Week 3 SVR

May 23, 2019

0.1 Apply different Regression algorithms

0.1.1 SVM

In [24]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, r2_score
import seaborn as sns
%matplotlib inline
```

In [25]:
```
data = pd.read_csv('reduced_var_data.csv', index_col = 0)
y = data['SalePrice']
x = data.drop(labels = 'SalePrice', axis=1)
```

- We will try first working on the actual value of the sale price, and then the log of sale price

In [3]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state
ss = StandardScaler()
ss.fit(x_train)
x_train = ss.transform(x_train)
x_test = ss.transform(x_test)
```

In [4]:
```
pipe = Pipeline(steps= [('ss', StandardScaler()), ('clf', SVR(gamma='scale'))])
```

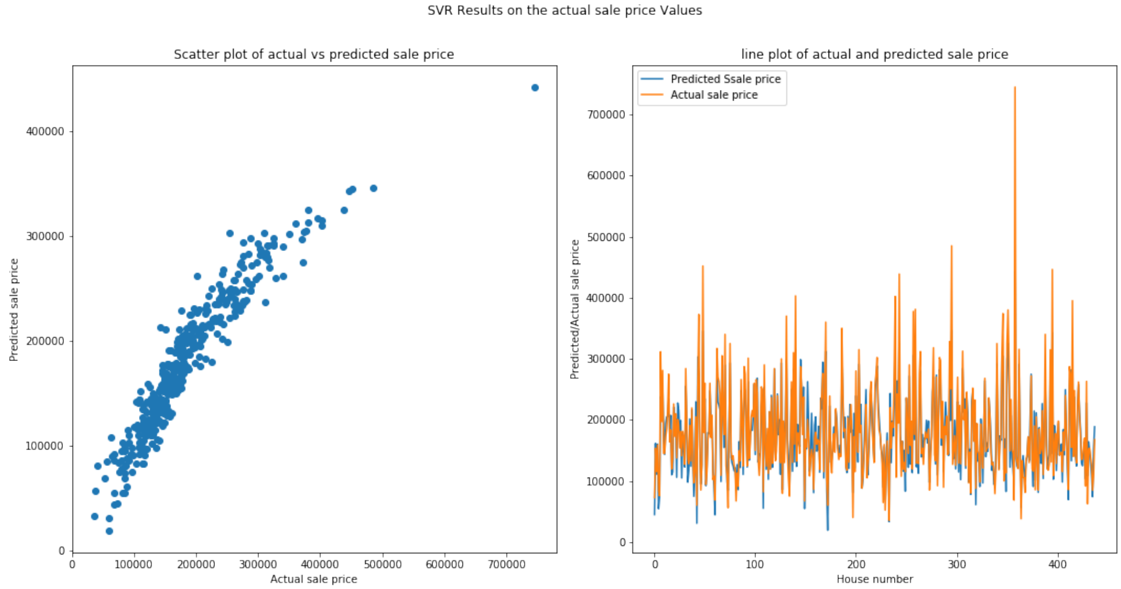
In [5]:
```
param_grid = {
    'clf__C':[0.1, 0.5, 1.0, 1.5, 10,100, 150],
    'clf__kernel': ['linear', 'rbf', 'sigmoid', 'poly']
}

search = GridSearchCV(pipe, param_grid, cv=5, iid=False, scoring='neg_mean_absolute_er
                      return_train_score=False)
search.fit(x, y)          # Here I am using the whole training data
print("Best parameter (CV score=%0.3f):" % search.best_score_)
print(search.best_params_)
```

```
Best parameter (CV score=-19736.160):
{'clf__C': 150, 'clf__kernel': 'linear'}
```

```
In [6]: best_svr = SVR(kernel='linear', gamma ='scale', C = 150)
        best_svr.fit(x_train, y_train)
        y_pred = best_svr.predict(x_test)
        print(mean_absolute_error(y_test, y_pred))
        print(r2_score(y_test, y_pred))
```

```
18799.026333339327
0.8607851431235201
```

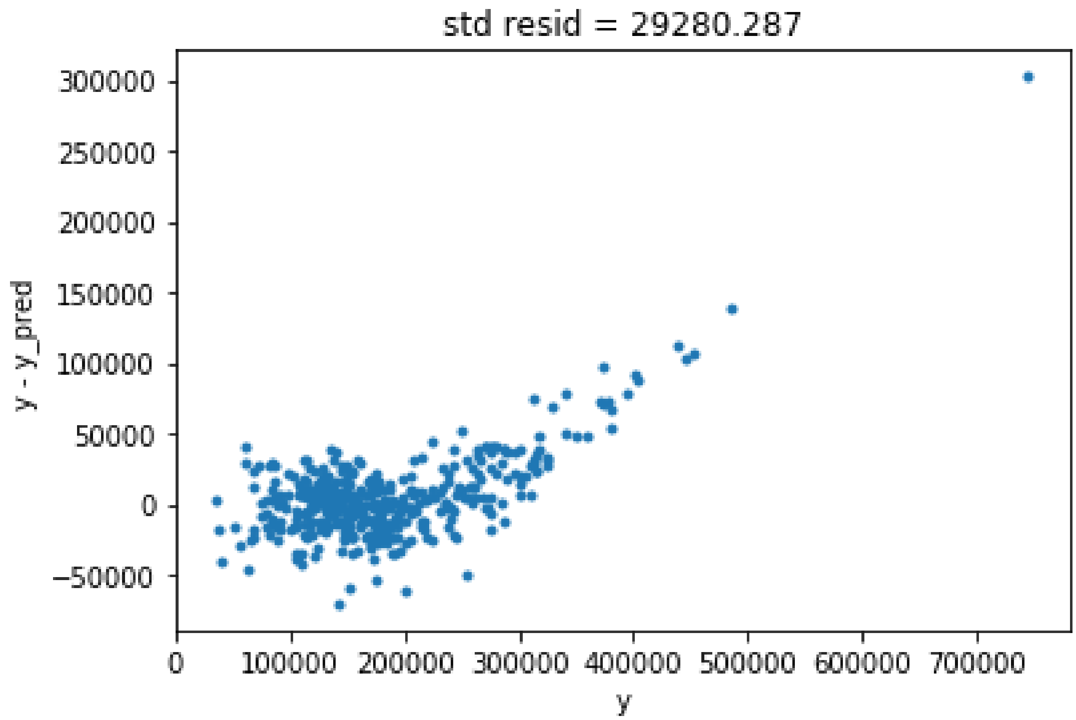
```
In [10]: y_pred = best_svr.predict(x_test)
         fig = plt.figure(figsize=(15,8))
         fig.suptitle('SVR Results on the actual sale price Values')
         plt.subplot(121)
         plt.scatter(y_test.values, y_pred)
         plt.xlabel('Actual sale price')
         plt.ylabel('Predicted sale price')
         plt.title('Scatter plot of actual vs predicted sale price')
         plt.subplot(122)
         plt.plot((y_pred), label='Predicted Ssale price')
         plt.plot((y_test.values), label='Actual sale price')
         plt.xlabel('House number')
         plt.ylabel('Predicted/Actual sale price')
         plt.title('line plot of actual and predicted sale price')
         plt.legend()
         plt.tight_layout()
         fig.subplots_adjust(top=0.88)
```



```
In [12]: print("Corrolation between true and predicted value using SVR on the actual sale price
                format(np.corrcoef(y_test,y_pred)[0][1]))
```

```
Corrolation between true and predicted value using SVR on the actual sale price is 0.9377106146
```

```
In [13]: resid = y_test - y_pred
         mean_resid = resid.mean()
         std_resid = resid.std()
         plt.plot(y_test,y_test-y_pred,'.')
         plt.xlabel('y')
         plt.ylabel('y - y_pred');
         plt.title('std resid = {:.3f}'.format(std_resid));
```



As shown in the figures above, There are some outliers which increase the value of the RMSE and the std of the residual.

0.1.2 Try working on log(Sale price)

```
In [14]: x_train, x_test, y_train, y_test = train_test_split(x, np.log(y), test_size = 0.3, ran
         ss = StandardScaler()
         ss.fit(x_train)
```

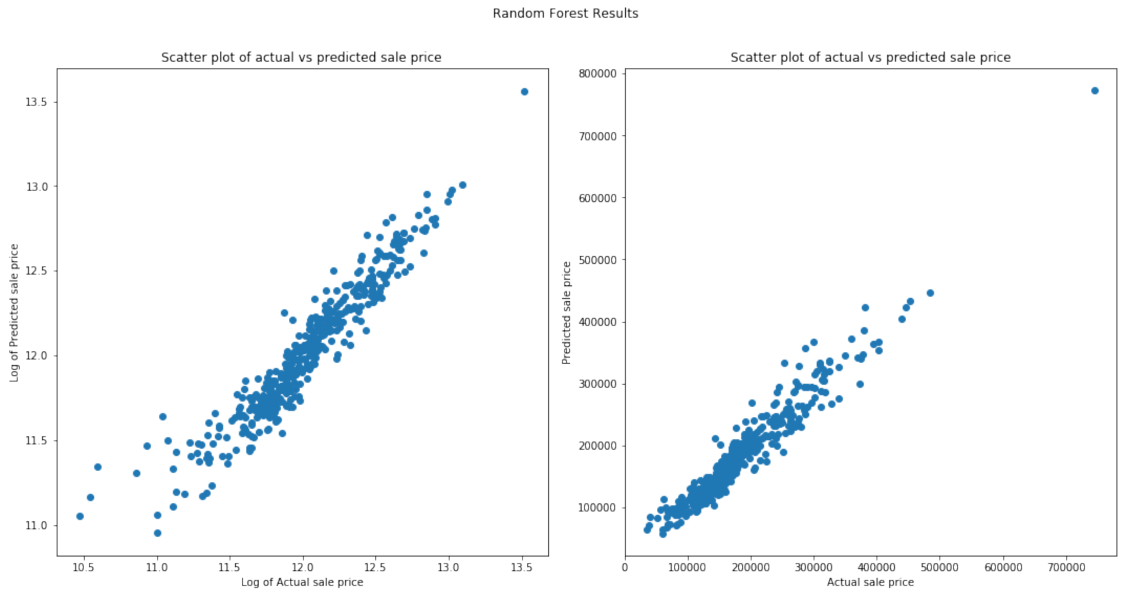
```
x_train = ss.transform(x_train)
x_test = ss.transform(x_test)
search.fit(x, np.log(y))          # Here I am using the whole training data
print("Best parameter (CV score=%0.3f):" % search.best_score_)
print(search.best_params_)
```

```
Best parameter (CV score=-0.092):
{'clf__C': 0.1, 'clf__kernel': 'linear'}
```

In [19]:
```
best_svr = SVR(kernel='linear', gamma ='scale', C = 0.1)
best_svr.fit(x_train, y_train)
y_pred = best_svr.predict(x_test)
print(mean_absolute_error(np.exp(y_test), np.exp(y_pred)))
print(r2_score(np.exp(y_test), np.exp(y_pred)))
```

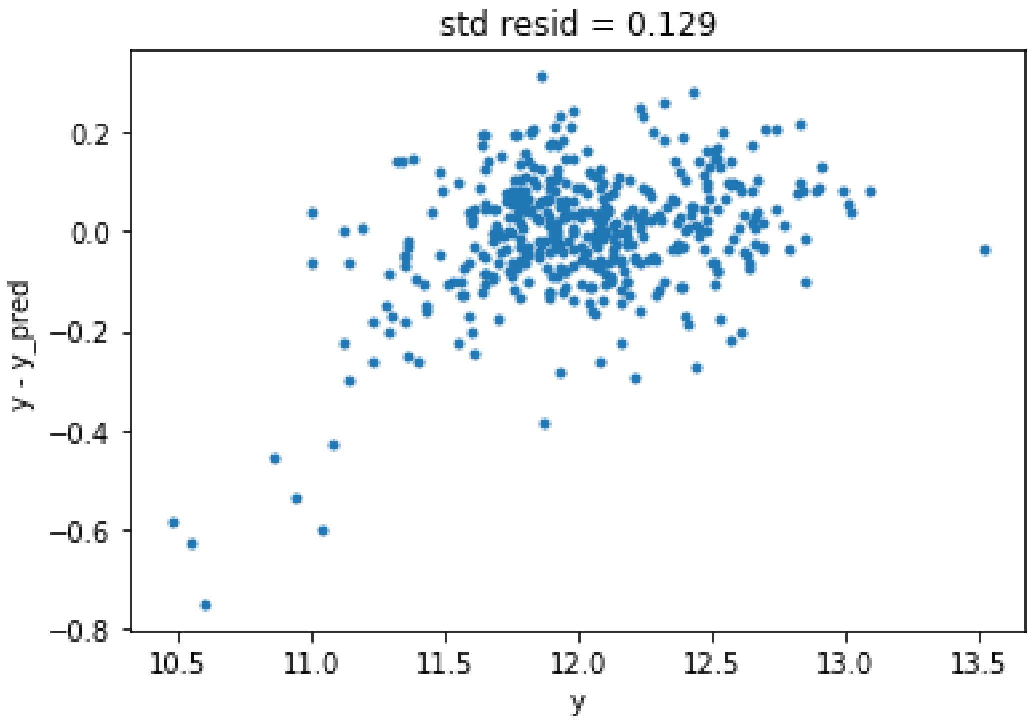
```
15236.845896887477
0.93274653988136
```

In [17]:
```
y_pred = best_svr.predict(x_test)
fig = plt.figure(figsize=(15,8))
fig.suptitle('Random Forest Results')
plt.subplot(121)
plt.scatter(y_test, y_pred)
plt.xlabel('Log of Actual sale price')
plt.ylabel('Log of Predicted sale price')
plt.title('Scatter plot of actual vs predicted sale price')
plt.subplot(122)
plt.scatter(np.exp(y_test.values), np.exp(y_pred))
plt.xlabel('Actual sale price')
plt.ylabel('Predicted sale price')
plt.title('Scatter plot of actual vs predicted sale price')
plt.tight_layout()
fig.subplots_adjust(top=0.88)
```



SVM algorithm with log of sale price gives a very good results

In [21]:
```
resid = y_test - y_pred
mean_resid = resid.mean()
std_resid = resid.std()
plt.plot(y_test,y_test-y_pred,'.')
plt.xlabel('y')
plt.ylabel('y - y_pred');
plt.title('std resid = {:.3f}'.format(std_resid));
```




```
In [23]: print("Corrolation between true and predicted value using SVR on the log of sale pric
            format(np.corrcoef(np.exp(y_test),np.exp(y_pred))[0][1]))
```

```
Corrolation between true and predicted value using SVR on the log of sale price is 0.965901765
```

Working on the actual value of the sale price is better than working on log od the sale price