AI ASSISTED CODING:

ASSIGNMENT(5.4)

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Task Description 1:

- Prompt GitHub Copilot to generate a Python script that collects user data (e.g., name, age, email). Then, ask Copilot to add comments on how to anonymize or protect this data. Expected Output #1:
- A script with inline Copilot-suggested code and comments explaining how to safeguard or anonymize user information (e.g., hashing emails, not storing data unencrypted)

Github copilot code:

```
import hashlib
def hash_email(email):
    return hashlib.sha256(email.encode()).hexdigest()
def collect_user_data():
   name = input("Enter your name: ")
   age = input("Enter your age: ")
   email = input("Enter your email: ")
   # Protect user data:
   anonymized_email = hash_email(email)
   user_data = {
        "name": name, # For full anonymity, do not store real names.
        "age": age, # Consider storing age ranges instead of exact value.
        "email_hash": anonymized_email # Store only the hashed email.
    }
    print("Anonymized user data:", user_data)
    # If saving to disk, use file encryption libraries (e.g., cryptography, Fernet).
if __name__ == "__main__":
    collect_user_data()
```

Copilot protection notes (inline):

- Hash emails before storage to anonymize.
- Encrypt files/databases containing user data.
- · Avoid storing raw names/emails.
- When possible, store minimum necessary info (e.g., age range instead of exact age).
- Always follow privacy best practices and legal requirements.

Task Description 2:

- Ask Copilot to generate a Python function for sentiment analysis. Then prompt Copilot to identify and handle potential biases in the data. Expected Output #2:
- Copilot-generated code with additions or comments addressing bias mitigation strategies (e.g., balancing dataset, removing offensive terms):

Copilot code:

```
from textblob import TextBlob
      def analyze_sentiment(text):
          blob = TextBlob(text)
          polarity = blob.sentiment.polarity
          if polarity > 0.1:
              return "positive"
          elif polarity < -0.1:
             return "negative"
             return "neutral"
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      def preprocess_text(text):
          offensive_terms = ['term1', 'term2'] # Populate with actual terms
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          for term in offensive terms:
             text = text.replace(term, '[REDACTED]')
          return text
      def safe_analyze_sentiment(text):
          # Preprocess to mitigate bias and offensive content.
          clean_text = preprocess_text(text)
          return analyze_sentiment(clean_text)
      if __name__ == "__main__":
    user_input = input("Enter text for sentiment analysis: ")
          result = safe_analyze_sentiment(user_input)
          print("Sentiment:", result)
```

Task Description 3:

• Use Copilot to write a Python program that recommends products based on user history.

Ask

it to follow ethical guidelines like transparency and fairness.

Expected Output #3:

• Copilot suggestions that include explanations, fairness checks (e.g., avoiding favoritism), and

user feedback options in the code:

Copilot Code:

```
from collections import Counter
     def recommend_products(user_history, all_products):
          top = Counter(user_history).most_common(1)
          new_items = [p for p in all_products if p not in user_history]
          result = [top[0][0]] if top else []
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          if new_items:
             result.append(new_items[0])
          reasons = [f"'{result[0]}' matches your history" if result else "",
                     f"'{result[1]}' adds diversity" if len(result) > 1 else ""]
          return result, reasons
      def feedback(recommendations):
          print("Recommended:", recommendations)
          resp = input("Feedback (yes/no/suggest): ")
          if resp == "suggest":
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              alt = input("Suggest a product: ")
              print(f"Thanks! '{alt}' noted.")
      if __name__ == "__main__":
          history = ['A', 'B', 'A']
          products = ['A', 'B', 'C']
          recs, why = recommend_products(history, products)
          print("\n".join(why))
          feedback(recs)
```

Task Description 4:

• Prompt Copilot to generate logging functionality in a Python web application. Then, ask it to

ensure the logs do not record sensitive information.

Expected Output #4:

• Logging code that avoids saving personal identifiers (e.g., passwords, emails), and includes comments about ethical logging practices:

Copilot Code:

```
# Logging functionality for a Python web app.
     # Copilot inline comments explain how to avoid logging sensitive info (e.g., passwords, emails).
     import logging
     logging.basicConfig(
         filename='app.log',
         level=logging.INFO,
         format='%(asctime)s %(levelname)s %(message)s'
     def log_event(event, details):
         Log an event with details.
         Ethical logging practice:
         - NEVER log sensitive info (passwords, emails, personal data).
         - Scrub details before logging.
20
         # Remove sensitive keys if present
         sensitive_keys = ['password', 'email', 'token']
          filtered_details = {k: v for k, v in details.items() if k not in sensitive_keys}
          logging.info(f"{event}: {filtered_details}")
     def user_login(username, password):
          # NEVER log raw passwords or emails.
         log_event('user_login_attempt', {'username': username}) # Only log non-sensitive info
     def password_reset(email):
          # Do NOT log the email address.
         log_event('password_reset_attempt', {}) # Log only the event, not the identifier
     # - Avoid logging personal identifiers.
```

Task Description 5:

• Ask Copilot to generate a machine learning model. Then, prompt it to add documentation on

how to use the model responsibly (e.g., explainability, accuracy limits). Expected Output #5:

• Copilot-generated model code with a README or inline documentation suggesting responsible usage, limitations, and fairness considerations:

Copilot Code:

```
# Simple machine learning model with responsible usage documentation.
# Copilot inline comments explain explainability, accuracy limits, and fairness.

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

def train_model():
# Load dataset (Iris for demonstration; review for bias before production use)
data = load_iris()
X_train, X_test, y_train, y_test = train_test_split(
data.data, data.target, test_size=0.2, random_state=42)
model = RandomForestClassifier()
model.fit(X_train, y_train)
accuracy = model.score(X_test, y_test)
print(f"Test Accuracy: {accuracy:.2f}")
return model

if __name__ == "__main__":
model = train_model()
# Responsible usage notes:
# - Explainability: Use model.feature_importances_ to understand which features matter most.
# - Accuracy limits: Always validate accuracy on representative data; don't overstate performance.
# - Fairness: Check for bias in training data; don't deploy without fairness review.
# - Never use predictions for critical decisions without human oversight.
# - Document intended uses and known limitations.
```