In [79]:
```
import numpy as np
import matplotlib.pyplot as plt
import os
import pandas as pd
```

In [80]:
```
df = pd.read_csv("./WA_Fn-UseC_-Telco-Customer-Churn.csv")
df.head(5)
```

Out[80]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multip
0	7590-VHVEG	Female	0	Yes	No	1	No	No ph service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No ph service
4	9237-HQITU	Female	0	No	No	2	Yes	No

5 rows × 21 columns

notice that "TotalCharges" is object, so it may have nan values

In [81]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
customerID          7043 non-null object
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
PhoneService        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
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
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [82]:
```
df.shape
```

Out[82]: (7043, 21)

Clean up the data

In [83]:
```
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'],errors='coerce')
```

In [84]:
```
# one-hot encoding:
# categorical variables are converted into a form that could be provided
 to ML algorithms

columns = list(df)
catg_obj =[]
for attr in columns:
    if df[attr].dtype =='object':
        if attr != 'customerID':
            catg_obj.append(attr)

df = pd.get_dummies(df, columns = catg_obj, drop_first=True)
df.head()
```

Out[84]:

	customerID	SeniorCitizen	tenure	MonthlyCharges	TotalCharges	gender_Male	Partr
0	7590-VHVEG	0	1	29.85	29.85	0	1
1	5575-GNVDE	0	34	56.95	1889.50	1	0
2	3668-QPYBK	0	2	53.85	108.15	1	0
3	7795-CFOCW	0	45	42.30	1840.75	1	0
4	9237-HQITU	0	2	70.70	151.65	0	0

5 rows × 32 columns

drop 'customerID' column

In [85]:
```
df.columns
df.drop(['customerID'], axis = 1, inplace = True)
```

drop nans

In [86]:
```
df.isna().sum()
```

Out[86]:
```
SeniorCitizen                             0
tenure                                    0
MonthlyCharges                            0
TotalCharges                             11
gender_Male                               0
Partner_Yes                               0
Dependents_Yes                            0
PhoneService_Yes                          0
MultipleLines_No phone service            0
MultipleLines_Yes                         0
InternetService_Fiber optic               0
InternetService_No                        0
OnlineSecurity_No internet service        0
OnlineSecurity_Yes                        0
OnlineBackup_No internet service          0
OnlineBackup_Yes                          0
DeviceProtection_No internet service      0
DeviceProtection_Yes                      0
TechSupport_No internet service           0
TechSupport_Yes                           0
StreamingTV_No internet service           0
StreamingTV_Yes                           0
StreamingMovies_No internet service       0
StreamingMovies_Yes                       0
Contract_One year                         0
Contract_Two year                         0
PaperlessBilling_Yes                      0
PaymentMethod_Credit card (automatic)     0
PaymentMethod_Electronic check            0
PaymentMethod_Mailed check                0
Churn_Yes                                 0
dtype: int64
```

In [87]:
```
df.dropna(inplace=True)
df.shape # drop 11 rows that has nan values
```

Out[87]:
```
(7032, 31)
```

In [88]:
```
# df.info()
```

Train Test split

In [89]:
```
from sklearn.model_selection import train_test_split

x = df.loc[:, df.columns != 'Churn_Yes']
y = df['Churn_Yes']
x_train, x_test, y_train, y_test = train_test_split(x, y) # default test
_size = 0.25
```

See if data is balance or not

In [90]:
```
sum_1 = sum(y_train==1)
sum_0 = sum(y_train==0)
print sum_1
print sum_0
print (sum_1/float(sum_0+sum_1)) # Percentage churn
```

```
1415
3859
0.268297307546
```

Use SMOTE Oversampling to balance data

In [91]:
```
from imblearn.over_sampling import SMOTE
smo = SMOTE()
x_train_, y_train_ = smo.fit_resample(x_train, y_train.ravel())
```

Fitting multiple models using KFold

In [92]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold

scoring = 'accuracy'
models = []
models.append(('LogR', LogisticRegression()))
models.append(('DT', DecisionTreeClassifier()))
models.append(('RF', RandomForestClassifier()))
rslts = []
names = []
for name, model in models:
    kf = KFold(n_splits=10, random_state=None)
    scores = cross_val_score(model, x_train_, y_train_, cv=kf, scoring=s
coring)
    rslts.append(scores)
    names.append(name)
    print"%s: %f" % (name, scores.mean())
```

```
LogR: 0.749289
DT: 0.807634
RF: 0.845593
```

Random Forest

In [93]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
rf = RandomForestClassifier()
rf.fit(x_train_, y_train_)
y_pred = rf.predict(x_test)
print(accuracy_score(y_test, y_pred))
```

```
0.779294653015
```

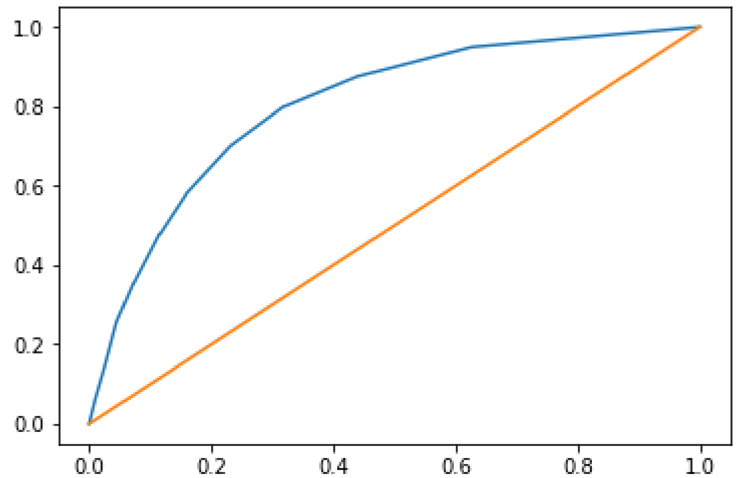
Random Forest Confusion Matrix

In [94]:
```
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[1153  151]
 [ 237  217]]
              precision    recall  f1-score   support

           0       0.83      0.88      0.86      1304
           1       0.59      0.48      0.53       454

   micro avg       0.78      0.78      0.78      1758
   macro avg       0.71      0.68      0.69      1758
weighted avg       0.77      0.78      0.77      1758
```

Random Forest ROC Curve

In [95]:
```
from sklearn import metrics

rf_pre_prob = rf.predict_proba(x_test)[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, rf_pre_prob)
roc_auc = metrics.auc(fpr, tpr)
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1])
plt.savefig("RF_ROC")
```



Logistic Regression

In [96]:
```
lr = LogisticRegression()
lr.fit(x_train_, y_train_)
y_pred = lr.predict(x_test)
print(accuracy_score(y_test, y_pred))
```

```
0.766211604096
```

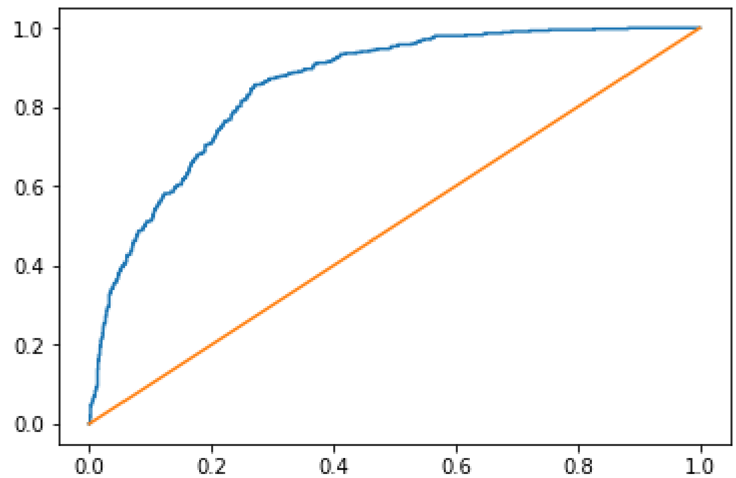
Logistic Regression Confusion Matrix

In [97]:
```
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[977 327]
 [ 84 370]]
              precision    recall  f1-score   support

           0       0.92      0.75      0.83      1304
           1       0.53      0.81      0.64       454

   micro avg       0.77      0.77      0.77      1758
   macro avg       0.73      0.78      0.73      1758
weighted avg       0.82      0.77      0.78      1758
```

Logistic Regression ROC Curve

In [98]:
```
lr_pre_prob = lr.predict_proba(x_test)[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, lr_pre_prob)
roc_auc = metrics.auc(fpr, tpr)
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1])
plt.savefig("LR_ROC")
```



Using Cross validation to get a validation score

In [99]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(rf, x_train_, y_train_, cv = 5)
print("Cross Validation Scores: " + str(scores))
print("Mean Cross Validation Score: " + str(scores.mean()))
```

```
Cross Validation Scores: [ 0.65544041  0.71567358  0.92940415  0.924222
8   0.91763943]
Mean Cross Validation Score: 0.828476072391
```

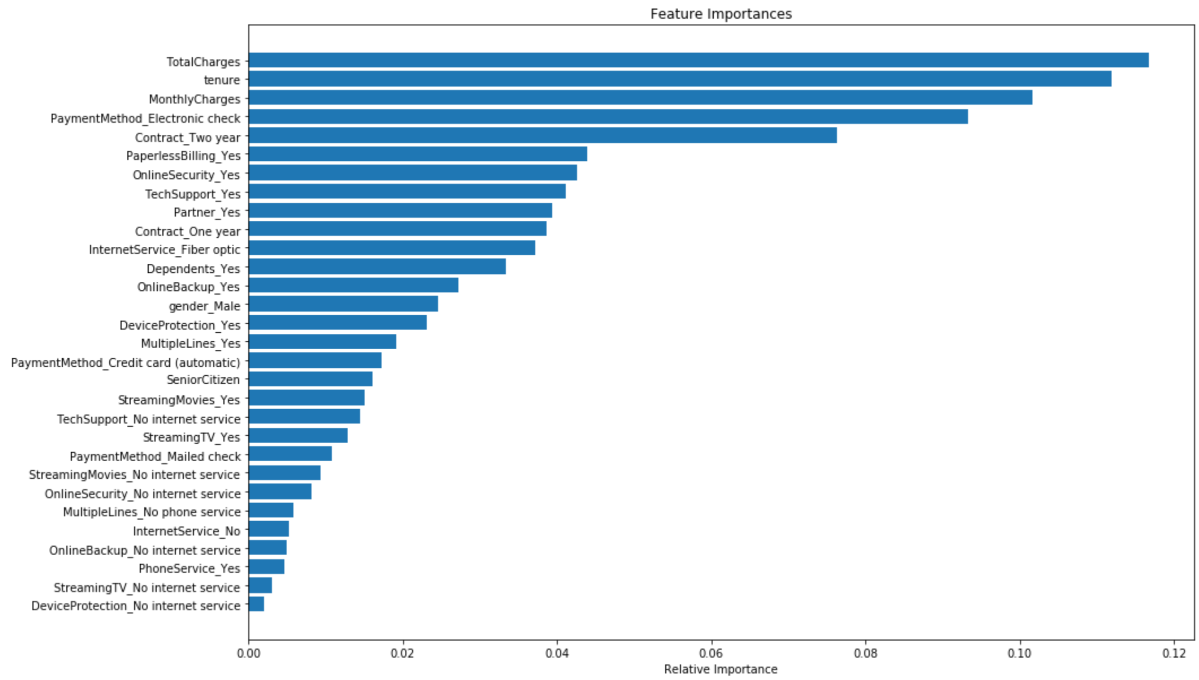
Feature importances with forests of trees

In [100]:
```
features = x_train.columns
importances = rf.feature_importances_
indices = np.argsort(importances)

feature_importances = pd.DataFrame(importances,index = features,columns=
['importance']).sort_values('importance',ascending=False)
feature_importances
```

Out[100]:

	importance
TotalCharges	0.116805
tenure	0.111848
MonthlyCharges	0.101589
PaymentMethod_Electronic check	0.093270
Contract_Two year	0.076361
PaperlessBilling_Yes	0.043977
OnlineSecurity_Yes	0.042574
TechSupport_Yes	0.041188
Partner_Yes	0.039395
Contract_One year	0.038659
InternetService_Fiber optic	0.037211
Dependents_Yes	0.033305
OnlineBackup_Yes	0.027226
gender_Male	0.024512
DeviceProtection_Yes	0.023113
MultipleLines_Yes	0.019178
PaymentMethod_Credit card (automatic)	0.017200
SeniorCitizen	0.016131
StreamingMovies_Yes	0.015063
TechSupport_No internet service	0.014450
StreamingTV_Yes	0.012866
PaymentMethod_Mailed check	0.010781
StreamingMovies_No internet service	0.009302
OnlineSecurity_No internet service	0.008184
MultipleLines_No phone service	0.005781
InternetService_No	0.005288
OnlineBackup_No internet service	0.004998
PhoneService_Yes	0.004662
StreamingTV_No internet service	0.003061
DeviceProtection_No internet service	0.002024

In [101]:
```
plt.figure(figsize=(15,10))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.savefig("Feature Importances", dpi=150)
plt.show()
```



Top two features are TotalCharges and Tenures

In [102]:
```
df.groupby(['Churn_Yes']).TotalCharges.describe()
```

Out[102]:

	count	mean	std	min	25%	50%	75%	max
Churn_Yes								
0	5163.0	2555.344141	2329.456984	18.80	577.825	1683.60	4264.125	8672.45
1	1869.0	1531.796094	1890.822994	18.85	134.500	703.55	2331.300	8684.80

In [103]:
```
df.groupby(['Churn_Yes']).tenure.describe()
```

Out[103]:

	count	mean	std	min	25%	50%	75%	max
Churn_Yes								
0	5163.0	37.650010	24.076940	1.0	15.0	38.0	61.0	72.0
1	1869.0	17.979133	19.531123	1.0	2.0	10.0	29.0	72.0

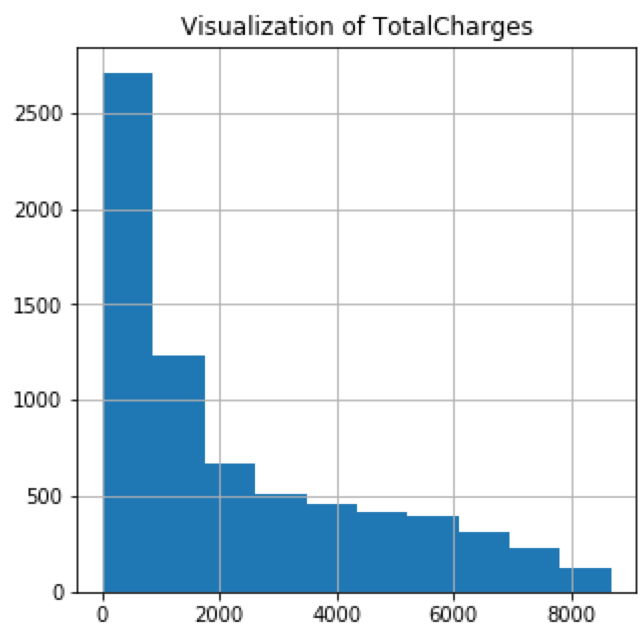
In [104]:
```
num = ['float64', 'int64']
num_data = df.select_dtypes(include=num)
cat_data = df.select_dtypes(exclude=num)
```

In [105]:
```
num_data.describe().T
```

Out[105]:

	count	mean	std	min	25%	50%	75%
SeniorCitizen	7032.0	0.162400	0.368844	0.00	0.0000	0.000	0.0000
tenure	7032.0	32.421786	24.545260	1.00	9.0000	29.000	55.0000
MonthlyCharges	7032.0	64.798208	30.085974	18.25	35.5875	70.350	89.8625
TotalCharges	7032.0	2283.300441	2266.771362	18.80	401.4500	1397.475	3794.7375

In [106]:
```
df["TotalCharges"].hist(figsize=(5,5))
plt.title('Visualization of TotalCharges')
plt.plot
plt.savefig("TotalCharges", dpi=300)
```



In [107]:
```
df["tenure"].hist(figsize=(5,5))
plt.title('Visualization of tenure')
plt.plot
plt.savefig("tenure", dpi=300)
```