ChiPy Mentorship Program

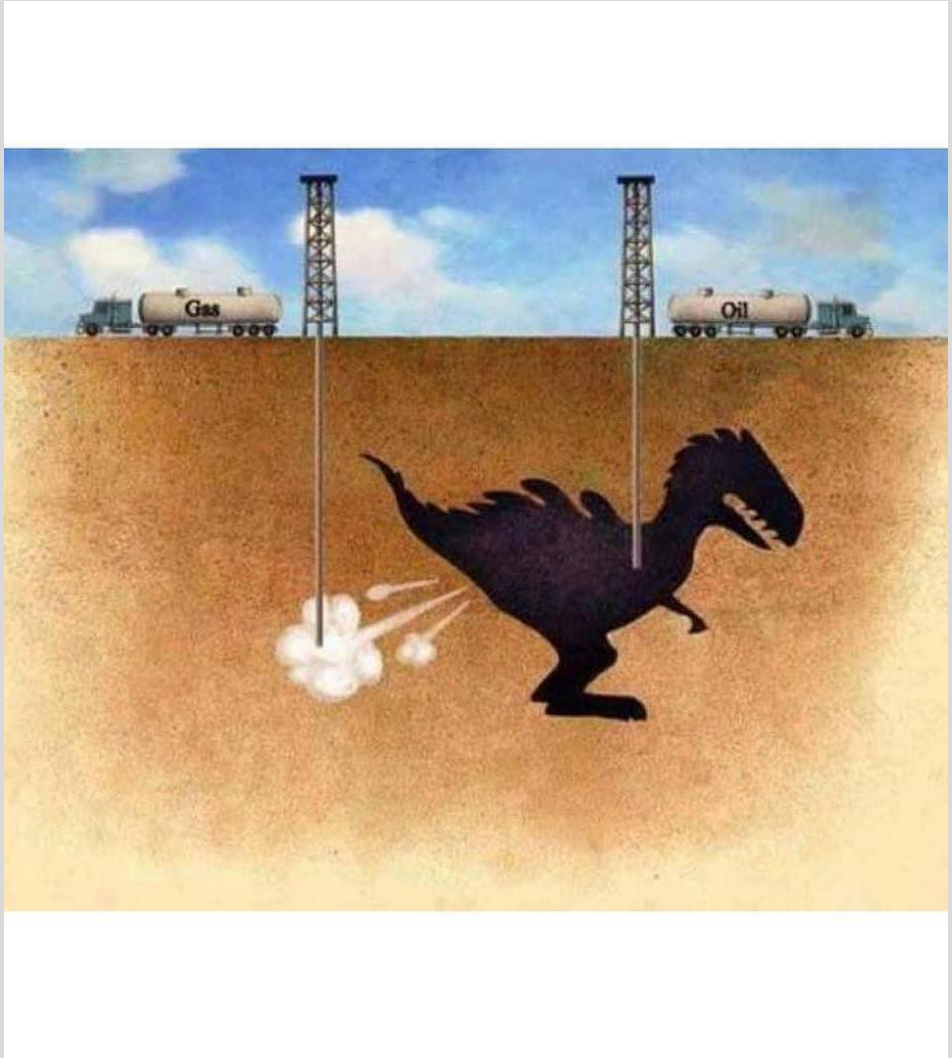
Spring 2017

https://github.com/kurtiskerstein/Chipy_Mentorship

Goals for my project

- Very large dataset
- Machine Learning
- High Level Quantitative Analysis
- Make Predictions
- Distributed Computing

Crude Oil



Disclosure

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- Past performance is not indicative of future results.

Topics

- Feature elimination
  - 54,000+ Features
- Prediction
  - Scikit-learn train/test split
    - Limitations
  - Seasonality
    - Optimizing
    - Forecasting

JSON Data


```
{
  "series_id":"NG.RL2R04SOK_1.A",
  "name":"Oklahoma Natural Gas Plant Liquids, Reserves Revision Decreases, Annual",
  "units":"Million Barrels",
  "f":"A",
  "unitsshort":"MMbbl",
  "description":"Oklahoma Natural Gas Plant Liquids, Reserves Revision Decreases",
  "copyright":"None","source":"EIA, U.S. Energy Information Administration",
  "iso3166":"USA-OK",
  "start":"1979",
  "end":"2008",
  "last_updated":"13-AUG-13 11.49.51 AM",
  "data":[
     ["2008","136"],
     ["2007","73"],
     ...
     ["1980","69"],
     ["1979","54"]
  ]
}
```

$$ Price Data $$

Let's make sure that the Price data is available

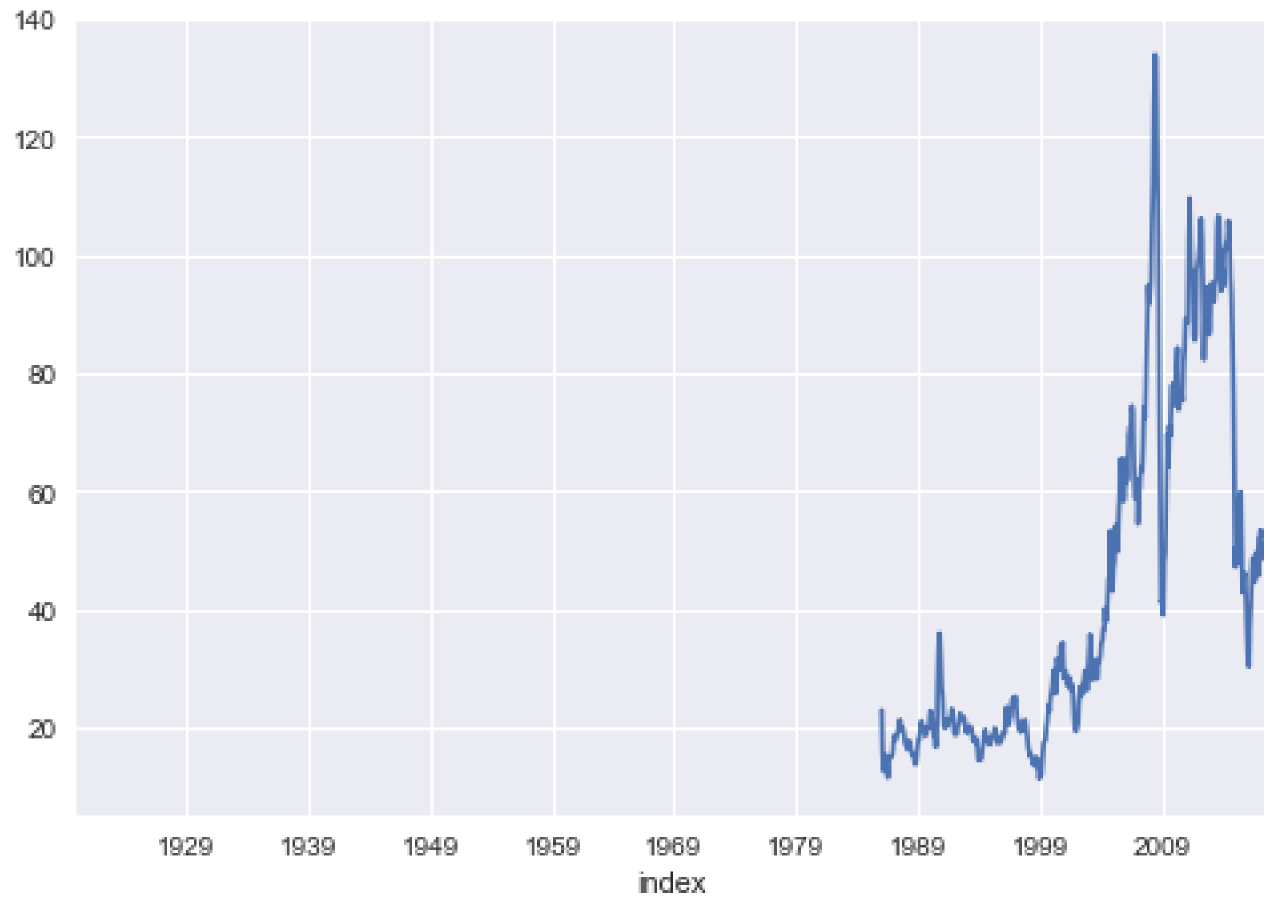
In [7]:
```
df = monthly_crude[['PET.RCLC1.M','PET.RCLC2.M','PET.RCLC3.M','PET.RCLC4.M','PET.RWTC.M']]
df.tail()
```

Out[7]:

index	PET.RCLC1.M	PET.RCLC2.M	PET.RCLC3.M	PET.RCLC4.M	PET.RWTC.M
2017-02-28	53.46	53.93	54.32	54.64	53.47
2017-03-31	49.67	50.22	50.61	50.91	49.33
2017-04-30	51.12	51.52	51.84	52.09	51.06
2017-05-31	48.54	48.86	49.12	49.34	48.48
2017-06-30	NaN	NaN	NaN	NaN	NaN

'PET.RWTC.M' Will be the value we are trying to predict

```
In [10]: monthly_crude['PET.RWTC.M'].plot()

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x11174d4e0>
```



In [5]:
```
monthly_crude = pd.read_csv('./monthly_crude_data.csv',index_col='index',parse_dates=True,infer_datetime_format=True)
monthly_crude.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1170 entries, 1920-01-31 to 2017-06-30
Columns: 54309 entries, PET.EMM_EPMM_PTE_SFL_DPG.M to PET.MBAEXUS2.M
dtypes: float64(54309)
memory usage: 484.8 MB
```

Prepare dateset for Dimensionality Reduction

In [9]:
```
# Set all data series to start January 1986
monthly_crude = monthly_crude.loc['1986-01-31':]

# Remove columns that are missing more than 10% of values
monthly_dataset = monthly_crude[monthly_crude.columns[monthly_crude.count() >= (.90 * monthly_crude['PET.RWTC.M'].count(


#fill in values instead of NaN's
monthly_dataset.fillna(method='ffill',axis=0,inplace=True)
monthly_dataset.fillna(0,inplace=True)

# Drop price Data
monthly_dataset = monthly_dataset.drop(['PET.RCLC1.M','PET.RCLC2.M','PET.RCLC3.M','PET.RCLC4.M','PET.RWTC.M'],axis=1)

monthly_dataset.tail(10)
```

Removed Thousands of features just by filtering!

In [10]:
```
monthly_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 378 entries, 1986-01-31 to 2017-06-30
Columns: 3864 entries, PET.C130013451.M to PET.MPFEXP32.M
dtypes: float64(3864)
memory usage: 11.1 MB
```

Feature Elimination

- scikit-learn
  - Linear Regression
  - RFE
- Train/test split
- Score
- Test set

Recursive Feature Elimination (RFE)

In [15]:

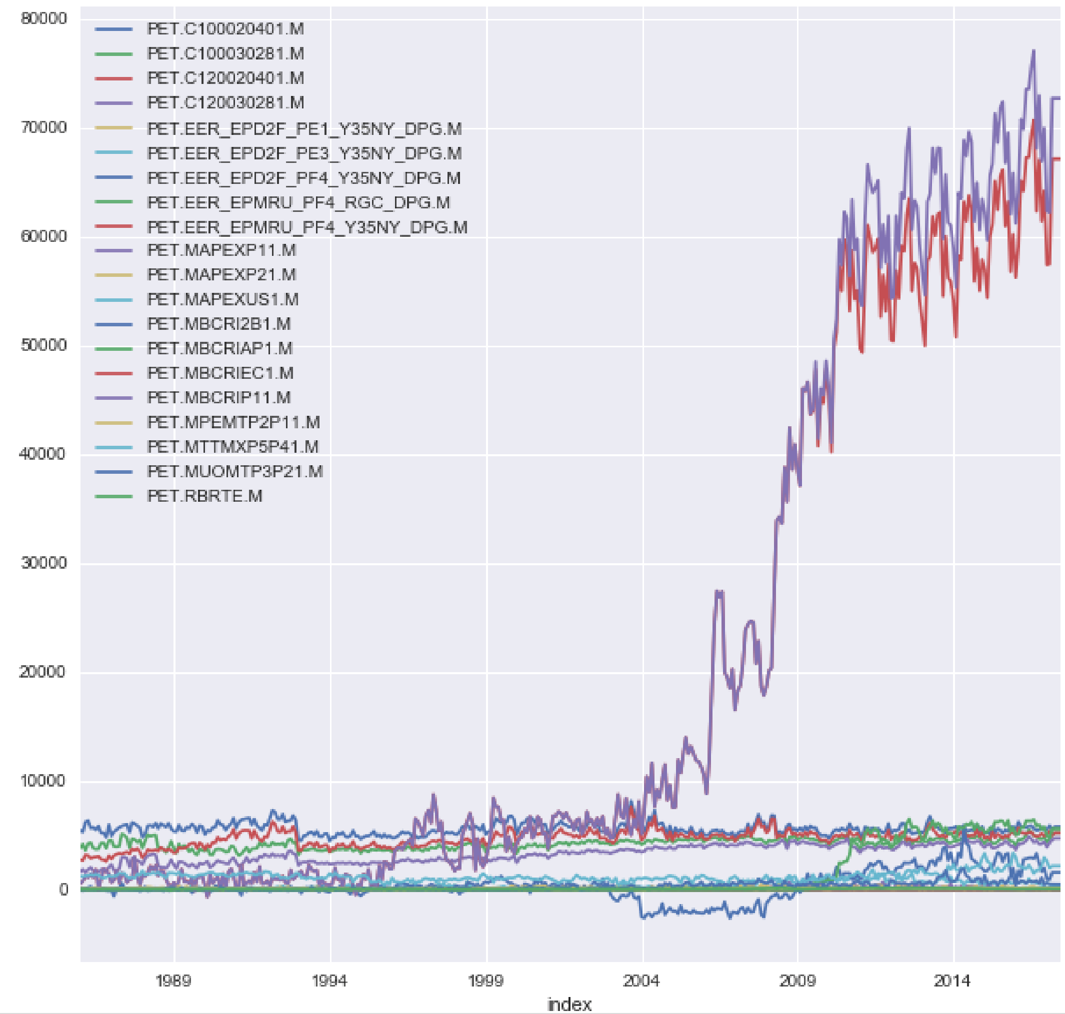
```
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
```

In [36]:

```
#use linear regression as the model
lr_rfe = LinearRegression()
rank all features, i.e continue the elimination until the last one
rfe = RFE(lr_rfe,step=20, n_features_to_select=20)
rfe.fit(monthly_dataset,y)

with open('RFE_linearregression.pickle','wb') as f:
    pickle.dump(rfe, f)

# pickle_in = open('RFE_linearregression.pickle','rb')
# rfe = pickle.load(pickle_in)
```

Remaining Features

```
In [19]: results_rfe.plot(figsize=(10,10))

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x10cfb3400>
```



Some info about these features

PET.MAPEXP11.M	East Coast (PADD 1) Exports of Asphalt and Roa...	Thousand Barrels	East Coast (PADD 1) Exports of Asphalt and Roa...	Mbbl	M	1970-01-03 07:01:41	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MAPEXP21.M	Midwest (PADD 2) Exports of Asphalt and Road O...	Thousand Barrels	Midwest (PADD 2) Exports of Asphalt and Road Oil	Mbbl	M	1970-01-03 07:01:41	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MAPEXUS1.M	U.S. Exports of Asphalt and Road Oil, Monthly	Thousand Barrels	U.S. Exports of Asphalt and Road Oil	Mbbl	M	1970-01-03 07:01:41	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MBCRI2B1.M	Refining District Minnesota-Wisconsin-North Da...	Thousand Barrels	Refining District Minnesota-Wisconsin-North Da...	Mbbl	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MBCRIAP1.M	Refining District Appalachian No. 1 Refinery a...	Thousand Barrels	Refining District Appalachian No. 1 Refinery a...	Mbbl	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MBCRIEC1.M	Refining District East Coast Refinery and Blen...	Thousand Barrels	Refining District East Coast Refinery and Blen...	Mbbl	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MBCRIP11.M	East Coast (PADD 1) Refinery and Blender Net I...	Thousand Barrels	East Coast (PADD 1) Refinery and Blender Net I...	Mbbl	M	1970-01-03 07:01:41	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MPEMTP2P11.M	Midwest (PADD 2) Receipts by Tanker and Barge ...	Thousand Barrels	Midwest (PADD 2) Receipts by Tanker and Barge ...	MBBL	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MTTMXP5P41.M	West Coast (PADD 5) Receipts by Pipeline, Tank...	Thousand Barrels	West Coast (PADD 5) Receipts by Pipeline, Tank...	MBBL	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.MUOMTP3P21.M	Gulf Coast (PADD 3) Receipts by Tanker and Bar...	Thousand Barrels	Gulf Coast (PADD 3) Receipts by Tanker and Bar...	MBBL	M	1970-01-03 07:10:01	1970-01-03 08:01:42	2017-05-02T14:54:09-04:00
PET.RBRTE.M	Europe Brent Spot Price FOB, Monthly	Dollars per Barrel	Europe Brent Spot Price FOB	$/bbl	M	1970-01-03 07:11:45	1970-01-03 08:01:44	2017-05-10T13:24:45-04:00

Train/Test

```
from sklearn.model_selection import train_test_split
from sklearn import cross_validation
X_train, X_test, y_train, y_test = cross_validation.train_test_split(results_rfe, y, test_size=0.2)
lr_rfe.fit(X_train,y_train)

lr_rfe.score(X_test,y_test)
```

```
/Users/Prometheus/Code/Chipy_Mentorship/venv3.6/lib/python3.6/site-packages/scipy/linalg/basic.py:1018: RuntimeWarnin
g: internal gelsd driver lwork query error, required iwork dimension not returned. This is likely the result of LAPAC
K bug 0038, fixed in LAPACK 3.2.2 (released July 21, 2010). Falling back to 'gelss' driver.
  warnings.warn(mesg, RuntimeWarning)
```

```
0.99361657190795627
```

Full Dataset

	ind1	ind2	ind3	ind4	ind5	dependent
2017-07-04	0	1	2	3	4	0
2017-07-05	5	6	7	8	9	1
2017-07-06	10	11	12	13	14	2
2017-07-07	15	16	17	18	19	3
2017-07-08	20	21	22	23	24	4
2017-07-09	25	26	27	28	29	5
2017-07-10	30	31	32	33	34	6
2017-07-11	35	36	37	38	39	7
2017-07-12	40	41	42	43	44	8
2017-07-13	45	46	47	48	49	9

Training set

	ind1	ind2	ind3	ind4	ind5	dependent
2017-07-04	0	1	2	3	4	0
2017-07-05	5	6	7	8	9	1
2017-07-06	10	11	12	13	14	2
2017-07-07	15	16	17	18	19	3
2017-07-08	20	21	22	23	24	4
2017-07-09	25	26	27	28	29	5
2017-07-10	30	31	32	33	34	6

Test set

	ind1	ind2	ind3	ind4	ind5	dependent
2017-07-11	35	36	37	38	39	7
2017-07-12	40	41	42	43	44	8
2017-07-13	45	46	47	48	49	9

Test Set Dilemma

- What about tomorrow or end of month?
  - Out of sample values (AKA Steps)

	ind1	ind2	ind3	ind4	ind5
2017-07-14	50	51	52	53	54
2017-07-15	55	56	57	58	59

- Forecast my inputs
  - How do we do this?

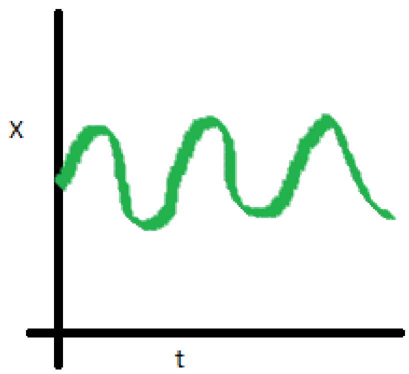
	prediction
2017-07-14	10
2017-07-15	11

With Trends!!!

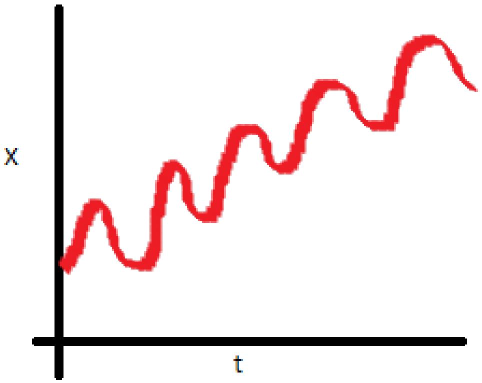
Seasonality

- Cyclical nature of the commodities markets

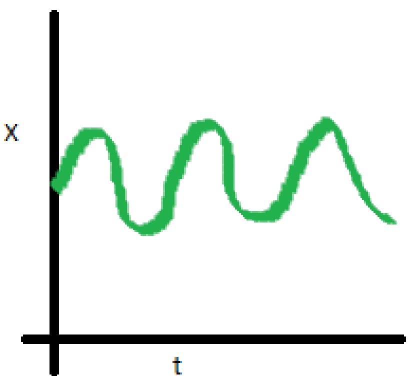
- Past data can give us information about the future



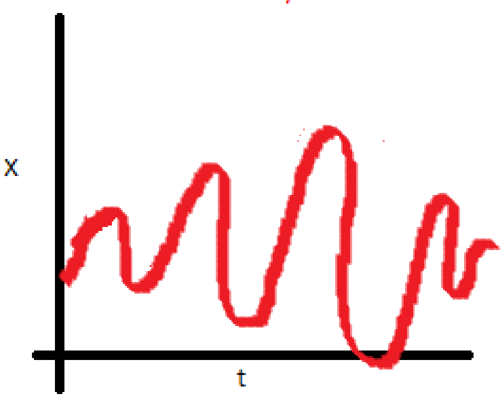
Stationary series



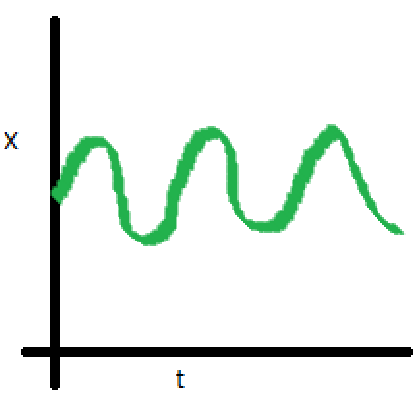
Non-Stationary series



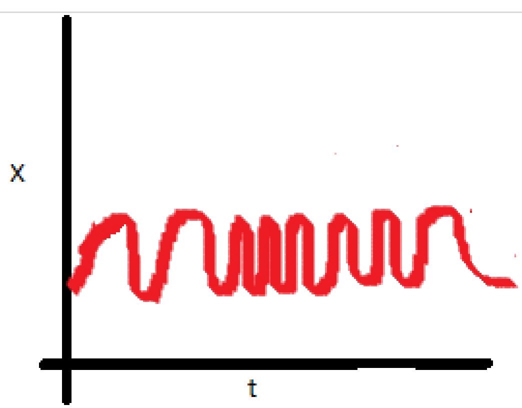
Stationary series



Non-Stationary series



Stationary series



Non-Stationary series

SARIMAX

```
def curve_fit(series):
    # Define the p, d and q parameters to take any value between 0 and 2
    p = d = q = range(0, 2)

    # Generate all different combinations of p, d and q triplets
    pdq = list(itertools.product(p, d, q))

    # Generate all different combinations of seasonal p, q and q triplets
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

#     warnings.filterwarnings("ignore") # specify to ignore warning messages
    param_list=[]
    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(series,
                                                order=param,
                                                seasonal_order=param_seasonal,
                                                enforce_stationarity=False,
                                                enforce_invertibility=False)
                results = mod.fit()
                param_list.append([results.aic,(param,param_seasonal)])
    #             print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))
            except:
                continue
    return param_list
```

Forecast Series

```
def predict_SARIMAX(series,num_months=False):
    #return optimized paramaters
    value = curve_fit(series)
    value.sort()
    value

    #pass optimized paramater to ARIMA
    mod = sm.tsa.statespace.SARIMAX(series,
                                    order=value[0][1][0],
                                    seasonal_order=value[0][1][1],
                                    enforce_stationarity=False,
                                    enforce_invertibility=False)

    results = mod.fit()
    #print(series)
    #print(results.summary().tables[1])

    #predict number of months out of sample data
    pred = results.predict(start=results_rfe.iloc[-1].name,
                                    end=results_rfe.iloc[-1].name+relativedelta(months=num_months))
    return pred
```

Forecast each column in dataset

In [40]:

```
#new dataframe for forcasted values
forecast =pd.DataFrame()

#for each column in the dataframe pass through column to ARIMA
all_cols = results_rfe.columns
for col in all_cols:
    # call function for ARIMA here and assign this to a new series
#     forecast[col] = forecast_ARIMA(results_rfe[col],5)
    forecast[col] = predict_SARIMAX(results_rfe[col],5)

forecast.to_csv('forecast.csv')
```

Created Values are now inputs

In [406]:
```
forecast
```

Out[406]:

	PET.C100020401.M	PET.C100030281.M	PET.C120020401.M	PET.C120030281.M	PET.EER_EPD2F_PE1_Y35NY_DPG.M	PET.EER_EPD2F_PE3_Y35NY_DPG.M	PI
2017-06-30	5890.865124	5301.409809	5321.678974	4774.269053	1.490431	1.497725	
2017-07-31	5553.488049	5158.627631	5012.344295	4650.170890	1.514000	1.527000	
2017-08-31	5664.631864	5115.721876	5124.599226	4649.745606	1.514000	1.527000	
2017-09-30	5610.167845	5019.991918	5140.943956	4590.451244	1.514000	1.527000	
2017-10-31	5603.478772	4986.363739	5116.909493	4552.594836	1.514000	1.527000	
2017-11-30	5525.561020	4934.699350	5045.264594	4504.756093	1.514000	1.527000	

Linear Regression Prediction

lr_rfe fit model to predict price from forcasted features

```
In [45]: forecast['Prediction'] = lr_rfe.predict(forecast)
         forecast['Prediction']

Out[45]: 2017-06-30    58.484699
         2017-07-31    51.501940
         2017-08-31    51.693834
         2017-09-30    48.764816
         2017-10-31    45.354732
         2017-11-30    44.851821
         Freq: M, Name: Prediction, dtype: float64
```

For the future

- Find other alternatives for relevant features
- Optimizing the forecast for each feature
- Distributed Computing
- Scale the project

Thank you

Patrick Boland (Mentor)

U.S. Energy Information Administration (EIA)

Questions?