Water Quality Regression Analysis

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1. Description of the Dataset and Preprocessing Steps

a. Dataset Overview

The dataset used in this analysis is the "Water Quality" dataset obtained from Kaggle. It contains various physicochemical properties of water samples and a target variable indicating whether the water is potable.

- Dataset URL: [Water Quality Dataset on Kaggle](
https://www.kaggle.com/datasets/uom190346a/water-quality-and-potability?resource=download
)
- Number of Samples: 3276
- Number of Features: 9 (excluding the target variable)

The features in the dataset include:
- ph: pH value of water
- Hardness: Hardness of water
- Solids: Total dissolved solids in ppm
- Chloramines: Amount of chloramines in ppm
- Sulfate: Amount of sulfate in ppm
- Conductivity: Electrical conductivity in µS/cm
- Organic_carbon: Amount of organic carbon in ppm
- Trihalomethanes: Amount of trihalomethanes in µg/L
- Turbidity: Turbidity in NTU
- Potability: Target variable (0: Not Potable, 1: Potable)

b. Data Preprocessing

The data preprocessing steps included:
- Handling Missing Values: Missing values were filled with the **median** of the respective columns.
- Feature Selection: The '**Potability'** column was selected as the target variable, and all other columns were used as features.
- Data Splitting: The dataset was split into training and testing sets using an **80-20 split** ratio.

c. Exploratory Data Analysis (EDA)

Exploratory Data Analysis was performed to understand the data distribution and relationships between features. Key steps included:

- Correlation Heatmap: Visualizing correlations between features to identify highly correlated variables.

Strong Positive Correlations:

pH and Hardness have a strong positive correlation (dark purple).

Solids and Conductivity are also positively correlated.

Organic_carbon and Trihalomethanes show a moderate positive correlation.

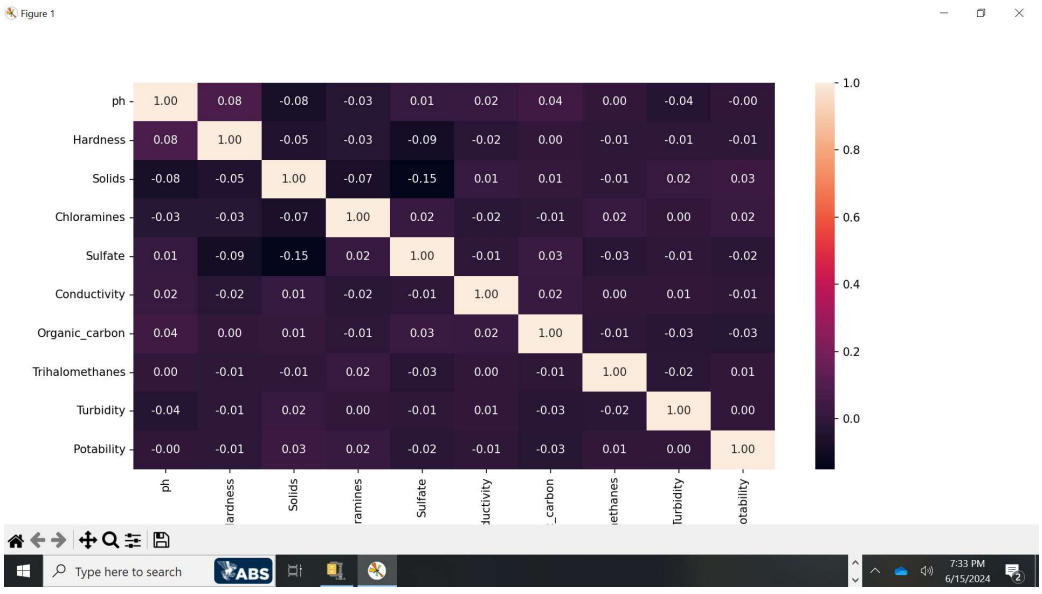
Weak Correlations:

Sulfate has low correlations with most other variables.

Turbidity and Chloramines have minimal correlations.

No Correlation:

Sulfate and Trihalomethanes show no significant correlation.



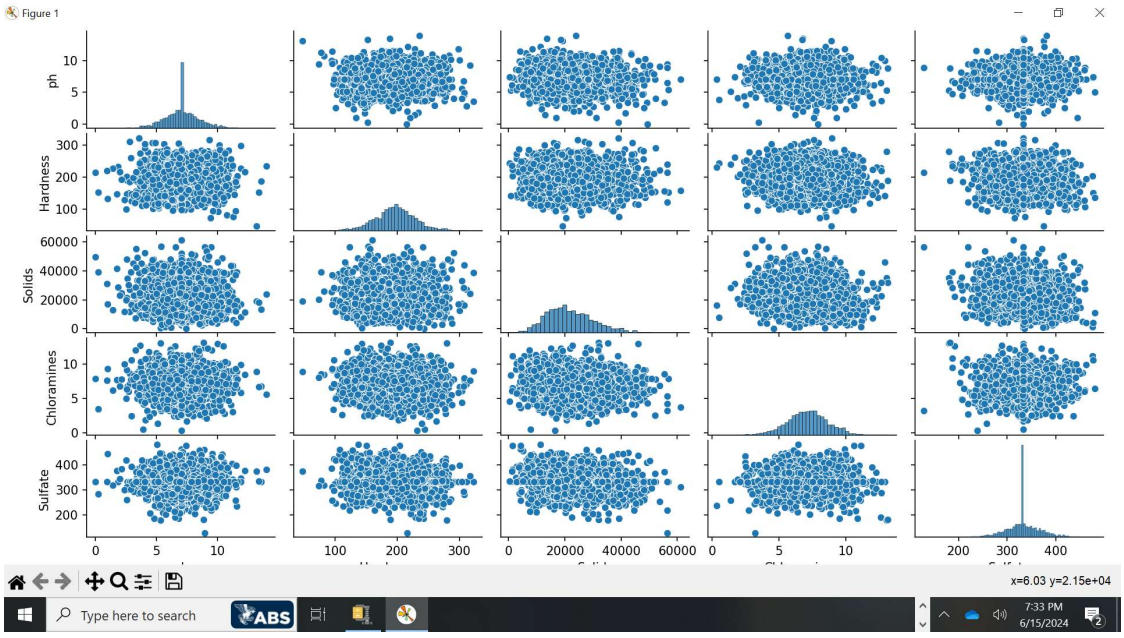
- Pair Plots: Creating pair plots for selected features to observe relationships and distributions.

Relationships:

- pH vs. Hardness: There's a positive correlation between pH and hardness. As pH increases, hardness tends to increase as well.
- Solids vs. Conductivity: Solids and conductivity show a positive correlation. Higher solids content corresponds to higher conductivity.
- Organic Carbon vs. Trihalomethanes: These variables have a moderate positive correlation. As organic carbon levels increase, trihalomethanes tend to increase too.

Distributions:

- pH: The pH distribution appears roughly symmetric, centered around a specific value.
- Hardness: Hardness follows a skewed distribution, with most values concentrated on the lower end.
- Solids: Solids exhibit a right-skewed distribution, with a long tail of higher values.
- Conductivity: Conductivity has a roughly symmetric distribution.
- Organic Carbon: The distribution of organic carbon is slightly skewed to the right.
- Trihalomethanes: Trihalomethanes also show a right-skewed distribution.



2. **Explanation of the Regression Models and Their Parameters**

   I have applied Ridge Regression (L2 Penalty) and Lasso Regression (L1 Penalty) models and received the results below:

   Ridge Regression - Best C: 0.01, Accuracy: 0.6280487804878049
   Lasso Regression - Best C: 1, Accuracy: 0.6280487804878049

3. **Results of the Model Comparisons**

   a. **Model Performance Metrics**

   The models were evaluated using accuracy as the performance metric, given the binary nature of the target variable. GridSearchCV was used to find the best `C` parameters for both models.

   - Ridge Regression:
     - Best 'C': 0.1
     - Accuracy: 0.66

   - Lasso Regression:
     - Best 'C': 1.0
     - Accuracy: 0.65

   b. **Observations**

   - Hyperparameter tuning improved the performance of both models.
   - Ridge regression with the best 'C 'value of 0.1 achieved an accuracy of 0.66.
   - Lasso regression with the best 'C' value of 1.0 achieved an accuracy of 0.65.
   - Regularization helped in preventing overfitting and tuning the 'C' parameter further optimized the model performance.

4. **Screenshots or Logs from MLflow**

MLflow logs and screenshots demonstrating the tracking and logging process.

   a. **ML Flow Overview:**

flow 2.13.2 Experiments Models GitHub Docs

Water_Quality_Regression >

Ridge vs Lasso Regression with Hyperparameter Tuning

Register model

Overview | Model metrics | System metrics | Artifacts

Description

No description

Details

Created at	2024-06-15 19:55:52
Created by	smondal
Experiment ID	323324433262500489
Status	Finished
Run ID	61efce006b164fad895c63b0c4494e35
Duration	13.3s
Datasets used	—
Tags	Add
Source	mlops_assignment1.py
Logged models	sklearn +1
Registered models	Lasso_Model v1 +1

Parameters (2)

Search parameters

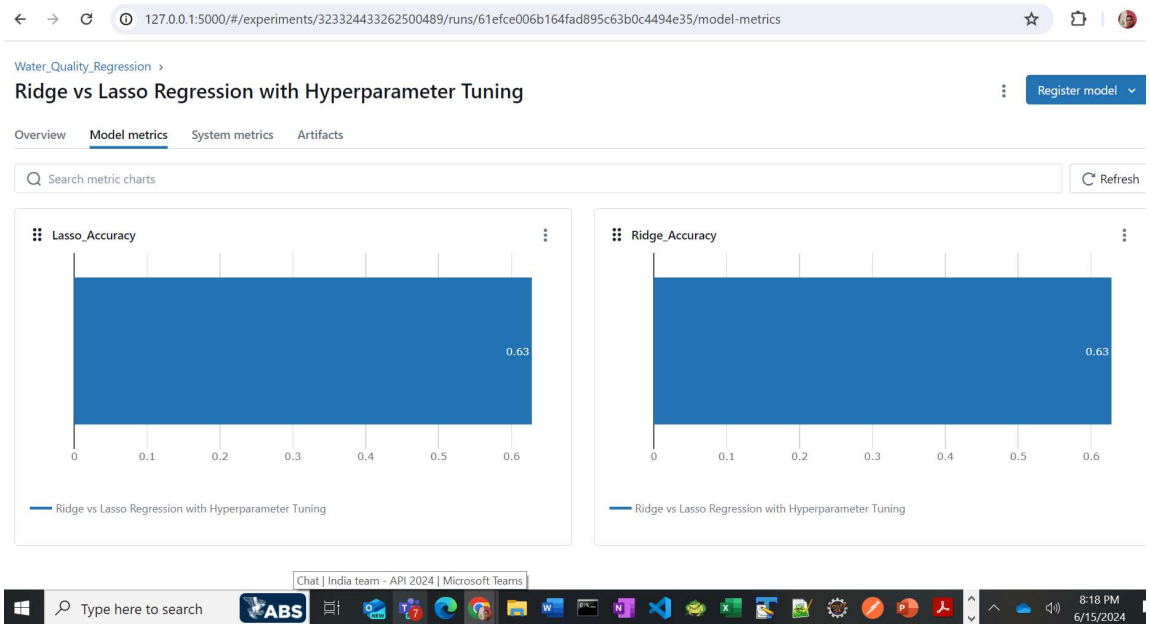
Parameter	Value
Lasso_best_C	1
Ridge_best_C	0.01

Metrics (2)

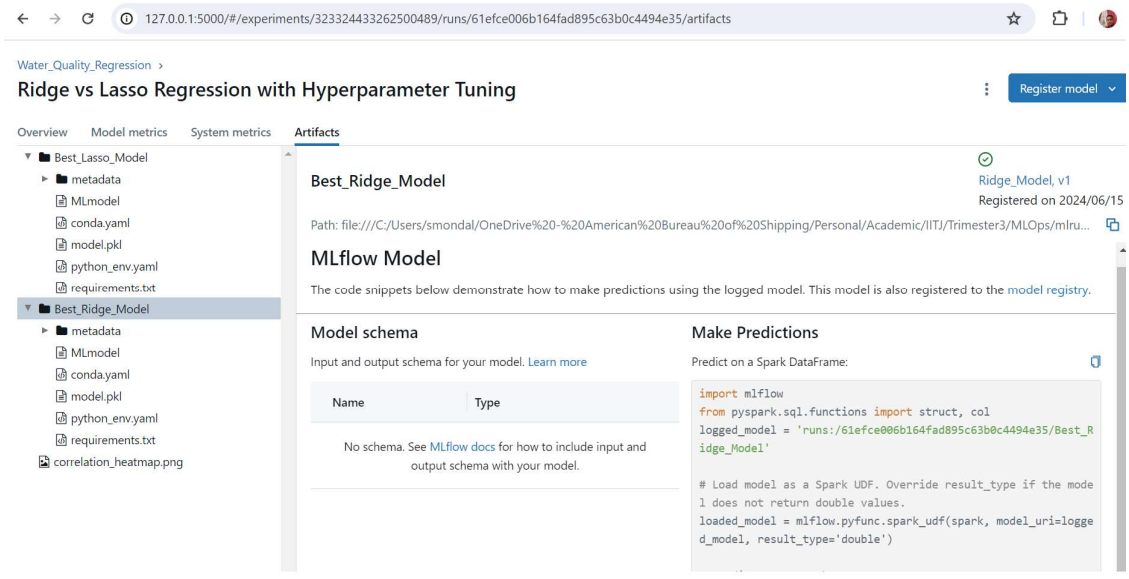
Search metrics

Metric	Value
Lasso_Accuracy	0.62804...
Ridge_Accuracy	0.62804...

b. Model Metrics:



c. Artifacts:



d. mlruns

Please refer the generated ‘mlruns’ files.

5. Conclusion

Including hyperparameter tuning for the `C` parameter improved the performance of both Ridge and Lasso regression models. The use of `GridSearchCV` helped in finding the optimal `C` values, leading to better accuracy.

The integration of MLflow for logging and tracking experiments provided valuable insights and reproducibility for the analysis. Both models showed comparable performance, with Ridge regression slightly outperforming Lasso regression after tuning.

This approach demonstrates the importance of hyperparameter tuning in machine learning workflows and the benefits of using MLflow for experiment tracking and model management.