

```
%pip install -q otter-grader
```

```

142.5/142.5 kB 5.1 MB/s eta 0:00:00
101.6/101.6 kB 5.6 MB/s eta 0:00:00
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2.2/2.2 MB 46.1 MB/s eta 0:00:00
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```

```
import sys
```

```
IN_COLAB = 'google.colab' in sys.modules
```

```

if IN_COLAB:
    !git clone https://github.com/porrashuang/CSE6740_CDA_HW0_Tests.git tests
    import otter
    grader = otter.Notebook()
else:
    print("Not running in Colab")

```

✓ Task 1: Basic Matrix Elimination

Purpose

- * Solve a linear equation system using Gaussian elimination by generating elimination matrices.
- * Understand what matrix multiplication is and how it can be used to perform row operations.

Goal

Write a Python function that returns the elimination matrix used to transform a given square matrix into upper triangular form.

An elimination matrix E is an identity matrix with specific entries modified such that when it is left-multiplied with the input matrix, it performs a row operation.

The goal is to output the list of elimination matrices that, when applied in sequence, will transform the input matrix into upper triangular form.

Constraints:

- * The input matrix is a list of lists (i.e., pure Python).
- * The matrix must be square ($n \times n$).
- * You may not use any external libraries like NumPy.
- * There will be no zero rows in the input matrix and only one solution exists.

Example:

```
A = [[2, 1], [4, 3]]
```

We want to get an upper Triangular matrix:

```
[2, 1], [0, 1]
```

Thus the Output:

```
[[ [1, 0], [-2, 1] ]]
```

Explanation:

We perform the operation $R_2 = R_2 - 2 * R_1$, which is represented by the elimination matrix.

Note that the output is a list of $n \times n$ matrices, where each matrix corresponds to an elimination step.

```

def elimination_matrices(matrix):
    dimension = len(matrix)

```

```
    ##Base case
```

```
    if (dimension == 2):
```

```
E_matrices = [[1,0],[- matrix[1][0]/matrix[0][0]], 1]
cornerNum = matrix[dimension - 1][dimension - 1] + matrix[0][n - 1]* E_matrices[n-1][n - 2]
else :
```

```
grader.check("q1")
```

What is the time complexity of your solution? Please return a string that describes the time complexity of your solution.

```
time_complexity = ... # (e.g "O(n)" "O(log n)" "O(nlog n)" "O(n^2)")
```

✓ Task 2: Matrix Inversion

Purpose

- Understand the mechanism behind matrix inversion before using libraries like NumPy.

Goal

Write a Python function that uses Gaussian-Jordan elimination to compute the inverse of a given square matrix.

Constraints:

- You may not use any external libraries like NumPy.
- The input matrix is a list of lists (i.e, pure Python).
- The matrix must be square (n x n).
- The matrix may not be invertible, if it is not invertible, return None.

```
def gauss_jordan_inverse(matrix):
    ...
```

```
grader.check("q3")
```

✓ What is the time complexity of a matrix inversion algorithm?

```
time_complexity_matrix_inv = ... # (e.g "O(n)" "O(log n)" "O(nlog n)" "O(n^2)")
```

✓ Task 3: Posterior Probability

Purpose

- Understand the concept of posterior probability.
- Understand how to compute posterior probability using Bayes' theorem.
- This will be useful for later tasks like EM algorithm and Naive Bayes classifier.

Goal

Write a Python function that computes the posterior probability of a given event using Bayes' theorem. You are a data scientist working for a company that sells ice cream. You have data on the sales of different flavors of ice cream, and you want to compute the posterior probability of a given flavor being sold given the sales data.

$$P(\text{Flavor}|\text{Observation}) = P(\text{Observation}|\text{Flavor}) * P(\text{Flavor})/P(\text{Observation})$$

Constraints:

- You can assume each feature in the observation is independent of each other, and no smoothing is needed.
- You don't need to worry about zero probabilities.

The data looks like this:

```
data = [
    {"flavor": "flavor1", "hot_day": 1, "weekend": 1, "sales": 100},
    {"flavor": "flavor2", "hot_day": 1, "weekend": 0, "sales": 200},
    ...
]
```

You are given the following observation:

```
observation = {"hot_day": 1, "weekend": 1}
```

You need to compute the posterior probability of each flavor being sold given the observation (see test cases for example).

```
output = {
    "flavor1": 0.4,
    "flavor2": 0.3,
    ...
}
```

```
data = [
    {"flavor": "chocolate", "hot_day": 1, "weekend": 1, "sales": 100},
    {"flavor": "chocolate", "hot_day": 0, "weekend": 1, "sales": 50},
    {"flavor": "vanilla", "hot_day": 1, "weekend": 0, "sales": 200},
    {"flavor": "vanilla", "hot_day": 0, "weekend": 1, "sales": 100},
    {"flavor": "strawberry", "hot_day": 0, "weekend": 1, "sales": 150},
    {"flavor": "strawberry", "hot_day": 1, "weekend": 0, "sales": 50},
    {"flavor": "strawberry", "hot_day": 1, "weekend": 1, "sales": 50},
]
def compute_posterior(data, observation):
    ...
```

```
grader.check("q5")
```

✓ Task 4: Numpy Refresh

Purpose

- Refresh your knowledge of NumPy.
- Able to perform basic operations using NumPy.

Goal

Fill in the Python function that performs the following operations using NumPy:

单元格类型不受支持。双击即可检查/修改内容。

```
import numpy as np
def q1_array_creation(data):
    """Return a NumPy array created from `data` (a Python list/tuple)."""
    ...

def q2_basic_slicing(A):
    """Return the middle 2x2 of A (assume 4x4), with columns reversed."""
    ...

def q3_boolean_indexing(A):
    """Return the elements of A that are smaller than mean."""
    ...

def q4_axis_operations(A):
    """Suppose A is 3x3, Return the sum of each column (3,) in A minus the sum of each row (3,) in A"""
    ...
```

```
def q5_matrix_operations(A):  
    """Return the transpose of A, inverse of A."""  
    ...  
  
def q6_more_matrix_operations(A):  
    """Return the rank of A, SVD decomposition of A."""  
    ...  
  
grader.check("q6")
```