SAM

October 21, 2022

1 A Simpler Method for Understanding Emergency Shelter Access Patterns

[1]:
```
%load_ext autoreload
%autoreload 1
```

[2]:
```
import numpy as np
import pandas as pd
import datetime, copy, imp
import time
import os
import re
import dask.dataframe as dd

from tqdm.auto import tqdm, trange
from tqdm.notebook import tqdm
tqdm.pandas()

from pandas.tseries.offsets import DateOffset
from sklearn.cluster import KMeans
from util import KMeansCluster as kmGeoff
```

```python
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import matplotlib as mpl

import sys
sys.path.insert(0, '../util/')

%aimport di_data
%aimport data_cache

from di_data import *
from data_cache import CacheResult
```

[3]:
```python
dataDirStr = '/Users/gmessier/data/plwh/gb/'
cacheDirStr = '/Users/gmessier/data/plwh/gb/cache/'
```

1.1 Create Sleep Tables

The event table contains all the individual sleep events indexed by `ClientId` and `Date`.

[4]:
```python
@CacheResult
def gen_event_table(field):

    # Multiple events in a 24 hour period are counted only once.
    def merge_events_24hr(tbl,field):
        dates = tbl.Date.drop_duplicates()
        nEntry = len(dates)
        return pd.DataFrame({
            'ClientId': [ tbl.iloc[0].ClientId ]*nEntry,
            'Date': dates,
            'EventType': [ field ]*nEntry
        })

    rawTblCols = [ 'ClientId', 'Date', 'EventType' ]

    rawTbl = pd.read_hdf(dataDirStr + 'Event-Anonymized-UpTo-Q1-2022.hdf',␣
↪key='Data')
    rawTbl = rawTbl[rawTblCols]
    rawTbl = rawTbl.assign(Date = rawTbl.Date.dt.normalize())

    tbl = rawTbl.loc[ rawTbl.EventType == field ].groupby('ClientId').
↪progress_apply(merge_events_24hr,field=field).reset_index(drop=True)

    return tbl
```

[5]:
```
eTbl = gen_event_table('Sleep',path=cacheDirStr,filename='Metrics-EventTable.
↪hdf')
```

[ ]:
```

```

Access and episode sequences are lists that give the date and index number of individual shelter sleeps and episodes of shelter sleeps, respectively.

[6]:
```
def calculate_access_sequence(tbl,field):

    validRecs =  tbl.EventType == field
    dates = tbl.loc[validRecs].Date.drop_duplicates().sort_values()

    return pd.DataFrame({
        'Date': dates.values,                  # Date of each access.
        'Ind': range(1,len(dates)+1)    # Index of each access.
    },index = range(0,len(dates)))
```

[7]:
```
episodeGap = 30   # Min number of days between episodes.

def calculate_episode_sequence(tbl,field):

    validRecs = tbl.EventType == field
    accDates = tbl.loc[validRecs].Date.drop_duplicates().sort_values()

    gapVals = accDates.diff().astype('timedelta64[D]')
    gapInd = (gapVals >= episodeGap).astype('int').cumsum().
↪drop_duplicates(keep='first')

    return pd.DataFrame({
        'Date': tbl.loc[gapInd.index].Date.values, # Date of first day of each␣
↪episode.
        'Ind': range(1,len(gapInd)+1)       # Episode index.
    },index=range(0,len(gapInd)))
```

[8]:
```
@CacheResult
def gen_access_pattern_table(tbl,typeStr):

    acc = tbl.groupby('ClientId').
↪progress_apply(calculate_access_sequence,field=typeStr)
    epi = tbl.groupby('ClientId').
↪progress_apply(calculate_episode_sequence,field=typeStr)

    lastAcc = acc.groupby(level=0).max()
    firstAcc = acc.groupby(level=0).min()
    lastEpi = epi.groupby(level=0).max()
```

```
    return pd.DataFrame({
        'NAcc': lastAcc.Ind,
        'NEpi': lastEpi.Ind,
        'StartDate': firstAcc.Date,
        'EndDate': lastAcc.Date,
    })
```

[9]:
```
sleepTbl = gen_access_pattern_table(eTbl, typeStr='Sleep', path=cacheDirStr,␣
 ↪filename='Metrics-SleepTable.hdf')
```

[10]:
```
studyStartDate = pd.to_datetime('2009-07-01')
studyEndDate = pd.to_datetime('2022-03-31')

validClients = ((sleepTbl.StartDate >= studyStartDate) & (sleepTbl.EndDate <=␣
 ↪studyEndDate))
sleepTbl = sleepTbl.loc[validClients]

nEntry = (eTbl.ClientId.isin(sleepTbl.index)).sum()

print(f'Clients: {len(sleepTbl.index)}, Entries: {nEntry}')
```

```
Clients: 24512, Entries: 1904044
```

[ ]:
```

```

1.2 Define Eras

- Define a cohort of clients with record start/end dates that fit within each era.

[11]:
```
eraDates = {
    'HousingReady':  { 'start': pd.to_datetime('2009-07-01'), 'end': pd.
 ↪to_datetime('2017-07-31') },
    'All' : { 'start': studyStartDate, 'end': studyEndDate }
}
```

[12]:
```
def create_cohorts(era, tbl):
    nClient = len(tbl.index)
    cohort = {}
    for e in era.keys():
        cohort[e] = tbl.loc[ (tbl.StartDate >= era[e]['start']) & (tbl.EndDate␣
 ↪<= era[e]['end']) ].index
        print(f'{e} Cohort Size: {len(cohort[e])}/{nClient}␣
 ↪({100*len(cohort[e])/nClient:.2f}%)')
    return cohort
```

[13]:
```
cohort = create_cohorts(eraDates, sleepTbl)
```

```
HousingReady Cohort Size: 13295/24512 (54.24%)
All Cohort Size: 24512/24512 (100.00%)
```

[ ]:

```

```

1.3 Clustering

[14]:

```
def generate_cluster_cohorts(cohort,tbl):

    cohortClstr = { k : {} for k in cohort.keys() }

    for k in cohort.keys():

        idx = tbl.index.isin(cohort[k])

        dat = tbl.loc[idx][ [ 'NAcc', 'NEpi' ] ].to_numpy()
        nrm = (dat - dat.mean(axis=0))/np.sqrt(dat.var(axis=0))

        kmeans = KMeans(n_clusters=3, random_state=0).fit(nrm)
        labels = kmeans.labels_
        srtInds = np.argsort(kmeans.cluster_centers_[:,0])

        print(f'--- {k} ---')
        nTot = sum(idx)

        cStr = [ 'Trn', 'Epi', 'Chr' ]
        for cInd in range(len(cStr)):
            cohortClstr[k][cStr[cInd]] = tbl.loc[idx].loc[labels ==␣
↪srtInds[cInd]].index.to_numpy()
            nCoh = sum(labels == srtInds[cInd])
            print(f' {cStr[cInd]}: {nCoh}/{nTot} ({100*nCoh/nTot:.2f}%)')


    return cohortClstr
```

[15]:

```
clstr = generate_cluster_cohorts(cohort,sleepTbl)
```

```
--- HousingReady ---
 Trn: 11984/13295 (90.14%)
 Epi: 1092/13295 (8.21%)
 Chr: 219/13295 (1.65%)
--- All ---
 Trn: 21211/24512 (86.53%)
 Epi: 2713/24512 (11.07%)
 Chr: 588/24512 (2.40%)
```

[ ]:

```

```

1.4 SAM

[16]:
```
def calc_sam_metrics(tbl,obsWin,actvThrsh):

    duration = np.nan
    inShelterFrc = np.nan

    daysInShelter = (tbl.Date - tbl.Date.min()).dt.days

    obsDay = daysInShelter.loc[ (daysInShelter <= obsWin) & (daysInShelter >␣
 ↪obsWin - actvThrsh) ].max()

    if(obsDay != obsDay):
        valid = False

    else:
        valid = True
        duration = obsDay
        nAccesses = tbl.loc[daysInShelter < obsDay].EventType.count()
        inShelterFrc = nAccesses / duration

    return pd.Series({ 'StartDate': tbl.Date.min(), 'Valid': valid, 'Duration':␣
 ↪duration, 'InShelterFrc': inShelterFrc })
```

[17]:
```
idx = eTbl.ClientId.isin(cohort['HousingReady']) & (eTbl.EventType == 'Sleep')
samMets = eTbl.loc[idx].groupby('ClientId').
 ↪progress_apply(calc_sam_metrics,obsWin=90,actvThrsh=30)
```

```
 0%|          | 0/13295 [00:00<?, ?it/s]
```

[ ]:
```

```

1.5 Evaluate SAM

[ ]:
```

```

1.5.1 Accuracy

[18]:
```
trueLbl = clstr['HousingReady']    # Assume the cluster labels are "true".
```

[19]:
```
nClients = len(cohort['HousingReady'])
```

[20]:
```
def assign_sam_labels(alpha, mets):
    coh = {}

    # Inactive clients are considered transitional.
    coh['Trn'] = list( mets.loc[ ~mets.Valid ].index )
```

```
    # Active clients above/below threshold are frequent/infrequent.
    coh['Chr'] = list( mets.loc[ mets.Valid & (mets.InShelterFrc > alpha) ].
↪index )
    coh['Epi'] = list( mets.loc[ mets.Valid & (mets.InShelterFrc <= alpha) ].
↪index )

    return coh
```

[21]:
```
def calc_confusion_matrix(alpha,mets,trueLbl):

    hatLbl = assign_sam_labels(alpha,mets)

    cMtx = np.zeros((3,3),dtype='int')
    key = [ 'Trn', 'Epi', 'Chr' ]
    for i in range(3):
        for j in range(3):
            cMtx[i,j] = np.isin(hatLbl[key[i]],trueLbl[key[j]]).sum()

    return cMtx
```

[22]:
```
def sweep_alpha(alphas, mets, trueLbl):

    res = np.empty((0,2))
    pbar = tqdm(total=len(alphas))
    for alpha in alphas:

        cMtx = calc_confusion_matrix(alpha,mets,trueLbl)

        acc = cMtx.diagonal().sum()/cMtx.sum().sum()

        nuRes = [[ alpha, acc ]]

        res = np.append(res,nuRes,axis=0)
        pbar.update(1)

    pbar.close()

    return res
```

[23]:
```
sweepRes = sweep_alpha(
    alphas = np.arange(0.05,1,0.05),
    mets = samMets, trueLbl = trueLbl)
```

```
  0%|          | 0/19 [00:00<?, ?it/s]
```

[24]:
```
# Select the value of alpha that gives maximum accuracy.
mxAcc = np.argmax(sweepRes[:,1])
```

```
print(f'Max Accuracy: {sweepRes[mxAcc,1]:.3f} (alpha = {sweepRes[mxAcc,0]:.
 ↪2f})')
```

```
Max Accuracy: 0.816 (alpha = 0.85)
```

[ ]:

```

```

1.5.2 Shelter Access Characteristics

[25]:

```
samLbl = assign_sam_labels(alpha = 0.85, mets = samMets)
```

[26]:

```
def gen_access_stats(coh,tbl):
    cohTbl = tbl.loc[tbl.index.isin(coh)]

    stats = {}
    n = len(coh)
    stats['N'] = n

    stats['NAccMn'] = cohTbl.NAcc.mean()
    stats['NAccMd'] = cohTbl.NAcc.median()
    stats['NAcc10'] = cohTbl.NAcc.sort_values(ascending=False).iloc[int(n*0.1)]

    stats['NEpiMn'] = cohTbl.NEpi.mean()
    stats['NEpiMd'] = cohTbl.NEpi.median()
    stats['NEpi10'] = cohTbl.NEpi.sort_values(ascending=False).iloc[int(n*0.1)]

    return stats
```

[27]:

```
def gen_header(lWdth,cWdth,sepStr=' ',endStr=''):

    hStr = f'{" ":>{lWdth}}' + sepStr
    hStr += f'{" ":^{cWdth}}' + sepStr
    hStr += f'{"Stays":^{cWdth}}' + sepStr
    hStr += f'{"Episodes":^{cWdth}}'
    hStr += endStr + '\n'

    hStr += f'{" ":>{lWdth}}' + sepStr
    hStr += f'{"N":^{cWdth}}' + sepStr
    hStr += f'{"(mean/median/10th pctl)":^{cWdth}}' + sepStr
    hStr += f'{"(mean/median/10th pctl)":^{cWdth}}'

    return hStr + endStr
```

[28]:

```
def gen_stat_row(labelStr,stat,nClients,lWdth,cWdth,sepStr=' ',endStr=''):

    rStr = f'{labelStr:>{lWdth}}' + sepStr
    nStr = f'{stat["N"]}/{nClients} ({100*stat["N"]/nClients:.2f}\%)'
    rStr += f'{nStr:^{cWdth}}' + sepStr
```

```
    nStr = f'{stat["NAccMn"]:.2f} / {stat["NAccMd"]:.0f} / {stat["NAcc10"]:.0f}'
    rStr += f'{nStr:^{cWdth}}' + sepStr

    nStr = f'{stat["NEpiMn"]:.2f} / {stat["NEpiMd"]:.0f} / {stat["NEpi10"]:.0f}'
    rStr += f'{nStr:^{cWdth}}'

    return rStr + endStr
```

[29]:
```
labels = { 'Trn': 'Transitional', 'Epi': 'Episodic', 'Chr': 'Chronic' }

lWdth = 24
cWdth = 24

print(gen_header(lWdth,cWdth,sepStr=' & ',endStr='\\\\'))

for k in labels.keys():
    tStat = gen_access_stats(trueLbl[k],sleepTbl)
    eStat = gen_access_stats(samLbl[k],sleepTbl)

    rStr = gen_stat_row(labels[k]+' -␣
↪cluster',tStat,nClients,lWdth,cWdth,sepStr=' & ',endStr='\\\\')
    print(rStr)

    rStr = gen_stat_row(labels[k]+' - SAM',eStat,nClients,lWdth,cWdth,sepStr='␣
↪& ',endStr='\\\\')
    print(rStr)
```

```
                         &                          &          Stays          &
Episodes        \\
                         &            N             & (mean/median/10th pctl) &
(mean/median/10th pctl) \\
  Transitional - cluster &  11984/13295 (90.14\%)   &      20.62 / 2 / 53     &
1.52 / 1 / 3      \\
      Transitional - SAM &  11007/13295 (82.79\%)   &      16.29 / 2 / 28     &
1.78 / 1 / 3      \\
      Episodic - cluster &   1092/13295 (8.21\%)    &    115.34 / 65 / 311    &
7.01 / 6 / 10      \\
          Episodic - SAM &   1668/13295 (12.55\%)   &    102.40 / 49 / 255    &
3.36 / 3 / 7      \\
       Chronic - cluster &    219/13295 (1.65\%)    &   1018.11 / 843 / 1782  &
2.50 / 2 / 5      \\
           Chronic - SAM &    620/13295 (4.66\%)    &    396.75 / 218 / 947   &
2.02 / 1 / 4      \\
```

[ ]:

```

```

1.6 Access Pattern Timeline

[30]:

```
startDate = pd.to_datetime('2013-08-01')
endDate = pd.to_datetime('2022-02-01')
```

[31]:

```
idx = eTbl.ClientId.isin(cohort['All']) & (eTbl.EventType == 'Sleep')
```

[32]:

```
samMets = eTbl.loc[idx].groupby('ClientId').
 ↪progress_apply(calc_sam_metrics,obsWin=90,actvThrsh=30)
```

```
0%|          | 0/24512 [00:00<?, ?it/s]
```

[33]:

```
def real_time_sam(tbl,alpha):
    labelStr = 'Trn'
    row = tbl.iloc[0]
    if row.Valid:
        if row.InShelterFrc > alpha:
            labelStr = 'Chr'
        else:
            labelStr = 'Epi'

    return pd.Series({ 'Date': row.StartDate, 'Label': labelStr })
```

[34]:

```
labels = samMets.groupby(level=0).progress_apply(real_time_sam,alpha=0.85)
```

```
0%|          | 0/24512 [00:00<?, ?it/s]
```

[35]:

```
dateIdx = (labels.Date >= startDate) & (labels.Date <= endDate)
c = labels.loc[(labels.Label=='Chr') & dateIdx].resample('3M',on='Date').
 ↪count().Label
e = labels.loc[(labels.Label=='Epi') & dateIdx].resample('3M',on='Date').
 ↪count().Label
t = labels.loc[(labels.Label=='Trn') & dateIdx].resample('3M',on='Date').
 ↪count().Label

n = c+e+t
```

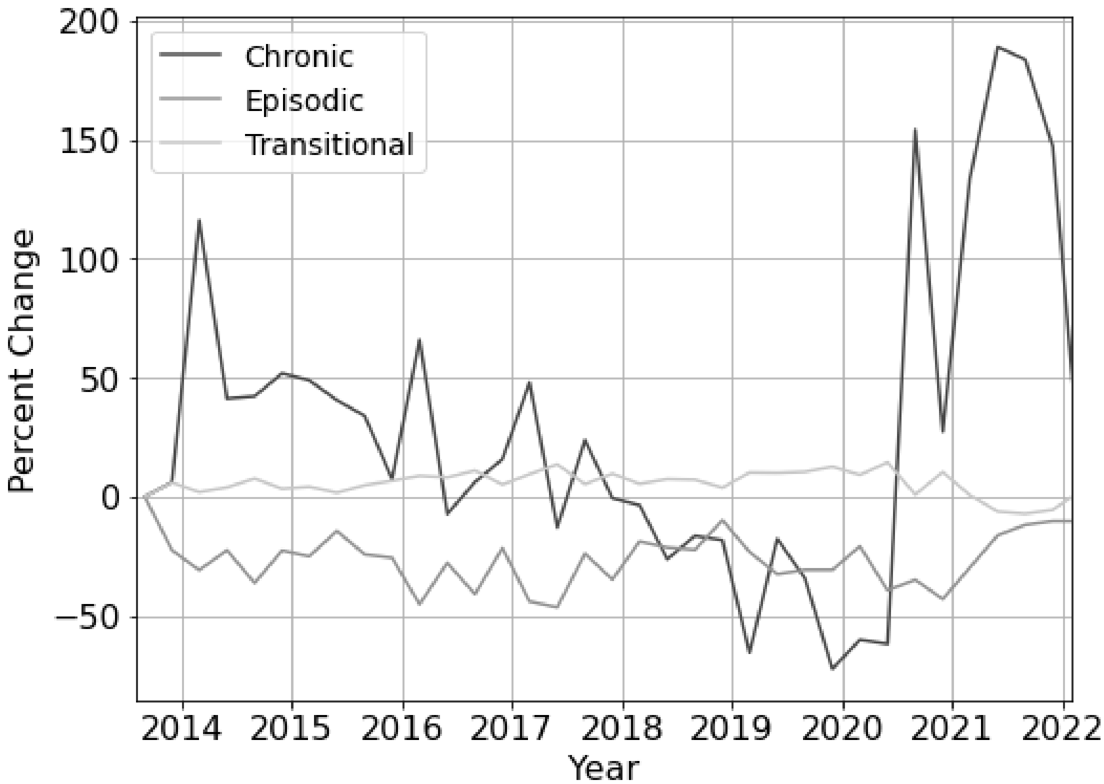
[36]:

```
cPct = c/n*100
ePct = e/n*100
tPct = t/n*100

cPctChg = (cPct/cPct.iloc[0]-1)*100
ePctChg = (ePct/ePct.iloc[0]-1)*100
tPctChg = (tPct/tPct.iloc[0]-1)*100
```

[42]:

```
plt.rcParams['font.size'] = 16
fig,ax = plt.subplots(figsize=(8,6))

dates = n.index
plt.plot(dates,cPctChg,color='#474747',label='Chronic')
plt.plot(dates,ePctChg,color='#919191',label='Episodic')
plt.plot(dates,tPctChg,color='#c7c7c7',label='Transitional')
plt.legend(fontsize=14)

plt.ylabel('Percent Change',fontsize=16)
plt.xlabel('Year',fontsize=16)
plt.grid()

_ = ax.set_xlim([ startDate, endDate ])
plt.savefig('PercentChange.eps')
```

```
The PostScript backend does not support transparency; partially transparent
artists will be rendered opaque.
The PostScript backend does not support transparency; partially transparent
artists will be rendered opaque.
```



[ ]:

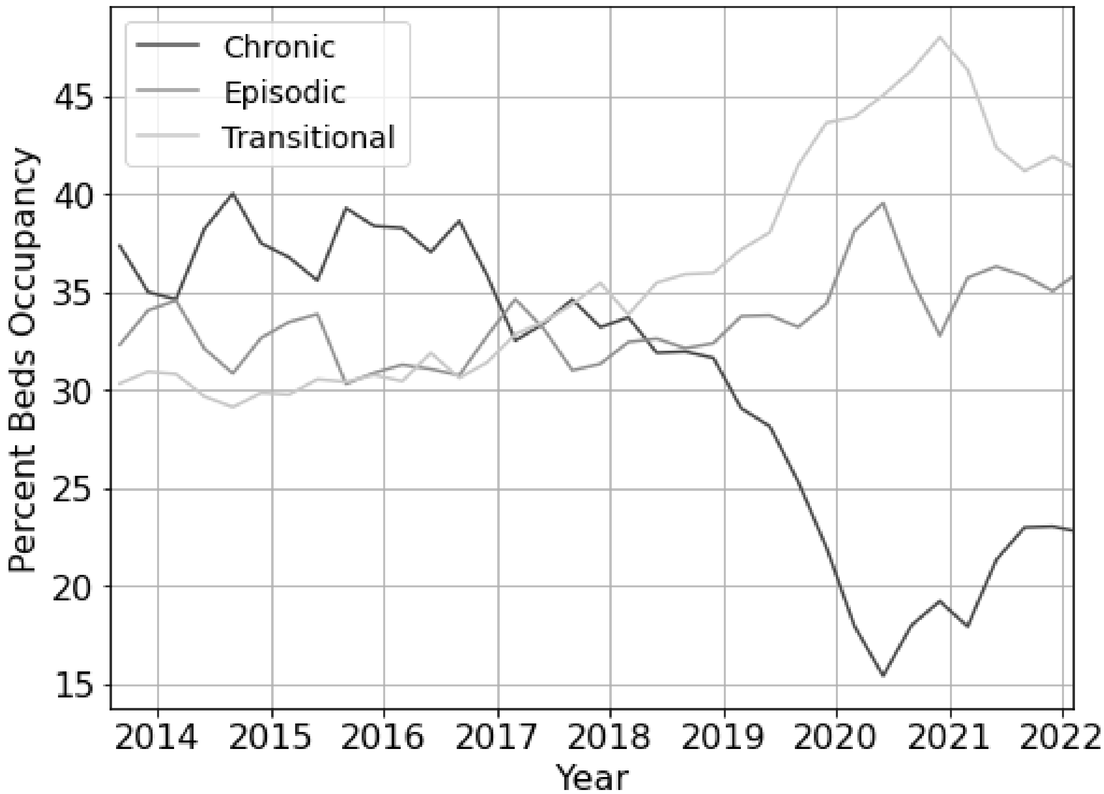
1.7 Shelter Usage Timeline

[38]:
```
cohT = labels.loc[labels.Label == 'Trn'].index
cohE = labels.loc[labels.Label == 'Epi'].index
cohC = labels.loc[labels.Label == 'Chr'].index
```

[39]:
```
sleepsT = eTbl.loc[eTbl.ClientId.isin(cohT) & (eTbl.Date >= startDate) & (eTbl.
 ↪Date <= endDate)].resample('3M',on='Date').count().EventType
sleepsE = eTbl.loc[eTbl.ClientId.isin(cohE) & (eTbl.Date >= startDate) & (eTbl.
 ↪Date <= endDate)].resample('3M',on='Date').count().EventType
sleepsC = eTbl.loc[eTbl.ClientId.isin(cohC) & (eTbl.Date >= startDate) & (eTbl.
 ↪Date <= endDate)].resample('3M',on='Date').count().EventType
sleepsN = sleepsT + sleepsE + sleepsC

sleepsTPct = sleepsT/sleepsN*100
sleepsEPct = sleepsE/sleepsN*100
sleepsCPct = sleepsC/sleepsN*100
```

[40]:
```
fig,ax = plt.subplots(figsize=(8,6))
plt.rcParams['font.size'] = 16
width = 25

dates = sleepsN.index

plt.plot(dates,sleepsCPct,color='#474747',label='Chronic')
plt.plot(dates,sleepsEPct,color='#919191',label='Episodic')
plt.plot(dates,sleepsTPct,color='#c7c7c7',label='Transitional')

plt.legend(fontsize=14)

plt.ylabel('Percent Beds Occupancy',fontsize=16)
plt.xlabel('Year',fontsize=16)
plt.grid()

_ = ax.set_xlim([ startDate, endDate ])
plt.savefig('BedOccupancy.eps')
```

```
The PostScript backend does not support transparency; partially transparent
artists will be rendered opaque.
The PostScript backend does not support transparency; partially transparent
artists will be rendered opaque.
```


Chronic
Episodic
Transitional
Percent Beds Occupancy
45
40
35
30
25
20
15
2014
2015
2016
2017
2018
2019
2020
2021
2022
Year

[ ]:

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[ ]: