APSC-5984 Lab 7: API and Database

0. Overview

API stands for Application Programming Interface. It is a set of tools meant to interact with other software or database. In this lab, we will use `requests` to interact with two USDA APIs. Later this week, we will also use `sqlite3` to practice building a database on our own.

```
import pandas as pd
import numpy as np
import requests
```

1. USDA local food portal API

Configuration

Before you can use the API, you need to get an API key and essentail parameters, such as the database you want to interact with and the query you want to run. Please treat the API key as a password and do not share it with others. Go to the USDA local food portal to register for an API key.

```
API = "xxxxxxx" # fill in your API key
headers = {
    "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/96.0.4664.110 Safari/537.36",
    "Referer": "https://www.google.com/",
}
params = {"apikey": API, "y": 37.221508, "x": -80.423857, "radius": 100}
base_url = "https://www.usdalocalfoodportal.com/api/farmersmarket/"
```

Request responses

The responses are usually coded as 3-digit numbers. The most common ones are:

- 1xx - Informational response - the request was received, continuing process
- 2xx - Success - the request was successfully received, understood, and accepted
- 3xx - Redirection - further action needs to be taken in order to complete the request
- 4xx - Client error - the request contains bad syntax or cannot be fulfilled
- 5xx - Server error - the server failed to fulfill an apparently valid request

In most cases, you want to get a 2xx response. If you get a 4xx or 5xx response, you need to check your code and make sure you are using the API correctly.

```
response = requests.get(base_url, headers=headers, params=params)
response
```

```
<Response [200]>
```

Parsing JSON

The response from the API is usually in JSON format. JSON stands for JavaScript Object Notation. It is a lightweight data-interchange format. It is not easy for humans to read and write, hense we can call `.json()` and `pd.DataFrame()` to parse the response into a tabular format.

```
json = response.json()
df = pd.DataFrame(json["data"])
df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	directory_type	directory_name	updatetime	listing_image	listing_id	listing_name	listing_desc	brief_desc	mydesc	conta
0	farmersmarket	farmers market	Jan 26th, 2021	default-farmersmarket-4-3.jpg	300156	Salem Farmers Market	None	Open: April to December; January to March; <br...		Marke Mana
1	farmersmarket	farmers market	Feb 1st, 2021	default-farmersmarket-4-3.jpg	300469	Grandin Village Farmers Market	None	Open: April to November; November to March; <b...		Sam L
2	farmersmarket	farmers market	Sep 27th, 2021	default-farmersmarket-4-3.jpg	301601	The Historic City Market	None	Open: Year-round Available Products: Fresh ...		Eric L Pendl
3	farmersmarket	farmers market	Aug 23rd, 2021	default-farmersmarket-4-3.jpg	301590	Rocky Mount Farmers Market	None	Open: April to December; Available Product...		Paul C
4	farmersmarket	farmers market	Jan 7th, 2021	default-farmersmarket-4-3.jpg	300467	Wytheville Farmers Market	None	Open: Year-round Available Products: Fresh ...		Joanr McNu

5 rows × 28 columns

Rearranging the data

The data might contain more information than you need. We can use Pandas techniques we learned before to rearrange the data.

```
cols = [
    "listing_name",
    "brief_desc",
    "contact_name",
    "contact_phone",
    "media_website",
    "media_facebook",
    "media_twitter",
    "location_city",
    "location_state",
    "location_y",
    "location_x",
]

df.loc[:, cols]
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	listing_name	brief_desc	contact_name	contact_phone	media_website	media_facebook
0	Salem Farmers Market	Open: April to December; January to March; <br...	Market Manager	540-375-4098	market.salemva.gov	https://www.facebook.com/Salem
1	Grandin Village Farmers Market	Open: April to November; November to March; <b...	Sam Lev	540-632-1360	www.leapforlocalfood.org/grandin	facebook.com/grandinvillagecom
2	The Historic City Market	Open: Year-round Available Products: Fresh ...	Eric L Pendleton	5403422028	Downtownroanoke.org	The Historic City Market
3	Rocky Mount Farmers Market	Open: April to December; Available Product...	Paul Cauley	540-488-2023	None	None
4	Wytheville Farmers Market	Open: Year-round Available Products: Fresh ...	Joanne McNulty	276-620-4095	www.wythevillefarmersmarket.com	Wytheville Farmers Market
5	Galax Farmers Market	Open: 05/11/2023 to 10/28/2023; Available ...	Jordan Shaw	276.733.4145	https://visitgalax.com/	https://www.facebook.com/searc
6	Forest farmers market	Open: April to October; November to December; ...	Dorothy McIntyre	434-665-5475	www.forestfarmersmarket.com	https://www.facebook.com/pages
7	King Farmers' Market	Open: May to September; Available Products...	Deb Fox	336-618-1086	www.kingfarmersmarket.com	www.facebook.com/KingFarmers
8	Lynchburg Community Market	Open: Year-round Available Products: Fresh ...	Ricky Kowalewski	434.455.3962	http://lynchburgcommunitymarket.com/	https://www.facebook.com/Lynch
9	The Market at Second Stage	Open: May to October; November to April; A...	Mary Hurst	434.941.0997	https://secondstageamherst.org/markets	https://www.facebook.com/The-M
10	Piedmont Triad Farmers Market	Open: Year-round Available Products: Fresh ...	Rick Cecil	(336) 605-9157	www.triadfarmersmarket.com	https://www.facebook.com/pages
11	Wilkes County Farmers' Market	Open: April to October; ; Available Produc...	Garrett Griffin	3366677129	www.downtownnorthwilkesboro.com	https://www.facebook.com/wilkes
12	The Corner Farmers Market	Open: Year-round Available Products: Fresh ...	Kathy Newsom	3365586924	www.cornermarketgso.com	https://www.facebook.com/walke
13	Webster Springs Farmer's Market	Open: July to October; Available Products:...	Mike Hall	304-847-2727	None	None

	listing_name	brief_desc	contact_name	contact_phone	media_website	media_facebook
14	Boone Winter Farmers Market	Open: 12/03/2022 to 03/25/2023; Available ...	Rachel Kinard	803-429-3943	https://www.brwia.org/wintermarket.html	https://www.facebook.com/Boon
15	King Street Farmers Market	Open: 05/03/2022 to 10/25/2022; Available ...	Rachel Kinard	8034293943	https://www.brwia.org/ksm.html	https://www.facebook.com/KingS
16	Verona Farmers Market	Open: May to October; Available Products: ...	Georgia Meyer	651-356-2410	https://www.projectgrows.org/food-access/north...	https://www.facebook.com/NAFa
17	Carrboro Farmers' Market	Open: January to March; March to October; Nove...	Maggie Funkhouser	9192803326	www.carrborofarmersmarket.com	https://www.facebook.com/carrb
18	The Chapel Hill Farmers' Market	Open: 04/02/2022 to 11/19/2022; 12/03/2022 to ...	Kate Underhill	9195339496	https://www.thechapelhillfarmersmarket.com/	https://www.facebook.com/TheC

2. Agricultural Resource Management Survey (ARMS) API

API key

Go to ARMS API to obtain an API key for the USDA ARMS API.

```
API = "xxxxxxx" # fill in your API key
params = {"api_key": API}
```

Use `arms/year` to get the list of available years

This API has a lot of data. Based on the documentation https://www.ers.usda.gov/developer/data-apis/arms-data-api/#apiForm, we can use `arms/year` to get the list of available years.

```
# arms/year
url = "https://api.ers.usda.gov/data/arms/year"
response = requests.get(url, headers=headers, params=params)
json_data = response.json()
json_data
```


```
{'status': 'ok',
 'info': {'timing': {'executing': 93, 'unit': 'ms'},
  'result_coverage': 'total',
  'total': {'record_count': 26}},
 'data': [2021,
  2020,
  2019,
  2018,
  2017,
  2016,
  2015,
  2014,
  2013,
  2012,
  2011,
  2010,
  2009,
  2008,
  2007,
  2006,
  2005,
  2004,
  2003,
  2002,
  2001,
  2000,
  1999,
  1998,
```

```
  1997,
  1996]}
```

Use `arms/report` to get the list of available reports

To make sure we are using the API correctly, we can use `arms/report` to get the list of available reports. We will later need to use the correct report name to get the data.

```
# get all report
url = "https://api.ers.usda.gov/data/arms/report"
response = requests.get(url, headers=headers, params=params)
js = response.json()
df = pd.DataFrame(response.json()["data"])
df
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	id	name	desc
0	1	Farm Business Balance Sheet	None
1	2	Farm Business Income Statement	None
2	3	Farm Business Financial Ratios	None
3	4	Structural Characteristics	None
4	5	Farm Business Debt Repayment Capacity	None
5	6	Government Payments	None
6	7	Operator Household Income	None
7	8	Operator Household Balance Sheet	None

Farm Business Income Statement

Let's say we want to get the farm business income statement for all farms in the US for the years 2008 to 2022. We can start with a single year, say 2018.

```
params = {
    "api_key": API,
    "Year": 2018,
    "report": "Farm Business Income Statement",
}
url = "https://api.ers.usda.gov/data/arms/surveydata"
response = requests.get(url, headers=headers, params=params)
json_data = response.json()
data = pd.DataFrame(json_data["data"])
data
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	year	state	report	farmtype	category	category_value	category2	category2_value	variable_id	variable_name	...
0	2018	All survey states	Farm Business Income Statement	All Farms	Operator Age	55 to 64 years old	All Farms	TOTAL	kount	Farms	...

	year	state	report	farmtype	category	category_value	category2	category2_value	variable_id	variable_name	...
1	2018	All survey states	Farm Business Income Statement	All Farms	Farm Typology	Retirement farms (2011 to present)	All Farms	TOTAL	kount	Farms	...
2	2018	All survey states	Farm Business Income Statement	All Farms	Farm Typology	Farming occupation/lower-sales farms (2011 to ...	All Farms	TOTAL	kount	Farms	...
3	2018	All survey states	Farm Business Income Statement	All Farms	Collapsed Farm Typology	Intermediate farms	All Farms	TOTAL	kount	Farms	...
4	2018	All survey states	Farm Business Income Statement	All Farms	NASS Region	Atlantic region	All Farms	TOTAL	kount	Farms	...
...	...	...	...	...	...	...	...	...	...	...	...
1483	2018	All survey states	Farm Business Income Statement	All Farms	Economic Class	Less than $100,000	All Farms	TOTAL	infi	Net farm income	...
1484	2018	All survey states	Farm Business Income Statement	All Farms	Production Specialty	Soybean	All Farms	TOTAL	infi	Net farm income	...
1485	2018	All survey states	Farm Business Income Statement	All Farms	Production Specialty	Tobacco, Cotton, Peanuts	All Farms	TOTAL	infi	Net farm income	...
1486	2018	All survey states	Farm Business Income Statement	All Farms	Production Specialty	Poultry	All Farms	TOTAL	infi	Net farm income	...
1487	2018	All survey states	Farm Business Income Statement	All Farms	Production Specialty	All other livestock	All Farms	TOTAL	infi	Net farm income	...

1488 rows × 23 columns

Check the data

You can check the data by inspecting the unique values of each column of interest. For example, if you want to know any category other than "Operator Age", you can use the following code:

```
data["category"].unique()
```

```
array(['Operator Age', 'Farm Typology', 'Collapsed Farm Typology',
       'NASS Region', 'Farm Resource Region', 'Economic Class',
       'Production Specialty', 'All Farms'], dtype=object)
```

You may also want to know what `Production Specialty` was recorded as. You can combine `df.query()` and `df.unique()`.

```
data.query("category == 'Production Specialty'").loc[:, "category_value"].unique()
```

```
array(['Corn', 'Tobacco, Cotton, Peanuts', 'Other Field Crops', 'Cattle',
       'Hogs', 'Dairy', 'All other livestock', 'General Cash Grains',
       'Wheat', 'Soybean', 'Specialty Crops (F,V,N)', 'Poultry'],
      dtype=object)
```

We can check variables to know what attributes are available for that category.

```
data.query("category == 'Production Specialty'").loc[:, "variable_name"].unique()
```

```
array(['Farms', 'Gross cash farm income', 'Livestock income',
       'Crop sales', 'Government payments', 'Other farm-related income',
       'Total cash expenses', 'Variable expenses', 'Livestock purchases',
       'Feed', 'Other livestock-related', 'Seed and plants',
       'Fertilizer and chemicals', 'Utilities', 'Labor', 'Fuels and oils',
       'Repairs and maintenance', 'Machine-hire and custom work',
       'Other variable expenses', 'Fixed expenses',
       'Real estate and property taxes', 'Interest', 'Insurance premiums',
       'Rent and lease payments', 'Net cash farm income',
       'Nonmoney income', 'Value of inventory change', 'Depreciation',
       'Labor, non-cash benefits', 'Adjusted breeding livestock income',
       'Net farm income'], dtype=object)
```

Functions

It is a good idea to wrap up the code into functions so that you can reuse them later. Especially when we deal with the queries with repeated patterns, we can use functions to make the code more concise.

To design a function, first thing we can to define is the input and output. In our case, we provide API key and parameters (year, report name, etc.) as input and get a parsed dataframe as output.

```
def query_data(year, API, report="Farm Business Income Statement"):
    # inputs
    params = {
        "api_key": API,
        "Year": year,
        "report": report,
    }
    headers = {
        "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko)
Chrome/96.0.4664.110 Safari/537.36",
        "Referer": "https://www.google.com/",
    }
    url = "https://api.ers.usda.gov/data/arms/surveydata"
    # query
    response = requests.get(url, headers=headers, params=params)
    print("status code:", response.status_code)
    json_data = response.json()
    data = pd.DataFrame(json_data["data"])
    # parse output
    data = data.query("variable_name == 'Gross cash farm income'")
    return data
```

Validate the function

```
data = query_data(2018, API)
data.head()
```

```
status code: 200
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	year	state	report	farmtype	category	category_value	category2	category2_value	variable_id	variable_name	...	vari

	year	state	report	farmtype	category	category_value	category2	category2_value	variable_id	variable_name	...	vari
48	2018	All survey states	Farm Business Income Statement	All Farms	Operator Age	34 years or younger	All Farms	TOTAL	igcfi	Gross cash farm income	...	Non
49	2018	All survey states	Farm Business Income Statement	All Farms	Operator Age	55 to 64 years old	All Farms	TOTAL	igcfi	Gross cash farm income	...	Non
50	2018	All survey states	Farm Business Income Statement	All Farms	Operator Age	65 years or older	All Farms	TOTAL	igcfi	Gross cash farm income	...	Non
51	2018	All survey states	Farm Business Income Statement	All Farms	Farm Typology	Farming occupation/lower-sales farms (2011 to ...	All Farms	TOTAL	igcfi	Gross cash farm income	...	Non
52	2018	All survey states	Farm Business Income Statement	All Farms	Farm Typology	Very large farms (2011 to present)	All Farms	TOTAL	igcfi	Gross cash farm income	...	Non

5 rows × 23 columns

We can define another function to process the data we get from the API. In this example, we will do the following processing:

- Select the columns of interest
- calculate standard deviation of the income statement
- calculate 95% confidence interval of the standard deviation

```
def post_process(data):
    cols = ["year", "category", "category_value", "estimate", "median", "rse"]
    datasub = data.loc[:, cols]
    datasub["se"] = datasub["estimate"] * (datasub["rse"] / 100)
    datasub["upper"] = datasub["estimate"] + datasub["se"] * 1.96  # 95% CI
    datasub["lower"] = datasub["estimate"] - datasub["se"] * 1.96  # 95% CI
    return datasub
```

Always check the results to make sure the function works as expected.

```
data18 = query_data(2018, API)
data18 = post_process(data18)
data18.head()
```

```
status code: 200
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	year	category	category_value	estimate	median	rse	se	upper	lower
48	2018	Operator Age	34 years or younger	212459.0	30102.0	11.8	25070.162	2.615965e+05	1.633215e+05
49	2018	Operator Age	55 to 64 years old	188384.0	7140.0	4.0	7535.360	2.031533e+05	1.736147e+05
50	2018	Operator Age	65 years or older	108034.0	8865.0	6.3	6806.142	1.213740e+05	9.469396e+04

	year	category	category_value	estimate	median	rse	se	upper	lower
51	2018	Farm Typology	Farming occupation/lower-sales farms (2011 to ...	27750.0	9800.0	4.1	1137.750	2.997999e+04	2.552001e+04
52	2018	Farm Typology	Very large farms (2011 to present)	11634254.0	7404800.0	11.3	1314670.702	1.421101e+07	9.057499e+06

Query multiple years

With the functions we defined, it is now easier to query multiple years. We can use a for loop to iterate through the years and use the functions we defined to get the data. To avoid overloading the server, we can use `time.sleep()` to pause the code for one second between each query.

```
import time

data = pd.DataFrame()
for year in range(2008, 2022):  # only 2008-2021
    print("Loading data for year", year)
    data_query = query_data(year, API)
    data_query = post_process(data_query)
    data = pd.concat([data, data_query], axis=0)
    time.sleep(1)
```

```
Loading data for year 2008
status code: 200
Loading data for year 2009
status code: 200
Loading data for year 2010
status code: 200
Loading data for year 2011
status code: 200
Loading data for year 2012
status code: 200
Loading data for year 2013
status code: 200
Loading data for year 2014
status code: 200
Loading data for year 2015
status code: 200
Loading data for year 2016
status code: 200
Loading data for year 2017
status code: 200
Loading data for year 2018
status code: 200
Loading data for year 2019
status code: 200
Loading data for year 2020
status code: 200
Loading data for year 2021
status code: 200
```

Check the result

```
data
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	year	category	category_value	estimate	median	rse	se	upper	lower
47	2008	Operator Age	45 to 54 years old	155557.0	6892.0	4.1	6377.837	1.680576e+05	1.430564e+05

	year	category	category_value	estimate	median	rse	se	upper	lower
48	2008	Farm Typology	Retirement farms (1996 through 2010)	13992.0	4000.0	4.3	601.656	1.517125e+04	1.281275e+04
49	2008	Collapsed Farm Typology	Intermediate farms	57234.0	22000.0	2.4	1373.616	5.992629e+04	5.454171e+04
50	2008	Collapsed Farm Typology	Commercial farms	813566.0	414011.0	2.4	19525.584	8.518361e+05	7.752959e+05
51	2008	NASS Region	Atlantic region	67912.0	5200.0	3.6	2444.832	7.270387e+04	6.312013e+04
...	...	...	...	...	...	...	...	...	...
91	2021	Production Specialty	Tobacco, Cotton, Peanuts	886937.0	522000.0	14.0	124171.180	1.130313e+06	6.435615e+05
92	2021	Production Specialty	Other Field Crops	53155.0	5000.0	9.7	5156.035	6.326083e+04	4.304917e+04
93	2021	Production Specialty	Specialty Crops (F,V,N)	447255.0	16904.0	13.3	59484.915	5.638454e+05	3.306646e+05
94	2021	Production Specialty	Poultry	183738.0	21000.0	16.8	30867.984	2.442392e+05	1.232368e+05
95	2021	Production Specialty	Dairy	1565673.0	332890.0	7.2	112728.456	1.786621e+06	1.344725e+06

669 rows × 9 columns

Visualize the data

Now, let's focus on the two categories: `NASS Region` and `Production Specialty`. We will use ggplot2 (`plotnine` library) to visualize the income statement for each category across years.

```
from plotnine import *
dataplot = data.query("category in ['NASS Region', 'Production Specialty']")
dataplot["group"] = dataplot["category"] + " - " + dataplot["category_value"]
dataplot
```

```
/var/folders/0k/_fn4_dgn04b2b44_sfhbshzr0000gp/T/ipykernel_59862/1007048301.py:3: 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-copy
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

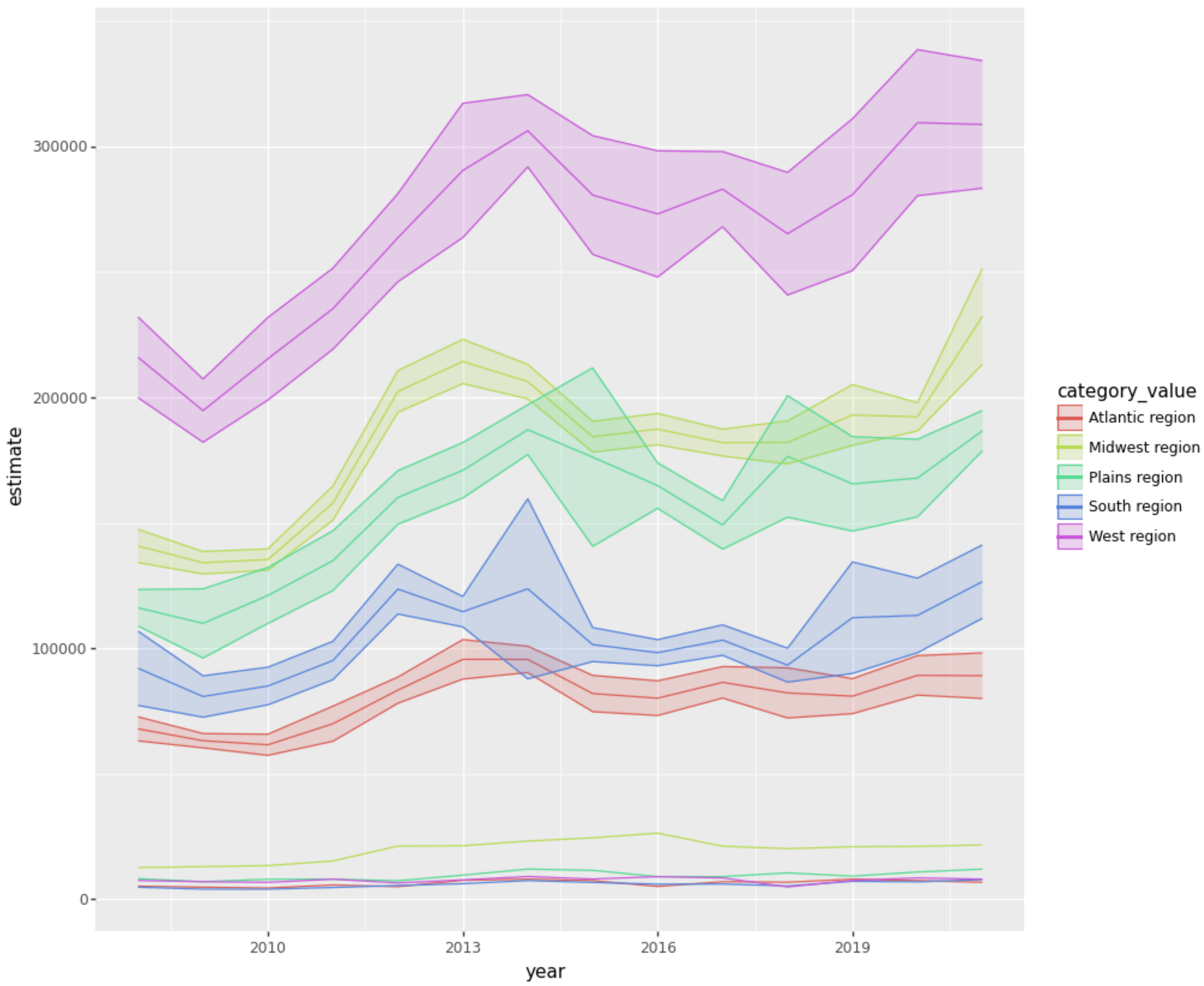
	year	category	category_value	estimate	median	rse	se	upper	lower	group
51	2008	NASS Region	Atlantic region	67912.0	5200.0	3.6	2444.832	7.270387e+04	6.312013e+04	NASS Region - Atlantic region
52	2008	NASS Region	South region	92042.0	4800.0	8.2	7547.444	1.068350e+05	7.724901e+04	NASS Region - South region
53	2008	NASS Region	Midwest region	140805.0	12600.0	2.4	3379.320	1.474285e+05	1.341815e+05	NASS Region - Midwest region
54	2008	NASS Region	Plains region	116175.0	8203.0	3.2	3717.600	1.234615e+05	1.088885e+05	NASS Region - Plains region
55	2008	NASS Region	West region	215985.0	7465.0	3.8	8207.430	2.320716e+05	1.998984e+05	NASS Region - West region
...	...	...	...	...	...	...	...	...	...	...
91	2021	Production Specialty	Tobacco, Cotton, Peanuts	886937.0	522000.0	14.0	124171.180	1.130313e+06	6.435615e+05	Production Specialty - Tobacco, Cotton, Peanuts

	year	category	category_value	estimate	median	rse	se	upper	lower	group
92	2021	Production Specialty	Other Field Crops	53155.0	5000.0	9.7	5156.035	6.326083e+04	4.304917e+04	Production Specialty - Other Field Crops
93	2021	Production Specialty	Specialty Crops (F,V,N)	447255.0	16904.0	13.3	59484.915	5.638454e+05	3.306646e+05	Production Specialty - Specialty Crops (F,V,N)
94	2021	Production Specialty	Poultry	183738.0	21000.0	16.8	30867.984	2.442392e+05	1.232368e+05	Production Specialty - Poultry
95	2021	Production Specialty	Dairy	1565673.0	332890.0	7.2	112728.456	1.786621e+06	1.344725e+06	Production Specialty - Dairy

238 rows × 10 columns

By region

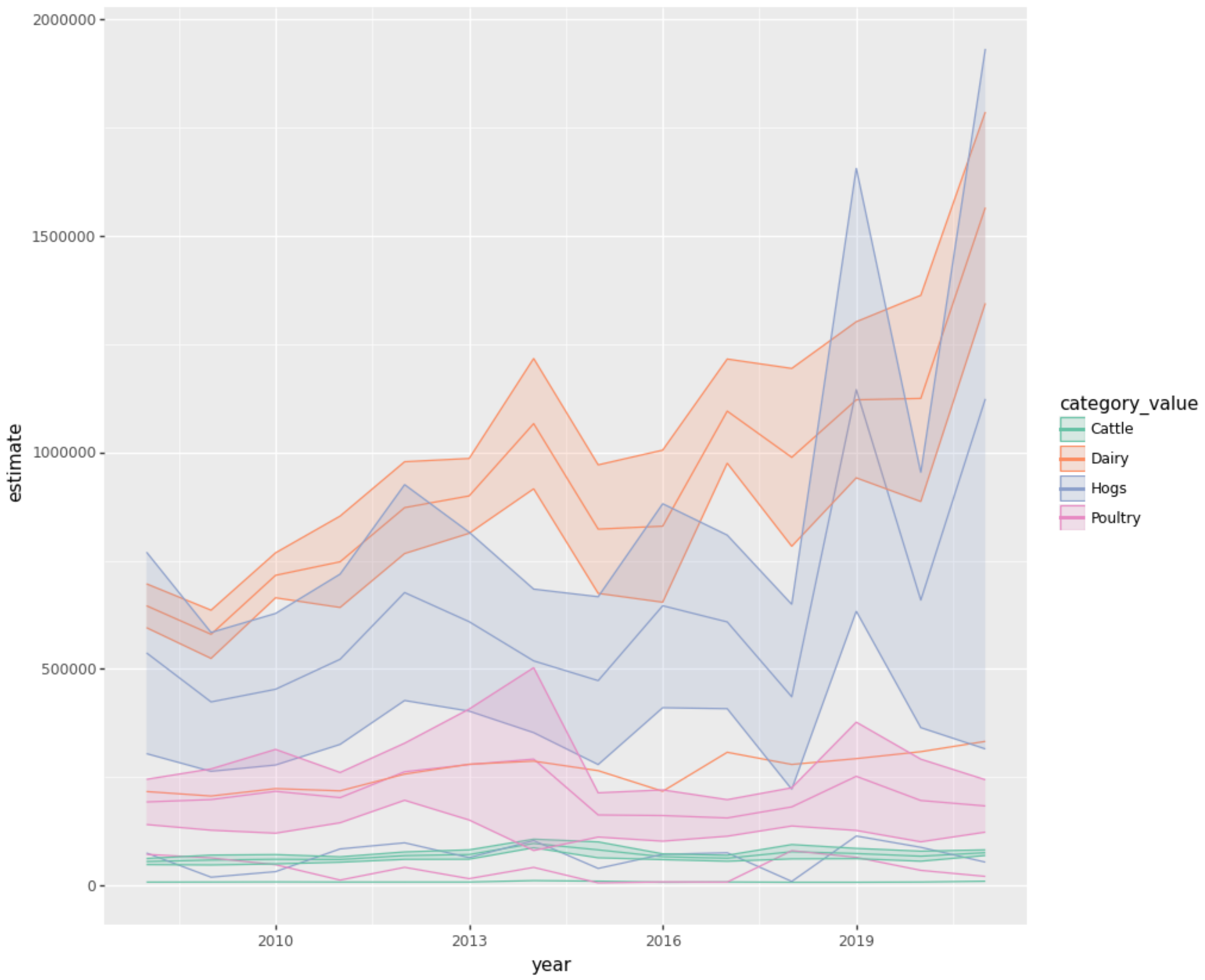
```
(
    ggplot(
        dataplot.query("category == 'NASS Region'"),
        aes(x="year", color="category_value", group="group"),
    )
    + geom_line(aes(y="estimate", color="category_value"))
    + geom_line(aes(y="median", color="category_value"))
    + geom_ribbon(aes(ymin="lower", ymax="upper", fill="category_value"), alpha=0.2)
    + theme(figure_size=(10, 10))
)
```



```
<ggplot: (685146251)>
```

By production specialty. We only show the livestock categories.

```
(
    ggplot(
        dataplot.query(
            "category == 'Production Specialty' and category_value in ['Dairy', 'Cattle', 'Hogs', 'Poultry']"
        ),
        aes(
            x="year",
            color="category_value",
            fill="category_value",
            group="category_value",
        ),
    )
    + geom_line(aes(y="estimate"))
    + geom_line(aes(y="median"))
    + geom_ribbon(aes(ymin="lower", ymax="upper"), alpha=0.2)
    # color theme
    + scale_color_brewer(type="qual", palette="Set2")
    + scale_fill_brewer(type="qual", palette="Set2")
    + theme(figure_size=(10, 10))
)
```




```
<ggplot: (685147956)>
```

We can apply a log transformation to the data to make the plot more readable.

```python
import numpy as np

dataplot["log_estimate"] = np.log(dataplot["estimate"])
dataplot["log_upper"] = np.log(dataplot["upper"])
dataplot["log_lower"] = np.log(dataplot["lower"])
dataplot["log_median"] = np.log(dataplot["median"])
(
    ggplot(
        dataplot.query(
            "category == 'Production Specialty' and category_value in ['Dairy', 'Cattle', 'Hogs', 'Poultry']"
        ),
        aes(
            x="year",
            color="category_value",
            fill="category_value",
            group="category_value",
        ),
    )
    + geom_line(aes(y="log_estimate"), size=1)
    + geom_line(aes(y="log_median"))
    + geom_ribbon(aes(ymin="log_lower", ymax="log_upper"), alpha=0.2)
    + scale_color_brewer(type="qual", palette="Set2")
    + scale_fill_brewer(type="qual", palette="Set2")
    + theme(figure_size=(10, 10))
)
```

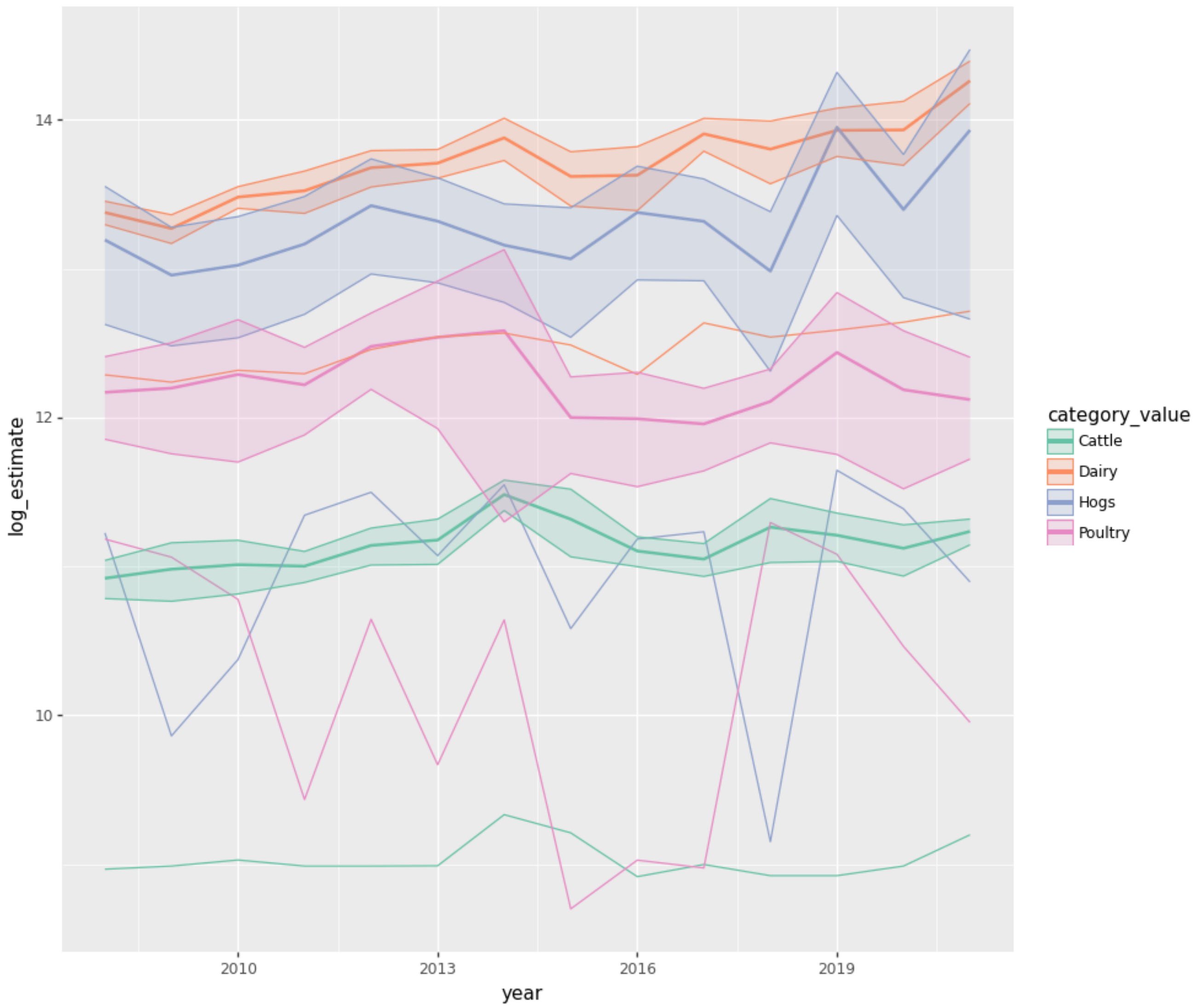
```
/var/folders/0k/_fn4_dgn04b2b44_sfhbshzr0000gp/T/ipykernel_59862/885553557.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
/var/folders/0k/_fn4_dgn04b2b44_sfhbshzr0000gp/T/ipykernel_59862/885553557.py:4: 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-copy
/Users/niche/miniforge3/envs/niche/lib/python3.9/site-packages/pandas/core/arraylike.py:402: RuntimeWarning: invalid
value encountered in log
/var/folders/0k/_fn4_dgn04b2b44_sfhbshzr0000gp/T/ipykernel_59862/885553557.py:5: 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-copy
/Users/niche/miniforge3/envs/niche/lib/python3.9/site-packages/pandas/core/arraylike.py:402: RuntimeWarning: divide
by zero encountered in log
/var/folders/0k/_fn4_dgn04b2b44_sfhbshzr0000gp/T/ipykernel_59862/885553557.py:6: 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-copy
```




```
<ggplot: (685725654)>
```

3. SQLite3

After we learn how to interact with an existing database through API, we can also build our own database using our own data. In this section, we will use `sqlite3` to build a database and query the data.

```
import sqlite3
```

Create a database

Creating a database is as simple as creating a file. We can use `sqlite3.connect()` to create a database file.

```
conn = sqlite3.connect("demo.db") # conn stands for connection
```

Like we learned in the previous section, a database can contain multiple tables (or surveys, reports). To craete a table, we need to specify the name of the columns and the data type. We also need to specify the primary key, which is a unique identifier for each row. We can create a table named `users` with the following columns:

- `id` - INTEGER (PRIMARY KEY)
- `name` - TEXT
- `gender` - TEXT
- `age` - INTEGER

```
cur = conn.cursor() # cur stands for cursor
cur.execute(
    """
    CREATE TABLE users (
```

```
        id INTEGER PRIMARY KEY,
        name TEXT NOT NULL,
        gender TEXT,
        age INTEGER
    )
    """
)
```

```
<sqlite3.Cursor at 0x28fdb7c70>
```

Check the table columns

```
cur.execute("PRAGMA table_info(users)")
cur.fetchall()
```

```
[(0, 'id', 'INTEGER', 0, None, 1),
 (1, 'name', 'TEXT', 1, None, 0),
 (2, 'gender', 'TEXT', 0, None, 0),
 (3, 'age', 'INTEGER', 0, None, 0)]
```

If you think the command is too complicated, we can use a function to simplify the process.

```
def list_cols(cur, table):
    cur.execute("PRAGMA table_info(%s)" % table)
    return display([x[1:3] for x in cur.fetchall()])

list_cols(cur, "users")
```

```
[('id', 'INTEGER'), ('name', 'TEXT'), ('gender', 'TEXT'), ('age', 'INTEGER')]
```

Save the database

We can use `conn.commit()` to save the changes to the database. Like how we deal with a file, we need to close `conn.close()` the database after we are done with it.

```
conn.commit()
conn.close()
```

Or we can use a `with` statement to automatically close the database after we are done with it.

```
with sqlite3.connect("demo.db") as conn:
    cur = conn.cursor()
    list_cols(cur, "users")
```

```
[('id', 'INTEGER'), ('name', 'TEXT'), ('gender', 'TEXT'), ('age', 'INTEGER')]
```

Insert data

There are two ways to insert data into a table:

Provide information for all columns

- `INSERT INTO users VALUES (1, 'John', 'M', 20)`

Provide information for some columns

- `INSERT INTO users (name, gender) VALUES ('John', 'M')`

```
cur.execute("INSERT INTO users VALUES (1, 'Mary', 'F', 25)")
cur.execute("INSERT INTO users (name) VALUES ('John')")
```

```
<sqlite3.Cursor at 0x28fdb7c70>
```

Check the data

```
cur.execute("SELECT * FROM users")
cur.fetchall()
```

```
[(1, 'Mary', 'F', 25), (2, 'John', None, None)]
```

Or wrap it up in a function

```
def print_table(cur, table):
    cur.execute("SELECT * FROM %s" % table)
    display(cur.fetchall())

print_table(cur, "users")
```

```
[(1, 'Mary', 'F', 25),
 (2, 'John', None, None),
 (3, 'Camille', 'female', 40),
 (4, 'Mike', 'male', 25),
 (5, 'Jason', 'male', 35),
 (6, 'Maria', 'female', 20)]
```

You can actually use `df.to_sql()` to insert data into a table. Parameters we need to consider:

- `if_exists`: If the table already exists, we can choose to `replace` the table, or `append` the data to the existing table.
- `index`: whether to include the index of the dataframe as a column in the table.

```
df = pd.DataFrame(
    {
        "name": ["Camille", "Mike", "Jason", "Maria"],
        "gender": ["female", "male", "male", "female"],
        "age": [40, 25, 35, 20],
    }
)
df.to_sql("users", conn, if_exists="append", index=False)  # if_exists="replace"
```

```
4
```

```
print_table(cur, "users")
```

```
[(1, 'Mary', 'F', 25),
 (2, 'John', None, None),
 (3, 'Camille', 'female', 40),
 (4, 'Mike', 'male', 25),
 (5, 'Jason', 'male', 35),
 (6, 'Maria', 'female', 20)]
```

Add constraints to columns

You might notice that the gender values were not in a consistent format, which should either be [`M`, `F`] or [`Male`, `Female`]. We can use `CHECK` to add constraints to the columns.

Before re-creating the table, we need to drop the table first.

```
cur.execute("DROP TABLE users")
```

```
<sqlite3.Cursor at 0x28fdb7b20>
```

Then create a new table with the constraints:

- id - INTEGER (PRIMARY KEY)
- name - TEXT - NOT NULL
- gender - TEXT - can only be either 'male' or 'female'
- age - INTEGER - must be in the range of 0 to 150
- weight - REAL - must be in the range of 0 to 300

```
cur.execute(
    """
    CREATE TABLE users (
        id INTEGER PRIMARY KEY,
        name TEXT NOT NULL,
        gender TEXT CHECK(gender IN ("male", "female")),
        age INTEGER CHECK(age >= 0 AND age <= 150),
        weight REAL CHECK(weight >= 0 AND weight <= 300)
    )
    """
)
```

```
<sqlite3.Cursor at 0x28fdb7b20>
```

Now, let's try to insert data again. We can start with expected values:

```
cur.execute("INSERT INTO users VALUES (1, 'Mary', 'female', 25, 150)")
```

```
<sqlite3.Cursor at 0x28fdb7b20>
```

```
print_table(cur, "users")
```

```
[(1, 'Mary', 'female', 25, 150.0)]
```

Let's try different exceptions:

```
cur.execute("INSERT INTO users VALUES (2, 'Mary', 'f', 25, 150)")
```

```
---------------------------------------------------------------------------

IntegrityError                            Traceback (most recent call last)

Cell In[112], line 1
----> 1 cur.execute("INSERT INTO users VALUES (2, 'Mary', 'f', 25, 150)")


IntegrityError: CHECK constraint failed: gender IN ("male", "female")
```

```
cur.execute("INSERT INTO users VALUES (2, 'Mary', 'female', -3, 200)")
```

```
---------------------------------------------------------------------------

IntegrityError                            Traceback (most recent call last)

Cell In[114], line 1
```

```
----> 1 cur.execute("INSERT INTO users VALUES (2, 'Mary', 'female', -3, 200)")


IntegrityError: CHECK constraint failed: age >= 0 AND age <= 150
```

By setting constraints to the columns, it is easier to ensure the data quality when the database is growing. Here is a complete code for creating a `user` table with data inserted.

```
with sqlite3.connect("demo.db") as conn:
    cur = conn.cursor()
    cur.execute(
    """
    CREATE TABLE users (
        id INTEGER PRIMARY KEY,
        name TEXT NOT NULL,
        gender TEXT CHECK(gender IN ("male", "female")),
        age INTEGER CHECK(age >= 0 AND age <= 150),
        weight REAL CHECK(weight >= 0 AND weight <= 300)
    )
    """)

    df = pd.DataFrame(
        {
            "name": ["Camille", "Mike", "Jason", "Maria"],
            "gender": ["female", "male", "male", "female"],
            "age": [40, 25, 35, 20],
            "weight": [150, 200, 180, 120],
        }
    )
    df.to_sql("users", conn, if_exists="append", index=False)
    print_table(cur, "users")
```

Reference integrity

We already have a table `users` to define users' information. Now, let's create another table `walks` to record the walking activity.

```
conn = sqlite3.connect("demo.db")
cur = conn.cursor()
cur.execute(
    """
    CREATE TABLE walks (
        id INTEGER PRIMARY KEY,
        user_id INTEGER NOT NULL,
        date TEXT NOT NULL,
        distance FLOAT NOT NULL,
        duration INTEGER NOT NULL,
        FOREIGN KEY (user_id) REFERENCES users (id))
    """
)
```

You may notice that we set `user_id` as the foreign key. This means that the value of `user_id` must correspond to the value of `id` in the `users` table when we need to consider the relationship between the two tables. This is called a `reference integrity`. We can use `REFERENCES` to set the reference integrity.

The `walks` table include the information of the walking date, distance, and duration.Let's insert data into this `walks` table.

```
data = pd.DataFrame(
    data={
        "user_id": [1, 1, 1, 2, 2, 3, 3, 4, 4, 4],
        "date": [
            "02-26-2023",
            "02-27-2023",
            "02-28-2023",
            "02-26-2023",
            "02-27-2023",
            "02-26-2023",
            "02-27-2023",
            "02-26-2023",
            "02-27-2023",
            "02-28-2023",
        ],
        "distance": [1.2, 1.5, 1.7, 2.2, 2.5, 3.2, 3.5, 4.2, 4.5, 4.7],
        "duration": [30, 40, 50, 60, 70, 80, 90, 100, 110, 120],
    }
```

```
)
data.to_sql("walks", conn, if_exists="append", index=False)
```

```
10
```

```
print_table(cur, "walks")
```

```
[(1, '02-26-2023', 1.2, 30),
 (1, '02-27-2023', 1.5, 40),
 (1, '02-28-2023', 1.7, 50),
 (2, '02-26-2023', 2.2, 60),
 (2, '02-27-2023', 2.5, 70),
 (3, '02-26-2023', 3.2, 80),
 (3, '02-27-2023', 3.5, 90),
 (4, '02-26-2023', 4.2, 100),
 (4, '02-27-2023', 4.5, 110),
 (4, '02-28-2023', 4.7, 120)]
```

Ok, now we have two tables with data inserted. We can use `JOIN` to put the data from two tables together.

```
cur.execute(
    """
    SELECT * FROM walks JOIN users
    ON walks.user_id = users.id
    """
)
cur.fetchall()
```

```
[(1, '02-26-2023', 1.2, 30, 1, 'Camille', 'female', 40, 150.0),
 (1, '02-27-2023', 1.5, 40, 1, 'Camille', 'female', 40, 150.0),
 (1, '02-28-2023', 1.7, 50, 1, 'Camille', 'female', 40, 150.0),
 (2, '02-26-2023', 2.2, 60, 2, 'Mike', 'male', 25, 200.0),
 (2, '02-27-2023', 2.5, 70, 2, 'Mike', 'male', 25, 200.0),
 (3, '02-26-2023', 3.2, 80, 3, 'Jason', 'male', 35, 180.0),
 (3, '02-27-2023', 3.5, 90, 3, 'Jason', 'male', 35, 180.0),
 (4, '02-26-2023', 4.2, 100, 4, 'Maria', 'female', 20, 120.0),
 (4, '02-27-2023', 4.5, 110, 4, 'Maria', 'female', 20, 120.0),
 (4, '02-28-2023', 4.7, 120, 4, 'Maria', 'female', 20, 120.0)]
```

You see that the user information was added to the `walks` table. This is similar to how we use `df.merge()` to combine two dataframes in Pandas.

```
df_users = pd.read_sql("SELECT * FROM users", conn)
df_walks = pd.read_sql("SELECT * FROM walks", conn)
pd.merge(df_walks, df_users, left_on="user_id", right_on="id")
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	user_id	date	distance	duration	id	name	gender	age	weight
0	1	02-26-2023	1.2	30	1	Camille	female	40	150.0
1	1	02-27-2023	1.5	40	1	Camille	female	40	150.0
2	1	02-28-2023	1.7	50	1	Camille	female	40	150.0
3	2	02-26-2023	2.2	60	2	Mike	male	25	200.0

	user_id	date	distance	duration	id	name	gender	age	weight
4	2	02-27-2023	2.5	70	2	Mike	male	25	200.0
5	3	02-26-2023	3.2	80	3	Jason	male	35	180.0
6	3	02-27-2023	3.5	90	3	Jason	male	35	180.0
7	4	02-26-2023	4.2	100	4	Maria	female	20	120.0
8	4	02-27-2023	4.5	110	4	Maria	female	20	120.0
9	4	02-28-2023	4.7	120	4	Maria	female	20	120.0

SQlite3 VS. Pandas

Here we will put the major functionalities of SQLite3 and Pandas side by side to see how they compare.

Sorting

SQLite3

```
cur.execute("SELECT * FROM users ORDER BY age DESC")  # or ASC
cur.fetchall()
```

```
[(1, 'Camille', 'female', 40, 150.0),
 (3, 'Jason', 'male', 35, 180.0),
 (2, 'Mike', 'male', 25, 200.0),
 (4, 'Maria', 'female', 20, 120.0)]
```

Pandas

```
df_users.sort_values(by="age", ascending=False)
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	id	name	gender	age	weight
0	1	Camille	female	40	150.0
2	3	Jason	male	35	180.0
1	2	Mike	male	25	200.0
3	4	Maria	female	20	120.0

Filtering

SQLite3

```
cur.execute("SELECT age, gender FROM users WHERE age > 30")
cur.fetchall()
```

```
[(40, 'female'), (35, 'male')]
```

Pandas

```
df_users.loc[:, ["age", "gender"]].query("age > 30")
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	age	gender
0	40	female
2	35	male

SQLite3

```
cur.execute(
    """
    SELECT name, weight FROM users
    WHERE name LIKE '%m%'
    OR name LIKE '%n%'
    """
)
cur.fetchall()
```

```
[('Camille', 150.0), ('Mike', 200.0), ('Jason', 180.0), ('Maria', 120.0)]
```

Pandas

```
df_users.loc[:, ["name", "weight"]].query(
    """
    name.str.upper().str.contains('M') |\
    name.str.upper().str.contains('N')
    """
)
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	name	weight
0	Camille	150.0
1	Mike	200.0
2	Jason	180.0
3	Maria	120.0

Grouping

SQLite3

```
cur.execute(
    """
    SELECT user_id, avg(distance), sum(duration), count(distance)
    FROM walks GROUP BY user_id
    """
)
cur.fetchall()
```

```
[(1, 1.4666666666666668, 120, 3),
 (2, 2.35, 130, 2),
 (3, 3.35, 170, 2),
 (4, 4.466666666666666, 330, 3)]
```

Pandas

```
df_walks.groupby("user_id").aggregate(
    distance_mean=("distance", "mean"),
    duration_sum=("duration", "sum"),
    distance_count=("distance", "count"),
)
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	distance_mean	duration_sum	distance_count
user_id			
1	1.466667	120	3
2	2.350000	130	2
3	3.350000	170	2
4	4.466667	330	3

sqlite_master

`sqliet_master` is a system table that contains the information of all tables in the database. We can use `SELECT * FROM sqlite_master` to get the information of all tables. The output will look like this:

- `type`: the type of the object. In this case, it is `table`.
- `name`: the name of the table.
- `tbl_name`: the name of the table.
- `rootpage`: the page number of the root b-tree page for the table.
- `sql`: the SQL statement used to create the table.

```
cur.execute("SELECT * FROM sqlite_master")
cur.fetchall()
```

```
[('table',
  'users',
  'users',
  2,
  'CREATE TABLE users (\n        id INTEGER PRIMARY KEY,\n        name TEXT NOT NULL,\n        gender TEXT
CHECK(gender IN ("male", "female")),\n        age INTEGER CHECK(age >= 0 AND age <= 150),\n        weight REAL
CHECK(weight >= 0 AND weight <= 300)\n    )'),
 ('table',
  'walks',
  'walks',
  3,
  'CREATE TABLE "walks" (\n"user_id" INTEGER,\n  "date" TEXT,\n  "distance" REAL,\n  "duration" INTEGER\n)')]
```

Or simply list all the tables in the database.

```
cur.execute("SELECT name FROM sqlite_master WHERE type='table'")
cur.fetchall()
```

```
[('users',), ('walks',)]
```

Collection of functions

```
def list_cols(cur, table):
    cur.execute("PRAGMA table_info(%s)" % table)
    cols = [x[1:3] for x in cur.fetchall()]
    return display(cols)

def print_table(cur, table):
    cur.execute("SELECT * FROM %s" % table)
    output = cur.fetchall()
    display(output)

def clean_table(cur, table):
    cur.execute("DELETE FROM %s" % table)

def drop_table(cur, table):
    cur.execute("DROP TABLE %s" % table)
```