Final Project

Group F 2021-11-06

Introduction

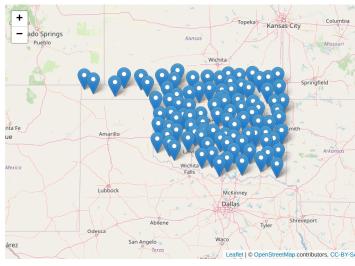
In this project we will work with a partly preprocessed dataset created from the original data given in the Kaggle platform corresponding to the "AMS 2013-2014 Solar Energy Prediction Contest". For more information on the dataset it can be found here https://www.kaggle.com/c/ams-2014-solar-energy-prediction-contest/overview

Dataset

- A total dimension of 6909 rows and 456 columns
- $\bullet \ \ \, \text{Each row corresponds to information of a particular day, ranging from 1994-01-01 to 2012-11-30. The first column, 'Date', } \\$ informs you of which day corresponds to each row.
- The next 98 columns (from 2nd to 99th position) gives the real values of solar production recorded in 98 different weather stations. These columns are only informed until 2007-12-31 (row 5113); after this date these 98 columns contain NA or missing values. These missing values we will attempt to **predict** to achieve the final goal of the project.
- The remaining columns are variables created from different weather predictors given in the Kaggle competition. They are the result of performing Principal Component Analysis, PCA, over the original data.

WEATHER STATIONS LOCATIONS

We thought it was important to visualize how spread out these 98 different whether stations are across the state of Oklahoma. We took advantage of the leaflet package in order to do this



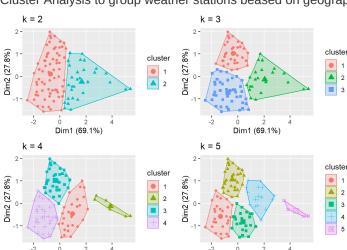


Elevation increases significantly in the northwest

EDA

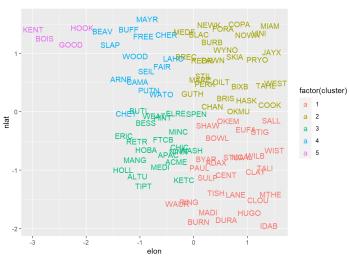
Cluster Analysis to group weather stations beased on geographic coordinates

Dim1 (69.1%)



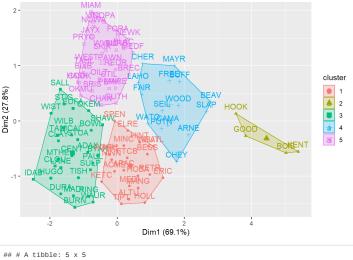
Clustering with k= 5

Dim1 (69.1%)



Based on these clusters, we decided to go wth 5 clusters since it is the one that best represents the Oklahoma map

```
## K-means clustering with 5 clusters of sizes 22, 4, 28, 15, 29
## Cluster means:
## nlat elon elev
## 1 -0.5728740 -0.6445489 0.2900088
## 2 1.3141019 -2.5323351 3.4817824
## 3 -1.0495895 0.7234280 -0.6998768
## 4 0.8787289 -0.9868012 0.9000444
## 5 0.8122205 0.6501879 -0.4900496
### Clustering vector:
## ACME ADAX ALTU APAC ARNE BEAV BESS BIXB BLAC BOIS BOWL BREC BRIS BUFF BURB BURN
4 4 1 5 5 2 3 5 5 4 5 3
## 1 3 1 1 4 4 1 5 5 2 3 5 5 4 5 3 ## BUTL BYAR CAMA CENT CHAN CHER CHEY CHIC CLAY CLOU COOK COPA DURA ELRE ERIC EUFA
## 1 3 4 3 5 4 4 1 3 3 5 5 3 1 1 3 ## FAIR FORA FREE FTCB GOOD GUTH HASK HINT HOBA HOLL HOOK HUGO IDAB JAYX KENT KETC
                    4
                                                5
## LAHO LANE MADI MANG MARE MAYR MCAL MEDF MEDI MIAM MINC MTHE NEWK NINN NOWA OILT
                                                        5
## 4 3 3 1 5 4 3 5 1 5 1 3 5 1 5 5 5 ## OKEM OKMU PAUL PAWN PERK PRYO PUTN REDR RETR RING SALL SEIL SHAW SKIA SLAP SPEN
## STIG STIL STUA SULP TAHL TALI TIPT TISH VINI WASH WATO WAUR WEAT WEST WILB WIST
## WOOD WYNO
""" ## Within cluster sum of squares by cluster:
## [1] 9.299395 3.244412 17.614317 10.179914 15.491898
## (between_SS / total_SS = 80.8 %)
## Available components:
## [1] "cluster"
                              "centers"
                                                                        "withinss"
                                                   "totss"
                                                                                             "tot.withinss"
## [1] "cluster" "center
## [6] "betweenss" "size"
                                                                        "ifault"
```

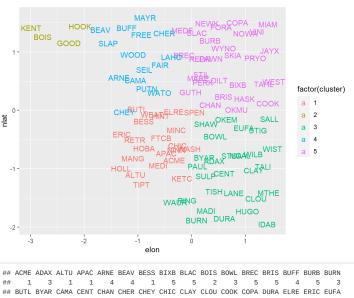


```
## cluster nlat elon elev stations
## <nh>elon elev stations
4bl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> NA

## 1 1 -0.573 -0.645 0.290 NA

## 2 2 1 31 -2 53 3 48 NA
                                                                     NA
                    2 1.31 -2.53 3.48
3 -1.05 0.723 -0.700
  ## 2
                                                                         NA
  ## 4
                     4 0.879 -0.987 0.900
                                                                         NA
  ## 5
                     5 0.812 0.650 -0.490
                                                                         NA
Final clusters
```

Cluster plot



```
5
                                                                                                                                                                                                                                                                                                                                                     3
        ## FAIR FORA FREE FTCB GOOD GUTH HASK HINT HOBA HOLL HOOK HUGO IDAB JAYX KENT KETC
        ## 4 5 4 1 2 5 5 1 1 1 2 3 3 3 5 2 1 ## LAHO LANE MADI MANG MARE MAYR MCAL MEDF MEDI MIAM MINC MTHE NEWK NINN NOWA OILT
        ## 4 3 3 1 5 4 3 5 1 5 1 3 5 1 5 5 5 5 6 1 5 1 5 1 5 1 5 1 5 5 5 6 1 5 5 5 6 1 5 5 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5 6 1 5
      ## STIG STIL STUA SULP TAHL TALI TIPT TISH VINI WASH WATO WAUR WEAT WEST WILB WISH ## 3 5 3 3 5 3 1 3 5 1 4 3 1 5 3 3
        ## WOOD WYNO
Summary
```

##	Date	ACME	ADAX	ALTU
##	Length:6909	Min. : 12000	Min. : 510000	Min. : 900
##	Class :character	1st Qu.:11404200	1st Qu.:10611000	1st Qu.:11674500
##	Mode :character	Median :16946400	Median :16299300	Median :17073600
##		Mean :16877462	Mean :16237534	Mean :17119189
##		3rd Qu.:23734800	3rd Qu.:23027400	3rd Qu.:23903700
##		Max. :31347900	Max. :31227000	Max. :31411500
##		NA's :1796	NA's :1796	NA's :1796
##	APAC	ARNE	BEAV	BESS
##	Min. : 3300	Min. : 477300	Min. : 300	Min. : 510600
##	1st Qu.:11637000	1st Qu.:11666400	1st Qu.:11493600	1st Qu.:11712600
##	Median :17062500	Median :17578500	Median :17520900	Median :17176500
##	Mean :17010565	Mean :17560173	Mean :17612143	Mean :17304074
##	3rd Qu.:23909400	3rd Qu.:24503700	3rd Qu.:24683100	3rd Qu.:24241200
##	Max. :31616100	Max. :32645700	Max. :32884800	Max. :31887900
44.44	NΔ's ·1796	NΔ's ·1796	NΔ'c ·1796	NΔ'c ·1706

PC353 PC354 Min. :-23.66467 1st Qu.: -1.58636 Min. :-21.90907 1st Qu.: -1.66117 Min. :-29.65249 1st Qu.: -1.60810 Median : -0.07761 Mean : -0.02131 Median : 0.01887 Mean : -0.04450 Median : 3rd Qu.: 1.52298 3rd Qu.: 1.56665 3rd Qu.: 1.74447 : 22.87146 PC356 Min. 1s⁺ PC357 Min. 15* ## Min. :-20.50932 1st Qu.: -1.56128 Median : -0.03687 :-22.30097 1st Qu.: -1.52905 Median : 0.04224 Mean : -0.02142 3rd Qu.: 1.51265 3rd Qu.: 1.61865 : 18.59593 Counting missing values count_nas <- function(x){
 ret <- sum(is.na(x));</pre> return(ret);sapply(dat, count_nas); Date 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 BRIS BURN BUTL CAMA CENT CHAN CHER CHEY CHIC 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 CLOU COOK COPA DURA ELRE ERIC EUFA FAIR FORA FREE FTCB GOOD GUTH 1796 1796 ## HASK HINT HOBA HOLL H00K **HUGO** IDAB JAYX KENT KETC LAH0 LANE MADI 1796 MCAL 1796 MEDI 1796 NEWK 1796 1796 1796 1796 1796 1796 1796 MEDF ## ## 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 OKMU PAUL PUTN REDR RETR RING 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 1796 SKIA SLAP SPEN STIG STIL STUA SULP TAHL TALI TIPT TISH VINI WASH 1796 WAT0 WAUR WEAT WEST WILB WIST WOOD WYNO PC1 PC2 PC3 PC4 PC5 1796 1796 PC10 1796 PC11 1796 PC12 1796 PC13 1796 1796 1796 PC7 PC8 PC9 PC16 ## ## PC19 PC20 PC21 PC22 PC23 PC24 PC25 PC26 PC27 PC28 PC29 PC30 PC31 ## PC32 PC33 PC34 PC35 PC36 PC37 PC38 PC39 PC40 PC41 PC42 PC43 PC44 PC51 ## PC45 PC46 PC47 PC48 PC49 PC50 PC52 PC53 PC54 PC55 PC56 PC57 PC58 PC59 PC60 PC61 PC62 PC63 PC64 PC65 PC66 PC67 PC68 PC69 ## PC78 PC79 PC80 PC71 PC72 PC73 PC74 PC75 PC76 PC77 PC81 PC82 PC84 PC85 PC86 PC87 PC88 PC89 PC90 0 0 0 0 0 0 0 ## PC91 PC92 PC93 PC94 PC95 PC96 PC97 PC98 PC99 PC100 PC101 PC102 PC103 PC104 PC105 PC106 PC107 PC108 PC109 ## ## PC123 PC124 PC125 PC126 PC127 PC128 PC129 PC130 PC131 PC132 PC133 PC134 PC135 ## PC136 PC137 PC138 PC139 PC140 PC141 PC142 PC143 PC144 PC145 PC146 PC147 PC148 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC149 PC150 PC151 PC152 PC153 PC154 PC155 PC156 PC157 PC158 PC159 PC160 PC161 ## PC162 PC163 PC164 PC165 PC166 PC167 PC168 PC169 PC170 PC171 PC172 PC173 PC174 ## PC175 PC176 PC177 PC178 PC179 PC180 PC181 PC182 PC183 PC184 PC185 PC186 PC187 ## PC188 PC189 PC190 PC191 PC192 PC193 PC194 PC195 PC196 PC197 PC198 PC199 PC200 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC201 PC202 PC203 PC204 PC205 PC206 PC207 PC208 PC209 PC210 PC211 PC212 PC213 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

PC214 PC215 PC216 PC217 PC218 PC219 PC220 PC221 PC222 PC223 PC224 PC225 PC226 ## PC227 PC228 PC229 PC230 PC231 PC232 PC233 PC234 PC235 PC236 PC237 PC238 PC239 ## PC240 PC241 PC242 PC243 PC244 PC245 PC246 PC247 PC248 PC249 PC250 PC251 PC252 ## PC253 PC254 PC255 PC256 PC257 PC258 PC259 PC260 PC261 PC262 PC263 PC264 PC265 ## PC266 PC267 PC268 PC269 PC270 PC271 PC272 PC273 PC274 PC275 PC276 PC277 PC278 ## PC279 PC280 PC281 PC282 PC283 PC284 PC285 PC286 PC287 PC288 PC289 PC290 PC291 ## PC292 PC293 PC294 PC295 PC296 PC297 PC298 PC299 PC300 PC301 PC302 PC303 PC304 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC305 PC306 PC307 PC308 PC309 PC310 PC311 PC312 PC313 PC314 PC315 PC316 PC317 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC318 PC319 PC320 PC321 PC322 PC323 PC324 PC325 PC326 PC327 PC328 PC329 PC330 ## PC331 PC332 PC333 PC334 PC335 PC336 PC337 PC338 PC339 PC340 PC341 PC342 PC343

BRIS BUFF BURB BURN BUTL BYAR CAMA CENT CLOU COOK COPA DURA ELRE ERIC EUFA FAIR ## HASK HINT HOBA HOLL H00K HUG0 IDAB JAYX

PAWN

ALTU APAC

ARNE BEAV

MAYR MCAL MEDF MEDI MIAM MINC MTHE NEWK

BESS BIXB BLAC

CHAN CHER CHEY

FORA FREE FTCB GOOD GUTH

KENT KETC LAH0 LANE MADI

REDR

BOIS BOWL

NINN

NOWA

OILT

removing rows with missing DATA df_red <- df[1:5113,]
sapply(df_red, function(x){sum(is.na(x))});</pre>

PC357

Date ACME ADAX

MANG MARE

4e+07

3e+07

2e+07

1e+07

0e+00

200

-200

-400

##

##

##

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##

##

##

Correlation Analysis Correlation plot

plot that PC2 & above have plenty of outliers

OKMU

##

OKEM PAUL PERK PRY0 PUTN STIG STIL STUA SULP TIPT TISH VINI TAHL PC2 PC3 WATO WAUR WEAT WEST WILB WIST WOOD WYNO PC1 PC4 PC5 0 0 0 0 0 PC13 PC14 PC15 PC16 PC17 PC9 PC10 PC11 PC12 PC6 PC7 PC8 PC19 PC20 PC21 PC22 PC23 PC24 PC25 PC26 PC31 ## ## ## PC32 ## PC45 PC46 PC47 PC48 PC49 PC50 PC51 PC52 PC53 PC54 PC55 PC56 PC57 PC58 PC59 PC60 PC61 PC62 PC63 PC64 PC65 PC66 PC67 PC68 PC69 PC70 ## ## ## ## PC74 PC75 PC76 PC71 PC72 PC73 PC77 PC78 PC79 PC80 PC81 PC82 PC83 ## PC84 PC85 PC86 PC87 PC88 PC89 PC90 PC91 PC92 PC93 PC97 PC99 PC100 PC101 PC102 PC103 PC104 PC105 PC106 PC107 PC108 PC109 ## PC110 PC111 PC112 PC113 PC114 PC115 PC116 PC117 PC118 PC119 PC120 PC121 PC122 ## PC123 PC124 PC125 PC126 PC127 PC128 PC129 PC130 PC131 PC132 PC133 PC134 PC135 PC136 PC137 PC138 PC139 PC140 PC141 PC142 PC143 PC144 PC145 PC146 PC147 PC148 ## PC149 PC150 PC151 PC152 PC153 PC154 PC155 PC156 PC157 PC158 PC159 PC160 PC161 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC162 PC163 PC164 PC165 PC166 PC167 PC168 PC169 PC170 PC171 PC172 PC173 PC174 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC175 PC176 PC177 PC178 PC179 PC180 PC181 PC182 PC183 PC184 PC185 PC186 PC187 PC188 PC189 PC190 PC191 PC192 PC193 PC194 PC195 PC196 PC197 PC198 PC199 PC200 ## PC201 PC202 PC203 PC204 PC205 PC206 PC207 PC208 PC209 PC210 PC211 PC212 PC213 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC214 PC215 PC216 PC217 PC218 PC219 PC220 PC221 PC222 PC223 PC224 PC225 PC226 ## PC227 PC228 PC229 PC230 PC231 PC232 PC233 PC234 PC235 PC236 PC237 PC238 PC239 PC240 PC241 PC242 PC243 PC244 PC245 PC246 PC247 PC248 PC249 PC250 PC251 PC252 ## PC253 PC254 PC255 PC256 PC257 PC258 PC259 PC260 PC261 PC262 PC263 PC264 PC265 ## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ## PC266 PC267 PC268 PC269 PC270 PC271 PC272 PC273 PC274 PC275 PC276 PC277 PC278 ## PC279 PC280 PC281 PC282 PC283 PC284 PC285 PC286 PC287 PC288 PC289 PC290 PC291 ## PC305 PC306 PC307 PC308 PC309 PC310 PC311 PC312 PC313 PC314 PC315 PC316 PC317 ## PC318 PC319 PC320 PC321 PC322 PC323 PC324 PC325 PC326 PC327 PC328 PC329 PC330 ## PC331 PC332 PC333 PC334 PC335 PC336 PC337 PC338 PC339 PC340 PC341 PC342 PC343 ## Visualize data distribution of weather stations

400

Visualize data distribution of top 100 Principal Components

ACME BRIS CHIC FREE JAYX MEDI PERK SPEN WAUR

PC1 PC11 PC22 PC33 PC44 PC55 PC66 PC77 PC88 PC99 It is evidenced in this

Finding Outliers 1.200000e+04 5.100000e+05 9.000000e+02 3.300000e+03 4.773000e+05 BIXB 3.000000e+02 5.106000e+05 7.470000e+04 3.600000e+04 BOWL BREC BRIS BUFF BURN BUTL BYAR CAMA 5.457000e+05 6.300000e+03 1.500000e+03 CHEY CHIC CLAY 3.000000e+02 CHAN 1.017000e+05 5.190000e+05 3.993000e+05 5.580000e+04 3.945000e+05 1.230000e+04 CLOU COOK COPA DURA ELRE 3.160350e+07 3.145350e+07 3.171360e+07 5.427000e+05 4.794000e+05 ERIC EUFA FAIR FORA FREE GOOD FTCB GUTH HASK HINT 4.380000e+04 1.281000e+05 1.281000e+05 HOBA HOLL HOOK 1.500000e+03 5.052000e+05 HUGO IDAB 3.600000e+03 3.291000e+05 3.201000e+05 3.282300e+07 3.944280e+07 KETC 3.237450e+07 7.938000e+05 2.730000e+04 5.202000e+05 3.000000e+02 MADI MANG MARE MAYR 6.600000e+03 5.511000e+05 5.640000e+05 1.500000e+03 3.774000e+05 MEDF MEDI MIAM MINC MTHE 5.802000e+05 1.500000e+03 3.200880e+07 NINN NOWA OKEM NEWK OILT 3.840000e+05 6.861000e+05 3.229740e+07 4.227000e+05 1.200000e+03 3.000000e+02 4.437000e+05 2.949000e+05 6.987000e+05 3.000000e+02 PUTN REDR RETR RING SALL 6.600000e+04 7.830000e+04 1.365000e+05 1.800000e+03 3.155520e+07 SEIL SHAW SKIA SLAP SPEN 4.794000e+05 3.069000e+05 STIG STIL STUA SULP 3.163350e+07 3.157290e+07 3.169590e+07 5.691000e+05 3.138360e+07 TALI TIPT TISH 3.143400e+07 5.760000e+05 9.000000e+02 1.746000e+05 7.800000e+04 WATO WAUR WEAT
6.162000e+05 3.300000e+03 7.593000e+05 WEST WILB 3.203010e+07 6.300000e+03 WIST WOOD WYNO PC1 PC2 1.680000e+04 1.884000e+05 PC3 PC4 8.700000e+04 -6.158103e+02 -5.355114e+02 PC5 PC6 3.642267e+02 -3.050638e+02 2.250383e+02 -2.865765e+02 2.074084e+02 PC8 PC9 PC10 PC11 PC12 2.317553e+02 2.453236e+02 2.012154e+02 -1.553629e+02 -1.551643e+02 PC13 PC14 PC15 PC16 PC17
1.600801e+02 -1.640057e+02 -1.764960e+02 1.417673e+02 -1.937855e+02 PC18 PC19 PC20 PC21 PC22 1.616515e+02 1.388195e+02 1.410499e+02 2.027049e+02 1.161806e+02 PC23 PC24 PC25 PC26 ## -1.683955e+02 2.199148e+02 1.395319e+02 -9.702311e+01 -1.417869e+02 1.120534e+02 1.200663e+02 -1.290919e+02 -1.087599e+02 1.243084e+02 PC33 PC34 PC35 PC36 PC33 PC34 PC35 PC36 PC37
1.162189e+02 1.012680e+02 -1.027788e+02 1.692115e+02 1.147545e+02 PC38 PC39 PC40 PC41 PC42 8.228080e+01 -1.291575e+02 -1.290914e+02 1.249909e+02 1.035214e+02 PC44 PC43 PC45 PC46 PC47 -1.042286e+02 6.959360e+01 8.471449e+01 -9.715078e+01 8.903736e+01 PC49 PC50 PC51 PC52

 -6.455406e+01 -9.266506e+01
 9.256876e+01 -1.128904e+02
 6.967469e+01

 PC53
 PC54
 PC55
 PC56
 PC57

 8.994106e+01 -7.266175e+01
 1.033283e+02
 9.668562e+01
 8.041210e+01

 PC58 PC59 PC60 PC61 -7.561729e+01 -6.448290e+01 8.791393e+01 9.188996e+01 -8.758565e+01 PC63 PC64 PC65 PC66 PC67 -7.563266e+01 5.065436e+01 -6.041020e+01 6.339131e+01 9.556350e+01 PC68 PC69 PC70 PC71 PC72 -9.707587e+01 8.272304e+01 -7.896915e+01 -7.826387e+01 6.975846e+01 PC74 PC75 8.428817e+01 6.518741e+01 -6.044956e+01 -7.308455e+01 -7.695525e+01 PC78 PC79 PC80 PC81 6.674916e+01 -6.843903e+01 -6.448964e+01 -6.826343e+01 -5.616706e+01 PC83 PC84 PC85 PC86 8.152141e+01 5.064356e+01 6.237217e+01 -6.317895e+01 -5.674073e+01 PC92 PC91 PC92 ## -6.322324e+01 -7.966507e+01 -6.470725e+01 5.431693e+01 7.076370e+01 PC94 PC95 ## -6.574163e+01 5.110237e+01 -4.663167e+01 5.728569e+01 7.087758e+01 PC98 PC99 PC100 6.867961e+01 6.868623e+01 6.178891e+01 Create a function to tipify the dataset (substract the mean & divide by standard deviation)

0.6

0.2 0 -0.2 -0.4

-0.8

4000

400

Weather Station data

From WILB weather station

500

5000

We can clearly notice

3000

Time

y<-df_red[,2][1:5113] nlags = 50ts.plot(y)

3.0e+07

2.0e+07

1.0e+07

0.0e+00

par(mfrow=c(2,1)) acf(y, nlags) pacf(y, nlags)

Partial ACF 9.0

0

Weather Station data

From HOBA weather station

1000

100

Time Series Model

Series y 0.5 ACF 0 100 200 300 400 500 Lag

200

the data is stationary, and it has seasonality. Estimating a potential forecasting time series model $\frac{1}{2}$

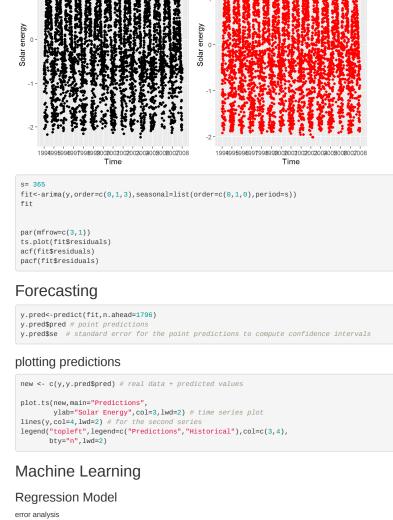
Illustration for two weather stations data per year

Series y

Lag

300

2000



Compute MSE ## [1] "MSE = NA" Train & test split ## [1] 5113 456

Get model predictions for test

library(e1071); # LIBSVM ### train standard SVM model

Check model info print(model);

predictions_test <- predict(model_l1_train, newdata = test);</pre>

model <- svm(HOBA ~ PC1, data = train) # . all columns except the target

[1] 3579 456

##

Compute MAE ## [1] "MAE = NA"

[1] 1534 456 Train model # build linear regression model to predict HOBA using as predictor variable PC1 $model_1l_train <- lm(HOBA \sim PC1, data = train);$ # Get model predictions for train predictions_train <- predict(model_l1_train, newdata = train);</pre>

331619.1 1439548.7 -1467137.8 -1916356.1 2421672.1 4428116.6

errors_train <- predictions_train - train\$HOBA;
errors_test <- predictions_test - test\$HOBA;</pre> # Compute Metrics mse_train <- round(mean(errors_train^2), 2);
mae_train <- round(mean(abs(errors_train)), 2);</pre> mse_test <- round(mean(errors_test^2), 2);
mae_test <- round(mean(abs(errors_test)), 2);</pre>

Call: ## svm(formula = HOBA ~ PC1, data = train) ## Parameters: ## SVM-Type: eps-regression
SVM-Kernel: radial
cost: 1 gamma: 1 epsilon: 0.1 ## ## Number of Support Vectors: 3050 # Get model predictions
predictions_train <- predict(model, newdata = train); # There is no formula here! Less straightforward</pre> to explain (Accuracy-'explainability' tradeoff) predictions_test <- predict(model, newdata = test);</pre> errors_train <- predictions_train - train\$HOBA; errors_test <- predictions_test - test\$HOBA; mse_train <- round(mean(errors_train^2), 2);
mae_train <- round(mean(abs(errors_train)), 2);</pre>

mse_test <- round(mean(errors_test^2), 2);
mae_test <- round(mean(abs(errors_test)), 2);</pre> comp <- rbind(comp,</pre> data.table(model = c("standard svm"), mse_train = mse_train, mae_train = mae_train, mse_test = mse_test, mae_test = mae_test));
comp; # Worse than linear regression. What is wrong