

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 1

1 pts

Once the data is read, look at summary statistics to answer the question below

The average Tenure of all the customers in the data is \_\_\_\_ (Calculate the Average Tenure and round it to two decimal places)



## Question 2

2 pts

Once the data is read, look at summary statistics to answer the question below

The average Tenure of the customers who churn is  and those who do not churn is  (round the answer to two decimal places)



## Question 3

1 pts

Once the data is read, look at summary statistics to answer the question below

3. The Feature MonthlyCharges has \_\_\_\_ missing observations

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 5

2 pts

Once the data is read, look at summary statistics to answer the questions below

lies at or below 99% of the data for the feature

MonthlyCharges and

lies at or below 99% of the data for the feature Tenure round the answer to two decimal places wherever applicable)



## Question 6

1 pts

Now that we have taken a look at some continuous features, lets take a look at some categorical features and their relationship with the target ('Churn')

\_\_\_\_% is the total percentage of churned customers in the data. [Numeric Input. Example – if 0.67 or 67% write 67 as answer]



## Question 7

2 pts

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 7

2 pts

Now that we have taken a look at some continuous features, lets take a look at some categorical features and their relationship with the target ('Churn')

Amongst those who churned,  % of the customers who have

Dependents tend to churn and  of the customers who do not have Dependents tend not to churn. Hence, we observe that there is a variation in Churn behaviour by this feature "Dependents". [Numeric Input. Example – if 0.67 or 67% write 67 as answer]



## Question 8

1 pts

Now that we have taken a look at some continuous features, lets take a look at some categorical features and their relationship with the target ('Churn')

Amongst those customers who churned, customers who opt for \_\_\_\_ Internet Service have the least percentage of churn. [Character Input - Use the same label as given in the data]



## Question 9

1 pts

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 11

1 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

1. Treat the missing values in the Feature MonthlyCharges by replacing them with the average value of the Monthly Charges column. Is there a change in overall average value of the Feature Monthly Charges after the missing value treatment?\_\_\_[Yes/No – Character Input].(In the average values consider changes (if any) only upto two decimals places)

Yes 1.85



## Question 12

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

2. Treat the outliers in the column Tenure. All the values that are greater than 72 in this feature, convert those values to 72. There are only two such values. The new average after the outlier treatment for the column Tenure is \_\_\_\_ [Numeric Input – Round upto two decimals]

32.37

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 12

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

2. Treat the outliers in the column Tenure. All the values that are greater than 72 in this feature, convert those values to 72. There are only two such values. The new average after the outlier treatment for the column Tenure is \_\_\_\_ [Numeric Input – Round upto two decimals]



## Question 13

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

3. To prepare the data for modelling, we will need to convert all the categorical variables into quantitative by using one hot encoding. But before we do that, we will also need to bring out information from the features that possible only by combining features. Its seems that customers who have no Partners and no Dependents tend to churn a lot. Instead of having two separate columns – Partner and Dependents in the data, create a feature that has a flag for those with no Partners and no Dependents. Lets call this feature – “Singles”.\_\_\_\_% is the percentage of singles that tend to churn.[Numeric Input –Example- If the answer is 0.67 or 67% write it as 67 in the blank]

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 14

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

4. The data shows that customers who opt for Month to Month contract and those with short tenure have a high percentage of churn. In order to optimise the information about the features in these two columns do the following –

4(a.) Create a column where those with Month-to-Month Contract are flagged as 1 and all other labels in the Contract column are flagged as 0. This column has a count of  for 1's and a count of  for 0's. [Numeric Input]



## Question 15

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

4. The data shows that customers who opt for Month to Month contract and those with short tenure have a high percentage of churn. In order to optimise



## Question 3

1 pts

Once the data is read, look at summary statistics to answer the question below

3. The Feature MonthlyCharges has \_\_\_ missing observations



## Question 4

1 pts

Once the data is read, look at summary statistics to answer the question below

Looking at the summary statistics (using the describe function of pandas)\_\_\_\_\_ seems to be a potential outlier for tenure.

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 15

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

4. The data shows that customers who opt for Month to Month contract and those with short tenure have a high percentage of churn. In order to optimise the information about the features in these two columns do the following –

4(b.) Create a bucketed feature for Tenure (Make sure you used the new Tenure column that is treated for outliers). Those with less than 12 months, flag these as “short”, Those with tenure between 12 and 36 months, flag them as

“medium” and the rest of the values as “long”.  is the count for

the “short” label,  is the count for the “medium” label and

is the count for the “long” label. [Numeric Input]



## Question 16

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

4. The data shows that customers who opt for Month to Month contract and those with short tenure have a high percentage of churn. In order to optimise the information about the features in these two columns do the following –

4(c.) Create a new column called (Short\_Contracts) that's a combination of Month-to-Month Contracts and customers with short tenures (less than 12 months). \_\_ is the churn percentage for this column Short\_Contracts? .[Numeric Input –Example- If the answer is 0.67 or 67% write it as 67 in the blank]



## Question 17

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

5. Create a dummy for Payment Method column is such a way that label Electronic Check is flagged as 1 and all the other labels are flagged as zero.\_\_\_\_\_ is the percentage of churn who opt for Electronic Check as a Payment method vs. automatic payment methods.[Numeric Input –Example- If the answer is 0.67 or 67% write it as 67 in the blank]



# QUESTIONS AND ANSWERS ON FEATURE ENGINEERING ON THIS CUSTOMER DATA SET:



## Question 19

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

7. Its also seen from the data, that those who pay high monthly charges are likely to churn as compared to those who pay less monthly charges. To bring out this information in the model, flag those rows with monthly charges less than 35 as low, 35 to 55 as medium and above 55 as High. \_\_\_\_\_ is the churn percentage amongst those who pay high monthly charges.[Numeric Input –Example- If the answer is 0.67 or 67% write it as 67 in the blank]

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## Question 18

2 pts

Once the step of Feature Understanding is complete, lets now start Engineering the Features based on the insights about the feature that tend to impact the churn.

6. Create a new column to flag those with No Online Security, No Tech Support, No Device Protection and No Online Backup. \_\_\_\_\_ is the churn percentage for this column? [Numeric Input –Example- If the answer is 0.67 or 67% write it as 67 in the blank]



## Question 19

2 pts