590-02 Final Project

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30-Day Readmission

A hospital readmission is an situation when a patient who had been discharged from a hospital is readmitted within a specified time interval. Readmission rates have increasingly been used as an outcome measure in health services research and as a quality benchmark for health systems. Higher readmission rate means ineffectiveness of treatment during the hospitalizations. Hospital readmission rates were formally included in reimbursement decisions for the Centers for Medicare and Medicaid Services (CMS) as part of the Patient Protection and Affordable Care Act (ACA) of 2010, which penalizes health systems with higher than expected readmission rates through the Hospital Readmission Reduction Program. Due to this penalty, there have been other programs that have been introduced, with the aim to decrease hospital readmission. The most common time frame is within 30-day of discharge, and this is what CMS uses. To predict 30-day readmission, I use 3 datasets, ADIMISSIONS.csv, PATIENTS.csv, ICUSTAYS.csv from MIMIC-III Clinical Database Demo ([https://physionet.org/content/mimiciii-demo/1.4/ (https://physionet.org/content/mimiciii-demo/1.4/)](https://physionet.org/content/mimiciii-demo/1.4/))

In [1]:
```
import pandas as pd
import numpy as np
import string
import re
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sco
from sklearn.metrics import precision_recall_curve, auc
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

1. Datasets

These are datasets for this project.

In [2]:
```
df1 = pd.read_csv('ADMISSIONS.csv')
df2 = pd.read_csv('PATIENTS.csv')
df3 = pd.read_csv('ICUSTAYS.csv')
```

In [3]:
```
# ADIMISSIONS
df1.head(5)
```

Out[3]:

	ROW_ID	SUBJECT_ID	HADM_ID	ADMITTIME	DISCHTIME	DEATHTIME	ADMISSION_TYPE	ADM
0	21	22	165315	2196-04-09 12:26:00	2196-04-10 15:54:00	NaN	EMERGENCY	E
1	22	23	152223	2153-09-03 07:15:00	2153-09-08 19:10:00	NaN	ELECTIVE	F
2	23	23	124321	2157-10-18 19:34:00	2157-10-25 14:00:00	NaN	EMERGENCY	
3	24	24	161859	2139-06-06 16:14:00	2139-06-09 12:48:00	NaN	EMERGENCY	
4	25	25	129635	2160-11-02 02:06:00	2160-11-05 14:55:00	NaN	EMERGENCY	E

In [4]:
```
# PATIENTS
df2.head(5)
```

Out[4]:

	ROW_ID	SUBJECT_ID	GENDER	DOB	DOD	DOD_HOSP	DOD_SSN	EXPIRE_FLAG
0	234	249	F	2075-03-13 00:00:00	NaN	NaN	NaN	0
1	235	250	F	2164-12-27 00:00:00	2188-11-22 00:00:00	2188-11-22 00:00:00	NaN	1
2	236	251	M	2090-03-15 00:00:00	NaN	NaN	NaN	0
3	237	252	M	2078-03-06 00:00:00	NaN	NaN	NaN	0
4	238	253	F	2089-11-26 00:00:00	NaN	NaN	NaN	0

In [5]:
```
# ICUSTAYS
df3.head(5)
```

Out[5]:

	ROW_ID	SUBJECT_ID	HADM_ID	ICUSTAY_ID	DBSOURCE	FIRST_CAREUNIT	LAST_CAREUNIT
0	365	268	110404	280836	carevue	MICU	MICU
1	366	269	106296	206613	carevue	MICU	MICU
2	367	270	188028	220345	carevue	CCU	CCU
3	368	271	173727	249196	carevue	MICU	SICU
4	369	272	164716	210407	carevue	CCU	CCU

In [6]:
```
df1.shape
```

Out[6]: (58976, 19)

In [7]:
```
df2.shape
```

Out[7]: (46520, 8)

In [8]:
```
df3.shape
```

Out[8]: (61532, 12)

Merge ADMISSIONS, PATIENTS and ICUSTAYS datasets upon SUBJECT_ID

In [9]:
```
df4 = pd.merge(df1,df2,on='SUBJECT_ID')
```

In [10]:
```
df = pd.merge(df4,df3,on='SUBJECT_ID')
```

2. Exploratory Data Analysis

In [11]:
```
df.shape
```

Out[11]: (116426, 37)

In [12]:
```
df.head()
```

Out[12]:

	ROW_ID_x	SUBJECT_ID	HADM_ID_x	ADMITTIME	DISCHTIME	DEATHTIME	ADMISSION_TYPE
0	21	22	165315	2196-04-09 12:26:00	2196-04-10 15:54:00	NaN	EMERGENCY
1	22	23	152223	2153-09-03 07:15:00	2153-09-08 19:10:00	NaN	ELECTIVE
2	22	23	152223	2153-09-03 07:15:00	2153-09-08 19:10:00	NaN	ELECTIVE
3	23	23	124321	2157-10-18 19:34:00	2157-10-25 14:00:00	NaN	EMERGENCY
4	23	23	124321	2157-10-18 19:34:00	2157-10-25 14:00:00	NaN	EMERGENCY

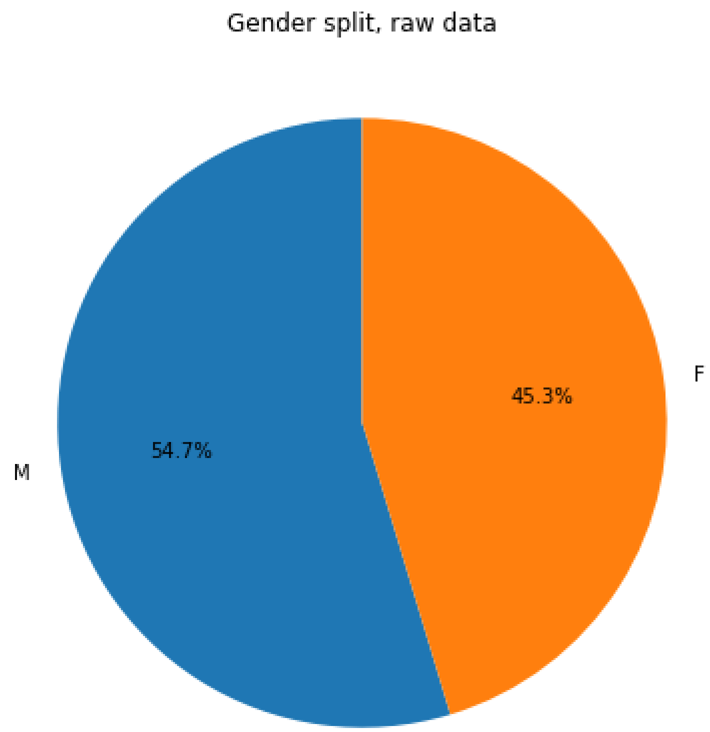
5 rows × 37 columns

In [13]:
```
print('Number of unique patient ids: {}'.format(len(df.SUBJECT_ID.unique())))
```

```
Number of unique patient ids: 46476
```

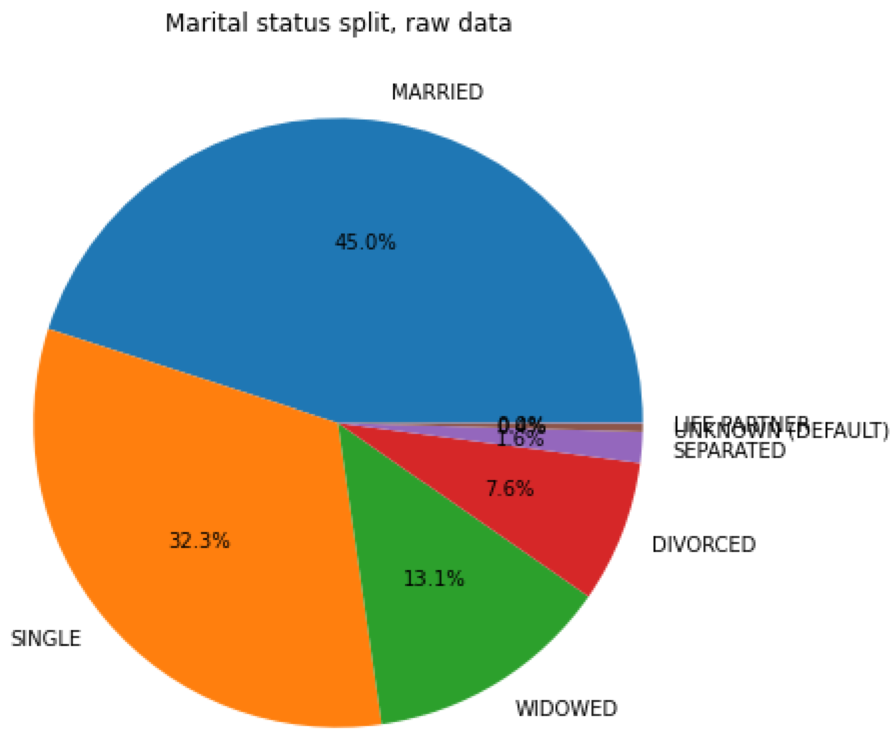
In [14]:
```
fig = plt.figure(figsize=(7,7))
df.GENDER.value_counts().plot.pie(startangle = 90, autopct='%1.1f%%')
plt.title('Gender split, raw data')
plt.ylabel('')
```

Out[14]: Text(0, 0.5, '')



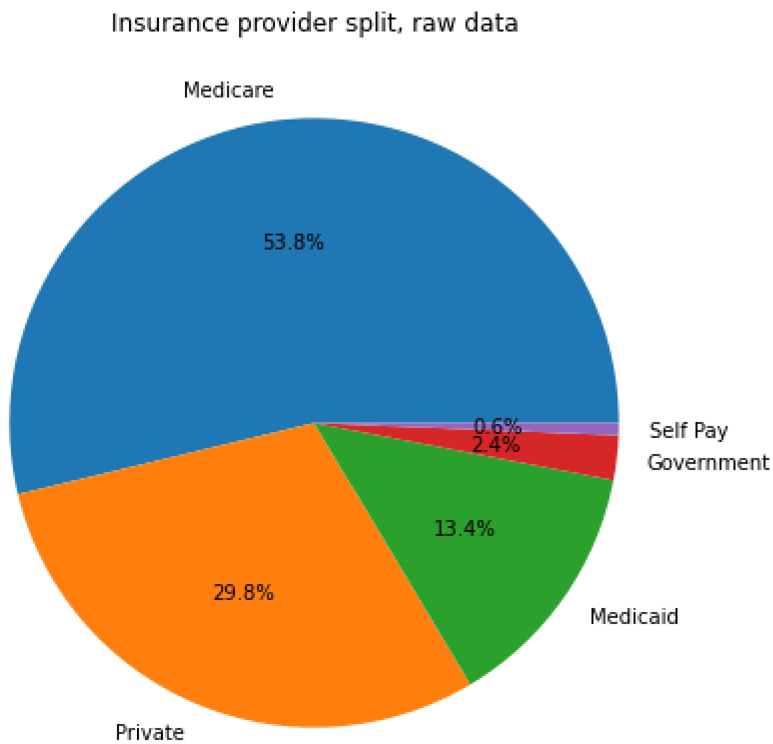
In [15]:
```
fig = plt.figure(figsize=(7,7))
df.MARITAL_STATUS.value_counts().plot.pie(startangle = 0, autopct='%1.1f%%')
plt.title('Marital status split, raw data')
plt.ylabel('')
```

Out[15]: Text(0, 0.5, '')



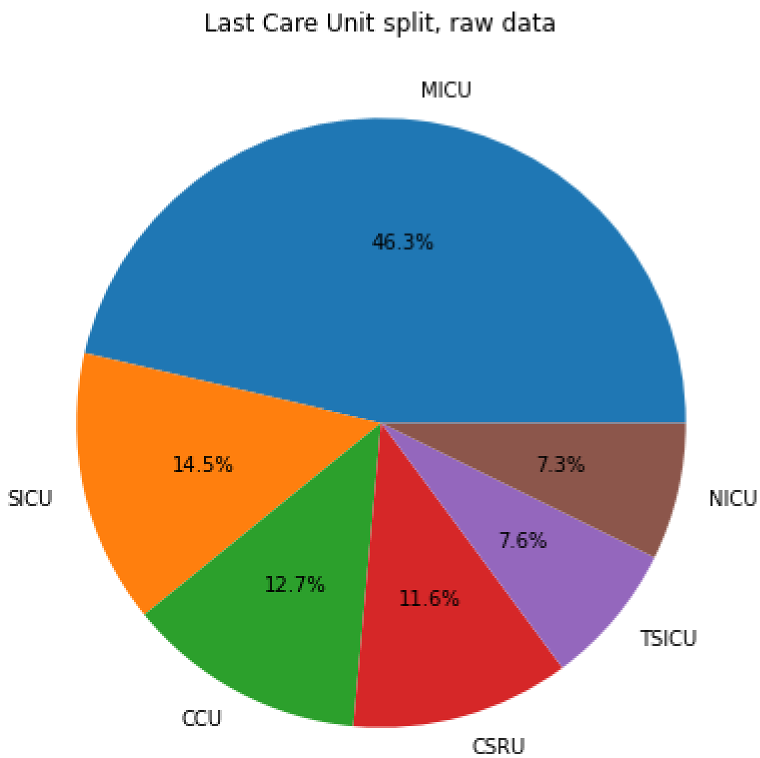
In [16]:
```
fig = plt.figure(figsize=(7,7))
df.INSURANCE.value_counts().plot.pie(startangle = 0, autopct='%1.1f%%')
plt.title('Insurance provider split, raw data')
plt.ylabel('')
```

Out[16]: Text(0, 0.5, '')



In [17]:
```
fig = plt.figure(figsize=(7,7))
df.LAST_CAREUNIT.value_counts().plot.pie(startangle = 0, autopct='%1.1f%%')
plt.title('Last Care Unit split, raw data')
plt.ylabel('')
```

Out[17]: Text(0, 0.5, '')



In [18]:
```
df.LAST_CAREUNIT.value_counts()
```

Out[18]:
```
MICU      53935
SICU      16891
CCU       14804
CSRU      13491
TSICU      8833
NICU       8472
Name: LAST_CAREUNIT, dtype: int64
```

3. Preprocessing

3-1. Extract readmission time information

In [19]:
```
df['DISCHTIME'] = df['DISCHTIME'].astype('datetime64[ns]')
df['ADMITTIME'] = df['ADMITTIME'].astype('datetime64[ns]')
```

In [20]:
```
# calculate time delta between subsequent readmissions of the same patient
df['readmit_dt'] = np.zeros(df.shape[0])
df['next_readmit_dt'] = np.zeros(df.shape[0])
```

In [21]:
```
for idx in np.arange(1,df.shape[0]):
    if df.SUBJECT_ID[idx] == df.SUBJECT_ID[idx - 1]:
        prev_disch = df.DISCHTIME[idx-1]
        curr_adm = df.ADMITTIME[idx]
        dt = curr_adm - prev_disch
        dt_hrs_calc = np.round(dt.value/3600.0/1e9,2)

        df.at[idx, 'readmit_dt'] = dt_hrs_calc
        df.at[idx-1, 'next_readmit_dt'] = dt_hrs_calc
```

Define time threshold and corresponding labels

In [22]:
```
# Define threshold in hours
threshold = 30*24
df['future_readmit'] = None
df['future_readmit'] = ['No' if dt == 0.0 else 'Yes' if dt>=threshold else 'No' f
```

In [23]:
```
df.iloc[:,-3:].head()
```

Out[23]:

	readmit_dt	next_readmit_dt	future_readmit
0	0.00	0.00	No
1	0.00	-131.92	No
2	-131.92	36024.40	Yes
3	36024.40	-162.43	No
4	-162.43	0.00	No

In [24]:
```
print('Value counts:')
print(df.future_readmit.value_counts())

print ('\nValue proportions:')
print(df.future_readmit.value_counts()/df.shape[0])
```

```
Value counts:
No     107436
Yes      8990
Name: future_readmit, dtype: int64

Value proportions:
No     0.922784
Yes    0.077216
Name: future_readmit, dtype: float64
```

Type *Markdown* and LaTeX: α^2

In [25]:
```
df.columns
```

Out[25]:
```
Index(['ROW_ID_x', 'SUBJECT_ID', 'HADM_ID_x', 'ADMITTIME', 'DISCHTIME',
       'DEATHTIME', 'ADMISSION_TYPE', 'ADMISSION_LOCATION',
       'DISCHARGE_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'EDREGTIME', 'EDOUTTIME', 'DIAGNOSIS',
       'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA', 'ROW_ID_y', 'GENDER',
       'DOB', 'DOD', 'DOD_HOSP', 'DOD_SSN', 'EXPIRE_FLAG', 'ROW_ID',
       'HADM_ID_y', 'ICUSTAY_ID', 'DBSOURCE', 'FIRST_CAREUNIT',
       'LAST_CAREUNIT', 'FIRST_WARDID', 'LAST_WARDID', 'INTIME', 'OUTTIME',
       'LOS', 'readmit_dt', 'next_readmit_dt', 'future_readmit'],
      dtype='object')
```

In [26]:
```
df = df.drop(['ROW_ID_x', 'SUBJECT_ID', 'HADM_ID_x', 'ADMITTIME', 'DISCHTIME','DE
              'EDOUTTIME', 'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA', \
              'ROW_ID_y','DOB', 'DOD', 'DOD_HOSP', 'DOD_SSN', 'EXPIRE_FLAG',\
              'ROW_ID','HADM_ID_y', 'ICUSTAY_ID', 'DBSOURCE', 'FIRST_WARDID', \
              'LAST_WARDID', 'INTIME', 'OUTTIME','LOS','readmit_dt','next_readmit
```

3-2. Check and Clean up missing or invalid values

In [27]:
```
np.sum(df.isnull())
```

Out[27]:
```
ADMISSION_TYPE             0
ADMISSION_LOCATION         0
DISCHARGE_LOCATION         0
INSURANCE                  0
LANGUAGE               39787
RELIGION                 525
MARITAL_STATUS         10929
ETHNICITY                  0
DIAGNOSIS                 55
GENDER                     0
FIRST_CAREUNIT             0
LAST_CAREUNIT              0
future_readmit             0
dtype: int64
```

In [28]:
```
is_NaN = df. isnull()
row_has_NaN = is_NaN. any(axis=1)
rows_with_NaN = df[row_has_NaN]
print(rows_with_NaN)
```

```
       ADMISSION_TYPE        ADMISSION_LOCATION        DISCHARGE_LOCATION  \
0           EMERGENCY       EMERGENCY ROOM ADMIT  DISC-TRAN CANCER/CHLDRN H
1           ELECTIVE   PHYS REFERRAL/NORMAL DELI          HOME HEALTH CARE
2           ELECTIVE   PHYS REFERRAL/NORMAL DELI          HOME HEALTH CARE
5           EMERGENCY  TRANSFER FROM HOSP/EXTRAM                      HOME
6           EMERGENCY       EMERGENCY ROOM ADMIT                      HOME
...               ...                        ...                       ...
116180      EMERGENCY  CLINIC REFERRAL/PREMATURE                      HOME
116216      EMERGENCY  TRANSFER FROM HOSP/EXTRAM                       SNF
116301      EMERGENCY  CLINIC REFERRAL/PREMATURE              DEAD/EXPIRED
116302      EMERGENCY  CLINIC REFERRAL/PREMATURE              DEAD/EXPIRED
116333      EMERGENCY  CLINIC REFERRAL/PREMATURE              DEAD/EXPIRED

       INSURANCE LANGUAGE          RELIGION MARITAL_STATUS  \
0        Private      NaN      UNOBTAINABLE        MARRIED
1       Medicare      NaN          CATHOLIC        MARRIED
2       Medicare      NaN          CATHOLIC        MARRIED
5        Private      NaN  PROTESTANT QUAKER         SINGLE
6        Private      NaN      UNOBTAINABLE        MARRIED
...          ...      ...               ...            ...
116180   Private     ENGL      UNOBTAINABLE            NaN
116216  Medicare     ENGL      UNOBTAINABLE            NaN
116301  Medicare     ENGL      UNOBTAINABLE            NaN
116302  Medicare     ENGL      UNOBTAINABLE            NaN
116333  Medicare     ENGL      UNOBTAINABLE            NaN

                     ETHNICITY  \
0                        WHITE
1                        WHITE
2                        WHITE
5                        WHITE
6                        WHITE
...                        ...
116180         UNABLE TO OBTAIN
116216  UNKNOWN/NOT SPECIFIED
116301  UNKNOWN/NOT SPECIFIED
116302  UNKNOWN/NOT SPECIFIED
116333         UNABLE TO OBTAIN

                                                DIAGNOSIS GENDER  \
0                                   BENZODIAZEPINE OVERDOSE      F
1       CORONARY ARTERY DISEASE\CORONARY ARTERY BYPASS...      M
2       CORONARY ARTERY DISEASE\CORONARY ARTERY BYPASS...      M
5                              INTERIOR MYOCARDIAL INFARCTION      M
6                                   ACUTE CORONARY SYNDROME      M
...                                                     ...    ...
116180                        ST ELEVATED MYOCARDIAL INFARCTION      M
116216                                    PORTAL VEIN THROMBUS      M
116301                                          ACUTE LEUKEMIA      F
116302                                          ACUTE LEUKEMIA      F
116333                                 SUBARACHNOID HEMORRHAGE      F
```

```
       FIRST_CAREUNIT LAST_CAREUNIT future_readmit
0                MICU          MICU             No
1                CSRU          CSRU             No
2                SICU          SICU            Yes
5                 CCU           CCU             No
6                 CCU           CCU             No
...               ...           ...            ...
116180            CCU           CCU             No
116216           SICU          SICU             No
116301           MICU          MICU             No
116302           MICU          MICU             No
116333          TSICU          SICU             No

[41238 rows x 13 columns]
```

In [29]:
```
# remove null
df = df.dropna()
```

In [30]:
```
np.sum(df.isnull())
```

Out[30]:
```
ADMISSION_TYPE        0
ADMISSION_LOCATION    0
DISCHARGE_LOCATION    0
INSURANCE             0
LANGUAGE              0
RELIGION              0
MARITAL_STATUS        0
ETHNICITY             0
DIAGNOSIS             0
GENDER                0
FIRST_CAREUNIT        0
LAST_CAREUNIT         0
future_readmit        0
dtype: int64
```

3-3. Labeling categorical values

In [31]:
```
df = df.astype('category')
```

In [32]:
```
labelencoder = LabelEncoder()
```

In [33]:
```
for col in df.columns:
    df[col+'_cat'] = labelencoder.fit_transform(df[col])
```

In [34]:
```
df.head()
```

Out[34]:

	ADMISSION_TYPE	ADMISSION_LOCATION	DISCHARGE_LOCATION	INSURANCE	LANGUAGE
3	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	HOME HEALTH CARE	Medicare	ENGL
4	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	HOME HEALTH CARE	Medicare	ENGL
14	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	HOME	Medicare	ENGL
15	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	HOME	Medicare	ENGL
16	EMERGENCY	CLINIC REFERRAL/PREMATURE	HOME HEALTH CARE	Medicare	ENGL

5 rows × 26 columns

In [35]:
```
df.keys()
```

Out[35]:
```
Index(['ADMISSION_TYPE', 'ADMISSION_LOCATION', 'DISCHARGE_LOCATION',
       'INSURANCE', 'LANGUAGE', 'RELIGION', 'MARITAL_STATUS', 'ETHNICITY',
       'DIAGNOSIS', 'GENDER', 'FIRST_CAREUNIT', 'LAST_CAREUNIT',
       'future_readmit', 'ADMISSION_TYPE_cat', 'ADMISSION_LOCATION_cat',
       'DISCHARGE_LOCATION_cat', 'INSURANCE_cat', 'LANGUAGE_cat',
       'RELIGION_cat', 'MARITAL_STATUS_cat', 'ETHNICITY_cat', 'DIAGNOSIS_cat',
       'GENDER_cat', 'FIRST_CAREUNIT_cat', 'LAST_CAREUNIT_cat',
       'future_readmit_cat'],
      dtype='object')
```

In [36]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 75188 entries, 3 to 116425
Data columns (total 26 columns):
 #   Column                  Non-Null Count  Dtype   
---  ------                  --------------  -----   
 0   ADMISSION_TYPE          75188 non-null  category
 1   ADMISSION_LOCATION      75188 non-null  category
 2   DISCHARGE_LOCATION      75188 non-null  category
 3   INSURANCE               75188 non-null  category
 4   LANGUAGE                75188 non-null  category
 5   RELIGION                75188 non-null  category
 6   MARITAL_STATUS          75188 non-null  category
 7   ETHNICITY               75188 non-null  category
 8   DIAGNOSIS               75188 non-null  category
 9   GENDER                  75188 non-null  category
 10  FIRST_CAREUNIT          75188 non-null  category
 11  LAST_CAREUNIT           75188 non-null  category
 12  future_readmit          75188 non-null  category
 13  ADMISSION_TYPE_cat      75188 non-null  int32   
 14  ADMISSION_LOCATION_cat  75188 non-null  int32   
 15  DISCHARGE_LOCATION_cat  75188 non-null  int32   
 16  INSURANCE_cat           75188 non-null  int32   
 17  LANGUAGE_cat            75188 non-null  int32   
 18  RELIGION_cat            75188 non-null  int32   
 19  MARITAL_STATUS_cat      75188 non-null  int32   
 20  ETHNICITY_cat           75188 non-null  int32   
 21  DIAGNOSIS_cat           75188 non-null  int32   
 22  GENDER_cat              75188 non-null  int32   
 23  FIRST_CAREUNIT_cat      75188 non-null  int32   
 24  LAST_CAREUNIT_cat       75188 non-null  int32   
 25  future_readmit_cat      75188 non-null  int32   
dtypes: category(13), int32(13)
memory usage: 5.7 MB
```

In [37]:
```
df_new = df.drop(['ADMISSION_TYPE', 'ADMISSION_LOCATION', 'DISCHARGE_LOCATION',
       'INSURANCE', 'LANGUAGE', 'RELIGION', 'MARITAL_STATUS', 'ETHNICITY',
       'DIAGNOSIS', 'GENDER', 'FIRST_CAREUNIT', 'LAST_CAREUNIT',
       'future_readmit'], axis = 1)
```

In [38]:
```
df_new.head()
```

Out[38]:

	ADMISSION_TYPE_cat	ADMISSION_LOCATION_cat	DISCHARGE_LOCATION_cat	INSURANCE_cat
3	1	5	5	2
4	1	5	5	2
14	1	5	4	2
15	1	5	4	2
16	1	1	5	2

In [39]:
```
print('Value counts:')
print(df_new.future_readmit_cat.value_counts())
```

```
Value counts:
0    69104
1     6084
Name: future_readmit_cat, dtype: int64
```

This is an imbalanced dataset. Perform upsampling for minor sample (Label = 1)

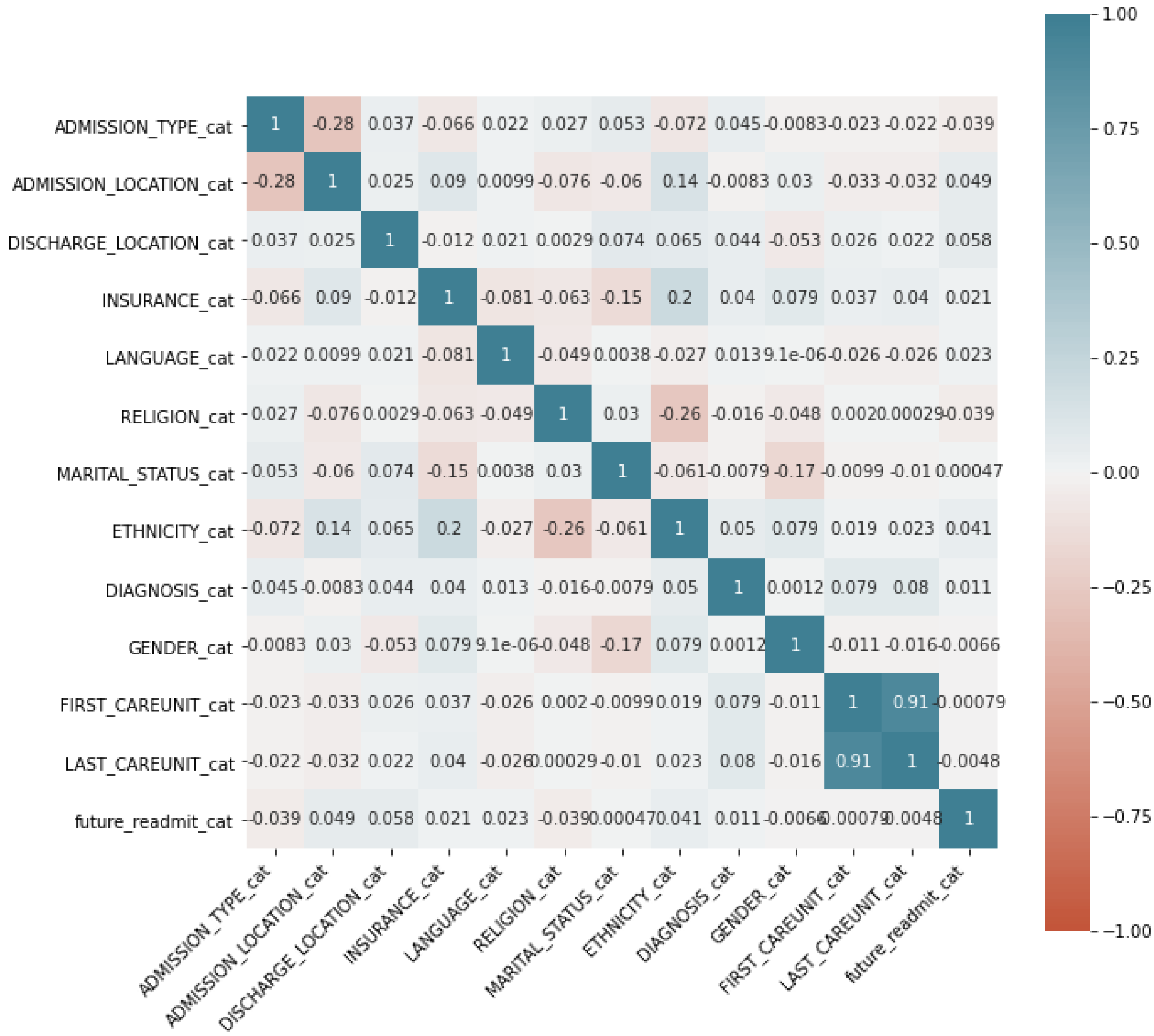
In [40]:
```
from sklearn.utils import resample
df_major = df_new[df_new.future_readmit_cat == 0]
df_minor = df_new[df_new.future_readmit_cat == 1]

df_minor_upsample  = resample(df_minor, replace = True, \
                              n_samples=69104, random_state = 123)
df_up = pd.concat([df_minor_upsample, df_major])
```

In [41]:
```
print('Value counts:')
print(df_up.future_readmit_cat.value_counts())
```

```
Value counts:
1    69104
0    69104
Name: future_readmit_cat, dtype: int64
```

3-4. Correlation Matrix

In [42]:
```
corr = df_up.corr()
plt.figure(figsize=(10,10))
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200), annot=True,
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



FIRST_CAREUNIT and LAST_CAREUNIT are highly correlated and will remove FIRST_CAREUNIT feature

In [43]:
```
X = df_up.iloc[:,0:12]
y = df_up.iloc[:,-1]
```

In [44]:
```
# remove FIRST_CAREUNIT_cat feature
X = X.drop(['FIRST_CAREUNIT_cat'], axis =1)
```

In [45]:
```
# splittin dataset into train and test sets
x_tr, x_test, y_tr, y_test = train_test_split(X, y)
```

In [ ]:
```

```

4. Models

4-1. Logistic Regression

As a baseline model, I trained Logsitic regression model.

In [46]:
```
lr = LogisticRegression(penalty='l2', C=1)
# Fit the model
lr.fit(x_tr, y_tr)

# probabilities for the target
lr_pred_prob = lr.predict_proba(x_test)
# prediction
lr_pred = lr.predict(x_test)
```

Cross Validations

In [47]:
```
scores = cross_val_score(lr, X, y, scoring='accuracy', cv=5)
print('Cross-Validation Accuracy Scores', scores)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:76
2: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  n_iter_i = _check_optimize_result(

Cross-Validation Accuracy Scores [0.55603791 0.51063599 0.50350915 0.51199305
0.50522774]
```

In [48]:
```
scores = pd.Series(scores)
print("min accuracy: ", scores.min())
print("mean accuracy: ", scores.mean())
print("max accuracy: ", scores.max())
```

```
min accuracy:  0.5035091527385862
mean accuracy:  0.5174807699934535
max accuracy:  0.5560379133203097
```

Accuracy score

In [49]:
```
# accuracy score
accuracy_score(y_test, lr_pred)
```

Out[49]:
```
0.5347881454040287
```

Confusion Matrix

In [50]:
```
# confusion matrix
confusion = confusion_matrix(y_test, lr_pred)
confusion
```

Out[50]:
```
array([[9119, 8270],
       [7804, 9359]], dtype=int64)
```

Classification Report

In [51]:
```
#Classification Report
print(classification_report(y_test, lr_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.54      0.52      0.53     17389
           1       0.53      0.55      0.54     17163

    accuracy                           0.53     34552
   macro avg       0.53      0.53      0.53     34552
weighted avg       0.53      0.53      0.53     34552
```

In [52]:
```
# calculation for ROC/PR curve => plots are below
l_fpr, l_tpr, _ = roc_curve(y_test, lr_pred_prob[:,1], pos_label=1)

random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

In [53]:
```
l_precision, l_recall, _ = precision_recall_curve(y_test, lr_pred_prob[:,1])
```

In [54]:
```
AUC = roc_auc_score(y_test, lr_pred_prob[:, 1])
AUC
```

Out[54]:
```
0.5512224001329655
```

In [ ]:

4-2 Random Forest

In [55]:
```
forest = RandomForestClassifier()
```

In [56]:
```
#exhaustive grid search is a good way to determine the best hyperparameter values

n_estimators = [20,25,30, 35]
max_depth = [15, 25, 30]
min_samples_split = [20,30,50,100]
min_samples_leaf = [2,5, 10, 15]

hyperPar = dict(n_estimators = n_estimators, max_depth = max_depth,
              min_samples_split = min_samples_split,
             min_samples_leaf = min_samples_leaf)
```

In [57]:
```
# k=5-fold
rf_grid = GridSearchCV(forest, hyperPar, cv = 5, verbose = 1, n_jobs = -1)
```

In [58]:
```
rf_best = rf_grid.fit(x_tr, y_tr)
```

```
Fitting 5 folds for each of 192 candidates, totalling 960 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   36.7s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  6.3min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed: 11.4min
[Parallel(n_jobs=-1)]: Done 960 out of 960 | elapsed: 14.0min finished
```

In [59]:
```
# find optimal hyper-parameters
rf_best.best_params_
```

Out[59]:
```
{'max_depth': 30,
 'min_samples_leaf': 2,
 'min_samples_split': 20,
 'n_estimators': 35}
```

In [60]:
```
# fitting with optimal hyperparameters
rf_opt = RandomForestClassifier(random_state = 1, max_depth = 30,\
                                   n_estimators = 35, min_samples_split = 20, mir
rf_opt.fit(x_tr, y_tr)
```

Out[60]:
```
RandomForestClassifier(max_depth=30, min_samples_leaf=2, min_samples_split=20,
                       n_estimators=35, random_state=1)
```

In [61]:
```
# prediction
rf_pred = rf_opt.predict(x_test)
```

In [62]:
```
# probabilities for the target
rf_pred_prob = rf_opt.predict_proba(x_test)
```

Crosss Validation

In [63]:
```
scores_r = cross_val_score(rf_opt, x_tr, y_tr, scoring='accuracy', cv=5)
print('Cross-Validation Accuracy Scores', scores_r)
```

```
Cross-Validation Accuracy Scores [0.82355779 0.82239159 0.8230669  0.81862911
 0.82634702]
```

In [64]:
```
rfscores = pd.Series(scores_r)
print("min accuracy: ", rfscores.min())
print("mean accuracy: ", rfscores.mean())
print("max accuracy: ", rfscores.max())
```

```
min accuracy:  0.8186291061695046
mean accuracy:  0.8227984799789198
max accuracy:  0.8263470165452703
```

Accuracy score

In [65]:
```
# accuracy score
accuracy_score(y_test, rf_pred)
```

Out[65]:
```
0.8437717064135216
```

Confusion Matrix

In [66]:
```
# confusion matrix
confusion = confusion_matrix(y_test, rf_pred)
confusion
```

Out[66]:
```
array([[13447,  3942],
       [ 1456, 15707]], dtype=int64)
```

Classification Report

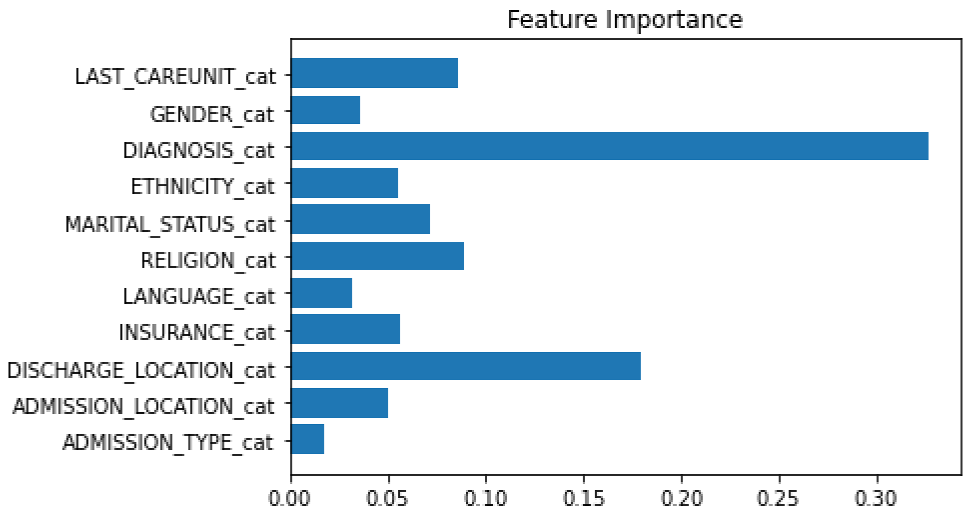
In [67]:
```
print(classification_report(y_test, rf_pred, target_names=['0', '1']))
```

```
              precision    recall  f1-score   support

           0       0.90      0.77      0.83     17389
           1       0.80      0.92      0.85     17163

    accuracy                           0.84     34552
   macro avg       0.85      0.84      0.84     34552
weighted avg       0.85      0.84      0.84     34552
```

Variable Importance

In [68]:
```
import matplotlib.pyplot as plt
plt.barh(x_tr.columns, rf_opt.feature_importances_)
plt.title('Feature Importance')
```

Out[68]: `Text(0.5, 1.0, 'Feature Importance')`



DIAGNOSIS feature is most important for the accuracy of model ad DISCHARGE_LOCATION is also important.

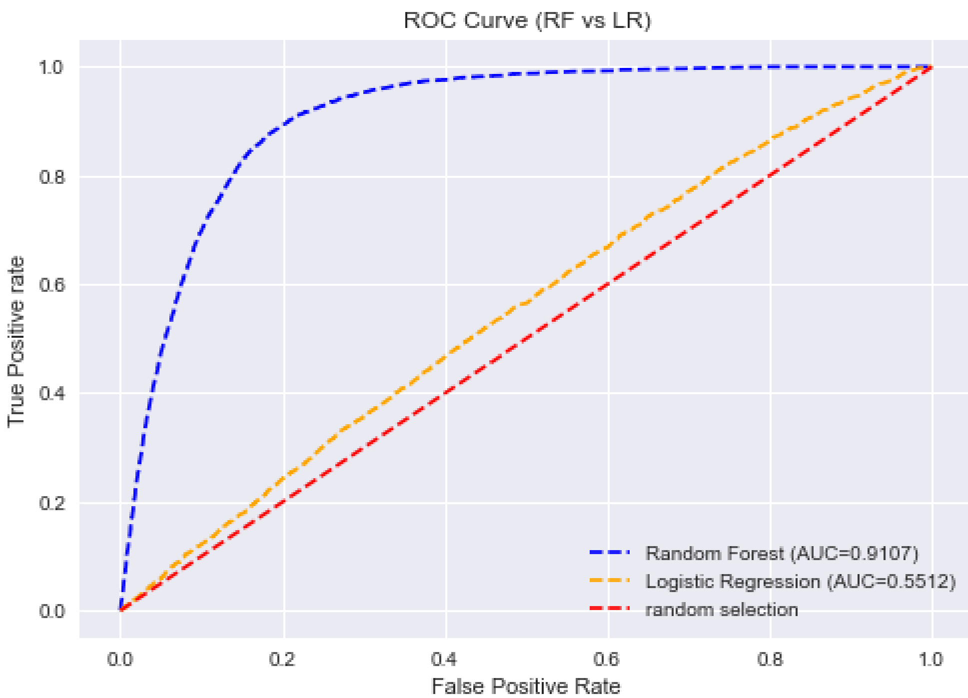
In [69]:
```
# RF ROC AUC calculation
AUC = roc_auc_score(y_test, rf_pred_prob[:, 1])
AUC
```

Out[69]: `0.910673971779557`

4-3. Model Comparison Logistic Regression vs Random Forest

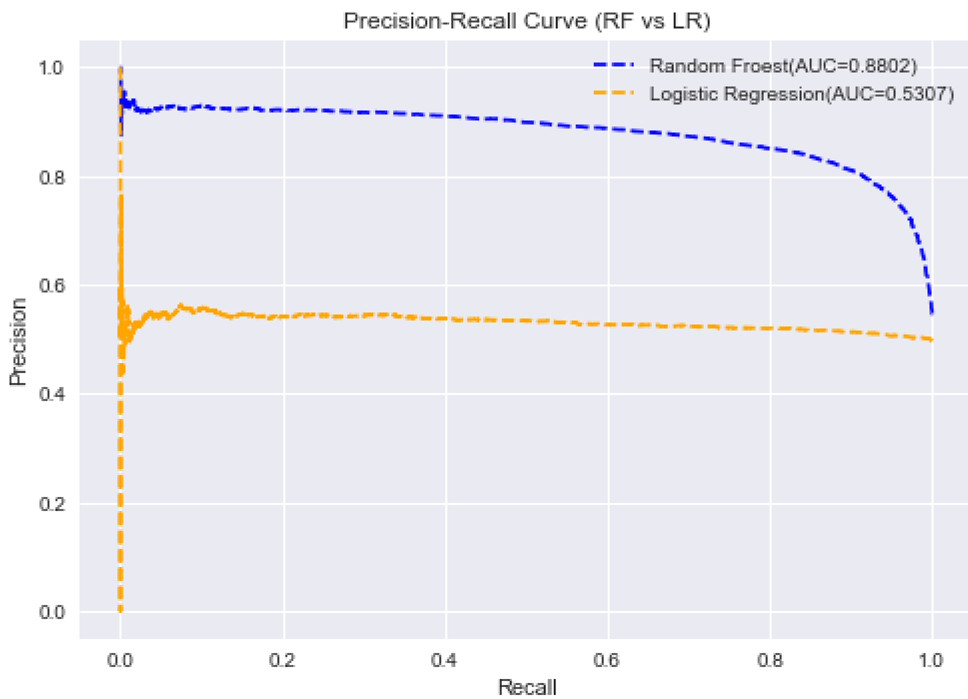
ROC curve (receiver operating characteristic curve)

In [70]:
```
fpr, tpr, _ = roc_curve(y_test, rf_pred_prob[:,1], pos_label=1)

plt.style.use('seaborn')

# plot roc curves
plt.plot(fpr, tpr, linestyle='--',color='blue', label=f'Random Forest (AUC={auc(f
plt.plot(l_fpr, l_tpr, linestyle='--',color='orange', label=f'Logistic Regression
plt.plot(p_fpr, p_tpr, linestyle='--', color='red', label = 'random selection')
plt.title('ROC Curve (RF vs LR)')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')
plt.show();
```



PR Curve (Precision-Recall curves)

In [71]:
```
precision, recall, thresholds = precision_recall_curve(y_test, rf_pred_prob[:,1])
# plot pr curves
plt.plot(recall, precision, linestyle='--',color='blue', label=f'Random Froest(AU
plt.plot(l_recall, l_precision, linestyle='--',color='orange', label=f'Logistic R
plt.title('Precision-Recall Curve (RF vs LR)')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.legend(loc='best')
plt.show();
```



5. Conclusion

In this project, I tried to predict 30-day readmission with two machine learning models, Logistic Regression and Random Forest. From the evaluation metrics that accuracy, recall, precision, ROC curve, PR curve, etc., I could see that overall performance of Random Forest outperforms Logistic Regression model. Dataset which is used in this project consists of mostly categorical features. I could see that Random Forest works better when dataset consists of categorical features and Logistic Regression model works poorly in this case. As future works, we can use or combine other datasets to imporve the performance and try deep-learning model.

References

1. https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program

(https://www.cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program)
2. https://www.kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/ (https://www.kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/)

In [ ]: