1 House Prices: Advanced Regression Techniques

1.1 Description

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.

1.2 Acknowledgments

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.

1.3 Data set ¶

Here's a brief version of what you'll find in the data description file.

- `SalePrice` - the property's sale price in dollars. This is the target variable * that you're trying to predict.
- `MSSubClass` : The building class
- `MSZoning` : The general zoning classification
- `LotFrontage` : Linear feet of street connected to property
- `LotArea` : Lot size in square feet
- `Street` : Type of road access
- `Alley` : Type of alley access
- `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 main road or railroad
- `Condition2` : Proximity to main road or railroad (if a second is present)
- `BldgType` : Type of dwelling
- `HouseStyle` : Style of dwelling
- `OverallQual` : Overall material and finish quality
- `OverallCond` : Overall condition rating
- `YearBuilt` : Original construction date
- `YearRemodAdd` : Remodel date
- `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` : Exterior material quality

- `ExterCond` : Present condition of the material on the exterior
- `Foundation` : Type of foundation
- `BsmtQual` : Height of the basement
- `BsmtCond` : General condition of the basement
- `BsmtExposure` : Walkout or garden level basement walls
- `BsmtFinType1` : Quality of basement finished area
- `BsmtFinSF1` : Type 1 finished square feet
- `BsmtFinType2` : Quality of second finished area (if present)
- `BsmtFinSF2` : Type 2 finished square feet
- `BsmtUnfSF` : Unfinished square feet of basement area
- `TotalBsmtSF` : Total square feet of basement area
- `Heating` : Type of heating
- `HeatingQC` : Heating quality and condition
- `CentralAir` : Central air conditioning
- `Electrical` : Electrical system
- `1stFlrSF` : First Floor square feet
- `2ndFlrSF` : Second floor square feet
- `LowQualFinSF` : 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` : Number of bedrooms above basement level
- `Kitchen` : Number of kitchens
- `KitchenQual` : Kitchen quality
- `TotRmsAbvGrd` : Total rooms above grade (does not include bathrooms)
- `Functional` : Home functionality rating
- `Fireplaces` : Number of fireplaces
- `FireplaceQu` : Fireplace quality
- `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` : USD Value of miscellaneous feature
- `MoSold` : Month Sold
- `YrSold` : Year Sold
- `SaleType` : Type of sale
- `SaleCondition` : Condition of sale

1.4 Goal

Predict sales prices and practice feature engineering, RFs, and gradient boosting Type: supervised machine learning - regression

---

2 Exploratory Analysis¶

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split
```

In [3]:

```
# keep only relevant imports based on the regresssion or classification goals
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score, GridSearchCV, RandomizedSe
```

In [4]:

```
# common classifiers
#from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
#from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.svm import SVC, LinearSVC
```

In [5]:

```
import xgboost as xgb
import lightgbm as lgbm
```

In [6]:

```
# common regresssors
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet, SG
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,
from sklearn.svm import SVR
```

In [7]:

```
from sklearn.pipeline import Pipeline
```

In [8]:

```
# skip future warnings and display enough columns for wide data sets
import warnings
warnings.simplefilter(action='ignore') #, category=FutureWarning)
pd.set_option('display.max_columns', 100)
```

2.1 Data set first insight

Let's see wath the data set looks like

In [9]:

```
df = pd.read_csv('../input/train.csv', index_col='Id' )
df.head()
```

Out[9]:

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

Number of samples (lines) and features (colunms including the target)

In [10]:

```
df.shape
```

Out[10]:

```
(1460, 80)
```

Basic infos

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 1 to 1460
Data columns (total 80 columns):
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(34), object(43)
memory usage: 923.9+ KB
```

Number of columns for each type of data

In [12]:

```
df.dtypes.value_counts()
```

Out[12]:

```
object     43
int64      34
float64     3
dtype: int64
```

Unique values for each type of data

In [13]:

```
df.select_dtypes('object').apply(pd.Series.nunique, axis = 0)
```

Out[13]:

```
MSZoning          5
Street            2
Alley             2
LotShape          4
LandContour       4
Utilities         2
LotConfig         5
LandSlope         3
Neighborhood     25
Condition1        9
Condition2        8
BldgType          5
HouseStyle        8
RoofStyle         6
RoofMatl          8
Exterior1st      15
Exterior2nd      16
MasVnrType        4
ExterQual         4
ExterCond         5
Foundation        6
BsmtQual          4
BsmtCond          4
BsmtExposure      4
BsmtFinType1      6
BsmtFinType2      6
Heating           6
HeatingQC         5
CentralAir        2
Electrical        5
KitchenQual       4
Functional        7
FireplaceQu       5
GarageType        6
GarageFinish      3
GarageQual        5
GarageCond        5
PavedDrive        3
PoolQC            3
Fence             4
MiscFeature       4
SaleType          9
SaleCondition     6
dtype: int64
```

Ratio of missing values by column

In [14]:

```
def missing_values_table(df):
        """Function to calculate missing values by column# Funct // credits Wil

        # Total missing values
        mis_val = df.isnull().sum()

        # Percentage of missing values
        mis_val_percent = 100 * df.isnull().sum() / len(df)

        # Make a table with the results
        mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)

        # Rename the columns
        mis_val_table_ren_columns = mis_val_table.rename(
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})

        # Sort the table by percentage of missing descending
        mis_val_table_ren_columns = mis_val_table_ren_columns[
            mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)

        # Print some summary information
        print ("Le jeu de données a " + str(df.shape[1]) + " colonnes.\n"
            "Il y a " + str(mis_val_table_ren_columns.shape[0]) +
              " colonnes avec des valeurs manquantes.")

        # Return the dataframe with missing information
        return mis_val_table_ren_columns
```

In [15]:

```
missing_values = missing_values_table(df)
missing_values.head(10)
```

```
Le jeu de données a 80 colonnes.
Il y a 19 colonnes avec des valeurs manquantes.
```

Out[15]:

	Missing Values	% of Total Values
PoolQC	1453	99.5
MiscFeature	1406	96.3
Alley	1369	93.8
Fence	1179	80.8
FireplaceQu	690	47.3
LotFrontage	259	17.7
GarageType	81	5.5
GarageYrBlt	81	5.5
GarageFinish	81	5.5
GarageQual	81	5.5

In [16]:

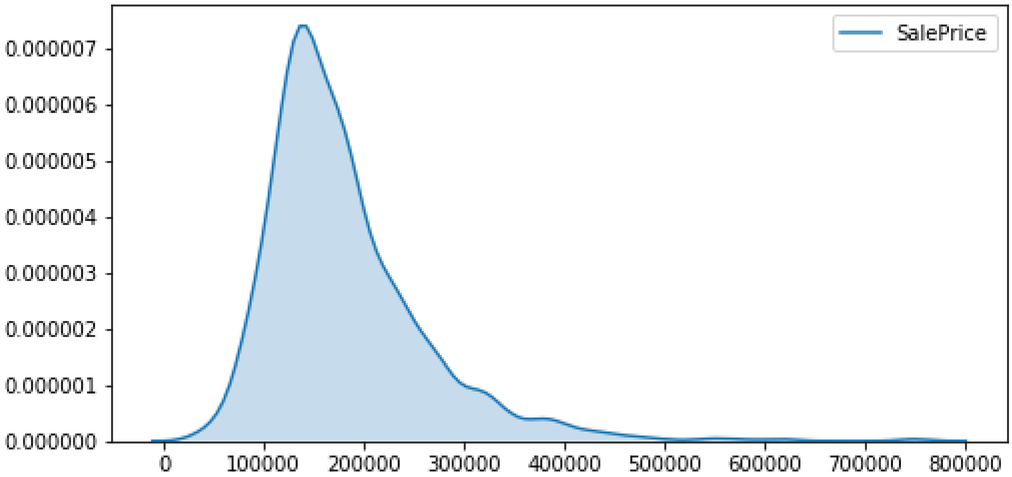
```
cat_feat = list(df.select_dtypes('object').columns)
num_feat = list(df.select_dtypes(exclude='object').columns)
```

2.2 Data Visualization

informations on the target

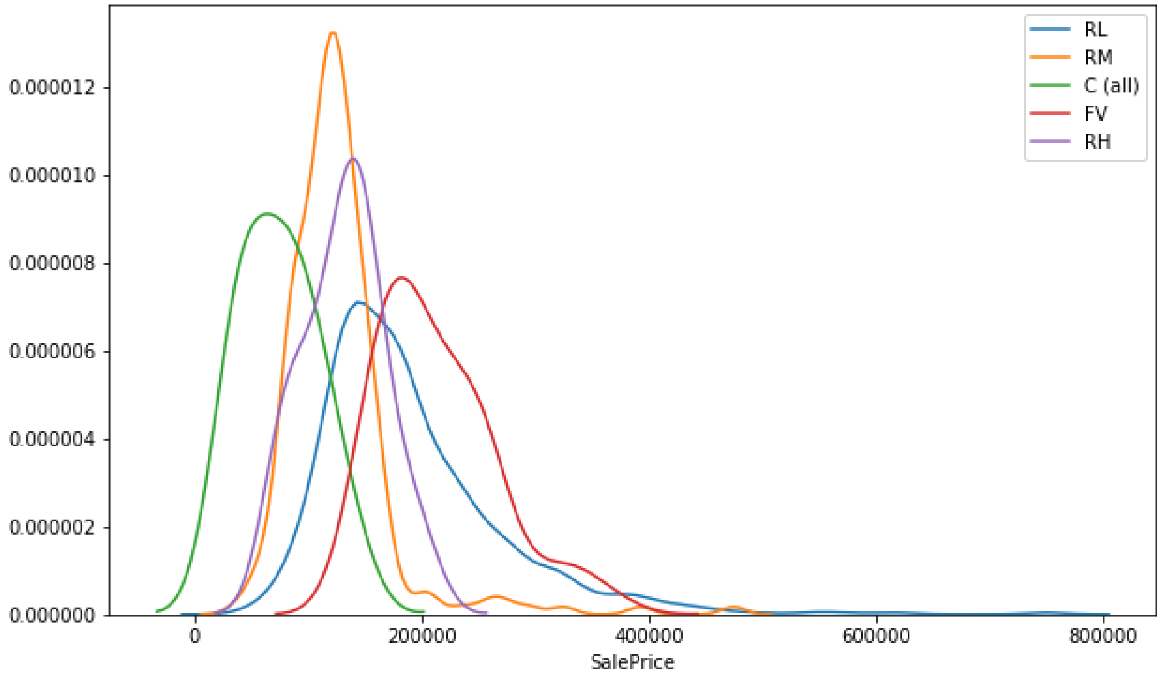
In [17]:

```
plt.figure(figsize=(8, 4))
sns.kdeplot(df.SalePrice, shade=True)
plt.show()
```



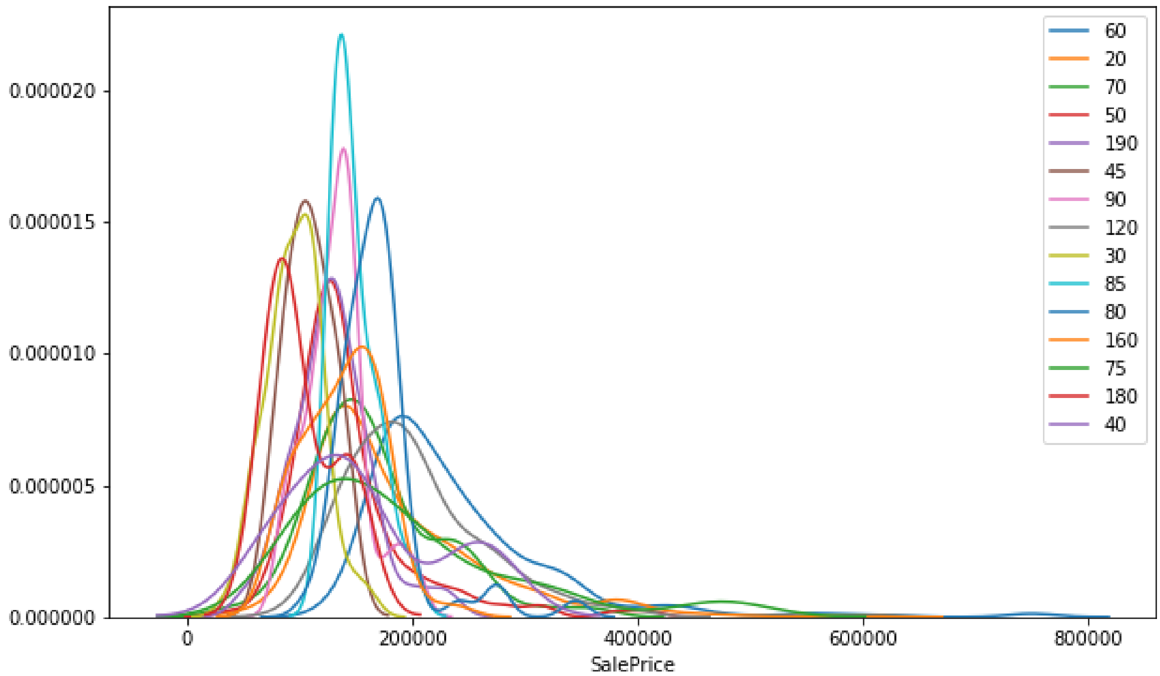
In [18]:

```
plt.figure(figsize=(10, 6))
for zone in list(df.MSZoning.unique()):
    sns.distplot(df[df.MSZoning==zone].SalePrice, label=zone, hist=False)
plt.show()
```



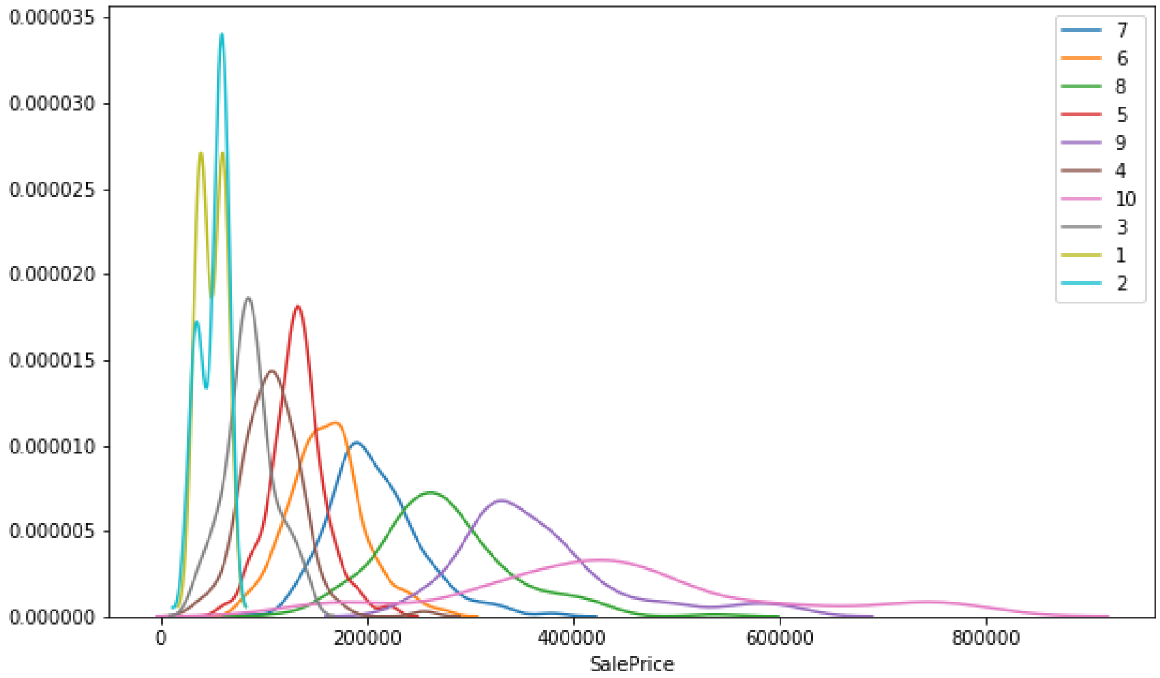
In [19]:

```
plt.figure(figsize=(10, 6))
for ms_sub_class in list(df.MSSubClass.unique()):
    sns.distplot(df[df.MSSubClass==ms_sub_class].SalePrice, label=ms_sub_class,
plt.show()

```



In [20]:

```
plt.figure(figsize=(10, 6))
for qual in list(df.OverallQual.unique()):
    sns.distplot(df[df.OverallQual==qual].SalePrice, label=qual, hist=False)
plt.show()
```



In [21]:

```
df.SalePrice.describe()
```

Out[21]:

```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

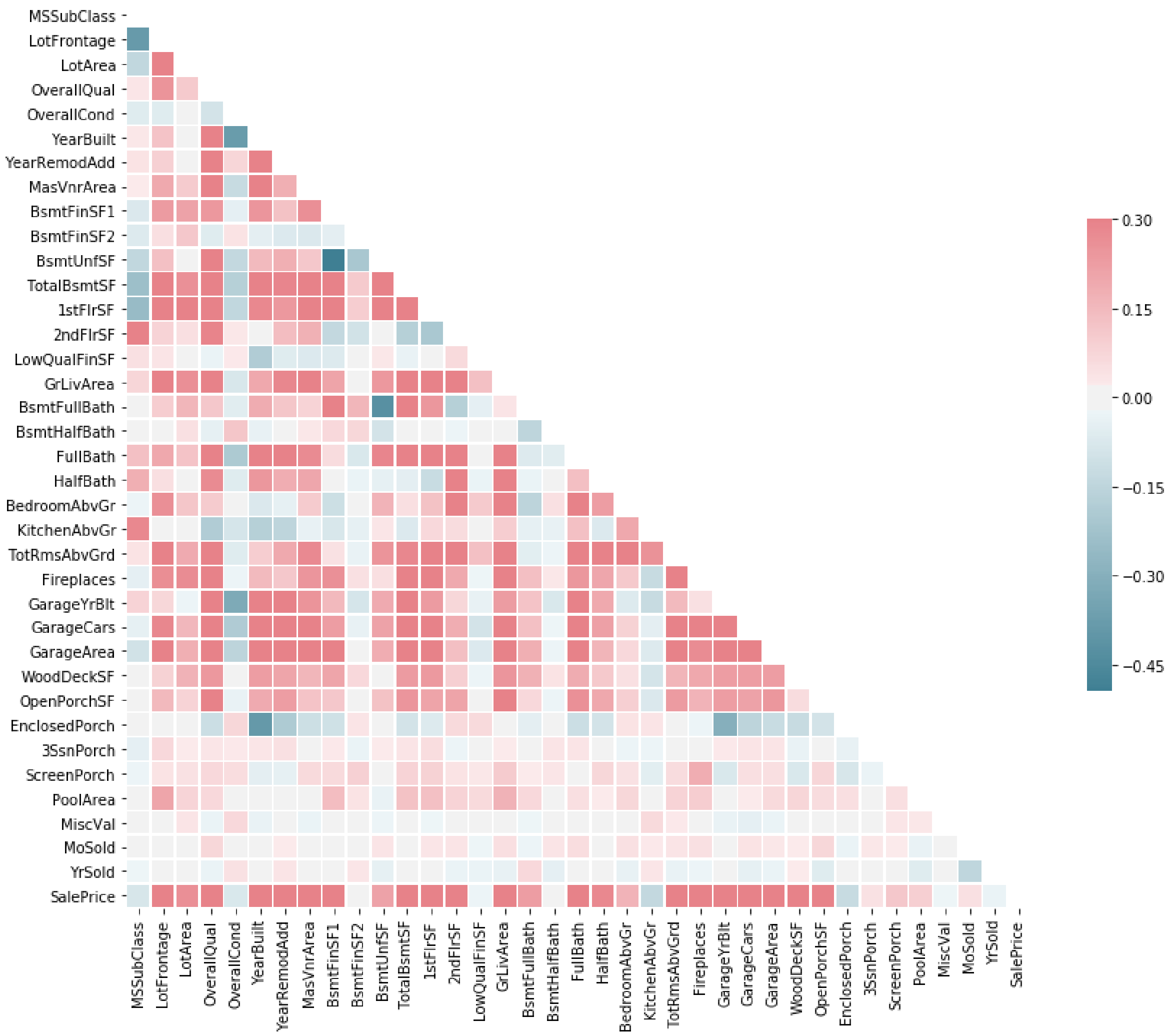
2.3 Correlations

In [22]:

```
corr = df.corr()
corr

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(14, 12))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0, square=True, linewid
```

Out[22]:

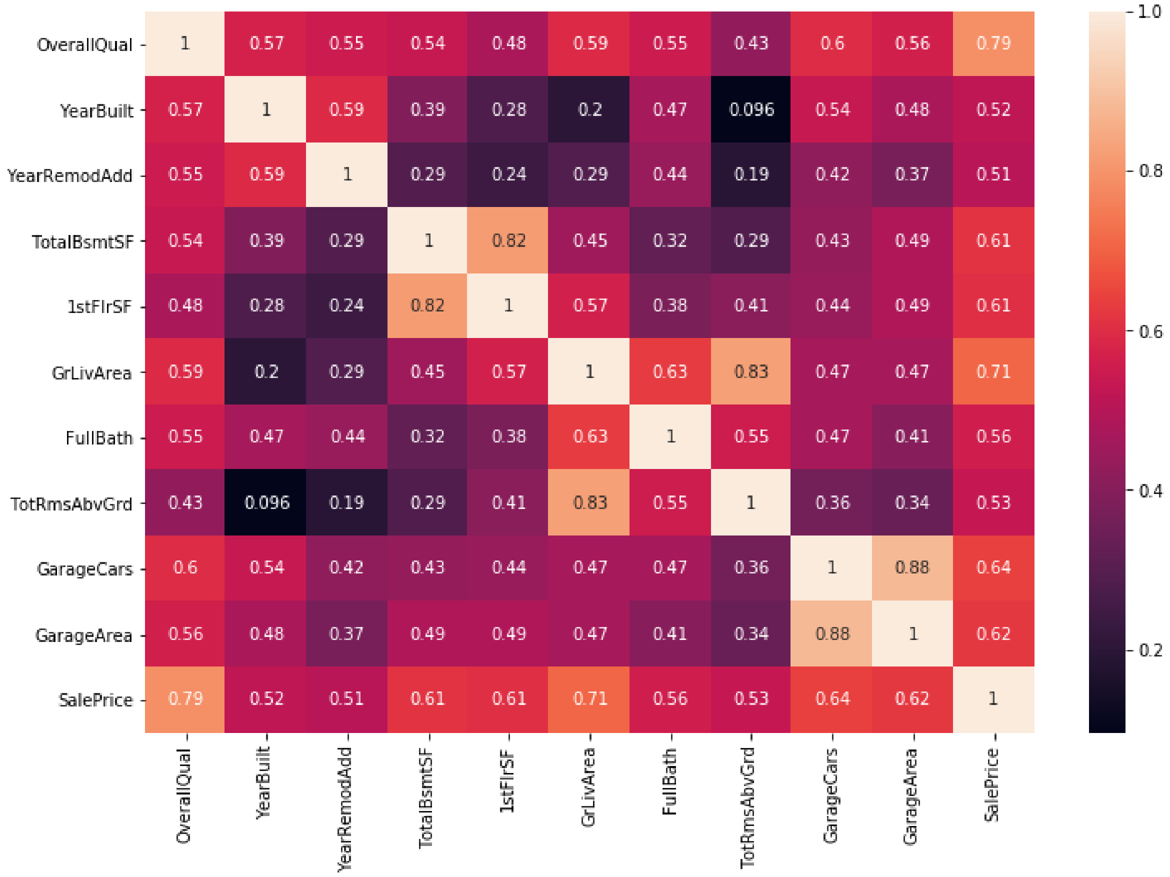
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf318cfd0>
```



Top 50% Corralation train attributes with sale-price

In [23]:

```python
top_feature = corr.index[abs(corr['SalePrice']>0.5)]
plt.subplots(figsize=(12, 8))
top_corr = df[top_feature].corr()
sns.heatmap(top_corr, annot=True)
plt.show()
```



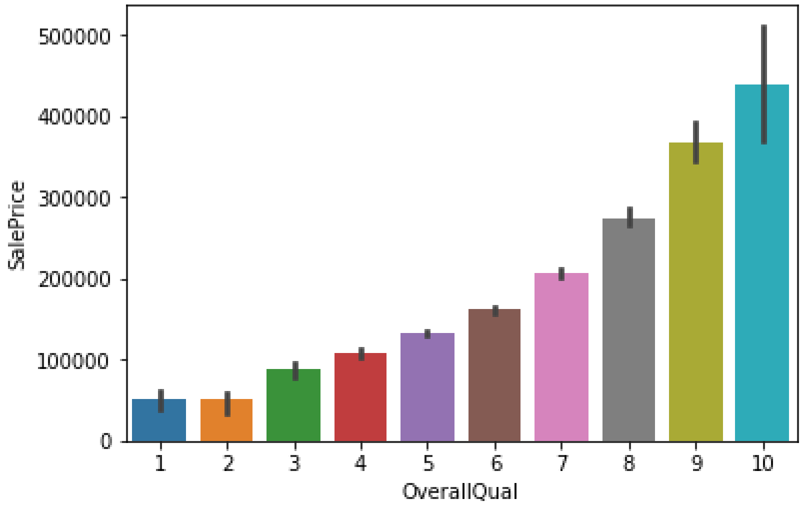
OverallQual is highly correlated with target feature of saleprice by near 80%

In [24]:

```
sns.barplot(df.OverallQual, df.SalePrice)
```

Out[24]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf16a0550>

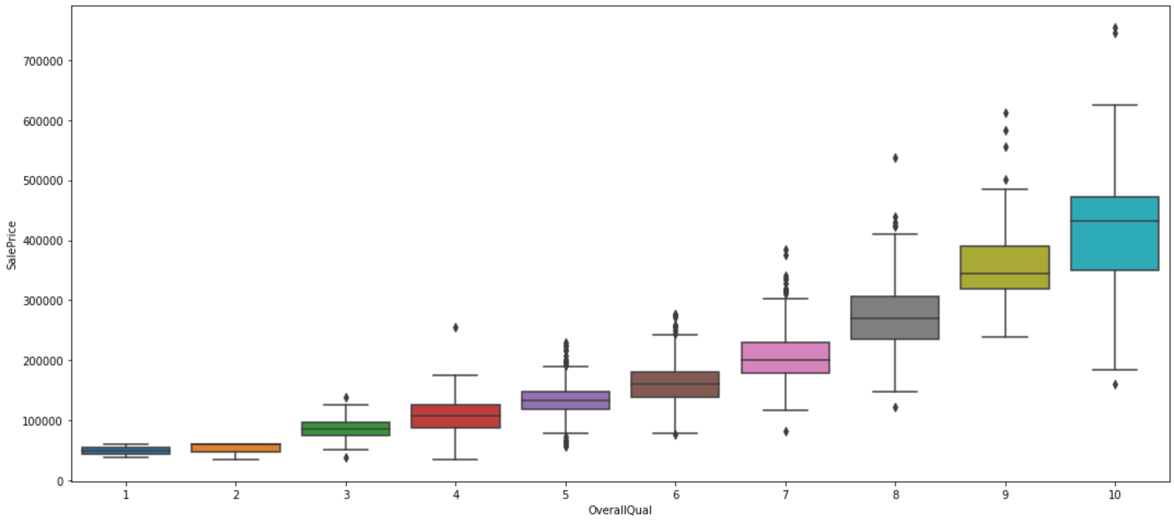


In [25]:

```
plt.figure(figsize=(18, 8))
sns.boxplot(x=df.OverallQual, y=df.SalePrice)
```

Out[25]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fbbf1335a20>

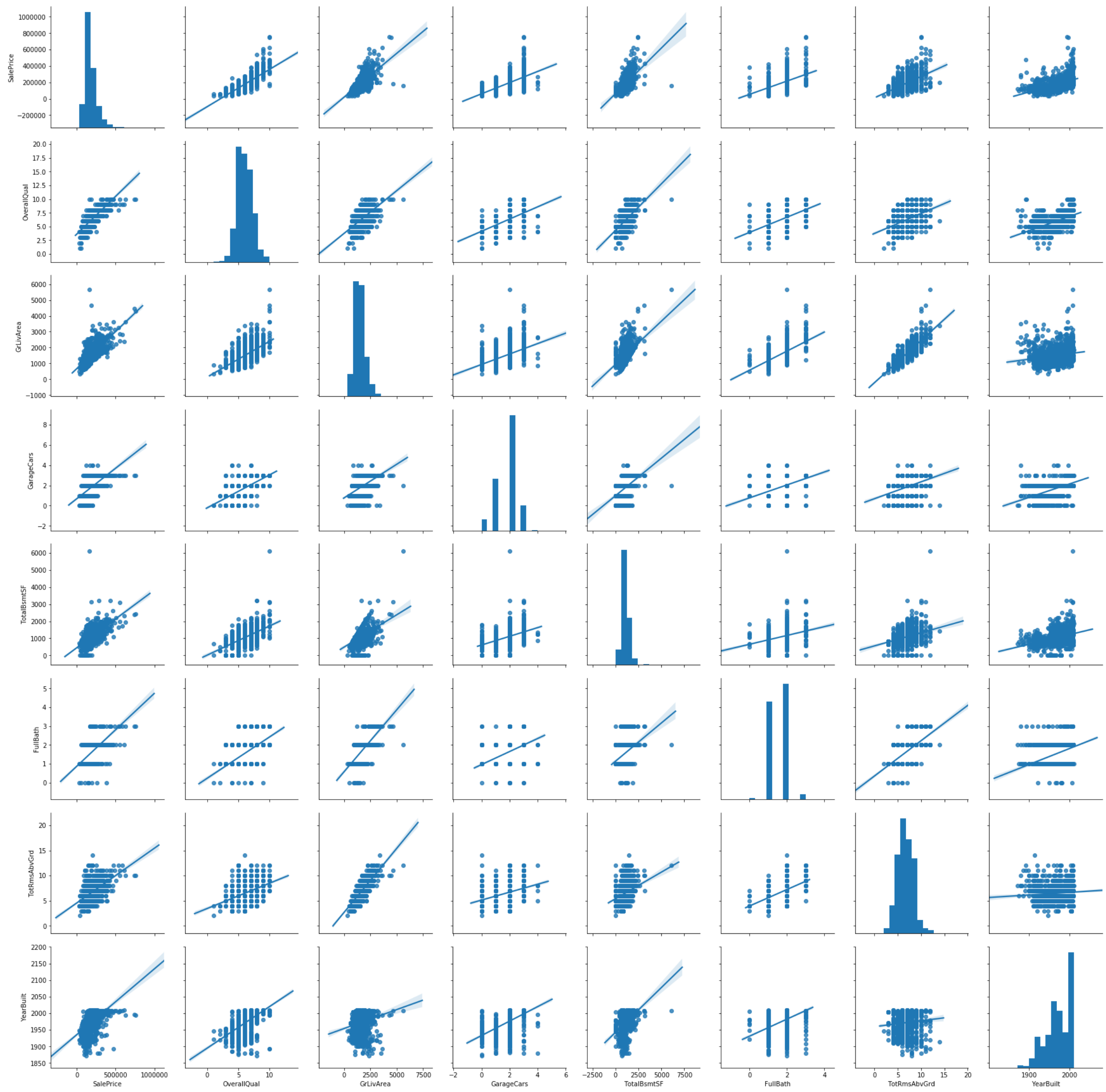


In [26]:

```
col = ['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'TotalBsmtSF', 'F
sns.pairplot(df[col], height=3, kind='reg')
```

Out[26]:

<seaborn.axisgrid.PairGrid at 0x7fbbf1668898>



In [27]:

```
print("Most postively correlated features with the target")
corr = df.corr()
corr.sort_values(['SalePrice'], ascending=False, inplace=True)
corr.SalePrice
```

```
Most postively correlated features with the target
```

Out[27]:

```
SalePrice        1.000000
OverallQual      0.790982
GrLivArea        0.708624
GarageCars       0.640409
GarageArea       0.623431
TotalBsmtSF      0.613581
1stFlrSF         0.605852
FullBath         0.560664
TotRmsAbvGrd     0.533723
YearBuilt        0.522897
YearRemodAdd     0.507101
GarageYrBlt      0.486362
MasVnrArea       0.477493
Fireplaces       0.466929
BsmtFinSF1       0.386420
LotFrontage      0.351799
WoodDeckSF       0.324413
2ndFlrSF         0.319334
OpenPorchSF      0.315856
HalfBath         0.284108
LotArea          0.263843
BsmtFullBath     0.227122
BsmtUnfSF        0.214479
BedroomAbvGr     0.168213
ScreenPorch      0.111447
PoolArea         0.092404
MoSold           0.046432
3SsnPorch        0.044584
BsmtFinSF2      -0.011378
BsmtHalfBath    -0.016844
MiscVal         -0.021190
LowQualFinSF    -0.025606
YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

---

3 Data preparation & feature engineering

3.1 Dealing with abnormal values

Not relevant here, we can assume that all values are been well integrated.

3.2 Data cleaning & Label encoding of categorical features

No duplicated rows

In [28]:

```
df.duplicated().sum()
```

Out[28]:

```
0
```

Let's remove columns with a high ratio of missing values

We don't have much samples, so instead of removing rows with nan, missing values are then replaced by the median

In [29]:

```
from sklearn.preprocessing import LabelEncoder
```

In [30]:

```
def prepare_data(dataframe):

    dataframe = dataframe.drop(columns=['PoolQC', 'MiscFeature', 'Alley', 'Fenc

    cat_feat = list(dataframe.select_dtypes('object').columns)
    num_feat = list(dataframe.select_dtypes(exclude='object').columns)

    dataframe[num_feat] = dataframe[num_feat].fillna(dataframe[num_feat].median
    dataframe[cat_feat] = dataframe[cat_feat].fillna("Not communicated")

    for c in cat_feat:
        lbl = LabelEncoder()
        lbl.fit(list(dataframe[c].values))
        dataframe[c] = lbl.transform(list(dataframe[c].values))

    return dataframe
```

At first sight, there isn't any value in the wrong type / format

Those features can't be used as they are (in string format), this is why we need to convert them in a numerical way...

In [31]:

```
df = prepare_data(df)
```

3.3 Creation of new features

- In this case, it's complicated to add features from an other dataset because no information is provided with the CSV file we're using.
- All columns except the id (used as index) seems to be relevant, so all of them are kept at first.
- We can also combine features to create new ones - but in this case it doesn't seem to be really usefull.

3.4 Standardization / normalization

Not needed here

In [32]:

```
#df[num_feat] = MinMaxScaler().fit_transform(df[num_feat])
```

3.5 Feature selection & and data preparation for models

In [33]:

```
y = df['SalePrice']
X = df.drop(columns=['SalePrice'])
X.shape, y.shape
```

Out[33]:

```
((1460, 74), (1460,))
```

Let's split the data into a train and a test set

In [34]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[34]:

```
((1168, 74), (292, 74), (1168,), (292,))
```

3.6 Feature importance

Top 10 most important features:

In [35]:

```
rnd_reg = RandomForestRegressor(n_estimators=500, n_jobs=-1)
rnd_reg.fit(X, y)

feature_importances = pd.DataFrame(rnd_reg.feature_importances_, index = X.colu
                                    columns=['importance']).sort_values('import
```

In [36]:

```
feature_importances[:10]
```

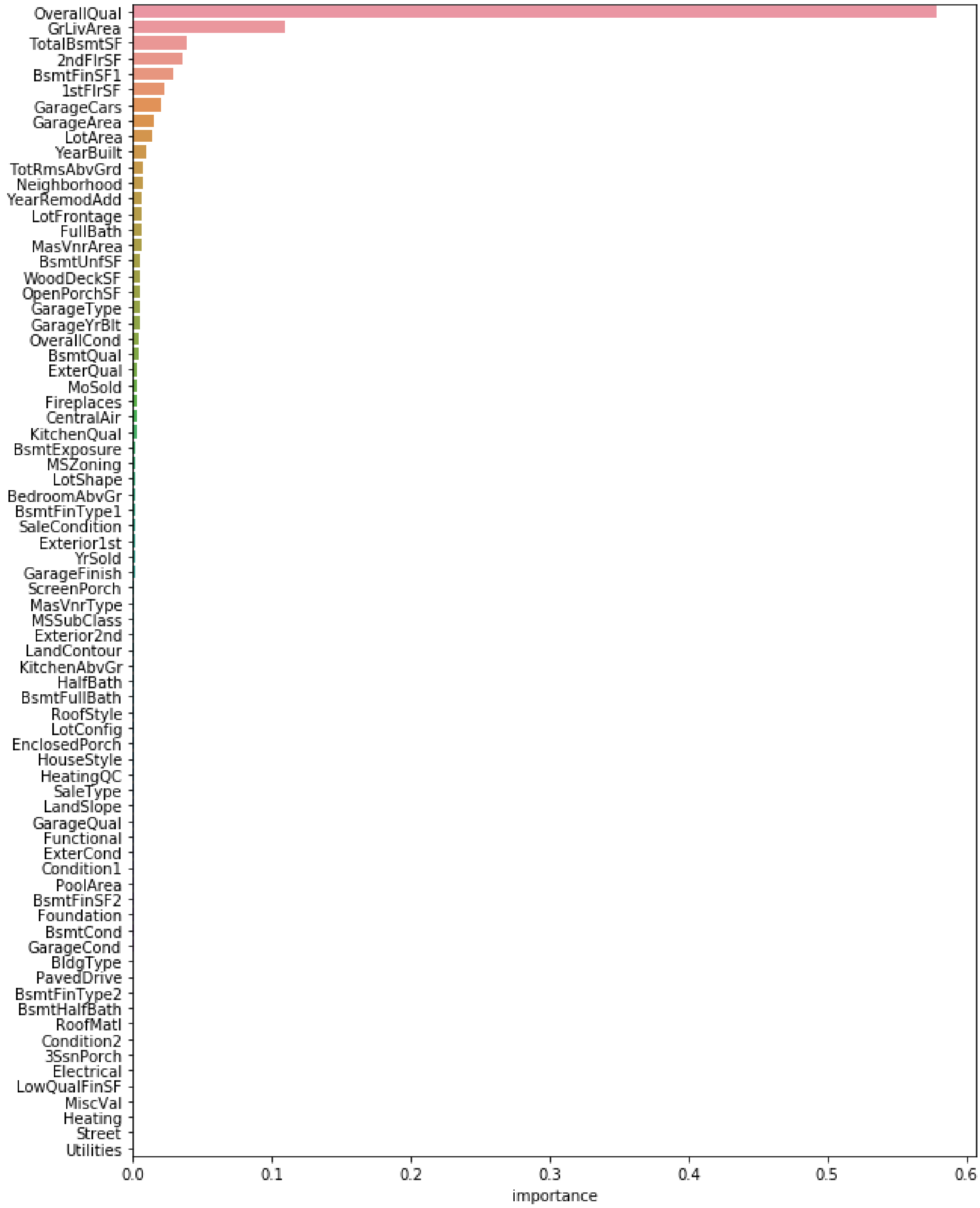
Out[36]:

	importance
OverallQual	0.578202
GrLivArea	0.109874
TotalBsmtSF	0.039231
2ndFlrSF	0.035708
BsmtFinSF1	0.029386
1stFlrSF	0.022536
GarageCars	0.020744
GarageArea	0.015562
LotArea	0.013600
YearBuilt	0.009355

Graph with features sorted by importance

In [37]:

```
plt.figure(figsize=(10, 14))
sns.barplot(x="importance", y=feature_importances.index, data=feature_importanc
plt.show()
```



4 Training models and results

4.1 Baselines - first selection of models

In [38]:

```python
# f1_score binary by default
def get_rmse(reg, model_name):
    """Print the score for the model passed in argument and retrun scores for t

    y_train_pred, y_pred = reg.predict(X_train), reg.predict(X_test)
    rmse_train, rmse_test = np.sqrt(mean_squared_error(y_train, y_train_pred)),
    print(model_name, f'\t - RMSE on Training  = {rmse_train:.0f} / RMSE on Tes

    return rmse_train, rmse_test
```

In [39]:

```python
model_list = [
    LinearRegression(), Lasso(), SVR(),
    RandomForestRegressor(), GradientBoostingRegressor(), Ridge(), ElasticNet()
    BayesianRidge(), ExtraTreesRegressor()
            ]
```

In [40]:

```python
model_names = [str(m)[:str(m).index('(')] for m in model_list]
rmse_train, rmse_test = [], []
```

In [41]:

```python
model_names
```

Out[41]:

```
['LinearRegression',
 'Lasso',
 'SVR',
 'RandomForestRegressor',
 'GradientBoostingRegressor',
 'Ridge',
 'ElasticNet',
 'LinearSVC',
 'BayesianRidge',
 'ExtraTreesRegressor']
```

In [42]:

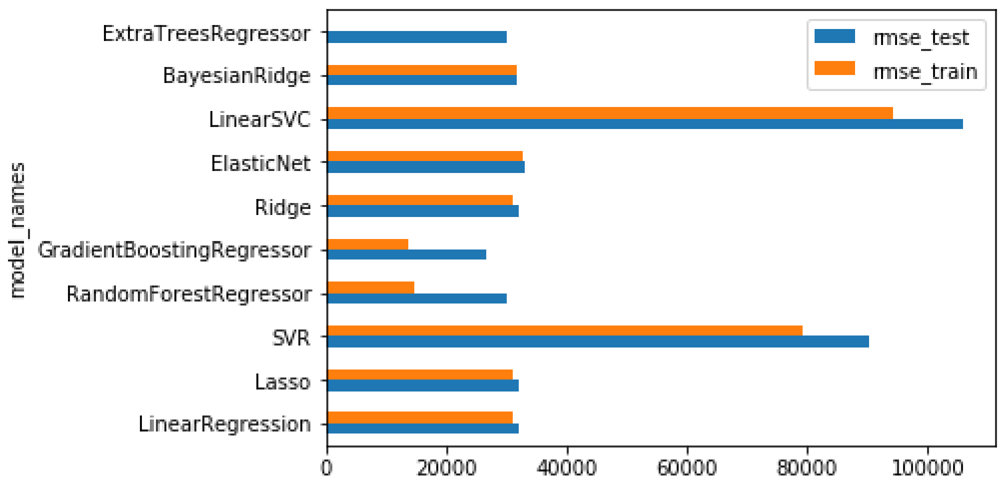
```
for model, name in zip(model_list, model_names):
    model.fit(X_train, y_train)
    sc_train, sc_test = get_rmse(model, name)
    rmse_train.append(sc_train)
    rmse_test.append(sc_test)
```

```
LinearRegression         - RMSE on Training  = 31163 / RMSE on Test =
32162
Lasso    - RMSE on Training  = 31163 / RMSE on Test = 32158
SVR      - RMSE on Training  = 79338 / RMSE on Test = 90251
RandomForestRegressor    - RMSE on Training  = 14748 / RMSE on Test =
30100
GradientBoostingRegressor        - RMSE on Training  = 13689 / RMSE on
Test = 26783
Ridge    - RMSE on Training  = 31176 / RMSE on Test = 32091
ElasticNet       - RMSE on Training  = 32547 / RMSE on Test = 33122
LinearSVC        - RMSE on Training  = 94350 / RMSE on Test = 105986
BayesianRidge    - RMSE on Training  = 31599 / RMSE on Test = 31864
ExtraTreesRegressor      - RMSE on Training  = 0 / RMSE on Test = 3002
3
```

Results comparison chart

In [43]:

```
df_score = pd.DataFrame({'model_names' : model_names,
                         'rmse_train' : rmse_train,
                         'rmse_test'  : rmse_test})
ax = df_score.plot.barh(y=['rmse_test', 'rmse_train'], x='model_names')
```



The LinearSVC model isn't performing well because data haven't been scaled before, let's do it with a pipeline:

In [44]:

```
svm_reg = Pipeline([
    ("scaler", StandardScaler()),
    ("svm_regresssor", LinearSVC())
])
svm_reg.fit(X_train, y_train)
_, _ = get_rmse(svm_reg, "svr_rbf")
```

```
svr_rbf          - RMSE on Training  = 2158 / RMSE on Test = 70136
```

That's much better, although it seems the linear kernel is the best option here:

In [45]:

```
svr_rbf = SVR(kernel = 'rbf')
svr_rbf.fit(X_train, y_train)
_, _ = get_rmse(svr_rbf, "svr_rbf")
```

```
svr_rbf          - RMSE on Training  = 79338 / RMSE on Test = 90251
```

In [46]:

```
svm_reg = Pipeline([
    ("scaler", StandardScaler()),
    ("svm_regresssor", SVR())
])
svm_reg.fit(X_train, y_train)
_, _ = get_rmse(svm_reg, "svr_rbf")

svm_reg = Pipeline([
    ("scaler", StandardScaler()),
    ("svm_regresssor", SVR(kernel="poly"))
])
svm_reg.fit(X_train, y_train)
_, _ = get_rmse(svm_reg, "svr_poly")

sgd_reg = Pipeline([
    ("scaler", StandardScaler()),
    ("sgd_regresssor", SGDRegressor())
])
sgd_reg.fit(X_train, y_train)
_, _ = get_rmse(sgd_reg, "sgd_reg")
```

```
svr_rbf          - RMSE on Training  = 79310 / RMSE on Test = 90222
svr_poly         - RMSE on Training  = 79315 / RMSE on Test = 90224
sgd_reg          - RMSE on Training  = 31546 / RMSE on Test = 34055
```

The same remark comes true also for the SGD Regressor model

Let's try XGBoost !

In [47]:

```
xgb_reg = xgb.XGBRegressor()
xgb_reg.fit(X_train, y_train)
_, _ = get_rmse(xgb_reg, "xgb_reg")
```

```
xgb_reg          - RMSE on Training  = 14601 / RMSE on Test = 27209
```

Looks promissing, here we can conclude that RandomForestRegressor, GradientBoostingRegressor and XGBoost seems to be the models we'll keep for hyperparameters tuning !

4.2 Model optimisation

4.2.1 RandomForrestReg

In [48]:

```
from sklearn.model_selection import GridSearchCV


rf = RandomForestRegressor()
param_grid = {
    'n_estimators': [80, 100, 120],
    'max_features': [14, 15, 16, 17],
    'max_depth' : [14, 16, 18]
}


rfc_cv = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1)
rfc_cv.fit(X_train, y_train)
print(rfc_cv.best_params_)
_, _ = get_rmse(rfc_cv, "rfc_reg")
```

```
{'max_depth': 18, 'max_features': 17, 'n_estimators': 100}
rfc_reg          - RMSE on Training  = 11404 / RMSE on Test = 29079
```

4.2.2 GradientBoostingReg

In [49]:

```
gb = GradientBoostingRegressor()
param_grid = {
    'n_estimators': [100, 400],
    'max_features': [14, 15, 16, 17],
    'max_depth' : [1, 2, 8, 14, 18]
}


gb_cv = GridSearchCV(estimator=gb, param_grid=param_grid, cv=5, n_jobs=-1)
gb_cv.fit(X_train, y_train)
print(gb_cv.best_params_)
_, _ = get_rmse(gb_cv, "gb_cv")
```

```
{'max_depth': 8, 'max_features': 15, 'n_estimators': 100}
gb_cv     - RMSE on Training  = 1180 / RMSE on Test = 25624
```

4.2.3 XGBoostReg

In [50]:

```
xg = xgb.XGBRegressor()
param_grid = {
     'n_estimators': [100, 400],
     'max_features': [10, 14, 16],
     'max_depth' : [1, 2, 8, 18]
}


xg_cv = GridSearchCV(estimator=xg, param_grid=param_grid, cv=5, n_jobs=-1)
xg_cv.fit(X_train, y_train)
print(xg_cv.best_params_)
_, _ = get_rmse(xg_cv, "xg_cv")
```

```
{'max_depth': 8, 'max_features': 10, 'n_estimators': 100}
xg_cv    - RMSE on Training  = 2478 / RMSE on Test = 28332
```

4.3 Combination of the best models & submission

In [51]:

```
df_test = pd.read_csv('../input/test.csv', index_col='Id' )
df_test.head()
```

Out[51]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
Id									
1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	A
1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	A
1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	A
1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	A
1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	A

In [52]:

```
df_test = prepare_data(df_test)
df_test.shape
```

Out[52]:

```
(1459, 74)
```

In [53]:

```
rfc_sub, gb_sub, xg_sub = rfc_cv.predict(df_test), gb_cv.predict(df_test), xg_c
```

In [54]:

```
sub = pd.DataFrame()
sub['Id'] = df_test.index
sub['SalePrice'] = np.mean([rfc_sub, gb_sub, xg_sub], axis=0) / 3
sub.to_csv('submission.csv',index=False)
```

If you found this notebook helpful or you just liked it , some upvotes would be very much appreciated - That will keep me motivated to update it on a regular basis :-)