#### Africa Soil Property Prediction – Kaggle Challenge

Graduate Project ECE/CS 498 DSG

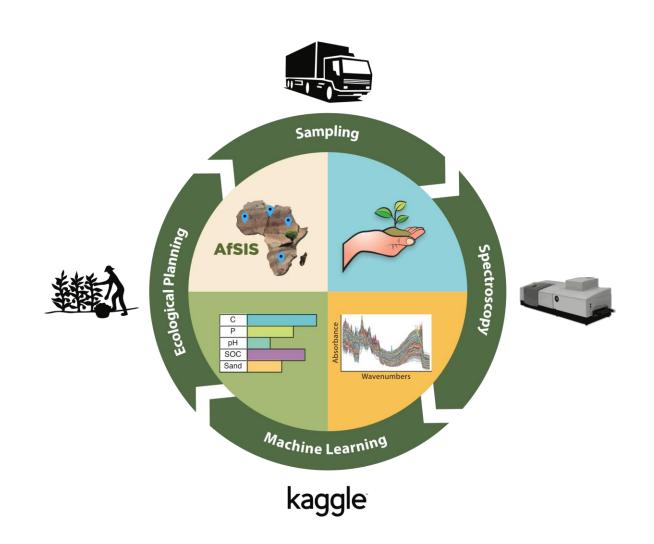
### Background

- Soil functional properties
  - Give information about primary productivity, nutrient and water retention, and resistance to soil erosion
  - Ecological planning
- Conventional reference tests to extract soil properties
  - Require much effort and time, slow, expensive, use chemicals
- Infrared Spectroscopy Approach
  - Have shown potential to provide a highly repeatable, rapid and low cost measurement of many soil functional properties
- Kaggle Challenge
  - Hosted a challenge to develop an accurate prediction model from spectroscopy data

#### **Problem Statement**

- 5 soil functional properties
  - Ca, P, pH, SOC, Sand

 Predict 5 target soil functional properties from infrared spectroscopy measurements

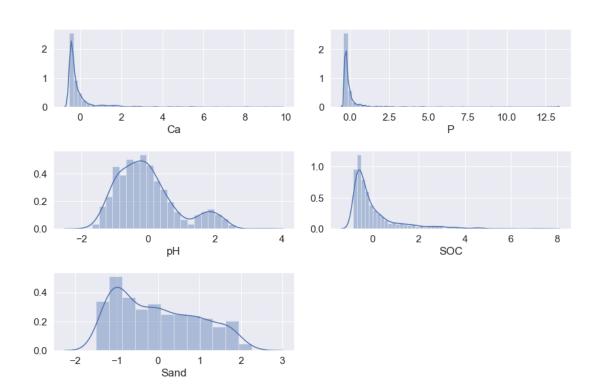


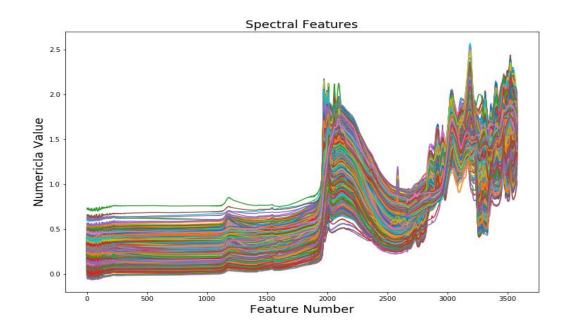
#### Data

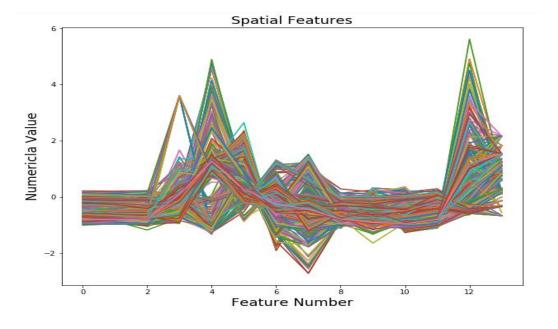
- Data Source: Kaggle competition
- Number of samples: 1157 (train data), 728 (test data)
- Number of features: 3594
  - 3578 Spectral Features from spectroscopy Numerical
  - 15 Spatial Features from remote sensing data Numerical
  - 1 Depth of Soil Categorical (topsoil & subsoil)
- Target Variables
  - SOC, pH, Ca, P, Sand are 5 target variables
  - Continuous/numerical in nature (Regression Problem)

# Challenges

- High Dimensional Data
- Finding the relevant features
- Overfitting (Small number of samples)
- Low correlations with target variables



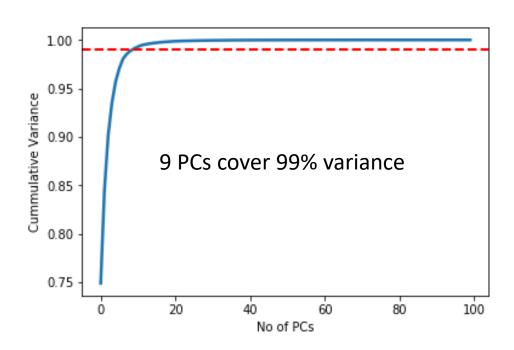




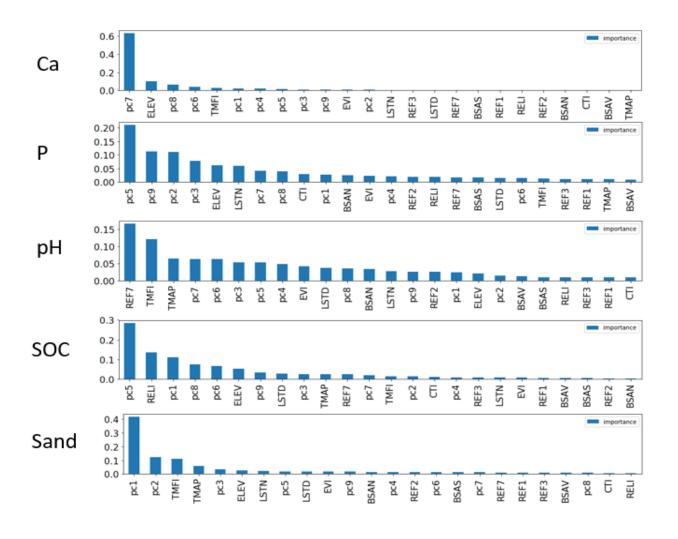
## Solution approach

- Broad solution approach
  - Dimensionality Reduction
    - PCA
    - Feature Selection
  - Train Regression models
    - Linear, non-linear, ensemble
  - k-fold Cross validation
  - Model Selection
  - Hyperparameter tuning
  - Final Prediction
  - Comparison with existing solutions
  - Clustering

### Solution approach

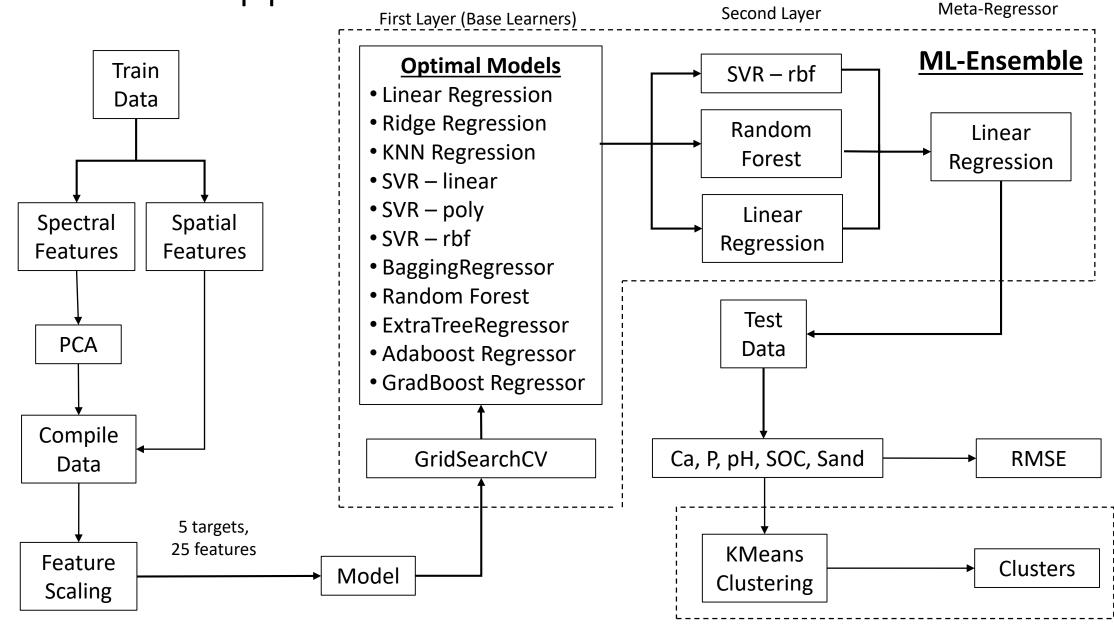


- Non-linear models performed better
- Feature Selection methods didn't work.
  Slightly improved results in case of linear models.
- PCA already reduced 3578 features to 9 PCs
- Decided to go with 25 features



Relative Feature Importance from Random Forest Regressor

Solution approach

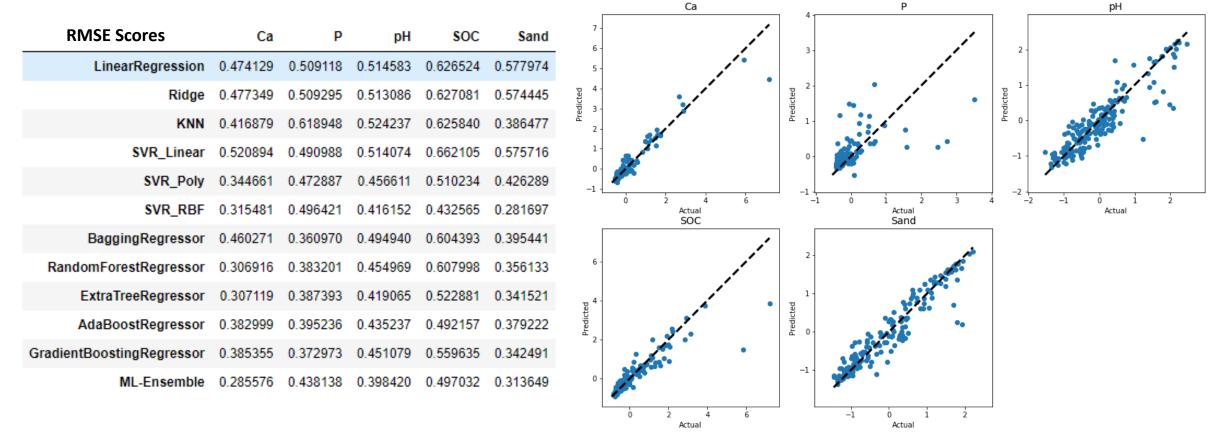


## Baseline approach – existing methods

- Kaggle top solutions mentioned overfitting as a problem
- There is no signal model that provided best results.
- Some sort of ensemble was created from best performing models.
- Mean column wise RMSE was the scoring criteria

MCRMSE = 
$$\frac{1}{5} \sum_{j=1}^{5} \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{ij} - \hat{y}_{ij})^2}$$

## Regression Results



Kaggle Test Data:

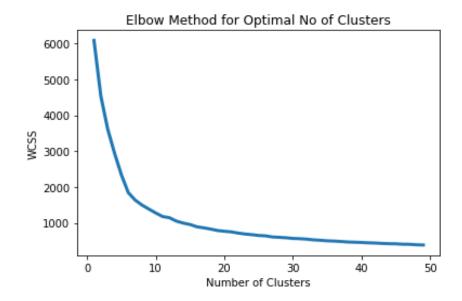
Top MCRMSE Score = **0.46892**,

Our MCRMSE Score = **0.5605** 

# Relationships among Target Variables

#### **Clustering Results:**

- There seemed to be 8 optimal clusters
- Grouped data by clusters and calculated means
- Gave interpretable Description for each cluster



Ca	P	pH	SOC	Sand	Cluster	Description
-0.377770	-0.219385	-0.449092	-0.388017	-0.074105	0	Low-Ca Low-P Neg-pH Low-SOC Mid-Sand
-0.040148	-0.124162	-0.574790	2.896514	-0.928389	1	Low-Ca Low-P Neg-pH High-SOC Low-Sand
0.747014	0.068563	1.537137	-0.304553	-0.389595	2	Mid-Ca Mid-P Pos-pH Low-SOC Mid-Sand
0.258263	3.141500	0.430292	0.317031	-0.174210	3	Mid-Ca Mid-P Pos-pH Mid-SOC Mid-Sand
4.859856	-0.190742	1.900154	2.483493	-0.967938	4	High-Ca Low-P Pos-pH High-SOC Low-Sand
-0.404145	-0.172640	-0.130470	-0.609670	1.282962	5	Low-Ca Low-P Neg-pH Low-SOC High-Sand
-0.137051	-0.209962	-0.449387	0.459577	-0.983348	6	Low-Ca Low-P Neg-pH Mid-SOC Low-Sand
1.040350	9.840077	0.638322	2.813268	-0.654799	7	Mid-Ca High-P Pos-pH High-SOC Low-Sand

