Nithin S 221IT085

IT464 Practice Assignment

Q1. 1. Generate a matrix with random entries of a size 4*4 and nd and show i. The transpose of the matrix ii. Inverse iii. Trace iv. Eigenvalues v. Eigenvectors

```
import numpy as np
                      _random_matrix(n, low=0, high=100):
       return np.random.randint(low, high, size=(n, n))
matrix = generate_random_matrix(n)
 print(matrix)
[[75 93 99 63]
[84 56 78 42]
[ 6 72 84 64]
[48 33 60 87]]
matrix.T
array([[75, 84, 6, 48],
[93, 56, 72, 33],
[99, 78, 84, 60],
[63, 42, 64, 87]])
np.linalg.inv(matrix)
array([[ 0.01057316, 0.00147231, -0.01654584, 0.00380445],
        [ 0.05496434, -0.04600385, -0.02000872, -0.00287395],
        [-0.05803068, 0.05615986, 0.03687552, -0.01221626],
        [ 0.01333914, -0.02209351, -0.00871314, 0.01891037]])
int(np.trace(matrix))
eigen_values,eigen_vectors=np.linalg.eig(matrix)
print(eigen_values)
[254.77761222 -21.73004059 25.28505106 43.66737732]
print(eigen vectors)
 [-0.51261618 0.7312642 -0.46795235 -0.57766986]
[-0.39714946 -0.61314973 0.74401777 0.44691069]
[-0.42377429 0.21018507 -0.11268535 0.41882312]]
```

Q2. Verify and show the adherence of the following vector operations to vector algebra laws (like commutative, associative, and distributive laws) by testing each law. Formulate a table to depict the results of this test. (i) Vector addition (ii) Vector subtraction (iii) Scalar-Vector multiplication (iv) Vector-Vector multiplication (Inner product)

```
import numpy as np

def test vector laws():
    # Test vectors
    a = np.array({1, 2, 3})
    b = np.array({2, 5, 6})
    c = np.array({2, 6, 6})
    c = np.array({2, 6, 9})
    k = 2  # scalar
    # Results dictionary to store all test results
    results = {
        "Vector Addition": {},
        "scalar-Vector Multiplication": {},
        "Inner Product": {}
}

# 1. Vector Addition Tests
# Commutative: a + b = b + a
results("vector Addition"["Commutative"] = {
        "low: "a + b = b + a',
        "left side": a + b,
        "Right Side": b + a,
        "Result: np.array_equal(a + b, b + a)
}

# Associative: (a + b) + c = a + (b + c)
results("Vector Addition"]["Associative"] = {
        "low: "a + b + c = a + (b + c)
        results(side: (a + b) + c = a + (b + c))
        "Result: np.array_equal((a + b) + c, a + (b + c))
}

# 2. Vector Subtraction Tests
# Non-commutative: a - b + b - a',
        "left Side": a - b,
        "right Side": a - b,
        "low: "a - b + b - a',
        "left Side": a - b,
        "light Side": b - a,
        "Result: not np.array_equal(a - b, b - a)
}
```

```
# Associative: Kia * b) = ka + kb
results': Scalar-Vector Multiplication']['Distributive'] = {
    'Law': *(a + b) = ka + kb',
    'Left Side': k * (a + b),
    'Right Side': k * a + k * b,
    'Result': np.array.equal(k * (a + b), k * a + k * b)
}

# 4. Inner Product Tests
# Commutative: ab = b-a
results' Inner Product']['Commutative'] = {
    'Law': *a' b * b * b'',
    'Left Side': np.dot(a, b),
    'Right Side': np.dot(b, a),
    'Result': np.dot(a, b) = np.dot(b, a)
}

# Distributive: a' (b * c) = a * b * a * c
results' Inner Product']['Distributive'] = {
    'Law': *a' (b * c) = a * b * a * c
    'Left Side': np.dot(a, b) + np.dot(a, c),
    'Right Side': np.dot(a, b) + np.dot(a, c),
    'Result': np.dot(a, (b * c)) = (np.dot(a, b) * np.dot(a, c))
}

# Print results in table format
print('Evector Algebra Laws Verification Table')
print("-*sb)

for operation, laws in results.items():
    print('Fundoperation):')
    print('Fundoperation):')
    print('Tundoperation):')
    print('Tundoperation):')
    print('Tundoperation):')
    print('Tundoperation):')
    return results

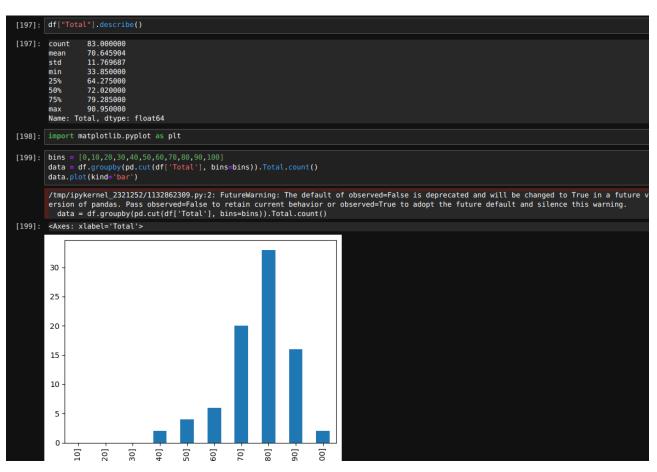
# Run the tests
test_vector_laws()
```

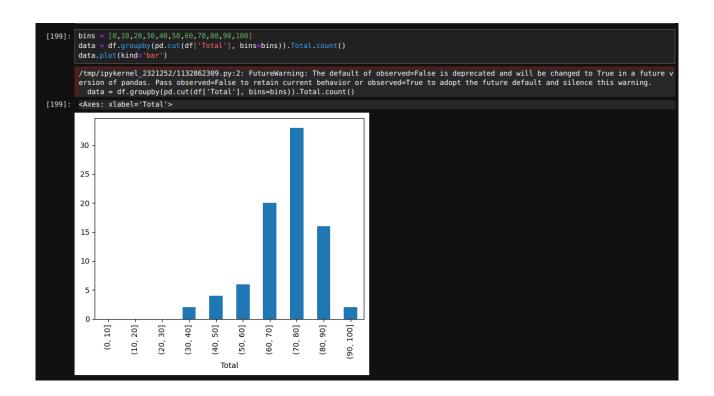
```
Vector Algebra Laws Verification Table
_____
Vector Addition:
                | Result
Law
Vector Subtraction:
                    | Result
Law
a - b ≠ b - a
Scalar-Vector Multiplication:
                 | Result
k(a + b) = ka + kb
Inner Product:
Law
                  | Result
a \cdot b = b \cdot a
a \cdot (b + c) = a \cdot b + a \cdot c
```

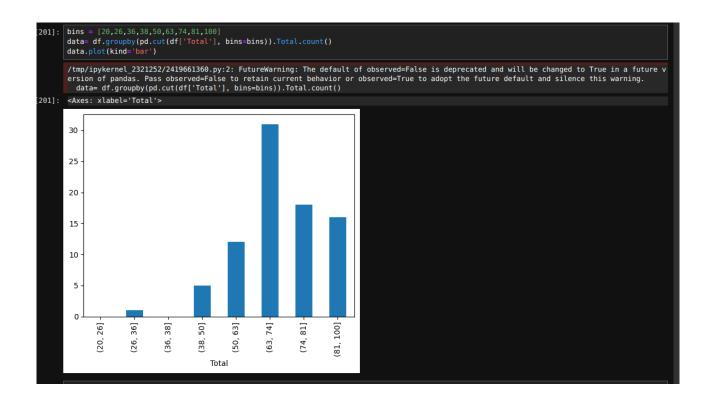
Q3. Consider marks obtained by a class of Engg. students for three assignments, a mid-sem, one mini-project work and an end-sem are mentioned in .xlxs les that can be downloaded from the moodle portal to make the nal report for grading the students of the class. Course evaluation plan is made by giving a weightage of 20% each to the assignments (for all the three), the mid-sem exam and the mini-project work. Remaining 40% weightage is given to the end-sem exam. Now using the vector operations calculate and show the nal consolidated marks (normalized to hundred) of the class using vector operations. Statics to show/display: i. Final scores of each assignment, mid, end-sem and project after normalization of nal score to 100. (ii). Find mean, variance and standard deviation along with the maximum and minimum of the normalization nal marks. (iii) Apply barchart on #students obtaining scores in dierent ranges like 0-10, 11-20,...,91-100. (iv) Apply barchart for the score ranges 100-81, 80-74, 73-63, 62-50, 49-38, 36-27 and 26-20 to nd the number of students obtained the scores in those ranges. (v) Plot the marks distribution of the students using Normal distribution

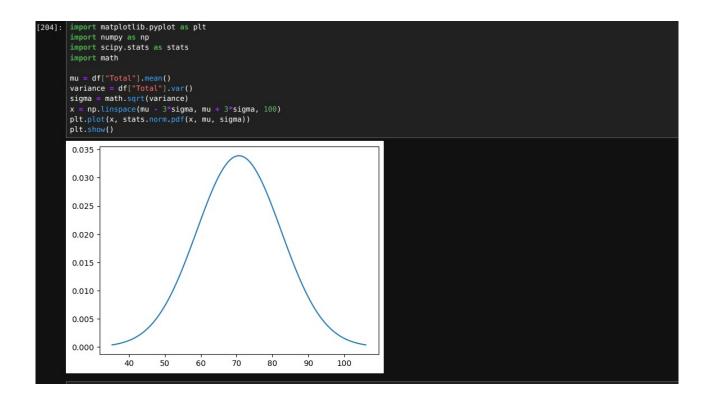
```
import pandas as pd
df=pd.read_excel("StudentsMarks.xlsx",header=3)
dtype='object')
df.rename(columns={"Mid-Semester (50 -> 20.0)":"MidSem","End_Semester (100 -> 40.0)":"EndSem","Project (100 -> 20.0)":"Project","Lab Assigned
df
   Sl. No. MidSem EndSem Project Lab1 Lab2 Lab3
                                      6.67
                       17.45 6.20 6.27 6.34
                       18.95 6.43 6.67 6.60
                 19.8 18.00 6.20 6.67 6.67
78
                       17.80 3.33 6.47
79
                       18.78 5.74 6.67
80
                       17.35 2.87 6.64 6.67
82
83 rows × 7 columns
df
```

[191]: df														
[191]:		Sl. No.	MidSem	EndSem	Project	Lab1	Lab2	Lab3	Total					
	0		12.2	31.6		6.20								
	1	2	6.0	21.6	17.45	6.20			63.86					
	2	3	9.4	28.4	17.95		6.67		75.42					
	3	4	14.4	26.4	18.95		6.67		79.45					
	4	5	10.4	19.8	18.00	6.20			67.74					
	78	79	8.6	24.4	17.80	3.33	6.47	6.67	67.27					
	79	80	12.2	21.4	18.78	5.74	6.67		71.46					
	80	81	9.2	18.8	17.35	2.87	6.64		61.53					
	81	82	6.4	24.4	17.68	2.87	6.54		64.56					
	82	83	10.8	25.2	17.68			6.67						
	83 rc	ows × 8 c	olumns											
[192]:	dfl	"Total	"1 var()											
[192]:	138	3.52553	66735233											
[193]:	3]: df["Total"].std()													
[193]:	93]: 11.769687195228398													
[194]:	float(df["Total"].mean())													
[194]:	94]: 70.64590361445782													
[195]:	df	"Total	"].max()											
			J. max ()											
[195]:	90.	.95												
[196]:	df["].min()											
[196]:	33.	.85												

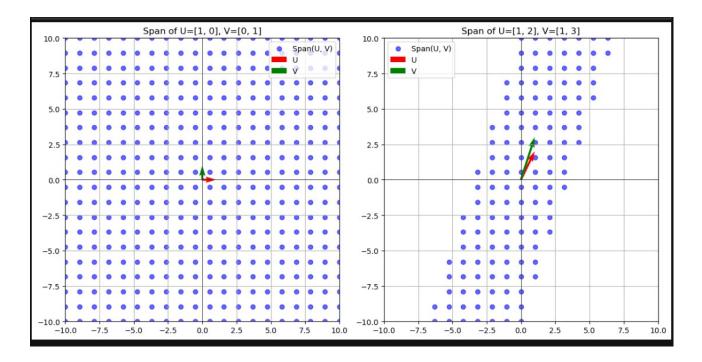








Q4. Compute linear combinations of the following vectors to nd the span and visualize the vector span in a higher dimensional plane. (i) $U = [1\ 0]$; $V = [0\ 1]$; (ii) $U = [1\ 2]$; $V = [1\ 3]$;



```
U1, V1 = np.array([1, 0]), np.array([0, 1])
U2, V2 = np.array([1, 2]), np.array([1, 3])
def generate_combinations(U, V, scalar_range=(-10, 10), steps=20):
    scalars = np.linspace(*scalar_range, steps)
    combinations = [a * U + b * V for a in scalars for b in scalars]
        return np.array(combinations)
span1 = generate_combinations(U1, V1)
span2 = generate_combinations(U2, V2)
fig, axes = plt.subplots(1, 2, figsize=(12, 6))
axes[0].scatter(span1[:, 0], span1[:, 1], alpha=0.6, c='blue', label="Span(U, V)")
axes[0].quiver(0, 0, U1[0], U1[1], angles='xy', scale_units='xy', scale=1, color='red', label="U")
axes[0].quiver(0, 0, V1[0], V1[1], angles='xy', scale_units='xy', scale=1, color='green', label="V")
axes[0].set_title("Span of U=[1, 0], V=[0, 1]")
axes[0].set_xlim(-10, 10)
axes[0].set_xlim(-10, 10)
axes[0].set_ylim(-10, 10)
axes[0].axhline(0, color='black', linewidth=0.5)
axes[0].axvline(0, color='black', linewidth=0.5)
axes[0].legend()
axes[0].grid()
axes[1].scatter(span2[:, 0], span2[:, 1], alpha=0.6, c='blue', label="Span(U, V)")
axes[1].quiver(0, 0, U2[0], U2[1], angles='xy', scale_units='xy', scale=1, color='red', label="U")
axes[1].quiver(0, 0, V2[0], V2[1], angles='xy', scale_units='xy', scale=1, color='green', label="V")
axes[1].set_title("Span of U=[1, 2], V=[1, 3]")
axes[1].set_xlim(-10, 10)
axes[1].set_ylim(-10, 10)
axes[1].axhline(0, color='black', linewidth=0.5)
axes[1].axvline(0, color='black', linewidth=0.5)
axes[1].legend()
axes[1].grid()
plt.tight_layout()
plt.show()
```

Q5. Generate a random matrix of size 30*50 and write a Python code to nd the no.of independent vectors or columns of the matrix. Find the rank of the matrix using Python code. Make your comment.

```
matrix=np.random.randint(1, 100, size=(30, 50))
matrix

array([[94, 43, 33, ..., 77, 1, 31],
       [61, 73, 74, ..., 86, 59, 60],
       [17, 35, 1, ..., 27, 2, 48],
       ...,
       [31, 65, 76, ..., 29, 13, 87],
       [32, 41, 80, ..., 74, 33, 32],
       [58, 40, 31, ..., 97, 88, 1]])

int(np.linalg.matrix_rank(matrix))

30
```

The rank represents the maximum number of linearly independent rows or columns.

The number of independent columns is equal to the rank of the matrix.

The rank is the same for rows and columns in a matrix, so independent rows = independent columns.