CSC487: Data Mining - Homework #2

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1. Find the distance between objects 1 and 3. Notice that we have mixed type of attributes. ***(25 points)***

The following python code has will find the distance between any two objects for this dataset.

```
# Build the dataframe.
table1 = {
  "Object Identifier": [1,2,3,4],
  "test-1 (nominal)" : ["A","B","C","A"],
  "test-2 (ordinal)" : ["excellent","fair","good","excellent"],
  "test-3 (numeric)" : [45,22,64,28]
  }

df1 = pd.DataFrame(table1)

# Set the index.
df1.set_index("Object Identifier",inplace=True)
df1
```

```
##                   test-1 (nominal) test-2 (ordinal)  test-3 (numeric)
## Object Identifier
## 1                                A        excellent                45
## 2                                B             fair                22
## 3                                C             good                64
## 4                                A        excellent                28
```

```
# Replace nominal values.
df1["test-1 (nominal)"].replace("A",3,inplace=True)
df1["test-1 (nominal)"].replace("B",2,inplace=True)
df1["test-1 (nominal)"].replace("C",1,inplace=True)

t1_range = (df1["test-1 (nominal)"].max()-df1["test-1 (nominal)"].min())
df1["test-1 (nominal)"] = (df1["test-1 (nominal)"]-1)/t1_range
df1
```

```
##                    test-1 (nominal) test-2 (ordinal)  test-3 (numeric)
## Object Identifier
## 1                               1.0        excellent                45
## 2                               0.5             fair                22
## 3                               0.0             good                64
## 4                               1.0        excellent                28
```

```
# Replace ordinal values.
df1["test-2 (ordinal)"].replace("excellent",3,inplace=True)
df1["test-2 (ordinal)"].replace("good",2,inplace=True)
df1["test-2 (ordinal)"].replace("fair",1,inplace=True)
```

```
t2_range = (df1["test-2 (ordinal)"].max()-df1["test-2 (ordinal)"].min())
df1["test-2 (ordinal)"] = (df1["test-2 (ordinal)"]-1)/t2_range
df1
```

```
##                    test-1 (nominal)  test-2 (ordinal)  test-3 (numeric)
## Object Identifier
## 1                               1.0               1.0                45
## 2                               0.5               0.0                22
## 3                               0.0               0.5                64
## 4                               1.0               1.0                28
```

```
# Replace numeric values.
t3_range = (df1["test-3 (numeric)"].max()-df1["test-3 (numeric)"].min())
df1["test-3 (numeric)"] = (
  df1["test-3 (numeric)"]-df1["test-3 (numeric)"].min()
  )/t3_range
df1
```

```
##                    test-1 (nominal)  test-2 (ordinal)  test-3 (numeric)
## Object Identifier
## 1                               1.0               1.0          0.547619
## 2                               0.5               0.0          0.000000
## 3                               0.0               0.5          1.000000
## 4                               1.0               1.0          0.142857
```

```
# Define our distance function.
def dist(i,j, df):
  neum = 0
  denom = 0
  for col in df.columns:
    print(col)
    if 'nominal' in col:
      if df[col].iloc[j-1] != df[col].iloc[i-1]:
        dist = 1
      else:
        dist = 0
    else:
      dist = np.abs(df[col].iloc[j-1] - df[col].iloc[i-1])
    print('feature distance:',dist)
    neum += dist
    denom += 1
    print()
  print('numerator:',neum)
  print('denomenator:',denom)
  print('\ntotal distance:')
  return neum/denom
```

```r
# Compute the distance between object 1 & 3
dist(1,3, df1)
```

```
## test-1 (nominal)
## feature distance: 1
##
## test-2 (ordinal)
## feature distance: 0.5
##
## test-3 (numeric)
## feature distance: 0.45238095238095233
##
## numerator: 1.9523809523809523
## denomenator: 3
##
## total distance:
## 0.6507936507936508
```

We can see that the distance between object 1 and object 3 is 0.651 .

2. Write a program in any language which can compute Manhattan and Euclidean distances between any two given vectors with any length. You can pass the length to your function, but please don't limit the dimension to 2. You can test your function on vectors you fill in your code without asking user input. *(25 points)*

The following python code has independent functions that will find the Manhattan and Euclidean distance between any two given numpy vectors.

```python
# Create test vector 1.
test_v1 = np.array([0,1,2,3,5,4])
test_v1
```

```
## array([0, 1, 2, 3, 5, 4])
```

```python
# Create test vector 2.
test_v2 = np.array([1,0,3,2,4,6])
test_v2
```

```
## array([1, 0, 3, 2, 4, 6])
```

```python
# Build our Manhattan Function
def manhattaan(v1,v2):
  return np.sum(np.abs(v2-v1))

# Test our Manhattan Function
manhattaan(test_v1,test_v2)
```

```
## 7
```

```python
# Build our Euclidean function.
def euclidian(v1,v2):
  return np.sqrt(np.sum(np.square(v2-v1)))

# Test our Euclidean function.
euclidian(test_v1,test_v2)
```

```
## 3.0
```

We can see that the simple test vectors pass for both functions.

3. In the table below, determine whether passing a class has a dependency on attendance by using Chi-square test. ***(25 points)***

```
# Build the dataframe.
table2 = {
  ""     : ["Attended","Skipped","Total"],
  "Pass" : [25,8,33],
  "Fail" : [6,15,21]
  }

df2 = pd.DataFrame(table2)
df2
```

```
##              Pass  Fail
## 0  Attended    25     6
## 1   Skipped     8    15
## 2     Total    33    21
```

```
# Total on attendance status.
df2["Total"] = df2["Pass"] + df2["Fail"]
df2
```

```
##              Pass  Fail  Total
## 0  Attended    25     6     31
## 1   Skipped     8    15     23
## 2     Total    33    21     54
```

```
# Create an expectation dataframe as a copy of the original.
expectation_df2 = df2.copy()
expectation_df2
```

```
##              Pass  Fail  Total
## 0  Attended    25     6     31
## 1   Skipped     8    15     23
## 2     Total    33    21     54
```

```
# Compute probabilities on attendance status
expectation_df2["Total"] = expectation_df2["Total"].apply(
  lambda x: x / expectation_df2["Total"].max()
  )
expectation_df2
```

```
##              Pass  Fail     Total
## 0  Attended    25     6  0.574074
## 1   Skipped     8    15  0.425926
## 2     Total    33    21  1.000000
```

```python
# Compute passing expectations.
expectation_df2["Pass"] = (
  expectation_df2["Pass"].max()*expectation_df2["Total"])
expectation_df2
```

```
##                    Pass  Fail     Total
## 0  Attended  18.944444     6  0.574074
## 1   Skipped  14.055556    15  0.425926
## 2     Total  33.000000    21  1.000000
```

```python
# Compute failing expectations
expectation_df2["Fail"] = (
  expectation_df2["Fail"].max()*expectation_df2["Total"])
expectation_df2
```

```
##                    Pass       Fail     Total
## 0  Attended  18.944444  12.055556  0.574074
## 1   Skipped  14.055556   8.944444  0.425926
## 2     Total  33.000000  21.000000  1.000000
```

```python
# Trim our original dataframe.
df2 = df2.iloc[:-1,:-1]
df2
```

```
##               Pass  Fail
## 0  Attended    25     6
## 1   Skipped     8    15
```

```python
# Trim our expectation dataframe
expectation_df2 = expectation_df2.iloc[:-1,:-1]
expectation_df2
```

```
##                    Pass       Fail
## 0  Attended  18.944444  12.055556
## 1   Skipped  14.055556   8.944444
```

```python
# Compute passing portion of chi squared.
pass_ = np.sum(
  np.square(
    (df2["Pass"] - expectation_df2["Pass"])
    )/expectation_df2["Pass"]
  )
pass_
```

```
## 4.544562029835523
```

```
# Compute failing portion of chi square.
fail_ = np.sum(
  np.square(
    (df2["Fail"] - expectation_df2["Fail"])
    )/expectation_df2["Fail"]
  )
fail_
```

```
## 7.141454618312963
```

```
# Sum for our chi squared value.
chi_squared_ = pass_ + fail_
chi_squared_
```

```
## 11.686016648148486
```

We can see that we yield $\chi^2 = 11.686$.

4. In R, there is a built-in data frame called `mtcars`. Please calculate the correlation between `mpg` and `wt` attributes of `mtcars` by using `cor()` function. Then generate scatter plot based on these two attributes. ***(25 points)***

```r
# Preview mtcars dataset.
mtcars
```

```
##                      mpg cyl  disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4           21.0   6 160.0 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag       21.0   6 160.0 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710          22.8   4 108.0  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive      21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout   18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
## Valiant             18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
## Duster 360          14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
## Merc 240D           24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2
## Merc 230            22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
## Merc 280            19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
## Merc 280C           17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
## Merc 450SE          16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
## Merc 450SL          17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
## Merc 450SLC         15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
## Cadillac Fleetwood  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
## Chrysler Imperial   14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
## Fiat 128            32.4   4  78.7  66 4.08 2.200 19.47  1  1    4    1
## Honda Civic         30.4   4  75.7  52 4.93 1.615 18.52  1  1    4    2
## Toyota Corolla      33.9   4  71.1  65 4.22 1.835 19.90  1  1    4    1
## Toyota Corona       21.5   4 120.1  97 3.70 2.465 20.01  1  0    3    1
## Dodge Challenger    15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
## AMC Javelin         15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
## Camaro Z28          13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
## Pontiac Firebird    19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
## Fiat X1-9           27.3   4  79.0  66 4.08 1.935 18.90  1  1    4    1
## Porsche 914-2       26.0   4 120.3  91 4.43 2.140 16.70  0  1    5    2
## Lotus Europa        30.4   4  95.1 113 3.77 1.513 16.90  1  1    5    2
## Ford Pantera L      15.8   8 351.0 264 4.22 3.170 14.50  0  1    5    4
## Ferrari Dino        19.7   6 145.0 175 3.62 2.770 15.50  0  1    5    6
## Maserati Bora       15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
## Volvo 142E          21.4   4 121.0 109 4.11 2.780 18.60  1  1    4    2
```

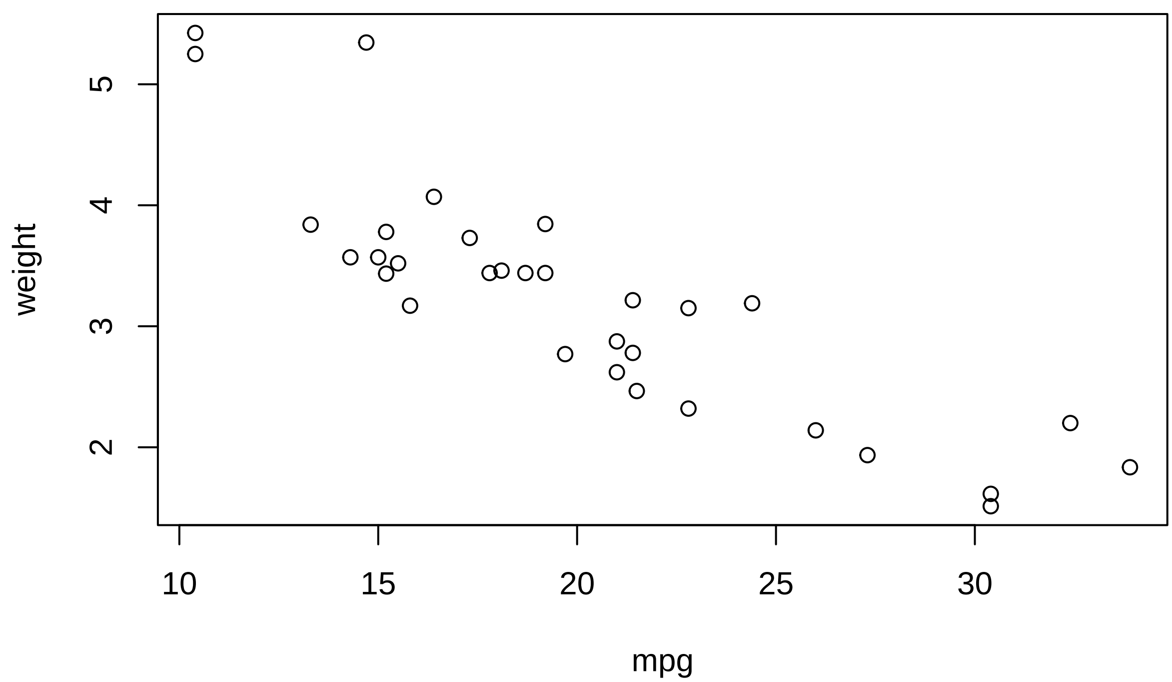
```r
# Set variables for naming.
mpg = mtcars$mpg
weight = mtcars$wt
```

```r
# Find Correlation.
cor(mpg, weight)
```

```
## [1] -0.8676594
```

We can see that the correlation between vehicle miles per gallon and vehicle weight in the mtcars dataset is $r_{mpg,weight} = -0.868$ What this explains is that as one variable (weight/mpg) increases, the other (mpg/weight) decreases.

```r
# Make scatterplot.
plot(mpg, weight)
```



```r
# To coincide with the example given in the assignment. (:
plot(weight, mpg)
```