johanna_fernandez_eval

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0.1 Biota Skills Evaluation - Staff Reservoir Engineer / Staff Geologist

The goal of this notebook is to assess several sets of skills that are required for Staff Reservoir Engineer & Staff Geologist roles at Biota.

Instructions: * Each section contains its own set of questions which should be answered to the best of your ability * Completing the Resevoir Engineering / Geology questions are required. Unix and GitHub questions are bonus questions. * If the answer to a question is not known to you currently, state that you have not seen that command or usage before. Then search the internet for the answer and provide it to your best ability. * If you cannot answer a question, provide a list of your thought processes, and what you tried along the way. This is important for Biota since we often want to accomplish the right thing, but may need help on the execution. This is materially different from not knowing what the most appropriate thing to do is in the first place.

Packages: * This evaluation should be completable with only the basic packages listed below. If you find yourself needing different packages, please install them and note what and why you are using something specifically.

Execute the cells below to import the relevant packages and functions

[383]:
```
%matplotlib inline
```

[384]:
```
# general packages
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn as sk
import scipy as sp
```

[ ]:
```

```

0.2 Reservoir Engineering / Geology

0.2.1 Part 1)

1) What are the main elements of a `petroleum system`? Which element is produced from in conventional vs. unconventional field development? The main elements of a conventional petroleum system are:

- Source rock: potential to generate hydrocarbons within the basin.
- Migration: formations of enough permeability to allow the hydrocarbons from the source beds to the reservoir.
- Reservoir: formation of sufficient areal extent, height and porosity to store volumes of hydrocarbons, as well as enough permeability to allow the hydrocarbons to migrate to the wellbore.
- Trap: configuration of rocks suitable for containing hydrocarbons. Can be either structural, stratigraphical or a combination of the two.
- Seal: impermeable intervals precluding further upward migration.

In terms of unconventional plays, some elements of the petroleum system needs to be adjusted:

- Source rocks also act as a reservoir: due to the low permeabilities, most of these unconventional plays are self-sourcing.
- Little to no migration occurs from the source rock to the reservoir.
- Traps have no effect on the accumulation and migration: unconventional accumulations are extensive and consecutive with no defined boundaries within the source rock. kitchen; traps are generally inconsequential.

In conventional field development, the production comes from the reservoir rock. On the other hand, in unconventional reservoirs, usually the production comes from the self-sourcing rock (source acting as a reservoir).

2) What are the main `drive mechanisms` of production from conventional and unconventional reservoirs? As the reservoir pressure declines, we have the following main drive mechanisms of production from conventional reservoirs:

- Water drive: the aquifer water expands slightly, displacing the oil or gas from the reservoir toward the borehole.
- Gas expansion: the free gas expands to replace produced hydrocarbons.
- Solution gas: there is an expansion of the oil due to the solution gas expanding. Therefore, the oil is moved to the wellbore.
- Rock and liquid expansion: the withdrawal of liquid or gas from a reservoir results in a decline of the fluid pressure followed by a consequent increase in the grain pressure. Both factors tend to reduce the pore volume and the fluids will be forced out towards the wellbore.
- Gravity drainage: the oil drains downward through the reservoir under the influence of gravity.

In terms of unconventional, low permeability reservoirs, the main drive mechanisms vary. These accumulations are pervasive throughout a large area and are not generally affected by hydrodynamic influences, being called 'continuous type deposits'. Among the main drive mechanisms for these reservoirs we have the following:

- Shale oil: the tightness of the rock provides impermeable barriers. As the reservoir pressure drops, the exsolution and expansion of the **dissolved gas** in the oil provide the main reservoir drive energy,
- Shale gas: a drive mechanism that is associated with certain unconventional gas reservoirs is **gas desorption**. In these cases, there is a high content of organic material in the reservoir rock. This organic rich rock material has the ability to adsorb gas onto its surface. As pressure is depleted, this adsorbed gas is released to the pore-volume of the reservoir by the desorption Process.

- In general, the drive mechanisms in unconventional reservoirs are supplemented by additional energy derived from the **expansion of the rock and water**.

3) How does the `In Situ` stress state affect the complexity of resulting hydraulic fracture system? What is the role of pre-existing natural fracturs/faults?

- In-situ stress represents the factor that most influences the fracture propagation.
- The plane along which the fracture is first possible is the one perpendicular to the least principal stress.

It is necessary to create as much contact area between the unconventional gas reservoir and fracture system as possible.

- The success of the hydraulic fracture system depends upon the intersections between induced hydraulic fractures and natural fractures.
- The interaction between induced hydraulic fractures and the natural fractures by the fracture stimulation provides enhanced permeability in order to increase the hydrocarbon production.
- Therefore, the more pre-existing natural fractures or faults, the more connectivity within the reservoir.

4) Unconventional wells are known for their large decline rates. What are some potential ways of extending the life of an unconventional well?

- Hydraulic fracturing has become a critical component in the successful development of unconventional reservoir and extending the life of an unconventional well. It enables the extraction of natural gas or oil from shale and other forms of tight rock.
- Refracturing restores well productivity to near original or even higher rates of production and extends the productive life of a well.
- There are additional methods for extending the life of an unconventional well, such as wellbore clean-outs, chemical treatments, recompletion, and artificial lift, but not as effective as fracuring the well.
- To be successful, the companies must understand what type of method is required to meet his specific recovery and business objectives.

5) Write a brief `Technical Roadmap` for integrating DNA Diagnostic with production/pressure data, petro-physical logs and reservoir models?

[ ]:

```

```

0.2.2 Part 2)

1) Create a variable named `WellData` by reading in the well metadata as a `pandas` dataframe from the file `WellData.csv`. Set the index as the `WellName` column. (The well metadata includes average geologic and completions parameters for 115 wells in addition to their 2-year cumulative oil production.)

[122]:

```
WellData = pd.read_csv('WellData.csv')
WellData
```

[122]:
```
    WellName TargetFormation  TargetFormationThickness       BVW      PHIT  \
0     Well 1               A                 48.099029  2.319936  0.080282
1     Well 2               A                 47.661448  2.287712  0.079972
2     Well 3               B                 87.939873  3.380522  0.096938
3     Well 4               B                 88.051987  3.390739  0.097546
4     Well 5               B                 88.040865  3.898508  0.101526
..       …             …                      …       …       …
110 Well 111               B                 91.054007  3.476534  0.098800
111 Well 112               B                117.802525  4.230607  0.067927
112 Well 113               B                 85.416697  2.858090  0.089659
113 Well 114               A                 45.150803  2.542320  0.090833
114 Well 115               B                 48.812965  1.757787  0.104128

           PR       SWT       VCL         YM     PGRAD  …  3D_Spacing  \
0    0.080282  0.600788  0.147393  38.672344  0.845430  …  1123.998119
1    0.079972  0.600198  0.145248  38.963685  0.846117  …  1273.997571
2    0.218695  0.396555  0.231885  34.838832  0.837477  …   834.240524
3    0.219903  0.394770  0.229876  34.619501  0.837942  …  1180.581605
4    0.219746  0.436152  0.257077  32.950645  0.846151  …   822.702861
..        …         …         …         …        …    …         …
110  0.228029  0.386448  0.234235  34.302323  0.834730  …  1087.282417
111  0.192165  0.528692  0.182282  46.592040  0.705602  …  1400.000000
112  0.200040  0.373199  0.244244  35.611307  0.848498  …  1400.000000
113  0.090833  0.619899  0.180936  39.084307  0.848514  …   424.760334
114  0.194399  0.345829  0.230363  33.131378  0.848506  …   526.938307

     LAT_LENGTH       PPG      Prop_ft   Fluid_ft  Avg_Stg_Len  Avg_Clust_Spc  \
0          4579  1.236471   390.265123   7.514960   508.777778     508.777778
1          4625  1.181445   391.161081   7.883027   513.888889     513.888889
2          4036  0.709314  1434.960357  48.167245   168.166667      33.633333
3          4141  0.730231  1391.224342  45.361507   295.785714      32.865079
4          4472  0.690833  1488.193202  51.290474   165.629630      32.172662
..            …         …            …          …            …              …
110        4875  0.972418  1440.480000  35.269949   195.000000      32.500000
111        4095  0.948113  1449.098901  36.390535   195.000000      32.500000
112        4833  0.972172  1404.961722  34.409019   201.375000      33.562500
113        4800  1.040158  2486.583333  56.918613   200.000000      33.333333
114        4800  1.054747  2493.135417  56.279267   200.000000      33.333333

     Clusters_per_Stage  Rate_per_cluster  CumOil_24Months
0                     1         48.780000      85767.71658
1                     1         49.780000     165623.71340
2                     5         17.580833     194886.78360
3                     9         11.073016     172405.75800
4                     5         17.888148     207418.55400
..                    …                 …                …
110                   6          8.347200     166501.82300
```

```
111                   6         8.747619     149973.75810
112                   6         9.570833     280928.83440
113                   6        10.000000     287423.95940
114                   6         9.833333     193090.72260

[115 rows x 22 columns]
```

[123]:
```python
WellData.set_index('WellName', inplace=True)
WellData
```

[123]:
```
         TargetFormation  TargetFormationThickness       BVW      PHIT  \
WellName
Well 1                 A                 48.099029  2.319936  0.080282
Well 2                 A                 47.661448  2.287712  0.079972
Well 3                 B                 87.939873  3.380522  0.096938
Well 4                 B                 88.051987  3.390739  0.097546
Well 5                 B                 88.040865  3.898508  0.101526
…                    …                         …         …         …
Well 111               B                 91.054007  3.476534  0.098800
Well 112               B                117.802525  4.230607  0.067927
Well 113               B                 85.416697  2.858090  0.089659
Well 114               A                 45.150803  2.542320  0.090833
Well 115               B                 48.812965  1.757787  0.104128

                PR       SWT       VCL         YM     PGRAD        P_Res  …  \
WellName                                                                  …
Well 1    0.080282  0.600788  0.147393  38.672344  0.845430  9470.505426  …
Well 2    0.079972  0.600198  0.145248  38.963685  0.846117  9475.665033  …
Well 3    0.218695  0.396555  0.231885  34.838832  0.837477  9651.080534  …
Well 4    0.219903  0.394770  0.229876  34.619501  0.837942  9665.658490  …
Well 5    0.219746  0.436152  0.257077  32.950645  0.846151  9774.742082  …
…              …         …         …          …         …            …  …
Well 111  0.228029  0.386448  0.234235  34.302323  0.834730  9428.276073  …
Well 112  0.192165  0.528692  0.182282  46.592040  0.705602  7261.350625  …
Well 113  0.200040  0.373199  0.244244  35.611307  0.848498  9822.209526  …
Well 114  0.090833  0.619899  0.180936  39.084307  0.848514  9662.027483  …
Well 115  0.194399  0.345829  0.230363  33.131378  0.848506  9915.645113  …

           3D_Spacing  LAT_LENGTH       PPG      Prop_ft   Fluid_ft  \
WellName
Well 1    1123.998119        4579  1.236471   390.265123   7.514960
Well 2    1273.997571        4625  1.181445   391.161081   7.883027
Well 3     834.240524        4036  0.709314  1434.960357  48.167245
Well 4    1180.581605        4141  0.730231  1391.224342  45.361507
Well 5     822.702861        4472  0.690833  1488.193202  51.290474
…                 …           …         …            …          …
Well 111  1087.282417        4875  0.972418  1440.480000  35.269949
```

```
Well 112  1400.000000        4095  0.948113  1449.098901  36.390535
Well 113  1400.000000        4833  0.972172  1404.961722  34.409019
Well 114   424.760334        4800  1.040158  2486.583333  56.918613
Well 115   526.938307        4800  1.054747  2493.135417  56.279267

          Avg_Stg_Len  Avg_Clust_Spc  Clusters_per_Stage  Rate_per_cluster  \
WellName
Well 1     508.777778     508.777778                   1         48.780000
Well 2     513.888889     513.888889                   1         49.780000
Well 3     168.166667      33.633333                   5         17.580833
Well 4     295.785714      32.865079                   9         11.073016
Well 5     165.629630      32.172662                   5         17.888148
…                 …              …                 …               …
Well 111   195.000000      32.500000                   6          8.347200
Well 112   195.000000      32.500000                   6          8.747619
Well 113   201.375000      33.562500                   6          9.570833
Well 114   200.000000      33.333333                   6         10.000000
Well 115   200.000000      33.333333                   6          9.833333

          CumOil_24Months
WellName
Well 1        85767.71658
Well 2       165623.71340
Well 3       194886.78360
Well 4       172405.75800
Well 5       207418.55400
…                  …
Well 111     166501.82300
Well 112     149973.75810
Well 113     280928.83440
Well 114     287423.95940
Well 115     193090.72260

[115 rows x 21 columns]
```

2) Perform a groupby function to show how many wells are landed in formations A and B. Which target formation seems to be the main focus of the operator?

[243]:
```python
WellData['COUNTER'] =1
WellGroups = WellData.groupby(['TargetFormation'])['COUNTER'].count()
WellGroups
```

[243]:
```
TargetFormation
A    21
B    94
Name: COUNTER, dtype: int64
```

3) Why do you think the operator is putting more capital in developing the formation you determined in task 2) above? Using `matplotlib` and/or `seaborn`, create a visual to summarize how main geologic parameters (porosity, saturation, thickness, pressure) differ between formation `A` and `B`. The operator is putting more capital in Formation B, according to the number of wells completed: * Formation A: 21 * Formation B: 94

Plots were performed for the geologic parameters, in order to compare the properties between the Formations. The following was observed in terms of each parameter: * Thickness:formation B almost doubles the average thickness of formation A, which is an important factor for putting more capital. * Water Saturation: formation B presents a lower Water Saturation, which increases the chances of producing oil and therefore an additional incentive for putting more capital. * Porosity and Reservoir Pressure: not a relevant difference between average data.

[551]:
```
WellGroups = WellData.groupby(['TargetFormation'])
WellGroups['PHIT','P_Res','TargetFormationThickness','SWT'].mean()
```

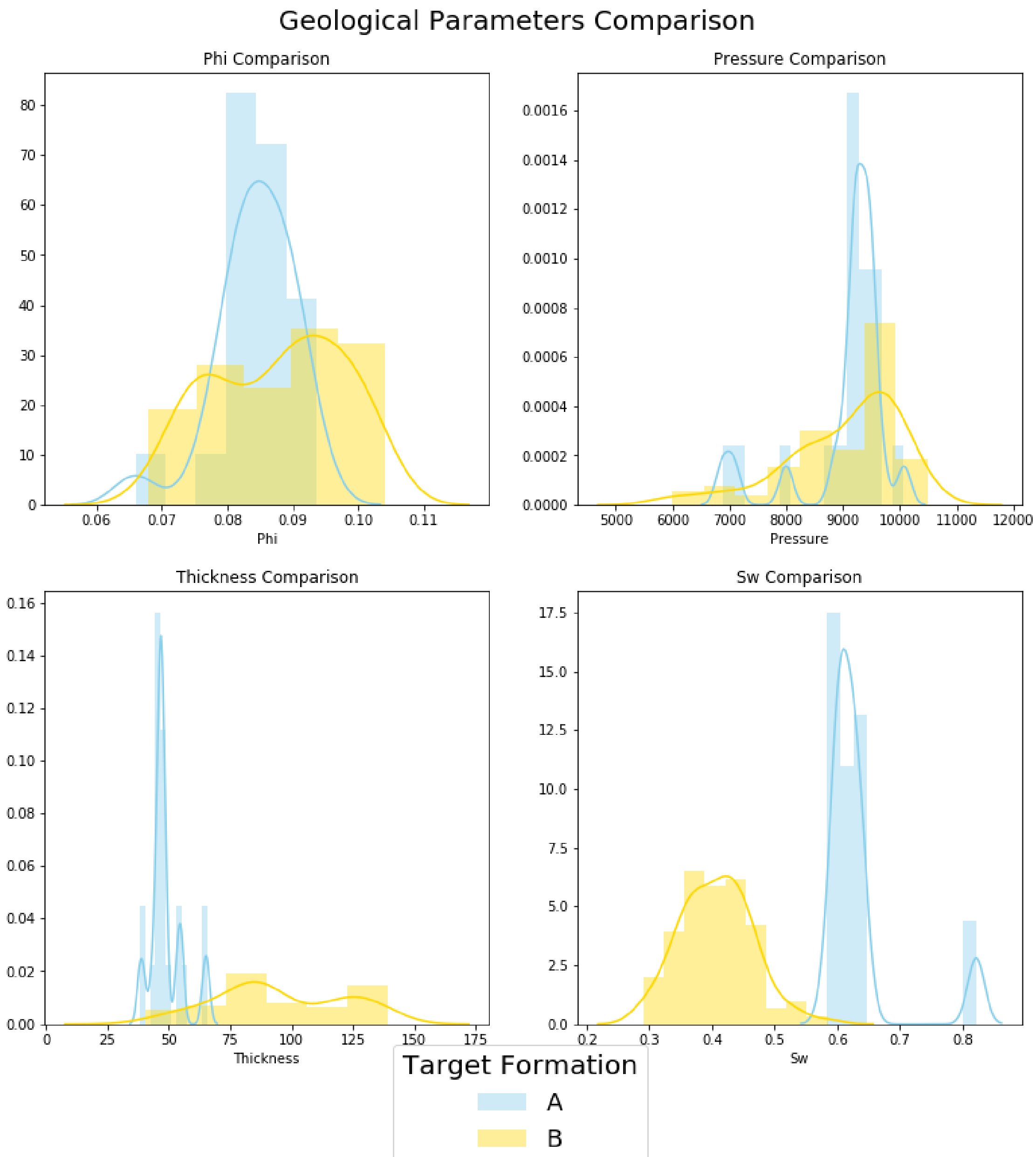
[551]:

TargetFormation	PHIT	P_Res	TargetFormationThickness	SWT
A	0.084317	9061.413038	48.776890	0.634352
B	0.087749	9019.228491	95.115332	0.406843

[474]:
```
# plot
f, axes = plt.subplots(2, 2, figsize=(13, 13), sharex=False)



hist_phi_a = WellData[WellData.TargetFormation == 'A']
sns.distplot(hist_phi_a['PHIT'], color="skyblue", label='A', ax=axes[0, 0])
hist_phi_b = WellData[WellData.TargetFormation == 'B']
sns.distplot(hist_phi_b['PHIT'], color="gold", label='B', ax=axes[0, 0])
axes[0][0].set_title("Phi Comparison")
axes[0][0].set_xlabel("Phi")

hist_p_a = WellData[WellData.TargetFormation == 'A']
sns.distplot(hist_p_a['P_Res'], norm_hist=True, kde=True, color="skyblue",␣
↪label='A', ax=axes[0, 1])
hist_p_b = WellData[WellData.TargetFormation == 'B']
sns.distplot(hist_p_b['P_Res'], norm_hist=True, kde=True, color="gold",␣
↪label='B', ax=axes[0, 1])
axes[0][1].set_title("Pressure Comparison")
axes[0][1].set_xlabel("Pressure")

hist_th_a = WellData[WellData.TargetFormation == 'A']
sns.distplot(hist_th_a['TargetFormationThickness'], color="skyblue", label='A',␣
↪ax=axes[1, 0])
hist_th_b = WellData[WellData.TargetFormation == 'B']
sns.distplot(hist_th_b['TargetFormationThickness'], color="gold", label='B',␣
↪ax=axes[1, 0])
axes[1][0].set_title("Thickness Comparison")
```

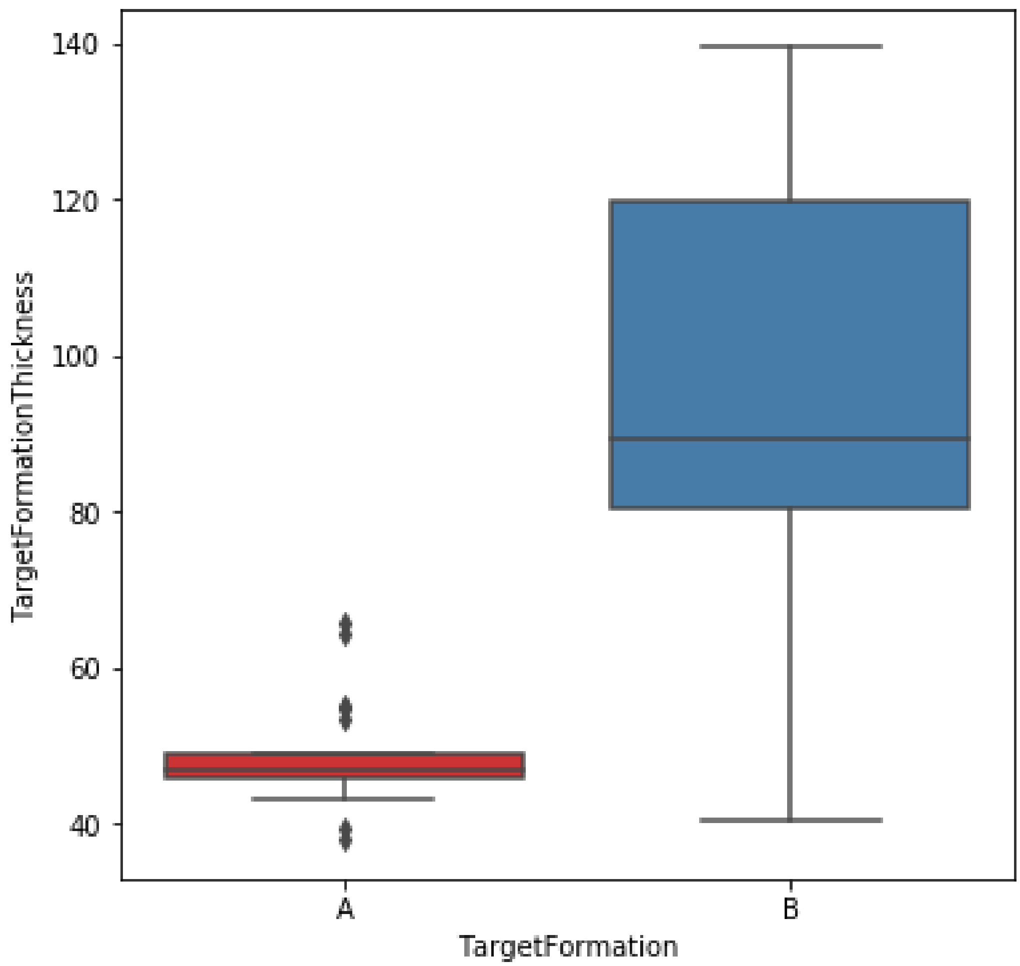
```
axes[1][0].set_xlabel("Thickness")

hist_sw_a = WellData[WellData.TargetFormation == 'A']
sns.distplot(hist_sw_a['SWT'], color="skyblue", label='A', ax=axes[1, 1])
hist_sw_b = WellData[WellData.TargetFormation == 'B']
sns.distplot(hist_sw_b['SWT'], color="gold", label='B', ax=axes[1, 1])
axes[1][1].set_title("Sw Comparison")
axes[1][1].set_xlabel("Sw")

line_labels = ["A", "B"]
f.legend(labels=line_labels, loc="lower center", borderaxespad=0.6,␣
↪title="Target Formation", fontsize=18, title_fontsize=20)
f.suptitle('Geological Parameters Comparison', fontsize=20, y = 0.93)
```

[474]:
```
Text(0.5, 0.93, 'Geological Parameters Comparison')
```




```
[477]: f, axes = plt.subplots(1, 1, figsize=(6, 6), sharex=False)
       sns.boxplot(x="TargetFormation", y="TargetFormationThickness", data=WellData,␣
        ↪palette="Set1")
```

```
[477]: <matplotlib.axes._subplots.AxesSubplot at 0x20d72d54c08>
```



4) Is there a significant difference in how formation `A` vs. formation `B` wells have been completed? Using `matplotlib` and/or `seaborn`, create a visual to summarize how main completions parameters (lateral length, injected fluid, injected proppant, average stage length) differ between formation `A`- and formation `B`-landed wells. There is a significant difference in how wells have been completed in Formation A vs. Formation B.

The following differences were observed:

```
* Lateral Length: Formation B presents longer lateral lengths for its wells compared to Format
* Injected Proppant and Fluid: Formation B presents higher volumes of injected Proppant and Fl
* Average Stage Length: Formation B presents shorter Stage Lengths compared to Formation A.
* Average Clusters Spacing: Formation B presents shorter Cluster Spacings compared to Formatio
* Average Clusters per Stage: Formation B presents mores Clusters per Stage compared to Formati
```

Please see below the details for average values and plots for Formation A and B.

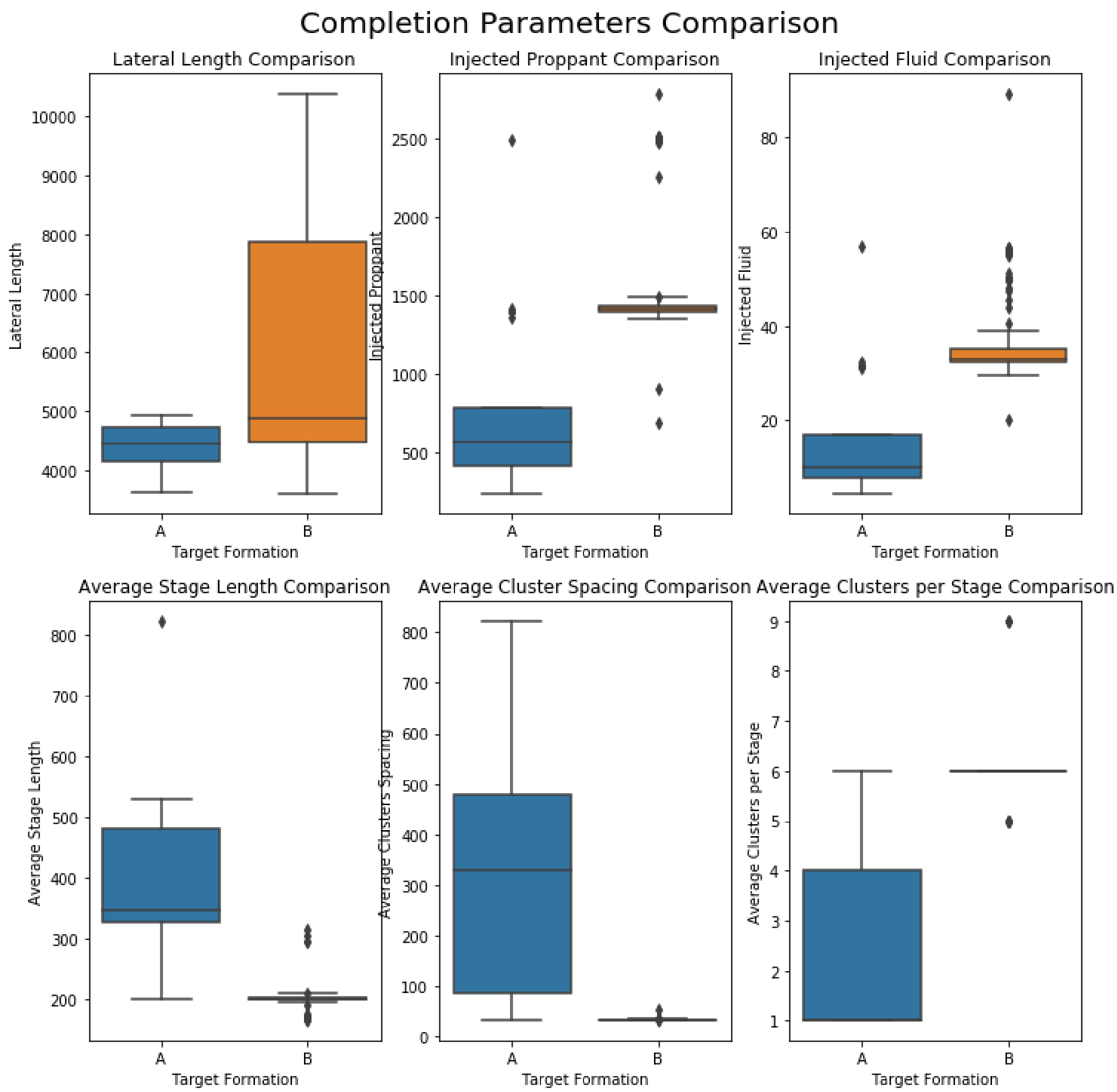
[168]:
```
WellGroups = WellData.groupby(['TargetFormation'])
WellGroups['LAT_LENGTH','Prop_ft','Fluid_ft','Avg_Stg_Len', 'Avg_Clust_Spc',␣
↪'Clusters_per_Stage'].mean()
```

[168]:
```
                 LAT_LENGTH      Prop_ft   Fluid_ft  Avg_Stg_Len  \
TargetFormation
A               4385.714286   774.637046  16.381845   387.919779
B               6130.095745  1526.288421  37.007634   203.651828

                 Avg_Clust_Spc  Clusters_per_Stage
TargetFormation
A                   299.198301            2.714286
B                    33.794418            6.021277
```

[478]:
```
# plot
f, axes = plt.subplots(2, 3, figsize=(12, 12), sharex=False)

sns.boxplot(x="TargetFormation", y="LAT_LENGTH", data=WellData, ax=axes[0, 0])
axes[0][0].set_title("Lateral Length Comparison")
axes[0][0].set_xlabel("Target Formation")
axes[0][0].set_ylabel("Lateral Length")

sns.boxplot(x="TargetFormation", y="Prop_ft", data=WellData, ax=axes[0, 1])
axes[0][1].set_title("Injected Proppant Comparison")
axes[0][1].set_xlabel("Target Formation")
axes[0][1].set_ylabel("Injected Proppant")

sns.boxplot(x="TargetFormation", y="Fluid_ft", data=WellData, ax=axes[0, 2])
axes[0][2].set_title("Injected Fluid Comparison")
axes[0][2].set_xlabel("Target Formation")
axes[0][2].set_ylabel("Injected Fluid")


sns.boxplot(x="TargetFormation", y="Avg_Stg_Len", data=WellData, ax=axes[1, 0])
axes[1][0].set_title("Average Stage Length Comparison")
axes[1][0].set_xlabel("Target Formation")
axes[1][0].set_ylabel("Average Stage Length")


sns.boxplot(x="TargetFormation", y="Avg_Clust_Spc", data=WellData, ax=axes[1,␣
↪1])
axes[1][1].set_title("Average Cluster Spacing Comparison")
axes[1][1].set_xlabel("Target Formation")
axes[1][1].set_ylabel("Average Clusters Spacing")
```

```
sns.boxplot(x="TargetFormation", y="Clusters_per_Stage", data=WellData,␣
↪ax=axes[1, 2])
axes[1][2].set_title("Average Clusters per Stage Comparison")
axes[1][2].set_xlabel("Target Formation")
axes[1][2].set_ylabel("Average Clusters per Stage")

f.suptitle('Completion Parameters Comparison', fontsize=20, y = 0.93)
```

[478]: Text(0.5, 0.93, 'Completion Parameters Comparison')



5) How does the production response vary between formation `A`- and formation `B`-landed wells? Create visualization as necessary. What do you think is causing the observed difference in production response from these two formations? Formation B exhibits more cumulative production than Formation A (41% more). This production response is related to both Reservoir Parameters and Completion Parameters.

```
* Reservoir Parameters: In terms of the information provided in WellData.csv, Formation B evide
* Completion Parameters: Several parameters were observed in Formation B that favor its Cumula

    - Lateral Length: Formation B Lateral Lengths are longer, which favors the well production
    - Injected Propant/Fluid: Formation B wells received higher volumes of proppant and fluid.
    - Average Stage Length: Formation B exhibits lower stage lengths, allowing more energy for
    - Cluster Spacing:
        + Formation A exhibits larger cluster spacings compared to Formation B.
        + For large spacings, the area between major fractures cannot be stimulated completely
        + Most likely, fractures in Formation A are not stimulated completely and cluster spaci
    - Clusters per Stage: Formation B consistently presents a higher value of clusters per stag
        + Most likely, Formation B presents a higher amount of fractures with larger SRVs.
```

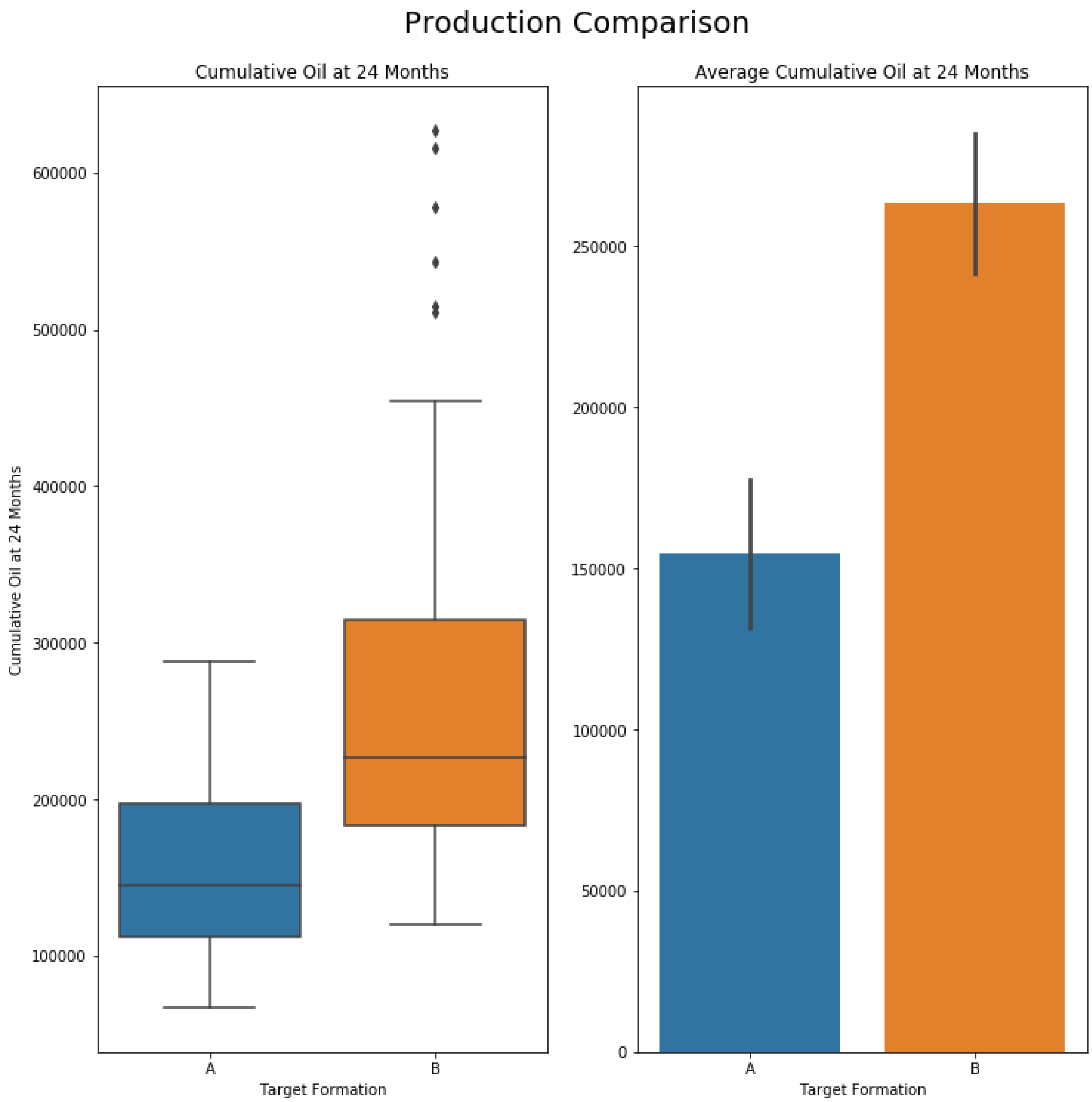
Please see below details of Cumulative Production averave and plots for Formation A and B.

[163]:
```python
WellGroups['CumOil_24Months'].mean()
```

[163]:
```
TargetFormation
A    154560.389025
B    263306.633845
Name: CumOil_24Months, dtype: float64
```

[493]:
```python
# plot
f, axes = plt.subplots(1, 2, figsize=(12, 12), sharex=False)

sns.boxplot(x="TargetFormation", y="CumOil_24Months", data=WellData, ax=axes[0])
axes[0].set_title("Cumulative Oil at 24 Months")
axes[0].set_xlabel("Target Formation")
axes[0].set_ylabel("Cumulative Oil at 24 Months")

#sns.boxplot(x="TargetFormation", y="Prop_ft", data=WellData, ax=axes[1])
sns.barplot(x="TargetFormation", y="CumOil_24Months", data=WellData, ax=axes[1])
axes[1].set_title("Average Cumulative Oil at 24 Months")
axes[1].set_xlabel("Target Formation")
axes[1].set_ylabel("")

f.suptitle('Production Comparison', fontsize=20, y = 0.94)
```

[493]:
```
Text(0.5, 0.94, 'Production Comparison')
```

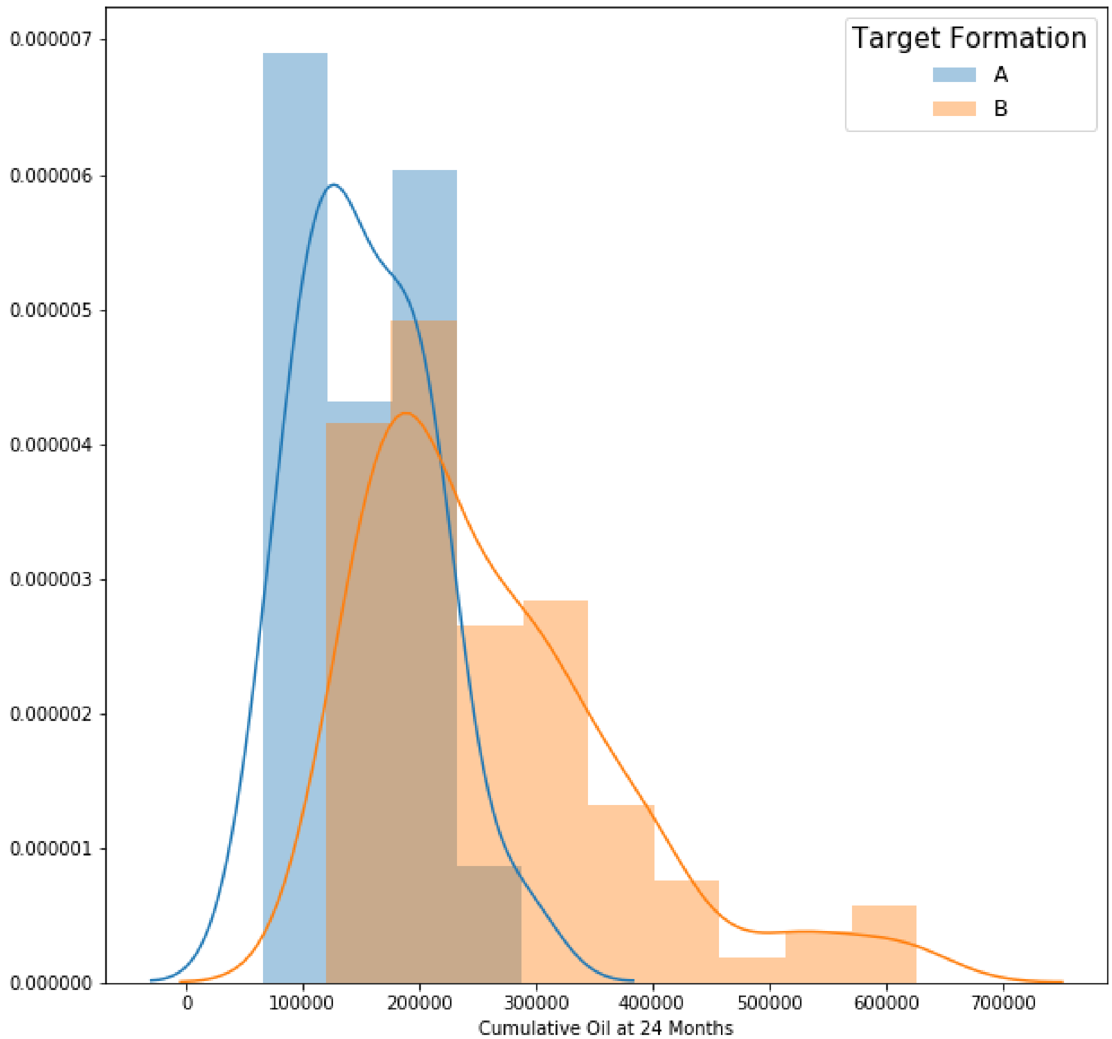


6) Perform a statistical test to determine if the observed difference in mean production response (between formations `A` and `B`) is statistically significant. First, it is necessary to determine wether the Production Response follows an approximate normal distribution for each formation:

[473]:
```
# plot
f, axes = plt.subplots(1, 1, figsize=(10, 10), sharex=False)

hist = WellData[WellData.TargetFormation == 'A']
sns.distplot(hist['CumOil_24Months'], label='A')
hist = WellData[WellData.TargetFormation == 'B']
```

```
sns.distplot(hist['CumOil_24Months'], label='B', axlabel='Cumulative Oil at 24␣
↪Months')


plt.legend(title="Target Formation", title_fontsize= 15, fontsize='larger')
```

[473]: <matplotlib.legend.Legend at 0x20d70663208>



Having verified this, we calculate the T-test for the means of two independent samples.

We will use the **ttest_ind** module from scipy.stats: * This is a two-sided test for the null hypothesis that 2 independent samples have identical average (expected) values. * This test assumes that the populations have identical variances by default.

We will select a p value of 5% or 0.05.

The results show that the Null Hypothesis is rejected and that the difference is statistically significant

[211]:
```
#from scipy import stats

CumOil_A = WellData[WellData['TargetFormation'] == 'A']['CumOil_24Months']
CumOil_B = WellData[WellData['TargetFormation'] == 'B']['CumOil_24Months']

# Calculate the T-test for the means of two independent samples of scores.
# t-tests are used when one or both of the groups have fewer than 30 members.
# This is a two-sided test for the null hypothesis that 2 independent samples␣
↪have identical average (expected) values.
# This test assumes that the populations have identical variances by default.
# p value: The two-tailed p-value.

t, p = stats.ttest_ind(CumOil_A,CumOil_B)
print("t = " + str(t))
print("p = " + str(p))

if p<0.05:
    print("Reject null hypothesis")
else:
    print("Accept null hypothesis")
```

```
t = -4.281592055934412
p = 3.910261959001755e-05
Reject null hypothesis
```

7) Using scikit-learn, divide the data into training and testing sets (75% training, 25% testing).

[293]:
```
WellData=WellData.drop(['COUNTER'], axis=1)
WellData
```

[293]:
```
          TargetFormation  TargetFormationThickness       BVW      PHIT  \
WellName
Well 1                  A                 48.099029  2.319936  0.080282
Well 2                  A                 47.661448  2.287712  0.079972
Well 3                  B                 87.939873  3.380522  0.096938
Well 4                  B                 88.051987  3.390739  0.097546
Well 5                  B                 88.040865  3.898508  0.101526
…                     …                        …         …         …
Well 111                B                 91.054007  3.476534  0.098800
Well 112                B                117.802525  4.230607  0.067927
Well 113                B                 85.416697  2.858090  0.089659
Well 114                A                 45.150803  2.542320  0.090833
Well 115                B                 48.812965  1.757787  0.104128
```

	PR	SWT	VCL	YM	PGRAD	P_Res	…
WellName							…
Well 1	0.080282	0.600788	0.147393	38.672344	0.845430	9470.505426	…
Well 2	0.079972	0.600198	0.145248	38.963685	0.846117	9475.665033	…
Well 3	0.218695	0.396555	0.231885	34.838832	0.837477	9651.080534	…
Well 4	0.219903	0.394770	0.229876	34.619501	0.837942	9665.658490	…
Well 5	0.219746	0.436152	0.257077	32.950645	0.846151	9774.742082	…
…	…	…	…	…	…	…	…
Well 111	0.228029	0.386448	0.234235	34.302323	0.834730	9428.276073	…
Well 112	0.192165	0.528692	0.182282	46.592040	0.705602	7261.350625	…
Well 113	0.200040	0.373199	0.244244	35.611307	0.848498	9822.209526	…
Well 114	0.090833	0.619899	0.180936	39.084307	0.848514	9662.027483	…
Well 115	0.194399	0.345829	0.230363	33.131378	0.848506	9915.645113	…

	3D_Spacing	LAT_LENGTH	PPG	Prop_ft	Fluid_ft
WellName					
Well 1	1123.998119	4579	1.236471	390.265123	7.514960
Well 2	1273.997571	4625	1.181445	391.161081	7.883027
Well 3	834.240524	4036	0.709314	1434.960357	48.167245
Well 4	1180.581605	4141	0.730231	1391.224342	45.361507
Well 5	822.702861	4472	0.690833	1488.193202	51.290474
…	…	…	…	…	…
Well 111	1087.282417	4875	0.972418	1440.480000	35.269949
Well 112	1400.000000	4095	0.948113	1449.098901	36.390535
Well 113	1400.000000	4833	0.972172	1404.961722	34.409019
Well 114	424.760334	4800	1.040158	2486.583333	56.918613
Well 115	526.938307	4800	1.054747	2493.135417	56.279267

	Avg_Stg_Len	Avg_Clust_Spc	Clusters_per_Stage	Rate_per_cluster
WellName				
Well 1	508.777778	508.777778	1	48.780000
Well 2	513.888889	513.888889	1	49.780000
Well 3	168.166667	33.633333	5	17.580833
Well 4	295.785714	32.865079	9	11.073016
Well 5	165.629630	32.172662	5	17.888148
…	…	…	…	…
Well 111	195.000000	32.500000	6	8.347200
Well 112	195.000000	32.500000	6	8.747619
Well 113	201.375000	33.562500	6	9.570833
Well 114	200.000000	33.333333	6	10.000000
Well 115	200.000000	33.333333	6	9.833333

	CumOil_24Months
WellName	
Well 1	85767.71658
Well 2	165623.71340
Well 3	194886.78360

```
Well 4       172405.75800
Well 5       207418.55400
…                  …
Well 111     166501.82300
Well 112     149973.75810
Well 113     280928.83440
Well 114     287423.95940
Well 115     193090.72260

[115 rows x 21 columns]
```

[294]:

```python
import sklearn as sk
#from sklearn.model_selection import train_test_split

x = WellData.drop(['CumOil_24Months'], axis=1)
y = WellData.CumOil_24Months

x_train, x_test, y_train, y_test = train_test_split(x, y,test_size=0.25)
print("\nx_train:\n")
print(x_train.head())
print(x_train.shape)

print("\nx_test:\n")
print(x_test.head())
print(x_test.shape)
```

```
x_train:

         TargetFormation  TargetFormationThickness       BVW      PHIT  \
WellName
Well 59                B                127.386360  4.301639  0.075717
Well 66                B                 97.582009  3.240405  0.093692
Well 87                B                 82.869652  3.406000  0.095202
Well 35                B                 83.337339  3.382836  0.093640
Well 113               B                 85.416697  2.858090  0.089659

                PR       SWT       VCL         YM     PGRAD        P_Res  \
WellName
Well 59   0.201597  0.445981  0.191612  47.262512  0.615320  6055.359682
Well 66   0.203521  0.354425  0.221820  41.683697  0.767584  8398.901951
Well 87   0.189237  0.431720  0.228748  36.828458  0.844870  9786.126233
Well 35   0.188690  0.433493  0.236519  37.069167  0.844239  9824.410558
Well 113  0.200040  0.373199  0.244244  35.611307  0.848498  9822.209526

                  GOR  3D_Spacing  LAT_LENGTH        PPG      Prop_ft  \
WellName
```

```
Well 59   6296.881247  1400.000000        6971  1.069861  2505.872902
Well 66   2533.917391   406.983093        8992  1.059646  1432.693505
Well 87   1638.863638   599.997949        7551  1.074668  1433.595550
Well 35   1689.832685  1400.000000        4863  1.042196  1408.213037
Well 113  1446.207436  1400.000000        4833  0.972172  1404.961722

           Fluid_ft  Avg_Stg_Len  Avg_Clust_Spc  Clusters_per_Stage  \
WellName
Well 59   55.767660   199.171429      33.195238                   6
Well 66   32.191634   199.822222      33.303704                   6
Well 87   31.761637   198.710526      33.118421                   6
Well 35   32.171386   202.625000      33.770833                   6
Well 113  34.409019   201.375000      33.562500                   6

          Rate_per_cluster
WellName
Well 59          10.166667
Well 66          10.166667
Well 87          10.166667
Well 35           8.833333
Well 113          9.570833
(86, 20)

x_test:

         TargetFormation  TargetFormationThickness       BVW      PHIT  \
WellName
Well 17                B                135.827778  3.902390  0.075160
Well 81                B                 70.112376  2.334124  0.089834
Well 16                B                135.832981  3.903333  0.075170
Well 2                 A                 47.661448  2.287712  0.079972
Well 89                A                 38.123147  2.079783  0.093650

                PR       SWT       VCL         YM     PGRAD        P_Res  \
WellName
Well 17   0.183370  0.382258  0.224776  43.852663  0.757299  7916.044712
Well 81   0.192017  0.370586  0.248182  38.233971  0.847893  9834.715361
Well 16   0.183384  0.382285  0.224678  43.855391  0.757346  7924.112108
Well 2    0.079972  0.600198  0.145248  38.963685  0.846117  9475.665033
Well 89   0.093650  0.582535  0.108778  44.758233  0.761176  7999.202935

                  GOR   3D_Spacing  LAT_LENGTH       PPG      Prop_ft  \
WellName
Well 17   4090.483270   869.388712        4379  1.085306  2498.839918
Well 81   1482.366658   424.018287        7074  1.033756  1427.027142
Well 16   4090.418197   873.487663        4385  1.083061  2504.944128
Well 2    1491.233642  1273.997571        4625  1.181445   391.161081
Well 89   2537.687521   766.289530        3922  1.041382  1392.554819
```

```
          Fluid_ft  Avg_Stg_Len  Avg_Clust_Spc  Clusters_per_Stage  \
WellName
Well 17   54.819758   199.045455      33.174242                   6
Well 81   32.867381   202.114286      33.685714                   6
Well 16   55.067585   199.318182      33.219697                   6
Well 2     7.883027   513.888889     513.888889                   1
Well 89   31.838511   206.421053      34.403509                   6

          Rate_per_cluster
WellName
Well 17          10.166667
Well 81          10.000000
Well 16          10.000000
Well 2           49.780000
Well 89          10.166667
(29, 20)
```

8) Using `scikit-learn`, train a `multiple linear regression` model for `CumOil_24Months` using all the geologic and completions parameters as your explanatory variables. Test the model, plot the results, and summarize relative statistics.

[297]:
```
# Checking columns with NaN values
WellData.isnull().any()
```

[297]:
```
TargetFormation             False
TargetFormationThickness    False
BVW                         False
PHIT                        False
PR                          False
SWT                         False
VCL                         False
YM                          False
PGRAD                       False
P_Res                       False
GOR                         False
3D_Spacing                  False
LAT_LENGTH                  False
PPG                         False
Prop_ft                     False
Fluid_ft                    False
Avg_Stg_Len                 False
Avg_Clust_Spc               False
Clusters_per_Stage          False
Rate_per_cluster            False
CumOil_24Months             False
dtype: bool
```

[307]:
```
# Converting data from 'TargerFormation' (Categorical Variables) to Binary␣
↪Variables.
WellData_LReg=pd.get_dummies(WellData)
WellData_LReg
```

[307]:
```
             TargetFormationThickness       BVW      PHIT        PR       SWT  \
WellName
Well 1                      48.099029  2.319936  0.080282  0.080282  0.600788
Well 2                      47.661448  2.287712  0.079972  0.079972  0.600198
Well 3                      87.939873  3.380522  0.096938  0.218695  0.396555
Well 4                      88.051987  3.390739  0.097546  0.219903  0.394770
Well 5                      88.040865  3.898508  0.101526  0.219746  0.436152
…                                 …         …         …         …         …
Well 111                    91.054007  3.476534  0.098800  0.228029  0.386448
Well 112                   117.802525  4.230607  0.067927  0.192165  0.528692
Well 113                    85.416697  2.858090  0.089659  0.200040  0.373199
Well 114                    45.150803  2.542320  0.090833  0.090833  0.619899
Well 115                    48.812965  1.757787  0.104128  0.194399  0.345829

                VCL         YM     PGRAD        P_Res          GOR  …  \
WellName                                                           …
Well 1     0.147393  38.672344  0.845430  9470.505426  1468.748419  …
Well 2     0.145248  38.963685  0.846117  9475.665033  1491.233642  …
Well 3     0.231885  34.838832  0.837477  9651.080534  1548.827181  …
Well 4     0.229876  34.619501  0.837942  9665.658490  1503.367385  …
Well 5     0.257077  32.950645  0.846151  9774.742082  1500.119838  …
…               …          …         …            …            …  …
Well 111   0.234235  34.302323  0.834730  9428.276073  1437.805232  …
Well 112   0.182282  46.592040  0.705602  7261.350625  4890.431130  …
Well 113   0.244244  35.611307  0.848498  9822.209526  1446.207436  …
Well 114   0.180936  39.084307  0.848514  9662.027483  1445.604822  …
Well 115   0.230363  33.131378  0.848506  9915.645113  1445.885001  …

                PPG      Prop_ft    Fluid_ft  Avg_Stg_Len  Avg_Clust_Spc  \
WellName
Well 1     1.236471   390.265123   7.514960   508.777778     508.777778
Well 2     1.181445   391.161081   7.883027   513.888889     513.888889
Well 3     0.709314  1434.960357  48.167245   168.166667      33.633333
Well 4     0.730231  1391.224342  45.361507   295.785714      32.865079
Well 5     0.690833  1488.193202  51.290474   165.629630      32.172662
…               …            …          …            …              …
Well 111   0.972418  1440.480000  35.269949   195.000000      32.500000
Well 112   0.948113  1449.098901  36.390535   195.000000      32.500000
Well 113   0.972172  1404.961722  34.409019   201.375000      33.562500
Well 114   1.040158  2486.583333  56.918613   200.000000      33.333333
Well 115   1.054747  2493.135417  56.279267   200.000000      33.333333
```

```
          Clusters_per_Stage  Rate_per_cluster  CumOil_24Months  \
WellName
Well 1                     1         48.780000      85767.71658
Well 2                     1         49.780000     165623.71340
Well 3                     5         17.580833     194886.78360
Well 4                     9         11.073016     172405.75800
Well 5                     5         17.888148     207418.55400
…                        …               …               …
Well 111                   6          8.347200     166501.82300
Well 112                   6          8.747619     149973.75810
Well 113                   6          9.570833     280928.83440
Well 114                   6         10.000000     287423.95940
Well 115                   6          9.833333     193090.72260

          TargetFormation_A  TargetFormation_B
WellName
Well 1                    1                  0
Well 2                    1                  0
Well 3                    0                  1
Well 4                    0                  1
Well 5                    0                  1
…                       …                  …
Well 111                  0                  1
Well 112                  0                  1
Well 113                  0                  1
Well 114                  1                  0
Well 115                  0                  1

[115 rows x 22 columns]
```

[308]:

```
# To avoid collinearity, we have to drop one of the dummy columns.
# Drop TargetFormation_B column.
WellData_LReg.drop('TargetFormation_B',axis=1,inplace=True)

# Rename TargetFormation_A column.
WellData_LReg.rename(columns={'TargetFormation_A':'TargetFormation'},␣
 ↪inplace=True)

# dataframe first 5 columns.
WellData_LReg.head()
```

[308]:

```
          TargetFormationThickness       BVW      PHIT        PR       SWT  \
WellName
Well 1                   48.099029  2.319936  0.080282  0.080282  0.600788
Well 2                   47.661448  2.287712  0.079972  0.079972  0.600198
Well 3                   87.939873  3.380522  0.096938  0.218695  0.396555
Well 4                   88.051987  3.390739  0.097546  0.219903  0.394770
```

```
Well 5                   88.040865  3.898508  0.101526  0.219746  0.436152

               VCL         YM     PGRAD        P_Res          GOR  …  \
WellName                                                          …
Well 1    0.147393  38.672344  0.845430  9470.505426  1468.748419  …
Well 2    0.145248  38.963685  0.846117  9475.665033  1491.233642  …
Well 3    0.231885  34.838832  0.837477  9651.080534  1548.827181  …
Well 4    0.229876  34.619501  0.837942  9665.658490  1503.367385  …
Well 5    0.257077  32.950645  0.846151  9774.742082  1500.119838  …

          LAT_LENGTH       PPG      Prop_ft   Fluid_ft  Avg_Stg_Len  \
WellName
Well 1          4579  1.236471   390.265123   7.514960   508.777778
Well 2          4625  1.181445   391.161081   7.883027   513.888889
Well 3          4036  0.709314  1434.960357  48.167245   168.166667
Well 4          4141  0.730231  1391.224342  45.361507   295.785714
Well 5          4472  0.690833  1488.193202  51.290474   165.629630

          Avg_Clust_Spc  Clusters_per_Stage  Rate_per_cluster  \
WellName
Well 1       508.777778                   1         48.780000
Well 2       513.888889                   1         49.780000
Well 3        33.633333                   5         17.580833
Well 4        32.865079                   9         11.073016
Well 5        32.172662                   5         17.888148

          CumOil_24Months  TargetFormation
WellName
Well 1        85767.71658                1
Well 2       165623.71340                1
Well 3       194886.78360                0
Well 4       172405.75800                0
Well 5       207418.55400                0

[5 rows x 21 columns]
```

[315]:

```python
# Now we proceed to create the variables and train the Multiple Linear
 ↪Regression Model
x = WellData_LReg.drop('CumOil_24Months', axis=1)
y = WellData_LReg.CumOil_24Months

x_train, x_test, y_train, y_test = train_test_split(x, y,test_size=0.25)

mlr = LinearRegression()
mlr.fit(x_train, y_train)
```

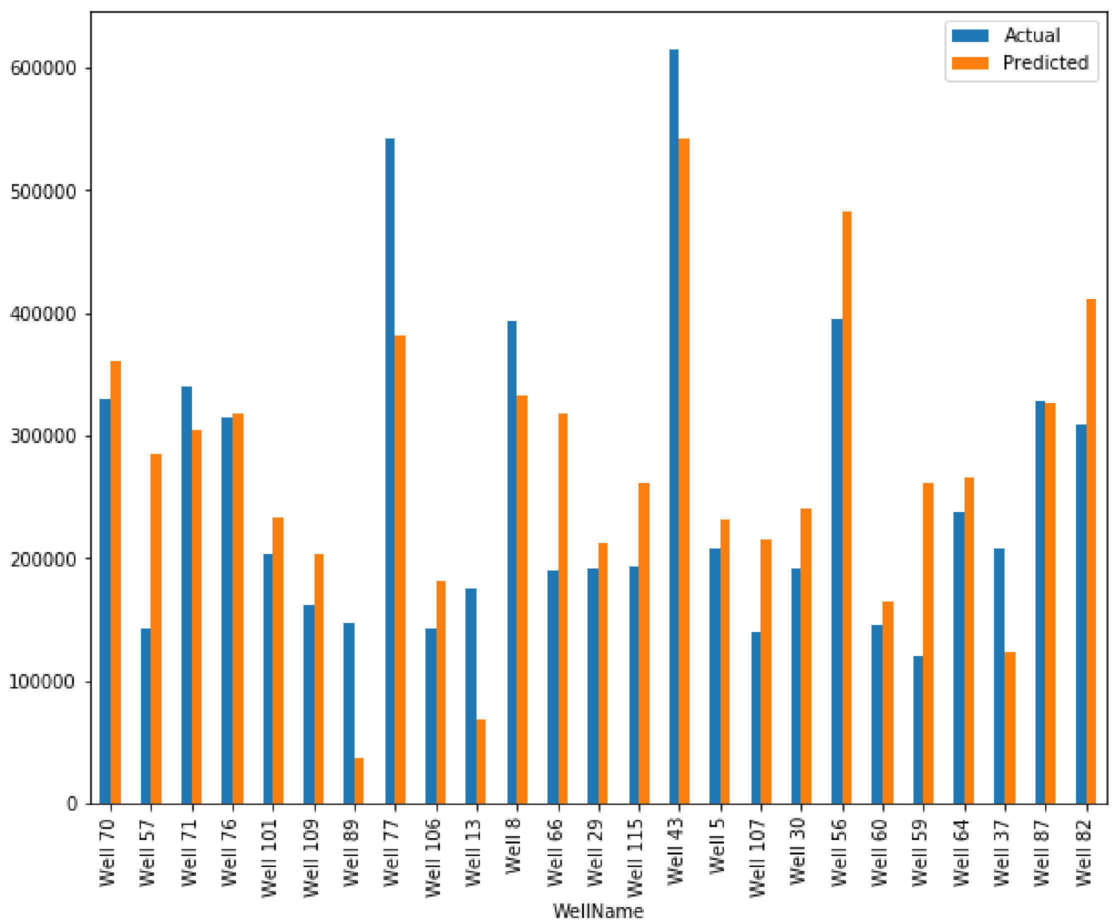
[315]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[335]:
```python
print(mlr.coef_)
print(mlr.intercept_)
```

```
[-3.98101096e+03  1.27470775e+05 -6.63480676e+06 -8.63497830e+05
 -8.31491175e+05  6.99395878e+05  5.35557259e+03  7.76958576e+05
 -1.82032178e+01 -2.80602701e+01  1.33690342e+01  3.44866785e+01
  4.61366389e+04  5.15006131e+01  2.32383441e+03  3.86354651e+02
 -3.77901710e+02 -8.08873339e+03  1.00652746e+03 -4.37283392e+04]
95383.60747694972
```

[390]:
```python
# Plot the results
y_pred = mlr.predict(x_test)

Comparison = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
Comparison1 = Comparison.head(25)

Comparison1.plot(kind='bar',figsize=(10,8))
plt.show()
```



[359]:
```python
# Summarize relative statistics
# This score is the R squared of our model

mlr.score(x,y)
```

[359]: 0.6398415816562699

[370]:
```python
WellData_LReg.corr()
```

[370]:

```
                          TargetFormationThickness       BVW      PHIT  \
TargetFormationThickness                  1.000000  0.857824 -0.290272
BVW                                       0.857824  1.000000 -0.255826
PHIT                                     -0.290272 -0.255826  1.000000
PR                                        0.602774  0.370434  0.169797
SWT                                      -0.394183  0.021734 -0.402812
VCL                                       0.079140 -0.040355  0.313720
YM                                        0.468060  0.390150 -0.763772
PGRAD                                    -0.306447 -0.134622  0.421525
P_Res                                    -0.167979 -0.042748  0.412136
GOR                                       0.534763  0.365038 -0.493668
3D_Spacing                               -0.037044 -0.055354 -0.053598
LAT_LENGTH                                0.359981  0.138274 -0.026923
PPG                                      -0.256499 -0.176092 -0.273536
Prop_ft                                   0.503176  0.317514 -0.083463
Fluid_ft                                  0.481788  0.318907  0.035042
Avg_Stg_Len                              -0.450055 -0.277040 -0.073043
Avg_Clust_Spc                            -0.450943 -0.271110 -0.084687
Clusters_per_Stage                        0.486282  0.281411  0.102773
Rate_per_cluster                         -0.471192 -0.286402 -0.061836
CumOil_24Months                           0.353170  0.218873 -0.135013
TargetFormation                          -0.610194 -0.316331 -0.141273

                                PR       SWT       VCL        YM     PGRAD  \
TargetFormationThickness  0.602774 -0.394183  0.079140  0.468060 -0.306447
BVW                       0.370434  0.021734 -0.040355  0.390150 -0.134622
PHIT                      0.169797 -0.402812  0.313720 -0.763772  0.421525
PR                        1.000000 -0.778769  0.612500 -0.024953 -0.177776
SWT                      -0.778769  1.000000 -0.515960  0.186085  0.127049
VCL                       0.612500 -0.515960  1.000000 -0.384293  0.201684
YM                       -0.024953  0.186085 -0.384293  1.000000 -0.565810
PGRAD                    -0.177776  0.127049  0.201684 -0.565810  1.000000
P_Res                     0.034848 -0.018156  0.312851 -0.506850  0.895238
GOR                       0.239878 -0.134162 -0.241417  0.684387 -0.825115
3D_Spacing                0.007373 -0.023877  0.175851 -0.018345 -0.073799
LAT_LENGTH                0.306685 -0.405835  0.058941  0.263211 -0.112227
PPG                      -0.554125  0.430732 -0.381356  0.235529  0.002689
Prop_ft                   0.563283 -0.416370  0.233816  0.208975 -0.315233
```

```
Fluid_ft                   0.616888 -0.459278  0.294122  0.065350 -0.231946
Avg_Stg_Len               -0.706856  0.529906 -0.406293 -0.061026  0.211115
Avg_Clust_Spc             -0.697769  0.532442 -0.400802 -0.048768  0.202130
Clusters_per_Stage         0.741235 -0.587585  0.414514  0.061215 -0.199773
Rate_per_cluster          -0.698817  0.528239 -0.397627 -0.080563  0.205255
CumOil_24Months            0.356846 -0.279589  0.265382  0.209488  0.097847
TargetFormation           -0.966686  0.836568 -0.599549 -0.001424  0.239258

                              P_Res       GOR  …  LAT_LENGTH       PPG  \
TargetFormationThickness -0.167979  0.534763  …    0.359981 -0.256499
BVW                       -0.042748  0.365038  …    0.138274 -0.176092
PHIT                       0.412136 -0.493668  …   -0.026923 -0.273536
PR                         0.034848  0.239878  …    0.306685 -0.554125
SWT                       -0.018156 -0.134162  …   -0.405835  0.430732
VCL                        0.312851 -0.241417  …    0.058941 -0.381356
YM                        -0.506850  0.684387  …    0.263211  0.235529
PGRAD                      0.895238 -0.825115  …   -0.112227  0.002689
P_Res                      1.000000 -0.773709  …   -0.018632 -0.158405
GOR                       -0.773709  1.000000  …    0.198634 -0.014322
3D_Spacing                -0.051036  0.023338  …   -0.150609  0.082334
LAT_LENGTH                -0.018632  0.198634  …    1.000000 -0.009744
PPG                       -0.158405 -0.014322  …   -0.009744  1.000000
Prop_ft                   -0.135085  0.360630  …    0.267443 -0.280220
Fluid_ft                  -0.037666  0.278388  …    0.202187 -0.616211
Avg_Stg_Len               -0.019082 -0.206641  …   -0.248637  0.479925
Avg_Clust_Spc             -0.030654 -0.224841  …   -0.265974  0.543433
Clusters_per_Stage         0.021934  0.280513  …    0.275012 -0.610778
Rate_per_cluster          -0.024202 -0.242593  …   -0.301125  0.513912
CumOil_24Months            0.226213 -0.025537  …    0.616531 -0.143675
TargetFormation            0.016803 -0.294095  …   -0.350081  0.527877

                            Prop_ft  Fluid_ft  Avg_Stg_Len  Avg_Clust_Spc  \
TargetFormationThickness  0.503176  0.481788    -0.450055      -0.450943
BVW                        0.317514  0.318907    -0.277040      -0.271110
PHIT                      -0.083463  0.035042    -0.073043      -0.084687
PR                         0.563283  0.616888    -0.706856      -0.697769
SWT                       -0.416370 -0.459278     0.529906       0.532442
VCL                        0.233816  0.294122    -0.406293      -0.400802
YM                         0.208975  0.065350    -0.061026      -0.048768
PGRAD                     -0.315233 -0.231946     0.211115       0.202130
P_Res                     -0.135085 -0.037666    -0.019082      -0.030654
GOR                        0.360630  0.278388    -0.206641      -0.224841
3D_Spacing                -0.155175 -0.157518     0.144338       0.173399
LAT_LENGTH                 0.267443  0.202187    -0.248637      -0.265974
PPG                       -0.280220 -0.616211     0.479925       0.543433
Prop_ft                    1.000000  0.902838    -0.685099      -0.664034
Fluid_ft                   0.902838  1.000000    -0.677695      -0.666101
```

```
Avg_Stg_Len              -0.685099 -0.677695     1.000000       0.946486
Avg_Clust_Spc            -0.664034 -0.666101     0.946486       1.000000
Clusters_per_Stage        0.637985  0.661428    -0.776266      -0.889317
Rate_per_cluster         -0.661790 -0.633123     0.841054       0.951022
CumOil_24Months           0.445139  0.415044    -0.373362      -0.357587
TargetFormation          -0.584519 -0.614910     0.731414       0.724938

                          Clusters_per_Stage  Rate_per_cluster  \
TargetFormationThickness            0.486282         -0.471192
BVW                                 0.281411         -0.286402
PHIT                                0.102773         -0.061836
PR                                  0.741235         -0.698817
SWT                                -0.587585          0.528239
VCL                                 0.414514         -0.397627
YM                                  0.061215         -0.080563
PGRAD                              -0.199773          0.205255
P_Res                               0.021934         -0.024202
GOR                                 0.280513         -0.242593
3D_Spacing                         -0.127872          0.182348
LAT_LENGTH                          0.275012         -0.301125
PPG                                -0.610778          0.513912
Prop_ft                             0.637985         -0.661790
Fluid_ft                            0.661428         -0.633123
Avg_Stg_Len                        -0.776266          0.841054
Avg_Clust_Spc                      -0.889317          0.951022
Clusters_per_Stage                  1.000000         -0.929186
Rate_per_cluster                   -0.929186          1.000000
CumOil_24Months                     0.332024         -0.369662
TargetFormation                    -0.770793          0.728925

                          CumOil_24Months  TargetFormation
TargetFormationThickness         0.353170        -0.610194
BVW                              0.218873        -0.316331
PHIT                            -0.135013        -0.141273
PR                               0.356846        -0.966686
SWT                             -0.279589         0.836568
VCL                              0.265382        -0.599549
YM                               0.209488        -0.001424
PGRAD                            0.097847         0.239258
P_Res                            0.226213         0.016803
GOR                             -0.025537        -0.294095
3D_Spacing                      -0.112217        -0.004037
LAT_LENGTH                       0.616531        -0.350081
PPG                             -0.143675         0.527877
Prop_ft                          0.445139        -0.584519
Fluid_ft                         0.415044        -0.614910
Avg_Stg_Len                     -0.373362         0.731414
```

```
Avg_Clust_Spc                      -0.357587         0.724938
Clusters_per_Stage                  0.332024        -0.770793
Rate_per_cluster                   -0.369662         0.728925
CumOil_24Months                     1.000000        -0.373611
TargetFormation                    -0.373611         1.000000

[21 rows x 21 columns]
```

9) Is it a good practice to include all features in the model? Explain how model complexity may impact in-sample and out-of-sample accuracy? This may not be necessarily is a good practice. Simplicity and theoretical foundations needs to be combined.

- When several models with similar predictive power are available, it is better to choose the simplest model. This is because simplification usually produces more precise models.
- In addition, the foundations of the model selection process should depend largely on theoretical concerns. Theory supports the collection of the right data and also benefits the best regression.

A good approach is to start simple and the add complexity only when it is actually needed. As complexity increases, the in-sample accuracy increases since the model is likely to be tailored for the particular dataset. However, the out-of-sample accuracy may be affected negatively since overfitting reduces generalizability, generating unreliable results instead of actual relationships in the population.

10) What would be your strategy for building the `best parsimonious model`? How would you choose the most important features? Parsimonious models explain data with a minimum number of independent variables. While working with multiple linear regression models, finding the right balance between parsimony and goodness of fit can be challenging.

There are statistical parameters able to help selecting variables to Include or exclude in the regression:

- R-squared:
  - When R-squared is less than 0.8, generally the match is not good. However, there may still be redundant variables when R-squared is above 0.8
  - This parameter tends to rise as more variables are added, even if they have no significant contribution.
- Adjusted R-squared: penalizes R-squared values that include non-useful predictors.
  - If it is much less than R-squared, it is a sign that a variable might be unnecessary.
  - Monitor changes when including or excluding variables in the regression model.
- F-statistic: suggests the strength of the entire model. If some of the predictors are correlated, F-tests can come out significant.
- T-test: looks at the relationship between the target variable, and every predictor variable, independently.
  - In this case, the p-value for each variable needs to be checked.
  - The null hypothesis is rejected when the p-value is small
- Multicollinearity: check high correlation between two variables such that the two variables contribute redundant information to the model.

Finally, there are variable selection methods to help choose which variables to include in multiple regressions:

- Backward elimination: all independent variables begin in the model and subsequent variables are eliminated.
- Forward selection: one independent variable is added at a time that increases the R2 value.
- Stepwise selection: a combination of the previous mentioned methods.

11) Using `scikit-learn`, perform principal coordinates analysis of the geologic features. Plot the resulting PC1 and PC2 as a scatter plot and color the points based on `TargetFormation`.

[466]:
```
from sklearn.decomposition import PCA

# PCA is affected by scale so you need to scale the features in your data␣
↪before applying PCA.
# The principal components are supplied with normalized version of original␣
↪predictors.
# This is because, the original predictors may have different scales
# from sklearn.preprocessing import StandardScaler

# Geologic parameters: porosity, saturation, thickness, pressure
# Target: TargetFormation

# Separating out the features
#x = WellData.loc[:, features].values
x = WellData[['PHIT', 'SWT', 'TargetFormationThickness', 'P_Res']]

# Separating out the target
y = WellData[['TargetFormation']]

## Standardizing the features
x = StandardScaler().fit_transform(x)

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents, columns = ['PC1', 'PC2'])
principalDf
```

[466]:

	PC1	PC2
0	0.266810	2.066143
1	0.281039	2.076178
2	-1.233661	-0.410609
3	-1.291819	-0.430253
4	-1.544611	-0.173551
..	…	…
110	-1.238990	-0.602643
111	3.026321	-0.182717

```
112 -0.872862 -0.409833
113 -0.622018  2.173910
114 -2.478622  0.084722

[115 rows x 2 columns]
```

[468]:

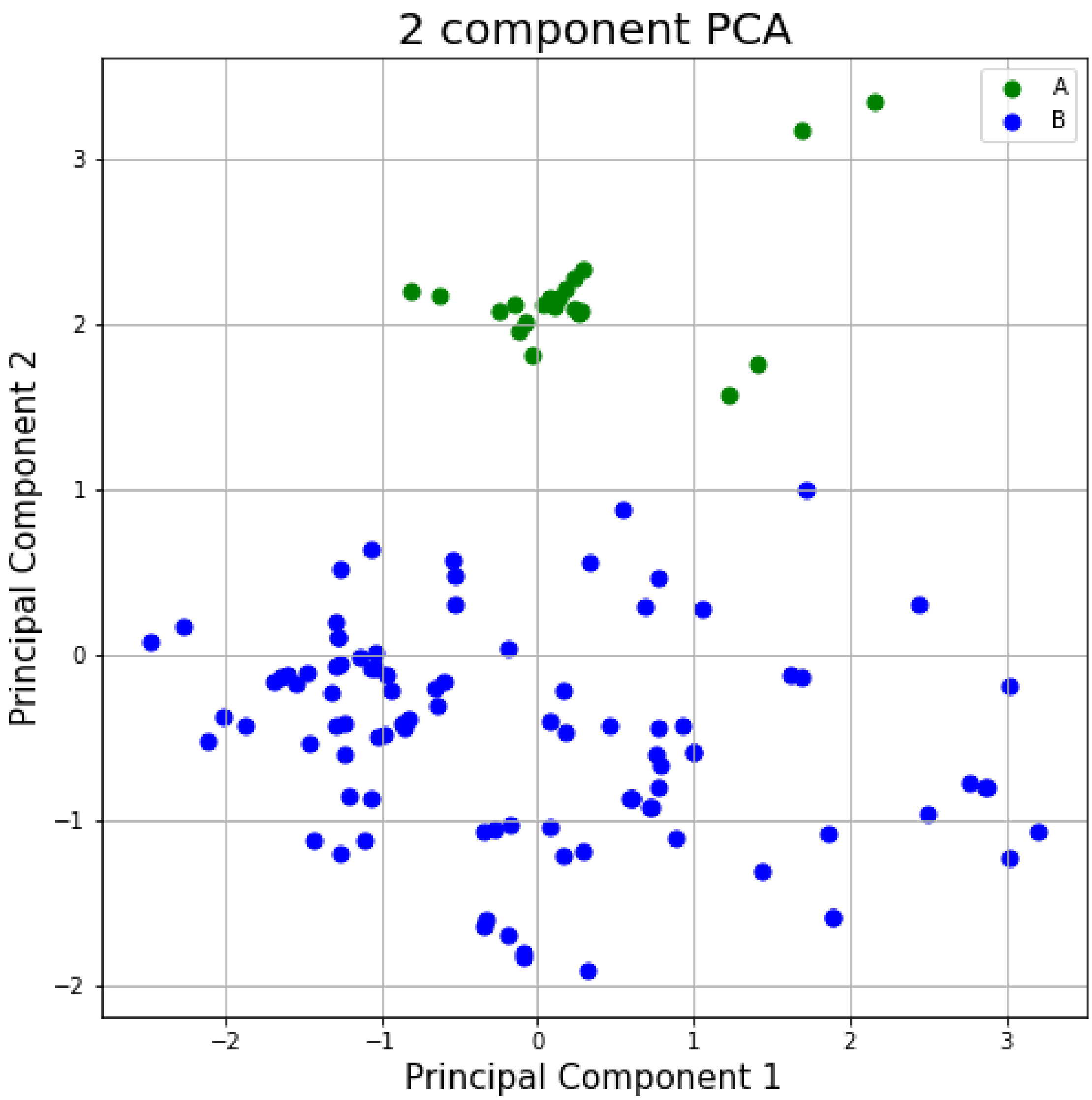
```
# We need to reset the index in order to create a new dataframe by␣
↪concatenating the Target Formation and the PCs
WellData_resetindex = WellData.reset_index()
WellData_resetindex[['TargetFormation']]

finalDf = pd.concat([principalDf, WellData_resetindex[['TargetFormation']]],␣
↪axis = 1)
finalDf
```

[468]:

```
          PC1       PC2 TargetFormation
0    0.266810  2.066143               A
1    0.281039  2.076178               A
2   -1.233661 -0.410609               B
3   -1.291819 -0.430253               B
4   -1.544611 -0.173551               B
..        …         …             …
110 -1.238990 -0.602643               B
111  3.026321 -0.182717               B
112 -0.872862 -0.409833               B
113 -0.622018  2.173910               A
114 -2.478622  0.084722               B

[115 rows x 3 columns]
```

[469]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
targets = ['A', 'B']
colors = ['g', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['TargetFormation'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'PC1'], finalDf.loc[indicesToKeep,␣
↪'PC2'], c = color, s = 50)
ax.legend(targets)
ax.grid()
```

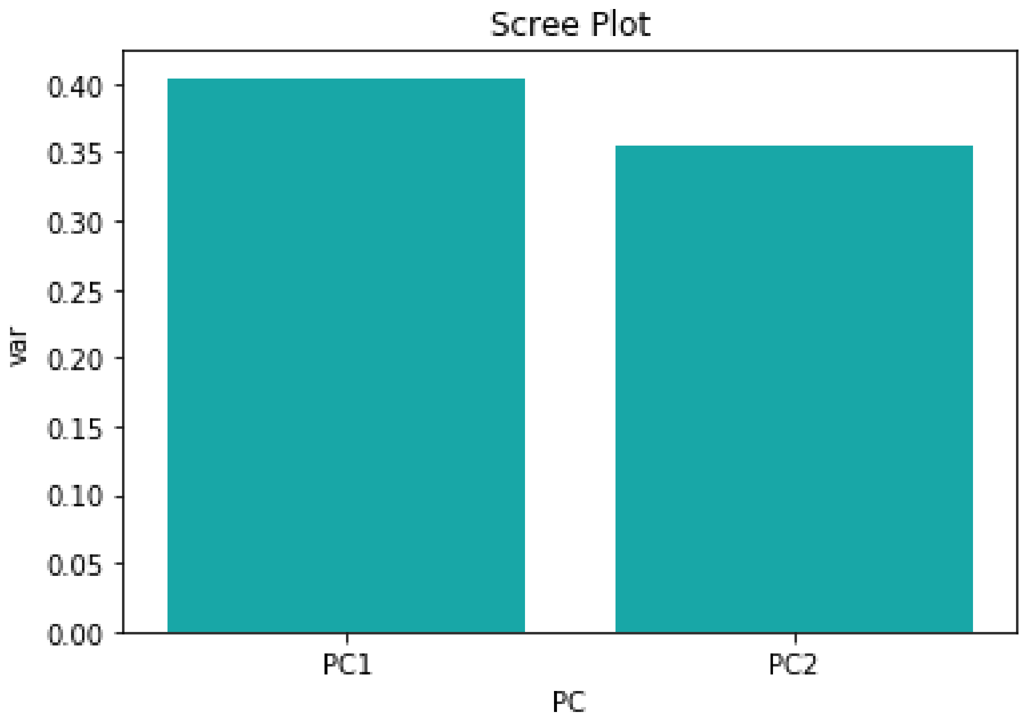


[470]:
```
pca.explained_variance_ratio_
```

[470]: array([0.40402517, 0.35425437])

[472]:
```
ScreeDf = pd.DataFrame({'var':pca.explained_variance_ratio_,
             'PC':['PC1','PC2']})
sns.barplot(x='PC',y="var", data=ScreeDf, color="c")
plt.title('Scree Plot')
```

[472]: Text(0.5, 1.0, 'Scree Plot')



12) Is PCA successful in unsupervised clustering of wells into formation `A` vs. formation `B` wells? If yes, which principal component separates formation A from Formation B wells?

- For this particular exercise, the PCA was successful in clustering of Wells into Formation A vs. Formation B.
  - The principal components correspond to the directions of maximum variability. However, it is important to mention that they do not guarantee maximum discrimination or separation between classes.
- For this exercise, PC2 separates formation A from Formation B wells. PC1 accounts for almost all the variance, but has no discriminatory power.

0.2.3 Part 3)

1) Read the following data files for a given well:

- `WellLogs.csv` which includes petro-physical well logs. Each zone (formation) is identified with a label.
- `Formations.csv` which includes top and bottom MDs of each zone.
- `DNAFormationContributions.csv` which includes an estimate of how much each zone contributes to total liquid production.

[570]:
```
WellLogs = pd.read_csv('WellLogs.csv')
Formations = pd.read_csv('Formations.csv')
DNA = pd.read_csv('DNAFormationContributions.csv')
```

2) Calculate Brittleness Index for each depth as defined by the fraction of total rock volume that is made of quartz and calcite. Hint: Use the last 6 columns of `WellLogs.csv`.

[526]:
```
# Last 6 columns do not include TOC
WellLogs_BI=WellLogs
WellLogs_BI['TRV']=WellLogs_BI['VQTZ']+WellLogs_BI['VPYR']+WellLogs_BI['VCL']+WellLogs_BI['VCA
WellLogs_BI['Q+C']=WellLogs_BI['VQTZ']+WellLogs_BI['VCALC']
WellLogs_BI['BI']=WellLogs_BI['Q+C']/WellLogs_BI['TRV']
WellLogs_BI
```

[526]:
```
       MD Zone          GR      KAIR       NEU        PE      PHIT       SWT  \
0   10050   A1  101.697227  0.000201  0.167445  4.000277  0.062168  0.375907
1   10060   A1  107.797100  0.000086  0.134535  4.177762  0.049613  0.530793
2   10070   A2   99.086056  0.000044  0.131360  3.726822  0.053083  0.576101
3   10080   A2  108.058048  0.000183  0.167135  3.517681  0.070519  0.375680
4   10090   A2  113.019047  0.000113  0.169545  3.935149  0.064609  0.423886
..    ...  ...         ...       ...       ...       ...       ...       ...
89  11260    C  112.550102  0.000405  0.223433  3.234017  0.083424  0.450923
90  11280    C  110.705902  0.000147  0.180583  4.800201  0.068065  0.762003
91  11300    C  104.672749  0.000080  0.155010  3.696765  0.059227  0.792062
92  11320    C  109.123848  0.000013  0.169026  4.386390  0.041564  1.000000
93  11340    C  131.968803  0.000085  0.186534  4.190419  0.060967  1.000000

         TOC     VCALC       VCL      VKER      VOIL      VPYR      VQTZ  \
0   0.027114  0.427140  0.102950  0.064822  0.038820  0.014632  0.332666
1   0.019847  0.559585  0.065400  0.047952  0.023350  0.008231  0.271999
2   0.021809  0.172476  0.083956  0.055361  0.022467  0.015788  0.625215
3   0.031486  0.089278  0.125994  0.075352  0.044127  0.022451  0.625227
4   0.026631  0.044797  0.160126  0.065208  0.037230  0.019117  0.657353
..       ...       ...       ...       ...       ...       ...       ...
89  0.025771  0.003641  0.286483  0.060343  0.045831  0.020217  0.565495
90  0.015327  0.015974  0.213699  0.039618  0.016181  0.012214  0.665046
91  0.015672  0.069522  0.158378  0.040922  0.012661  0.012505  0.670274
92  0.007348  0.030593  0.254298  0.020034  0.000000  0.006034  0.664855
93  0.012818  0.000000  0.232981  0.035993  0.000000  0.010324  0.675649

         TRV       Q+C        BI
0   0.877388  0.759806  0.865986
1   0.905215  0.831585  0.918660
2   0.897436  0.797691  0.888856
3   0.862950  0.714505  0.827980
4   0.881393  0.702150  0.796637
```

```
..        …         …         …
89  0.875835  0.569136  0.649821
90  0.906933  0.681020  0.750905
91  0.910678  0.739795  0.812357
92  0.955779  0.695448  0.727624
93  0.918954  0.675649  0.735237

[94 rows x 18 columns]
```

3) Calculate average properties for each zone using groupby function.

[529]:
```
WellLogs_BI.groupby(['Zone']).mean()
```

[529]:
```
                MD          GR      KAIR       NEU        PE      PHIT  \
Zone
A1    10055.000000  104.747164  0.000144  0.150990  4.089019  0.055891
A2    10100.000000   97.567045  0.000090  0.142152  3.942242  0.057819
A3    10155.000000   96.394148  0.000047  0.130900  3.934197  0.051825
A4    10238.000000   73.638632  0.000010  0.091603  4.797253  0.036302
A5    10285.000000   74.017006  0.000034  0.099701  4.646792  0.045228
A6    10325.000000   79.165456  0.000114  0.118086  4.683020  0.051411
B1    10400.000000   99.389460  0.000215  0.160935  4.598812  0.065537
B2    10511.818182   93.535800  0.000140  0.177770  4.296407  0.063145
B3    10600.000000   89.334879  0.000182  0.210283  4.462783  0.066876
B4    10652.500000   79.839968  0.000189  0.150339  4.243116  0.051475
B5    10710.000000   85.870205  0.000383  0.179507  4.210856  0.078485
B6    10801.666667   95.240988  0.000222  0.187569  4.329374  0.071050
C     11103.461538   96.015332  0.000112  0.155254  4.016482  0.053423

           SWT       TOC     VCALC       VCL      VKER      VOIL      VPYR  \
Zone
A1    0.453350  0.023480  0.493363  0.084175  0.056387  0.031085  0.011432
A2    0.425592  0.025402  0.186274  0.096923  0.062225  0.033504  0.018255
A3    0.544223  0.020106  0.197811  0.091817  0.051163  0.023567  0.014551
A4    0.471404  0.012132  0.410623  0.044297  0.031626  0.017654  0.008777
A5    0.362570  0.018785  0.403404  0.032325  0.045347  0.027225  0.013469
A6    0.731424  0.015184  0.360822  0.064800  0.038914  0.016761  0.010987
B1    0.643939  0.016368  0.103660  0.169780  0.040016  0.023558  0.012947
B2    0.602159  0.018240  0.096263  0.213281  0.042640  0.026476  0.014621
B3    0.925829  0.010911  0.133720  0.289361  0.023763  0.002952  0.008998
B4    0.929620  0.008746  0.249429  0.177361  0.018985  0.003321  0.007900
B5    0.717582  0.016833  0.128585  0.180704  0.039133  0.021331  0.013434
B6    0.723963  0.015261  0.049687  0.227878  0.034711  0.017953  0.012302
C     0.733334  0.014353  0.161186  0.185241  0.034959  0.018169  0.011640

          VQTZ       TRV       Q+C        BI
Zone
```

```
A1    0.302333  0.891302  0.795695  0.892323
A2    0.585289  0.886741  0.771563  0.869173
A3    0.599253  0.903433  0.797065  0.882445
A4    0.471467  0.935164  0.882090  0.943042
A5    0.462481  0.911680  0.865886  0.948803
A6    0.477582  0.914192  0.838405  0.916211
B1    0.619879  0.906265  0.723538  0.798397
B2    0.584866  0.909031  0.681129  0.750265
B3    0.497352  0.929431  0.631072  0.678613
B4    0.507139  0.941829  0.756568  0.801620
B5    0.572163  0.894886  0.700748  0.784435
B6    0.620117  0.909984  0.669804  0.737825
C     0.566264  0.924332  0.727450  0.785119
```

4) Create a visualization with 5 log tracks vs. depth: `gamma ray, brittleness index, oil volume, water volume, and formation contribution to liquid production.`

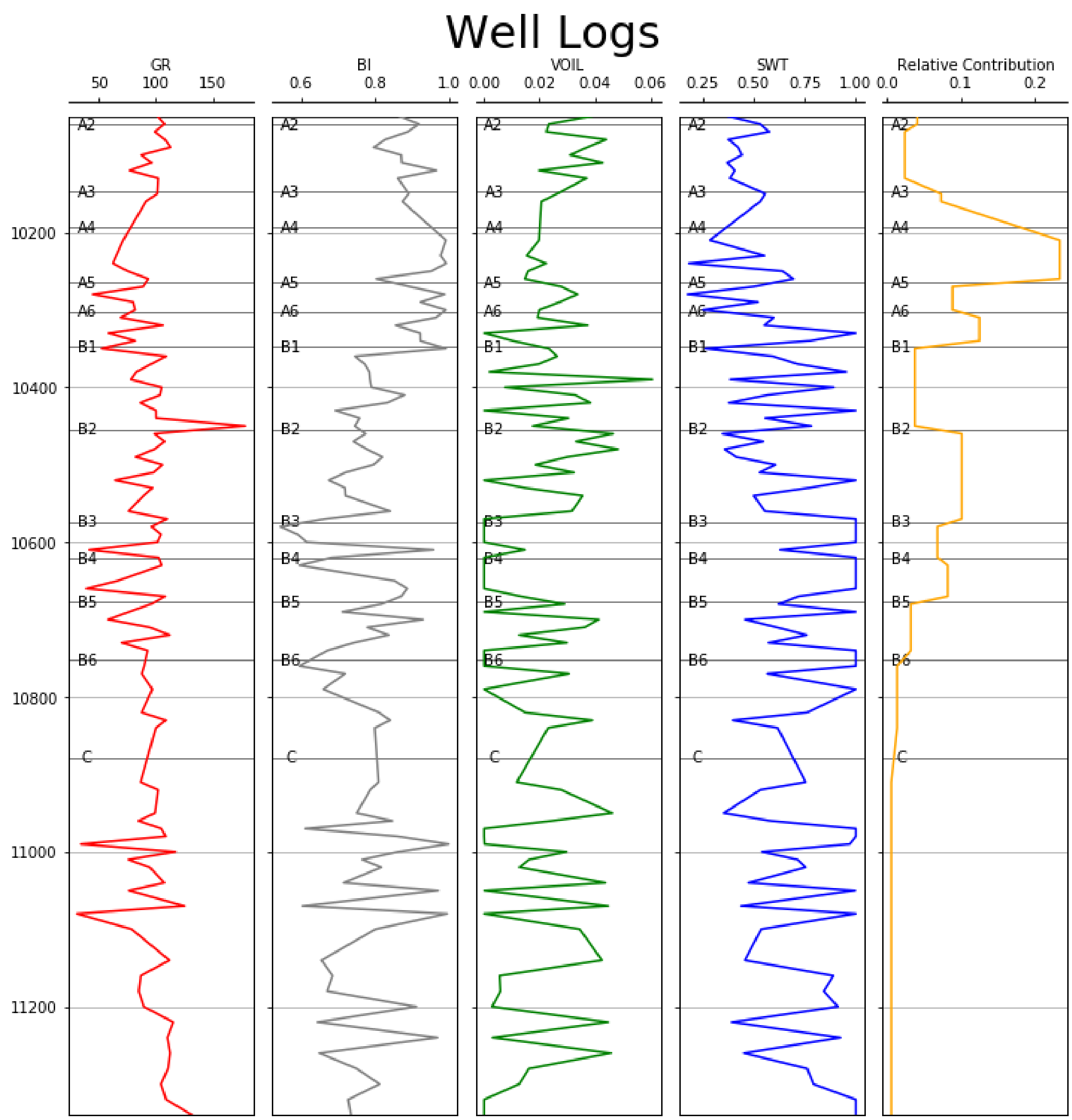
[700]:
```
# We have to merge the DNA Relative Contribution with the WellLogs data.
# This will be done merging the 'Zone' in WellLogs, with 'Formation' in DNA.␣
 ↪This is similar to a LOOKUP function in Excel.

WLplot=WellLogs_BI.merge(DNA, left_on='Zone', right_on='Formation')

# Now we choose the Logs we want to plot
WLplot=WellLogs_BI_plot[['MD', 'Zone', 'GR', 'BI', 'VOIL', 'SWT',␣
 ↪'RelativeContribution']]
WLplot
```

[700]:
```
       MD Zone          GR        BI      VOIL       SWT  RelativeContribution
0   10050   A1  101.697227  0.865986  0.038820  0.375907              0.040967
1   10060   A1  107.797100  0.918660  0.023350  0.530793              0.040967
2   10070   A2   99.086056  0.888856  0.022467  0.576101              0.024071
3   10080   A2  108.058048  0.827980  0.044127  0.375680              0.024071
4   10090   A2  113.019047  0.796637  0.037230  0.423886              0.024071
..    …   …           …         …         …         …                   …
89  11260    C  112.550102  0.649821  0.045831  0.450923              0.005853
90  11280    C  110.705902  0.750905  0.016181  0.762003              0.005853
91  11300    C  104.672749  0.812357  0.012661  0.792062              0.005853
92  11320    C  109.123848  0.727624  0.000000  1.000000              0.005853
93  11340    C  131.968803  0.735237  0.000000  1.000000              0.005853

[94 rows x 7 columns]
```

[701]:
```
tops = Formations.Formation
tops_depths=Formations.TopMD

# Create the figure and subplots
```

```
def logs_plot(top_depth,bottom_depth):

#  logs = plot[(plot.MD >= top_depth) & (plot.MD <= bottom_depth)]
  fig, ax = plt.subplots(nrows=1, ncols=5, figsize=(12,12), sharey=True)
  fig.suptitle('Well Logs', fontsize=30)
  fig.subplots_adjust(top=0.90, wspace=0.1)

#General setting for all axis
  for axes in ax:
     axes.set_ylim (top_depth,bottom_depth)
     axes.invert_yaxis()
     axes.yaxis.grid(True)
     axes.get_xaxis().set_visible(False)
     for (i,j) in zip(tops_depths,tops):
         if ((i>=top_depth) and (i<=bottom_depth)):
             axes.axhline(y=i, linewidth=0.5, color='black')
             axes.text(0.1, i ,j,␣
 ↪horizontalalignment='center',verticalalignment='center')

#track 1
  ax01=ax[0].twiny()
#  ax01.invert_yaxis()
#  ax01.set_xlim(-100,10)
  ax01.spines['top'].set_position(('outward',10))
  ax01.set_xlabel('GR', color='black')
  ax01.plot(WLplot.GR, WLplot.MD, label='GR', color='red')
#  ax01.set_xlabel('GR',color='blue')
#  ax01.tick_params(axis='x', colors='blue')
#  ax01.grid(True)

#track 2
  ax02=ax[1].twiny()
#  ax02.invert_yaxis()
  ax02.plot(WLplot.BI, WLplot.MD, color='gray')
  #ax02.set_xlim(25, 155)
  ax02.set_xlabel('BI', color='black')
  ax02.spines['top'].set_position(('outward', 10))

#track 3
  ax03=ax[2].twiny()
#  ax03.invert_yaxis()
  ax03.plot(WLplot.VOIL, WLplot.MD, color='green')
  #ax03.set_xlim(25, 155)
  ax03.set_xlabel('VOIL', color='black')
  ax03.spines['top'].set_position(('outward', 10))

#track 4
```

```
  ax04=ax[3].twiny()
#  ax04.invert_yaxis()
  ax04.plot(WLplot.SWT, WLplot.MD, color='blue')
  ax04.set_xlabel('SWT', color='black')
  ax04.spines['top'].set_position(('outward', 10))

#track 5
  ax05=ax[4].twiny()
#  ax05.invert_yaxis()
  ax05.plot(WLplot.RelativeContribution, WLplot.MD, color='orange')
  ax05.set_xlabel('Relative Contribution', color='black')
  ax05.spines['top'].set_position(('outward', 10))

logs_plot(WLplot.MD.min(),WLplot.MD.max())
```



5) How does the brittleness index for zones A4-A6 compare with other zones? How about contribution to production according DNA diagnostics?

- The BI for zones A4-A6 is higher compared with the rest of the zones.
- This is directly proportional to the DNA Formation Contribution: the higher the BI, the higher the Relative Contribution.

6) Generally speaking, how does formation contribution (to liquid production) correlate with formation-average brittleness index? How would you explain the observed relationship?

- Generally speaking, Formation Contribution to liquid production should increase directly proportional to BI.
- The observed relationship supports the higher contribution due to higher BI. For reservoir rocks including shale, the BI measures their fracturability, theferore, they tend to form a complex network of fractures, which favors the liquid movement towards the well.

Please find below the supporting scatter plot for Formation Contribution vs. Brittleness Index. While BI increases, the Formation Contribution increases as well.

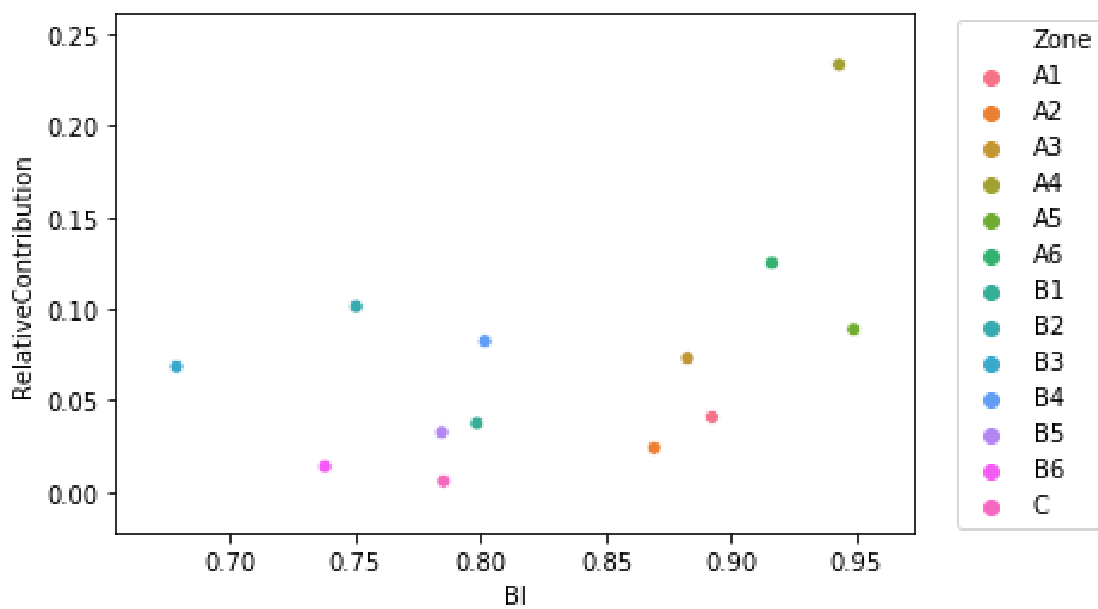
[703]:
```
meanWLplot = WLplot.groupby(['Zone']).mean()
meanWLplot.reset_index(inplace=True)
meanWLplot
```

[703]:
```
   Zone            MD          GR        BI      VOIL       SWT  \
0    A1  10055.000000  104.747164  0.892323  0.031085  0.453350
1    A2  10100.000000   97.567045  0.869173  0.033504  0.425592
2    A3  10155.000000   96.394148  0.882445  0.023567  0.544223
3    A4  10238.000000   73.638632  0.943042  0.017654  0.471404
4    A5  10285.000000   74.017006  0.948803  0.027225  0.362570
5    A6  10325.000000   79.165456  0.916211  0.016761  0.731424
6    B1  10400.000000   99.389460  0.798397  0.023558  0.643939
7    B2  10511.818182   93.535800  0.750265  0.026476  0.602159
8    B3  10600.000000   89.334879  0.678613  0.002952  0.925829
9    B4  10652.500000   79.839968  0.801620  0.003321  0.929620
10   B5  10710.000000   85.870205  0.784435  0.021331  0.717582
11   B6  10801.666667   95.240988  0.737825  0.017953  0.723963
12    C  11103.461538   96.015332  0.785119  0.018169  0.733334

    RelativeContribution
0               0.040967
1               0.024071
2               0.073145
3               0.233410
4               0.088705
```

```
5              0.125099
6              0.037503
7              0.101365
8              0.068528
9              0.082264
10             0.032565
11             0.013939
12             0.005853
```

[704]:
```
scatplot=sns.scatterplot(x="BI", y="RelativeContribution", hue="Zone",␣
 ↪data=meanWLplot)
scatplot.legend(loc='right', bbox_to_anchor=(1.25, 0.5), ncol=1)
```

[704]:
```
<matplotlib.legend.Legend at 0x20d76e08208>
```



7) Are zones B3 and B4 more likely to contribute to water production or oil production? Why?

- According to the Well Log plot, Zones B3 and B4 more likely contribute water production
- The oil contribution from these zones is likely to be negligible, since the VOIL is very low.

0.3 Unix

Unix commands are often used at Biota and data science in general.

Write the commands necessary to: 1. Create a directory named "test" 2. Create an empty file name "foo.txt" 3. Create a directory inside of "test" called "temp" 3. Copy "foo.txt" into "temp" 4. Change the name of "foo.txt" to "bar.txt" 5. Print the path to the current working directory 5. Change the current working directory to home 5. Explain the difference between a relative and absolute path

[ ]:

```

```

0.4 GitHub

1. Write the command to clone a directory called "git@github.com:user/foo" (not a real repository)
2. Change into that directory
3. Create a branch called "test"
4. change into that branch
5. Create an empty file name "foo.txt"
6. Add that file to the staging area
7. Commit that file
8. Push that file to the master branch on github

[ ]:

```

```

Thanks! Please save this jupyter notebook with inline images, and email the resulting jupyter notebook to jsawadogo@biota.com AND mschlecht@biota.com (name this file "firstname_lastname_eval.ipynb" for example mine would be "mathias_schlecht_eval.ipynb")

[1]:

```
jupyter nbconvert --execute my_notebook.ipynb --to pdf
```

```
  File "<ipython-input-1-a8f56e77774b>", line 1
    jupyter nbconvert --execute my_notebook.ipynb --to pdf
                    ^
SyntaxError: invalid syntax
```

[2]:

```
import nbconvert
```

[3]:

```
jupyter nbconvert --johanna_fernandez_eval.ipynb --to pdf
```

```
  File "<ipython-input-3-0eb3726a22fa>", line 1
    jupyter nbconvert --johanna_fernandez_eval.ipynb --to pdf
                    ^
SyntaxError: invalid syntax
```

```
[ ]:
```