Data Manipulation Challenge

A Mental Model for Method Chaining in Pandas

Data Manipulation Challenge - A Mental Model for Method Chaining in Pandas

! Challenge Requirements In Section Student Analysis Section

- Complete all discussion questions for the seven mental models (plus some extra requirements for higher grades)

! Note on Python Usagew

Recommended Workflow: Use Your Existing Virtual Environment If you completed the Tech Setup Challenge Part 2, you already have a virtual environment set up! Here's how to use it for this new challenge:

1. **Clone this new challenge repository** (see Getting Started section below)
2. **Open the cloned repository in Cursor**
3. **Set this project to use your existing Python interpreter:**
   - Press `Ctrl+Shift+P` → "Python: Select Interpreter"
   - Navigate to and choose the interpreter from your existing virtual environment (e.g., `your-previous-project/venv/Scripts/python.exe`)
4. **Activate the environment in your terminal:**
   - Open terminal in Cursor ('Ctrl + ")
   - Navigate to your previous project folder where you have the `venv` folder
   - **Pro tip:** You can quickly navigate by typing `cd` followed by dragging the folder from your file explorer into the terminal
   - Activate using the appropriate command for your system:
     - **Windows Command Prompt:** `venv\Scripts\activate`

    - **Windows PowerShell:** `.\venv\Scripts\Activate.ps1`
    - **Mac/Linux:** `source venv/bin/activate`
  - You should see `(venv)` at the beginning of your terminal prompt

5. **Install additional packages if needed:** `pip install pandas numpy matplotlib seaborn`

Cloud Storage Warning

Avoid using Google Drive, OneDrive, or other cloud storage for Python projects! These services can cause issues with: - Package installations failing due to file locking - Virtual environment corruption - Slow performance during pip operations

Best practice: Keep your Python projects in a local folder like `C:\Users\YourName\Documents\` or `~/Documents/` instead of cloud-synced folders.

Alternative: Create a New Virtual Environment If you prefer a fresh environment, follow the Quarto documentation: https://quarto.org/docs/projects/virtual-environments.html. Be sure to follow the instructions to activate the environment, set it up as your default Python interpreter for the project, and install the necessary packages (e.g. pandas) for this challenge. For installing the packages, you can use the `pip install -r requirements.txt` command since you already have the requirements.txt file in your project. Some steps do take a bit of time, so be patient.
Why This Works: Virtual environments are portable - you can use the same environment across multiple projects, and Cursor automatically activates it when you select the interpreter!

The Problem: Mastering Data Manipulation Through Method Chaining

Core Question: How can we efficiently manipulate datasets using `pandas` method chaining to answer complex business questions?

The Challenge: Real-world data analysis requires combining multiple data manipulation techniques in sequence. Rather than creating intermediate variables at each step, method chaining allows us to write clean, readable code that flows logically from one operation to the next.

Our Approach: We'll work with ZappTech's shipment data to answer critical business questions about service levels and cross-category orders, using the seven mental models of data manipulation through pandas method chaining.

AI Partnership Required

This challenge pushes boundaries intentionally. You'll tackle problems that normally require weeks of study, but with Cursor AI as your partner (and your brain keeping it honest), you can accomplish more than you thought possible.
The new reality: The four stages of competence are Ignorance → Awareness → Learning → Mastery. AI lets us produce Mastery-level work while operating primarily in the Awareness stage. I focus on awareness training, you leverage AI for execution, and together we create outputs that used to require years of dedicated study.

The Seven Mental Models of Data Manipulation

The seven most important ways we manipulate datasets are:

1. **Assign:** Add new variables with calculations and transformations
2. **Subset:** Filter data based on conditions or select specific columns
3. **Drop:** Remove unwanted variables or observations
4. **Sort:** Arrange data by values or indices
5. **Aggregate:** Summarize data using functions like mean, sum, count
6. **Merge:** Combine information from multiple datasets
7. **Split-Apply-Combine:** Group data and apply functions within groups

Data and Business Context

We analyze ZappTech's shipment data, which contains information about product deliveries across multiple categories. This dataset is ideal for our analysis because:

- **Real Business Questions:** CEO wants to understand service levels and cross-category shopping patterns
- **Multiple Data Sources:** Requires merging shipment data with product category information
- **Complex Relationships:** Service levels may vary by product category, and customers may order across categories
- **Method Chaining Practice:** Perfect for demonstrating all seven mental models in sequence

Data Loading and Initial Exploration

Let's start by loading the ZappTech shipment data and understanding what we're working with.

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta

# Load the shipment data
shipments_df = pd.read_csv(
    "https://raw.githubusercontent.com/flyaflya/persuasive/main/shipments.csv",
    parse_dates=['plannedShipDate', 'actualShipDate']
)

# Load product line data
product_line_df = pd.read_csv(
    "https://raw.githubusercontent.com/flyaflya/persuasive/main/productLine.csv"
)

# Reduce dataset size for faster processing (4,000 rows instead of 96,805 rows)
shipments_df = shipments_df.head(4000)

print("Shipments data shape:", shipments_df.shape)
print("\nShipments data columns:", shipments_df.columns.tolist())
print("\nFirst few rows of shipments data:")
print(shipments_df.head(10))

print("\n" + "="*50)
print("Product line data shape:", product_line_df.shape)
print("\nProduct line data columns:", product_line_df.columns.tolist())
print("\nFirst few rows of product line data:")
print(product_line_df.head(10))
```

```
Shipments data shape: (4000, 5)

Shipments data columns: ['shipID', 'plannedShipDate', 'actualShipDate', 'partID', 'quantity'

First few rows of shipments data:
   shipID plannedShipDate actualShipDate       partID  quantity
0   10001      2013-11-06     2013-10-04  part92b16c5         6
1   10002      2013-10-15     2013-10-04   part66983b         2
2   10003      2013-10-25     2013-10-07  part8e36f25         1
3   10004      2013-10-14     2013-10-08  part30f5de0         1
4   10005      2013-10-14     2013-10-08  part9d64d35         6
```

```
5   10006      2013-10-14     2013-10-08  part6cd6167        15
6   10007      2013-10-14     2013-10-08  parta4d5fd1         2
7   10008      2013-10-14     2013-10-08  part08cadf5         1
8   10009      2013-10-14     2013-10-08  part5cc4989        10
9   10010      2013-10-14     2013-10-08  part912ae4c         1

==================================================
Product line data shape: (11997, 3)

Product line data columns: ['partID', 'productLine', 'prodCategory']

First few rows of product line data:
        partID productLine prodCategory
0  part00005ba      line4c      Liquids
1  part000b57d      line61     Machines
2  part00123bf      linec1  Marketables
3  part0021fc9      line61     Machines
4  part0027e86      line2f     Machines
5  part002ed95      line4c      Liquids
6  part0030856      lineb8     Machines
7  part0033dfd      line49      Liquids
8  part0037a2a      linea3  Marketables
9  part003caee      linea3  Marketables
```

Understanding the Data

Shipments Data: Contains individual line items for each shipment, including: - `shipID`: Unique identifier for each shipment - `partID`: Product identifier - `plannedShipDate`: When the shipment was supposed to go out - `actualShipDate`: When it actually shipped - `quantity`: How many units were shipped
Product Category and Line Data: Contains product category information: - `partID`: Links to shipments data - `productLine`: The category each product belongs to - `prodCategory`: The category each product belongs to
Business Questions We'll Answer: 1. Does service level (on-time shipments) vary across product categories? 2. How often do orders include products from more than one category?

The Seven Mental Models: A Progressive Learning Journey

Now we'll work through each of the seven mental models using method chaining, starting simple and building complexity.

1. Assign: Adding New Variables

Mental Model: Create new columns with calculations and transformations.

Let's start by calculating whether each shipment was late:

```
# Simple assignment - calculate if shipment was late
shipments_with_lateness = (
    shipments_df
    .assign(
        is_late=lambda df: df['actualShipDate'] > df['plannedShipDate'],
        days_late=lambda df: (df['actualShipDate'] - df['plannedShipDate']).dt.days
    )
)

print("Added lateness calculations:")
print(shipments_with_lateness[['shipID', 'plannedShipDate', 'actualShipDate', 'is_late', 'da
```

```
Added lateness calculations:
   shipID plannedShipDate actualShipDate  is_late  days_late
0   10001      2013-11-06     2013-10-04    False        -33
1   10002      2013-10-15     2013-10-04    False        -11
2   10003      2013-10-25     2013-10-07    False        -18
3   10004      2013-10-14     2013-10-08    False         -6
4   10005      2013-10-14     2013-10-08    False         -6
```

Method Chaining Tip for New Python Users

Why use `lambda df:`? When chaining methods, we need to reference the current state of the dataframe. The `lambda df:` tells pandas "use the current dataframe in this calculation." Without it, pandas would look for a variable called `df` that doesn't exist.
Alternative approach: You could also write this as separate steps, but method chaining keeps related operations together and makes the code more readable.

Discussion Questions: Assign Mental Model

Question 1: Data Types and Date Handling - What is the `dtype` of the `actualShipDate` series? How can you find out using code?
Answer: The dtype of the `actualShipDate` series is `datetime64[ns]`. I found this by running the code `print(shipments_df['actualShipDate'].dtype)`.

```
print(shipments_df['actualShipDate'].dtype)
```

```
datetime64[ns]
```

- Why is it important that both `actualShipDate` and `plannedShipDate` have the same data type for comparison? Comparison may not work if the datatypes are different. For example, if `actualShipDate` is a string and `plannedShipDate` is a datetime, the comparison will not work because the string cannot be compared to a datetime.

Question 2: String vs Date Comparison - Can you give an example where comparing two dates as strings would yield unintuitive results, e.g. what happens if you try to compare "04-11-2025" and "05-20-2024" as strings vs as dates?
Answer: Results would be unintuitive since the strings are not in the correct format. If you try to compare "04-11-2025" and "05-20-2024" as strings, the comparison will not work because the strings are not in the correct format.

```
print("04-11-2025" > "05-20-2024")
```

```
False
```

Returns `False` because the strings are not in the correct format.

```
print(datetime.strptime("04-11-2025", "%m-%d-%Y") > datetime.strptime("05-20-2024", "%m-%d-
```

```
True
```

Returns `True` because the strings are in the correct format.
Question 3: Debug This Code

```
# This code has an error - can you spot it?
shipments_with_lateness = (
    shipments_df
    .assign(
        is_late=lambda df: df['actualShipDate'] > df['plannedShipDate'],
        days_late=lambda df: (df['actualShipDate'] - df['plannedShipDate']).dt.days,
        lateStatement="Darn Shipment is Late" if shipments_df['is_late'] else "Shipment is
    )
)
```

What's wrong with the `lateStatement` assignment and how would you fix it?
Answer: The `lateStatement` assignment is wrong as the `is_late` column is a boolean series, not a single boolean value.

```
shipments_with_lateness = (
    shipments_df
    .assign(
        is_late=lambda df: df['actualShipDate'] > df['plannedShipDate'],
        days_late=lambda df: (df['actualShipDate'] - df['plannedShipDate']).dt.days,
        lateStatement=lambda df: np.where(
            df['actualShipDate'] > df['plannedShipDate'],
            "Darn Shipment is Late",
            "Shipment is on Time"
        )
    )
)
print(shipments_with_lateness['lateStatement'])
```

```
0         Shipment is on Time
1         Shipment is on Time
2         Shipment is on Time
3         Shipment is on Time
4         Shipment is on Time
                ...
3995      Shipment is on Time
3996      Shipment is on Time
3997    Darn Shipment is Late
3998      Shipment is on Time
3999      Shipment is on Time
Name: lateStatement, Length: 4000, dtype: object
```

Understanding the Methods

- **`.query()`**: Query rows based on conditions (like SQL WHERE clause)
- **`.filter()`**: Filter to keep specific columns by name
- **Alternative**: You could use `.loc[]` for more complex row querying, but `.query()` is often more readable

Discussion Questions: Subset Mental Model

Question 1: Query vs Boolean Indexing - What's the difference between using `.query('is_late == True')` and `[df['is_late'] == True]`? - Which approach is more readable and why?

Question 2: Additional Row Querying - Can you show an example of using a variable like `late_threshold` to query rows for shipments that are at least `late_threshold` days late, e.g. what if you wanted to query rows for shipments that are at least 5 days late?

Briefly Give Answers to the Discussion Questions In This Section

Question 1: Query vs Boolean Indexing

Answer: There is no difference in results between using `.query('is_late == True')` and `[df['is_late'] == True]` is that `.query('is_late == True')` is more readable and easier to understand.

Question 2: Additional Row Querying

Answer: `late_threshold` can be used to query rows for shipments that are at least `late_threshold` days late.

```
late_threshold = 5
print(shipments_with_lateness[shipments_with_lateness['days_late'] >= late_threshold])
```

```
      shipID plannedShipDate actualShipDate       partID  quantity  is_late  \
776    10192      2013-10-09     2013-10-14  part0164a70         2     True
777    10192      2013-10-09     2013-10-14  part9259836         1     True
778    10192      2013-10-09     2013-10-14  part4526c73         1     True
779    10192      2013-10-09     2013-10-14  partbb47e81         2     True
780    10192      2013-10-09     2013-10-14  part008482f         1     True
...      ...             ...            ...          ...       ...      ...
3896   10956      2013-09-24     2013-10-15  part98c1c48         1     True
3897   10956      2013-09-24     2013-10-15  part82e69e9         1     True
3898   10956      2013-09-24     2013-10-15  partf23fd1e         2     True
3899   10956      2013-09-24     2013-10-15  part825873c         1     True
3997   11001      2013-10-04     2013-10-15  partd4952a8         1     True

      days_late          lateStatement
776           5  Darn Shipment is Late
777           5  Darn Shipment is Late
778           5  Darn Shipment is Late
779           5  Darn Shipment is Late
780           5  Darn Shipment is Late
...         ...                    ...
3896         21  Darn Shipment is Late
3897         21  Darn Shipment is Late
3898         21  Darn Shipment is Late
3899         21  Darn Shipment is Late
3997         11  Darn Shipment is Late

[186 rows x 8 columns]
```

Returns the rows where the `days_late` column is greater than or equal to `late_threshold`.

3. Drop: Removing Unwanted Data

Mental Model: Remove columns or rows you don't need.
Let's clean up our data by removing unnecessary columns:

```
# Create a cleaner dataset by dropping unnecessary columns
clean_shipments = (
    shipments_with_lateness
    .drop(columns=['quantity'])  # Drop quantity column (not needed for our analysis)
    .dropna(subset=['plannedShipDate', 'actualShipDate'])  # Remove rows with missing dates
)

print(f"Cleaned dataset: {len(clean_shipments)} rows, {len(clean_shipments.columns)} colum
print("Remaining columns:", clean_shipments.columns.tolist())
```

```
Cleaned dataset: 4000 rows, 7 columns
Remaining columns: ['shipID', 'plannedShipDate', 'actualShipDate', 'partID', 'is_late', 'da
```

Discussion Questions: Drop Mental Model

Question 1: Drop vs Filter Strategies - What's the difference between `.drop(columns=['quantity'])` and `.filter()` with a list of columns you want to keep? - When would you choose to drop columns vs filter to keep specific columns?

Question 2: Handling Missing Data - What happens if you use `.dropna()` without specifying `subset`? How is this different from `.dropna(subset=['plannedShipDate', 'actualShipDate'])`? - Why might you want to be selective about which columns to check for missing values?

Briefly Give Answers to the Discussion Questions In This Section

Question 1: Drop vs Filter Strategies

Answer: The difference between `.drop(columns=['quantity'])` and `.filter()` with a list of columns you want to keep is that `.drop(columns=['quantity'])` drops the `quantity` column from the dataframe, while `.filter()` keeps the columns in the list.

```
print(clean_shipments.columns.tolist())
```

```
['shipID', 'plannedShipDate', 'actualShipDate', 'partID', 'is_late', 'days_late', 'lat
```

Returns the columns in the dataframe.

```
print(clean_shipments.filter(['shipID', 'partID', 'plannedShipDate', 'actualShipDate',
```

```
      shipID       partID plannedShipDate actualShipDate  days_late
0      10001  part92b16c5      2013-11-06     2013-10-04        -33
1      10002   part66983b      2013-10-15     2013-10-04        -11
2      10003  part8e36f25      2013-10-25     2013-10-07        -18
3      10004  part30f5de0      2013-10-14     2013-10-08         -6
4      10005  part9d64d35      2013-10-14     2013-10-08         -6
...      ...          ...             ...            ...        ...
3995   10999  part0275794      2013-10-15     2013-10-15          0
3996   10999  part04da31b      2013-10-15     2013-10-15          0
3997   11001  partd4952a8      2013-10-04     2013-10-15         11
3998   11002  parta8850c7      2013-10-15     2013-10-15          0
3999   11003  part7114b3c      2013-10-15     2013-10-15          0

[4000 rows x 5 columns]
```

Returns the columns in the list.

Question 2: Handling Missing Data

Answer: Not all columns having missing values need to be dropped all times. If you only need to check for missing values in certain columns. For example, if you only need to check for missing values in the `plannedShipDate` and `actualShipDate` columns, you can use `.dropna(subset=['plannedShipDate', 'actualShipDate'])`.

4. Sort: Arranging Data

Mental Model: Order data by values or indices.
Let's sort by lateness to see the worst offenders:

```
# Sort by days late (worst first)
sorted_by_lateness = (
    clean_shipments
    .sort_values('days_late', ascending=False)  # Sort by days_late, highest first
    .reset_index(drop=True)  # Reset index to be sequential
)

print("Shipments sorted by lateness (worst first):")
print(sorted_by_lateness[['shipID', 'partID', 'days_late', 'is_late']].head(10))
```

```
Shipments sorted by lateness (worst first):
   shipID       partID  days_late  is_late
0   10956  part795d1a4         21     True
1   10956  partf23fd1e         21     True
2   10956  partc653823         21     True
3   10956  partb6208b5         21     True
4   10956  parte820e31         21     True
5   10956  part50c6b9a         21     True
6   10956  part1fedfcf         21     True
7   10956  part3017fa1         21     True
8   10956  part66bb851         21     True
9   10956  partd5b19e4         21     True
```

Discussion Questions: Sort Mental Model

Question 1: Sorting Strategies - What's the difference between `ascending=False` and `ascending=True` in sorting? - How would you sort by multiple columns (e.g., first by `is_late`, then by `days_late`)?

Abhijeet's answer:

Question 2: Index Management - Why do we use `.reset_index(drop=True)` after sorting? - What happens to the original index when you sort? Why might this be problematic?

Briefly Give Answers to the Discussion Questions In This Section

Question 1: Sorting Strategies

Answer: `ascending=False` sorts in descending order, `ascending=True` sorts in ascending order.

```
print(sorted_by_lateness.sort_values('days_late', ascending=False))
```

```
      shipID plannedShipDate actualShipDate       partID  is_late  days_late  \
0      10956      2013-09-24     2013-10-15  part795d1a4     True         21
12     10956      2013-09-24     2013-10-15  part825873c     True         21
1      10956      2013-09-24     2013-10-15  partf23fd1e     True         21
21     10956      2013-09-24     2013-10-15  part54d1a21     True         21
20     10217      2013-09-23     2013-10-14  part2081be9     True         21
...      ...             ...            ...          ...      ...        ...
3974   10059      2013-11-05     2013-10-11  part5bd94b1    False        -
25
3975   10059      2013-11-05     2013-10-11  partb5c97bc    False        -
25
```

```
3976   10059      2013-11-05     2013-10-11  part0945ee9    False         -
25
3977   10059      2013-11-05     2013-10-11  part5f63c90    False         -
25
3999   10001      2013-11-06     2013-10-04  part92b16c5    False         -
33

              lateStatement
0     Darn Shipment is Late
12    Darn Shipment is Late
1     Darn Shipment is Late
21    Darn Shipment is Late
20    Darn Shipment is Late
...                     ...
3974    Shipment is on Time
3975    Shipment is on Time
3976    Shipment is on Time
3977    Shipment is on Time
3999    Shipment is on Time

[4000 rows x 7 columns]
```

Returns the dataframe sorted by `days_late` in descending order.

```
print(sorted_by_lateness.sort_values('days_late', ascending=True))
```

```
      shipID plannedShipDate actualShipDate       partID  is_late  days_late  \
3999   10001      2013-11-06     2013-10-04  part92b16c5    False         -
33
3977   10059      2013-11-05     2013-10-11  part5f63c90    False         -
25
3976   10059      2013-11-05     2013-10-11  part0945ee9    False         -
25
3975   10059      2013-11-05     2013-10-11  partb5c97bc    False         -
25
3974   10059      2013-11-05     2013-10-11  part5bd94b1    False         -
25
...      ...             ...            ...          ...      ...        ...
18     10956      2013-09-24     2013-10-15  parta27d449     True         21
20     10217      2013-09-23     2013-10-14  part2081be9     True         21
21     10956      2013-09-24     2013-10-15  part54d1a21     True         21
11     10956      2013-09-24     2013-10-15  part82e69e9     True         21
```

```
0      10956      2013-09-24     2013-10-15  part795d1a4     True         21

              lateStatement
3999    Shipment is on Time
3977    Shipment is on Time
3976    Shipment is on Time
3975    Shipment is on Time
3974    Shipment is on Time
...                     ...
18    Darn Shipment is Late
20    Darn Shipment is Late
21    Darn Shipment is Late
11    Darn Shipment is Late
0     Darn Shipment is Late

[4000 rows x 7 columns]
```

Returns the dataframe sorted by `days_late` in ascending order.

- Use lists to sort by multiple columns

```python
sorted_shipments = clean_shipments.sort_values(
    by=['is_late', 'days_late'],
    ascending=[False, False]   # both in descending order
)
```

Question 2: Index Management
Answer: - use .reset_index(drop=True) to get a clean, continuous index after sorting. - Without it, the old index values remain and can make the table look messy or cause confusion when referencing rows.

```python
sorted_shipments = sorted_shipments.reset_index(drop=True)
print("\nAfter resetting index:")
print(sorted_shipments)
```

```
After resetting index:
      shipID plannedShipDate actualShipDate       partID  is_late  days_late  \
0      10217      2013-09-23     2013-10-14  part2081be9     True         21
1      10956      2013-09-24     2013-10-15  part54d1a21     True         21
2      10956      2013-09-24     2013-10-15  part0666061     True         21
3      10956      2013-09-24     2013-10-15  parta27d449     True         21
```

```
4      10956      2013-09-24     2013-10-15  partc63f9bc     True         21
...      ...             ...            ...          ...      ...        ...
3995   10059      2013-11-05     2013-10-11  part0945ee9    False          -
25
3996   10059      2013-11-05     2013-10-11  part5bd94b1    False          -
25
3997   10059      2013-11-05     2013-10-11  part0d00ec6    False          -
25
3998   10059      2013-11-05     2013-10-11  part9b3abf3    False          -
25
3999   10001      2013-11-06     2013-10-04  part92b16c5    False          -
33

              lateStatement
0     Darn Shipment is Late
1     Darn Shipment is Late
2     Darn Shipment is Late
3     Darn Shipment is Late
4     Darn Shipment is Late
...                     ...
3995    Shipment is on Time
3996    Shipment is on Time
3997    Shipment is on Time
3998    Shipment is on Time
3999    Shipment is on Time

[4000 rows x 7 columns]
```

5. Aggregate: Summarizing Data

Mental Model: Calculate summary statistics across groups or the entire dataset. Let's calculate overall service level metrics:

```
# Calculate overall service level metrics
service_metrics = (
    clean_shipments
    .agg({
        'is_late': ['count', 'sum', 'mean'],  # Count total, count late, calculate percenta
        'days_late': ['mean', 'max']  # Average and maximum days late
    })
    .round(3)
)

print("Overall Service Level Metrics:")
print(service_metrics)

# Calculate percentage on-time directly from the data
on_time_rate = (1 - clean_shipments['is_late'].mean()) * 100
print(f"\nOn-time delivery rate: {on_time_rate:.1f}%")
```

```
Overall Service Level Metrics:
        is_late  days_late
count  4000.000        NaN
sum     456.000        NaN
mean      0.114     -0.974
max         NaN     21.000

On-time delivery rate: 88.6%
```

Discussion Questions: Aggregate Mental Model

Question 1: Boolean Aggregation - Why does `sum()` work on boolean values? What does it count?

Briefly Give Answers to the Discussion Questions In This Section

Answer: `sum()` works on boolean values because it counts the number of True values (as 1) in the series.

```
print(clean_shipments['is_late'].sum())
```

```
456
```

Returns the number of True values in the `is_late` column.

6. Merge: Combining Information

Mental Model: Join data from multiple sources to create richer datasets.
Now let's analyze service levels by product category. First, we need to merge our data:

```python
# Merge shipment data with product line data
shipments_with_category = (
    clean_shipments
    .merge(product_line_df, on='partID', how='left')  # Left join to keep all shipments
    .assign(
        category_late=lambda df: df['is_late'] & df['prodCategory'].notna()  # Only count a
    )
)

print("\nProduct categories available:")
print(shipments_with_category['prodCategory'].value_counts())
```

```

Product categories available:
prodCategory
Marketables    1850
Machines        846
SpareParts      767
Liquids         537
Name: count, dtype: int64
```

Discussion Questions: Merge Mental Model

Question 1: Join Types and Data Loss - Why does your professor think we should use `how='left'` in most cases? - How can you check if any shipments were lost during the merge?

Question 2: Key Column Matching - What happens if there are duplicate `partID` values in the `product_line_df`?

Briefly Give Answers to the Discussion Questions In This Section
Question 1: Join Types and Data Loss
Answer: - Using how='left' keeps all rows from the left DataFrame (e.g., shipments) even if there's no match in the right DataFrame (e.g., productLine). This prevents losing shipments that don't have matching product information. - Check for data loss by comparing row counts or counting NaN values after the merge.

```
print("Before merge:", len(clean_shipments))
print("After merge:", len(shipments_with_category))
missing = shipments_with_category["prodCategory"].isna().sum()
print("Shipments without matching category:", missing)
```

```
Before merge: 4000
After merge: 4000
Shipments without matching category: 0
```

Question 2: Key Column Matching
Answer: Duplicate partID values cause row multiplication — each shipment gets repeated for every matching duplicate entry. This can inflate data and affect counts or aggregations, so it's best to deduplicate before merging.

~~~
### 7. Split-Apply-Combine: Group Analysis

**Mental Model:** Group data and apply functions within each group.

Now let's analyze service levels by category:

::: {#mental-model-7-groupby .cell execution_count=20}
``` {.python .cell-code}
# Analyze service levels by product category
service_by_category = (
    shipments_with_category
    .groupby('prodCategory')  # Split by product category
    .agg({
        'is_late': ['any', 'count', 'sum', 'mean'],  # Count, late count, percentage late
        'days_late': ['mean', 'max']  # Average and max days late
    })
    .round(3)
)

print("Service Level by Product Category:")
print(service_by_category)

Service Level by Product Category:
             is_late                   days_late
                 any count  sum   mean      mean max
prodCategory
Liquids         True   537   22  0.041    -0.950  19
Machines        True   846  152  0.180    -1.336  21
~~~

```
Marketables     True  1850  145  0.078    -0.804  21
SpareParts      True   767  137  0.179    -1.003  21
```

! Discussion Questions: Split-Apply-Combine Mental Model

Question 1: GroupBy Mechanics - What does `.groupby('prodCategory')` actually do? How does it "split" the data? - Why do we need to use `.agg()` after grouping? What happens if you don't?
Question 2: Multi-Level Grouping - Explore grouping by `['shipID', 'prodCategory']`? What question does this answer versus grouping by `'prodCategory'` alone? (HINT: There may be many rows with identical shipID's due to a particular order having multiple partID's.)

Briefly Give Answers to the Discussion Questions In This Section

Answer for Question 1: GroupBy Mechanics

- .groupby() splits the data into category-based groups and .agg() combines them again with summary statistics.
- Without .agg(), no calculations are performed — it just have the grouping structure.

Answer for Question 2: Multi-Level Grouping

- Grouping by [‘shipID’, ‘prodCategory’] breaks the data down by both shipment and category, letting to see per-shipment category details.
- while grouping by ‘prodCategory’ alone only shows overall category trends.

Answering A Business Question

Mental Model: Combine multiple data manipulation techniques to answer complex business questions.

Let's create a comprehensive analysis by combining shipment-level data with category information:

```python
# Create a comprehensive analysis dataset
comprehensive_analysis = (
    shipments_with_category
    .groupby(['shipID', 'prodCategory'])  # Group by shipment and category
    .agg({
        'is_late': 'any',  # True if any item in this shipment/category is late
        'days_late': 'max'  # Maximum days late for this shipment/category
    })
    .reset_index()
    .assign(
        has_multiple_categories=lambda df: df.groupby('shipID')['prodCategory'].transform('nu
    )
)

print("Comprehensive analysis - shipments with multiple categories:")
multi_category_shipments = comprehensive_analysis[comprehensive_analysis['has_multiple_catego
print(f"Shipments with multiple categories: {multi_category_shipments['shipID'].nunique()}")
print(f"Total unique shipments: {comprehensive_analysis['shipID'].nunique()}")
print(f"Percentage with multiple categories: {multi_category_shipments['shipID'].nunique() /
```

```
Comprehensive analysis - shipments with multiple categories:
Shipments with multiple categories: 232
Total unique shipments: 997
Percentage with multiple categories: 23.3%
```

! Discussion Questions: Answering A Business Question

Question 1: Business Question Analysis - What business question does this comprehensive analysis answer?
Question 2: Multi-Level Grouping

- How does grouping by `['shipID', 'prodCategory']` differ from grouping by just `'prodCategory'`?
- What insights can ZappTech's management gain from knowing the percentage of multi-category shipments?

Briefly Give Answers to the Discussion Questions In This Section

Question 1: Business Question Analysis

Answer: This comprehensive analysis answers the business question of how many shipments have multiple product categories.

```
print(comprehensive_analysis['has_multiple_categories'].sum())
```

```
594
```

Returns the number of shipments with multiple product categories.

Question 2: Multi-Level Grouping

Answer: - Grouping by `['shipID', 'prodCategory']` differs from grouping by just `'prodCategory'` in that it breaks the data down by both shipment and category, letting you see per-shipment category details. While grouping by 'prodCategory' alone only shows overall category trends. - The insights that ZappTech's management can gain from knowing the percentage of multi-category shipments is that they can see how many shipments have multiple product categories and what categories are most common. This can help them identify which categories are most problematic and need to be addressed.

Student Analysis Section: Mastering Data Manipulation

Your Task: Demonstrate your mastery of the seven mental models through comprehensive discussion and analysis. The bulk of your grade comes from thoughtfully answering the discussion questions for each mental model. See below for more details.

Core Challenge: Discussion Questions Analysis

For each mental model, provide: - Clear, concise answers to all discussion questions - Code examples where appropriate to support your explanations

! Discussion Questions Requirements

Complete all discussion question sections: 1. **Assign Mental Model:** Data types, date handling, and debugging 2. **Subset Mental Model:** Filtering strategies and complex queries 3. **Drop Mental Model:** Data cleaning and quality management 4. **Sort Mental Model:** Data organization and business logic 5. **Aggregate Mental Model:** Summary statistics and business metrics 6. **Merge Mental Model:** Data integration and quality control 7. **Split-Apply-Combine Mental Model:** Group analysis and advanced operations 8. **Answering A Business Question:** Combining multiple data manipulation techniques to answer a business question

Professional Visualizations (For 100% Grade)

Your Task: Create a professional visualization that supports your analysis and demonstrates your understanding of the data.

Create visualizations showing: - Service level (on-time percentage) by product category

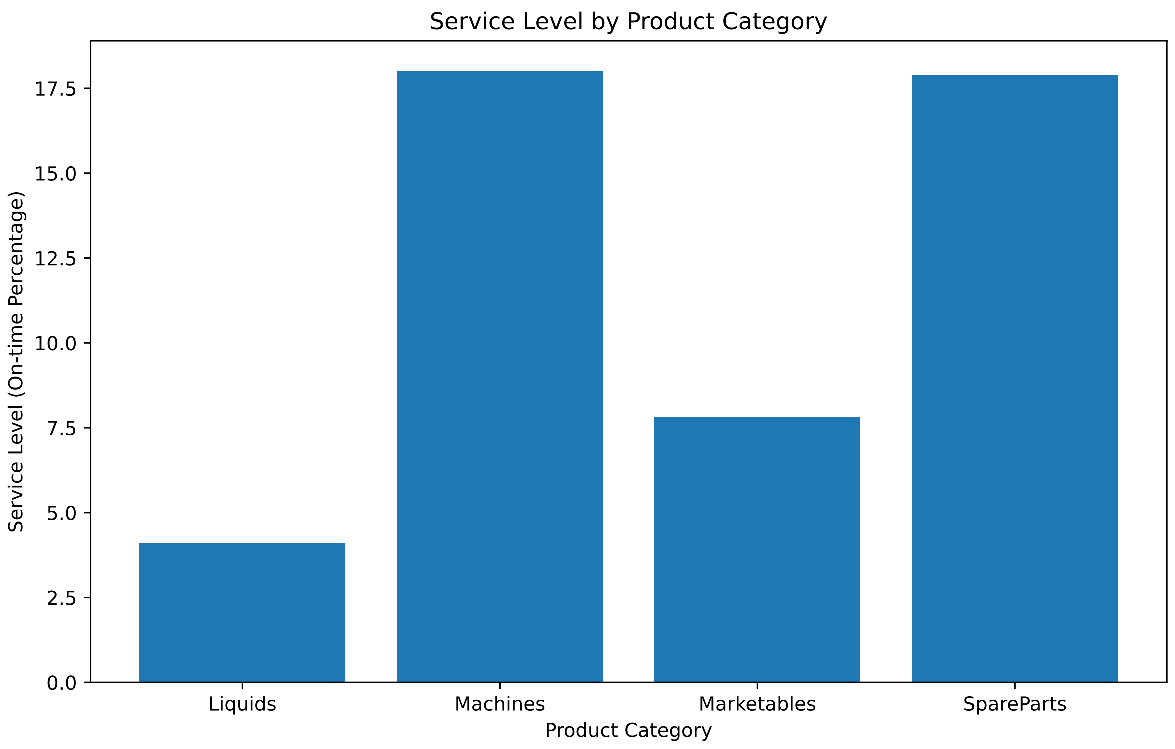
Your visualizations should: - Use clear labels and professional formatting - Support the insights from your discussion questions - Be appropriate for a business audience - Do not `echo` the code that creates the visualizations

Answer:

- Service level (on-time percentage) by product category

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
plt.bar(service_by_category.index, service_by_category['is_late']['mean'] * 100)
plt.xlabel('Product Category')
plt.ylabel('Service Level (On-time Percentage)')
plt.title('Service Level by Product Category')
plt.savefig('service_level_by_product_category.png')
plt.show()
```



Returns a bar chart showing the service level (on-time percentage) by product category. This helps to identify which categories are most problematic and need to be addressed.

Challenge Requirements

Your Primary Task: Answer all discussion questions for the seven mental models with thoughtful, well-reasoned responses that demonstrate your understanding of data manipulation concepts.

Key Requirements: - Complete discussion questions for each mental model - Demonstrate clear understanding of pandas concepts and data manipulation techniques - Write clear, business-focused analysis that explains your findings

Getting Started: Repository Setup

❗ Getting Started

Step 1: Fork and clone this challenge repository - Go to the course repository and find the "dataManipulationChallenge" folder - Fork it to your GitHub account, or clone it directly - Open the cloned repository in Cursor
Step 2: Set up your Python environment - Follow the Python setup instructions above (use your existing venv from Tech Setup Challenge Part 2) - Make sure your virtual environment is activated and the Python interpreter is set
Step 3: You're ready to start! The data loading code is already provided in this file.
Note: This challenge uses the same `index.qmd` file you're reading right now - you'll edit it to complete your analysis.

Getting Started Tips

ℹ Method Chaining Philosophy

> "Each operation should build naturally on the previous one"

Think of method chaining like building with LEGO blocks - each piece connects to the next, creating something more complex and useful than the individual pieces.

⚠ Important: Save Your Work Frequently!

Before you start: Make sure to commit your work often using the Source Control panel in Cursor (Ctrl+Shift+G or Cmd+Shift+G). This prevents the AI from overwriting your progress and ensures you don't lose your work.
Commit after each major step:

- After completing each mental model section
- After adding your visualizations
- After completing your advanced method chain
- Before asking the AI for help with new code

How to commit:

1. Open Source Control panel (Ctrl+Shift+G)
2. Stage your changes (+ button)
3. Write a descriptive commit message
4. Click the checkmark to commit

Remember: Frequent commits are your safety net!

Grading Rubric

75% Grade: Complete discussion questions for at least 5 of the 7 mental models with clear, thoughtful responses.

85% Grade: Complete discussion questions for all 7 mental models with comprehensive, well-reasoned responses.

95% Grade: Complete all discussion questions plus the "Answering A Business Question" section.

100% Grade: Complete all discussion questions plus create a professional visualization showing service level by product category.

Submission Checklist

Minimum Requirements (Required for Any Points):

- ☐ Created repository named "dataManipulationChallenge" in your GitHub account
- ☐ Cloned repository locally using Cursor (or VS Code)
- ☐ Completed discussion questions for at least 5 of the 7 mental models
- ☐ Document rendered to HTML successfully
- ☐ HTML files uploaded to your repository
- ☐ GitHub Pages enabled and working
- ☐ Site accessible at `https://[your-username].github.io/dataManipulationChallenge/`

75% Grade Requirements:

- ☐ Complete discussion questions for at least 5 of the 7 mental models

- ☐ Clear, thoughtful responses that demonstrate understanding
- ☐ Code examples where appropriate to support explanations

85% Grade Requirements:

- ☐ Complete discussion questions for all 7 mental models
- ☐ Comprehensive, well-reasoned responses showing deep understanding
- ☐ Business context for why concepts matter
- ☐ Examples of real-world applications

95% Grade Requirements:

- ☐ Complete discussion questions for all 7 mental models
- ☐ Complete the "Answering A Business Question" discussion questions
- ☐ Comprehensive, well-reasoned responses showing deep understanding
- ☐ Business context for why concepts matter

100% Grade Requirements:

- ☐ All discussion questions completed with professional quality
- ☐ Professional visualization showing service level by product category
- ☐ Professional presentation style appropriate for business audience
- ☐ Clear, engaging narrative that tells a compelling story
- ☐ Practical insights that would help ZappTech's management

Report Quality (Critical for Higher Grades):

- ☐ Professional writing style (no AI-generated fluff)
- ☐ Concise analysis that gets to the point