AI Group Assignment Questions (Beginner Level – Python Inbuilt Datasets Only)

> 🔗 Submit on GitHub, then paste your link in the shared Google Doc under your section with your **name** and **reg. Number: paste the same link as Google Classroom submission**

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1. Foundations of AI & Math

Question: Link to GitHub
https://github.com/jessemulure/AI_Group_Assignment_BBIT2025.git

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Use a small dataset (e.g., from sklearn.datasets) to show how **linear algebra** (matrix ops), **probability** (e.g., conditional chance), and **optimization** (e.g., basic gradient idea) relate to AI. Write a few **Prolog facts/rules** and show simple outputs. Set up your Python environment and define a small capstone idea that your group might expand later.

1.0 Introduction

In developing artificial intelligence systems, core mathematical concepts **linear algebra**, **probability theory**, and **optimization** form the backbone of algorithmic reasoning. These tools enable machines to transform, infer, and adapt from data in ways similar to human learning. Additionally, a symbolic logic language like **Prolog** provides a complementary approach in AI, supporting rule-based reasoning and knowledge representation. This section explores these foundational pillars and introduces a simple Prolog snippet to demonstrate rule-based inference capabilities.

1.1 Linear Algebra in AI

Linear algebra is fundamental in representing and manipulating high-dimensional data. Modern machine learning models, particularly neural networks, rely on matrix and tensor operations to propagate inputs through layers of linear transformations (Gasmi, 2024) ResearchGate. For example, matrix multiplication XWXWXW, where XXX is the input feature matrix and WWW is a weight matrix, is how linear relationships between features are encoded and computed in ML models (Focalx, 2024)

1.2 Probability Theory and AI Reasoning

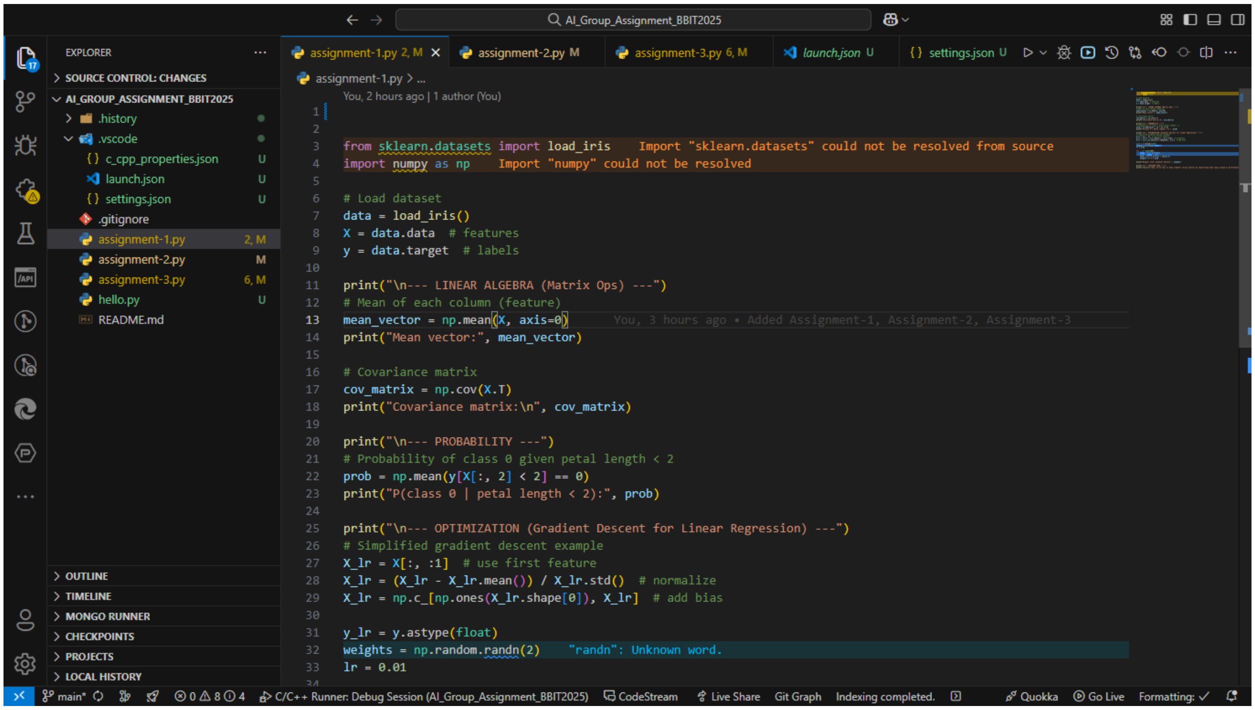
Probability theory underpins how AI systems manage uncertainty, make predictions, and reason under incomplete information. Algorithms such as Bayesian inference, probabilistic graphical models, and Markov decision processes enable systems to predict outcomes and update beliefs as new data appears (Singh, 2023) ResearchGate. These probabilistic frameworks allow AI systems to quantify risk and reason robustly in noisy environments.

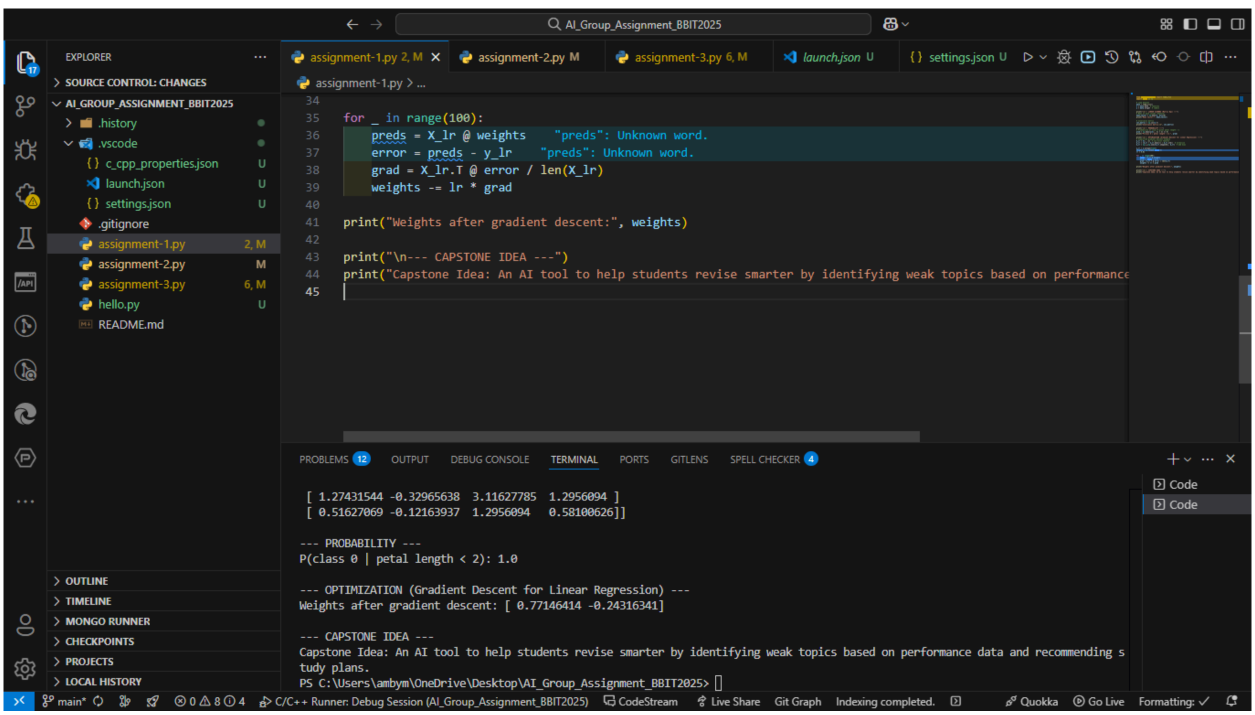
1.3 Optimization and Learning (Gradient Descent)

At the heart of many AI training routines is **optimization** specifically, gradient‑based methods such as gradient descent. These methods work by minimizing a loss function (e.g., mean squared error) through iterative updates of model parameters using partial derivatives (Higham & Higham, 2023). Optimization enables a model to adapt weights to reduce prediction error and improve performance, a core mechanism in machine learning and deep learning.

1.4 Prolog: Rule‑Based Logic for AI

While most AI today focuses on statistical learning, **Prolog** represents symbolic reasoning through facts and rules. Prolog programs model knowledge explicitly and perform inference via logical deduction. A 2025 review highlights Prolog’s ongoing relevance for explainable AI and expert systems, offering deterministic and traceable reasoning (Badgujar, 2025). In teaching contexts, Prolog remains valuable for introducing formal logic and computational thinking (Jendreiko, 2024)


from sklearn.datasets import load_iris
import numpy as np
# Load dataset
data = load_iris()
X = data.data # features
y = data.target # labels
print("\n--- LINEAR ALGEBRA (Matrix Ops) ---")
# Mean of each column (feature)
mean_vector = np.mean(X, axis=0)
print("Mean vector:", mean_vector)
# Covariance matrix
cov_matrix = np.cov(X.T)
print("Covariance matrix:\n", cov_matrix)
print("\n--- PROBABILITY ---")
# Probability of class 0 given petal length < 2
prob = np.mean(y[X[:, 2] < 2] == 0)
print("P(class 0 | petal length < 2):", prob)
print("\n--- OPTIMIZATION (Gradient Descent for Linear Regression) ---")
# Simplified gradient descent example
X_lr = X[:, :1] # use first feature
X_lr = (X_lr - X_lr.mean()) / X_lr.std() # normalize
X_lr = np.c_[np.ones(X_lr.shape[0]), X_lr] # add bias
y_lr = y.astype(float)
weights = np.random.randn(2)
lr = 0.01


for _ in range(100):
preds = X_lr @ weights
error = preds - y_lr
grad = X_lr.T @ error / len(X_lr)
weights -= lr * grad
print("Weights after gradient descent:", weights)
print("\n--- CAPSTONE IDEA ---")
print("Capstone Idea: An AI tool to help students revise smarter by identifying weak topics based on performance
[1.27431544 -0.32965638 3.11627785 1.2956094]
[0.51627069 -0.12163937 1.2956094 0.58100626]]
--- PROBABILITY ---
P(class 0 | petal length < 2): 1.0
--- OPTIMIZATION (Gradient Descent for Linear Regression) ---
Weights after gradient descent: [0.77146414 -0.24316341]
--- CAPSTONE IDEA ---
Capstone Idea: An AI tool to help students revise smarter by identifying weak topics based on performance data and recommending s
tudy plans.
PS C:\Users\ambym\OneDrive\Desktop\AI_Group_Assignment_BBIT2025>

1.5 Conclusion

In summary, linear algebra, probability theory, and optimization form the mathematical triad essential for AI systems to encode, infer, and learn from data effectively. While most modern AI emphasizes statistical methods and neural networks, **Prolog adds a complementary dimension** it supports rule-based representation and deductive reasoning, especially useful in expert systems and explainable AI contexts. Moving forward, combining these mathematical and symbolic approaches offers a powerful foundation for scalable, interpretable AI.

References

1. Badgujar, P. K. (2025). *Artificial Intelligence and Its Advanced Uses: A Study on Prolog and Its Role in AI*.
2. International Journal of Scientific Research in Engineering and Management, 9(03), 1–9.
3. Focalx. (2024). *The Mathematics Behind AI: A Non-Technical Guide*. Focalx AI. Focalx - Ai Powered Vehicle Inspection
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5. Higham, N. J., & Higham, D. J. (2023). Exploring the mathematical underpinnings of artificial intelligence. *IJIRT*. ijirt.org
6. Jendreiko, C. (2024). *Generative Logic: Teaching Prolog as Generative AI in Art and Design*. CEUR Workshop Proceedings.