AI ASSISTED CODING: ASSIGNMENT: 5.4

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TASK1:

PROMPT:

create a Python script that collects user data like name, age, email, add comments on how to protect/anonymize the data.

CODE & OUTPUT:

```
name = input("Enter your name: ")
age = input("Enter your age: ")
      email = input("Enter your email: ")
  6 print("\n--- User Data Collected ---")
      print(f"Name: {name}")
      print(f"Age: {age}")
      print(f"Email: {email}")
 # - Do not store raw personal data; use pseudonyms or user IDs.
# - Hash or encrypt sensitive fields like email before saving.
 15 # - Remove or mask identifying information before
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS CODE REFERENCE LOG
PS C:\Users\P\Desktop\AIcoding> & C:\Users\P\AppData\Local\Programs\
                                                                                  ▶ powershell
Python\Python313\python.exe c:/Users/P/Desktop/AIcoding/TASK1.py
                                                                                 ∑ pow... [] iii
Enter your name: KITTU
Enter your age: 19
Enter your email: adc@gmail.com
--- User Data Collected ---
Name: KITTU
Age: 19
Email: adc@gmail.com
PS C:\Users\P\Desktop\AIcoding>
```

TASK2:

PROMPT:

write a Python function that does sentiment analysis, identify and handle biases in training data or results.

CODE:

```
def simple_sentiment(text):
     """Return sentiment label for the given text using a basic rule-based approach."""
     positive_words = ['good', 'happy', 'excellent', 'great', 'love', 'wonderful', 'best', 'fantastic']
     negative_words = ['bad', 'sad', 'terrible', 'worst', 'hate', 'awful', 'poor', 'horrible']
     text_lower = text.lower()
     pos = sum(word in text_lower for word in positive_words)
     neg = sum(word in text_lower for word in negative_words)
     if pos > neg:
        return 'positive'
     elif neg > pos:
        return 'negative'
     else:
        return 'neutral'
 if __name__ == "_
                 _main__":
     text = input("Enter text for sentiment analysis: ")
     print(f"Sentiment: {simple_sentiment(text)}")
 # 2. Review data sources for demographic or topical bias
 # 3. Use diverse and representative datasets for training and testing.
if __name__ == "__main__":
    text = input("Enter text for sentiment analysis: ")
    print(f"Sentiment: {simple_sentiment(text)}")
# --- Identifying and Handling Potential Biases in Data ---
# 1. Check for class imbalance (e.g., more positive than negative samples).
# 2. Review data sources for demographic or topical bias.
# 3. Use diverse and representative datasets for training and testing.
# 4. Regularly evaluate model predictions for fairness and accuracy.
# 5. Apply techniques like re-sampling, re-weighting, or data augmentation to mitigate bias.
# Example: Check class distribution in a dataset
# from collections import Counter
# labels = ['positive', 'negative', 'neutral', 'positive', 'positive'] # Example labels
# If imbalance is found, consider collecting more data for underrepresented classes.
```

OUTPUT:

```
PS C:\AIcoding> & "C:/Program Files/Python313/python.exe" c:/AIcoding/lab3_1.py
Enter text for sentiment analysis: I am very happy doing this assignment
Sentiment: positive

PS C:\AIcoding> & "C:/Program Files/Python313/python.exe" c:/AIcoding/lab3_1.py
Enter text for sentiment analysis: Hi!i am good.what about you?Are you sad?
Sentiment: neutral

PS C:\AIcoding> & "C:/Program Files/Python313/python.exe" c:/AIcoding/lab3_1.py
Enter text for sentiment analysis: the test was too horrible
Sentiment: negative

PS C:\AIcoding>
```

TASK 3:

PROMPT:

Generate a Python program that recommends products based on user history,Add comments about ethical guidelines like transparency and fairness and give users feedback options.

CODE:

```
task3.py > ...
     # Simple product recommendation system based on user history
     def recommend_products(user_history, all_products):
         Recommend products based on user's purchase/view history.
         Ensures transparency by showing why products are recommended.
         recommendations = [product for product in all_products if product not in user_histo
         print("Recommended products (based on items you haven't tried):")
         for product in recommendations:
           print(f"- {product} (recommended because you haven't interacted with it yet)")
         return recommendations
     def get_user_feedback(recommendations):
         Allow users to provide feedback on recommendations.
         print("\nPlease provide feedback on the recommendations (like/dislike):")
         feedback = {}
         for product in recommendations:
             response = input(f"Do you like '{product}'? (like/dislike): ").strip().lower()
             feedback[product] = response
         print("\nThank you for your feedback! It will help improve future recommendations."
         return feedback
```

```
task3.py > ...

def get_user_feedback(recommendations):

feedback = {}

for product in recommendations:

response = input(f"Do you like '{product}'? (like/dislike): ").strip().lower()

feedback[product] = response

print("\nThank you for your feedback! It will help improve future recommendations."

return feedback

# Example usage

if __name__ == "__main__":

user_history = ['Laptop', 'Headphones']

all_products = ['Laptop', 'Headphones', 'Smartphone', 'Tablet', 'Smartwatch']

recommendations = recommend_products(user_history, all_products)

feedback = get_user_feedback(recommendations)

# --- Ensuring Transparency and Fairness ---

# Recommendations are explained to the user.

# - Products are not filtered by demographic or personal attributes.

# - Users can give feedback to improve fairness and relevance.

# - Regularly review recommendation logic for bias or unfairness.
```

OUTPUT:

```
Thank you for your feedback! It will help improve future recommendations.

PS C:\Users\P\Desktop\AIcoding> & C:\Users\P\AppData\Local\Programs\Python\Python313\pytho

n.exe c:/Users/P/Desktop/AIcoding/task3.py

Recommended products (based on items you haven't tried):

- Smartphone (recommended because you haven't interacted with it yet)

- Tablet (recommended because you haven't interacted with it yet)

- Smartwatch (recommended because you haven't interacted with it yet)

Please provide feedback on the recommendations (like/dislike):

Do you like 'Smartphone'? (like/dislike): like

Do you like 'Tablet'? (like/dislike): dislike

Do you like 'Smartwatch'? (like/dislike): like

Thank you for your feedback! It will help improve future recommendations.

PS C:\Users\P\Desktop\AIcoding>
```

TASK4:

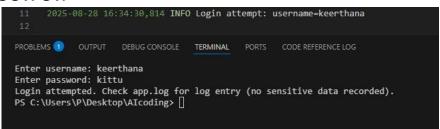
PROMPT:

generate logging for a Python web app, Then ensure no sensitive information is logged.

CODE:

```
ta4.py > ...
    import logging
   logging.basicConfig(
        filename='app.log',
        level=logging.INFO,
        format='%(asctime)s %(levelname)s %(message)s'
   # 2. Log only necessary information for debugging and monitoring.
   # 4. Restrict access to log files to authorized personnel only.
   # Example function in a web application
   def login_user(username, password):
       logging.info(f"Login attempt: username={username}") # Acceptable if username is no
    if __name__ == "__main__":
        user = input("Enter username: ")
        pwd = input("Enter password: ")
        login_user(user, pwd)
        print("Login attempted. Check app.log for log entry (no sensitive data recorded).")
```

OUTPUT:



TASK 5:

PROMPT:

generate a machine learning model, add documentation on how to use the model responsibly (e.g., explainability, accuracy limits).

OUTPUT&CODE:

```
# ai_ml_model.py
Copilot-Generated Machine Learning Model with Responsible Usage Guidelines
This example uses a Logistic Regression classifier.
The documentation explains:
- How to use the model responsibly
- Fairness and explainability considerations
from sklearn.model_selection import train_test_split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
import pandas as pd
data = {
   "hours_studied": [1, 2, 3, 4, 5, 6, 7, 8],
   "passed_exam": [0, 0, 0, 1, 1, 1, 1, 1]
# Load into DataFrame
df = pd.DataFrame(data)
X = df[["hours_studied", "sleep_hours"]]
y = df["passed_exam"]
```

```
# Load into DataFrame
df = pd.DataFrame(data)

X = df[["hours_studied", "sleep_hours"]]
y = df["passed_exam"]

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

# Initialize Logistic Regression model
model = LogisticRegression()

# Train the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

"""
Responsible Usage & Documentation
```

```
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
Responsible Usage & Documentation
   - Logistic Regression is a linear model: predictions are based on learned coefficients.
   - Coefficients can be inspected using `model.coef_` for interpretability.
2. Accuracy Limits:
   - Accuracy depends heavily on dataset size and quality.
   - Small or biased datasets may lead to misleading performance metrics.
   - This toy dataset is for demonstration only → DO NOT use in real-world exams prediction.
3. Fairness Considerations:
   - Ensure the dataset is diverse and representative to avoid bias.
   - Regularly validate the model on unseen data to prevent unfair outcomes.
   - Provide transparency: communicate that predictions are probabilistic, not absolute truths.
4. Human Oversight:
   - This model should *assist* decision-making, not replace human judgment.
   - Always provide users with explanations of predictions and allow feedback.
Summary:
This model is a simple demo of how ML works.
Use responsibly with awareness of accuracy limits, dataset bias, and fairness issues.
```

lassifi	cation	Report: precision	recall	f1-score	support
	9	1.00	1.00	1.00	1
	1	1.00	1.00	1.00	1
accu	racy			1.00	2
macro	avg	1.00	1.00	1.00	2
weighted	avg	1.00	1.00	1.00	2

EPLANATION&DOCUMENTATION:

Overview

This project provides a basic template for training and evaluating a logistic regression model using scikit-learn.

Responsible Usage Guidelines

Explainability:

This model uses logistic regression, which is relatively interpretable. You can check model.coef_ and model.intercept_ to understand feature importance and decision boundaries.

- *Accuracy Limits:*

- The model's performance depends on the quality, balance, and representativeness of the provided dataset.
- Always validate metrics (precision, recall, F1, etc.) using the provided classification report.
- Do not use the model in critical applications without thorough evaluation.

- *Fairness Considerations:*

- Ensure your dataset does not contain biases (e.g., demographic or gender imbalance) that might be learned by the model and reflected in its predictions.
- Regularly audit predictions for disparate impact and retrain with a balanced dataset if necessary.

- *Transparency:*

- Document the data sources and preprocessing steps.
- Clearly communicate the model's intended use cases and limitations to stakeholders.

- *Privacy:*

- Do not include personally identifiable information (PII) in training data without appropriate consent and anonymization.

Limitations

- This model is a simple baseline and may not capture complex relationships in data.
- It may perform poorly on unbalanced datasets or in the presence of outliers.
- The model is not robust to adversarial examples or novel, out-of-distribution data.

Usage

- 1. Place your CSV data in the project directory as data.csv.
- 2. Run python simple ml model.py to train and evaluate the model.
- 3. Adapt the code for your own datasets, being mindful of responsible ML practices.