In [1]:

```
import lasio
import pandas as pd
import numpy as np
from sklearn.neighbors import KNeighborsRegressor # for KNN regression

import matplotlib.pyplot as plt # for data visualization
import plotly.express as px # for data visualization
```

In [2]:

```
las = lasio.read("ColvilleUnit1.LAS")
well = las.df()
df =well.dropna(how="any")
print(df.shape)
```

```
(6055, 8)
```

In [3]:

```
df.isnull().sum()
```

Out[3]:

```
CALI    0
GR      0
ILD     0
ILM     0
LL8     0
RHOB    0
SP      0
SWL     0
dtype: int64
```

In [4]:

```
from sklearn.model_selection import train_test_split
train , test = train_test_split(df, test_size = 0.3)

x_train = train.drop('GR', axis=1)
y_train = train['GR']

x_test = test.drop('GR', axis = 1)
y_test = test['GR']
```

In [5]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))

x_train_scaled = scaler.fit_transform(x_train)
x_train = pd.DataFrame(x_train_scaled)

x_test_scaled = scaler.fit_transform(x_test)
x_test = pd.DataFrame(x_test_scaled)
```

In [6]:

```
#import required packages
from sklearn import neighbors
from sklearn.metrics import mean_squared_error
from math import sqrt
import matplotlib.pyplot as plt
%matplotlib inline
```

In [7]:

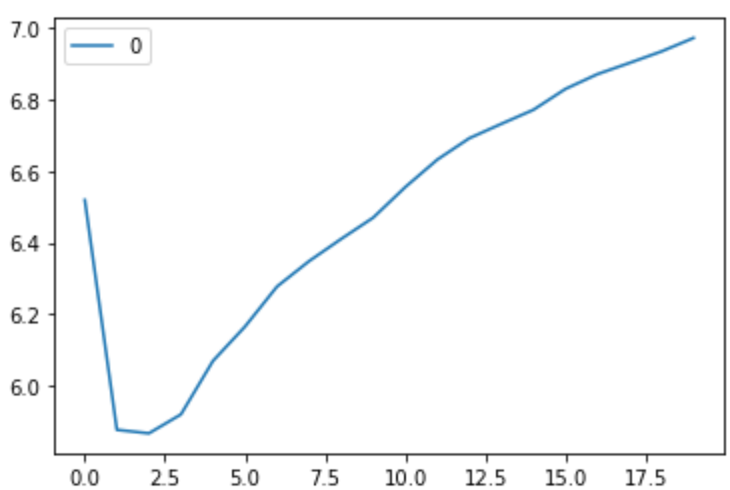
```
rmse_val = [] #to store rmse values for different k
for K in range(20):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)

    model.fit(x_train, y_train)  #fit the model
    pred=model.predict(x_test) #make prediction on test set
    error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 6.519317827135389
RMSE value for k=  2 is: 5.8759443369196305
RMSE value for k=  3 is: 5.866107225811023
RMSE value for k=  4 is: 5.919093694756719
RMSE value for k=  5 is: 6.0688633820424265
RMSE value for k=  6 is: 6.165032298710593
RMSE value for k=  7 is: 6.277147871293805
RMSE value for k=  8 is: 6.348198430960938
RMSE value for k=  9 is: 6.41025601225977
RMSE value for k=  10 is: 6.4698670596886325
RMSE value for k=  11 is: 6.555274682804502
RMSE value for k=  12 is: 6.632277999174153
RMSE value for k=  13 is: 6.692191057158776
RMSE value for k=  14 is: 6.732478875281051
RMSE value for k=  15 is: 6.77174368502252
RMSE value for k=  16 is: 6.830192652040286
RMSE value for k=  17 is: 6.871645141579368
RMSE value for k=  18 is: 6.903040291319884
RMSE value for k=  19 is: 6.935320445199133
RMSE value for k=  20 is: 6.972919487527774
```

In [8]:

```
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[8]: <AxesSubplot:>



In [9]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}

knn = neighbors.KNeighborsRegressor()

model = GridSearchCV(knn, params, cv=5)
model.fit(x_train,y_train)
model.best_params_
```

Out[9]:

```
{'n_neighbors': 2}
```

In [10]:

```
modelR = KNeighborsRegressor(n_neighbors=2, #default=2
                             weights='uniform', #{'uniform', 'distance'} or callable,
                             algorithm='auto', #{'auto', 'ball_tree', 'kd_tree', 'bru
                             #leaf_size=30, #default=30, Leaf size passed to BallTree
                             #p=2, #default=2, Power parameter for the Minkowski metr
                             #metric='minkowski', #default='minkowski', with p=2 is e
                             metric_params=None, #dict, default=None, Additional keyw
                             n_jobs=-1 #default=None, The number of parallel jobs to
                            )
```

In [11]:

```
reg = modelR.fit(x_train, y_train)
```

In [12]:

```
# Predict on training data

pred_values_tr = modelR.predict(x_train)

# Predict on a test data

pred_values_te = modelR.predict(x_test)
```

In [13]:

```
# Basic info about the model
print("")
print('****************** KNN Regression ******************')

print("")
scoreR_te = modelR.score(x_test, y_test)
print('Test Accuracy Score: ', scoreR_te)
scoreR_tr = modelR.score(x_train, y_train)
print('Training Accuracy Score: ', scoreR_tr)

print('---------------------------------------------------------')
```

```
****************** KNN Regression ******************

Test Accuracy Score:  0.8754898272808345
Training Accuracy Score:  0.9696118262736437
---------------------------------------------------------
```

In [14]:

```
# Create a copy of each dataframe before modifying
df_train_new=train.copy()
df_test_new=test.copy()

# ------- Training DataFrame -------
# Attach predicted class labels and values

df_train_new['Predicted GR']=pred_values_tr



# ------- Test DataFrame -------
# Attach predicted class labels and values

df_test_new['Predicted GR']=pred_values_te




# ------- Combined DataFrame -------
# Combine training and testing dataframes back into one
df_new=pd.concat([df_train_new, df_test_new], ignore_index=False, axis=0, sort=False)
df_new
```

Out[14]:

| | CALI | GR | ILD | ILM | LL8 | RHOB | SP | SWL | Predicted GR |
|---|---|---|---|---|---|---|---|---|---|
| **DEPTH** | | | | | | | | | |
| **2450.0** | 8.371 | 72.871 | 14.984 | 16.373 | 19.698 | 2.553 | 54.188 | 24.116 | 73.1925 |
| **1989.0** | 8.290 | 59.409 | 32.702 | 36.681 | 37.297 | 2.634 | 55.445 | 11.519 | 59.5205 |
| **3006.5** | 8.464 | 67.354 | 33.907 | 36.167 | 35.683 | 2.659 | 60.417 | 11.144 | 60.2440 |
| **3311.0** | 8.042 | 32.544 | 45.822 | 50.419 | 38.891 | 2.453 | 66.370 | 13.173 | 31.7090 |
| **3373.0** | 8.219 | 49.611 | 25.729 | 26.421 | 26.948 | 2.465 | 56.610 | 16.550 | 52.8445 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2637.5** | 8.350 | 65.750 | 26.711 | 31.032 | 31.199 | 2.619 | 58.796 | 11.532 | 63.7450 |
| **4116.5** | 8.244 | 66.181 | 30.151 | 39.143 | 40.813 | 2.605 | 82.725 | 13.654 | 67.2790 |
| **1397.5** | 8.298 | 73.459 | 18.471 | 19.014 | 17.840 | 2.566 | 43.572 | 16.760 | 69.6450 |
| **1395.0** | 8.328 | 104.638 | 14.583 | 14.929 | 13.505 | 2.520 | 43.517 | 21.343 | 73.0400 |
| **1262.5** | 8.095 | 61.523 | 41.517 | 46.780 | 41.335 | 2.609 | 34.887 | 11.307 | 61.2685 |

6055 rows × 9 columns

In [15]:

```
data= df_new.sort_index(ascending=True)
data
```

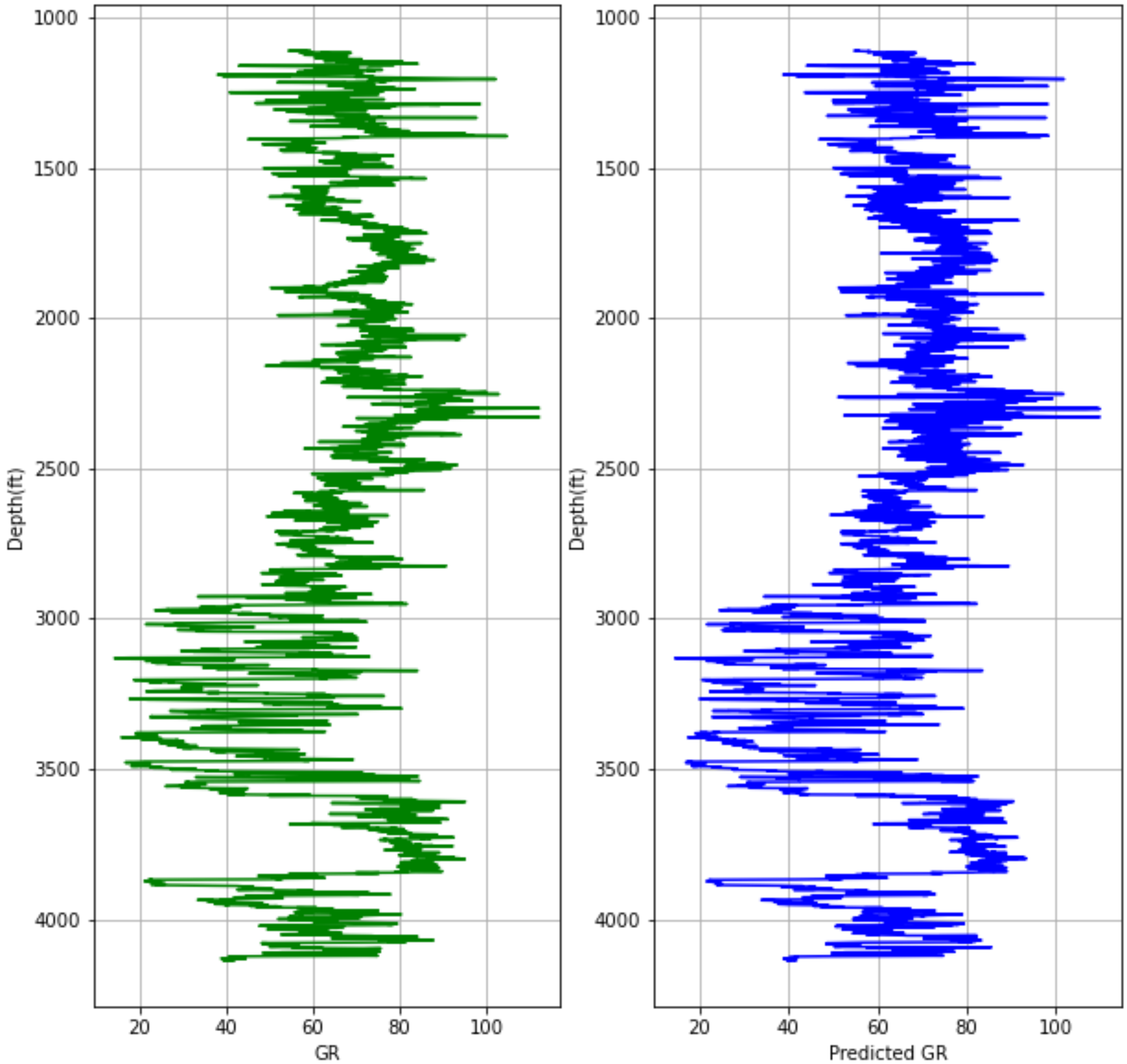
Out[15]:

| | CALI | GR | ILD | ILM | LL8 | RHOB | SP | SWL | Predicted GR |
|---|---|---|---|---|---|---|---|---|---|
| **DEPTH** | | | | | | | | | |

| | CALI | GR | ILD | ILM | LL8 | RHOB | SP | SWL | Predicted GR |
|---|---|---|---|---|---|---|---|---|---|
| **DEPTH** | | | | | | | | | |
| **1110.0** | 13.907 | 59.206 | 2.996 | 2.572 | 3.121 | 1.852 | 28.073 | 29.676 | 55.4650 |
| **1110.5** | 14.354 | 56.543 | 2.893 | 2.574 | 3.047 | 1.802 | 28.022 | 31.547 | 55.4650 |
| **1111.0** | 14.037 | 54.387 | 2.952 | 2.613 | 2.992 | 1.748 | 28.033 | 33.854 | 54.7025 |
| **1111.5** | 13.877 | 55.018 | 3.013 | 2.675 | 2.973 | 1.709 | 28.078 | 36.162 | 55.4745 |
| **1112.0** | 14.156 | 55.931 | 3.082 | 2.769 | 2.954 | 1.712 | 28.126 | 38.469 | 55.4745 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **4135.0** | 8.123 | 39.606 | 22.608 | 28.664 | 27.949 | 2.481 | 64.309 | 11.841 | 40.4935 |
| **4135.5** | 8.127 | 39.293 | 22.738 | 28.939 | 28.138 | 2.470 | 64.294 | 12.295 | 39.5670 |
| **4136.0** | 8.131 | 39.841 | 22.871 | 29.216 | 28.303 | 2.462 | 64.258 | 12.579 | 39.5670 |
| **4136.5** | 8.129 | 40.555 | 22.971 | 29.440 | 28.409 | 2.483 | 64.211 | 12.332 | 39.9240 |
| **4137.0** | 8.131 | 41.694 | 23.066 | 29.578 | 28.506 | 2.461 | 64.169 | 11.887 | 40.4935 |

In [17]:

```
def plotter():
 f, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,10))
 logs = ['GR','Predicted GR']
 colors = ['green','blue']
 for i,log,color in zip(range(2),logs,colors):
   ax[i].plot(data[log], data.index ,color=color)
   ax[i].invert_yaxis()
   ax[i].set_xlabel(log)
   ax[i].set_ylabel("Depth(ft)")
   ax[i].grid()
plotter()
```



Depth(ft)
1000
1500
2000
2500
3000
3500
4000
20
40
60
80
100
GR
Predicted GR


In [ ]:

In [ ]:

In [ ]: