In [1]:
```
%config IPCompleter.greedy=True
```

Phase 3 Project

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SyriaTel Customer Churn

- Build a classifier to predict whether a customer will ("soon") stop doing business with SyriaTel, a telecommunications company. Note that this is a binary classification problem.
- Most naturally, your audience here would be the telecom business itself, interested in losing money on customers who don't stick around very long. Are there any predictable patterns here?

In this investigation on churn for SyriaTel, we will be predicting whether or not a customer will be cancelling their phone plan with SyriaTel. In order to accomplish this, we have been provided with a dataset that includes information regarding customers' phone plan specifics, their phone usage, and their service history.

Furthermore, we will be providing recommendations on how SyriaTel may retain customers more efficiently through the lens of our model. We will inspect which variables had large impacts on customers' decisions to cancel their plan, and suggest campaigns or incentives that will most likely change our customers decisions to leave the service, or retain existing customers for a longer period.

Finally, we will request additional resources or information for SyriaTel to gather in order to show how this process could have been, or could be, improved upon for further investiations.

Data Info

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from scipy import stats

df = pd.read_csv('Data/telecom_data.csv')
df.shape

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In [3]:
```
# we rename columns to work with pandas

df.columns = df.columns.str.strip().str.replace(' ', '_')
```

Our data is collected from a telecom provider with national coverage, representing one month's worth of data on a customer, describing the plan, usage, and service details. The data is split into three types: customer data, plan specifics, and usage data.

Customer Data:

- state
- area_code

- phone_number
- customer_service_calls

Plan Specifics:

- international_plan
- voice_mail_plan

Usage Data:

- number_vmail_messages
- total_day_minutes
- total_day_calls
- total_day_charge
- total_eve_minues
- total_eve_calls
- total_eve_charge
- total_night_minutes
- total_night_calls
- total_night_charge
- total_intl_minutes
- total_intl_calls
- total_intl_charge

In [4]:
```
# we establish placeholder cat/num lists for use in later for loops

catts = []
numms = []

# we fill the lists

for i in df.columns:
    if df[i].dtype == 'object':
        catts.append(i)
    else:
        numms.append(i)
```

In [5]:
```
# we move 'area_code' to categorical

catts.append('area_code')
numms.remove('area_code')

df['area_code'] = df['area_code'].astype('object')
```

Data Cleaning

In [37]:
```
# we inspect our dataframe

df.account_length.describe()
```

Out[37]:
```
count    3333.000000
mean      101.064806
std        39.822106
min         1.000000
25%        74.000000
50%       101.000000
75%       127.000000
max       243.000000
Name: account_length, dtype: float64
```

In [7]:
```
# we define a function for dropping columns safely. We drop 'phone_number' beca

def drop_cols(df, columns):
    for col in columns:
        if col in df.columns:
            df.drop(columns = col, inplace = True)
        if col in catts:
            catts.remove(col)
        if col in numms:
            numms.remove(col)
        else:
            pass
drop_cols(df, ['phone_number'])
df
```

Out[7]:

	state	account_length	area_code	international_plan	voice_mail_plan	number_vmail_messa
0	KS	128	415	no	yes	
1	OH	107	415	no	yes	
2	NJ	137	415	no	no	
3	OH	84	408	yes	no	
4	OK	75	415	yes	no	
...	...	...	...	...	...	
3328	AZ	192	415	no	yes	
3329	WV	68	415	no	no	
3330	RI	28	510	no	no	
3331	CT	184	510	yes	no	
3332	TN	74	415	no	yes	

3333 rows × 20 columns

We need to address 'area_code', a problematic column. There are only three unique values in this column, all area codes belonging to the San Francisco Bay area, while we also have the 'states' column that contradicts this fact, as there are customers all over the US. Because of

this, we will be dropping 'area_code' and utilizing 'state' as our sole location predictor.

In [8]:
```
# we drop "area_code", due to it's inherent conflict with 'states'

df = df.drop('area_code', axis = 1)
```

In [9]:
```
# we change 'churn' from bool to int

df['churn'] *= 1

# we change 'international_plan' and 'voice_mail_plan' from object to int and \

for i in range(len(df)):

    if df['international_plan'][i] == 'yes':
        df['international_plan'][i] = 1
    else:
        df['international_plan'][i] = 0

    if df['voice_mail_plan'][i] == 'yes':
        df['voice_mail_plan'][i] = 1
    else:
        df['voice_mail_plan'][i] = 0

df[['churn', 'international_plan', 'voice_mail_plan']].astype(int)
```

```
C:\Users\rmcar\Anaconda\envs\learn-env\lib\site-packages\ipykernel_launcher.p
y:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  if sys.path[0] == '':
C:\Users\rmcar\Anaconda\envs\learn-env\lib\site-packages\ipykernel_launcher.p
y:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  from ipykernel import kernelapp as app
C:\Users\rmcar\Anaconda\envs\learn-env\lib\site-packages\ipykernel_launcher.p
y:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
C:\Users\rmcar\Anaconda\envs\learn-env\lib\site-packages\ipykernel_launcher.p
y:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  # Remove the CWD from sys.path while we load stuff.
```

Out[9]:

	churn	international_plan	voice_mail_plan
0	0	0	1
1	0	0	1
2	0	0	0
3	0	1	0
4	0	1	0
...	...	...	...
3328	0	0	1
3329	0	0	0
3330	0	0	0
3331	0	1	0
3332	0	0	1

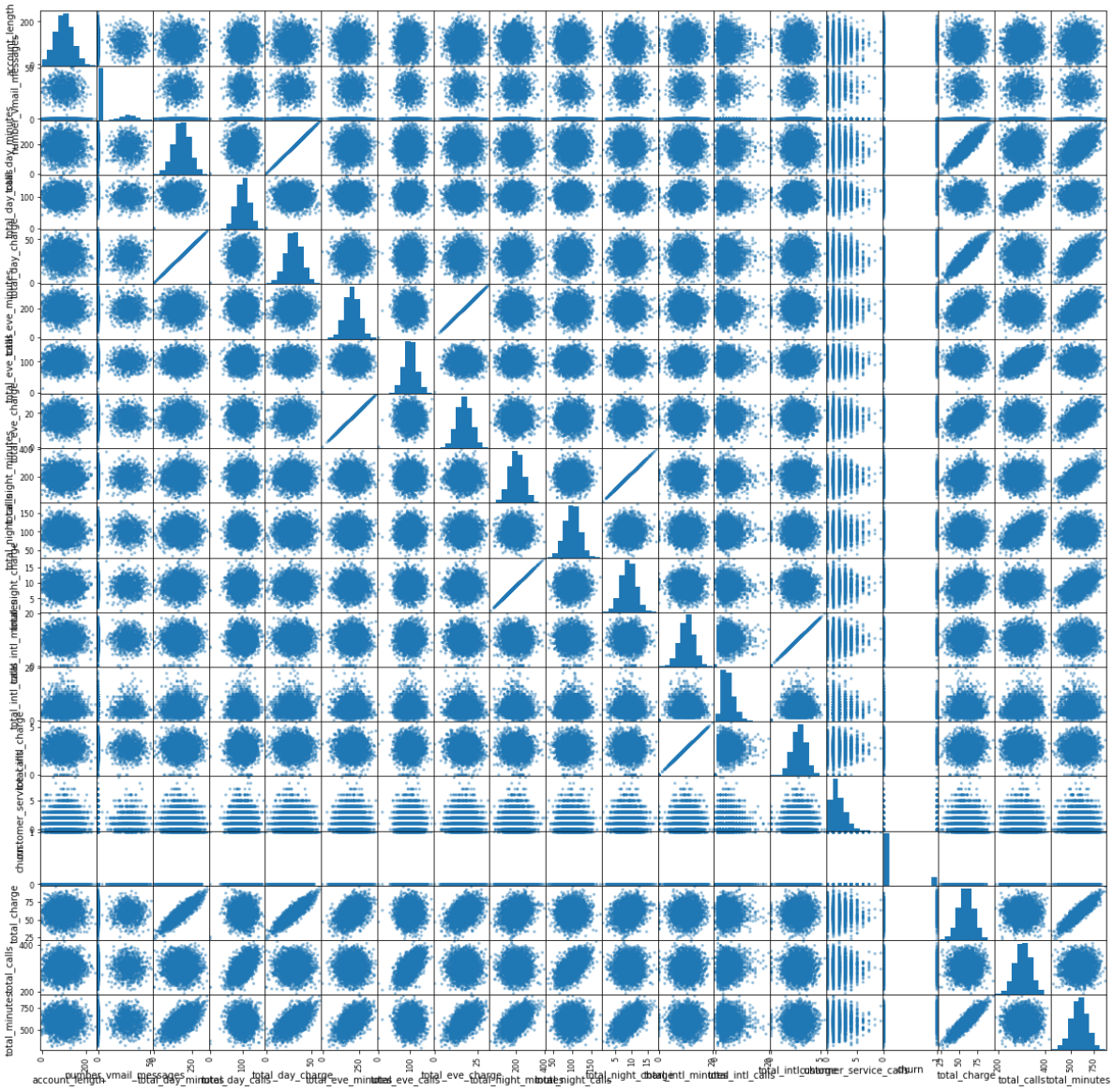
3333 rows × 3 columns

In [10]:
```
# we construct features 'total_charge', 'total_calls', 'total_minutes' and add

df['total_charge'] = df.total_day_charge+df.total_eve_charge+df.total_night_cha
df['total_calls'] = df.total_day_calls+df.total_eve_calls+df.total_night_calls
df['total_minutes'] = df.total_day_minutes+df.total_eve_minutes+df.total_night_

numms.append('total_charge')
numms.append('total_minutes')
numms.append('total_calls')
```

In [11]:
```
# we check for any null values or any duplicate values and find neither

df.columns[df.isnull().any()]

df.duplicated().sum()
```

Out[11]:
```
0
```

In [12]:
```
# we plot a scatter matrix to inspect distributions of predictors

pd.plotting.scatter_matrix(df, figsize = (20, 20))
plt.show()
```



The followig columns are not normally distributed:

- number_vmail_messages
- customer_service_calls

Exploratory Data Analysis

Total Charge investigation

How does Total Charge relate to customer churn?

In [13]:
```
# we compare descriptive statistics for customers who churn vs customers who do

df['total_charge'].where(df['churn'] == 1).describe()
```

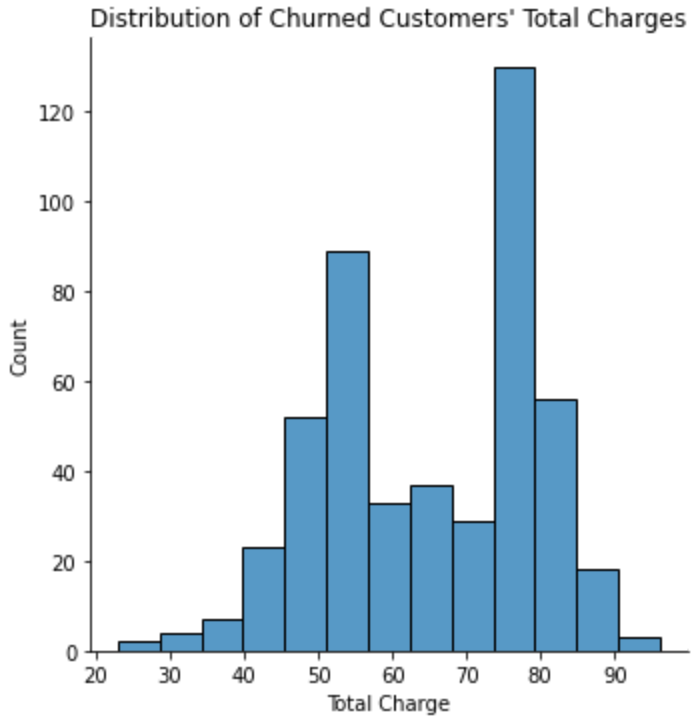
Out[13]:
```
count    483.000000
mean      65.355963
std       13.885268
min       22.930000
25%       53.425000
50%       66.910000
75%       76.655000
max       96.150000
Name: total_charge, dtype: float64
```

In [14]:
```
df['total_charge'].where(df['churn']==0).describe()
```

Out[14]:
```
count    2850.000000
mean       58.448807
std         9.458436
min        23.250000
25%        52.220000
50%        58.920000
75%        65.137500
max        87.290000
Name: total_charge, dtype: float64
```

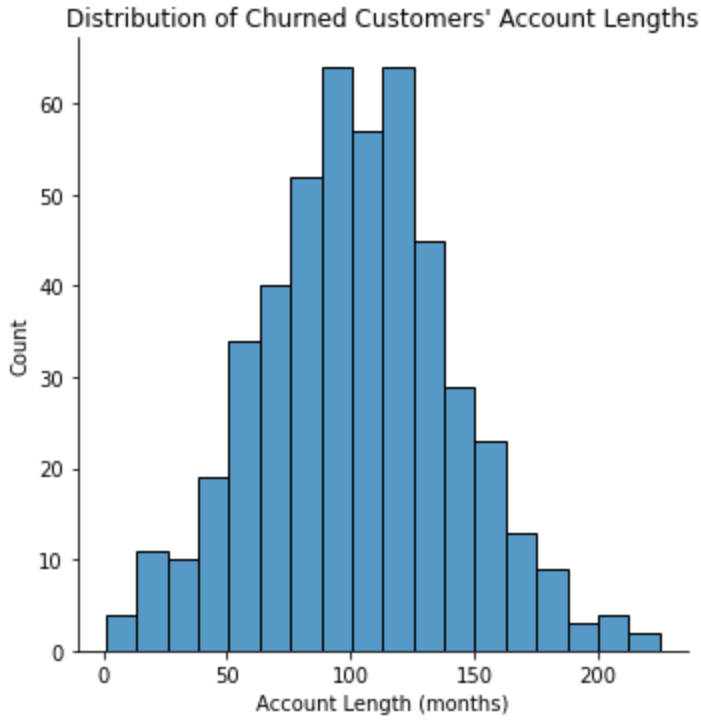
In [38]:
```
# we visualize the distribution of our churned customers charges

sns.displot(data = df.where(df['churn']==1), x = 'total_charge')
plt.title("Distribution of Churned Customers' Total Charges")
plt.xlabel('Total Charge')
```

Out[38]:
```
Text(0.5, 6.79999999999999, 'Total Charge')
```



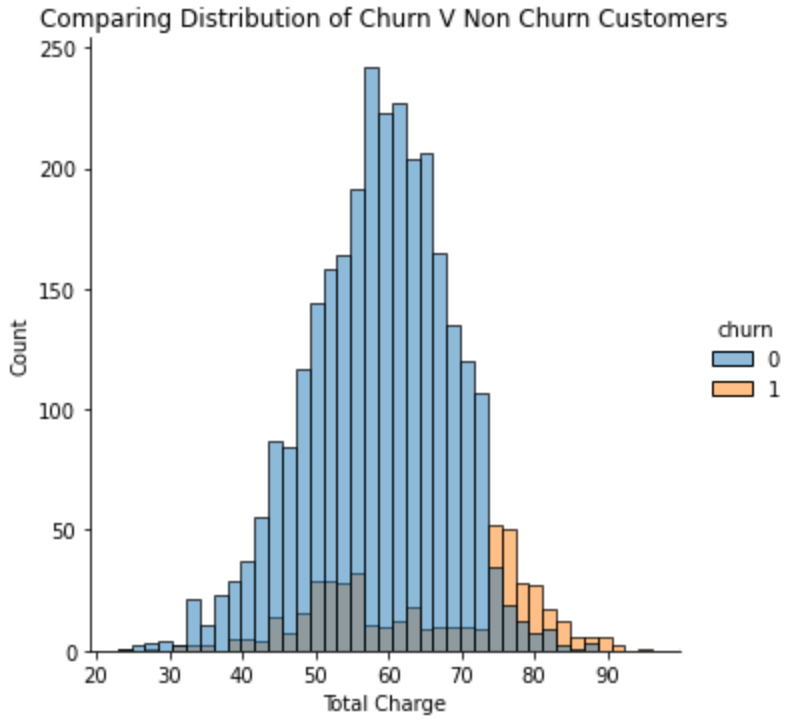
In [41]:
```
# we visualize the distribution of churned customers account_length

sns.displot(data = df.where(df['churn']==1), x = 'account_length')
plt.title("Distribution of Churned Customers' Account Lengths")
plt.xlabel('Account Length (months)')
```

Out[41]:
```
Text(0.5, 6.79999999999999, 'Account Length (months)')
```



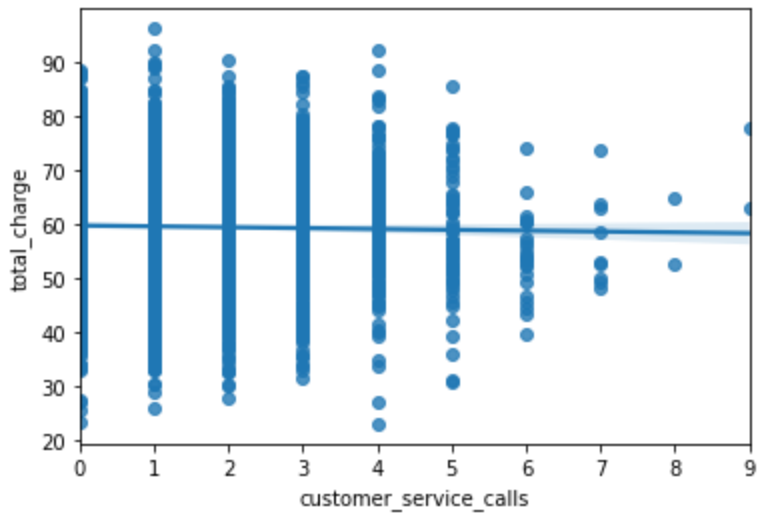
In [16]:
```
# we compare churned customers v retained customers

sns.displot(data = df, x = 'total_charge', hue = 'churn')
plt.title('Comparing Distribution of Churn V Non Churn Customers')
plt.xlabel('Total Charge')
```

Out[16]:
```
Text(0.5, 6.79999999999999, 'Total Charge')
```



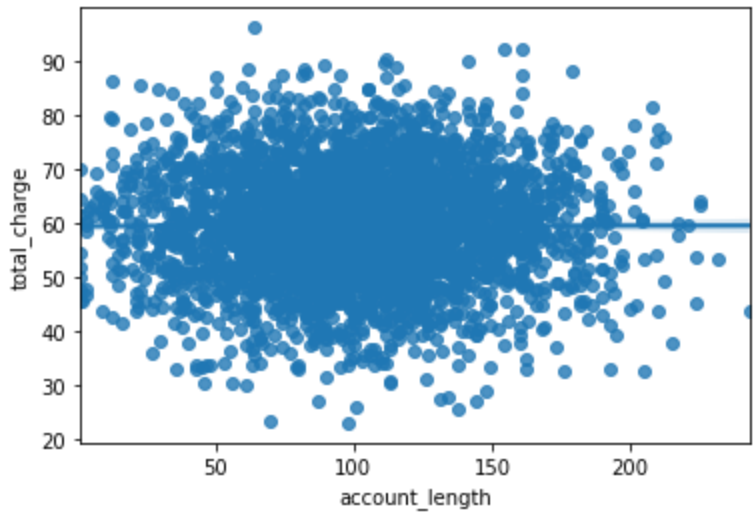
In [17]:
```
# we check for relationships between total_charge and other predictors, finding

sns.regplot(data = df, x = 'customer_service_calls', y = 'total_charge')
```

Out[17]:
```
<AxesSubplot:xlabel='customer_service_calls', ylabel='total_charge'>
```



In [18]:
```
sns.regplot(data = df, x = 'account_length', y = 'total_charge')
```

Out[18]:
```
<AxesSubplot:xlabel='account_length', ylabel='total_charge'>
```



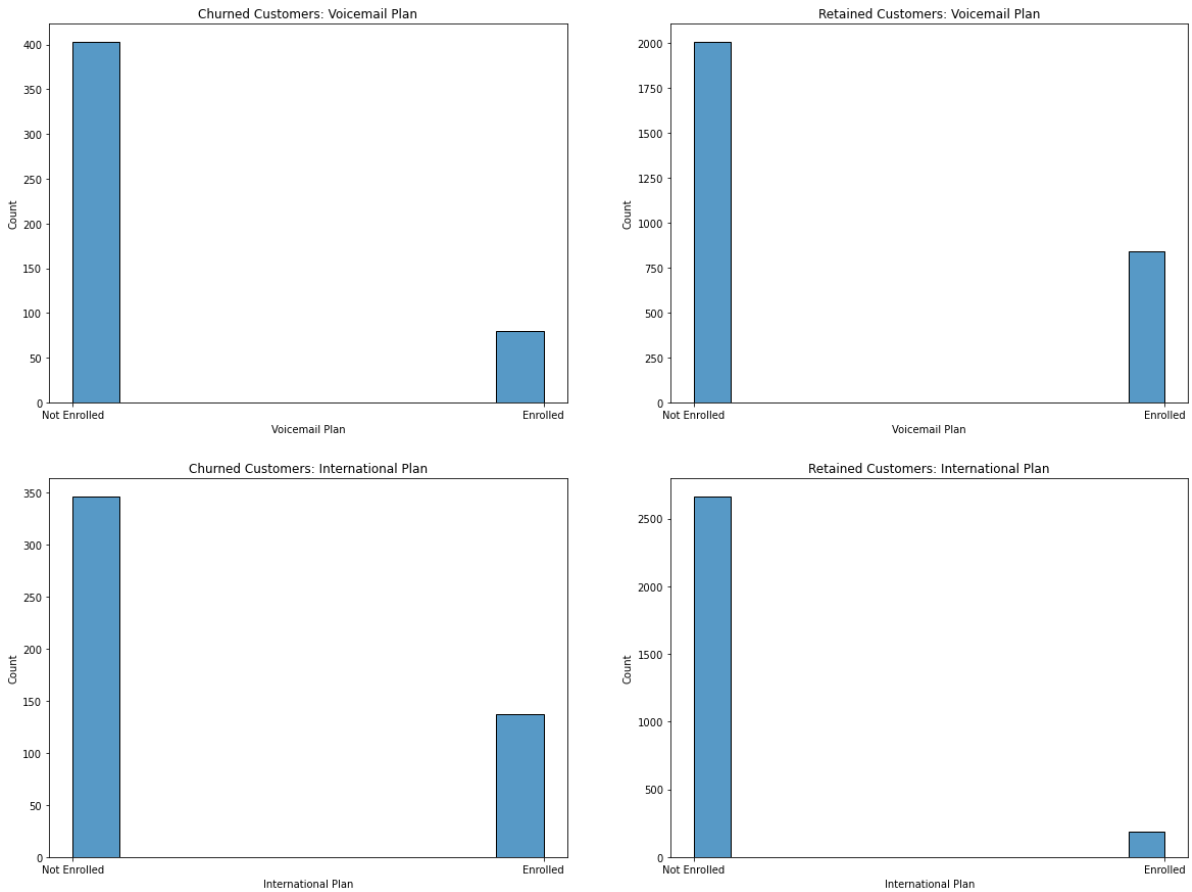
Conclusions on Total_Cost investigation

- The distribution of churned customers suggests that there are two different clusters of payments. Because of this, we expect that some sort of promotional campaign was in place during the last month for SyriaTel customers. These customers were paying less for a promotional period, then either churned out, resulting in the lower of the two clusters, or stayed on and churned later on, resulting in the second cluster.
- On average, customers who churn pay more than retained customers.

Extra Plan Investigation

Does being enrolled in an additional service (Voicemail or International) contribute to churn or retention?

In [29]:
```
# we visualize the different types of customers and plans, finding that interna

fig, axes = plt.subplots(nrows = 2, ncols = 2, figsize = (20, 15))

x_range = [0, 1]
x_labels = ['Not Enrolled', 'Enrolled']

sns.histplot(ax = axes[0][0], data = df.where(df['churn']==1), x = 'voice_mail_
sns.histplot(ax = axes[0][1], data = df.where(df['churn']==0), x = 'voice_mail_
sns.histplot(ax = axes[1][0], data = df.where(df['churn']==1), x = 'internatio
sns.histplot(ax = axes[1][1], data = df.where(df['churn']==0), x = 'internatio
plt.show()
```



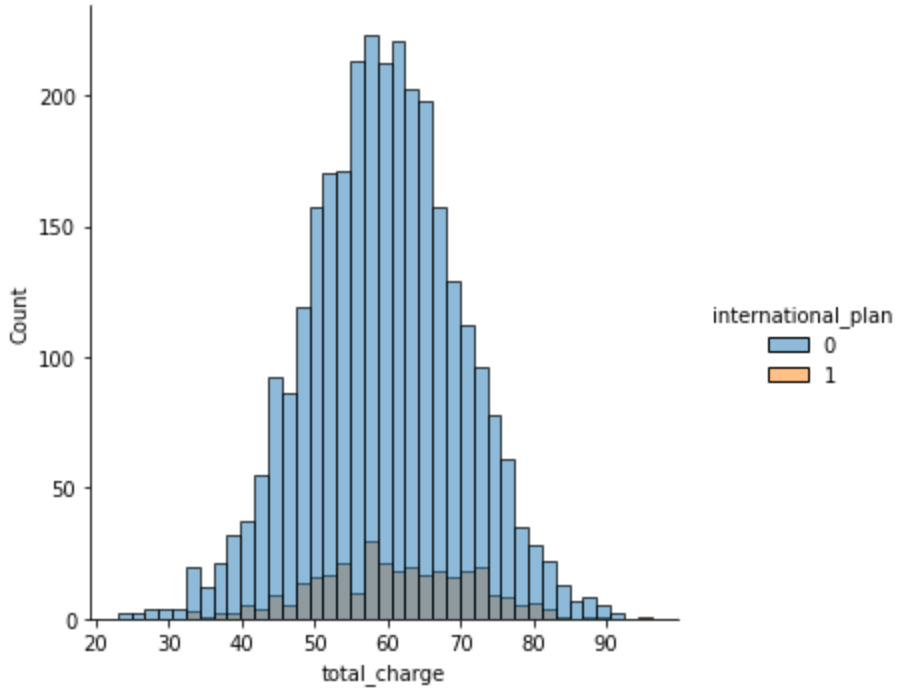
In [36]:
```
# we find the percentage of international customers who churned this month

df_intl = df.where(df['international_plan'] == 1)
df_intl = df_intl.dropna()

df_intl['churn'].sum() / len(df_intl)
```

Out[36]:
```
0.4241486068111455
```

Type *Markdown* and LaTeX: α^2

In [20]:
```
sns.displot(data = df, x = 'total_charge', hue = 'international_plan')
```

Out[20]:
```
<seaborn.axisgrid.FacetGrid at 0x252f2520748>
```



Conclusions on Plan Investigation:

- Customers are genearally satisfied with SyriaTel's voicemail plan. This is shown by rthe high ratio of enrolled customers in our 'Retained Customers: Voicemail Plan' visualization.
- Conversely, customers are very unsatisfied with SyriaTel's international plan. This is shown for the same reason, the high ratio of enrolled customers in our 'Churned Customers: International Plan' visualization.

Location Investigation

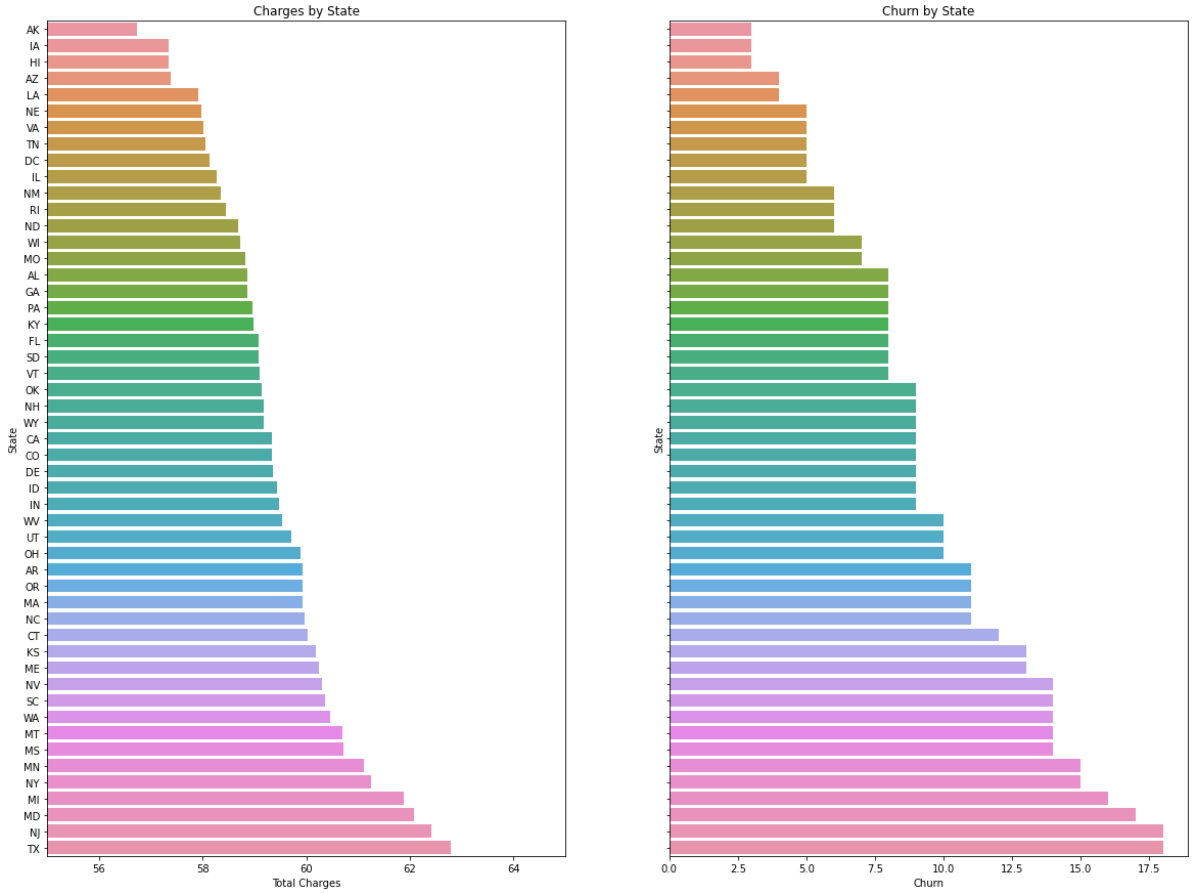
What does each state pay for their phone service on average?

What is the churn rate by state?

How does churn relate to total charge?

In [21]:
```
# we construct a dataframe that contains state and total charge by state

df_states = pd.DataFrame(df.groupby('state')['total_charge'].mean())
df_states = df_states.sort_values(['total_charge'])
df_states = df_states.reset_index()

# we add a column for number of churned customers by state

df_states_churn = pd.DataFrame(df.groupby('state')['churn'].sum())
df_states_churn = df_states_churn.sort_values(['churn'])
df_states_churn = df_states_churn.reset_index()
df_states['churn_sum'] = df_states_churn['churn']
```

In [22]:
```
# we visualize the above dataframe

fig, axes = plt.subplots(nrows = 1, ncols = 2, figsize = (20, 15), sharey = Tru
sns.barplot(ax = axes[0], y = df_states['state'], x = df_states['total_charge']
sns.barplot(ax = axes[1], y = df_states_churn['state'], x = df_states_churn['ch
plt.show()
```



Conclusions on Location Investigation

- While there is no real trend for churn or payments geographically (the distribution of payments is generally random), we can see that the relationship between large charges and churn is positive.

A note on our features:

- We need to choose between using totals versus breakdowns of minutes, charge, and calls. Including all of these columns will lead to intense multicollinearity issues, so it is best to drop what will impede us now.
- let us drop charge breakdowns, using only Total_charge.
- let us keep minutes and call breakdowns, dropping Total_minutes and Total_calls.

In [23]:
```
# we drop columns that we know will have independence issues

drop_cols(df, ['total_day_charge', 'total_night_charge', 'total_eve_charge', '
```

In [24]:
```
# we inspect the final dataframe to ensure that it is fully cleaned and ready t

df.columns
```

Out[24]:
```
Index(['state', 'account_length', 'international_plan', 'voice_mail_plan',
       'number_vmail_messages', 'total_day_minutes', 'total_day_calls',
       'total_eve_minutes', 'total_eve_calls', 'total_night_minutes',
       'total_night_calls', 'total_intl_minutes', 'total_intl_calls',
       'customer_service_calls', 'churn', 'total_charge'],
      dtype='object')
```

In [25]:
```
df.shape
```

Out[25]:
```
(3333, 16)
```

In [26]:
```
df.head()
```

Out[26]:

	state	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_day_
0	KS	128	0	1	25	
1	OH	107	0	1	26	
2	NJ	137	0	0	0	
3	OH	84	1	0	0	
4	OK	75	1	0	0	

In [27]:
```
catts, numms
```

Out[27]:
```
(['state', 'international_plan', 'voice_mail_plan', 'area_code'],
 ['account_length',
  'number_vmail_messages',
  'total_day_minutes',
  'total_day_calls',
  'total_eve_minutes',
  'total_eve_calls',
  'total_night_minutes',
  'total_night_calls',
  'total_intl_minutes',
  'total_intl_calls',
  'customer_service_calls',
  'churn',
  'total_charge'])
```

In [28]:
```
# finally, we save our cleaned dataframe to our data folder.

df.to_csv(r'..\dsc-phase-3-project\Data\cleaned_data.csv')
```