

Pinelli_Gisler

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Install Packages

```
library(dplyr)
library(tinytex)
library(ggplot2)
library(ggrepel)
library(gridExtra)
library(gganimate)
library(gifski)
library(av)
```

Data Cleaning

```
names(df)[names(df) == "NSA.Code"] <- "Nation"
names(df)[names(df) == "i..Rank" ] <- "Rank"
names(df)[names(df) == "Year.of.Birth" ] <- "Year_of_birth"
names(df)[names(df) == "Distance..m." ] <- "Distance_in_meters"
names(df)[names(df) == "Race.Points" ] <- "Race_points"
names(df)[names(df) == "Race.Day" ] <- "Race_day"
names(df)[names(df) == "FIS.Code" ] <- "FIS_code"
names(df)[names(df) == "Last.Name" ] <- "Last_name"
names(df)[names(df) == "First.Name" ] <- "First_name"
df$FIS_code <- as.factor(df$FIS_code)
df$Race_day <- as.factor(df$Race_day)
df$Race_day <- as.Date(df$Race_day, "%d.%m.%Y")
df$Race_year <- format(df$Race_day, '%Y')
df$Race_year <- as.numeric(df$Race_year)
```

Add Additional Columns

```
###Number of participations
df_part <- table(df$FIS_code)
df_part <- as.data.frame(df_part)
names(df_part)[names(df_part) == "Var1"] <- "FIS_code"
names(df_part)[names(df_part) == "Freq"] <- "Number_of_participations"
df <- left_join(df, df_part, by='FIS_code', keep=FALSE)
```

```

###Age of Rider at Race
df$year_of_race <- format(as.Date(df$Race_day, format="%d.%m.%Y"), "%Y")
df$year_of_race <- as.integer(df$year_of_race)
df$Age_of_rider <- df$year_of_race - df$Year_of_birth

###Number of wins
df_winner <- filter(df, df$Rank == 1)
df_winner_count <- table(df_winner$FIS_code)
df_winner_count <- as.data.frame(df_winner_count)
names(df_winner_count)[names(df_winner_count) == "Var1"] <- "FIS_code"
names(df_winner_count)[names(df_winner_count) == "Freq"] <- "Number_of_wins"
df <- left_join(df, df_winner_count, by='FIS_code', keep=FALSE)

###Number of wins/nation
df_winner_count_nation <- table(df_winner$Nation)
df_winner_count_nation <- as.data.frame(df_winner_count_nation)

names(df_winner_count_nation)[names(df_winner_count_nation) == "Var1"] <- "Nation"
names(df_winner_count_nation)[names(df_winner_count_nation) == "Freq"] <- "Number_of_wins_nation"
df <- left_join(df, df_winner_count_nation, by='Nation', keep=FALSE)
df$Number_of_wins_nation[is.na(df$Number_of_wins_nation)] <- 0

### Number of Participations / nation
nations <- table(df$Nation)
nations <- as.data.frame(nations)
names(nations)[names(nations) == "Var1"] <- "Nation"
names(nations)[names(nations) == "Freq"] <- "Number_of_participations_Nation"
df <- left_join(df, nations, by='Nation', keep=FALSE)

###Number of wins/ski
df_winner_ski <- table(df_winner$Ski)
df_winner_ski <- as.data.frame(df_winner_ski)
names(df_winner_ski)[names(df_winner_ski) == "Var1"] <- "Ski"
names(df_winner_ski)[names(df_winner_ski) == "Freq"] <- "Number_of_wins_ski"
df <- left_join(df, df_winner_ski, by='Ski', keep=FALSE)
df$Number_of_wins_ski[is.na(df$Number_of_wins_ski)] <- 0

### Number of Participations / ski
Ski <- table(df$Ski)
Ski <- as.data.frame(Ski)
names(Ski)[names(Ski) == "Var1"] <- "Ski"
names(Ski)[names(Ski) == "Freq"] <- "Number_of_participations_Ski"
df <- left_join(df, Ski, by='Ski', keep=FALSE)

###Number of podiums
df_podium <- filter(df, df$Rank < 4)
df_podium <- table(df_podium$FIS_code)
df_podium <- as.data.frame(df_podium)
names(df_podium)[names(df_podium) == "Var1"] <- "FIS_code"
names(df_podium)[names(df_podium) == "Freq"] <- "Number_of_podiums"
df <- left_join(df, df_podium, by='FIS_code', keep=FALSE)

```

```

###Best Rank

df_rank = df %>%
  select(FIS_code, Rank, Last_name)
df_rank <- df_rank[order(df_rank$Rank),]
df_rank <- df_rank[!duplicated(df_rank$FIS_code), ]
names(df_rank)[names(df_rank) == "Rank"] <- "Best_Rank"
df_rank$Last_name <- NULL
df <- left_join(df, df_rank,by='FIS_code', keep=FALSE)

head(df)

```

```

## Rank Bib FIS_code Last_name First_name Year_of_birth Nation Time
## 1 13 30 510993 ALBRECHT Daniel 1983 SUI 2:33.80
## 2 27 24 510993 ALBRECHT Daniel 1983 SUI 2:33.74
## 3 45 51 370031 ALESSANDRIA Arnaud 1993 MON 2:34.06
## 4 64 71 370031 ALESSANDRIA Arnaud 1993 MON 1:37.48
## 5 19 42 104537 ALEXANDER Cameron 1997 CAN 1:44.10
## 6 15 21 194858 ALLEGRE Nils 1994 FRA 1:44.07
## Difference Distance_in_meters Race_points Ski Race_day Race_year
## 1 1.82 53.01 15.81 Atomic 2009-01-17 2009
## 2 3.34 97.33 29.98 Atomic 2008-01-13 2008
## 3 5.70 157.98 48.03 Salomon 2019-01-19 2019
## 4 4.82 132.61 71.26 Unknown 2014-01-18 2014
## 5 1.57 44.49 19.14 Rossignol 2020-01-18 2020
## 6 1.54 43.65 18.77 Salomon 2020-01-18 2020
## Number_of_participations year_of_race Age_of_rider Number_of_wins
## 1 2 2009 26 0
## 2 2 2008 25 0
## 3 2 2019 26 0
## 4 2 2014 21 0
## 5 1 2020 23 0
## 6 2 2020 26 0
## Number_of_wins_nation Number_of_participations_Nation Number_of_wins_ski
## 1 6 88 1
## 2 6 88 1
## 3 0 2 4
## 4 0 2 0
## 5 0 45 2
## 6 0 76 4
## Number_of_participations_Ski Number_of_podiums Best_Rank
## 1 144 0 13
## 2 144 0 13
## 3 68 0 45
## 4 26 0 45
## 5 91 0 19
## 6 68 0 15

```

Add additional Dataframes

```

### Dataframe Podium
df_podium <- filter(df, df$Rank <4)

### Dataframe Winner

df_winner <- filter(df, df$Rank == 1)

### Dataframe Top 10
df_top_10 <- filter(df, df$Rank <11)

### Riders with more than 5 Participations
df_participations <- filter(df, df$Number_of_participations >6)
df_participations <- df_participations[order(df_participations$Rank),]
df_participations <- df_participations[!duplicated(df_participations$FIS_code), ]

```

Data Visualisation: Nations most participated

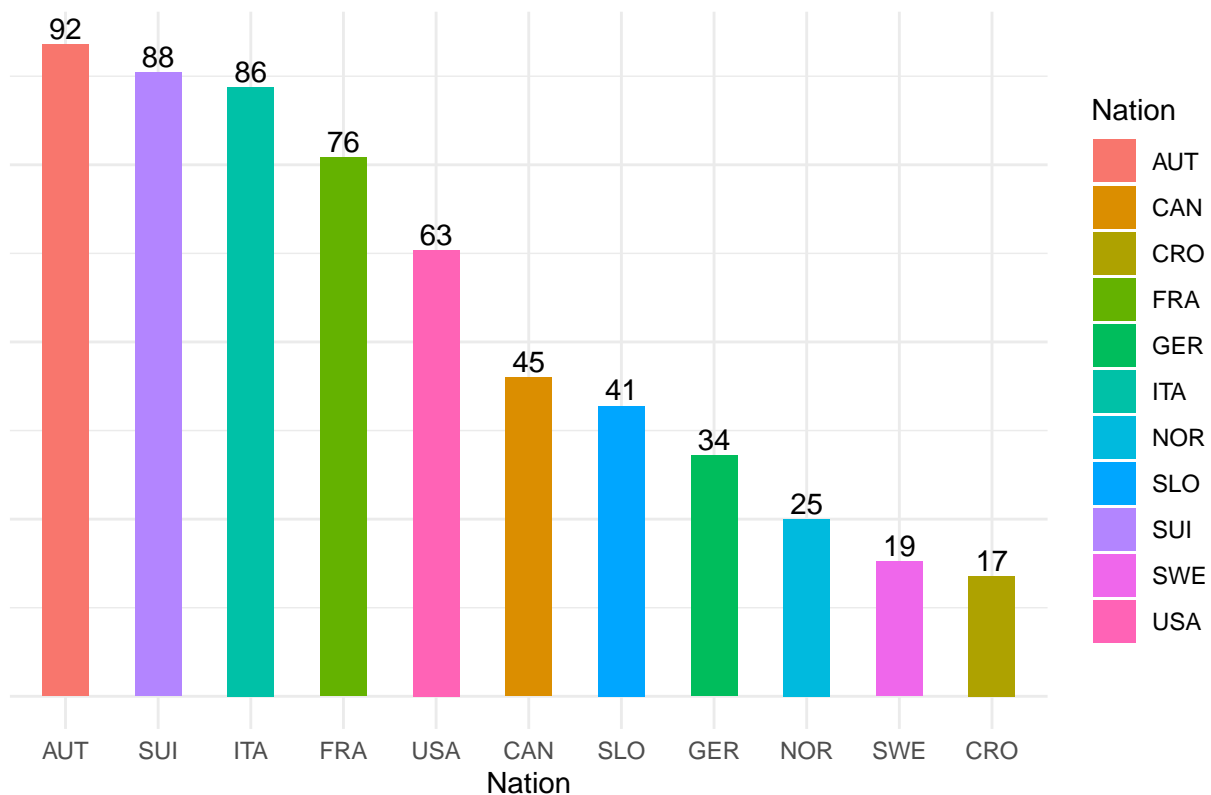
```

### Nations number of Participants
nations <- table(df$Nation)
nations <- as.data.frame(nations)
names(nations)[names(nations) == "Var1"] <- "Nation"
names(nations)[names(nations) == "Freq"] <- "Number_of_participations_Nation"

nations <- filter(nations, nations$Number_of_participations_Nation >9)
ggplot(data = nations, aes(x=reorder(Nation, -Number_of_participations_Nation), y=Number_of_participations_Nation)) +
  theme_minimal() +
  geom_bar(stat="identity", width=0.5, aes(fill = Nation)) +
  ggtitle("Number of Participations per Nation") +
  xlab("Nation") +
  ylab("Number of Participations") +
  geom_text(aes(label=Number_of_participations_Nation), position=position_dodge(width=0.9), vjust=-0.25) +
  theme(axis.title.y=element_blank(),
        axis.text.y=element_blank(),
        axis.ticks.y=element_blank())

```

Number of Participations per Nation



Data Visualisation: Comparison participations, wins and wins per number of participations

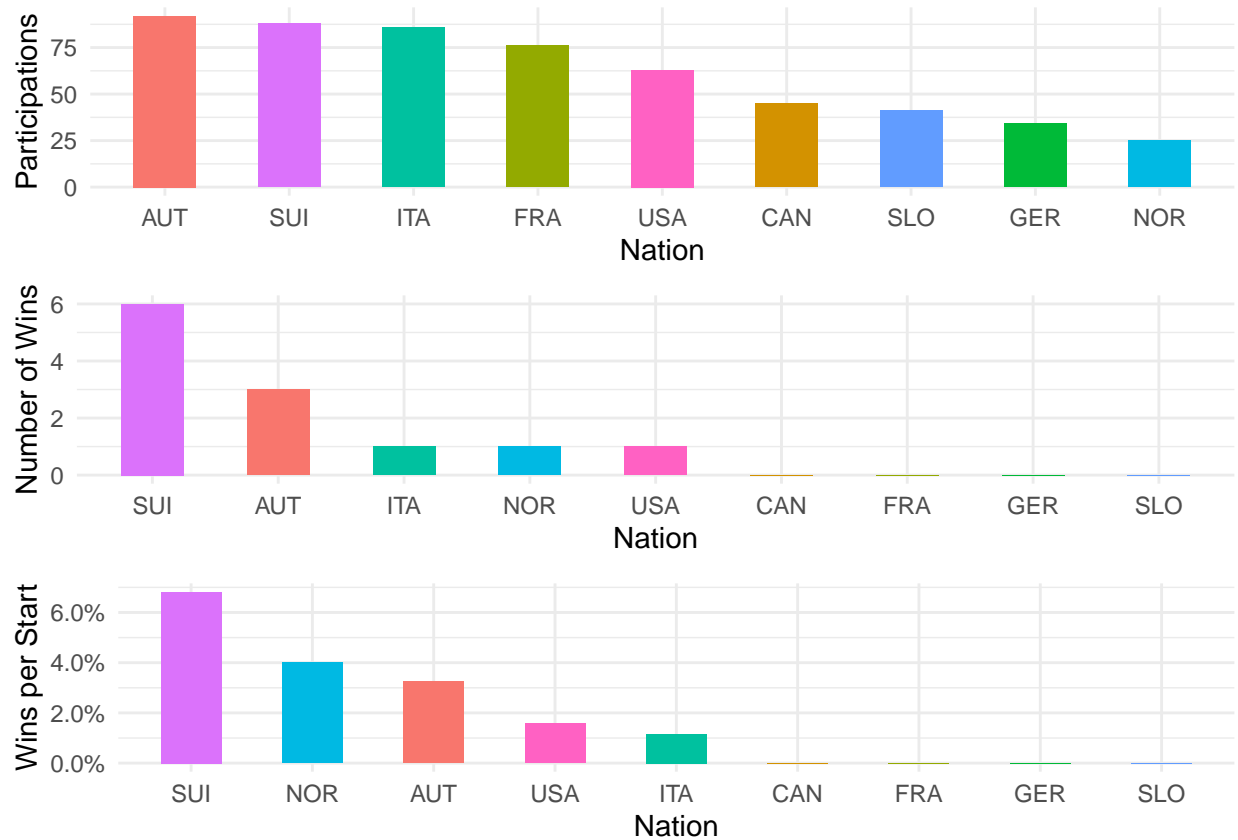
```
df$Wins_per_Start_nation <- df$Number_of_wins_nation/df$Number_of_participations_Nation
nations <- filter(df, df$Number_of_participations_Nation >24)

plot_nations_1 <- ggplot(data = nations, aes(x=reorder(Nation, -Number_of_participations_Nation), y=Number_of_participations_Nation)) +
  theme_minimal() +
  geom_bar(stat="identity", width=0.5, position = "dodge", aes(fill = Nation), show.legend = FALSE) +
  ylab("Participations") +
  xlab("Nation")

plot_nations_2 <- ggplot(data = nations, aes(x=reorder(Nation, -Number_of_wins_nation), y=Number_of_wins_nation)) +
  theme_minimal() +
  geom_bar(stat="identity", width=0.5, position = "dodge", aes(fill = Nation), show.legend = FALSE) +
  ylab("Number of Wins") +
  xlab("Nation")

plot_nations_3 <- ggplot(data = nations, aes(x=reorder(Nation, -Wins_per_Start_nation), y=Wins_per_Start_nation)) +
  theme_minimal() +
  geom_bar(stat="identity", width=0.5, position = "dodge", aes(fill = Nation), show.legend = FALSE) +
  ylab("Wins per Start") +
  xlab("Nation") +
  scale_y_continuous(labels = scales::percent)
```

```
grid.arrange(plot_nations_1, plot_nations_2, plot_nations_3, ncol=1)
```

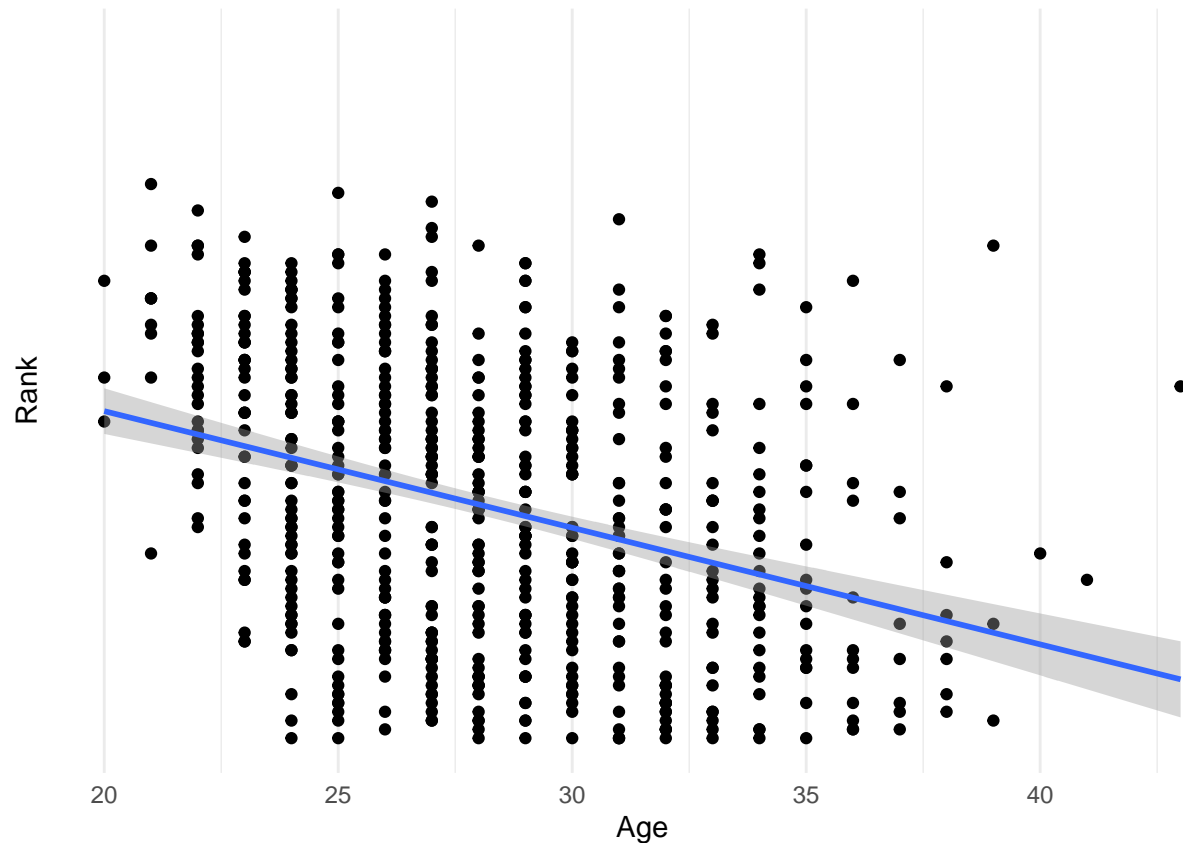


Austria has participated the most, however the Swiss won more races. Interestingly the Norwegians have a better rating in Wins divided by number of participations, this might indicate that the small norwegian team is strong or has had a lucky day by wining a race.

Data Visualisation: Age and Rank over time

```
ggplot(data = df, aes(x=Age_of_rider, y=Rank)) +
  geom_point()+
  coord_cartesian(ylim = c(1, 80))+
  scale_y_reverse()+
  geom_smooth(method = "lm")+
  theme_minimal()+
  xlab("Age")+
  ylab("Rank")
```

```
## 'geom_smooth()' using formula 'y ~ x'
```



Data Visualisation: Age Comparison

```
age_average <- ggplot(data = df, aes(y=Age_of_rider))+
  geom_boxplot(color="black", fill="brown", alpha=0.2)+
  ylab("Age of all Athletes")+
  coord_cartesian(ylim = c(18, 40))+
  theme(axis.title.x=element_blank(),
        axis.text.x=element_blank(),
        axis.ticks.x=element_blank())

age_podium_average <- ggplot(data = df_podium, aes(y=Age_of_rider))+
  geom_boxplot(color="black", fill="gold", alpha=0.2)+
  ylab("Age of Athletes on Podium")+
  coord_cartesian(ylim = c(18, 40))+
  theme(axis.title.x=element_blank(),
        axis.text.x=element_blank(),
        axis.ticks.x=element_blank())

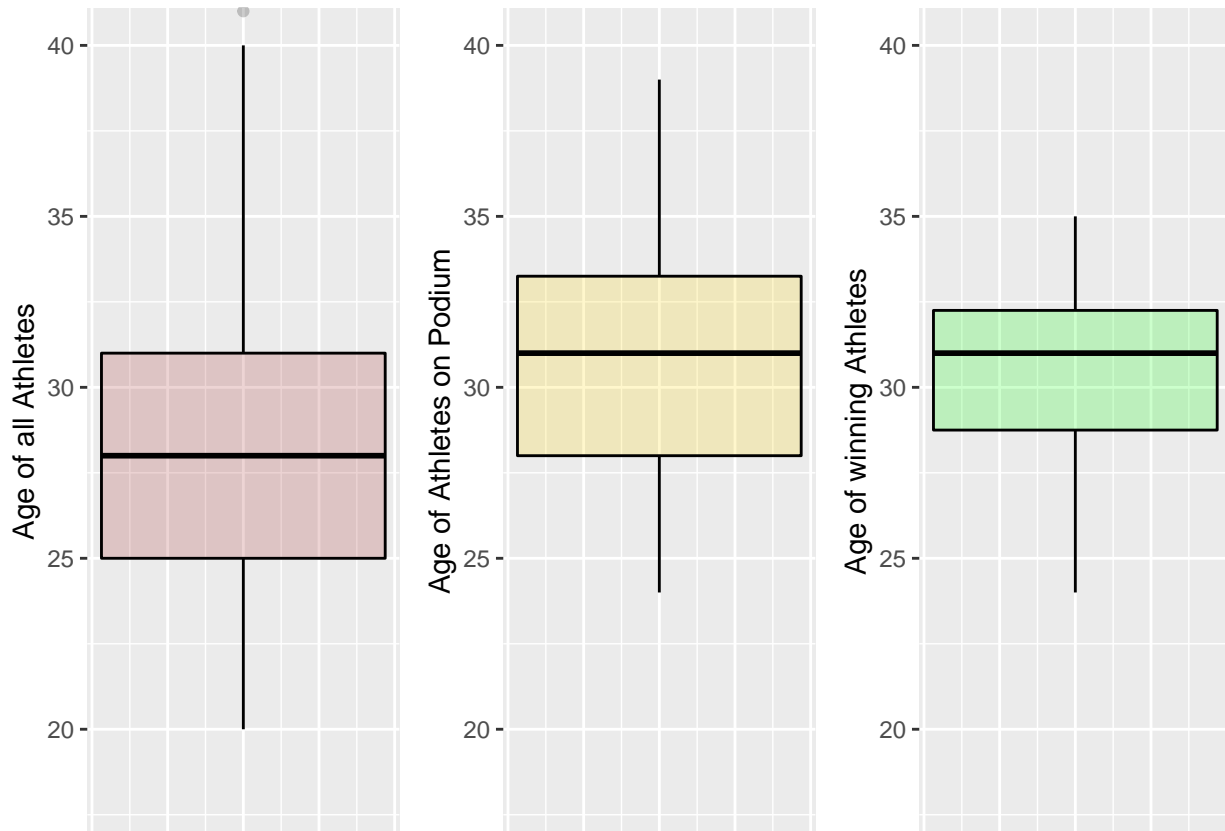
age_winner_average <- ggplot(data = df_winner, aes(y=Age_of_rider, fill = Age_of_rider))+
  geom_boxplot(color="black", fill="green", alpha=0.2)+
  ylab("Age of winning Athletes")+
  coord_cartesian(ylim = c(18, 40))+
```

```

theme(axis.title.x=element_blank(),
      axis.text.x=element_blank(),
      axis.ticks.x=element_blank())

grid.arrange(age_average, age_podium_average, age_winner_average, ncol=3)

```



The age of the winning athletes and the athletes on the podium seem to be higher than the overall age of all athletes.

Data Visualisation: Athletes with more than 6 starts, what is the highest rank reached?

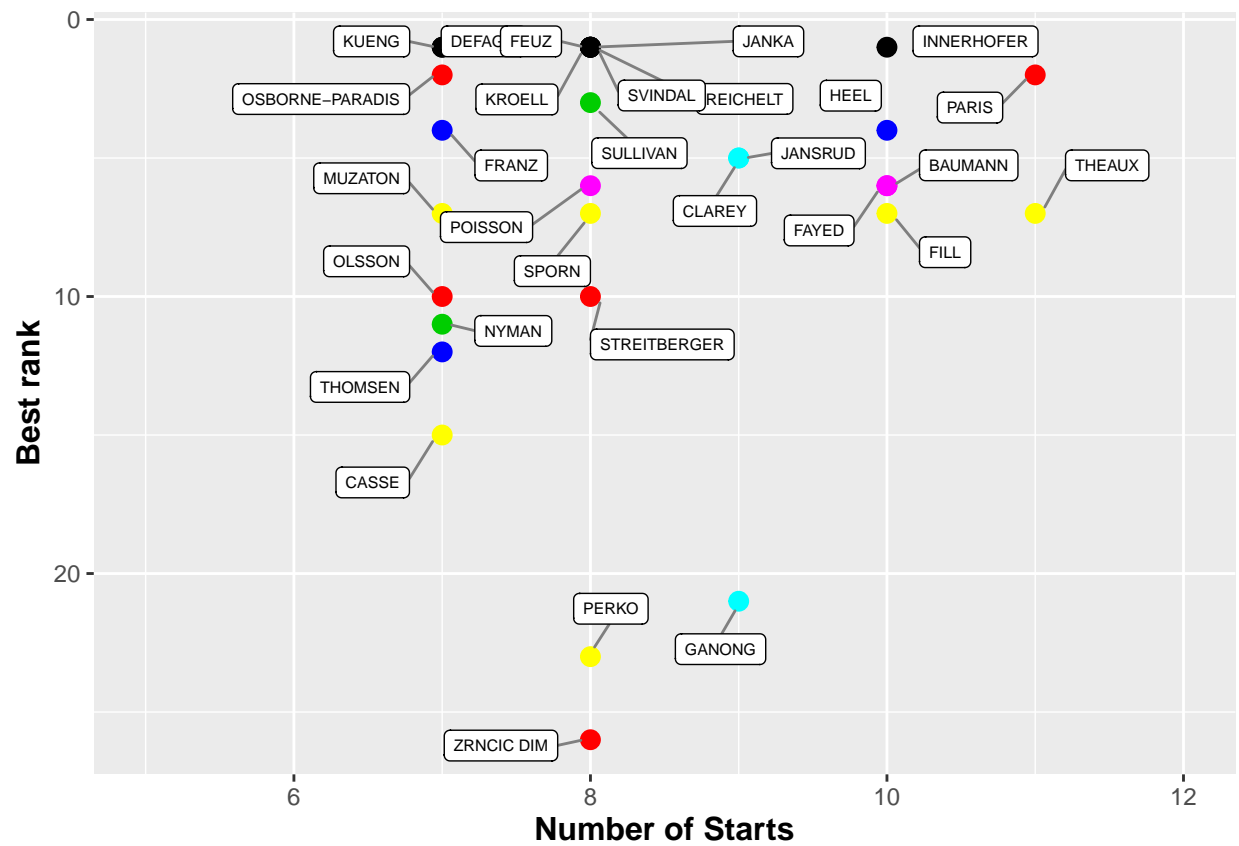
```

ggplot(df_participations, aes(y= Best_Rank, x = Number_of_participations)) +
  geom_point(color = df_participations$Best_Rank, size = 3, show.legend = TRUE)+
  geom_label_repel(aes(label = Last_name),
                  box.padding = 0.35,
                  point.padding = 0.5,
                  segment.color = 'grey50',
                  size = 2) +
  theme(axis.text=element_text(size=9),
        axis.title=element_text(size=12,face="bold"))+
  coord_cartesian(xlim = c(5, 12))+
  scale_y_reverse()+

```

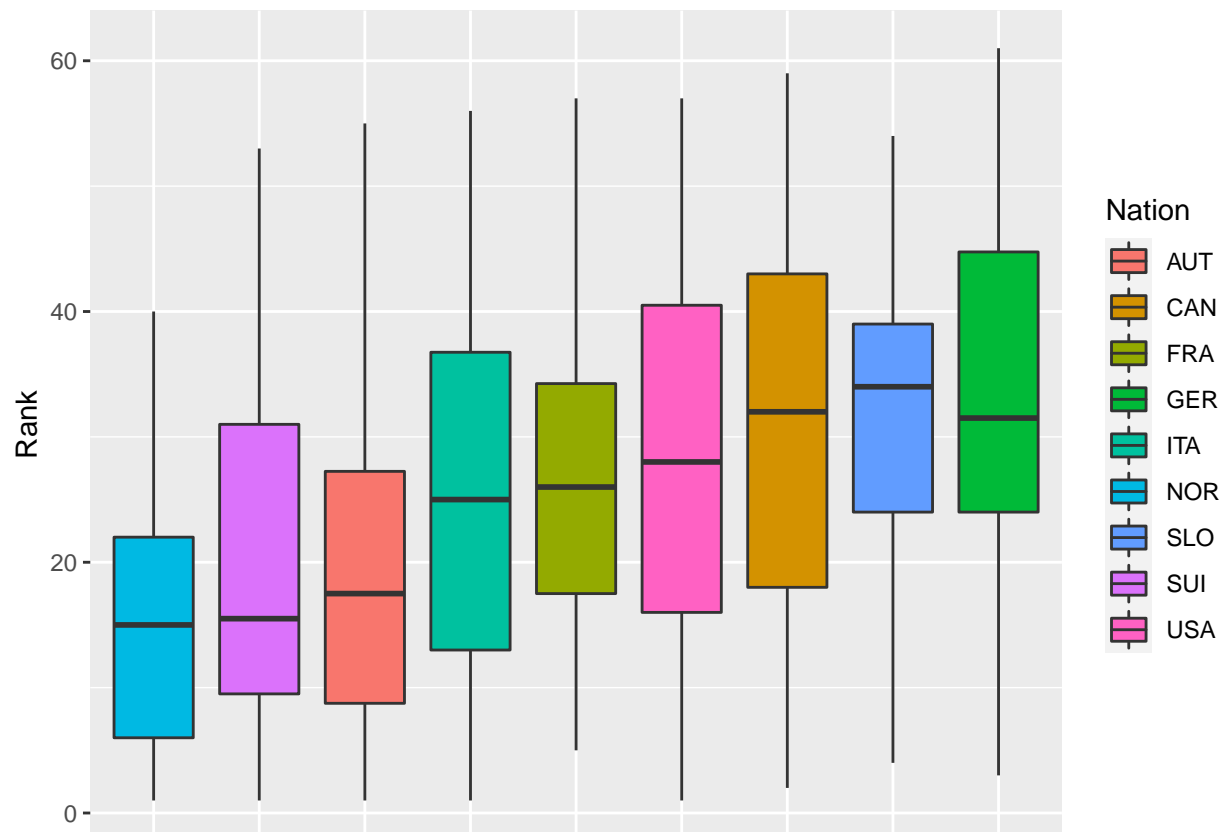


```
ylab("Best rank")+
xlab("Number of Starts")
```



Data Analysis: How do the nations perform on average?

```
ggplot(data = nations, mapping = aes(x=reorder(Nation, Rank), y = Rank, fill=Nation))+
  geom_boxplot()+
  theme(axis.title.x=element_blank(),
        axis.text.x=element_blank(),
        axis.ticks.x=element_blank())
```



```
lm_nations <- lm(nations$Rank ~ nations$Nation)
summary(lm_nations)
```

```
##
## Call:
## lm(formula = nations$Rank ~ nations$Nation)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -29.85 -11.18  -1.24   10.48   34.53
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    20.4674     1.4917  13.721 < 2e-16 ***
## nations$NationCAN     9.8882     2.6027   3.799 0.000162 ***
## nations$NationFRA     6.0458     2.2178   2.726 0.006618 **
## nations$NationGER    12.3855     2.8715   4.313 1.91e-05 ***
## nations$NationITA     5.0675     2.1460   2.361 0.018562 *
## nations$NationNOR    -4.2274     3.2270  -1.310 0.190744
## nations$NationSLO    11.1911     2.6866   4.166 3.62e-05 ***
## nations$NationSUI    -0.8538     2.1334  -0.400 0.689173
## nations$NationUSA     7.5485     2.3397   3.226 0.001330 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 14.31 on 541 degrees of freedom
## Multiple R-squared:  0.1002, Adjusted R-squared:  0.08693
## F-statistic: 7.534 on 8 and 541 DF,  p-value: 1.466e-09
```

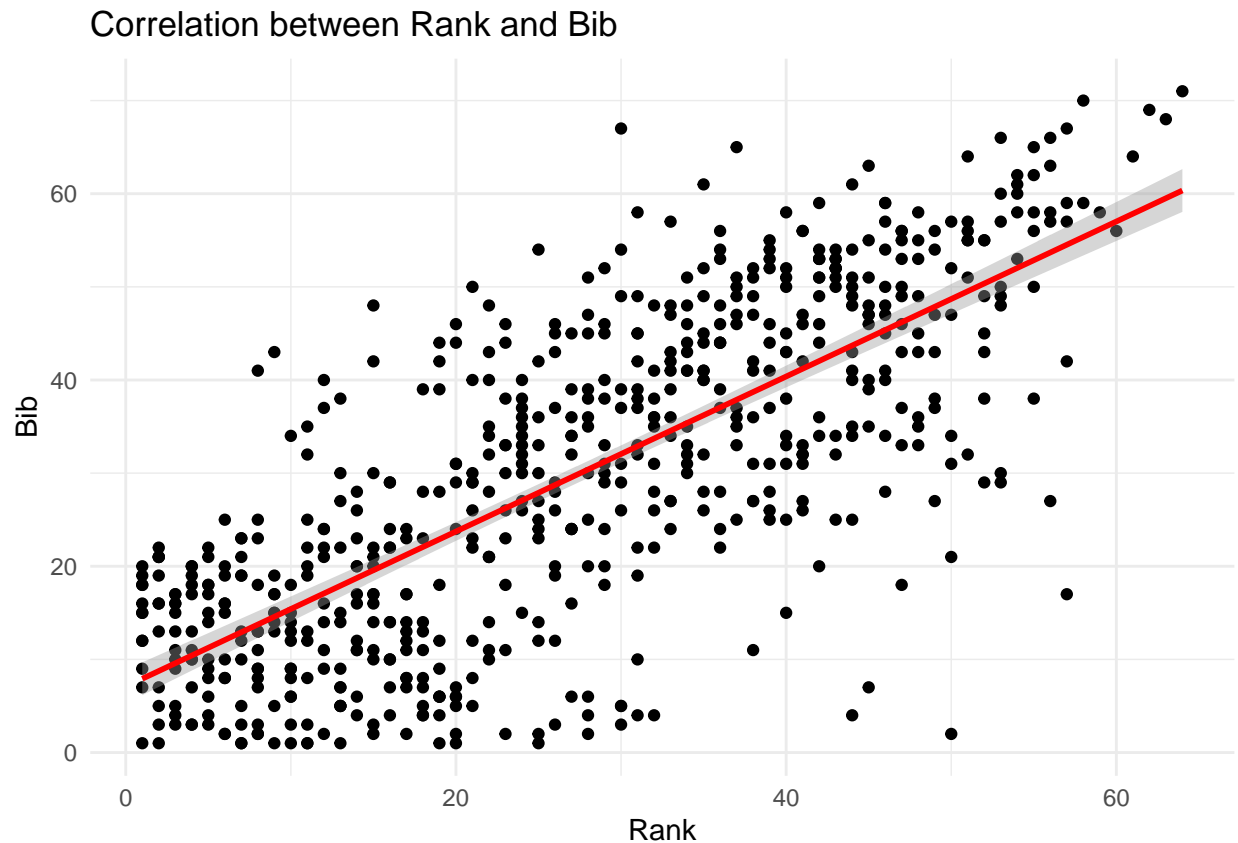
Data Analysis: Are there correlations between Rank and Bib?

```
cor(df$Rank, df$Bib)
```

```
## [1] 0.7484561
```

```
ggplot(df, aes(x=Rank, y=Bib))+
  geom_point()+
  stat_smooth(method = 'lm', col = 'red')+
  ylab("Bib")+
  xlab("Rank")+
  ggtitle('Correlation between Rank and Bib')+
  theme_minimal()
```

```
## 'geom_smooth()' using formula 'y ~ x'
```



```
lm.rank_1 <- lm(Rank ~ Bib, data = df)
summary(lm.rank_1)
```

```
##
## Call:
## lm(formula = Rank ~ Bib, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -27.170  -6.914  -0.576   6.751  41.433
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.22097    0.81897   8.817  <2e-16 ***
## Bib          0.67323    0.02367  28.439  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.51 on 635 degrees of freedom
## Multiple R-squared:  0.5602, Adjusted R-squared:  0.5595
## F-statistic: 808.8 on 1 and 635 DF,  p-value: < 2.2e-16
```

Data Analysis: Are there correlations between Rank and Number of Participations?

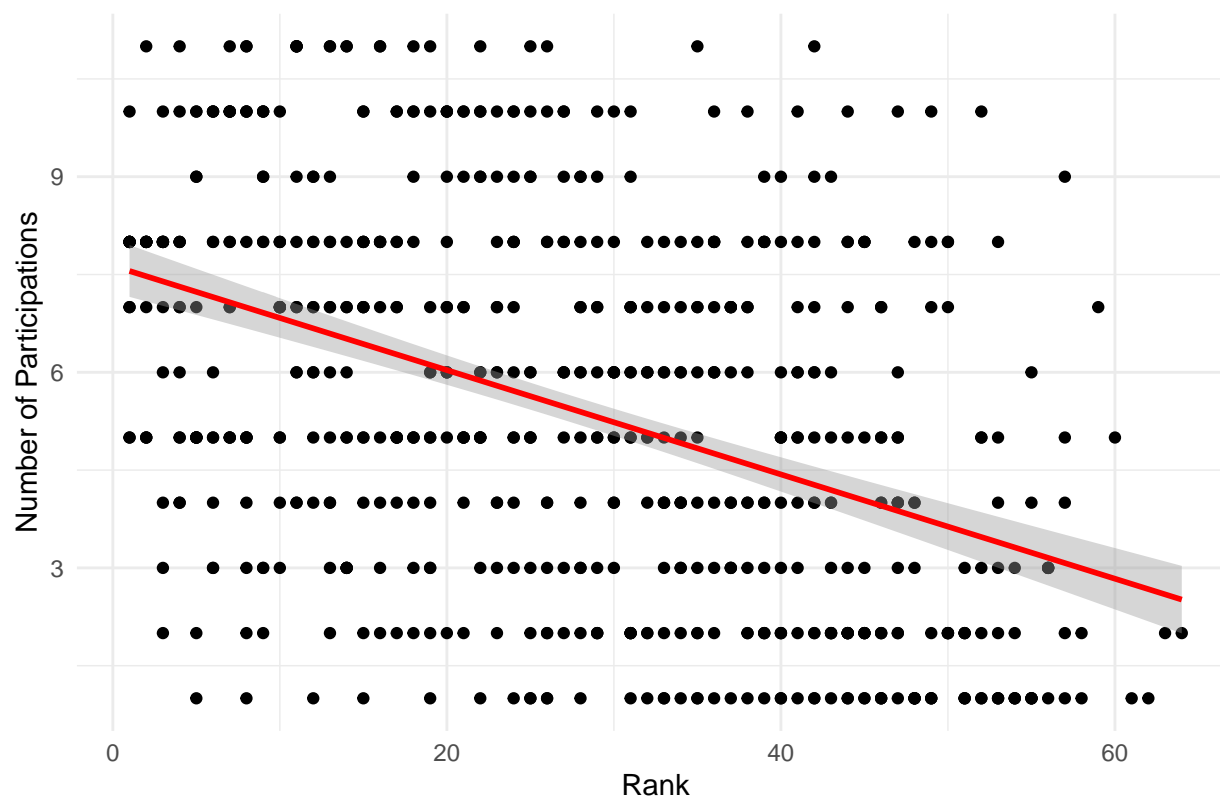
```
cor(df$Rank, df$Number_of_participations)
```

```
## [1] -0.4339373
```

```
ggplot(df, aes(x=Rank, y=Number_of_participations))+
  geom_point()+
  stat_smooth(method = 'lm', col = 'red')+
  ylab("Number of Participations")+
  xlab("Rank")+
  ggtitle('Correlation between Rank and Bib')+
  theme_minimal()
```

```
## 'geom_smooth()' using formula 'y ~ x'
```

Correlation between Rank and Bib



```
lm.rank_2 <- lm(Rank ~ Number_of_participations, data = df)
summary(lm.rank_2)
```

```
##
## Call:
## lm(formula = Rank ~ Number_of_participations, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -32.752 -11.045   0.955  10.602  38.077
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    40.1058     1.1993   33.44  <2e-16 ***
## Number_of_participations -2.3537     0.1939  -12.14  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.28 on 635 degrees of freedom
## Multiple R-squared:  0.1883, Adjusted R-squared:  0.187
## F-statistic: 147.3 on 1 and 635 DF, p-value: < 2.2e-16
```

Comparison of models: Which one is better?

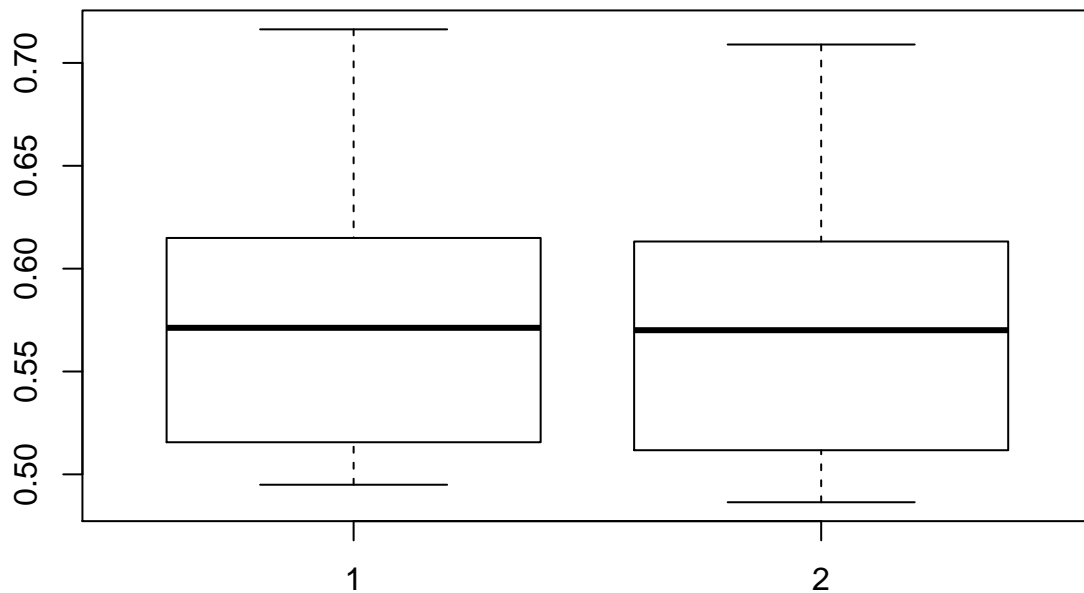
A 10n fold cross validation is applied and the R-squareds are compared.

```
r.squared.simple <- c()
r.squared.few <- c()
set.seed(12)
for(i in 1:10){
  ## 1) prepare data
  smp_size <- floor(0.9*nrow(df))
  train <- sample(seq_len(nrow(df)), size = smp_size)
  df_train <- df[train,]
  df_test <- df[-train,]

  ## model 1
  ## 2) fit the model with "train" data
  lm.all <- lm(Rank ~ Bib + Number_of_participations, data = df)
  ##
  ## 3) make prediction on the test data
  predicted_lm_all <- predict(lm.all,
                             newdata = df_test)
  ##
  ## 4) compute  $R^2$ 
  r.squared.simple[i] <- cor(predicted_lm_all,
                             df_test$Rank)^2

  ## model 2
  ## 2) fit the model with "train" data
  lm.few <- lm(Rank ~ Bib, data = df_train)
  ##
  ## 3) make prediction on the test data
  predicted_lm_few <- predict(lm.few,
                              newdata = df_test)
  ##
  ## 4) compute  $R^2$ 
  r.squared.few[i] <- cor(predicted_lm_few,
                           df_test$Rank)^2
}

mean_rsquared_lm_all <- mean(r.squared.simple)
mean_rsquared_lm_few <- mean(r.squared.few)
boxplot(r.squared.simple, r.squared.few)
```



```
print(mean_rsquared_lm_all)
```

```
## [1] 0.5770742
```

```
print(mean_rsquared_lm_few)
```

```
## [1] 0.5724064
```

The r-squared seem to do not differ significantly.

Own Chapter

Application of gganimate, gifski, and av.

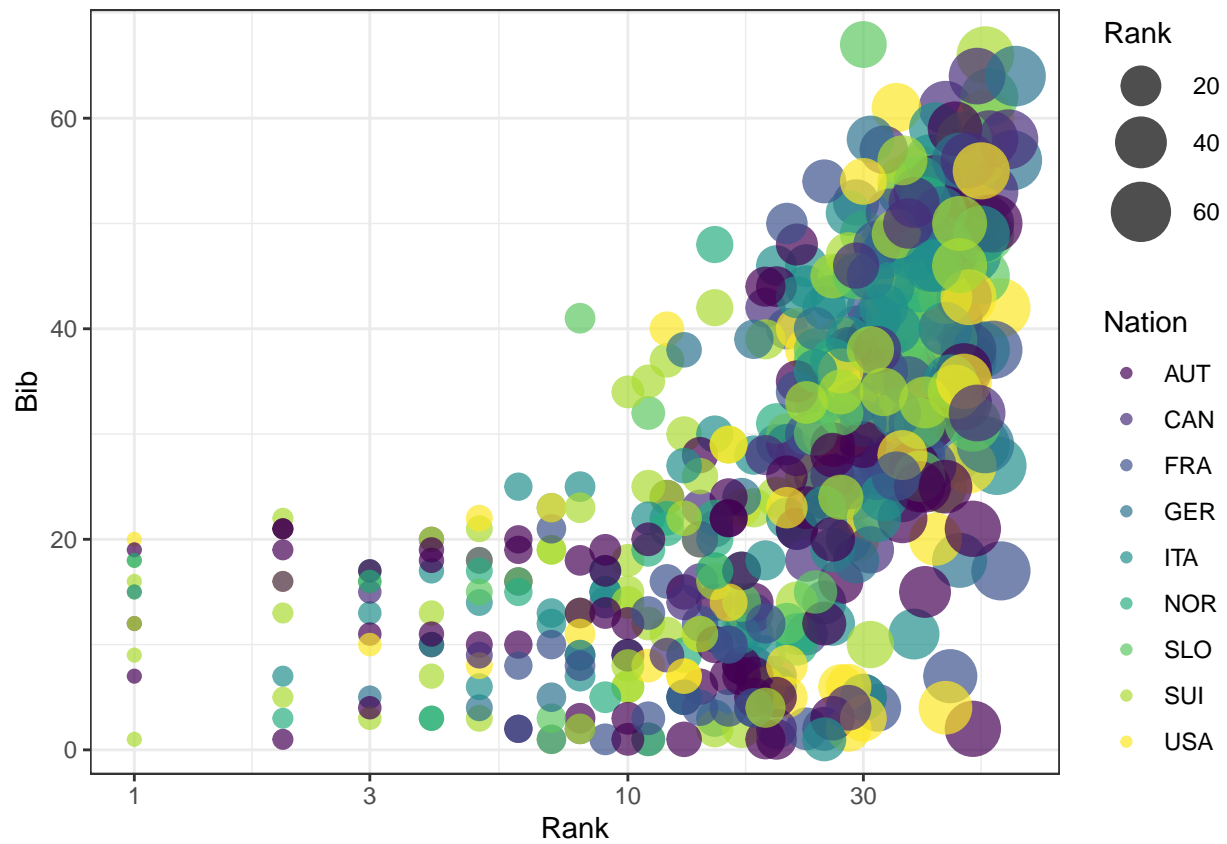
```
theme_set(theme_bw())
```

```
country <- c("SUI" = "red", "USA" = "blue", "ITA" = "green", "NOR" = "grey", "SLO" = "yellow", "LIE" = "black",  
             "CAN" = "black", "AUT" = "pink", "SWE" = "beige", "FRA" = "brown", "GER" = "cyan" )
```

```
p <- ggplot(  
  nations,  
  aes(x = Rank , y=Bib, size = Rank , colour = Nation)  
) +
```

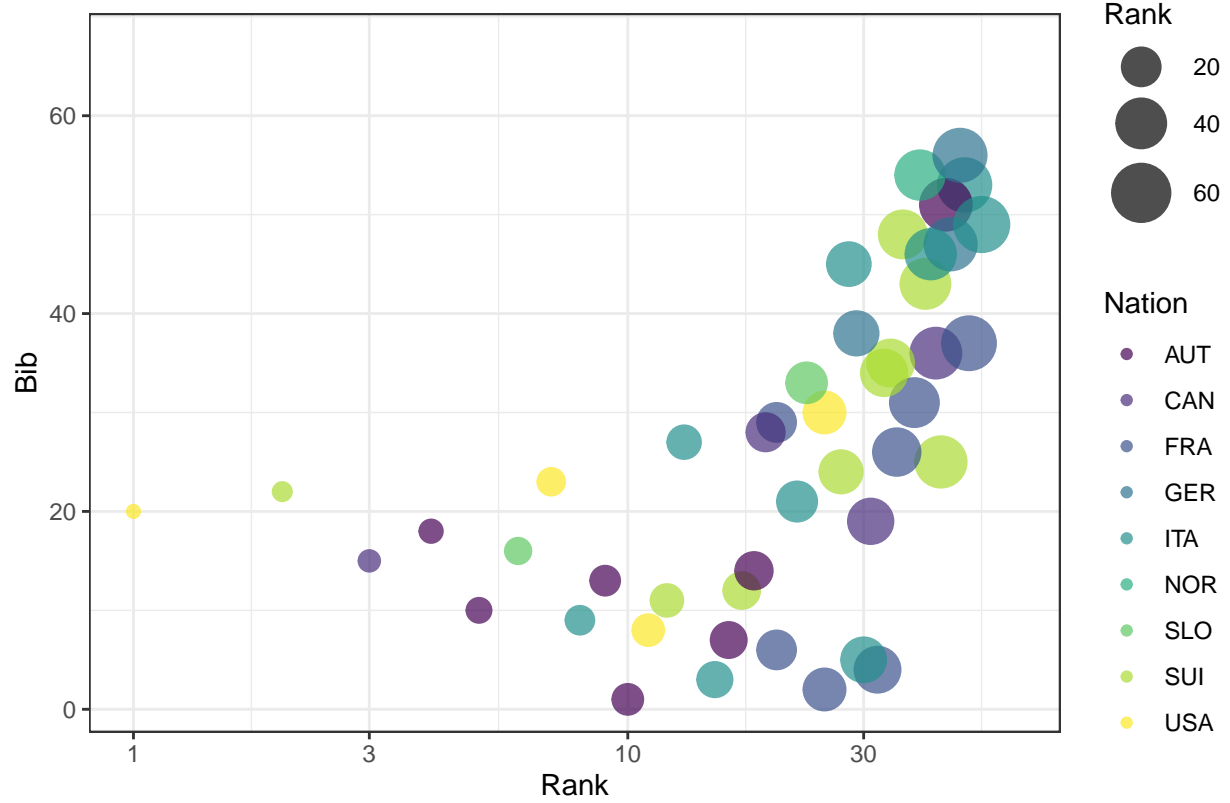
```
geom_point(show.legend = TRUE, alpha = 0.7) +
scale_color_viridis_d() +
scale_size(range = c(2, 10)) +
scale_x_log10() +
labs(x = "Rank", y = "Bib")
```

p

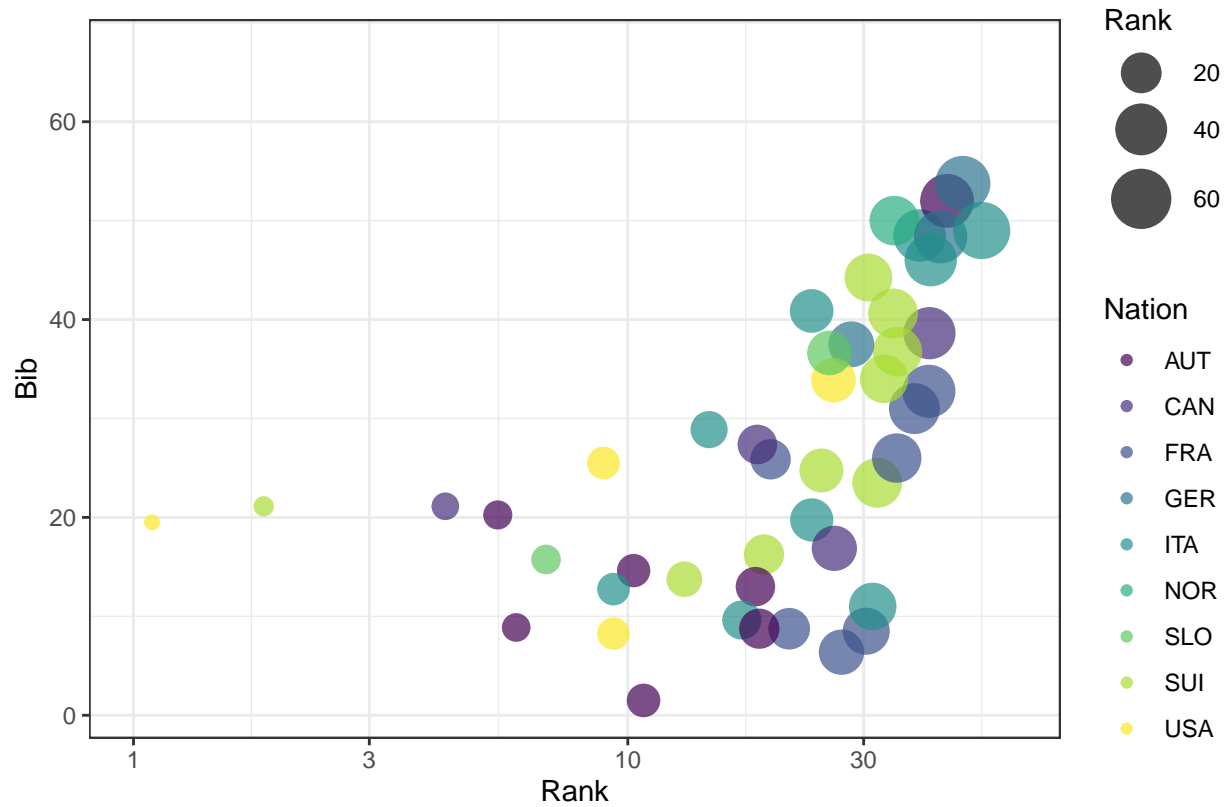


```
p + transition_time(Race_year) +
labs(title = "Year: {frame_time}")
```

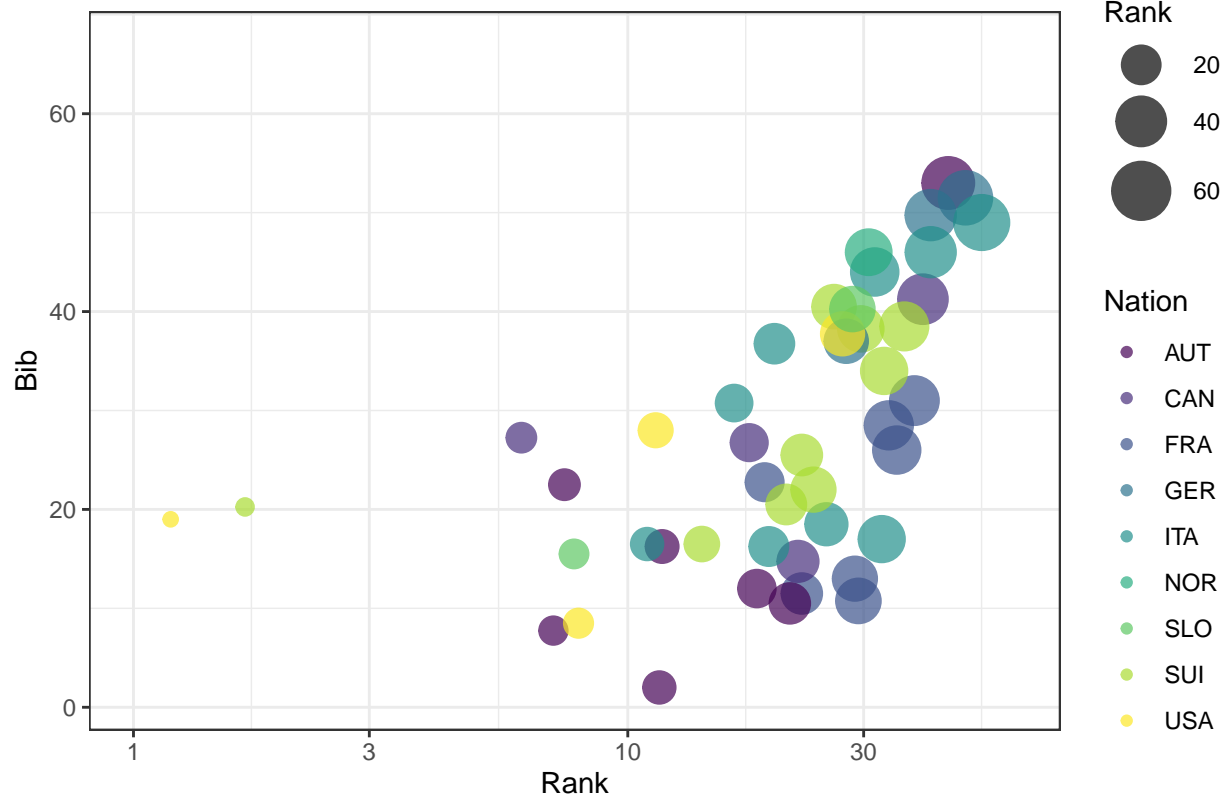

Year: 2008



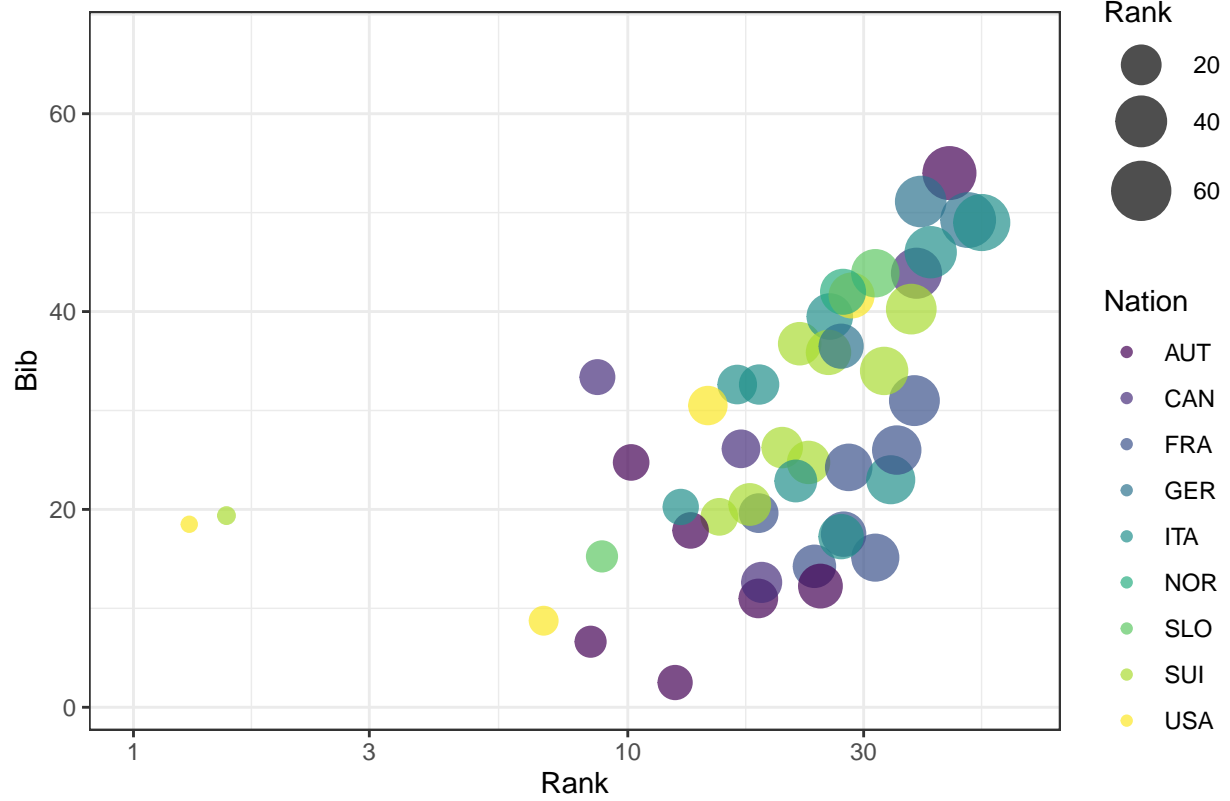
Year: 2008.12121212121



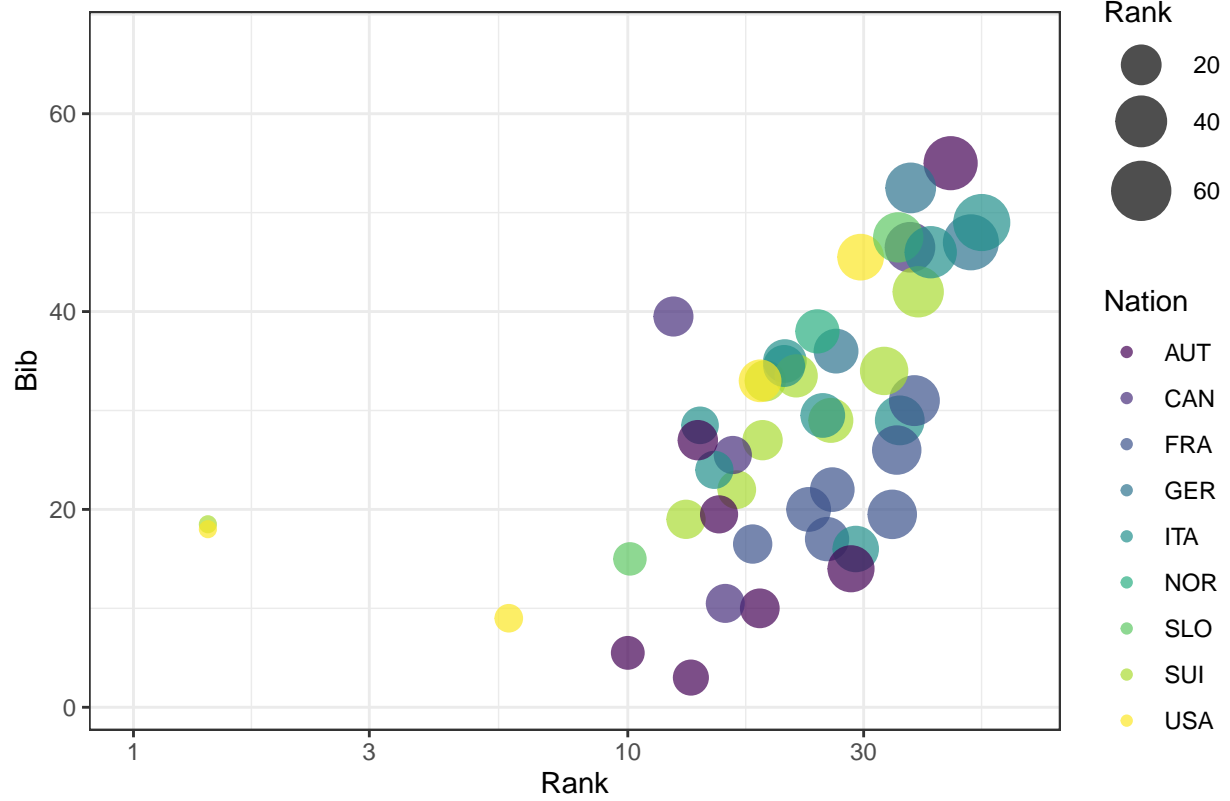
Year: 2008.24242424242



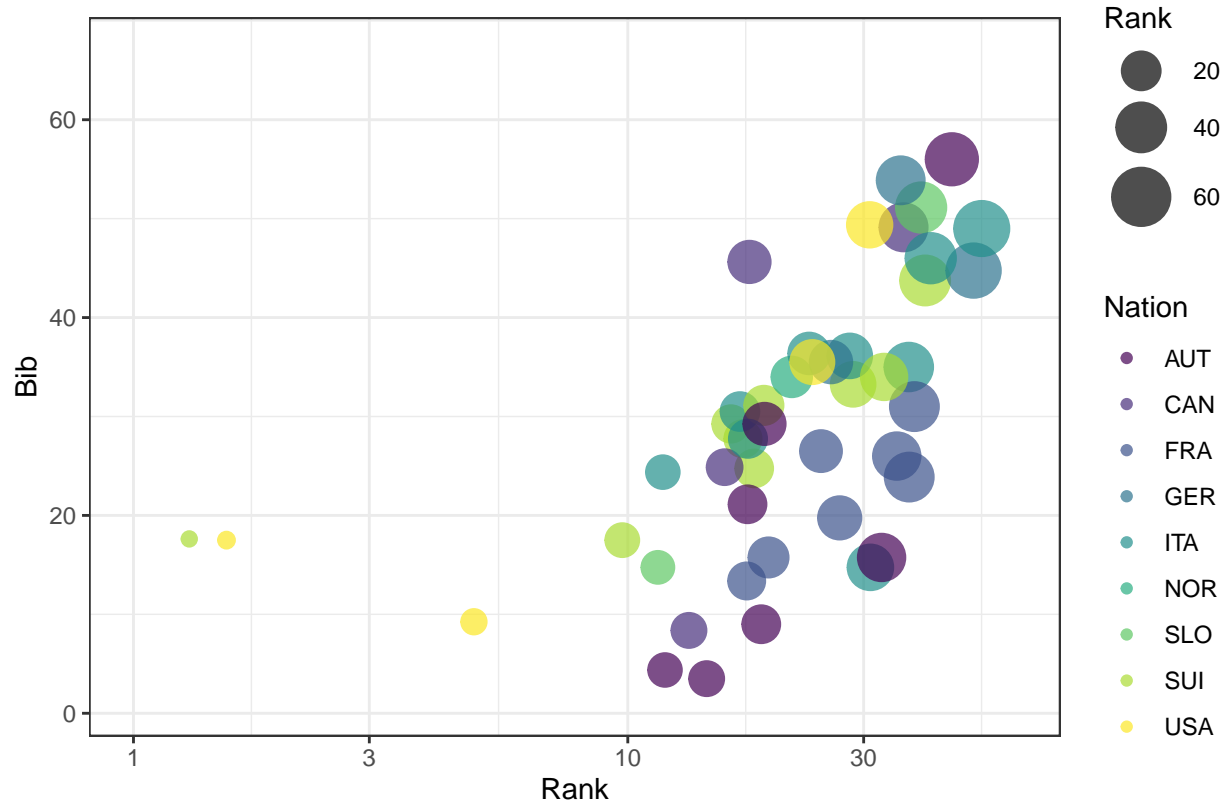
Year: 2008.36363636364



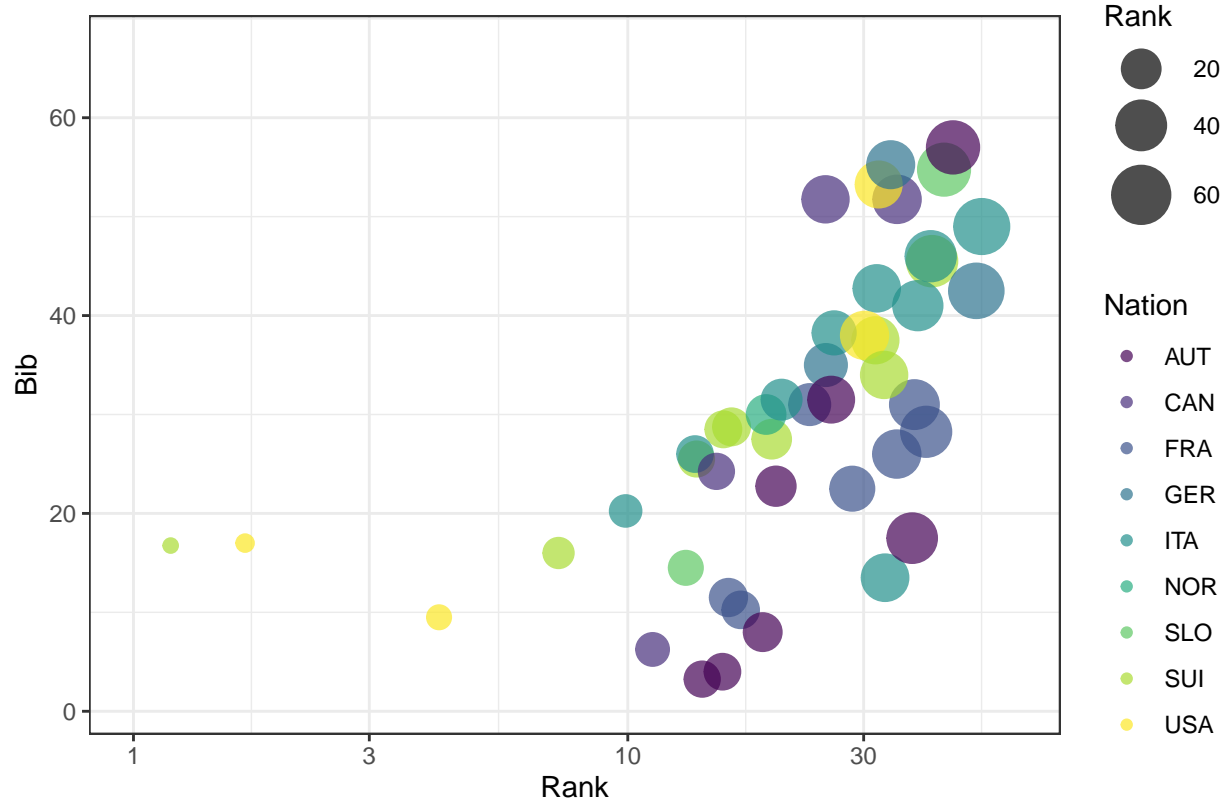
Year: 2008.48484848485



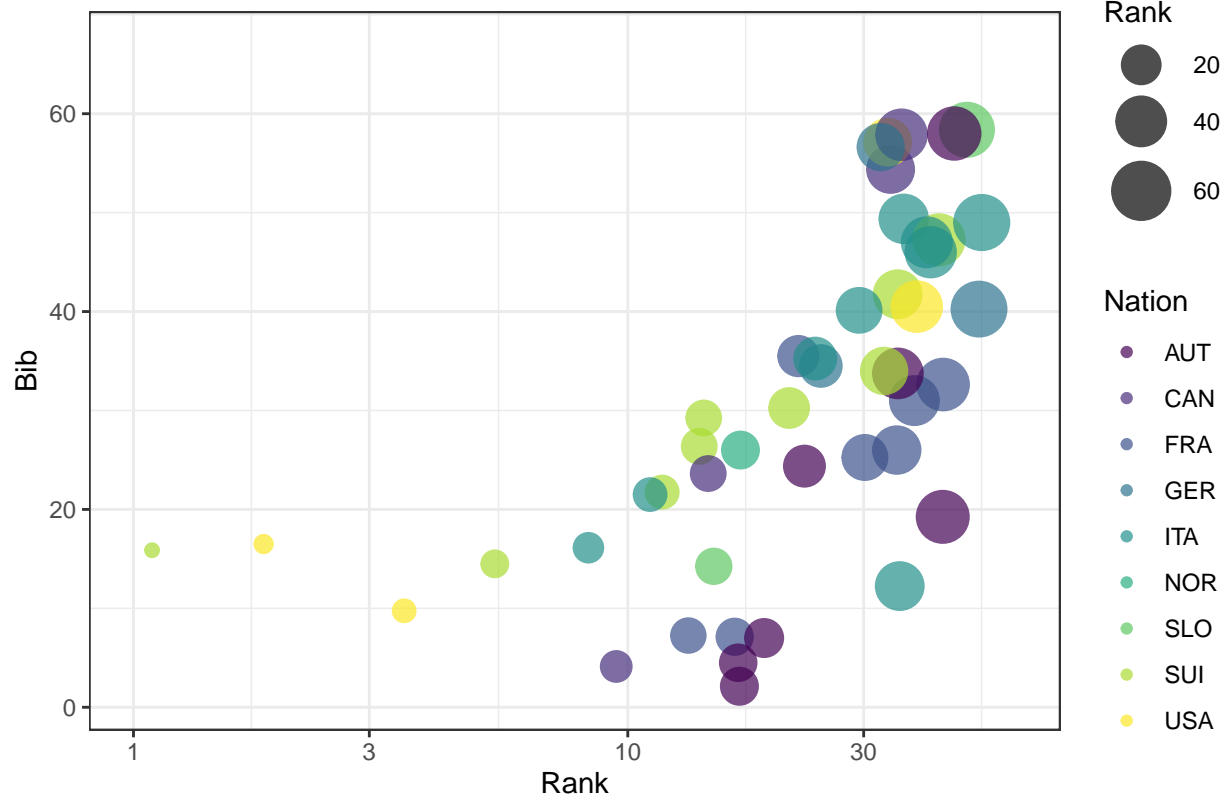
Year: 2008.60606060606



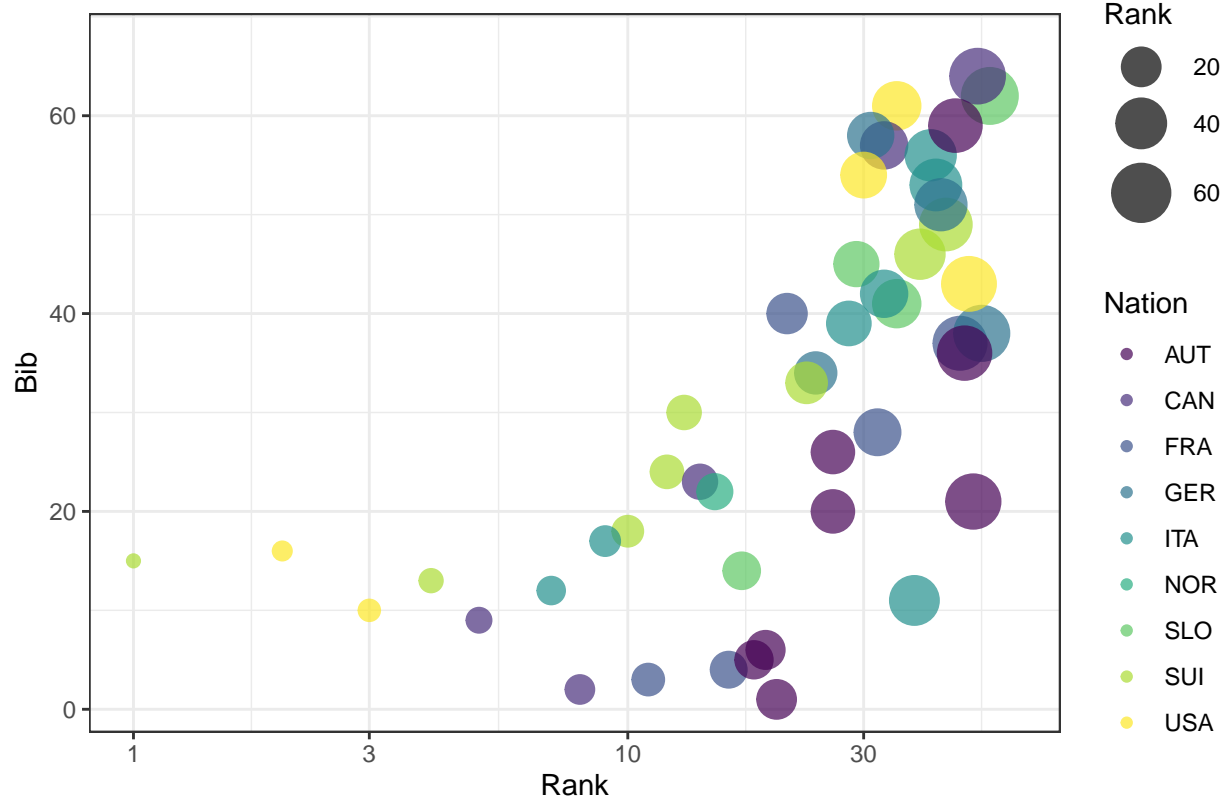
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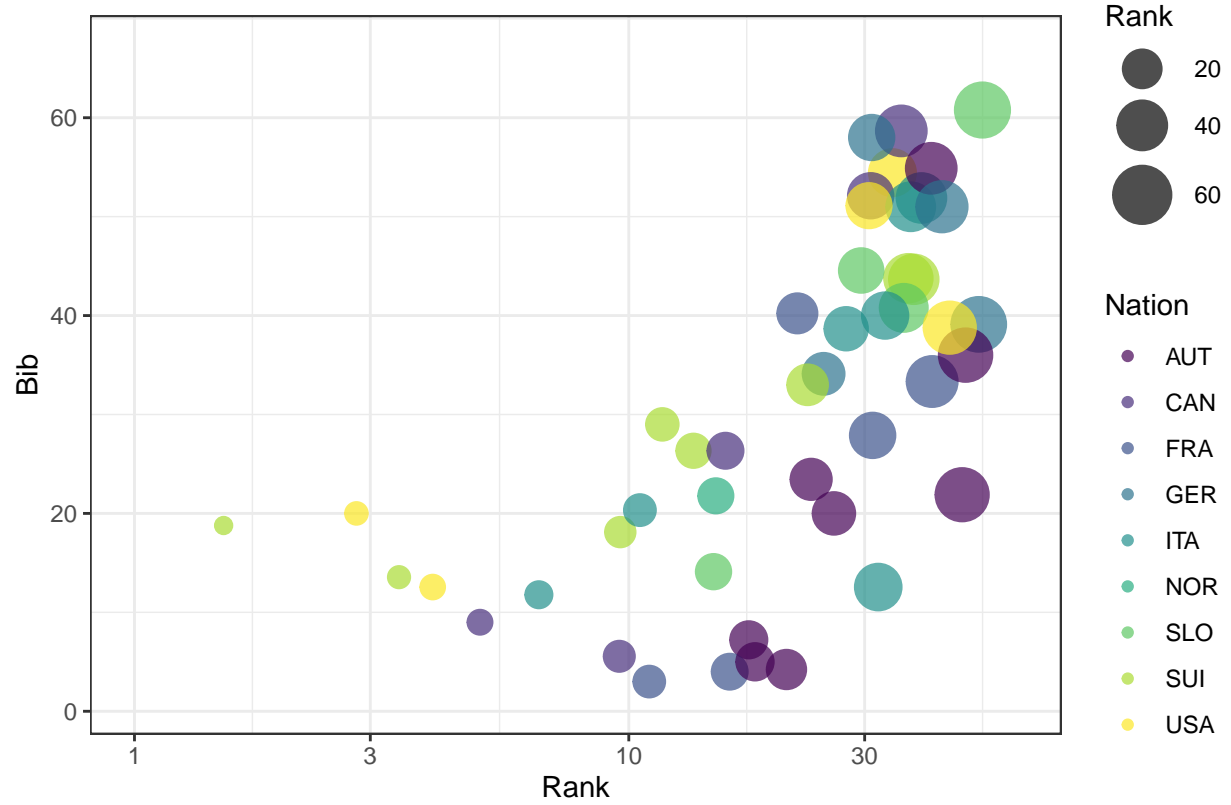
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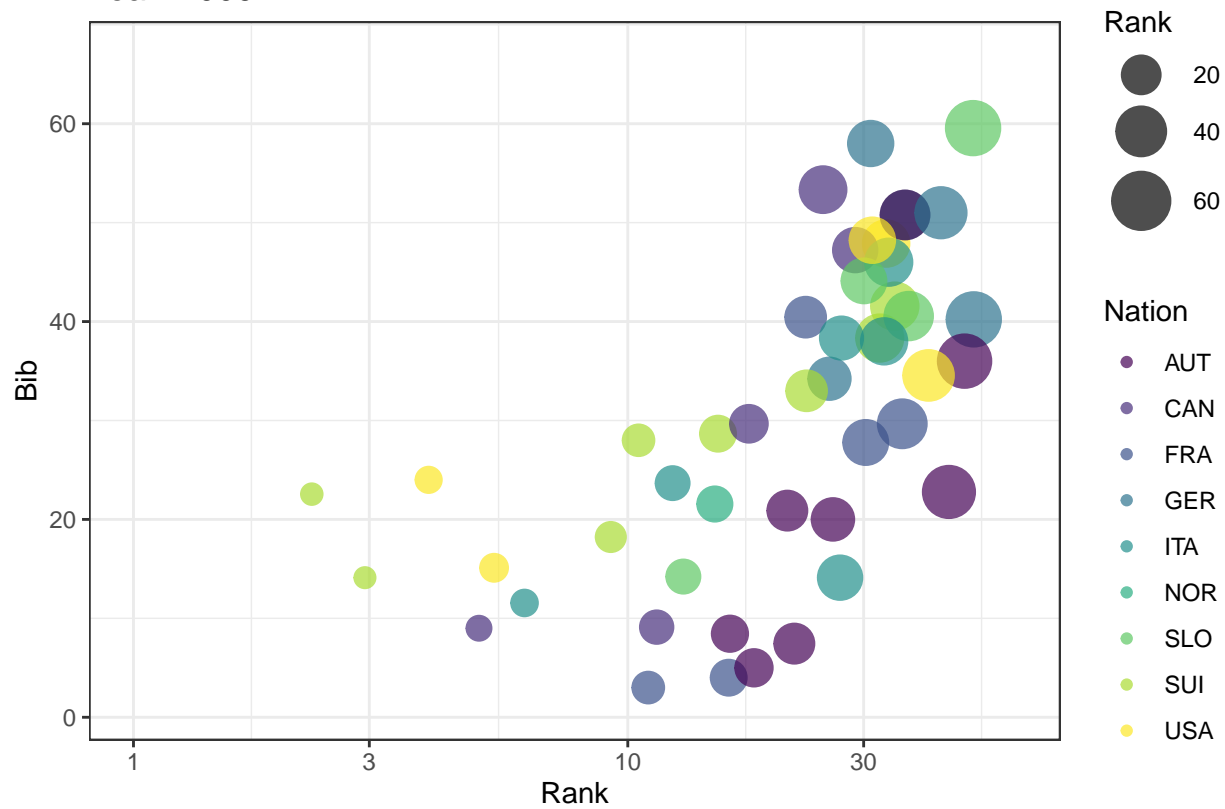
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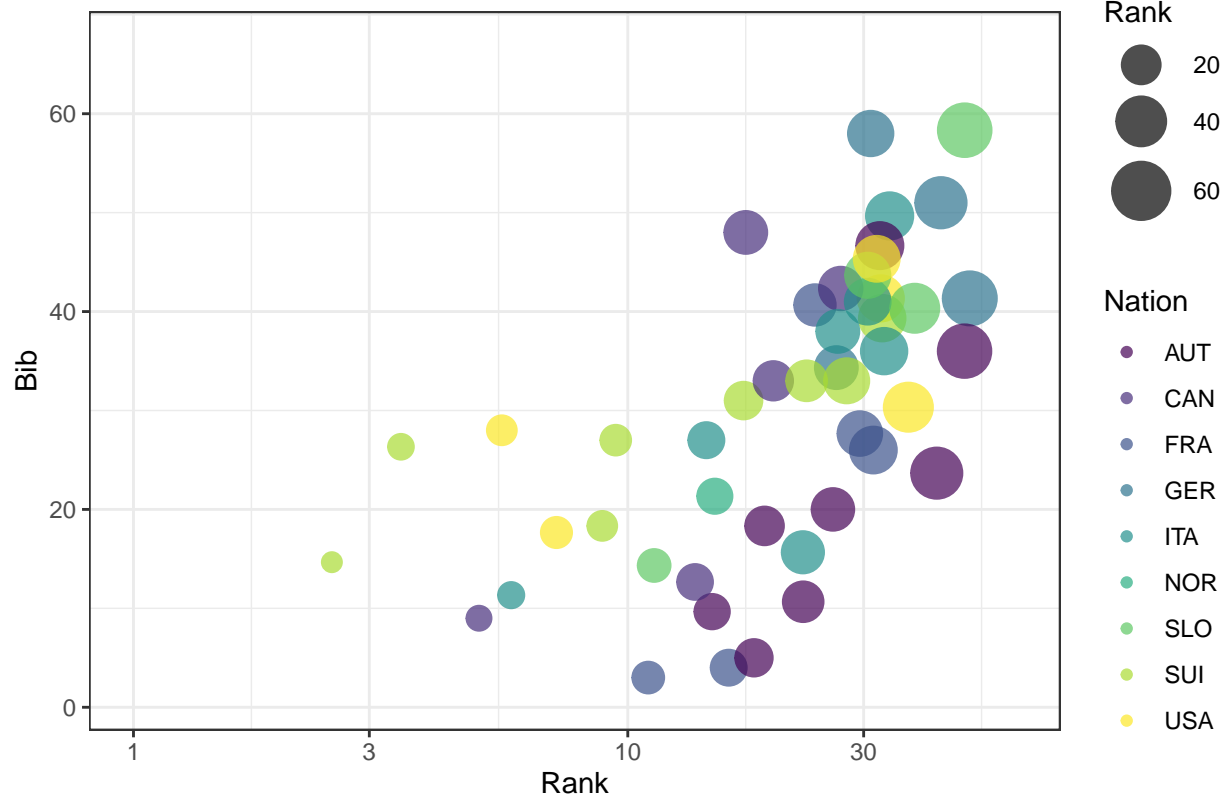
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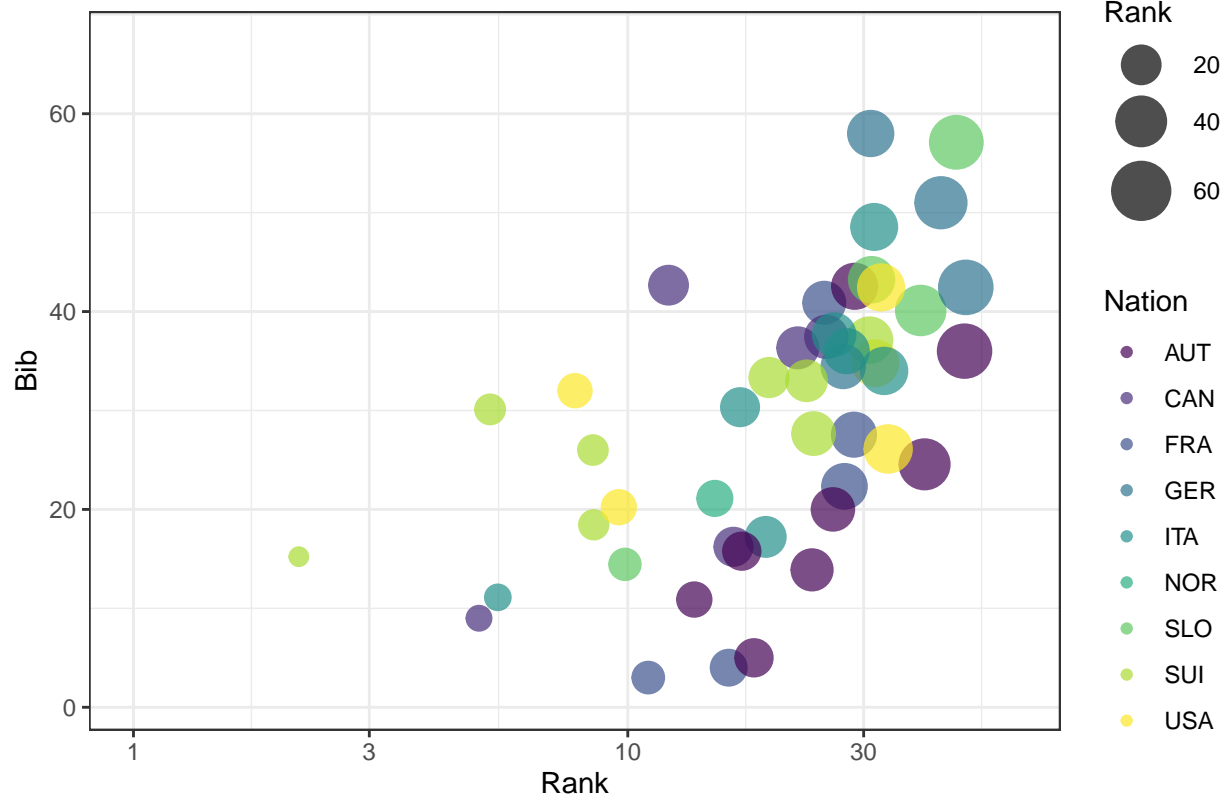
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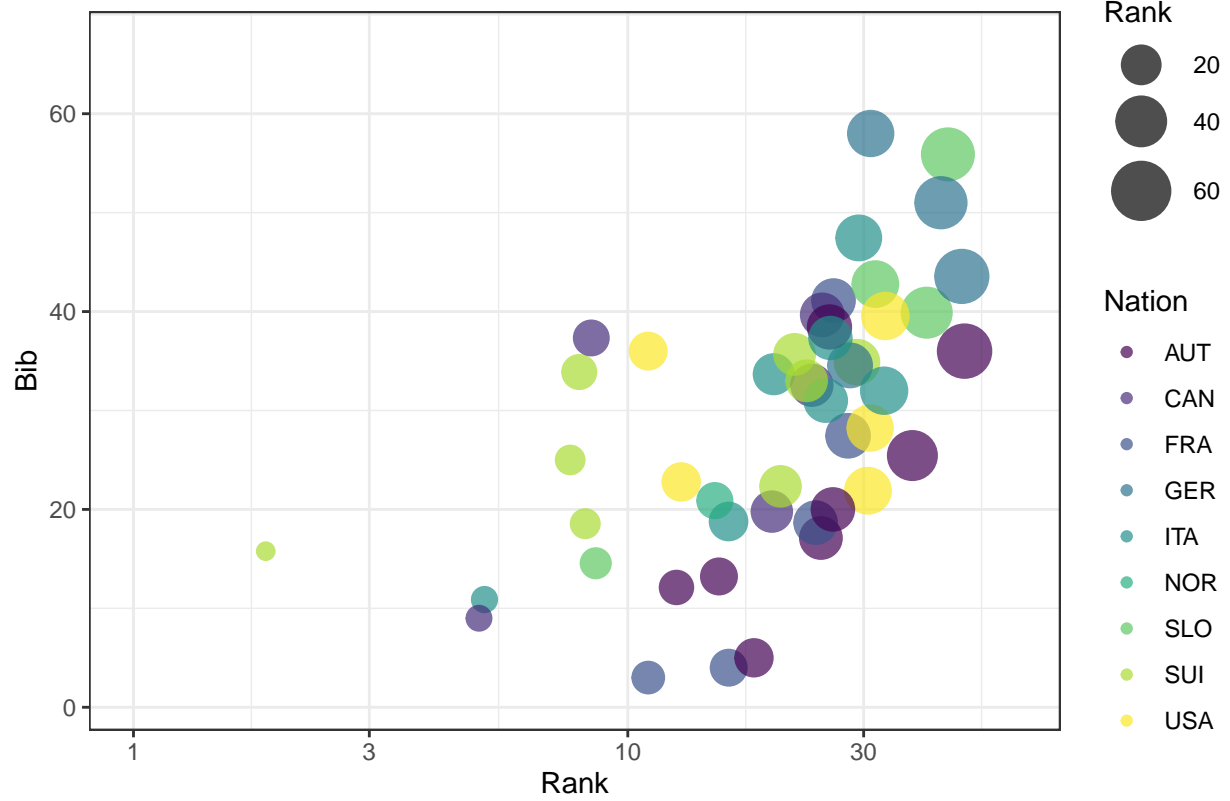
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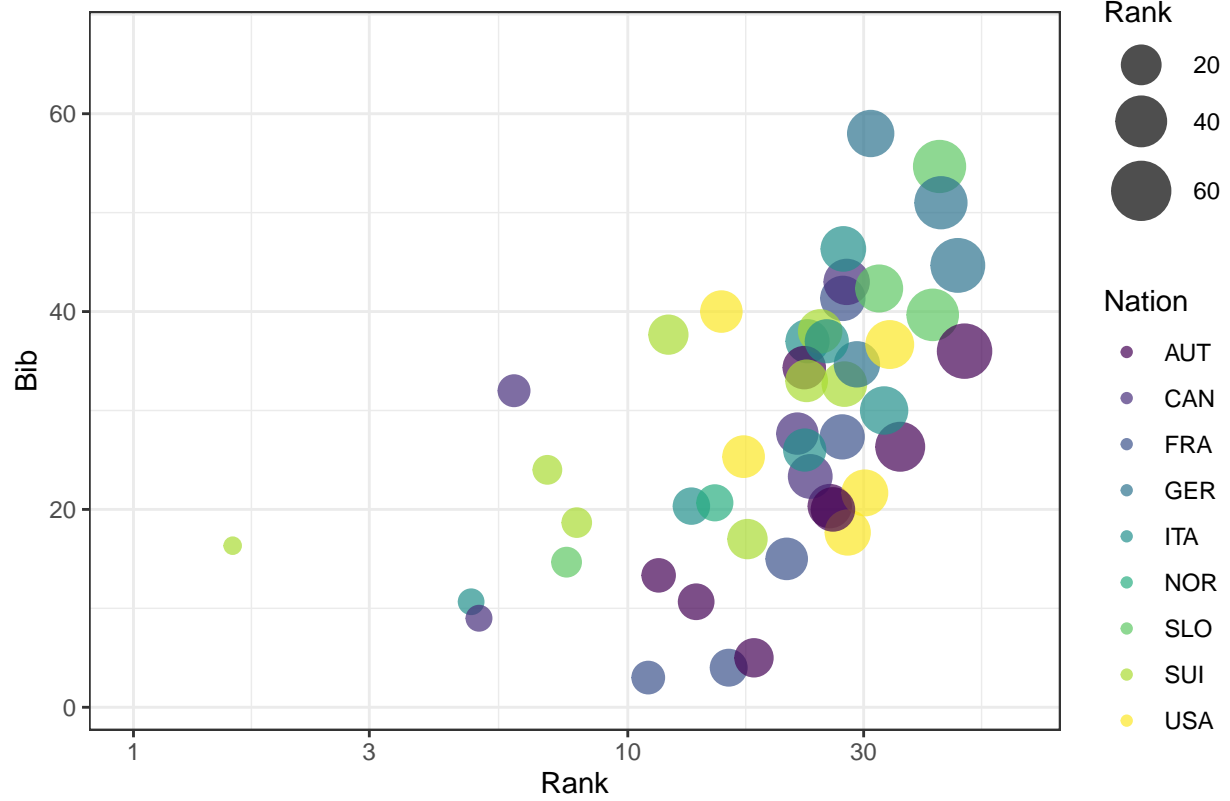
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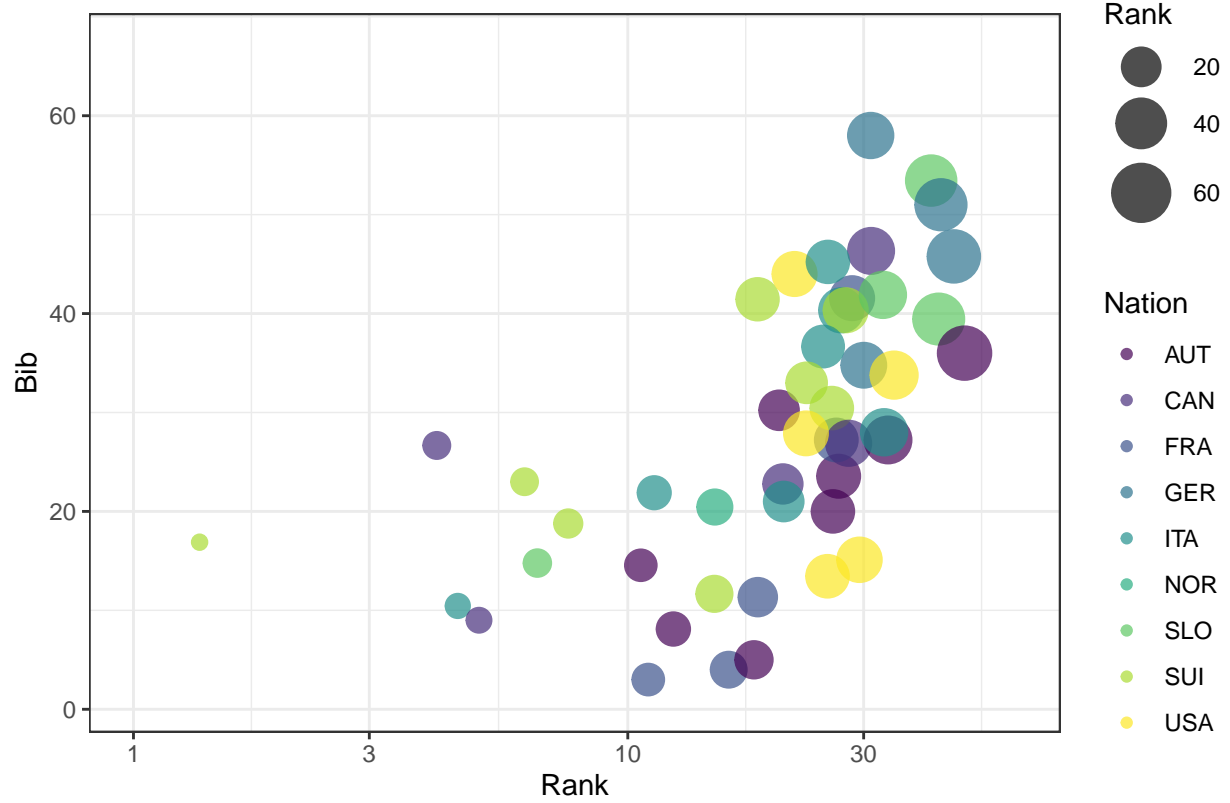
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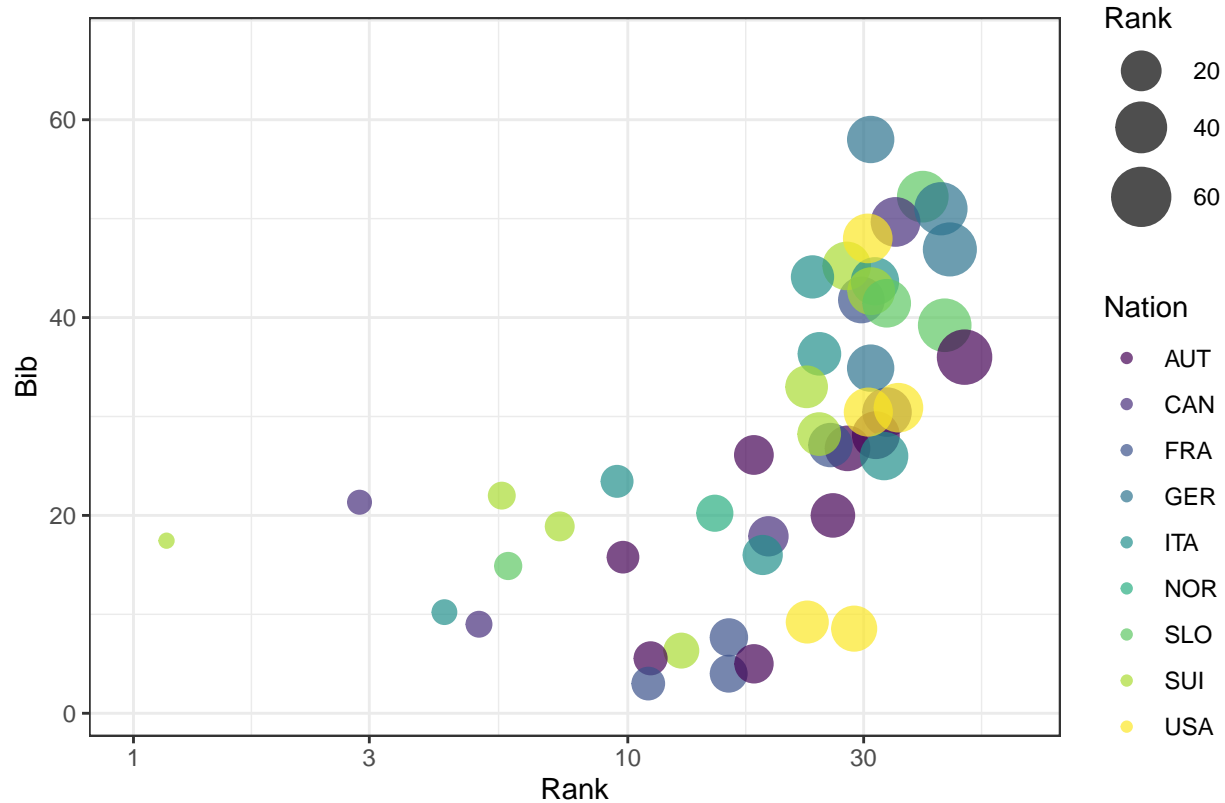
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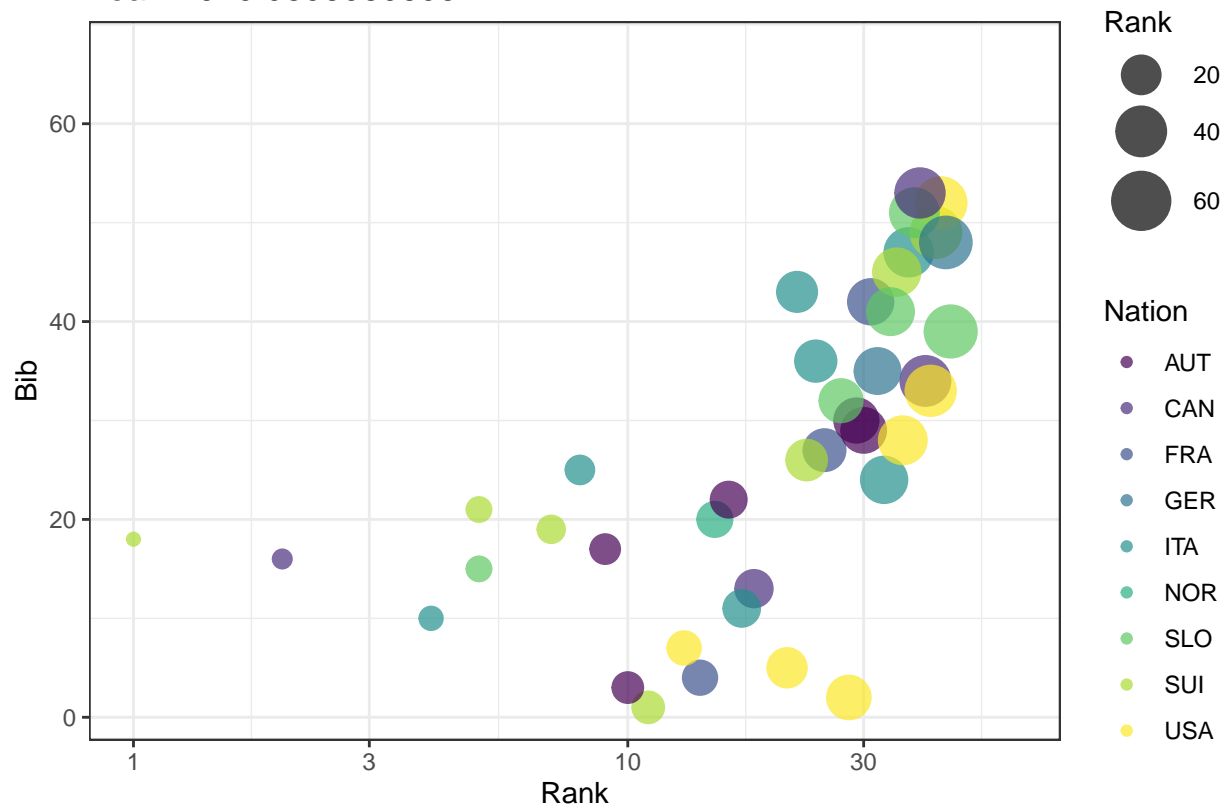
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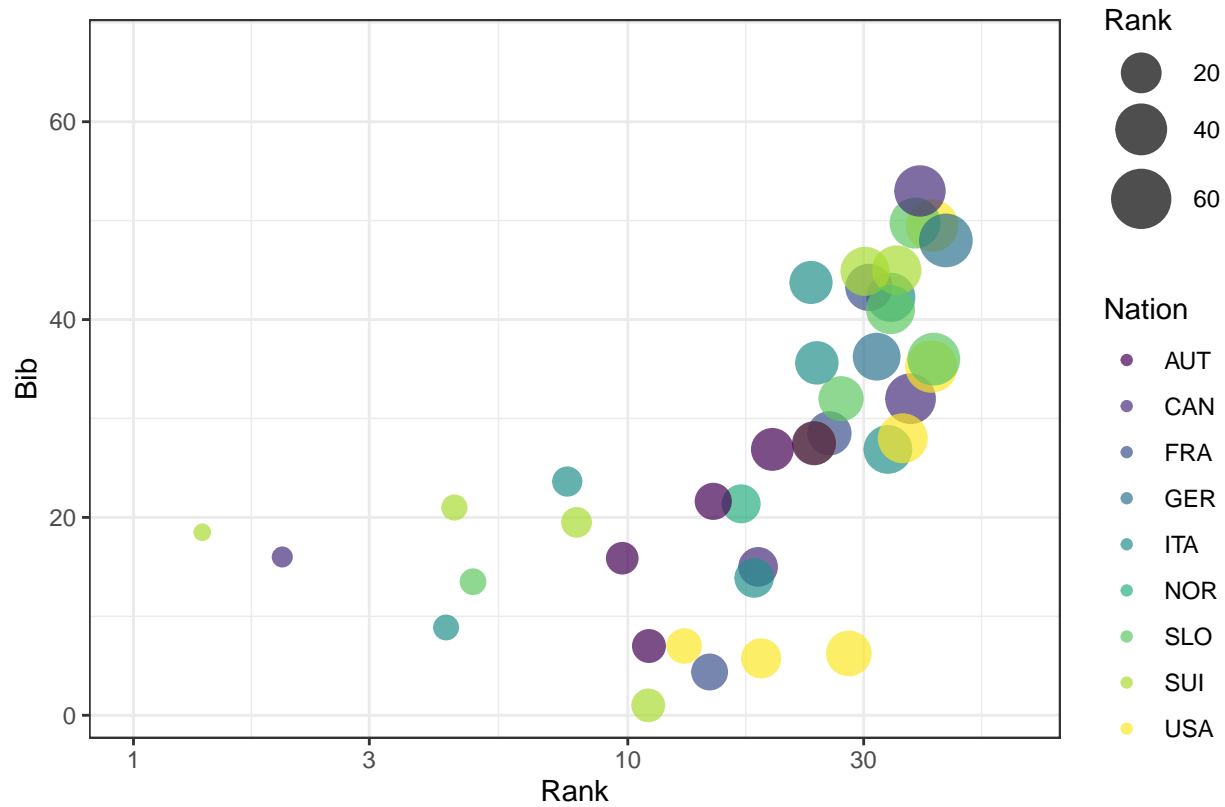
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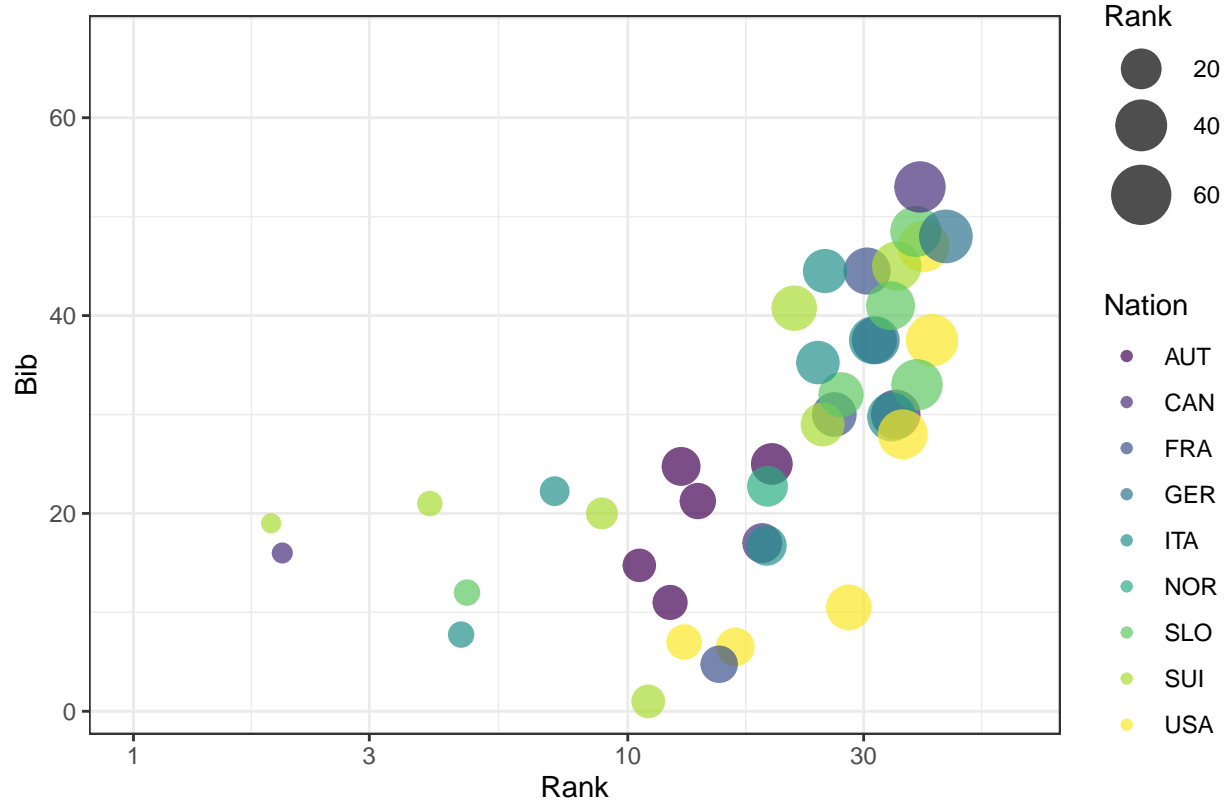
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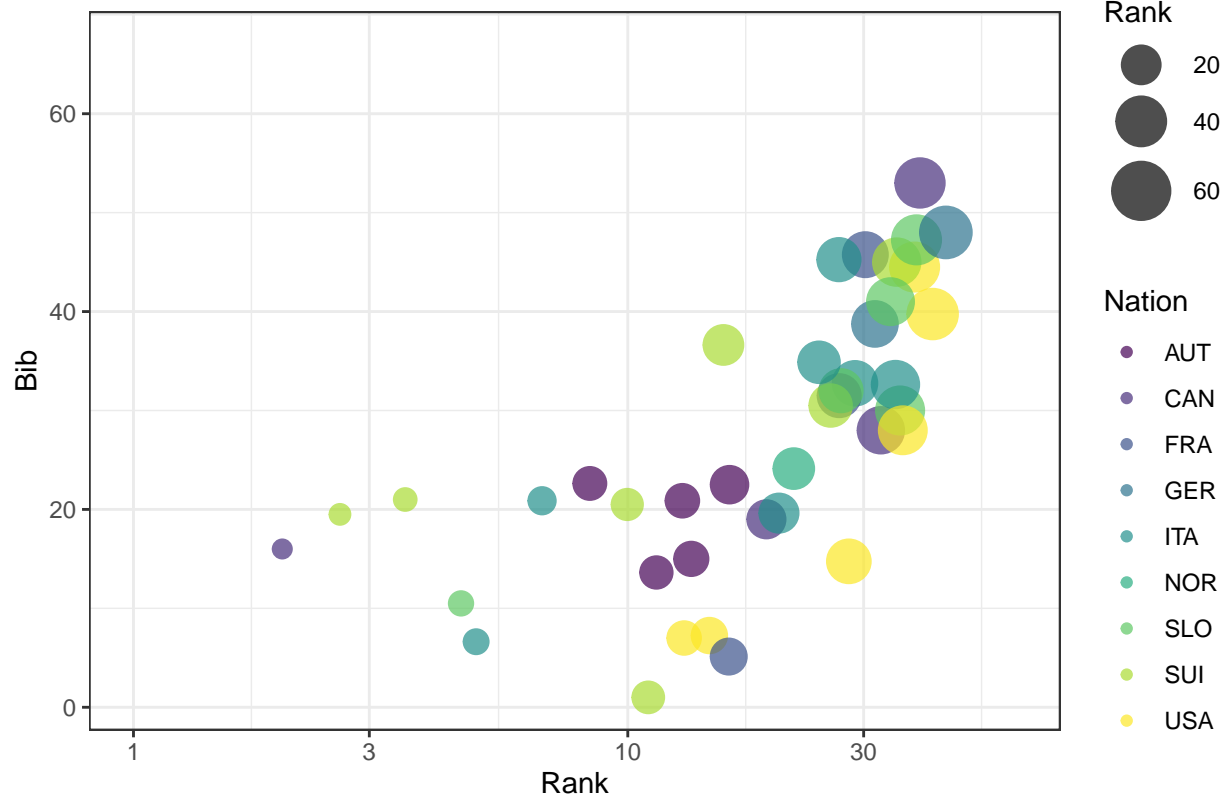
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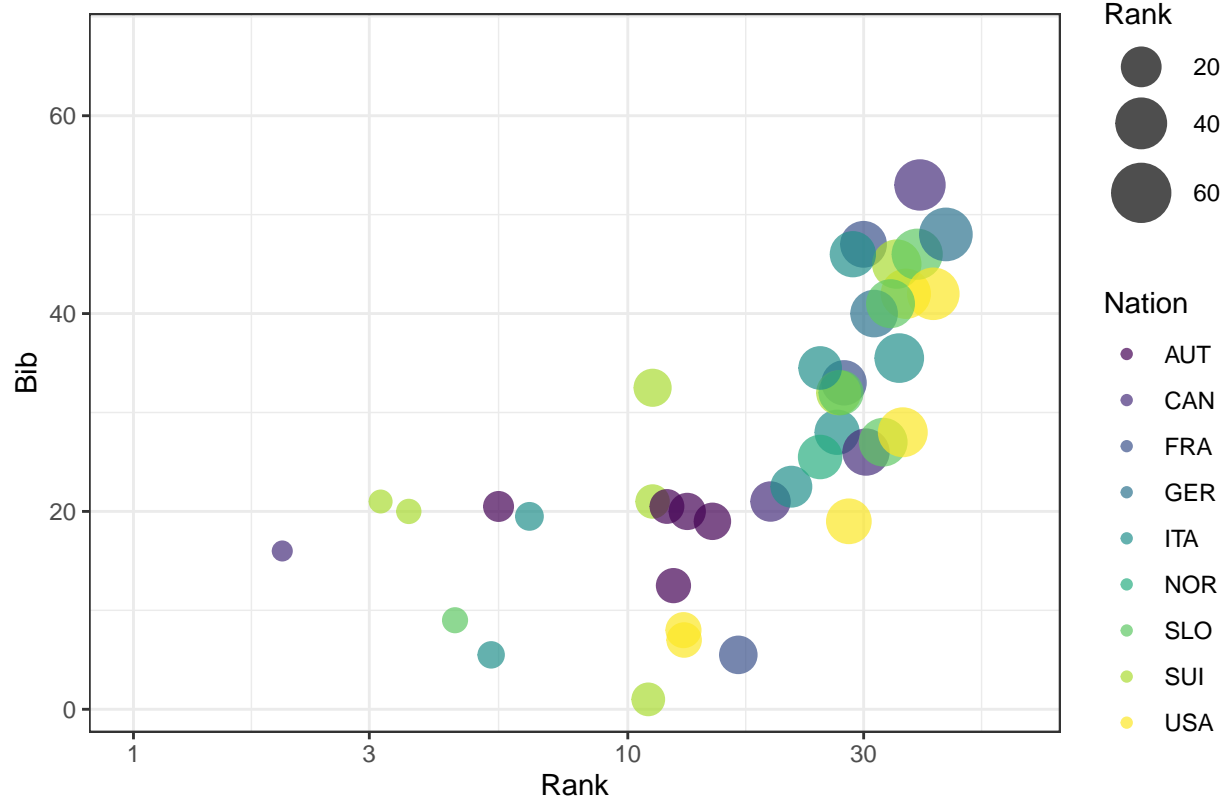
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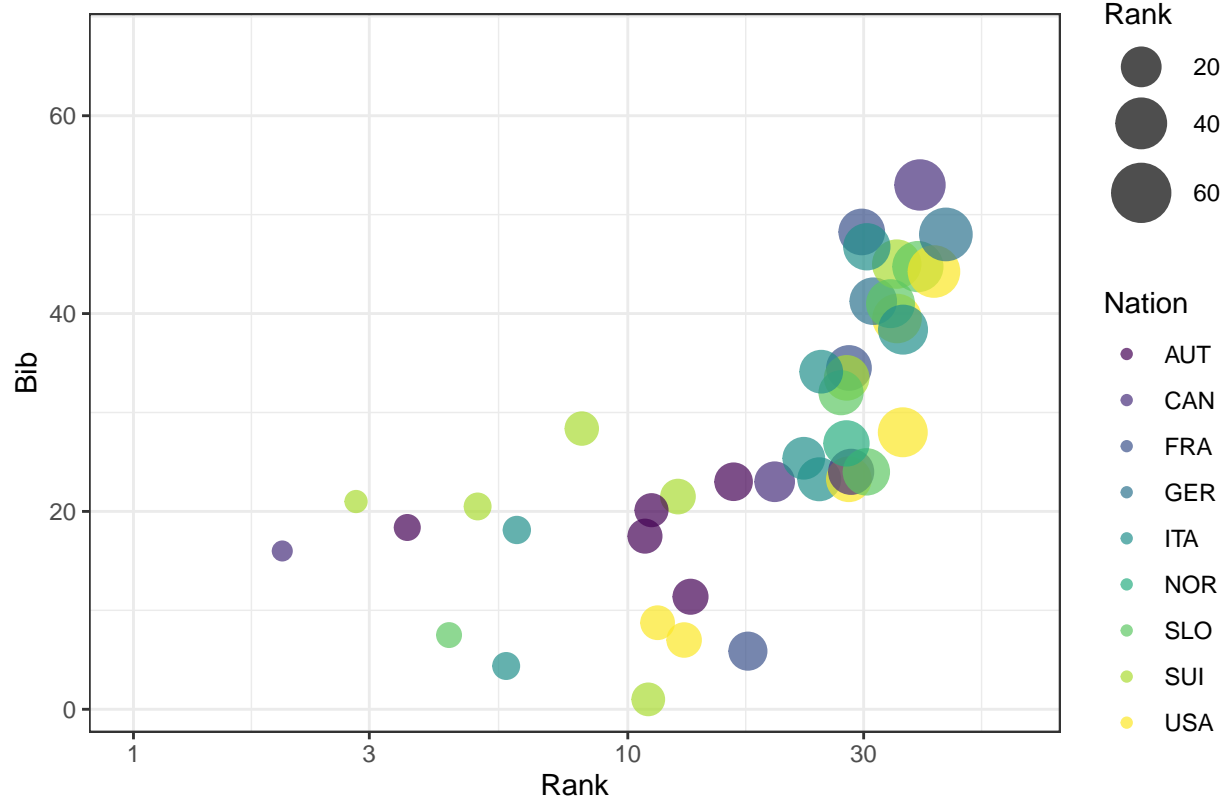
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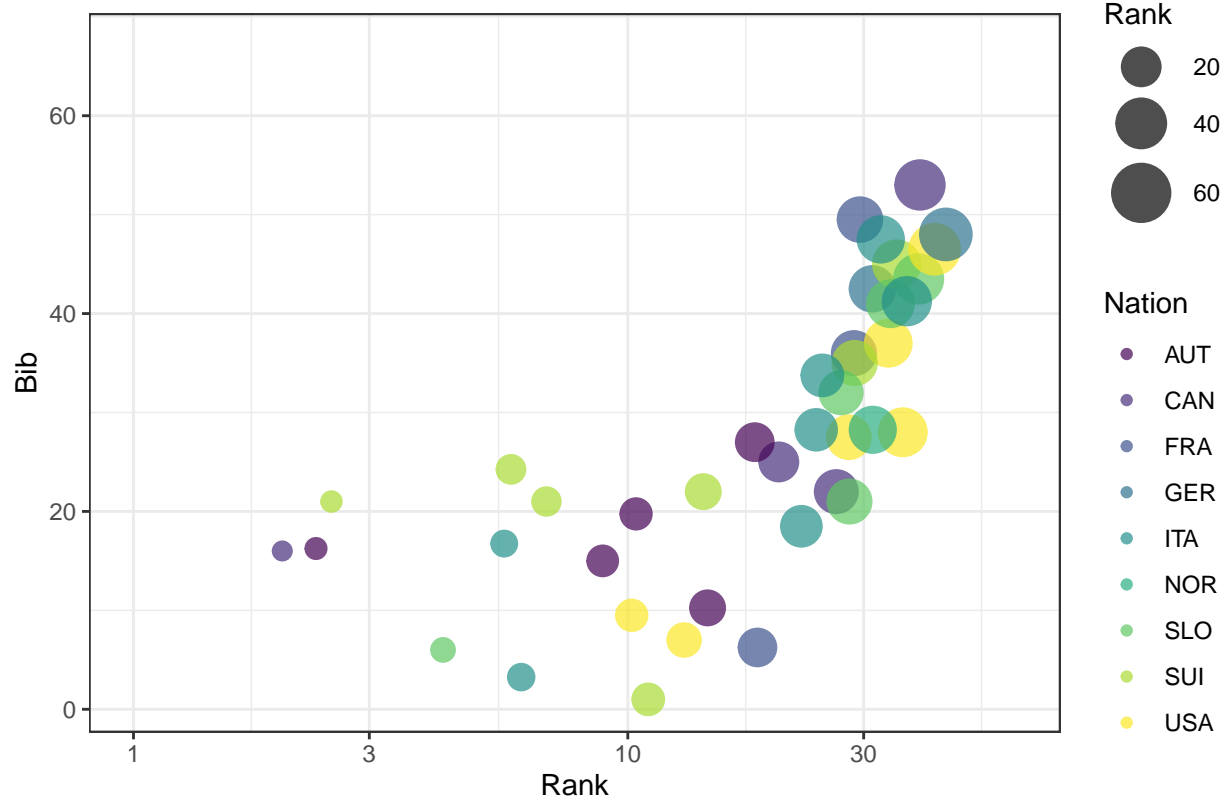
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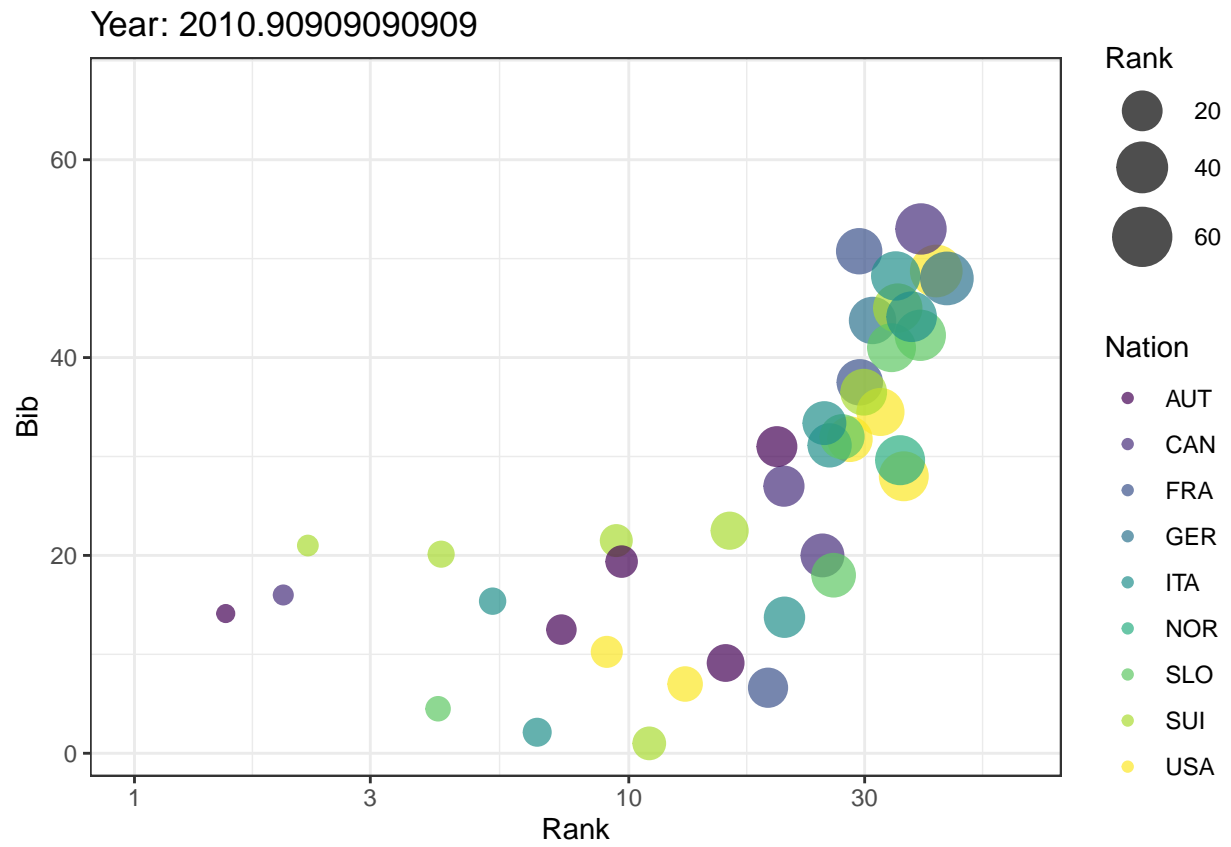


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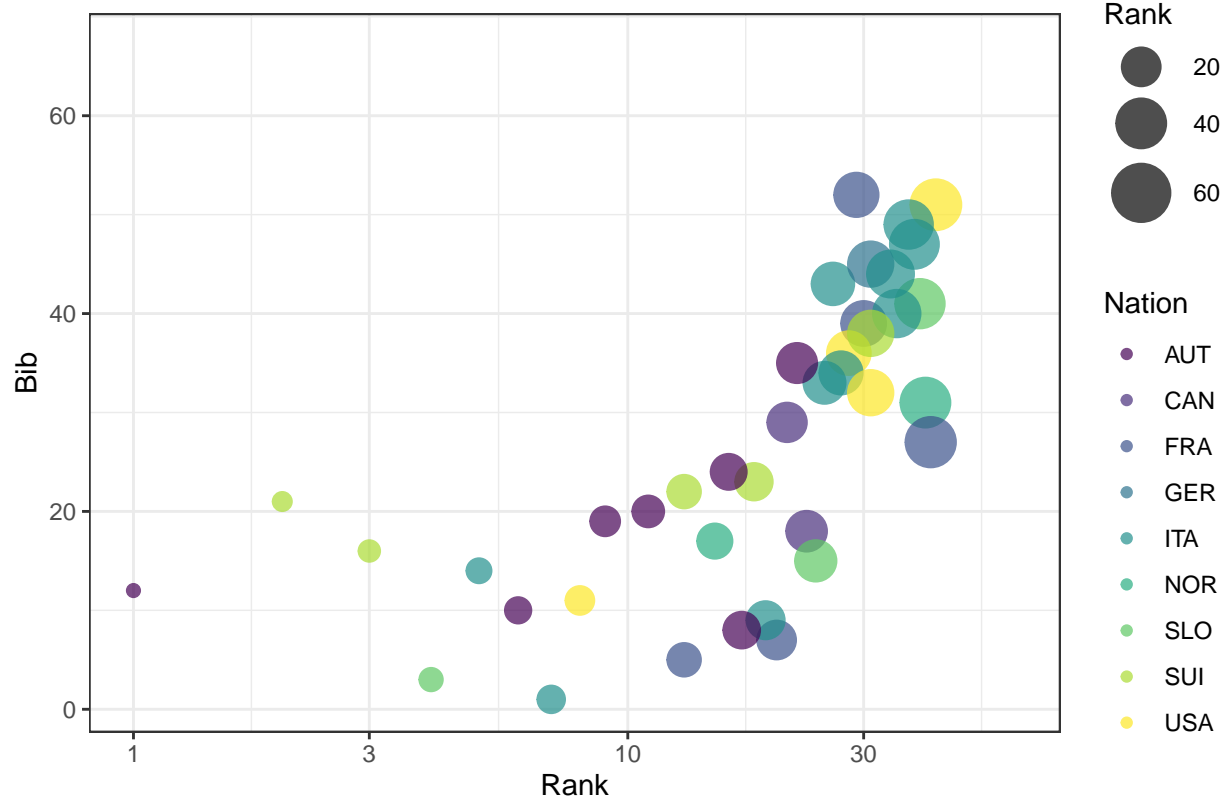


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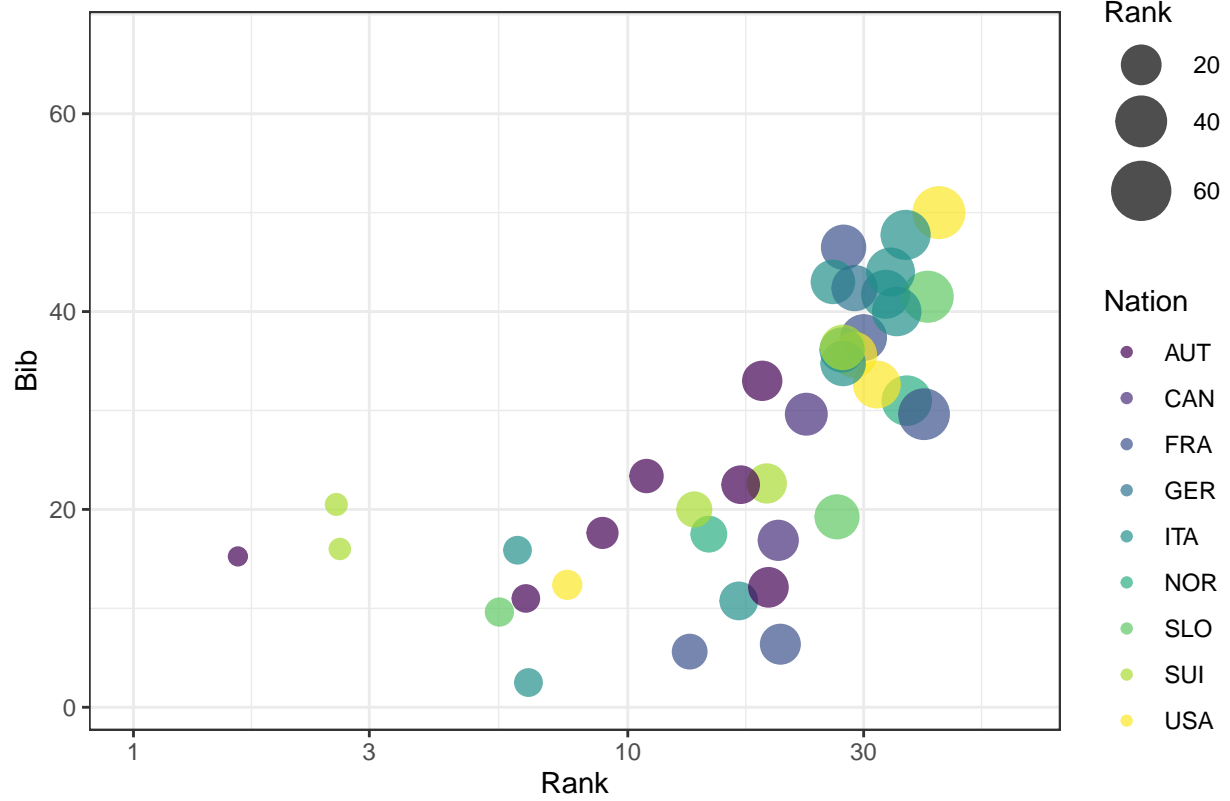




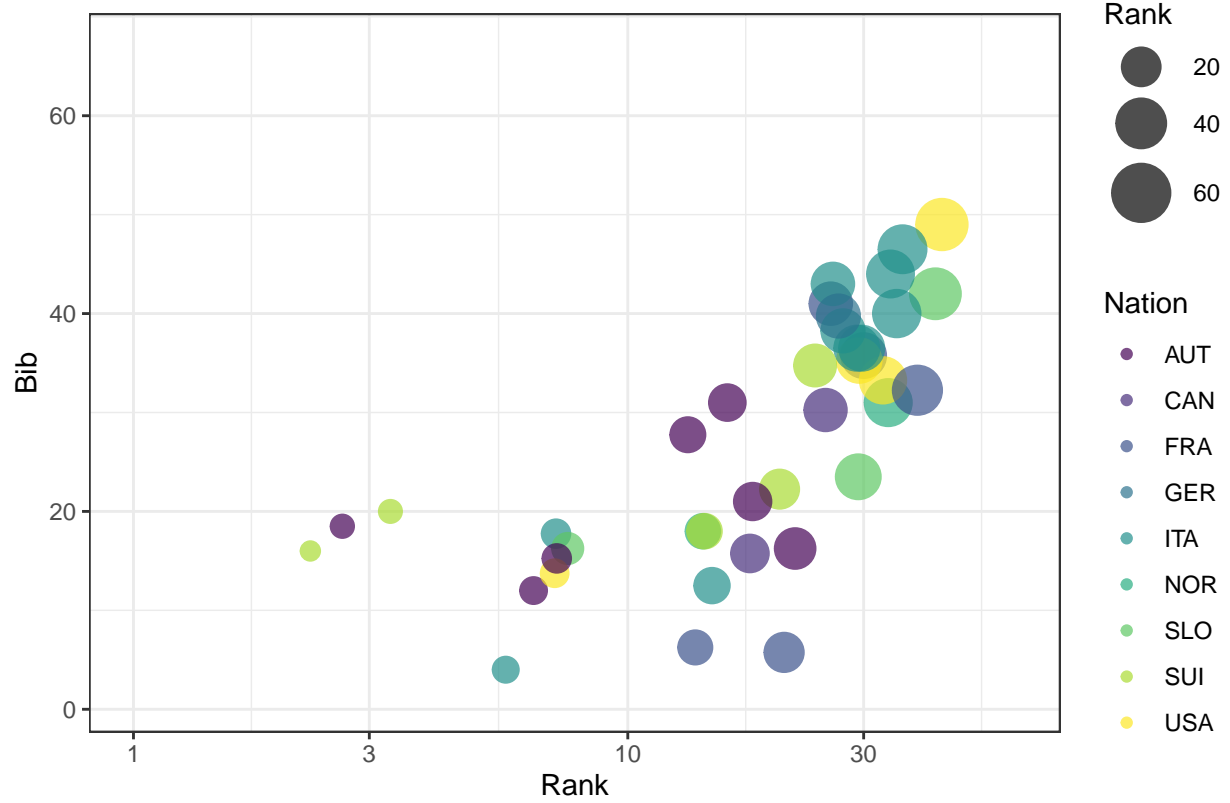
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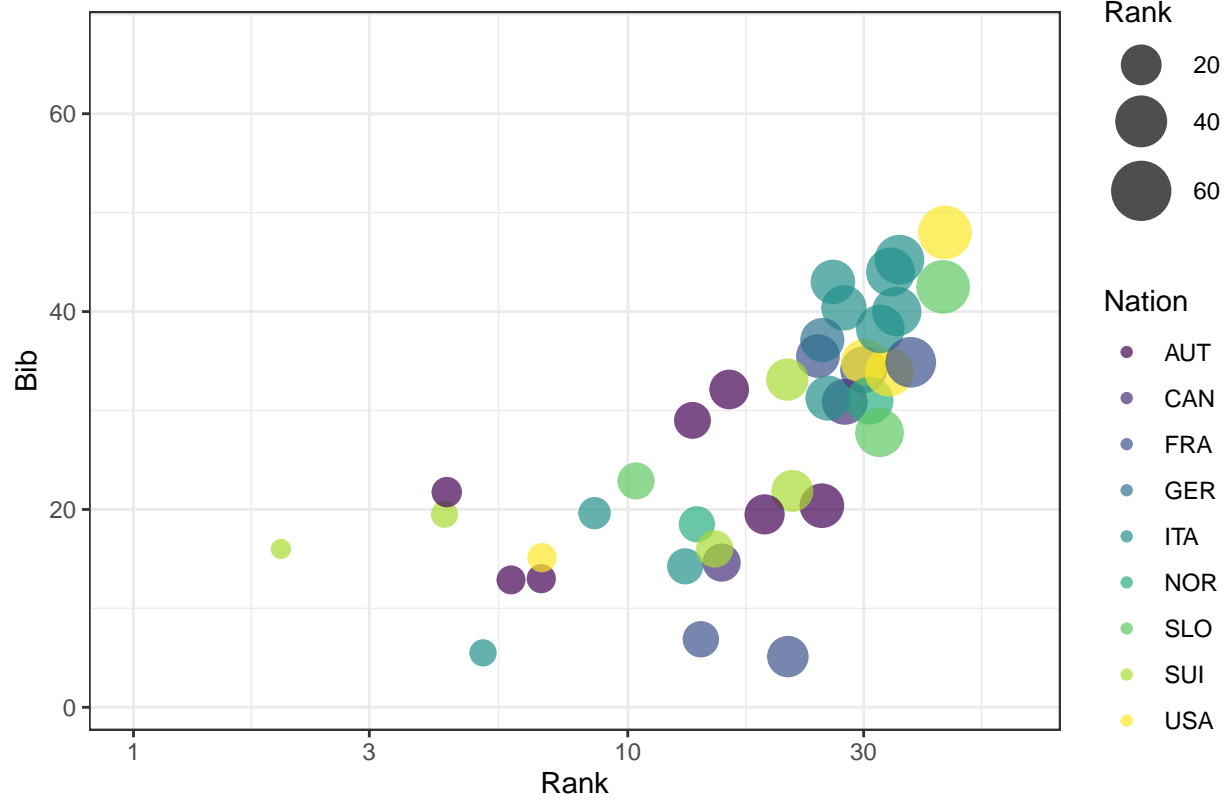
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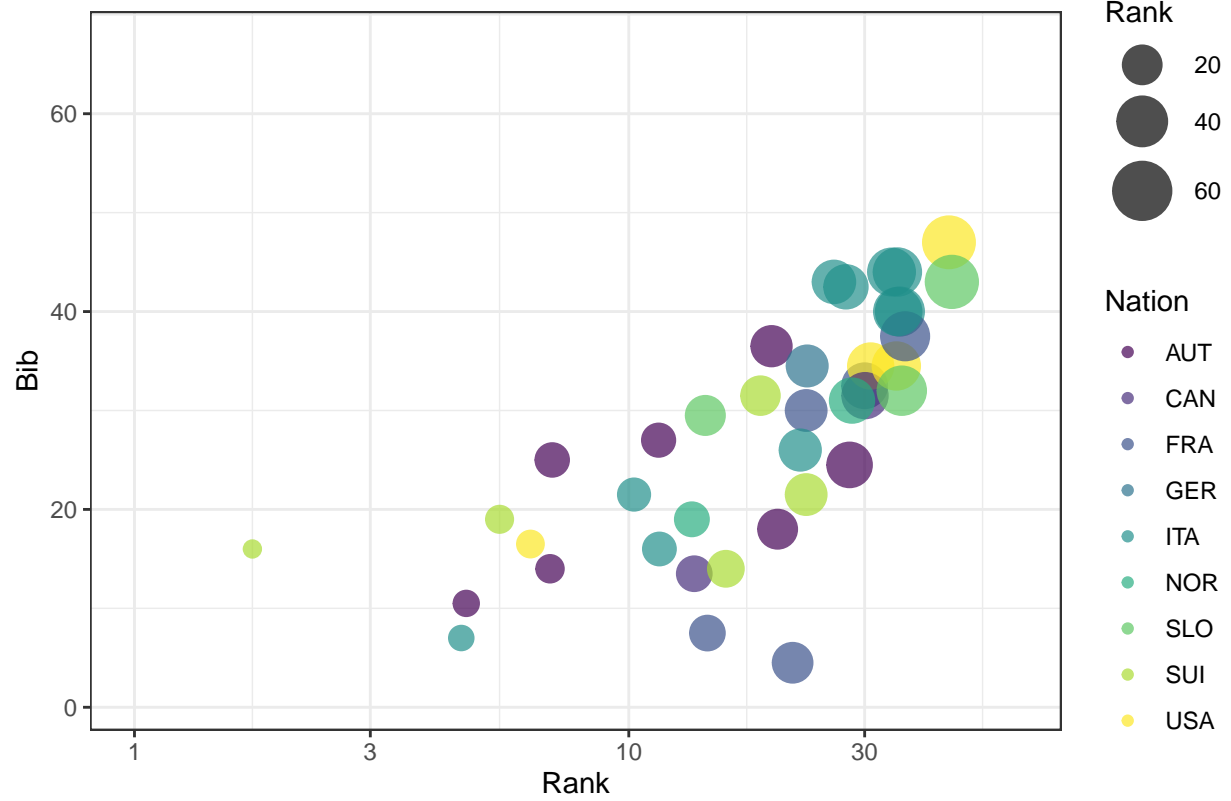
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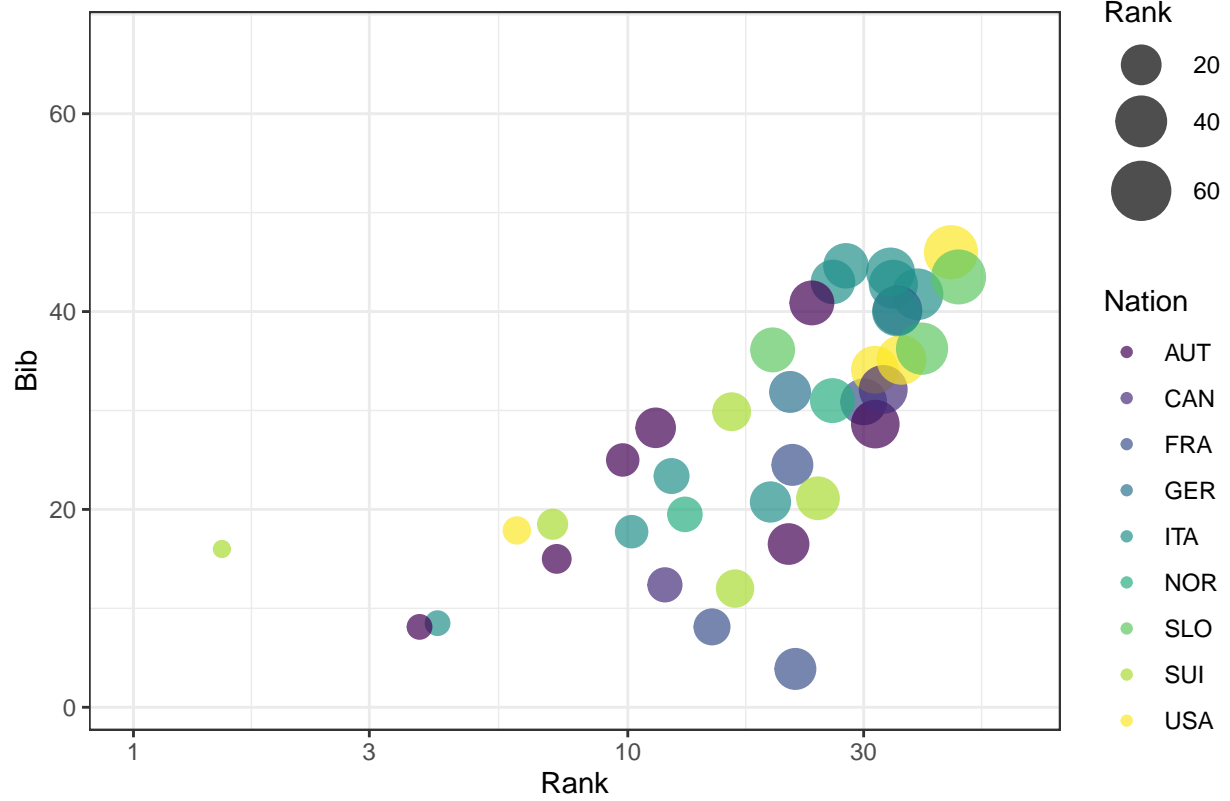
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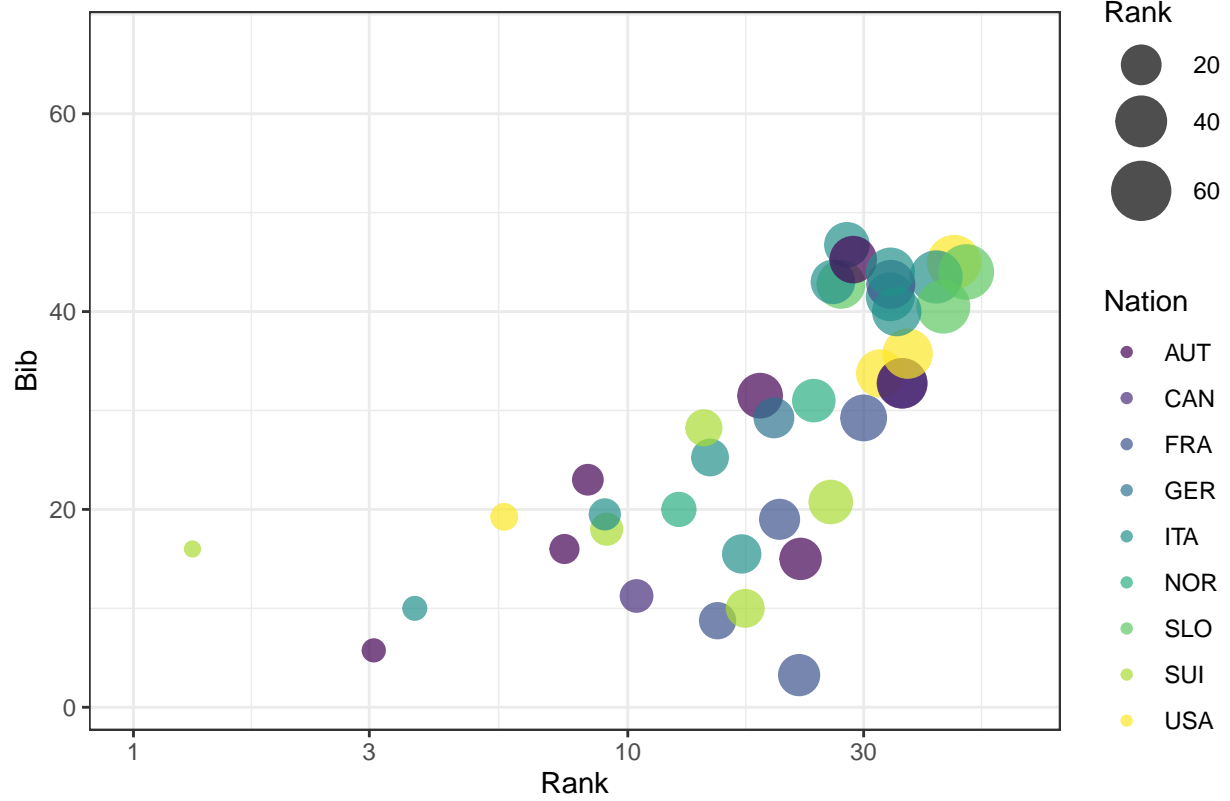
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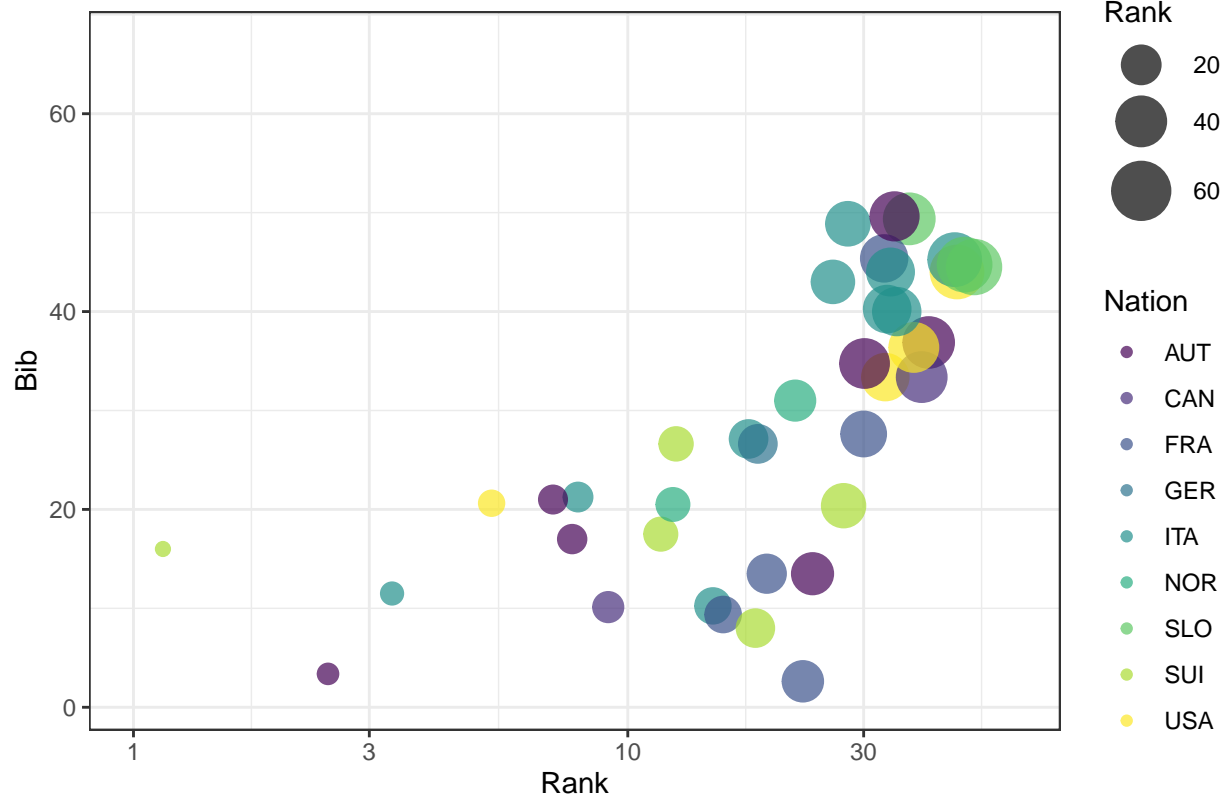
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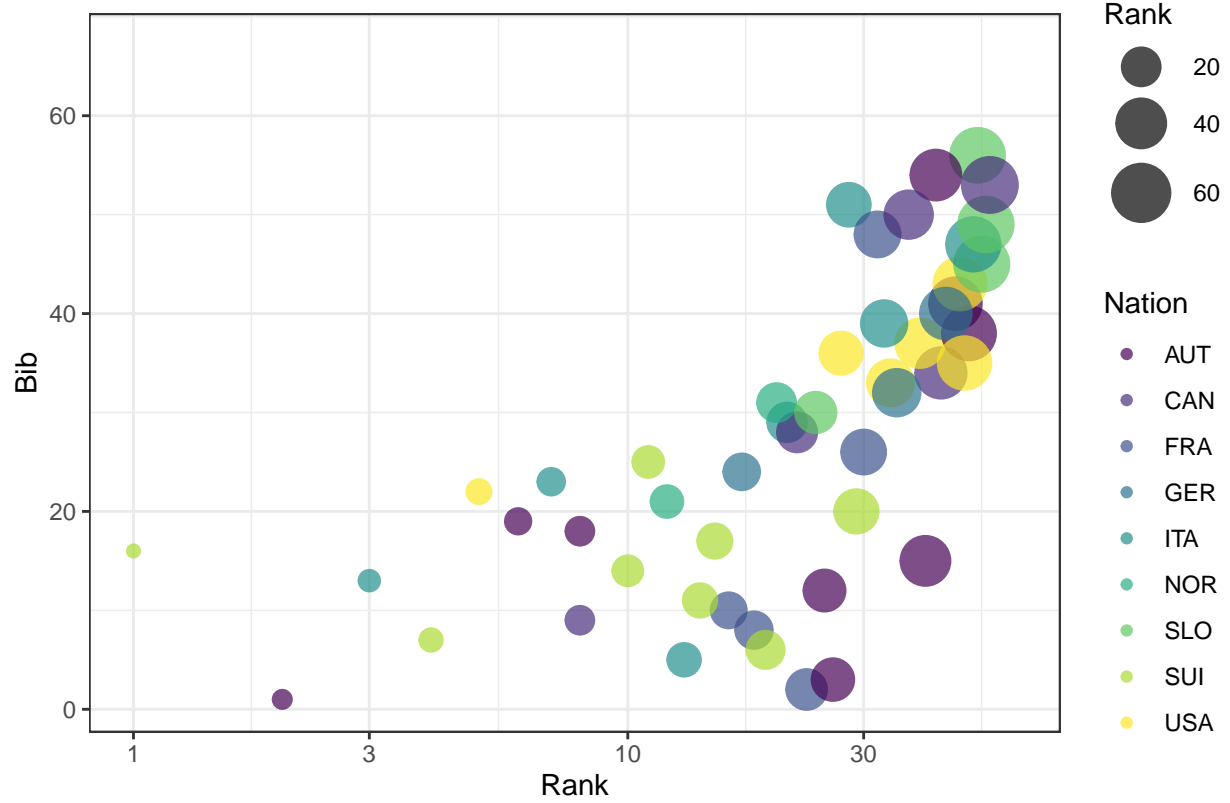
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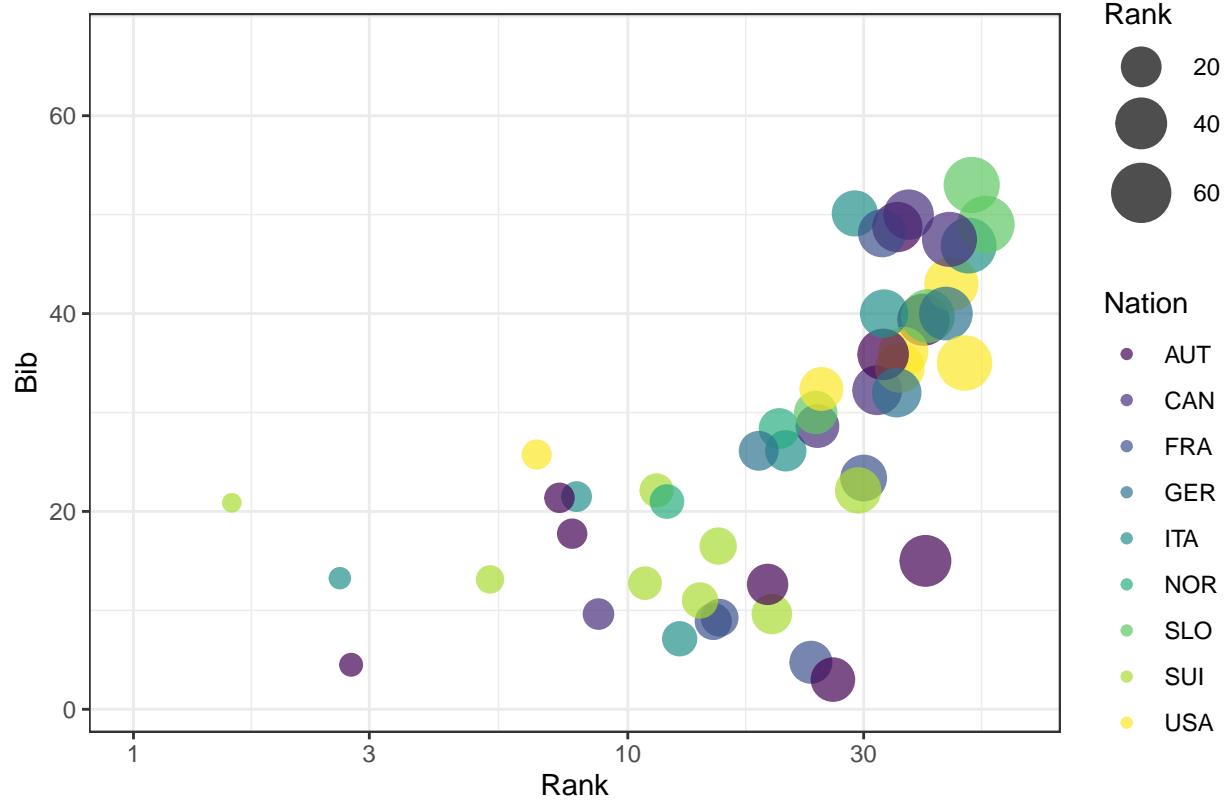
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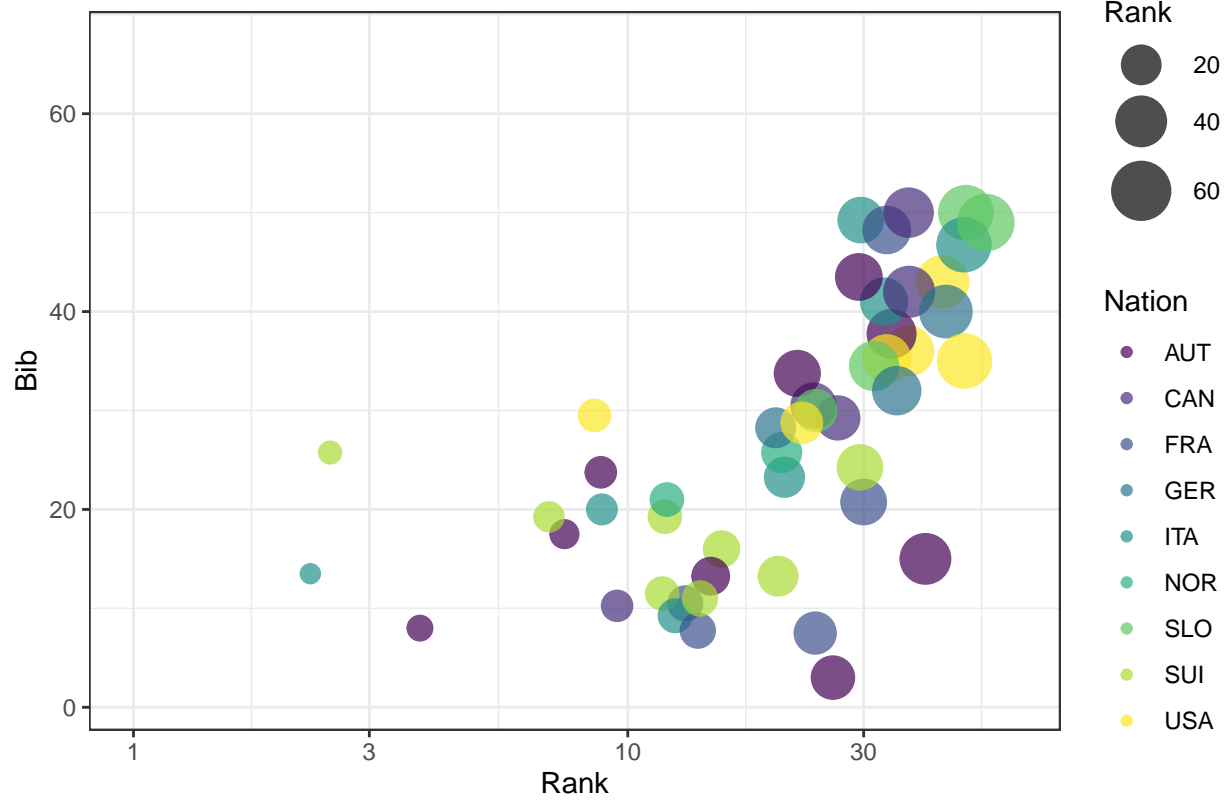
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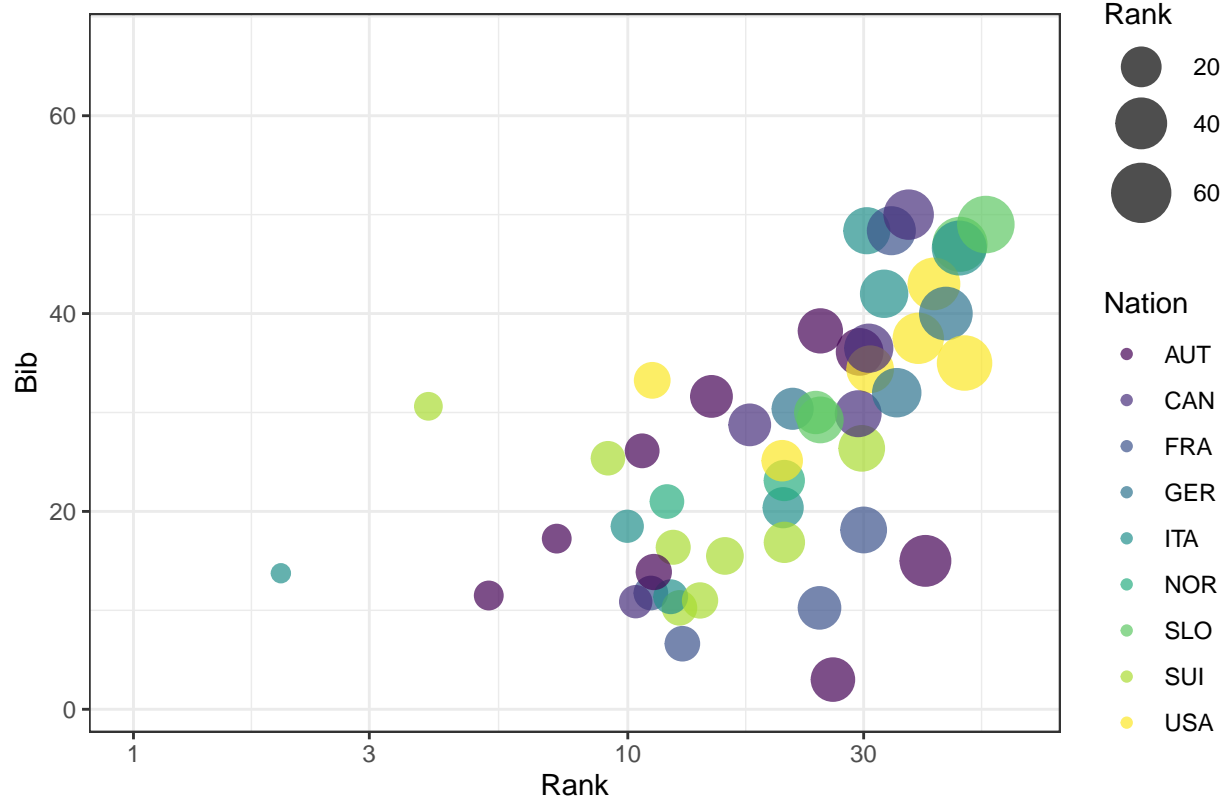
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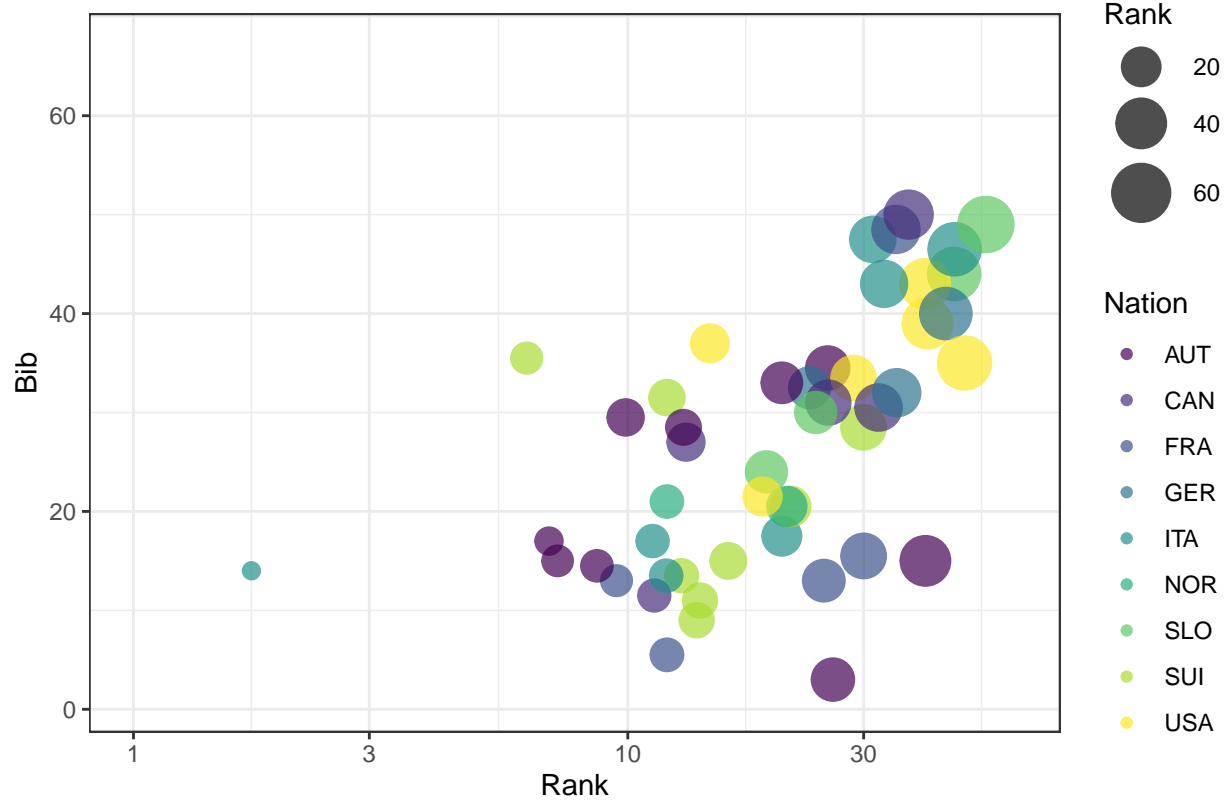
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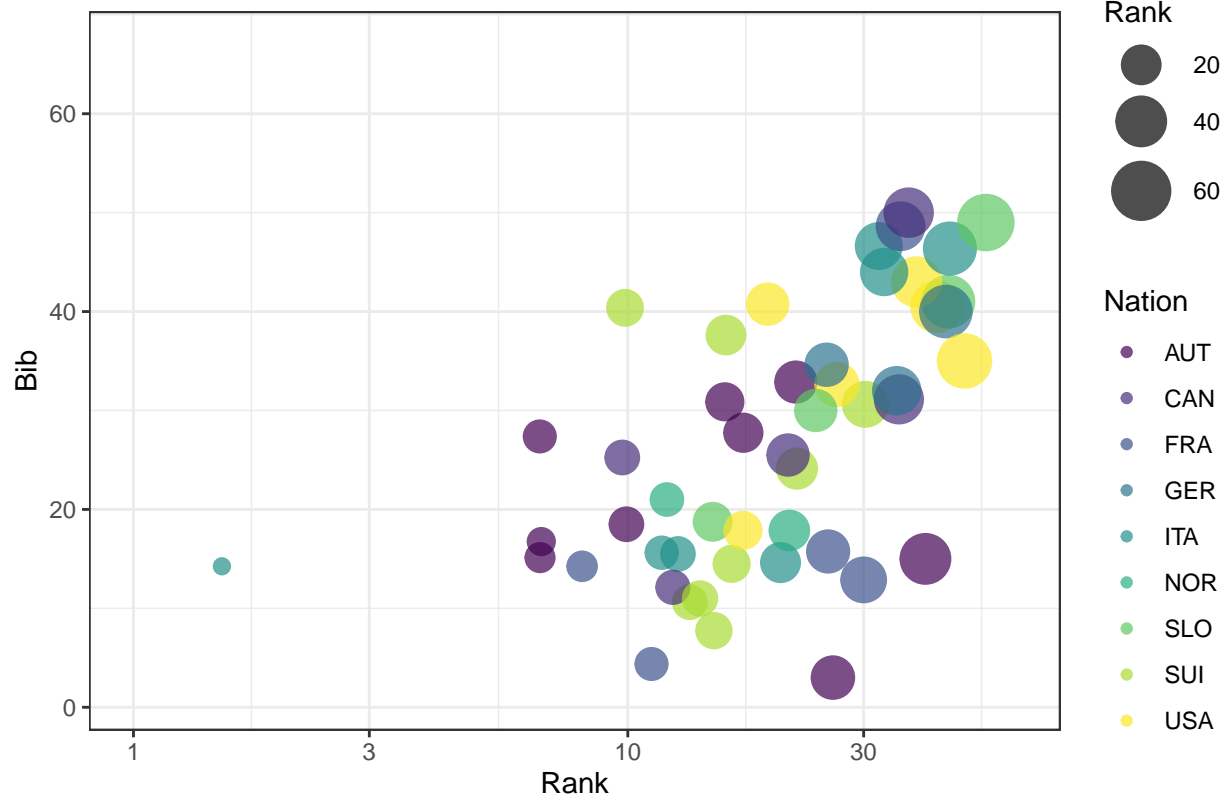
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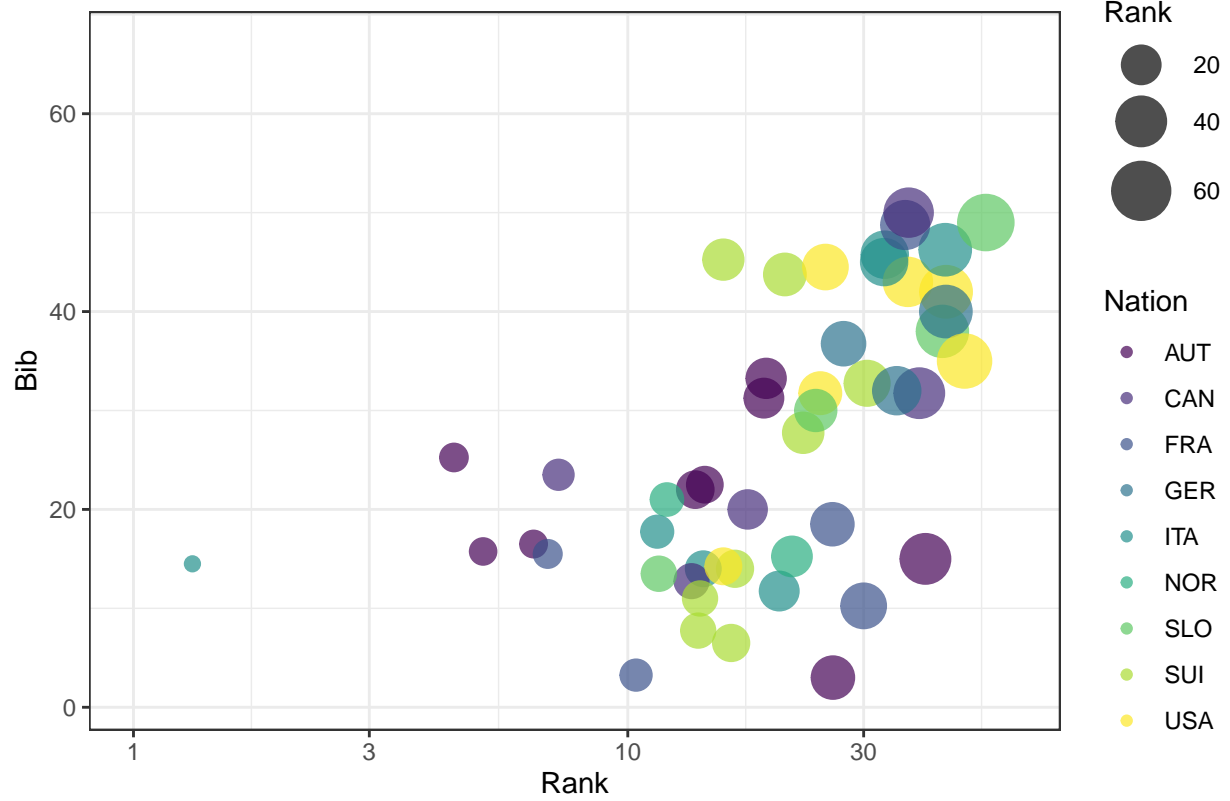
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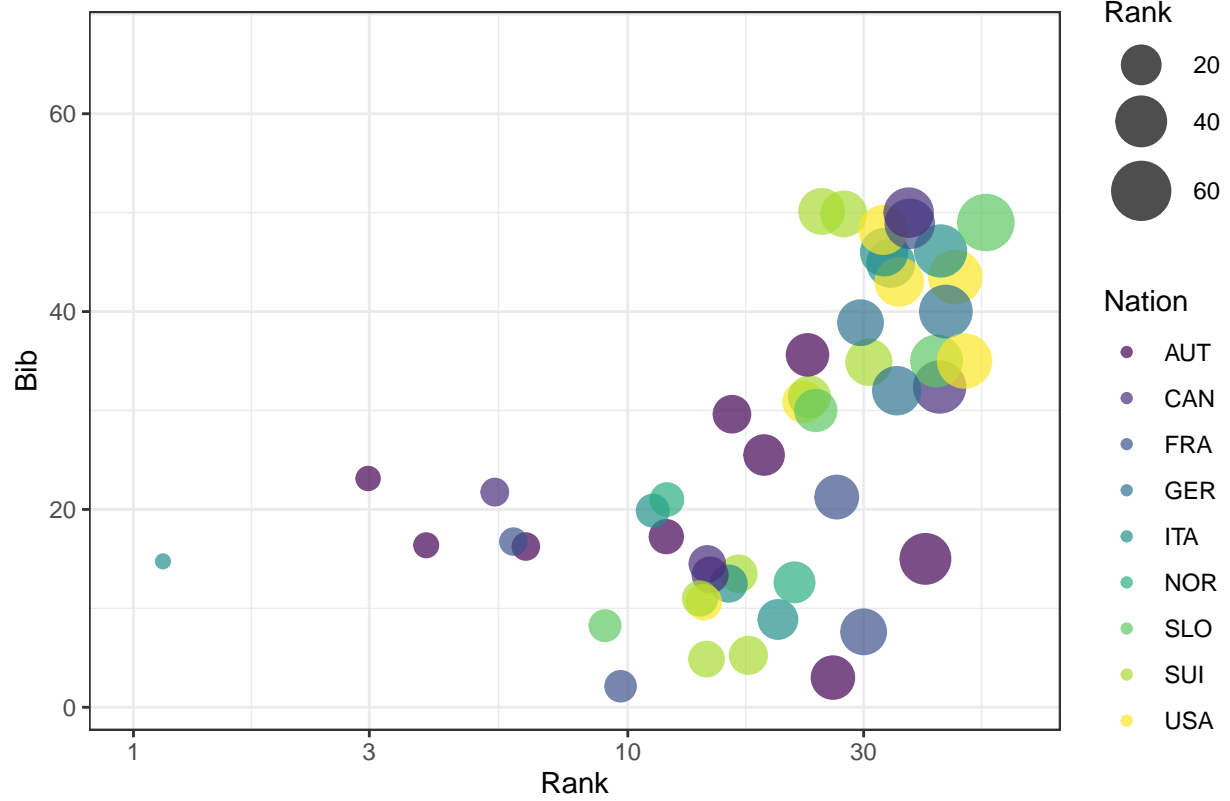
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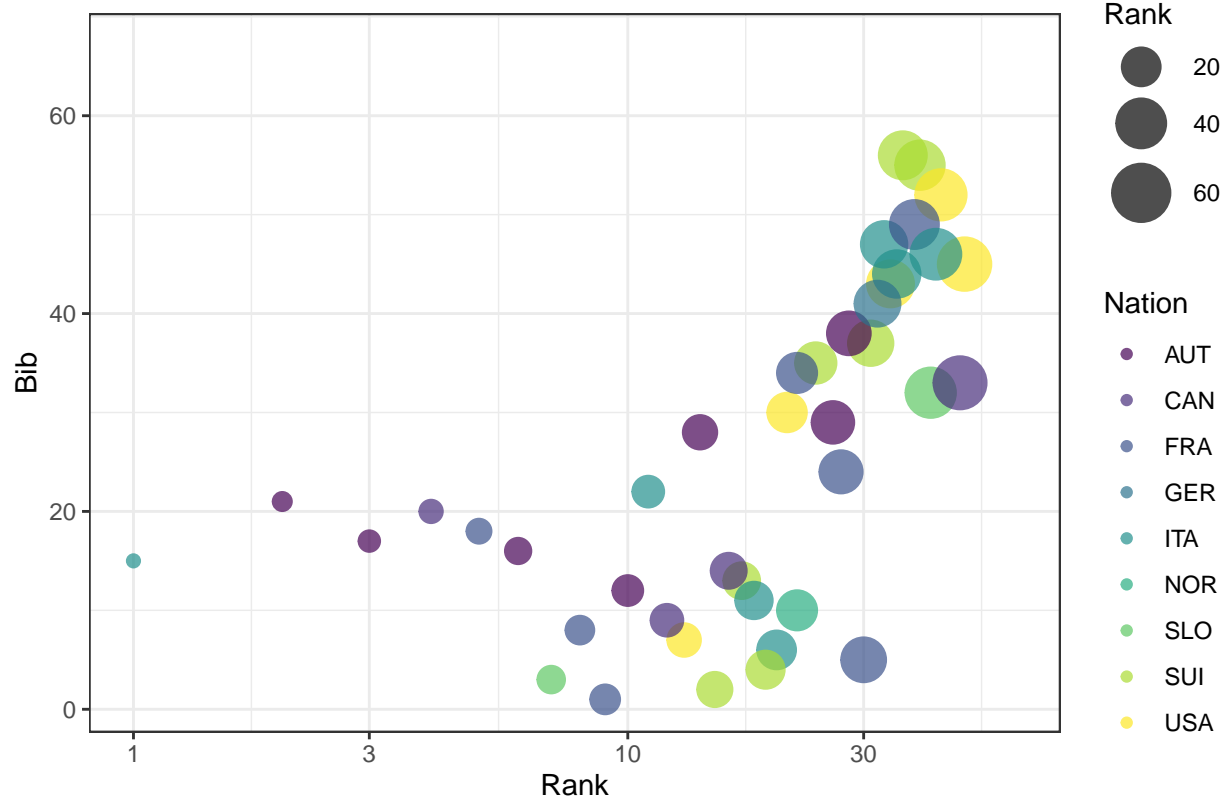
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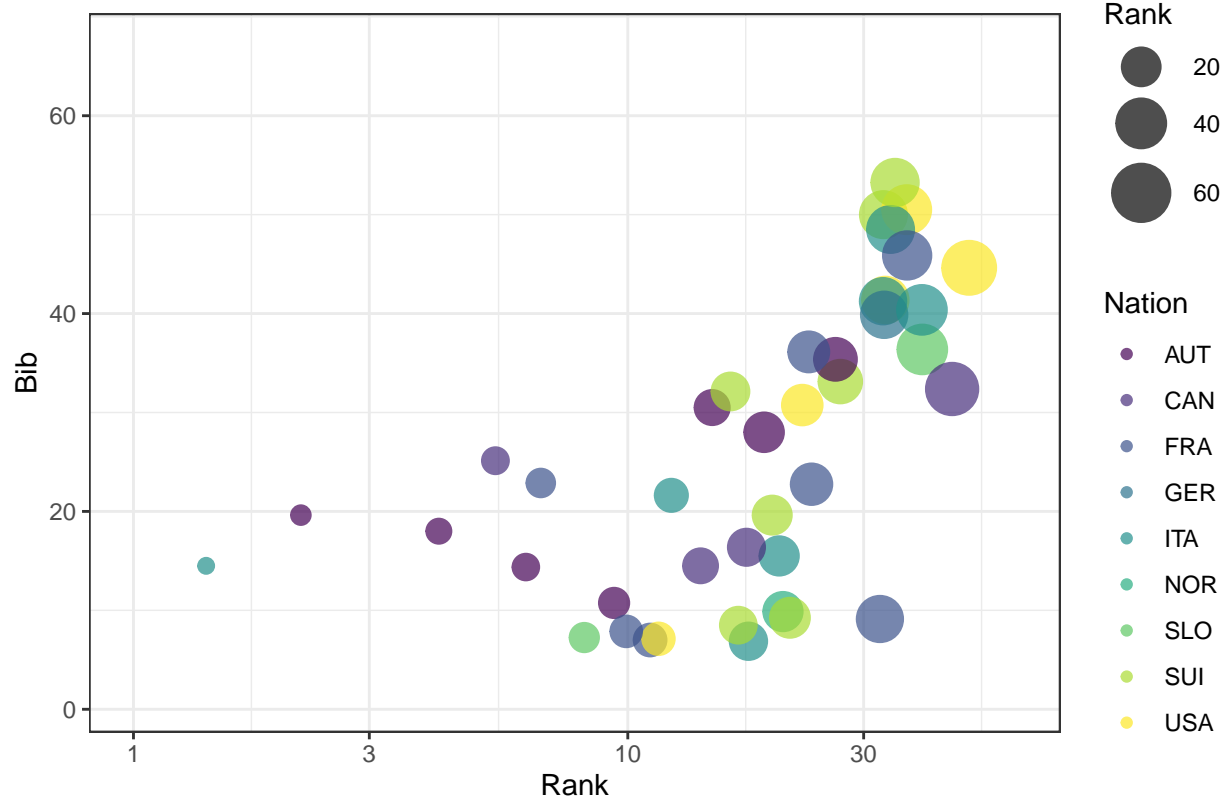
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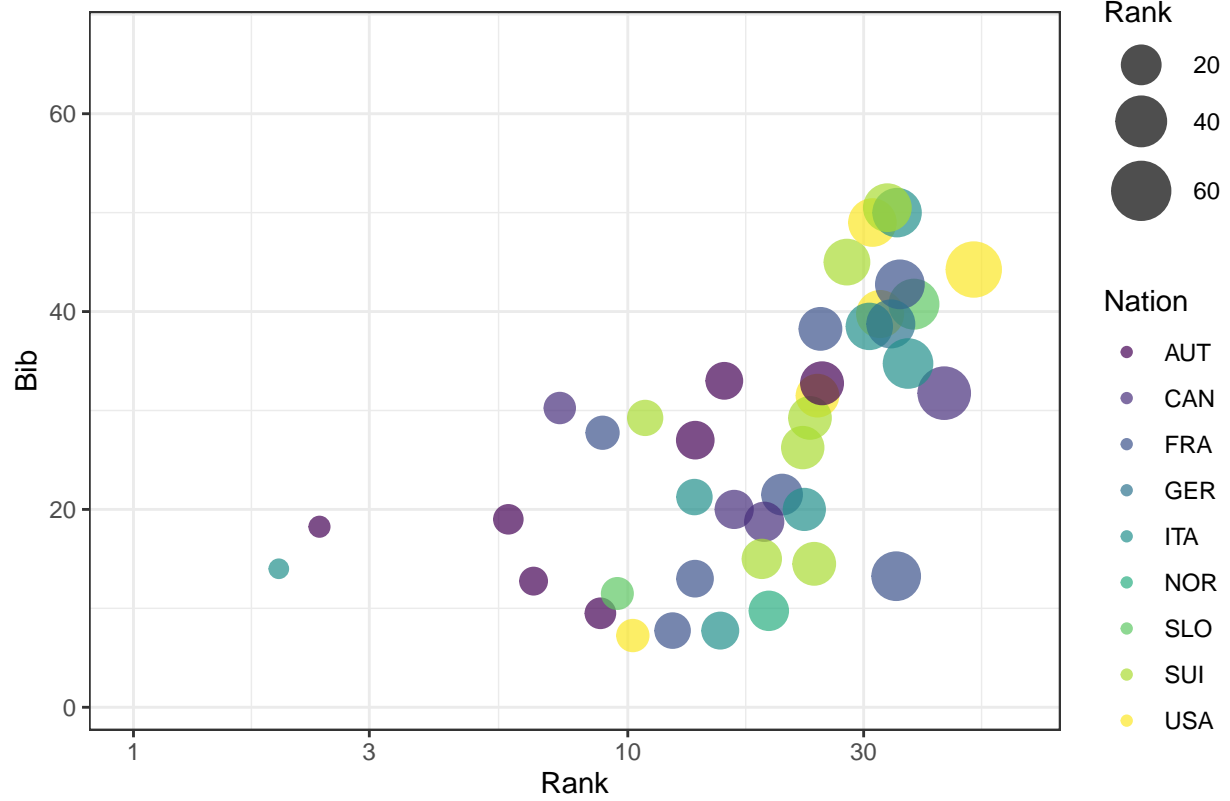
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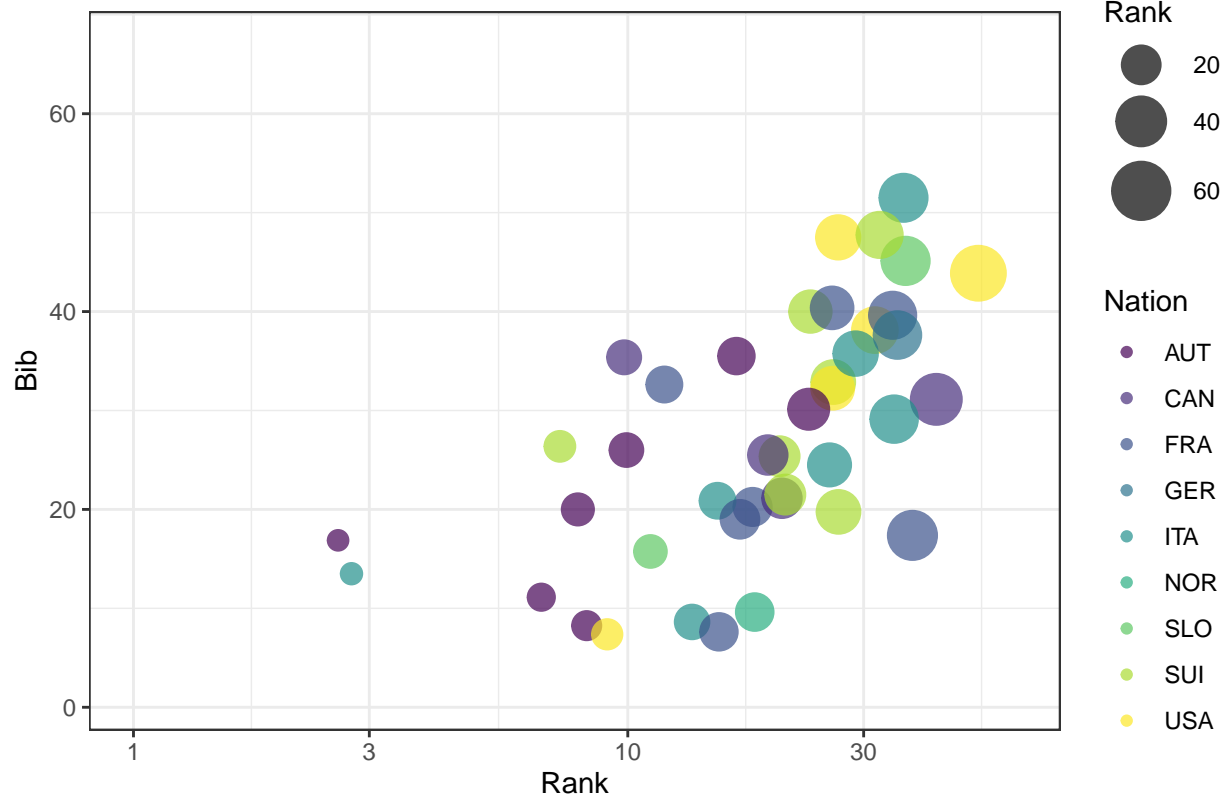
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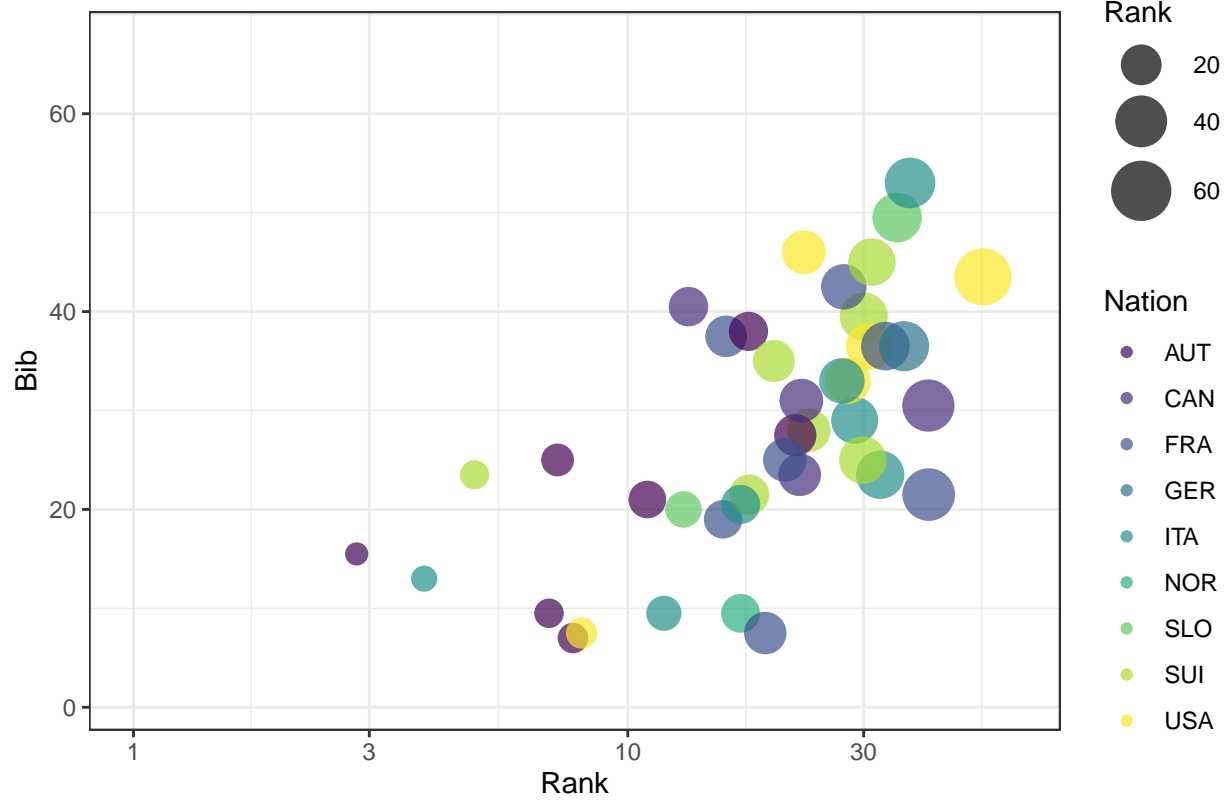
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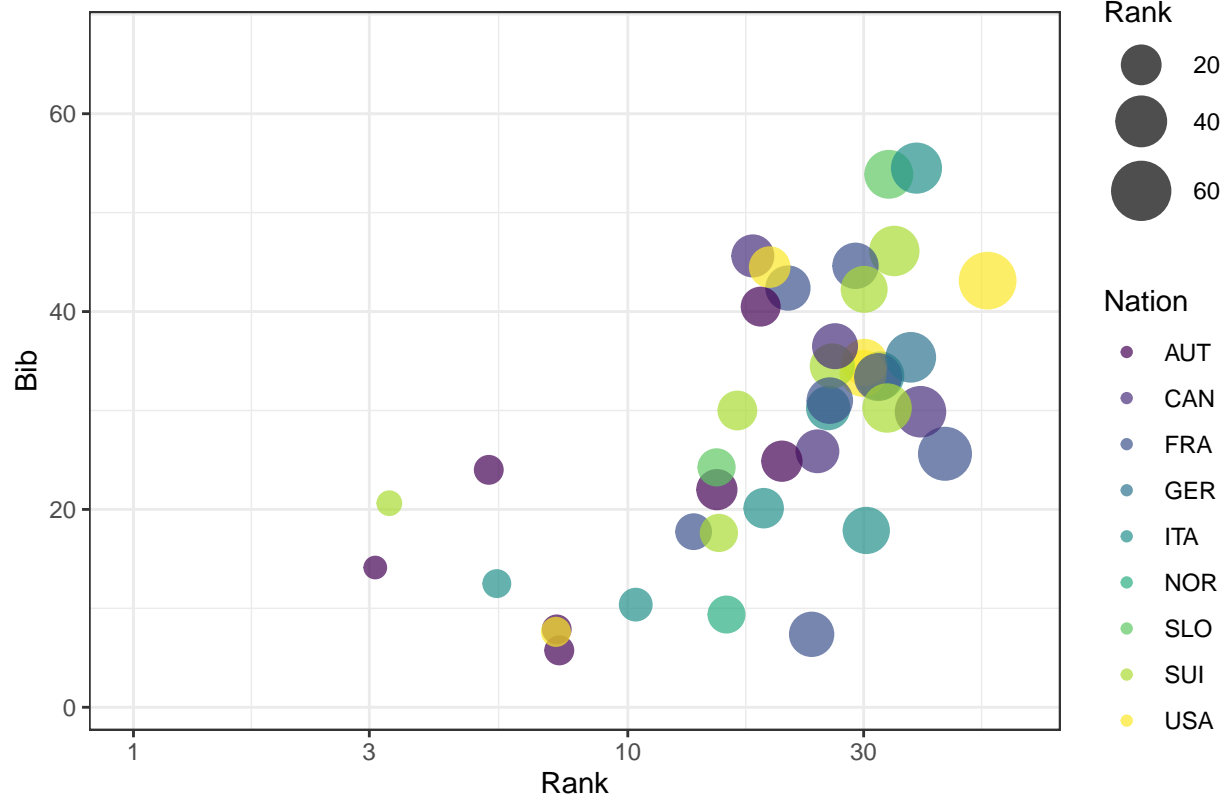
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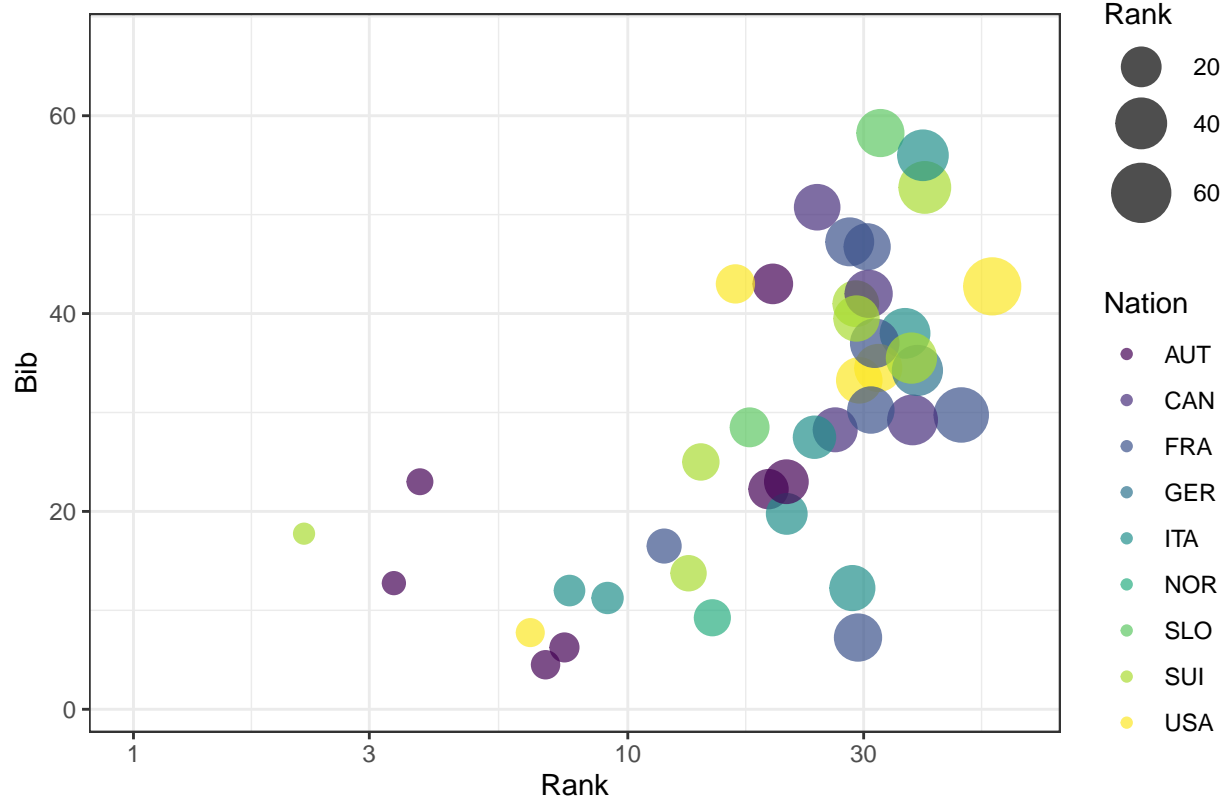
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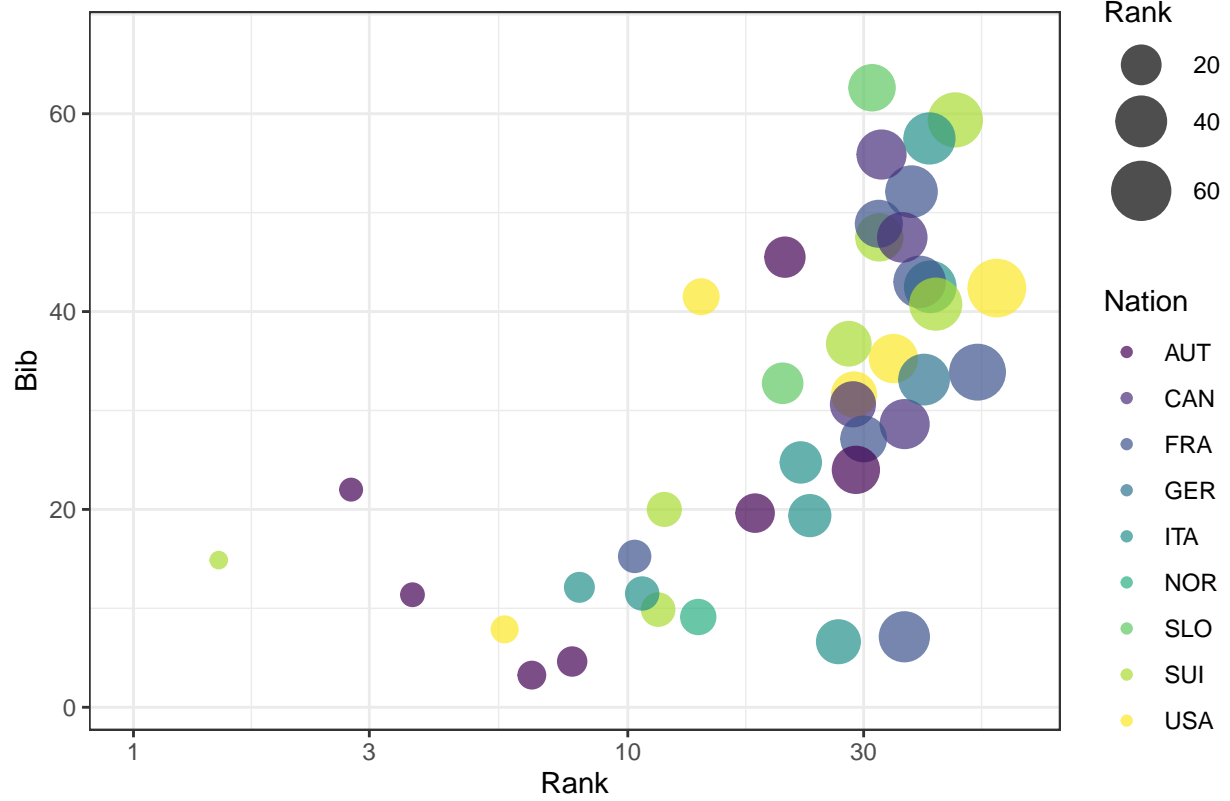
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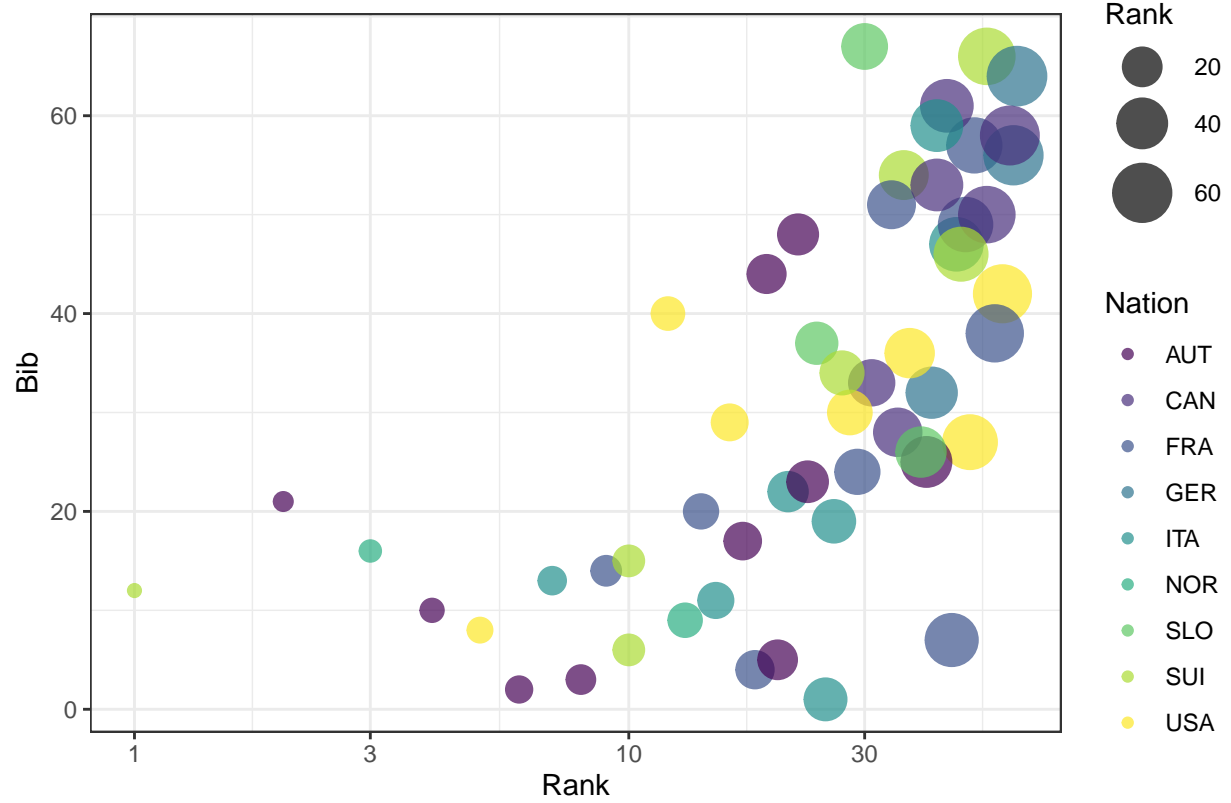
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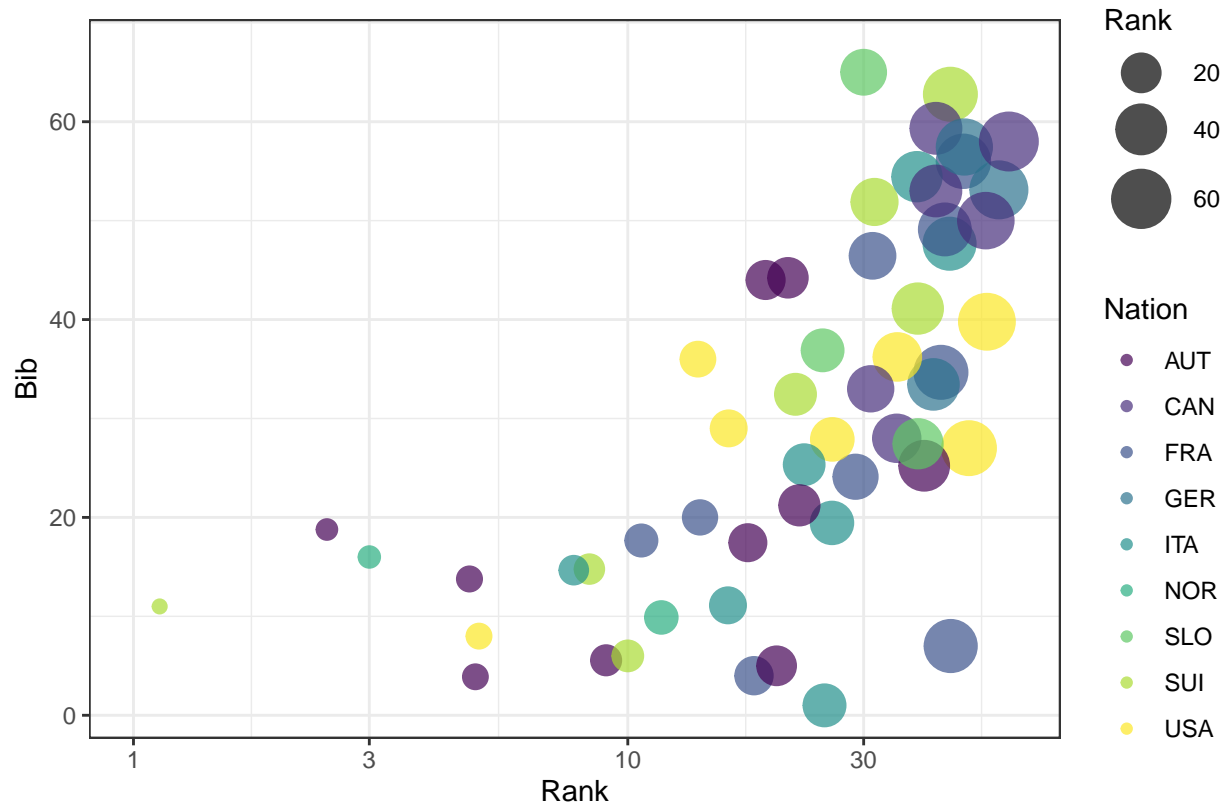
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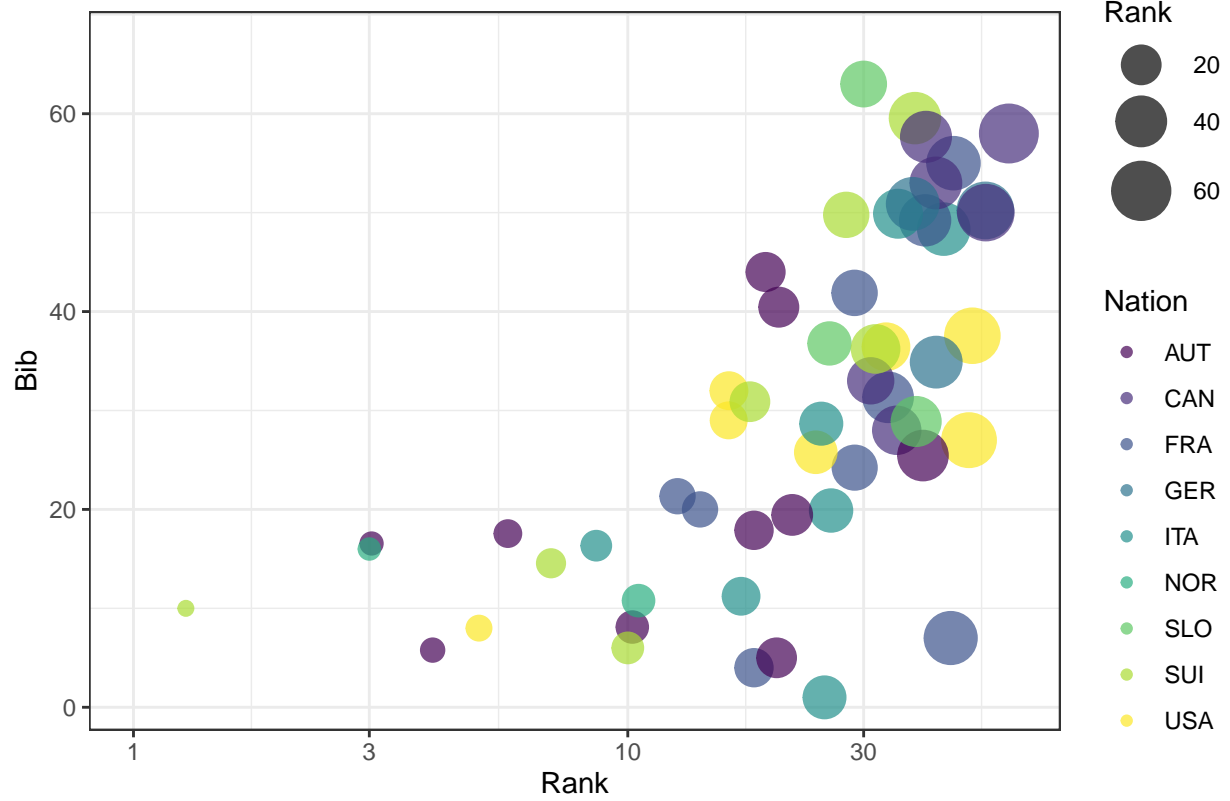
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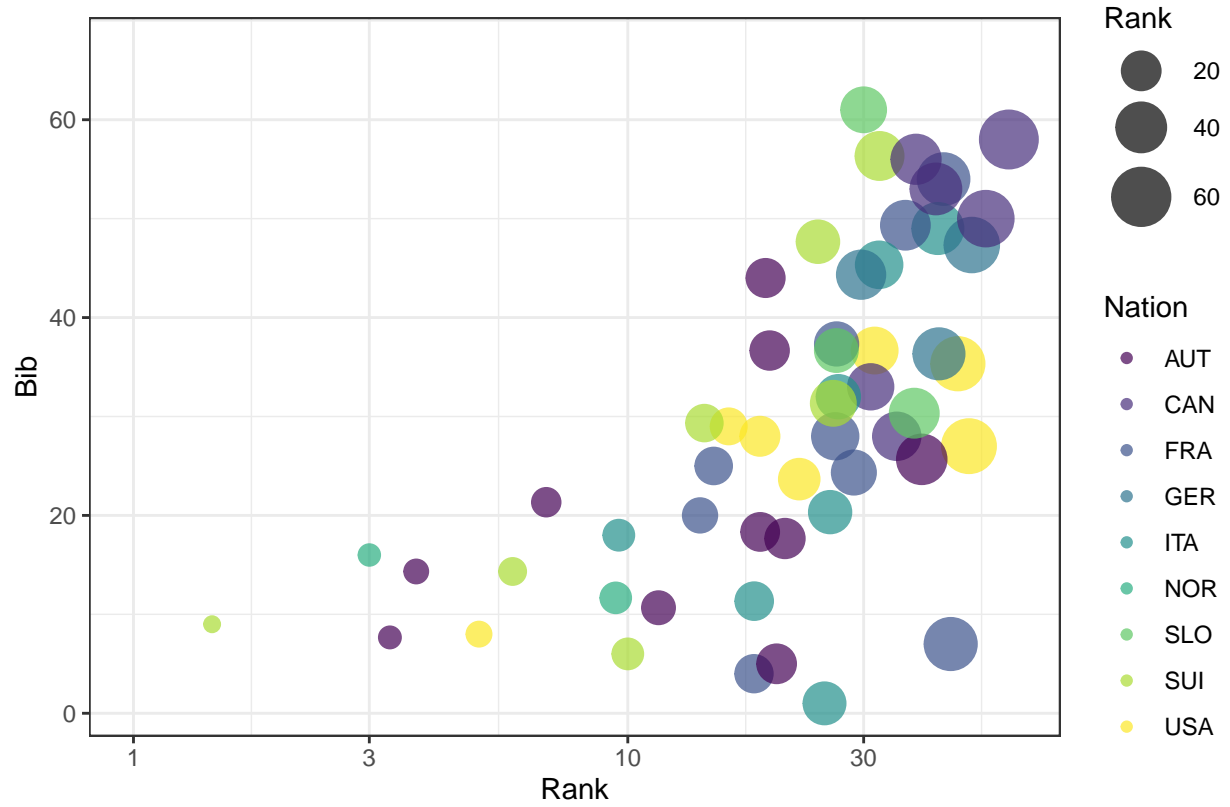
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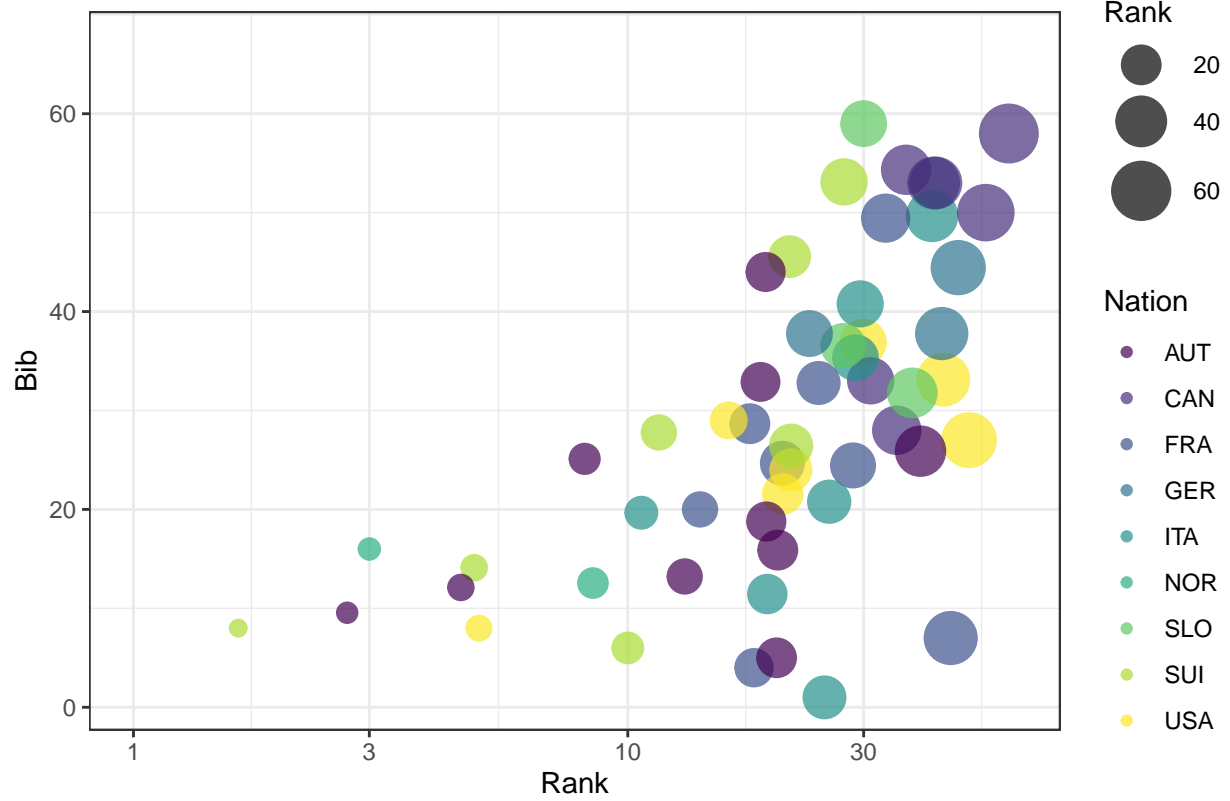
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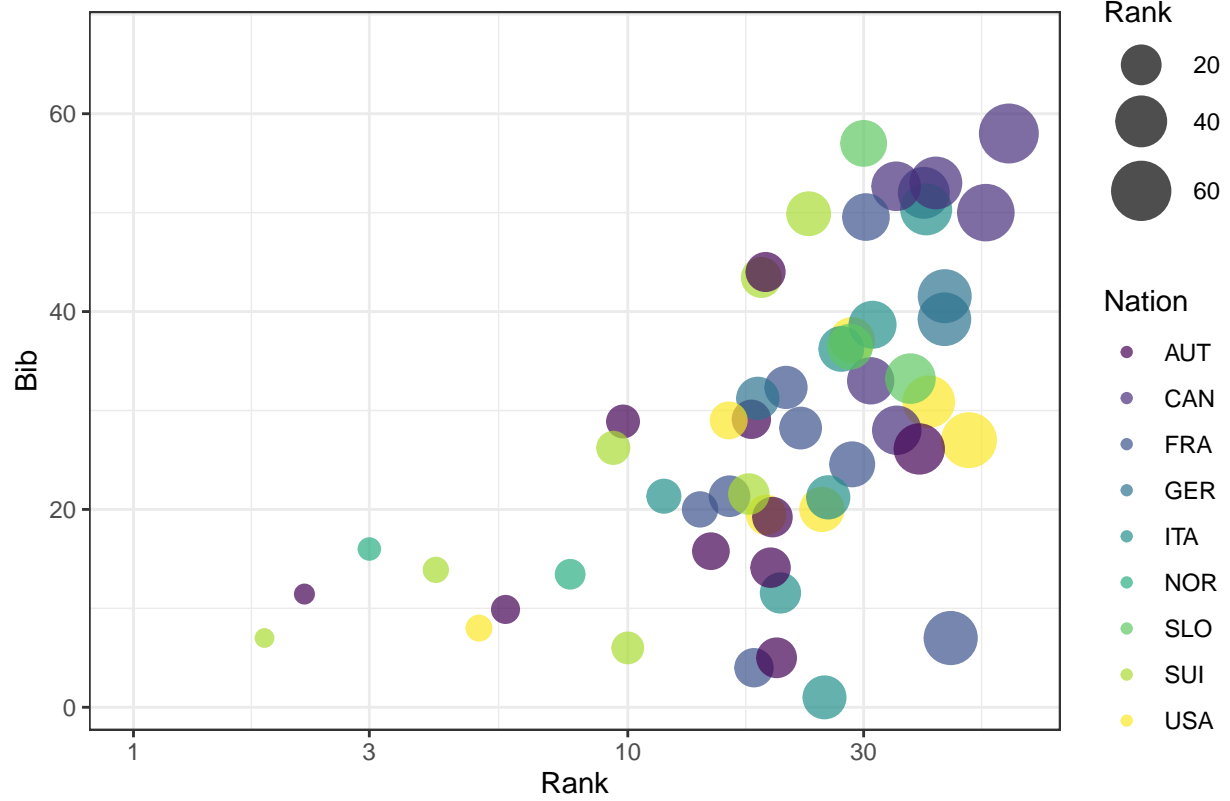
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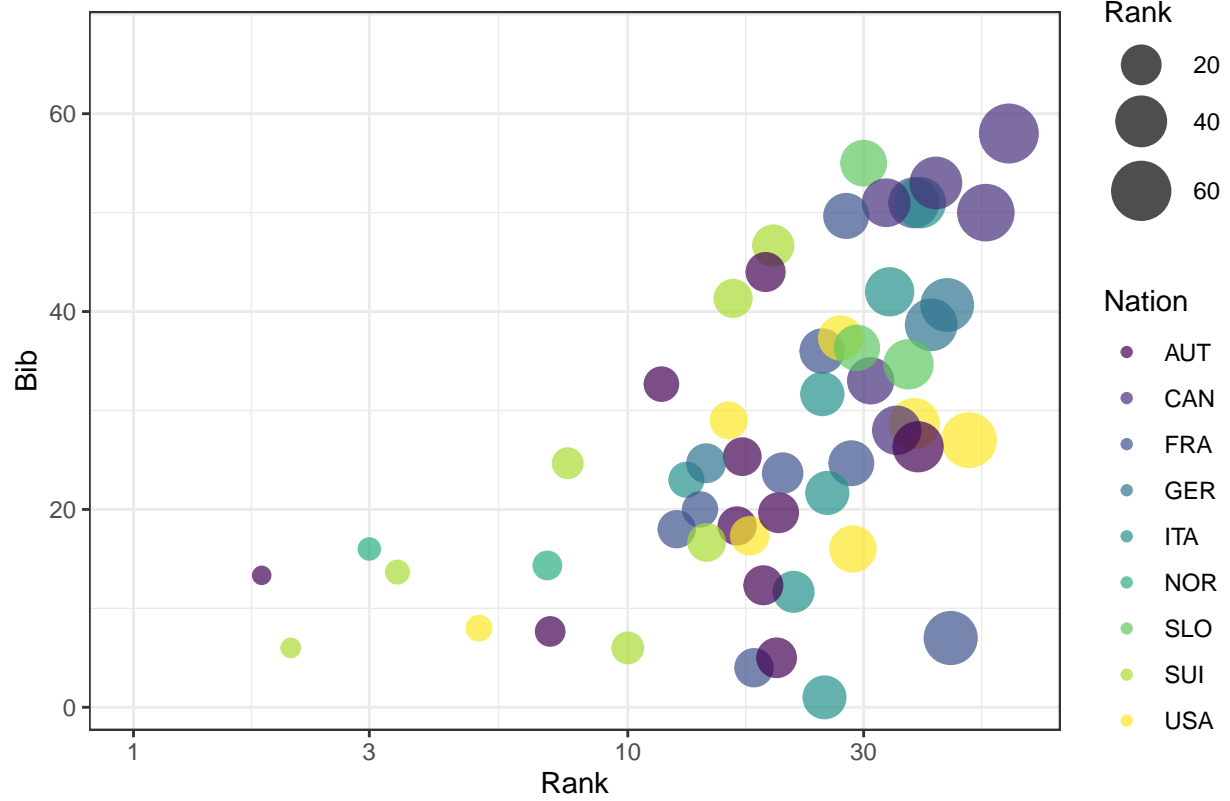
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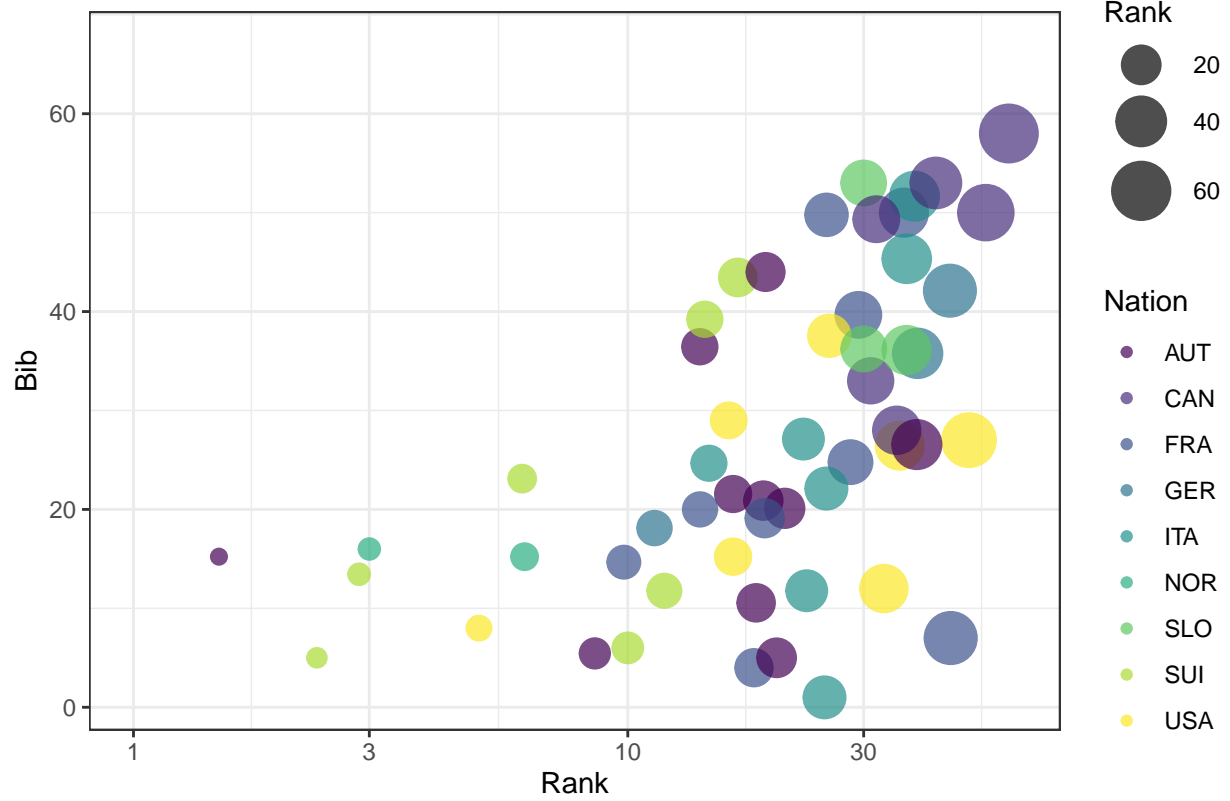
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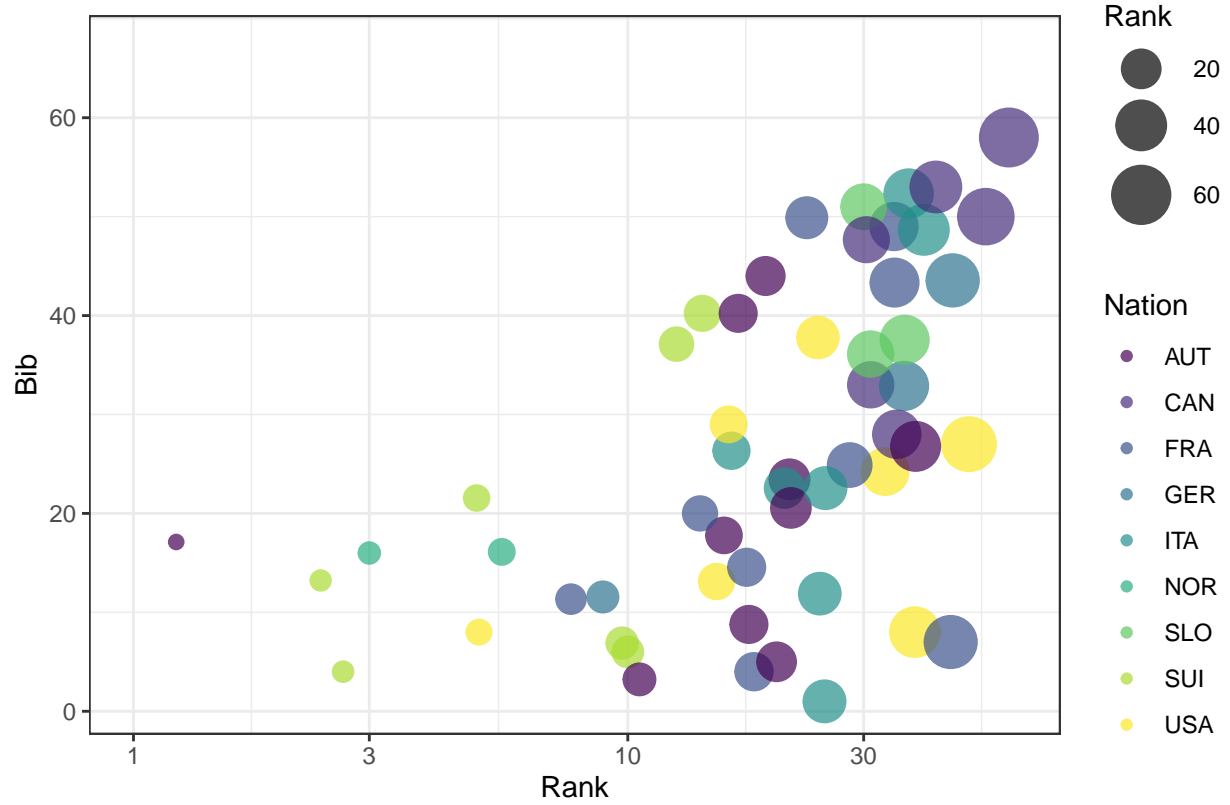
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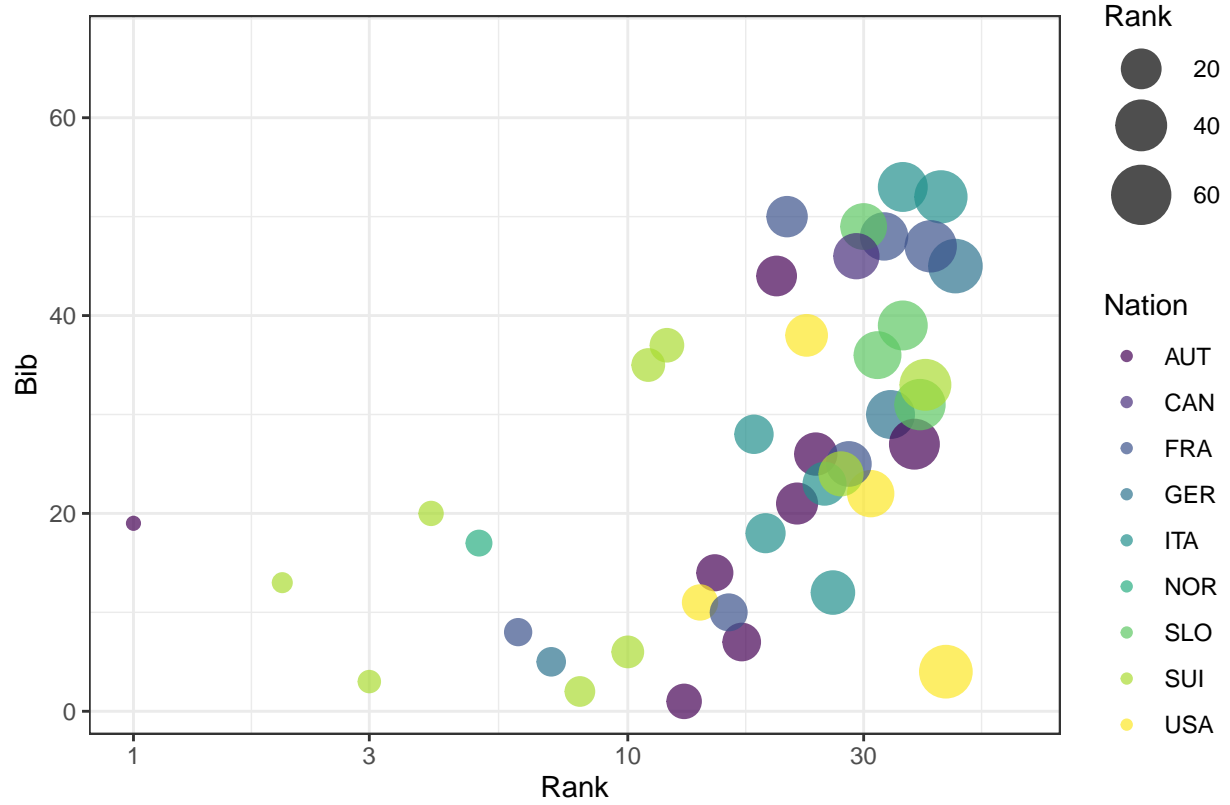
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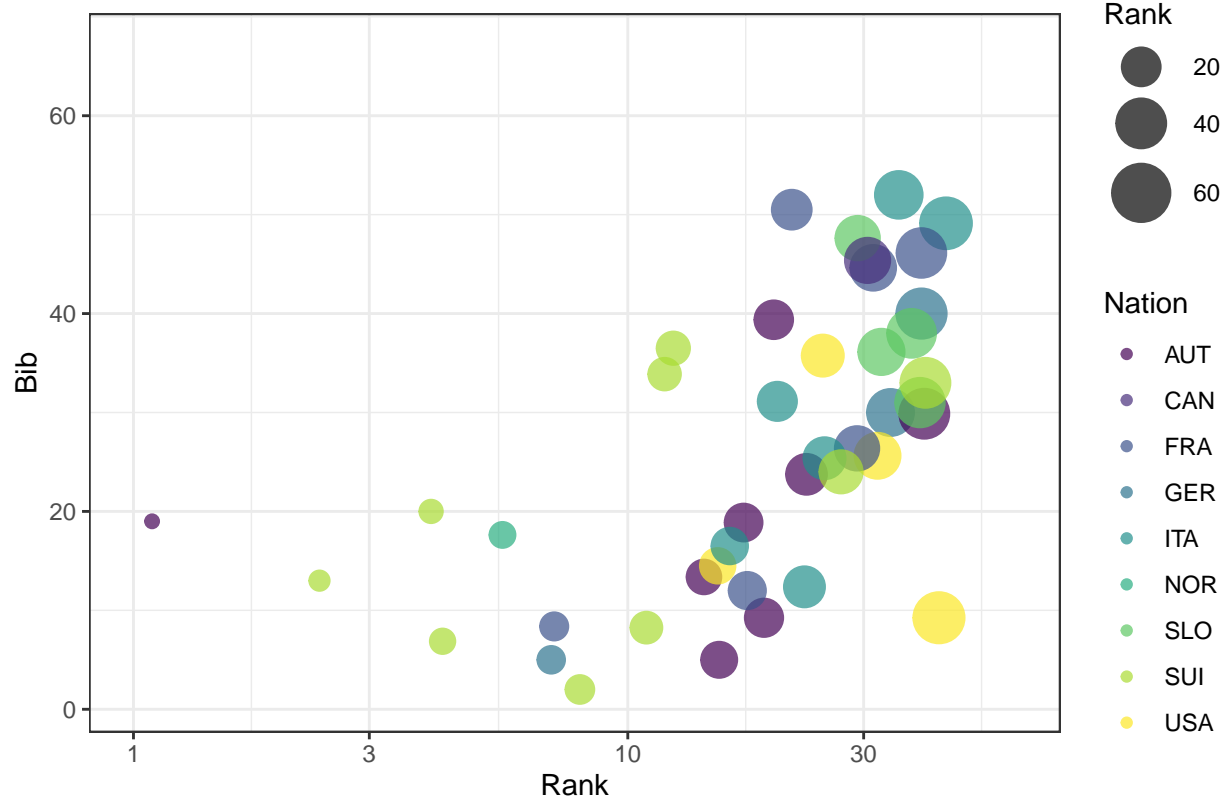
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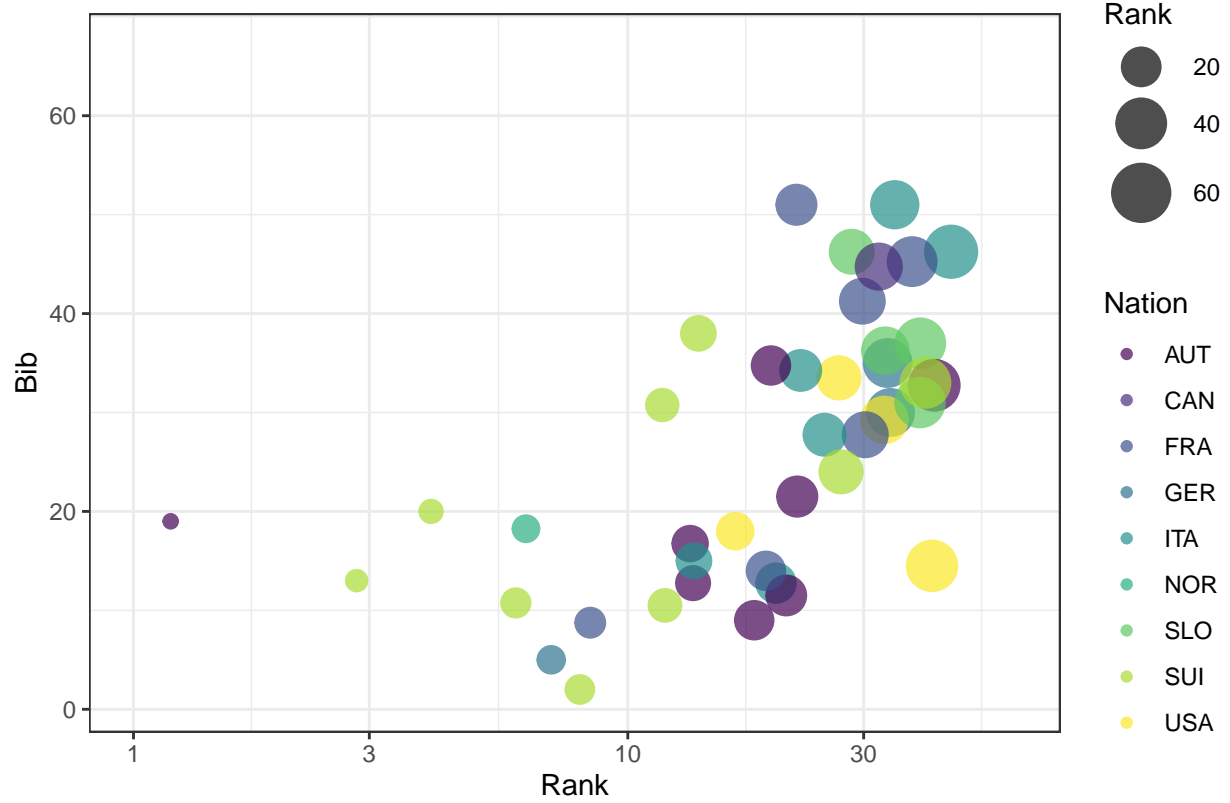
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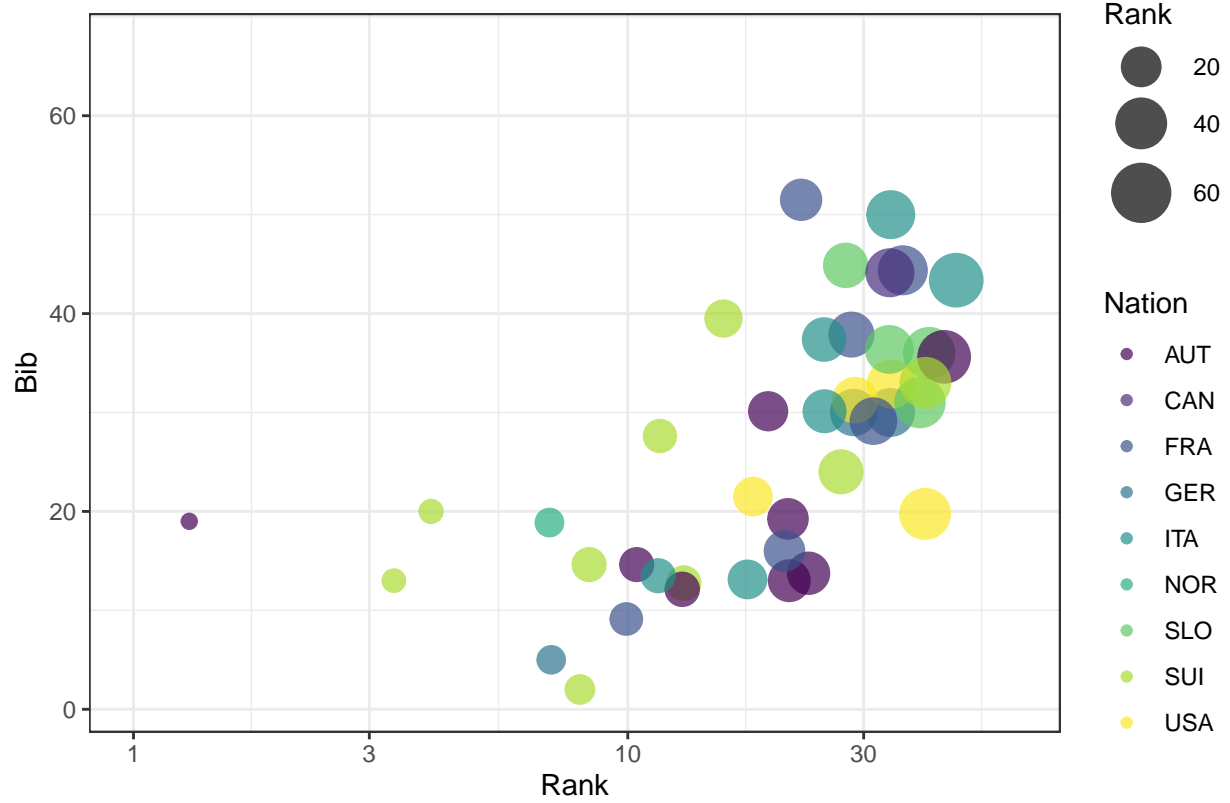
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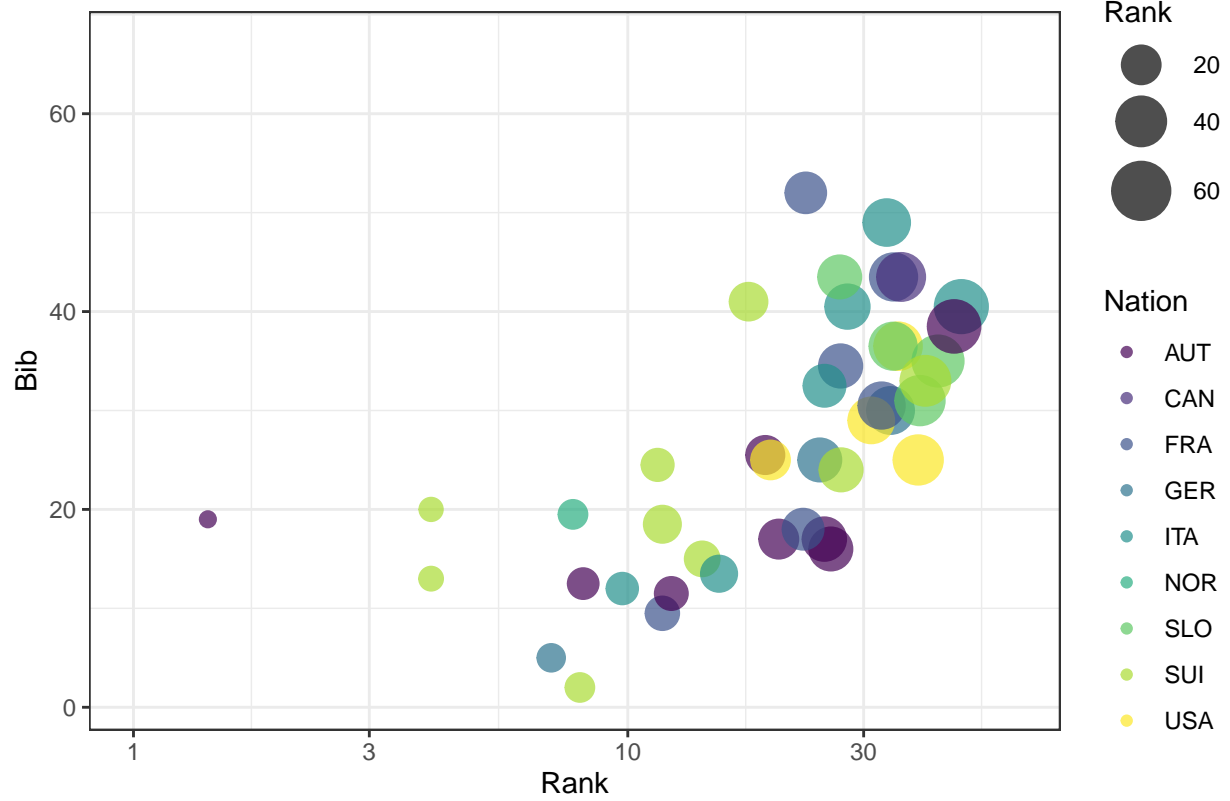
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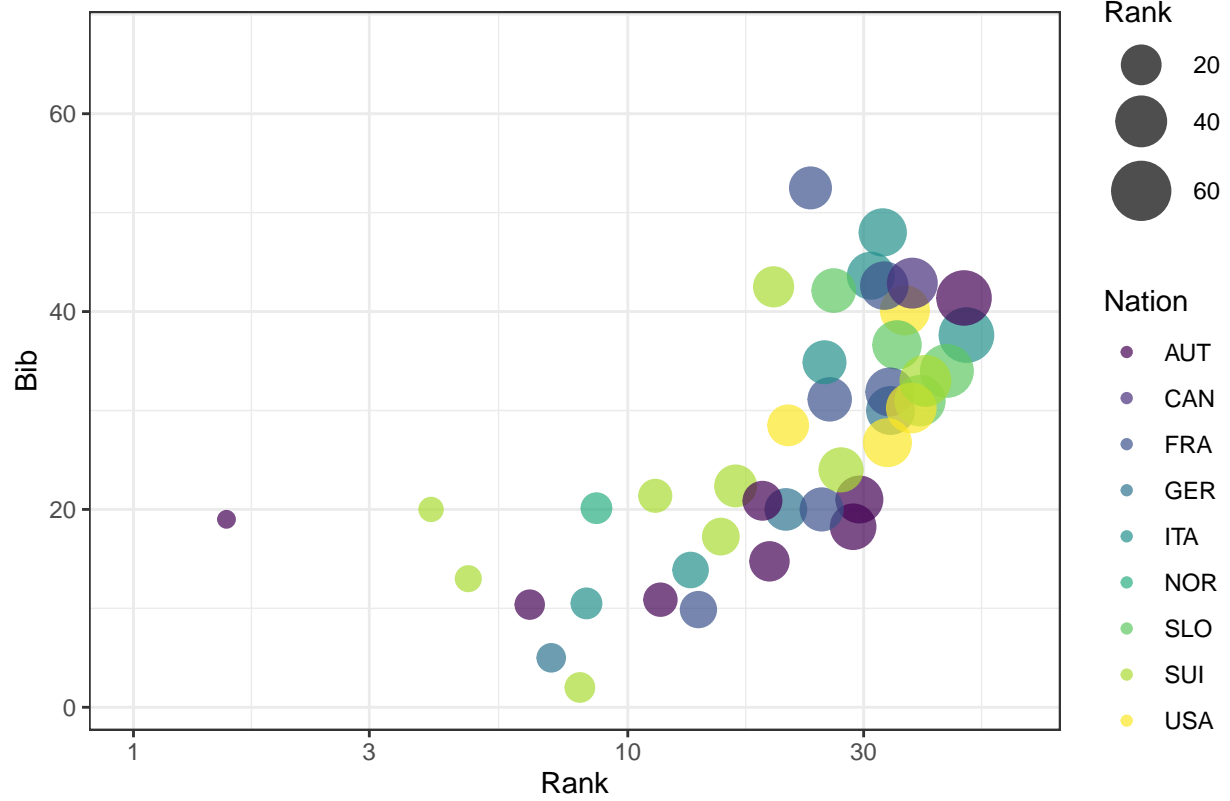
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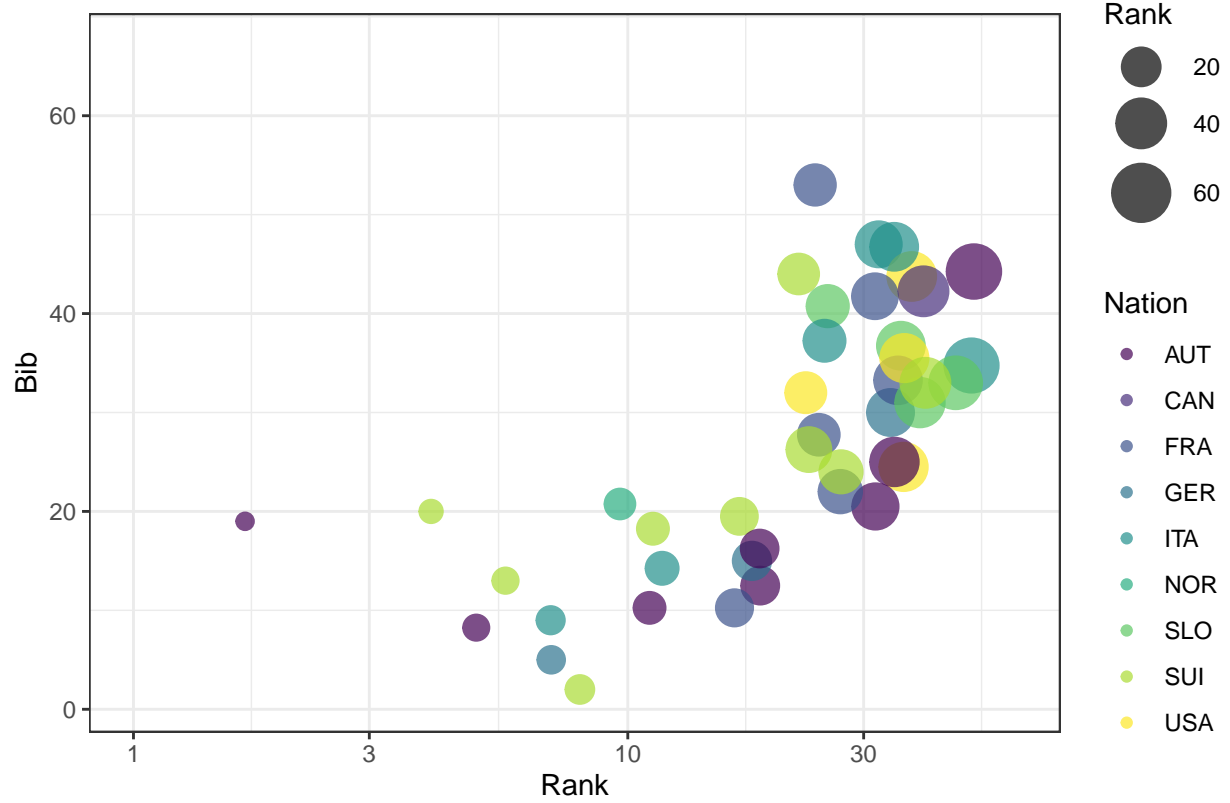
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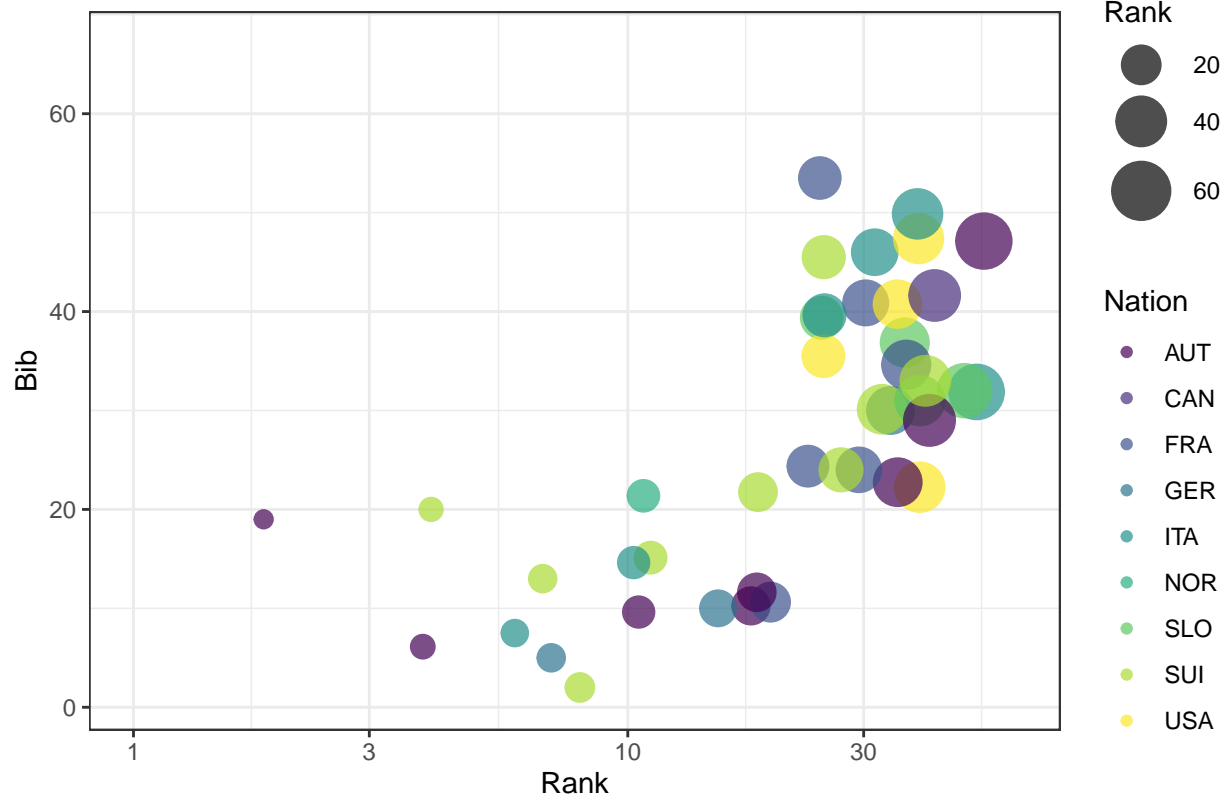
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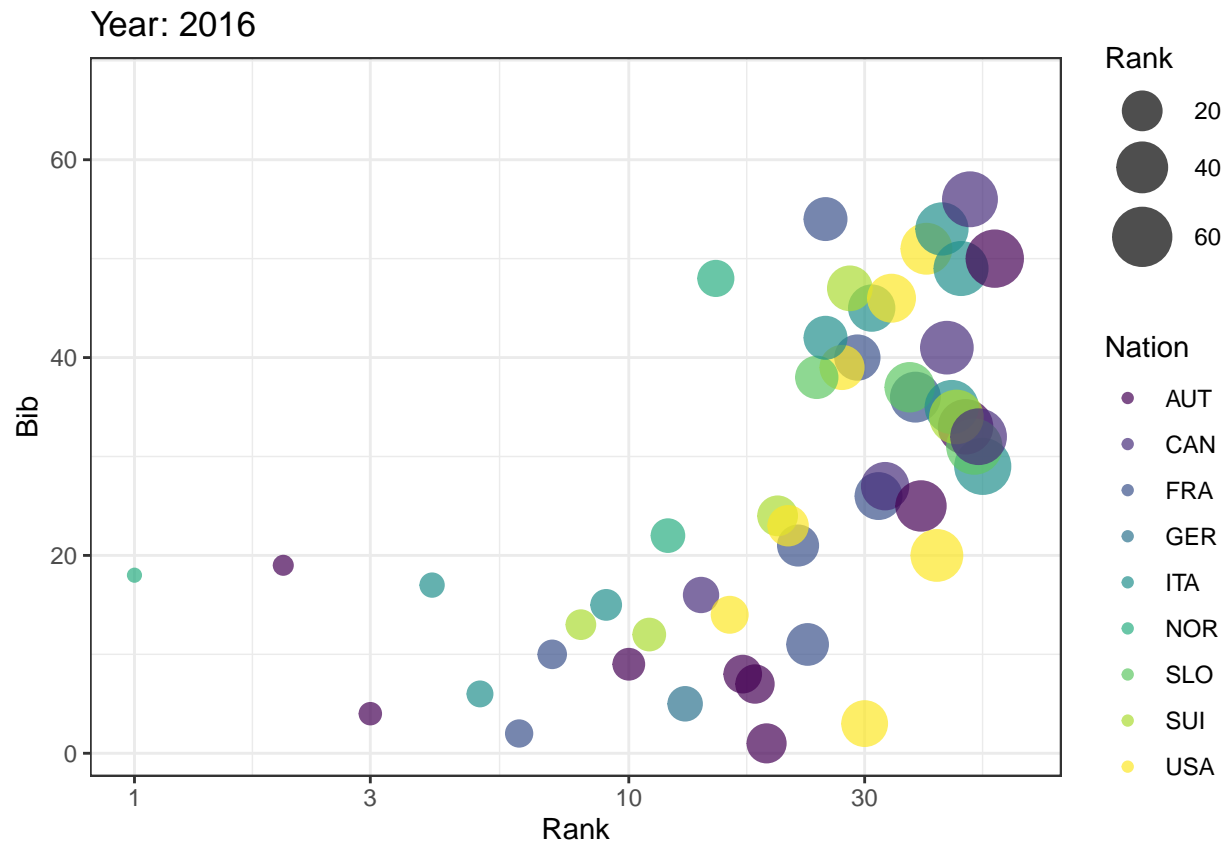


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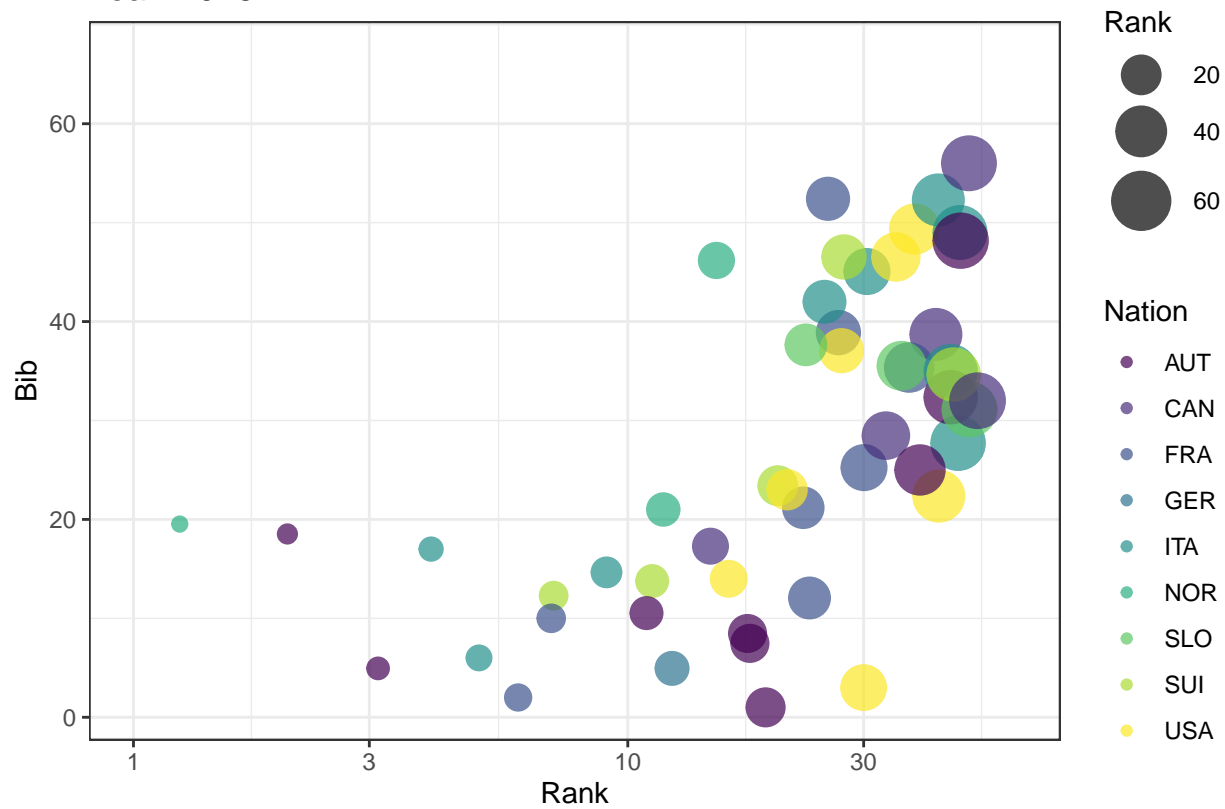


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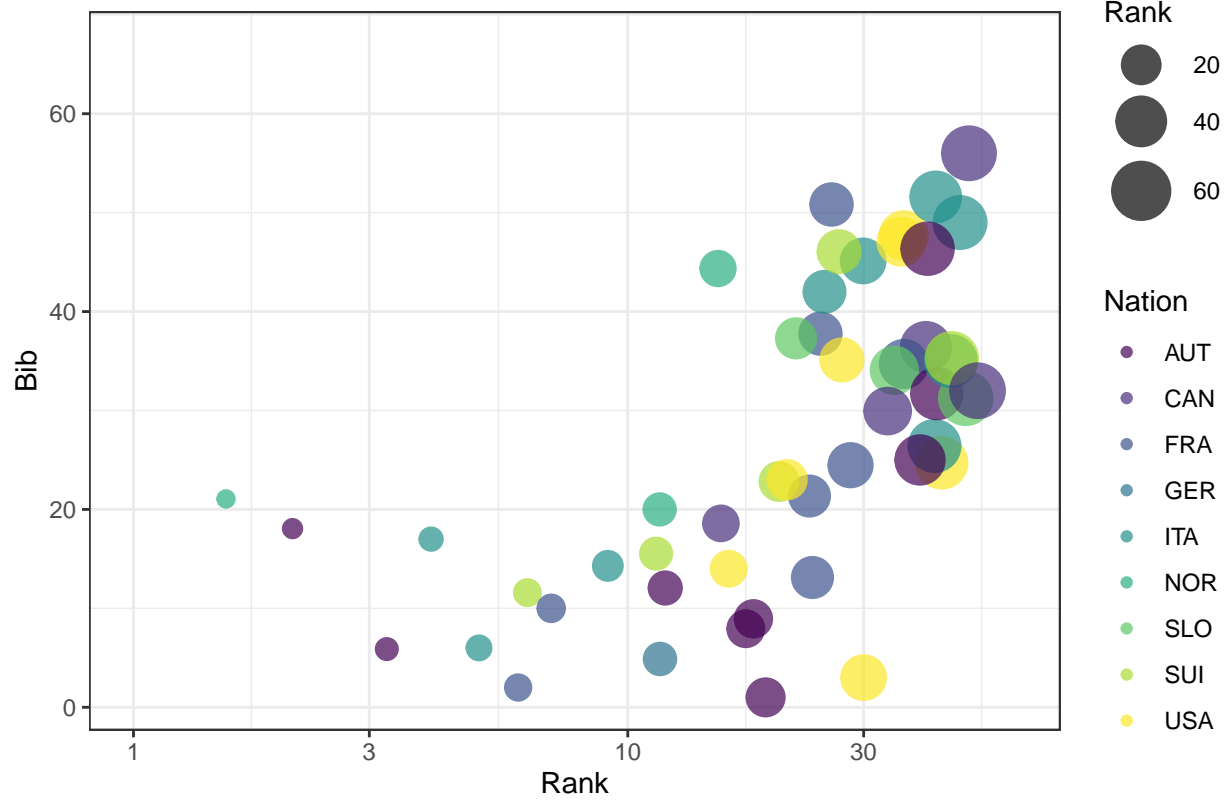




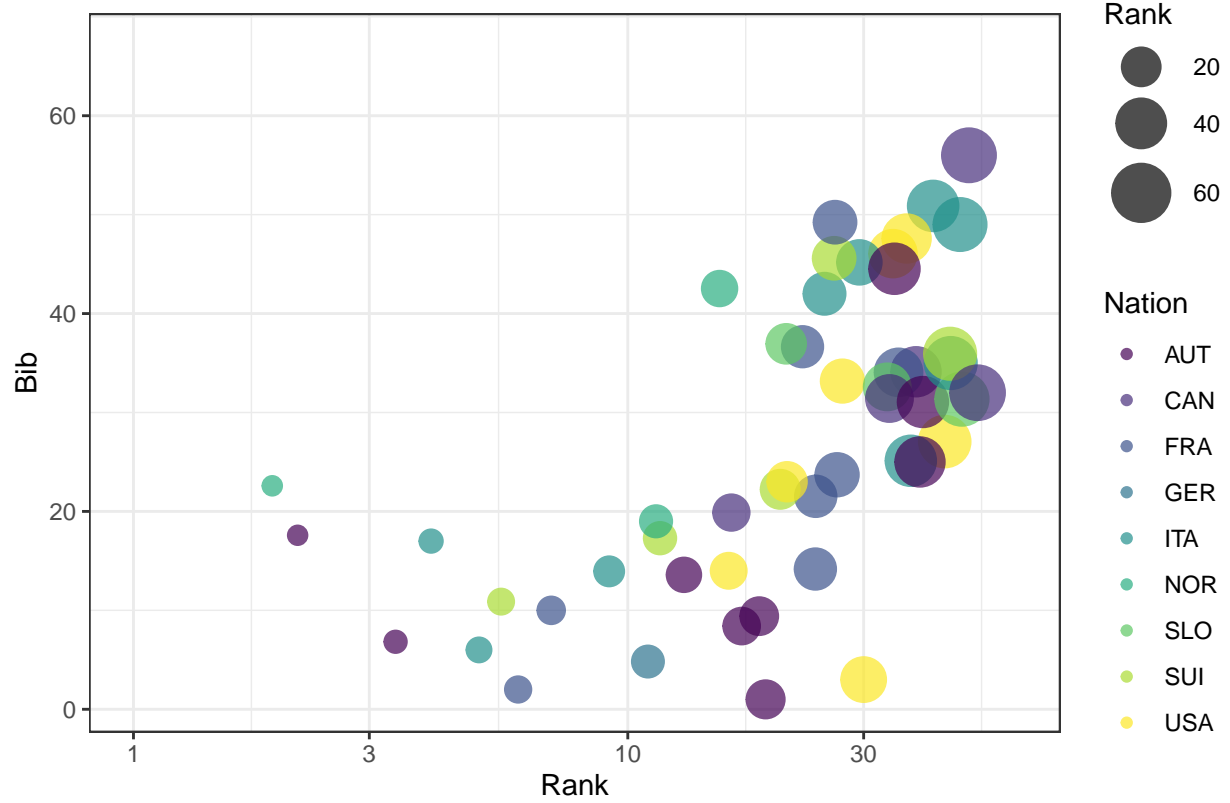
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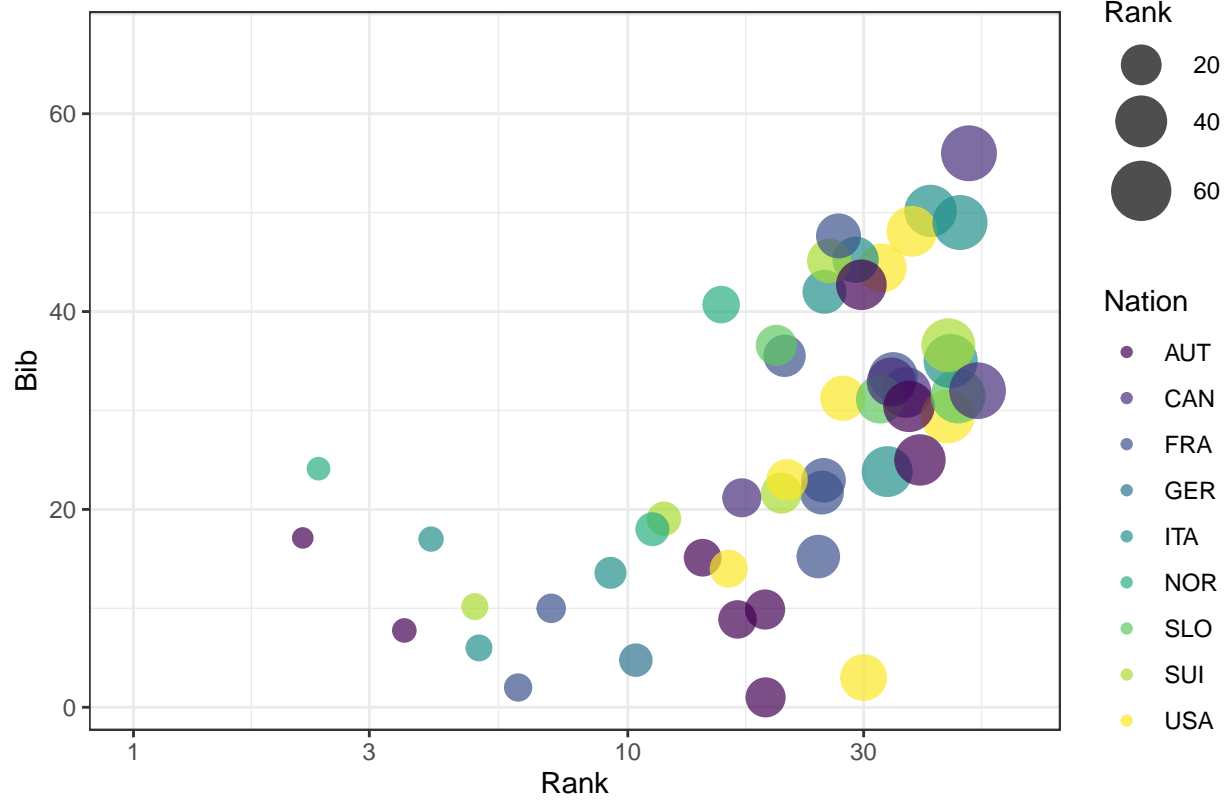
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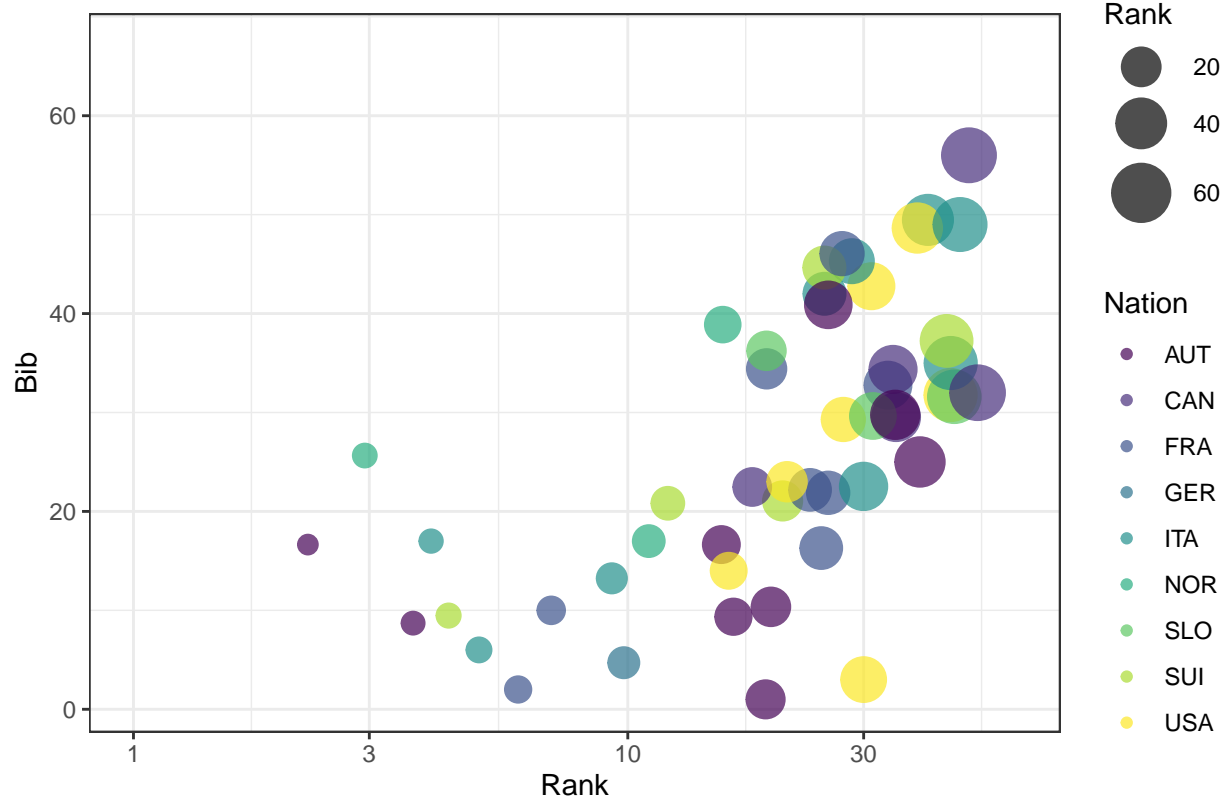
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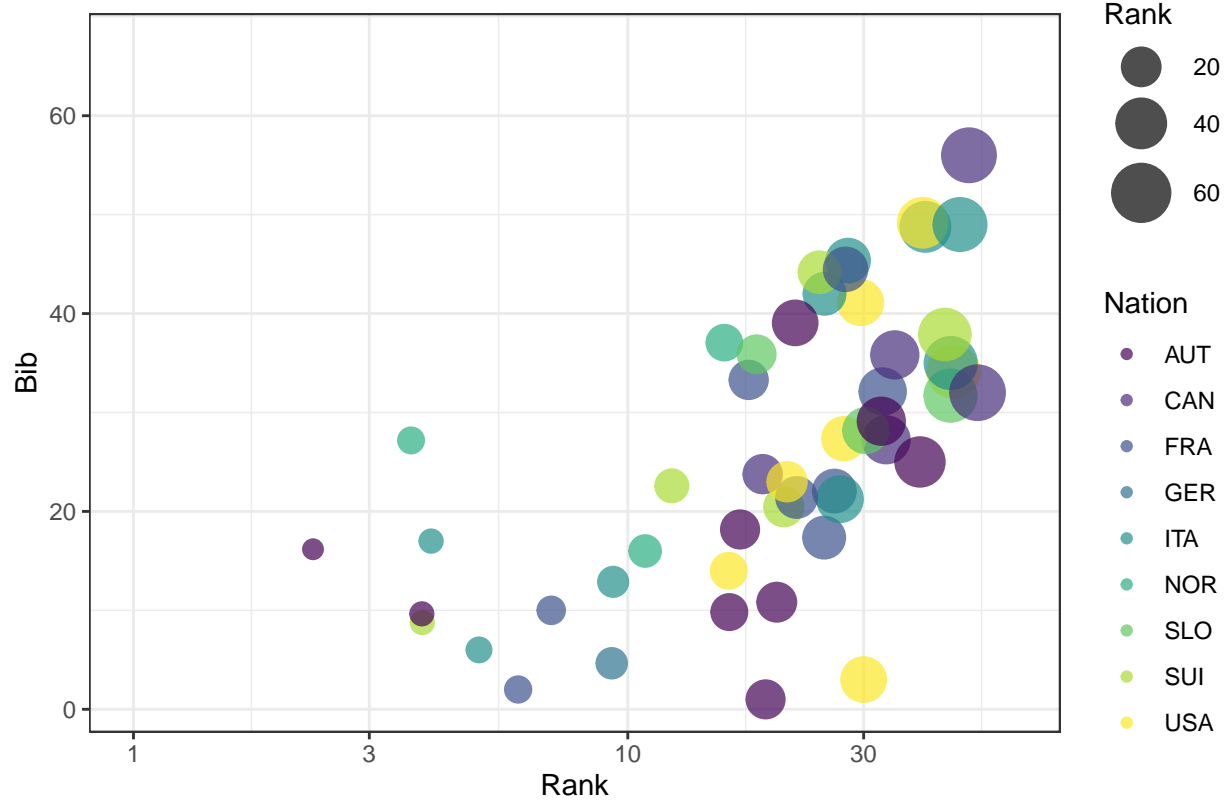
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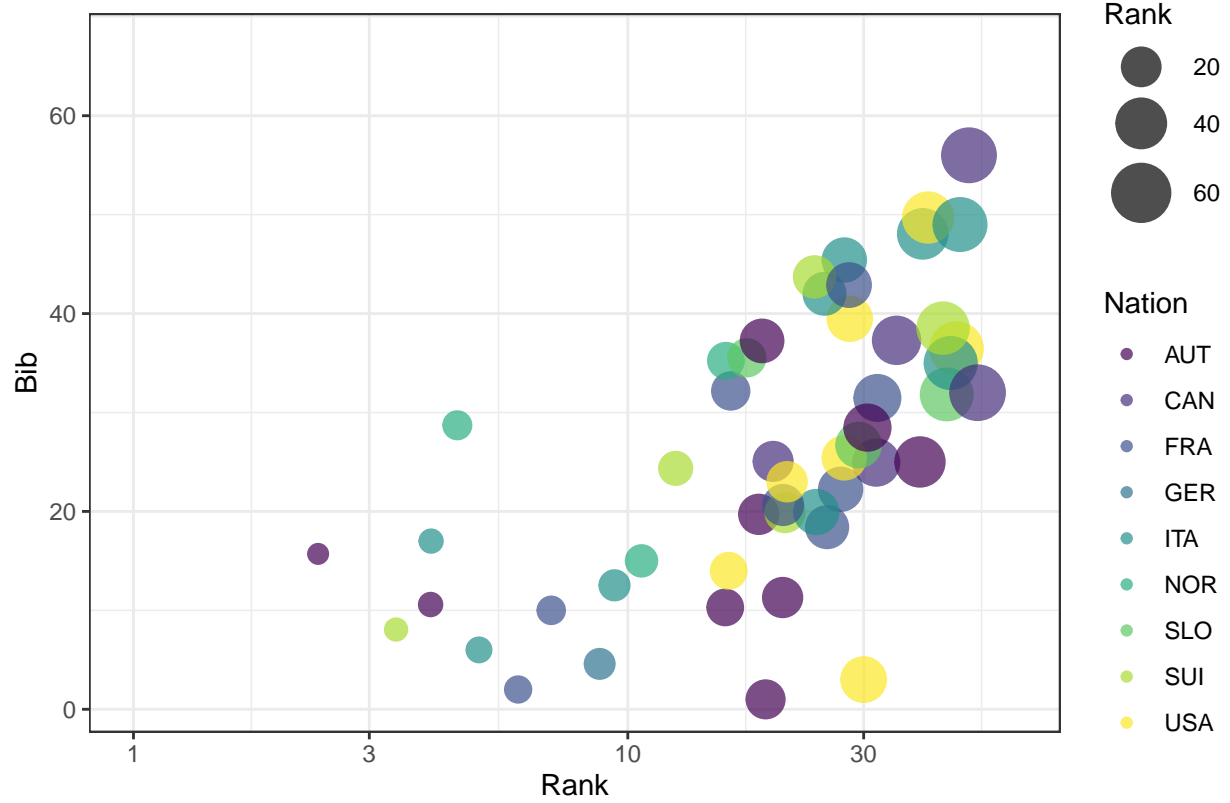
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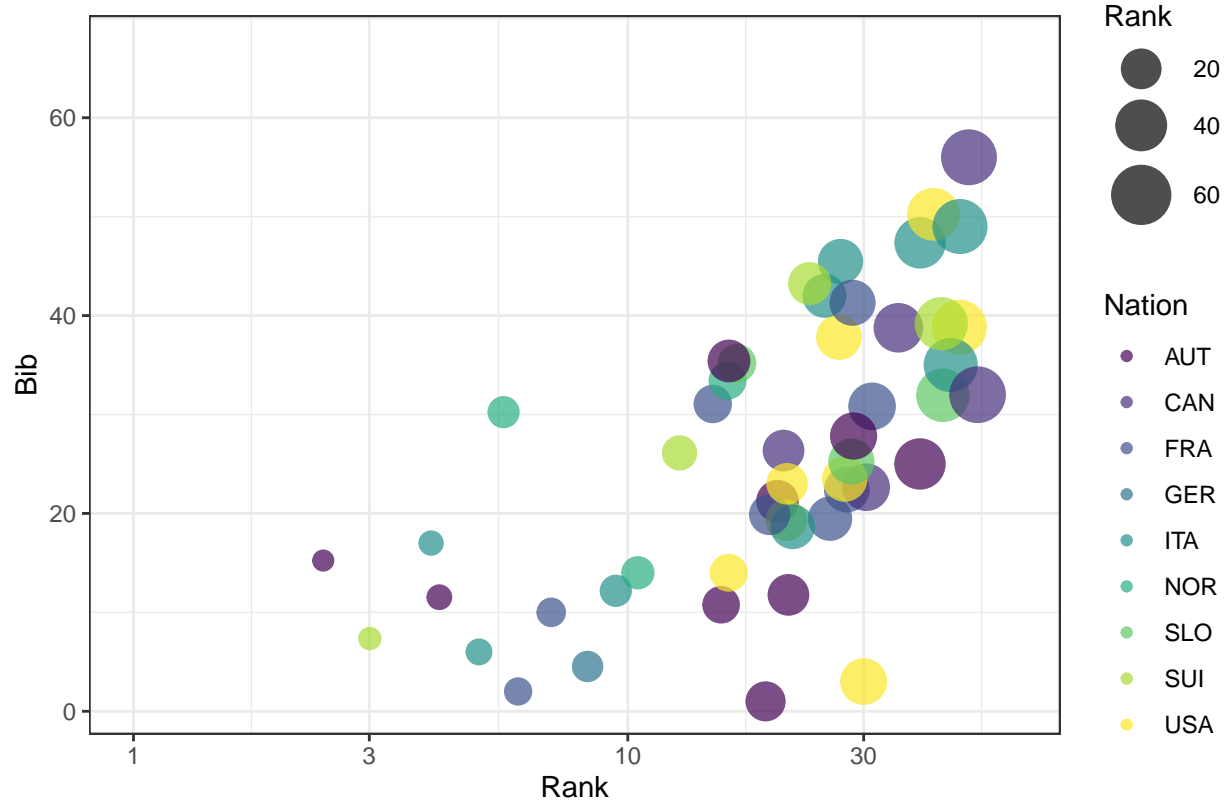
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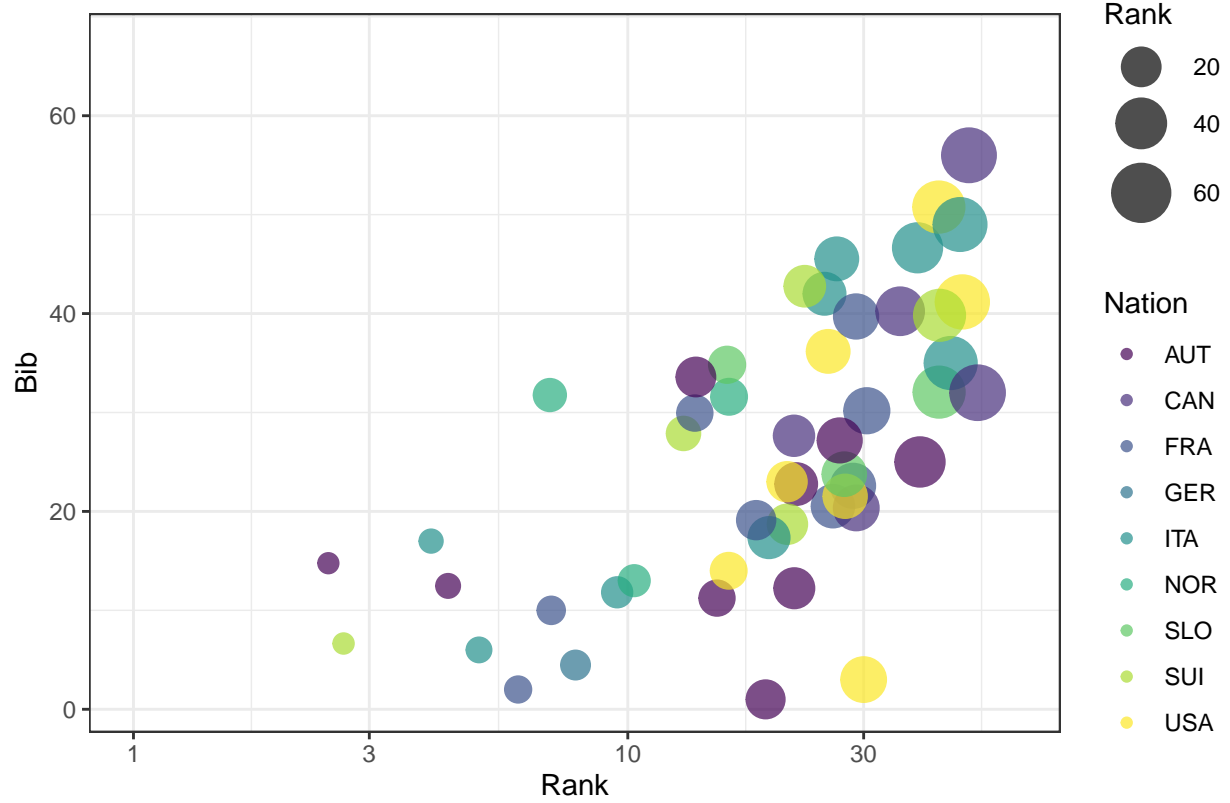
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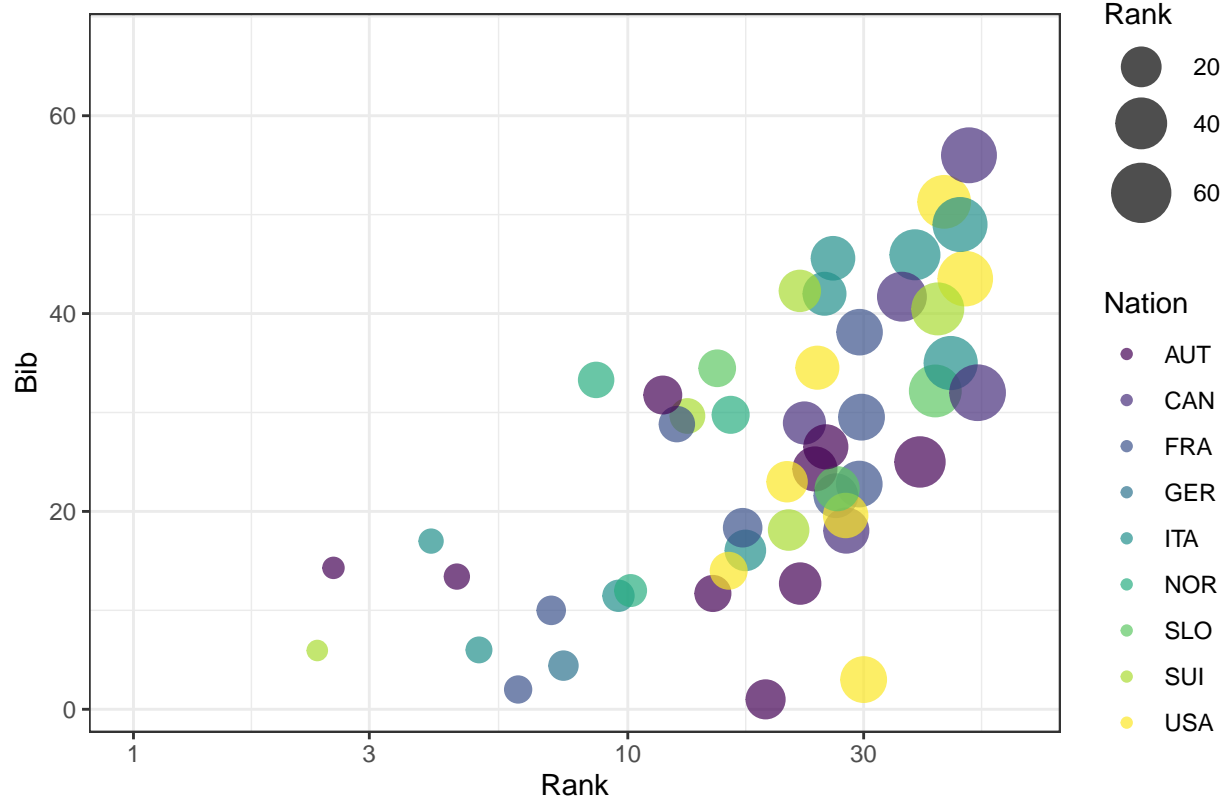
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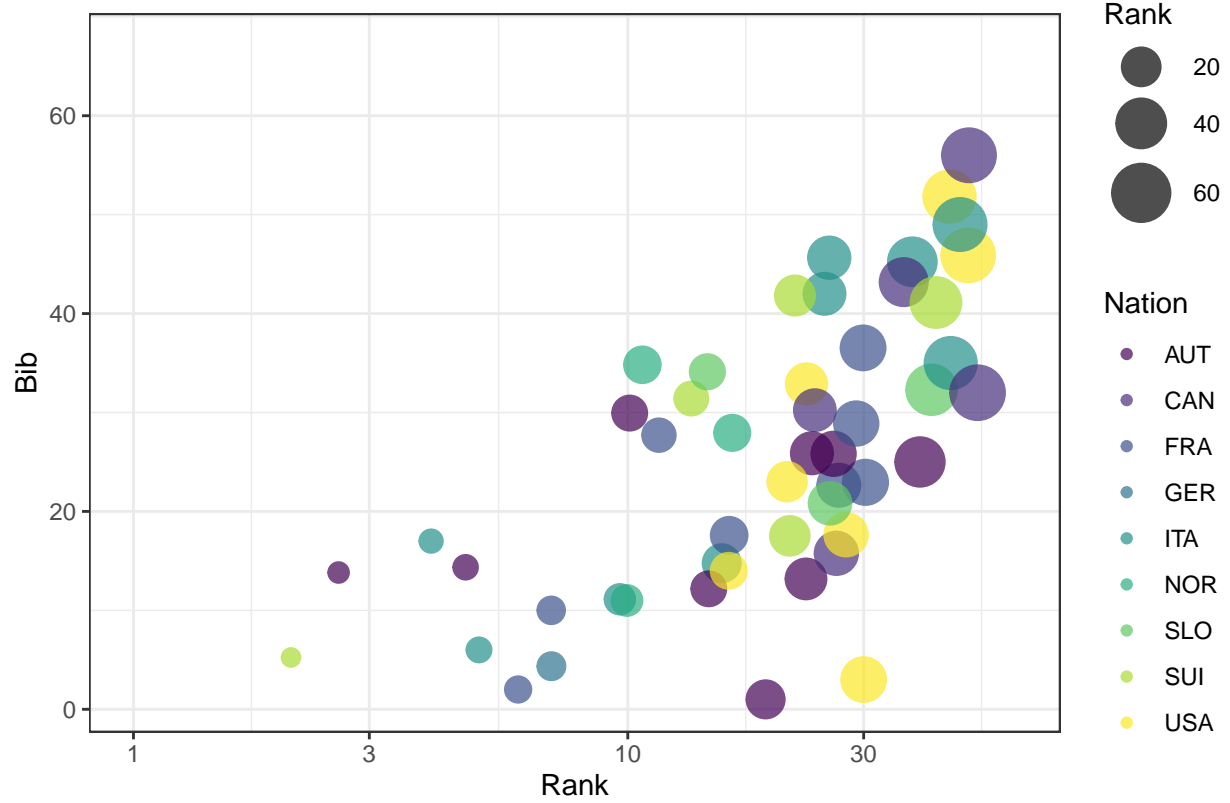
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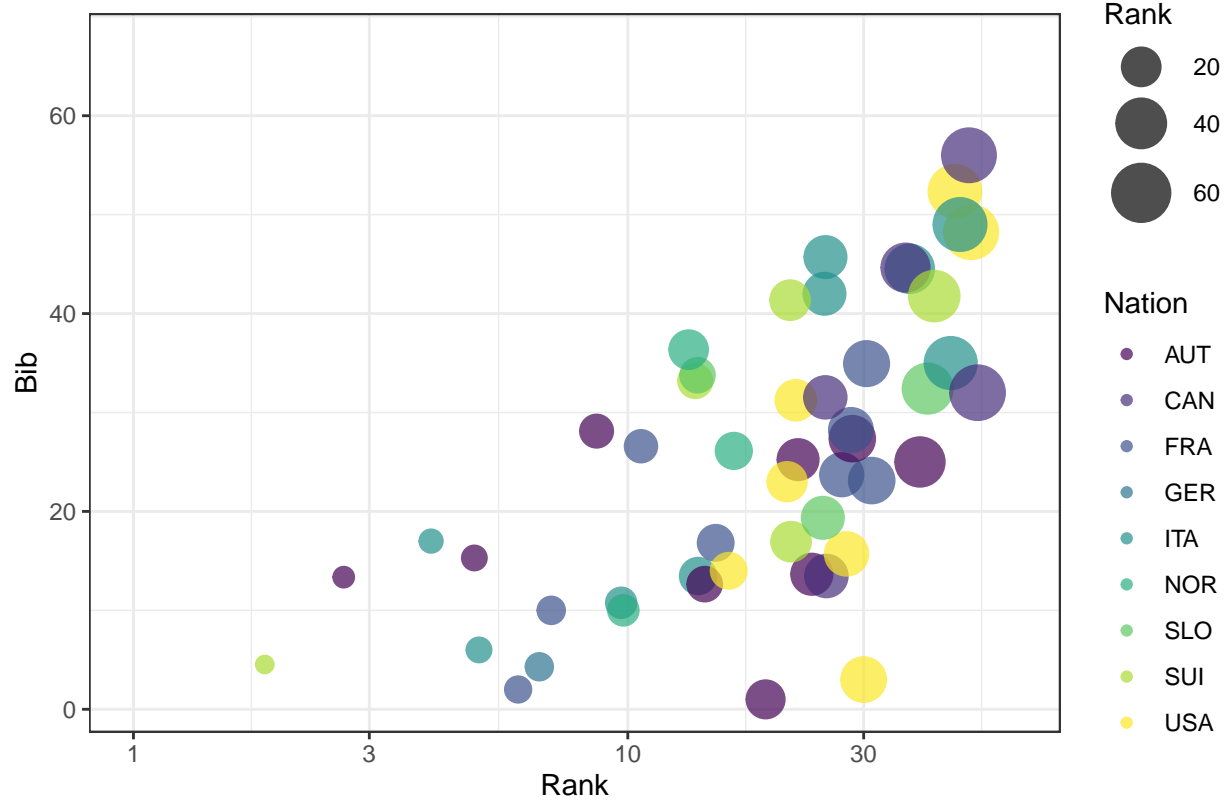
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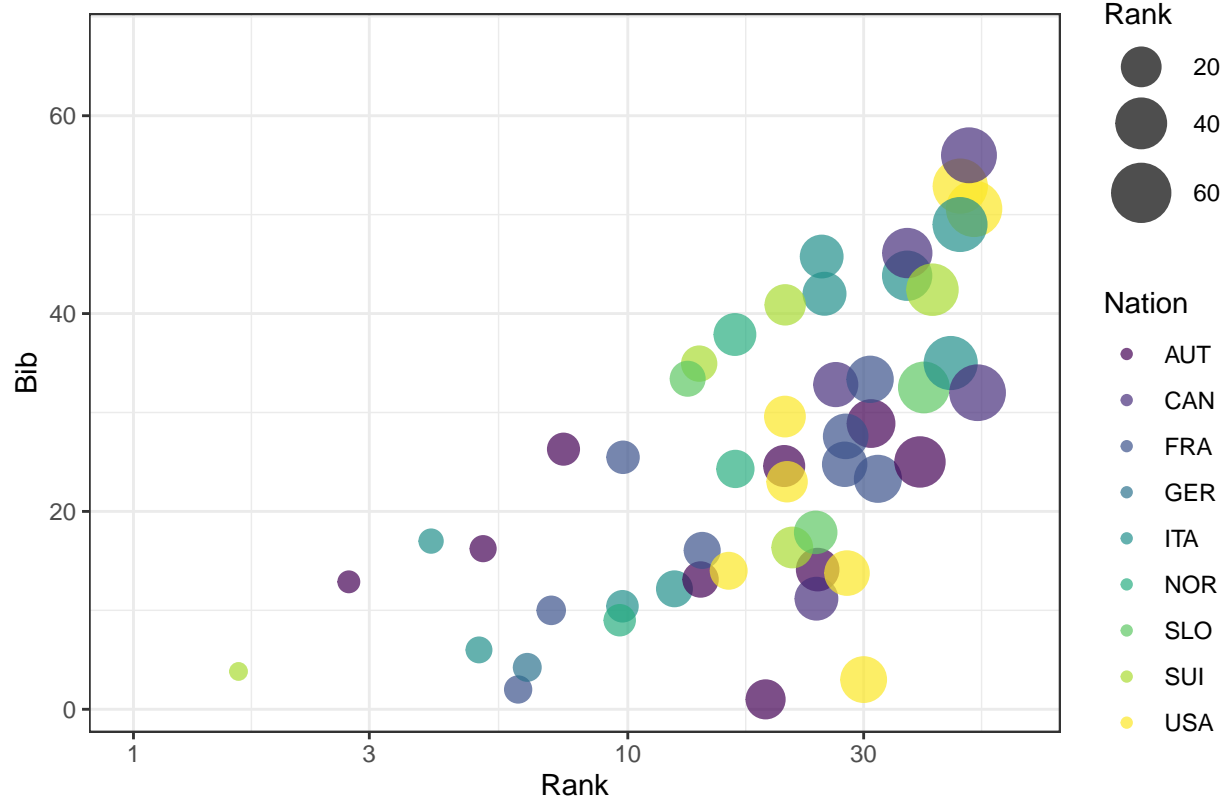
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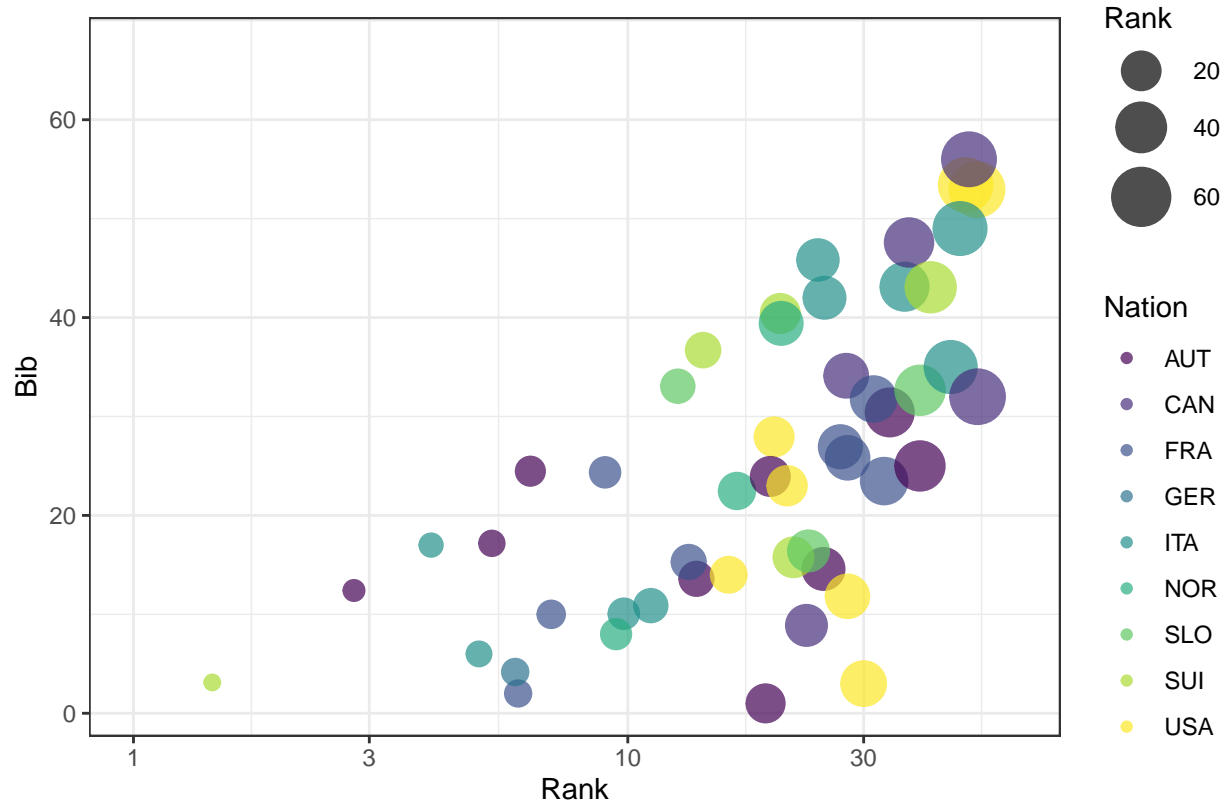
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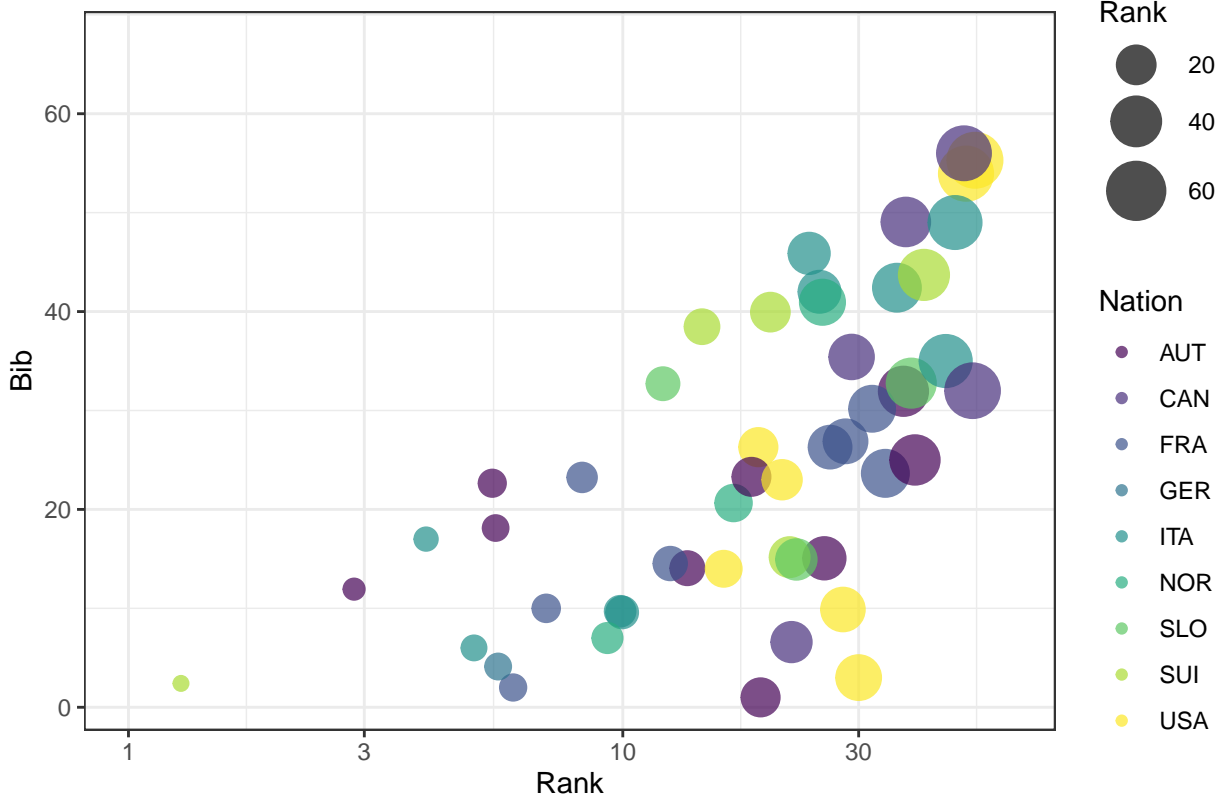
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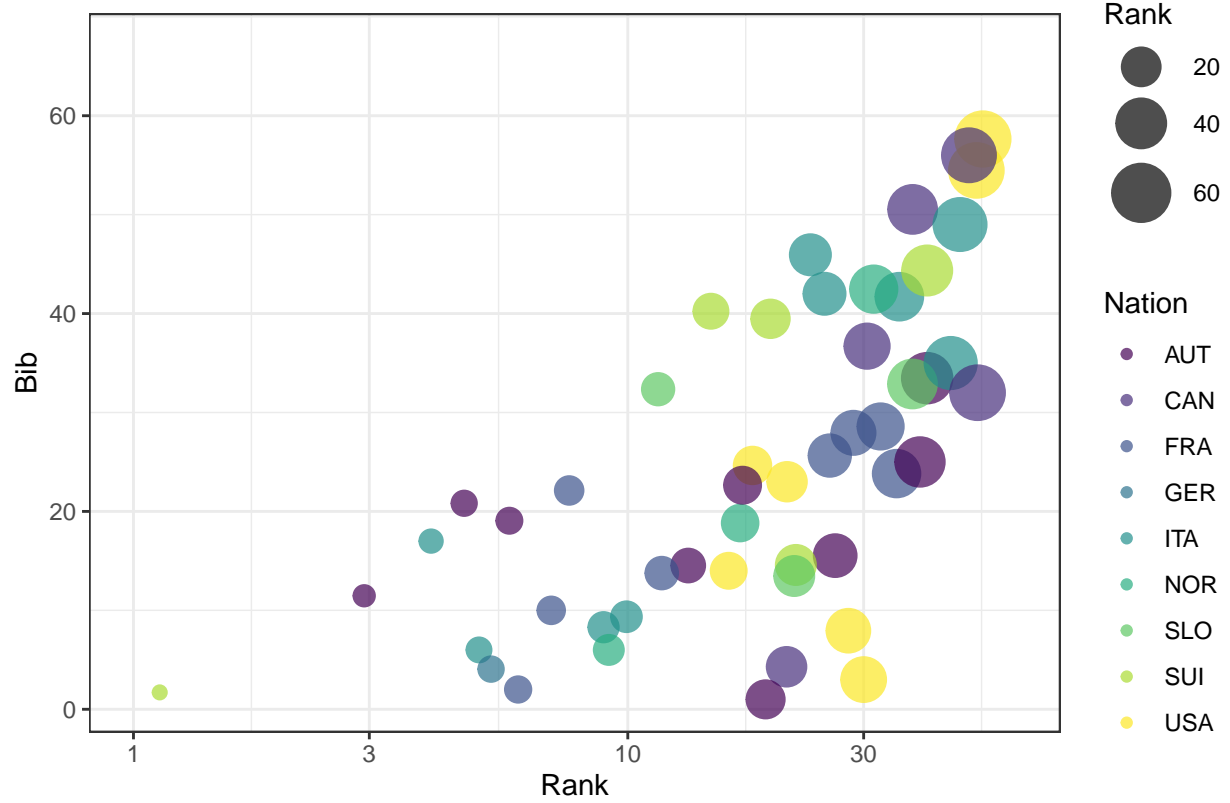
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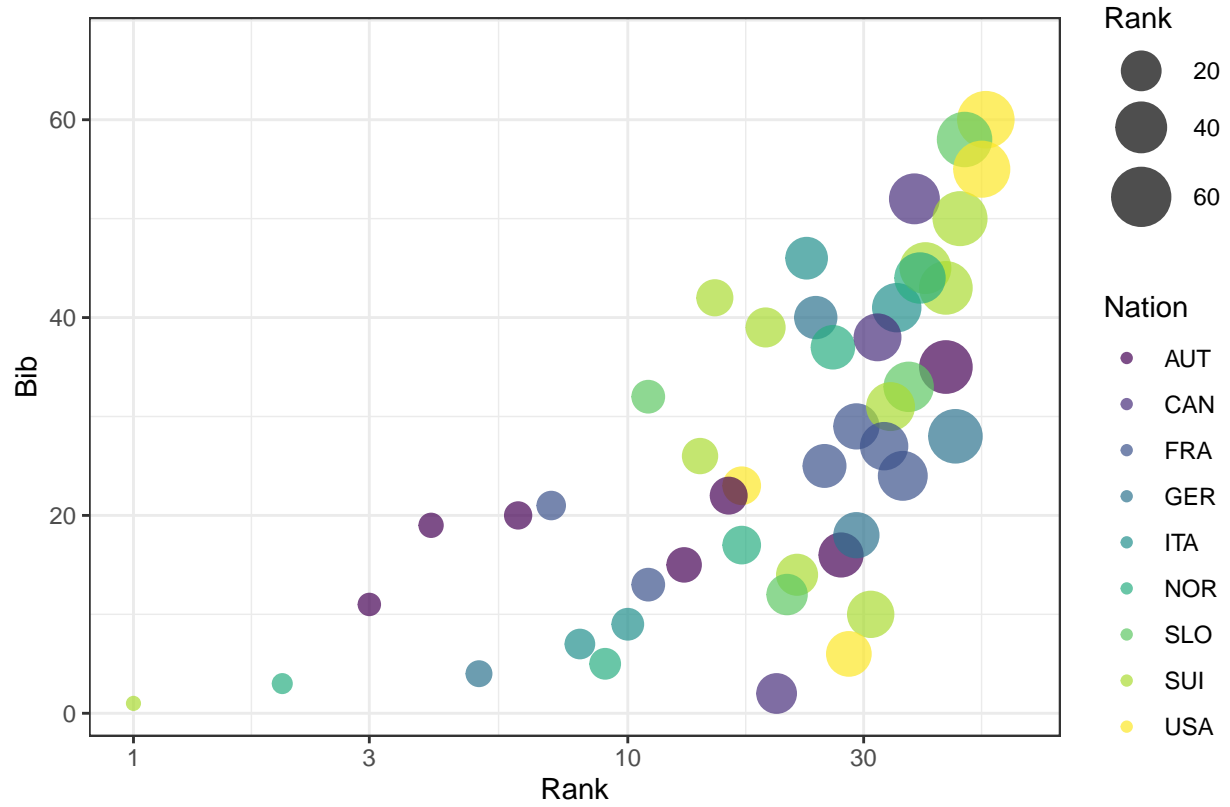
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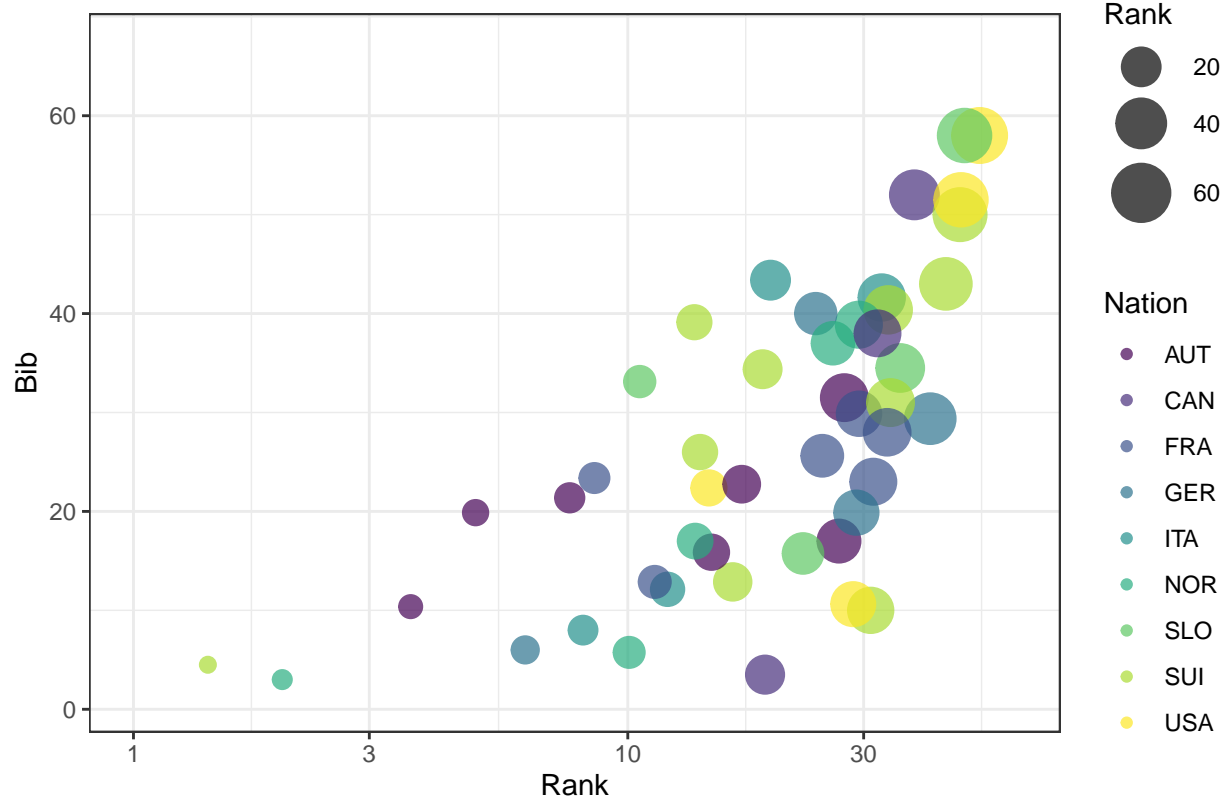
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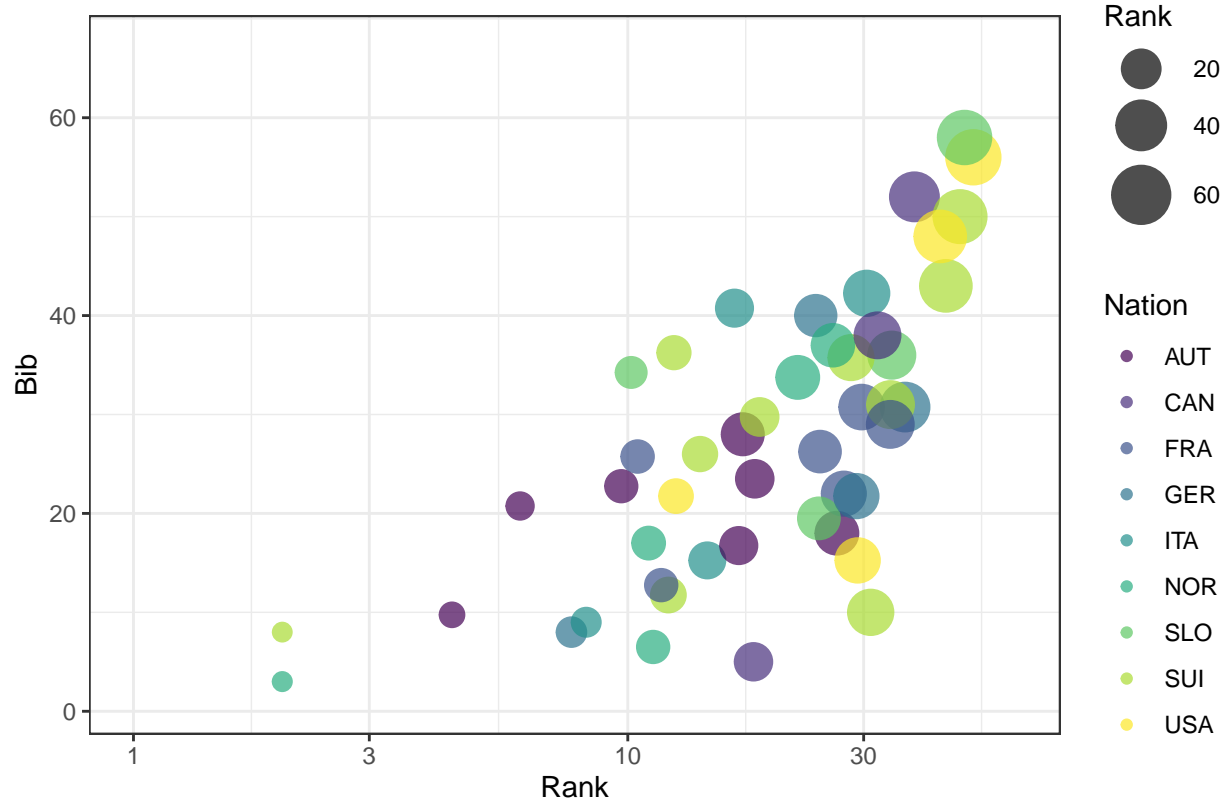
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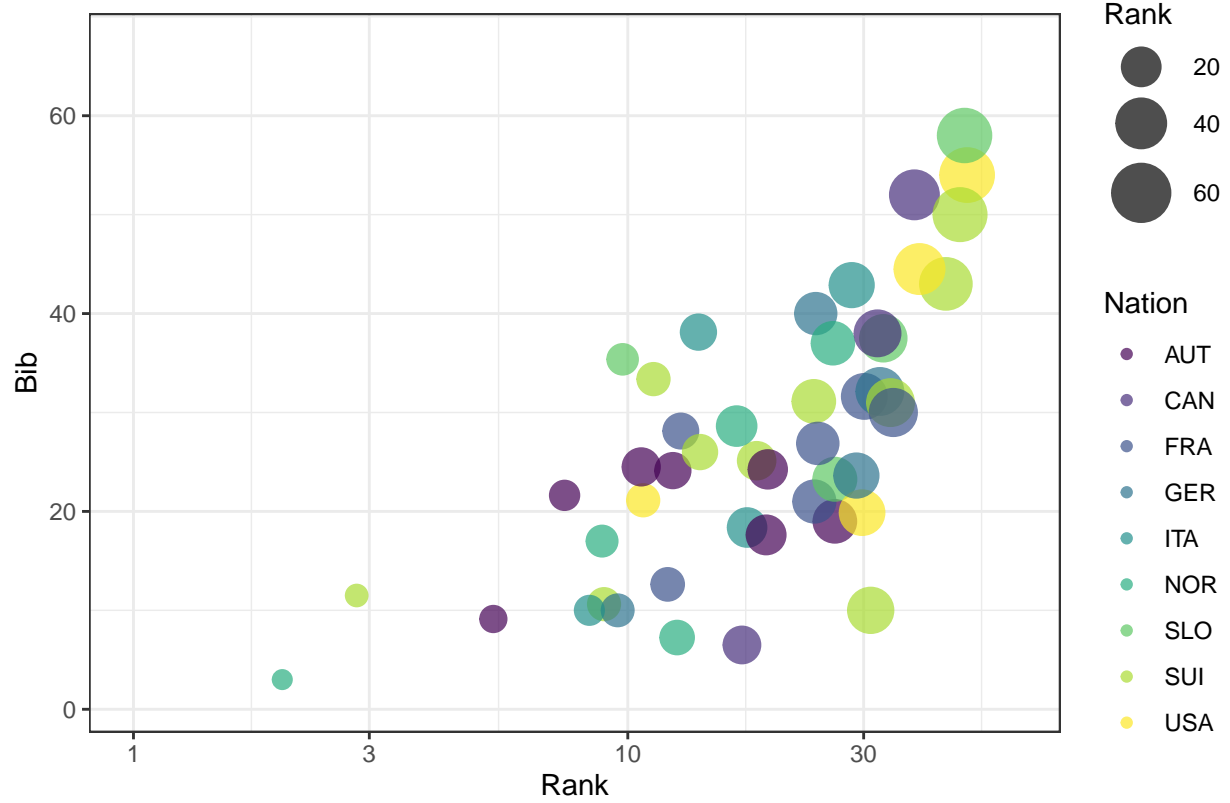
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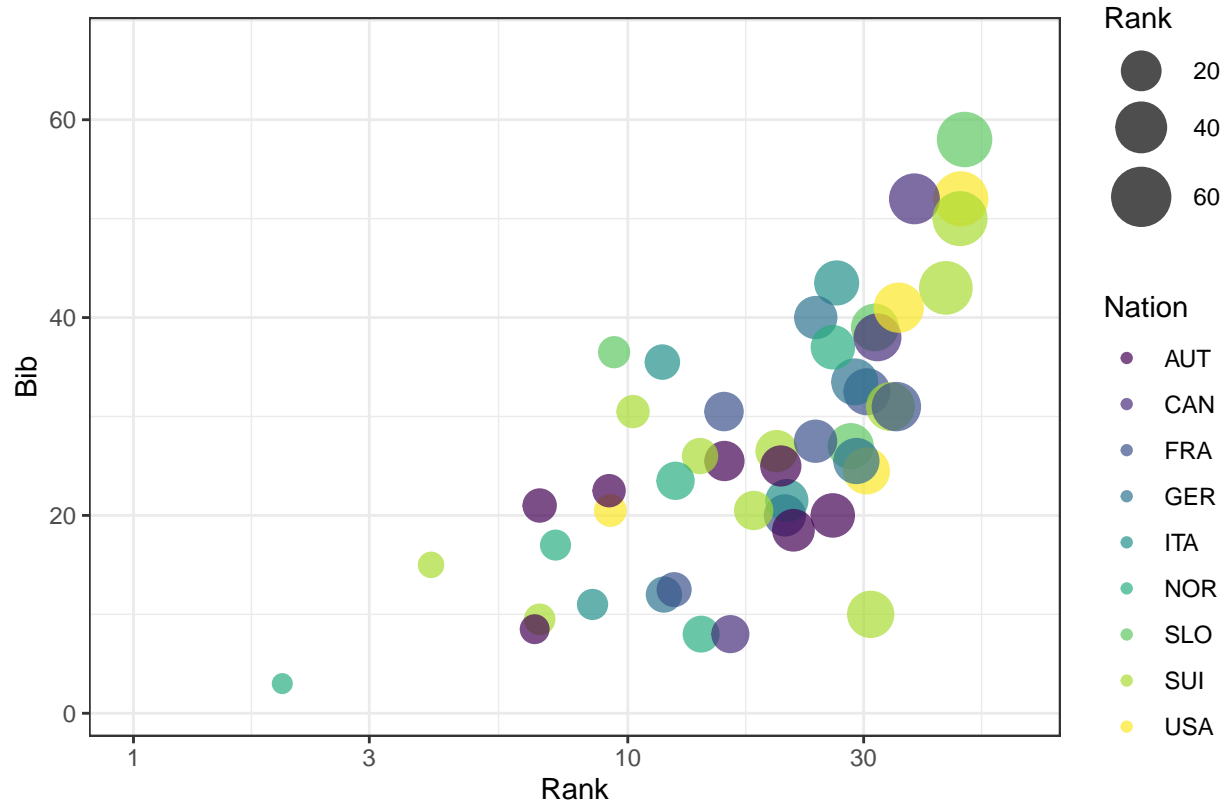
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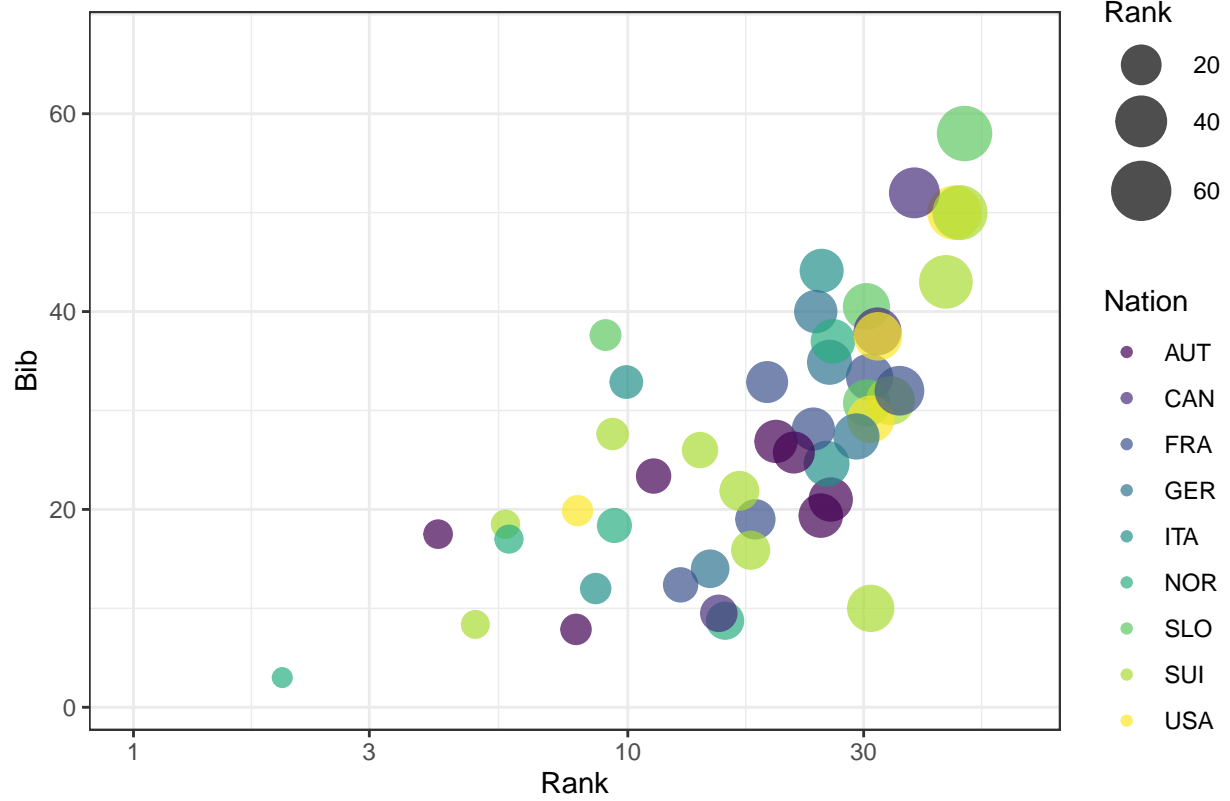
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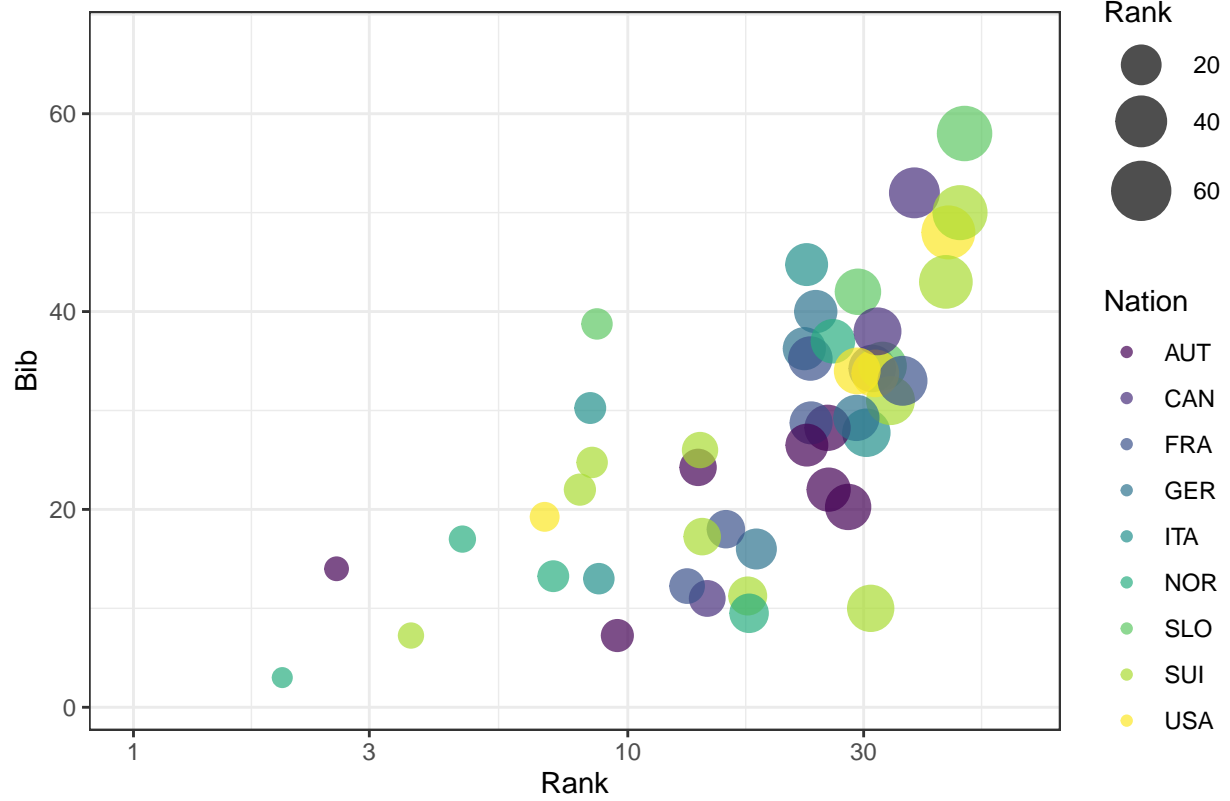
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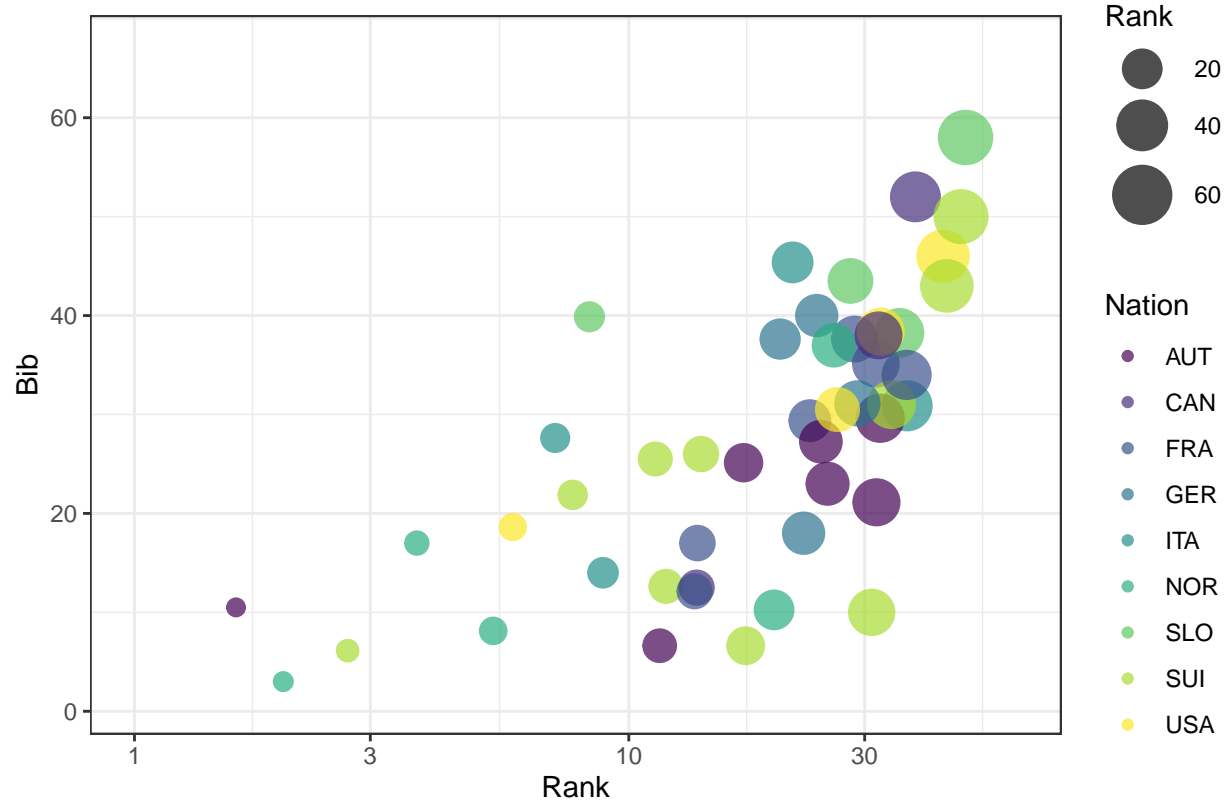
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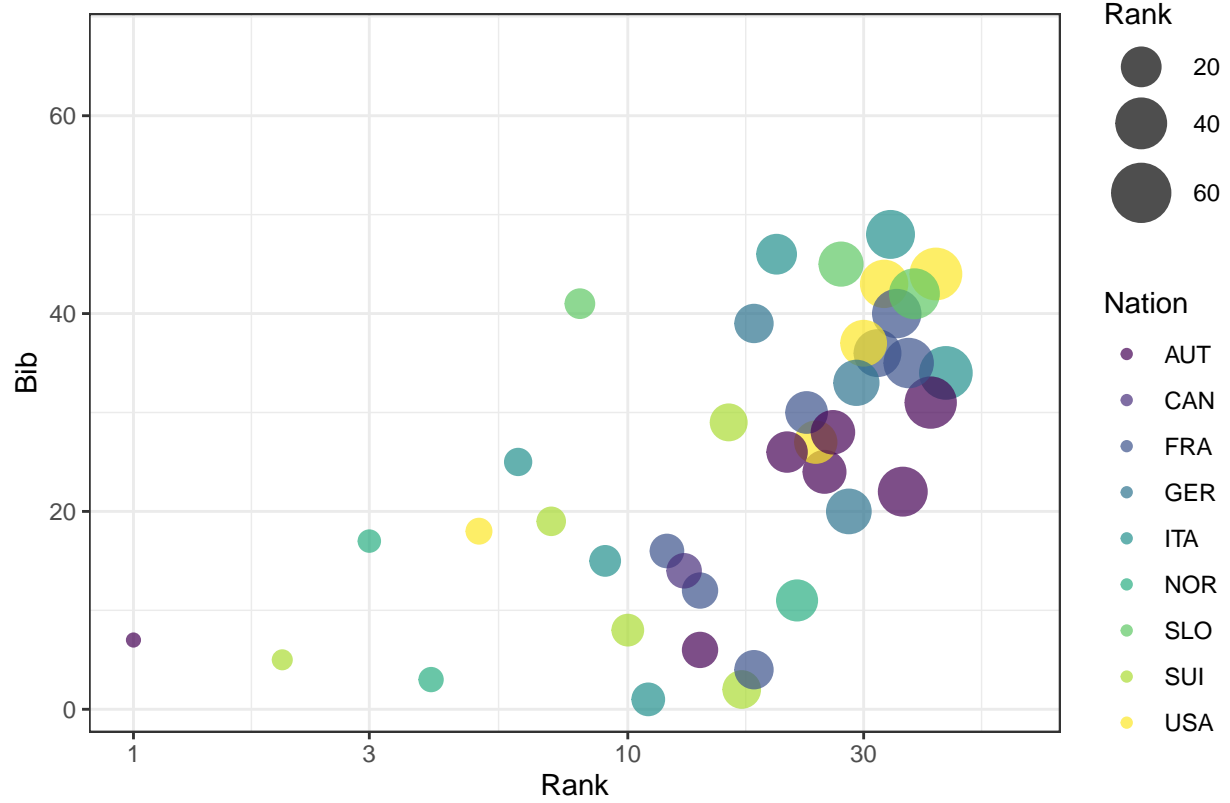
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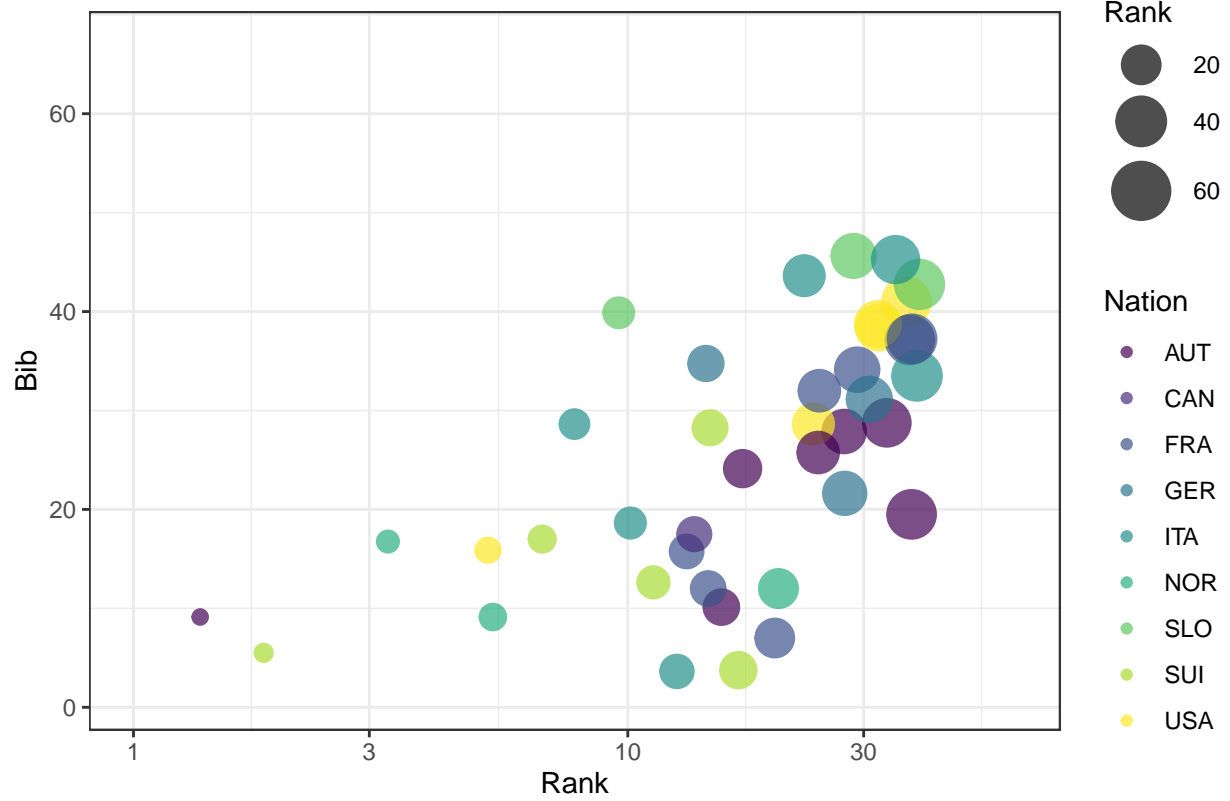
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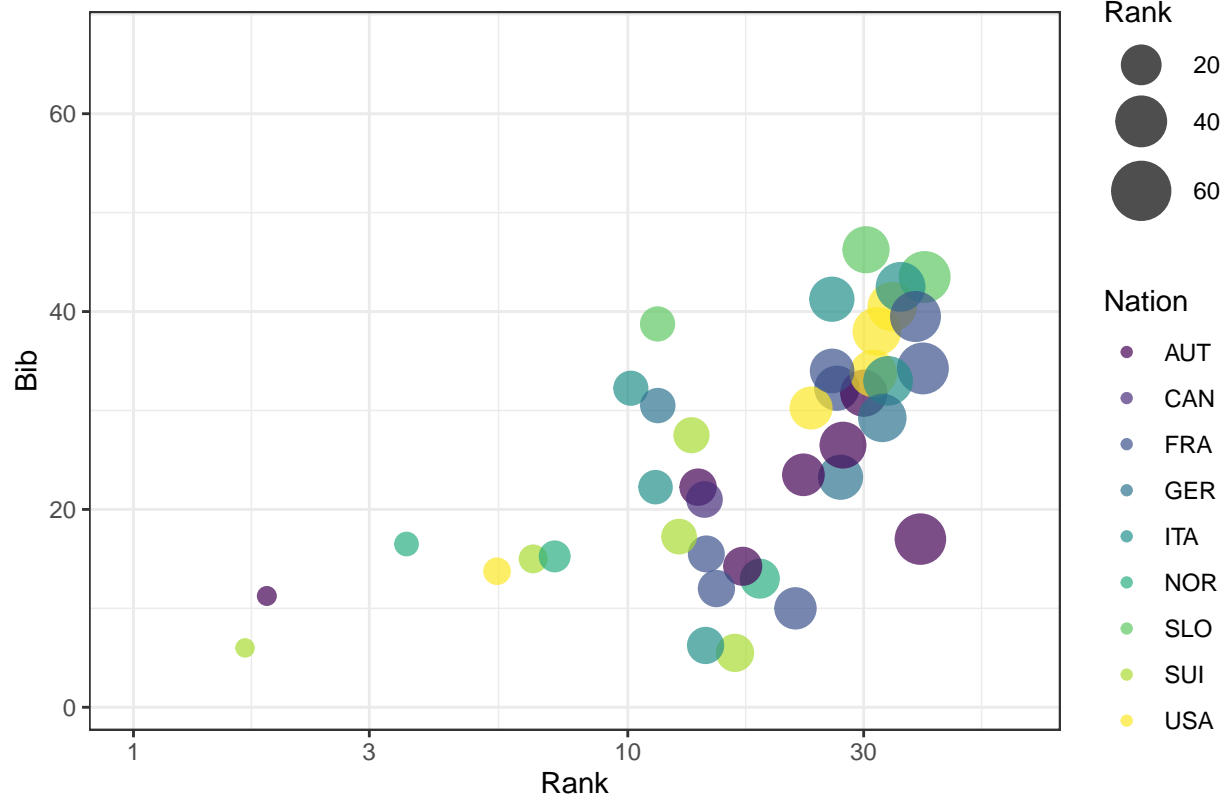
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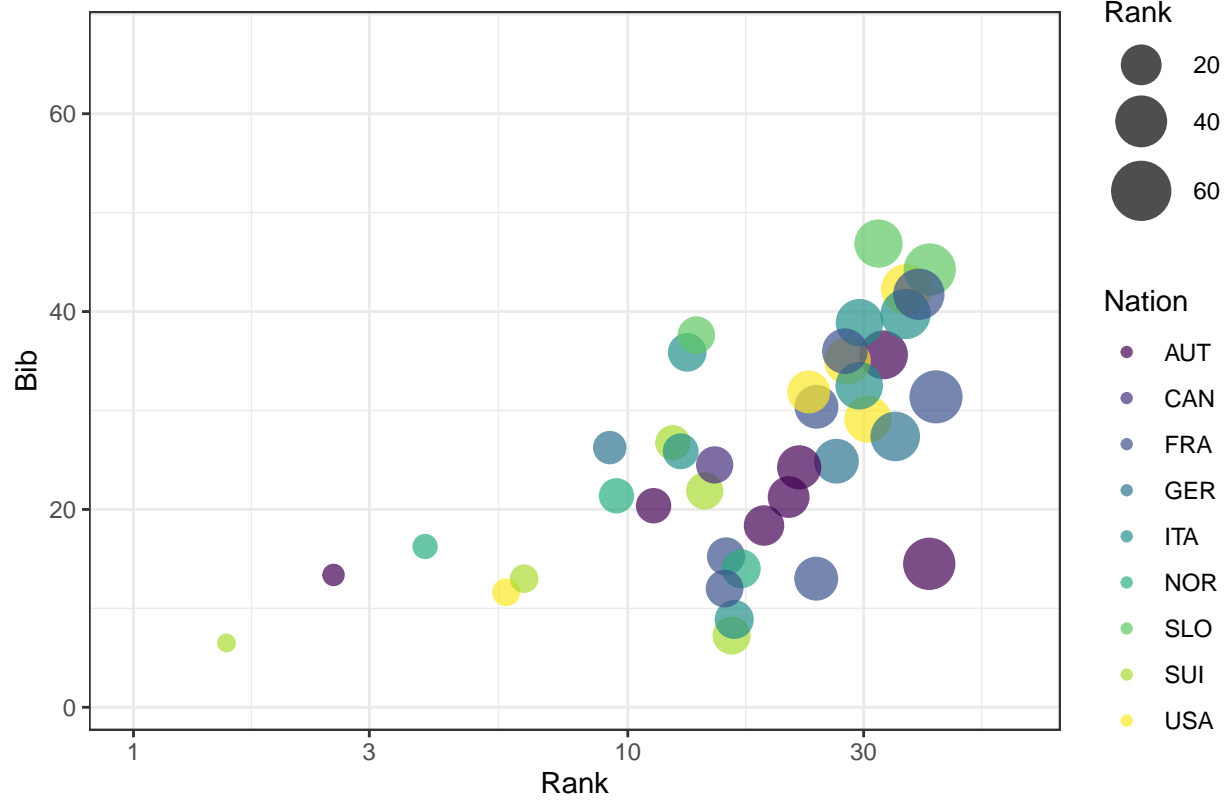
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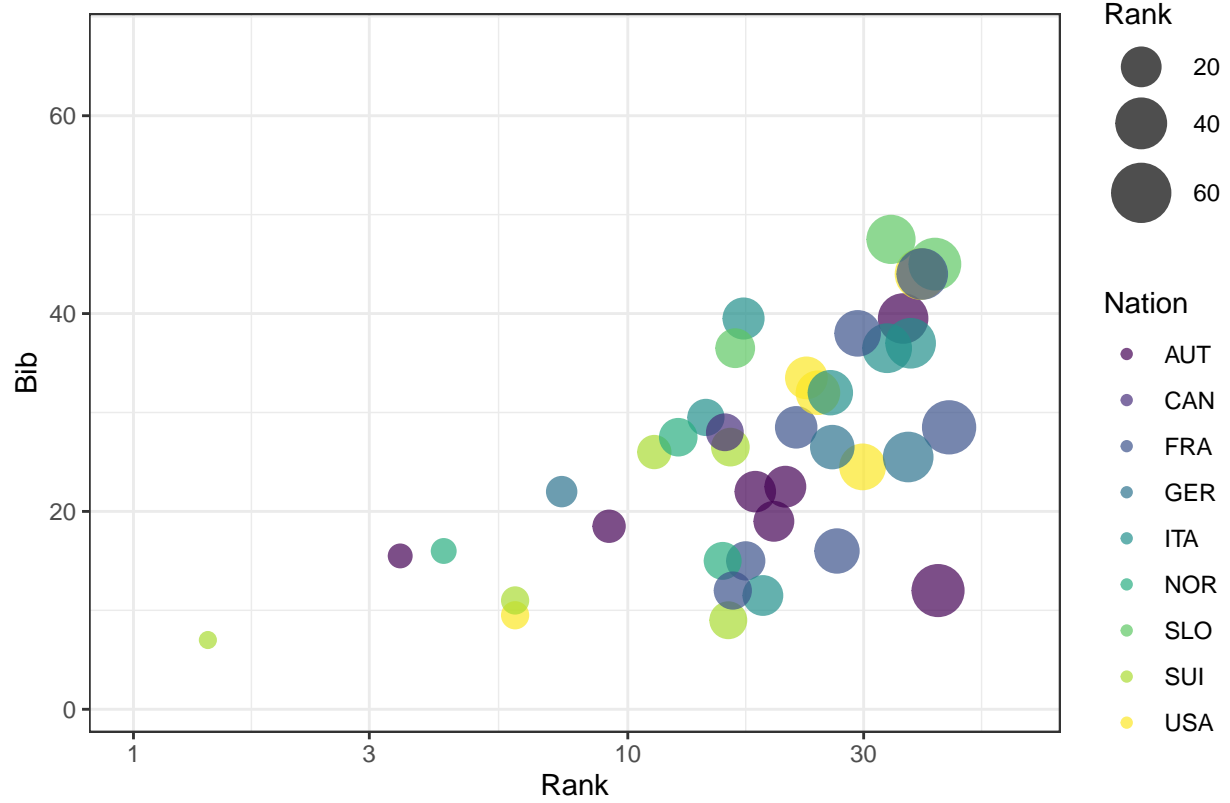
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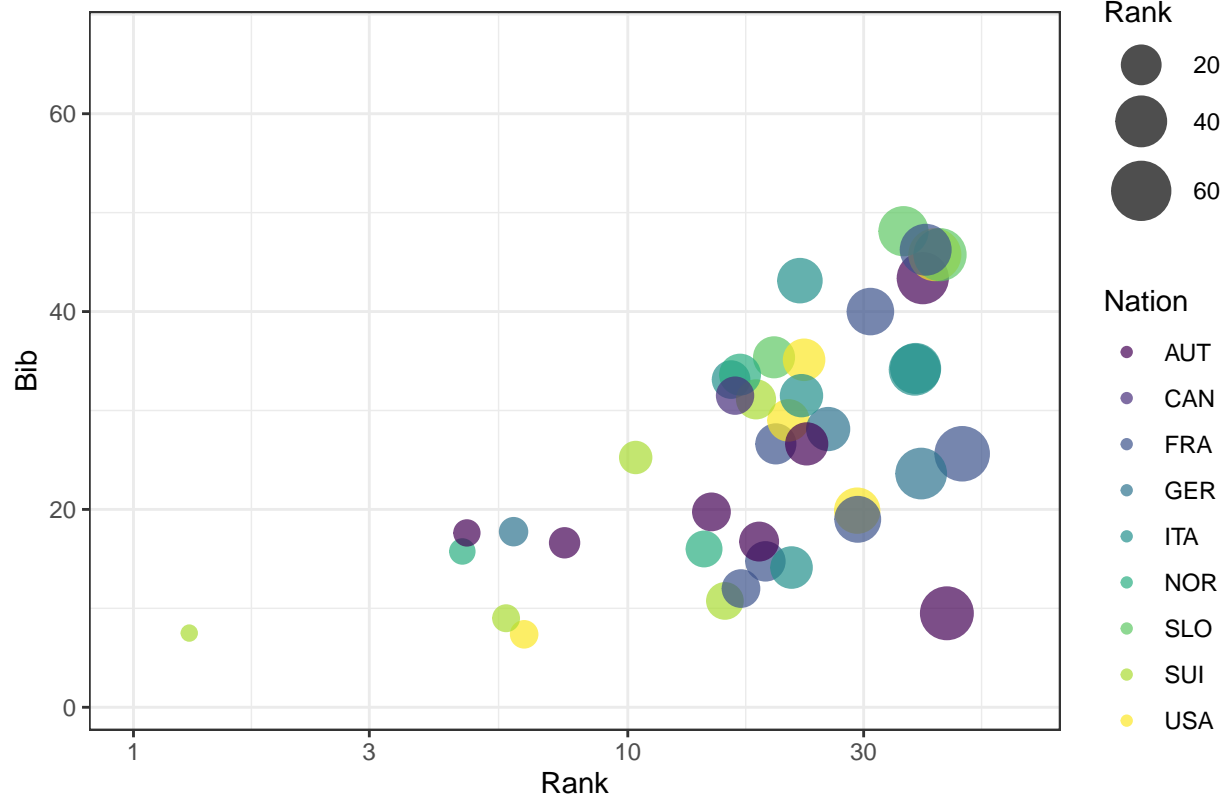
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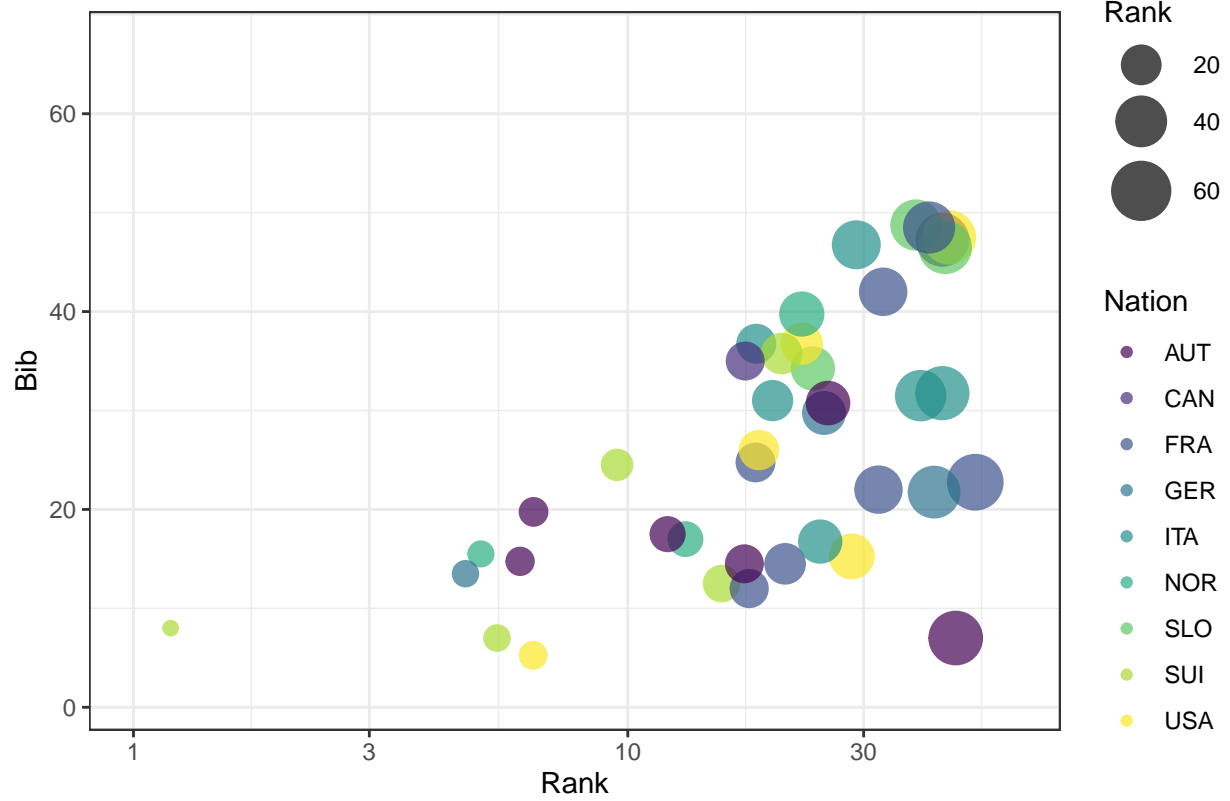
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