Inventory Data Cleaning & Standardization Project

Objective:

The aim of this project is to clean, standardize, and analyze product-level inventory data for better reporting and business insight.

Common Issues Identified:

- Multiple naming variations for the **same product** (e.g., *CocaCola - 500ml*, *Coke 0.5L*, *Coca-Cola 500ml*)
- Inconsistent or missing **SKU codes**
- **Price variations** for identical products (e.g., same SKU or name priced differently at different hubs)
- Duplicate or non-standard **hub/location** names
- Need for **clear visual insights** across hubs

What We'll Do:

1. Load and explore the raw inventory data.
2. Standardize product names (to "Coca-Cola 500ml").
3. Standardize SKUs for similar products.
4. Set a consistent price (e.g., €2.5 for Coca-Cola 500ml).
5. Aggregate total stock per hub.
6. Visualize stock distribution by location.
7. Highlight top and bottom performing hubs.
8. Export a cleaned dataset for dashboarding or reporting.

Let's begin!

```
!pip install pandas pandasql
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-pac
Collecting pandasql
  Downloading pandasql-0.7.3.tar.gz (26 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/d
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/pyt
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/di
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/
Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.11/dist
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-p
Requirement already satisfied: greenlet>=1 in /usr/local/lib/python3.11/dis
Requirement already satisfied: typing-extensions>=4.6.0 in /usr/local/lib/p
Building wheels for collected packages: pandasql
  Building wheel for pandasql (setup.py) ... done
  Created wheel for pandasql: filename=pandasql-0.7.3-py3-none-any.whl size
  Stored in directory: /root/.cache/pip/wheels/68/5d/a5/edc271b998f909801d7
Successfully built pandasql
Installing collected packages: pandasql
Successfully installed pandasql-0.7.3
```

```
# Importing libraries
import pandas as pd
import pandasql as ps
```

```
# Loading CSV File
df = pd.read_csv("product.csv")
df.head()
```

	sku	product_name	location	stock	price
0	COKE500MLUK	Coca Cola 0.5L	Paris Hub	30	1.66
1	COKE500MLUK	CocaCola - 500ml	Tokyo Hub	232	1.54
2	CC500PAR	Coca-Cola 500ml	New York Hub	213	1.09
3	COCA500	Coke 0.5L	Johannesburg Hub	475	3.10
4	CC_JHB500	Coke 0.5L	Doha Hub	36	3.54

Next steps: Generate code with df | View recommended plots | New interactive sheet

Step 1: Standardize Product Names

Many SKUs have slightly different product names like "Coke 0.5L", "Coca Cola 500ml", or "CocaCola - 500 ML".

To clean this, we use a SQL `CASE` statement to create a `standard_name` field where all variations are renamed to **'Coca-Cola 500ml'**.

```
query = """
SELECT
  CASE
    WHEN LOWER(product_name) LIKE '%coke%' OR LOWER(product_name) LIKE '%cola%'
    THEN 'Coca-Cola 500ml'
    ELSE product_name
  END AS standard_name,
  sku,
  price,
  stock,
  location
FROM df
"""

cleaned_df = ps.sqldf(query)
cleaned_df.head()
```

	standard_name	sku	price	stock	location
0	Coca-Cola 500ml	COKE500MLUK	1.66	30	Paris Hub
1	Coca-Cola 500ml	COKE500MLUK	1.54	232	Tokyo Hub
2	Coca-Cola 500ml	CC500PAR	1.09	213	New York Hub
3	Coca-Cola 500ml	COCA500	3.10	475	Johannesburg Hub
4	Coca-Cola 500ml	CC_JHB500	3.54	36	Doha Hub

Next steps: Generate code with `cleaned_df` View recommended plots New interactive sheet

Step 2: Standardize SKUs

Even if the product names are standardized, there can still be different SKUs for the same item.

Here, we assign a single `standard_sku` for Coca-Cola 500ml using the same logic.

```
query = """
SELECT
  CASE
    WHEN LOWER(product_name) LIKE '%coke%' OR LOWER(product_name) LIKE '%cola%'
    THEN 'Coca-Cola 500ml'
    ELSE product_name
  END AS standard_name,
  CASE
    WHEN LOWER(product_name) LIKE '%coke%' OR LOWER(product_name) LIKE '%cola%'
    THEN 'COKE500'
    ELSE sku
  END AS standard_sku,
  price,
  stock,
  location
FROM df
"""

sku_cleaned_df = ps.sqldf(query)
sku_cleaned_df.head()
```

	standard_name	standard_sku	price	stock	location
0	Coca-Cola 500ml	COKE500	1.66	30	Paris Hub
1	Coca-Cola 500ml	COKE500	1.54	232	Tokyo Hub
2	Coca-Cola 500ml	COKE500	1.09	213	New York Hub
3	Coca-Cola 500ml	COKE500	3.10	475	Johannesburg Hub
4	Coca-Cola 500ml	COKE500	3.54	36	Doha Hub

Next steps: Generate code with `sku_cleaned_df` View recommended plots New interactive sh

Step 3: Detect Price Inconsistencies

After standardizing SKUs and names, we want to find if there are **multiple prices for the same product**.

This can happen if pricing was entered differently at each location. We use `GROUP BY` and `HAVING` to find products with more than one price.

```
query = """
SELECT
  standard_name,
  standard_sku,
  COUNT(DISTINCT price) AS price_variations
FROM sku_cleaned_df
GROUP BY standard_name, standard_sku
HAVING COUNT(DISTINCT price) > 1
"""

price_issues = ps.sqldf(query)
price_issues
```

	standard_name	standard_sku	price_variations
0	Coca-Cola 500ml	COKE500	292

Step 4: Standardize Price to €2.5

After standardizing product names and SKUs, we now clean the pricing data.

Due to inconsistent pricing across different locations, we set a flat price of **€2.5** for all entries of "Coca-Cola 500ml". This simplifies reporting and ensures price consistency across the inventory system.

```
query = """
SELECT
  standard_name,
  standard_sku,
  location,
  stock,
  CASE
    WHEN standard_name = 'Coca-Cola 500ml' THEN 2.5
    ELSE price
  END AS standard_price_eur
FROM sku_cleaned_df
"""

final_cleaned_df = ps.sqldf(query)
final_cleaned_df.head()
```

	standard_name	standard_sku	location	stock	standard_price_eur
0	Coca-Cola 500ml	COKE500	Paris Hub	30	2.5
1	Coca-Cola 500ml	COKE500	Tokyo Hub	232	2.5
2	Coca-Cola 500ml	COKE500	New York Hub	213	2.5
3	Coca-Cola 500ml	COKE500	Johannesburg Hub	475	2.5
4	Coca-Cola 500ml	COKE500	Doha Hub	36	2.5

Next steps: Generate code with `final_cleaned_df` View recommended plots New interactive

Step 5: Aggregate Stock by Location

We now want to analyze the stock levels across different locations.

This helps in:

- Understanding how much stock is available per hub.
- Spotting overstocked or understocked locations.

We group the data by location and calculate the total stock of Coca-Cola 500ml at each hub.

```
query = """
SELECT
  location,
  SUM(stock) AS total_stock
FROM final_cleaned_df
WHERE standard_name = 'Coca-Cola 500ml'
GROUP BY location
ORDER BY total_stock DESC
"""

stock_by_location_df = ps.sqldf(query)
stock_by_location_df
```

	location	total_stock
0	New York Hub	49387
1	Doha Hub	48320
2	Dubai Hub	44732
3	Singapore Hub	42889
4	Paris Hub	41553
5	Tokyo Hub	39466
6	Madrid Hub	39454
7	London Hub	37682
8	Delhi Hub	35523
9	Johannesburg Hub	33171

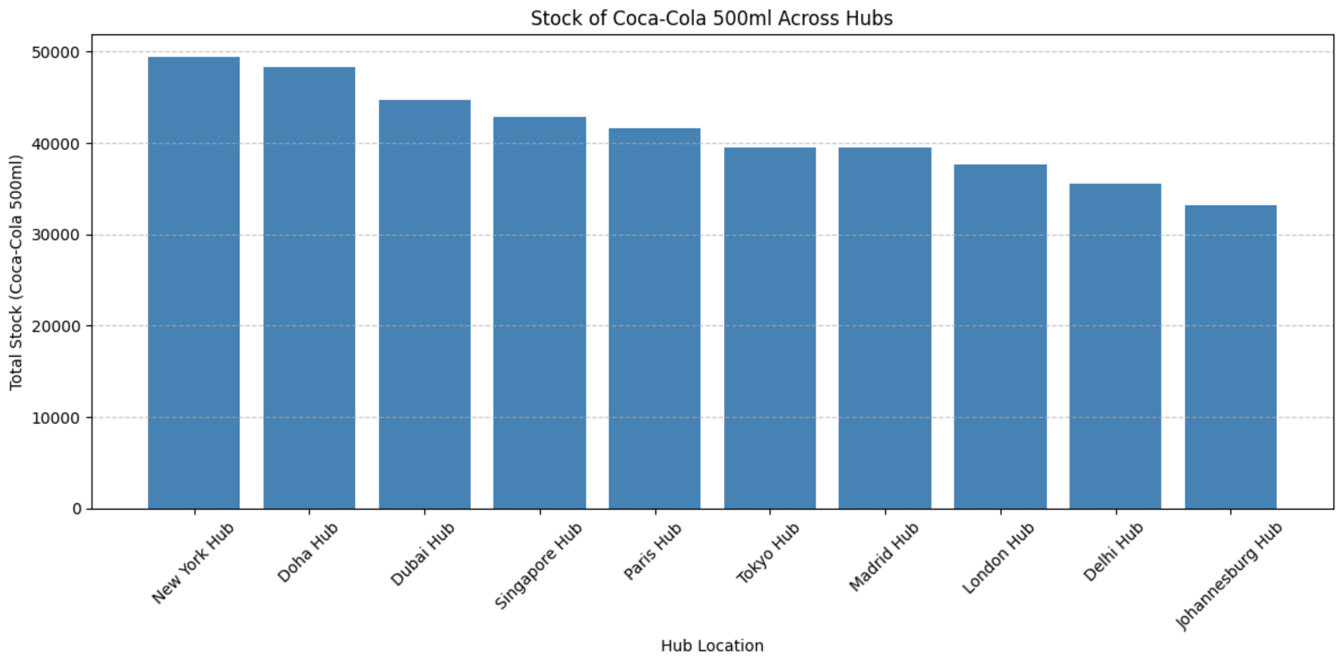
Next steps: Generate code with `stock_by_location_df` View recommended plots New intera

Step 5.1: Visualize Stock by Hub

Now that we have the total Coca-Cola 500ml stock by location, let's plot it in a bar chart to clearly see how stock is distributed across hubs.

```
import matplotlib.pyplot as plt

# Plotting
plt.figure(figsize=(12, 6))
plt.bar(stock_by_location_df['location'], stock_by_location_df['total_stock'],
plt.xlabel("Hub Location")
plt.ylabel("Total Stock (Coca-Cola 500ml)")
plt.title("Stock of Coca-Cola 500ml Across Hubs")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Step 6: Highlight Top & Bottom Performing Hubs

After visualizing stock levels across all hubs, we'll now identify:

- The hub with the **highest stock**
- The hub with the **lowest stock**

This helps in quickly spotting inventory imbalances across locations.

Why This Step Matters

While this dataset is small and it's easy to visually spot top and bottom performing hubs, in **real-world datasets** that contain thousands of rows, it's not always obvious.

Adding this step helps to:

- Quickly identify **stock imbalances**
- Take **action faster** without scanning the full data
- Make your dashboards more insightful

This approach is especially useful when working with **live inventory dashboards** or when needing to track performance at scale.

```
# Sort by total stock
sorted_stock = stock_by_location_df.sort_values(by='total_stock', ascending=Fal

# Top and Bottom performing hubs
top_hub = sorted_stock.iloc[0]
bottom_hub = sorted_stock.iloc[-1]

st_top = f"Top Hub: {top_hub['location']} with {top_hub['total_stock']} units"
st_bottom = f"Bottom Hub: {bottom_hub['location']} with {bottom_hub['total_stoc

print(st_top)
print(st_bottom)
```

```
Top Hub: New York Hub with 49387 units
Bottom Hub: Johannesburg Hub with 33171 units
```

Step 7: Export Cleaned Data

We'll now export the cleaned product inventory data (with standardized product names, SKUs, price, and locations) for reporting or dashboarding purposes.

```
# Save cleaned dataframe to CSV
cleaned_df.to_csv("cleaned_inventory.csv", index=False)
print("✅ Cleaned data exported as cleaned_inventory.csv")
```

```
✅ Cleaned data exported as cleaned_inventory.csv
```

```
Start coding or generate with AI.
```