

# Lab 17 AI for Data Processing: Data Cleaning and Preprocessing Scripts

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**Task :** Use AI to generate a Python script for cleaning an employee dataset

**Prompt:**Generate a Python script to clean an employee dataset by handling missing values, formatting joining\_date, standardizing department names, and encoding categorical variables.

**Code:**

```
mean.py > inventory.py > ...
1 import pandas as pd
2 import os
3
4 # Print current working directory
5 print("Current working directory:", os.getcwd())
6
7 # Load dataset
8 df = pd.read_csv(r"C:\Users\Saniya Tahseen\OneDrive\Desktop\AI assistant coding\employee_data_cleaning\employees.csv")
9
10 # Handle missing values (safe assignment)
11 df = df.fillna({
12     'SALARY': df['SALARY'].median(),
13     'DEPARTMENT_ID': 'Unknown',
14     'HIRE_DATE': '1900-01-01'
15 })
16
17 # Convert HIRE_DATE to datetime with format hint (optional but safer)
18 df['HIRE_DATE'] = pd.to_datetime(df['HIRE_DATE'], errors='coerce')
19
20 # Standardize DEPARTMENT_ID
21 df['DEPARTMENT_ID'] = df['DEPARTMENT_ID'].astype(str).str.lower().replace({
22     'human resources': 'hr',
23     'hr': 'hr',
24     'finance': 'finance',
25     'sales': 'sales',
26     'marketing': 'marketing'
27 })
28
29 # Encode categorical variables
30 df_encoded = pd.get_dummies(df, columns=['DEPARTMENT_ID', 'JOB_ID'])
31
32 # Save cleaned data
33 df_encoded.to_csv("cleaned_employees.csv", index=False)
34
35 # Display cleaned DataFrame
36 print(df_encoded.head())
37 # Optionally print the raw CSV file contents
```

**Output:**

	EMPLOYEE_ID	FIRST_NAME	LAST_NAME	EMAIL	PHONE_NUMBER	HIRE_DATE	SALARY	...	JOB_ID_MK_REP	JOB_ID_PR_REP	JOB_ID_PU_CLERK	JOB_ID_PU_MAN	JOB_ID_SH_CLERK	JOB_ID_ST_CLERK	JOB_ID_ST_MAN
0	198	Donald	O'Connell	DOCONNEL	650.507.9833	2007-06-21	2600	...	False	False	False	False	True	False	False
1	199	Douglas	Grant	DGRANT	650.507.9844	2008-01-13	2600	...	False	False	False	False	True	False	False
2	200	Jennifer	Whalen	JWHALEN	515.123.4444	2003-09-17	4400	...	False	False	False	False	False	False	False
3	201	Michael	Hartstein	MHARTSTE	515.123.5555	2004-02-17	13000	...	False	False	False	False	False	False	False
4	202	Pat	Fay	PFAY	603.123.6666	2005-08-17	6000	...	True	False	False	False	False	False	False

[5 rows x 36 columns]

## Observations:

The AI help me clean the the database and it handled all the missing value and made the database ready to use **Task 2 :**

## Task:

Use AI to generate a script for preprocessing a sales transaction dataset

## Prompt:

Preprocess a sales dataset by parsing dates, extracting Month-Year, removing invalid amounts, and normalizing values.

## Code:

```
mean.py > inventory.py > ...
1 import pandas as pd
2 from sklearn.preprocessing import MinMaxScaler
3
4 # Load dataset
5 df = pd.read_csv(r"C:\Users\Saniya Tahseen\OneDrive\Desktop\AI assistant coding\sales_data_cleaning\transactions.csv")
6
7 # Convert transaction_date to datetime
8 df['transaction_date'] = pd.to_datetime(df['transaction_date'], format='%Y-%m-%d', errors='coerce')
9
10 # Create Month-Year column
11 df['Month_Year'] = df['transaction_date'].dt.to_period('M').astype(str)
12
13 # Remove rows with zero or negative transaction_amount
14 df = df[df['transaction_amount'] > 0]
15
16 # Normalize transaction_amount using Min-Max scaling
17 scaler = MinMaxScaler()
18 df['normalized_amount'] = scaler.fit_transform(df[['transaction_amount']])
19
20 # Save cleaned data
21 df.to_csv("cleaned_transactions.csv", index=False)
22
23 # Display first few rows
24 print(df.head())
25
26 # Optional: Read and print the saved cleaned file
27 with open(r"C:\Users\Saniya Tahseen\OneDrive\Desktop\AI assistant coding\sales_data_cleaning\transactions.csv", "r") as f:
28     print(f.read())
29
```

## Output:

	transaction_id	customer_id	transaction_date	transaction_amount	product_category	Month_Year	normalized_amount
0	1	C001	2025-01-15	250	Electronics	2025-01	0.095238
3	4	C004	2025-02-18	1200	Electronics	2025-02	1.000000
4	5	C005	2025-03-10	300	Fashion	2025-03	0.142857
5	6	C006	2025-03-15	450	Grocery	2025-03	0.285714
7	8	C008	2025-04-12	800	Fashion	2025-04	0.619048

```

transaction_id,customer_id,transaction_date,transaction_amount,product_category
1,C001,2025-01-15,250,Electronics
2,C002,2025-01-20,0,Fashion
3,C003,2025-02-05,-50,Grocery
4,C004,2025-02-18,1200,Electronics
5,C005,2025-03-10,300,Fashion
6,C006,2025-03-15,450,Grocery
7,C007,2025-04-01,0,Electronics
8,C008,2025-04-12,800,Fashion
9,C009,2025-05-05,150,Grocery
10,C010,2025-05-20,600,Electronics

```

## Observation:

- The AI helped me in cleaning the data, handle the missing value and irrelevant information in my database
- It made my database readable and ready to process

## Task 3 Task:

Use AI to generate a script for cleaning healthcare patient records.

## Prompt:

Clean healthcare patient records by imputing numeric means, standardizing height units, fixing gender labels, and dropping IDs.

## Code:

```

healthcare_data_cleaning > clean_patient_records.py > ...
1 import pandas as pd
2 from io import StringIO
3
4 # Step 1: Rebuild the CSV data inside Python
5 csv_data = """patient_id,gender,height_cm,blood_pressure,heart_rate
6 101,M,175,120,80
7 102,Female,160,,72
8 103,male,180,130,
9 104,f,165,110,75
10 105,Male,170,,78
11 106,F,158,125,70
12 107,m,172,118,
13 108,female,168,122,74
14 109,M,177,135,82
15 110,F,162,,76
16 """
17
18 # Step 2: Load CSV data directly (no file issues)
19 df = pd.read_csv(StringIO(csv_data))
20
21 # Step 3: Fill missing values in numeric columns with column mean
22 numeric_cols = ['blood_pressure', 'heart_rate']
23 for col in numeric_cols:
24     df[col] = df[col].fillna(df[col].mean())
25
26 # Step 4: Convert height from cm to meters
27 if 'height_cm' in df.columns:
28     df['height_m'] = df['height_cm'] / 100
29     df.drop(columns=['height_cm'], inplace=True)
30
31 # Step 5: Standardize gender labels
32 if 'gender' in df.columns:
33     df['gender'] = df['gender'].astype(str).str.lower().replace({
34         'm': 'Male',
35         'male': 'Male',
36         'f': 'Female',
37         'female': 'Female'
38     })
39
40 # Step 6: Drop irrelevant columns
41 df.drop(columns=['patient_id'], inplace=True)
42
43 # Step 7: Save cleaned data
44 df.to_csv("cleaned_patient_records.csv", index=False)
45
46 # Step 8: Display cleaned DataFrame
47 print("✅ Cleaned data saved as 'cleaned_patient_records.csv'\n")
48 print(df)
49

```

## Output:

✓ Cleaned data saved as 'cleaned\_patient\_records.csv'

	gender	blood_pressure	heart_rate	height_m
0	Male	120.000000	80.000	1.75
1	Female	122.857143	72.000	1.60
2	Male	130.000000	75.875	1.80
3	Female	110.000000	75.000	1.65
4	Male	122.857143	78.000	1.70
5	Female	125.000000	70.000	1.58
6	Male	118.000000	75.875	1.72
7	Female	122.000000	74.000	1.68
8	Male	135.000000	82.000	1.77
9	Female	122.857143	76.000	1.62

### Observation:

- It standardized height units from centimeters to meters with a simple conversion, ensuring consistency for downstream analysis like BMI calculation.
- AI corrected inconsistent gender labels (e.g., "M", "Male", "male") into a unified format, improving data quality and enabling reliable categorical encoding.

### Task 4 :

#### Task:

Use AI to write a script to preprocess a social media text dataset.

#### Prompt:

Clean and prepare social media text for sentiment analysis by removing noise, normalizing, and lemmatizing

#### Code:

```
import pandas as pd
import re

# Step 1: Example dataset (you can replace this with your CSV)
data = {
    'post_id': [1, 2, 3, 4],
    'text': [
        "I loooove this product!!! 🥰🥰 Check it out: https://example.com",
        "Ugh, this app keeps crashing :( #annoyed",
        "Best update ever. Totally worth it! 🌟🌟",
        "Not happy with the service... too slow!!! 😡"
    ]
}

df = pd.DataFrame(data)

# Step 2: Basic stopword list (simple version)
stop_words = {'a', 'the', 'is', 'it', 'this', 'that', 'i', 'with', 'for', 'to', 'and', 'of', 'in', 'on', 'too'}

# Step 3: Text cleaning function (no external libraries)
def clean_text(text):
    # Remove URLs
    text = re.sub(r'http\S+|www\S+', '', text)
    # Remove emojis and non-alphanumeric characters
    text = re.sub(r'[^\w\s-]', '', text)
    # Convert to lowercase
    text = text.lower()
    # Tokenize by splitting
    words = text.split()
    # Remove stopwords
    words = [w for w in words if w not in stop_words]
    # (Optional) Simple lemmatization-like cleanup for plural forms
    cleaned = []
    for w in words:
        if w.endswith('s') and len(w) > 3: # crude lemmatization
            w = w[:-1]
        cleaned.append(w)
    # Join back into sentence
    return ' '.join(cleaned)

# Step 4: Apply function
df['clean_text'] = df['text'].apply(clean_text)

# Step 5: Save cleaned data
df.to_csv("cleaned_social_media_posts_simple.csv", index=False)

# Step 6: Display cleaned dataset
print("✓ Cleaned dataset saved as 'cleaned_social_media_posts_simple.csv'\n")
print(df[['text', 'clean_text']])
```

### Output:



```

✓ Cleaned dataset saved as 'cleaned_social_media_posts_simple.csv'

                                text                                clean_text
0  I loooove this product!!! 🍕🔥 Check it out: htt...      loooove product check out
1      Ugh, this app keeps crashing :( #annoyed      ugh app keep crashing annoyed
2      Best update ever. Totally worth it! 🍌🍌      best update ever totally worth
3      Not happy with the service... too slow!!! 🙄      not happy service slow

```

## Observation:

- AI helped strip out clutter like emojis, URLs, and special characters so your text is clean and analysis-ready.
- AI converted everything to lowercase and removed common stopwords to focus on meaningful words.
- AI applied lemmatization to standardize word forms, making your sentiment model smarter and more accurate.

## Task 5 Task:

Use AI to create a preprocessing script for a financial dataset

### Prompt:

Preprocess financial data by handling missing values, engineering moving averages, normalizing, and encoding categories.

### Code:

```

assignment 17.4 > task5.py > ...
1  import pandas as pd
2  from io import StringIO
3  from sklearn.preprocessing import StandardScaler
4  from sklearn.impute import SimpleImputer
5
6  # Simulated CSV content
7  csv_data = """date,company_name,sector,stock_price,volume
8  2025-10-01,AlphaTech,Technology,120.5,10000
9  2025-10-02,AlphaTech,Technology,121.0,9800
10  2025-10-03,BetaCorp,Finance,,10500
11  2025-10-04,BetaCorp,Finance,118.0,
12  2025-10-05,GammaInc,Healthcare,119.5,11000
13  2025-10-06,GammaInc,Healthcare,120.0,10800
14  2025-10-07,AlphaTech,Technology,122.0,10200
15  2025-10-08,BetaCorp,Finance,123.5,10700
16  2025-10-09,GammaInc,Healthcare,124.0,10900
17  2025-10-10,AlphaTech,Technology,125.0,11100
18  2025-10-11,BetaCorp,Finance,126.5,11200
19  2025-10-12,GammaInc,Healthcare,127.0,11300
20  2025-10-13,AlphaTech,Technology,128.0,11400
21  2025-10-14,BetaCorp,Finance,129.5,11500
22  2025-10-15,GammaInc,Healthcare,130.0,11600
23  """
24
25  # Load the CSV from string
26  df = pd.read_csv(StringIO(csv_data), parse_dates=['date'])
27
28  # Handle missing values
29  imputer = SimpleImputer(strategy='mean')
30  df['stock_price'] = imputer.fit_transform(df[['stock_price']])
31  df['volume'] = imputer.fit_transform(df[['volume']])
32
33  # Create moving averages
34  df['MA_7'] = df['stock_price'].rolling(window=7).mean()
35  df['MA_30'] = df['stock_price'].rolling(window=30).mean()
36
37  # Encode categorical variables
38  df = pd.get_dummies(df, columns=['company_name', 'sector'], drop_first=True)
39
40  # Normalize continuous variables
41  scaler = StandardScaler()
42  df[['stock_price', 'volume', 'MA_7', 'MA_30']] = scaler.fit_transform(df[['stock_price', 'volume', 'MA_7', 'MA_30']])
43
44  # Display the final feature-engineered DataFrame
45  print(df.head())
46

```

## Output:

	date	stock_price	volume	MA_7	MA_30	company_name_BetaCorp	company_name_GammaInc	sector_Healthcare	sector_Technology
0	2025-10-01	-0.938392	-1.640627	NaN	NaN	False	False	False	True
1	2025-10-02	-0.800103	-2.023440	NaN	NaN	False	False	False	True
2	2025-10-03	0.000000	-0.683594	NaN	NaN	True	False	False	False
3	2025-10-04	-1.629839	0.000000	NaN	NaN	True	False	False	False
4	2025-10-05	-1.214971	0.273438	NaN	NaN	False	True	True	False

### Observation:

- AI filled in missing stock price and volume data using column averages, so your model won't stumble on gaps.
- AI added 7-day and 30-day moving averages to give your model trend awareness for smarter predictions.
- AI normalized all numeric features and encoded company and sector labels, making your dataset clean and ML-ready.