Pipeline Data Analysis

December 24, 2020

[1]:
```
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
from scipy.stats import boxcox
from sklearn.preprocessing import RobustScaler
import missingno as msno
```

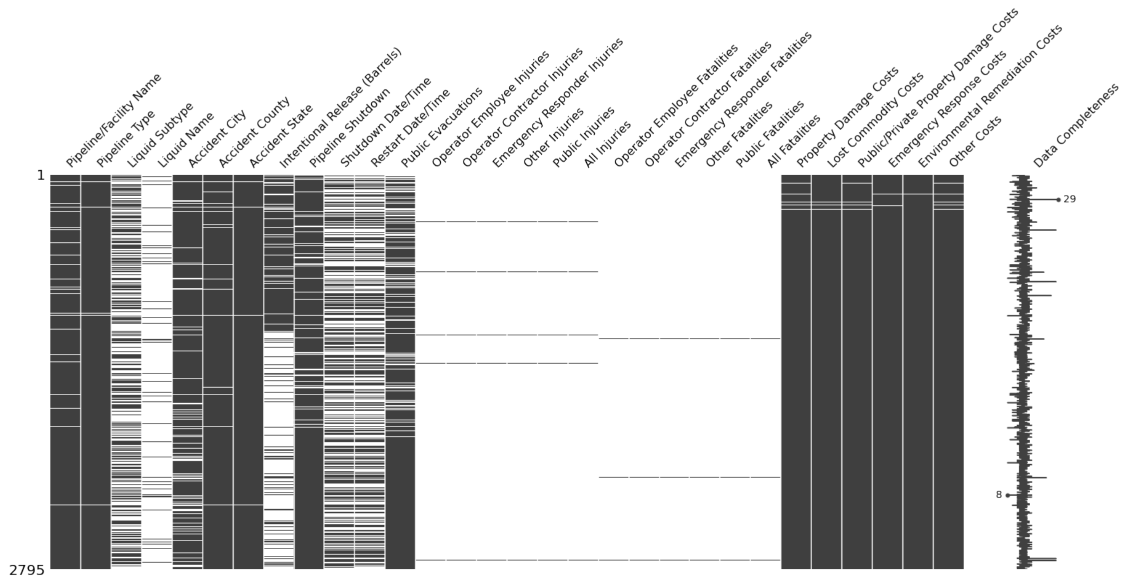
[2]:
```
pipeline_df = pd.read_csv(r'C:\Users\mmotd\OneDrive\Documents\Boot Camp␣
↪Files\Shiny Project\Shiny_Project\Pipeline_Incidents.csv')
```

Assessing missingness patterns in pipeline dataframe and handling them accordingly

[3]:
```
missing_data = pipeline_df.columns[pipeline_df.isnull().any()].tolist()

msno.matrix(pipeline_df[missing_data], labels = True)
```

[3]: <matplotlib.axes._subplots.AxesSubplot at 0x2073996c880>



Imputing 0 for incidents where Nan represents that no injuries/fatalities occurred

[4]:
```
def imputation():
    pipeline_df.loc[:,'Public Evacuations':'Other Costs'] = pipeline_df.loc[:,
                                                        'Public␣
↪Evacuations':'Other Costs'].fillna(0)
    pipeline_df.loc[:,
                'Pipeline/Facility Name':'Accident State'] = pipeline_df.loc[:,
                                                        'Pipeline/
↪Facility Name':'Accident State'].fillna('Unknown')
    pipeline_df.loc[:, 'Intentional Release (Barrels)'] = pipeline_df.loc[:,
                                                        'Unintentional␣
↪Release (Barrels)'].fillna(0)
    pipeline_df['Pipeline Shutdown'] = pipeline_df['Pipeline Shutdown'].
↪fillna('NO')
    shutdown_null = pipeline_df.loc[:,['Shutdown Date/Time',
                                    'Restart Date/Time']][pipeline_df['Shutdown␣
↪Date/Time'].isna()].index
    pipeline_df.loc[shutdown_null,['Shutdown Date/Time', 'Restart Date/Time']]␣
↪= pipeline_df.loc[shutdown_null,
                                                                            ␣
↪           'Accident Date/Time']
    shutdown_null = pipeline_df.loc[:,['Shutdown Date/Time',
                                    'Restart Date/Time']][pipeline_df['Restart␣
↪Date/Time'].isna()].index
    pipeline_df.loc[shutdown_null,['Shutdown Date/Time', 'Restart Date/Time']]␣
↪= pipeline_df.loc[shutdown_null,
```

```
                                                                         ␣
↪          'Accident Date/Time']
    return pipeline_df
```

[5]:
```
pipeline_df = imputation()
```

[6]:
```
pipeline_df.loc[:,['Accident Date/Time','Shutdown Date/Time',
       'Restart Date/Time']] = pipeline_df.loc[:,['Accident Date/
↪Time','Shutdown Date/Time',
       'Restart Date/Time']].apply(lambda x: pd.to_datetime(x), axis = 1)
```

[7]:
```
pipeline_df = pipeline_df.set_index('Accident Date/Time')
```

[8]:
```
monthly_incidents = pd.DataFrame(pipeline_df.groupby(pd.Grouper(freq =␣
↪'m'))['Report Number'].count())
```

[9]:
```
monthly_incidents['year'] = monthly_incidents.index.year
```

[10]:
```
monthly_incidents.columns = ['incidents_num', 'year']
```

[11]:
```
yearly_incidents = pd.DataFrame(pipeline_df.groupby(pd.Grouper(freq =␣
↪'y'))['Report Number'].count())
```

[12]:
```
yearly_incidents.index = yearly_incidents.index.year
yearly_incidents = yearly_incidents.loc['2010':'2016',:]
```

[13]:
```
yearly_incidents.columns = ['num_incidents']
```

[14]:
```
yearly_graph = px.line(yearly_incidents, x = yearly_incidents.index,
                       y= 'num_incidents', title = 'Yearly Number of Incidents')
yearly_graph.update_xaxes(title = 'Year')
yearly_graph.update_yaxes(title = '# of Incidents')
```

The trend of incidents shows an exponential upwards trend between 2011 and 2014. From 2014 to 2015, there is a slight upwards linear trend followed by a decresing linear trend in 2016. This may suggest the implemetation of more robust reliability systems such as predictive maintenance or leak detection systems.

What are the growth trends of accident categories

[15]:
```
yearly_category = pipeline_df.groupby([pd.Grouper(freq = 'y'),
                                       'Cause Category'])['Report Number'].
↪count()
```

[16]:
```
yearly_category = yearly_category.reset_index().set_index('Accident Date/Time')
yearly_category.index = yearly_category.index.year
yearly_category = yearly_category.loc[:2016, :]
```

[17]:
```
yearly_cause = px.line(yearly_category, x = yearly_category.index,
                       y= 'Report Number', title = 'Yearly Number of Incidents␣
↪by Cause Category', color = 'Cause Category')
yearly_cause.update_xaxes(title = 'Year')
yearly_cause.update_yaxes(title = '# of Incidents')
```

Delving deeper into the primary causes of pipeline incidents over time reveals that Material/Weld/Equipment failures followed by corrosion are the primary culprits. This can further be mitigated by by more robust reliability measures

[18]:
```
px.histogram(pipeline_df,
             y = 'Cause Category',
             title = 'Total Number of Incidents by Cause Category').
↪update_yaxes(categoryorder = 'total ascending')
```

[19]:
```
causes_df = pipeline_df.loc[:,['Cause Category', 'Cause Subcategory']]
```

[20]:
```
causes_df = causes_df[(causes_df['Cause Category'] == 'CORROSION') |␣
↪(causes_df['Cause Category'] == 'MATERIAL/WELD/EQUIP FAILURE')]
```

[21]:
```
px.histogram(causes_df, y = 'Cause Subcategory',
             title = 'Total Number of Incidents by Cause Subcategory').
↪update_yaxes(categoryorder = 'total ascending')
```

Some of the most common modes of failure are related to corrosion and mechanical/coupling related equipment failures. It would be useful to assess if the modes of failure have a seasonality aspect.

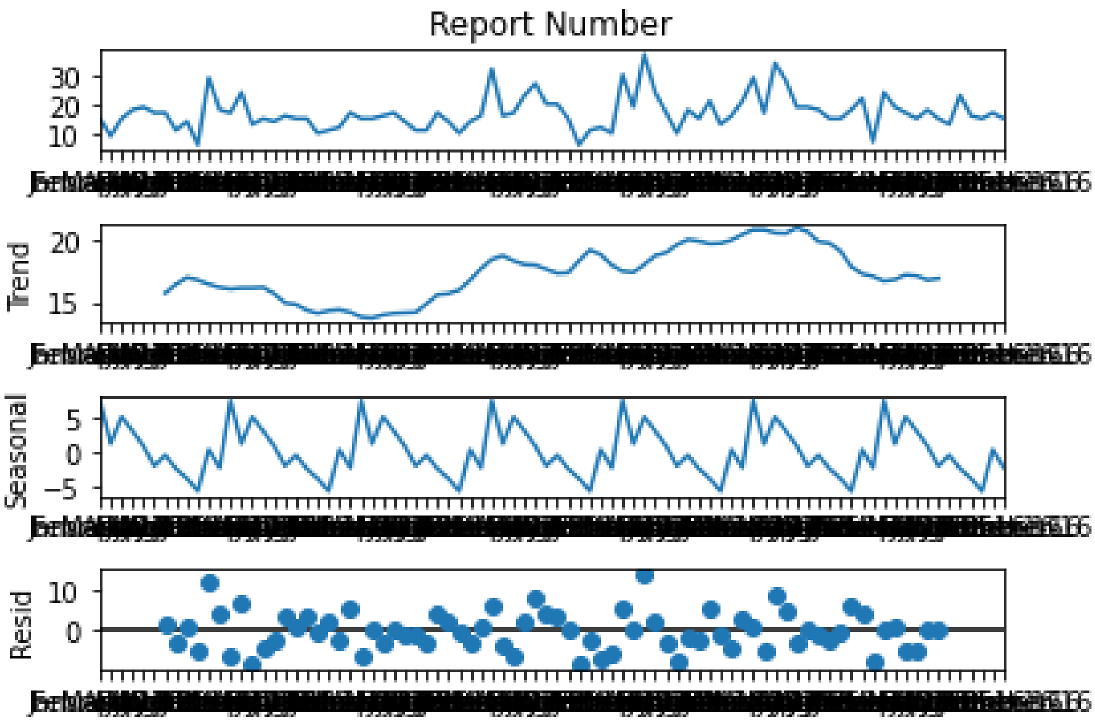
[22]:
```
equip_failure = pipeline_df[pipeline_df['Cause Category'] == 'MATERIAL/WELD/
↪EQUIP FAILURE']
```

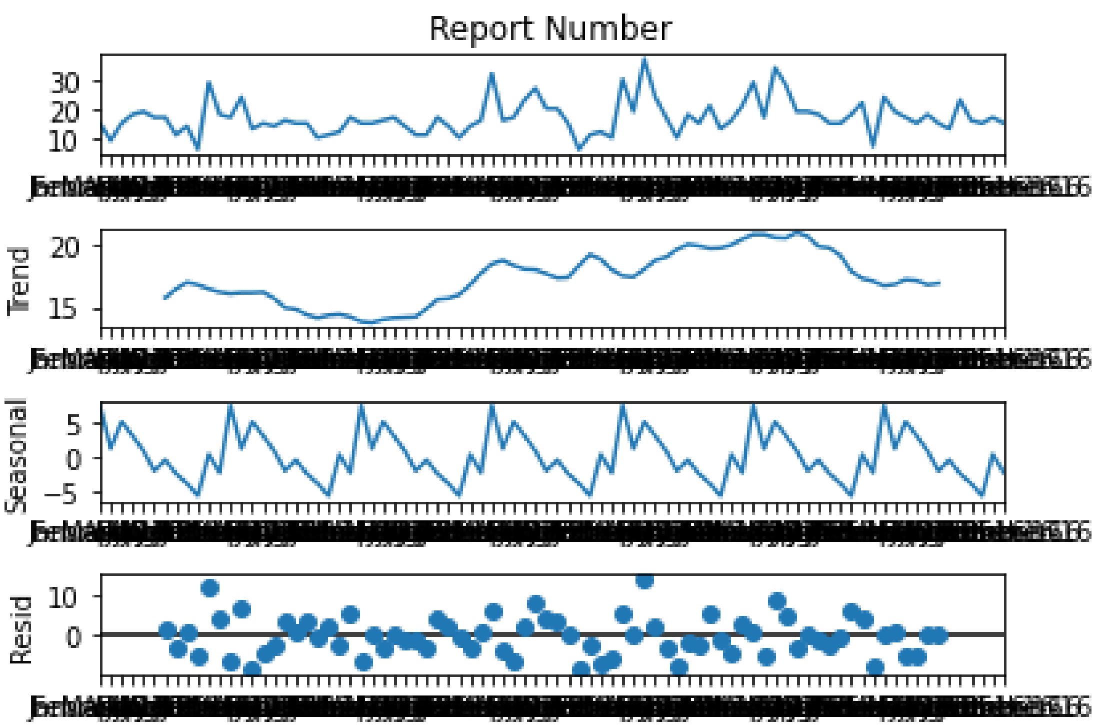
[23]:
```
equip_failure = equip_failure.groupby([pd.Grouper(freq = 'm')])['Report␣
↪Number'].count()
```

[24]:
```
equip_failure.index = equip_failure.index.strftime('%B-%y')
```

[25]:
```
equip_seasonal = seasonal_decompose(equip_failure, model = 'Multiplicative',␣
↪period = 12)
equip_seasonal.plot()
```

[25]:


Report Number
30
20
10
Trend
20
15
Seasonal
5
0
−5
Resid
10
0


Report Number
30
20
10
Trend
20
15
Seasonal
5
0
−5
Resid
10
0

```
[26]: seasonal_equipment = px.histogram(equip_failure, x = equip_failure.index,
                 y= equip_seasonal.seasonal,histfunc = 'avg', nbins= 120, title =␣
 ↪'Seasonality of Equipment/Seal Failure')
seasonal_equipment.update_yaxes(title = 'Average Change in Incidents by Month')
seasonal_equipment.show()
```

It would appear that most equipment related failures occur during the transition from winter to spring. This could be caused by change in temperature between seasons. Mechanical equipments contracts in the winter and expands with heat. As the equipment stabilizes to temperature, the incidence rate decreases.

```
[27]: yearly_costs = pd.DataFrame(pipeline_df.groupby([pd.Grouper(freq = 'y')])['All␣
 ↪Costs'].sum())
```

```
[28]: yearly_costs = yearly_costs[:2016]
```

```
[29]: yearly_costs.index = yearly_costs.index.year
```

```
[30]: yearly_equipcosts = pipeline_df[(pipeline_df['Cause Category'] == 'CORROSION')␣
 ↪| \
                                (pipeline_df['Cause Category'] == \
                                 'MATERIAL/WELD/EQUIP FAILURE')].groupby(pd.
 ↪Grouper(freq = 'y'))['All Costs'].sum()
```

```
[31]: yearly_equipcosts.index = yearly_equipcosts.index.year
```

```
[32]: yearly_costs['Equip Failure Cost'] = yearly_equipcosts
```

```
[33]: yearly_costs = yearly_costs.loc[:2016,:]
```

```
[34]: yearly_costs['Ratio'] = yearly_costs['Equip Failure Cost'] / yearly_costs['All␣
 ↪Costs']
```

```
[35]: px.histogram(pipeline_df, x = 'All Costs', title = 'Histogram of Cost␣
 ↪Distribution', nbins = 10000).update_yaxes(title = 'Frequency')
```

Based on the price distribution histogram, it is evident that the data has severe right skew and significant kurtosis. A majority of pipeline incidents yield losses of under 100k USD.

```
[36]: px.histogram(pipeline_df, x = 'All Costs', title = 'Histogram of Cost␣
 ↪Distribution', nbins = 10000, color = 'Accident Year')
```

```
[37]: px.bar(yearly_costs, x = yearly_costs.index,
        y = 'Ratio', title = 'Ratio of Equipment/Corrosion Costs to Total␣
 ↪Costs').update_xaxes(title = 'Year')
```

[38]:
```python
px.histogram(pipeline_df, x = pipeline_df.index.strftime('%B-%y'), y = 'All Costs', title = 'Cost Over Time')
```

[39]:
```python
pipeline_df['Down Time'] = (pipeline_df['Restart Date/Time'] - pipeline_df['Shutdown Date/Time'])
pipeline_df['Down Time'] = pipeline_df['Down Time'] / np.timedelta64(1, 'h')
```

[52]:
```python
px.histogram(pipeline_df, x = 'Down Time', nbins = 500,
             title = 'Distribution of Downtime').update_xaxes(title = 'Hours').update_yaxes(title = 'Frequency')
```

[41]:
```python
px.histogram(pipeline_df,
             x = 'Accident State',
             title = 'Distribution of Incidents by State').update_xaxes(categoryorder = \
                                                                          'total descending').update_yaxes(title = 'Frequency')
```

[51]:
```python
px.histogram(pipeline_df, x = 'Net Loss (Barrels)',
             title = 'Distribution of Net Product Loss', nbins = 1500).update_yaxes(title = 'Frequency')
```

[43]:
```python
operator_counts = pipeline_df.groupby(['Operator Name'])['Report Number'].count().sort_values(ascending = False).head(20)
```

[44]:
```python
px.histogram(operator_counts, y = operator_counts.index,
             x = operator_counts, title = \
             'Top 20 Operators with Highest Incident Rate'\
            ).update_yaxes(categoryorder = 'total ascending').update_xaxes(title = 'Total Number of Incidents')
```

[45]:
```python
operators_price = pipeline_df.groupby(['Operator Name'])['All Costs'].sum().sort_values(ascending = False).head(20)
```

[46]:
```python
px.histogram(operators_price, y = operators_price.index,
             x = operators_price, title = \
             'Top 20 Operators with Highest Incident Costs'\
            ).update_yaxes(categoryorder = 'total ascending').update_xaxes(title = 'Total Cost in Dollars')
```