

Data Preparation Assignment

Preparing the Data

I would begin by importing the packages and features necessary in order to prepare the given data for modeling and then I would read the CSV file containing the data and look at its shape (how many rows and columns), which would then tell how many samples and features the data contains. After that, I would check to see if there are any samples with null values, and if so, which features have an abundance of them as if certain features had a lot of null values, I would see what the best options are to supplement them. Following that, I would check the data types of each feature and if anything was a type other than a float or integer and could be made binary, I would use the replace function to give a numerical representation. By doing so, the data can be used by various functions and address each feature, as if the feature was for instance a string, it wouldn't be able to compare each feature to other ones that are represented by numbers. Once I've replaced the sample values that aren't numbers, I would get descriptive statistics of the data to look at values like the mean, count, and standard deviation of each feature. Similarly, I would check the balance of the target feature because if it's very unbalanced, the model may incorrectly learn some things and create assumptions during its training. After that, I would look at each feature's correlation with other features, as well as use a heatmap which would effectively do the same thing except that it would be more clear to the viewer. Next, I would look at a variety of plots to see the distribution of each feature and determine if there are any outlier samples that may need to be removed from the data by also looking at skewness. Lastly, I would rescale and then standardize the data for modeling, as normalizing can't be done without treating null values.

Data Exploration

⇒ see figures of results at end of document

⇒ imports

```
import pandas as pd
import numpy as np
import seaborn as sea
from matplotlib import pyplot
from pandas import read_csv
from numpy import unique
from numpy import set_printoptions
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
```

⇒ read the file and see the data's shape and head

```
fileName = "/Users/mtjen/Desktop/Churn_Train.csv"
customerDF = read_csv(fileName)
shape = customerDF.shape
head = customerDF.head
print(shape)
print(head)
```

⇒ check for null values and each features data type

```
isNullValues = customerDF.isnull().sum()
types = customerDF.dtypes
print(isNullValues)
print(types)
```

⇒ replace churn values with binary values

```
customerDF = customerDF.replace(['no', 'yes'], [0, 1])
```

⇒ simple descriptive statistics

```
description = customerDF.describe()
print(description)
```

⇒ get the balance of the target feature

```
churnBalance = customerDF.groupby('churn').size()
print(churnBalance)
```

⇒ get the correlations between each feature

```
correlation = customerDF.corr(method = 'pearson')
print(correlation)
```

⇒ create a heatmap of correlations

```
matrix = np.triu(customerDF.corr())
sea.heatmap(customerDF.corr(), annot = True, fmt = '0.1g', mask = matrix)
```

⇒ use plots to find feature distribution

```
customerDF.hist(layout = (6,3), figsize = (10,10))
customerDF.plot(kind = 'box', layout = (6,3), subplots = True, sharex = False, sharey = False,
                figsize = (10,10))
pyplot.show()
```

⇒ get skew values

```
skew = customerDF.skew()
print(skew)
```

⇒ scale and normalize the data

```
customer = customerDF.drop(['area_code', 'state'], 1) # remove to scale the numerical features
customer = customer.replace(['no', 'yes'], [0, 1])
array = customer.values
X = array[:,0:17]
Y = array[:,17]
scaler = MinMaxScaler(feature_range=(0, 1))
rescaledX = scaler.fit_transform(X)
set_printoptions(precision=3)
print(rescaledX[0:5,:])
print()
scaler = StandardScaler().fit(X)
rescaledX = scaler.transform(X)
set_printoptions(precision=3)
print(rescaledX[0:5,:])
```

Overview of Data

By doing basic exploratory data analysis, it was found that there are a number of samples with some missing data, although relative to the entire data set, it is a small percentage. With that though, the leading feature of missing values is the sample's account length, which is one of the most important factors to know. The 'churn rate' of the samples is also unbalanced and leans towards not churning. However, the percentage of people is somewhat alarming as about 14.5% of the samples have switched to a competition's services. A couple of features within the data also have high correlation, telling how some of the features studied were not that necessary because of the overlap with others. Even though some of them are highly correlated though, most of the features may still play a large role as they allow the company to see if the customers that they are losing are high value ones that they should be trying to retain. While looking at histograms of the distribution of the samples by each feature, most of the features are relatively evenly distributed which is good for studying the data. Combining the histograms with the descriptive statistics shows a small problem though, as a couple of the features have a high standard deviation and the data is not distributed very evenly. As such, looking at the box plots, a number of the features like total international calls, total number of day minutes, and number of voicemail messages have a lot of outliers. With those outliers, the data is skewed and the model may not be able to be trained as accurately as possible, particularly when figuring out which features are the most important to weigh. To further the idea of outliers and how the data may be skewed, a couple of features were heavily skewed and needed to be fixed. There were only four features that were heavily skewed, but there were also five other features that were also skewed to a lesser degree but still need to be fixed.

Recommendations and Potential Corrective Action

To fully prepare the data set for modeling, there are a couple of corrective actions that I would take to hopefully make the model more accurate. The first thing that I would do is to make sure that every feature's values are numerical by assigning a numerical value for instances like state and area code and by giving binary values for yes or no questions. By doing this, each feature would be able to be compared with each other and graphics like map overlays would convey more useful and effective information. The next thing that I would do is figure out the best way to handle samples with null values within the data. Some of the features may be able to have extrapolated values used, but others with numerous null values may have to just be removed because of the randomness of other samples' values. Moreover, null values within features that are skewed would likely not be able to be accurately extrapolated based on other samples' values. After that, I would remove a couple of the features from the data because of its high correlation and overlap with others. There are four features in particular that have very high correlation, and as such can be removed to improve efficiency within the model. I would also scale and normalize the data, as even though most of the features are evenly distributed, a number of them are skewed to one side or another. Furthermore, the scale and range of some of the features are much greater than others, so it would be useful to have all the data on the same scale. Lastly, I would remove heavy outliers from the data set so that the data is more evenly distributed. Without heavy outliers that greatly skew the data, the model would be able to more accurately and precisely predict whether or not a customer may leave for another provider.

Data Figures

<pre>(3333, 20) >bound method NDFrame.head of voice_mail_plan \ 0 HI 125.0 area_code_510 no no 1 HI 180.0 area_code_415 no no 2 HI 82.0 area_code_415 no no 3 HI 80.0 area_code_480 no yes 4 OH 83.0 area_code_415 no no ... 3328 OH 144.0 area_code_415 no yes 3329 LA 65.0 area_code_415 no yes 3330 SD 80.0 area_code_415 no no 3331 NV 70.0 area_code_480 no no 3332 WI 41.0 area_code_480 no no</pre>	<pre>total_day_charge total_eve_minutes total_eve_calls total_eve_charge \ 0 28.86 1107.0 107.0 14.93 1 40.57 221.1 93.0 18.79 2 51.85 181.0 100.0 15.39 3 18.75 182.4 100.0 15.50 4 57.30 227.4 116.0 19.33 ... 3328 18.89 100.1 113.0 9.19 3329 26.35 NaN 105.0 12.10 3330 29.67 180.2 103.0 15.32 3331 27.27 1034.6 103.0 8.72 3332 34.49 153.0 104.0 13.07</pre>	<pre>total_intl_minutes total_intl_calls total_intl_charge \ 0 18.9 7.0 2.84 1 14.0 9.0 3.78 2 11.7 4.0 3.10 3 11.4 8.0 2.97 4 15.0 7.0 4.27 ... 3328 10.1 5.0 2.73 3329 5.9 4.0 1.10 3330 10.7 2.0 2.89 3331 9.1 5.0 2.46 3332 0.0 3.0 2.43</pre>
<pre>number_vmail_messages total_day_minutes total_day_calls \ 0 0.0 2013.4 99.0 1 0.0 291.6 99.0 2 0.0 180.3 189.0 3 30.0 118.3 71.0 4 0.0 337.4 120.0 ... 3328 10.0 105.4 109.0 3329 37.0 155.8 98.0 3330 0.0 174.5 90.0 3331 0.0 2039.6 68.0 3332 0.0 202.9 97.0</pre>	<pre>total_night_minutes total_night_calls total_night_charge \ 0 243.3 92 18.95 1 229.2 110 18.21 2 270.1 73 12.15 3 183.0 80 8.27 4 153.9 114 8.93 ... 3328 200.4 111 9.30 3329 143.7 117 6.47 3330 179.0 89 8.80 3331 235.3 106 10.59 3332 113.5 92 5.11</pre>	<pre>number_customer_service_calls churn 0 0.0 no 1 2.0 yes 2 0.0 yes 3 2.0 no 4 0.0 yes ... 3328 1.0 no 3329 1.0 no 3330 2.0 no 3331 2.0 no 3332 3.0 no [3333 rows x 20 columns]</pre>
<pre>state 0 account_length 501 area_code 0 international_plan 0 voice_mail_plan 0 number_vmail_messages 200 total_day_minutes 200 total_day_calls 200 total_day_charge 200 total_eve_minutes 301 total_eve_calls 200 total_eve_charge 200 total_night_minutes 200 total_night_calls 0 total_night_charge 200 total_intl_minutes 200 total_intl_calls 301 total_intl_charge 200 number_customer_service_calls 200 churn 0 dtype: int64</pre>	<pre>state object account_length float64 area_code object international_plan object voice_mail_plan object number_vmail_messages float64 total_day_minutes float64 total_day_calls float64 total_day_charge float64 total_eve_minutes float64 total_eve_calls float64 total_eve_charge float64 total_night_minutes float64 total_night_calls int64 total_night_charge float64 total_intl_minutes float64 total_intl_calls float64 total_intl_charge float64 number_customer_service_calls float64 churn object dtype: object</pre>	<p>Top 3 : Head of Data</p> <p>Bottom 2 : null values and data types</p>

Figure 1

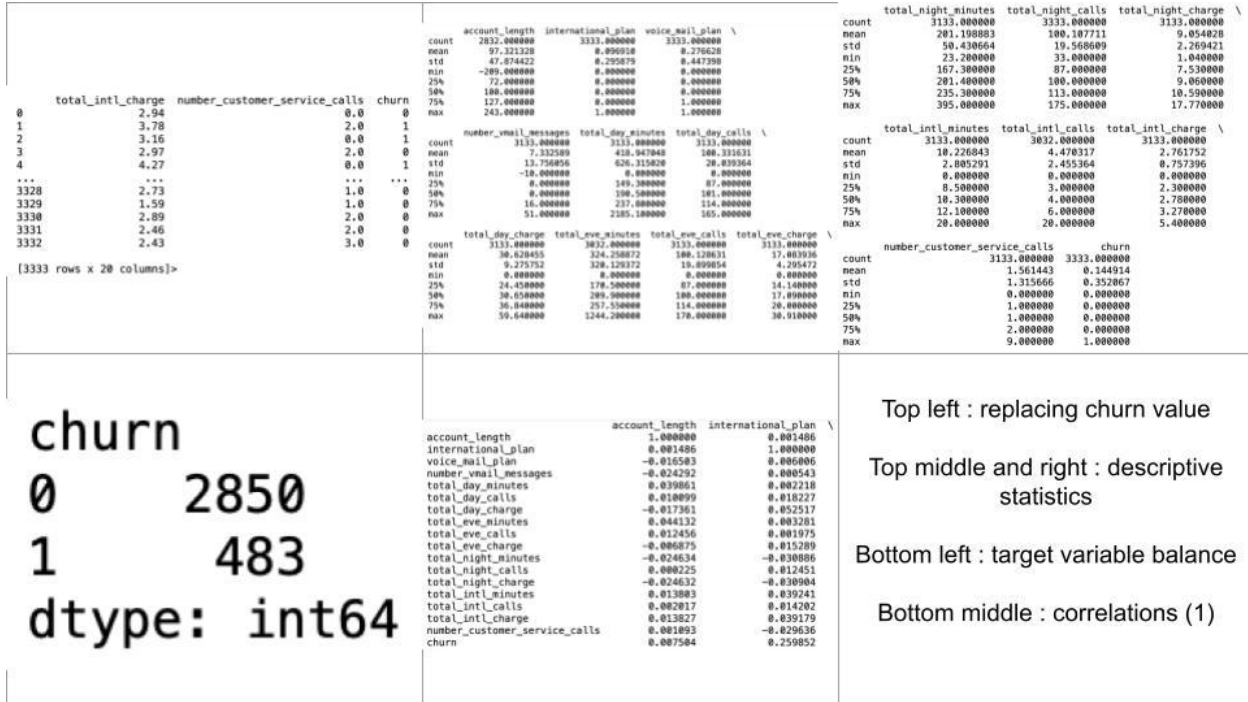


Figure 2



Figure 3

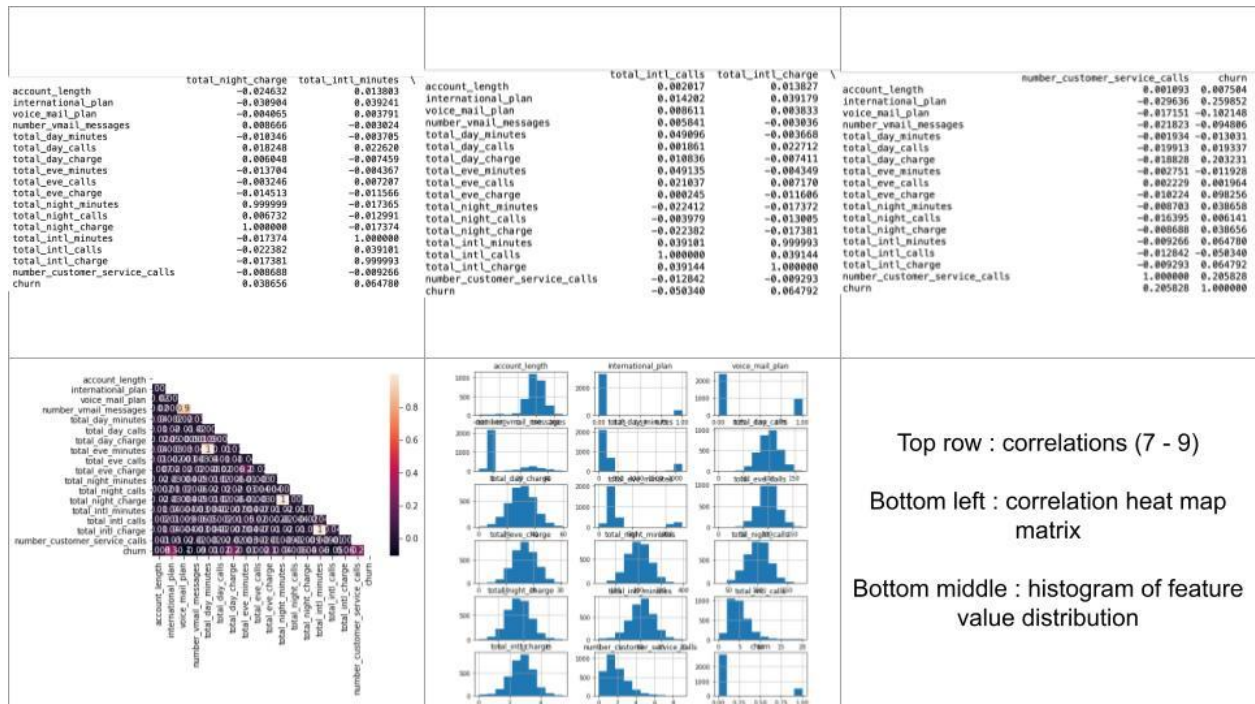


Figure 4

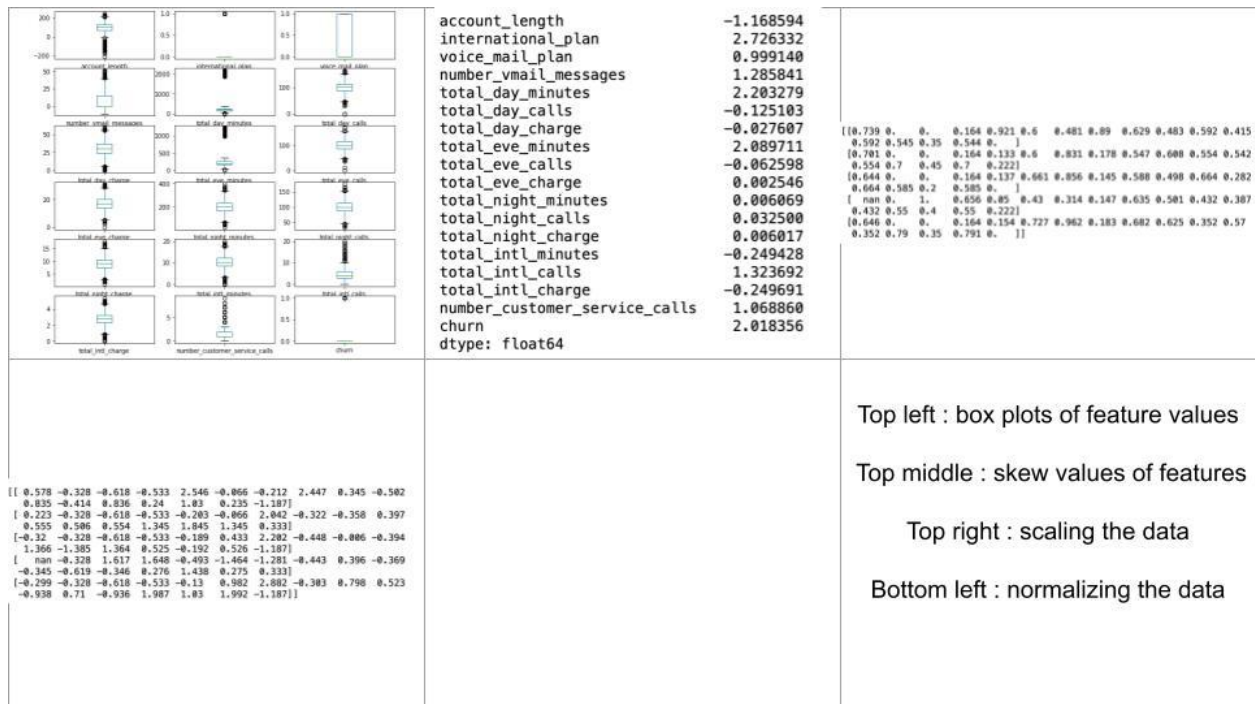


Figure 5