Machine Learning from Blood Donations Prediction:

1. Introduction

Blood transfusion saves lives - from replacing lost blood during major surgery or a serious injury to treating various illnesses and blood disorders. Ensuring that there's enough blood in supply whenever needed is a serious challenge for the health professionals. The demand for blood fluctuates throughout the year. As one prominent example, blood donations slow down during busy holiday seasons. An accurate forecast for the future supply of blood allows for an appropriate action to be taken ahead of time and therefore saving more lives.

Aim Of Project:

To build a model which can identify who is likely to donate blood again using TPOT. TPOT can eliminate the most tedious part of machine learning seemlessly and effortlessly more than ever.

You can reach TPOT website and documentation from [TPOT (http://epistasislab.github.io/tpot/)](http://epistasislab.github.io/tpot/).

Let's get started exploring the data

1) **Importing Libraries**

In [2]:

```
# Importing necessary libraries

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from sklearn.model_selection import train_test_split
from tpot import TPOTClassifier
from sklearn.metrics import confusion_matrix,accuracy_score,roc_auc_score

#Importing library for visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
C:\ProgramData\Anaconda3\lib\site-packages\tpot\builtins\__init__.py:36: U
serWarning: Warning: optional dependency `torch` is not available. - skipp
ing import of NN models.
  warnings.warn("Warning: optional dependency `torch` is not available. -
skipping import of NN models.")
```

In [3]:

```
#Filter the unwanted warning
import warnings
warnings.simplefilter("ignore")
```

2) **Loading the blood donations data**

We now know that we are working with a typical CSV file (i.e., the delimiter is ,, etc.). We proceed to loading the data into memory.

In [4]:

```
#Lets get started exploring the data.

train = pd.read_csv("C:\\Leina\\Data_sets\\blood_donation\\blood-train.csv")
test=pd.read_csv("C:\\Leina\\Data_sets\\blood_donation\\blood-test.csv")
train.head()
```

Out[4]:

	Unnamed: 0	Months since Last Donation	Number of Donations	Total Volume Donated (c.c.)	Months since First Donation	Made Donation in March 2007
0	619	2	50	12500	98	1
1	664	0	13	3250	28	1
2	441	1	16	4000	35	1
3	160	2	20	5000	45	1
4	358	1	24	6000	77	0

3) **Inspecting transfusion DataFrame**

The RFM model stands for Recency, Frequency and Monetary Value and it is commonly used in marketing for identifying the best customers. In this case, the customers are blood donors.

RFMTC is a variation of the RFM model. Below is a description of what each column means in the dataset:

R (Recency - months since the last donation) F (Frequency - total number of donation) M (Monetary - total volume blood donated in c.c.) T (Time - months since the first donation) a binary variable representing whether he/she donated blood in March 2007 (1 stands for donating blood; 0 stands for not donating blood) It will be helpful to rename these columns as such; except for the last column, which will be the Target column, as the aim is to predict whether someone donated blood in March 2007.

In [5]:

```
#Printing the train and test size
print("Train Shape : ",train.shape)
print("Test Shape : ",test.shape)
```

```
Train Shape :  (576, 6)
Test Shape :  (200, 5)
```

NOTE:

> We can see that there are 576 rows and 6 columns in our training dataset
>
> We can see that there are 200 rows and 5 columns in our test dataset

In [6]:

```
# Print a concise summary of transfusion DataFrame
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 576 entries, 0 to 575
Data columns (total 6 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Unnamed: 0                   576 non-null    int64
 1   Months since Last Donation   576 non-null    int64
 2   Number of Donations          576 non-null    int64
 3   Total Volume Donated (c.c.)  576 non-null    int64
 4   Months since First Donation  576 non-null    int64
 5   Made Donation in March 2007  576 non-null    int64
dtypes: int64(6)
memory usage: 27.1 KB
```

NOTE:

> We can see that there is no missing vale for any row.
>
> The datatype for all features is integer.

1. **Creating target column**

We are aiming to predict the value in whether he/she donated blood in March 2007 column. Let's rename this it to target so that it's more convenient to work with

In [7]:

```
# Rename target column as 'target' for brevity
train.rename(
    columns={'Made Donation in March 2007':'Target'},
    inplace=True
)
```

5.**Checking target incidence**

We want to predict whether or not the same donor will give blood the next time the vehicle comes to campus. The model for this is a binary classifier, meaning that there are only 2 possible outcomes:

0 - the donor will not give blood 1 - the donor will give blood Target incidence is defined as the number of cases of each individual target value in a dataset. That is, how many 0s in the target column compared to how many 1s? Target incidence gives us an idea of how balanced (or imbalanced) is our dataset.

In [8]:

```
#Counting the number of people who donated and not donated
train["Target"].value_counts()
```

Out[8]:

```
0    438
1    138
Name: Target, dtype: int64
```

Note:

> This is an imbalance dataset.

6) **Looking into the testing dataset**

In [9]:

```
test.head()
```

Out[9]:

	Unnamed: 0	Months since Last Donation	Number of Donations	Total Volume Donated (c.c.)	Months since First Donation
0	659	2	12	3000	52
1	276	21	7	1750	38
2	263	4	1	250	4
3	303	11	11	2750	38
4	83	4	12	3000	34

Note:

> Made Donation in March 2007 is not present in Test data.
>
> We have to train our classifier using the Train data and generate predictions (Made Donation in March 2007) on Test data.

In [10]:

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Unnamed: 0                   200 non-null    int64
 1   Months since Last Donation   200 non-null    int64
 2   Number of Donations          200 non-null    int64
 3   Total Volume Donated (c.c.)  200 non-null    int64
 4   Months since First Donation  200 non-null    int64
dtypes: int64(5)
memory usage: 7.9 KB
```

NOTE:

> We can see that there is no missing vale for any row.
>
> The datatype for all features is an integer.

Data Exploration

7) **Describing training dataset**

describe() method can show different values like count, mean, standard deviation, etc. of numeric data types.

In [11]:

```
# Statistics of the data
train.describe()
```

Out[11]:

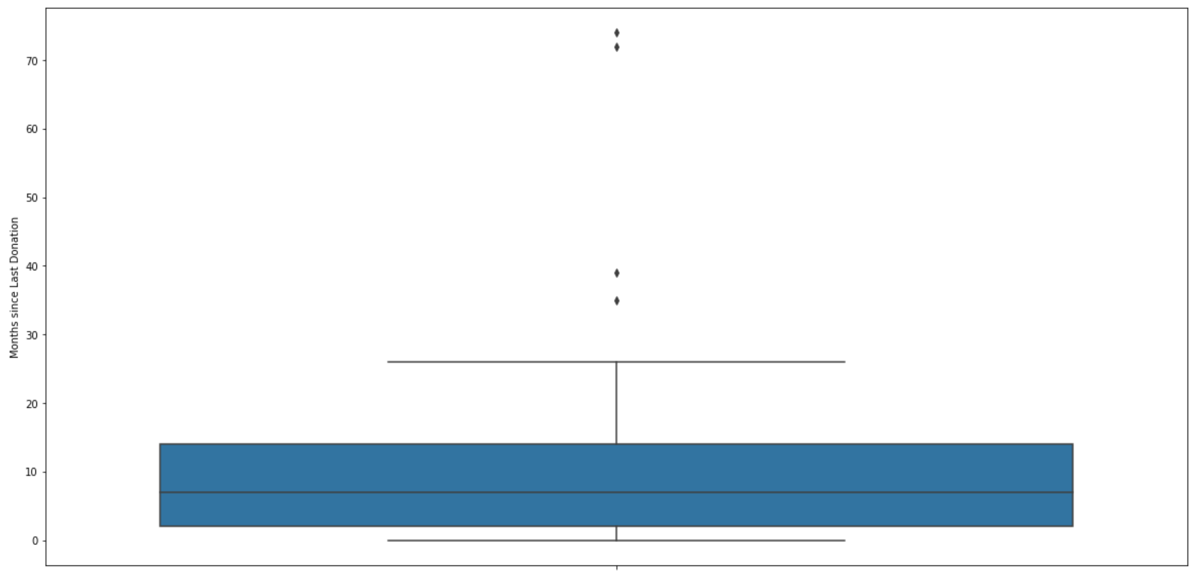
	Unnamed: 0	Months since Last Donation	Number of Donations	Total Volume Donated (c.c.)	Months since First Donation	Target
count	576.000000	576.000000	576.000000	576.000000	576.000000	576.000000
mean	374.034722	9.439236	5.427083	1356.770833	34.050347	0.239583
std	216.947773	8.175454	5.740010	1435.002556	24.227672	0.427200
min	0.000000	0.000000	1.000000	250.000000	2.000000	0.000000
25%	183.750000	2.000000	2.000000	500.000000	16.000000	0.000000
50%	375.500000	7.000000	4.000000	1000.000000	28.000000	0.000000
75%	562.500000	14.000000	7.000000	1750.000000	49.250000	0.000000
max	747.000000	74.000000	50.000000	12500.000000	98.000000	1.000000

In [12]:

```
#Boxplot for Months since Last Donation
plt.figure(figsize=(20,10))
sns.boxplot(y="Months since Last Donation",data=train)
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e684193ca0>
```



Note:

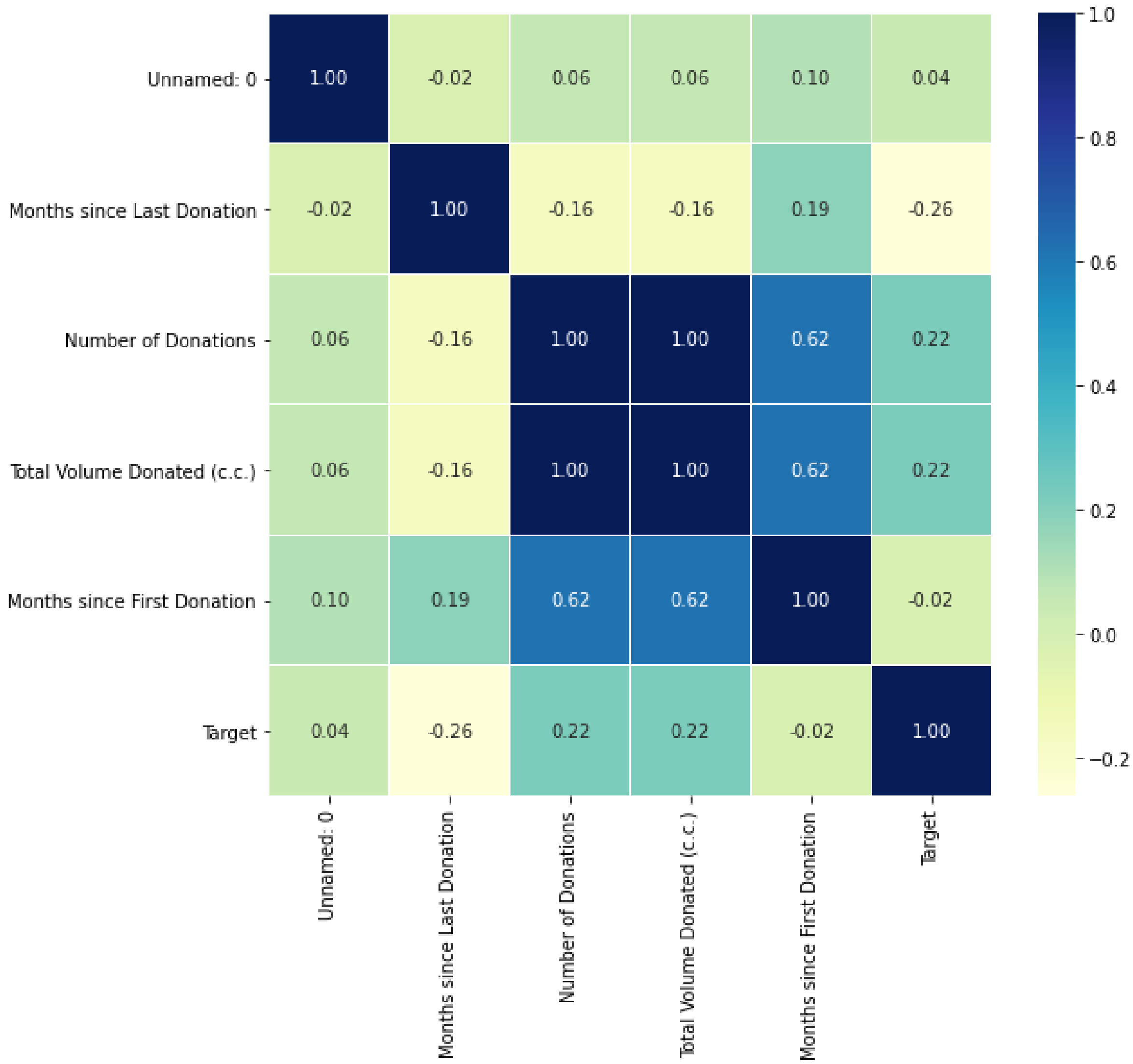
> We can see that most of donations happened around 10th month There are some outliers

In [13]:

```
#Correlation between all variables [Checking how different variable are related]
corrmat=train.corr()
f, ax = plt.subplots(figsize =(9, 8))
sns.heatmap(corrmat, ax = ax, cmap ="YlGnBu", linewidths = 0.1,fmt = ".2f",annot=True)
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e6848fd0d0>
```



NOTE: Heatmap of Correlation between different features:

Positive numbers = Positive correlation, i.e. increase in one feature will increase the other feature & vice-versa. Negative numbers = Negative correlation, i.e. increase in one feature will decrease the other feature & vice-versa.

In our case, we focus on which features have strong positive or negative correlation with the Target feature.

Model Building

1. **Splitting dataset into train and test datasets**

We'll now use train_test_split() method to split DataFrame.This is very easy to do using the train_test_split() method from the scikit learn library - all we need to do is specify the stratify parameter. In our case, we'll stratify on the target column.

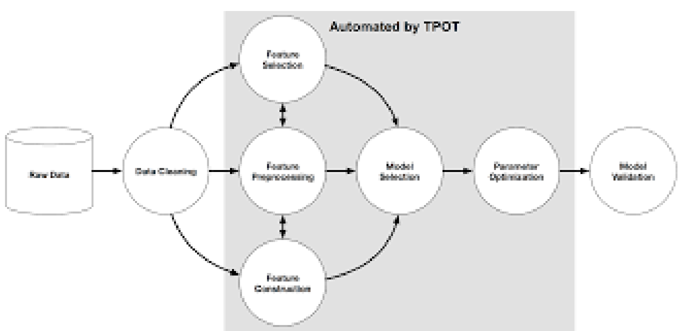
In [14]:

```
# Import train_test_split method
from sklearn.model_selection import train_test_split

# Split transfusion DataFrame into
# X_train, X_test, y_train and y_test datasets,
# stratifying on the `target` column
X_train, X_test, y_train, y_test = train_test_split(
    train.drop(columns=['Target','Unnamed: 0']),
    train.Target,
    test_size=0.2,
    random_state=0)
```

1. **Selecting model using TPOT**

TPOT is a Python Automated Machine Learning tool that optimizes machine learning pipelines using genetic programming.



TPOT will automatically explore hundreds of possible pipelines to find the best one for our dataset. Note, the outcome of this search will be a scikit-learn pipeline, meaning it will include any pre-processing steps as well as the model.

We are using TPOT to help us zero in on one model that we can then explore and optimize further.

In [15]:

```
# Import TPOTClassifier and roc_auc_score
from tpot import TPOTClassifier
from sklearn.metrics import roc_auc_score

# Instantiate TPOTClassifier
tpot = TPOTClassifier(
    generations=5,
    population_size=20,
    verbosity=2,
    scoring='roc_auc',
    random_state=42,
    disable_update_check=True,
    config_dict='TPOT light'
)
tpot.fit(X_train, y_train)

# AUC score for tpot model
tpot_auc_score = roc_auc_score(y_test, tpot.predict_proba(X_test)[:, 1])
print(f'\nAUC score: {tpot_auc_score:.4f}')


# Print best pipeline steps
print('\nBest pipeline steps:', end='\n')
for idx, (name, transform) in enumerate(tpot.fitted_pipeline_.steps, start=1):
    # Print idx and transform
    print(f'{idx}. {transform}')
```

```
Generation 1 - Current best internal CV score: 0.7355558350100603

Generation 2 - Current best internal CV score: 0.7355558350100603

Generation 3 - Current best internal CV score: 0.7355558350100603

Generation 4 - Current best internal CV score: 0.7355558350100603

Generation 5 - Current best internal CV score: 0.7355558350100603

Best pipeline: LogisticRegression(input_matrix, C=25.0, dual=False, penalt
y=l2)

AUC score: 0.8042

Best pipeline steps:
1. LogisticRegression(C=25.0, random_state=42)
```

In [16]:

```
tpot.fitted_pipeline_
```

Out[16]:

```
Pipeline(steps=[('logisticregression',
                 LogisticRegression(C=25.0, random_state=42))])
```

TPOT picked LogisticRegression as the best model for our dataset with no pre-processing , giving us the AUC score of 0.8042. This is a great starting point. Let's see if we can make it better.

1. Training the linear regression model¶

We are now ready to train the linear regression model.

In [17]:

```
# Importing modules
from sklearn.linear_model import LogisticRegression
# Instantiate LogisticRegression
logreg = LogisticRegression(C=25.0, random_state=42)
#Fitting the model
logreg.fit(X_train,y_train)
```

Out[17]:

```
LogisticRegression(C=25.0, random_state=42)
```

In [20]:

```
#Predicting on the test data
pred=logreg.predict(X_test)
```

In [21]:

```
#printing the confusion matrix
confusion_matrix(pred,y_test)
```

Out[21]:

```
array([[80, 29],
       [ 1,  6]], dtype=int64)
```

In [22]:

```
# AUC score for tpot model
logreg_auc_score = roc_auc_score(y_test, logreg.predict_proba(X_test)[:, 1])
print(f'\nAUC score: {logreg_auc_score:.4f}')
```

```
AUC score: 0.8042
```

1. **Conclusion**

In this notebook, we explored automatic model selection using TPOT and AUC score we got was 0.8042.