Assignment 1: Data Preprocessing and Visualization

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July 2024

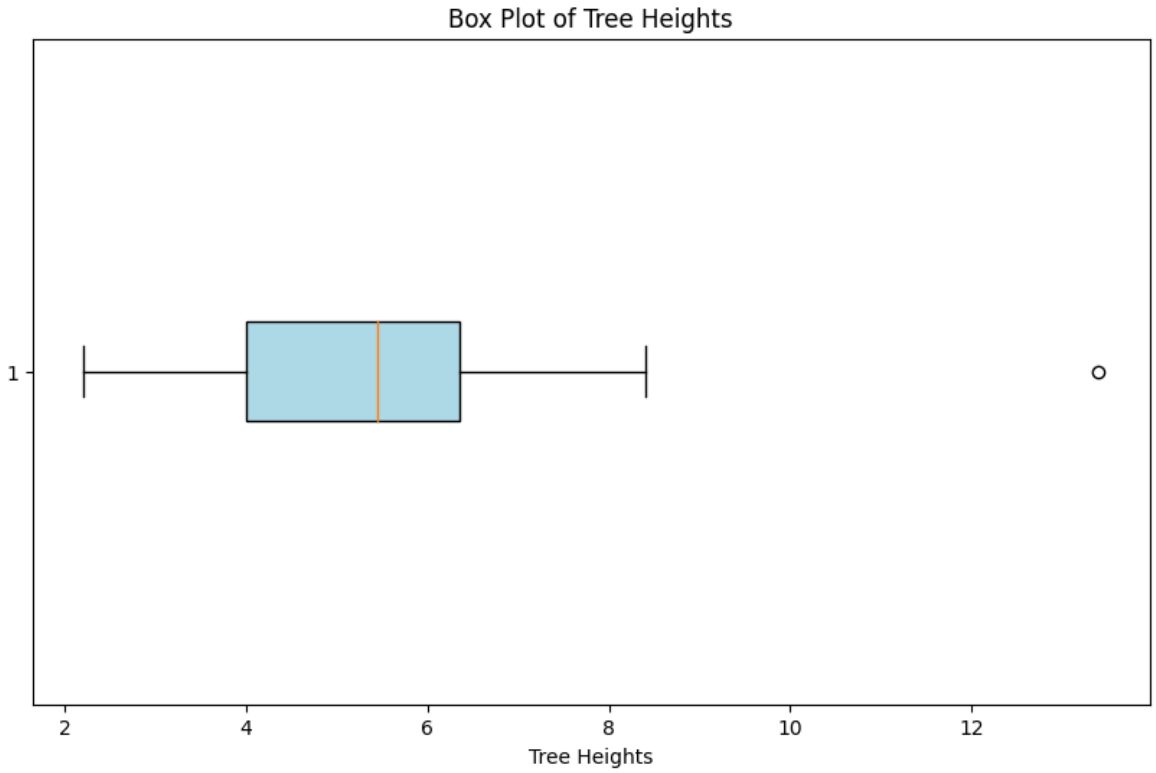
Contents

1 Problem 1

1.1

Minimum: 2.2
Q1 (25th percentile): 4.0
Median (50th percentile): 5.45
Q3 (75th percentile): 6.35
Maximum: 13.4

1.2



1.3

ordered data: 2.2, 2.5, 2.5, 2.7, 4.0, 4.0, 4.2, 4.3, 4.8, 5.4, 5.5, 5.5, 5.5, 5.8, 6.3, 6.5, 7.9, 7.9, 8.4, 13.4

Equal Frequency Partitioning:
bin 1: [2.2, 2.5, 2.5, 2.7, 4.0]
bin 2: [4.0, 4.2, 4.3, 4.8, 5.4]
bin 3: [5.5, 5.5, 5.5, 5.8, 6.3]
bin 4: [6.5, 7.9, 7.9, 8.4, 13.4]
Equal Width Partitioning:
bin 1: [2.2, 2.5, 2.5, 2.7, 4.0, 4.0, 4.2, 4.3, 4.8]
bin 2: [5.4, 5.5, 5.5, 5.5, 5.8, 6.3, 6.5]
bin 3: [7.9, 7.9, 8.4]
bin 4: [13.4]

1.4

The outliers can be inferred from the box plot, any value lying outside 3Q + 1.5x(IQR) is considered an outlier which for this specific data set is just one value: 13.4.

1.5

The missing values in the following data can be dealt with in two ways

4.3, 2.5, 2.5, ?, ?, 5.4, 6.3, ?, 4.0, 4.0, ?, ?, 13.4, 8.4, ?, 5.5, 5.5, 5.5, 2.7, 6.5

Since the missing values are missing completely at random, the following methods can be used to deal with them:

Imputation: The missing values can be replaced(imputed) with the mean(average), median(middle value) or mode(most repeated value) of the remaining data and then the completed dataset can be used for data analysis but this could lead to some loss of variation.

Deletion: The missing values can be deleted and not considered for data analysis and since they are missing completely at random, the resulting data analysis will be unbiased.

2 Problem 2

2.1

Answers:

Mean: 58.8
Median: 60.0
Mode: ModeResult(mode=45.0, count=2)
5% Trimmed Mean: 59.7
10% Trimmed Mean: 60.5
(Python) Code for 2.1

```
import numpy as np
from scipy import stats

exam_data = [56.7, 45, 65, 77, 75, 78, 56, 73, 75, 24, 0, 10, 100,
95, 45, 52, 65, 66, 58, 58.5, 59, 61]

mean = round(np.mean(exam_data), 1)
median = np.median(exam_data)
mode = stats.mode(exam_data)
trimmedfive = round(stats.trim_mean(exam_data, 0.05), 1)
trimmedten = round(stats.trim_mean(exam_data, 0.1), 1)

print(f"Mean: {mean}")
print(f"Median: {median}")
print(f"Mode: {mode}")
print(f"5% Trimmed Mean: {trimmedfive}")
print(f"10% Trimmed Mean: {trimmedten}")
```

Measure of centrality:

I think that median is the better measure of centrality because it is the least effected by outliers in the data.

Robust:

I think that median is more robust than others because it does not take into account the outliers and is least effected by outliers in all scenarios.

2.2

Values:

Mean: 2.7
Median: 2.5
Mode: 1.2
5% Trimmed Mean: 2.6
10% Trimmed Mean: 2.6

(Python) Code for 2.2

```
    import numpy as np
from scipy import stats

random_numbers = np.random.uniform(low=1, high=5, size=20)

mean = round(np.mean(random_numbers), 1)
median = round(np.median(random_numbers), 1)
mode_result = stats.mode(random_numbers)
mode_value = mode_result.mode
mode= round(mode_value, 1)

trimmedfive = round(stats.trim_mean(random_numbers, 0.05), 1)
trimmedten = round(stats.trim_mean(random_numbers, 0.1), 1)

print(f"Mean: {mean}")
print(f"Median: {median}")
print(f"Mode: {mode}")
print(f"5% Trimmed Mean: {trimmedfive}")
print(f"10% Trimmed Mean: {trimmedten}")
```

Comments:

The mean and median should be close to 3 as this is a uniformed set of numbers; the mode of this dataset is not much meaningful due to the random nature of it. As expected, the trimmed means are very close to the mean because of the absence of much outliers.

3 Problem 3:

3.1

Numerical Attributes: age, fnlwgt, education-num, capital-gain, capital-loss, hours-per-week
Nominal Attributes: race, sex, native-country
Categorical Attributes: workclass, education, marital-status, occupation, relationship, race, sex, native country

Unique values per attribute:
age: 73
workclass: 9
fnlwgt: 21648
education: 16
education-num: 16
marital-status: 7
occupation: 15
relationship: 6
race: 5
sex: 2
capital-gain: 119
capital-loss: 92
hours-per-week: 94
native-country: 42
income: 2

3.2

Age:
Minimum: 17
Q1 (25th percentile): 28.0
Median (50th percentile): 37.0
Q3 (75th percentile): 48.0
Maximum: 90
Mode: 36
Mean: 38.6

fnlwgt(Final Weight):
Minimum: 12285
Q1 (25th percentile): 117827.0
Median (50th percentile): 178356.0
Q3 (75th percentile): 237051.0
Maximum: 1484705
Mode: 123011

Mean: 189778.4

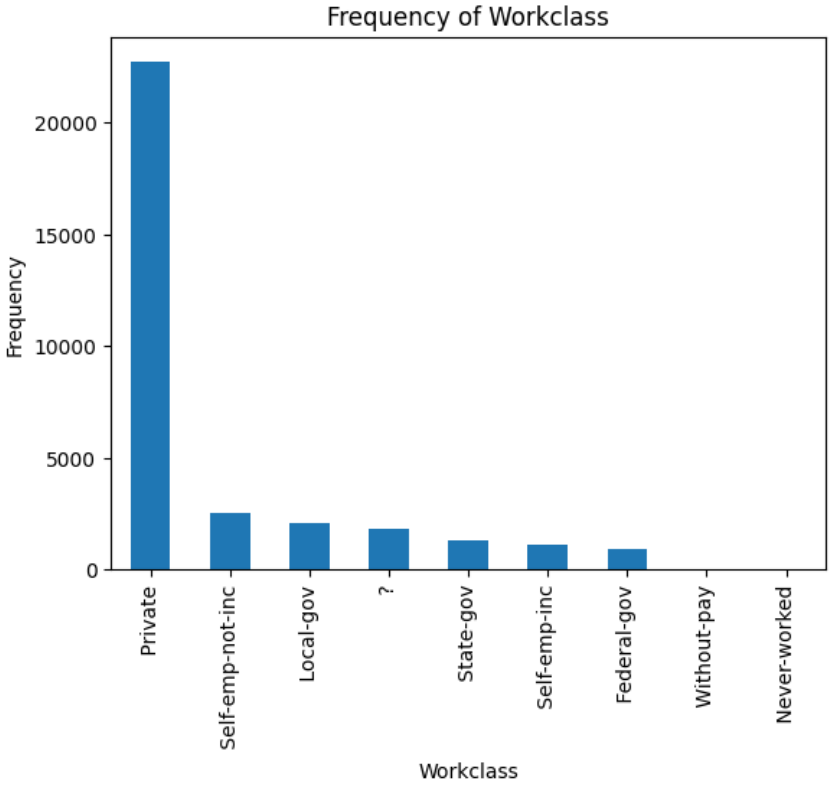
education-num:
Minimum: 1
Q1 (25th percentile): 9.0
Median (50th percentile): 10.0
Q3 (75th percentile): 12.0
Maximum: 16
Mode: 9
Mean: 10.1

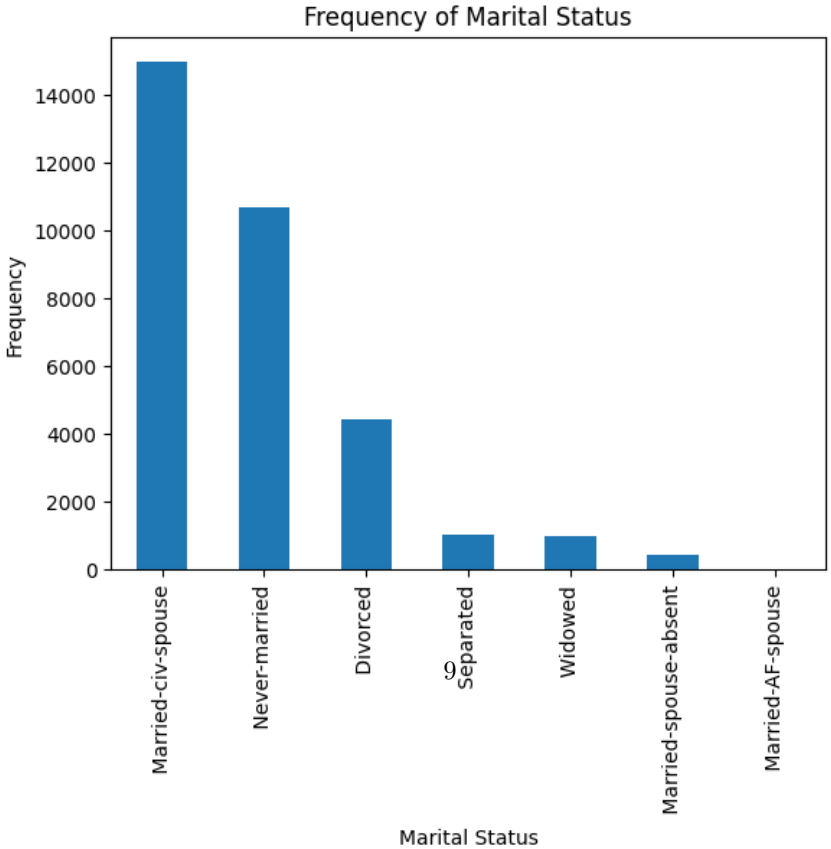
capital-gain:
Minimum: 0
Q1 (25th percentile): 0.0
Median (50th percentile): 0.0
Q3 (75th percentile): 0.0
Maximum: 99999
Mode: 0
Mean: 1077.6

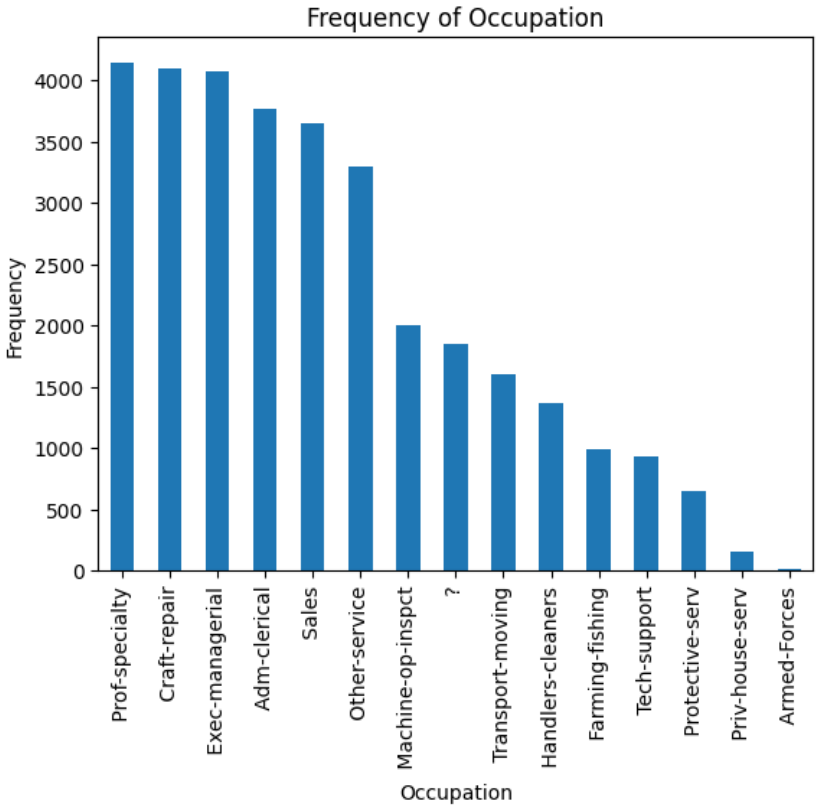
capital-loss:
Minimum: 0
Q1 (25th percentile): 0.0
Median (50th percentile): 0.0
Q3 (75th percentile): 0.0
Maximum: 4356
Mode: 0
Mean: 87.3

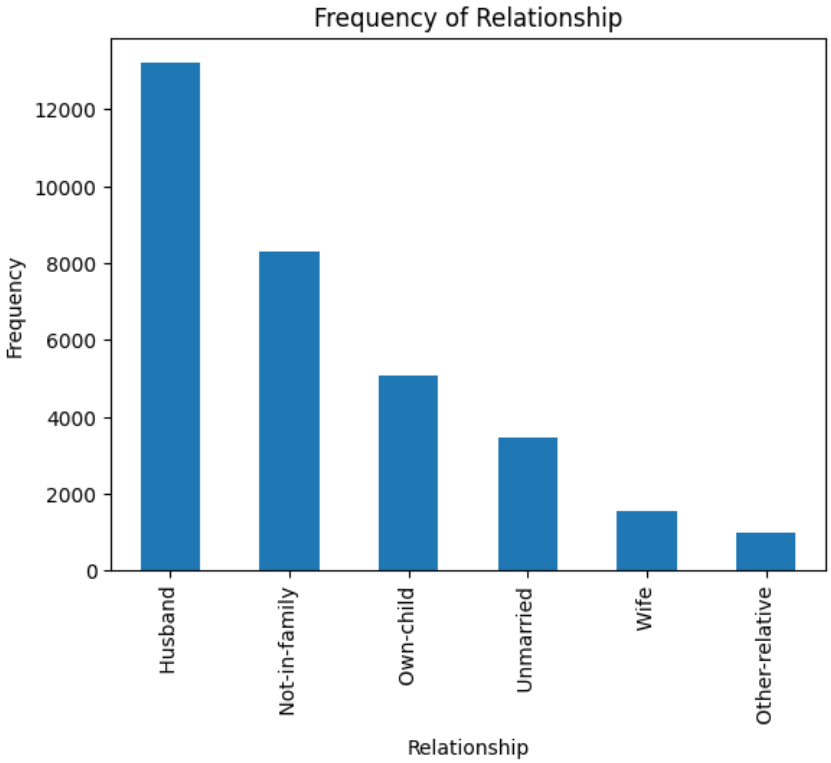
hours-per-week:
Minimum: 1
Q1 (25th percentile): 40.0
Median (50th percentile): 40.0
Q3 (75th percentile): 45.0
Maximum: 99
Mode: 40
Mean: 40.4

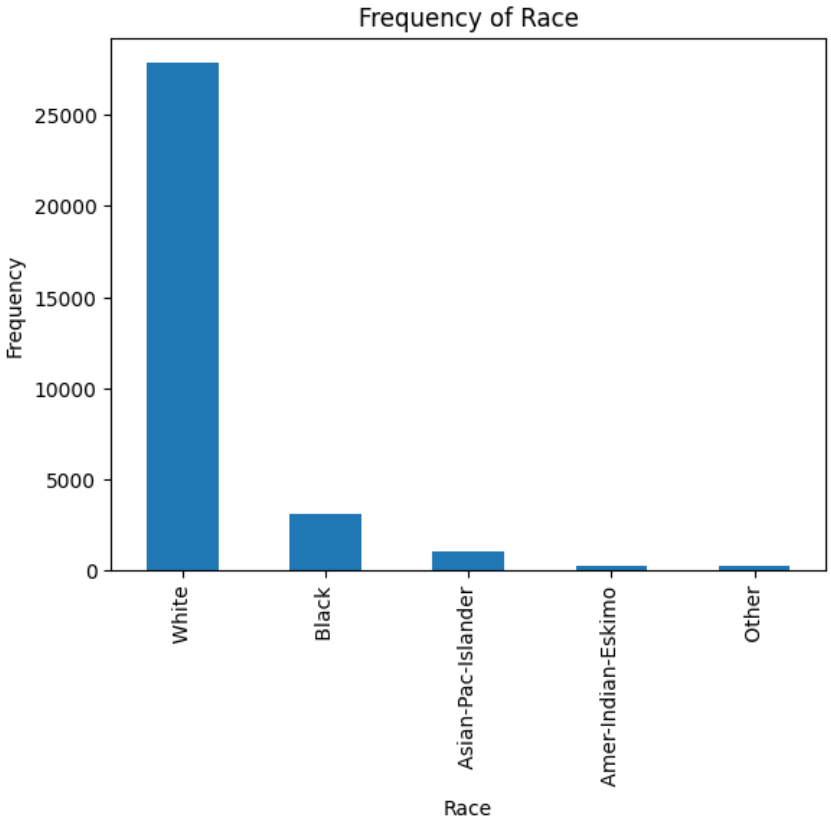
3.3

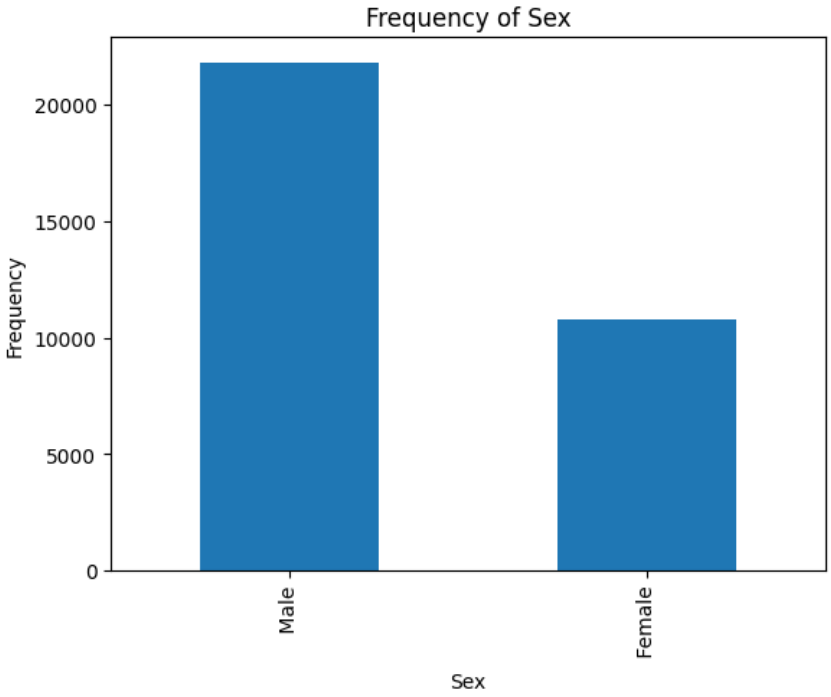

Frequency of Workclass
Frequency
20000
15000
10000
5000
0
Private
Self-emp-not-inc
Local-gov
?
State-gov
Self-emp-inc
Federal-gov
Without-pay
Never-worked
Workclass

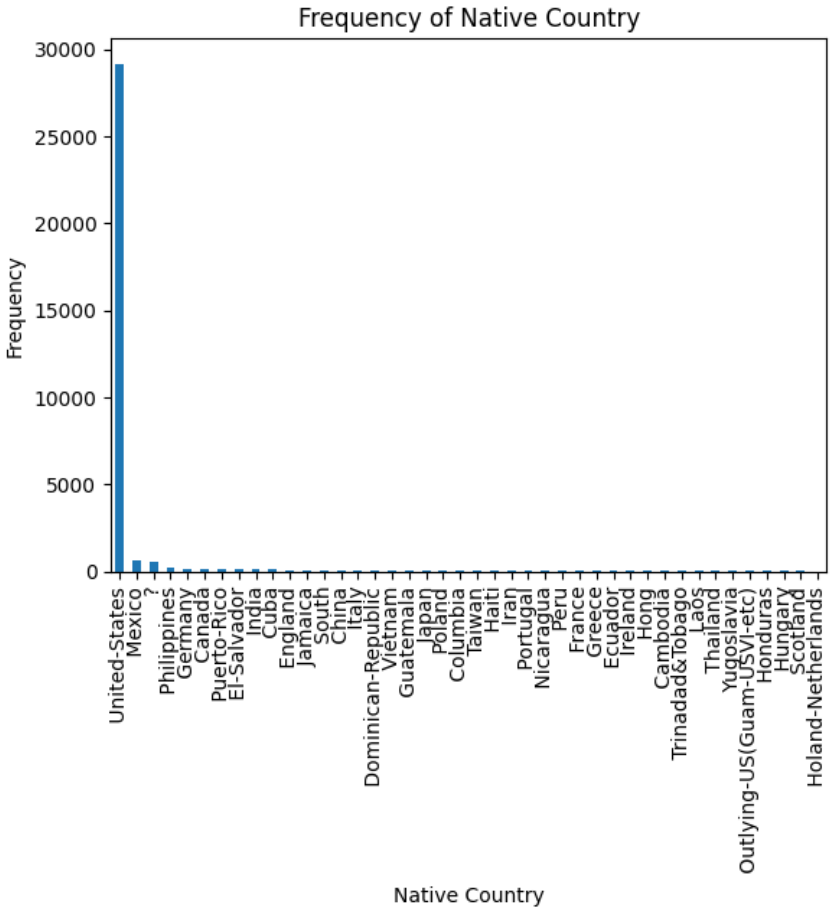

Frequency of Marital Status
Frequency
14000
12000
10000
8000
6000
4000
2000
0
Married-civ-spouse
Never-married
Divorced
Separated
Widowed
Married-spouse-absent
Married-AF-spouse
Marital Status


Frequency of Occupation
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
Prof-specialty
Craft-repair
Exec-managerial
Adm-clerical
Sales
Other-service
Machine-op-inspct
?
Transport-moving
Handlers-cleaners
Farming-fishing
Tech-support
Protective-serv
Priv-house-serv
Armed-Forces
Occupation


Frequency of Relationship
Frequency
12000
10000
8000
6000
4000
2000
0
Husband
Not-in-family
Own-child
Unmarried
Wife
Other-relative
Relationship


Frequency of Race
Frequency
25000
20000
15000
10000
5000
0
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
Race


Frequency of Sex
Frequency
20000
15000
10000
5000
0
Male
Female
Sex



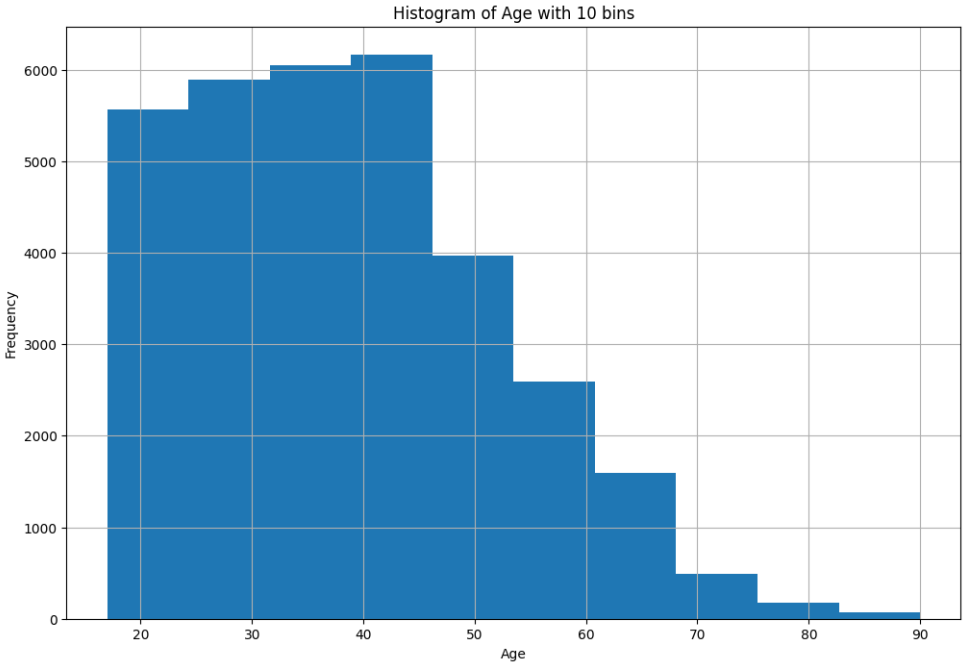
3.4

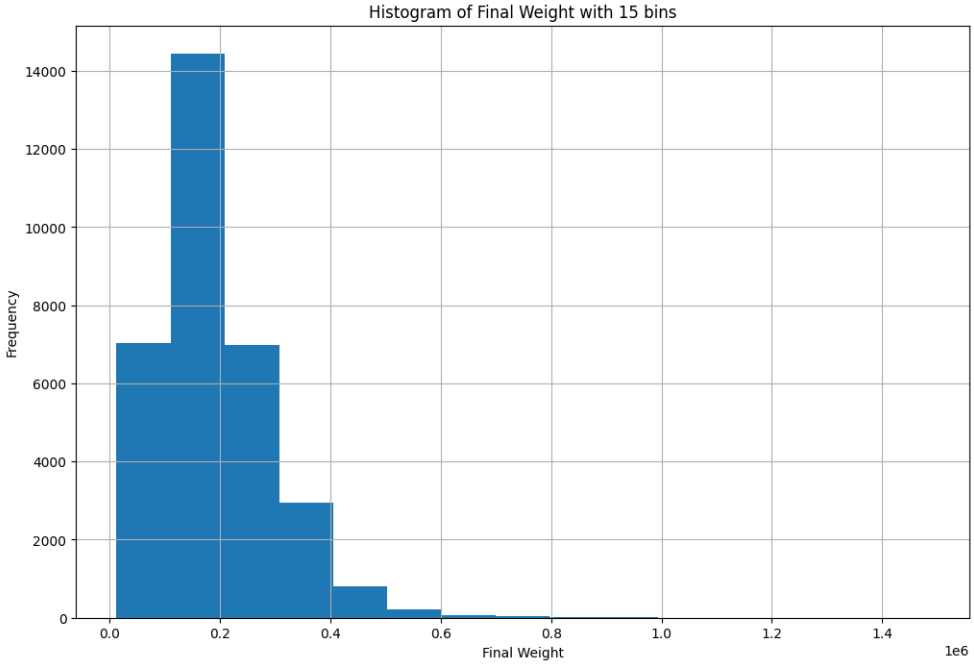
Unable to find missing data.

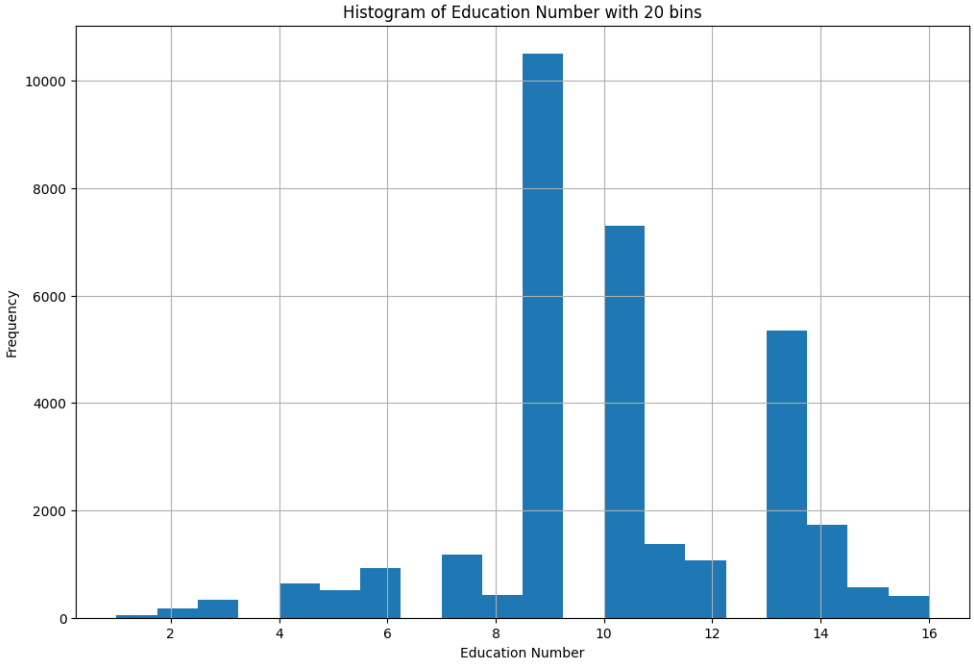
3.5

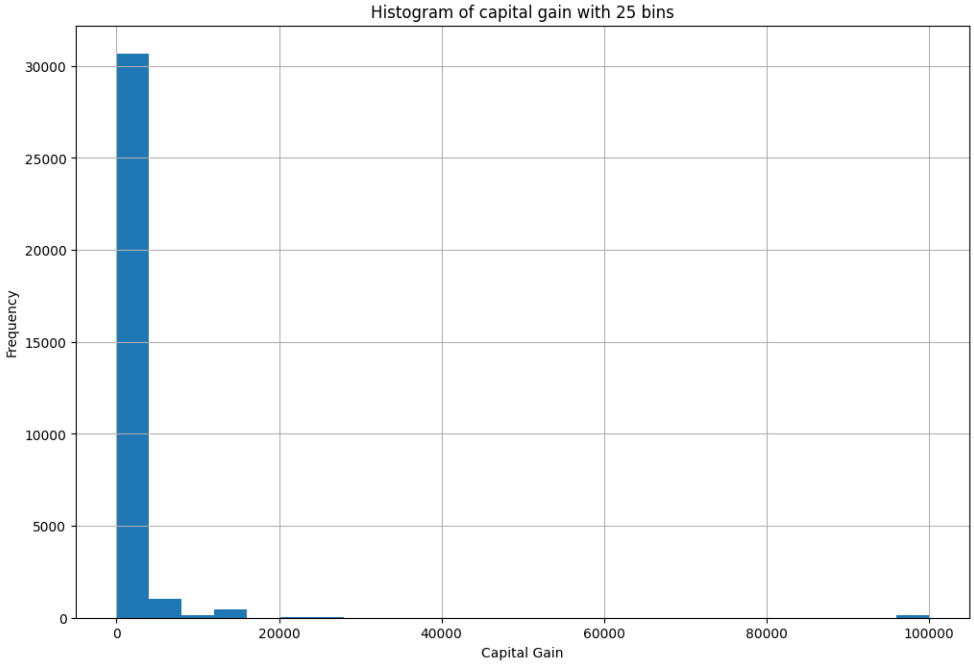
Mean Values:
age: 38.6
fnlwgt: 189778.4
education-num: 10.1
capital-gain: 1077.6
capital-loss: 87.3
hours-per-week: 40.4

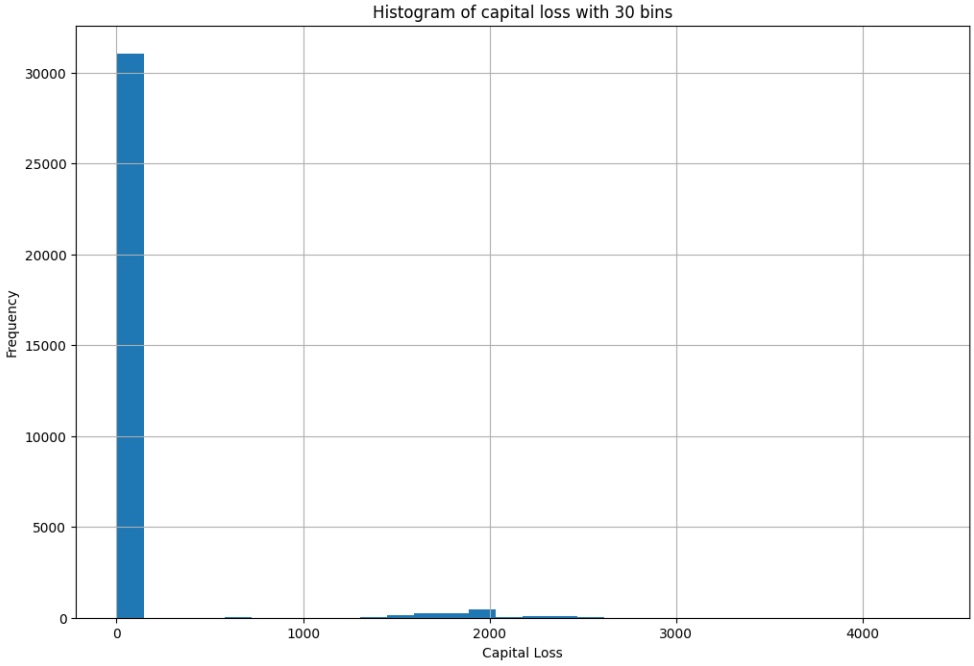
Standard Deviation Values:
age: 13.6
fnlwgt: 105550.0
education-num: 2.6
capital-gain: 7385.3
capital-loss: 403.0
hours-per-week: 12.3

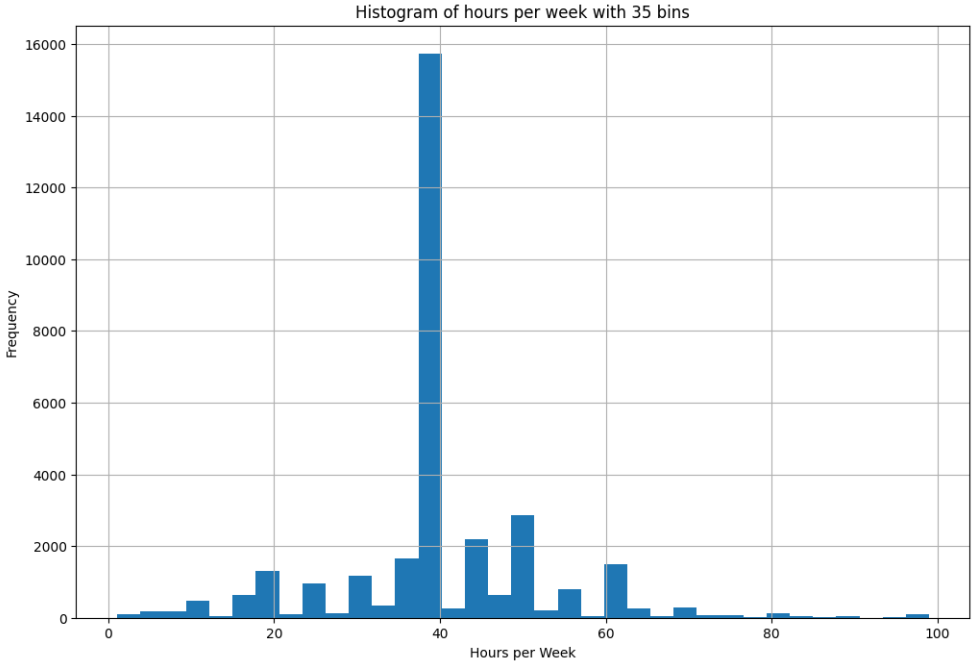



Histogram of Final Weight with 15 bins
Frequency
Final Weight
1e6
0
2000
4000
6000
8000
10000
12000
14000
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4

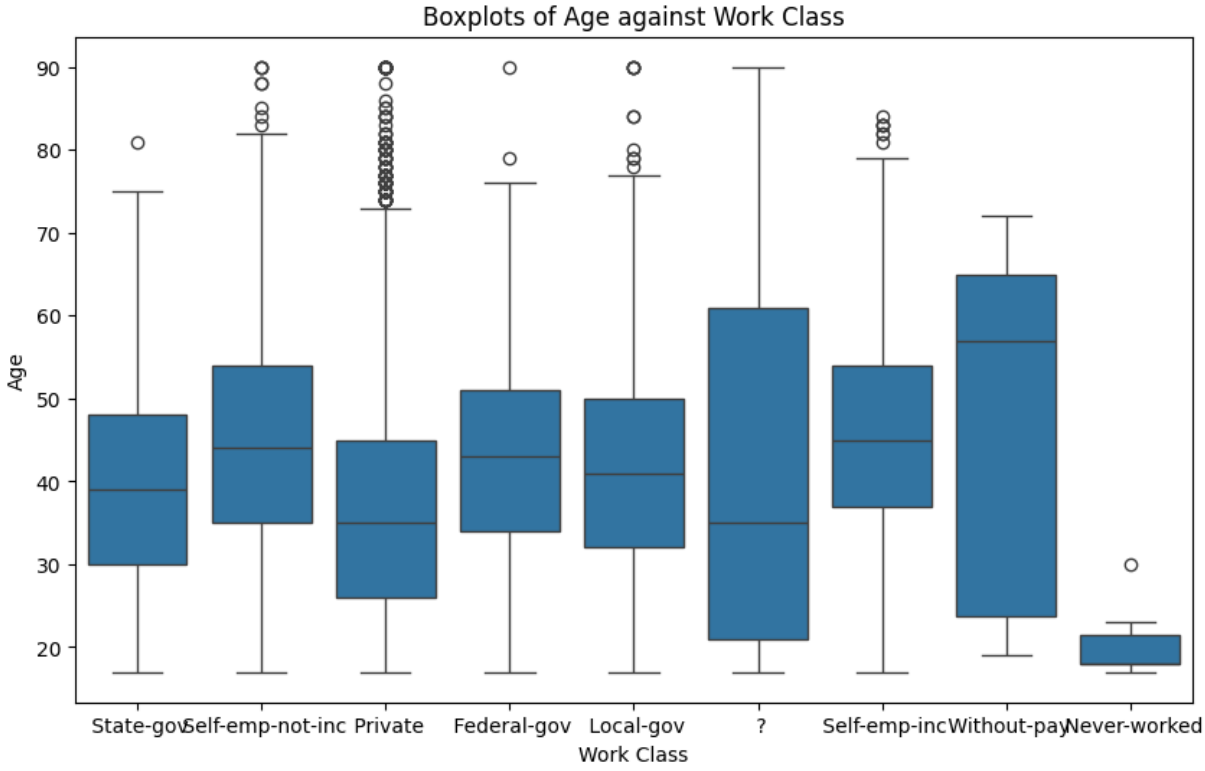

Histogram of Education Number with 20 bins
Frequency
Education Number
0
2000
4000
6000
8000
10000
2
4
6
8
10
12
14
16

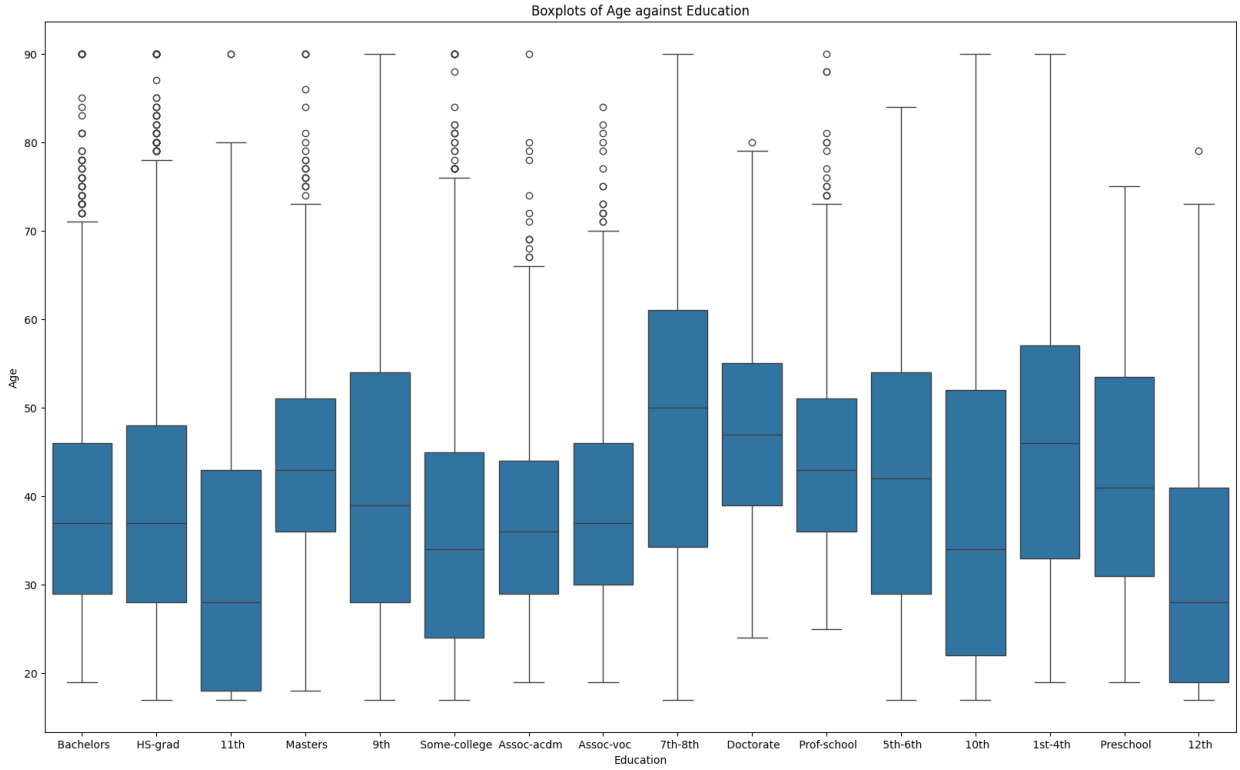

Histogram of capital gain with 25 bins
Frequency
Capital Gain
0
5000
10000
15000
20000
25000
30000
0
20000
40000
60000
80000
100000

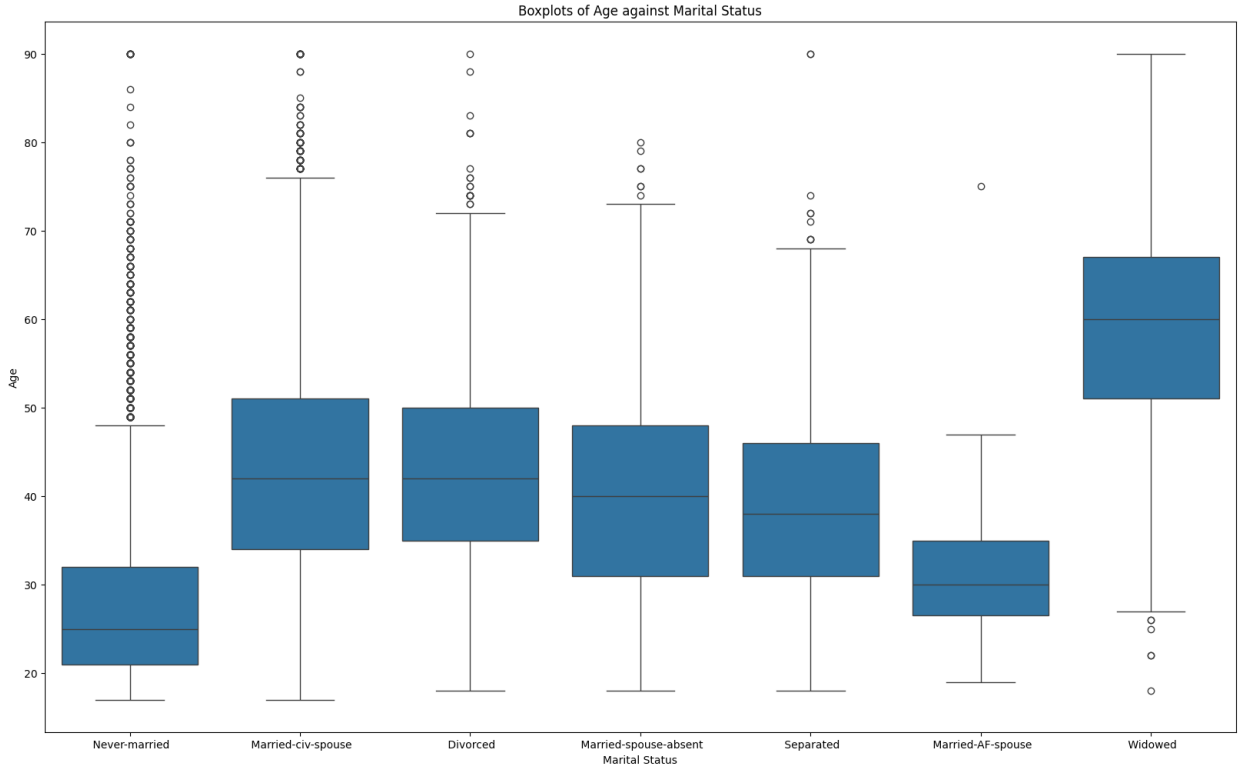

Histogram of capital loss with 30 bins
Frequency
Capital Loss
0
5000
10000
15000
20000
25000
30000
0
1000
2000
3000
4000

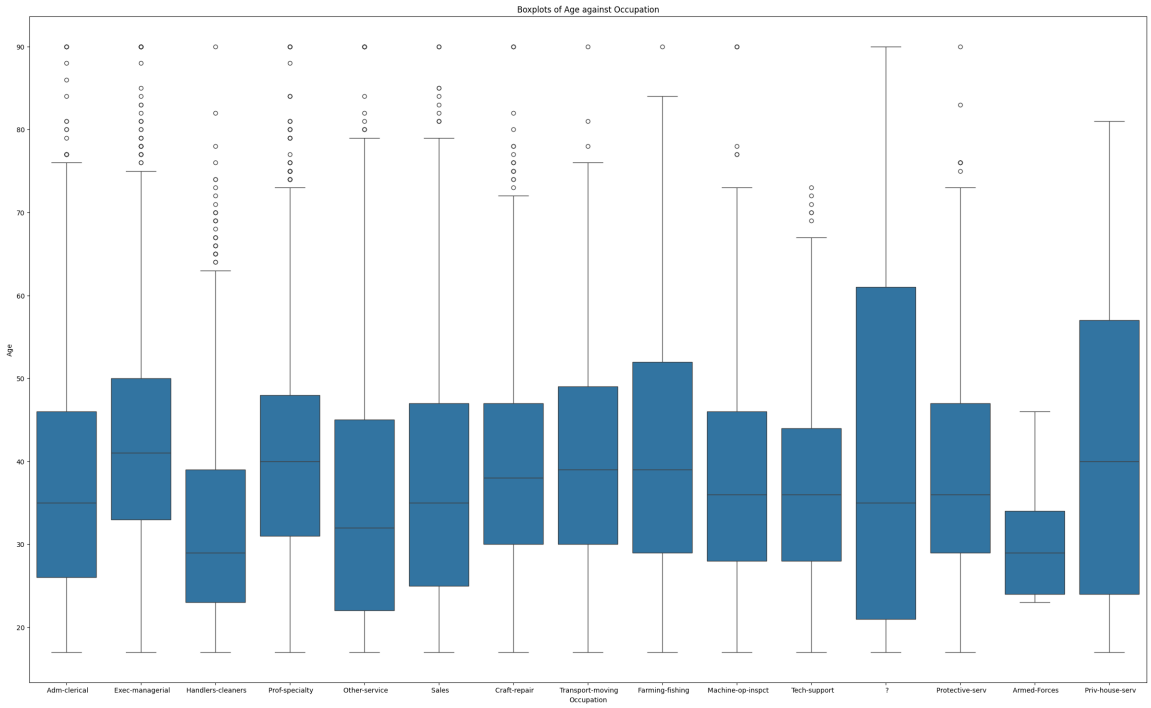

Histogram of hours per week with 35 bins
Frequency
Hours per Week
0
2000
4000
6000
8000
10000
12000
14000
16000
0
20
40
60
80
100

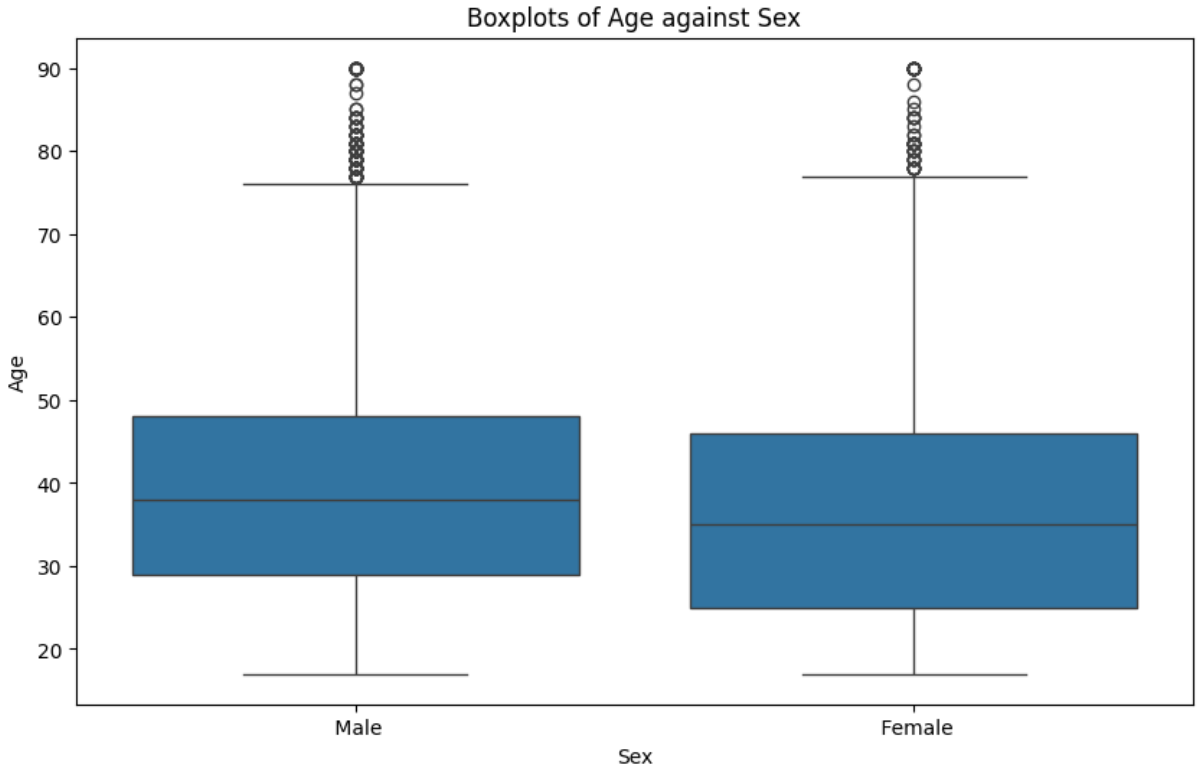
3.6


Boxplots of Age against Work Class
Age
90
80
70
60
50
40
30
20
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
?
Self-emp-inc
Without-pay
Never-worked
Work Class


Boxplots of Age against Education
Age
90
80
70
60
50
40
30
20
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
Education


Boxplots of Age against Marital Status
Age
90
80
70
60
50
40
30
20
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
Marital Status


Boxplots of Age against Occupation
Age
90
80
70
60
50
40
30
20
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
?
Protective-serv
Armed-Forces
Priv-house-serv
Occupation



3.7

Age and Work Class

workclass	?	Federal-gov	Local-gov	Never-worked	Private
age					
17	64	1	14	1	300
18	92	3	10	3	413
19	113	5	11	0	540
20	115	9	12	1	581
21	89	3	9	0	577
...	...	...	...	...	...
86	0	0	0	0	1
87	1	0	0	0	0
88	0	0	0	0	1
90	7	1	4	0	28
Total	1836	960	2093	7	22696

workclass	Self-emp-inc	Self-emp-not-inc	State-gov	Without-pay	Total
age					
17	7	6	2	0	395
18	6	14	9	0	550
19	3	17	21	2	712
20	3	11	21	0	753
21	1	10	30	1	720
...	...	...	...	...	...
86	0	0	0	0	1
87	0	0	0	0	1
88	0	2	0	0	3
90	0	3	0	0	43
Total	1116	2541	1298	14	32561

Age and Education

education	10th	11th	12th	1st-4th	5th-6th	7th-8th	9th
age							
17	138	180	37	0	1	3	25
18	38	166	60	0	4	5	8
19	16	45	29	3	2	9	6
20	15	27	14	1	5	3	12
21	17	16	8	1	4	7	10
...	...	...	...	...	...	...	...
86	0	0	0	0	0	0	0
87	0	0	0	0	0	0	0
88	0	0	0	0	0	0	0
90	1	2	0	1	0	3	1
Total	933	1175	433	168	333	646	514

education	Assoc-acdm	Assoc-voc	Bachelors	Doctorate	HS-grad
age					
17	0	0	0	0	8
18	0	0	0	0	152
19	1	3	2	0	266
20	13	10	1	0	237
21	21	29	7	0	225
...	...	...	...	...	...
86	0	0	0	0	0
87	0	0	0	0	1
88	0	0	0	0	0
90	1	0	9	0	14
Total	1067	1382	5355	413	10501

education	Masters	Preschool	Prof-school	Some-college	Total
age					
17	0	0	0	3	395
18	1	0	0	116	550
19	0	1	0	329	712
20	1	1	0	413	753
21	1	2	0	372	720
...	...	...	...	...	...
86	1	0	0	0	1
87	0	0	0	0	1
88	0	0	2	1	3
90	4	0	1	6	43
Total	1723	51	576	7291	32561

Age and Marital Status

marital-status	Divorced	Married-AF-spouse	Married-civ-spouse
age			
17	0	0	2
18	1	0	7
19	6	2	15
20	7	0	38
21	4	0	53
...	...	...	...
86	0	0	0
87	0	0	0
88	1	0	2
90	1	0	20
Total	4443	23	14976

marital-status	Married-spouse-absent	Never-married	Separated	Widowed
age				
17	0	393	0	0
18	1	539	1	1
19	3	681	5	0
20	5	695	8	0
21	6	651	6	0
...	...	...	...	...
86	0	1	0	0
87	0	0	0	1
88	0	0	0	0
90	0	14	2	6
Total	418	10683	1025	993

marital-status	Total
age	
17	395
18	550
19	712
20	753
21	720
...	...
86	1
87	1
88	3
90	43
Total	32561

Age and Occupation

occupation	?	Adm-clerical	Armed-Forces	Craft-repair
age				
17	65	23	0	14
18	95	55	0	17
19	113	102	0	40
20	116	117	0	35
21	89	121	0	59
...	...	...	...	...
86	0	1	0	0
87	1	0	0	0
88	0	1	0	0
90	7	4	0	3
Total	1843	3770	9	4099

occupation	Exec-managerial	Farming-fishing	Handlers-cleaners
age			
17	1	9	40
18	6	14	50
19	12	24	65
20	15	23	81
21	18	25	51
...	...	...	...
86	0	0	0
87	0	0	0
88	1	0	0
90	8	1	1
Total	4066	994	1370

occupation age	Machine-op-inspct	Other-service	Priv-house-serv
17	2	129	8
18	17	152	4
19	30	166	3
20	41	139	3
21	51	142	4
...	...	...	...
86	0	0	0
87	0	0	0
88	0	0	0
90	3	6	0
Total	2002	3295	149

occupation age	Prof-specialty	Protective-serv	Sales	Tech-support
17	10	3	87	1
18	10	5	115	2
19	18	3	112	8
20	28	9	108	14
21	30	7	93	16
...	...	...	...	...
86	0	0	0	0
87	0	0	0	0
88	1	0	0	0
90	5	1	3	0
Total	4140	649	3650	928

occupation age	Transport-moving	Total
17	3	395
18	8	550
19	16	712
20	24	753
21	14	720
...	...	...
86	0	1
87	0	1
88	0	3
90	1	43
Total	1597	32561

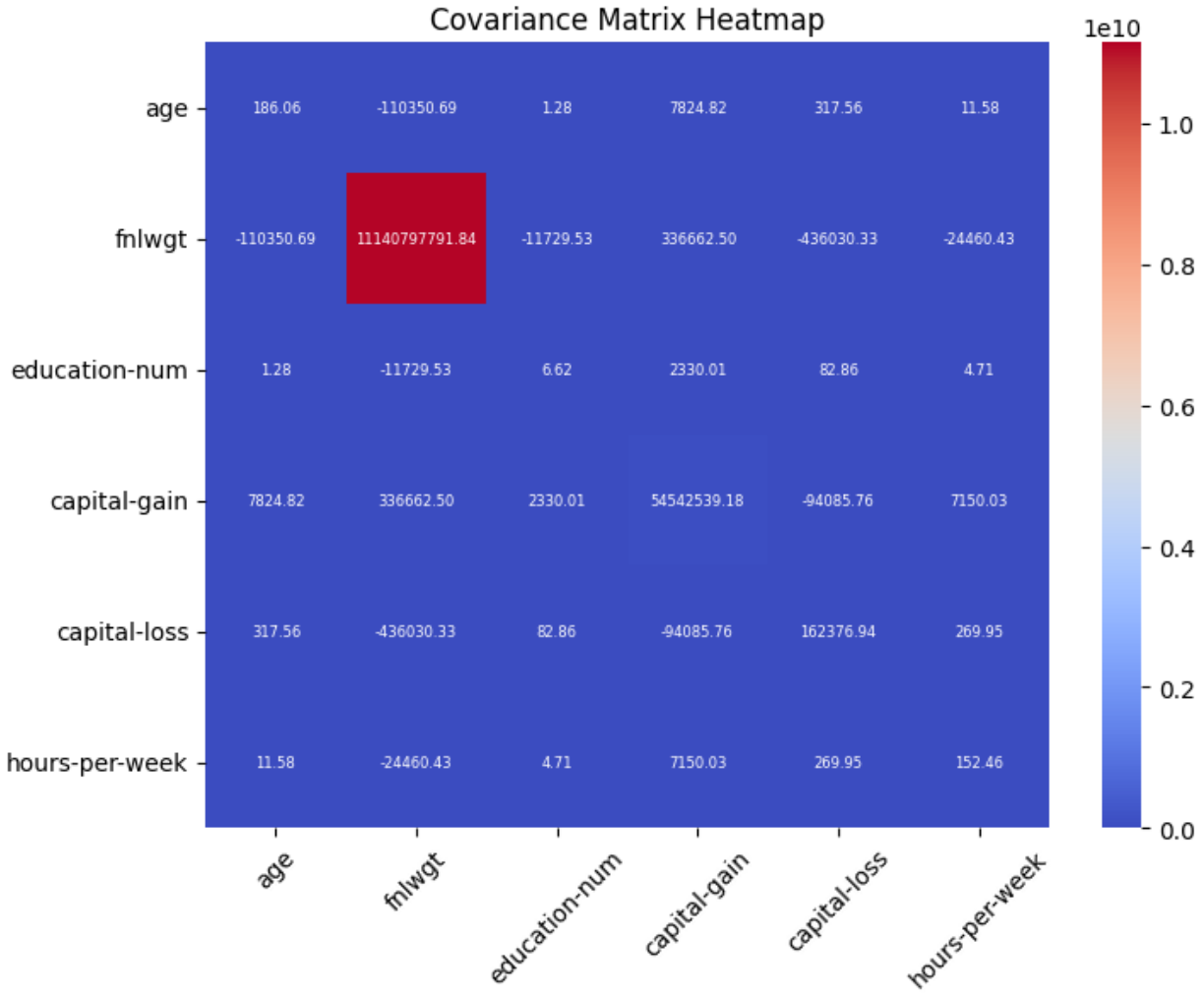
Age and Sex

sex	Female	Male	Total
age			
17	186	209	395
18	268	282	550
19	356	356	712
20	363	390	753
21	329	391	720
...	...	...	...
86	1	0	1
87	0	1	1
88	1	2	3
90	14	29	43
Total	10771	21790	32561

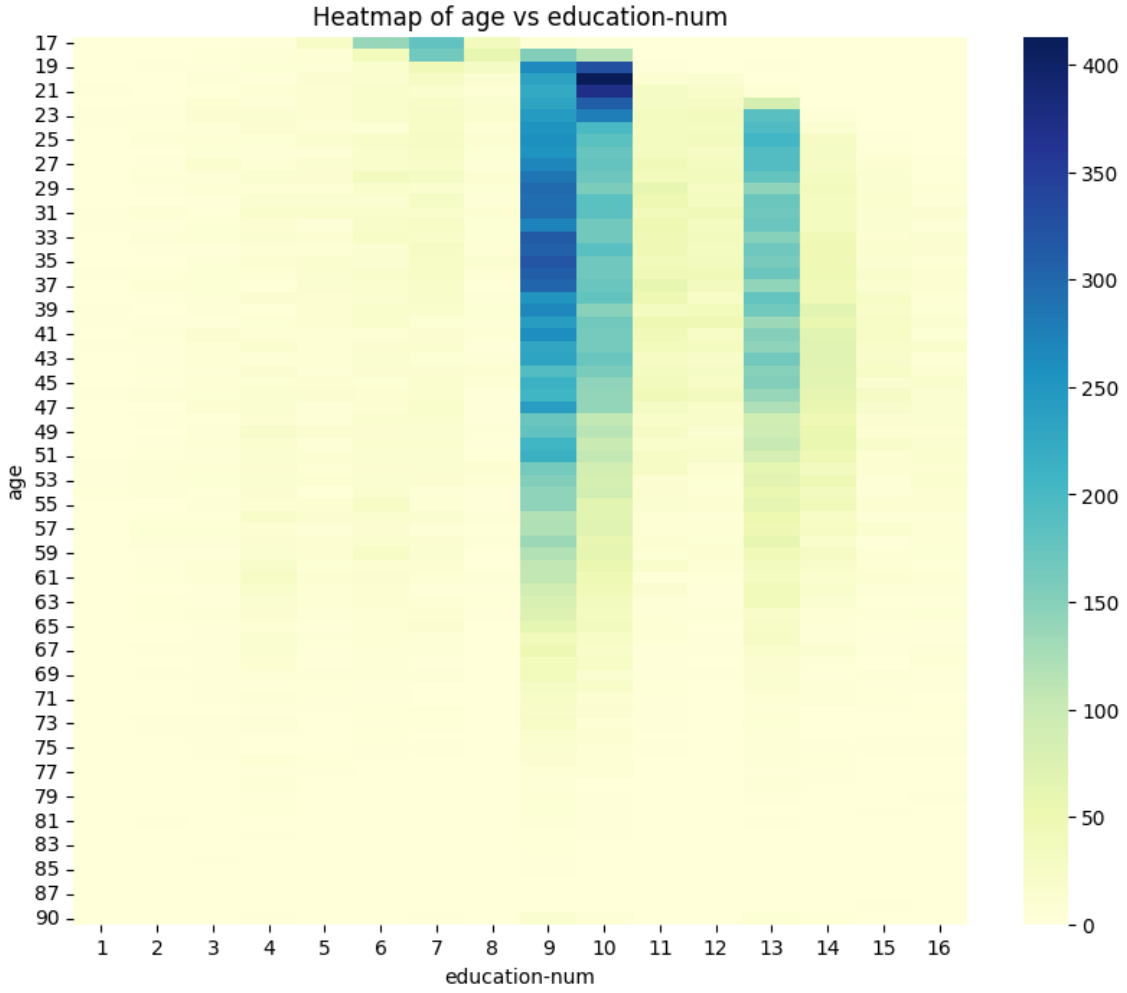
3.8

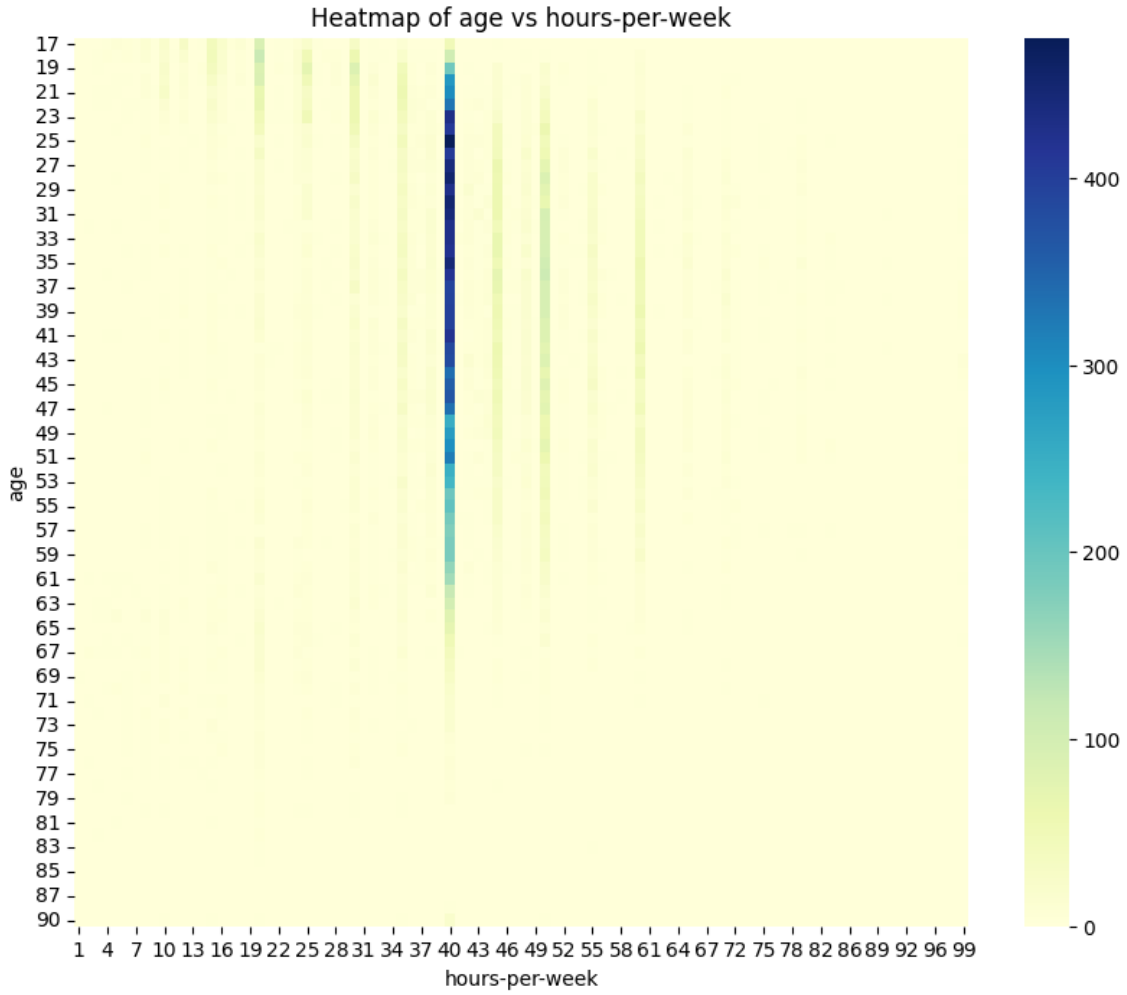
	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
age	186.06	-110350.69	1.28	7824.82	317.56	11.58
fnlwgt	-110350.69	11140797791.84	-11729.53	336662.50	-436030.33	-24460.43
education-num	1.28	-11729.53	6.62	2330.01	82.86	4.71
capital-gain	7824.82	336662.50	2330.01	54542539.18	-94085.76	7150.03
capital-loss	317.56	-436030.33	82.86	-94085.76	162376.94	269.95
hours-per-week	11.58	-24460.43	4.71	7150.03	269.95	152.46

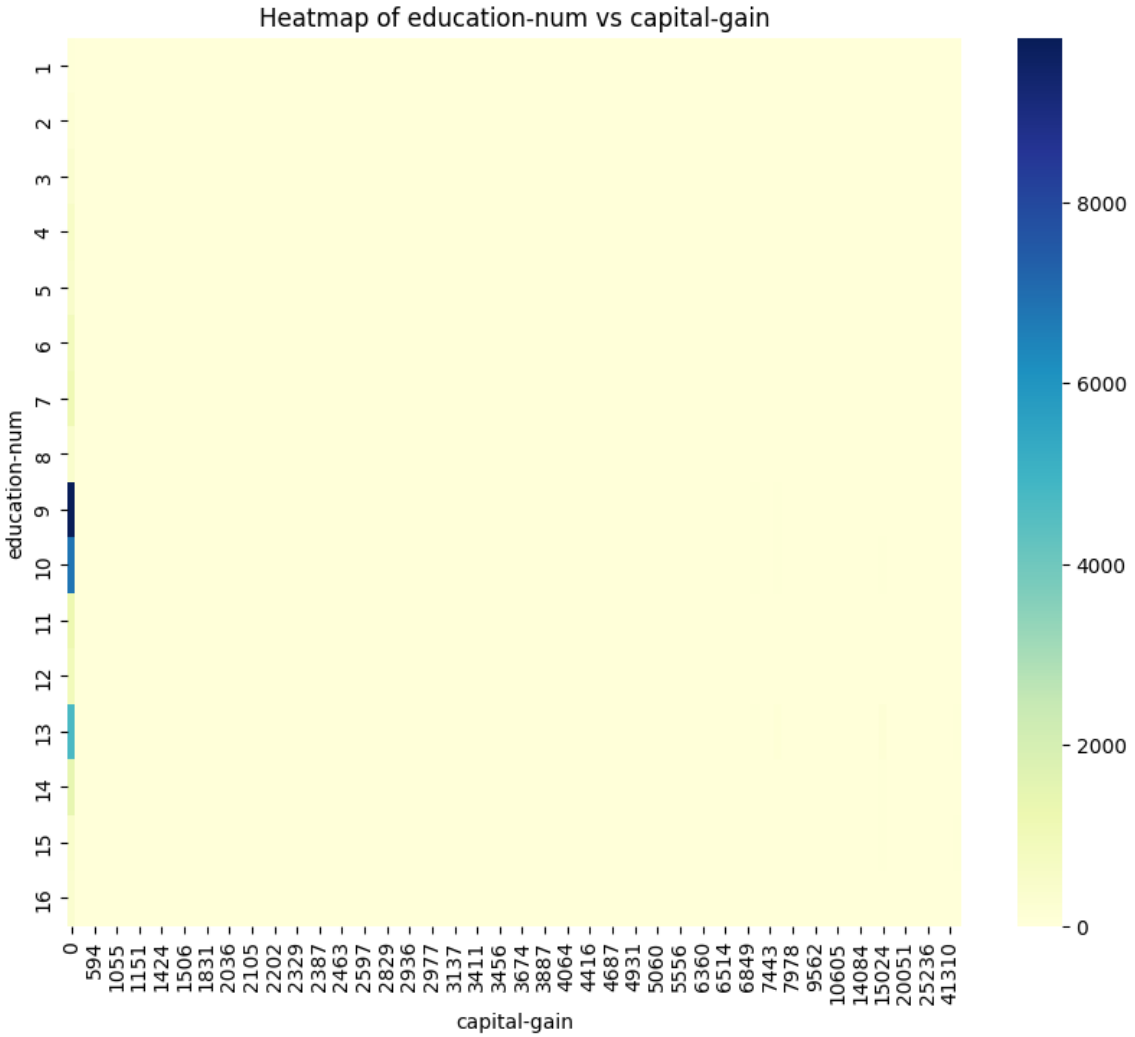
3.9

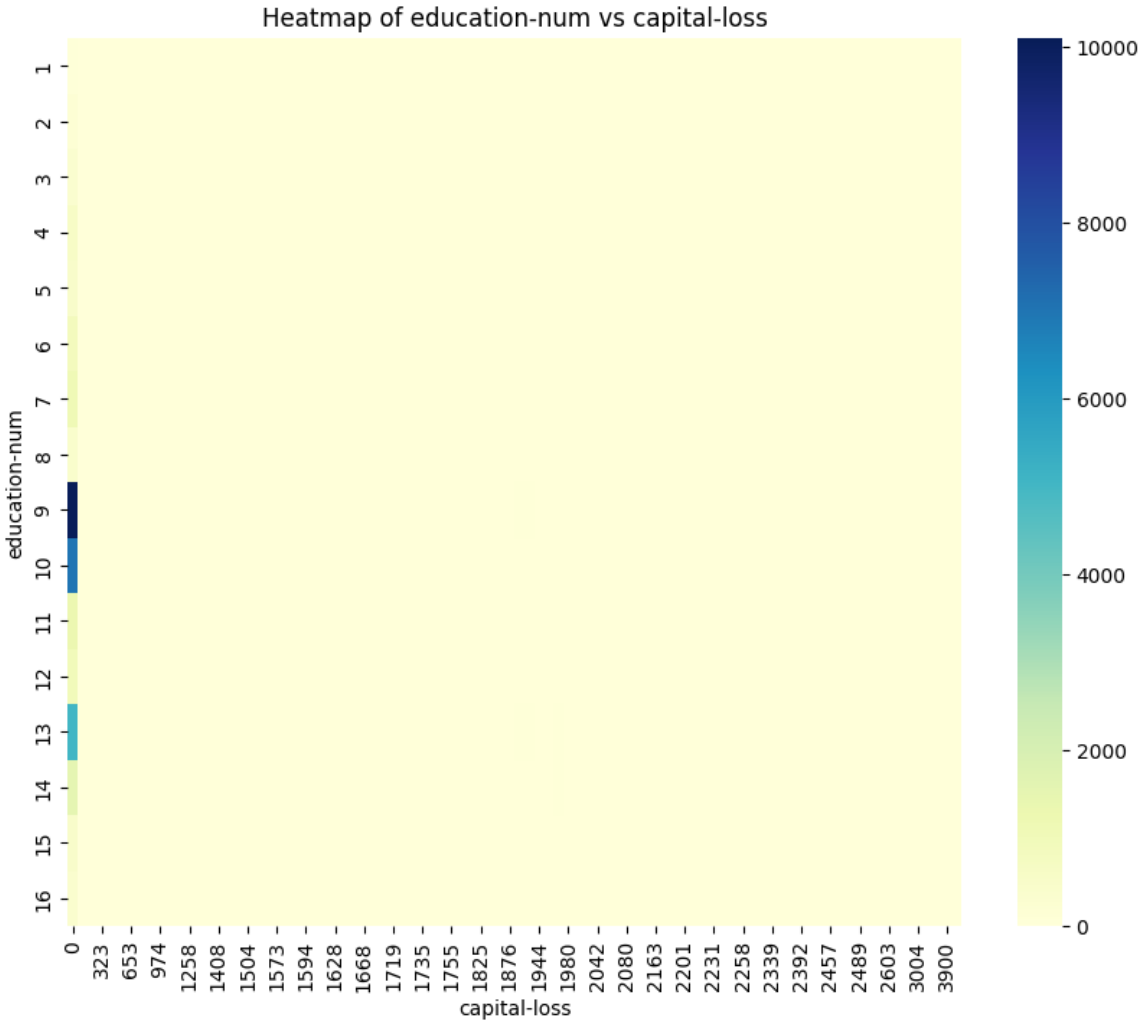

Covariance Matrix Heatmap
1e10
1.0
0.8
0.6
0.4
0.2
0.0
age
fnlwgt
education-num
capital-gain
capital-loss
hours-per-week
186.06
-110350.69
1.28
7824.82
317.56
11.58
-110350.69
11140797791.84
-11729.53
336662.50
-436030.33
-24460.43
1.28
-11729.53
6.62
2330.01
82.86
4.71
7824.82
336662.50
2330.01
54542539.18
-94085.76
7150.03
317.56
-436030.33
82.86
-94085.76
162376.94
269.95
11.58
-24460.43
4.71
7150.03
269.95
152.46

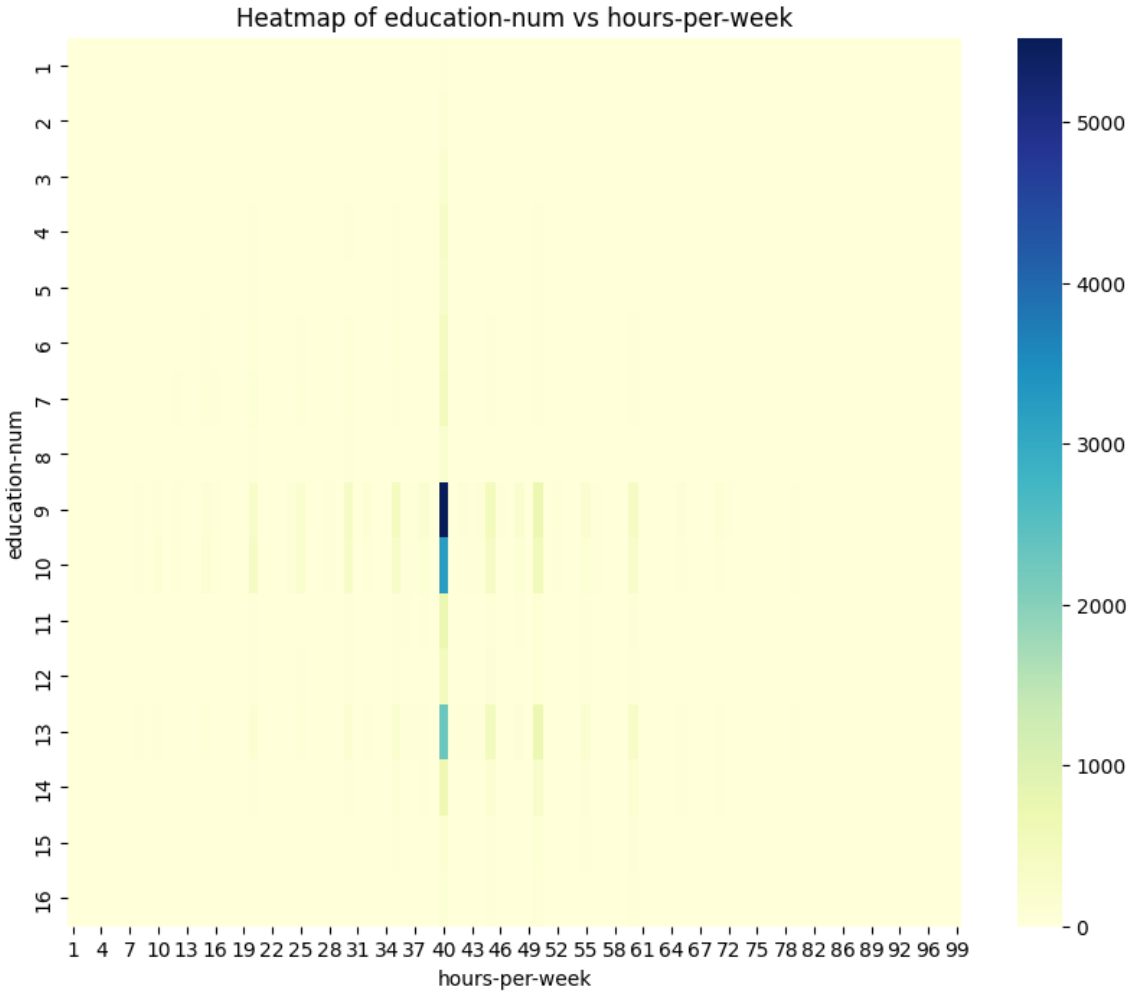
3.10


Heatmap of age vs education-num
age
education-num
17
19
21
23
25
27
29
31
33
35
37
39
41
43
45
47
49
51
53
55
57
59
61
63
65
67
69
71
73
75
77
79
81
83
85
87
90
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
400
350
300
250
200
150
100
50
0


Heatmap of age vs hours-per-week
age
hours-per-week
17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69 71 73 75 77 79 81 83 85 87 90
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 72 75 78 82 86 89 92 96 99
0 100 200 300 400

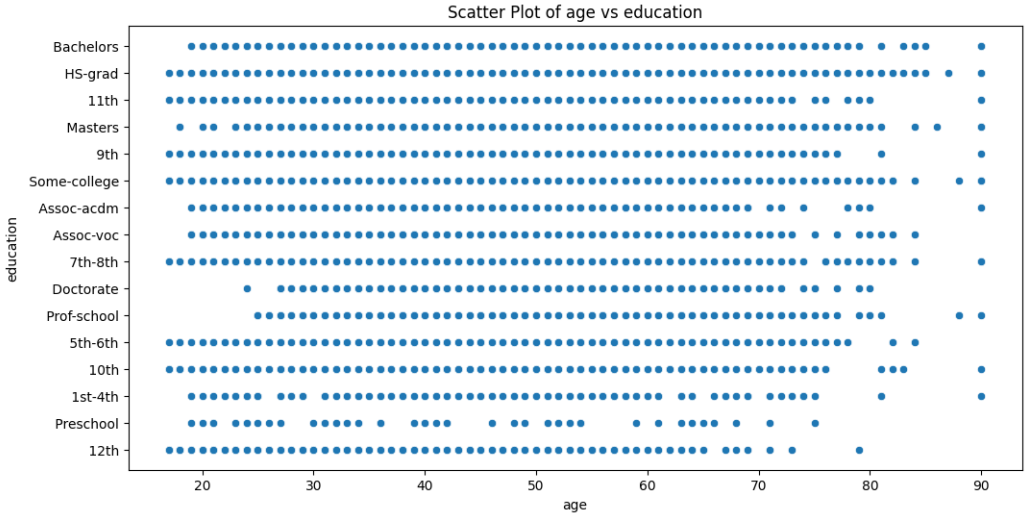

Heatmap of education-num vs capital-gain
education-num
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
capital-gain
0
594
1055
1151
1424
1506
1831
2036
2105
2202
2329
2387
2463
2597
2829
2936
2977
3137
3411
3456
3674
3887
4064
4416
4687
4931
5060
5556
6360
6514
6849
7443
7978
9562
10605
14084
15024
20051
25236
41310
8000
6000
4000
2000
0

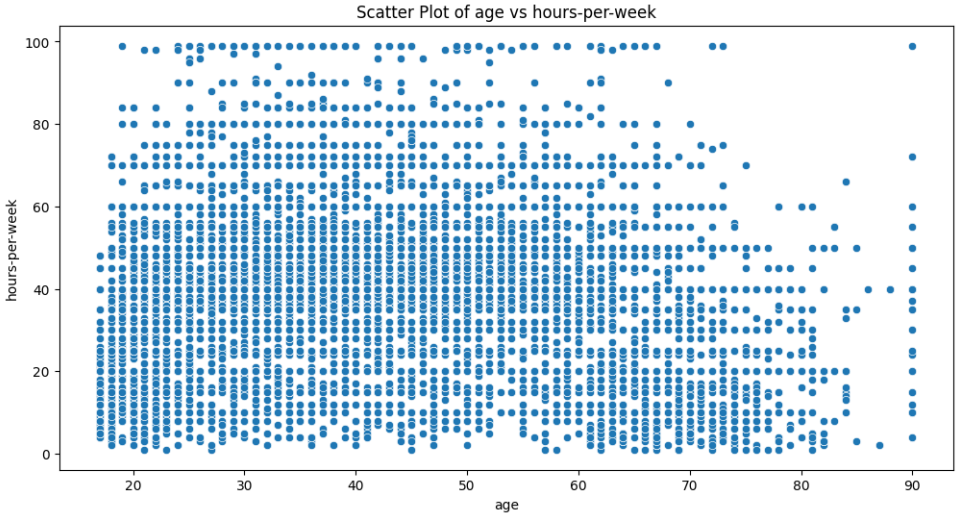

Heatmap of education-num vs capital-loss
education-num
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
capital-loss
0
323
653
974
1258
1408
1504
1573
1594
1628
1668
1719
1735
1755
1825
1876
1944
1980
2042
2080
2163
2201
2231
2258
2339
2392
2457
2489
2603
3004
3900
10000
8000
6000
4000
2000
0

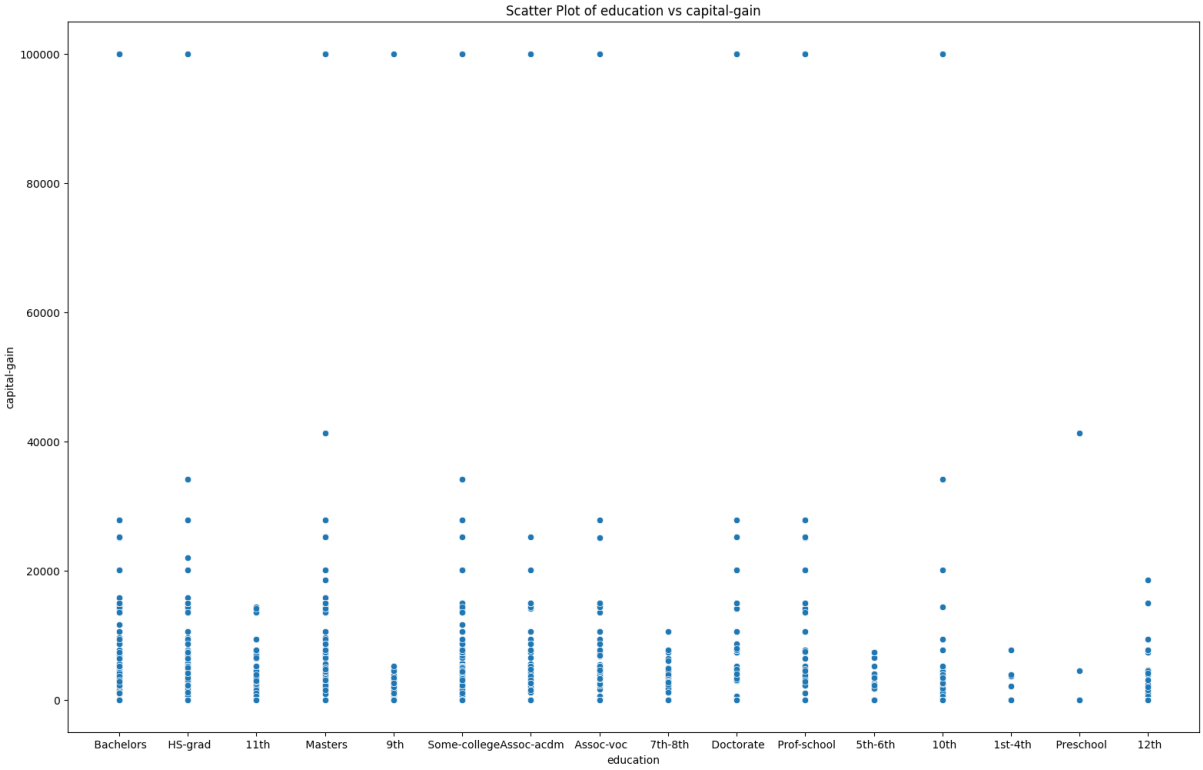

Heatmap of education-num vs hours-per-week
education-num
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
hours-per-week
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49 52 55 58 61 64 67 72 75 78 82 86 89 92 96 99
5000
4000
3000
2000
1000
0

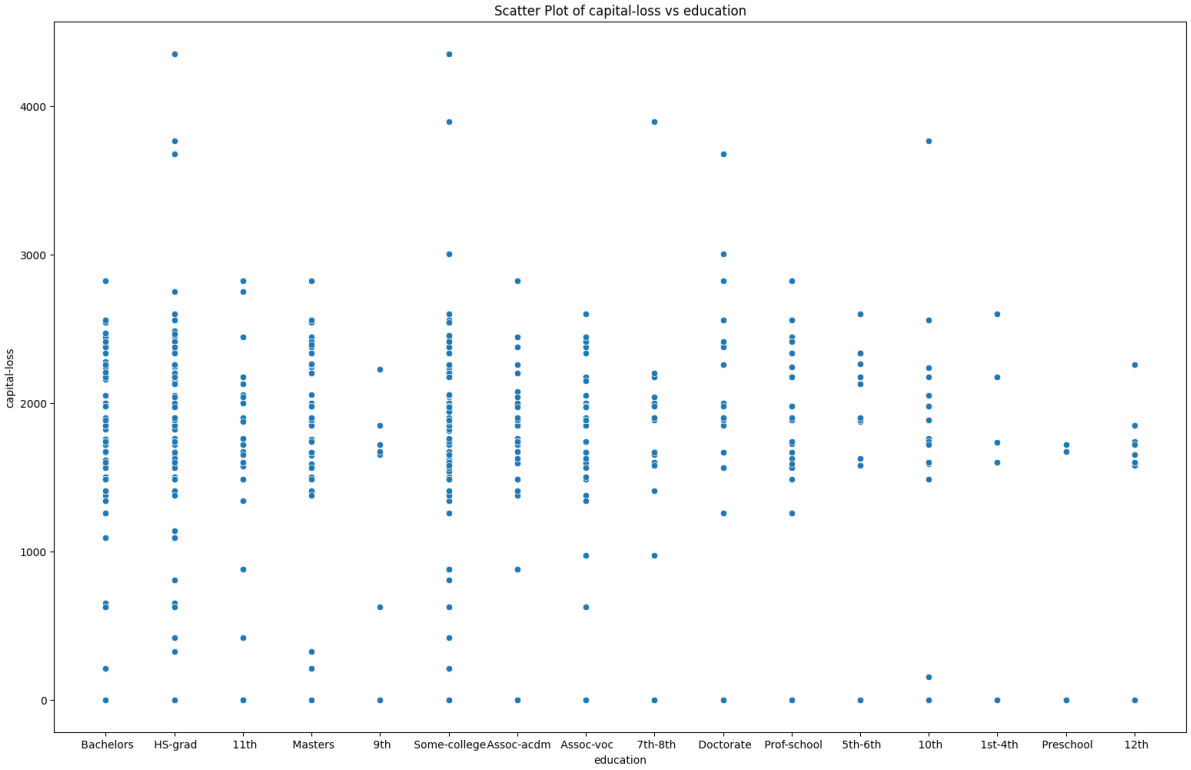
3.11

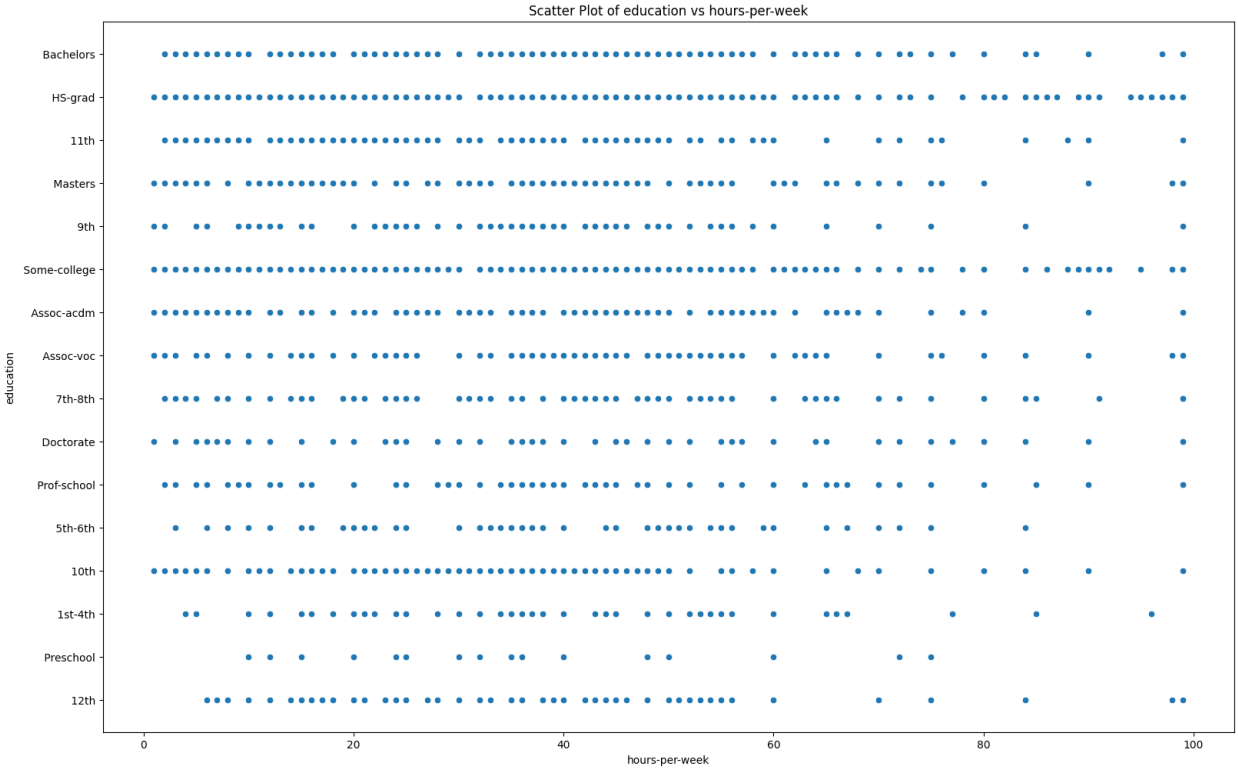
Scatter Plots



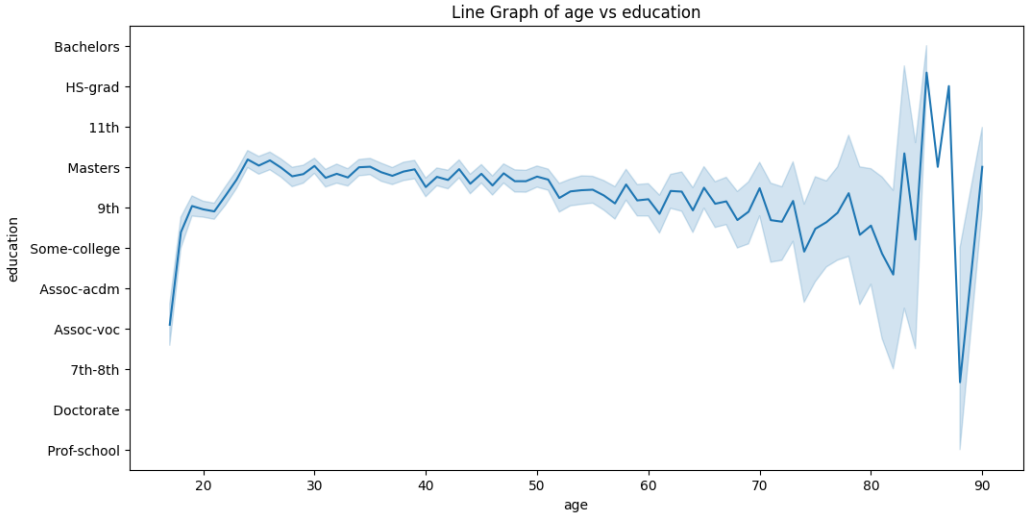


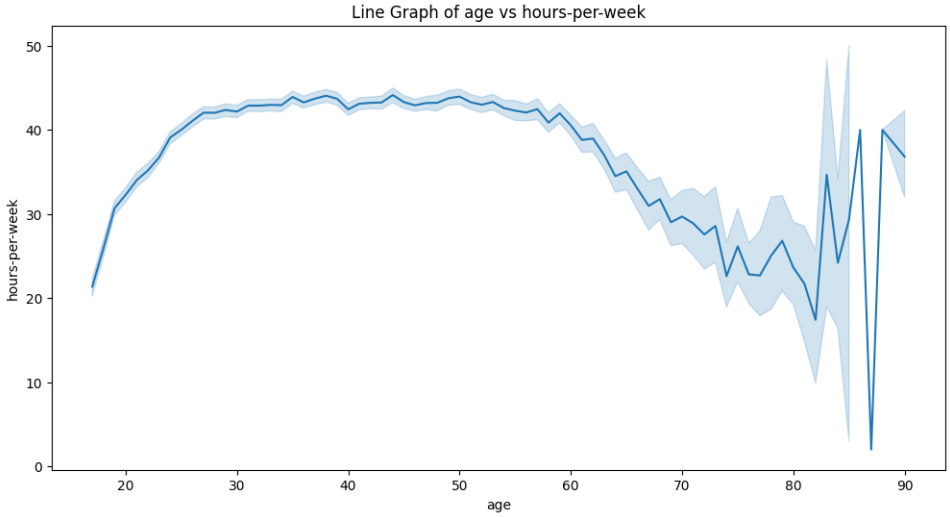

Scatter Plot of education vs capital-gain
capital-gain
100000
80000
60000
40000
20000
0
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education

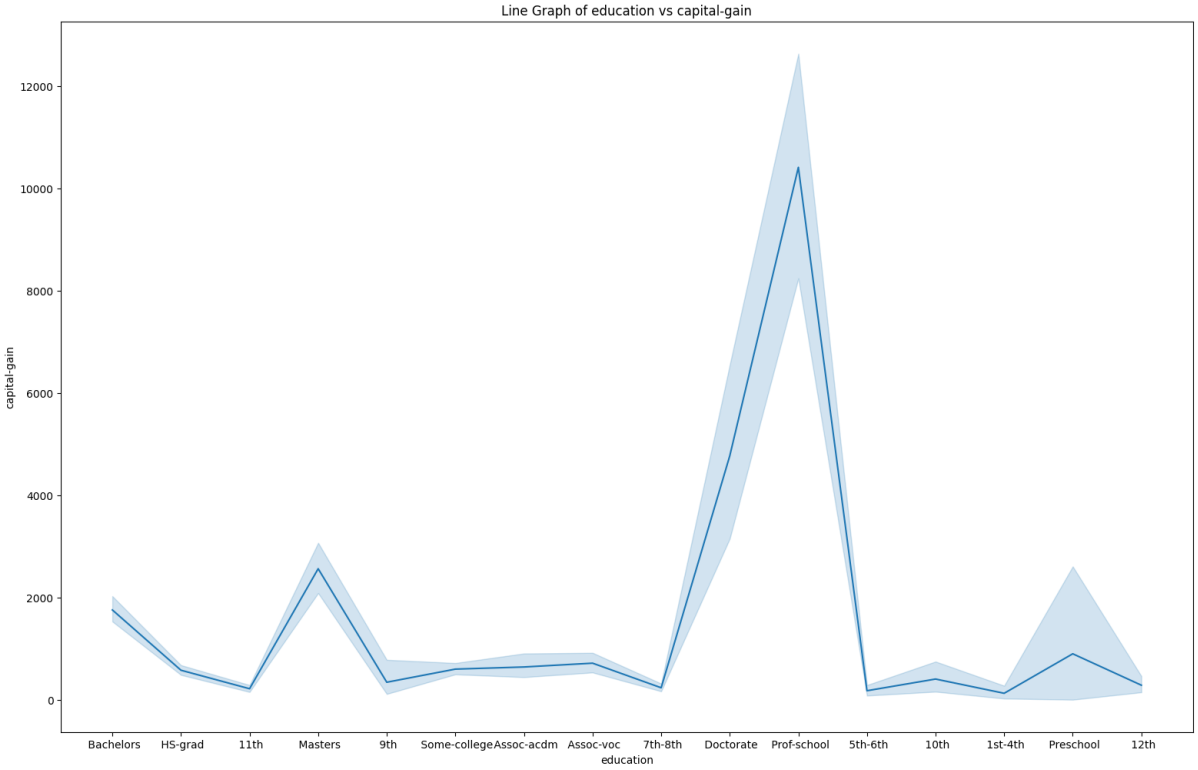

Scatter Plot of capital-loss vs education
capital-loss
4000
3000
2000
1000
0
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education

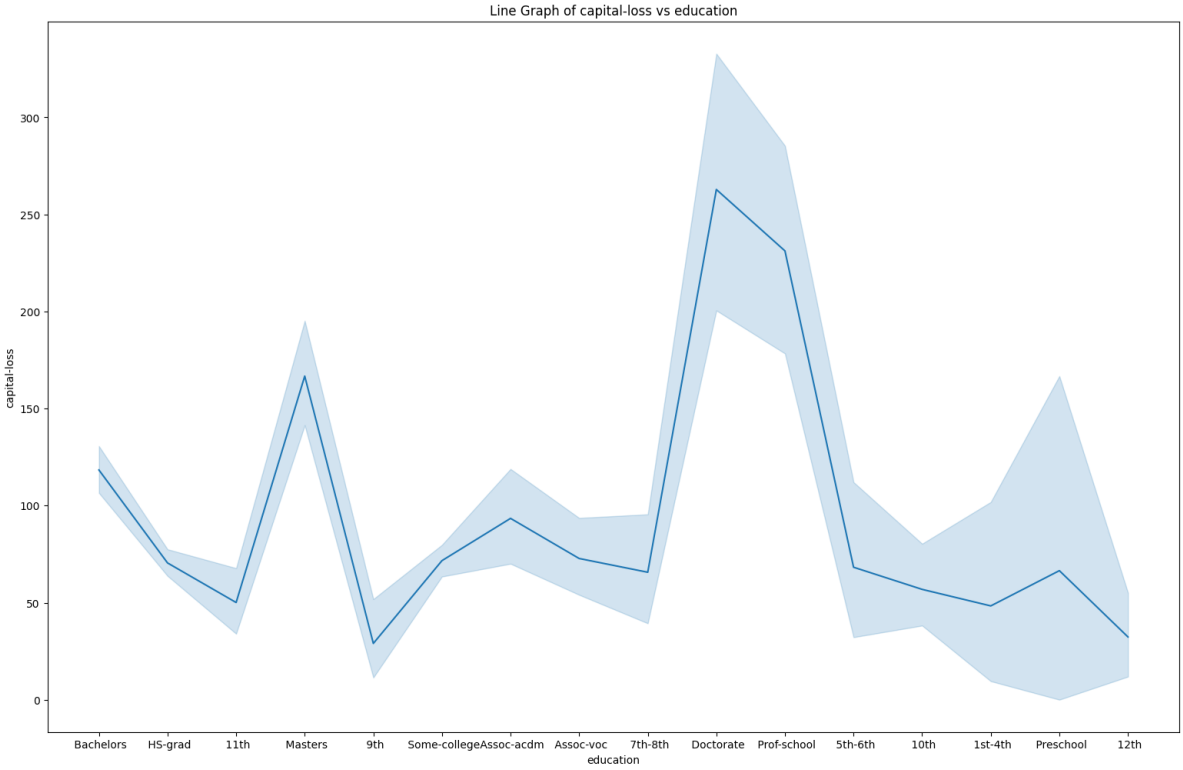

Scatter Plot of education vs hours-per-week
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education
0
20
40
60
80
100
hours-per-week

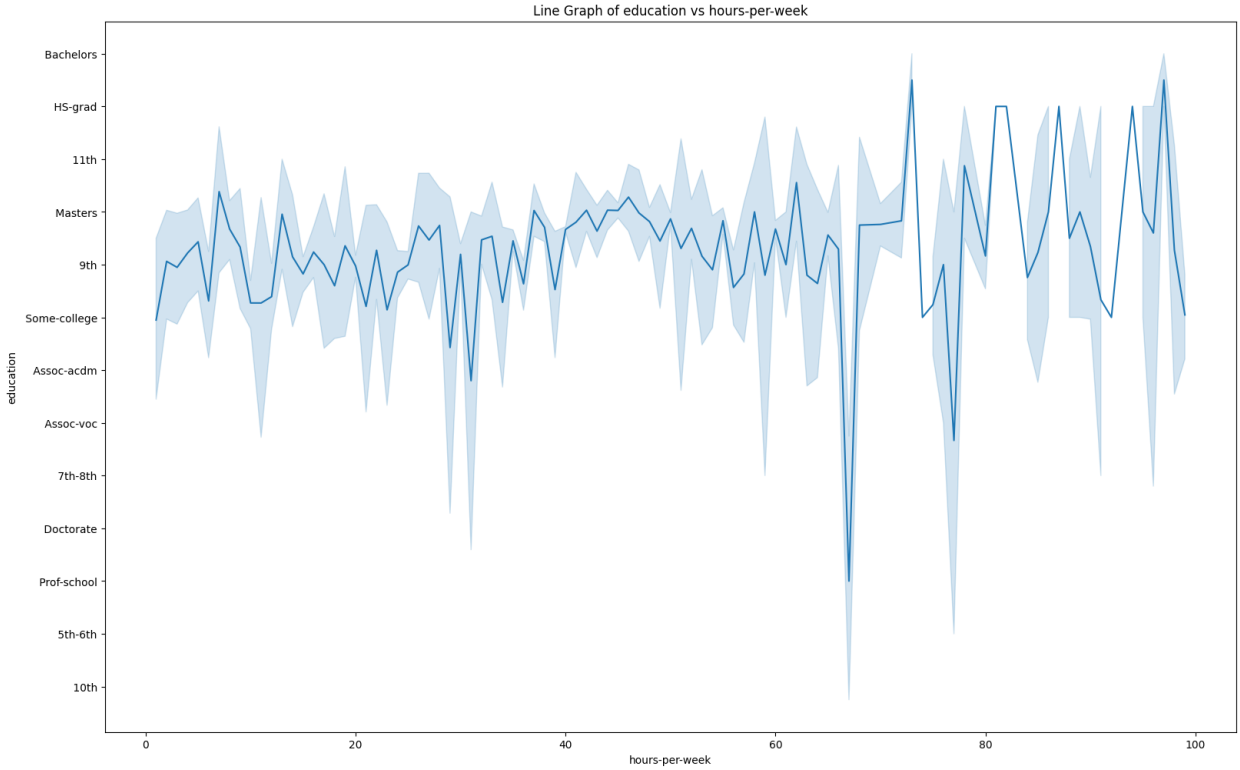
Line Graphs


Line Graph of age vs education
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
education
20
30
40
50
60
70
80
90
age


Line Graph of age vs hours-per-week
hours-per-week
age
0
10
20
30
40
50
20
30
40
50
60
70
80
90

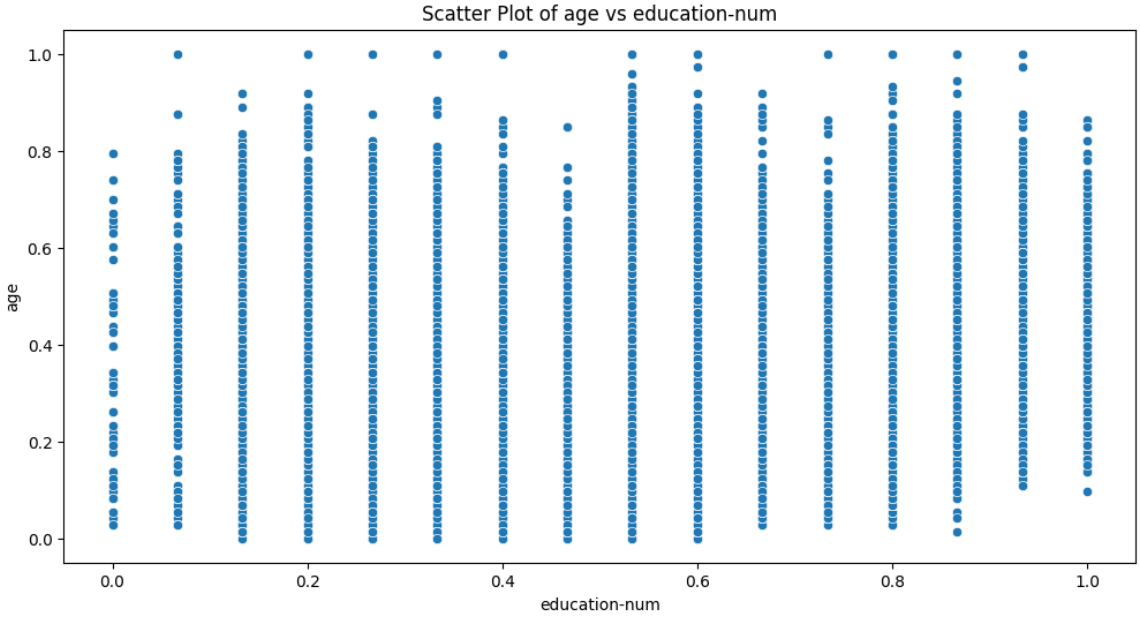

Line Graph of education vs capital-gain
capital-gain
education
0
2000
4000
6000
8000
10000
12000
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th

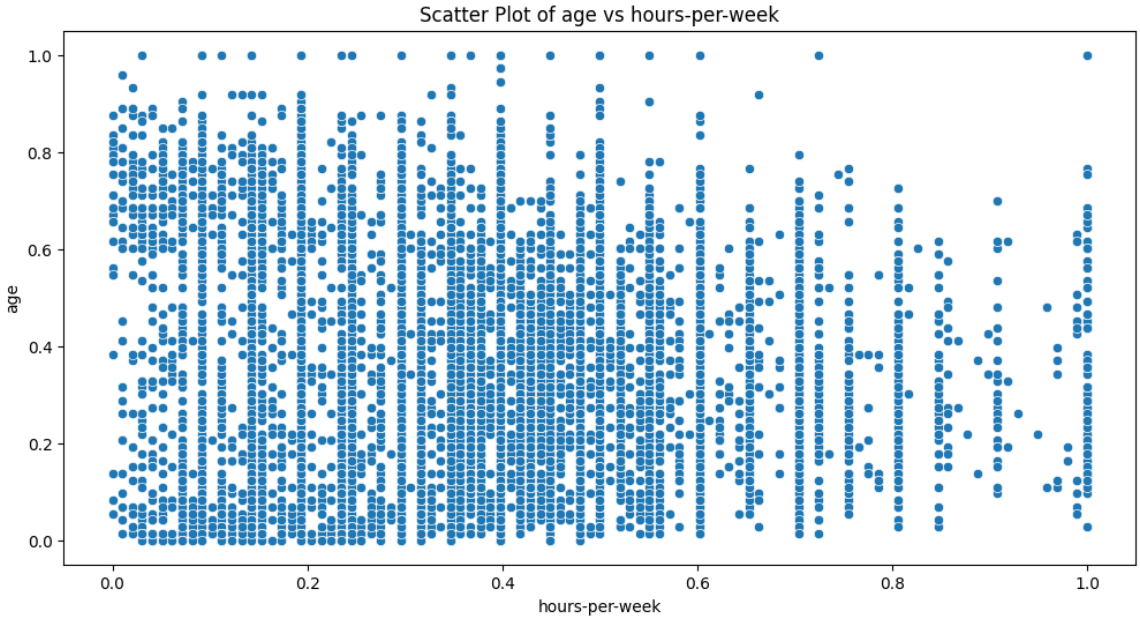

Line Graph of capital-loss vs education
capital-loss
0
50
100
150
200
250
300
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education

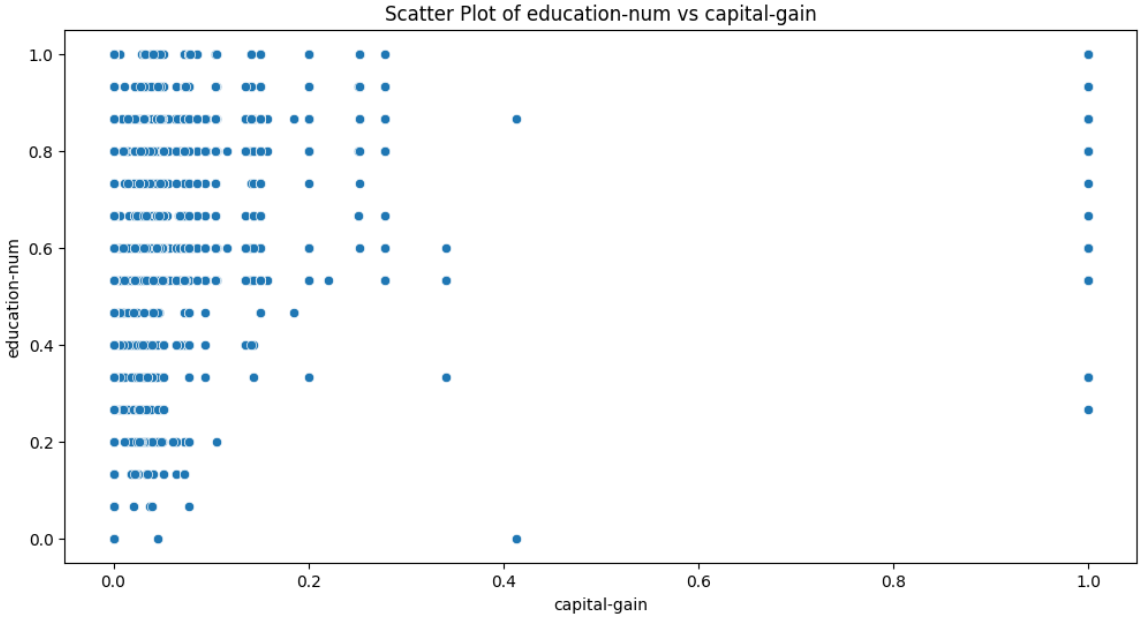

Line Graph of education vs hours-per-week
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
education
0
20
40
60
80
100
hours-per-week

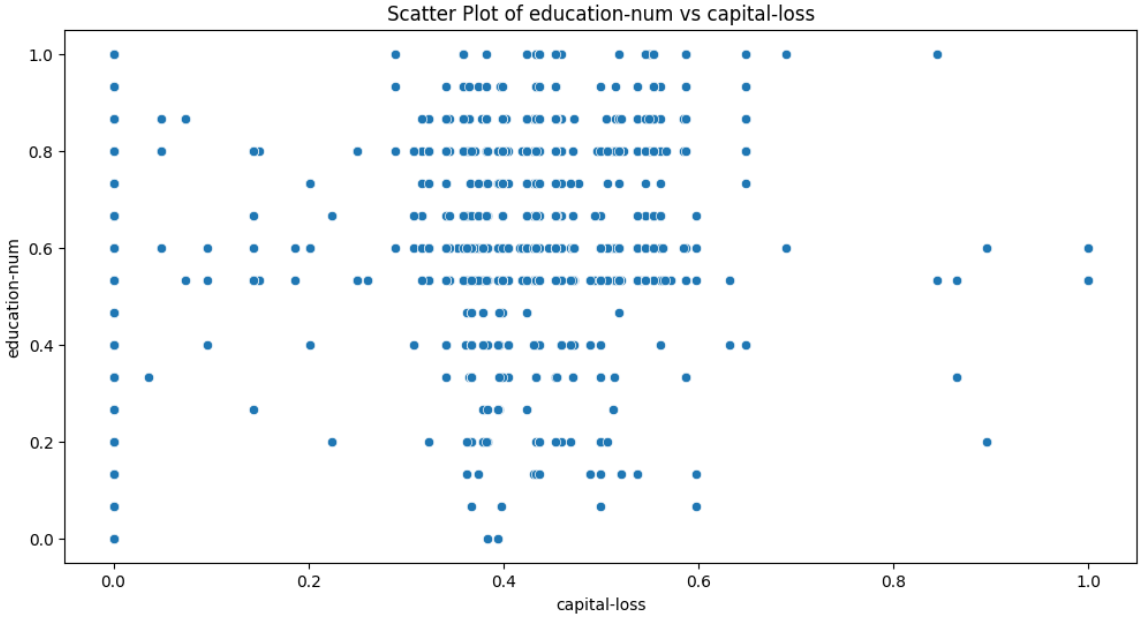
3.12

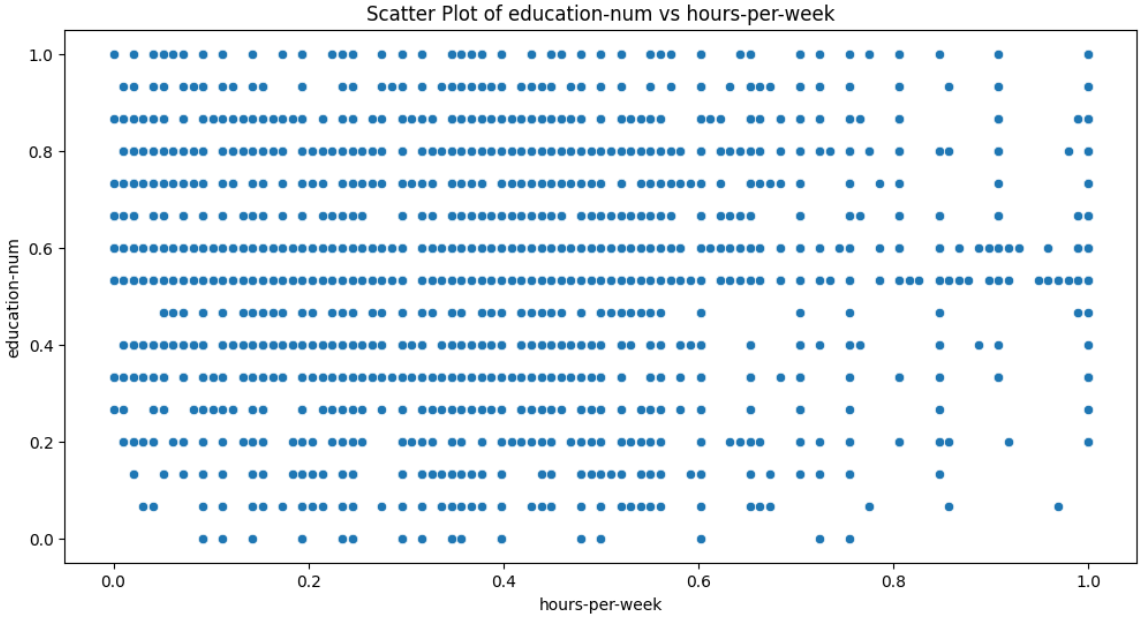
Min-Max Scaled Scatter Plots



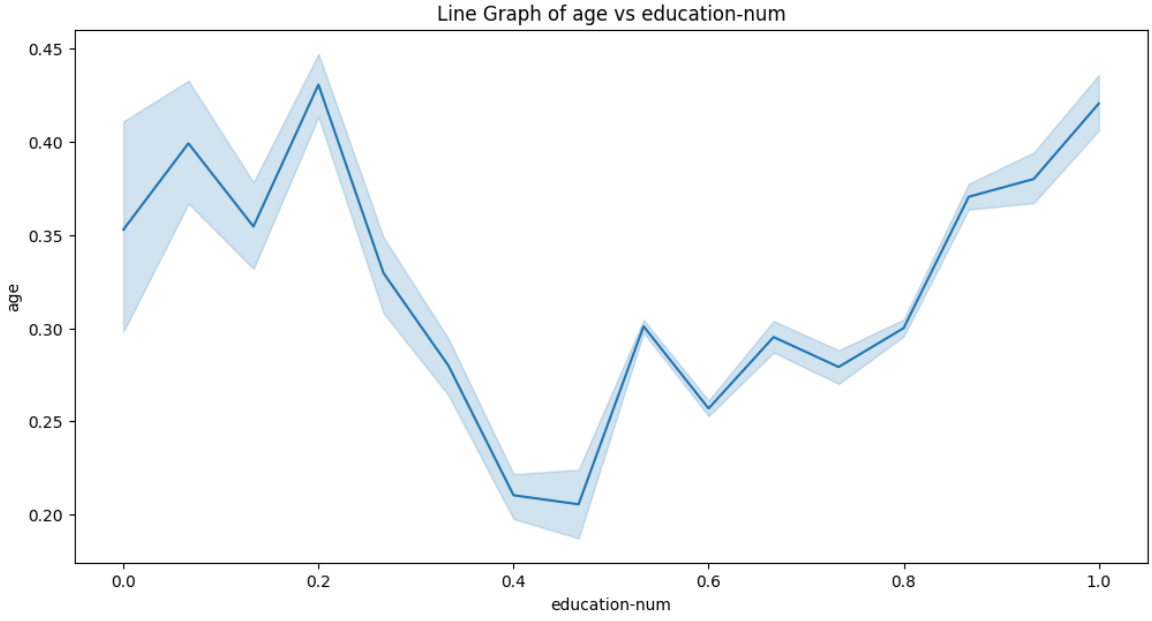


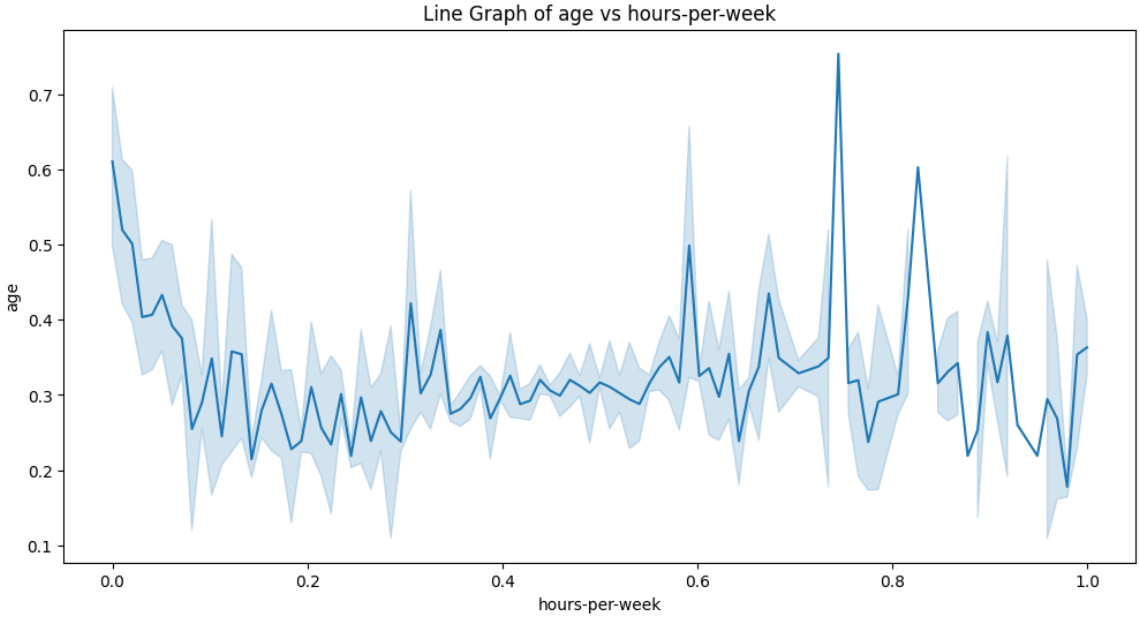

Scatter Plot of education-num vs capital-gain
education-num
capital-gain
0.0
0.2
0.4
0.6
0.8
1.0

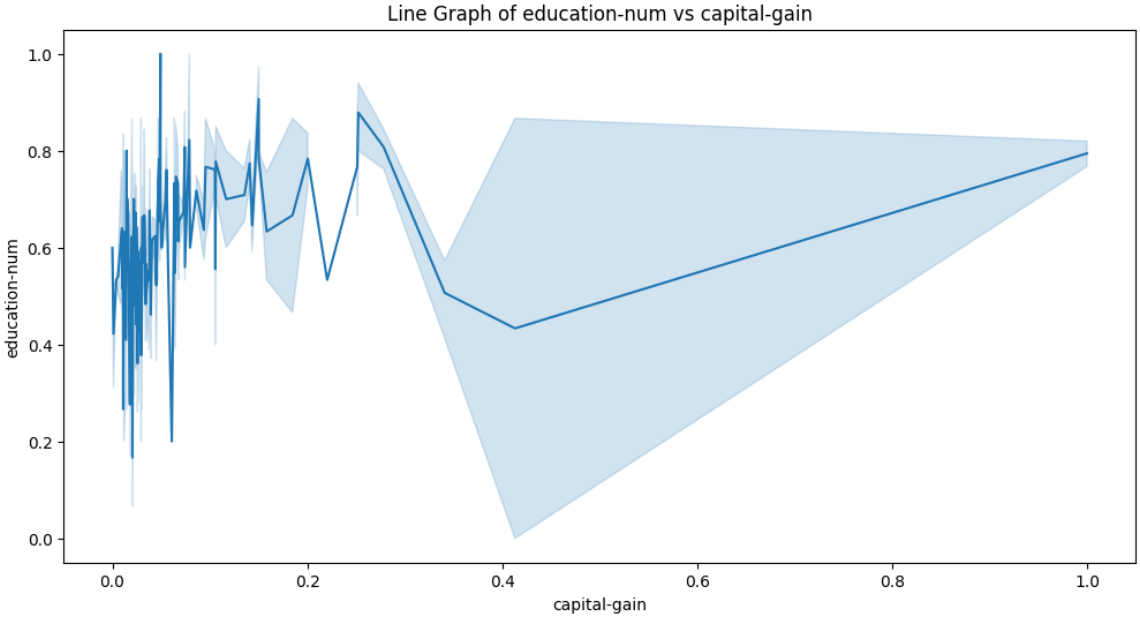

Scatter Plot of education-num vs capital-loss
education-num
capital-loss
0.0
0.2
0.4
0.6
0.8
1.0

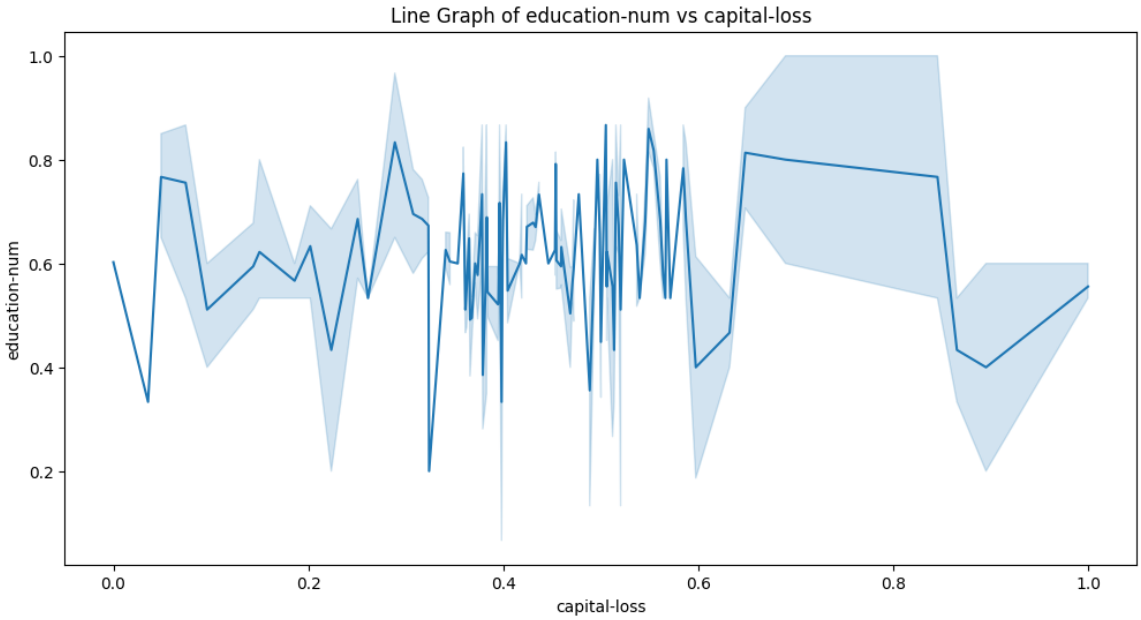


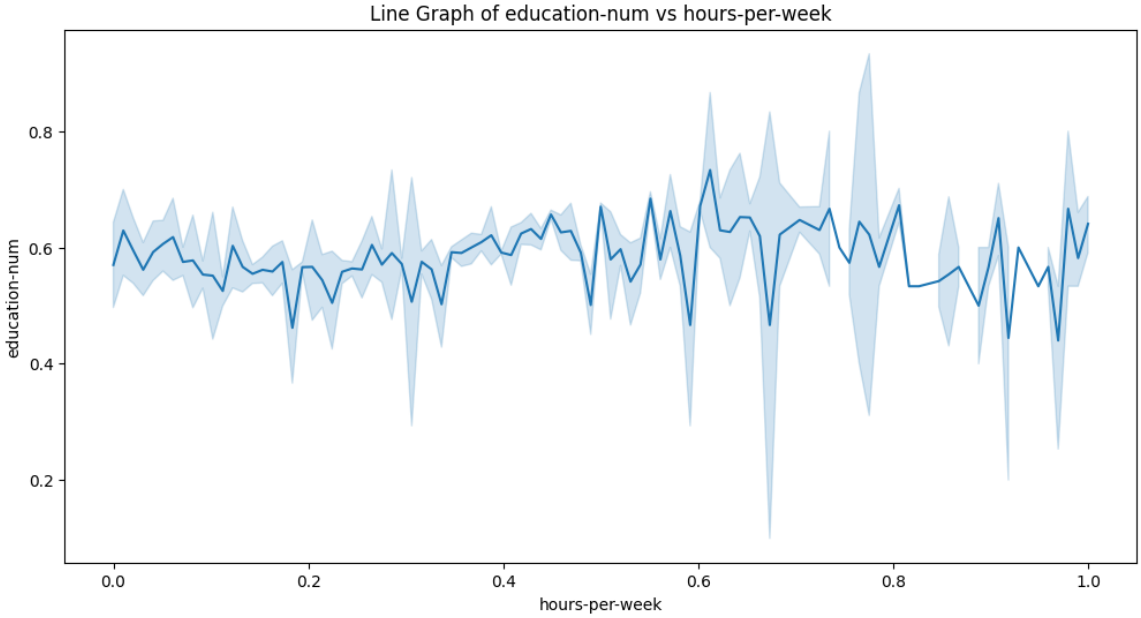
Min-Max Scaled Line Graphs



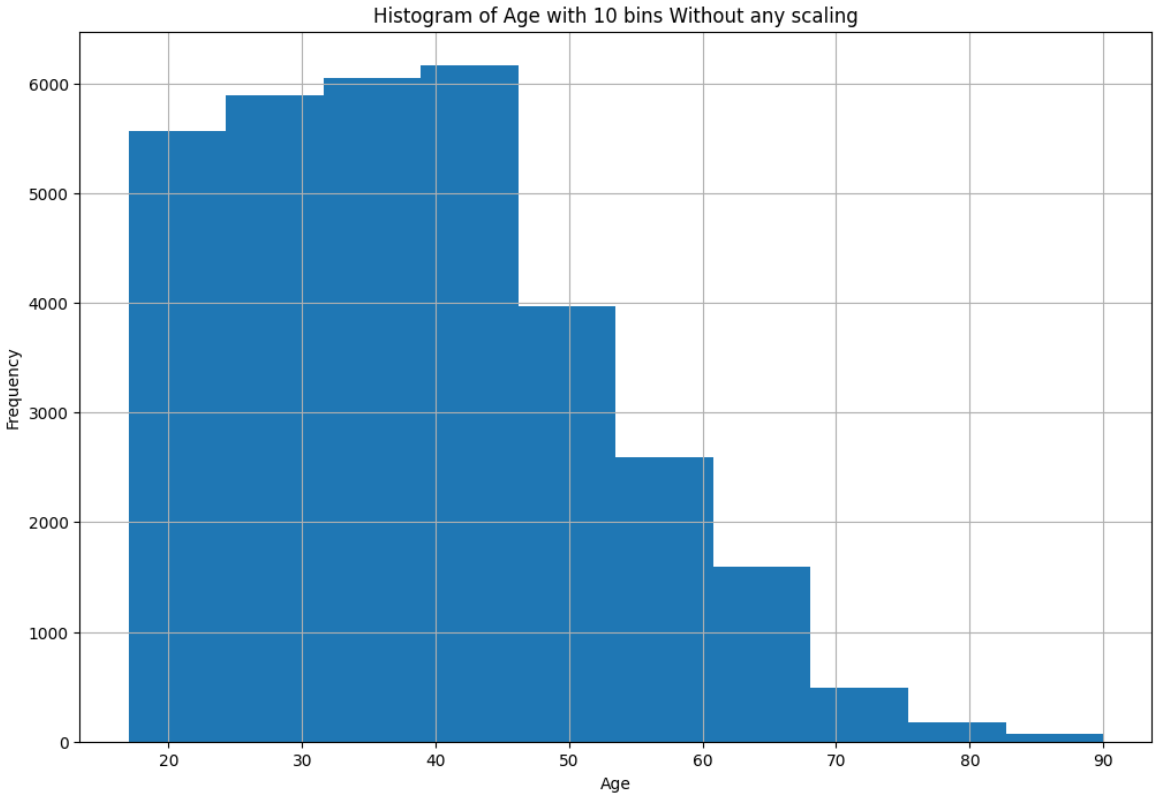

Line Graph of age vs hours-per-week
age
hours-per-week
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.0
0.2
0.4
0.6
0.8
1.0

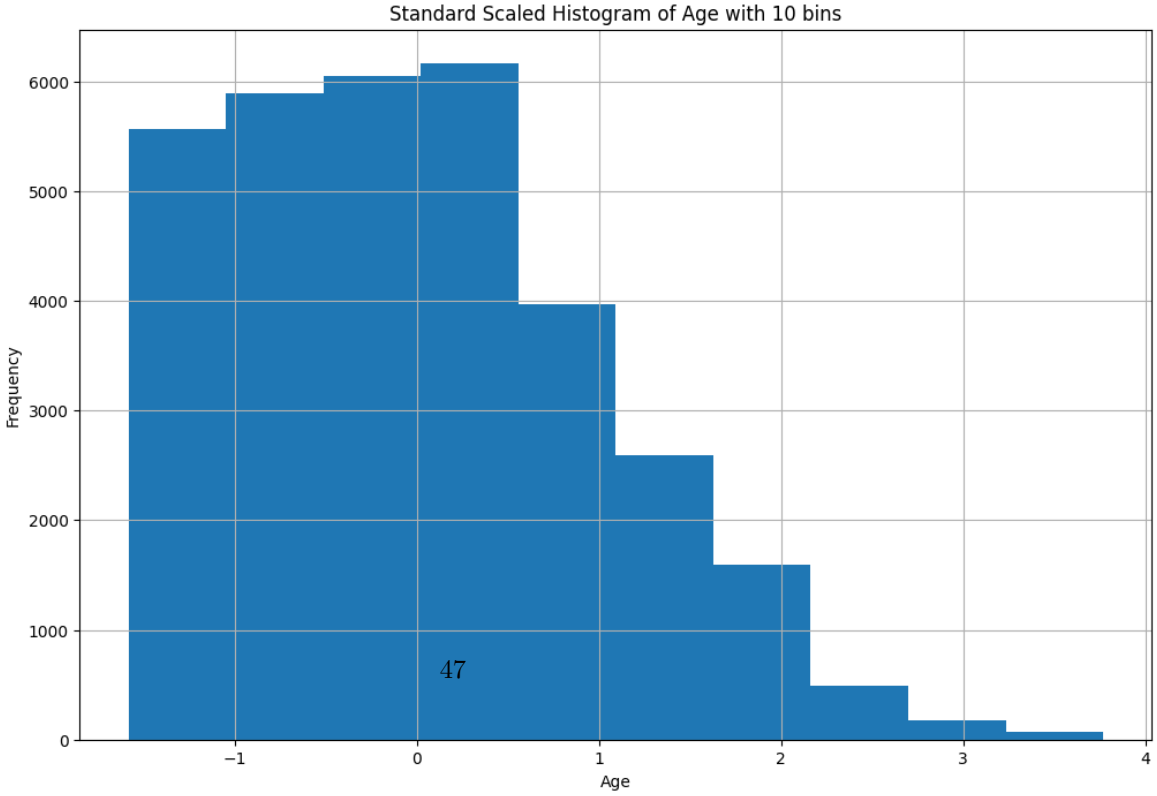

Line Graph of education-num vs capital-gain
education-num
capital-gain
0.0
0.2
0.4
0.6
0.8
1.0

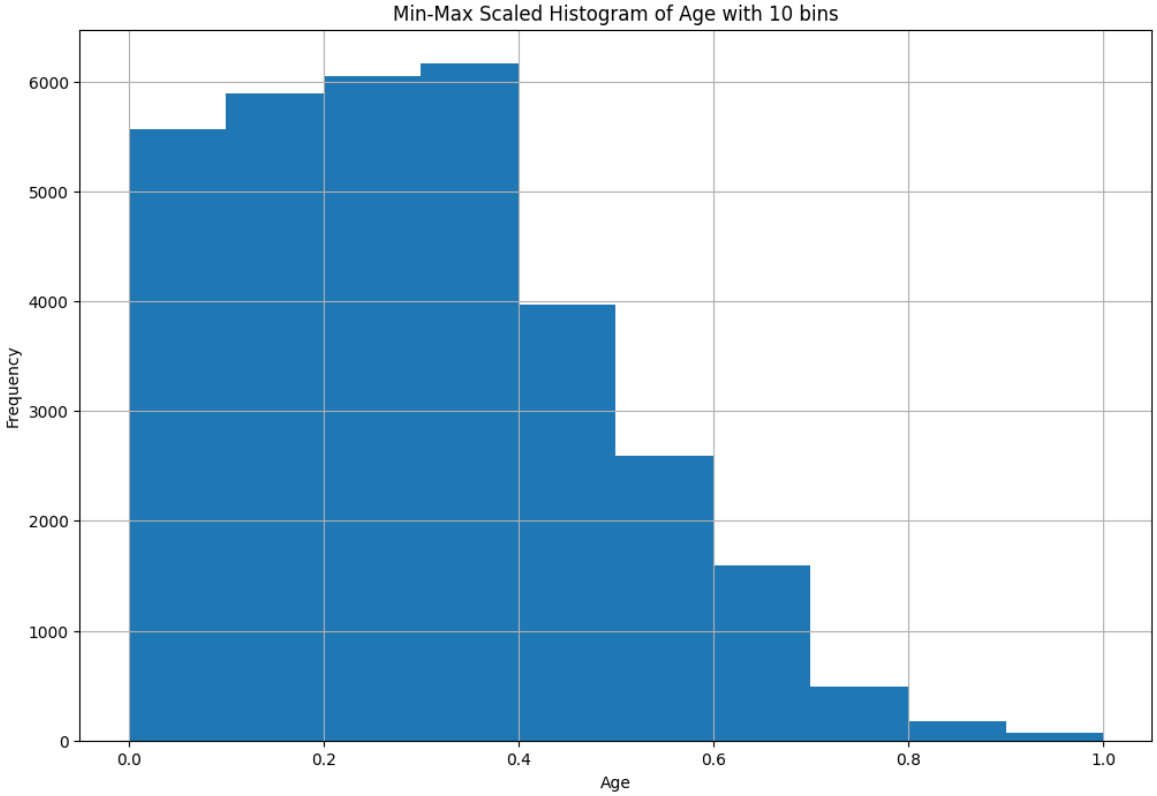

Line Graph of education-num vs capital-loss
education-num
capital-loss
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0


Line Graph of education-num vs hours-per-week
education-num
hours-per-week
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0

3.13


Histogram of Age with 10 bins Without any scaling
Frequency
Age
0
1000
2000
3000
4000
5000
6000
20
30
40
50
60
70
80
90


Standard Scaled Histogram of Age with 10 bins
Frequency
Age
0
1000
2000
3000
4000
5000
6000
−1
0
1
2
3
4



The above histogram are of the 'age' numerical attribute of the Adult dataset. Through obserservation it can be concluded that the normal, min-max scaled and standard scaled histograms of the same numerical attribute are of the same shape.

3.14

Before normalization: The heat map shows the raw L2 distances between numeric attributes. Attributes with larger numerical ranges (e.g., 'capital-gain', 'capital-loss') tend to have larger distances compared to attributes with smaller ranges (e.g., 'age', 'education-num'). This can skew the interpretation of distances due to the differing scales.

After Min-Max normalization: After Min-Max scaling, attributes are scaled to a fixed range. The heat map shows distances normalized within the [0, 1] range. It preserves the shape of the distances but compresses them into a uniform scale.

After Z-score normalization: After standard scaling, the heat map shows distances that are more balanced across all attributes. It emphasizes rel-

ative distances based on their distribution rather than their absolute magnitude.

3.15

This database was organised in .name and .data filetypes. The .data filetype contained the data without attribute names while the .name file contained the names of the attributes and some additional information. Data was arranged in columns and rows, the names provided sufficient description for ease of understanding for the reader.
In some use cases the data retrieval from the file took more time than usual i.e when making heatmaps for the numerical attributes but in general the speed of data retrieval was quick.
The data contained 32561 rows and 15 columns which desribed attributes like age, education level, relationship status etc of adults from varying demographics.

3.16

```
from google.colab import drive
import pandas as pd

drive.mount('/content/drive')
path= '/content/drive/MyDrive/adult/adult.data'

names = ['age', 'workclass', 'fnlwgt', 'education', 'education-num',
         'marital-status', 'occupation', 'relationship', 'race', 'sex',
         'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
'income']

df = pd.read_csv(path, header=None, names=names)

Q1 = df['age'].quantile(0.25)
Q3 = df['age'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = df[(df['age'] < lower_bound) | (df['age'] > upper_bound)]

print("Outliers detected using IQR method:")
print(outliers)
```

Using the above python code, the outliers were detected to be:
Age: 143

Final Weight(fnlwgt): 992
Education Number(education-num): 1198
Capital Gain: 2712
Capital Loss: 1519
Hours Per Week: 9008

3.17

Age:
Minimum: 17
Q1 (25th percentile): 28.0
Median (50th percentile): 37.0
Q3 (75th percentile): 47.0
Maximum: 78
Mode: 36
Mean: 38.4

Final Weight:
Minimum: 12285
Q1 (25th percentile): 116508.0
Median (50th percentile): 175935.0
Q3 (75th percentile): 228570.0
Maximum: 415847
Mode: 123011
Mean: 179631.3

Education Number:
Minimum: 5
Q1 (25th percentile): 9.0
Median (50th percentile): 10.0
Q3 (75th percentile): 13.0
Maximum: 16
Mode: 9
Mean: 10.3

Capital Gain:
Minimum: 0
Q1 (25th percentile): 0.0
Median (50th percentile): 0.0
Q3 (75th percentile): 0.0
Maximum: 0
Mode: 0
Mean: 0.0

Capital Loss:
Minimum: 0
Q1 (25th percentile): 0.0
Median (50th percentile): 0.0
Q3 (75th percentile): 0.0
Maximum: 0
Mode: 0
Mean: 0.0

Hours Per Week:
Minimum: 33
Q1 (25th percentile): 40.0
Median (50th percentile): 40.0
Q3 (75th percentile): 42.0
Maximum: 52
Mode: 40
Mean: 41.6