04_readmission

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1 Hospital Readmission

What do we mean by readmission? We mean an admission to the hospital for a patient that is already been hospitalized within a certain period of time.

1.1 1. Problem Statement

The goal is to create a model that predicts which patients are at risk for 30-day, 90-day or 365-day unplanned readmission utilizing patients demographics, diagnoses and icustays.

1.2 2. Type of model used for prediction

"Re-Admission" is a categorical attribute (YES,NO), so a classification model is used.

1.3 3. Metrics used for validation

For validation we use the metrics derived from the Confusion Matrix. The structure of this kinf o matrix for a binary classifier is the following:

There are 4 important terms in this performance: - True Positives (TP): The cases in which we predicted YES and the actual output was also YES. - True Negatives (TN): The cases in which we predicted NO and the actual output was NO. - False Positives (FP): The cases in which we predicted YES and the actual output was NO. - False Negatives (FN): The cases in which we predicted NO and the actual output was YES.

From these terms we can compute our metrics used for validate the model: - **Accuracy**: it means how well the models predict all of the labels correctly. **Higher accuracy means better performance**. - **Precision**: it describes how well the model can predict the labels correctly. - **Recall**: it describes how the model can retrieve all of the labels correctly. - **AUC (Area Under the ROC Curve)**: AUC measures the entire two-dimensional area underneath the entire ROC curve where the ROC curve is a graph showing the performance of a classification model at all classification thresholds, that plots precision and recall. AUC provides an aggregate measure of performance across all possible classification thresholds. One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example.

We start importing our baseline dataset extracted selecting only the necessary tables from MIMIC dataset.

[188]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[189]:
```
# Import baseline dataset constructed in data extraction and preparation phase
admits_patients_diag = pd.read_csv('admits_patients_diag.csv')

#convert dates
admits_patients_diag.admittime = pd.to_datetime(admits_patients_diag.admittime)
admits_patients_diag.dischtime = pd.to_datetime(admits_patients_diag.dischtime)
admits_patients_diag.deathtime = pd.to_datetime(admits_patients_diag.deathtime)

admits_patients_diag.head()
```

[189]:
```
   Unnamed: 0  subject_id   hadm_id           admittime           dischtime  \
0           0    14679932  21038362 2139-09-26 14:16:00 2139-09-28 11:30:00
1           1    15585972  24941086 2123-10-07 23:56:00 2123-10-12 11:22:00
2           2    15078341  23272159 2122-08-28 08:48:00 2122-08-30 12:32:00
3           3    17301855  29732723 2140-06-06 14:23:00 2140-06-08 14:25:00
4           4    17991012  24298836 2181-07-10 20:28:00 2181-07-12 15:49:00

  deathtime admission_type insurance               ethnicity  \
0       NaT       ELECTIVE     Other           OTHER/UNKNOWN
1       NaT       ELECTIVE     Other                   WHITE
2       NaT       ELECTIVE     Other  BLACK/AFRICAN AMERICAN
3       NaT       ELECTIVE     Other                   WHITE
4       NaT       ELECTIVE     Other                   WHITE

   died_at_the_hospital  … injury  mental misc  muscular  neoplasms  \
0                     0  …      2       0    0         0          0
1                     0  …      2       0    0         0          0
2                     0  …      3       0    0         0          0
3                     0  …      2       0    0         0          0
4                     0  …      2       0    0         0          0

   nervous  pregnancy  prenatal  respiratory  skin
0        0          0         0            0     0
1        0          0         0            0     0
2        0          0         0            0     0
3        0          0         1            0     0
4        0          0         0            0     0

[5 rows x 30 columns]
```

[190]:
```python
# check to see if there are any missing dates
print('Number of missing date admissions:', admits_patients_diag.admittime.
 ↪isnull().sum())
print('Number of missing date discharges:', admits_patients_diag.dischtime.
 ↪isnull().sum())
```

```
Number of missing date admissions: 0
Number of missing date discharges: 0
```

Since we want to predict a readmission we have to get the next admission date for a patient if it exists.

[191]:
```python
# first we sort by subject_id and admission date
admits_patients_diag = admits_patients_diag.
 ↪sort_values(['subject_id','admittime'])
admits_patients_diag = admits_patients_diag.reset_index(drop = True)
```

[192]:
```python
# verify that the previous operation was successful
admits_patients_diag.loc[admits_patients_diag.subject_id ==␣
 ↪10000032,['subject_id','admittime','admission_type']]
```

[192]:
```
   subject_id           admittime admission_type
1    10000032 2180-05-06 22:23:00      EMERGENCY
2    10000032 2180-06-26 18:27:00      EMERGENCY
3    10000032 2180-07-23 12:35:00      EMERGENCY
4    10000032 2180-08-05 23:44:00      EMERGENCY
```

[193]:
```python
# add the next admission date and type for each subject using groupby and shift␣
 ↪function
admits_patients_diag['next_admittime'] = admits_patients_diag.
 ↪groupby('subject_id').admittime.shift(-1)
# get the next admission type using groupby and shift function
admits_patients_diag['next_admission_type'] = admits_patients_diag.
 ↪groupby('subject_id').admission_type.shift(-1)
```

[194]:
```python
# verify that the previous operation was successful
admits_patients_diag.loc[admits_patients_diag.subject_id ==␣
 ↪10000032,['subject_id','admittime','admission_type','next_admittime','next_admission_type']]
```

[194]:
```
   subject_id           admittime admission_type      next_admittime  \
1    10000032 2180-05-06 22:23:00      EMERGENCY 2180-06-26 18:27:00
2    10000032 2180-06-26 18:27:00      EMERGENCY 2180-07-23 12:35:00
3    10000032 2180-07-23 12:35:00      EMERGENCY 2180-08-05 23:44:00
4    10000032 2180-08-05 23:44:00      EMERGENCY                 NaT

  next_admission_type
1           EMERGENCY
2           EMERGENCY
```

```
3          EMERGENCY
4                NaN
```

[195]:
```
#analyze admission_type
admits_patients_diag['admission_type'].value_counts()
```

[195]:
```
EMERGENCY                      178476
OBSERVATION                     84779
ELECTIVE                        45952
SURGICAL SAME DAY ADMISSION     26171
Name: admission_type, dtype: int64
```

Since we want to predict UNPLANNED re-admissions, so we should filter out the ELECTIVE (planned) next admissions.

[196]:
```
# get rows where next admission is elective and replace with naT or nan
elective_rows = admits_patients_diag.next_admission_type == 'ELECTIVE'
admits_patients_diag.loc[elective_rows,'next_admittime'] = pd.NaT
admits_patients_diag.loc[elective_rows,'next_admission_type'] = np.NaN
```

[197]:
```
# backfill in the values that we removed

# sort by subject_ID and admission date
admits_patients_diag = admits_patients_diag.
↪sort_values(['subject_id','admittime'])

# back fill (this will take a little while)
admits_patients_diag[['next_admittime','next_admission_type']] =␣
↪admits_patients_diag.
↪groupby(['subject_id'])[['next_admittime','next_admission_type']].
↪fillna(method = 'bfill')
```

[198]:
```
# verify
admits_patients_diag['admission_type'].value_counts()
```

[198]:
```
EMERGENCY                      178476
OBSERVATION                     84779
ELECTIVE                        45952
SURGICAL SAME DAY ADMISSION     26171
Name: admission_type, dtype: int64
```

[199]:
```
admits_patients_diag.head()
```

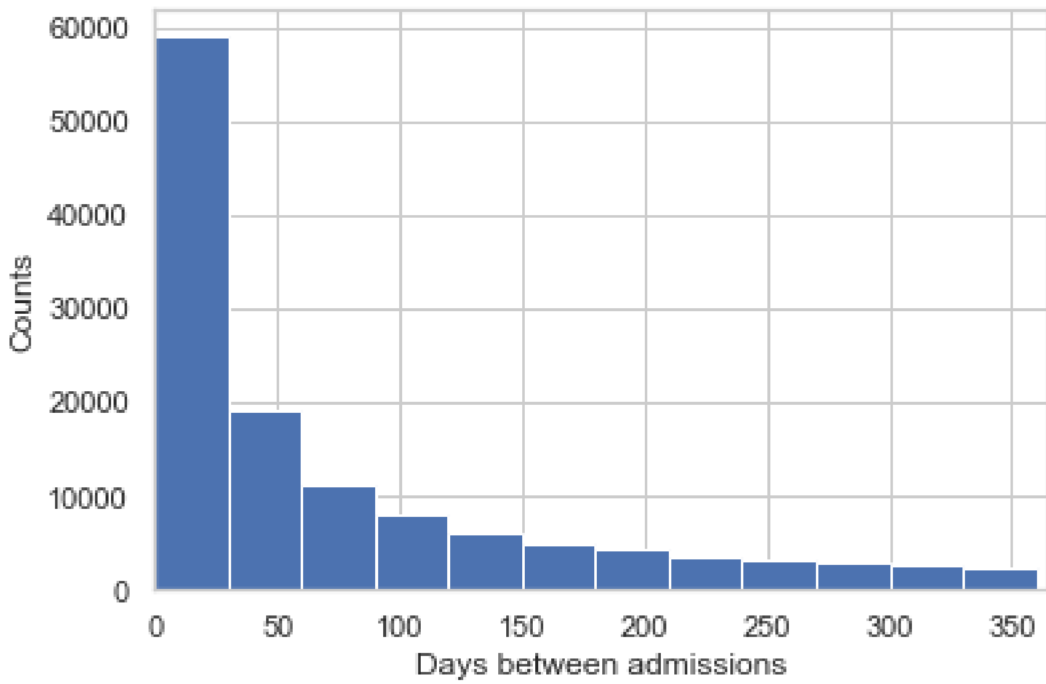
[199]:
```
   Unnamed: 0  subject_id   hadm_id           admittime           dischtime  \
0      170509    10000019  25058216 2129-05-21 19:16:00 2129-05-23 18:30:00
1      285967    10000032  22595853 2180-05-06 22:23:00 2180-05-07 17:15:00
2      285968    10000032  22841357 2180-06-26 18:27:00 2180-06-27 18:49:00
3      285966    10000032  29079034 2180-07-23 12:35:00 2180-07-25 17:55:00
```

```
4      285969    10000032  25742920 2180-08-05 23:44:00 2180-08-07 17:50:00

  deathtime admission_type insurance ethnicity  died_at_the_hospital  …  \
0       NaT       ELECTIVE     Other     WHITE                     0  …
1       NaT      EMERGENCY     Other     WHITE                     0  …
2       NaT      EMERGENCY  Medicaid     WHITE                     0  …
3       NaT      EMERGENCY  Medicaid     WHITE                     0  …
4       NaT      EMERGENCY  Medicaid     WHITE                     0  …

  misc  muscular neoplasms  nervous  pregnancy  prenatal  respiratory  skin  \
0    0         0         0        0          0         0            0     0
1    1         0         0        0          0         0            1     0
2    1         0         0        0          0         0            1     0
3    2         0         0        0          0         0            1     0
4    2         0         0        0          0         0            1     0

       next_admittime  next_admission_type
0                 NaT                  NaN
1 2180-06-26 18:27:00            EMERGENCY
2 2180-07-23 12:35:00            EMERGENCY
3 2180-08-05 23:44:00            EMERGENCY
4                 NaT                  NaN

[5 rows x 32 columns]
```

Now we calculate days until next admission, because we want to predict unplanned re-admission within a specific range of days (30, 90, 365).

[200]:
```python
# calculate the number of days between discharge and next admission
admits_patients_diag['days_next_admit']=  (admits_patients_diag.next_admittime␣
↪- admits_patients_diag.dischtime).dt.total_seconds()/(24*60*60)
```

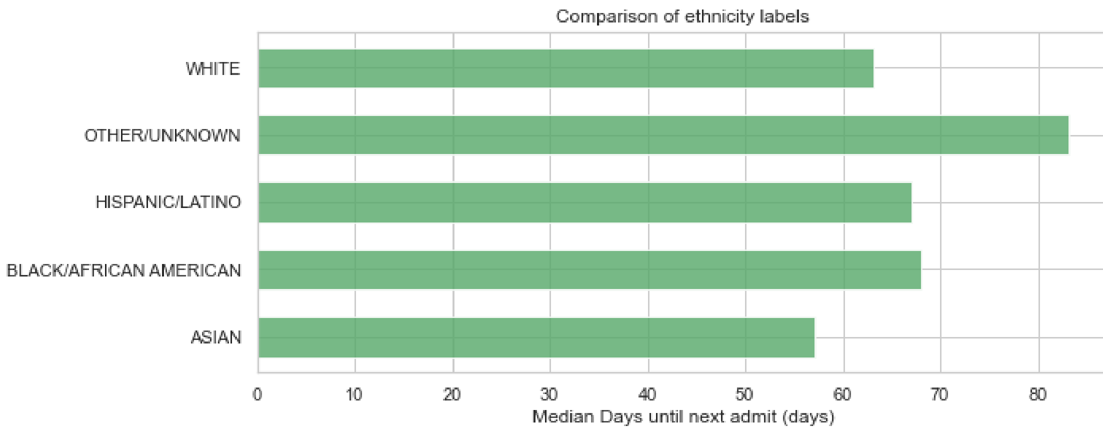
[201]:
```python
# plot a histogram of days between readmissions if they exist
plt.hist(admits_patients_diag.loc[~admits_patients_diag.days_next_admit.
↪isnull(),'days_next_admit'], bins =range(0,365,30))
plt.xlim([0,365])
plt.xlabel('Days between admissions')
plt.ylabel('Counts')
plt.show()
```



Ethnicity attribute correlation

[202]:
```
# Re-usable plotting function
def plot_los_groupby(variable, size=(7,4)):
    '''
    Plot Median 'Days_Next_Admit" by dataframe categorical series name
    '''
    results = admits_patients_diag[[variable, 'days_next_admit']].
↪groupby(variable).median().reset_index()
    values = list(results['days_next_admit'].values)
    labels = list(results[variable].values)

    fig, ax = plt.subplots(figsize=size)
    ind = range(len(results))
    ax.barh(ind, values, align='center', height=0.6, color = '#55a868', alpha=0.
↪8)
    ax.set_yticks(ind)
    ax.set_yticklabels(labels)
    ax.set_xlabel('Median Days until next admit (days)')
    ax.tick_params(left=False, top=False, right=False)
    ax.set_title('Comparison of {} labels'.format(variable))

    plt.tight_layout()
    plt.show();
```

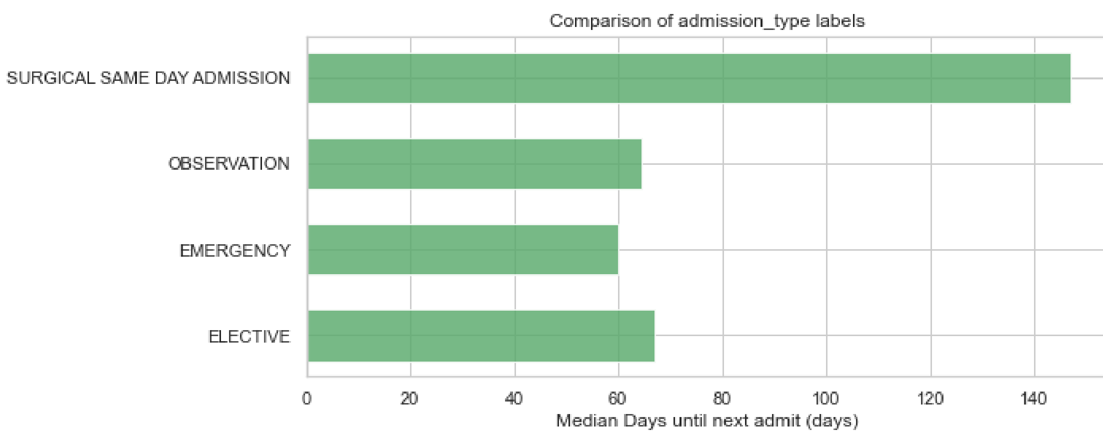
```
# Look at median "days_next_admit" for groups ETHNICITY
plot_los_groupby('ethnicity', size=(10,4))
```



To notice that "ASIAN" patients have the lowest median of days until next admission.

ADMISSION_TYPE attribute

[203]:
```
plot_los_groupby('admission_type', size=(10,4))
```

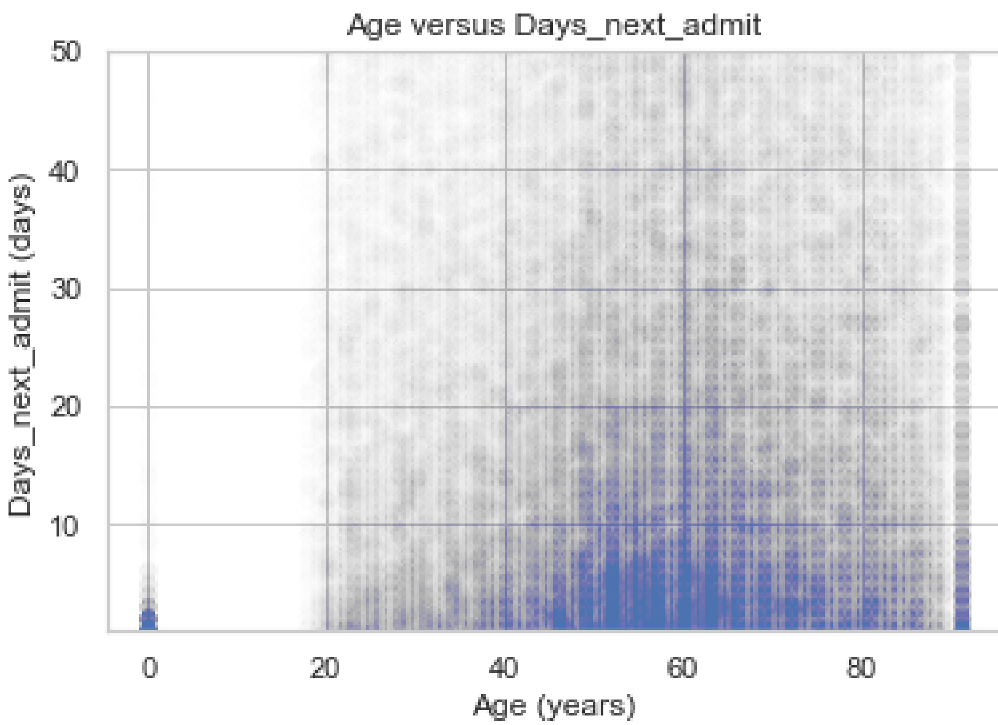


As we could expect we a larger median of days until next admission for those admission which the patients had a surgical operation in the same day. This is expected because after a surgical operation is probable to be readmitted in a short time of period for observation usually.

1.3.1 Age attribute

[204]:
```
plt.scatter(admits_patients_diag['anchor_age'],␣
↪admits_patients_diag['days_next_admit'], alpha=0.005)
plt.ylabel('Days_next_admit (days)')
plt.xlabel('Age (years)')
plt.title('Age versus Days_next_admit')
plt.ylim(1, 50)
```

[204]:
```
(1.0, 50.0)
```



As we did for our previous tasks, because of the discrete-like distribution of data on the extremes of age, it could be useful to convert all ages into the categories of **newborn, young adult, middle adult, and senior** for use in the prediction model.

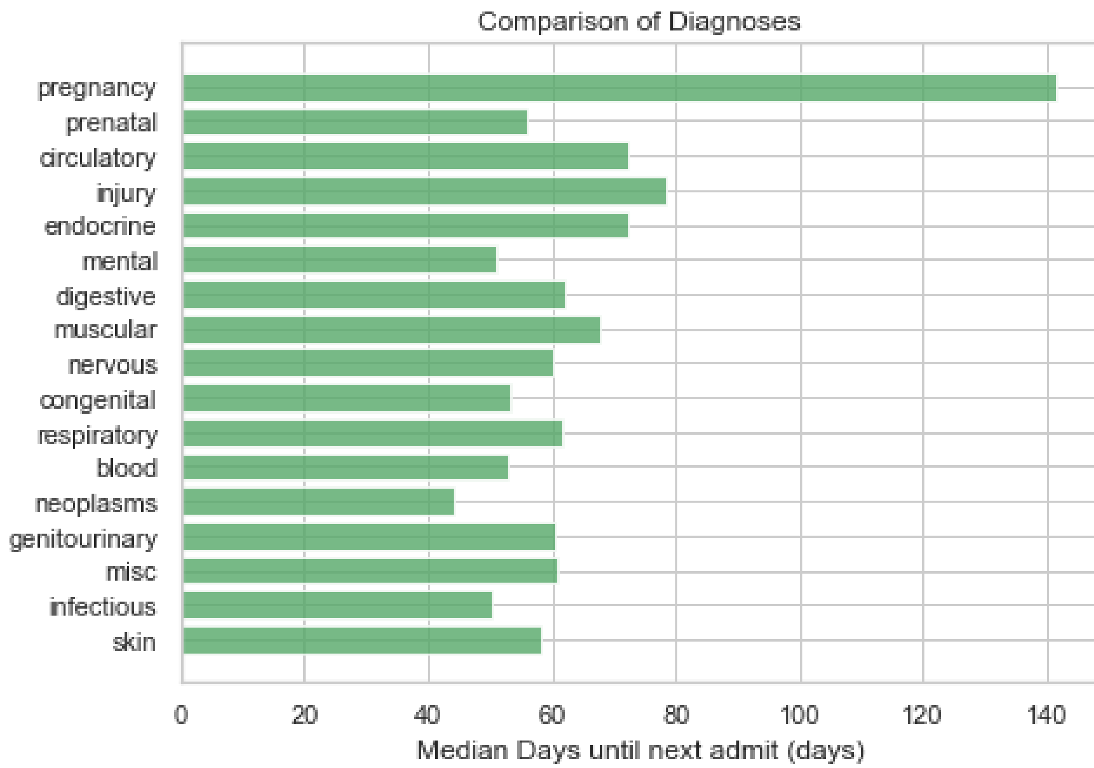
[205]:
```
age_ranges = [(0, 13), (14, 36), (37, 56), (57, 100)]
for num, cat_range in enumerate(age_ranges):
    admits_patients_diag['anchor_age'] = np.
↪where(admits_patients_diag['anchor_age'].between(cat_range[0],cat_range[1]),␣
↪num, admits_patients_diag['anchor_age'])

age_dict = {0: 'NEWBORN', 1: 'YOUNG_ADULT', 2: 'MIDDLE_ADULT', 3: 'SENIOR'}
admits_patients_diag['anchor_age'] = admits_patients_diag['anchor_age'].
↪replace(age_dict)
```

```
admits_patients_diag.anchor_age.value_counts()
```

[205]:
```
SENIOR          155500
MIDDLE_ADULT     88506
YOUNG_ADULT      52902
NEWBORN          38470
Name: anchor_age, dtype: int64
```

Now, let's analyze the diagnosis in correlation to the number of day until next admission.

[206]:
```
import seaborn as sns

# Look at the median Days_next_Admit by diagnosis category
diag_cat_list = ['skin', 'infectious',  'misc', 'genitourinary', 'neoplasms',␣
↪'blood', 'respiratory',
                  'congenital','nervous', 'muscular', 'digestive', 'mental',␣
↪'endocrine', 'injury',
                 'circulatory', 'prenatal',  'pregnancy']

results = []
for variable in diag_cat_list:
    results.append(admits_patients_diag[[variable, 'days_next_admit']].
↪groupby(variable).median().reset_index().values[1][1])

sns.set(style="whitegrid")
fig, ax = plt.subplots(figsize=(7,5))
ind = range(len(results))
ax.barh(ind, results, color = '#55a868', alpha=0.8)
ax.set_yticks(ind)
ax.set_yticklabels(diag_cat_list)
ax.set_xlabel('Median Days until next admit (days)')
ax.tick_params(left=False, right=False, top=False)
ax.set_title('Comparison of Diagnoses'.format(variable))
plt.show();
```



We notice that: - Patients in pregnancy have a really high median, namely the days until next admission are a lot and this is expected because if the birth of the child goes well there is no need for the patient to be readmitted shortly at the hospital. - Patients diagnosed in the *neoplasms** category, instead, have the lower median. It means that they can more likely be readmitted in a short time.

The data in the ICUSTAYS table could be useful because indicates if a patient during an admission was in an ICU (Intensive Care Unit). This could be a factor that could increment the possibility that a patient is readmitted to the hospital within a certain period of time.

[207]:
```
mimic4_path = '../../mimic-iv-1.0/'

# read icustays table
def read_icustays_table(mimic4_path):
    icustays = pd.read_csv(mimic4_path + 'icu/icustays.csv')
    return icustays

icustays = read_icustays_table(mimic4_path)
icustays.head()
```

[207]:
```
   subject_id   hadm_id   stay_id       first_careunit        last_careunit  \
0    17867402  24528534  31793211  Trauma SICU (TSICU)  Trauma SICU (TSICU)
1    14435996  28960964  31983544  Trauma SICU (TSICU)  Trauma SICU (TSICU)
```

```
2    17609946  27385897  33183475  Trauma SICU (TSICU)  Trauma SICU (TSICU)
3    18966770  23483021  34131444  Trauma SICU (TSICU)  Trauma SICU (TSICU)
4    12776735  20817525  34547665       Neuro Stepdown       Neuro Stepdown

                intime             outtime       los
0  2154-03-03 04:11:00  2154-03-04 18:16:56  1.587454
1  2150-06-19 17:57:00  2150-06-22 18:33:54  3.025625
2  2138-02-05 18:54:00  2138-02-15 12:42:05  9.741725
3  2123-10-25 10:35:00  2123-10-25 18:59:47  0.350544
4  2200-07-12 00:33:00  2200-07-13 16:44:40  1.674769
```

[208]:
```python
icustays['category'] = icustays['first_careunit']
icu_list = icustays.groupby('hadm_id')['category'].apply(list).reset_index()
icu_list.head()
```

[208]:
```
    hadm_id                                           category
0  20000094                         [Coronary Care Unit (CCU)]
1  20000147                         [Coronary Care Unit (CCU)]
2  20000351  [Medical/Surgical Intensive Care Unit (MICU/SI…
3  20000397                         [Coronary Care Unit (CCU)]
4  20000808  [Surgical Intensive Care Unit (SICU), Surgical…
```

[209]:
```python
icustays['first_careunit'].value_counts()
```

[209]:
```
Medical Intensive Care Unit (MICU)                  16729
Medical/Surgical Intensive Care Unit (MICU/SICU)    13421
Cardiac Vascular Intensive Care Unit (CVICU)        12169
Surgical Intensive Care Unit (SICU)                 11765
Trauma SICU (TSICU)                                  9165
Coronary Care Unit (CCU)                             8746
Neuro Surgical Intensive Care Unit (Neuro SICU)      1851
Neuro Intermediate                                   1823
Neuro Stepdown                                        871
Name: first_careunit, dtype: int64
```

[210]:
```python
# Create admission-ICU matrix
icu_item = pd.get_dummies(icu_list['category'].apply(pd.Series).stack()).
 ↪sum(level=0)
icu_item[icu_item >= 1] = 1
icu_item = icu_item.join(icu_list['hadm_id'], how="outer")
icu_item.head()
```

[210]:
```
   Cardiac Vascular Intensive Care Unit (CVICU)  Coronary Care Unit (CCU)  \
0                                             0                         1
1                                             0                         1
2                                             0                         0
3                                             0                         1
```

```
4                                              0                          0

   Medical Intensive Care Unit (MICU)  \
0                                   0
1                                   0
2                                   0
3                                   0
4                                   0

   Medical/Surgical Intensive Care Unit (MICU/SICU)  Neuro Intermediate  \
0                                                 0                   0
1                                                 0                   0
2                                                 1                   0
3                                                 0                   0
4                                                 0                   0

   Neuro Stepdown  Neuro Surgical Intensive Care Unit (Neuro SICU)  \
0               0                                                 0
1               0                                                 0
2               0                                                 0
3               0                                                 0
4               0                                                 0

   Surgical Intensive Care Unit (SICU)  Trauma SICU (TSICU)   hadm_id
0                                    0                    0  20000094
1                                    0                    0  20000147
2                                    0                    0  20000351
3                                    0                    0  20000397
4                                    1                    0  20000808
```

[211]:

```python
# Merge ICU data with main dataFrame
final_df = admits_patients_diag.merge(icu_item, how='outer', on='hadm_id')
final_df.head()
```

[211]:

```
   Unnamed: 0  subject_id   hadm_id           admittime           dischtime  \
0    170509.0  10000019.0  25058216 2129-05-21 19:16:00 2129-05-23 18:30:00
1    285967.0  10000032.0  22595853 2180-05-06 22:23:00 2180-05-07 17:15:00
2    285968.0  10000032.0  22841357 2180-06-26 18:27:00 2180-06-27 18:49:00
3    285966.0  10000032.0  29079034 2180-07-23 12:35:00 2180-07-25 17:55:00
4    285969.0  10000032.0  25742920 2180-08-05 23:44:00 2180-08-07 17:50:00

  deathtime admission_type insurance ethnicity  died_at_the_hospital  …  \
0       NaT       ELECTIVE     Other     WHITE                   0.0  …
1       NaT      EMERGENCY     Other     WHITE                   0.0  …
2       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …
3       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …
4       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …
```

```
  days_next_admit Cardiac Vascular Intensive Care Unit (CVICU)  \
0             NaN                                           NaN
1       50.050000                                           NaN
2       25.740278                                           NaN
3       11.242361                                           0.0
4             NaN                                           NaN

  Coronary Care Unit (CCU)  Medical Intensive Care Unit (MICU)  \
0                      NaN                                 NaN
1                      NaN                                 NaN
2                      NaN                                 NaN
3                      0.0                                 1.0
4                      NaN                                 NaN

   Medical/Surgical Intensive Care Unit (MICU/SICU)  Neuro Intermediate  \
0                                               NaN                 NaN
1                                               NaN                 NaN
2                                               NaN                 NaN
3                                               0.0                 0.0
4                                               NaN                 NaN

   Neuro Stepdown  Neuro Surgical Intensive Care Unit (Neuro SICU)  \
0             NaN                                              NaN
1             NaN                                              NaN
2             NaN                                              NaN
3             0.0                                              0.0
4             NaN                                              NaN

   Surgical Intensive Care Unit (SICU)  Trauma SICU (TSICU)
0                                  NaN                  NaN
1                                  NaN                  NaN
2                                  NaN                  NaN
3                                  0.0                  0.0
4                                  NaN                  NaN

[5 rows x 42 columns]
```

[212]:
```
# Replace NaNs with 0
final_df['Cardiac Vascular Intensive Care Unit (CVICU)'].fillna(value=0,␣
↪inplace=True)
final_df['Coronary Care Unit (CCU)'].fillna(value=0, inplace=True)
final_df['Medical Intensive Care Unit (MICU)'].fillna(value=0, inplace=True)
final_df['Medical/Surgical Intensive Care Unit (MICU/SICU)'].fillna(value=0,␣
↪inplace=True)
final_df['Neuro Intermediate'].fillna(value=0, inplace=True)
final_df['Neuro Stepdown'].fillna(value=0, inplace=True)
```

```
final_df['Neuro Surgical Intensive Care Unit (Neuro SICU)'].fillna(value=0,␣
 ↪inplace=True)
final_df['Surgical Intensive Care Unit (SICU)'].fillna(value=0, inplace=True)
final_df['Trauma SICU (TSICU)'].fillna(value=0, inplace=True)
```

[213]:

```
final_df.head()
```

[213]:

```
   Unnamed: 0  subject_id   hadm_id           admittime           dischtime  \
0    170509.0  10000019.0  25058216 2129-05-21 19:16:00 2129-05-23 18:30:00
1    285967.0  10000032.0  22595853 2180-05-06 22:23:00 2180-05-07 17:15:00
2    285968.0  10000032.0  22841357 2180-06-26 18:27:00 2180-06-27 18:49:00
3    285966.0  10000032.0  29079034 2180-07-23 12:35:00 2180-07-25 17:55:00
4    285969.0  10000032.0  25742920 2180-08-05 23:44:00 2180-08-07 17:50:00

  deathtime admission_type insurance ethnicity  died_at_the_hospital  …  \
0       NaT       ELECTIVE     Other     WHITE                   0.0  …
1       NaT      EMERGENCY     Other     WHITE                   0.0  …
2       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …
3       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …
4       NaT      EMERGENCY  Medicaid     WHITE                   0.0  …

  days_next_admit Cardiac Vascular Intensive Care Unit (CVICU)  \
0             NaN                                          0.0
1       50.050000                                          0.0
2       25.740278                                          0.0
3       11.242361                                          0.0
4             NaN                                          0.0

  Coronary Care Unit (CCU)  Medical Intensive Care Unit (MICU)  \
0                      0.0                                 0.0
1                      0.0                                 0.0
2                      0.0                                 0.0
3                      0.0                                 1.0
4                      0.0                                 0.0

   Medical/Surgical Intensive Care Unit (MICU/SICU)  Neuro Intermediate  \
0                                               0.0                 0.0
1                                               0.0                 0.0
2                                               0.0                 0.0
3                                               0.0                 0.0
4                                               0.0                 0.0

   Neuro Stepdown  Neuro Surgical Intensive Care Unit (Neuro SICU)  \
0             0.0                                              0.0
1             0.0                                              0.0
2             0.0                                              0.0
3             0.0                                              0.0
```

```
4            0.0                                           0.0

   Surgical Intensive Care Unit (SICU)  Trauma SICU (TSICU)
0                                  0.0                  0.0
1                                  0.0                  0.0
2                                  0.0                  0.0
3                                  0.0                  0.0
4                                  0.0                  0.0

[5 rows x 42 columns]
```

1.4 5. Data cleaning

[214]:
```python
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 363071 entries, 0 to 363070
Data columns (total 42 columns):
 #   Column                                              Non-Null Count   Dtype
---  ------                                              --------------   -----
 0   Unnamed: 0                                          335378 non-null  float64
 1   subject_id                                          335378 non-null  float64
 2   hadm_id                                             363071 non-null  int64
 3   admittime                                           335378 non-null
datetime64[ns]
 4   dischtime                                           335378 non-null
datetime64[ns]
 5   deathtime                                           5670 non-null
datetime64[ns]
 6   admission_type                                      335378 non-null  object
 7   insurance                                           335378 non-null  object
 8   ethnicity                                           335378 non-null  object
 9   died_at_the_hospital                                335378 non-null  float64
 10  gender                                              335378 non-null  object
 11  anchor_age                                          335378 non-null  object
 12  dod                                                 24651 non-null   object
 13  blood                                               335378 non-null  float64
 14  circulatory                                         335378 non-null  float64
 15  congenital                                          335378 non-null  float64
 16  digestive                                           335378 non-null  float64
 17  endocrine                                           335378 non-null  float64
 18  genitourinary                                       335378 non-null  float64
 19  infectious                                          335378 non-null  float64
 20  injury                                              335378 non-null  float64
 21  mental                                              335378 non-null  float64
 22  misc                                                335378 non-null  float64
 23  muscular                                            335378 non-null  float64
 24  neoplasms                                           335378 non-null  float64
```

```
 25   nervous                                          335378 non-null  float64
 26   pregnancy                                        335378 non-null  float64
 27   prenatal                                         335378 non-null  float64
 28   respiratory                                      335378 non-null  float64
 29   skin                                             335378 non-null  float64
 30   next_admittime                                   160565 non-null
datetime64[ns]
 31   next_admission_type                              160565 non-null  object
 32   days_next_admit                                  160565 non-null  float64
 33   Cardiac Vascular Intensive Care Unit (CVICU)     363071 non-null  float64
 34   Coronary Care Unit (CCU)                         363071 non-null  float64
 35   Medical Intensive Care Unit (MICU)               363071 non-null  float64
 36   Medical/Surgical Intensive Care Unit (MICU/SICU) 363071 non-null  float64
 37   Neuro Intermediate                               363071 non-null  float64
 38   Neuro Stepdown                                   363071 non-null  float64
 39   Neuro Surgical Intensive Care Unit (Neuro SICU)  363071 non-null  float64
 40   Surgical Intensive Care Unit (SICU)              363071 non-null  float64
 41   Trauma SICU (TSICU)                              363071 non-null  float64
dtypes: datetime64[ns](4), float64(30), int64(1), object(7)
memory usage: 119.1+ MB
```

[215]:
```
# Remove deceased persons because for for sure they will not be readmitted again
final_df = final_df[final_df['died_at_the_hospital'] == 0.0]
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 329708 entries, 0 to 335377
Data columns (total 42 columns):
 #    Column                                           Non-Null Count   Dtype
---   ------                                           --------------   -----
 0    Unnamed: 0                                       329708 non-null  float64
 1    subject_id                                       329708 non-null  float64
 2    hadm_id                                          329708 non-null  int64
 3    admittime                                        329708 non-null
datetime64[ns]
 4    dischtime                                        329708 non-null
datetime64[ns]
 5    deathtime                                        0 non-null
datetime64[ns]
 6    admission_type                                   329708 non-null  object
 7    insurance                                        329708 non-null  object
 8    ethnicity                                        329708 non-null  object
 9    died_at_the_hospital                             329708 non-null  float64
 10   gender                                           329708 non-null  object
 11   anchor_age                                       329708 non-null  object
 12   dod                                              18981 non-null   object
 13   blood                                            329708 non-null  float64
 14   circulatory                                      329708 non-null  float64
```

```
 15   congenital                                         329708 non-null  float64
 16   digestive                                          329708 non-null  float64
 17   endocrine                                          329708 non-null  float64
 18   genitourinary                                      329708 non-null  float64
 19   infectious                                         329708 non-null  float64
 20   injury                                             329708 non-null  float64
 21   mental                                             329708 non-null  float64
 22   misc                                               329708 non-null  float64
 23   muscular                                           329708 non-null  float64
 24   neoplasms                                          329708 non-null  float64
 25   nervous                                            329708 non-null  float64
 26   pregnancy                                          329708 non-null  float64
 27   prenatal                                           329708 non-null  float64
 28   respiratory                                        329708 non-null  float64
 29   skin                                               329708 non-null  float64
 30   next_admittime                                     160543 non-null
datetime64[ns]
 31   next_admission_type                                160543 non-null  object
 32   days_next_admit                                    160543 non-null  float64
 33   Cardiac Vascular Intensive Care Unit (CVICU)       329708 non-null  float64
 34   Coronary Care Unit (CCU)                           329708 non-null  float64
 35   Medical Intensive Care Unit (MICU)                 329708 non-null  float64
 36   Medical/Surgical Intensive Care Unit (MICU/SICU)   329708 non-null  float64
 37   Neuro Intermediate                                 329708 non-null  float64
 38   Neuro Stepdown                                     329708 non-null  float64
 39   Neuro Surgical Intensive Care Unit (Neuro SICU)    329708 non-null  float64
 40   Surgical Intensive Care Unit (SICU)                329708 non-null  float64
 41   Trauma SICU (TSICU)                                329708 non-null  float64
dtypes: datetime64[ns](4), float64(30), int64(1), object(7)
memory usage: 108.2+ MB
```

[216]:
```python
# Drop unused or no longer needed columns
final_df.drop(columns=['Unnamed: 0', 'subject_id', 'hadm_id', 'admittime',␣
 ↪'dischtime', 'deathtime','dod', 'died_at_the_hospital'], inplace=True)

final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 329708 entries, 0 to 335377
Data columns (total 34 columns):
 #    Column                                             Non-Null Count   Dtype
---   ------                                             --------------   -----
 0    admission_type                                     329708 non-null  object
 1    insurance                                          329708 non-null  object
 2    ethnicity                                          329708 non-null  object
 3    gender                                             329708 non-null  object
 4    anchor_age                                         329708 non-null  object
 5    blood                                              329708 non-null  float64
```

```
 6   circulatory                                       329708 non-null  float64
 7   congenital                                        329708 non-null  float64
 8   digestive                                         329708 non-null  float64
 9   endocrine                                         329708 non-null  float64
 10  genitourinary                                     329708 non-null  float64
 11  infectious                                        329708 non-null  float64
 12  injury                                            329708 non-null  float64
 13  mental                                            329708 non-null  float64
 14  misc                                              329708 non-null  float64
 15  muscular                                          329708 non-null  float64
 16  neoplasms                                         329708 non-null  float64
 17  nervous                                           329708 non-null  float64
 18  pregnancy                                         329708 non-null  float64
 19  prenatal                                          329708 non-null  float64
 20  respiratory                                       329708 non-null  float64
 21  skin                                              329708 non-null  float64
 22  next_admittime                                    160543 non-null
datetime64[ns]
 23  next_admission_type                               160543 non-null  object
 24  days_next_admit                                   160543 non-null  float64
 25  Cardiac Vascular Intensive Care Unit (CVICU)      329708 non-null  float64
 26  Coronary Care Unit (CCU)                          329708 non-null  float64
 27  Medical Intensive Care Unit (MICU)                329708 non-null  float64
 28  Medical/Surgical Intensive Care Unit (MICU/SICU)  329708 non-null  float64
 29  Neuro Intermediate                                329708 non-null  float64
 30  Neuro Stepdown                                    329708 non-null  float64
 31  Neuro Surgical Intensive Care Unit (Neuro SICU)   329708 non-null  float64
 32  Surgical Intensive Care Unit (SICU)               329708 non-null  float64
 33  Trauma SICU (TSICU)                               329708 non-null  float64
dtypes: datetime64[ns](1), float64(27), object(6)
memory usage: 88.0+ MB
```

[217]:
```
final_df.head()
```

[217]:
```
  admission_type insurance ethnicity gender    anchor_age  blood  circulatory  \
0       ELECTIVE     Other     WHITE      M       NEWBORN    0.0          0.0
1      EMERGENCY     Other     WHITE      F  MIDDLE_ADULT    0.0          0.0
2      EMERGENCY  Medicaid     WHITE      F  MIDDLE_ADULT    1.0          0.0
3      EMERGENCY  Medicaid     WHITE      F  MIDDLE_ADULT    0.0          1.0
4      EMERGENCY  Medicaid     WHITE      F  MIDDLE_ADULT    0.0          0.0

   congenital  digestive  endocrine  …  days_next_admit  \
0         0.0        0.0        0.0  …              NaN
1         0.0        2.0        0.0  …        50.050000
2         0.0        1.0        1.0  …        25.740278
3         0.0        1.0        2.0  …        11.242361
4         0.0        1.0        2.0  …              NaN
```

```
   Cardiac Vascular Intensive Care Unit (CVICU)  Coronary Care Unit (CCU)  \
0                                           0.0                       0.0
1                                           0.0                       0.0
2                                           0.0                       0.0
3                                           0.0                       0.0
4                                           0.0                       0.0

   Medical Intensive Care Unit (MICU)  \
0                                 0.0
1                                 0.0
2                                 0.0
3                                 1.0
4                                 0.0

   Medical/Surgical Intensive Care Unit (MICU/SICU)  Neuro Intermediate  \
0                                               0.0                 0.0
1                                               0.0                 0.0
2                                               0.0                 0.0
3                                               0.0                 0.0
4                                               0.0                 0.0

   Neuro Stepdown  Neuro Surgical Intensive Care Unit (Neuro SICU)  \
0             0.0                                              0.0
1             0.0                                              0.0
2             0.0                                              0.0
3             0.0                                              0.0
4             0.0                                              0.0

   Surgical Intensive Care Unit (SICU)  Trauma SICU (TSICU)
0                                  0.0                  0.0
1                                  0.0                  0.0
2                                  0.0                  0.0
3                                  0.0                  0.0
4                                  0.0                  0.0

[5 rows x 34 columns]
```

[218]:
```python
# Convert gender into numeric boolean attribute
final_df['gender'].replace({'M': 0, 'F':1}, inplace=True)
final_df.head()
```

[218]:
```
  admission_type insurance ethnicity  gender    anchor_age  blood  \
0       ELECTIVE     Other     WHITE       0       NEWBORN    0.0
1      EMERGENCY     Other     WHITE       1  MIDDLE_ADULT    0.0
2      EMERGENCY  Medicaid     WHITE       1  MIDDLE_ADULT    1.0
3      EMERGENCY  Medicaid     WHITE       1  MIDDLE_ADULT    0.0
```

```
4      EMERGENCY  Medicaid     WHITE       1  MIDDLE_ADULT    0.0

   circulatory  congenital  digestive  endocrine  …  days_next_admit  \
0          0.0         0.0        0.0        0.0  …              NaN
1          0.0         0.0        2.0        0.0  …        50.050000
2          0.0         0.0        1.0        1.0  …        25.740278
3          1.0         0.0        1.0        2.0  …        11.242361
4          0.0         0.0        1.0        2.0  …              NaN

   Cardiac Vascular Intensive Care Unit (CVICU)  Coronary Care Unit (CCU)  \
0                                           0.0                       0.0
1                                           0.0                       0.0
2                                           0.0                       0.0
3                                           0.0                       0.0
4                                           0.0                       0.0

   Medical Intensive Care Unit (MICU)  \
0                                 0.0
1                                 0.0
2                                 0.0
3                                 1.0
4                                 0.0

   Medical/Surgical Intensive Care Unit (MICU/SICU)  Neuro Intermediate  \
0                                               0.0                 0.0
1                                               0.0                 0.0
2                                               0.0                 0.0
3                                               0.0                 0.0
4                                               0.0                 0.0

   Neuro Stepdown  Neuro Surgical Intensive Care Unit (Neuro SICU)  \
0             0.0                                              0.0
1             0.0                                              0.0
2             0.0                                              0.0
3             0.0                                              0.0
4             0.0                                              0.0

   Surgical Intensive Care Unit (SICU)  Trauma SICU (TSICU)
0                                  0.0                  0.0
1                                  0.0                  0.0
2                                  0.0                  0.0
3                                  0.0                  0.0
4                                  0.0                  0.0

[5 rows x 34 columns]
```

[219]:
```python
# Create dummy columns for categorical variables
prefix_cols = ['ADM', 'INS', 'ETH', 'AGE']
dummy_cols = ['admission_type', 'insurance','ethnicity', 'anchor_age']
final_df = pd.get_dummies(final_df, prefix=prefix_cols, columns=dummy_cols)
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 329708 entries, 0 to 335377
Data columns (total 46 columns):
 #   Column                                         Non-Null Count   Dtype
---  ------                                         --------------   -----
 0   gender                                         329708 non-null  int64
 1   blood                                          329708 non-null  float64
 2   circulatory                                    329708 non-null  float64
 3   congenital                                     329708 non-null  float64
 4   digestive                                      329708 non-null  float64
 5   endocrine                                      329708 non-null  float64
 6   genitourinary                                  329708 non-null  float64
 7   infectious                                     329708 non-null  float64
 8   injury                                         329708 non-null  float64
 9   mental                                         329708 non-null  float64
 10  misc                                           329708 non-null  float64
 11  muscular                                       329708 non-null  float64
 12  neoplasms                                      329708 non-null  float64
 13  nervous                                        329708 non-null  float64
 14  pregnancy                                      329708 non-null  float64
 15  prenatal                                       329708 non-null  float64
 16  respiratory                                    329708 non-null  float64
 17  skin                                           329708 non-null  float64
 18  next_admittime                                 160543 non-null
datetime64[ns]
 19  next_admission_type                            160543 non-null  object
 20  days_next_admit                                160543 non-null  float64
 21  Cardiac Vascular Intensive Care Unit (CVICU)   329708 non-null  float64
 22  Coronary Care Unit (CCU)                       329708 non-null  float64
 23  Medical Intensive Care Unit (MICU)             329708 non-null  float64
 24  Medical/Surgical Intensive Care Unit (MICU/SICU) 329708 non-null  float64
 25  Neuro Intermediate                             329708 non-null  float64
 26  Neuro Stepdown                                 329708 non-null  float64
 27  Neuro Surgical Intensive Care Unit (Neuro SICU)  329708 non-null  float64
 28  Surgical Intensive Care Unit (SICU)            329708 non-null  float64
 29  Trauma SICU (TSICU)                            329708 non-null  float64
 30  ADM_ELECTIVE                                   329708 non-null  uint8
 31  ADM_EMERGENCY                                  329708 non-null  uint8
 32  ADM_OBSERVATION                                329708 non-null  uint8
 33  ADM_SURGICAL SAME DAY ADMISSION                329708 non-null  uint8
 34  INS_Medicaid                                   329708 non-null  uint8
 35  INS_Medicare                                   329708 non-null  uint8
```

```
 36  INS_Other                                     329708 non-null  uint8
 37  ETH_ASIAN                                     329708 non-null  uint8
 38  ETH_BLACK/AFRICAN AMERICAN                    329708 non-null  uint8
 39  ETH_HISPANIC/LATINO                           329708 non-null  uint8
 40  ETH_OTHER/UNKNOWN                             329708 non-null  uint8
 41  ETH_WHITE                                     329708 non-null  uint8
 42  AGE_MIDDLE_ADULT                              329708 non-null  uint8
 43  AGE_NEWBORN                                   329708 non-null  uint8
 44  AGE_SENIOR                                    329708 non-null  uint8
 45  AGE_YOUNG_ADULT                               329708 non-null  uint8
dtypes: datetime64[ns](1), float64(27), int64(1), object(1), uint8(16)
memory usage: 83.0+ MB
```

[220]:

```
# Check for any remaining NaNs
final_df.isnull().sum()
```

[220]:

```
gender                                                  0
blood                                                   0
circulatory                                             0
congenital                                              0
digestive                                               0
endocrine                                               0
genitourinary                                           0
infectious                                              0
injury                                                  0
mental                                                  0
misc                                                    0
muscular                                                0
neoplasms                                               0
nervous                                                 0
pregnancy                                               0
prenatal                                                0
respiratory                                             0
skin                                                    0
next_admittime                                     169165
next_admission_type                                169165
days_next_admit                                    169165
Cardiac Vascular Intensive Care Unit (CVICU)            0
Coronary Care Unit (CCU)                                0
Medical Intensive Care Unit (MICU)                      0
Medical/Surgical Intensive Care Unit (MICU/SICU)        0
Neuro Intermediate                                      0
Neuro Stepdown                                          0
Neuro Surgical Intensive Care Unit (Neuro SICU)         0
Surgical Intensive Care Unit (SICU)                     0
Trauma SICU (TSICU)                                     0
ADM_ELECTIVE                                            0
```

```
ADM_EMERGENCY                                        0
ADM_OBSERVATION                                      0
ADM_SURGICAL SAME DAY ADMISSION                      0
INS_Medicaid                                         0
INS_Medicare                                         0
INS_Other                                            0
ETH_ASIAN                                            0
ETH_BLACK/AFRICAN AMERICAN                           0
ETH_HISPANIC/LATINO                                  0
ETH_OTHER/UNKNOWN                                    0
ETH_WHITE                                            0
AGE_MIDDLE_ADULT                                     0
AGE_NEWBORN                                          0
AGE_SENIOR                                           0
AGE_YOUNG_ADULT                                      0
dtype: int64
```

[221]:
```python
# Drop rows that contain NaN values
final_df.dropna(axis=0, inplace=True)
```

[222]:
```python
# Check for any remaining NaNs
final_df.isnull().values.sum()
```

[222]: 0

[223]:
```python
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160543 entries, 1 to 335375
Data columns (total 46 columns):
 #   Column                                         Non-Null Count   Dtype
---  ------                                         --------------   -----
 0   gender                                         160543 non-null  int64
 1   blood                                          160543 non-null  float64
 2   circulatory                                    160543 non-null  float64
 3   congenital                                     160543 non-null  float64
 4   digestive                                      160543 non-null  float64
 5   endocrine                                      160543 non-null  float64
 6   genitourinary                                  160543 non-null  float64
 7   infectious                                     160543 non-null  float64
 8   injury                                         160543 non-null  float64
 9   mental                                         160543 non-null  float64
 10  misc                                           160543 non-null  float64
 11  muscular                                       160543 non-null  float64
 12  neoplasms                                      160543 non-null  float64
 13  nervous                                        160543 non-null  float64
 14  pregnancy                                      160543 non-null  float64
 15  prenatal                                       160543 non-null  float64
```

```
 16   respiratory                                       160543 non-null  float64
 17   skin                                              160543 non-null  float64
 18   next_admittime                                    160543 non-null
datetime64[ns]
 19   next_admission_type                               160543 non-null  object
 20   days_next_admit                                   160543 non-null  float64
 21   Cardiac Vascular Intensive Care Unit (CVICU)      160543 non-null  float64
 22   Coronary Care Unit (CCU)                          160543 non-null  float64
 23   Medical Intensive Care Unit (MICU)                160543 non-null  float64
 24   Medical/Surgical Intensive Care Unit (MICU/SICU)  160543 non-null  float64
 25   Neuro Intermediate                                160543 non-null  float64
 26   Neuro Stepdown                                    160543 non-null  float64
 27   Neuro Surgical Intensive Care Unit (Neuro SICU)   160543 non-null  float64
 28   Surgical Intensive Care Unit (SICU)               160543 non-null  float64
 29   Trauma SICU (TSICU)                               160543 non-null  float64
 30   ADM_ELECTIVE                                      160543 non-null  uint8
 31   ADM_EMERGENCY                                     160543 non-null  uint8
 32   ADM_OBSERVATION                                   160543 non-null  uint8
 33   ADM_SURGICAL SAME DAY ADMISSION                   160543 non-null  uint8
 34   INS_Medicaid                                      160543 non-null  uint8
 35   INS_Medicare                                      160543 non-null  uint8
 36   INS_Other                                         160543 non-null  uint8
 37   ETH_ASIAN                                         160543 non-null  uint8
 38   ETH_BLACK/AFRICAN AMERICAN                        160543 non-null  uint8
 39   ETH_HISPANIC/LATINO                               160543 non-null  uint8
 40   ETH_OTHER/UNKNOWN                                 160543 non-null  uint8
 41   ETH_WHITE                                         160543 non-null  uint8
 42   AGE_MIDDLE_ADULT                                  160543 non-null  uint8
 43   AGE_NEWBORN                                       160543 non-null  uint8
 44   AGE_SENIOR                                        160543 non-null  uint8
 45   AGE_YOUNG_ADULT                                   160543 non-null  uint8
dtypes: datetime64[ns](1), float64(27), int64(1), object(1), uint8(16)
memory usage: 40.4+ MB
```

1.4.1 Compute the OUTPUT LABELs to predict

[224]:
```python
final_df['READMISSION_30'] = (final_df.days_next_admit < 30).astype('int')
final_df['READMISSION_90'] = (final_df.days_next_admit < 90).astype('int')
final_df['READMISSION_365'] = (final_df.days_next_admit < 365).astype('int')
```

[225]:
```python
# READMISSION_30 rates
print('Number of positive samples:', (final_df.READMISSION_30 == 1).sum())
print('Number of negative samples:',  (final_df.READMISSION_30 == 0).sum())
print('Total samples:', len(final_df))
```

```
Number of positive samples: 58980
Number of negative samples: 101563
Total samples: 160543
```

[226]:
```python
# READMISSION_90 rates
print('Number of positive samples:', (final_df.READMISSION_90 == 1).sum())
print('Number of negative samples:',  (final_df.READMISSION_90 == 0).sum())
print('Total samples:', len(final_df))
```

```
Number of positive samples: 89167
Number of negative samples: 71376
Total samples: 160543
```

[227]:
```python
# READMISSION_365 rates
print('Number of positive samples:', (final_df.READMISSION_365 == 1).sum())
print('Number of negative samples:',  (final_df.READMISSION_365 == 0).sum())
print('Total samples:', len(final_df))
```

```
Number of positive samples: 127181
Number of negative samples: 33362
Total samples: 160543
```

[228]:
```python
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160543 entries, 1 to 335375
Data columns (total 49 columns):
 #   Column                                      Non-Null Count   Dtype
---  ------                                      --------------   -----
 0   gender                                      160543 non-null  int64
 1   blood                                       160543 non-null  float64
 2   circulatory                                 160543 non-null  float64
 3   congenital                                  160543 non-null  float64
 4   digestive                                   160543 non-null  float64
 5   endocrine                                   160543 non-null  float64
 6   genitourinary                               160543 non-null  float64
 7   infectious                                  160543 non-null  float64
 8   injury                                      160543 non-null  float64
 9   mental                                      160543 non-null  float64
 10  misc                                        160543 non-null  float64
 11  muscular                                    160543 non-null  float64
 12  neoplasms                                   160543 non-null  float64
 13  nervous                                     160543 non-null  float64
 14  pregnancy                                   160543 non-null  float64
 15  prenatal                                    160543 non-null  float64
 16  respiratory                                 160543 non-null  float64
 17  skin                                        160543 non-null  float64
 18  next_admittime                              160543 non-null
datetime64[ns]
 19  next_admission_type                         160543 non-null  object
 20  days_next_admit                             160543 non-null  float64
 21  Cardiac Vascular Intensive Care Unit (CVICU)  160543 non-null  float64
 22  Coronary Care Unit (CCU)                    160543 non-null  float64
```

```
 23  Medical Intensive Care Unit (MICU)                 160543 non-null  float64
 24  Medical/Surgical Intensive Care Unit (MICU/SICU)   160543 non-null  float64
 25  Neuro Intermediate                                 160543 non-null  float64
 26  Neuro Stepdown                                     160543 non-null  float64
 27  Neuro Surgical Intensive Care Unit (Neuro SICU)    160543 non-null  float64
 28  Surgical Intensive Care Unit (SICU)                160543 non-null  float64
 29  Trauma SICU (TSICU)                                160543 non-null  float64
 30  ADM_ELECTIVE                                       160543 non-null  uint8
 31  ADM_EMERGENCY                                      160543 non-null  uint8
 32  ADM_OBSERVATION                                    160543 non-null  uint8
 33  ADM_SURGICAL SAME DAY ADMISSION                    160543 non-null  uint8
 34  INS_Medicaid                                       160543 non-null  uint8
 35  INS_Medicare                                       160543 non-null  uint8
 36  INS_Other                                          160543 non-null  uint8
 37  ETH_ASIAN                                          160543 non-null  uint8
 38  ETH_BLACK/AFRICAN AMERICAN                         160543 non-null  uint8
 39  ETH_HISPANIC/LATINO                                160543 non-null  uint8
 40  ETH_OTHER/UNKNOWN                                  160543 non-null  uint8
 41  ETH_WHITE                                          160543 non-null  uint8
 42  AGE_MIDDLE_ADULT                                   160543 non-null  uint8
 43  AGE_NEWBORN                                        160543 non-null  uint8
 44  AGE_SENIOR                                         160543 non-null  uint8
 45  AGE_YOUNG_ADULT                                    160543 non-null  uint8
 46  READMISSION_30                                     160543 non-null  int32
 47  READMISSION_90                                     160543 non-null  int32
 48  READMISSION_365                                    160543 non-null  int32
dtypes: datetime64[ns](1), float64(27), int32(3), int64(1), object(1), uint8(16)
memory usage: 42.3+ MB
```

[229]:

```python
# Drop no longer needed columns
final_df.drop(columns=['next_admittime', 'next_admission_type',␣
 ↪'days_next_admit'], inplace=True)

final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160543 entries, 1 to 335375
Data columns (total 46 columns):
 #   Column                                             Non-Null Count   Dtype
---  ------                                             --------------   -----
 0   gender                                             160543 non-null  int64
 1   blood                                              160543 non-null  float64
 2   circulatory                                        160543 non-null  float64
 3   congenital                                         160543 non-null  float64
 4   digestive                                          160543 non-null  float64
 5   endocrine                                          160543 non-null  float64
 6   genitourinary                                      160543 non-null  float64
 7   infectious                                         160543 non-null  float64
```

```
 8   injury                                            160543 non-null  float64
 9   mental                                            160543 non-null  float64
 10  misc                                              160543 non-null  float64
 11  muscular                                          160543 non-null  float64
 12  neoplasms                                         160543 non-null  float64
 13  nervous                                           160543 non-null  float64
 14  pregnancy                                         160543 non-null  float64
 15  prenatal                                          160543 non-null  float64
 16  respiratory                                       160543 non-null  float64
 17  skin                                              160543 non-null  float64
 18  Cardiac Vascular Intensive Care Unit (CVICU)      160543 non-null  float64
 19  Coronary Care Unit (CCU)                          160543 non-null  float64
 20  Medical Intensive Care Unit (MICU)                160543 non-null  float64
 21  Medical/Surgical Intensive Care Unit (MICU/SICU)  160543 non-null  float64
 22  Neuro Intermediate                                160543 non-null  float64
 23  Neuro Stepdown                                    160543 non-null  float64
 24  Neuro Surgical Intensive Care Unit (Neuro SICU)   160543 non-null  float64
 25  Surgical Intensive Care Unit (SICU)               160543 non-null  float64
 26  Trauma SICU (TSICU)                               160543 non-null  float64
 27  ADM_ELECTIVE                                      160543 non-null  uint8
 28  ADM_EMERGENCY                                     160543 non-null  uint8
 29  ADM_OBSERVATION                                   160543 non-null  uint8
 30  ADM_SURGICAL SAME DAY ADMISSION                   160543 non-null  uint8
 31  INS_Medicaid                                      160543 non-null  uint8
 32  INS_Medicare                                      160543 non-null  uint8
 33  INS_Other                                         160543 non-null  uint8
 34  ETH_ASIAN                                         160543 non-null  uint8
 35  ETH_BLACK/AFRICAN AMERICAN                        160543 non-null  uint8
 36  ETH_HISPANIC/LATINO                               160543 non-null  uint8
 37  ETH_OTHER/UNKNOWN                                 160543 non-null  uint8
 38  ETH_WHITE                                         160543 non-null  uint8
 39  AGE_MIDDLE_ADULT                                  160543 non-null  uint8
 40  AGE_NEWBORN                                       160543 non-null  uint8
 41  AGE_SENIOR                                        160543 non-null  uint8
 42  AGE_YOUNG_ADULT                                   160543 non-null  uint8
 43  READMISSION_30                                    160543 non-null  int32
 44  READMISSION_90                                    160543 non-null  int32
 45  READMISSION_365                                   160543 non-null  int32
dtypes: float64(26), int32(3), int64(1), uint8(16)
memory usage: 38.6 MB
```

[230]:
```
df_cleaned = final_df.astype(int)
```

The final DataFrame size resulted in 43 feature columns and 1 target column (READMISSION_30) or (READMISSION_90) or (READMISSION_365) alternatively with an entry count of 160543.

1.5 6. Prediction Model

We use a **Supervised Learning ML model**. First of all what is it? Supervised learning is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. It uses a training set to teach models to yield the desired output. This training dataset includes inputs and correct outputs, which allow the model to learn over time. The algorithm measures its accuracy through the loss function, adjusting until the error has been sufficiently minimized.

Why do we choose it? Because in our case we have the corret output for each dataset entry: "READMISSION_30" (Yes or No - 1 or 0) and we want to create a model that predicts this output for new entries, in other words that it "generalize well".

We will implement the supervised learning prediction model using the **Scikit-Learn** machine learning library.

To implement the prediction model, our dataset is splitted into training and test sets at an 80:20 ratio using the scikit-learn *train_test_split* function.

Why split in training and test set? Because to detect a machine learning model behavior, we need to use observations that aren't used in the training process. Otherwise, the evaluation of the model would be biased as a matter of fact when we build a predictive model, we want the model to work well on data that the model has never seen, so that's the reason why we use a training set to train the model and a test set to evaulate the model accuaracy.

Searching on the Internet for the best train-test ratio, the first answer is 80:20. This means we use 80% of the observations for training and the rest for testing. This approach is taken in this case. zability)

[231]:
```
# Target Variable READMISSION_30
READMISSION_30 = df_cleaned['READMISSION_30'].values
# Prediction Features
features = df_cleaned.drop(columns=['READMISSION_30', 'READMISSION_90',␣
↪'READMISSION_365'])
```

[232]:
```
from sklearn.model_selection import train_test_split

# Split into training set 80% and test set 20%
X_train, X_test, y_train, y_test = train_test_split(features,
                                                    READMISSION_30,
                                                    test_size = .20,
                                                    random_state = 0)

# Show the results of the split
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 128434 samples.
Testing set has 32109 samples.
```

[233]:
```
from sklearn.linear_model import LogisticRegression
```

```
# We'll use a simple classifier for this task
clf=LogisticRegression(C = 0.0001, penalty = 'l2', random_state = 42)
clf.fit(X_train, y_train)
```

[233]: LogisticRegression(C=0.0001, random_state=42)

Logistic regression, despite its name, is a linear model for classification rather than regression. In this model, the probabilities describing the possible outcomes of a single trial are modeled using a logistic function.

[234]:
```
# Calculate probability of re-admission within 30 days
model = clf
y_train_preds = model.predict_proba(X_train)[:,1]
y_test_preds = model.predict_proba(X_test)[:,1]
```

[235]:
```
print(y_train[:10])
print(y_train_preds[:10])
```

```
[1 1 0 0 0 1 0 0 0 0]
[0.48290955 0.40408915 0.30761995 0.33062243 0.39206664 0.31875484
 0.38196265 0.29467634 0.2974451  0.40647122]
```

1.6 7. Model Evalutaion & Parameter Tuning

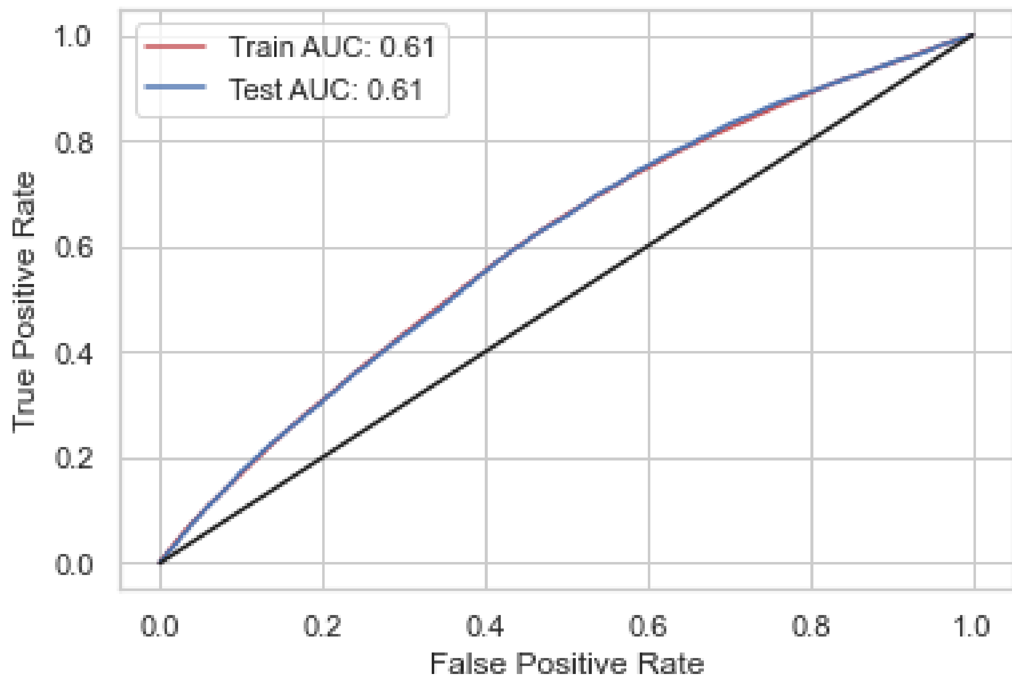
1.6.1 Calculate Performance metrics

[236]:
```
def calc_accuracy(y_actual, y_pred, thresh):
    # this function calculates the accuracy with probability threshold at thresh
    return (sum((y_pred > thresh) & (y_actual == 1))+sum((y_pred < thresh) &␣
 ↪(y_actual == 0))) /len(y_actual)

def calc_recall(y_actual, y_pred, thresh):
    # calculates the recall
    return sum((y_pred > thresh) & (y_actual == 1)) /sum(y_actual)

def calc_precision(y_actual, y_pred, thresh):
    # calculates the precision
    return sum((y_pred > thresh) & (y_actual == 1)) /sum(y_pred > thresh)
```

[237]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

fpr_train, tpr_train, thresholds_train = roc_curve(y_train, y_train_preds)
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_preds)



thresh = 0.5

auc_train = roc_auc_score(y_train, y_train_preds)
```

```
auc_test = roc_auc_score(y_test, y_test_preds)

print('Train AUC:%.3f'%auc_train)
print('Test AUC:%.3f'%auc_test)

print('Train accuracy:%.3f'%calc_accuracy(y_train, y_train_preds, thresh))
print('Test accuracy:%.3f'%calc_accuracy(y_test, y_test_preds, thresh))

print('Train recall:%.3f'%calc_recall(y_train, y_train_preds, thresh))
print('Test recall:%.3f'%calc_recall(y_test, y_test_preds, thresh))

print('Train precision:%.3f'%calc_precision(y_train, y_train_preds, thresh))
print('Test precision:%.3f'%calc_precision(y_test, y_test_preds, thresh))

plt.plot(fpr_train, tpr_train,'r-', label = 'Train AUC: %.2f'%auc_train)
plt.plot(fpr_test, tpr_test,'b-',label = 'Test AUC: %.2f'%auc_test)
plt.plot([0,1],[0,1],'-k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
Train AUC:0.605
Test AUC:0.605
Train accuracy:0.636
Test accuracy:0.630
Train recall:0.048
Test recall:0.043
Train precision:0.537
Test precision:0.522
```



1.6.2 Parameter Tuning

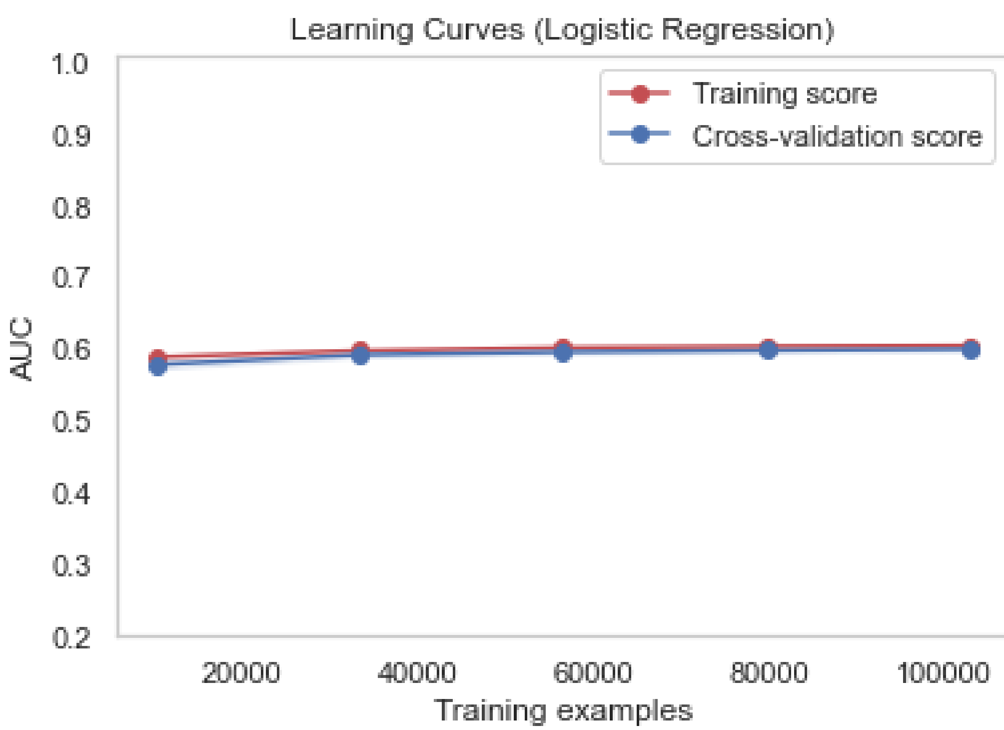
All decisions will have a trade-off on the metrics described above. Let's choose AUC for this task as it balances FPR and TPR.

[238]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit


def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
    """
    Generate a simple plot of the test and training learning curve.

    Parameters
    ----------
    estimator : object type that implements the "fit" and "predict" methods
        An object of that type which is cloned for each validation.

    title : string
        Title for the chart.

    X : array-like, shape (n_samples, n_features)
        Training vector, where n_samples is the number of samples and
        n_features is the number of features.
```

```
    y : array-like, shape (n_samples) or (n_samples, n_features), optional
        Target relative to X for classification or regression;
        None for unsupervised learning.

    ylim : tuple, shape (ymin, ymax), optional
        Defines minimum and maximum yvalues plotted.

    cv : int, cross-validation generator or an iterable, optional
        Determines the cross-validation splitting strategy.
        Possible inputs for cv are:
          - None, to use the default 3-fold cross-validation,
          - integer, to specify the number of folds.
          - An object to be used as a cross-validation generator.
          - An iterable yielding train/test splits.

        For integer/None inputs, if ``y`` is binary or multiclass,
        :class:`StratifiedKFold` used. If the estimator is not a classifier
        or if ``y`` is neither binary nor multiclass, :class:`KFold` is used.

        Refer :ref:`User Guide <cross_validation>` for the various
        cross-validators that can be used here.

    n_jobs : integer, optional
        Number of jobs to run in parallel (default 1).
    """
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("AUC")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes, scoring␣
↪= 'roc_auc')
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="b")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
```

```
                 label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="b",
                 label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

[239]:
```
title = "Learning Curves (Logistic Regression)"
# Cross validation with 5 iterations to get smoother mean test and train
# score curves, each time with 20% data randomly selected as a validation set.
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=42)
estimator = LogisticRegression( C = 0.0001, penalty = 'l2')
plot_learning_curve(estimator, title, X_train, y_train, ylim=(0.2, 1.01),␣
 ↪cv=cv, n_jobs=4)

plt.show()
```



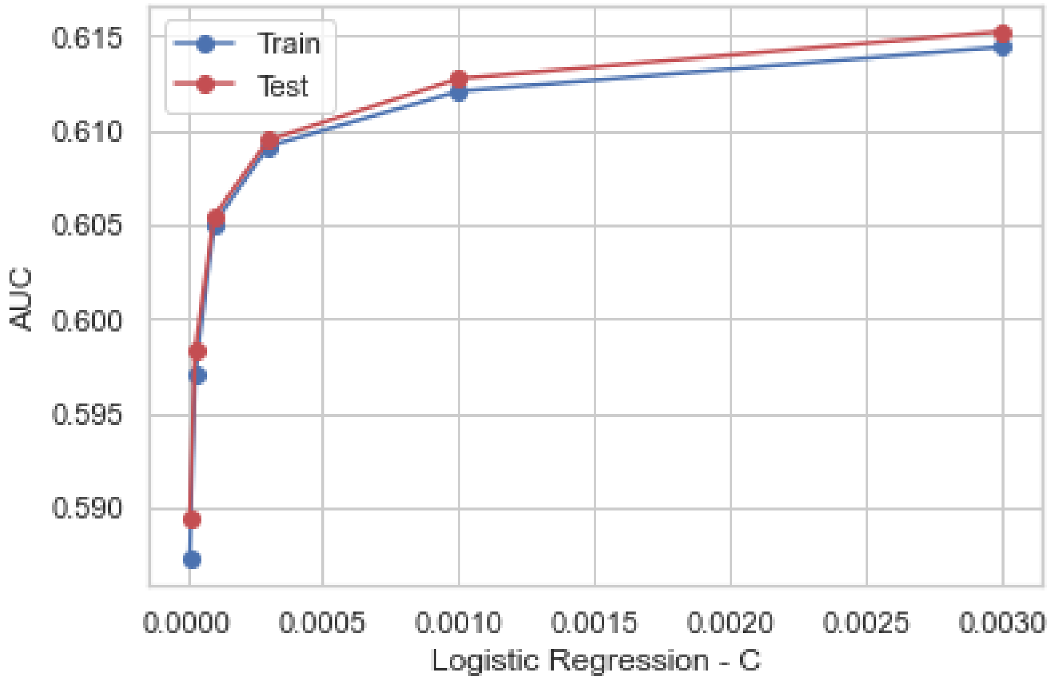
[240]:
```
# let's try and visualize different hypermparamters

Cs = [0.00001, 0.00003, 0.0001, 0.0003, 0.001, 0.003]
train_aucs = np.zeros(len(Cs))
test_aucs = np.zeros(len(Cs))
```

```
for ii in range(len(Cs)):
    C = Cs[ii]
    print('\n C:', C)

    # logistic regression

    clf=LogisticRegression(C = C, penalty = 'l2', random_state = 42)
    clf.fit(X_train, y_train)

    model = clf
    y_train_preds = model.predict_proba(X_train)[:,1]
    y_test_preds = model.predict_proba(X_test)[:,1]

    auc_train = roc_auc_score(y_train, y_train_preds)
    auc_test = roc_auc_score(y_test, y_test_preds)
    print('Train AUC:%.3f'%auc_train)
    print('Test AUC:%.3f'%auc_test)
    train_aucs[ii] = auc_train
    test_aucs[ii] = auc_test
```

```
 C: 1e-05
Train AUC:0.587
Test AUC:0.589

 C: 3e-05
Train AUC:0.597
Test AUC:0.598

 C: 0.0001
Train AUC:0.605
Test AUC:0.605

 C: 0.0003
Train AUC:0.609
Test AUC:0.609

 C: 0.001
Train AUC:0.612
Test AUC:0.613

 C: 0.003
Train AUC:0.614
Test AUC:0.615
```

[241]:
```
plt.plot(Cs, train_aucs,'bo-', label ='Train')
plt.plot(Cs, test_aucs, 'ro-', label='Test')
```

```
plt.legend()
plt.xlabel('Logistic Regression - C')
plt.ylabel('AUC')
plt.show()
```



Let's execute againg the prediction with the tuned hyperparamter of LogisticRegression C =0.003 that maximize our performance metric AUC curve.

[242]:
```
from sklearn.linear_model import LogisticRegression

# Logistic regression with tuned paramter C = 0.003
clf=LogisticRegression(C = 0.003, penalty = 'l2', random_state = 42)
clf.fit(X_train, y_train)
```

[242]:
```
LogisticRegression(C=0.003, random_state=42)
```

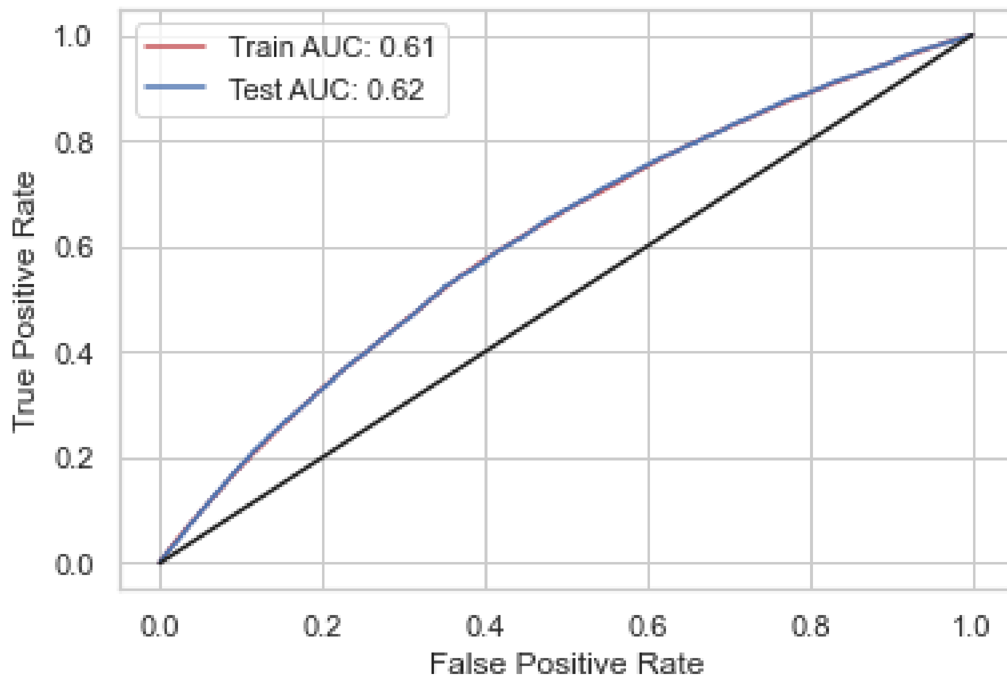
[244]:
```
# Calculate probability of re-admission within 30 days
model = clf
y_train_preds = model.predict_proba(X_train)[:,1]
y_test_preds = model.predict_proba(X_test)[:,1]
print(y_train[:10])
print(y_train_preds[:10])
```

```
[1 1 0 0 0 1 0 0 0 0]
[0.51703183 0.45155691 0.31220777 0.35475367 0.39630306 0.29985046
```

0.40903701 0.27001664 0.25939752 0.44125596]

[245]:
```python
# recalculate the performance metrics
fpr_train, tpr_train, thresholds_train = roc_curve(y_train, y_train_preds)
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_preds)


thresh = 0.5

auc_train = roc_auc_score(y_train, y_train_preds)
auc_test = roc_auc_score(y_test, y_test_preds)

print('Train AUC:%.3f'%auc_train)
print('Test AUC:%.3f'%auc_test)

print('Train accuracy:%.3f'%calc_accuracy(y_train, y_train_preds, thresh))
print('Test accuracy:%.3f'%calc_accuracy(y_test, y_test_preds, thresh))

print('Train recall:%.3f'%calc_recall(y_train, y_train_preds, thresh))
print('Test recall:%.3f'%calc_recall(y_test, y_test_preds, thresh))

print('Train precision:%.3f'%calc_precision(y_train, y_train_preds, thresh))
print('Test precision:%.3f'%calc_precision(y_test, y_test_preds, thresh))

plt.plot(fpr_train, tpr_train,'r-', label = 'Train AUC: %.2f'%auc_train)
plt.plot(fpr_test, tpr_test,'b-',label = 'Test AUC: %.2f'%auc_test)
plt.plot([0,1],[0,1],'-k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
Train AUC:0.614
Test AUC:0.615
Train accuracy:0.637
Test accuracy:0.633
Train recall:0.103
Test recall:0.101
Train precision:0.527
Test precision:0.531
```



We can see that we tuned parameters, the AUC score is improved.

1.7 8. Result Discussion

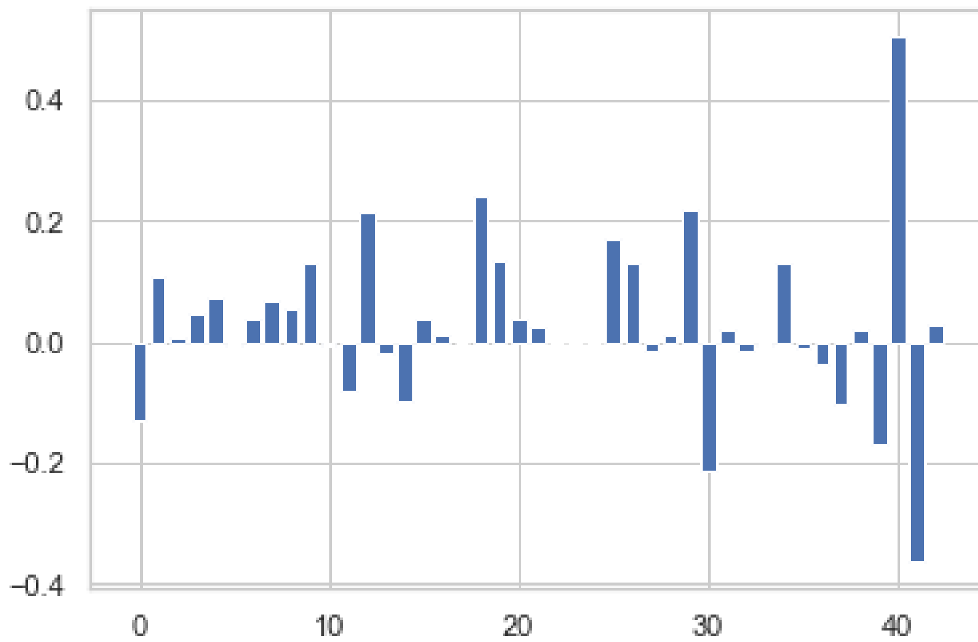
In the previous section we already saw the perfomrance metrics of the model. Now let's try to see what features were most important in predicting 30 days hospital readmission when using the logistic regression classifier model.

[247]:
```
clf=LogisticRegression(C = 0.003, penalty = 'l2', random_state = 42)
clf.fit(X_train, y_train)
model = clf
```

[248]:
```
from matplotlib import pyplot

# get importance
importance = model.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: -0.12856
Feature: 1, Score: 0.10846
Feature: 2, Score: 0.00975
```

```
Feature: 3, Score: 0.04628
Feature: 4, Score: 0.07533
Feature: 5, Score: -0.00587
Feature: 6, Score: 0.04073
Feature: 7, Score: 0.06821
Feature: 8, Score: 0.05410
Feature: 9, Score: 0.13245
Feature: 10, Score: -0.00732
Feature: 11, Score: -0.07943
Feature: 12, Score: 0.21556
Feature: 13, Score: -0.01840
Feature: 14, Score: -0.09642
Feature: 15, Score: 0.03879
Feature: 16, Score: 0.01127
Feature: 17, Score: -0.00156
Feature: 18, Score: 0.24049
Feature: 19, Score: 0.13414
Feature: 20, Score: 0.04057
Feature: 21, Score: 0.02513
Feature: 22, Score: 0.00000
Feature: 23, Score: 0.00000
Feature: 24, Score: 0.00000
Feature: 25, Score: 0.17311
Feature: 26, Score: 0.12955
Feature: 27, Score: -0.01309
Feature: 28, Score: 0.01255
Feature: 29, Score: 0.21770
Feature: 30, Score: -0.21508
Feature: 31, Score: 0.02207
Feature: 32, Score: -0.01630
Feature: 33, Score: -0.00370
Feature: 34, Score: 0.12936
Feature: 35, Score: -0.00948
Feature: 36, Score: -0.03608
Feature: 37, Score: -0.10125
Feature: 38, Score: 0.01953
Feature: 39, Score: -0.16998
Feature: 40, Score: 0.50760
Feature: 41, Score: -0.36494
Feature: 42, Score: 0.02939
```



[249]:
```
# Feature 40 was the most important in prediction
print(features.columns[40])
```

```
AGE_NEWBORN
```

30 DAYS-READMISSION result: the result from our study is that "Newborn patients" are more likely to be readmitted after 30 days from last discarge from hospital. This could be expected for newborn patients due to usual observatory purposes.

1.7.1 Readmission_90 , Readmission_365

Now we do the same prediction with "LogisticRegression" and with the same paramters, but now we want to predict readmission to the hospital within 90 and 365 days from the last discharge.

[250]:
```
df_cleaned.head()
```

[250]:
```
    gender  blood  circulatory  congenital  digestive  endocrine  \
1        1      0            0           0          2          0
2        1      1            0           0          1          1
3        1      0            1           0          1          2
17       1      0            0           0          0          0
22       1      1            0           0          4          3

    genitourinary  infectious  injury  mental  …  ETH_HISPANIC/LATINO  \
1               0           1       1       2  …                    0
2               0           1       1       1  …                    0
3               0           1       3       2  …                    0
```

```
17              0          0       1       0  ...                     0
22              1          0       0       2  ...                     0

    ETH_OTHER/UNKNOWN  ETH_WHITE  AGE_MIDDLE_ADULT  AGE_NEWBORN  AGE_SENIOR  \
1                   0          1                 1            0           0
2                   0          1                 1            0           0
3                   0          1                 1            0           0
17                  0          1                 0            1           0
22                  0          1                 0            0           0

    AGE_YOUNG_ADULT  READMISSION_30  READMISSION_90  READMISSION_365
1                 0               0               1                1
2                 0               1               1                1
3                 0               1               1                1
17                0               1               1                1
22                1               1               1                1

[5 rows x 46 columns]
```

[251]:

```
# Target Variable READMISSION_90
READMISSION_90 = df_cleaned['READMISSION_90'].values
# Prediction Features
features = df_cleaned.drop(columns=['READMISSION_90', 'READMISSION_30',␣
 ↪'READMISSION_365'])
```

[252]:

```
from sklearn.model_selection import train_test_split

# Split into training set 80% and test set 20%
X_train, X_test, y_train, y_test = train_test_split(features,
                                                    READMISSION_90,
                                                    test_size = .20,
                                                    random_state = 0)

# Show the results of the split
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 128434 samples.
Testing set has 32109 samples.
```

[253]:

```
clf=LogisticRegression(C = 0.003, penalty = 'l2', random_state = 42)
clf.fit(X_train, y_train)
```

[253]:

```
LogisticRegression(C=0.003, random_state=42)
```

[255]:

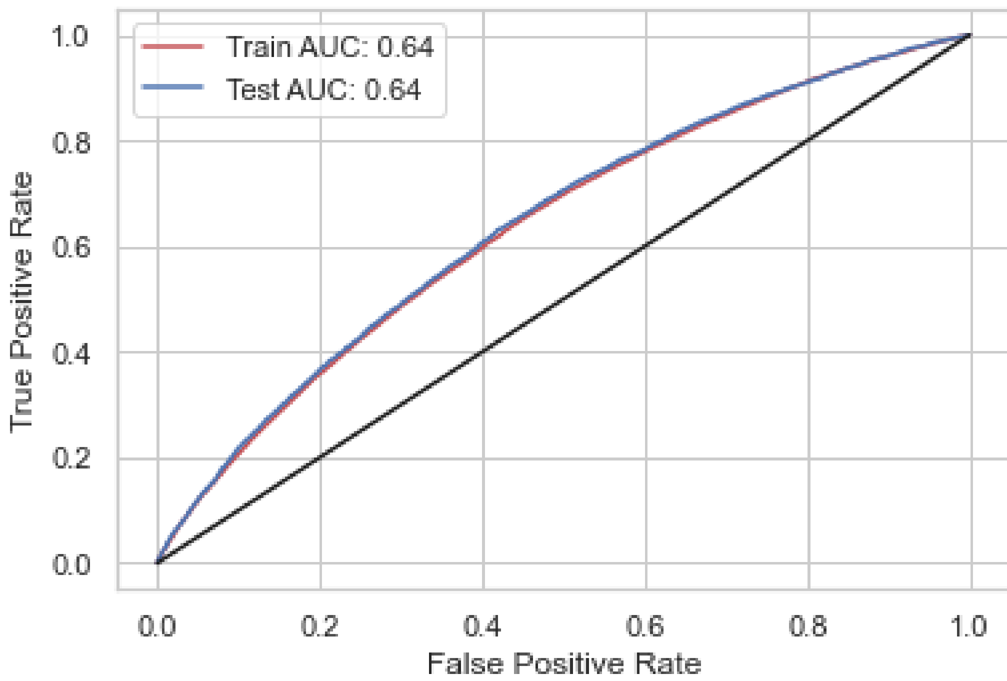
```
# calculate probabilities
model = clf
y_train_preds = model.predict_proba(X_train)[:,1]
```

```
y_test_preds = model.predict_proba(X_test)[:,1]
print(y_train[:10])
print(y_train_preds[:10])
```

```
[1 1 1 1 0 1 0 0 1 0]
[0.77487392 0.60949116 0.46756107 0.48497073 0.63474014 0.44503751
 0.59959792 0.46913974 0.52507816 0.67952589]
```

[256]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

fpr_train, tpr_train, thresholds_train = roc_curve(y_train, y_train_preds)
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_preds)


thresh = 0.5

auc_train = roc_auc_score(y_train, y_train_preds)
auc_test = roc_auc_score(y_test, y_test_preds)

print('Train AUC:%.3f'%auc_train)
print('Test AUC:%.3f'%auc_test)

print('Train accuracy:%.3f'%calc_accuracy(y_train, y_train_preds, thresh))
print('Test accuracy:%.3f'%calc_accuracy(y_test, y_test_preds, thresh))

print('Train recall:%.3f'%calc_recall(y_train, y_train_preds, thresh))
print('Test recall:%.3f'%calc_recall(y_test, y_test_preds, thresh))

print('Train precision:%.3f'%calc_precision(y_train, y_train_preds, thresh))
print('Test precision:%.3f'%calc_precision(y_test, y_test_preds, thresh))

plt.plot(fpr_train, tpr_train,'r-', label = 'Train AUC: %.2f'%auc_train)
plt.plot(fpr_test, tpr_test,'b-',label = 'Test AUC: %.2f'%auc_test)
plt.plot([0,1],[0,1],'-k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

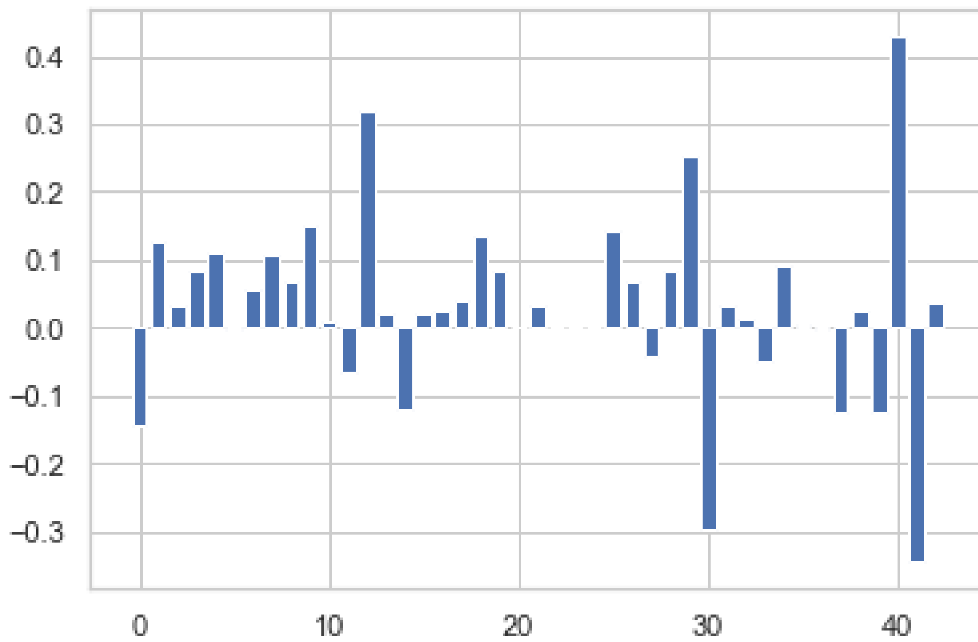
```
Train AUC:0.637
Test AUC:0.642
Train accuracy:0.611
Test accuracy:0.615
Train recall:0.759
Test recall:0.761
Train precision:0.623
Test precision:0.627
```



[257]:
```python
from matplotlib import pyplot

# get importance
importance = model.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: -0.14218
Feature: 1, Score: 0.12667
Feature: 2, Score: 0.03341
Feature: 3, Score: 0.08523
Feature: 4, Score: 0.11130
Feature: 5, Score: -0.00028
Feature: 6, Score: 0.05741
Feature: 7, Score: 0.10620
Feature: 8, Score: 0.06917
Feature: 9, Score: 0.15032
Feature: 10, Score: 0.01086
Feature: 11, Score: -0.06523
Feature: 12, Score: 0.31814
Feature: 13, Score: 0.02175
```

```
Feature: 14, Score: -0.12024
Feature: 15, Score: 0.02338
Feature: 16, Score: 0.02614
Feature: 17, Score: 0.04280
Feature: 18, Score: 0.13522
Feature: 19, Score: 0.08605
Feature: 20, Score: 0.00360
Feature: 21, Score: 0.03133
Feature: 22, Score: 0.00000
Feature: 23, Score: 0.00000
Feature: 24, Score: 0.00000
Feature: 25, Score: 0.14205
Feature: 26, Score: 0.06981
Feature: 27, Score: -0.04164
Feature: 28, Score: 0.08315
Feature: 29, Score: 0.25358
Feature: 30, Score: -0.29666
Feature: 31, Score: 0.03469
Feature: 32, Score: 0.01240
Feature: 33, Score: -0.04866
Feature: 34, Score: 0.09251
Feature: 35, Score: 0.00488
Feature: 36, Score: -0.00083
Feature: 37, Score: -0.12211
Feature: 38, Score: 0.02399
Feature: 39, Score: -0.12354
Feature: 40, Score: 0.43049
Feature: 41, Score: -0.34500
Feature: 42, Score: 0.03648
```



[264]:
```
print(features.columns[40])
print(features.columns[12])
```

```
AGE_NEWBORN
neoplasms
```

90 DAYS-READMISSION result: the result is similar from 30-DAYS-READMISSION so also in this case "Newborn patients" are more likely to be readmitted after 90 days from last discarge from hospital. But we can see how also the feature "neoplasm" has an importance pretty high in prediction. This means that, in addition to "newborn patients", also patients diagnosed in the category "neoplasm" are more likely to be readmitted to the hospital after 90 days from discharge.

Finally let's check with 365 time limit.

[258]:
```
# Target Variable READMISSION_365
READMISSION_365 = df_cleaned['READMISSION_365'].values
# Prediction Features
features = df_cleaned.drop(columns=['READMISSION_90', 'READMISSION_30',␣
 ↪'READMISSION_365'])
```

[259]:
```
# Split into training set 80% and test set 20%
X_train, X_test, y_train, y_test = train_test_split(features,
                                                    READMISSION_365,
                                                    test_size = .20,
                                                    random_state = 0)


# Show the results of the split
```

```
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 128434 samples.
Testing set has 32109 samples.
```

[260]:
```
clf=LogisticRegression(C = 0.003, penalty = 'l2', random_state = 42)
clf.fit(X_train, y_train)
```

[260]:
```
LogisticRegression(C=0.003, random_state=42)
```

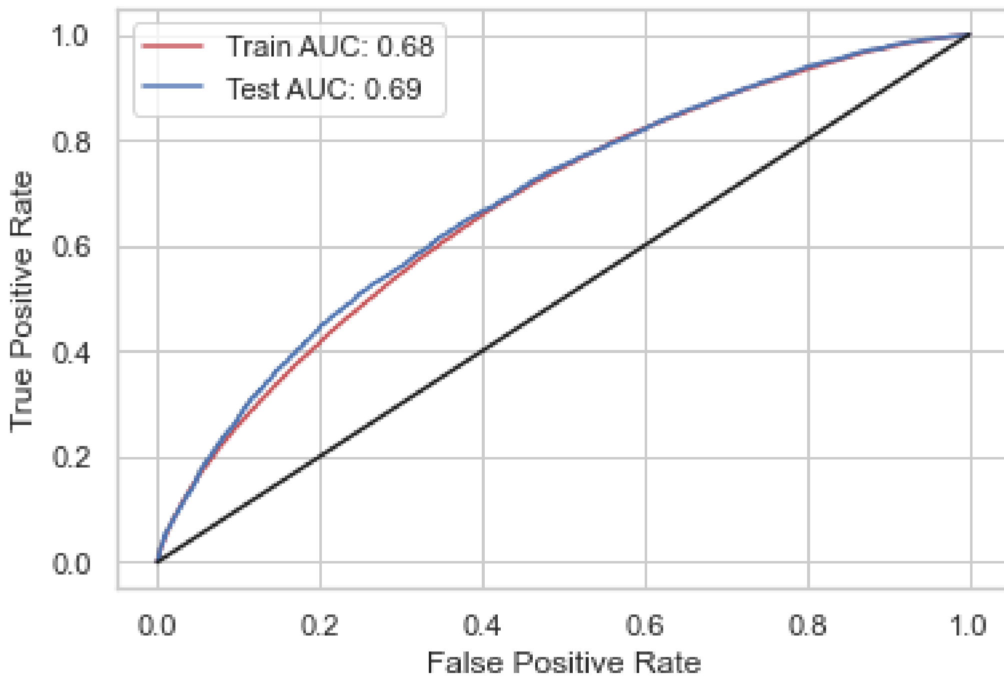
[261]:
```
# calculate probabilities
model = clf
y_train_preds = model.predict_proba(X_train)[:,1]
y_test_preds = model.predict_proba(X_test)[:,1]
print(y_train[:10])
print(y_train_preds[:10])
```

```
[1 1 1 1 0 1 0 1 1 0]
[0.94940836 0.83320845 0.7246811  0.65752376 0.86696649 0.71031022
 0.83328796 0.76929901 0.84373479 0.88425083]
```

[262]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

fpr_train, tpr_train, thresholds_train = roc_curve(y_train, y_train_preds)
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_preds)


thresh = 0.5

auc_train = roc_auc_score(y_train, y_train_preds)
auc_test = roc_auc_score(y_test, y_test_preds)

print('Train AUC:%.3f'%auc_train)
print('Test AUC:%.3f'%auc_test)

print('Train accuracy:%.3f'%calc_accuracy(y_train, y_train_preds, thresh))
print('Test accuracy:%.3f'%calc_accuracy(y_test, y_test_preds, thresh))

print('Train recall:%.3f'%calc_recall(y_train, y_train_preds, thresh))
print('Test recall:%.3f'%calc_recall(y_test, y_test_preds, thresh))

print('Train precision:%.3f'%calc_precision(y_train, y_train_preds, thresh))
print('Test precision:%.3f'%calc_precision(y_test, y_test_preds, thresh))

plt.plot(fpr_train, tpr_train,'r-', label = 'Train AUC: %.2f'%auc_train)
plt.plot(fpr_test, tpr_test,'b-',label = 'Test AUC: %.2f'%auc_test)
```

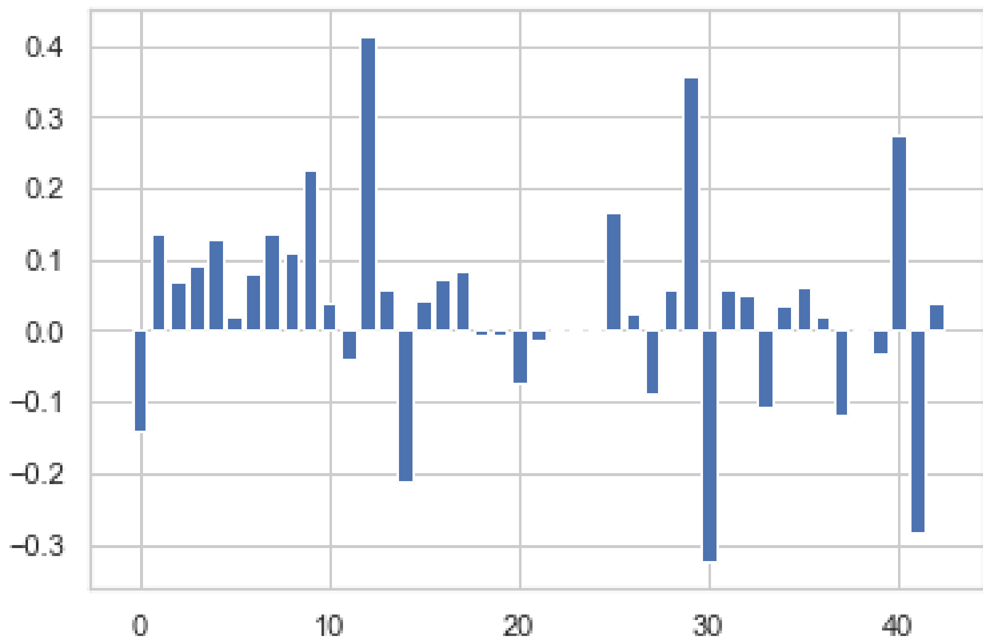
```
plt.plot([0,1],[0,1],'-k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
Train AUC:0.678
Test AUC:0.685
Train accuracy:0.794
Test accuracy:0.797
Train recall:0.993
Test recall:0.993
Train precision:0.797
Test precision:0.800
```



[263]:
```
from matplotlib import pyplot

# get importance
importance = model.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: -0.14189
Feature: 1, Score: 0.13782
Feature: 2, Score: 0.06893
Feature: 3, Score: 0.09262
Feature: 4, Score: 0.12718
Feature: 5, Score: 0.02110
Feature: 6, Score: 0.07883
Feature: 7, Score: 0.13439
Feature: 8, Score: 0.10940
Feature: 9, Score: 0.22671
Feature: 10, Score: 0.03832
Feature: 11, Score: -0.04088
Feature: 12, Score: 0.41417
Feature: 13, Score: 0.05612
Feature: 14, Score: -0.21269
Feature: 15, Score: 0.04293
Feature: 16, Score: 0.07094
Feature: 17, Score: 0.08253
Feature: 18, Score: -0.00676
Feature: 19, Score: -0.00509
Feature: 20, Score: -0.07217
Feature: 21, Score: -0.01496
Feature: 22, Score: 0.00000
Feature: 23, Score: 0.00000
Feature: 24, Score: 0.00000
Feature: 25, Score: 0.16787
Feature: 26, Score: 0.02518
Feature: 27, Score: -0.08892
Feature: 28, Score: 0.05635
Feature: 29, Score: 0.35854
Feature: 30, Score: -0.32575
Feature: 31, Score: 0.05574
Feature: 32, Score: 0.05040
Feature: 33, Score: -0.10592
Feature: 34, Score: 0.03557
Feature: 35, Score: 0.06125
Feature: 36, Score: 0.01918
Feature: 37, Score: -0.11954
Feature: 38, Score: 0.00376
Feature: 39, Score: -0.03201
Feature: 40, Score: 0.27479
Feature: 41, Score: -0.28256
Feature: 42, Score: 0.04001
```



[265]:
```
print(features.columns[12])
print(features.columns[29])
```

```
neoplasms
ADM_OBSERVATION
```

365 DAYS-READMISSION result: in this task's result we can see how the feature "neoplasm" has the highest importance prediction. It is followed by the feature of admissions to the hospital for observation. So we could say that patients diagnosed diagnosed in the category "neoplasm" and patients admitted for observation purposes are more likely to be readmitted to the hospital after 365 days from discharge.

1.8 Conclusions for Hospital Readmission

We saw how the probability of readmission to the hospital after discharge changes if we consider different period of time. But most important, we saw that in all of the three time interval considered (30, 90, 365 days after discharge) patients diagnosed in category "neoplasm" has always an high probability to be readmitted, expecially in the 65-days.hasattr

With this kinf of insights it is possible to plan and better manage admissions and hospital stays avoiding crowds and consequently the possibility of getting infections on the hospital.