Minor in AI

Vectors, Matrices, and Markov Models

1 Introduction: The Matrix in Real Life

Imagine shopping online. Every product you see has multiple attributes: price, size, color, rating. At the backend, this data is organized as a **matrix** where rows represent products and columns represent features. Similarly, digital images are matrices of pixel values, with three matrices (red, green, blue) combining to form colors. These real-world examples show how matrices structure complex data.

In AI, we use matrices for:

- Linear regression: Predicting house prices from features
- Image recognition: Processing pixel matrices in CNNs
- Recommendation systems: User-item interaction matrices
- Markov models: Predicting next states (e.g., focused/distracted students)

2 Core Concepts and Implementation

2.1 The Great List vs Array Debate

```
Key Difference

Lists = Mixed data types (heterogeneous)

Arrays = Same data type (homogeneous)
```

Why does this matter? Arrays are 100x faster for mathematical operations. Here's why:

- 1. Memory efficiency: Arrays use contiguous memory blocks
- 2. Implicit addressing: Calculate positions via base address + (index \times data size)
- 3. Optimized operations: Single instruction for all elements

```
import numpy as np

# List (heterogeneous - mixed types)

list_ex = [5.2, "hello", 1.4, 'a']

print(list_ex) # Output: [5.2, 'hello', 1.4, 'a']

# Array with mixed types $->$ converts to string

arr_mixed = np.array([5.2, 3.5, "hello", 1.7])

print(arr_mixed) # Output: ['5.2' '3.5' 'hello' '1.7']

# Pure numeric array $->$ retains float type

arr_num = np.array([5.2, 3.5, 4.5, 1.7])

print(arr_num) # Output: [5.2 3.5 4.5 1.7]
```

Listing 1: Lists vs Arrays in Python

2.2 Matrix Operations in Machine Learning

2.2.1 Dot Product: The AI Workhorse

Used in linear regression and neural networks. Calculates weighted sums: $dot(w, x) = w_1x_1 + w_2x_2 + \cdots + w_nx_n$

```
w = [3, 4, 5, 2] # Model weights
x = [1, 2, 5, 3] # Input features

# Method 1: Using np.dot()
prediction = np.dot(w, x) # 3*1 + 4*2 + 5*5 + 2*3 = 42

# Method 2: Convert to arrays and use @ operator
w_arr = np.array(w)
x_arr = np.array(x)
pred = w_arr @ x_arr # Also 42
```

Listing 2: Dot Product Implementation

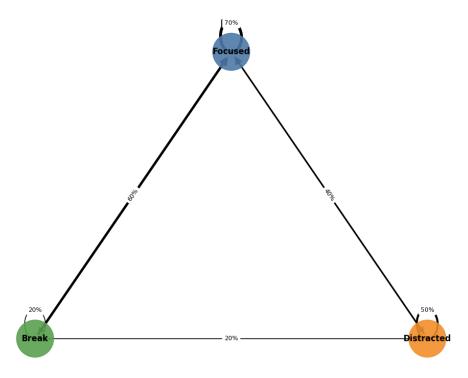
2.2.2 Matrix Multiplication: Neural Network Brains

Each layer in a neural network uses matrix multiplication. Shape matters: $(m \times n)$ matrix $\times (n \times p)$ matrix $- > (m \times p)$ result.

2.2.3 Transpose and Inverse

- Transpose: Swap rows/columns $(A_{ij} \to A_{ji})$
- Inverse: Matrix "division" $(A^{-1} \text{ where } A \times A^{-1} = I)$

Student Focus State Transitions



2.3 Markov Models: Predicting the Present

Core Principle

"The future depends only on the present, not the past."

Real-world applications:

- Student focus states (focused -> distracted -> break)
- Weather prediction (sunny > rainy)
- PageRank algorithm

Implementation components:

- 1. States: Possible conditions (e.g., focused, distracted, break)
- 2. Transition Matrix: Probabilities of moving between states

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```
for step in range(5):
    next_state = np.random.choice([0,1,2], p=tm[current_state])
    print(f"Step {step}: {states[current_state]} $->$ {states[next_state]}")
    current_state = next_state

# Example output:
# Step 0: Focused $->$ Distracted
# Step 1: Distracted $->$ Focused
# Step 2: Focused $->$ Focused
# Step 3: Focused $->$ Break
```

Listing 3: Student Focus Markov Model

3 Why This Matters

- Efficiency: Arrays process ML data 100x faster than lists
- AI Foundations: Matrix operations power neural networks and deep learning
- Real-time prediction: Markov models enable quick decisions based on current state
- Exam focus: These concepts are crucial for Module B and offline exams

Pro Tip

Always convert data to NumPy arrays before ML processing. The speed difference becomes crucial with real-world datasets!