Predicting Hospital Readmission with Discharge Summaries

Problem

Prediction of hospital readmission at admission time, within 24 hours, lacks information that would be included in discharge summaries

Solution

Build machine learning models improve hospital resource utilization and reduce cost of unplanned readmission solely on discharge summaries.

In [1]:
```
import os, sys, math, csv, datetime, time, pickle, json
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
```

Load and analyse the ADMSSION dataset

In [2]:
```
admissions = pd.read_csv('ADMISSIONS.csv.gz', compression='gzip')
```

In [3]:
```
admissions.columns
```

Out[3]:
```
Index(['ROW_ID', 'SUBJECT_ID', 'HADM_ID', 'ADMITTIME', 'DISCHTIME',
       'DEATHTIME', 'ADMISSION_TYPE', 'ADMISSION_LOCATION',
       'DISCHARGE_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'EDREGTIME', 'EDOUTTIME', 'DIAGNO
SIS',
       'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA'],
      dtype='object')
```

Check for the NaN values on each column

In [4]:
```
for col in admissions.columns:
  print(col)
  print(admissions[col].isna().value_counts())
  print('----------------------------------------------------')
```

```
ROW_ID
False    58976
Name: ROW_ID, dtype: int64
------------------------------------------------
SUBJECT_ID
False    58976
Name: SUBJECT_ID, dtype: int64
------------------------------------------------
HADM_ID
False    58976
Name: HADM_ID, dtype: int64
------------------------------------------------
ADMITTIME
False    58976
Name: ADMITTIME, dtype: int64
------------------------------------------------
DISCHTIME
False    58976
Name: DISCHTIME, dtype: int64
------------------------------------------------
DEATHTIME
True     53122
False     5854
Name: DEATHTIME, dtype: int64
------------------------------------------------
ADMISSION_TYPE
False    58976
Name: ADMISSION_TYPE, dtype: int64
------------------------------------------------
ADMISSION_LOCATION
False    58976
Name: ADMISSION_LOCATION, dtype: int64
------------------------------------------------
DISCHARGE_LOCATION
False    58976
Name: DISCHARGE_LOCATION, dtype: int64
------------------------------------------------
INSURANCE
False    58976
Name: INSURANCE, dtype: int64
------------------------------------------------
LANGUAGE
False    33644
True     25332
Name: LANGUAGE, dtype: int64
------------------------------------------------
RELIGION
False    58518
True       458
Name: RELIGION, dtype: int64
------------------------------------------------
MARITAL_STATUS
False    48848
True     10128
Name: MARITAL_STATUS, dtype: int64
------------------------------------------------
ETHNICITY
```

```
False    58976
Name: ETHNICITY, dtype: int64
--------------------------------------------------
EDREGTIME
False    30877
True     28099
Name: EDREGTIME, dtype: int64
--------------------------------------------------
EDOUTTIME
False    30877
True     28099
Name: EDOUTTIME, dtype: int64
--------------------------------------------------
DIAGNOSIS
False    58951
True        25
Name: DIAGNOSIS, dtype: int64
--------------------------------------------------
HOSPITAL_EXPIRE_FLAG
False    58976
Name: HOSPITAL_EXPIRE_FLAG, dtype: int64
--------------------------------------------------
HAS_CHARTEVENTS_DATA
False    58976
Name: HAS_CHARTEVENTS_DATA, dtype: int64
--------------------------------------------------
```

In [5]:
```
admissions.shape
```

Out[5]:
```
(58976, 19)
```

In [6]:
```
admissions.head()
```

Out[6]:

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

In [7]:
```
admissions.SUBJECT_ID.unique().shape
```

Out[7]:
```
(46520,)
```

In [8]:
```
len(set(map(lambda x: tuple(x), admissions[['SUBJECT_ID', 'HADM_ID']].values.tolist())))
```

Out[8]:
```
58976
```

In [9]:
```
admissions[['HADM_ID', 'SUBJECT_ID']].duplicated().value_counts()
```

Out[9]:
```
False    58976
dtype: int64
```

Get the next admission date if it exists

We can get this with the shift() function, but we need to verify the dates are in order.

In [10]:
```
# get the NEXTADMITTIME for each patient
admissions.loc[:, 'NEXT_ADMITTIME'] = admissions.groupby('SUBJECT_ID')['ADMITTIME'].shift(-1)
```

In [11]:
```
admissions.head(5)
```

Out[11]:

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

In [12]:
```
# sort by subject_ID and check for duplicates
admissions[admissions.duplicated('SUBJECT_ID', keep=False)].sort_values
(['SUBJECT_ID', 'ADMITTIME'])
```

Out[12]:

	ROW_ID	SUBJECT_ID	HADM_ID	ADMITTIME	DISCHTIME	DEATHTIME	ADMISSION_TYP
224	14	17	194023	2134-12-27 07:15:00	2134-12-31 16:05:00	NaN	ELECTIV
225	15	17	161087	2135-05-09 14:11:00	2135-05-13 14:40:00	NaN	EMERGENC
229	19	21	109451	2134-09-11 12:17:00	2134-09-24 16:15:00	NaN	EMERGENC
230	20	21	111970	2135-01-30 20:50:00	2135-02-08 02:08:00	2135-02-08 02:08:00	EMERGENC
1	22	23	152223	2153-09-03 07:15:00	2153-09-08 19:10:00	NaN	ELECTIV
...	...	...	...	...	...	...	
56415	58952	99923	164914	2201-02-23 20:42:00	2201-03-03 16:00:00	NaN	EMERGENC
56416	58953	99923	192053	2201-05-15 13:12:00	2201-05-25 14:51:00	NaN	EMERGENC
56431	58968	99982	151454	2156-11-28 11:56:00	2156-12-08 13:45:00	NaN	EMERGENC
56432	58969	99982	112748	2157-01-05 17:27:00	2157-01-12 13:00:00	NaN	EMERGENC
56433	58970	99982	183791	2157-02-16 17:31:00	2157-02-22 20:36:00	NaN	EMERGENC

19993 rows × 20 columns

pd.to_datetime converts the date time string to date-time datatype

In [13]:
```
admissions['NEXT_ADMITTIME'] = pd.to_datetime(admissions['NEXT_ADMITTIM
E'])
```

In [14]:
```
admissions['ADMITTIME'] = pd.to_datetime(admissions['ADMITTIME'])
```

In [15]:
```
admissions['DISCHTIME'] = pd.to_datetime(admissions['DISCHTIME'])
```

In [16]:
```
# get the total number of days on hospital
admissions.loc[:, 'DAYS_IN_HOSPITAL'] = (admissions['DISCHTIME'] - admis
sions['ADMITTIME']).dt.days
```

In [17]:
```
# sort by subject_ID and admission date
adm = admissions.sort_values(['SUBJECT_ID', 'ADMITTIME'])
```

In [18]:
```
# get the days within next admit
adm['DAYS_WITHIN_NEXT_ADMIT'] = (adm['NEXT_ADMITTIME'] - adm['ADMITTIME'
]).dt.days
```

In [19]:
```
adm.DAYS_IN_HOSPITAL.isna().value_counts()
```

Out[19]:
```
False    58976
Name: DAYS_IN_HOSPITAL, dtype: int64
```

In [20]:
```
# filling the negative values with
adm.loc[adm['DAYS_WITHIN_NEXT_ADMIT'] < 0, 'DAYS_WITHIN_NEXT_ADMIT'] = p
d.NaT
```

In [21]:
```
adm['DAYS_WITHIN_NEXT_ADMIT'].isna().value_counts()
```

Out[21]:
```
True     46622
False    12354
Name: DAYS_WITHIN_NEXT_ADMIT, dtype: int64
```

In [22]:
```
# gine the counts of the patient admits within 30 days.
(adm.DAYS_WITHIN_NEXT_ADMIT <= 30).value_counts()
```

Out[22]:
```
False    56449
True      2527
Name: DAYS_WITHIN_NEXT_ADMIT, dtype: int64
```

In [23]:
```
adm[['ADMITTIME', 'SUBJECT_ID', 'HADM_ID', 'DAYS_WITHIN_NEXT_ADMIT']]
```

Out[23]:

	ADMITTIME	SUBJECT_ID	HADM_ID	DAYS_WITHIN_NEXT_ADMIT
211	2138-07-17 19:04:00	2	163353	NaN
212	2101-10-20 19:08:00	3	145834	NaN
213	2191-03-16 00:28:00	4	185777	NaN
214	2103-02-02 04:31:00	5	178980	NaN
215	2175-05-30 07:15:00	6	107064	NaN
...	...	...	...	...
56435	2181-01-27 02:47:00	99985	176670	NaN
56436	2184-12-24 08:30:00	99991	151118	NaN
56437	2144-07-25 18:03:00	99992	197084	NaN
56565	2147-02-08 08:00:00	99995	137810	NaN
56566	2117-12-30 07:15:00	99999	113369	NaN

58976 rows × 4 columns

In [24]:
```
adm.head(5)
```

Out[24]:

	ROW_ID	SUBJECT_ID	HADM_ID	ADMITTIME	DISCHTIME	DEATHTIME	ADMISSION_TYPE
211	1	2	163353	2138-07-17 19:04:00	2138-07-21 15:48:00	NaN	NEWBORN
212	2	3	145834	2101-10-20 19:08:00	2101-10-31 13:58:00	NaN	EMERGENCY
213	3	4	185777	2191-03-16 00:28:00	2191-03-23 18:41:00	NaN	EMERGENCY
214	4	5	178980	2103-02-02 04:31:00	2103-02-04 12:15:00	NaN	NEWBORN
215	5	6	107064	2175-05-30 07:15:00	2175-06-15 16:00:00	NaN	ELECTIVE

5 rows × 22 columns

In [25]:
```
adm['HOSPITAL_EXPIRE_FLAG'].value_counts()
```

Out[25]:
```
0    53122
1     5854
Name: HOSPITAL_EXPIRE_FLAG, dtype: int64
```

In [26]:
```
adm.shape, admissions.shape
```

Out[26]:
```
((58976, 22), (58976, 21))
```

In [27]:
```
cols = [
        'HOSPITAL_EXPIRE_FLAG',
        'HAS_CHARTEVENTS_DATA',
        'DAYS_IN_HOSPITAL',
        'DAYS_WITHIN_NEXT_ADMIT'
]
```

In [28]:
```
for col in cols:
  print(col)
  print(adm[col].unique())
  print('-----------------------------------------------')
```

```
HOSPITAL_EXPIRE_FLAG
[0 1]
-----------------------------------------------
HAS_CHARTEVENTS_DATA
[1 0]
-----------------------------------------------
DAYS_IN_HOSPITAL
[  3  10   7   2  16   4   8  25  12   6   5  13   1  19   9  27  32  2
9
   0  15  14  18  58  17  80  91  22  28  33  24  20  11  31  75  70 10
7
  26  89  35  -1  76  23  61  21  49  30  54  47  59  85  60  56  81  4
6
  71  38 117  74  36  72  62  53  44  63  52  45  55  51  34  41  65  6
6
  97  87  37 145  64  50  42 108  39  43 113  84  48  69  40  86 137  9
5
  90  96 106 128  83 135 126 150  79 164  78  57 112 129  68  88 119  6
7
  82  99  73 101  94 123 100  93 173 155 191  77 151 138 140 131 125 20
2
 181 134 111 124 102 133 105  98 153 114 148 294 127 142 104  92 109 17
1
 118 120 132 144 167 166 115 116 103 110 163 161 122 121 141 169 136 20
6]
-----------------------------------------------
DAYS_WITHIN_NEXT_ADMIT
[nan 133.0 141.0 ... 3045.0 721.0 1627.0]
-----------------------------------------------
```

In [29]:
```
adm[adm.DAYS_WITHIN_NEXT_ADMIT.isna()].sort_values(['SUBJECT_ID', 'HADM_ID'])
```

Out[29]:

	ROW_ID	SUBJECT_ID	HADM_ID	ADMITTIME	DISCHTIME	DEATHTIME	ADMISSION_TYP
211	1	2	163353	2138-07-17 19:04:00	2138-07-21 15:48:00	NaN	NEWBOR
212	2	3	145834	2101-10-20 19:08:00	2101-10-31 13:58:00	NaN	EMERGENC
213	3	4	185777	2191-03-16 00:28:00	2191-03-23 18:41:00	NaN	EMERGENC
214	4	5	178980	2103-02-02 04:31:00	2103-02-04 12:15:00	NaN	NEWBOR
215	5	6	107064	2175-05-30 07:15:00	2175-06-15 16:00:00	NaN	ELECTIV
...	...	...	...	...	...	...	
56435	58972	99985	176670	2181-01-27 02:47:00	2181-02-12 17:05:00	NaN	EMERGENC
56436	58973	99991	151118	2184-12-24 08:30:00	2185-01-05 12:15:00	NaN	ELECTIV
56437	58974	99992	197084	2144-07-25 18:03:00	2144-07-28 17:56:00	NaN	EMERGENC
56565	58975	99995	137810	2147-02-08 08:00:00	2147-02-11 13:15:00	NaN	ELECTIV
56566	58976	99999	113369	2117-12-30 07:15:00	2118-01-04 16:30:00	NaN	ELECTIV

46622 rows × 22 columns

In [30]:
```
# get the max days between admits
adm['DAYS_WITHIN_NEXT_ADMIT'].max(), adm['DAYS_WITHIN_NEXT_ADMIT'].max()
// 365
```

Out[30]:
```
(4121.0, 11.0)
```

In [31]:
```
# fill the DAYS_WITHIN_NEXT_ADMIT NaN values with the 2 times the MAXIMU
M vlaue in the same column - this means that the NaN means the patient t
akes around 22 years to get admit again which is of less importance
adm.loc[adm.DAYS_WITHIN_NEXT_ADMIT.isna(), 'DAYS_WITHIN_NEXT_ADMIT'] = 2
*adm['DAYS_WITHIN_NEXT_ADMIT'].max()
```

In [32]:
```
for col in cols:
  print(col)
  print(adm[col].unique())
  adm[col] = adm[col].astype(float)
  print('-----------------------------------------')
```

```
HOSPITAL_EXPIRE_FLAG
[0 1]
-----------------------------------------
HAS_CHARTEVENTS_DATA
[1 0]
-----------------------------------------
DAYS_IN_HOSPITAL
[  3  10   7   2  16   4   8  25  12   6   5  13   1  19   9  27  32  2
9
   0  15  14  18  58  17  80  91  22  28  33  24  20  11  31  75  70 10
7
  26  89  35  -1  76  23  61  21  49  30  54  47  59  85  60  56  81  4
6
  71  38 117  74  36  72  62  53  44  63  52  45  55  51  34  41  65  6
6
  97  87  37 145  64  50  42 108  39  43 113  84  48  69  40  86 137  9
5
  90  96 106 128  83 135 126 150  79 164  78  57 112 129  68  88 119  6
7
  82  99  73 101  94 123 100  93 173 155 191  77 151 138 140 131 125 20
2
 181 134 111 124 102 133 105  98 153 114 148 294 127 142 104  92 109 17
1
 118 120 132 144 167 166 115 116 103 110 163 161 122 121 141 169 136 20
6]
-----------------------------------------
DAYS_WITHIN_NEXT_ADMIT
[8242  133  141 ... 3045  721 1627]
-----------------------------------------
```

In [33]:
```
adm.dtypes
```

Out[33]:
```
ROW_ID                          int64
SUBJECT_ID                      int64
HADM_ID                         int64
ADMITTIME                datetime64[ns]
DISCHTIME                datetime64[ns]
DEATHTIME                       object
ADMISSION_TYPE                  object
ADMISSION_LOCATION              object
DISCHARGE_LOCATION              object
INSURANCE                       object
LANGUAGE                        object
RELIGION                        object
MARITAL_STATUS                  object
ETHNICITY                       object
EDREGTIME                       object
EDOUTTIME                       object
DIAGNOSIS                       object
HOSPITAL_EXPIRE_FLAG           float64
HAS_CHARTEVENTS_DATA           float64
NEXT_ADMITTIME           datetime64[ns]
DAYS_IN_HOSPITAL               float64
DAYS_WITHIN_NEXT_ADMIT         float64
dtype: object
```

convert the time of the EMERGENCY IN AND OUT TIME to datetime datatype

In [34]:
```
adm['EDOUTTIME'] = pd.to_datetime(adm['EDOUTTIME'])
```

In [35]:
```
adm['EDREGTIME'] = pd.to_datetime(adm['EDREGTIME'])
```

In [36]:
```
(adm['EDOUTTIME'] - adm['EDREGTIME']).dt.total_seconds() / 86400
```

Out[36]:
```
211           NaN
212      0.093750
213      0.500000
214           NaN
215           NaN
             ...
56435    0.196528
56436         NaN
56437    0.215278
56565         NaN
56566         NaN
Length: 58976, dtype: float64
```

In [37]:
```
# get the TIME_IN_EMERGENCY_WARD IN DAYS, since all the columns are in d
ate unit
adm['TIME_IN_EMERGENCY_WARD'] = (adm['EDOUTTIME'] - adm['EDREGTIME']).dt
.total_seconds() / 86400
```

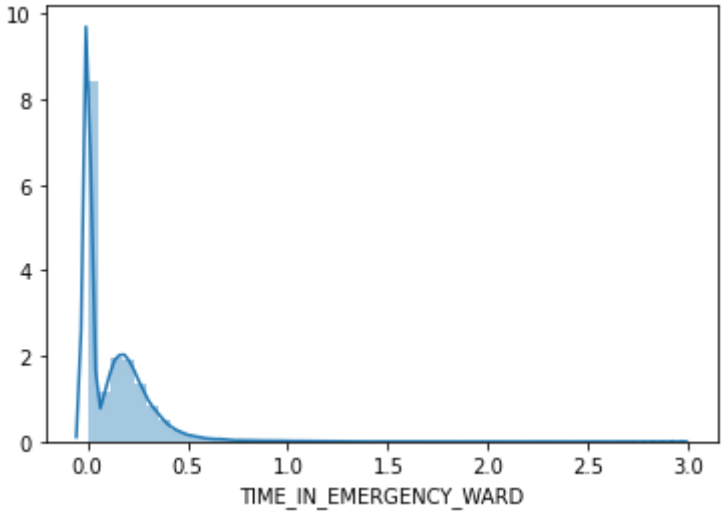
fill NaN values and negative values with 0 - means the patient stayed 0 days in the EMERGENCY WARD, means the patient did not stayed in emergency ward

In [38]:
```
adm.loc[adm['TIME_IN_EMERGENCY_WARD'] < 0, 'TIME_IN_EMERGENCY_WARD'] = 0
```

In [39]:
```
adm.loc[adm['TIME_IN_EMERGENCY_WARD'].isna(), 'TIME_IN_EMERGENCY_WARD']
= 0
```

In [40]:
```
sns.distplot(adm['TIME_IN_EMERGENCY_WARD'])
```

Out[40]: <AxesSubplot:xlabel='TIME_IN_EMERGENCY_WARD'>



In [41]:
```
# convert date string to pd.datetime
adm['DEATHTIME'] = pd.to_datetime(adm['DEATHTIME'])
```

In [42]:
```
(adm['DEATHTIME'] - adm['DISCHTIME']).value_counts()
```

Out[42]:
```
0 days 00:00:00       5789
1 days 00:00:00         29
-1 days +00:00:00       13
2 days 00:00:00          3
-7 days +00:00:00        2
-30 days +00:00:00       1
33 days 00:00:00         1
20 days 00:00:00         1
-1 days +06:53:00        1
-31 days +00:00:00       1
54 days 00:00:00         1
-4 days +00:00:00        1
65 days 00:00:00         1
-1 days +04:35:00        1
3 days 00:00:00          1
-10 days +00:00:00       1
-1 days +12:23:00        1
-3 days +00:00:00        1
-1 days +08:10:00        1
-9 days +00:00:00        1
-1 days +13:30:00        1
12 days 00:00:00         1
-1 days +12:00:00        1
dtype: int64
```

Obtain the difference between the death time and discharge time

In [43]:
```
# get the difference between the death time and discharge time
adm['DIFF_TIME_DEATH_DISCH'] = (adm['DISCHTIME'] - adm['DEATHTIME']).dt.
days
```

In [44]:
```
adm['DIFF_TIME_DEATH_DISCH'].isna().value_counts()
```

Out[44]:
```
True     53122
False     5854
Name: DIFF_TIME_DEATH_DISCH, dtype: int64
```

In [45]:
```
adm['DIFF_TIME_DEATH_DISCH'].value_counts()
```

Out[45]:
```
 0.0     5795
-1.0       29
 1.0       13
-2.0        3
 7.0        2
-54.0       1
 4.0        1
-65.0       1
 9.0        1
 30.0       1
-20.0       1
 31.0       1
-3.0        1
 10.0       1
 3.0        1
-12.0       1
-33.0       1
Name: DIFF_TIME_DEATH_DISCH, dtype: int64
```

Plot correlation value of the columns

In [46]:
```
adm.corr()
```

Out[46]:

	ROW_ID	SUBJECT_ID	HADM_ID	HOSPITAL_EXPIRE_FLAG	HAS_C
ROW_ID	1.000000	0.943991	0.007482	0.004480	
SUBJECT_ID	0.943991	1.000000	0.007082	0.004339	
HADM_ID	0.007482	0.007082	1.000000	-0.003120	
HOSPITAL_EXPIRE_FLAG	0.004480	0.004339	-0.003120	1.000000	
HAS_CHARTEVENTS_DATA	0.023013	0.023264	-0.002019	0.045495	
DAYS_IN_HOSPITAL	-0.062274	-0.062315	0.000280	0.000269	
DAYS_WITHIN_NEXT_ADMIT	0.037872	0.040350	-0.001477	0.163618	
TIME_IN_EMERGENCY_WARD	0.026858	0.029537	-0.001514	0.069405	
DIFF_TIME_DEATH_DISCH	0.001039	0.003959	-0.006720	NaN	

In [47]:
```
# get the value counts of the rows that have DAYS_WITHIN_NEXT
(adm['DAYS_WITHIN_NEXT_ADMIT'] <= 30).value_counts()
```

Out[47]:
```
False    56449
True      2527
Name: DAYS_WITHIN_NEXT_ADMIT, dtype: int64
```

get the target values - The readmissions within next 30 days

In [48]:
```
adm.loc[:, 'TARGET'] = (adm['DAYS_WITHIN_NEXT_ADMIT'] <= 30).astype(int)
```

In [49]:
```
# count the value of the TARGET variable
adm.TARGET.value_counts()
```

Out[49]:
```
0    56449
1     2527
Name: TARGET, dtype: int64
```

In [50]:
```
# verify for NaN values
adm.TARGET.isna().value_counts()
```

Out[50]:
```
False    58976
Name: TARGET, dtype: int64
```

In [51]:
```
cols = [
        'ADMISSION_TYPE',
        'ADMISSION_LOCATION',
        'DISCHARGE_LOCATION',
        'INSURANCE',
        'LANGUAGE',
        'RELIGION',
        'ETHNICITY',
        'DIAGNOSIS'
      ]
```

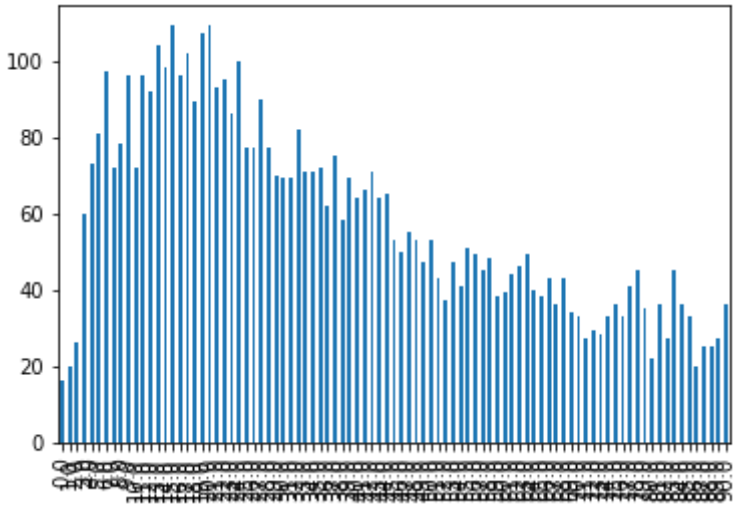
In [52]:
```
# verfiy NaN values for each of the above columns
for col in cols:
  print(col)
  print(adm[col].isna().value_counts())
  print('----------------------------------------')
```

```
ADMISSION_TYPE
False    58976
Name: ADMISSION_TYPE, dtype: int64
----------------------------------------
ADMISSION_LOCATION
False    58976
Name: ADMISSION_LOCATION, dtype: int64
----------------------------------------
DISCHARGE_LOCATION
False    58976
Name: DISCHARGE_LOCATION, dtype: int64
----------------------------------------
INSURANCE
False    58976
Name: INSURANCE, dtype: int64
----------------------------------------
LANGUAGE
False    33644
True     25332
Name: LANGUAGE, dtype: int64
----------------------------------------
RELIGION
False    58518
True       458
Name: RELIGION, dtype: int64
----------------------------------------
ETHNICITY
False    58976
Name: ETHNICITY, dtype: int64
----------------------------------------
DIAGNOSIS
False    58951
True        25
Name: DIAGNOSIS, dtype: int64
----------------------------------------
```

Now we plot and visualize the columns above and decide how the NaN values needs to be filled up

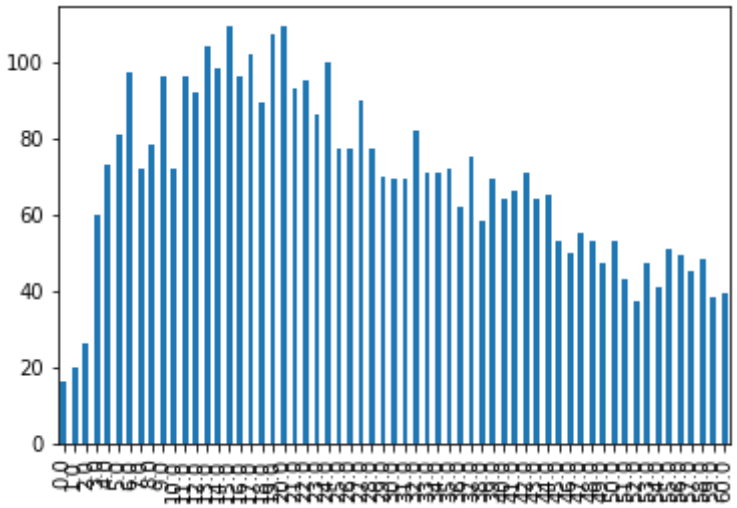
In [53]:
```
# plot the top 90 values (90 DAYS Readmission days) and its counts as bar plot
adm['DAYS_WITHIN_NEXT_ADMIT'].value_counts().sort_index()[:90].plot.bar()
```

Out[53]: <AxesSubplot:>



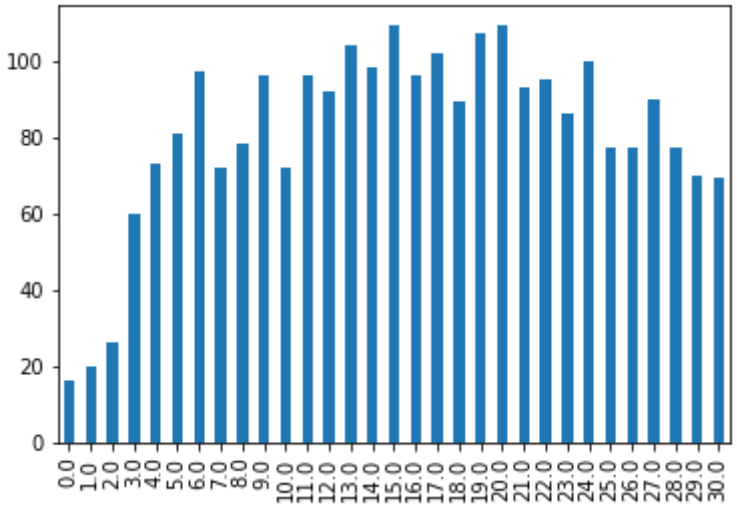
In [54]:
```
# plot the top 90 values (60 DAYS Readmission days) and its counts as bar plot
adm['DAYS_WITHIN_NEXT_ADMIT'].value_counts().sort_index()[:60].plot.bar()
```

Out[54]: <AxesSubplot:>



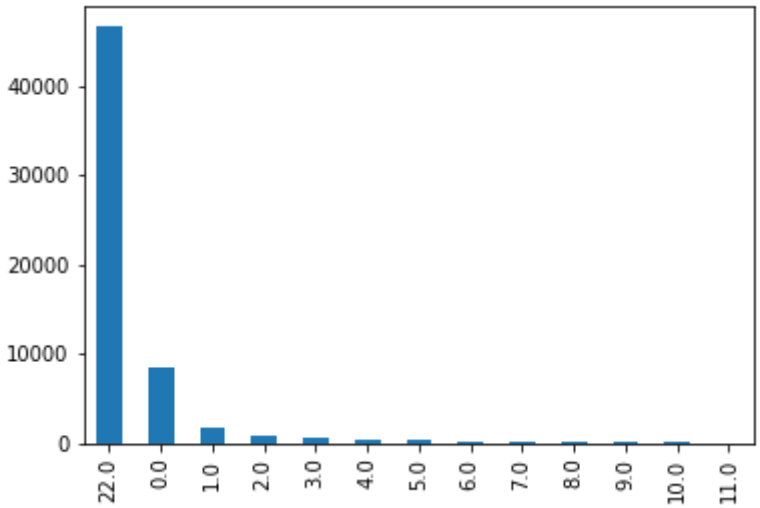
In [55]:
```
# plot the top 30 values (30 DAYS Readmission days) and its counts as ba
r plot
adm['DAYS_WITHIN_NEXT_ADMIT'].value_counts().sort_index()[:30].plot.bar
()
```

Out[55]: <AxesSubplot:>



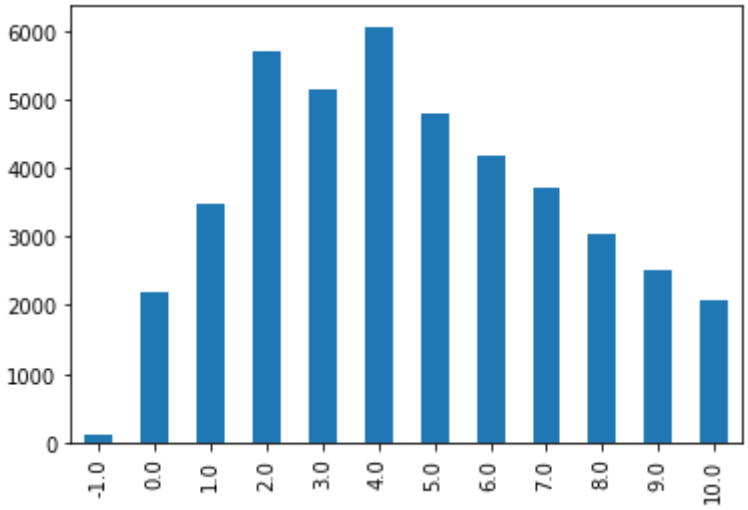
In [56]:
```
# plot years unit for the next readmission and its counts as bar plot
(adm['DAYS_WITHIN_NEXT_ADMIT'] // 365).value_counts().plot.bar()
```

Out[56]: <AxesSubplot:>



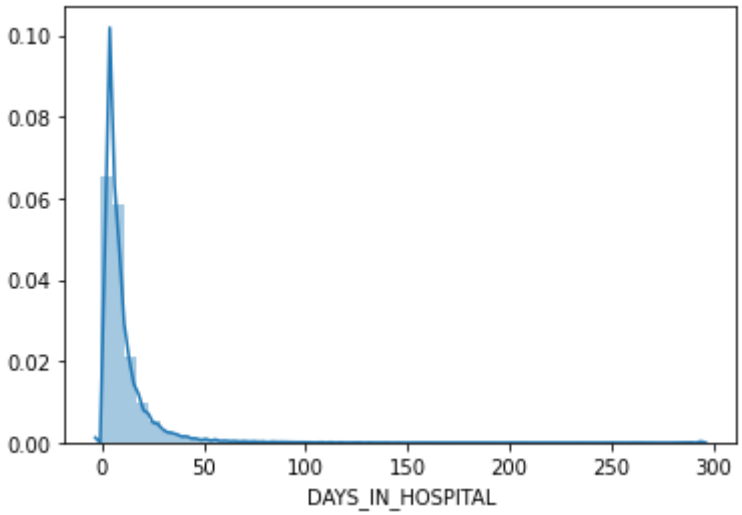
In [57]:
```
# plot the sorted top 10 days in hospital ant its value counts as bar pl
ot
adm['DAYS_IN_HOSPITAL'].value_counts().sort_index()[:10].plot.bar()
```

Out[57]: <AxesSubplot:>



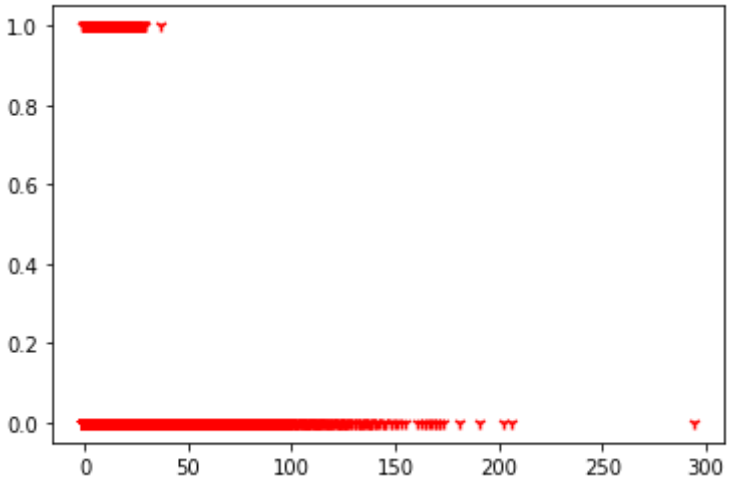
In [58]:
```
# get the distribution plot of the DAYS IN HOSPITAL values
sns.distplot(adm.DAYS_IN_HOSPITAL)
```

Out[58]: <AxesSubplot:xlabel='DAYS_IN_HOSPITAL'>



In [59]:
```
# get the scatter plot of the TARGET values and the DAYS IN HOSPITAL
plt.scatter(adm.DAYS_IN_HOSPITAL, adm.TARGET, c='r', marker='1')
```

Out[59]:
```
<matplotlib.collections.PathCollection at 0x12ac7ef50>
```

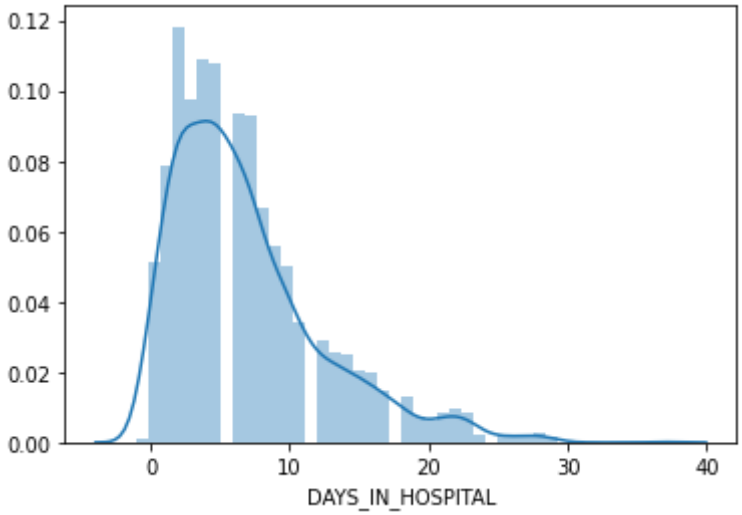


In [60]:
```
# get the correlation of the TARGET variables
adm.corr()['TARGET']
```

Out[60]:
```
ROW_ID                    0.003362
SUBJECT_ID                0.006839
HADM_ID                  -0.001086
HOSPITAL_EXPIRE_FLAG     -0.057916
HAS_CHARTEVENTS_DATA     -0.061368
DAYS_IN_HOSPITAL         -0.045178
DAYS_WITHIN_NEXT_ADMIT   -0.435745
TIME_IN_EMERGENCY_WARD    0.042624
DIFF_TIME_DEATH_DISCH    -0.014700
TARGET                    1.000000
Name: TARGET, dtype: float64
```

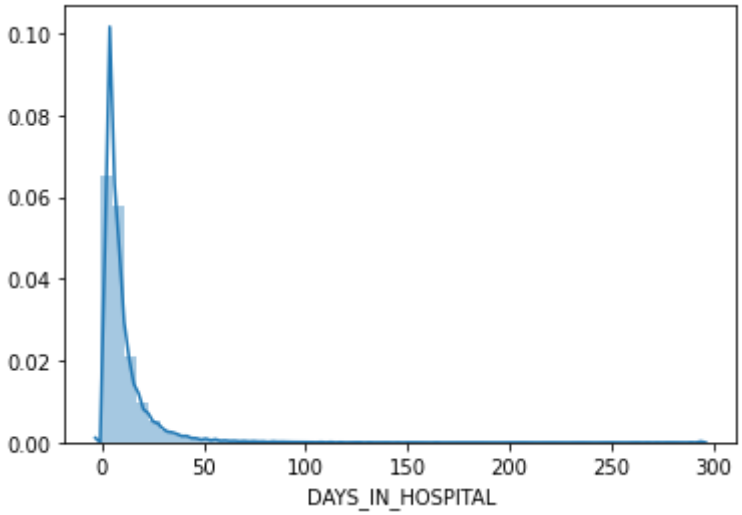
In [61]:
```
# the distribution plot of the TARGET variable with the DAYS IN HOSPITAL
sns.distplot(adm.loc[adm.TARGET == 1, 'DAYS_IN_HOSPITAL'])
```

Out[61]:
```
<AxesSubplot:xlabel='DAYS_IN_HOSPITAL'>
```



In [62]:
```
## the distribution plot of the TARGET variable with the DAYS IN HOSPITAL
sns.distplot(adm.loc[adm.TARGET == 0, 'DAYS_IN_HOSPITAL'].fillna(-1))
```

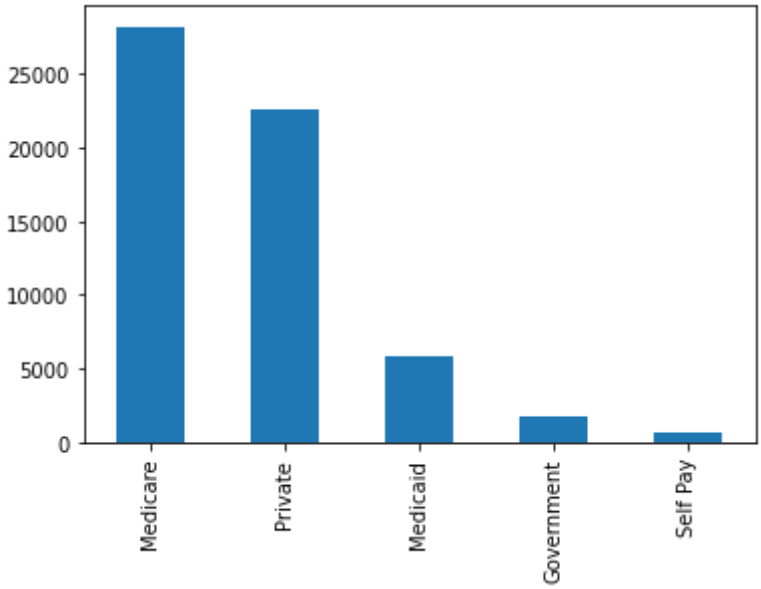
Out[62]: <AxesSubplot:xlabel='DAYS_IN_HOSPITAL'>



Now we check the different columns and the corresponding value counts of them and decide for them what NaN values needs to be filled and consequently make hypothesis and test them using correlation analysis, regression analayis, chi-square test

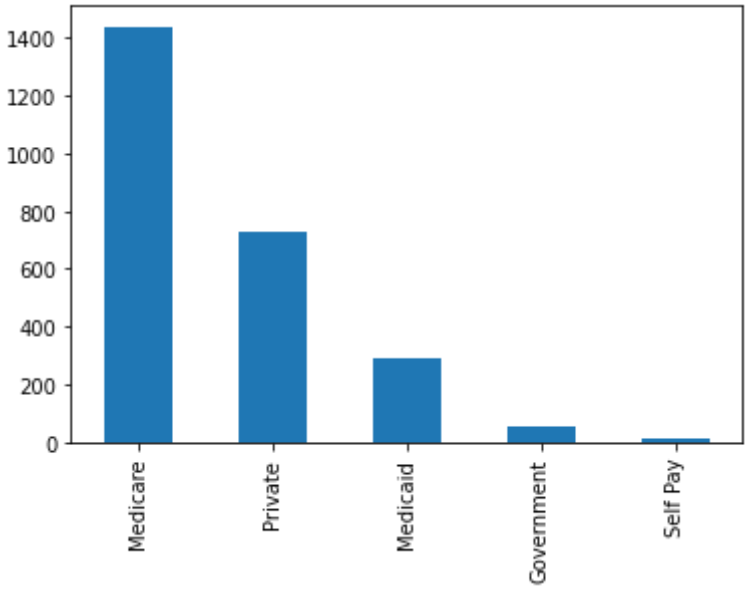
In [63]:
```
## get insurance plots
adm.INSURANCE.value_counts().plot.bar()
```

Out[63]: <AxesSubplot:>



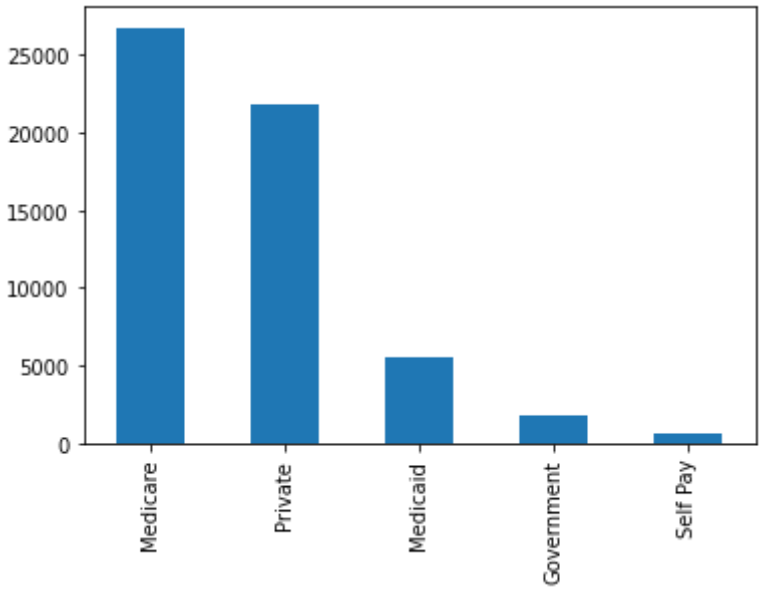
In [64]:
```
## get insurance plot when TARGET == 1
## there is a high chance that the TARGET == 1 when INSURANCE is MEdicar
e
adm.loc[adm.TARGET == 1, 'INSURANCE'].value_counts().plot.bar()
```

Out[64]: <AxesSubplot:>



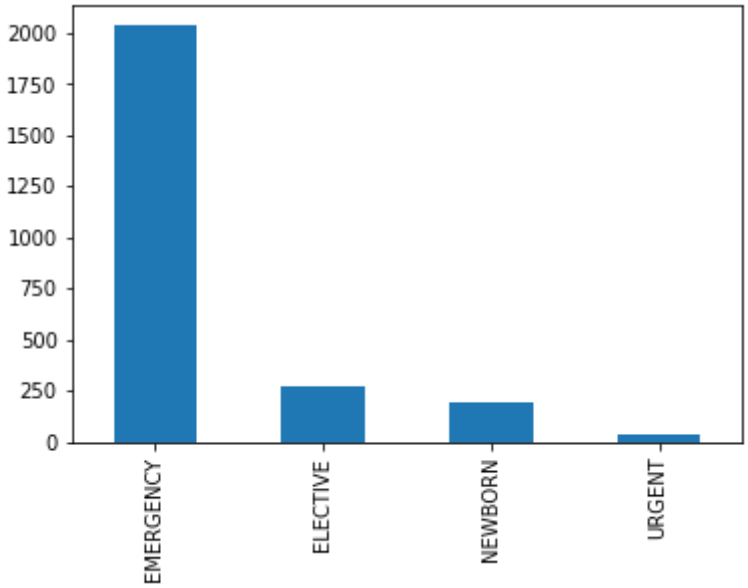
In [65]:
```
## get insurance plot when TARGET == 0
adm.loc[adm.TARGET == 0, 'INSURANCE'].value_counts().plot.bar()
```

Out[65]: <AxesSubplot:>



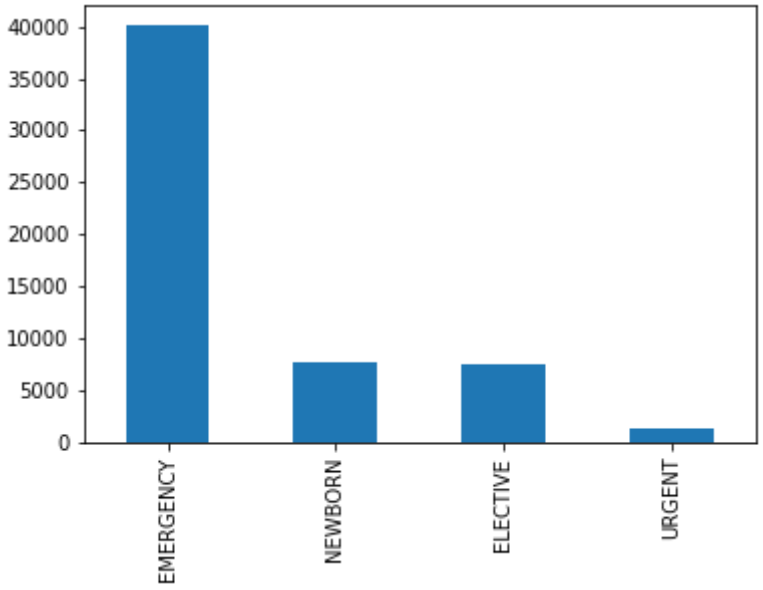
In [66]:
```
## get the ADMISSION TYPES when TARGET == 1
## most of the ADMISSIONS are EMERGENCY
adm.loc[adm.TARGET == 1].ADMISSION_TYPE.value_counts().plot.bar()
```

Out[66]: <AxesSubplot:>



In [67]:
```
## get the ADMISSION TYPE plot when TARGET == 0
adm.loc[adm.TARGET == 0].ADMISSION_TYPE.value_counts().plot.bar()
```

Out[67]: <AxesSubplot:>



In [68]:
```
adm.columns
```

Out[68]:
```
Index(['ROW_ID', 'SUBJECT_ID', 'HADM_ID', 'ADMITTIME', 'DISCHTIME',
       'DEATHTIME', 'ADMISSION_TYPE', 'ADMISSION_LOCATION',
       'DISCHARGE_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'EDREGTIME', 'EDOUTTIME', 'DIAGNO
SIS',
       'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA', 'NEXT_ADMITTIM
E',
       'DAYS_IN_HOSPITAL', 'DAYS_WITHIN_NEXT_ADMIT', 'TIME_IN_EMERGENCY
_WARD',
       'DIFF_TIME_DEATH_DISCH', 'TARGET'],
      dtype='object')
```

In [69]:
```
adm.TARGET
```

Out[69]:
```
211      0
212      0
213      0
214      0
215      0
        ..
56435    0
56436    0
56437    0
56565    0
56566    0
Name: TARGET, Length: 58976, dtype: int64
```

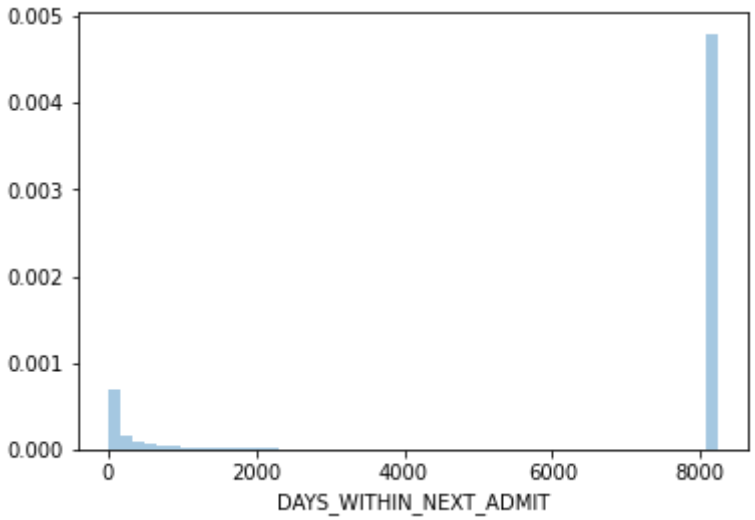
In [70]:
```
adm.columns
```

Out[70]:
```
Index(['ROW_ID', 'SUBJECT_ID', 'HADM_ID', 'ADMITTIME', 'DISCHTIME',
       'DEATHTIME', 'ADMISSION_TYPE', 'ADMISSION_LOCATION',
       'DISCHARGE_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'EDREGTIME', 'EDOUTTIME', 'DIAGNO
SIS',
       'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA', 'NEXT_ADMITTIM
E',
       'DAYS_IN_HOSPITAL', 'DAYS_WITHIN_NEXT_ADMIT', 'TIME_IN_EMERGENCY
_WARD',
       'DIFF_TIME_DEATH_DISCH', 'TARGET'],
      dtype='object')
```

In [71]:
```
## get the distribution plot for the DAYS_WITHIN_NEXT_ADMIT
sns.distplot(adm.DAYS_WITHIN_NEXT_ADMIT)
```

```
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/seaborn/
distributions.py:369: UserWarning: Default bandwidth for data is 0; ski
pping density estimation.
  warnings.warn(msg, UserWarning)
```

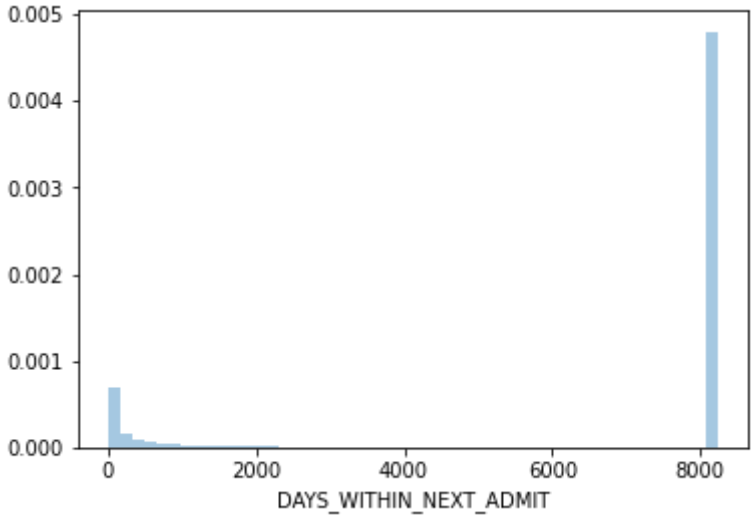
Out[71]: <AxesSubplot:xlabel='DAYS_WITHIN_NEXT_ADMIT'>



In [72]:
```
## get the DAYS_WITHIN_NEXT_ADMIT for when DAYS_WITHIN_NEXT_ADMIT is not
NaN
sns.distplot(adm.loc[adm.DAYS_WITHIN_NEXT_ADMIT.notna()].DAYS_WITHIN_NEX
T_ADMIT)
```

```
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/seaborn/
distributions.py:369: UserWarning: Default bandwidth for data is 0; ski
pping density estimation.
  warnings.warn(msg, UserWarning)
```

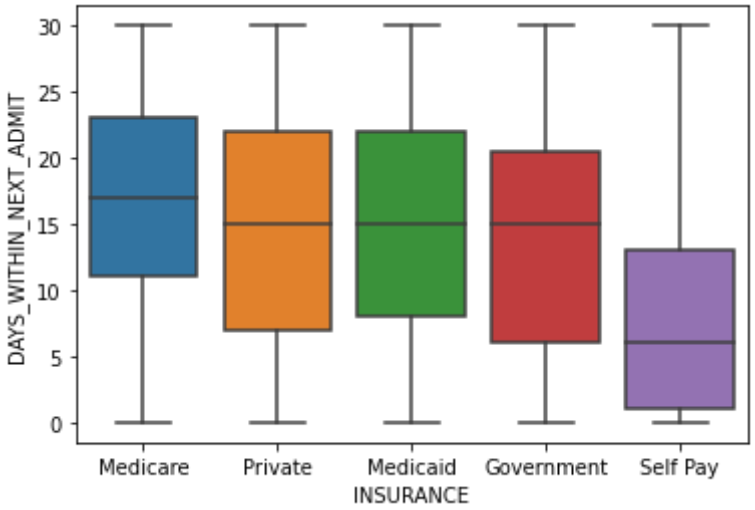
Out[72]: <AxesSubplot:xlabel='DAYS_WITHIN_NEXT_ADMIT'>



In [73]:
```
# box plot of the INSURANCE for DAYS WITHIN NEXT ADMIT

sns.boxplot(x='INSURANCE', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.
TARGET == 1])
```

Out[73]: <AxesSubplot:xlabel='INSURANCE', ylabel='DAYS_WITHIN_NEXT_ADMIT'>



In [74]:
```
# get spearman correlation for the INSURANCE One hot encoded values with
the TARGET values
pd.get_dummies(adm.INSURANCE).corrwith(adm.TARGET, method='spearman')
```

Out[74]:
```
Government   -0.010463
Medicaid      0.012702
Medicare      0.038558
Private      -0.041441
Self Pay     -0.010898
dtype: float64
```

In [75]:
```
# get the INSRUANCE correlation one hot representation for the DAYS IN H
OSPITAL
pd.get_dummies(adm.INSURANCE).corrwith(adm.DAYS_IN_HOSPITAL, method='spe
arman')
```

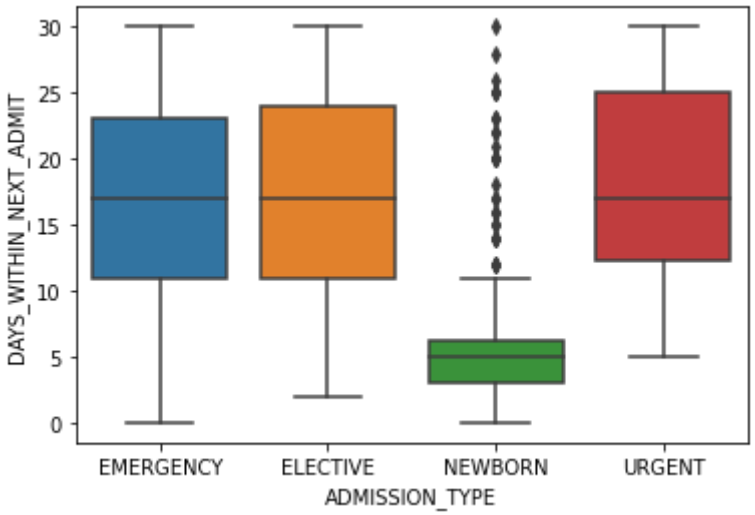
Out[75]:
```
Government   -0.023306
Medicaid     -0.007343
Medicare      0.097673
Private      -0.077255
Self Pay     -0.050004
dtype: float64
```

In [76]:
```
# get the INSURANCE correlation with the TIME IN EMERGENCY WARD
pd.get_dummies(adm.INSURANCE).corrwith(adm.TIME_IN_EMERGENCY_WARD, metho
d='spearman')
```

Out[76]:
```
Government   -0.002078
Medicaid      0.028020
Medicare      0.195138
Private      -0.222653
Self Pay      0.027396
dtype: float64
```

In [77]:
```
## the boxplot of the ADMISSION TYPE with the DAYS WITHIN NEXT ADMIT
sns.boxplot(x='ADMISSION_TYPE', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc
[adm.TARGET == 1])
```

Out[77]:
```
<AxesSubplot:xlabel='ADMISSION_TYPE', ylabel='DAYS_WITHIN_NEXT_ADMIT'>
```

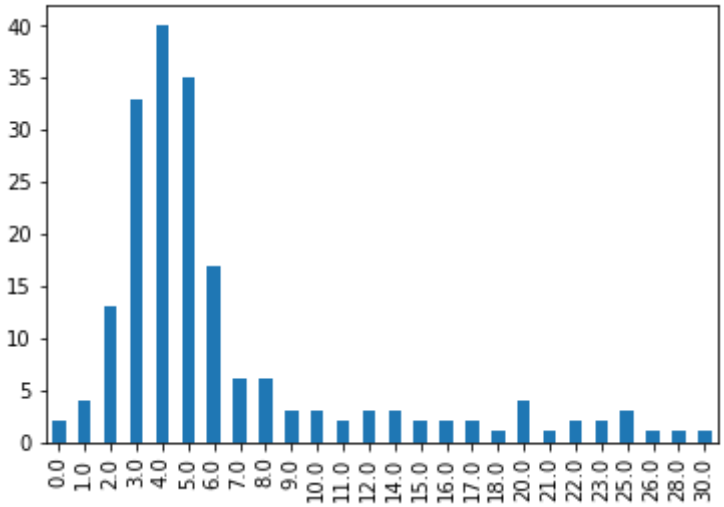


In [78]:
```
# the ADMISSION TYPE correlation with the TARGET correlation
pd.get_dummies(adm.ADMISSION_TYPE).corrwith(adm.TARGET, method='spearma
n')
```

Out[78]:
```
ELECTIVE    -0.015946
EMERGENCY    0.043021
NEWBORN     -0.035694
URGENT      -0.013080
dtype: float64
```

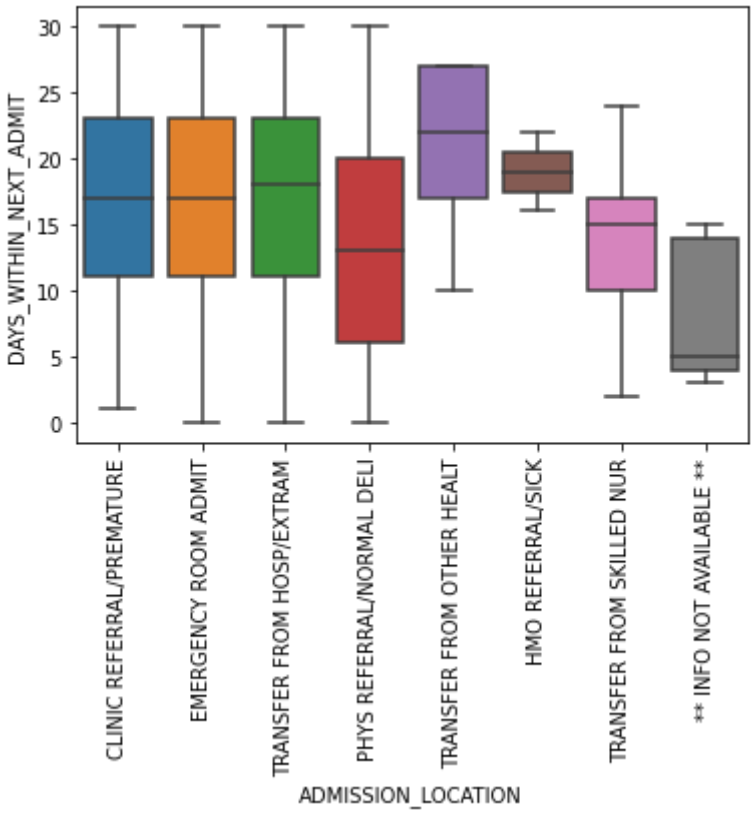
In [79]:
```
# plot the TARGET == 1 and ADMISSION TYPE == NEWBORN with the DAYS WITHI
N NEXT ADMIT bar plot to see the value count distribution
adm.loc[(adm.TARGET == 1) & (adm.ADMISSION_TYPE == 'NEWBORN'), 'DAYS_WIT
HIN_NEXT_ADMIT'].value_counts().sort_index().plot.bar()
```

Out[79]: <AxesSubplot:>



In [80]:
```
# boxplot for the ADMISSION LOCATION AND THE DAYS WITHIN NEXT ADMIT
sns.boxplot(x='ADMISSION_LOCATION', y='DAYS_WITHIN_NEXT_ADMIT', data=adm
.loc[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[80]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7]),
 [Text(0, 0, 'CLINIC REFERRAL/PREMATURE'),
  Text(1, 0, 'EMERGENCY ROOM ADMIT'),
  Text(2, 0, 'TRANSFER FROM HOSP/EXTRAM'),
  Text(3, 0, 'PHYS REFERRAL/NORMAL DELI'),
  Text(4, 0, 'TRANSFER FROM OTHER HEALT'),
  Text(5, 0, 'HMO REFERRAL/SICK'),
  Text(6, 0, 'TRANSFER FROM SKILLED NUR'),
  Text(7, 0, '** INFO NOT AVAILABLE **')])
```

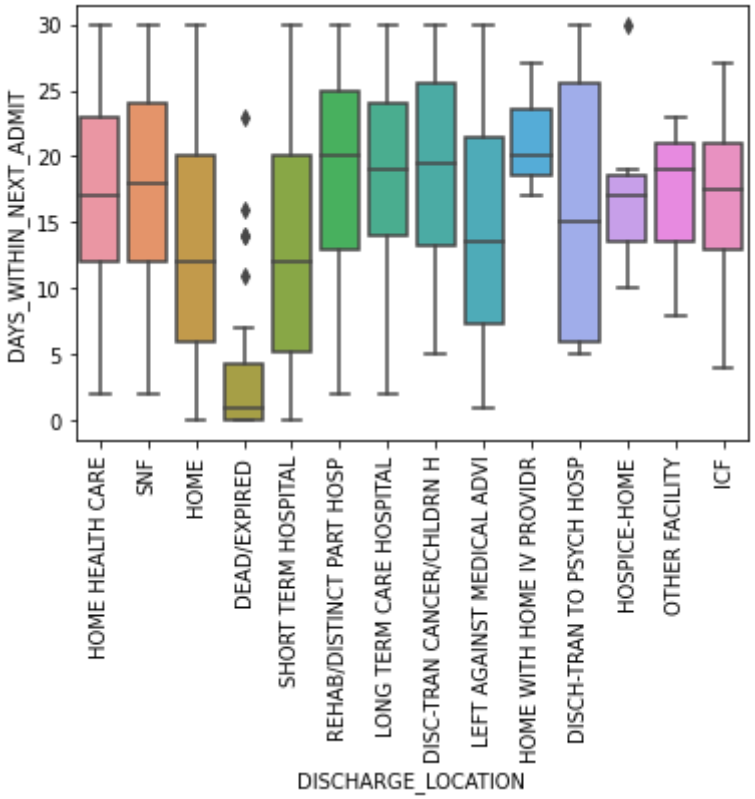


In [82]:
```
# the DISCHARGE LOCATION and the TARGET correlation
pd.get_dummies(adm.DISCHARGE_LOCATION).corrwith(adm.TARGET, method='spea
rman')
```

Out[82]:
```
DEAD/EXPIRED                -0.057916
DISC-TRAN CANCER/CHLDRN H   -0.010013
DISC-TRAN TO FEDERAL HC     -0.002890
DISCH-TRAN TO PSYCH HOSP    -0.011704
HOME                        -0.017296
HOME HEALTH CARE             0.003489
HOME WITH HOME IV PROVIDR    0.000321
HOSPICE-HOME                -0.010405
HOSPICE-MEDICAL FACILITY    -0.010791
ICF                          0.005893
LEFT AGAINST MEDICAL ADVI    0.023872
LONG TERM CARE HOSPITAL      0.047627
OTHER FACILITY               0.000770
REHAB/DISTINCT PART HOSP     0.009277
SHORT TERM HOSPITAL          0.004351
SNF                          0.037230
SNF-MEDICAID ONLY CERTIF    -0.000871
dtype: float64
```

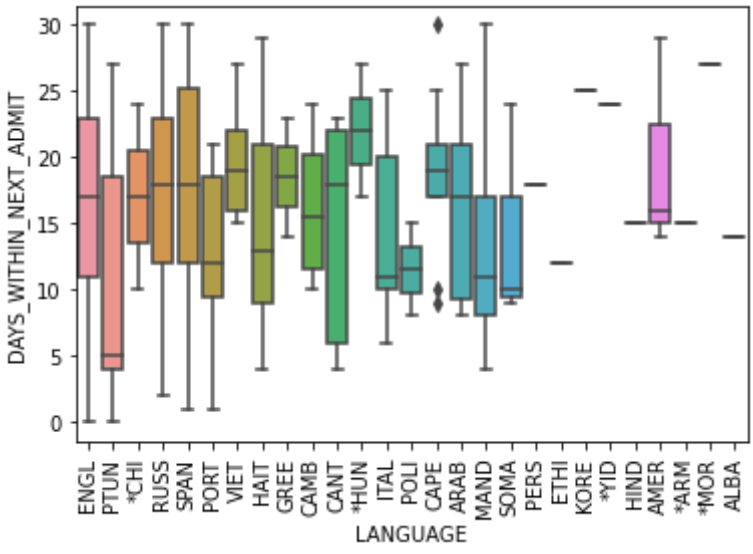
In [83]:
```
# the DISCHARGE LOCATION box plot with the DAYS WITHIN NEXT ADMIT when f
or the patient who are admitted again
sns.boxplot(x='DISCHARGE_LOCATION', y='DAYS_WITHIN_NEXT_ADMIT', data=adm
.loc[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[83]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 [Text(0, 0, 'HOME HEALTH CARE'),
  Text(1, 0, 'SNF'),
  Text(2, 0, 'HOME'),
  Text(3, 0, 'DEAD/EXPIRED'),
  Text(4, 0, 'SHORT TERM HOSPITAL'),
  Text(5, 0, 'REHAB/DISTINCT PART HOSP'),
  Text(6, 0, 'LONG TERM CARE HOSPITAL'),
  Text(7, 0, 'DISC-TRAN CANCER/CHLDRN H'),
  Text(8, 0, 'LEFT AGAINST MEDICAL ADVI'),
  Text(9, 0, 'HOME WITH HOME IV PROVIDR'),
  Text(10, 0, 'DISCH-TRAN TO PSYCH HOSP'),
  Text(11, 0, 'HOSPICE-HOME'),
  Text(12, 0, 'OTHER FACILITY'),
  Text(13, 0, 'ICF')])
```



In [84]:
```
# boxplot for the LANGUAGE and the DAYS WITHIN NEXT ADMIT for the patien
t who are admitted again
sns.boxplot(x='LANGUAGE', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.T
ARGET == 1])
plt.xticks(rotation=90)
```

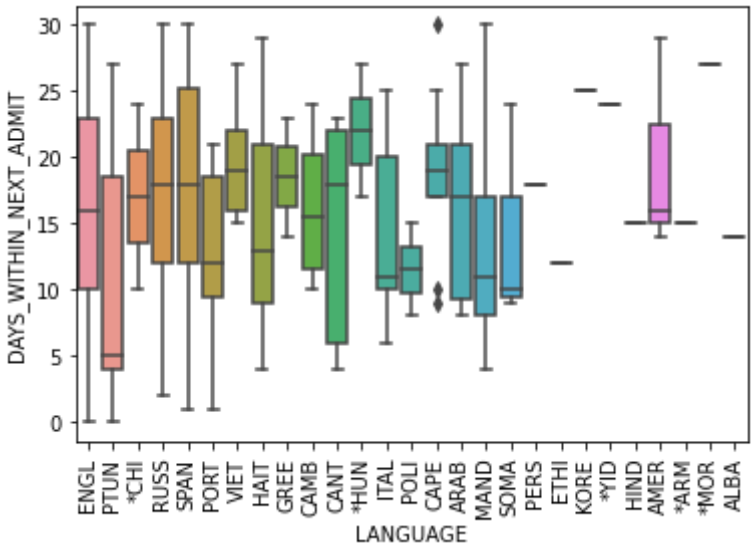
Out[84]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26]),
 [Text(0, 0, 'ENGL'),
  Text(1, 0, 'PTUN'),
  Text(2, 0, '*CHI'),
  Text(3, 0, 'RUSS'),
  Text(4, 0, 'SPAN'),
  Text(5, 0, 'PORT'),
  Text(6, 0, 'VIET'),
  Text(7, 0, 'HAIT'),
  Text(8, 0, 'GREE'),
  Text(9, 0, 'CAMB'),
  Text(10, 0, 'CANT'),
  Text(11, 0, '*HUN'),
  Text(12, 0, 'ITAL'),
  Text(13, 0, 'POLI'),
  Text(14, 0, 'CAPE'),
  Text(15, 0, 'ARAB'),
  Text(16, 0, 'MAND'),
  Text(17, 0, 'SOMA'),
  Text(18, 0, 'PERS'),
  Text(19, 0, 'ETHI'),
  Text(20, 0, 'KORE'),
  Text(21, 0, '*YID'),
  Text(22, 0, 'HIND'),
  Text(23, 0, 'AMER'),
  Text(24, 0, '*ARM'),
  Text(25, 0, '*MOR'),
  Text(26, 0, 'ALBA')])
```



In [85]:
```
# fill the language column with the maximum value occuring in the datase
t
adm.loc[adm.LANGUAGE.isna(), 'LANGUAGE'] = adm.LANGUAGE.value_counts().n
largest(1).index[0]
```

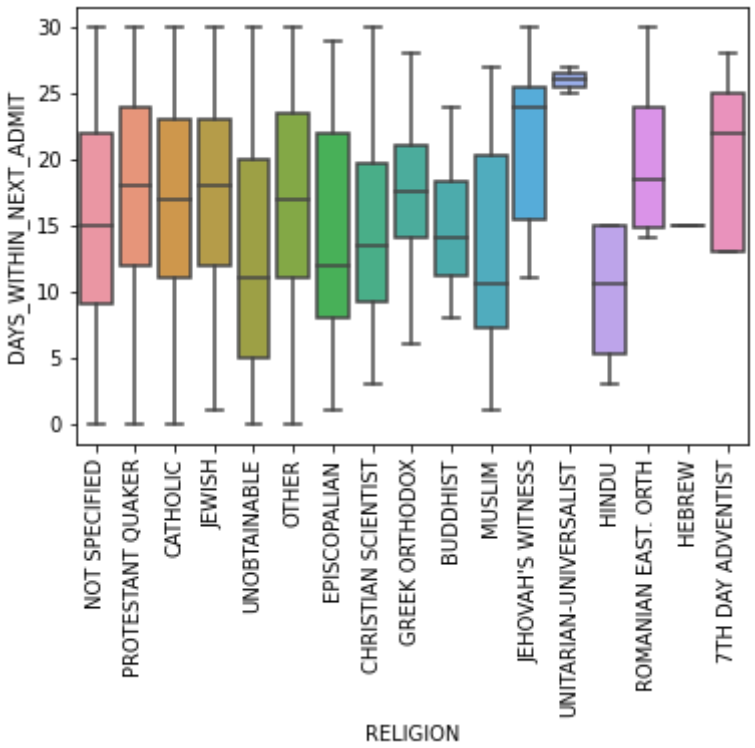
In [86]:
```
# the BOXPLOT for the LANGUAGE and the DAYS WITHIN NEXT ADMIT for the patient who are admitted again
sns.boxplot(x='LANGUAGE', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[86]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26]),
 [Text(0, 0, 'ENGL'),
  Text(1, 0, 'PTUN'),
  Text(2, 0, '*CHI'),
  Text(3, 0, 'RUSS'),
  Text(4, 0, 'SPAN'),
  Text(5, 0, 'PORT'),
  Text(6, 0, 'VIET'),
  Text(7, 0, 'HAIT'),
  Text(8, 0, 'GREE'),
  Text(9, 0, 'CAMB'),
  Text(10, 0, 'CANT'),
  Text(11, 0, '*HUN'),
  Text(12, 0, 'ITAL'),
  Text(13, 0, 'POLI'),
  Text(14, 0, 'CAPE'),
  Text(15, 0, 'ARAB'),
  Text(16, 0, 'MAND'),
  Text(17, 0, 'SOMA'),
  Text(18, 0, 'PERS'),
  Text(19, 0, 'ETHI'),
  Text(20, 0, 'KORE'),
  Text(21, 0, '*YID'),
  Text(22, 0, 'HIND'),
  Text(23, 0, 'AMER'),
  Text(24, 0, '*ARM'),
  Text(25, 0, '*MOR'),
  Text(26, 0, 'ALBA')])
```



In [87]:
```
# the boxplot for the RELIGION and the DAYS WITHIN NEXT ADMIT for the pa
tient who are admiited again
sns.boxplot(x='RELIGION', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.T
ARGET == 1])
plt.xticks(rotation=90)
```

Out[87]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16]),
 [Text(0, 0, 'NOT SPECIFIED'),
  Text(1, 0, 'PROTESTANT QUAKER'),
  Text(2, 0, 'CATHOLIC'),
  Text(3, 0, 'JEWISH'),
  Text(4, 0, 'UNOBTAINABLE'),
  Text(5, 0, 'OTHER'),
  Text(6, 0, 'EPISCOPALIAN'),
  Text(7, 0, 'CHRISTIAN SCIENTIST'),
  Text(8, 0, 'GREEK ORTHODOX'),
  Text(9, 0, 'BUDDHIST'),
  Text(10, 0, 'MUSLIM'),
  Text(11, 0, "JEHOVAH'S WITNESS"),
  Text(12, 0, 'UNITARIAN-UNIVERSALIST'),
  Text(13, 0, 'HINDU'),
  Text(14, 0, 'ROMANIAN EAST. ORTH'),
  Text(15, 0, 'HEBREW'),
  Text(16, 0, '7TH DAY ADVENTIST')])
```



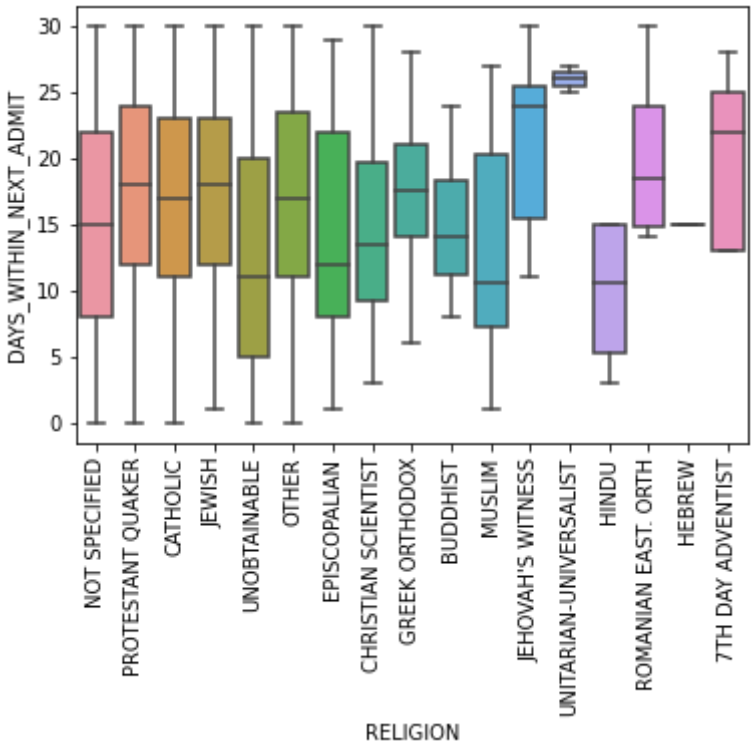
In [88]:
```
adm.RELIGION.value_counts()
```

Out[88]:
```
CATHOLIC                20606
NOT SPECIFIED           11753
UNOBTAINABLE             8269
PROTESTANT QUAKER        7134
JEWISH                   5314
OTHER                    2696
EPISCOPALIAN              774
GREEK ORTHODOX            459
CHRISTIAN SCIENTIST       429
BUDDHIST                  267
MUSLIM                    225
JEHOVAH'S WITNESS         139
UNITARIAN-UNIVERSALIST    124
HINDU                     113
ROMANIAN EAST. ORTH        83
7TH DAY ADVENTIST          81
BAPTIST                    28
HEBREW                     16
METHODIST                   7
LUTHERAN                    1
Name: RELIGION, dtype: int64
```

In [89]:
```
# fill RELIGION column value with 'NOT SPECIFIED'
adm.loc[adm.RELIGION.isna(), 'RELIGION'] = 'NOT SPECIFIED'
```

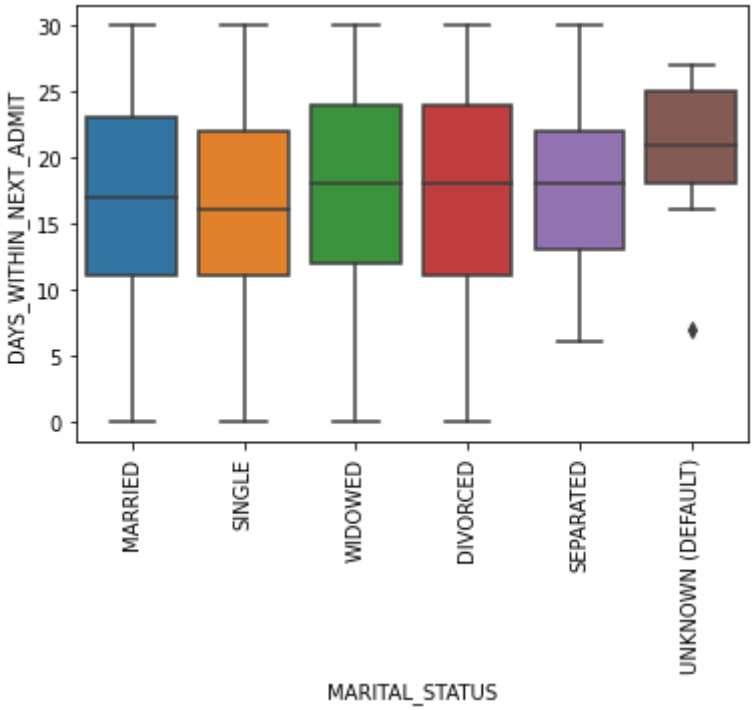
In [90]:
```
# plot the box plot again after filling NaN values
sns.boxplot(x='RELIGION', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[90]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16]),
 [Text(0, 0, 'NOT SPECIFIED'),
  Text(1, 0, 'PROTESTANT QUAKER'),
  Text(2, 0, 'CATHOLIC'),
  Text(3, 0, 'JEWISH'),
  Text(4, 0, 'UNOBTAINABLE'),
  Text(5, 0, 'OTHER'),
  Text(6, 0, 'EPISCOPALIAN'),
  Text(7, 0, 'CHRISTIAN SCIENTIST'),
  Text(8, 0, 'GREEK ORTHODOX'),
  Text(9, 0, 'BUDDHIST'),
  Text(10, 0, 'MUSLIM'),
  Text(11, 0, "JEHOVAH'S WITNESS"),
  Text(12, 0, 'UNITARIAN-UNIVERSALIST'),
  Text(13, 0, 'HINDU'),
  Text(14, 0, 'ROMANIAN EAST. ORTH'),
  Text(15, 0, 'HEBREW'),
  Text(16, 0, '7TH DAY ADVENTIST')])
```



In [91]:
```
# boxplot of the MARITAL STATUS and the DAYS WITHIN NEXT ADMIT for the p
atient who are admitted again
sns.boxplot(x='MARITAL_STATUS', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc
[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[91]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'MARRIED'),
  Text(1, 0, 'SINGLE'),
  Text(2, 0, 'WIDOWED'),
  Text(3, 0, 'DIVORCED'),
  Text(4, 0, 'SEPARATED'),
  Text(5, 0, 'UNKNOWN (DEFAULT)')])
```



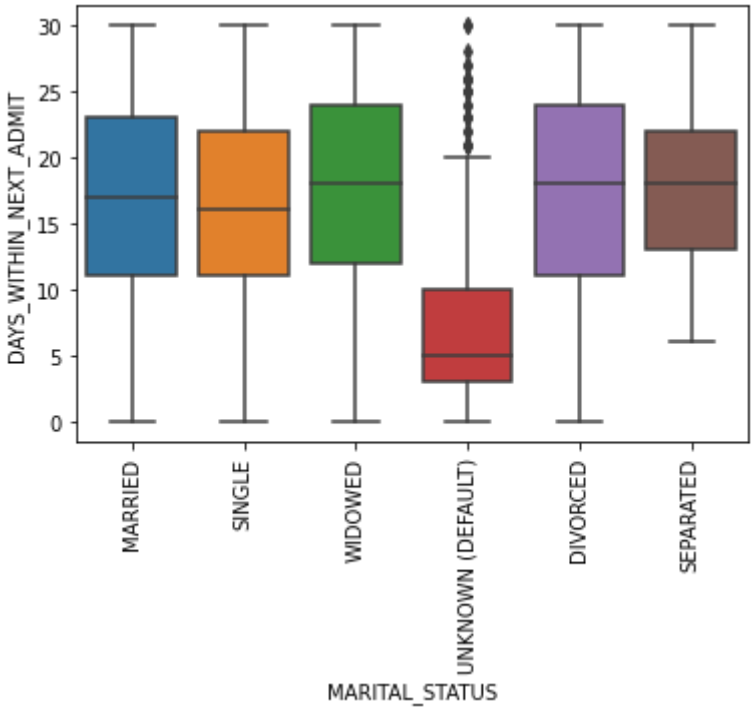
In [92]:
```
# check the NaN values
adm.MARITAL_STATUS.isna().value_counts()
```

Out[92]:
```
False    48848
True     10128
Name: MARITAL_STATUS, dtype: int64
```

In [93]:
```
# fill the NaN values with the 'UNKNOWN (DEFAULT)' values as analysed ab
ove
adm.loc[adm.MARITAL_STATUS.isna(), 'MARITAL_STATUS'] = 'UNKNOWN (DEFAUL
T)'
```

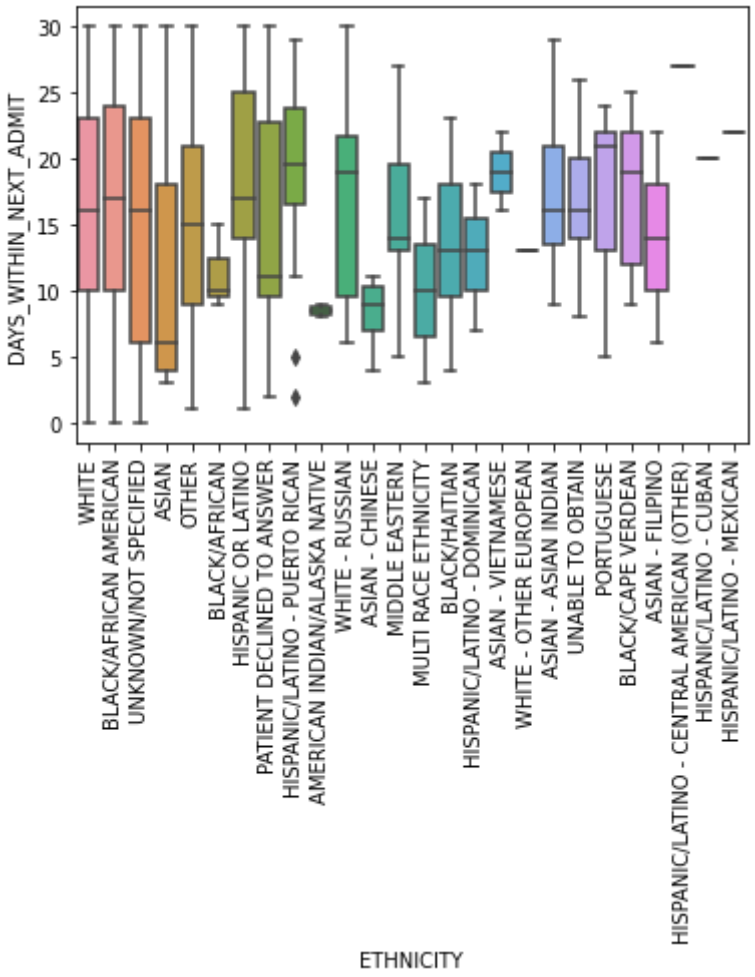
In [94]:
```
# plot it again after filling NaN values
sns.boxplot(x='MARITAL_STATUS', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc
[adm.TARGET == 1])
plt.xticks(rotation=90)
```

Out[94]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'MARRIED'),
  Text(1, 0, 'SINGLE'),
  Text(2, 0, 'WIDOWED'),
  Text(3, 0, 'UNKNOWN (DEFAULT)'),
  Text(4, 0, 'DIVORCED'),
  Text(5, 0, 'SEPARATED')])
```



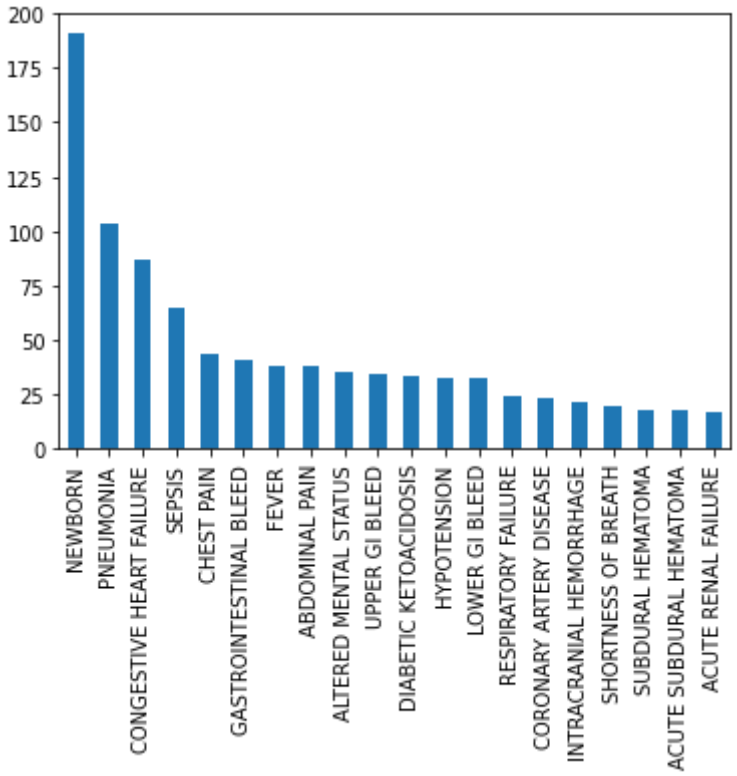
In [95]:
```
# bxoplot for the ETHINICY and DAYS WITHIN NEXT ADMIT for patient readmi
tted again
sns.boxplot(x='ETHNICITY', y='DAYS_WITHIN_NEXT_ADMIT', data=adm.loc[adm.
TARGET == 1])
plt.xticks(rotation=90)
```

Out[95]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16,
        17, 18, 19, 20, 21, 22, 23, 24, 25]),
 [Text(0, 0, 'WHITE'),
  Text(1, 0, 'BLACK/AFRICAN AMERICAN'),
  Text(2, 0, 'UNKNOWN/NOT SPECIFIED'),
  Text(3, 0, 'ASIAN'),
  Text(4, 0, 'OTHER'),
  Text(5, 0, 'BLACK/AFRICAN'),
  Text(6, 0, 'HISPANIC OR LATINO'),
  Text(7, 0, 'PATIENT DECLINED TO ANSWER'),
  Text(8, 0, 'HISPANIC/LATINO - PUERTO RICAN'),
  Text(9, 0, 'AMERICAN INDIAN/ALASKA NATIVE'),
  Text(10, 0, 'WHITE - RUSSIAN'),
  Text(11, 0, 'ASIAN - CHINESE'),
  Text(12, 0, 'MIDDLE EASTERN'),
  Text(13, 0, 'MULTI RACE ETHNICITY'),
  Text(14, 0, 'BLACK/HAITIAN'),
  Text(15, 0, 'HISPANIC/LATINO - DOMINICAN'),
  Text(16, 0, 'ASIAN - VIETNAMESE'),
  Text(17, 0, 'WHITE - OTHER EUROPEAN'),
  Text(18, 0, 'ASIAN - ASIAN INDIAN'),
  Text(19, 0, 'UNABLE TO OBTAIN'),
  Text(20, 0, 'PORTUGUESE'),
  Text(21, 0, 'BLACK/CAPE VERDEAN'),
  Text(22, 0, 'ASIAN - FILIPINO'),
  Text(23, 0, 'HISPANIC/LATINO - CENTRAL AMERICAN (OTHER)'),
  Text(24, 0, 'HISPANIC/LATINO - CUBAN'),
  Text(25, 0, 'HISPANIC/LATINO - MEXICAN')])
```


DAYS_WITHIN_NEXT_ADMIT
0
5
10
15
20
25
30
WHITE
BLACK/AFRICAN AMERICAN
UNKNOWN/NOT SPECIFIED
ASIAN
OTHER
BLACK/AFRICAN
HISPANIC OR LATINO
PATIENT DECLINED TO ANSWER
HISPANIC/LATINO - PUERTO RICAN
AMERICAN INDIAN/ALASKA NATIVE
WHITE - RUSSIAN
ASIAN - CHINESE
MIDDLE EASTERN
MULTI RACE ETHNICITY
BLACK/HAITIAN
HISPANIC/LATINO - DOMINICAN
ASIAN - VIETNAMESE
WHITE - OTHER EUROPEAN
ASIAN - ASIAN INDIAN
UNABLE TO OBTAIN
PORTUGUESE
BLACK/CAPE VERDEAN
ASIAN - FILIPINO
HISPANIC/LATINO - CENTRAL AMERICAN (OTHER)
HISPANIC/LATINO - CUBAN
HISPANIC/LATINO - MEXICAN
ETHNICITY

In [96]:
```
# do analysis on DIAGNOSIS value counts
adm.loc[adm.TARGET == 1]['DIAGNOSIS'].value_counts().nlargest(20).plot.bar()
```

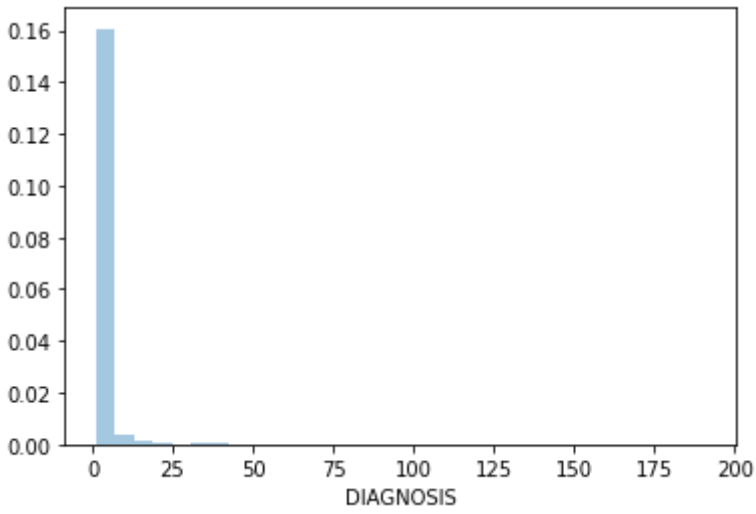
Out[96]: <AxesSubplot:>



In [97]:
```
# plot distribution graph for the DIAGNOSIS value counts
sns.distplot(adm.loc[adm.TARGET == 1]['DIAGNOSIS'].value_counts())
```

```
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/seaborn/distributions.py:369: UserWarning: Default bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
```

Out[97]: <AxesSubplot:xlabel='DIAGNOSIS'>



Clean the DIAGNOSIS column for further use as a feature

In [98]:
```
import re, string
```

In [99]:
```
# remove the extra punctuations / sysmbols
diagnosis_re = re.compile(r"[\"#$%&\'\(\)\*+,.:<=>?@\[\\\]^_`\{|\}~]")
```

In [100]:
```
# remove the extra -;/ etc which occurs in DIAGNOSIS column
diagnosis_re1 = re.compile(r"[-;/]")
```

In [101]:
```
# check the DIAGNOSIS NaN values
adm.DIAGNOSIS.isna().value_counts()
```

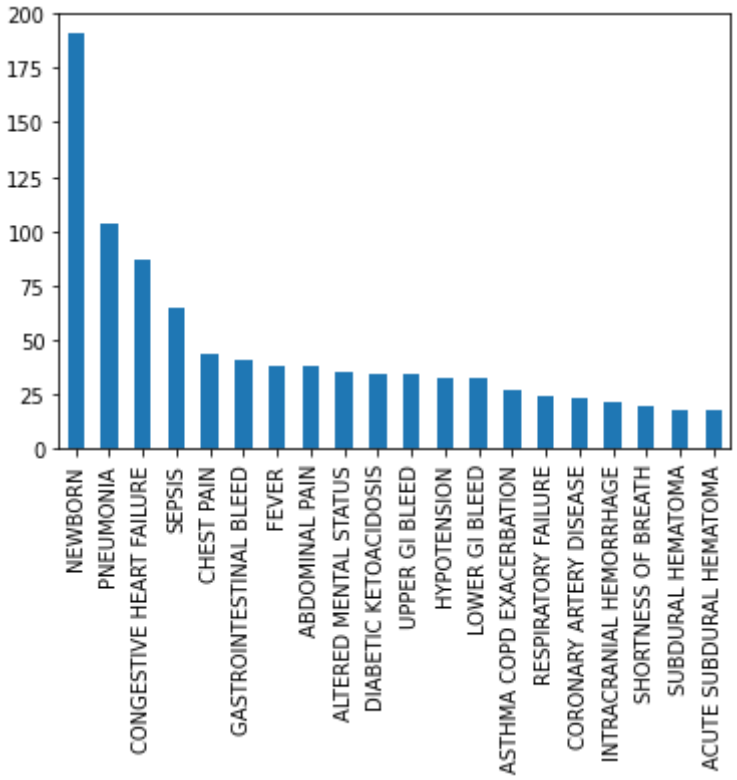
Out[101]:
```
False    58951
True        25
Name: DIAGNOSIS, dtype: int64
```

In [102]:
```
# fill the DIAGNOSIS vlaues with UNKNOWN default value
adm.loc[adm.DIAGNOSIS.isna(), 'DIAGNOSIS'] = 'UNKNOWN'
```

In [103]:
```
# remove extra spaces and extra punctuation characters
adm.DIAGNOSIS = adm.DIAGNOSIS.apply(lambda x: diagnosis_re1.sub(' ', x))
.apply(lambda x: diagnosis_re.sub('', x))
```

In [104]:
```
# plot the largest occuring DIAGNOSIS vlaues
adm.loc[adm.TARGET == 1]['DIAGNOSIS'].value_counts().nlargest(20).plot.bar()
```

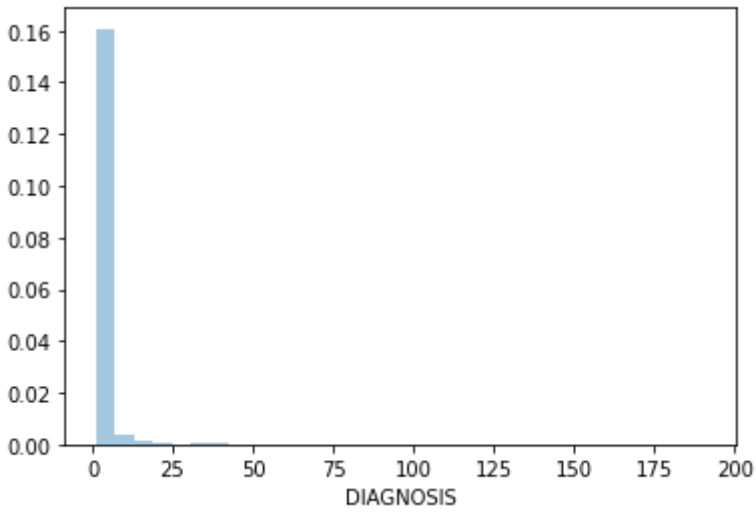
Out[104]: <AxesSubplot:>



In [105]:
```
# plot the distribution graph of the DIAGNOSIS values
sns.distplot(adm.loc[adm.TARGET == 1]['DIAGNOSIS'].value_counts())
```

```
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/seaborn/distributions.py:369: UserWarning: Default bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
```

Out[105]: <AxesSubplot:xlabel='DIAGNOSIS'>



Do feature engineering on the DIAGNOSIS values

In [106]:
```
# import TfidfVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [107]:
```
tfidf = TfidfVectorizer()
```

In [108]:
```
# train the TfidfVectorizer object
diagnosis_features = tfidf.fit_transform(adm.DIAGNOSIS.fillna('UNKNOWN')
.values).toarray()
```

In [109]:
```
# get it into a dataframe for further analysis with TARGET columns
tfidf_df = pd.DataFrame(diagnosis_features, columns=tfidf.get_feature_na
mes())
```

In [110]:
```
del tfidf, diagnosis_features
```

In [111]:
```
# copy the TARGET column
tfidf_df.loc[:, 'TARGET'] = adm.TARGET
```

In [112]:
```
import gc
gc.collect()
```

Out[112]:
```
75
```

In [113]:
```
# get the correlation of each diagnosis feature with the Target column
corr = []

for col in tfidf_df.columns:
  corr.append(tfidf_df[col].corr(tfidf_df['TARGET'], method='spearman'))
```

In [114]:
```
# plot the most correlation wise diagnosis feature with the TARGET colum
n
pd.Series(corr, index=tfidf_df.columns).sort_values(ascending=False)
```

Out[114]:
```
TARGET                   1.000000
ft                       0.019462
obstructivepulmonary     0.019462
cellulitiscolonoscopy    0.019462
aniogram                 0.019462
                             ...
embolis                 -0.007362
fibrillation            -0.007768
gangrene                -0.007991
stemi                   -0.008557
airway                  -0.009025
Length: 6294, dtype: float64
```

In [115]:
```
# plot the least correlated features wise DIAGNOSIS feature with the TAR
GET columns
pd.Series(corr, index=tfidf_df.columns).sort_values()
```

Out[115]:
```
airway                   -0.009025
stemi                    -0.008557
gangrene                 -0.007991
fibrillation             -0.007768
embolis                  -0.007362
                              ...
aniogram                  0.019462
cellulitiscolonoscopy     0.019462
obstructivepulmonary      0.019462
ft                        0.019462
TARGET                    1.000000
Length: 6294, dtype: float64
```

In [116]:
```
# get the bool value whether there is any failure word in the diagnosis
 column
adm.loc[:, 'in_failure'] = adm.DIAGNOSIS.apply(lambda x: int('failure' i
n x.lower()))
```

In [117]:
```
# corelation of in_failure with the targte col
adm.in_failure.corr(adm.TARGET)
```

Out[117]:
```
0.03032207780279582
```

In [118]:
```
# correlation fo in_failure feature with HOSPITAL_EXPIRE_FLAG
adm.in_failure.corr(adm.HOSPITAL_EXPIRE_FLAG)
```

Out[118]:
```
0.062478071812382394
```

In [119]:
```
# correlation of HOSPITAL_EXPIRE_FLAG with the TARGET columns
adm['HOSPITAL_EXPIRE_FLAG'].astype(int).corr(adm.TARGET)
```

Out[119]:
```
-0.057915975095876454
```

In [120]:
```
del tfidf_df
```

In [121]:
```
gc.collect()
```

Out[121]:
```
100
```

In [122]:
```
# check the correlation of the columns by doing LabelEncoding them
from sklearn.preprocessing import LabelEncoder
```

In [123]:
```
le = LabelEncoder()
```

In [124]:
```
new_adm = adm.copy()
```

In [125]:
```
# verifyu the NaN values in the columns
for col in new_adm.columns:
  print(col)
  print(new_adm[col].isna().value_counts().index)
  print('------------------------------------------------')
```

```
ROW_ID
Index([False], dtype='object')
------------------------------------------------
SUBJECT_ID
Index([False], dtype='object')
------------------------------------------------
HADM_ID
Index([False], dtype='object')
------------------------------------------------
ADMITTIME
Index([False], dtype='object')
------------------------------------------------
DISCHTIME
Index([False], dtype='object')
------------------------------------------------
DEATHTIME
Index([True, False], dtype='object')
------------------------------------------------
ADMISSION_TYPE
Index([False], dtype='object')
------------------------------------------------
ADMISSION_LOCATION
Index([False], dtype='object')
------------------------------------------------
DISCHARGE_LOCATION
Index([False], dtype='object')
------------------------------------------------
INSURANCE
Index([False], dtype='object')
------------------------------------------------
LANGUAGE
Index([False], dtype='object')
------------------------------------------------
RELIGION
Index([False], dtype='object')
------------------------------------------------
MARITAL_STATUS
Index([False], dtype='object')
------------------------------------------------
ETHNICITY
Index([False], dtype='object')
------------------------------------------------
EDREGTIME
Index([False, True], dtype='object')
------------------------------------------------
EDOUTTIME
Index([False, True], dtype='object')
------------------------------------------------
DIAGNOSIS
Index([False], dtype='object')
------------------------------------------------
HOSPITAL_EXPIRE_FLAG
Index([False], dtype='object')
------------------------------------------------
HAS_CHARTEVENTS_DATA
Index([False], dtype='object')
------------------------------------------------
```

```
NEXT_ADMITTIME
Index([True, False], dtype='object')
------------------------------------------------
DAYS_IN_HOSPITAL
Index([False], dtype='object')
------------------------------------------------
DAYS_WITHIN_NEXT_ADMIT
Index([False], dtype='object')
------------------------------------------------
TIME_IN_EMERGENCY_WARD
Index([False], dtype='object')
------------------------------------------------
DIFF_TIME_DEATH_DISCH
Index([True, False], dtype='object')
------------------------------------------------
TARGET
Index([False], dtype='object')
------------------------------------------------
in_failure
Index([False], dtype='object')
------------------------------------------------
```

In [126]:
```
cols = [
        'ADMISSION_TYPE',
        'ADMISSION_LOCATION',
        'DISCHARGE_LOCATION',
        'INSURANCE',
        'LANGUAGE',
        'RELIGION',
        'ETHNICITY',
        'DIAGNOSIS'
]
```

In [127]:
```
# LabelEncode only the above columns
for col in cols:
  new_adm[col + '_le'] = le.fit_transform(new_adm[col])
```

In [128]:
```
new_adm.columns
```

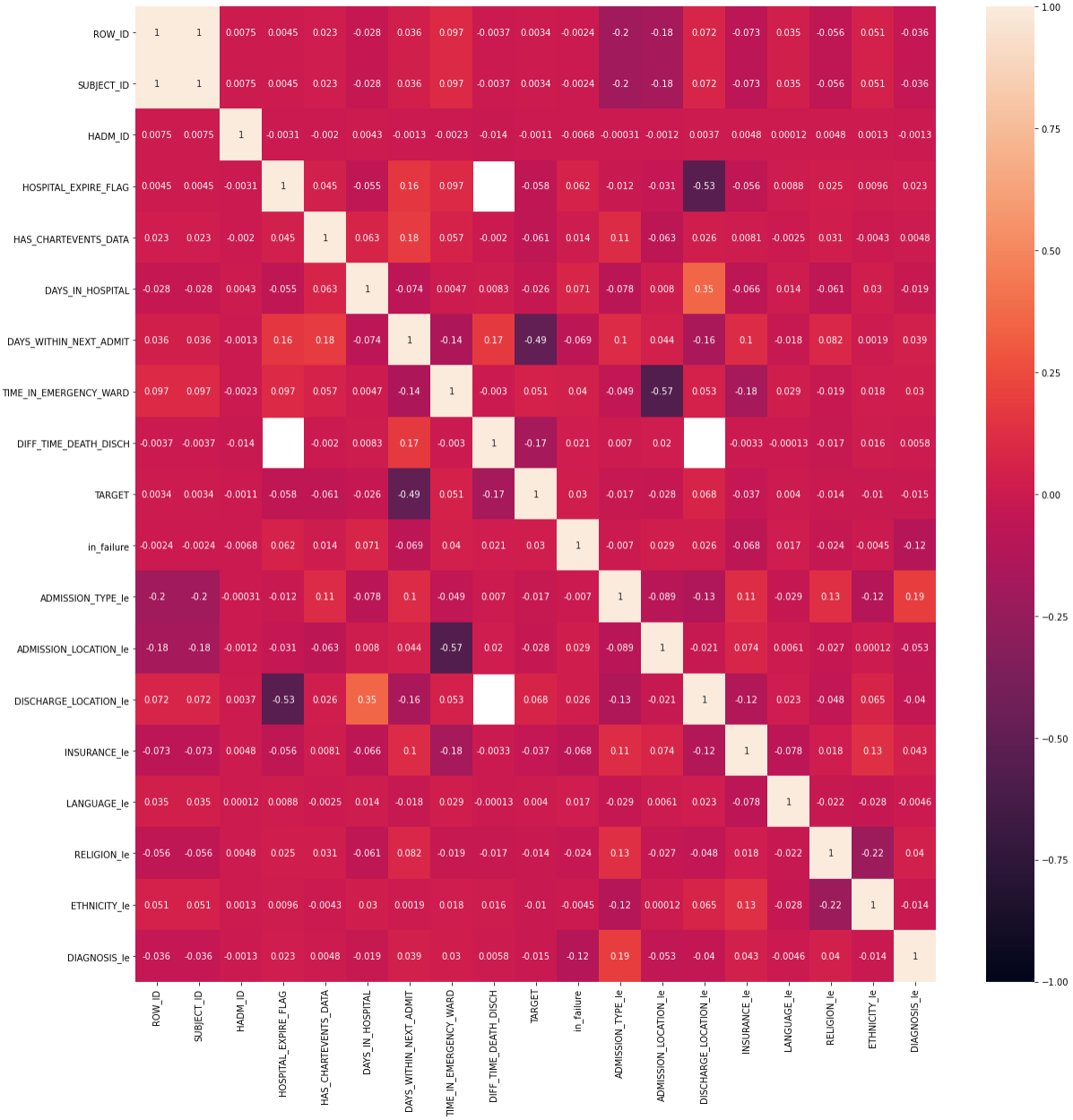
Out[128]:
```
Index(['ROW_ID', 'SUBJECT_ID', 'HADM_ID', 'ADMITTIME', 'DISCHTIME',
       'DEATHTIME', 'ADMISSION_TYPE', 'ADMISSION_LOCATION',
       'DISCHARGE_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'EDREGTIME', 'EDOUTTIME', 'DIAGNO
SIS',
       'HOSPITAL_EXPIRE_FLAG', 'HAS_CHARTEVENTS_DATA', 'NEXT_ADMITTIM
E',
       'DAYS_IN_HOSPITAL', 'DAYS_WITHIN_NEXT_ADMIT', 'TIME_IN_EMERGENCY
_WARD',
       'DIFF_TIME_DEATH_DISCH', 'TARGET', 'in_failure', 'ADMISSION_TYPE
_le',
       'ADMISSION_LOCATION_le', 'DISCHARGE_LOCATION_le', 'INSURANCE_l
e',
       'LANGUAGE_le', 'RELIGION_le', 'ETHNICITY_le', 'DIAGNOSIS_le'],
      dtype='object')
```

In [129]:
```
# check the correlation of the above label encoded column with the TARGE
T columns
new_adm.corr(method="spearman")['TARGET'].filter(like='le')
```

Out[129]:
```
ADMISSION_TYPE_le       -0.016746
ADMISSION_LOCATION_le   -0.028276
DISCHARGE_LOCATION_le    0.068068
INSURANCE_le            -0.037283
LANGUAGE_le              0.003980
RELIGION_le             -0.014266
ETHNICITY_le            -0.009986
DIAGNOSIS_le            -0.014893
Name: TARGET, dtype: float64
```

In [130]:
```
# plot the heatmap to get a sense of correlation distribution
plt.figure(figsize=(20, 20))
sns.heatmap(new_adm.corr(method="spearman"), vmin=-1, vmax=1, annot=True
)
```

Out[130]: <AxesSubplot:>



In [131]:
```
cols = [
        'ADMISSION_TYPE',
        'ADMISSION_LOCATION',
        'DISCHARGE_LOCATION',
        'INSURANCE',
        'LANGUAGE',
        'RELIGION',
        'ETHNICITY',
        # 'DIAGNOSIS'
]
```

In [132]:
```
# check the correlation by doing One hot encoding the above cols only
from sklearn.preprocessing import OneHotEncoder
```

In [133]:
```
ohe = OneHotEncoder()
```

In [134]:
```
new_adm1 = adm.copy()
```

In [135]:
```
# verify for NaN values and change the representation to the One Hot enc
oding
for index, col in enumerate(cols):
  # print(col, new_adm1[col].isna().value_counts().index)
  sp_mat = ohe.fit_transform(new_adm1[col].values.reshape((-1, 1)))
  new_adm1 = pd.concat([new_adm1, pd.DataFrame(sp_mat.toarray(), columns
=[col + 'ohe_{}'.format(i) for i in range(sp_mat[0].shape[1])])], axis=1
)
  # print(new_adm[col].isna().value_counts().index)
  # print(new_adm[cols[index + 1:index + 2]].value_counts().index)
  # print('----------------------')
```

In [136]:
```
new_adm1.DAYS_WITHIN_NEXT_ADMIT.isna().value_counts()
```

Out[136]:
```
False    58976
Name: DAYS_WITHIN_NEXT_ADMIT, dtype: int64
```

In [137]:
```
new_adm1.TARGET.isna().value_counts()
```

Out[137]:
```
False    58976
Name: TARGET, dtype: int64
```

In [138]:
```
# import for chisquare tests
from scipy.stats import chisquare
```

In [139]:
```
# do chisquare test for the DAYS_WITHIN_NEXT_ADMIT and TARGET values
chisquare(new_adm1[['DAYS_WITHIN_NEXT_ADMIT', 'TARGET']].astype(float))
```

Out[139]:
```
Power_divergenceResult(statistic=array([9.13548875e+07, 5.64490000e+0
4]), pvalue=array([0., 1.]))
```

In [140]:
```
# do the chisquare test for the numeric columns with the TARGET columns
for each_col in new_adm1.columns:
  if pd.api.types.is_numeric_dtype(new_adm1[each_col]):
    print(each_col, chisquare(new_adm1[[each_col, 'TARGET']]))
```

```
ROW_ID Power_divergenceResult(statistic=array([5.79684933e+08, 5.644900
00e+04]), pvalue=array([0., 1.]))
SUBJECT_ID Power_divergenceResult(statistic=array([1.37882804e+09, 5.64
490000e+04]), pvalue=array([0., 1.]))
HADM_ID Power_divergenceResult(statistic=array([3.28056523e+08, 5.64490
000e+04]), pvalue=array([0., 1.]))
HOSPITAL_EXPIRE_FLAG Power_divergenceResult(statistic=array([53122., 56
449.]), pvalue=array([1., 1.]))
HAS_CHARTEVENTS_DATA Power_divergenceResult(statistic=array([ 1592., 56
449.]), pvalue=array([1., 1.]))
DAYS_IN_HOSPITAL Power_divergenceResult(statistic=array([951547.5621075
5,  56449.        ]), pvalue=array([0., 1.]))
DAYS_WITHIN_NEXT_ADMIT Power_divergenceResult(statistic=array([9.135488
75e+07, 5.64490000e+04]), pvalue=array([0., 1.]))
TIME_IN_EMERGENCY_WARD Power_divergenceResult(statistic=array([13480.02
120254, 56449.        ]), pvalue=array([1., 1.]))
DIFF_TIME_DEATH_DISCH Power_divergenceResult(statistic=array([   nan, 5
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TARGET Power_divergenceResult(statistic=array([56449., 56449.]), pvalue
=array([1., 1.]))
in_failure Power_divergenceResult(statistic=array([55541., 56449.]), pv
alue=array([1., 1.]))
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ADMISSION_TYPEohe_1 Power_divergenceResult(statistic=array([16905., 564
49.]), pvalue=array([1., 1.]))
ADMISSION_TYPEohe_2 Power_divergenceResult(statistic=array([51113., 564
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ADMISSION_TYPEohe_3 Power_divergenceResult(statistic=array([57640., 564
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ADMISSION_LOCATIONohe_1 Power_divergenceResult(statistic=array([46944.,
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ADMISSION_LOCATIONohe_2 Power_divergenceResult(statistic=array([36222.,
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ADMISSION_LOCATIONohe_3 Power_divergenceResult(statistic=array([58874.,
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ADMISSION_LOCATIONohe_5 Power_divergenceResult(statistic=array([50520.,
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ADMISSION_LOCATIONohe_6 Power_divergenceResult(statistic=array([58905.,
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DISCHARGE_LOCATIONohe_4 Power_divergenceResult(statistic=array([40014.,
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LANGUAGEohe_9 Power_divergenceResult(statistic=array([58975., 56449.]),
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LANGUAGEohe_22 Power_divergenceResult(statistic=array([58969., 5644
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```

```
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/scipy/st
ats/_distn_infrastructure.py:903: RuntimeWarning: invalid value encount
ered in greater
  return (a < x) & (x < b)
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/scipy/st
ats/_distn_infrastructure.py:903: RuntimeWarning: invalid value encount
ered in less
  return (a < x) & (x < b)
/Users/jeradwilliams/opt/anaconda3/lib/python3.7/site-packages/scipy/st
ats/_distn_infrastructure.py:1912: RuntimeWarning: invalid value encoun
tered in less_equal
  cond2 = cond0 & (x <= _a)
```

```
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9.]), pvalue=array([0.51896772, 1.        ]))
ETHNICITYohe_30 Power_divergenceResult(statistic=array([57464., 5644
9.]), pvalue=array([0.99999541, 1.        ]))
ETHNICITYohe_31 Power_divergenceResult(statistic=array([58417., 5644
9.]), pvalue=array([0.9482328, 1.       ]))
ETHNICITYohe_32 Power_divergenceResult(statistic=array([58915., 5644
9.]), pvalue=array([0.56860422, 1.        ]))
ETHNICITYohe_33 Power_divergenceResult(statistic=array([58968., 5644
9.]), pvalue=array([0.50735677, 1.        ]))
ETHNICITYohe_34 Power_divergenceResult(statistic=array([58162., 5644
9.]), pvalue=array([0.99125541, 1.        ]))
ETHNICITYohe_35 Power_divergenceResult(statistic=array([54453., 5644
9.]), pvalue=array([1., 1.]))
ETHNICITYohe_36 Power_divergenceResult(statistic=array([17980., 5644
9.]), pvalue=array([1., 1.]))
ETHNICITYohe_37 Power_divergenceResult(statistic=array([58917., 5644
9.]), pvalue=array([0.56631277, 1.        ]))
ETHNICITYohe_38 Power_divergenceResult(statistic=array([58951., 5644
9.]), pvalue=array([0.52708719, 1.        ]))
ETHNICITYohe_39 Power_divergenceResult(statistic=array([58895., 5644
9.]), pvalue=array([0.59138237, 1.        ]))
ETHNICITYohe_40 Power_divergenceResult(statistic=array([58812., 5644
9.]), pvalue=array([0.68193203, 1.        ]))
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