Global Yearly Data Analysis

Team Cowboys

4/16/2022

Data Preparation

- No near zero variance predictors. No action necessary.
- No NA values. No action necessary.
- There are a significant number of 0 Values

```
#Confirmation of No Near Zero Variance for Predictor Variables
globalYearly <- read.csv('data/GlobalYearly.csv')
str(globalYearly)
```

```
## 'data.frame':    34 obs. of  29 variables:
##  $ X                                        : int  0 1 2 3 4 5 6 7 8 9 ...
##  $ Year                                     : int  1980 1981 1982 1983 1984 1985 1986 1987 1988 1989
##  $ Population                               : num  3.52e+09 3.58e+09 3.65e+09 3.71e+09 3.78e+09 ...
##  $ Gas.consumption                          : num  1.02e+12 1.01e+12 9.85e+11 9.72e+11 1.06e+12 ...
##  $ Coal.consumption                         : num  2.32e+09 2.36e+09 2.43e+09 2.54e+09 2.70e+09 ...
##  $ Oil.consumption                          : num  2.80e+09 2.69e+09 2.62e+09 2.58e+09 2.65e+09 ...
##  $ FossilFuelGrowth                         : num  -938 -956 -980 312 2400 ...
##  $ CoalGrowth                               : num  569 264 185 552 895 ...
##  $ GasGrowth                                : num  15.5 -49.2 -230.4 -118.8 735.8 ...
##  $ OilGrowth                                : num  -1522 -1171 -935 -122 769 ...
##  $ AverageTemperature                       : num  16 16.1 16 16.1 15.9 ...
##  $ AverageTemperatureUncertainty            : num  0.272 0.296 0.291 0.293 0.284 ...
##  $ TempMinus1                               : num  NA 16 16.1 16 16.1 ...
##  $ TempMinus2                               : num  NA NA 16 16.1 16 ...
##  $ TempMinus5                               : num  NA NA NA NA NA ...
##  $ Gas.cumsum                               : num  1.02e+12 2.03e+12 3.01e+12 3.98e+12 5.04e+12 ...
##  $ Coal.cumsum                              : num  2.32e+09 4.68e+09 7.11e+09 9.65e+09 1.24e+10 ...
##  $ Oil.cumsum                               : num  2.80e+09 5.50e+09 8.11e+09 1.07e+10 1.33e+10 ...
##  $ log_Gas                                  : num  27.6 27.6 27.6 27.6 27.7 ...
##  $ log_Coal                                 : num  21.6 21.6 21.6 21.7 21.7 ...
##  $ log_Oil                                  : num  21.8 21.7 21.7 21.7 21.7 ...
##  $ LandAverageTemperature                   : num  8.98 9.17 8.64 9.03 8.69 ...
##  $ LandAverageTemperatureUncertainty        : num  0.1067 0.0872 0.0827 0.094 0.1026 ...
##  $ LandMaxTemperature                       : num  14.7 14.9 14.3 14.7 14.3 ...
##  $ LandMaxTemperatureUncertainty            : num  0.153 0.139 0.171 0.115 0.134 ...
##  $ LandMinTemperature                       : num  3.4 3.64 3.24 3.55 3.19 ...
##  $ LandMinTemperatureUncertainty            : num  0.15 0.147 0.207 0.124 0.13 ...
##  $ LandAndOceanAverageTemperature           : num  15.5 15.5 15.3 15.5 15.3 ...
##  $ LandAndOceanAverageTemperatureUncertainty: num  0.0537 0.0523 0.0548 0.0558 0.0572 ...
```

```
globalYearly
```

```
##     X Year Population Gas.consumption Coal.consumption Oil.consumption
```

```
## 1   0 1980 3520742300    1.019004e+12       2315428970      2803656200
## 2   1 1981 3583075700    1.007001e+12       2364801500      2693236100
## 3   2 1982 3646517300    9.846384e+11       2432822500      2615004600
## 4   3 1983 3710593700    9.717523e+11       2541397200      2584808700
## 5   4 1984 3777333600    1.057065e+12       2702477130      2648520400
## 6   5 1985 3846210100    1.073513e+12       2864156440      2653958300
## 7   6 1986 3916121000    1.064809e+12       2912022650      2743546700
## 8   7 1987 3988082800    1.117415e+12       3057345890      2816492100
## 9   8 1988 4060976000    1.166109e+12       3183591818      2927792500
## 10  9 1989 4131562800    1.233739e+12       3218605526      3002605300
## 11 10 1990 4200976700    1.240325e+12       3199232567      3050522600
## 12 11 1991 4346403500    1.366019e+12       3588274763      3231984700
## 13 12 1992 4683993600    2.073445e+12       4134134263      3725955400
## 14 13 1993 4751563700    2.136247e+12       4154657297      3722056800
## 15 14 1994 4812298600    2.129221e+12       4192215208      3801156800
## 16 15 1995 4873091500    2.183895e+12       4304571210      3875198100
## 17 16 1996 4933433000    2.229984e+12       4397396386      3991828000
## 18 17 1997 4993099200    2.235532e+12       4327900734      4056028800
## 19 18 1998 5051628400    2.248265e+12       4308377990      4099391900
## 20 19 1999 5110804700    2.308788e+12       4336480033      4192458500
## 21 20 2000 5168914300    2.397643e+12       4553035770      4262540800
## 22 21 2001 5224751400    2.401179e+12       4620818176      4292982400
## 23 22 2002 5280483900    2.509842e+12       4740015730      4340406500
## 24 23 2003 5337153700    2.575515e+12       5127172813      4428659900
## 25 24 2004 5393134200    2.648937e+12       5572996742      4606191700
## 26 25 2005 5449196200    2.718143e+12       5944836616      4663917500
## 27 26 2006 5503821300    2.807988e+12       6281123170      4726676000
## 28 27 2007 5560803100    2.908187e+12       6592559050      4804681000
## 29 28 2008 5617899300    2.991946e+12       6722365277      4763964900
## 30 29 2009 5673676600    2.902559e+12       6787239130      4712376100
## 31 30 2010 5729765200    3.174016e+12       7305800372      4866602700
## 32 31 2011 5785304800    3.264771e+12       7729972480      4904080400
## 33 32 2012 5842191500    3.333059e+12       7961497351      4973526400
## 34 33 2013 5898014800    3.373866e+12       8033213439      5051870600
##    FossilFuelGrowth CoalGrowth GasGrowth OilGrowth AverageTemperature
## 1          -937.510    568.843    15.456 -1521.806           15.96485
## 2          -955.931    264.405   -49.198 -1171.134           16.05891
## 3          -979.571    185.496  -230.437  -934.624           15.98645
## 4           311.553    551.937  -118.796  -121.585           16.11157
## 5          2399.844    895.197   735.751   768.904           15.86553
## 6           968.970    970.534    61.939   -63.502           15.83764
## 7          1157.716    276.564   -36.092   917.241           15.93650
## 8          2121.008    935.856   526.132   659.019           16.17134
## 9          2552.947    836.316   483.658  1232.973           16.27646
## 10         1736.035    440.454   607.512   688.065           16.31738
## 11          592.211    -44.582   308.957   327.834           16.56269
## 12          867.664    152.353   471.802   243.509           16.01661
## 13          780.331     10.267    66.419   703.637           14.71804
## 14          163.440    165.949   229.810  -232.314           14.51090
## 15         1128.927    180.532   129.135   819.258           15.04993
## 16         1318.643    199.608   678.476   440.563           14.94695
## 17         2542.419    646.875  1021.638   873.905           14.47993
## 18          756.529    -42.101  -174.829   973.464           14.90067
## 19          381.536   -149.004   377.285   153.249           15.25699
```

```
## 20         1603.640    193.837   672.215   737.595           15.26706
## 21         2170.029    828.727   888.026   453.277           15.28678
## 22         1011.723    432.297   270.083   309.340           15.21260
## 23         2102.935   1094.043   687.156   321.741           15.37752
## 24         4088.631   2528.479   652.914   907.241           15.24131
## 25         4643.544   2151.649   937.086  1554.811           15.15012
## 26         3688.942   2515.612   689.525   483.806           15.15431
## 27         3050.710   1880.572   673.293   496.855           15.32645
## 28         3827.642   2194.614  1094.340   538.695           15.45695
## 29          762.846    531.097   693.312  -461.568           15.28611
## 30        -2063.064   -558.672  -586.854  -917.537           15.33661
## 31         5350.160   1837.893  2110.871  1401.398           15.28995
## 32         3290.304   2019.350   768.775   502.187           15.25549
## 33         1591.055    190.067   835.661   565.328           15.24738
## 34         1876.422    828.760   530.413   517.259           15.90694
##    AverageTemperatureUncertainty TempMinus1 TempMinus2 TempMinus5   Gas.cumsum
## 1                      0.2717218         NA         NA         NA 1.019004e+12
## 2                      0.2962352   15.96485         NA         NA 2.026005e+12
## 3                      0.2911895   16.05891   15.96485         NA 3.010644e+12
## 4                      0.2930336   15.98645   16.05891         NA 3.982396e+12
## 5                      0.2843831   16.11157   15.98645         NA 5.039461e+12
## 6                      0.2946761   15.86553   16.11157   15.96485 6.112974e+12
## 7                      0.2765336   15.83764   15.86553   16.05891 7.177783e+12
## 8                      0.2627231   15.93650   15.83764   15.98645 8.295198e+12
## 9                      0.2527742   16.17134   15.93650   16.11157 9.461307e+12
## 10                     0.2833683   16.27646   16.17134   15.86553 1.069505e+13
## 11                     0.2882755   16.31738   16.27646   15.83764 1.193537e+13
## 12                     0.2438902   16.56269   16.31738   15.93650 1.330139e+13
## 13                     0.2931111   16.01661   16.56269   16.17134 1.537484e+13
## 14                     0.2623026   14.71804   16.01661   16.27646 1.751108e+13
## 15                     0.2602621   14.51090   14.71804   16.31738 1.964030e+13
## 16                     0.2487774   15.04993   14.51090   16.56269 2.182420e+13
## 17                     0.2493114   14.94695   15.04993   16.01661 2.405418e+13
## 18                     0.2663629   14.47993   14.94695   14.71804 2.628971e+13
## 19                     0.2519605   14.90067   14.47993   14.51090 2.853798e+13
## 20                     0.2428300   15.25699   14.90067   15.04993 3.084677e+13
## 21                     0.2616776   15.26706   15.25699   14.94695 3.324441e+13
## 22                     0.2639792   15.28678   15.26706   14.47993 3.564559e+13
## 23                     0.2644726   15.21260   15.28678   14.90067 3.815543e+13
## 24                     0.2976656   15.37752   15.21260   15.25699 4.073095e+13
## 25                     0.2705680   15.24131   15.37752   15.26706 4.337988e+13
## 26                     0.2511919   15.15012   15.24131   15.28678 4.609803e+13
## 27                     0.2872456   15.15431   15.15012   15.21260 4.890601e+13
## 28                     0.2521656   15.32645   15.15431   15.37752 5.181420e+13
## 29                     0.2563783   15.45695   15.32645   15.24131 5.480615e+13
## 30                     0.2688333   15.28611   15.45695   15.15012 5.770871e+13
## 31                     0.2655756   15.33661   15.28611   15.15431 6.088272e+13
## 32                     0.2758158   15.28995   15.33661   15.32645 6.414749e+13
## 33                     0.3612599   15.25549   15.28995   15.45695 6.748055e+13
## 34                     0.4589432   15.24738   15.25549   15.28611 7.085442e+13
##    Coal.cumsum  Oil.cumsum  log_Gas log_Coal  log_Oil LandAverageTemperature
## 1   2315428970  2803656200 27.64985 21.56286 21.75419               8.980333
## 2   4680230470  5496892300 27.63800 21.58396 21.71401               9.165833
## 3   7113052970  8111896900 27.61554 21.61232 21.68453               8.639167
```

```
## 4    9654450170  10696705600 27.60237 21.65598 21.67292               9.028167
## 5   12356927300  13345226000 27.68652 21.71743 21.69727               8.691833
## 6   15221083740  15999184300 27.70196 21.77554 21.69932               8.658000
## 7   18133106390  18742731000 27.69382 21.79211 21.73252               8.833583
## 8   21190452280  21559223100 27.74204 21.84081 21.75876               8.994417
## 9   24374044098  24487015600 27.78469 21.88128 21.79751               9.201583
## 10  27592649624  27489620900 27.84107 21.89221 21.82275               8.922000
## 11  30791882190  30540143500 27.84639 21.88618 21.83858               9.234167
## 12  34380156953  33772128200 27.94292 22.00094 21.89636               9.179417
## 13  38514291216  37498083600 28.36023 22.14254 22.03859               8.836583
## 14  42668948514  41220140400 28.39007 22.14750 22.03754               8.866583
## 15  46861163721  45021297200 28.38678 22.15650 22.05857               9.038750
## 16  51165734931  48896495300 28.41213 22.18294 22.07786               9.347083
## 17  55563131316  52888323300 28.43302 22.20428 22.10752               9.038917
## 18  59891032050  56944352100 28.43550 22.18835 22.12347               9.202583
## 19  64199410040  61043744000 28.44118 22.18383 22.13410               9.522667
## 20  68535890074  65236202500 28.46774 22.19033 22.15655               9.285083
## 21  73088925844  69498743300 28.50551 22.23906 22.17313               9.201167
## 22  77709744019  73791725700 28.50698 22.25384 22.18025               9.414583
## 23  82449759749  78132132200 28.55124 22.27931 22.19123               9.570417
## 24  87576932562  82560792100 28.57707 22.35782 22.21136               9.525583
## 25  93149929304  87166983800 28.60518 22.44120 22.25067               9.324583
## 26  99094765920  91830901300 28.63097 22.50579 22.26312               9.700917
## 27 105375889090  96557577300 28.66349 22.56081 22.27649               9.532500
## 28 111968448140 101362258300 28.69855 22.60921 22.29286               9.732167
## 29 118690813417 106126223200 28.72695 22.62871 22.28435               9.431750
## 30 125478052548 110838599300 28.69661 22.63831 22.27346               9.505250
## 31 132783852919 115705202000 28.78602 22.71193 22.30566               9.703083
## 32 140513825399 120609282400 28.81421 22.76837 22.31333               9.516000
## 33 148475322750 125582808800 28.83491 22.79788 22.32739               9.507333
## 34 156508536189 130634679400 28.84708 22.80685 22.34302               9.606500
##    LandAverageTemperatureUncertainty LandMaxTemperature
## 1                         0.10666667           14.67292
## 2                         0.08725000           14.85517
## 3                         0.08266667           14.30092
## 4                         0.09400000           14.67983
## 5                         0.10258333           14.34267
## 6                         0.09325000           14.26717
## 7                         0.08500000           14.51683
## 8                         0.08516667           14.69983
## 9                         0.08008333           14.89000
## 10                        0.08800000           14.62150
## 11                        0.08633333           14.95767
## 12                        0.06208333           14.83958
## 13                        0.08333333           14.47133
## 14                        0.08133333           14.51975
## 15                        0.07091667           14.72925
## 16                        0.07641667           15.02642
## 17                        0.08475000           14.73725
## 18                        0.08858333           14.86800
## 19                        0.07391667           15.16942
## 20                        0.07925000           14.98275
## 21                        0.08350000           14.89883
## 22                        0.08741667           15.15917
```

```
## 23                 0.07241667          15.31233
## 24                 0.09066667          15.24933
## 25                 0.08341667          15.01800
## 26                 0.07516667          15.34983
## 27                 0.09000000          15.26200
## 28                 0.08950000          15.53308
## 29                 0.07891667          15.19175
## 30                 0.08591667          15.26658
## 31                 0.08341667          15.44900
## 32                 0.08200000          15.28483
## 33                 0.08341667          15.33283
## 34                 0.09766667          15.37383
##    LandMaxTemperatureUncertainty LandMinTemperature
## 1                      0.1525833           3.404667
## 2                      0.1389167           3.635917
## 3                      0.1710000           3.239917
## 4                      0.1146667           3.552417
## 5                      0.1340833           3.186750
## 6                      0.1196667           3.175667
## 7                      0.1205000           3.319333
## 8                      0.1107500           3.431417
## 9                      0.1336667           3.654000
## 10                     0.1118333           3.334333
## 11                     0.1298333           3.658750
## 12                     0.1012500           3.622167
## 13                     0.0990000           3.263500
## 14                     0.0785000           3.284583
## 15                     0.1092500           3.396083
## 16                     0.1325833           3.703500
## 17                     0.1179167           3.381167
## 18                     0.1206667           3.590167
## 19                     0.1047500           3.949167
## 20                     0.0967500           3.662333
## 21                     0.1226667           3.581833
## 22                     0.1037500           3.740667
## 23                     0.1240833           3.864583
## 24                     0.1137500           3.851583
## 25                     0.1090833           3.664417
## 26                     0.1130833           4.113833
## 27                     0.1495833           3.864833
## 28                     0.1288333           4.009250
## 29                     0.1035000           3.724833
## 30                     0.1077500           3.796917
## 31                     0.1034167           4.023917
## 32                     0.1143333           3.827667
## 33                     0.1073333           3.756167
## 34                     0.1155000           3.911333
##    LandMinTemperatureUncertainty LandAndOceanAverageTemperature
## 1                      0.1500833                       15.49183
## 2                      0.1474167                       15.51617
## 3                      0.2070833                       15.34192
## 4                      0.1242500                       15.52025
## 5                      0.1303333                       15.34417
## 6                      0.1054167                       15.34067
```

```
## 7                          0.1282500                          15.38400
## 8                          0.1445833                          15.52450
## 9                          0.1115000                          15.55575
## 10                         0.1291667                          15.44158
## 11                         0.1197500                          15.62933
## 12                         0.1056667                          15.59800
## 13                         0.1025000                          15.45300
## 14                         0.1063333                          15.46642
## 15                         0.1267500                          15.53500
## 16                         0.1580000                          15.63783
## 17                         0.1124167                          15.52467
## 18                         0.1115000                          15.71383
## 19                         0.1249167                          15.82600
## 20                         0.1135000                          15.60033
## 21                         0.1154167                          15.61067
## 22                         0.1200833                          15.76750
## 23                         0.1171667                          15.82917
## 24                         0.1261667                          15.82658
## 25                         0.1059167                          15.75725
## 26                         0.1120833                          15.87925
## 27                         0.1383333                          15.81350
## 28                         0.1371667                          15.82733
## 29                         0.1298333                          15.72125
## 30                         0.1260000                          15.82717
## 31                         0.1156667                          15.89550
## 32                         0.1365833                          15.76950
## 33                         0.1453333                          15.80233
## 34                         0.1498333                          15.85442
##    LandAndOceanAverageTemperatureUncertainty
## 1                                 0.05366667
## 2                                 0.05233333
## 3                                 0.05475000
## 4                                 0.05583333
## 5                                 0.05716667
## 6                                 0.05391667
## 7                                 0.05325000
## 8                                 0.05333333
## 9                                 0.05325000
## 10                                0.05591667
## 11                                0.05725000
## 12                                0.05508333
## 13                                0.05816667
## 14                                0.05916667
## 15                                0.05858333
## 16                                0.06041667
## 17                                0.05950000
## 18                                0.05916667
## 19                                0.06300000
## 20                                0.06333333
## 21                                0.06350000
## 22                                0.06458333
## 23                                0.06291667
## 24                                0.06433333
## 25                                0.06125000
```

```
## 26                                0.06083333
## 27                                0.06100000
## 28                                0.05908333
## 29                                0.05725000
## 30                                0.05891667
## 31                                0.05858333
## 32                                0.05900000
## 33                                0.06150000
## 34                                0.06466667
```

```r
predictors <- globalYearly[c(2, 3, 4, 5, 6, 7, 8, 9, 10, 16, 17, 18, 19, 20, 21)]
y <- globalYearly[c("AverageTemperature")]
predictors
```

```
##    Year Population Gas.consumption Coal.consumption Oil.consumption
## 1  1980 3520742300    1.019004e+12       2315428970      2803656200
## 2  1981 3583075700    1.007001e+12       2364801500      2693236100
## 3  1982 3646517300    9.846384e+11       2432822500      2615004600
## 4  1983 3710593700    9.717523e+11       2541397200      2584808700
## 5  1984 3777333600    1.057065e+12       2702477130      2648520400
## 6  1985 3846210100    1.073513e+12       2864156440      2653958300
## 7  1986 3916121000    1.064809e+12       2912022650      2743546700
## 8  1987 3988082800    1.117415e+12       3057345890      2816492100
## 9  1988 4060976000    1.166109e+12       3183591818      2927792500
## 10 1989 4131562800    1.233739e+12       3218605526      3002605300
## 11 1990 4200976700    1.240325e+12       3199232567      3050522600
## 12 1991 4346403500    1.366019e+12       3588274763      3231984700
## 13 1992 4683993600    2.073445e+12       4134134263      3725955400
## 14 1993 4751563700    2.136247e+12       4154657297      3722056800
## 15 1994 4812298600    2.129221e+12       4192215208      3801156800
## 16 1995 4873091500    2.183895e+12       4304571210      3875198100
## 17 1996 4933433000    2.229984e+12       4397396386      3991828000
## 18 1997 4993099200    2.235532e+12       4327900734      4056028800
## 19 1998 5051628400    2.248265e+12       4308377990      4099391900
## 20 1999 5110804700    2.308788e+12       4336480033      4192458500
## 21 2000 5168914300    2.397643e+12       4553035770      4262540800
## 22 2001 5224751400    2.401179e+12       4620818176      4292982400
## 23 2002 5280483900    2.509842e+12       4740015730      4340406500
## 24 2003 5337153700    2.575515e+12       5127172813      4428659900
## 25 2004 5393134200    2.648937e+12       5572996742      4606191700
## 26 2005 5449196200    2.718143e+12       5944836616      4663917500
## 27 2006 5503821300    2.807988e+12       6281123170      4726676000
## 28 2007 5560803100    2.908187e+12       6592559050      4804681000
## 29 2008 5617899300    2.991946e+12       6722365277      4763964900
## 30 2009 5673676600    2.902559e+12       6787239130      4712376100
## 31 2010 5729765200    3.174016e+12       7305800372      4866602700
## 32 2011 5785304800    3.264771e+12       7729972480      4904080400
## 33 2012 5842191500    3.333059e+12       7961497351      4973526400
## 34 2013 5898014800    3.373866e+12       8033213439      5051870600
##    FossilFuelGrowth CoalGrowth GasGrowth OilGrowth   Gas.cumsum  Coal.cumsum
## 1          -937.510    568.843    15.456 -1521.806 1.019004e+12   2315428970
## 2          -955.931    264.405   -49.198 -1171.134 2.026005e+12   4680230470
## 3          -979.571    185.496  -230.437  -934.624 3.010644e+12   7113052970
## 4           311.553    551.937  -118.796  -121.585 3.982396e+12   9654450170
## 5          2399.844    895.197   735.751   768.904 5.039461e+12  12356927300
```

```
## 6          968.970    970.534    61.939    -63.502 6.112974e+12  15221083740
## 7         1157.716    276.564   -36.092    917.241 7.177783e+12  18133106390
## 8         2121.008    935.856   526.132    659.019 8.295198e+12  21190452280
## 9         2552.947    836.316   483.658   1232.973 9.461307e+12  24374044098
## 10        1736.035    440.454   607.512    688.065 1.069505e+13  27592649624
## 11         592.211    -44.582   308.957    327.834 1.193537e+13  30791882190
## 12         867.664    152.353   471.802    243.509 1.330139e+13  34380156953
## 13         780.331     10.267    66.419    703.637 1.537484e+13  38514291216
## 14         163.440    165.949   229.810   -232.314 1.751108e+13  42668948514
## 15        1128.927    180.532   129.135    819.258 1.964030e+13  46861163721
## 16        1318.643    199.608   678.476    440.563 2.182420e+13  51165734931
## 17        2542.419    646.875  1021.638    873.905 2.405418e+13  55563131316
## 18         756.529    -42.101  -174.829    973.464 2.628971e+13  59891032050
## 19         381.536   -149.004   377.285    153.249 2.853798e+13  64199410040
## 20        1603.640    193.837   672.215    737.595 3.084677e+13  68535890074
## 21        2170.029    828.727   888.026    453.277 3.324441e+13  73088925844
## 22        1011.723    432.297   270.083    309.340 3.564559e+13  77709744019
## 23        2102.935   1094.043   687.156    321.741 3.815543e+13  82449759749
## 24        4088.631   2528.479   652.914    907.241 4.073095e+13  87576932562
## 25        4643.544   2151.649   937.086   1554.811 4.337988e+13  93149929304
## 26        3688.942   2515.612   689.525    483.806 4.609803e+13  99094765920
## 27        3050.710   1880.572   673.293    496.855 4.890601e+13 105375889090
## 28        3827.642   2194.614  1094.340    538.695 5.181420e+13 111968448140
## 29         762.846    531.097   693.312   -461.568 5.480615e+13 118690813417
## 30       -2063.064   -558.672  -586.854   -917.537 5.770871e+13 125478052548
## 31        5350.160   1837.893  2110.871   1401.398 6.088272e+13 132783852919
## 32        3290.304   2019.350   768.775    502.187 6.414749e+13 140513825399
## 33        1591.055    190.067   835.661    565.328 6.748055e+13 148475322750
## 34        1876.422    828.760   530.413    517.259 7.085442e+13 156508536189
##      Oil.cumsum  log_Gas log_Coal  log_Oil
## 1    2803656200 27.64985 21.56286 21.75419
## 2    5496892300 27.63800 21.58396 21.71401
## 3    8111896900 27.61554 21.61232 21.68453
## 4   10696705600 27.60237 21.65598 21.67292
## 5   13345226000 27.68652 21.71743 21.69727
## 6   15999184300 27.70196 21.77554 21.69932
## 7   18742731000 27.69382 21.79211 21.73252
## 8   21559223100 27.74204 21.84081 21.75876
## 9   24487015600 27.78469 21.88128 21.79751
## 10  27489620900 27.84107 21.89221 21.82275
## 11  30540143500 27.84639 21.88618 21.83858
## 12  33772128200 27.94292 22.00094 21.89636
## 13  37498083600 28.36023 22.14254 22.03859
## 14  41220140400 28.39007 22.14750 22.03754
## 15  45021297200 28.38678 22.15650 22.05857
## 16  48896495300 28.41213 22.18294 22.07786
## 17  52888323300 28.43302 22.20428 22.10752
## 18  56944352100 28.43550 22.18835 22.12347
## 19  61043744000 28.44118 22.18383 22.13410
## 20  65236202500 28.46774 22.19033 22.15655
## 21  69498743300 28.50551 22.23906 22.17313
## 22  73791725700 28.50698 22.25384 22.18025
## 23  78132132200 28.55124 22.27931 22.19123
## 24  82560792100 28.57707 22.35782 22.21136
```

```
## 25  87166983800 28.60518 22.44120 22.25067
## 26  91830901300 28.63097 22.50579 22.26312
## 27  96557577300 28.66349 22.56081 22.27649
## 28 101362258300 28.69855 22.60921 22.29286
## 29 106126223200 28.72695 22.62871 22.28435
## 30 110838599300 28.69661 22.63831 22.27346
## 31 115705202000 28.78602 22.71193 22.30566
## 32 120609282400 28.81421 22.76837 22.31333
## 33 125582808800 28.83491 22.79788 22.32739
## 34 130634679400 28.84708 22.80685 22.34302
```

```
#Summary Statistics
summary(predictors)
```

```
##       Year        Population        Gas.consumption     Coal.consumption
##  Min.   :1980   Min.   :3.521e+09   Min.   :9.718e+11   Min.   :2.315e+09
##  1st Qu.:1988   1st Qu.:4.079e+09   1st Qu.:1.183e+12   1st Qu.:3.188e+09
##  Median :1996   Median :4.963e+09   Median :2.233e+12   Median :4.318e+09
##  Mean   :1996   Mean   :4.806e+09   Mean   :2.084e+12   Mean   :4.603e+09
##  3rd Qu.:2005   3rd Qu.:5.435e+09   3rd Qu.:2.701e+12   3rd Qu.:5.852e+09
##  Max.   :2013   Max.   :5.898e+09   Max.   :3.374e+12   Max.   :8.033e+09
##  Oil.consumption     FossilFuelGrowth    CoalGrowth       GasGrowth
##  Min.   :2.585e+09   Min.   :-2063.1   Min.   :-558.7   Min.   :-586.9
##  1st Qu.:2.946e+09   1st Qu.:  758.1   1st Qu.: 186.6   1st Qu.:  82.1
##  Median :4.024e+09   Median : 1454.8   Median : 541.5   Median : 528.3
##  Mean   :3.842e+09   Mean   : 1585.4   Mean   : 756.3   Mean   : 471.2
##  3rd Qu.:4.649e+09   3rd Qu.: 2506.8   3rd Qu.: 961.9   3rd Qu.: 692.4
##  Max.   :5.052e+09   Max.   : 5350.2   Max.   :2528.5   Max.   :2110.9
##    OilGrowth          Gas.cumsum          Coal.cumsum          Oil.cumsum
##  Min.   :-1521.8   Min.   :1.019e+12   Min.   :2.315e+09   Min.   :2.804e+09
##  1st Qu.:  175.8   1st Qu.:9.770e+12   1st Qu.:2.518e+10   1st Qu.:2.524e+10
##  Median :  499.5   Median :2.517e+13   Median :5.773e+10   Median :5.492e+10
##  Mean   :  357.9   Mean   :2.882e+13   Mean   :6.435e+10   Mean   :5.918e+10
##  3rd Qu.:  761.1   3rd Qu.:4.542e+13   3rd Qu.:9.761e+10   3rd Qu.:9.066e+10
##  Max.   : 1554.8   Max.   :7.085e+13   Max.   :1.565e+11   Max.   :1.306e+11
##     log_Gas          log_Coal         log_Oil
##  Min.   :27.60   Min.   :21.56   Min.   :21.67
##  1st Qu.:27.80   1st Qu.:21.88   1st Qu.:21.80
##  Median :28.43   Median :22.19   Median :22.12
##  Mean   :28.28   Mean   :22.18   Mean   :22.04
##  3rd Qu.:28.62   3rd Qu.:22.49   3rd Qu.:22.26
##  Max.   :28.85   Max.   :22.81   Max.   :22.34
```

```
print(nearZeroVar(predictors))
```

```
## integer(0)
```

```
#Check for missing values
#Confirmed No Missing Values
sapply(predictors, function(x) sum(is.na(x)))
```

```
##             Year       Population  Gas.consumption Coal.consumption
##                0                0                0                0
##  Oil.consumption FossilFuelGrowth       CoalGrowth        GasGrowth
##                0                0                0                0
##        OilGrowth       Gas.cumsum      Coal.cumsum       Oil.cumsum
```

```
##                0                0                0                0
##          log_Gas         log_Coal          log_Oil
##                0                0                0
```

Skewness

Generally values between -1 and 1 are acceptable. Insulin, Age and Pedigree have skewness values beyond these thresholds. Using the log of these functions removes the skewness. *Note doesn't boxcox correct for this?

```
#skewness
skewness(y$AverageTemperature) #0.898
```

```
## [1] 0.09924692
```

```
skewness(predictors$Gas.consumption) #0.529
```

```
## [1] -0.08930246
```

```
skewness(predictors$Coal.consumption) #0.145
```

```
## [1] 0.5274291
```

```
skewness(predictors$Oil.consumption) #2.026
```

```
## [1] -0.2035202
```

```
skewness(predictors$CoalGrowth) #1.912
```

```
## [1] 0.827991
```

```
skewness(predictors$OilGrowth) #1.912
```

```
## [1] -0.9227753
```

```
skewness(predictors$GasGrowth) #1.912
```

```
## [1] 0.6249069
```

```
skewness(predictors$Gas.cumsum) #0.595
```

```
## [1] 0.4091472
```

```
skewness(predictors$Coal.cumsum) #1.912
```

```
## [1] 0.4084866
```

```
skewness(predictors$Oil.cumsum) #1.125
```

```
## [1] 0.2496961
```

```
skewness(predictors$log_Gas) #0.595
```

```
## [1] -0.3912521
```

```
skewness(predictors$log_Coal) #1.912
```

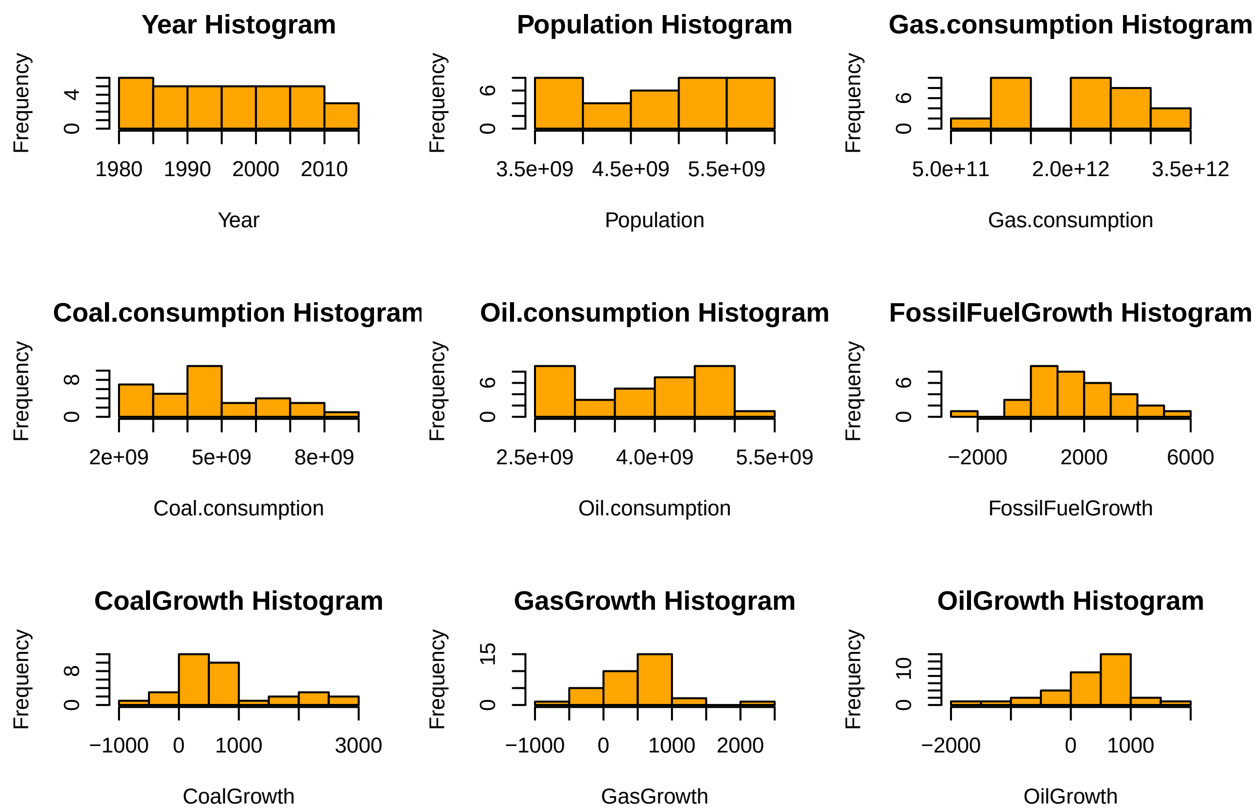
```
## [1] 0.03770163
```

```
skewness(predictors$log_Oil) #1.125
```

```
## [1] -0.3583972
```

Graphical Review of data

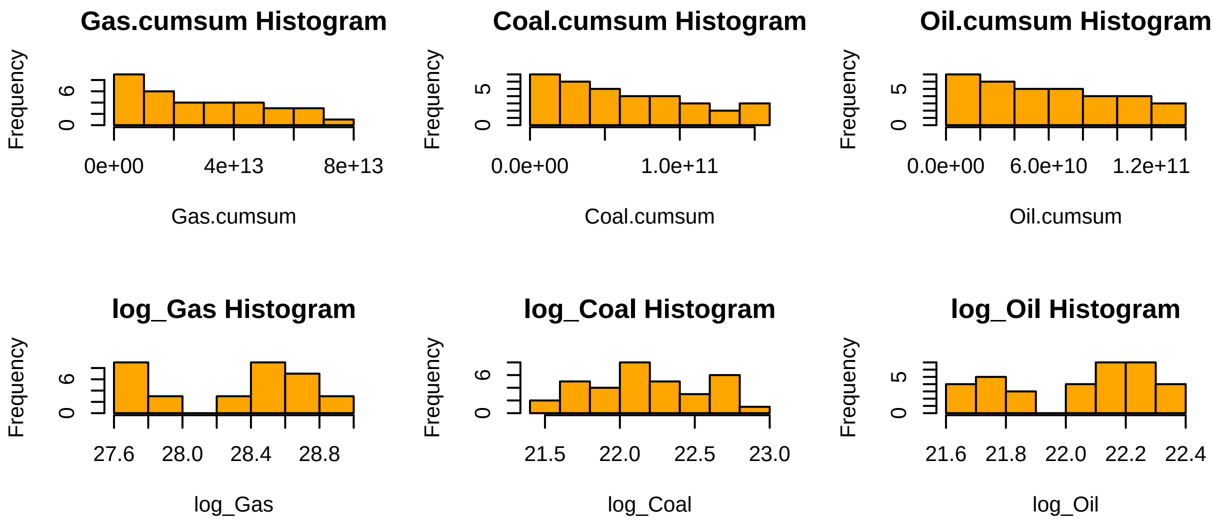
```r
#Histograms : Predictor Variables
par(mfrow = c(3,3)) #Histograms will be 3x3
for (i in 1:ncol(predictors))
{hist(predictors[ ,i], xlab = names(predictors[i]), main = paste(names(predictors[i]), "Histogram"), co
}
```

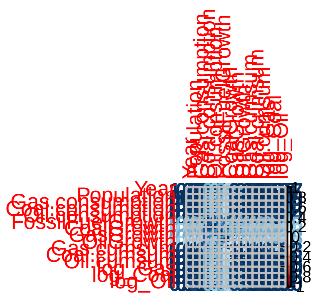



```r
#Correlation Plot:
#pairs(df)

corrplot(cor(predictors), method="number")

pca <-prcomp(predictors)
summary(pca)
```

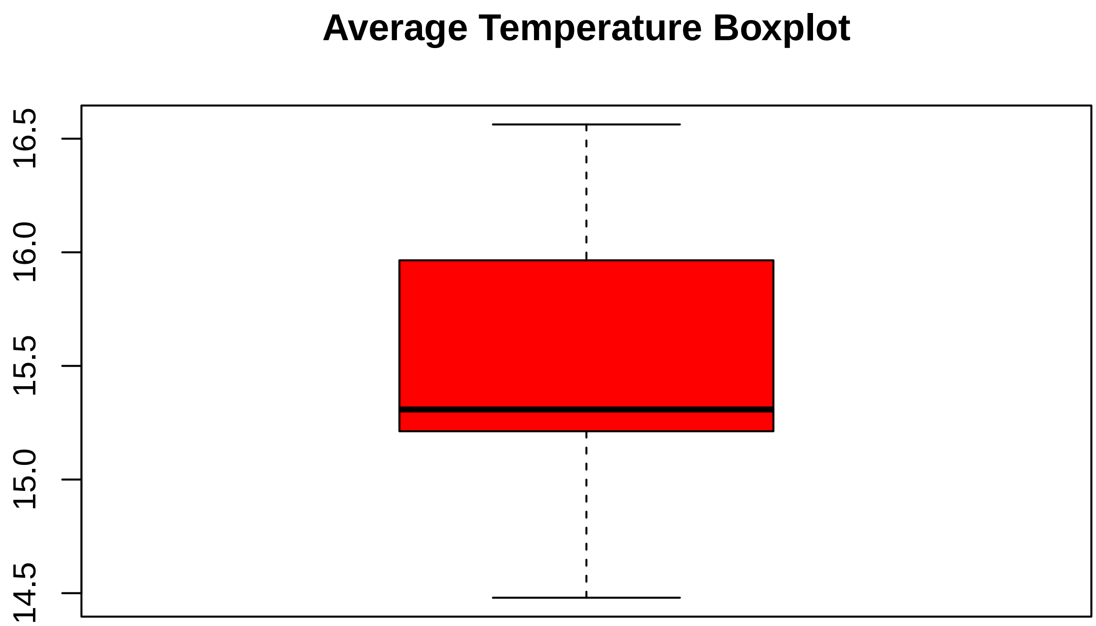
```
## Importance of components:
##                              PC1       PC2       PC3       PC4       PC5
## Standard deviation     2.150e+13 2.149e+11 2.213e+09 1.604e+09 186475703
## Proportion of Variance 9.999e-01 1.000e-04 0.000e+00 0.000e+00         0
## Cumulative Proportion  9.999e-01 1.000e+00 1.000e+00 1.000e+00         1
##                             PC6      PC7  PC8   PC9  PC10    PC11     PC12
## Standard deviation     63237765 17259992 1446 324.7 259.7 0.05215 0.008529
## Proportion of Variance        0        0    0   0.0   0.0 0.00000 0.000000
## Cumulative Proportion         1        1    1   1.0   1.0 1.00000 1.000000
##                            PC13     PC14     PC15
## Standard deviation     0.004095 0.002737 0.001588
```

```
## Proportion of Variance 0.000000 0.000000 0.000000
## Cumulative Proportion  1.000000 1.000000 1.000000
```

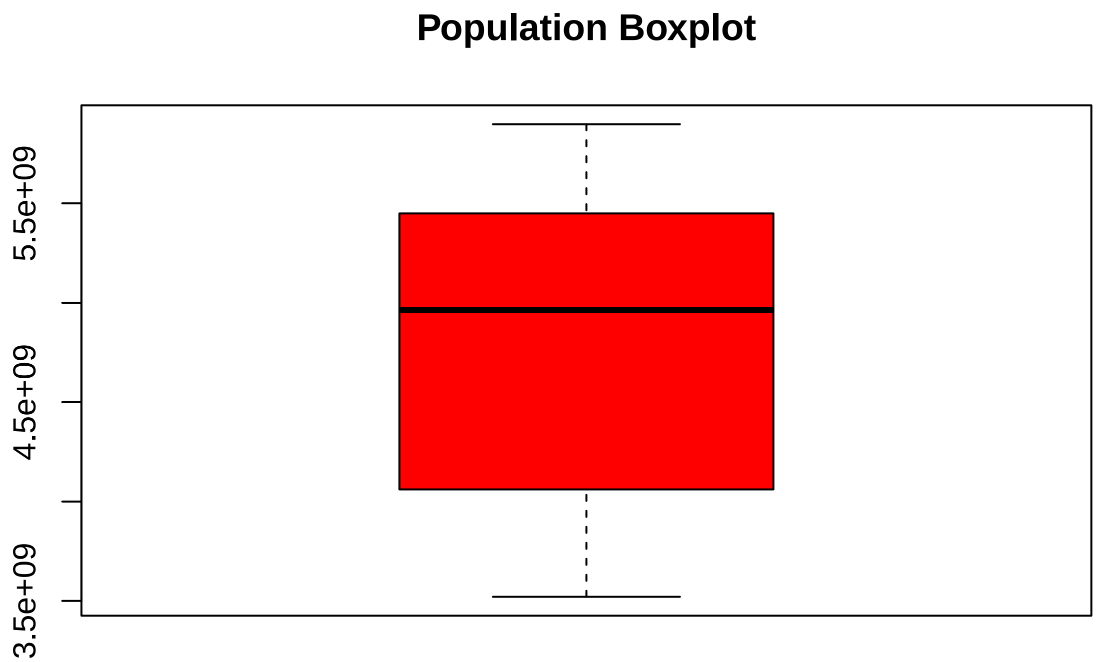




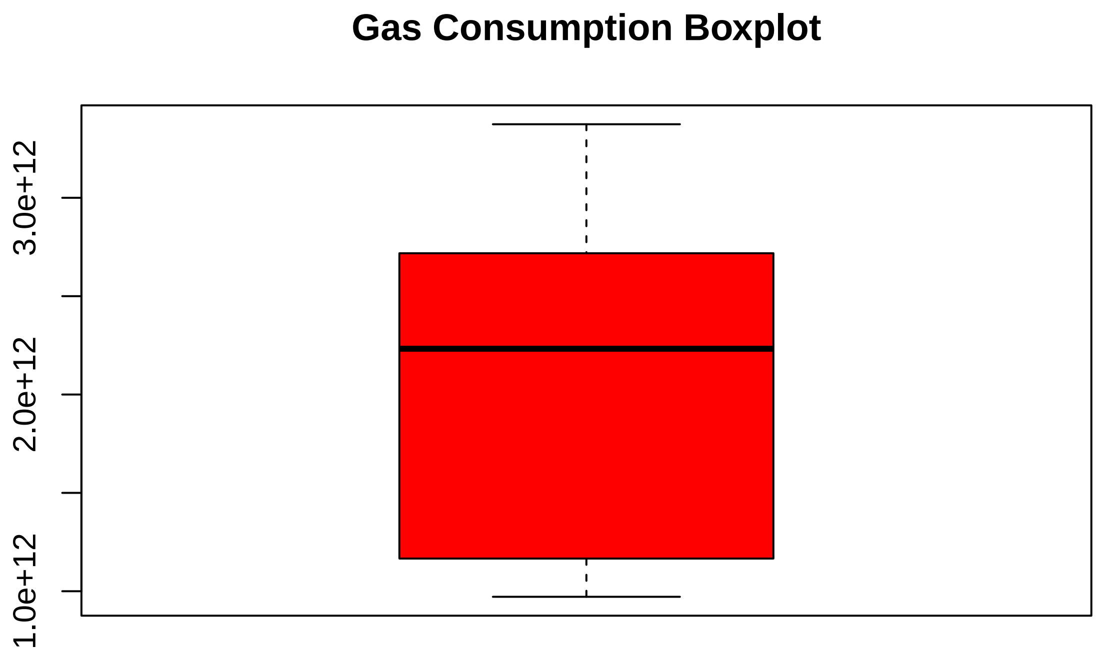
```r
#Box Plots of Diabetes: Predictor Variables
boxplot(y$AverageTemperature , main = "Average Temperature Boxplot", col = "red")
```



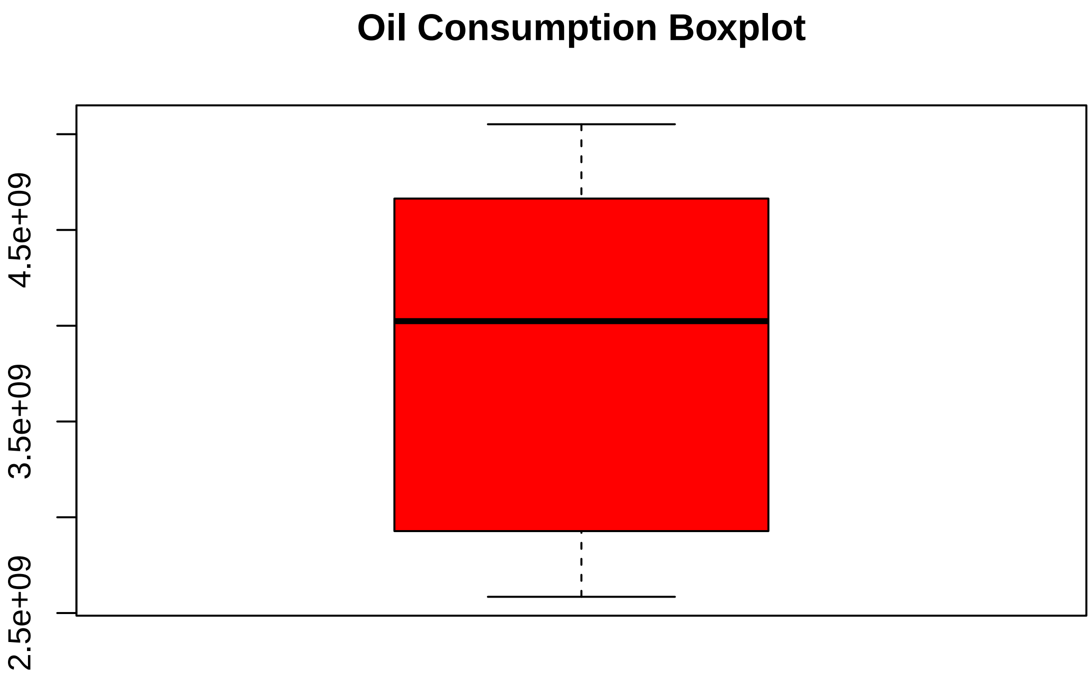

```
boxplot(predictors$Population, main = "Population Boxplot", col = "red")
```



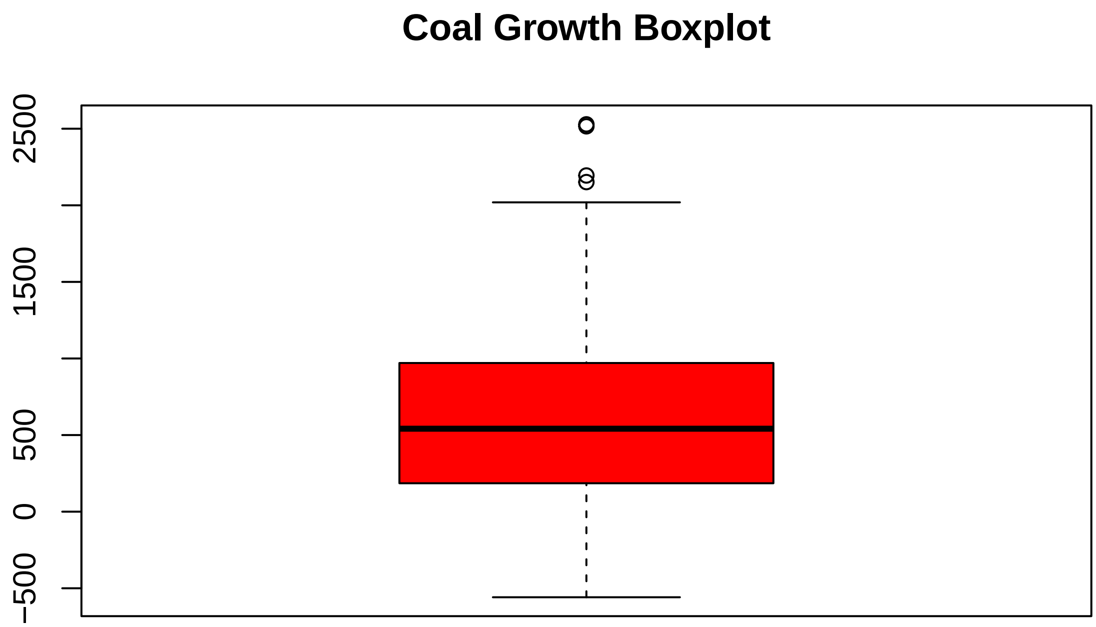

```
boxplot(predictors$Gas.consumption, main = "Gas Consumption Boxplot", col = "red")
```



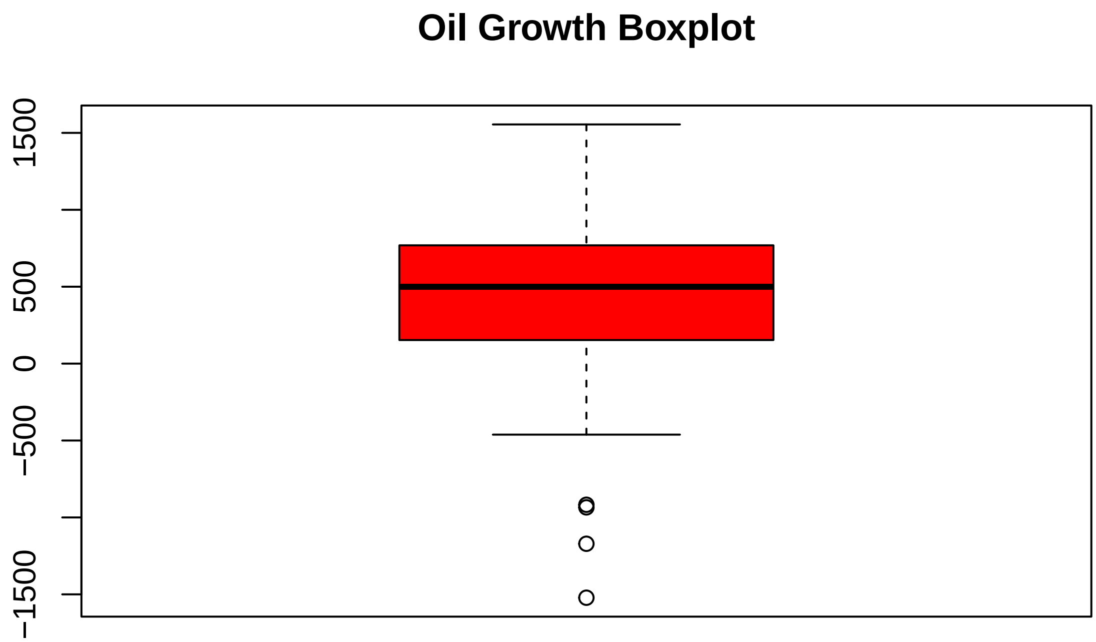

```
boxplot(predictors$Oil.consumption, main = "Oil Consumption Boxplot", col = "red")
```



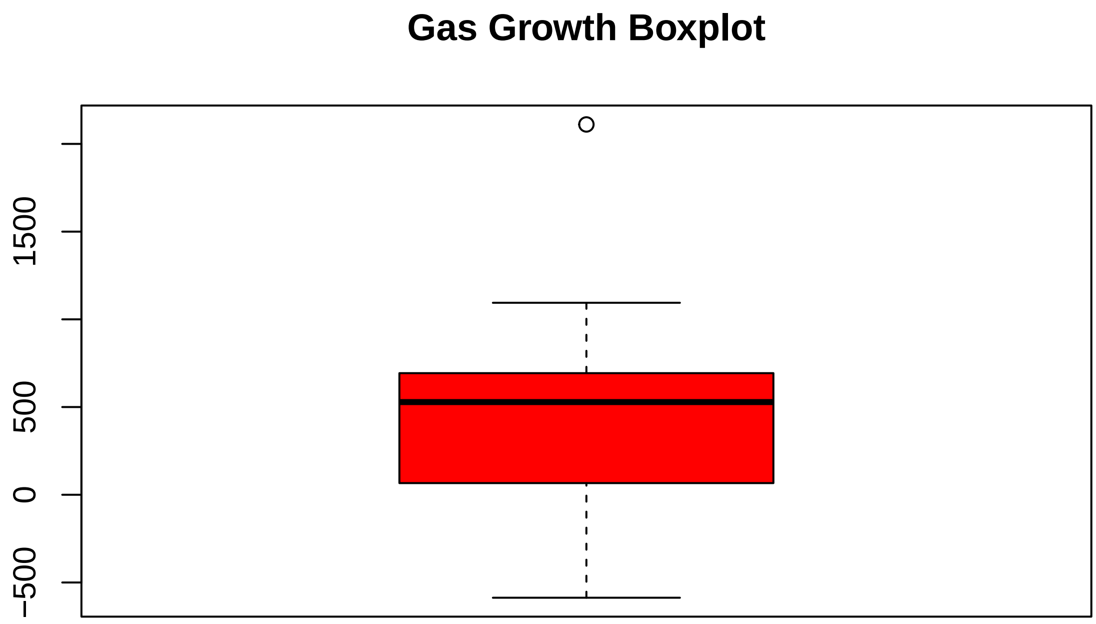

```
boxplot(predictors$CoalGrowth, main = "Coal Growth Boxplot", col = "red")
```



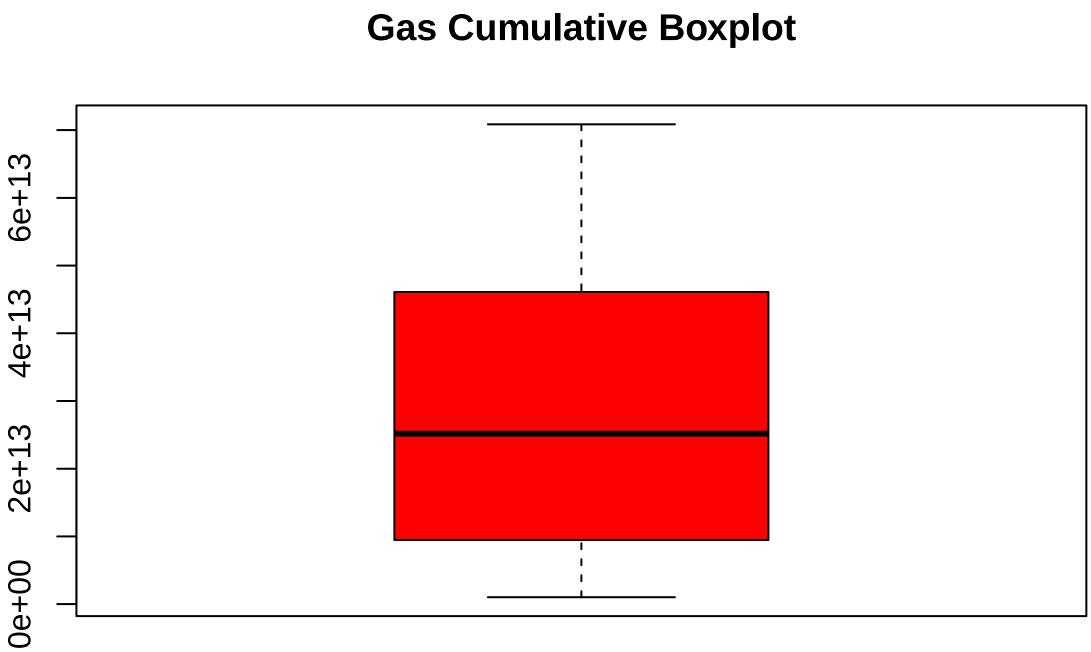

```
boxplot(predictors$OilGrowth, main = "Oil Growth Boxplot", col = "red")
```



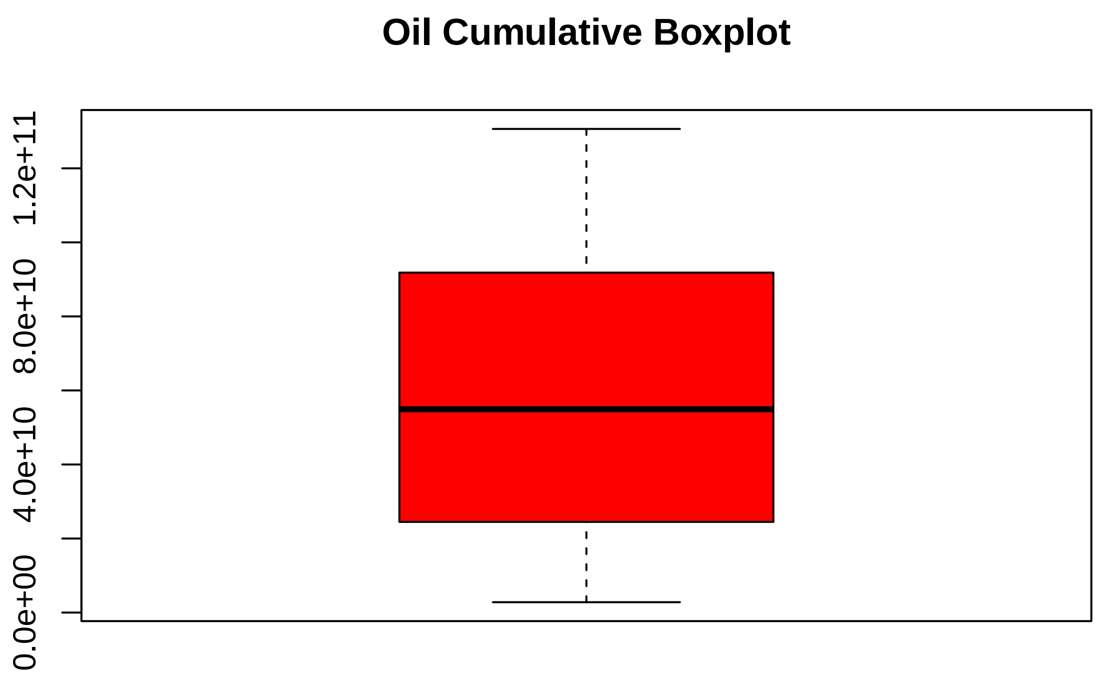

```
boxplot(predictors$GasGrowth, main = "Gas Growth Boxplot", col = "red")
```



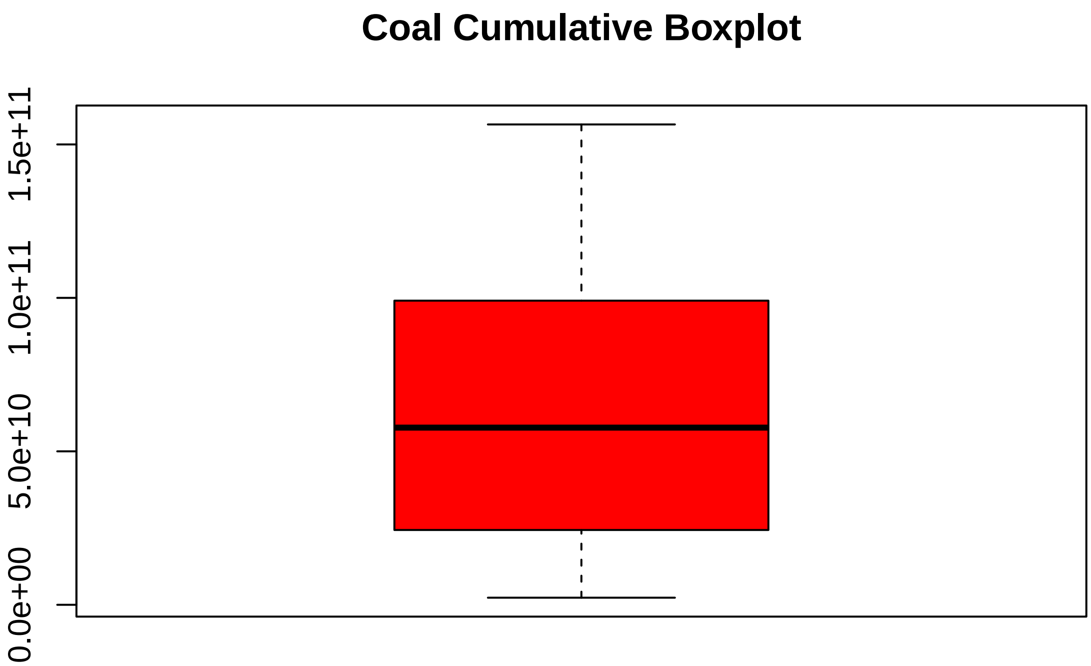

```
boxplot(predictors$Gas.cumsum, main = "Gas Cumulative Boxplot", col = "red")
```




```r
boxplot(predictors$Oil.cumsum, main = "Oil Cumulative Boxplot", col = "red")
```




```
boxplot(predictors$Coal.cumsum, main = "Coal Cumulative Boxplot", col = "red")
```



Data Splitting

Data will be split 80%/20% train/testing.

```
#Split Training and Test Data, 80/20
df <- merge(y, predictors)
set.seed(1)
split <- caret::createDataPartition(y = df$AverageTemperature , times = 1, p = 0.8, list = FALSE)
#Train_data Split, 80%
train_data <- df[split,]
#Test_data Split, 20%
test_data <- df[-split,]
#Summary Statistics
summary(train_data)
```

```
##  AverageTemperature      Year        Population         Gas.consumption
##  Min.   :14.48      Min.   :1980   Min.   :3.521e+09   Min.   :9.718e+11
##  1st Qu.:15.21      1st Qu.:1988   1st Qu.:4.061e+09   1st Qu.:1.166e+12
##  Median :15.31      Median :1997   Median :4.993e+09   Median :2.236e+12
##  Mean   :15.49      Mean   :1997   Mean   :4.826e+09   Mean   :2.107e+12
##  3rd Qu.:15.96      3rd Qu.:2005   3rd Qu.:5.449e+09   3rd Qu.:2.718e+12
##  Max.   :16.56      Max.   :2013   Max.   :5.898e+09   Max.   :3.374e+12
##  Coal.consumption    Oil.consumption     FossilFuelGrowth    CoalGrowth
##  Min.   :2.315e+09   Min.   :2.585e+09   Min.   :-2063.1   Min.   :-558.7
##  1st Qu.:3.184e+09   1st Qu.:2.928e+09   1st Qu.:  756.5   1st Qu.: 185.5
##  Median :4.328e+09   Median :4.056e+09   Median : 1591.1   Median : 551.9
##  Mean   :4.645e+09   Mean   :3.866e+09   Mean   : 1596.1   Mean   : 764.7
```

```
##  3rd Qu.:5.945e+09   3rd Qu.:4.664e+09   3rd Qu.: 2542.4   3rd Qu.: 970.5
##  Max.   :8.033e+09   Max.   :5.052e+09   Max.   : 5350.2   Max.   :2528.5
##    GasGrowth          OilGrowth          Gas.cumsum          Coal.cumsum
##  Min.   :-586.85   Min.   :-1521.8   Min.   :1.019e+12   Min.   :2.315e+09
##  1st Qu.:  66.42   1st Qu.:  153.2   1st Qu.:9.461e+12   1st Qu.:2.437e+10
##  Median : 530.41   Median :  496.9   Median :2.629e+13   Median :5.989e+10
##  Mean   : 481.67   Mean   :  349.7   Mean   :2.933e+13   Mean   :6.542e+10
##  3rd Qu.: 693.31   3rd Qu.:  768.9   3rd Qu.:4.610e+13   3rd Qu.:9.909e+10
##  Max.   :2110.87   Max.   : 1554.8   Max.   :7.085e+13   Max.   :1.565e+11
##    Oil.cumsum            log_Gas          log_Coal          log_Oil
##  Min.   :2.804e+09   Min.   :27.60   Min.   :21.56   Min.   :21.67
##  1st Qu.:2.449e+10   1st Qu.:27.78   1st Qu.:21.88   1st Qu.:21.80
##  Median :5.694e+10   Median :28.44   Median :22.19   Median :22.12
##  Mean   :6.011e+10   Mean   :28.29   Mean   :22.19   Mean   :22.05
##  3rd Qu.:9.183e+10   3rd Qu.:28.63   3rd Qu.:22.51   3rd Qu.:22.26
##  Max.   :1.306e+11   Max.   :28.85   Max.   :22.81   Max.   :22.34
```

```r
dim(train_data)
```

```
## [1] 926  16
```

Model Training

The following models will be trained on the training data.

```r
##################Training Models##########################
#Linear Regression: Training Model
#No Tuning Parameters for Simple Logistic Regression
set.seed(1)
lr_train_data <- caret::train(AverageTemperature~., data = train_data,
                          method = "lm",
                          tuneLength = 10,
                          trControl = trainControl(method = "cv", number = 10),
                          preProcess = c("center","scale", "BoxCox"))
lr_train_data$preProcess
```

```
## Created from 926 samples and 15 variables
##
## Pre-processing:
##   - Box-Cox transformation (11)
##   - centered (15)
##   - ignored (0)
##   - scaled (15)
##
## Lambda estimates for Box-Cox transformation:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.550   0.900   1.164   2.000   2.000
```

```r
lr_train_data
```

```
## Linear Regression
##
## 926 samples
##  15 predictor
##
## Pre-processing: centered (15), scaled (15), Box-Cox transformation (11)
## Resampling: Cross-Validated (10 fold)
```

```
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results:
##
##   RMSE       Rsquared    MAE
##   0.5221692  0.02378245  0.4475645
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
summary(lr_train_data)
```

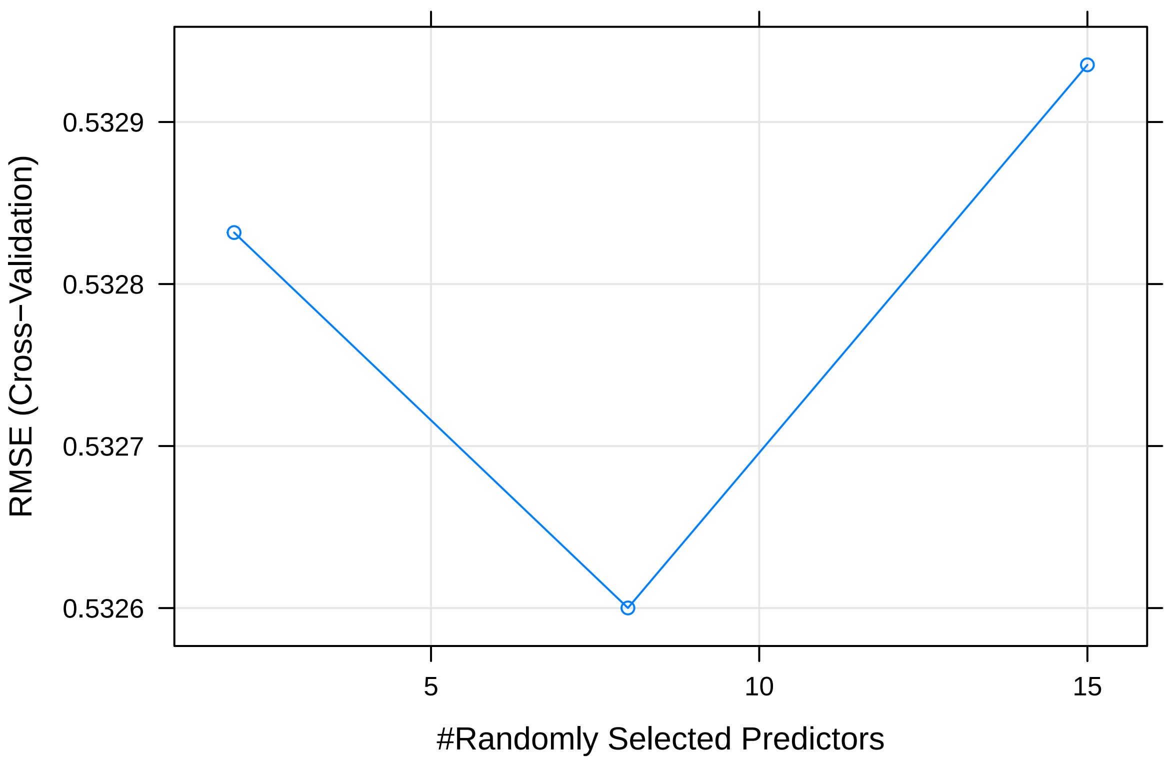
```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.0590 -0.2917 -0.1748  0.4718  1.1080
##
## Coefficients: (1 not defined because of singularities)
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.549e+01  1.704e-02 909.235   <2e-16 ***
## Year              2.041e+00  2.995e+00   0.681    0.496
## Population       -5.091e-02  1.443e+00  -0.035    0.972
## Gas.consumption  -1.339e-01  1.297e+00  -0.103    0.918
## Coal.consumption -1.125e-01  3.205e-01  -0.351    0.726
## Oil.consumption  -1.084e-01  1.207e+00  -0.090    0.928
## FossilFuelGrowth  2.745e+03  8.222e+03   0.334    0.739
## CoalGrowth       -1.361e+03  4.077e+03  -0.334    0.739
## GasGrowth        -8.167e+02  2.447e+03  -0.334    0.739
## OilGrowth        -1.162e+03  3.482e+03  -0.334    0.739
## Gas.cumsum        1.919e+00  3.220e+00   0.596    0.551
## Coal.cumsum       8.826e-01  1.976e+00   0.447    0.655
## Oil.cumsum       -4.598e+00  5.458e+00  -0.842    0.400
## log_Gas           1.390e-01  1.404e+00   0.099    0.921
## log_Coal                 NA         NA      NA       NA
## log_Oil           2.135e-02  1.266e+00   0.017    0.987
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5185 on 911 degrees of freedom
## Multiple R-squared:  0.003581,   Adjusted R-squared:  -0.01173
## F-statistic: 0.2338 on 14 and 911 DF,  p-value: 0.9984
```

```
#Random Forest: Training Model
set.seed(1)
rf_train_data <- caret::train(AverageTemperature ~., data = train_data,
                             method = "rf",
                             trControl = trainControl(method = "cv", number = 10),
                             preProcess = c("center","scale"))
rf_train_data
```

```
## Random Forest
##
## 926 samples
##  15 predictor
```

```
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE       Rsquared    MAE
##    2    0.5328318  0.05199912  0.4561321
##    8    0.5326001  0.05128867  0.4558554
##   15    0.5329353  0.05250372  0.4560572
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 8.
```

```
plot(rf_train_data)
```




```
rf_train_data$finalModel$importance
```

```
##                    IncNodePurity
## Year                   0.3300828
## Population             0.3282590
## Gas.consumption        0.4417320
## Coal.consumption       0.3699572
## Oil.consumption        0.4921677
## FossilFuelGrowth       1.5773091
## CoalGrowth             1.7036737
## GasGrowth              1.4323933
```

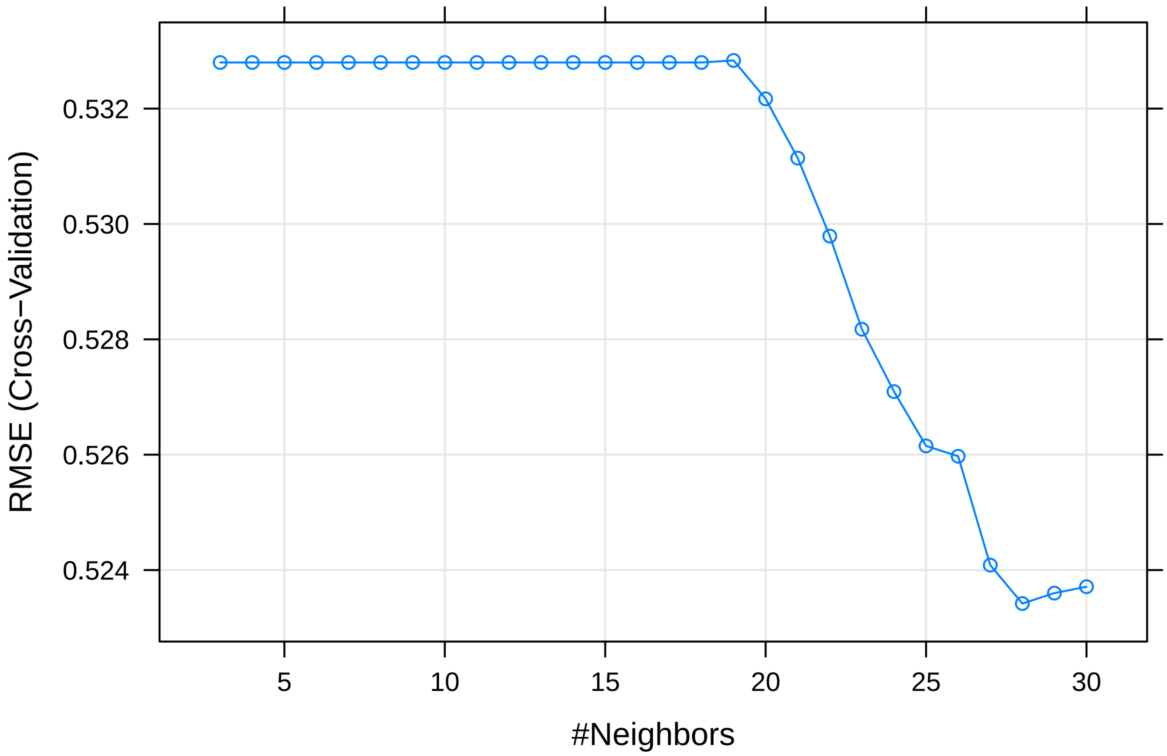
```
## OilGrowth           1.5876075
## Gas.cumsum          0.3755633
## Coal.cumsum         0.3187935
## Oil.cumsum          0.3047421
## log_Gas             0.4716346
## log_Coal            0.4788041
## log_Oil             0.5597839
```

```r
#K Nearest Neighbor: Training Model
set.seed(1)
knn_train_data <- caret::train(AverageTemperature ~., data = train_data,
                               method = "knn",
                               tuneGrid = expand.grid(.k = c(3:30)),
                               trControl = trainControl(method = "cv", number = 10),
                               preProcess = c("center","scale"))
knn_train_data
```

```
## k-Nearest Neighbors
##
## 926 samples
##  15 predictor
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
##
##   k   RMSE       Rsquared    MAE
##    3  0.5328000  0.05182978  0.4560099
##    4  0.5328000  0.05182978  0.4560099
##    5  0.5328000  0.05182978  0.4560099
##    6  0.5328000  0.05182978  0.4560099
##    7  0.5328000  0.05182978  0.4560099
##    8  0.5328000  0.05182978  0.4560099
##    9  0.5328000  0.05182978  0.4560099
##   10  0.5328000  0.05182978  0.4560099
##   11  0.5328000  0.05182978  0.4560099
##   12  0.5328000  0.05182978  0.4560099
##   13  0.5328000  0.05182978  0.4560099
##   14  0.5328000  0.05182978  0.4560099
##   15  0.5328000  0.05182978  0.4560099
##   16  0.5328000  0.05182978  0.4560099
##   17  0.5328000  0.05182978  0.4560099
##   18  0.5328000  0.05182978  0.4560099
##   19  0.5328358  0.05215851  0.4560242
##   20  0.5321696  0.05113216  0.4554489
##   21  0.5311414  0.04755453  0.4539739
##   22  0.5297897  0.04459315  0.4526117
##   23  0.5281754  0.04073472  0.4514423
##   24  0.5270947  0.04160246  0.4515233
##   25  0.5261523  0.03759524  0.4509884
##   26  0.5259730  0.03913722  0.4505999
##   27  0.5240858  0.03220912  0.4490498
##   28  0.5234196  0.02974657  0.4486011
##   29  0.5236005  0.03019404  0.4489798
```

```
##   30  0.5237114  0.03063802  0.4490555
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 28.
```

```r
plot(knn_train_data)
```




```r
#Classification and Regression Trees (CART): Training Model
set.seed(1)
cart_train_data <- caret::train(AverageTemperature ~., data = train_data,
                                method = "rpart",
                                tuneLength = 20,
                                trControl = trainControl(method = "cv", number = 10),
                                preProcess = c("center","scale"))
cart_train_data
```

```
## CART
##
## 926 samples
##  15 predictor
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
##
##   cp            RMSE       Rsquared    MAE
```

```
##   1.508839e-06  0.5327644  0.05171901  0.4559827
##   5.262059e-06  0.5326801  0.05126053  0.4559138
##   1.014084e-05  0.5325887  0.05076454  0.4558504
##   1.342267e-05  0.5325627  0.05070953  0.4558152
##   1.965799e-05  0.5323707  0.04963818  0.4556424
##   2.304350e-05  0.5323605  0.04961488  0.4556451
##   2.564169e-05  0.5323830  0.04983966  0.4556933
##   3.160431e-05  0.5324084  0.05038600  0.4556881
##   7.087998e-05  0.5319219  0.04829540  0.4553462
##   7.359431e-05  0.5320172  0.04901343  0.4554388
##   7.802040e-05  0.5319113  0.04859280  0.4553656
##   8.291483e-05  0.5318876  0.04864273  0.4552919
##   9.909704e-05  0.5316539  0.04723751  0.4550557
##   1.112719e-04  0.5316253  0.04740353  0.4549954
##   1.277299e-04  0.5315746  0.04708839  0.4550616
##   6.663113e-04  0.5284348  0.04030325  0.4522650
##   8.499504e-04  0.5268058  0.03281471  0.4514234
##   9.045555e-04  0.5264765  0.03105844  0.4512008
##   1.091845e-03  0.5251499  0.02834497  0.4499597
##   1.230829e-03  0.5244680  0.03099430  0.4492707
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 0.001230829.
```

```
FinalTree = cart_train_data$finalModel
rpartTree = as.party(FinalTree)
dev.new()
plot(rpartTree)
#Neural Net
registerDoParallel(cores=7)
nnetGrid <- expand.grid(.decay = c(0, 0.01, 0.1,0.5),
                        .size = c(1:10),
                        .bag = FALSE
)
set.seed(1)
nnet_train_data <- caret::train(AverageTemperature ~., data = train_data,
                               method = "avNNet",
                               tuneGrid = nnetGrid,
                               trControl = trainControl(method = "cv", number = 10),
                               preProcess = c("center","scale"),
                               linout = TRUE,
                               trace = FALSE,
                               MaxNWts = 10 * (ncol(train_data) + 1) + 10 + 1,
                               maxit = 500)
nnet_train_data
```

```
## Model Averaged Neural Network
##
## 926 samples
##  15 predictor
##
## Pre-processing: centered (15), scaled (15)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
```

```
##
##   decay  size  RMSE       Rsquared    MAE
##   0.00    1    0.5167856  0.02710320  0.4432566
##   0.00    2    0.5243326  0.05591935  0.4496936
##   0.00    3    0.5303730  0.05204293  0.4543698
##   0.00    4    0.5323901  0.05240382  0.4558553
##   0.00    5    0.5319061  0.05094962  0.4552918
##   0.00    6    0.5321200  0.05168481  0.4554036
##   0.00    7    0.5320936  0.05049755  0.4555411
##   0.00    8    0.5320629  0.05126051  0.4555288
##   0.00    9    0.5324410  0.05132792  0.4558348
##   0.00   10    0.5327792  0.05216868  0.4560140
##   0.01    1    0.5205350  0.01931820  0.4460347
##   0.01    2    0.5255159  0.04312569  0.4506501
##   0.01    3    0.5300084  0.05402660  0.4541498
##   0.01    4    0.5317946  0.05331221  0.4552899
##   0.01    5    0.5322814  0.05253561  0.4556499
##   0.01    6    0.5324385  0.05287343  0.4557609
##   0.01    7    0.5324845  0.05302095  0.4556294
##   0.01    8    0.5324091  0.05268905  0.4557515
##   0.01    9    0.5323877  0.05281533  0.4556900
##   0.01   10    0.5324144  0.05310762  0.4557046
##   0.10    1    0.5184244  0.01320753  0.4441988
##   0.10    2    0.5225793  0.03521409  0.4480357
##   0.10    3    0.5243718  0.04377381  0.4496294
##   0.10    4    0.5260569  0.05259983  0.4508955
##   0.10    5    0.5276990  0.05505708  0.4522593
##   0.10    6    0.5279889  0.05495217  0.4524968
##   0.10    7    0.5284447  0.05547823  0.4527500
##   0.10    8    0.5291192  0.05656069  0.4532954
##   0.10    9    0.5289386  0.05544143  0.4531470
##   0.10   10    0.5293428  0.05685968  0.4535620
##   0.50    1    0.5179287  0.01189233  0.4429189
##   0.50    2    0.5200019  0.02471530  0.4450298
##   0.50    3    0.5203883  0.02670554  0.4455088
##   0.50    4    0.5204733  0.02661162  0.4456570
##   0.50    5    0.5204676  0.02611874  0.4457049
##   0.50    6    0.5204220  0.02547166  0.4457081
##   0.50    7    0.5203853  0.02500252  0.4457078
##   0.50    8    0.5207280  0.02679548  0.4460153
##   0.50    9    0.5207850  0.02696104  0.4461005
##   0.50   10    0.5209893  0.02752403  0.4463959
##
## Tuning parameter 'bag' was held constant at a value of FALSE
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were size = 1, decay = 0 and bag = FALSE.
```

```r
plot(nnet_train_data)
################# Support Vector Machines ####################
set.seed(1)
svmFit <- train(AverageTemperature ~., data = train_data,
                method = "svmRadial",
                tuneLength = 14,
                preProcess = c("center","scale", "BoxCox"),
```

```r
                 trControl = trainControl(method = "cv", number = 10))
svmFit
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 926 samples
##  15 predictor
##
## Pre-processing: centered (15), scaled (15), Box-Cox transformation (11)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
##
##   C        RMSE       Rsquared    MAE
##      0.25  0.5429114  0.03384051  0.4189485
##      0.50  0.5436702  0.03246348  0.4203144
##      1.00  0.5441964  0.03212132  0.4213267
##      2.00  0.5446705  0.03037026  0.4227085
##      4.00  0.5457520  0.02816179  0.4244072
##      8.00  0.5462479  0.02948530  0.4250113
##     16.00  0.5467691  0.02883888  0.4260788
##     32.00  0.5473630  0.02851446  0.4267892
##     64.00  0.5473616  0.02851950  0.4267881
##    128.00  0.5473612  0.02848675  0.4267842
##    256.00  0.5473612  0.02851021  0.4267842
##    512.00  0.5473604  0.02848107  0.4267844
##   1024.00  0.5473644  0.02853139  0.4267916
##   2048.00  0.5473662  0.02851743  0.4267924
##
## Tuning parameter 'sigma' was held constant at a value of 0.1784708
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were sigma = 0.1784708 and C = 0.25.
```

```r
plot(svmFit)

################# Elastinet #####################
glmnGrid <- expand.grid(.alpha = c(0, .1, .2, .4, .6, .8, 1),
                       .lambda = seq(.01, .2, length = 40))
set.seed(1)
glmnFit <- train(AverageTemperature ~., data = train_data,
                 method = "glmnet",
                 tuneGrid = glmnGrid,
                 preProcess = c("center","scale", "BoxCox"),
                 trControl = trainControl(method = "cv", number = 10))
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

```r
glmnFit
```

```
## glmnet
##
## 926 samples
##  15 predictor
##
```

```
## Pre-processing: centered (15), scaled (15), Box-Cox transformation (11)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 834, 832, 833, 834, 833, 833, ...
## Resampling results across tuning parameters:
##
##   alpha  lambda      RMSE       Rsquared      MAE
##   0.0    0.01000000  0.5173743  0.0108400786  0.4436790
##   0.0    0.01487179  0.5172250  0.0101493356  0.4435486
##   0.0    0.01974359  0.5171163  0.0096457599  0.4434555
##   0.0    0.02461538  0.5170296  0.0092555264  0.4433828
##   0.0    0.02948718  0.5169581  0.0089484308  0.4433240
##   0.0    0.03435897  0.5168979  0.0087075616  0.4432752
##   0.0    0.03923077  0.5168446  0.0085049189  0.4432326
##   0.0    0.04410256  0.5167970  0.0083309107  0.4431954
##   0.0    0.04897436  0.5167558  0.0081931140  0.4431646
##   0.0    0.05384615  0.5167184  0.0080803587  0.4431388
##   0.0    0.05871795  0.5166836  0.0079790339  0.4431148
##   0.0    0.06358974  0.5166497  0.0078807586  0.4430914
##   0.0    0.06846154  0.5166206  0.0078111738  0.4430714
##   0.0    0.07333333  0.5165949  0.0077590284  0.4430542
##   0.0    0.07820513  0.5165689  0.0077012650  0.4430368
##   0.0    0.08307692  0.5165445  0.0076493938  0.4430205
##   0.0    0.08794872  0.5165224  0.0076127889  0.4430059
##   0.0    0.09282051  0.5165011  0.0075761451  0.4429916
##   0.0    0.09769231  0.5164806  0.0075402005  0.4429779
##   0.0    0.10256410  0.5164618  0.0075141270  0.4429657
##   0.0    0.10743590  0.5164437  0.0074909645  0.4429538
##   0.0    0.11230769  0.5164260  0.0074674513  0.4429420
##   0.0    0.11717949  0.5164091  0.0074472972  0.4429307
##   0.0    0.12205128  0.5163933  0.0074320538  0.4429202
##   0.0    0.12692308  0.5163782  0.0074193019  0.4429103
##   0.0    0.13179487  0.5163635  0.0074073958  0.4429006
##   0.0    0.13666667  0.5163497  0.0073982192  0.4428915
##   0.0    0.14153846  0.5163362  0.0073897540  0.4428825
##   0.0    0.14641026  0.5163232  0.0073825938  0.4428739
##   0.0    0.15128205  0.5163108  0.0073772675  0.4428657
##   0.0    0.15615385  0.5162986  0.0073723310  0.4428577
##   0.0    0.16102564  0.5162869  0.0073685210  0.4428499
##   0.0    0.16589744  0.5162757  0.0073660948  0.4428425
##   0.0    0.17076923  0.5162647  0.0073639166  0.4428352
##   0.0    0.17564103  0.5162540  0.0073625117  0.4428281
##   0.0    0.18051282  0.5162439  0.0073623156  0.4428213
##   0.0    0.18538462  0.5162339  0.0073623350  0.4428147
##   0.0    0.19025641  0.5162241  0.0073627462  0.4428081
##   0.0    0.19512821  0.5162148  0.0073640320  0.4428019
##   0.0    0.20000000  0.5162057  0.0073659278  0.4427958
##   0.1    0.01000000  0.5165956  0.0068355946  0.4430871
##   0.1    0.01487179  0.5163630  0.0061856943  0.4429308
##   0.1    0.01974359  0.5162436  0.0060638126  0.4428660
##   0.1    0.02461538  0.5161320  0.0059376694  0.4428080
##   0.1    0.02948718  0.5160221  0.0057520514  0.4427393
##   0.1    0.03435897  0.5159102  0.0055604989  0.4426668
##   0.1    0.03923077  0.5158059  0.0054222922  0.4425977
##   0.1    0.04410256  0.5157166  0.0055058250  0.4425317
```

```
##   0.1    0.04897436  0.5156370  0.0060264727  0.4424675
##   0.1    0.05384615  0.5155696  0.0065573791  0.4424084
##   0.1    0.05871795  0.5155083  0.0069901846  0.4423508
##   0.1    0.06358974  0.5154499  0.0068160699  0.4422914
##   0.1    0.06846154  0.5153917  0.0042628751  0.4422306
##   0.1    0.07333333  0.5153356  0.0039886090  0.4421729
##   0.1    0.07820513  0.5152919  0.0038319378  0.4421286
##   0.1    0.08307692  0.5152514  0.0035569361  0.4420944
##   0.1    0.08794872  0.5152133  0.0032546259  0.4420624
##   0.1    0.09282051  0.5151784  0.0029749773  0.4420332
##   0.1    0.09769231  0.5151505  0.0029949491  0.4420100
##   0.1    0.10256410  0.5151302  0.0028965308  0.4419958
##   0.1    0.10743590  0.5151133  0.0018699155  0.4419835
##   0.1    0.11230769  0.5150996  0.0017908098  0.4419741
##   0.1    0.11717949  0.5150867  0.0017001104  0.4419647
##   0.1    0.12205128  0.5150741  0.0015950633  0.4419555
##   0.1    0.12692308  0.5150620  0.0014772468  0.4419464
##   0.1    0.13179487  0.5150504  0.0013497359  0.4419376
##   0.1    0.13666667  0.5150392  0.0012031780  0.4419289
##   0.1    0.14153846  0.5150291  0.0011070063  0.4419232
##   0.1    0.14641026  0.5150192  0.0009883562  0.4419194
##   0.1    0.15128205  0.5150096  0.0008511571  0.4419155
##   0.1    0.15615385  0.5150034  0.0008500952  0.4419141
##   0.1    0.16102564  0.5149975  0.0010183070  0.4419122
##   0.1    0.16589744  0.5149919  0.0023914917  0.4419079
##   0.1    0.17076923  0.5149872  0.0023914917  0.4419027
##   0.1    0.17564103  0.5149827  0.0023914917  0.4418977
##   0.1    0.18051282  0.5149783  0.0023914917  0.4418927
##   0.1    0.18538462  0.5149739  0.0023914917  0.4418877
##   0.1    0.19025641  0.5149705  0.0038608506  0.4418850
##   0.1    0.19512821  0.5149680  0.0038608506  0.4418855
##   0.1    0.20000000  0.5149656  0.0038608506  0.4418860
##   0.2    0.01000000  0.5162720  0.0060214891  0.4428867
##   0.2    0.01487179  0.5160549  0.0057035181  0.4427648
##   0.2    0.01974359  0.5158394  0.0053816431  0.4426235
##   0.2    0.02461538  0.5156701  0.0060268655  0.4424943
##   0.2    0.02948718  0.5155374  0.0069390067  0.4423748
##   0.2    0.03435897  0.5154146  0.0041216546  0.4422491
##   0.2    0.03923077  0.5153104  0.0037439796  0.4421419
##   0.2    0.04410256  0.5152306  0.0031991267  0.4420733
##   0.2    0.04897436  0.5151651  0.0029119463  0.4420177
##   0.2    0.05384615  0.5151222  0.0017380759  0.4419869
##   0.2    0.05871795  0.5150944  0.0015694391  0.4419678
##   0.2    0.06358974  0.5150689  0.0013655991  0.4419493
##   0.2    0.06846154  0.5150452  0.0011083635  0.4419311
##   0.2    0.07333333  0.5150250  0.0009434156  0.4419225
##   0.2    0.07820513  0.5150085  0.0008500952  0.4419179
##   0.2    0.08307692  0.5149955  0.0023914917  0.4419107
##   0.2    0.08794872  0.5149850  0.0023914917  0.4418991
##   0.2    0.09282051  0.5149750  0.0023914917  0.4418877
##   0.2    0.09769231  0.5149683  0.0038608506  0.4418855
##   0.2    0.10256410  0.5149656           NaN  0.4418860
##   0.2    0.10743590  0.5149656           NaN  0.4418860
##   0.2    0.11230769  0.5149656           NaN  0.4418860
```

```
##   0.2    0.11717949  0.5149656          NaN  0.4418860
##   0.2    0.12205128  0.5149656          NaN  0.4418860
##   0.2    0.12692308  0.5149656          NaN  0.4418860
##   0.2    0.13179487  0.5149656          NaN  0.4418860
##   0.2    0.13666667  0.5149656          NaN  0.4418860
##   0.2    0.14153846  0.5149656          NaN  0.4418860
##   0.2    0.14641026  0.5149656          NaN  0.4418860
##   0.2    0.15128205  0.5149656          NaN  0.4418860
##   0.2    0.15615385  0.5149656          NaN  0.4418860
##   0.2    0.16102564  0.5149656          NaN  0.4418860
##   0.2    0.16589744  0.5149656          NaN  0.4418860
##   0.2    0.17076923  0.5149656          NaN  0.4418860
##   0.2    0.17564103  0.5149656          NaN  0.4418860
##   0.2    0.18051282  0.5149656          NaN  0.4418860
##   0.2    0.18538462  0.5149656          NaN  0.4418860
##   0.2    0.19025641  0.5149656          NaN  0.4418860
##   0.2    0.19512821  0.5149656          NaN  0.4418860
##   0.2    0.20000000  0.5149656          NaN  0.4418860
##   0.4    0.01000000  0.5158521  0.0053555041  0.4426331
##   0.4    0.01487179  0.5155502  0.0069316128  0.4423844
##   0.4    0.01974359  0.5153194  0.0036832905  0.4421477
##   0.4    0.02461538  0.5151717  0.0028624446  0.4420209
##   0.4    0.02948718  0.5150987  0.0015182441  0.4419696
##   0.4    0.03435897  0.5150478  0.0010426328  0.4419314
##   0.4    0.03923077  0.5150110  0.0008500952  0.4419201
##   0.4    0.04410256  0.5149861  0.0023914917  0.4418995
##   0.4    0.04897436  0.5149682  0.0038608506  0.4418855
##   0.4    0.05384615  0.5149656          NaN  0.4418860
##   0.4    0.05871795  0.5149656          NaN  0.4418860
##   0.4    0.06358974  0.5149656          NaN  0.4418860
##   0.4    0.06846154  0.5149656          NaN  0.4418860
##   0.4    0.07333333  0.5149656          NaN  0.4418860
##   0.4    0.07820513  0.5149656          NaN  0.4418860
##   0.4    0.08307692  0.5149656          NaN  0.4418860
##   0.4    0.08794872  0.5149656          NaN  0.4418860
##   0.4    0.09282051  0.5149656          NaN  0.4418860
##   0.4    0.09769231  0.5149656          NaN  0.4418860
##   0.4    0.10256410  0.5149656          NaN  0.4418860
##   0.4    0.10743590  0.5149656          NaN  0.4418860
##   0.4    0.11230769  0.5149656          NaN  0.4418860
##   0.4    0.11717949  0.5149656          NaN  0.4418860
##   0.4    0.12205128  0.5149656          NaN  0.4418860
##   0.4    0.12692308  0.5149656          NaN  0.4418860
##   0.4    0.13179487  0.5149656          NaN  0.4418860
##   0.4    0.13666667  0.5149656          NaN  0.4418860
##   0.4    0.14153846  0.5149656          NaN  0.4418860
##   0.4    0.14641026  0.5149656          NaN  0.4418860
##   0.4    0.15128205  0.5149656          NaN  0.4418860
##   0.4    0.15615385  0.5149656          NaN  0.4418860
##   0.4    0.16102564  0.5149656          NaN  0.4418860
##   0.4    0.16589744  0.5149656          NaN  0.4418860
##   0.4    0.17076923  0.5149656          NaN  0.4418860
##   0.4    0.17564103  0.5149656          NaN  0.4418860
##   0.4    0.18051282  0.5149656          NaN  0.4418860
```

```
##   0.4    0.18538462  0.5149656           NaN  0.4418860
##   0.4    0.19025641  0.5149656           NaN  0.4418860
##   0.4    0.19512821  0.5149656           NaN  0.4418860
##   0.4    0.20000000  0.5149656           NaN  0.4418860
##   0.6    0.01000000  0.5155510  0.0069187807  0.4423838
##   0.6    0.01487179  0.5152400  0.0031204848  0.4420770
##   0.6    0.01974359  0.5150994  0.0014928646  0.4419696
##   0.6    0.02461538  0.5150281  0.0008992334  0.4419246
##   0.6    0.02948718  0.5149861  0.0023914917  0.4418992
##   0.6    0.03435897  0.5149656           NaN  0.4418860
##   0.6    0.03923077  0.5149656           NaN  0.4418860
##   0.6    0.04410256  0.5149656           NaN  0.4418860
##   0.6    0.04897436  0.5149656           NaN  0.4418860
##   0.6    0.05384615  0.5149656           NaN  0.4418860
##   0.6    0.05871795  0.5149656           NaN  0.4418860
##   0.6    0.06358974  0.5149656           NaN  0.4418860
##   0.6    0.06846154  0.5149656           NaN  0.4418860
##   0.6    0.07333333  0.5149656           NaN  0.4418860
##   0.6    0.07820513  0.5149656           NaN  0.4418860
##   0.6    0.08307692  0.5149656           NaN  0.4418860
##   0.6    0.08794872  0.5149656           NaN  0.4418860
##   0.6    0.09282051  0.5149656           NaN  0.4418860
##   0.6    0.09769231  0.5149656           NaN  0.4418860
##   0.6    0.10256410  0.5149656           NaN  0.4418860
##   0.6    0.10743590  0.5149656           NaN  0.4418860
##   0.6    0.11230769  0.5149656           NaN  0.4418860
##   0.6    0.11717949  0.5149656           NaN  0.4418860
##   0.6    0.12205128  0.5149656           NaN  0.4418860
##   0.6    0.12692308  0.5149656           NaN  0.4418860
##   0.6    0.13179487  0.5149656           NaN  0.4418860
##   0.6    0.13666667  0.5149656           NaN  0.4418860
##   0.6    0.14153846  0.5149656           NaN  0.4418860
##   0.6    0.14641026  0.5149656           NaN  0.4418860
##   0.6    0.15128205  0.5149656           NaN  0.4418860
##   0.6    0.15615385  0.5149656           NaN  0.4418860
##   0.6    0.16102564  0.5149656           NaN  0.4418860
##   0.6    0.16589744  0.5149656           NaN  0.4418860
##   0.6    0.17076923  0.5149656           NaN  0.4418860
##   0.6    0.17564103  0.5149656           NaN  0.4418860
##   0.6    0.18051282  0.5149656           NaN  0.4418860
##   0.6    0.18538462  0.5149656           NaN  0.4418860
##   0.6    0.19025641  0.5149656           NaN  0.4418860
##   0.6    0.19512821  0.5149656           NaN  0.4418860
##   0.6    0.20000000  0.5149656           NaN  0.4418860
##   0.8    0.01000000  0.5153180  0.0036315840  0.4421447
##   0.8    0.01487179  0.5150991  0.0014746493  0.4419690
##   0.8    0.01974359  0.5150113  0.0008500952  0.4419211
##   0.8    0.02461538  0.5149676  0.0038608506  0.4418856
##   0.8    0.02948718  0.5149656           NaN  0.4418860
##   0.8    0.03435897  0.5149656           NaN  0.4418860
##   0.8    0.03923077  0.5149656           NaN  0.4418860
##   0.8    0.04410256  0.5149656           NaN  0.4418860
##   0.8    0.04897436  0.5149656           NaN  0.4418860
##   0.8    0.05384615  0.5149656           NaN  0.4418860
```

```
##   0.8    0.05871795  0.5149656          NaN  0.4418860
##   0.8    0.06358974  0.5149656          NaN  0.4418860
##   0.8    0.06846154  0.5149656          NaN  0.4418860
##   0.8    0.07333333  0.5149656          NaN  0.4418860
##   0.8    0.07820513  0.5149656          NaN  0.4418860
##   0.8    0.08307692  0.5149656          NaN  0.4418860
##   0.8    0.08794872  0.5149656          NaN  0.4418860
##   0.8    0.09282051  0.5149656          NaN  0.4418860
##   0.8    0.09769231  0.5149656          NaN  0.4418860
##   0.8    0.10256410  0.5149656          NaN  0.4418860
##   0.8    0.10743590  0.5149656          NaN  0.4418860
##   0.8    0.11230769  0.5149656          NaN  0.4418860
##   0.8    0.11717949  0.5149656          NaN  0.4418860
##   0.8    0.12205128  0.5149656          NaN  0.4418860
##   0.8    0.12692308  0.5149656          NaN  0.4418860
##   0.8    0.13179487  0.5149656          NaN  0.4418860
##   0.8    0.13666667  0.5149656          NaN  0.4418860
##   0.8    0.14153846  0.5149656          NaN  0.4418860
##   0.8    0.14641026  0.5149656          NaN  0.4418860
##   0.8    0.15128205  0.5149656          NaN  0.4418860
##   0.8    0.15615385  0.5149656          NaN  0.4418860
##   0.8    0.16102564  0.5149656          NaN  0.4418860
##   0.8    0.16589744  0.5149656          NaN  0.4418860
##   0.8    0.17076923  0.5149656          NaN  0.4418860
##   0.8    0.17564103  0.5149656          NaN  0.4418860
##   0.8    0.18051282  0.5149656          NaN  0.4418860
##   0.8    0.18538462  0.5149656          NaN  0.4418860
##   0.8    0.19025641  0.5149656          NaN  0.4418860
##   0.8    0.19512821  0.5149656          NaN  0.4418860
##   0.8    0.20000000  0.5149656          NaN  0.4418860
##   1.0    0.01000000  0.5151699  0.0028062749  0.4420188
##   1.0    0.01487179  0.5150272  0.0008819114  0.4419246
##   1.0    0.01974359  0.5149673  0.0038608506  0.4418857
##   1.0    0.02461538  0.5149656          NaN  0.4418860
##   1.0    0.02948718  0.5149656          NaN  0.4418860
##   1.0    0.03435897  0.5149656          NaN  0.4418860
##   1.0    0.03923077  0.5149656          NaN  0.4418860
##   1.0    0.04410256  0.5149656          NaN  0.4418860
##   1.0    0.04897436  0.5149656          NaN  0.4418860
##   1.0    0.05384615  0.5149656          NaN  0.4418860
##   1.0    0.05871795  0.5149656          NaN  0.4418860
##   1.0    0.06358974  0.5149656          NaN  0.4418860
##   1.0    0.06846154  0.5149656          NaN  0.4418860
##   1.0    0.07333333  0.5149656          NaN  0.4418860
##   1.0    0.07820513  0.5149656          NaN  0.4418860
##   1.0    0.08307692  0.5149656          NaN  0.4418860
##   1.0    0.08794872  0.5149656          NaN  0.4418860
##   1.0    0.09282051  0.5149656          NaN  0.4418860
##   1.0    0.09769231  0.5149656          NaN  0.4418860
##   1.0    0.10256410  0.5149656          NaN  0.4418860
##   1.0    0.10743590  0.5149656          NaN  0.4418860
##   1.0    0.11230769  0.5149656          NaN  0.4418860
##   1.0    0.11717949  0.5149656          NaN  0.4418860
##   1.0    0.12205128  0.5149656          NaN  0.4418860
```

```
##   1.0    0.12692308  0.5149656          NaN  0.4418860
##   1.0    0.13179487  0.5149656          NaN  0.4418860
##   1.0    0.13666667  0.5149656          NaN  0.4418860
##   1.0    0.14153846  0.5149656          NaN  0.4418860
##   1.0    0.14641026  0.5149656          NaN  0.4418860
##   1.0    0.15128205  0.5149656          NaN  0.4418860
##   1.0    0.15615385  0.5149656          NaN  0.4418860
##   1.0    0.16102564  0.5149656          NaN  0.4418860
##   1.0    0.16589744  0.5149656          NaN  0.4418860
##   1.0    0.17076923  0.5149656          NaN  0.4418860
##   1.0    0.17564103  0.5149656          NaN  0.4418860
##   1.0    0.18051282  0.5149656          NaN  0.4418860
##   1.0    0.18538462  0.5149656          NaN  0.4418860
##   1.0    0.19025641  0.5149656          NaN  0.4418860
##   1.0    0.19512821  0.5149656          NaN  0.4418860
##   1.0    0.20000000  0.5149656          NaN  0.4418860
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 0.2 and lambda = 0.2.
```

```r
############################ LDA ##############################

#Compare ROC Value by Training Model
allmodels <- list(Logistic_Regression = lr_train_data, Random_Forest = rf_train_data, KNN = knn_train_da
trainresults <- resamples(allmodels)
bwplot(trainresults)
```

```r
###########################Test Data###########################
#Logistic Regression: Testing Data
set.seed(1)
lrpredict <- predict(lr_train_data, test_data)
```

```
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading
```

```r
lrresults <- postResample(pred = lrpredict, test_data$AverageTemperature)
lrresults
```

```
##       RMSE   Rsquared        MAE
## 0.54696378 0.05398734 0.47346096
```

```r
#Random Forest: Testing Data
set.seed(1)
rfpredict <- predict(rf_train_data, test_data)

rfresults <-postResample(pred = rfpredict, test_data$AverageTemperature)
rfresults
```

```
##      RMSE  Rsquared       MAE
## 0.5582194 0.1292098 0.4829114
```

```r
#K Nearest Neighbor: Testing Data
set.seed(1)
knnpredict <- predict(knn_train_data, test_data)

knnresults <-postResample(pred = knnpredict, test_data$AverageTemperature)
knnresults
```

```
##       RMSE   Rsquared        MAE
## 0.55381260 0.09498403 0.47930131
```

```
#Classification and Regression Trees (CART): Testing Data
set.seed(1)
cartpredict <- predict(cart_train_data, test_data)
#Confusion Matrix Accuracy
cartresults <- postResample(pred = cartpredict, test_data$AverageTemperature)
cartresults
```

```
##      RMSE  Rsquared       MAE
## 0.5390572        NA 0.4674725
```

```
#Neural Net: Testing Data
set.seed(1)
nnetpredict <- predict(nnet_train_data, test_data)
#Confusion Matrix Accuracy
nnetresults <- postResample(nnetpredict, test_data$AverageTemperature)
nnetresults
```

```
##       RMSE   Rsquared        MAE
## 0.54187868 0.06424787 0.46981953
```

```
#Support Vector Machines
set.seed(1)
svmpredict <- predict(svmFit, test_data)
#Confusion Matrix Accuracy
svmresults <- postResample(svmpredict, test_data$AverageTemperature)
svmresults
```

```
##       RMSE   Rsquared        MAE
## 0.56939443 0.08729363 0.45079948
```

```
# Elastinet
set.seed(1)
glmnpredict <- predict(glmnFit, test_data)
#Confusion Matrix Accuracy
glmnresults <- postResample(glmnpredict, test_data$AverageTemperature)
glmnresults
```

```
##      RMSE  Rsquared       MAE
## 0.5390572        NA 0.4674725
```

```
#Comparing Test Results

lrfinal<- c(lrresults[1], lrresults[2], lrresults[3])
rffinal <- c(rfresults[1], rfresults[2], rfresults[3])
knnfinal <- c(knnresults[1], knnresults[2], knnresults[3])
cartfinal <- c(cartresults[1], cartresults[2], cartresults[3])
nnetfinal <- c(nnetresults[1], nnetresults[2], nnetresults[3])
svmfinal <- c(svmresults[1], svmresults[2], svmresults[3])
glmnfinal <- c(glmnresults[1], glmnresults[2], glmnresults[3])
allmodelsfinal <- data.frame(rbind(lrfinal, rffinal, knnfinal, cartfinal, nnetfinal, svmfinal, glmnfinal
names(allmodelsfinal) <- c("RSME", "Rsquared", "MAE")
allmodelsfinal
```

```
##                RSME   Rsquared       MAE
## lrfinal   0.5469638 0.05398734 0.4734610
## rffinal   0.5582194 0.12920977 0.4829114
```

```
## knnfinal  0.5538126 0.09498403 0.4793013
## cartfinal 0.5390572         NA 0.4674725
## nnetfinal 0.5418787 0.06424787 0.4698195
## svmfinal  0.5693944 0.08729363 0.4507995
## glmnfinal 0.5390572         NA 0.4674725
```

```
#To find the Most Important Predictors within the Diabetes Dataset
set.seed(1)
importance <- randomForest(AverageTemperature ~., data = train_data, importance=TRUE) # fit the random
caret::varImp(importance) # get variable importance, based on mean decrease in accuracy
```

```
##                     Overall
## Year              -3.332437
## Population        -4.257055
## Gas.consumption   -4.384206
## Coal.consumption  -4.038590
## Oil.consumption   -5.090087
## FossilFuelGrowth  -8.419754
## CoalGrowth       -12.489948
## GasGrowth        -10.761649
## OilGrowth        -12.655051
## Gas.cumsum        -3.456780
## Coal.cumsum       -5.084109
## Oil.cumsum        -4.831225
## log_Gas           -5.192255
## log_Coal          -4.526770
## log_Oil           -4.682388
```