#### In [1]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

### In [2]:

```
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn
from datetime import datetime, timedelta
from fredapi import Fred
import quandl
```

#### In [3]:

```
# https://github.com/mortada/fredapi
fred = Fred(api_key="a02df0a22c57860f5f7cf25edc70ffb3")
quandl.ApiConfig.api_key = "QZLZXdHDDPZna9Yw48NP"
```

```
### National Analysis
Define the variables to be used in analysis:
X Attributes:
* *Monthly* Stocks
    * S&P 500 (MULTPL/SP500 REAL PRICE MONTH)
* *Quarterly* Gross Domestic Product (GDP)
* *Annual* Age Dependency Ratio (SPPOPDPNDOLUSA)
    * Ratio of Older Dependents to Working-Age Population for the
United States
* *Monthly* Civilian Noninstitutional Population
    * Population who are not inmates of institutions (penal,
mental facilities, homes for the aged), and who are not on active
duty in the Armed Forces
        * 20 to 24 years (LNU00000036)
        * 25 to 54 years (LNU00000060)
        * 55 years and over (LNU00024230)
* *Monthly* Unemployment Rate (UNRATE)
* *Quarterly* Homeownership Rate for the United States
(RHORUSO156N)
* *Annual* Home Vacancy Rate for the United States (USHVAC)
у:
* *Monthly* Case-Shiller U.S. National Home Price Index
(CSUSHPINSA)
```

Connect to APIs and create a dataframe with information from each dataset:

```
In [4]:
```

```
def get_info(names):
    data = []
    for i in range(len(names)):
        data.append(fred.get_series(names[i]).to_frame().rename(col
        data[i] = data[i].groupby(data[i].index.year).mean().dropna
    return data
```

### In [5]:

```
sp500 = quandl.get('MULTPL/SP500_REAL_PRICE_MONTH').rename(columns=
names = ["GDP", "SPP0PDPND0LUSA", "LNU000000036", "LNU000000060", "LN
sp500 = sp500.groupby(sp500.index.year).mean().dropna()
us_data_series = get_info(names) + [sp500]
```

# In [6]:

```
usHPI = fred.get_series('CSUSHPINSA').to_frame().rename(columns={0:
usHPI_annual = usHPI.groupby(usHPI.index.year).mean().dropna()
```

### In [7]:

```
us_annual = usHPI_annual.copy()
for df in us_data_series:
    us_annual = us_annual.merge(df, left_index=True, right_index=Trus_annual.tail()
```

#### Out[7]:

	CSUSHPINSA	GDP	SPPOPDPNDOLUSA	LNU00000036	LNU
2014	164.699833	17527.25825	21.514698	22079.500000	1245 <sup>-</sup>
2015	172.211417	18224.78025	22.141440	21970.916667	1251(
2016	180.984333	18715.04050	22.797998	21720.666667	12576
2017	191.519250	19519.42350	23.461460	21395.750000	12569
2018	202.666667	20580.22300	24.139975	21239.166667	12639

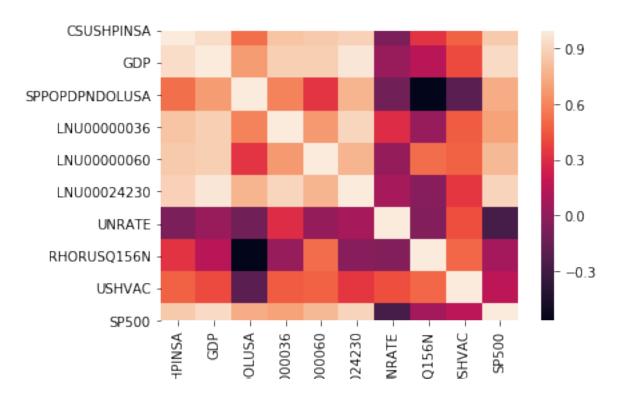
Analyze the correlation coefficient for each indicator we have specified:

# In [8]:

corr = us\_annual.corr().round(4)
sns.heatmap(data=corr)

# Out[8]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x11d38f0b8>



#### In [9]:

corr

#### Out [9]:

	CSUSHPINSA	GDP	SPPOPDPNDOLUSA	LNU00000C
CSUSHPINSA	1.0000	0.9406	0.5246	0.83
GDP	0.9406	1.0000	0.6828	0.87
SPPOPDPNDOLUSA	0.5246	0.6828	1.0000	0.59
LNU00000036	0.8381	0.8786	0.5923	1.00
LNU00000060	0.8647	0.8790	0.3385	0.67
LNU00024230	0.8925	0.9803	0.7784	0.91
UNRATE	-0.0822	0.0329	-0.1147	0.30
RHORUSQ156N	0.3273	0.1456	-0.5667	0.02
USHVAC	0.4852	0.4091	-0.1954	0.46
SP500	0.8625	0.9273	0.7486	0.71

Create a model using linear regression to express the Case-Schiller index as dependent on the other datasets we have downloaded:

### In [10]:

```
X = us_annual.drop(columns=['CSUSHPINSA'], axis=1)
Y = us_annual['CSUSHPINSA']
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size lin_model = LinearRegression() lin_model.fit(X_train, Y_train)
```

# Out [10]:

LinearRegression(copy\_X=True, fit\_intercept=True, n\_jo
bs=None, normalize=False)

```
In [11]:
# model evaluation for training set
v train predict = lin model.predict(X train)
rmse = (np.sqrt(mean squared error(Y train, y train predict)))
r2 = r2 score(Y train, y train predict)
print("The model performance for training set")
print("----
print('Root Mean Squared Error is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")
# model evaluation for testing set
y test predict = lin model.predict(X test)
rmse = (np.sgrt(mean squared error(Y test, y test predict)))
r2 = r2_score(Y_test, y_test_predict)
print("The model performance for testing set")
print("----
print('Root Mean Squared Error is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

In [1]:

```
In [2]:
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National Analysis
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    Monthly Stocks

    S&P 500 (MULTPL/SP500 REAL PRICE MONTH)

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    Quarterly Homeownership Rate for the United States (RHORUSQ156N)

    Annual Home Vacancy Rate for the United States (USHVAC)

y:

    Monthly Case-Shiller U.S. National Home Price Index (CSUSHPINSA)

Connect to APIs and create a dataframe with information from each dataset:
In [4]:
In [5]:
```

# In [6]:

### In [7]:

# Out[7]:

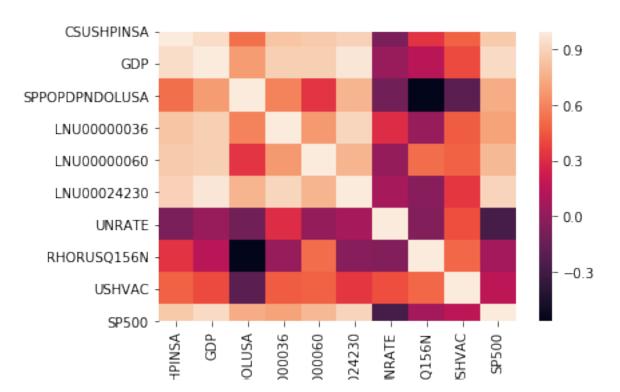
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Create a model using linear regression to express the Case-Schiller index as dependent on the other datasets we have downloaded:

## In [10]:

# Out[10]:

LinearRegression(copy\_X=True, fit\_intercept=True, n\_jo
bs=None, normalize=False)

## In [11]:

The model performance for training set

Root Mean Squared Error is 4.347607380219566 R2 score is 0.9893143554524647

The model performance for testing set

-----

Root Mean Squared Error is 10.188044637012396 R2 score is 0.9468582800978659