House Prices: Advanced Regression Techniques

Work developed by: Manuel Robalinho

21-7-2018

https://www.kaggle.com/c/house-prices-advanced-regression-techniques (https://www.kaggle.com/c/house-prices-advanced-regression-techniques)

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence. With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

The Ames Housing dataset was compiled by Dean De Cock for use in data science education. It's an incredible alternative for data scientists looking for a modernized and expanded version of the often cited Boston Housing dataset.

Query Documentation

http://alanpryorjr.com/visualizations/seaborn/heatmap/heatmap/ (http://alanpryorjr.com/visualizations/seaborn/heatmap/heatmap/)
https://seaborn.pydata.org/tutorial/categorical.html (https://seaborn.pydata.org/tutorial/categorical.html)
http://pbpython.com/pandas-pivot-table-explained.html (http://pbpython.com/pandas-pivot-table-explained.html)

Data Description

MSSubClass: Identifies the type of dwelling involved in the sale.

MSZoning: Identifies the general zoning classification of the sale.

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Alley: Type of alley access to property

LotShape: General shape of property

LandContour: Flatness of the property

Utilities: Type of utilities available

LotConfig: Lot configuration

LandSlope: Slope of property

Neighborhood: Physical locations within Ames city limits

Condition1: Proximity to various conditions

Condition2: Proximity to various conditions (if more than one is present)

BldgType: Type of dwelling

Conversion; originally built as one-family dwelling

HouseStyle: Style of dwelling

OverallQual: Rates the overall material and finish of the house

OverallCond: Rates the overall condition of the house

YearBuilt: Original construction date Year

RemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

RoofMatl: Roof material

Exterior1st: Exterior covering on house

Exterior2nd: Exterior covering on house (if more than one material)

MasVnrType: Masonry veneer type

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

ExterCond: Evaluates the present condition of the material on the exterior

Foundation: Type of foundation

BsmtQual: Evaluates the height of the basement

BsmtCond: Evaluates the general condition of the basement

BsmtExposure: Refers to walkout or garden level walls

BsmtFinType1: Rating of basement finished area

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area Total

BsmtSF: Total square feet of basement area

Heating: Type of heating

HeatingQC: Heating quality and condition

CentralAir: Central air conditioning

Electrical: Electrical system

Romex wiring (Average)

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

Low QualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

Fireplace in main living area or Masonry Fireplace in basement

GarageType: Garage location

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

GarageCond: Garage condition

PavedDrive: Paved driveway

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Fence: Fence quality

MiscFeature: Miscellaneous feature not covered in other categories

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

SaleCondition: Condition of sale

In [3]:

```
# Load the python packages
import sys
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
%matplotlib inline
```

In the Kaggle House Prices challenge we are given two sets of data:

1. A training set which contains data about houses and their sale prices.
2. A test set which contains data about a different set of houses, for which we would like to predict sale price.

In [4]:

```
# Read files
df_train = pd.read_csv("house_prices_train.csv")
df_test  = pd.read_csv('house_prices_test.csv')
```

1. Pre Processing

In [5]:

```
# Scan information files
df = df_train
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
Id               1460 non-null int64
MSSubClass       1460 non-null int64
MSZoning         1460 non-null object
LotFrontage      1201 non-null float64
LotArea          1460 non-null int64
Street           1460 non-null object
Alley            91 non-null object
LotShape         1460 non-null object
LandContour      1460 non-null object
Utilities        1460 non-null object
LotConfig        1460 non-null object
LandSlope        1460 non-null object
Neighborhood     1460 non-null object
Condition1       1460 non-null object
Condition2       1460 non-null object
BldgType         1460 non-null object
HouseStyle       1460 non-null object
OverallQual      1460 non-null int64
OverallCond      1460 non-null int64
YearBuilt        1460 non-null int64
YearRemodAdd     1460 non-null int64
RoofStyle        1460 non-null object
RoofMatl         1460 non-null object
Exterior1st      1460 non-null object
Exterior2nd      1460 non-null object
MasVnrType       1452 non-null object
MasVnrArea       1452 non-null float64
ExterQual        1460 non-null object
ExterCond        1460 non-null object
Foundation       1460 non-null object
BsmtQual         1423 non-null object
BsmtCond         1423 non-null object
BsmtExposure     1422 non-null object
BsmtFinType1     1423 non-null object
BsmtFinSF1       1460 non-null int64
BsmtFinType2     1422 non-null object
BsmtFinSF2       1460 non-null int64
BsmtUnfSF        1460 non-null int64
TotalBsmtSF      1460 non-null int64
Heating          1460 non-null object
HeatingQC        1460 non-null object
CentralAir       1460 non-null object
Electrical       1459 non-null object
1stFlrSF         1460 non-null int64
2ndFlrSF         1460 non-null int64
LowQualFinSF     1460 non-null int64
GrLivArea        1460 non-null int64
BsmtFullBath     1460 non-null int64
BsmtHalfBath     1460 non-null int64
FullBath         1460 non-null int64
HalfBath         1460 non-null int64
BedroomAbvGr     1460 non-null int64
KitchenAbvGr     1460 non-null int64
KitchenQual      1460 non-null object
TotRmsAbvGrd     1460 non-null int64
Functional       1460 non-null object
Fireplaces       1460 non-null int64
FireplaceQu      770 non-null object
```

```
GarageType       1379 non-null object
GarageYrBlt      1379 non-null float64
GarageFinish     1379 non-null object
GarageCars       1460 non-null int64
GarageArea       1460 non-null int64
GarageQual       1379 non-null object
GarageCond       1379 non-null object
PavedDrive       1460 non-null object
WoodDeckSF       1460 non-null int64
OpenPorchSF      1460 non-null int64
EnclosedPorch    1460 non-null int64
3SsnPorch        1460 non-null int64
ScreenPorch      1460 non-null int64
PoolArea         1460 non-null int64
PoolQC           7 non-null object
Fence            281 non-null object
MiscFeature      54 non-null object
MiscVal          1460 non-null int64
MoSold           1460 non-null int64
YrSold           1460 non-null int64
SaleType         1460 non-null object
SaleCondition    1460 non-null object
SalePrice        1460 non-null int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

Numeric informations:

SalePrice - Preço

YrSold - Ano de venda
MoSold - Mes de venda
MiscVal: $Value of miscellaneous feature - Valor de melhorias aplicadas no imovel

PoolArea - are de piscina
OpenPorchSF- Área de varanda aberta
WoodDeckS - Área de deck de madeira
GarageCars: Size of garage in car capacity
GarageArea: Size of garage
Fireplaces - Number of fireplaces - NUmero lareiras
1stFlrSF: First Floor square feet (m2 do 1 andar)
TotRmsAbvGrd: Total de quartos acima do nível (não inclui banheiros)
FullBath: banheiros completos acima do nível
Kitchen: Kitchens above grade (n. cozinhas)
LotFrontage: Pés lineares de rua conectados à propriedade
LotArea: Tamanho do lote em pés quadrados

$Wehave: 1460, entries$:

we have records with various null information, the most significant being::
- PoolQC(piscina) 7 non-null object
- Fence(cerca) 281 non-null objec
- MiscFeature(melhorias) 54 non-null object
- FireplaceQu(lareira) 770 non-null object
- Alley(rua) 91 non-null object

In [6]:

```
# Count null data in each column
df.isnull().sum()
```

Out[6]:

```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
Street             0
Alley           1369
LotShape           0
LandContour        0
Utilities          0
LotConfig          0
LandSlope          0
Neighborhood       0
Condition1         0
Condition2         0
BldgType           0
HouseStyle         0
OverallQual        0
OverallCond        0
YearBuilt          0
YearRemodAdd       0
RoofStyle          0
RoofMatl           0
Exterior1st        0
Exterior2nd        0
MasVnrType         8
MasVnrArea         8
ExterQual          0
ExterCond          0
Foundation         0
                ... 
BedroomAbvGr       0
KitchenAbvGr       0
KitchenQual        0
TotRmsAbvGrd       0
Functional         0
Fireplaces         0
FireplaceQu      690
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageCars         0
GarageArea         0
GarageQual        81
GarageCond        81
PavedDrive         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
PoolQC          1453
Fence           1179
MiscFeature     1406
MiscVal            0
MoSold             0
YrSold             0
SaleType           0
```

```
SaleCondition       0
SalePrice           0
Length: 81, dtype: int64
```

In [7]:

```
# visualization some lines
df.head()
```

Out[7]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Land
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl

5 rows × 81 columns

In [8]:

```
# statistical measures
df.describe()
```

Out[8]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	Overa
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.(
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000

8 rows × 38 columns

Analysis of numerical columns

Note that there are very disparate columns in the column-by-column evaluation. This can be observed by the minimum and maximum values of the numeric columns

-----------------------min --- max

LotFrontage = 21.0 - 313.0

LotArea = 1300.0 - 215245.0

MasVnrArea(area alvenaria) = 0.0 - 1600.0

MiscVal(melhorias) = 0.0 - 15500.0

In [9]:

```
# Type data information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
Id               1460 non-null int64
MSSubClass       1460 non-null int64
MSZoning         1460 non-null object
LotFrontage      1201 non-null float64
LotArea          1460 non-null int64
Street           1460 non-null object
Alley            91 non-null object
LotShape         1460 non-null object
LandContour      1460 non-null object
Utilities        1460 non-null object
LotConfig        1460 non-null object
LandSlope        1460 non-null object
Neighborhood     1460 non-null object
Condition1       1460 non-null object
Condition2       1460 non-null object
BldgType         1460 non-null object
HouseStyle       1460 non-null object
OverallQual      1460 non-null int64
OverallCond      1460 non-null int64
YearBuilt        1460 non-null int64
YearRemodAdd     1460 non-null int64
RoofStyle        1460 non-null object
RoofMatl         1460 non-null object
Exterior1st      1460 non-null object
Exterior2nd      1460 non-null object
MasVnrType       1452 non-null object
MasVnrArea       1452 non-null float64
ExterQual        1460 non-null object
ExterCond        1460 non-null object
Foundation       1460 non-null object
BsmtQual         1423 non-null object
BsmtCond         1423 non-null object
BsmtExposure     1422 non-null object
BsmtFinType1     1423 non-null object
BsmtFinSF1       1460 non-null int64
BsmtFinType2     1422 non-null object
BsmtFinSF2       1460 non-null int64
BsmtUnfSF        1460 non-null int64
TotalBsmtSF      1460 non-null int64
Heating          1460 non-null object
HeatingQC        1460 non-null object
CentralAir       1460 non-null object
Electrical       1459 non-null object
1stFlrSF         1460 non-null int64
2ndFlrSF         1460 non-null int64
LowQualFinSF     1460 non-null int64
GrLivArea        1460 non-null int64
BsmtFullBath     1460 non-null int64
BsmtHalfBath     1460 non-null int64
FullBath         1460 non-null int64
HalfBath         1460 non-null int64
BedroomAbvGr     1460 non-null int64
KitchenAbvGr     1460 non-null int64
KitchenQual      1460 non-null object
TotRmsAbvGrd     1460 non-null int64
Functional       1460 non-null object
Fireplaces       1460 non-null int64
FireplaceQu      770 non-null object
```

```
GarageType       1379 non-null object
GarageYrBlt      1379 non-null float64
GarageFinish     1379 non-null object
GarageCars       1460 non-null int64
GarageArea       1460 non-null int64
GarageQual       1379 non-null object
GarageCond       1379 non-null object
PavedDrive       1460 non-null object
WoodDeckSF       1460 non-null int64
OpenPorchSF      1460 non-null int64
EnclosedPorch    1460 non-null int64
3SsnPorch        1460 non-null int64
ScreenPorch      1460 non-null int64
PoolArea         1460 non-null int64
PoolQC           7 non-null object
Fence            281 non-null object
MiscFeature      54 non-null object
MiscVal          1460 non-null int64
MoSold           1460 non-null int64
YrSold           1460 non-null int64
SaleType         1460 non-null object
SaleCondition    1460 non-null object
SalePrice        1460 non-null int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [10]:

```
# For the columns that have missing data, one option is delete column because have many
 null itens,
# or replace the num entry by a default code.

# - PoolQC(piscina) 7 non-null object
# - Fence(cerca) 281 non-null objec
# - MiscFeature(melhorias) 54 non-null object
# - FireplaceQu(lareira) 770 non-null object
# - Alley(rua) 91 non-null object

# to erase the column use:
# del df['PoolQC']
```

In [11]:

```
#del df['Fence']
```

In [12]:

```
#del df['MiscFeature']
```

In [13]:

```
#del df['FireplaceQu']
```

Missing Data

To get an overview of this, let’s find all columns with missing values and count how many each of them has:

In [315]:

```
# Counting missing values in X_Test and X_Train
def count_missing(data):
    null_cols = data.columns[data.isnull().any(axis=0)]
    X_null = data[null_cols].isnull().sum()
    X_null = X_null.sort_values(ascending=False)
    print(X_null)

# Concatenate df_train and df_test
data_X = pd.concat([df_train, df_test])

count_missing(data_X)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9: Future
Warning: Sorting because non-concatenation axis is not aligned. A future v
ersion
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  if __name__ == '__main__':

PoolQC          2909
MiscFeature     2814
Alley           2721
Fence           2348
SalePrice       1459
FireplaceQu     1420
LotFrontage      486
GarageQual       159
GarageCond       159
GarageFinish     159
GarageYrBlt      159
GarageType       157
BsmtExposure      82
BsmtCond          82
BsmtQual          81
BsmtFinType2      80
BsmtFinType1      79
MasVnrType        24
MasVnrArea        23
MSZoning           4
BsmtFullBath       2
BsmtHalfBath       2
Utilities          2
Functional         2
Electrical         1
BsmtUnfSF          1
Exterior1st        1
Exterior2nd        1
TotalBsmtSF        1
GarageCars         1
BsmtFinSF2         1
BsmtFinSF1         1
KitchenQual        1
SaleType           1
GarageArea         1
dtype: int64
```

Some of the missing values are indeed significant. For example, missing values for features related to garage, pool or basement simply indicate that the house does not have a garage, pool or basement, respectively. In this case, it makes sense to fill in these missing values with something that captures this information.

For categorical resources, for example, we can replace missing values in such cases with a new value called "None":

In [316]:

```
catfeats_fillnaNone = \
    ['Alley',
    'BsmtCond','BsmtQual','BsmtExposure',
    'BsmtFinType1', 'BsmtFinType2',
    'FireplaceQu',
    'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
    'PoolQC',
    'Fence',
    'MiscFeature']

data_X.loc[:,catfeats_fillnaNone] = \
    data_X[catfeats_fillnaNone].fillna('None')
```

In [317]:

```
# Counting missing values in X_Test and X_Train

count_missing(data_X)
```

```
SalePrice       1459
LotFrontage      486
GarageYrBlt      159
MasVnrType        24
MasVnrArea        23
MSZoning           4
Utilities          2
BsmtFullBath       2
BsmtHalfBath       2
Functional         2
Exterior1st        1
BsmtFinSF2         1
BsmtUnfSF          1
Electrical         1
GarageCars         1
Exterior2nd        1
GarageArea         1
TotalBsmtSF        1
KitchenQual        1
SaleType           1
BsmtFinSF1         1
dtype: int64
```

We see that the features no longer appear with null values:
'Alley', 'BsmtCond','BsmtQual','BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond', 'PoolQC', 'Fence', 'MiscFeature'

For most numerical features of this kind, it makes sense to replace the missing values with zero:

In [318]:

```
numfeats_fillnazero = \
    ['BsmtFullBath', 'BsmtHalfBath', 'TotalBsmtSF',
     'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
     'GarageArea', 'GarageCars']

data_X.loc[:,numfeats_fillnazero] = \
    data_X[numfeats_fillnazero].fillna(0)
```

In [319]:

```
# Counting missing values in X_Test and X_Train

count_missing(data_X)
```

```
SalePrice      1459
LotFrontage     486
GarageYrBlt     159
MasVnrType       24
MasVnrArea       23
MSZoning          4
Utilities         2
Functional        2
SaleType          1
KitchenQual       1
Exterior2nd       1
Exterior1st       1
Electrical        1
dtype: int64
```

We see that the features no longer appear with null values:
'BsmtFullBath', 'BsmtHalfBath', 'TotalBsmtSF', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'GarageArea', 'GarageCars'

For the GarageYrBuilt field, where the best course of action is less clear. If the house does not have a garage, how can we tell when it was built? The best solution will probably depend on the model we decided to use and now let's fill it with YearBuilt:

In [320]:

```
# Data Missing for GarageYrBlt
data_X.loc[:,'GarageYrBlt'] = \
    data_X['GarageYrBlt'].fillna(data_X.YearBuilt)
```

In [321]:

```
# Counting missing values in X_Test and X_Train

count_missing(data_X)
```

```
SalePrice      1459
LotFrontage     486
MasVnrType       24
MasVnrArea       23
MSZoning          4
Utilities         2
Functional        2
SaleType          1
KitchenQual       1
Exterior2nd       1
Exterior1st       1
Electrical        1
dtype: int64
```

Some values still missing. We may assume that they are missing at random. In this case, there are three main options open to us: delete, impute or leave.

The crudest option is to simply replace each missing entry by the mean, median or mode of the given feature, which gives us the roughest possible estimate for what the missing value might be. We can implement this for our house prices dataset as follows (using mode and median for categorical and numerical features respectively):

In [322]:

```
# Fill Missing Values with MODE

catfeats_fillnamode = \
    ['Electrical', 'MasVnrType', 'MSZoning', 'Functional', 'Utilities',
     'Exterior1st', 'Exterior2nd', 'KitchenQual', 'SaleType']

data_X.loc[:, catfeats_fillnamode] = \
    data_X[catfeats_fillnamode].fillna(data_X[catfeats_fillnamode].mode().iloc[0])
```

In [323]:

```
# Fill Missing Values with MEDIAN

numfeats_fillnamedian = ['MasVnrArea', 'LotFrontage']

data_X.loc[:, numfeats_fillnamedian] = \
    data_X[numfeats_fillnamedian].fillna(data_X[numfeats_fillnamedian].median())
```

In [324]:

```
# Counting missing values in X_Test and X_Train

count_missing(data_X)
```

```
SalePrice    1459
dtype: int64
```

In [326]:

```
# Fill Missing Values with MEAN

numfeats_fillnamedian = ['SalePrice']

data_X.loc[:, numfeats_fillnamedian] = \
    data_X[numfeats_fillnamedian].fillna(data_X[numfeats_fillnamedian].mean())
```

In [327]:

```
# Counting missing values in X_Test and X_Train

count_missing(data_X)
```

```
Series([], dtype: float64)
```

In [328]:

```
# Count the number of features we have of each type:
data_X.dtypes.value_counts()
```

Out[328]:

```
object     43
int64      26
float64    12
dtype: int64
```

In [329]:

```
# We can retrieve the names of features that are in fact non-numerical ‘objects’ as fol
lows:
data_X.select_dtypes(include = [object]).columns
```

Out[329]:

```
Index(['Alley', 'BldgType', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
       'BsmtFinType2', 'BsmtQual', 'CentralAir', 'Condition1', 'Condition
2',
       'Electrical', 'ExterCond', 'ExterQual', 'Exterior1st', 'Exterior2n
d',
       'Fence', 'FireplaceQu', 'Foundation', 'Functional', 'GarageCond',
       'GarageFinish', 'GarageQual', 'GarageType', 'Heating', 'HeatingQC',
       'HouseStyle', 'KitchenQual', 'LandContour', 'LandSlope', 'LotConfi
g',
       'LotShape', 'MSZoning', 'MasVnrType', 'MiscFeature', 'Neighborhoo
d',
       'PavedDrive', 'PoolQC', 'RoofMatl', 'RoofStyle', 'SaleCondition',
       'SaleType', 'Street', 'Utilities'],
      dtype='object')
```

Ordinal features

Since ordinal features are inherently ordered, they lend themselves naturally to numerical encoding. For example, the possible values for LotShape are Reg (regular), IR1 (slightly irregular), IR2 (moderately irregular) and IR3 (irregular), to which we could assign the values (0,1,2,3) respectively:

In [330]:

```
# Convert LotShape to numbers
data_X.LotShape = \
    data_X.LotShape.replace({'Reg':0, 'IR1':1, 'IR2':2, 'IR3':3})
```

In [331]:

```
data_X.LotShape.head()
```

Out[331]:

```
0    0
1    0
2    1
3    1
4    1
Name: LotShape, dtype: int64
```

In [332]:

```
# Verify all distinct values for a column - Utilities
data_X["Utilities"].value_counts()
```

Out[332]:

```
AllPub    2918
NoSeWa       1
Name: Utilities, dtype: int64
```

In [333]:

```
# We have all values with the same carecteristic AllPub.
# We could delete this column

del data_X["Utilities"]
```

In [334]:

```
# Verify all distinct values for a column - Street
data_X["Street"].value_counts()
```

Out[334]:

```
Pave    2907
Grvl      12
Name: Street, dtype: int64
```

In [335]:

```
# We have the most values with the same carecteristic Pave.
# We could delete this column - Street

del data_X["Street"]
```

Ordinal encoding

There is nothing to stop us from applying ordinal encoding to categorical features as well. For instance, we could assign integers to each possible category in alphabetical order or in order of appearance in the dataset. As an example, let’s have a look at the first few Neighborhood entries in the test set:

In [336]:

```
data_X.Neighborhood.head(10)
```

Out[336]:

```
0    CollgCr
1    Veenker
2    CollgCr
3    Crawfor
4    NoRidge
5    Mitchel
6    Somerst
7     NWAmes
8    OldTown
9    BrkSide
Name: Neighborhood, dtype: object
```

Applying ordinal encoding (in order of appearance), we get the following:

In [337]:

```
# Verify all distinct values for a column - Neighborhood
data_X["Neighborhood"].value_counts()
```

Out[337]:

```
NAmes      443
CollgCr    267
OldTown    239
Edwards    194
Somerst    182
NridgHt    166
Gilbert    165
Sawyer     151
NWAmes     131
SawyerW    125
Mitchel    114
BrkSide    108
Crawfor    103
IDOTRR      93
Timber      72
NoRidge     71
StoneBr     51
SWISU       48
ClearCr     44
MeadowV     37
BrDale      30
Blmngtn     28
Veenker     24
NPkVill     23
Blueste     10
Name: Neighborhood, dtype: int64
```

In [338]:

```
# Create a List whith Values
target_names = data_X["Neighborhood"].unique()
target_names
```

Out[338]:

```
array(['CollgCr', 'Veenker', 'Crawfor', 'NoRidge', 'Mitchel', 'Somerst',
       'NWAmes', 'OldTown', 'BrkSide', 'Sawyer', 'NridgHt', 'NAmes',
       'SawyerW', 'IDOTRR', 'MeadowV', 'Edwards', 'Timber', 'Gilbert',
       'StoneBr', 'ClearCr', 'NPkVill', 'Blmngtn', 'BrDale', 'SWISU',
       'Blueste'], dtype=object)
```

In [346]:

```
# Create a dictionary whith Values and index
target_dict = {n:i for i, n in enumerate(target_names)}
target_dict
```

Out[346]:

```
{'Blmngtn': 21,
 'Blueste': 24,
 'BrDale': 22,
 'BrkSide': 8,
 'ClearCr': 19,
 'CollgCr': 0,
 'Crawfor': 2,
 'Edwards': 15,
 'Gilbert': 17,
 'IDOTRR': 13,
 'MeadowV': 14,
 'Mitchel': 4,
 'NAmes': 11,
 'NPkVill': 20,
 'NWAmes': 6,
 'NoRidge': 3,
 'NridgHt': 10,
 'OldTown': 7,
 'SWISU': 23,
 'Sawyer': 9,
 'SawyerW': 12,
 'Somerst': 5,
 'StoneBr': 18,
 'Timber': 16,
 'Veenker': 1}
```

In [340]:

```
# Convert to numbers - Neighborhood
data_X.Neighborhood = data_X.Neighborhood.replace(target_dict)
```

In [341]:

```
data_X.Neighborhood.head()
```

Out[341]:

```
0    0
1    1
2    0
3    2
4    3
Name: Neighborhood, dtype: int64
```

In [148]:

```
# Create dataframe backup
#data_Back = data_X
# Create dataframe with Neighborhood caracteristics
data_X1 = pd.get_dummies(data_X.Neighborhood, drop_first=True)
```

In [149]:

```
data_X1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2919 entries, 0 to 1458
Data columns (total 24 columns):
Blueste    2919 non-null uint8
BrDale     2919 non-null uint8
BrkSide    2919 non-null uint8
ClearCr    2919 non-null uint8
CollgCr    2919 non-null uint8
Crawfor    2919 non-null uint8
Edwards    2919 non-null uint8
Gilbert    2919 non-null uint8
IDOTRR     2919 non-null uint8
MeadowV    2919 non-null uint8
Mitchel    2919 non-null uint8
NAmes      2919 non-null uint8
NPkVill    2919 non-null uint8
NWAmes     2919 non-null uint8
NoRidge    2919 non-null uint8
NridgHt    2919 non-null uint8
OldTown    2919 non-null uint8
SWISU      2919 non-null uint8
Sawyer     2919 non-null uint8
SawyerW    2919 non-null uint8
Somerst    2919 non-null uint8
StoneBr    2919 non-null uint8
Timber     2919 non-null uint8
Veenker    2919 non-null uint8
dtypes: uint8(24)
memory usage: 171.2 KB
```

In [150]:

```
data_X1.head()
```

Out[150]:

	Blueste	BrDale	BrkSide	ClearCr	CollgCr	Crawfor	Edwards	Gilbert	IDOTRR	M
0	0	0	0	0	1	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	1	0	0	0	0	0
3	0	0	0	0	0	1	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0

5 rows × 24 columns

In [151]:

```
# Concatenate data_X and data_X1 and delete column Neighborhood
#data_X = pd.concat([data_X, data_X1])

#del data_X["Neighborhood"]
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: Future
Warning: Sorting because non-concatenation axis is not aligned. A future v
ersion
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.
```

In [347]:

```
data_X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2919 entries, 0 to 1458
Data columns (total 79 columns):
1stFlrSF         2919 non-null int64
2ndFlrSF         2919 non-null int64
3SsnPorch        2919 non-null int64
Alley            2919 non-null object
BedroomAbvGr     2919 non-null int64
BldgType         2919 non-null object
BsmtCond         2919 non-null object
BsmtExposure     2919 non-null object
BsmtFinSF1       2919 non-null float64
BsmtFinSF2       2919 non-null float64
BsmtFinType1     2919 non-null object
BsmtFinType2     2919 non-null object
BsmtFullBath     2919 non-null float64
BsmtHalfBath     2919 non-null float64
BsmtQual         2919 non-null object
BsmtUnfSF        2919 non-null float64
CentralAir       2919 non-null object
Condition1       2919 non-null object
Condition2       2919 non-null object
Electrical       2919 non-null object
EnclosedPorch    2919 non-null int64
ExterCond        2919 non-null object
ExterQual        2919 non-null object
Exterior1st      2919 non-null object
Exterior2nd      2919 non-null object
Fence            2919 non-null object
FireplaceQu      2919 non-null object
Fireplaces       2919 non-null int64
Foundation       2919 non-null object
FullBath         2919 non-null int64
Functional       2919 non-null object
GarageArea       2919 non-null float64
GarageCars       2919 non-null float64
GarageCond       2919 non-null object
GarageFinish     2919 non-null object
GarageQual       2919 non-null object
GarageType       2919 non-null object
GarageYrBlt      2919 non-null float64
GrLivArea        2919 non-null int64
HalfBath         2919 non-null int64
Heating          2919 non-null object
HeatingQC        2919 non-null object
HouseStyle       2919 non-null object
Id               2919 non-null int64
KitchenAbvGr     2919 non-null int64
KitchenQual      2919 non-null object
LandContour      2919 non-null object
LandSlope        2919 non-null object
LotArea          2919 non-null int64
LotConfig        2919 non-null object
LotFrontage      2919 non-null float64
LotShape         2919 non-null int64
LowQualFinSF     2919 non-null int64
MSSubClass       2919 non-null int64
MSZoning         2919 non-null object
MasVnrArea       2919 non-null float64
MasVnrType       2919 non-null object
MiscFeature      2919 non-null object
```

```
MiscVal          2919 non-null int64
MoSold           2919 non-null int64
Neighborhood     2919 non-null int64
OpenPorchSF      2919 non-null int64
OverallCond      2919 non-null int64
OverallQual      2919 non-null int64
PavedDrive       2919 non-null object
PoolArea         2919 non-null int64
PoolQC           2919 non-null object
RoofMatl         2919 non-null object
RoofStyle        2919 non-null object
SaleCondition    2919 non-null object
SalePrice        2919 non-null float64
SaleType         2919 non-null object
ScreenPorch      2919 non-null int64
TotRmsAbvGrd     2919 non-null int64
TotalBsmtSF      2919 non-null float64
WoodDeckSF       2919 non-null int64
YearBuilt        2919 non-null int64
YearRemodAdd     2919 non-null int64
YrSold           2919 non-null int64
dtypes: float64(12), int64(28), object(39)
memory usage: 1.8+ MB
```

However, we have introduced an artificial structure to our variable. This encoding effectively says that Northwest Ames < Gilbert < Stone Brook, etc, which has no basis in reality.

In [348]:

```
# Verify all distinct values for a column - BldgType
data_X["BldgType"].value_counts()
```

Out[348]:

```
1Fam      2425
TwnhsE     227
Duplex     109
Twnhs       96
2fmCon      62
Name: BldgType, dtype: int64
```

In [350]:

```
# Convert BldgType to numbers
# Create a List whith Values
target_names = data_X["BldgType"].unique()
# Create a dictionary whith Values and index
target_dict = {n:i for i, n in enumerate(target_names)}
# Replace Values
data_X.BldgType = data_X.BldgType.replace(target_dict)
```

In [351]:

```
# Verify all distinct values for a column - BldgType
data_X["BldgType"].value_counts()
```

Out[351]:

```
0    2425
3     227
2     109
4      96
1      62
Name: BldgType, dtype: int64
```

Dummy encoding (aka one-hot encoding)

This method avoids the problem of imposing a numerical ordering on our categories altogether, though it comes at the expense of turning one feature into many. The basic idea is to create a new binary feature for each possible value of the original. This is easiest to understand with an example, so let’s return to the small snippet of Neighborhood data we looked at before. We can apply dummy encoding to this as follows:

In [30]:

```
# Transform caracteristics with columns with 0 or 1
pd.get_dummies(data_X.Neighborhood.head(15), drop_first=True)
```

Out[30]:

	CollgCr	Crawfor	Mitchel	NAmes	NWAmes	NoRidge	NridgHt	OldTown	Saw
0	1	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	0
4	0	0	0	0	0	1	0	0	0
5	0	0	1	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	1	0	0	0	0
8	0	0	0	0	0	0	0	1	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1
11	0	0	0	0	0	0	1	0	0
12	0	0	0	0	0	0	0	0	1
13	1	0	0	0	0	0	0	0	0
14	0	0	0	1	0	0	0	0	0

2. Data exploration and visualization

1. Univariate analysis

The distribution of the target variable and the individual characteristics

To get an idea of the distribution of the numerical variables, make the histograms.
Let's start by generating one for SalePrice, our target variable.

In [31]:

```
plt.title("Number of houses per price")
plt.xlabel("$ Price")
plt.ylabel("Number of Houses")
plt.hist(df.SalePrice, bins=30,  align=('mid'), color=['red'], label=['A'])
```

Out[31]:

```
(array([  11.,   38.,   99.,  232.,  273.,  218.,  176.,  104.,   93.,
          58.,   42.,   35.,   24.,   10.,   17.,    8.,    7.,    4.,
           2.,    1.,    1.,    2.,    1.,    0.,    2.,    0.,    0.,
           0.,    0.,    2.]),
 array([  34900.        ,   58903.33333333,   82906.66666667,
        106910.        ,  130913.33333333,  154916.66666667,
        178920.        ,  202923.33333333,  226926.66666667,
        250930.        ,  274933.33333333,  298936.66666667,
        322940.        ,  346943.33333333,  370946.66666667,
        394950.        ,  418953.33333333,  442956.66666667,
        466960.        ,  490963.33333333,  514966.66666667,
        538970.        ,  562973.33333333,  586976.66666667,
        610980.        ,  634983.33333333,  658986.66666667,
        682990.        ,  706993.33333333,  730996.66666667,  755000.
    ]),
 <a list of 30 Patch objects>)
```

The largest number of offers is registered in houses with a price between $100, 000.00, and$: 200,000.00

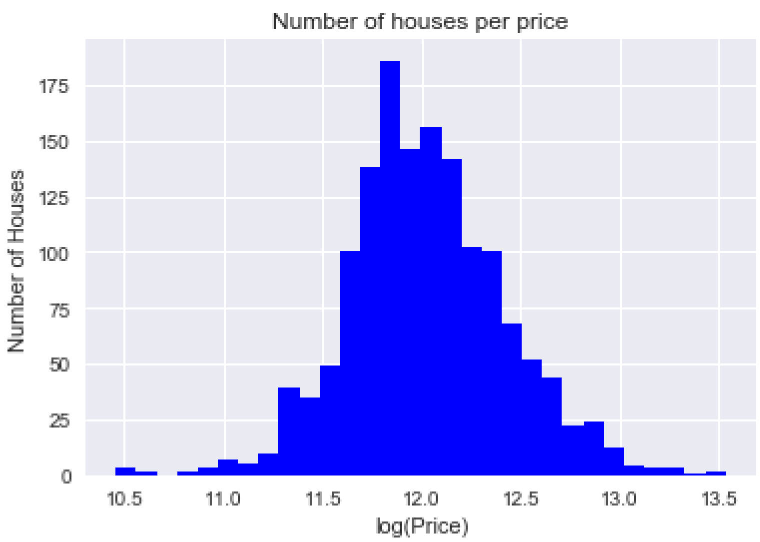
Immediately we see that the distribution is for cheaper houses, with a relatively long tail for homes with high prices. To make the distribution more symmetric, we can make the histogram of the logarithm:

In [32]:

```
plt.title("Number of houses per price")
plt.xlabel("log(Price)")
plt.ylabel("Number of Houses")
plt.hist(np.log(df.SalePrice), bins=30,  align=('mid'), color=['blue'], label=['A'])
```

Out[32]:

```
(array([   3.,    2.,    0.,    2.,    3.,    7.,    5.,   10.,   39.,
          35.,   49.,  100.,  138.,  186.,  146.,  156.,  142.,  102.,
         100.,   68.,   52.,   44.,   22.,   24.,   12.,    4.,    3.,
           3.,    1.,    2.]),
 array([ 10.46024211,  10.56271647,  10.66519084,  10.7676652 ,
         10.87013956,  10.97261393,  11.07508829,  11.17756266,
         11.28003702,  11.38251138,  11.48498575,  11.58746011,
         11.68993448,  11.79240884,  11.8948832 ,  11.99735757,
         12.09983193,  12.2023063 ,  12.30478066,  12.40725502,
         12.50972939,  12.61220375,  12.71467812,  12.81715248,
         12.91962684,  13.02210121,  13.12457557,  13.22704994,
         13.3295243 ,  13.43199866,  13.53447303]),
 <a list of 30 Patch objects>)
```



In addition to making the distribution more symmetrical, working with the logarithm of the selling price will also ensure that relative errors of cheaper and more expensive houses are treated equally.

Analysis of Categorical Variables

For categorical variables, bar graphs and frequency counts are the natural analyzes for histograms

In [33]:

```
# Analyzing the Type of Construction (Foundation)
x= df.Foundation.value_counts()
x
```

Out[33]:

```
PConc     647
CBlock    634
BrkTil    146
Slab       24
Stone       6
Wood        3
Name: Foundation, dtype: int64
```

Foundation: Type of foundation:

-BrkTil= Brick & Tile

-CBlock= Cinder Block

-PConc= Poured Contrete

-Slab= Slab

-Stone= Stone

-Wood= Wood

Almost all homes are made of concrete, being concrete or concrete blocks only.

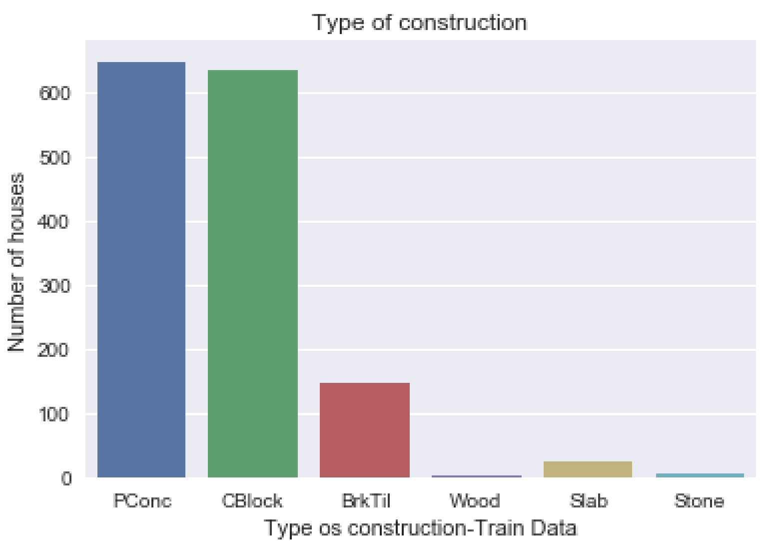
In [34]:

```
ax=sns.countplot(df.Foundation)
ax.set_title('Type of construction')
ax.set_ylabel('Number of houses')
ax.set_xlabel('Type os construction-Train Data')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

Out[34]:

```
<matplotlib.text.Text at 0x2ace6ea77f0>
```



Analyzing the same information in the test data (df_test), below, we see that they have the same behavior of the training data

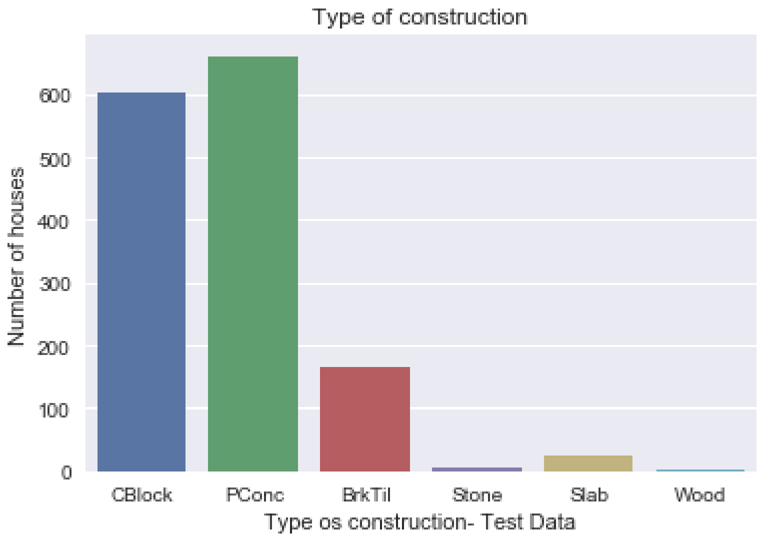
In [35]:

```
ax=sns.countplot(df_test.Foundation)
ax.set_title('Type of construction')
ax.set_ylabel('Number of houses')
ax.set_xlabel('Type os construction- Test Data')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

Out[35]:

```
<matplotlib.text.Text at 0x2ace7013d68>
```



2. Bivariate analysis

Having analyzed some of the variables individually, let's explore the relationships between them. Of course, the most interesting will be the relationship between the target variable (selling price) and the resources we will use for forecasting.

For numerical resources, scatter plots are the reference tool. As the total living area of a home is probably an important factor in determining its price, we will create one for GrLivArea and SalePrice. We will plot the seating area against the log of the sale price as well as for comparison.

In [36]:

```
# Plot the area versus the price
plt.plot(df_train.GrLivArea, df_train.SalePrice,'.', alpha = 0.3)
plt.title("Area and houses per price")
plt.ylabel("$ Price")
plt.xlabel("Area")
```

Out[36]:

<matplotlib.text.Text at 0x2ace6d75ac8>

In [37]:

```
# Plot the area versus the price
plt.plot(df_train.GrLivArea, np.log(df_train.SalePrice),'o', color=('green'),alpha = 0.
3)
plt.title("Area and houses per price")
plt.ylabel("log(Price)")
plt.xlabel("Area")
```

Out[37]:

<matplotlib.text.Text at 0x2ace70a04a8>

There is a strong dependence on the sale price of the total living area. As expected, the larger the home, the more expensive it tends to be. There is clearly a tendency to increase the selling price with the area, but we also see some points that do not seem to fit the rest. There are (a few) houses where the area / price pattern does not fit.

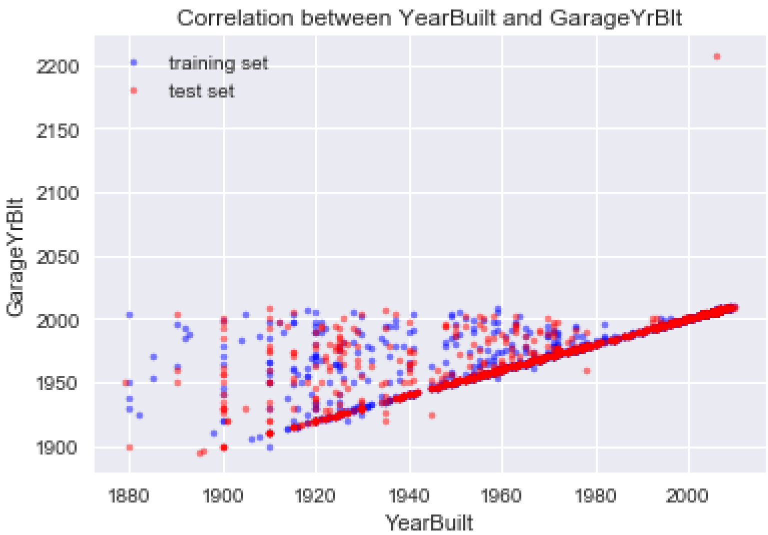
We would expect YearBuilt (year of construction) and GarageYrBlt (year of garage construction) to be perfectly related, so let's create a scatter chart for them. Since we are not considering SalePrice, we can use training and test data.

In [38]:

```
# Plot train Data
plt.plot(df_train.YearBuilt, df_train.GarageYrBlt,
         '.', alpha=0.5, color=('blue'), label = 'training set')
# Plot test Data
plt.plot(df_test.YearBuilt, df_test.GarageYrBlt,
         '.', alpha=0.5, color=('red'), label = 'test set')

plt.title("Correlation between YearBuilt and GarageYrBlt")
plt.ylabel("GarageYrBlt")
plt.xlabel("YearBuilt")
plt.legend()
```

Out[38]:

```
<matplotlib.legend.Legend at 0x2ace729a3c8>
```



As you would expect, the figure tells us that most garages were built at the same time as the houses to which they belong: they form the diagonal line that crosses the terrain. A significant number was also added later: these are the dots above the line.

In both training and test sets, we have several garages that were built up to 20 years before their homes (the points below the diagonal line), and in the training set we have a garage in the future where the record shows that it was built in year of 2018 (current). These amounts could be corrected to stay at least in the year of construction of the house.

Categorical variables

Let's take a look at some examples of selling price depending on the neighborhood. Another feature that is likely to be important for our predictive models.

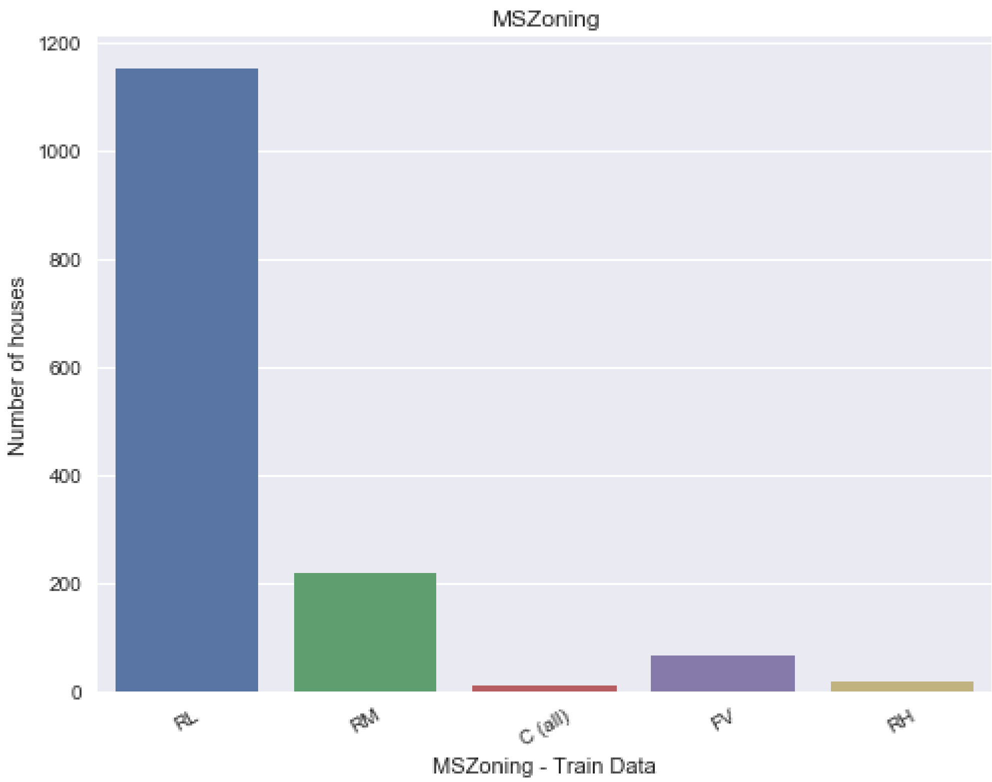
In [39]:

```
# Plot Number of houses for MSZoning
a4_dims = (8, 6)
fig, ax = plt.subplots(figsize=a4_dims)
g = sns.countplot(df_train.MSZoning)
ax.set_title('MSZoning')
ax.set_ylabel('Number of houses')
ax.set_xlabel('MSZoning - Train Data')
# Labels Rotation
g.set_xticklabels(g.get_xticklabels(), rotation=30)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

Out[39]:

```
[<matplotlib.text.Text at 0x2ace7314be0>,
 <matplotlib.text.Text at 0x2ace7318470>,
 <matplotlib.text.Text at 0x2ace7364898>,
 <matplotlib.text.Text at 0x2ace736b390>,
 <matplotlib.text.Text at 0x2ace736be48>]
```



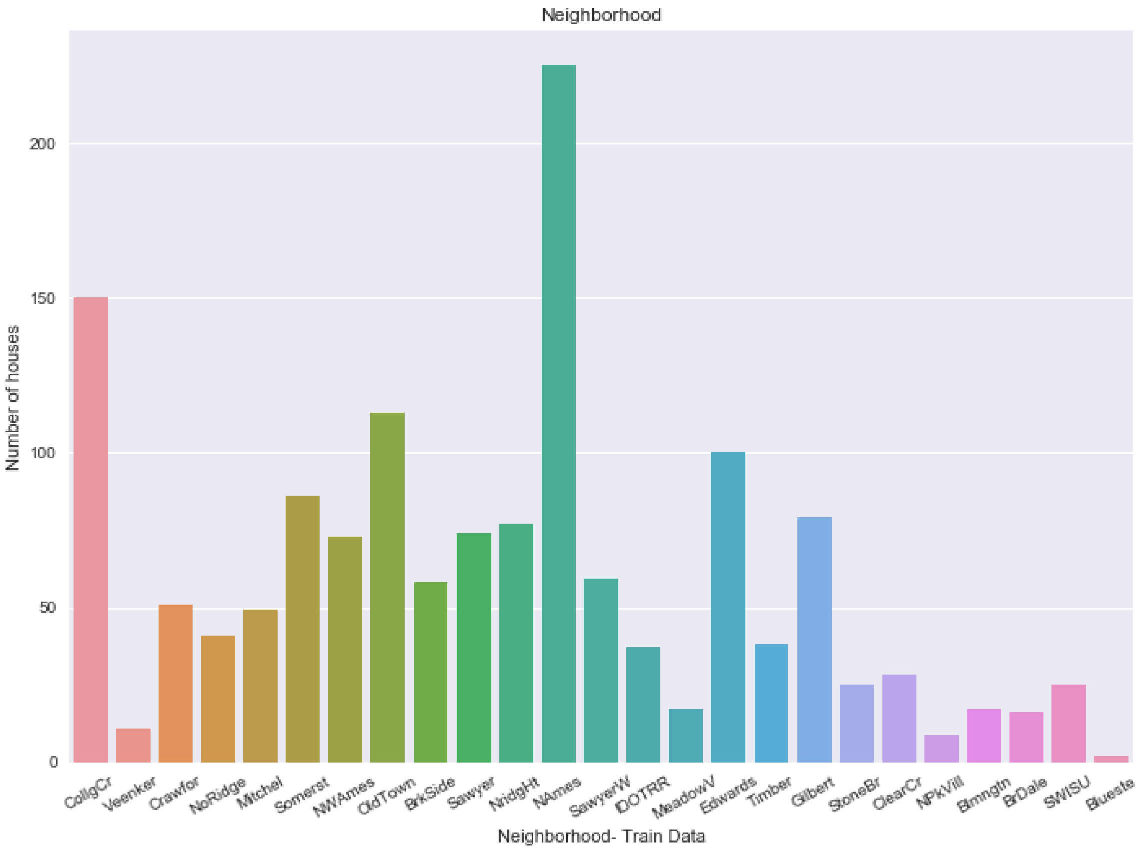
In [40]:

```
a4_dims = (11.7, 8.27)
fig, ax = plt.subplots(figsize=a4_dims)
#sns.violinplot(ax=ax, data=df_test.Neighborhood)
g = sns.countplot(df_train.Neighborhood)
ax.set_title('Neighborhood')
ax.set_ylabel('Number of houses')
ax.set_xlabel('Neighborhood- Train Data')
# labels Rotation
g.set_xticklabels(g.get_xticklabels(), rotation=30)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

Out[40]:

```
[<matplotlib.text.Text at 0x2ace73b9278>,
 <matplotlib.text.Text at 0x2ace73c13c8>,
 <matplotlib.text.Text at 0x2ace7460be0>,
 <matplotlib.text.Text at 0x2ace74686d8>,
 <matplotlib.text.Text at 0x2ace746c1d0>,
 <matplotlib.text.Text at 0x2ace746cc88>,
 <matplotlib.text.Text at 0x2ace7471780>,
 <matplotlib.text.Text at 0x2ace7478278>,
 <matplotlib.text.Text at 0x2ace7478d30>,
 <matplotlib.text.Text at 0x2ace747e828>,
 <matplotlib.text.Text at 0x2ace7483320>,
 <matplotlib.text.Text at 0x2ace7483dd8>,
 <matplotlib.text.Text at 0x2ace74898d0>,
 <matplotlib.text.Text at 0x2ace74903c8>,
 <matplotlib.text.Text at 0x2ace7490e80>,
 <matplotlib.text.Text at 0x2ace7497978>,
 <matplotlib.text.Text at 0x2ace749c470>,
 <matplotlib.text.Text at 0x2ace749cf28>,
 <matplotlib.text.Text at 0x2ace74a2a20>,
 <matplotlib.text.Text at 0x2ace74a9518>,
 <matplotlib.text.Text at 0x2ace74a9fd0>,
 <matplotlib.text.Text at 0x2ace74afac8>,
 <matplotlib.text.Text at 0x2ace74b45c0>,
 <matplotlib.text.Text at 0x2ace74bd0b8>,
 <matplotlib.text.Text at 0x2ace74bdb70>]
```



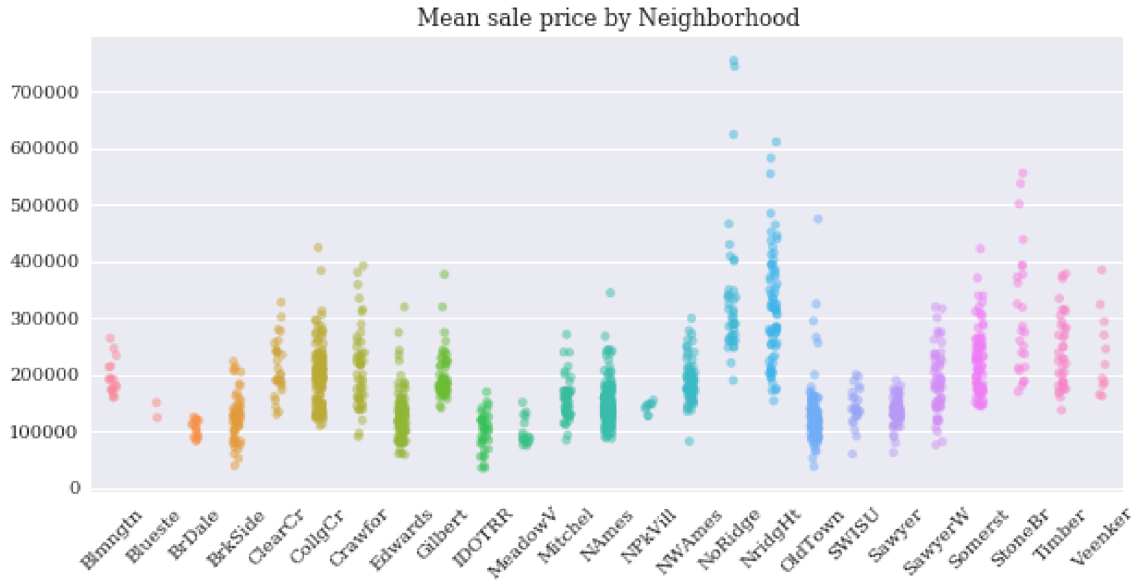
The largest number of homes is located in NAames, followed by Old Town and CollgCr.

In [84]:

```
g=sns.stripplot(x = df_train.Neighborhood.values, y = df_train.SalePrice.values,
              order = np.sort(df_train.Neighborhood.unique()),
              jitter=0.1, alpha=0.5)
g.set_title('Mean sale price by Neighborhood')
plt.xticks(rotation=45)
```

Out[84]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 1
6,
        17, 18, 19, 20, 21, 22, 23, 24]),
 <a list of 25 Text xticklabel objects>)
```



We can see the accumulation of prices in each neighborhood and the average prices where it is most reasonable.

In [353]:

```
# Mean Sales price by Neighborhood

df1 = df_train.groupby('Neighborhood')['SalePrice'].mean()

df1 = df1.sort_values()
df1
```

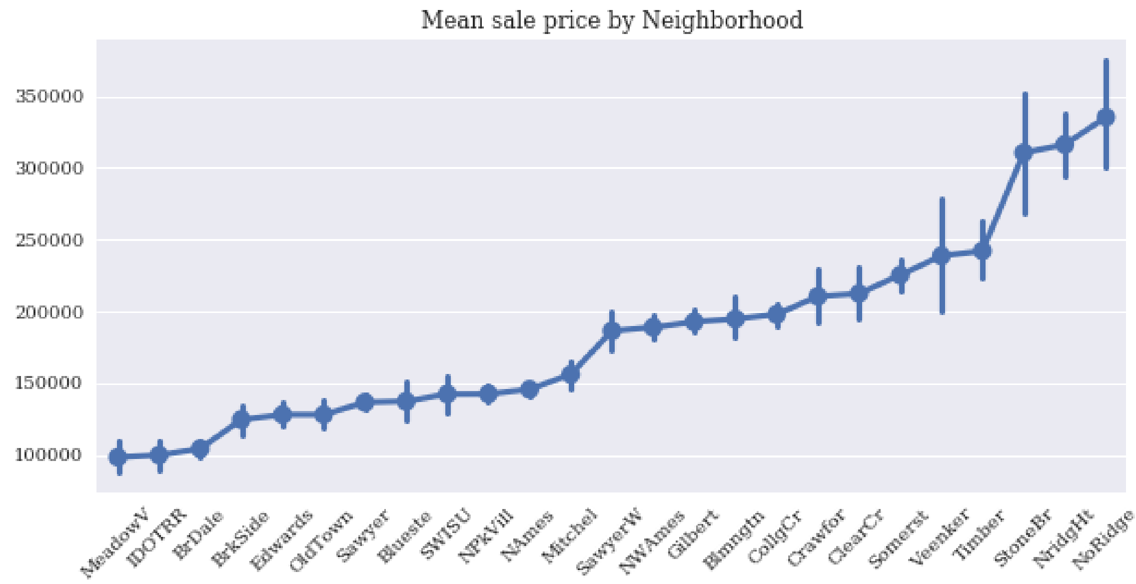
Out[353]:

```
Neighborhood
MeadowV     98576.470588
IDOTRR     100123.783784
BrDale     104493.750000
BrkSide    124834.051724
Edwards    128219.700000
OldTown    128225.300885
Sawyer     136793.135135
Blueste    137500.000000
SWISU      142591.360000
NPkVill    142694.444444
NAmes      145847.080000
Mitchel    156270.122449
SawyerW    186555.796610
NWAmes     189050.068493
Gilbert    192854.506329
Blmngtn    194870.882353
CollgCr    197965.773333
Crawfor    210624.725490
ClearCr    212565.428571
Somerst    225379.837209
Veenker    238772.727273
Timber     242247.447368
StoneBr    310499.000000
NridgHt    316270.623377
NoRidge    335295.317073
Name: SalePrice, dtype: float64
```

In [354]:

```
# Plot Mean SalesPrice by Neighborhood Ordered
g = sns.pointplot(x = df_train.Neighborhood.values, y = df_train.SalePrice.values,
              order = df1.index)
g.set_title('Mean sale price by Neighborhood')
plt.xticks(rotation=45)
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

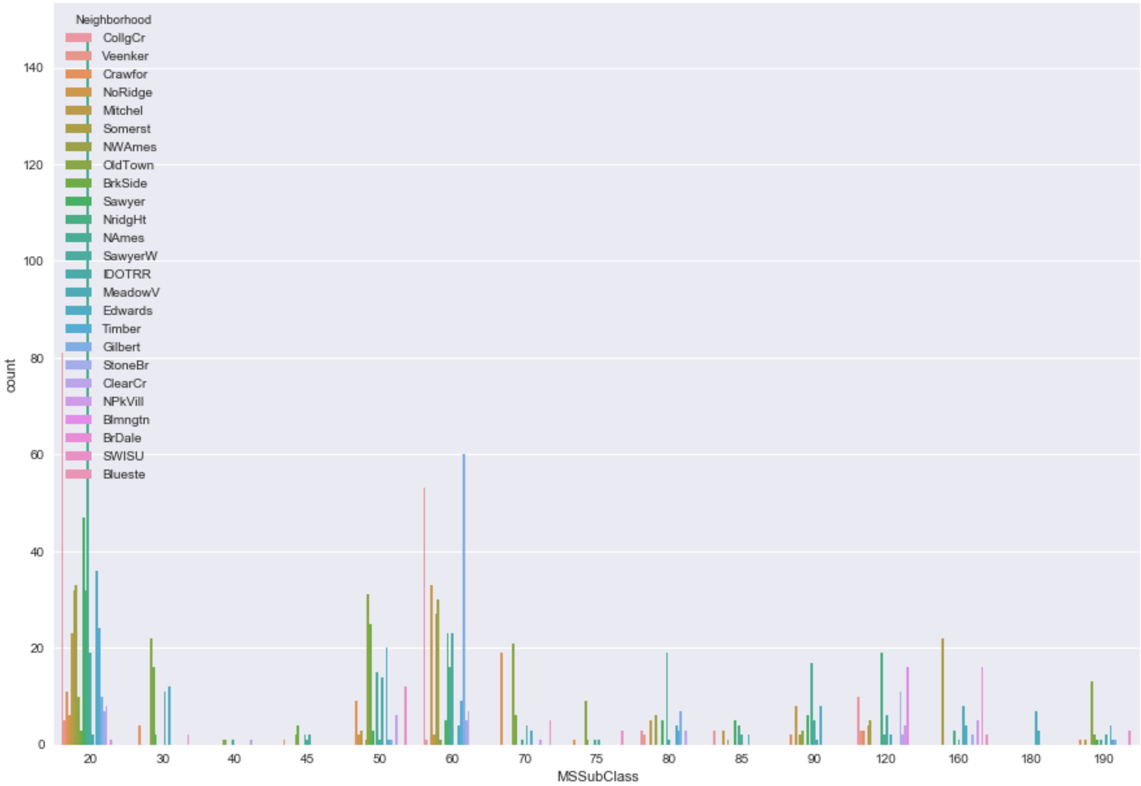


We have an idea of the average price per neighborhood. NoRidge has the highest price and MeadowV has de lowest. The points represent the average sale price for each neighbourhood, while the vertical bars indicate the uncertainty in this value.

In [44]:

```
# Plot Multi-Characteristics with Counting

plt.rcParams['figure.figsize'] = (15.0, 10.5)
ax = sns.countplot(x="MSSubClass", hue="Neighborhood", data=df)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1468: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data[hue_mask])
```



In [ ]:

There is a great offer of houses of type:
- 20 = 1-STORY 1946 & NEWER ALL STYLES),
- followed by 60 = 2-STORY 1946 & NEWER
- and after 50 = 1-1 / 2 STORY FINISHED ALL AGES.
The other types are less representative.

They are usually located in:
--Bluestem
--Sawyer
--Timberland
--Old Town

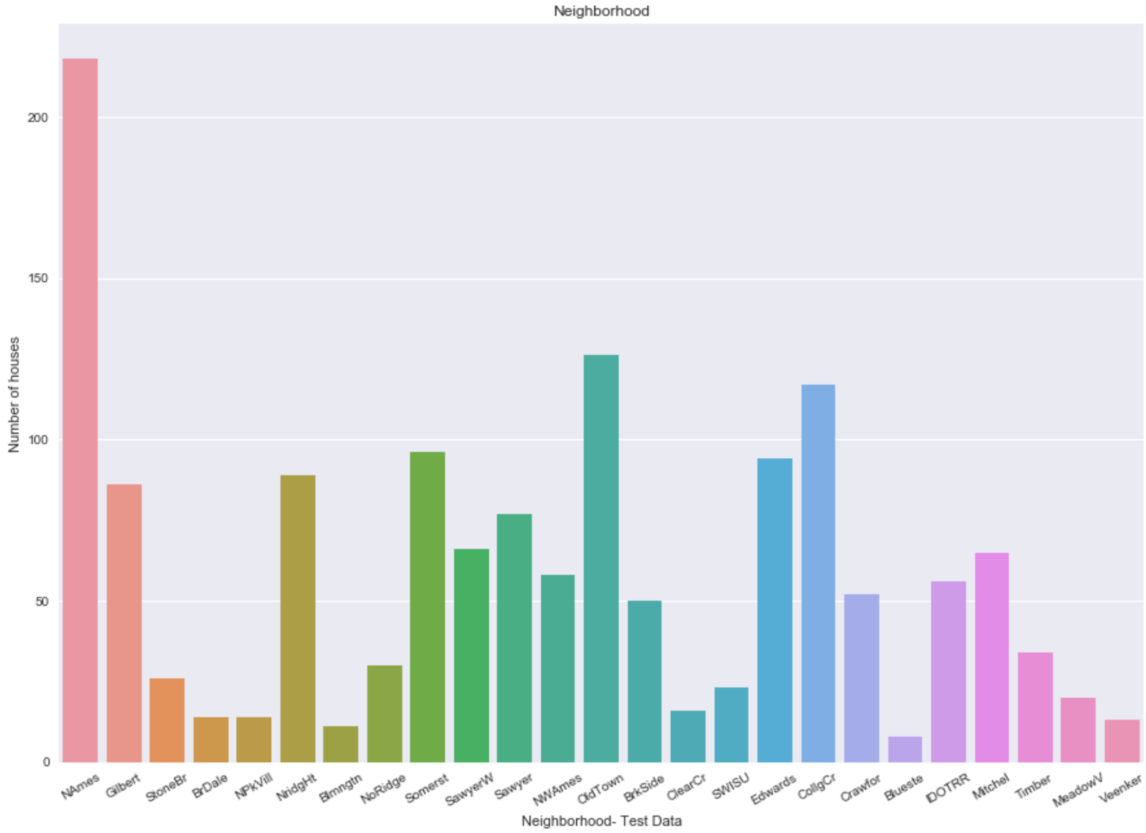
In [45]:

```
#  Plot number of houses by Neighborhood

ax=sns.countplot(df_test.Neighborhood)
ax.set_title('Neighborhood')
ax.set_ylabel('Number of houses')
ax.set_xlabel('Neighborhood- Test Data')
# Labels Rotation
ax.set_xticklabels(ax.get_xticklabels(), rotation=30)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```

Out[45]:

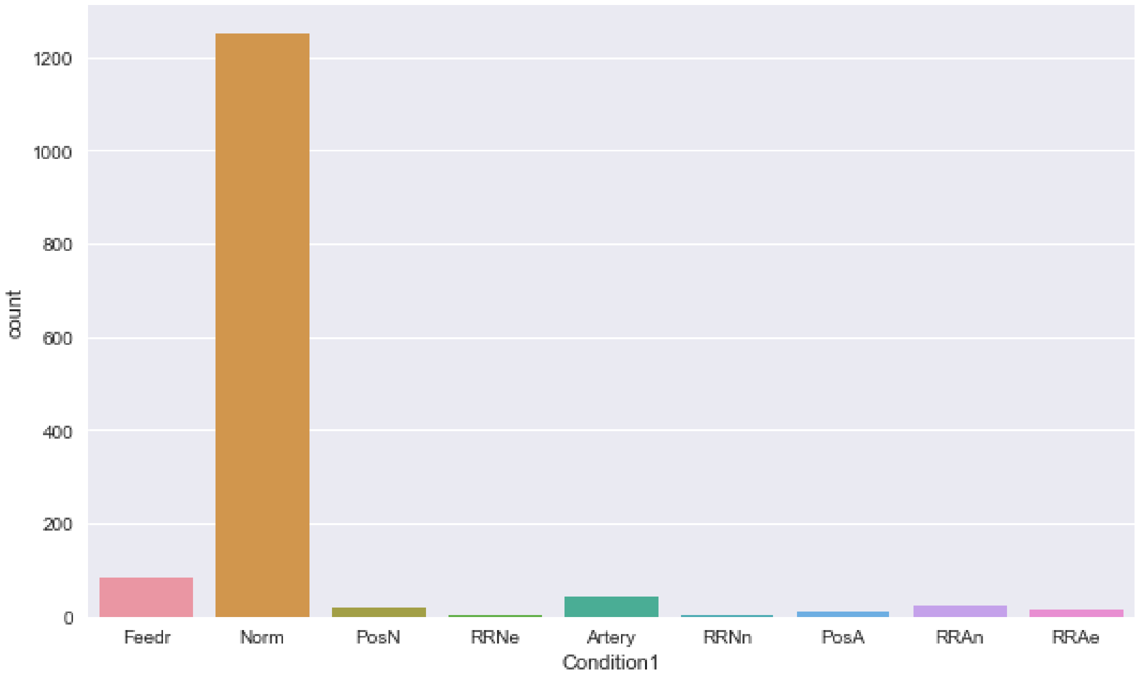
```
[<matplotlib.text.Text at 0x2ace8ceff28>,
 <matplotlib.text.Text at 0x2ace8baf908>,
 <matplotlib.text.Text at 0x2ace8b49cf8>,
 <matplotlib.text.Text at 0x2ace8a4ae80>,
 <matplotlib.text.Text at 0x2ace96e20f0>,
 <matplotlib.text.Text at 0x2ace96e2ba8>,
 <matplotlib.text.Text at 0x2ace96e76a0>,
 <matplotlib.text.Text at 0x2ace96ee198>,
 <matplotlib.text.Text at 0x2ace96eec50>,
 <matplotlib.text.Text at 0x2ace96f1748>,
 <matplotlib.text.Text at 0x2ace96fa240>,
 <matplotlib.text.Text at 0x2ace96facf8>,
 <matplotlib.text.Text at 0x2ace97037f0>,
 <matplotlib.text.Text at 0x2ace970c2e8>,
 <matplotlib.text.Text at 0x2ace970cda0>,
 <matplotlib.text.Text at 0x2ace9715898>,
 <matplotlib.text.Text at 0x2ace9739390>,
 <matplotlib.text.Text at 0x2ace9739e48>,
 <matplotlib.text.Text at 0x2ace972f940>,
 <matplotlib.text.Text at 0x2ace9737438>,
 <matplotlib.text.Text at 0x2ace9737ef0>,
 <matplotlib.text.Text at 0x2ace97349e8>,
 <matplotlib.text.Text at 0x2ace973d4e0>,
 <matplotlib.text.Text at 0x2ace973df98>,
 <matplotlib.text.Text at 0x2ace9745a90>]
```


Neighborhood
Number of houses
0
50
100
150
200
NAmes
Gilbert
StoneBr
BrDale
NPkVill
NridgHt
Blmngtn
NoRidge
Somerst
SawyerW
Sawyer
NWAmes
OldTown
BrkSide
ClearCr
SWISU
Edwards
CollgCr
Crawfor
Blueste
IDOTRR
Mitchel
Timber
MeadowV
Veenker
Neighborhood- Test Data

In [46]:

```
# Plot features with count.

ax.set_title('Proximity to various conditions')
ax.set_ylabel('Number of houses')
ax.set_xlabel('Proximity to- Test Data')
plt.rcParams['figure.figsize'] = (10.0, 6.0)
ax = sns.countplot(df_test.Condition1)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1428: Fu
tureWarning: remove_na is deprecated and is a private function. Do not us
e.
  stat_data = remove_na(group_data)
```



Proximity information is not very relevant, since practically all of them are Norm = normal.
There is some classification of houses (100 houses) with: Adjacent to feeder street
There is some classification of houses (50 houses) with: Adjacent to arterial street

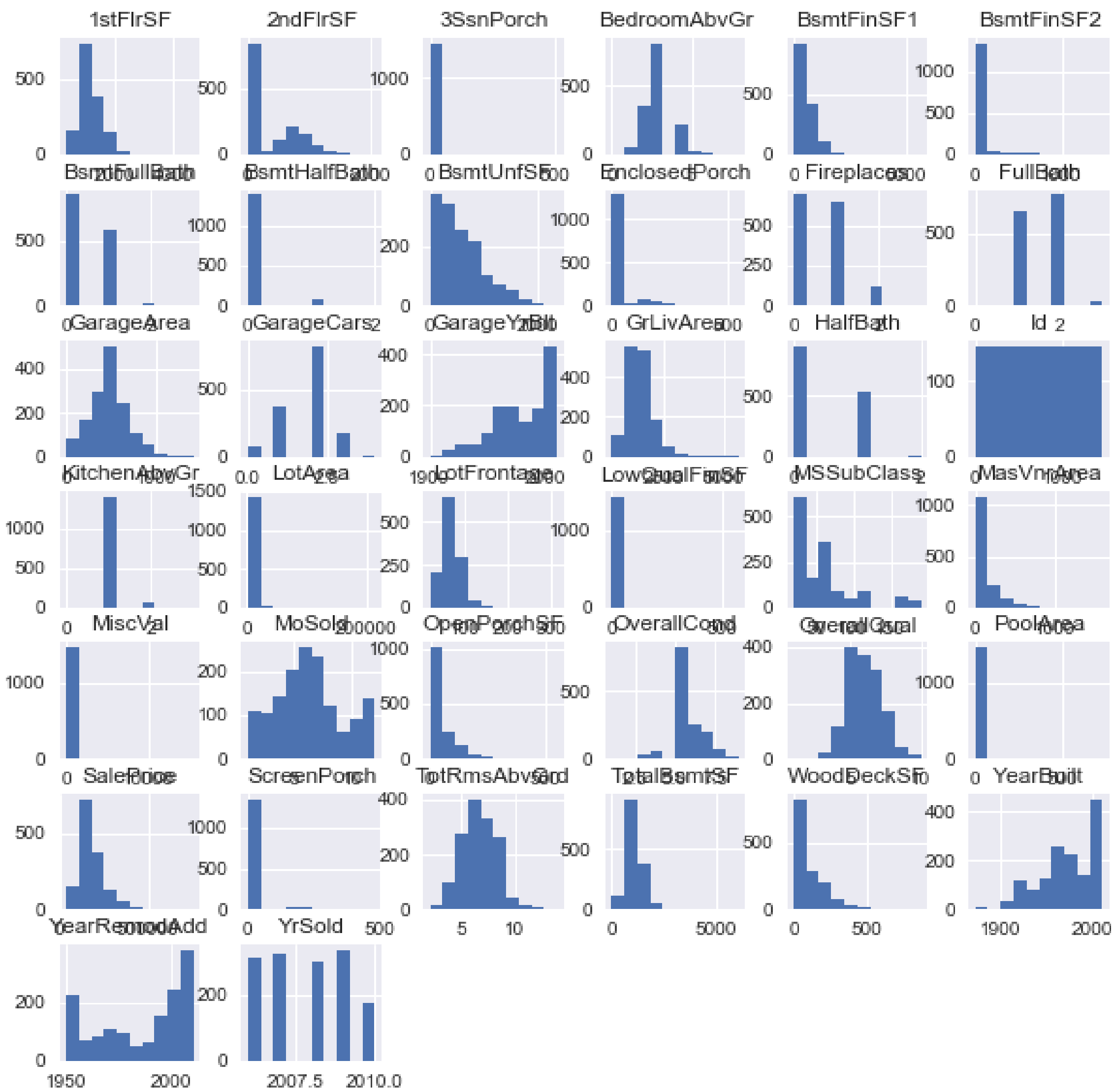
In [47]:

```
df.hist(figsize = (10,10))
```

Out[47]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE90DDA5
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE912555
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE973466
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE91E6A5
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE924C24
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE924C27
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE93684A
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE99EFDD
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9A7CA5
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9A90F6
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9B4E51
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9BAD24
0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9C15F9
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9C7C89
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9CF4B7
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE78CEEF
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8FE37B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE738F90
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE89BC8D
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8A5B24
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8A6C71
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8B3B2E
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8B9F90
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8C1E12
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8C83A9
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8D107F
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8D811D
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8DC42B
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE905C47
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8E656D
```

```
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8F404A
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE8FA47B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE93F6C5
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE88E763
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE94C9A2
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE94FB51
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE955B35
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE95A0AC
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE95D4F2
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9653B7
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE96635F
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002ACE9D824E
0>]], dtype=object)
```



In [48]:

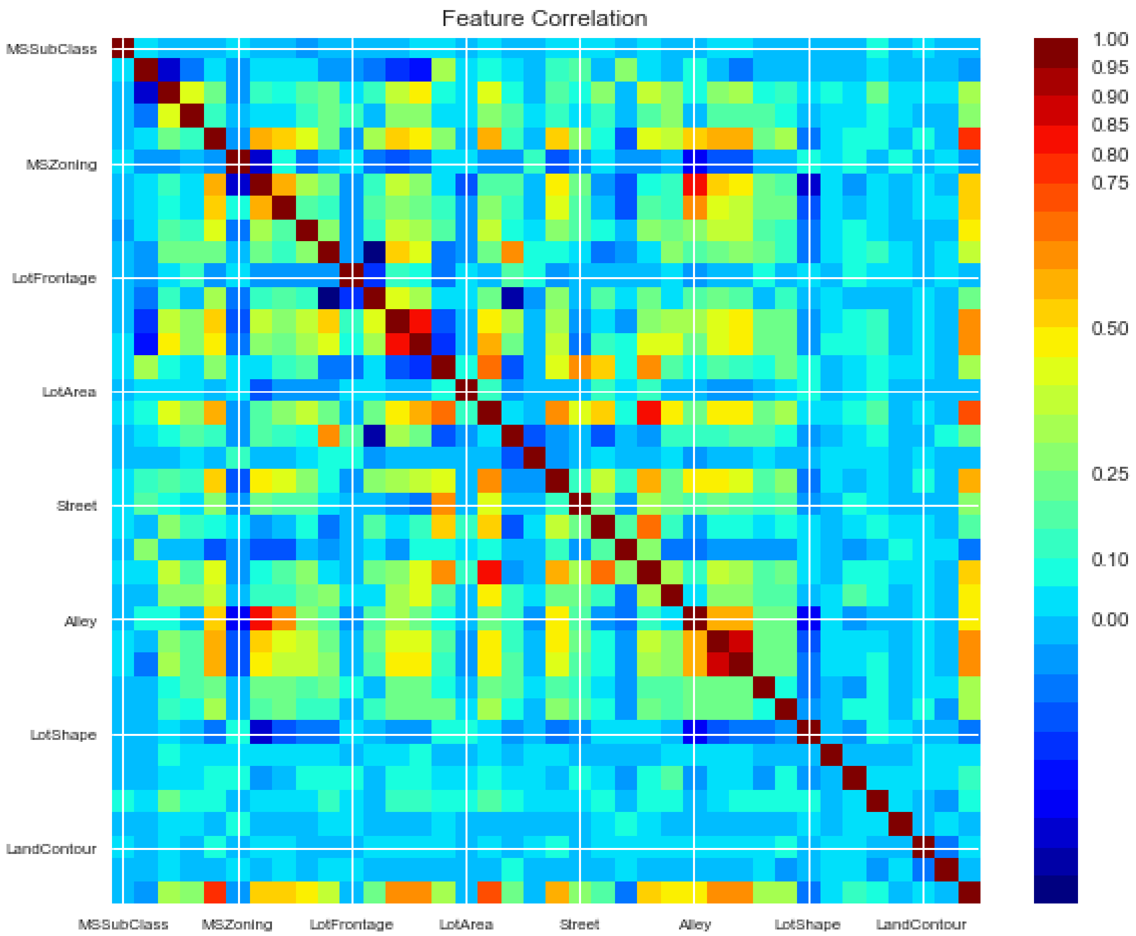
```
alpha = df.columns
alpha
```

Out[48]:

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgTyp
e',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemod
Add',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrTyp
e',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heatin
g',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullB
ath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageT
ype',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQ
ual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [49]:

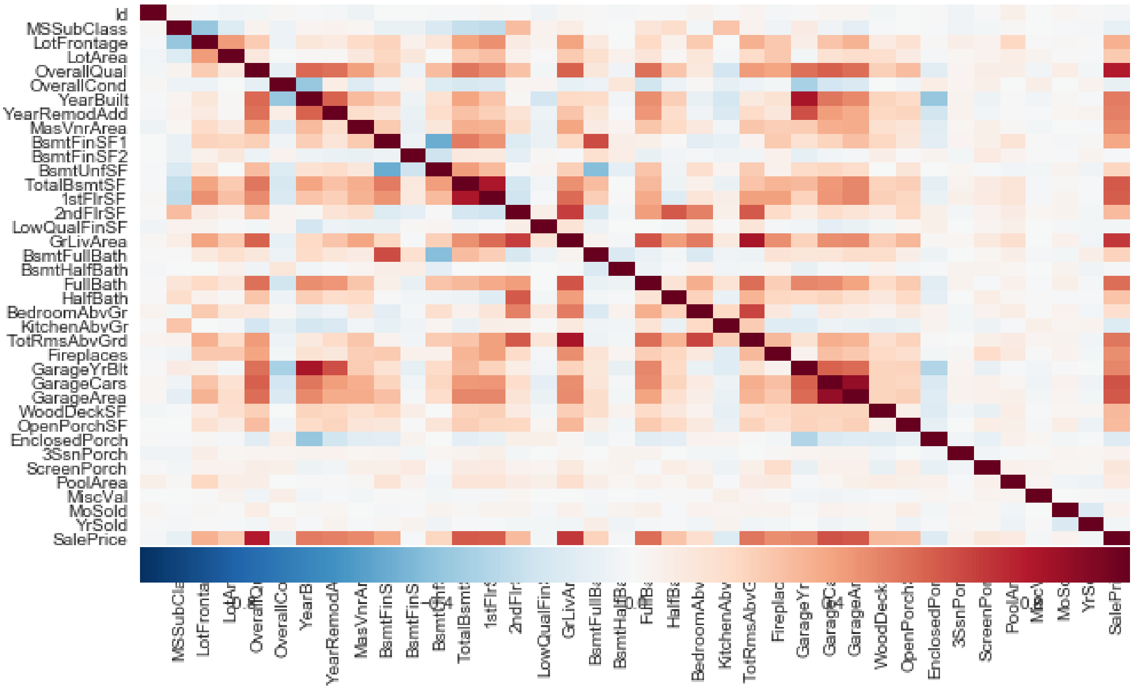
```
# Correlation of characteristics
# how much closer to 1 more related are the characteristics
alpha = df.columns

def correlation_matrix(df):
    from matplotlib import pyplot as plt
    from matplotlib import cm as cm

    fig = plt.figure(figsize=(10,8))
    ax1 = fig.add_subplot(111)
    cmap = cm.get_cmap('jet', 30)
    cax = ax1.imshow(df.corr(), interpolation="nearest", cmap=cmap)
    ax1.grid(True)
    plt.title('Feature Correlation')
    labels=alpha
    ax1.set_xticklabels(labels,fontsize=8)
    ax1.set_yticklabels(labels,fontsize=8)
    # Add colorbar, make sure to specify tick locations to match desired ticklabels
    fig.colorbar(cax, ticks=[0,5,0.10,0.25,0.50,.75,.8,.85,.90,.95,1])
    plt.show()

correlation_matrix(df)
```



Based on this graph, the dark points show the correlation of variables.
MSZoning (zone) is related to Alley (type access to the property) Home

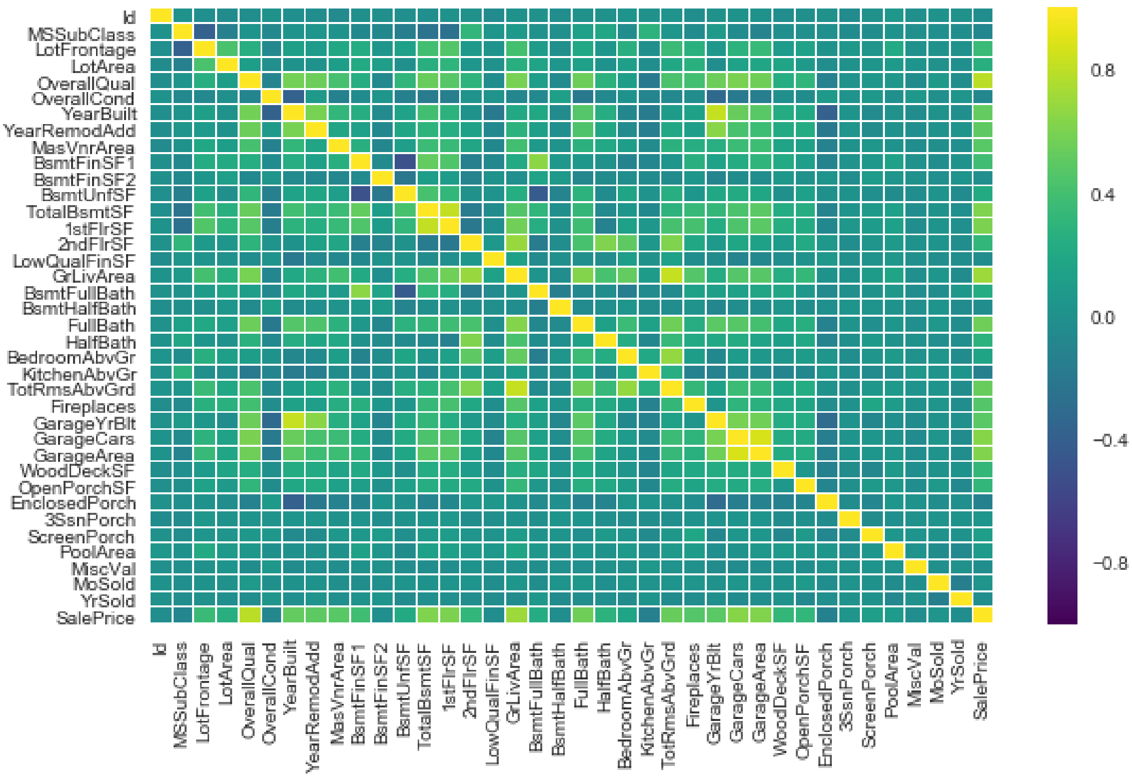
In [50]:

```
grid_kws = {"height_ratios": (1.5, 0.1), "hspace": 0.01}
f, (ax, cbar_ax) = plt.subplots(2, gridspec_kw=grid_kws)
ax = sns.heatmap(df.corr(), ax=ax,
                 cbar_ax=cbar_ax,
                 cbar_kws={"orientation": "horizontal"})
```



In [51]:

```
result = df.corr()
sns.heatmap(result, annot=False, fmt="g", cmap='viridis', cbar=True, linewidths=.05)
plt.show()
```



Based on this graph, the clearest points show the correlation of variables.
MSZoning (zone) is related to Alley (type access to the property)
The overall quality (OverallQual) is related to the Price (Salesprice)
Other important correlations for the price are:
- Area 1 floor and area 2 floor
- the year in which improvements were made
- The year of construction
- m2 living area
- number of rooms
- number of bathrooms
- number of fireplaces
- garage area and number of parking spaces

In general, the year of construction, the general quality of the property, the area and the number of rooms, lead the standard for price determination.

In [52]:

```
# Correlation analysis between data
# df.corr () determines the correlation between the variables
# clearer is higher correlation
# how much closer to 1 more related are the characteristics

# Alternative form to obtain plot of correlation
# sns.heatmap(df.corr(), annot = False)
```

In [53]:

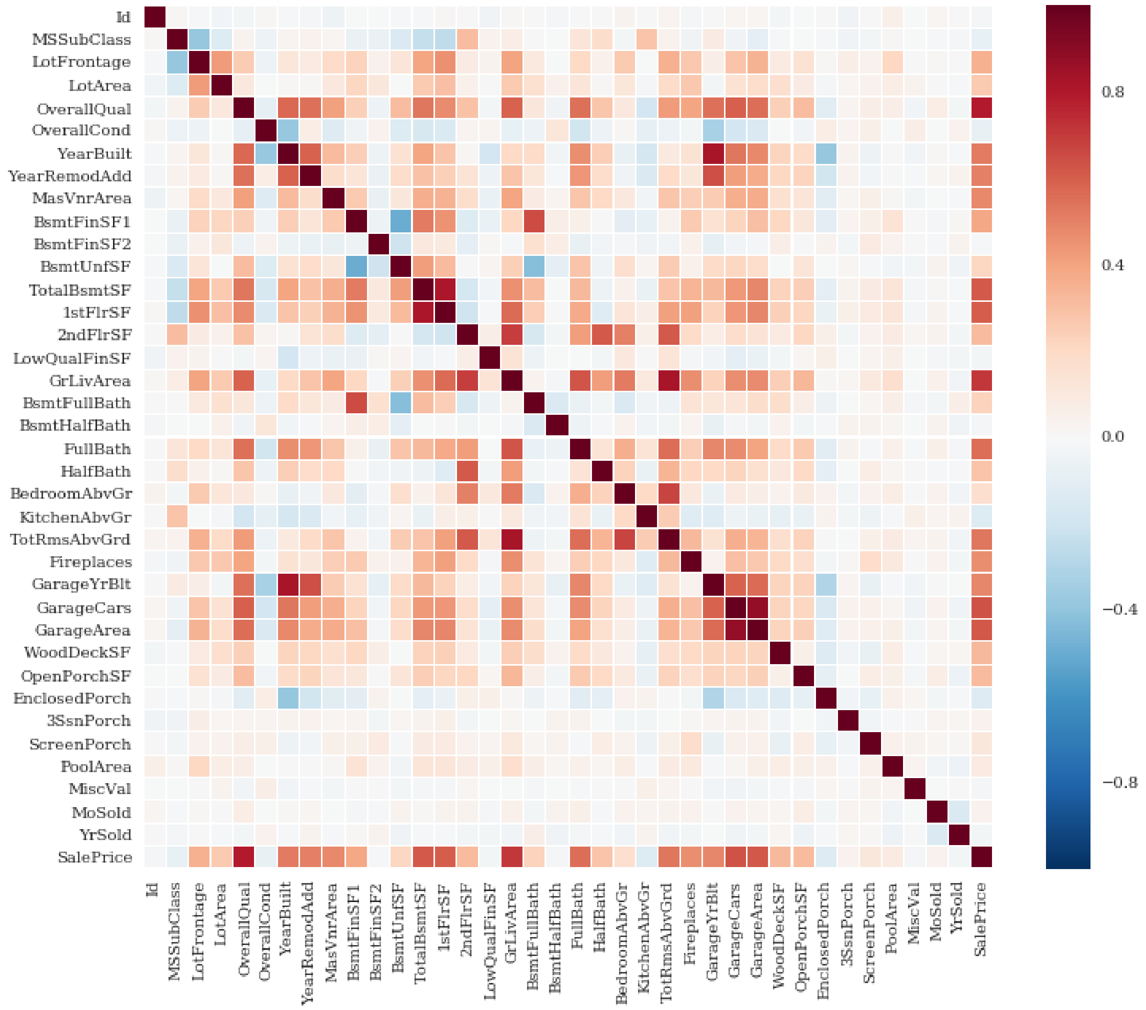
```
# Correlation analysis between data
# df.corr () determines the correlation between the variables
# clearer is higher correlation
# how much closer to 1 more related are the characteristics

# Alternative form to obtain plot of correlation
# corr = df.corr()
# sns.heatmap(corr,
#            xticklabels=corr.columns.values,
#            yticklabels=corr.columns.values)
```

In [54]:

```
# Correlation analysis between data
# df.corr () determines the correlation between the variables
# clearer is higher correlation
# how much closer to 1 more related are the characteristics

# Alternative form to obtain plot of correlation
# Bigger plot because we have many columns
corr = df.corr()
plt.rcParams['figure.figsize'] = (12.0, 10.0)
plt.rcParams['font.family'] = "serif"
sns.heatmap(corr,linewidths=.05)
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2acea97b4e0>
```



Based on this graph, the darker points show the correlation of variables.
MSZoning (zone) is related to Alley (type access to the property)
The overall quality (OverallQual) is related to the Price (Salesprice)
Other important correlations for the price are:
- Area 1 floor and area 2 floor
- the year in which improvements were made
- The year of construction
- m2 living area
- number of rooms
- number of bathrooms
- number of fireplaces
- garage area and number of parking spaces

In general, the year of construction, the general quality of the property, the area and the number of rooms, lead the standard for price determination.

In [55]:

```
list = df.columns
list
```

Out[55]:

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgTyp
e',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemod
Add',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrTyp
e',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heatin
g',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullB
ath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageT
ype',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQ
ual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [56]:

```
# Of the 1460 training lines, we practically do not have values for the columns:
# - PoolQC, Fence, MiscFeature, and Alley
# Let's delete these columns

df1 = pd.DataFrame(df)
# df1 = pd.DataFrame(df)
# list = ['Alley','PoolQC','Fence','MiscFeature']
# df1 = df1.drop(list, axis=1)
df1.head()
```

Out[56]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandCo
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl

5 rows × 81 columns

In [57]:

```
list = df1.columns
list
```

Out[57]:

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgTyp
e',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemod
Add',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrTyp
e',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heatin
g',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullB
ath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageT
ype',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQ
ual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [58]:

```
# Analysis of Variables MSZoning ',' MSSubClass ',' SalePrice

df2 = df1[['MSZoning','MSSubClass','SalePrice']]
```

In [59]:

```
df2.head()
```

Out[59]:

	MSZoning	MSSubClass	SalePrice
0	RL	60	208500
1	RL	20	181500
2	RL	60	223500
3	RL	70	140000
4	RL	60	250000

In [60]:

```
# put to plot the class under analysis "SalePrice"
# sns.pairplot(df2, hue = "SalePrice")
```

In [61]:

```
# Table with average prices in each zone, and count by type of property
X_pvt1 = pd.pivot_table(df, index=['MSSubClass'],
                              columns=['MSZoning'],
                               values=['SalePrice'],
                       aggfunc=[np.mean,np.count_nonzero], margins=True)
X_pvt1.head(25)
```

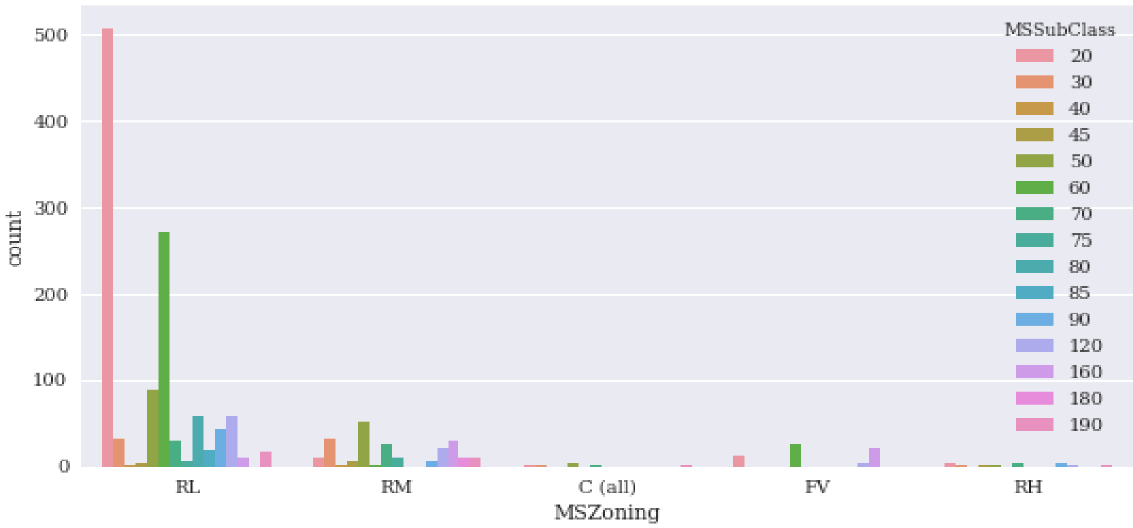
Out[61]:

	mean				
	SalePrice				
MSZoning	**C (all)**	**FV**	**RH**	**RL**	**RM**
MSSubClass					
20	45652.0	226289.538462	102966.666667	186467.039370	121327.500000
30	57950.0	NaN	79000.000000	96481.212121	97983.969697
40	NaN	NaN	NaN	196500.000000	115750.000000
45	NaN	NaN	76000.000000	110050.000000	112414.285714
50	91044.0	NaN	159434.000000	156277.477273	124698.039216
60	NaN	248558.600000	NaN	239544.457875	135000.000000
70	40000.0	NaN	124533.333333	199808.733333	138403.192308
75	NaN	NaN	NaN	184750.000000	197050.000000
80	NaN	NaN	NaN	169736.551724	NaN
85	NaN	NaN	NaN	147810.000000	NaN
90	NaN	NaN	144666.666667	132379.906977	136300.000000
120	NaN	226140.000000	157000.000000	210029.491525	172920.952381
160	NaN	164749.318182	NaN	164909.090909	109876.666667
180	NaN	NaN	NaN	NaN	102300.000000
190	133900.0	NaN	180000.000000	134662.500000	112718.181818
All	74528.0	214014.061538	131558.375000	191004.994787	126316.830275

In [62]:

```
# Plot Multi-Characteristics with Counting Subclass
plt.rcParams['figure.figsize'] = (10.0, 4.5)
ax = sns.countplot(x="MSZoning", hue="MSSubClass", data=df2)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py:1468: FutureWarning: remove_na is deprecated and is a private function. Do not use.
  stat_data = remove_na(group_data[hue_mask])
```



The houses are located mostly in the RL (Residential Low Density) Zone.

In this context the classes of preferential houses are:
20 - STORY 1946 & NEWER ALL STYLES
50 - 1-1 / 2 STORY FINISHED ALL AGES
60 - 2-STORY 1946 & NEWER

In [63]:

```
# Table with average prices in each zone, by type of property and count number of house
s
X_pvt1 = pd.pivot_table(df, index=['MSZoning'],
                              columns=['MSSubClass'],
                                values=['SalePrice'],
                      aggfunc=[np.mean,np.count_nonzero], margins=True)
X_pvt1
```

Out[63]:

	mean				
	SalePrice				
MSSubClass	20	30	40	45	50
MSZoning					
C (all)	45652.000000	57950.000000	NaN	NaN	91044.000000
FV	226289.538462	NaN	NaN	NaN	NaN
RH	102966.666667	79000.000000	NaN	76000.000000	159434.000000
RL	186467.039370	96481.212121	196500.0	110050.000000	156277.477273
RM	121327.500000	97983.969697	115750.0	112414.285714	124698.039216
All	185224.811567	95829.724638	156125.0	108591.666667	143302.972222

6 rows × 32 columns

In [64]:

```
# Average price table in each zone
X_pvt2 = pd.pivot_table(df, index=['MSZoning'],
                                values=['SalePrice'],
                      aggfunc=[np.mean,np.count_nonzero],margins=True)
X_pvt2
```

Out[64]:

	mean	count_nonzero
	SalePrice	SalePrice
MSZoning		
C (all)	74528.000000	10
FV	214014.061538	65
RH	131558.375000	16
RL	191004.994787	1151
RM	126316.830275	218
All	180921.195890	1460

In [65]:

```
# Rename Columns
X_pvt2.columns = ['MeanSalePrice','CountHouses']
X_pvt2
```

Out[65]:

	MeanSalePrice	CountHouses
MSZoning		
C (all)	74528.000000	10
FV	214014.061538	65
RH	131558.375000	16
RL	191004.994787	1151
RM	126316.830275	218
All	180921.195890	1460

In [66]:

```
# Multiply Number houses by 10 to plot
X_pvt3 = X_pvt2
X_pvt3.CountHouses = X_pvt3.CountHouses * 10
```

In [67]:

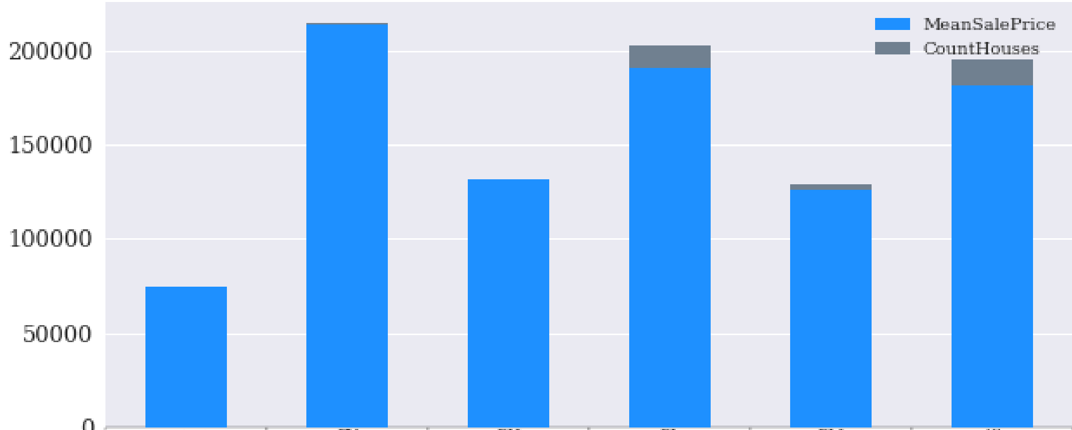
```
X_pvt3
```

Out[67]:

	MeanSalePrice	CountHouses
MSZoning		
C (all)	74528.000000	100
FV	214014.061538	650
RH	131558.375000	160
RL	191004.994787	11510
RM	126316.830275	2180
All	180921.195890	14600

In [68]:

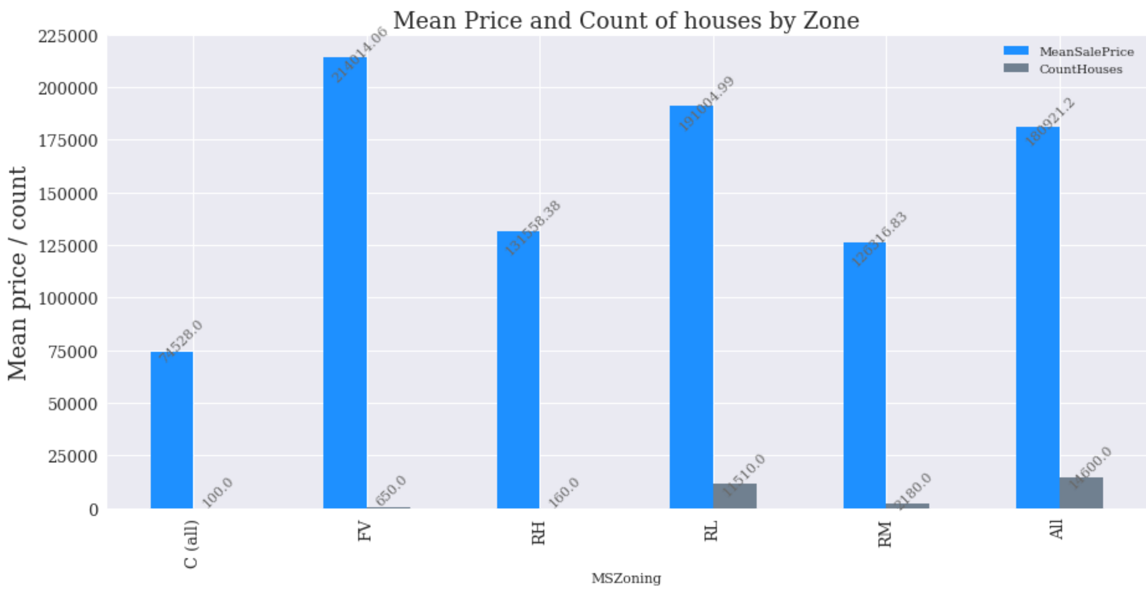
```
# PLOT 2 columns in one bar (stacked=true)
myplot = X_pvt3.plot(kind='bar',  stacked='True',table=True,
                     color=['dodgerblue', 'slategray'], fontsize=13)
myplot.axes.get_xaxis().set_visible(False)
plt.show()
```



	C (all)	FV	RH	RL	RM	All
MeanSalePrice	74528.0	214014.061538	131558.375	191004.994787	126316.830275	180921.19589
CountHouses	100.0	650.0	160.0	11510.0	2180.0	14600.0

In [69]:

```
ax = X_pvt3[['MeanSalePrice', 'CountHouses']].plot(kind='bar',
              figsize=(15,7), color=['dodgerblue', 'slategray'], fontsize=13);
ax.set_alpha(0.8)
ax.set_title("Mean Price and Count of houses by Zone",
fontsize=18)
ax.set_ylabel("Mean price / count", fontsize=18);

# set individual bar lables using above list
for i in ax.patches:
    # get_x pulls left or right; get_height pushes up or down
    ax.text(i.get_x()+.04, i.get_height()+12000, \
            str(round((i.get_height()), 2)), fontsize=11, color='dimgrey',
                rotation=45)
```



In [70]:

```
# Bar chart plot
X_pvt2.plot(kind='bar', figsize=(8,6), grid=True, fontsize=12)
plt.title('Average Price of Real Estate by Zone and number houses',fontsize=12)
plt.xlabel('Zon',fontsize=12)
plt.ylabel('Mean Price',fontsize=12)
plt.show()
```

The RL zone is the one with the most houses available, and it is the second most expensive zone.
The FV zone with very little supply of houses has the most expensive prices.

In [71]:

```
# Table with average prices in each zone, and count number of houses in each Zone
X_pvt3 = pd.pivot_table(df_train, index=['MSZoning'],
                               values=['SalePrice'],
                        aggfunc=[np.mean,len], margins=True)
X_pvt3
```

Out[71]:

	mean	len
	SalePrice	**SalePrice**
MSZoning		
C (all)	74528.000000	10
FV	214014.061538	65
RH	131558.375000	16
RL	191004.994787	1151
RM	126316.830275	218
All	180921.195890	1460

In [72]:

```
X_pvt3.columns[0]
```

Out[72]:

```
('mean', 'SalePrice')
```

In [73]:

```
# Rename columns
X_pvt3.columns = ['MeanPrice', 'Count']
X_pvt3
```

Out[73]:

	MeanPrice	Count
MSZoning		
C (all)	74528.000000	10
FV	214014.061538	65
RH	131558.375000	16
RL	191004.994787	1151
RM	126316.830275	218
All	180921.195890	1460

In [74]:

```
# Divide price by 100 for better presentation
X_pvt4 = X_pvt3
X_pvt4.MeanPrice = X_pvt4.MeanPrice / 100
X_pvt4
```

Out[74]:

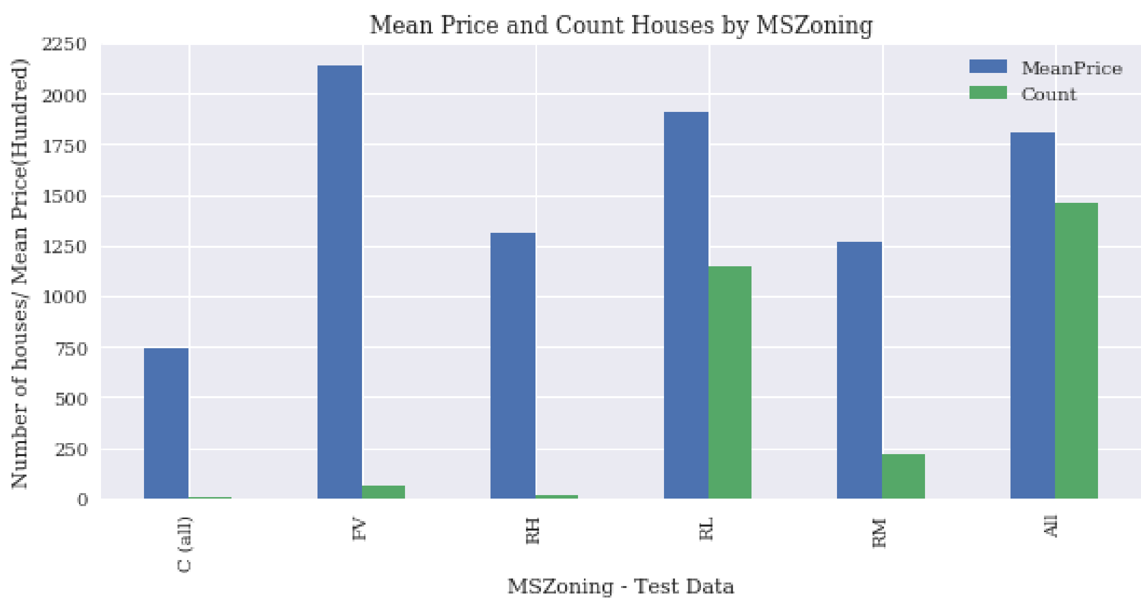
	MeanPrice	Count
MSZoning		
C (all)	745.280000	10
FV	2140.140615	65
RH	1315.583750	16
RL	1910.049948	1151
RM	1263.168303	218
All	1809.211959	1460

In [75]:

```
# Plot number houses and mean price by MSZoning
df = X_pvt4
ax=df.plot.bar()
ax.set_title('Mean Price and Count Houses by MSZoning')
ax.set_ylabel('Number of houses/ Mean Price(Hundred)')
ax.set_xlabel('MSZoning - Test Data')
# Rotação das Labels
g.set_xticklabels(g.get_xticklabels(), rotation=30)
```

Out[75]:

```
[<matplotlib.text.Text at 0x2ace75ee550>,
 <matplotlib.text.Text at 0x2ace763e240>,
 <matplotlib.text.Text at 0x2ace76dc390>,
 <matplotlib.text.Text at 0x2ace7616ef0>,
 <matplotlib.text.Text at 0x2ace75ee2b0>,
 <matplotlib.text.Text at 0x2ace76dcf60>,
 <matplotlib.text.Text at 0x2ace76e8978>,
 <matplotlib.text.Text at 0x2ace76ec470>,
 <matplotlib.text.Text at 0x2ace76ecf28>,
 <matplotlib.text.Text at 0x2ace76f2a20>,
 <matplotlib.text.Text at 0x2ace76f7518>,
 <matplotlib.text.Text at 0x2ace76f7fd0>,
 <matplotlib.text.Text at 0x2ace76fdac8>,
 <matplotlib.text.Text at 0x2ace78865c0>,
 <matplotlib.text.Text at 0x2ace78890b8>,
 <matplotlib.text.Text at 0x2ace7889b70>,
 <matplotlib.text.Text at 0x2ace788f668>,
 <matplotlib.text.Text at 0x2ace7898160>,
 <matplotlib.text.Text at 0x2ace7898c18>,
 <matplotlib.text.Text at 0x2ace78a0710>,
 <matplotlib.text.Text at 0x2ace78a4208>,
 <matplotlib.text.Text at 0x2ace78a4cc0>,
 <matplotlib.text.Text at 0x2ace78ab7b8>,
 <matplotlib.text.Text at 0x2ace78b02b0>,
 <matplotlib.text.Text at 0x2ace78b0d68>]
```



Comparative analysis between the number of houses and their average price per Zone.

3. Transform Data

In [360]:

```
# Erase columns whithout Correlation analysis between data

#del data_X["BsmtFinType1"]
#del data_X["BsmtFinType2"]
#del data_X["BsmtQual"]
#del data_X["CentralAir"]
#del data_X["Condition1"]
#del data_X["Condition2"]
#del data_X["Electrical"]
#del data_X["Exterior1st"]
#del data_X["Exterior2nd"]
#del data_X["GarageQual"]
```

In [361]:

```
# We can retrieve the names of features that are in fact non-numerical ‘objects’ as fol
lows,
# to analyse all object columns and transform them.

data_X.select_dtypes(include = [object]).columns
```

Out[361]:

```
Index(['Alley', 'BsmtCond', 'BsmtExposure', 'ExterCond', 'ExterQual', 'Fen
ce',
       'FireplaceQu', 'Foundation', 'Functional', 'GarageCond', 'GarageFin
ish',
       'GarageType', 'Heating', 'HeatingQC', 'HouseStyle', 'KitchenQual',
       'LandContour', 'LandSlope', 'LotConfig', 'MSZoning', 'MasVnrType',
       'MiscFeature', 'PavedDrive', 'PoolQC', 'RoofMatl', 'RoofStyle',
       'SaleCondition', 'SaleType'],
      dtype='object')
```

In [362]:

```
# Show object columns
columns = data_X.select_dtypes(include = [object]).columns

dfz = pd.DataFrame(data_X, columns=columns)
dfz.head()
```

Out[362]:

	Alley	BsmtCond	BsmtExposure	ExterCond	ExterQual	Fence	FireplaceQu	Foun
0	None	TA	No	TA	Gd	None	None	PCor
1	None	TA	Gd	TA	TA	None	TA	CBlo
2	None	TA	Mn	TA	Gd	None	TA	PCor
3	None	Gd	No	TA	TA	None	Gd	BrkTi
4	None	TA	Av	TA	Gd	None	TA	PCor

5 rows × 28 columns

In [363]:

```
# Verify all distinct values for a column - RoofStyle
data_X["RoofStyle"].value_counts()
```

Out[363]:

```
Gable      2310
Hip         551
Gambrel      22
Flat         20
Mansard      11
Shed          5
Name: RoofStyle, dtype: int64
```

In [364]:

```
# Convert to numbers - RoofStyle
# Create a List whith Values
target_names = data_X["RoofStyle"].unique()
# Create a dictionary whith Values and index
target_dict = {n:i for i, n in enumerate(target_names)}
# Replace values
data_X.RoofStyle = data_X.RoofStyle.replace(target_dict)
```

In [365]:

```
# Verify all distinct values for a column - RoofMatl
data_X["RoofMatl"].value_counts()
```

Out[365]:

```
CompShg    2876
Tar&Grv      23
WdShake       9
WdShngl       7
ClyTile       1
Membran       1
Roll          1
Metal         1
Name: RoofMatl, dtype: int64
```

In [366]:

```
# Convert to numbers - RoofMatl
# Create a List whith Values
target_names = data_X["RoofMatl"].unique()
# Create a dictionary whith Values and index
target_dict = {n:i for i, n in enumerate(target_names)}
# Replace values
data_X.RoofMatl = data_X.RoofMatl.replace(target_names)
```

In [440]:

```
# Convert to numbers - RoofMatl
data_X.RoofMatl = \
    data_X.RoofMatl.replace({'CompShg':1})
```

In [367]:

```
# Verify all distinct values for a column - PoolQC
data_X["PoolQC"].value_counts()
```

Out[367]:

```
None    2909
Gd         4
Ex         4
Fa         2
Name: PoolQC, dtype: int64
```

In [368]:

```
# Most of them are the same values 'None' , let's erase the column
del data_X["PoolQC"]
```

In [372]:

```
# Verify all distinct values for a column - PavedDrive
data_X["PavedDrive"].value_counts()
```

Out[372]:

```
0    2641
1     216
2      62
Name: PavedDrive, dtype: int64
```

In [374]:

```
# Convert to numbers - PavedDrive
#data_X.PavedDrive = data_X.PavedDrive.replace({'Y':0, 'N':1, 'P':2})
```

In [375]:

```
# Verify all distinct values for a column - MiscFeature
data_X["MiscFeature"].value_counts()
```

Out[375]:

```
None    2814
Shed      95
Gar2       5
Othr       4
TenC       1
Name: MiscFeature, dtype: int64
```

In [376]:

```
# Most of them are the same values 'None' , let's erase the column
del data_X["MiscFeature"]
```

In [377]:

```
# Verify all distinct values for a column - MasVnrType
data_X["MasVnrType"].value_counts()
```

Out[377]:

```
None       1766
BrkFace     879
Stone       249
BrkCmn       25
Name: MasVnrType, dtype: int64
```

In [378]:

```
# Convert to numbers - MasVnrType
data_X.MasVnrType = \
    data_X.MasVnrType.replace({'None':0, 'BrkFace':1, 'Stone':2, 'BrkCmn':3})
```

In [379]:

```
# Verify all distinct values for a column - MSZoning
data_X["MSZoning"].value_counts()
```

Out[379]:

```
RL         2269
RM          460
FV          139
RH           26
C (all)      25
Name: MSZoning, dtype: int64
```

In [380]:

```
# Convert to numbers - MSZoning
data_X.MSZoning = \
    data_X.MSZoning.replace({'RL':0, 'RM':1, 'FV':2, 'RH':3, 'C (all)':4})
```

In [381]:

```
# Verify all distinct values for a column - LotConfig
data_X["LotConfig"].value_counts()
```

Out[381]:

```
Inside     2133
Corner      511
CulDSac     176
FR2          85
FR3          14
Name: LotConfig, dtype: int64
```

In [382]:

```
# Convert to numbers - LotConfig
data_X.LotConfig = \
    data_X.LotConfig.replace({'Inside':0, 'Corner':1, 'CulDSac':2, 'FR2':3, 'FR3':4})
```

In [383]:

```
# Verify all distinct values for a column - LandSlope
data_X["LandSlope"].value_counts()
```

Out[383]:

```
Gtl    2778
Mod     125
Sev      16
Name: LandSlope, dtype: int64
```

In [384]:

```
# Most of them are the same values 'Gtl' , let's erase the column
del data_X["LandSlope"]
```

In [385]:

```
# Verify all distinct values for a column - LandContour
data_X["LandContour"].value_counts()
```

Out[385]:

```
Lvl    2622
HLS     120
Bnk     117
Low      60
Name: LandContour, dtype: int64
```

In [386]:

```
# Convert to numbers - LandContour
data_X.LandContour = \
    data_X.LandContour.replace({'Lvl':0, 'HLS':1, 'Bnk':2, 'Low':3})
```

In [387]:

```
# Verify all distinct values for a column - KitchenQual
data_X["KitchenQual"].value_counts()
```

Out[387]:

```
TA    1493
Gd    1151
Ex     205
Fa      70
Name: KitchenQual, dtype: int64
```

In [388]:

```
# Convert to numbers - KitchenQual
data_X.KitchenQual = \
    data_X.KitchenQual.replace({'TA':0, 'Gd':1, 'Ex':2, 'Fa':3})
```

In [389]:

```
# Verify all distinct values for a column - HouseStyle
data_X["HouseStyle"].value_counts()
```

Out[389]:

```
1Story    1471
2Story     872
1.5Fin     314
SLvl       128
SFoyer      83
2.5Unf      24
1.5Unf      19
2.5Fin       8
Name: HouseStyle, dtype: int64
```

In [390]:

```
# Convert to numbers - HouseStyle
data_X.HouseStyle = \
    data_X.HouseStyle.replace({'1Story':0, '2Story':1, '1.5Fin':2, 'SLvl':3, 'SFoyer':4
, '2.5Unf':5, '1.5Unf':6, '2.5Fin':7})
```

In [391]:

```
# Verify all distinct values for a column - GarageFinish
data_X["GarageFinish"].value_counts()
```

Out[391]:

```
Unf     1230
RFn      811
Fin      719
None     159
Name: GarageFinish, dtype: int64
```

In [392]:

```
# Convert to numbers - GarageType
data_X.GarageFinish = \
    data_X.GarageFinish.replace({'Unf':0, 'RFn':1, 'Fin':2, 'None':3})
```

In [393]:

```
# Verify all distinct values for a column - HeatingQC
data_X["HeatingQC"].value_counts()
```

Out[393]:

```
Ex    1493
TA     857
Gd     474
Fa      92
Po       3
Name: HeatingQC, dtype: int64
```

In [394]:

```
# Convert to numbers - GarageType
data_X.HeatingQC = \
    data_X.HeatingQC.replace({'Ex':0, 'TA':1, 'Gd':2, 'Fa':3, 'Po':4})
```

In [395]:

```
# Verify all distinct values for a column - Heating
data_X["Heating"].value_counts()
```

Out[395]:

```
GasA     2874
GasW       27
Grav        9
Wall        6
OthW        2
Floor       1
Name: Heating, dtype: int64
```

In [396]:

```
# Most of them are the same values 'GasA     ' , let's erase the column
del data_X["Heating"]
```

In [397]:

```
# Verify all distinct values for a column - GarageType
data_X["GarageType"].value_counts()
```

Out[397]:

```
Attchd     1723
Detchd      779
BuiltIn     186
None        157
Basment      36
2Types       23
CarPort      15
Name: GarageType, dtype: int64
```

In [398]:

```
# Convert to numbers - GarageType
data_X.GarageType = \
    data_X.GarageType.replace({'Attchd':0, 'Detchd':1, 'BuiltIn':2, 'None':3, 'Basment'
:4, '2Types':5, 'CarPort':6})
```

In [399]:

```
# Verify all distinct values for a column - GarageCond
data_X["GarageCond"].value_counts()
```

Out[399]:

```
TA      2654
None     159
Fa        74
Gd        15
Po        14
Ex         3
Name: GarageCond, dtype: int64
```

In [ ]:

```

```

In [400]:

```
# Most of them are the same values ' TA' , let's erase the column
del data_X["GarageCond"]
```

In [401]:

```
# Verify all distinct values for a column - Functional
data_X["Functional"].value_counts()
```

Out[401]:

```
Typ     2719
Min2      70
Min1      65
Mod       35
Maj1      19
Maj2       9
Sev        2
Name: Functional, dtype: int64
```

In [402]:

```
# Most of them are Typ, let's erase the column
del data_X["Functional"]
```

In [403]:

```
# Verify all distinct values for a column - Foundation
data_X["Foundation"].value_counts()
```

Out[403]:

```
PConc     1308
CBlock    1235
BrkTil     311
Slab        49
Stone       11
Wood         5
Name: Foundation, dtype: int64
```

In [404]:

```
# Convert to numbers - Foundation
data_X.Foundation = \
    data_X.Foundation.replace({'PConc':0, 'CBlock':1, 'BrkTil':2, 'Slab':3, 'Stone':4,
'Wood':5})
```

In [405]:

```
# Verify all distinct values for a column - FireplaceQu
data_X["FireplaceQu"].value_counts()
```

Out[405]:

```
None    1420
Gd       744
TA       592
Fa        74
Po        46
Ex        43
Name: FireplaceQu, dtype: int64
```

In [406]:

```
# Convert to numbers - FireplaceQu
data_X.FireplaceQu = \
    data_X.FireplaceQu.replace({'None':0, 'Gd':1, 'TA':2, 'Fa':3, 'Po':4, 'Ex':5})
```

In [407]:

```
# Verify all distinct values for a column - ExterQual
data_X["Fence"].value_counts()
```

Out[407]:

```
None     2348
MnPrv     329
GdPrv     118
GdWo      112
MnWw       12
Name: Fence, dtype: int64
```

In [408]:

```
# Most of them are None, let's erase the column
del data_X["Fence"]
```

In [409]:

```
# Verify all distinct values for a column - ExterQual
data_X["ExterQual"].value_counts()
```

Out[409]:

```
TA    1798
Gd     979
Ex     107
Fa      35
Name: ExterQual, dtype: int64
```

In [410]:

```
# Convert to numbers - ExterQua
data_X.ExterQual = \
    data_X.ExterQual.replace({'TA':0, 'Gd':1, 'Ex':2, 'Fa':3})
```

In [411]:

```
# Verify all distinct values for a column - ExterCond
data_X["ExterCond"].value_counts()
```

Out[411]:

```
TA    2538
Gd     299
Fa      67
Ex      12
Po       3
Name: ExterCond, dtype: int64
```

In [412]:

```
# Most of them are TA, let's erase the column
del data_X["ExterCond"]
```

In [414]:

```
# Verify all distinct values for a column - BsmtExposure
data_X["BsmtExposure"].value_counts()
```

Out[414]:

```
No      1904
Av       418
Gd       276
Mn       239
None      82
Name: BsmtExposure, dtype: int64
```

In [415]:

```
# Convert to numbers - BsmtExposure
data_X.BsmtExposure = \
    data_X.BsmtExposure.replace({'No':0, 'Av':1, 'Gd':2, 'Mn':3, 'None':4})
```

In [416]:

```
# Verify all distinct values for a column - BsmtExposure
data_X["BsmtExposure"].value_counts()
```

Out[416]:

```
0    1904
1     418
2     276
3     239
4      82
Name: BsmtExposure, dtype: int64
```

In [417]:

```
# Verify all distinct values for a column - BsmtCond
data_X["BsmtCond"].value_counts()
```

Out[417]:

```
TA      2606
Gd       122
Fa       104
None      82
Po         5
Name: BsmtCond, dtype: int64
```

In [418]:

```
# Most of them are TA, let's erase the column
del data_X["BsmtCond"]
```

In [419]:

```
# Verify all distinct values for a column - Alley
data_X["Alley"].value_counts()
```

Out[419]:

```
None    2721
Grvl     120
Pave      78
Name: Alley, dtype: int64
```

In [420]:

```
# Most of them are empty, let's erase the column
del data_X["Alley"]
```

In [421]:

```
# Verify all distinct values for a column - SaleType
data_X["SaleType"].value_counts()
```

Out[421]:

```
WD       2526
New       239
COD        87
ConLD      26
CWD        12
ConLI       9
ConLw       8
Oth         7
Con         5
Name: SaleType, dtype: int64
```

In [422]:

```
# Convert to numbers - SaleType
data_X.SaleType = \
    data_X.SaleType.replace({'WD':0, 'New':1, 'COD':2, 'ConLD':3, 'CWD':4, 'ConLI':5,
'ConLw':6, 'Oth':7, 'Con':8})
```

In [423]:

```
# Verify all distinct values for a column - SaleType
data_X["SaleType"].value_counts()
```

Out[423]:

```
0    2526
1     239
2      87
3      26
4      12
5       9
6       8
7       7
8       5
Name: SaleType, dtype: int64
```

In [424]:

```
# Convert to numbers - SaleCondition
# Verify all distinct values for a column - SaleCondition
data_X["SaleCondition"].value_counts()
```

Out[424]:

```
Normal     2402
Partial     245
Abnorml     190
Family       46
Alloca       24
AdjLand      12
Name: SaleCondition, dtype: int64
```

In [425]:

```
# Convert to numbers - SaleCondition
data_X.SaleCondition = \
    data_X.SaleCondition.replace({'Normal':0, 'Partial':1, 'Abnorml':2, 'Family':3, 'Al
loca':4, 'AdjLand':5})
```

In [426]:

```
# Verify all distinct values for a column - SaleCondition
data_X["SaleCondition"].value_counts()
```

Out[426]:

```
0    2402
1     245
2     190
3      46
4      24
5      12
Name: SaleCondition, dtype: int64
```

4. Modeling

Using a simple linear model with the sci-kit learn library available for python
Using scikit-learn module for linear models

In [427]:

```
from sklearn import linear_model
```

In [441]:

```
X = data_X.drop('SalePrice',1)
#y = np.log(data_X.SalePrice)
y = data_X["SalePrice"].values
```

In [442]:

```
X.head()
```

Out[442]:

	1stFlrSF	2ndFlrSF	3SsnPorch	BedroomAbvGr	BldgType	BsmtExposure	BsmtFi
0	856	854	0	3	0	0	706.0
1	1262	0	0	3	0	2	978.0
2	920	866	0	3	0	3	486.0
3	961	756	0	3	0	0	216.0
4	1145	1053	0	4	0	1	655.0

5 rows × 58 columns

In [443]:

```
y
```

Out[443]:

```
array([ 208500.        ,  181500.        ,  223500.        , ...,
        180921.19589041,  180921.19589041,  180921.19589041])
```

In [444]:

```
scaler = linear_model.LinearRegression()
```

In [445]:

```
count_missing(data_X)
```

```
Series([], dtype: float64)
```

In [446]:

```
# Count null data in each column
data_X.isnull().sum()
```

Out[446]:

```
1stFlrSF         0
2ndFlrSF         0
3SsnPorch        0
BedroomAbvGr     0
BldgType         0
BsmtExposure     0
BsmtFinSF1       0
BsmtFinSF2       0
BsmtFullBath     0
BsmtHalfBath     0
BsmtUnfSF        0
EnclosedPorch    0
ExterQual        0
FireplaceQu      0
Fireplaces       0
Foundation       0
FullBath         0
GarageArea       0
GarageCars       0
GarageFinish     0
GarageType       0
GarageYrBlt      0
GrLivArea        0
HalfBath         0
HeatingQC        0
HouseStyle       0
Id               0
KitchenAbvGr     0
KitchenQual      0
LandContour      0
LotArea          0
LotConfig        0
LotFrontage      0
LotShape         0
LowQualFinSF     0
MSSubClass       0
MSZoning         0
MasVnrArea       0
MasVnrType       0
MiscVal          0
MoSold           0
Neighborhood     0
OpenPorchSF      0
OverallCond      0
OverallQual      0
PavedDrive       0
PoolArea         0
RoofMatl         0
RoofStyle        0
SaleCondition    0
SalePrice        0
SaleType         0
ScreenPorch      0
TotRmsAbvGrd     0
TotalBsmtSF      0
WoodDeckSF       0
YearBuilt        0
YearRemodAdd     0
```

```
YrSold          0
dtype: int64
```

In [447]:

```
scaler.fit(X,y)
```

Out[447]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Fals
e)
```

In [449]:

```
y_test_predicted = scaler.predict(X)
```

In [450]:

```
y_test_predicted_dollars = np.exp(y_test_predicted)
```

In [451]:

```
# Analyse scores
from sklearn.model_selection import cross_val_score
```

In [452]:

```
scores = cross_val_score(scaler, X, y, cv=5,
                         scoring = 'neg_mean_squared_error')

scores = np.sqrt(abs(scores))

print("CV score: ", scores.mean())
```

```
CV score:  49963.4063342
```

In [453]:

```
# Creating data division for Test and Train
from sklearn.model_selection import train_test_split
```

In [454]:

```
X_test, X_train, y_test, y_train = \
train_test_split(X, y, test_size=0.8, shuffle = True)

scaler.fit(X_train, y_train)
y_test_predicted = scaler.predict(X_test)
```

In [459]:

```
#y_test_predicted
```

In [460]:

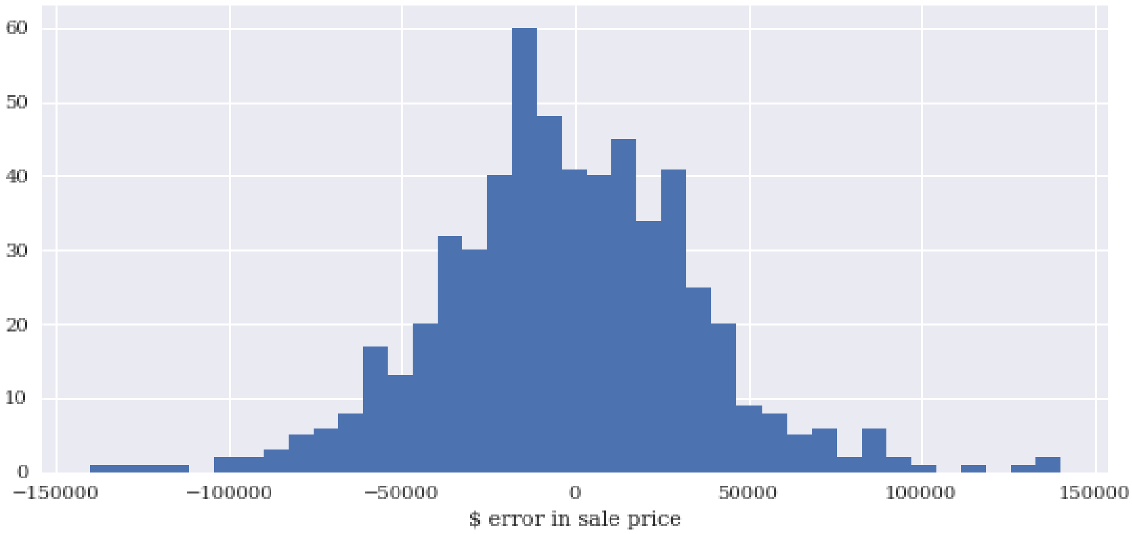
```
# Compute the errors made by our model both as dollar values and as percentages
# of the true sale price:

#USD_errors = np.exp(y_test) - np.exp(y_test_predicted)
USD_errors = y_test - y_test_predicted
percent_errors = USD_errors/np.exp(y_test) * 100
```

In [463]:

```
# Plot results
plt.hist(USD_errors, bins = np.linspace(-140000, 140000, 40))
plt.xlabel('$ error in sale price')
```

Out[463]:

```
<matplotlib.text.Text at 0x2acfdfb3eb8>
```

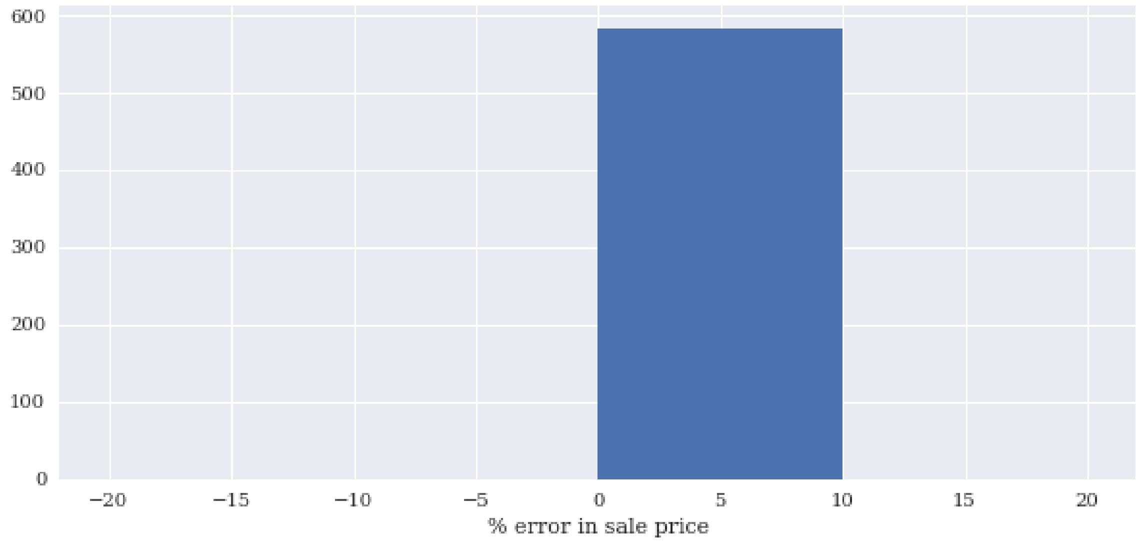


In [467]:

```
# Plot results
plt.hist(percent_errors, bins = np.linspace(-20,20,5))
plt.xlabel('% error in sale price')
```

Out[467]:

<matplotlib.text.Text at 0x2acecb6b160>



In [ ]:

```
```