GIGO in Practice: Data Quality Pipelines for Reliable Data Science

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Course: INFO 7390 – Advanced Data Science and Architecture

1. Why GIGO Matters

In data science, you face a hard truth:

GIGO – Garbage In, Garbage Out

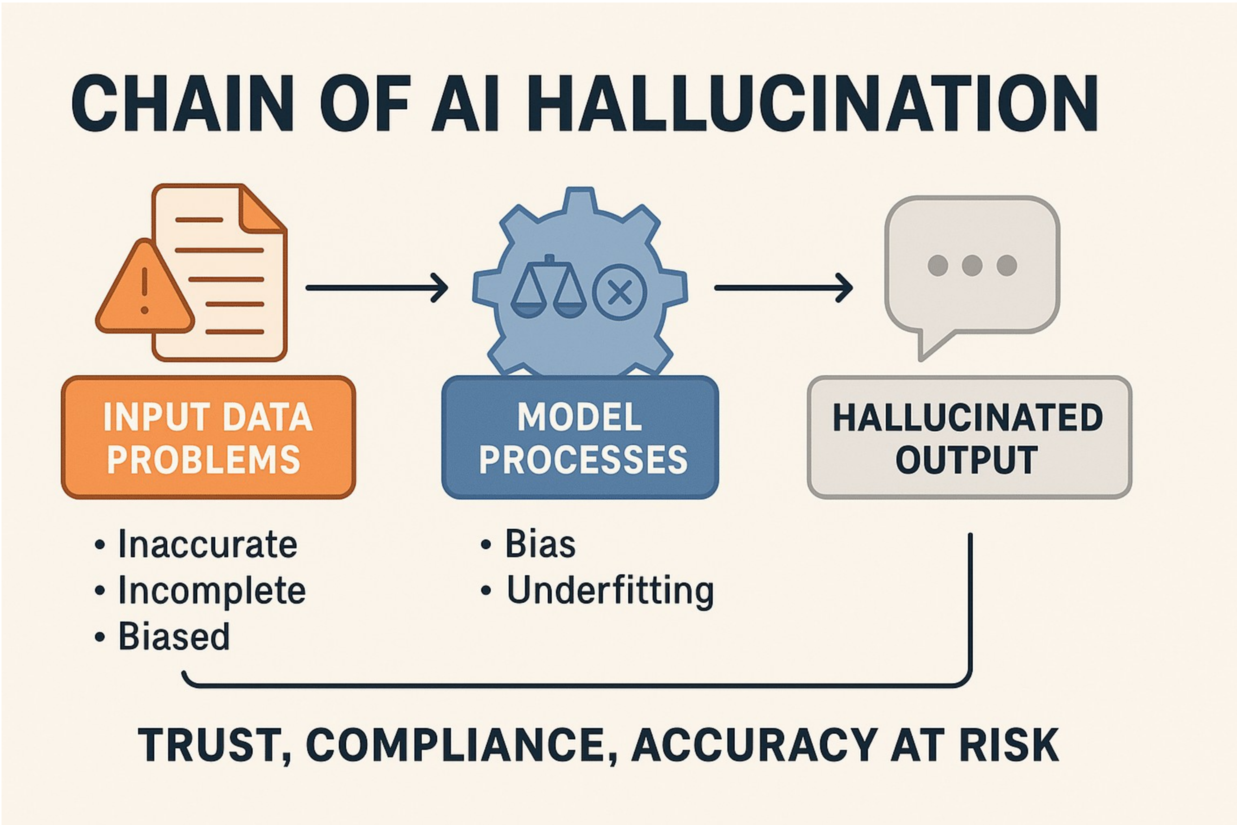
If your data's junk, then whatever you get out - like reports or charts - is gonna be junk too.

Even strong models - like XGBoost or deep nets - might fail if fed poor data, since garbage in means garbage out; worse yet, LLMs amplify those flaws fast

- Bad choices in running the company
- Models that favor one side or aren't fair
- Misleading dashboards
- Losing faith in AI

In this notebook, we're going to -

1. Get what GIGO means along with why good data matters
2. Create a practical data-checking system using Python
3. Check what happens when tidying up shifts the way you see your work



##2. Theoretical Foundations: GIGO & Data Quality

2.1 What is GIGO?

GIGO (Garbage In, Garbage Out) is a principle from early computing:

If things are off, missing stuff, leaning one way, or don't match up, The result'll miss the mark - even if the math looks slick

GIGO matters a lot in data science workflows - especially since we usually pay attention to:

- "Which model should I use?"
- "What hyperparameters are best?"

and ignore:

- "Is my data even valid?"
- "Do the values make sense?"
- "What assumptions am I making about the data?"

2.2 Data Quality Dimensions

To turn a saying into action, you'll want clear traits for good data. While ideas sound nice, real results depend on measurable parts. Several options exist - here's an easy pick for this guide:

1. Completeness

Got some values missing?

- Like, age shows up as NaN in lots of spots.

1. Validity

Check if values fit within permitted limits or correct forms.

- Like age below 0 or above 120, also transactions with minus values.

1. Consistency

- Do the numbers match up between areas or follow company guidelines?
- Like: Area tags missing from the okay pile.

1. Uniqueness

- Any accidental copies hanging around?

Same line shows up more than once.

1. Reasonableness / Outliers

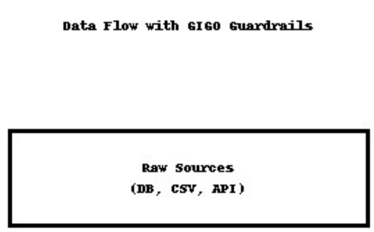
Could certain numbers seem way off? Might a few figures look too wild to be true?

A transaction worth 1 million shows up in a tiny store's data set.

We'll put together a little system which looks at those aspects, then makes them better.

2.3 Data Quality in a DS Pipeline

Conceptual data flow diagram:



What we will build

We'll simulate a **transaction dataset** with:

- `customer_id`
- `age`
- `country`
- `product_category`
- `transaction_amount`

Then we will:

1. **Inject garbage** into it (missing values, invalid ranges, etc.).

2. Implement a **data quality report** (diagnose).

3. Implement a **cleaning pipeline** (treat).

4. Compare **average transaction amount per country** before vs after cleaning.

4. Environment Setup

Run the following cell to import Python libraries.

```
!pip install pandas numpy matplotlib

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

plt.rcParams["figure.figsize"] = (10, 4)
plt.rcParams["axes.grid"] = True

pd.set_option("display.max_rows", 10)
pd.set_option("display.max_columns", 20)
```

```
Requirement already satisfied: pandas in
/usr/local/lib/python3.12/dist-packages (2.2.2)
Requirement already satisfied: numpy in
/usr/local/lib/python3.12/dist-packages (2.0.2)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.12/dist-packages (3.10.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.12/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
```

```
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (1.3.3)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (4.61.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (1.4.9)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (25.0)
Requirement already satisfied: pillow>=8 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (3.2.5)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2-
>pandas) (1.17.0)
```

5. Step 1 – Create a Base (Reasonably Clean) Dataset

We simulate a simple dataset representing **customer transactions**:

- Each row = one transaction
- `customer_id` = integer ID
- `age` = customer age
- `country` = country code from a small set
- `product_category` = type of product
- `transaction_amount` = purchase amount

We start with a **reasonable** dataset, then we will **corrupt it on purpose** to demonstrate GIGO.

```
np.random.seed(42)

n_rows = 500

customer_ids = np.random.randint(1000, 2000, size=n_rows)
ages = np.random.randint(18, 80, size=n_rows)
countries = np.random.choice(
    ["US", "UK", "IN", "DE", "CA"],
    size=n_rows,
    p=[0.3, 0.2, 0.2, 0.15, 0.15]
)
product_categories = np.random.choice(
```

```
    ["Electronics", "Clothing", "Grocery", "Beauty"],
    size=n_rows
)
transaction_amounts = np.round(np.random.exponential(scale=50,
size=n_rows) + 10, 2)

base_df = pd.DataFrame({
    "customer_id": customer_ids,
    "age": ages,
    "country": countries,
    "product_category": product_categories,
    "transaction_amount": transaction_amounts
})

base_df.head()
```


{"summary":"{\n \"name\": \"base_df\",\n \"rows\": 500,\n \"fields\": [\n   {\n   \"column\": \"customer_id\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 288,\n   \"min\": 1001,\n   \"max\": 1996,\n   \"num_unique_values\": 372,\n   \"samples\": [\n   1579,\n   1313,\n   1372\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"age\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 17,\n   \"min\": 18,\n   \"max\": 79,\n   \"num_unique_values\": 62,\n   \"samples\": [\n   21,\n   48,\n   20\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"country\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 5,\n   \"samples\": [\n   \"DE\",\n   \"IN\",\n   \"CA\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"product_category\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 4,\n   \"samples\": [\n   \"Clothing\",\n   \"Beauty\",\n   \"Grocery\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"transaction_amount\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 52.67274586078298,\n   \"min\": 10.25,\n   \"max\": 382.09,\n   \"num_unique_values\": 491,\n   \"samples\": [\n   45.61,\n   110.88,\n   58.33\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"base_df"}


```
print("Base dataset info:")
print(base_df.info())

print("\nSummary stats for base dataset:")
```

```
display(base_df.describe())

print("\nSample rows:")
display(base_df.sample(5, random_state=0))
```

```
Base dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   customer_id         500 non-null    int64
 1   age                 500 non-null    int64
 2   country             500 non-null    object
 3   product_category    500 non-null    object
 4   transaction_amount  500 non-null    float64
dtypes: float64(1), int64(2), object(2)
memory usage: 19.7+ KB
None

Summary stats for base dataset:
```


```
{"summary":"{\n  \"name\": \"display(base_df\",\n  \"rows\": 8,\n
\"fields\": [\n    {\n      \"column\": \"customer_id\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
593.3314303872578,\n        \"min\": 288.26707402673617,\n
\"max\": 1996.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          1497.062,\n          1494.0,\n
500.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"age\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 162.3012127448394,\n        \"min\": 17.998764152631264,\n
\"max\": 500.0,\n        \"num_unique_values\": 8,\n
\"samples\": [\n          49.82,\n          50.0,\n          500.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"transaction_amount\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
187.40187963909423,\n        \"min\": 10.25,\n        \"max\": 500.0,\
n        \"num_unique_values\": 8,\n        \"samples\": [\n
60.29272,\n          44.515,\n          500.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```


```
Sample rows:
```


```
{"summary":"{\n  \"name\": \"display(base_df\",\n  \"rows\": 5,\n
\"fields\": [\n    {\n      \"column\": \"customer_id\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
108,\n        \"min\": 1001,\n        \"max\": 1282,\n
```

```
\"num_unique_values\": 5,\n        \"samples\": [\n          1224,\n
1191,\n          1112\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"age\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 18,\n        \"min\": 29,\n        \"max\": 75,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          52,\n
75,\n          39\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"country\",\n      \"properties\": {\n        \"dtype\": \"string\",\
n        \"num_unique_values\": 3,\n        \"samples\": [\n
\"US\",\n          \"CA\",\n          \"IN\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"product_category\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 3,\n        \"samples\": [\n
\"Grocery\",\n          \"Electronics\",\n          \"Beauty\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"transaction_amount\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
117.88872961398812,\n        \"min\": 13.11,\n        \"max\":
295.64,\n        \"num_unique_values\": 5,\n        \"samples\": [\n
13.11,\n          295.64,\n          60.14\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe"}
```

6. Step 2 – Inject GIGO: Make the Data Messy

To demonstrate GIGO, we **deliberately inject problems** into the data:

- **Completeness issues:**
  - Missing ages
  - Missing countries
- **Validity issues:**
  - Negative ages
  - Age > 120
  - Negative transaction amounts
- **Reasonableness / outliers:**
  - Extremely large transaction amounts
- **Consistency issues:**
  - Invalid country codes
  - Invalid product categories (e.g., `UnknownCategory`)
- **Uniqueness issues:**
  - Duplicated rows

This simulates messy data from real-world pipelines.

```python
df = base_df.copy()

# 1. Missing ages
missing_age_idx = np.random.choice(df.index, size=20, replace=False)
df.loc[missing_age_idx, "age"] = np.nan

# 2. Impossible ages
df.loc[np.random.choice(df.index, size=5, replace=False), "age"] = -5
# negative
df.loc[np.random.choice(df.index, size=5, replace=False), "age"] = 150
# too large

# 3. Missing countries
missing_country_idx = np.random.choice(df.index, size=15,
replace=False)
df.loc[missing_country_idx, "country"] = np.nan

# 4. Invalid product categories
df.loc[np.random.choice(df.index, size=10, replace=False),
"product_category"] = "UnknownCategory"

# 5. Negative transaction amounts
df.loc[np.random.choice(df.index, size=8, replace=False),
"transaction_amount"] *= -1

# 6. Extreme outliers (multiply some by 20)
df.loc[np.random.choice(df.index, size=5, replace=False),
"transaction_amount"] = \
    df["transaction_amount"].max() * 20

# 7. Duplicate some rows
duplicates = df.sample(10, random_state=1)
df = pd.concat([df, duplicates], ignore_index=True)

df.head(10)
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 510,\n  \"fields\": [\
n    {\n      \"column\": \"customer_id\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 288,\n        \"min\": 1001,\
n        \"max\": 1996,\n        \"num_unique_values\": 372,\n
\"samples\": [\n          1579,\n          1313,\n          1372\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"age\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 21.19471270350303,\n
\"min\": -5.0,\n        \"max\": 150.0,\n
\"num_unique_values\": 64,\n        \"samples\": [\n          36.0,\n
48.0,\n          57.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"country\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 5,\n        \"samples\":
```

```
[\n          \"DE\",\n          \"IN\",\n          \"CA\"\n        ],\
n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"product_category\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 5,\n        \"samples\": [\n
\"Clothing\",\n          \"UnknownCategory\",\n
\"Electronics\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"transaction_amount\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 750.0006519343574,\n        \"min\": -
185.18,\n        \"max\": 7641.799999999999,\n
\"num_unique_values\": 487,\n        \"samples\": [\n          13.75,\
n          20.89,\n          85.88\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    }\n  ]\n}","type":"dataframe","variable_name":"df"}
```


```
import os

os.makedirs("data", exist_ok=True)
df.to_csv("data/transactions_dirty.csv", index=False)
print("Saved dirty dataset to data/transactions_dirty.csv")
```

```
Saved dirty dataset to data/transactions_dirty.csv
```

```
from google.colab import files
files.download("data/transactions_dirty.csv")
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>
```

Saving the Dirty Example Dataset

So far, `df` exists only inside this notebook as our **corrupted (dirty)** transaction data.

To make this usable as an **example dataset** for learners and scripts (and to satisfy the *"Example scenarios/datasets"* requirement), we save it to a CSV file:

- `os.makedirs("data", exist_ok=True)`
  → Creates a folder called `data` in the project if it doesn't already exist.

- `df.to_csv("data/transactions_dirty.csv", index=False)`
  → Saves the current **dirty transaction data** as `data/transactions_dirty.csv`, which serves as our **example dataset** for the GIGO tutorial.

Later, we (or learners) can load this example dataset with:

```
df = pd.read_csv("data/transactions_dirty.csv")
```

instead of regenerating the corrupted data from scratch.

7. Step 3 – First Diagnostics: How Bad Is the Data?

Now we pretend this is **real raw data** arriving from upstream systems.

We will:

- Check table shape and types
- Count missing values
- Count duplicates
- Inspect basic stats to see if anything looks suspicious

This is the **first GIGO check**: before modeling, understand how "dirty" the data is.

```
print("Current shape:", df.shape)
print("\nInfo:")
print(df.info())

print("\nMissing values per column:")
print(df.isna().sum())

print("\nNumber of duplicated rows:", df.duplicated().sum())
```

```
Current shape: (510, 5)

Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 510 entries, 0 to 509
Data columns (total 5 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   customer_id         510 non-null    int64
 1   age                 490 non-null    float64
 2   country             495 non-null    object
 3   product_category    510 non-null    object
 4   transaction_amount  510 non-null    float64
dtypes: float64(2), int64(1), object(2)
memory usage: 20.1+ KB
None

Missing values per column:
customer_id            0
age                   20
country               15
product_category       0
transaction_amount     0
dtype: int64
```

```
Number of duplicated rows: 10

print("Age stats:")
display(df["age"].describe())

print("\nTransaction amount stats:")
display(df["transaction_amount"].describe())

print("\nUnique countries:", df["country"].unique())
print("Unique product categories:", df["product_category"].unique())

Age stats:

count    490.000000
mean      50.410204
std       21.194713
min       -5.000000
25%       34.000000
50%       50.000000
75%       66.000000
max      150.000000
Name: age, dtype: float64


Transaction amount stats:

count     510.000000
mean      132.639941
std       750.000652
min      -185.180000
25%        22.490000
50%        43.720000
75%        75.717500
max      7641.800000
Name: transaction_amount, dtype: float64


Unique countries: ['UK' 'DE' 'CA' 'US' 'IN' nan]
Unique product categories: ['Grocery' 'Clothing' 'Electronics'
'Beauty' 'UnknownCategory']
```

Data Contract & Validation Plan

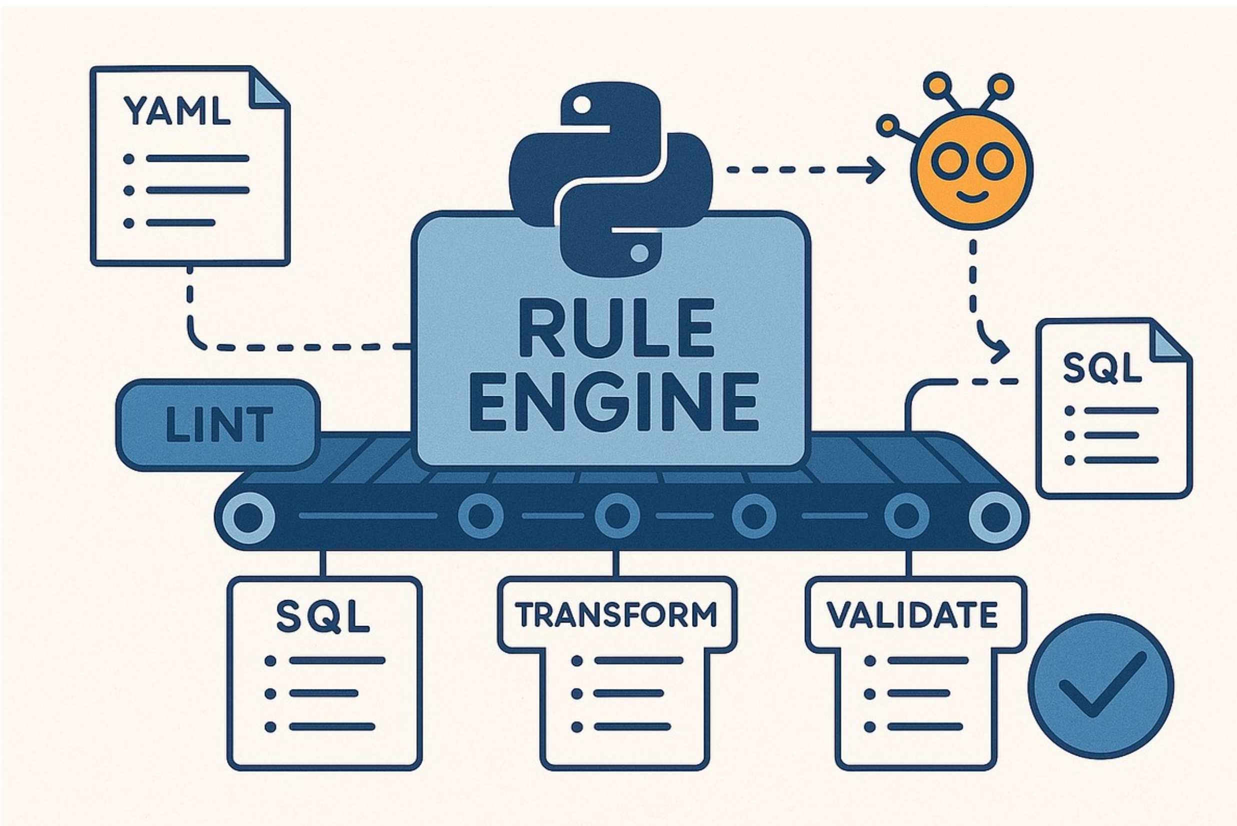
To turn GIGO into something concrete, we define what **valid data** means:

- `age`: between 18 and 100
- `country`: one of {US, UK, IN, DE, CA}

- `product_category`: one of {Electronics, Clothing, Grocery, Beauty}
- `transaction_amount`: > 0 and ≤ 1000

We will:

1. Build a **data quality report** (missing + invalid % per column)
2. Build a **cleaning pipeline**
3. Compare a simple business metric **before vs after cleaning**
   → average transaction amount per country




```
# Validation rules (simple data contract)
allowed_countries = ["US", "UK", "IN", "DE", "CA"]
allowed_categories = ["Electronics", "Clothing", "Grocery", "Beauty"]

validation_rules = {
    "age": {"min": 18, "max": 100},
    "transaction_amount": {"min": 0, "max": 1000},
    "country": {"allowed": allowed_countries},
    "product_category": {"allowed": allowed_categories},
}

def data_quality_report(df: pd.DataFrame, rules: dict) ->
```

```
pd.DataFrame:
    """
    Simple data quality report:
    - missing_count / missing_pct
    - invalid_count / invalid_pct
    for key columns.
    """
    total_rows = len(df)
    records = []

    # Age
    if "age" in df.columns:
        col = "age"
        missing = df[col].isna().sum()
        invalid = df[col].notna() & (
            (df[col] < rules["age"]["min"]) | (df[col] > rules["age"]
["max"])
        )
        records.append({
            "column": col,
            "missing_pct": missing / total_rows * 100,
            "invalid_pct": invalid.sum() / total_rows * 100,
        })

    # Country
    if "country" in df.columns:
        col = "country"
        missing = df[col].isna().sum()
        invalid = df[col].notna() & (~df[col].isin(rules["country"]
["allowed"]))
        records.append({
            "column": col,
            "missing_pct": missing / total_rows * 100,
            "invalid_pct": invalid.sum() / total_rows * 100,
        })

    # Product category
    if "product_category" in df.columns:
        col = "product_category"
        missing = df[col].isna().sum()
        invalid = df[col].notna() &
(~df[col].isin(rules["product_category"]["allowed"]))
        records.append({
            "column": col,
            "missing_pct": missing / total_rows * 100,
            "invalid_pct": invalid.sum() / total_rows * 100,
        })

    # Transaction amount
    if "transaction_amount" in df.columns:
```

```python
        col = "transaction_amount"
        missing = df[col].isna().sum()
        invalid = df[col].notna() & (
            (df[col] <= rules["transaction_amount"]["min"]) |
            (df[col] > rules["transaction_amount"]["max"])
        )
        records.append({
            "column": col,
            "missing_pct": missing / total_rows * 100,
            "invalid_pct": invalid.sum() / total_rows * 100,
        })

    return pd.DataFrame(records)

dq_before = data_quality_report(df, validation_rules)
print("Data quality report BEFORE cleaning:")
display(dq_before)

dup_count = df.duplicated().sum()
print(f"\nDuplicate rows: {dup_count} ({dup_count / len(df) * 100:.2f}
%)")
```

```
Data quality report BEFORE cleaning:
```


```
{"summary":"{\n  \"name\": \"dq_before\",\n  \"rows\": 4,\n
\"fields\": [\n    {\n      \"column\": \"column\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n
\"country\",\n          \"transaction_amount\",\n          \"age\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"missing_pct\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
2.021130208636108,\n        \"min\": 0.0,\n        \"max\":
3.9215686274509802,\n        \"num_unique_values\": 3,\n
\"samples\": [\n          3.9215686274509802,\n
2.941176470588235,\n          0.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"invalid_pct\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1.1135114403529949,\n        \"min\": 0.0,\n        \"max\":
2.549019607843137,\n        \"num_unique_values\": 3,\n
\"samples\": [\n          1.9607843137254901,\n          0.0,\n
2.549019607843137\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"dq_before"}
```


```
Duplicate rows: 10 (1.96%)
```

Question: Which column seems dirtiest and why?

```python
clean_df = df.copy()

# 1. Drop duplicates
clean_df = clean_df.drop_duplicates()

# 2. Fix age: out-of-range -> NaN, then fill with median
age_min, age_max = validation_rules["age"]["min"],
validation_rules["age"]["max"]
invalid_age = clean_df["age"].notna() & (
    (clean_df["age"] < age_min) | (clean_df["age"] > age_max)
)
clean_df.loc[invalid_age, "age"] = np.nan
clean_df["age"] = clean_df["age"].fillna(clean_df["age"].median())

# 3. Fix country: invalid -> NaN, then fill with mode
valid_countries = validation_rules["country"]["allowed"]
clean_df.loc[~clean_df["country"].isin(valid_countries), "country"] =
np.nan
clean_df["country"] =
clean_df["country"].fillna(clean_df["country"].mode().iloc[0])

# 4. Fix product_category: invalid -> NaN, then fill with mode
valid_cats = validation_rules["product_category"]["allowed"]
clean_df.loc[~clean_df["product_category"].isin(valid_cats),
"product_category"] = np.nan
clean_df["product_category"] = clean_df["product_category"].fillna(
    clean_df["product_category"].mode().iloc[0]
)

# 5. Fix transaction_amount:
#    - non-positive or > max -> NaN, then fill with median
ta_min, ta_max = validation_rules["transaction_amount"]["min"],
validation_rules["transaction_amount"]["max"]
invalid_ta = clean_df["transaction_amount"].notna() & (
    (clean_df["transaction_amount"] <= ta_min) |
    (clean_df["transaction_amount"] > ta_max)
)
clean_df.loc[invalid_ta, "transaction_amount"] = np.nan
clean_df["transaction_amount"] =
clean_df["transaction_amount"].fillna(
    clean_df["transaction_amount"].median()
)

dq_after = data_quality_report(clean_df, validation_rules)
print("Data quality report AFTER cleaning:")
display(dq_after)
```

```
Data quality report AFTER cleaning:
```

```
{"summary":"{\n  \"name\": \"dq_after\",\n  \"rows\": 4,\n
\"fields\": [\n    {\n      \"column\": \"column\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n
\"country\",\n          \"transaction_amount\",\n          \"age\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"missing_pct\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.0,\n        \"min\": 0.0,\n        \"max\": 0.0,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          0.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"invalid_pct\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.0,\n        \"min\": 0.0,\n        \"max\": 0.0,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          0.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"dq_after"}
```


Question: Did the cleaning fully fix all invalids?

##**Example Scenario:**

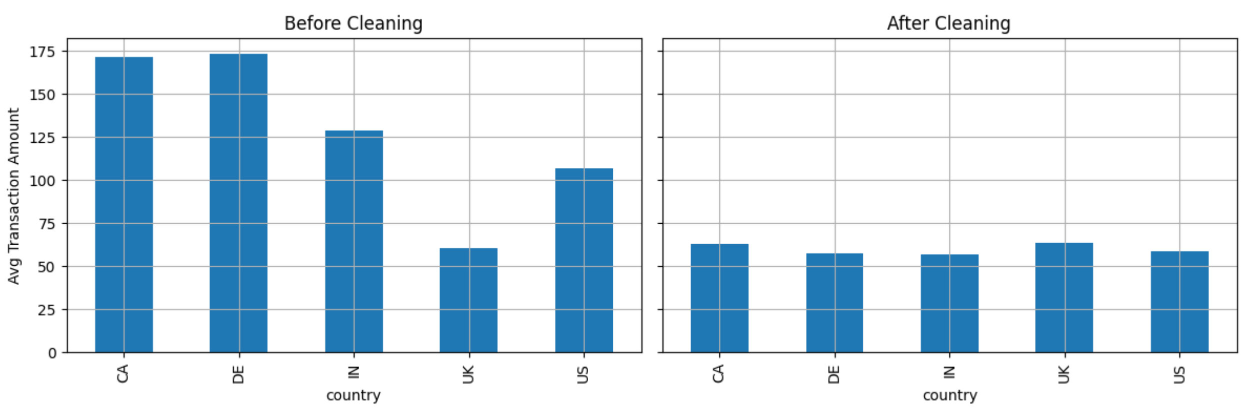
Retail Transactions GIGO Demo

Imagine you are a data analyst at an online retailer. You receive a transactions export with customer age, country, product category, and transaction amount. The data is messy: missing values, impossible ages, invalid categories, negative and extreme amounts, duplicates. Your job is to:

- Diagnose the data quality issues (GIGO),
- Clean the data,
- And then compute reliable metrics like average transaction amount by country.

```
# Simple business metric: avg transaction amount by country

avg_before = df.groupby("country")["transaction_amount"].mean()
avg_after = clean_df.groupby("country")["transaction_amount"].mean()

print("Average transaction amount by country (BEFORE cleaning):")
display(avg_before)

print("\nAverage transaction amount by country (AFTER cleaning):")
display(avg_after)

fig, axes = plt.subplots(1, 2, figsize=(12, 4), sharey=True)

avg_before.plot(kind="bar", ax=axes[0], title="Before Cleaning")
axes[0].set_ylabel("Avg Transaction Amount")
```

```
avg_after.plot(kind="bar", ax=axes[1], title="After Cleaning")

plt.tight_layout()
plt.show()

Average transaction amount by country (BEFORE cleaning):

country
CA    171.662899
DE    173.686406
IN    129.042500
UK     60.557216
US    106.935342
Name: transaction_amount, dtype: float64


Average transaction amount by country (AFTER cleaning):

country
CA    62.871014
DE    57.587460
IN    57.177723
UK    63.666947
US    58.774070
Name: transaction_amount, dtype: float64
```



Step 4: From Hardcoded Rules → Config-Driven Pipeline

Instead of manually writing code for each check, we can define our rules in a **configuration dictionary**.

This makes it easier to:

- Reuse for multiple datasets
- Store rules in JSON/YAML
- Modify rules without changing code

```python
VALID_COUNTRIES = [
    "United Kingdom",
    "Germany",
    "France",
    "Netherlands",
    "Spain",
    "Portugal",
    "Italy",
    "Belgium",
    "Sweden",
    "Norway",
    "Finland",
    "Denmark",
    # add/adjust based on your dataset
]

VALID_COUNTRIES = ["US", "UK", "IN", "DE", "CA"]
VALID_CATEGORIES = ["Electronics", "Clothing", "Grocery", "Beauty"]

QUALITY_CONFIG = {
    "age": {
        "min": 18,
        "max": 100
    },
    "transaction_amount": {
        "min": 0.01,
        "max": 1000
    },
    "customer_id": {
        "not_null": True
    },
    "country": {
        "allowed_values": VALID_COUNTRIES
    },
    "product_category": {
        "allowed_values": VALID_CATEGORIES
    }
}
```

Generic Check Engine


```
df.columns

Index(['customer_id', 'age', 'country', 'product_category',
       'transaction_amount'],
      dtype='object')

def validate_column(df, col, rules):
    s = df[col]
    checks = {}

    if "min" in rules:
        checks["min"] = s >= rules["min"]
    if "max" in rules:
        checks["max"] = s <= rules["max"]
    if rules.get("not_null"):
        checks["not_null"] = s.notna()
    if "allowed_values" in rules:
        checks["allowed_values"] = s.isin(rules["allowed_values"])
    if "range" in rules:
        start, end = rules["range"]
        s_dates = pd.to_datetime(s, errors="coerce")
        checks["range"] = s_dates.between(start, end,
inclusive="both")

    # Combine into a single Series (all checks for this column)
    if checks:
        col_result = pd.DataFrame(checks).all(axis=1)
    else:
        col_result = pd.Series(True, index=df.index)

    return col_result, checks  # second output is detailed per-rule if
needed


def run_config_checks(df, config):
    results = pd.DataFrame(index=df.index)
    detail = {}
```

```python
    for col, rules in config.items():
        col_valid, col_detail = validate_column(df, col, rules)
        results[f"{col}_valid"] = col_valid
        detail[col] = col_detail

    results["row_valid"] = results.all(axis=1)
    return results, detail

config_results, config_detail = run_config_checks(df, QUALITY_CONFIG)
config_results.head()
```


```
{"summary":"{\n  \"name\": \"config_results\",\n  \"rows\": 510,\n
\"fields\": [\n    {\n      \"column\": \"age_valid\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          true,\n
false\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"transaction_amount_valid\",\n      \"properties\": {\n
\"dtype\": \"boolean\",\n        \"num_unique_values\": 2,\n
\"samples\": [\n          false,\n          true\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"customer_id_valid\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 1,\n        \"samples\": [\n          true\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"country_valid\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          false\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"product_category_valid\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          false\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"row_valid\",\n
\"properties\": {\n        \"dtype\": \"boolean\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          true\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"config_results"}
```


3.3 Compare Basic vs Config Pipeline (Quick Sanity Check)

```python
df_with_checks = df.copy()
df_with_checks["check_row_valid"] = config_results["row_valid"]

(df_with_checks["check_row_valid"] ==
config_results["row_valid"]).value_counts()
```

```
True    510
Name: count, dtype: int64
```

Mini Exercise 3

1. Add a `max` rule for `quantity` (e.g., maximum 100 units per order).

2. Add a new column `discount_rate` between 0 and 1, then:
   - Inject some invalid values (e.g., -0.5, 1.5)
   - Add rules for it in `QUALITY_CONFIG`
3. Re-run `run_config_checks` and compute how many rows are invalid because of `discount_rate`.

Step 5: From Row Flags → Data Quality Metrics

We'll transform our boolean validation results into metrics like:

- `% valid quantity`
- `% valid unit_price`
- `% rows fully valid`
- `% missing per column`

These can be tracked over time or per batch.

```
def compute_quality_metrics(df, validation_results):
    metrics = {}

    # per-column validity
    for col in validation_results.columns:
        metrics[f"{col}_valid_pct"] = validation_results[col].mean() *
100

    # missingness per raw column
    for col in df.columns:
        metrics[f"{col}_missing_pct"] = df[col].isna().mean() * 100

    return pd.Series(metrics)

quality_metrics = compute_quality_metrics(df, config_results)
quality_metrics
```

```
age_valid_valid_pct                    94.117647
transaction_amount_valid_valid_pct     97.450980
customer_id_valid_valid_pct           100.000000
country_valid_valid_pct                97.058824
product_category_valid_valid_pct       98.039216
                                         ...
customer_id_missing_pct                 0.000000
age_missing_pct                         3.921569
country_missing_pct                     2.941176
product_category_missing_pct            0.000000
transaction_amount_missing_pct          0.000000
Length: 11, dtype: float64
```

5.2 Batch-Level Summary

```python
def summarize_quality(df, validation_results, batch_name="batch_1"):
    metrics = compute_quality_metrics(df, validation_results)
    metrics["batch_name"] = batch_name
    metrics["num_rows"] = len(df)
    return metrics

batch_summary = summarize_quality(df, config_results,
batch_name="2024-11-01_ingest")
batch_summary
```

```
age_valid_valid_pct                                    94.117647
transaction_amount_valid_valid_pct                      97.45098
customer_id_valid_valid_pct                                100.0
country_valid_valid_pct                                97.058824
product_category_valid_valid_pct                       98.039216
                                                 ...
country_missing_pct                                     2.941176
product_category_missing_pct                                 0.0
transaction_amount_missing_pct                               0.0
batch_name                                     2024-11-01_ingest
num_rows                                                     510
Length: 13, dtype: object
```

Mini Exercise 4

1. Imagine you run this pipeline **daily**. Which 3 metrics would you put on a dashboard?
2. Write 1–2 sentences about **thresholds** (e.g., "if `row_valid_pct` < 95%, trigger an alert").
3. (Optional) Create a simple bar plot of a few metrics using `matplotlib` or `seaborn`.

Simple Anomaly Detection for “Weird but Valid” Data (Advanced Taste)

Even if data passes validation rules, it can still be weird (e.g., very high order values). We’ll create a simple transaction_amount field and use a z-score approach to flag anomalies.

Z-Score Based Anomaly Flag

```python
def flag_amount_outliers(df, col="transaction_amount", z_thresh=3.0):
    # only on non-null, valid rows
    vals = df[col].astype(float)
    mean = vals.mean()
    std = vals.std()

    z_scores = (vals - mean) / std
    return np.abs(z_scores) > z_thresh
```

```
df["amount_anomaly"] = flag_amount_outliers(df)
df["amount_anomaly"].value_counts()
```

```
amount_anomaly
False    505
True       5
Name: count, dtype: int64
```

6.2 Combine Validation + Anomaly Flags

```
# 1) Rebuild row_valid directly from the current df + rules
allowed_countries = ["US", "UK", "IN", "DE", "CA"]
allowed_categories = ["Electronics", "Clothing", "Grocery", "Beauty"]

df["row_valid"] = (
    df["age"].between(18, 100) &
    df["transaction_amount"].between(0, 1000) &
    df["country"].isin(allowed_countries) &
    df["product_category"].isin(allowed_categories)
)

# 2) Define an amount anomaly flag (top 1% as "suspicious")
threshold = df["transaction_amount"].quantile(0.99)
df["amount_anomaly"] = df["transaction_amount"] > threshold

# 3) Assign quality labels
df["quality_label"] = np.select(
    [
        ~df["row_valid"],                              # any validation
failed
        df["row_valid"] & df["amount_anomaly"]  # valid but anomalous
amount
    ],
    [
        "INVALID",
        "SUSPICIOUS"
    ],
    default="OK"
)

df["quality_label"].value_counts()
```

```
quality_label
OK            443
INVALID        66
SUSPICIOUS      1
Name: count, dtype: int64
```

Now that things are clear, let's put your mind to a test.

Reflection & Progressive Exercises

Reflection

1. Look at the **data quality report before cleaning** (`dq_before`) and **after cleaning** (`dq_after`):
   - Which column had the most problems originally?
   - Did any column still look suspicious even after cleaning?
2. Look at the **average transaction amount by country** before vs after:
   - Did any country's average change a lot?
   - What wrong conclusion could a manager make if they only saw the "before" chart?

Exercise 1 – Read What the Data Is Telling You (Easy!!)

Goal: Practice *interpreting* the data-quality report.

1. For each column in `dq_before`:
   - Write down the `missing_pct` and `invalid_pct`.
2. Do the same for `dq_after`.
3. In your own words, answer:
   - "Which column was dirtiest before cleaning?"
   - "Which column improved the most after cleaning?"

Deliverable: 3–5 bullet points summarizing what you learned about the raw vs clean data.

Exercise 2 – Change One Rule, Watch the Ripple (Medium!)

Goal: See how changing rules changes what counts as “garbage”.

1. Change the age rule in `validation_rules` from:

   ```python "age": {"min": 18, "max": 100}

to:

```python
"age": {"min": 21, "max": 90}
```

Re-run:

- dq_before = data_quality_report(df, validation_rules)
- The cleaning pipeline
- The before vs after country-average code

Answer:

- Did invalid_pct for age go up or down?
- Did any country’s average transaction amount change noticeably?

Exercise 3 – Add a New Field to the GIGO Pipeline (Hard!!!!!)

Extend your GIGO pipeline to handle a new column called `loyalty_score`.

Question:

You now receive a new field `loyalty_score` that is supposed to be a value between 0 and 1 for each customer.

1. How would you:
   - Add `loyalty_score` into your existing data-quality contract (validation rules)?
   - Update your data-quality report so it also checks missing and invalid values for `loyalty_score`?
   - Modify your cleaning pipeline so invalid `loyalty_score` values are fixed or imputed?
2. Finally, explain in 3–4 sentences:
   - How could uncleaned or invalid `loyalty_score` values affect any downstream model (for example, churn prediction or customer segmentation)?

##**References**

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```

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