TRG_Census_datasets_DataArts

June 6, 2020

1 TRGDW Database

In this notebook, we document and give a high level description of the Household level data we have collected in our database. Accessing this data require an userid and a password. The database is hosted on a SQL server. Connecting to it through an API using for example, python, would require necessary odbc driver.

Import the general libraries first and connect to the SQL server

[1]:
```
import pyodbc
import numpy as np
import pandas as pd
import os,sys
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(font_scale=1.5)
%matplotlib inline
import datetime
```

[2]:
```
#- Reading my userid and password from the environment variables
trguid=os.environ['TRGUID']
trgpwd=os.environ['TRGPWD']
#- Now we establish a connection so that we will be able to perform a query␣
 ↪using pandas read_sql module
#- in python one can use pyodbc or create an engine using sqlalchemy
driver='/usr/local/lib/libmsodbcsql.17.dylib' #- local odbc drive
server='129.119.63.219'
dbname='TRGDW'
port=1433
cnxnTRG=pyodbc.connect(driver=driver,server=server,database=dbname,uid=trguid,\
                       pwd=trgpwd,port=port)
```

Check the tables in the database

[3]:
```
cursor = cnxnTRG.cursor()
for row in cursor.tables(tableType='TABLE'):
    if row[1]=='dbo': #- avoiding system tables
        print(row[2])
```

```
Activity
Activity_20200501
FipsstateMap
HouseHold
HouseHold_20200501
Household2020_clean
Organization
OrgGenre
OrgMap
OrgMapTEST
sysdiagrams
TradeSummary
TRGCompany
TRGCompanyStats
TRGMap
TRGOrgInteg
```

To avoid redundancy, we have already cleaned and integrated static TRG information. So the only tables of interest are **TRGOrgInteg, Activity_20200501, Household2020_clean, TRGCompany and TRGCompanyStats. NO NEED!!! to check other tables**. We will explore each of these tables below.

[4]:
```python
def load_data(cnxn,sqlquery):
    """
    cnxn: pyodbc.Connection object
    sqlquery: sql query string
    returns pandas dataframe from the sqlquery.
    Use only for small databases if running from stanalone node-- to make␣
 ↪efficient
    need distributed architecture for larger databases
    """
    cursor=cnxn.cursor()
    data=pd.read_sql(sqlquery,cursor.connection)
    return data
```

For data description we will limit our queries to a few rows. If one expects to extract the full table, it may be slow with the above function. One may increase the data loading efficiency by some form of parallel processing.

1.0.1 TRGOrgInteg

[5]:
```python
#- look at the schema
for row in cursor.columns(table='TRGOrgInteg'):
    print(row[3],row[5])
```

```
NCARID float
OrgID bigint
ORGName varchar
```

```
ADDRESS varchar
CITY varchar
STATE varchar
ZIP float
ZIP9 varchar
STATENO float
County float
FTRACT float
CensusBlock float
CNTYNM varchar
CBSA float
LATITUDE float
LONGITUDE float
NetworkCode varchar
NetworkName varchar
Active bigint
InactiveDate float
AnnualRevenue float
AnnualRevenueYear float
PostalCode varchar
TRG_Genre varchar
sec_no float
```

COLUMN_NAME	DATA_TYPE	DESCRIPTION
NCARID	float	Primary Key, NCAR ID number for organization
OrgID	bigint	Primary key
ORGName	varchar	Organization full name
ADDRESS	varchar	Organizations reported address
CITY	varchar	Organizations reported city
STATE	varchar	Organizations reported state
ZIP	float	Organizations reported 5-digit zip code
ZIP9	varchar	Orgnizations 9-digt zip code
STATENO	float	State identifier
County	float	Organizations 4-digit county number
FTRACT	float	Organizations tract number
CensusBlock	float	Census Block group number
CNTYNM	varchar	Organization reported county
CBSA	float	CBSA Number
LATITUDE	float	Geo-latitiude coordinate
LONGITUDE	float	Geo-longitude coordinate
NetworkCode	varchar	TRG's Community Network code
NetworkName	varchar	TRG's Community Network name
Active	bigint	Indicates if organization is currently active in TRG's database
InactiveDate	float	Date[YYYYMM] Organization became inactive
AnnualRevenue	float	Budget reported by organization
AnnualRevenueYear	float	Year budget reported for
PostalCode	varchar	Organizations reported postal code
TRG_Genre	varchar	Reported Genre
sec_no	float	The sector which the organization belongs to

[6]:
```
sqlquery='select * from TRGOrgInteg'
trgIntDF=load_data(cnxnTRG,sqlquery)
trgIntDF.head()
```

[6]:
```
     NCARID  OrgID                      ORGName                  ADDRESS  \
0  154202.0   1516                Barter Theatre               PO Box 867
1  150159.0    186            WaterTower Theatre         15650 Addison Rd
2  162722.0    851       Front Porch Theatricals  112 Sewickley Ridge Cir
3  146464.0   1083            Baum School of Art           510 W Linden St
4  146462.0   1084  Lehigh Valley Arts Council          840 Hamilton St

        CITY STATE      ZIP        ZIP9  STATENO   County  …  LONGITUDE  \
0   ABINGDON    VA  24212.0  24212-0867     51.0  51191.0  … -81.974386
1    ADDISON    TX  75001.0  75001-3285     48.0  48113.0  … -96.829781
2  ALEPPO TWP   PA  15143.0  15143-8978     42.0  42003.0  … -80.147076
3  ALLENTOWN    PA  18101.0  18101-1416     42.0  42077.0  … -75.469017
4  ALLENTOWN    PA  18101.0  18101-2455     42.0  42077.0  … -75.474660

  NetworkCode                    NetworkName  Active  InactiveDate  \
0        None                           None       0      201807.0
```

```
1         CNNT     TRG Community: North Texas       1          NaN
2         GPAC  Greater Pittsburgh Arts Counc       0     201711.0
3         CNPH    TRG Community: Philadelphia       0     201709.0
4         CNPH    TRG Community: Philadelphia       1          NaN

   AnnualRevenue AnnualRevenueYear  PostalCode                     TRG_Genre  \
0      8392321.0            2016.0  24210-3202  Education - Performing Arts
1      1418207.0            2018.0  75001-3285                       Theater
2       145000.0            2016.0  15143-8978                       Theater
3            0.0               0.0  18101-1416  Museum - Visual Art/Gallery
4       253347.0            2017.0  18101-2456    Community/Cultural Center

   sec_no
0    11.0
1    11.0
2     8.0
3     1.0
4     3.0

[5 rows x 25 columns]
```

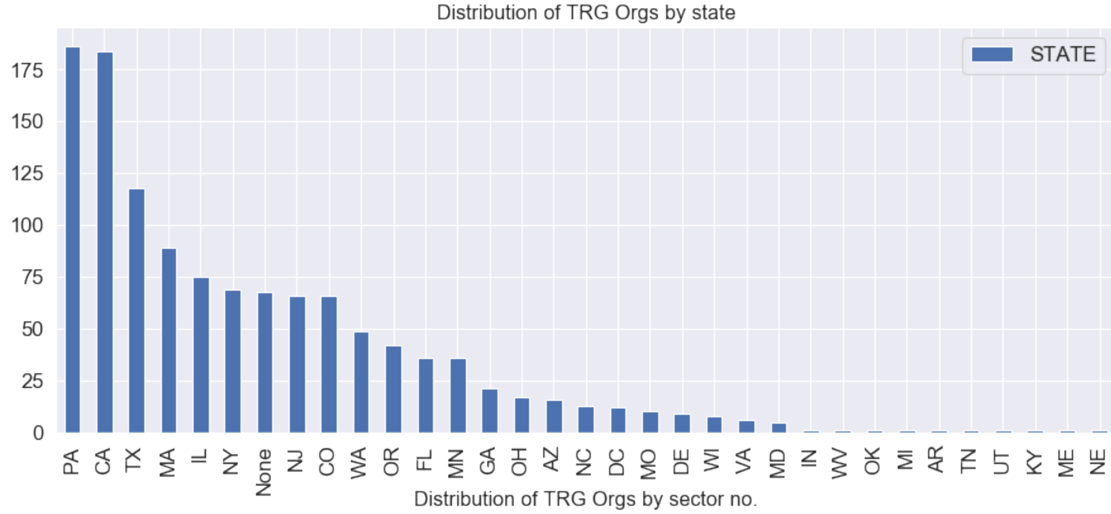
[7]:

```
#- Categorical Distributions
fig=plt.figure(figsize=(15,20))
ax1=plt.subplot(311)
trgIntDF['STATE'].astype(str).value_counts().plot(kind='bar')
ax1.legend()
plt.title('Distribution of TRG Orgs by state',fontsize=16)
ax2=plt.subplot(312)
trgIntDF['sec_no'].astype(str).value_counts().plot(kind='bar',color='r')
ax2.legend()
plt.title('Distribution of TRG Orgs by sector no.',fontsize=16)
ax3=plt.subplot(313)
trgIntDF['Active'].astype(str).value_counts().plot.bar(color=['Black','Green'])
#trgIntDF['Active'].astype(str).value_counts().
↪plot(kind='bar',color=['Black','Green'],label='Inactive')
ax3.set_xticklabels(['Inactive','Active'],rotation=0)
plt.title('Distribution of TRG Orgs by Active/Inactive status',fontsize=16)
```

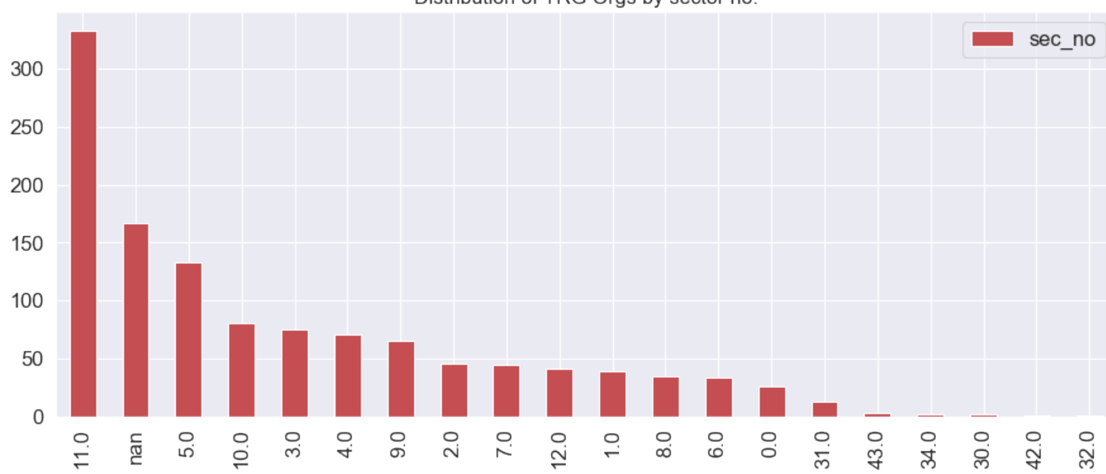
[7]:

```
Text(0.5, 1.0, 'Distribution of TRG Orgs by Active/Inactive status')
```

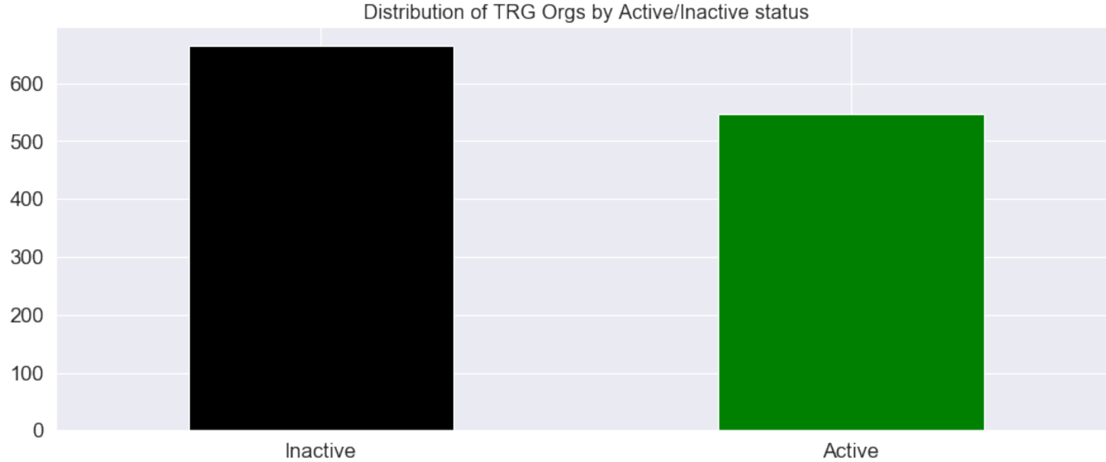
Distribution of TRG Orgs by state



Distribution of TRG Orgs by sector no.



Distribution of TRG Orgs by Active/Inactive status



1.0.2 Household data

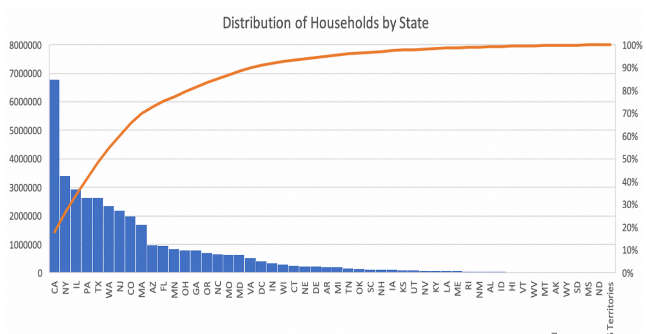
[8]:
```python
#- look at the schema
for row in cursor.columns(table='Household2020_clean'):
    if row[1]=='dbo':
        print(row[3],row[5])
```

```
HouseholdID bigint
CountyCode varchar
FTract varchar
BlockGroup varchar
City varchar
State varchar
PostalCode varchar
Fipsstatecode float
```

COLUMN_NAME	DATA_TYPE	DESCRIPTION
HouseholdID	bigint	Primary Key, TRG's Household ID
CountyCode	varchar	Concatenation of FipsStateCode & FipsCountyCode from Acxiom
FTract	varchar	Concatenation of FipsStateCode, FipsCountyCode, & CensusTract from Acxiom
BlockGroup	varchar	Concatenation of FipsStateCode, FipsCountyCode, CensusTract, & CensusBlockCode from Acxiom
City	varchar	City
State	varchar	State Code
PostalCode	varchar	Postal Code
Fipsstatecode	float	FipsStateCode from Acxiom- mapped with State

Distinct Households:

- **Total: 43,280,081**
- **State not NULL: 38,445,632**
- **US state+Territory: 38,048,817**



[9]:
```python
sqlquery='select top 100 * from Household2020_clean'
hshldDF=load_data(cnxnTRG,sqlquery)
hshldDF.head()
```

[9]:
```
   HouseholdID  CountyCode                          FTract                BlockGroup  \
0     19872353  42043       42043022502            420430225021
1     19971394  42007       42007600700            420076007001
2     20709578  42101       42101008701            421010087012
3     21338944  36061       36061015200            360610152002
4     22481676  12105       12105012503            121050125031

          City State PostalCode  Fipsstatecode
0   Harrisburg    PA      17112           42.0
```

```
1  Beaver Falls    PA      15010          42.0
2  Philadelphia    PA      19104          42.0
3      New York    NY      10128          36.0
4     Kissimmee    FL      34759          12.0
```

1.0.3 Activity_20200501

[10]:
```
#- look at the schema
for row in cursor.columns(table='Activity_20200501'):
    if row[1]=='dbo':
        print(row[3],row[5])
```

```
OrgID int
HouseholdID int
SegmentYear smallint
SegmentTypeCode varchar
SegmentDesc varchar
TransactionAmount money
TransactionQty int
OrderDate datetime
EventDate datetime
```

COLUMN_NAME	DATA_TYPE	DESCRIPTION
OrgID	int	TRG's Org ID, Key to Organization
HouseholdID	int	TRG's Household ID, Key to Household
SegmentYear	smallint	Year of Activity
SegmentTypeCode	varchar	Type of Activity
SegmentDesc	varchar	Description of Activity
TransactionAmount	money	Total Amount assiciated with the Activity
TransactionQty	int	Number of Transactions (tickets, donations)
OrderDate	datetime	Date Transaction Occurred
EventDate	datetime	Date of Event

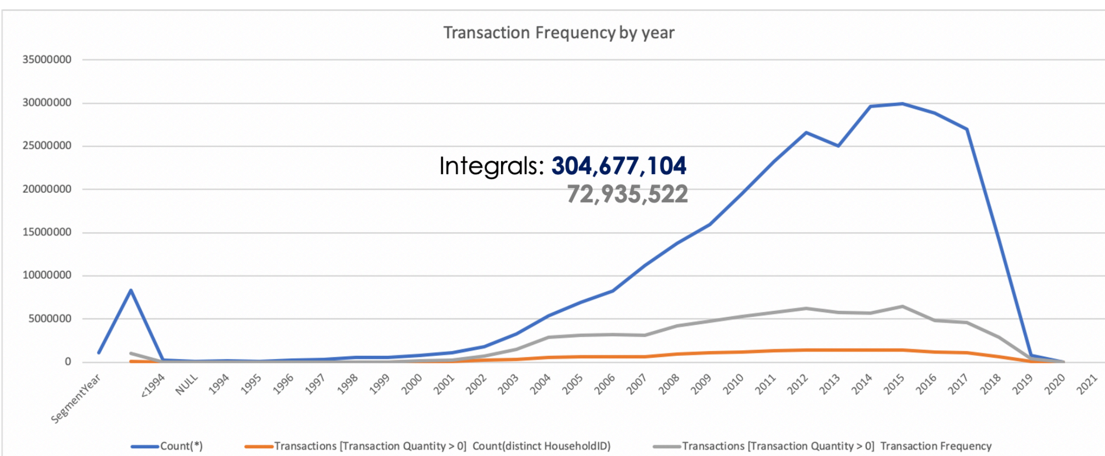
[11]:
```
sqlquery='select top 100 * from Activity_20200501'
ActDF=load_data(cnxnTRG,sqlquery)
ActDF.head()
```

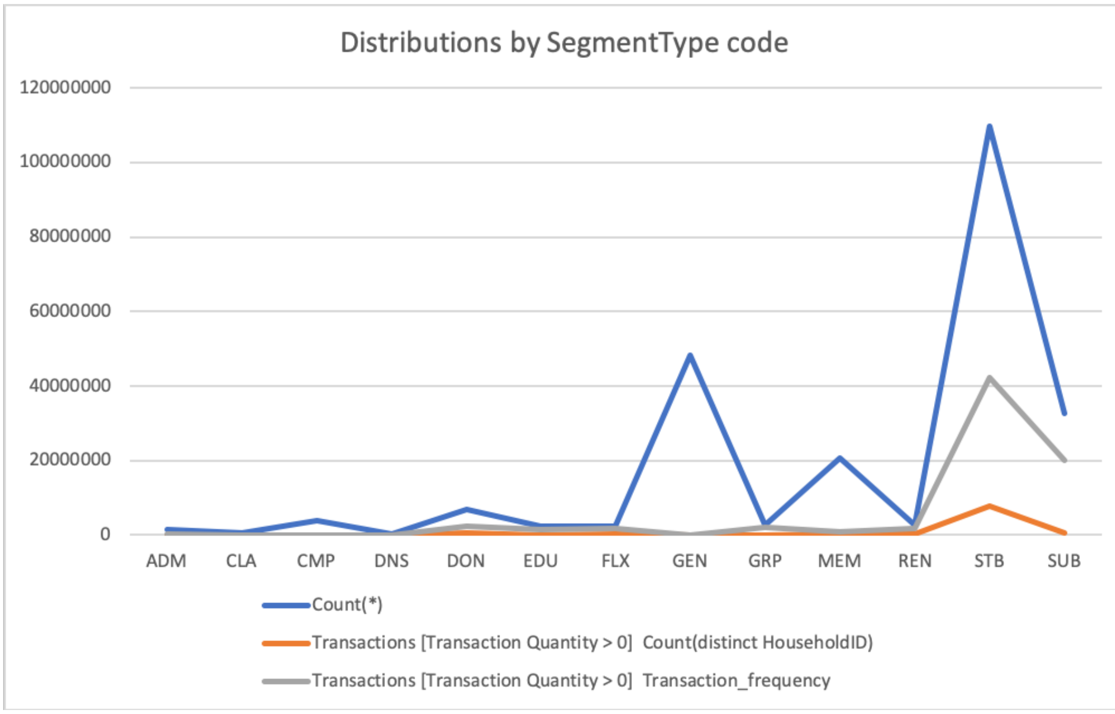
[11]:
```
   OrgID  HouseholdID  SegmentYear SegmentTypeCode    SegmentDesc  \
0    593     16340093         2011             GRP  MOLLY EPSTEIN
1    593     15542333         2011             GRP  MOLLY EPSTEIN
2    593     15537361         2011             GRP  MOLLY EPSTEIN
3    593     15222737         2011             GRP  MOLLY EPSTEIN
4    593     15320003         2011             GRP  MOLLY EPSTEIN

  TransactionAmount TransactionQty OrderDate EventDate
0              None           None      None      None
1              None           None      None      None
```

```
2               None            None       None       None
3               None            None       None       None
4               None            None       None       None
```

[12]:
```python
#Checking where Transaction information is available
sqlquery='select top 100 * from Activity_20200501 where TransactionQty>0'
ActDF=load_data(cnxnTRG,sqlquery)
ActDF.head()
```

[12]:
```
   OrgID  HouseholdID  SegmentYear SegmentTypeCode    SegmentDesc  \
0    280       591215         2013             STB        Bethany
1    280      7688452         2014             STB  Row After Row
2    280     14598194         2013             STB        Bethany
3    280       694624         2013             STB         Jackie
4    280      7614365         2013             STB       Collapse

   TransactionAmount  TransactionQty           OrderDate           EventDate
0               75.0               1 2013-01-30 11:51:00 2013-02-17 14:30:00
1               60.0               3 2014-01-21 09:13:00 2014-02-09 14:30:00
2               45.0               2 2013-01-27 20:19:00 2013-02-02 14:30:00
3               45.0               2 2013-02-19 21:25:00 2013-03-17 14:30:00
4               40.0               2 2013-01-31 15:11:00 2013-04-27 19:30:00
```





1.0.4 TRGCompany

[13]:
```
#- look at the schema
n=0
for row in cursor.columns(table='TRGCompany'):
    if n<=20:  #- only looking at the first 20 fields. Total 411
        if row[1]=='dbo':
            print(row[3],row[5])
    n+=1
```

```
OrgID bigint
year bigint
CNTART float
MKTADV float
ARTSATCD float
FRATNDTO float
PDATND float
ALLATTTO float
BOARDCD float
TRUSTNCD float
ENDTOTCD float
FTEMPS float
FTSEAS float
FTVOLS float
DEVSATCD float
GASAT float
HITIX float
```

```
LOTIX float
DMAILN float
MKTTOT float
MKTSAT float
```

TRGCompany Table consists of 411 variables with OrgID, year and the the remaining 409 numeric variables for the TRG organizations spanning from 2008 through 2019. The description of the numeric fields are given in the TRGCompanyStats table. But let's see some description below as well.

[14]:
```
#Load the TRG company
sqlquery='select * from TRGCompany'
TRGcompDF=load_data(cnxnTRG,sqlquery)
TRGcompDF.head()
```

[14]:
```
   OrgID  year   CNTART  MKTADV  ARTSATCD  FRATNDTO    PDATND  ALLATTTO  \
0   1012  2008  36598.0  7026.0       NaN     100.0    5003.0    5103.0
1   1012  2009  57887.0  8755.0       NaN     300.0    3925.0    4225.0
2   1012  2010  37799.0  2219.0       NaN       0.0  105260.0  105260.0
3   1012  2011      0.0   400.0       NaN       0.0  120545.0  120545.0
4   1012  2012  33819.0   713.0   76718.0     491.0       0.0    4100.0

   BOARDCD  TRUSTNCD  …  GABENCD  PRGBENCD  UWEBVIS  ArtsActivity  \
0     10.0       8.0  …  10268.0   21800.0      0.0      0.233247
1     10.0       9.0  …   4325.0   25390.0      0.0      0.524995
2     10.0       7.0  …   1662.0   22111.0      0.0      0.509109
3      9.0       9.0  …   2088.0   26273.0      0.0      0.518762
4      8.0       8.0  …   2983.0   24379.0      0.0      0.497554

   ArtsProviders  GrantActivity  Hospitality  Substitute  SocioEcon  \
0       0.310376      -0.027368     0.187422   -0.147217  -0.093418
1       0.191257      -0.017818     0.327811   -0.200109  -0.096941
2       0.221737       0.444290     0.205557   -0.152727   0.383591
3       0.341954      -0.444695     0.204866   -0.135336   0.431744
4       0.184335      -0.444695     0.177981   -0.245605   0.528201

         TOTPOP
0  11406.837973
1  11406.837973
2  11485.493201
3  11553.009420
4  11590.029118

[5 rows x 410 columns]
```

[15]:
```
#- For display, let's take a subset and look at some correlation
selected_fields=['ArtsActivity', 'ArtsProviders',
       'GrantActivity', 'Hospitality', 'Substitute', 'SocioEcon',
```

```
        'TOTPOP']
TRGcomp_subset=TRGcompDF[selected_fields]
TRGcomp_subset.describe()
```

[15]:

```
       ArtsActivity  ArtsProviders  GrantActivity   Hospitality    Substitute  \
count  13246.000000   13246.000000   13246.000000  13246.000000  13246.000000
mean       0.974061       2.271096       1.723004      1.094885      1.448059
std        0.381326       1.519767       2.821947      0.798728      1.603717
min       -1.655881      -1.041982      -0.444695     -1.328030     -0.879976
25%        0.791436       1.200293       0.351602      0.504058      0.376510
50%        0.994557       2.009976       1.047828      1.047564      1.275327
75%        1.207564       2.867896       1.939133      1.691370      2.495204
max        1.786953       6.376923      25.179070      3.550326      9.360109

          SocioEcon        TOTPOP
count  13246.000000  1.324600e+04
mean       1.096317  2.470085e+05
std        0.900768  2.000732e+05
min       -1.422394  1.538331e+03
25%        0.420591  1.273388e+05
50%        1.082471  1.902962e+05
75%        1.760716  3.074388e+05
max        3.935416  1.051378e+06
```

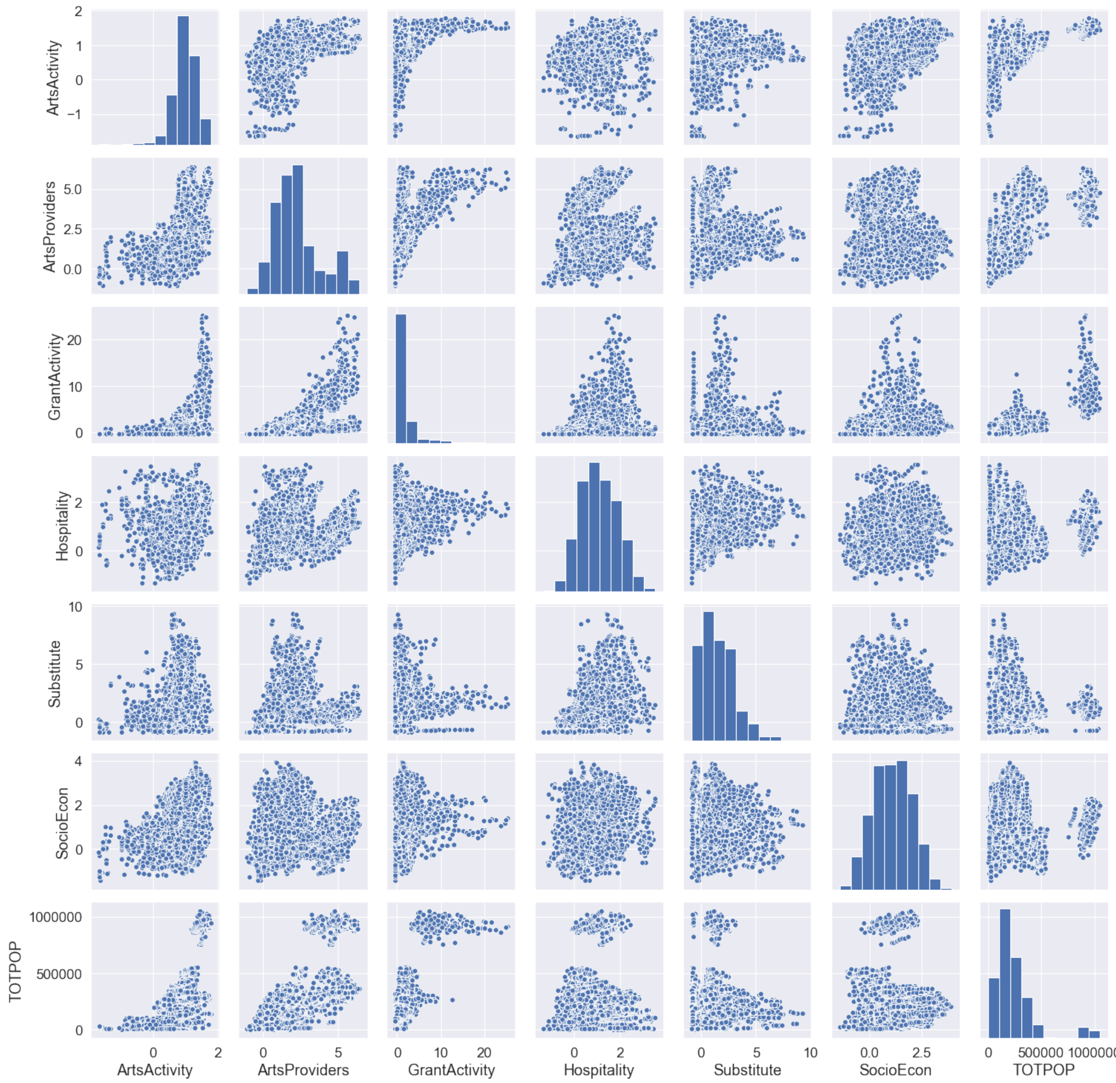
One can look at the correlations in a pair plot

[16]:

```
sns.pairplot(TRGcomp_subset)
```

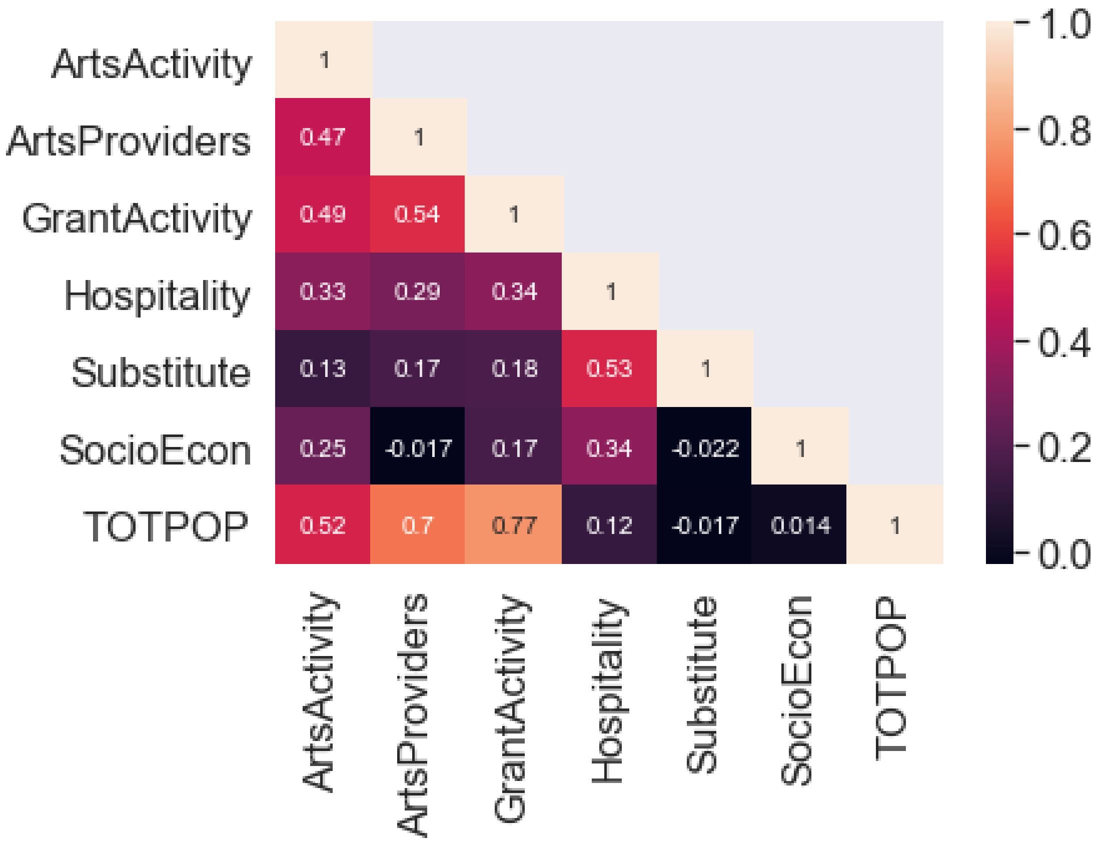
[16]:

```
<seaborn.axisgrid.PairGrid at 0x1a2a0f4150>
```



Or one can also create a correlation matrix/see the overall correlation coefficients across the variables

[17]:
```
corrMatrix=TRGcomp_subset.corr()
corrMatrix=corrMatrix.where(np.tril(np.ones(corrMatrix.shape)).astype(np.bool))
#mask = np.triu(np.ones_like(corrMatrix, dtype=np.bool))
sns.heatmap(corrMatrix,annot=True)
plt.show()
```



The tables above can be joined by the ORGID/householdID. In this framework the join can be performed in the SQL query itself, or at the dataframe level. For larger tables, it is more efficient to perform the join operations in the SQL query itself

[18]:
```
TRGcomp_subset
```

[18]:
```
       ArtsActivity  ArtsProviders  GrantActivity  Hospitality  Substitute  \
0          0.233247       0.310376      -0.027368     0.187422   -0.147217
1          0.524995       0.191257      -0.017818     0.327811   -0.200109
2          0.509109       0.221737       0.444290     0.205557   -0.152727
3          0.518762       0.341954      -0.444695     0.204866   -0.135336
4          0.497554       0.184335      -0.444695     0.177981   -0.245605
…               …            …             …            …           …
13241      0.487631      -0.085477      -0.444695    -0.256045    0.176473
13242      0.521980      -0.112383      -0.444695    -0.257550    0.224276
13243      0.378935      -0.198211      -0.444695    -0.220531    0.326361
13244      0.559540      -0.506832      -0.443646    -0.855271   -0.818810
13245      0.491091      -0.506832      -0.443646    -0.855271   -0.818810

       SocioEcon         TOTPOP
```

```
0      -0.093418  11406.837973
1      -0.096941  11406.837973
2       0.383591  11485.493201
3       0.431744  11553.009420
4       0.528201  11590.029118
…          …            …
13241   0.371721  71287.656183
13242   0.370371  71744.895173
13243   0.399870  72133.488822
13244   0.510956  73720.210891
13245   0.514528  73720.210891

[13246 rows x 7 columns]
```

2 CensusDB

We also have cleaned and integrated Census TRACT and Block Group level data that can be merged with the TRG data for TRACT and Block group level analyses. For this, the database is CensusDB

[19]:
```
#- We create a new connection instance
censusdb='CensusDB'
cnxnCNS=pyodbc.
 ↪connect(driver=driver,server=server,database=censusdb,uid=trguid,pwd=trgpwd,port=port)
```

[20]:
```
#- checking the tables
cursor = cnxnCNS.cursor()
for row in cursor.tables(tableType='TABLE'):
    if row[1]=='dbo': #- avoiding system tables
        print(row[2])
```

```
BlkGrpcommute
BlkGrpecon
BlkGrpeduc
BlkGrplatin
BlkGrpmedhhinc
BlkGrppoverty
BlkGrprace
Tractdemo
Tractecon
Tracteduc
```

The table names indicate the kinds of data in each table. The BlkGrp data span 2013-2019 and tract level data span from 2008-2019. Lets see some of the data

2.0.1 BlkGrpcommute

[21]:
```
sqlquery='select * from BlkGrpcommute'
BlkComDF=load_data(cnxnCNS,sqlquery)
BlkComDF.head()
```

[21]:

	BlkGrp	YEAR	CommuteN	AvgCommute	STATE
0	270332701002	2018	401	13.264339	Minnesota
1	270332701003	2018	503	16.127237	Minnesota
2	270332702002	2018	307	22.446254	Minnesota
3	270332702003	2018	208	22.817308	Minnesota
4	270332703002	2018	412	16.371359	Minnesota

So that shows the average commute time by year for each BlkGrp.

2.0.2 BlkGrpecon

[22]:
```
sqlquery='select * from BlkGrpecon'
BlkeconDF=load_data(cnxnCNS,sqlquery)
BlkeconDF.head()
```

[22]:

	BlkGrp	YEAR	TotHse	LT50p	GT100p	GT125p	GT150p	\
0	270332701002	2018	435	0.450575	0.055172	0.022989	0.018391	
1	270332701003	2018	539	0.551020	0.072356	0.040816	0.040816	
2	270332702002	2018	288	0.423611	0.197917	0.093750	0.052083	
3	270332702003	2018	218	0.399083	0.142202	0.055046	0.032110	
4	270332703002	2018	322	0.285714	0.298137	0.121118	0.077640	

	GT200p	STATE
0	0.002299	Minnesota
1	0.024119	Minnesota
2	0.038194	Minnesota
3	0.027523	Minnesota
4	0.012422	Minnesota

This shows the economy data for each BlkGrp by year. And so on is the data for education, ethnicity, race and poverty. The tract level data also include the same information for the tract levels.

3 Combining aka merging aka joining data sets

We show two ways to merge the data sets and pick Tract level census data to do so as an example

[23]:
```
#- Tract level Census data
Tracttables=['Tractdemo','Tractecon','Tracteduc']
for tab in Tracttables:
    print("Table schema: ", tab)
    for row in cursor.columns(table=tab):
```

```
        print(row[3],row[5])
```

```
Table schema:  Tractdemo
TRACT bigint
TOTPOP bigint
WHIT bigint
BLCK bigint
AMIND bigint
ASIA bigint
HAWA bigint
LATIN bigint
YEAR bigint
STATE varchar
Table schema:  Tractecon
TRACT bigint
POP16 bigint
LT50P varchar
GT100P varchar
GT150P varchar
GT200P varchar
PovPerc varchar
YEAR bigint
STATE varchar
Table schema:  Tracteduc
TRACT bigint
POP25 bigint
BACHP varchar
GRADP varchar
BachPlusP varchar
YEAR bigint
STATE varchar
```

As we see, we have TRACT, YEAR, STATE in all Tract tables, so we will use these to join the tables.

Using SQL join query – fast

[24]:
```
sqlquery='select a.TRACT,a.YEAR,a.STATE,TOTPOP,WHIT,BLCK,AMIND,ASIA,HAWA,LATIN,\
          POP16,LT50P,GT100P,GT150P,GT200P,PovPerc,\
          POP25,BACHP,GRADP,BachPlusP from Tractecon a \
          full outer join Tracteduc b \
          on a.TRACT=b.TRACT and a.YEAR=b.YEAR and a.STATE=b.STATE \
          full outer join Tractdemo c \
          on a.TRACT=c.TRACT and a.YEAR=c.YEAR and a.STATE=c.STATE'
```

[25]:
```
#%%timeit
#TRACT_dataDF=load_data(cnxnCNS,sqlquery)
#==> 2min 16s ± 12.5 s per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

[26]:
```
t1 = datetime.datetime.now()
TRACT_dataDF=load_data(cnxnCNS,sqlquery)
t2 = datetime.datetime.now()
print("Time taken to execute the query and load to DF  [Seconds] ", (t2-t1).
 ↪seconds)
```

```
Time taken to execute the query and load to DF  [Seconds]  107
```

[27]:
```
print(TRACT_dataDF.shape)
TRACT_dataDF.head()
```

```
(814013, 20)
```

[27]:
```
        TRACT  YEAR    STATE  TOTPOP    WHIT   BLCK  AMIND  ASIA  HAWA  LATIN  \
0  1001020100  2009  Alabama  1856.0  1547.0  316.0   73.0   0.0   0.0   15.0
1  1001020100  2012  Alabama  1812.0  1600.0  230.0   54.0   3.0   0.0    0.0
2  1001020100  2014  Alabama  1900.0  1742.0  156.0   25.0  31.0   0.0   14.0
3  1001020100  2015  Alabama  1948.0  1780.0  157.0   29.0  25.0  17.0   17.0
4  1001020100  2017  Alabama  1845.0  1727.0  134.0   31.0  31.0  13.0   44.0

  POP16              LT50P             GT100P             GT150P  \
0  1392  14.699999999999999               21.5                2.0
1  1412               13.6               19.6                5.2
2  1492               12.8                 22                6.5
3  1554                8.5               19.5                4.5
4  1483  5.7000000000000002  20.800000000000001  10.800000000000001

              GT200P            PovPerc   POP25              BACHP  \
0                7.0               10.5  1253.0  12.800000000000001
1                3.2                9.2  1206.0               12.9
2                3.1                 10  1209.0               14.3
3                  1                8.1  1243.0               13.4
4  1.6000000000000001  10.699999999999999  1259.0  20.699999999999999

               GRADP          BachPlusP
0               11.0  23.800000000000001
1               10.9               23.8
2               12.3               26.6
3               14.2               27.5
4  17.100000000000001  37.799999999999997
```

Using individual dataframe – slow

[28]:
```
#%%timeit
#squery='select * from Tractecon'
#testDF=load_data(cnxnCNS,squery)
```

[29]:
```
t3 = datetime.datetime.now()
squery1='select * from Tractecon'
squery2='select * from Tracteduc'
squery3='select * from Tractdemo'

print("Reading Tract economy data")
econDF=load_data(cnxnCNS,squery1)
print("Reading Tract education data")
educDF=load_data(cnxnCNS,squery2)
print("Reading Tract demographics data")
demoDF=load_data(cnxnCNS,squery3)

tract_mergeDF1=econDF.merge(educDF,on=['TRACT','YEAR','STATE'],how='outer')
tract_mergeDF2=tract_mergeDF1.
↪merge(demoDF,on=['TRACT','YEAR','STATE'],how='outer')

t4 = datetime.datetime.now()
print("Time taken on full data queries and DF merge [Seconds] ", (t4-t3).
↪seconds)
```

```
Reading Tract economy data
Reading Tract education data
Reading Tract demographics data
Time taken on full data queries and DF merge [Seconds]  118
```

[30]:
```
print(tract_mergeDF2.shape)
tract_mergeDF2.head()
```

```
(814013, 20)
```

[30]:
```
        TRACT  POP16              LT50P              GT100P  \
0  1001020100   1396  14.699999999999999  18.021468290000001
1  1001020200   1516  17.300000000000001  13.474851320000001
2  1001020300   2549  21.800000000000001          11.4979377
3  1001020400   3638               15.6         13.65610053
4  1001020500   6948               12.5  18.500227150000001

               GT150P              GT200P             PovPerc  YEAR  \
0  1.8803097219999998  5.9569049620000003  9.0918167759999999  2008
1 0.29874091199999997  1.5685701780000001         12.96785751  2008
2  3.6633025469999998 0.45844473399999996         6.914585679  2008
3  3.4820126600000001  1.3284576959999999  5.4389412429999995  2008
4  5.3617976160000005 0.97059919500000003  5.3786507590000001  2008

     STATE   POP25               BACHP               GRADP  \
0  Alabama  1234.0  11.050633270000001  9.7291630170000012
1  Alabama  1254.0  14.157830929999999         7.590958616
```

2	Alabama	2175.0	11.32799376	1.362691852
3	Alabama	3120.0	13.756875389999999	6.8137658339999998
4	Alabama	5619.0	21.31521575	9.9805559810000002

	BachPlusP	TOTPOP	WHIT	BLCK	AMIND	ASIA	HAWA	LATIN
0	20.750948409999999	1852.0	1552.0	291.0	67.0	0.0	0.0	15.0
1	21.930149579999998	2045.0	855.0	1128.0	0.0	22.0	0.0	6.0
2	12.643148160000001	3443.0	2891.0	539.0	0.0	31.0	0.0	39.0
3	20.713600530000001	4639.0	4486.0	85.0	22.0	14.0	0.0	128.0
4	31.834601150000001	9339.0	8067.0	1131.0	88.0	146.0	0.0	471.0