COVID Global Forecast: SIR model + ML regressions

In the context of the global COVID-19 pandemic, Kaggle has launched several challenges in order to provide useful insights that may answer some of the open scientific questions about the virus. This is the case of the COVID19 Global Forecasting, in which participants are encouraged to fit worldwide data in order to predict the pandemic evolution, hopefully helping to determine which factors impact the transmission behavior of COVID-19.

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Disclaimer 1: this notebook is being updated frequently with the objective of improving predictions by using new models.

Disclaimer 2: the training dataset is also updated on a daily basis in order to include the most recent cases. In order to be up to date and prevent data leaking and other potential problems, daily updates on "filtered dates" will be applied.

Disclaimer 3: the COVID Global Forecasting competition is updated week by week (with a new competition). I'll move the notebook from previous weeks to the new one, so that it only appears in the most recent competition.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import time
from datetime import datetime
from scipy import integrate, optimize
import warnings
warnings.filterwarnings('ignore')

# ML libraries
import lightgbm as lgb
import xgboost as xgb
from xgboost import plot_importance, plot_tree
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn import linear_model
from sklearn.metrics import mean_squared_error
```

1. Exploratory data analysis (EDA)

First of all, let's take a look on the data structure:

In [2]:
```
submission_example = pd.read_csv("../input/covid19-global-forecasting-week-4/submission.csv")
test = pd.read_csv("../input/covid19-global-forecasting-week-4/test.csv")
train = pd.read_csv("../input/covid19-global-forecasting-week-4/train.csv")
train.Province_State.fillna("None", inplace=True)
display(train.head(5))
display(train.describe())
print("Number of Country_Region: ", train['Country_Region'].nunique())
print("Dates go from day", max(train['Date']), "to day", min(train['Date']), ", a total of", train['Dat
e'].nunique(), "days")
print("Countries with Province/State informed: ", train.loc[train['Province_State']!='None']['Country_R
egion'].unique())
```

	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities
0	1	None	Afghanistan	2020-01-22	0.0	0.0
1	2	None	Afghanistan	2020-01-23	0.0	0.0
2	3	None	Afghanistan	2020-01-24	0.0	0.0
3	4	None	Afghanistan	2020-01-25	0.0	0.0
4	5	None	Afghanistan	2020-01-26	0.0	0.0

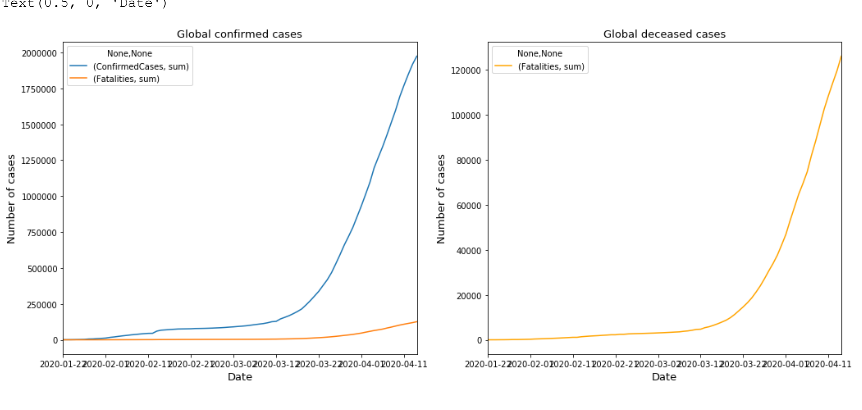
	Id	ConfirmedCases	Fatalities
count	26292.000000	26292.000000	26292.000000
mean	17826.500000	1186.183896	62.265594
std	10300.678012	8549.128727	695.049077
min	1.000000	0.000000	0.000000
25%	8913.750000	0.000000	0.000000
50%	17826.500000	1.000000	0.000000
75%	26739.250000	117.000000	1.000000
max	35652.000000	203020.000000	21067.000000

```
Number of Country_Region:  184
Dates go from day 2020-04-14 to day 2020-01-22 , a total of 84 days
Countries with Province/State informed:  ['Australia' 'Canada' 'China' 'Denmark' 'France' 'Netherland
s' 'US'
 'United Kingdom']
```

The dataset covers 163 countries and almost 2 full months from 2020, which is enough data to get some clues about the pandemic. Let's see a few plots of the worldwide tendency to see if we can extract some insights:

In [3]:
```
#confirmed_country = train.groupby(['Country/Region', 'Province/State']).agg({'ConfirmedCases':['su
m']})
#fatalities_country = train.groupby(['Country/Region', 'Province/State']).agg({'Fatalities':['sum']})
confirmed_total_date = train.groupby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date = train.groupby(['Date']).agg({'Fatalities':['sum']})
total_date = confirmed_total_date.join(fatalities_total_date)

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(17,7))
total_date.plot(ax=ax1)
ax1.set_title("Global confirmed cases", size=13)
ax1.set_ylabel("Number of cases", size=13)
ax1.set_xlabel("Date", size=13)
fatalities_total_date.plot(ax=ax2, color='orange')
ax2.set_title("Global deceased cases", size=13)
ax2.set_ylabel("Number of cases", size=13)
ax2.set_xlabel("Date", size=13)
```

Out[3]: `Text(0.5, 0, 'Date')`



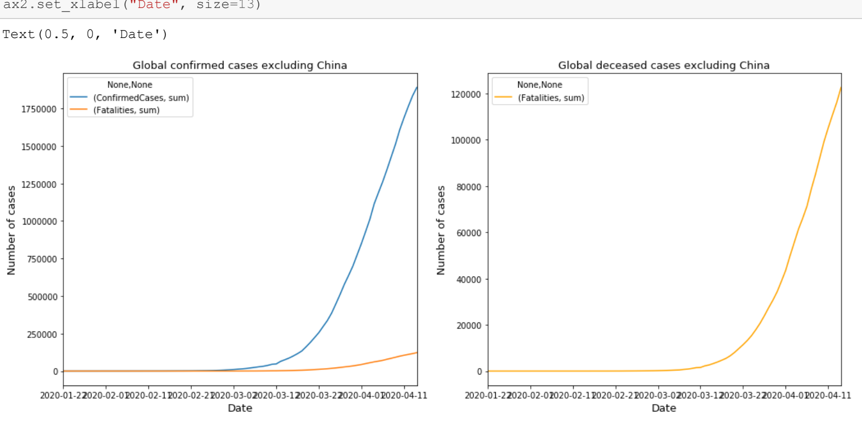
Observations: The global curve shows a rich fine structure, but these numbers are strongly affected by the vector zero country, China. Given that COVID-19 started there, during the initial expansion of the virus there was no reliable information about the real infected cases. In fact, the criteria to consider infection cases was modified around 2020-02-11, which strongly perturbed the curve as you can see from the figure.

1.1. COVID-19 global tendency excluding China

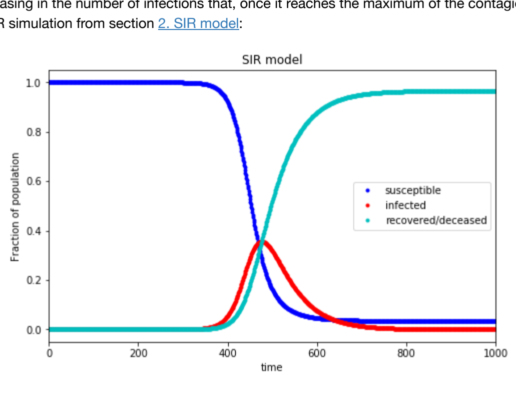
Since details of the initial breakthrough strongly interfere with the results, it's recomended to analyze China independently. Let's first see the results without China:

In [4]:
```
#confirmed_country_noChina = train[train['Country_Region']!='China'].groupby(['Country_Region', 'Provin
ce_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_noChina = train[train['Country_Region']!='China'].groupby(['Country_Region', 'Provi
nce_State']).agg({'Fatalities':['sum']})
confirmed_total_date_noChina = train[train['Country_Region']!='China'].groupby(['Date']).agg({'Confirme
dCases':['sum']})
fatalities_total_date_noChina = train[train['Country_Region']!='China'].groupby(['Date']).agg({'Fatalit
ies':['sum']})
total_date_noChina = confirmed_total_date_noChina.join(fatalities_total_date_noChina)

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(17,7))
total_date_noChina.plot(ax=ax1)
ax1.set_title("Global confirmed cases excluding China", size=13)
ax1.set_ylabel("Number of cases", size=13)
ax1.set_xlabel("Date", size=13)
fatalities_total_date_noChina.plot(ax=ax2, color='orange')
ax2.set_title("Global deceased cases excluding China", size=13)
ax2.set_ylabel("Number of cases", size=13)
ax2.set_xlabel("Date", size=13)
```

Out[4]: `Text(0.5, 0, 'Date')`



Observations: In this case the general behavior looks cleaner, and in fact the curve resembles a typical epidemiology model like SIR. SIR models present a large increasing in the number of infections that, once it reaches the maximum of the contagion, decreases with a lower slope. For comparison, a SIR simulation from section 2. SIR model:

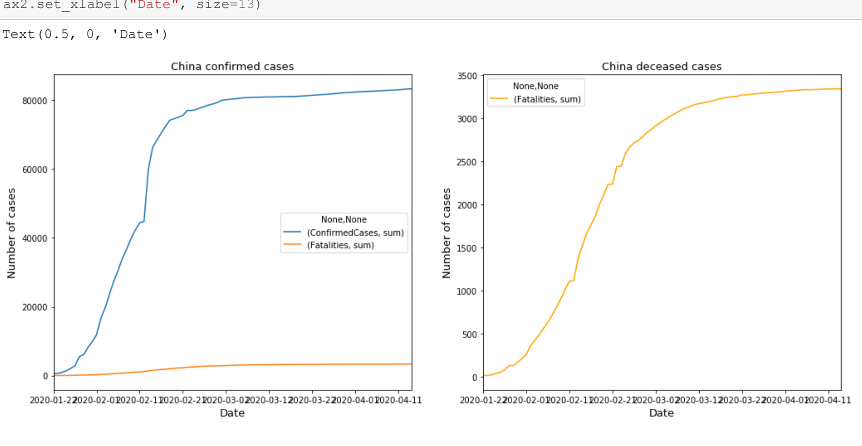


1.2. COVID-19 tendency in China

Since China was the initial infected country, the COVID-19 behavior is different from the rest of the world. The medical system was not prepared for the pandemic, in fact no one was aware of the virus until several cases were reported. Moreover, China government took strong contention measures in a considerable short period of time and, while the virus is widely spread, they have been able to control the increasing of the infections.

In [5]:
```
#confirmed_country_China = train[train['Country_Region']=='China'].groupby(['Country_Region', 'Province
_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_China = train[train['Country_Region']=='China'].groupby(['Country_Region', 'Provinc
e_State']).agg({'Fatalities':['sum']})
confirmed_total_date_China = train[train['Country_Region']=='China'].groupby(['Date']).agg({'ConfirmedC
ases':['sum']})
fatalities_total_date_China = train[train['Country_Region']=='China'].groupby(['Date']).agg({'Fatalitie
s':['sum']})
total_date_China = confirmed_total_date_China.join(fatalities_total_date_China)

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(17,7))
total_date_China.plot(ax=ax1)
ax1.set_title("China confirmed cases", size=13)
ax1.set_ylabel("Number of cases", size=13)
ax1.set_xlabel("Date", size=13)
fatalities_total_date_China.plot(ax=ax2, color='orange')
ax2.set_title("China deceased cases", size=13)
ax2.set_ylabel("Number of cases", size=13)
ax2.set_xlabel("Date", size=13)
```

Out[5]: `Text(0.5, 0, 'Date')`



Observations:

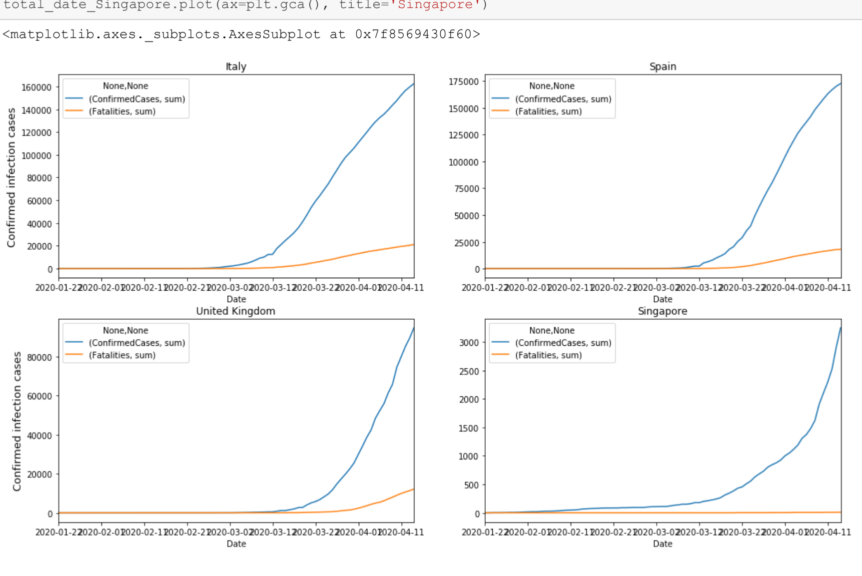
- **Smoothness**. Both plots are less smooth than theoretical simulations or the curve from the rest of the world cumulative
- **Infected criteria**. The moment in which the criteria to consider an infected case was changed is direclty spotted
- **Irregularities**. There are some irregularities. I should check the literature in depth to look for evidences, but the reasons may be that both the resources spent to monitor the epidemy and the security measures to stop ot have been changing over time
- **Plateaux**. It looks like the curve has reached a plateaux, which would imply that China is on their maximum of contagion

1.3. Italy, Spain, UK and Singapore

Both Italy and Spain are experiencing the larger increase in COVID-19 positives in Europe. At the same time, UK is a unique case given that it's one of the most important countries in Europe but recently has left the European Union, which has create an effective barrier to human mobility from other countries. The fourth country we will study in this section is Singapore, since it's an asiatic island, is closer to China and its socio-economic conditions is different from the other three countries.

In [6]:
```
#confirmed_country_Italy = train[train['Country_Region']=='Italy'].groupby(['Country_Region', 'Province
_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Italy = train[train['Country_Region']=='Italy'].groupby(['Country_Region', 'Provinc
e_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Italy = train[train['Country_Region']=='Italy'].groupby(['Date']).agg({'ConfirmedC
ases':['sum']})
fatalities_total_date_Italy = train[train['Country_Region']=='Italy'].groupby(['Date']).agg({'Fatalitie
s':['sum']})
total_date_Italy = confirmed_total_date_Italy.join(fatalities_total_date_Italy)

#confirmed_country_Spain = train[train['Country_Region']=='Spain'].groupby(['Country_Region', 'Province
_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Spain = train[train['Country_Region']=='Spain'].groupby(['Country_Region', 'Provinc
e_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Spain = train[train['Country_Region']=='Spain'].groupby(['Date']).agg({'ConfirmedC
ases':['sum']})
fatalities_total_date_Spain = train[train['Country_Region']=='Spain'].groupby(['Date']).agg({'Fatalitie
s':['sum']})
total_date_Spain = confirmed_total_date_Spain.join(fatalities_total_date_Spain)

#confirmed_country_UK = train[train['Country_Region']=='United Kingdom'].groupby(['Country_Region', 'Pr
ovince_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_UK = train[train['Country_Region']=='United Kingdom'].groupby(['Country_Region', 'P
rovince_State']).agg({'Fatalities':['sum']})
confirmed_total_date_UK = train[train['Country_Region']=='United Kingdom'].groupby(['Date']).agg({'Conf
irmedCases':['sum']})
fatalities_total_date_UK = train[train['Country_Region']=='United Kingdom'].groupby(['Date']).agg({'Fat
alities':['sum']})
total_date_UK = confirmed_total_date_UK.join(fatalities_total_date_UK)

#confirmed_country_Australia = train[train['Country_Region']=='Australia'].groupby(['Country_Region',
 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Australia = train[train['Country_Region']=='Australia'].groupby(['Country_Region',
 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Australia = train[train['Country_Region']=='Australia'].groupby(['Date']).agg({'Co
nfirmedCases':['sum']})
fatalities_total_date_Australia = train[train['Country_Region']=='Australia'].groupby(['Date']).agg({'F
atalities':['sum']})
total_date_Australia = confirmed_total_date_Australia.join(fatalities_total_date_Australia)

#confirmed_country_Singapore = train[train['Country_Region']=='Singapore'].groupby(['Country_Region',
 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Singapore = train[train['Country_Region']=='Singapore'].groupby(['Country_Region',
 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Singapore = train[train['Country_Region']=='Singapore'].groupby(['Date']).agg({'Co
nfirmedCases':['sum']})
fatalities_total_date_Singapore = train[train['Country_Region']=='Singapore'].groupby(['Date']).agg({'F
atalities':['sum']})
total_date_Singapore = confirmed_total_date_Singapore.join(fatalities_total_date_Singapore)

plt.figure(figsize=(17,10))
plt.subplot(2, 2, 1)
total_date_Italy.plot(ax=plt.gca(), title='Italy')
plt.ylabel("Confirmed infection cases", size=13)

plt.subplot(2, 2, 2)
total_date_Spain.plot(ax=plt.gca(), title='Spain')

plt.subplot(2, 2, 3)
total_date_UK.plot(ax=plt.gca(), title='United Kingdom')
plt.ylabel("Confirmed infection cases", size=13)

plt.subplot(2, 2, 4)
total_date_Singapore.plot(ax=plt.gca(), title='Singapore')
```

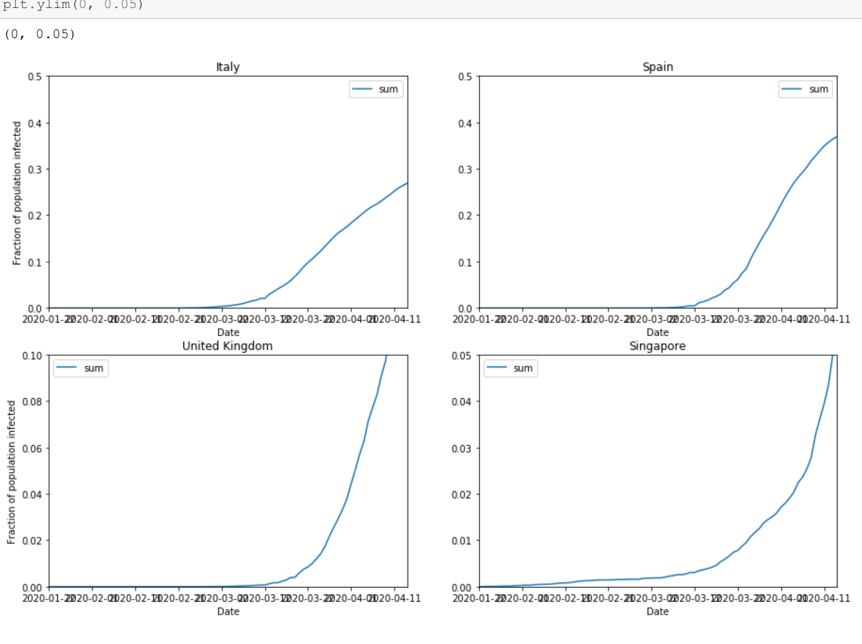
Out[6]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f8569430f60>`



As a fraction of the total population of each country:

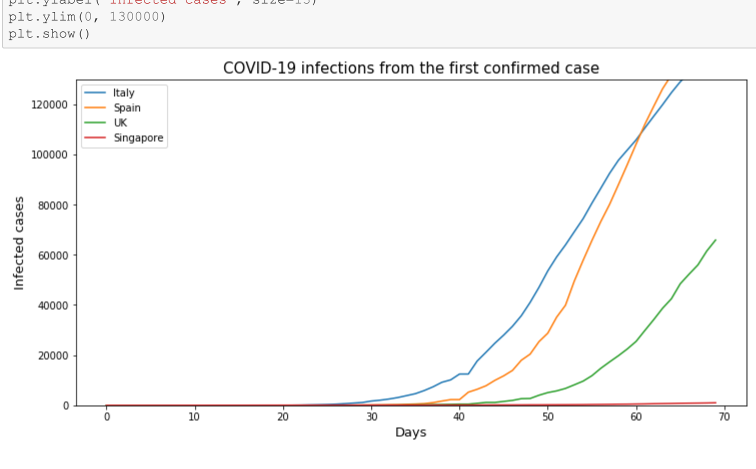
In [7]:
```
pop_italy = 60486683.
pop_spain = 46749696.
pop_UK = 67784927.
pop_singapore = 5837230.

total_date_Italy.ConfirmedCases = total_date_Italy.ConfirmedCases/pop_italy*100.
total_date_Italy.Fatalities = total_date_Italy.ConfirmedCases/pop_italy*100.
total_date_Spain.ConfirmedCases = total_date_Spain.ConfirmedCases/pop_spain*100.
total_date_Spain.Fatalities = total_date_Spain.ConfirmedCases/pop_spain*100.
total_date_UK.ConfirmedCases = total_date_UK.ConfirmedCases/pop_UK*100.
total_date_UK.Fatalities = total_date_UK.ConfirmedCases/pop_UK*100.
total_date_Singapore.ConfirmedCases = total_date_Singapore.ConfirmedCases/pop_singapore*100.
total_date_Singapore.Fatalities = total_date_Singapore.ConfirmedCases/pop_singapore*100.

plt.figure(figsize=(15,10))
plt.subplot(2, 2, 1)
total_date_Italy.ConfirmedCases.plot(ax=plt.gca(), title='Italy')
plt.ylabel("Fraction of population infected")
plt.ylim(0, 0.5)

plt.subplot(2, 2, 2)
total_date_Spain.ConfirmedCases.plot(ax=plt.gca(), title='Spain')
plt.ylim(0, 0.5)

plt.subplot(2, 2, 3)
total_date_UK.ConfirmedCases.plot(ax=plt.gca(), title='United Kingdom')
plt.ylabel("Fraction of population infected")
plt.ylim(0, 0.1)

plt.subplot(2, 2, 4)
total_date_Singapore.ConfirmedCases.plot(ax=plt.gca(), title='Singapore')
plt.ylim(0, 0.05)
```

Out[7]: `(0, 0.05)`



In order to compare the 4 countries, it's also interesting to see the evolution of the infections from the first confirmed case:

In [8]:
```
#confirmed_country_Italy = train[(train['Country_Region']=='Italy') & train['ConfirmedCases']!=0].group
by(['Country_Region', 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Italy = train[(train['Country_Region']=='Italy') & train['ConfirmedCases']!=0].grou
pby(['Country_Region', 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Italy = train[(train['Country_Region']=='Italy') & train['ConfirmedCases']!=0].gro
upby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date_Italy = train[(train['Country_Region']=='Italy') & train['ConfirmedCases']!=0].gr
oupby(['Date']).agg({'Fatalities':['sum']})
total_date_Italy = confirmed_total_date_Italy.join(fatalities_total_date_Italy)

#confirmed_country_Spain = train[(train['Country_Region']=='Spain') & (train['ConfirmedCases']!=0)].gro
upby(['Country_Region', 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Spain = train[(train['Country_Region']=='Spain') & (train['ConfirmedCases']!=0)].gr
oupby(['Country_Region', 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Spain = train[(train['Country_Region']=='Spain') & (train['ConfirmedCases']!=0)].g
roupby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date_Spain = train[(train['Country_Region']=='Spain') & (train['ConfirmedCases']!=0)].
groupby(['Date']).agg({'Fatalities':['sum']})
total_date_Spain = confirmed_total_date_Spain.join(fatalities_total_date_Spain)

#confirmed_country_UK = train[(train['Country_Region']=='United Kingdom') & (train['ConfirmedCases']!=
0)].groupby(['Country_Region', 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_UK = train[(train['Country_Region']=='United Kingdom') & (train['ConfirmedCases']!=
0)].groupby(['Country_Region', 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_UK = train[(train['Country_Region']=='United Kingdom') & (train['ConfirmedCases']!
=0)].groupby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date_UK = train[(train['Country_Region']=='United Kingdom') & (train['ConfirmedCases']
!=0)].groupby(['Date']).agg({'Fatalities':['sum']})
total_date_UK = confirmed_total_date_UK.join(fatalities_total_date_UK)

#confirmed_country_Australia = train[(train['Country_Region']=='Australia') & (train['ConfirmedCases']!
=0)].groupby(['Country_Region', 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Australia = train[(train['Country_Region']=='Australia') & (train['ConfirmedCase
s']!=0)].groupby(['Country_Region', 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Australia = train[(train['Country_Region']=='Australia') & (train['ConfirmedCases'
]!=0)].groupby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date_Australia = train[(train['Country_Region']=='Australia') & (train['ConfirmedCase
s']!=0)].groupby(['Date']).agg({'Fatalities':['sum']})
total_date_Australia = confirmed_total_date_Australia.join(fatalities_total_date_Australia)

#confirmed_country_Singapore = train[(train['Country_Region']=='Singapore') & (train['ConfirmedCases']!
=0)].groupby(['Country_Region', 'Province_State']).agg({'ConfirmedCases':['sum']})
#fatalities_country_Singapore = train[(train['Country_Region']=='Singapore') & (train['ConfirmedCase
s']!=0)].groupby(['Country_Region', 'Province_State']).agg({'Fatalities':['sum']})
confirmed_total_date_Singapore = train[(train['Country_Region']=='Singapore') & (train['ConfirmedCases'
]!=0)].groupby(['Date']).agg({'ConfirmedCases':['sum']})
fatalities_total_date_Singapore = train[(train['Country_Region']=='Singapore') & (train['ConfirmedCase
s']!=0)].groupby(['Date']).agg({'Fatalities':['sum']})
total_date_Singapore = confirmed_total_date_Singapore.join(fatalities_total_date_Singapore)

italy = [i for i in total_date_Italy.ConfirmedCases['sum'].values]
italy_30 = italy[0:70]
spain = [i for i in total_date_Spain.ConfirmedCases['sum'].values]
spain_30 = spain[0:70]
UK = [i for i in total_date_UK.ConfirmedCases['sum'].values]
UK_30 = UK[0:70]
singapore = [i for i in total_date_Singapore.ConfirmedCases['sum'].values]
singapore_30 = singapore[0:70]


# Plots
plt.figure(figsize=(12,6))
plt.plot(italy_30)
plt.plot(spain_30)
plt.plot(UK_30)
plt.plot(singapore_30)
plt.legend(["Italy", "Spain", "UK", "Singapore"], loc='upper left')
plt.title("COVID-19 infections from the first confirmed case", size=15)
plt.xlabel("Days", size=13)
plt.ylabel("Infected cases", size=13)
plt.ylim(0, 130000)
plt.show()
```



Observations:

- **Italy**. With almost 120.000 confirmed cases, Italy shows one of the most alarming scenarios of COVID-19. The infections curve is very steep, and more than 2% of population has been infected
- **Spain**. Spain has the same number of cumulative infected cases than Italy, near 120.000. However, Spain's total population is lower (around 42 millions) and hence the percentage of population that has been infected rises up to 3%.
- **United Kingdom**. Despite not being very far from them, the UK shows less cases. This may be due to the number of tests performed, but it's soon to know for sure. The number of cases is around 40.000, this is, a 0.6 of the total population.
- **Singapore**. Singapore is relatively isolated given that is an island, and the number of international travels is lower than for the other 3 countries. The number of cases is still very low (>1000), despite the general tendency is to increase. However, the infections started faster in the beginning, but the slope of the infections curve hasn't increased very much in the past weeks. A 0.2% of the population was infected

2. SIR model

We have seen some general behavior of the virus in agregated data, for the country where the coronavirus was originated and for four other interesting countries. There's a lot of information to be extracted from this data; for example, we haven't analyzed the effects of long/lat of countries. However, since our main purpose is to develop a predective model in order to understand the key factors that impact the COVID-19 transmission, I'll move on to one of the most famous epidemiologic models: SIR.

SIR is a simple model that considers a population that belongs to one of the following states:

1. **Susceptible (S)**. The individual hasn't contracted the disease, but she can be infected due to transmisison from infected people
2. **Infected (I)**. This person has contracted the disease
3. **Recovered/Deceased (R)**. The disease may lead to one of two destinies: either the person survives, hence developing inmunity to the disease, or the person is deceased.

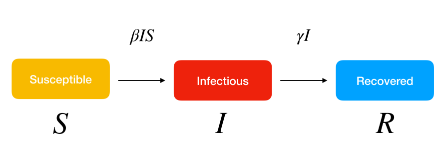


Image by Kai Sasaki from lewuathe.com

There are many versions of this model, considering birth and death (SIRD with demography), with intermediate states, etc. However, since we are in the early stages of the COVID-19 expansion and our interest is focused in the short term, we will consider that people develops immunity (in the long term, immunity may be lost and the COVID-19 may come back within a certain seasonality like the common flu) and there is no transition from recovered to the remaining two states. With this, the differential equations that govern the system are:

$$\frac{dS}{dt} = -\frac{\beta SI}{N}$$
$$\frac{dI}{dt} = \frac{\beta SI}{N} - \gamma I$$
$$\frac{dR}{dt} = \gamma I$$

Where β is the contagion rate of the pathogen and γ is the recovery rate.

2.1. Implementing the SIR model

SIR model can be implemented in many ways: from the differential equations governing the system, within a mean field approximation or running the dynamics in a social network (graph). For the sake of simplicity, I'vem chosen the first option, and we will simply run a numerical method (Runge-Kutta) to solve the differential equations system.

The functions governing the dif.eqs. are:

In [9]:
```
# Susceptible equation
def fa(N, a, b, beta):
    fa = -beta*a*b
    return fa

# Infected equation
def fb(N, a, b, beta, gamma):
    fb = beta*a*b - gamma*b
    return fb

# Recovered/deceased equation
def fc(N, b, gamma):
    fc = gamma*b
    return fc
```

In order to solve the differential equations system, we develop a 4rth order Runge-Kutta method:

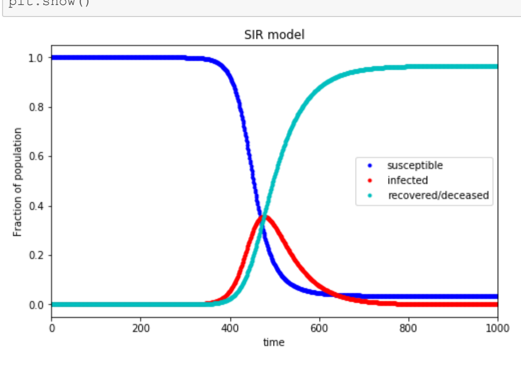
In [10]:
```
# Runge-Kutta method of 4rth order for 3 dimensions (susceptible a, infected b and recovered r)
def rK4(N, a, b, c, fa, fb, fc, beta, gamma, hs):
    a1 = fa(N, a, b, beta)*hs
    b1 = fb(N, a, b, beta, gamma)*hs
    c1 = fc(N, b, gamma)*hs
    ak = a + a1*0.5
    bk = b + b1*0.5
    ck = c + c1*0.5
    a2 = fa(N, ak, bk, beta)*hs
    b2 = fb(N, ak, bk, beta, gamma)*hs
    c2 = fc(N, bk, gamma)*hs
    ak = a + a2*0.5
    bk = b + b2*0.5
    ck = c + c2*0.5
    a3 = fa(N, ak, bk, beta)*hs
    b3 = fb(N, ak, bk, beta, gamma)*hs
    c3 = fc(N, bk, gamma)*hs
    ak = a + a3
    bk = b + b3
    ck = c + c3
    a4 = fa(N, ak, bk, beta)*hs
    b4 = fb(N, ak, bk, beta, gamma)*hs
    c4 = fc(N, bk, gamma)*hs
    a = a + (a1 + 2*(a2 + a3) + a4)/6
    b = b + (b1 + 2*(b2 + b3) + b4)/6
    c = c + (c1 + 2*(c2 + c3) + c4)/6
    return a, b, c
```

And finally, to obtain the evolution of the disease we simply define the initial conditions and call the rk4 method:

In [11]:
```
def SIR(N, b0, beta, gamma, hs):

    """
    N = total number of population
    beta = transition rate S->I
    gamma = transition rate I->R
    k =  denotes the constant degree distribution of the network (average value for networks in which
    the probability of finding a node with a different connectivity decays exponentially fast
    hs = jump step of the numerical integration
    """

    # Initial condition
    a = float(N-1)/N -b0
    b = float(1)/N +b0
    c = 0.

    sus, inf, rec= [],[],[]
    for i in range(10000): # Run for a certain number of time-steps
        sus.append(a)
        inf.append(b)
        rec.append(c)
        a,b,c = rK4(N, a, b, c, fa, fb, fc, beta, gamma, hs)

    return sus, inf, rec
```

Results obtained for N=world population, only one initial infected case, $\beta = 0.3$, $\gamma = 0.5$ and a leap pass $h_s = 0.1$ are shown below:

In [12]:
```
# Parameters of the model
N = 7800*(10**6)
b0 = 0
beta = 0.7
gamma = 0.2
hs = 0.1

sus, inf, rec = SIR(N, b0, beta, gamma, hs)

f = plt.figure(figsize=(8,5))
plt.plot(sus, 'b.', label='susceptible');
plt.plot(inf, 'r.', label='infected');
plt.plot(rec, 'c.', label='recovered/deceased');
plt.title("SIR model")
plt.xlabel("time", fontsize=10);
plt.ylabel("Fraction of population", fontsize=10);
plt.legend(loc='best')
plt.xlim(0,1000)
plt.savefig('SIR_example.png')
plt.show()
```



Observations:

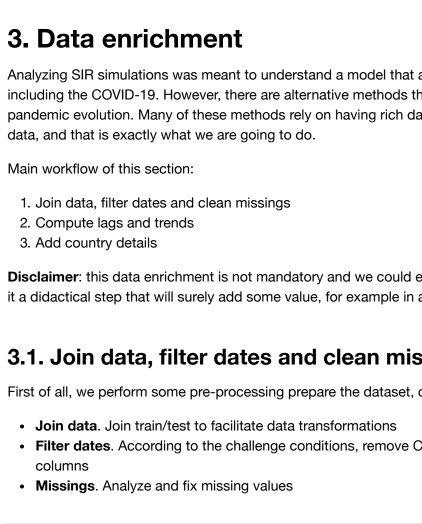
- The number of infected cases increases for a certain time period, and then eventually decreases given that individuals recover/decease from the disease
- The susceptible fraction of population decreases as the virus is transmited, to eventually drop to the absorbent state 0
- The oposite happens for the recovered/deceased case

Notice that different initial conditions and parameter values will lead to other scenarios, feel free to play with these numbers to study the system.

2.2. Fit SIR parameters to real data

The SIR model is purely theoretical, and we are interested into a real approximation of the COVID-19 expansion in order to extract insights and understand the transmission of the virus. Hence, we need to extract the β and γ paramaters for each case if we hope to be able to predict the evolution of the system.

```
In [13]: population = float(46750238)
country_df = pd.DataFrame()
country_df['ConfirmedCases'] = train.loc[train['Country_Region']=='Spain'].ConfirmedCases.diff().fillna(0)
country_df = country_df[10:]
country_df['day_count'] = list(range(1,len(country_df)+1))

ydata = [i for i in country_df.ConfirmedCases]
xdata = country_df.day_count
ydata = np.array(ydata, dtype=float)
xdata = np.array(xdata, dtype=float)

N = population
inf0 = ydata[0]
sus0 = N - inf0
rec0 = 0.0

def sir_model(y, x, beta, gamma):
    sus = -beta * y[0] * y[1] / N
    rec = gamma * y[1]
    inf = -(sus + rec)
    return sus, inf, rec

def fit_odeint(x, beta, gamma):
    return integrate.odeint(sir_model, (sus0, inf0, rec0), x, args=(beta, gamma))[:,1]

popt, pcov = optimize.curve_fit(fit_odeint, xdata, ydata)
fitted = fit_odeint(xdata, *popt)

plt.plot(xdata, ydata, 'o')
plt.plot(xdata, fitted)
plt.title("Fit of SIR model for Spain infected cases")
plt.ylabel("Population infected")
plt.xlabel("Days")
plt.show()
print("Optimal parameters: beta =", popt[0], " and gamma = ", popt[1])
```




```
Optimal parameters: beta = 9.44923389303625  and gamma =  9.27220462762098
```

I'm not happy with the fit of parameters and I want to work more on this, since I'm not properly reproducing the curves. I'll keep working on this for curiosity, but in the meanwhile I'll develop a data-centric approach to the prediction.

3. Data enrichment

Analyzing SIR simulations was meant to understand a model that approximately resembles the transmission mechanism of many virus, including the COVID-19. However, there are alternative methods that may prove being equally useful both to predict and to understand the pandemic evolution. Many of these methods rely on having rich data to extract conclusions and allow algorithms to extrapolate patterns in data, and that is exactly what we are going to do.

Main workflow of this section:

1. Join data, filter dates and clean missings
2. Compute lags and trends
3. Add country details

Disclaimer: this data enrichment is not mandatory and we could end up not using all of the new features in our models. However I consider it a didactical step that will surely add some value, for example in an in-depth exploratory analysis.

3.1. Join data, filter dates and clean missings

First of all, we perform some pre-processing prepare the dataset, consisting on:

- **Join data**. Join train/test to facilitate data transformations
- **Filter dates**. According to the challenge conditions, remove ConfirmedCases and Fatalities post 2020-03-12. Create additional date columns
- **Missings**. Analyze and fix missing values

```
In [14]: # Merge train and test, exclude overlap
dates_overlap = ['2020-04-01', '2020-04-02', '2020-04-03', '2020-04-04', '2020-04-05', '2020-04-06', '2020-04-07', '2020-04-08',
                 '2020-04-09', '2020-04-10', '2020-04-11', '2020-04-12', '2020-04-13', '2020-04-14']
train2 = train.loc[~train['Date'].isin(dates_overlap)]
all_data = pd.concat([train2, test], axis = 0, sort=False)

# Double check that there are no informed ConfirmedCases and Fatalities after 2020-03-11
all_data.loc[all_data['Date'] >= '2020-04-01', 'ConfirmedCases'] = 0
all_data.loc[all_data['Date'] >= '2020-04-01', 'Fatalities'] = 0
all_data['Date'] = pd.to_datetime(all_data['Date'])

# Create date columns
le = preprocessing.LabelEncoder()
all_data['Day_num'] = le.fit_transform(all_data.Date)
all_data['Day'] = all_data['Date'].dt.day
all_data['Month'] = all_data['Date'].dt.month
all_data['Year'] = all_data['Date'].dt.year

# Fill null values given that we merged train-test datasets
all_data['Province_State'].fillna("None", inplace=True)
all_data['ConfirmedCases'].fillna(0, inplace=True)
all_data['Fatalities'].fillna(0, inplace=True)
all_data['Id'].fillna(-1, inplace=True)
all_data['ForecastId'].fillna(-1, inplace=True)

display(all_data)
display(all_data.loc[all_data['Date'] == '2020-04-01'])
```

	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	Day	Month	Year
0	1.0	None	Afghanistan	2020-01-22	0.0	0.0	-1.0	0	22	1	2020
1	2.0	None	Afghanistan	2020-01-23	0.0	0.0	-1.0	1	23	1	2020
2	3.0	None	Afghanistan	2020-01-24	0.0	0.0	-1.0	2	24	1	2020
3	4.0	None	Afghanistan	2020-01-25	0.0	0.0	-1.0	3	25	1	2020
4	5.0	None	Afghanistan	2020-01-26	0.0	0.0	-1.0	4	26	1	2020
...	...	...	...	...	...	...	...	...	...	...	...
13454	-1.0	None	Zimbabwe	2020-05-10	0.0	0.0	13455.0	108	10	5	2020
13455	-1.0	None	Zimbabwe	2020-05-11	0.0	0.0	13456.0	109	11	5	2020
13456	-1.0	None	Zimbabwe	2020-05-12	0.0	0.0	13457.0	110	12	5	2020
13457	-1.0	None	Zimbabwe	2020-05-13	0.0	0.0	13458.0	111	13	5	2020
13458	-1.0	None	Zimbabwe	2020-05-14	0.0	0.0	13459.0	112	14	5	2020

35369 rows × 11 columns

Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	Day	Month	Year

Observations:

- "ConfirmedCases" and "Fatalities" are now only informed for dates previous to 2020-03-12
- The dataset includes all countries and dates, which is required for the lag/trend step
- Missing values for "ConfirmedCases" and "Fatalities" have been replaced by 0, which may be dangerous if we do not remember it at the end of the process. However, since we will train only on dates previous to 2020-03-12, this won't impact our prediction algorithm
- A new column "Day" has been created, as a day counter starting from the first date

Double-check that there are no remaining missing values:

```
In [15]: missings_count = {col:all_data[col].isnull().sum() for col in all_data.columns}
missings = pd.DataFrame.from_dict(missings_count, orient='index')
print(missings.nlargest(30, 0))
```

```
                0
Id              0
Province_State  0
Country_Region  0
Date            0
ConfirmedCases  0
Fatalities      0
ForecastId      0
Day_num         0
Day             0
Month           0
Year            0
```

3.2. Compute lags and trends

Enriching a dataset is key to obtain good results. In this case we will apply 2 different transformations:

Lag. Lags are a way to compute the previous value of a column, so that the lag 1 for ConfirmedCases would inform the this column from the previous day. The lag 3 of a feature X is simply:

$$X_{lag3}(t) = X(t-3)$$

Trend. Transformig a column into its trend gives the natural tendency of this column, which is different from the raw value. The definition of trend I will apply is:

$$Trend_X = \frac{X(t) - X(t-1)}{X(t-1)}$$

The backlog of lags I'll apply is 14 days, while for trends is 7 days. For ConfirmedCases and Fatalities:

```
In [16]: def calculate_lag(df, lag_list, column):
    for lag in lag_list:
        column_lag = column + "_" + str(lag)
        df[column_lag] = df.groupby(['Country_Region', 'Province_State'])[column].shift(lag, fill_value=0)
    return df

def calculate_trend(df, lag_list, column):
    for lag in lag_list:
        trend_column_lag = "Trend_" + column + "_" + str(lag)
        df[trend_column_lag] = (df.groupby(['Country_Region', 'Province_State'])[column].shift(0, fill_value=0) -
                                df.groupby(['Country_Region', 'Province_State'])[column].shift(lag, fill_value=0))/df.groupby(['Country_Region', 'Province_State'])[column].shift(lag, fill_value=0.001)
    return df


ts = time.time()
all_data = calculate_lag(all_data.reset_index(), range(1,7), 'ConfirmedCases')
all_data = calculate_lag(all_data, range(1,7), 'Fatalities')
all_data = calculate_trend(all_data, range(1,7), 'ConfirmedCases')
all_data = calculate_trend(all_data, range(1,7), 'Fatalities')
all_data.replace([np.inf, -np.inf], 0, inplace=True)
all_data.fillna(0, inplace=True)
print("Time spent: ", time.time()-ts)
```

```
Time spent:  6.311013221740723
```

As you see, the process is really fast. An example of some of the lag/trend columns for Spain:

```
In [17]: all_data[all_data['Country_Region']=='Spain'].iloc[40:50][['Id', 'Province_State', 'Country_Region', 'Date',
       'ConfirmedCases', 'Fatalities', 'ForecastId', 'Day_num', 'ConfirmedCases_1',
       'ConfirmedCases_2', 'ConfirmedCases_3', 'Fatalities_1', 'Fatalities_2',
       'Fatalities_3']]
```

Out[17]:

	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	ConfirmedCases_1	ConfirmedCa
15580	25349.0	None	Spain	2020-03-02	120.0	0.0	-1.0	40	84.0	
15581	25350.0	None	Spain	2020-03-03	165.0	1.0	-1.0	41	120.0	
15582	25351.0	None	Spain	2020-03-04	222.0	2.0	-1.0	42	165.0	
15583	25352.0	None	Spain	2020-03-05	259.0	3.0	-1.0	43	222.0	
15584	25353.0	None	Spain	2020-03-06	400.0	5.0	-1.0	44	259.0	
15585	25354.0	None	Spain	2020-03-07	500.0	10.0	-1.0	45	400.0	
15586	25355.0	None	Spain	2020-03-08	673.0	17.0	-1.0	46	500.0	
15587	25356.0	None	Spain	2020-03-09	1073.0	28.0	-1.0	47	673.0	
15588	25357.0	None	Spain	2020-03-10	1695.0	35.0	-1.0	48	1073.0	
15589	25358.0	None	Spain	2020-03-11	2277.0	54.0	-1.0	49	1695.0	

3.3. Add country details

Variables like the total population of a country, the average age of citizens or the fraction of peoople living in cities may strongly impact on the COVID-19 transmission behavior. Hence, it's important to consider these factors. I'm using Tanu's dataset based on Web Scrapping for this purpose.

```
In [18]: # Load countries data file
world_population = pd.read_csv("/kaggle/input/population-by-country-2020/population_by_country_2020.csv")

# Select desired columns and rename some of them
world_population = world_population[['Country (or dependency)', 'Population (2020)', 'Density (P/Km²)', 'Land Area (Km²)', 'Med. Age', 'Urban Pop %']]
world_population.columns = ['Country (or dependency)', 'Population (2020)', 'Density', 'Land Area', 'Med Age', 'Urban Pop']

# Replace United States by US
world_population.loc[world_population['Country (or dependency)']=='United States', 'Country (or dependency)'] = 'US'

# Remove the % character from Urban Pop values
world_population['Urban Pop'] = world_population['Urban Pop'].str.rstrip('%')

# Replace Urban Pop and Med Age "N.A" by their respective modes, then transform to int
world_population.loc[world_population['Urban Pop']=='N.A.', 'Urban Pop'] = int(world_population.loc[world_population['Urban Pop']!='N.A.', 'Urban Pop'].mode()[0])
world_population['Urban Pop'] = world_population['Urban Pop'].astype('int16')
world_population.loc[world_population['Med Age']=='N.A.', 'Med Age'] = int(world_population.loc[world_population['Med Age']!='N.A.', 'Med Age'].mode()[0])
world_population['Med Age'] = world_population['Med Age'].astype('int16')

print("Cleaned country details dataset")
display(world_population)

# Now join the dataset to our previous DataFrame and clean missings (not match in left join)- label encode cities
print("Joined dataset")
all_data = all_data.merge(world_population, left_on='Country_Region', right_on='Country (or dependency)', how='left')
all_data[['Population (2020)', 'Density', 'Land Area', 'Med Age', 'Urban Pop']] = all_data[['Population (2020)', 'Density', 'Land Area', 'Med Age', 'Urban Pop']].fillna(0)
display(all_data)

print("Encoded dataset")
# Label encode countries and provinces. Save dictionary for exploration purposes
all_data.drop('Country (or dependency)', inplace=True, axis=1)
all_data['Country_Region'] = le.fit_transform(all_data['Country_Region'])
number_c = all_data['Country_Region']
countries = le.inverse_transform(all_data['Country_Region'])
country_dict = dict(zip(countries, number_c))
all_data['Province_State'] = le.fit_transform(all_data['Province_State'])
number_p = all_data['Province_State']
province = le.inverse_transform(all_data['Province_State'])
province_dict = dict(zip(province, number_p))
display(all_data)
```

```
Cleaned country details dataset
```

	Country (or dependency)	Population (2020)	Density	Land Area	Med Age	Urban Pop
0	China	1438116346	153	9388211	38	61
1	India	1377011281	464	2973190	28	35
2	US	330578810	36	9147420	38	83
3	Indonesia	272884327	151	1811570	30	56
4	Pakistan	219922471	287	770880	23	35
...	...	...	...	...	...	...
230	Montserrat	4991	50	100	19	10
231	Falkland Islands	3457	0	12170	19	66
232	Niue	1624	6	260	19	46
233	Tokelau	1353	136	10	19	0
234	Holy See	801	2003	0	19	57

235 rows × 6 columns

```
Joined dataset
```

	index	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	Day	...	Trend_Fatalities_3
0	0	1.0	None	Afghanistan	2020-01-22	0.0	0.0	-1.0	0	22	...	0.0
1	1	2.0	None	Afghanistan	2020-01-23	0.0	0.0	-1.0	1	23	...	0.0
2	2	3.0	None	Afghanistan	2020-01-24	0.0	0.0	-1.0	2	24	...	0.0
3	3	4.0	None	Afghanistan	2020-01-25	0.0	0.0	-1.0	3	25	...	0.0
4	4	5.0	None	Afghanistan	2020-01-26	0.0	0.0	-1.0	4	26	...	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...
35364	13454	-1.0	None	Zimbabwe	2020-05-10	0.0	0.0	13455.0	108	10	...	0.0
35365	13455	-1.0	None	Zimbabwe	2020-05-11	0.0	0.0	13456.0	109	11	...	0.0
35366	13456	-1.0	None	Zimbabwe	2020-05-12	0.0	0.0	13457.0	110	12	...	0.0
35367	13457	-1.0	None	Zimbabwe	2020-05-13	0.0	0.0	13458.0	111	13	...	0.0
35368	13458	-1.0	None	Zimbabwe	2020-05-14	0.0	0.0	13459.0	112	14	...	0.0

35369 rows × 42 columns

```
Encoded dataset
```

	index	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	Day	...	Trend_Fatalities_2
0	0	1.0	83	0	2020-01-22	0.0	0.0	-1.0	0	22	...	0.0
1	1	2.0	83	0	2020-01-23	0.0	0.0	-1.0	1	23	...	0.0
2	2	3.0	83	0	2020-01-24	0.0	0.0	-1.0	2	24	...	0.0
3	3	4.0	83	0	2020-01-25	0.0	0.0	-1.0	3	25	...	0.0
4	4	5.0	83	0	2020-01-26	0.0	0.0	-1.0	4	26	...	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...
35364	13454	-1.0	83	183	2020-05-10	0.0	0.0	13455.0	108	10	...	0.0
35365	13455	-1.0	83	183	2020-05-11	0.0	0.0	13456.0	109	11	...	0.0
35366	13456	-1.0	83	183	2020-05-12	0.0	0.0	13457.0	110	12	...	0.0
35367	13457	-1.0	83	183	2020-05-13	0.0	0.0	13458.0	111	13	...	0.0
35368	13458	-1.0	83	183	2020-05-14	0.0	0.0	13459.0	112	14	...	0.0

35369 rows × 41 columns

4. Predictions for the early stages of the transmission

Our obective in this section consists on predicting the evolution of the expansion from a data-centric perspective, like any other regression problem. To do so, remember that the challenge specifies that submissions on the public LB shouldn only contain data previous to 2020-03-26.

Models to apply:

1. Linear Regression for one country
2. Linear Regression for all countries (method 1)
3. Linear Regression for all countries (method 2)

4.1. Linear Regression for one country

Since we are interested into predicting the future time evolution of the pandemic, our first approach consists on a simple Linear Regression. However, remind that **the evolution is** not linear but **exponential** (only in the beginning of the infection), so that a preliminar log transformation is needed.

Visual comparison of both cases for Spain and with data from last 10 days informed, starting on March 1st:

```
In [19]: fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,6))

# Day_num = 38 is March 1st
y1 = all_data[(all_data['Country_Region']==country_dict['Spain']) & (all_data['Day_num']>39) & (all_data['Day_num']<=49)][['ConfirmedCases']]
x1 = range(0, len(y1))
ax1.plot(x1, y1, 'bo--')
ax1.set_title("Spain ConfirmedCases between days 39 and 49")
ax1.set_xlabel("Days")
ax1.set_ylabel("ConfirmedCases")

y2 = all_data[(all_data['Country_Region']==country_dict['Spain']) & (all_data['Day_num']>39) & (all_data['Day_num']<=49)][['ConfirmedCases']].apply(lambda x: np.log(x))
x2 = range(0, len(y2))
ax2.plot(x2, y2, 'bo--')
ax2.set_title("Spain Log ConfirmedCases between days 39 and 49")
ax2.set_xlabel("Days")
ax2.set_ylabel("Log ConfirmedCases")
```

```
Out[19]: Text(0, 0.5, 'Log ConfirmedCases')
```

As you see, the log transformation results in a fancy straight-like line, which is awesome for Linear Regression. However, let me clarify two important points:

- This "roughly **exponential behavior" is only true for the initial infection stages of the pandemic** (the initial increasing of infections on the SIR model), but that's exactly the point where most countries are at the moment.
- Why do I only extract the last 10 days of data? For three reasons:
  1. In order to capture exactly the very short term component of the evolution
  2. To prevent the effects of certain variables that have been impacting the transmition speed (quarantine vs free circulation)
  3. To prevent differences on criteria when confirming cases (remember that weird slope on the China plot?)

This first model is very simple, and only elemental features will be considered: Country/Region, date information, Long and Lat. Lags. Engineered columns like lags, trends and country details are not introduced as an input. Finally, the workflow for the Basic Linear Regression model is:

1. **Features**. Select features
2. **Dates**. Filter train data from 2020-03-01 to 2020-03-18
3. **Log transformation**. Apply log transformation to ConfirmedCases and Fatalities
4. **Infinites**. Replace infinites from the logarithm with 0. Given the asymptotic behavior of the logarithm for log(0),this implies that when applying the inverse transformation (exponential) a 1 will be returned instead of a 0. This problem does not impact many countries, but still needs to be tackled sooner or later in order to obtain a clean solution.
5. **Train/test split**. Split into train/valid/test
6. **Prediction**. Linear Regression, training country by country and joining data
7. **Submit**. Submit results in the correct format, and applying exponential to reverse log transformation

```
In [20]: # Filter selected features
data = all_data.copy()
features = ['Id', 'ForecastId', 'Country_Region', 'Province_State', 'ConfirmedCases', 'Fatalities',
       'Day_num']
data = data[features]

# Apply log transformation to all ConfirmedCases and Fatalities columns, except for trends
data[['ConfirmedCases', 'Fatalities']] = data[['ConfirmedCases', 'Fatalities']].astype('float64')
data[['ConfirmedCases', 'Fatalities']] = data[['ConfirmedCases', 'Fatalities']].apply(lambda x: np.log1p(x))

# Replace infinites
data.replace([np.inf, -np.inf], 0, inplace=True)


# Split data into train/test
def split_data(df, train_lim, test_lim):

    df.loc[df['Day_num']<=train_lim , 'ForecastId'] = -1
    df = df[df['Day_num']<=test_lim]

    # Train set
    x_train = df[df.ForecastId == -1].drop(['ConfirmedCases', 'Fatalities'], axis=1)
    y_train_1 = df[df.ForecastId == -1]['ConfirmedCases']
    y_train_2 = df[df.ForecastId == -1]['Fatalities']

    # Test set
    x_test = df[df.ForecastId != -1].drop(['ConfirmedCases', 'Fatalities'], axis=1)

    # Clean Id columns and keep ForecastId as index
    x_train.drop('Id', inplace=True, errors='ignore', axis=1)
    x_train.drop('ForecastId', inplace=True, errors='ignore', axis=1)
    x_test.drop('Id', inplace=True, errors='ignore', axis=1)
    x_test.drop('ForecastId', inplace=True, errors='ignore', axis=1)

    return x_train, y_train_1, y_train_2, x_test


# Linear regression model
def lin_reg(X_train, Y_train, X_test):
    # Create linear regression object
    regr = linear_model.LinearRegression()

    # Train the model using the training sets
    regr.fit(X_train, Y_train)

    # Make predictions using the testing set
    y_pred = regr.predict(X_test)

    return regr, y_pred


# Submission function
def get_submission(df, target1, target2):

    prediction_1 = df[target1]
    prediction_2 = df[target2]

    # Submit predictions
    prediction_1 = [int(item) for item in list(map(round, prediction_1))]
    prediction_2 = [int(item) for item in list(map(round, prediction_2))]

    submission = pd.DataFrame({
        "ForecastId": df['ForecastId'].astype('int32'),
        "ConfirmedCases": prediction_1,
        "Fatalities": prediction_2
    })
    submission.to_csv('submission.csv', index=False)
```

Let's try to see results when training with a single country:

- **Spain**

```
In [21]: # Select train (real) data from March 1 to last day updated
dates_list = ['2020-03-01', '2020-03-02', '2020-03-03', '2020-03-04', '2020-03-05', '2020-03-06', '2020-03-07', '2020-03-08', '2020-03-09',
                 '2020-03-10', '2020-03-11','2020-03-12','2020-03-13','2020-03-14','2020-03-15','2020-03-16','2020-03-17','2020-03-18',
                 '2020-03-19','2020-03-20','2020-03-21','2020-03-22','2020-03-23', '2020-03-24', '2020-03-25', '2020-03-26', '2020-03-27',
                 '2020-03-28', '2020-03-29', '2020-03-30', '2020-03-31', '2020-04-01', '2020-04-02', '2020-04-03', '2020-04-04', '2020-04-05',
                 '2020-04-06', '2020-04-07', '2020-04-08', '2020-04-09', '2020-04-10', '2020-04-11', '2020-04-12', '2020-04-13', '2020-04-14']
```

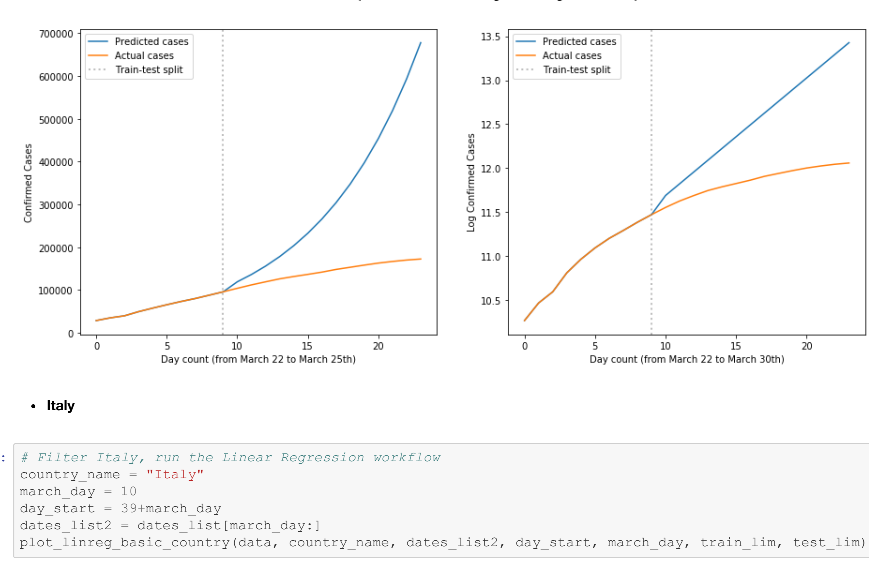
```
In [22]: all_data.loc[all_data['Country_Region']==country_dict['Spain']][50:70]
```

Out[22]:

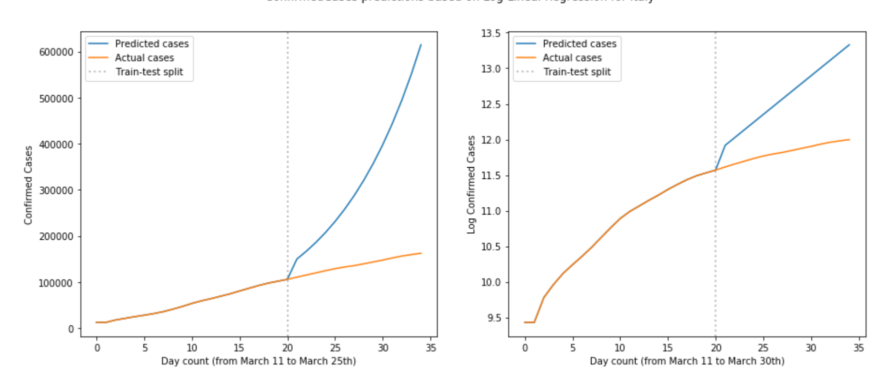
	index	Id	Province_State	Country_Region	Date	ConfirmedCases	Fatalities	ForecastId	Day_num	Day	...	Trend_Fatalities
15590	18698	25359.0	83	156	2020-03-12	2277.0	55.0	-1.0	50	12	...	0.5714
15591	18699	25360.0	83	156	2020-03-13	5232.0	133.0	-1.0	51	13	...	1.4629
15592	18700	25361.0	83	156	2020-03-14	6391.0	195.0	-1.0	52	14	...	2.5454
15593	18701	25362.0	83	156	2020-03-15	7798.0	289.0	-1.0	53	15	...	1.1729
15594	18702	25363.0	83	156	2020-03-16	9942.0	342.0	-1.0	54	16	...	0.7538
15595	18703	25364.0	83	156	2020-03-17	11748.0	533.0	-1.0	55	17	...	0.8442
15596	18704	25365.0	83	156	2020-03-18	13910.0	623.0	-1.0	56	18	...	0.8216
15597	18705	25366.0	83	156	2020-03-19	17963.0	830.0	-1.0	57	19	...	0.5572
15598	18706	25367.0	83	156	2020-03-20	20410.0	1043.0	-1.0	58	20	...	0.6741
15599	18707	25368.0	83	156	2020-03-21	25374.0	1375.0	-1.0	59	21	...	0.6566
15600	18708	25369.0	83	156	2020-03-22	28768.0	1772.0	-1.0	60	22	...	0.6989
15601	18709	25370.0	83	156	2020-03-23	35136.0	2311.0	-1.0	61	23	...	0.6807
15602	18710	25371.0	83	156	2020-03-24	39885.0	2808.0	-1.0	62	24	...	0.5846
15603	18711	25372.0	83	156	2020-03-25	49515.0	3647.0	-1.0	63	25	...	0.5781
15604	18712	25373.0	83	156	2020-03-26	57786.0	4365.0	-1.0	64	26	...	0.5544
15605	18713	25374.0	83	156	2020-03-27	65719.0	5138.0	-1.0	65	27	...	0.4088
15606	18714	25375.0	83	156	2020-03-28	73235.0	5982.0	-1.0	66	28	...	0.3704
15607	18715	25376.0	83	156	2020-03-29	80110.0	6803.0	-1.0	67	29	...	0.3240
15608	18716	25377.0	83	156	2020-03-30	87956.0	7716.0	-1.0	68	30	...	0.2898
15609	18717	25378.0	83	156	2020-03-31	95923.0	8464.0	-1.0	69	31	...	0.2441

20 rows × 41 columns

```
In [23]: def plot_linreg_basic_country(data, country_name, dates_list, day_start, shift, train_lim, test_lim):

    data_country = data[data['Country_Region']==country_dict[country_name]]
    data_country = data_country.loc[data_country['Day_num']>=day_start]
    X_train, Y_train_1, Y_train_2, X_test = split_data(data_country, train_lim, test_lim)
    model, pred = lin_reg(X_train, Y_train_1, X_test)

    # Create a df with both real cases and predictions (predictions starting on March 12th)
    X_train_check = X_train.copy()
    X_train_check['Target'] = Y_train_1

    X_test_check = X_test.copy()
    X_test_check['Target'] = pred

    X_final_check = pd.concat([X_train_check, X_test_check])

    # Select predictions from March 1st to March 25th
    predicted_data = X_final_check.loc[(X_final_check['Day_num'].isin(list(range(day_start, day_start+len(dates_list)))))].Target
    real_data = train.loc[(train['Country_Region']==country_name) & (train['Date'].isin(dates_list))]['ConfirmedCases']
    dates_list_num = list(range(0,len(dates_list)))

    # Plot results
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,6))

    ax1.plot(dates_list_num, np.expm1(predicted_data))
    ax1.plot(dates_list_num, real_data)
    ax1.axvline(30-shift, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax1.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax1.set_xlabel("Day count (from March " + str(1+shift) + " to March 25th)")
    ax1.set_ylabel("Confirmed Cases")

    ax2.plot(dates_list_num, predicted_data)
    ax2.plot(dates_list_num, np.log1p(real_data))
    ax2.axvline(30-shift, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax2.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax2.set_xlabel("Day count (from March " + str(1+shift) + " to March 30th)")
    ax2.set_ylabel("Log Confirmed Cases")

    plt.suptitle(("ConfirmedCases predictions based on Log-Lineal Regression for "+country_name))



# Filter Spain, run the Linear Regression workflow
country_name = "Spain"
march_day = 10
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
train_lim, test_lim = 69, 112
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

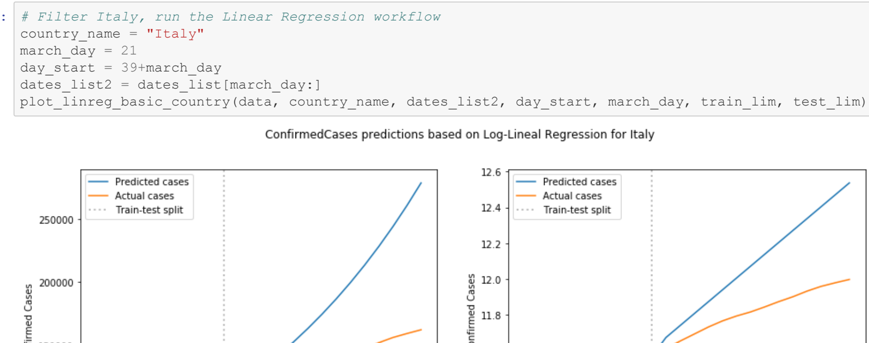



```
In [24]: # Filter Spain, run the Linear Regression workflow
country_name = "Spain"
march_day = 21
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

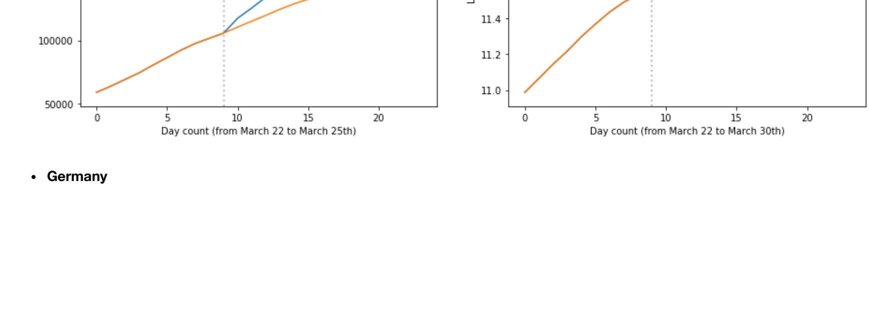


- **Italy**

```
In [25]: # Filter Italy, run the Linear Regression workflow
country_name = "Italy"
march_day = 10
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```



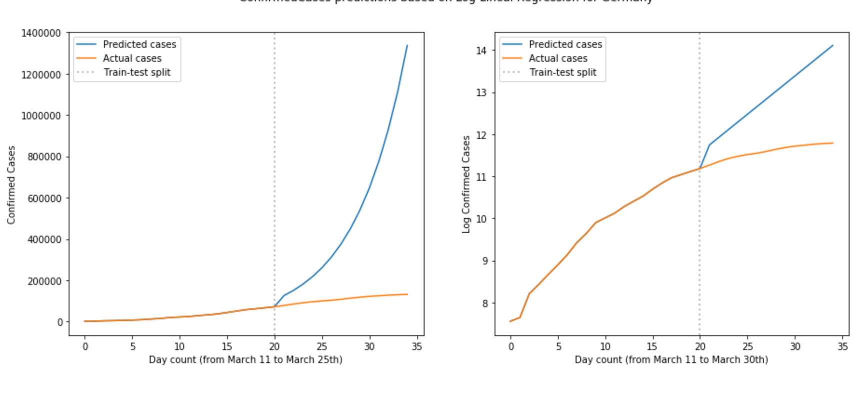

```
In [26]: # Filter Italy, run the Linear Regression workflow
country_name = "Italy"
march_day = 21
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```



- **Germany**

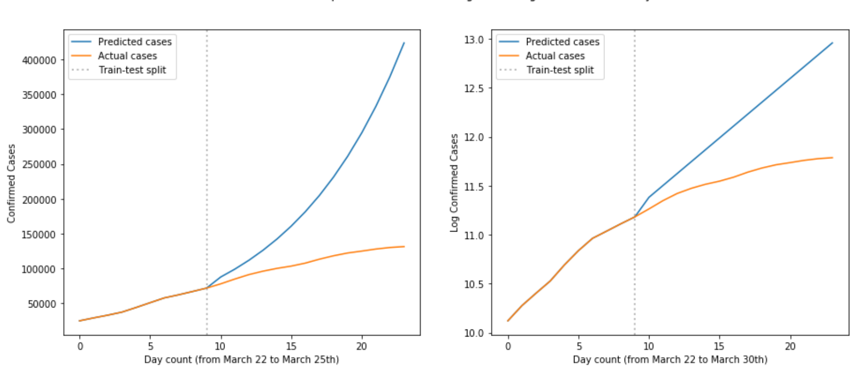
```
In [27]: # Filter Germany, run the Linear Regression workflow
country_name = "Germany"
march_day = 10
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

ConfirmedCases predictions based on Log-Lineal Regression for Germany




```
In [28]: # Filter Germany, run the Linear Regression workflow
country_name = "Germany"
march_day = 21
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

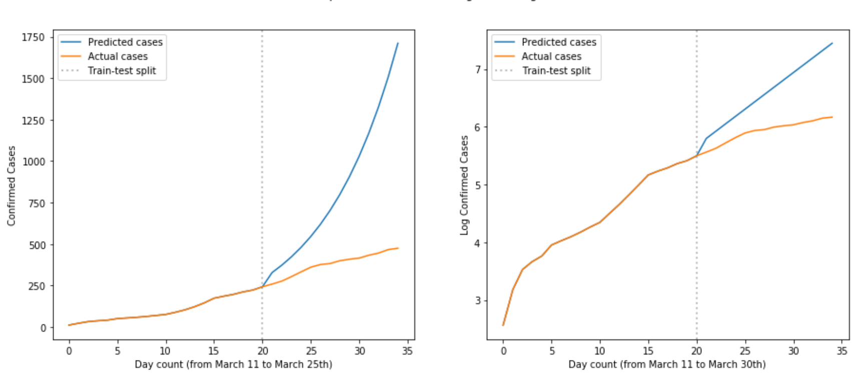
ConfirmedCases predictions based on Log-Lineal Regression for Germany



- **Albania**

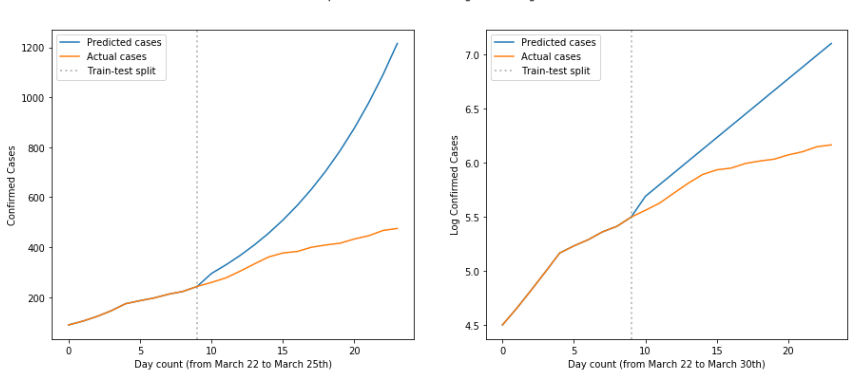
```
In [29]: # Filter Albania, run the Linear Regression workflow
country_name = "Albania"
march_day = 10
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

ConfirmedCases predictions based on Log-Lineal Regression for Albania




```
In [30]: # Filter Albania, run the Linear Regression workflow
country_name = "Albania"
march_day = 21
day_start = 39+march_day
dates_list2 = dates_list[march_day:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, march_day, train_lim, test_lim)
```

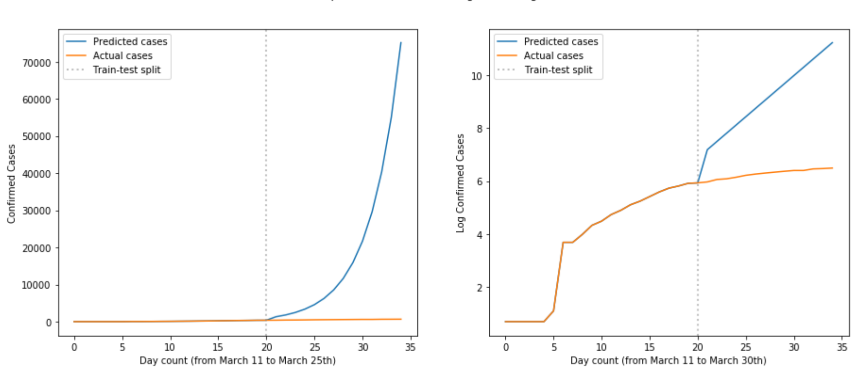
ConfirmedCases predictions based on Log-Lineal Regression for Albania



- **Andorra**

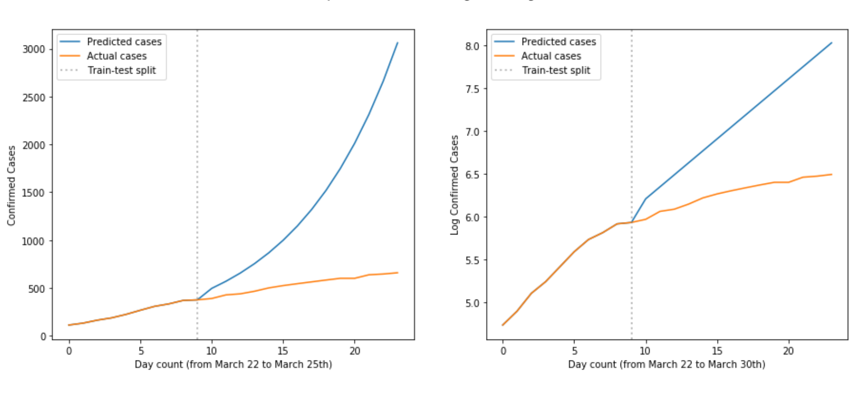
```
In [31]: # Filter Andorra, run the Linear Regression workflow
country_name = "Andorra"
shift = 10
day_start = 39+shift
dates_list2 = dates_list[shift:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, shift, train_lim, test_lim)
```

ConfirmedCases predictions based on Log-Lineal Regression for Andorra




```
In [32]: # Filter Andorra, run the Linear Regression workflow
country_name = "Andorra"
shift = 21
day_start = 39+shift
dates_list2 = dates_list[shift:]
plot_linreg_basic_country(data, country_name, dates_list2, day_start, shift, train_lim, test_lim)
```

ConfirmedCases predictions based on Log-Lineal Regression for Andorra



Observations:

- The general evolution is captured despite the simplicity of the model
- The cumulative infected cases has been changing in March, so that using thw whole month data for training results in overestimated predictions. When reducing the training set to only a few days prior the testing region, results are better. This is capturing the problem of the exponential behavior, that is only true for the early stages of the spreading. Now the behavior is more complex, and in order to predict the evolution with large portions of the historic evolution, alternative models are required (sigmoid, ARIMA...)
- Estimations are increasingly worse as time passes (harder to extrapolate)
- Countries that recently confirmed their first contagions are difficult to predict (less data points)
- Countries with 0 cases in the whole training dataset are predicted as non-infected (no datapoints)

Questions to tackle in next subsections:

- How to obtain the full submission set?
- What to do for countries with different Provinces/State informed?
- Is there any alternative to manually setting the size of the train data?

4.2 Linear Regression for all countries (method 1)

We've recently discovered that when fitting only with 10 historical datapoints some problematic scenarios appear, that impact the performance of our Linear Regressor. Let's generalize the model for all countries to verify if it's an unavoidable problem. Steps to run for all countries:

1. Loop for each country
2. Compute provinces list
3. If there are provinces, run the Linear Regressor for each of them
4. Otherwise just run the Linear Regressor

```
In [33]: ts = time.time()

def linreg_basic_all_countries(data, day_start, train_lim, test_lim):

    data2 = data.loc[data.Day_num >= day_start]

    # Set the dataframe where we will update the predictions
    data_pred = data[data.ForecastId != -1][['Country_Region', 'Province_State', 'Day_num', 'ForecastId']]
    data_pred = data_pred.loc[data_pred['Day_num']>=day_start]
    data_pred['Predicted_ConfirmedCases'] = [0]*len(data_pred)
    data_pred['Predicted_Fatalities'] = [0]*len(data_pred)

    print("Currently running Linear Regression for all countries")

    # Main loop for countries
    for c in data2['Country_Region'].unique():

        # List of provinces
        provinces_list = data2[data2['Country_Region']==c]['Province_State'].unique()

        # If the country has several Province/State informed
        if len(provinces_list)>1:
            for p in provinces_list:
                data_cp = data2[(data2['Country_Region']==c) & (data2['Province_State']==p)]
                X_train, Y_train_1, Y_train_2, X_test = split_data(data_cp, train_lim, test_lim)
                model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
                model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
                data_pred.loc[((data_pred['Country_Region']==c) & (data2['Province_State']==p)), 'Predicted_ConfirmedCases'] = pred_1
                data_pred.loc[((data_pred['Country_Region']==c) & (data2['Province_State']==p)), 'Predicted_Fatalities'] = pred_2

        # No Province/State informed
        else:
            data_c = data2[(data2['Country_Region']==c)]
            X_train, Y_train_1, Y_train_2, X_test = split_data(data_c, train_lim, test_lim)
            model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
            model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
            data_pred.loc[(data_pred['Country_Region']==c), 'Predicted_ConfirmedCases'] = pred_1
            data_pred.loc[(data_pred['Country_Region']==c), 'Predicted_Fatalities'] = pred_2

    # Apply exponential transf. and clean potential infinites due to final numerical precision
    data_pred[['Predicted_ConfirmedCases', 'Predicted_Fatalities']] = data_pred[['Predicted_ConfirmedCases', 'Predicted_Fatalities']].apply(lambda x: np.expm1(x))
    data_pred.replace([np.inf, -np.inf], 0, inplace=True)

    return data_pred


day_start = 65
#data_pred = linreg_basic_all_countries(data, day_start, train_lim, test_lim)
#get_submission(data_pred, 'Predicted_ConfirmedCases', 'Predicted_Fatalities')

print("Process finished in ", round(time.time() - ts, 2), " seconds")
```

```
Process finished in  0.0  seconds
```

Final LMSE score for week 2, with training data prior to 2020-03-19 and measures on date 2020-04-01:

1.19681

4.3 Linear Regression for all countries (method 2)

An alternative method to setting the number of days for the training step is to simply keep all data for each country since the first case was confirmed. However, since there are certain countries were the initial outbreak was very smooth (i.e. in Spain there was only one confirmed case for 7 days in a row), predictions may be biased by these initial periods.

```
In [34]: ts = time.time()

# Set the dataframe where we will update the predictions
day_start = 65
data2 = data.loc[data.Day_num >= day_start]
data_pred3 = data2[data2.ForecastId != -1][['Country_Region', 'Province_State', 'Day_num', 'ForecastId']]
data_pred3['Predicted_ConfirmedCases'] = [0]*len(data_pred3)
data_pred3['Predicted_Fatalities'] = [0]*len(data_pred3)
how_many_days = test.Date.nunique()

print("Currently running Linear Regression for all countries")

# Main loop for countries
for c in data['Country_Region'].unique():

    # List of provinces
    provinces_list = data2[data2['Country_Region']==c]['Province_State'].unique()

    # If the country has several Province/State informed
    if len(provinces_list)>1:

        for p in provinces_list:
            # Only fit starting from the first confirmed case in the country
            train_countries_no0 = data.loc[(data['Country_Region']==c) & (data['Province_State']==p) & (data.ConfirmedCases!=0) & (data.ForecastId==-1)]
            test_countries_no0 = data.loc[(data['Country_Region']==c) & (data['Province_State']==p) & (data.ForecastId!=-1)]
            data2 = pd.concat([train_countries_no0, test_countries_no0])

            # If there are no previous cases, predict 0
            if len(train_countries_no0) == 0:
                data_pred3.loc[((data_pred2['Country_Region']==c) & (data_pred3['Province_State']==p)), 'Predicted_ConfirmedCases'] = [0]*how_many_days
                data_pred3.loc[((data_pred2['Country_Region']==c) & (data_pred3['Province_State']==p)), 'Predicted_Fatalities'] = [0]*how_many_days

            # Else run LinReg
            else:
                data_cp = data2[(data2['Country_Region']==c) & (data2['Province_State']==p)]
                X_train, Y_train_1, Y_train_2, X_test = split_data(data_cp, train_lim, test_lim)
                model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
                model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
                data_pred3.loc[((data_pred3['Country_Region']==c) & (data_pred3['Province_State']==p)), 'Predicted_ConfirmedCases'] = pred_1
                data_pred3.loc[((data_pred3['Country_Region']==c) & (data_pred3['Province_State']==p)), 'Predicted_Fatalities'] = pred_2

    # No Province/State informed
    else:
        # Only fit starting from the first confirmed case in the country
        train_countries_no0 = data.loc[(data['Country_Region']==c) & (data.ConfirmedCases!=0) & (data.ForecastId==-1)]
        test_countries_no0 = data.loc[(data['Country_Region']==c) &  (data.ForecastId!=-1)]
        data2 = pd.concat([train_countries_no0, test_countries_no0])

        # If there are no previous cases, predict 0
        if len(train_countries_no0) == 0:
            data_pred3.loc[((data_pred3['Country_Region']==c)), 'Predicted_ConfirmedCases'] = [0]*how_many_days
            data_pred3.loc[((data_pred3['Country_Region']==c)), 'Predicted_Fatalities'] = [0]*how_many_days

        # Else, run LinReg
        else:
            data_c = data2[(data2['Country_Region']==c)]
            X_train, Y_train_1, Y_train_2, X_test = split_data(data_c, train_lim, test_lim)
            model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
            model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
            data_pred3.loc[(data_pred3['Country_Region']==c), 'Predicted_ConfirmedCases'] = pred_1
            data_pred3.loc[(data_pred3['Country_Region']==c), 'Predicted_Fatalities'] = pred_2

# Aplly exponential transf. and clean potential infinites due to final numerical precision
#data_pred3[['Predicted_ConfirmedCases', 'Predicted_Fatalities']] = data_pred3[['Predicted_ConfirmedCases', 'Predicted_Fatalities']].apply(lambda x: np.expm1(x))
#data_pred3.replace([np.inf, -np.inf], 0, inplace=True)

#get_submission(data_pred3, 'Predicted_ConfirmedCases', 'Predicted_Fatalities')

print("Process finished in ", round(time.time() - ts, 2), " seconds")
```

```
Currently running Linear Regression for all countries
Process finished in  6.01  seconds
```

From my experiments, this apporach is not suitable for our linear regression model. In many cases there are strong transitional periods at the beginning, which frequently biases the regression. Hence, I will not apply this method on following sections, but you are welcome to use it for any other purposes.

Final LMSE score for week 2, with training data prior to 2020-03-19 and measures on date 2020-04-01:

1.62190

4.4. Linear regression with lags

With all the previous results in mind, I quite believe that Linear Regression is a good approach for the early stages of the COVID-19 spread. Of course, this is only true for the initial outbreak we are analysing, and there's no way our model could predict when the number of new infections is going to decrease. But for short-term prediction purposes everything is fine, and we are in disposition to try to improve the results.

Remember those lagged variables we computed some sections before? Now it's time to use them, but first there's a problem to solve. If we use our dataset to predict the next following days of contagions, for the first day all the lags will be reported (from the previous days), but what about the next days? **Many of the lags will be unknown** (flagged as 0), since the number of ConfirmedCases is only known for the train subset. The most simple approach to overcome this is:

1. Begin with the train dataset, with all cases and lags reported
2. Forecast only the following day, through the Linear Regression
3. Set the new prediction as a confirmed case
4. Recompute lags
5. Repeat from step 2 to step 4 for all remaining days

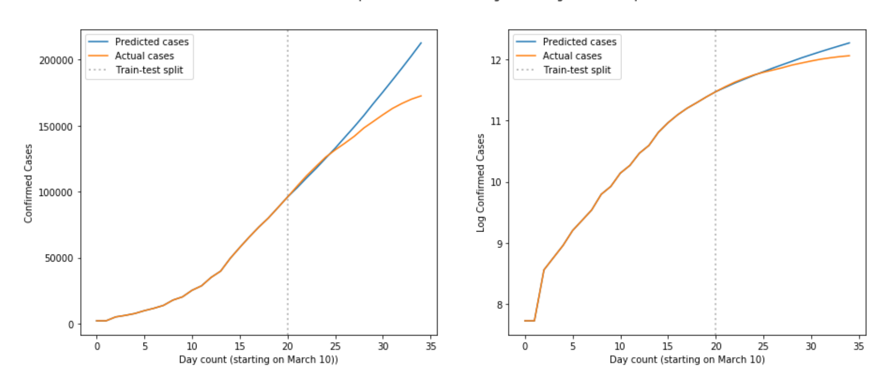
As usual, I'll start training on single countries in order to analyze the behavior of the model with these new features.

```
In [35]: # New split function, for one forecast day
def split_data_one_day(df, d, train_lim, test_lim):

    df.loc[df['Day_num']<=train_lim , 'ForecastId'] = -1
    df = df[df['Day_num']<=test_lim]

    #Train
    x_train = df[df.Day_num<d]
    y_train_1 = x_train.ConfirmedCases
    y_train_2 = x_train.Fatalities
    x_train.drop(['ConfirmedCases', 'Fatalities'], axis=1, inplace=True)

    #Test
    x_test = df[df.Day_num==d]
    x_test.drop(['ConfirmedCases', 'Fatalities'], axis=1, inplace=True)

    # Clean Id columns and keep ForecastId as index
    x_train.drop('Id', inplace=True, errors='ignore', axis=1)
    x_train.drop('ForecastId', inplace=True, errors='ignore', axis=1)
    x_test.drop('Id', inplace=True, errors='ignore', axis=1)
    x_test.drop('ForecastId', inplace=True, errors='ignore', axis=1)

    return x_train, y_train_1, y_train_2, x_test


def plot_real_vs_prediction_country(data, train, country_name, day_start, dates_list, march_day):

    # Select predictions from March 1st to March 25th
    predicted_data = data.loc[(data['Day_num'].isin(list(range(day_start, day_start+len(dates_list)))))].ConfirmedCases
    real_data = train.loc[(train['Country_Region']==country_name) & (train['Date'].isin(dates_list))]['ConfirmedCases']
    dates_list_num = list(range(0,len(dates_list)))

    # Plot results
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,6))

    ax1.plot(dates_list_num, np.expm1(predicted_data))
    ax1.plot(dates_list_num, real_data)
    ax1.axvline(30-march_day, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax1.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax1.set_xlabel("Day count (starting on March " + str(march_day) + "))")
    ax1.set_ylabel("Confirmed Cases")

    ax2.plot(dates_list_num, predicted_data)
    ax2.plot(dates_list_num, np.log1p(real_data))
    ax2.axvline(30-march_day, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax2.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax2.set_xlabel("Day count (starting on March " + str(march_day) + ")")
    ax2.set_ylabel("Log Confirmed Cases")

    plt.suptitle(("ConfirmedCases predictions based on Log-Lineal Regression for "+country_name))


def plot_real_vs_prediction_country_fatalities(data, train, country_name, day_start, dates_list, march_day):

    # Select predictions from March 1st to March 25th
    predicted_data = data.loc[(data['Day_num'].isin(list(range(day_start, day_start+len(dates_list)))))].Fatalities
    real_data = train.loc[(train['Country_Region']==country_name) & (train['Date'].isin(dates_list))]['Fatalities']
    dates_list_num = list(range(0,len(dates_list)))

    # Plot results
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,6))

    ax1.plot(dates_list_num, np.expm1(predicted_data))
    ax1.plot(dates_list_num, real_data)
    ax1.axvline(30-march_day, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax1.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax1.set_xlabel("Day count (starting on March " + str(march_day) + ")")
    ax1.set_ylabel("Fatalities Cases")

    ax2.plot(dates_list_num, predicted_data)
    ax2.plot(dates_list_num, np.log1p(real_data))
    ax2.axvline(30-march_day, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax2.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax2.set_xlabel("Day count (starting on March " + str(march_day) + ")")
    ax2.set_ylabel("Log Fatalities Cases")

    plt.suptitle(("Fatalities predictions based on Log-Lineal Regression for "+country_name))
```

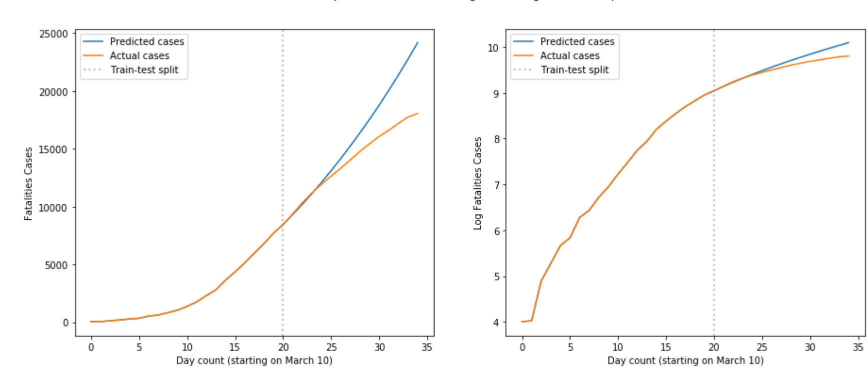
- **Spain**

```
In [36]: # Function to compute the Linear Regression predictions with lags, for a certain Country/Region
def lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim, test_lim):

    ts = time.time()

    # Filter country and features from all_data (dataset without data leaking)
    data = all_data.copy()
    features = ['Id', 'Province_State', 'Country_Region',
           'ConfirmedCases', 'Fatalities', 'ForecastId', 'Day_num']
    data = data[features]

    # Select country an data start (all days)
    data = data[data['Country_Region']==country_dict[country_name]]
    data = data.loc[data['Day_num']>=day_start]

    # Lags
    data = calculate_lag(data, range(1,lag_size), 'ConfirmedCases')
    data = calculate_lag(data, range(1,8), 'Fatalities')

    filter_col_confirmed = [col for col in data if col.startswith('Confirmed')]
    filter_col_fatalities= [col for col in data if col.startswith('Fataliti')]
    filter_col = np.append(filter_col_confirmed, filter_col_fatalities)

    # Apply log transformation
    data[filter_col] = data[filter_col].apply(lambda x: np.log1p(x))
    data.replace([np.inf, -np.inf], 0, inplace=True)
    data.fillna(0, inplace=True)


    # Start/end of forecast
    start_fcst = all_data[all_data['Id']==-1].Day_num.min()
    end_fcst = all_data[all_data['Id']==-1].Day_num.max()

    for d in list(range(start_fcst, end_fcst+1)):
        X_train, Y_train_1, Y_train_2, X_test = split_data_one_day(data, d, train_lim, test_lim)
        model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
        data.loc[(data['Country_Region']==country_dict[country_name])
                 & (data['Day_num']==d), 'ConfirmedCases'] = pred_1[0]
        model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
        data.loc[(data['Country_Region']==country_dict[country_name])
                 & (data['Day_num']==d), 'Fatalities'] = pred_2[0]

        # Recompute lags
        data = calculate_lag(data, range(1,lag_size), 'ConfirmedCases')
        data = calculate_lag(data, range(1,8), 'Fatalities')
        data.replace([np.inf, -np.inf], 0, inplace=True)
        data.fillna(0, inplace=True)

    #print("Process for ", country_name, "finished in ", round(time.time() - ts, 2), " seconds")

    return data


# Function to compute the Linear Regression predictions with lags, for a certain Country/Region and State/province
def lin_reg_with_lags_country_province(all_data, country_name, province_name, day_start, lag_size, country_dict, train_lim, test_lim):

    ts = time.time()

    # Filter country and features from all_data (dataset without data leaking)
    data = all_data.copy()
    features = ['Id', 'Province_State', 'Country_Region',
           'ConfirmedCases', 'Fatalities', 'ForecastId', 'Day_num']
    data = data[features]

    # Select country an data start (all days)
    data = data[(data['Country_Region']==country_dict[country_name]) & (data['Province_State']==province_dict[province_name])]
    data = data.loc[data['Day_num']>=day_start]

    # Lags
    data = calculate_lag(data, range(1,lag_size), 'ConfirmedCases')
    data = calculate_lag(data, range(1,lag_size), 'Fatalities')

    # Apply log transformation
    filter_col_confirmed = [col for col in data if col.startswith('Confirmed')]
    filter_col_fatalities= [col for col in data if col.startswith('Fataliti')]
    filter_col = np.append(filter_col_confirmed, filter_col_fatalities)
    data[filter_col] = data[filter_col].apply(lambda x: np.log1p(x))
    data.replace([np.inf, -np.inf], 0, inplace=True)
    data.fillna(0, inplace=True)

    # Start/end of forecast
    start_fcst = all_data[all_data['Id']==-1].Day_num.min()
    end_fcst = all_data[all_data['Id']==-1].Day_num.max()

    for d in list(range(start_fcst, end_fcst+1)):
        X_train, Y_train_1, Y_train_2, X_test = split_data_one_day(data, d, train_lim, test_lim)
        model_1, pred_1 = lin_reg(X_train, Y_train_1, X_test)
        data.loc[(data['Country_Region']==country_dict[country_name]) & (data['Province_State']==province_dict[province_name])
                 & (data['Day_num']==d), 'ConfirmedCases'] = pred_1[0]
        model_2, pred_2 = lin_reg(X_train, Y_train_2, X_test)
        data.loc[(data['Country_Region']==country_dict[country_name]) & (data['Province_State']==province_dict[province_name])
                 & (data['Day_num']==d), 'Fatalities'] = pred_2[0]

        # Recompute lags
        data = calculate_lag(data, range(1,lag_size), 'ConfirmedCases')
        data = calculate_lag(data, range(1,lag_size), 'Fatalities')
        data.replace([np.inf, -np.inf], 0, inplace=True)
        data.fillna(0, inplace=True)

    #print("Process for ", country_name, "/", province_name, "finished in ", round(time.time() - ts, 2), " seconds")

    return data



# Run the model for Spain
country_name = 'Spain'
march_day = 10
day_start = 39 + march_day
dates_list2 = dates_list[march_day:]
lag_size = 30

data_c = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim, test_lim)
plot_real_vs_prediction_country(data_c, train, country_name, day_start, dates_list2, march_day)
plot_real_vs_prediction_country_fatalities(data_c, train, country_name, day_start, dates_list2, march_day)
```

ConfirmedCases predictions based on Log-Lineal Regression for Spain



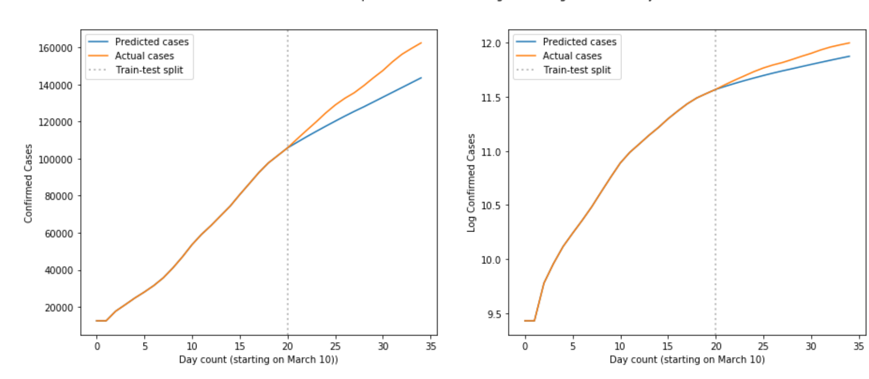
Fatalities predictions based on Log-Lineal Regression for Spain



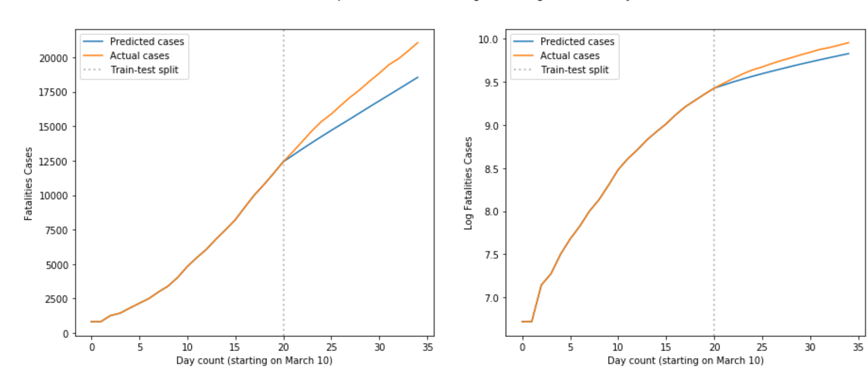
- **Italy**

```
In [37]: ts = time.time()

# Inputs
country_name = "Italy"
march_day = 10
day_start = 39 + march_day
dates_list2 = dates_list[march_day:]
lag_size = 30

data_c = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim, test_lim)
plot_real_vs_prediction_country(data_c, train, country_name, day_start, dates_list2, march_day)
plot_real_vs_prediction_country_fatalities(data_c, train, country_name, day_start, dates_list2, march_day)
```

ConfirmedCases predictions based on Log-Lineal Regression for Italy



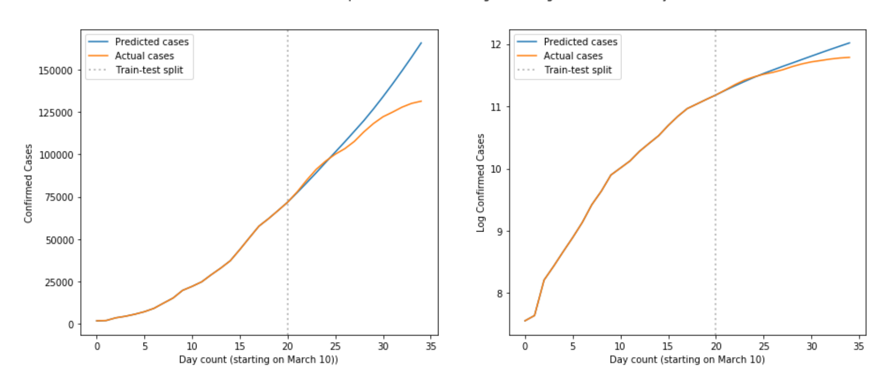
Fatalities predictions based on Log-Lineal Regression for Italy



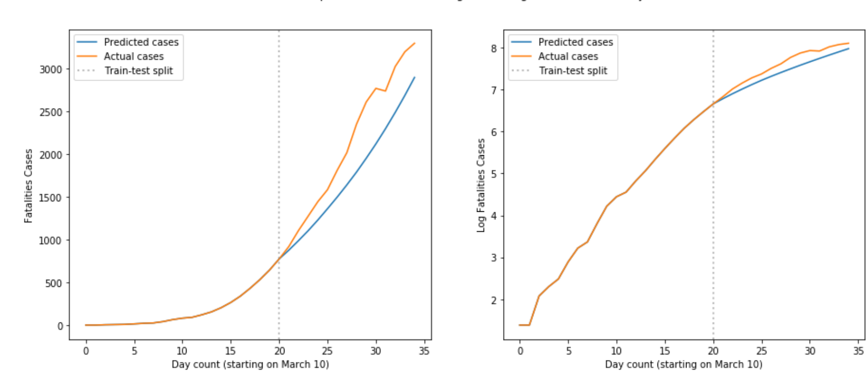
- **Germany**

```
In [38]: # Inputs
country_name = "Germany"
march_day = 10
day_start = 39 + march_day
dates_list2 = dates_list[march_day:]
lag_size = 30

data_c = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim, test_lim)
plot_real_vs_prediction_country(data_c, train, country_name, day_start, dates_list2, march_day)
plot_real_vs_prediction_country_fatalities(data_c, train, country_name, day_start, dates_list2, march_day)
```

ConfirmedCases predictions based on Log-Lineal Regression for Germany

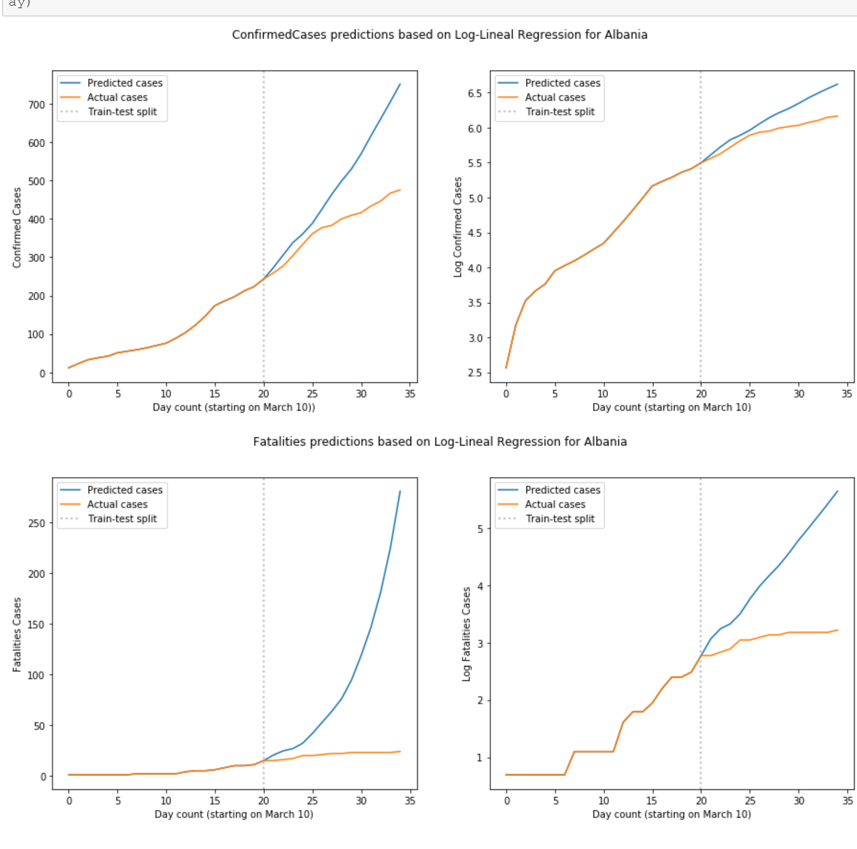


Fatalities predictions based on Log-Lineal Regression for Germany



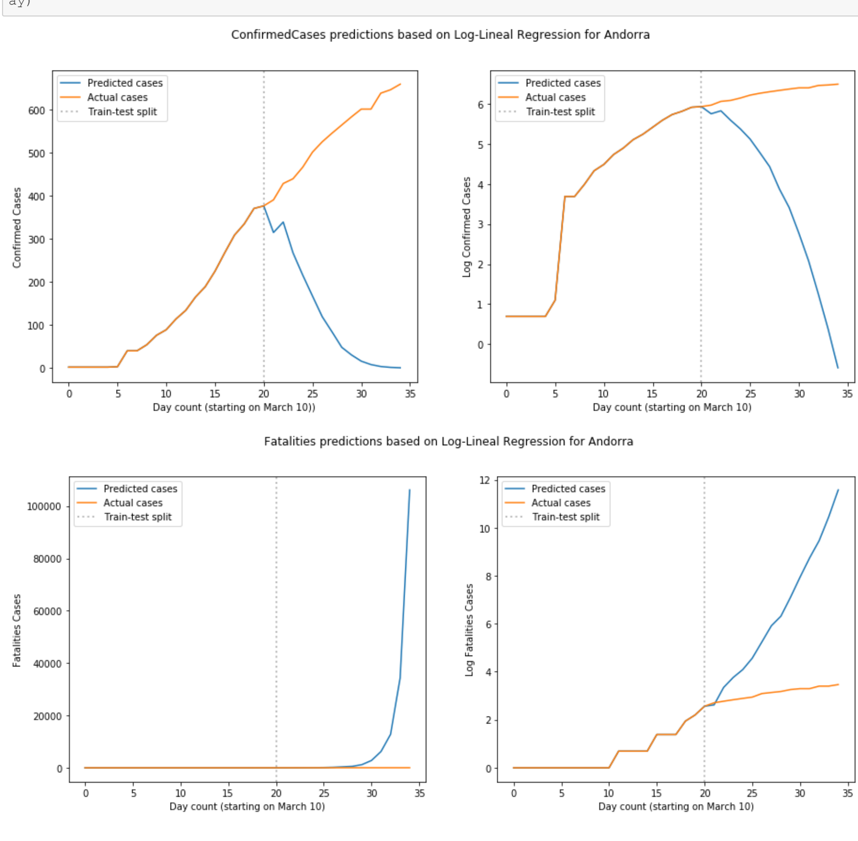
- **Albania**

```
In [39]: # Inputs
country_name = "Albania"
march_day = 10
day_start = 39 + march_day
dates_list2 = dates_list[march_day:]
lag_size = 7

data_c = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim
, test_lim)
plot_real_vs_prediction_country(data_c, train, country_name, day_start, dates_list2, march_day)
plot_real_vs_prediction_country_fatalities(data_c, train, country_name, day_start, dates_list2, march_d
ay)
```



- **Andorra**

```
In [40]: # Inputs
country_name = "Andorra"
march_day = 10
day_start = 39 + march_day
dates_list2 = dates_list[march_day:]
lag_size = 1

data_c = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_dict, train_lim
, test_lim)
plot_real_vs_prediction_country(data_c, train, country_name, day_start, dates_list2, march_day)
plot_real_vs_prediction_country_fatalities(data_c, train, country_name, day_start, dates_list2, march_d
ay)
```



Observations:

- **Parameters**. Two full weeks of training used (from February 26th to March 11th), with their previous 30 lags
- **Enough data**. (Spain, Italy, Germany). For countries with several ConfirmedCases!=0 in the train dataset (prior to March 11th), predictions are very precise and similar to actual confirmed data
- **Poor data**. (Algeria, Andorra). Countries with a small number of datapoints in the train dataset show a potentially disastrous prediction. Given the small number of cases, the log transformation followed by a Linear Regression is not able to capture the future behavior
- **No data**. When the number of confirmed cases in the train dataset is 0 or negligible, the model predicts always no infections

Let's generalize the model with lags for training each country day by day:

```
In [41]: """
# Inputs
day_start = 39
lag_size = 30

train3 = train.copy()
train3.Province_State.fillna("None", inplace=True)

results_df = pd.DataFrame()

tp = time.time()

# Main loop for countries
for country_name in train3['Country_Region'].unique():

    # List of provinces
    provinces_list = train3[train3['Country_Region']==country_name]['Province_State'].unique()

    # If the country has several Province/State informed
    if len(provinces_list)>1:
        for province_name in provinces_list:
            pred_province = lin_reg_with_lags_country_province(all_data, country_name, province_name, d
ay_start, lag_size, country_dict, train_lim, test_lim)
            results_df = pd.concat([results_df, pred_province])

    else:
        pred_country = lin_reg_with_lags_country(all_data, country_name, day_start, lag_size, country_d
ict, train_lim, test_lim)
        results_df = pd.concat([results_df, pred_country])

results_df_submit = results_df.copy()
results_df_submit['ConfirmedCases'] = results_df_submit['ConfirmedCases'].apply(lambda x: np.expm1(x))
results_df_submit['Fatalities'] = results_df_submit['Fatalities'].apply(lambda x: np.expm1(x))

#get_submission(results_df_submit.loc[results_df_submit['ForecastId']!=-1], 'ConfirmedCases', 'Fataliti
es')
print("Complete process finished in ", time.time()-tp)
"""
```

```
Out[41]: '\n# Inputs\nday_start = 39 \nlag_size = 30\n\ntrain3 = train.copy()\ntrain3.Province_State.fillna("N
one", inplace=True)\n\nresults_df = pd.DataFrame()\n\ntp = time.time()\n\n# Main loop for countries\n
for country_name in train3[\'Country_Region\'].unique():\n\n    # List of provinces\n    provinces_li
st = train3[train3[\'Country_Region\']==country_name][\'Province_State\'].unique()\n\n    # I
f the country has several Province/State informed\n    if len(provinces_list)>1:\n        for provinc
e_name in provinces_list:\n            pred_province = lin_reg_with_lags_country_province(all_data, c
ountry_name, province_name, day_start, lag_size, country_dict, train_lim, test_lim)\n            resu
lts_df = pd.concat([results_df, pred_province])\n\n    else:\n        pred_country = lin_reg_with_lag
s_country(all_data, country_name, day_start, lag_size, country_dict, train_lim, test_lim)\n        re
sults_df = pd.concat([results_df, pred_country])\n        \nresults_df_submit = results_df.copy()\nre
sults_df_submit[\'ConfirmedCases\'] = results_df_submit[\'ConfirmedCases\'].apply(lambda x: np.expm1
(x))\nresults_df_submit[\'Fatalities\'] = results_df_submit[\'Fatalities\'].apply(lambda x: np.expm1
(x))\n        \n#get_submission(results_df_submit.loc[results_df_submit[\'ForecastId\']!=-1], \'Confi
rmedCases\', \'Fatalities\')\nprint("Complete process finished in ", time.time()-tp)\n'
```

Nice, extending the model for all countries and days has been quite easy, but a tricky part needs to be addressed. As we saw when analyzing the results for certain countries, some of them have too few training datapoints different from 0, and these scenarios sometimes end up with the regression algorithm predicting absurd values.

For the sake of simplicity, my proposal to overcome this problem consists on mixing the current results with those from [section 4.2.](#), where we trained the model for all countries without lags. All countries with too few confirmed cases in the training dataset will be predicted with results from section 4.2.

```
In [42]: """
results_df_2 = results_df.copy()

day_start = 39
data_pred2 = linreg_basic_all_countries(data, day_start, train_lim, test_lim)
day_num_test = 57    # Day 2020-04-18


# Main loop for countries
for country_name in train3['Country_Region'].unique():

    # List of provinces
    provinces_list = train3[train3['Country_Region']==country_name]['Province_State'].unique()

    # Countries with several Province_State informed
    if len(provinces_list)>1:
        for province_name in provinces_list:

            tmp_index = all_data.index[(all_data['Country_Region']==country_dict[country_name]) &
                           (all_data['Province_State']==province_dict[province_name]) &
                           (all_data['Day_num']<day_num_test) &
                           (all_data['ConfirmedCases']!=0)]

            # When there is not enough data
            if len(tmp_index) < 30:

                # ConfirmedCases
                results_df_2.loc[((results_df_2['Country_Region']==country_dict[country_name]) &
                                  (results_df_2['Province_State']==province_dict[province_name]) &
                                  (results_df_2['Day_num']>=day_num_test)), 'ConfirmedCases'] = data_pr
ed2.loc[((data_pred2['Country_Region']==country_dict[country_name]) &
                                  (data_pred2['Province_State']==province_dict[province_name]) &
                                  (data_pred2['Day_num']>=day_num_test)), 'Predicted_ConfirmedCases'].a
pply(lambda x: np.log1p(x))

                #Fatalities
                results_df_2.loc[((results_df_2['Country_Region']==country_dict[country_name]) &
                                  (results_df_2['Province_State']==province_dict[province_name]) &
                                  (results_df_2['Day_num']>=day_num_test)), 'Fatalities'] = data_pred2.
loc[((data_pred2['Country_Region']==country_dict[country_name]) &
                                  (data_pred2['Province_State']==province_dict[province_name]) &
                                  (data_pred2['Day_num']>=day_num_test)), 'Predicted_Fatalities'].apply
(lambda x: np.log1p(x))

    # Countries without Province_State
    else:
        tmp_index = all_data.index[(all_data['Country_Region']==country_dict[country_name]) &
                           (all_data['Day_num']<day_num_test) &
                           (all_data['ConfirmedCases']!=0)]

        # When there is not enough data
        if len(tmp_index) < 30:

            #Confirmed Cases
            results_df_2.loc[((results_df_2['Country_Region']==country_dict[country_name]) &
                              (results_df_2['Day_num']>=day_num_test)), 'ConfirmedCases'] = data_pred2.lo
c[((data_pred2['Country_Region']==country_dict[country_name]) &
                              (data_pred2['Day_num']>=day_num_test)), 'Predicted_ConfirmedCases'].apply(l
ambda x: np.log1p(x))

            results_df_2.loc[((results_df_2['Country_Region']==country_dict[country_name]) &
                              (results_df_2['Day_num']>=day_num_test)), 'Fatalities'] = data_pred2.loc
[((data_pred2['Country_Region']==country_dict[country_name]) &
                              (data_pred2['Day_num']>=day_num_test)), 'Predicted_Fatalities'].apply(lambd
a x: np.log1p(x))

results_df_2 = results_df_2.loc[results_df_2['Day_num']>=day_num_test]
#results_df_2[['ConfirmedCases', 'Fatalities']] = results_df_2[['ConfirmedCases', 'Fatalities']].apply
(lambda x: np.expm1(x))
#get_submission(results_df_2, 'ConfirmedCases', 'Fatalities')
"""
```

```
Out[42]: "\nresults_df_2 = results_df.copy()\n\nday_start = 39\ndata_pred2 = linreg_basic_all_countries(data,
day_start, train_lim, test_lim)\nday_num_test = 57    # Day 2020-04-18\n\n\n# Main loop for countries
\nfor country_name in train3['Country_Region'].unique():\n\n    # List of provinces\n    provinces_li
st = train3[train3['Country_Region']==country_name]['Province_State'].unique()\n\n    # Countries wit
h several Province_State informed\n    if len(provinces_list)>1:\n        for province_name in provin
ces_list:\n        \n            tmp_index = all_data.index[(all_data['Country_Region']==country_dict
[country_name]) & \n                           (all_data['Province_State']==province_dict[province_na
me]) & \n                           (all_data['Day_num']<day_num_test) & \n
(all_data['ConfirmedCases']!=0)]\n\n            # When there is not enough data\n            if len(t
mp_index) < 30:\n                \n                # ConfirmedCases\n                results_df_2.loc
[((results_df_2['Country_Region']==country_dict[country_name]) & \n
(results_df_2['Province_State']==province_dict[province_name]) &\n
(results_df_2['Day_num']>=day_num_test)), 'ConfirmedCases'] = data_pred2.loc[((data_pred2['Country_Re
gion']==country_dict[country_name]) & \n                                  (data_pred2['Province_Stat
e']==province_dict[province_name]) & \n                                  (data_pred2['Day_num']>=day_
num_test)), 'Predicted_ConfirmedCases'].apply(lambda x: np.log1p(x))\n                \n
   #Fatalities\n                results_df_2.loc[((results_df_2['Country_Region']==country_dict[count
ry_name]) & \n                                  (results_df_2['Province_State']==province_dict[provin
ce_name]) &\n                                  (results_df_2['Day_num']>=day_num_test)), 'Fatalitie
s'] = data_pred2.loc[((data_pred2['Country_Region']==country_dict[country_name]) & \n
            (data_pred2['Province_State']==province_dict[province_name]) & \n
          (data_pred2['Day_num']>=day_num_test)), 'Predicted_Fatalities'].apply(lambda x: np.lo
g1p(x))\n                \n    # Countries without Province_State\n    else:\n        tmp_index = all
_data.index[(all_data['Country_Region']==country_dict[country_name]) & \n
(all_data['Day_num']<day_num_test) & \n                           (all_data['ConfirmedCases']!=0)]\n
\n        # When there is not enough data\n        if len(tmp_index) < 30:\n            \n
#Confirmed Cases\n            results_df_2.loc[((results_df_2['Country_Region']==country_dict[country
_name]) & \n                              (results_df_2['Day_num']>=day_num_test)), 'ConfirmedCases'] =
data_pred2.loc[((data_pred2['Country_Region']==country_dict[country_name]) & \n
      (data_pred2['Day_num']>=day_num_test)), 'Predicted_ConfirmedCases'].apply(lambda x: np.log1p
(x))\n            \n            results_df_2.loc[((results_df_2['Country_Region']==country_dict[count
ry_name]) & \n                              (results_df_2['Day_num']>=day_num_test)), 'Fatalities'] = d
ata_pred2.loc[((data_pred2['Country_Region']==country_dict[country_name]) & \n
     (data_pred2['Day_num']>=day_num_test)), 'Predicted_Fatalities'].apply(lambda x: np.log1p(x))\n
          \nresults_df_2 = results_df_2.loc[results_df_2['Day_num']>=day_num_test]\n#results_df_2[['C
onfirmedCases', 'Fatalities']] = results_df_2[['ConfirmedCases', 'Fatalities']].apply(lambda x: np.ex
pm1(x))\n#get_submission(results_df_2, 'ConfirmedCases', 'Fatalities')\n"
```

5. Predictions for the late stages of the transmission (under construction)

As the transmission progresses, **the exponential regime is left behind** and the Linear Regressor we developed begins to predict worse results. We were aware of this limitation, and now **alternative methods are required** in order to capture the new behavior.

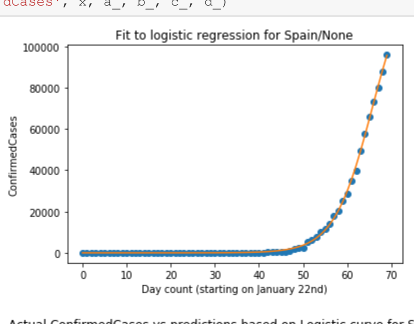
I'd like to clarify that the aim of this section will be to predict the immediate future evolution of the number of cases, not to estimate when the peack of infections will happen or to which extent the COVID-19 will spread in each country.

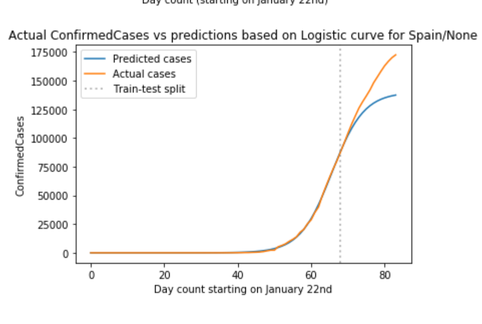
Models considered in this section:

1. Logistic curve fit
2. Logistic curve fit for all countries
3. ARIMA

5.1. Logistic curve fit

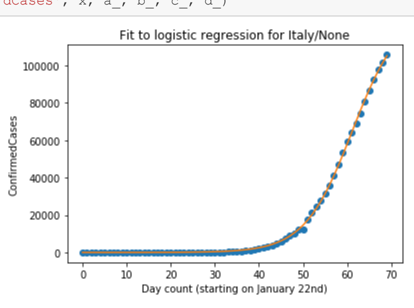
```
In [43]: def logistic_function(x, a, b, c, d):
    return a / (1. + np.exp(-c * (x - d))) + b

def fit_logistic(all_data, country_name, province_name, train_lim, target):
    data_cp = all_data.loc[(all_data['Country_Region']==country_dict[country_name]) & (all_data['Provin
ce_State']==province_dict[province_name])]
    y = data_cp.loc[(data_cp['Day_num'])<=train_lim, target].astype(np.int32)
    x = list(range(0, len(y)))

    # Initial guess
    p0 = [0,1,1,0]

    (a_, b_, c_, d_), cov = optimize.curve_fit(logistic_function, x, y, bounds=(0, [500000., 10., 1000.
, 1000., ]), p0=p0, maxfev=10**9)
    y_fit = logistic_function(x, a_, b_, c_, d_)

    return x, y, y_fit, (a_, b_, c_, d_), cov

def plot_logistic(x, y, y_fit, country_name, province_name, target):
    fig, ax = plt.subplots(1, 1, figsize=(6, 4))
    ax.plot(x, y, 'o')
    ax.plot(x, y_fit, '-')
    ax.set_xlabel("Day count (starting on January 22nd)")
    ax.set_ylabel(target)
    ax.set_title("Fit to logistic regression for "+ country_name+"/"+province_name)


def plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, targe
t, x, a_, b_, c_, d_):
    forecast = logistic_function(list(range(len(x)+60)), a_, b_, c_, d_)
    df_train = train.loc[(train['Country_Region']==country_name) & (train['Province_State']==province_n
ame), target]
    df_fcst = forecast[:len(df_train)]
    dates = list(range(0,len(df_train)))

    # Plot results
    fig, (ax1) = plt.subplots(1, 1, figsize=(6,4))
    ax1.plot(dates, df_fcst)
    ax1.plot(dates, df_train)
    ax1.axvline(len(df_train)-valid_num-1, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax1.set_title("Actual ConfirmedCases vs predictions based on Logistic curve for "+country_name +
"/"+province_name)
    ax1.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax1.set_xlabel("Day count starting on January 22nd")
    ax1.set_ylabel("ConfirmedCases")


# Fit country to logistic curve
country_name = 'Spain'
province_name = 'None'
train_lim = 69
valid_lim = 84 # needs to be changed as more days of training data are included
test_lim = 112
valid_num=valid_lim-train_lim

x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```

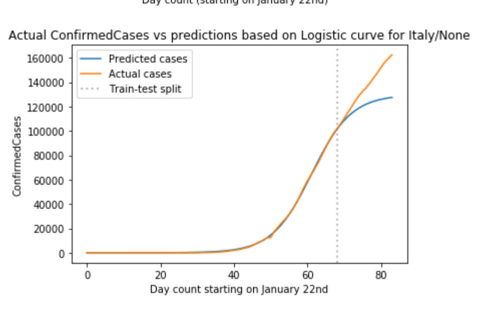




- **Italy**

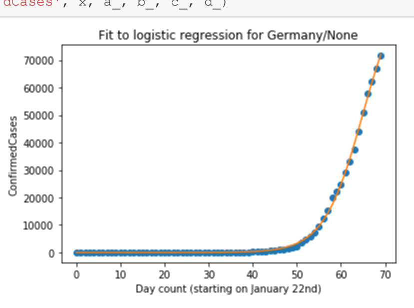
```
In [44]: # Fit country to logistic curve
country_name = 'Italy'
province_name = 'None'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```

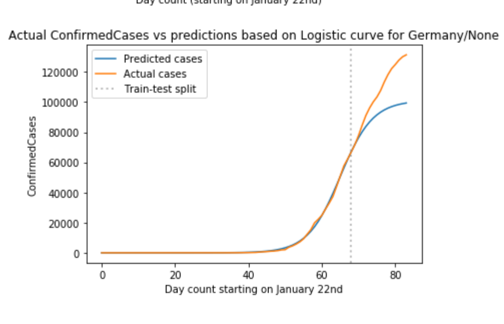




- **Germany**

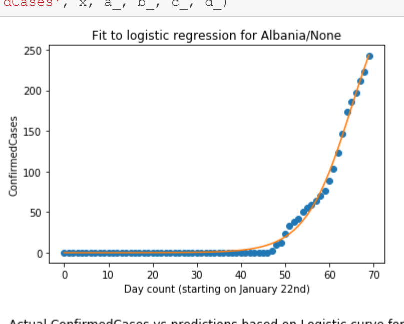
```
In [45]: # Fit country to logistic curve
country_name = 'Germany'
province_name = 'None'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```

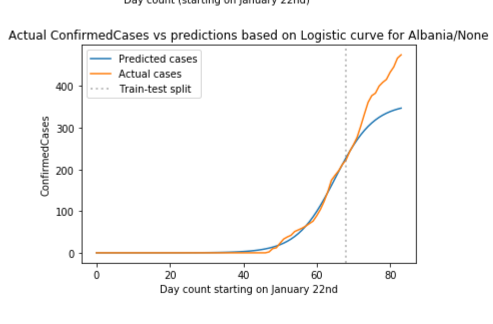




- **Albania**

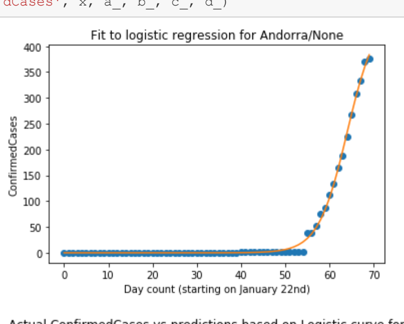
```
In [46]: # Fit country to logistic curve
country_name = 'Albania'
province_name = 'None'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```

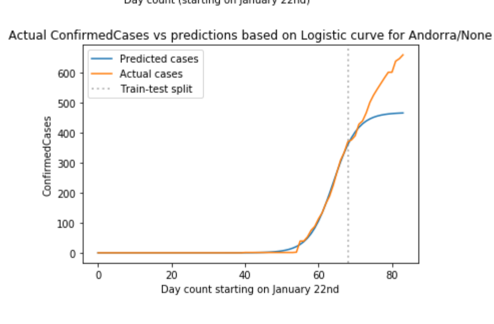




- **Andorra**

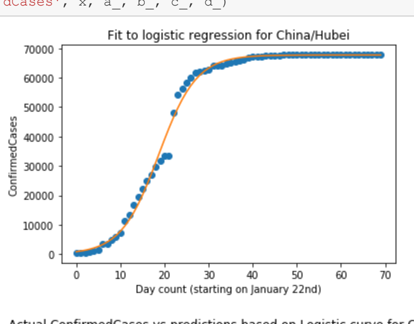
```
In [47]: # Fit country to logistic curve
country_name = 'Andorra'
province_name = 'None'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```

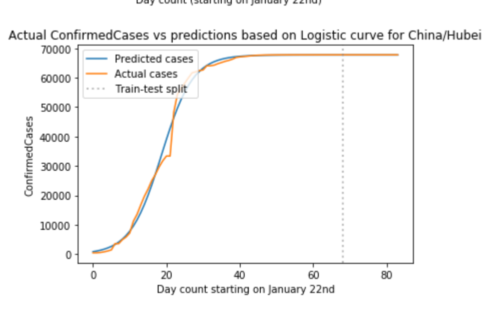




*** China/Hubei**

```
In [48]: # Fit country to logistic curve
country_name = 'China'
province_name = 'Hubei'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, 'Co
nfirmedCases')
plot_logistic(x, y, y_fit, country_name, province_name, 'ConfirmedCases')
plot_logistic_country(all_data, train, dates_overlap, country_name, province_name, valid_num, 'Confirme
dCases', x, a_, b_, c_, d_)
```





5.2. Logistic curve fit for all countries

```
In [49]: train_lim = 69
test_lim = 112

def logistic_forecast_allcountries(all_data, train, train_lim, test_lim):

    ts = time.time()
    data_pred = all_data[all_data.ForecastId != -1][['Country_Region', 'Province_State', 'Day_num', 'Fo
recastId']]
    data_pred['Predicted_ConfirmedCases'] = [0]*len(data_pred)
    data_pred['Predicted_Fatalities'] = [0]*len(data_pred)

    # Main loop for countries
    for country_name in train['Country_Region'].unique():
        for province_name in train[train['Country_Region']==country_name]['Province_State'].unique():

            # ConfirmedCases
            x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, tr
ain_lim, 'ConfirmedCases')
            pred_1 = [logistic_function(t, a_, b_, c_, d_) for t in list(range(train_lim+1, test_lim+1
))]
            data_pred.loc[((data_pred['Country_Region']==country_dict[country_name]) & (data_pred['Prov
ince_State']==province_dict[province_name])), 'Predicted_ConfirmedCases'] = pred_1

            # Fatalities
            x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, tr
ain_lim, 'Fatalities')
            pred_2 = [logistic_function(t, a_, b_, c_, d_) for t in list(range(train_lim+1, test_lim+1
))]
            data_pred.loc[((data_pred['Country_Region']==country_dict[country_name]) & (data_pred['Prov
ince_State']==province_dict[province_name])), 'Predicted_Fatalities'] = pred_2


    print("Logistic function fit for all countries finished in ", round(time.time() - ts, 2), " second
s")
    return data_pred

logistic_forecast = logistic_forecast_allcountries(all_data, train, train_lim, test_lim)
get_submission(logistic_forecast, 'Predicted_ConfirmedCases', 'Predicted_Fatalities')
```

```
Logistic function fit for all countries finished in  2050.0  seconds
```

5.3. ARIMA

Autoregressive integrated moving average (ARIMA) models are mainly used for time-series analysis, since they are capable to predict the future values of a variable based only on its historical evolution. ARIMA models can be understood by dividing them in three main concepts, each of them with a related parameter:

- **AR**: the regression of the predicted variable is based on its previous values (lags). The p parameter defines the number of these terms.
$$\sum_{i=1}^{p} \phi_i y_{t-i}$$
- **I**: data values used for the regression are differenciated until they are stationary. Instead of working with y_t, it uses terms of . Parameter d is related to the number of differences need for stationarity.
$$y'_t \sim y_t - y_{t-1}$$
- **MA**: the error of the regression is based on a linear combination of error terms from the past (lags of errors). Parameter q is the number of lagged forecast errors in the prediction equation.
$$\sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

In general, the model can be written as:

$$y'_t = c + \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \epsilon_{t-1} \ldots + \theta_q \epsilon_{t-q} - \epsilon_t$$

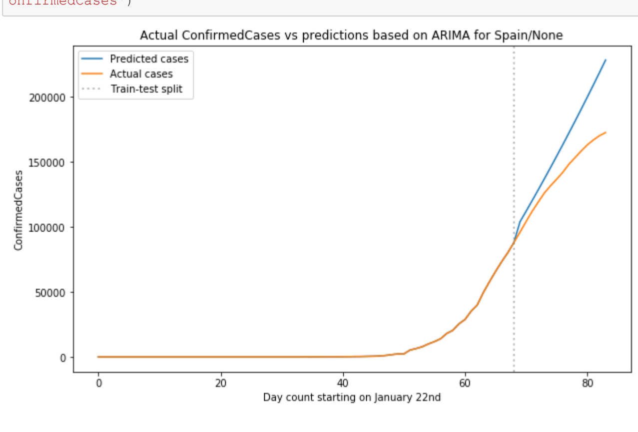
In order to keep the notebook clean and don't overextend, I won't go into further details of the model. For a rich explanation of ARIMA models you can visit the [Monash University online textbook](#).

```
In [50]: !pip install pyramid.arima
from pyramid.arima import auto_arima
```

```
Collecting pyramid.arima
  Downloading pyramid_arima-0.9.0-cp36-cp36m-manylinux1_x86_64.whl (597 kB)
     |████████████████████████████████| 597 kB 2.9 MB/s
Requirement already satisfied: scikit-learn>=0.17 in /opt/conda/lib/python3.6/site-packages (from pyr
amid.arima) (0.22.2.post1)
Requirement already satisfied: Cython>=0.23 in /opt/conda/lib/python3.6/site-packages (from pyramid.a
rima) (0.29.15)
Requirement already satisfied: scipy>=0.9 in /opt/conda/lib/python3.6/site-packages (from pyramid.ari
ma) (1.4.1)
Requirement already satisfied: pandas>=0.19 in /opt/conda/lib/python3.6/site-packages (from pyramid.a
rima) (0.25.3)
Requirement already satisfied: numpy>=1.10 in /opt/conda/lib/python3.6/site-packages (from pyramid.ar
ima) (1.18.1)
Requirement already satisfied: statsmodels>=0.9.0 in /opt/conda/lib/python3.6/site-packages (from pyr
amid.arima) (0.11.0)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.6/site-packages (from scikit-le
arn>=0.17->pyramid.arima) (0.14.1)
Requirement already satisfied: python-dateutil>=2.6.1 in /opt/conda/lib/python3.6/site-packages (from
pandas>=0.19->pyramid.arima) (2.8.0)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.6/site-packages (from pandas>=
0.19->pyramid.arima) (2019.3)
Requirement already satisfied: patsy>=0.5 in /opt/conda/lib/python3.6/site-packages (from statsmodels
>=0.9.0->pyramid.arima) (0.5.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.6/site-packages (from python-dateut
il>=2.6.1->pandas>=0.19->pyramid.arima) (1.14.0)
Installing collected packages: pyramid.arima
Successfully installed pyramid.arima
```

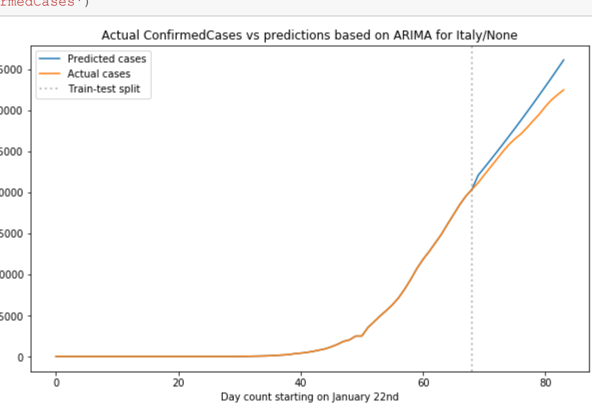
- **Spain**

```
In [51]: # Define a general function to run ARIMA regression
def arima_cp(all_data, country_name, province_name, target, train_lim, test_lim):

    #Select data for the Country/Region, splitting train/test days
    data_cp = all_data.loc[(all_data['Country_Region']==country_dict[country_name]) & (all_data['Provin
ce_State']==province_dict[province_name])]
    data_cp_train = data_cp.loc[(data_cp['Day_num'])<=train_lim, target].astype(np.int32)
    data_cp_test = data_cp.loc[(data_cp['Day_num'])>test_lim, target].astype(np.int32)

    # Set the range of parameters to use
    stepwise_model = auto_arima(data_cp[target], start_p=1, start_q=1, max_p=30, max_q=30,
                                start_P=0, seasonal=False, d=2, trace=False, error_action='ignore', ste
pwise=True)

    # Train and predict
    stepwise_model.fit(data_cp_train, start_ar_lags=2*max(30, 30))
    forecast = stepwise_model.predict(n_periods=test_lim-train_lim)
    return forecast


# Plot the actual values vs predictions
def plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num
, target):
    df_train = train.loc[(train['Country_Region']==country_name) & (train['Province_State']==province_n
ame), target]
    df_fcst = np.append(df_train[:-valid_num], forecast[:valid_num])
    dates = list(range(0,len(df_train)))

    # Plot results
    fig, (ax1) = plt.subplots(1, 1, figsize=(10,6))
    ax1.plot(dates, df_fcst)
    ax1.plot(dates, df_train)
    ax1.axvline(len(df_train)-valid_num-1, linewidth=2, ls = ':', color='grey', alpha=0.5)
    ax1.set_title("Actual ConfirmedCases vs predictions based on ARIMA for "+country_name + "/"+provinc
e_name)
    ax1.legend(['Predicted cases', 'Actual cases', 'Train-test split'], loc='upper left')
    ax1.set_xlabel("Day count starting on January 22nd")
    ax1.set_ylabel("ConfirmedCases")



# Inputs
country_name = 'Spain'
province_name = 'None'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```



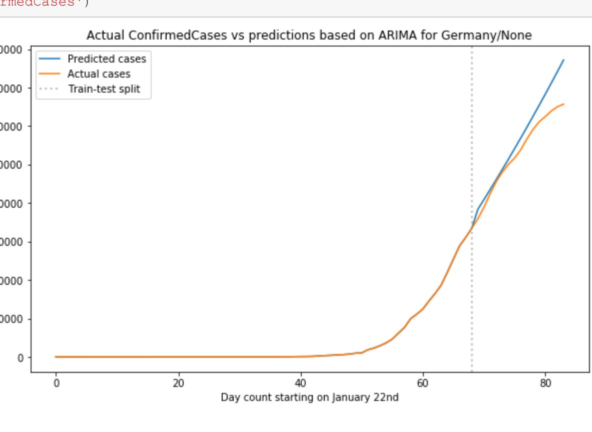
- **Italy**

```
In [52]: # Inputs
country_name = 'Italy'
province_name = 'None'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```



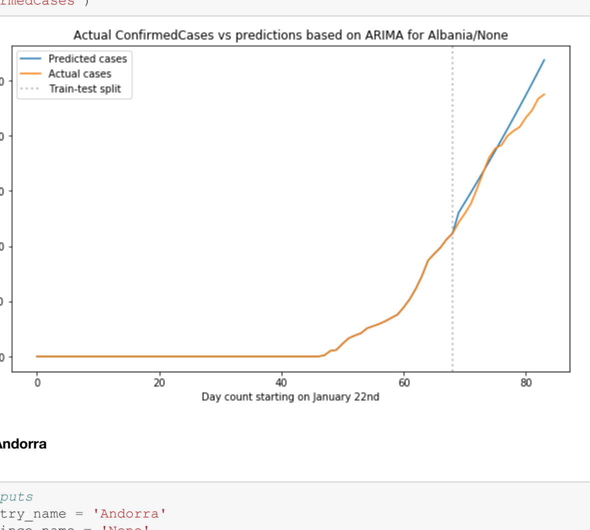
- **Germany**

```
In [53]: # Inputs
country_name = 'Germany'
province_name = 'None'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```



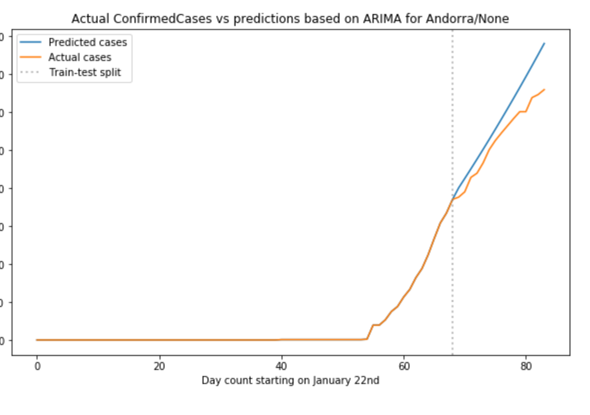
- **Albania**

```
In [54]: # Inputs
country_name = 'Albania'
province_name = 'None'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```



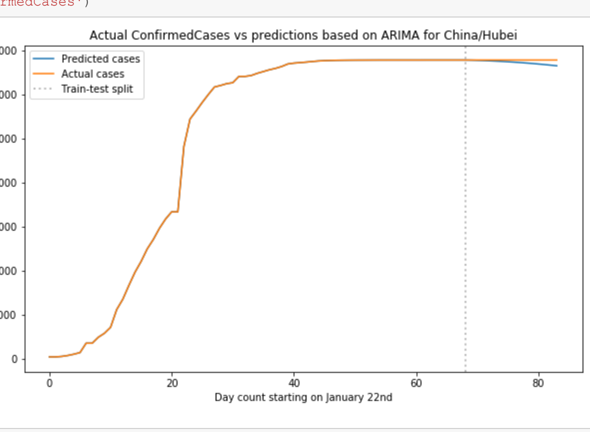
- **Andorra**

```
In [55]: # Inputs
country_name = 'Andorra'
province_name = 'None'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```



- **China/Hubei**

```
In [56]: # Inputs
country_name = 'China'
province_name = 'Hubei'

forecast = arima_cp(all_data, country_name, province_name, 'ConfirmedCases', train_lim, test_lim)
plot_arima_country(all_data, train, forecast, dates_overlap, country_name, province_name, valid_num, 'C
onfirmedCases')
```




```
In [57]: """
train_lim = 69
test_lim = 112

ARIMA_forecast = all_data[all_data.ForecastId != -1][['Country_Region', 'Province_State', 'Day_num', 'F
orecastId']]
ARIMA_forecast['Predicted_ConfirmedCases'] = [0]*len(ARIMA_forecast)
ARIMA_forecast['Predicted_Fatalities'] = [0]*len(ARIMA_forecast)

# Main loop for countries
for c in train['Country_Region'].unique():
        for p in train[train['Country_Region']==c]['Province_State'].unique():
            print(c, p)
            pred_1 = arima_cp(all_data, c, p, 'ConfirmedCases', train_lim, test_lim)
            #pred_2 = arima_cp(all_data, c, p, 'Fatalities', train_lim, test_lim)
            ARIMA_forecast.loc[((ARIMA_forecast['Country_Region']==country_dict[c]) & (ARIMA_forecast
['Province_State']==province_dict[p])), 'Predicted_ConfirmedCases'] = pred_1
            #ARIMA_forecast.loc[((ARIMA_forecast['Country_Region']==country_dict[c]) & (ARIMA_forecast
['Province_State']==province_dict[p])), 'Predicted_Fatalities'] = pred_2

"""
```

```
Out[57]: "\ntrain_lim = 69\ntest_lim = 112\n\nARIMA_forecast = all_data[all_data.ForecastId != -1][['Country_R
egion', 'Province_State', 'Day_num', 'ForecastId']]\nARIMA_forecast['Predicted_ConfirmedCases'] = [0]
*len(ARIMA_forecast)\nARIMA_forecast['Predicted_Fatalities'] = [0]*len(ARIMA_forecast)\n\n# Main loop
for countries\nfor c in train['Country_Region'].unique():\n        for p in train[train['Country_Regi
on']==c]['Province_State'].unique():\n            print(c, p)\n            pred_1 = arima_cp(all_dat
a, c, p, 'ConfirmedCases', train_lim, test_lim)\n            #pred_2 = arima_cp(all_data, c, p, 'Fata
lities', train_lim, test_lim)\n            ARIMA_forecast.loc[((ARIMA_forecast['Country_Region']==cou
ntry_dict[c]) & (ARIMA_forecast['Province_State']==province_dict[p])), 'Predicted_ConfirmedCases'] =
pred_1\n            #ARIMA_forecast.loc[((ARIMA_forecast['Country_Region']==country_dict[c]) & (ARIMA
_forecast['Province_State']==province_dict[p])), 'Predicted_Fatalities'] = pred_2\n            \n"
```

6. Statement of the author

- The **objective of this notebook** is to provide some insights about the COVID-19 transmission from a data-centric perspective in a didactical and simple way. Predicted results **should not be considered in any way an affirmation of what will happen in the future**. Observations obtained from data exploration are personal opinions.
- Models tailored specifically for epidemic spreading (i.e. SIR and its versions) are designed to reproduce a certain phenomenology, in order to understand the underlying mechanics of a contagion process. On the other hand, the simple machine learning approaches I used aim to predict the short term evolution of the infection in the current regime. They might eventually help to find some features or parameters that are particularly important for the model's fitting, but by no means they should be confused with scientific epidemic models.
- The success of the current predictions is **strongly dependent on the current spreading regime**, in which the number of infections is still increasing exponentially for many countries. However, they cannot provide a reliable expected day by which the maximum contagion peak will be reached. Epidemic models are closer to obtaining such estimations, but there's a large number of variables that need to be considered for this (quarantines, quality of the medical resources deployed, environmental measures…).
- In order to achieve such results, a considerable amount of **tuning is required**. We filter how many previous dates should be used for the fitting step, when to use lags or not, and even missings replacements were very rough due to the log transformation.
- **Predictive models** can be used for several purposes, but they **never** (try to) **substitute recommendations from experts**.

```
In [58]: """ WEIRD OVERESTIMATED CASE
# Fit country to logistic curve
country_name = 'South Africa'
province_name = 'None'
target = 'ConfirmedCases'
#target='Fatalities'
x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, tar
get)
plot_logistic(x, y, y_fit, country_name, province_name, target)

#x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, country_name, province_name, train_lim, ta
rget)
pred_1 = [logistic_function(t, a_, b_, c_, d_) for t in list(range(train_lim+1, test_lim+1))]

pred_1

logistic_forecast[(logistic_forecast['Country_Region']==66) & (logistic_forecast['Province_State']==8
1)]
"""
```

```
Out[58]: " WEIRD OVERESTIMATED CASE\n# Fit country to logistic curve\ncountry_name = 'South Africa'\nprovince_
name = 'None'\ntarget = 'ConfirmedCases'\n#target='Fatalities'\nx, y, y_fit, (a_, b_, c_, d_), cov =
fit_logistic(all_data, country_name, province_name, train_lim, target)\nplot_logistic(x, y, y_fit, co
untry_name, province_name, target)\n\n#x, y, y_fit, (a_, b_, c_, d_), cov = fit_logistic(all_data, co
untry_name, province_name, train_lim, target)\npred_1 = [logistic_function(t, a_, b_, c_, d_) for t i
n list(range(train_lim+1, test_lim+1))]\n\npred_1\n\nlogistic_forecast[(logistic_forecast['Country_Re
gion']==66) & (logistic_forecast['Province_State']==81)]\n"
```