Data for Good Challenge 2 - Climate Change

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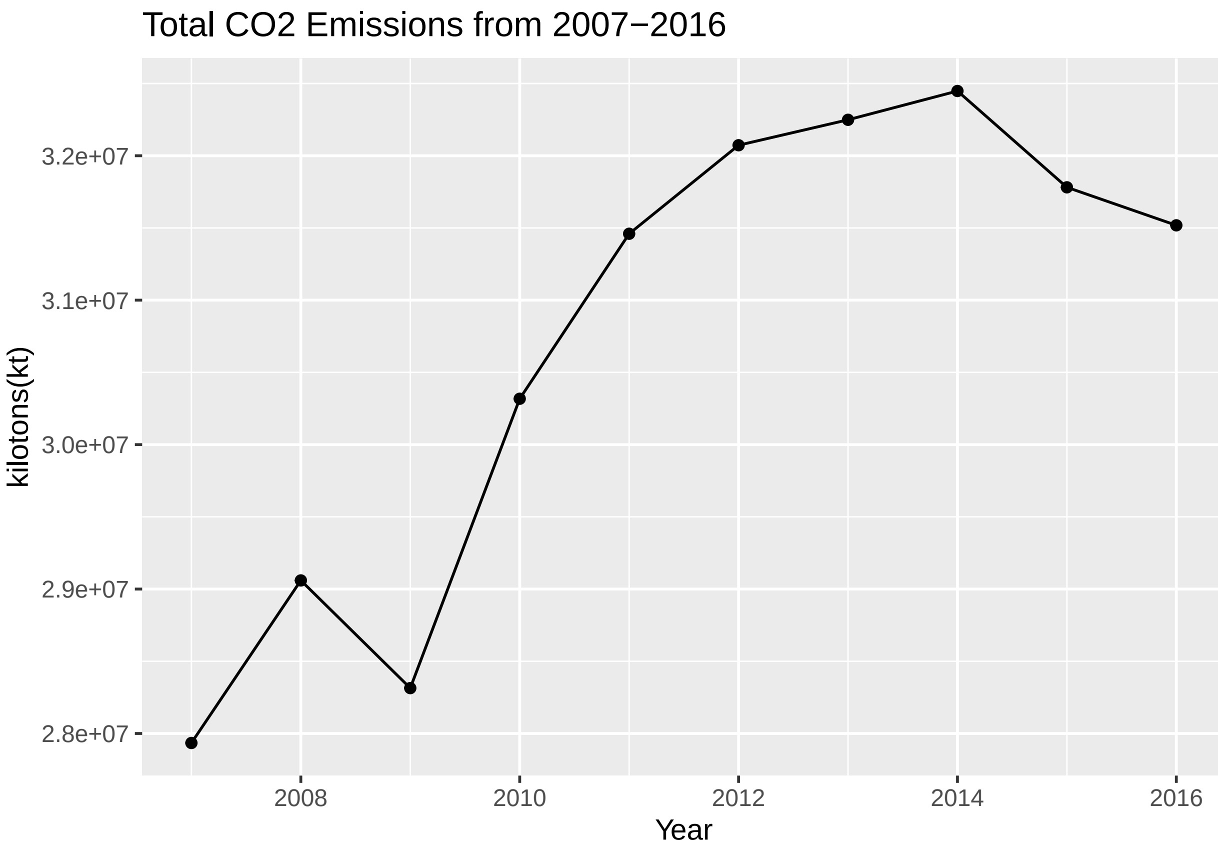
```
metaColC <- c( "Year", "Country.Name", "Country.Code", "agricultural.land", "land.area", "surface.area"

metaColR <- c( "Year", "Region.Name", "Region.Code", "agricultural.land", "land.area", "surface.area",

colnames(country_data) <- metaColC
colnames(region_data) <- metaColR
```

Are we on track to meet the 2030 Sustainable Development Goal?

```
CO2emissions <- country_data %>% group_by(Year) %>%
  summarize(totalCO2 = sum(CO2.emissions.kt, na.rm=TRUE))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
CO2emissions %>%
  ggplot() +
  geom_point(aes(x=Year, y=totalCO2)) +
  geom_line(aes(x=Year, y=totalCO2)) +
  ggtitle("Total CO2 Emissions from 2007-2016") +
  ylab("kilotons(kt)")
```




```
CO2_2014 <- country_data %>% filter(Year==2014) %>% select("CO2.emissions.kt") %>% sum(na.rm=TRUE)
CO2_2015 <- country_data %>% filter(Year==2015) %>% select("CO2.emissions.kt") %>% sum(na.rm=TRUE)
CO2_2016 <- country_data %>% filter(Year==2016) %>% select("CO2.emissions.kt") %>% sum(na.rm=TRUE)

r1 <- (CO2_2015 - CO2_2014) / CO2_2014
r2 <- (CO2_2016 - CO2_2015) / CO2_2015
avg <- (r1+r2)/2
goal <-(CO2_2014 * (1-0.076)^(2030-2014))
new_rate <- 1 - (goal/ CO2_2016)^(1/14)
new_rate
```

```
## [1] 0.08447576
```

The graph shows that from 2007 to 2014, total CO2 emissions were growing exponentially. However, they started to decrease from 2014 to 2016. From 2014 to 2015, total CO2 emissions decreased by 2.05% and from 2015 to 2016, decreased by 0.83%. This averages to a 1.44% decrease in carbon emissions per year. This does not match the targeted 7.6% annual emissions reduction goal set for 2030.

This means we need to implement stricter policies and increase awareness for climate change if we want to accomplish our 7.6% annual target rate.

```
data2016 <- country_data %>% filter(Year==2016) %>% mutate(CO22016=CO2.emissions.kt) %>%
  select(Country.Name, CO22016)
data2015 <- country_data %>% filter(Year==2015) %>% mutate(CO22015=CO2.emissions.kt) %>%
  select(Country.Name, CO22015)
data2014 <- country_data %>% filter(Year==2014) %>% mutate(CO22014=CO2.emissions.kt) %>%
  select(Country.Name, CO22014)
rates <- data2016 %>% full_join(data2015) %>% full_join(data2014)
```

```
## Joining, by = "Country.Name"
## Joining, by = "Country.Name"
```

```r
rates %<>% mutate(rt1415 = (CO22015-CO22014)/CO22014,
                  rt1516 = (CO22016-CO22015)/CO22015,
                  rt1416 = (CO22016-CO22014)/CO22014)
rates %<>% select(-c(2:4)) %>% melt(id.vars=c("Country.Name"))

# Which countries decreased the most from 2014-2015?
rates %>% filter(variable == "rt1415") %>% filter(value < 0) %>% mutate(value=abs(value)) %>% top_n(10)
```

```
## Selecting by value
```

```
##          Country.Name variable     value
## 1             Albania   rt1415 0.1589846
## 2              Angola   rt1415 0.2289265
## 3            Botswana   rt1415 0.2080214
## 4   Brunei Darussalam   rt1415 0.2187120
## 5    Congo, Dem. Rep.   rt1415 0.3924647
## 6            Mongolia   rt1415 0.2142062
## 7          Mozambique   rt1415 0.2308696
## 8               Nepal   rt1415 0.2214612
## 9            Suriname   rt1415 0.2320261
## 10        Yemen, Rep.   rt1415 0.4660324
```

```r
# Which countries decreased the most from 2015-2016?
rates %>% filter(variable == "rt1516") %>% filter(value < 0) %>% mutate(value=abs(value)) %>% top_n(10)
```

```
## Selecting by value
```

```
##         Country.Name variable      value
## 1             Brazil   rt1516 0.08344723
## 2   Congo, Dem. Rep.   rt1516 0.28811370
## 3      Cote d'Ivoire   rt1516 0.11743058
## 4              Libya   rt1516 0.11284823
## 5             Norway   rt1516 0.13110680
## 6       Saudi Arabia   rt1516 0.12928616
## 7          Singapore   rt1516 0.38918725
## 8         Uzbekistan   rt1516 0.10801952
## 9        Yemen, Rep.   rt1516 0.19459911
## 10          Zimbabwe   rt1516 0.10836558
```

```r
# Which countries decreased the most from 2014-2016?
rates %>% filter(variable == "rt1416") %>% filter(value < 0) %>% mutate(value=abs(value)) %>% top_n(10)
```

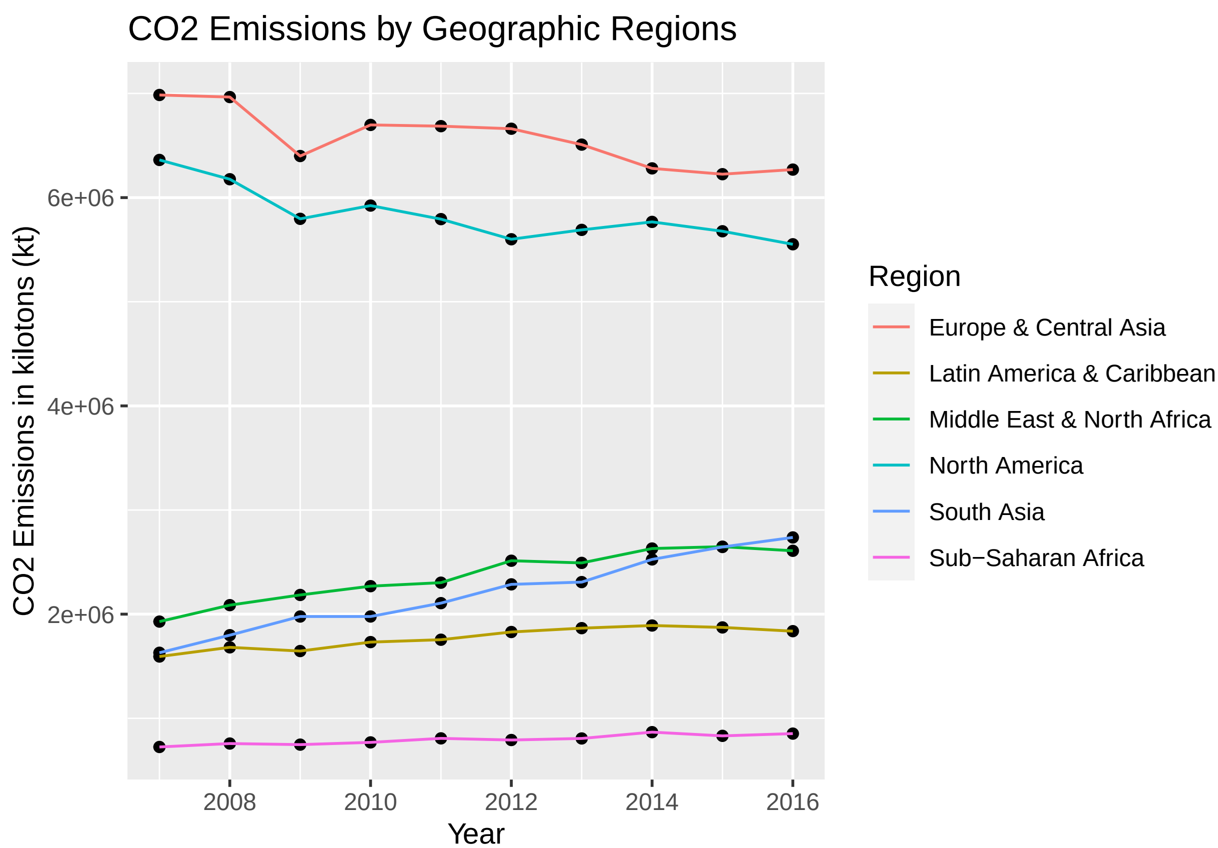
```
## Selecting by value
```

```
##          Country.Name variable     value
## 1             Albania   rt1416 0.1736807
## 2              Angola   rt1416 0.2264737
## 3   Brunei Darussalam   rt1416 0.1535034
## 4    Congo, Dem. Rep.   rt1416 0.5675039
## 5               Libya   rt1416 0.1500339
## 6            Mongolia   rt1416 0.1439178
## 7              Norway   rt1416 0.1440049
## 8           Singapore   rt1416 0.3373471
## 9            Suriname   rt1416 0.2254902
## 10        Yemen, Rep.   rt1416 0.5699420
```

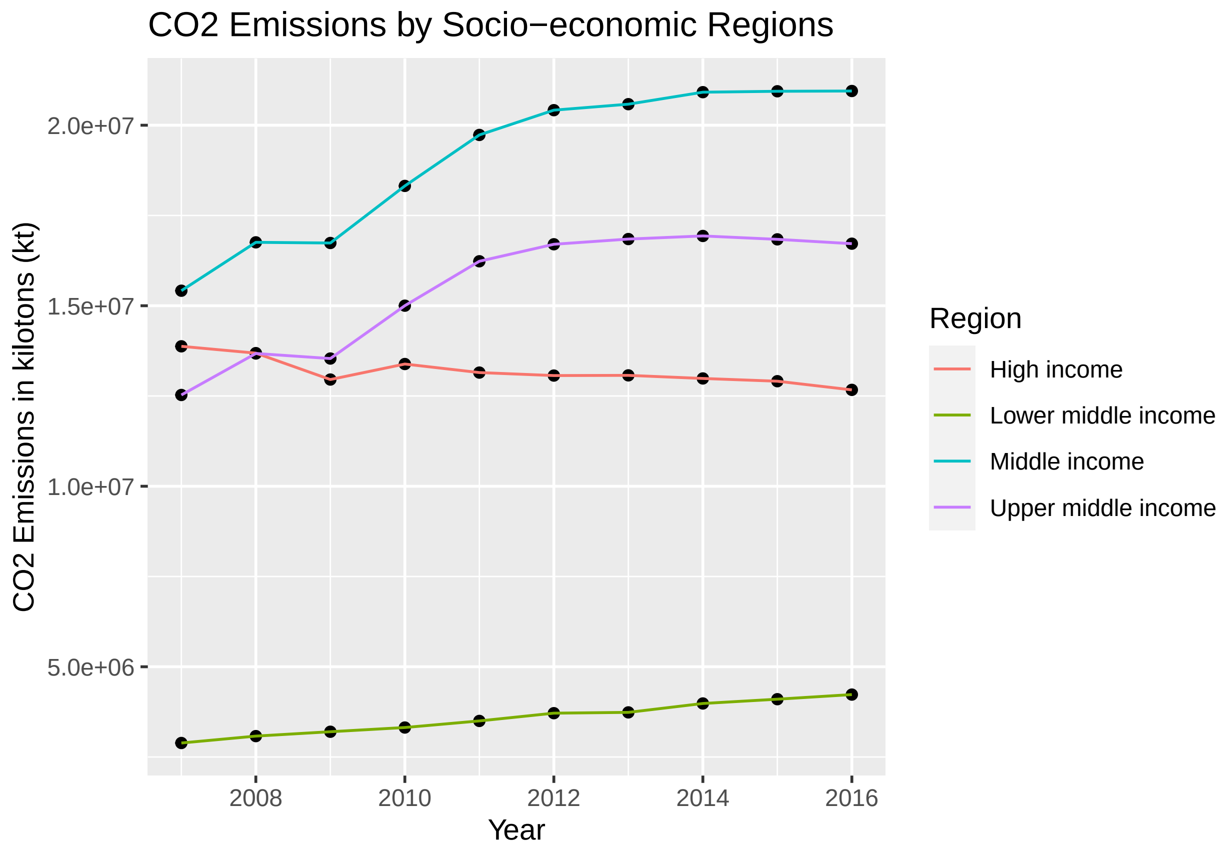
The countries that have decreased the most in CO2 emissions are Albania, Angola, Brunei Darussalam, Congo Dem. Rep., Libya, Mongolia, Norway, Singapore, Suriname, Yemen. Surprisingly, these would not traditionally be considered the biggest or most influential countries in the world.

Regions with the Highest CO2 Emissions

```
region_data %>% filter(Region.Code %in% c("LCN", "SAS", "NAC", "ECS", "SSF","MEA")) %>%
  ggplot() +
  geom_point(aes(x=Year, y=CO2.emissions.kt)) +
  geom_line(aes(x=Year, y=CO2.emissions.kt, color=Region.Name)) +
  ggtitle("CO2 Emissions by Geographic Regions") +
  ylab("CO2 Emissions in kilotons (kt)") +
  scale_color_discrete("Region")
```

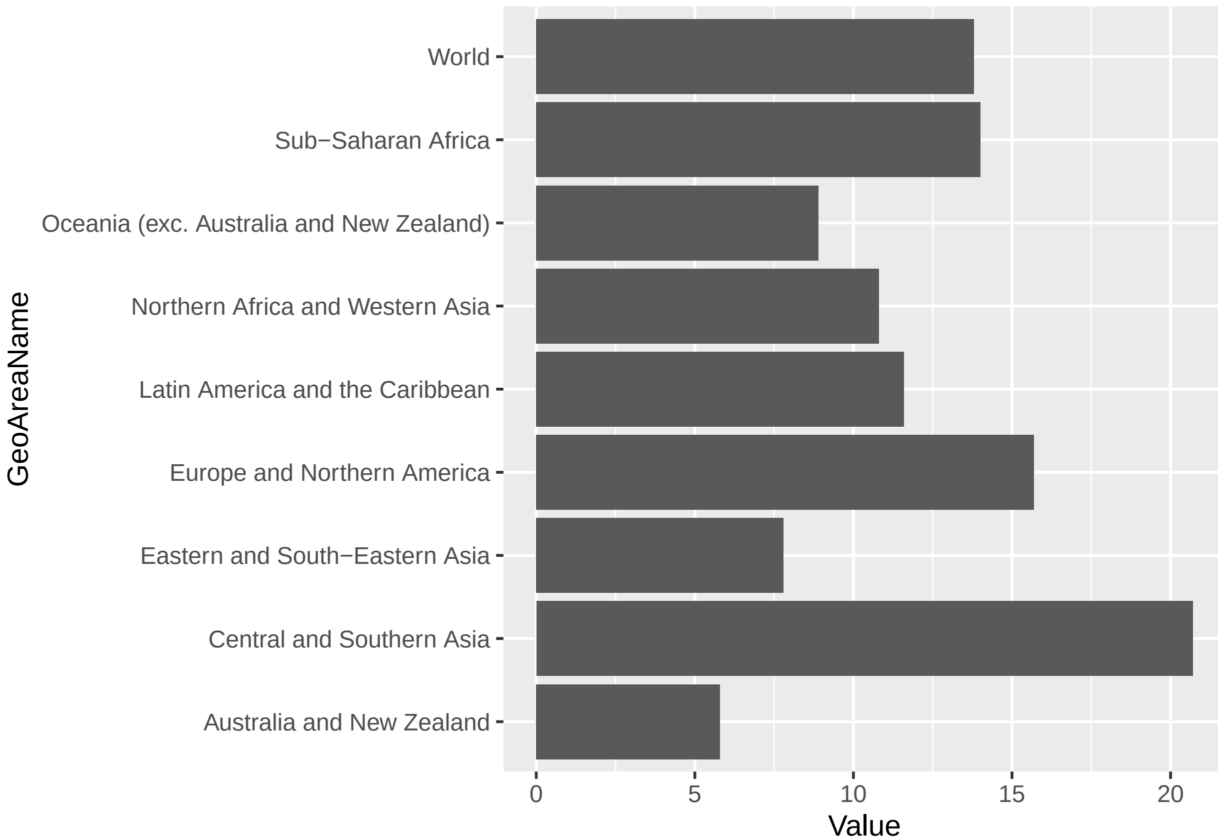



```
region_data %>% filter(Region.Name %in% c("High income", "Lower middle income","Middle income", "Upper m
  ggplot() +
  geom_point(aes(x=Year, y=CO2.emissions.kt)) +
  geom_line(aes(x=Year, y=CO2.emissions.kt, color=Region.Name)) +
  ggtitle("CO2 Emissions by Socio-economic Regions") +
  ylab("CO2 Emissions in kilotons (kt)") +
  scale_color_discrete("Region")
```



Food Waste Regions

```
foodRegions <- read.csv("12.3.1.aFood_loss_percentage.csv")

foodRegions %>%
  ggplot() +
  geom_bar(aes(y=GeoAreaName, x=Value), stat='identity')
```




```
x<-c("LCN", "SAS", "NAC", "ECS", "SSF", "MEA")
y<-c(11.6, 7.8, 15.7, 15.7, 14, 10.8)
foodwasteperc <- data.frame(Region.Code=x, foodWastePercent=y)

regions <- left_join(region_data, foodwasteperc) %>% filter(Region.Code %in% c("LCN", "SAS", "NAC", "EC
```

```
## Joining, by = "Region.Code"
```

Correlations

```
cor(region_data$CO2.emissions.kt, region_data$agricultural.land)
```

```
## [1] 0.8962335
```

```
cor(regions$CO2.emissions.kt, regions$foodWastePercent)
```

```
## [1] 0.6225621
```

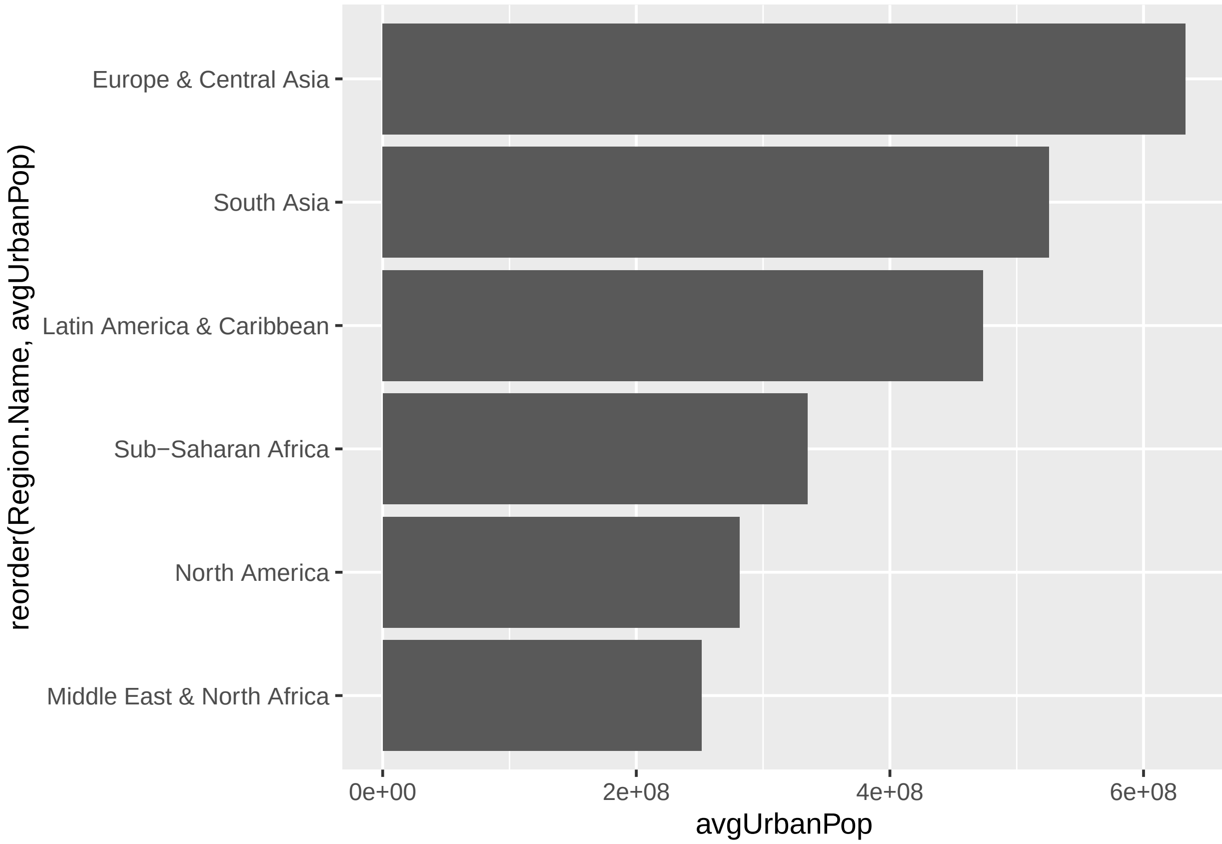
```
cor(region_data$CO2.emissions.kt, region_data$urban.pop)
```

```
## [1] 0.9430723
```

```
regions %>% group_by(Region.Name) %>% summarize(avgUrbanPop = mean(urban.pop)) %>% top_n(10) %>%
  ggplot() +
  geom_bar(aes(y=reorder(Region.Name,avgUrbanPop), x=avgUrbanPop), stat="identity")
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## Selecting by avgUrbanPop
```



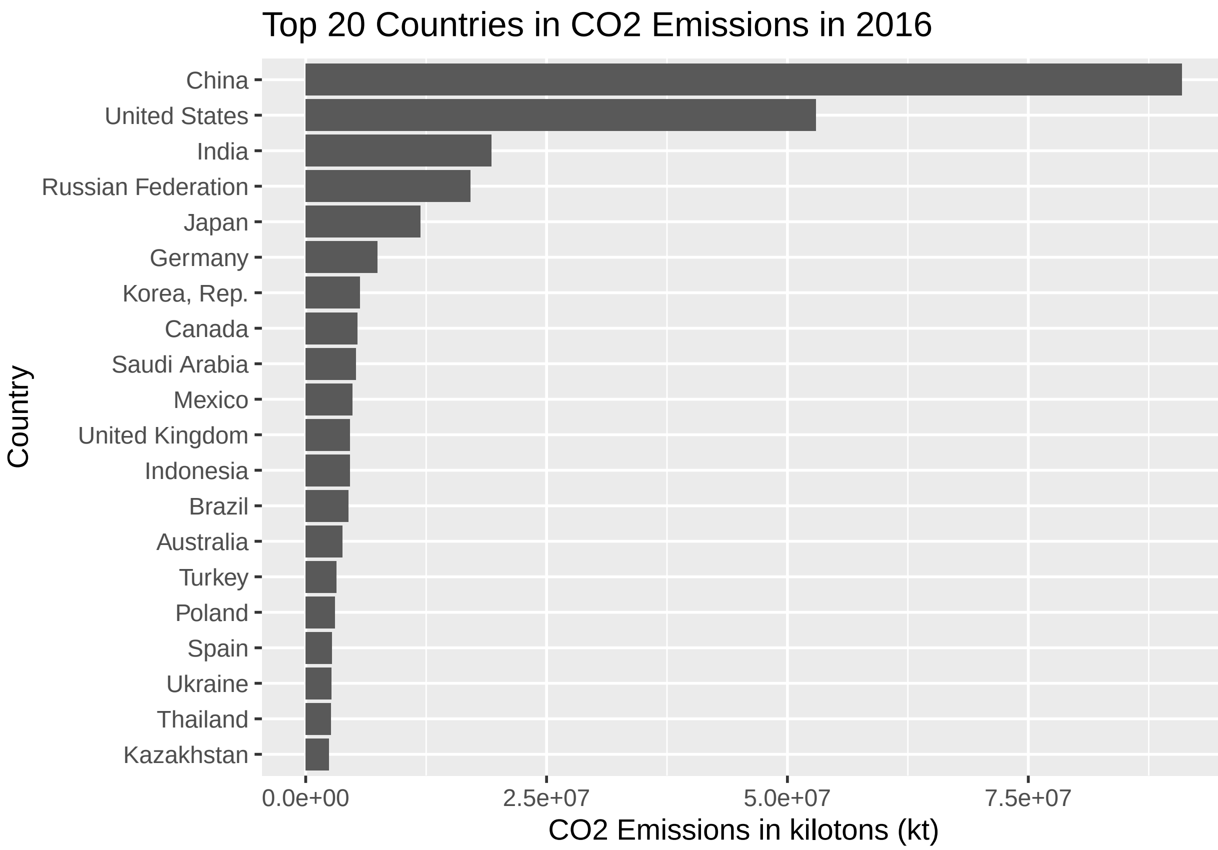
20 Countries with highest CO2 emissions in 2016

```
top20 <- country_data %>% group_by(Country.Name) %>%
  summarize(totalCO2 = sum(CO2.emissions.kt)) %>% arrange(desc(totalCO2)) %>% top_n(20)
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## Selecting by totalCO2
```

```
top20 %>%
  ggplot() +
  geom_bar(aes(reorder(Country.Name,totalCO2), x=totalCO2), stat='identity') +
  ggtitle("Top 20 Countries in CO2 Emissions in 2016") +
  xlab("CO2 Emissions in kilotons (kt)") +
  ylab("Country")
```



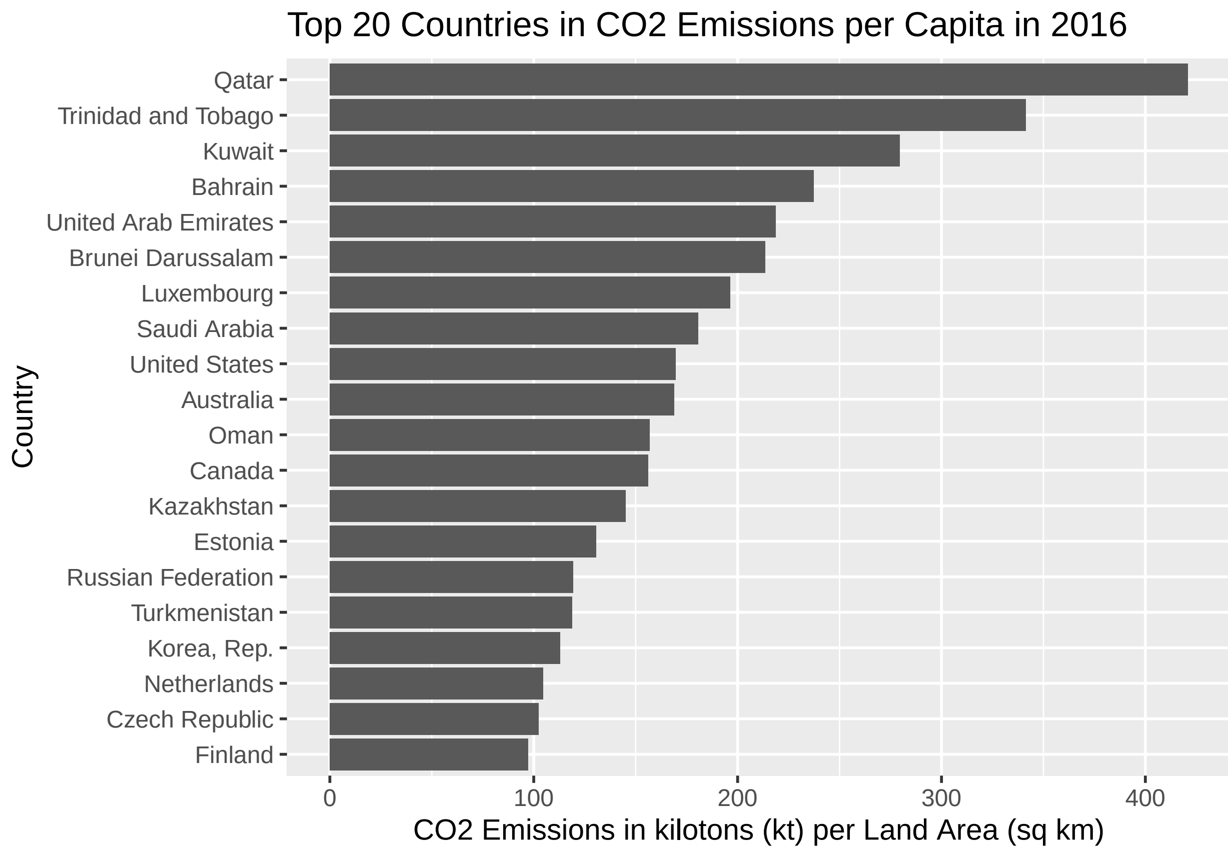
20 Countries with highest CO2 emissions per sq km in 2016

```
top20 <- country_data %>% group_by(Country.Name) %>%
  summarize(totalCO2 = sum(CO2.emissions.tonsPerCapita)) %>% arrange(desc(totalCO2)) %>% top_n(20)
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## Selecting by totalCO2
```

```
top20 %>%
  ggplot() +
  geom_bar(aes(reorder(Country.Name,totalCO2), x=totalCO2), stat='identity') +
  ggtitle("Top 20 Countries in CO2 Emissions per Capita in 2016") +
  xlab("CO2 Emissions in kilotons (kt) per Land Area (sq km)") +
  ylab("Country")
```


Top 20 Countries in CO2 Emissions per Capita in 2016
Qatar
Trinidad and Tobago
Kuwait
Bahrain
United Arab Emirates
Brunei Darussalam
Luxembourg
Saudi Arabia
United States
Australia
Oman
Canada
Kazakhstan
Estonia
Russian Federation
Turkmenistan
Korea, Rep.
Netherlands
Czech Republic
Finland
Country
0
100
200
300
400
CO2 Emissions in kilotons (kt) per Land Area (sq km)