

Congratulations! You passed!

**Keep Learning** 

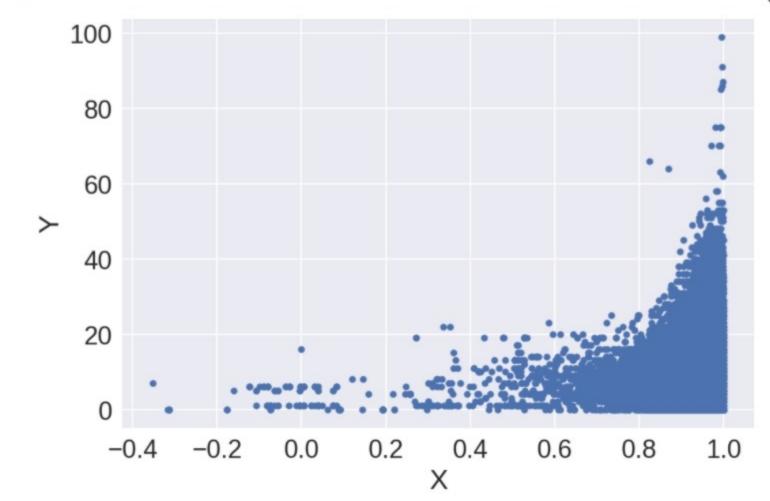
GRADE 100%

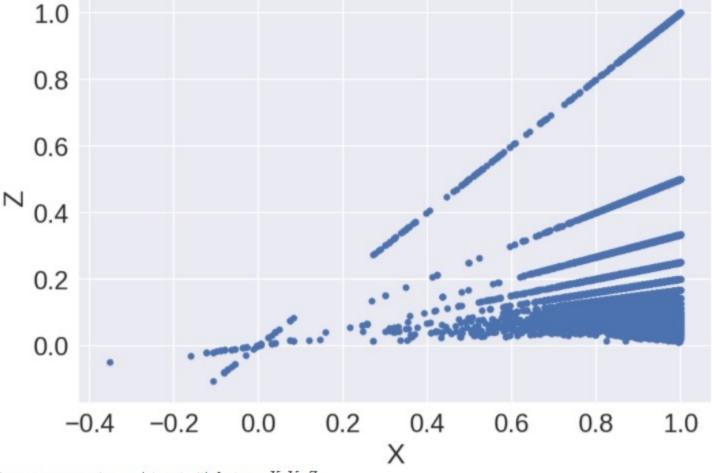
# **Exploratory data analysis**

LATEST SUBMISSION GRADE

TO PASS 75% or higher

100%





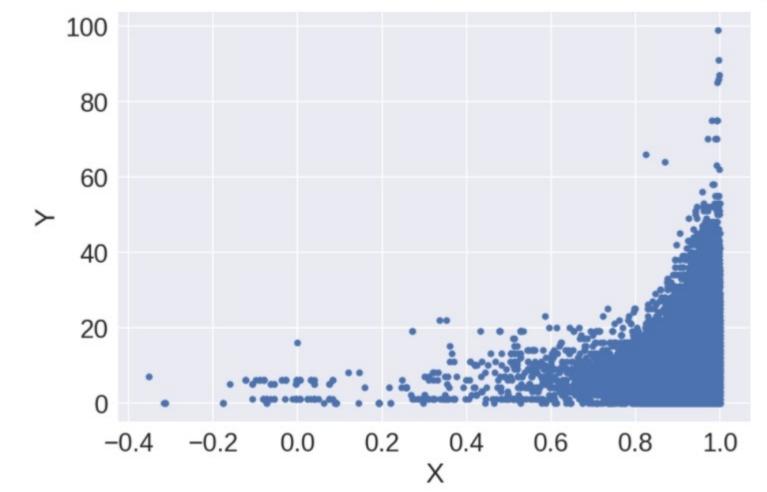
Suppose we are given a data set with features X, Y, Z.

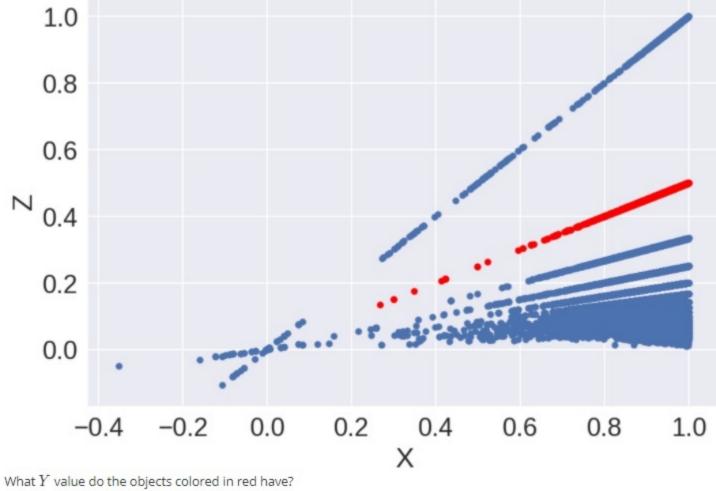
On the top figure you see a scatter plot for variables X and Y. Variable Z is a function of X and Y and on the bottom figure a scatter plot between X and Z is shown. Can you recover Z as a function of X and Y?

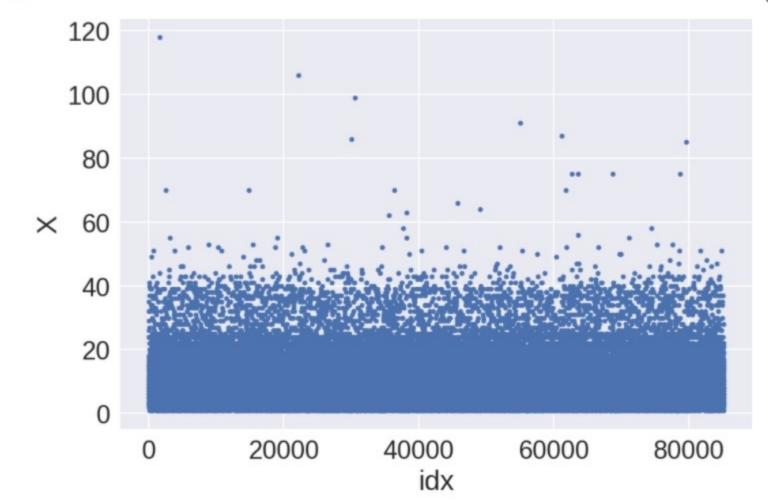


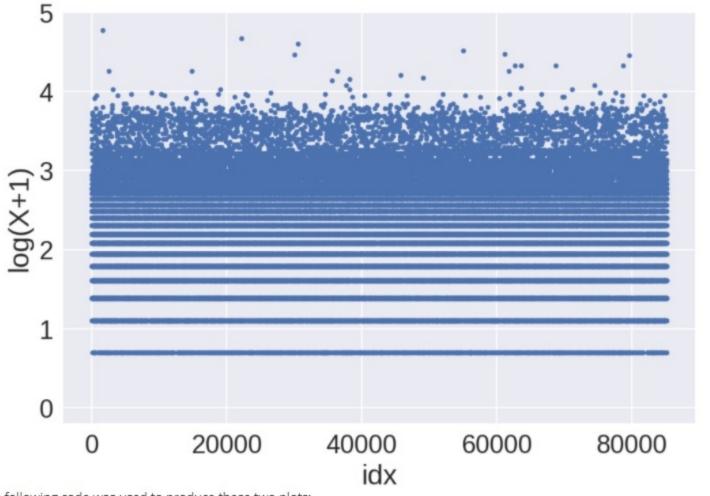


Correct!









The following code was used to produce these two plots:

```
1  # top plot
2  plt.plot(x, '.')
3
4  # bottom plot
5  logX = np.log1p(x) # no NaNs after this operation
6  plt.plot(logX, '.')
```

(note that it is not the same variable X as in previous questions).

Which hypotheses about variable X do NOT contradict with the plots? In other words: what hypotheses we can't reject (not in statistical sense) based on the plots and our intuition?



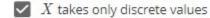
### ✓ Correct

Yes! The values are integers and start from 1. It could be e.g. a counter how many times a used opened website. Or it could be a a categorical features encoded with label encoder, which starts with label 1 (in pandas and sklearn label encoders usually start with 0).

- X can take a value of zero
- ${f Z} = 2 \le X < 3$  happens more frequently than  $3 \le X < 4$

#### ✓ Correct

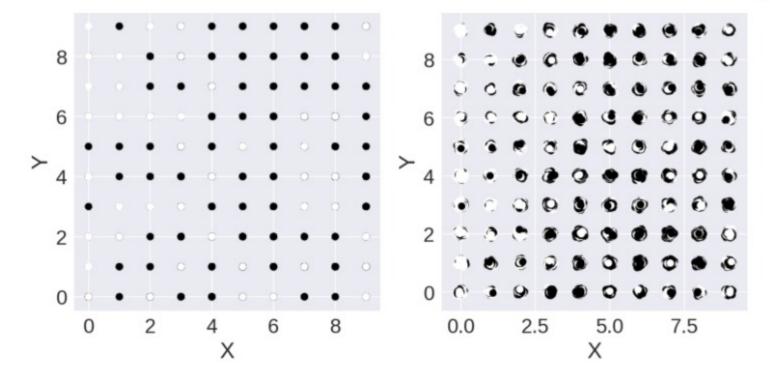
Yes! It can be the case, we cannot understand it from these plots, more exploration is needed, but such hypothesis does not contradicts with the plots.

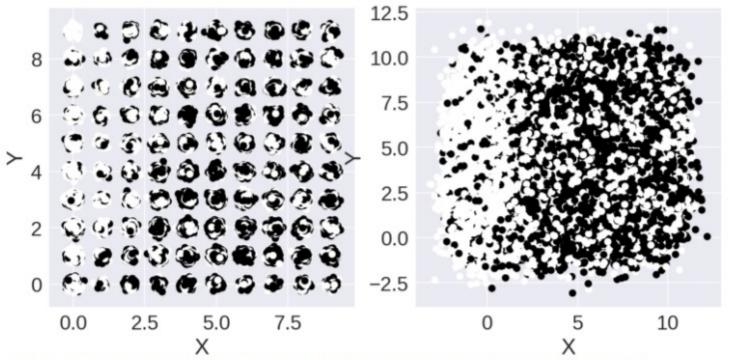


#### ✓ Correct

In fact, horizontal lines indicate a lot or repeated values. The most bottom horizontal line on log(X+1) plot corresponds to the value 1, the next to the value 2 and so on.

 $oxedsymbol{\square}$  X can be the temperature (in Celsius) in different cities at different times





Suppose we are given a dataset with features X and Y and need to learn to classify objects into 2 classes. The corresponding targets for the objects from the dataset are denoted as y.

Top left plot shows X vs Y scatter plot, produced with the following code:

```
1 # y is a target vector
2 plt.scatter(X, Y, c = y)
```

We use target variable y to colorcode the points.

The other three plots were produced by jittering X and Y values:

```
def jitter(data, stdev):
    N = len(data)
    return data + np.random.randn(N) * stdev

# sigma is a given std. dev. for Gaussian distribution
    plt.scatter(jitter(X, sigma), jitter(Y, sigma), c = y)
```

That is, we add Gaussian noise to the features before drawing scatter plot.

Select the correct statements.

We need to jitter variables not only for a sake of visualization, but also because it is beneficial for a model.



,		$\label{eq:correct} \text{Yes! On the top left plot we only see, that pairs } (x,y) \text{ lie on the grid. Top right also shows target distribution for each } (x,y) \text{ and density in } (x,y).$
	poi	rget is completely determined by coordinates $(x,y)$ , i.e. the label of the point is <i>completely determined</i> by int's position $(x,y)$ . Saying the same in other words: if we only had two features $(x,y)$ , we could build a ssifier, that is accurate 100% of time.
	It is	s <i>always</i> beneficial to jitter variables before building a scatter plot

## ✓ Correct

Yes! We can't even see, that  $X,\,Y$  originally have small number of unique values.

Standard deviation for Jittering is the largest on the bottom right plot.