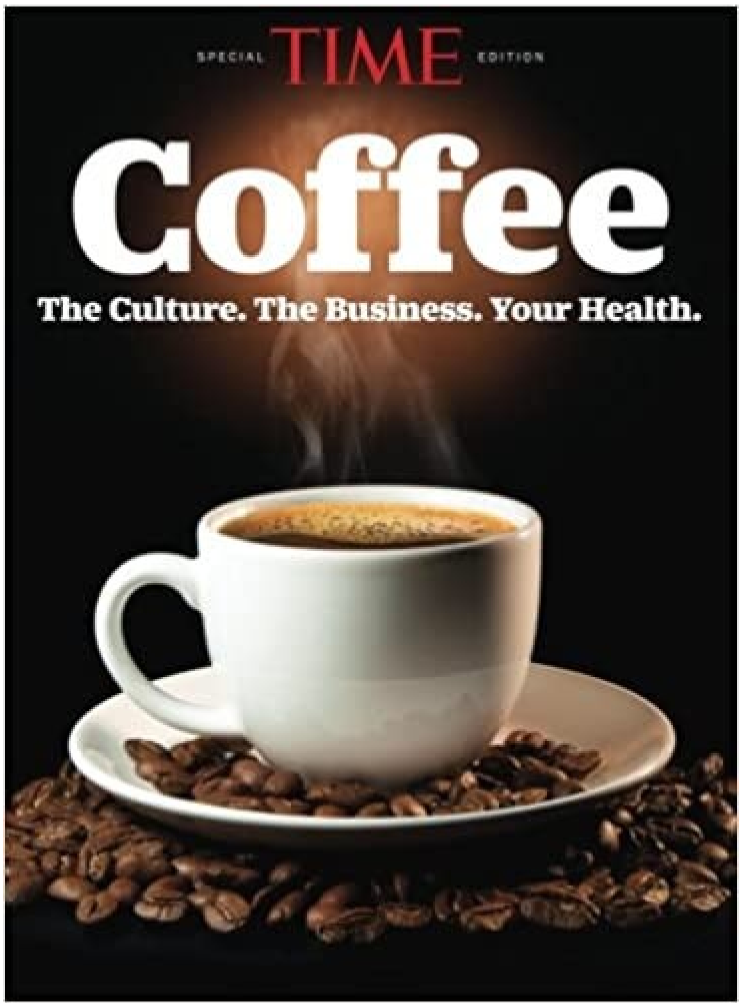
Introduction



Around four years ago I was given a copy of Time Magazine's specialty issue on Coffee together with a French press as a gift. At the time, I was satisfied with a regular instant cup of joe and did not know much about the vastness and culture of the industry. However, it was thanks to these gifts that I was able to learn a lot about coffee, such as the two major species of beans (Arabica and Robusta),the tasting process done by connoisseurs to rank various coffees(called "cupping"), about the altitude, climate and countries various coffees grow around the world. If you read this specialty issue by Time, you probably not only got a more expensive interest piqued (if you haven't already), but also probably learned enough to hold your own with the the best of the coffee snobs out there.

(PSA- this blog is not sponsored by Time Magazine, but I won't say no if I got an offer!)

In this blog post we're going to examine the `coffee_ratings` dataset released back in the beginning of July 2020 in the Tidy Tuesday Project by R4DS. I initially started analyzing this dataset seeking to answer a lot of questions. But, because there is so much to discover and analyze from this relatively small dataset, I thought it is best to try to focus my question on a very simple one:

> Where in the world can I find the best coffee beans?

While this question seems simple enough. There is a lot to uncover to answer this question.

Our Data (Some Exploratory Data Analysis)

Loading our data

I am loading the data with the `tidytuesdayR` package, if you want you can load the raw data with the `readr` package's `read_csv()` function as well.

A Quick Glimpse

```
library(tidyverse)
coffee_ratings<-tuesdata$coffee_ratings
glimpse(coffee_ratings)
```

```
## Rows: 1,339
## Columns: 43
## $ total_cup_points       90.58, 89.92, 89.75, 89.00, 88.83, 88.83,
88.75, 88.67, 88.42, 88.25, 88.08, 87.92, 87.92, 87.92, 87.8...
## $ species                "Arabica", "Arabica", "Arabica", "Arabica",
"Arabica", "Arabica", "Arabica", "Arabica", "Arabica", "Ar...
## $ owner                  "metad plc", "metad plc", "grounds for
health admin", "yidnekachew dabessa", "metad plc", "ji-ae ahn",...
## $ country_of_origin      "Ethiopia", "Ethiopia", "Guatemala",
"Ethiopia", "Ethiopia", "Brazil", "Peru", "Ethiopia", "Ethiopia",...
## $ farm_name              "metad plc", "metad plc", "san marcos
barrancas \"san cristobal cuch", "yidnekachew dabessa coffee pla...
## $ lot_number             NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, "YNC-06114", NA, NA, NA, NA, N...
## $ mill                   "metad plc", "metad plc", NA, "wolensu",
"metad plc", NA, "hvc", "c.p.w.e", "c.p.w.e", "tulla coffee f...
## $ ico_number             "2014/2015", "2014/2015", NA, NA,
"2014/2015", NA, NA, "010/0338", "010/0338", "2014/15", NA, "unknown...
## $ company                "metad agricultural developmet plc", "metad
agricultural developmet plc", NA, "yidnekachew debessa cof...
## $ altitude               "1950-2200", "1950-2200", "1600 - 1800 m",
"1800-2200", "1950-2200", NA, NA, "1570-1700", "1570-1700",...
## $ region                 "guji-hambela", "guji-hambela", NA,
"oromia", "guji-hambela", NA, NA, "oromia", "oromiya", "snnp/kaffa...
## $ producer               "METAD PLC", "METAD PLC", NA, "Yidnekachew
Dabessa Coffee Plantation", "METAD PLC", NA, "HVC", "Bazen ...
## $ number_of_bags         300, 300, 5, 320, 300, 100, 100, 300, 300,
50, 300, 10, 10, 1, 300, 10, 1, 150, 3, 250, 10, 250, 14, 1...
## $ bag_weight             "60 kg", "60 kg", "1", "60 kg", "60 kg",
"30 kg", "69 kg", "60 kg", "60 kg", "60 kg", "60 kg", "1 kg",...
## $ in_country_partner     "METAD Agricultural Development plc",
"METAD Agricultural Development plc", "Specialty Coffee Associat...
## $ harvest_year           "2014", "2014", NA, "2014", "2014", "2013",
"2012", "March 2010", "March 2010", "2014", "2014", "2014"...
## $ grading_date           "April 4th, 2015", "April 4th, 2015", "May
31st, 2010", "March 26th, 2015", "April 4th, 2015", "Septem...
## $ owner_1                "metad plc", "metad plc", "Grounds for
```

```
Health Admin", "Yidnekachew Dabessa", "metad plc", "Ji-Ae Ahn",...
## $ variety                NA, "Other", "Bourbon", NA, "Other", NA,
"Other", NA, NA, "Other", NA, "Other", "Other", NA, NA, "Othe...
## $ processing_method      "Washed / Wet", "Washed / Wet", NA,
"Natural / Dry", "Washed / Wet", "Natural / Dry", "Washed / Wet", ...
## $ aroma                  8.67, 8.75, 8.42, 8.17, 8.25, 8.58, 8.42,
8.25, 8.67, 8.08, 8.17, 8.25, 8.08, 8.33, 8.25, 8.00, 8.33, ...
## $ flavor                 8.83, 8.67, 8.50, 8.58, 8.50, 8.42, 8.50,
8.33, 8.67, 8.58, 8.67, 8.42, 8.67, 8.42, 8.33, 8.50, 8.25, ...
## $ aftertaste             8.67, 8.50, 8.42, 8.42, 8.25, 8.42, 8.33,
8.50, 8.58, 8.50, 8.25, 8.17, 8.33, 8.08, 8.50, 8.58, 7.83, ...
## $ acidity                8.75, 8.58, 8.42, 8.42, 8.50, 8.50, 8.50,
8.42, 8.42, 8.50, 8.50, 8.33, 8.42, 8.25, 8.25, 8.17, 7.75, ...
## $ body                   8.50, 8.42, 8.33, 8.50, 8.42, 8.25, 8.25,
8.33, 8.33, 7.67, 7.75, 8.08, 8.00, 8.25, 8.58, 8.17, 8.50, ...
## $ balance                8.42, 8.42, 8.42, 8.25, 8.33, 8.33, 8.25,
8.50, 8.42, 8.42, 8.17, 8.17, 8.08, 8.00, 8.75, 8.00, 8.42, ...
## $ uniformity             10.00, 10.00, 10.00, 10.00, 10.00, 10.00,
10.00, 10.00, 9.33, 10.00, 10.00, 10.00, 10.00, 10.00, 9.33,...
## $ clean_cup              10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10,
10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10...
## $ sweetness              10.00, 10.00, 10.00, 10.00, 10.00, 10.00,
10.00, 9.33, 9.33, 10.00, 10.00, 10.00, 10.00, 10.00, 9.33, ...
## $ cupper_points          8.75, 8.58, 9.25, 8.67, 8.58, 8.33, 8.50,
9.00, 8.67, 8.50, 8.58, 8.50, 8.33, 8.58, 8.50, 8.17, 8.33, ...
## $ moisture               0.12, 0.12, 0.00, 0.11, 0.12, 0.11, 0.11,
0.03, 0.03, 0.10, 0.10, 0.00, 0.00, 0.00, 0.05, 0.00, 0.03, ...
## $ category_one_defects   0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ quakers                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ color                  "Green", "Green", NA, "Green", "Green",
"Bluish-Green", "Bluish-Green", NA, NA, "Green", NA, NA, NA, N...
## $ category_two_defects   0, 1, 0, 2, 2, 1, 0, 0, 0, 4, 1, 0, 0, 2,
2, 0, 0, 2, 0, 8, 0, 2, 0, 0, 1, 2, 2, 1, 3, 0, 2, 1, 2, 0, ...
## $ expiration             "April 3rd, 2016", "April 3rd, 2016", "May
31st, 2011", "March 25th, 2016", "April 3rd, 2016", "Septem...
## $ certification_body     "METAD Agricultural Development plc",
"METAD Agricultural Development plc", "Specialty Coffee Associat...
## $ certification_address  "309fcf77415a3661ae83e027f7e5f05dad786e44",
"309fcf77415a3661ae83e027f7e5f05dad786e44", "36d0d00a37243...
## $ certification_contact  "19fef5a731de2db57d16da10287413f5f99bc2dd",
"19fef5a731de2db57d16da10287413f5f99bc2dd", "0878a7d4b9d35...
## $ unit_of_measurement    "m", "m", "m", "m", "m", "m", "m", "m",
"m", "m", "m", "m", "m", "ft", "m", "m", "m", "m", "m", "m", "...
## $ altitude_low_meters    1950.0, 1950.0, 1600.0, 1800.0, 1950.0, NA,
NA, 1570.0, 1570.0, 1795.0, 1855.0, 1872.0, 1943.0, 609.6,...
## $ altitude_high_meters   2200.0, 2200.0, 1800.0, 2200.0, 2200.0, NA,
NA, 1700.0, 1700.0, 1850.0, 1955.0, 1872.0, 1943.0, 609.6,...
## $ altitude_mean_meters   2075.0, 2075.0, 1700.0, 2000.0, 2075.0, NA,
NA, 1635.0, 1635.0, 1822.5, 1905.0, 1872.0, 1943.0, 609.6,...
```

A quick glimpse of our data (no pun intended) is enough to indicate that our dataset is far from clean.
It also looks like there is missing data everywhere. Lets see how much.

Missing Data

```
library(naniar)

vis_miss(coffee_ratings)
```

Thankfully, it's not as bad as I thought it was going to be. For the nature of my question I am only going to using the `total_cupper_points`, `country_of_origin`, `grading_date` and `species` variables which all have little to no missing data (I thought this would be more of an issue, but looking back at it I'm thankful it isn't for this case.)

Quantites of Coffee per Country

As stated in the description of our dataset (see the readme.md)

> "These data were collected from the Coffee Quality Institute's review pages in January 2018."

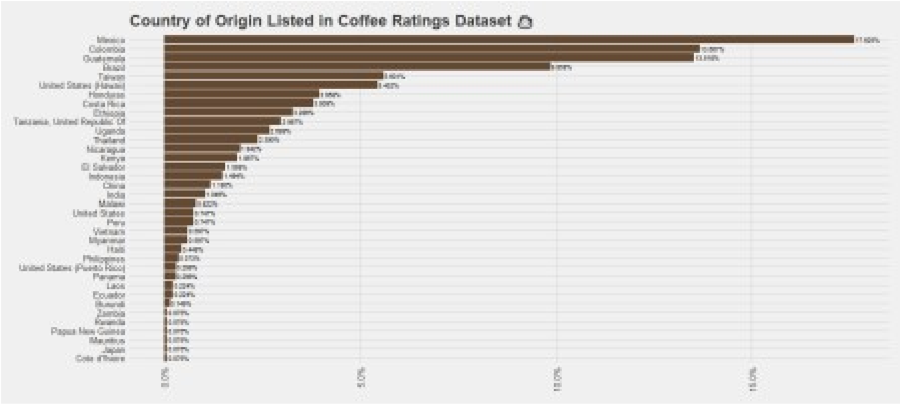
(I am not sure how grammatical that phrase is but ok.)

To better understand our data, lets look at the frequencies of our data in terms of countries listed in our data set. Because there is only one instance of missing data, we will remove it from our plots for aesthetic reasons.

```
library(ggthemes)

# Need to make a new transformed dataset for this visualization

(
  country_table<-coffee_ratings %>%
    count(country_of_origin = factor(country_of_origin)) %>%
    mutate(pct = prop.table(n)) %>%
    arrange(-pct) %>%
    tibble()
)
```

```
## # A tibble: 37 x 3
##    country_of_origin                n    pct
##
##  1 Mexico                          236 0.176
##  2 Colombia                        183 0.137
##  3 Guatemala                       181 0.135
##  4 Brazil                          132 0.0986
##  5 Taiwan                           75 0.0560
##  6 United States (Hawaii)           73 0.0545
##  7 Honduras                         53 0.0396
##  8 Costa Rica                       51 0.0381
##  9 Ethiopia                         44 0.0329
## 10 Tanzania, United Republic Of     40 0.0299
## # ... with 27 more rows
```

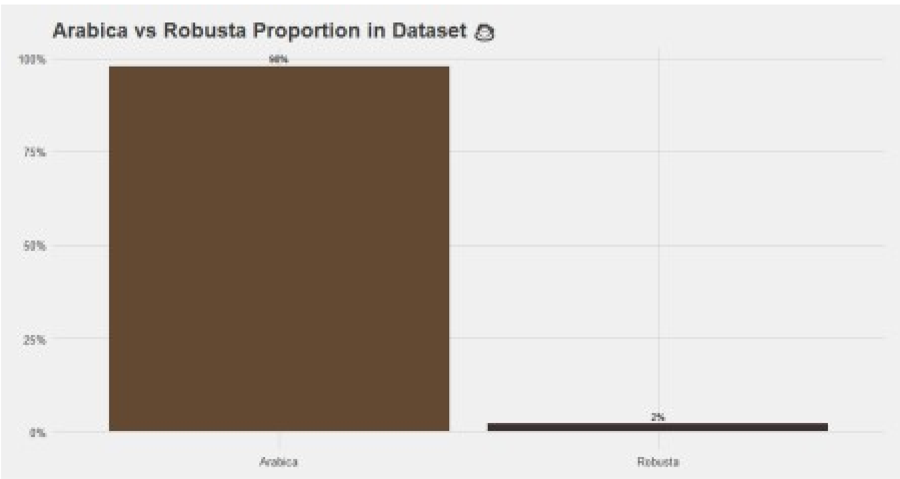
```
# Together with my knowledge of ggplot and google, these visualizations
became possible

ggplot(
  country_table %>% filter(country_of_origin != "NA"),
  mapping = aes(
    x = reorder(country_of_origin, n),
    y = pct,
    group = 1,
    label = scales::percent(pct)
  )
) +
  theme_fivethirtyeight() +
  geom_bar(stat = "identity",
           fill = "#634832") +
  geom_text(position = position_dodge(width = 0.9),
            # move to center of bars
            hjust = -0.05,
            #Have Text just above bars
            size = 2.5) +
  labs(x = "Country of Origin",
       y = "Proportion of Dataset") +
  theme(axis.text.x = element_text(
    angle = 90,
    vjust = 0.5,
    hjust = 1
  )) +
  ggtitle("Country of Origin Listed in Coffee Ratings Dataset " ) +   #
This Emoji messes up this line in R markdown but hey, it
  scale_y_continuous(labels = scales::percent) +
# looks good.
  coord_flip()
```



From a brief look at our table and bar chart we see that **over 54% of our dataset consists of coffees from Mexico, Columbia, Guatemala and Brazil**. But this only tells us part of the story, what species of coffees do we have in our dataset from each country?

Before looking at that lets look at the overall Arabica/Robusta proportion in our dataset:

```
# Need to make a new transformed dataset for this visualization

species_table<-coffee_ratings %>%
    count(species = factor(species)) %>%
    mutate(pct = prop.table(n)) %>% tibble()

ggplot(species_table,mapping=aes(x=species,y=pct,group=1,
label=scales::percent(pct)))+
   theme_fivethirtyeight()+
  geom_bar(stat="identity",
           fill=c("#634832","#3b2f2f"))+
    geom_text(position = position_dodge(width=0.9),    # move to center
of bars
              vjust=-0.5, #Have Text just above bars
              size = 3)+
  scale_y_continuous(labels = scales::percent)+
  ggtitle("Arabica vs Robusta Proportion in Dataset ")
```



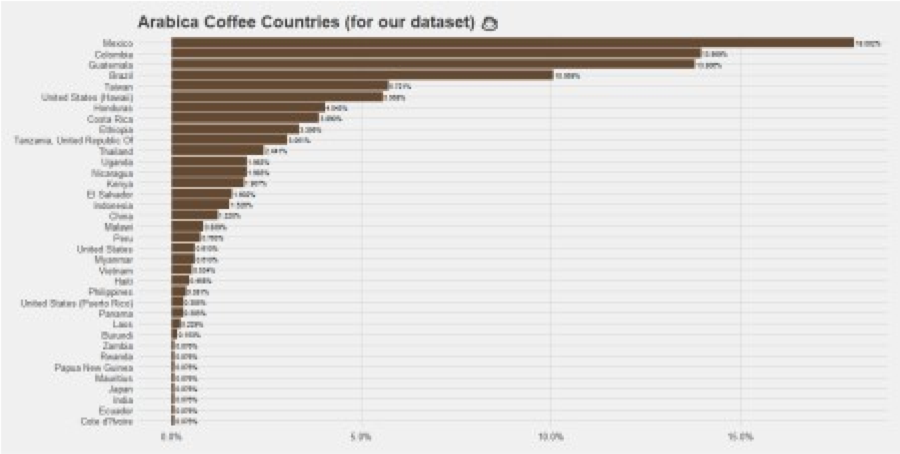
Wow! only 2% of Coffee in our dataset is from Robusta beans! But if you think about this in context, this shouldn't be too much of a suprise. Robusta coffee is primarily used in instant coffee,espresso and filler for coffee blends. The reason why Robusta coffee beans are not graded proportionately as Arabica beans are is due to the fact that the quality of these bitter, earthy beans are usually not as desirable to coffee drinkers as their smoother, richer Arabica counterparts.

With that in mind, lets see how the breakdown proportionally per country:

```
# Need to make a new transformed datasets for this visualization

(
  arabica_countries<-coffee_ratings %>%
  filter(species =="Arabica") %>%
    count(species=factor(species),
          country=country_of_origin) %>%
    mutate(pct = prop.table(n)) %>%
    arrange(-n) %>%
  tibble()
)
```

```
## # A tibble: 37 x 4
##    species country                          n    pct
##
##  1 Arabica Mexico                         236 0.180
##  2 Arabica Colombia                       183 0.140
##  3 Arabica Guatemala                      181 0.138
##  4 Arabica Brazil                         132 0.101
##  5 Arabica Taiwan                          75 0.0572
##  6 Arabica United States (Hawaii)          73 0.0557
##  7 Arabica Honduras                        53 0.0404
##  8 Arabica Costa Rica                      51 0.0389
##  9 Arabica Ethiopia                        44 0.0336
## 10 Arabica Tanzania, United Republic Of    40 0.0305
## # ... with 27 more rows
```

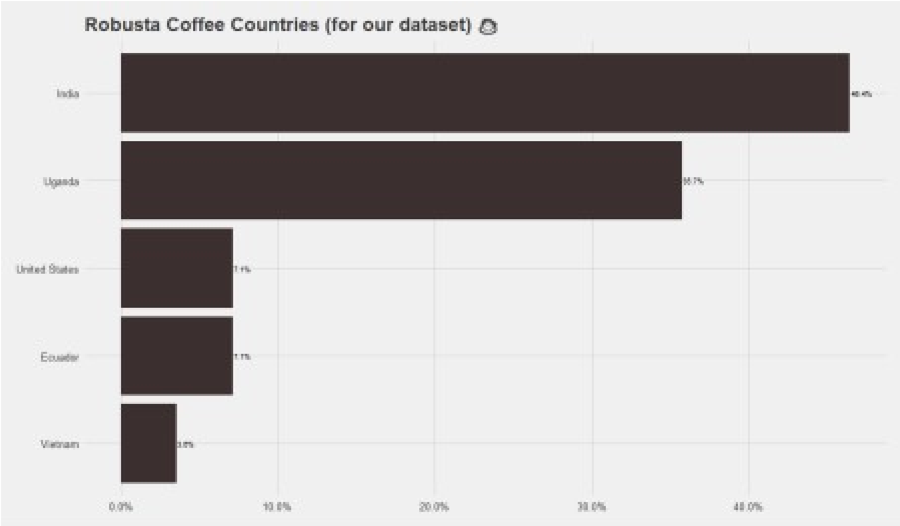
```
ggplot(arabica_countries %>% filter(country!="NA"),
       mapping=aes(x=reorder(country,n),y=pct,group=1,label=scales:
:percent(pct))) +
  theme_fivethirtyeight()+
  geom_bar(stat="identity",
           fill="#634832")+
  geom_text(position = position_dodge(width = 0.9),
            # move to center of bars
            hjust = -0.05,
            #Have Text just above bars
            size = 2.5) +
  ggtitle("Arabica Coffee Countries (for our dataset) ") +
   scale_y_continuous(labels = scales::percent) +
  coord_flip()
```




```
(
  robusta_countries<-coffee_ratings %>%
    filter(species =="Robusta") %>%
    count(species = factor(species),
          country=country_of_origin) %>%
    mutate(pct = prop.table(n)) %>%
    arrange(-n) %>%
  tibble()
)
```

```
## # A tibble: 5 x 4
##   species country           n    pct
##
## 1 Robusta India            13 0.464
## 2 Robusta Uganda           10 0.357
## 3 Robusta Ecuador           2 0.0714
## 4 Robusta United States     2 0.0714
## 5 Robusta Vietnam           1 0.0357
```

```
ggplot(robusta_countries %>% filter(country!="NA"),
       mapping=aes(x=reorder(country,n),y=pct,group=1,label=scales:
:percent(pct))) +
  theme_fivethirtyeight()+
  geom_bar(stat="identity",
           fill="#3b2f2f")+
  geom_text(position = position_dodge(width = 0.9),
            # move to center of bars
            hjust = -0.05,
            #Have Text just above bars
            size = 2.5) +
  ggtitle("Robusta Coffee Countries (for our dataset) ") +
   scale_y_continuous(labels = scales::percent) +
  coord_flip()
```

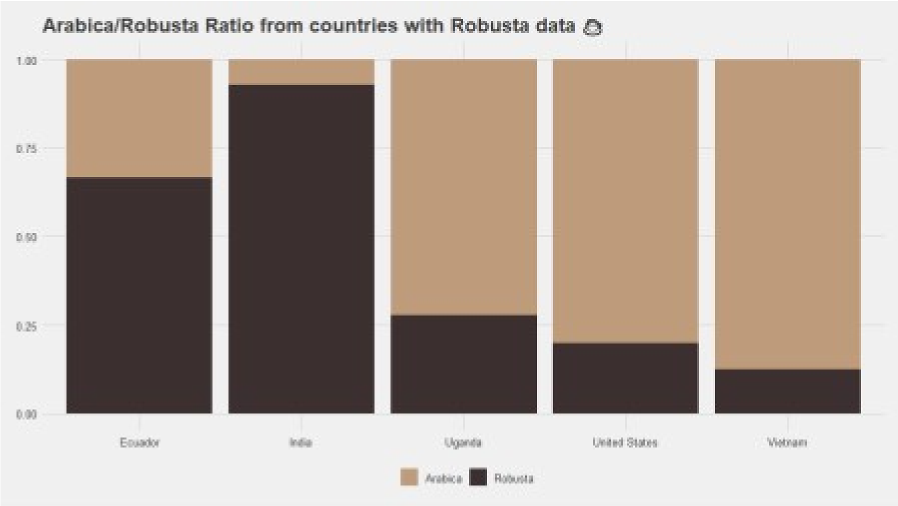


The Robusta coffees that we have in this dataset are mostly from India and Uganda, with a few coffees from the Ecuador, the United States and Vietnam. With that being known, Lets look at the Arabica/Robusta ratio for countries that we have Robusta Data on.

```
coffee_ratings %>%
  filter(country_of_origin %in% c("India","Uganda","Ecuador","United
States","Vietnam")) %>%
  count(country_of_origin,species) %>%
  group_by(country_of_origin)
```

```
## # A tibble: 10 x 3
## # Groups:   country_of_origin [5]
##    country_of_origin species     n
##
##  1 Ecuador           Arabica     1
##  2 Ecuador           Robusta     2
##  3 India             Arabica     1
##  4 India             Robusta    13
##  5 Uganda            Arabica    26
##  6 Uganda            Robusta    10
##  7 United States     Arabica     8
##  8 United States     Robusta     2
##  9 Vietnam           Arabica     7
## 10 Vietnam           Robusta     1
```

```
ggplot(coffee_ratings %>% filter(country_of_origin %in%
c("India","Uganda","Ecuador","United States","Vietnam")),
       mapping=aes(x=country_of_origin,fill=species))+
  theme_fivethirtyeight()+
  geom_bar(position="fill")+
  scale_fill_manual(values=c("#BE9B7B", "#3b2f2f"))+
  theme(legend.title = element_blank())+
  ggtitle("Arabica/Robusta Ratio from countries with Robusta data ")
```



Now that we have better understanding of where our coffees come from, we can get into trying to answer the question of **where** the best coffee beans are in the world.

Well, it depends.

What type? What year?

It would be nice to just pick out the highest rated coffee and be done with it, but that wouldn't tell us anything (or really motivate a blog post). We need to consider is when was a given coffee graded. That can tell us the performance of a given country's over time. Additionally, we need to consider the species of bean- where is the best ranked Arabica coffee from? Where is the best Robusta coffee from?

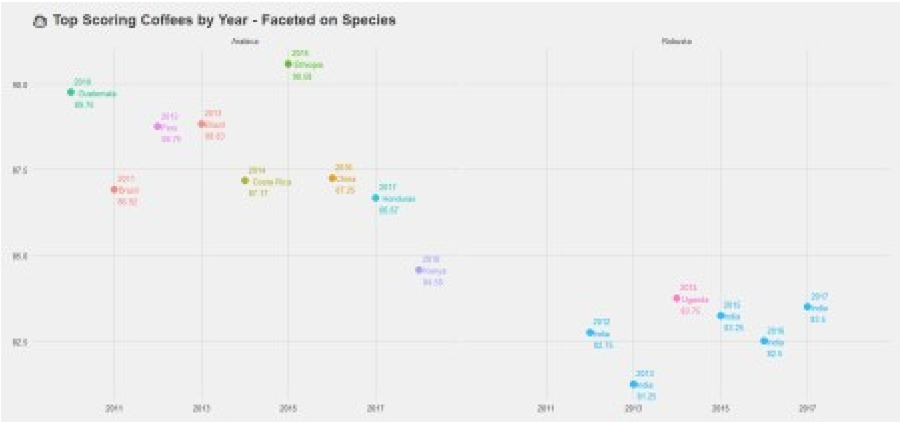
Before we can answer this question, we need to clean the `grading_date` and convert them into the `date` data from. Thankfully, the lubridate package will help us with doing this relatively easy. After that we will formulate our data set with the `dplyr` package to get the data in the form we need for our visualization.

```
library(lubridate)

# Getting the year data
coffee_ratings$new_dates<-coffee_ratings$grading_date %>% mdy()
coffee_ratings$score_year<- coffee_ratings$new_dates %>% year()

# Dataset for visualizations

(
  top_annual_score<- coffee_ratings %>%
  group_by(species,
           score_year,
           country_of_origin) %>%
  summarise(max_points = max(total_cup_points)) %>%
  filter(max_points == max(max_points)) %>%
  arrange(-max_points)
)
```

```
## # A tibble: 15 x 4
## # Groups:   species, score_year [15]
##    species score_year country_of_origin max_points
##
##  1 Arabica       2015 Ethiopia                90.6
##  2 Arabica       2010 Guatemala               89.8
##  3 Arabica       2013 Brazil                  88.8
##  4 Arabica       2012 Peru                    88.8
##  5 Arabica       2016 China                   87.2
##  6 Arabica       2014 Costa Rica              87.2
##  7 Arabica       2011 Brazil                  86.9
##  8 Arabica       2017 Honduras                86.7
##  9 Arabica       2018 Kenya                   84.6
## 10 Robusta       2014 Uganda                  83.8
## 11 Robusta       2017 India                   83.5
## 12 Robusta       2015 India                   83.2
## 13 Robusta       2012 India                   82.8
## 14 Robusta       2016 India                   82.5
## 15 Robusta       2013 India                   81.2
```

```
ggplot(top_annual_score,
       mapping=aes(x=score_year,
                   y=max_points,
                   label=paste0(score_year,"\n",country_of_origin,"\n",
max_points),
                   color=country_of_origin))+
  theme_fivethirtyeight()+
  geom_text(position = position_dodge(width = 0.9),
            # move to center of bars
            hjust =-0.2,
```

```
            #Have Text just above bars
            size =3.5) +
  geom_point(size=4,
             alpha=0.8)+
  theme(legend.position = "none")+
  facet_wrap(~species)+
  ggtitle(" Top Scoring Coffees by Year - Faceted on Species ")
```



From our visualization and table we see for Arabica beans, the top coffee varied from country to country for a given year. However for Robusta, India seemed to have dominated with consistent wins from 2012 – 2017 with an exception of Uganda beating them in 2014.

Overall, for our given timespan in our dataset, for Arabica beans (as well as our entire dataset) Ethiopia scored the highest with a score of 90.58 and for Robusta Beans Uganda had the highest score of 83.75.

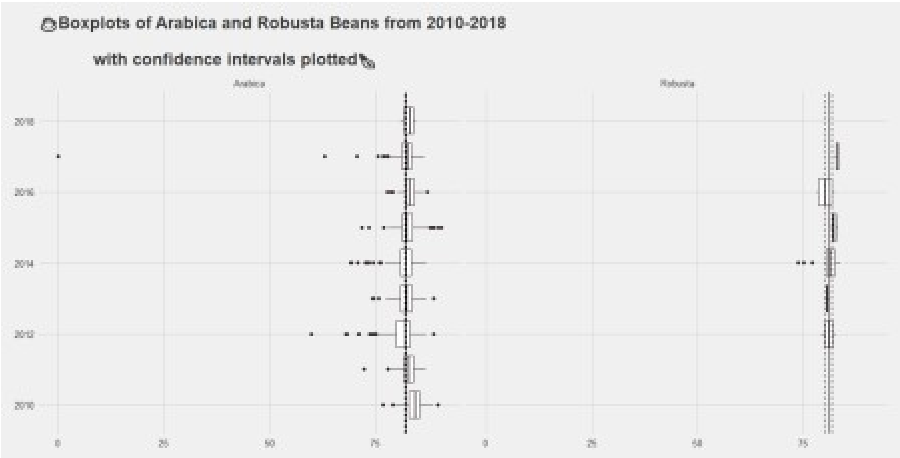
The overall summary for of scores for Arabica and Robusta beans accross the years is plotted in the below visualization with boxplots.

```
(arabica_robusta_average_score<-
   coffee_ratings %>%
  group_by(species) %>%
  summarise(average_score = mean(total_cup_points),
            lower_ci = mean(total_cup_points) -
1.96*sqrt(var(total_cup_points)/length(total_cup_points)),
            upper_ci = mean(total_cup_points) +
1.96*sqrt(var(total_cup_points)/length(total_cup_points)))
  )
```

```
## # A tibble: 2 x 4
##   species average_score lower_ci upper_ci
##
## 1 Arabica          82.1     81.9     82.3
## 2 Robusta          80.9     80.0     81.8
```

```
ggplot(coffee_ratings,mapping=aes(x=score_year,y=total_cup_
```

```
points,group=score_year))+
  theme_fivethirtyeight()+
  geom_boxplot(color="#3b2f2f")+
  coord_flip()+
  facet_wrap(~species)+
  geom_hline(data=arabica_robusta_average_score,
             mapping=aes(yintercept=average_score),
             size= 0.5)+
  geom_hline(data=arabica_robusta_average_score,
             mapping=aes(yintercept=lower_ci),
             linetype="dashed",
             size= 0.5)+
   geom_hline(data=arabica_robusta_average_score,
             mapping=aes(yintercept=upper_ci),
             linetype="dashed",
             size= 0.5)+
  ggtitle("Boxplots of Arabica and Robusta Beans from 2010-2018 \n
           with confidence intervals plotted")
```



Besides for some outliers on the lower end of the scoring range, most of these coffees in this dataset are on average score around 80 or above. What can be implied from here is that the coffees that come in to be graded by the Coffee Quality Institute are usually those which have are assumed to be high in quality. This shouldn't be a surprise because it appears that beans graded by the CQI are usually those which are submitted as it says it on the site's banner

> Welcome to the Coffee Quality Institute (CQI) database, **which allows users to submit a sample for Q Grading** …

Conclusion

Its not surprising for our data set that Robusta beans scored poorer than their Arabica counterparts. That is something that anyone with some background in coffee will tell you- Arabica is generally more desirable by coffee drinkers and Robusta is usually used for instant coffee, Espresso and filler for coffee blends.