In [47]:
```
from google.colab import files
uploaded = files.upload()

#import some necessary librairies

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
%matplotlib inline
import matplotlib.pyplot as plt  # Matlab-style plotting
import seaborn as sns
color = sns.color_palette()
sns.set_style('darkgrid')
import warnings
def ignore_warn(*args, **kwargs):
    pass
warnings.warn = ignore_warn #ignore annoying warning (from sklearn and seabor
n)


from scipy import stats
from scipy.stats import norm, skew #for some statistics


pd.set_option('display.float_format', lambda x: '{:.3f}'.format(x)) #Limiting
 floats output to 3 decimal points


from subprocess import check_output
print(check_output(["ls", "."]).decode("utf8")) #check the files available in
 the directory
```

```
sample_data
submission.csv
test.csv
train.csv
```

In [0]:
```
#Now let's import and put the train and test datasets in  pandas dataframe

train = pd.read_csv('./train.csv')
test = pd.read_csv('./test.csv')
```

In [0]:
```
#display the first five rows of the train dataset.
train.head(5)
```

Out[0]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Util
0	1	60	RL	65.000	8450	Pave	NaN	Reg	Lvl	Al
1	2	20	RL	80.000	9600	Pave	NaN	Reg	Lvl	Al
2	3	60	RL	68.000	11250	Pave	NaN	IR1	Lvl	Al
3	4	70	RL	60.000	9550	Pave	NaN	IR1	Lvl	Al
4	5	60	RL	84.000	14260	Pave	NaN	IR1	Lvl	Al

5 rows × 81 columns

In [4]:
```
#display the first five rows of the test dataset.
test.head(5)
```

Out[4]:

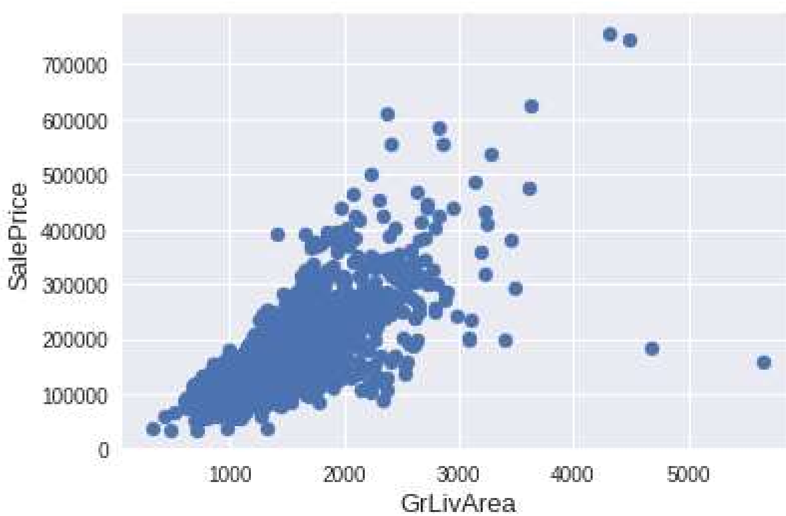
	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1461	20	RH	80.000	11622	Pave	NaN	Reg	Lvl
1	1462	20	RL	81.000	14267	Pave	NaN	IR1	Lvl
2	1463	60	RL	74.000	13830	Pave	NaN	IR1	Lvl
3	1464	60	RL	78.000	9978	Pave	NaN	IR1	Lvl
4	1465	120	RL	43.000	5005	Pave	NaN	IR1	HLS

5 rows × 80 columns

In [5]:
```
#check the numbers of samples and features
print("The train data size before dropping Id feature is : {} ".format(train.shape))
print("The test data size before dropping Id feature is : {} ".format(test.shape))

#Save the 'Id' column
train_ID = train['Id']
test_ID = test['Id']

#Now drop the  'Id' colum since it's unnecessary for  the prediction process.
train.drop("Id", axis = 1, inplace = True)
test.drop("Id", axis = 1, inplace = True)

#check again the data size after dropping the 'Id' variable
print("\nThe train data size after dropping Id feature is : {} ".format(train.shape))
print("The test data size after dropping Id feature is : {} ".format(test.shape))
```

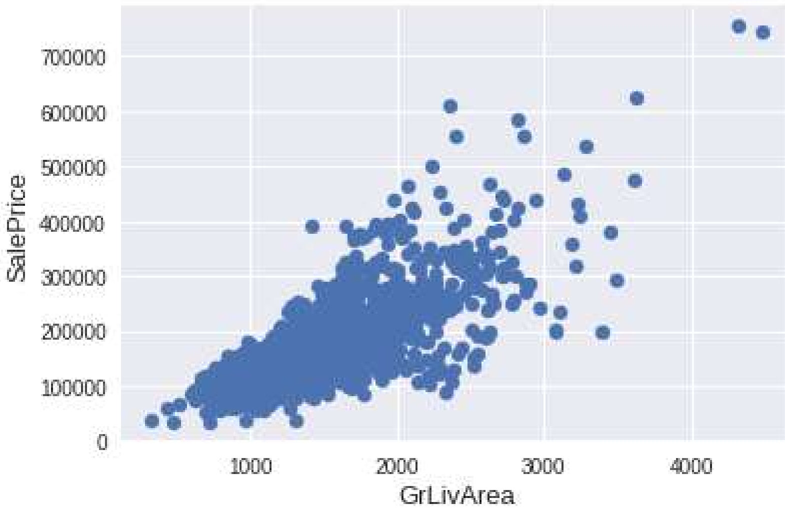
```
The train data size before dropping Id feature is : (1460, 81)
The test data size before dropping Id feature is : (1459, 80)

The train data size after dropping Id feature is : (1460, 80)
The test data size after dropping Id feature is : (1459, 79)
```

In [6]:
```
#outliers
fig, ax = plt.subplots()
ax.scatter(x = train['GrLivArea'], y = train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.show()
```



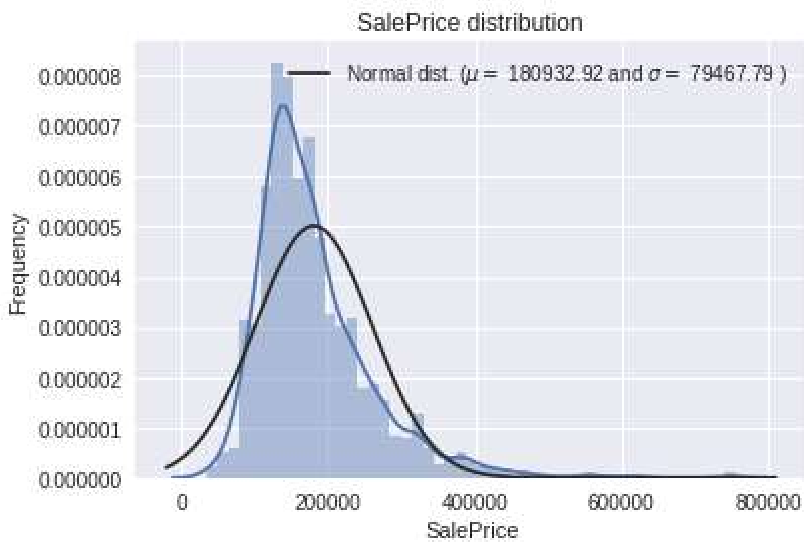
In [7]:

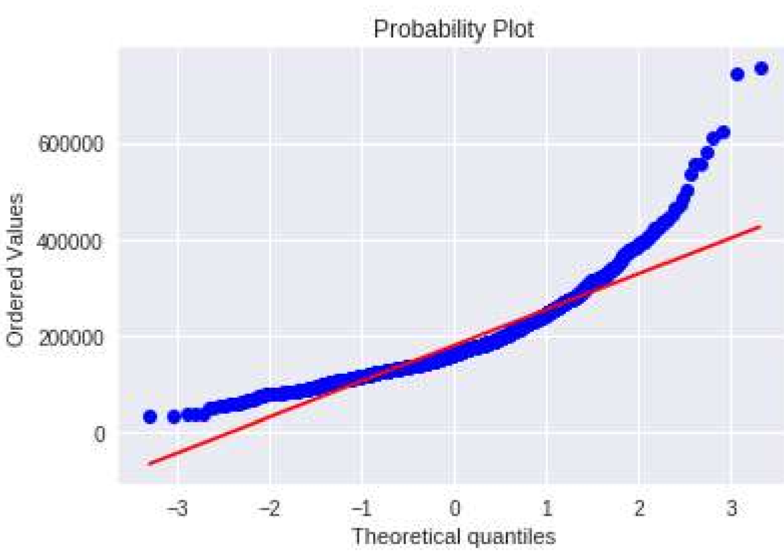
```
#Deleting outliers
train = train.drop(train[(train['GrLivArea']>4000) & (train['SalePrice']<30000
0)].index)

#Check the graphic again
fig, ax = plt.subplots()
ax.scatter(train['GrLivArea'], train['SalePrice'])
plt.ylabel('SalePrice', fontsize=13)
plt.xlabel('GrLivArea', fontsize=13)
plt.show()
```



In [8]:
```
#Target Variable
sns.distplot(train['SalePrice'] , fit=norm);

# Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Now plot the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, si
gma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')

#Get also the QQ-plot
fig = plt.figure()
res = stats.probplot(train['SalePrice'], plot=plt)
plt.show()
```

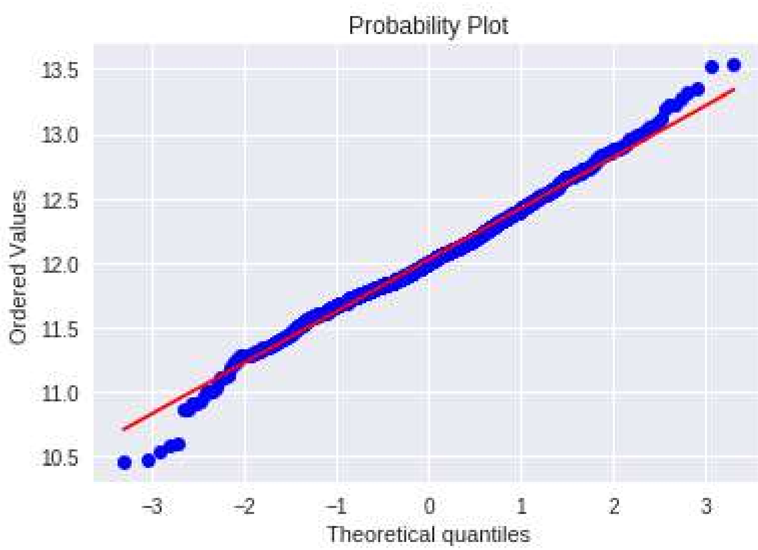
```
 mu = 180932.92 and sigma = 79467.79
```





In [9]:
```
#Log-transformation of the target variable

#We use the numpy fuction log1p which  applies log(1+x) to all elements of the
column
train["SalePrice"] = np.log1p(train["SalePrice"])

#Check the new distribution
sns.distplot(train['SalePrice'] , fit=norm);

# Get the fitted parameters used by the function
(mu, sigma) = norm.fit(train['SalePrice'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))

#Now plot the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, si
gma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('SalePrice distribution')

#Get also the QQ-plot
fig = plt.figure()
res = stats.probplot(train['SalePrice'], plot=plt)
plt.show()
```

```
mu = 12.02 and sigma = 0.40
```



In [10]:

```
#Features engineering

ntrain = train.shape[0]
ntest = test.shape[0]
y_train = train.SalePrice.values
all_data = pd.concat((train, test)).reset_index(drop=True)
all_data.drop(['SalePrice'], axis=1, inplace=True)
print("all_data size is : {}".format(all_data.shape))
```

```
all_data size is : (2917, 79)
```

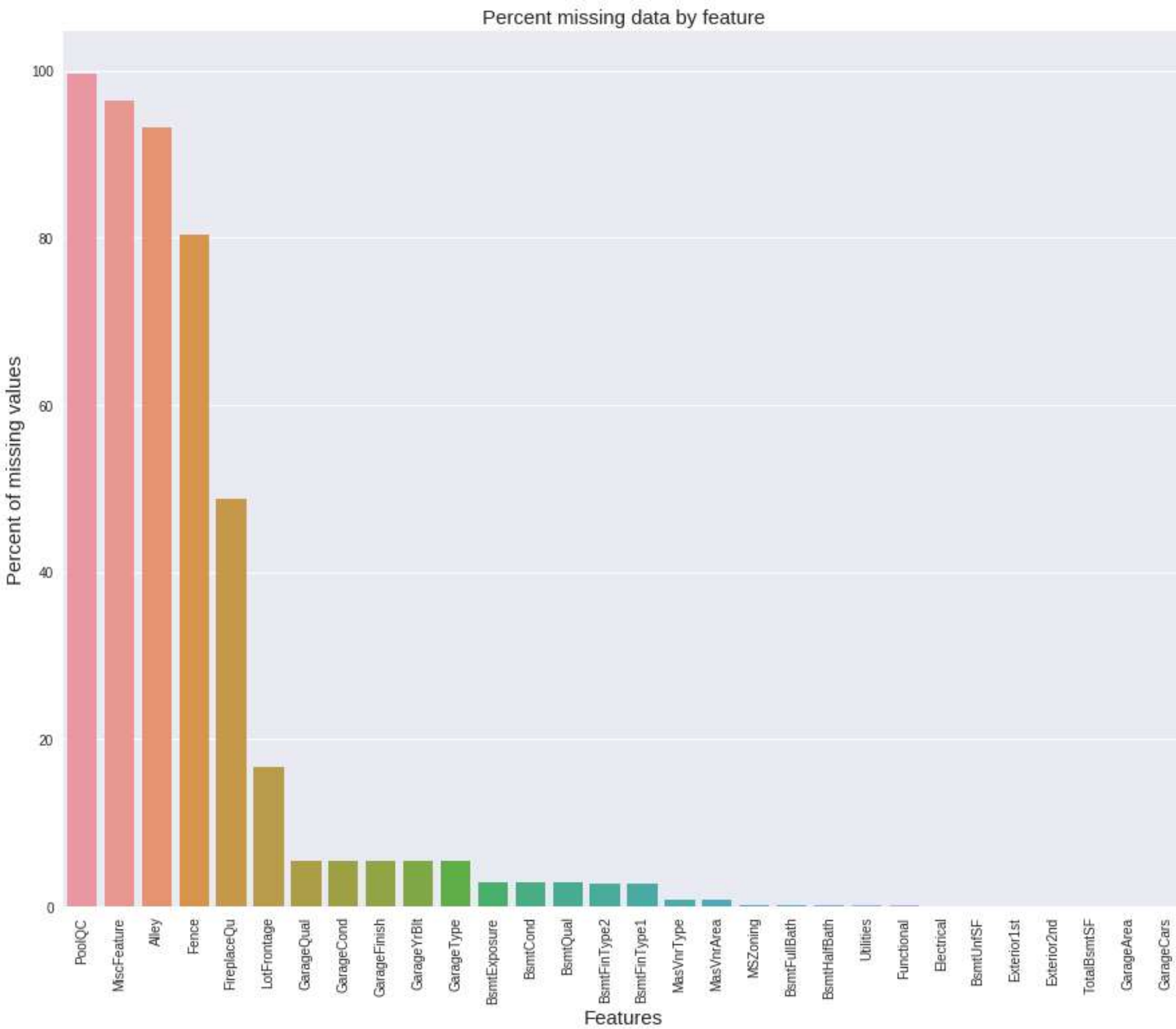
In [11]:
```
#Missing Data

all_data_na = (all_data.isnull().sum() / len(all_data)) * 100
all_data_na = all_data_na.drop(all_data_na[all_data_na == 0].index).sort_value
s(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :all_data_na})
missing_data.head(20)
```

Out[11]:

	Missing Ratio
PoolQC	99.691
MiscFeature	96.400
Alley	93.212
Fence	80.425
FireplaceQu	48.680
LotFrontage	16.661
GarageQual	5.451
GarageCond	5.451
GarageFinish	5.451
GarageYrBlt	5.451
GarageType	5.382
BsmtExposure	2.811
BsmtCond	2.811
BsmtQual	2.777
BsmtFinType2	2.743
BsmtFinType1	2.708
MasVnrType	0.823
MasVnrArea	0.788
MSZoning	0.137
BsmtFullBath	0.069

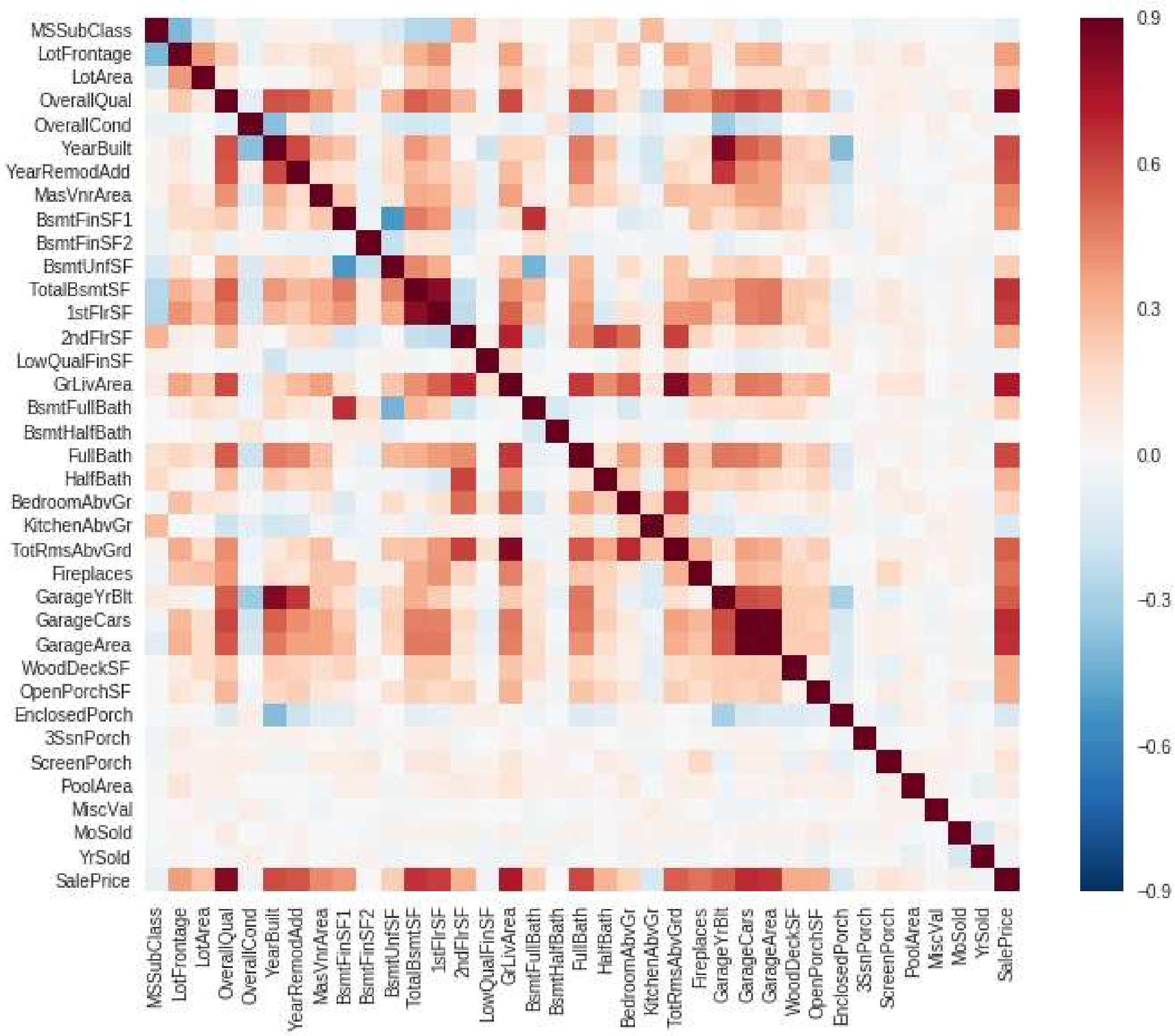
In [12]:
```
f, ax = plt.subplots(figsize=(15, 12))
plt.xticks(rotation='90')
sns.barplot(x=all_data_na.index, y=all_data_na)
plt.xlabel('Features', fontsize=15)
plt.ylabel('Percent of missing values', fontsize=15)
plt.title('Percent missing data by feature', fontsize=15)
```

Out[12]:
```
Text(0.5, 1.0, 'Percent missing data by feature')
```



In [13]:
```
#Data Correlation

#Correlation map to see how features are correlated with SalePrice
corrmat = train.corr()
plt.subplots(figsize=(12,9))
sns.heatmap(corrmat, vmax=0.9, square=True)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f819be34208>



In [0]:
```
#Input missing values

all_data["PoolQC"] = all_data["PoolQC"].fillna("None")
all_data["MiscFeature"] = all_data["MiscFeature"].fillna("None")
all_data["Alley"] = all_data["Alley"].fillna("None")
all_data["Fence"] = all_data["Fence"].fillna("None")
all_data["FireplaceQu"] = all_data["FireplaceQu"].fillna("None")

#Group by neighborhood and fill in missing value by the median LotFrontage of
 all the neighborhood
all_data["LotFrontage"] = all_data.groupby("Neighborhood")["LotFrontage"].tran
sform(
    lambda x: x.fillna(x.median()))

for col in ('GarageType', 'GarageFinish', 'GarageQual', 'GarageCond'):
    all_data[col] = all_data[col].fillna('None')

for col in ('GarageYrBlt', 'GarageArea', 'GarageCars'):
    all_data[col] = all_data[col].fillna(0)

for col in ('BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF','TotalBsmtSF', 'BsmtFullBa
th', 'BsmtHalfBath'):
    all_data[col] = all_data[col].fillna(0)

for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinTy
pe2'):
    all_data[col] = all_data[col].fillna('None')

all_data["MasVnrType"] = all_data["MasVnrType"].fillna("None")
all_data["MasVnrArea"] = all_data["MasVnrArea"].fillna(0)

all_data['MSZoning'] = all_data['MSZoning'].fillna(all_data['MSZoning'].mode()
[0])

all_data = all_data.drop(['Utilities'], axis=1)

all_data["Functional"] = all_data["Functional"].fillna("Typ")

all_data['Electrical'] = all_data['Electrical'].fillna(all_data['Electrical'].
mode()[0])

all_data['KitchenQual'] = all_data['KitchenQual'].fillna(all_data['KitchenQua
l'].mode()[0])

all_data['Exterior1st'] = all_data['Exterior1st'].fillna(all_data['Exterior1s
t'].mode()[0])
all_data['Exterior2nd'] = all_data['Exterior2nd'].fillna(all_data['Exterior2n
d'].mode()[0])

all_data['SaleType'] = all_data['SaleType'].fillna(all_data['SaleType'].mode()
[0])

all_data['MSSubClass'] = all_data['MSSubClass'].fillna("None")
```

In [15]:
```
#Check remaining missing values if any
all_data_na = (all_data.isnull().sum() / len(all_data)) * 100
all_data_na = all_data_na.drop(all_data_na[all_data_na == 0].index).sort_value
s(ascending=False)
missing_data = pd.DataFrame({'Missing Ratio' :all_data_na})
missing_data.head()
```

Out[15]:

Missing Ratio

In [0]:
```
#More features engeneering

#Transforming some numerical variables that are really categorical

#MSSubClass=The building class
all_data['MSSubClass'] = all_data['MSSubClass'].apply(str)


#Changing OverallCond into a categorical variable
all_data['OverallCond'] = all_data['OverallCond'].astype(str)


#Year and month sold are transformed into categorical features.
all_data['YrSold'] = all_data['YrSold'].astype(str)
all_data['MoSold'] = all_data['MoSold'].astype(str)
```

In [17]:
```
#Label Encoding some categorical variables that may contain information in the
ir ordering set

from sklearn.preprocessing import LabelEncoder
cols = ('FireplaceQu', 'BsmtQual', 'BsmtCond', 'GarageQual', 'GarageCond',
        'ExterQual', 'ExterCond','HeatingQC', 'PoolQC', 'KitchenQual', 'BsmtFi
nType1',
        'BsmtFinType2', 'Functional', 'Fence', 'BsmtExposure', 'GarageFinish',
'LandSlope',
        'LotShape', 'PavedDrive', 'Street', 'Alley', 'CentralAir', 'MSSubClas
s', 'OverallCond',
        'YrSold', 'MoSold')
# process columns, apply LabelEncoder to categorical features
for c in cols:
    lbl = LabelEncoder()
    lbl.fit(list(all_data[c].values))
    all_data[c] = lbl.transform(list(all_data[c].values))

# shape
print('Shape all_data: {}'.format(all_data.shape))
```

```
Shape all_data: (2917, 78)
```

In [0]:
```
# Adding total sqfootage feature
all_data['TotalSF'] = all_data['TotalBsmtSF'] + all_data['1stFlrSF'] + all_dat
a['2ndFlrSF']
```

In [19]:
```
#Skewed features

numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index

# Check the skew of all numerical features
skewed_feats = all_data[numeric_feats].apply(lambda x: skew(x.dropna())).sort_
values(ascending=False)
print("\nSkew in numerical features: \n")
skewness = pd.DataFrame({'Skew' :skewed_feats})
skewness.head(10)
```

```
Skew in numerical features:
```

Out[19]:

	Skew
MiscVal	21.940
PoolArea	17.689
LotArea	13.109
LowQualFinSF	12.085
3SsnPorch	11.372
LandSlope	4.973
KitchenAbvGr	4.301
BsmtFinSF2	4.145
EnclosedPorch	4.002
ScreenPorch	3.945

In [20]:
```
#Box Cox Transformation of (highly) skewed features

skewness = skewness[abs(skewness) > 0.75]
print("There are {} skewed numerical features to Box Cox transform".format(ske
wness.shape[0]))

from scipy.special import boxcox1p
skewed_features = skewness.index
lam = 0.15
for feat in skewed_features:
    #all_data[feat] += 1
    all_data[feat] = boxcox1p(all_data[feat], lam)

#all_data[skewed_features] = np.log1p(all_data[skewed_features])
```

```
There are 59 skewed numerical features to Box Cox transform
```

In [21]:
```
#Getting dummy categorical features

all_data = pd.get_dummies(all_data)
print(all_data.shape)
```

```
(2917, 220)
```

In [0]:
```
#Getting the new train and test sets

train = all_data[:ntrain]
test = all_data[ntrain:]
```

Modelling

In [0]:
```
#Import librairies

from sklearn.linear_model import ElasticNet, Lasso,  BayesianRidge, LassoLarsI
C
from sklearn.ensemble import RandomForestRegressor,  GradientBoostingRegressor
from sklearn.kernel_ridge import KernelRidge
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clon
e
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
import lightgbm as lgb
```

In [0]:
```
#Validation function
n_folds = 5

def rmsle_cv(model):
    kf = KFold(n_folds, shuffle=True, random_state=42).get_n_splits(train.valu
es)
    rmse= np.sqrt(-cross_val_score(model, train.values, y_train, scoring="neg_
mean_squared_error", cv = kf))
    return(rmse)
```

In [0]:
```
lasso = make_pipeline(RobustScaler(), Lasso(alpha =0.0005, random_state=1))
ENet = make_pipeline(RobustScaler(), ElasticNet(alpha=0.0005, l1_ratio=.9, ran
dom_state=3))
KRR = KernelRidge(alpha=0.6, kernel='polynomial', degree=2, coef0=2.5)
GBoost = GradientBoostingRegressor(n_estimators=3000, learning_rate=0.05,
                                   max_depth=4, max_features='sqrt',
                                   min_samples_leaf=15, min_samples_split=10,
                                   loss='huber', random_state =5)
model_xgb = xgb.XGBRegressor(colsample_bytree=0.4603, gamma=0.0468,
                             learning_rate=0.05, max_depth=3,
                             min_child_weight=1.7817, n_estimators=2200,
                             reg_alpha=0.4640, reg_lambda=0.8571,
                             subsample=0.5213, silent=1,
                             random_state =7, nthread = -1)
model_lgb = lgb.LGBMRegressor(objective='regression',num_leaves=5,
                              learning_rate=0.05, n_estimators=720,
                              max_bin = 55, bagging_fraction = 0.8,
                              bagging_freq = 5, feature_fraction = 0.2319,
                              feature_fraction_seed=9, bagging_seed=9,
                              min_data_in_leaf =6, min_sum_hessian_in_leaf = 1
1)
```

In [26]:
```
score = rmsle_cv(lasso)
print("\nLasso score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
```

```
Lasso score: 0.1115 (0.0074)
```

In [27]:
```
score = rmsle_cv(ENet)
print("ElasticNet score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
```

```
ElasticNet score: 0.1116 (0.0074)
```

In [28]:
```
score = rmsle_cv(KRR)
print("Kernel Ridge score: {:.4f} ({:.4f})\n".format(score.mean(), score.std
()))
```

```
Kernel Ridge score: 0.1153 (0.0075)
```

In [29]:
```
score = rmsle_cv(GBoost)
print("Gradient Boosting score: {:.4f} ({:.4f})\n".format(score.mean(), score.
std()))
```

```
Gradient Boosting score: 0.1177 (0.0080)
```

In [30]:
```
score = rmsle_cv(model_xgb)
print("Xgboost score: {:.4f} ({:.4f})\n".format(score.mean(), score.std()))
```

```
Xgboost score: 0.1164 (0.0069)
```

In [31]:
```
score = rmsle_cv(model_lgb)
print("LGBM score: {:.4f} ({:.4f})\n" .format(score.mean(), score.std()))
```

```
LGBM score: 0.1167 (0.0072)
```

In [0]:
```
# Stacking models

# Averaging base models

class AveragingModels(BaseEstimator, RegressorMixin, TransformerMixin):
    def __init__(self, models):
        self.models = models

    # we define clones of the original models to fit the data in
    def fit(self, X, y):
        self.models_ = [clone(x) for x in self.models]

        # Train cloned base models
        for model in self.models_:
            model.fit(X, y)

        return self

    #Now we do the predictions for cloned models and average them
    def predict(self, X):
        predictions = np.column_stack([
            model.predict(X) for model in self.models_
        ])
        return np.mean(predictions, axis=1)
```

In [33]:
```
# Averaged base models score

averaged_models = AveragingModels(models = (ENet, GBoost, KRR, lasso))

score = rmsle_cv(averaged_models)
print(" Averaged base models score: {:.4f} ({:.4f})\n".format(score.mean(), sc
ore.std()))
```

```
 Averaged base models score: 0.1091 (0.0075)
```

In [0]:

```
# Stacking averaged Models Class

class StackingAveragedModels(BaseEstimator, RegressorMixin, TransformerMixin):
    def __init__(self, base_models, meta_model, n_folds=5):
        self.base_models = base_models
        self.meta_model = meta_model
        self.n_folds = n_folds

    # We again fit the data on clones of the original models
    def fit(self, X, y):
        self.base_models_ = [list() for x in self.base_models]
        self.meta_model_ = clone(self.meta_model)
        kfold = KFold(n_splits=self.n_folds, shuffle=True, random_state=156)

        # Train cloned base models then create out-of-fold predictions
        # that are needed to train the cloned meta-model
        out_of_fold_predictions = np.zeros((X.shape[0], len(self.base_models
)))
        for i, model in enumerate(self.base_models):
            for train_index, holdout_index in kfold.split(X, y):
                instance = clone(model)
                self.base_models_[i].append(instance)
                instance.fit(X[train_index], y[train_index])
                y_pred = instance.predict(X[holdout_index])
                out_of_fold_predictions[holdout_index, i] = y_pred

        # Now train the cloned  meta-model using the out-of-fold predictions a
s new feature
        self.meta_model_.fit(out_of_fold_predictions, y)
        return self

    #Do the predictions of all base models on the test data and use the averag
ed predictions as
    #meta-features for the final prediction which is done by the meta-model
    def predict(self, X):
        meta_features = np.column_stack([
            np.column_stack([model.predict(X) for model in base_models]).mean(
axis=1)
            for base_models in self.base_models_ ])
        return self.meta_model_.predict(meta_features)
```

In [37]:

```
# Stacking Averaged models Score

stacked_averaged_models = StackingAveragedModels(base_models = (ENet, GBoost,
KRR),
                                                 meta_model = lasso)

score = rmsle_cv(stacked_averaged_models)
print("Stacking Averaged models score: {:.4f} ({:.4f})".format(score.mean(), s
core.std()))
```

```
Stacking Averaged models score: 0.1084 (0.0074)
```

In [0]:
```
def rmsle(y, y_pred):
    return np.sqrt(mean_squared_error(y, y_pred))
```

Final Training and Prediction

In [40]:
```
# StackedRegressor
stacked_averaged_models.fit(train.values, y_train)
stacked_train_pred = stacked_averaged_models.predict(train.values)
stacked_pred = np.expm1(stacked_averaged_models.predict(test.values))
print(rmsle(y_train, stacked_train_pred))
```

```
0.07814905151549066
```

In [41]:
```
# XGBoost
model_xgb.fit(train, y_train)
xgb_train_pred = model_xgb.predict(train)
xgb_pred = np.expm1(model_xgb.predict(test))
print(rmsle(y_train, xgb_train_pred))
```

```
0.07898668813465673
```

In [42]:
```
# LightGBM
model_lgb.fit(train, y_train)
lgb_train_pred = model_lgb.predict(train)
lgb_pred = np.expm1(model_lgb.predict(test.values))
print(rmsle(y_train, lgb_train_pred))
```

```
0.07343743130986105
```

In [43]:
```
'''RMSE on the entire Train data when averaging'''

print('RMSLE score on train data:')
print(rmsle(y_train,stacked_train_pred*0.70 +
               xgb_train_pred*0.15 + lgb_train_pred*0.15 ))
```

```
RMSLE score on train data:
0.07548543390046325
```

In [0]:
```
# Ensemble prediction
ensemble = stacked_pred*0.70 + xgb_pred*0.15 + lgb_pred*0.15
```

In [0]:
```
# Submission
sub = pd.DataFrame()
sub['Id'] = test_ID
sub['SalePrice'] = ensemble
sub.to_csv('submission.csv',index=False)
```

In [0]:
```
# Download submission file
files.download('submission.csv')
```