Stat 380 Final Project

Group Beta

Introduction

Carbon Dioxide (CO2) emissions are the leading cause of human induced climate change. According to the IPCC, humanity's greenhouse gas emissions have already raised the planets temperature 1.1 degrees Celsius over pre-industrial levels, with CO2 in the atmosphere being 50% higher than pre-industrial levels (420 PPM compared with 280 in pre industrial times). Because of this, various countries signed onto the Paris Climate Agreement which aimed to implement policies to curb CO2 emissions to cap warming at 1.5 degrees Celsius over pre industrial levels. However, whether the necessary policies are being implemented is called into question with CO2 emissions continuing to rise and the probability of the planet exceeding 1.5 degrees growing over time.

With this in mind, we aim to model CO2 emissions in the United States using various relevant human activities as predictors. Through this we aim to identify which human activities are the strongest predictors of future CO2 emissions. In particular, we employed two models: a Neural Network and Extreme Gradient Boosting.

```
Warning: Row 1 does not provide unique names. Consider running clean_names()
after row_to_names().
```

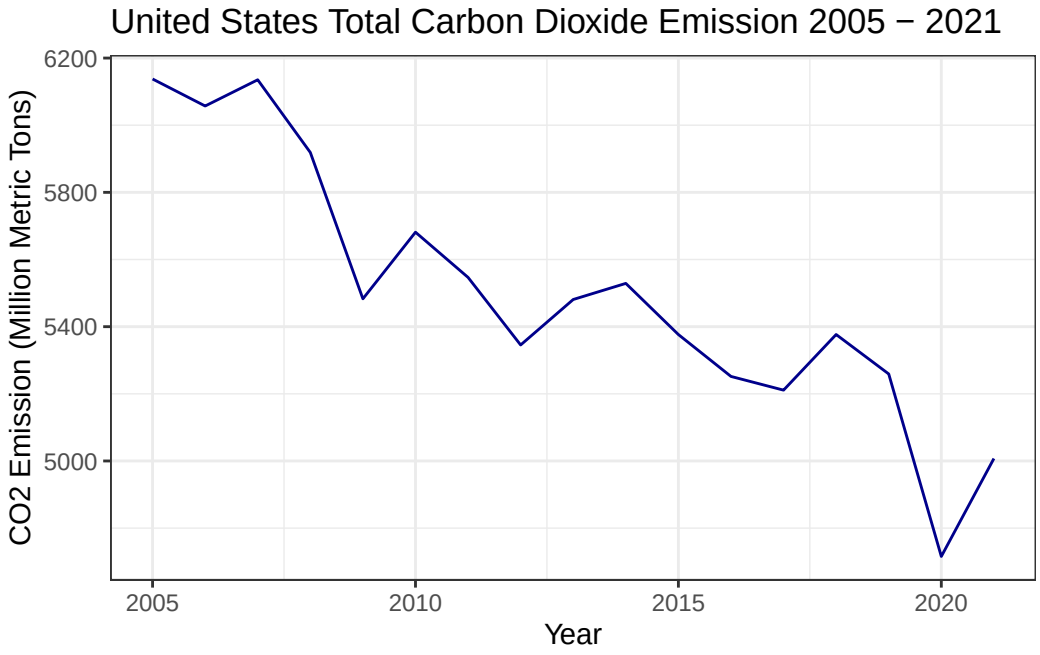
Explotory Data Analysis

Carbon Emissions

We produced a line graph for the total yearly carbon dioxide emission in the United States from 2005 to 2021.

From the graph, we found that the Carbon Dioxide emission is in steadily declining since 2005, which is a direct result of efforts made on reducing co2 emission since the recognition of global warming. There is a slight increase in emission in 2021. This aligns with the "Build America Buy America Act", a legislation made in the same year, stating that all construction material used for infrastructure must be manufactured in the united states. Also, after COVID-19,

global trade was greatly hindered, and the need for reliable goods produced domestically increased.



Industrial Output

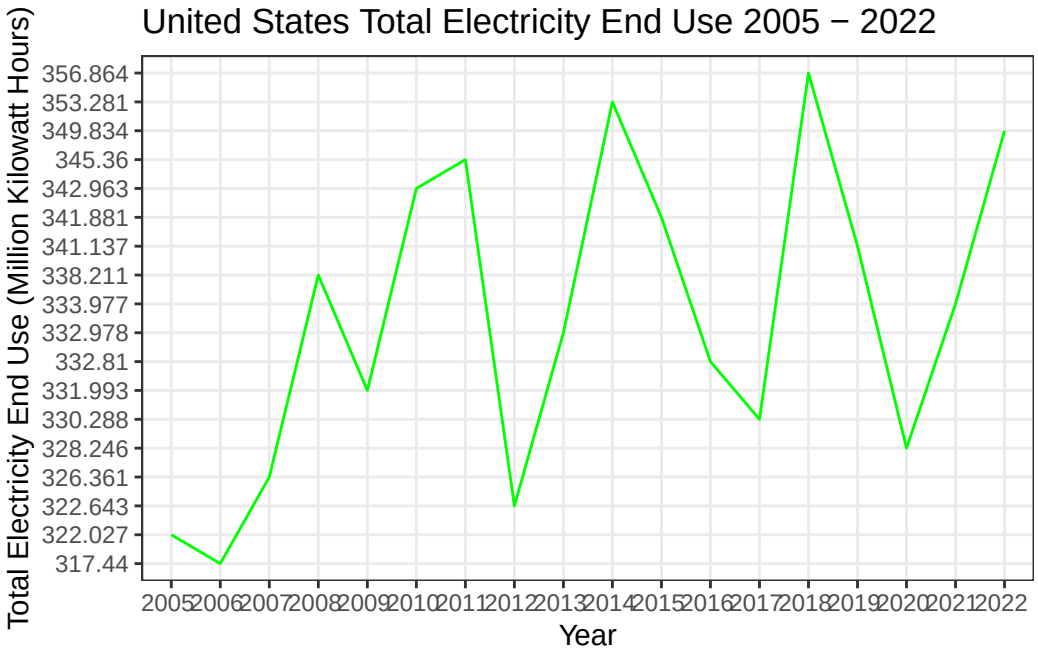
We produced a line graph for the Gross Manufacturing Output in the United States from 2005 to 2021.

From the graph, we found that the gross manufacturing output have increased roughly 55% since 2005, with slight dips in 2008, 2014, and 2020. This aligns with the global financial crisis, the energy crisis, and the COVID-19 pandemic respectively. It is speculated that this is due to the Manufacturing Enterprise Integration Act of 2002, which promoted the rise of smart manufacturing, and later digital manufacturing and robotic use. Data suggests that this act eliminated jobs, but increased the production capacity by a large margin.

Electricity Use

We produced a line graph for the electricity end use in the United States from 2005 to 2021.

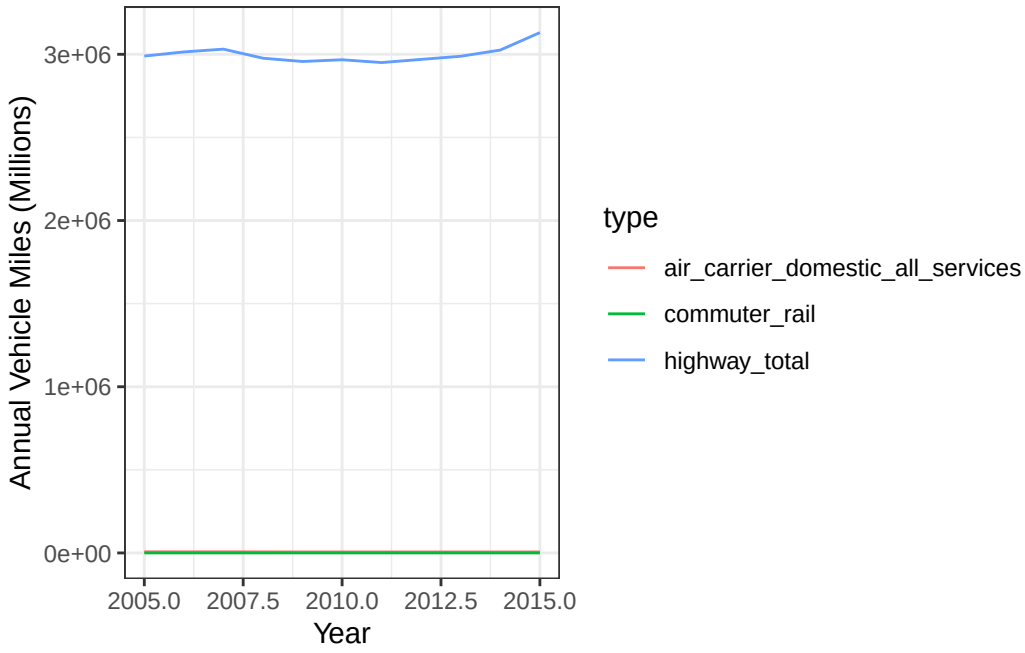
From the graph, we can see that there is no obvious trend observed for this variable, as the measure fluctuates between 317 million and 350 million kilowatt hours over the observed period. CO2 emission from the electricity sector is still extremely relevant, since that despite tremendous amount of investments made in clean energy, 60% of electricity generated in the US are still from traditional sources like natural gas, coal and petroleum.

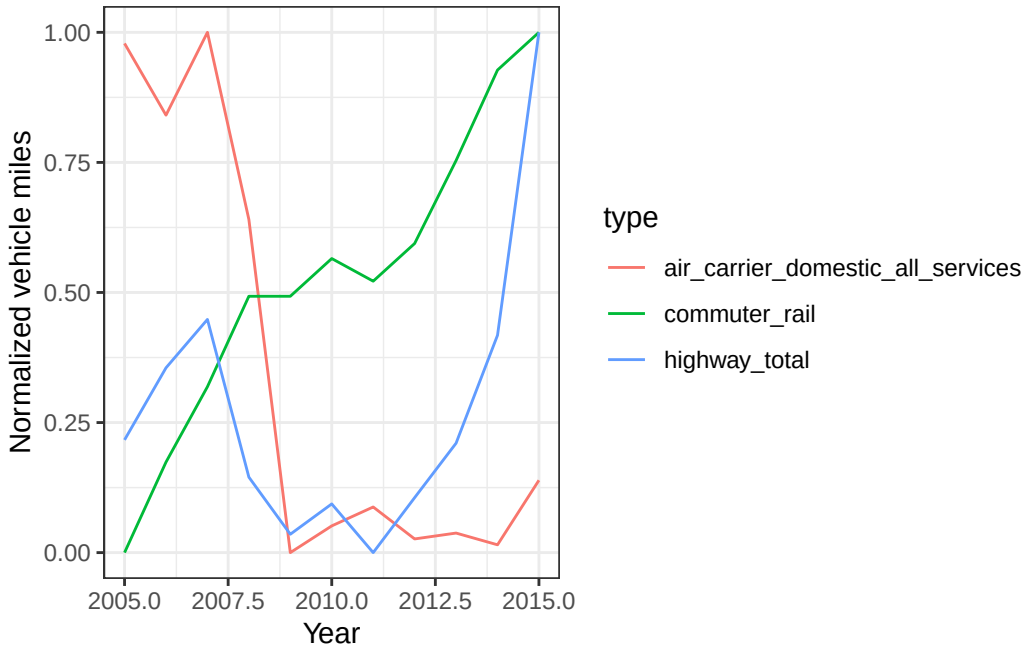


Transportation

We produced a line graph for the transportation usage in the United States from 2005 to 2015

Finally we looked at the vehicle usage which is measure in million miles. We normalized the data for uniformity in comparison, as the magnitude of data differ significantly between the different sectors. We found that over the ten year observation period, air travel millage dropped 16%. In the mean time, travel by rail increased 25%, and total highway millage increased 5%. We speculate that this is not related to 911, instead, it is due to the poor customer service provided by airlines, and increased airline fares, as air travel millage peaked in 2007, at a 20% increase from 2001.


Annual Vehicle Miles (Millions)
3e+06
2e+06
1e+06
0e+00
2005.0
2007.5
2010.0
2012.5
2015.0
Year
type
air_carrier_domestic_all_services
commuter_rail
highway_total


Normalized vehicle miles
1.00
0.75
0.50
0.25
0.00
2005.0
2007.5
2010.0
2012.5
2015.0
Year
type
air_carrier_domestic_all_services
commuter_rail
highway_total

Modelling part 1:

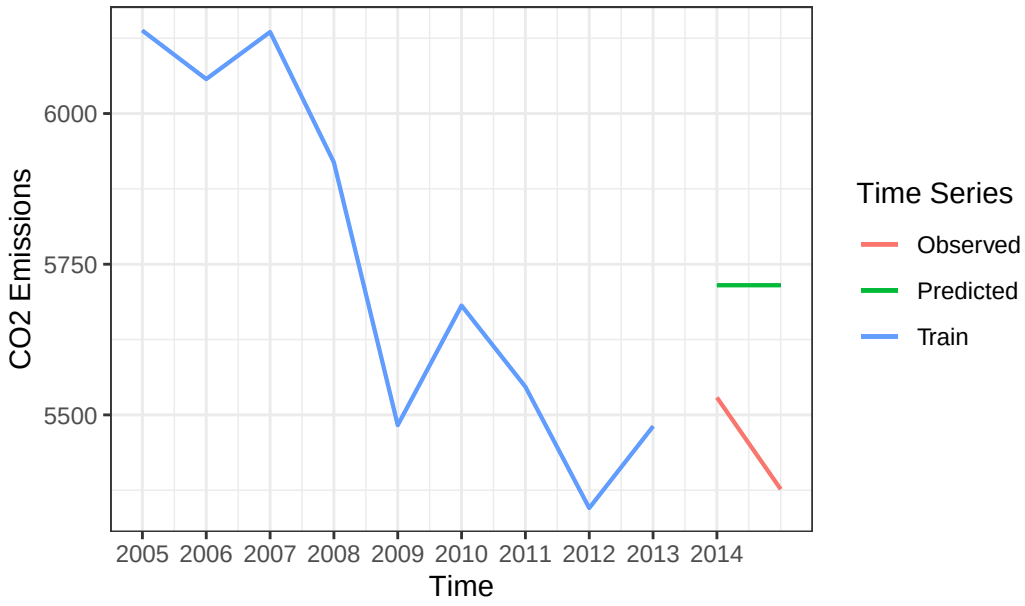
Finally, we took two approaches to modelling. Firstly, we constructed a two layer neural networ, consisting of 64 nodes in first layer and 32 nodes in the second layer, with MSE loss and ReLU activations. Ultimately, our goal was to use this model to identify which variables were most important for our analysis. We first built the full model with all four predictors to see how it performed. However, we then repeatedly trained the model excluding one predictor at a time then saw how each models loss was affected. Our idea was that the model in which loss was most impacted would indicate that the given excluded variable was most important to predicting CO2.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_2 (Dense)             (None, 64)                320
 dense_1 (Dense)             (None, 32)                2080
 dense (Dense)               (None, 1)                 33
=================================================================
Total params: 2,433
Trainable params: 2,433
Non-trainable params: 0
_________________________________________________________________
```

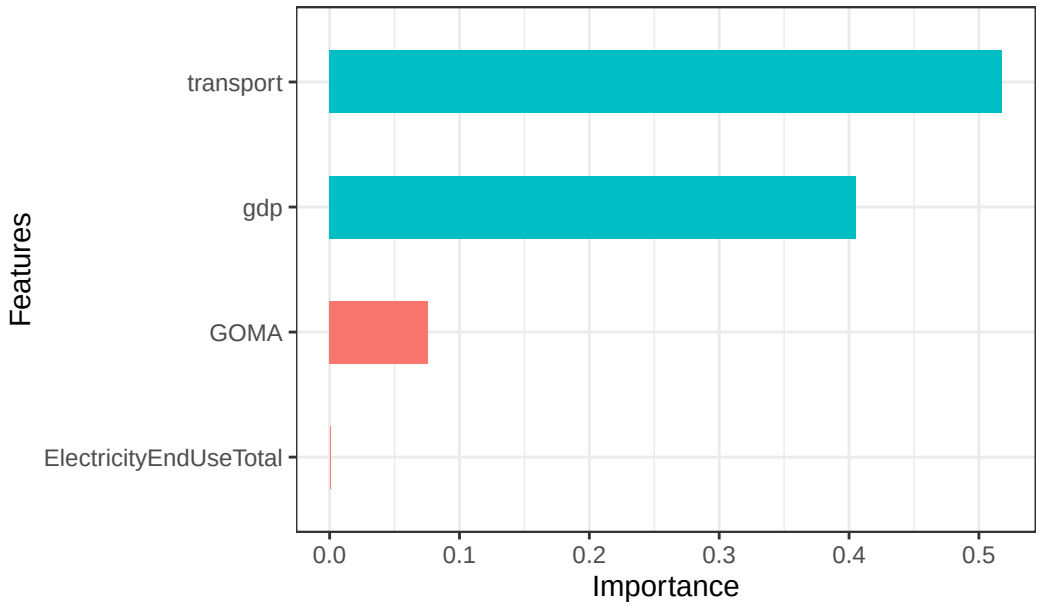
Looking at the loss performance for each of our models, we see that the model that exclude electricity has the highest loss value, followed by the model without transportation. That electricity followed by transportation are the most important predictors of Carbon Dioxide emissions.

Modeling Part 2

The second model we used was an Extreme Gradient Boost model, also known as XGBoost. This model works by first generating a layer of decision tree models and averaging them out to minimize the variance associated with the decision tree model type. After that, it attempts to make a new layer of decision trees that tries to account for as much of the previous layer's error as possible. It continues to do this process, using a loss function and gradient descent. We chose this model because it fit our particular problem pretty well: it can account for time series data relatively easily, it is one of the models that is very popular in real data science currently, it wasn't too hard to work with, and it has built-in feature importance generation, allowing us to easily compare which predictors had the greatest effect on the model.




```
Warning: package 'Ckmeans.1d.dp' was built under R version 4.2.3
```




```
[1] 0.5180465303 0.4056273088 0.0756505753 0.0006755855
```

XGBoost Results

Unfortunately, our second model does a poor job predicting our data, as seen in the time series line graph above. We believe this is due to the model being trained on such a small dataset, as this type of machine learning is best suited for huge datasets with many more data points than we had here. Regardless, it indicates that transportation is our most important predictor, followed by GDP.

Conclusion

Removing electricity use had the greatest impact on the performance of our first model. Transportation had the second most. On our second model transportation was the most important predictor.

Because of the consistent prevalence of transportation we consider it to be the most important feature when predicting climate change. This is also backed up by a similar studies from the Environmental Protection Agency in 2021 that also found transportation to be the largest contributor to the united states carbon output.

This means that according to our project climate policies should be focusing on limiting wasteful electricity use and reconsidering our car based infrastructure as our default way of transportation. Which we can already see happening as concepts like 15 minute cities and walkable cities become more popular online as more people begin to search for alternative modes of transport.

Limitations

We did this project with 4 different datasets, some only started at 2005 and others ended at 2015, meaning that we only have about a decade's worth of usable data. We also had a somewhat low number of predictors, each pulled from a different dataset. And so because of this we cannot draw full causal conclusions, only correlations.

Dealing with timeseries data also proved challenging. With the transportation dataset ending at 2015, our information is not fully up to date, leaving out recent events that may sway data such as the Coronavirus pandemic which would have definietly provided greater insights into how our behaviour and consumptions habits changed during the pandemic. Also because we chose to use time series data the initial data cleaning was time consuming and there was always the chance of noise in the data which neural networks have a hard time accounting for.

In regards to our analysis, we found a method for k-fold cross validation with time series data that we wanted to use. However, because our data wasn't large enough we didn't pursue that method.

Overall, our greatest limitation was the size our of data. Had it been larger we could have pursued other methods that might have yielded other results. This issue was also made worse by the fact we were using time series data. Some of our data sets were measured by day, month, quarter, and year. Meaning that me had to use the largest measure in order to normalize our data. This led to our data becoming even smaller.

Source Code

```
packages <- c(
  "dplyr",
  "readr",
  "tidyr",
  "purrr",
  "broom",
  "magrittr",
  "corrplot",
  "caret",
  "rpart",
  "rpart.plot",
  "e1071",
  "torch",
  "luz",
  "ramify",
  "stringr",
  "janitor",
  "reshape2",
  "ggpubr",
  "ggplot2",
  "keras"
)

# renv::install(packages)
sapply(packages, require, character.only=T)
```

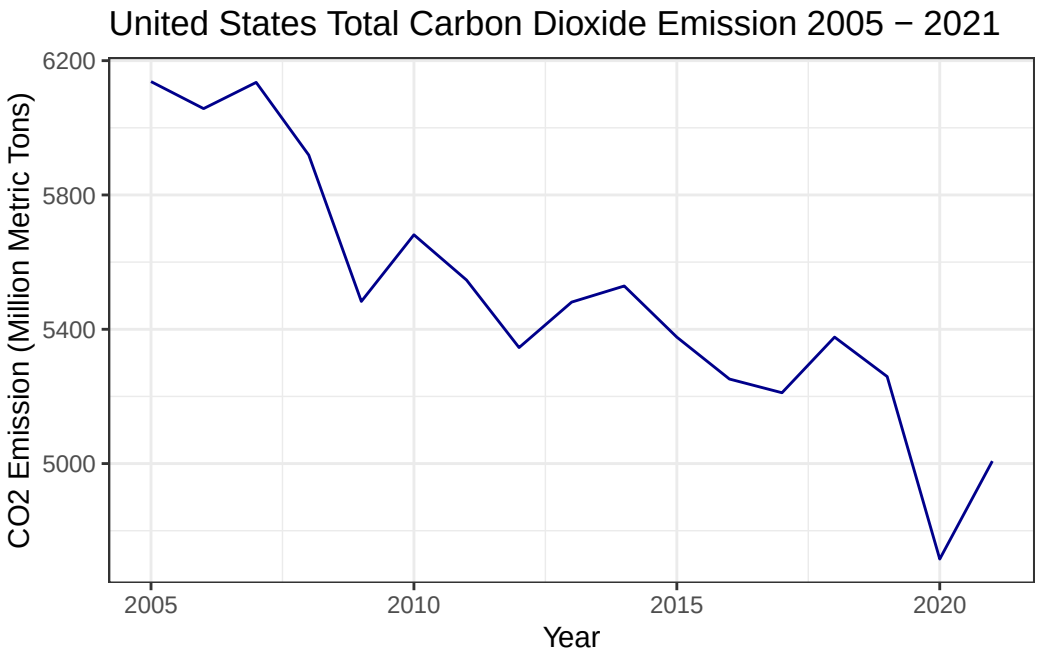
```
   dplyr      readr      tidyr      purrr      broom   magrittr   corrplot
    TRUE       TRUE       TRUE       TRUE       TRUE       TRUE       TRUE
   caret      rpart rpart.plot      e1071      torch        luz     ramify
    TRUE       TRUE       TRUE       TRUE       TRUE       TRUE       TRUE
 stringr    janitor   reshape2     ggpubr    ggplot2      keras
    TRUE       TRUE       TRUE       TRUE       TRUE       TRUE
```

```r
owid <- read.csv("https://raw.githubusercontent.com/JackBenadon/Stat-380-group-project/mai
goma <- read.csv("https://raw.githubusercontent.com/JackBenadon/Stat-380-group-project/mai
eo <- read.csv("https://raw.githubusercontent.com/JackBenadon/Stat-380-group-project/main/
tran <- read.csv("https://raw.githubusercontent.com/JackBenadon/Stat-380-group-project/mai
```

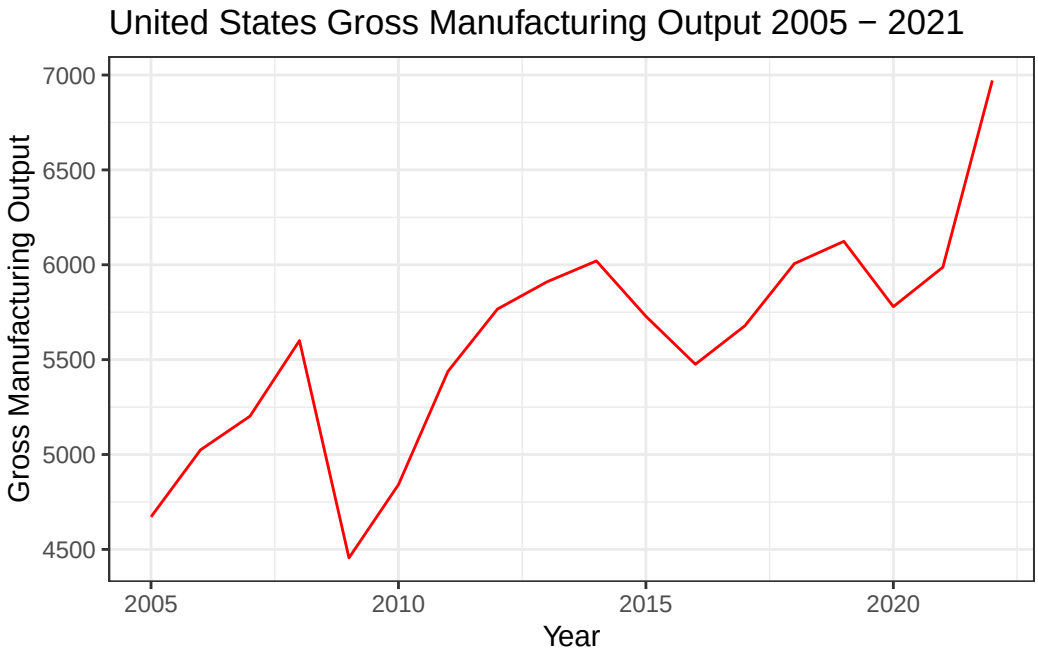
```r
zowidyearly1800_2021 <- owid%>%
  select(c(country,year,co2,gdp,population))%>%
  filter(country=="United States")
zowideyearly2005_2022 <- zowidyearly1800_2021%>%
  filter(year>=2005)
goma$DATE <- as.Date(goma$DATE)
goma$year <- as.numeric(format(goma$DATE, "%Y"))
zGOMAYearly2005_2022 <- goma%>%
  filter(str_detect(DATE, "01-01"))
zeosmonthly1973_2022 <- eo[10:610,]
zeosmonthly1973_2022 <- zeosmonthly1973_2022%>%
  row_to_names(row_number = 1)
zeosmonthly1973_2022 <- zeosmonthly1973_2022[-c(1),]
zeosyearly1973_2022 <- zeosmonthly1973_2022%>%
  filter(str_detect(Month, "January"))
zeosyearly2005_2022 <- zeosyearly1973_2022
zeosyearly2005_2022$Month <- gsub("January","",zeosyearly2005_2022$Month)
zeosyearly2005_2022 <- zeosyearly2005_2022%>%
  filter(Month>=2005)
ztransyearly1990_2015 <- tran %>%
  select(-c(X,X.1,X.2,X.3,X.4,X.5)) %>%
  t() %>%
  as.data.frame() %>%
  row_to_names(row_number = 1) %>%
  clean_names()%>%
  select(-c(2,23))
```

```
Warning: Row 1 does not provide unique names. Consider running clean_names()
after row_to_names().
```

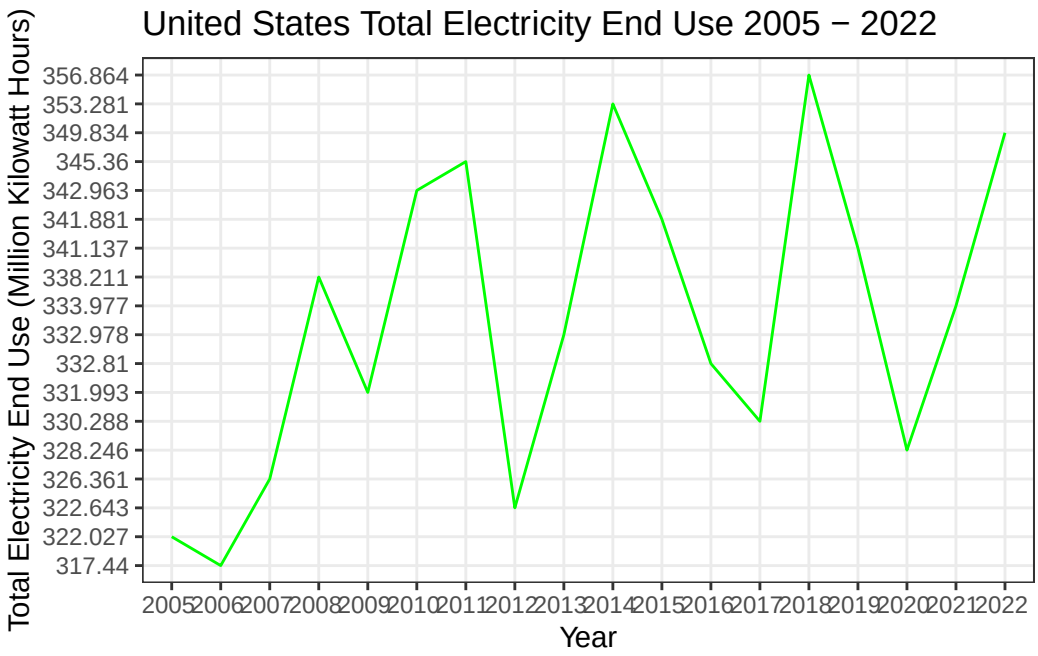
```r
zzlowid2005_2021<- ggplot(zowideyearly2005_2022,aes(x=year,y=co2))+geom_line(color="darkbl
zzlowid2005_2021
```



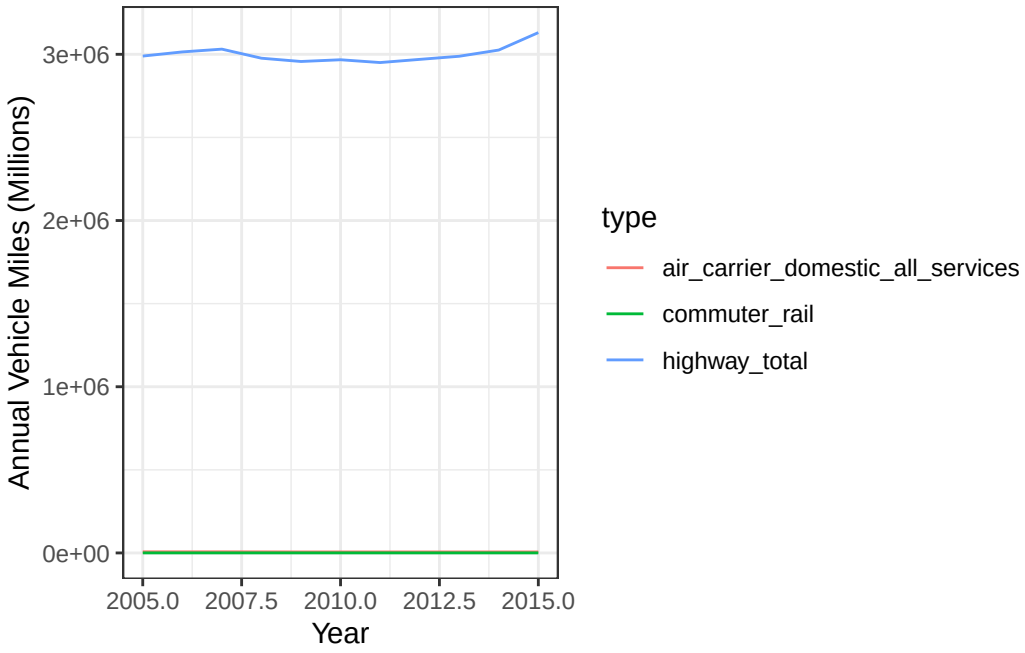

```
zzlgoma2005_2022 <- ggplot(zGOMAYearly2005_2022,aes(x=year,y=GOMA))+geom_line(color="red")
zzlgoma2005_2022
```



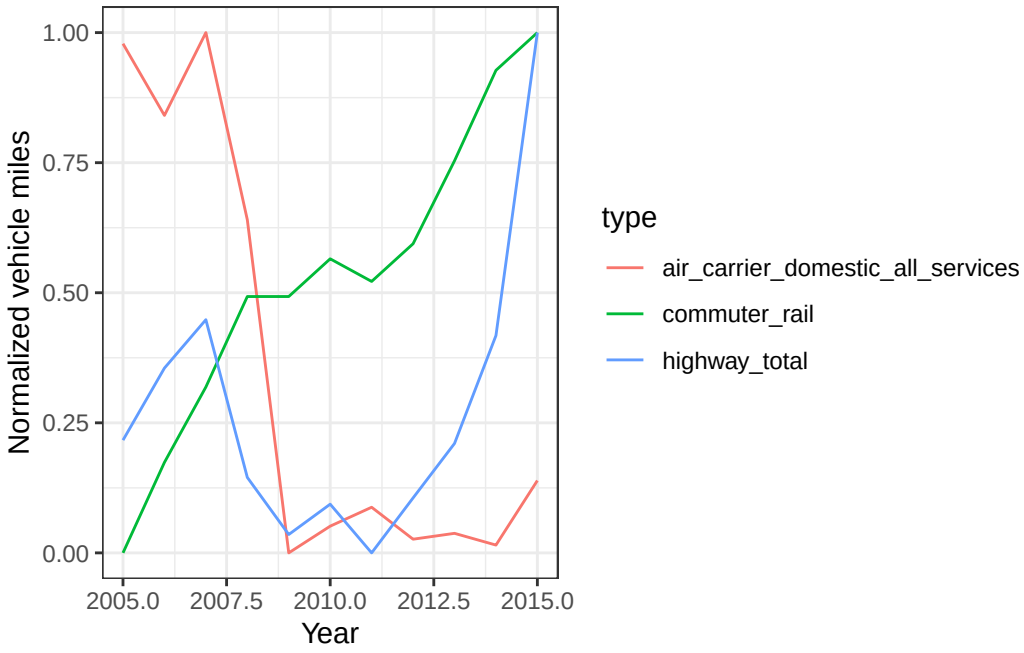
```
colnames(zeosyearly2005_2022)[12] <- "ElectricityEndUseTotal"
zzleosyearly2005_2022eu <- ggplot(zeosyearly2005_2022, aes(x=Month,y = ElectricityEndUseTo
zzleosyearly2005_2022eu
```




```
colnames(ztransyearly1990_2015)[1] <- "Year"
z2transyearly1990_2015 <- ztransyearly1990_2015 %>%
  pivot_longer(!Year, names_to = "type", values_to = "value")%>%
  filter(type %in% c("air_carrier_domestic_all_services","highway_total","commuter_rail"))
  mutate(Year = as.numeric(Year), value)
zztransyearly2005_2015 <- z2transyearly1990_2015%>%
  filter(Year>=2005)%>%
  mutate(value = gsub(",","",value))%>%
  mutate(value=gsub("\\(R\\) ","",value))%>%
  mutate(value=as.numeric(value))
ggplot(zztransyearly2005_2015, aes(x=Year, y=value, color=type,group=type))+geom_line()+th
```




```
zztransyearly2005_2015 <- zztransyearly2005_2015%>%
  group_by(type)%>%
  mutate(value=((value - min(value))/(max(value)-min(value))))
ggplot(zztransyearly2005_2015, aes(x=Year,y=value,color=type,group=type))+geom_line()+them
```




```
zztranshighway <- zztransyearly2005_2015 %>%
  filter(type=="Highway, total")
zztransair <- zztransyearly2005_2015 %>%
  filter(type=="Air carrier, domestic, all services")
zztransrail <- zztransyearly2005_2015 %>%
  filter(type=="Commuter rail")
```

```
#loading the data
data = read.csv("https://raw.githubusercontent.com/JackBenadon/Stat-380-group-project/main
#removing NA values
data <- data %>%
    na.omit()
#removing the (R) in the commuter.rail column
data$Commuter.rail[11] <- 372
#removing the commas in Highway..total because its special
data$Highway..total <- gsub(",", "", data$Highway..total)
# making the all the columns into numeric variables
data$Commuter.rail <- as.numeric(sub(",","",data$Commuter.rail))
data$Air.carrier..domestic..all.services <- as.numeric(sub(",","",data$Air.carrier..domest
data$Highway..total <- as.numeric(data$Highway..total)
#making sure the transport data is only one column
```

```r
data$transport <- data$Air.carrier..domestic..all.services + data$Commuter.rail + data$Hig
#duplicating data object so both models function properly
data2 <- data
```

```r
#Cleaning for model 1


#selecting variables
data = data %>%
  select(year,co2,transport, ElectricityEndUseTotal, GOMA, gdp)
#Creating predictor and response variables
xdata <- data %>%
  select(transport, ElectricityEndUseTotal, GOMA, gdp)
corrdata <- data %>%
  select(co2,transport, ElectricityEndUseTotal, GOMA, gdp)

ydata <- data %>%
  select(co2)
#Normalizing variables
mean <- apply(data, 2, mean)
std <- apply(data, 2, sd)
std<-case_when(std==0 ~ 1,
          std !=0 ~ std)

meanx <- apply(xdata, 2, mean)
stdx <- apply(xdata, 2, sd)
stdx<-case_when(stdx==0 ~ 1,
          stdx !=0 ~ stdx)

meany <- apply(ydata, 2, mean)
stdy <- apply(ydata, 2, sd)
stdy<-case_when(stdy==0 ~ 1,
          stdy !=0 ~ stdy)



data <- scale(data, center = mean, scale = std)
xdata <- scale(xdata,center = meanx, scale = stdx)
ydata = scale(ydata,center = meany, scale = stdy)

set.seed(380)
```

```r
#Full Model 4 inputs
model = keras_model_sequential() %>%
   layer_dense(units=64, activation="relu", input_shape=4) %>%
   layer_dense(units=32, activation = "relu") %>%
   layer_dense(units=1, activation="linear")

#Loss Testing 3 inputs:
modelt = keras_model_sequential() %>%
    layer_dense(units=64, activation="relu", input_shape=3) %>%
    layer_dense(units=32, activation = "relu") %>%
    layer_dense(units=1, activation="linear")

model %>% compile(
   loss = "mse",
   optimizer =  "adam",
   metrics = list("mean_absolute_error")
 )

modelt %>% compile(
   loss = "mse",
   optimizer =  "adam",
   metrics = list("mean_absolute_error")
 )


model %>% summary()
```

```
Model: "sequential_2"
_________________________________________________________________________________
 Layer (type)                        Output Shape                      Param #
=================================================================================
 dense_8 (Dense)                     (None, 64)                        320
 dense_7 (Dense)                     (None, 32)                        2080
 dense_6 (Dense)                     (None, 1)                         33
=================================================================================
Total params: 2,433
Trainable params: 2,433
Non-trainable params: 0
_________________________________________________________________________________
```

```r
x = as.matrix(data[1:11,3:6])

xNoElec = as.matrix(data[1:11,3:6][,-2])
xNoMan = as.matrix(data[1:11,3:6][,-3])
xNoTrans = as.matrix(data[1:11,3:6][,-1])
xNoGDP = as.matrix(data[1:11,3:6][,-4])


y = as.matrix(data[1:11,2])

#Full Model loss
model %>% fit(x, y, epochs = 100,verbose = 1)

#Testing models
modelt %>% fit(xNoElec, y, epochs = 100,verbose = 1)
#0.0407

modelt %>% fit(xNoMan, y, epochs = 100,verbose = 1)
#0.0196

modelt %>% fit(xNoTrans, y, epochs = 100,verbose = 1)
#0.0317

modelt %>% fit(xNoGDP, y, epochs = 100,verbose = 1)
#0.017

#historyFull <- model %>% fit(x, y, epochs = 100, verbose = 1)
#historyT <- modelt %>% fit(xNoMan, y, epochs = 100, verbose = 1)
```

```r
library(xgboost)

data2 <- as.data.frame(data2)

train <- data2[1:9,]
test <- data2[10:11,]

train_Dmatrix <- train %>%
                 dplyr::select(transport,gdp,GOMA,ElectricityEndUseTotal) %>%
                 as.matrix()
```

```r
pred_Dmatrix <- test %>%
                dplyr::select(transport,gdp,GOMA,ElectricityEndUseTotal) %>%
                as.matrix()

targets <- train$co2

#Cross-validation
library(caret)

xgb_trcontrol <- trainControl(
  method = "cv",
  number = 5,
  allowParallel = TRUE,
  verboseIter = FALSE,
  returnData = FALSE
)

#Building parameters set
xgb_grid <- base::expand.grid(
  list(
    nrounds = c(5,10,50, 100,200,500,1000),
    max_depth = c(1:6),
    colsample_bytree = 1,
    eta = 0.5,
    gamma = 0,
    min_child_weight = 1,
    subsample = 1)
)

#Building the model
model_xgb <- caret::train(
  train_Dmatrix,targets,
  trControl = xgb_trcontrol,
  tuneGrid = xgb_grid,
  method = "xgbTree",
  nthread = 10,
  verbosity=0
)
```

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

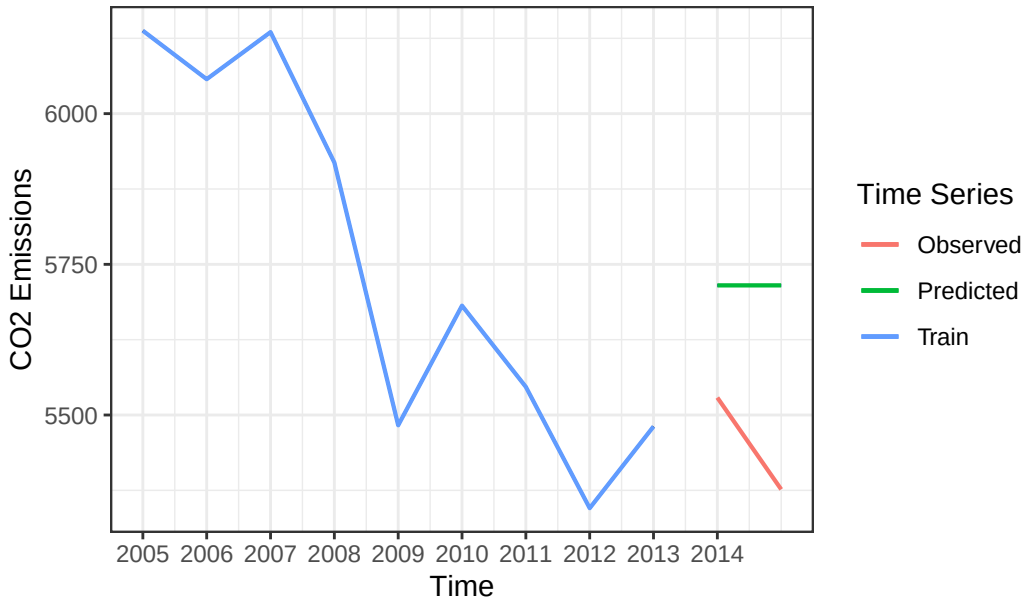
```
model_xgb$bestTune
```

```
  nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
6     500         1 0.5     0                1                1         1
```

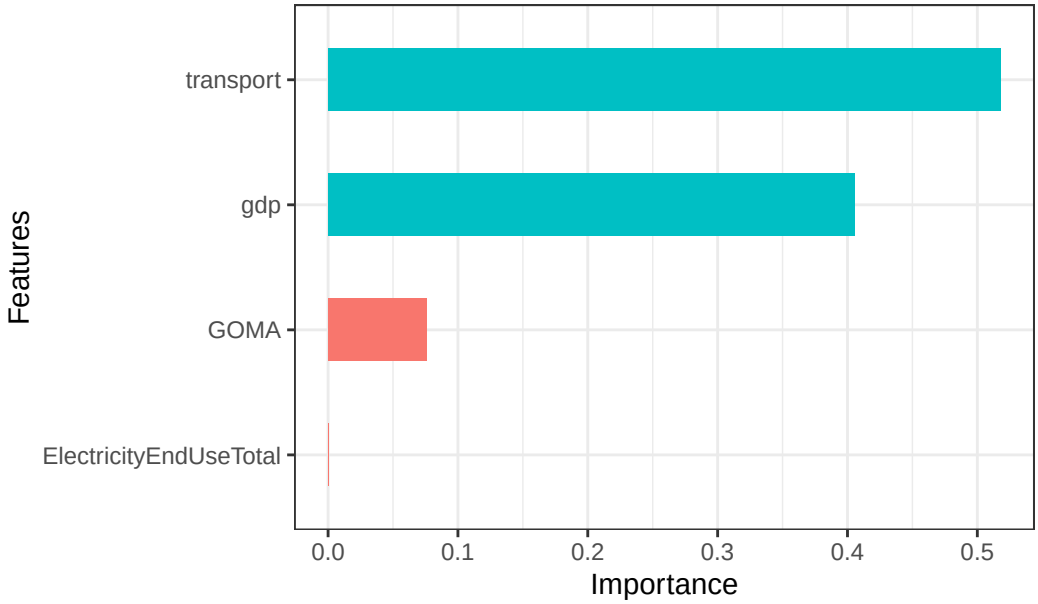
```
#Making the variables used in forecast object
fitted <- model_xgb %>%
  stats::predict(train_Dmatrix) %>%
  stats::ts(start = c(2005,1),frequency = 1)

ts_co2 <- ts(targets,start=c(2005,1),frequency=1)
forecast_xgb <- model_xgb %>% stats::predict(pred_Dmatrix)
forecast_ts <- ts(forecast_xgb,start=c(2014,1),frequency=1)

#Preparing forecast object
forecast_co2 <- list(
  model = model_xgb$modelInfo,
  method = model_xgb$method,
  mean = forecast_ts,
  x = ts_co2,
  fitted = fitted,
  residuals = as.numeric(ts_co2) - as.numeric(fitted)
)
class(forecast_co2) <- "forecast"

#The function to convert decimal time label to wanted format
library(lubridate)
date_transform <- function(x) {format(date_decimal(x), "%Y")}
#Making a time series varibale for observed data
observed_values <- ts(test$co2,start=c(2014,1),frequency=1)

#Plot forecasting
library(ggplot2)
library(forecast)

autoplot(forecast_co2)+
  autolayer(forecast_co2$mean,series="Predicted",size=0.75) +
  autolayer(forecast_co2$x,series ="Train",size=0.75 ) +
  autolayer(observed_values,series = "Observed",size=0.75) +
  scale_x_continuous(labels =date_transform,breaks = seq(2005,2014,1) ) +
  guides(colour=guide_legend(title = "Time Series")) +
```

```
  ylab("CO2 Emissions") + xlab("Time") +
  ggtitle("") +
  theme_bw()
```

```
Scale for x is already present.
Adding another scale for x, which will replace the existing scale.
```




```
#Feature importance
library(Ckmeans.1d.dp)

xgb_imp <- xgb.importance(
  feature_names = colnames(train_Dmatrix),
  model = model_xgb$finalModel)

xgb.ggplot.importance(xgb_imp,n_clusters = c(2))+
  ggtitle("") +
  theme_bw()+
  theme(legend.position="none")
```




```
xgb_imp$Importance
```

```
[1] 0.5180465303 0.4056273088 0.0756505753 0.0006755855
```