CS112 - R Competency

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NB: Each graph is followed by a few italic sentences describing the association portrayed as well as it's relevance. They should be taken as part of the graphs, not associated with nearby text.

```
In [1]:
```

```
# Step 1: Read in the data
data = read.csv("data.csv")
```

In [3]:

```
# Step 2: Omit rows with missing values
na.omit(data)

# Step 3: Read date values as dates
data$Last_Reporting_Date <- as.Date(data$Last_Reporting_Date, format="%d/%m/%Y")</pre>
```

A data.frame: 147626 × 9

	Contribution_ID	ISOCode3	M49_Code	Contributing_Country	Mission_Acronym	Personnel_Type	Female_Personnel	Male_Pers
	<int></int>	<chr></chr>	<int></int>	<chr></chr>	<chr></chr>	<chr></chr>	<int></int>	
1	427903	DZA	12	Algeria	MONUSCO	Experts on Mission	0	
2	427904	ARG	32	Argentina	MINURSO	Experts on Mission	0	
3	427905	ARG	32	Argentina	UNFICYP	Troops	15	
4	427906	ARG	32	Argentina	UNFICYP	Staff Officer	3	
5	427907	ARG	32	Argentina	UNMISS	Individual Police	1	
6	427908	ARG	32	Argentina	UNTSO	Experts on Mission	0	
7	427909	ARG	32	Argentina	UNVMC	Individual Police	5	
8	427910	ARM	51	Armenia	MINUSMA	Staff Officer	0	
9	427911	ARM	51	Armenia	UNIFIL	Troops	2	
10	427912	ARM	51	Armenia	UNIFIL	Staff Officer	0	
11	427913	AUS	36	Australia	UNDOF	Staff Officer	0	
12	427914	AUS	36	Australia	UNFICYP	Staff Officer	1	
13	427915	AUS	36	Australia	UNMISS	Experts on Mission	0	
14	427916	AUS	36	Australia	UNMISS	Staff Officer	9	
15	427917	AUS	36	Australia	UNTSO	Experts on Mission	0	
16	427918	AUT	40	Austria	MINURSO	Experts on Mission	0	
17	427919	AUT	40	Austria	MINUSMA	Staff Officer	0	
18	427920	AUT	40	Austria	UNFICYP	Staff Officer	0	
19	427921	AUT	40	Austria	UNIFIL	Troops	9	
20	427922	AUT	40	Austria	UNIFIL	Staff Officer	0	
21	427923	AUT	40	Austria	UNMIK	Individual Police	1	
22	427924	AUT	40	Austria	UNTSO	Experts on Mission	1	
23	427925	AZE	31	Azerbaijan	UNMISS	Experts on Mission	0	

24	Contribut <u>iong∯</u>	ISOC pode3	M49_Code	Contributing Contribution	Mission_AARTOREEM	Personnel _L -Type	Female_Personne	Male_Pers
25	<int> 427927</int>	<chr> BGD</chr>	<int> 50</int>	<chr> Bangladesh</chr>	<chr> MINURSO</chr>	Expension	<int></int>	
26	427928	BGD	50	Bangladesh	MINUSCA	Troops	13	
27	427929	BGD	50	Bangladesh	MINUSCA	Experts on Mission	0	
28	427930	BGD	50	Bangladesh	MINUSCA	Staff Officer	5	
29	427931	BGD	50	Bangladesh	MINUSMA	Troops	10	
30	427932	BGD	50	Bangladesh	MINUSMA	Experts on Mission	1	
:	:	:	!	: -	:	:	:	
147602	411514	ROU	642	Romania	MONUC	Troops Formed Police	0	
147603	411515	ROU	642	Romania	MONUC	Units	0	
147604	411519	TUR	792	Turkey	UNMIK	Formed Police Units	0	
147605	411523	ZMB	894	Zambia	UNMIK	Formed Police Units	0	
147606	411526	TUN	788	Tunisia	MONUC	Troops	0	
147607	411527	TUN	788	Tunisia	MONUC	Formed Police Units	0	
147608	411531	TUR	792	Turkey	MONUC	Formed Police Units	0	
147609	411539	NGA	566	Nigeria	MINURSO	Formed Police Units	0	
147610	411543	ARG	32	Argentina	UNMISET	Formed Police Units	0	
147611	411546	BRA	76	Brazil	UNMISET	Troops	0	
147612	411547	BRA	76	Brazil	UNMISET	Formed Police Units	0	
147613	411551	CAN	124	Canada	UNMISET	Formed Police Units	0	
147614	411554	NZL	554	New Zealand	UNMISET	Troops	0	
147615	411559	NER	562	Niger (the)	UNMISET	Formed Police Units	0	
147616	411562	PRT	620	Portugal	UNMISET	Troops	0	
147617	411563	PRT	620	Portugal	UNMISET	Formed Police Units	0	
147618	411567	SEN	686	Senegal	UNMISET	Formed Police Units	0	
147619	411571	GBR	826	United Kingdom of Great Britain and Northern Ireland (the)	UNMISET	Formed Police Units	0	
147620	411575	USA	840	United States of America (the)	UNMISET	Formed Police Units	0	
147621	411578	JPN	392	Japan	UNDOF	Troops	0	
147622	411587	GRC	300	Greece	UNMIBH	Formed Police Units	0	
147623	411591	ISL	352	Iceland	UNMIBH	Formed Police Units	0	
147624	411595	IRL	372	Ireland	UNMIBH	Formed Police Units	0	
147625	411599	ARG	32	Argentina	UNMIK	Formed Police Units	0	
147626	411603	NOR	578	Norway	UNMIBH	Formed Police Units	0	
147627	411607	USA	840	United States of America (the)	UNMIBH	Formed Police Units	0	
147628	411611	BEL	56	Belgium	UNMIK	Formed Police Units	0	
147629	411615	FRA	250	France	UNMIK	Formed Police Units	0	



In [4]:

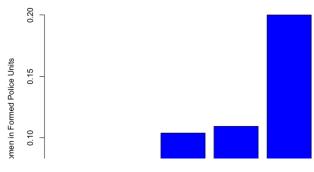
0.10929203539823

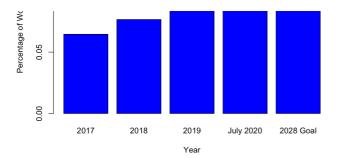
No, the UN did not meet its 2028 diversity goal for formed police units in July. Their goal was 20%, and they only had 10.9% as shown output above.

In [5]:

```
# Step 5: Plotting
bars = c(
    percent_women_police("2017/01/01", "2017/12/31"),
    percent_women_police("2018/01/01", "2018/12/31"),
percent_women_police("2019/01/01", "2019/12/31"),
    percent women police("2020/07/01", "2020/07/31"),
    0.2
names = c(
    "2017",
    "2018",
    "2019",
    "July 2020",
    "2028 Goal"
barplot (bars,
         main="Women in Formed Police Units",
         ylab="Percentage of Women in Formed Police Units",
         xlab="Year",
         names=names,
         col='blue')
```

Women in Formed Police Units





This bar plot shows the percentage of women in formed police units in UN missions in the dataset. Although the numbers are improving, they are not close to the 2028 goal. Notice the nonlinear x-axis.

In [6]:

19

```
# Step 6: Countries from the Rotation
missions for country = function(country code) {
    # this line subsets the primary data frame to find only missions from the country
    country_missions = subset(data, data$ISOCode3==country_code)$Mission_Acronym
    \# this line removes whitespace and get the unique missions
    \# removing whitespace ensures that trailing spaces won;t result in doubles
    country missions unique = unique(lapply(country missions, trimws))
    # print country code and number of missions
    cat(country code, fill=TRUE)
    cat(length(country missions unique), fill=TRUE)
    # iterate over missions and print
    # this is the prettiest low-effort way I found to print them
    for (val in country_missions_unique) {
       cat(val)
       cat(", ")
    }
    # newline for readability
    cat("\n\n")
```

```
In [21]:
countries iso = c("USA", "KOR", "IND", "DEU", "ARG", "GBR")
for (val in countries iso) {
    missions for country(val)
USA
BINUH, MINUSCA, MINUSMA, MONUSCO, UNMISS, UNSMIL, UNTSO, MINUJUSTH, UNMIL, MINUSTAH, UNAMA, MINURC
AT, UNMIS, UNMIK, UNIOSIL, UNAMID, UNMIT, UNOTIL, UNAMSIL, UNMISET, UNIKOM, UNMEE, UNMIBH,
KOR
MINURSO, UNAMID, UNIFIL, UNMISS, UNMOGIP, UNMHA, MINUJUSTH, UNMIL, UNOCI, MINUSTAH, UNMIT, UNISFA,
UNMIS, UNMIN, UNAMA, UNMISET, UNFICYP,
IND
MINURSO, MONUSCO, UNDOF, UNFICYP, UNIFIL, UNISFA, UNMISS, UNTSO, UNSOM, MINUJUSTH, MINUSTAH, UNMIL
, UNAMA, UNOCI, UNAMI, UNMIT, UNMIS, MONUC, UNMIK, UNIOSIL, UNMEE, ONUB, UNOMIG, UNAMSIL, UNIKOM,
UNMIBH,
DEU
MINURSO, MINUSMA, UNAMID, UNIFIL, UNMIK, UNMISS, UNSOM, UNMHA, MINUJUSTH, UNSMIL, UNMIL, UNAMA, MI
NUSTAH, UNMIS, UNOMIG, UNAMSIL, UNIKOM, UNMIBH,
ARG
```

MINURSO, UNFICYP, UNMISS, UNTSO, UNVMC, MINUSCA, MINUJUSTH, UNAMI, MINUSTAH, UNMC, UNOCI, UNMIL, UNMIS, MONUC, UNMIK, UNMISET, UNIKOM, UNIMOG, UNMIBH,

GBR 2.4

MINUSMA, UNAMA, UNFICYP, UNMISS, UNSMIL, UNSOM, UNSOS, MONUSCO, UNVMC, UNMC, UNMIL, MINUSTAH, UNAMI, UNISFA, UNMIS, MONUC, UNAMID, UNMIK, UNMEE, UNIOSIL, UNAMSIL, UNMISET, UNIKOM, UNMIBH,

In [8]:

```
# sum male and female personnel
data$personnel = data$Male_Personnel + data$Female_Personnel

# subset and aggregate
data_MINUSMA = subset(data, Mission_Acronym=="MINUSMA")
agg_data = aggregate(personnel ~ Last_Reporting_Date, data_MINUSMA, sum)
```

In [9]:

```
# summary statistics on aggregated data
cat("Mean", mean(agg_data$personnel), fill=TRUE)
cat("Median", median(agg_data$personnel), fill=TRUE)

quantiles = quantile(agg_data$personnel)
cat("Min", quantiles[1], fill=TRUE)
cat("25th percentile", quantiles[2], fill=TRUE)
cat("75th percentile", quantiles[4], fill=TRUE)
cat("Max", quantiles[5], fill=TRUE)
```

Mean 11768.85 Median 12039.5 Min 5872 25th percentile 10125.25 75th percentile 13882 Max 14871

In [26]:

```
# Optional Challenge
```

In [35]:

```
# read gpd data from dataset
gdp_data = read.csv('gdp_data.csv')
gdp_data$GDP = gdp_data$GDP.per.capita..int.....constant.2011.international...
gdp_data_2017 = subset(gdp_data, gdp_data$Year==2017)
```

In [113]:

```
# assemble list of all countries for looping
all_countries_iso = unique(data$ISOCode3)[1:147]
```

In [100]:

```
# get the 2017 gdp for each country and put it in a vector
countries_gdp = c()
counter = 1
for (country in all_countries_iso) {

    # there a lots of gaps in the 2017 gdp data, so I hardcoded them
    if (country == "DJI") {
        countries_gdp[counter] = 2931
    } else if (country == "CUB") {
        countries_gdp[counter] = 8541
    } else if (country == "YEM") {
        countries_gdp[counter] = 964
    } else if (country == "BDS") {
        countries_gdp[counter] = 17432
    } else {
        # all_countries_that_aren!t_bardcoded_access_the_dataframe
```

```
countries_gdp[counter] = subset(gdp_data_2017, gdp_data_2017$Code==country)$GDP
}
counter = counter + 1
}
```

In [101]:

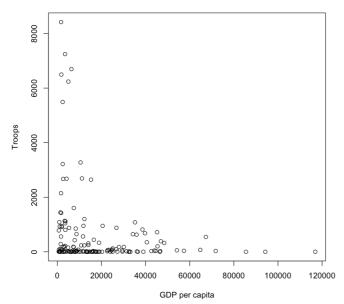
In [102]:

```
#assemble the dataframe
people_vs_purchase = data.frame(all_countries_iso, countries_gdp, countries_troops)
```

In [104]:

```
# mandatory scatterplot
plot(
    people_vs_purchase$countries_gdp,
    people_vs_purchase$countries_troops,
    main="GDP per capita vs Troops on UN Missions",
    xlab="GDP per capita",
    ylab="Troops"
)
```

GDP per capita vs Troops on UN Missions



There does appear to be an association between the variables, but it is far from linear. Judging from the high number of low-troop, low-gdp countries and the strong inverse correlation, we are probably dealing with a log-linear relationship.

The instructions for this assignment recommend a linear regression here, but frankly, that seems like a really bad model for this data. It doesn't look linear at all, and I think a linear regression would probably just be misleading.

Instead, I will try logging the data and fitting an (implicit) powerlaw model. Just eyeballing it, the data looks log-linear. So, I expect this to yield good results.

```
In [ ]:
```

```
pvp = people_vs_purchase # for quality of life
```

In [120]:

```
# getting log data
pvp$log_gdp = log(pvp$countries_gdp)
pvp$log_troops = log(pvp$countries_troops)

# purge -infs
counter = 1
for (num in pvp$log_troops) {
    if (num == '-Inf') {
        pvp$log_troops[counter] = 0
      }
      counter = counter + 1
}
```

I thought about removing the countries with zero troop contributions in December 2017, because their inclusion in the dataset feels a little arbitrary. After all, all they did to get in the list of countries I have is to contribute troops at some point, possibly years or decades before or after December 2017.

However, I decided to include them on second thought though because zero is totally a valid troop contribution, and I didn't to exclude many valid datapoints just because a few might not quite capture what I am trying to measure. So, I wanted to make it clear that the reference population for this statistic is the population of countries who have sent troops on a UN mission at some time.

In [125]:

In [133]:

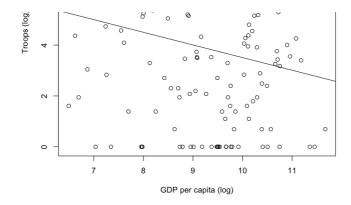
```
# Another scatterplot

# log data and titles
plot(
    pvp$log_gdp,
    pvp$log_troops,
    main="GDP per capita vs Troops on UN Missions",
    xlab="GDP per capita (log)",
    ylab="Troops (log)"
)

# regression result
abline(log_troops_from_log_gdp)
```

GDP per capita vs Troops on UN Missions

```
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```



A plot showing the relationship between log GDP per capita and log troop contributions. The line shown is a linear regression for log Troops given log GDP per capita. Interestingly, the data appear almost uncorrelated, although it looks like they have a slight inverse relationship.

The scatter plot appears more linear here, and the line looks like a not unreasonable fit for the data. So, I am content with this model.

The only thing that still worries me is the countries with zero troop contributions still appear distinct from the rest of the distribution. If I were going to dive deeper with this, I might try to first fit a logistic regression model to predict whether a contry's contribution would be zero. Then, I could fit a linear model on the remaining (log) data to predict troops from GDP given nonzero contribution.

If I were actually trying to solve a prediction problem, I would compare all of these options with cross validation and pick the best.

In []: