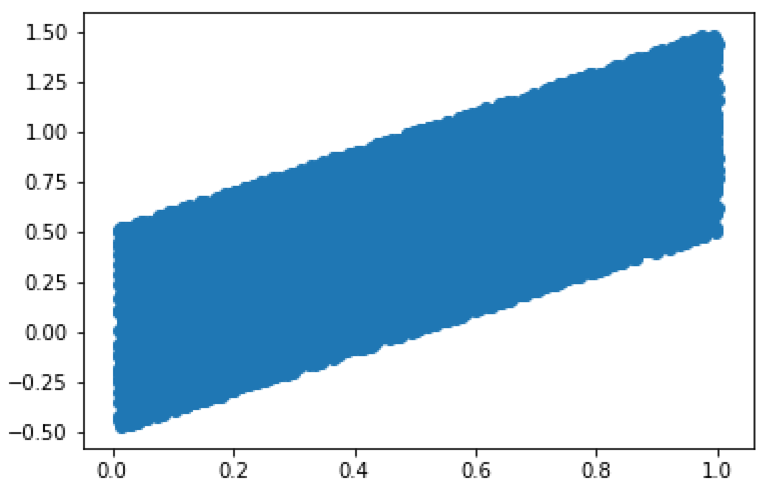
In [1]:
```
from sklearn.linear_model import LinearRegression
import numpy as np
import matplotlib.pylab as plt
%matplotlib inline
from sklearn import linear_model
```

In [2]:
```
n = 10000
x = np.linspace(0.01, 1, n).reshape(-1, 1)
y = np.linspace(0.01, 1, n)  + np.random.rand(n) - .5


plt.scatter(x,y)
```

Out[2]: <matplotlib.collections.PathCollection at 0x22dca7cda20>



Assignment 5

1. Create and fit a Linear Regression Model

Calculate the Training error and Testing error using sklearn with a .50 split

For error, use `mean_squared`, but if you want to experiment with other mean errors, please do!

In [37]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.5)

lr = LinearRegression()
lr.fit(xtrain,ytrain)

train_err = mean_squared_error(ytrain, np.dot(xtrain, lr.coef_) + lr.intercept
_)
test_err =  mean_squared_error(ytest, np.dot(xtest,lr.coef_) + lr.intercept_)

print('train error: {0}'.format(train_err))
print('test error: {0}'.format(test_err))
print('slope:{0}'.format(lr.coef_))
```

```
train error: 0.08447252784478264
test error: 0.08368899099673137
slope:[1.02132297]
```

2. Repeat #1 for a Ridge Regression

In [4]:
```
from sklearn.linear_model import Ridge
ridge = Ridge(fit_intercept=True)
ridge.fit(xtrain, ytrain)

train_err = mean_squared_error(ytrain, np.dot(xtrain, ridge.coef_) + ridge.int
ercept_)
test_err =  mean_squared_error(ytest, np.dot(xtest,ridge.coef_) + ridge.interc
ept_)

print('train error: {0}'.format(train_err))
print('test error: {0}'.format(test_err))
```

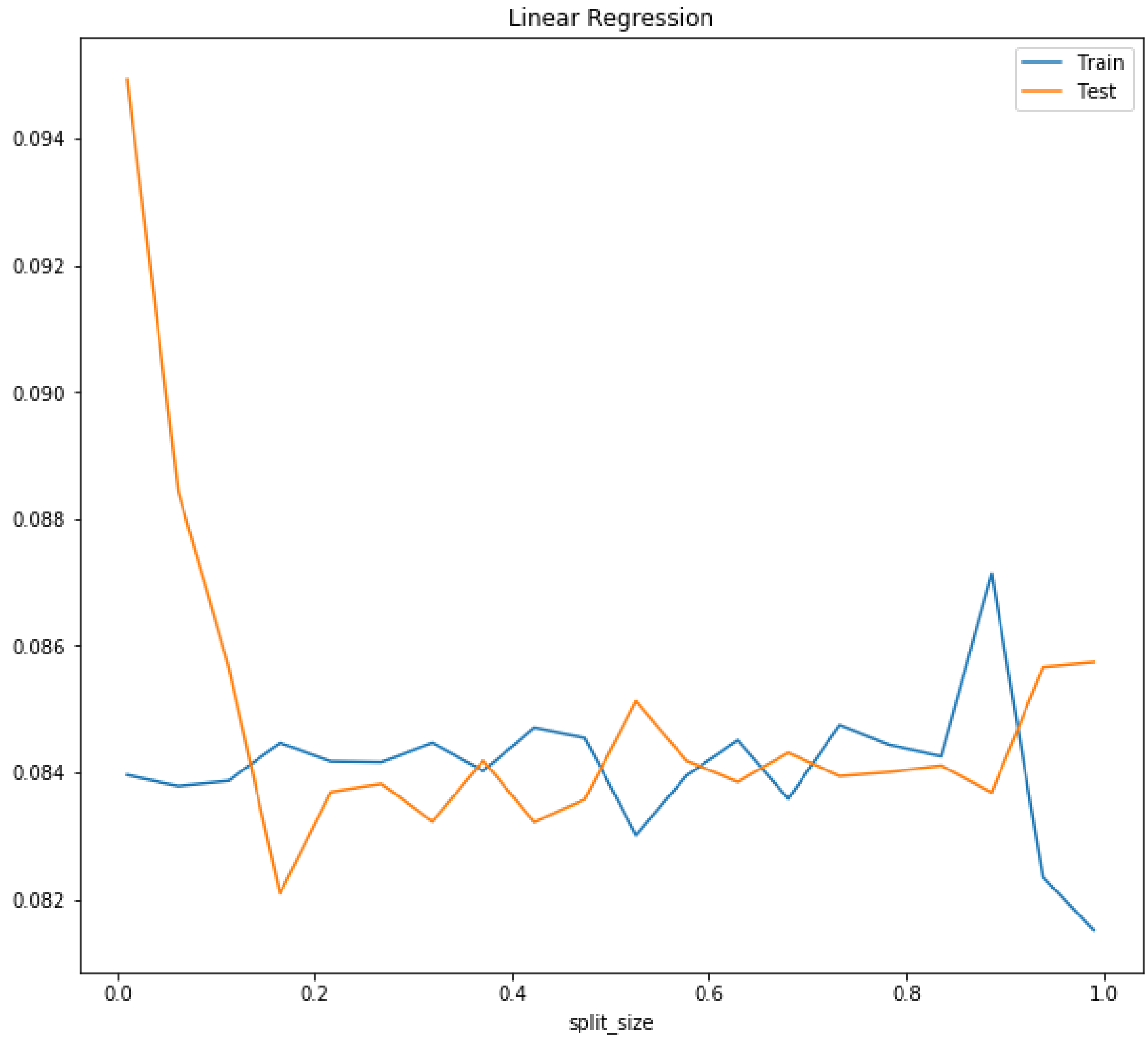
```
train error: 0.08402671905858511
test error: 0.08417675172400539
```

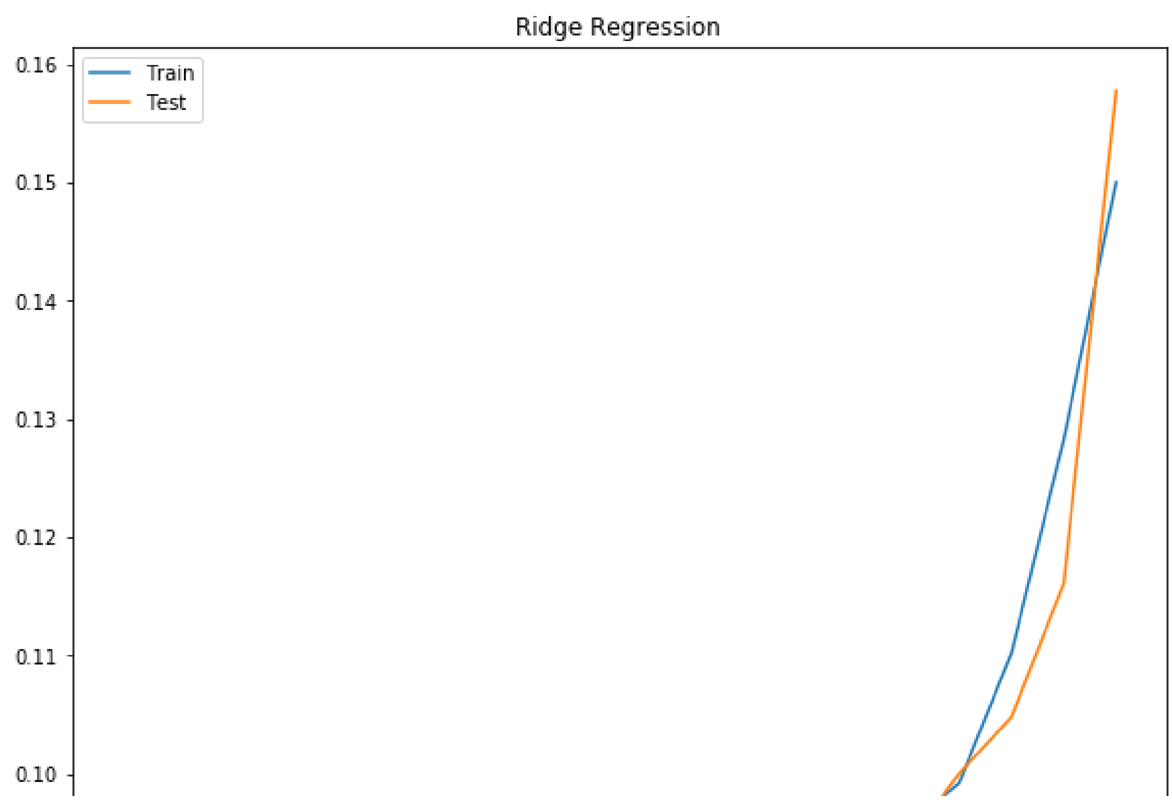
3. Vary the `split` size from .01 to .99 with at least 10 values (the more the merrier!). Plot the resulting Training error and Testing error vs. `split` size. Create separate plots for Linear and Ridge

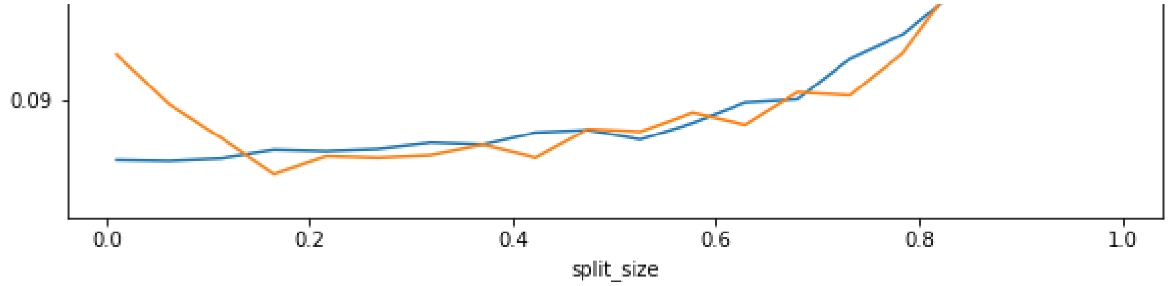
In [29]:
```
import sys
splits = np.linspace(.01, .99,20)
np.random.seed(1256)
errValuesRegression = []
errValuesRidge = []

min_err = (sys.float_info.max, 0.0) #min err, split

for split in splits:
    xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=split)

    lr = LinearRegression()
    lr.fit(xtrain,ytrain)

    train_err = mean_squared_error(ytrain, np.dot(xtrain, lr.coef_) + lr.inter
cept_)
    test_err =  mean_squared_error(ytest, np.dot(xtest,lr.coef_) + lr.intercep
t_)

    errValuesRegression.append((train_err, test_err))

    ridge = Ridge(alpha=100.0,fit_intercept=True)
    ridge.fit(xtrain, ytrain)

    train_err2 = mean_squared_error(ytrain, np.dot(xtrain, ridge.coef_) + ridg
e.intercept_)
    test_err2 =  mean_squared_error(ytest, np.dot(xtest,ridge.coef_) + ridge.i
ntercept_)

    #track min error for ridge
    if test_err2 < min_err[0]:
        min_err = (test_err2, split)

    errValuesRidge.append((train_err2, test_err2))

fig = plt.figure(figsize=(10,8))


xerrTrain = [e[0] for e in errValuesRegression]
xerrTest = [e[1] for e in errValuesRegression]

ax = fig.add_subplot(2,1,1)
ax.set_xlabel('split_size')
ax.set_title('Linear Regression')
ax.plot(splits, xerrTrain,label='Train' )
ax.plot(splits, xerrTest,label='Test' )
ax.legend()

xerrTrain2 = [e[0] for e in errValuesRidge]
xerrTest2 = [e[1] for e in errValuesRidge]

ax = fig.add_subplot(2,1,2)
ax.plot(splits, xerrTrain2,label='Train' )
ax.plot(splits, xerrTest2,label='Test' )
ax.set_xlabel('split_size')
ax.set_title('Ridge Regression')
```

```
ax.legend()

fig.subplots_adjust(top=2.0)

print('min error {0}'.format(min_err[0]))
print('optimal split at {0}'.format(min_err[1]))
```

```
min error 0.08380034400734329
optimal split at 0.16473684210526315
```


Linear Regression
Train
Test
0.094
0.092
0.090
0.088
0.086
0.084
0.082
0.0
0.2
0.4
0.6
0.8
1.0
split_size

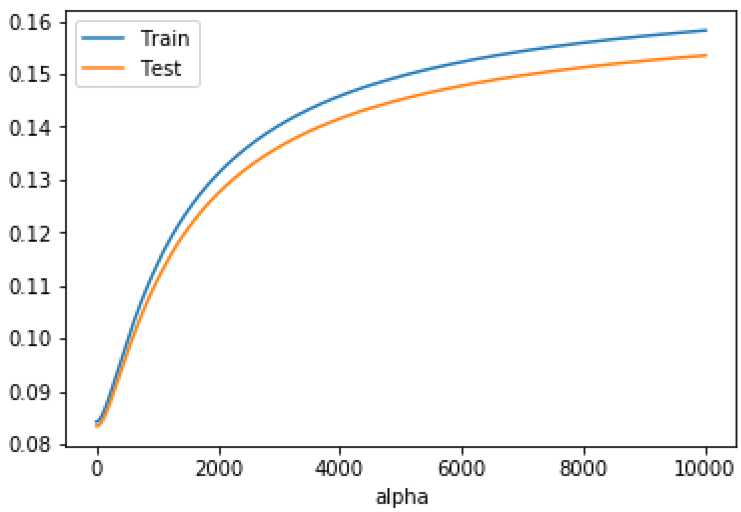

Ridge Regression
Train
Test
0.16
0.15
0.14
0.13
0.12
0.11
0.10



4. Chose an ideal split size based on the previous plot for Ridge.

Vary the Ridge parameter `alpha` from 0 to any value you'd like above 1. Plot the Train and Test error. Describe what you see based on the `alpha` parameter's stiffness.

In [35]:
```
np.random.seed(1256)
alpha = np.linspace(0.0, 10000, 1000)
errValuesRidge = []

split = min_err[1]
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=split)

for a in alpha:
    ridge = Ridge(alpha=a,fit_intercept=True)
    ridge.fit(xtrain, ytrain)

    train_err = mean_squared_error(ytrain, np.dot(xtrain, ridge.coef_) + ridge
.intercept_)
    test_err =  mean_squared_error(ytest, np.dot(xtest,ridge.coef_) + ridge.in
tercept_)

    errValuesRidge.append([train_err, test_err])

xerrTrain = [e[0] for e in errValuesRidge]
xerrTest = [e[1] for e in errValuesRidge]

plt.plot(alpha, xerrTrain,label='Train' )
plt.plot(alpha, xerrTest,label='Test' )
plt.xlabel('alpha')
plt.legend()
plt.show()
```



Bonus. Either: Generate data with a polynomial shape or use real data that you find on your own. Choose whatever regression model and process you'd like (Ridge, polynomial, etc.) and plot the Train-Test errors vs. any parameter your Model depends on (e.g. `alpha`, `degree`, etc.)