healthcare_analytics_demo

January 18, 2022

1 Healthcare Analytics Demonstration

1.1 Analysis of CMS Enrollment and Claims Data

Description: We will analyze CMS SynPUF enrollment and claims data using Python pandas. From the enrollment data, we can calculate high-level expense rates and analyze by demographic or condition categories.

Data Source: CMS 2008-2010 Data Entrepreneurs Synthetic Public Use File, a.k.a., CMS SynPUF

1.2 Part 1: Enrollment Data and Per Person per Month/Year (PMPM/PMPY) Analysis

1.2.1 Setup

[1]:
```
import pandas as pd
import logging
import seaborn as sns

# pandas/logging/seaborn configuration for jupyter
pd.set_option('max_columns', None), pd.set_option('max_rows', 1000), pd.
 ↪set_option('max_colwidth', None)
logging.basicConfig(level=logging.INFO, format='%(asctime)s - %(message)s',␣
 ↪datefmt='%d-%b-%y %H:%M:%S')
sns.set()

# this disables unnecessary matplotlib/seaborng logging
logging.getLogger('matplotlib.font_manager').disabled = True

# helper class to allow displaying multiple dataframes side-by-side in jupyter
class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier, monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
```

```
        return '\n'.join(self.template.format(a, eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

1.2.2 Import data

[2]:
```
# read 2008 Beneficiary Summary File from CMS URL
    # we can retrieve additional years and samples (01-20) if we want within␣
↪memory constraints
    # by parameterizing the URL
url = r'https://www.cms.gov/Research-Statistics-Data-and-Systems/
↪Downloadable-Public-Use-Files/SynPUFs/Downloads/
↪DE1_0_2008_Beneficiary_Summary_File_Sample_1.zip'
benes_df = pd.read_csv(url, dtype={'BENE_DEATH_DT': 'Int32', 'BENE_ESRD_IND':␣
↪'category'})
logging.info(f'Read file from: {url}')
```

```
12-Jan-22 01:03:47 - Read file from: https://www.cms.gov/Research-Statistics-
Data-and-Systems/Downloadable-Public-Use-
Files/SynPUFs/Downloads/DE1_0_2008_Beneficiary_Summary_File_Sample_1.zip
```

1.2.3 Preview Data

[3]:
```
import io

# pipe df.info() to logging
buffer = io.StringIO()
benes_df.info(buf=buffer)
s = buffer.getvalue()
s = 'Summary of `benes_df` dataframe:\n\n\t' + s.replace('\n', '\n\t')
logging.info(s)
```

```
12-Jan-22 01:03:47 - Summary of `benes_df` dataframe:

        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 116352 entries, 0 to 116351
        Data columns (total 32 columns):
         #   Column                    Non-Null Count   Dtype
        ---  ------                    --------------   -----
         0   DESYNPUF_ID               116352 non-null  object
         1   BENE_BIRTH_DT             116352 non-null  int64
         2   BENE_DEATH_DT             1814 non-null    Int32
         3   BENE_SEX_IDENT_CD         116352 non-null  int64
         4   BENE_RACE_CD              116352 non-null  int64
         5   BENE_ESRD_IND             116352 non-null  category
```

```
 6   SP_STATE_CODE             116352 non-null  int64
 7   BENE_COUNTY_CD            116352 non-null  int64
 8   BENE_HI_CVRAGE_TOT_MONS   116352 non-null  int64
 9   BENE_SMI_CVRAGE_TOT_MONS  116352 non-null  int64
 10  BENE_HMO_CVRAGE_TOT_MONS  116352 non-null  int64
 11  PLAN_CVRG_MOS_NUM         116352 non-null  int64
 12  SP_ALZHDMTA               116352 non-null  int64
 13  SP_CHF                    116352 non-null  int64
 14  SP_CHRNKIDN               116352 non-null  int64
 15  SP_CNCR                   116352 non-null  int64
 16  SP_COPD                   116352 non-null  int64
 17  SP_DEPRESSN               116352 non-null  int64
 18  SP_DIABETES               116352 non-null  int64
 19  SP_ISCHMCHT               116352 non-null  int64
 20  SP_OSTEOPRS               116352 non-null  int64
 21  SP_RA_OA                  116352 non-null  int64
 22  SP_STRKETIA               116352 non-null  int64
 23  MEDREIMB_IP               116352 non-null  float64
 24  BENRES_IP                 116352 non-null  float64
 25  PPPYMT_IP                 116352 non-null  float64
 26  MEDREIMB_OP               116352 non-null  float64
 27  BENRES_OP                 116352 non-null  float64
 28  PPPYMT_OP                 116352 non-null  float64
 29  MEDREIMB_CAR              116352 non-null  float64
 30  BENRES_CAR                116352 non-null  float64
 31  PPPYMT_CAR                116352 non-null  float64
dtypes: Int32(1), category(1), float64(9), int64(20), object(1)
memory usage: 27.3+ MB
```

[4]:

```
benes_df.head()
```

[4]:

```
        DESYNPUF_ID  BENE_BIRTH_DT  BENE_DEATH_DT  BENE_SEX_IDENT_CD  \
0  00013D2EFD8E45D1       19230501           <NA>                  1
1  00016F745862898F       19430101           <NA>                  1
2  0001FDD721E223DC       19360901           <NA>                  2
3  00021CA6FF03E670       19410601           <NA>                  1
4  00024B3D2352D2D0       19360801           <NA>                  1

   BENE_RACE_CD BENE_ESRD_IND  SP_STATE_CODE  BENE_COUNTY_CD  \
0             1             0             26             950
1             1             0             39             230
2             1             0             39             280
3             5             0              6             290
4             1             0             52             590

   BENE_HI_CVRAGE_TOT_MONS  BENE_SMI_CVRAGE_TOT_MONS  \
```

```
0                        12                         12
1                        12                         12
2                        12                         12
3                         0                          0
4                        12                         12

   BENE_HMO_CVRAGE_TOT_MONS  PLAN_CVRG_MOS_NUM  SP_ALZHDMTA  SP_CHF  \
0                        12                 12            2       2
1                         0                  0            2       2
2                         0                 12            2       2
3                         0                  0            2       2
4                         0                  0            2       2

   SP_CHRNKIDN  SP_CNCR  SP_COPD  SP_DEPRESSN  SP_DIABETES  SP_ISCHMCHT  \
0            2        2        2            2            2            2
1            2        2        2            2            2            2
2            2        2        2            2            2            2
3            2        2        2            2            2            2
4            2        2        2            2            2            2

   SP_OSTEOPRS  SP_RA_OA  SP_STRKETIA  MEDREIMB_IP  BENRES_IP  PPPYMT_IP  \
0            2         2            2          0.0        0.0        0.0
1            2         2            2          0.0        0.0        0.0
2            2         2            2          0.0        0.0        0.0
3            2         2            2          0.0        0.0        0.0
4            1         2            2          0.0        0.0        0.0

   MEDREIMB_OP  BENRES_OP  PPPYMT_OP  MEDREIMB_CAR  BENRES_CAR  PPPYMT_CAR
0         50.0       10.0        0.0           0.0         0.0         0.0
1          0.0        0.0        0.0         700.0       240.0         0.0
2          0.0        0.0        0.0           0.0         0.0         0.0
3          0.0        0.0        0.0           0.0         0.0         0.0
4         30.0       40.0        0.0         220.0        80.0         0.0
```

1.2.4 Preprocess

[5]:
```python
# downsize integer types
benes_df[benes_df.select_dtypes('int64').columns] = benes_df.
↪select_dtypes('int64').astype('Int32')

# restrict columns
columns_to_keep = [
    # demographic
    'DESYNPUF_ID', 'BENE_BIRTH_DT', 'BENE_DEATH_DT', 'BENE_SEX_IDENT_CD',␣
↪'BENE_RACE_CD', 'BENE_ESRD_IND', 'SP_STATE_CODE',

    # condition flags
```

```
    'SP_CNCR', 'SP_COPD', 'SP_DEPRESSN', 'SP_DIABETES', 'SP_ISCHMCHT',␣
 ↪'SP_OSTEOPRS', 'SP_RA_OA', 'SP_STRKETIA',

    # payment variables, member months
    'MEDREIMB_IP', 'MEDREIMB_OP', 'MEDREIMB_CAR', 'PLAN_CVRG_MOS_NUM',
]

benes_df = benes_df[columns_to_keep]

# convert column names to lower case
benes_df.columns = [col.lower() for col in benes_df.columns]
```

[6]:
```
# remap condition flags
    # from: 1 (Yes) and 2 (No)
    # to: 1 (Yes) and 0 (No)

condition_cols = ['sp_cncr', 'sp_copd', 'sp_depressn', 'sp_diabetes',␣
 ↪'sp_ischmcht', 'sp_osteoprs', 'sp_ra_oa', 'sp_strketia']
benes_df[condition_cols] = benes_df[condition_cols].apply(lambda x: x.map({1:␣
 ↪1, 2: 0}))
```

1.2.5 Data Exploration, Data Quality Checks

Check unique member vs row counts

[7]:
```
if benes_df['desynpuf_id'].nunique() == benes_df.shape[0]:
    logging.info('TEST PASSED - Beneficiary file unique member count matches␣
 ↪row count.')
else:
    logging.info('TEST FAILED - Beneficiary file unique member count does not␣
 ↪match row count.')
```

```
12-Jan-22 01:03:48 - TEST PASSED - Beneficiary file unique member count matches
row count.
```

Inspect value counts (up to top 5 values) for each categorical column

- This is a little hacky in how we call pd.Series.value_counts() on several columns and display at once. This is just to keep the notebook pretty (avoid lengthy/tall output).
- e.g., we can see 92.9% of members do not have end-stage renal disease (bene_esrd_in==0)

[8]:
```
cols_to_check = ['bene_sex_ident_cd', 'bene_race_cd', 'bene_esrd_ind',
                 'sp_state_code', 'sp_cncr', 'sp_copd', 'sp_depressn',
                 'sp_diabetes', 'sp_ischmcht', 'sp_osteoprs', 'sp_ra_oa',␣
 ↪'sp_strketia',]

for col in cols_to_check:
    globals()[col] = pd.DataFrame(benes_df[col].value_counts(normalize=True).
 ↪iloc[:5])
```

```
display(*cols_to_check)
```

[8]:
```
bene_sex_ident_cd
   bene_sex_ident_cd
2           0.553037
1           0.446963

bene_race_cd
   bene_race_cd
1      0.828082
2      0.106083
3       0.04238
5      0.023455

bene_esrd_ind
   bene_esrd_ind
0          0.929
Y          0.071

sp_state_code
    sp_state_code
5        0.087871
10       0.066565
45        0.05761
33       0.055951
39       0.044683

sp_cncr
    sp_cncr
0  0.936271
1  0.063729

sp_copd
    sp_copd
0  0.864695
1  0.135305

sp_depressn
   sp_depressn
0      0.78651
1      0.21349

sp_diabetes
   sp_diabetes
0     0.621322
1     0.378678
```

```
sp_ischmcht
   sp_ischmcht
0     0.579363
1     0.420637

sp_osteoprs
   sp_osteoprs
0     0.826587
1     0.173413

sp_ra_oa
   sp_ra_oa
0  0.846019
1  0.153981

sp_strketia
   sp_strketia
0      0.95511
1      0.04489
```

Summarize condition prevalence

[9]:
```
# get condition prevalence as sum of 1s (Yes indicator) divided by row count␣
↪(members)
condition_prevalence = (benes_df[condition_cols].sum() /␣
↪benes_df[condition_cols].shape[0])

# format to %
condition_prevalence = pd.DataFrame(condition_prevalence.apply(lambda s: '{:.
↪2f}%'.format(s*100)), columns=['prevalence'])
condition_prevalence
```

[9]:

	prevalence
sp_cncr	6.37%
sp_copd	13.53%
sp_depressn	21.35%
sp_diabetes	37.87%
sp_ischmcht	42.06%
sp_osteoprs	17.34%
sp_ra_oa	15.40%
sp_strketia	4.49%

2 Analytical Calculations

- analyze age distribution based on birth date
- calculate Per Person Per Month (PMPM) for Inpatient, Outpatient, and Professional claims
- show PMPM by demographic categories: age, sex, race, ESRD status, chronic condition

Age Distribution

- We calculate age using `relativedelta` module, which should be more accurate.
- `age_basic` gets to a similar result but may run into edge cases.
- We have to define an `age_as_of_date` to bound the age to a reference date
- For simplicity, we are ignoring the death date

[10]:
```python
from datetime import datetime
from dateutil.relativedelta import relativedelta
import numpy as np

# set reference date
age_as_date = datetime(year=2008, month=12, day=31)

# convert from source integer smarter datetime object
benes_df['bene_birth_dt'] = pd.to_datetime(benes_df['bene_birth_dt'],␣
 ↪format='%Y%m%d')

# calculate age using relative delta
benes_df['age'] = benes_df['bene_birth_dt'].apply(lambda dob:␣
 ↪relativedelta(age_as_date, dob).years)

# basic/naive method using 365.25; might have incorrect edge cases
benes_df['age_basic'] = (age_as_date - benes_df['bene_birth_dt']).dt.days / 365.
 ↪25
benes_df['age_basic'] = np.floor(benes_df['age_basic']).astype('Int32')

# cut age value into categorical bins
bins = range(25, 115, 10)
benes_df['age_bin'] = pd.cut(benes_df['age'], bins, include_lowest=True)
```

[11]:
```python
# preview age columns
benes_df[['bene_birth_dt', 'age', 'age_basic', 'age_bin']].head()
```

[11]:

	bene_birth_dt	age	age_basic	age_bin
0	1923-05-01	85	85	(75.0, 85.0]
1	1943-01-01	65	65	(55.0, 65.0]
2	1936-09-01	72	72	(65.0, 75.0]
3	1941-06-01	67	67	(65.0, 75.0]
4	1936-08-01	72	72	(65.0, 75.0]

[12]:
```python
# age distribution
benes_df['age_bin'].value_counts(dropna=False).sort_values()
```

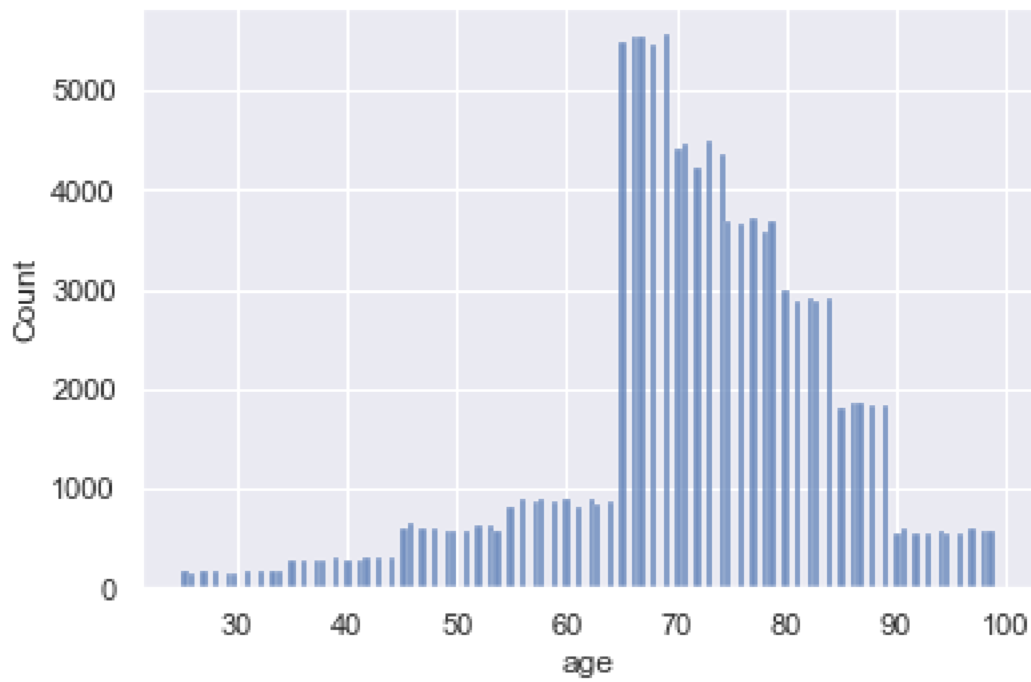
[12]:
```
(24.999, 35.0]     1876
(95.0, 105.0]      2266
(35.0, 45.0]       3219
(45.0, 55.0]       6199
```

```
(85.0, 95.0]      10727
(55.0, 65.0]      13323
(75.0, 85.0]      31016
(65.0, 75.0]      47726
Name: age_bin, dtype: int64
```

Different ways to plot a histogram with seaborn

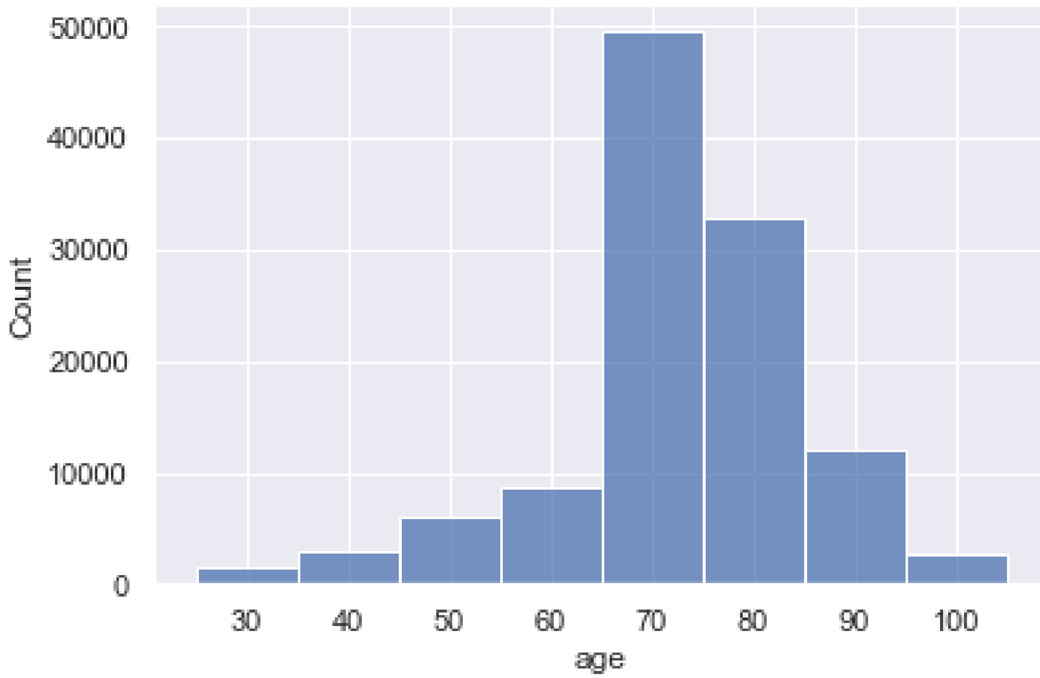
[13]:
```
sns.histplot(data=benes_df, x='age')
```

[13]: <AxesSubplot:xlabel='age', ylabel='Count'>



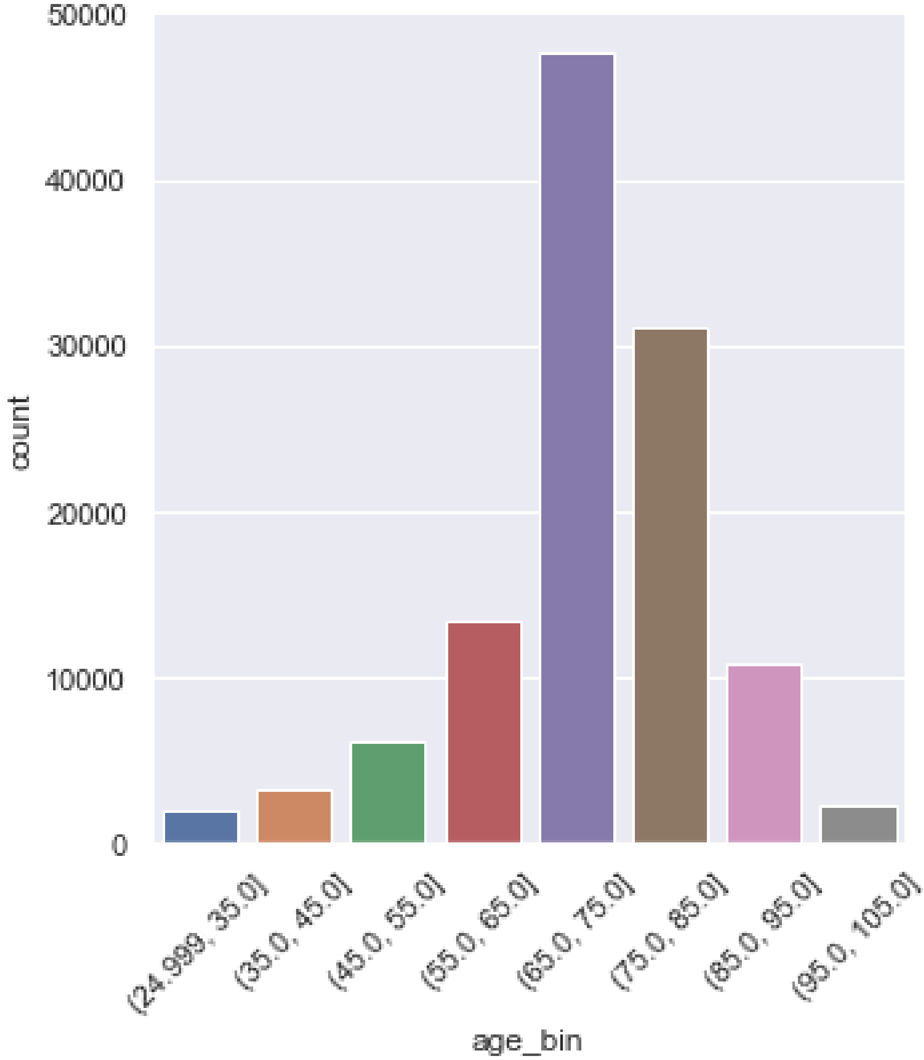
[14]:
```
sns.histplot(data=benes_df, x='age', bins=bins)
```

[14]: <AxesSubplot:xlabel='age', ylabel='Count'>




```
[15]: sns.catplot(data=benes_df.sort_values(by=['age_bin']),
                  x='age_bin',
                  kind='count') \
                  .set_xticklabels(rotation=45)
```

```
[15]: <seaborn.axisgrid.FacetGrid at 0x7fd86246f940>
```



2.0.1 Calculate PMPM and PMPY (Per Person Per Month/Year) expenses

- calculation: total expense divided by total member months (or year)
- the payments by Medicare are represented in columns: 'medreimb_ip', 'medreimb_op', 'medreimb_car'
- 'car' is short for "carrier" claims; a legacy term that refers to non-facility professional

2.0.2 PMPM by Claim Type and Total PMPM

[16]:
```
# paid amounts by claim type
payment_columns = ['medreimb_ip', 'medreimb_op', 'medreimb_car']
benes_df['medreimb_total'] = benes_df[payment_columns].sum(axis=1)
benes_df[payment_columns].sum() / benes_df['plan_cvrg_mos_num'].sum()
```

```
[16]: medreimb_ip     324.352408
      medreimb_op      91.149139
      medreimb_car    170.233887
      dtype: float64
```

```python
[17]: # paid amount total
      benes_df['medreimb_total'].sum() / benes_df['plan_cvrg_mos_num'].sum()
```

```
[17]: 585.7354335348174
```

2.0.3 Total PMPY

QA check: ~$7,000 paid amount per beneficiary seems reasonable

```python
[18]: # paid amount total
      benes_df['medreimb_total'].sum() / benes_df['plan_cvrg_mos_num'].sum() * 12
```

```
[18]: 7028.825202417809
```

2.0.4 PMPM by demographic category

First we calculate PMPM by Sex/Gender. We will generalize this into a function into which we can "pipe" a dataframe.

```python
[19]: grouped = benes_df.groupby(['bene_sex_ident_cd'], as_index=False).
       ↪agg({'medreimb_total': 'sum', 'plan_cvrg_mos_num': 'sum'})
      grouped['pmpm'] = grouped['medreimb_total'] / grouped['plan_cvrg_mos_num']
      grouped
```

[19]:

	bene_sex_ident_cd	medreimb_total	plan_cvrg_mos_num	pmpm
0	1	202596470.0	323386	626.484975
1	2	262637370.0	470887	557.75031

```python
[20]: def pmpm_by_category(benes_df, category=None) -> pd.DataFrame:
          """Takes any categorical column from beneficiary file and returns PMPM␣
       ↪dataframe grouped on that column."""
          grouped = benes_df.groupby([category]).agg({'medreimb_total': 'sum',␣
       ↪'plan_cvrg_mos_num': 'sum'})
          grouped['pmpm'] = grouped['medreimb_total'] / grouped['plan_cvrg_mos_num']
          return grouped[['pmpm']]
```

```python
[21]: benes_df.pipe(pmpm_by_category, category='bene_sex_ident_cd')
```

```
[21]:                         pmpm
      bene_sex_ident_cd
      1                 626.484975
      2                  557.75031
```

Here we can tabulate the PMPM by various demographic categories. For example, we can see the extent to which PMPM increases/decrease when a beneficiary has a particluar chronic condition.

[22]:
```
pmpm_by_sex = benes_df.pipe(pmpm_by_category, category='bene_sex_ident_cd')
pmpm_by_race = benes_df.pipe(pmpm_by_category, category='bene_race_cd')
pmpm_by_diabetes_status = benes_df.pipe(pmpm_by_category,␣
 ↪category='sp_diabetes')
pmpm_by_esrd_status = benes_df.pipe(pmpm_by_category, category='bene_esrd_ind')

# display dataframes using special helper class defined earlier
display('pmpm_by_sex', 'pmpm_by_race', 'pmpm_by_diabetes_status',␣
 ↪'pmpm_by_esrd_status')
```

[22]:
```
pmpm_by_sex
                          pmpm
bene_sex_ident_cd
1                   626.484975
2                    557.75031

pmpm_by_race
                     pmpm
bene_race_cd
1              605.190157
2              565.455487
3              406.413847
5              396.407894

pmpm_by_diabetes_status
                    pmpm
sp_diabetes
0             210.430212
1             1113.52066

pmpm_by_esrd_status
                      pmpm
bene_esrd_ind
0               456.995155
Y               2029.32543
```

3 Part 2: Inpatient Claims Data and Calculating Expenses per Inpatient Admission

The grain of this data set is member-claimID level. Diagnoses (Dx'es) in the source are pivoted into separate columns, which we will fix.

Simplifying assumption: we will equate 1 facility inpatient claim ID with an admission. * In reality, multiple claims may be associated with an admission. * We would require additional medical grouper logic to check admission and discharge dates to capture related claims while separating episodes. * For example, a Rehab DRG may proceed a Surgery DRG. Those would generally be considered separate admission events for purposes of economic analysis.

3.0.1 Load the data

[23]:
```
ip_claims_df = pd.read_csv('https://www.cms.gov/
↪Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/SynPUFs/
↪Downloads/DE1_0_2008_to_2010_Inpatient_Claims_Sample_1.zip')

# convert column labels to lower case
ip_claims_df.columns = [col.lower() for col in ip_claims_df.columns]
```

3.0.2 Inspect

[24]:
```
ip_claims_df.head()
```

[24]:
```
        desynpuf_id           clm_id  segment  clm_from_dt  clm_thru_dt  \
0  00013D2EFD8E45D1  196661176988405        1   20100312.0   20100313.0
1  00016F745862898F  196201177000368        1   20090412.0   20090418.0
2  00016F745862898F  196661177015632        1   20090831.0   20090902.0
3  00016F745862898F  196091176981058        1   20090917.0   20090920.0
4  00016F745862898F  196261176983265        1   20100626.0   20100701.0

  prvdr_num  clm_pmt_amt  nch_prmry_pyr_clm_pd_amt  at_physn_npi  \
0    2600GD       4000.0                       0.0  3.139084e+09
1    3900MB      26000.0                       0.0  6.476809e+09
2    3900HM       5000.0                       0.0  6.119985e+08
3    3913XU       5000.0                       0.0  4.971603e+09
4    3900MB      16000.0                       0.0  6.408400e+09

   op_physn_npi  ot_physn_npi  clm_admsn_dt admtng_icd9_dgns_cd  \
0           NaN           NaN      20100312                4580
1           NaN           NaN      20090412                7866
2  6.119985e+08           NaN      20090831                6186
3           NaN  1.119000e+09      20090917               29590
4  1.960860e+09           NaN      20100626                5849

   clm_pass_thru_per_diem_amt  nch_bene_ip_ddctbl_amt  \
0                         0.0                  1100.0
1                         0.0                  1068.0
2                         0.0                  1068.0
3                         0.0                  1068.0
4                         0.0                  1100.0

   nch_bene_pta_coinsrnc_lblty_am  nch_bene_blood_ddctbl_lblty_am  \
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

   clm_utlztn_day_cnt  nch_bene_dschrg_dt clm_drg_cd icd9_dgns_cd_1  \
0                 1.0            20100313        217           7802
1                 6.0            20090418        201           1970
2                 2.0            20090902        750           6186
3                 3.0            20090920        883          29623
4                 5.0            20100701        983           3569

  icd9_dgns_cd_2 icd9_dgns_cd_3 icd9_dgns_cd_4 icd9_dgns_cd_5 icd9_dgns_cd_6  \
0          78820          V4501           4280           2720           4019
1           4019           5853           7843           2768          71590
2           2948          56400            NaN            NaN            NaN
3          30390          71690          34590          V1581          32723
4           4019           3542          V8801          78820           2639

  icd9_dgns_cd_7 icd9_dgns_cd_8 icd9_dgns_cd_9 icd9_dgns_cd_10  \
0          V4502          73300          E9330             NaN
1           2724          19889           5849             NaN
2            NaN            NaN            NaN             NaN
3            NaN            NaN            NaN             NaN
4           7840           7856           4271             NaN

   icd9_prcdr_cd_1 icd9_prcdr_cd_2 icd9_prcdr_cd_3 icd9_prcdr_cd_4  \
0              NaN             NaN             NaN             NaN
1              NaN             NaN             NaN             NaN
2           7092.0            6186           V5866             NaN
3              NaN             NaN             NaN             NaN
4              NaN           E8889             NaN             NaN

  icd9_prcdr_cd_5 icd9_prcdr_cd_6  hcpcs_cd_1  hcpcs_cd_2  hcpcs_cd_3  \
0             NaN             NaN         NaN         NaN         NaN
1             NaN             NaN         NaN         NaN         NaN
2             NaN             NaN         NaN         NaN         NaN
3             NaN             NaN         NaN         NaN         NaN
4             NaN             NaN         NaN         NaN         NaN

   hcpcs_cd_4  hcpcs_cd_5  hcpcs_cd_6  hcpcs_cd_7  hcpcs_cd_8  hcpcs_cd_9  \
0         NaN         NaN         NaN         NaN         NaN         NaN
1         NaN         NaN         NaN         NaN         NaN         NaN
2         NaN         NaN         NaN         NaN         NaN         NaN
3         NaN         NaN         NaN         NaN         NaN         NaN
4         NaN         NaN         NaN         NaN         NaN         NaN

   hcpcs_cd_10  hcpcs_cd_11  hcpcs_cd_12  hcpcs_cd_13  hcpcs_cd_14  \
```

```
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_15  hcpcs_cd_16  hcpcs_cd_17  hcpcs_cd_18  hcpcs_cd_19  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_20  hcpcs_cd_21  hcpcs_cd_22  hcpcs_cd_23  hcpcs_cd_24  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_25  hcpcs_cd_26  hcpcs_cd_27  hcpcs_cd_28  hcpcs_cd_29  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_30  hcpcs_cd_31  hcpcs_cd_32  hcpcs_cd_33  hcpcs_cd_34  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_35  hcpcs_cd_36  hcpcs_cd_37  hcpcs_cd_38  hcpcs_cd_39  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN

   hcpcs_cd_40  hcpcs_cd_41  hcpcs_cd_42  hcpcs_cd_43  hcpcs_cd_44  \
0          NaN          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN          NaN
```

```
   hcpcs_cd_45
0          NaN
1          NaN
2          NaN
3          NaN
4          NaN
```

[25]:
```
ip_claims_df.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 66773 entries, 0 to 66772
Data columns (total 81 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   desynpuf_id                     66773 non-null  object
 1   clm_id                          66773 non-null  int64
 2   segment                         66773 non-null  int64
 3   clm_from_dt                     66705 non-null  float64
 4   clm_thru_dt                     66705 non-null  float64
 5   prvdr_num                       66773 non-null  object
 6   clm_pmt_amt                     66773 non-null  float64
 7   nch_prmry_pyr_clm_pd_amt        66773 non-null  float64
 8   at_physn_npi                    66100 non-null  float64
 9   op_physn_npi                    39058 non-null  float64
 10  ot_physn_npi                    7683 non-null   float64
 11  clm_admsn_dt                    66773 non-null  int64
 12  admtng_icd9_dgns_cd             66174 non-null  object
 13  clm_pass_thru_per_diem_amt      66773 non-null  float64
 14  nch_bene_ip_ddctbl_amt          64595 non-null  float64
 15  nch_bene_pta_coinsrnc_lblty_am  66773 non-null  float64
 16  nch_bene_blood_ddctbl_lblty_am  66773 non-null  float64
 17  clm_utlztn_day_cnt              66705 non-null  float64
 18  nch_bene_dschrg_dt              66773 non-null  int64
 19  clm_drg_cd                      66773 non-null  object
 20  icd9_dgns_cd_1                  66678 non-null  object
 21  icd9_dgns_cd_2                  66247 non-null  object
 22  icd9_dgns_cd_3                  65492 non-null  object
 23  icd9_dgns_cd_4                  64005 non-null  object
 24  icd9_dgns_cd_5                  61639 non-null  object
 25  icd9_dgns_cd_6                  58369 non-null  object
 26  icd9_dgns_cd_7                  54407 non-null  object
 27  icd9_dgns_cd_8                  49947 non-null  object
 28  icd9_dgns_cd_9                  45032 non-null  object
 29  icd9_dgns_cd_10                 5455 non-null   object
 30  icd9_prcdr_cd_1                 38231 non-null  float64
 31  icd9_prcdr_cd_2                 22733 non-null  object
 32  icd9_prcdr_cd_3                 14462 non-null  object
```

33	icd9_prcdr_cd_4	9377 non-null	object
34	icd9_prcdr_cd_5	6446 non-null	object
35	icd9_prcdr_cd_6	4622 non-null	object
36	hcpcs_cd_1	0 non-null	float64
37	hcpcs_cd_2	0 non-null	float64
38	hcpcs_cd_3	0 non-null	float64
39	hcpcs_cd_4	0 non-null	float64
40	hcpcs_cd_5	0 non-null	float64
41	hcpcs_cd_6	0 non-null	float64
42	hcpcs_cd_7	0 non-null	float64
43	hcpcs_cd_8	0 non-null	float64
44	hcpcs_cd_9	0 non-null	float64
45	hcpcs_cd_10	0 non-null	float64
46	hcpcs_cd_11	0 non-null	float64
47	hcpcs_cd_12	0 non-null	float64
48	hcpcs_cd_13	0 non-null	float64
49	hcpcs_cd_14	0 non-null	float64
50	hcpcs_cd_15	0 non-null	float64
51	hcpcs_cd_16	0 non-null	float64
52	hcpcs_cd_17	0 non-null	float64
53	hcpcs_cd_18	0 non-null	float64
54	hcpcs_cd_19	0 non-null	float64
55	hcpcs_cd_20	0 non-null	float64
56	hcpcs_cd_21	0 non-null	float64
57	hcpcs_cd_22	0 non-null	float64
58	hcpcs_cd_23	0 non-null	float64
59	hcpcs_cd_24	0 non-null	float64
60	hcpcs_cd_25	0 non-null	float64
61	hcpcs_cd_26	0 non-null	float64
62	hcpcs_cd_27	0 non-null	float64
63	hcpcs_cd_28	0 non-null	float64
64	hcpcs_cd_29	0 non-null	float64
65	hcpcs_cd_30	0 non-null	float64
66	hcpcs_cd_31	0 non-null	float64
67	hcpcs_cd_32	0 non-null	float64
68	hcpcs_cd_33	0 non-null	float64
69	hcpcs_cd_34	0 non-null	float64
70	hcpcs_cd_35	0 non-null	float64
71	hcpcs_cd_36	0 non-null	float64
72	hcpcs_cd_37	0 non-null	float64
73	hcpcs_cd_38	0 non-null	float64
74	hcpcs_cd_39	0 non-null	float64
75	hcpcs_cd_40	0 non-null	float64
76	hcpcs_cd_41	0 non-null	float64
77	hcpcs_cd_42	0 non-null	float64
78	hcpcs_cd_43	0 non-null	float64
79	hcpcs_cd_44	0 non-null	float64
80	hcpcs_cd_45	0 non-null	float64

```
dtypes: float64(58), int64(4), object(19)
memory usage: 95.2 MB
```

3.0.3 Drop HCPCS columns

[26]:
```
hcpcs_columns = [f'hcpcs_cd_{n}' for n in range(1, 46)]
ip_claims_df = ip_claims_df.drop(columns=hcpcs_columns)
```

3.0.4 Re-shape data from claim header level (wide) to diagnosis-level (tall)

- Retain the memberid (desynpuf_id) and clm_id as the primary key.
- Reshaping the data this way makes it easier to return queries like "retrieve all members with this Dx"
  - We usually do not care if the diagnosis was in the 1st, 2nd, … 10th field and so on

[27]:
```
# list of dx cols from icd9_dgns_cd_{1-10}
dx_cols = ['icd9_dgns_cd_1', 'icd9_dgns_cd_2', 'icd9_dgns_cd_3']

# Small demo on single member. Limit columns and limit to single row from␣
↪source.
ip_claims_wide = ip_claims_df[['desynpuf_id', 'clm_id']+dx_cols].head(1)

ip_claims_tall = (ip_claims_wide.melt(id_vars=['desynpuf_id', 'clm_id'],
                                      value_vars=dx_cols,
                                      value_name='dx_code')
                                .drop(columns=['variable'])
                 )

display('ip_claims_wide', 'ip_claims_tall')
```

[27]:
```
ip_claims_wide
        desynpuf_id           clm_id icd9_dgns_cd_1 icd9_dgns_cd_2  \
0  00013D2EFD8E45D1  196661176988405           7802          78820

  icd9_dgns_cd_3
0          V4501

ip_claims_tall
        desynpuf_id           clm_id dx_code
0  00013D2EFD8E45D1  196661176988405    7802
1  00013D2EFD8E45D1  196661176988405   78820
2  00013D2EFD8E45D1  196661176988405   V4501
```

3.0.5 Facility Inpatient Case Rate and Per Diem (Per Day, Daily) Expense Calculation

$9,500 paid per case seems realistic

[28]:
```python
# simplifying assumption; 1 claim = 1 case/admission
ip_claims_df['cases'] = 1

ip_case_rate = ip_claims_df['clm_pmt_amt'].sum() / ip_claims_df['cases'].sum()
ip_per_diem = ip_claims_df['clm_pmt_amt'].sum() /␣
 ↪ip_claims_df['clm_utlztn_day_cnt'].sum()

print('ip_case_rate\t', ip_case_rate)
print('ip_per_diem\t', ip_per_diem)
```

```
ip_case_rate     9573.632755754572
ip_per_diem      1716.5632762005012
```

Let's generalize so we can group by DRG, admitting diagnosis, provider, or some other aggregation of interest

[29]:
```python
def ip_case_rate(ip_claims_df, category):
    """Pipes inpatient case rate calculation to dataframe of IP claims."""
    grouped = ip_claims_df.groupby(category)[['clm_pmt_amt', 'cases']].sum()
    grouped['ip_case_rate'] =  grouped['clm_pmt_amt'] / grouped['cases']
    return grouped

```

3.0.6 Top 10 DRGs by Case Rate

[30]:
```python
(ip_claims_df.pipe(ip_case_rate, category='clm_drg_cd')
             .sort_values('ip_case_rate', ascending=False)
             .head(10)
)
```

[30]:

clm_drg_cd	clm_pmt_amt	cases	ip_case_rate
009	1247000.0	23	54217.391304
002	1297000.0	24	54041.666667
007	697000.0	13	53615.384615
013	1049000.0	20	52450.000000
003	1094000.0	21	52095.238095
008	1493000.0	29	51482.758621
001	1647000.0	32	51468.750000
006	1306000.0	26	50230.769231
004	748000.0	15	49866.666667
012	1415000.0	29	48793.103448

3.0.7 Top 10 Providers by Case Rate (Attending Physician NPI)

[31]:
```python
# convert float to integer (pandas "nullable" ints)
ip_claims_df['at_physn_npi'] = ip_claims_df['at_physn_npi'].astype('Int64')

(ip_claims_df.pipe(ip_case_rate, category='at_physn_npi')
              .sort_values('ip_case_rate', ascending=False)
              .head(10)
)
```

[31]:

	clm_pmt_amt	cases	ip_case_rate
at_physn_npi			
2504216159	57000.0	1	57000.0
4832410339	57000.0	1	57000.0
5255908246	57000.0	1	57000.0
8862064428	57000.0	1	57000.0
5216021000	57000.0	1	57000.0
1128735743	57000.0	1	57000.0
3728749348	57000.0	1	57000.0
407618680	57000.0	1	57000.0
9749687266	57000.0	1	57000.0
8911704513	57000.0	1	57000.0

4 End