

# Surgical Complications

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## Import the necessary libraries

```
In [1]: import csv
import pandas as pd
import numpy as np
import datetime
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

## Load the files into dataframes

```
In [2]: #Inpatient

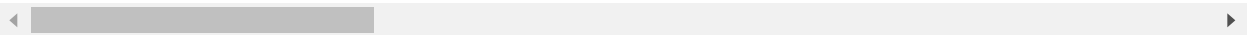
inpatient_raw = pd.read_csv('Data_Files/inpatient_master.csv', low_memory=False)

inpatient_raw.head(5)
```

Out[2]:

	DESYNPUF_ID	CLM_ID	SEGMENT	CLM_FROM_DT	CLM_THRU_DT	PRVDR_NUM
0	00013D2EFD8E45D1	196661176988405	1	20100312.0	20100313.0	2600GD
1	00016F745862898F	196201177000368	1	20090412.0	20090418.0	3900MB
2	00016F745862898F	196661177015632	1	20090831.0	20090902.0	3900HM
3	00016F745862898F	196091176981058	1	20090917.0	20090920.0	3913XU
4	00016F745862898F	196261176983265	1	20100626.0	20100701.0	3900MB

5 rows × 81 columns



In [3]: *# Beneficiary*

```
ben_2008_raw = pd.read_csv('Data_Files/master_2008_csv.csv', low_memory=False)
ben_2009_raw = pd.read_csv('Data_Files/master_2009_csv.csv', low_memory=False)
ben_2010_raw = pd.read_csv('Data_Files/master_2010_csv.csv', low_memory=False)

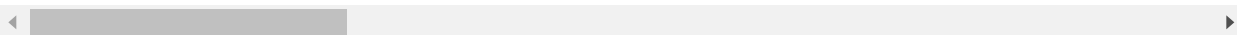
ben_raw = pd.concat([ben_2008_raw, ben_2009_raw, ben_2010_raw])

ben_raw.head(5)
```

Out[3]:

	DESNPUF_ID	BENE_BIRTH_DT	BENE_DEATH_DT	BENE_SEX_IDENT_CD	BENE_RACE_CD
0	0000141F2FECE9BC	19740401	NaN	2	.
1	0000B27E77EE1987	19550201	NaN	1	.
2	0000C1386AE2C2A2	19591101	NaN	2	!
3	0000EC65FBBF94AB8	19370401	NaN	1	.
4	00020C9F73FD7F45	19430601	NaN	2	.

5 rows × 32 columns

In [4]: *#clean up unnecessary variables from the script to create more memory*

```
del ben_2008_raw
del ben_2009_raw
del ben_2010_raw
```

## Data Profiling

```

In [5]: # Data Profile analysis for Inpatient.
ip_dataprofile_results_df = pd.DataFrame([], columns = ["column_name", "col_count", "unique_count", "column_mode", "null_count", "null_pct"])
li = inpatient_raw.columns
row_num = inpatient_raw.shape[0]

for val in li:
    if inpatient_raw[val].count() == 0:
        column_name = val
        col_count = inpatient_raw[val].count()
        unique_count = len(pd.unique(inpatient_raw[val]))
        column_mode = inpatient_raw[val].mode()
        null_count = inpatient_raw[val].isnull().sum()
        null_pct = (null_count / row_num)*100
    else:
        column_name = val
        col_count = inpatient_raw[val].count()
        unique_count = len(pd.unique(inpatient_raw[val]))
        column_mode = inpatient_raw[val].mode()
        null_count = inpatient_raw[val].isnull().sum()
        null_pct = (null_count / row_num)*100 # Needs to be tweaked.
    stage = [column_name, col_count, unique_count, column_mode, null_count, null_pct]
    a_series = pd.Series(stage, index=ip_dataprofile_results_df.columns)
    ip_dataprofile_results_df = ip_dataprofile_results_df.append(a_series, ignore_index=True)

```

```

In [6]: # Data Profile results inpatient.
pd.set_option("display.max_rows", None)

ip_dataprofile_results_df

```

Out[6]:

	column_name	col_count	unique_count	column_mode	null_count	null_pct
0	DESYNPUF_ID	4008836	755214	91948E46E2DF89A1 dtype: object	0	0.0
1	CLM_ID	4008836	1331533	0 90011100088330 1 90031100088821 ...	0	0.0
2	SEGMENT	4008836	2	0 1 dtype: int64	0	0.0
3	CLM_FROM_DT	4004965	1132	0 20080704.0 dtype: float64	0	0.0
4	CLM_THRU_DT	4004965	1097	0 20080709.0 dtype: float64	0	0.0
5	PRVDR_NUM	4008836	2895	0 23006G dtype: object	0	0.0
6	CLM_PMT_AMT	4008836	100	0 4000.0 dtype: float64	0	0.0

```

In [7]: # Data Profile analysis for Beneficiary.
bene_dataprofile_results_df = pd.DataFrame([], columns = ["column_name", "col_count", "unique_count", "column_mode", "null_count", "null_pct"])
li = ben_raw.columns
row_num = ben_raw.shape[0]

for val in li:
    if ben_raw[val].count() == 0:
        column_name = val
        col_count = ben_raw[val].count()
        unique_count = len(pd.unique(ben_raw[val]))
        column_mode = ben_raw[val].mode()
        null_count = ben_raw[val].isnull().sum()
        null_pct = (null_count / row_num)*100
    else:
        column_name = val
        col_count = ben_raw[val].count()
        unique_count = len(pd.unique(ben_raw[val]))
        column_mode = ben_raw[val].mode()
        null_count = ben_raw[val].isnull().sum()
        null_pct = (null_count / row_num)*100 # Needs to be tweaked.
    stage = [column_name, col_count, unique_count, column_mode, null_count, null_pct]
    a_series = pd.Series(stage, index=bene_dataprofile_results_df.columns)
    bene_dataprofile_results_df = bene_dataprofile_results_df.append(a_series, ignore_index=True)

```

```

In [8]: # Data Profile results beneficiary.
bene_dataprofile_results_df.head(5)

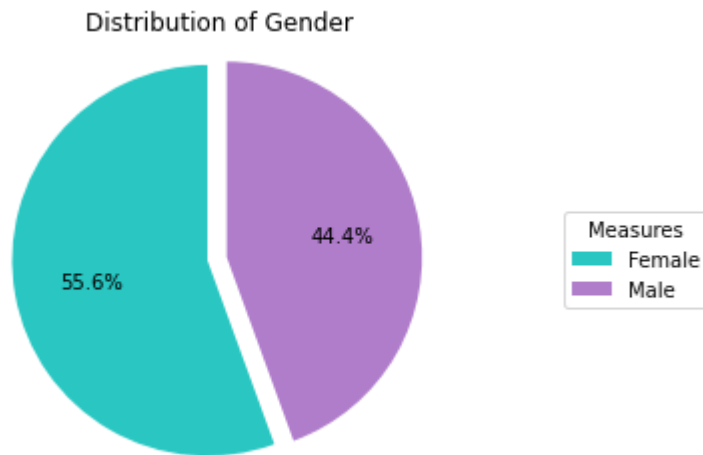
```

Out[8]:

	column_name	col_count	unique_count	column_mode	null_count	null_pct
0	DESYNPUF_ID	15573396	2326856	0 0000438E79D01BEA 100015BF6509...	0	0.000000
1	BENE_BIRTH_DT	15573396	900	0 19431001 dtype: int64	0	0.000000
2	BENE_DEATH_DT	242991	37	0 20080901.0 dtype: float64	15330405	98.439704
3	BENE_SEX_IDENT_CD	15573396	2	0 2 dtype: int64	0	0.000000
4	BENE_RACE_CD	15573396	4	0 1 dtype: int64	0	0.000000

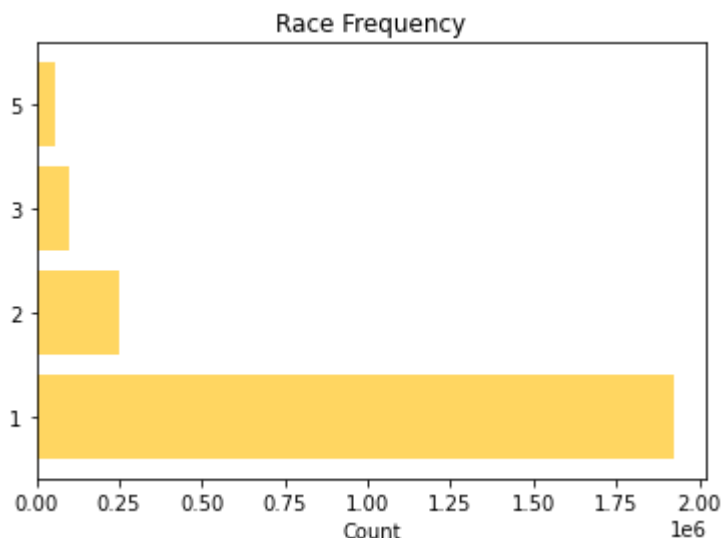
In [9]: `## ADD GRAPHS -`

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
labels = ['Female', 'Male']
sizes = [1292861, 1033995]
explode = (0.1, 0) # only "explode" the 2nd slice (i.e. 'Hogs')
colors = ['#2AC7C2', '#B07DCB', '#EB5A5A', '#FFD661', '#ABC7FC']
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, colors=colors, autopct='%1.1f%%',
        shadow=False, startangle=90)
ax1.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.
ax1.legend(labels,
            title="Measures",
            loc="center left",
            bbox_to_anchor=(1, 0, 0.5, 1))
plt.title('Distribution of Gender')
plt.show()
```



```
In [10]: plt.barh(range(0,4), [1926708, 247723, 97972, 54453],
                color='#FFD661',
                tick_label=['1','2','3','5'])
plt.title("Race Frequency")
plt.xlabel("Count")
```

Out[10]: Text(0.5, 0, 'Count')



After reviewing the data profiling results, the columns that we found to be valuable and worth keeping are kept while the others are removed.

```
In [11]: # Inpatient dataset after reviewing the data profiling results.
narrow_inpatient_raw = inpatient_raw[["DESYNPUF_ID", "CLM_ID", "SEGMENT", "CLM_FROM_DT",
"NCH_BENE_IP_DDCTBL_AMT", "NCH_BENE_DSCHRG_DT", "ICD9_DGNS_CD_1", "ICD9_DGNS_CD_2",
"ICD9_PRCDR_CD_2", "ICD9_PRCDR_CD_3", "ICD9_PRCDR_CD_4", "ICD9_PRCDR_CD_5"]]

narrow_inpatient_raw.head(5)
```

Out[11]:

	DESYNPUF_ID	CLM_ID	SEGMENT	CLM_FROM_DT	CLM_THRU_DT	CLM_PMT_AMT
0	00013D2EFD8E45D1	196661176988405	1	20100312.0	20100313.0	4000
1	00016F745862898F	196201177000368	1	20090412.0	20090418.0	26000
2	00016F745862898F	196661177015632	1	20090831.0	20090902.0	5000
3	00016F745862898F	196091176981058	1	20090917.0	20090920.0	5000
4	00016F745862898F	196261176983265	1	20100626.0	20100701.0	16000

5 rows × 23 columns

```
In [12]: # Beneficiary dataset after reviewing the data profiling results.

ben_master = ben_raw[["DESYNPUF_ID", "BENE_BIRTH_DT", "BENE_DEATH_DT", "BENE_SEX_IDE
ben_master.head(5)
```

```
Out[12]:
```

	DESYNPUF_ID	BENE_BIRTH_DT	BENE_DEATH_DT	BENE_SEX_IDENT_CD	BENE_RACE_CD
0	0000141F2FECE9BC	19740401	NaN	2	
1	0000B27E77EE1987	19550201	NaN	1	
2	0000C1386AE2C2A2	19591101	NaN	2	
3	0000EC65FBF94AB8	19370401	NaN	1	
4	00020C9F73FD7F45	19430601	NaN	2	

### Format the data

```
In [13]: #Inpatient

narrow_inpatient_raw['NCH_BENE_DSCHRG_DT'] = pd.to_datetime(narrow_inpatient_raw[
narrow_inpatient_raw['CLM_FROM_DT'] = pd.to_datetime(narrow_inpatient_raw['CLM_F
narrow_inpatient_raw['CLM_THRU_DT'] = pd.to_datetime(narrow_inpatient_raw['CLM_TH
narrow_inpatient_raw['CLM_ADMSN_DT'] = pd.to_datetime(narrow_inpatient_raw['CLM_A
```

```
In [14]: # Beneficiary

ben_master['BENE_BIRTH_DT'] = pd.to_datetime(ben_master['BENE_BIRTH_DT'].astype('t
ben_master['BENE_DEATH_DT'] = pd.to_datetime(ben_master['BENE_DEATH_DT'].astype('t

ben_master.rename(columns = {'BENE_BIRTH_DT': 'BIRTH_DT', 'BENE_DEATH_DT': 'DEATH_DT
```

### Datasets

```
In [15]: # Create a dataframe of unique DESYNPUF_IDs from beneficiary dataset.
ben_master_sorted = ben_master.sort_values(by=['DEATH_DT', 'DESYNPUF_ID'], ascending=[
unique_ben = ben_master_sorted.drop_duplicates(subset = ["DESYNPUF_ID"])

# Create a dataframe of only the DESYNPUF_IDs who have a DEATH_DT.
dead_ben = unique_ben[unique_ben.DEATH_DT.notnull()]
```

**Create the general and vascular surgery procedure list for filtering.**

```
In [16]: # Load the procedure code list provided by Ram.
proc_reference = pd.read_csv('Data_Files/surgery_flags_i9_2015.csv', low_memory=False)
proc_reference = proc_reference.rename(columns = {'ICD-9-CM CODE': 'ICD9_PROCEDURE_CD'})

proc_reference.head(5)
```

Out[16]:

	ICD9_PROCEDURE_CD	SURGERY_FLAG	ICD9_DX_DESCRIPTION
0	'0050'	'2'	IMPLA RESYNCHR PACEMAKER W/0 (Begin 2002)
1	'0051'	'2'	IMPLA RESYNCHRONIZATION DEFI (Begin 2002)
2	'0052'	'2'	IMPL/REPL TRANSVENOUS LEAD L (Begin 2002)
3	'0053'	'2'	IMPL/REPL PACEMAKER PLSE GE (Begin 2002)
4	'0054'	'2'	IMPL/REPL DEFIBRIL GENERATOR (Begin 2002)

```
In [17]: # Clean up procedure code list.

# Remove all quotes around the surgery flag number.
proc_reference['SURGERY_FLAG'] = proc_reference['SURGERY_FLAG'].str.replace(r"['\""]", "")
proc_reference['ICD9_PROCEDURE_CD'] = proc_reference['ICD9_PROCEDURE_CD'].str.replace(r"['\""]", "")

proc_reference2 = proc_reference[proc_reference['SURGERY_FLAG'] == '2']

# Creating the selected surgeries and turning them into a list.
proc_list = proc_reference2['ICD9_PROCEDURE_CD'].to_list()
rams_procedure_codes = [float(i) for i in proc_list] #converting string to float

proc_reference2.head(5)
```

Out[17]:

	ICD9_PROCEDURE_CD	SURGERY_FLAG	ICD9_DX_DESCRIPTION
0	0050	2	IMPLA RESYNCHR PACEMAKER W/0 (Begin 2002)
1	0051	2	IMPLA RESYNCHRONIZATION DEFI (Begin 2002)
2	0052	2	IMPL/REPL TRANSVENOUS LEAD L (Begin 2002)
3	0053	2	IMPL/REPL PACEMAKER PLSE GE (Begin 2002)
4	0054	2	IMPL/REPL DEFIBRIL GENERATOR (Begin 2002)



```
In [18]: # Applicable measure procedure codes.
procedure_codes = 46.0,46.01,46.02,46.03,46.04,46.13,46.23,46.20,45.76,45.03,45.4

#preparing the list of codes for next filter
P_codes = []
for number in procedure_codes:
    code = str(number).replace('.', '')
    P_codes.append(code)
print(P_codes)
```

['460', '4601', '4602', '4603', '4604', '4613', '4623', '462', '4576', '4503', '4541', '4542', '4543', '4571', '4572', '4573', '4574', '4575', '4581', '4582', '4583']

```
In [19]: # Concatenate the measure procedure code List with Ram's procedure codes.
our_proc_codes = ['46.0', '4601.0', '4602.0', '4603.0', '4604.0', '4613.0', '4623.0', '4

for i in rams_procedure_codes:
    if i in rams_procedure_codes != our_proc_codes:
        our_proc_codes.append(i)
```

```
In [20]: del proc_reference
```

### Denominator Calculation

```
In [21]: # Filter the inpatient file with the identified procedure codes.
P_codes = our_proc_codes

#Denominator file
inpatient_denominator = narrow_inpatient_raw[narrow_inpatient_raw['ICD9_PRCDR_CD_1'].isin(P_codes) &
                                              narrow_inpatient_raw['ICD9_PRCDR_CD_3'].isin(P_codes) &
                                              narrow_inpatient_raw['ICD9_PRCDR_CD_5'].isin(P_codes)]

# Add diagnosis and procedure flag if the row has a qualifying Dx or Px code.
inpatient_denominator['qualified_diagnosis'] = 0
inpatient_denominator['qualified_procedures'] = 1

inpatient_denominator.head(5)
```

Out[21]:

	DESYNPUF_ID	CLM_ID	SEGMENT	CLM_FROM_DT	CLM_THRU_DT	CLM_PMT_A
2	00016F745862898F	196661177015632	1	2009-08-31	2009-09-02	500
9	0007F12A492FD25D	196831176966961	1	2010-06-16	2010-06-19	2900
11	000C7486B11E7030	196641176984178	1	2008-10-15	2008-10-21	3000
19	00157F1570C74E09	196381176974293	1	2009-06-26	2009-06-30	900
26	001AFA59A08ABBF1	196331177006825	1	2008-06-21	2008-06-25	1100

5 rows × 25 columns

### Numerator Calculation

```
In [22]: # Filtering the inpatient dataset with the identified measure qualifying diagnosis
D_codes = ('480', '481', '482', '483', '485', '486', '487', '51881', '51882', '51884', '799')

inpatient_numerator = narrow_inpatient_raw[narrow_inpatient_raw['ICD9_DGNS_CD_1'].isin(D_codes) &
                                              narrow_inpatient_raw['ICD9_DGNS_CD_3'].isin(D_codes) &
                                              narrow_inpatient_raw['ICD9_DGNS_CD_5'].isin(D_codes)]

inpatient_numerator['qualified_diagnosis'] = 1
inpatient_numerator['qualified_procedures'] = 0
```

```
In [23]: #deleting unnecessary variables from script to create memory
del inpatient_raw
```

### Create a combined Numerator and Denominator Dataset

```
In [24]: # Join the numerator and denominator.
readmission = pd.concat([inpatient_numerator,inpatient_denominator], ignore_index=True)

# Remove records that qualify in both the numerator and denominator datasets.
readmission = readmission.drop_duplicates(subset=['DESYNPUF_ID', 'NCH_BENE_DSCHRG_DT'])

readmission.head(5)
```

Out[24]:

	DESYNPUF_ID	CLM_ID	SEGMENT	CLM_FROM_DT	CLM_THRU_DT	CLM_PMT_AMT
0	00052705243EA128	196991176971757	1	2008-09-12	2008-09-12	14000
1	00139C345A104F72	196691176984309	1	2009-12-07	2009-12-13	17000
2	001EA2F4DB30F105	196601176970568	1	2009-07-19	2009-07-22	5000
3	0021D4CDAFC0609F	196031176965445	1	2008-04-19	2008-04-23	5000
4	00271F7DF9C2B88A	196711177025513	1	2010-01-13	2010-01-14	28000

5 rows × 7 columns

### Create custom columns needed in future calculations.

The discharge date from the previous record is put one row below it on the next most recent one claim the patient has. This pattern repeats until the patient no longer has encounters.

```
In [25]: # Create a column to place the previous encounter discharge date by patient.
readmission['PreviousDischargeDTS'] = (readmission.sort_values(by=['DESYNPUF_ID', 'CLM_ID'],
                                                                .groupby(['DESYNPUF_ID']))['NCH_BENE_DSCHRG_DT'].shift(1, axis=1))
readmission[['DESYNPUF_ID', 'CLM_ID', 'NCH_BENE_DSCHRG_DT', 'PreviousDischargeDTS']]
```

Out[25]:

	DESYNPUF_ID	CLM_ID	NCH_BENE_DSCHRG_DT	PreviousDischargeDTS
0	00052705243EA128	196991176971757	2008-09-12	NaT
1	00139C345A104F72	196691176984309	2009-12-13	NaT
2	001EA2F4DB30F105	196601176970568	2009-07-22	NaT
3	0021D4CDAFC0609F	196031176965445	2008-04-23	NaT
4	00271F7DF9C2B88A	196711177025513	2010-01-14	NaT

Similar to discharge date, a patient's previous procedure is put on the following line (where applicable) so that it can be used to confirm if a patient qualifies as a NSQIP measure. This is determined when a qualifying diagnosis (in the list above) is on the same line as a previous qualifying procedure.

```
In [26]: # Create a column to place the previous procedure on the next line if it is consi
readmission['previous_qualified_procedures'] = (readmission.sort_values(by=['DESYNPUF_ID', 'qualified_procedures'],
                                   .groupby(['DESYNPUF_ID'])['qualified_procedures'].shift(1,

# Review the results.
readmission[['DESYNPUF_ID', 'qualified_diagnosis', 'qualified_procedures', 'previous_qualified_procedures']]
```

Out[26]:

	DESYNPUF_ID	qualified_diagnosis	qualified_procedures	previous_qualified_procedures
0	00052705243EA128	1	0	NaN
1	00139C345A104F72	1	0	NaN
2	001EA2F4DB30F105	1	0	NaN
3	0021D4CDAFC0609F	1	0	NaN
4	00271F7DF9C2B88A	1	0	NaN

**Calculate the number of days that elapsed between a patient's discharge dates.**

```
In [27]: # Creating a column with difference of days between claims.
readmission['difference_days'] = readmission['NCH_BENE_DSCHRG_DT'] - readmission['PreviousDischargeDTS']
readmission[['DESYNPUF_ID', 'CLM_ID', 'NCH_BENE_DSCHRG_DT', 'PreviousDischargeDTS', 'difference_days']]
```

Out[27]:

	DESYNPUF_ID	CLM_ID	NCH_BENE_DSCHRG_DT	PreviousDischargeDTS	difference_days
0	00052705243EA128	196991176971757	2008-09-12	NaT	
1	00139C345A104F72	196691176984309	2009-12-13	NaT	
2	001EA2F4DB30F105	196601176970568	2009-07-22	NaT	
3	0021D4CDAFC0609F	196031176965445	2008-04-23	NaT	
4	00271F7DF9C2B88A	196711177025513	2010-01-14	NaT	

```
In [28]: # Creating a column that has 'x days' as a float (using a float rather than an int)
readmission['days_float'] = readmission['difference_days'].dt.days.astype(float)
```

NSQIP is concerned about patients who had a qualifying procedure and came back with a qualifying diagnosis as long as it is within 30 days. Therefore, claims that have a gap in visits longer than 30 days are removed as well as same day claims.

```
In [29]: # Filter the dataset by selecting the rows that have a difference in days between
readmission_30days = readmission[(readmission['days_float'] >= 1.0) & (readmission

# Review the data after filtering.
readmission_30days[['DESYNPUF_ID', 'CLM_ID', 'NCH_BENE_DSCHRG_DT', 'PreviousDischargeDTS', 'differe
```

Out[29]:

	DESYNPUF_ID	CLM_ID	NCH_BENE_DSCHRG_DT	PreviousDischargeDTS	differe
7	002AB71D3224BE66	196351177026160	2008-09-01	2008-08-12	
18	007928DE5B0C4AA5	196601176961455	2010-01-18	2010-01-07	
88	02D6BF1BB02FAC15	196881176959734	2008-07-24	2008-07-23	
107	0342E8D226B4E3FC	196471177009155	2008-05-27	2008-05-18	
150	046A3EAEF33204E1	196061177019627	2008-01-05	2008-01-03	

### Are there patients that had died within 30 days from their procedure?

- In order to find this, we merged our beneficiary dataset with our readmission dataset. At which point, we created a column "Days before death" to count the number of days in order to see if there were any patients that died within 30 days of have a qualified surgery.

```
In [30]: readmissions within 30 days with the beneficiary dataset of those who died.
n_death = pd.merge(readmission_30days, dead_ben, how='left', on='DESYNPUF_ID')

n_death['Days_Before_Death'] = (readmission_death['PreviousDischargeDTS'] - readm

n_death_2 = readmission_death[(readmission_death['Days_Before_Death'] >= 1.0) & (

results. Any patients that come back would qualify as a NSQIP patient for dieing
n_death_2
```

Out[30]:

DESYNPUF_ID	CLM_ID	SEGMENT	CLM_FROM_DT	CLM_THRU_DT	CLM_PMT_AMT	AT_PHYSN_
-------------	--------	---------	-------------	-------------	-------------	-----------

0 rows × 34 columns

**Findings:** There were no patients who died within 30 days of receiving a qualifying procedure.

Now that the datasets of those who had a qualifying diagnosis and a qualifying procedure have been merged. Filtered for only discharge dates that are within 30 days of each other, patients can be identified as a NSQIP individual if they have a 1 in the qualified\_diagnosis column and a 1 in the qualified\_procedure column.

```
In [31]: # Create a NSQIP column based on the qualified diagnosis & previous qualified procedure
readmission_30days['nsqip_person'] = readmission_30days['qualified_diagnosis'].as
numerator = (readmission_30days['nsqip_person'] == 2).value_counts()
denominator = readmission_30days['DESYNPUF_ID'].count()

print(numerator)
```

```
False    18181
True       5111
Name: nsqip_person, dtype: int64
```

**Calculate the overall rate of individuals who have been identified as a NSQIP patient as compared to everyone.**

```
In [32]: # Calculate the overall rate:
rate = numerator/denominator *100
rate
```

```
Out[32]: False    78.056844
         True     21.943156
         Name: nsqip_person, dtype: float64
```

**Join in the beneficiary data so that patient demographic can be used with the main dataset. This is done using the DESYNPUF\_ID as a join column between the two datasets.**

```
In [33]: # Bring in the patient information.
readmission_with_pat_info = pd.merge(readmission_30days,unique_ben, how='inner',
readmission_with_pat_info.shape[0]
```

```
Out[33]: 23292
```

**Findings:** The denominator count remained the same after joining in the beneficiary list so we know that we did not inadvertently increase our dataset size.

### Explore the NSQIP individuals

In order to further understand the patients who were identified as a NSQIP patient, a dataset is created with just those who have a value of 2 in the nsqip\_person column.

In [34]: *the columns of interest.*  
 readmission\_with\_pat\_info[['DESYNPUF\_ID', 'qualified\_diagnosis', 'qualified\_procedures', 'previous\_qualified\_procedures', 'nsqip\_person']]

Out[34]:

	DESYNPUF_ID	qualified_diagnosis	qualified_procedures	previous_qualified_procedures	nsqip_person
0	002AB71D3224BE66	1	0	1.0	
1	007928DE5B0C4AA5	1	0	1.0	
2	02D6BF1BB02FAC15	1	0	0.0	
3	0342E8D226B4E3FC	1	0	1.0	
4	046A3EAEF33204E1	1	0	0.0	

In [35]: *# Create a dataframe of patients with a nsqip\_person value equal to 2.*  
 nsqip\_people = readmission\_with\_pat\_info[readmission\_with\_pat\_info['nsqip\_person'] == 2]

**Classify each NSQIP patient into their qualifying measure.**

Loop through different diagnosis code columns (1 - 7) to find which measure category each individual belongs to (i.e. uti, pneumonia, etc.)

```
In [36]: from numpy import NaN
#ICD codes that we want to find
uti = ['390', '5990']
sepsis = ['99591', '99592', '78552']
pneumonia = ['480', '481', '482', '483', '485', '486', '487', '51881', '51882', '51884', '7
colon = ['4299', '4280', '41511', '45340', '9972', '9971', '99749', '9989', '56962', '4349
deep_vein = ['453400', '453900', '453410', '45342', '9971', '99749', '99739', '9972', '99

#creating an empty list of our data
NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_1']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_1"] = NSQIP_Measure
```

```
In [37]: #creating an empty list of our data
NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_2']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_2"] = NSQIP_Measure
```



```
In [38]: NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_3']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_3"] = NSQIP_Measure
```

```
In [39]: NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_4']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_4"] = NSQIP_Measure
```

```
In [40]: NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_5']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_5"] = NSQIP_Measure
```

```
In [41]: NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_6']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our List, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_6"] = NSQIP_Measure
```

```
In [42]: NSQIP_Measure = []
for i in nsqip_people['ICD9_DGNS_CD_7']:
    if i in uti:
        NSQIP_Measure.append('Urinary Tract Infection')
    elif i in sepsis:
        NSQIP_Measure.append('Sepsis')
    elif i in pneumonia:
        NSQIP_Measure.append('Pneumonia')
    elif i in colon:
        NSQIP_Measure.append('Colon')
    elif i in (deep_vein):
        NSQIP_Measure.append('deep_vein')
    else:
        NSQIP_Measure.append(NaN)

#using our list, we create a column in the dataframe with it
nsqip_people["NSQIP_Measure_7"] = NSQIP_Measure
```

**Consolidate the newly created NSQIP\_Measure\_1-7 columns into 1 where all the rows will be populated.**

```
In [43]: # Create a column that summarizes the patient's qualifying diagnosis category.
nsqip_people['diagnosis'] = np.nan
nsqip_people['diagnosis'] = nsqip_people.diagnosis.fillna(nsqip_people.NSQIP_Meas
```

## Findings

```
In [44]: # Frequency count of each diagnosis.
diagnosis_freq = nsqip_people['diagnosis'].value_counts()

# Total amount of people who have a matched diagnosis.
nsqip_people.shape[0]

# Creating a dataframe of the frequencies.
diagnosis_freq.to_frame()

# Diagnosis/diagnosis_total.
diagnosis_freq['diagnosis_total'] = nsqip_people.shape[0]

# Do a ratio of diagnosis/numerator (2000ish people)
diagnosis_freq['numerator_total'] = readmission_with_pat_info.shape[0]

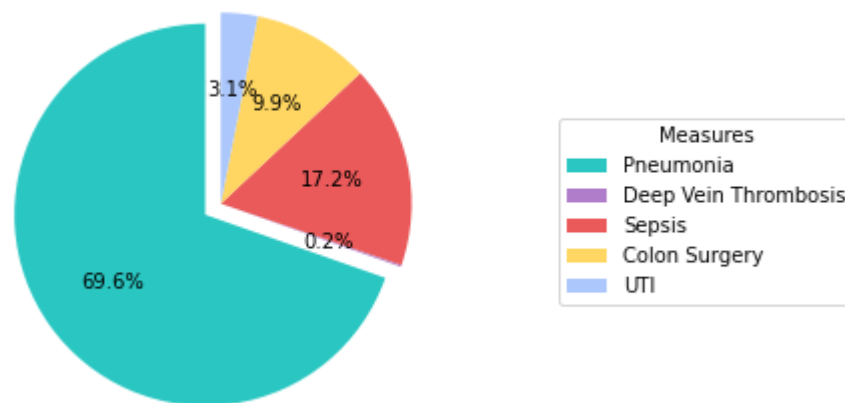
diagnosis_freq
```

```
Out[44]: Pneumonia          3542
Sepsis              847
Colon              515
Urinary Tract Infection  162
deep_vein           8
diagnosis_total    5111
numerator_total    23292
Name: diagnosis, dtype: int64
```

Look at the breakdown of identified NSQIP individuals and how they are distributed across the various measures. In this particular instance, the denominator is the "numerator" and the individual measures are the numerator.

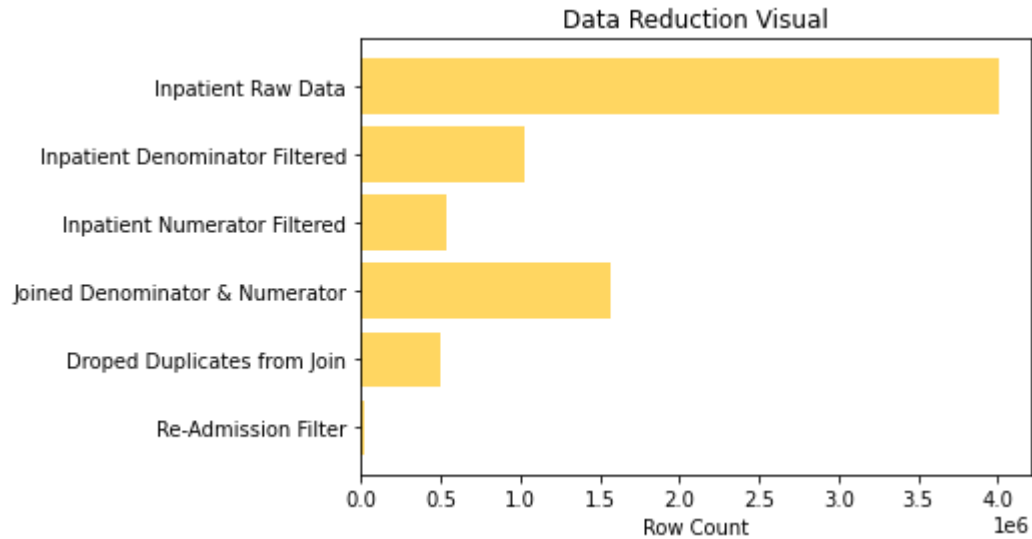
```
In [45]: # Pie chart, where the slices will be ordered and plotted counter-clockwise:
labels = ['Pneumonia', 'Deep Vein Thrombosis', 'Sepsis', 'Colon Surgery', 'UTI']
sizes = [3678, 8, 908, 524, 164]
explode = (0.1, 0, 0, 0, 0) # only "explode" the 2nd slice (i.e. 'Hogs')
colors = ['#2AC7C2', '#B07DCB', '#EB5A5A', '#FFD661', '#ABC7FC']
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, colors=colors, autopct='%1.1f%%',
        shadow=False, startangle=90)
ax1.axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle.
ax1.legend(labels,
           title="Measures",
           loc="center left",
           bbox_to_anchor=(1, 0, 0.5, 1))
plt.title('Qualified Patients by NSQIP Measure')
plt.show()
```

Qualified Patients by NSQIP Measure



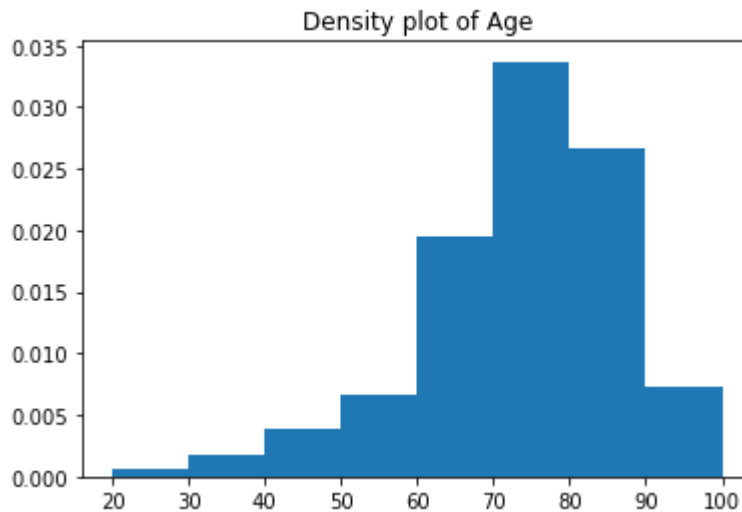
```
In [46]: plt.barh(range(0,6), [23557,494344,1564154,533220,1030934,4008836],
        color='#FFD661',
        tick_label=["Re-Admission Filter","Dropped Duplicates from Join",
                    "Joined Denominator & Numerator","Inpatient Numerator Filter",
                    "Inpatient Denominator Filtered","Inpatient Raw Data"])
plt.title("Data Reduction Visual")
plt.xlabel("Row Count")
```

Out[46]: Text(0.5, 0, 'Row Count')



```
In [47]: #Calculating the age for patients
readmission_with_pat_info['age'] = readmission_with_pat_info['NCH_BENE_DSCHRG_DT']
readmission_with_pat_info['age'] = (readmission_with_pat_info['age'].dt.days.asty
```

```
In [48]: #Creating histogram of age range in dataset
bins = [20,30,40,50,60,70,80,90,100]
fig = plt.figure()
ax = fig.add_subplot(111)
n, bins, rectangles = ax.hist(readmission_with_pat_info['age'], bins, density=True)
fig.canvas.draw()
plt.title('Density plot of Age')
plt.show()
```



## Conclusion

While we found patients who qualified for 5 of the 6 measures we sought after to find, the amount of data that is available through the CMS PUF files is not complete enough to submit to NSQIP. This project highlighted the plausibility of building a dataset out and identifying patients who might fit the different measure definitions but that is the extent of this dataset. The other limitation with using the CMS files is that they are more than 10 years old and healthcare codes have changed from ICD9 diagnosis and procedure to ICD10 diagnosis and procedure. This means that the codes used in this analysis would not be transferrable directly but would rather need to be translated into the respective ICD-10 equivalents.