# KNN_Hydropower_Cnsumption

February 28, 2025

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import seaborn as sns
```

[2]:
```python
df = pd.read_csv("Practice dataset 1 KNN regression Hydropower_Consumption.csv")
```

[3]:
```python
df
```

[3]:
```
         Country   2000   2001   2002   2003   2004   2005   2006   2007  \
0    Afghanistan    312    498    555     63    565     59    637    748
1         Africa  75246  80864  85181  82873  87405  89066  92241  95341
2        Albania   4548   3519   3477   5117   5411   5319   4951    276
3        Algeria     54     69     57    265    251    555    218    226
4         Angola    903   1007   1132   1229   1733   2197   2638   2472
..           …      …      …      …      …      …      …      …      …
148   Uzbekistan   5879   6017   6186   7155   6493   6876    585   6457
149    Venezuela  62886  60441  59534  60532  70075  77088  81413  83034
150      Vietnam  14551   1821  18198      0  17818  16535      0  22437
151       Zambia   7673   7814   8021   8174   8375   8794   9572   9535
152     Zimbabwe   3227   2968   3786   5305   5466   4866   5257   5329

      2008  …    2010    2011    2012    2013    2014    2015    2016  \
0      542  …     751     595      71     804     895     989    1025
1    97157  …  107427  110445  110952  117673  123727  115801  123816
2     3759  …    7673    4036    4725    6959    4726    5866    7136
3      283  …     173     378     389      99     193     145      72
4     3103  …    3666    3967    3734    4719    4991    5037    5757
..      …  …      …       …       …       …       …       …       …
148   4386  …    8192    5721    6355     627    6185     602    7327
149  86713  …    7666   83155   81736   83405   78747   73397   61699
150  25984  …   28524   41076   53305    5782   62165   57171   66048
151   9427  …   10331   11368   12227   13148   13902   12907   10915
152   5651  …    5741    5149    5336    4946    5377     494    2955
```

```
       2017    2018   2019
0       105     105    107
1    130388  132735      0
2       448     448   4018
3        56     117    152
4      7576    7576   8422
..      …       …     …
148    8427    5897     65
149   59296   56987  63267
150   88762   84485  65563
151   12076   12076  11799
152    3929    3929   3592

[153 rows x 21 columns]
```

[4]:
```
df.shape
```

[4]:
```
(153, 21)
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153 entries, 0 to 152
Data columns (total 21 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Country  153 non-null    object
 1   2000     153 non-null    int64
 2   2001     153 non-null    int64
 3   2002     153 non-null    int64
 4   2003     153 non-null    int64
 5   2004     153 non-null    int64
 6   2005     153 non-null    int64
 7   2006     153 non-null    int64
 8   2007     153 non-null    int64
 9   2008     153 non-null    int64
 10  2009     153 non-null    int64
 11  2010     153 non-null    int64
 12  2011     153 non-null    int64
 13  2012     153 non-null    int64
 14  2013     153 non-null    int64
 15  2014     153 non-null    int64
 16  2015     153 non-null    int64
 17  2016     153 non-null    int64
 18  2017     153 non-null    int64
 19  2018     153 non-null    int64
 20  2019     153 non-null    int64
```

```
dtypes: int64(20), object(1)
memory usage: 25.2+ KB
```

[6]:
```python
df.isna().sum()
```

[6]:
```
Country    0
2000       0
2001       0
2002       0
2003       0
2004       0
2005       0
2006       0
2007       0
2008       0
2009       0
2010       0
2011       0
2012       0
2013       0
2014       0
2015       0
2016       0
2017       0
2018       0
2019       0
dtype: int64
```

[7]:
```python
df.columns
```

[7]:
```
Index(['Country', '2000', '2001', '2002', '2003', '2004', '2005', '2006',
       '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015',
       '2016', '2017', '2018', '2019'],
      dtype='object')
```

[8]:
```python
X = df.drop(columns = ['2019', 'Country'])
y = df['2019']
```

[9]:
```python
X = pd.get_dummies(X, drop_first=True)
```

[10]:
```python
sc = StandardScaler()
X = sc.fit_transform(X)
```

[11]:
```python
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 42, shuffle = True)
```

[12]:
```python
params = {
    'n_neighbors':[3,5,7,12],
```

```
    'weights' : ['uniform', 'distance'],
    'metric':['minkowski','manhattan','euclidean']
}
```

[13]:
```
dia_reg = GridSearchCV(KNeighborsRegressor(), params, cv = 10)
```

[14]:
```
dia_reg.fit(X_train, y_train)
```

```
c:\Users\Neil\anaconda3\Lib\site-
packages\joblib\externals\loky\backend\context.py:136: UserWarning: Could not
find the number of physical cores for the following reason:
[WinError 2] The system cannot find the file specified
Returning the number of logical cores instead. You can silence this warning by
setting LOKY_MAX_CPU_COUNT to the number of cores you want to use.
  warnings.warn(
  File "c:\Users\Neil\anaconda3\Lib\site-
packages\joblib\externals\loky\backend\context.py", line 257, in
_count_physical_cores
    cpu_info = subprocess.run(
               ^^^^^^^^^^^^^^^

  File "c:\Users\Neil\anaconda3\Lib\subprocess.py", line 548, in run
    with Popen(*popenargs, **kwargs) as process:
         ^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "c:\Users\Neil\anaconda3\Lib\subprocess.py", line 1026, in __init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "c:\Users\Neil\anaconda3\Lib\subprocess.py", line 1538, in _execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
                       ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
```

[14]:
```
GridSearchCV(cv=10, estimator=KNeighborsRegressor(),
             param_grid={'metric': ['minkowski', 'manhattan', 'euclidean'],
                         'n_neighbors': [3, 5, 7, 12],
                         'weights': ['uniform', 'distance']})
```

[15]:
```
dia_reg.best_score_
```

[15]:
```
-0.7084955694221238
```

[16]:
```
dia_reg.best_params_
```

[16]:
```
{'metric': 'minkowski', 'n_neighbors': 12, 'weights': 'uniform'}
```

[17]:
```
regressor = KNeighborsRegressor(metric = 'manhattan', n_neighbors= 5,␣
 ↪weights='distance')
regressor.fit(X_train, y_train)
```

[17]:
```
KNeighborsRegressor(metric='manhattan', weights='distance')
```

[18]:
```
y_pred = regressor.predict(X_val)
```

[19]:
```
rmse = np.sqrt(mean_squared_error(y_val, y_pred))
rmse
```

[19]: 3884.94001975831

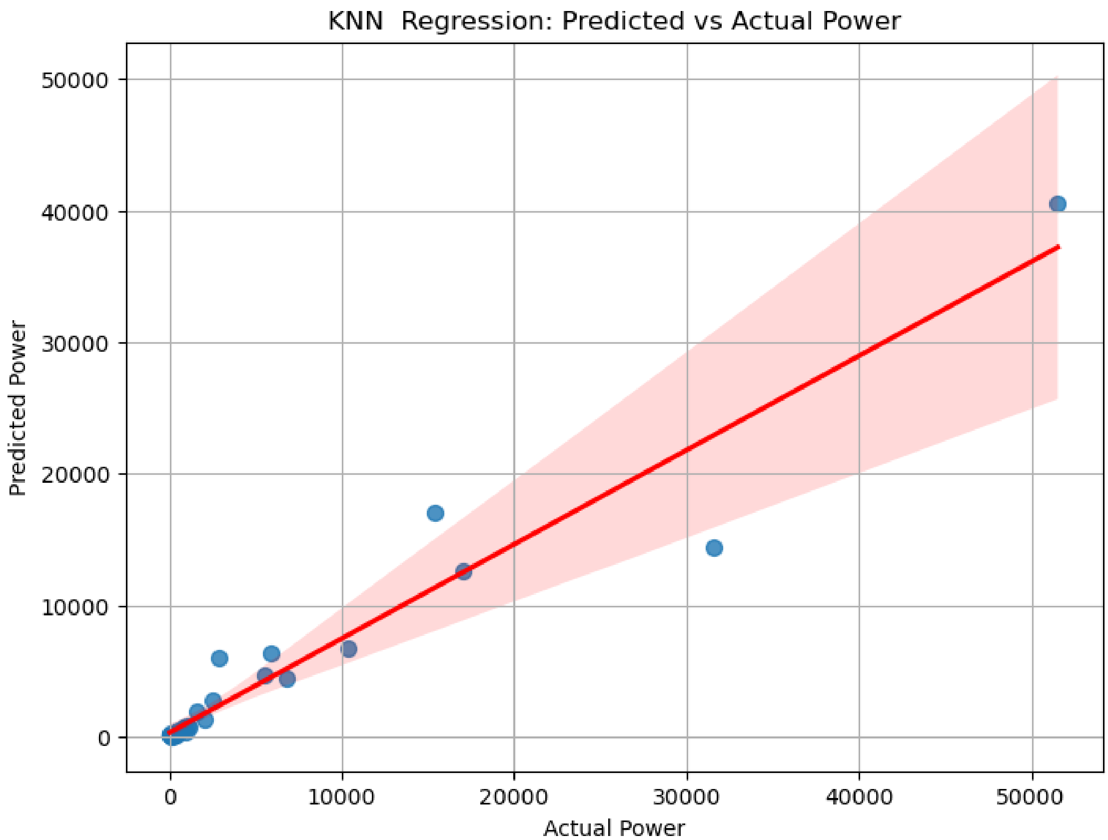
[20]:
```
from sklearn.metrics import mean_squared_error
# Calculate and display Mean Squared Error (MSE)
mse = mean_squared_error(y_val, y_pred)
print("MSE value : {:.4f}".format(mse))
from sklearn.metrics import mean_squared_error
# Calculate and display Root Mean Squared Error (RMSE)
mse = mean_squared_error(y_val, y_pred)
rmse = np.sqrt(mse)
print("RMSE value : {:.4f}".format(rmse))

from sklearn.metrics import r2_score
# Calculate and display R2 score (R2)
print("R2 score value : {:.4f}".format(r2_score(y_val, y_pred)))

from sklearn.metrics import mean_absolute_error
# Calculate and display Mean Absolute Error (MAE)
mae = mean_absolute_error(y_val, y_pred)
print("MAE value : {:.4f}".format(mae))
```

```
MSE value : 15092758.9571
RMSE value : 3884.9400
R2 score value : 0.8700
MAE value : 1572.8438
```

[21]:
```
plt.figure(figsize=(8,6))
sns.regplot(x=y_val, y=y_pred, scatter_kws={"s":50}, line_kws={"color": "red"})
plt.xlabel("Actual Power")
plt.ylabel("Predicted Power")
plt.title("KNN  Regression: Predicted vs Actual Power")
plt.grid(True)
plt.show()
```



KNN  Regression: Predicted vs Actual Power
Predicted Power
Actual Power
0
10000
20000
30000
40000
50000