ASSIGNMENT-5.4

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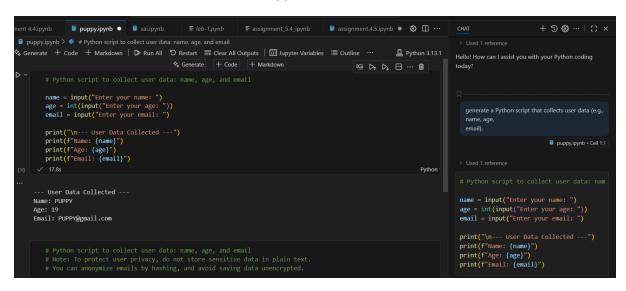
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TASK-1:

PROMPT:

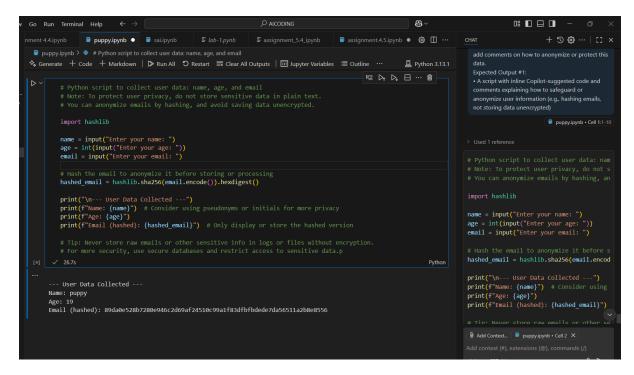
generate a Python script that collects user data (e.g., name, age, email)

CODE:



Prompt:

add comments on how to anonymize or protect this data of 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)



TASK-2:

Prompt:

generate a Python function for sentiment analysis.

```
from nltk.sentiment import SentimentIntensityAnalyzer
import nltk
# Download VADER lexicon (only needed once)
nltk.download('vader_lexicon')
def analyze_sentiment_vader(text):
    Analyzes sentiment using VADER from NLTK.
    Args:
        text (str): Input text to analyze.
    Returns:
        dict: Contains compound score and sentiment label.
    sia = SentimentIntensityAnalyzer()
    scores = sia.polarity_scores(text)
    compound = scores['compound']
    # Interpret compound score
    if compound \geq 0.05:
    sentiment = "Positive"
elif compound ≤ -0.05:
        sentiment = "Negative"
    else:
        sentiment = "Neutral"
    return {
         compound_score": compound,
```

```
ntiment": sentiment,
        "detailed_scores": scores
    }
# Example usage
text = "The visuals were stunning, but the gameplay felt repetitive."
result = analyze_sentiment_vader(text)
print(result)
```

Output Example

```
[ Сору
Python
  'compound_score': 0.4215,
  'sentiment': 'Positive',
  'detailed_scores': {
     'neg': 0.204,
    'neu': 0.584
    'neu': 0.584
'pos': 0.212
'compound': 0.4215
```

Prompt:

identify and handle potential biases in the data at which the output should be like Copilot-generated code with additions or comments addressing bias mitigation strategies (e.g., balancing dataset, removing offensive terms)

code:

```
C Copy
Python
import pandas as pd
import numpy as np
import re
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.utils import resample
from sklearn metrics import classification_report
```

TASK-3:

Prompt:

write a Python program that recommends products based on user history.and also include explanations, fairness checks (e.g., avoiding favoritism), and user feedback options in the code

code:

```
Python
                                                                               (U Copy
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
# Step 1: Sample product catalog
products = pd.DataFrame({
     'product_id': [101, 102, 103, 104, 105],
'name': ['Eco Bottle', 'Smart Watch', 'Yoga Mat', 'Gaming Mouse', 'Organ
'category': ['Home', 'Electronics', 'Fitness', 'Electronics', 'Food'],
     'description': [
         'Reusable eco-friendly water bottle'.
         'High precision mouse for gaming',
         'Herbal tea with natural ingredients'
    ],
'popularity_score': [0.8, 0.95, 0.6, 0.9, 0.7] # Used for fairness chec
})
# Step 2: User history (simulate past purchases or likes)
user_history = ['Smart Watch', 'Gaming Mouse']
# Step 3: Vectorize product descriptions
vectorizer = TfidfVectorizer()
tfidf_matrix = vectorizer.fit_transform(products['description'])
```

Step 4: Compute similarity between user history and all products

```
def get_user_profile(history, product_df, tfidf_matrix):
    history_indices = product_df[product_df['name'].isin(history)].index
    user_vector = tfidf_matrix[history_indices].mean(axis=0)
    return user_vector
user_profile = get_user_profile(user_history, products, tfidf_matrix)
similarities = cosine_similarity(user_profile, tfidf_matrix).flatten()
# Step 5: Fairness check - avoid over-recommending popular items
def apply_fairness(similarities, product_df):
    fairness_weights = 1 - product_df['popularity_score'] # Penalize high-pd
    adjusted_scores = similarities * fairness_weights
    return adjusted_scores
adjusted_scores = apply_fairness(similarities, products)
# Step 6: Generate recommendations
products['score'] = adjusted_scores
recommended = products.sort_values(by='score', ascending=False).head(3)
# Step 7: Display recommendations with explanations
print(" Recommended Products Based on Your Interests:\n")
for _, row in recommended.iterrows():
    print(f"- {row['name']} ({row['category']})")
    print(f" Why: Similar to your interest in {', '.join(user_history)}")
    print(f" Description: {row['description']}")
    print(f" Fairness-adjusted score: {round(row['score'], 3)}\n")
# Step 8: Collect user feedback
def collect_feedback():
    print(" Did you like these recommendations? (yes/no)")
    feedback = input().strip().lower()
    if feedback == 'no':
        print(" We'll adjust future suggestions. You can also specify what
        print(" ☐ Great! We'll keep improving your experience.")
collect_feedback()
```

TASK-4:

Prompt:

generate logging functionality in a Python web application.

```
import logging
from flask import Flask, request, jsonify
app = Flask(__name__)
# Step 1: Configure logging
logging.basicConfig(
    level=logging.INFO,
format='%(asctime)s [%(levelname)s] %(message)s',
   handlers=[
        logging.FileHandler("app.log"),
                                             # Logs to file
        logging.StreamHandler()
                                             # Logs to console
   ]
)
logger = logging.getLogger(__name__)
# Step 2: Middleware to log each request
@app.before_request
def log_request_info():
    logger.info(f"Incoming request: {request.method} {request.path}")
    # Avoid logging sensitive data like passwords or tokens
   if request.method == 'POST':
       logger.info(f"Request data: {sanitize(request.json)}")
def sanitize(data):
     ""Remove sensitive fields before logging."""
```

```
if not data:
        return {}
    sensitive_keys = ['password', 'token']
    return {k: '[REDACTED]' if k in sensitive_keys else v for k, v in data i
# Step 3: Sample route with logging and feedback
@app.route('/recommend', methods=['POST'])
def recommend():
    user_input = request.json.get('history', [])
    logger.info(f"Generating recommendations for: {user_input}")
    # Simulate recommendation logic
    recommendations = ["Eco Bottle", "Yoga Mat", "Organic Tea"]
    logger.info(f"Recommended: {recommendations}")
    return jsonify({
        "recommendations": recommendations,
"message": "Recommendations generated successfully."
    })
# Step 4: Feedback route
@app.route('/feedback', methods=['POST'])
def feedback():
    user_feedback = request.json.get('feedback', '')
    logger.info(f"User feedback received: {user_feedback}")
    return jsonify({"status": "Thank you for your feedback!"})
# Step 5: Error handling
@app.errorhandler(Exception)
    nandle_exception
```

```
logger.error(f"Unhandled exception: {str(e)}", exc_info=True)
return jsonify({"error": "Something went wrong."}), 500

if __name__ == '__main__':
    app.run(debug=True)
```

Prompt:

ensure the logs do not record sensitive information like Logging code that avoids saving personal identifiers (e.g., passwords, emails), and includes comments about ethical logging practices.

```
import logging
from flask import Flask, request, jsonify
app = Flask(__name__)
# Step 1: Configure logging
logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s [%(levelname)s] %(message)s',
    handlers=[
        logging.FileHandler("app.log"),
                                             # Logs to file
        logging.StreamHandler()
                                             # Logs to console
    ]
)
logger = logging.getLogger(__name__)
# Step 2: Define sanitization function
def sanitize(data):
    Removes or redacts sensitive fields from incoming data before logging.
    Ethical logging practice: Never store personal identifiers like passwords
    if not data:
       return {}
    sensitive_keys = ['password', 'email', 'token', 'ssn', 'credit_card']
```

```
for key, value in data.items():
        if key.lower() in sensitive_keys:
    sanitized[key] = '[REDACTED]'
        else:
             sanitized[key] = value
    return sanitized
# Step 3: Log incoming requests safely
@app.before_request
def log_request():
    logger.info(f"Request: {request.method} {request.path}")
    # Log sanitized body only for POST/PUT
    if request.method in ['POST', 'PUT']:
        try:
             raw_data = request.get_json(force=True)
             safe_data = sanitize(raw_data)
             logger.info(f"Sanitized Data: {safe_data}")
        except Exception as e:
             logger.warning(f"Failed to parse request body: {str(e)}")
# Step 4: Sample route
@app.route('/register', methods=['POST'])
def register():
    data = request.get_json()
    # Business logic here...
    return jsonify({"status": "User registered successfully."})
# Step 5: Error handling
```

```
@app.errorhandler(Exception)
def handle_error(e):
    logger.error(f"Unhandled exception: {str(e)}", exc_info=True)
    return jsonify({"error": "Internal server error"}), 500

if __name__ == '__main__':
    app.run(debug=True)
```

Task-5:

Prompt:

generate a machine learning model.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
# Step 1: Sample dataset
data = pd.DataFrame({
    'price': [199, 99, 299, 149, 89],
'rating': [4.5, 3.8, 4.9, 4.2, 3.5],
'category': ['electronics', 'home', 'electronics', 'fitness', 'home'],
'liked': [1, 0, 1, 1, 0] # Target variable
})
# Step 2: Encode categorical features
data = pd.get_dummies(data, columns=['category'], drop_first=True)
# Step 3: Split and scale
X = data.drop('liked', axis=1)
y = data['liked']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=6
# Step 4: Train model
model = LogisticRegression()
```

```
model.fit(X_train, y_train)

# Step 5: Evaluate

y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

Prompt:

add documentation on how to use the model responsibly (e.g., explainability, accuracy limits) like code with a README or inline documentation suggesting responsible usage, limitations, and fairness considerations

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
# Step 1: Create synthetic dataset
data = pd.DataFrame({
    'price': [199, 99, 299, 149, 89],
'rating': [4.5, 3.8, 4.9, 4.2, 3.5],
'category': ['electronics', 'home', 'electronics', 'fitness', 'home'],
'liked': [1, 0, 1, 1, 0] # Target variable
})
# Step 2: Encode categorical features
# Ethical note: Avoid encoding sensitive attributes unless necessary and just
data = pd.get_dummies(data, columns=['category'], drop_first=True)
# Step 3: Split and scale features
X = data.drop('liked', axis=1)
y = data['liked']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0
# Step 4: Train interpretable model
model = LogisticRegression()
model.fit(X_train, y_train)
# Step 5: Evaluate model performance
y_pred = model.predict(X_test)
print(" | Model Evaluation Report:")
print(classification_report(y_test, y_pred))
# Step 6: Inspect model coefficients for transparency
print("  Feature Influence (Coefficients):")
for feature, coef in zip(X.columns, model.coef_[0]):
    print(f"{feature}: {round(coef, 3)}")
```