COVID-19 Model Simulation

April 8, 2021

[1]:
```
#!pip install --upgrade covsirphy
```

[2]:
```
import covsirphy as cs
cs.__version__
```

[2]: '2.15.0'

[3]:
```
from IPython.display import IFrame, display
#filepath = "http://wikipedia.org" # works with websites too!
filepath = "../Images/CrispFramework.PNG"
IFrame(filepath, width=800, height=300)
```

[3]: <IPython.lib.display.IFrame at 0x1c783b7d208>

0.0.1 Business Understanding

1. The scope of this project is to develop a SIR Model for CANADA.
2. Simulate the Effectiveness of Lockdown.

0.0.2 General Packages

[4]:
```
from collections import defaultdict
from datetime import timedelta
from dateutil.relativedelta import relativedelta
import functools
from IPython.display import display, Markdown
import math
import os
from pprint import pprint
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib
from matplotlib.ticker import ScalarFormatter
%matplotlib inline
import numpy as np
import pandas as pd
# import dask.dataframe as dd
pd.plotting.register_matplotlib_converters()
```

```python
import seaborn as sns
import scipy as sci
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
import sympy as sym
from scipy.integrate import odeint
```

0.0.3 Plotting Configuration

[5]:
```python
# Ramdam
np.random.seed(123)
os.environ["PYTHONHASHSEED"] = "123"
# Matplotlib
plt.style.use("seaborn-ticks")
plt.rcParams["xtick.direction"] = "in"
plt.rcParams["ytick.direction"] = "in"
plt.rcParams["font.size"] = 11.0
plt.rcParams["figure.figsize"] = (15, 10)
# Pandas
pd.set_option("display.max_colwidth", 1000)
```

0.0.4 Load Dataset

[6]:
```python
data_loader = cs.DataLoader("input")
jhu_data = data_loader.jhu()
```

```
Retrieving datasets from COVID-19 Data Hub: https://covid19datahub.io/

Please set verbose=2 to see the detailed citation list.


Retrieving COVID-19 dataset in Japan from
https://github.com/lisphilar/covid19-sir/data/japan
```

0.0.5 Cleaned dataset is saved in jhu_data, lets load the dataset.

[7]:
```python
jhu_data.cleaned().head()
```

[7]:

	Date	Country	Province	Confirmed	Infected	Fatal	Recovered
0	2020-01-01	Afghanistan	-	0	0	0	0
1	2020-01-02	Afghanistan	-	0	0	0	0
2	2020-01-03	Afghanistan	-	0	0	0	0
3	2020-01-04	Afghanistan	-	0	0	0	0
4	2020-01-05	Afghanistan	-	0	0	0	0

0.0.6 Creating Canada wide subset of data

[8]:
```
jhu_data.subset("Canada", province=None)
```

[8]:
```
           Date  Confirmed  Infected  Fatal  Recovered
0    2020-03-26       4018      3749     39        230
1    2020-03-27       4675      4366     53        256
2    2020-03-28       5386      4825     59        502
3    2020-03-29       6255      5672     61        522
4    2020-03-30       7424      6267     89       1068
..          …          …        …      …          …
368  2021-03-29     971719     45212  22900     903607
369  2021-03-30     976597     46394  22926     907277
370  2021-03-31     982110     47858  22959     911293
371  2021-04-01     987918     49568  23002     915348
372  2021-04-02     987918     49568  23002     915348

[373 rows x 5 columns]
```

0.0.7 How many days have passed

[9]:
```
df = jhu_data.cleaned()
jhu_first_date, jhu_last_date = df["Date"].min(), df["Date"].max()
jhu_elapsed = (jhu_last_date - jhu_first_date).days
print(f"{jhu_elapsed} days have passed from the date of the first record.")
```

```
457 days have passed from the date of the first record.
```

0.0.8 Total Population

We need population values to calculate the number of "susceptible" cases. Susceptible = Total population - Confirmed

[10]:
```
#Make use of dataloader to get population of Countries.
population_data = data_loader.population()
# Show cleaned dataset
population_data.cleaned().tail()
# show cleaned Canada data
population_data.value("Canada", province = None)
```

[10]: 37057765

0.0.9 Population pyramid

To estimate the average number of days people go out we going to use population pyramid

[11]:
```
pyramid_data = data_loader.pyramid()
```

0.0.10 Template Data (The average number of days people go out)

We are using the average number of days a person of each age group usually go out. The template is provided by @marcoferrante.

[12]:
```
# Estmation by marcoferrante

_period_of_life_list = [
    "nursery", "nursery school", "elementary school", "middle school", "high␣
↪school", "university/work" , "work", "work", "work",
    "work", "retired", "retired", "retired"
]

df = pd.DataFrame({

    "Age_first": [0, 3, 6, 11, 14, 19, 26, 36, 46, 56, 66, 76, 86],
        "Age_last": [2, 5, 10, 13, 18, 25, 35, 45, 55, 65, 75, 85, 95],
        "Period_of_life": _period_of_life_list,
        "Days": [3, 5, 6, 6, 7, 7, 6, 5, 5, 5, 4, 3, 2]



})

# Adjustment by @marcoferrante
df["Types"] = df["Period_of_life"].replace(
    {
        "nursery": "school",
        "nursery school": "school",
        "elementary school": "school",
        "middle school": "school",
        "high school": "school",
        "university/work": "school/work"
    }
)


df["School"] = df[["Types","Days"]].apply(lambda x : x[1] if "school" in x[0]␣
↪else 0, axis = 1)
df["Office"] = df[["Types", "Days"]].apply(lambda x : x[1] if "work" in x[0]␣
↪else 0, axis =1)
df["Others"] = df["Days"] - df[["School", "Office"]].sum(axis=1)

df.loc[df["Others"]<0, "Others"]=0
df.loc[df.index[1:5],"School"] -=1
df.loc[df.index[1:5],"Others"] +=1
df.loc[df.index[5], ["School", "Office", "Others"]] = [3, 3, 1]
```

```
df[["School", "Office", "Others"]] = df[["Days", "School", "Office", "Others"]].
↪apply(lambda x : x[1:]/sum(x[1:])*x[0],
                                                                            ␣
↪      axis=1).astype(np.int64)
df.loc[df.index[6:10], "Others"] += 1
# df = df.drop(["Days", "Types"], axis=1)



#show dataset
_out_df = df.copy()

_out_df.head(10)
```

[12]:

```
   Age_first  Age_last     Period_of_life  Days         Types  School  Office  \
0          0         2            nursery     3        school       3       0
1          3         5     nursery school     5        school       4       0
2          6        10  elementary school     6        school       5       0
3         11        13      middle school     6        school       5       0
4         14        18        high school     7        school       6       0
5         19        25    university/work     7   school/work       3       3
6         26        35               work     6          work       0       6
7         36        45               work     5          work       0       5
8         46        55               work     5          work       0       5
9         56        65               work     5          work       0       5

   Others
0       0
1       1
2       1
3       1
4       1
5       1
6       1
7       1
8       1
9       1
```

- Now this Pyramid data will be combined with Canada Specific Data.

[13]:

```
def go_out(country, pyramid_data=pyramid_data):
    """
    Return the estimated number of days people usually go out.
    Args:
        country (str): coutry name
        pyramid_data (covsirphy.PopulationPyramidData): pyramid dataset

```

```python
    Returns:
        pandas.DataFrame
    """
    p_df = pyramid_data.subset(country)
    p_df["Cumsum"] = p_df["Population"].cumsum()
    df = pd.merge(_out_df, p_df, left_on="Age_last", right_on="Age", how="left")
    df["Population"] = df["Cumsum"].diff()
    df.loc[df.index[0], "Population"] = df.loc[df.index[0], "Cumsum"]
    df["Population"] = df["Population"].astype(np.int64)
    df["Portion"] = df["Population"] / df["Population"].sum()
    return df.drop(["Per_total", "Cumsum"], axis=1)

go_out("Canada")
```

[13]:

```
    Age_first  Age_last     Period_of_life  Days        Types  School  Office  \
0           0         2            nursery     3       school       3       0
1           3         5     nursery school     5       school       4       0
2           6        10  elementary school     6       school       5       0
3          11        13      middle school     6       school       5       0
4          14        18        high school     7       school       6       0
5          19        25    university/work     7  school/work       3       3
6          26        35               work     6         work       0       6
7          36        45               work     5         work       0       5
8          46        55               work     5         work       0       5
9          56        65               work     5         work       0       5
10         66        75            retired     4      retired       0       0
11         76        85            retired     3      retired       0       0
12         86        95            retired     2      retired       0       0

    Others  Age  Population   Portion
0        0    2     1193571  0.034264
1        1    5     1193646  0.034266
2        1   10     1987203  0.057047
3        1   13     1186425  0.034059
4        1   18     2007971  0.057643
5        1   25     3365119  0.096603
6        1   35     5302920  0.152232
7        1   45     5012608  0.143898
8        1   55     4961567  0.142432
9        1   65     5165771  0.148294
10       4   75     1918186  0.055066
11       3   85     1158996  0.033271
12       2   95      380580  0.010925
```

0.0.11 Data Cleaning: Linelist (COVID19_line_list_data.csv) Link

This dataset contains clinical trails of many reported case.

[14]:
```
# linelist_raw = pd.read_csv("..\\data\\raw\\Covid-19_line_data.xlsx",header=0,␣
↪encoding = 'unicode_escape')
# linelist_raw.head()

# import csv

# data = open(r"C://Users//yrsin//Desktop//w2021//SIRModel//sirmodel//data//raw/
↪/NewData.xlsx", encoding = 'unicode_escape')
# data = pd.read_csv(data)
# # print(data)


linelist_raw = pd.read_csv("../data/raw/test.csv")
linelist_raw.head()
```

[14]:
```
  reporting date            location country  gender   age symptom_onset  \
0      1/20/2020  Shenzhen, Guangdong   China    male  66.0      1/3/2020
1      1/20/2020            Shanghai   China  female  56.0     1/15/2020
2      1/21/2020            Zhejiang   China    male  46.0      1/4/2020
3      1/21/2020             Tianjin   China  female  60.0           NaN
4      1/21/2020             Tianjin   China    male  58.0           NaN

   If_onset_approximated hosp_visit_date  international_traveler  \
0                    0.0       1/11/2020                     NaN
1                    0.0       1/15/2020                     NaN
2                    0.0       1/17/2020                     NaN
3                    NaN       1/19/2020                     NaN
4                    NaN       1/14/2020                     NaN

   domestic_traveler exposure_start exposure_end  traveler  visiting Wuhan  \
0                NaN     12/29/2019     1/4/2020       NaN             1.0
1                NaN            NaN    1/12/2020       NaN             0.0
2                NaN            NaN     1/3/2020       NaN             0.0
3                NaN            NaN          NaN       NaN             1.0
4                NaN            NaN          NaN       NaN             0.0

   from Wuhan death recovered symptom
0         0.0     0         0     NaN
1         1.0     0         0     NaN
2         1.0     0         0     NaN
3         0.0     0         0     NaN
4         0.0     0         0     NaN
```

[15]:
```
linelist_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3397 entries, 0 to 3396
```

```
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   reporting date          3396 non-null   object
 1   location                3167 non-null   object
 2   country                 3234 non-null   object
 3   gender                  1685 non-null   object
 4   age                     1507 non-null   float64
 5   symptom_onset           684 non-null    object
 6   If_onset_approximated   655 non-null    float64
 7   hosp_visit_date         620 non-null    object
 8   international_traveler  826 non-null    float64
 9   domestic_traveler       802 non-null    float64
 10  exposure_start          194 non-null    object
 11  exposure_end            488 non-null    object
 12  traveler                660 non-null    float64
 13  visiting Wuhan          1606 non-null   float64
 14  from Wuhan              1602 non-null   float64
 15  death                   1619 non-null   object
 16  recovered               1606 non-null   object
 17  symptom                 338 non-null    object
dtypes: float64(7), object(11)
memory usage: 477.8+ KB
```

[16]:

```
df = linelist_raw.loc[:, ~linelist_raw.columns.str.startswith("Unnamed:")]
# df = df.drop(["id", "case_in_country", "summary", "source", "link"], axis=1)
# Date
case_date_dict = {
    "reporting date": "Confirmed_date",
    "exposure_start": "Exposed_date",
    "exposure_end": "Quarantined_date",
    "hosp_visit_date": "Hospitalized_date",
    "symptom_onset": "Onset_date",
    "death": "Deaths_date",
    "recovered": "Recovered_date"
}
df["death"] = df["death"].replace({"0": "", "1": ""})
df["recovered"] = df["recovered"].replace({"0": "", "1": "", "12/30/1899": "12/
↪30/2019"})
# for (col, _) in case_date_dict.items():
#     df[col] = pd.to_datetime(df[col])
# df = df.rename(case_date_dict, axis=1)
df = df.rename(columns={"reporting date": "Confirmed_date",
    "exposure_start": "Exposed_date",
    "exposure_end": "Quarantined_date",
    "hosp_visit_date": "Hospitalized_date",
    "symptom_onset": "Onset_date",
```

```
    "death": "Deaths_date",
    "recovered": "Recovered_date" })
# df.head()
# Location
df["Country"] = df["country"].fillna("-")
df["Province"] = df["location"].fillna("-")
df["Province"] = df[["Country", "Province"]].apply(lambda x: "-" if x[0] ==␣
↪x[1] else x[1], axis=1)
# Personal
df["Gender"] = df["gender"].fillna("-").str.capitalize()
df["Age"] = df["age"].fillna(df["age"].median()).astype(np.int64) ## Fill in NA␣
↪with median
df["From_Wuhan"] = df["from Wuhan"]
df["To_Wuhan"] = df["visiting Wuhan"]
# Medical
df["Events"] = df["symptom"].fillna("-")
# Order of columns
linelist_df = df.loc[
    :,
    [
        "Country", "Province",
        "Exposed_date", "Onset_date", "Hospitalized_date", "Confirmed_date",␣
↪"Quarantined_date", "Deaths_date", "Recovered_date",
        "Events",
        "Gender", "Age", "From_Wuhan", "To_Wuhan"
    ]
]
linelist_df.head()

# df.head()
```

[16]:

```
  Country            Province Exposed_date Onset_date Hospitalized_date  \
0   China  Shenzhen, Guangdong   12/29/2019   1/3/2020         1/11/2020
1   China            Shanghai          NaN  1/15/2020         1/15/2020
2   China            Zhejiang          NaN   1/4/2020         1/17/2020
3   China             Tianjin          NaN        NaN         1/19/2020
4   China             Tianjin          NaN        NaN         1/14/2020

  Confirmed_date Quarantined_date Deaths_date Recovered_date Events  Gender  \
0      1/20/2020         1/4/2020                                 -    Male
1      1/20/2020        1/12/2020                                 -  Female
2      1/21/2020         1/3/2020                                 -    Male
3      1/21/2020              NaN                                 -  Female
4      1/21/2020              NaN                                 -    Male

   Age  From_Wuhan  To_Wuhan
0   66         0.0       1.0
```

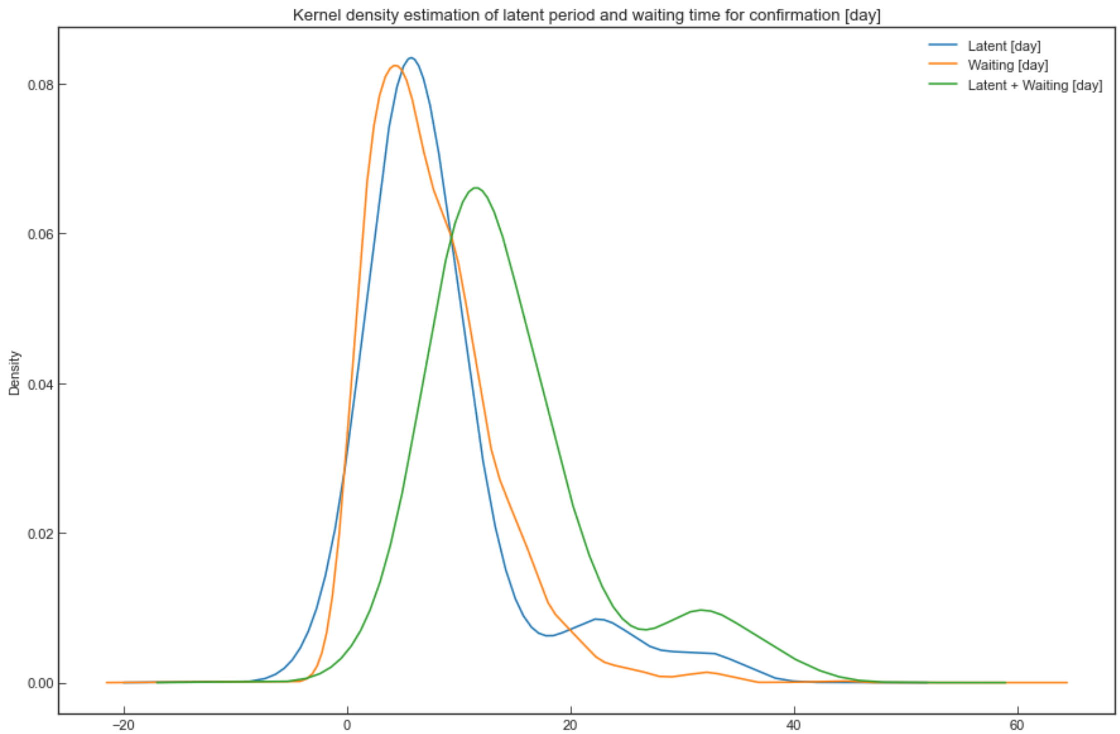
```
1   56          1.0        0.0
2   46          1.0        0.0
3   60          0.0        1.0
4   58          0.0        0.0
```

[17]:
```
# linelist_df.info()
# linelist_df.describe(include="all").fillna("-")
period_df = linelist_df.loc[:, ["Exposed_date", "Onset_date", "Confirmed_date"]]
period_df['Onset_date'] = pd.
 ↪to_datetime(period_df['Onset_date'],errors='coerce')
period_df['Exposed_date'] = pd.
 ↪to_datetime(period_df['Exposed_date'],errors='coerce')
period_df['Confirmed_date'] = pd.
 ↪to_datetime(period_df['Confirmed_date'],errors='coerce')
period_df["Latent [min]"] = (period_df["Onset_date"] -␣
 ↪period_df["Exposed_date"]).dt.total_seconds() / 60
period_df["Waiting [min]"] = (period_df["Confirmed_date"] -␣
 ↪period_df["Onset_date"]).dt.total_seconds() / 60
period_df["Latent [day]"] = period_df["Latent [min]"] / 60 / 24
period_df["Waiting [day]"] = period_df["Waiting [min]"] / 60 / 24
period_df["Latent + Waiting [day]"] = period_df["Latent [day]"] +␣
 ↪period_df["Waiting [day]"]
period_df.dropna(axis=0).tail()



period_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3397 entries, 0 to 3396
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Exposed_date            194 non-null    datetime64[ns]
 1   Onset_date              683 non-null    datetime64[ns]
 2   Confirmed_date          3396 non-null   datetime64[ns]
 3   Latent [min]            92 non-null     float64
 4   Waiting [min]           683 non-null    float64
 5   Latent [day]            92 non-null     float64
 6   Waiting [day]           683 non-null    float64
 7   Latent + Waiting [day]  92 non-null     float64
dtypes: datetime64[ns](3), float64(5)
memory usage: 212.4 KB
```

[18]:
```
cols = ["Latent [day]", "Waiting [day]", "Latent + Waiting [day]"]
period_df[cols].plot.kde()
```

```
plt.title("Kernel density estimation of latent period and waiting time for␣
↪confirmation [day]")
plt.show()
period_df[cols].describe().T
```



[18]:

```
                        count       mean       std  min   25%   50%    75%  \
Latent [day]             92.0   8.163043  6.934984 -2.0   4.0   6.0   9.00
Waiting [day]           683.0   7.590044  5.582389  0.0   3.0   6.0  10.00
Latent + Waiting [day]   92.0  14.793478  7.838392  2.0  10.0  13.0  17.25

                         max
Latent [day]            34.0
Waiting [day]           43.0
Latent + Waiting [day]  40.0
```

0.0.12 Lets take a look at what are the measures implemented by Canada

Government of Canada took multiple intervention measures to stop the spread of COVID-19. Lets have a look at the same.

[19]:

```
canada_action_raw = pd.read_excel("input/
↪covid-19-intervention-scan-data-tables-en.xlsx", sheet_name = "Intervention␣
↪scan", header=2)
```

```
# canada_action_raw.head()
```

Data Cleaning

```
[20]: def canada_action(canada_action_raw):

          #Removing the columns
          canada_action_raw = canada_action_raw.loc[:,:'Indigenous \npopulation␣
       ↪group']
      #     print(canada_action_raw.columns)
      #     canada_action_raw.head()

          canada_action_raw[canada_action_raw['Jurisdiction ']=='Can.']

          # Slicing Intervention Summary to get Who implemented the policy what was␣
       ↪the policy and how long it will be effective.

          Intervention_summary = canada_action_raw['Intervention summary'].str.
       ↪split("Who: |\nWhat: |\nEffective until:",
                                                                                ␣
       ↪    expand=True)


          # Sliced Columns are expanded into individual columns.

          Intervention_summary.rename(columns={1: "Who Implemented", 2: "What␣
       ↪Implemented", 3: "Effective Until"},
                                      inplace = True)
          # Intervention_summary.head()

          # concatinating intervention_scan data and intervention summary data.

          canada_action_raw = pd.
       ↪concat([canada_action_raw,Intervention_summary],axis=1)
          canada_action_raw.head()

          # Dropping Secondary source

          canada_action_raw.drop(['Secondary source',0],axis=1,inplace=True)

          # Renaming the columns

          canada_action_raw.rename(columns = {"Indigenous \npopulation group":␣
       ↪"Indigenous population group",'Primary source\n(news release or specific␣
       ↪resource)': 'Primary source'},inplace=True)
          # canada_action_raw.head()
```

```
    #converting the date column to datetime format and extracting month from it.

    canada_action_raw[canada_action_raw['Date announced']=='No data']

    DateColumns = ['Date announced','Date implemented', 'Effective Until']

    for column in DateColumns:

        canada_action_raw[column] = pd.to_datetime(canada_action_raw[column],␣
↪infer_datetime_format=True,errors='coerce')
    #intervention_scan_data['Date implemented'] = pd.
↪to_datetime(intervention_scan_data['Date implemented'],␣
↪infer_datetime_format=True,errors='coerce')
    #intervention_scan_data['Effective Until'] = pd.
↪to_datetime(intervention_scan_data['Effective Until'],␣
↪infer_datetime_format=True,errors='coerce')

    # Rearranging the columns

    canada_action_raw = canada_action_raw[['Entry ID', 'Jurisdiction␣
↪','Level','Date announced','Date implemented',
                                            'Intervention␣
↪category','Intervention type','Who Implemented',
                                            'What␣
↪Implemented','Effective Until','Indigenous population group',
                                            'Primary source']]

    return(canada_action_raw)

canada_action(canada_action_raw)
```

[20]:

```
     Entry ID Jurisdiction                    Level Date announced  \
0       BC007         B.C.  Provincial/territorial     2020-03-15
1       ON021         Ont.  Provincial/territorial     2020-03-17
2       ON022         Ont.  Provincial/territorial     2020-03-17
3       ON023         Ont.  Provincial/territorial     2020-03-17
4       ON111         Ont.  Provincial/territorial     2020-03-17
…         …            …                       …              …
1495    SK057        Sask.  Provincial/territorial            NaT
1496    SK058        Sask.  Provincial/territorial            NaT
1497    YT002         Y.T.  Provincial/territorial            NaT
1498   CAN080         Can.                 Federal            NaT
1499    NS061         N.S.  Provincial/territorial            NaT

     Date implemented   Intervention category  \
```

```
0          2020-03-16        Case management
1          2020-03-17               Closures
2          2020-03-17               Closures
3          2020-03-17               Closures
4          2020-03-17               Closures
…               …                      …
1495              NaT       Health workforce
1496              NaT       Health workforce
1497       2020-03-13  Contextual information
1498              NaT     State of emergency
1499              NaT       Health workforce

                                              Intervention type  \
0                                 Case management - test criteria
1                                           Closures - recreation
2                                           Closures - recreation
3                                Closures - non-essential services
4                                             Closures - daycares
…                                                               …
1495  Health workforce - licence reinstatement/reclassification
1496  Health workforce - licence reinstatement/reclassification
1497                            Contextual information - holiday
1498                                           State of emergency
1499  Health workforce - licence reinstatement/reclassification

                                                        Who Implemented  \
0     BC Centre for Disease Control, Provincial Health Services Authority
1                                                  Office of the Premier
2                                                  Office of the Premier
3                                                  Office of the Premier
4                                                  Office of the Premier
…                                                                     …
1495            Saskatchewan Society of Medical Laboratory Technologists
1496                  College of Physicians and Surgeons of Saskatchewan
1497                                                       Yukon schools
1498                                                 Government of Canada
1499                    College of Occupational Therapists of Nova Scotia

        What Implemented  \
0     Testing criteria first published. Testing is prioritized for patients with
respiratory symptoms who are hospitalized or likely to be hospitalized; health
care workers; residents of long term care facilities; part of an investigation
of a cluster or outbreak.
1
Closed all facilities providing indoor recreational programs and public
libraries, with subsequent extensions (see secondary source column)
2                                                   Closed all theatres
```

```
including those offering live performances of music, dance and other art forms,
as well as cinemas that show movies and concert venues, with subsequent
extensions (see secondary source column)
3
Closures of all bars and restaurants, except to the extent that such facilities
provide takeout food and delivery, with subsequent extensions (see secondary
source column)
4
Closures of all licensed child care facilities and EarlyON programs, with
subsequent extensions (see secondary source column)
…
…
1495                                                         Waived or modified
registration requirements for former registered medical laboratory
technologists, allowing them to apply for temporary registration during the
pandemic on an expedited basis and at no cost
1496                                    Published information on modification of
registration requirements for non-practising/retired/out-of-province physicians,
allowing them to apply for return to practice during the pandemic on an
expedited basis and at no cost
1497
Spring breaks in Y.T. vary by region.
1498
Activated the federal/provincial/territorial health response plan for biologic
events
1499
Provided a 30-day temporary provisional registration for cross-jurisdictional
telepractice services and waived registration fee

     Effective Until Indigenous population group  \
0              NaT                           No
1       2020-06-12                           No
2       2020-06-12                           No
3       2020-06-12                           No
4       2020-06-12                           No
…              …                           …
1495           NaT                           No
1496           NaT                           No
1497    2020-03-27                           No
1498           NaT                           No
1499           NaT                           No

                                             Primary source
0                                       http://www.bccdc.ca/health-info/diseases-
conditions/covid-19/testing/phases-of-covid-19-testing-in-bc
1
https://news.ontario.ca/opo/en/2020/03/ontario-enacts-declaration-of-emergency-
```

```
to-protect-the-public.html
2
https://news.ontario.ca/opo/en/2020/03/ontario-enacts-declaration-of-emergency-
to-protect-the-public.html
3
https://news.ontario.ca/opo/en/2020/03/ontario-enacts-declaration-of-emergency-
to-protect-the-public.html
4
https://news.ontario.ca/opo/en/2020/03/ontario-enacts-declaration-of-emergency-
to-protect-the-public.html
…
…
1495
https://ssmlt.org/document/3967/Covid%20Callout%20website.pdf
1496  https://www.cps.sk.ca/imis/CPSS/News___Events/News/News_Items/COVID-19_-_E
mergency_Changes_to_Physician_Registration_Requirements.aspx
1497
https://yukon.ca/sites/yukon.ca/files/edu/edu-school-calendar-important-
dates-2019-2020.pdf
1498           https://www.canada.ca/en/public-
health/services/diseases/2019-novel-coronavirus-infection/canadas-
reponse.html?topic=tilelink
1499                                             https://cotns.ca/registration/new-
registration/occupational-therapists-from-other-jurisdictions/

[1500 rows x 12 columns]
```

0.0.13 Visualization of cases all over the world

[21]:
```python
# columns
data_cols = ["Infected", "Fatal", "Recovered"]
#calculating rate
rate_cols = ["Fatal per Confirmed", "Recovered per Confirmed", "Fatal per␣
↪(Fatal or Recovered)"]
```

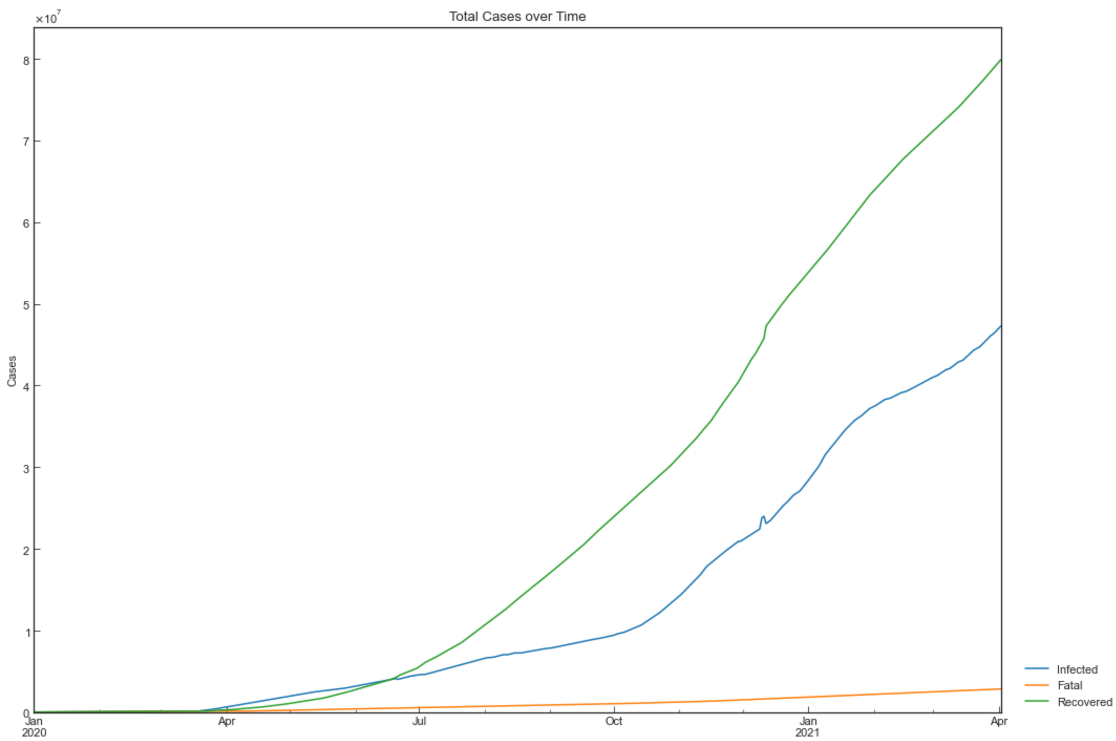
[22]:
```python
total_df = jhu_data.total()
total_df = total_df.loc[total_df.index<=jhu_last_date, :]
total_df.tail()
```

[22]:
```
             Confirmed  Infected    Fatal  Recovered  Fatal per Confirmed  \
Date
2021-03-29  127747356  46211805  2794268   78741283             0.021873
2021-03-30  128316320  46447609  2805450   79063261             0.021864
2021-03-31  128977720  46744597  2817212   79415911             0.021843
2021-04-01  129668609  47096176  2828594   79743839             0.021814
2021-04-02  129979714  47263661  2833234   79882819             0.021798
```

```
            Recovered per Confirmed  Fatal per (Fatal or Recovered)
Date
2021-03-29                 0.616383                        0.034271
2021-03-30                 0.616159                        0.034268
2021-03-31                 0.615734                        0.034259
2021-04-01                 0.614982                        0.034256
2021-04-02                 0.614579                        0.034253
```

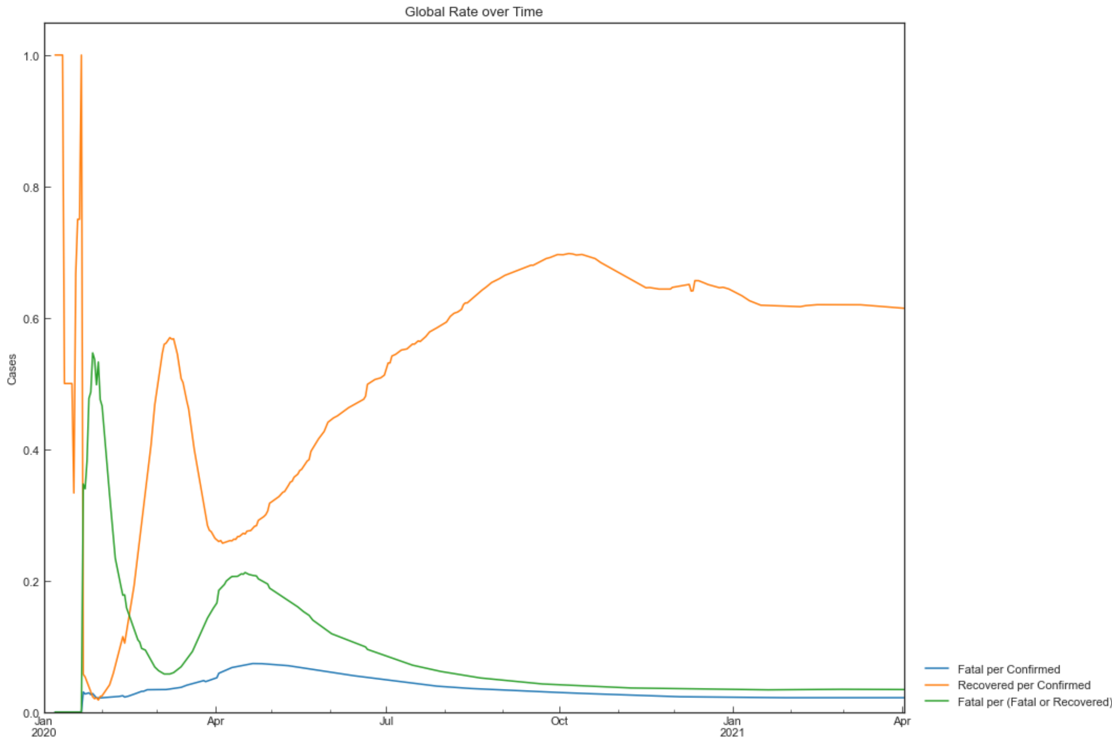
0.0.14 Total Cases over Time

[23]:
```python
cs.line_plot(total_df[data_cols], "Total Cases over Time")
```



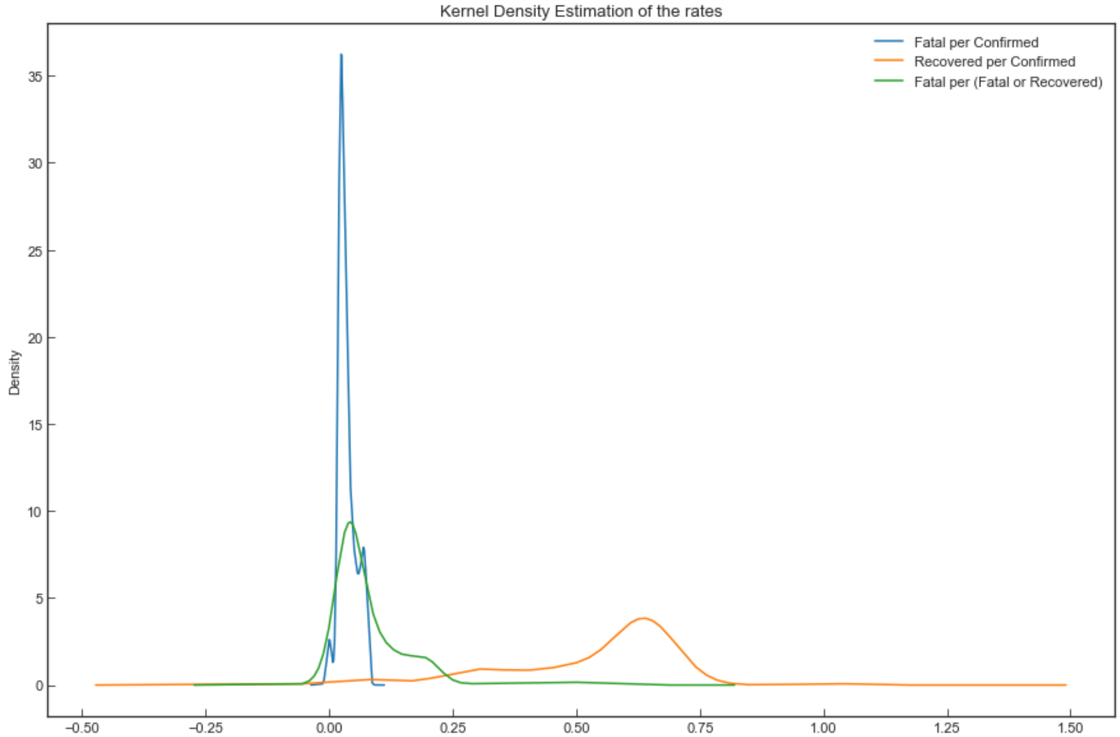
0.0.15 Rate over Time

[24]:
```python
cs.line_plot(total_df[rate_cols], "Global Rate over Time")
```



0.0.16 Kernel Density Estimation

[25]:
```
total_df[rate_cols].plot.kde()
plt.title("Kernel Density Estimation of the rates")
plt.show()
```



[26]:
```
total_df[rate_cols].describe().T
```

[26]:
```
                                count      mean       std       min       25%  \
Fatal per Confirmed             452.0  0.034960  0.017222  0.000000  0.022218
Recovered per Confirmed         452.0  0.530950  0.181616  0.018246  0.443017
Fatal per (Fatal or Recovered)  452.0  0.085122  0.087088  0.000000  0.034543

                                     50%       75%       max
Fatal per Confirmed             0.029646  0.043878  0.074186
Recovered per Confirmed         0.616973  0.646632  1.000000
Fatal per (Fatal or Recovered)  0.047167  0.106401  0.546667
```

0.0.17 Grouping by growth factor

We are going to group countries, by the rate of their confirmed cases. 1. Countries where growth factor is > 1 2. Countries where growth factor < 1

For calculating growth factor we will use Growth Factor = ΔCn/ΔCn-1

[27]:
```
covid_df = jhu_data.cleaned()
df = covid_df.pivot_table(
index="Date", columns="Country", values="Confirmed", aggfunc="sum").
 ↪fillna(method='ffill').fillna(0)
```

```python
#growth factor

df = df.diff()/df.diff().shift(freq="D")
df = df.replace(np.inf,np.nan).fillna(1.0)

#Rolling mean (window: 7 days)

df = df.rolling(7).mean().dropna().loc[:covid_df["Date"].max(),:]

growth_value_df = df.round(2)

growth_value_df
```

```
[27]: Country     Afghanistan  Albania  Algeria  American Samoa  Andorra  Angola  \
      Date
      2020-01-07         1.00     1.00     1.00             1.0     1.00    1.00
      2020-01-08         1.00     1.00     1.00             1.0     1.00    1.00
      2020-01-09         1.00     1.00     1.00             1.0     1.00    1.00
      2020-01-10         1.00     1.00     1.00             1.0     1.00    1.00
      2020-01-11         1.00     1.00     1.00             1.0     1.00    1.00
      …                     …        …        …               …        …       …
      2021-03-29         1.80     1.01     1.03             1.0     1.11    1.47
      2021-03-30         2.05     1.03     1.04             1.0     1.09    1.48
      2021-03-31         2.12     1.03     1.07             1.0     1.11    1.32
      2021-04-01         1.92     0.99     1.02             1.0     1.06    1.24
      2021-04-02         1.81     0.85     0.87             1.0     0.92    1.16

      Country     Antigua and Barbuda  Argentina  Armenia  Australia  …  \
      Date                                                            …
      2020-01-07                 1.00       1.00     1.00       1.00  …
      2020-01-08                 1.00       1.00     1.00       1.00  …
      2020-01-09                 1.00       1.00     1.00       1.00  …
      2020-01-10                 1.00       1.00     1.00       1.00  …
      2020-01-11                 1.00       1.00     1.00       1.00  …
      …                             …          …        …          …  …
      2021-03-29                 0.62       1.19     1.04       1.27  …
      2021-03-30                 0.59       1.09     1.06       1.34  …
      2021-03-31                 0.74       1.19     1.07       1.15  …
      2021-04-01                 0.74       1.17     1.06       1.31  …
      2021-04-02                 0.62       0.95     0.94       1.19  …

      Country     United States  Uruguay  Uzbekistan  Vanuatu  Venezuela  Vietnam  \
      Date
      2020-01-07           1.00     1.00        1.00      1.0       1.00     1.00
      2020-01-08           1.00     1.00        1.00      1.0       1.00     1.00
      2020-01-09           1.00     1.00        1.00      1.0       1.00     1.00
      2020-01-10           1.00     1.00        1.00      1.0       1.00     1.00
```

```
2020-01-11             1.00      1.00        1.00      1.0       1.00      1.00
…                    …      …          …      …       …       …
2021-03-29             1.08      1.02        1.08      1.0       1.10      1.13
2021-03-30             1.06      1.11        0.88      1.0       1.12      1.13
2021-03-31             1.00      1.12        1.06      1.0       1.09      1.13
2021-04-01             1.05      1.11        1.05      1.0       1.07      0.93
2021-04-02             0.89      0.86        0.91      1.0       0.95      0.59

Country     Virgin Islands, U.S.  Yemen  Zambia  Zimbabwe
Date
2020-01-07                  1.00   1.00    1.00      1.00
2020-01-08                  1.00   1.00    1.00      1.00
2020-01-09                  1.00   1.00    1.00      1.00
2020-01-10                  1.00   1.00    1.00      1.00
2020-01-11                  1.00   1.00    1.00      1.00
…                          …     …      …       …
2021-03-29                  2.09   0.99    1.08      1.37
2021-03-30                  2.09   1.08    0.86      1.12
2021-03-31                  2.09   1.07    0.90      1.13
2021-04-01                  2.23   1.11    0.77      1.04
2021-04-02                  0.81   1.01    0.66      0.91

[374 rows x 199 columns]
```

[28]:

```
df = growth_value_df

df = df.iloc[-7:,:].T

day_cols = df.columns.strftime("%d%b%Y")
df.columns = day_cols
last_date = day_cols[-1]

#Grouping
more_col, less_col = "GrowthFactor>1[straight days]","GrowthFactor<1[straight␣
↪days]"
df[more_col] = ((growth_value_df)>1).iloc[::-1].cumprod().sum(axis=0)
df[less_col] = ((growth_value_df)<1).iloc[::-1].cumprod().sum(axis=0)
df["Group"] = df[[more_col,less_col]].apply(lambda x : "outbreaking" if x[0] >=␣
↪7 else "Stopping" if x[1] >=7 else "Crossroad", axis=1)

#Sorting
df = df.loc[:,["Group", more_col, less_col, *day_cols]]
df = df.sort_values(["Group", more_col, less_col], ascending = False)
growth_df = df.copy()
growth_df
```

[28]:
```
Date                   Group  GrowthFactor>1[straight days]  \
Country
Slovakia          outbreaking                            236
Spain             outbreaking                            229
Bulgaria          outbreaking                            173
North Macedonia   outbreaking                            150
Czech Republic    outbreaking                            124
…                       …                              …
Tajikistan          Crossroad                              0
Tanzania            Crossroad                              0
Thailand            Crossroad                              0
Timor-Leste         Crossroad                              0
Vanuatu             Crossroad                              0

Date             GrowthFactor<1[straight days]  27Mar2021  28Mar2021  \
Country
Slovakia                                     0       1.21       1.23
Spain                                        0       2.32       2.30
Bulgaria                                     0       1.38       1.38
North Macedonia                              0       1.12       1.12
Czech Republic                               0       1.20       1.20
…                                          …         …         …
Tajikistan                                   0       1.00       1.00
Tanzania                                     0       1.00       1.00
Thailand                                     0       1.52       1.55
Timor-Leste                                  0       1.47       1.12
Vanuatu                                      0       1.00       1.00

Date             29Mar2021  30Mar2021  31Mar2021  01Apr2021  02Apr2021
Country
Slovakia              1.20       1.59       1.58       1.57       1.46
Spain                 1.99       1.95       2.12       1.79       1.69
Bulgaria              1.36       1.37       1.36       1.35       1.20
North Macedonia       1.08       1.35       1.34       1.33       1.17
Czech Republic        1.28       1.27       1.27       1.27       1.13
…                     …         …         …         …         …
Tajikistan            1.00       1.00       1.00       1.00       1.00
Tanzania              1.00       1.00       1.00       1.00       1.00
Thailand              1.50       0.89       0.99       0.88       1.00
Timor-Leste           1.37       1.46       1.39       1.37       1.00
Vanuatu               1.00       1.00       1.00       1.00       1.00

[199 rows x 10 columns]
```

[29]:
```
# merging both the columns

df = pd.merge(covid_df, growth_df["Group"].reset_index(), on="Country")
```

```
covid_df = df.loc[:, ["Date", "Group", *covid_df.columns[1:]]]
covid_df
```

[29]:

```
              Date         Group      Country Province  Confirmed  Infected  \
0       2020-01-01  outbreaking  Afghanistan        -          0         0
1       2020-01-02  outbreaking  Afghanistan        -          0         0
2       2020-01-03  outbreaking  Afghanistan        -          0         0
3       2020-01-04  outbreaking  Afghanistan        -          0         0
4       2020-01-05  outbreaking  Afghanistan        -          0         0
…              …           …            …      …        …         …
453511  2021-03-29    Crossroad        Japan        -     468614     17184
453512  2021-03-30    Crossroad        Japan        -     470175     17449
453513  2021-03-31    Crossroad        Japan        -     472112     17975
453514  2021-04-01    Crossroad        Japan        -     474773     19195
453515  2021-04-02    Crossroad        Japan        -     477458     20558

        Fatal  Recovered
0           0          0
1           0          0
2           0          0
3           0          0
4           0          0
…         …          …
453511   9061     442369
453512   9086     443640
453513   9113     445024
453514   9162     446416
453515   9185     447715

[453516 rows x 8 columns]
```

0.0.18 Grouping Outbreaking Countries

[30]:

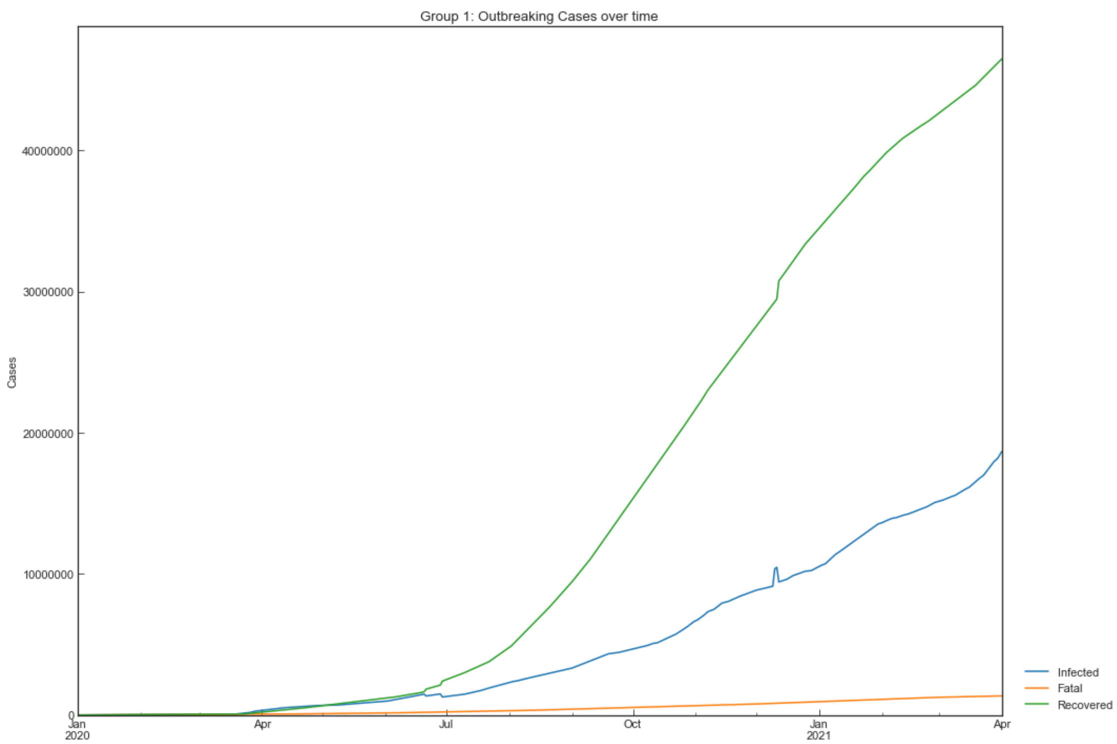
```
growth_df[growth_df["Group"] == "outbreaking"].head()
```

[30]:

```
Date                      Group  GrowthFactor>1[straight days]  \
Country
Slovakia            outbreaking                            236
Spain               outbreaking                            229
Bulgaria            outbreaking                            173
North Macedonia     outbreaking                            150
Czech Republic      outbreaking                            124

Date             GrowthFactor<1[straight days]  27Mar2021  28Mar2021  \
Country
Slovakia                                     0       1.21       1.23
Spain                                        0       2.32       2.30
```

```
Bulgaria                                     0      1.38      1.38
North Macedonia                              0      1.12      1.12
Czech Republic                               0      1.20      1.20

Date             29Mar2021  30Mar2021  31Mar2021  01Apr2021  02Apr2021
Country
Slovakia              1.20       1.59       1.58       1.57       1.46
Spain                 1.99       1.95       2.12       1.79       1.69
Bulgaria              1.36       1.37       1.36       1.35       1.20
North Macedonia       1.08       1.35       1.34       1.33       1.17
Czech Republic        1.28       1.27       1.27       1.27       1.13
```

[31]:
```python
df = covid_df.loc[covid_df["Group"] == "outbreaking", ["Date", *data_cols]]
df = df.groupby("Date").sum()
df = df.iloc[:-1,:]
if not df.empty:
    cs.line_plot(df,"Group 1: Outbreaking Cases over time", y_integer=True)
df.tail()
```



[31]:

Date	Infected	Fatal	Recovered
2021-03-28	17930824	1343667	45861403
2021-03-29	18038018	1347304	46019852

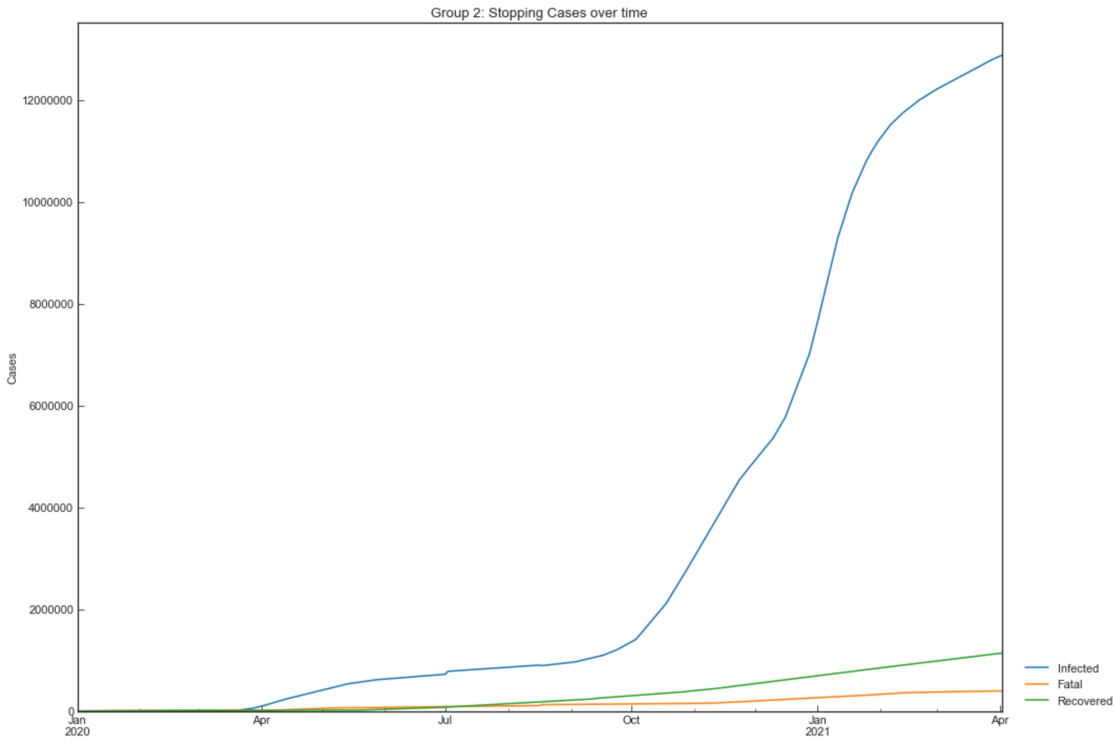
```
2021-03-30  18197789  1351066   46175230
2021-03-31  18446174  1354744   46326258
2021-04-01  18673226  1358382   46490025
```

0.0.19 Grouping Stopping Country

[32]:
```
growth_df[growth_df["Group"]=="Stopping"].head()
```

[32]:
```
Date                    Group  GrowthFactor>1[straight days]  \
Country
Gabon                Stopping                              0
Oman                 Stopping                              0
Equatorial Guinea    Stopping                              0
Costa Rica           Stopping                              0
El Salvador          Stopping                              0

Date                 GrowthFactor<1[straight days]  27Mar2021  28Mar2021  \
Country
Gabon                                          243       0.71       0.57
Oman                                           205       0.78       0.78
Equatorial Guinea                              181       0.57       0.57
Costa Rica                                     173       0.71       0.71
El Salvador                                    162       0.71       0.71

Date                 29Mar2021  30Mar2021  31Mar2021  01Apr2021  02Apr2021
Country
Gabon                     0.57       0.57       0.57       0.57       0.57
Oman                      0.77       0.81       0.83       0.79       0.79
Equatorial Guinea         0.57       0.57       0.57       0.71       0.57
Costa Rica                0.71       0.71       0.71       0.71       0.71
El Salvador               0.86       0.71       0.71       0.86       0.86
```

[33]:
```
df = covid_df.loc[covid_df["Group"] == "Stopping", ["Date", *data_cols]]
df = df.groupby("Date").sum()
if not df.empty:
    cs.line_plot(df,"Group 2: Stopping Cases over time", y_integer=True)
df.head()
```



[33]:

Date	Infected	Fatal	Recovered
2020-01-01	0	0	0
2020-01-02	0	0	0
2020-01-03	0	0	0
2020-01-04	0	0	0
2020-01-05	0	0	0

0.0.20 Grouping crossroad Countries

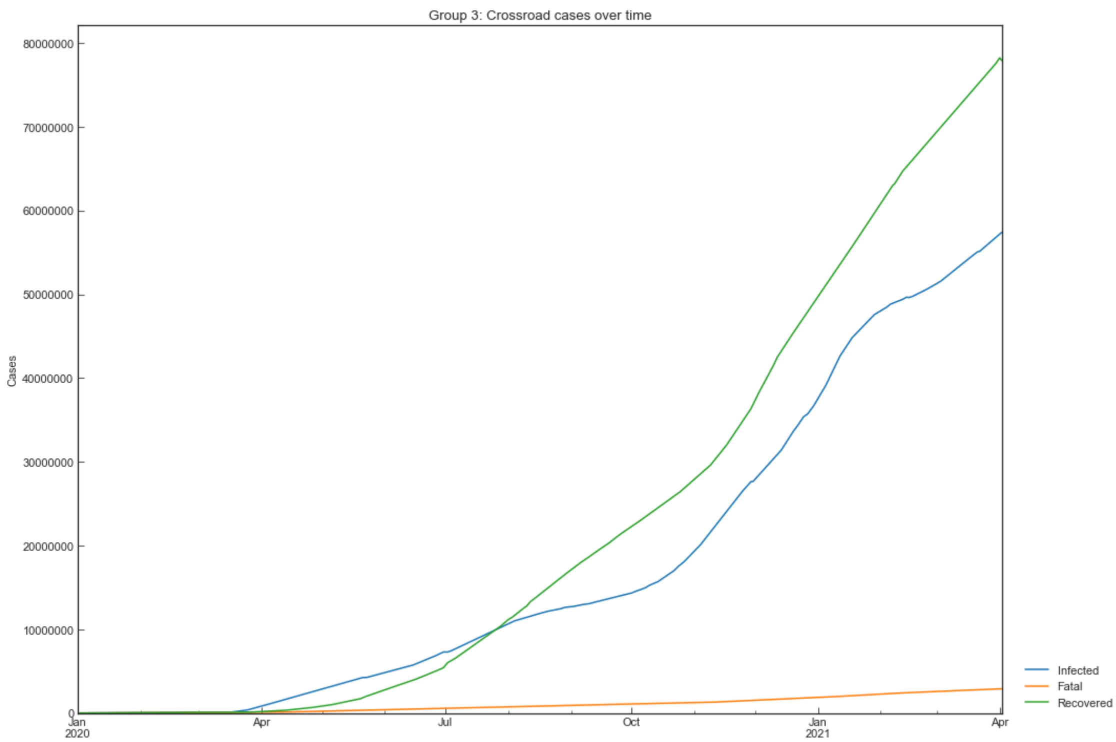
[34]:
```
growth_df[growth_df["Group"]=="Crossroad"]
```

[34]:

Date Country	Group	GrowthFactor>1[straight days] \
Barbados	Crossroad	6
Monaco	Crossroad	6
New Zealand	Crossroad	6
Saint Vincent and the Grenadines	Crossroad	6
Togo	Crossroad	6
…	…	…
Tajikistan	Crossroad	0
Tanzania	Crossroad	0
Thailand	Crossroad	0

```
Timor-Leste                      Crossroad                         0
Vanuatu                          Crossroad                         0

Date                             GrowthFactor<1[straight days]  27Mar2021  \
Country
Barbados                                                     0       0.94
Monaco                                                       0       0.94
New Zealand                                                  0       0.63
Saint Vincent and the Grenadines                             0       0.79
Togo                                                         0       1.00
…                                                          …        …
Tajikistan                                                   0       1.00
Tanzania                                                     0       1.00
Thailand                                                     0       1.52
Timor-Leste                                                  0       1.47
Vanuatu                                                      0       1.00

Date                             28Mar2021  29Mar2021  30Mar2021  31Mar2021  \
Country
Barbados                              1.30       1.27       1.23       1.33
Monaco                                1.06       1.09       1.23       1.18
New Zealand                           2.06       2.09       2.09       2.26
Saint Vincent and the Grenadines      1.86       1.73       1.59       1.59
Togo                                  1.07       1.01       1.36       1.36
…                                    …        …        …        …
Tajikistan                            1.00       1.00       1.00       1.00
Tanzania                              1.00       1.00       1.00       1.00
Thailand                              1.55       1.50       0.89       0.99
Timor-Leste                           1.12       1.37       1.46       1.39
Vanuatu                               1.00       1.00       1.00       1.00

Date                             01Apr2021  02Apr2021
Country
Barbados                              1.23       1.10
Monaco                                1.37       1.19
New Zealand                           2.19       2.24
Saint Vincent and the Grenadines      1.37       1.30
Togo                                  1.36       1.30
…                                    …        …
Tajikistan                            1.00       1.00
Tanzania                              1.00       1.00
Thailand                              0.88       1.00
Timor-Leste                           1.37       1.00
Vanuatu                               1.00       1.00

[131 rows x 10 columns]
```

[35]:
```python
df = covid_df.loc[covid_df['Group']=="Crossroad",["Date",*data_cols]].
↪groupby("Date").sum()

if not df.empty:
    cs.line_plot(df, "Group 3: Crossroad cases over time", y_integer=True)
df.tail()
```



[35]:

Date	Infected	Fatal	Recovered
2021-03-29	56658026	2864968	77233221
2021-03-30	56868076	2878542	77536939
2021-03-31	57056343	2893385	77918306
2021-04-01	57353053	2907332	78230305
2021-04-02	57400190	2904550	77892214

0.0.21 SIR Model

The SIR epidemic model is a simple mathematical description of the spread of disease in a population. It divides the population into 3 compartments which may vary as a fucntion of time t, and space x:

S(t) = are those who are susceptible but not infected yet. I(t) = are those who are infected. R(t) = are those who have recovered from the disease and now have immunity to it.

The SIR model describes the changes in the population of each of three compartments using and .

describes the effective contact rate of the disease.   describes the mean recovery rate. An infected individual comes into contact with N other individuals per unit time (of which the fraction that are a susceptible to contracting the disease of S/N). 1/ is the mean period of time during which an infected individual can pass it on.

The differential equations describing this model were first derived by Kermack and McKendrick:

dS/dT = SI/N dI/dT = SI/N - I dR/dT = I

N = S+I+R is the total population, T is the elapsed time from the start date.

Non-dimensional SIR Model To make our model we will remove the units of the variable from ODE. set (S,I,R) = N x (x,y,z) and (T, ,) = (t, -1 , -1)

This results in the ODE

dx/dt = - xy dy/dt = xy - y dz/dt = y

where N is the total population and   is coefficient ([min], is an integer to simplify)

The range of variables and parameters:

0 <= (x,y,z, ,) <=1 1<=   <= 1440

Basic reproduction number, Non-dimensional parameter, is defined as

Ro = -1 = -1

Estimated Mean Values of Ro: Ro means "the average number of secondary infections caused by an infected host"

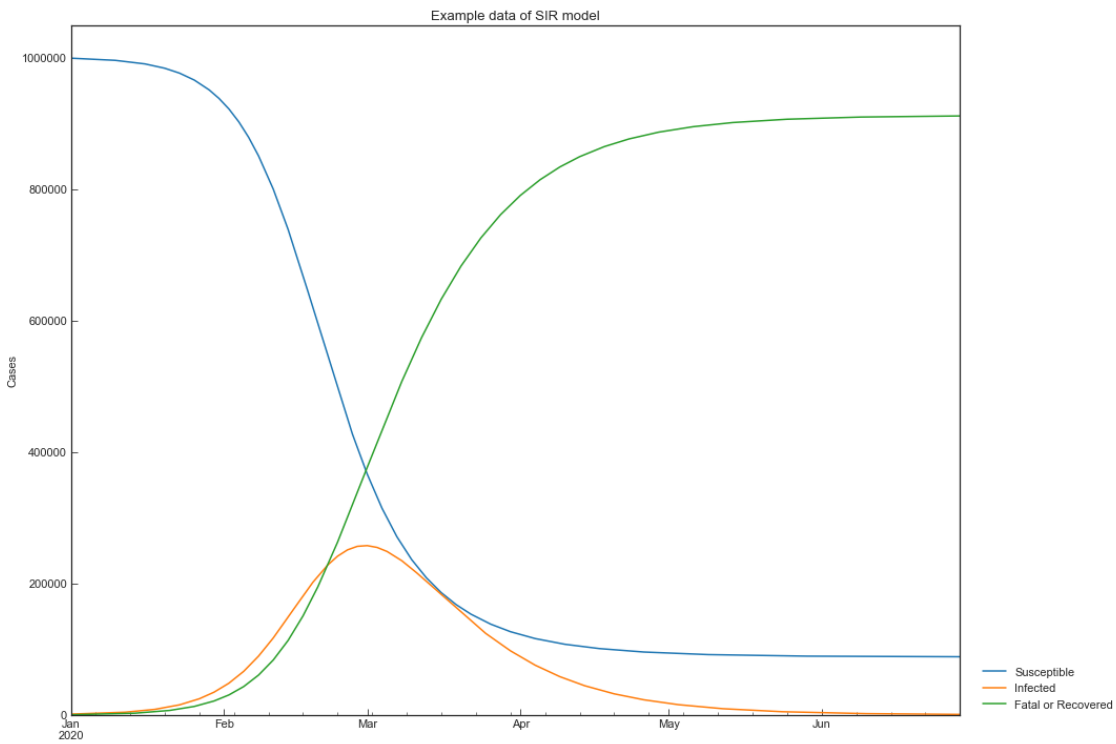
[36]:
```
# this is example data to simulate the SIR Model with tau = 1440 (max) and␣
↪start date 01Jan2020

example_data = cs.ExampleData(tau=1440,start_date='01Jan2020')
example_data.cleaned()
```

[36]:
```
Empty DataFrame
Columns: [Date, Country, Province, Confirmed, Infected, Fatal, Recovered]
Index: []
```

[37]:
```
# Model name
print(cs.SIR.NAME)
# Example parameter values
pprint(cs.SIR.EXAMPLE, compact=True)
```

```
SIR
{'param_dict': {'rho': 0.2, 'sigma': 0.075},
 'population': 1000000,
 'step_n': 180,
 'y0_dict': {'Fatal or Recovered': 0, 'Infected': 1000, 'Susceptible': 999000}}
```

[38]:
```
model = cs.SIR
area = {"country": "Full", "province": model.NAME}
# Add records with SIR model
example_data.add(model, **area)
# Records with model variables
df = example_data.specialized(model, **area)
cs.line_plot(
    df.set_index("Date"),
    title=f"Example data of {model.NAME} model",
    y_integer=True
)
```



There is an inflection point of number of currently infected cases per total population(y). At this point value of susceptible cases (x) per total population is nearly equal to 1/

[39]:
```
eg_r0 = model(model.EXAMPLE["population"], **model.EXAMPLE["param_dict"]).
↪calc_r0()
df = example_data.specialized(model, **area)
x_max = df.loc[df["Infected"].idxmax(), "Susceptible"] / cs.SIR.
↪EXAMPLE["population"]
(x_max, 1/eg_r0)
```

[39]:
```
(0.366211, 0.37453183520599254)
```

0.0.22 SIR model Implementation

We'll use differential equations to calculate the population change over time.

[40]:
```
# The differentail equation to define SIR Model:

def deriv(state, t, N, beta, gamma):

    S, I, R = state

    #change in S population over time
    dsdt = -beta * S* I / N
    #change in I population over time
    dIdt = beta * S * I / N - gamma * I
    #change in R population over time
    dRdt = gamma * I

    return dsdt, dIdt, dRdt
```

0.0.23 Preparing data for the model

We'll start by taking only the canadian population as our data frame.

Effective contact rate is transmission rate * contact rate, so: - 5% transmission rate and 5 contacts a day is 0.05*5 = 0.25

Recovery rate is 1/day - 4 day recovery rate 1/4 = 0.25

[41]:
```
effective_contact_rate = 0.25
recovery_rate = 1/14

#calculate R0
print("R0 is", effective_contact_rate/recovery_rate)
total_population = population_data.value("Canada", province = None)
print(total_population)
recovered = 0
infected = 1
susceptible = total_population - infected - recovered

# number of days
# days = len(jhu_data.subset("Canada", province=None))
days = range(0,len(jhu_data.subset("Canada", province=None)))

#use of differentail equation

ret = odeint(deriv,
             [susceptible, infected, recovered],
             days,
             args = (total_population, effective_contact_rate, recovery_rate))
```

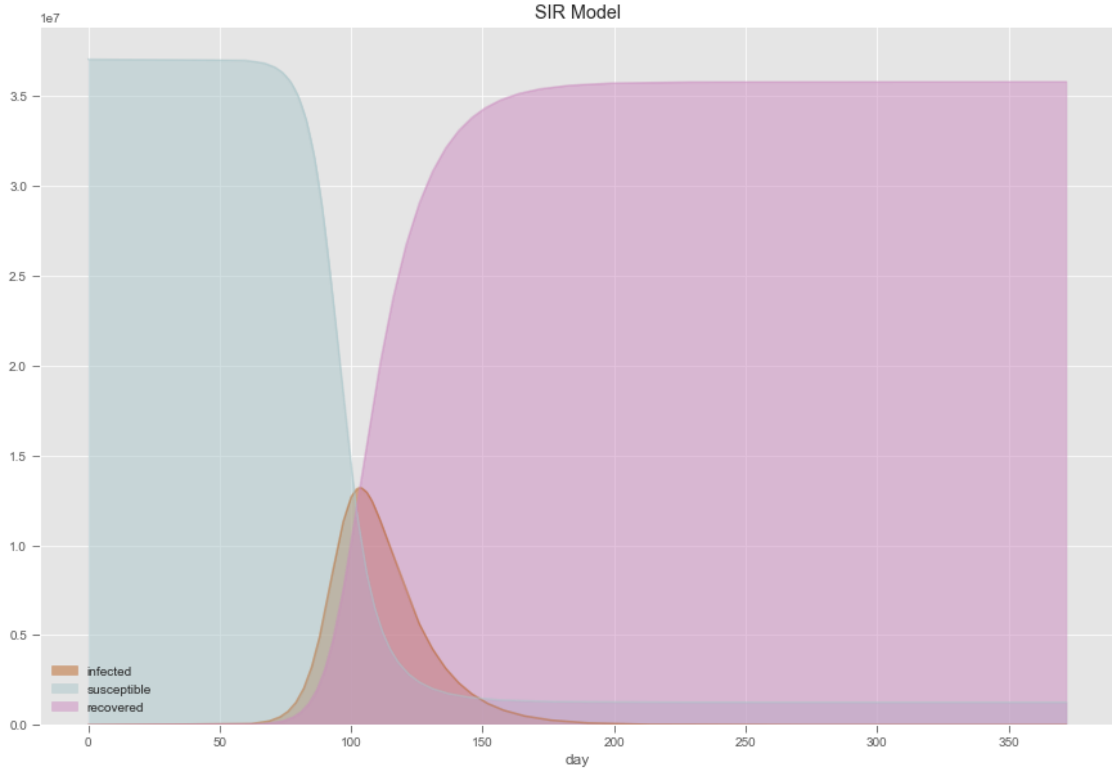
```python
S, I , R = ret.T

#Build a dataframe

df = pd.DataFrame({
    'susceptible': S,
    'infected': I,
    'recovered': R,
    'day': days
})

plt.style.use('ggplot')
plt.figure(figsize=(15,10))
df.plot(x='day',
        y=['infected', 'susceptible', 'recovered'],
        color=['#bb6424', '#aac6ca', '#cc8ac0'],
        kind='area',
        stacked=False)
plt.title("SIR Model")
df
```

```
R0 is 3.5
37057765
```

[41]:

```
      susceptible  infected     recovered  day
0    3.705776e+07  1.000000  0.000000e+00    0
1    3.705776e+07  1.195508  7.820330e-02    1
2    3.705776e+07  1.429240  1.716960e-01    2
3    3.705776e+07  1.708668  2.834673e-01    3
4    3.705776e+07  2.042727  4.170908e-01    4
..            ...       ...           ...  ...
368  1.260529e+06  1.516762  3.579723e+07  368
369  1.260529e+06  1.424260  3.579723e+07  369
370  1.260529e+06  1.337401  3.579723e+07  370
371  1.260529e+06  1.255838  3.579723e+07  371
372  1.260529e+06  1.179250  3.579723e+07  372

[373 rows x 4 columns]
```

```
<Figure size 1080x720 with 0 Axes>
```



0.0.24 Infected and Recovered

- Lets take a look at Infected and Recovered

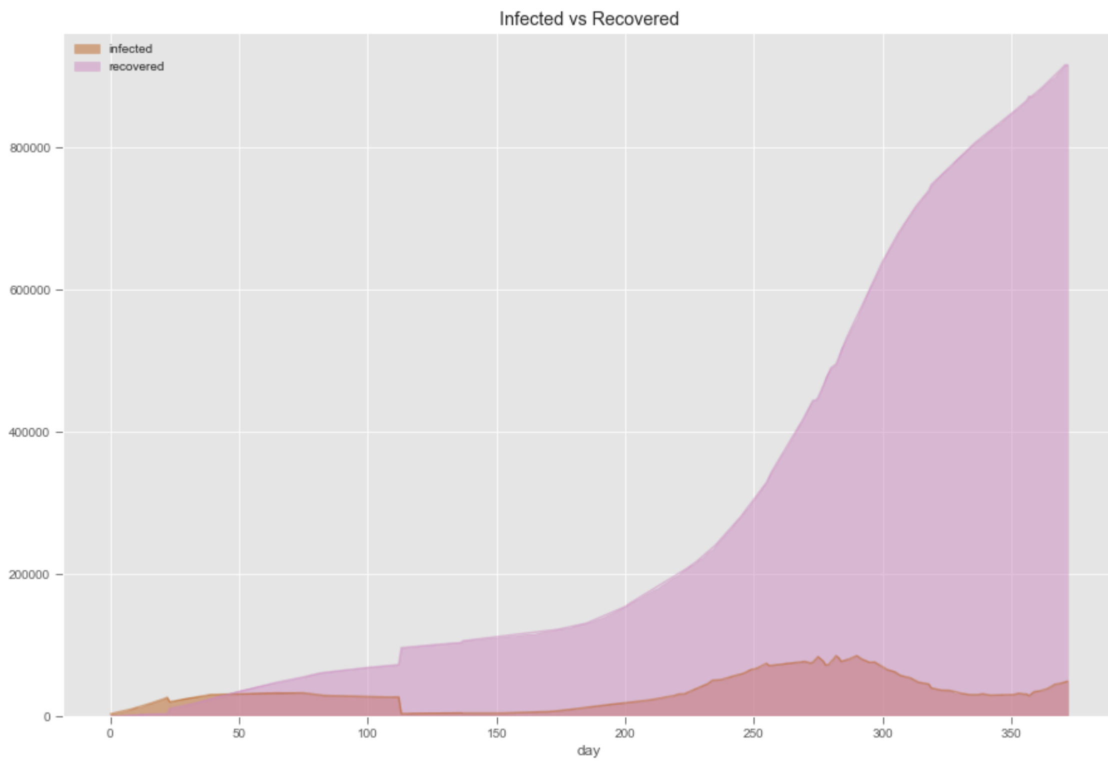
[42]:
```
canada_subset = jhu_data.subset("Canada", province=None)
# canada_subset.head()


#total population
total_population = population_data.value("Canada", province = None)
print("Total population is", total_population)
#susceptible  = Total_population - infected - recovered

canada_subset["Susceptible"] = total_population - canada_subset["Infected"] -
 ↪canada_subset["Recovered"]
canada_subset['day'] = range(0,len(canada_subset))

SIR_Model_subset = canada_subset[["Susceptible","Infected", "Recovered", "day"]]
SIR_Model_subset.columns = map(str.lower, SIR_Model_subset.columns)

SIR_Model_subset.plot(x='day',
        y=['infected','recovered'],
        color=['#bb6424', '#cc8ac0'],
```

```
        kind='area',
        stacked=False)
plt.title('Infected vs Recovered')
SIR_Model_subset
```

```
Total population is 37057765
```

[42]:

```
     susceptible  infected  recovered  day
0       37053786      3749        230    0
1       37053143      4366        256    1
2       37052438      4825        502    2
3       37051571      5672        522    3
4       37050430      6267       1068    4
..           …         …        …   …
368     36108946     45212     903607  368
369     36104094     46394     907277  369
370     36098614     47858     911293  370
371     36092849     49568     915348  371
372     36092849     49568     915348  372

[373 rows x 4 columns]
```



0.0.25 SIR-D Model

As we are measuring the number of fatal cases and recovered cases separately, we will use recovered and deaths separately.

The SIR-D epidemic model is also a simple mathematical description of the spread of disease in a population. It divides the population into 4 compartments which may vary as a fucntion of time t, and space x:

S(t) = are those who are susceptible but not infected yet. I(t) = are those who are infected. R(t) = are those who have recovered from the disease and now have immunity to it. D(t) = those who died

The SIR-D model describes the changes in the population of each of 4 compartments using and . describes the effective contact rate of the disease. describes the mean recovery rate. describes the number of Mortality rate. An infected individual comes into contact with N other individuals per unit time (of which the fraction that are a susceptible to contracting the disease of S/N). 1/ is the mean period of time during which an infected individual can pass it on.

The differential equations describing this model:

dS/dT = SI/N dI/dT = SI/N - + I dR/dT = I dR/dT = I

N = S+I+R+D is the total population, T is the elapsed time from the start date.

[43]:
```python
# The differentail equation to define SIR-D Model:

def derivSIRD(state, t, N, beta, gamma, alpha):

    S, I, R, D = state

    #change in S population over time
    dsdt = -beta * S* I / N
    #change in I population over time
    dIdt = beta * S * I / N - (gamma+alpha) * I
    #change in R population over time
    dRdt = gamma * I
    #change in Fatalities over time
    dDdt =  alpha * I

    return dsdt, dIdt, dRdt, dDdt
```

We'll start by taking only the canadian population as our data frame.

Effective contact rate is transmission rate * contact rate, so: - 5% transmission rate and 5 contacts a day is 0.05*5 = 0.25

Recovery rate is 1/day - 4 day recovery rate 1/4 = 0.25

Mortality rate is 1/day - mortality rate for canada is 2.5% ("Mortality Rate for Countries")

[44]:

```
effective_contact_rate = 0.25
recovery_rate = 1/14
mortality_rate = 0.025

#calculate R0
print("R0 is", effective_contact_rate/recovery_rate)
total_population = population_data.value("Canada", province = None)
print(total_population)
recovered = 0
infected = 1
susceptible = total_population - infected - recovered
fatal = 40

# number of days
# days = len(jhu_data.subset("Canada", province=None))
days = range(0,len(jhu_data.subset("Canada", province=None)))

#use of differentail equation

ret = odeint(derivSIRD,
            [susceptible, infected, recovered, fatal],
            days,
            args = (total_population, effective_contact_rate, recovery_rate,␣
↪mortality_rate))

S, I , R, D = ret.T

#Build a dataframe

df = pd.DataFrame({
    'susceptible': S,
    'infected': I,
    'recovered': R,
    'fatal': D,
    'day': days
})

plt.style.use('ggplot')
plt.figure(figsize=(15,10))
df.plot(x='day',
        y=['infected', 'susceptible', 'recovered', 'fatal'],
        color=['#bb6424', '#aac6ca', '#cc8ac0', '#F15E3F'],
        kind='area',
        stacked=False)
plt.title("SIR-D Model")
df
```

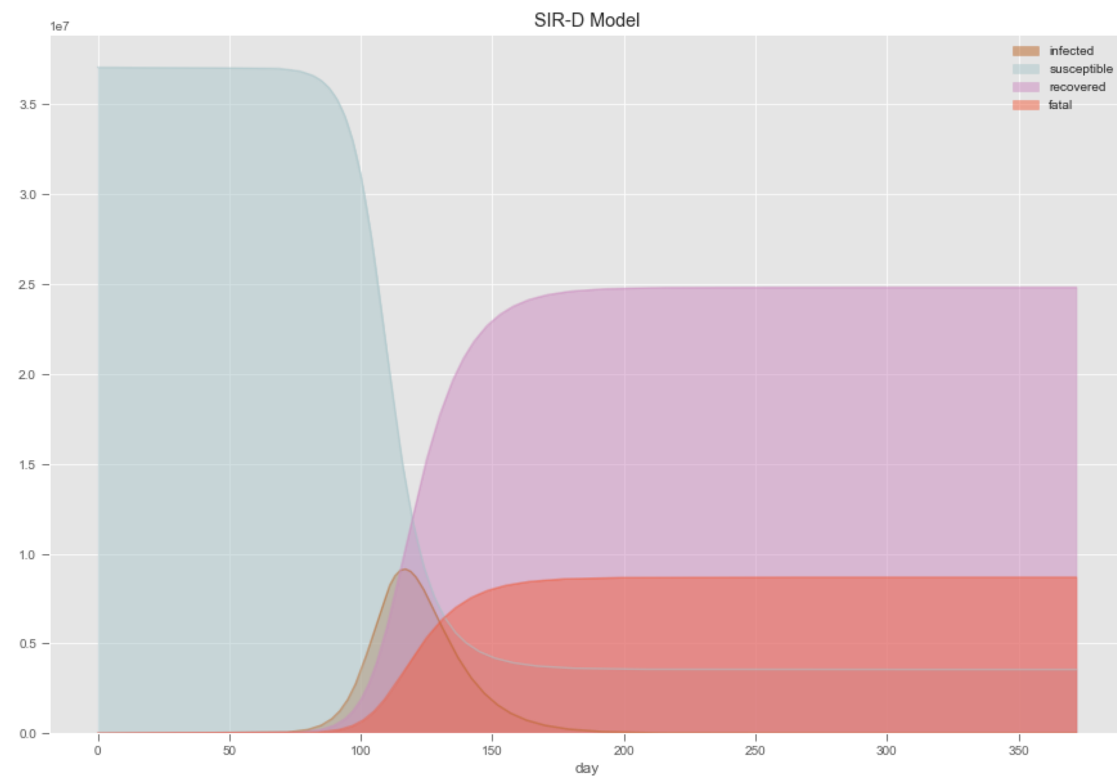
```
R0 is 3.5
37057765
```

[44]:

	susceptible	infected	recovered	fatal	day
0	3.705776e+07	1.000000	0.000000e+00	4.000000e+01	0
1	3.705776e+07	1.165991	7.720514e-02	4.002702e+01	1
2	3.705776e+07	1.359535	1.672257e-01	4.005853e+01	2
3	3.705776e+07	1.585206	2.721888e-01	4.009527e+01	3
4	3.705776e+07	1.848336	3.945748e-01	4.013810e+01	4
..	…	…	…	…	…
368	3.556141e+06	0.268248	2.481602e+07	8.685646e+06	368
369	3.556141e+06	0.249504	2.481602e+07	8.685646e+06	369
370	3.556141e+06	0.232070	2.481602e+07	8.685646e+06	370
371	3.556141e+06	0.215853	2.481602e+07	8.685646e+06	371
372	3.556141e+06	0.200770	2.481602e+07	8.685646e+06	372

[373 rows x 5 columns]

<Figure size 1080x720 with 0 Axes>



0.0.26 Lets take a look at infected and fatal

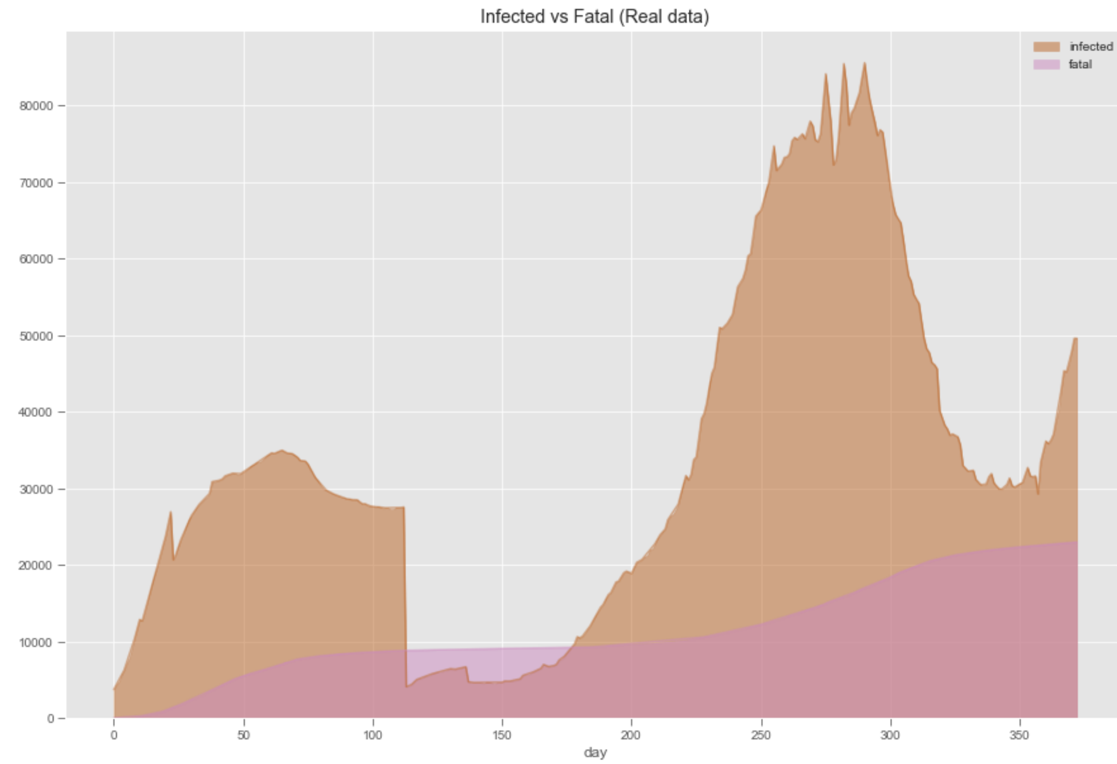
[45]:
```
canada_subset = jhu_data.subset("Canada", province=None)
# canada_subset.head()



#total population
total_population = population_data.value("Canada", province = None)
print("Total population is", total_population)
#susceptible  = Total_population - infected - recovered

canada_subset["Susceptible"] = total_population - canada_subset["Infected"] -␣
↪canada_subset["Recovered"]
canada_subset['day'] = range(0,len(canada_subset))

SIR_Model_subset = canada_subset[["Susceptible","Infected","Fatal",␣
↪"Recovered", "day"]]
SIR_Model_subset.columns = map(str.lower, SIR_Model_subset.columns)
# print(SIR_Model_subset.head())

SIR_Model_subset.plot(x='day',
        y=['infected','fatal'],
        color=['#bb6424', '#cc8ac0'],
        kind='area',
        stacked=False)
plt.title("Infected vs Fatal (Real data)")
SIR_Model_subset
```

```
Total population is 37057765
```

[45]:

	susceptible	infected	fatal	recovered	day
0	37053786	3749	39	230	0
1	37053143	4366	53	256	1
2	37052438	4825	59	502	2
3	37051571	5672	61	522	3
4	37050430	6267	89	1068	4
..	…	…	…	…	…
368	36108946	45212	22900	903607	368
369	36104094	46394	22926	907277	369
370	36098614	47858	22959	911293	370
371	36092849	49568	23002	915348	371
372	36092849	49568	23002	915348	372

[373 rows x 5 columns]



0.0.27 SIR-F Model

Initially many cases were confirmed after they died in case of COVID-19. To take this into consideration we will add S*: confirmed and uncategorized.

- S: Suceptible (Population - confirmed)
- S*: Confirmed and uncategorized
- I: Confirmed and categorized as Infected
- R: Confirmed and categorized as Recovered
- F: Confirmed and categorized as Fatal

we are measuring these below mentioned variables:

Confirmed = I+R+F Recovered = R Deaths = F

The mathematical model describing these equations are:

dS/dT = SI/N dI/dT = SI*(1- 1)/N - +(2)* I dR/dT = I dF/dT = (1 SI)/N + (2)* I

When 1 = 0, SIR-F model is the same as SIR-D model.

1: Probability of direct fatality 2: Moratality rate Effective contact rate Recovery rate

The value of 1 is very small because performance of PCR tesets were improved significantly

Some important notes on S*: S* describes those cases who were actually the carriers of the disease, who either die and were confirmed positive after their death or were moved to infected after being confirmed. In our JHU dataset we know the COVID-19 confirmed cases, but we don't know about the cases who died without it. 1 is small at this time and our new SIR-F model can be taken as an enhanced model of SIR-D model.

[46]:
```python
# The differentail equation to define SIR-F Model:

def derivSIRF(state, t, N, beta, gamma, alpha1, alpha2):

    S, I, R, F = state

    #change in S population over time
    dsdt = -beta * S* I / N
    #change in I population over time
    dIdt = (beta * S * I*(1 - alpha1) / N) - ((gamma+alpha2) * I)
    #change in R population over time
    dRdt = gamma * I
    #change in Fatalities over time
    dFdt = (beta * S* I*alpha1 / N) + alpha2 * I

    return dsdt, dIdt, dRdt, dFdt
```

[47]:
```python
effective_contact_rate = 0.25
recovery_rate = 1/14
probability_of_direct_fatality = 0.0001
mortality_rate = 0.025

#calculate R0
print("R0 is", effective_contact_rate/recovery_rate)
total_population = population_data.value("Canada", province = None)
print(total_population)
recovered = 0
infected = 1
susceptible = total_population - infected - recovered
fatal = 40

# number of days
# days = len(jhu_data.subset("Canada", province=None))
days = range(0,len(jhu_data.subset("Canada", province=None)))

#use of differentail equation

ret = odeint(derivSIRF,
            [susceptible, infected, recovered, fatal],
            days,
            args = (total_population, effective_contact_rate, recovery_rate,␣
 ↪probability_of_direct_fatality, mortality_rate))
```

```python
S, I , R, F = ret.T

#Build a dataframe

df = pd.DataFrame({
    'susceptible': S,
    'infected': I,
    'recovered': R,
    'fatal': F,
    'day': days
})

plt.style.use('ggplot')
plt.figure(figsize=(15,10))
df.plot(x='day',
        y=['infected', 'susceptible', 'recovered', 'fatal'],
        color=['#bb6424', '#aac6ca', '#cc8ac0', '#F15E3F'],
        kind='area',
        stacked=False)
plt.title("SIR-F Model")
df
```

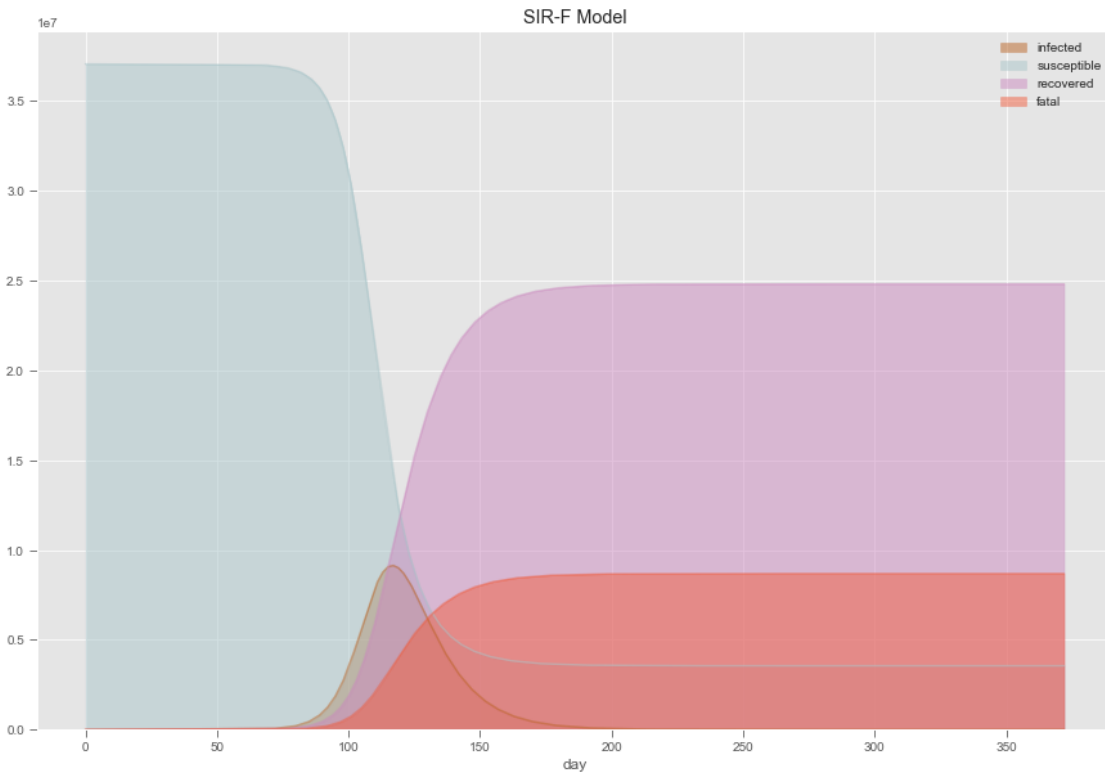
```
R0 is 3.5
37057765
```

[47]:

	susceptible	infected	recovered	fatal	day
0	3.705776e+07	1.000000	0.000000e+00	4.000000e+01	0
1	3.705776e+07	1.165962	7.720415e-02	4.002705e+01	1
2	3.705776e+07	1.359467	1.672213e-01	4.005859e+01	2
3	3.705776e+07	1.585087	2.721778e-01	4.009536e+01	3
4	3.705776e+07	1.848151	3.945531e-01	4.013823e+01	4
..	…	…	…	…	…
368	3.557251e+06	0.268872	2.481271e+07	8.687840e+06	368
369	3.557251e+06	0.250086	2.481271e+07	8.687840e+06	369
370	3.557251e+06	0.232612	2.481271e+07	8.687840e+06	370
371	3.557251e+06	0.216359	2.481271e+07	8.687840e+06	371
372	3.557251e+06	0.201241	2.481271e+07	8.687840e+06	372

[373 rows x 5 columns]

```
<Figure size 1080x720 with 0 Axes>
```



0.0.28 Example of non-dimensional SIR-F model.

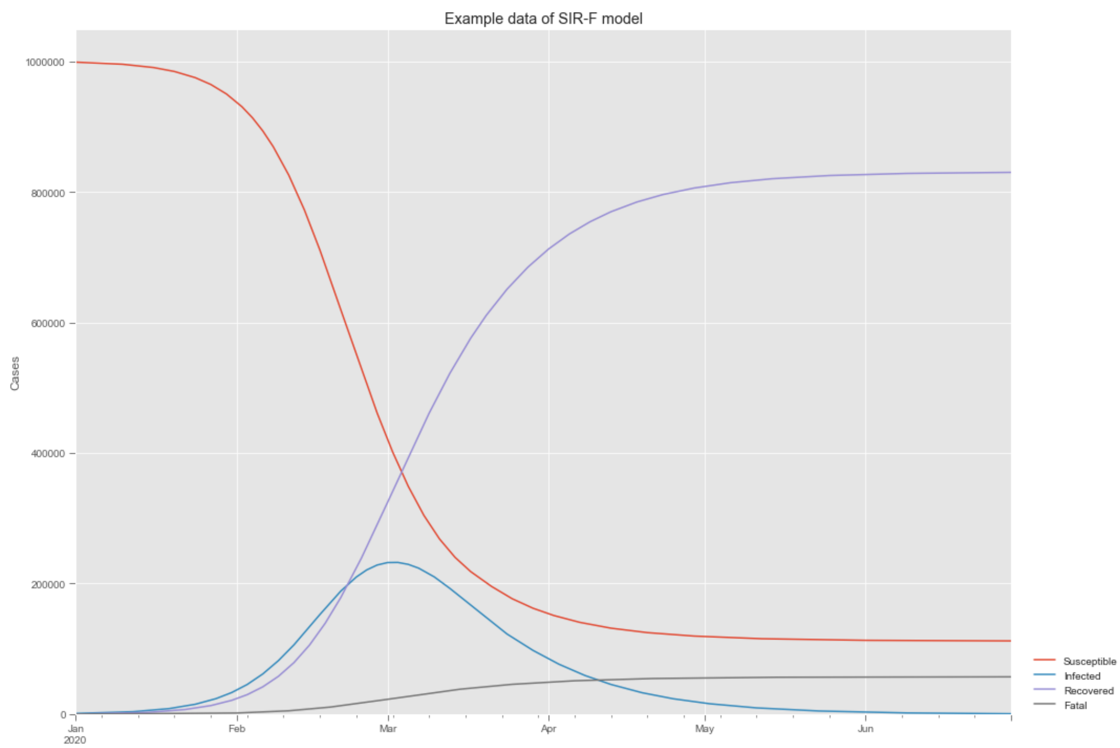
So now our model is built and we know how all the compartments influence each other. We will now use covsirphy package to explore the SIR-F model. To know more about CovsirPhy Click here

[48]:
```
# model name
print(cs.SIRF.NAME)
# parameter values
pprint(cs.SIRF.EXAMPLE, compact=True)
```

```
SIR-F
{'param_dict': {'kappa': 0.005, 'rho': 0.2, 'sigma': 0.075, 'theta': 0.002},
 'population': 1000000,
 'step_n': 180,
 'y0_dict': {'Fatal': 0,
             'Infected': 1000,
             'Recovered': 0,
             'Susceptible': 999000}}
```

[49]:
```
model = cs.SIRF
area = {"country":"Full","province":model.NAME}
```

```
# adding records
example_data.add(model,**area)

## creating record
df = example_data.specialized(model, **area)
cs.line_plot(
    df.set_index("Date"),
    title=f"Example data of {model.NAME} model",
    y_integer=True
)
```



The inflection point of y number of currently infected cases per total population and x the number of susceptible cases per total population is nearly equal to 1/R0.

[50]:
```
eg_r0 = model(model.EXAMPLE["population"], **model.EXAMPLE['param_dict']).
↪calc_r0()
df = example_data.specialized(model, **area)
x_max = df.loc[df["Infected"].idxmax(), "Susceptible"] / cs.SIR.
↪EXAMPLE["population"]
(x_max, 1/eg_r0)
```

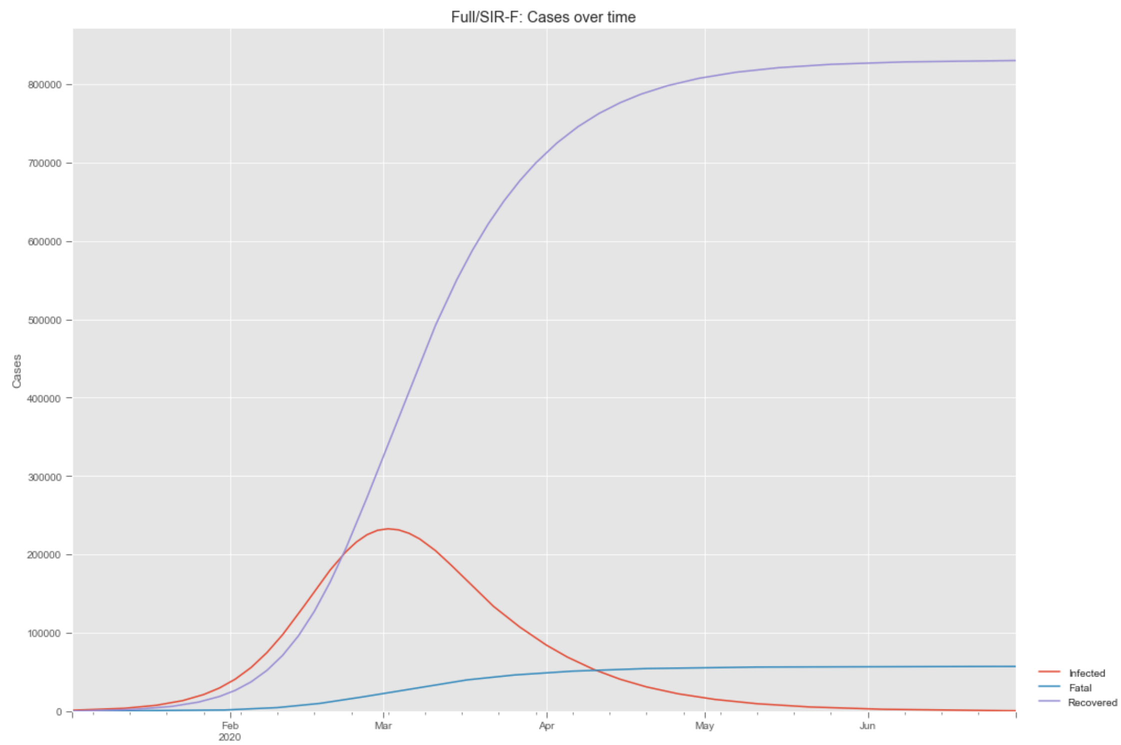
[50]: (0.401442, 0.4)

0.0.29 Hyperparameter optimization using optuna package

[51]:
```
# Example data setting population
population_data.update(cs.SIRF.EXAMPLE["population"],**area)
population_data.value(**area)
```

[51]:
```
1000000
```

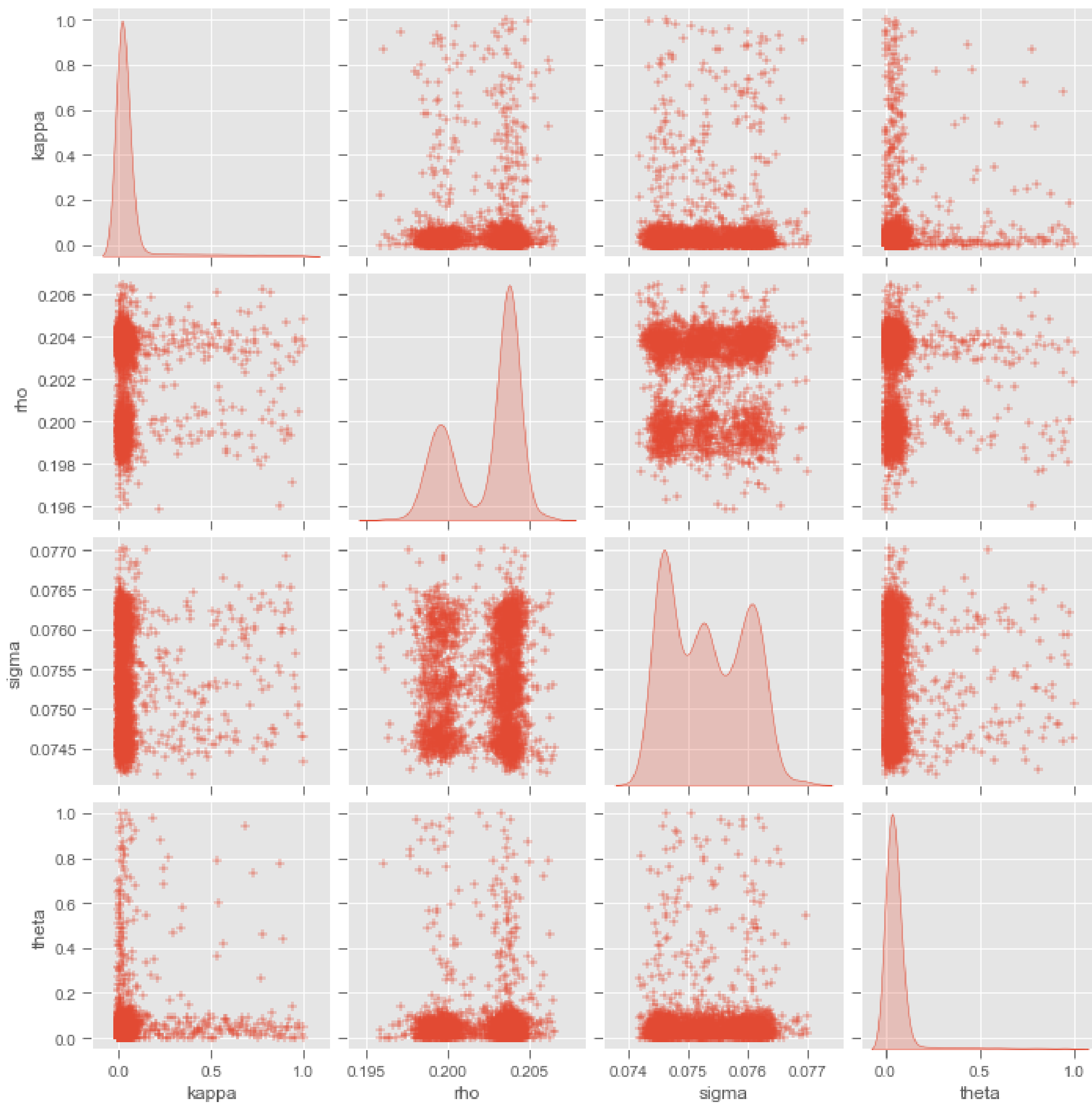
[52]:
```
#JHU-style records

sirf_snl = cs.Scenario(example_data, population_data, tau=1440, **area)
_ = sirf_snl.records()
```



[53]:
```
# Parameter estimation

sirf_snl.add().summary()
sirf_snl.estimate(cs.SIRF, timeout=120)
```

```
<SIR-F model: parameter estimation>
Running optimization with 12 CPUs…
Completed optimization. Total: 2 min  4 sec
```

[54]:
```
# distribution of variables

sirf_snl.estimate_history("0th")
```



[55]:
```
# table for estimated values

df = sirf_snl.summary()
setting_model = cs.SIRF(population=cs.SIRF.EXAMPLE["population"],**cs.SIRF.
↪EXAMPLE["param_dict"])

setting_dict = {
    "Population": cs.SIRF.EXAMPLE["population"],
    "ODE":cs.SIRF.NAME,
```

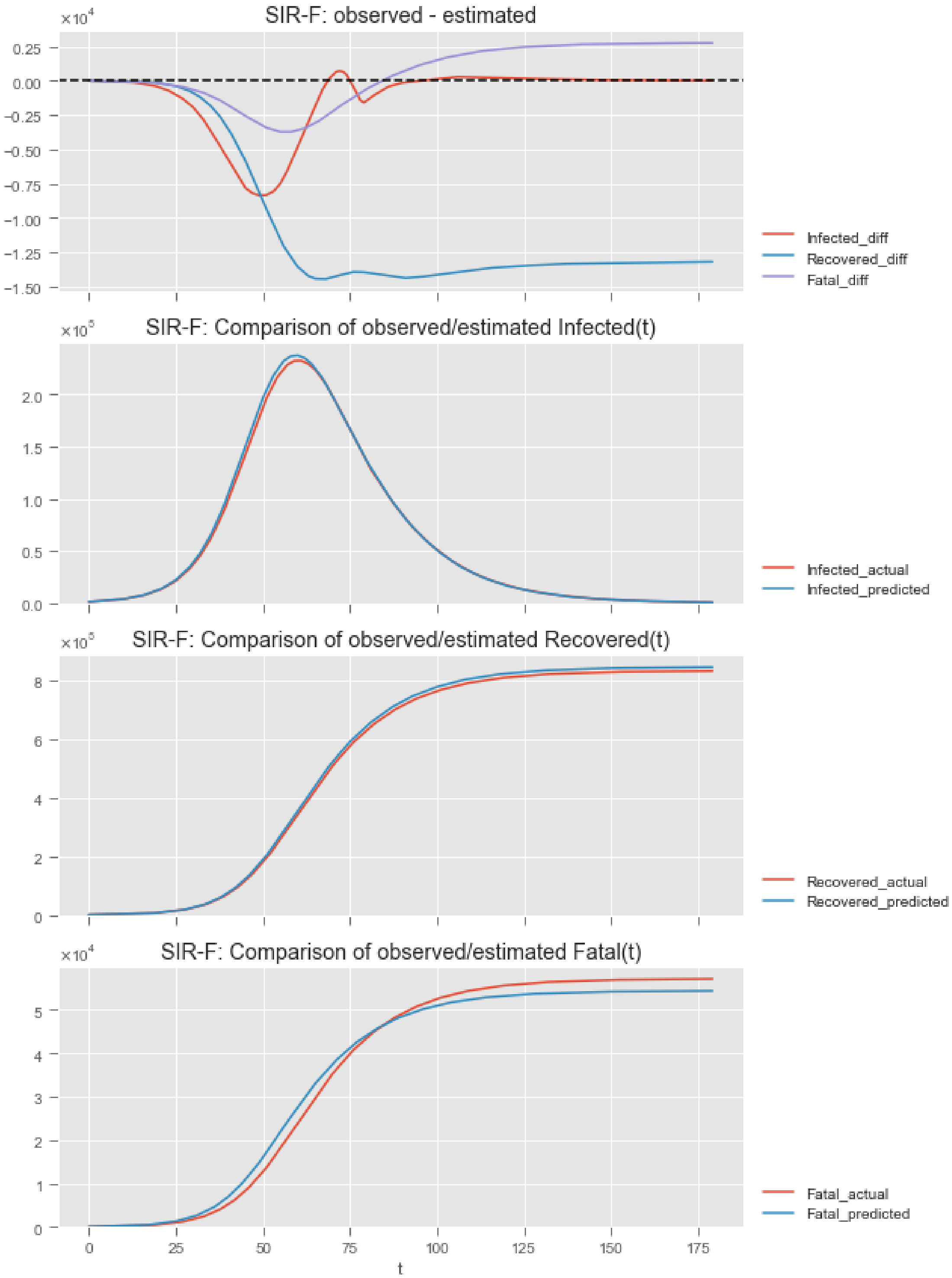
```python
    "Rt":setting_model.calc_r0(),
    "tau": 1440,
    **setting_model.calc_days_dict(1440),
    **cs.SIRF.EXAMPLE["param_dict"]
}

df = df.append(pd.Series(setting_dict, name="setting"))
df.fillna("-")
```

[55]:

```
           Type      Start        End  Population    ODE    Rt     theta  \
0th        Past  02Jan2020  29Jun2020     1000000  SIR-F  2.56  0.019557
setting       -          -          -     1000000  SIR-F  2.50  0.002000

              kappa       rho     sigma   tau  alpha1 [-]  1/alpha2 [day]  \
0th        0.003262  0.203457  0.074732  1440       0.020             306
setting    0.005000  0.200000  0.075000  1440       0.002             200

         1/beta [day]  1/gamma [day]      RMSLE Trials       Runtime
0th                 4             13  0.0972948   2458  2 min  0 sec
setting             5             13          -      -             -
```

[56]:

```python
sirf_snl.estimate_accuracy("0th")
```


×10⁴
SIR-F: observed - estimated
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
Infected_diff
Recovered_diff
Fatal_diff
×10⁵
SIR-F: Comparison of observed/estimated Infected(t)
2.0
1.5
1.0
0.5
0.0
Infected_actual
Infected_predicted
×10⁵
SIR-F: Comparison of observed/estimated Recovered(t)
8
6
4
2
0
Recovered_actual
Recovered_predicted
×10⁴
SIR-F: Comparison of observed/estimated Fatal(t)
5
4
3
2
1
0
Fatal_actual
Fatal_predicted
0
25
50
75
100
125
150
175
t

0.0.30 Control factors of SIR-F model parameters

Here we will define the control factors for our example data. =1440, the start date is 01Jan2020, population is set to 1,000,000 and country name is “Theoretical”.

[57]:
```
# Preset of SIR-F parameters

preset_dict = cs.SIRF.EXAMPLE["param_dict"]
preset_dict
```

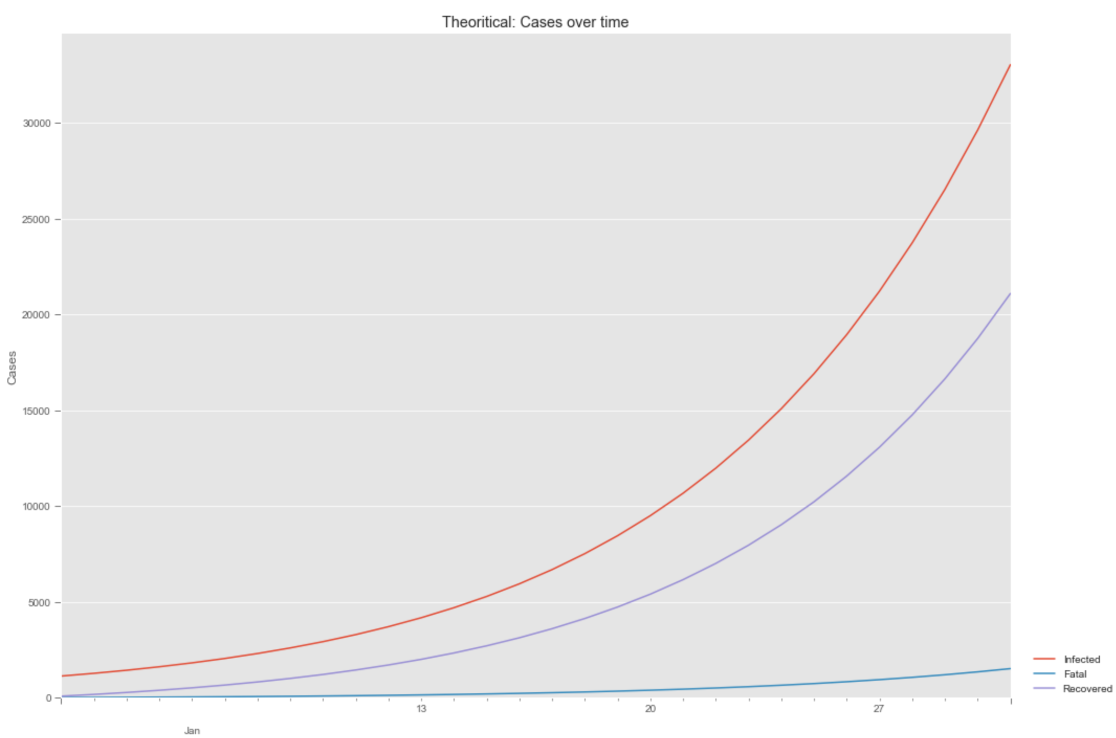
[57]:
```
{'theta': 0.002, 'kappa': 0.005, 'rho': 0.2, 'sigma': 0.075}
```

[58]:
```
area = {"country":"Theoritical"}
example_data.add(cs.SIRF, step_n=30, **area)
```

[59]:
```
#Register population value
population_data.update(cs.SIRF.EXAMPLE["population"], **area)
population_data.value(**area)
```

[59]:
```
1000000
```

[60]:
```
# show records with scenario class

snl = cs.Scenario(example_data,population_data, tau=1440,**area)
record_df =snl.records()
display(record_df.head())
display(record_df.tail())
```



```
         Date  Infected  Fatal  Recovered
0  2020-01-02      1127      6         80
1  2020-01-03      1270     12        169
2  2020-01-04      1430     19        271
3  2020-01-05      1612     28        385
4  2020-01-06      1816     37        513
```

```
          Date  Infected  Fatal  Recovered
25  2020-01-27     21210    940      13068
26  2020-01-28     23730   1061      14753
27  2020-01-29     26524   1196      16637
28  2020-01-30     29616   1347      18741
29  2020-01-31     33030   1515      21088
```

0.0.31 Defining Control factors of effective contact rate 1

gs: Number of days susceptible person go out in a week. gw: Numbe of days waiting but un-quarantined persons go out. gi: Number of days currently infected but un-quarantined persons go out. q: Quarantine rate of currently infected cases. v: Probability of existance of virus. m: Rate of persons wearing masks effectively. we: Washing hands. wn: Hand washing frequency. h1: HEalth condition of susceptible and contacted persons(cellular immunity). h2: Health condition of susceptible and contacted persons(humoral immunity). c: Number of contacts between patients and susceptible persons in a minute. : unkown factors

The above equations is derived from SEWIR-F model. For more info click here . We are not working with SEIR models because for SEWIR-F predictions we need to calculate 1 and 2 with linelist dataset for each country which is very difficult. For more info on SEIR model visit click here

Predicting the impact of lockdown by minimising the number of days a susceptible person goes out.

[61]:
```python
# beta value before any action was taken

rho_before = cs.SIRF.EXAMPLE["param_dict"]["rho"]
rho_before
```

[61]: 0.2

Calculation of gs value before lockdown using population pyramid

[62]:
```python
going_out_df = go_out("Canada")
going_out_df
```

[62]:

	Age_first	Age_last	Period_of_life	Days	Types	School	Office	\
0	0	2	nursery	3	school	3	0	
1	3	5	nursery school	5	school	4	0	
2	6	10	elementary school	6	school	5	0	
3	11	13	middle school	6	school	5	0	
4	14	18	high school	7	school	6	0	
5	19	25	university/work	7	school/work	3	3	
6	26	35	work	6	work	0	6	
7	36	45	work	5	work	0	5	
8	46	55	work	5	work	0	5	
9	56	65	work	5	work	0	5	
10	66	75	retired	4	retired	0	0	
11	76	85	retired	3	retired	0	0	
12	86	95	retired	2	retired	0	0	

	Others	Age	Population	Portion
0	0	2	1193571	0.034264
1	1	5	1193646	0.034266
2	1	10	1987203	0.057047
3	1	13	1186425	0.034059
4	1	18	2007971	0.057643
5	1	25	3365119	0.096603
6	1	35	5302920	0.152232
7	1	45	5012608	0.143898
8	1	55	4961567	0.142432
9	1	65	5165771	0.148294
10	4	75	1918186	0.055066
11	3	85	1158996	0.033271
12	2	95	380580	0.010925

[63]:

```
gs_before = (going_out_df[["School","Office","Others"]].
↪sum(axis=1)*going_out_df["Portion"]).sum()
gs_before
```

[63]: 5.915772475744851

Calculation of gs value after lockdown assuming below mentioned conditions: - All schools were closed. - Offices were closed and only 50% of employee were working onsite - People will go out only 1 day instead of going to office, school

[64]:

```
df = going_out_df.copy()
df.loc[df["School"]+df["Office"]>0, "Others"] +=1
df["School"] = 0
df["Office"] *= 0.5
going_out_after = df.copy()
going_out_after
```

```
[64]:     Age_first  Age_last      Period_of_life  Days        Types  School  Office  \
      0           0         2             nursery     3       school       0     0.0
      1           3         5      nursery school     5       school       0     0.0
      2           6        10   elementary school     6       school       0     0.0
      3          11        13       middle school     6       school       0     0.0
      4          14        18         high school     7       school       0     0.0
      5          19        25     university/work     7  school/work       0     1.5
      6          26        35                work     6         work       0     3.0
      7          36        45                work     5         work       0     2.5
      8          46        55                work     5         work       0     2.5
      9          56        65                work     5         work       0     2.5
      10         66        75             retired     4      retired       0     0.0
      11         76        85             retired     3      retired       0     0.0
      12         86        95             retired     2      retired       0     0.0

          Others  Age  Population   Portion
      0        1    2     1193571  0.034264
      1        2    5     1193646  0.034266
      2        2   10     1987203  0.057047
      3        2   13     1186425  0.034059
      4        2   18     2007971  0.057643
      5        2   25     3365119  0.096603
      6        2   35     5302920  0.152232
      7        2   45     5012608  0.143898
      8        2   55     4961567  0.142432
      9        2   65     5165771  0.148294
      10       4   75     1918186  0.055066
      11       3   85     1158996  0.033271
      12       2   95      380580  0.010925
```

```
[65]: df = going_out_after.copy()
      gs_after = (df[["School","Office","Others"]].sum(axis=1)*df["Portion"]).sum()
      gs_after
```

```
[65]: 3.7972982896326273
```

```
[66]: rho_after = rho_before * (gs_after/gs_before)
      print(rho_after)
      print(rho_after/rho_before)
```

```
0.12837878080003448
0.6418939040001723
```

```
[67]: # set 0th phase from 02Jan2020 to 31Jan2020 with preset parameter values
      snl.clear(include_past=True)
      snl.add(end_date="31Jan2020", model=cs.SIRF, **preset_dict)
      snl.summary()
```

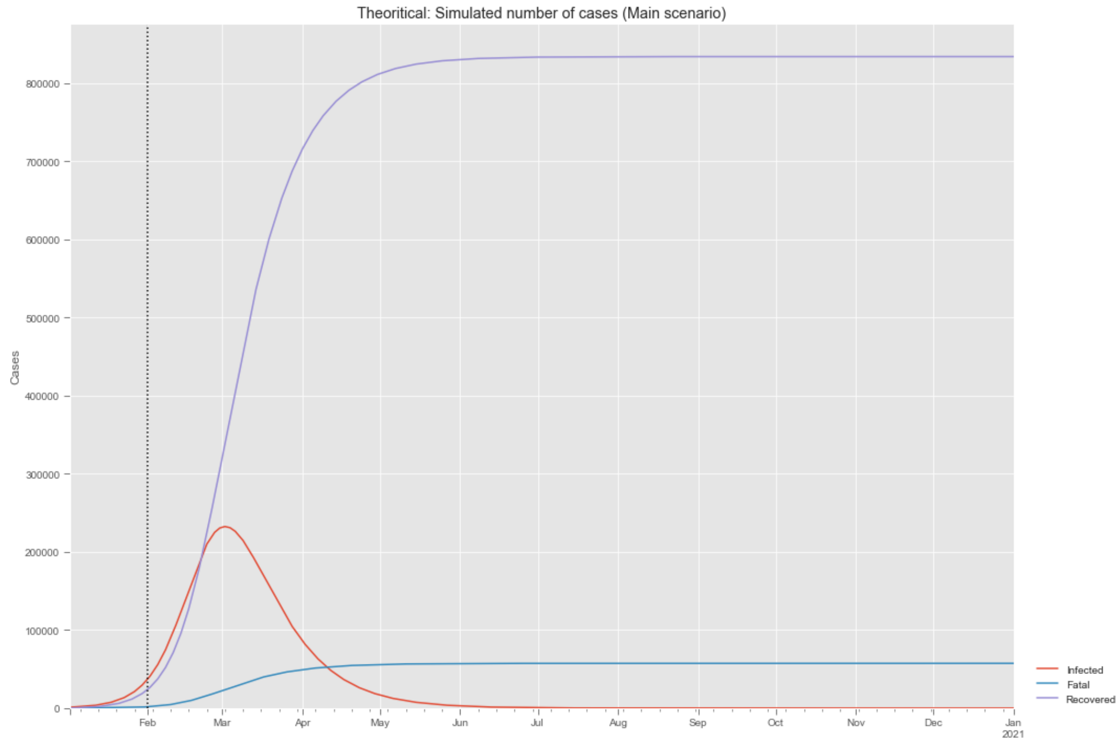
```python
# Add main scenario after 31Dec2020
snl.add(end_date="31Dec2020", name="Main")
#Add Lockdown Scenario
snl.clear(include_past=False, name="Lockdown")
snl.add(end_date="31Dec2020", name="Lockdown", rho=rho_after).summary()
```

[67]:

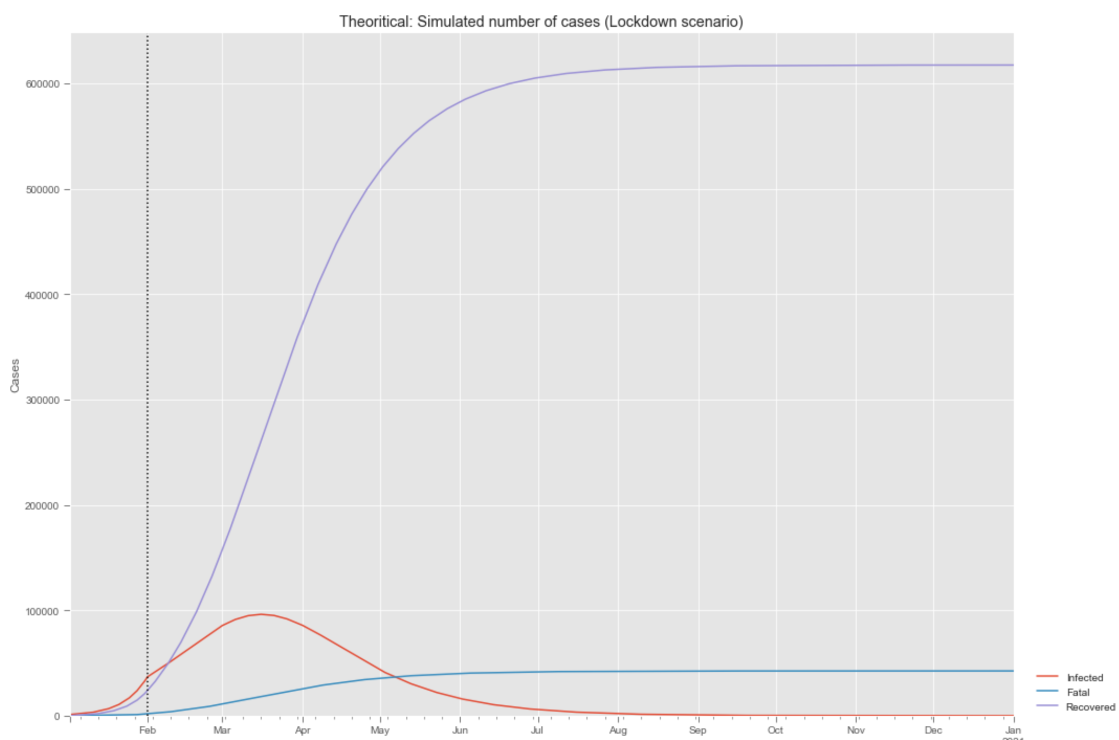
```
                     Type      Start        End  Population    ODE   Rt  theta  \
Scenario Phase
Main     0th         Past  02Jan2020  31Jan2020     1000000  SIR-F  2.5  0.002
         1st       Future  01Feb2020  31Dec2020     1000000  SIR-F  2.5  0.002
Lockdown 0th         Past  02Jan2020  31Jan2020     1000000  SIR-F  2.5  0.002
         1st       Future  01Feb2020  31Dec2020     1000000  SIR-F  1.6  0.002

                kappa       rho  sigma   tau  alpha1 [-]  1/alpha2 [day]  \
Scenario Phase
Main     0th    0.005  0.200000  0.075  1440       0.002             200
         1st    0.005  0.200000  0.075  1440       0.002             200
Lockdown 0th    0.005  0.200000  0.075  1440       0.002             200
         1st    0.005  0.128379  0.075  1440       0.002             200

                1/beta [day]  1/gamma [day]
Scenario Phase
Main     0th               5             13
         1st               5             13
Lockdown 0th               5             13
         1st               7             13
```

[68]:

```python
_ = snl.simulate(name="Main")
```



[69]:
```
_ = snl.simulate(name="Lockdown")
```



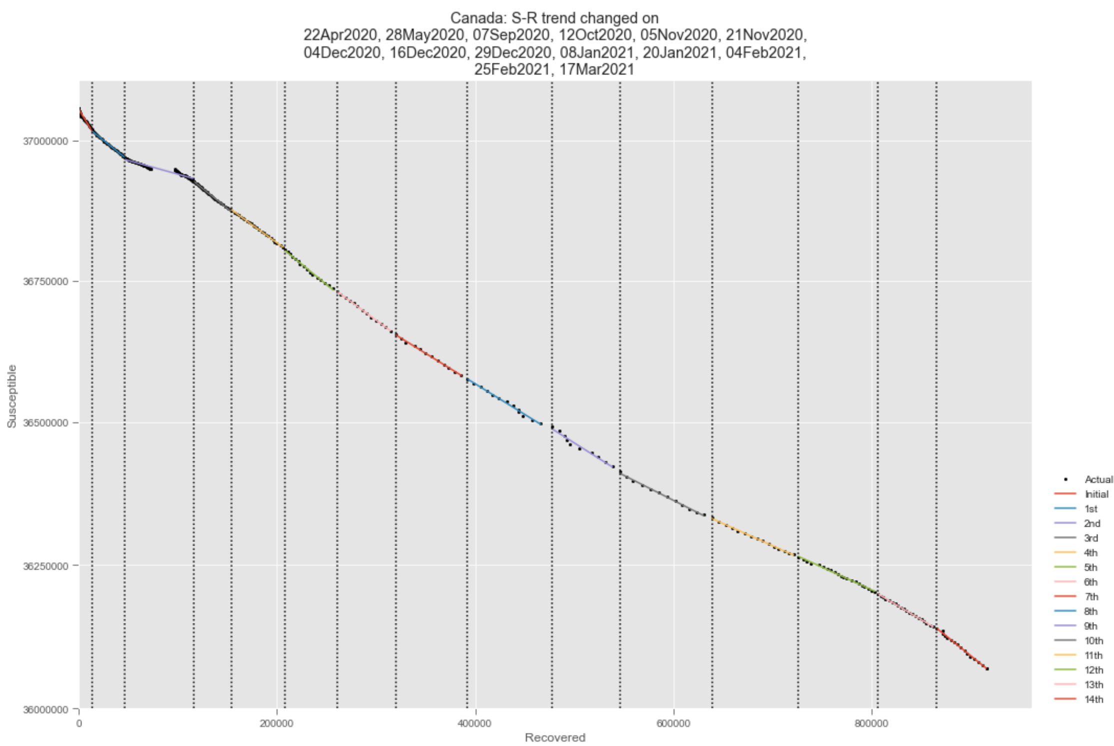
[70]:
```
snl.describe()
```

[70]:
```
          max(Infected) argmax(Infected)  Confirmed on 01Jan2021  \
Main             232568        02Mar2020                  891643
Lockdown          96224        16Mar2020                  660040

          Infected on 01Jan2021  Fatal on 01Jan2021  1st_Rt
Main                          0               57398     2.5
Lockdown                      7               42488     1.6
```

0.0.32 S-R trend of actual data in Canada

Plotting S-R trend

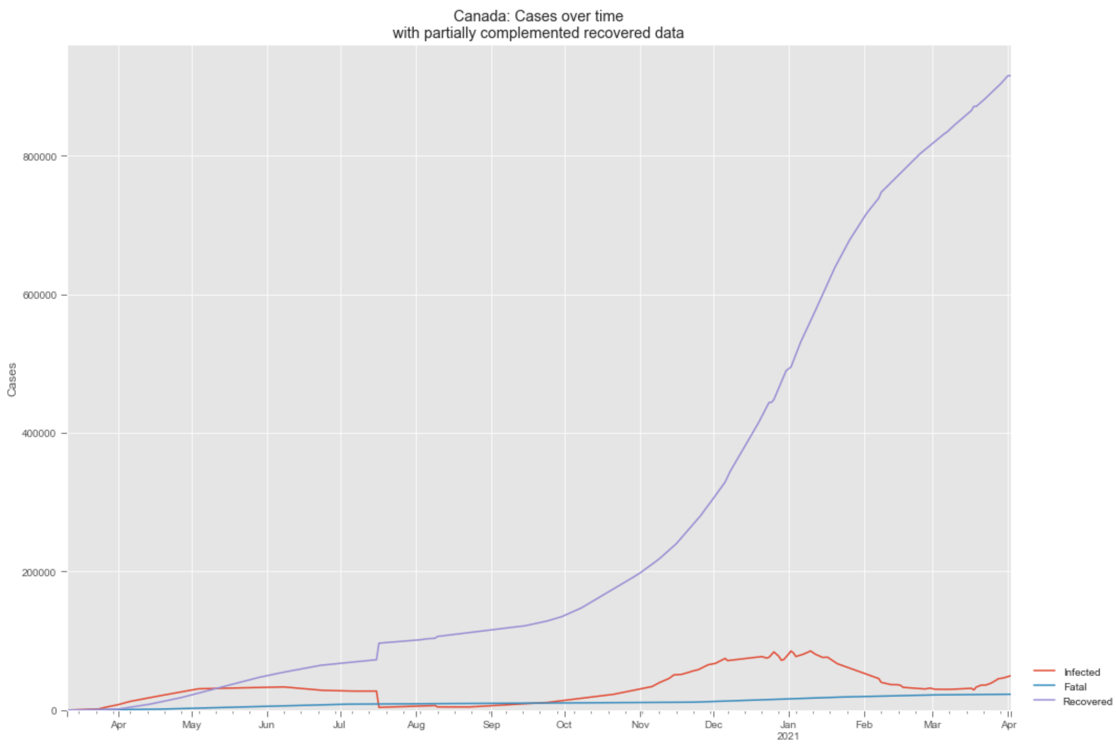
[71]:
```
can_scenario = cs.Scenario(jhu_data, population_data, "Canada")
_ = can_scenario.trend()
```



- From this graph we can see that SIR-F parameters were changed at some time-points. Assuming that there are 4 change points in Canada dataset we will find time points for them.

0.0.33 Scenario Analysis

[72]:
```
can_scenario.records().tail()
```



[72]:

	Date	Infected	Fatal	Recovered
383	2021-03-29	45212	22900	903607
384	2021-03-30	46394	22926	907277
385	2021-03-31	47858	22959	911293
386	2021-04-01	49568	23002	915348
387	2021-04-02	49568	23002	915348

0.0.34 Phases in Canada

Change points will be used as start date of phases. For each phase, we will apply SIR-F model. values will remain same.

[73]:
```
can_scenario.summary()
```

[73]:

	Type	Start	End	Population
0th	Past	11Mar2020	21Apr2020	37057765
1st	Past	22Apr2020	27May2020	37057765
2nd	Past	28May2020	06Sep2020	37057765
3rd	Past	07Sep2020	11Oct2020	37057765
4th	Past	12Oct2020	04Nov2020	37057765

```
5th   Past  05Nov2020  20Nov2020    37057765
6th   Past  21Nov2020  03Dec2020    37057765
7th   Past  04Dec2020  15Dec2020    37057765
8th   Past  16Dec2020  28Dec2020    37057765
9th   Past  29Dec2020  07Jan2021    37057765
10th  Past  08Jan2021  19Jan2021    37057765
11th  Past  20Jan2021  03Feb2021    37057765
12th  Past  04Feb2021  24Feb2021    37057765
13th  Past  25Feb2021  16Mar2021    37057765
14th  Past  17Mar2021  02Apr2021    37057765
```

0.0.35 Estimate SIR-F parameters

[74]:
```
can_scenario.estimate(cs.SIRF, timeout=150)
```

```
<SIR-F model: parameter estimation>
Running optimization with 12 CPUs…
        10th phase (17Mar2021 - 02Apr2021): finished 1757 trials in 1 min 30 sec
Completed optimization. Total: 4 min 39 sec
```

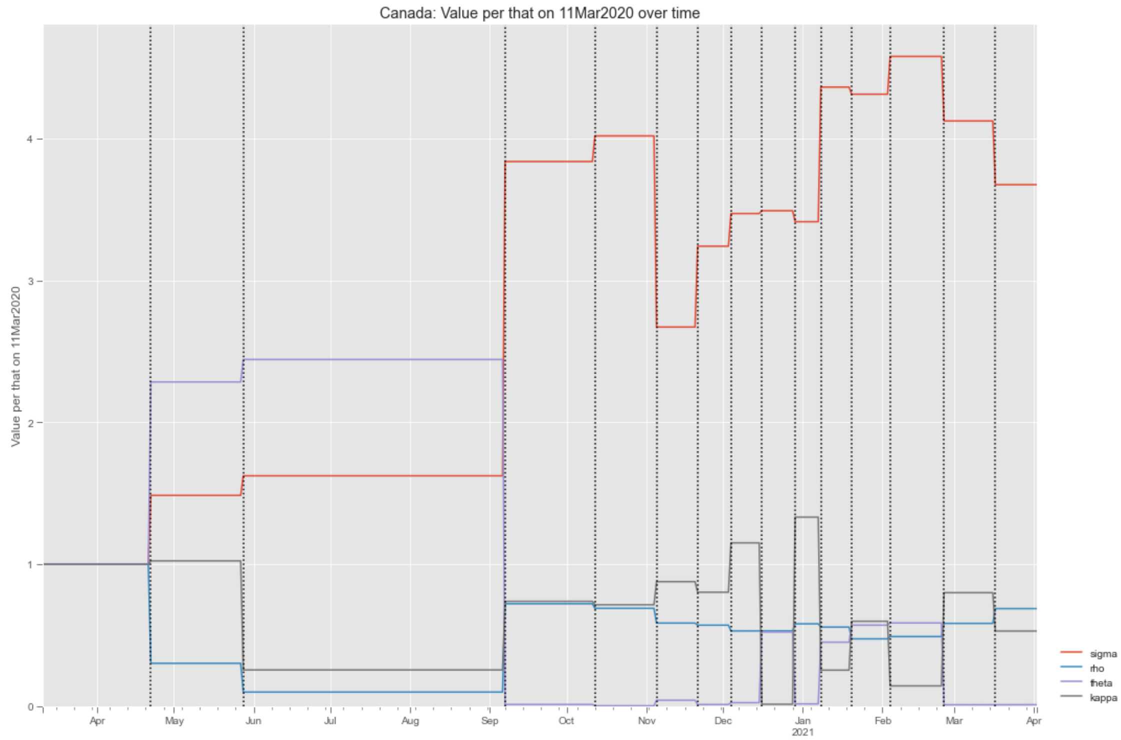
0.0.36 Compare parameters

[75]:
```
can_scenario.summary()
```

[75]:
```
      Type      Start        End  Population    ODE    Rt     theta     kappa  \
0th   Past  11Mar2020  21Apr2020    37057765  SIR-F  6.78  0.034481  0.000320
1st   Past  22Apr2020  27May2020    37057765  SIR-F  1.34  0.078768  0.000327
2nd   Past  28May2020  06Sep2020    37057765  SIR-F  0.41  0.084218  0.000082
3rd   Past  07Sep2020  11Oct2020    37057765  SIR-F  1.38  0.000443  0.000236
4th   Past  12Oct2020  04Nov2020    37057765  SIR-F  1.26  0.000121  0.000229
5th   Past  05Nov2020  20Nov2020    37057765  SIR-F  1.59  0.001467  0.000281
6th   Past  21Nov2020  03Dec2020    37057765  SIR-F  1.29  0.000433  0.000257
7th   Past  04Dec2020  15Dec2020    37057765  SIR-F  1.11  0.000867  0.000368
8th   Past  16Dec2020  28Dec2020    37057765  SIR-F  1.11  0.018024  0.000005
9th   Past  29Dec2020  07Jan2021    37057765  SIR-F  1.23  0.000574  0.000426
10th  Past  08Jan2021  19Jan2021    37057765  SIR-F  0.93  0.015560  0.000081
11th  Past  20Jan2021  03Feb2021    37057765  SIR-F  0.79  0.019697  0.000191
12th  Past  04Feb2021  24Feb2021    37057765  SIR-F  0.78  0.020229  0.000046
13th  Past  25Feb2021  16Mar2021    37057765  SIR-F  1.04  0.000362  0.000256
14th  Past  17Mar2021  02Apr2021    37057765  SIR-F  1.38  0.000382  0.000169

           rho     sigma  tau  1/gamma [day]  1/beta [day]  1/alpha2 [day]  \
0th   0.042211  0.005692  360             43             5             781
1st   0.012768  0.008456  360             29            19             763
2nd   0.004214  0.009240  360             27            59            3056
3rd   0.030477  0.021842  360             11             8            1057
```

```
4th   0.029118  0.022869  360              10            8            1093
5th   0.024726  0.015204  360              16           10             890
6th   0.024110  0.018446  360              13           10             973
7th   0.022389  0.019757  360              12           11             679
8th   0.022424  0.019868  360              12           11           54836
9th   0.024516  0.019428  360              12           10             586
10th  0.023536  0.024827  360              10           10            3073
11th  0.020044  0.024541  360              10           12            1305
12th  0.020717  0.026056  360               9           12            5455
13th  0.024642  0.023469  360              10           10             977
14th  0.029028  0.020914  360              11            8            1475

      alpha1 [-]     RMSLE  Trials       Runtime
0th        0.034  1.055565    1588  2 min 31 sec
1st        0.079  0.051503    1885  2 min 30 sec
2nd        0.084  0.262894    1541  2 min 31 sec
3rd        0.000  0.029902    1591  2 min 31 sec
4th        0.000  0.014688     249  0 min 20 sec
5th        0.001  0.025654    1597  2 min 30 sec
6th        0.000  0.008732    1608  2 min 30 sec
7th        0.001  0.010306     829  1 min 10 sec
8th        0.018  0.019936     368  0 min 30 sec
9th        0.001  0.027432     370  0 min 30 sec
10th       0.016  0.016512    1604  2 min 31 sec
11th       0.020  0.011408     259  0 min 20 sec
12th       0.020  0.023115     475  0 min 40 sec
13th       0.000  0.012934    1598  2 min 31 sec
14th       0.000  0.019174    1757  1 min 30 sec
```

[76]:
```
_ = can_scenario.history_rate()
```



[77]:
```python
canada_action_df = canada_action(canada_action_raw)
print("Measures taken in Canada")
canada_action_df[(canada_action_df["Jurisdiction "]=="Can.
↪")&(canada_action_df["Intervention category"]=="Closures")]
```

```
Measures taken in Canada
```

[77]:
```
    Entry ID Jurisdiction    Level Date announced Date implemented  \
470   CAN034          Can.  Federal     2020-03-17       2020-03-19
653   CAN039          Can.  Federal     2020-03-24       2020-03-25
786   CAN052          Can.  Federal     2020-04-02       2020-04-02
937   CAN016          Can.  Federal     2020-04-15       2020-04-15

    Intervention category                   Intervention type  \
470              Closures              Closures - recreation
653              Closures              Closures - recreation
786              Closures  Closures - non-essential services
937              Closures              Closures - recreation

          Who Implemented  \
470           Parks Canada
653           Parks Canada
786  Public Safety Canada
937           Parks Canada
```

```
                        What Implemented  \
470
Temporarily suspending all visitor services in all national parks, national
historic sites and national marine conservation areas across the country
653
Temporarily suspending all motor vehicle access by visitors at all national
parks, national historic sites and national marine conservation areas
786  Released a guidance document to assist various jurisdictions and businesses
in their decision-making around the types of employees considered essential
across Canada's 10 critical infrastructure sectors: energy and utilities,
information and communication technologies, finance, health, food, water,
transportation, safety, government and manufacturing
937
Suspended camping, group activities and events at all national parks, national
historic sites, heritage canals and national marine conservation areas

    Effective Until Indigenous population group  \
470             NaT                           No
653             NaT                           No
786             NaT                           No
937      2020-06-21                           No

                              Primary source
470
https://www.canada.ca/en/parks-canada/news/2020/03/parks-canada-temporarily-
suspends-all-visitor-services-across-the-country-until-further-notice.html
653
https://www.pc.gc.ca/en/voyage-travel/securite-safety/covid-19-info
786  https://www.canada.ca/en/public-safety-canada/news/2020/04/government-of-
canada-provides-guidance-on-services-and-functions-deemed-essential-to-canadas-
critical-infrastructure-during-covid-19.html
937  https://www.canada.ca/en/parks-canada/news/2020/04/to-help-limit-the-
spread-of-covid-19-parks-canada-suspends-camping-group-activities-and-events-
across-the-country-until-at-least-may-31-2020.html
```

From the graph and measures taken from canada government it seems school closures and lockdown reduced th effective contact rate.

0.0.37 Effect of school closure and lockdown

From the above table we can see that government of canada declared nationwide lockdown on 17Mar2020 and all the people were asked to remain home. From this we will predict the effect of closures after 3rd phase.

[78]:
```
can_scenario.get("Start", name="Main", phase="3rd")
```

[78]:
```
'07Sep2020'
```

0.0.38 Value of control factors of 1 before after the national lockdown

A national lockdown will effect on gs and c. Using the Google Mobility report generated on Mar 28, 2020 we can assume average reduction of potential encounters of 13%-15%

[79]:
```
c_before, c_after = 1.0, 0.85
```

gs before the lockdown We will estimate average number people going out using @marcoferrante estimation and population pyramiad data for canada

[80]:
```
going_out_df
```

[80]:

	Age_first	Age_last	Period_of_life	Days	Types	School	Office	\
0	0	2	nursery	3	school	3	0	
1	3	5	nursery school	5	school	4	0	
2	6	10	elementary school	6	school	5	0	
3	11	13	middle school	6	school	5	0	
4	14	18	high school	7	school	6	0	
5	19	25	university/work	7	school/work	3	3	
6	26	35	work	6	work	0	6	
7	36	45	work	5	work	0	5	
8	46	55	work	5	work	0	5	
9	56	65	work	5	work	0	5	
10	66	75	retired	4	retired	0	0	
11	76	85	retired	3	retired	0	0	
12	86	95	retired	2	retired	0	0	

	Others	Age	Population	Portion
0	0	2	1193571	0.034264
1	1	5	1193646	0.034266
2	1	10	1987203	0.057047
3	1	13	1186425	0.034059
4	1	18	2007971	0.057643
5	1	25	3365119	0.096603
6	1	35	5302920	0.152232
7	1	45	5012608	0.143898
8	1	55	4961567	0.142432
9	1	65	5165771	0.148294
10	4	75	1918186	0.055066
11	3	85	1158996	0.033271
12	2	95	380580	0.010925

[81]:
```
df = going_out_df.copy()
gs_before = (df[["School","Office","Others"]].sum(axis=1)*df["Portion"]).sum()
print("Number of days susceptible person go out: {}".format(gs_before))
```

```
Number of days susceptible person go out: 5.915772475744851
```

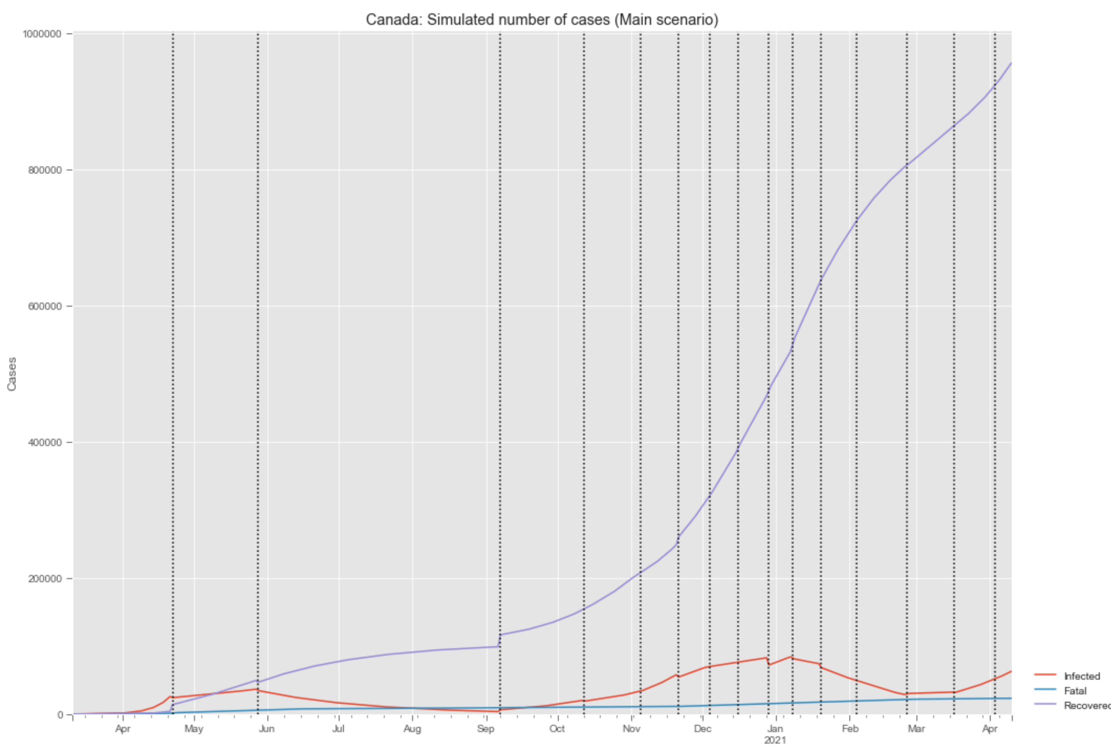
Estimating gs after school closure and lockdown using:

[82]:
```
rho_before = can_scenario.get("rho", name="Main", phase="1st")
rho_after = can_scenario.get("rho", name="Main", phase="3rd")
gs_after = (rho_after / (rho_before * c_after)) * (gs_before * c_before)/10
print("Number of days susceptible person go out after lockdown: {}".
 ↪format(round(gs_after,1)))
```

```
Number of days susceptible person go out after lockdown: 1.7
```

A week scenario

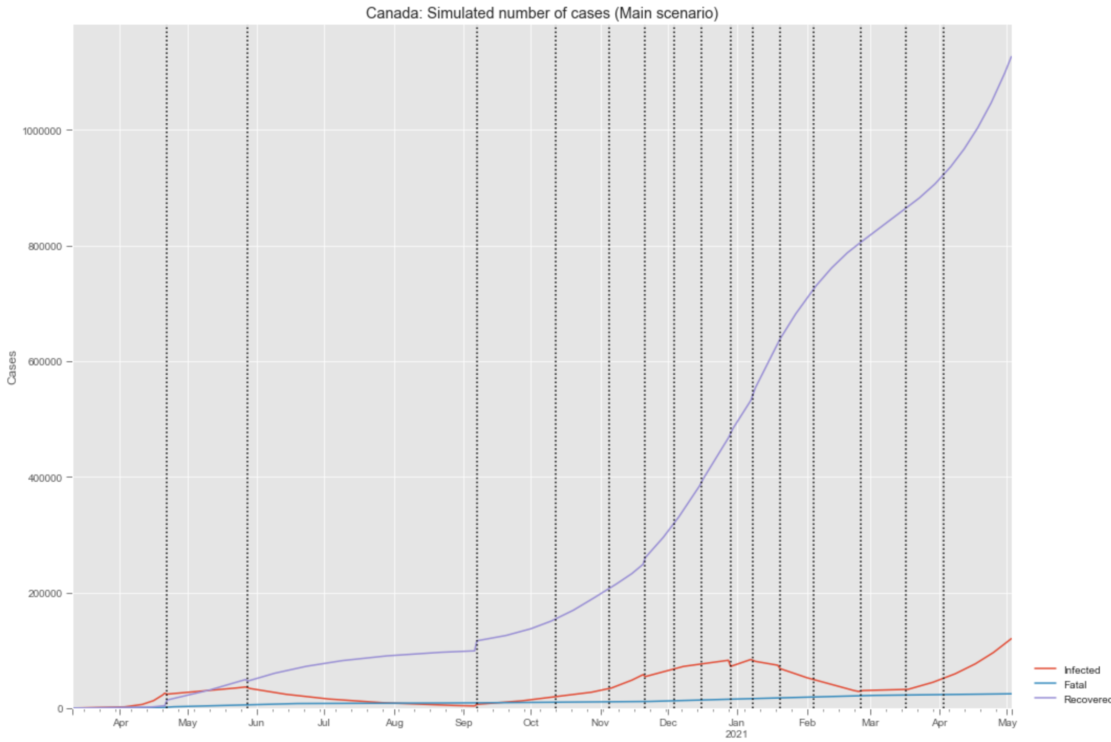
[83]:
```
can_scenario.clear()
can_scenario.add(days=7)
can_scenario.simulate().tail(7).style.background_gradient(axis=0)
```



[83]: <pandas.io.formats.style.Styler at 0x1c810f6a888>

A month scenario

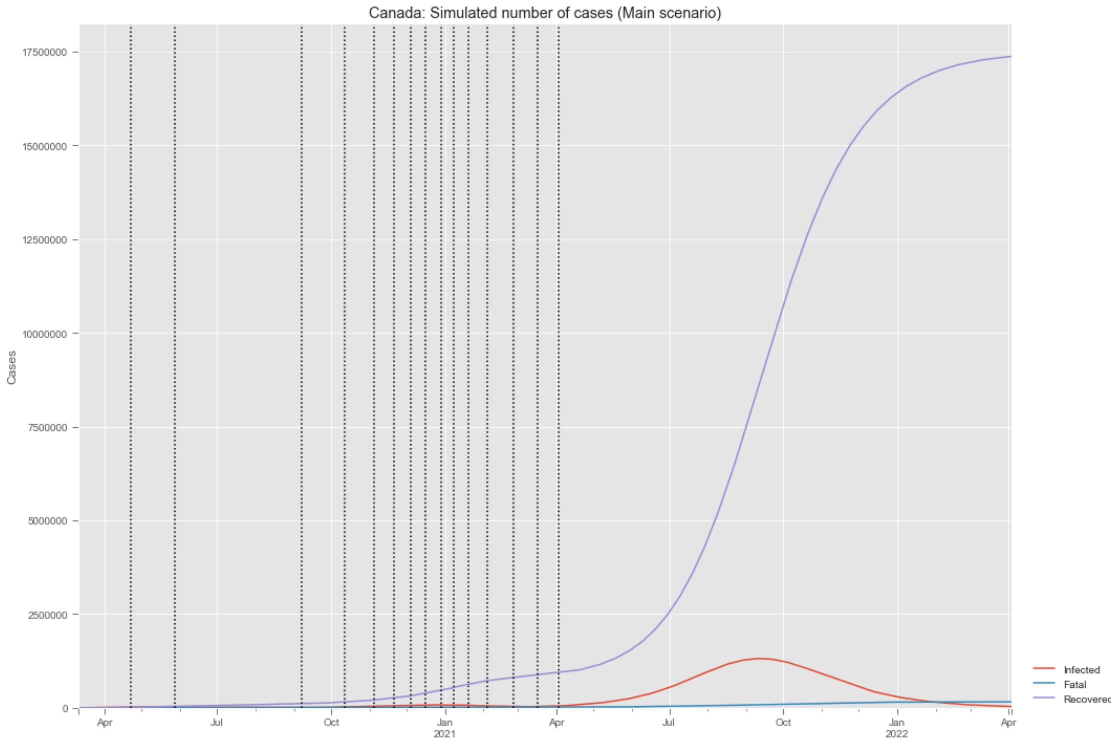
[84]:
```
can_scenario.clear()
can_scenario.add(days=30)
can_scenario.simulate().tail(7).style.background_gradient(axis=0)
```



[84]: <pandas.io.formats.style.Styler at 0x1c810db3dc8>

In long term

[85]:
```
can_scenario.clear()
can_scenario.add(days=365)
can_scenario.simulate().tail(7).style.background_gradient(axis=0)
```



[85]: <pandas.io.formats.style.Styler at 0x1c80f9cb848>

In this graph we can see that if lockdown and school closures are implemented then infected and fatal cases will significantly drop after 1 year. We can also see that we will see a rise in number of infected person soon after cases drops to zero and people again decide to go out.

0.0.39 Conclusion

- With lockdown we were able to reduce the potential encounter by 13%-15%.
- With lockdown (effective contact rate) we saw a 40% decrease from 0.2 to 0.12.
- With lockdown gs (number of days susceptible person goes out) also reduced by ~71%.
- With lockdown number of infected person also reduced by 58%. In real world it is in a range of (20%-30%).

0.0.40 Model Deployement (AWS)

- The above explained SIR and SIR-F model were also deployed on AWS cloud to easily simulate the scenarios for any country.
- Front End was made using HTML & CSS.
- Back End was made using Flask.
- Model was made using Python.
- Github Link click here

0.0.41 References

- Github Repo COVID-19 Model Simulation: https://github.com/isohels/SIRModel
- Github Repo for AWS Model: https://github.com/isohels/SIRModelDeployement
- Github Repo for CovsirPhy Model: https://github.com/lisphilar/covid19-sir
- COVID19_line_list_data.csv: https://github.com/beoutbreakprepared/nCoV2019/blob/master/latest_da
- Mortality Rate: https://coronavirus.jhu.edu/data/mortality
- SEWIR-F Model: https://github.com/lisphilar/covid19-sir
- SEIR Model: http://indico.ictp.it/event/7960/session/3/contribution/19/material/slides/
- Google Mobility Report: https://www.gstatic.com/covid19/mobility/2021-03-28_CA_Mobility_Report_en.pdf
- Intervention Scan Data: https://www.cihi.ca/en/covid-19-intervention-scan