26-6-2022

COVID-19 Global Forecasting

Midterm Project

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PREDICTIVE MODELS

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Problem

The Covid-19 virus and the consequent pandemic broke into the world quickly and with very serious consequences, causing a large number of deaths and illnesses, blocking and paralyzing economies, countries and entire continents.

For this project I'm trying to predict or forecast future covid-19 daily cases of various locations.

Significance

If I'm able to build models that reliably predict future covid-19 cases I will be able to anticipate the pandemic, being able to plan resources more efficiently. By knowing when we will get a spike in the number of cases, we can dedicate more resources to hospitals in order to treat all patients.

Data Description

The Time series is divided between countries, having a total of 187 different ones, from Afghanistan to Zimbabwe.

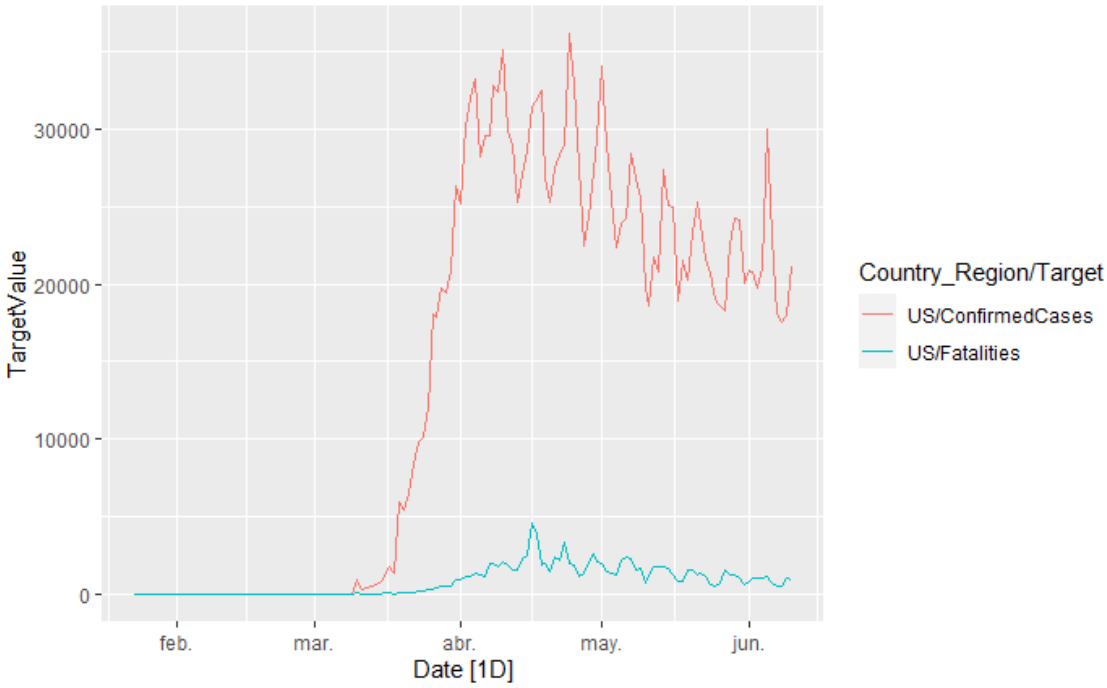
But some of these countries are divided into provinces, that being the case for 8 countries: Australia, Canada, China, Denmark, France, Netherlands, United Kingdom and US. For each of these ones we have a dataset for the hole country as well as for his provinces. The one with the highest number of provinces is the United States with 54, this is because it is including the District of Columbia, Guam, Puerto Rico and the Virgin Islands. The second country with the most provinces in China with 33, followed by Canada with 12, France and the UK with 10, Australia with 8, the Netherlands with 4 and Denmark with 2.

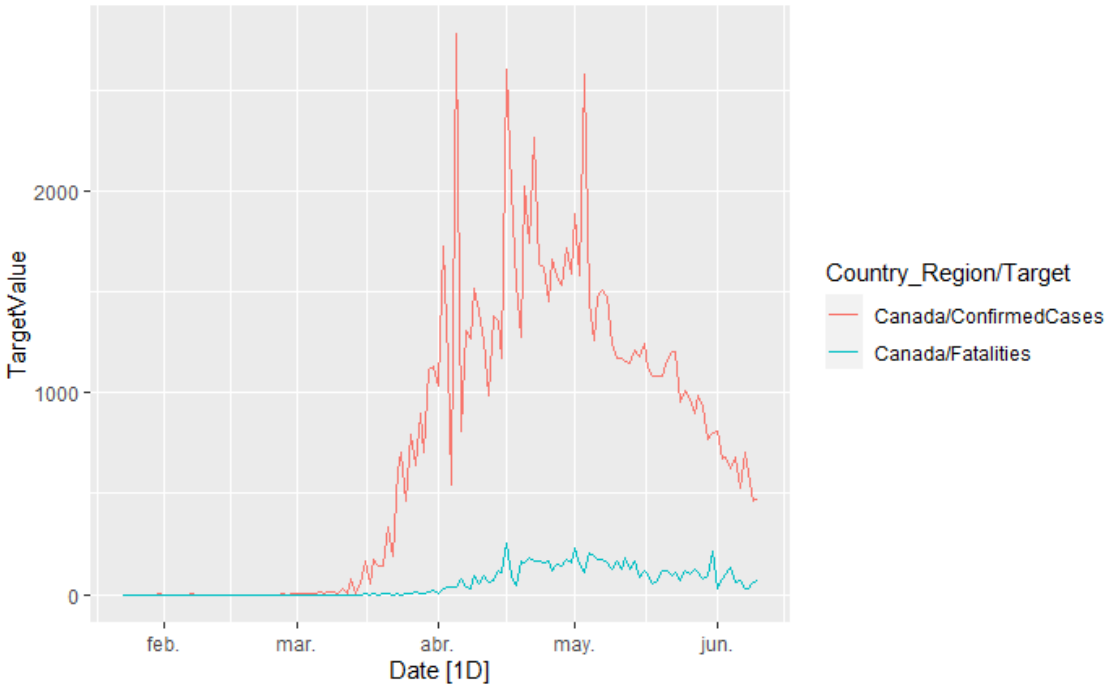
The last territorial subdivision is counties, there are 1841 different ones. All of them belongs to the US, the list of provinces or states with subdivisions has a size of 51, this is because in this case Guam, Puerto Rico and the Virgin Islands do not have counties.

Lastly for each of these countries, provinces, counties we have two types of data, that being Confirmed Cases and Fatalities.

I decided to plot some countries to see how the data behaves, I choose US, Canada, Italy, Germany:

First a normal line plot to see the evolution of the data:


30000
20000
10000
0
TargetValue
feb.
mar.
abr.
may.
jun.
Date [1D]
Country_Region/Target
US/ConfirmedCases
US/Fatalities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1000
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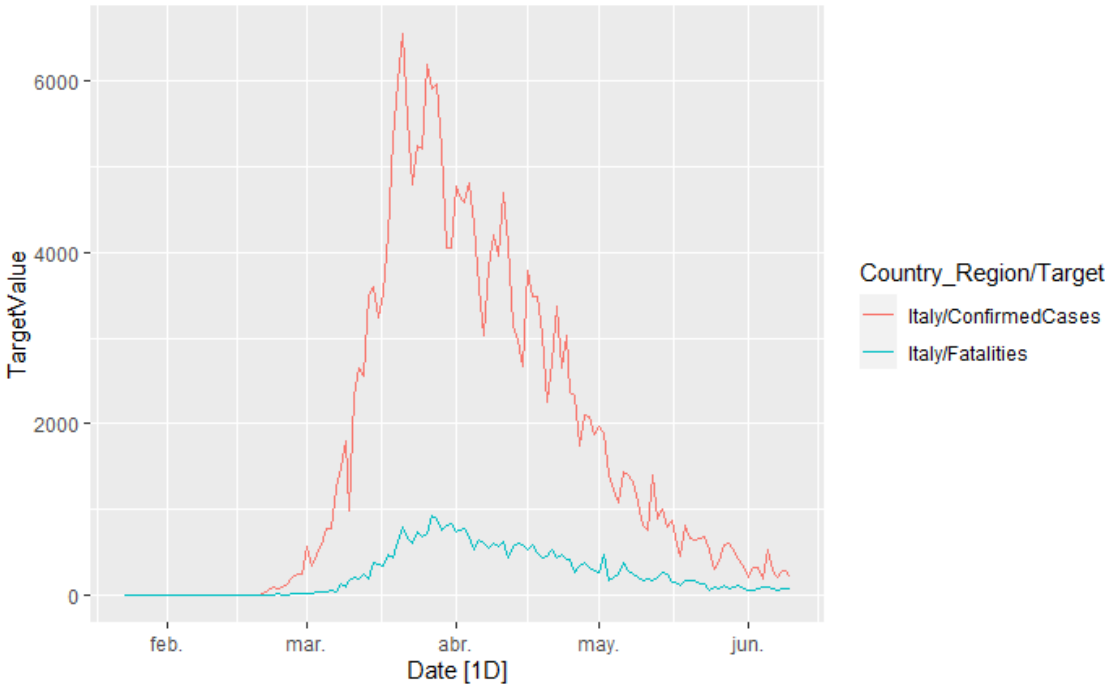
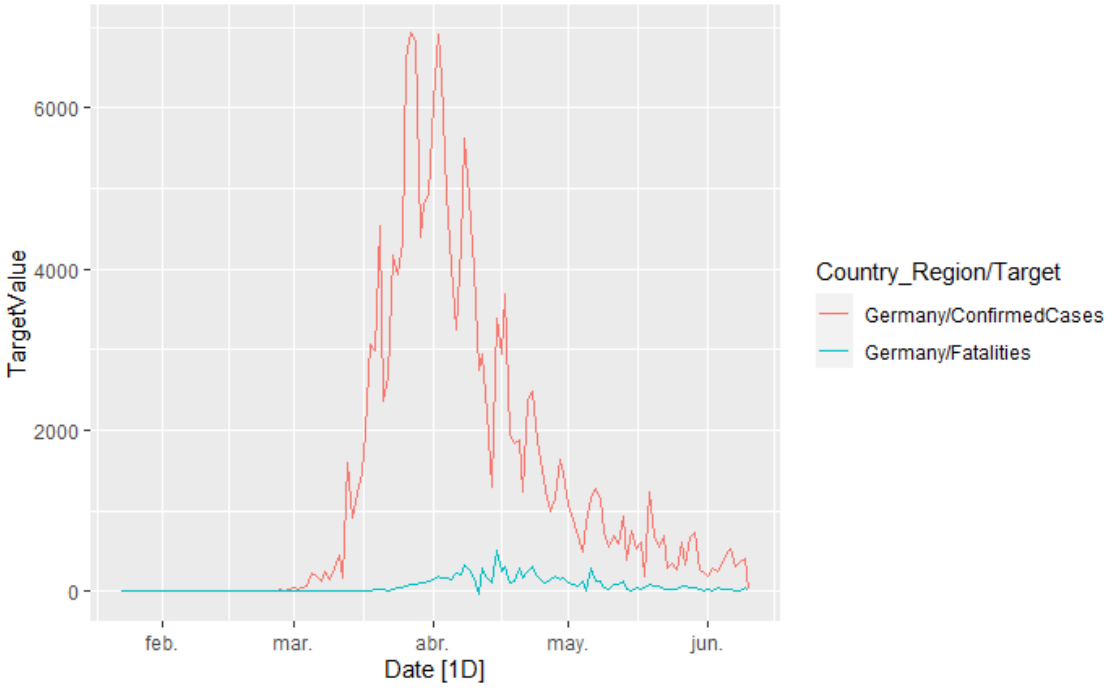
TargetValue
feb.
mar.
abr.
may.
jun.
Date [1D]
Country_Region/Target
Canada/ConfirmedCases
Canada/Fatalities

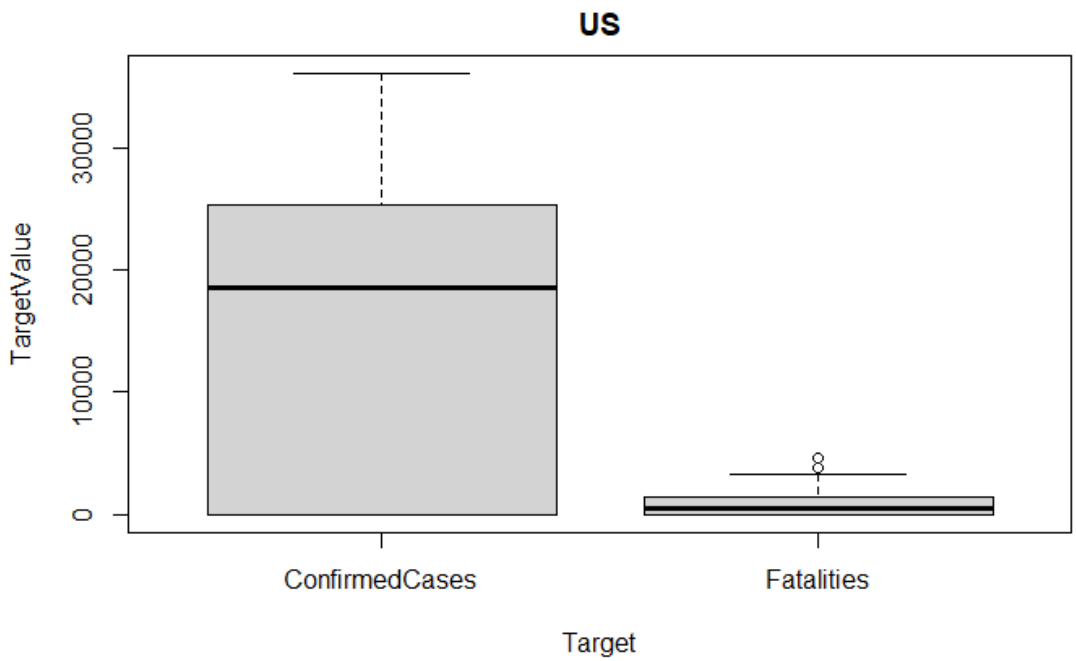


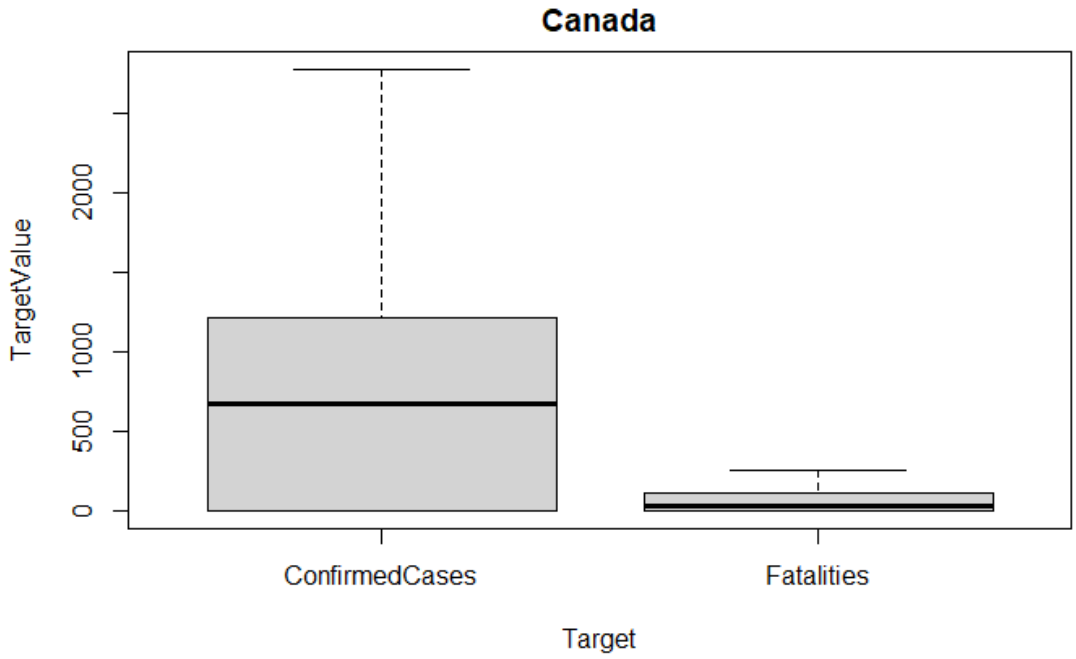


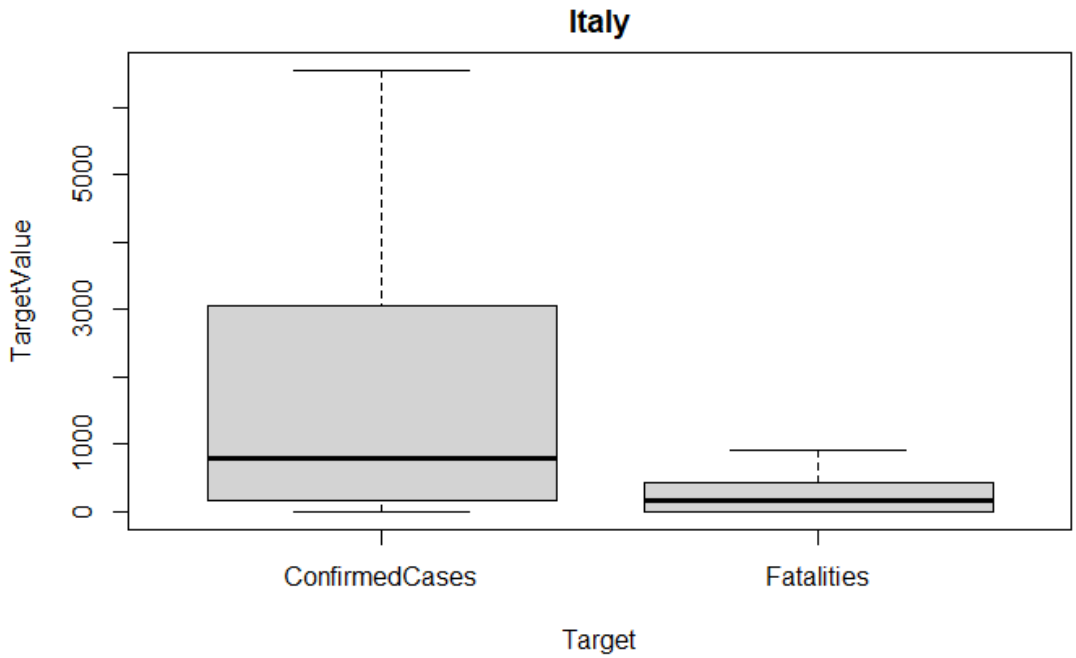
We can see that the confirmed cases datasets have higher values than the fatalities one, that's expected, since the deaths needs to be infected beforehand, but being infected doesn't means death.

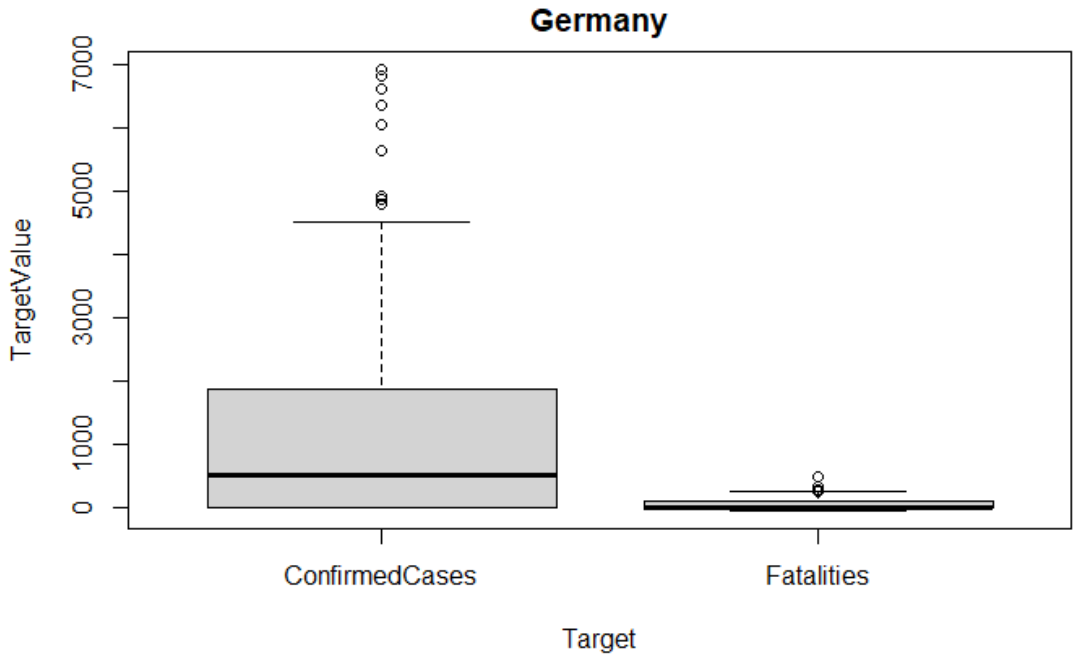
We can also see some short of waive pattern in all the datasets.

Then I plotted a normal boxplot:


US
TargetValue
0
10000
20000
30000
ConfirmedCases
Fatalities
Target

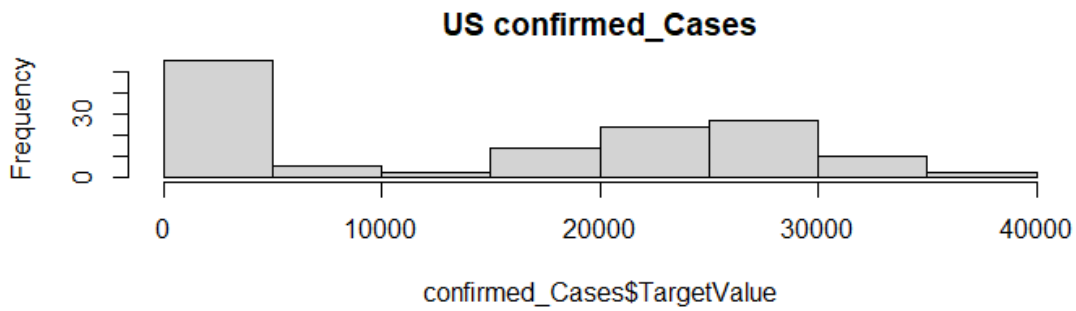

Canada
TargetValue
0
500
1000
2000
ConfirmedCases
Fatalities
Target

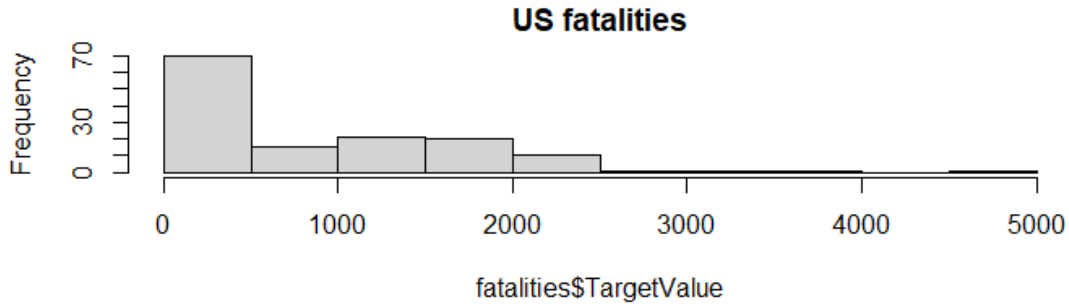


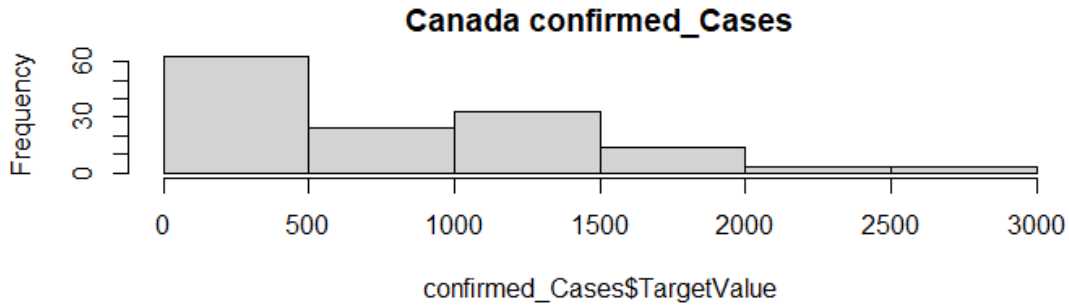


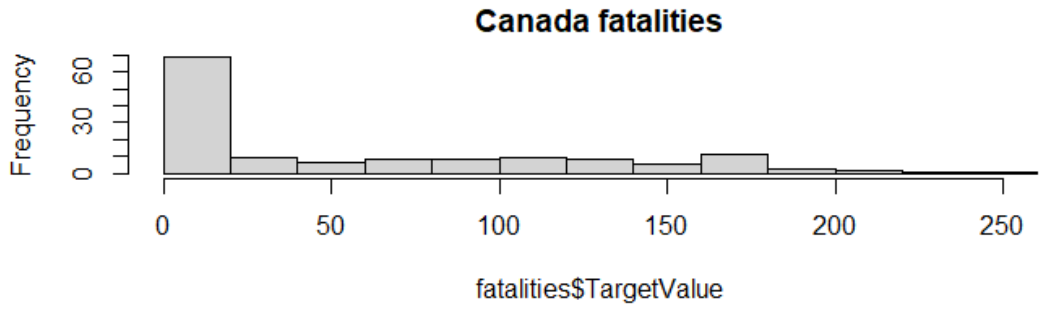
As above we can see that fatalities are closest to the 0 value than confirmed Cases. We also see that the bulk of the values for confirmed cases are close to the 0 mark, this is because the first months of the year 2020 there weren't infected people in most of the countries.

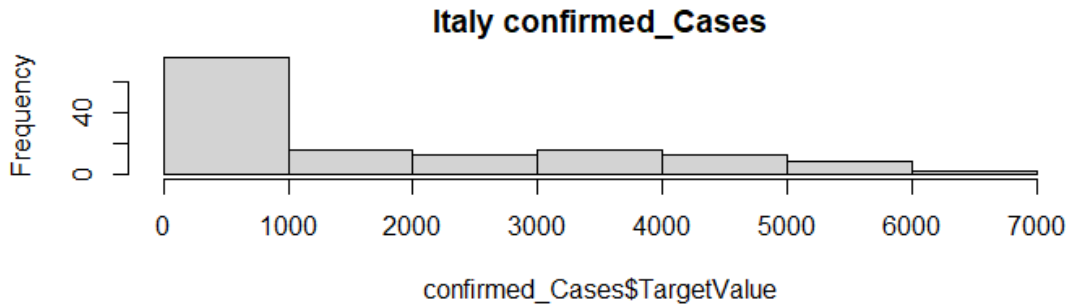
Lastly the histogram of these countries differentiating by confirmed cases and fatalities:

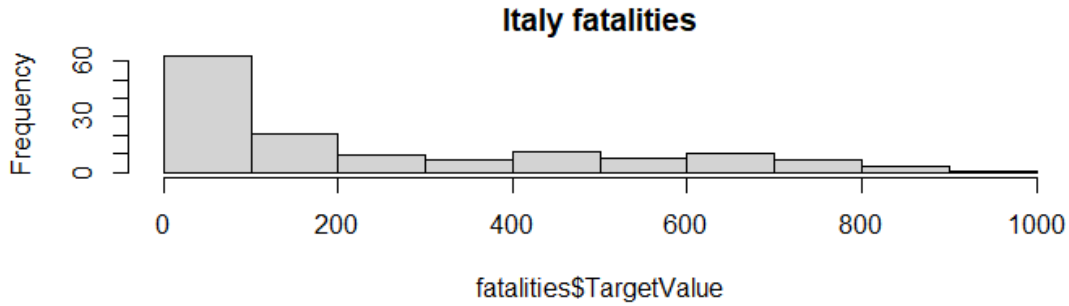

US confirmed_Cases
Frequency
0
30
0
10000
20000
30000
40000
confirmed_Cases$TargetValue

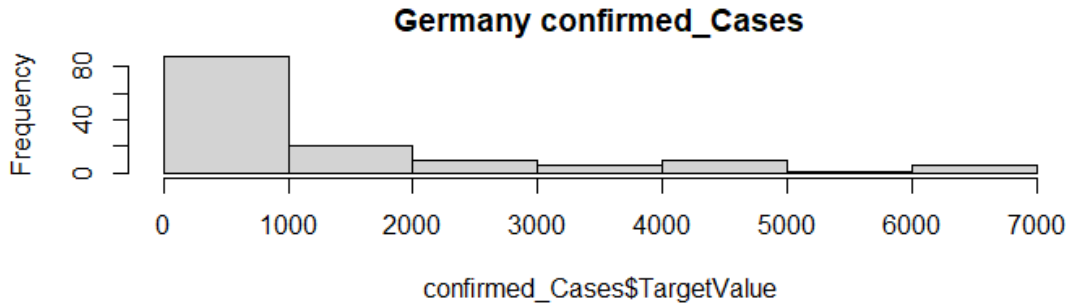

US fatalities
Frequency
0
30
70
0
1000
2000
3000
4000
5000
fatalities$TargetValue

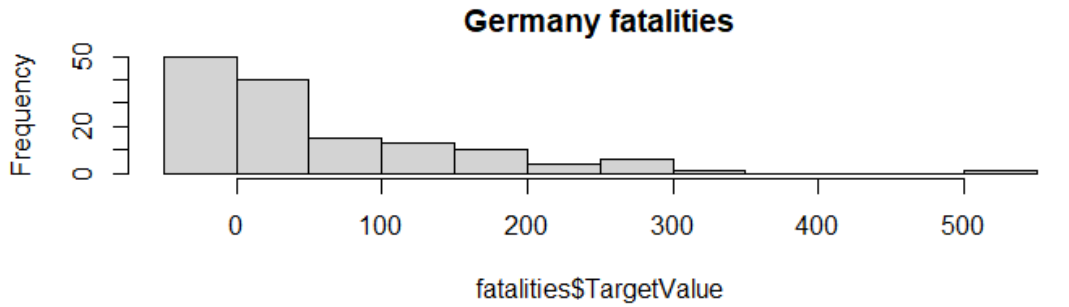

Canada confirmed_Cases
Frequency
0
30
60
0
500
1000
1500
2000
2500
3000
confirmed_Cases$TargetValue


Canada fatalities
Frequency
0
30
60
0
50
100
150
200
250
fatalities$TargetValue





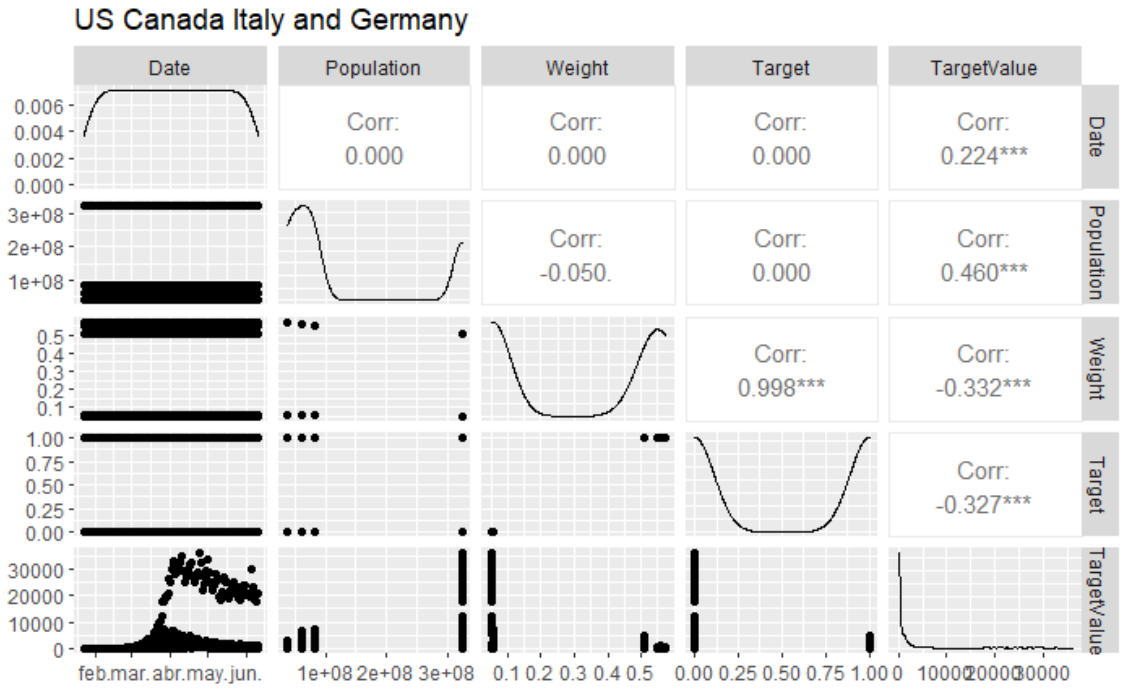


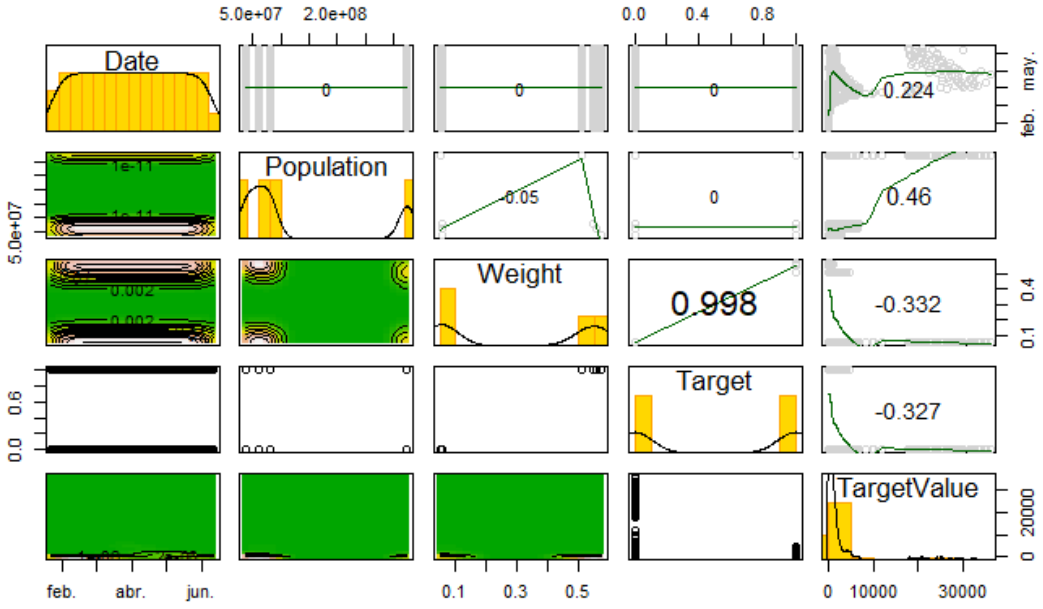


We can see a big number of the values really close to the 0 mark, this is because of the same reason as above, where the covid crisis started at different times in each country. Therefore, it will be interesting to add a dummy variable in order to represent this difference.

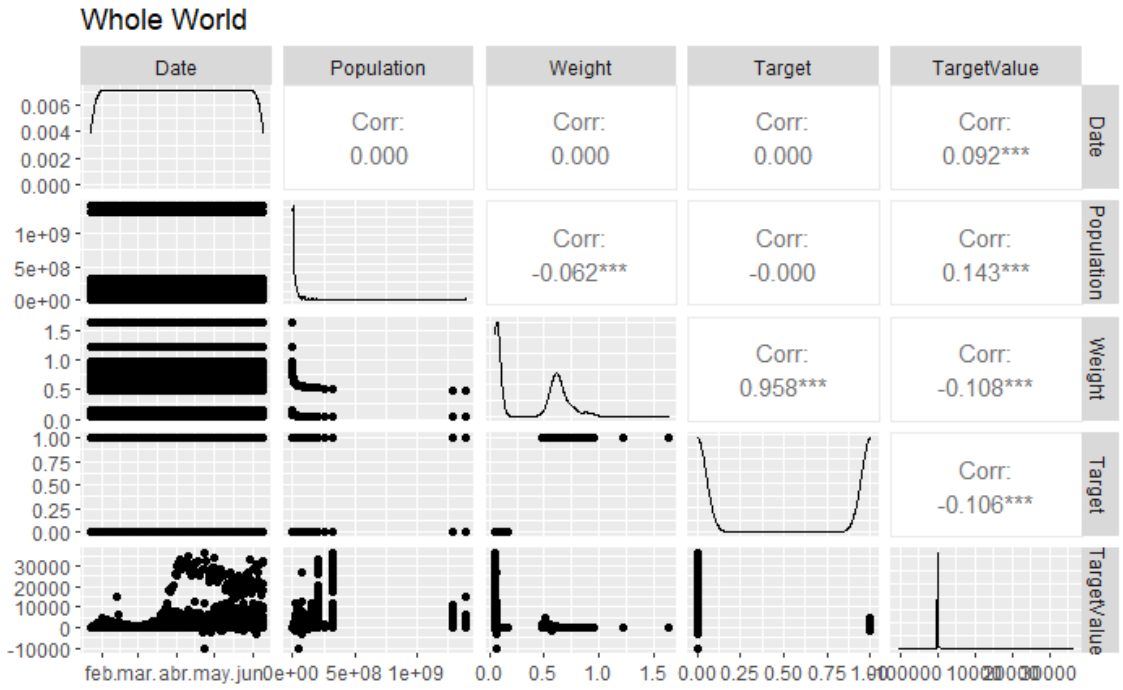
Now let's get the Scatterplot Matrix:

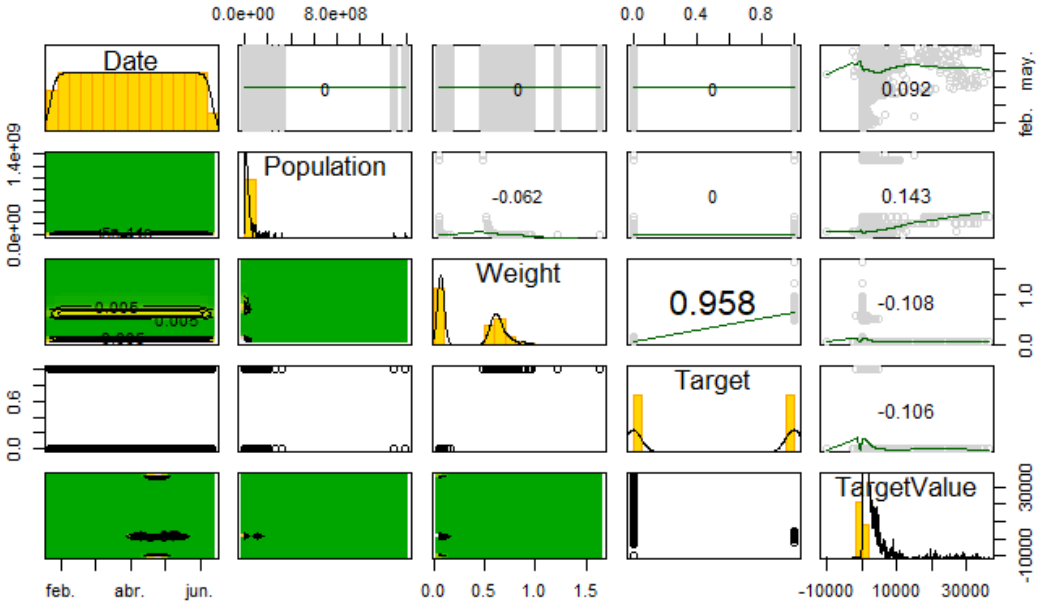
First for the 4 countries we were exploring before, US, Canada, Italy and Germany



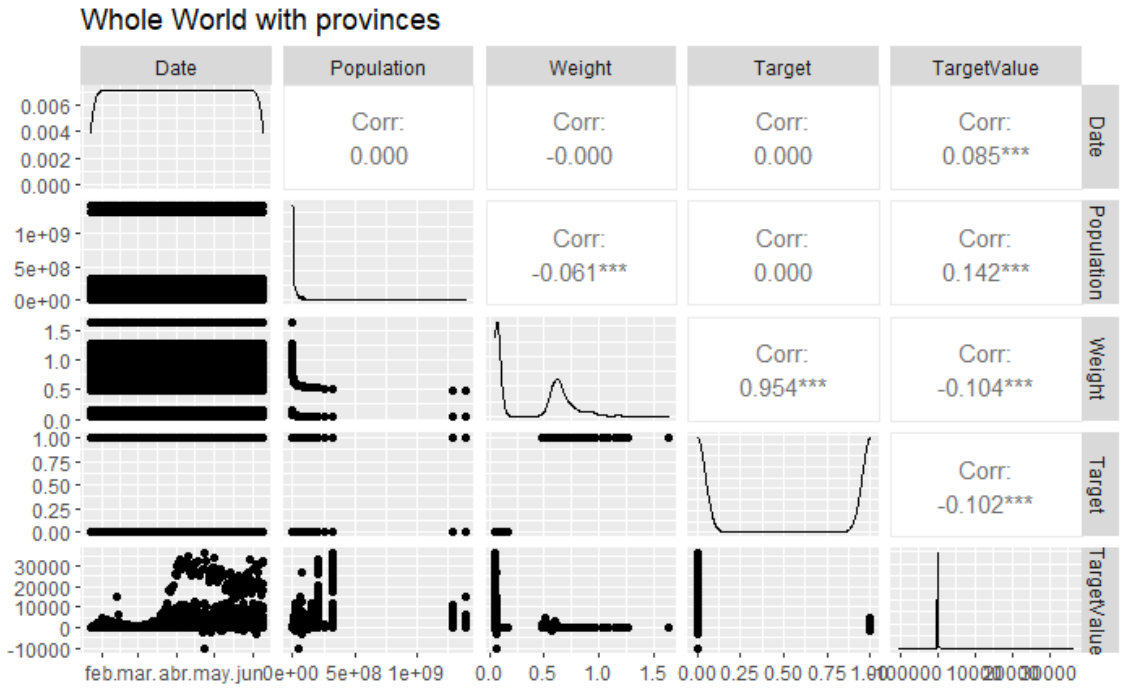


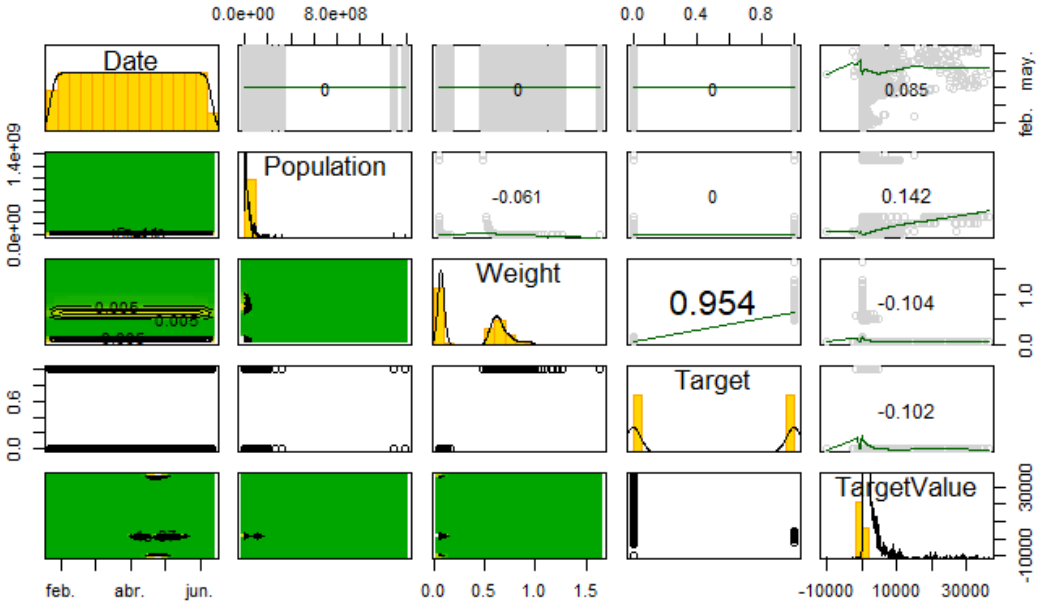
For all the countries:





Now including the provinces on top of the countries:





We can see that all of the variables are uncorrelated except for Weight and Target, this is because the weight is calculated using one formula or another depending on the target variable, that is why they are mostly correlated.

Types of Models

The typical model will be a linear regression, although this will fail to capture the true nature of the data, as we have seen in the graphs the data does not follow a straight line.

We can use a multiple linear regression using multiple inputs, such as population, weight, or outside factors such as country GDP. This short of models would be able to predict with a higher precision.

It will be interesting to add other predictors in order to try to increase the accuracy of the model. This predictor could be the trend in order to capture the time dimension into the predictions. also using dummy variables such as one marking the start of the pandemic for each country, since the start date differs by country, meaning that for an initial period all values will be 0 in the target variable, also trying to apply seasonality, since all the dataset is contain within one year we cannot use the month as seasons, it will be wiser to use days of the week, this is important since some countries do not offer data on a daily basis.

We could also apply transformations to the predictors and or the forecast variables, such as logarithms, if we apply it to both sizes, it's called log-log, if we apply it to only the forecast variable it is log-linear, and if it is applied only to the predictors is linear-log. In this case, if we want to apply the log functions to the forecast variable, we first will need to change the negative values to 0 and use log(x+1) in order to take into account, the zeros.

Another interesting model will be autocorrelation, we can give as predictors previous values of the dataset, since todays values are influenced by previous ones

Literature

From reading the book and some of the discussions on the Kaggle competition we are able to get some insight into other people approaches.

For the thread about sharing datasets, we are able to find some complete dataset containing not only the original information but even more, for example from the user "Sadhaklal" (https://www.kaggle.com/code/sambitmukherjee/covid-19-data-adding-world-development-indicators/data?select=indicator_dictionary.csv), he compose a dataset including the World Bank world Development Indicators, including things like GDP in purchasing power parity (PPP), when comparing different countries from different socioeconomics factors it is better to use PPP than normal nominal GDP, since it takes into account the different prices of needs in the different economies. We can also get access to other variables like access to electricity, passengers carried, etc.

Another interesting source is the user CPMP thread about "Linear Regression Is All you Need" (https://www.kaggle.com/competitions/covid19-global-forecasting-week-5/discussion/151461), where he uses auto regression, using past values as input. As well as using the logarithm of the variables instead of the normal variables.

Models

For the models that I have built first a normal model using only trend and season, lag weight and Pandemic Start in order to make the forecast. The 'PandemicStart' variable was created in as a dummy or Intervention variable, its value is 0 from the start until the first case is diagnosed, after that then it changes to 1 until the end. I decided to create this variable because for some countries the pandemic starts after a while, meaning that for the initial period the values of the series are 0.

The data is split into 80% for train (Before 2020-05-14) and 20% to validate (After and including 2020-05-14).

This are the models I built, for each of the models that used the lag parameter, I built multiple ones with different lag, 1, 2, 4, 6 and 8. The exceptions are the log-log models where the lags I tested are 1, 2, 4 and 6. This resulted in 37 different models.

TargetValue ~ Trend + season

TargetValue ~ Trend + season + Weight

TargetValue ~ lag(TargetValue)

TargetValue ~ Trend + lag(TargetValue)

TargetValue ~ Season + lag(TargetValue)

TargetValue ~ Trend + season + lag(TargetValue)

TargetValue ~ Trend + season + PandemicStart

TargetValue ~ Trend + season + PandemicStart + lag(TargetValue)

log(TargetValue) ~ Trend + season + lag(log(TargetValue))

log(TargetValue) ~ Trend + season + PandemicStart + lag(log(TargetValue))

First, I decided to build the models using only the data for 4 countries, US, Canada, Italy and Germany, this is done because my computer is old and slow, so running the hole dataset will take a lot of time. The results are averaged by Fatalities and Confirmed Cases, because if we don't do it, it will give the results for each of the countries, and in return the results will be harder to compare. Models' names: t → trend, s → season, w → weight, S → PandemicStart, l<number> → lag, log → using log.

	.model	Target	avg_ME	avg_RMSE	avg_MAE	avg_ACF1
1	tsl1	Fatalities	-28.525028	163.3275	98.73008	-0.01366571
2	tsSl1	Fatalities	-28.525028	163.3275	98.73008	-0.01366571
3	sl1	Fatalities	-10.018446	168.5459	90.91792	-0.09996614
4	tl1	Fatalities	-30.647154	172.1925	98.51192	0.02185236
5	l1	Fatalities	-9.495386	177.0179	88.07641	-0.07202595
6	log_tsl1	Fatalities	-64.212480	186.6867	98.72109	0.01834980
7	log_tsSl1	Fatalities	-64.212480	186.6867	98.72109	0.01834980
8	tsl2	Fatalities	-44.960059	212.0099	134.07896	0.45841095
9	tsSl2	Fatalities	-44.960059	212.0099	134.07896	0.45841095
10	sl2	Fatalities	-19.330207	219.2942	123.36310	0.42444220

Figure 1 - First 10 models by Avg RMSE for fatalities (US, Canada, Italy, Germany)

	.model	Target	avg_ME	avg_RMSE	avg_MAE	avg_ACF1
	All	Confirm	All	All	All	All
1	sl1	ConfirmedCases	-24.12986	869.3031	646.9643	-0.18935173
2	tsl1	ConfirmedCases	-71.96926	882.4826	671.5628	-0.02686585
3	tsSl1	ConfirmedCases	-73.78713	884.9706	673.0000	-0.01796508
4	l1	ConfirmedCases	-19.44688	966.0954	626.6308	-0.11695359
5	tl1	ConfirmedCases	-82.36727	980.9424	651.1861	0.05284333
6	sl2	ConfirmedCases	-62.28571	1106.6756	863.4872	0.34679003
7	tsl2	ConfirmedCases	-124.01895	1119.9826	873.2019	0.42891730
8	tsSl2	ConfirmedCases	-125.87413	1123.0440	874.8552	0.43541588
9	l2	ConfirmedCases	-48.17795	1305.6727	921.9317	0.37170541
10	tl2	ConfirmedCases	-149.61144	1323.9735	927.0803	0.46449019

Figure 2 - First 10 models by Avg RMSE for Conformed Cases (US, Canada, Italy, Germany)

	.model	Target	avg_adj_r_squared	avg_CV	avg_AIC	avg_AICc	avg_BIC
	All	fata	All	All	All	All	All
1	log_tsl1	Fatalities	0.9392826	4.162010e-01	-146.14341	-143.94341	-119.04810
2	log_tsSl1	Fatalities	0.9392826	4.162010e-01	-146.14341	-143.94341	-119.04810
3	log_tsl2	Fatalities	0.9382990	4.310375e-01	-127.86263	-125.64041	-100.85783
4	log_tsSl2	Fatalities	0.9382990	4.310375e-01	-127.86263	-125.64041	-100.85783
5	log_tsl4	Fatalities	0.9222619	5.569073e-01	-85.00993	-82.74189	-58.18862
6	log_tsSl4	Fatalities	0.9222619	5.569073e-01	-85.00993	-82.74189	-58.18862
7	log_tsl6	Fatalities	0.9052116	6.852423e-01	-53.44438	-51.12860	-26.80999
8	log_tsSl6	Fatalities	0.9052116	6.852423e-01	-53.44438	-51.12860	-26.80999
9	tsl1	Fatalities	0.7946312	4.437687e+04	999.26740	1001.46740	1026.36270
10	tsSl1	Fatalities	0.7946312	4.437687e+04	999.26740	1001.46740	1026.36270

Figure 3 - First 10 models by Avg Adj. R^2 for fatalities (US, Canada, Italy, Germany)

	.model	Target	avg_adj_r_squared	avg_CV	avg_AIC	avg_AICc	avg_BIC
	All	Confirm	All	All	All	All	All
1	log_tsl1	ConfirmedCases	0.9730563	3.835597e-01	-114.60609	-112.40609	-87.510785
2	log_tsSl1	ConfirmedCases	0.9729571	3.850315e-01	-114.13066	-111.81399	-86.357972
3	log_tsl2	ConfirmedCases	0.9664480	5.149612e-01	-81.07232	-78.85010	-54.067515
4	log_tsSl2	ConfirmedCases	0.9663709	Inf	-80.57966	-78.23952	-52.899737
5	log_tsl4	ConfirmedCases	0.9404083	9.204206e-01	-18.02290	-15.75486	8.798412
6	log_tsSl4	ConfirmedCases	0.9404083	9.204206e-01	-18.02290	-15.75486	8.798412
7	log_tsl6	ConfirmedCases	0.9069856	1.409873e+00	26.68785	29.00364	53.322246
8	log_tsSl6	ConfirmedCases	0.9069856	1.409873e+00	26.68785	29.00364	53.322246
9	tsSl1	ConfirmedCases	0.9030373	1.298063e+06	1450.07578	1452.39244	1477.848461
10	tsl1	ConfirmedCases	0.9029590	1.298412e+06	1449.88858	1452.08858	1476.983883

Figure 4 - First 10 models by Avg Adj. R2 for Confirmed Cases (US, Canada, Italy, Germany)

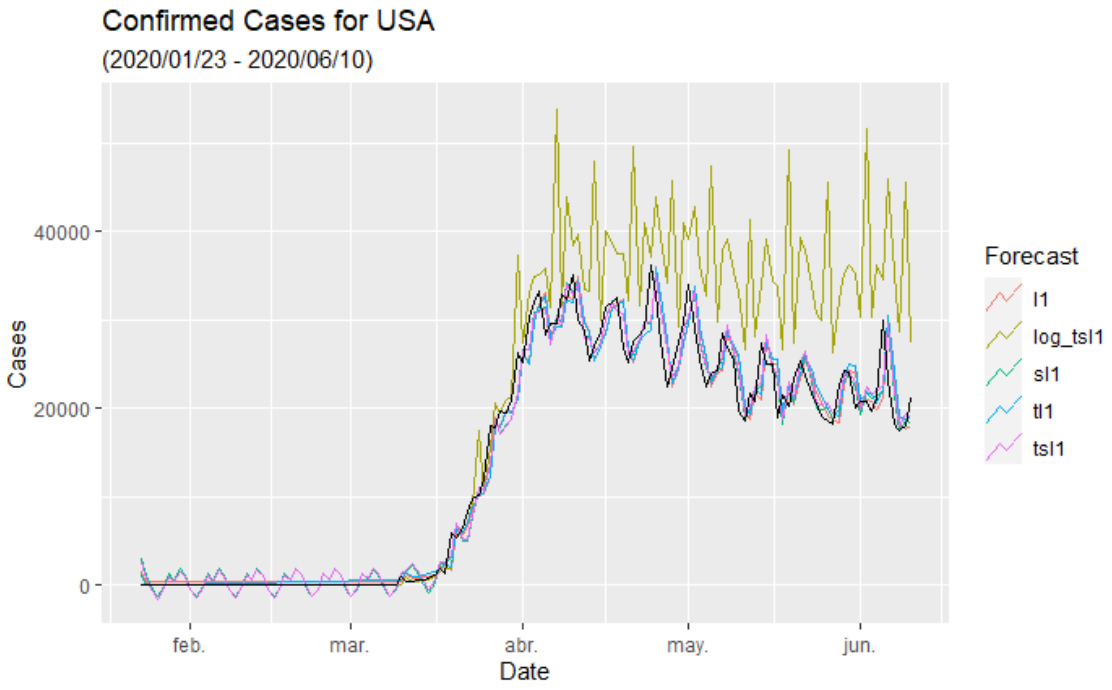
Weight variable: We can see that the models that used the variable weights as a predictor obtained the worst results, this is expected since this variable do not change in any scenario, and only changed between scenarios, thus resulting in not a good predictor.

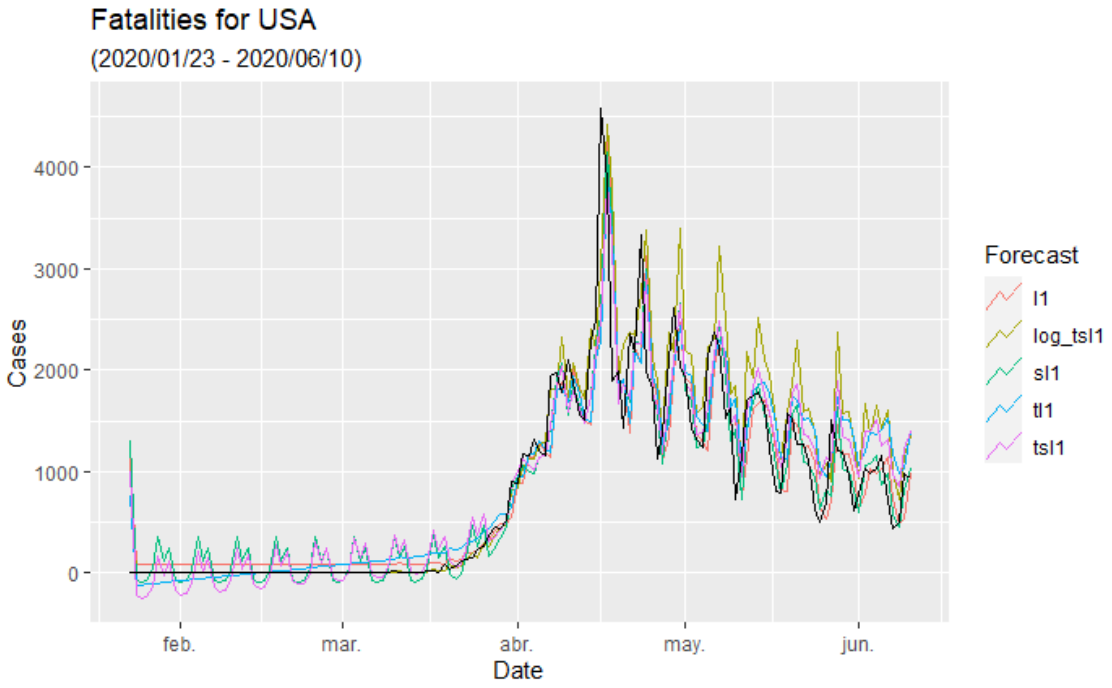
PandemicStart variable: we can see that using or not using this variable in the models don't really make a big difference in the results, but overall, we can see that the models that used this variable underperformed with respect to their counterparts.

Lag: We can see that using lag increase the performance of the model, we can see that all the models with l<number lag> outperform the models without it, this means that the current value depends on previous ones, we also see that a the lower the lag is the greater performance we get, meaning that a lag of 1 achieved the best results. We can see that the best models in each of the tables uses a lag of 1.

Log: We can see that the log models where able to outperform the rest of them if we rank them using the adj. R^2, achieving values of over 0.9. But if we look at the ranking using the RMSE, we can see that the log models no longer top the ranking.

We can plot the predictions for the USA:





We can see that the log transformation didn't perform well on the Confirmed cases, but it did a better job in the fatalities. We can see that the other models are really close the real graph, except for the beginning when the values are 0, in this case the variable Pandemic Start will be useful.

Now we run the same models for the whole countries (We still don't use the provinces or counties), now we get the following results:

	.model	Target	avg_ME	avg_RMSE	avg_MAE	avg_ACF1
	All	fata	All	All	All	All
1	log_tsl1	Fatalities	-3.1868496	13.24391	6.579311	NaN
2	log_tsSl1	Fatalities	-3.1868496	13.24391	6.579311	NaN
3	tsl1	Fatalities	-1.1705797	13.44046	6.540320	NaN
4	tsSl1	Fatalities	-1.1705797	13.44046	6.540320	NaN
5	tl1	Fatalities	-1.2351178	13.82610	6.527182	NaN
6	sl1	Fatalities	-0.6206886	15.13842	6.332690	NaN
7	l1	Fatalities	-0.5773800	15.43620	6.298264	NaN
8	log_tsl2	Fatalities	-4.7354594	16.21297	8.241159	NaN
9	log_tsSl2	Fatalities	-4.7354594	16.21297	8.241159	NaN
10	tsl2	Fatalities	-1.9360711	17.05356	8.294644	NaN

Figure 5 - First 10 models by Avg RMSE for fatalities (all countries)

	.model	Target	avg_ME	avg_RMSE	avg_MAE	avg_ACF1
	All	confirme	All	All	All	All
1	tsl1	ConfirmedCases	-2.3707049	135.6561	76.67873	-0.006790852
2	tsSl1	ConfirmedCases	-2.3457210	135.6745	76.68386	-0.005954164
3	sl1	ConfirmedCases	0.1386551	136.2610	73.00651	-0.087405626
4	tl1	ConfirmedCases	-2.3459063	139.5836	75.17326	0.004620093
5	l1	ConfirmedCases	0.5201520	140.0439	71.61392	-0.077311847
6	tsl2	ConfirmedCases	-3.6184889	151.2075	88.33608	0.335138383
7	tsSl2	ConfirmedCases	-3.5918833	151.2173	88.34099	0.335603046
8	sl2	ConfirmedCases	-2.7465657	153.2768	85.82700	0.325580993
9	tl2	ConfirmedCases	-3.4519638	158.2898	88.78162	0.343933305
10	l2	ConfirmedCases	-1.7353530	160.1760	86.54414	0.332295886

Figure 6 - First 10 models by Avg RMSE for Conformed Cases (all countries)

	.model	Target	avg_adj_r_squared	avg_CV	avg_AIC	avg_AICc	avg_BIC
	All	fata	All	All	All	All	All
1	l1	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
2	l2	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
3	l4	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
4	l6	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
5	l8	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
6	log_tsl1	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
7	log_tsl2	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
8	log_tsl4	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
9	log_tsl6	Fatalities	NaN	Inf	-Inf	-Inf	-Inf
10	log_tsSl1	Fatalities	NaN	Inf	-Inf	-Inf	-Inf

Figure 7 - First 10 models by Avg Adj. R2 for fatalities (all countries)

	.model	Target	avg_adj_r_squared	avg_CV	avg_AIC	avg_AICc	avg_BIC
	All	confirm	All	All	All	All	All
1	log_tsSl2	ConfirmedCases	0.5989418	6.230087e-01	-92.59657	-90.37182	-65.57732
2	log_tsl2	ConfirmedCases	0.5988970	6.232103e-01	-92.55080	-90.32858	-65.54600
3	log_tsSl1	ConfirmedCases	0.5898533	6.289095e-01	-94.18466	-91.98217	-67.07487
4	log_tsl1	ConfirmedCases	0.5897722	6.292848e-01	-94.11105	-91.91105	-67.01574
5	log_tsSl4	ConfirmedCases	0.5740575	7.012282e-01	-76.00099	-73.73037	-49.16534
6	log_tsl4	ConfirmedCases	0.5739501	7.017299e-01	-75.90582	-73.63778	-49.08451
7	log_tsSl6	ConfirmedCases	0.5478697	8.008068e-01	-61.63551	-59.31709	-34.98688
8	log_tsl6	ConfirmedCases	0.5478283	8.009977e-01	-61.59440	-59.27861	-34.96001
9	tsSl2	ConfirmedCases	0.4657731	1.614349e+05	594.82039	597.04514	621.83964
10	tsl2	ConfirmedCases	0.4657280	1.614353e+05	594.84524	597.06746	621.85005

Figure 8 - - First 10 models by Avg Adj. R2 for Confirmed Cases (all countries)

It appears that there was some error, since some of the outputs are NaN, this looks like it happens in the fatality's series, this could be due to a missing value or some weird anomaly, but since this part took so long to run, I preferred to run everything for the hole world, but using only 4 models, this way we can fixed faster the errors.

Now that we have the results of the hole countries, we need to build the model for the hole dataset, including provinces and counties, but since it took a lot of time to run the models on only the countries, in this case I'm only running one model:

TargetValue ~ Trend + season + lag(TargetValue, n=1)

And this are the results:

<PHOTOS>

(My computer is unable to run it, since now its 24:00 of the Sunday I am afraid I won't be able to show these results or make the predictions on the test set.)

Limitations

In all of this models we haven't used external datasets, this is short of a limitation since there are outside factors that affect the model, such as travel intensity, investments in healthcare, temperature and many other variables. Even factors that are extremely hard to categorize as variables, such as culture habits which is hard to represent in a numeric variable. Some cultures have a lot of person closeness like Mediterranean cultures, and other are the opposite like Scandinavian ones, and many other differences.

Another big difference is how does each country and region categories it's diagnose cases and fatalities, some regions are going to make test to dead people to see if they had the virus, other countries won't do it, also some countries won't count the same way, as if a person dies form some other cause but tested positive some countries will add it to the covid statistics and others not.

Also, the number of diagnosed cases is not the same as the true infected population, this is because of not enough tests and asymptomatic people, this results in having a smaller sample of the actual infected population, but the new cases come from the actual infected population and not the diagnose one.

Future Work

Future work can come from three different places. First, we can use more predictor variables in order to try to increase the performance of the models, such as the ones mentioned in the previous section.

Second, we can try to use more complex models such as neural networks and advance AI in order to build better models that are able to adapt to multiple waves and different covid strains.

Third, by trying to obtain better information by increasing testing and trying to standardize the procedures and systems different countries used. This will result in having better data and this will in turn result in better forecasting.

What was learned/Conclusions

I learn how to work with big datasets in R and being able to construct models in order to make forecast or predictions into the future. This is a useful tool since this allows to get a glimpse into the future, by doing this we are able to prepare and plan accordingly, this means that we are able to reduce the impact of negative events and increase the impact of positive ones.

In this case the best models where the ones using trend season and lag, we have seen that using a lag of 1 is the best option.