Project 1

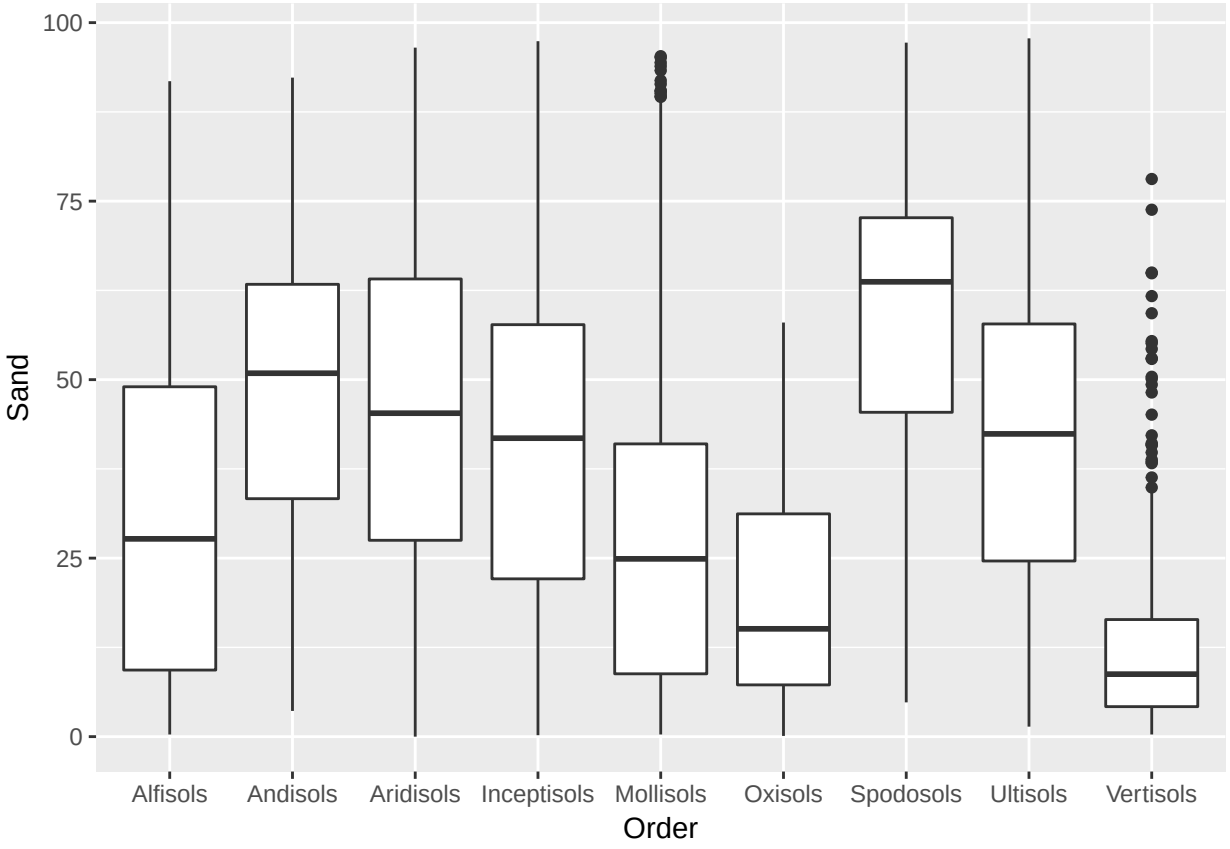
Introduction

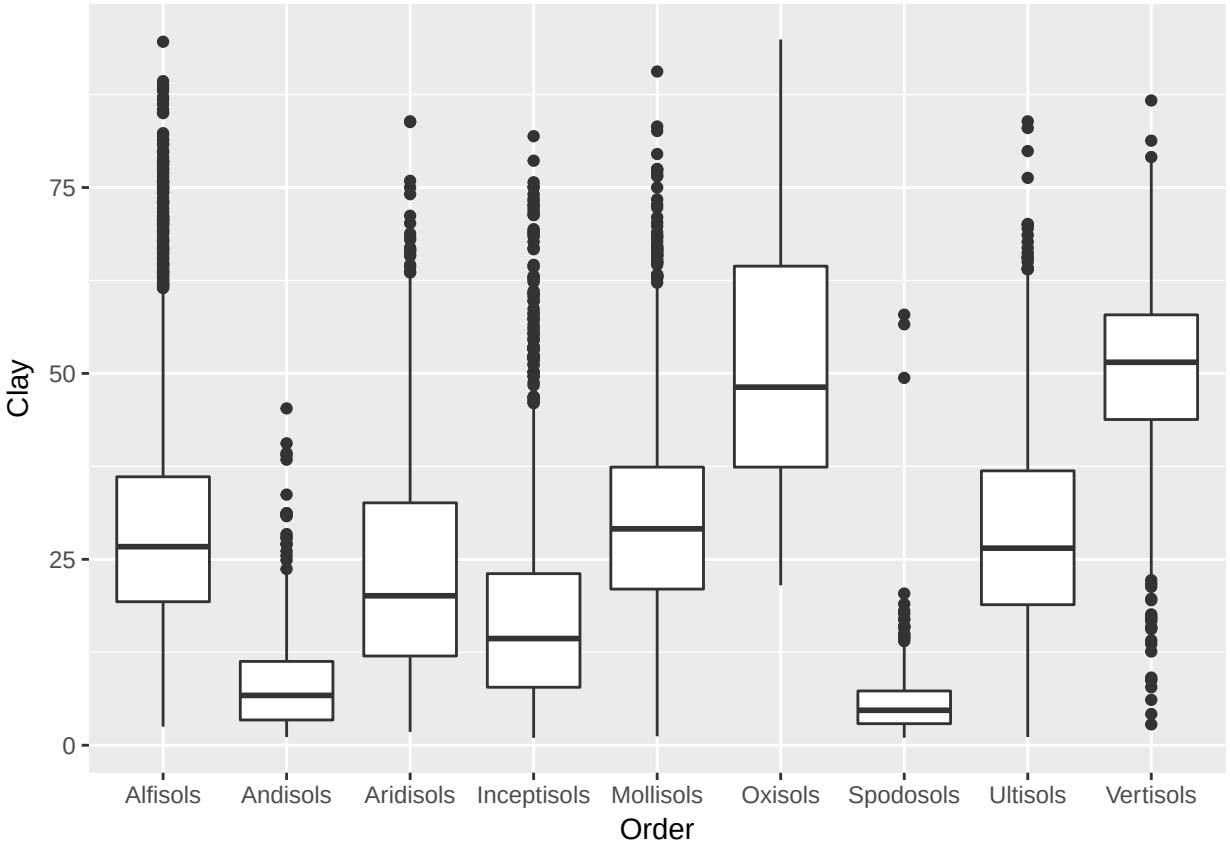
This is Project 1 for STAT 557 2018 Spring by Meridith Bartley and Fei. The aim of this project is to practice linear classification methods and QDA and study basic techniques of dimension reduction.In this project we (1) apply LDA, QDA, and multinomial logistic regression to soil sample data in order to calssify into separate soil group (Orders).

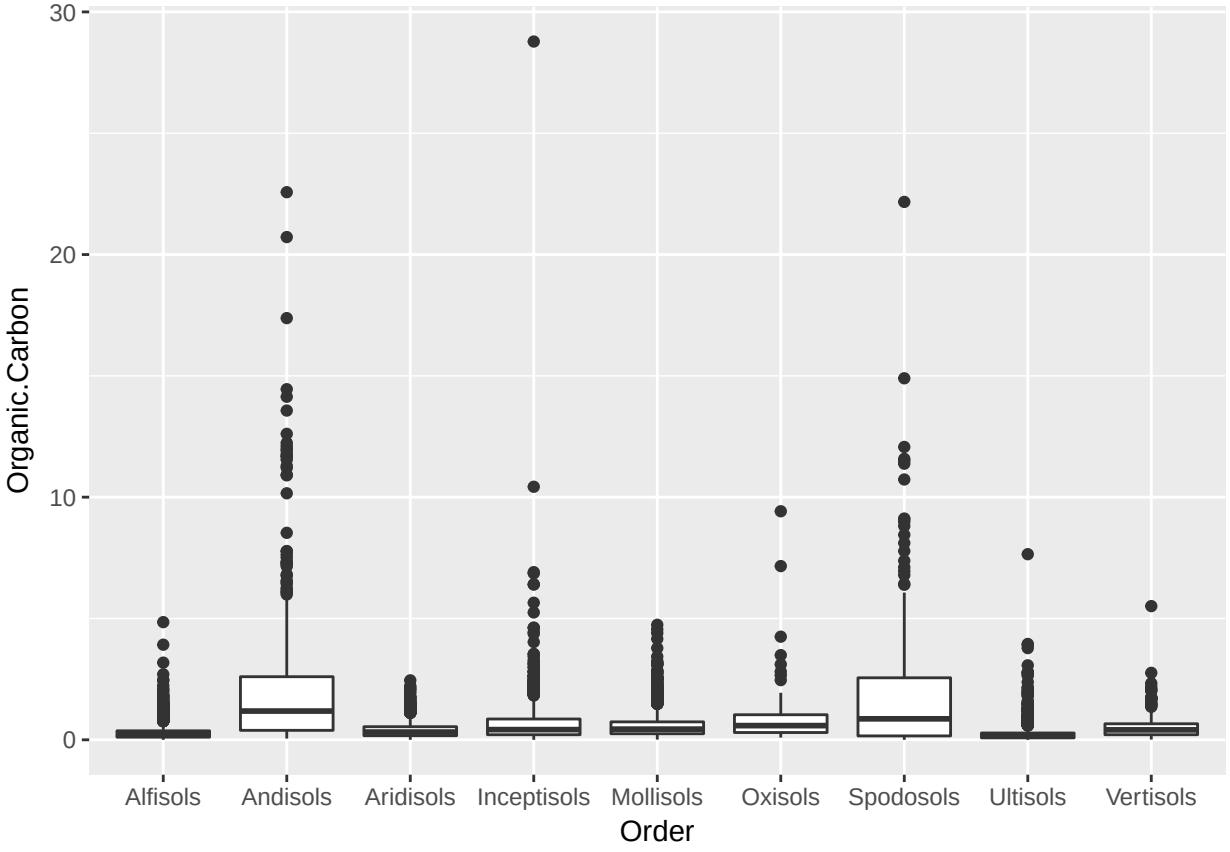
Description of Data

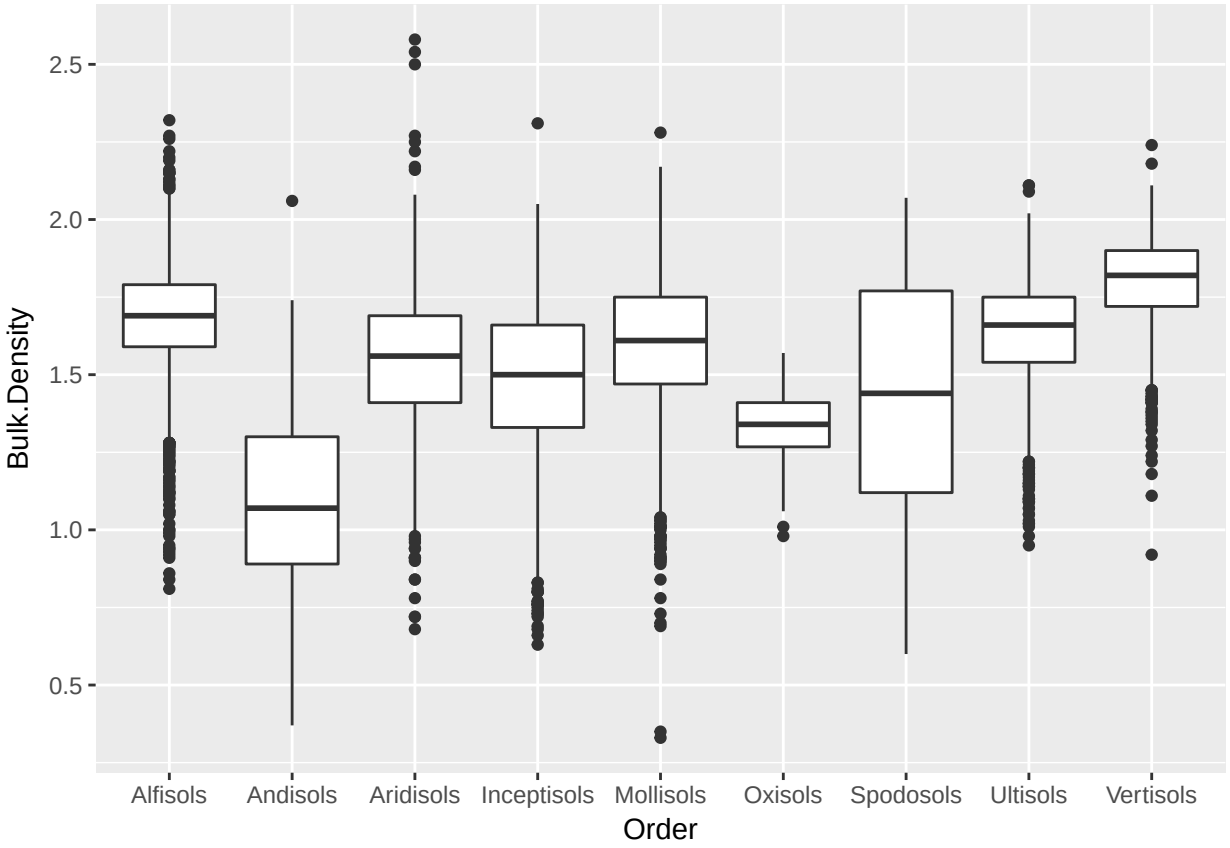
This is Fei's research data. It's about soil sample data over the US downloaded from NRCS, including the physical and chemical properties of soil samples (sand, silt, clay, oganic carbon, bulk density, CEC soil, CEC clay, base satuaration, and pH) and the corresponding soil classification group (soil order).

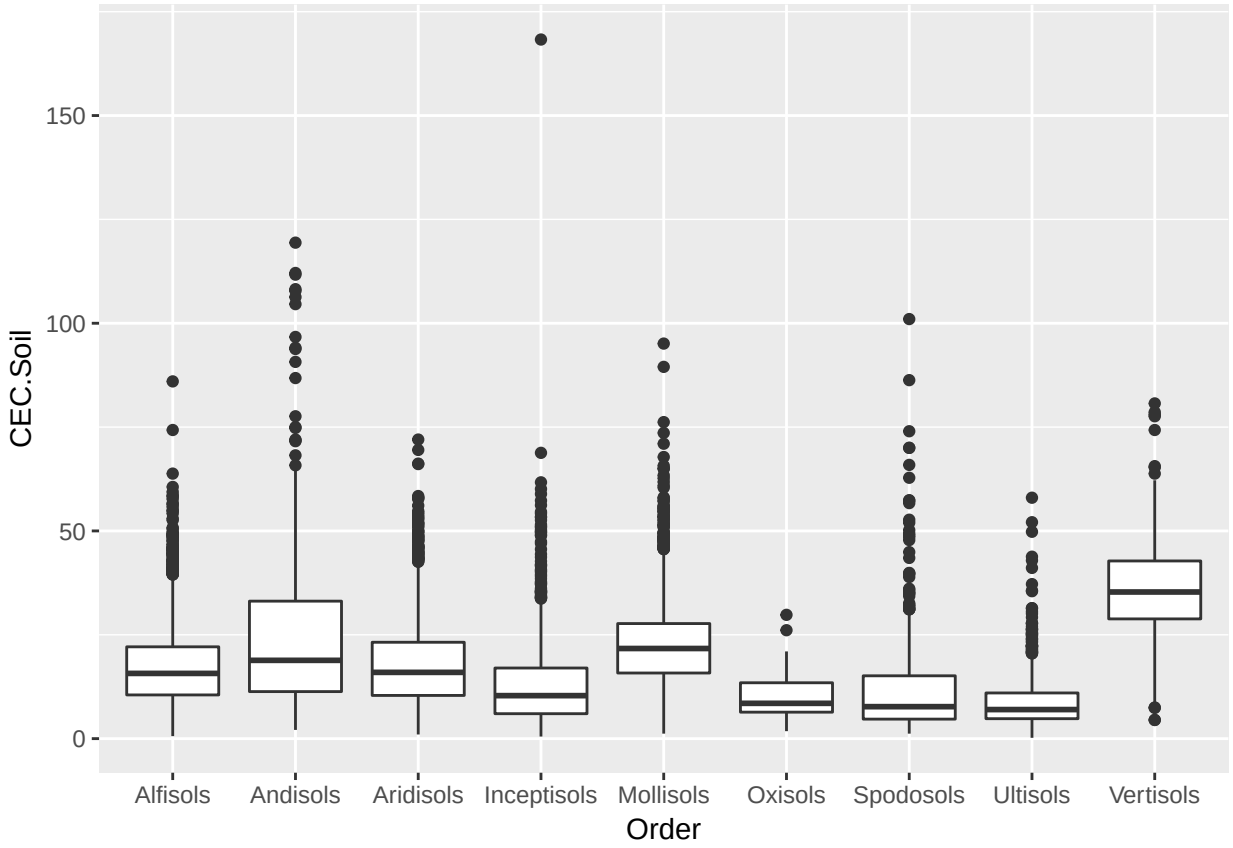
Boxplots for each physical and chemical property used as explanitory variables in the subsequent classification models are included below. This EDA allows for early indication of which variables may possibly be ommitted during dimention reduction. That is, what properties do not differ significantly between soil Orders.

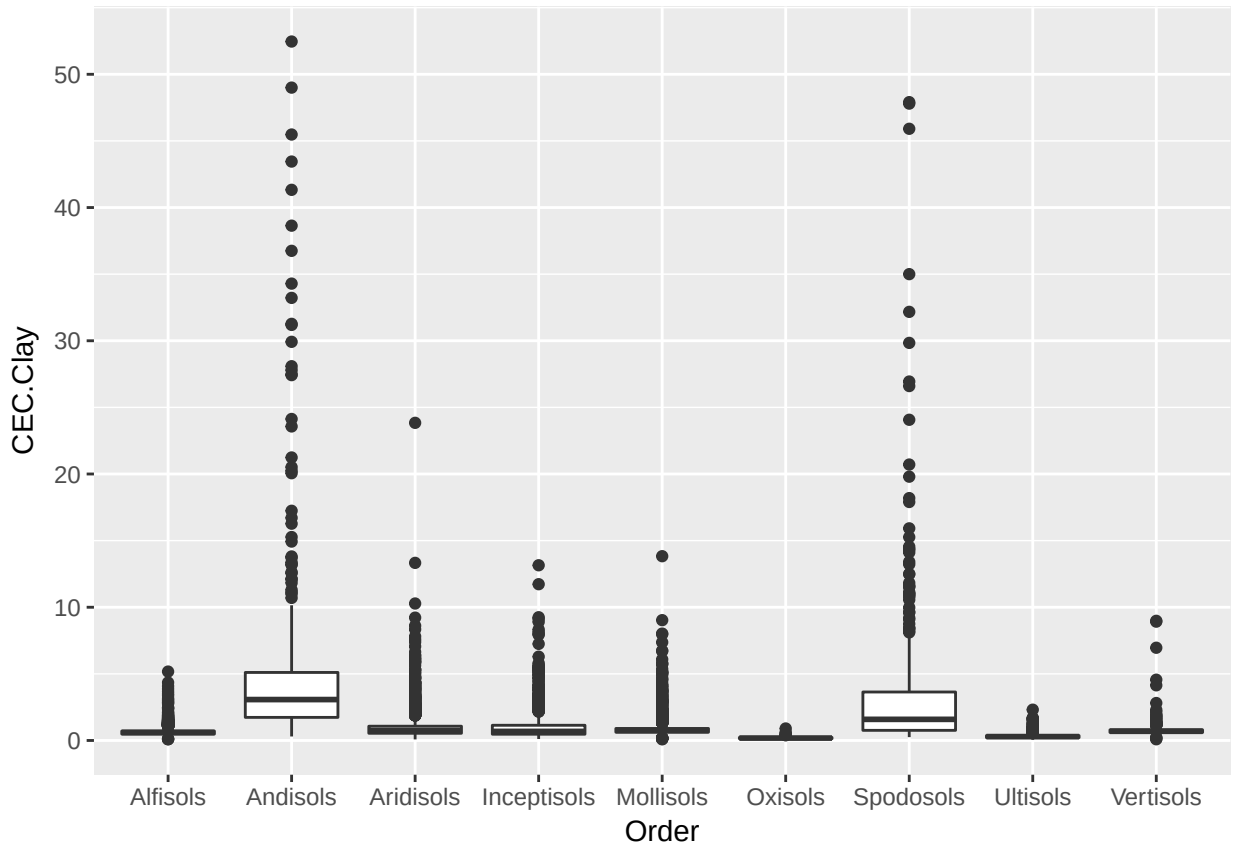


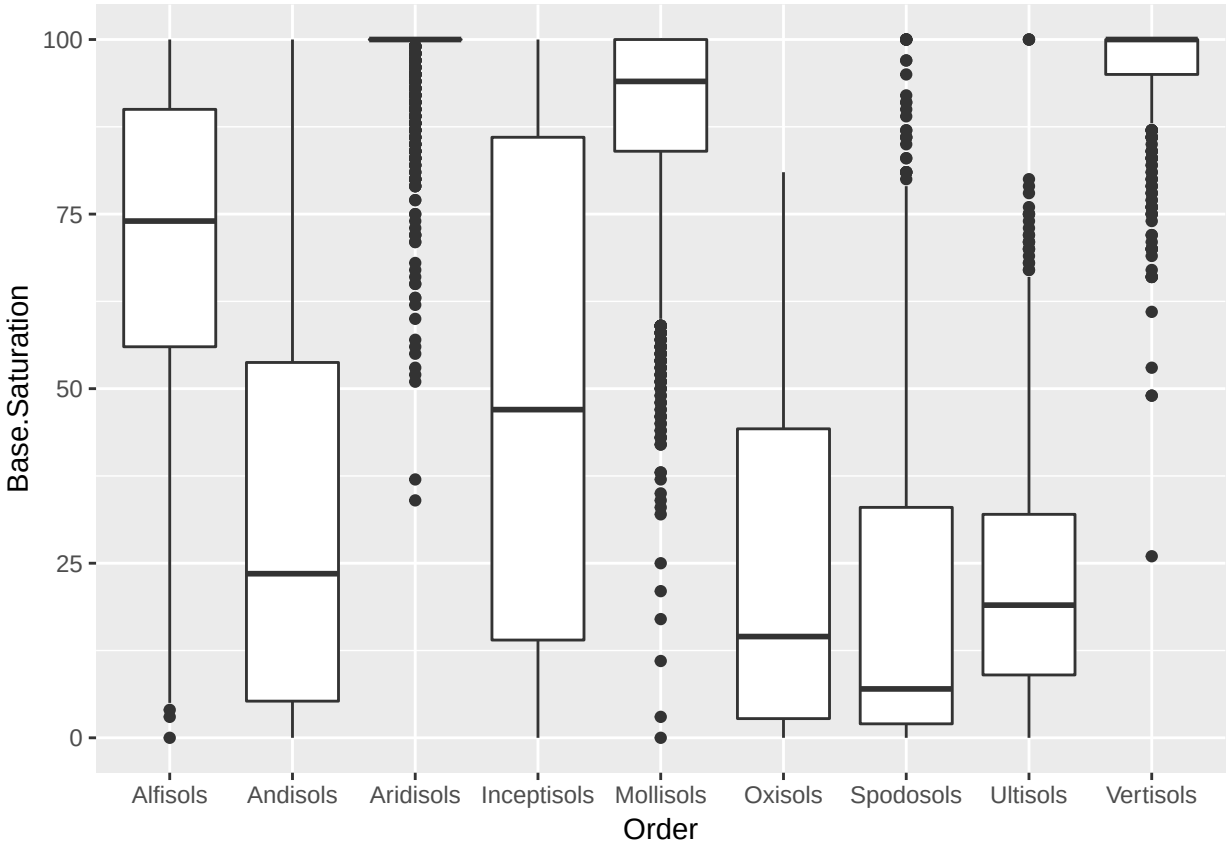

Clay
75
50
25
0
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order

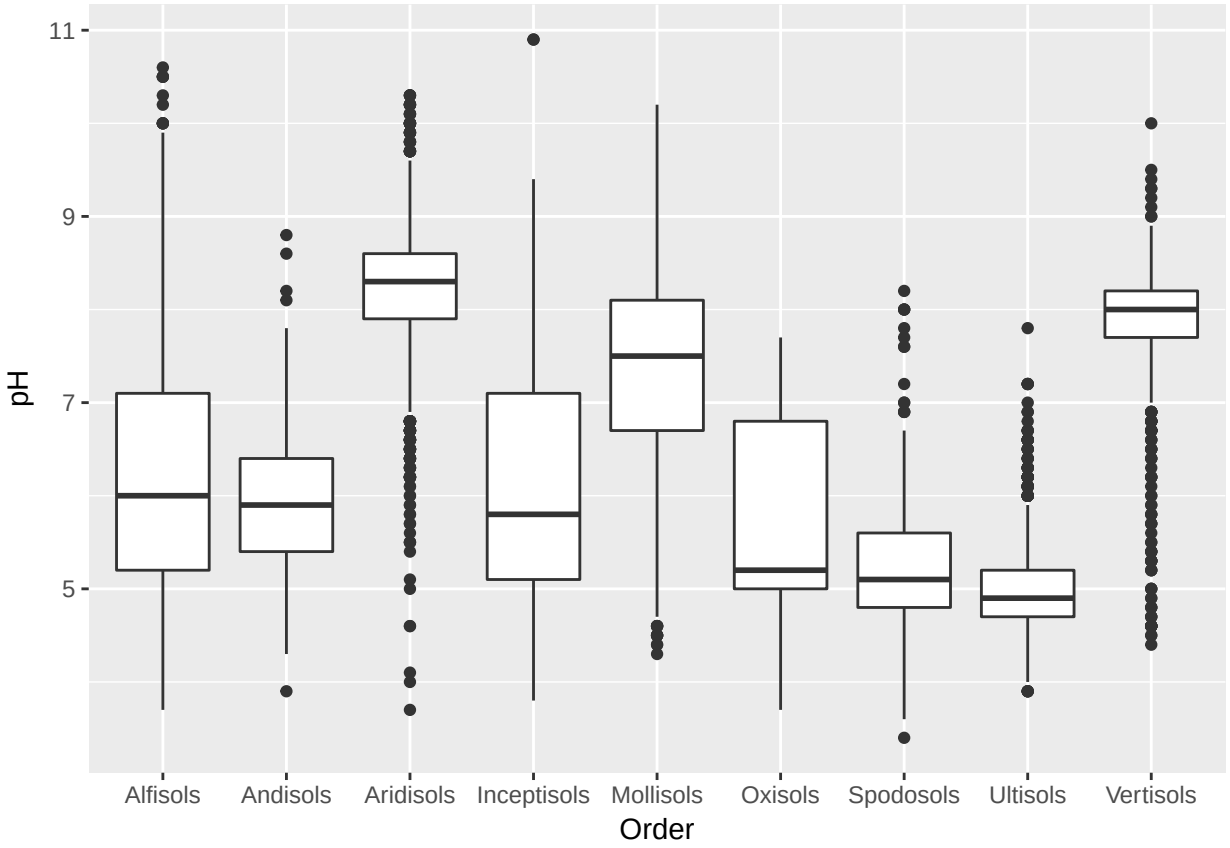

30
20
10
0
Organic.Carbon
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order


2.5
2.0
1.5
1.0
0.5
Bulk.Density
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order


CEC.Soil
150
100
50
0
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order


CEC.Clay
50
40
30
20
10
0
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order


100
75
50
25
0
Base.Saturation
Alfisols
Andisols
Aridisols
Inceptisols
Mollisols
Oxisols
Spodosols
Ultisols
Vertisols
Order

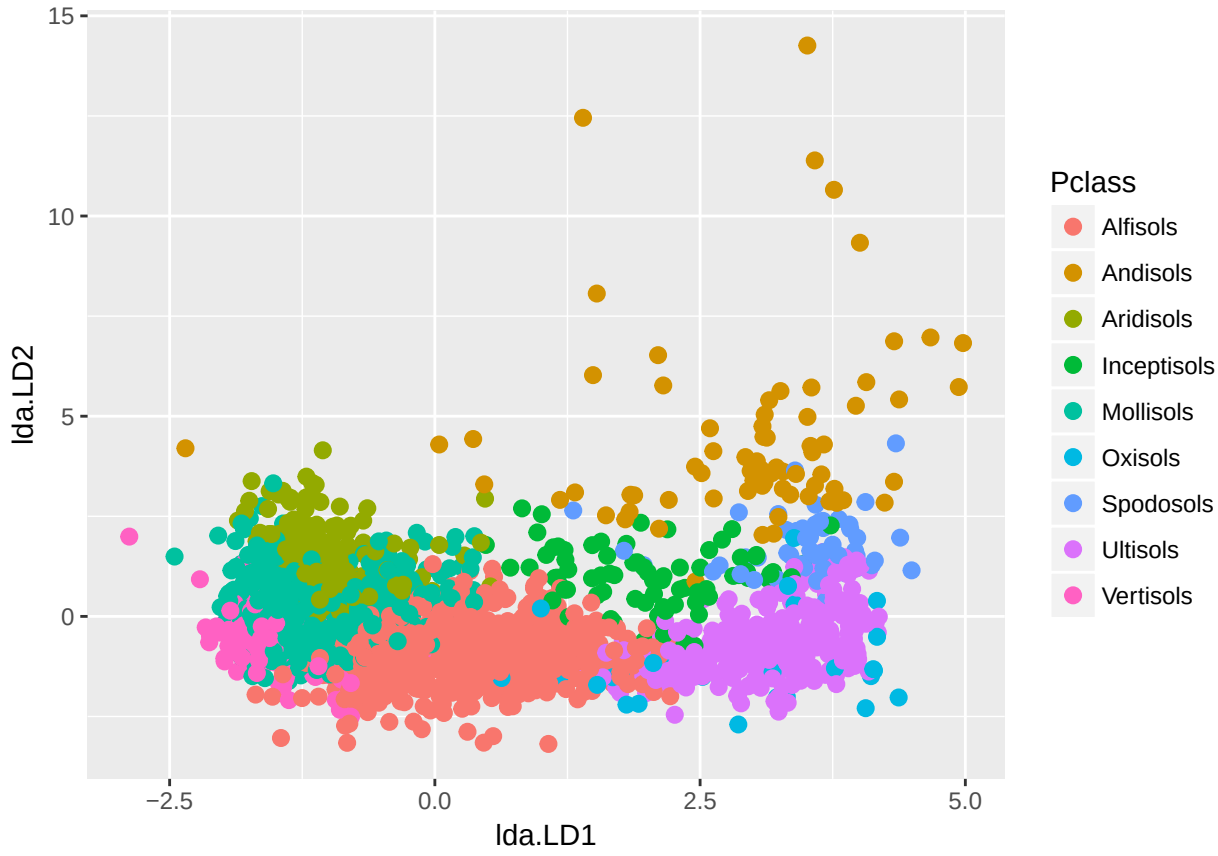


Analysis

Linear Discriminant Analysis (LDA)

```
##    Alfisols    Andisols   Aridisols Inceptisols   Mollisols     Oxisols
##   0.5756410   0.5135135   0.5312500   0.1226415   0.6719902   0.7058824
##   Spodosols    Ultisols   Vertisols
##   0.2674419   0.7413793   0.6056338
```

```
## [1] 0.5676163
```



Quadratic Discriminant Analysis

```
##    Alfisols    Andisols   Aridisols Inceptisols   Mollisols     Oxisols
##   0.7025641   0.3648649   0.5528846   0.1745283   0.5233415   0.8235294
##   Spodosols    Ultisols   Vertisols
##   0.3720930   0.8362069   0.6830986
```

```
## [1] 0.5787955
```

Multinomial Logistic Regression

```
## # weights:  90 (72 variable)
## initial  value 24413.362279
## iter  10 value 15571.788617
## iter  20 value 15002.934730
## iter  30 value 14478.067709
## iter  40 value 13342.947004
## iter  50 value 12895.100142
## iter  60 value 11964.921219
## iter  70 value 11392.960138
## iter  80 value 11092.884124
## iter  90 value 11073.376567
## iter 100 value 11068.820796
## final  value 11068.820796
```

```
## stopped after 100 iterations
```

```
## Call:
## nnet::multinom(formula = Order ~ ., data = project1data, subset = logr_train)
##
## Coefficients:
##             (Intercept)         Sand        Clay Organic.Carbon
## Andisols      -1.257580  0.004604636 -0.14837098      1.4814836
## Aridisols    -16.647205  0.037371622  0.01397444      1.8354158
## Inceptisols   -1.546126 -0.001386762 -0.02952812      1.5541408
## Mollisols     -4.784262 -0.010040832 -0.03849970      2.1073975
## Oxisols       -1.228724 -0.036673998  0.12533802      1.5804614
## Spodosols      3.154741 -0.002459725 -0.30013019      2.0265253
## Ultisols       4.176125  0.020686544  0.02329184      0.9611524
## Vertisols    -25.756763 -0.032795642  0.02686232      1.1029453
##             Bulk.Density     CEC.Soil   CEC.Clay Base.Saturation
## Andisols      -3.3268648  0.090699690  0.7283956     -0.05400634
## Aridisols     -2.9977783  0.017788300  0.7767474      0.08904043
## Inceptisols   -1.5721995 -0.033087145  0.6996854     -0.05024397
## Mollisols     -1.1448023  0.047291014  0.5020496      0.04673994
## Oxisols       -5.4297005 -0.384503261 -0.9479182     -0.14023916
## Spodosols      0.8954668  0.002404581  0.7267122     -0.02971002
## Ultisols      -0.5523640 -0.029525291 -6.0788610     -0.07628861
## Vertisols      3.7233981  0.101828103  0.8685522      0.07153714
##                     pH
## Andisols     1.03564767
## Aridisols    1.25567438
## Inceptisols  0.98149835
## Mollisols    0.30925835
## Oxisols      2.07863101
## Spodosols   -0.46243105
## Ultisols     0.06223332
## Vertisols    0.96201601
##
## Std. Errors:
##             (Intercept)        Sand        Clay Organic.Carbon
## Andisols      1.0310036 0.005048637 0.017763183      0.1323038
## Aridisols     0.7567081 0.002603326 0.006319524      0.1391297
## Inceptisols   0.5795942 0.002545976 0.007085791      0.1273438
## Mollisols     0.4033562 0.001836661 0.005258040      0.1095274
## Oxisols       0.2767875 0.014934380 0.017266353      0.2450583
## Spodosols     1.1548783 0.004945074 0.025558550      0.1459979
## Ultisols      1.0390342 0.003520762 0.010589521      0.1903680
## Vertisols     1.1395826 0.005597663 0.007548138      0.1939263
##             Bulk.Density    CEC.Soil  CEC.Clay Base.Saturation         pH
## Andisols       0.4291549 0.012529912 0.1603186     0.005764099 0.14309326
## Aridisols      0.2374184 0.008514832 0.1549128     0.007760952 0.07389334
## Inceptisols    0.2665768 0.010696741 0.1580458     0.003296969 0.07042780
## Mollisols      0.1922521 0.007539809 0.1536843     0.003460284 0.04776292
## Oxisols        0.7171407 0.065117056 1.2830235     0.013121106 0.24593297
## Spodosols      0.4031730 0.019898739 0.1622694     0.005147604 0.15985335
## Ultisols       0.3992114 0.025454237 0.7309696     0.004329235 0.12335749
## Vertisols      0.3997487 0.009602013 0.1887096     0.012469922 0.10947987
##
```

```
## Residual Deviance: 22137.64
## AIC: 22281.64
```

Results

The results from these three approaches show that…

In order to compare the reults it is important to recall the diffences between these three classification approaches. The difference between LDA and logistic regression is that linear coefficients are estimated differently. MLE for logistic models and estimated mean and variance based on Gaussian assumptions for the LDA. LDA makes more restrictive Gaussian assumptions and therefore often expected to work better than logistic models IF they are met. QDA serves as a compromise between non-parametric methods (not explored in this project) and the linear LDA and logistic regression approaches. Since QDA assumes a quadratic decision boundary, it can accurately model a wider range of problems than can the linear methods. QDA can perform better in the presence of a limited number of training observations because it does make some assumptions about the form of the decision boundary.

Contributions