

# Telecom\_Churn\_Model

June 8, 2019

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## 2 1.Data Import and Cleanup ( index )

```
[35]: import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from IPython.display import display # Allows the use of display() for
↳DataFrames
%matplotlib inline
```

## 2.0.1 1.1 Data Overview ( index )

```
[36]: #path to data source file
source_path = '/home/gino/Documents/Udacity/MLEnano/machine-learning-master/
↳projects/capstone/Final/WA_Fn-UseC_-Telco-Customer-Churn.csv'

raw_data = pd.read_csv(source_path)

print raw_data.shape
raw_data
```

(7043, 21)

```
[36]:
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	\
0	7590-VHVEG	Female	0	Yes	No	1	
1	5575-GNVDE	Male	0	No	No	34	
2	3668-QPYBK	Male	0	No	No	2	
3	7795-CFOCW	Male	0	No	No	45	
4	9237-HQITU	Female	0	No	No	2	
5	9305-CDSKC	Female	0	No	No	8	
6	1452-KIOVK	Male	0	No	Yes	22	
7	6713-OKOMC	Female	0	No	No	10	
8	7892-POOKP	Female	0	Yes	No	28	
9	6388-TABGU	Male	0	No	Yes	62	
10	9763-GRSKD	Male	0	Yes	Yes	13	
11	7469-LKBCI	Male	0	No	No	16	
12	8091-TTVAX	Male	0	Yes	No	58	
13	0280-XJGEX	Male	0	No	No	49	
14	5129-JLPIS	Male	0	No	No	25	
15	3655-SNQYZ	Female	0	Yes	Yes	69	
16	8191-XWSZG	Female	0	No	No	52	
17	9959-WOFKT	Male	0	No	Yes	71	
18	4190-MFLUW	Female	0	Yes	Yes	10	
19	4183-MYFRB	Female	0	No	No	21	
20	8779-QRDMV	Male	1	No	No	1	
21	1680-VDCWW	Male	0	Yes	No	12	
22	1066-JKSGK	Male	0	No	No	1	
23	3638-WEABW	Female	0	Yes	No	58	
24	6322-HRPFA	Male	0	Yes	Yes	49	
25	6865-JZSKO	Female	0	No	No	30	
26	6467-CHFZW	Male	0	Yes	Yes	47	
27	8665-UTDHZ	Male	0	Yes	Yes	1	
28	5248-YGIJN	Male	0	Yes	No	72	
29	8773-HHUOZ	Female	0	No	Yes	17	
...	...	...	...	...	...	...	
7013	1685-BQULA	Female	0	No	No	40	
7014	9053-EJUNL	Male	0	No	No	41	
7015	0666-UCTJO	Male	1	Yes	No	34	

7016	1471-GIQKQ	Female	0	No	No	1
7017	4807-IZYOZ	Female	0	No	No	51
7018	1122-JWTJW	Male	0	Yes	Yes	1
7019	9710-NJERN	Female	0	No	No	39
7020	9837-FWLCH	Male	0	Yes	Yes	12
7021	1699-HPSBG	Male	0	No	No	12
7022	7203-OYKCT	Male	0	No	No	72
7023	1035-IPQPU	Female	1	Yes	No	63
7024	7398-LXGYX	Male	0	Yes	No	44
7025	2823-LKABH	Female	0	No	No	18
7026	8775-CEBBJ	Female	0	No	No	9
7027	0550-DCXLH	Male	0	No	No	13
7028	9281-CEDRU	Female	0	Yes	No	68
7029	2235-DWLJU	Female	1	No	No	6
7030	0871-OPBXW	Female	0	No	No	2
7031	3605-JISKB	Male	1	Yes	No	55
7032	6894-LFHLY	Male	1	No	No	1
7033	9767-FFLEM	Male	0	No	No	38
7034	0639-TSIQW	Female	0	No	No	67
7035	8456-QDAVC	Male	0	No	No	19
7036	7750-EYXWZ	Female	0	No	No	12
7037	2569-WGERO	Female	0	No	No	72
7038	6840-RESVB	Male	0	Yes	Yes	24
7039	2234-XADUH	Female	0	Yes	Yes	72
7040	4801-JZAZL	Female	0	Yes	Yes	11
7041	8361-LTMKD	Male	1	Yes	No	4
7042	3186-AJIEK	Male	0	No	No	66

	PhoneService	MultipleLines	InternetService	OnlineSecurity \
0	No	No phone service	DSL	No
1	Yes	No	DSL	Yes
2	Yes	No	DSL	Yes
3	No	No phone service	DSL	Yes
4	Yes	No	Fiber optic	No
5	Yes	Yes	Fiber optic	No
6	Yes	Yes	Fiber optic	No
7	No	No phone service	DSL	Yes
8	Yes	Yes	Fiber optic	No
9	Yes	No	DSL	Yes
10	Yes	No	DSL	Yes
11	Yes	No	No	No internet service
12	Yes	Yes	Fiber optic	No
13	Yes	Yes	Fiber optic	No
14	Yes	No	Fiber optic	Yes
15	Yes	Yes	Fiber optic	Yes
16	Yes	No	No	No internet service
17	Yes	Yes	Fiber optic	Yes

18	Yes	No	DSL	No
19	Yes	No	Fiber optic	No
20	No	No phone service	DSL	No
21	Yes	No	No	No internet service
22	Yes	No	No	No internet service
23	Yes	Yes	DSL	No
24	Yes	No	DSL	Yes
25	Yes	No	DSL	Yes
26	Yes	Yes	Fiber optic	No
27	No	No phone service	DSL	No
28	Yes	Yes	DSL	Yes
29	Yes	No	DSL	No
...	...	...	...	...
7013	Yes	Yes	Fiber optic	No
7014	Yes	Yes	Fiber optic	No
7015	Yes	No	Fiber optic	No
7016	Yes	No	DSL	No
7017	Yes	No	No	No internet service
7018	Yes	No	Fiber optic	No
7019	Yes	No	No	No internet service
7020	Yes	No	No	No internet service
7021	Yes	No	DSL	No
7022	Yes	Yes	Fiber optic	No
7023	Yes	Yes	Fiber optic	No
7024	Yes	Yes	Fiber optic	Yes
7025	Yes	Yes	Fiber optic	No
7026	Yes	No	DSL	No
7027	Yes	No	DSL	No
7028	Yes	No	DSL	No
7029	No	No phone service	DSL	No
7030	Yes	No	No	No internet service
7031	Yes	Yes	DSL	Yes
7032	Yes	Yes	Fiber optic	No
7033	Yes	No	Fiber optic	No
7034	Yes	Yes	Fiber optic	Yes
7035	Yes	No	Fiber optic	No
7036	No	No phone service	DSL	No
7037	Yes	No	No	No internet service
7038	Yes	Yes	DSL	Yes
7039	Yes	Yes	Fiber optic	No
7040	No	No phone service	DSL	Yes
7041	Yes	Yes	Fiber optic	No
7042	Yes	No	Fiber optic	Yes
...	DeviceProtection		TechSupport	StreamingTV \
0	...	No	No	No
1	...	Yes	No	No

2	...	No	No	No
3	...	Yes	Yes	No
4	...	No	No	No
5	...	Yes	No	Yes
6	...	No	No	Yes
7	...	No	No	No
8	...	Yes	Yes	Yes
9	...	No	No	No
10	...	No	No	No
11	...	No internet service	No internet service	No internet service
12	...	Yes	No	Yes
13	...	Yes	No	Yes
14	...	Yes	Yes	Yes
15	...	Yes	Yes	Yes
16	...	No internet service	No internet service	No internet service
17	...	Yes	No	Yes
18	...	Yes	Yes	No
19	...	Yes	No	No
20	...	Yes	No	No
21	...	No internet service	No internet service	No internet service
22	...	No internet service	No internet service	No internet service
23	...	No	Yes	No
24	...	No	Yes	No
25	...	No	No	No
26	...	No	No	Yes
27	...	No	No	No
28	...	Yes	Yes	Yes
29	...	No	No	Yes
...	...	...	...	...
7013	...	Yes	No	Yes
7014	...	No	No	Yes
7015	...	Yes	No	Yes
7016	...	No	No	No
7017	...	No internet service	No internet service	No internet service
7018	...	No	No	No
7019	...	No internet service	No internet service	No internet service
7020	...	No internet service	No internet service	No internet service
7021	...	No	Yes	Yes
7022	...	Yes	No	Yes
7023	...	Yes	No	Yes
7024	...	Yes	No	No
7025	...	Yes	Yes	No
7026	...	No	No	No
7027	...	No	Yes	Yes
7028	...	No	Yes	Yes
7029	...	No	No	Yes
7030	...	No internet service	No internet service	No internet service

7031	...	No	No	No
7032	...	No	No	No
7033	...	No	No	No
7034	...	Yes	No	Yes
7035	...	No	No	Yes
7036	...	Yes	Yes	Yes
7037	...	No internet service	No internet service	No internet service
7038	...	Yes	Yes	Yes
7039	...	Yes	No	Yes
7040	...	No	No	No
7041	...	No	No	No
7042	...	Yes	Yes	Yes

	StreamingMovies	Contract	PaperlessBilling \
0	No	Month-to-month	Yes
1	No	One year	No
2	No	Month-to-month	Yes
3	No	One year	No
4	No	Month-to-month	Yes
5	Yes	Month-to-month	Yes
6	No	Month-to-month	Yes
7	No	Month-to-month	No
8	Yes	Month-to-month	Yes
9	No	One year	No
10	No	Month-to-month	Yes
11	No internet service	Two year	No
12	Yes	One year	No
13	Yes	Month-to-month	Yes
14	Yes	Month-to-month	Yes
15	Yes	Two year	No
16	No internet service	One year	No
17	Yes	Two year	No
18	No	Month-to-month	No
19	Yes	Month-to-month	Yes
20	Yes	Month-to-month	Yes
21	No internet service	One year	No
22	No internet service	Month-to-month	No
23	No	Two year	Yes
24	No	Month-to-month	No
25	No	Month-to-month	Yes
26	Yes	Month-to-month	Yes
27	No	Month-to-month	No
28	Yes	Two year	Yes
29	Yes	Month-to-month	Yes
...	...	...	...
7013	No	Month-to-month	Yes
7014	No	Month-to-month	Yes

7015	No	Month-to-month	Yes
7016	No	Month-to-month	No
7017	No internet service	Two year	No
7018	No	Month-to-month	Yes
7019	No internet service	Two year	No
7020	No internet service	Month-to-month	Yes
7021	No	One year	Yes
7022	Yes	One year	Yes
7023	Yes	Month-to-month	Yes
7024	No	Month-to-month	Yes
7025	Yes	Month-to-month	Yes
7026	No	Month-to-month	Yes
7027	Yes	Month-to-month	No
7028	No	Two year	No
7029	Yes	Month-to-month	Yes
7030	No internet service	Month-to-month	Yes
7031	No	One year	No
7032	No	Month-to-month	Yes
7033	No	Month-to-month	Yes
7034	No	Month-to-month	Yes
7035	No	Month-to-month	Yes
7036	Yes	One year	No
7037	No internet service	Two year	Yes
7038	Yes	One year	Yes
7039	Yes	One year	Yes
7040	No	Month-to-month	Yes
7041	No	Month-to-month	Yes
7042	Yes	Two year	Yes

	PaymentMethod	MonthlyCharges	TotalCharges	Churn
0	Electronic check	29.85	29.85	No
1	Mailed check	56.95	1889.5	No
2	Mailed check	53.85	108.15	Yes
3	Bank transfer (automatic)	42.30	1840.75	No
4	Electronic check	70.70	151.65	Yes
5	Electronic check	99.65	820.5	Yes
6	Credit card (automatic)	89.10	1949.4	No
7	Mailed check	29.75	301.9	No
8	Electronic check	104.80	3046.05	Yes
9	Bank transfer (automatic)	56.15	3487.95	No
10	Mailed check	49.95	587.45	No
11	Credit card (automatic)	18.95	326.8	No
12	Credit card (automatic)	100.35	5681.1	No
13	Bank transfer (automatic)	103.70	5036.3	Yes
14	Electronic check	105.50	2686.05	No
15	Credit card (automatic)	113.25	7895.15	No
16	Mailed check	20.65	1022.95	No

17	Bank transfer (automatic)	106.70	7382.25	No
18	Credit card (automatic)	55.20	528.35	Yes
19	Electronic check	90.05	1862.9	No
20	Electronic check	39.65	39.65	Yes
21	Bank transfer (automatic)	19.80	202.25	No
22	Mailed check	20.15	20.15	Yes
23	Credit card (automatic)	59.90	3505.1	No
24	Credit card (automatic)	59.60	2970.3	No
25	Bank transfer (automatic)	55.30	1530.6	No
26	Electronic check	99.35	4749.15	Yes
27	Electronic check	30.20	30.2	Yes
28	Credit card (automatic)	90.25	6369.45	No
29	Mailed check	64.70	1093.1	Yes
...	...	...	...	...
7013	Bank transfer (automatic)	93.40	3756.4	No
7014	Electronic check	89.20	3645.75	No
7015	Credit card (automatic)	85.20	2874.45	No
7016	Electronic check	49.95	49.95	No
7017	Bank transfer (automatic)	20.65	1020.75	No
7018	Mailed check	70.65	70.65	Yes
7019	Mailed check	20.15	826	No
7020	Electronic check	19.20	239	No
7021	Electronic check	59.80	727.8	Yes
7022	Electronic check	104.95	7544.3	No
7023	Electronic check	103.50	6479.4	No
7024	Credit card (automatic)	84.80	3626.35	No
7025	Bank transfer (automatic)	95.05	1679.4	No
7026	Bank transfer (automatic)	44.20	403.35	Yes
7027	Mailed check	73.35	931.55	No
7028	Bank transfer (automatic)	64.10	4326.25	No
7029	Electronic check	44.40	263.05	No
7030	Mailed check	20.05	39.25	No
7031	Credit card (automatic)	60.00	3316.1	No
7032	Electronic check	75.75	75.75	Yes
7033	Credit card (automatic)	69.50	2625.25	No
7034	Credit card (automatic)	102.95	6886.25	Yes
7035	Bank transfer (automatic)	78.70	1495.1	No
7036	Electronic check	60.65	743.3	No
7037	Bank transfer (automatic)	21.15	1419.4	No
7038	Mailed check	84.80	1990.5	No
7039	Credit card (automatic)	103.20	7362.9	No
7040	Electronic check	29.60	346.45	No
7041	Mailed check	74.40	306.6	Yes
7042	Bank transfer (automatic)	105.65	6844.5	No

[7043 rows x 21 columns]



```
[3]: raw_data.describe()
```

```
[3]:      SeniorCitizen      tenure  MonthlyCharges
count      7043.000000  7043.000000      7043.000000
mean         0.162147    32.371149         64.761692
std          0.368612    24.559481         30.090047
min          0.000000     0.000000         18.250000
25%          0.000000     9.000000         35.500000
50%          0.000000    29.000000         70.350000
75%          0.000000    55.000000         89.850000
max          1.000000    72.000000        118.750000
```

## 3 2.Data Manipulation ( index )

### 3.0.1 Blanks and NA's in the data

```
[4]: #Look for NA's, missing datapoints.
display(raw_data.isna().any())

#count of all non-NA values
display(raw_data.count())
```

```
customerID      False
gender           False
SeniorCitizen    False
Partner          False
Dependents       False
tenure           False
PhoneService     False
MultipleLines    False
InternetService  False
OnlineSecurity   False
OnlineBackup     False
DeviceProtection False
TechSupport      False
StreamingTV      False
StreamingMovies  False
Contract         False
PaperlessBilling False
PaymentMethod    False
MonthlyCharges   False
TotalCharges     False
Churn            False
dtype: bool
```

```
customerID      7043
```

```

gender          7043
SeniorCitizen   7043
Partner         7043
Dependents      7043
tenure          7043
PhoneService    7043
MultipleLines   7043
InternetService 7043
OnlineSecurity  7043
OnlineBackup    7043
DeviceProtection 7043
TechSupport     7043
StreamingTV     7043
StreamingMovies 7043
Contract        7043
PaperlessBilling 7043
PaymentMethod   7043
MonthlyCharges  7043
TotalCharges    7043
Churn           7043
dtype: int64

```

```
[5]: raw_data.columns
```

```
[5]: Index([u'customerID', u'gender', u'SeniorCitizen', u'Partner', u'Dependents',
u'tenure', u'PhoneService', u'MultipleLines', u'InternetService',
u'OnlineSecurity', u'OnlineBackup', u'DeviceProtection', u'TechSupport',
u'StreamingTV', u'StreamingMovies', u'Contract', u'PaperlessBilling',
u'PaymentMethod', u'MonthlyCharges', u'TotalCharges', u'Churn'],
dtype='object')
```

```
[6]: #Find indexes of empty cells
blanks = np.where(raw_data.applymap(lambda x: x==' '))
print np.array(blanks).reshape(2, len(blanks[0]))

#11 blanks on column 19, Total Charges
#drop blank rows
raw_data.drop(blanks[0], inplace = True)
raw_data.reset_index(drop=True, inplace = True)

#drop customerID column
raw_data.drop('customerID', axis=1, inplace = True)

#change data types on some columns
cleaned_data = raw_data.astype({'TotalCharges': 'float64', 'tenure': 'int64',
    → 'SeniorCitizen': 'object',
    → 'gender': 'object', 'SeniorCitizen': 'int64', 'Partner': 'object',
    → 'Dependents': 'object',
```

```

        'PhoneService':'object', 'MultipleLines':'object', 'InternetService':
        →'object',
        'OnlineSecurity':'object', 'OnlineBackup':'object', 'DeviceProtection':
        →'object', 'TechSupport':'object',
        'StreamingTV':'object', 'StreamingMovies':'object', 'Contract':'object',
        →'PaperlessBilling':'object',
        'PaymentMethod':'object', 'Churn':'category'})

cleaned_data.info()
cleaned_data.describe()
cleaned_data

```

```

[[ 488  753  936 1082 1340 3331 3826 4380 5218 6670 6754]
 [ 19   19   19   19   19   19   19   19   19   19   19]]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7032 entries, 0 to 7031
Data columns (total 20 columns):
gender                7032 non-null object
SeniorCitizen         7032 non-null int64
Partner               7032 non-null object
Dependents            7032 non-null object
tenure                7032 non-null int64
PhoneService          7032 non-null object
MultipleLines         7032 non-null object
InternetService       7032 non-null object
OnlineSecurity        7032 non-null object
OnlineBackup          7032 non-null object
DeviceProtection      7032 non-null object
TechSupport           7032 non-null object
StreamingTV           7032 non-null object
StreamingMovies       7032 non-null object
Contract              7032 non-null object
PaperlessBilling      7032 non-null object
PaymentMethod         7032 non-null object
MonthlyCharges        7032 non-null float64
TotalCharges          7032 non-null float64
Churn                 7032 non-null category
dtypes: category(1), float64(2), int64(2), object(15)
memory usage: 1.0+ MB

```

```

[6]:      gender  SeniorCitizen  Partner  Dependents  tenure  PhoneService  \
0    Female                0     Yes         No         1           No
1     Male                0     No         No        34           Yes
2     Male                0     No         No         2           Yes
3     Male                0     No         No        45           No
4    Female                0     No         No         2           Yes
5    Female                0     No         No         8           Yes

```

6	Male	0	No	Yes	22	Yes
7	Female	0	No	No	10	No
8	Female	0	Yes	No	28	Yes
9	Male	0	No	Yes	62	Yes
10	Male	0	Yes	Yes	13	Yes
11	Male	0	No	No	16	Yes
12	Male	0	Yes	No	58	Yes
13	Male	0	No	No	49	Yes
14	Male	0	No	No	25	Yes
15	Female	0	Yes	Yes	69	Yes
16	Female	0	No	No	52	Yes
17	Male	0	No	Yes	71	Yes
18	Female	0	Yes	Yes	10	Yes
19	Female	0	No	No	21	Yes
20	Male	1	No	No	1	No
21	Male	0	Yes	No	12	Yes
22	Male	0	No	No	1	Yes
23	Female	0	Yes	No	58	Yes
24	Male	0	Yes	Yes	49	Yes
25	Female	0	No	No	30	Yes
26	Male	0	Yes	Yes	47	Yes
27	Male	0	Yes	Yes	1	No
28	Male	0	Yes	No	72	Yes
29	Female	0	No	Yes	17	Yes
...	...	...	...	...	...	...
7002	Female	0	No	No	40	Yes
7003	Male	0	No	No	41	Yes
7004	Male	1	Yes	No	34	Yes
7005	Female	0	No	No	1	Yes
7006	Female	0	No	No	51	Yes
7007	Male	0	Yes	Yes	1	Yes
7008	Female	0	No	No	39	Yes
7009	Male	0	Yes	Yes	12	Yes
7010	Male	0	No	No	12	Yes
7011	Male	0	No	No	72	Yes
7012	Female	1	Yes	No	63	Yes
7013	Male	0	Yes	No	44	Yes
7014	Female	0	No	No	18	Yes
7015	Female	0	No	No	9	Yes
7016	Male	0	No	No	13	Yes
7017	Female	0	Yes	No	68	Yes
7018	Female	1	No	No	6	No
7019	Female	0	No	No	2	Yes
7020	Male	1	Yes	No	55	Yes
7021	Male	1	No	No	1	Yes
7022	Male	0	No	No	38	Yes
7023	Female	0	No	No	67	Yes

7024	Male	0	No	No	19	Yes
7025	Female	0	No	No	12	No
7026	Female	0	No	No	72	Yes
7027	Male	0	Yes	Yes	24	Yes
7028	Female	0	Yes	Yes	72	Yes
7029	Female	0	Yes	Yes	11	No
7030	Male	1	Yes	No	4	Yes
7031	Male	0	No	No	66	Yes

	MultipleLines	InternetService	OnlineSecurity \
0	No phone service	DSL	No
1	No	DSL	Yes
2	No	DSL	Yes
3	No phone service	DSL	Yes
4	No	Fiber optic	No
5	Yes	Fiber optic	No
6	Yes	Fiber optic	No
7	No phone service	DSL	Yes
8	Yes	Fiber optic	No
9	No	DSL	Yes
10	No	DSL	Yes
11	No	No	No internet service
12	Yes	Fiber optic	No
13	Yes	Fiber optic	No
14	No	Fiber optic	Yes
15	Yes	Fiber optic	Yes
16	No	No	No internet service
17	Yes	Fiber optic	Yes
18	No	DSL	No
19	No	Fiber optic	No
20	No phone service	DSL	No
21	No	No	No internet service
22	No	No	No internet service
23	Yes	DSL	No
24	No	DSL	Yes
25	No	DSL	Yes
26	Yes	Fiber optic	No
27	No phone service	DSL	No
28	Yes	DSL	Yes
29	No	DSL	No
...	...	...	...
7002	Yes	Fiber optic	No
7003	Yes	Fiber optic	No
7004	No	Fiber optic	No
7005	No	DSL	No
7006	No	No	No internet service
7007	No	Fiber optic	No

7008	No	No	No internet service
7009	No	No	No internet service
7010	No	DSL	No
7011	Yes	Fiber optic	No
7012	Yes	Fiber optic	No
7013	Yes	Fiber optic	Yes
7014	Yes	Fiber optic	No
7015	No	DSL	No
7016	No	DSL	No
7017	No	DSL	No
7018	No phone service	DSL	No
7019	No	No	No internet service
7020	Yes	DSL	Yes
7021	Yes	Fiber optic	No
7022	No	Fiber optic	No
7023	Yes	Fiber optic	Yes
7024	No	Fiber optic	No
7025	No phone service	DSL	No
7026	No	No	No internet service
7027	Yes	DSL	Yes
7028	Yes	Fiber optic	No
7029	No phone service	DSL	Yes
7030	Yes	Fiber optic	No
7031	No	Fiber optic	Yes

	OnlineBackup	DeviceProtection	TechSupport \
0	Yes	No	No
1	No	Yes	No
2	Yes	No	No
3	No	Yes	Yes
4	No	No	No
5	No	Yes	No
6	Yes	No	No
7	No	No	No
8	No	Yes	Yes
9	Yes	No	No
10	No	No	No
11	No internet service	No internet service	No internet service
12	No	Yes	No
13	Yes	Yes	No
14	No	Yes	Yes
15	Yes	Yes	Yes
16	No internet service	No internet service	No internet service
17	No	Yes	No
18	No	Yes	Yes
19	Yes	Yes	No
20	No	Yes	No

21	No internet service	No internet service	No internet service
22	No internet service	No internet service	No internet service
23	Yes	No	Yes
24	Yes	No	Yes
25	Yes	No	No
26	Yes	No	No
27	Yes	No	No
28	Yes	Yes	Yes
29	No	No	No
...	...	...	...
7002	Yes	Yes	No
7003	Yes	No	No
7004	No	Yes	No
7005	Yes	No	No
7006	No internet service	No internet service	No internet service
7007	No	No	No
7008	No internet service	No internet service	No internet service
7009	No internet service	No internet service	No internet service
7010	No	No	Yes
7011	Yes	Yes	No
7012	Yes	Yes	No
7013	No	Yes	No
7014	No	Yes	Yes
7015	No	No	No
7016	Yes	No	Yes
7017	Yes	No	Yes
7018	No	No	No
7019	No internet service	No internet service	No internet service
7020	Yes	No	No
7021	No	No	No
7022	No	No	No
7023	Yes	Yes	No
7024	No	No	No
7025	Yes	Yes	Yes
7026	No internet service	No internet service	No internet service
7027	No	Yes	Yes
7028	Yes	Yes	No
7029	No	No	No
7030	No	No	No
7031	No	Yes	Yes

	StreamingTV	StreamingMovies	Contract \
0	No	No	Month-to-month
1	No	No	One year
2	No	No	Month-to-month
3	No	No	One year
4	No	No	Month-to-month

5		Yes	Yes	Month-to-month
6		Yes	No	Month-to-month
7		No	No	Month-to-month
8		Yes	Yes	Month-to-month
9		No	No	One year
10		No	No	Month-to-month
11	No internet service	No internet service		Two year
12		Yes	Yes	One year
13		Yes	Yes	Month-to-month
14		Yes	Yes	Month-to-month
15		Yes	Yes	Two year
16	No internet service	No internet service		One year
17		Yes	Yes	Two year
18		No	No	Month-to-month
19		No	Yes	Month-to-month
20		No	Yes	Month-to-month
21	No internet service	No internet service		One year
22	No internet service	No internet service		Month-to-month
23		No	No	Two year
24		No	No	Month-to-month
25		No	No	Month-to-month
26		Yes	Yes	Month-to-month
27		No	No	Month-to-month
28		Yes	Yes	Two year
29		Yes	Yes	Month-to-month
...		...	...	...
7002		Yes	No	Month-to-month
7003		Yes	No	Month-to-month
7004		Yes	No	Month-to-month
7005		No	No	Month-to-month
7006	No internet service	No internet service		Two year
7007		No	No	Month-to-month
7008	No internet service	No internet service		Two year
7009	No internet service	No internet service		Month-to-month
7010		Yes	No	One year
7011		Yes	Yes	One year
7012		Yes	Yes	Month-to-month
7013		No	No	Month-to-month
7014		No	Yes	Month-to-month
7015		No	No	Month-to-month
7016		Yes	Yes	Month-to-month
7017		Yes	No	Two year
7018		Yes	Yes	Month-to-month
7019	No internet service	No internet service		Month-to-month
7020		No	No	One year
7021		No	No	Month-to-month
7022		No	No	Month-to-month



7023	Yes	No	Month-to-month
7024	Yes	No	Month-to-month
7025	Yes	Yes	One year
7026	No internet service	No internet service	Two year
7027	Yes	Yes	One year
7028	Yes	Yes	One year
7029	No	No	Month-to-month
7030	No	No	Month-to-month
7031	Yes	Yes	Two year

	PaperlessBilling	PaymentMethod	MonthlyCharges \
0	Yes	Electronic check	29.85
1	No	Mailed check	56.95
2	Yes	Mailed check	53.85
3	No	Bank transfer (automatic)	42.30
4	Yes	Electronic check	70.70
5	Yes	Electronic check	99.65
6	Yes	Credit card (automatic)	89.10
7	No	Mailed check	29.75
8	Yes	Electronic check	104.80
9	No	Bank transfer (automatic)	56.15
10	Yes	Mailed check	49.95
11	No	Credit card (automatic)	18.95
12	No	Credit card (automatic)	100.35
13	Yes	Bank transfer (automatic)	103.70
14	Yes	Electronic check	105.50
15	No	Credit card (automatic)	113.25
16	No	Mailed check	20.65
17	No	Bank transfer (automatic)	106.70
18	No	Credit card (automatic)	55.20
19	Yes	Electronic check	90.05
20	Yes	Electronic check	39.65
21	No	Bank transfer (automatic)	19.80
22	No	Mailed check	20.15
23	Yes	Credit card (automatic)	59.90
24	No	Credit card (automatic)	59.60
25	Yes	Bank transfer (automatic)	55.30
26	Yes	Electronic check	99.35
27	No	Electronic check	30.20
28	Yes	Credit card (automatic)	90.25
29	Yes	Mailed check	64.70
...	...	...	...
7002	Yes	Bank transfer (automatic)	93.40
7003	Yes	Electronic check	89.20
7004	Yes	Credit card (automatic)	85.20
7005	No	Electronic check	49.95
7006	No	Bank transfer (automatic)	20.65

7007	Yes	Mailed check	70.65
7008	No	Mailed check	20.15
7009	Yes	Electronic check	19.20
7010	Yes	Electronic check	59.80
7011	Yes	Electronic check	104.95
7012	Yes	Electronic check	103.50
7013	Yes	Credit card (automatic)	84.80
7014	Yes	Bank transfer (automatic)	95.05
7015	Yes	Bank transfer (automatic)	44.20
7016	No	Mailed check	73.35
7017	No	Bank transfer (automatic)	64.10
7018	Yes	Electronic check	44.40
7019	Yes	Mailed check	20.05
7020	No	Credit card (automatic)	60.00
7021	Yes	Electronic check	75.75
7022	Yes	Credit card (automatic)	69.50
7023	Yes	Credit card (automatic)	102.95
7024	Yes	Bank transfer (automatic)	78.70
7025	No	Electronic check	60.65
7026	Yes	Bank transfer (automatic)	21.15
7027	Yes	Mailed check	84.80
7028	Yes	Credit card (automatic)	103.20
7029	Yes	Electronic check	29.60
7030	Yes	Mailed check	74.40
7031	Yes	Bank transfer (automatic)	105.65

	TotalCharges	Churn
0	29.85	No
1	1889.50	No
2	108.15	Yes
3	1840.75	No
4	151.65	Yes
5	820.50	Yes
6	1949.40	No
7	301.90	No
8	3046.05	Yes
9	3487.95	No
10	587.45	No
11	326.80	No
12	5681.10	No
13	5036.30	Yes
14	2686.05	No
15	7895.15	No
16	1022.95	No
17	7382.25	No
18	528.35	Yes
19	1862.90	No

20	39.65	Yes
21	202.25	No
22	20.15	Yes
23	3505.10	No
24	2970.30	No
25	1530.60	No
26	4749.15	Yes
27	30.20	Yes
28	6369.45	No
29	1093.10	Yes
...	...	...
7002	3756.40	No
7003	3645.75	No
7004	2874.45	No
7005	49.95	No
7006	1020.75	No
7007	70.65	Yes
7008	826.00	No
7009	239.00	No
7010	727.80	Yes
7011	7544.30	No
7012	6479.40	No
7013	3626.35	No
7014	1679.40	No
7015	403.35	Yes
7016	931.55	No
7017	4326.25	No
7018	263.05	No
7019	39.25	No
7020	3316.10	No
7021	75.75	Yes
7022	2625.25	No
7023	6886.25	Yes
7024	1495.10	No
7025	743.30	No
7026	1419.40	No
7027	1990.50	No
7028	7362.90	No
7029	346.45	No
7030	306.60	Yes
7031	6844.50	No

[7032 rows x 20 columns]

```
[7]: #Simplify columns by replacing 'No Internet Service' to 'No' for
      ↳ 'OnlineSecurity', 'OnlineBackup',
      # 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies'
```

```
cols = ['OnlineSecurity', 'OnlineBackup',
        'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies']

for i in cols:
    cleaned_data[i] = cleaned_data[i].replace({'No internet service': 'No'})

cleaned_data
```

```
[7]:
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	\
0	Female	0	Yes	No	1	No	
1	Male	0	No	No	34	Yes	
2	Male	0	No	No	2	Yes	
3	Male	0	No	No	45	No	
4	Female	0	No	No	2	Yes	
5	Female	0	No	No	8	Yes	
6	Male	0	No	Yes	22	Yes	
7	Female	0	No	No	10	No	
8	Female	0	Yes	No	28	Yes	
9	Male	0	No	Yes	62	Yes	
10	Male	0	Yes	Yes	13	Yes	
11	Male	0	No	No	16	Yes	
12	Male	0	Yes	No	58	Yes	
13	Male	0	No	No	49	Yes	
14	Male	0	No	No	25	Yes	
15	Female	0	Yes	Yes	69	Yes	
16	Female	0	No	No	52	Yes	
17	Male	0	No	Yes	71	Yes	
18	Female	0	Yes	Yes	10	Yes	
19	Female	0	No	No	21	Yes	
20	Male	1	No	No	1	No	
21	Male	0	Yes	No	12	Yes	
22	Male	0	No	No	1	Yes	
23	Female	0	Yes	No	58	Yes	
24	Male	0	Yes	Yes	49	Yes	
25	Female	0	No	No	30	Yes	
26	Male	0	Yes	Yes	47	Yes	
27	Male	0	Yes	Yes	1	No	
28	Male	0	Yes	No	72	Yes	
29	Female	0	No	Yes	17	Yes	
...	...	...	...	...	...	...	
7002	Female	0	No	No	40	Yes	
7003	Male	0	No	No	41	Yes	
7004	Male	1	Yes	No	34	Yes	
7005	Female	0	No	No	1	Yes	
7006	Female	0	No	No	51	Yes	
7007	Male	0	Yes	Yes	1	Yes	
7008	Female	0	No	No	39	Yes	

7009	Male	0	Yes	Yes	12	Yes
7010	Male	0	No	No	12	Yes
7011	Male	0	No	No	72	Yes
7012	Female	1	Yes	No	63	Yes
7013	Male	0	Yes	No	44	Yes
7014	Female	0	No	No	18	Yes
7015	Female	0	No	No	9	Yes
7016	Male	0	No	No	13	Yes
7017	Female	0	Yes	No	68	Yes
7018	Female	1	No	No	6	No
7019	Female	0	No	No	2	Yes
7020	Male	1	Yes	No	55	Yes
7021	Male	1	No	No	1	Yes
7022	Male	0	No	No	38	Yes
7023	Female	0	No	No	67	Yes
7024	Male	0	No	No	19	Yes
7025	Female	0	No	No	12	No
7026	Female	0	No	No	72	Yes
7027	Male	0	Yes	Yes	24	Yes
7028	Female	0	Yes	Yes	72	Yes
7029	Female	0	Yes	Yes	11	No
7030	Male	1	Yes	No	4	Yes
7031	Male	0	No	No	66	Yes

	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	\
0	No phone service	DSL	No	Yes	
1	No	DSL	Yes	No	
2	No	DSL	Yes	Yes	
3	No phone service	DSL	Yes	No	
4	No	Fiber optic	No	No	
5	Yes	Fiber optic	No	No	
6	Yes	Fiber optic	No	Yes	
7	No phone service	DSL	Yes	No	
8	Yes	Fiber optic	No	No	
9	No	DSL	Yes	Yes	
10	No	DSL	Yes	No	
11	No	No	No	No	
12	Yes	Fiber optic	No	No	
13	Yes	Fiber optic	No	Yes	
14	No	Fiber optic	Yes	No	
15	Yes	Fiber optic	Yes	Yes	
16	No	No	No	No	
17	Yes	Fiber optic	Yes	No	
18	No	DSL	No	No	
19	No	Fiber optic	No	Yes	
20	No phone service	DSL	No	No	
21	No	No	No	No	

22	No	No	No	No
23	Yes	DSL	No	Yes
24	No	DSL	Yes	Yes
25	No	DSL	Yes	Yes
26	Yes	Fiber optic	No	Yes
27	No phone service	DSL	No	Yes
28	Yes	DSL	Yes	Yes
29	No	DSL	No	No
...	...	...	...	...
7002	Yes	Fiber optic	No	Yes
7003	Yes	Fiber optic	No	Yes
7004	No	Fiber optic	No	No
7005	No	DSL	No	Yes
7006	No	No	No	No
7007	No	Fiber optic	No	No
7008	No	No	No	No
7009	No	No	No	No
7010	No	DSL	No	No
7011	Yes	Fiber optic	No	Yes
7012	Yes	Fiber optic	No	Yes
7013	Yes	Fiber optic	Yes	No
7014	Yes	Fiber optic	No	No
7015	No	DSL	No	No
7016	No	DSL	No	Yes
7017	No	DSL	No	Yes
7018	No phone service	DSL	No	No
7019	No	No	No	No
7020	Yes	DSL	Yes	Yes
7021	Yes	Fiber optic	No	No
7022	No	Fiber optic	No	No
7023	Yes	Fiber optic	Yes	Yes
7024	No	Fiber optic	No	No
7025	No phone service	DSL	No	Yes
7026	No	No	No	No
7027	Yes	DSL	Yes	No
7028	Yes	Fiber optic	No	Yes
7029	No phone service	DSL	Yes	No
7030	Yes	Fiber optic	No	No
7031	No	Fiber optic	Yes	No

	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract \
0	No	No	No	No	Month-to-month
1	Yes	No	No	No	One year
2	No	No	No	No	Month-to-month
3	Yes	Yes	No	No	One year
4	No	No	No	No	Month-to-month
5	Yes	No	Yes	Yes	Month-to-month

6	No	No	Yes	No	Month-to-month
7	No	No	No	No	Month-to-month
8	Yes	Yes	Yes	Yes	Month-to-month
9	No	No	No	No	One year
10	No	No	No	No	Month-to-month
11	No	No	No	No	Two year
12	Yes	No	Yes	Yes	One year
13	Yes	No	Yes	Yes	Month-to-month
14	Yes	Yes	Yes	Yes	Month-to-month
15	Yes	Yes	Yes	Yes	Two year
16	No	No	No	No	One year
17	Yes	No	Yes	Yes	Two year
18	Yes	Yes	No	No	Month-to-month
19	Yes	No	No	Yes	Month-to-month
20	Yes	No	No	Yes	Month-to-month
21	No	No	No	No	One year
22	No	No	No	No	Month-to-month
23	No	Yes	No	No	Two year
24	No	Yes	No	No	Month-to-month
25	No	No	No	No	Month-to-month
26	No	No	Yes	Yes	Month-to-month
27	No	No	No	No	Month-to-month
28	Yes	Yes	Yes	Yes	Two year
29	No	No	Yes	Yes	Month-to-month
...	...	...	...	...	...
7002	Yes	No	Yes	No	Month-to-month
7003	No	No	Yes	No	Month-to-month
7004	Yes	No	Yes	No	Month-to-month
7005	No	No	No	No	Month-to-month
7006	No	No	No	No	Two year
7007	No	No	No	No	Month-to-month
7008	No	No	No	No	Two year
7009	No	No	No	No	Month-to-month
7010	No	Yes	Yes	No	One year
7011	Yes	No	Yes	Yes	One year
7012	Yes	No	Yes	Yes	Month-to-month
7013	Yes	No	No	No	Month-to-month
7014	Yes	Yes	No	Yes	Month-to-month
7015	No	No	No	No	Month-to-month
7016	No	Yes	Yes	Yes	Month-to-month
7017	No	Yes	Yes	No	Two year
7018	No	No	Yes	Yes	Month-to-month
7019	No	No	No	No	Month-to-month
7020	No	No	No	No	One year
7021	No	No	No	No	Month-to-month
7022	No	No	No	No	Month-to-month
7023	Yes	No	Yes	No	Month-to-month

7024	No	No	Yes	No	Month-to-month
7025	Yes	Yes	Yes	Yes	One year
7026	No	No	No	No	Two year
7027	Yes	Yes	Yes	Yes	One year
7028	Yes	No	Yes	Yes	One year
7029	No	No	No	No	Month-to-month
7030	No	No	No	No	Month-to-month
7031	Yes	Yes	Yes	Yes	Two year

	PaperlessBilling	PaymentMethod	MonthlyCharges \
0	Yes	Electronic check	29.85
1	No	Mailed check	56.95
2	Yes	Mailed check	53.85
3	No	Bank transfer (automatic)	42.30
4	Yes	Electronic check	70.70
5	Yes	Electronic check	99.65
6	Yes	Credit card (automatic)	89.10
7	No	Mailed check	29.75
8	Yes	Electronic check	104.80
9	No	Bank transfer (automatic)	56.15
10	Yes	Mailed check	49.95
11	No	Credit card (automatic)	18.95
12	No	Credit card (automatic)	100.35
13	Yes	Bank transfer (automatic)	103.70
14	Yes	Electronic check	105.50
15	No	Credit card (automatic)	113.25
16	No	Mailed check	20.65
17	No	Bank transfer (automatic)	106.70
18	No	Credit card (automatic)	55.20
19	Yes	Electronic check	90.05
20	Yes	Electronic check	39.65
21	No	Bank transfer (automatic)	19.80
22	No	Mailed check	20.15
23	Yes	Credit card (automatic)	59.90
24	No	Credit card (automatic)	59.60
25	Yes	Bank transfer (automatic)	55.30
26	Yes	Electronic check	99.35
27	No	Electronic check	30.20
28	Yes	Credit card (automatic)	90.25
29	Yes	Mailed check	64.70
...	...	...	...
7002	Yes	Bank transfer (automatic)	93.40
7003	Yes	Electronic check	89.20
7004	Yes	Credit card (automatic)	85.20
7005	No	Electronic check	49.95
7006	No	Bank transfer (automatic)	20.65
7007	Yes	Mailed check	70.65



7008	No	Mailed check	20.15
7009	Yes	Electronic check	19.20
7010	Yes	Electronic check	59.80
7011	Yes	Electronic check	104.95
7012	Yes	Electronic check	103.50
7013	Yes	Credit card (automatic)	84.80
7014	Yes	Bank transfer (automatic)	95.05
7015	Yes	Bank transfer (automatic)	44.20
7016	No	Mailed check	73.35
7017	No	Bank transfer (automatic)	64.10
7018	Yes	Electronic check	44.40
7019	Yes	Mailed check	20.05
7020	No	Credit card (automatic)	60.00
7021	Yes	Electronic check	75.75
7022	Yes	Credit card (automatic)	69.50
7023	Yes	Credit card (automatic)	102.95
7024	Yes	Bank transfer (automatic)	78.70
7025	No	Electronic check	60.65
7026	Yes	Bank transfer (automatic)	21.15
7027	Yes	Mailed check	84.80
7028	Yes	Credit card (automatic)	103.20
7029	Yes	Electronic check	29.60
7030	Yes	Mailed check	74.40
7031	Yes	Bank transfer (automatic)	105.65

	TotalCharges	Churn
0	29.85	No
1	1889.50	No
2	108.15	Yes
3	1840.75	No
4	151.65	Yes
5	820.50	Yes
6	1949.40	No
7	301.90	No
8	3046.05	Yes
9	3487.95	No
10	587.45	No
11	326.80	No
12	5681.10	No
13	5036.30	Yes
14	2686.05	No
15	7895.15	No
16	1022.95	No
17	7382.25	No
18	528.35	Yes
19	1862.90	No
20	39.65	Yes

21	202.25	No
22	20.15	Yes
23	3505.10	No
24	2970.30	No
25	1530.60	No
26	4749.15	Yes
27	30.20	Yes
28	6369.45	No
29	1093.10	Yes
...	...	...
7002	3756.40	No
7003	3645.75	No
7004	2874.45	No
7005	49.95	No
7006	1020.75	No
7007	70.65	Yes
7008	826.00	No
7009	239.00	No
7010	727.80	Yes
7011	7544.30	No
7012	6479.40	No
7013	3626.35	No
7014	1679.40	No
7015	403.35	Yes
7016	931.55	No
7017	4326.25	No
7018	263.05	No
7019	39.25	No
7020	3316.10	No
7021	75.75	Yes
7022	2625.25	No
7023	6886.25	Yes
7024	1495.10	No
7025	743.30	No
7026	1419.40	No
7027	1990.50	No
7028	7362.90	No
7029	346.45	No
7030	306.60	Yes
7031	6844.50	No

[7032 rows x 20 columns]

## 4 3. Data Preparation and Exploratory Data Analysis ( index )

[8]: *# separate features and labels dataframe*

```
y = cleaned_data['Churn']
X = cleaned_data.drop('Churn', axis = 1)
```

[9]: *#display some basic statistics*

```
display(cleaned_data.describe())
display(X.drop(['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges'],
→axis=1).describe())
display(pd.DataFrame(y, columns=['Churn']).describe())
```

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000	7032.000000
mean	0.162400	32.421786	64.798208	2283.300441
std	0.368844	24.545260	30.085974	2266.771362
min	0.000000	1.000000	18.250000	18.800000
25%	0.000000	9.000000	35.587500	401.450000
50%	0.000000	29.000000	70.350000	1397.475000
75%	0.000000	55.000000	89.862500	3794.737500
max	1.000000	72.000000	118.750000	8684.800000

	gender	Partner	Dependents	PhoneService	MultipleLines	InternetService	\
count	7032	7032	7032	7032	7032	7032	
unique	2	2	2	2	3	3	
top	Male	No	No	Yes	No	Fiber optic	
freq	3549	3639	4933	6352	3385	3096	

	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	\
count	7032	7032	7032	7032	7032	
unique	2	2	2	2	2	
top	No	No	No	No	No	
freq	5017	4607	4614	4992	4329	

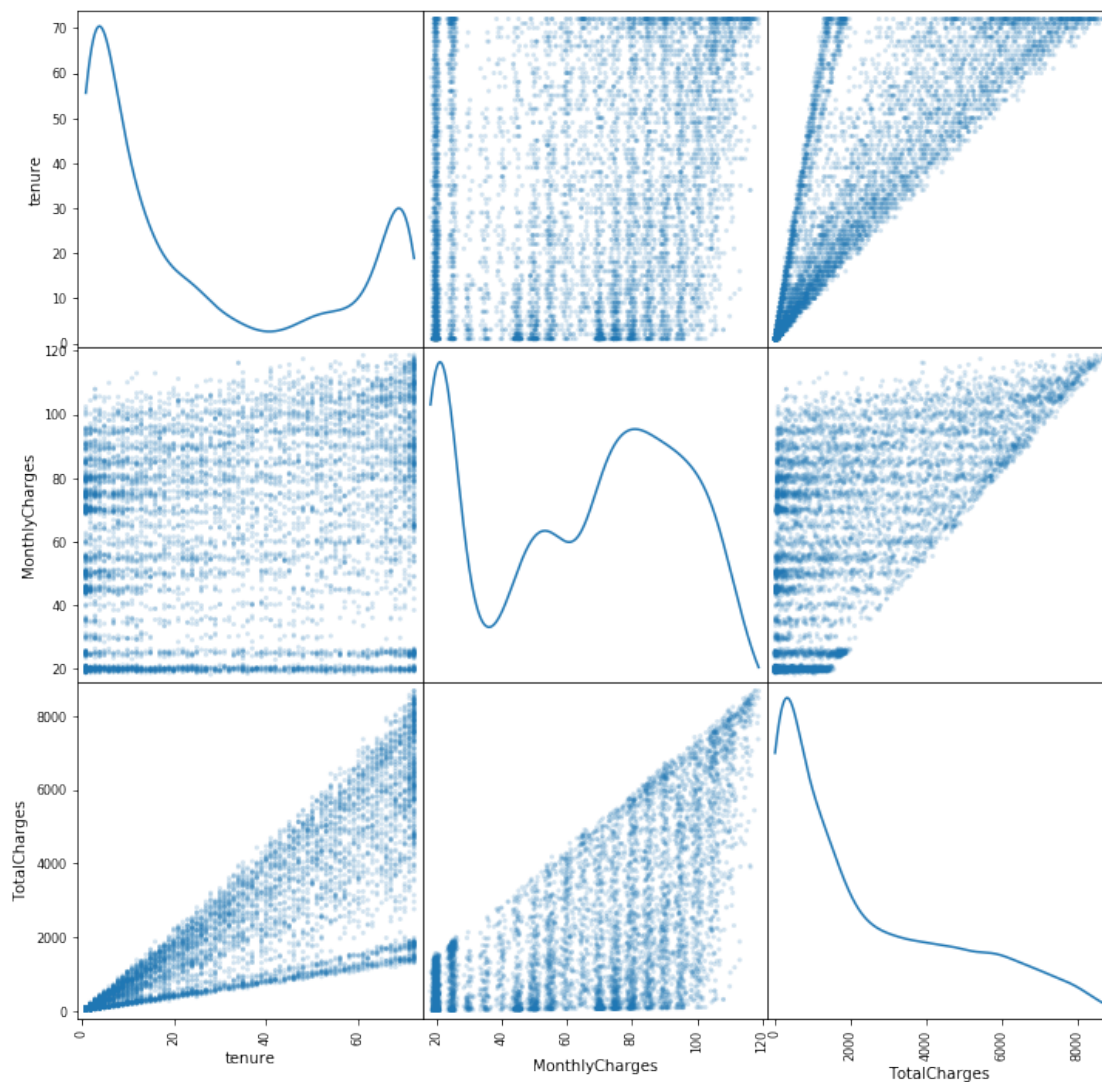
	StreamingMovies	Contract	PaperlessBilling	PaymentMethod
count	7032	7032	7032	7032
unique	2	3	2	4
top	No	Month-to-month	Yes	Electronic check
freq	4301	3875	4168	2365

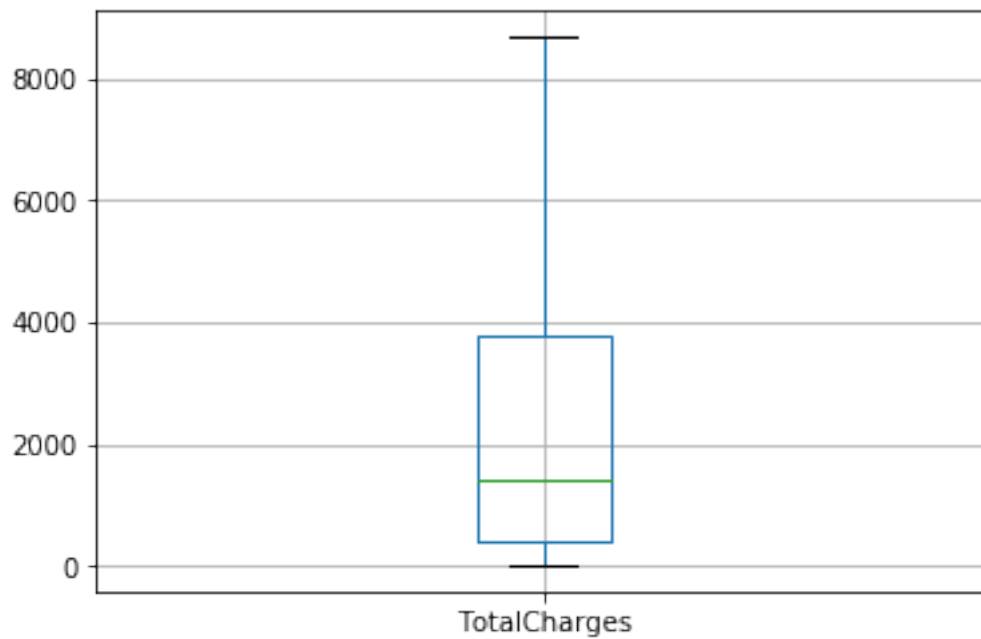
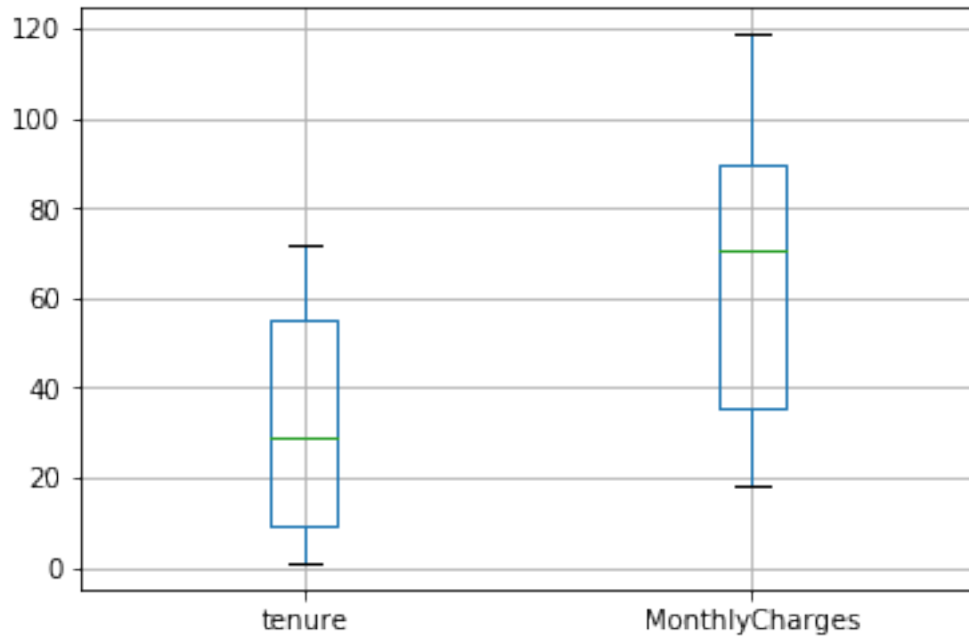
	Churn
count	7032
unique	2
top	No
freq	5163

```
[10]: #explore data distribution
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
pd.plotting.scatter_matrix(cleaned_data[num_cols], alpha = 0.2,
                           figsize = (12,12), diagonal = 'kde')

plt.show()

# inspect for outliers, boxplots for numerical fields
cleaned_data.boxplot(column = ['tenure', 'MonthlyCharges'])
plt.show()
cleaned_data.boxplot(column = ['TotalCharges'])
plt.show()
```





```
[11]: #scale numerical fields
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
```

```
X[num_cols] = scaler.fit_transform(X[num_cols])
```

```
/home/gino/anaconda2/lib/python2.7/site-
packages/sklearn/preprocessing/data.py:625: DataConversionWarning: Data with
input dtype int64, float64 were all converted to float64 by StandardScaler.
    return self.partial_fit(X, y)
/home/gino/anaconda2/lib/python2.7/site-packages/sklearn/base.py:462:
DataConversionWarning: Data with input dtype int64, float64 were all converted
to float64 by StandardScaler.
    return self.fit(X, **fit_params).transform(X)
```

[12]: *#One-Hot encode relevant fields*

```
from sklearn.preprocessing import LabelEncoder

#transform y to binary
lb = LabelEncoder()

y = lb.fit_transform(y).ravel()
#convert back to DF
y = pd.DataFrame(y, columns = ['Churn'])

#transform Binary category columns of X to 1's and 0's
bin_cols = X.nunique()[X.nunique() == 2].keys().tolist()

for i in bin_cols:
    X[i] = lb.fit_transform(X[i])

#transform Non-Binary category columns of X to one hot encode
non_bin_cols = ['MultipleLines', 'InternetService', 'Contract', 'PaymentMethod']

X = pd.get_dummies(data = X, columns = non_bin_cols)
```

[13]: *#view newly created one-hot features*

```
X.describe()
```

[13]:

	gender	SeniorCitizen	Partner	Dependents	tenure \
count	7032.000000	7032.000000	7032.000000	7032.000000	7.032000e+03
mean	0.504693	0.162400	0.482509	0.298493	-1.214741e-16
std	0.500014	0.368844	0.499729	0.457629	1.000071e+00
min	0.000000	0.000000	0.000000	0.000000	-1.280248e+00
25%	0.000000	0.000000	0.000000	0.000000	-9.542963e-01
50%	1.000000	0.000000	0.000000	0.000000	-1.394171e-01
75%	1.000000	0.000000	1.000000	1.000000	9.199259e-01
max	1.000000	1.000000	1.000000	1.000000	1.612573e+00

	PhoneService	OnlineSecurity	OnlineBackup	DeviceProtection	\
count	7032.000000	7032.000000	7032.000000	7032.000000	
mean	0.903299	0.286547	0.344852	0.343857	
std	0.295571	0.452180	0.475354	0.475028	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

	TechSupport	...	InternetService_DSL	\
count	7032.000000	...	7032.000000	
mean	0.290102	...	0.343572	
std	0.453842	...	0.474934	
min	0.000000	...	0.000000	
25%	0.000000	...	0.000000	
50%	0.000000	...	0.000000	
75%	1.000000	...	1.000000	
max	1.000000	...	1.000000	

	InternetService_Fiber optic	InternetService_No	\
count	7032.000000	7032.000000	
mean	0.440273	0.216155	
std	0.496455	0.411650	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	1.000000	0.000000	
max	1.000000	1.000000	

	Contract_Month-to-month	Contract_One year	Contract_Two year	\
count	7032.000000	7032.000000	7032.000000	
mean	0.551052	0.209329	0.239619	
std	0.497422	0.406858	0.426881	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	
75%	1.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	

	PaymentMethod_Bank transfer (automatic)	\
count	7032.000000	
mean	0.219283	
std	0.413790	
min	0.000000	
25%	0.000000	
50%	0.000000	

75%	0.000000
max	1.000000

	PaymentMethod_Credit card (automatic)	PaymentMethod_Electronic check \
count	7032.000000	7032.000000
mean	0.216297	0.336320
std	0.411748	0.472483
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	1.000000	1.000000

	PaymentMethod_Mailed check
count	7032.000000
mean	0.228100
std	0.419637
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

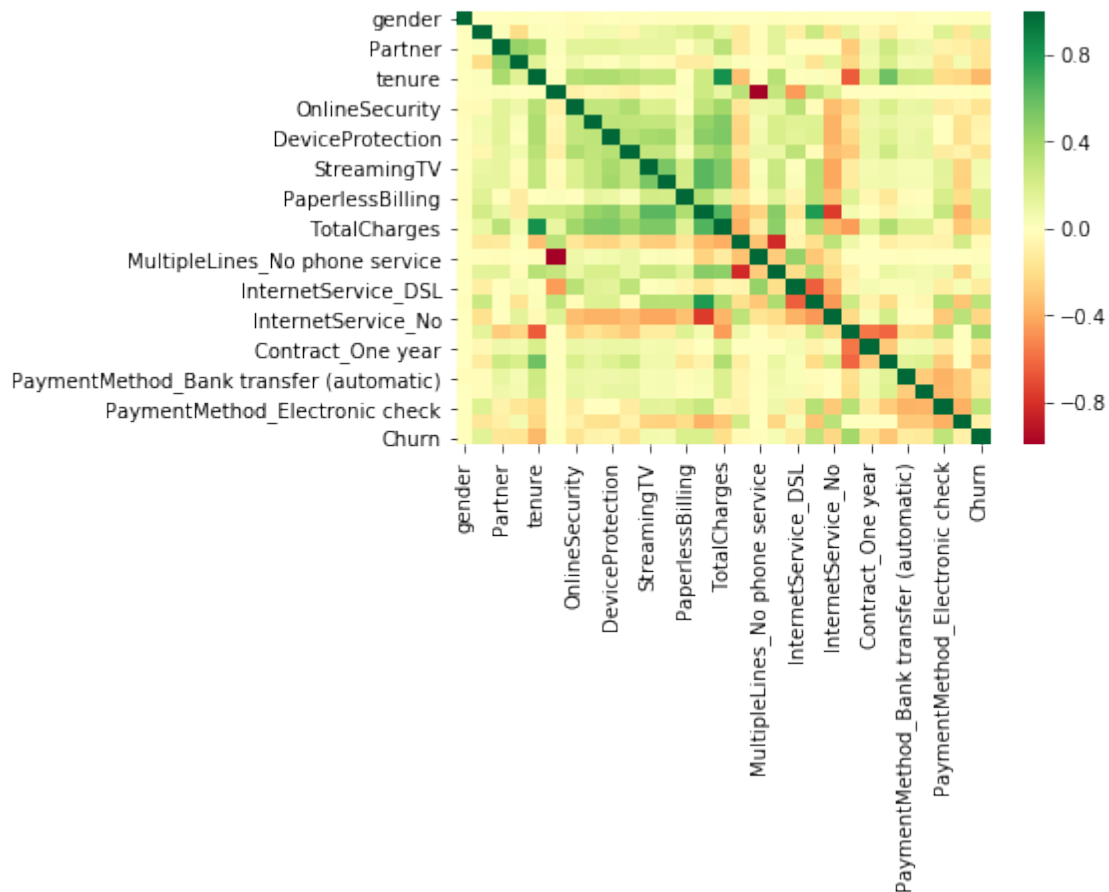
[8 rows x 28 columns]

#### 4.0.1 3.1 Correlation Matrix ( index )

```
[14]: import seaborn as sns

joined = X.join(y)
gr = sns.heatmap(joined.corr(),annot=False,cmap="RdYlGn")
sns.set(rc={'figure.figsize':(22,14)})
plt.show()
```





#### 4.0.2 3.2 Variables Distribution ( index )

```
[15]: # default plot settings
labels = 'Churn', 'No Churn'
colors = ['gold', 'lightskyblue']
explode = (0.1, 0) # explode 1st slice
labels = 15
titlesize = 30
valuesize = 15

#function for pie chart to show BOTH value and %
def absolute_value(val):
    a = np.round(val/100.*np.array(values).sum(), 0)
    return '%.0f%%' % val, '%.0f' % a

#function to create pie chart
def plot_pie(values, colors, title):
```

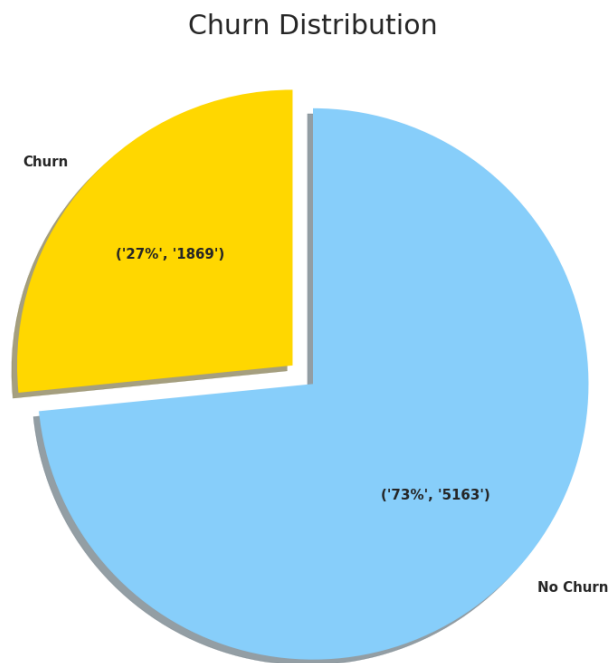
```

plt.title(title, size = titlesize)
plt.axis('equal')
font = {'family' : 'Sans Serif',
        'weight' : 'bold',
        'size'    : valuesize}
plt.rc('xtick', labels=labels)
plt.rc('font', **font)
plt.pie(values, explode=explode, labels=labels, colors=colors,
        autopct=absolute_value, shadow=True, startangle=90)
return plt.show()

# Plot Data

values = [y.sum(), len(y) - y.sum()] #[churn, no churn]
plot_pie(values, colors, 'Churn Distribution')

```



```

[16]: # default plot settings
labels = 'Churn', 'No Churn'
colors = ['gold', 'lightskyblue']
explode = (0.1, 0) # explode 1st slice
labelsize = 9
titlesize = 10
valuesize = 8

```

```

grid = plt.GridSpec(2,2)

#by Gender
male_churn = y['Churn'][X['gender'] == 1].sum()
female_churn = y['Churn'][X['gender'] == 0].sum()

# by Gender
plt.subplot(grid[0, 0])
values = [male_churn, female_churn]
labels = 'Male', 'Female'
plot_pie(values, colors, 'Churn Rate by Gender')

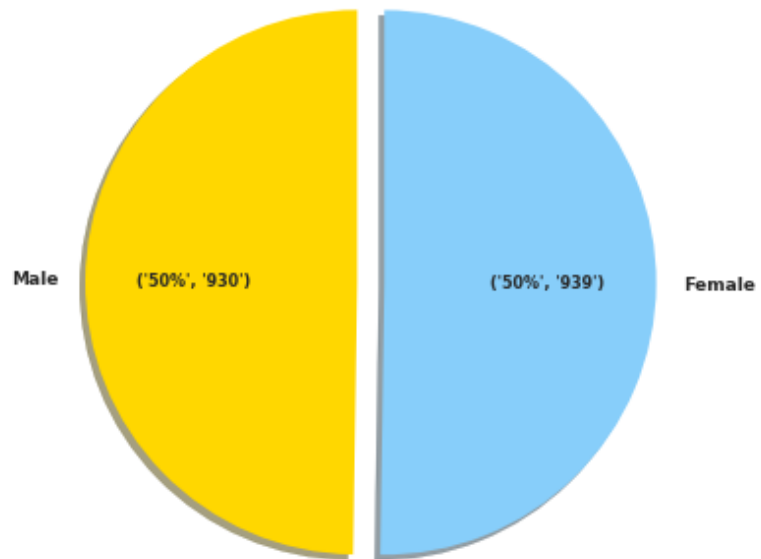

# by Senior Citizen
plt.subplot(grid[0, 1])
senior = pd.DataFrame()
senior['Churn'] = y['Churn'][X['SeniorCitizen'] == 1]
values = [senior['Churn'][senior['Churn'] == 1].
    →sum(), len(senior['Churn'][senior['Churn'] == 0])]
labels = 'Churn', 'No Churn'
plot_pie(values, colors, 'Senior Citizen Churn Rate')


# by Partner
plt.subplot(grid[1, 0])
partner = pd.DataFrame()
partner['Churn'] = y['Churn'][X['Partner'] == 1]
values = [partner['Churn'][partner['Churn'] == 1].
    →sum(), len(partner['Churn'][partner['Churn'] == 0])]
labels = 'Churn', 'No Churn'
plot_pie(values, colors, 'With Partner Churn Rate')

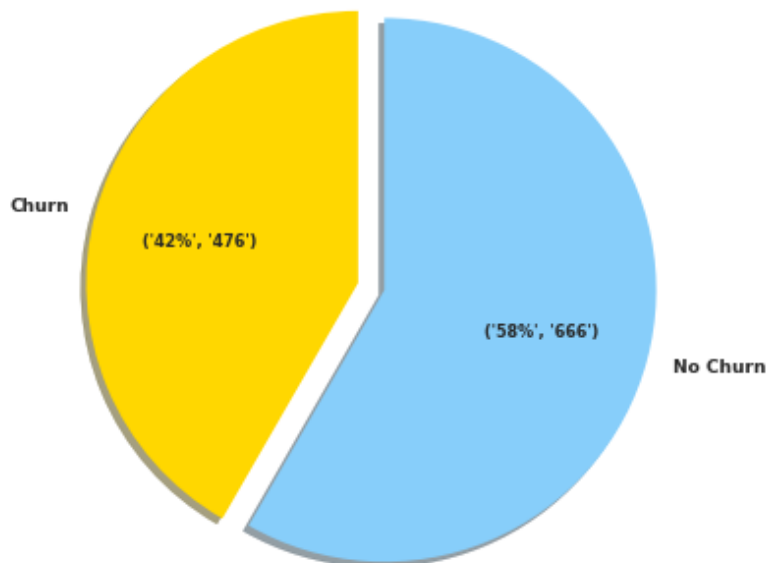

# by Dependents
plt.subplot(grid[1, 1])
dependents = pd.DataFrame()
dependents['Churn'] = y['Churn'][X['Dependents'] == 1]
values = [dependents['Churn'][dependents['Churn'] == 1].sum(),
    →len(dependents['Churn'][dependents['Churn'] == 0])]
labels = 'Churn', 'No Churn'
plot_pie(values, colors, 'With Dependents Churn Rate')

```

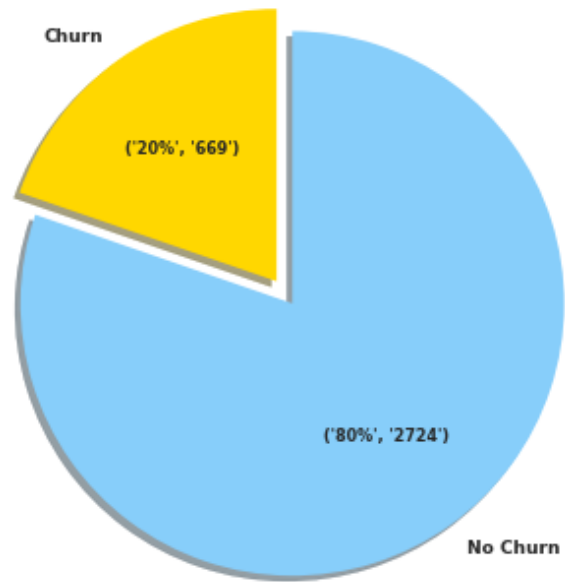
Churn Rate by Gender



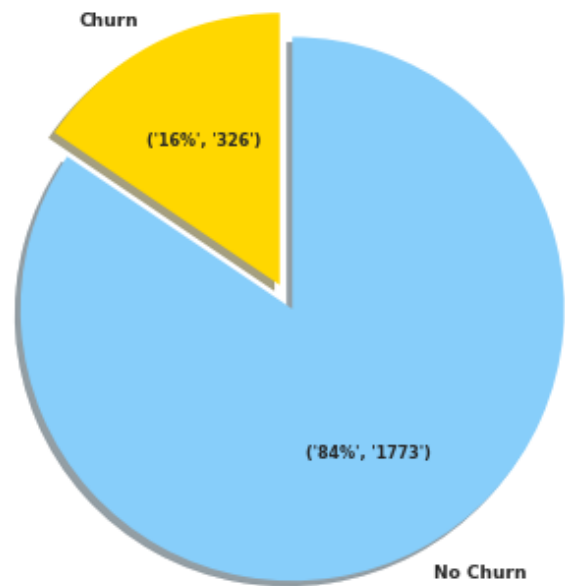
Senior Citizen Churn Rate



With Partner Churn Rate



With Dependents Churn Rate



### 4.0.3 3.3 Principal Component Analysis ( index )

```
[17]: from sklearn.decomposition import PCA
pca = PCA(n_components = 28, random_state=1)
pca.fit(X)
reduced_data = pca.transform(X)

#convert back to Dataframe
reduced_data = pd.DataFrame(reduced_data)

#show 1st n_components that comprises 98% of variance
print "1st 21 Components represent", pca.explained_variance_ratio_[0:20].
    ↳sum(), '% of Variance'

#use only 1st 21 components
drop = reduced_data.columns[21:].values.tolist()
reduced_data.drop(drop, axis = 1, inplace=True)
```

1st 21 Components represent 0.983002583600193 % of Variance

## 5 4. Model Creation and Testing

### 5.0.1 4.1 Baseline Model ( index )

```
[18]: from sklearn.metrics import fbeta_score, recall_score, precision_score,
    ↳accuracy_score

'''NAIVE BASELINE MODEL'''
#Assume all customers will churn

#True total number of Churn customers
num_churn = float(np.sum(y))

#Naive Prediction: Assume all customers will churn
pred = float(len(y))

print "**** BASIC NAIVE Benchmark ****"

naive_acc = num_churn / pred
print "Naive Benchmark Accuracy = ", naive_acc

naive_f2beta = fbeta_score(y, np.ones((len(y),)), beta= 2)
print "Naive Benchmark F2 Beta Score = ", naive_f2beta

naive_recall = recall_score(y , np.ones((len(y),)))
print "Naive Benchmark Recall Score = ", naive_recall
```

```

naive_precision = precision_score(y , np.ones((len(y),)))
print "Naive Benchmark Precision Score = ", naive_precision

'''IMPROVED NAIVE MODEL'''
# predictions of customers with less than 12 months tenure

# scale the tenure value of 12 months
transformed_12 = scaler.transform([[12,0,0]])

tenure = y.copy()

#initiate all values to 0
tenure['Prediction'] = 0

#set prediction to 1 if less than 12 months tenure
tenure['Prediction'][X['tenure'] < transformed_12[0][0]] = 1

acc = accuracy_score(tenure['Churn'], tenure['Prediction'])

print "\n**** IMPROVED NAIVE Benchmark ****"
print "Naive Tenure-based Benchmark Accuracy = ", acc

naive_tenure_f2beta = fbeta_score(tenure['Churn'], tenure['Prediction'], beta=1
→2)
print "Naive Tenure-based Benchmark F2 Beta Score = ", naive_tenure_f2beta

naive_tenure_recall = recall_score(tenure['Churn'], tenure['Prediction'])
print "Naive Tenure-based Benchmark Recall Score = ", naive_tenure_recall

naive_tenure_precision = precision_score(tenure['Churn'], tenure['Prediction'])
print "Naive Tenure-based Benchmark Precision Score = ", naive_tenure_precision

```

\*\*\*\* BASIC NAIVE Benchmark \*\*\*\*

```

Naive Benchmark Accuracy = 0.265784982935
Naive Benchmark F2 Beta Score = 0.6441273779983457
Naive Benchmark Recall Score = 1.0
Naive Benchmark Precision Score = 0.26578498293515357

```

\*\*\*\* IMPROVED NAIVE Benchmark \*\*\*\*

```

Naive Tenure-based Benchmark Accuracy = 0.7256825938566553
Naive Tenure-based Benchmark F2 Beta Score = 0.5239144115796098
Naive Tenure-based Benchmark Recall Score = 0.5345104333868379
Naive Tenure-based Benchmark Precision Score = 0.48542274052478135

```

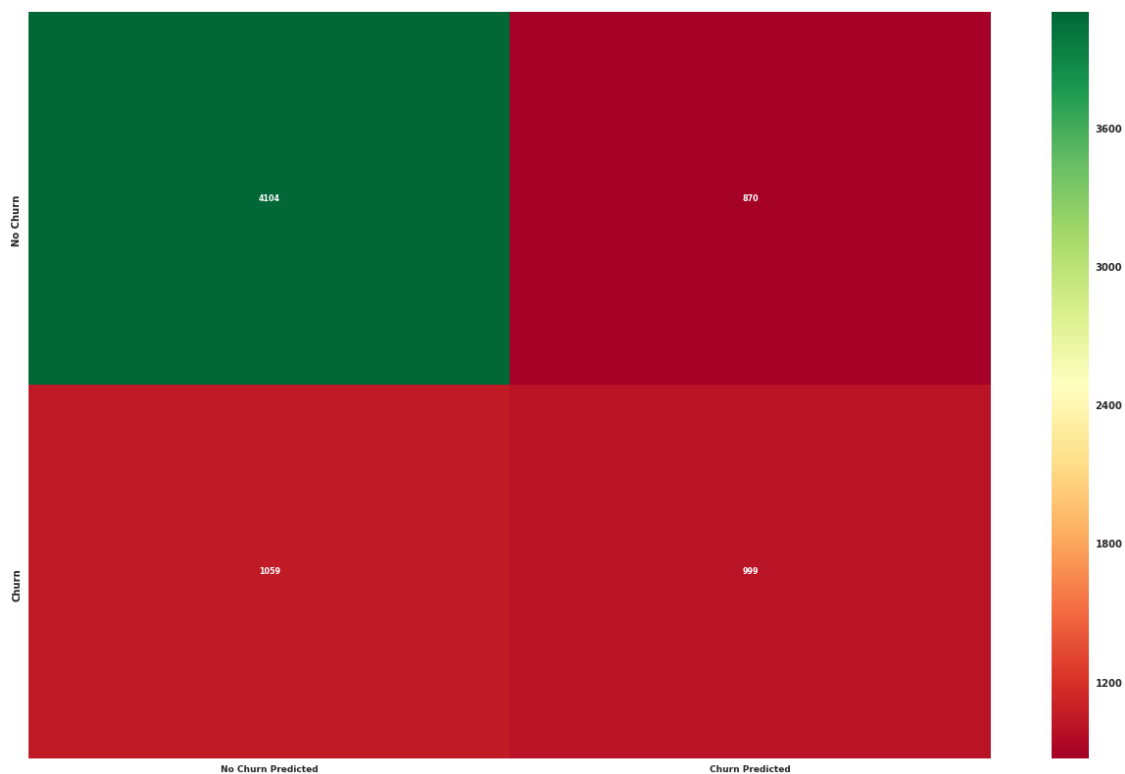
```
[19]: #create confusion matrix for Improved Naive Benchmark
from sklearn.metrics import confusion_matrix

#conf_matrix_naive = confusion_matrix(y, np.ones((len(y),)))
conf_matrix_naive = confusion_matrix(tenure['Prediction'], tenure['Churn'])

#convert to DF
df_cf_naive = pd.DataFrame(conf_matrix_naive, columns = ['No Churn',
→'Predicted', 'Churn Predicted'],
                           index = ['No Churn', 'Churn'])

print '\n **** Improved Naive Benchmark Confusion Matrix ***'
fig = sns.heatmap(df_cf_naive, annot=True, fmt = 'd', cmap="RdYlGn")
sns.set(rc={'figure.figsize':(12,8)})
```

\*\*\*\* Improved Naive Benchmark Confusion Matrix \*\*\*



```
[20]: from sklearn.model_selection import train_test_split
from sklearn.metrics import make_scorer, accuracy_score
from sklearn.model_selection import GridSearchCV, StratifiedShuffleSplit
import pickle
```



```

# make y into 1d array
y = y.values
y = y.ravel()

#create training and test split
X_train, X_test, y_train, y_test = train_test_split(reduced_data, y,
                                                    test_size=0.15,
                                                    random_state=42)

#Create scorer for Grid Search
f2scorer = make_scorer(fbeta_score, beta = 2)

#create Stratified Shuffle Split for cross validation
cv = StratifiedShuffleSplit(n_splits=5, test_size=0.20, random_state=1)

```

## 5.0.2 4.2 Support Vector Machine ( index )

```

[21]: from sklearn.svm import SVC
svc = SVC(random_state=1)
svc_parameters = {'kernel': ['rbf'],
                  'C': [1e07, 1e09, 1000.],
                  'gamma': [1e-09, 1e-10]
                  }

# Store in Pickle file. Uncomment below to rerun classifier with new
→parameters
#clf_gs = GridSearchCV(svc, svc_parameters, scoring = f2scorer, cv =cv, n_jobs
→= -1)

#clf_gs.fit(X_train, y_train)

#with open('grid_searchcv_svc.pickle','wb') as f:
#    pickle.dump(clf_gs, f)

pickle_in = open('grid_searchcv_svc.pickle','rb')
clf_gs = pickle.load(pickle_in)
print clf_gs.best_estimator_
print clf_gs.best_params_

```

```

SVC(C=10000000.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma=1e-10, kernel='rbf',
    max_iter=-1, probability=False, random_state=1, shrinking=True,
    tol=0.001, verbose=False)
{'kernel': 'rbf', 'C': 10000000.0, 'gamma': 1e-10}

```

```
[22]: svc = SVC(kernel = clf_gs.best_params_['kernel'],
               C = clf_gs.best_params_['C'],
               gamma = clf_gs.best_params_['gamma'],
               random_state = 1
               )
```

```
svc.fit(X_train,y_train)
```

```
[22]: SVC(C=10000000.0, cache_size=200, class_weight=None, coef0=0.0,
        decision_function_shape='ovr', degree=3, gamma=1e-10, kernel='rbf',
        max_iter=-1, probability=False, random_state=1, shrinking=True,
        tol=0.001, verbose=False)
```

### 5.0.3 4.3. Decision Tree ( index )

```
[23]: from sklearn import tree
```

```
dt = tree.DecisionTreeClassifier(random_state=1, class_weight= 'balanced')
```

```
[24]: #Parameters for Decision Tree
```

```
dt_parameters = {'criterion':['gini', 'entropy'],
                 'max_depth':[3, 5, 8,12],
                 'splitter':['random','best'],
                 'min_samples_leaf':[1,2,5,10]
                 }
```

```
# Store in Pickle file. Uncomment below to rerun classifier with new
→parameters
```

```
#clf_gs = GridSearchCV(dt, dt_parameters, scoring = f2scorer, cv =cv, n_jobs =
→-1)
```

```
#clf_gs.fit(X_train, y_train)
```

```
#with open('grid_searchcv_dt.pickle','wb') as f:
# pickle.dump(clf_gs, f)
```

```
pickle_in = open('grid_searchcv_dt.pickle','rb')
clf_gs = pickle.load(pickle_in)
print clf_gs.best_estimator_
print clf_gs.best_params_
```

```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_depth=3,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=10, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False, random_state=1,
```

```

        splitter='random')
{'splitter': 'random', 'criterion': 'gini', 'max_depth': 3, 'min_samples_leaf':
10}

```

```

[25]: dt = tree.DecisionTreeClassifier(criterion = clf_gs.best_params_['criterion'],
        max_depth = clf_gs.best_params_['max_depth'],
        splitter = clf_gs.best_params_['splitter'],
        min_samples_leaf = clf_gs.best_params_['min_samples_leaf'],
        random_state = 1,
        class_weight= 'balanced'
    )

dt.fit(X_train,y_train)

```

```

[25]: DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_depth=3,
        max_features=None, max_leaf_nodes=None,
        min_impurity_decrease=0.0, min_impurity_split=None,
        min_samples_leaf=10, min_samples_split=2,
        min_weight_fraction_leaf=0.0, presort=False, random_state=1,
        splitter='random')

```

#### 5.0.4 4.4. XGBoost ( index )

```

[26]: from xgboost import XGBClassifier
xgb = XGBClassifier(random_state=1)

```

```

[27]: xgb_parameters = {'booster':['gblinear', 'gbtree','dart'],
        'learning_rate':[0.1, 0.01, 0.3, 0.6],
        'max_depth': [1,3,9],
        'scale_pos_weight': [2.76, 5.5, 6.0]
    }

# Store in Pickle file. Uncomment below to rerun classifier with new
    ↪ parameters
#clf_gs = GridSearchCV(xgb, xgb_parameters, scoring = f2scorer, cv = cv, n_jobs
    ↪ = -1)

#clf_gs.fit(X_train, y_train)

#with open('grid_searchcv_xgb.pickle','wb') as f:
#    pickle.dump(clf_gs, f)

pickle_in = open('grid_searchcv_xgb.pickle','rb')
clf_gs = pickle.load(pickle_in)
print clf_gs.best_estimator_
print clf_gs.best_params_

```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bytree=1, gamma=0, learning_rate=0.3, max_delta_step=0,
              max_depth=1, min_child_weight=1, missing=nan, n_estimators=100,
              n_jobs=1, nthread=None, objective='binary:logistic', random_state=1,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=6.0, seed=None,
              silent=True, subsample=1)
{'scale_pos_weight': 6.0, 'learning_rate': 0.3, 'max_depth': 1, 'booster':
'gbtree'}
```

```
[28]: xgb = XGBClassifier(booster=clf_gs.best_params_['booster'],
                          learning_rate=clf_gs.best_params_['learning_rate'],
                          max_depth = clf_gs.best_params_['max_depth'],
                          scale_pos_weight=clf_gs.best_params_['scale_pos_weight'],
                          random_state = 1)

xgb.fit(X_train,y_train)
```

```
[28]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                    colsample_bytree=1, gamma=0, learning_rate=0.3, max_delta_step=0,
                    max_depth=1, min_child_weight=1, missing=None, n_estimators=100,
                    n_jobs=1, nthread=None, objective='binary:logistic', random_state=1,
                    reg_alpha=0, reg_lambda=1, scale_pos_weight=6.0, seed=None,
                    silent=True, subsample=1)
```

## 5.0.5 4.5. LightGBM ( index )

```
[29]: from lightgbm import LGBMClassifier
lgbm = LGBMClassifier(random_state = 1, is_unbalance = True, objective='binary')
```

```
[30]: lgbm_parameters = {'boosting': ['gbdt', 'goss', 'dart'],
                        'min_data_per_leaf': [5,10,30,500],
                        'num_leaves': [5,31,80,150],
                        'max_depth': [1,3,7,9],
                        'is_unbalance': [True],
                        'objective': ['binary'],
                        'random_state': [1]
                        }

# Store in Pickle file. Uncomment below to rerun classifier with new
→parameters
#clf_gs = GridSearchCV(lgbm, lgbm_parameters, scoring = f2scorer, cv = cv,
→n_jobs = -1)

#clf_gs.fit(X_train, y_train)

#with open('grid_searchcv_lgbm.pickle','wb') as f:
#    pickle.dump(clf_gs, f)
```

```

pickle_in = open('grid_searchcv_lgbm.pickle','rb')
clf_gs = pickle.load(pickle_in)
print clf_gs.best_estimator_
print clf_gs.best_params_

```

```

LGBMClassifier(boosting='dart', boosting_type='gbdt', class_weight=None,
               colsample_bytree=1.0, importance_type='split', is_unbalance=True,
               learning_rate=0.1, max_depth=3, min_child_samples=20,
               min_child_weight=0.001, min_data_per_leaf=5, min_split_gain=0.0,
               n_estimators=100, n_jobs=-1, num_leaves=5, objective='binary',
               random_state=1, reg_alpha=0.0, reg_lambda=0.0, silent=True,
               subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
{'num_leaves': 5, 'min_data_per_leaf': 5, 'random_state': 1, 'is_unbalance':
True, 'boosting': 'dart', 'objective': 'binary', 'max_depth': 3}

```

```

[31]: lgbm = LGBMClassifier(boosting = clf_gs.best_params_['boosting'],
                           num_leaves = clf_gs.best_params_['num_leaves'],
                           max_depth = clf_gs.best_params_['max_depth'],
                           min_data_per_leaf = clf_gs.
→best_params_['min_data_per_leaf'],
                           random_state = 1,
                           is_unbalance = True,
                           objective='binary'
                           )

lgbm.fit(X_train,y_train)

```

```

[31]: LGBMClassifier(boosting='dart', boosting_type='gbdt', class_weight=None,
               colsample_bytree=1.0, importance_type='split', is_unbalance=True,
               learning_rate=0.1, max_depth=3, min_child_samples=20,
               min_child_weight=0.001, min_data_per_leaf=5, min_split_gain=0.0,
               n_estimators=100, n_jobs=-1, num_leaves=5, objective='binary',
               random_state=1, reg_alpha=0.0, reg_lambda=0.0, silent=True,
               subsample=1.0, subsample_for_bin=200000, subsample_freq=0)

```

## 6 5. Model Evaluation and Performance Metrics

### 6.0.1 5.1 Confusion Matrices for Models ( index )

```

[32]: #create confusion matrices

models = {svc:'Support Vector Machine', dt:'Decision Tree', xgb:'XGBoost_
→Classifier', lgbm:'LightGB Classifier'}
fig = plt.GridSpec(2,2)

#SVC Confusion Matrix

```

```

model = svc

conf_matrix = confusion_matrix(y_test, model.predict(X_test))
plt.subplot(grid[0,0])
#convert to DF
df_cf = pd.DataFrame(conf_matrix, columns = ['No Churn Predicted', 'Churn_
→Predicted'],
                      index = ['No Churn', 'Churn'])
a = sns.heatmap(df_cf, annot=True, fmt = 'd', cmap="RdYlGn")
sns.set(rc={'figure.figsize':(12,8)})
a.set_title('%s Confusion Matrix' % models[model])

#Record metrics for the model
f2 = fbeta_score(y_test, model.predict(X_test), beta = 2)
recall = recall_score(y_test, model.predict(X_test))
precision = precision_score(y_test, model.predict(X_test))
accuracy = accuracy_score(y_test, model.predict(X_test))
svc_metrics = {'Model': models[model], 'F2 Score': [f2], 'Recall': [recall],
               'Precision': [precision], 'Accuracy': [accuracy]}
all_metrics = pd.DataFrame(svc_metrics)


#Decision Tree Confusion Matrix
model = dt

conf_matrix = confusion_matrix(y_test, model.predict(X_test))
plt.subplot(grid[0,1])
#convert to DF
df_cf = pd.DataFrame(conf_matrix, columns = ['No Churn Predicted', 'Churn_
→Predicted'],
                      index = ['No Churn', 'Churn'])
a = sns.heatmap(df_cf, annot=True, fmt = 'd', cmap="RdYlGn")
sns.set(rc={'figure.figsize':(12,8)})
a.set_title('%s Confusion Matrix' % models[model])

#Record metrics for the model
f2 = fbeta_score(y_test, model.predict(X_test), beta = 2)
recall = recall_score(y_test, model.predict(X_test))
precision = precision_score(y_test, model.predict(X_test))
accuracy = accuracy_score(y_test, model.predict(X_test))
data = {'Model': models[model], 'F2 Score': [f2], 'Recall': [recall],
        'Precision': [precision], 'Accuracy': [accuracy]}
dt_metrics = pd.DataFrame(data)
all_metrics = all_metrics.append(dt_metrics)

```

```

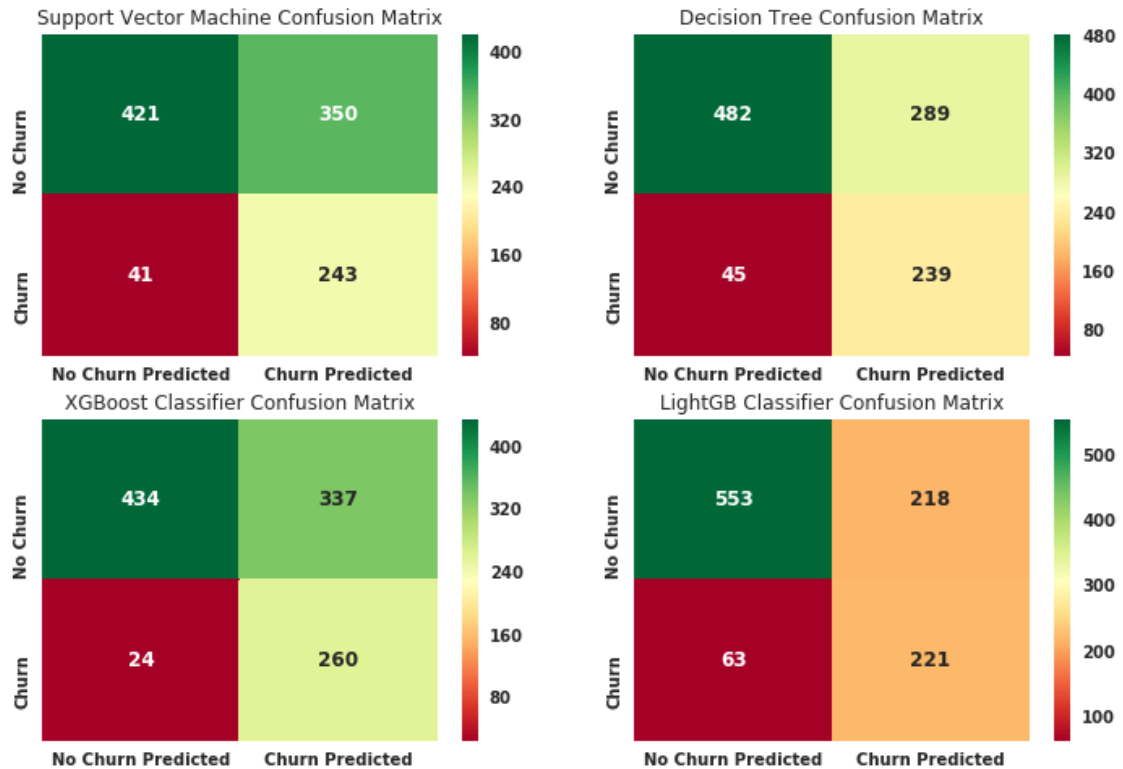
#XGBoost Confusion Matrix
model = xgb
conf_matrix = confusion_matrix(y_test, model.predict(X_test))
plt.subplot(grid[1,0])
#convert to DF
df_cf = pd.DataFrame(conf_matrix,columns = ['No Churn Predicted','Churn_
→Predicted'],
                        index = ['No Churn', 'Churn'])
a = sns.heatmap(df_cf,annot=True,fmt = 'd',cmap="RdYlGn")
sns.set(rc={'figure.figsize':(12,8)})
a.set_title('%s Confusion Matrix' % models[model])

#Record metrics for the model
f2 = fbeta_score(y_test, model.predict(X_test), beta = 2)
recall = recall_score(y_test, model.predict(X_test))
precision = precision_score(y_test, model.predict(X_test))
accuracy = accuracy_score(y_test, model.predict(X_test))
data = {'Model': models[model], 'F2 Score':[f2], 'Recall': [recall],
        'Precision':[precision], 'Accuracy':[accuracy]}
xgb_metrics = pd.DataFrame(data)
all_metrics = all_metrics.append(xgb_metrics)

#LightBM Confusion Matrix
model = lgbm
conf_matrix = confusion_matrix(y_test, model.predict(X_test))
plt.subplot(grid[1,1])
#convert to DF
df_cf = pd.DataFrame(conf_matrix,columns = ['No Churn Predicted','Churn_
→Predicted'],
                        index = ['No Churn', 'Churn'])
a = sns.heatmap(df_cf,annot=True,fmt = 'd',cmap="RdYlGn")
sns.set(rc={'figure.figsize':(12,8)})
a.set_title('%s Confusion Matrix' % models[model])

#Record metrics for the model
f2 = fbeta_score(y_test, model.predict(X_test), beta = 2)
recall = recall_score(y_test, model.predict(X_test))
precision = precision_score(y_test, model.predict(X_test))
accuracy = accuracy_score(y_test, model.predict(X_test))
data = {'Model': models[model], 'F2 Score':[f2], 'Recall': [recall],
        'Precision':[precision], 'Accuracy':[accuracy]}
lgbm_metrics = pd.DataFrame(data)
all_metrics = all_metrics.append(lgbm_metrics)

```



## 6.0.2 5.2 Compare Model Metrics ( index )

```
[33]: #Prepare Metric Results to display

#Add Naive Benchmark Metrics
data = {'Model': ['Naive Benchmark'], 'F2 Score': naive_f2beta, 'Recall': naive_recall,
        'Precision': naive_precision, 'Accuracy': naive_acc}
naive_metrics = pd.DataFrame(data)
all_metrics = all_metrics.append(naive_metrics)

#Add Improved Benchmark Metrics
data = {'Model': ['Improved Naive Benchmark'], 'F2 Score': naive_tenure_f2beta,
        'Recall': naive_tenure_recall,
        'Precision': naive_tenure_precision, 'Accuracy': acc}
imp_naive_metrics = pd.DataFrame(data)
all_metrics = all_metrics.append(imp_naive_metrics)

#order headers in DF
all_metrics = all_metrics[['Model', 'F2 Score', 'Recall', 'Precision', 'Accuracy']]
```



```
#Display Table of Metrics
from IPython.display import HTML
HTML(all_metrics.to_html(index=False))
```

[33]: <IPython.core.display.HTML object>

```
[34]: #plot important features
from xgboost import plot_importance

xgb = xgb.fit(X,y)
plot_importance(xgb, importance_type='gain')
```

[34]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f29fafb5fd0>

