

## **Learning Objective**

By the end of this lesson, learners will be able to:

- Map data through its lifecycle from collection to deletion in an AI project.
- Implement hands-on coding to simulate each stage of the lifecycle.
- Identify key consulting considerations when working with clients on data governance, security, and compliance.

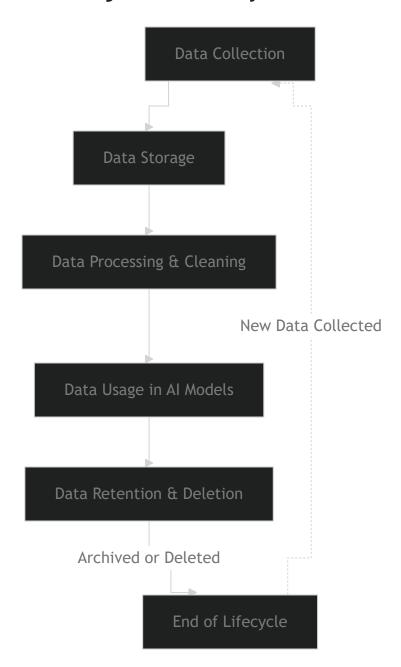
# 1. Introduction: Understanding the Data Lifecycle $\mathscr S$

Data in Al projects moves through distinct stages:

- 1. **Collection** Gathering raw data from sources.
- 2. **Storage** Saving data in appropriate formats.
- 3. **Processing & Cleaning** Preparing data for Al models.
- 4. **Usage** Leveraging data for insights and predictions.

5. Retention & Deletion – Managing long-term data policies.

#### Visualizing the Data Lifecycle



## Key considerations when working with clients:

- What data privacy laws (e.g., GDPR, CCPA) apply to this project?
- Does the client need real-time data processing or batch updates?
- What security and access controls should be in place for sensitive data?

# 2. Hands-On: Simulating the Data Lifecycle with Code

#### Step 1: Data Collection (Simulating Client Data)

**Scenario:** Your client is an e-commerce company. They want to analyze customer transaction data for personalized recommendations.

#### **Code: Generate Synthetic Data**

```
import pandas as pd
import numpy as np

np.random.seed(42)

data = {
    "customer_id": np.random.randint(1000, 9999, 100),
    "purchase_amount": np.random.uniform(10, 500, 100),
    "purchase_category": np.random.choice(["Electronics", "Clothing", "Home"], 10
    "purchase_date": pd.date_range(start="2023-01-01", periods=100, freq="D"),
}

df = pd.DataFrame(data)
```

## Key considerations when working with clients:

- What sources does the client collect data from (APIs, databases, external providers)?
- How frequently should new data be collected?

## Step 2: Data Storage & Format Considerations

Clients often store data in different formats. Choosing the right format impacts **speed, cost, and scalability.** 

#### **Code: Save Data in Different Formats**

```
df.to_csv("transactions.csv", index=False)
df.to_json("transactions.json", orient="records")
df.to_parquet("transactions.parquet", index=False)
```

#### Key considerations when working with clients:

- Does the client need high-speed querying (Parquet) or compatibility (CSV)?
- Should storage be on-premises, cloud-based, or hybrid?

#### Step 3: Data Processing & Cleaning

**Challenge:** Real-world data is often **messy**—it contains duplicates, missing values, or incorrect formats.

#### **Code: Data Cleaning & Validation**

```
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df.drop_duplicates(inplace=True)

df["purchase_amount"] = df["purchase_amount"].round(2)
```

#### Key considerations when working with clients:

- What data quality checks are required before analysis?
- Who is responsible for data validation—Al engineers, data analysts, or business users?

#### Step 4: Data Usage in Al Models

Al models require structured, preprocessed data. We simulate a **basic classification model** predicting whether a customer will make another purchase.

#### Code: Prepare Data for Al Model

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```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.ensemble import RandomForestClassifier

X = df.drop(columns=["customer_id", "purchase_date"])
y = np.random.choice([0, 1], 100) # Simulated repurchase prediction

# Encode categorical variables
encoder = OneHotEncoder(sparse_output=False)
```

```
X_encoded = encoder.fit_transform(df[["purchase_category"]])

# Scale numerical data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df[["purchase_amount"]])

# Combine processed data
X_final = np.hstack((X_scaled, X_encoded))

# Train a basic model
X_train, X_test, y_train, y_test = train_test_split(X_final, y, test_size=0.2, ramodel = RandomForestClassifier()
model fit(X train y train)
```

#### Key considerations when working with clients:

- What business outcomes does the client expect from Al insights?
- How frequently should AI models be retrained with fresh data?

#### Step 5: Data Retention & Deletion Policies

Not all data needs to be kept indefinitely. Companies must balance **storage costs**, **compliance**, **and business needs**.

Code: Filter Out Old Data

```
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df = df[df["purchase_date"] > "2023-03-01"] # Remove old data

df.to_csv("updated_transactions.csv", index=False)
```

#### Key considerations when working with clients:

- How long should different types of data be retained?
- What compliance regulations (e.g., GDPR Right to Erasure) must be followed?

# 3. Recap & Key Takeaways

- ightharpoonup Data moves through a lifecycle from **collection** ightharpoonup **storage** ightharpoonup **processing** ightharpoonup **usage** ightharpoonup **deletion**.
- ☑ Different **storage formats** impact performance and cost.
- ✓ Cleaning and preprocessing ensure data quality before AI modeling.
- ✓ Al models need **structured**, **processed data** to generate insights.
- ✓ Compliance, governance, and business needs shape data retention policies.

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