Bigdata_Final

May 13, 2022

1 Setup

[ ]:
```
# A few graphs cannot be displayed in the PDF. If you require full access,␣
↪please contact jd4573@nyu.edu to be added to the share list.
```

[ ]:
```
!python -m pip install dask[dataframe] --upgrade
!pip install memory_profiler
```

```
Requirement already satisfied: dask[dataframe] in /usr/local/lib/python3.7/dist-
packages (2.12.0)
Requirement already satisfied: pandas>=0.23.0 in /usr/local/lib/python3.7/dist-
packages (from dask[dataframe]) (1.3.5)
Requirement already satisfied: numpy>=1.13.0 in /usr/local/lib/python3.7/dist-
packages (from dask[dataframe]) (1.21.6)
Requirement already satisfied: toolz>=0.7.3 in /usr/local/lib/python3.7/dist-
packages (from dask[dataframe]) (0.11.2)
Requirement already satisfied: fsspec>=0.6.0 in /usr/local/lib/python3.7/dist-
packages (from dask[dataframe]) (2022.3.0)
Requirement already satisfied: partd>=0.3.10 in /usr/local/lib/python3.7/dist-
packages (from dask[dataframe]) (1.2.0)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.23.0->dask[dataframe])
(2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=0.23.0->dask[dataframe]) (2022.1)
Requirement already satisfied: locket in /usr/local/lib/python3.7/dist-packages
(from partd>=0.3.10->dask[dataframe]) (1.0.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7.3->pandas>=0.23.0->dask[dataframe]) (1.15.0)
Requirement already satisfied: memory_profiler in /usr/local/lib/python3.7/dist-
packages (0.60.0)
Requirement already satisfied: psutil in /usr/local/lib/python3.7/dist-packages
(from memory_profiler) (5.4.8)
```

[ ]:
```
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os
import dask
import dask.array as da
import dask.dataframe as dd
from dask.diagnostics import ProgressBar
```

[ ]:
```
# print("Pandas version: ", pd.__version__)
# print("Dask   version: ", dask.__version__)
```

2 Data Loading

[ ]:
```
!gdown --id 1g7MhWITLHw1o0akGyCztcJSZxFsVxlMK
!unzip -q '/content/bigdata_dataset.zip'
```

```
/usr/local/lib/python3.7/dist-packages/gdown/cli.py:131: FutureWarning: Option
`--id` was deprecated in version 4.3.1 and will be removed in 5.0. You don't
need to pass it anymore to use a file ID.
  category=FutureWarning,
Downloading…
From: https://drive.google.com/uc?id=1g7MhWITLHw1o0akGyCztcJSZxFsVxlMK
To: /content/bigdata_dataset.zip
100% 44.4M/44.4M [00:00<00:00, 146MB/s]
replace 2020_CA_Region_Mobility_Report.csv? [y]es, [n]o, [A]ll, [N]one,
[r]ename: a
error:  invalid response [a]
replace 2020_CA_Region_Mobility_Report.csv? [y]es, [n]o, [A]ll, [N]one,
[r]ename: a
error:  invalid response [a]
replace 2020_CA_Region_Mobility_Report.csv? [y]es, [n]o, [A]ll, [N]one,
[r]ename: A
```

3 Data Cleaning

3.0.1 GDP Dataset

[ ]:
```
dd_GDP_world = dd.read_csv("/content/World_GDP.csv")
dd_GDP_world = dd_GDP_world[['LOCATION','TIME','Value']]
```

[ ]:
```
dd_GDP_world.compute()
```

[ ]:
```
    LOCATION     TIME     Value
0        KOR  2018-Q1  1.148519
1        KOR  2018-Q2  0.633609
2        KOR  2018-Q3  0.688282
3        KOR  2018-Q4  0.822000
4        KOR  2019-Q1 -0.199688
..       …      …       …
859      CRI  2020-Q4  4.412640
860      CRI  2021-Q1  1.869415
861      CRI  2021-Q2  1.896151
862      CRI  2021-Q3  3.776817
863      CRI  2021-Q4  1.308014

[864 rows x 3 columns]
```

[ ]:
```
mask = (dd_GDP_world['LOCATION'].str.len() == 3) & (dd_GDP_world['LOCATION'] !=␣
↪'G-7')
dd_GDP_world_sort = dd_GDP_world.loc[(mask) & (~dd_GDP_world["TIME"].
↪isin(["2018-Q1","2018-Q2","2018-Q3","2018-Q4","2019-Q1","2019-Q2","2019-Q3","2019-Q4","2022
dd_GDP_world_sort = dd_GDP_world_sort.reset_index()
dd_GDP_world_sort = dd_GDP_world_sort.drop(['index'],axis = 1)
dd_GDP_world_sort = dd_GDP_world_sort.rename(columns={"LOCATION": "Code",␣
↪"TIME":"Time","Value":"Quarterly GDP Growth Rate"})
dd_GDP_world_sort['Time'] = dd_GDP_world_sort['Time'].replace('-', '',␣
↪regex=True)
```

[ ]:
```
dd_GDP_world_sort.compute()
```

[ ]:
```
    Code    Time  Quarterly GDP Growth Rate
0    KOR  2020Q1                  -1.261507
1    KOR  2020Q2                  -3.150738
2    KOR  2020Q3                   2.233424
3    KOR  2020Q4                   1.142221
4    KOR  2021Q1                   1.740407
..   …      …                        …
378  CRI  2020Q4                   4.412640
379  CRI  2021Q1                   1.869415
380  CRI  2021Q2                   1.896151
381  CRI  2021Q3                   3.776817
382  CRI  2021Q4                   1.308014

[383 rows x 3 columns]
```

[ ]:
```
dd_GDP_rank = dd_GDP_world_sort.groupby(by = 'Code').mean().compute().
↪sort_values(by = 'Quarterly GDP Growth Rate',ascending = False)
```

```
[ ]: dd_five = dd_GDP_world.loc[(dd_GDP_world["LOCATION"].isin(["JPN", "USA", "GBR",␣
      ↪"TUR", "CAN"])) & (~dd_GDP_world["TIME"].
      ↪isin(["2018-Q1","2018-Q2","2018-Q3","2018-Q4","2022-Q1"]))]
     dd_five = dd_five.reset_index()
     dd_five = dd_five.drop(['index'],axis = 1)
     dd_five = dd_five.rename(columns={"LOCATION": "Code"})
     dd_five['TIME'] = dd_five['TIME'].replace('-', '', regex=True)
```

3.0.2 Policy Dataset

```
[ ]: dd_fc = dd.read_csv("/content/face-covering-policies-covid.
      ↪csv",parse_dates=['Day'])
     dd_is = dd.read_csv("/content/income-support-covid.csv",parse_dates=['Day'])
     dd_pt = dd.read_csv("/content/public-transport-covid.csv",parse_dates=['Day'])
     dd_sc = dd.read_csv("/content/school-closures-covid.csv",parse_dates=['Day'])
     dd_vp = dd.read_csv("/content/covid-vaccination-policy.csv",parse_dates=['Day'])
     dd_sah = dd.read_csv("/content/stay-at-home-covid.csv",parse_dates=['Day'])
```

```
[ ]: dd_fc['Day'] = dd.to_datetime(dd_fc['Day'])
     dd_is['Day'] = dd.to_datetime(dd_is['Day'])
     dd_pt['Day'] = dd.to_datetime(dd_pt['Day'])
     dd_sc['Day'] = dd.to_datetime(dd_sc['Day'])
     dd_vp['Day'] = dd.to_datetime(dd_vp['Day'])
     dd_sah['Day'] = dd.to_datetime(dd_sah['Day'])
```

```
[ ]: dd_fc.compute().info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 154352 entries, 0 to 154351
Data columns (total 4 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Entity            154352 non-null  object
 1   Code              154352 non-null  object
 2   Day               154352 non-null  datetime64[ns]
 3   facial_coverings  154352 non-null  int64
dtypes: datetime64[ns](1), int64(1), object(2)
memory usage: 4.7+ MB
```

```
[ ]: def convertQ(dd_name):
       dd_name['Time'] = dd_name['Day'].dt.to_period('Q').astype('string')
       return dd_name.groupby(['Code','Time']).mean().reset_index()
```

```
[ ]: def combine(dd_fc_Q,dd_is_Q,dd_pt_Q,dd_sc_Q,dd_vp_Q,dd_GDP_world_sort):
```

```
  dd_combine = dd_fc_Q.merge(dd_is_Q, how ='left').merge(dd_pt_Q, how = 'left').
↪merge(dd_sc_Q, how = 'left').merge(dd_vp_Q, how = 'left').
↪merge(dd_GDP_world_sort,how ='left')
  dd_combine = dd_combine.dropna().reset_index()
  dd_combine = dd_combine.loc[dd_combine['Code'] != 'RUS']
  dd_combine = dd_combine.drop(['index'],axis = 1)
  return dd_combine
```

[ ]:
```
dd_fc_Q = convertQ(dd_fc)
dd_is_Q = convertQ(dd_is)
dd_pt_Q = convertQ(dd_pt)
dd_sc_Q = convertQ(dd_sc)
dd_vp_Q = convertQ(dd_vp)
dd_combine = combine(dd_fc_Q,dd_is_Q,dd_pt_Q,dd_sc_Q,dd_vp_Q,dd_GDP_world_sort)
```

[ ]:
```
dd_combine.compute()
```

[ ]:

	Code	Time	facial_coverings	income_support	close_public_transport	school_closures	vaccination_policy	Quarterly GDP Growth Rate
0	ARG	2020Q1	0.000000	0.098901	0.197802	0.676056	0.000000	-4.089572
1	ARG	2020Q2	2.571429	1.000000	2.000000	3.000000	0.000000	-14.913956
2	ARG	2020Q3	3.000000	1.000000	2.000000	3.000000	0.000000	11.875660
3	ARG	2020Q4	3.000000	1.000000	2.000000	3.000000	0.032609	4.455026
4	ARG	2021Q1	3.000000	1.000000	2.000000	2.466667	1.422222	3.216986
..	…	…	…	…	…	…	…	…
378	ZAF	2020Q4	3.000000	1.000000	0.489130	0.597826	0.000000	2.548717
379	ZAF	2021Q1	3.077778	1.000000	1.000000	1.400000	0.655556	1.040859
380	ZAF	2021Q2	3.000000	0.835165	0.912088	1.307692	1.857143	1.317869
381	ZAF	2021Q3	3.000000	0.858696	1.000000	1.271739	4.108696	-1.727377
382	ZAF	2021Q4	3.000000	1.000000	1.000000	1.000000	5.000000	1.163439

[376 rows x 8 columns]

[ ]:
```
us_fc = dd_fc.loc[dd_fc['Code'] == "USA"]
us_pt = dd_pt.loc[dd_pt['Code'] == "USA"]
```

```
us_sc = dd_sc.loc[dd_sc['Code'] == "USA"]
us_sah = dd_sah.loc[dd_sah['Code'] == "USA"]

tr_fc = dd_fc.loc[dd_fc['Code'] == "TUR"]
tr_pt = dd_pt.loc[dd_pt['Code'] == "TUR"]
tr_sc = dd_sc.loc[dd_sc['Code'] == "TUR"]
tr_sah = dd_sah.loc[dd_sah['Code'] == "TUR"]

jp_fc = dd_fc.loc[dd_fc['Code'] == "JPN"]
jp_pt = dd_pt.loc[dd_pt['Code'] == "JPN"]
jp_sc = dd_sc.loc[dd_sc['Code'] == "JPN"]
jp_sah = dd_sah.loc[dd_sah['Code'] == "JPN"]
```

[ ]:
```
df_stringency = dd.read_csv("/content/owid-covid-data.csv", sample=25000000)
df_stringency['date'] = dd.to_datetime(df_stringency['date'],␣
↪infer_datetime_format=True)
```

[ ]:
```
df_stringency_us = df_stringency.loc[df_stringency['location'] == "United␣
↪States"].compute()
df_stringency_us = df_stringency_us.fillna(0)
df_stringency_us = df_stringency_us[['date', 'stringency_index']]
df_stringency_us.rename(columns={'stringency_index': 'us_stringency_index'},␣
↪inplace=True)

df_stringency_gb = df_stringency.loc[df_stringency['location'] == "United␣
↪Kingdom"].compute()
df_stringency_gb = df_stringency_gb.fillna(0)
df_stringency_gb = df_stringency_gb[['date', 'stringency_index']]
df_stringency_gb.rename(columns={'stringency_index': 'gb_stringency_index'},␣
↪inplace=True)

df_stringency_jp = df_stringency.loc[df_stringency['location'] == "Japan"].
↪compute()
df_stringency_jp = df_stringency_jp.fillna(0)
df_stringency_jp = df_stringency_jp[['date', 'stringency_index']]
df_stringency_jp.rename(columns={'stringency_index': 'jp_stringency_index'},␣
↪inplace=True)

df_stringency_ca = df_stringency.loc[df_stringency['location'] == "Canada"].
↪compute()
df_stringency_ca = df_stringency_ca.fillna(0)
df_stringency_ca = df_stringency_ca[['date', 'stringency_index']]
df_stringency_ca.rename(columns={'stringency_index': 'ca_stringency_index'},␣
↪inplace=True)
```

```
df_stringency_tr = df_stringency.loc[df_stringency['location'] == "Turkey"].
 ↪compute()
df_stringency_tr = df_stringency_tr.fillna(0)
df_stringency_tr = df_stringency_tr[['date', 'stringency_index']]
df_stringency_tr.rename(columns={'stringency_index': 'tr_stringency_index'},␣
 ↪inplace=True)
```

3.0.3 Mobility Dataset

[ ]:
```
df_us_mobility_2020 = dd.read_csv("/content/2020_US_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_us_mobility_2021 = dd.read_csv("/content/2021_US_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_us_mobility_2022 = dd.read_csv("/content/2022_US_Region_Mobility_Report.
 ↪csv", sample=25000000)

df_us_mobility = dd.concat([df_us_mobility_2020, df_us_mobility_2021])
df_us_mobility = dd.concat([df_us_mobility, df_us_mobility_2022])

df_us_mobility['date'] = dd.to_datetime(df_us_mobility['date'],␣
 ↪infer_datetime_format=True)
df_us_mobility = df_us_mobility.loc[df_us_mobility['sub_region_1'].isnull()].
 ↪compute()
df_us_mobility = df_us_mobility.drop(columns=['sub_region_1', 'sub_region_2',␣
 ↪'metro_area', 'iso_3166_2_code', 'census_fips_code', 'place_id'])

us_transit = df_us_mobility[['date',␣
 ↪'transit_stations_percent_change_from_baseline']]
us_park = df_us_mobility[['date', 'parks_percent_change_from_baseline']]
us_residential = df_us_mobility[['date',␣
 ↪'residential_percent_change_from_baseline']]


df_us_case = dd.read_csv(["/content/
 ↪United_States_COVID-19_Cases_and_Deaths_by_State_over_Time.csv"],␣
 ↪sample=25000000)
df_us_vaccine = dd.read_csv(["/content/
 ↪COVID-19_Vaccinations_in_the_United_States_Jurisdiction.csv"],␣
 ↪sample=25000000)
```

[ ]:
```
def convertPolicy(dd_name):
  dd_name['Time'] = dd_name['Day'].dt.to_period('Q').astype('string')
  return dd_name.groupby(['Time']).mean().reset_index()
```

```
[ ]: def convertMobility(dd_name):
       dd_name['Time'] = dd_name['date'].dt.to_period('Q').astype('string')
       return dd_name.groupby(['Time']).mean().reset_index()
```

```
[ ]: us_fc_convert = convertPolicy(us_fc)
     us_pt_convert = convertPolicy(us_pt)
     us_sc_convert = convertPolicy(us_sc)
     us_sah_convert = convertPolicy(us_sah)
     us_transit_convert = convertMobility(us_transit)
     us_park_convert = convertMobility(us_park)
     us_residential_convert = convertMobility(us_residential)
```

```
[ ]: def␣
      ↪combine_policy_with_mobility(fc_convert,pt_convert,sc_convert,sah_convert,transit_convert,p
      ↪
       dd_combine = fc_convert.merge(pt_convert, how ='left').merge(sc_convert, how␣
      ↪= 'left')\
            .merge(sah_convert, how = 'left').merge(transit_convert, how = 'left').
      ↪merge(park_convert,how ='left')\
            .merge(residential_convert, how = 'left')
       dd_combine = dd_combine.dropna().reset_index()
       dd_combine = dd_combine.drop(['index'],axis = 1)
       return dd_combine
```

```
[ ]: def␣
      ↪combine_mobility_with_GDP(stringency_convert,transit_convert,park_convert,residential_conve
      ↪
       dd_combine = stringency_convert.merge(transit_convert, how ='left').
      ↪merge(park_convert, how ='left').merge(residential_convert, how = 'left')\
            .merge(workplace_convert, how = 'left').merge(grocery_convert, how =␣
      ↪'left').merge(country_GDP,how ='left')
       dd_combine = dd_combine.dropna().reset_index()
       dd_combine = dd_combine.drop(['index'],axis = 1)
       return dd_combine
```

```
[ ]: df_tr_mobility_2020 = dd.read_csv("/content/2020_TR_Region_Mobility_Report.
      ↪csv", sample=25000000)
     df_tr_mobility_2021 = dd.read_csv("/content/2021_TR_Region_Mobility_Report.
      ↪csv", sample=25000000)
     df_tr_mobility_2022 = dd.read_csv("/content/2022_TR_Region_Mobility_Report.
      ↪csv", sample=25000000)

     df_tr_mobility = dd.concat([df_tr_mobility_2020, df_tr_mobility_2021])
     df_tr_mobility = dd.concat([df_tr_mobility, df_tr_mobility_2022])
```

```
df_tr_mobility['date'] = dd.to_datetime(df_tr_mobility['date'],␣
 ↪infer_datetime_format=True)
df_tr_mobility = df_tr_mobility.loc[df_tr_mobility['sub_region_1'].isnull()].
 ↪compute()
df_tr_mobility = df_tr_mobility.drop(columns=['sub_region_1', 'sub_region_2',␣
 ↪'metro_area', 'iso_3166_2_code', 'census_fips_code', 'place_id'])

tr_transit = df_tr_mobility[['date',␣
 ↪'transit_stations_percent_change_from_baseline']]
tr_park = df_tr_mobility[['date', 'parks_percent_change_from_baseline']]
tr_residential = df_tr_mobility[['date',␣
 ↪'residential_percent_change_from_baseline']]
tr_workplace = df_tr_mobility[['date',␣
 ↪'workplaces_percent_change_from_baseline']]
tr_grocery = df_tr_mobility[['date',␣
 ↪'grocery_and_pharmacy_percent_change_from_baseline']]

tr_GDP = dd_GDP_world_sort.loc[dd_GDP_world_sort['Code'] == "TUR"]
tr_GDP = tr_GDP.drop(columns=['Code'])

tr_stringency_data = df_stringency.loc[df_stringency['location'] == "Turkey"]
tr_stringency_data = tr_stringency_data.fillna(0)
tr_stringency_data = tr_stringency_data[['date', 'stringency_index']]
```

[ ]:
```
tr_fc_convert = convertPolicy(tr_fc)
tr_pt_convert = convertPolicy(tr_pt)
tr_sc_convert = convertPolicy(tr_sc)
tr_sah_convert = convertPolicy(tr_sah)
tr_transit_convert = convertMobility(tr_transit)
tr_park_convert = convertMobility(tr_park)
tr_residential_convert = convertMobility(tr_residential)
tr_workplace_convert = convertMobility(tr_workplace)
tr_grocery_convert = convertMobility(tr_grocery)
tr_stringency_convert = convertMobility(tr_stringency_data)
```

[ ]:
```
df_jp_mobility_2020 = dd.read_csv("/content/2020_JP_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_jp_mobility_2021 = dd.read_csv("/content/2021_JP_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_jp_mobility_2022 = dd.read_csv("/content/2022_JP_Region_Mobility_Report.
 ↪csv", sample=25000000)

df_jp_mobility = dd.concat([df_jp_mobility_2020, df_jp_mobility_2021])
df_jp_mobility = dd.concat([df_jp_mobility, df_jp_mobility_2022])
```

```
df_jp_mobility['date'] = dd.to_datetime(df_jp_mobility['date'],␣
↪infer_datetime_format=True)
df_jp_mobility = df_jp_mobility.loc[df_jp_mobility['sub_region_1'].isnull()].
↪compute()
df_jp_mobility = df_jp_mobility.drop(columns=['sub_region_1', 'sub_region_2',␣
↪'metro_area', 'iso_3166_2_code', 'census_fips_code', 'place_id'])

jp_transit = df_jp_mobility[['date',␣
↪'transit_stations_percent_change_from_baseline']]
jp_park = df_jp_mobility[['date', 'parks_percent_change_from_baseline']]
jp_residential = df_jp_mobility[['date',␣
↪'residential_percent_change_from_baseline']]
jp_workplace = df_jp_mobility[['date',␣
↪'workplaces_percent_change_from_baseline']]
jp_grocery = df_jp_mobility[['date',␣
↪'grocery_and_pharmacy_percent_change_from_baseline']]

jp_GDP = dd_GDP_world_sort.loc[dd_GDP_world_sort['Code'] == "JPN"]
jp_GDP = jp_GDP.drop(columns=['Code'])


jp_stringency_data = df_stringency.loc[df_stringency['location'] == "Japan"]
jp_stringency_data = jp_stringency_data.fillna(0)
jp_stringency_data = jp_stringency_data[['date', 'stringency_index']]
```

[ ]:
```
jp_fc_convert = convertPolicy(jp_fc)
jp_pt_convert = convertPolicy(jp_pt)
jp_sc_convert = convertPolicy(jp_sc)
jp_sah_convert = convertPolicy(jp_sah)
jp_transit_convert = convertMobility(jp_transit)
jp_park_convert = convertMobility(jp_park)
jp_residential_convert = convertMobility(jp_residential)
jp_workplace_convert = convertMobility(jp_workplace)
jp_grocery_convert = convertMobility(jp_grocery)
jp_stringency_convert = convertMobility(jp_stringency_data)
```

[ ]:
```
df_gb_mobility_2020 = dd.read_csv("/content/2020_GB_Region_Mobility_Report.
↪csv", sample=25000000)
df_gb_mobility_2021 = dd.read_csv("/content/2021_GB_Region_Mobility_Report.
↪csv", sample=25000000)
df_gb_mobility_2022 = dd.read_csv("/content/2022_GB_Region_Mobility_Report.
↪csv", sample=25000000)

df_gb_mobility = dd.concat([df_gb_mobility_2020, df_gb_mobility_2021])
df_gb_mobility = dd.concat([df_gb_mobility, df_gb_mobility_2022])
```

```
df_gb_mobility['date'] = dd.to_datetime(df_gb_mobility['date'],␣
 ↪infer_datetime_format=True)
df_gb_mobility = df_gb_mobility.loc[df_gb_mobility['sub_region_1'].isnull()].
 ↪compute()
df_gb_mobility = df_gb_mobility.drop(columns=['sub_region_1', 'sub_region_2',␣
 ↪'metro_area', 'iso_3166_2_code', 'census_fips_code', 'place_id'])
```

[ ]:
```
df_ca_mobility_2020 = dd.read_csv("/content/2020_CA_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_ca_mobility_2021 = dd.read_csv("/content/2021_CA_Region_Mobility_Report.
 ↪csv", sample=25000000)
df_ca_mobility_2022 = dd.read_csv("/content/2022_CA_Region_Mobility_Report.
 ↪csv", sample=25000000)

df_ca_mobility = dd.concat([df_ca_mobility_2020, df_ca_mobility_2021])
df_ca_mobility = dd.concat([df_ca_mobility, df_ca_mobility_2022])

df_ca_mobility['date'] = dd.to_datetime(df_ca_mobility['date'],␣
 ↪infer_datetime_format=True)
df_ca_mobility = df_ca_mobility.loc[df_ca_mobility['sub_region_1'].isnull()].
 ↪compute()
df_ca_mobility = df_ca_mobility.drop(columns=['sub_region_1', 'sub_region_2',␣
 ↪'metro_area', 'iso_3166_2_code', 'census_fips_code', 'place_id'])
df_ca_mobility.head(1000)
```

[ ]:
```
    country_region_code country_region       date  \
0                    CA         Canada 2020-02-15
1                    CA         Canada 2020-02-16
2                    CA         Canada 2020-02-17
3                    CA         Canada 2020-02-18
4                    CA         Canada 2020-02-19
..                  …             …        …
111                  CA         Canada 2022-04-22
112                  CA         Canada 2022-04-23
113                  CA         Canada 2022-04-24
114                  CA         Canada 2022-04-25
115                  CA         Canada 2022-04-26

     retail_and_recreation_percent_change_from_baseline  \
0                                                   4.0
1                                                  13.0
2                                                 -12.0
3                                                  -1.0
4                                                   1.0
..                                                  …
111                                                -5.0
```

```
112                                                 2.0
113                                                 6.0
114                                                -5.0
115                                                -4.0

     grocery_and_pharmacy_percent_change_from_baseline  \
0                                                   2.0
1                                                   8.0
2                                                 -15.0
3                                                   4.0
4                                                   1.0
..                                                  …
111                                                 1.0
112                                                 4.0
113                                                 3.0
114                                                 2.0
115                                                 5.0

     parks_percent_change_from_baseline  \
0                                  10.0
1                                  41.0
2                                  63.0
3                                   6.0
4                                   9.0
..                                  …
111                                35.0
112                                47.0
113                                86.0
114                                27.0
115                                28.0

     transit_stations_percent_change_from_baseline  \
0                                              3.0
1                                              4.0
2                                            -28.0
3                                             -1.0
4                                              0.0
..                                             …
111                                          -40.0
112                                          -30.0
113                                          -29.0
114                                          -42.0
115                                          -41.0

     workplaces_percent_change_from_baseline  \
0                                        1.0
1                                        0.0
```

```
2                                        -52.0
3                                         -1.0
4                                          0.0
..                                         …
111                                      -21.0
112                                        0.0
113                                       -3.0
114                                      -22.0
115                                      -21.0

     residential_percent_change_from_baseline
0                                           0.0
1                                          -2.0
2                                          11.0
3                                           1.0
4                                           0.0
..                                          …
111                                         7.0
112                                         2.0
113                                         1.0
114                                         7.0
115                                         7.0

[802 rows x 9 columns]
```

[ ]:
```
dd_develop = df_stringency[['iso_code','human_development_index']]
dd_combine_country = dd_combine[['Code']].drop_duplicates().reset_index()
dd_combine_country = dd_combine_country.drop(['index'],axis = 1)
country_list = []
for _,i in dd_combine_country.iterrows():
    country_list.append(i.item())
dd_develop = dd_develop.loc[dd_develop['iso_code'].isin(country_list)].dropna()
dd_develop = dd_develop.drop_duplicates().reset_index()
dd_develop = dd_develop.drop(['index'],axis = 1)

dd_temp = dd_develop.set_index('human_development_index')
dd_develop_sort = dd_temp.map_partitions(lambda df: df.
 ↪sort_values(['human_development_index'], ascending=False)).reset_index()
```

4 Data Visualization

[ ]:
```
# basic visualization package
import matplotlib.pyplot as plt
import matplotlib.cm as cm
# advanced ploting
```

```
import seaborn as sns

# interactive visualization
import plotly.express as px
import plotly.graph_objects as go
# import plotly.figure_factory as ff
from plotly.subplots import make_subplots
```

[ ]:
```
def plot_map(df, policy):
    fig = px.choropleth(df, locations=df.Entity,
                        color=policy,
                        range_color=[0,4],
                        locationmode='country names',
                        animation_frame=df["Day"].dt.strftime('%Y-%m-%d'),
                        title='Change Over Time', color_continuous_scale=px.colors.
 ↪sequential.Teal
                        )
    fig.update_layout(coloraxis_showscale=True)
    fig.show()
```

4.1 GDP

[ ]:
```
px.histogram(dd_combine, x=dd_combine['Code'], y=dd_combine['Quarterly GDP␣
 ↪Growth Rate']/8,color=dd_combine['Code'], text_auto=True).update_layout(
    title={"text": '2020-2021 GDP Growth Rate Rank'}, yaxis_title="AVG of GDP␣
 ↪Growth Rate", xaxis_title="Country"
).update_xaxes(categoryorder="total descending")
```

[ ]:
```
fig_gdp = px.line(dd_combine, x= dd_combine.Time, y= dd_combine['Quarterly GDP␣
 ↪Growth Rate'],
                  color= dd_combine.Code,
                  labels={'x':'Time(Quarterly)','y':'% change'},
                  title = '2020-2021 Quarterly GDP', markers=True)
fig_gdp.show()
```

4.2 Policies Change Over Time

4.2.1 1. Facial Covering Policy

[ ]:
```
plot_map(dd_fc, dd_fc.facial_coverings)
```

The color range from dark to light indicates the severity of the policy. Light blue as none to dark blue as the most severe.

We can see that China is the first country in the world to start the facial covering policy. From the end of 2019 to 2021, China's mask policy has always been the highest.

As Covid-19 is spreading around the world, many other countries are also started the facial covering policy.

4.2.2 2. Income Support Policy

[ ]:
```
plot_map(dd_is,dd_is.income_support)
```

In terms of income support, we can see that some countries are doing very well, such as the United States, Canada, and most countries in Europe which have helped people a lot in the first place. Of course, this also promotes their economic to a certain extent.

4.2.3 3. Public Transport Policy

[ ]:
```
plot_map(dd_pt, dd_pt.close_public_transport)
```

4.2.4 4. School and Workplace Closures Policy

[ ]:
```
plot_map(dd_sc, dd_sc.school_closures)
```

4.2.5 5. Vaccination Policy

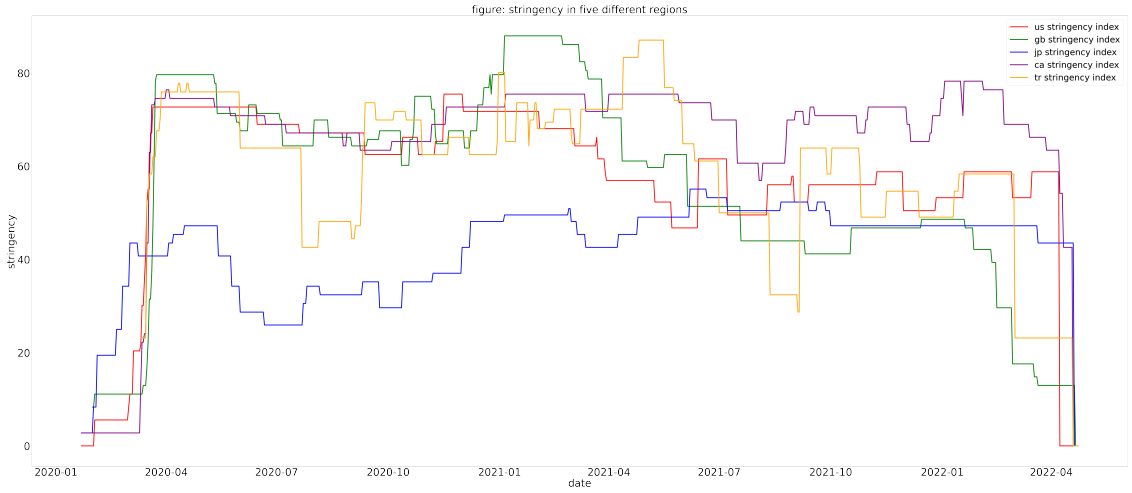
[ ]:
```
plot_map(dd_vp, dd_vp.vaccination_policy)
```

4.2.6 6. Stringency Index

[ ]:
```
plt.figure(figsize=(250,450))
plt.rc('xtick', labelsize=60)
plt.rc('ytick', labelsize=60)
plt.subplot(823)
plt.plot(df_stringency_us['date'], df_stringency_us['us_stringency_index'],␣
 ↪color='red', label='us stringency index', linewidth=5)
plt.plot(df_stringency_gb['date'], df_stringency_gb['gb_stringency_index'],␣
 ↪color='green', label='gb stringency index', linewidth=5)
plt.plot(df_stringency_jp['date'], df_stringency_jp['jp_stringency_index'],␣
 ↪color='blue', label='jp stringency index', linewidth=5)
plt.plot(df_stringency_ca['date'], df_stringency_ca['ca_stringency_index'],␣
 ↪color='purple', label='ca stringency index', linewidth=5)
plt.plot(df_stringency_tr['date'], df_stringency_tr['tr_stringency_index'],␣
 ↪color='orange', label='tr stringency index', linewidth=5)
```

```
plt.legend(prop={'size': 50})
plt.title('figure: stringency in five different regions', fontsize=60)
plt.ylabel('stringency', fontsize=60)
plt.xlabel('date', fontsize=60)
```

[ ]: Text(0.5, 0, 'date')



4.3 Correlation of Policies to GDP

[ ]:
```
policy_corrMatrix = dd_combine.corr()
policy_corrMatrix.compute()
```

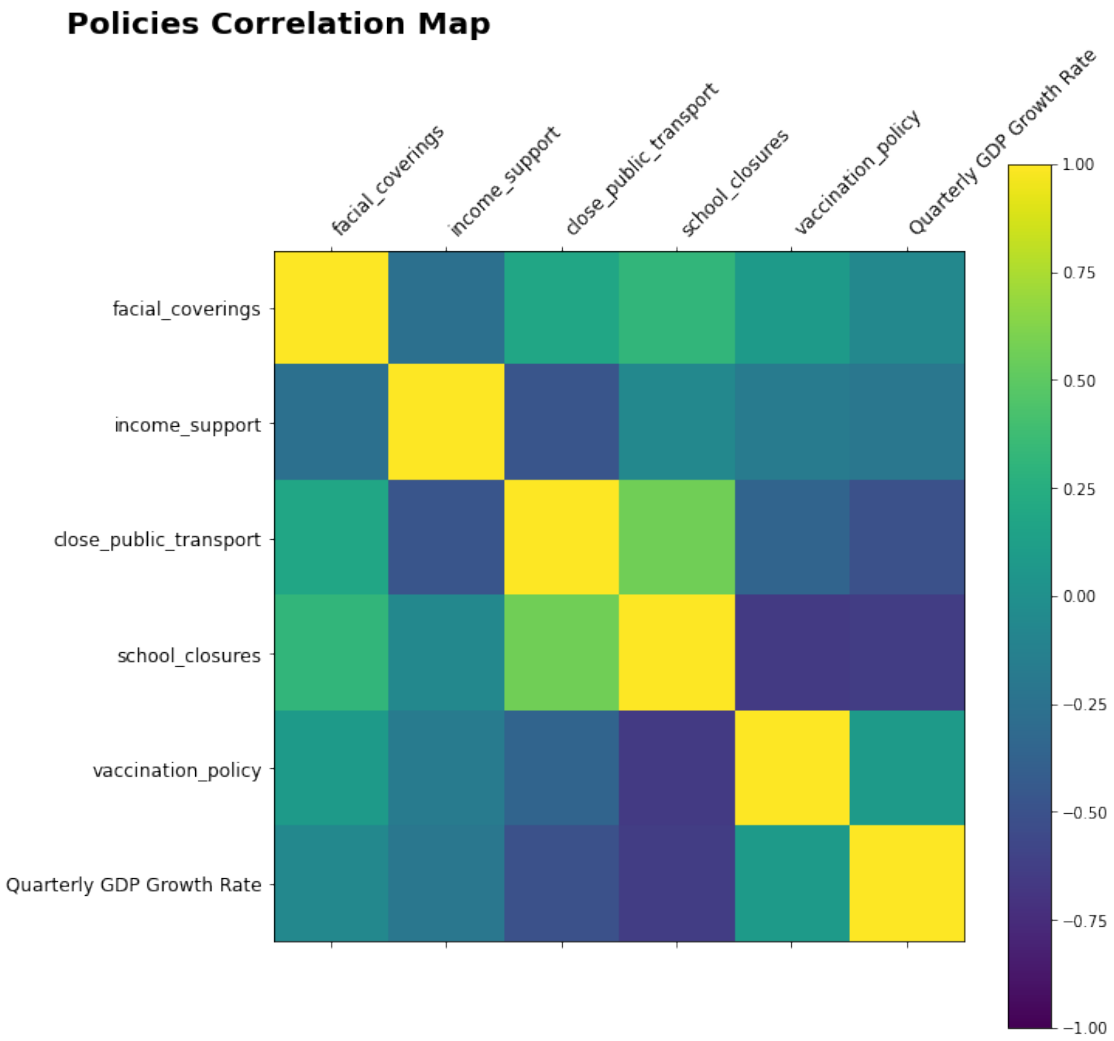
[ ]:

	facial_coverings	income_support	close_public_transport	school_closures	vaccination_policy	Quarterly GDP Growth Rate
facial_coverings	1.000000	0.182133	0.328882	0.415951	0.330302	0.252419
income_support	0.182133	1.000000	-0.029609	0.157894	0.091541	0.056180
close_public_transport	0.328882	-0.029609	1.000000	0.428539	0.055371	-0.030723
school_closures	0.415951	0.157894	0.428539	1.000000	-0.161641	-0.142244
vaccination_policy	0.330302	0.091541	0.055371	-0.161641	1.000000	0.252419
Quarterly GDP Growth Rate	0.252419	0.056180	-0.030723	-0.142244	0.252419	1.000000

facial_coverings	0.330302	0.252419
income_support	0.091541	0.056180
close_public_transport	0.055371	-0.030723
school_closures	-0.161641	-0.142244
vaccination_policy	1.000000	0.137702
Quarterly GDP Growth Rate	0.137702	1.000000

[ ]:
```
from numpy.core.fromnumeric import size
def heat_map(df,title):

    df_Matrix = df.corr()
    plt.figure(figsize=(10,10))
    plt.matshow(df_Matrix,fignum =1)
    plt.xticks(ticks = range(df_Matrix.shape[1]), labels = df_Matrix.columns,␣
↪fontsize = 12, rotation = 45, ha = "left")
    plt.yticks(ticks = range(df_Matrix.shape[1]), labels = df_Matrix.columns,␣
↪fontsize = 12)
    plt.title(f'{title}',y=1.3,x=-0.3,loc='Left',fontweight="bold",size=20)
    plt.clim(-1,1)

    cb = plt.colorbar()
    cb.ax.tick_params(labelsize=10)
```

[ ]:
```
heat_map(policy_corrMatrix, 'Policies Correlation Map')
```



GDP is positively affected by the face-covering policy and the covid vaccination policy. The former has a 0.250567 impact and the latter has a 0.13877 impact.

4.3.1 Policy Rank

[ ]:
```
px.histogram(dd_combine, x=dd_combine['Code'], y=dd_combine['facial_coverings']/
↪8,title='2020-2021 Facial Coverings Policy Rank',color=dd_combine['Code'],␣
↪text_auto=True)\
.update_layout(yaxis_title="AVG of Facial Coverings Policy",␣
↪xaxis_title="Country")\
.update_xaxes(categoryorder="total descending")
```

[ ]:
```

```

```
px.histogram(dd_combine, x=dd_combine['Code'], y=dd_combine['income_support']/
↪8,title='2020-2021 Income Support Policy Rank',color=dd_combine['Code'],␣
↪text_auto=True)\
.update_layout(yaxis_title="AVG of Income Support Policy",␣
↪xaxis_title="Country")\
.update_xaxes(categoryorder="total descending")
```

[ ]:
```
px.histogram(dd_combine, x=dd_combine['Code'], y=dd_combine['school_closures']/
↪8,title='2020-2021 School Closures Policy Rank',color=dd_combine['Code'],␣
↪text_auto=True)\
.update_layout(yaxis_title="AVG of School Closures Policy",␣
↪xaxis_title="Country")\
.update_xaxes(categoryorder="total descending")
```

[ ]:
```
px.histogram(dd_combine, x=dd_combine['Code'],␣
↪y=dd_combine['close_public_transport']/8,title='2020-2021 Close Public␣
↪Transport Policy Rank',color=dd_combine['Code'], text_auto=True)\
.update_layout(yaxis_title="AVG of Close Public Transport Policy",␣
↪xaxis_title="Country")\
.update_xaxes(categoryorder="total descending")
```

[ ]:
```
px.histogram(dd_develop_sort, x=dd_develop_sort['iso_code'],␣
↪y=dd_develop_sort['human_development_index'], text_auto=True).update_layout(
    title={"text": 'human_development_index Rank'},␣
↪yaxis_title="human_development_index", xaxis_title="Country")
```

[ ]:
```
px.histogram(dd_combine, x=dd_combine['Code'],␣
↪y=dd_combine['vaccination_policy']/8,title='2020-2021 Vaccination Policy␣
↪Rank',color=dd_combine['Code'], text_auto=True)\
.update_layout(yaxis_title="AVG of Vaccination Policy", xaxis_title="Country")\
.update_xaxes(categoryorder="total descending")
```

4.3.2 Country Analysis

[ ]:
```
def country_policy_scatter(dd_combine,name):
  dd_target = dd_combine.loc[dd_combine['Code'].isin([name])]
  fig = go.Figure()

  # Add traces
  fig.add_trace(go.Scatter(x=dd_target['Time'],␣
↪y=dd_target['facial_coverings'],mode='lines+markers',name='facial_coverings'))
  fig.add_trace(go.Scatter(x=dd_target['Time'],␣
↪y=dd_target['income_support'],mode='lines+markers',name='income_support'))
  fig.add_trace(go.Scatter(x=dd_target['Time'],␣
↪y=dd_target['close_public_transport'],mode='lines+markers',name='close_public_transport'))
```

```
  fig.add_trace(go.Scatter(x=dd_target['Time'],␣
 ↪y=dd_target['school_closures'],mode='lines+markers',name='school_closures'))
  fig.add_trace(go.Scatter(x=dd_target['Time'],␣
 ↪y=dd_target['vaccination_policy'],mode='lines+markers',name='vaccination_policy'))

  fig.update_layout(
    title=f'{name} 2020-2021 Policy Rank',
    xaxis_title="Time",
    yaxis_title="Policy level"
)
  fig.show()
```

[ ]:
```
country_policy_scatter(dd_combine,'CAN')
```

[ ]:
```
country_policy_scatter(dd_combine,'JPN')
```

[ ]:
```
country_policy_scatter(dd_combine,'USA')
```

[ ]:
```
country_policy_scatter(dd_combine,'TUR')
```

4.4 Policies Impacts to Mobility

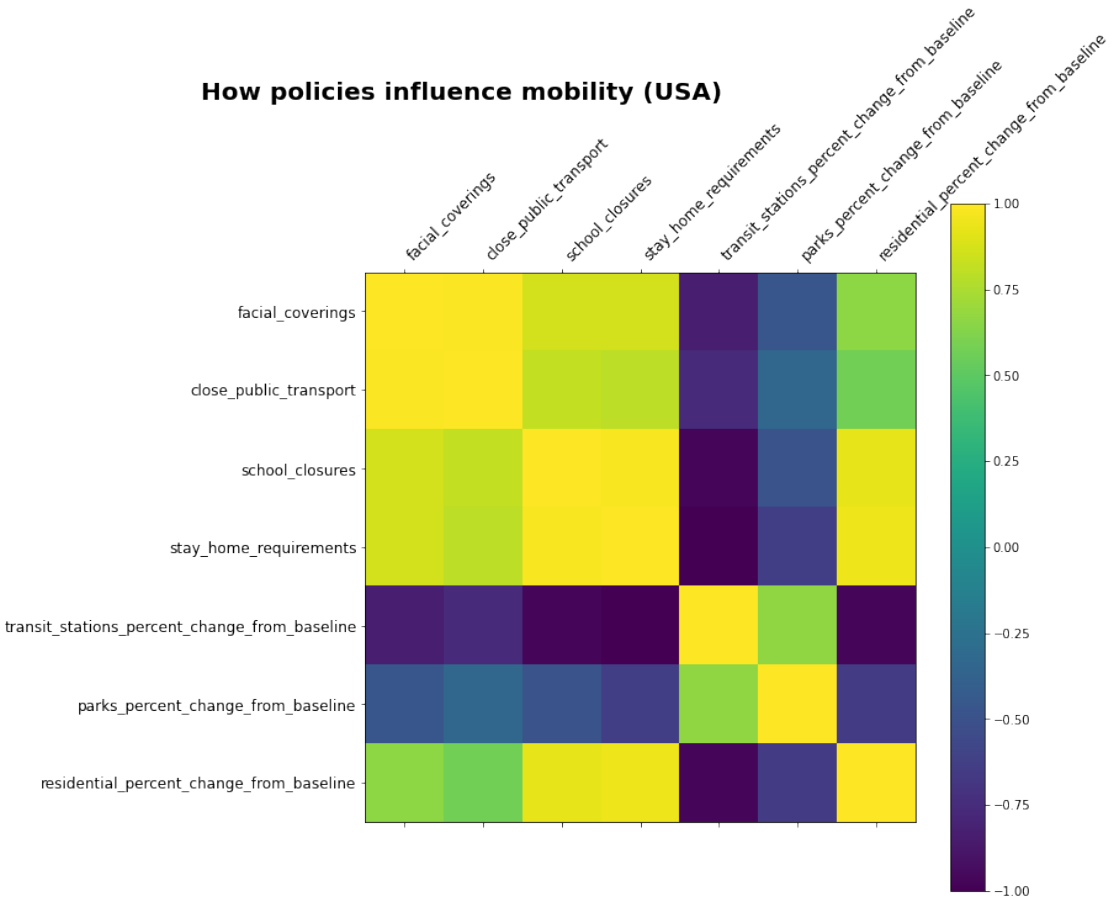
4.4.1 1. Policy Impacts to Mobility

[ ]:
```
df_us_case = df_us_case.compute()
df_us_case['submission_date_str'] = df_us_case['submission_date']
df_us_case['submission_date'] = dd.to_datetime(df_us_case['submission_date'],␣
 ↪infer_datetime_format=True)
df_us_case = df_us_case.sort_values(by='submission_date')
df_us_case.head(100)
fig = px.choropleth(df_us_case,
                    locations='state',
                    locationmode="USA-states",
                    color='tot_cases',
                    color_continuous_scale="Viridis_r",
                    scope="usa",
                    animation_frame='submission_date_str')␣
 ↪#make sure 'period_begin' is string type and sorted in ascending order
fig.show()
```

[ ]:
```
df_us_vaccine = df_us_vaccine.compute()
df_us_vaccine['DateStr'] = df_us_vaccine['Date']
df_us_vaccine['Date'] = dd.to_datetime(df_us_vaccine['Date'],␣
 ↪infer_datetime_format=True)
df_us_vaccine = df_us_vaccine.sort_values(by='Date')
```

```
fig = px.choropleth(df_us_vaccine,
                    locations='Location',
                    locationmode="USA-states",
                    color='Dist_Per_100K',
                    color_continuous_scale="Viridis_r",
                    scope="usa",
                    animation_frame='DateStr') #make sure 'period_begin' is␣
 ↪string type and sorted in ascending order

fig.show()
```

[ ]:
```
combine_US_df =␣
 ↪combine_policy_with_mobility(us_fc_convert,us_pt_convert,us_sc_convert,us_sah_convert,us_tr
policy_corrMatrix_US = combine_US_df.corr()
heat_map(policy_corrMatrix_US, 'How policies influence mobility (USA)')
```



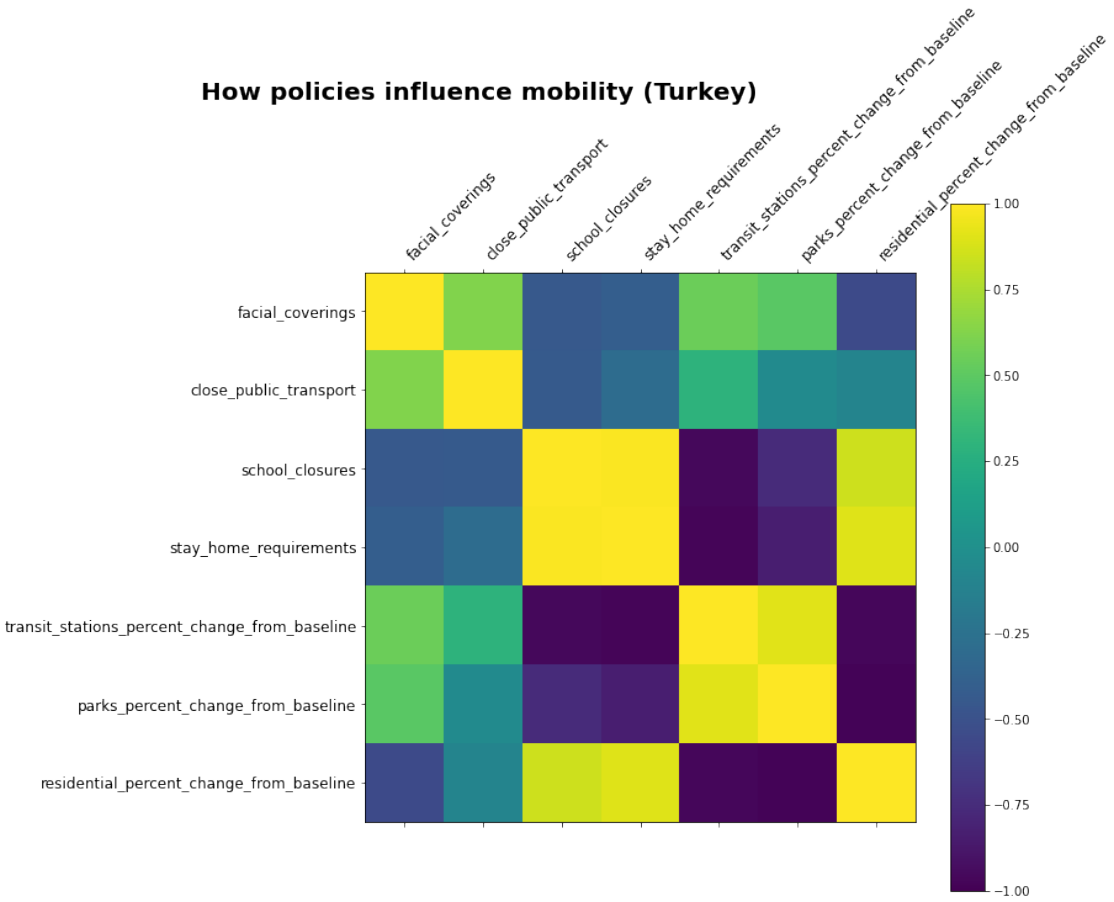
[ ]:
```
combine_TR_df =␣
↪combine_policy_with_mobility(tr_fc_convert,tr_pt_convert,tr_sc_convert,tr_sah_convert,tr_tr
policy_corrMatrix_TR = combine_TR_df.corr()
policy_corrMatrix_TR.compute()
```

[ ]:

```
                                                facial_coverings  \
facial_coverings                                        1.000000
close_public_transport                                  0.570022
school_closures                                         0.061221
stay_home_requirements                                  0.098612
transit_stations_percent_change_from_baseline           0.266954
parks_percent_change_from_baseline                      0.285890
residential_percent_change_from_baseline               -0.314448

                                                close_public_transport  \
facial_coverings                                              0.570022
close_public_transport                                        1.000000
school_closures                                              -0.191578
stay_home_requirements                                       -0.045500
transit_stations_percent_change_from_baseline                 0.201351
parks_percent_change_from_baseline                           -0.128432
residential_percent_change_from_baseline                      0.132637

                                                school_closures  \
facial_coverings                                       0.061221
close_public_transport                                -0.191578
school_closures                                        1.000000
stay_home_requirements                                 0.902259
transit_stations_percent_change_from_baseline         -0.773361
parks_percent_change_from_baseline                    -0.242487
residential_percent_change_from_baseline               0.561045

                                                stay_home_requirements  \
facial_coverings                                              0.098612
close_public_transport                                       -0.045500
school_closures                                               0.902259
stay_home_requirements                                        1.000000
transit_stations_percent_change_from_baseline                -0.872607
parks_percent_change_from_baseline                           -0.419963
residential_percent_change_from_baseline                      0.646110

                                                transit_stations_percent_change_from_baseline  \
facial_coverings
0.266954
close_public_transport
0.201351
school_closures
```

```
-0.773361
stay_home_requirements
-0.872607
transit_stations_percent_change_from_baseline
1.000000
parks_percent_change_from_baseline
0.734920
residential_percent_change_from_baseline
-0.854219

parks_percent_change_from_baseline  \
facial_coverings
0.285890
close_public_transport
-0.128432
school_closures
-0.242487
stay_home_requirements
-0.419963
transit_stations_percent_change_from_baseline
0.734920
parks_percent_change_from_baseline
1.000000
residential_percent_change_from_baseline
-0.861975

residential_percent_change_from_baseline
facial_coverings
-0.314448
close_public_transport
0.132637
school_closures
0.561045
stay_home_requirements
0.646110
transit_stations_percent_change_from_baseline
-0.854219
parks_percent_change_from_baseline
-0.861975
residential_percent_change_from_baseline
1.000000
```

[ ]:
```
heat_map(policy_corrMatrix_TR,'How policies influence mobility (Turkey)')
```



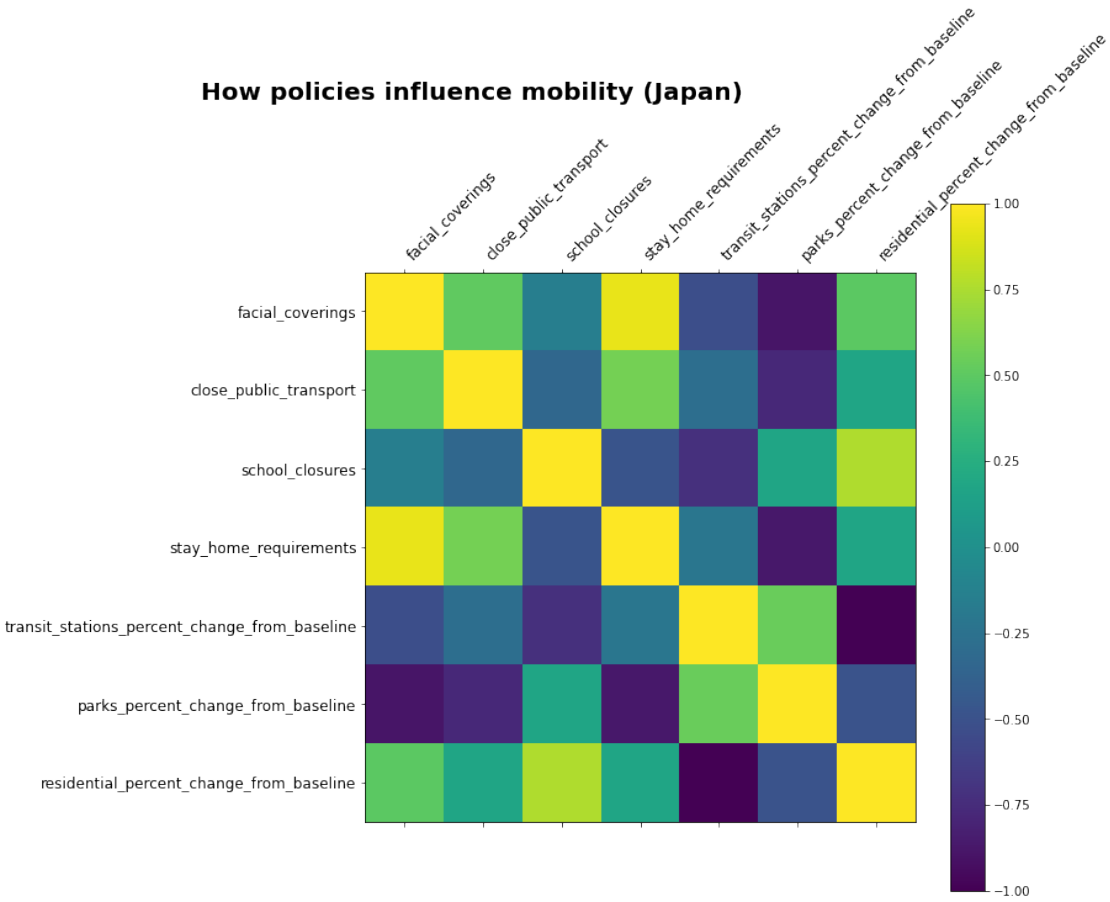
[ ]:
```
combine_JP_df =␣
↪combine_policy_with_mobility(jp_fc_convert,jp_pt_convert,jp_sc_convert,jp_sah_convert,jp_tr
policy_corrMatrix_JP = combine_JP_df.corr()
policy_corrMatrix_JP.compute()
```

[ ]:
```
                                                facial_coverings  \
facial_coverings                                        1.000000
close_public_transport                                  0.211227
school_closures                                        -0.085827
stay_home_requirements                                  0.876412
transit_stations_percent_change_from_baseline          -0.372120
parks_percent_change_from_baseline                     -0.477824
residential_percent_change_from_baseline                0.389551

                                                close_public_transport  \
facial_coverings                                              0.211227
close_public_transport                                        1.000000
school_closures                                              -0.240949
stay_home_requirements                                        0.248470
```

```
transit_stations_percent_change_from_baseline              -0.211092
parks_percent_change_from_baseline                         -0.475103
residential_percent_change_from_baseline                    0.049246

                                                    school_closures  \
facial_coverings                                          -0.085827
close_public_transport                                    -0.240949
school_closures                                            1.000000
stay_home_requirements                                    -0.437628
transit_stations_percent_change_from_baseline             -0.672302
parks_percent_change_from_baseline                         0.230306
residential_percent_change_from_baseline                   0.716400

                                                    stay_home_requirements  \
facial_coverings                                                  0.876412
close_public_transport                                            0.248470
school_closures                                                  -0.437628
stay_home_requirements                                            1.000000
transit_stations_percent_change_from_baseline                    -0.105036
parks_percent_change_from_baseline                               -0.657895
residential_percent_change_from_baseline                          0.100117

transit_stations_percent_change_from_baseline  \
facial_coverings
-0.372120
close_public_transport
-0.211092
school_closures
-0.672302
stay_home_requirements
-0.105036
transit_stations_percent_change_from_baseline
1.000000
parks_percent_change_from_baseline
0.406230
residential_percent_change_from_baseline
-0.974913

parks_percent_change_from_baseline  \
facial_coverings
-0.477824
close_public_transport
-0.475103
school_closures
0.230306
stay_home_requirements
-0.657895
```

```
transit_stations_percent_change_from_baseline
0.406230
parks_percent_change_from_baseline
1.000000
residential_percent_change_from_baseline
-0.356409

residential_percent_change_from_baseline
facial_coverings
0.389551
close_public_transport
0.049246
school_closures
0.716400
stay_home_requirements
0.100117
transit_stations_percent_change_from_baseline
-0.974913
parks_percent_change_from_baseline
-0.356409
residential_percent_change_from_baseline
1.000000
```

[ ]:
```
heat_map(policy_corrMatrix_JP,'How policies influence mobility (Japan)')
```

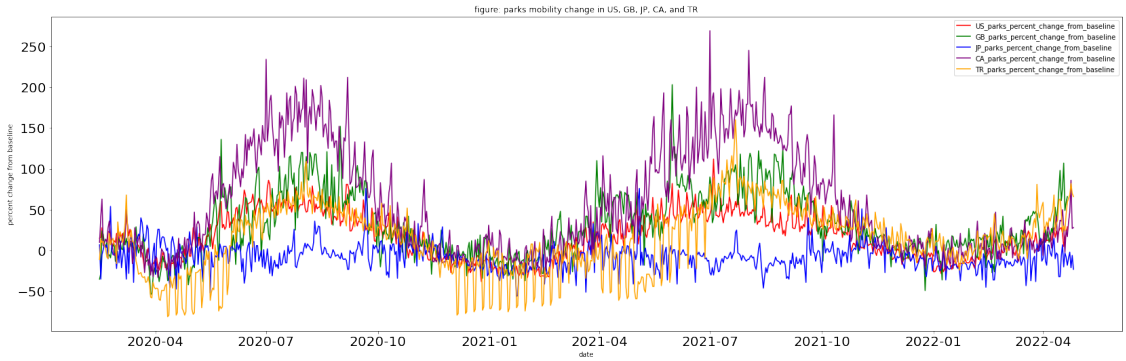


4.4.2 2. Parks Mobility

[ ]:
```
plt.figure(figsize=(300, 70))
plt.rc('xtick', labelsize=20)
plt.rc('ytick', labelsize=20)
plt.subplot(797)
plt.plot(df_us_mobility['date'],␣
 ↪df_us_mobility['parks_percent_change_from_baseline'], color="red",␣
 ↪label='US_parks_percent_change_from_baseline')
plt.plot(df_gb_mobility['date'],␣
 ↪df_gb_mobility['parks_percent_change_from_baseline'], color="green",␣
 ↪label='GB_parks_percent_change_from_baseline')
plt.plot(df_jp_mobility['date'],␣
 ↪df_jp_mobility['parks_percent_change_from_baseline'], color="blue",␣
 ↪label='JP_parks_percent_change_from_baseline')
```

```
plt.plot(df_ca_mobility['date'],␣
 ↪df_ca_mobility['parks_percent_change_from_baseline'], color="purple",␣
 ↪label='CA_parks_percent_change_from_baseline')
plt.plot(df_tr_mobility['date'],␣
 ↪df_tr_mobility['parks_percent_change_from_baseline'], color="orange",␣
 ↪label='TR_parks_percent_change_from_baseline')

plt.legend()
plt.title('figure: parks mobility change in US, GB, JP, CA, and TR')
plt.ylabel('percent change from baseline')
plt.xlabel('date')
```

[ ]: Text(0.5, 0, 'date')

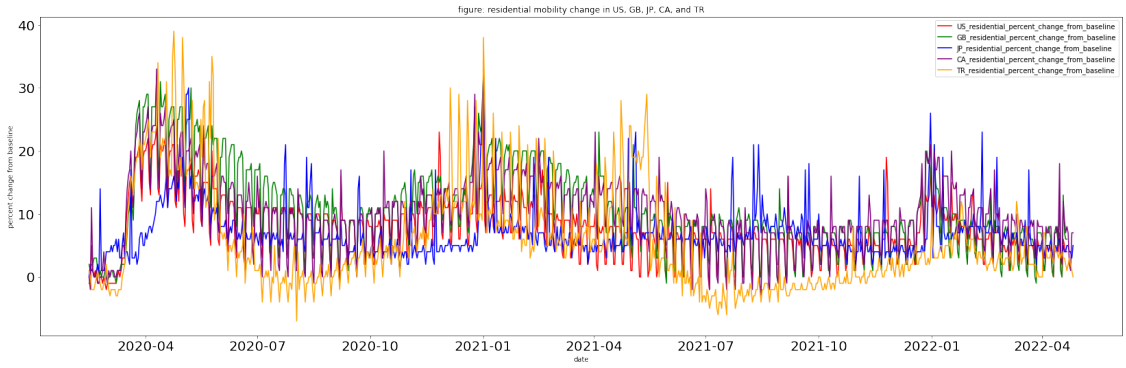


4.4.3 3. Residential Mobility

[ ]:
```
plt.figure(figsize=(300, 70))
plt.rc('xtick', labelsize=20)
plt.rc('ytick', labelsize=20)
plt.subplot(797)
plt.plot(df_us_mobility['date'],␣
 ↪df_us_mobility['residential_percent_change_from_baseline'], color="red",␣
 ↪label='US_residential_percent_change_from_baseline')
plt.plot(df_gb_mobility['date'],␣
 ↪df_gb_mobility['residential_percent_change_from_baseline'], color="green",␣
 ↪label='GB_residential_percent_change_from_baseline')
plt.plot(df_jp_mobility['date'],␣
 ↪df_jp_mobility['residential_percent_change_from_baseline'], color="blue",␣
 ↪label='JP_residential_percent_change_from_baseline')
plt.plot(df_ca_mobility['date'],␣
 ↪df_ca_mobility['residential_percent_change_from_baseline'], color="purple",␣
 ↪label='CA_residential_percent_change_from_baseline')
```

```
plt.plot(df_tr_mobility['date'],␣
 ↪df_tr_mobility['residential_percent_change_from_baseline'], color="orange",␣
 ↪label='TR_residential_percent_change_from_baseline')

plt.legend()
plt.title('figure: residential mobility change in US, GB, JP, CA, and TR')
plt.ylabel('percent change from baseline')
plt.xlabel('date')
```

[ ]: Text(0.5, 0, 'date')

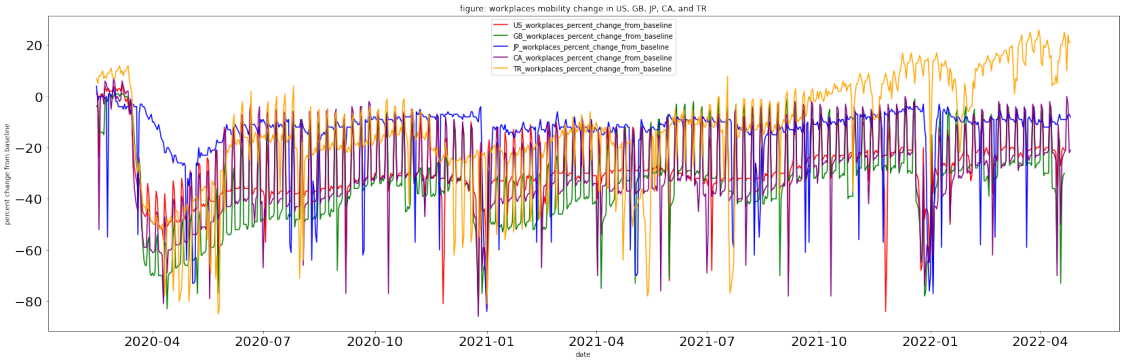


4.4.4 4. Workplaces Mobility

[ ]:
```
plt.figure(figsize=(300, 70))
plt.rc('xtick', labelsize=20)
plt.rc('ytick', labelsize=20)
plt.subplot(797)
plt.plot(df_us_mobility['date'],␣
 ↪df_us_mobility['workplaces_percent_change_from_baseline'], color="red",␣
 ↪label='US_workplaces_percent_change_from_baseline')
plt.plot(df_gb_mobility['date'],␣
 ↪df_gb_mobility['workplaces_percent_change_from_baseline'], color="green",␣
 ↪label='GB_workplaces_percent_change_from_baseline')
plt.plot(df_jp_mobility['date'],␣
 ↪df_jp_mobility['workplaces_percent_change_from_baseline'], color="blue",␣
 ↪label='JP_workplaces_percent_change_from_baseline')
plt.plot(df_ca_mobility['date'],␣
 ↪df_ca_mobility['workplaces_percent_change_from_baseline'], color="purple",␣
 ↪label='CA_workplaces_percent_change_from_baseline')
plt.plot(df_tr_mobility['date'],␣
 ↪df_tr_mobility['workplaces_percent_change_from_baseline'], color="orange",␣
 ↪label='TR_workplaces_percent_change_from_baseline')
```

```
plt.legend()
plt.title('figure: workplaces mobility change in US, GB, JP, CA, and TR')
plt.ylabel('percent change from baseline')
plt.xlabel('date')
```

[ ]: Text(0.5, 0, 'date')

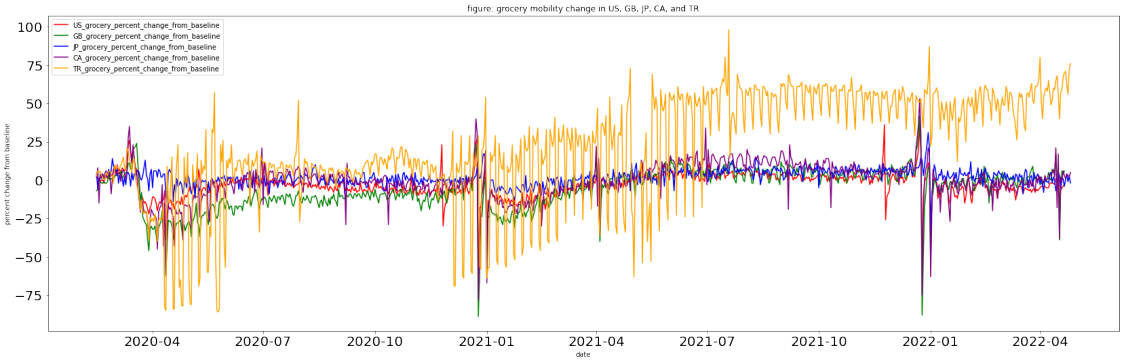


4.4.5 5. Grocery Mobility

[ ]:
```
plt.figure(figsize=(300, 70))
plt.rc('xtick', labelsize=20)
plt.rc('ytick', labelsize=20)
plt.subplot(797)
plt.plot(df_us_mobility['date'],␣
 ↪df_us_mobility['grocery_and_pharmacy_percent_change_from_baseline'],␣
 ↪color="red", label='US_grocery_percent_change_from_baseline')
plt.plot(df_gb_mobility['date'],␣
 ↪df_gb_mobility['grocery_and_pharmacy_percent_change_from_baseline'],␣
 ↪color="green", label='GB_grocery_percent_change_from_baseline')
plt.plot(df_jp_mobility['date'],␣
 ↪df_jp_mobility['grocery_and_pharmacy_percent_change_from_baseline'],␣
 ↪color="blue", label='JP_grocery_percent_change_from_baseline')
plt.plot(df_ca_mobility['date'],␣
 ↪df_ca_mobility['grocery_and_pharmacy_percent_change_from_baseline'],␣
 ↪color="purple", label='CA_grocery_percent_change_from_baseline')
plt.plot(df_tr_mobility['date'],␣
 ↪df_tr_mobility['grocery_and_pharmacy_percent_change_from_baseline'],␣
 ↪color="orange", label='TR_grocery_percent_change_from_baseline')

plt.legend()
plt.title('figure: grocery mobility change in US, GB, JP, CA, and TR')
```

```
plt.ylabel('percent change from baseline')
plt.xlabel('date')
```

[ ]: Text(0.5, 0, 'date')



4.5 Mobility to GDP

4.5.1 1. GDP in five countries

[ ]:
```
fig_gdp = px.line(dd_five, x= dd_five.TIME, y= dd_five.Value,
                  color= dd_five.Code,
                  labels={'x':'Time(Quarterly)','y':'% change'},
                  title = '2019-2021 Quarterly GDP', markers=True)
fig_gdp.show()
```

4.5.2 2. Mobility to GDP in Turkey

[ ]:
```
def country_mobility_scatter(dd_trans, dd_park, dd_resid, dd_workplace,␣
↪dd_grocery, name):
 fig = go.Figure()

 # Add traces
 fig.add_trace(go.Scatter(x=dd_trans['Time'],␣
↪y=dd_trans['transit_stations_percent_change_from_baseline'],mode='lines+markers',name='tran
 fig.add_trace(go.Scatter(x=dd_park['Time'],␣
↪y=dd_park['parks_percent_change_from_baseline'],mode='lines+markers',name='parks_percent_ch
 fig.add_trace(go.Scatter(x=dd_resid['Time'],␣
↪y=dd_resid['residential_percent_change_from_baseline'],mode='lines+markers',name='residenti
 fig.add_trace(go.Scatter(x=dd_workplace['Time'],␣
↪y=dd_workplace['workplaces_percent_change_from_baseline'],mode='lines+markers',name='workpl
```

```
  fig.update_layout(
    title=f'{name} 2020-2022 Mobility change',
    xaxis_title="Time",
    yaxis_title="Mobility change"
)
  fig.show()
```

[ ]:
```
country_mobility_scatter(tr_transit_convert, tr_park_convert,␣
↪tr_residential_convert, tr_workplace_convert, tr_grocery_convert,'Turkey')
```

[ ]:
```
combine_tr_mobility_gdp =␣
↪combine_mobility_with_GDP(tr_stringency_convert,tr_transit_convert,tr_park_convert,tr_resid
↪
corrMatrix_TR_GDP = combine_tr_mobility_gdp.corr()
corrMatrix_TR_GDP.compute()
```

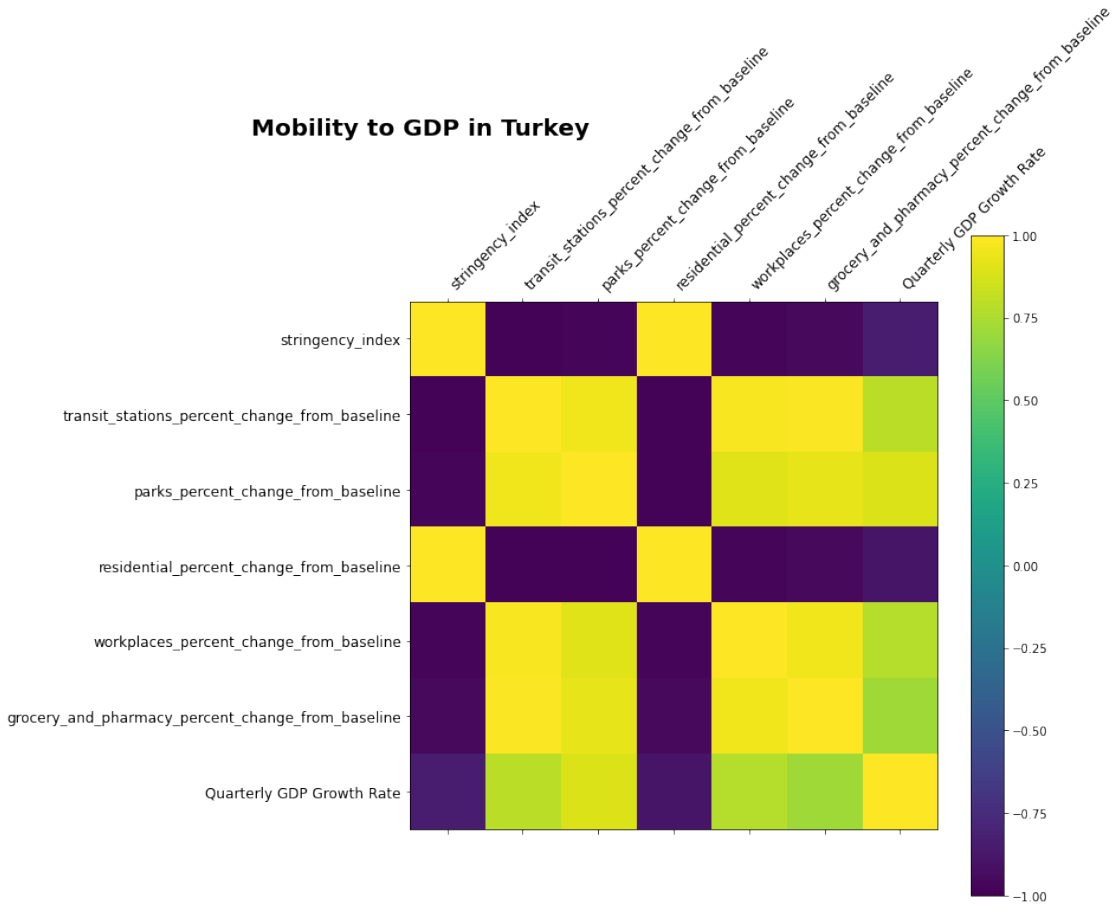
[ ]:
```
                                                stringency_index  \
stringency_index                                        1.000000
transit_stations_percent_change_from_baseline          -0.799876
parks_percent_change_from_baseline                     -0.775071
residential_percent_change_from_baseline                0.888529
workplaces_percent_change_from_baseline                -0.762960
grocery_and_pharmacy_percent_change_from_baseline      -0.568602
Quarterly GDP Growth Rate                              -0.434208

                                                transit_stations_percent_change_from_baseline  \
stringency_index
-0.799876
transit_stations_percent_change_from_baseline
1.000000
parks_percent_change_from_baseline
0.758519
residential_percent_change_from_baseline
-0.908267
workplaces_percent_change_from_baseline
0.860580
grocery_and_pharmacy_percent_change_from_baseline
0.935902
Quarterly GDP Growth Rate
0.403217

                                                parks_percent_change_from_baseline  \
stringency_index
-0.775071
transit_stations_percent_change_from_baseline
0.758519
parks_percent_change_from_baseline
```

```
1.000000
residential_percent_change_from_baseline
-0.881647
workplaces_percent_change_from_baseline
0.460667
grocery_and_pharmacy_percent_change_from_baseline
0.660931
Quarterly GDP Growth Rate
0.615187

residential_percent_change_from_baseline  \
stringency_index
0.888529
transit_stations_percent_change_from_baseline
-0.908267
parks_percent_change_from_baseline
-0.881647
residential_percent_change_from_baseline
1.000000
workplaces_percent_change_from_baseline
-0.797226
grocery_and_pharmacy_percent_change_from_baseline
-0.746038
Quarterly GDP Growth Rate
-0.685645

workplaces_percent_change_from_baseline  \
stringency_index
-0.762960
transit_stations_percent_change_from_baseline
0.860580
parks_percent_change_from_baseline
0.460667
residential_percent_change_from_baseline
-0.797226
workplaces_percent_change_from_baseline
1.000000
grocery_and_pharmacy_percent_change_from_baseline
0.695333
Quarterly GDP Growth Rate
0.386329

grocery_and_pharmacy_percent_change_from_baseline  \
stringency_index
-0.568602
transit_stations_percent_change_from_baseline
0.935902
```

```
parks_percent_change_from_baseline
0.660931
residential_percent_change_from_baseline
-0.746038
workplaces_percent_change_from_baseline
0.695333
grocery_and_pharmacy_percent_change_from_baseline
1.000000
Quarterly GDP Growth Rate
0.229598
```

	Quarterly GDP Growth Rate
stringency_index	-0.434208
transit_stations_percent_change_from_baseline	0.403217
parks_percent_change_from_baseline	0.615187
residential_percent_change_from_baseline	-0.685645
workplaces_percent_change_from_baseline	0.386329
grocery_and_pharmacy_percent_change_from_baseline	0.229598
Quarterly GDP Growth Rate	1.000000

[ ]:
```
heat_map(corrMatrix_TR_GDP, 'Mobility to GDP in Turkey')
```



4.5.3 3. Mobility to GDP in Japan

[ ]:
```
country_mobility_scatter(jp_transit_convert, jp_park_convert,␣
↪jp_residential_convert, jp_workplace_convert, jp_grocery_convert,'Japan')
```

[ ]:
```
combine_jp_mobility_gdp =␣
↪combine_mobility_with_GDP(jp_stringency_convert,jp_transit_convert,jp_park_convert,jp_resid
↪
corrMatrix_JP_GDP = combine_jp_mobility_gdp.corr()
corrMatrix_JP_GDP.compute()
```

[ ]:
```
                                                    stringency_index  \
stringency_index                                            1.000000
transit_stations_percent_change_from_baseline              -0.294161
parks_percent_change_from_baseline                         -0.768314
residential_percent_change_from_baseline                    0.272136
workplaces_percent_change_from_baseline                    -0.367624
grocery_and_pharmacy_percent_change_from_baseline           0.235336
Quarterly GDP Growth Rate                                  -0.179369

transit_stations_percent_change_from_baseline  \
stringency_index
-0.294161
transit_stations_percent_change_from_baseline
1.000000
parks_percent_change_from_baseline
0.490539
residential_percent_change_from_baseline
-0.974447
workplaces_percent_change_from_baseline
0.924055
grocery_and_pharmacy_percent_change_from_baseline
0.534635
Quarterly GDP Growth Rate
0.695671

parks_percent_change_from_baseline  \
stringency_index
-0.768314
transit_stations_percent_change_from_baseline
0.490539
parks_percent_change_from_baseline
1.000000
```

```
residential_percent_change_from_baseline
-0.384019
workplaces_percent_change_from_baseline
0.490904
grocery_and_pharmacy_percent_change_from_baseline
0.312015
Quarterly GDP Growth Rate
0.155644

residential_percent_change_from_baseline  \
stringency_index
0.272136
transit_stations_percent_change_from_baseline
-0.974447
parks_percent_change_from_baseline
-0.384019
residential_percent_change_from_baseline
1.000000
workplaces_percent_change_from_baseline
-0.940619
grocery_and_pharmacy_percent_change_from_baseline
-0.390237
Quarterly GDP Growth Rate
-0.720047

workplaces_percent_change_from_baseline  \
stringency_index
-0.367624
transit_stations_percent_change_from_baseline
0.924055
parks_percent_change_from_baseline
0.490904
residential_percent_change_from_baseline
-0.940619
workplaces_percent_change_from_baseline
1.000000
grocery_and_pharmacy_percent_change_from_baseline
0.409604
Quarterly GDP Growth Rate
0.461258

grocery_and_pharmacy_percent_change_from_baseline  \
stringency_index
0.235336
transit_stations_percent_change_from_baseline
0.534635
parks_percent_change_from_baseline
```

```
0.312015
residential_percent_change_from_baseline
-0.390237
workplaces_percent_change_from_baseline
0.409604
grocery_and_pharmacy_percent_change_from_baseline
1.000000
Quarterly GDP Growth Rate
0.172966
```

	Quarterly GDP Growth Rate
stringency_index	-0.179369
transit_stations_percent_change_from_baseline	0.695671
parks_percent_change_from_baseline	0.155644
residential_percent_change_from_baseline	-0.720047
workplaces_percent_change_from_baseline	0.461258
grocery_and_pharmacy_percent_change_from_baseline	0.172966
Quarterly GDP Growth Rate	1.000000

[ ]:
```
heat_map(corrMatrix_JP_GDP, 'Mobility to GDP in Japan')
```