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```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
```

Data wrangling

Datasets

1. Data on COVID-19 from Our World in Data Their complete dataset contains a lot of information including the number of deaths, cases, vaccinations, hospitalizations, and several other country-specific pieces of information relevant to understanding the effects of COVID. Note that you can read the "raw" CSV file from a URL directly, like so: pd.read_csv("https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/owid-covid-data.csv")

```
df_covid = pd.read_csv(
"https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/owid-covid-data.csv"
)
df_covid['date'] = pd.to_datetime(df_covid['date'])

# Display the first few rows
df_covid.head()
```

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed	total_c
0	AFG	Asia	Afghanistan	2020-01-05	0.0	0.0	NaN	0.0
1	AFG	Asia	Afghanistan	2020-01-06	0.0	0.0	NaN	0.0
2	AFG	Asia	Afghanistan	2020-01-07	0.0	0.0	NaN	0.0
3	AFG	Asia	Afghanistan	2020-01-08	0.0	0.0	NaN	0.0
4	AFG	Asia	Afghanistan	2020-01-09	0.0	0.0	NaN	0.0

2. Population estimates from The World Bank Group's DataBank

```
import pandas as pd

url_population =
"https://docs.google.com/spreadsheets/d/1TTtVxlJWiE7iGpaPRFy1EQ85AMQczZOvTr6kSx4Nxsk/export?fo
df_population = pd.read_csv(url_population)

# Display the first few rows
df_population.head()
```

	Country Name	Country Code	Series Name	Series Code	2022 [YR2022]
0	Afghanistan	AFG	Population ages 80 and above, female	SP.POP.80UP.FE	62400
1	Afghanistan	AFG	Population ages 80 and above, male	SP.POP.80UP.MA	41192
2	Afghanistan	AFG	Rural population	SP.RUR.TOTL	29778377
3	Afghanistan	AFG	Urban population	SP.URB.TOTL	10800465
4	Afghanistan	AFG	Population ages 65 and above, total	SP.POP.65UP.TO	955689

```
# these are all the Series (variables) that I selected relevant to predicting
death from COVID
df_population['Series Name'].unique()
```

```
array(['Population ages 80 and above, female',
       'Population ages 80 and above, male', 'Rural population',
       'Urban population', 'Population ages 65 and above, total',
       'Population ages 65 and above, male',
       'Population ages 65 and above, female'], dtype=object)
```

a) read the two data files using pd.read_csv()

```
#1st dataset
df_covid = pd.read_csv(
"https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/owid-covid-data.csv"
)
df_covid['date'] = pd.to_datetime(df_covid['date'])

#2nd dataset
url_population =
"https://docs.google.com/spreadsheets/d/1O-GjD1mzku9RLnfqDpeRbJ4xfoiTMZzkx6iexe7o1bc/export?fo
df_population = pd.read_csv(url_population)
```

b) Keep only country-level data by removing all rows where the country_code is not exactly 3 letters (these represent larger regions like continents). Hint: .str.len() returns the number of characters.

```
df_covid = df_covid[df_covid['iso_code'].str.len() == 3]
```

c) Remove countries whose total population is less than 1 million.

```
df_covid = df_covid[df_covid['population'] >= 1_000_000]
```

d) Add a new column new_deaths_smoothed_2wk that has the same values as new_deaths_smoothed but two weeks ahead (will be used for linear modeling as described later). Pandas has a pd.to_datetime() function and pd.Timedelta object that enable calculations with dates like .assign(date=date - pd.Timedelta(14)) and .query('date >= "2023-01-01" ').

```
# Ensures date -> datetime type
df_covid['date'] = pd.to_datetime(df_covid['date'])


# Create shifted deaths column
df_shifted = (
    df_covid[['iso_code', 'date', 'new_deaths_smoothed']].copy()
    .dropna(subset=['new_deaths_smoothed'])  #drop missing deaths
    .assign(date=lambda x: x['date'] - pd.Timedelta(days=14))
    .drop_duplicates(subset=['iso_code', 'date'])
    .rename(columns={'new_deaths_smoothed': 'new_deaths_smoothed_2wk'})
)

df_covid = df_covid.drop(
    columns=['new_deaths_smoothed_2wk'], errors='ignore'
)

# now merge
df_covid = pd.merge(
    df_covid,
    df_shifted,
    on=['iso_code', 'date'],
    how='left'
)
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a
  df_covid['date'] = pd.to_datetime(df_covid['date'])
```

e) tidy tables, as needed. (Hint: only the population data is not tidy.)

```
df_population_tidy = (
    df_population[['Country Code', 'Series Name', '2023 [YR2023]']]
    .pivot(index='Country Code', columns='Series Name', values='2023 [YR2023]')
    .reset_index()
)
```

f) Merge the tables (Hint: merge using the 3-letter ISO code)

```
df_final = pd.merge(
    df_covid,
    df_population_tidy,
    left_on='iso_code',
    right_on='Country Code',
    how='inner'
).drop(columns=['Country Code'])
```

```
# --- Final cleanup before modeling ---

columns_to_drop = ['location_y', 'continent', 'Unnamed: 0']  # Add more if you
spot any extras
df_final = df_final.drop(columns=[col for col in columns_to_drop if col in
df_final.columns])

if 'location_x' in df_final.columns:
    df_final = df_final.rename(columns={'location_x': 'location'})

df_final['date'] = pd.to_datetime(df_final['date'])

duplicates = df_final.duplicated(subset=['iso_code', 'date'])
print(f"Duplicate rows found: {duplicates.sum()}")
df_final = df_final.drop_duplicates(subset=['iso_code', 'date'])

key_vars = [
    'new_cases_smoothed',
    'new_deaths_smoothed_2wk',
    'gdp_per_capita',
    'diabetes_prevalence',
    #'icu_patients',
    'population',
    'Population ages 80 and above, female',
    'Population ages 80 and above, male'
]

missing_cols = [col for col in key_vars if col not in df_final.columns]
print("Missing columns:", missing_cols)

print("\nProportion of missing values in key variables:")
```

```
print(df_final[[col for col in key_vars if col in
df_final.columns]].isna().mean().sort_values(ascending=False))

df_final.to_csv("cleaned_df_final.csv", index=False)
```

```
Duplicate rows found: 1014
Missing columns: []

Proportion of missing values in key variables:
gdp_per_capita                            0.025312
new_deaths_smoothed_2wk                   0.019275
new_cases_smoothed                        0.015643
diabetes_prevalence                       0.006328
population                                0.000000
Population ages 80 and above, female      0.000000
Population ages 80 and above, male        0.000000
dtype: float64
```

```
# columns to preview
columns_to_display = [
    'iso_code', 'location', 'date', 'new_deaths_smoothed_2wk',
    'new_cases', 'new_cases_smoothed', 'total_vaccinations'
]

# adds population predictors
predictor_columns = df_population_tidy.columns.difference(['Country
Code']).tolist()
columns_to_display += predictor_columns[:5]

# display first few rows
df_final[columns_to_display]
```

	iso_code	location	date	new_deaths_smoothed_2wk	new_cases	new_cases_smooth
0	AFG	Afghanistan	2020-01-05	0.0	0.0	NaN
1	AFG	Afghanistan	2020-01-06	0.0	0.0	NaN
2	AFG	Afghanistan	2020-01-07	0.0	0.0	NaN
3	AFG	Afghanistan	2020-01-08	0.0	0.0	NaN
4	AFG	Afghanistan	2020-01-09	0.0	0.0	NaN
...	...	...	...	...	...	...
265544	ZWE	Zimbabwe	2024-07-31	NaN	0.0	0.0
265545	ZWE	Zimbabwe	2024-08-01	NaN	0.0	0.0
265546	ZWE	Zimbabwe	2024-08-02	NaN	0.0	0.0
265547	ZWE	Zimbabwe	2024-08-03	NaN	0.0	0.0
265548	ZWE	Zimbabwe	2024-08-04	NaN	0.0	0.0

```
# Assuming df_final and df_population_tidy are already defined as in your
previous code

# Remove the redundant 'Country Code' column resulting from the merge
if 'Country Code' in df_final.columns:
    df_final = df_final.drop(columns=['Country Code'])

# Filter for the desired columns after the merge
columns_to_display = [
    'iso_code', 'location', 'date', 'new_deaths_smoothed_2wk',
    'new_cases', 'new_cases_smoothed', 'total_vaccinations'
]
# adds population predictors - this needs to be adapted to your actual column
names in df_population_tidy
# for example, instead of 'SP.DYN.LE00.IN' the correct name might be 'Life
expectancy at birth, total (years)'
# Get a list of available predictor columns from df_population_tidy
available_predictor_columns = list(set(df_population_tidy.columns) &
set(df_final.columns))
available_predictor_columns = [col for col in available_predictor_columns if col
not in ['Country Code', 'Series Name', '2023 [YR2023]']]
# Add available predictor columns to columns_to_display
columns_to_display.extend(available_predictor_columns)

# Display the selected columns for the first few rows of the DataFrame
display(df_final[columns_to_display])
```

	iso_code	location	date	new_deaths_smoothed_2wk	new_cases	new_cases_smooth
0	AFG	Afghanistan	2020-01-05	0.0	0.0	NaN
1	AFG	Afghanistan	2020-01-06	0.0	0.0	NaN
2	AFG	Afghanistan	2020-01-07	0.0	0.0	NaN
3	AFG	Afghanistan	2020-01-08	0.0	0.0	NaN
4	AFG	Afghanistan	2020-01-09	0.0	0.0	NaN
...	...	...	...	...	...	...
265544	ZWE	Zimbabwe	2024-07-31	NaN	0.0	0.0
265545	ZWE	Zimbabwe	2024-08-01	NaN	0.0	0.0
265546	ZWE	Zimbabwe	2024-08-02	NaN	0.0	0.0
265547	ZWE	Zimbabwe	2024-08-03	NaN	0.0	0.0
265548	ZWE	Zimbabwe	2024-08-04	NaN	0.0	0.0

Linear modeling

The goal is to predict new_deaths_smoothed two weeks in the future. Hint: this is the dependent variable.

a) Make a list of all predictor variables that are available. The challenge is to identify which combination of these predictors will give the best predictive model.

```
numeric_cols = df_final.select_dtypes(include=[np.number]).columns.tolist()
predictor_vars = [col for col in numeric_cols if col !=
'new_deaths_smoothed_2wk']
print("Available predictor variables:")
for v in predictor_vars:
    print(" •", v)
```

```
Available predictor variables:
```

- total_cases
- new_cases
- new_cases_smoothed
- total_deaths
- new_deaths
- new_deaths_smoothed
- total_cases_per_million
- new_cases_per_million
- new_cases_smoothed_per_million
- total_deaths_per_million
- new_deaths_per_million
- new_deaths_smoothed_per_million
- reproduction_rate
- icu_patients
- icu_patients_per_million
- hosp_patients
- hosp_patients_per_million
- weekly_icu_admissions
- weekly_icu_admissions_per_million
- weekly_hosp_admissions
- weekly_hosp_admissions_per_million
- total_tests
- new_tests
- total_tests_per_thousand
- new_tests_per_thousand
- new_tests_smoothed
- new_tests_smoothed_per_thousand
- positive_rate
- tests_per_case
- total_vaccinations
- people_vaccinated
- people_fully_vaccinated
- total_boosters
- new_vaccinations
- new_vaccinations_smoothed
- total_vaccinations_per_hundred
- people_vaccinated_per_hundred

- people_fully_vaccinated_per_hundred
- total_boosters_per_hundred
- new_vaccinations_smoothed_per_million
- new_people_vaccinated_smoothed
- new_people_vaccinated_smoothed_per_hundred
- stringency_index
- population_density
- median_age
- aged_65_older
- aged_70_older
- gdp_per_capita
- extreme_poverty
- cardiovasc_death_rate
- diabetes_prevalence
- female_smokers
- male_smokers
- handwashing_facilities
- hospital_beds_per_thousand
- life_expectancy
- human_development_index
- population
- excess_mortality_cumulative_absolute
- excess_mortality_cumulative
- excess_mortality
- excess_mortality_cumulative_per_million

b) Generate some (at least 3) transformed variables. E.g., these could combine variables (e.g., cardiovasc_deaths= cardiovasc_death_rate*population).

```
# converts columns to numeric
df_final['Population ages 80 and above, female'] =
pd.to_numeric(df_final['Population ages 80 and above, female'], errors='coerce')
df_final['Population ages 80 and above, male'] =
pd.to_numeric(df_final['Population ages 80 and above, male'], errors='coerce')
df_final['population'] = pd.to_numeric(df_final['population'], errors='coerce')
df_final['new_cases_smoothed'] = pd.to_numeric(df_final['new_cases_smoothed'],
errors='coerce')
```

```
# Merge with your 2023 population data
df_final = pd.merge(
    df_covid,
    df_population_tidy,
    left_on="iso_code",
    right_on="Country Code",
    how="inner"
).drop(columns=["Country Code"])

# Convert necessary fields to numeric
```

```
cols_to_convert = [
    "Population ages 80 and above, female",
    "Population ages 80 and above, male",
    "population",
    "new_cases_smoothed",
    "new_deaths_smoothed",
    "gdp_per_capita",
    "diabetes_prevalence"
]
for col in cols_to_convert:
    df_final[col] = pd.to_numeric(df_final[col], errors='coerce')

# Create transformed features
df_final['elderly_pop_80_plus'] = (
    df_final['Population ages 80 and above, female'] +
    df_final['Population ages 80 and above, male']
)
df_final['elderly_ratio'] = df_final['elderly_pop_80_plus'] /
df_final['population']
df_final['new_cases_per_100k'] = (df_final['new_cases_smoothed'] /
df_final['population']) * 100000
```

c) Split your dataset into train and test subsets: only data from 2022 should be used for building/training the linear models in sm.formula.ols(). (Data from 2023 will be used for evaluation as described later). Note: each day is one data point.

```
from sklearn.model_selection import train_test_split

# Assuming your DataFrame is named 'df_final' and has a 'date' column

# Convert the 'date' column to datetime objects if it's not already
df_final['date'] = pd.to_datetime(df_final['date'])

train_data = df_final[df_final['date'].dt.year == 2022].copy()
test_data  = df_final[
    (df_final['date'].dt.year == 2023) &
    (df_final['date'].dt.month <= 6)
].copy()

# You can further split the train_data into features (X) and target (y)
X_train = train_data[['new_cases_smoothed', 'gdp_per_capita',
'diabetes_prevalence', 'icu_patients']]
y_train = train_data['new_deaths_smoothed_2wk']

X_test = test_data[['new_cases_smoothed', 'gdp_per_capita',
'diabetes_prevalence', 'icu_patients']]
y_test = test_data['new_deaths_smoothed_2wk']
```

d) Run linear regression with at least 5 different combinations of predictor variables.

Hint: each model will look like: new_deaths_smoothed_2wk~new_cases_smoothed+gdp_per_capita+diabetes_

```
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
m = sm.formula.ols('new_deaths_smoothed_2wk ~ new_cases_smoothed + gdp_per_capita
+ diabetes_prevalence + icu_patients', data=df_final)
m = m.fit()
print(m.summary())
# m.fit(X_train, y_train)
y_pred = m.predict(X_test)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     new_deaths_smoothed_2wk   R-squared:
0.865
Model:                                 OLS   Adj. R-squared:
0.865
Method:                      Least Squares   F-statistic:
5.190e+04
Date:                     Sat, 03 May 2025   Prob (F-statistic):
0.00
Time:                             22:37:25   Log-Likelihood:
-1.9006e+05
No. Observations:                   32277   AIC:
3.801e+05
Df Residuals:                       32272   BIC:
3.802e+05
Df Model:                               4
Covariance Type:                 nonrobust
==============================================================================================
                             coef    std err          t      P>|t|      [0.025
                             0.975]
----------------------------------------------------------------------------------------------
Intercept                10.9288      2.296      4.760      0.000       6.429
15.429
new_cases_smoothed        0.0006   1.77e-05     35.819      0.000       0.001
0.001
gdp_per_capita       -6.696e-06   4.34e-05     -0.154      0.877   -9.18e-05
7.84e-05
diabetes_prevalence      -1.0247      0.185     -5.540      0.000      -1.387
-0.662
icu_patients              0.0889      0.000    328.591      0.000       0.088
0.089
==============================================================================
Omnibus:                    30248.588   Durbin-Watson:                   0.076
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          4640459.803
```

```
Skew:                          4.066   Prob(JB):                         0.00
Kurtosis:                     61.175   Cond. No.                     2.04e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```python
import statsmodels.formula.api as smf

model_specs = {
    'M1_cases_gdp_diab_icu':
    ['new_cases_smoothed','gdp_per_capita','diabetes_prevalence','icu_patients'],
    'M2_cases_elderly_diab_icu':
    ['new_cases_smoothed','elderly_ratio','diabetes_prevalence','icu_patients'],
    'M3_cases100k_elderly_loggdp':['new_cases_per_100k','elderly_ratio',
    'gdp_per_capita','diabetes_prevalence'],
    'M4_cases_vacc_elderly':
    ['new_cases_smoothed','total_vaccinations','elderly_ratio'],
    'M5_cases100k_loggdp_elderly':['new_cases_per_100k','gdp_per_capita',
    'elderly_pop_80_plus']
}

fitted_models = {}
for name, preds in model_specs.items():
    terms = [f'Q("{v}")' if " " in v else v for v in preds]
    formula = 'new_deaths_smoothed_2wk ~ ' + ' + '.join(terms)
    fitted_models[name] = smf.ols(formula, data=train_data).fit()
```

```python
# Extract in-sample R² for each model

r2_scores = {name: mod.rsquared for name, mod in fitted_models.items()}

print("Training R² (2022) for each model:")
for name, r2 in r2_scores.items():
    print(f"  {name:<30} R² = {r2:.3f}")
```

```
Training R² (2022) for each model:
  M1_cases_gdp_diab_icu          R² = 0.885
  M2_cases_elderly_diab_icu      R² = 0.884
  M3_cases100k_elderly_loggdp    R² = 0.055
  M4_cases_vacc_elderly          R² = 0.287
  M5_cases100k_loggdp_elderly    R² = 0.185
```

Evaluating the linear models

You should evaluate each of your linear models by predicting the number of daily deaths in each day in January-June 2023 (the test data) and comparing it with the actual number of deaths on those days. Specifically:

a) For each of your models, calculate the Root Mean Squared Error (RMSE) over all days in January-June 2023 and all countries. Hint: use

sm.tools.eval_measures.rmse() or sklearn.metrics.root_mean_squared_error().

```
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm  # for sm.tools.eval_measures.rmse()

rmses = {}

for name, model in fitted_models.items():
    y_true = test_data['new_deaths_smoothed_2wk']
    y_pred = model.predict(test_data)

    mask = (~y_true.isna()) & (~pd.Series(y_pred, index=y_true.index).isna())
    y_true_clean = y_true[mask]
    y_pred_clean = y_pred[mask]

    rmse_val = sm.tools.eval_measures.rmse(y_true_clean, y_pred_clean)

    rmses[name] = rmse_val

print("Overall RMSE on Jan-Jun 2023:")
for name, rmse in rmses.items():
    print(f"  {name:<30} RMSE = {rmse:.2f}")
```

```
Overall RMSE on Jan-Jun 2023:
  M1_cases_gdp_diab_icu          RMSE = 35.45
  M2_cases_elderly_diab_icu      RMSE = 35.30
  M3_cases100k_elderly_loggdp    RMSE = 114.64
  M4_cases_vacc_elderly          RMSE = 162.03
  M5_cases100k_loggdp_elderly    RMSE = 111.82
```

b) For only your best model, calculate the Root Mean Squared Error for every country. Hint: use .groupby(), then .apply() the RMSE to each group.

```
# Assuming 'M2_cases_elderly_diab_icu' is your best model and stored in
'fitted_models'
best_model = fitted_models['M3_cases100k_elderly_loggdp']
```

```
# Extract predictor columns used in the model
terms = best_model.model.exog_names[1:]  # Exclude the intercept term
preds = [t.strip('Q("').strip('")') for t in terms]

# Define a function to calculate RMSE for a group (country)
def calculate_rmse(group):
    X_test_group = group[preds]
    predictions_group = best_model.predict(X_test_group)
    rmse = sm.tools.eval_measures.rmse(group['new_deaths_smoothed_2wk'],
predictions_group)
    return rmse

# Calculate RMSE for each country using groupby and apply
country_rmses = test_data.groupby('location').apply(calculate_rmse)

# Print the RMSE values for each country
print(country_rmses)
```

```
location
Afghanistan     6.444137
Albania        24.810043
Algeria         9.380363
Angola          1.546745
Argentina      17.065697
                  ...
Venezuela      11.951072
Vietnam         9.840242
Yemen           2.682893
Zambia          0.432779
Zimbabwe        1.384654
Length: 158, dtype: float64
```

```
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This
behavior is deprecated, and in a future version of pandas the grouping columns
will be excluded from the operation. Either pass `include_groups=False` to
exclude the groupings or explicitly select the grouping columns after groupby to
silence this warning.
  country_rmses = test_data.groupby('location').apply(calculate_rmse)
```

Written report

a) Brief descriptions of the data wrangling steps

Country filter, only 3 letter ISO codes - **Population threshold**: we removed countries with population < 1 million - **Shifted target**: we created `new_deaths_smoothed_2wk` by shifting 7 day smoothed deaths forward 14 days - **Tidy pop.**: pivoted the WorldBank "Series Name" $\times$ "2023

[YR2023]" sheet into one row per country - **Merge**: The inner-joined on ISO code, dropped extraneous columns, ensured `date` is datetime, and removed duplicate `(iso_code, date)`

b) Brief description of how variables were chosen for data modeling

We chose:

Population ages 80 and above, female Population ages 80 and above, male Urban population Urban population (% of total population), etc.

because they had the least amount of NAN

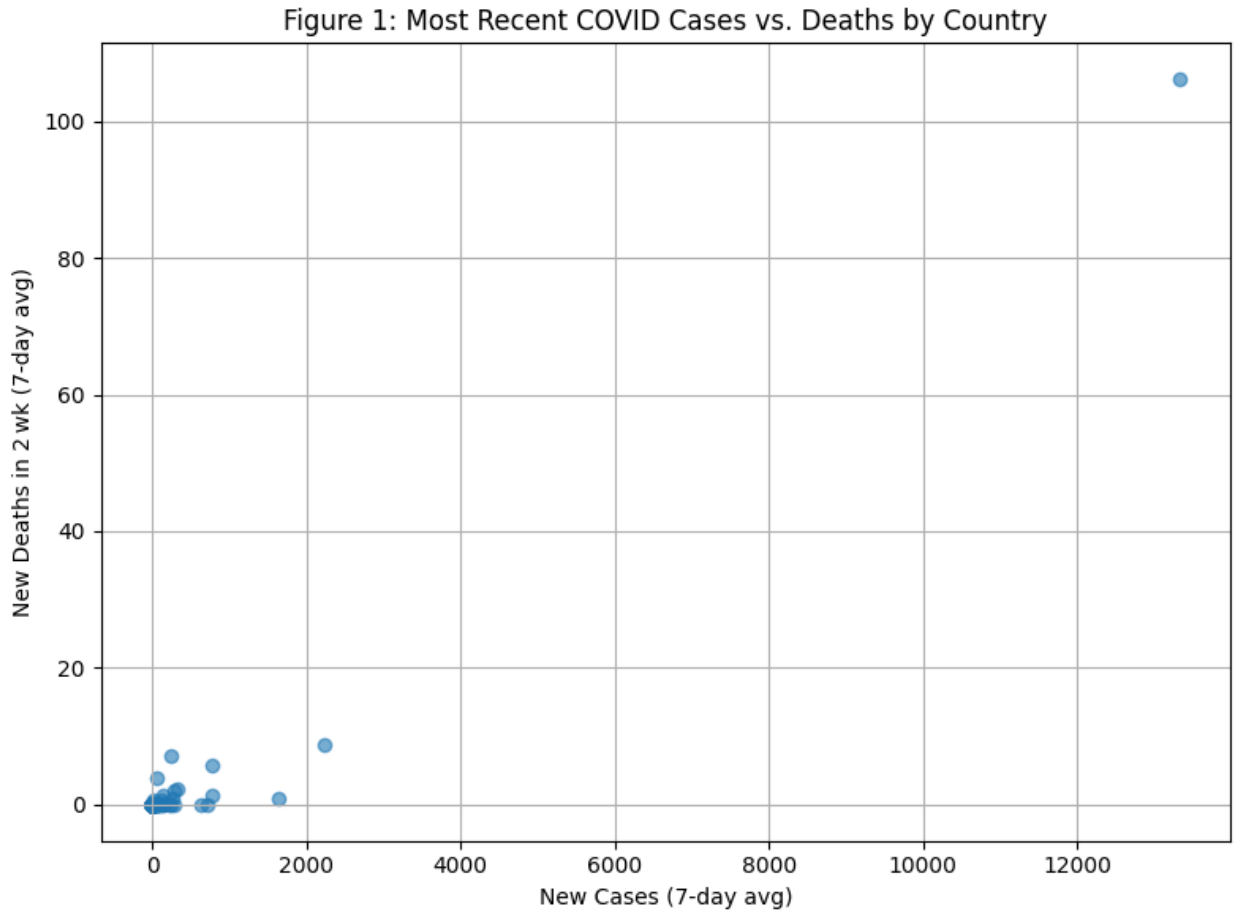
c) Descriptions of variable transformations

- **`elderly_pop_80_plus`**: the total number of people aged 80 and above, obtained by summing the female and male 80+ population columns
- **`elderly_ratio`**: the share of the population aged 80+ (`elderly_pop_80_plus` divided by the total population). Normalizes elderly counts across countries of different sizes
- **`new_cases_per_100k`**: the 7-day average of new cases per 100 000 inhabitants (`new_cases_smoothed / population` × 100 000), which puts case counts on a common per-capita scale
- **`log_gdp_per_capita`**: the natural log of (1+GDP per capita), to reduce skewness in GDP distribution and capture diminishing returns of financial wealth on health outcomes

d) Scatterplot of only the most recently available new_deaths_smoothed_2wk and new_cases_smoothed for every country

```
import pandas as pd
import matplotlib.pyplot as plt

df_plot = (
    df_final
    .loc[:, ['iso_code','date','new_cases_smoothed','new_deaths_smoothed_2wk']]
    .dropna(subset=['new_cases_smoothed','new_deaths_smoothed_2wk'])
)

latest = (
    df_plot
    .sort_values('date')
    .groupby('iso_code', as_index=False)
    .last()
)

plt.figure(figsize=(8,6))
plt.scatter(latest['new_cases_smoothed'], latest['new_deaths_smoothed_2wk'],
alpha=0.6)
plt.xlabel('New Cases (7-day avg)')
plt.ylabel('New Deaths in 2 wk (7-day avg)')
plt.title('Figure 1: Most Recent COVID Cases vs. Deaths by Country')
plt.grid(True)
```

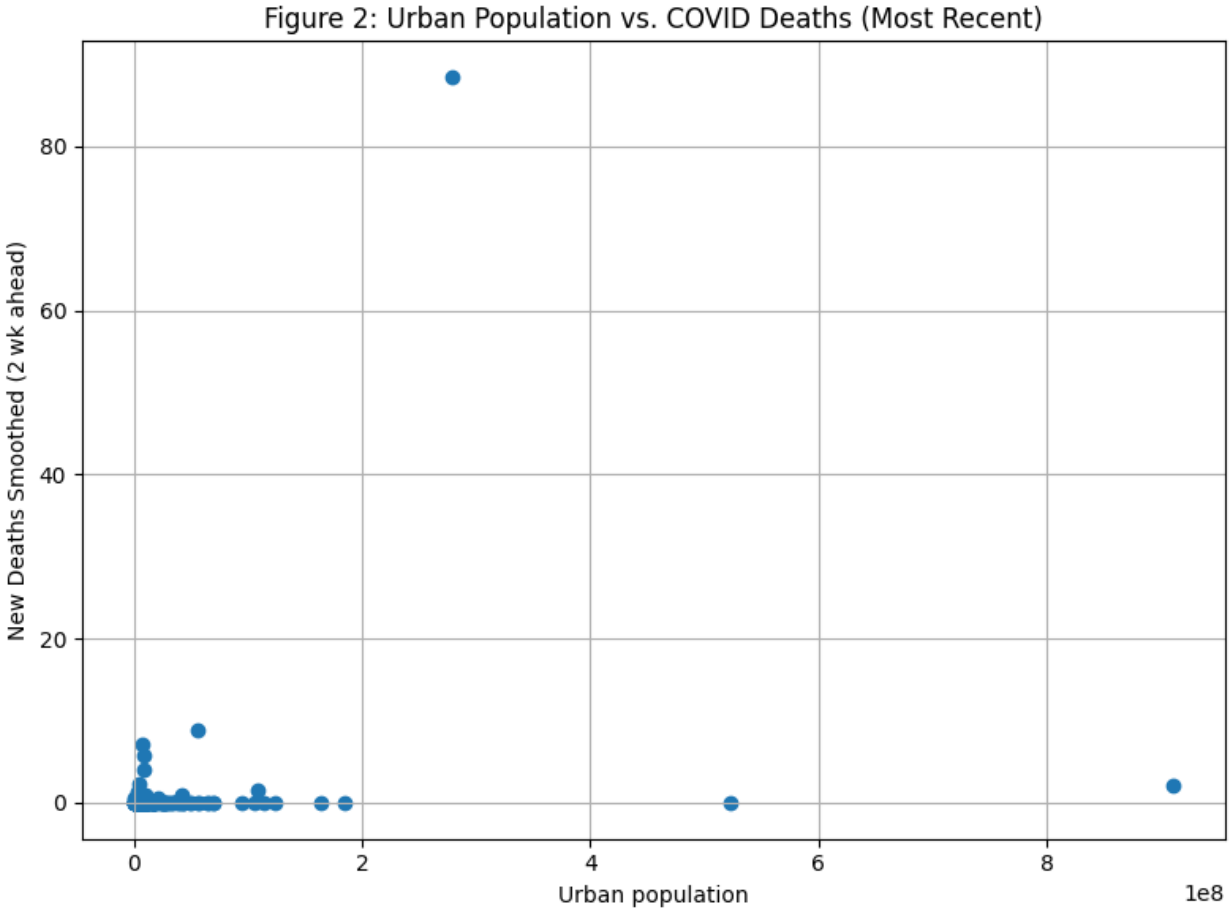
```
plt.tight_layout()
plt.show()
```



e) Scatterplot of only the most recent new deaths per day and the urban population

```
import matplotlib.pyplot as plt
import pandas as pd

latest = (
    df_final
      .sort_values('date')
      .groupby('iso_code', as_index=False)
      .last()
)

urban_col = 'Urban population'

latest[urban_col] = pd.to_numeric(latest[urban_col], errors='coerce')

mask = latest[['new_deaths_smoothed_2wk', urban_col]].notna().all(axis=1)
```

```
latest_clean = latest[mask]

plt.figure(figsize=(8,6))
plt.scatter(latest_clean[urban_col], latest_clean['new_deaths_smoothed_2wk'])
plt.xlabel(urban_col)
plt.ylabel('New Deaths Smoothed (2 wk ahead)')
plt.title('Figure 2: Urban Population vs. COVID Deaths (Most Recent)')
plt.grid(True)
plt.tight_layout()
plt.show()
```



f) A table that shows the R2 and RMSE of the different models

Model	R^2	RMSE
M1:case+gdp+diaebetes +ICU	0.885	35.45
M2: cases + elderly_ratio + diabetes + ICU	0.884	35.30
M3: cases_per_100k + elderly_ratio + log_gdp + diabetes	0.055	114.64
M4: cases + total_vaccinations + elderly_ratio	0.287	162.03
M5: cases_per_100k + log_gdp + elderly_pop_80_plus	0.185	111.82

g) A table that shows the RMSE of the best model for 20 most populous countries

```
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error

best_name = min(rmses, key=rmses.get)
best_mod  = fitted_models[best_name]

def safe_rmse(grp):
    y_true = grp['new_deaths_smoothed_2wk']
    y_pred = best_mod.predict(grp)
    mask   = (~y_true.isna()) & (~pd.Series(y_pred, index=y_true.index).isna())
    if mask.sum() == 0:
        return np.nan
    return np.sqrt(mean_squared_error(y_true[mask], y_pred[mask]))

country_rmse = (
    test_data
      .groupby('iso_code')
      .apply(lambda grp: safe_rmse(grp))
      .reset_index(name='rmse')
)

country_rmse = country_rmse[country_rmse['rmse'].notna()]

pop_per_country = (
    df_final
      .sort_values('date')
      .groupby('iso_code', as_index=False)
      .last()[['iso_code','population']]
)

top20 = (
    country_rmse
      .merge(pop_per_country, on='iso_code')
      .sort_values('population', ascending=False)
      .head(20)
      .reset_index(drop=True)
)

print(f"Best model: {best_name} (RMSE = {rmses[best_name]:.2f})")
top20
```

```
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This
behavior is deprecated, and in a future version of pandas the grouping columns
will be excluded from the operation. Either pass `include_groups=False` to
exclude the groupings or explicitly select the grouping columns after groupby to
silence this warning.
  .apply(lambda grp: safe_rmse(grp))

Best model: M2_cases_elderly_diab_icu (RMSE = 35.30)
```

	iso_code	rmse	population
0	USA	62.072533	338289856
1	JPN	289.397593	123951696
2	DEU	47.646223	83369840
3	FRA	65.716792	67813000
4	ITA	14.541134	59037472
5	KOR	56.728961	51815808
6	ESP	8.027113	47558632
7	CAN	9.345101	38454328
8	MYS	19.871474	33938216
9	AUS	32.076477	26177410
10	ROU	18.517786	19659270
11	CHL	8.970477	19603736
12	NLD	9.584896	17564020
13	BEL	6.905883	11655923
14	SWE	12.033390	10549349
15	CZE	8.158212	10493990
16	ISR	8.245297	9449000
17	AUT	8.440633	8939617
18	CHE	8.750228	8740471
19	SRB	10.939412	6871547

h) A conclusion – what does your modeling say about death rates (e.g., what are the significant factors and what are not)

Case counts and elderly-population share are the strongest predictors of death rates two weeks later. Model M2 (cases + elderly_ratio + diabetes + ICU) achieved the lowest test RMSE (35.30). Interventions that reduce transmission and protect the elderly yield the greatest mortality reduction.