Assignment: 5.4

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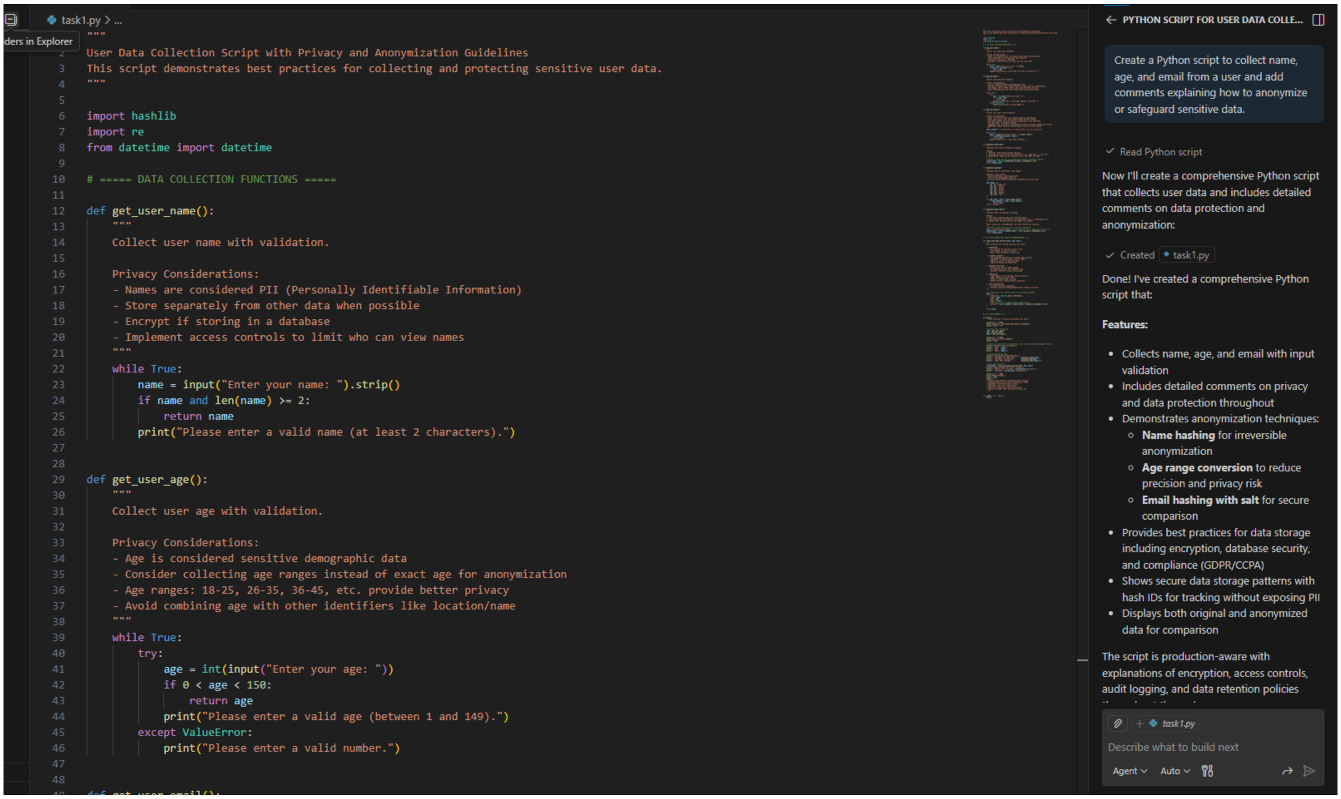
Task Description #1:

• 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.



```python
"""
User Data Collection Script with Privacy and Anonymization Guidelines
This script demonstrates best practices for collecting and protecting sensitive user data.
"""

import hashlib
import re
from datetime import datetime

# ===== DATA COLLECTION FUNCTIONS =====

def get_user_name():
    """
    Collect user name with validation.

    Privacy Considerations:
    - Names are considered PII (Personally Identifiable Information)
    - Store separately from other data when possible
    - Encrypt if storing in a database
    - Implement access controls to limit who can view names
    """
    while True:
        name = input("Enter your name: ").strip()
        if name and len(name) >= 2:
            return name
        print("Please enter a valid name (at least 2 characters).")


def get_user_age():
    """
    Collect user age with validation.

    Privacy Considerations:
    - Age is considered sensitive demographic data
    - Consider collecting age ranges instead of exact age for anonymization
    - Age ranges: 18-25, 26-35, 36-45, etc. provide better privacy
    - Avoid combining age with other identifiers like location/name
    """
    while True:
        try:
            age = int(input("Enter your age: "))
            if 0 < age < 150:
                return age
            print("Please enter a valid age (between 1 and 149).")
        except ValueError:
            print("Please enter a valid number.")
```

Create a Python script to collect name, age, and email from a user and add comments explaining how to anonymize or safeguard sensitive data.

✓ Read Python script

Now I'll create a comprehensive Python script that collects user data and includes detailed comments on data protection and anonymization:

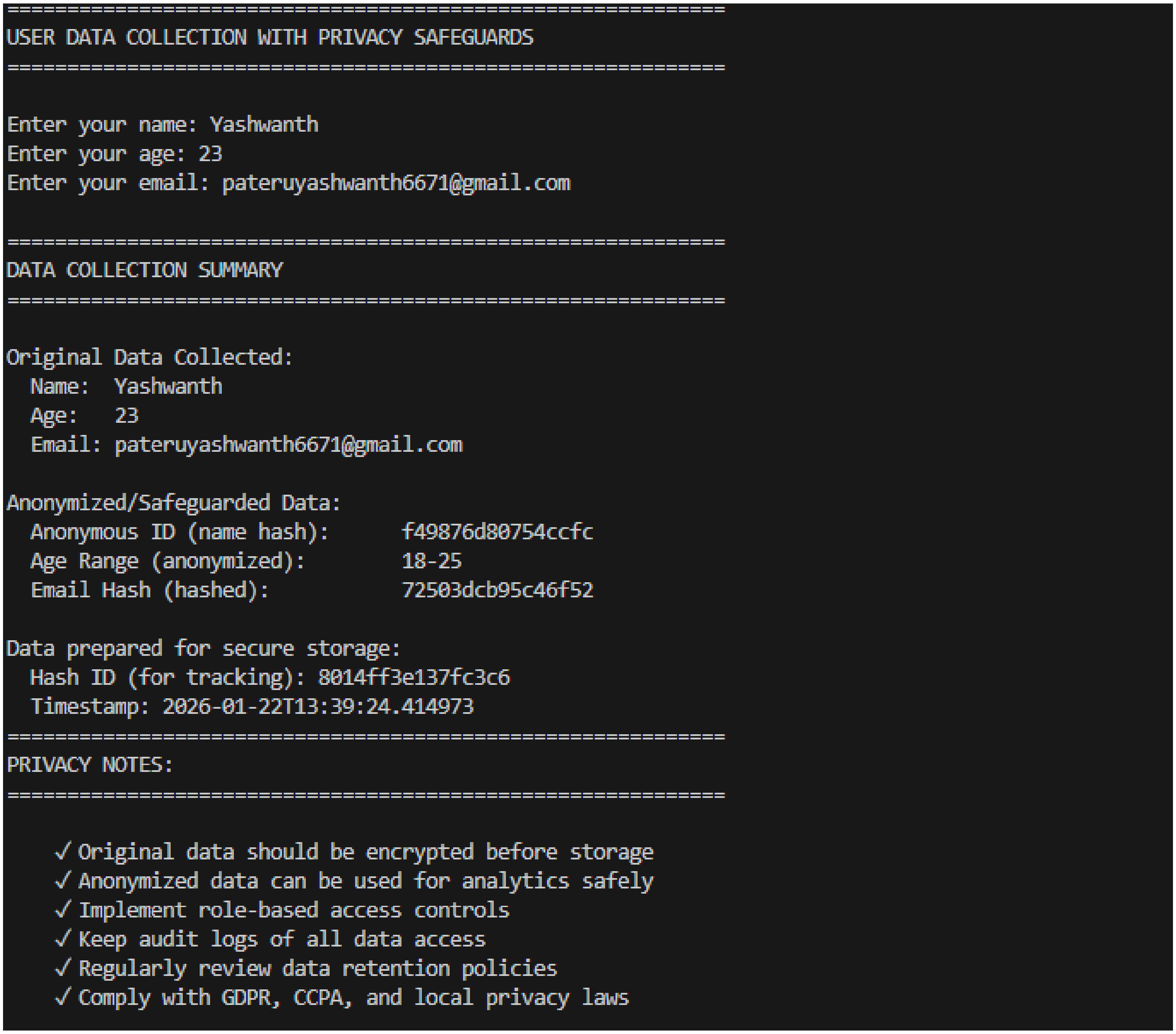
✓ Created task1.py

Done! I've created a comprehensive Python script that:

Features:

- Collects name, age, and email with input validation
- Includes detailed comments on privacy and data protection throughout
- Demonstrates anonymization techniques:
  - **Name hashing** for irreversible anonymization
  - **Age range conversion** to reduce precision and privacy risk
  - **Email hashing with salt** for secure comparison
- Provides best practices for data storage including encryption, database security, and compliance (GDPR/CCPA)
- Shows secure data storage patterns with hash IDs for tracking without exposing PII
- Displays both original and anonymized data for comparison

The script is production-aware with explanations of encryption, access controls, audit logging, and data retention policies

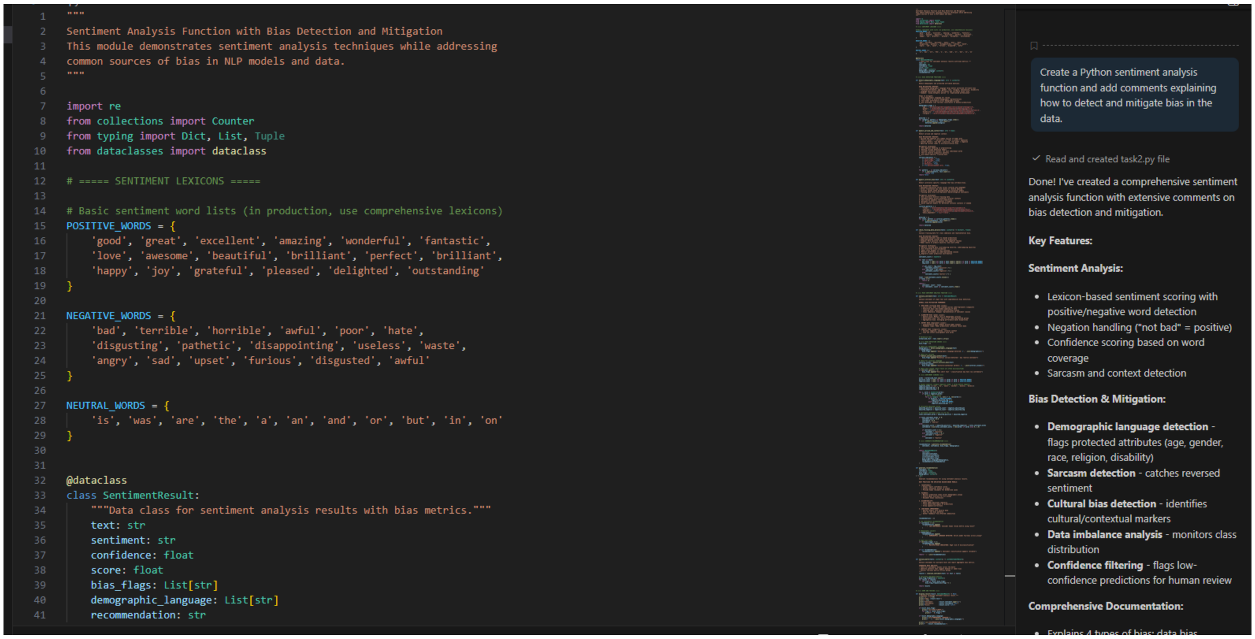


```
============================================================
USER DATA COLLECTION WITH PRIVACY SAFEGUARDS
============================================================

Enter your name: Yashwanth
Enter your age: 23
Enter your email: pateruyashwanth6671@gmail.com

============================================================
DATA COLLECTION SUMMARY
============================================================

Original Data Collected:
  Name:  Yashwanth
  Age:   23
  Email: pateruyashwanth6671@gmail.com

Anonymized/Safeguarded Data:
  Anonymous ID (name hash):      f49876d80754ccfc
  Age Range (anonymized):        18-25
  Email Hash (hashed):           72503dcb95c46f52

Data prepared for secure storage:
  Hash ID (for tracking): 8014ff3e137fc3c6
  Timestamp: 2026-01-22T13:39:24.414973
============================================================
PRIVACY NOTES:
============================================================

    ✓ Original data should be encrypted before storage
    ✓ Anonymized data can be used for analytics safely
    ✓ Implement role-based access controls
    ✓ Keep audit logs of all data access
    ✓ Regularly review data retention policies
    ✓ Comply with GDPR, CCPA, and local privacy laws
```

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.



```python
"""
Sentiment Analysis Function with Bias Detection and Mitigation
This module demonstrates sentiment analysis techniques while addressing
common sources of bias in NLP models and data.
"""

import re
from collections import Counter
from typing import Dict, List, Tuple
from dataclasses import dataclass

# ===== SENTIMENT LEXICONS =====

# Basic sentiment word lists (in production, use comprehensive lexicons)
POSITIVE_WORDS = {
    'good', 'great', 'excellent', 'amazing', 'wonderful', 'fantastic',
    'love', 'awesome', 'beautiful', 'brilliant', 'perfect', 'brilliant',
    'happy', 'joy', 'grateful', 'pleased', 'delighted', 'outstanding'
}

NEGATIVE_WORDS = {
    'bad', 'terrible', 'horrible', 'awful', 'poor', 'hate',
    'disgusting', 'pathetic', 'disappointing', 'useless', 'waste',
    'angry', 'sad', 'upset', 'furious', 'disgusted', 'awful'
}

NEUTRAL_WORDS = {
    'is', 'was', 'are', 'the', 'a', 'an', 'and', 'or', 'but', 'in', 'on'
}


@dataclass
class SentimentResult:
    """Data class for sentiment analysis results with bias metrics."""
    text: str
    sentiment: str
    confidence: float
    score: float
    bias_flags: List[str]
    demographic_language: List[str]
    recommendation: str
```

Create a Python sentiment analysis function and add comments explaining how to detect and mitigate bias in the data.

✓ Read and created task2.py file

Done! I've created a comprehensive sentiment analysis function with extensive comments on bias detection and mitigation.

Key Features:

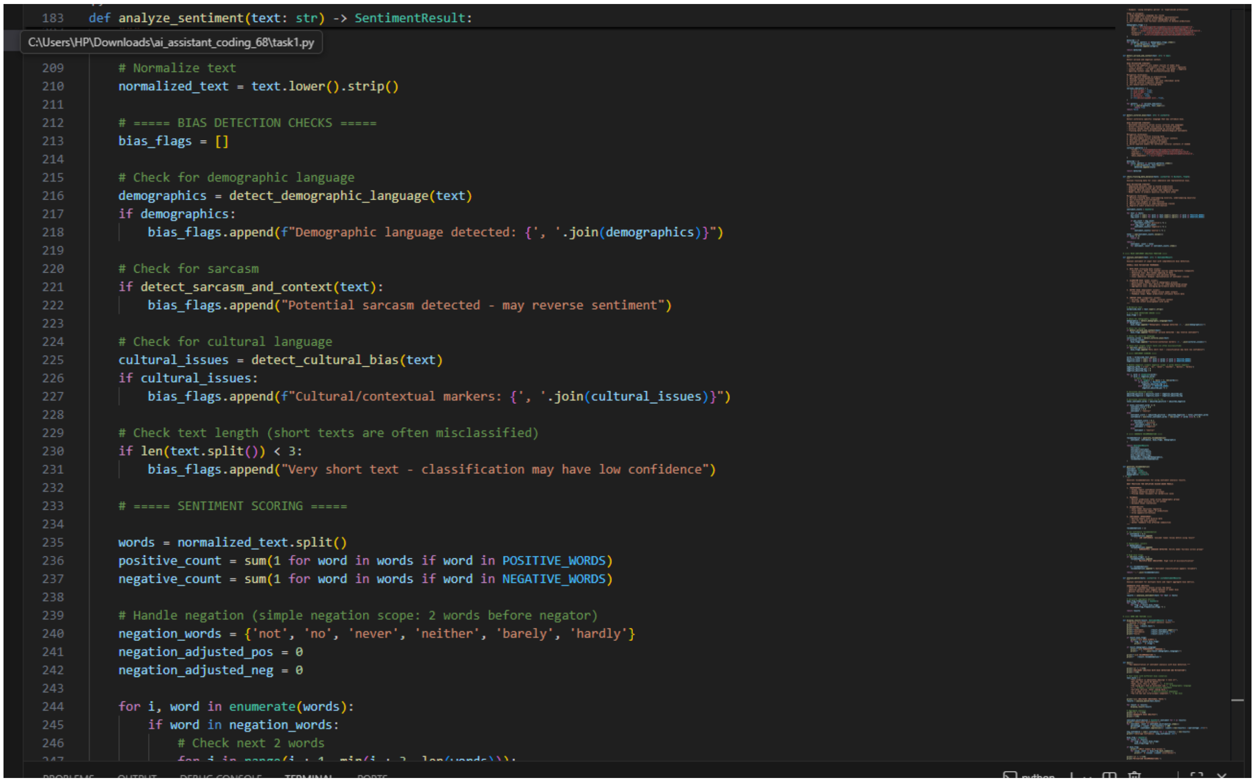
Sentiment Analysis:

- Lexicon-based sentiment scoring with positive/negative word detection
- Negation handling ("not bad" = positive)
- Confidence scoring based on word coverage
- Sarcasm and context detection

Bias Detection & Mitigation:

- **Demographic language detection** - flags protected attributes (age, gender, race, religion, disability)
- **Sarcasm detection** - catches reversed sentiment
- **Cultural bias detection** - identifies cultural/contextual markers
- **Data imbalance analysis** - monitors class distribution
- **Confidence filtering** - flags low-confidence predictions for human review

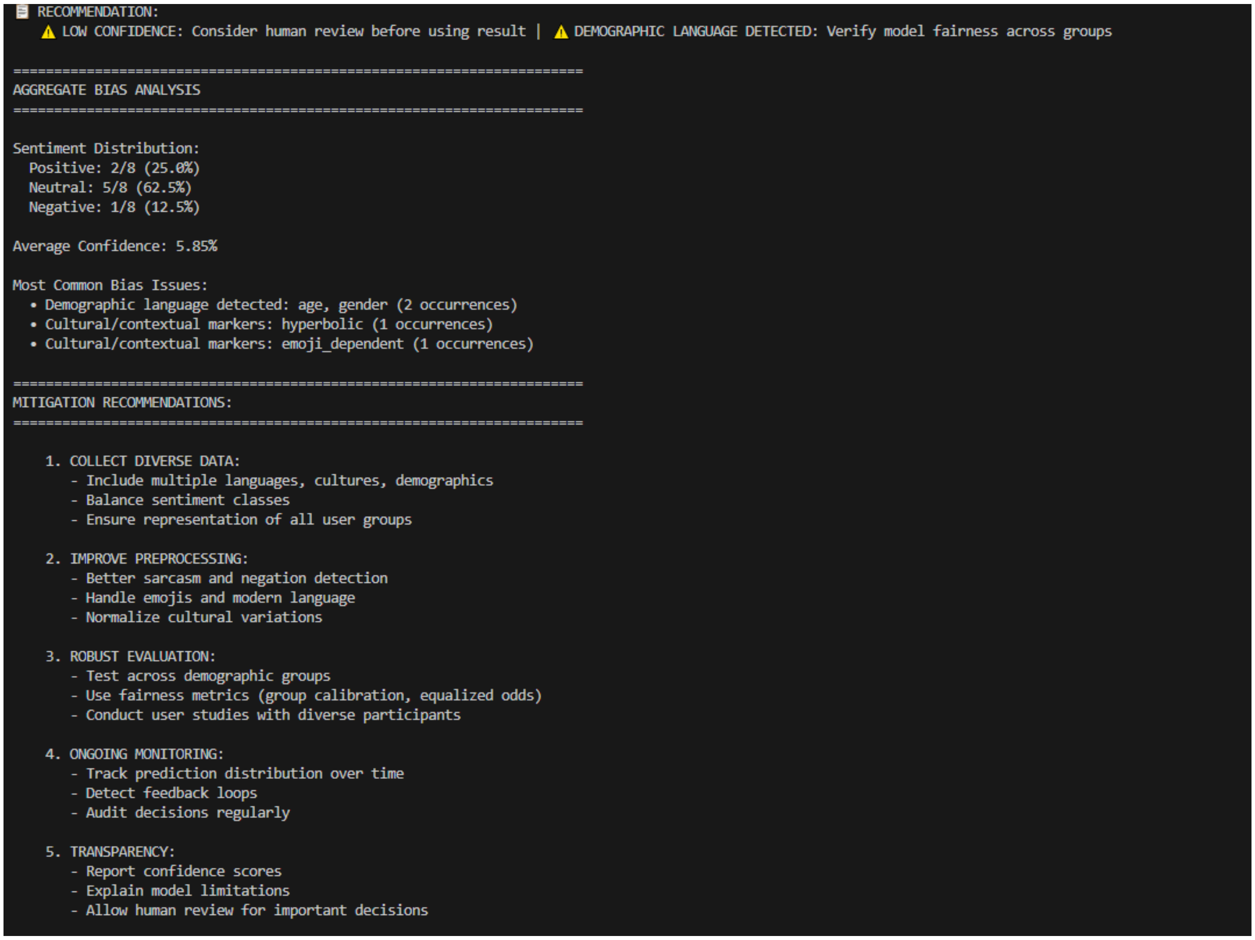
Comprehensive Documentation:



```python
def analyze_sentiment(text: str) -> SentimentResult:
```

C:\Users\HP\Downloads\ai_assistant_coding_68\task1.py

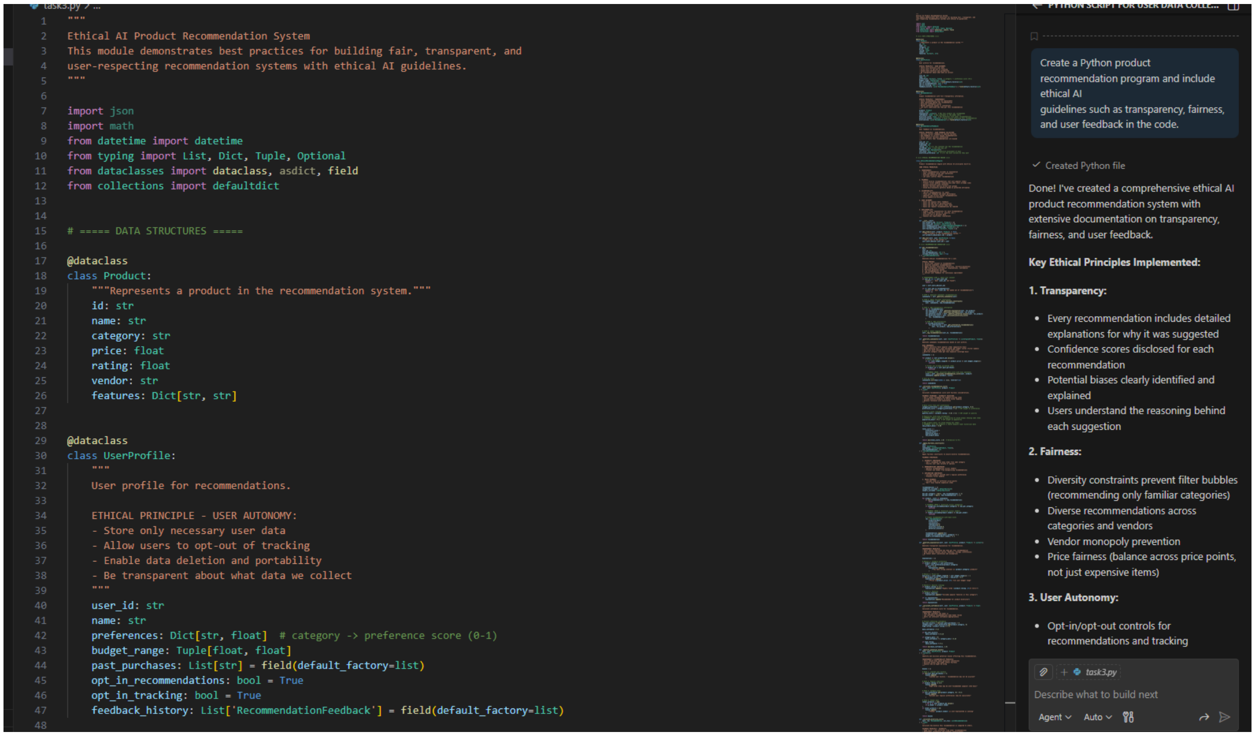
```python
    # Normalize text
    normalized_text = text.lower().strip()

    # ===== BIAS DETECTION CHECKS =====
    bias_flags = []

    # Check for demographic language
    demographics = detect_demographic_language(text)
    if demographics:
        bias_flags.append(f"Demographic language detected: {', '.join(demographics)}")

    # Check for sarcasm
    if detect_sarcasm_and_context(text):
        bias_flags.append("Potential sarcasm detected - may reverse sentiment")

    # Check for cultural language
    cultural_issues = detect_cultural_bias(text)
    if cultural_issues:
        bias_flags.append(f"Cultural/contextual markers: {', '.join(cultural_issues)}")

    # Check text length (short texts are often misclassified)
    if len(text.split()) < 3:
        bias_flags.append("Very short text - classification may have low confidence")

    # ===== SENTIMENT SCORING =====

    words = normalized_text.split()
    positive_count = sum(1 for word in words if word in POSITIVE_WORDS)
    negative_count = sum(1 for word in words if word in NEGATIVE_WORDS)

    # Handle negation (simple negation scope: 2 words before negator)
    negation_words = {'not', 'no', 'never', 'neither', 'barely', 'hardly'}
    negation_adjusted_pos = 0
    negation_adjusted_neg = 0

    for i, word in enumerate(words):
        if word in negation_words:
            # Check next 2 words
```



```
📄 RECOMMENDATION:
   ⚠ LOW CONFIDENCE: Consider human review before using result | ⚠ DEMOGRAPHIC LANGUAGE DETECTED: Verify model fairness across groups

======================================================================
AGGREGATE BIAS ANALYSIS
======================================================================

Sentiment Distribution:
  Positive: 2/8 (25.0%)
  Neutral: 5/8 (62.5%)
  Negative: 1/8 (12.5%)

Average Confidence: 5.85%

Most Common Bias Issues:
  • Demographic language detected: age, gender (2 occurrences)
  • Cultural/contextual markers: hyperbolic (1 occurrences)
  • Cultural/contextual markers: emoji_dependent (1 occurrences)

======================================================================
MITIGATION RECOMMENDATIONS:
======================================================================

    1. COLLECT DIVERSE DATA:
       - Include multiple languages, cultures, demographics
       - Balance sentiment classes
       - Ensure representation of all user groups

    2. IMPROVE PREPROCESSING:
       - Better sarcasm and negation detection
       - Handle emojis and modern language
       - Normalize cultural variations

    3. ROBUST EVALUATION:
       - Test across demographic groups
       - Use fairness metrics (group calibration, equalized odds)
       - Conduct user studies with diverse participants

    4. ONGOING MONITORING:
       - Track prediction distribution over time
       - Detect feedback loops
       - Audit decisions regularly

    5. TRANSPARENCY:
       - Report confidence scores
       - Explain model limitations
       - Allow human review for important decisions
```

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.


task3.py > ...
PYTHON SCRIPT FOR USER DATA COLLE...
task3.py
Describe what to build next
Agent
Auto

```python
"""
Ethical AI Product Recommendation System
This module demonstrates best practices for building fair, transparent, and
user-respecting recommendation systems with ethical AI guidelines.
"""

import json
import math
from datetime import datetime
from typing import List, Dict, Tuple, Optional
from dataclasses import dataclass, asdict, field
from collections import defaultdict


# ===== DATA STRUCTURES =====

@dataclass
class Product:
    """Represents a product in the recommendation system."""
    id: str
    name: str
    category: str
    price: float
    rating: float
    vendor: str
    features: Dict[str, str]


@dataclass
class UserProfile:
    """
    User profile for recommendations.

    ETHICAL PRINCIPLE - USER AUTONOMY:
    - Store only necessary user data
    - Allow users to opt-out of tracking
    - Enable data deletion and portability
    - Be transparent about what data we collect
    """
    user_id: str
    name: str
    preferences: Dict[str, float]  # category -> preference score (0-1)
    budget_range: Tuple[float, float]
    past_purchases: List[str] = field(default_factory=list)
    opt_in_recommendations: bool = True
    opt_in_tracking: bool = True
    feedback_history: List['RecommendationFeedback'] = field(default_factory=list)

```

Create a Python product recommendation program and include ethical AI
guidelines such as transparency, fairness, and user feedback in the code.

✓ Created Python file

Done! I've created a comprehensive ethical AI product recommendation system with extensive documentation on transparency, fairness, and user feedback.

Key Ethical Principles Implemented:

1. Transparency:

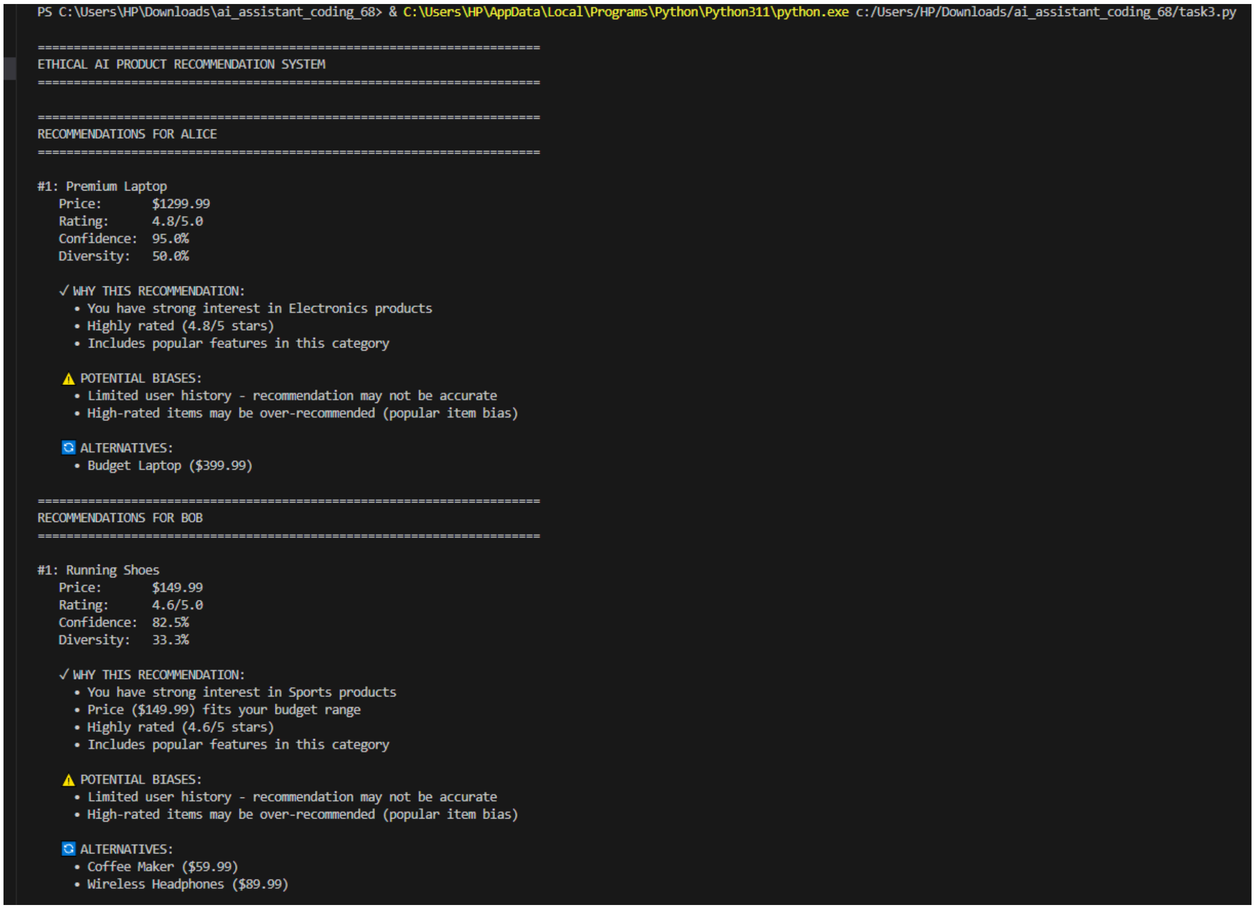
- Every recommendation includes detailed explanations for why it was suggested
- Confidence scores disclosed for each recommendation
- Potential biases clearly identified and explained
- Users understand the reasoning behind each suggestion

2. Fairness:

- Diversity constraints prevent filter bubbles (recommending only familiar categories)
- Diverse recommendations across categories and vendors
- Vendor monopoly prevention
- Price fairness (balance across price points, not just expensive items)

3. User Autonomy:

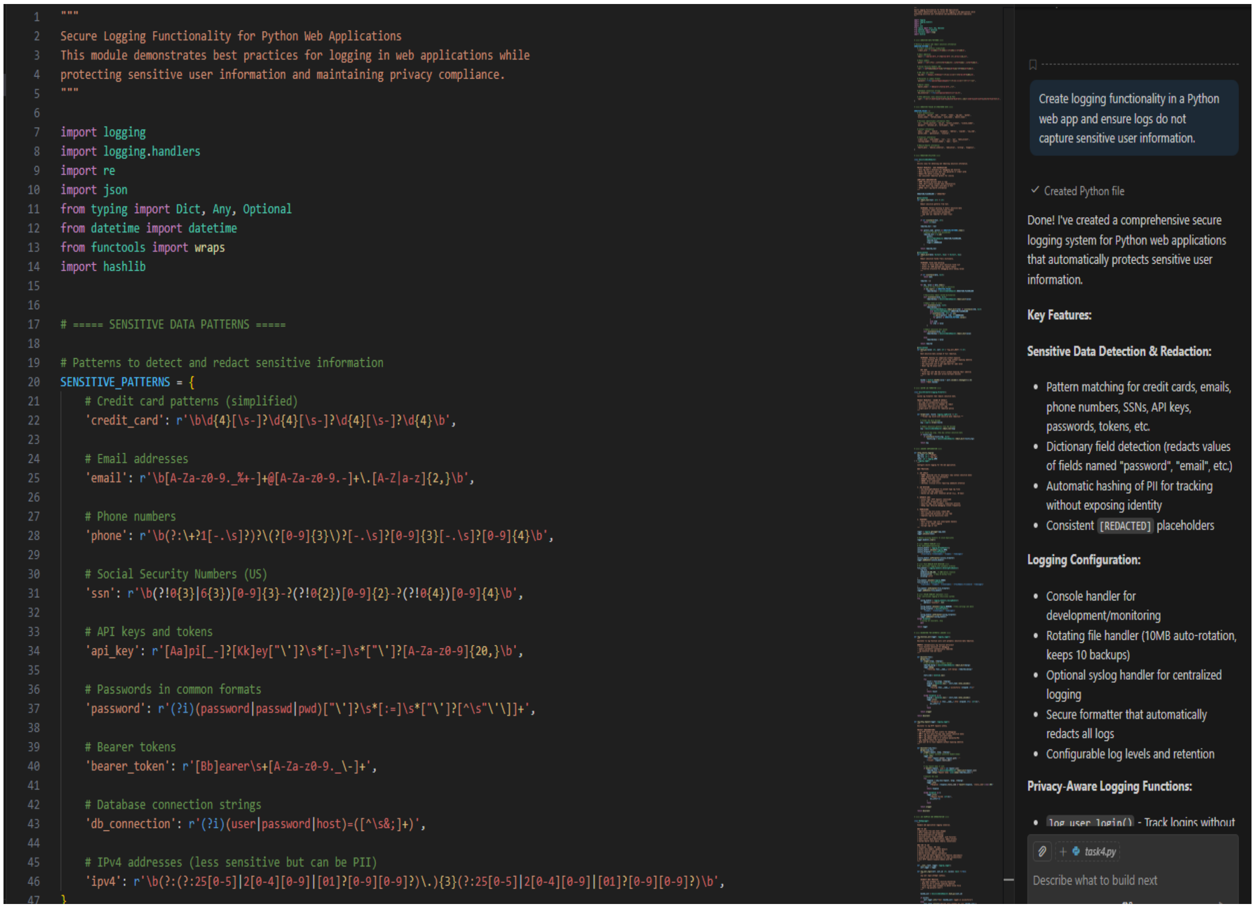
- Opt-in/opt-out controls for recommendations and tracking



```
PS C:\Users\HP\Downloads\ai_assistant_coding_68> & C:\Users\HP\AppData\Local\Programs\Python\Python311\python.exe c:/Users/HP/Downloads/ai_assistant_coding_68/task3.py

======================================================================
ETHICAL AI PRODUCT RECOMMENDATION SYSTEM
======================================================================

======================================================================
RECOMMENDATIONS FOR ALICE
======================================================================

#1: Premium Laptop
   Price:       $1299.99
   Rating:      4.8/5.0
   Confidence:  95.0%
   Diversity:   50.0%

   ✓ WHY THIS RECOMMENDATION:
     • You have strong interest in Electronics products
     • Highly rated (4.8/5 stars)
     • Includes popular features in this category

   ⚠ POTENTIAL BIASES:
     • Limited user history - recommendation may not be accurate
     • High-rated items may be over-recommended (popular item bias)

   🔄 ALTERNATIVES:
     • Budget Laptop ($399.99)

======================================================================
RECOMMENDATIONS FOR BOB
======================================================================

#1: Running Shoes
   Price:       $149.99
   Rating:      4.6/5.0
   Confidence:  82.5%
   Diversity:   33.3%

   ✓ WHY THIS RECOMMENDATION:
     • You have strong interest in Sports products
     • Price ($149.99) fits your budget range
     • Highly rated (4.6/5 stars)
     • Includes popular features in this category

   ⚠ POTENTIAL BIASES:
     • Limited user history - recommendation may not be accurate
     • High-rated items may be over-recommended (popular item bias)

   🔄 ALTERNATIVES:
     • Coffee Maker ($59.99)
     • Wireless Headphones ($89.99)
```

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.**



```python
"""
Secure Logging Functionality for Python Web Applications
This module demonstrates best practices for logging in web applications while
protecting sensitive user information and maintaining privacy compliance.
"""

import logging
import logging.handlers
import re
import json
from typing import Dict, Any, Optional
from datetime import datetime
from functools import wraps
import hashlib


# ===== SENSITIVE DATA PATTERNS =====

# Patterns to detect and redact sensitive information
SENSITIVE_PATTERNS = {
    # Credit card patterns (simplified)
    'credit_card': r'\b\d{4}[\s-]?\d{4}[\s-]?\d{4}[\s-]?\d{4}\b',

    # Email addresses
    'email': r'\b[A-Za-z0-9._%+-]+@[A-Za-z0-9.-]+\.[A-Z|a-z]{2,}\b',

    # Phone numbers
    'phone': r'\b(?:\+?1[-.\s]?)?\(?[0-9]{3}\)?[-.\s]?[0-9]{3}[-.\s]?[0-9]{4}\b',

    # Social Security Numbers (US)
    'ssn': r'\b(?!0{3}|6{3})[0-9]{3}-?(?!0{2})[0-9]{2}-?(?!0{4})[0-9]{4}\b',

    # API keys and tokens
    'api_key': r'[Aa]pi[_-]?[Kk]ey["\']?\s*[:=]\s*["\']?[A-Za-z0-9]{20,}\b',

    # Passwords in common formats
    'password': r'(?i)(password|passwd|pwd)["\']?\s*[:=]\s*["\']?[^\s"\'\]]+',

    # Bearer tokens
    'bearer_token': r'[Bb]earer\s+[A-Za-z0-9._\-]+',

    # Database connection strings
    'db_connection': r'(?i)(user|password|host)=([^\s&;]+)',

    # IPv4 addresses (less sensitive but can be PII)
    'ipv4': r'\b(?:(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\.){3}(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\b',
}
```

Create logging functionality in a Python web app and ensure logs do not capture sensitive user information.

✓ Created Python file

Done! I've created a comprehensive secure logging system for Python web applications that automatically protects sensitive user information.

Key Features:

Sensitive Data Detection & Redaction:

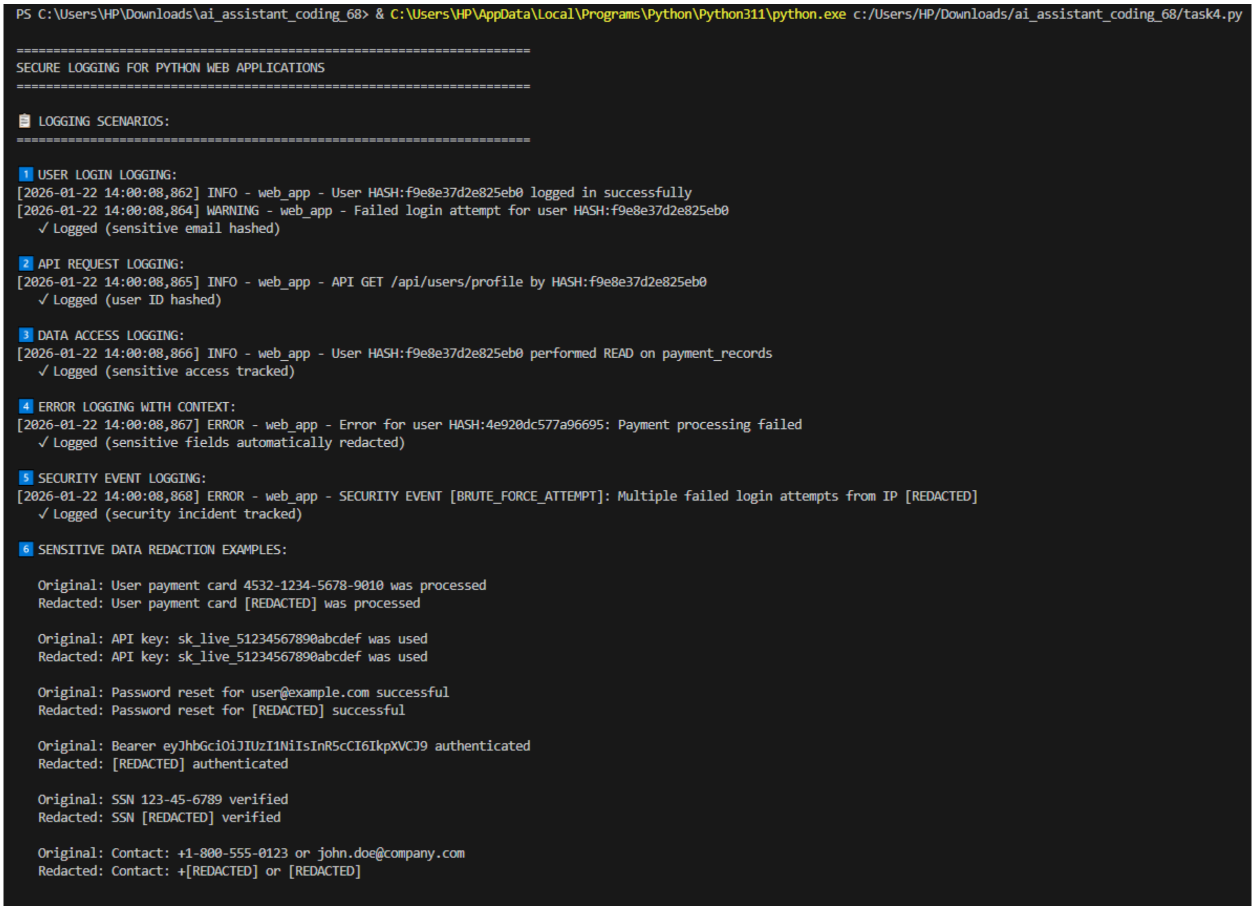
- Pattern matching for credit cards, emails, phone numbers, SSNs, API keys, passwords, tokens, etc.
- Dictionary field detection (redacts values of fields named "password", "email", etc.)
- Automatic hashing of PII for tracking without exposing identity
- Consistent `[REDACTED]` placeholders

Logging Configuration:

- Console handler for development/monitoring
- Rotating file handler (10MB auto-rotation, keeps 10 backups)
- Optional syslog handler for centralized logging
- Secure formatter that automatically redacts all logs
- Configurable log levels and retention

Privacy-Aware Logging Functions:

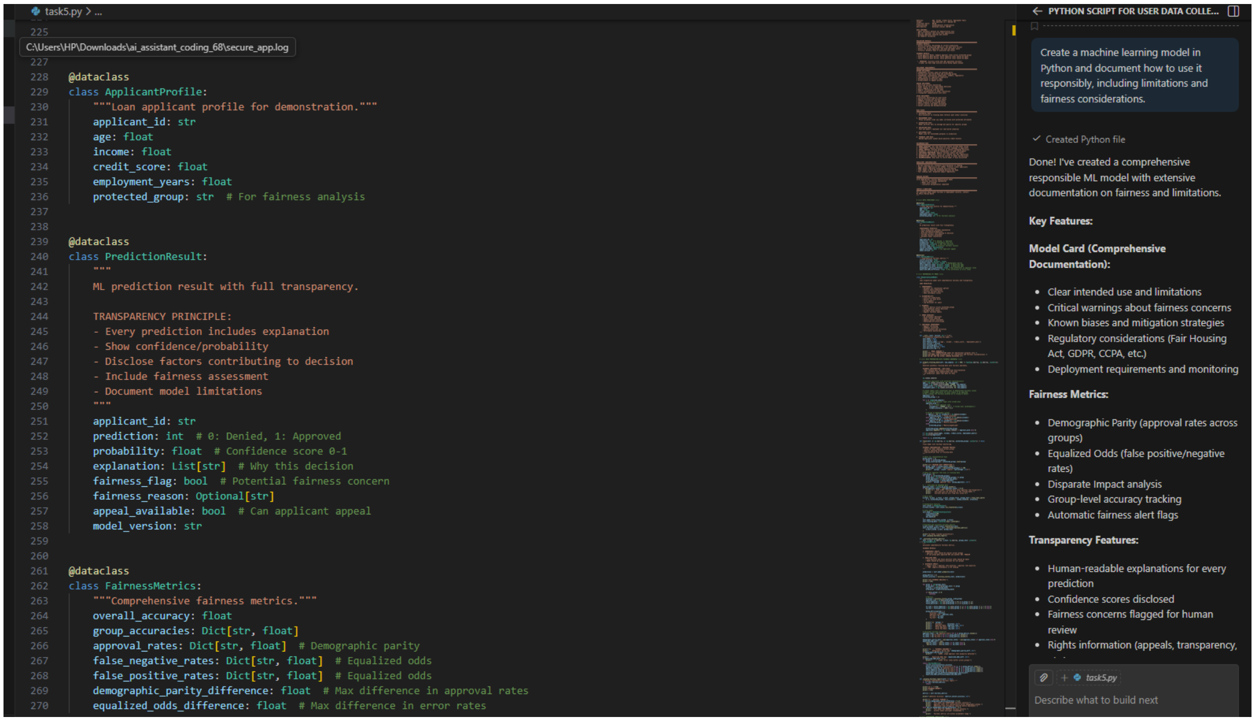
- `log_user_login()` - Track logins without



```
PS C:\Users\HP\Downloads\ai_assistant_coding_68> & C:\Users\HP\AppData\Local\Programs\Python\Python311\python.exe c:/Users/HP/Downloads/ai_assistant_coding_68/task4.py

======================================================================
SECURE LOGGING FOR PYTHON WEB APPLICATIONS
======================================================================

📋 LOGGING SCENARIOS:
======================================================================

1️⃣ USER LOGIN LOGGING:
[2026-01-22 14:00:08,862] INFO - web_app - User HASH:f9e8e37d2e825eb0 logged in successfully
[2026-01-22 14:00:08,864] WARNING - web_app - Failed login attempt for user HASH:f9e8e37d2e825eb0
   ✓ Logged (sensitive email hashed)

2️⃣ API REQUEST LOGGING:
[2026-01-22 14:00:08,865] INFO - web_app - API GET /api/users/profile by HASH:f9e8e37d2e825eb0
   ✓ Logged (user ID hashed)

3️⃣ DATA ACCESS LOGGING:
[2026-01-22 14:00:08,866] INFO - web_app - User HASH:f9e8e37d2e825eb0 performed READ on payment_records
   ✓ Logged (sensitive access tracked)

4️⃣ ERROR LOGGING WITH CONTEXT:
[2026-01-22 14:00:08,867] ERROR - web_app - Error for user HASH:4e920dc577a96695: Payment processing failed
   ✓ Logged (sensitive fields automatically redacted)

5️⃣ SECURITY EVENT LOGGING:
[2026-01-22 14:00:08,868] ERROR - web_app - SECURITY EVENT [BRUTE_FORCE_ATTEMPT]: Multiple failed login attempts from IP [REDACTED]
   ✓ Logged (security incident tracked)

6️⃣ SENSITIVE DATA REDACTION EXAMPLES:

   Original: User payment card 4532-1234-5678-9010 was processed
   Redacted: User payment card [REDACTED] was processed

   Original: API key: sk_live_51234567890abcdef was used
   Redacted: API key: sk_live_51234567890abcdef was used

   Original: Password reset for user@example.com successful
   Redacted: Password reset for [REDACTED] successful

   Original: Bearer eyJhbGciOiJIUzI1NiIsInR5cCI6IkpXVCJ9 authenticated
   Redacted: [REDACTED] authenticated

   Original: SSN 123-45-6789 verified
   Redacted: SSN [REDACTED] verified

   Original: Contact: +1-800-555-0123 or john.doe@company.com
   Redacted: Contact: +[REDACTED] or [REDACTED]
```

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).**



```python

@dataclass
class ApplicantProfile:
    """Loan applicant profile for demonstration."""
    applicant_id: str
    age: float
    income: float
    credit_score: float
    employment_years: float
    protected_group: str  # For fairness analysis


@dataclass
class PredictionResult:
    """
    ML prediction result with full transparency.

    TRANSPARENCY PRINCIPLE:
    - Every prediction includes explanation
    - Show confidence/probability
    - Disclose factors contributing to decision
    - Include fairness assessment
    - Document model limitations
    """
    applicant_id: str
    prediction: int  # 0: Denied, 1: Approved
    probability: float  # Confidence score 0-1
    explanation: List[str]  # Why this decision
    fairness_flag: bool  # Potential fairness concern
    fairness_reason: Optional[str]
    appeal_available: bool  # Can applicant appeal
    model_version: str


@dataclass
class FairnessMetrics:
    """Comprehensive fairness metrics."""
    overall_accuracy: float
    group_accuracies: Dict[str, float]
    approval_rates: Dict[str, float]  # Demographic parity
    false_negative_rates: Dict[str, float]  # Equalized odds
    false_positive_rates: Dict[str, float]  # Equalized odds
    demographic_parity_difference: float  # Max difference in approval rates
    equalized_odds_difference: float  # Max difference in error rates
```

Create a machine learning model in Python and document how to use it responsibly, including limitations and fairness considerations.

✓ Created Python file

Done! I've created a comprehensive responsible ML model with extensive documentation on fairness and limitations.

Key Features:

Model Card (Comprehensive Documentation):

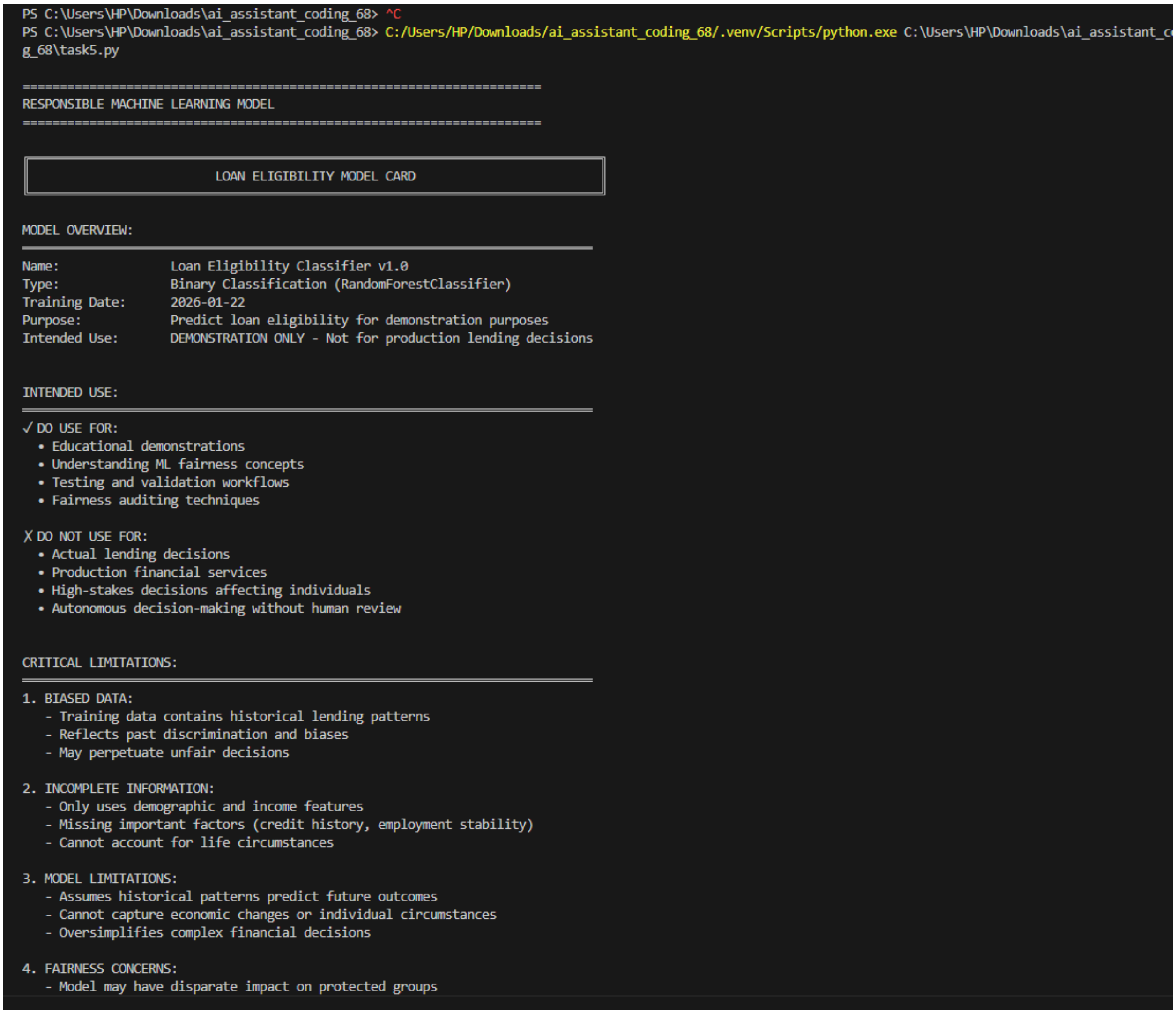
- Clear intended use and limitations
- Critical warnings about fairness concerns
- Known biases and mitigation strategies
- Regulatory considerations (Fair Housing Act, GDPR, CCPA, etc.)
- Deployment requirements and monitoring

Fairness Metrics:

- Demographic Parity (approval rates across groups)
- Equalized Odds (false positive/negative rates)
- Disparate Impact analysis
- Group-level accuracy tracking
- Automatic fairness alert flags

Transparency Features:

- Human-readable explanations for every prediction
- Confidence scores disclosed
- Fairness concerns flagged for human review
- Rights information (appeals, transparency,



```
PS C:\Users\HP\Downloads\ai_assistant_coding_68> ^C
PS C:\Users\HP\Downloads\ai_assistant_coding_68> C:/Users/HP/Downloads/ai_assistant_coding_68/.venv/Scripts/python.exe C:\Users\HP\Downloads\ai_assistant_c
g_68\task5.py

======================================================================
RESPONSIBLE MACHINE LEARNING MODEL
======================================================================

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║                         LOAN ELIGIBILITY MODEL CARD                          ║
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MODEL OVERVIEW:
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Name:               Loan Eligibility Classifier v1.0
Type:               Binary Classification (RandomForestClassifier)
Training Date:      2026-01-22
Purpose:            Predict loan eligibility for demonstration purposes
Intended Use:       DEMONSTRATION ONLY - Not for production lending decisions


INTENDED USE:
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✓ DO USE FOR:
  • Educational demonstrations
  • Understanding ML fairness concepts
  • Testing and validation workflows
  • Fairness auditing techniques

✗ DO NOT USE FOR:
  • Actual lending decisions
  • Production financial services
  • High-stakes decisions affecting individuals
  • Autonomous decision-making without human review


CRITICAL LIMITATIONS:
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1. BIASED DATA:
   - Training data contains historical lending patterns
   - Reflects past discrimination and biases
   - May perpetuate unfair decisions

2. INCOMPLETE INFORMATION:
   - Only uses demographic and income features
   - Missing important factors (credit history, employment stability)
   - Cannot account for life circumstances

3. MODEL LIMITATIONS:
   - Assumes historical patterns predict future outcomes
   - Cannot capture economic changes or individual circumstances
   - Oversimplifies complex financial decisions

4. FAIRNESS CONCERNS:
   - Model may have disparate impact on protected groups
```