earlier section, we converted all the data to dummy variables.

Fortunately, the data contains relatively few missing values. I used the methodology described in [Khotimah et al., 2019] for imputation. Briefly, in order to impute the data,

we create a Naive Bayes model to predict every binary independent variable using all other columns in independent variables. Then, we use the model to impute the missing values.

3 Methods

3.1 Models

I tried four different approaches to solve this problem. Namely:

1. Naive Bayes with independent component analysis
2. Logistic regression with principle component analysis
3. Random forest classifier
4. Gradient boosting classifier

Partly, a reason behind using these methods was availability of reliable implementations from scikit-learn [Pedregosa et al., 2011]

3.1.1 Naive Bayes with independent component analysis

Naive Bayes algorithm is often a preferred choice when dealing with binary data. Unfortunately, as the name of the method suggests, it makes a "naive" assumption about the distribution of the data which may often fail in practice. Naive Bayes assumes that all exogenous variables are independent of each other. To circumvent this issue, we can use Independent component analysis (ICA) described in [Hyvärinen and Oja, 2000]. ICA finds low-dimensional representation of the feature matrix in such a way that maximizes the statistical independence between the generated components. Thus, we move closer to the Naive Bayes assumption.

3.1.2 Logistic Regression with principle component analysis

Logistic regression classifier on binary feature has an add-on bonus in that we get to know the exact contribution of each feature to the output. Unfortunately, when inputs are highly multicollinear, it severely affect the performance of the logistic regression model. This is very similar to the independence assumption made by the Naive Bayes model. To circumvent this problem, I used Principle Component Analysis (PCA) to remove the multicollinearity in the input features. That significantly improved the accuracy on test data from 0.573 to 0.675.

3.1.3 Random Forest

Decision trees are a natural choice for categorical data. We can observe significant improvement in accuracy after switching to tree-based ensemble models in the results section below. As we can see that the the linear models could not perform very well for on the given task, we can conclude that the data is not linearly separable. Random forests work quite well to accommodate non-linearity by averaging multiple overfitted trees. An additional advantage is the feature importance scores obtained from OOB samples.

3.1.4 Gradient Boosting Classifier

Gradient boosting can effectively model non-linear data. We inherited all the advantages of trees on categorical data by using trees as base classifiers for gradient boosting.

3.1.5 Sample weights

As gradient boosting and random forest classifiers can perform better if sample weights are initialized, we considered using an independent method for initializing sample weights. We constructed a k-nearest neighbor classifier on the training data and predicted the classes for the same data. The correctly classified samples were given a weight of 1. The incorrect samples were given a weight of 2.

3.2 Training

I initially split the entire train set in two parts. One for model training and the other for testing the model parameters. Apart from the models listed below, I also evaluated at different models including Ridge classifier, K-nearest neighbors (which I later converted as a step for deriving the sample weights), decision trees with CART algorithm.

I've used the scikit-learn implementations for all the models described above. Data preprocessing was done using the transformations described in the earlier section. The final random forest model took around 45 seconds to train. The final boosting model took about 26 seconds.

Among the first two approaches, the classifiers were fairly simple and completed training in less than 3 seconds. The ICA transformation consumed a significant amount of time (approximately 2 minutes) while PCA completed in less than 3 seconds.

3.3 Hyper-parameter Selection

3.3.1 Logistic Regression and PCA

An important parameter to configure when using PCA is how to set the number of components from the eigenvalues. The scikit-learn implementation allows the end-user to specify the explained variance instead of specifying the components directly. There is a tradeoff between explained variance and number of components. I have set the explained variance at 0.99. Besides, I found that the output of logistic regression does not vary with the values of regularization term. A possible explanation can be that most of the features are binary, so the effect of slope is only marginal.

3.3.2 Random Forest

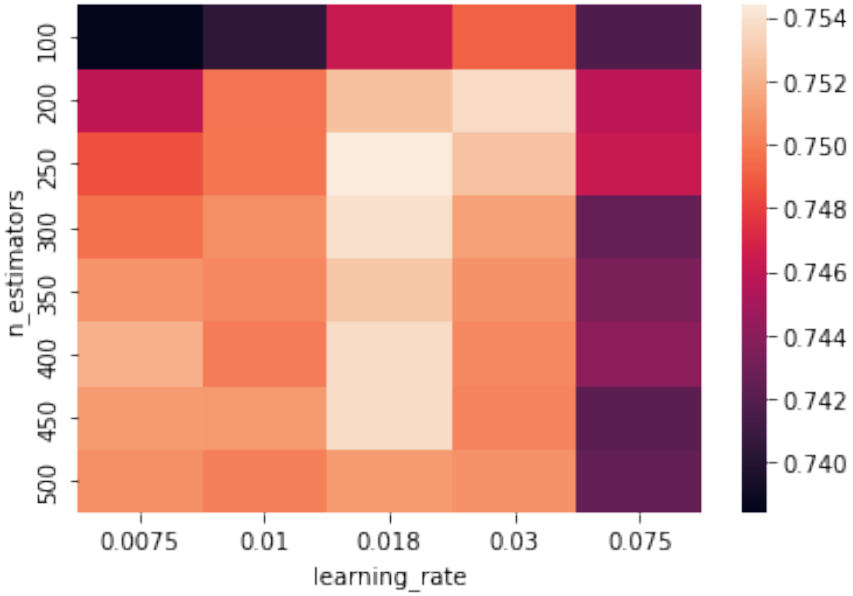
When tuning the hyperparameters for random forests, I realized the importance of overfitting of the individual trees. In the below table, we have given the accuracy scores of the random forest estimator for different values of max depth. We can consistently see that random forests with simple trees consistently perform poorer compared to the ones with complex trees (in terms of max depth). We found the best result at 1000, 64 so in the final model, we have set the parameters to 3000, 128 which gave the accuracy of 0.726 on the test set.

max_depth n_estimator	2	4	8	16	32	64
30	0.606284	0.680167	0.706186	0.713549	0.699804	0.699804
54	0.614875	0.674030	0.699804	0.715022	0.713795	0.713795
100	0.605793	0.681640	0.702504	0.721895	0.716249	0.716249
180	0.610211	0.676976	0.702995	0.722140	0.721404	0.721404
300	0.611193	0.676485	0.705695	0.721404	0.720422	0.720913
540	0.614875	0.677467	0.710358	0.721895	0.722631	0.723122
1000	0.613893	0.680167	0.713058	0.720913	0.723368	0.723613

3.3.3 Boosting Model

The implementation we used was stochastic in that at a time it only selects 30% from the available training data to train a model. This is set by setting the parameter "subsample" of the scikit-learn implementation.

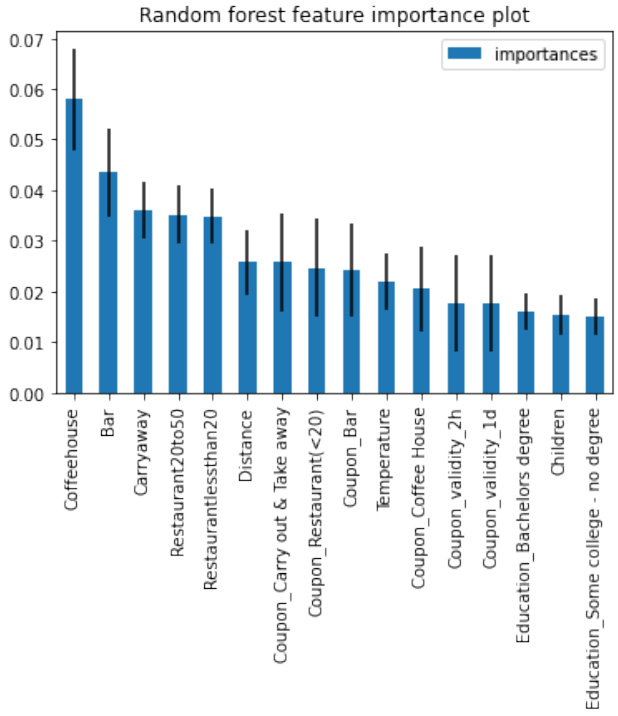
The other important parameter for a boosting classifier to is to chose the learning rate and number of estimators. The heatmap below shows the various configurations of these two parameters and their corresponding accuracy scores.



Notably, the scikit learn provides two options for the gradient boosting loss function. One is the exponential loss which reduces the model to Adaboost. The other is deviance loss, which is nothing but a logistic loss function. The deviance loss is the default configuration. Unfortunately, I did not get to thoroughly tune this parameter.

4 Results

Although I am not submitting for the interpretability track, I found the following feature importance chart an interesting result. Thus, adding this to the results section.



4.1 Prediction

We shall compare our models on the basis of three performance metrics: F1-score, ROC AUC score, and accuracy. Following table gives the comparison:

Model	Accuracy	ROC AUC	F-1 score
Naive Bayes with ICA	0.6465	0.6875	0.7152
Logistic Regression with PCA	0.6782	0.7287	0.7296
Random Forest	0.7408	0.8080	0.7855
Gradient Boosting	0.7459	0.8237	0.7851

4.2 Fixing Mistakes

Initially, I tried to drop the features that do not have a high value of correlation with the target variable. Specifically, I dropped all the features with absolute correlation less than 0.01. This significantly hurt the performance of the models such as random forest that significantly rely on overfitting of an individual estimator.

Scaling is important: while visualizing the t-SNE data without scaling, the data got segregated into three distinct clusters and I developed a feature to capture this variation and use it in the further modeling. Unfortunately, this was a consequence of unscaled temperature feature which had very high variance.

Notebooks are bad at maintaining the state! I completed most of the work in a Kaggle notebooks and multiple times during this work, I found me losing track of states. For instance variable X was declared in cell four but used in cell three. Because the notebook allows out of order execution, this does not cause a problem in the first run. But if one happens to restart

the notebook, code breaks. I learned that it is important to name each variable uniquely and restart and run all cells often.

Code

```
Put your code here.
```

Adding code to the bottom of the report.

References

[Hyvärinen and Oja, 2000] Hyvärinen, A. and Oja, E. (2000). Independent component analysis: algorithms and applications. *Neural Networks*, 13(4):411–430.

[Khotimah et al., 2019] Khotimah, B. K., Miswanto, and Suprajitno, H. (2019). Modeling naïve bayes imputation classification for missing data. *IOP Conference Series: Earth and Environmental Science*, 243:012111.

[Pedregosa et al., 2011] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

[Wang et al., 2017] Wang, T., Rudin, C., Doshi-Velez, F., Liu, Y., Klampfl, E., and MacNeille, P. (2017). A bayesian framework for learning rule sets for interpretable classification. *Journal of Machine Learning Research*, 18(70):1–37.

[Wang et al., 2021] Wang, Y., Huang, H., Rudin, C., and Shaposhnik, Y. (2021). Understanding how dimension reduction tools work: An empirical approach to deciphering t-sne, umap, trimap, and pacmap for data visualization. *Journal of Machine Learning Research*, 22(201):1–73.

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)
```

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

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

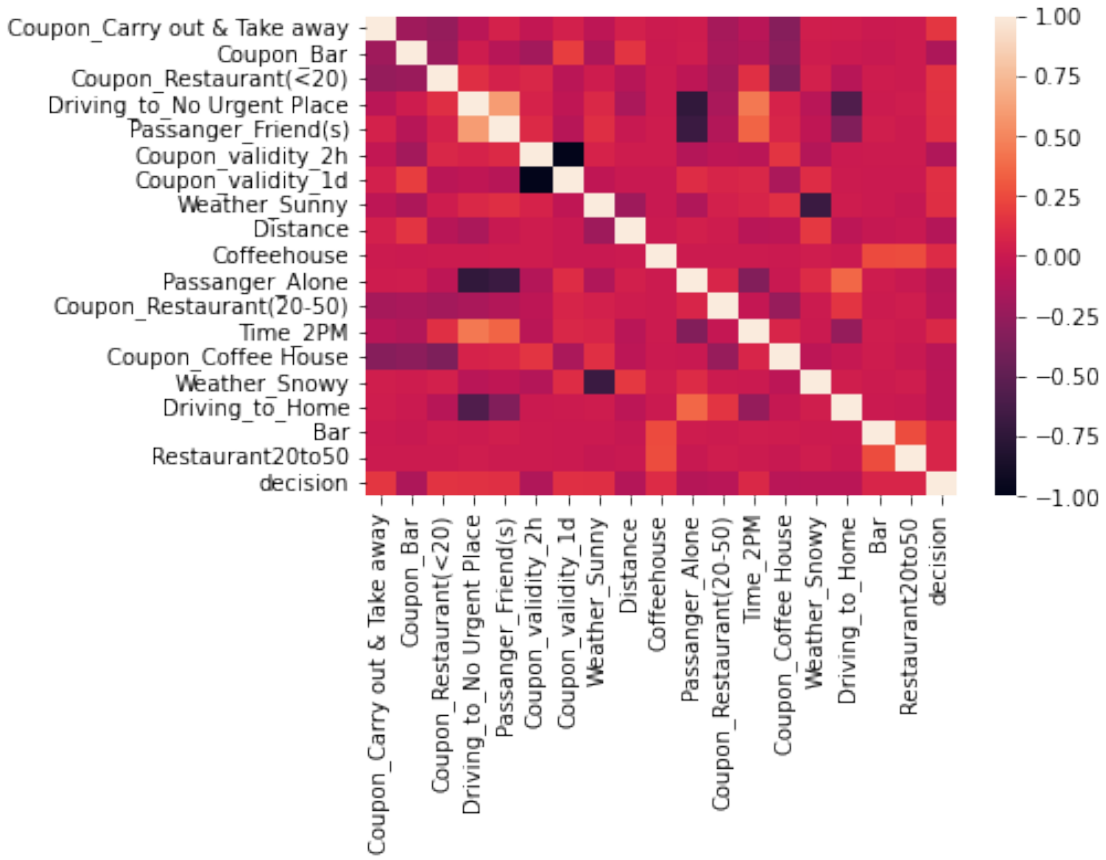
[9]:
```
# fig, ax = plt.subplots()
# ax.scatter(x2d[:, 0], x2d[:, 1], s=3)
# ax.set_title('t-SNE reduction')
# plt.show()
```

[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))
```

```
  0%|          | 0/8 [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]
```

```
  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
```

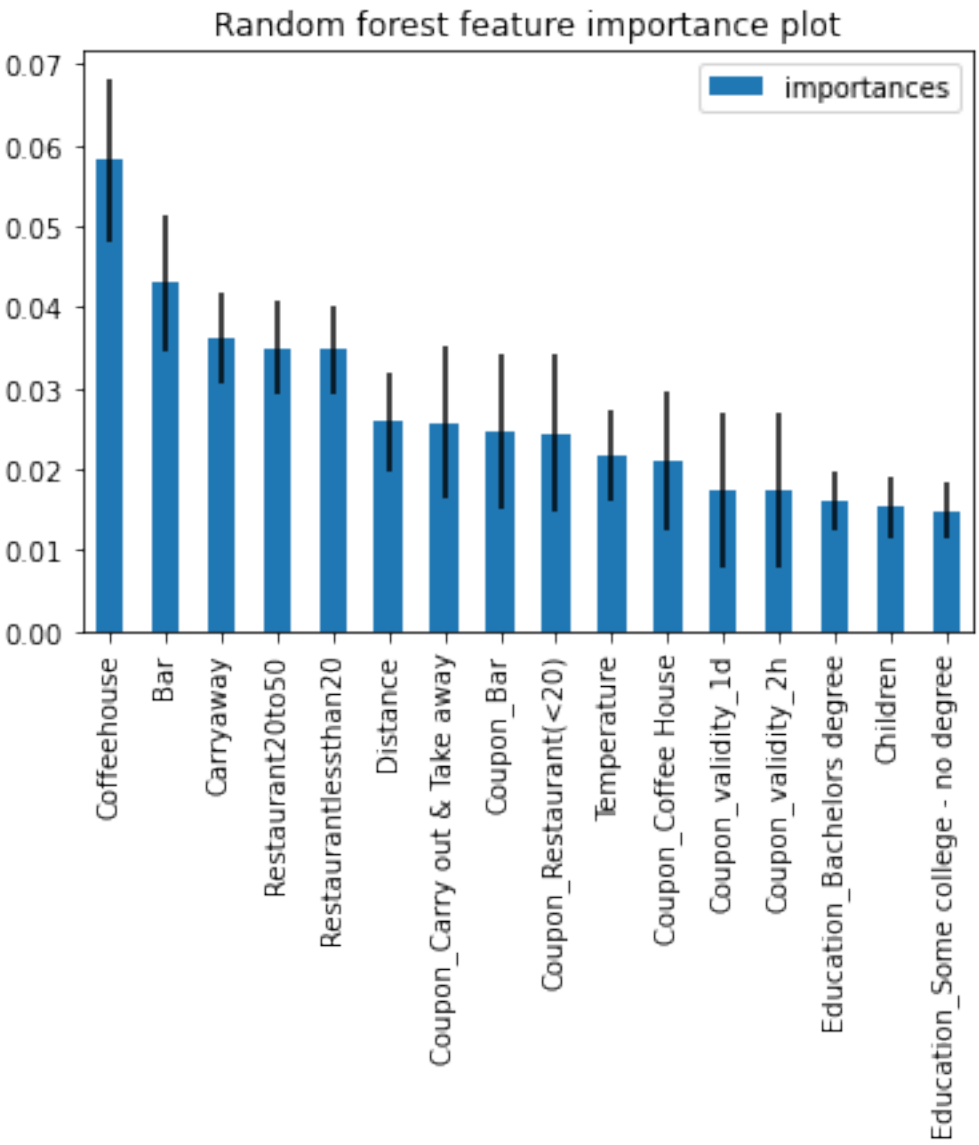
[23]:
```
big_forest_pred, big_forest_proba = (
    big_forest.predict(X_test), big_forest.predict_proba(X_test)[:, 1])
print('roc auc score:', roc_auc_score(Y_test, big_forest_proba))
print('f1 score:', f1_score(Y_test, big_forest_pred))
```

```
roc auc score: 0.8087146542777136
```

```
f1 score: 0.7861788617886178
```

[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')
```

[ ]:
```

```