Open in Colab

Telecom Churn Case Study

With 21 predictor variables we need to predict whether a particular customer will switch to another telecom provider or not. I used a dataset from Kaggle [https://www.kaggle.com] that included 7,043 unique customer records for a telecom company called Telco. You can read more about the dataset here [https://www.kaggle.com/blastchar/telco-customer-churn]

Importing and Merging Data

In [0]:

```
# Importing Pandas and NumPy
import pandas as pd
import numpy as np
```

In [0]:

```
#Running or Importing .py Files with Google Colab
from google.colab import drive
drive.mount('/content/drive/')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=94731898
9803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%
3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.tes
t%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2F
auth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readon
ly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive/
```

In [0]:

```
# Importing all datasets
churn_data = pd.read_csv("/content/drive/My Drive/app/churn_data.csv") #Churn Data
customer_data = pd.read_csv("/content/drive/My Drive/app/customer_data.csv") #Customer Da
ta
internet_data = pd.read_csv("/content/drive/My Drive/app/internet_data.csv") #Internet Da
ta
```

In [0]:

```
#Merging on 'customerID'(Mege Churn and Customer Data)
df_1 = pd.merge(churn_data, customer_data, how='inner', on='customerID')
df_1
```

Out[0]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	1889.5	No
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	108.15	Yes
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	151.65	Yes
5	9305-CDSKC	8	Yes	Month-to-month	Yes	Electronic check	99.65	820.5	Yes
6	1452-KIOVK	22	Yes	Month-to-month	Yes	Credit card (automatic)	89.10	1949.4	No
7	6713-OKOMC	10	No	Month-to-month	No	Mailed check	29.75	301.9	No
8	7892-POOKP	28	Yes	Month-to-month	Yes	Electronic check	104.80	3046.05	Yes
9	6388-TABGU	62	Yes	One year	No	Bank transfer (automatic)	56.15	3487.95	No
10	9763-GRSKD	13	Yes	Month-to-month	Yes	Mailed check	49.95	587.45	No
11	7469-LKBCI	16	Yes	Two year	No	Credit card (automatic)	18.95	326.8	No
12	8091-TTVAX	58	Yes	One year	No	Credit card (automatic)	100.35	5681.1	No
13	0280-XJGEX	49	Yes	Month-to-month	Yes	Bank transfer (automatic)	103.70	5036.3	Yes
14	5129-JLPIS	25	Yes	Month-to-month	Yes	Electronic check	105.50	2686.05	No
15	3655-SNQYZ	69	Yes	Two year	No	Credit card (automatic)	113.25	7895.15	No
16	8191-XWSZG	52	Yes	One year	No	Mailed check	20.65	1022.95	No
17	9959-WOFKT	71	Yes	Two year	No	Bank transfer (automatic)	106.70	7382.25	No
18	4190-MFLUW	10	Yes	Month-to-month	No	Credit card (automatic)	55.20	528.35	Yes
19	4183-MYFRB	21	Yes	Month-to-month	Yes	Electronic check	90.05	1862.9	No
20	8779-QRDMV	1	No	Month-to-month	Yes	Electronic check	39.65	39.65	Yes
21	1680-VDCWW	12	Yes	One year	No	Bank transfer (automatic)	19.80	202.25	No
22	1066-JKSGK	1	Yes	Month-to-month	No	Mailed check	20.15	20.15	Yes
23	3638-WEABW	58	Yes	Two year	Yes	Credit card (automatic)	59.90	3505.1	No
24	6322-HRPFA	49	Yes	Month-to-month	No	Credit card (automatic)	59.60	2970.3	No
25	6865-JZNKO	30	Yes	Month-to-month	Yes	Bank transfer (automatic)	55.30	1530.6	No
26	6467-CHFZW	47	Yes	Month-to-month	Yes	Electronic check	99.35	4749.15	Yes

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
27	8665-UTDHZ	1	No	Month-to-month	No	Electronic check	30.20	30.2	Yes
28	5248-YGIJN	72	Yes	Two year	Yes	Credit card (automatic)	90.25	6369.45	No
29	8773-HHUOZ	17	Yes	Month-to-month	Yes	Mailed check	64.70	1093.1	Yes
...	...	...	...	...	...	...	...	...	...
7013	1685-BQULA	40	Yes	Month-to-month	Yes	Bank transfer (automatic)	93.40	3756.4	No
7014	9053-EJUNL	41	Yes	Month-to-month	Yes	Electronic check	89.20	3645.75	No
7015	0666-UXTJO	34	Yes	Month-to-month	Yes	Credit card (automatic)	85.20	2874.45	No
7016	1471-GIQKQ	1	Yes	Month-to-month	No	Electronic check	49.95	49.95	No
7017	4807-IZYOZ	51	Yes	Two year	No	Bank transfer (automatic)	20.65	1020.75	No
7018	1122-JWTJW	1	Yes	Month-to-month	Yes	Mailed check	70.65	70.65	Yes
7019	9710-NJERN	39	Yes	Two year	No	Mailed check	20.15	826	No
7020	9837-FWLCH	12	Yes	Month-to-month	Yes	Electronic check	19.20	239	No
7021	1699-HPSBG	12	Yes	One year	Yes	Electronic check	59.80	727.8	Yes
7022	7203-OYKCT	72	Yes	One year	Yes	Electronic check	104.95	7544.3	No
7023	1035-IPQPU	63	Yes	Month-to-month	Yes	Electronic check	103.50	6479.4	No
7024	7398-LXGYX	44	Yes	Month-to-month	Yes	Credit card (automatic)	84.80	3626.35	No
7025	2823-LKABH	18	Yes	Month-to-month	Yes	Bank transfer (automatic)	95.05	1679.4	No
7026	8775-CEBBJ	9	Yes	Month-to-month	Yes	Bank transfer (automatic)	44.20	403.35	Yes
7027	0550-DCXLH	13	Yes	Month-to-month	No	Mailed check	73.35	931.55	No
7028	9281-CEDRU	68	Yes	Two year	No	Bank transfer (automatic)	64.10	4326.25	No
7029	2235-DWLJU	6	No	Month-to-month	Yes	Electronic check	44.40	263.05	No
7030	0871-OPBXW	2	Yes	Month-to-month	Yes	Mailed check	20.05	39.25	No
7031	3605-JISKB	55	Yes	One year	No	Credit card (automatic)	60.00	3316.1	No

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
7032	6894-LFHLY	1	Yes	Month-to-month	Yes	Electronic check	75.75	75.75	Yes
7033	9767-FFLEM	38	Yes	Month-to-month	Yes	Credit card (automatic)	69.50	2625.25	No
7034	0639-TSIQW	67	Yes	Month-to-month	Yes	Credit card (automatic)	102.95	6886.25	Yes
7035	8456-QDAVC	19	Yes	Month-to-month	Yes	Bank transfer (automatic)	78.70	1495.1	No
7036	7750-EYXWZ	12	No	One year	No	Electronic check	60.65	743.3	No
7037	2569-WGERO	72	Yes	Two year	Yes	Bank transfer (automatic)	21.15	1419.4	No
7038	6840-RESVB	24	Yes	One year	Yes	Mailed check	84.80	1990.5	No
7039	2234-XADUH	72	Yes	One year	Yes	Credit card (automatic)	103.20	7362.9	No
7040	4801-JZAZL	11	No	Month-to-month	Yes	Electronic check	29.60	346.45	No
7041	8361-LTMKD	4	Yes	Month-to-month	Yes	Mailed check	74.40	306.6	Yes
7042	3186-AJIEK	66	Yes	Two year	Yes	Bank transfer (automatic)	105.65	6844.5	No

7043 rows × 13 columns

In [0]:

```
#Final dataframe with all predictor variables
telecom = pd.merge(df_1, internet_data, how='inner', on='customerID')
telecom
```

Out[0]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	29.85	No
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	1889.5	No
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	108.15	Yes
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	151.65	Yes
5	9305-CDSKC	8	Yes	Month-to-month	Yes	Electronic check	99.65	820.5	Yes
6	1452-KIOVK	22	Yes	Month-to-month	Yes	Credit card (automatic)	89.10	1949.4	No
7	6713-OKOMC	10	No	Month-to-	No	Mailed check	29.75	301.9	No

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
8	7892-POOKP	28	Yes	Month-to-month	Yes	Electronic check	104.80	3046.05	Yes
9	6388-TABGU	62	Yes	One year	No	Bank transfer (automatic)	56.15	3487.95	No
10	9763-GRSKD	13	Yes	Month-to-month	Yes	Mailed check	49.95	587.45	No
11	7469-LKBCI	16	Yes	Two year	No	Credit card (automatic)	18.95	326.8	No
12	8091-TTVAX	58	Yes	One year	No	Credit card (automatic)	100.35	5681.1	No
13	0280-XJGEX	49	Yes	Month-to-month	Yes	Bank transfer (automatic)	103.70	5036.3	Yes
14	5129-JLPIS	25	Yes	Month-to-month	Yes	Electronic check	105.50	2686.05	No
15	3655-SNQYZ	69	Yes	Two year	No	Credit card (automatic)	113.25	7895.15	No
16	8191-XWSZG	52	Yes	One year	No	Mailed check	20.65	1022.95	No
17	9959-WOFKT	71	Yes	Two year	No	Bank transfer (automatic)	106.70	7382.25	No
18	4190-MFLUW	10	Yes	Month-to-month	No	Credit card (automatic)	55.20	528.35	Yes
19	4183-MYFRB	21	Yes	Month-to-month	Yes	Electronic check	90.05	1862.9	No
20	8779-QRDMV	1	No	Month-to-month	Yes	Electronic check	39.65	39.65	Yes
21	1680-VDCWW	12	Yes	One year	No	Bank transfer (automatic)	19.80	202.25	No
22	1066-JKSGK	1	Yes	Month-to-month	No	Mailed check	20.15	20.15	Yes
23	3638-WEABW	58	Yes	Two year	Yes	Credit card (automatic)	59.90	3505.1	No
24	6322-HRPFA	49	Yes	Month-to-month	No	Credit card (automatic)	59.60	2970.3	No
25	6865-JZNKO	30	Yes	Month-to-month	Yes	Bank transfer (automatic)	55.30	1530.6	No
26	6467-CHFZW	47	Yes	Month-to-month	Yes	Electronic check	99.35	4749.15	Yes
27	8665-UTDHZ	1	No	Month-to-month	No	Electronic check	30.20	30.2	Yes
28	5248-YGIJN	72	Yes	Two year	Yes	Credit card (automatic)	90.25	6369.45	No
29	8773-HHUOZ	17	Yes	Month-to-month	Yes	Mailed check	64.70	1093.1	Yes
...	...	...	...	...	...	...	...	...	...
	1685-			Month-		Bank transfer			

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
7013	1685-BQULA	40	Yes	Month-to-month	Yes	Bank transfer (automatic)	93.40	3756.4	No
7014	9053-EJUNL	41	Yes	Month-to-month	Yes	Electronic check	89.20	3645.75	No
7015	0666-UXTJO	34	Yes	Month-to-month	Yes	Credit card (automatic)	85.20	2874.45	No
7016	1471-GIQKQ	1	Yes	Month-to-month	No	Electronic check	49.95	49.95	No
7017	4807-IZYOZ	51	Yes	Two year	No	Bank transfer (automatic)	20.65	1020.75	No
7018	1122-JWTJW	1	Yes	Month-to-month	Yes	Mailed check	70.65	70.65	Yes
7019	9710-NJERN	39	Yes	Two year	No	Mailed check	20.15	826	No
7020	9837-FWLCH	12	Yes	Month-to-month	Yes	Electronic check	19.20	239	No
7021	1699-HPSBG	12	Yes	One year	Yes	Electronic check	59.80	727.8	Yes
7022	7203-OYKCT	72	Yes	One year	Yes	Electronic check	104.95	7544.3	No
7023	1035-IPQPU	63	Yes	Month-to-month	Yes	Electronic check	103.50	6479.4	No
7024	7398-LXGYX	44	Yes	Month-to-month	Yes	Credit card (automatic)	84.80	3626.35	No
7025	2823-LKABH	18	Yes	Month-to-month	Yes	Bank transfer (automatic)	95.05	1679.4	No
7026	8775-CEBBJ	9	Yes	Month-to-month	Yes	Bank transfer (automatic)	44.20	403.35	Yes
7027	0550-DCXLH	13	Yes	Month-to-month	No	Mailed check	73.35	931.55	No
7028	9281-CEDRU	68	Yes	Two year	No	Bank transfer (automatic)	64.10	4326.25	No
7029	2235-DWLJU	6	No	Month-to-month	Yes	Electronic check	44.40	263.05	No
7030	0871-OPBXW	2	Yes	Month-to-month	Yes	Mailed check	20.05	39.25	No
7031	3605-JISKB	55	Yes	One year	No	Credit card (automatic)	60.00	3316.1	No
7032	6894-LFHLY	1	Yes	Month-to-month	Yes	Electronic check	75.75	75.75	Yes
7033	9767-FFLEM	38	Yes	Month-to-month	Yes	Credit card (automatic)	69.50	2625.25	No
7034	0639-TSIQW	67	Yes	Month-to-month	Yes	Credit card (automatic)	102.95	6886.25	Yes
7035	8456-QDAVC	19	Yes	Month-to-month	Yes	Bank transfer (automatic)	78.70	1495.1	No

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	g
7036	7750-EYXWZ	12	No	One year	No	Electronic check	60.65	743.3	No	I
7037	2569-WGERO	72	Yes	Two year	Yes	Bank transfer (automatic)	21.15	1419.4	No	I
7038	6840-RESVB	24	Yes	One year	Yes	Mailed check	84.80	1990.5	No	
7039	2234-XADUH	72	Yes	One year	Yes	Credit card (automatic)	103.20	7362.9	No	I
7040	4801-JZAZL	11	No	Month-to-month	Yes	Electronic check	29.60	346.45	No	I
7041	8361-LTMKD	4	Yes	Month-to-month	Yes	Mailed check	74.40	306.6	Yes	
7042	3186-AJIEK	66	Yes	Two year	Yes	Bank transfer (automatic)	105.65	6844.5	No	

7043 rows × 21 columns

In [0]:

```
telecom.shape
```

Out[0]:

```
(7043, 21)
```

Let's understand the structure of our dataframe

In [0]:

```
# Let's see the head of our master dataset
telecom.head()
```

Out[0]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	gen
0	7590-VHVEG	1	No	Month-to-month	Yes	Electronic check	29.85	29.85	No	Fem
1	5575-GNVDE	34	Yes	One year	No	Mailed check	56.95	1889.5	No	M
2	3668-QPYBK	2	Yes	Month-to-month	Yes	Mailed check	53.85	108.15	Yes	M
3	7795-CFOCW	45	No	One year	No	Bank transfer (automatic)	42.30	1840.75	No	M
4	9237-HQITU	2	Yes	Month-to-month	Yes	Electronic check	70.70	151.65	Yes	Fem

In [0]:

```
telecom.describe()
```

Out[0]:

	tenure	MonthlyCharges	SeniorCitizen
count	7043.000000	7043.000000	7043.000000

	tenure	MonthlyCharges	SeniorCitizen
mean	32.371149	64.761692	0.162147
std	24.559481	30.090047	0.368612
min	0.000000	18.250000	0.000000
25%	9.000000	35.500000	0.000000
50%	29.000000	70.350000	0.000000
75%	55.000000	89.850000	0.000000
max	72.000000	118.750000	1.000000

In [0]:

```
# Let's see the type of each column
telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 21 columns):
customerID          7043 non-null object
tenure              7043 non-null int64
PhoneService        7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null object
Churn               7043 non-null object
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.2+ MB
```

Data Preparation

In [0]:

```
# Converting Yes to 1 and No to 0
telecom['PhoneService'] = telecom['PhoneService'].map({'Yes': 1, 'No': 0})
telecom['PaperlessBilling'] = telecom['PaperlessBilling'].map({'Yes': 1, 'No': 0})
telecom['Churn'] = telecom['Churn'].map({'Yes': 1, 'No': 0})
telecom['Partner'] = telecom['Partner'].map({'Yes': 1, 'No': 0})
telecom['Dependents'] = telecom['Dependents'].map({'Yes': 1, 'No': 0})
```

In [0]:

```
telecom
```

Out[0]:

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	7590-VHVEG	1	0	Month-to-month	1	Electronic check	29.85	29.85	0
1	5575-GNVDE	34	1	One year	0	Mailed check	56.95	1889.5	0
2	3668-	2	1	Month-to-	1	Mailed check	53.85	108.15	1

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
	QPYBK			month					
3	7795-CFOCW	45	0	One year	0	Bank transfer (automatic)	42.30	1840.75	0
4	9237-HQITU	2	1	Month-to-month	1	Electronic check	70.70	151.65	1
5	9305-CDSKC	8	1	Month-to-month	1	Electronic check	99.65	820.5	1
6	1452-KIOVK	22	1	Month-to-month	1	Credit card (automatic)	89.10	1949.4	0
7	6713-OKOMC	10	0	Month-to-month	0	Mailed check	29.75	301.9	0
8	7892-POOKP	28	1	Month-to-month	1	Electronic check	104.80	3046.05	1
9	6388-TABGU	62	1	One year	0	Bank transfer (automatic)	56.15	3487.95	0
10	9763-GRSKD	13	1	Month-to-month	1	Mailed check	49.95	587.45	0
11	7469-LKBCI	16	1	Two year	0	Credit card (automatic)	18.95	326.8	0
12	8091-TTVAX	58	1	One year	0	Credit card (automatic)	100.35	5681.1	0
13	0280-XJGEX	49	1	Month-to-month	1	Bank transfer (automatic)	103.70	5036.3	1
14	5129-JLPIS	25	1	Month-to-month	1	Electronic check	105.50	2686.05	0
15	3655-SNQYZ	69	1	Two year	0	Credit card (automatic)	113.25	7895.15	0
16	8191-XWSZG	52	1	One year	0	Mailed check	20.65	1022.95	0
17	9959-WOFKT	71	1	Two year	0	Bank transfer (automatic)	106.70	7382.25	0
18	4190-MFLUW	10	1	Month-to-month	0	Credit card (automatic)	55.20	528.35	1
19	4183-MYFRB	21	1	Month-to-month	1	Electronic check	90.05	1862.9	0
20	8779-QRDMV	1	0	Month-to-month	1	Electronic check	39.65	39.65	1
21	1680-VDCWW	12	1	One year	0	Bank transfer (automatic)	19.80	202.25	0
22	1066-JKSGK	1	1	Month-to-month	0	Mailed check	20.15	20.15	1
23	3638-WEABW	58	1	Two year	1	Credit card (automatic)	59.90	3505.1	0
24	6322-HRPFA	49	1	Month-to-month	0	Credit card (automatic)	59.60	2970.3	0
25	6865-JZNKO	30	1	Month-to-month	1	Bank transfer (automatic)	55.30	1530.6	0

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
26	6467-CHFZW	47	1	Month-to-month	1	Electronic check	99.35	4749.15	1
27	8665-UTDHZ	1	0	Month-to-month	0	Electronic check	30.20	30.2	1
28	5248-YGIJN	72	1	Two year	1	Credit card (automatic)	90.25	6369.45	0
29	8773-HHUOZ	17	1	Month-to-month	1	Mailed check	64.70	1093.1	1
...	...	...	...	...	...	...	...	...	...
7013	1685-BQULA	40	1	Month-to-month	1	Bank transfer (automatic)	93.40	3756.4	0
7014	9053-EJUNL	41	1	Month-to-month	1	Electronic check	89.20	3645.75	0
7015	0666-UXTJO	34	1	Month-to-month	1	Credit card (automatic)	85.20	2874.45	0
7016	1471-GIQKQ	1	1	Month-to-month	0	Electronic check	49.95	49.95	0
7017	4807-IZYOZ	51	1	Two year	0	Bank transfer (automatic)	20.65	1020.75	0
7018	1122-JWTJW	1	1	Month-to-month	1	Mailed check	70.65	70.65	1
7019	9710-NJERN	39	1	Two year	0	Mailed check	20.15	826	0
7020	9837-FWLCH	12	1	Month-to-month	1	Electronic check	19.20	239	0
7021	1699-HPSBG	12	1	One year	1	Electronic check	59.80	727.8	1
7022	7203-OYKCT	72	1	One year	1	Electronic check	104.95	7544.3	0
7023	1035-IPQPU	63	1	Month-to-month	1	Electronic check	103.50	6479.4	0
7024	7398-LXGYX	44	1	Month-to-month	1	Credit card (automatic)	84.80	3626.35	0
7025	2823-LKABH	18	1	Month-to-month	1	Bank transfer (automatic)	95.05	1679.4	0
7026	8775-CEBBJ	9	1	Month-to-month	1	Bank transfer (automatic)	44.20	403.35	1
7027	0550-DCXLH	13	1	Month-to-month	0	Mailed check	73.35	931.55	0
7028	9281-CEDRU	68	1	Two year	0	Bank transfer (automatic)	64.10	4326.25	0
7029	2235-DWLJU	6	0	Month-to-month	1	Electronic check	44.40	263.05	0
7030	0871-OPBXW	2	1	Month-to-	1	Mailed check	20.05	39.25	0

	customerID	tenure	PhoneService	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn
7031	3605-JISKB	55	1	One year	0	Credit card (automatic)	60.00	3316.1	0
7032	6894-LFHLY	1	1	Month-to-month	1	Electronic check	75.75	75.75	1
7033	9767-FFLEM	38	1	Month-to-month	1	Credit card (automatic)	69.50	2625.25	0
7034	0639-TSIQW	67	1	Month-to-month	1	Credit card (automatic)	102.95	6886.25	1
7035	8456-QDAVC	19	1	Month-to-month	1	Bank transfer (automatic)	78.70	1495.1	0
7036	7750-EYXWZ	12	0	One year	0	Electronic check	60.65	743.3	0
7037	2569-WGERO	72	1	Two year	1	Bank transfer (automatic)	21.15	1419.4	0
7038	6840-RESVB	24	1	One year	1	Mailed check	84.80	1990.5	0
7039	2234-XADUH	72	1	One year	1	Credit card (automatic)	103.20	7362.9	0
7040	4801-JZAZL	11	0	Month-to-month	1	Electronic check	29.60	346.45	0
7041	8361-LTMKD	4	1	Month-to-month	1	Mailed check	74.40	306.6	1
7042	3186-AJIEK	66	1	Two year	1	Bank transfer (automatic)	105.65	6844.5	0

7043 rows × 21 columns

Dummy Variable Creation(Converting Categorical to Dummy Variable)

In [0]:

```
# Creating a dummy variable for the variable 'Contract' and dropping the first one.
cont = pd.get_dummies(telecom['Contract'],prefix='Contract',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,cont],axis=1)

# Creating a dummy variable for the variable 'PaymentMethod' and dropping the first one.
pm = pd.get_dummies(telecom['PaymentMethod'],prefix='PaymentMethod',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,pm],axis=1)

# Creating a dummy variable for the variable 'gender' and dropping the first one.
gen = pd.get_dummies(telecom['gender'],prefix='gender',drop_first=True)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,gen],axis=1)

# Creating a dummy variable for the variable 'MultipleLines' and dropping the first one.
ml = pd.get_dummies(telecom['MultipleLines'],prefix='MultipleLines')
#  dropping MultipleLines_No phone service column
ml1 = ml.drop(['MultipleLines_No phone service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,ml1],axis=1)

# Creating a dummy variable for the variable 'InternetService' and dropping the first one
.
iser = pd.get_dummies(telecom['InternetService'],prefix='InternetService',drop_first=Tru
```

```
e)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,iser],axis=1)

# Creating a dummy variable for the variable 'OnlineSecurity'.
os = pd.get_dummies(telecom['OnlineSecurity'],prefix='OnlineSecurity')
os1= os.drop(['OnlineSecurity_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,os1],axis=1)

# Creating a dummy variable for the variable 'OnlineBackup'.
ob =pd.get_dummies(telecom['OnlineBackup'],prefix='OnlineBackup')
ob1 =ob.drop(['OnlineBackup_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,ob1],axis=1)

# Creating a dummy variable for the variable 'DeviceProtection'.
dp =pd.get_dummies(telecom['DeviceProtection'],prefix='DeviceProtection')
dp1 = dp.drop(['DeviceProtection_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,dp1],axis=1)

# Creating a dummy variable for the variable 'TechSupport'.
ts =pd.get_dummies(telecom['TechSupport'],prefix='TechSupport')
ts1 = ts.drop(['TechSupport_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,ts1],axis=1)

# Creating a dummy variable for the variable 'StreamingTV'.
st =pd.get_dummies(telecom['StreamingTV'],prefix='StreamingTV')
st1 = st.drop(['StreamingTV_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,st1],axis=1)

# Creating a dummy variable for the variable 'StreamingMovies'.
sm =pd.get_dummies(telecom['StreamingMovies'],prefix='StreamingMovies')
sm1 = sm.drop(['StreamingMovies_No internet service'],1)
#Adding the results to the master dataframe
telecom = pd.concat([telecom,sm1],axis=1)
```

In [0]:

```
telecom['MultipleLines'].value_counts()
```

Out[0]:

```
No                  3390
Yes                 2971
No phone service     682
Name: MultipleLines, dtype: int64
```

Dropping the repeated variables

In [0]:

```
# We have created dummies for the below variables, so we can drop them
telecom = telecom.drop(['Contract','PaymentMethod','gender','MultipleLines','InternetServ
ice', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies'], 1)
```

In [0]:

```
#The varaible was imported as a string we need to convert it to float
telecom['TotalCharges'] =telecom['TotalCharges'].convert_objects(convert_numeric=True)
#telecom['tenure'] = telecom['tenure'].astype(int).astype(float)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: FutureWarning: convert_ob
jects is deprecated.  To re-infer data dtypes for object columns, use Series.infer_object
s()
For all other conversions use the data-type specific converters pd.to_datetime, pd.to_tim
edelta and pd.to_numeric.
```

```
"""Entry point for launching an IPython kernel.
```

In [0]:

```
telecom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7043 entries, 0 to 7042
Data columns (total 32 columns):
customerID                                7043 non-null object
tenure                                    7043 non-null int64
PhoneService                              7043 non-null int64
PaperlessBilling                          7043 non-null int64
MonthlyCharges                            7043 non-null float64
TotalCharges                              7032 non-null float64
Churn                                     7043 non-null int64
SeniorCitizen                             7043 non-null int64
Partner                                   7043 non-null int64
Dependents                                7043 non-null int64
Contract_One year                         7043 non-null uint8
Contract_Two year                         7043 non-null uint8
PaymentMethod_Credit card (automatic)     7043 non-null uint8
PaymentMethod_Electronic check            7043 non-null uint8
PaymentMethod_Mailed check                7043 non-null uint8
gender_Male                               7043 non-null uint8
MultipleLines_No                          7043 non-null uint8
MultipleLines_Yes                         7043 non-null uint8
InternetService_Fiber optic               7043 non-null uint8
InternetService_No                        7043 non-null uint8
OnlineSecurity_No                         7043 non-null uint8
OnlineSecurity_Yes                        7043 non-null uint8
OnlineBackup_No                           7043 non-null uint8
OnlineBackup_Yes                          7043 non-null uint8
DeviceProtection_No                       7043 non-null uint8
DeviceProtection_Yes                      7043 non-null uint8
TechSupport_No                            7043 non-null uint8
TechSupport_Yes                           7043 non-null uint8
StreamingTV_No                            7043 non-null uint8
StreamingTV_Yes                           7043 non-null uint8
StreamingMovies_No                        7043 non-null uint8
StreamingMovies_Yes                       7043 non-null uint8
dtypes: float64(2), int64(7), object(1), uint8(22)
memory usage: 756.6+ KB
```

Now we can see we have all variables as integer.

Checking for Outliers

In [0]:

```
# Checking for outliers in the continuous variables
num_telecom = telecom[['tenure','MonthlyCharges','SeniorCitizen','TotalCharges']]
```

In [0]:

```
# Checking outliers at 25%,50%,75%,90%,95% and 99%
num_telecom.describe(percentiles=[.25,.5,.75,.90,.95,.99])
```

Out[0]:

	tenure	MonthlyCharges	SeniorCitizen	TotalCharges
count	7043.000000	7043.000000	7043.000000	7032.000000
mean	32.371149	64.761692	0.162147	2283.300441
std	24.559481	30.090047	0.368612	2266.771362
min	0.000000	18.250000	0.000000	18.800000
25%	9.000000	35.500000	0.000000	401.450000

	tenure	MonthlyCharges	SeniorCitizen	TotalCharges
50%	29.000000	70.350000	0.000000	1397.475000
75%	55.000000	89.850000	0.000000	3794.737500
90%	69.000000	102.600000	1.000000	5976.640000
95%	72.000000	107.400000	1.000000	6923.590000
99%	72.000000	114.729000	1.000000	8039.883000
max	72.000000	118.750000	1.000000	8684.800000

From the distribution shown above, you can see that there no outier in your data. The numbers are gradually increasing.

Checking for Missing Values and Inputing Them

In [0]:

```
# Adding up the missing values (column-wise)
telecom.isnull().sum()
```

Out[0]:

```
customerID                                0
tenure                                    0
PhoneService                              0
PaperlessBilling                          0
MonthlyCharges                            0
TotalCharges                             11
Churn                                     0
SeniorCitizen                             0
Partner                                   0
Dependents                                0
Contract_One year                         0
Contract_Two year                         0
PaymentMethod_Credit card (automatic)     0
PaymentMethod_Electronic check            0
PaymentMethod_Mailed check                0
gender_Male                               0
MultipleLines_No                          0
MultipleLines_Yes                         0
InternetService_Fiber optic               0
InternetService_No                        0
OnlineSecurity_No                         0
OnlineSecurity_Yes                        0
OnlineBackup_No                           0
OnlineBackup_Yes                          0
DeviceProtection_No                       0
DeviceProtection_Yes                      0
TechSupport_No                            0
TechSupport_Yes                           0
StreamingTV_No                            0
StreamingTV_Yes                           0
StreamingMovies_No                        0
StreamingMovies_Yes                       0
dtype: int64
```

It means that 11/7043 = 0.001561834 i.e 0.1%, best is to remove these observations from the analysis

In [0]:

```
# Checking the percentage of missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[0]:

```
customerID                              0.00
tenure                                  0.00
PhoneService                            0.00
PaperlessBilling                        0.00
```

```
MonthlyCharges                           0.00
TotalCharges                             0.16
Churn                                    0.00
SeniorCitizen                            0.00
Partner                                  0.00
Dependents                               0.00
Contract_One year                        0.00
Contract_Two year                        0.00
PaymentMethod_Credit card (automatic)    0.00
PaymentMethod_Electronic check           0.00
PaymentMethod_Mailed check               0.00
gender_Male                              0.00
MultipleLines_No                         0.00
MultipleLines_Yes                        0.00
InternetService_Fiber optic              0.00
InternetService_No                       0.00
OnlineSecurity_No                        0.00
OnlineSecurity_Yes                       0.00
OnlineBackup_No                          0.00
OnlineBackup_Yes                         0.00
DeviceProtection_No                      0.00
DeviceProtection_Yes                     0.00
TechSupport_No                           0.00
TechSupport_Yes                          0.00
StreamingTV_No                           0.00
StreamingTV_Yes                          0.00
StreamingMovies_No                       0.00
StreamingMovies_Yes                      0.00
dtype: float64
```

In [0]:

```
# Removing NaN TotalCharges rows
telecom = telecom[~np.isnan(telecom['TotalCharges'])]
```

In [0]:

```
# Checking percentage of missing values after removing the missing values
round(100*(telecom.isnull().sum()/len(telecom.index)), 2)
```

Out[0]:

```
customerID                               0.0
tenure                                   0.0
PhoneService                             0.0
PaperlessBilling                         0.0
MonthlyCharges                           0.0
TotalCharges                             0.0
Churn                                    0.0
SeniorCitizen                            0.0
Partner                                  0.0
Dependents                               0.0
Contract_One year                        0.0
Contract_Two year                        0.0
PaymentMethod_Credit card (automatic)    0.0
PaymentMethod_Electronic check           0.0
PaymentMethod_Mailed check               0.0
gender_Male                              0.0
MultipleLines_No                         0.0
MultipleLines_Yes                        0.0
InternetService_Fiber optic              0.0
InternetService_No                       0.0
OnlineSecurity_No                        0.0
OnlineSecurity_Yes                       0.0
OnlineBackup_No                          0.0
OnlineBackup_Yes                         0.0
DeviceProtection_No                      0.0
DeviceProtection_Yes                     0.0
TechSupport_No                           0.0
TechSupport_Yes                          0.0
StreamingTV_No                           0.0
StreamingTV_Yes                          0.0
```

```
StreamingMovies_No                         0.0
StreamingMovies_Yes                        0.0
dtype: float64
```

Now we don't have any missing values

Feature Standardisation

In [0]:

```
# Normalising continuous features
df = telecom[['tenure','MonthlyCharges','TotalCharges']]
```

In [0]:

```
normalized_df=(df-df.mean())/df.std()
```

In [0]:

```
telecom = telecom.drop(['tenure','MonthlyCharges','TotalCharges'], 1)
```

In [0]:

```
telecom = pd.concat([telecom,normalized_df],axis=1)
```

In [0]:

```
telecom
```

Out[0]:

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Dependents	Contract_One year	Contract_Two year	P
0	7590-VHVEG	0	1	0	0	1	0	0	0	
1	5575-GNVDE	1	0	0	0	0	0	1	0	
2	3668-QPYBK	1	1	1	0	0	0	0	0	
3	7795-CFOCW	0	0	0	0	0	0	1	0	
4	9237-HQITU	1	1	1	0	0	0	0	0	
5	9305-CDSKC	1	1	1	0	0	0	0	0	
6	1452-KIOVK	1	1	0	0	0	1	0	0	
7	6713-OKOMC	0	0	0	0	0	0	0	0	
8	7892-POOKP	1	1	1	0	1	0	0	0	
9	6388-TABGU	1	0	0	0	0	1	1	0	
10	9763-GRSKD	1	1	0	0	1	1	0	0	
11	7469-LKBCI	1	0	0	0	0	0	0	1	
12	8091-TTVAX	1	0	0	0	1	0	1	0	
13	0280-XJGEX	1	1	1	0	0	0	0	0	

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Dependents	Contract_One year	Contract_Two year	P
14	5129-JLPIS	1	1	0	0	0	0	0	0	
15	3655-SNQYZ	1	0	0	0	1	1	0	1	
16	8191-XWSZG	1	0	0	0	0	0	1	0	
17	9959-WOFKT	1	0	0	0	0	1	0	1	
18	4190-MFLUW	1	0	1	0	1	1	0	0	
19	4183-MYFRB	1	1	0	0	0	0	0	0	
20	8779-QRDMV	0	1	1	1	0	0	0	0	
21	1680-VDCWW	1	0	0	0	1	0	1	0	
22	1066-JKSGK	1	0	1	0	0	0	0	0	
23	3638-WEABW	1	1	0	0	1	0	0	1	
24	6322-HRPFA	1	0	0	0	1	1	0	0	
25	6865-JZNKO	1	1	0	0	0	0	0	0	
26	6467-CHFZW	1	1	1	0	1	1	0	0	
27	8665-UTDHZ	0	0	1	0	1	1	0	0	
28	5248-YGIJN	1	1	0	0	1	0	0	1	
29	8773-HHUOZ	1	1	1	0	0	1	0	0	
...	...	...	...	...	...	...	...	...	...	
7013	1685-BQULA	1	1	0	0	0	0	0	0	
7014	9053-EJUNL	1	1	0	0	0	0	0	0	
7015	0666-UXTJO	1	1	0	1	1	0	0	0	
7016	1471-GIQKQ	1	0	0	0	0	0	0	0	
7017	4807-IZYOZ	1	0	0	0	0	0	0	1	
7018	1122-JWTJW	1	1	1	0	1	1	0	0	
7019	9710-NJERN	1	0	0	0	0	0	0	1	
7020	9837-FWLCH	1	1	0	0	1	1	0	0	
7021	1699-HPSBG	1	1	1	0	0	0	1	0	
7022	7203-OYKCT	1	1	0	0	0	0	1	0	
7023	1035-IPQPU	1	1	0	1	1	0	0	0	
7024	7398-LXGYX	1	1	0	0	1	0	0	0	

	customerID	PhoneService	PaperlessBilling	Churn	SeniorCitizen	Partner	Dependents	Contract_One year	Contract_Two year	P
7025	2823-LKABH	1	1	0	0	0	0	0	0	
7026	8775-CEBBJ	1	1	1	0	0	0	0	0	
7027	0550-DCXLH	1	0	0	0	0	0	0	0	
7028	9281-CEDRU	1	0	0	0	1	0	0	1	
7029	2235-DWLJU	0	1	0	1	0	0	0	0	
7030	0871-OPBXW	1	1	0	0	0	0	0	0	
7031	3605-JISKB	1	0	0	1	1	0	1	0	
7032	6894-LFHLY	1	1	1	1	0	0	0	0	
7033	9767-FFLEM	1	1	0	0	0	0	0	0	
7034	0639-TSIQW	1	1	1	0	0	0	0	0	
7035	8456-QDAVC	1	1	0	0	0	0	0	0	
7036	7750-EYXWZ	0	0	0	0	0	0	1	0	
7037	2569-WGERO	1	1	0	0	0	0	0	1	
7038	6840-RESVB	1	1	0	0	1	1	1	0	
7039	2234-XADUH	1	1	0	0	1	1	1	0	
7040	4801-JZAZL	0	1	0	0	1	1	0	0	
7041	8361-LTMKD	1	1	1	1	1	0	0	0	
7042	3186-AJIEK	1	1	0	0	0	0	0	1	

7032 rows × 32 columns

Checking the Churn Rate

Now we will look what is the percentage of number of people who have really churn in the telecom company.Basically, I want to see whether it's a balanced dataset or an imbalance dataset.

In [0]:

```
churn = (sum(telecom['Churn'])/len(telecom['Churn'].index))*100
```

In [0]:

```
churn
```

Out[0]:

```
26.578498293515356
```

We have almost 27% churn rate. We have more people who don't churn.

Model Building

Let's start by splitting our data into a training set and a test set.

Splitting Data into Training and Test Sets

In [0]:

```
from sklearn.model_selection import train_test_split
```

In [0]:

```
# Putting feature variable to X
X = telecom.drop(['Churn','customerID'],axis=1)

# Putting response variable to y
y = telecom['Churn']
```

In [0]:

```
y.head()
```

Out[0]:

```
0    0
1    0
2    1
3    0
4    1
Name: Churn, dtype: int64
```

In [0]:

```
# Splitting the data into train and test
#70% Training and 30% Testing
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7,test_size=0.3,ra
ndom_state=100)
```

Running Your First Training Model

In [0]:

```
import statsmodels.api as sm
```

In [0]:

```
# Logistic regression model
logm1 = sm.GLM(y_train,(sm.add_constant(X_train)), family = sm.families.Binomial())
logm1.fit().summary()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Met
hod .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

Out[0]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4898
Model Family:	Binomial	**Df Model:**	23
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2004.7
Date:	Mon, 01 Jul 2019	**Deviance:**	4009.4
Time:	05:10:18	**Pearson chi2:**	6.07e+03

No. Iterations:	7
Covariance Type:	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.2783	1.187	-2.762	0.006	-5.605	-0.952
PhoneService	0.8213	0.588	1.396	0.163	-0.332	1.974
PaperlessBilling	0.3254	0.090	3.614	0.000	0.149	0.502
SeniorCitizen	0.3984	0.102	3.924	0.000	0.199	0.597
Partner	0.0374	0.094	0.399	0.690	-0.146	0.221
Dependents	-0.1430	0.107	-1.332	0.183	-0.353	0.067
Contract_One year	-0.6578	0.129	-5.106	0.000	-0.910	-0.405
Contract_Two year	-1.2455	0.212	-5.874	0.000	-1.661	-0.830
PaymentMethod_Credit card (automatic)	-0.2577	0.137	-1.883	0.060	-0.526	0.011
PaymentMethod_Electronic check	0.1615	0.113	1.434	0.152	-0.059	0.382
PaymentMethod_Mailed check	-0.2536	0.137	-1.845	0.065	-0.523	0.016
gender_Male	-0.0346	0.078	-0.442	0.658	-0.188	0.119
MultipleLines_No	0.1295	0.205	0.632	0.527	-0.272	0.531
MultipleLines_Yes	0.6918	0.392	1.763	0.078	-0.077	1.461
InternetService_Fiber optic	2.5124	0.967	2.599	0.009	0.618	4.407
InternetService_No	-3.4348	1.324	-2.594	0.009	-6.030	-0.839
OnlineSecurity_No	0.0905	0.058	1.558	0.119	-0.023	0.204
OnlineSecurity_Yes	0.0660	0.174	0.380	0.704	-0.275	0.407
OnlineBackup_No	-0.0088	0.055	-0.161	0.872	-0.116	0.098
OnlineBackup_Yes	0.1653	0.172	0.960	0.337	-0.172	0.503
DeviceProtection_No	-0.0832	0.056	-1.487	0.137	-0.193	0.026
DeviceProtection_Yes	0.2397	0.174	1.379	0.168	-0.101	0.580
TechSupport_No	0.0935	0.058	1.604	0.109	-0.021	0.208
TechSupport_Yes	0.0630	0.174	0.362	0.717	-0.278	0.404
StreamingTV_No	-0.4016	0.133	-3.027	0.002	-0.662	-0.142
StreamingTV_Yes	0.5581	0.267	2.094	0.036	0.036	1.081
StreamingMovies_No	-0.3459	0.133	-2.609	0.009	-0.606	-0.086
StreamingMovies_Yes	0.5024	0.266	1.886	0.059	-0.020	1.025
tenure	-1.5198	0.190	-8.015	0.000	-1.891	-1.148
MonthlyCharges	-2.1817	1.160	-1.880	0.060	-4.456	0.092
TotalCharges	0.7329	0.198	3.705	0.000	0.345	1.121

Correlation Matrix

In [0]:

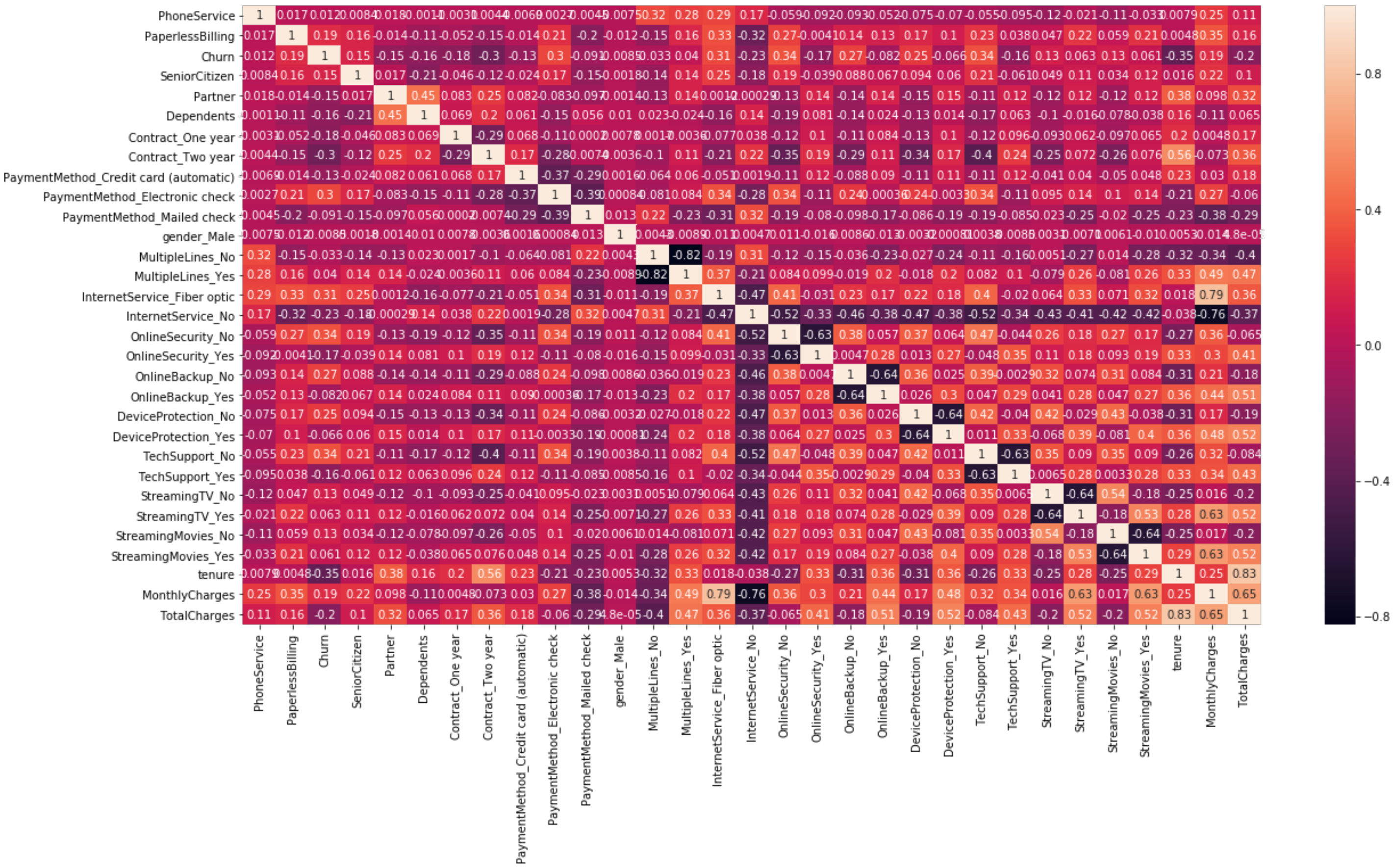
```
# Importing matplotlib and seaborn
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [0]:

```
# Let's see the correlation matrix
plt.figure(figsize = (20,10))# Size of the figure
sns.heatmap(telecom.corr(),annot = True)
```

Out [0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fc39413ab38>



Dropping highly correlated variables.

In [0]:

```
X_test2 = X_test.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','DevicePr
otection_No','TechSupport_No','StreamingTV_No','StreamingMovies_No'],1)
X_train2 = X_train.drop(['MultipleLines_No','OnlineSecurity_No','OnlineBackup_No','Device
Protection_No','TechSupport_No','StreamingTV_No','StreamingMovies_No'],1)
```

Checking the Correlation Matrix

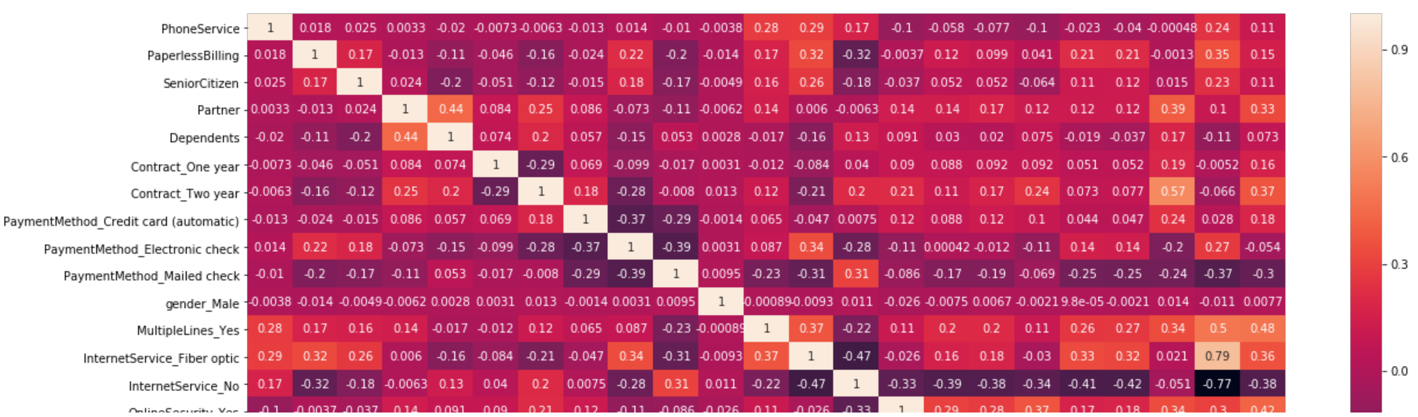
After dropping highly correlated variables now let's check the correlation matrix again.

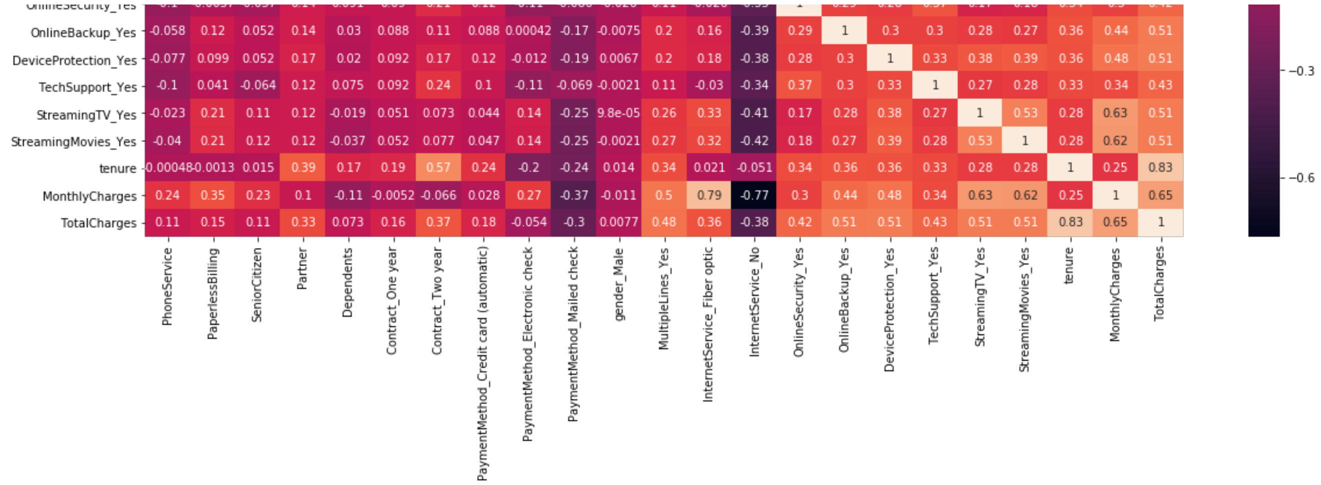
In [0]:

```
plt.figure(figsize = (20,10))
sns.heatmap(X_train2.corr(),annot = True)
```

Out [0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fc393b13a20>





Re-Running the Model

Now let's run our model again after dropping highly correlated variables

In [0]:

```
logm2 = sm.GLM(y_train,(sm.add_constant(X_train2)), family = sm.families.Binomial())
logm2.fit().summary()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

Out[0]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4898
Model Family:	Binomial	**Df Model:**	23
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2004.7
Date:	Mon, 01 Jul 2019	**Deviance:**	4009.4
Time:	05:14:53	**Pearson chi2:**	6.07e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.9338	1.545	-2.545	0.011	-6.963	-0.905
PhoneService	0.9507	0.789	1.205	0.228	-0.595	2.497
PaperlessBilling	0.3254	0.090	3.614	0.000	0.149	0.502
SeniorCitizen	0.3984	0.102	3.924	0.000	0.199	0.597
Partner	0.0374	0.094	0.399	0.690	-0.146	0.221
Dependents	-0.1430	0.107	-1.332	0.183	-0.353	0.067
Contract_One year	-0.6578	0.129	-5.106	0.000	-0.910	-0.405
Contract_Two year	-1.2455	0.212	-5.874	0.000	-1.661	-0.830
PaymentMethod_Credit card (automatic)	-0.2577	0.137	-1.883	0.060	-0.526	0.011
PaymentMethod_Electronic check	0.1615	0.113	1.434	0.152	-0.059	0.382
PaymentMethod_Mailed check	-0.2536	0.137	-1.845	0.065	-0.523	0.016
gender_Male	-0.0346	0.078	-0.442	0.658	-0.188	0.119

MultipleLines_Yes	0.5623	0.214	2.628	0.009	0.143	0.982
InternetService_Fiber optic	2.5124	0.967	2.599	0.009	0.618	4.407
InternetService_No	-2.7792	0.982	-2.831	0.005	-4.703	-0.855
OnlineSecurity_Yes	-0.0245	0.216	-0.113	0.910	-0.448	0.399
OnlineBackup_Yes	0.1740	0.212	0.822	0.411	-0.241	0.589
DeviceProtection_Yes	0.3229	0.215	1.501	0.133	-0.099	0.744
TechSupport_Yes	-0.0305	0.216	-0.141	0.888	-0.455	0.394
StreamingTV_Yes	0.9598	0.396	2.423	0.015	0.183	1.736
StreamingMovies_Yes	0.8484	0.396	2.143	0.032	0.072	1.624
tenure	-1.5198	0.190	-8.015	0.000	-1.891	-1.148
MonthlyCharges	-2.1817	1.160	-1.880	0.060	-4.456	0.092
TotalCharges	0.7329	0.198	3.705	0.000	0.345	1.121

Feature Selection Using Recursive Feature Elimination(RFE)

In [0]:

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
from sklearn.feature_selection import RFE
rfe = RFE(logreg, 13)          # running RFE with 13 variables as output
rfe = rfe.fit(X,y)
print(rfe.support_)            # Printing the boolean results
print(rfe.ranking_)            # Printing the ranking
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
```

```
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
```

```
[ True  True False False False  True  True False  True False False  True
 False  True  True False  True False False False False False  True False
 False  True False  True False  True]
[ 1  1  2 18  6  1  1 11  1 12 14  1  8  1  1  4  1 15  5 13 10  7  1  3
 16  1 17  1  9  1]
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
```

In [0]:

```
# Variables selected by RFE
col = ['PhoneService', 'PaperlessBilling', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fiber optic'
, 'InternetService_No',
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','TotalCharges
']
```

In [0]:

```
# Let's run the model using the selected variables
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logsk = LogisticRegression()
logsk.fit(X_train[col], y_train)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
```

Out[0]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [0]:

```python
#Comparing the model with StatsModels
logm4 = sm.GLM(y_train,(sm.add_constant(X_train[col])), family = sm.families.Binomial())
logm4.fit().summary()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Met
hod .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

Out[0]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4908
Model Family:	Binomial	**Df Model:**	13
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2024.2
Date:	Mon, 01 Jul 2019	**Deviance:**	4048.4
Time:	05:18:40	**Pearson chi2:**	6.19e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.0162	0.169	-6.017	0.000	-1.347	-0.685
PhoneService	-0.3090	0.173	-1.784	0.074	-0.648	0.030
PaperlessBilling	0.3595	0.089	4.029	0.000	0.185	0.534
Contract_One year	-0.7012	0.127	-5.516	0.000	-0.950	-0.452
Contract_Two year	-1.3187	0.210	-6.271	0.000	-1.731	-0.907
PaymentMethod_Electronic check	0.3668	0.083	4.446	0.000	0.205	0.529
MultipleLines_No	-0.2311	0.095	-2.435	0.015	-0.417	-0.045
InternetService_Fiber optic	0.7937	0.116	6.836	0.000	0.566	1.021
InternetService_No	-1.1832	0.182	-6.484	0.000	-1.541	-0.826
OnlineSecurity_Yes	-0.4107	0.102	-4.031	0.000	-0.610	-0.211
TechSupport_Yes	-0.4181	0.101	-4.135	0.000	-0.616	-0.220
StreamingMovies_No	-0.2024	0.094	-2.160	0.031	-0.386	-0.019
tenure	-1.4974	0.181	-8.251	0.000	-1.853	-1.142
TotalCharges	0.7373	0.186	3.965	0.000	0.373	1.102

In [0]:

```python
#To address multicollinearity problem
# UDF for calculating VIF value
#Detecting Multicollinearity using Variance Inflation Factor(VIF)
def vif_cal(input_data, dependent_col):
    vif_df = pd.DataFrame( columns = ['Var', 'Vif'])
    x_vars=input_data.drop([dependent_col], axis=1)
    xvar_names=x_vars.columns
    for i in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.OLS(y,x).fit().rsquared
        vif=round(1/(1-rsq),2)
        vif_df.loc[i] = [xvar_names[i], vif]
    return vif_df.sort_values(by = 'Vif', axis=0, ascending=False, inplace=False)
```

In [0]:

```
telecom.columns
['PhoneService', 'PaperlessBilling', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fiber optic'
, 'InternetService_No',
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','TotalCharges
']
```

Out[0]:

```
['PhoneService',
 'PaperlessBilling',
 'Contract_One year',
 'Contract_Two year',
 'PaymentMethod_Electronic check',
 'MultipleLines_No',
 'InternetService_Fiber optic',
 'InternetService_No',
 'OnlineSecurity_Yes',
 'TechSupport_Yes',
 'StreamingMovies_No',
 'tenure',
 'TotalCharges']
```

In [0]:

```
# Calculating Vif value
vif_cal(input_data=telecom.drop(['customerID','SeniorCitizen', 'Partner', 'Dependents',
                                  'PaymentMethod_Credit card (automatic)','PaymentMethod_
Mailed check',
                                  'gender_Male','MultipleLines_Yes','OnlineSecurity_No','
OnlineBackup_No',
                                  'OnlineBackup_Yes', 'DeviceProtection_No', 'DeviceProte
ction_Yes',
                                  'TechSupport_No','StreamingTV_No','StreamingTV_Yes','St
reamingMovies_Yes',
                                  'MonthlyCharges'], axis=1), dependent_col='Churn')
```

Out[0]:

	Var	Vif
0	PhoneService	10.87
12	TotalCharges	8.58
11	tenure	6.80
1	PaperlessBilling	2.61
7	InternetService_No	0.65
3	Contract_Two year	0.28
2	Contract_One year	0.24
9	TechSupport_Yes	0.24
8	OnlineSecurity_Yes	0.21
10	StreamingMovies_No	0.19
4	PaymentMethod_Electronic check	0.05
5	MultipleLines_No	0.05
6	InternetService_Fiber optic	0.03

Dropping Variable with high VIF

In [0]:

```
col = ['PaperlessBilling', 'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Electronic check','MultipleLines_No','InternetService_Fiber optic'
, 'InternetService_No',
```

```
       'OnlineSecurity_Yes','TechSupport_Yes','StreamingMovies_No','tenure','TotalCharges
']
```

In [0]:

```
logm5 = sm.GLM(y_train,(sm.add_constant(X_train[col])), family = sm.families.Binomial())
logm5.fit().summary()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/core/fromnumeric.py:2389: FutureWarning: Met
hod .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

Out[0]:

Generalized Linear Model Regression Results

Dep. Variable:	Churn	**No. Observations:**	4922
Model:	GLM	**Df Residuals:**	4909
Model Family:	Binomial	**Df Model:**	12
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2025.8
Date:	Mon, 01 Jul 2019	**Deviance:**	4051.5
Time:	05:21:11	**Pearson chi2:**	6.00e+03
No. Iterations:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.1915	0.138	-8.607	0.000	-1.463	-0.920
PaperlessBilling	0.3563	0.089	3.998	0.000	0.182	0.531
Contract_One year	-0.6965	0.127	-5.483	0.000	-0.945	-0.448
Contract_Two year	-1.3078	0.210	-6.230	0.000	-1.719	-0.896
PaymentMethod_Electronic check	0.3700	0.082	4.487	0.000	0.208	0.532
MultipleLines_No	-0.2990	0.087	-3.442	0.001	-0.469	-0.129
InternetService_Fiber optic	0.7227	0.108	6.666	0.000	0.510	0.935
InternetService_No	-1.2732	0.175	-7.276	0.000	-1.616	-0.930
OnlineSecurity_Yes	-0.4100	0.102	-4.025	0.000	-0.610	-0.210
TechSupport_Yes	-0.4202	0.101	-4.157	0.000	-0.618	-0.222
StreamingMovies_No	-0.2205	0.093	-2.366	0.018	-0.403	-0.038
tenure	-1.4276	0.177	-8.066	0.000	-1.774	-1.081
TotalCharges	0.6495	0.179	3.622	0.000	0.298	1.001

In [0]:

```
# Calculating Vif value
vif_cal(input_data=telecom.drop(['customerID','PhoneService','SeniorCitizen', 'Partner',
'Dependents',
                                 'PaymentMethod_Credit card (automatic)','PaymentMethod_
Mailed check',
                                 'gender_Male','MultipleLines_Yes','OnlineSecurity_No','
OnlineBackup_No',
                                 'OnlineBackup_Yes', 'DeviceProtection_No', 'DeviceProte
ction_Yes',
                                 'TechSupport_No','StreamingTV_No','StreamingTV_Yes','St
reamingMovies_Yes',
                                 'MonthlyCharges'], axis=1), dependent_col='Churn')
```

Out[0]:

	Var	Vif
11	TotalCharges	8.24
10	tenure	6.56
0	PaperlessBilling	2.44
6	InternetService_No	0.45
2	Contract_Two year	0.26
8	TechSupport_Yes	0.24
1	Contract_One year	0.23
7	OnlineSecurity_Yes	0.21
9	StreamingMovies_No	0.17
3	PaymentMethod_Electronic check	0.05
4	MultipleLines_No	0.04
5	InternetService_Fiber optic	0.02

In [0]:

```
# Let's run the model using the selected variables
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
logsk = LogisticRegression()
logsk.fit(X_train[col], y_train)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432: FutureWarnin
g: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this wa
rning.
  FutureWarning)
```

Out[0]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

Making Predictions

In [0]:

```
# Predicted probabilities
y_pred = logsk.predict_proba(X_test[col])
y_pred
```

Out[0]:

```
array([[0.50091675, 0.49908325],
       [0.62730407, 0.37269593],
       [0.99326151, 0.00673849],
       ...,
       [0.99619427, 0.00380573],
       [0.54140273, 0.45859727],
       [0.99756576, 0.00243424]])
```

In [0]:

```
# Converting y_pred to a dataframe which is an array
y_pred_df = pd.DataFrame(y_pred)
```

In [0]:

```
# Converting to column dataframe
y_pred_1 = y_pred_df.iloc[:,[1]]
y_pred_1
```

Out[0]:

	1
0	0.499083
1	0.372696
2	0.006738
3	0.635453
4	0.007533
5	0.673095
6	0.177610
7	0.005931
8	0.681964
9	0.118320
10	0.050400
11	0.109029
12	0.022472
13	0.453892
14	0.760527
15	0.801745
16	0.476952
17	0.702485
18	0.107699
19	0.120798
20	0.361009
21	0.625166
22	0.682284
23	0.517458
24	0.049125
25	0.003352
26	0.029837
27	0.004115
28	0.364597
29	0.212304
...	...
2080	0.012408
2081	0.344398
2082	0.214186
2083	0.008402
2084	0.398487
2085	0.288573
2086	0.728764
2087	0.435861
2088	0.067832
2089	0.324133
2090	0.032337

2091	0.434160
2092	0.003839
2093	0.270909
2094	0.155305
2095	0.374195
2096	0.023819
2097	0.245812
2098	0.089576
2099	0.002256
2100	0.690666
2101	0.002518
2102	0.071062
2103	0.421375
2104	0.288124
2105	0.015464
2106	0.056786
2107	0.003806
2108	0.458597
2109	0.002434

2110 rows × 1 columns

In [0]:

```
# Let's see the head
y_pred_1.head()
```

Out[0]:

	1
0	0.499083
1	0.372696
2	0.006738
3	0.635453
4	0.007533

In [0]:

```
# Converting y_test to dataframe
y_test_df = pd.DataFrame(y_test)
```

In [0]:

```
# Putting CustID to index
y_test_df['CustID'] = y_test_df.index
```

In [0]:

```
# Removing index for both dataframes to append them side by side
y_pred_1.reset_index(drop=True, inplace=True)
y_test_df.reset_index(drop=True, inplace=True)
```

In [0]:

```
# Appending y_test_df and y_pred_1
y_pred_final = pd.concat([y_test_df,y_pred_1],axis=1)
```

In [0]:

```
# Renaming the column
y_pred_final= y_pred_final.rename(columns={ 1 : 'Churn_Prob'})
```

In [0]:

```
# Rearranging the columns
y_pred_final = y_pred_final.reindex_axis(['CustID','Churn','Churn_Prob'], axis=1)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: FutureWarning: '.reindex_
axis' is deprecated and will be removed in a future version. Use '.reindex' instead.
  """Entry point for launching an IPython kernel.
```

In [0]:

```
# Let's see the head of y_pred_final
y_pred_final.head()
```

Out[0]:

	CustID	Churn	Churn_Prob
0	942	0	0.499083
1	3730	1	0.372696
2	1761	0	0.006738
3	2283	1	0.635453
4	1872	0	0.007533

In [0]:

```
# Creating new column 'predicted' with 1 if Churn_Prob>0.5 else 0
#Changing Churn_Prob to 0 and 1
y_pred_final['predicted'] = y_pred_final.Churn_Prob.map( lambda x: 1 if x > 0.5 else 0)
```

In [0]:

```
# Let's see the head
y_pred_final.head()
```

Out[0]:

	CustID	Churn	Churn_Prob	predicted
0	942	0	0.499083	0
1	3730	1	0.372696	0
2	1761	0	0.006738	0
3	2283	1	0.635453	1
4	1872	0	0.007533	0

Model Evaluation

In [0]:

```
from sklearn import metrics
```

In [0]:

```
# Confusion matrix
confusion = metrics.confusion_matrix( y_pred_final.Churn, y_pred_final.predicted )
confusion
```

Out[0]:

```
array([[1362,  166],
       [ 249,  333]])
```

In [0]:

```
# Predicted     not_churn    churn
# Actual
# not_churn        1326      166
# churn            249       333
```

In [0]:

```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.Churn, y_pred_final.predicted)
```

Out[0]:

```
0.8033175355450237
```

In [0]:

```
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives
```

In [0]:

```
# Let's see the sensitivity of our logistic regression model
TP / float(TP+FN)
```

Out[0]:

```
0.5721649484536082
```

In [0]:

```
# Let us calculate specificity
TN / float(TN+FP)
```

Out[0]:

```
0.8913612565445026
```

In [0]:

```
# Calculate false postive rate - predicting churn when customer does not have churned
print(FP/ float(TN+FP))
```

```
0.10863874345549739
```

In [0]:

```
# positive predictive value
print (TP / float(TP+FP))
```

```
0.6673346693386774
```

In [0]:

```
# Negative predictive value
print (TN / float(TN+ FN))
```

```
0.845437616387337
```

ROC Curve

An ROC curve demonstrates several things:

- **It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).**

decrease in specificity).

- The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.
- The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test.

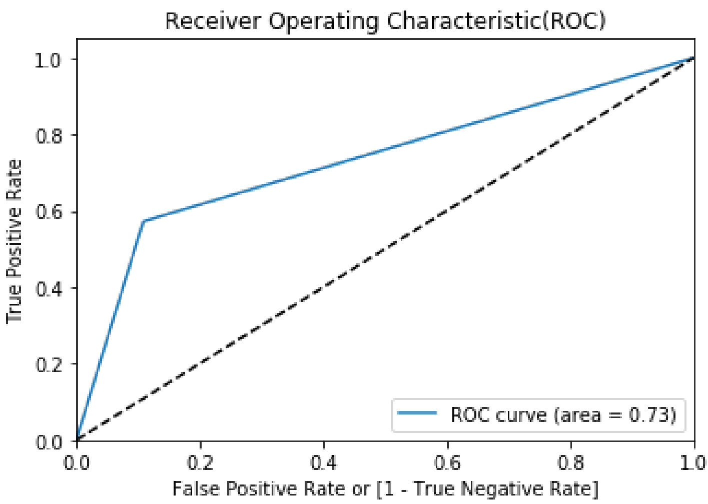
In [0]:

```
def draw_roc( actual, probs ):
    fpr, tpr, thresholds = metrics.roc_curve( actual, probs,drop_intermediate = False )
    auc_score = metrics.roc_auc_score(actual, probs)
    plt.figure(figsize=(6, 4))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic(ROC)')
    plt.legend(loc="lower right")
    plt.show()

    return fpr, tpr, thresholds
```

In [0]:

```
draw_roc(y_pred_final.Churn, y_pred_final.predicted)
```



Out[0]:

```
(array([0.        , 0.10863874, 1.        ]),
 array([0.        , 0.57216495, 1.        ]),
 array([2, 1, 0]))
```

Finding Optimal Cutoff Point

Optimal cutoff probability is that prob where we get balanced sensitivity and specificity

In [0]:

```
# Let's create columns with different probability cutoffs
numbers = [float(x)/10 for x in range(10)]
for i in numbers:
    y_pred_final[i]= y_pred_final.Churn_Prob.map( lambda x: 1 if x > i else 0)
y_pred_final.head()
```

Out[0]:

	CustID	Churn	Churn_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0	942	0	0.499083	0	1	1	1	1	1	0	0	0	0	0
1	3730	1	0.372696	0	1	1	1	1	0	0	0	0	0	0

	CustID	Churn	Churn_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
2	[illegible]	0	[illegible]	0	1	0	0	0	0	0	0	0	0	0
3	2283	1	0.635453	1	1	1	1	1	1	1	1	0	0	0
4	1872	0	0.007533	0	1	0	0	0	0	0	0	0	0	0

In [0]:

```
# Now let's calculate accuracy sensitivity and specificity for various probability cutoff
s.
cutoff_df = pd.DataFrame( columns = ['prob','accuracy','sensi','speci'])
from sklearn.metrics import confusion_matrix

# TP = confusion[1,1] # true positive
# TN = confusion[0,0] # true negatives
# FP = confusion[0,1] # false positives
# FN = confusion[1,0] # false negatives

num = [0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]
for i in num:
    cm1 = metrics.confusion_matrix( y_pred_final.Churn, y_pred_final[i] )
    total1=sum(sum(cm1))
    accuracy = (cm1[0,0]+cm1[1,1])/total1
    speci = cm1[0,0]/(cm1[0,0]+cm1[0,1])
    sensi = cm1[1,1]/(cm1[1,0]+cm1[1,1])
    cutoff_df.loc[i] =[ i ,accuracy,sensi,speci]
print(cutoff_df)
```

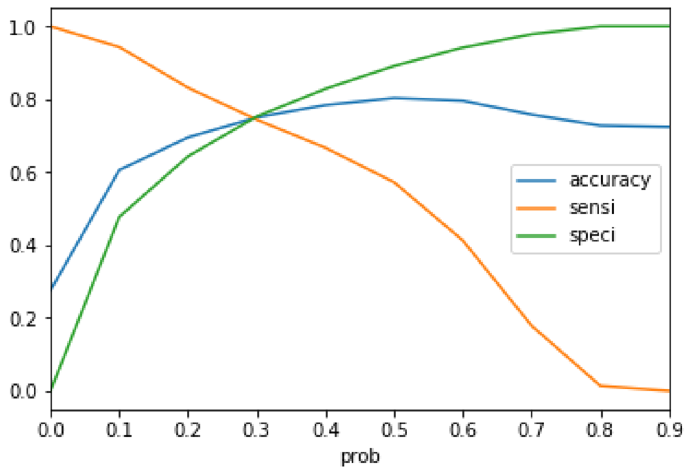
```
     prob  accuracy     sensi     speci
0.0   0.0  0.275829  1.000000  0.000000
0.1   0.1  0.605687  0.943299  0.477094
0.2   0.2  0.695261  0.831615  0.643325
0.3   0.3  0.750237  0.743986  0.752618
0.4   0.4  0.783886  0.666667  0.828534
0.5   0.5  0.803318  0.572165  0.891361
0.6   0.6  0.795735  0.412371  0.941754
0.7   0.7  0.757820  0.178694  0.978403
0.8   0.8  0.727962  0.013746  1.000000
0.9   0.9  0.724171  0.000000  1.000000
```

In [0]:

```
# Let's plot accuracy sensitivity and specificity for various probabilities.
cutoff_df.plot.line(x='prob', y=['accuracy','sensi','speci'])
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc38faca128>
```



From the curve above, 0.3 is the optimum point to take it as a cutoff probability.

In [0]:

```
y_pred_final['final_predicted'] = y_pred_final.Churn_Prob.map( lambda x: 1 if x > 0.3 el
```

```
se 0)
```

In [0]:

```
y_pred_final.head()
```

Out[0]:

	CustID	Churn	Churn_Prob	predicted	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	final_predicted
0	942	0	0.499083	0	1	1	1	1	1	0	0	0	0	0	1
1	3730	1	0.372696	0	1	1	1	1	0	0	0	0	0	0	1
2	1761	0	0.006738	0	1	0	0	0	0	0	0	0	0	0	0
3	2283	1	0.635453	1	1	1	1	1	1	1	1	0	0	0	1
4	1872	0	0.007533	0	1	0	0	0	0	0	0	0	0	0	0

In [0]:

```
#Let's check the overall accuracy.
metrics.accuracy_score( y_pred_final.Churn, y_pred_final.final_predicted)
```

Out[0]:

```
0.7502369668246446
```

In [0]:

```
metrics.confusion_matrix( y_pred_final.Churn, y_pred_final.final_predicted )
```

Out[0]:

```
array([[1150,  378],
       [ 149,  433]])
```

END