

## **ASSIGNMENT-17.2**

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**COURSE:AI ASSISTED CODING**

**BATCH:01**

## Task 1 – Social Media Data Cleaning

Task: Clean raw social media posts dataset.

Instructions:

- Remove stopwords, punctuation, and special symbols from post text.
- Handle missing values in likes and shares columns.
- Convert timestamp to datetime and extract features (hour, weekday).
- Detect and remove spam/duplicate posts.

**Expected Output:** A cleaned dataset with structured features for sentiment/engagement analysis

## Prompt:

Generate Social Media Data Cleaning

Task: Clean raw social media posts dataset.

Instructions:

- Remove stopwords, punctuation, and special symbols from post text.
- Handle missing values in likes and shares columns.
- Convert timestamp to datetime and extract features (hour, weekday).
- Detect and remove spam/duplicate posts

## Code:

```
1] 0s ➜ import pandas as pd
     import numpy as np

# Assuming the dataset is loaded into a DataFrame 'df' with columns: 'date', 'closing_price', 'volume'
# Example: df = pd.read_csv('stock_data.csv')
# For demonstration, I'll create a sample dataset. In practice, replace this with your actual data load

# Sample data creation (replace with actual data loading)
dates = pd.date_range('2020-01-01', periods=100, freq='D')
np.random.seed(42)
closing_prices = np.random.normal(100, 10, 100) # Simulated closing prices
volumes = np.random.poisson(1000000, 100) # Simulated volumes
df = pd.DataFrame({'date': dates, 'closing_price': closing_prices, 'volume': volumes})

# Introduce some missing values for demonstration
df.loc[10:15, 'closing_price'] = np.nan
df.loc[20:25, 'volume'] = np.nan

# Set date as index for time-series handling
df.set_index('date', inplace=True)
df.sort_index(inplace=True)

# Step 1: Handle missing values
# For closing_price: Use forward fill (assumes prices are continuous)
df['closing_price'].fillna(method='ffill', inplace=True)

# For volume: Use median imputation (robust to outliers)
df['volume'].fillna(df['volume'].median(), inplace=True)
```

```

# The preprocessed dataset is now ready for forecasting models
# It includes original columns, lag features, normalized volume, and outlier flags
print(df.head(10)) # Display first 10 rows for verification

...
      closing_price    volume  1_day_return  7_day_return \
date
2020-01-01    104.967142   999766.0       NaN        NaN
2020-01-02     98.617357   998640.0      -0.060493     NaN
2020-01-03    106.476885  1002095.0       0.079697     NaN
2020-01-04    115.230299  1000052.0       0.082210     NaN
2020-01-05     97.658466   999608.0      -0.152493     NaN
2020-01-06     97.658630  1002717.0       0.000002     NaN
2020-01-07    115.792128  999992.0       0.185682     NaN
2020-01-08    107.674347   999361.0      -0.070107    0.025791
2020-01-09     95.305256  1000312.0      -0.114875   -0.033585
2020-01-10    105.425600  997771.0       0.106189   -0.009873

      volume_normalized  is_outlier
date
2020-01-01          13.815278    False
2020-01-02          13.814151    False
2020-01-03          13.817604    False
2020-01-04          13.815564    False
2020-01-05          13.815119    False
2020-01-06          13.818225    False
2020-01-07          13.815504    False
2020-01-08          13.814872    False
2020-01-09          13.815824    False
2020-01-10          13.813280    False

/tmipython-input-1102876934.py:25: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inpl

```

```

import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Assuming the dataset is loaded into a DataFrame 'df' with columns: 'timestamp', 'sensor_id', 'temperature', 'humidity'
# Example: df = pd.read_csv('iot_sensor_logs.csv')
# For demonstration, I'll create a sample dataset. In practice, replace this with your actual data loading.

# Sample data creation (replace with actual data loading)
np.random.seed(42)
timestamps = pd.date_range('2023-01-01', periods=100, freq='H')
sensor_ids = np.random.choice(['Sensor_A', 'Sensor_B', 'Sensor_C'], 100)
temperatures = np.random.normal(25, 5, 100) + np.sin(np.arange(100) * 0.1) # Simulated with some drift
humidities = np.random.normal(60, 10, 100) + np.cos(np.arange(100) * 0.1)
df = pd.DataFrame({'timestamp': timestamps, 'sensor_id': sensor_ids, 'temperature': temperatures, 'humidity': humidities})

# Introduce some missing values for demonstration
df.loc[10:15, 'temperature'] = np.nan
df.loc[20:25, 'humidity'] = np.nan

# Set timestamp as index for time-series handling
df.set_index('timestamp', inplace=True)
df.sort_index(inplace=True)

# Step 1: Handle missing values using forward fill
df['temperature'].fillna(method='ffill', inplace=True)
df['humidity'].fillna(method='ffill', inplace=True)

```

is Terminal

The screenshot shows a Jupyter Notebook interface with two code cells and a terminal window.

**Code Cell 1:**

```
# The structured dataset is now optimized for anomaly detection
# It includes smoothed and normalized readings, encoded sensor IDs, and is ready for models like Isolation Forest or Autoencoders
print(df.head(10)) # Display first 10 rows for verification
```

**Code Cell 2:**

```
... timestamp sensor_id temperature humidity temperature_smoothed \
2023-01-01 00:00:00 Sensor_C 27.910614 57.755090 27.910614
2023-01-01 01:00:00 Sensor_A 29.538576 58.936337 29.538576
2023-01-01 02:00:00 Sensor_C 29.670331 46.579652 29.670331
2023-01-01 03:00:00 Sensor_C 29.070509 72.862609 29.070509
2023-01-01 04:00:00 Sensor_A 24.353589 73.915029 24.353589
2023-01-01 05:00:00 Sensor_A 22.362039 52.206121 26.063209
2023-01-01 06:00:00 Sensor_C 18.023876 67.001744 25.645289
2023-01-01 07:00:00 Sensor_B 31.142453 72.935550 25.064572
2023-01-01 08:00:00 Sensor_C 24.828695 62.959589 24.470680
2023-01-01 09:00:00 Sensor_C 23.731410 69.095624 23.936770

humidity_smoothed temperature_normalized \
timestamp
2023-01-01 00:00:00 57.755090 0.928742
2023-01-01 01:00:00 58.936337 1.586458
2023-01-01 02:00:00 46.579652 1.639689
2023-01-01 03:00:00 72.862609 1.397354
2023-01-01 04:00:00 73.915029 -0.508340
2023-01-01 05:00:00 63.424735 0.182368
2023-01-01 06:00:00 63.878089 0.013523
2023-01-01 07:00:00 62.812960 -0.221094
2023-01-01 08:00:00 65.240578 -0.461033
2023-01-01 09:00:00 65.306172 -0.676739
```

**Terminal Output:**

```
print("Cleaned DataFrame:")
print(df.head())
print("nSummary Report:")
print(report)

... Cleaned DataFrame:
   review_text rating cleaned_review rating_normalized \
0 <div>Great movie!</div> 8.0 great movie! 0.8
1 <div>Bad film</div> 8.0 bad film 0.8
2 NaN 6.0 nan 0.6
3 Okay 9.0 okay 0.9

tfidf_vector
0 [0.0, 0.0, 0.7071067811865476, 0.7071067811865...
1 [0.7071067811865476, 0.7071067811865476, 0.0, ...
2 [0.0, 0.0, 0.0, 0.0, 1.0, 0.0]
3 [0.0, 0.0, 0.0, 0.0, 0.0, 1.0]

Summary Report:
{'before_avg_words': np.float64(1.5), 'after_avg_words': np.float64(1.5), 'before_rating_mean': np.float64(7.75), 'after_rating_mean': np.float64(0.775), 'rating_median': 8.0
'/tmp/ipython-input-522370084.py:19: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the on
df['cleaned_review'].fillna("", inplace=True)
/tmp/ipython-input-522370084.py:24: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the on
is Terminal
```

## Task 2 – Financial Data Preprocessing

Task: Preprocess a stock market dataset.

Instructions:

- Handle missing values in closing\_price and volume.
- Create lag features (1-day, 7-day returns).
- Normalize volume column using log-scaling.
- Detect outliers in closing\_price using IQR method.

**Expected Output:** A time-series dataset ready for forecasting models

**Prompt:**

Generate a code for Financial Data Preprocessing

Task: Preprocess a stock market dataset. Instructions:

- Handle missing values in closing\_price and volume.
- Create lag features (1-day, 7-day returns).
- Normalize volume column using log-scaling. - Detect outliers in closing\_price using IQR method

## Code:

The screenshot shows a Jupyter Notebook cell containing Python code for financial data preprocessing. The code imports pandas and numpy, creates a sample dataset with simulated closing prices and volumes, introduces missing values, sets the date as the index, handles missing values for closing price using forward fill, handles missing values for volume using median imputation, and prints the resulting DataFrame. The DataFrame has columns: date, closing\_price, volume, 1\_day\_return, 7\_day\_return, volume\_normalized, and is\_outlier. The data shows various price points and returns over 10 days, with some missing values and outliers detected.

```
import pandas as pd
import numpy as np

# Assuming the dataset is loaded into a DataFrame 'df' with columns: 'date', 'closing_price', 'volume'
# Example: df = pd.read_csv('stock_data.csv')
# For demonstration, I'll create a sample dataset. In practice, replace this with your actual data loading.

# Sample data creation (replace with actual data loading)
dates = pd.date_range('2020-01-01', periods=100, freq='D')
np.random.seed(42)
closing_prices = np.random.normal(100, 10, 100) # Simulated closing prices
volumes = np.random.poisson(1000000, 100) # Simulated volumes
df = pd.DataFrame({'date': dates, 'closing_price': closing_prices, 'volume': volumes})

# Introduce some missing values for demonstration
df.loc[10:15, 'closing_price'] = np.nan
df.loc[20:25, 'volume'] = np.nan

# Set date as index for time-series handling
df.set_index('date', inplace=True)
df.sort_index(inplace=True)

# Step 1: Handle missing values
# For closing_price: Use forward fill (assumes prices are continuous)
df['closing_price'].fillna(method='ffill', inplace=True)

# For volume: Use median imputation (robust to outliers)
df['volume'].fillna(df['volume'].median(), inplace=True)
```

date	closing_price	volume	1_day_return	7_day_return	volume_normalized	is_outlier						
2020-01-01	104.967142	999766.0	Nan	Nan	13.815278	False						
2020-01-02	98.617357	998640.0	-0.060493	Nan	13.814151	False						
2020-01-03	106.450885	1002095.0	0.079997	Nan	13.817604	False						
2020-01-04	114.330299	1000052.0	0.092210	Nan	13.815564	False						
2020-01-05	97.658466	999680.0	-0.152493	Nan	13.815119	False						
2020-01-06	97.658030	1002717.0	0.000002	Nan	13.818225	False						
2020-01-07	115.792128	999992.0	0.185682	Nan	107.674347	999361.0	-0.070107	0.025791	13.815085	False		
2020-01-08	107.674347	999361.0	-0.070107	0.025791	95.305256	1000312.0	-0.114875	-0.033585	105.425600	997771.0	0.106189	-0.009873
2020-01-10	105.425600	997771.0	0.106189	-0.009873								

## Task 3 – IoT Sensor Data Preparation

Task: Clean and preprocess IoT temperature and humidity logs.

Instructions:

- Handle missing values using forward fill.
- Remove sensor drift (apply rolling mean).
- Normalize readings using standard scaling. - Encode categorical sensor IDs.

**Expected Output:** A structured dataset optimized for anomaly

detection

## Prompt:

Generate a python code for IoT Sensor Data Preparation Task:

Clean and preprocess IoT temperature and humidity logs.

Instructions:

- Handle missing values using forward fill.
- Remove sensor drift (apply rolling mean).
- Normalize readings using standard scaling. - Encode categorical sensor ID

## Code:

The screenshot shows a Jupyter Notebook interface with two code cells and a terminal window.

**Code Cell 1:**

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Assuming the dataset is loaded into a DataFrame 'df' with columns: 'timestamp', 'sensor_id', 'temperature', 'humidity'
# Example: df = pd.read_csv('iot_sensor_logs.csv')
# For demonstration, I'll create a sample dataset. In practice, replace this with your actual data loading.

# Sample data creation (replace with actual data loading)
np.random.seed(42)
timestamps = pd.date_range('2023-01-01', periods=100, freq='H')
sensor_ids = np.random.choice(['Sensor_A', 'Sensor_B', 'Sensor_C'], 100)
temperatures = np.random.normal(25, 5, 100) + np.sin(np.arange(100) * 0.1) # Simulated with some drift
humidities = np.random.normal(60, 10, 100) + np.cos(np.arange(100) * 0.1)
df = pd.DataFrame({'timestamp': timestamps, 'sensor_id': sensor_ids, 'temperature': temperatures, 'humidity': humidities})

# Introduce some missing values for demonstration
df.loc[10:15, 'temperature'] = np.nan
df.loc[20:25, 'humidity'] = np.nan

# Set timestamp as index for time-series handling
df.set_index('timestamp', inplace=True)
df.sort_index(inplace=True)

# Step 1: Handle missing values using forward fill
df['temperature'].fillna(method='ffill', inplace=True)
df['humidity'].fillna(method='ffill', inplace=True)
```

**Code Cell 2:**

```
# The structured dataset is now optimized for anomaly detection
# It includes smoothed and normalized readings, encoded sensor IDs, and is ready for models like Isolation Forest or Autoencoders
print(df.head(10)) # Display first 10 rows for verification
```

**Terminal:**

```
14:13 Python 3
```

**Data Preview:**

timestamp	humidity_smoothed	temperature_normalized
2023-01-01 00:00:00	57.755090	0.928742
2023-01-01 01:00:00	58.936337	1.586458
2023-01-01 02:00:00	46.579652	1.639689
2023-01-01 03:00:00	72.862609	1.397354
2023-01-01 04:00:00	73.915029	-0.508340
2023-01-01 05:00:00	63.424735	0.182368
2023-01-01 06:00:00	63.878089	0.013523
2023-01-01 07:00:00	62.812960	-0.221094
2023-01-01 08:00:00	65.240578	-0.461033
2023-01-01 09:00:00	65.306172	-0.676739

## Task 4 – Real-Time Application: Movie Reviews Data Cleaning

Task: A streaming platform wants to analyze customer reviews.

Instructions:

Standardize text (lowercase, remove HTML tags).

- Tokenize and encode reviews using AI-assisted methods (TF-IDF or embeddings).
- Handle missing ratings (fill with median).
- Normalize ratings (0–10 → 0–1 scale).
- Generate a before vs after summary report.

**Expected Output:** A cleaned dataset ready for sentiment classification.

Deliverables (For All Tasks)

1. AI-generated prompts for code and test case generation.
2. At least 3 assert test cases for each task.
3. AI-generated initial code and execution screenshots.
4. Analysis of whether code passes all tests.
5. Improved final version with inline comments and explanations.
6. Compiled report (Word/PDF) with prompts, test cases, assertions, code, and output.

## Prompt:

Generate A streaming platform wants to analyze customer reviews. Instructions:

Standardize text (lowercase, remove HTML tags).

- Tokenize and encode reviews using AI-assisted methods (TF-IDF or embeddings).
- Handle missing ratings (fill with median).
- Normalize ratings (0–10 → 0–1 scale).
- Generate a before vs after summary report.

## Code:

```

❶ import pandas as pd
import numpy as np
import re
from sklearn.feature_extraction.text import TfidfVectorizer

# Assuming the dataset is loaded into a DataFrame 'df' with columns: 'review_text', 'rating'
# Example: df = pd.read_csv('movie_reviews.csv')
# For demonstration, sample data is created. Replace with actual loading.

# Sample data creation (replace with actual data loading)
reviews = ['<b>Great movie!</b>', 'Bad <i>film</i>', np.nan, 'Okay']
ratings = [8.0, np.nan, 6.0, 9.0]
df = pd.DataFrame({'review_text': reviews, 'rating': ratings})

# Step 1: Standardize text (lowercase, remove HTML tags)
# Convert to lowercase and use regex to strip HTML tags for cleaner text
df['cleaned_review'] = df['review_text'].astype(str).str.lower().str.replace(r'<[^>]+>', '', regex=True).str.strip()
# Handle any remaining NaN by filling with empty string (avoids TF-IDF errors)
df['cleaned_review'].fillna('', inplace=True)

# Step 2: Handle missing ratings (fill with median)
# Calculate median and fill missing values to maintain distribution
median_rating = df['rating'].median()
df['rating'].fillna(median_rating, inplace=True)

# Step 3: Normalize ratings (0-10 → 0-1 scale)
# Simple min-max normalization assuming original range is 0-10
df['rating_normalized'] = df['rating'] / 10.0

{
    'after_avg_words': df['cleaned_review'].str.split().str.len().mean(),
    'before_rating_mean': df['rating'].mean(), # original (with fills)
    'after_rating_mean': df['rating_normalized'].mean(),
    'rating_median': median_rating,
    'total_reviews': len(df)
}

# The cleaned dataset is now ready for sentiment classification (e.g., feed into classifiers like logisticRegression)
print("Cleaned DataFrame:")
print(df.head())
print("\nSummary Report:")
print(report)

```

Cleaned DataFrame:

	review_text	rating	cleaned_review	rating_normalized
0	<b>Great movie!</b>	8.0	great movie!	0.8
1	Bad <i>film</i>	8.0	bad film	0.8
2	NaN	6.0	nan	0.6
3	Okay	9.0	okay	0.9

tfidf\_vector

```

0 [0.0, 0.0, 0.7071067811865476, 0.7071067811865...
1 [0.7071067811865476, 0.7071067811865476, 0.0, ...
2 [0.0, 0.0, 0.0, 0.0, 1.0, 0.0]
3 [0.0, 0.0, 0.0, 0.0, 0.0, 1.0]

```

Summary Report:

```

('before_avg_words': np.float64(1.5), 'after_avg_words': np.float64(1.5), 'before_rating_mean': np.float64(7.75), 'after_rating_mean': np.float64(0.775), 'rating_median': 8.0
/tmp/ipython-input-522370084.py:19: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

```