Final Project Submission

Please fill out:

- Student name: Guofa Shou
- Student pace: self paced
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Business Understanding

I firstly do the business understanding by the following questions and answers

In [218]:

```
# Q: Who are the stakeholders in this project? Who will be directly affected by the creatio
# A: The stakeholder is the SyriaTel, a telecommunications company.
# Q: What business problem(s) will this Data Science project solve for the organization?
# A: 1) Who will be stick on the company and who will stop doing business with the company
#       and classification models performed.
#    2) Based on identified patterns, suggestions in different aspects could be given to th
#       the customers stick on the company
# Q: What data sources are available to us?
# A: the file bigml_59c28831336c6604c800002a.csv includes information for different custome
```

Data Understanding

Now, I import the data and examine what data are available.

In [219]:

```
# Import necessary basic libraries
import warnings
warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import pandas as pd
import numpy as np
```

In [220]:

```
# load data into dataframe
df = pd.read_csv('./data/bigml_59c28831336c6604c800002a.csv')
# take a look the first 5 rows to get an idea about the data
df.head()
```

Out[220]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...

5 rows × 21 columns

In [221]:

```
# What data is available and is there any missing values in any columns
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
```

There are 20 features and one target, i.e., churn, and no missing data from all columns

Data Preparation

In [222]:

```
# Deal with column names:
# since there are spaces in the column names, I want to repalce it with '_' for better nami
df.columns = df.columns.str.replace(' ', '_')
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 [223]:

```
# Deal with phone number: drop it since it generally does not affect the customer churn
len(df['phone_number'].unique())
# all phone_number are unique
df = df.drop('phone_number',axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 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   international_plan      3333 non-null   object 
 4   voice_mail_plan         3333 non-null   object 
 5   number_vmail_messages   3333 non-null   int64  
 6   total_day_minutes       3333 non-null   float64
 7   total_day_calls         3333 non-null   int64  
 8   total_day_charge        3333 non-null   float64
 9   total_eve_minutes       3333 non-null   float64
 10  total_eve_calls         3333 non-null   int64  
 11  total_eve_charge        3333 non-null   float64
 12  total_night_minutes     3333 non-null   float64
 13  total_night_calls       3333 non-null   int64  
 14  total_night_charge      3333 non-null   float64
 15  total_intl_minutes      3333 non-null   float64
 16  total_intl_calls        3333 non-null   int64  
 17  total_intl_charge       3333 non-null   float64
 18  customer_service_calls  3333 non-null   int64  
 19  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 498.1+ KB
```

In [224]:

```
# Deal with 'state','international_plan' and 'voice_mail_plan':
objcols = ['state','international_plan','voice_mail_plan']
for i,col in enumerate(objcols):
    print(f"Unique values in {col}:  {df[col].unique()} \n")

# For international_plan and voice_mail_plan, convert 'yes' and 'no' into 1 and 0 for
df['international_plan'].replace(('yes', 'no'), (1, 0), inplace = True)
df['voice_mail_plan'].replace(('yes', 'no'), (1, 0), inplace = True)

# for 'state', use onehotencoder late since it has multiple values
for i,col in enumerate(objcols):
    print(f"Unique values in {col}:  {df[col].unique()} \n")
```

```
Unique values in state:  ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN'
'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']

Unique values in international_plan:  ['no' 'yes']

Unique values in voice_mail_plan:  ['yes' 'no']

Unique values in state:  ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN'
'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']

Unique values in international_plan:  [0 1]

Unique values in voice_mail_plan:  [1 0]
```

In [225]:

```
# Deal with 'churn': convert boolean into int
df['churn'] = df['churn'].astype(int)
df.churn.value_counts()
# it is imbalanced, might use SMOTE for imbalanced data
```

Out[225]:

```
0    2850
1     483
Name: churn, dtype: int64
```

In [226]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 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   international_plan      3333 non-null   int64  
 4   voice_mail_plan         3333 non-null   int64  
 5   number_vmail_messages   3333 non-null   int64  
 6   total_day_minutes       3333 non-null   float64
 7   total_day_calls         3333 non-null   int64  
 8   total_day_charge        3333 non-null   float64
 9   total_eve_minutes       3333 non-null   float64
 10  total_eve_calls         3333 non-null   int64  
 11  total_eve_charge        3333 non-null   float64
 12  total_night_minutes     3333 non-null   float64
 13  total_night_calls       3333 non-null   int64  
 14  total_night_charge      3333 non-null   float64
 15  total_intl_minutes      3333 non-null   float64
 16  total_intl_calls        3333 non-null   int64  
 17  total_intl_charge       3333 non-null   float64
 18  customer_service_calls  3333 non-null   int64  
 19  churn                   3333 non-null   int32  
dtypes: float64(8), int32(1), int64(10), object(1)
memory usage: 507.9+ KB
```

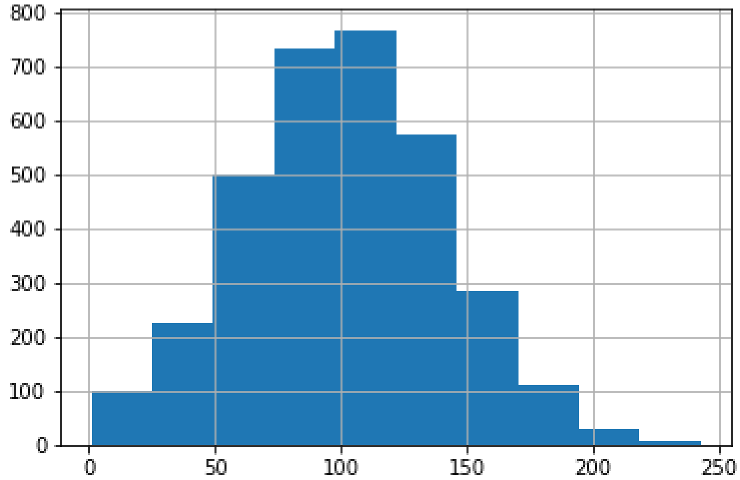
now all data except state are in good format

Feature examination

examine every features

In [227]:

```
# 'account_length'
df['account_length'].hist()
plt.savefig('figures/accountlen_hist.png')
# account_length is discrete values and follow a normal distribution, and it is more like t
```



In [228]:

```
# The area_code
print(f"Unique values in area_code:  {df['area_code'].unique()} \n")
# it has three unique values in area_code,
# it is interesting to see whether the churn rate is similar or not across three area_code
print(df.groupby(["area_code"])['churn'].mean())
# It seems the churn rates are similar across three area codes, therefore, this feature can
```

```
Unique values in area_code:  [415 408 510]

area_code
408    0.145585
415    0.142598
510    0.148810
Name: churn, dtype: float64
```

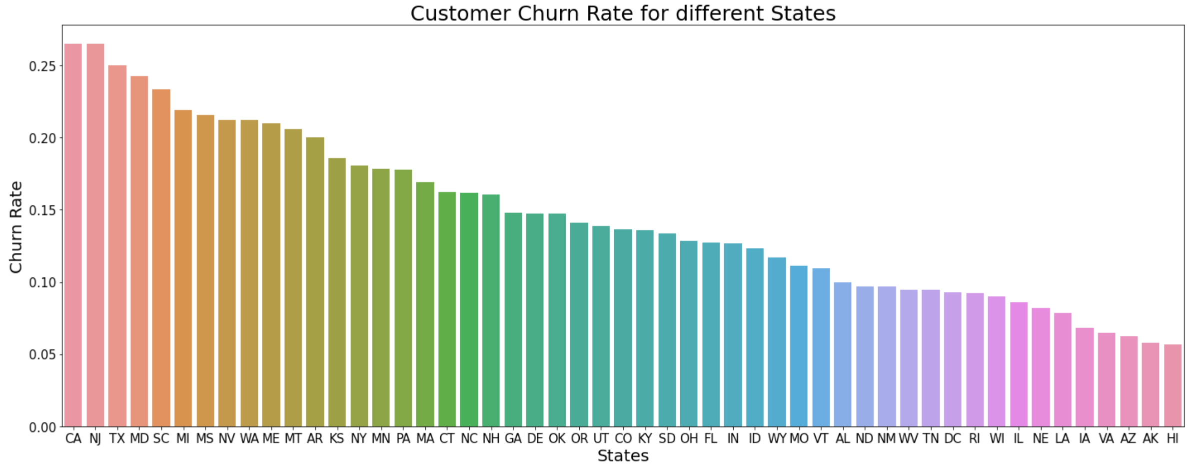
In [229]:

```
# The state: to see whether different states have different churn rate
churn_rate_state = pd.DataFrame(df.groupby(["state"])['churn'].mean().sort_values(ascending
print(churn_rate_state)
```

```
          churn
state
CA     0.264706
NJ     0.264706
TX     0.250000
MD     0.242857
SC     0.233333
MI     0.219178
MS     0.215385
NV     0.212121
WA     0.212121
ME     0.209677
MT     0.205882
AR     0.200000
KS     0.185714
NY     0.180723
MN     0.178571
PA     0.177778
MA     0.169231
CT     0.162162
NC     0.161765
NH     0.160714
GA     0.148148
DE     0.147541
OK     0.147541
OR     0.141026
UT     0.138889
CO     0.136364
KY     0.135593
SD     0.133333
OH     0.128205
FL     0.126984
IN     0.126761
ID     0.123288
WY     0.116883
MO     0.111111
VT     0.109589
AL     0.100000
ND     0.096774
NM     0.096774
WV     0.094340
TN     0.094340
DC     0.092593
RI     0.092308
WI     0.089744
IL     0.086207
NE     0.081967
LA     0.078431
IA     0.068182
VA     0.064935
AZ     0.062500
AK     0.057692
HI     0.056604
```

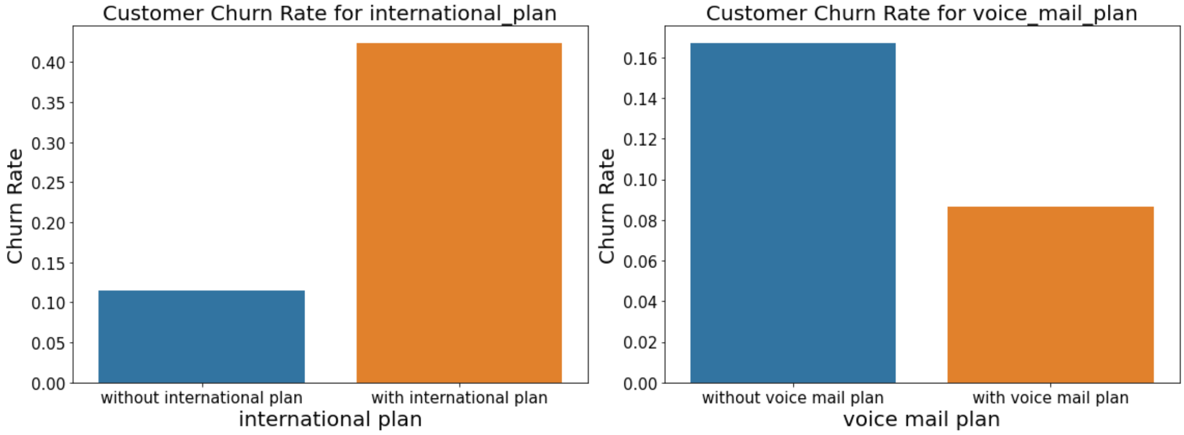
In [230]:

```
# visualization it since it have many states
fig, ax = plt.subplots(figsize=(20,8))
sns.barplot(x = np.linspace(0, len(churn_rate_state)-1, len(churn_rate_state), endpoint=Tru
            y = 'churn', data = churn_rate_state , ax = ax)
plt.title('Customer Churn Rate for different States', fontsize = 25)
ax.tick_params(axis = 'both', labelsize = 15)
plt.xlabel('States', fontsize = 20)
plt.ylabel('Churn Rate', fontsize = 20)
ax.set_xticklabels(churn_rate_state.index)
plt.tight_layout()
plt.savefig('figures/churnrate_states.png')
# Different states have different churn rate, CA and NJ are the two highest churn rate stat
# while AK and HI are the two lowest churn rate states < 6%
```



In [231]:

```
# international_plan and voice_mail_plan:
# whether the different conditions in these two have different churn rates?
churn_rate_interplan = pd.DataFrame(df.groupby(["international_plan"])['churn'].mean())
churn_rate_voiceplan = pd.DataFrame(df.groupby(["voice_mail_plan"])['churn'].mean())
fig, ax = plt.subplots(1,2,figsize=(16,6))
sns.barplot(x = [0,1], y = 'churn', data = churn_rate_interplan, ax = ax[0])
ax[0].set_title('Customer Churn Rate for international_plan', fontsize = 20)
ax[0].tick_params(axis = 'both', labelsize = 15)
ax[0].set_xlabel('international plan', fontsize = 20)
ax[0].set_ylabel('Churn Rate', fontsize = 20,)
ax[0].set_xticklabels(['without international plan','with international plan'])

sns.barplot(x = [0,1], y = 'churn', data = churn_rate_voiceplan, ax = ax[1])
ax[1].set_title('Customer Churn Rate for voice_mail_plan', fontsize = 20)
ax[1].tick_params(axis = 'both', labelsize = 15)
ax[1].set_xlabel('voice mail plan', fontsize = 20)
ax[1].set_ylabel('Churn Rate', fontsize = 20)
ax[1].set_xticklabels(['without voice mail plan','with voice mail plan'])
plt.tight_layout()
plt.savefig('figures/churnrate_intervoiceplans.png')
# The customer with international plan has a higher churn rate
# The customer with voice mail plan has a lower churn rate
```

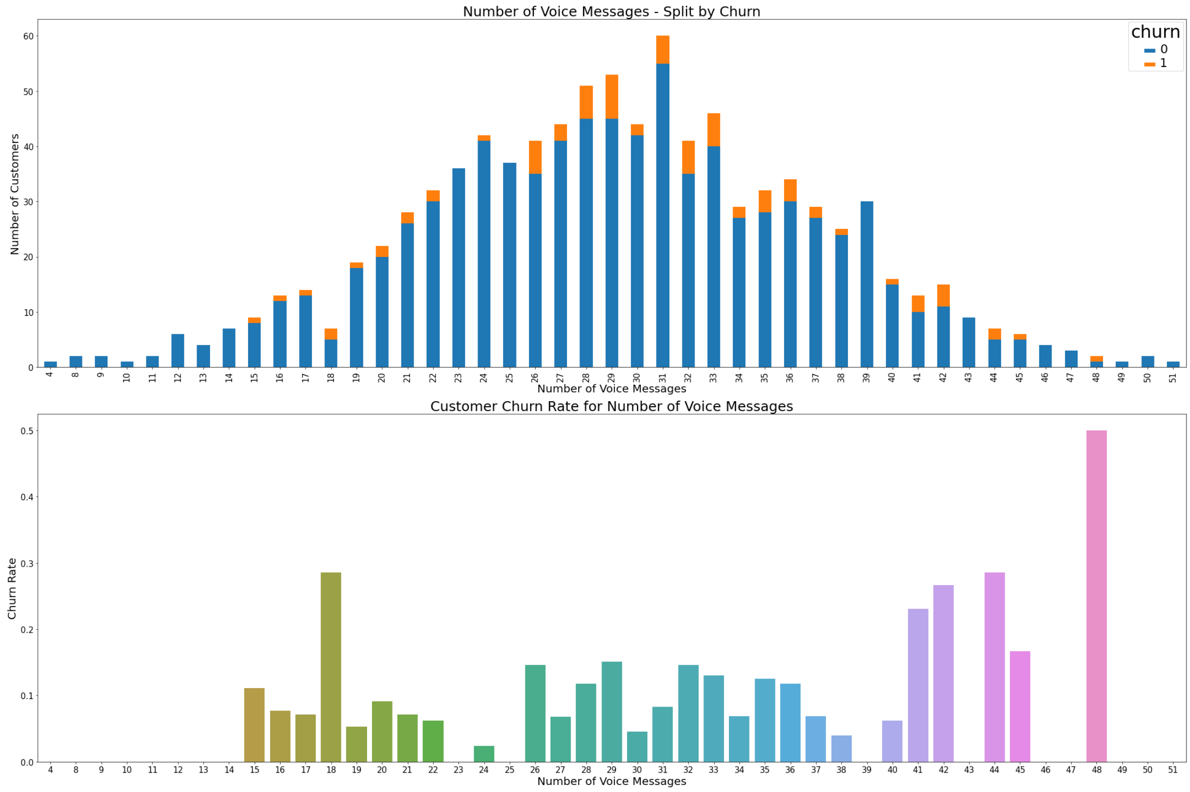


In [232]:

```
# number_vmail_messages:
print(df['number_vmail_messages'].value_counts())
# there is a larger number of customers with 0 number of voice messages
# I will drop the rows == 0 and only examine the customers with number of voice messages
df_nonzero = df[df['number_vmail_messages']>0]

fig, ax = plt.subplots(2,1,figsize = (30, 20))
# how many customers with churn=1 or 1 with respect to different number of voice messages
df_nonzero.groupby(['number_vmail_messages', 'churn']).size().unstack().plot(kind='bar', st
ax[0].set_title('Number of Voice Messages - Split by Churn', fontsize = 25)
ax[0].tick_params(axis = 'both', labelsize = 15)
ax[0].set_xlabel('Number of Voice Messages', fontsize = 20)
ax[0].set_ylabel('Number of Customers', fontsize = 20)
plt.setp(ax[0].get_legend().get_texts(), fontsize='22') # for legend text
plt.setp(ax[0].get_legend().get_title(), fontsize='32') # for legend title

# The churn rate for the customers with different number of voice messages
churn_rate_nvmail = pd.DataFrame(df_nonzero.groupby(["number_vmail_messages"])['churn'].mea
sns.barplot(x = np.linspace(0, len(churn_rate_nvmail)-1, len(churn_rate_nvmail), endpoint=T
            y = 'churn', data = churn_rate_nvmail , ax = ax[1])
ax[1].set_title('Customer Churn Rate for Number of Voice Messages', fontsize = 25)
ax[1].tick_params(axis = 'both', labelsize = 15)
ax[1].set_xlabel('Number of Voice Messages', fontsize = 20)
ax[1].set_ylabel('Churn Rate', fontsize = 20)
ax[1].set_xticklabels(churn_rate_nvmail.index)
plt.tight_layout()
plt.show()
plt.savefig('figures/churnrate_numvmailmges.png')
# This feature seems not well sampled, since there are too many customers in the survey has
# Meanwhile, this feature also have some relationship with the churn rate
```

```
0     2411
31      60
29      53
28      51
33      46
27      44
30      44
24      42
26      41
32      41
25      37
23      36
36      34
35      32
22      32
39      30
37      29
34      29
21      28
38      25
20      22
19      19
40      16
42      15
17      14
41      13
16      13
43       9
```

```
15        9
18        7
44        7
14        7
45        6
12        6
46        4
13        4
47        3
8         2
48        2
50        2
9         2
11        2
49        1
10        1
4         1
51        1
Name: number_vmail_messages, dtype: int64
```

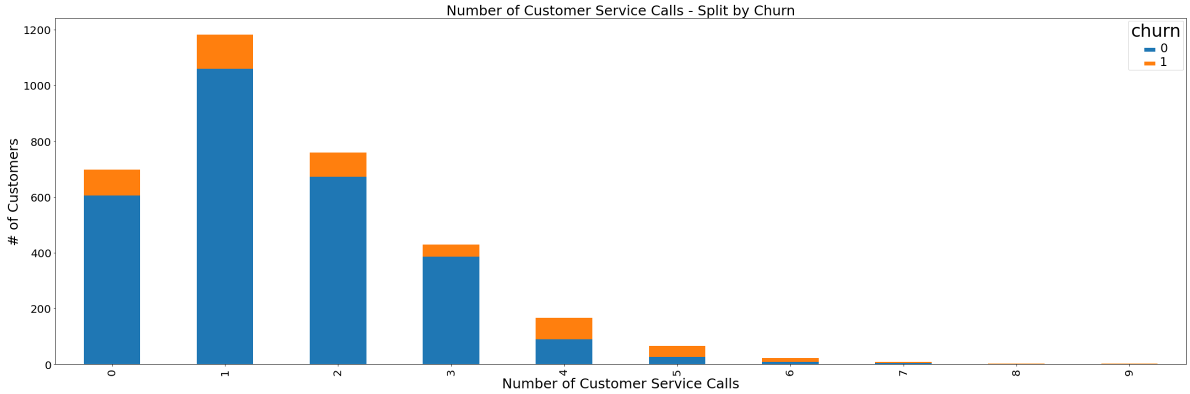


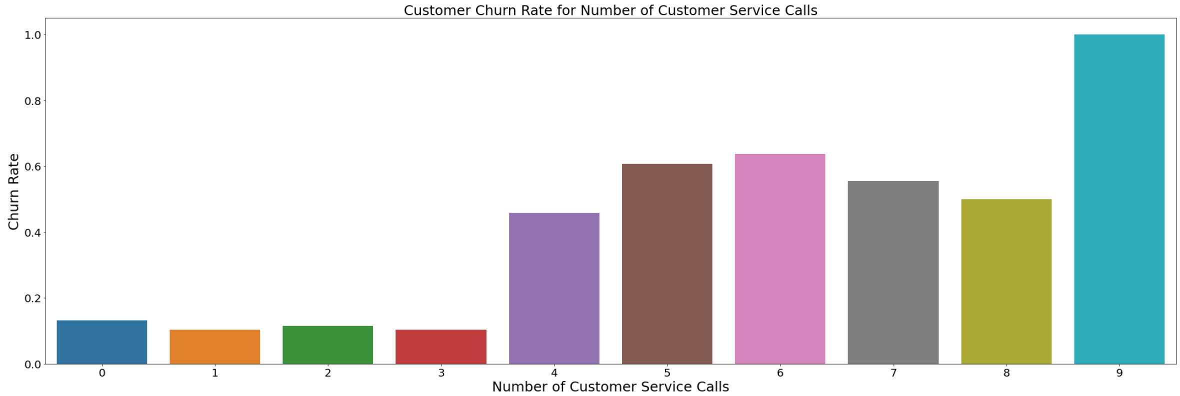

```
<Figure size 432x288 with 0 Axes>
```

In [233]:

```
# customer_service_calls: do the same plot as for number_vmail_message
print(df['customer_service_calls'].value_counts())

fig, ax = plt.subplots(2,1,figsize = (30, 20))
df.groupby(['customer_service_calls', 'churn']).size().unstack().plot(kind='bar', stacked=T
ax[0].set_title('Number of Customer Service Calls - Split by Churn', fontsize = 25)
ax[0].tick_params(axis = 'both', labelsize = 20)
ax[0].set_xlabel('Number of Customer Service Calls', fontsize = 25)
ax[0].set_ylabel('# of Customers', fontsize = 25)
plt.setp(ax[0].get_legend().get_texts(), fontsize='22') # for legend text
plt.setp(ax[0].get_legend().get_title(), fontsize='32') # for legend title
#plt.show()
churn_rate_csercalls = pd.DataFrame(df.groupby(["customer_service_calls"])['churn'].mean())

sns.barplot(x = np.linspace(0, len(churn_rate_csercalls)-1, len(churn_rate_csercalls), endp
            y = 'churn', data = churn_rate_csercalls , ax = ax[1])
ax[1].set_title('Customer Churn Rate for Number of Customer Service Calls', fontsize = 25)
ax[1].tick_params(axis = 'both', labelsize = 20)
ax[1].set_xlabel('Number of Customer Service Calls', fontsize = 25)
ax[1].set_ylabel('Churn Rate', fontsize = 25)
ax[1].set_xticklabels(churn_rate_csercalls.index)
plt.tight_layout()
plt.show()
plt.savefig('figures/churnrate_custsercalls.png')
# customers with number of service calls as 4,5,6 seems have larger churn rate
```

```
1    1181
2     759
0     697
3     429
4     166
5      66
6      22
7       9
9       2
8       2
Name: customer_service_calls, dtype: int64
```






```
<Figure size 432x288 with 0 Axes>
```

In [234]:

```
# The remaining features related to calls and charges within four different categories: day
# These items might have some correlation
call_cols = ['total_day_minutes', 'total_day_calls', 'total_day_charge',
             'total_eve_minutes', 'total_eve_calls', 'total_eve_charge',
             'total_night_minutes', 'total_night_calls', 'total_night_charge',
             'total_intl_minutes', 'total_intl_calls', 'total_intl_charge']

df_callrelated = df[call_cols]
df_callrelated.corr()
# It indicates the minutes and charge in each category has close to 1 correlation,
# so I will drop the columns of charge in the following classification models
```

Out[234]:

	total_day_minutes	total_day_calls	total_day_charge	total_eve_minutes	tota
total_day_minutes	1.000000	0.006750	1.000000	0.007043	
total_day_calls	0.006750	1.000000	0.006753	-0.021451	
total_day_charge	1.000000	0.006753	1.000000	0.007050	
total_eve_minutes	0.007043	-0.021451	0.007050	1.000000	
total_eve_calls	0.015769	0.006462	0.015769	-0.011430	
total_eve_charge	0.007029	-0.021449	0.007036	1.000000	
total_night_minutes	0.004323	0.022938	0.004324	-0.012584	
total_night_calls	0.022972	-0.019557	0.022972	0.007586	
total_night_charge	0.004300	0.022927	0.004301	-0.012593	
total_intl_minutes	-0.010155	0.021565	-0.010157	-0.011035	
total_intl_calls	0.008033	0.004574	0.008032	0.002541	
total_intl_charge	-0.010092	0.021666	-0.010094	-0.011067	

Building classification models

In [235]:

```
# import necessary modules
from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, AdaBoostClassifier,
from imblearn.over_sampling import SMOTE
from sklearn.metrics import accuracy_score,confusion_matrix,recall_score,f1_score,plot_conf
```

In [236]:

```
# Based on the feature exploration described above, I will build a initial model after drop
# Target y:
y = df['churn']
X = df.drop(['churn','area_code','total_day_charge','total_eve_charge','total_night_charge'
X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=42,test_size=0.25)
X_train.head()
```

Out[236]:

	state	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_
367	MD	45	0	0	0	
3103	DE	115	0	0	0	
549	OK	121	0	1	31	
2531	RI	180	0	0	0	
2378	OR	112	0	0	0	

In [237]:

```
# For 'state', I will do oneHotEncoder for both X_train and X_test
ohe = OneHotEncoder(sparse=False,handle_unknown = "ignore")
ohe.fit(X_train[['state']])
state_train_ohe = pd.DataFrame(ohe.transform(X_train[["state"]]),
                               index = X_train.index,
                               columns = ohe.categories_[0])
X_train = pd.concat([X_train.drop("state", axis = 1), state_train_ohe], axis = 1)
print('========== X_train ===========\n')
print(X_train.head())

ohe.fit(X_test[['state']])
state_test_ohe = pd.DataFrame(ohe.transform(X_test[["state"]]),
                               index = X_test.index,
                               columns = ohe.categories_[0])
X_test = pd.concat([X_test.drop("state", axis = 1), state_test_ohe], axis = 1)
print('========== X_test ===========\n')
X_test.head()
```

```
========== X_train ===========

      account_length  international_plan  voice_mail_plan  \
367               45                   0                0
3103             115                   0                0
549              121                   0                1
2531             180                   0                0
2378             112                   0                0

      number_vmail_messages  total_day_minutes  total_day_calls  \
367                       0               78.2              127
3103                      0              195.9              111
549                      31              237.1               63
2531                      0              143.3              134
2378                      0              206.2              122

      total_eve_minutes  total_eve_calls  total_night_minutes  \
367               253.4              108                255.0
3103              227.0              108                313.2
549               205.6              117                196.7
2531              180.5              113                184.2
2378              164.5               94                140.3

      total_night_calls  ...   SD   TN   TX   UT   VA   VT   WA   WI   WV
WY
367                 100  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0
3103                113  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0
549                  85  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0
2531                 87  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0
2378                101  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
0.0

[5 rows x 64 columns]
========== X_test ===========
```

Out[237]:

	account_length	international_plan	voice_mail_plan	number_vmail_messages	total_day_m
438	113	0	0	0	
2674	67	0	0	0	
1345	98	0	0	0	
1957	147	0	0	0	
2148	96	0	0	0	

5 rows × 64 columns

In [238]:

```
# Check the percentage of different churn numbers
y_train.value_counts()
# it is imbalanced and need SMOTE oversampling
```

Out[238]:

```
0    2141
1     358
Name: churn, dtype: int64
```

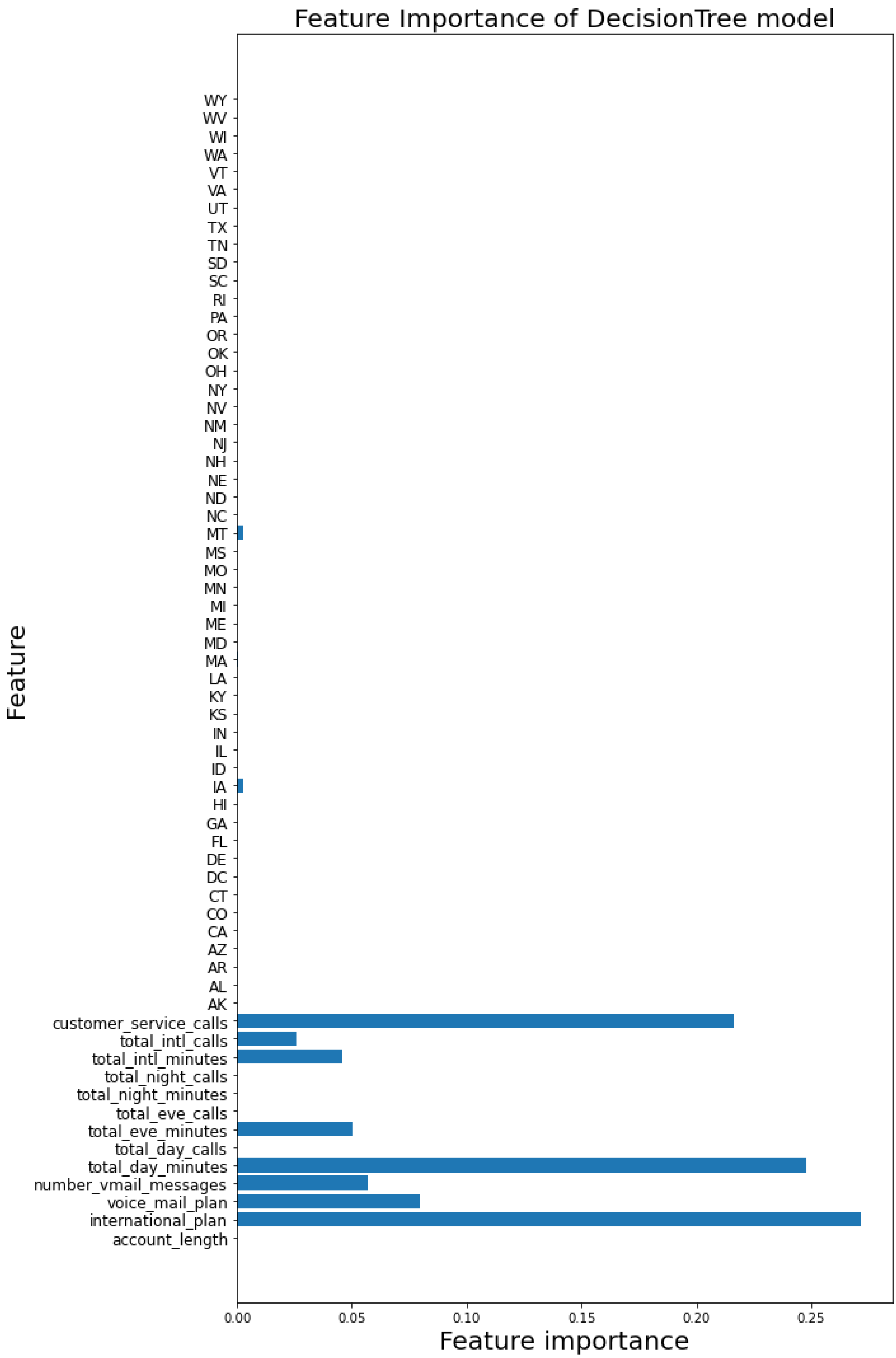
In [239]:

```
# create a baseline model using decision tree:
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
smote = SMOTE(random_state = 42)
X_train_scaled_bal,y_train_bal = smote.fit_resample(X_train_scaled,y_train)
clf_dt = DecisionTreeClassifier(max_depth = 5, random_state = 10)
clf_dt.fit(X_train_scaled_bal, y_train_bal)
y_train_pred = clf_dt.predict(X_train_scaled)
print(f"confusion matrix: \n {confusion_matrix(y_train,y_train_pred)}") # (tn, fp, fn, tp)
print(f"accuracy_score:  {round(accuracy_score(y_train,y_train_pred),3)}")
print(f"f1_score:  {round(f1_score(y_train,y_train_pred),3)}") # TP/(TP+FN)
print(f"recall_score:  {round(recall_score(y_train,y_train_pred),3)}") # TP/(TP+FN)
```

```
confusion matrix:
 [[1997  144]
 [  78  280]]
accuracy_score:  0.911
f1_score:  0.716
recall_score:  0.782
```

In [240]:

```
# It has 77 false negative, and out of all the predictions,
# 77/(2141+358) = 3.08% of predictions were false negatives, accuracy score is 91%, not bad
# Based on the classification model, let's take a look the importance of each feature
n_features = clf_dt.n_features_
plt.figure(figsize=(10, 15))
plt.barh(range(n_features), clf_dt.feature_importances_);
plt.yticks(np.arange(n_features), X_train.columns.values, fontsize = 12)
plt.xlabel('Feature importance', fontsize = 20)
plt.ylabel('Feature', fontsize = 20)
plt.title('Feature Importance of DecisionTree model', fontsize = 20)
plt.tight_layout()
plt.savefig('figures/dtbasic_feat_import.png')
```



It seems three features are the most important ones:

- customer_service_calls
- total_day_minutes
- international_plan

In [241]:

```
# I have examined customer_service_calls and international_plan above.
# Now examine total_day_minutes
tdm = pd.DataFrame(df.groupby(['total_day_minutes'])['churn'].mean().sort_values(ascending
tdm['churn'].value_counts()
```

Out[241]:

```
0.000000    1221
1.000000     189
0.500000     130
0.333333      48
0.250000      47
0.200000      13
0.666667       8
0.166667       5
0.400000       4
0.285714       1
0.125000       1
Name: churn, dtype: int64
```

In [242]:

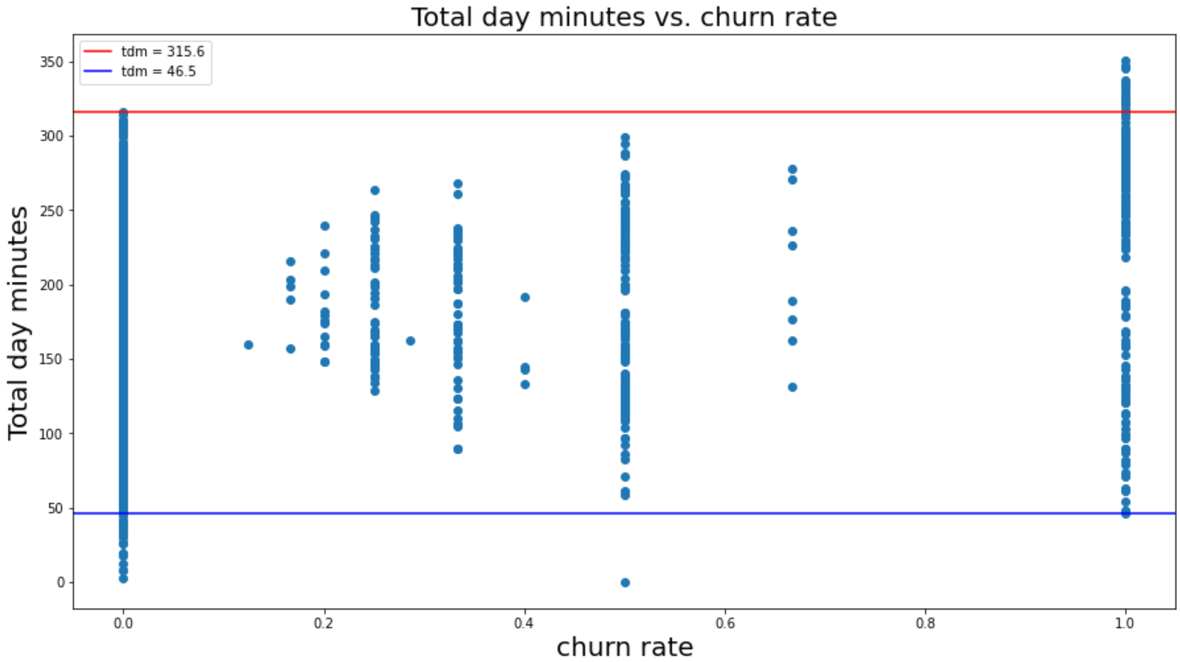
```
tdm.head()
```

Out[242]:

total_day_minutes	churn
180.8	0.0
186.8	0.0
186.7	0.0
186.6	0.0
186.5	0.0

In [243]:

```
# total day minutes as a function of churn rate
fig, ax = plt.subplots(figsize=(15,8))
plt.scatter(tdm.churn,tdm.index)
plt.axhline(y=tdm[tdm['churn']==0].index.sort_values(ascending = True)[-1], xmin=0, xmax=1,
            label = "tdm = " +str(tdm[tdm['churn']==0].index.sort_values(ascending = True)[
plt.axhline(y=tdm[tdm['churn']==1].index.sort_values(ascending = True)[0], xmin=0, xmax=1,c
            label = "tdm = " +str(tdm[tdm['churn']==1].index.sort_values(ascending = True)[
plt.xlabel('churn rate',fontsize=20)
plt.ylabel('Total day minutes', fontsize=20)
plt.title('Total day minutes vs. churn rate', fontsize=20)
plt.legend()
plt.savefig('figures/churnrate_totaldaymin.png')

# total day minutes > 315.6, churn rate is 100%, and total day minutes < 46.5, churn rate i
```



Classification Model Comparisons using different classifiers

- DecisonTreeClassifier()
- KNeighborsClassifier()
- RandomForestClassifier()
- AdaBoostClassifier()
- GradientBoostingClassifier()

In [244]:

```
# define a dataframe to save the metrics from different classification models
PerfDifClf = pd.DataFrame(columns=['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP
# DecisionTreeClassifier
clf_dt = DecisionTreeClassifier(max_depth = 5, random_state = 10)
dt_cv_score = cross_val_score(clf_dt, X_train_scaled_bal, y_train_bal, cv=5)
mean_dt_cv_score = np.mean(dt_cv_score)
y_train_pred = clf_dt.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
PerfDifClf.loc['DecisionTreeCls_dft',
                       ['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP','FN','TP'
         round(mean_dt_cv_score,3),
         round(accuracy_score(y_train,y_train_pred),3),
         round(recall_score(y_train,y_train_pred),3),
         round(f1_score(y_train,y_train_pred),3),
         round(confusion_matrix(y_train,y_train_pred)[0,0]),
         round(confusion_matrix(y_train,y_train_pred)[0,1]),
         round(confusion_matrix(y_train,y_train_pred)[1,0]),
         round(confusion_matrix(y_train,y_train_pred)[1,1])]
# KNeighborsClassifier
clf_kn = KNeighborsClassifier()
kn_cv_score = cross_val_score(clf_kn, X_train_scaled_bal, y_train_bal, cv=5)
mean_kn_cv_score = np.mean(kn_cv_score)
y_train_pred = clf_kn.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
PerfDifClf.loc['KNeighborsCls_dft',
                       ['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP','FN','TP'
         round(mean_kn_cv_score,3),
         round(accuracy_score(y_train,y_train_pred),3),
         round(recall_score(y_train,y_train_pred),3),
         round(f1_score(y_train,y_train_pred),3),
         round(confusion_matrix(y_train,y_train_pred)[0,0]),
         round(confusion_matrix(y_train,y_train_pred)[0,1]),
         round(confusion_matrix(y_train,y_train_pred)[1,0]),
         round(confusion_matrix(y_train,y_train_pred)[1,1])]
# RandomForestClassifier
clf_rf = RandomForestClassifier(max_depth=5)
rf_cv_score = cross_val_score(clf_rf, X_train_scaled_bal, y_train_bal, cv=5)
mean_rf_cv_score = np.mean(rf_cv_score)
y_train_pred = clf_rf.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
PerfDifClf.loc['RandomForestCls_dft',
                       ['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP','FN','TP'
         round(mean_rf_cv_score,3),
         round(accuracy_score(y_train,y_train_pred),3),
         round(recall_score(y_train,y_train_pred),3),
         round(f1_score(y_train,y_train_pred),3),
         round(confusion_matrix(y_train,y_train_pred)[0,0]),
         round(confusion_matrix(y_train,y_train_pred)[0,1]),
         round(confusion_matrix(y_train,y_train_pred)[1,0]),
         round(confusion_matrix(y_train,y_train_pred)[1,1])]
# AdaBoostClassifier()
clf_ab = AdaBoostClassifier()
ab_cv_score = cross_val_score(clf_ab, X_train_scaled_bal, y_train_bal, cv=5)
mean_ab_cv_score = np.mean(ab_cv_score)
y_train_pred = clf_ab.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
PerfDifClf.loc['AdaBoostCls_dft',
                       ['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP','FN','TP'
         round(mean_ab_cv_score,3),
         round(accuracy_score(y_train,y_train_pred),3),
         round(recall_score(y_train,y_train_pred),3),
         round(f1_score(y_train,y_train_pred),3),
         round(confusion_matrix(y_train,y_train_pred)[0,0]),
```

```
        round(confusion_matrix(y_train,y_train_pred)[0,1]),
        round(confusion_matrix(y_train,y_train_pred)[1,0]),
        round(confusion_matrix(y_train,y_train_pred)[1,1])]
#GradientBoostingClassifier()
clf_gb = GradientBoostingClassifier()
gb_cv_score = cross_val_score(clf_gb, X_train_scaled_bal, y_train_bal, cv=5)
mean_gb_cv_score = np.mean(gb_cv_score)
y_train_pred = clf_gb.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
PerfDifClf.loc['GradientBoostingCls_dft',
                       ['MeanCrsValScore','AccScore','RecallScore','F1','TN','FP','FN','TP'
        round(mean_gb_cv_score,3),
        round(accuracy_score(y_train,y_train_pred),3),
        round(recall_score(y_train,y_train_pred),3),
        round(f1_score(y_train,y_train_pred),3),
        round(confusion_matrix(y_train,y_train_pred)[0,0]),
        round(confusion_matrix(y_train,y_train_pred)[0,1]),
        round(confusion_matrix(y_train,y_train_pred)[1,0]),
        round(confusion_matrix(y_train,y_train_pred)[1,1])]
```

In [245]:

```
# check the peformance from different classification models
PerfDifClf
```

Out[245]:

	MeanCrsValScore	AccScore	RecallScore	F1	TN	FP	FN	TP
DecisionTreeCls_dft	0.865	0.911	0.782	0.716	1997	144	78	280
KNeighborsCls_dft	0.844	0.846	0.997	0.649	1756	385	1	357
RandomForestCls_dft	0.867	0.882	0.799	0.661	1919	222	72	286
AdaBoostCls_dft	0.874	0.871	0.637	0.585	1948	193	130	228
GradientBoostingCls_dft	0.915	0.948	0.804	0.816	2081	60	70	288

The GradientBoostingClassifier achieves the best results, So I will use this model in the following analysis

In [246]:

```
clf_gb = GradientBoostingClassifier()
gb_cv_score = cross_val_score(clf_gb, X_train_scaled_bal, y_train_bal, cv=5)
mean_gb_cv_score = np.mean(gb_cv_score)
y_train_pred = clf_gb.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
print('GradientBoostingClassifier:')
print(f"confusion matrix: \n {confusion_matrix(y_train,y_train_pred)}")
print(f"accuracy_score:  {round(accuracy_score(y_train,y_train_pred),3)}")
print(f"recall_score:  {round(recall_score(y_train,y_train_pred),3)}")
print(f"f1_score:  {round(f1_score(y_train,y_train_pred),3)}")
```

```
GradientBoostingClassifier:
confusion matrix:
 [[2081   60]
 [  70  288]]
accuracy_score:  0.948
recall_score:  0.804
f1_score:  0.816
```

In [247]:

```
clf_gb.get_params()
```

Out[247]:

```
{'ccp_alpha': 0.0,
 'criterion': 'friedman_mse',
 'init': None,
 'learning_rate': 0.1,
 'loss': 'deviance',
 'max_depth': 3,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_iter_no_change': None,
 'random_state': None,
 'subsample': 1.0,
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': 0,
 'warm_start': False}
```

In [248]:

```
# With GridSearch to find the optimal parameters
param_grid = {
    "loss":["exponential", "deviance"],
    "learning_rate": [0.01,0.1,0.2],
    "min_samples_split": [2,5],
    "min_samples_leaf":[1,2,5],
    'max_depth':[3,5]
    }

# create gradient boost object for grid searching
clf_gbc = GradientBoostingClassifier(random_state = 42)

# create search object
gridsearch = GridSearchCV(estimator = clf_gbc, param_grid = param_grid, n_jobs = -1, cv = 3

# Train search object
gridsearch.fit(X_train_scaled_bal,y_train_bal)

# Get best estimator
print('Best parameters: \n\n',gridsearch.best_params_,'\n')
```

```
Best parameters: 

 {'learning_rate': 0.1, 'loss': 'deviance', 'max_depth': 5, 'min_samples_lea
f': 1, 'min_samples_split': 2}
```

In [249]:

```
gridsearch.cv_results_
```

Out[249]:

```
{'mean_fit_time': array([2.48666461, 2.36665559, 2.23579844, 1.80323005,
1.62504824,
        1.54408964, 2.26722447, 2.20986621, 2.36338353, 2.2624379 ,
        2.64753421, 2.64390214, 1.57411766, 1.852712  , 1.67684905,
        1.65790892, 1.77061955, 2.20015653, 2.72415217, 3.02434595,
        2.47679051, 2.5824581 , 2.27947052, 3.01491531, 1.64890949,
        1.69820992, 2.2153887 , 1.77161614, 1.89460707, 1.99046628,
        3.20475729, 3.59099889, 3.13063606, 3.67885296, 3.32456851,
        3.61690021, 2.31586425, 2.41978661, 2.20137262, 2.5332574 ,
        2.55989114, 2.18344649, 3.08720239, 3.58211605, 3.46810397,
        3.67059898, 3.76785453, 4.12065951, 2.24698456, 2.23670991,
        2.16691279, 2.39506443, 2.86040401, 2.43481414, 3.35592469,
        4.21046996, 4.807851  , 4.11125541, 3.74437992, 3.36389852,
        2.2048382 , 1.92646591, 2.0106895 , 2.15380939, 2.21833531,
        2.52825514, 5.07744686, 5.32787657, 5.91616011, 4.8876965 ,
        4.18572187, 3.33121252]),
 'std_fit_time': array([0.14470041, 0.25588814, 0.51351567, 0.1971932 , 0.
12977016,
```

In [250]:

```
clf_gbcfinal = GradientBoostingClassifier(learning_rate = 0.1, loss = 'deviance', max_depth
                                        min_samples_split = 2, min_samples_leaf=1, random_s
y_train_pred = clf_gbcfinal.fit(X_train_scaled_bal,y_train_bal).predict(X_train_scaled)
print('GradientBoostingClassifier final:')
print(f"confusion matrix: \n {confusion_matrix(y_train,y_train_pred)}")
print(f"accuracy_score:  {round(accuracy_score(y_train,y_train_pred),3)}")
print(f"recall_score:  {round(recall_score(y_train,y_train_pred),3)}")
print(f"f1_score:  {round(f1_score(y_train,y_train_pred),3)}")
```

```
GradientBoostingClassifier final:
confusion matrix:
 [[2135    6]
 [  40  318]]
accuracy_score:  0.982
recall_score:  0.888
f1_score:  0.933
```

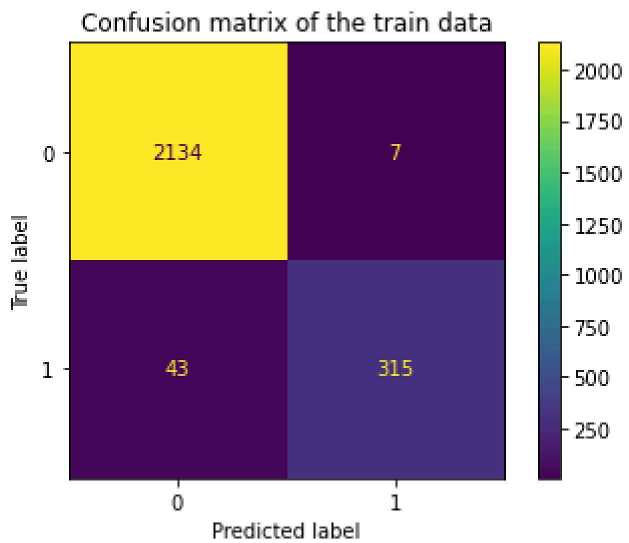
this result is pretty good, so I will use it as the final model to do the test:

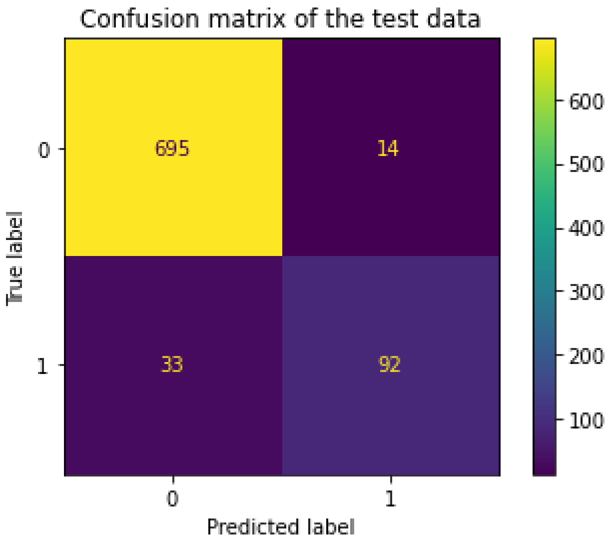
- Parameters:
- loss = 'deviance'
- learning_rate = 0.1
- min_samples_leaf = 1
- min_samples_split = 2
- max_depth = 5
- SMOTE balancing
- StandardScaler

In [251]:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

smote = SMOTE(random_state = 42)
X_train_scaled_bal,y_train_bal = smote.fit_resample(X_train_scaled,y_train)

clf_final = GradientBoostingClassifier(loss = 'deviance', learning_rate = 0.1,
                                   min_samples_leaf= 5, min_samples_split= 5,
                                   max_depth = 5, random_state = 42)
clf_final.fit(X_train_scaled_bal, y_train_bal)



print('Final model for train data:')
#print(f"confusion matrix: \n {confusion_matrix(y_train,clf_final.predict(X_train_scaled))}
print(f"accuracy_score:  {round(accuracy_score(y_train,clf_final.predict(X_train_scaled)),3
print(f"recall_score:  {round(recall_score(y_train,clf_final.predict(X_train_scaled)),3)}")
print(f"f1_score:  {round(f1_score(y_train,clf_final.predict(X_train_scaled)),3)}\n")

plot_confusion_matrix(clf_final, X_train_scaled,y_train)
plt.title('Confusion matrix of the train data')
plt.savefig('figures/clffinal_confmattrain.png')
print('Final model for test data:')
#print(f"confusion matrix: \n {confusion_matrix(y_test,clf_final.predict(X_test_scaled))}")
print(f"accuracy_score:  {round(accuracy_score(y_test,clf_final.predict(X_test_scaled)),3)}
print(f"recall_score:  {round(recall_score(y_test,clf_final.predict(X_test_scaled)),3)}")
print(f"f1_score:  {round(f1_score(y_test,clf_final.predict(X_test_scaled)),3)}\n")
plot_confusion_matrix(clf_final, X_test_scaled,y_test)
plt.title('Confusion matrix of the test data')
plt.savefig('figures/clffinal_confmattest.png')
```

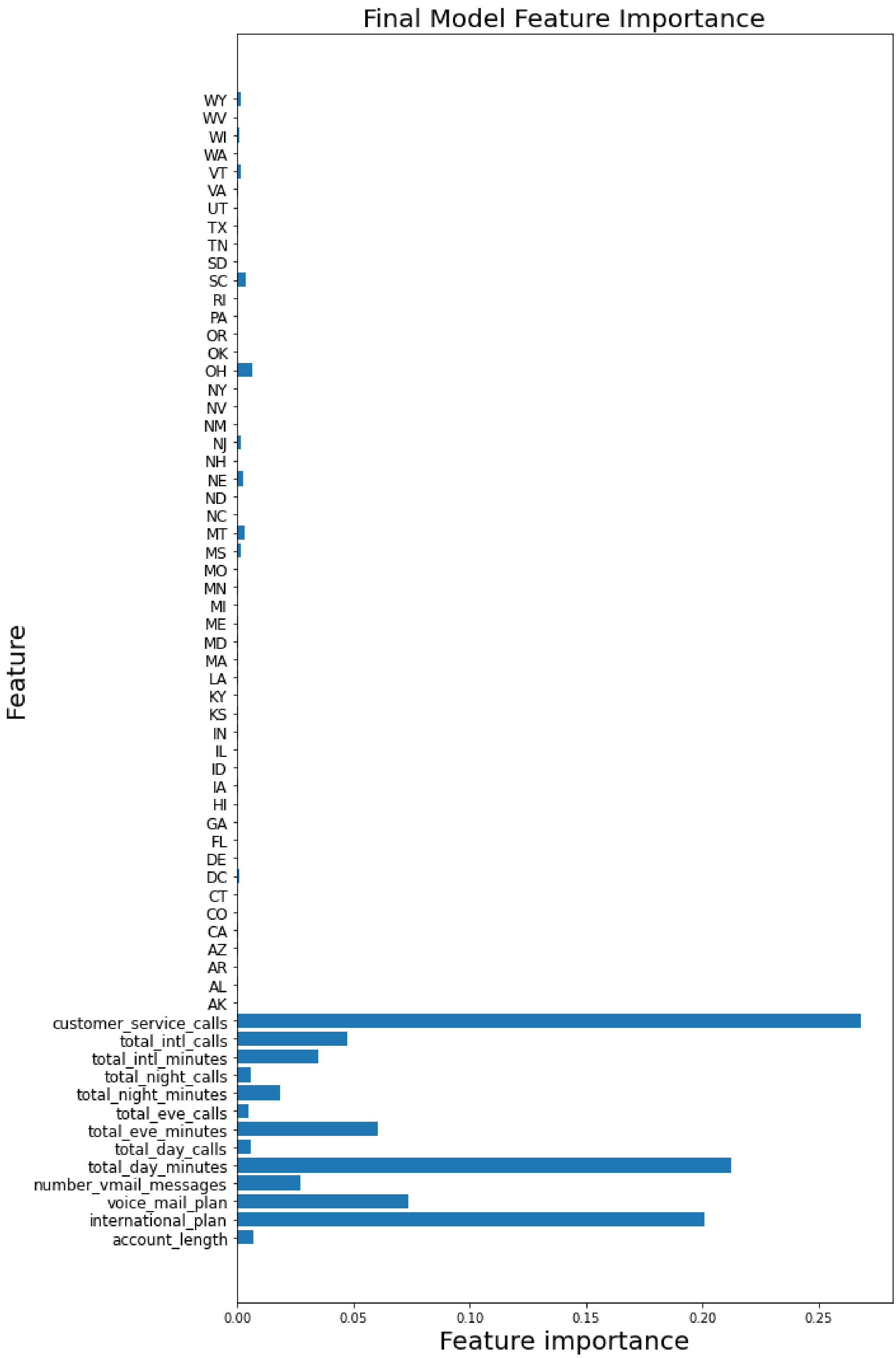
```
Final model for train data:
accuracy_score:  0.98
recall_score:  0.88
f1_score:  0.926

Final model for test data:
accuracy_score:  0.944
recall_score:  0.736
f1_score:  0.797
```




Confusion matrix of the test data
True label
Predicted label
0
1
0
1
695
14
33
92
600
500
400
300
200
100

In [252]:

```
# Plot feature importance for the final model
n_features = clf_final.n_features_
plt.figure(figsize=(10, 15))
plt.barh(range(n_features), clf_final.feature_importances_);
plt.yticks(np.arange(n_features), X_train.columns.values, fontsize = 12)
plt.xlabel('Feature importance', fontsize = 20)
plt.ylabel('Feature', fontsize = 20)
plt.title('Final Model Feature Importance', fontsize = 20)
plt.tight_layout()
plt.savefig('figures/clffinal_feat_import.png')
```



Summary from the model

From the classification models, we found that three features affected the customer churn rate most significantly:

- customer_service_calls: The customers with large number of service calls as 4,5,6 seems have the larger churn rate

- international_plan: The customers with international plan have the higher churn rate
- total_day_minutes: The customers with the total day minutes > 315.6, churn rate is 100%, and total day minutes < 46.5, churn rate is mostly 0, therefore, the company need to deal with the customers with the total day minutes between 46.5 to 316 mins

Regarding states: AZ, AK and HI have the lowest churn rate states, therefore, need to pay more attention on customers from these states