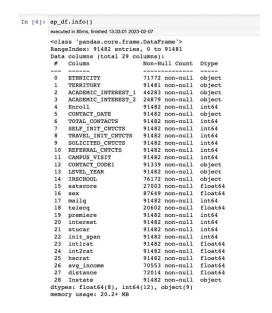
6211 Assignment 1

Question 1.)



c)

- Variables 'ACADEMIC_INTEREST_1', 'ACADEMIC_INTEREST_2', 'IRSCHOOL', 'CONTACT CODE1', 'CONTACT DATE' are dropped as mentioned in the question.
- Column 'Level_Year' is to be dropped as the variable has only 1 unique value 'FR22' and has no impact on the predictive models.
- 'Satscore' and 'telecq' have more than 70% missing values and will not make a good feature. Hence, dropping these two columns.
- Variables Total_Contacts, Mailq have been for the regression model as they have VIF values greater than the threshold value of 10 during model building in the later steps.
- d) Variable 'Enroll' is the target variable.

Question 2.)

- Categorical variables 'ETHNICITY', 'TERRITORY' and 'INSTATE' are to be dummied.
- Category 'A' from variable ETHNICITY is left out and similarly TERRITORY '0' along with INSTATE 'N' are left out.

Question 3.)

- Variable Imputation is required for model building but Transformation isn't required.
- Variable 'Ethnicity' has been imputed with value 'C' as it is the most frequently occurred value.
- Variable 'Territory' has been imputed with value '0' as the missing value percentage is close to 0, and so filling it with '0' won't make any difference to the model.
- Variable 'sex' has been imputed with value 1 as it is the most frequently occurred value.

- Variable 'avg_income has been imputed with its mean value as the variable is normally distributed.
- Variable 'distance' has been imputed with its mean value as the variable is right skewed.
- Variables 'Total_Contacts' and 'SELF_INIT_CNTCTS' have been grouped into bins of 0 and 1. (if value greater than 0 then assigned value as 1 else 0).

Question 4.)

a) Logit Model Summary

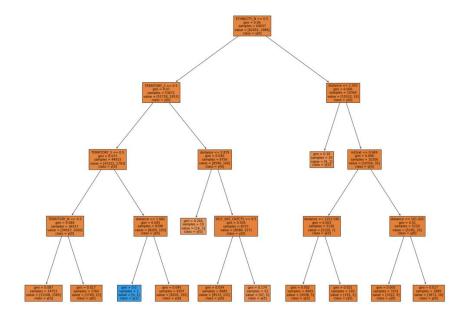
Optimization terminated successfully.

Current function value: 0.130450

Therations 10

Logic Regission Results							
Dep. Variable:		Enroll	No. Observations:		64037		
Model:			Df Residuals:		64005		
Method:			Df Model:		31		
Date:	Tue, 07 Feb 2023 Pseudo R-squ.:			0.05640			
Time:		21:14:28 Log-Likelihood:			-8353.6		
converged:	True LL-Null:			-8852.9			
Covariance Type:	no	nonrobust LLR p-value:			5.854e-190		
	coef	std err	z	P> z	[0.025	0.975]	
SELF INIT CNTCTS	-0.0074	0.053	-0.140	0.889	-0.111	0.096	
TRAVEL INIT CNTCTS	-0.0716	0.048		0.133	-0.165	0.022	
SOLICITED CNTCTS	0.0541	0.040		0.174	-0.024	0.132	
REFERRAL CNTCTS	-0.0357	0.105		0.733	-0.241	0.169	
CAMPUS VISIT	0.0662	0.124		0.594	-0.177	0.309	
sex	0.0154	0.048		0.751	-0.079	0.110	
premiere	0.0085	0.141		0.952	-0.269	0.286	
interest	0.0792	0.093	0.852	0.394	-0.103	0.261	
stucar	-0.0404	0.051		0.425	-0.140	0.059	
init span	-0.0021	0.003	-0.723	0.470	-0.008	0.004	
int1rat	-0.8614	1.350	-0.638	0.523	-3.507	1.784	
int2rat	1.9032	1.195	1.593	0.111	-0.438	4.245	
hscrat	0.3373	0.395	0.854	0.393	-0.437	1.111	
avg_income	-3.47e-06	1.38e-06	-2.510	0.012	-6.18e-06	-7.6e-07	
distance	-0.0002	9.14e-05	-2.084	0.037	-0.000	-1.13e-05	
ETHNICITY_B	-0.8502	0.116	-7.340	0.000	-1.077	-0.623	
ETHNICITY_C	-0.5111	0.089	-5.746	0.000	-0.685	-0.337	
ETHNICITY_H	-0.7468	0.109	-6.832	0.000	-0.961	-0.533	
ETHNICITY_I	-0.9763	0.318	-3.073	0.002	-1.599	-0.354	
ETHNICITY_N	-3.0555	0.194	-15.759	0.000	-3.435	-2.675	
ETHNICITY_O	-0.8985	0.172	-5.222	0.000	-1.236	-0.561	
TERRITORY_1	-2.0417	0.154	-13.290	0.000	-2.343	-1.741	
TERRITORY_2	-3.1630	0.165		0.000	-3.487	-2.839	
TERRITORY_3	-2.0986	0.154		0.000	-2.400	-1.797	
TERRITORY_4	-2.2930	0.158		0.000	-2.603	-1.983	
TERRITORY_5	-2.9224	0.163		0.000	-3.241	-2.604	
TERRITORY_6	-2.2118	0.158		0.000	-2.522	-1.902	
TERRITORY_7	-2.6265	0.160		0.000	-2.941	-2.312	
TERRITORY_8	-1.8844	0.158		0.000	-2.194	-1.575	
TERRITORY_A	-3.4108	0.238		0.000	-3.878	-2.943	
TERRITORY_N	-3.9805	0.297		0.000	-4.562	-3.399	
Instate_Y	-0.0544	0.087	-0.628	0.530	-0.224	0.115	

Logit Regression Results



Question 5.) I'll choose Logistic Regression as its ROC AUC value (0.685) is higher than Decision Tree ROC AUC value (0.636).

Question 6.)

- Given dataset is highly imbalanced and requires resampling for building better models.
- Based on the regression model, variables AVG_INCOME, DISTANCE, ETHNICITY and TERRITORY are the significant variables in the given dataset as their respective p-values are less than the threshold of 0.05 whereas the rest variables have higher p-values than 0.05. Keeping the rest variables constant, with every unit increase in either AVG_INCOME or DISTANCE or ETHNICITY or TERRITORY, the target value Enroll decreases.

```
Question 7.)
#!/usr/bin/env python
# coding: utf-8
# In[1]:
import pandas as pd
import numpy as np
from statsmodels.stats.outliers influence import variance inflation factor
from sklearn.model selection import train test split
import statsmodels.api as sm
from sklearn.metrics import confusion matrix
from sklearn.metrics import roc curve
from sklearn.metrics import roc auc score
from matplotlib import pyplot as plt
from sklearn import tree
from sklearn.tree import export text
# In[2]:
ap_df = pd.read_csv("inq2022.csv")
# In[3]:
ap_df.head()
# In[4]:
ap_df.info()
# In[5]:
ap df.describe(include = 'all')
```

```
# In[6]:
ap_df.isnull().sum()/len(ap_df)
# In[7]:
ap_df
ap_df.drop(columns=['ACADEMIC_INTEREST_1','ACADEMIC_INTEREST_2','IRSCHOOL',
'CONTACT CODE1','CONTACT DATE'])
# In[8]:
ap_df.describe(include='all')
# In[9]:
ap_df.info()
# In[10]:
ap_df.isna().sum()/len(ap_df)
# In[11]:
ap_df = ap_df.drop(columns=['satscore','telecq'])
# In[12]:
ap_df = ap_df.drop(columns=['LEVEL_YEAR'])
# In[13]:
```

```
ap df.Enroll.value counts()
# In[14]:
cat_columns = ['ETHNICITY','TERRITORY','Instate']
# In[15]:
for col in cat columns:
  print(ap df[col].value counts())
print(len(ap df))
print(ap df.isna().sum())
# In[16]:
ap df['ETHNICITY'] = ap df['ETHNICITY'].fillna('C') ## Most frequent occurence
ap df['TERRITORY'] = ap df['TERRITORY'].fillna('0') ## Null % is close to 0, so filling with
least occurence value as it doesn't have much impact on the model
ap df['sex'] = ap df['sex'].fillna(1) ## Highest occurence
ap df['avg income'] = ap df['avg income'].fillna(ap df['avg income'].mean()) ## Right skewed
so filling nulls with mean
ap df['distance'] = ap df['distance'].fillna(ap df['distance'].mean()) ## Right skewed so filling
nulls with mean
# In[17]:
ap df =pd.get dummies(ap df, drop first=True)
ap df tree = ap df.copy() ## Making a replica for Decision Tree Model
ap df.describe()
# In[18]:
```

```
ap df.info()
# In[19]:
ap df[['TOTAL CONTACTS','SELF INIT CNTCTS','TRAVEL INIT CNTCTS',
       'SOLICITED CNTCTS', 'REFERRAL CNTCTS', 'CAMPUS VISIT',
       'sex', 'mailq', 'premiere', 'interest', 'stucar', 'init span', 'intlrat',
       'int2rat', 'hscrat', 'avg income', 'distance']].skew(axis = 0, skipna = True)
# In[20]:
ap df[['TOTAL CONTACTS','SELF INIT CNTCTS','TRAVEL INIT CNTCTS',
       'SOLICITED CNTCTS', 'REFERRAL CNTCTS', 'CAMPUS VISIT',
       'sex', 'mailq', 'premiere', 'interest', 'stucar', 'init span', 'int1rat',
       'int2rat', 'hscrat', 'avg income', 'distance']].hist(bins=30, figsize=(20, 15))
# In[21]:
ap df['TOTAL CONTACTS'] = np.where(ap df['TOTAL CONTACTS']>0,1,0)
ap df['SELF INIT CNTCTS'] = np.where(ap df['SELF INIT CNTCTS']>0,1,0)
# In[22]:
ap df.drop(columns=['Enroll']).hist(bins=30, figsize=(20, 15))
# Considering VIF threshold as 10
# In[23]:
ap vif = pd.DataFrame()
ap vif["feature"] = ap df.drop(columns=['Enroll']).columns
ap vif["VIF"] = [variance inflation factor(ap df.drop(columns=['Enroll']).values, i)
               for i in range(len(ap_df.drop(columns=['Enroll']).columns))]
print(ap vif)
```

```
# In[24]:
ap df.corr()
# In[25]:
ap df = ap df.drop(columns=['TOTAL CONTACTS']) ### Highest VIF value
# In[26]:
ap vif = pd.DataFrame()
ap vif["feature"] = ap df.drop(columns=['Enroll']).columns
ap vif["VIF"] = [variance inflation factor(ap df.drop(columns=['Enroll']).values, i)
               for i in range(len(ap_df.drop(columns=['Enroll']).columns))]
print(ap vif)
# In[27]:
ap df.corr()
# In[28]:
ap df = ap df.drop(columns=['mailq']) ### Highest VIF value
# In[29]:
ap vif = pd.DataFrame()
ap vif["feature"] = ap df.drop(columns=['Enroll']).columns
ap vif["VIF"] = [variance inflation factor(ap df.drop(columns=['Enroll']).values, i)
               for i in range(len(ap df.drop(columns=['Enroll']).columns))]
```

```
print(ap vif)
### Regression Model
# In[30]:
ap X train,
                        ap X val,
                                                ap y train,
                                                                        ap y val
train test split(ap df.drop(columns=['Enroll']),ap df['Enroll'], test size=0.3,random state=0)
ap log reg = sm.Logit(ap y train, ap X train).fit()
print(ap log reg.summary())
# In[31]:
ap_prediction_prob = ap_log_reg.predict(ap_X_val)
ap prediction = list(map(round, ap prediction prob))
confusion matrix(ap y val,ap prediction)
# In[32]:
lr_auc = roc_auc_score(ap_y_val, ap_prediction_prob)
print('Logistic: ROC AUC=%.3f' % (lr auc))
# In[33]:
lr_fpr, lr_tpr, _ = roc_curve(ap_y_val, ap_prediction_prob)
plt.plot(lr fpr, lr tpr, marker='.')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
### Tree Model
# In[34]:
```

```
ap X train,
                         ap X val,
                                                 ap y train,
                                                                          ap_y_val
train test split(ap df tree.drop(columns=['Enroll']),ap df tree['Enroll'],
test size=0.3,random state=0)
ap dtree = tree.DecisionTreeClassifier(max depth=4,min_samples_split=30)
ap dtree = ap dtree.fit(ap X train, ap y train)
# In[35]:
ap r = \text{export text}(\text{ap dtree, feature names} = \text{list}(\text{ap } X \text{ train.columns.values}))
print(ap r)
# In[36]:
plt.figure(figsize=[25,20])
tree.plot tree(ap dtree,
         feature names=list(ap X train.columns.values),
         class names=True,
         filled=True)
plt.show()
# In[37]:
ap prediction = ap dtree.predict(ap X val)
confusion matrix(ap y val,ap prediction)
# In[38]:
ap dtree.score(ap X val,ap y val)
# In[39]:
ap prediction prob = ap dtree.predict proba(ap X val)
ap_tree_auc = roc_auc_score(ap_y_val, ap_prediction_prob[:,1])
print('Decision Tree: ROC AUC=%.3f' % (ap tree auc))
```

```
# In[40]:

tree_fpr, tree_tpr, _ = roc_curve(ap_y_val, ap_prediction_prob[:,1])
plt.plot(tree_fpr, tree_tpr, marker='.')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.show()
```