In [4]:
```
import os
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
```

In [5]:
```
#First let’s add the Python code to change directories – I was doing this using the Spyder Gl
#which is a bit lazy.

path = "C:\Work\Machine Learning experiments\Kaggle\House Price"
os.chdir(path)
```

In [7]:
```
train_data = pd.read_csv("train.csv")
test_data = pd.read_csv("test.csv")
```

In [8]:
```
#Let’s get our bearings by running some .head and .describe() commands on the training set an
#that we spot:

train_data.head(n=20)
```

Out[8]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	Po
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	
5	6	50	RL	85.0	14115	Pave	NaN	IR1	Lvl	AllPub	...	
6	7	20	RL	75.0	10084	Pave	NaN	Reg	Lvl	AllPub	...	
7	8	60	RL	NaN	10382	Pave	NaN	IR1	Lvl	AllPub	...	
8	9	50	RM	51.0	6120	Pave	NaN	Reg	Lvl	AllPub	...	
9	10	190	RL	50.0	7420	Pave	NaN	Reg	Lvl	AllPub	...	
10	11	20	RL	70.0	11200	Pave	NaN	Reg	Lvl	AllPub	...	
11	12	60	RL	85.0	11924	Pave	NaN	IR1	Lvl	AllPub	...	
12	13	20	RL	NaN	12968	Pave	NaN	IR2	Lvl	AllPub	...	
13	14	20	RL	91.0	10652	Pave	NaN	IR1	Lvl	AllPub	...	
14	15	20	RL	NaN	10920	Pave	NaN	IR1	Lvl	AllPub	...	
15	16	45	RM	51.0	6120	Pave	NaN	Reg	Lvl	AllPub	...	
16	17	20	RL	NaN	11241	Pave	NaN	IR1	Lvl	AllPub	...	
17	18	90	RL	72.0	10791	Pave	NaN	Reg	Lvl	AllPub	...	
18	19	20	RL	66.0	13695	Pave	NaN	Reg	Lvl	AllPub	...	
19	20	20	RL	70.0	7560	Pave	NaN	Reg	Lvl	AllPub	...	

20 rows × 81 columns

In [9]:

```
#We’ve certainly got lots of columns to work with – each row represents a sale, most of the
#columns describe the property itself, but over to the right we’ve also got some info on the
#sale (year sold, sale type, sale condition, etc.), and importantly – the variable we will be
#trying to predict – the sale price.

#Next let’s try the .describe command:

train_data.describe()
```

Out[9]:

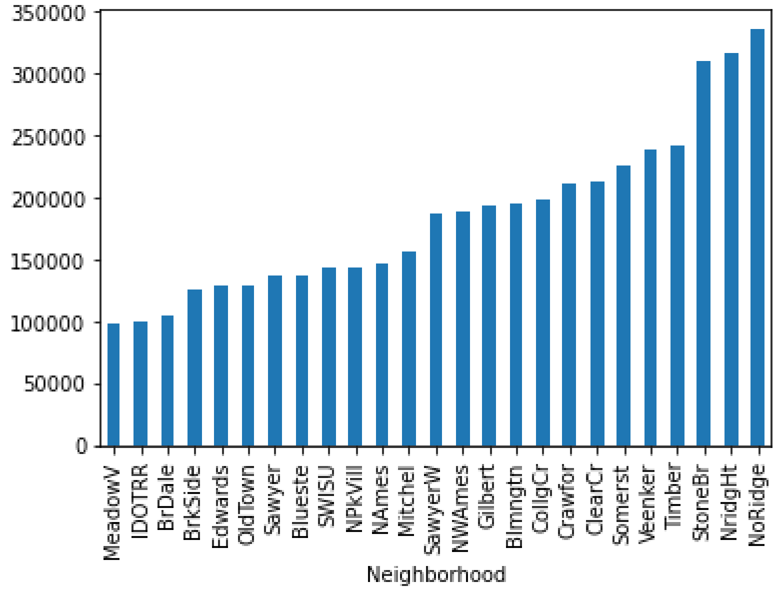
	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRen
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1460.000000	146(
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	1984
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	30.202904	2(
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	195(
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	1954.000000	1967
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	1973.000000	1994
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2000.000000	2004
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	201(

8 rows × 38 columns

In [10]:

```
#Let’s pick out a few important features of the above – we’ve for 1460 rows, each row has a s
# price – so far so good. The average sale price is $ 180,921. House prices in Iowa cira 200
# are certainly a lot lower than London! We can read off the min and max house price – 35k, a
# 750k respectively. In order to start to build up some intuition around the dataset, let’s s
# to pick out some variables we think will be useful and graph them against house price:

#Let’s start with neighbourhood:
#First we need to pivot on Neighbourhood, sort by sales price, and then produce a bar chart:


NeighbourhoodPivot = train_data.groupby("Neighborhood")['SalePrice'].mean()
NeighbourhoodPivot = NeighbourhoodPivot.sort_values()
NeighbourhoodPivot.plot.bar()
```

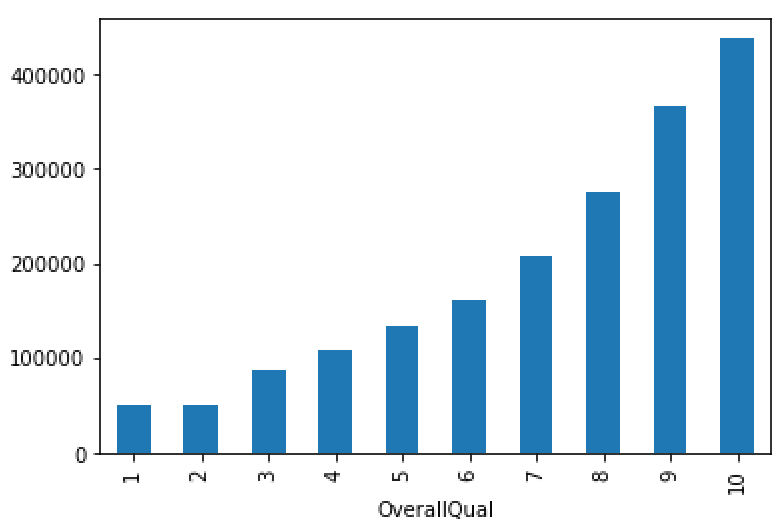
Out[10]: <AxesSubplot:xlabel='Neighborhood'>



In [11]:

```
#The built-in .plot functionality is definitely not the prettiest, but at least it seems to w
# well straight out of the box. I’ve used Seaborn in the past, but since this is just a rough
# cut, let’s not go to the effort right now just for the sake of appearance.

#So what can we deduce from the chart? We see that Neighbourhood is clearly going to be usefu
# NoRidge has an average sale price almost double that of the average across our entire datas
# MedaowV has an average almost half of the whole population. We’ll definitely want to includ
# this in our modelling.

#Let’s repeat the above with a few more variables, just eyeballing the list of variables, I
# the look of OverallQuality, OverallCondition, BuildingType, Housestyle, and YearSold


#Overall Quality:


OverallQualPivot = train_data.groupby("OverallQual")['SalePrice'].mean().sort_values()
OverallQualPivot.plot.bar()
```

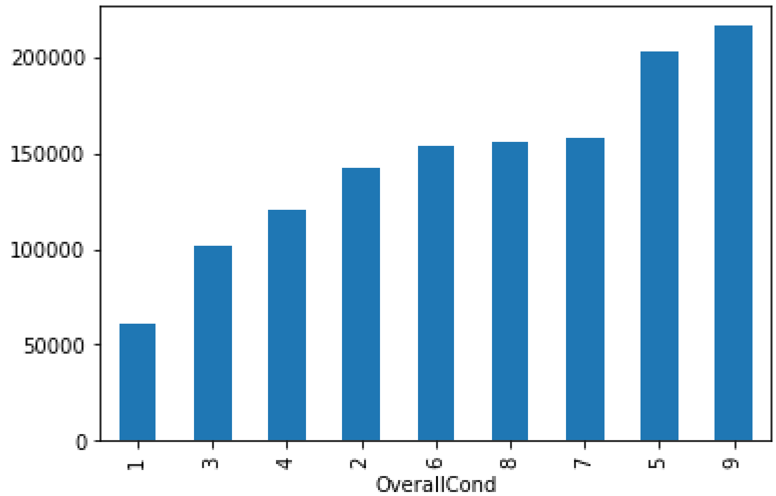
Out[11]: <AxesSubplot:xlabel='OverallQual'>



In [12]:

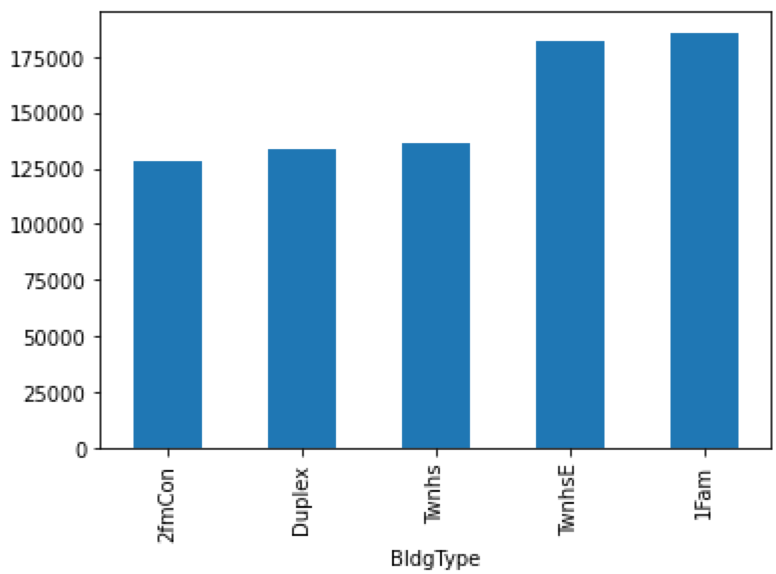
```
OverallCondPivot = train_data.groupby("OverallCond")['SalePrice'].mean().sort_values()
OverallCondPivot.plot.bar()
```

Out[12]: <AxesSubplot:xlabel='OverallCond'>



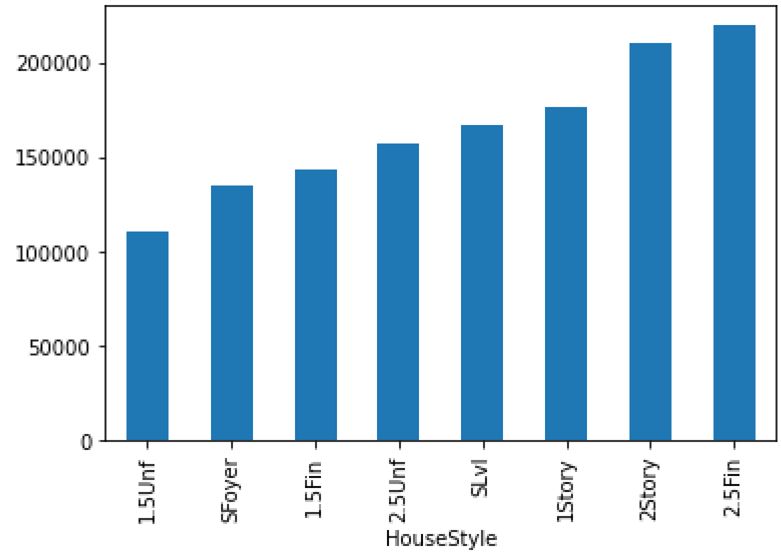
In [13]:
```
BldgTypePivot = train_data.groupby("BldgType")['SalePrice'].mean().sort_values()
BldgTypePivot.plot.bar()
```

Out[13]: <AxesSubplot:xlabel='BldgType'>



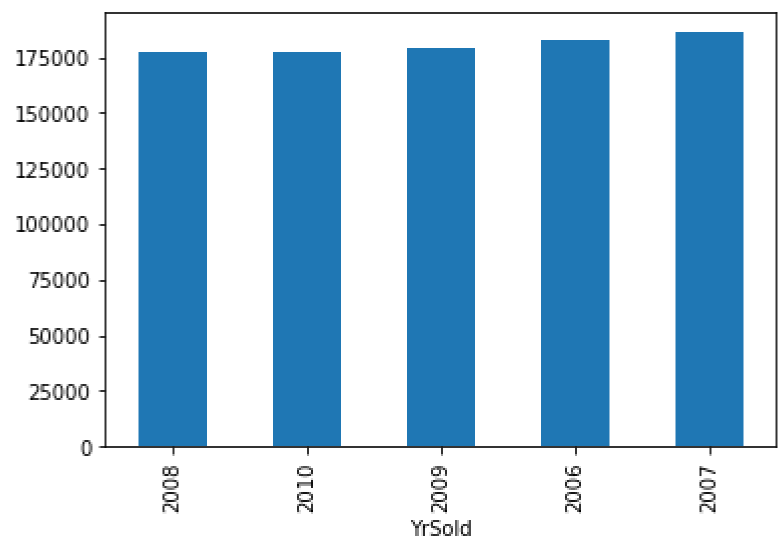
In [14]:
```
HouseStylePivot = train_data.groupby("HouseStyle")['SalePrice'].mean().sort_values()
HouseStylePivot.plot.bar()
```

Out[14]: <AxesSubplot:xlabel='HouseStyle'>



In [15]:
```
YrSoldPivot = train_data.groupby("YrSold")['SalePrice'].mean().sort_values()
YrSoldPivot.plot.bar()
```

Out[15]: <AxesSubplot:xlabel='YrSold'>



In [16]:
```
#Okay - we’ve done some data exploration, and there are clearly some useful variables in our

#Building a model:
#We want to build a supervised regression model - since we had so much success with Random Fo
# last time, I’m going to just use that this time - we’re going to only use the variables abo
# used useful and we’re not going to amend any data or tweak and hyperparameters - just to gi
# ourselves a naïve benchmark so reference against. The following is just code which I’ve tak
# the Titanic competition and amended to work here:


features = ['Neighborhood','OverallQual','OverallCond','BldgType','HouseStyle']
Y = train_data['SalePrice']
X = pd.get_dummies(train_data[features])
X_test = pd.get_dummies(test_data[features])

columns = X.columns
ColList = columns.tolist()
```

```python
missing_cols = set( X_test.columns ) - set( X.columns )
missing_cols2 = set( X.columns ) - set( X_test.columns )
# Add a missing column in test set with default value equal to 0
for c in missing_cols:
    X[c] = 0

for c in missing_cols2:
    X_test[c] = 0
# Ensure the order of column in the test set is in the same order than in train set
X = X[X_test.columns]
```

In [17]:
```python
RFmodel = RandomForestRegressor(random_state=1)
RFmodel.fit(X,Y)
predictions = RFmodel.predict(X_test)
```

In [ ]:
```python
output = pd.DataFrame({'ID': test_data.Id, 'SalePrice': predictions})
output.to_csv('my_submission - V1 - RF.csv',index=False)
```