Week 9 deliverable

I. Team members details

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II. Github repository link

https://github.com/tess92/Bank-Marketing-Campaign-

III. Problem description

We want to get some insight from the data of a bank called ABC that wants to sell it's term deposit product to customers and before launching the product they want to develop a model which help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

Business need: Buying Product for customer.

Method: using ML model to help companies shortlist customers whose chances of buying products is more so that their marketing channel can focus on them.


```
df.shape
```

```
(41188, 21)
```

```
print(df.describe())
```

```
                age      duration      campaign         pdays      previous  \
count  41188.00000  41188.000000  41188.000000  41188.000000  41188.000000
mean      40.02406    258.285010      2.567593    962.475454      0.172963
std       10.42125    259.279249      2.770014    186.910907      0.494901
min       17.00000      0.000000      1.000000      0.000000      0.000000
25%       32.00000    102.000000      1.000000    999.000000      0.000000
50%       38.00000    180.000000      2.000000    999.000000      0.000000
75%       47.00000    319.000000      3.000000    999.000000      0.000000
max       98.00000   4918.000000     56.000000    999.000000      7.000000

       emp.var.rate  cons.price.idx  cons.conf.idx     euribor3m   nr.employed
count  41188.000000    41188.000000   41188.000000  41188.000000  41188.000000
mean       0.081886       93.575664     -40.502600      3.621291   5167.035911
std        1.570960        0.578840       4.628198      1.734447     72.251528
min       -3.400000       92.201000     -50.800000      0.634000   4963.600000
25%       -1.800000       93.075000     -42.700000      1.344000   5099.100000
50%        1.100000       93.749000     -41.800000      4.857000   5191.000000
75%        1.400000       93.994000     -36.400000      4.961000   5228.100000
max        1.400000       94.767000     -26.900000      5.045000   5228.100000
```

IV. Problems in the data

- **Skewness**

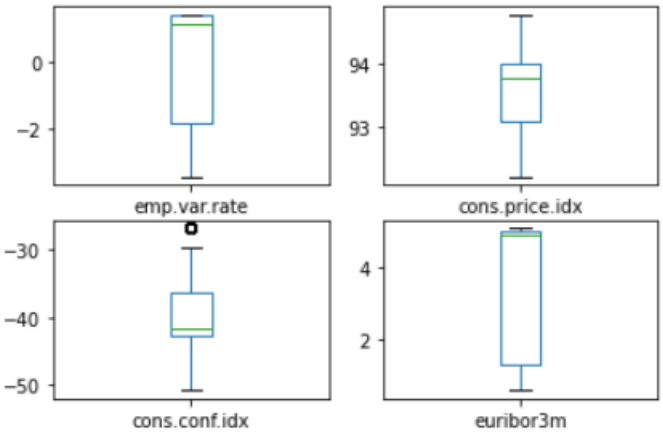
```
Entrée [6]: df.skew()
```

```
Out[6]: age              0.784697
        duration         3.263141
        campaign         4.762507
        pdays           -4.922190
        previous         3.832042
        emp.var.rate    -0.724096
        cons.price.idx  -0.230888
        cons.conf.idx    0.303180
        euribor3m       -0.709188
        nr.employed     -1.044262
        dtype: float64
```

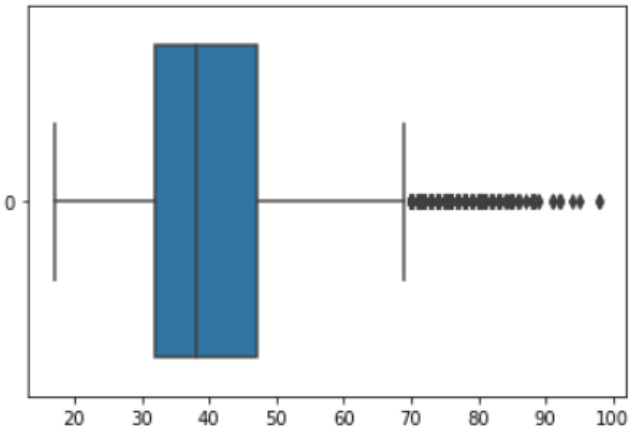
- **Outliers**

We calculate the z-score to detect outliers and we can also draw the box plot to check the eventual existence of outliers:

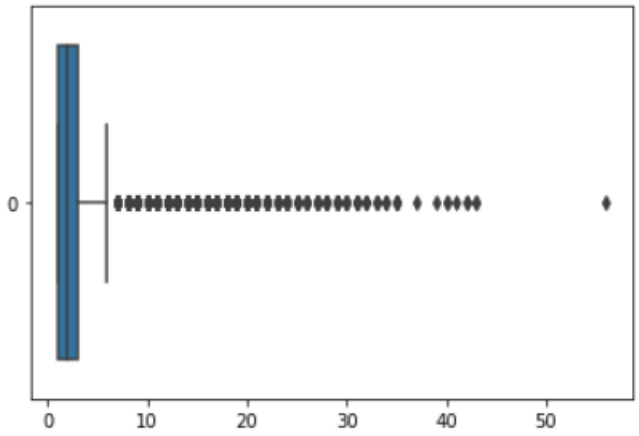
:
```
# box and whisker plots
df1=df.iloc[:,15:19]
df1.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
pyplot.show()
```



Entrée [8]:
```
sns.boxplot(data = df.age, orient ='h')
plt.show()
```




```
Entrée [14]: sns.boxplot(data = df.campaign, orient ='h')
             plt.show()
```



- **NA values:** There are no NA values in the data

```
Entrée [54]: df.isna().any()

Out[54]: age               False
         job               False
         marital           False
         education         False
         default           False
         housing           False
         loan              False
         contact           False
         month             False
         day_of_week       False
         duration          False
         campaign          False
         pdays             False
         previous          False
         poutcome          False
         emp.var.rate      False
         cons.price.idx    False
         cons.conf.idx     False
         euribor3m         False
         nr.employed       False
         y                 False
         dtype: bool
```

V. Problems overcoming techniques

- **Removing outliers:**

We can deal with outliers either by calculating the z-score or by calculating the interquartile range.

Using Z-score

The z-score is a numerical value that quatifies the relationship to the mean of of the values in our data. Z-score is measured in terms of standard deviations from the mean.

removing outliers

Entrée [44]:
```
#detecting outliers using z score

z = np.abs(stats.zscore(df.age))
print(z)
```

```
[1.53303429 1.62899323 0.29018564 ... 1.53303429 0.38152696 3.26029527]
```

Entrée [45]:
```
threshold = 3
print(np.where(z > 3))
```


```
(array([27757, 27780, 27800, 27802, 27805, 27808, 27810, 27811, 27812,
        27813, 27814, 27815, 27816, 27817, 27818, 27826, 27851, 27875,
        27930, 27950, 27951, 27963, 28220, 28221, 28312, 28456, 29263,
        29498, 29625, 29682, 29973, 29977, 29981, 29990, 30000, 30004,
        30006, 30072, 30078, 30079, 30103, 30110, 30133, 30171, 30214,
        30225, 30241, 30334, 30430, 30460, 30589, 35833, 35856, 35878,
        35973, 36183, 36285, 36311, 36383, 36384, 36816, 36998, 37136,
        37137, 37186, 37190, 37192, 37193, 37195, 37206, 37207, 37213,
        37219, 37235, 37237, 37239, 37257, 37260, 37341, 37355, 37403,
        37454, 37455, 37472, 37479, 37493, 37505, 37509, 37512, 37525,
        37532, 37597, 37601, 37602, 37604, 37635, 37675, 37679, 37690,
        37692, 37715, 37735, 37736, 37743, 37756, 37769, 37775, 37784,
        37818, 37819, 37820, 37861, 37868, 37870, 37873, 37905, 37920,
        37946, 37951, 37952, 37954, 37999, 38005, 38019, 38020, 38022,
        38032, 38033, 38045, 38052, 38054, 38065, 38136, 38166, 38178,
        38179, 38184, 38191, 38192, 38193, 38195, 38206, 38229, 38241,
        38246, 38252, 38260, 38279, 38288, 38314, 38316, 38322, 38326,
        38410, 38415, 38452, 38455, 38471, 38486, 38505, 38517, 38518,
        38536, 38548, 38549, 38556, 38557, 38577, 38580, 38582, 38587,
        38600, 38643, 38676, 38697, 38700, 38703, 38722, 38726, 38735,
        38740, 38744, 38751, 38783, 38810, 38824, 38825, 38831, 38846,
        38876, 38878, 38880, 38892, 38901, 38909, 38921, 38924, 38936,
        38942, 38943, 38944, 38946, 38953, 38960, 38967, 38968, 38984,
        39001, 39011, 39032, 39038, 39041, 39042, 39043, 39055, 39058,
        39061, 39062, 39093, 39115, 39124, 39133, 39184, 39186, 39190,
        39204, 39261, 39264, 39275, 39319, 39332, 39342, 39348, 39360,
        39377, 39402, 39410, 39411, 39415, 39444, 39452, 39466, 39471,
        39472, 39473, 39474, 39475, 39476, 39477, 39478, 39479, 39486,
        39487, 39488, 39489, 39493, 39495, 39498, 39504, 39577, 39578,
        39601, 39614, 39625, 39639, 39650, 39655, 39676, 39678, 39692,
        39719, 39722, 39724, 39730, 39734, 39737, 39752, 39762, 39766,
        39768, 39786, 39795, 39847, 39890, 39892, 39923, 39947, 39971,
        39974, 39975, 40001, 40045, 40050, 40060, 40076, 40078, 40080,
        40081, 40085, 40114, 40117, 40119, 40129, 40142, 40149, 40162,
        40194, 40195, 40196, 40197, 40201, 40218, 40219, 40220, 40262,
        40273, 40277, 40289, 40291, 40331, 40344, 40356, 40400, 40414,
        40421, 40437, 40445, 40450, 40468, 40469, 40470, 40484, 40488,
        40529, 40546, 40554, 40575, 40592, 40611, 40621, 40624, 40631,
        40636, 40638, 40639, 40651, 40667, 40669, 40686, 40702, 40714,
        40716, 40718, 40727, 40748, 40756, 40879, 40915, 40950, 40965,
        40966, 40969, 40982, 40983, 40986, 40996, 41004, 41183, 41187],
       dtype=int64),)
```


```
#shape before removing outliers
df.shape
```

```
(41188, 21)
```

```
# removing outliers
df1 = df[(z < 3)]
#shape after removing outliers
df1.shape
```

```
(40819, 21)
```

VI. Other transformations done on the data

- We checked that there are no intruders in the categorical data
- We checked that there are no durations that are equal to zero
- There are no NA values to be cleaned in the data
- We detected duplicated data and deleted them
- We drew some visualizations for the data understanding