

Expanding Machine Learning to Formation Evaluation

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Objectives

- To propose a model that would accurately determine the type of facies based on the log readings, speedily.
- To accurately determine the feature importances based of the machine learning model to aid in logging method selection
- Analyze the relationship between different log readings, and geological locations with facies classification

Presentation Flow

















TARGET

- 1: Non-Marine Sandstone
- 2: Non-Marine Coarse Siltstone
- 3: Non-Marine Fine Siltstone
- 4: Marine siltstone and shale
- 5 : Mudstone (Limestone)
- 6: Wackestone (Limestone)
- 7 : Dolomite
- 8 : Packstone Grainstone (Limestone)
- 9 : Phylloid-algal bafflestone (Limestone)



FEATURES

Log Readings:

- Gamma Ray (GR)
- Resistivity (ILD_log10)
- Photoelectric Effect (PE)
- Neutron-Density Porosity Difference (DeltaPHI)
- Neutron-Density Porosity (PHID)

Positional/Geological

Depth, Nonmarine-Marine Indicator (NM_M), relative position, Formation and well names





Basic



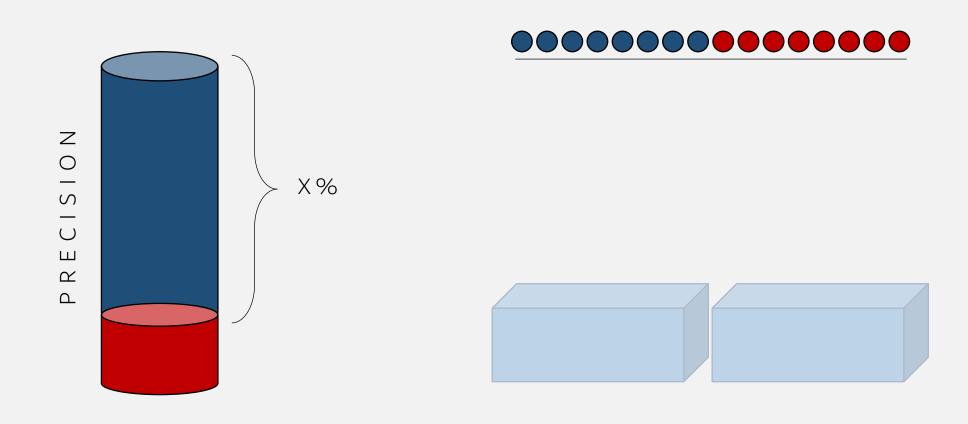






Model Basics – F1 Score

RECALL







Basic



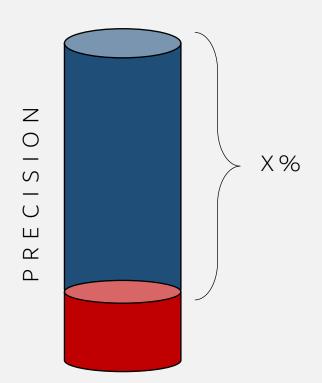


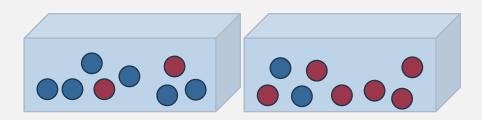




Model Basics – F1 Score

RECALL









Basic



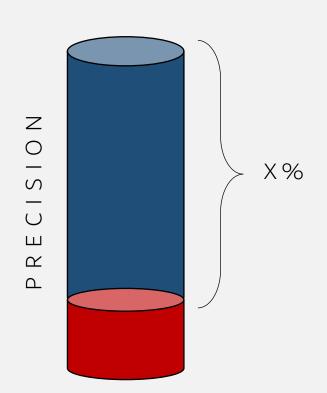


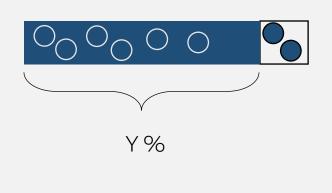


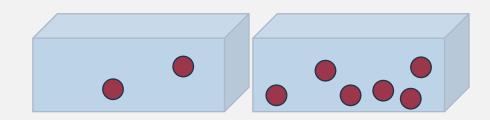


Model Basics – F1 Score

RECALL













Data Split

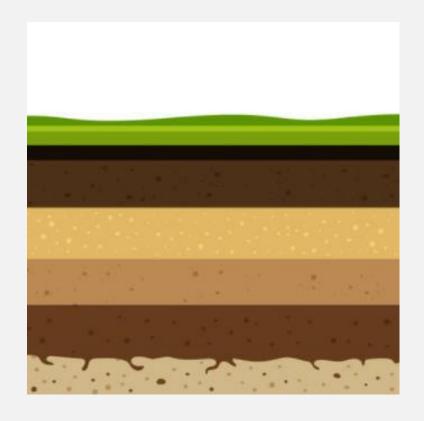
Preprocessing



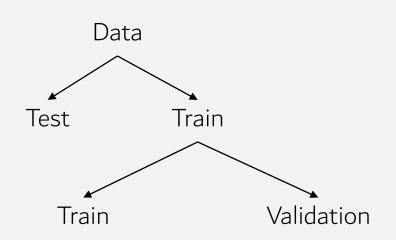




Data Split And Preprocessing



DATA SPLITTING



PREPROCESSING

Filling Missing Values: Using Distances

Scaling: Using Median









Model

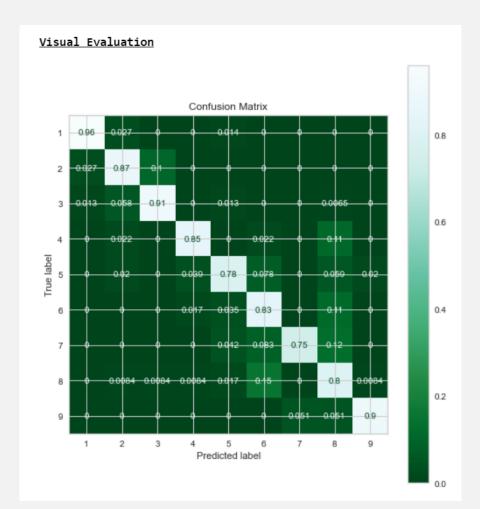
Results

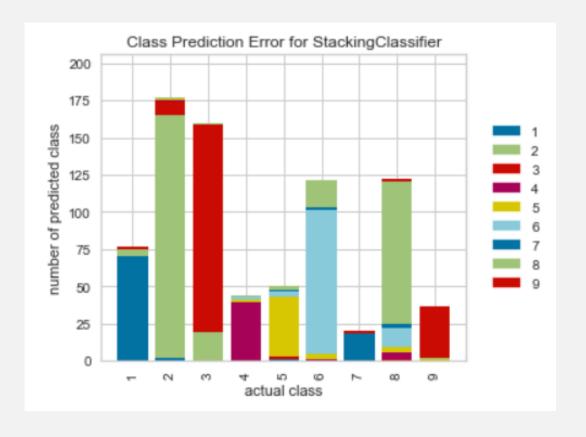




Results on the Test Data

Time taken: 9.7s

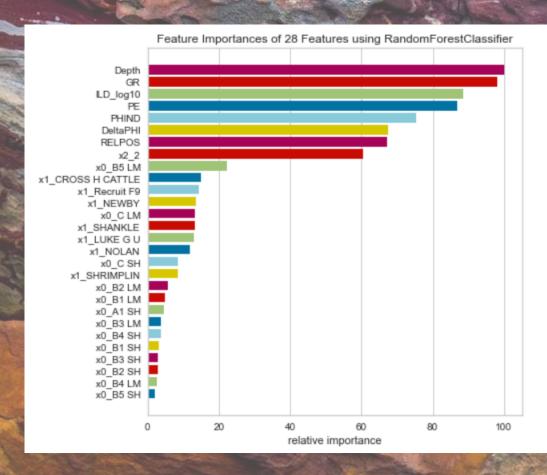


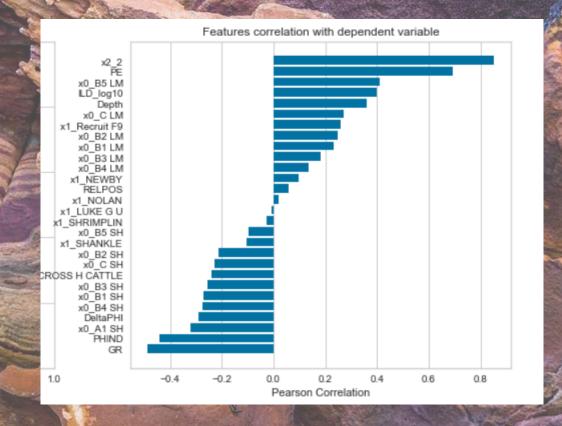


f1-SCORE: 0.86

Feature Rank and Importances







Relation with Target













Target Relation



Packstone -Grainstone (Limestone)

Dolomite



Mudstone (Limestone)

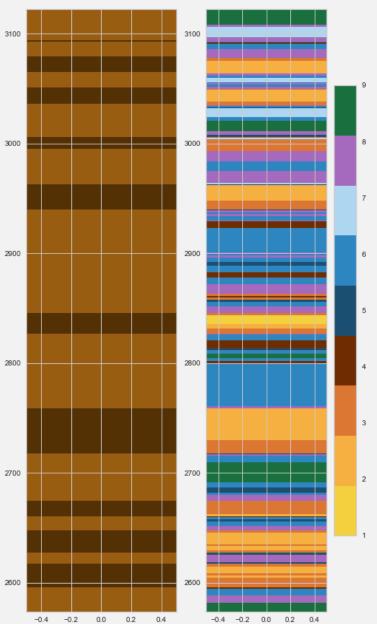
Marine siltstone and shale

Non-Marine Fine Siltstone

Non-Marine Coarse Siltstone

Non-Marine Sandstone





200

ILD_log10

GR

50

PHIND

-20

0

DeltaPHI

20

2600

2700

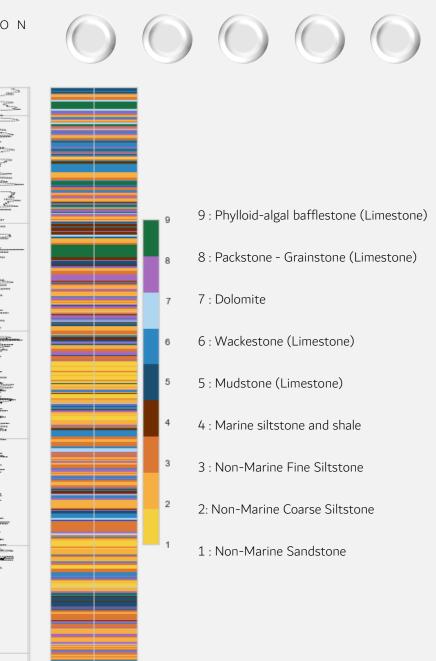
2800

2900

3000

3100

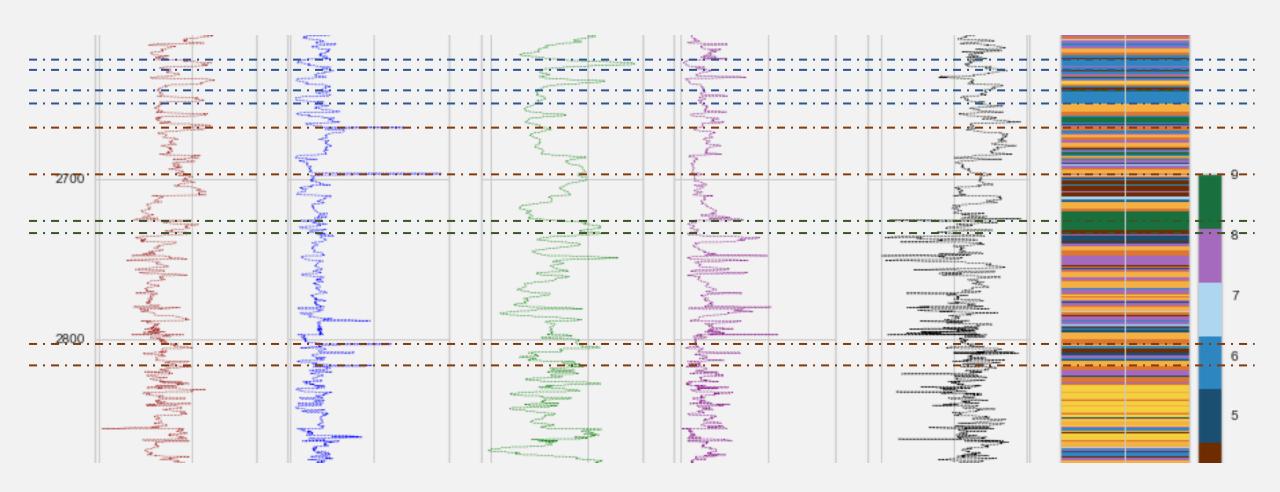
PE



Target Relation



Target Relation



Conclusions and Recommendations

- The best model took $9.7\,\,$ S E C S to classify the data into separate facies with F $1\,\,$ S C O R E of $0.86.\,$
- Machine learning model can be a very EFFICIENT and SPEEDY tool for facies classification compared to the cumbersome manual techniques currently used which take days to generate the results.
- The most important features that determine the accurate classification include the property of being MARINE or NON-MARINE, and the log values generated from PE, GR, N-D LOGS, RESISTIVITY and RELATIVE POSITION along with DEPTH. These show great influence since each of these values are unique to certain properties which define a facies.
- It is paramount, therefore, that these operations and data preprocessing is conducted meticulously before feeding in the data into the machine learning model.



Future Work



- Further IMPROVING the model to include other methods of DISTANCE CALCULATION since distance is proved to be a major factor in the results.
- Analyze the EFFECT OF CLASS IMBALANCE to further improve our model.
- Incorporate DEPTH MISMATCH and tail REMOVAL during preprocessing since it is time consuming.
- Expand and test this model for wells at DIFFERENT GEOLOGICAL LOCATIONS with other facies present to make this model applicable globally
- Use these PREDICTIONS AS A FEATURE in machine learning models to predict the main goal of facies classification.



Thank You!

Questions?

EXPANDING MACHINE LEARNING TO FORMATION EVALUATION