House Price Prediction

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Introduction

Welcome to our project! Our project of House price prediction in Georgia state is to use data science technology to translate a large amount of Zillow house data to meaningful insights.We use Zillow house data to train machine learning models that can help us to predict the Georgia house’s price. our model will serve as a predictive model that help user to decide whether the sale price of a unlisted house is higher or lower than its actual sale price, which will provide a good comparison for them to decide whether they should invest or not.

Data Explanation

The data for our project is provided in two files: GaCensus.xlsx and ForSaleData.xlsx.

- ForSaleData.xlsx contains 32056 rows and 48 columns.
- GaCensus.xlsx contains 949 rows 27 columns.
- we merge these two dataset together by the common feature of City.
- We also split our dataset in to training data set and testing dataset,which contains 30% of the total dataset.
- Each row represents a house in Georgia state,each column is a feature, either unique to the house.
- These data set contains both numerical features and categorical features,and we transfer categorical features in to numerical features.

Feature Introduction:

ForSaleData:

- 5 categories
- house pric:'city','ParcelId’, 'StreetAddress’, 'Zipcode’, 'Latitude','Longitude’
- Location:'Price','PriceChange','Zestimate', 'RentZestimate’,'Zpid'
- homesiatution:'Bathrooms','Bedrooms',''LivingArea','LotSize','Basement','Appliances','Cooling','Heating','Floori
- school information:'PrimarySchoolDistance', 'PrimarySchoolName','PrimarySchoolRating','MiddleSchoolDistance','MiddleSchoolName','MiddleSchoolRating 'HighSchoolName','HighSchoolRating'
- website information:'last_upd_dt','hoa','Url','OnMarketDate','last_upd_dt'

GaCensus:

- 5 categories
- populaiton:'FemalePopulation', 'HawaiianPopulation','HispanicPopulation','AmericanIndianPopulation','AsianPopulation','BlackPopulation','Wh
- household:'IncomePerHousehold','Households','PersonsPerHousehold','AverageHouseValue'
- age:'MaleMedianAge','FemaleMedianAge'
- employment:'BusinessMailboxes','NumberofBusinesses', 'NumberofEmployees'，‘AnnualPayroll’
- other:'BusinessMailboxes','ResidentialMailboxes','City', 'CountyFIPS','Latitude', 'Longitude'

Goal

Our goal is to predic the house price of Georgia state as precise as possible. we collected the data of each house,and each house has own unique information, and we also clloect the data of Population profile in Georgia state.

Metric

we want to build machine learning model that can predict the house price of Georgia state as precise as possible.Our predictions will be assessed by the following metric.

- MAE:Mean Absolute Error
- MSE:Mean Squared Error
- RMSE:Root Mean Square Error
- MAPE: Mean Absolute Percentage Error
- MPE:Mean Percentage Error
- R^2:R-squared

Model

Since the variables we predicted were continuous variables, we first used the linear regression model, and then used the lasso linear regression model to avoid overfitting.In order to get a better model, we use In order to get a better model, we use machine learning model of random forest, XGboost,LGBM.On the base of these underlying machine learning models we build our Ensemble Learning model to further improve the performance of models.

- Simple Model: linear regression, Lasso
- Complex Model:random forest, XGboost,LGBM
- Ensemble Learning

Default Model

We first tune our dataset on the default machine learning modle, which serve as the benchmark to further impromve our model and compare the result of our tunning models.

Grid search & RandomSearch

we use gridsearch and RandomSearch to tune the best combination of hyperparameter for each model by achieving the highest average metric score on each validation data set.

PART ONE

In [239]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
color = sns.color_palette()
from scipy import stats
from scipy.stats import norm, skew
from sklearn.model_selection import cross_val_score
from xgboost import XGBRegressor
from xgboost import plot_importance
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from scipy.stats import boxcox
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
import warnings
warnings.filterwarnings('ignore')
```

1. Collecting Data

In [240]:
```
sale_data_df = pd.read_excel('ForSaleData.xlsx')
gagensus_df = pd.read_excel('GaCensus.xlsx')
```

2. Data Browsing

In [241]:
```
sale_data_df.head()
gagensus_df.head()
```

Out[241]:

	Zpid	ParcelId	HomeStatus	HomeType	StreetAddress	City	State	Zipcode
0	90171327	6194384	FOR_SALE	CONDO	1809 Brookside Lay Cir	Norcross	GA	30093
1	14770166	6176A070	FOR_SALE	SINGLE_FAMILY	997 Carla Pl	Norcross	GA	30093
2	14773317	6187374	FOR_SALE	SINGLE_FAMILY	1371 Kings Ridge Dr	Norcross	GA	30093
3	124173626	6169331	FOR_SALE	TOWNHOUSE	6302 Story Cir	Norcross	GA	30093
4	14774647	6190064	FOR_SALE	SINGLE_FAMILY	1227 Gale Dr	Norcross	GA	30093

5 rows × 45 columns

Out[241]:

	ZipCode	City	Latitude	Longitude	CountyFIPS	BusinessMailboxes	ResidentialMailbox
0	30327	Atlanta	33.864887	-84.423887	121	424	103
1	30573	Tallulah Falls	34.736100	-83.391500	241	0	
2	30005	Alpharetta	34.090544	-84.218282	121	1567	134
3	30075	Roswell	34.056136	-84.379465	121	1476	214
4	30068	Marietta	33.972174	-84.441108	67	684	128

5 rows × 27 columns

3. Cleaning Data for Each Form to Be Ready for Merging

Step1: We need to find column names appear in both forms.

In [242]:
```
sale_name = list(sale_data_df.columns)
sale_name_lower = [sale.lower() for sale in sale_name]
gagensus_name = list(gagensus_df.columns)
gagensus_name_lower = [ga.lower() for ga in gagensus_name]
common = [x for x in sale_name_lower if x in gagensus_name_lower]
common
```

Out[242]:
```
['city', 'zipcode', 'latitude', 'longitude']
```

Step2: Merging key options include 'city', 'zipcode', 'latitude' and 'longitude'. We could foresee that 'zipcode', 'latitude' and 'longitude' are more specific than 'city'. If we choose one of those three as key, it is possible that there are lots of missing values we need to fill. However, if we choose 'city' as the key, that problem could be avoided. Another thing to support our choice is that the same city always has similar attributes. Thus, for gagensus_df, we need to groupby city. For sale_data_df, we could remain most of features inside until we merge two forms.

(1) Gagensus Form

Gagensus form is about city information in Georgia State.

In [243]:
```
gagensus_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 949 entries, 0 to 948
Data columns (total 27 columns):
ZipCode                     949 non-null int64
City                        949 non-null object
Latitude                    949 non-null float64
Longitude                   949 non-null float64
CountyFIPS                  949 non-null int64
BusinessMailboxes           949 non-null int64
ResidentialMailboxes        949 non-null int64
NumberofBusinesses          949 non-null int64
NumberofEmployees           949 non-null int64
Population2010              949 non-null int64
CurrentPopulation           949 non-null int64
AmericanIndianPopulation    949 non-null int64
AsianPopulation             949 non-null int64
BlackPopulation             949 non-null int64
HawaiianPopulation          949 non-null int64
HispanicPopulation          949 non-null int64
WhitePopulation             949 non-null int64
AnnualPayroll               949 non-null int64
AverageHouseValue           949 non-null int64
IncomePerHousehold          949 non-null int64
Households                  949 non-null int64
PersonsPerHousehold         949 non-null float64
FemaleMedianAge             949 non-null object
FemalePopulation            949 non-null int64
MaleMedianAge               949 non-null object
MalePopulation              949 non-null int64
MedianAge                   949 non-null object
dtypes: float64(3), int64(20), object(4)
memory usage: 200.3+ KB
```

a. Drop meaningless value

Value in 'ZipCode' and 'CountyFIPS' are artificially regulated. They are not naturally attribute for city. So we drop them.

In [244]:
```
g_a = gagensus_df.drop(['ZipCode','CountyFIPS'], axis = 1)
```

b. Convert object into numerical value

From data info we find 4 features in object type. To better take advantage of original dataset, we decide to convert possible object featues into numerical features. They are 'FemaleMedianAge', 'MaleMedianAge' and 'MedianAge'.

In [245]:
```
g_a['FemaleMedianAge'] = g_a['FemaleMedianAge'].str.strip(' years').astype(flo
at)
g_a['MaleMedianAge'] = g_a['MaleMedianAge'].str.strip(' years').astype(float)
g_a['MedianAge'] = g_a['MedianAge'].str.strip(' years').astype(float)
```

c. Compile features in same city

We find in orginal data form, some same city appears many times. In order to get an overview of the same city and merge them with the other form via key 'City', we decide to sum some of those features up.

In [246]:
```
g_b = g_a[['City', 'BusinessMailboxes', 'ResidentialMailboxes',
       'NumberofBusinesses', 'NumberofEmployees', 'Population2010',
       'CurrentPopulation', 'AmericanIndianPopulation', 'AsianPopulation',
       'BlackPopulation', 'HawaiianPopulation', 'HispanicPopulation',
       'WhitePopulation', 'AnnualPayroll', 'Households', 'FemalePopulation',
'MalePopulation']]
g_c = g_b.groupby('City').sum()
```

We find 'IncomePerHousehold' and 'PersonsPerHousehold' is the average value in different counties within the same city. So we cannot sum them up. In this case, we decide to take the weighted average for them in each city. Here are formulas:

IncomePerHousehold = $\sum_{i=1}^{n} IncomePerHousehold_i * Household_i$ / $\sum_{i=1}^{n} Household_i$

PersonsPerHousehold = $\sum_{i=1}^{n} PersonsPerHousehold_i * Household_i$ / $\sum_{i=1}^{n} Household_i$

In [247]:
```
g_c['IncomePerHousehold'] = g_a.groupby('City').apply(
    lambda g_a: np.average(g_a['IncomePerHousehold'], weights = g_a['Household
s'])
    if g_a['Households'].any() >0 else 0)
g_c['PersonsPerHousehold'] = g_a.groupby('City').apply(
    lambda g_a: np.average(g_a['PersonsPerHousehold'], weights = g_a['Househol
ds'])
    if g_a['Households'].any() >0 else 0)
```

For features 'AverageHouseValue', 'FemaleMedianAge', 'MaleMedianAge' and 'MedianAge', they are also average value. We cannot sum them up. Also there exist zero values. So a best way to compile them based on city is to calculate non-zero average for those features.

In [248]:
```
g_c['AverageHouseValue'] = g_a.groupby('City').apply(
    lambda g_a: np.array(g_a['AverageHouseValue'])[np.nonzero(np.array(g_a['Av
erageHouseValue']))].mean())
g_c['FemaleMedianAge'] = g_a.groupby('City').apply(
    lambda g_a: np.array(g_a['FemaleMedianAge'])[np.nonzero(np.array(g_a['Fema
leMedianAge']))].mean())
g_c['MaleMedianAge'] = g_a.groupby('City').apply(
    lambda g_a: np.array(g_a['MaleMedianAge'])[np.nonzero(np.array(g_a['MaleMe
dianAge']))].mean())
g_c['MedianAge'] = g_a.groupby('City').apply(
    lambda g_a: np.array(g_a['MedianAge'])[np.nonzero(np.array(g_a['MedianAge'
]))].mean())
```

d. Reset index

Since we process data based on groupby 'City'. The index right now is 'City'. We need to convert them into numerical range instead of 'City' for further convinience.

In [249]:
```
city_df = g_c.reset_index()
```

(2) Sales data Form

sale_data_df is about each house information and sales data on Zillow.

In [250]:
```
sale_data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32056 entries, 0 to 32055
Data columns (total 45 columns):
Zpid                     32056 non-null int64
ParcelId                 32049 non-null object
HomeStatus               32056 non-null object
HomeType                 32056 non-null object
StreetAddress            32056 non-null object
City                     32056 non-null object
State                    32056 non-null object
Zipcode                  32056 non-null int64
Latitude                 32056 non-null float64
Longitude                32056 non-null float64
Price                    32056 non-null int64
PriceChange              32056 non-null int64
Zestimate                32056 non-null int64
RentZestimate            32056 non-null int64
TaxAssessedValue         32056 non-null int64
DaysOnZillow             32056 non-null int64
PageViewCount            32056 non-null int64
FavoriteCount            32056 non-null int64
Bedrooms                 32056 non-null int64
Bathrooms                32056 non-null float64
Stories                  32056 non-null int64
LivingArea               32056 non-null int64
LotSize                  32056 non-null int64
Basement                 32056 non-null object
Appliances               21706 non-null object
Cooling                  24785 non-null object
Heating                  24644 non-null object
Flooring                 21553 non-null object
ExteriorFeatures         23659 non-null object
RoofType                 32056 non-null object
Utilities                14017 non-null object
YearBuilt                32056 non-null int64
Url                      32056 non-null object
PrimarySchoolDistance    30162 non-null float64
PrimarySchoolName        30162 non-null object
PrimarySchoolRating      30162 non-null float64
MiddleSchoolDistance     31652 non-null float64
MiddleSchoolName         31652 non-null object
MiddleSchoolRating       31652 non-null float64
HighSchoolDistance       31980 non-null float64
HighSchoolName           31980 non-null object
HighSchoolRating         31980 non-null float64
hoa                      6804 non-null object
OnMarketDate             22271 non-null datetime64[ns]
last_upd_dt              14447 non-null datetime64[ns]
dtypes: datetime64[ns](2), float64(9), int64(15), object(19)
memory usage: 11.0+ MB
```

Drop meaningless value

Step1: Value in 'Zpid','ParcelId' and 'Zipcode' are artificially regulated. They are not naturally attribute for city. So we drop them.

Step2: For other features 'HomeStatus','StreetAddress','Url','PrimarySchoolName','MiddleSchoolName','HighSchoolName', 'OnMarketDate' and 'last_upd_dt', they are all useless for price predicting. So we drop them.

Step3: We find there are many features about price, which is the y we want to predict. 'PriceChange' 'Zestimate', 'RentZestimate' are not that useful compared to actual 'Price' itself. So we drop them.

Step4: Since 'latitude', 'longitude' are also appears in gagensus form, we should only reserve one set of them.

In [251]:
```
s_a = sale_data_df.drop(columns=['Zpid','ParcelId','HomeStatus','StreetAddres
s',
                 'Zipcode','PriceChange', 'Zestimate', 'RentZestimate','Url',
'PrimarySchoolName',
                 'MiddleSchoolName','HighSchoolName','OnMarketDate','last_upd_
dt','Latitude','Longitude'])
```

We know there may exist some mistakes when conducting web crawling. To make sure all house in this form are in GA state, we decide to check feature state. If there are houses in other state, we drop them. Then we drop 'State' feature.

In [252]:
```
s_a['State'].value_counts()
```

Out[252]:
```
GA    32044
0         9
AL        1
LA        1
OH        1
Name: State, dtype: int64
```

In [253]:
```
s_a = s_a[s_a['State'].isin(['GA'])]
sales_df = s_a.drop(columns=['State'])
```

4. Merging Data

In [254]:
```
df = sales_df.merge(city_df, on=['City'], how='inner')
```

5. Cleaning Merged data

(1) Drop rows and columns

Step1: Drop rows. Because y-'price' is what we want to predict. If its value is NaN, we cannot just fill them based on other house prices. It is not helpful for building high performance model. So we decide to drop rows which 'price' is zero.

In [255]:
```
df['Price'].value_counts()
print('Is there any missing values in Price Column?',df['Price'].isnull().any
())
```

Out[255]:
```
0         644
250000    137
399900    137
299900    136
349900    127
         ...
425766      1
194343      1
814900      1
593720      1
339998      1
Name: Price, Length: 9741, dtype: int64

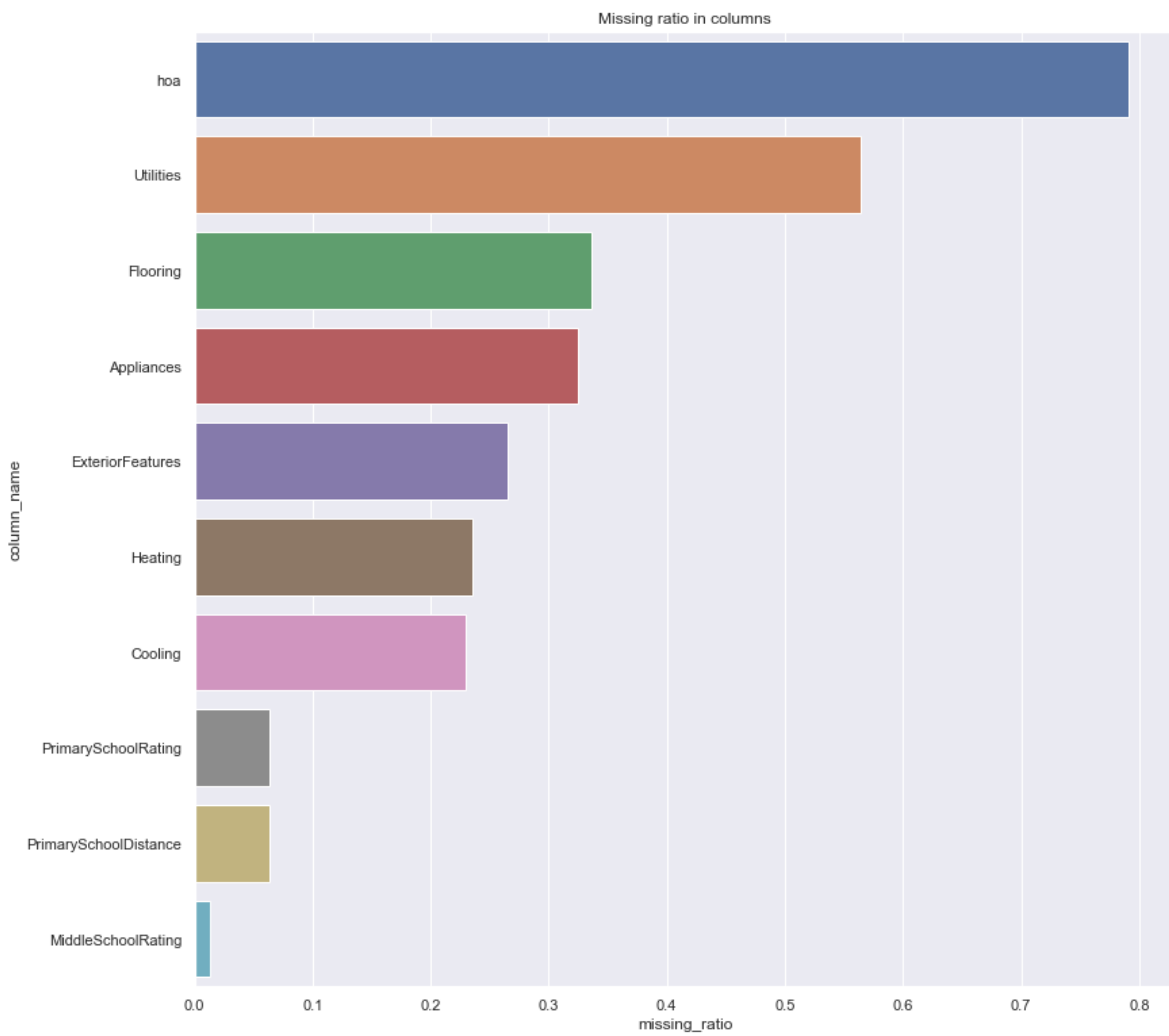
Is there any missing values in Price Column? False
```

In [256]:
```
df_1 = df.drop(index=list(np.where(df['Price']==0)[0]))
```

Step2: Drop columns. If there are so many missing values, we drop them directly.

In [257]:
```
missing_df = df.isnull().sum(axis=0).reset_index()
missing_df.columns = ['column_name', 'missing_count']
missing_df['missing_ratio'] = missing_df['missing_count'] / df.shape[0]
missing_df = missing_df.sort_values(by='missing_count', ascending=False)
sns.set(rc={'figure.figsize':(13,13)})
sns.barplot(data=missing_df[0:10], x='missing_ratio', y='column_name').set_tit
le('Missing ratio in columns')
```

Out[257]:
```
Text(0.5, 1.0, 'Missing ratio in columns')
```



We find missing values in 'hoa' and 'Utilities' are over 50%, so we drop them. Because if we fill missing values based on minority, it will have great bias.

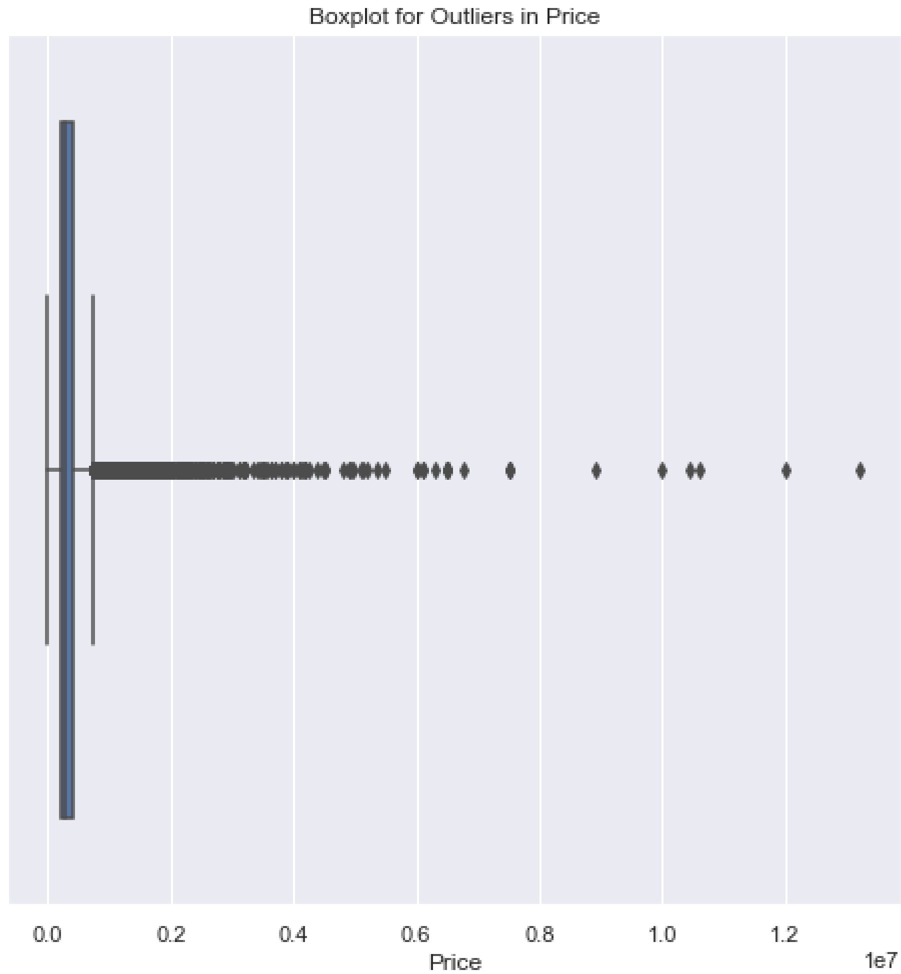
In [258]:
```
df_1 = df_1.drop(columns = ['hoa', 'Utilities'])
```

(2) Drop Outliers

We decide to drop values beyond 3 standard deviation in Price.

In [259]:
```
sns.set(rc={'figure.figsize':(8,8)})
sns.boxplot(x = df_1['Price']).set_title('Boxplot for Outliers in Price')
```

Out[259]:
```
Text(0.5, 1.0, 'Boxplot for Outliers in Price')
```



In [260]:
```
price = np.array(df_1['Price'])
mean = np.mean(price,axis=0)
sd = np.std(price, axis=0)
price_1 = [x for x in price if (x > mean - 3 * sd)]
price_2 = [x for x in price_1 if (x < mean + 3 * sd)]
print('Ratio of outliers removed in Price is %.2f' % ((len(price)-len(price_2
))/len(price)))
```

```
Ratio of outliers removed in Price is 0.01
```

In [261]:
```
df_2 = df_1[df_1['Price'].isin(list(price_2))]
```

(3) Convert object into numerical value

In [262]:
```
df_3 = df_2.select_dtypes(include='object')
df_3.head()
```

Out[262]:

	HomeType	City	Basement	Appliances	Cooling	Heating	
0	CONDO	Norcross	0	dishwasher Electric Range	Ceiling Fan S,Central Air	gas Forced Air Natural Gas	
1	SINGLE_FAMILY	Norcross	0	Range / Oven Refrigerator	Central	Forced air	Carpet
2	SINGLE_FAMILY	Norcross	Finished, Walk-Out Access, Walk-Up Access	Dishwasher Range/Oven Refrigerator Other	Central Air Ceiling Fan(s)	Other Central	H
3	TOWNHOUSE	Norcross	0	Dishwasher,Disposal,Electric Cooktop,Electric ...	Central Air	Central	Carpet,H
4	SINGLE_FAMILY	Norcross	Crawl Space	Other	Central Air	Forced Air,Natural Gas	

a. Count 'Appliances'

Fo convenience, we drop rows containing missing values of 'Appliances'. Since 'Appliances' is combined by different types, we could count them to replace string type values.

In [263]:
```
df_3 = df_2.dropna(subset = ['Appliances'])
adf =df_3['Appliances']
adf.iloc[np.where(df_3['Appliances']==0)[0]]='0'
df_al_p1=[]
for i in range(0,len(adf)):
    if adf.iloc[i] != 0:
        df_al_p1.append([len(adf.iloc[i]),adf.iloc[i].encode('raw_unicode_esca
pe'),adf.index[i]])
        df_al_pp1=[]
for i in range(0,len(df_al_p1)):
    df_al_pp1.append(df_al_p1[i][0])
for i in range(0,len(df_al_p1)):
    if df_al_p1[i][0]==max(df_al_pp1):
        print(df_al_p1[i])
```

```
[253, b'Dishwasher Range/Oven Refrigerator Disposal Double Oven Convection Ov
en Dryer Washer Central Vacuum Indoor Grill Ice Maker Gas Water Heater Cookto
p - Separate Microwave - Built In Oven - Wall ENERGY STAR Qualified Appliance
s Stainless Steel Appliance(s)', 10454]
```

In [264]:
```
df_3['Appliances']=adf
df_dpnew=df_3 # utility :u
df_dpnew.index=range(0,len(df_3))
sdsds=[]
for i in range(0,len(df_dpnew)):
    sdsds.append(0)
    if 'Dishwasher' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Range/Oven' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Refrigerator' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Disposal' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Double Oven' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Convection Oven' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Dryer' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Washer' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Central Vacuum' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Indoor Grill' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Ice Maker' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Gas Wa' in df_dpnew['Appliances'][i]: #ter Heater
        sdsds[i]=sdsds[i]+1
    if 'Cooktop - Separate' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Microwave - Built In' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'ENERGY STAR Qualified Appliances,' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Stainless Steel Appliance(s)' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Oven - Wall' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'dishwasher' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Range / Oven' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Electric Ran' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
    if 'Electric Cooktop' in df_dpnew['Appliances'][i]:
        sdsds[i]=sdsds[i]+1
```

In [265]:
```
df_3['Appliances']=sdsds
```

After filling missing value with average number, we count Appliance number again.

b. Encode other features

Step1: Encode 'HomeType' and 'City' via label encoder.

In [266]:
```
df_3['HomeType'].value_counts()
df_3['City'].value_counts()
```

Out[266]:
```
SINGLE_FAMILY    15540
TOWNHOUSE         2021
CONDO              988
LOT                508
MANUFACTURED        66
MULTI_FAMILY        48
APARTMENT            2
Name: HomeType, dtype: int64
```

Out[266]:
```
Marietta        1688
Atlanta         1315
Alpharetta       793
Lawrenceville    778
Smyrna           711
                ... 
Nelson             2
Emerson            2
Lithonia           1
Cobb               1
Mcdonough          1
Name: City, Length: 72, dtype: int64
```

In [267]:
```
encode= preprocessing.LabelEncoder()
for i in ['HomeType','City']:
    encode.fit(df_3[i])
    df_3[i]=np.array(encode.transform(df_3[i]))
```

Out[267]: `LabelEncoder()`

Out[267]: `LabelEncoder()`

Step2: Encode 'Basement', 'Cooling', 'Heating', 'Flooring', 'ExteriorFeatures' and 'RoofType'. Considering that NaN/0 may express the same thing-missing value or the house doesn't have that kind of decoration(a plain house), we decide to encode 0/Nan to 0, anything else as 1.

In [268]:
```
df_3[['Basement','Cooling','Heating','Flooring','ExteriorFeatures', 'RoofType'
]].fillna(0, inplace=True)
df_3[['Basement','Cooling','Heating','Flooring','ExteriorFeatures', 'RoofType'
]]= df_3[['Basement','Cooling','Heating','Flooring','ExteriorFeatures','RoofTy
pe']].astype(bool).astype(int)
```

(4) Fill numerical missing value

In [269]:
```
miss = list(df_3.columns[np.where(np.isnan(df_3))[1]].drop_duplicates())
miss
for i in miss:
    df_3[i].fillna(np.mean(df_3[i]),inplace=True)
df = df_3
```

Out[269]:
```
['HighSchoolDistance',
 'HighSchoolRating',
 'PrimarySchoolDistance',
 'PrimarySchoolRating',
 'MiddleSchoolDistance',
 'MiddleSchoolRating',
 'AverageHouseValue',
 'FemaleMedianAge',
 'MaleMedianAge',
 'MedianAge']
```

In [270]:
```
list(df.columns)
```

Out[270]:
```
['HomeType',
 'City',
 'Price',
 'TaxAssessedValue',
 'DaysOnZillow',
 'PageViewCount',
 'FavoriteCount',
 'Bedrooms',
 'Bathrooms',
 'Stories',
 'LivingArea',
 'LotSize',
 'Basement',
 'Appliances',
 'Cooling',
 'Heating',
 'Flooring',
 'ExteriorFeatures',
 'RoofType',
 'YearBuilt',
 'PrimarySchoolDistance',
 'PrimarySchoolRating',
 'MiddleSchoolDistance',
 'MiddleSchoolRating',
 'HighSchoolDistance',
 'HighSchoolRating',
 'BusinessMailboxes',
 'ResidentialMailboxes',
 'NumberofBusinesses',
 'NumberofEmployees',
 'Population2010',
 'CurrentPopulation',
 'AmericanIndianPopulation',
 'AsianPopulation',
 'BlackPopulation',
 'HawaiianPopulation',
 'HispanicPopulation',
 'WhitePopulation',
 'AnnualPayroll',
 'Households',
 'FemalePopulation',
 'MalePopulation',
 'IncomePerHousehold',
 'PersonsPerHousehold',
 'AverageHouseValue',
 'FemaleMedianAge',
 'MaleMedianAge',
 'MedianAge']
```

In [271]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19173 entries, 0 to 19172
Data columns (total 48 columns):
HomeType                    19173 non-null int64
City                        19173 non-null int64
Price                       19173 non-null int64
TaxAssessedValue            19173 non-null int64
DaysOnZillow                19173 non-null int64
PageViewCount               19173 non-null int64
FavoriteCount               19173 non-null int64
Bedrooms                    19173 non-null int64
Bathrooms                   19173 non-null float64
Stories                     19173 non-null int64
LivingArea                  19173 non-null int64
LotSize                     19173 non-null int64
Basement                    19173 non-null int64
Appliances                  19173 non-null int64
Cooling                     19173 non-null int64
Heating                     19173 non-null int64
Flooring                    19173 non-null int64
ExteriorFeatures            19173 non-null int64
RoofType                    19173 non-null int64
YearBuilt                   19173 non-null int64
PrimarySchoolDistance       19173 non-null float64
PrimarySchoolRating         19173 non-null float64
MiddleSchoolDistance        19173 non-null float64
MiddleSchoolRating          19173 non-null float64
HighSchoolDistance          19173 non-null float64
HighSchoolRating            19173 non-null float64
BusinessMailboxes           19173 non-null int64
ResidentialMailboxes        19173 non-null int64
NumberofBusinesses          19173 non-null int64
NumberofEmployees           19173 non-null int64
Population2010              19173 non-null int64
CurrentPopulation           19173 non-null int64
AmericanIndianPopulation    19173 non-null int64
AsianPopulation             19173 non-null int64
BlackPopulation             19173 non-null int64
HawaiianPopulation          19173 non-null int64
HispanicPopulation          19173 non-null int64
WhitePopulation             19173 non-null int64
AnnualPayroll               19173 non-null int64
Households                  19173 non-null int64
FemalePopulation            19173 non-null int64
MalePopulation              19173 non-null int64
IncomePerHousehold          19173 non-null float64
PersonsPerHousehold         19173 non-null float64
AverageHouseValue           19173 non-null float64
FemaleMedianAge             19173 non-null float64
MaleMedianAge               19173 non-null float64
MedianAge                   19173 non-null float64
dtypes: float64(13), int64(35)
memory usage: 7.0 MB
```

In [272]:
```
df
```

Out[272]:

	HomeType	City	Price	TaxAssessedValue	DaysOnZillow	PageViewCount	FavoriteCoun
0	1	51	201900	176500	9	929	3
1	5	51	110000	88800	38	2865	4
2	5	51	195000	157900	1	252	1
3	6	51	239900	227800	34	1227	8
4	5	51	210000	147000	53	1127	2
...	...	...	...	...	...	...	.
19168	5	15	89900	78970	456	588	2
19169	5	15	134990	0	396	441	2
19170	5	15	114400	98820	21	1260	7
19171	5	15	89900	59210	95	594	1
19172	5	15	83900	45220	19	1064	6

19173 rows × 48 columns

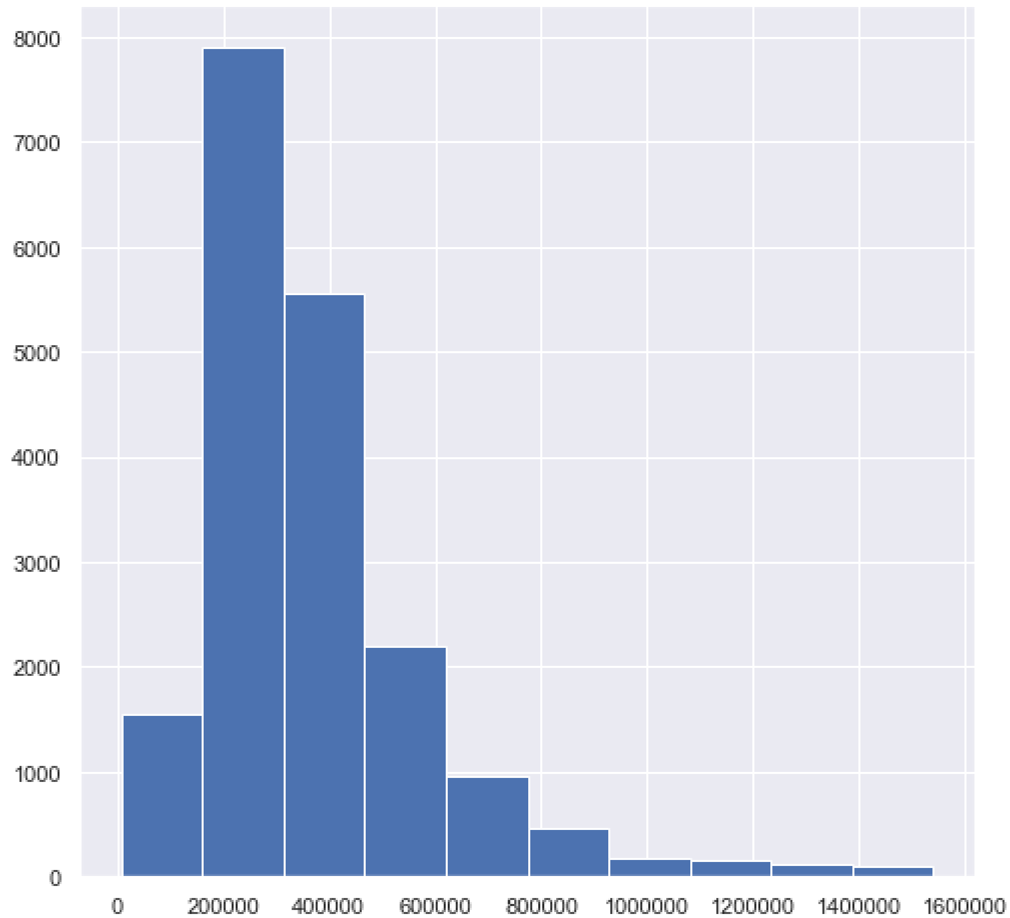
In [273]:
```
import copy
df_before_log=copy.deepcopy(df)
```

6. Transformation

For some models we may use, such as Linear Regression, there is an assumption that the data should be normal distributed. We check the most important feature y-Price, and find that it is skewed. So we decide to transform data based on powertransform method.

In [274]:
```
df['Price'].hist()
```

Out[274]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22b35b90>



In [275]:
```
from scipy.stats import boxcox
for i in list(df.columns):
    df[i], lmbda = boxcox(df[i]+1,lmbda=None)
```

In [276]:
```
df.shape
```

Out[276]: (19173, 48)

In [277]:
```
df
```

Out[277]:

	HomeType	City	Price	TaxAssessedValue	DaysOnZillow	PageViewCount	Fav
0	4.042986	20.009742	31.448482	49.051212	2.253184	14.399386	
1	410.281860	20.009742	28.366913	42.252075	3.539562	19.220562	
2	410.281860	20.009742	31.265064	47.886151	0.688625	10.002469	
3	778.460344	20.009742	32.371066	51.818083	3.438487	15.492890	
4	410.281860	20.009742	31.657014	47.151046	3.842274	15.152372	
...	...	...	...	...	...	...	
19168	410.281860	8.188015	27.398201	41.179339	5.783374	12.727179	
19169	410.281860	8.188015	29.377346	0.000000	5.657850	11.750272	
19170	410.281860	8.188015	28.558316	43.251298	3.002455	15.600367	
19171	410.281860	8.188015	27.398201	38.648009	4.372950	12.762680	
19172	410.281860	8.188015	27.072675	36.404198	2.912474	14.925177	

19173 rows × 48 columns

Log transformation

In [278]:
```
df_before_log
```

Out[278]:

	HomeType	City	Price	TaxAssessedValue	DaysOnZillow	PageViewCount	FavoriteCoun
0	1	51	201900	176500	9	929	3
1	5	51	110000	88800	38	2865	4
2	5	51	195000	157900	1	252	1
3	6	51	239900	227800	34	1227	8
4	5	51	210000	147000	53	1127	2
...	...	...	...	...	...	...	.
19168	5	15	89900	78970	456	588	2
19169	5	15	134990	0	396	441	2
19170	5	15	114400	98820	21	1260	7
19171	5	15	89900	59210	95	594	1
19172	5	15	83900	45220	19	1064	6

19173 rows × 48 columns

In [279]:
```
df_before_log_columns = ['HomeType','City','Price','TaxAssessedValue','DaysOnZ
illow','PageViewCount','FavoriteCount','Bedrooms',
                  'Bathrooms','Stories','LivingArea','LotSize','Basement','App
liances',
                  'Cooling','Heating','Flooring','ExteriorFeatures','RoofType'
                 ,'YearBuilt','PrimarySchoolDistance','PrimarySchoolRating','M
iddleSchoolDistance','MiddleSchoolRating','HighSchoolDistance',
                 'HighSchoolRating','BusinessMailboxes','ResidentialMailboxes'
,'NumberofBusinesses','NumberofEmployees','Population2010',
                  'CurrentPopulation','AmericanIndianPopulation','AsianPopulat
ion','BlackPopulation','HawaiianPopulation','HispanicPopulation',
                        'WhitePopulation','AnnualPayroll','Households','Female
Population','MalePopulation',
                        'IncomePerHousehold','PersonsPerHousehold','AverageHou
seValue',
                        'MaleMedianAge','MedianAge']
```

In [280]:
```
#Log Transformation
def process_num(d, col):
    #d.drop(d[d[col]<=0].index, inplace=True)
    d[col+'_log'] =  np.log1p(d[col])
    return d
```

In [281]:
```
num_df = df_before_log[df_before_log_columns]
num_df.info()
num_df
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19173 entries, 0 to 19172
Data columns (total 47 columns):
HomeType                    19173 non-null int64
City                        19173 non-null int64
Price                       19173 non-null int64
TaxAssessedValue            19173 non-null int64
DaysOnZillow                19173 non-null int64
PageViewCount               19173 non-null int64
FavoriteCount               19173 non-null int64
Bedrooms                    19173 non-null int64
Bathrooms                   19173 non-null float64
Stories                     19173 non-null int64
LivingArea                  19173 non-null int64
LotSize                     19173 non-null int64
Basement                    19173 non-null int64
Appliances                  19173 non-null int64
Cooling                     19173 non-null int64
Heating                     19173 non-null int64
Flooring                    19173 non-null int64
ExteriorFeatures            19173 non-null int64
RoofType                    19173 non-null int64
YearBuilt                   19173 non-null int64
PrimarySchoolDistance       19173 non-null float64
PrimarySchoolRating         19173 non-null float64
MiddleSchoolDistance        19173 non-null float64
MiddleSchoolRating          19173 non-null float64
HighSchoolDistance          19173 non-null float64
HighSchoolRating            19173 non-null float64
BusinessMailboxes           19173 non-null int64
ResidentialMailboxes        19173 non-null int64
NumberofBusinesses          19173 non-null int64
NumberofEmployees           19173 non-null int64
Population2010              19173 non-null int64
CurrentPopulation           19173 non-null int64
AmericanIndianPopulation    19173 non-null int64
AsianPopulation             19173 non-null int64
BlackPopulation             19173 non-null int64
HawaiianPopulation          19173 non-null int64
HispanicPopulation          19173 non-null int64
WhitePopulation             19173 non-null int64
AnnualPayroll               19173 non-null int64
Households                  19173 non-null int64
FemalePopulation            19173 non-null int64
MalePopulation              19173 non-null int64
IncomePerHousehold          19173 non-null float64
PersonsPerHousehold         19173 non-null float64
AverageHouseValue           19173 non-null float64
MaleMedianAge               19173 non-null float64
MedianAge                   19173 non-null float64
dtypes: float64(12), int64(35)
memory usage: 6.9 MB
```

Out[281]:

	HomeType	City	Price	TaxAssessedValue	DaysOnZillow	PageViewCount	FavoriteCoun
0	1	51	201900	176500	9	929	3
1	5	51	110000	88800	38	2865	4
2	5	51	195000	157900	1	252	1
3	6	51	239900	227800	34	1227	8
4	5	51	210000	147000	53	1127	2
...	...	...	...	...	...	...	.
19168	5	15	89900	78970	456	588	2
19169	5	15	134990	0	396	441	2
19170	5	15	114400	98820	21	1260	7
19171	5	15	89900	59210	95	594	1
19172	5	15	83900	45220	19	1064	6

19173 rows × 47 columns

In [282]:
```
for s in df_before_log_columns:
    num_df = process_num(num_df, s)
```

In [283]:
```
num_df_log = num_df.drop(df_before_log_columns, axis=1)
```

In [284]:
```
num_df_log
```

Out[284]:

	HomeType_log	City_log	Price_log	TaxAssessedValue_log	DaysOnZillow_log	PageView(
0	0.693147	3.951244	12.215533	12.081082	2.302585	
1	1.791759	3.951244	11.608245	11.394153	3.663562	
2	1.791759	3.951244	12.180760	11.969724	0.693147	
3	1.945910	3.951244	12.387982	12.336228	3.555348	
4	1.791759	3.951244	12.254868	11.898195	3.988984	
...	...	...	...	...	...	
19168	1.791759	2.772589	11.406464	11.276836	6.124683	
19169	1.791759	2.772589	11.812963	0.000000	5.983936	
19170	1.791759	2.772589	11.647465	11.501065	3.091042	
19171	1.791759	2.772589	11.406464	10.988863	4.564348	
19172	1.791759	2.772589	11.337393	10.719317	2.995732	

19173 rows × 47 columns

In [285]:
```
num_df_log.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19173 entries, 0 to 19172
Data columns (total 47 columns):
HomeType_log                   19173 non-null float64
City_log                       19173 non-null float64
Price_log                      19173 non-null float64
TaxAssessedValue_log           19173 non-null float64
DaysOnZillow_log               19173 non-null float64
PageViewCount_log              19173 non-null float64
FavoriteCount_log              19173 non-null float64
Bedrooms_log                   19173 non-null float64
Bathrooms_log                  19173 non-null float64
Stories_log                    19173 non-null float64
LivingArea_log                 19173 non-null float64
LotSize_log                    19173 non-null float64
Basement_log                   19173 non-null float64
Appliances_log                 19173 non-null float64
Cooling_log                    19173 non-null float64
Heating_log                    19173 non-null float64
Flooring_log                   19173 non-null float64
ExteriorFeatures_log           19173 non-null float64
RoofType_log                   19173 non-null float64
YearBuilt_log                  19173 non-null float64
PrimarySchoolDistance_log      19173 non-null float64
PrimarySchoolRating_log        19173 non-null float64
MiddleSchoolDistance_log       19173 non-null float64
MiddleSchoolRating_log         19173 non-null float64
HighSchoolDistance_log         19173 non-null float64
HighSchoolRating_log           19173 non-null float64
BusinessMailboxes_log          19173 non-null float64
ResidentialMailboxes_log       19173 non-null float64
NumberofBusinesses_log         19173 non-null float64
NumberofEmployees_log          19173 non-null float64
Population2010_log             19173 non-null float64
CurrentPopulation_log          19173 non-null float64
AmericanIndianPopulation_log   19173 non-null float64
AsianPopulation_log            19173 non-null float64
BlackPopulation_log            19173 non-null float64
HawaiianPopulation_log         19173 non-null float64
HispanicPopulation_log         19173 non-null float64
WhitePopulation_log            19173 non-null float64
AnnualPayroll_log              19173 non-null float64
Households_log                 19173 non-null float64
FemalePopulation_log           19173 non-null float64
MalePopulation_log             19173 non-null float64
IncomePerHousehold_log         19173 non-null float64
PersonsPerHousehold_log        19173 non-null float64
AverageHouseValue_log          19173 non-null float64
MaleMedianAge_log              19173 non-null float64
MedianAge_log                  19173 non-null float64
dtypes: float64(47)
memory usage: 6.9 MB
```

Metrics

In the beggining, we considered five regression metrics for model selection. They are MAE, MSE, RMSE, MAPE and MPE

In [286]:
```
def metrics(pred, truth):
    print("MAE: %.2f" % np.mean(np.abs(pred- truth))) #MAE
    print("MSE: %.2f" % np.mean((pred- truth) ** 2))   #MSE
    print("RMSE: %.2f" % np.sqrt(np.mean((pred - truth) ** 2))) #RMSE
    print("MAPE: %.2f" % (np.mean(np.abs((pred -truth) / truth)) * 100)) #MAPE
    print("MPE: %.2f" % (np.mean((pred - truth) /truth)* 100))  #MPE
```

MPE used for proxy on bias. The bias alone won't be enough to evaluate our forecast precision.

After data exploration and data preprocessing, we already removed outliers we defined. According to the paper (Georgios.D), MAE,MAPE (MAPE is considered as the weighted version of MAE the optimal constant predictions for MAPE it turns out to be the weighted median of the target value) can penalize huge errors that not as that badly as MSE does. Thus, they are not that sensitive to outliers as mean square error. In conclusin, MAE provides a protection against outliers whereas RMSE and MSE provides the assurance to get an unbiased forecast.If using MAE as a metric results in a high bias, we might want to use RMSE (Nicolas. V). If the dataset contains many outliers, resulting in a skewed forecast, we might want to use MAE. In this case, we do not have outliers anymore and also we prefer to care about model accuracy. Therefore, we prefer to use RMSE and MSE.

It is also hard to realize if our model is good or not by looking at the absolute values of MSE or RMSE. We want to measure how much our model is better than the constant baseline.

The coefficient of determination, or R^2, is the main metric we use to evaluate a model and it is closely related to MSE, but has the advantage of being scale-free — it doesn't matter if the output values are very large or very small, the R^2 is always going to be between $-\infty$ and 1.In conclusion, R^2 is the ratio between how good our model is vs how good is the naive mean model.

Therefore, Our main regresison metric for model selection will be R^2. We also will check model's MSE and RMSE.

In [287]:
```
from sklearn.metrics import r2_score
def metrics_new(pred, truth):
    #print("MAE: %.2f" % np.mean(np.abs(pred- truth))) #MAE
    print("MSE: %.2f" % np.mean((pred- truth) ** 2))   #MSE
    print("RMSE: %.2f" % np.sqrt(np.mean((pred - truth) ** 2))) #RMSE
    #print("MAPE: %.2f" % (np.mean(np.abs((pred -truth) / truth)) * 100)) #MAP
E
    #print("MPE: %.2f" % (np.mean((pred - truth) /truth)* 100))  #MPE
    print("R^2: %.3f" % (r2_score(truth, pred))) #R^2
```

Spliting Data into Training and Testing dataset

In [288]:
```
Y = num_df_log['Price_log']
X = num_df_log.drop(['Price_log'], axis=1)
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, rando
m_state=2020)
```

PART TWO-exploratory data analysis and test hypotheses

Dataset before transformation:num_df

1. general introduction

In [289]:
```
num_df.describe()
```

Out[289]:

	HomeType	City	Price	TaxAssessedValue	DaysOnZillow	PageViewCou
count	19173.000000	19173.000000	1.917300e+04	1.917300e+04	19173.000000	19173.000C
mean	4.809889	33.134825	3.684249e+05	1.822540e+05	353.773379	647.109C
std	1.072921	21.188028	2.153710e+05	1.969438e+05	1119.483445	768.9501
min	0.000000	0.000000	7.500000e+03	0.000000e+00	0.000000	0.000C
25%	5.000000	15.000000	2.300000e+05	0.000000e+00	26.000000	137.000C
50%	5.000000	36.000000	3.159900e+05	1.504000e+05	77.000000	410.000C
75%	5.000000	50.000000	4.430250e+05	2.777100e+05	165.000000	884.000C
max	6.000000	71.000000	1.540000e+06	5.050440e+06	14536.000000	14877.000C

8 rows × 94 columns

2. Missing Value:NO

After the data processing, we dealt with all the missing values, so there are no more missing values in the dataset.

In [290]:
```
mv=[]
for i in num_df.columns:
    mv.append(num_df[i].isnull().any())
```

In [291]:
```
pd.DataFrame({'Feature':num_df.columns,
              'Missing value':mv
             })
```

Out[291]:

	Feature	Missing value
0	HomeType	False
1	City	False
2	Price	False
3	TaxAssessedValue	False
4	DaysOnZillow	False
...	...	...
89	IncomePerHousehold_log	False
90	PersonsPerHousehold_log	False
91	AverageHouseValue_log	False
92	MaleMedianAge_log	False
93	MedianAge_log	False

94 rows × 2 columns

3.Outliers

3.1 scatter diagram

we will first use diagram to show whether features include outliers. For some of the features are categorical features before, so we choose some of the original numerical features to find the outliers.

In [228]:
```
col=[]
for i in num_df.columns:
    col.append(i)
```

In [229]:
```
for i in range(1,48):
    #yi = np.sin(2*np.pi*t)
    #y2 = np.sin(2*np.pi*t)
    plt.subplot(10,5,i)
    b=num_df[col[i-1]]
    #plt.figure(figsize=(1,1))
    plt.scatter(range(0,len(num_df)),b)
    #plt.subplots_adjust(wspace=0, hspace=0)
    #fig.subplots_adjust(wspace=0.5,hspace=0.5)
    plt.subplots_adjust(left=4, bottom=4, right=5, top=5,
                    wspace=1, hspace=1)
```

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a262d1850>

Out[229]: <matplotlib.collections.PathCollection at 0x1a270a1110>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2606f550>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26b87b10>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a262d14d0>

Out[229]: <matplotlib.collections.PathCollection at 0x1a27148c90>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a271b7110>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26390a90>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a26fff3d0>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26fffc50>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a271d9510>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26383cd0>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a271d9150>

Out[229]: <matplotlib.collections.PathCollection at 0x1a271c4990>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a26e6b350>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26e8b7d0>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2639b8d0>

Out[229]: <matplotlib.collections.PathCollection at 0x1a260f6bd0>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a271aa1d0>

Out[229]: <matplotlib.collections.PathCollection at 0x1a25a81410>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a25816a50>

Out[229]: <matplotlib.collections.PathCollection at 0x1a26e74b90>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2522c090>

Out[229]: <matplotlib.collections.PathCollection at 0x1a25a81f10>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a257597d0>

Out[229]: <matplotlib.collections.PathCollection at 0x1a25759950>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2578e090>

Out[229]: <matplotlib.collections.PathCollection at 0x1a2523db50>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a257b3990>

Out[229]: <matplotlib.collections.PathCollection at 0x1a257b3b90>

Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a262d1750>

Out[229]: <matplotlib.collections.PathCollection at 0x1a2586ed50>

```
Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a259bf550>
Out[229]: <matplotlib.collections.PathCollection at 0x1a259bf6d0>
Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a25ae2ed0>
Out[229]: <matplotlib.collections.PathCollection at 0x1a25afb350>
Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a26a4e410>
Out[229]: <matplotlib.collections.PathCollection at 0x1a26a55ed0>
Out[229]: <matplotlib.axes._subplots.AxesSubplot at 0x1a26a5ee50>
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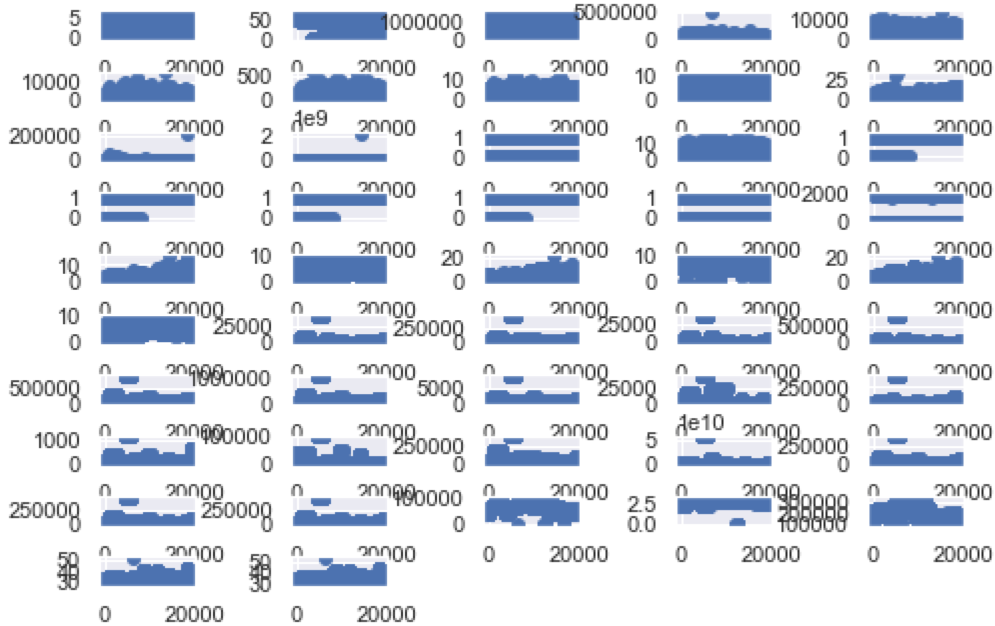
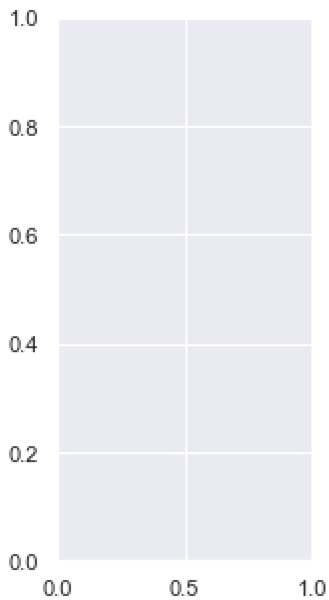
```

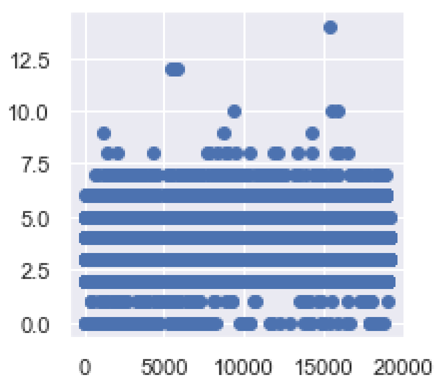


In [230]:
```
k=5
fig=plt.figure(figsize=(k,k))
ax1=fig.add_subplot(1,2,1)
plt.figure(figsize=(3,3))
plt.scatter(range(0,len(num_df['Bedrooms'])),num_df['Bedrooms'])
plt.subplots_adjust(wspace=0, hspace=0)
```

Out[230]: <Figure size 216x216 with 0 Axes>

Out[230]: <matplotlib.collections.PathCollection at 0x1a2392b8d0>





In [231]:
```
for i in num_df.columns:
    plt.figure(figsize=(3,3))
    plt.scatter(range(0,len(num_df[i])),num_df[i])
    plt.subplots_adjust(wspace=0, hspace=0)
    plt.title(i)
```

```
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a24004990>
Out[231]: Text(0.5, 1.0, 'HomeType')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a23fe3c10>
Out[231]: Text(0.5, 1.0, 'City')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a24067050>
Out[231]: Text(0.5, 1.0, 'Price')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a24073590>
Out[231]: Text(0.5, 1.0, 'TaxAssessedValue')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a2479e490>
Out[231]: Text(0.5, 1.0, 'DaysOnZillow')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a247b3410>
Out[231]: Text(0.5, 1.0, 'PageViewCount')
Out[231]: <Figure size 216x216 with 0 Axes>
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Out[231]: <matplotlib.collections.PathCollection at 0x1a24a628d0>
Out[231]: Text(0.5, 1.0, 'Bedrooms')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a24ba0290>
Out[231]: Text(0.5, 1.0, 'Bathrooms')
Out[231]: <Figure size 216x216 with 0 Axes>
Out[231]: <matplotlib.collections.PathCollection at 0x1a24cc1290>
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```
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Out[231]: <matplotlib.collections.PathCollection at 0x1a256d3f90>
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```

```
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```

```
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```
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```
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```

```
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Out[231]: Text(0.5, 1.0, 'WhitePopulation_log')
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```

```
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Out[231]: Text(0.5, 1.0, 'AnnualPayroll_log')

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Out[231]: Text(0.5, 1.0, 'Households_log')

Out[231]: <Figure size 216x216 with 0 Axes>

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Out[231]: Text(0.5, 1.0, 'FemalePopulation_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8c62150>

Out[231]: Text(0.5, 1.0, 'MalePopulation_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8d4e150>

Out[231]: Text(0.5, 1.0, 'IncomePerHousehold_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8ddb610>

Out[231]: Text(0.5, 1.0, 'PersonsPerHousehold_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8e68ad0>

Out[231]: Text(0.5, 1.0, 'AverageHouseValue_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8ef6410>

Out[231]: Text(0.5, 1.0, 'MaleMedianAge_log')

Out[231]: <Figure size 216x216 with 0 Axes>

Out[231]: <matplotlib.collections.PathCollection at 0x1aa8f8c490>

Out[231]: Text(0.5, 1.0, 'MedianAge_log')
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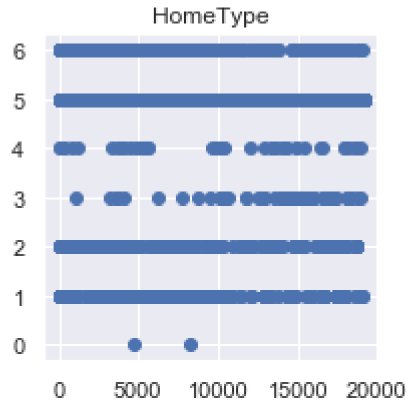
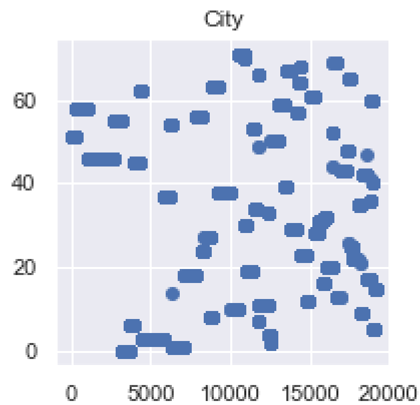
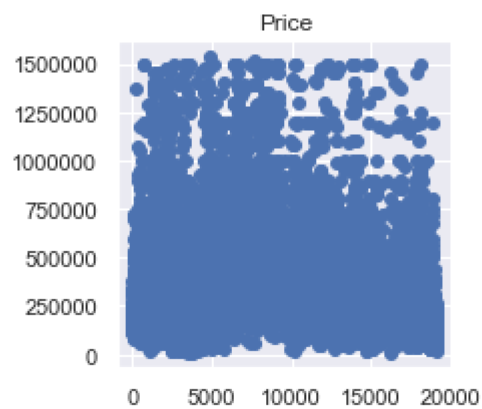
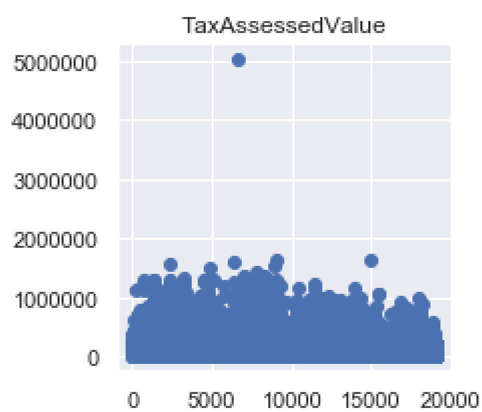
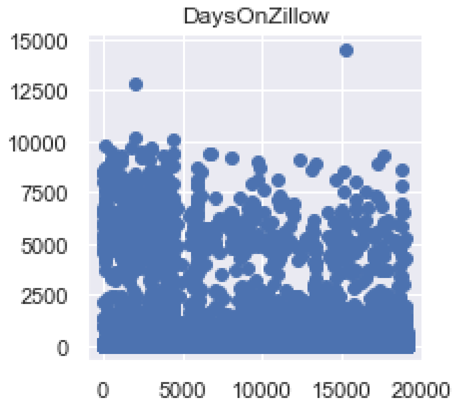
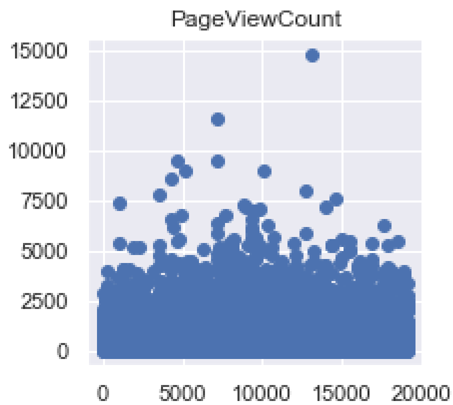

HomeType
6
5
4
3
2
1
0
0
5000
10000
15000
20000

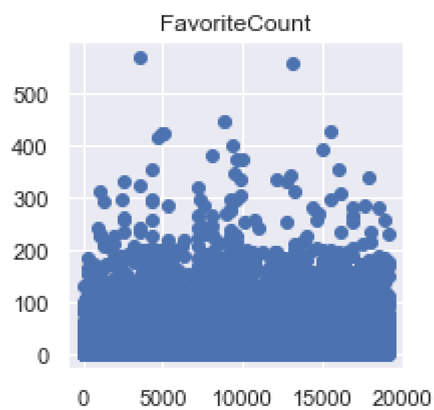

City
60
40
20
0
0
5000
10000
15000
20000

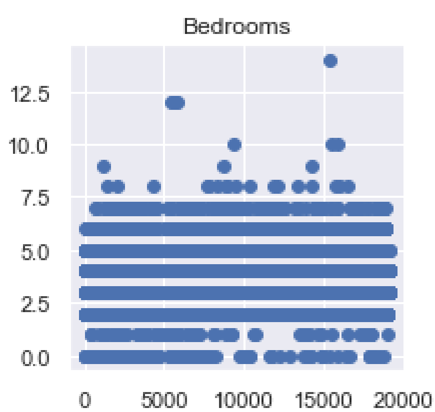

Price
1500000
1250000
1000000
750000
500000
250000
0
0
5000
10000
15000
20000

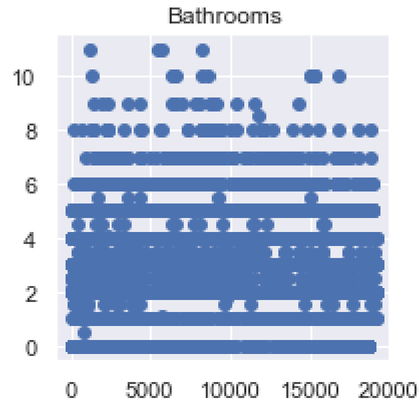

TaxAssessedValue
5000000
4000000
3000000
2000000
1000000
0
0
5000
10000
15000
20000

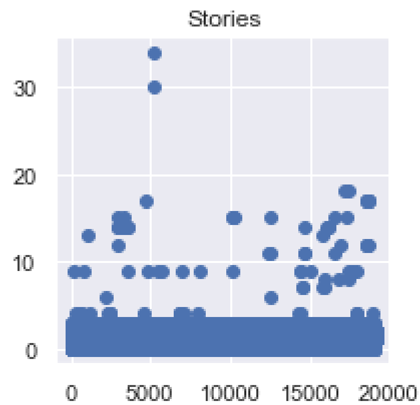

DaysOnZillow
15000
12500
10000
7500
5000
2500
0
0
5000
10000
15000
20000

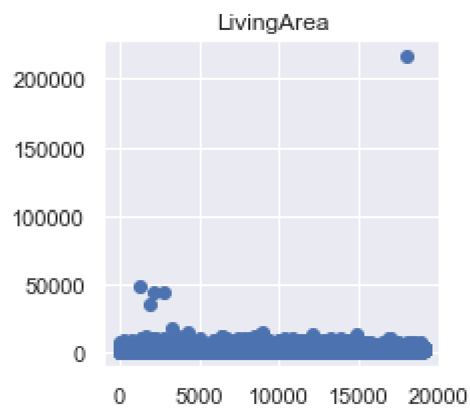

PageViewCount
15000
12500
10000
7500
5000
2500
0
0
5000
10000
15000
20000

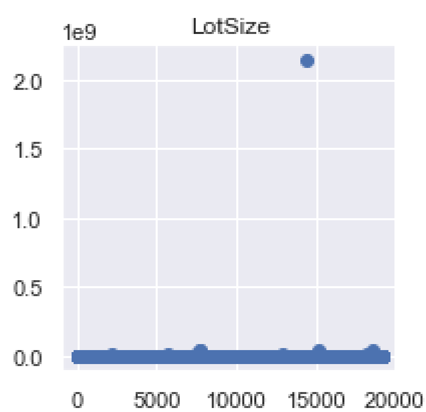

FavoriteCount
500
400
300
200
100
0
0
5000
10000
15000
20000


Bedrooms
12.5
10.0
7.5
5.0
2.5
0.0
0
5000
10000
15000
20000

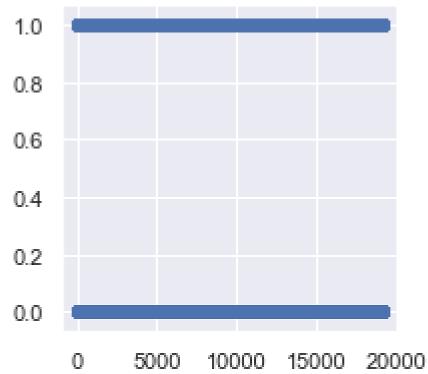

Bathrooms
10
8
6
4
2
0
0
5000
10000
15000
20000


Stories
30
20
10
0
0
5000
10000
15000
20000

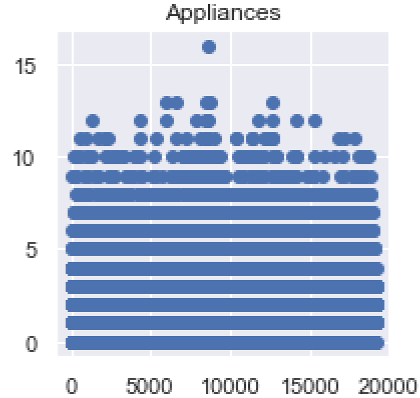

LivingArea
200000
150000
100000
50000
0
0
5000
10000
15000
20000


LotSize
1e9
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

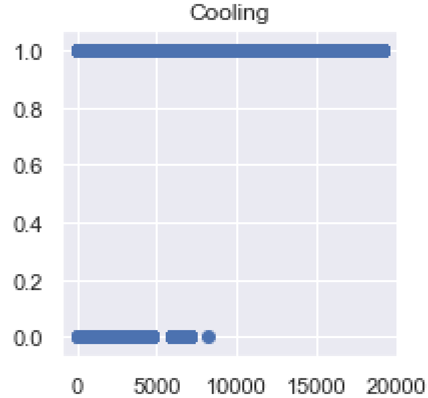
Basement



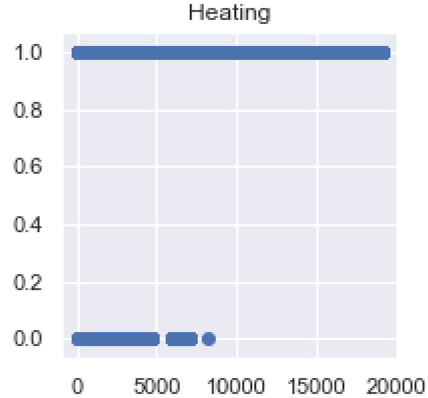
Appliances

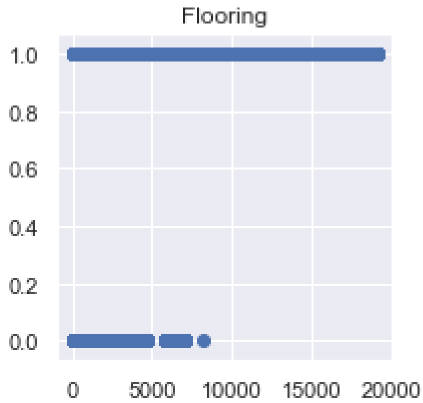


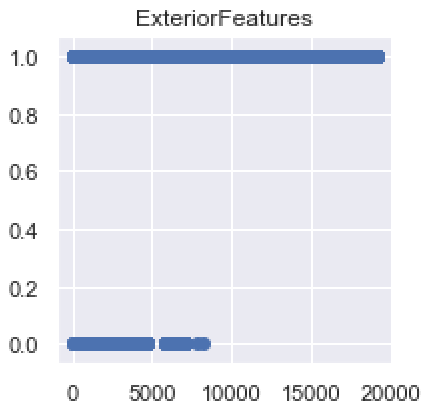
Cooling

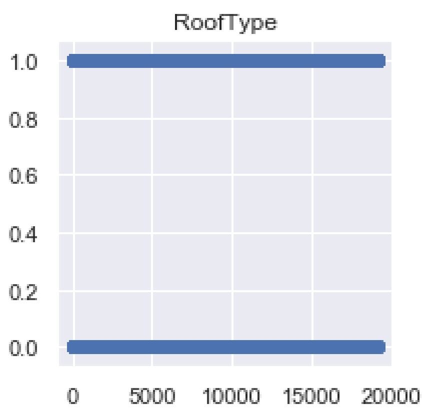


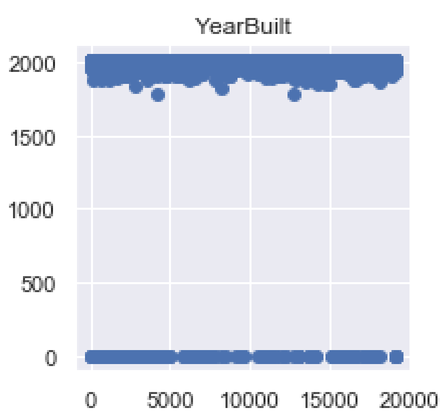
Heating

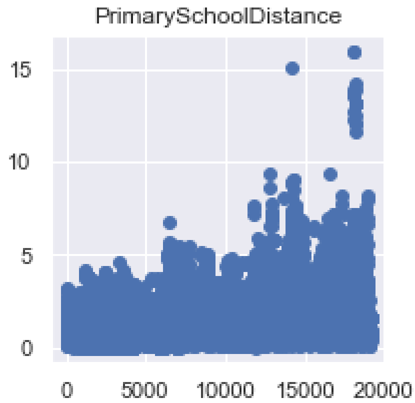


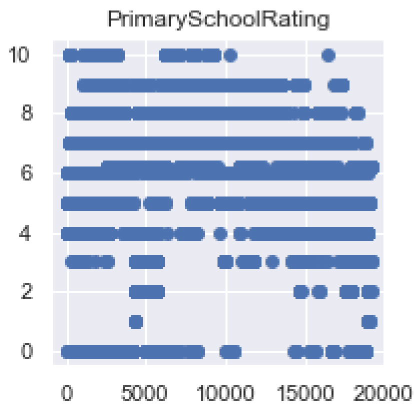

Flooring
1.0
0.8
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000


ExteriorFeatures
1.0
0.8
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000


RoofType
1.0
0.8
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000


YearBuilt
2000
1500
1000
500
0
0
5000
10000
15000
20000


PrimarySchoolDistance
15
10
5
0
0 5000 10000 15000 20000


PrimarySchoolRating
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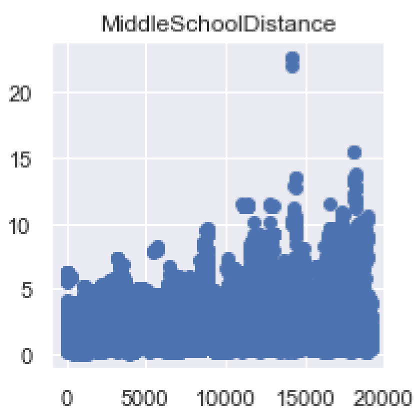
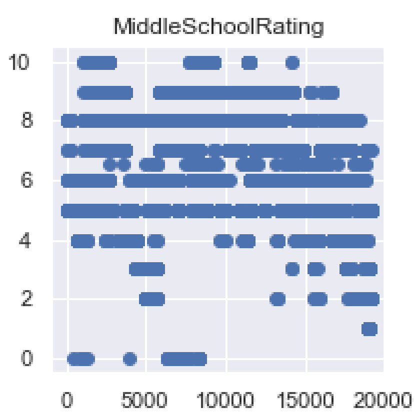
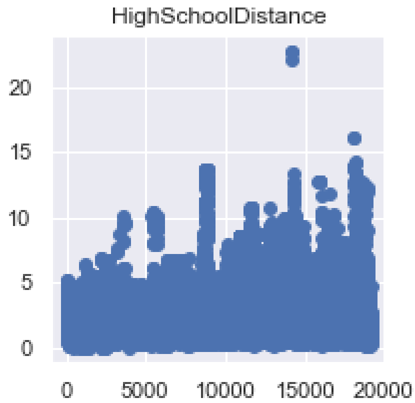
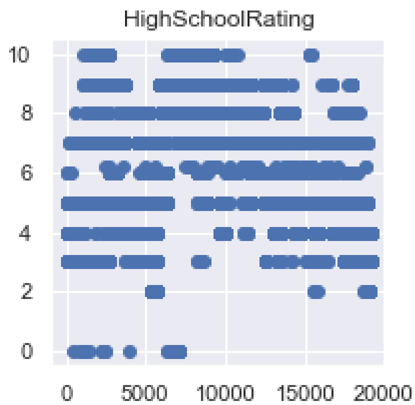
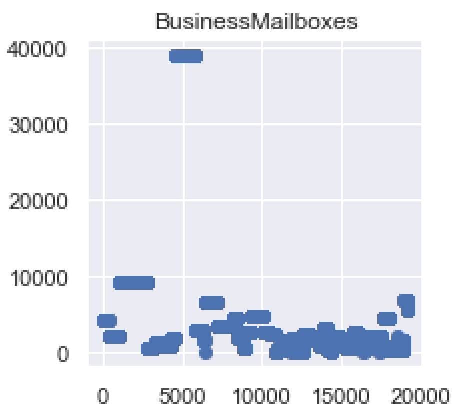
8
6
4
2
0
0 5000 10000 15000 20000

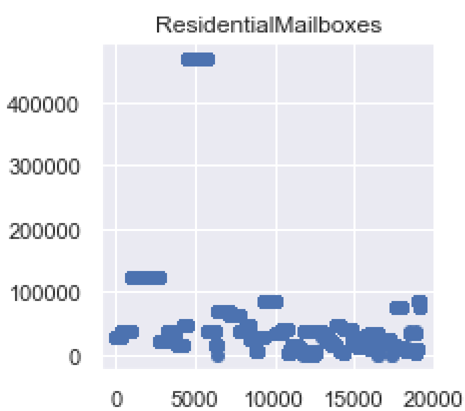

MiddleSchoolDistance
20
15
10
5
0
0 5000 10000 15000 20000

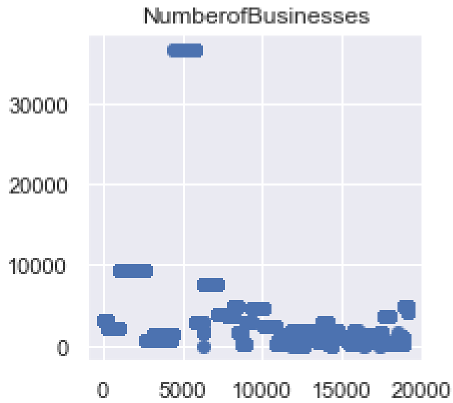

MiddleSchoolRating
10
8
6
4
2
0
0 5000 10000 15000 20000

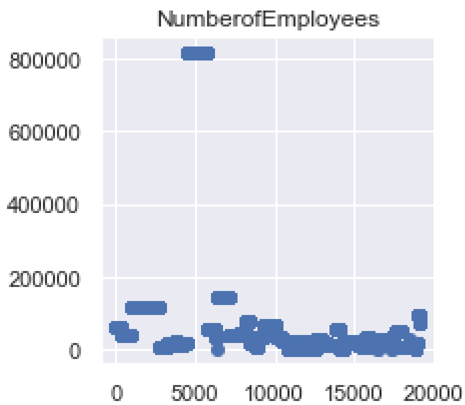

HighSchoolDistance
20
15
10
5
0
0
5000
10000
15000
20000

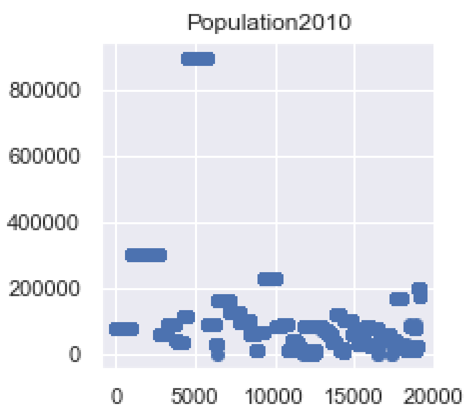

HighSchoolRating
10
8
6
4
2
0
0
5000
10000
15000
20000

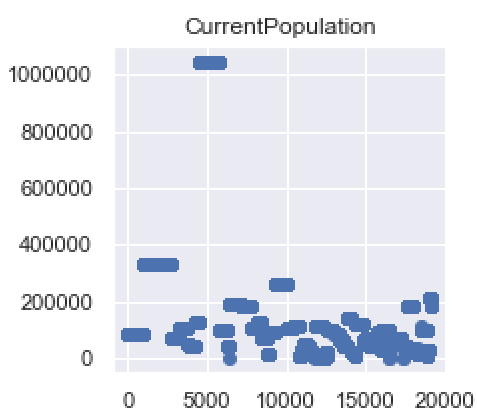

BusinessMailboxes
40000
30000
20000
10000
0
0
5000
10000
15000
20000

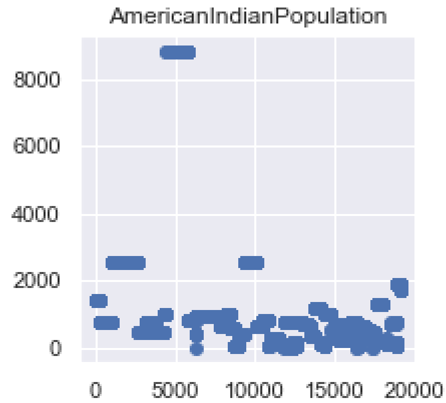

ResidentialMailboxes
400000
300000
200000
100000
0
0
5000
10000
15000
20000

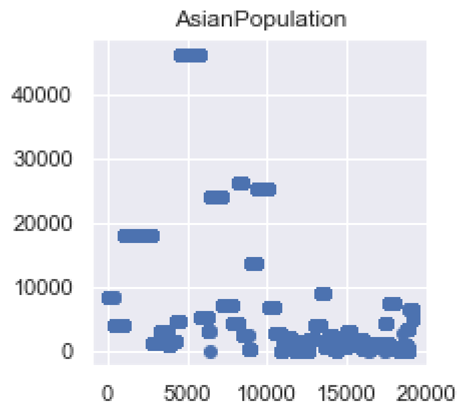

NumberofBusinesses
30000
20000
10000
0
0
5000
10000
15000
20000

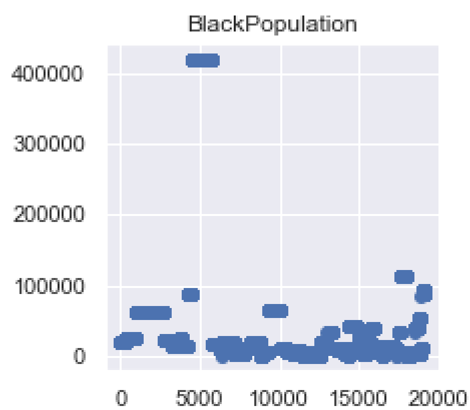

NumberofEmployees
800000
600000
400000
200000
0
0
5000
10000
15000
20000

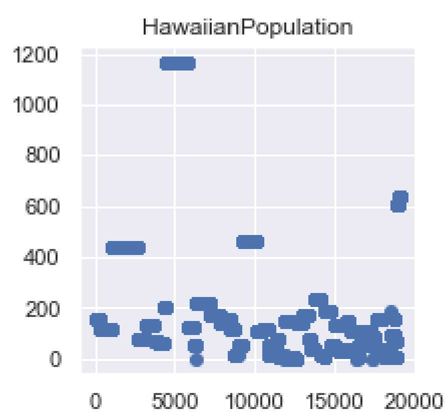

Population2010
800000
600000
400000
200000
0
0
5000
10000
15000
20000

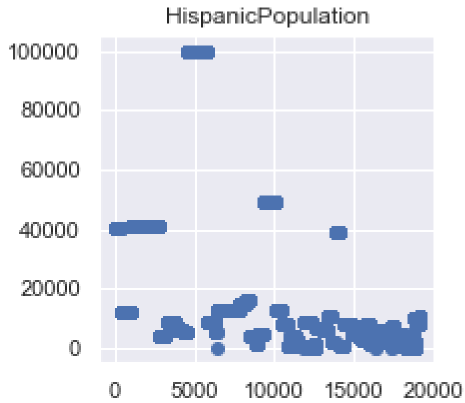

CurrentPopulation
1000000
800000
600000
400000
200000
0
0
5000
10000
15000
20000

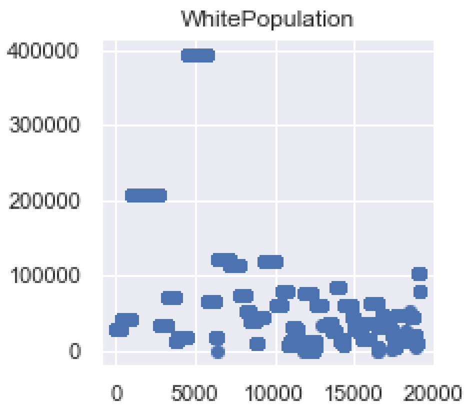

AmericanIndianPopulation
8000
6000
4000
2000
0
0
5000
10000
15000
20000

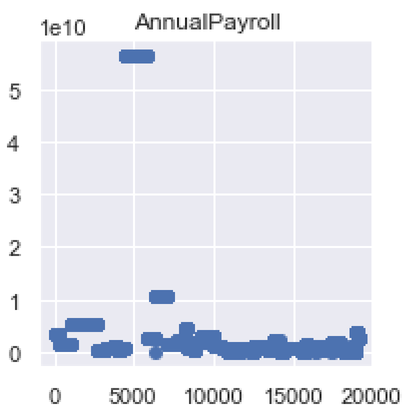

AsianPopulation
40000
30000
20000
10000
0
0
5000
10000
15000
20000

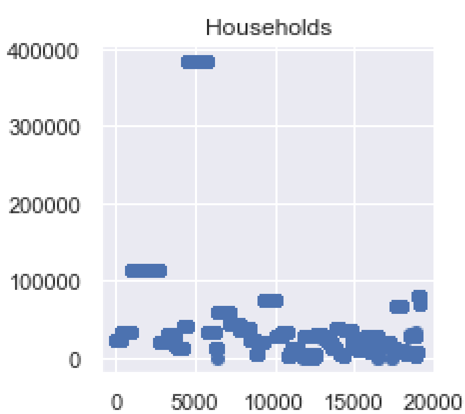

BlackPopulation
400000
300000
200000
100000
0
0
5000
10000
15000
20000

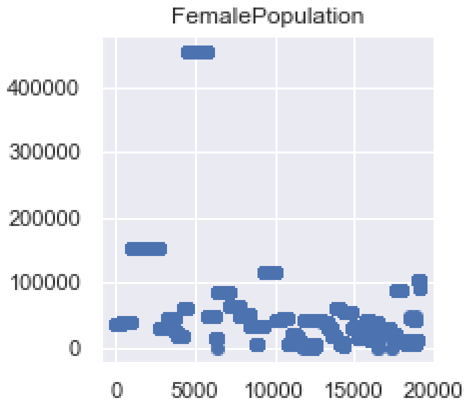

HawaiianPopulation
1200
1000
800
600
400
200
0
0
5000
10000
15000
20000

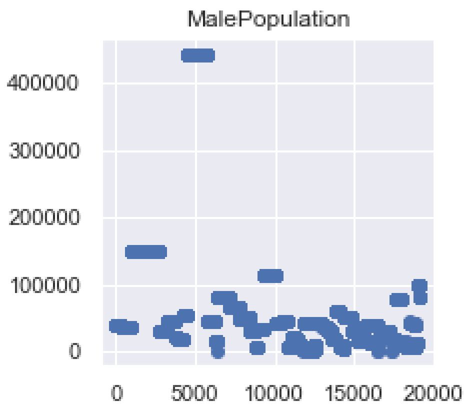

HispanicPopulation
100000
80000
60000
40000
20000
0
0
5000
10000
15000
20000

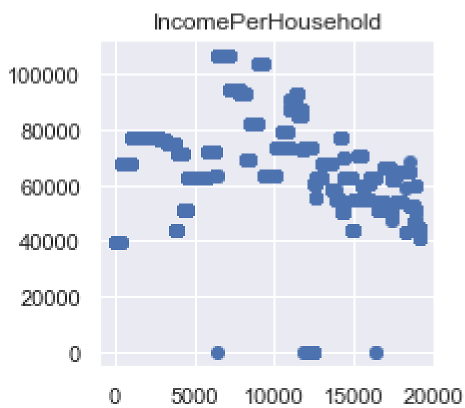

WhitePopulation
400000
300000
200000
100000
0
0
5000
10000
15000
20000

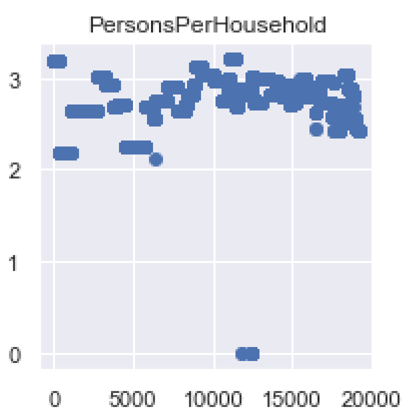

1e10
AnnualPayroll
5
4
3
2
1
0
0
5000
10000
15000
20000

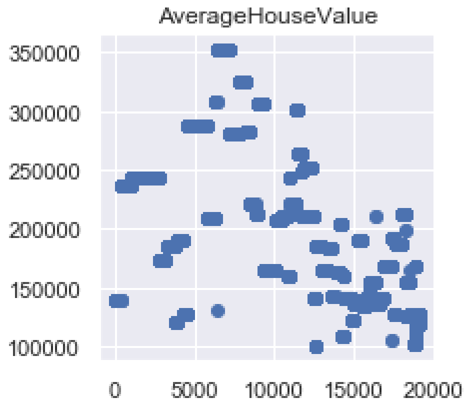

Households
400000
300000
200000
100000
0
0
5000
10000
15000
20000

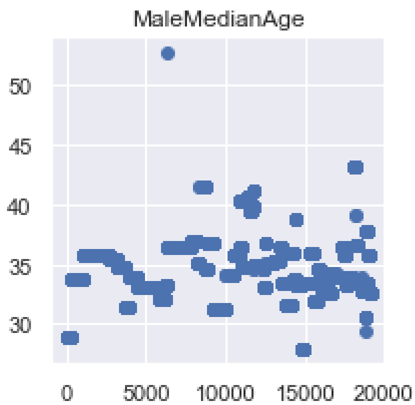

FemalePopulation
400000
300000
200000
100000
0
0
5000
10000
15000
20000

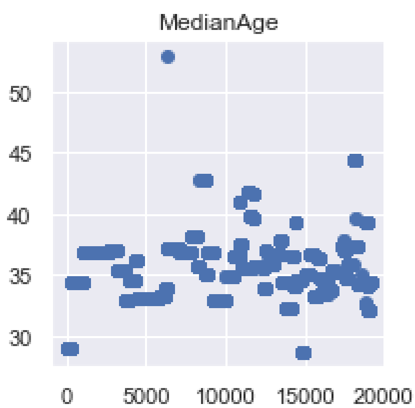

MalePopulation
400000
300000
200000
100000
0
0
5000
10000
15000
20000

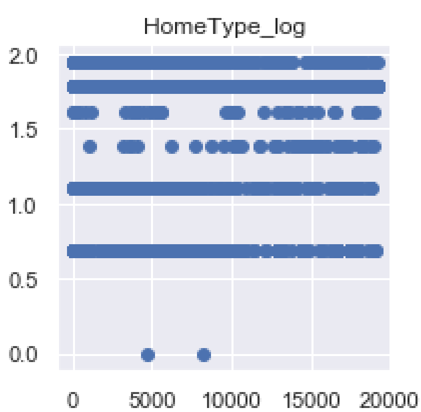

IncomePerHousehold
100000
80000
60000
40000
20000
0
0
5000
10000
15000
20000

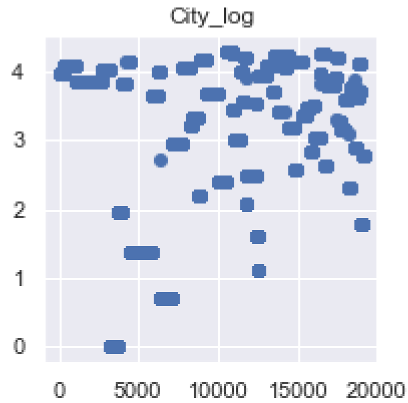

PersonsPerHousehold
3
2
1
0
0
5000
10000
15000
20000

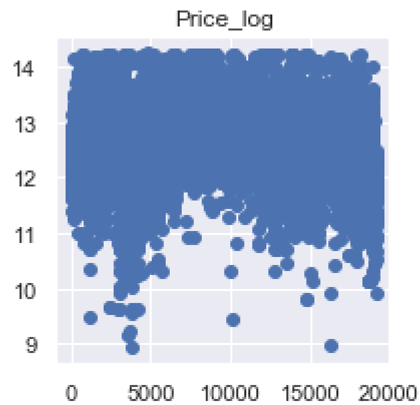

AverageHouseValue
350000
300000
250000
200000
150000
100000
0
5000
10000
15000
20000

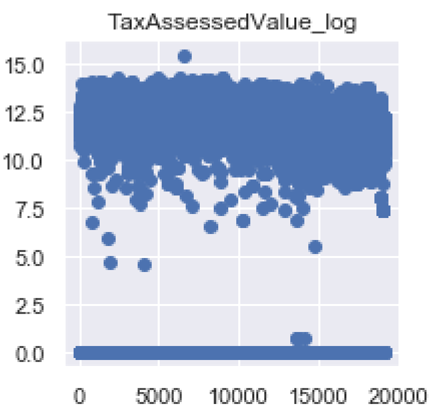

MaleMedianAge
50
45
40
35
30
0
5000
10000
15000
20000

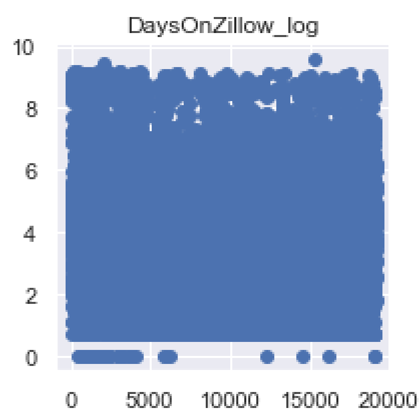

MedianAge
50
45
40
35
30
0
5000
10000
15000
20000

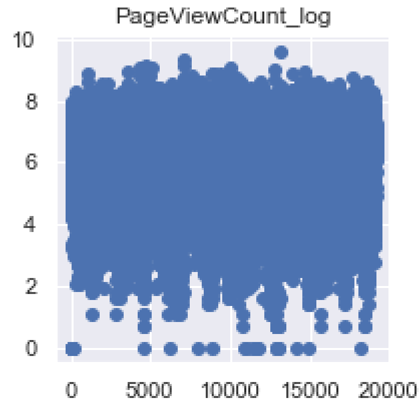

HomeType_log
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

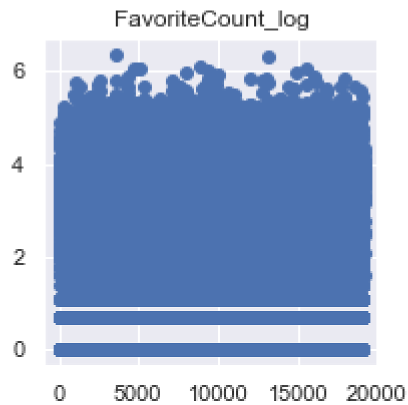

City_log
4
3
2
1
0
0
5000
10000
15000
20000

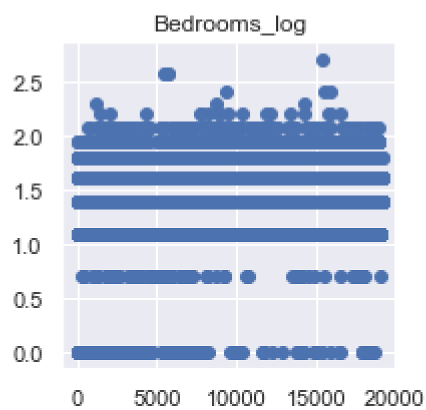

Price_log
14
13
12
11
10
9
0
5000
10000
15000
20000

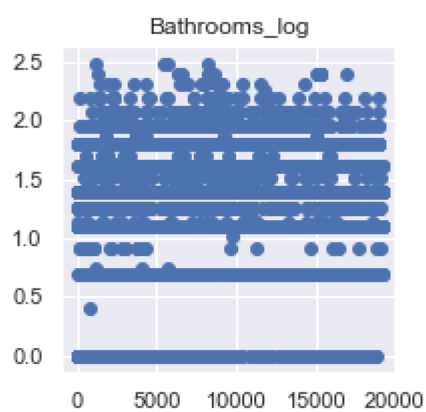

TaxAssessedValue_log
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
5000
10000
15000
20000

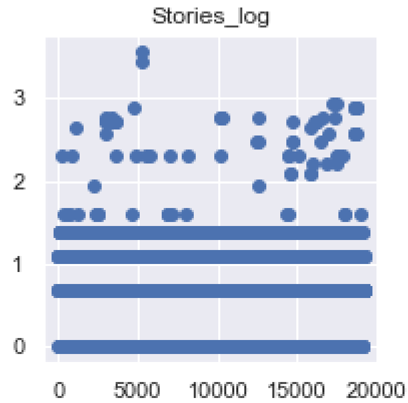

DaysOnZillow_log
10
8
6
4
2
0
0
5000
10000
15000
20000

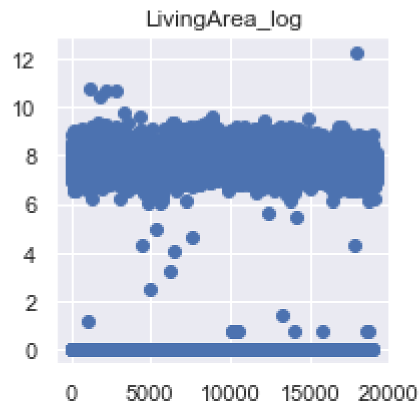

PageViewCount_log
10
8
6
4
2
0
0
5000
10000
15000
20000

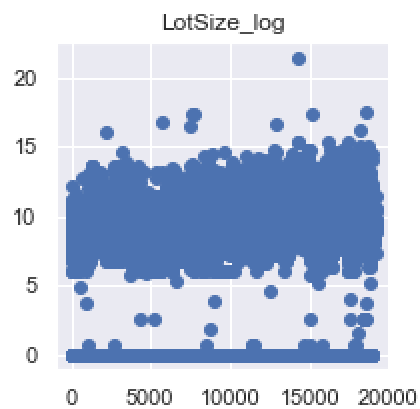

FavoriteCount_log
6
4
2
0
0
5000
10000
15000
20000

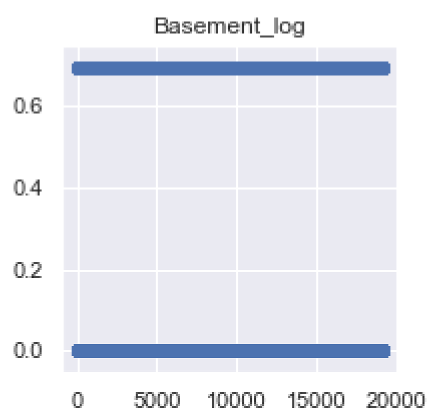

Bedrooms_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

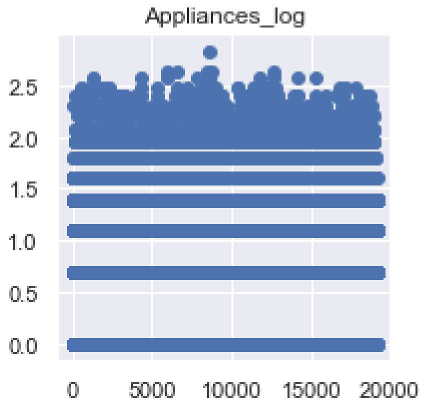

Bathrooms_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

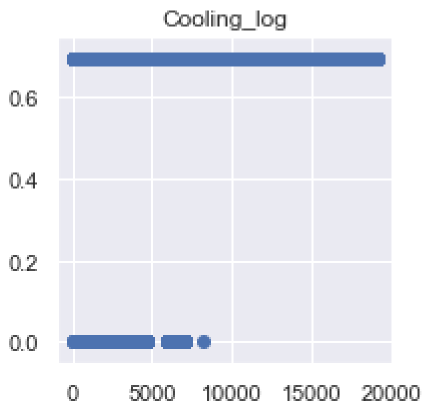

Stories_log
0
1
2
3
0
5000
10000
15000
20000

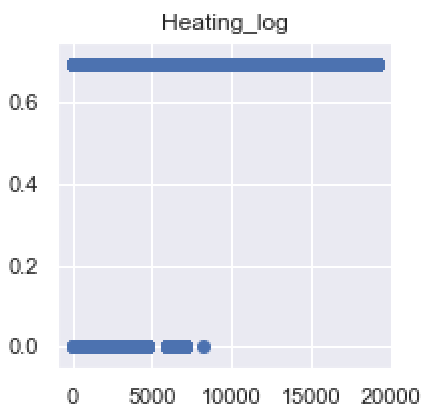

LivingArea_log
0
2
4
6
8
10
12
0
5000
10000
15000
20000

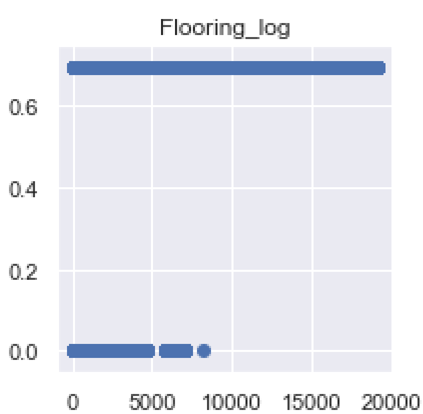

LotSize_log
0
5
10
15
20
0
5000
10000
15000
20000

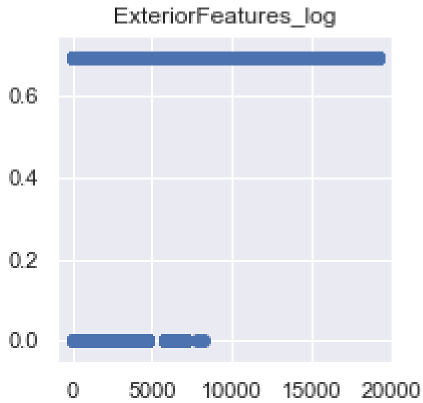

Basement_log
0.0
0.2
0.4
0.6
0
5000
10000
15000
20000

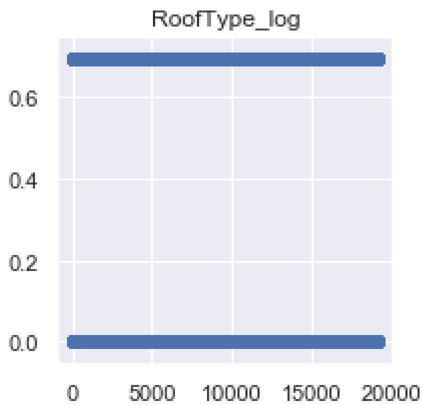

Appliances_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

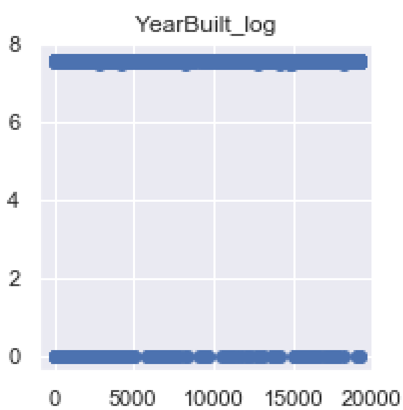

Cooling_log
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000

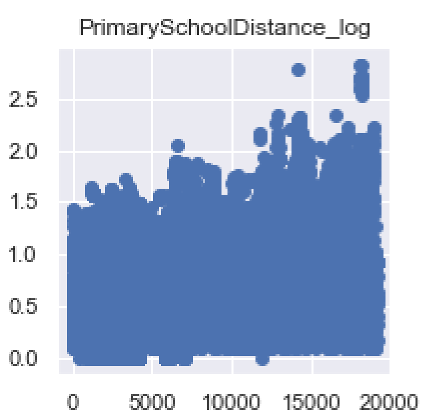

Heating_log
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000

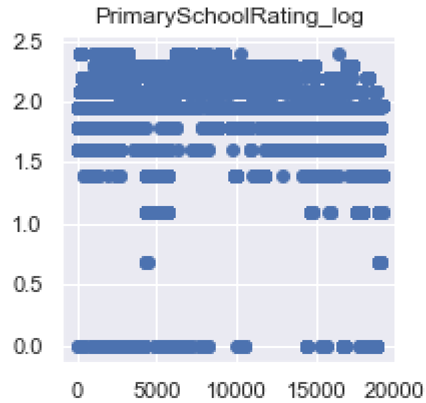

Flooring_log
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000

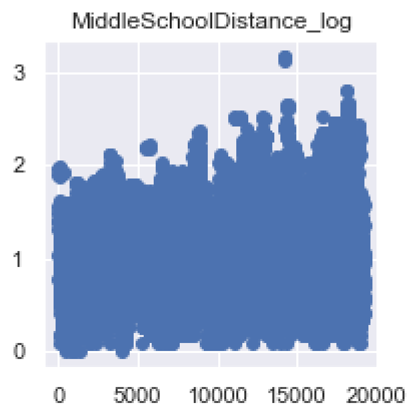

ExteriorFeatures_log
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000

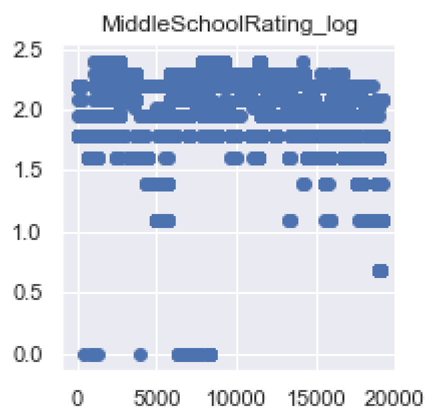

RoofType_log
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000

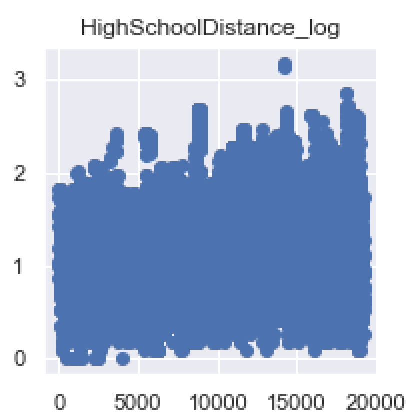

YearBuilt_log
8
6
4
2
0
0
5000
10000
15000
20000

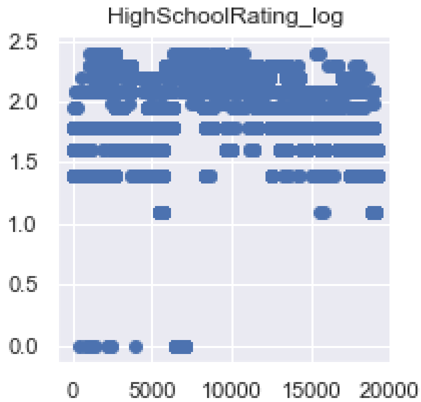

PrimarySchoolDistance_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

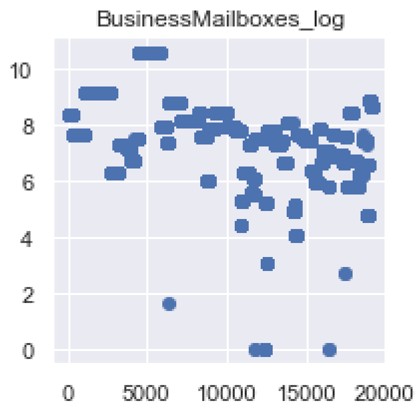

PrimarySchoolRating_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

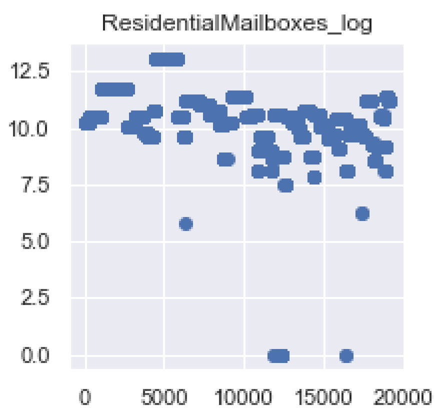

MiddleSchoolDistance_log
3
2
1
0
0
5000
10000
15000
20000

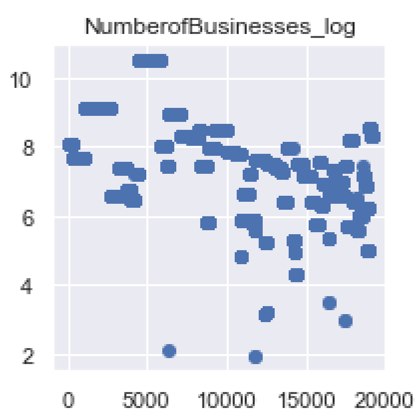

MiddleSchoolRating_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

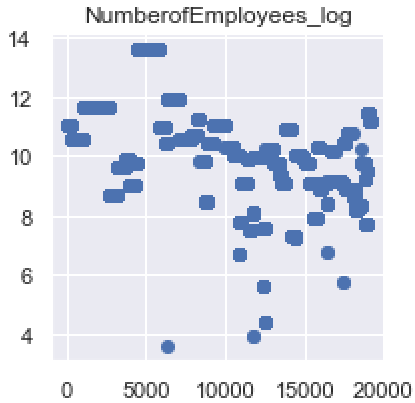

HighSchoolDistance_log
3
2
1
0
0
5000
10000
15000
20000

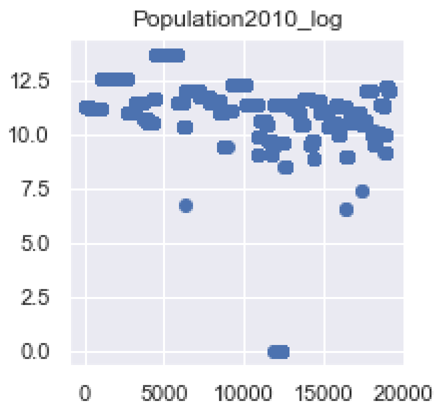

HighSchoolRating_log
2.5
2.0
1.5
1.0
0.5
0.0
0
5000
10000
15000
20000

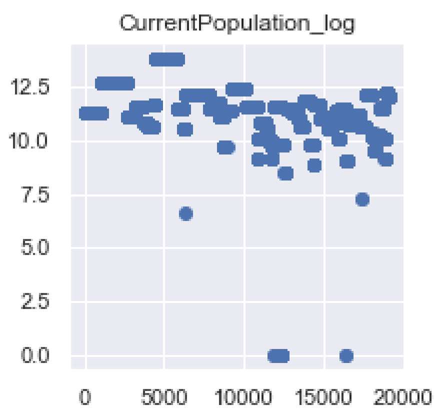

BusinessMailboxes_log
10
8
6
4
2
0
0
5000
10000
15000
20000

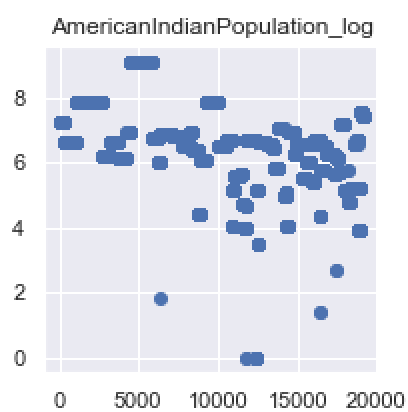

ResidentialMailboxes_log
12.5
10.0
7.5
5.0
2.5
0.0
0
5000
10000
15000
20000

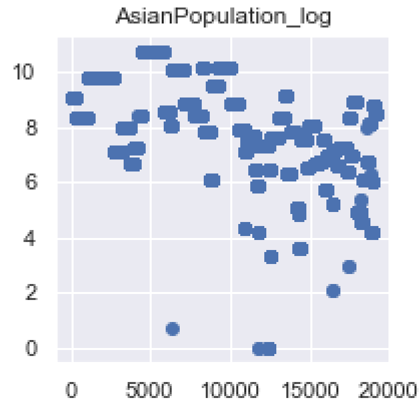

NumberofBusinesses_log
10
8
6
4
2
0
5000
10000
15000
20000

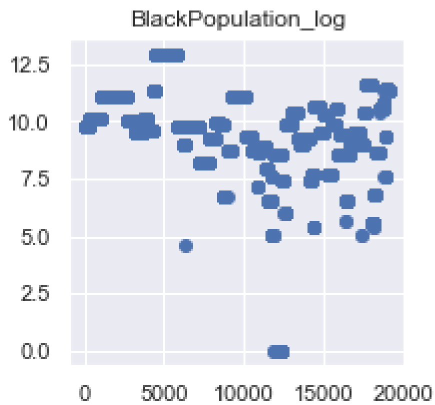

NumberofEmployees_log
14
12
10
8
6
4
0
5000
10000
15000
20000

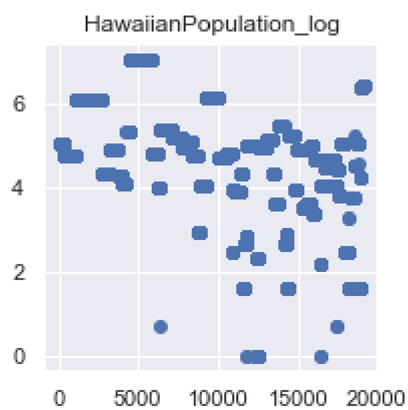

Population2010_log
12.5
10.0
7.5
5.0
2.5
0.0
0
5000
10000
15000
20000

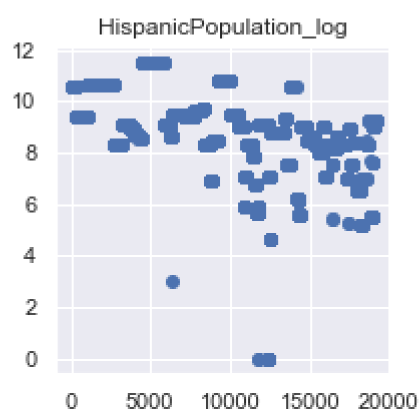

CurrentPopulation_log
12.5
10.0
7.5
5.0
2.5
0.0
0
5000
10000
15000
20000


AmericanIndianPopulation_log
8
6
4
2
0
0
5000
10000
15000
20000

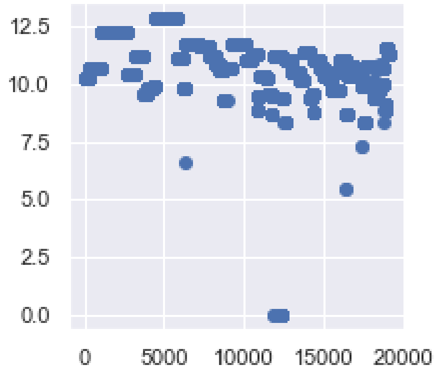

AsianPopulation_log
0
2
4
6
8
10
0 5000 10000 15000 20000


BlackPopulation_log
0.0
2.5
5.0
7.5
10.0
12.5
0 5000 10000 15000 20000

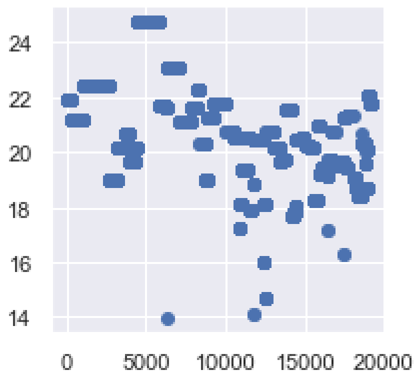

HawaiianPopulation_log
0
2
4
6
0 5000 10000 15000 20000


HispanicPopulation_log
0
2
4
6
8
10
12
0 5000 10000 15000 20000

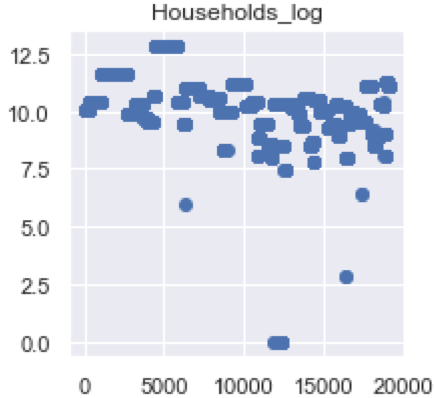
WhitePopulation_log



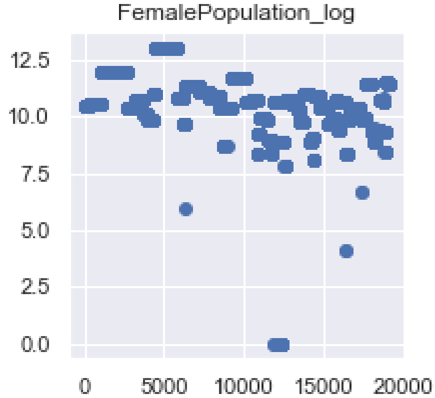
AnnualPayroll_log



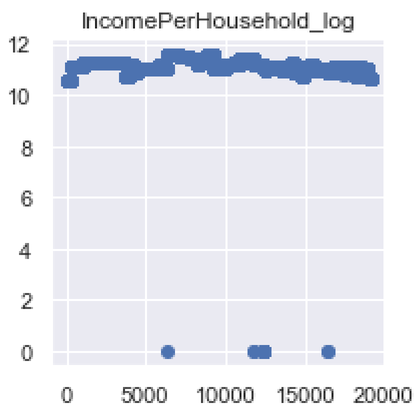
Households_log

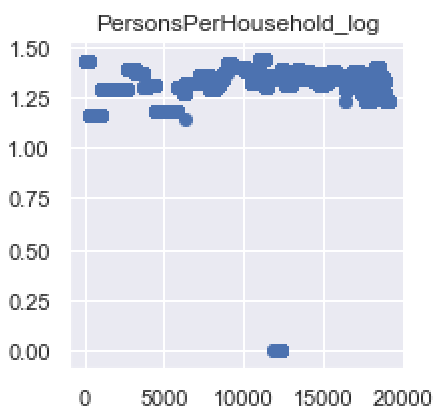


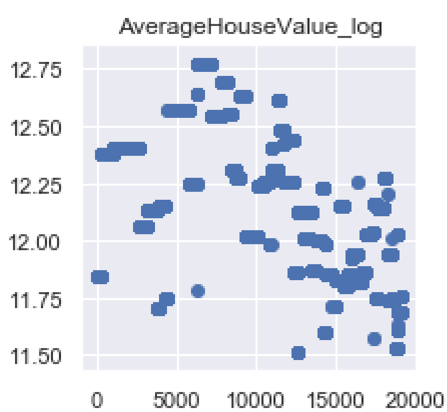
FemalePopulation_log

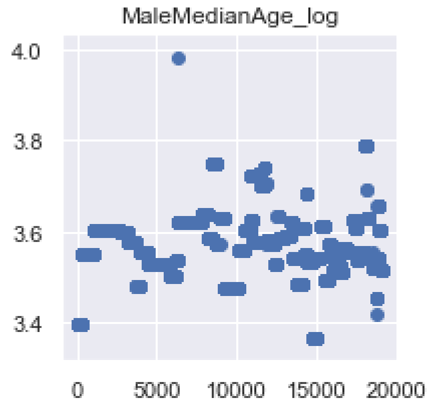


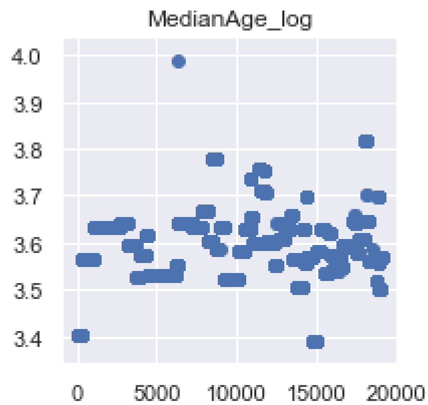

MalePopulation_log
12.5
10.0
7.5
5.0
2.5
0.0
0 5000 10000 15000 20000


IncomePerHousehold_log
12
10
8
6
4
2
0
0 5000 10000 15000 20000


PersonsPerHousehold_log
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0 5000 10000 15000 20000


AverageHouseValue_log
12.75
12.50
12.25
12.00
11.75
11.50
0 5000 10000 15000 20000





According to the scatter plot, we find most of the features contain outliers.

3.2 Delete Outliers

We keep value of features within three standard deviations, because that's essentially 99% of the range.

In [232]:
```
numdf=num_df
for i in numdf.columns:
    feature = np.array(numdf[i])
    mean = np.mean(feature,axis=0)
    sd = np.std(feature, axis=0)
num_df=numdf
```

4. Skewed distribution

4.1 Graph

Observe the skewness distribution of the features through the graph.

In [233]:
```
for k in ['Appliances','Price','TaxAssessedValue','DaysOnZillow',
          'PageViewCount', 'FavoriteCount','Bedrooms', 'Bathrooms', 'Stories',
          'LivingArea', 'LotSize', 'Basement', 'YearBuilt',
       'PrimarySchoolDistance', 'PrimarySchoolRating', 'MiddleSchoolDistance',
       'MiddleSchoolRating', 'HighSchoolDistance', 'HighSchoolRating',
       'BusinessMailboxes', 'ResidentialMailboxes', 'NumberofBusinesses',
       'NumberofEmployees', 'Population2010', 'CurrentPopulation',
       'AmericanIndianPopulation', 'AsianPopulation', 'BlackPopulation',
       'HawaiianPopulation', 'HispanicPopulation', 'WhitePopulation',
       'AnnualPayroll', 'Households', 'FemalePopulation', 'MalePopulation',
       'IncomePerHousehold', 'PersonsPerHousehold', 'AverageHouseValue',
       'MaleMedianAge', 'MedianAge']:
    df1=numdf

    fig = plt.figure()
    plt.figure(figsize=(5,5))
    sns.distplot(df1[k] , fit=norm) #画出数据的分布图
    (mu, sigma) = norm.fit(df1[k])  #求mu，sigma
    plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu
, sigma)], loc='best') #画图例
    plt.ylabel('Frequency')
    plt.title(k)

    fig = plt.figure()
    plt.figure(figsize=(5,5))
    res = stats.probplot(df1[k], plot=plt) #画拟合曲线
    plt.show()
```

Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaae10fd0>

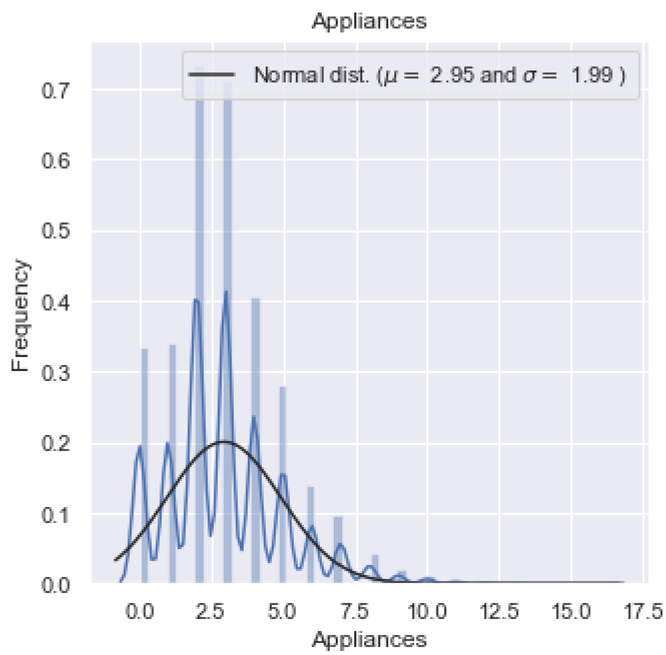
Out[233]: <matplotlib.legend.Legend at 0x1a26436490>

Out[233]: Text(0, 0.5, 'Frequency')

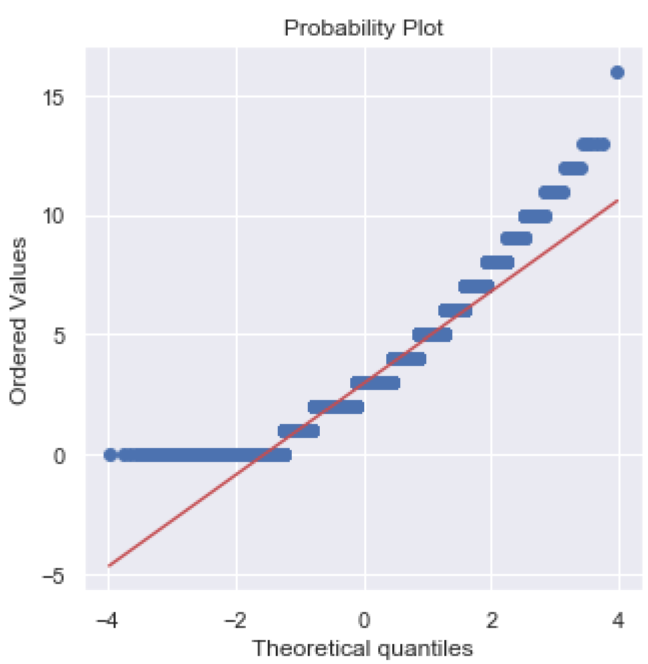
Out[233]: Text(0.5, 1.0, 'Appliances')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa6032610>

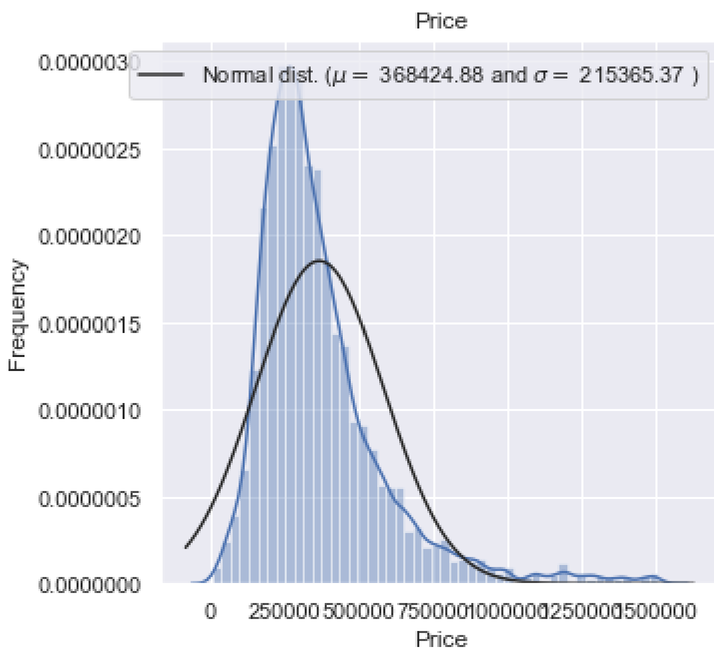
Out[233]: <matplotlib.legend.Legend at 0x1aa5db0d90>

Out[233]: Text(0, 0.5, 'Frequency')

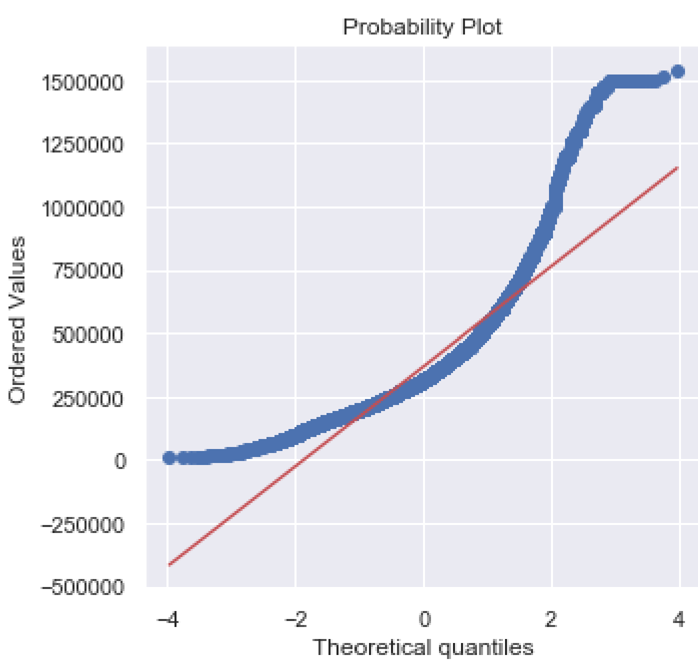
Out[233]: Text(0.5, 1.0, 'Price')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa64e9e10>

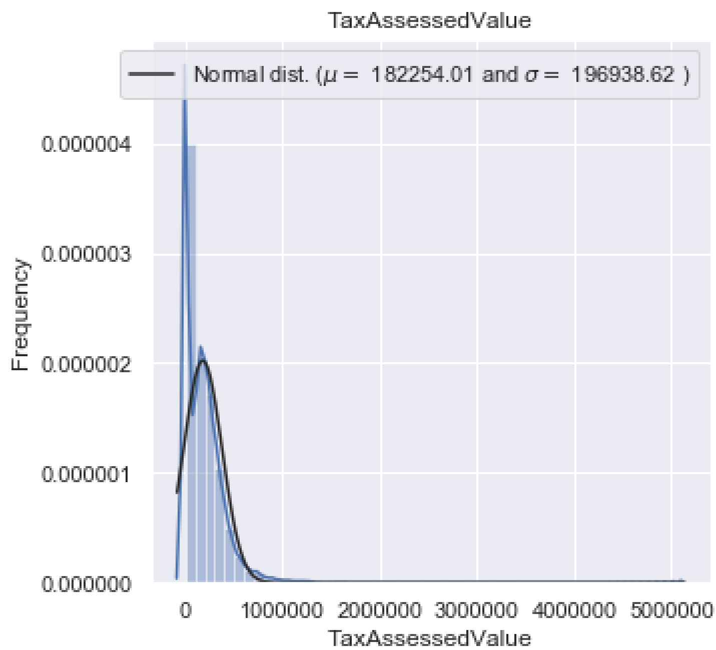
Out[233]: <matplotlib.legend.Legend at 0x1aa60a7890>

Out[233]: Text(0, 0.5, 'Frequency')

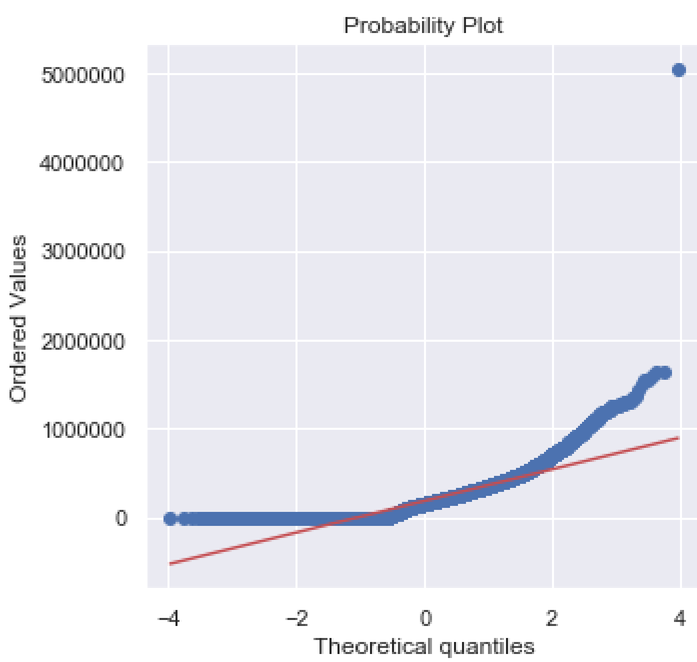
Out[233]: Text(0.5, 1.0, 'TaxAssessedValue')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa65a2ad0>

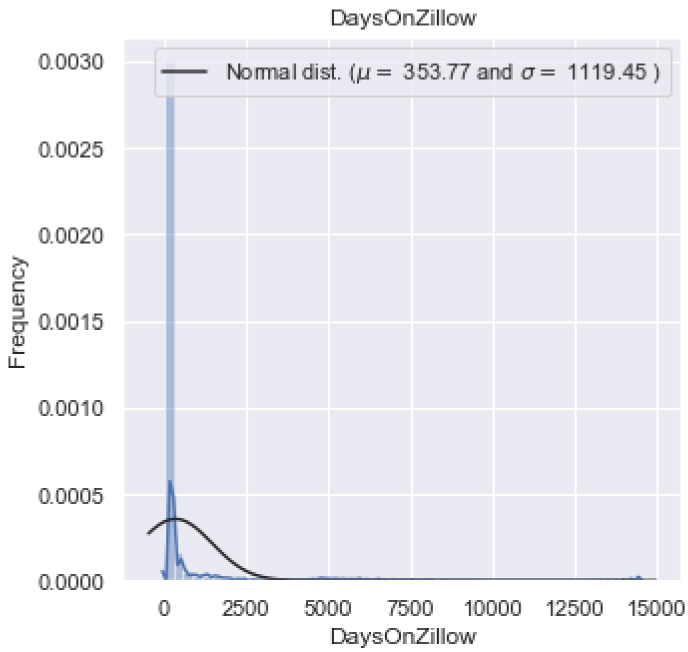
Out[233]: <matplotlib.legend.Legend at 0x1aa64e18d0>

```
Out[233]: Text(0, 0.5, 'Frequency')

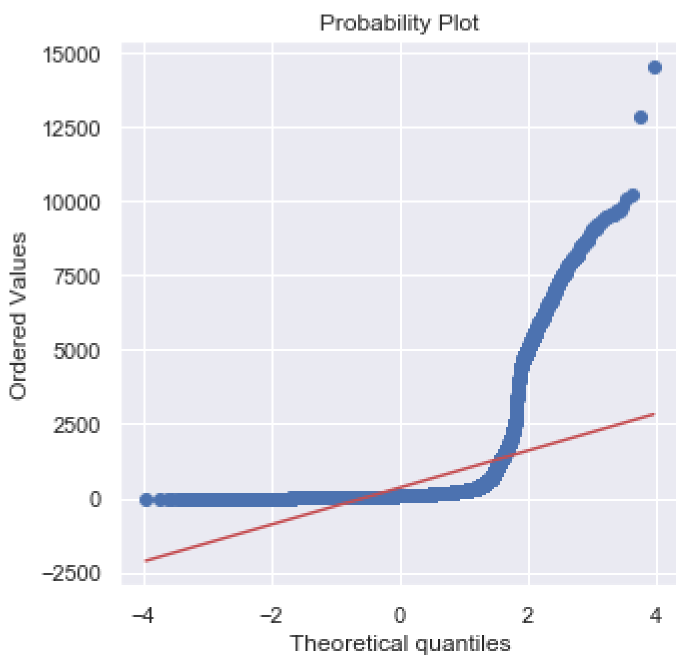
Out[233]: Text(0.5, 1.0, 'DaysOnZillow')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




```
Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aab72d450>

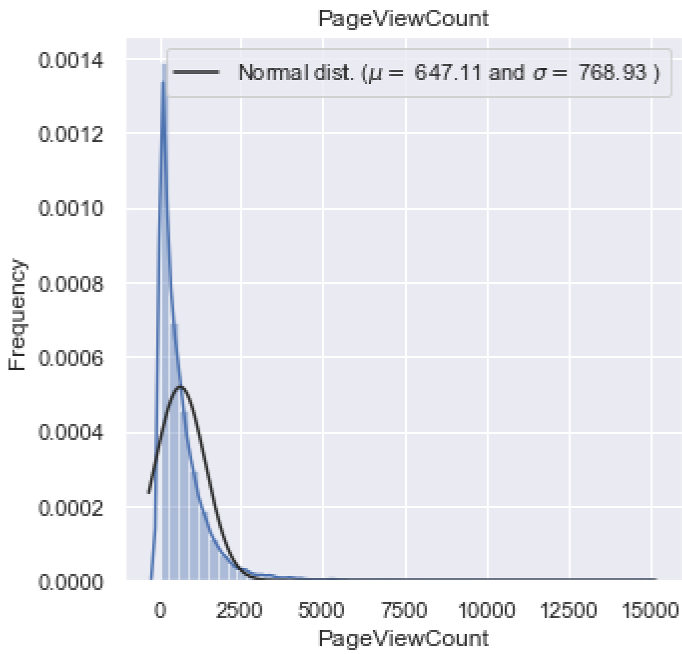
Out[233]: <matplotlib.legend.Legend at 0x1aa69fde10>

Out[233]: Text(0, 0.5, 'Frequency')
```

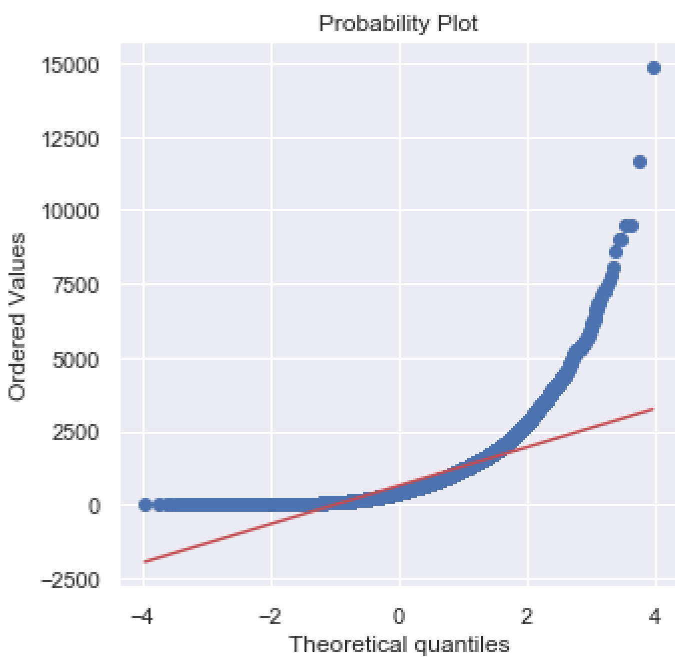
Out[233]: Text(0.5, 1.0, 'PageViewCount')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aab8a8a10>

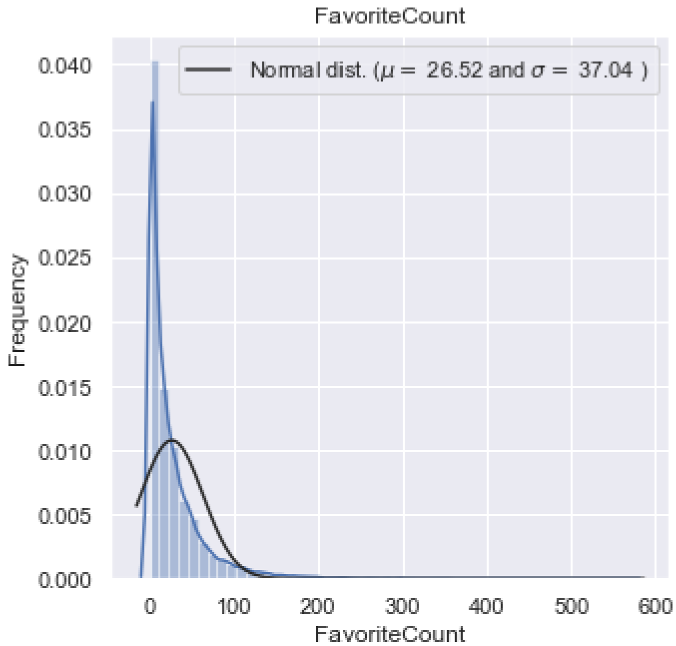
Out[233]: <matplotlib.legend.Legend at 0x1aab686ad0>

Out[233]: Text(0, 0.5, 'Frequency')

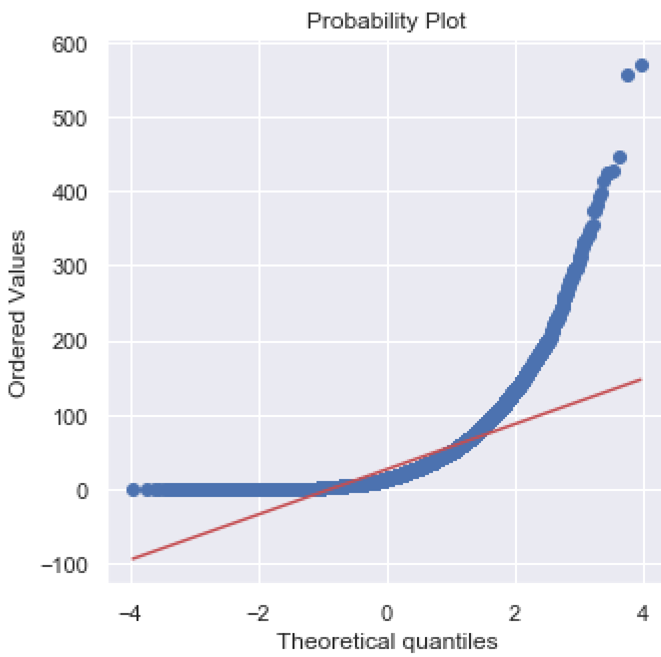
Out[233]: Text(0.5, 1.0, 'FavoriteCount')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aabc91790>

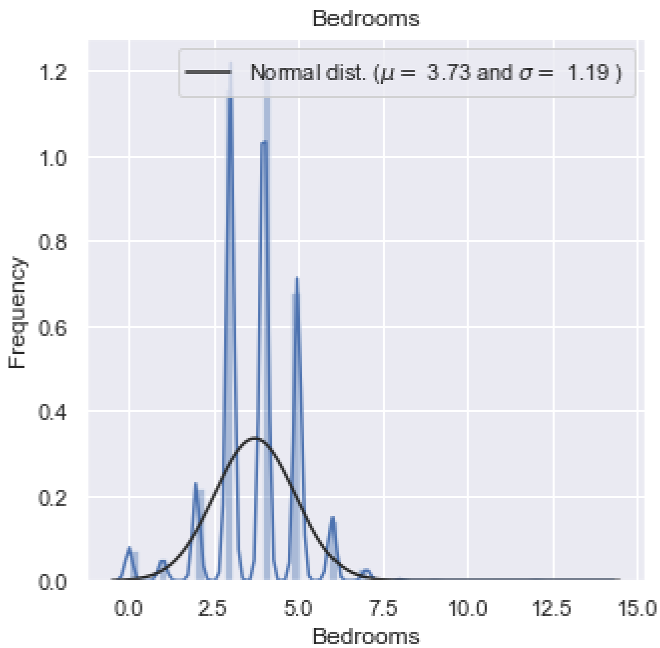
Out[233]: <matplotlib.legend.Legend at 0x1aabe18710>

Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'Bedrooms')

Out[233]: <Figure size 360x360 with 0 Axes>

```
<Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
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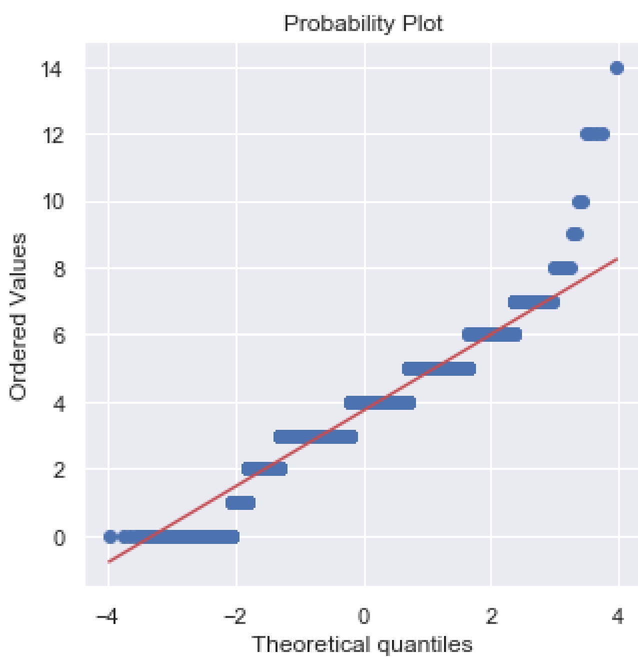


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Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aabff4810>

Out[233]: <matplotlib.legend.Legend at 0x1aac3b0d50>

Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'Bathrooms')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>
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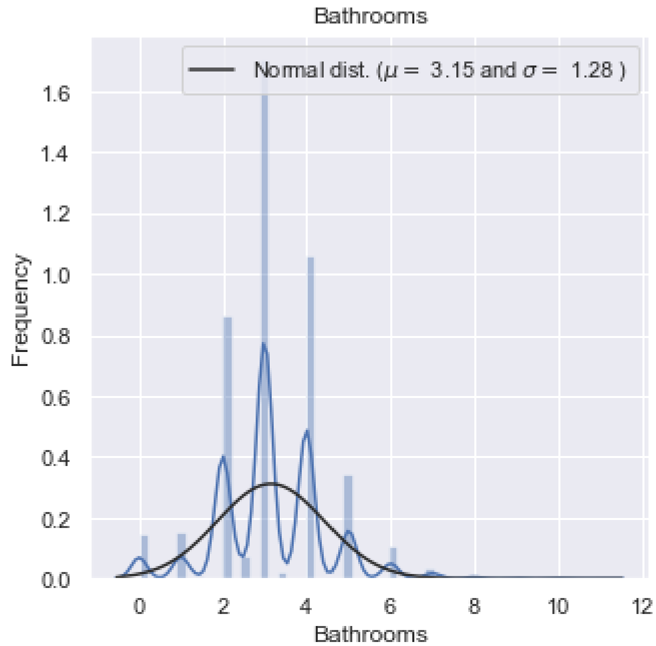
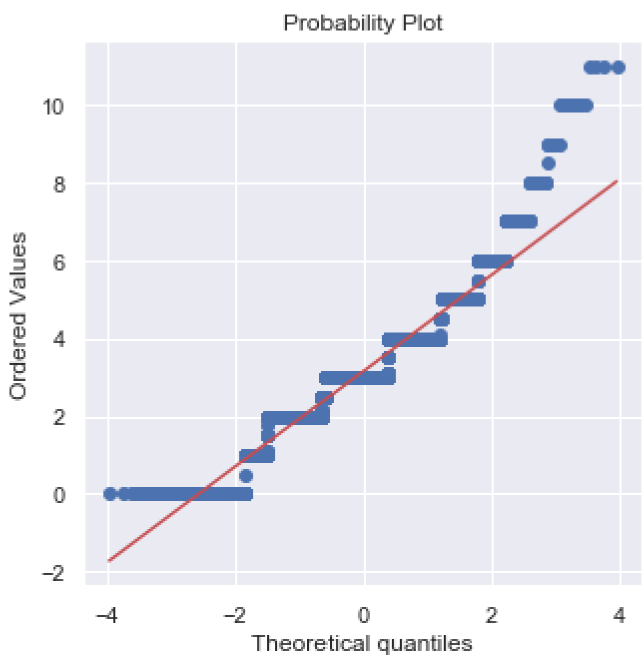


<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aac8e3f10>

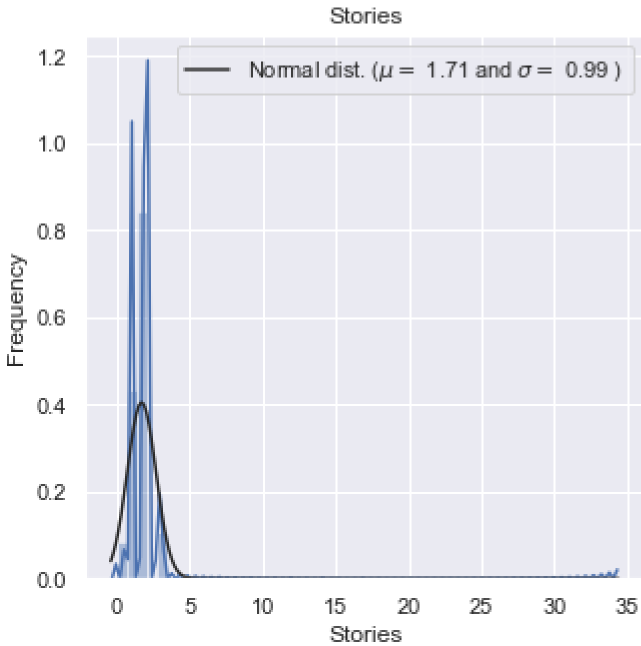
Out[233]: <matplotlib.legend.Legend at 0x1aac8e3d50>

Out[233]: Text(0, 0.5, 'Frequency')

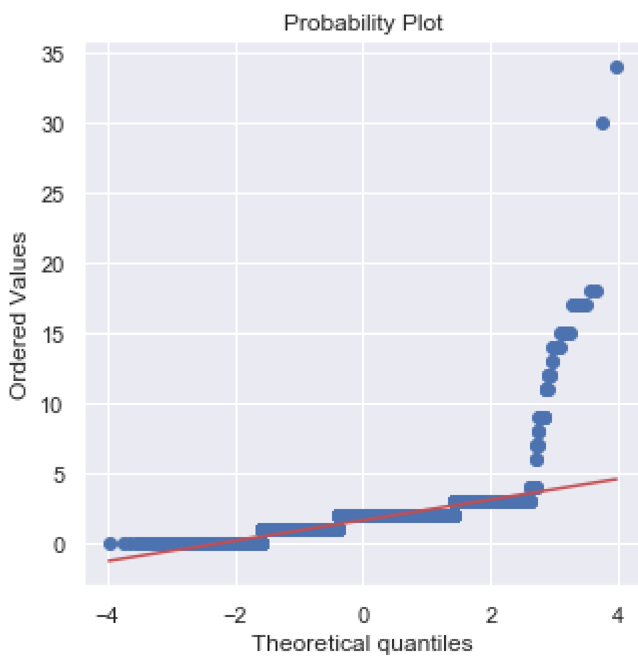
Out[233]: Text(0.5, 1.0, 'Stories')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

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Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aacd40490>
Out[233]: <matplotlib.legend.Legend at 0x1aacde46d0>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'LivingArea')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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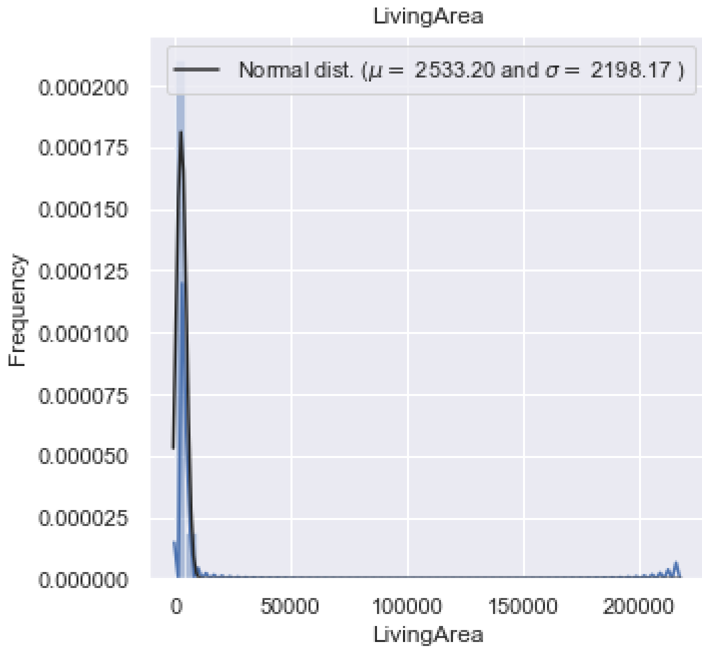


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<Figure size 432x288 with 0 Axes>
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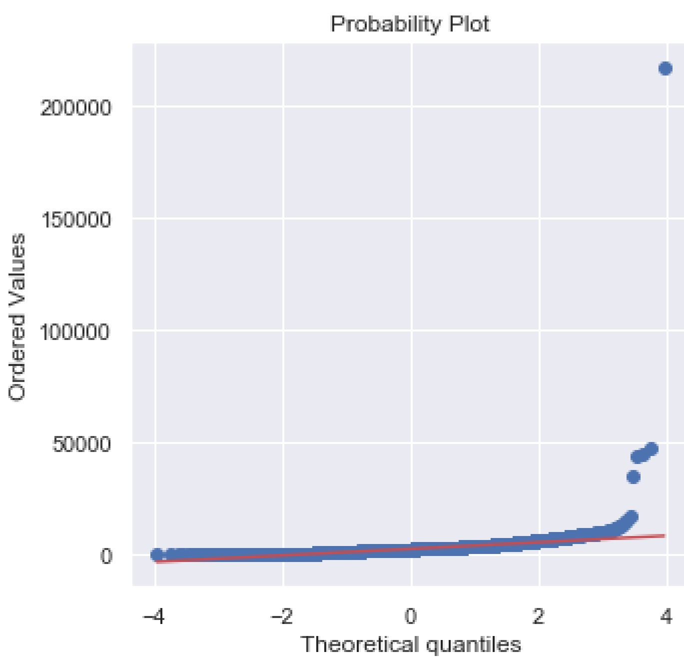


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Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aacab3850>

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Out[233]: Text(0.5, 1.0, 'LotSize')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>
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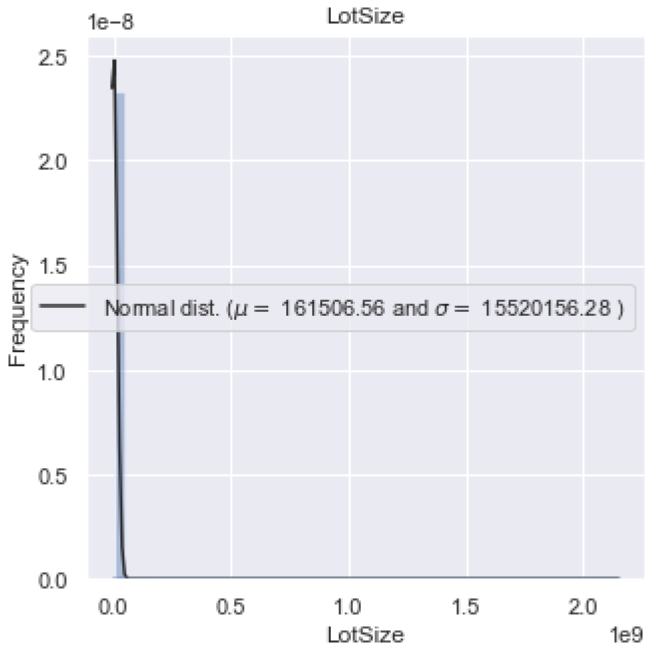
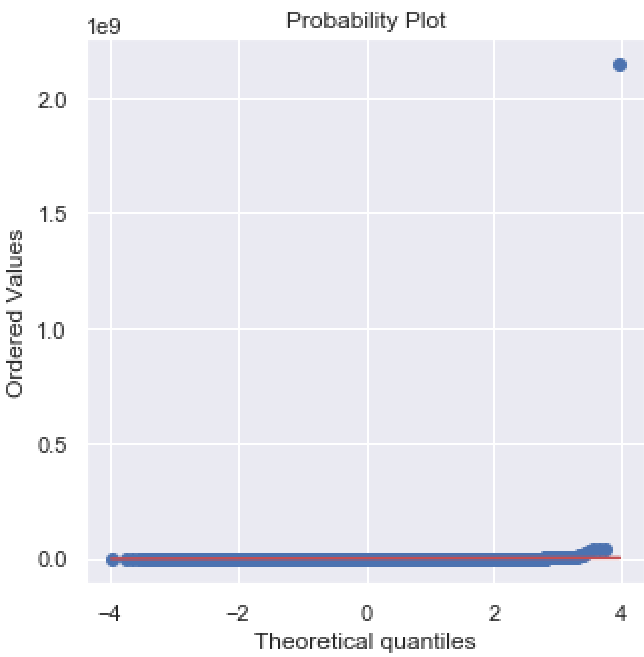


<Figure size 432x288 with 0 Axes>



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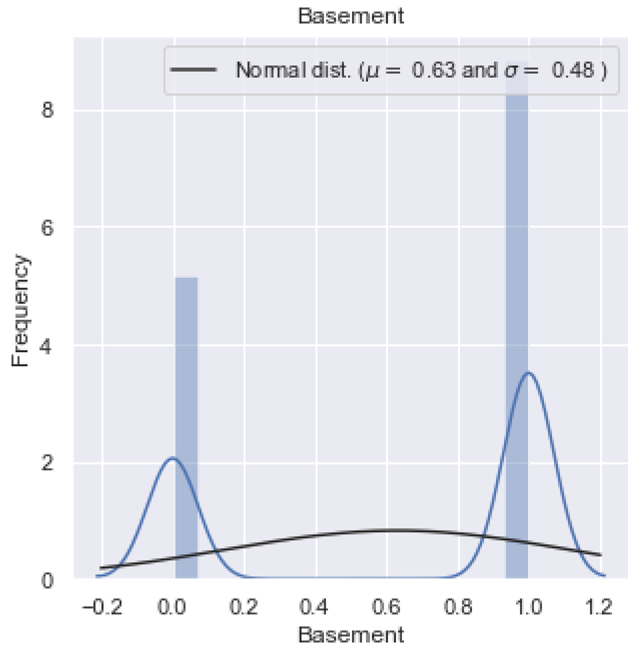
Out[233]: <matplotlib.legend.Legend at 0x1aacefa5d0>

Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'Basement')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



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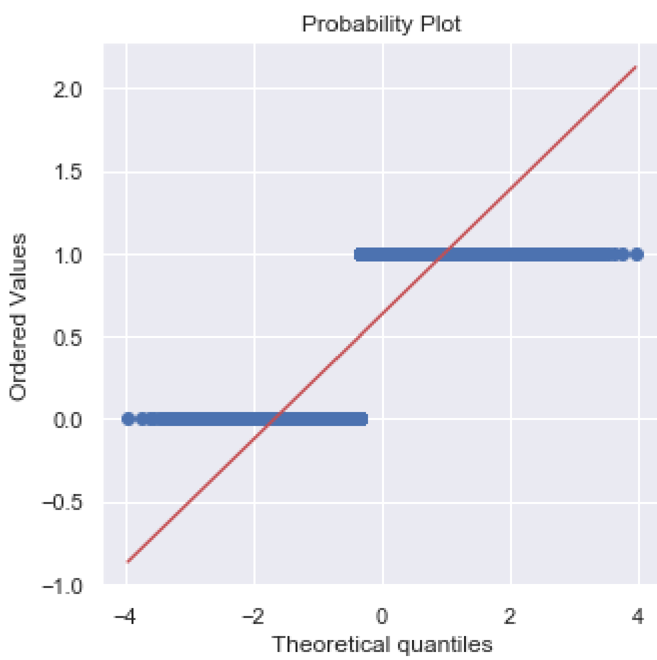

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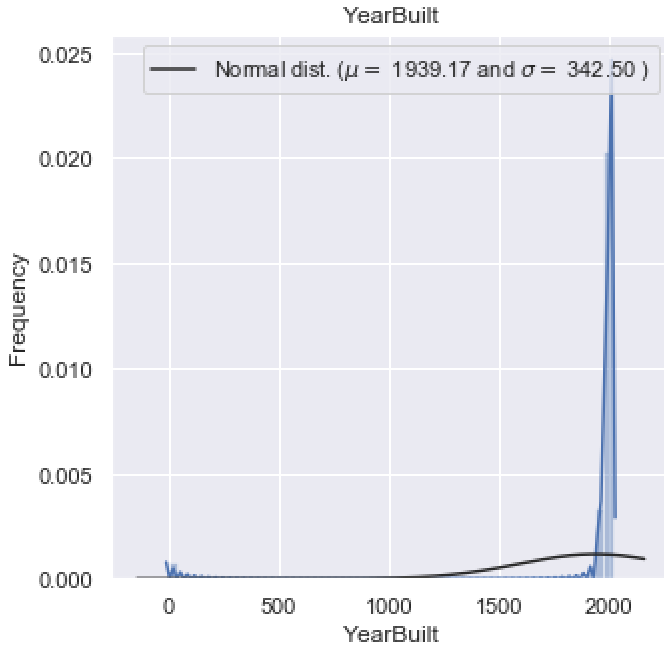
Out[233]: <matplotlib.legend.Legend at 0x1aa5da3850>

Out[233]: Text(0, 0.5, 'Frequency')

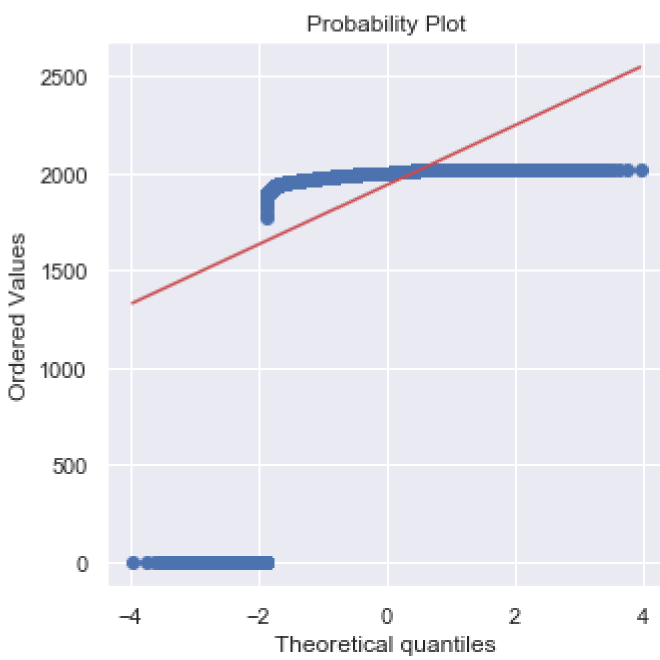
Out[233]: Text(0.5, 1.0, 'YearBuilt')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

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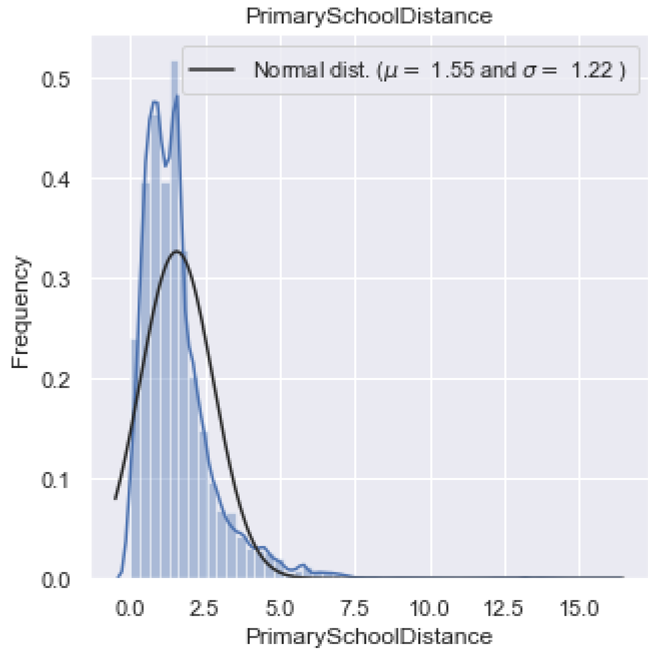
Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaaa3ee90>
Out[233]: <matplotlib.legend.Legend at 0x1aaaa3eb90>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'PrimarySchoolDistance')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
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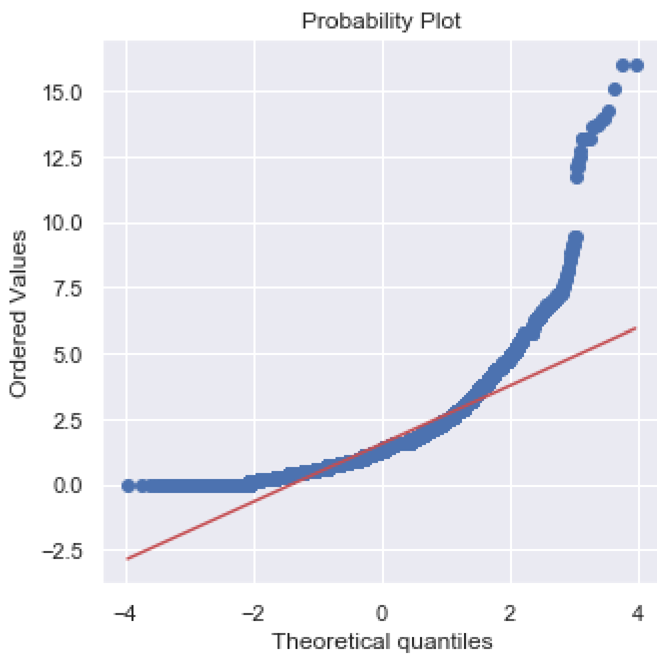


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Out[233]: <matplotlib.legend.Legend at 0x1a246139d0>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'PrimarySchoolRating')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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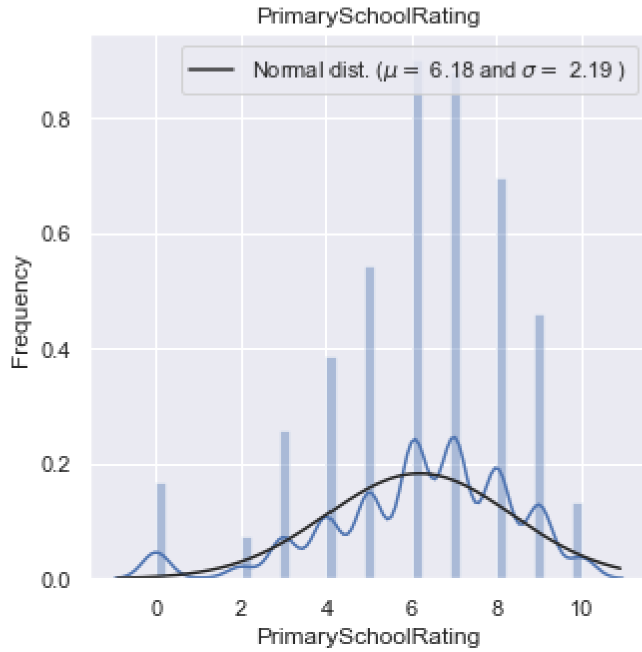

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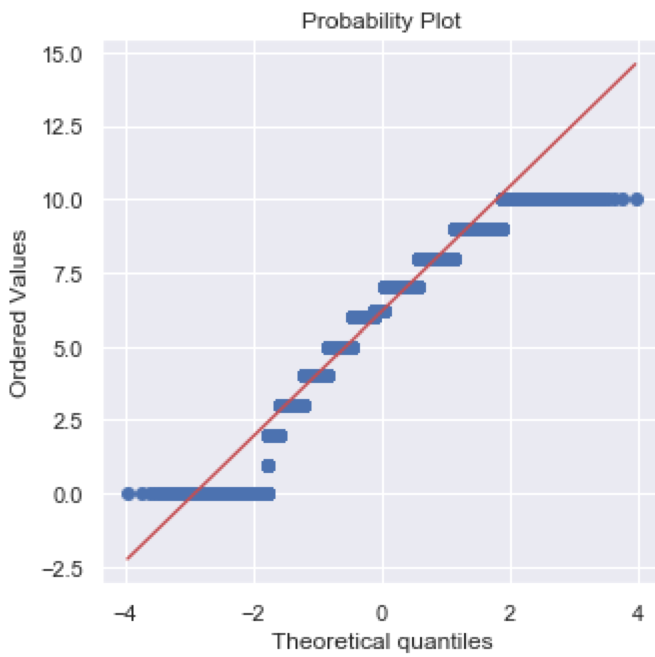

Out[233]: <Figure size 360x360 with 0 Axes>

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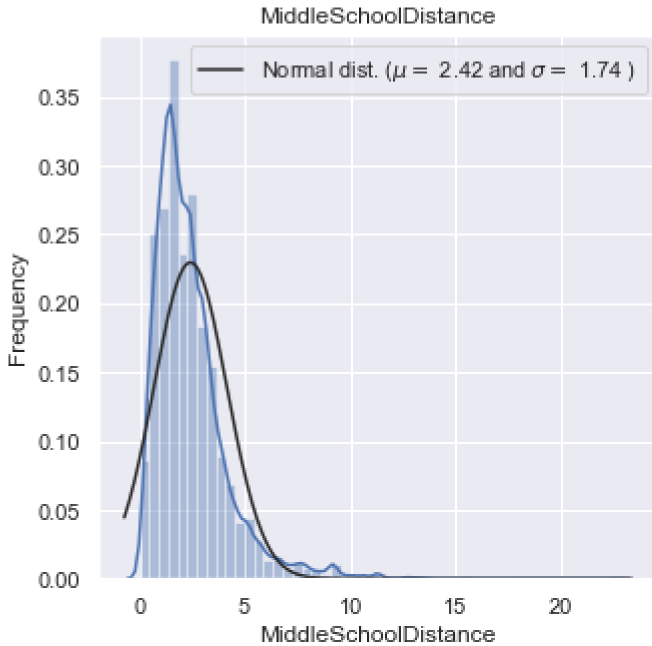
Out[233]: <matplotlib.legend.Legend at 0x1a23780b50>

Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'MiddleSchoolDistance')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
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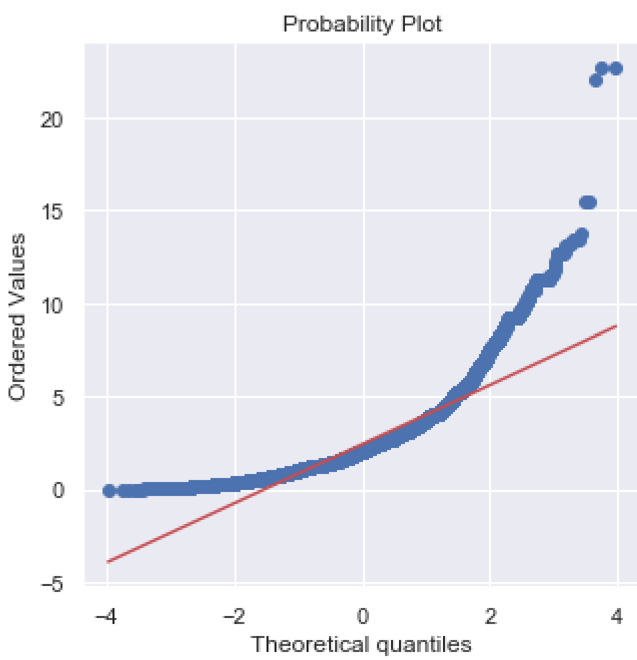


```
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Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1a25b95450>

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Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'MiddleSchoolRating')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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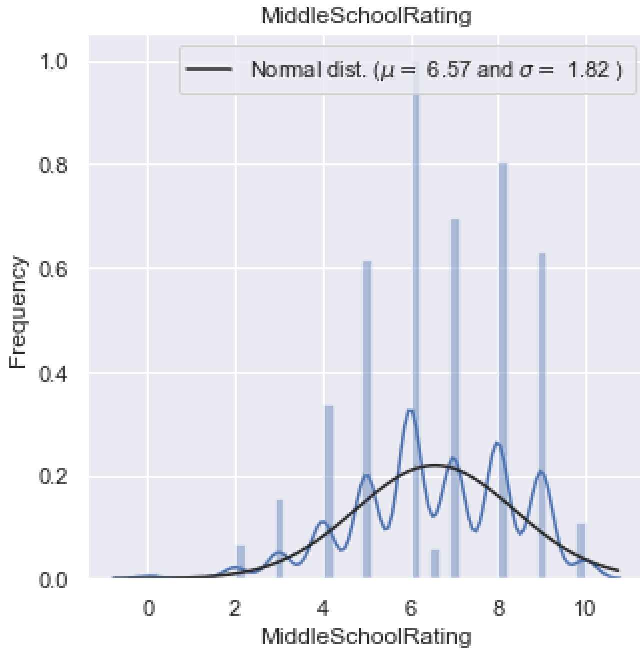
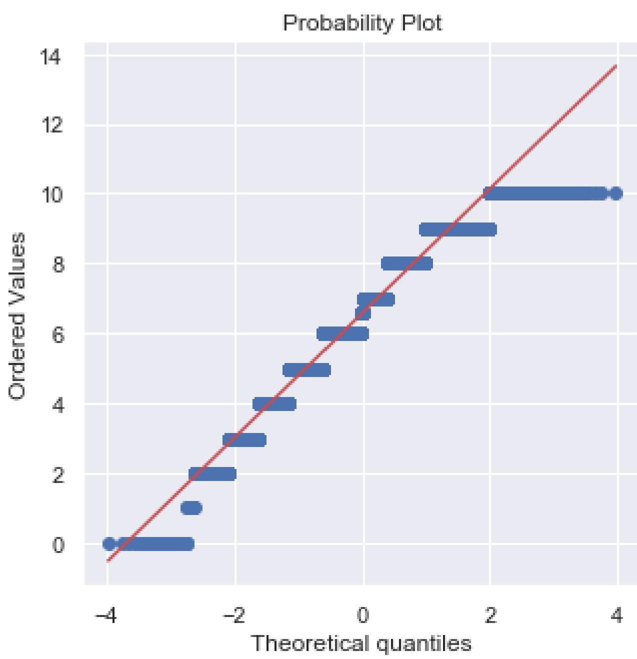


<Figure size 432x288 with 0 Axes>

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Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaab03ed0>
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Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'HighSchoolDistance')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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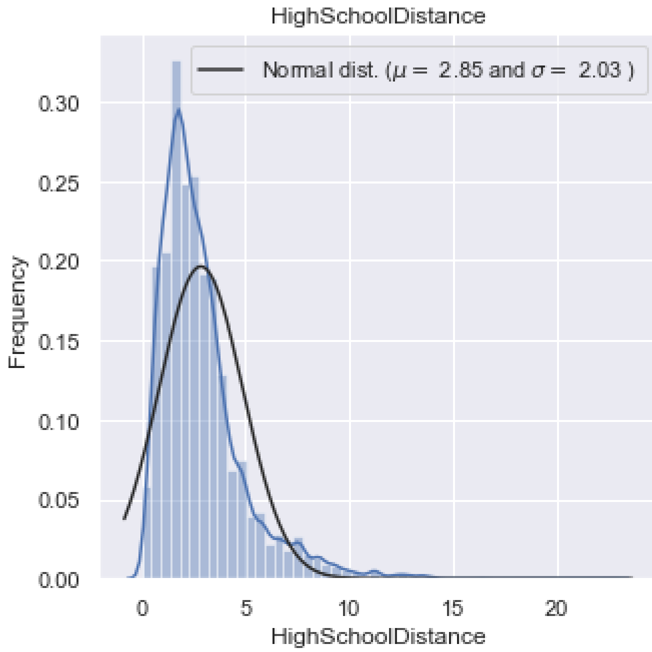

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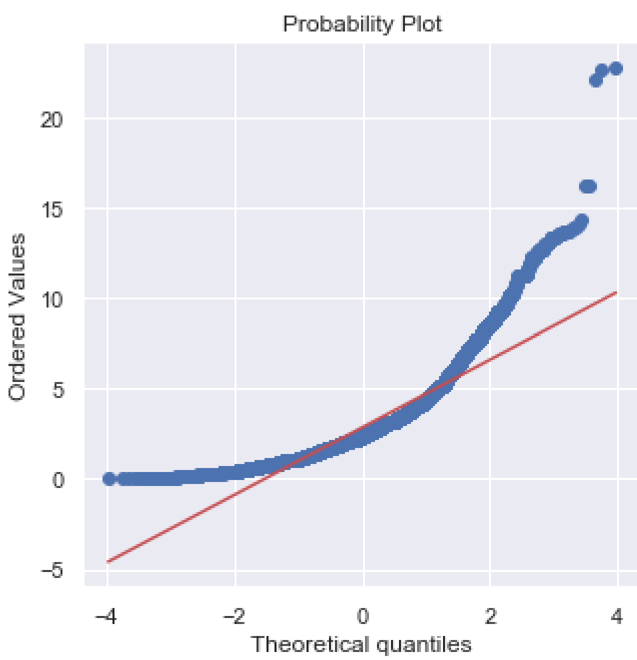

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Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'HighSchoolRating')

Out[233]: <Figure size 360x360 with 0 Axes>

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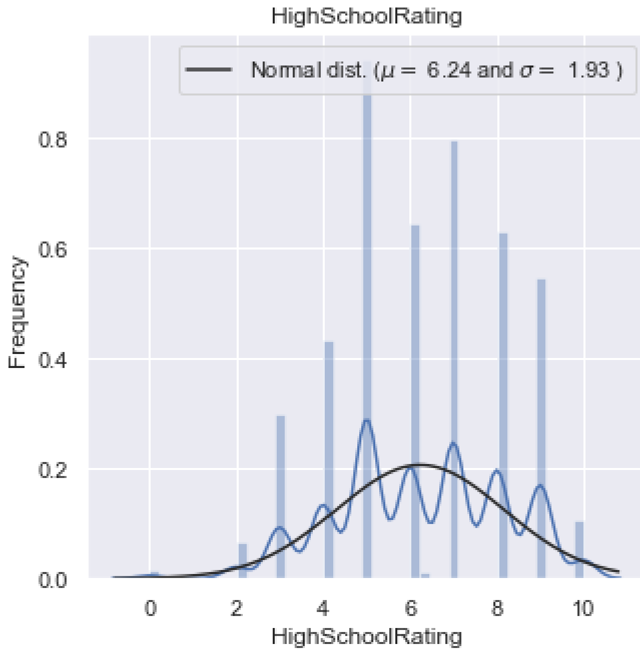
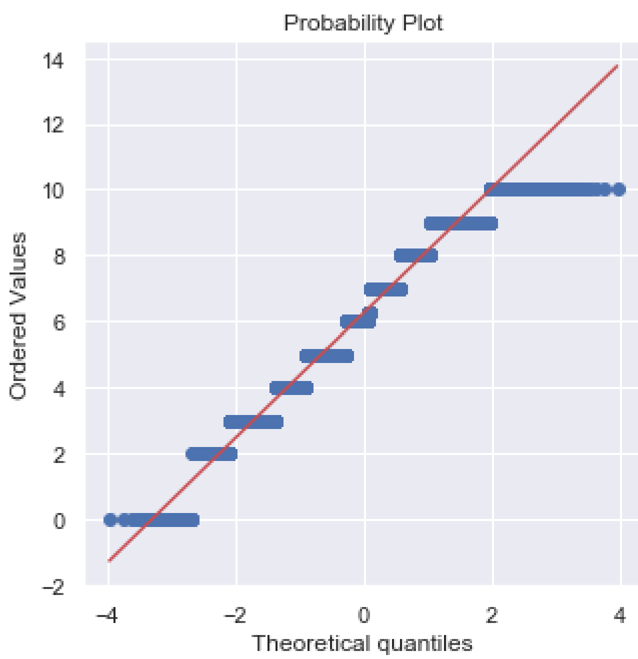



```
<Figure size 432x288 with 0 Axes>
```




```
Out[233]: <Figure size 360x360 with 0 Axes>

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Out[233]: <matplotlib.legend.Legend at 0x1aac047950>

Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'BusinessMailboxes')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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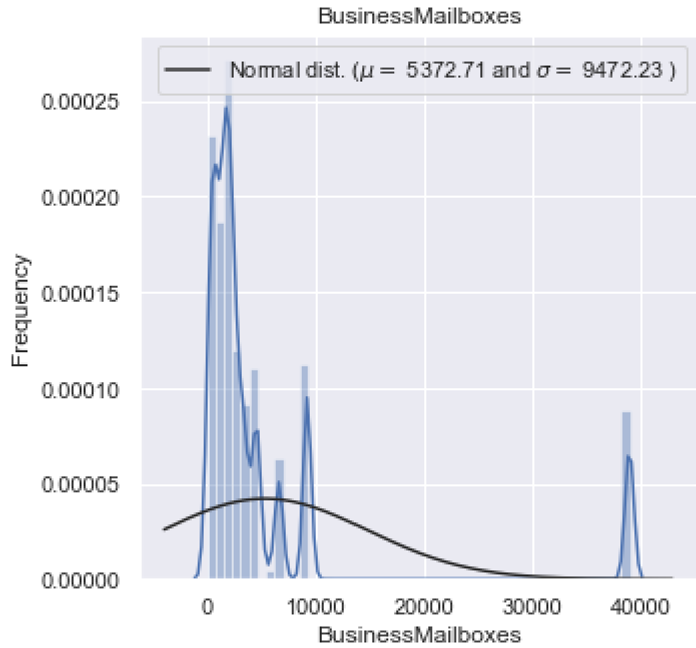
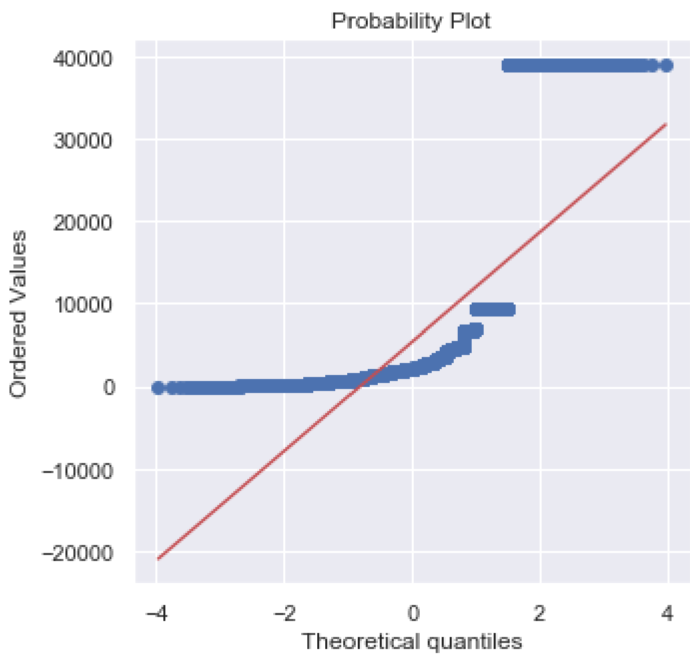


<Figure size 432x288 with 0 Axes>

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Out[233]: Text(0.5, 1.0, 'ResidentialMailboxes')
Out[233]: <Figure size 360x360 with 0 Axes>
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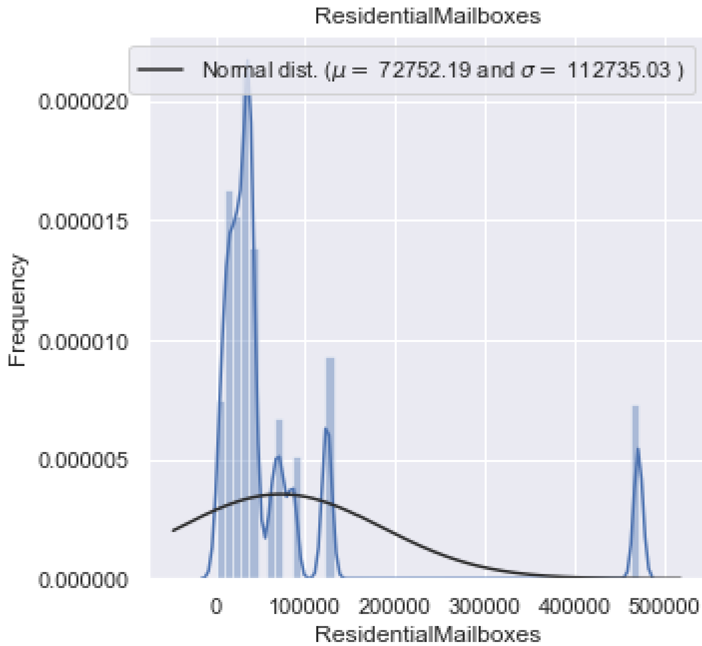

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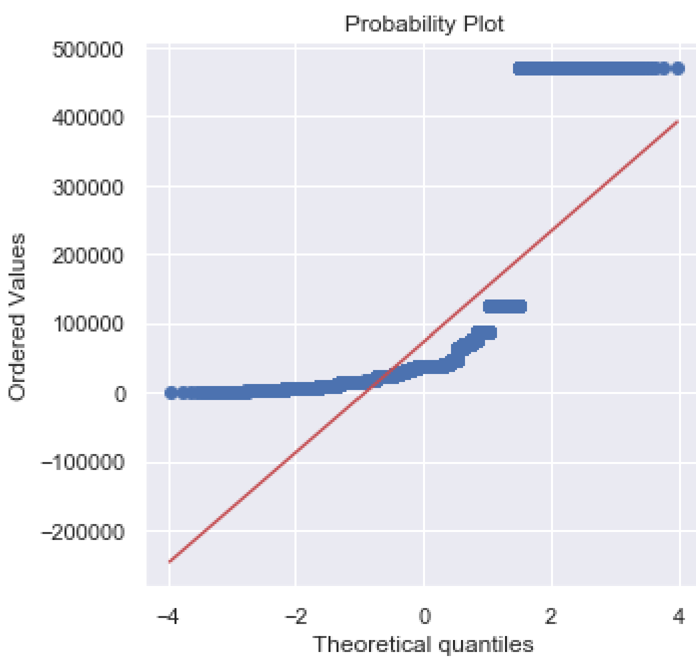


```
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Out[233]: Text(0.5, 1.0, 'NumberofBusinesses')
Out[233]: <Figure size 360x360 with 0 Axes>
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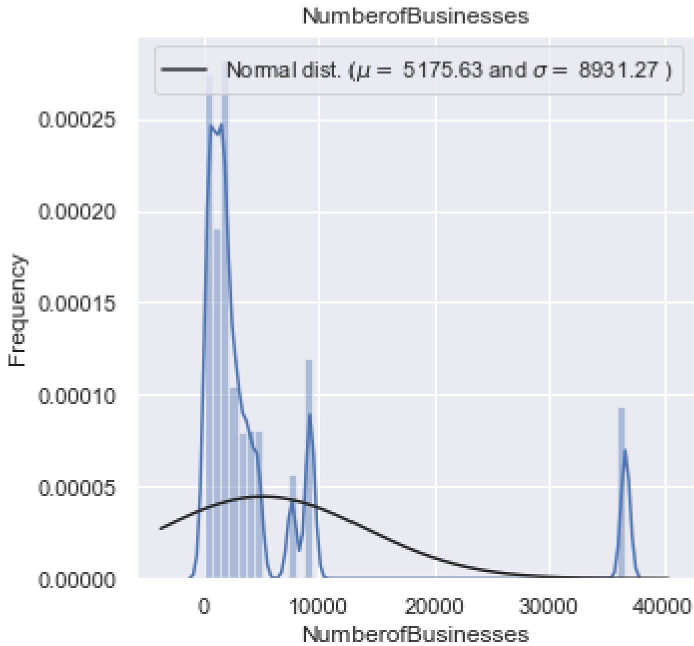
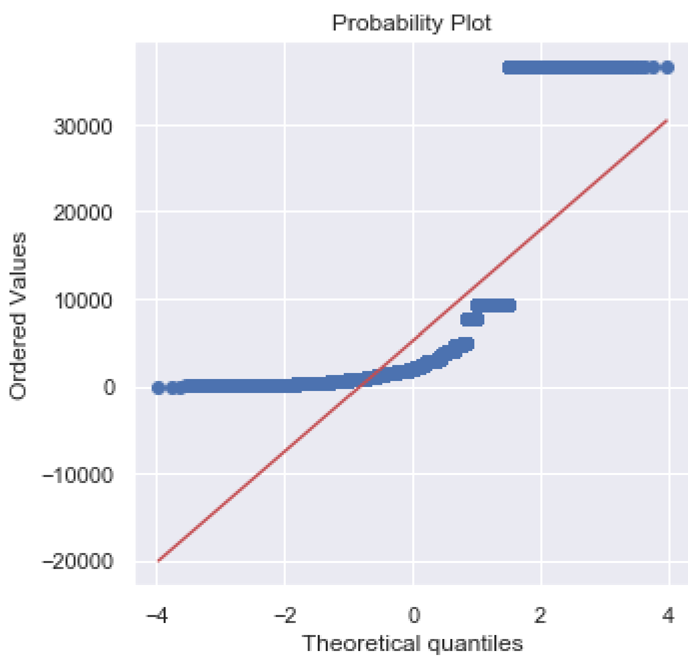



```
<Figure size 432x288 with 0 Axes>
```




```
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Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'NumberofEmployees')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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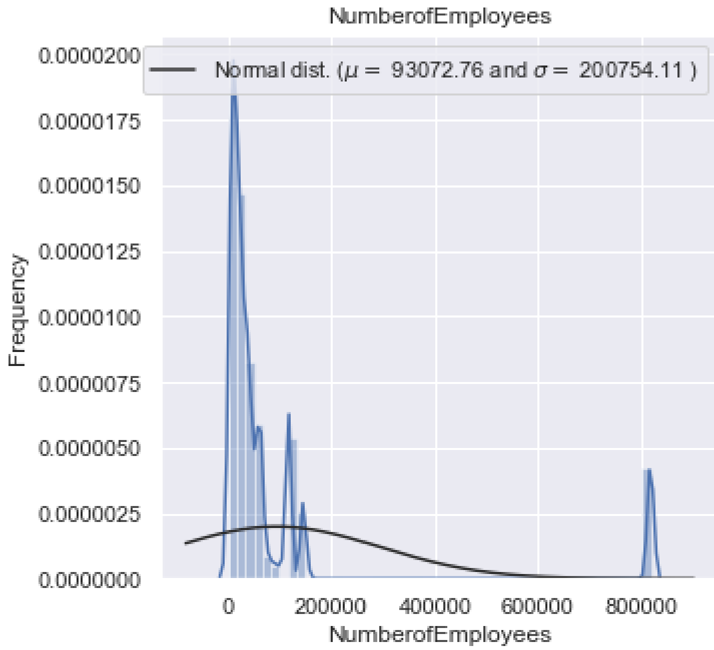


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<Figure size 432x288 with 0 Axes>
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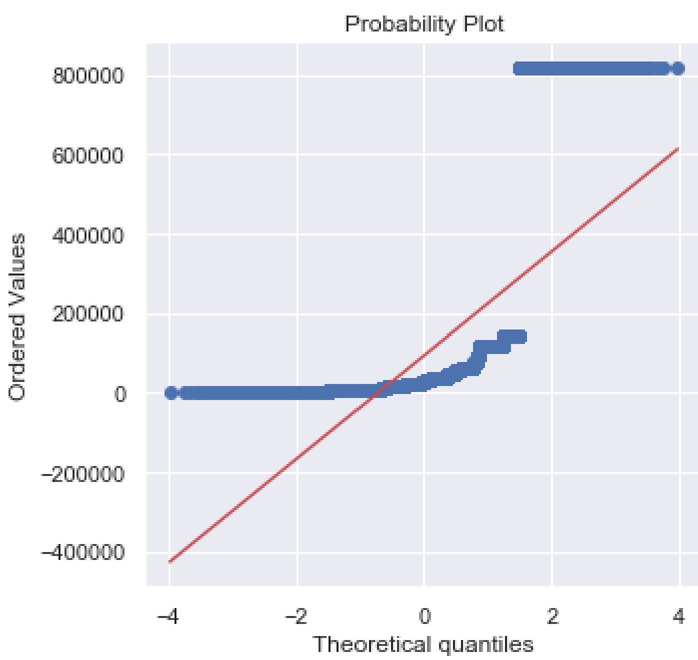


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Out[233]: Text(0, 0.5, 'Frequency')

Out[233]: Text(0.5, 1.0, 'Population2010')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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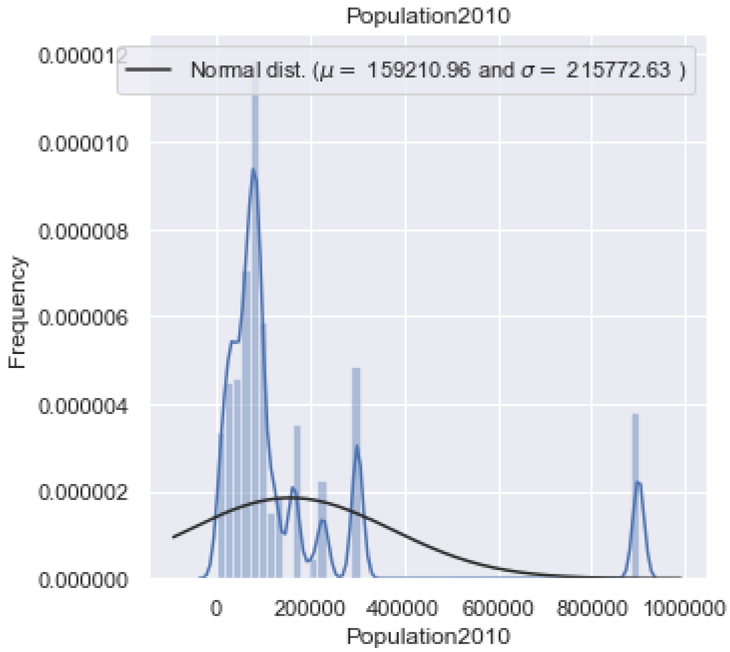


```
<Figure size 432x288 with 0 Axes>
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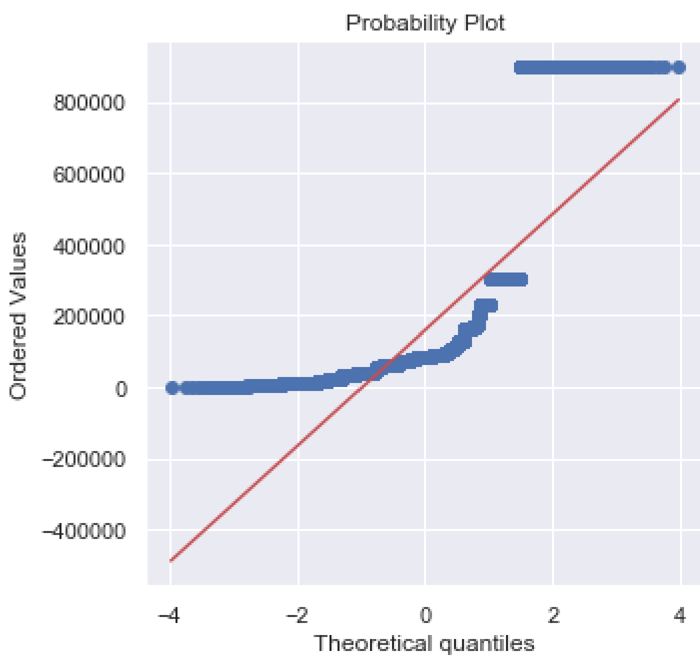


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Out[233]: <Figure size 360x360 with 0 Axes>
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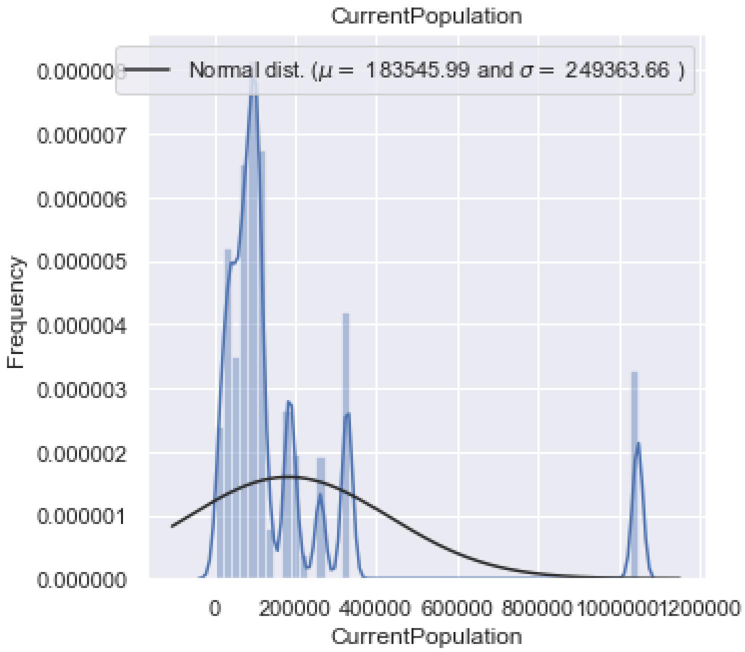


```
<Figure size 432x288 with 0 Axes>
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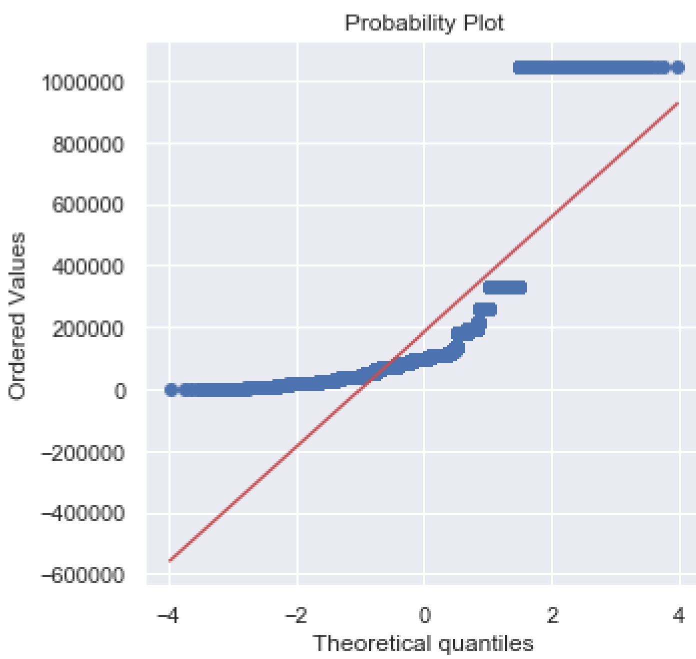


```
Out[233]: <Figure size 360x360 with 0 Axes>
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Out[233]: <matplotlib.legend.Legend at 0x1aaced0d90>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'AmericanIndianPopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
           <Figure size 432x288 with 0 Axes>
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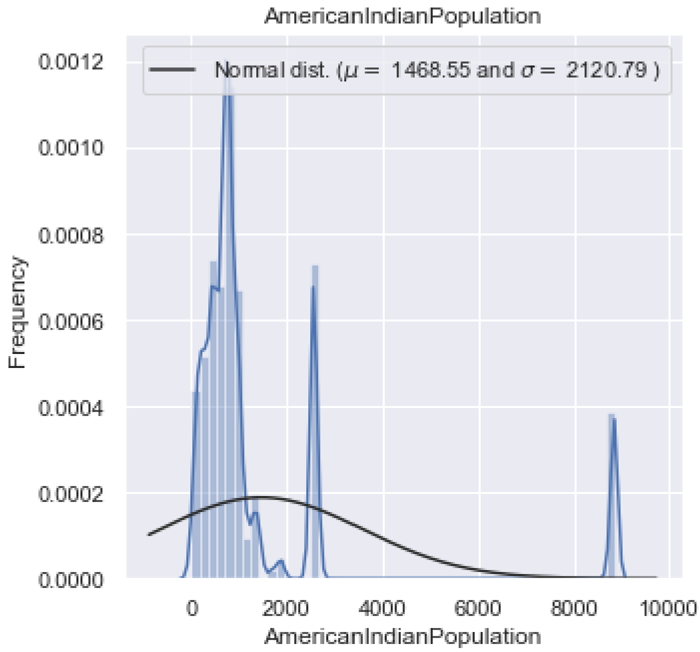


```
<Figure size 432x288 with 0 Axes>
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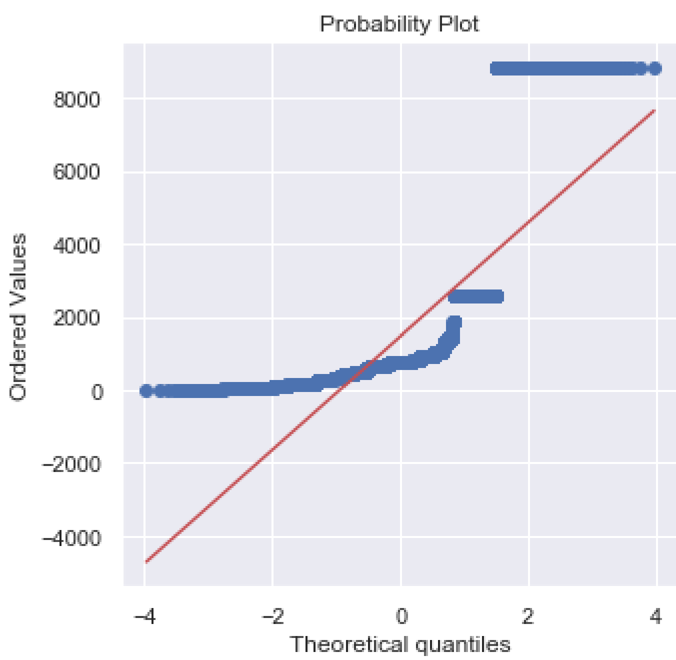


```
Out[233]: <Figure size 360x360 with 0 Axes>
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Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'AsianPopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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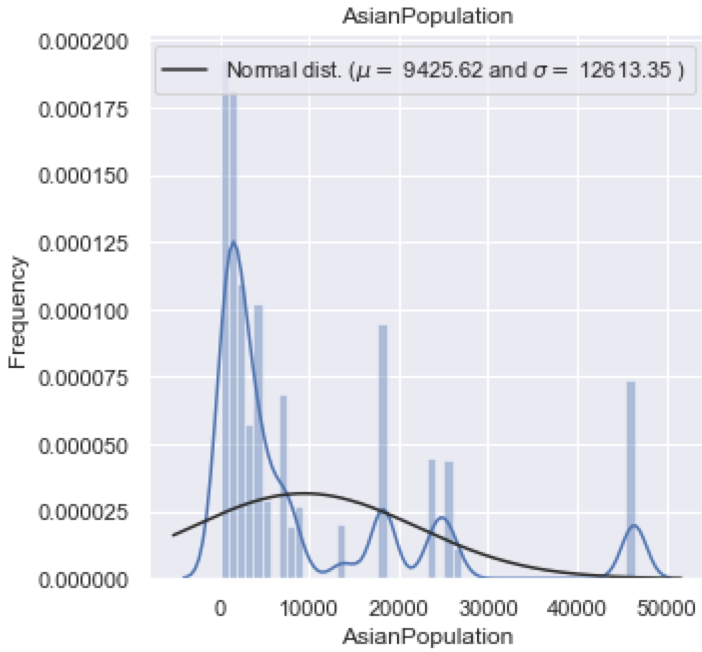


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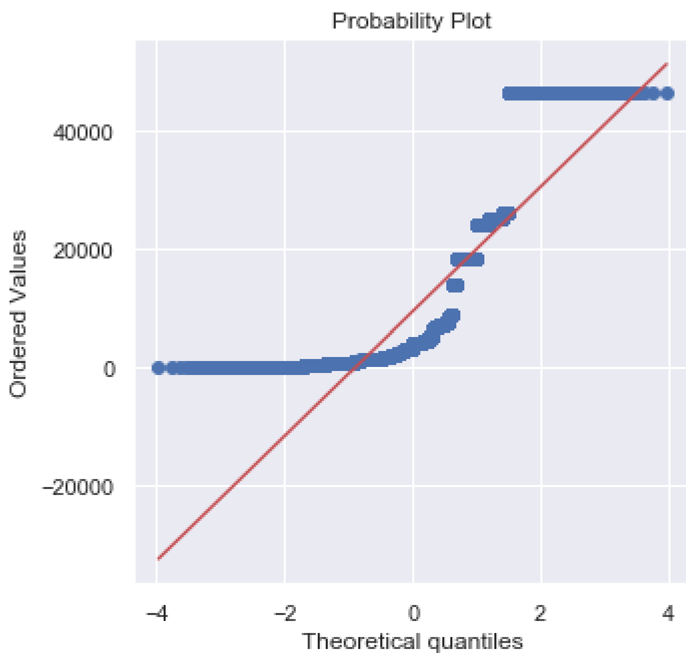


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Out[233]: Text(0.5, 1.0, 'BlackPopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
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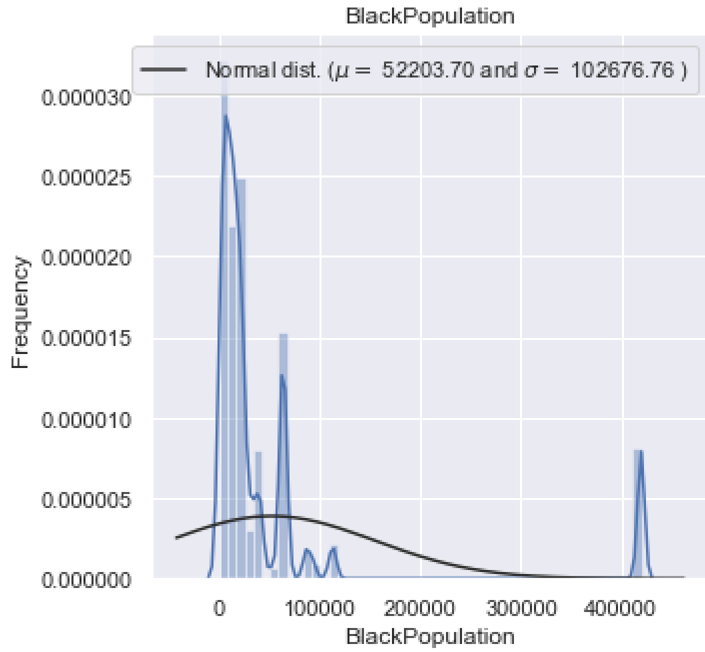
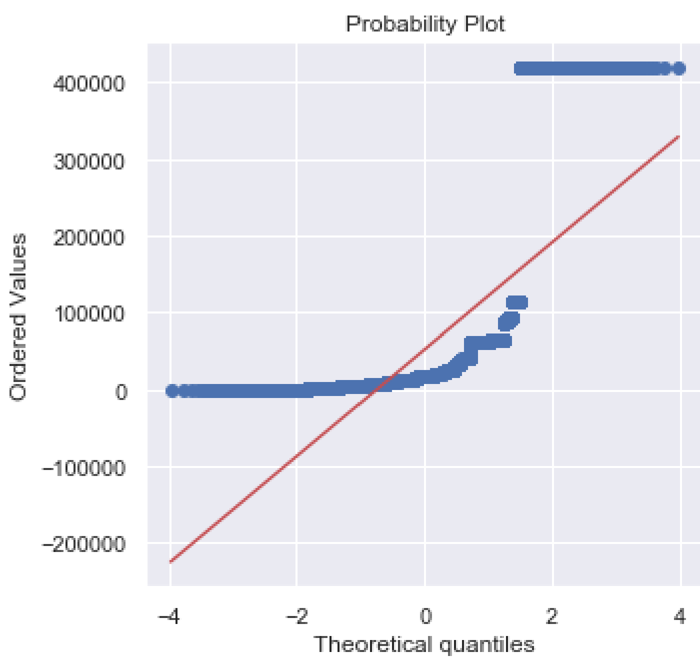


<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa5f53c10>

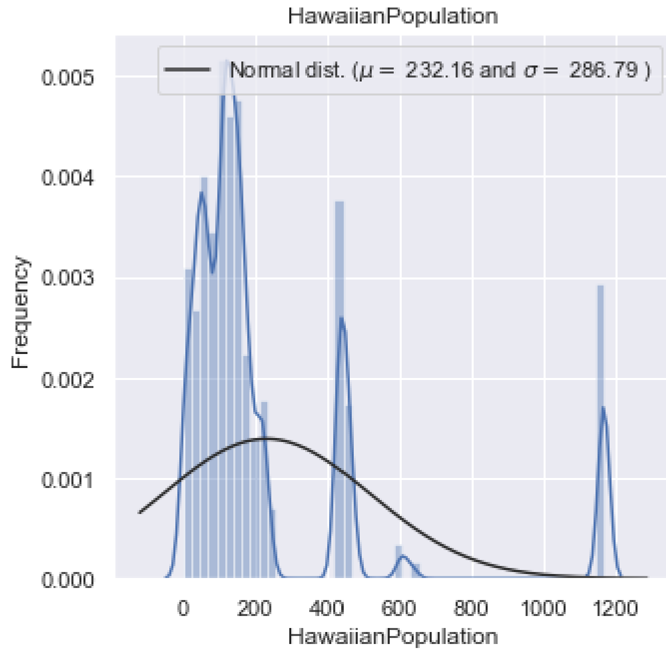
Out[233]: <matplotlib.legend.Legend at 0x1aa6423f10>

Out[233]: Text(0, 0.5, 'Frequency')

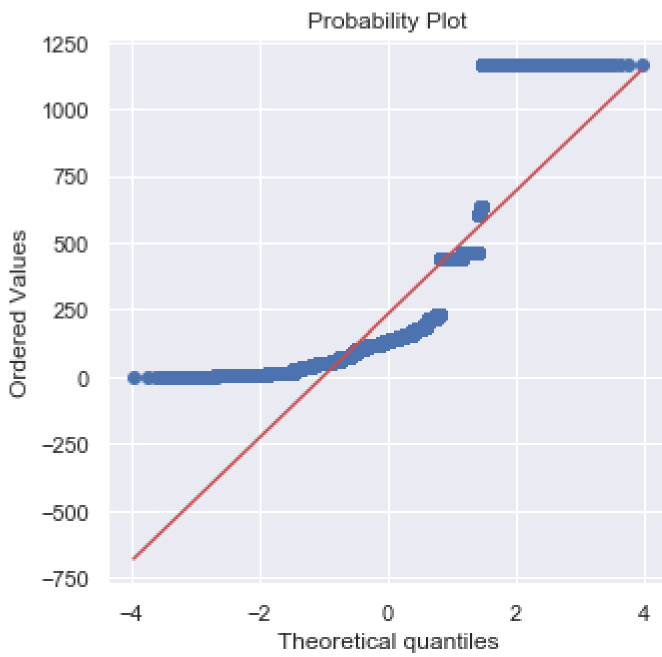
Out[233]: Text(0.5, 1.0, 'HawaiianPopulation')

Out[233]: <Figure size 360x360 with 0 Axes>

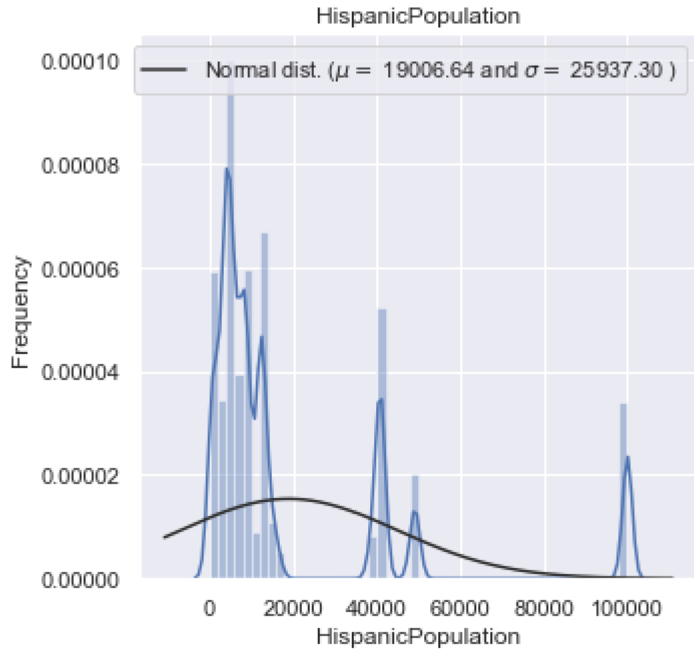
<Figure size 432x288 with 0 Axes>



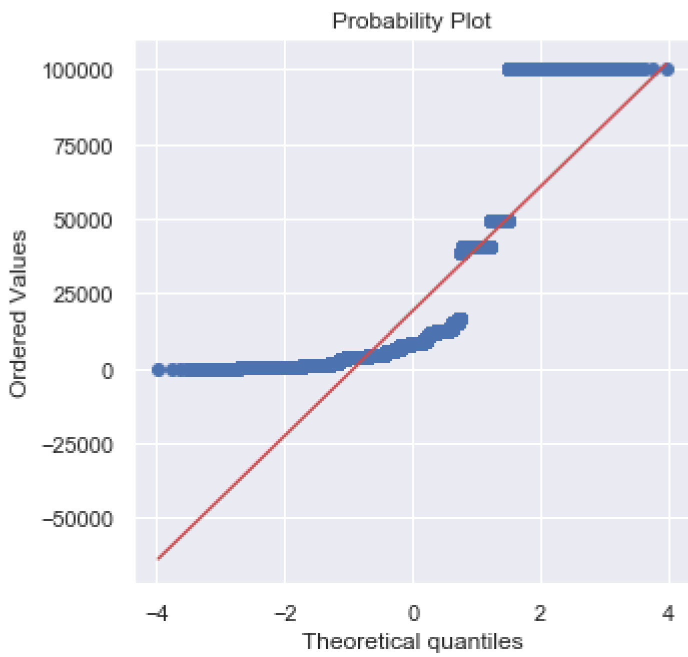
<Figure size 432x288 with 0 Axes>



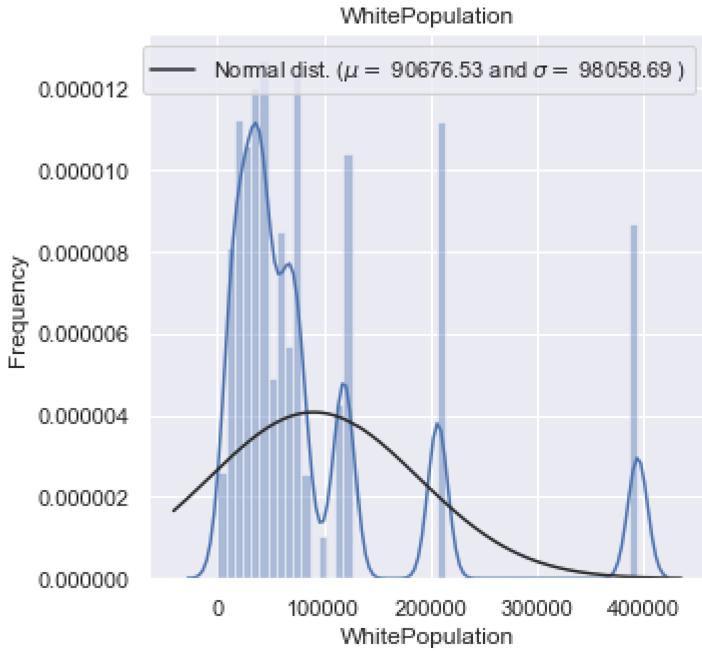

```
Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa8bd41d0>
Out[233]: <matplotlib.legend.Legend at 0x1aa8f10310>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'HispanicPopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```



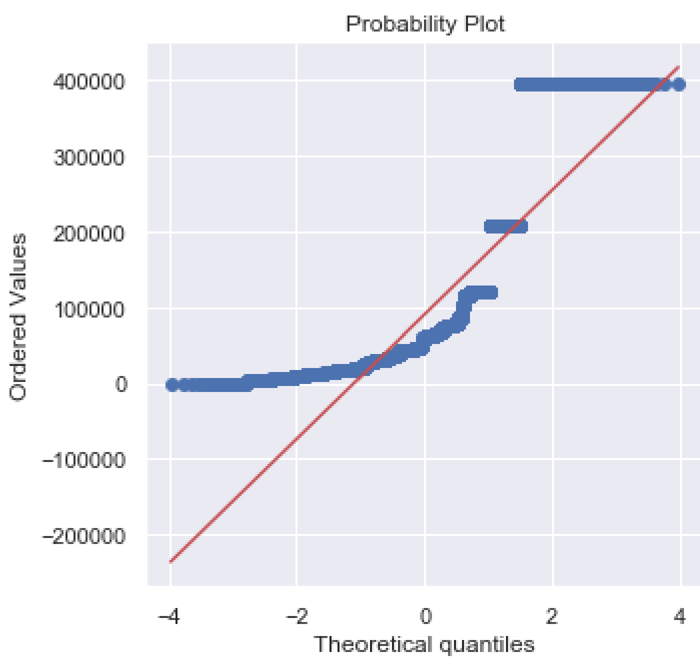

```
<Figure size 432x288 with 0 Axes>
```



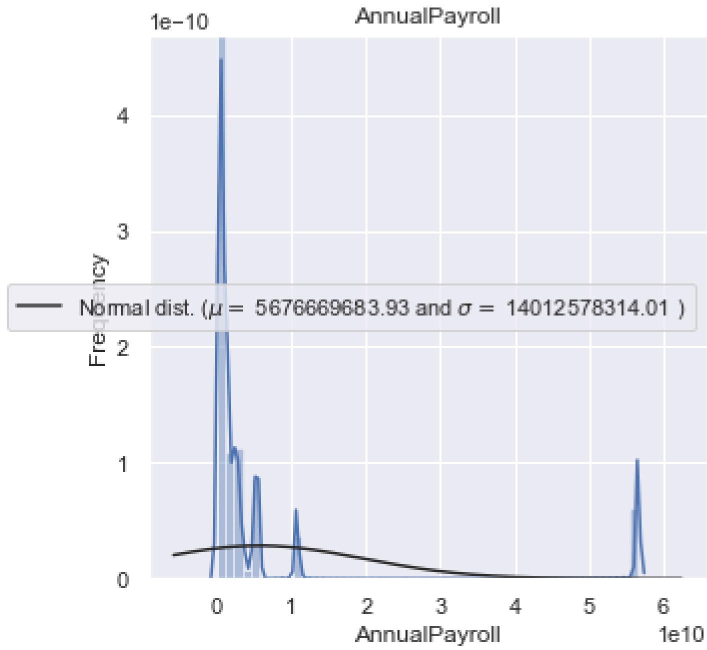

```
Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaac91f50>
Out[233]: <matplotlib.legend.Legend at 0x1a24859410>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'WhitePopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




```
Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1a25b31f10>
Out[233]: <matplotlib.legend.Legend at 0x1aaa24d090>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'AnnualPayroll')
Out[233]: <Figure size 360x360 with 0 Axes>
<Figure size 432x288 with 0 Axes>
```




```
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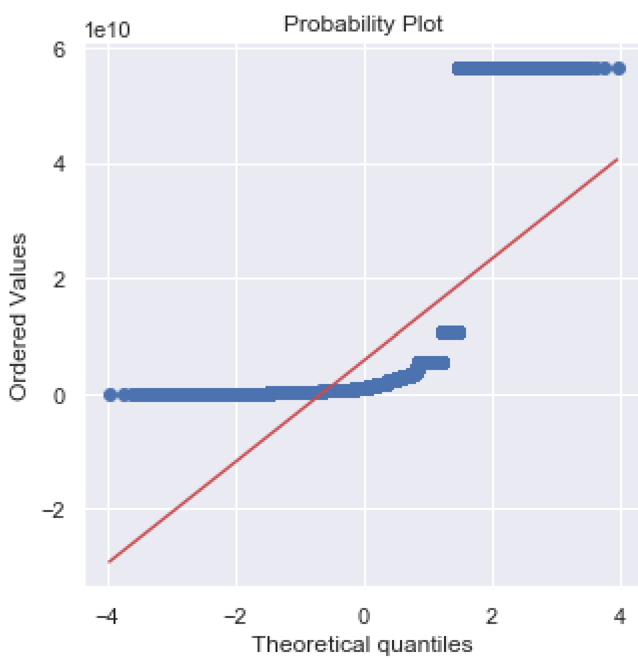
```




```
Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa9d6fb50>

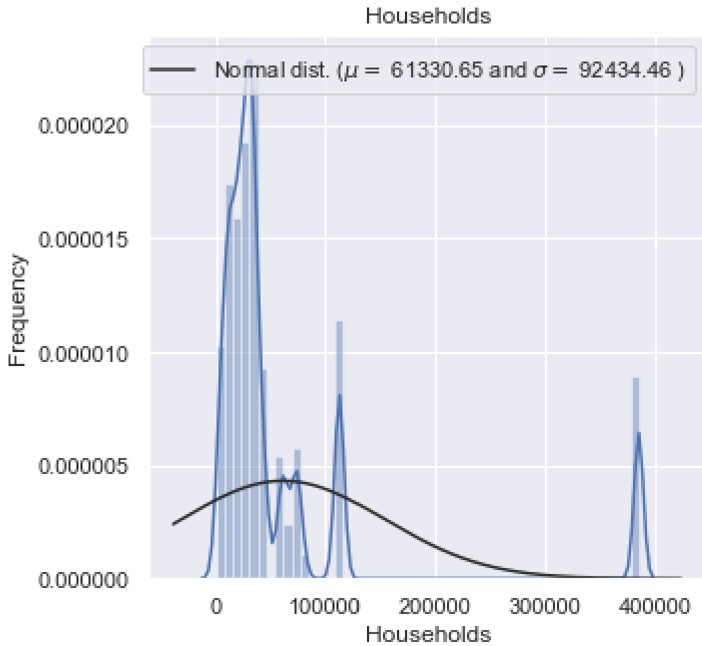
Out[233]: <matplotlib.legend.Legend at 0x1a26c3fdd0>

Out[233]: Text(0, 0.5, 'Frequency')

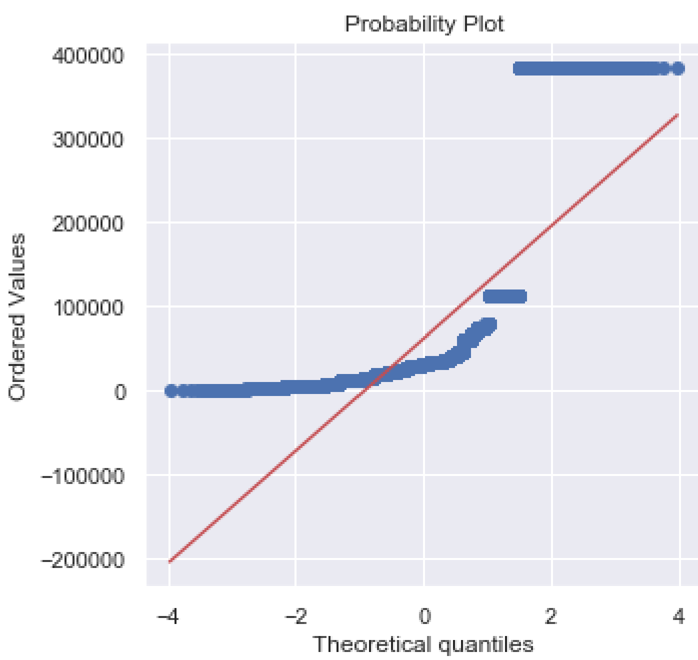
Out[233]: Text(0.5, 1.0, 'Households')

Out[233]: <Figure size 360x360 with 0 Axes>

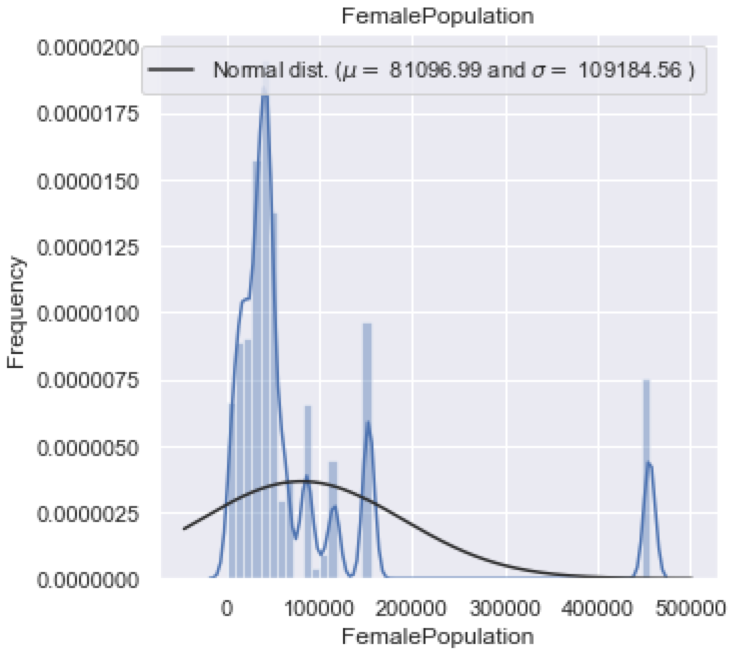
          <Figure size 432x288 with 0 Axes>
```



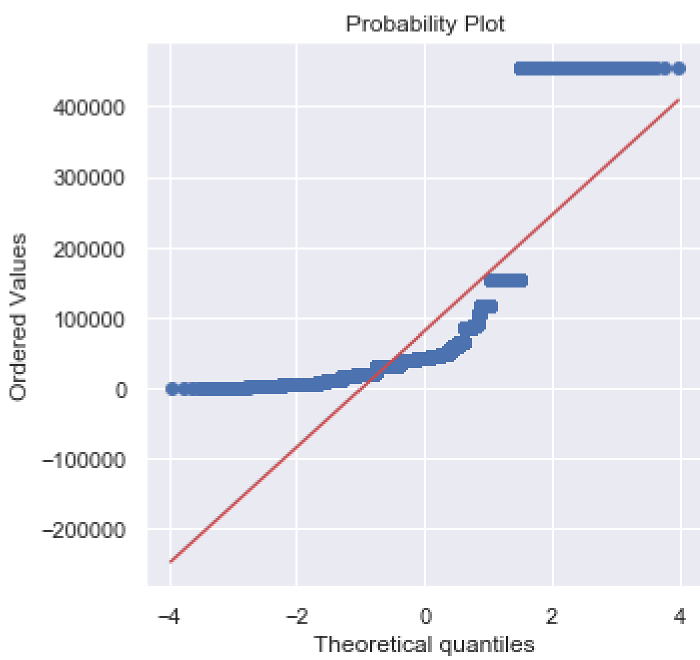
<Figure size 432x288 with 0 Axes>




```
Out[233]: <Figure size 360x360 with 0 Axes>
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1a24056c10>
Out[233]: <matplotlib.legend.Legend at 0x1aa9d7d690>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'FemalePopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
           <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




```
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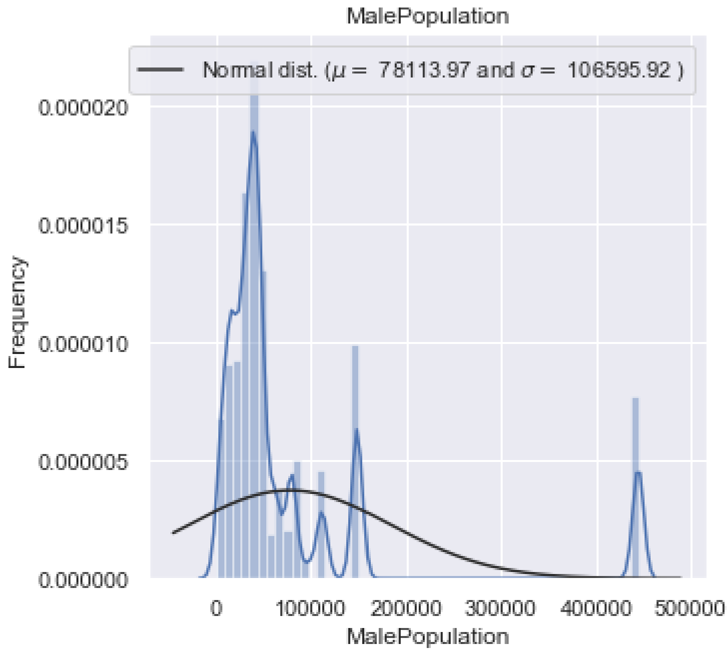
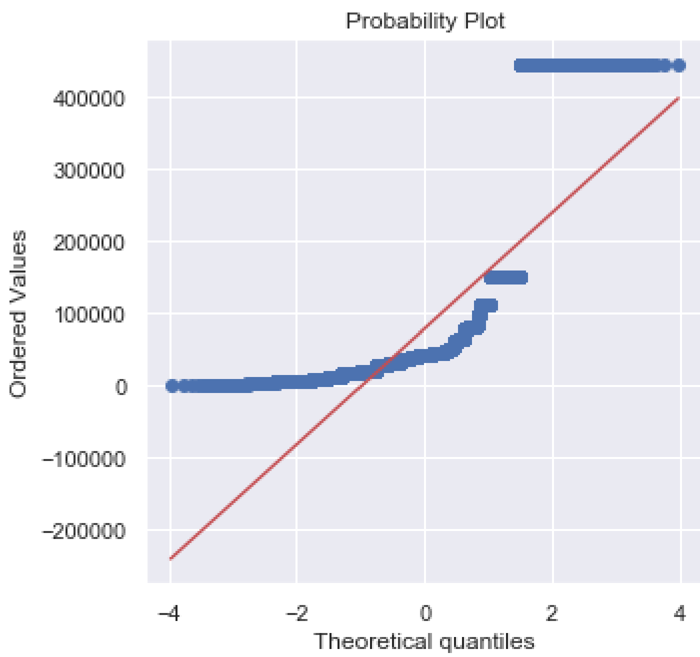
Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa9287f90>
Out[233]: <matplotlib.legend.Legend at 0x1aaa3d7410>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'MalePopulation')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




```
Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aac3b0190>

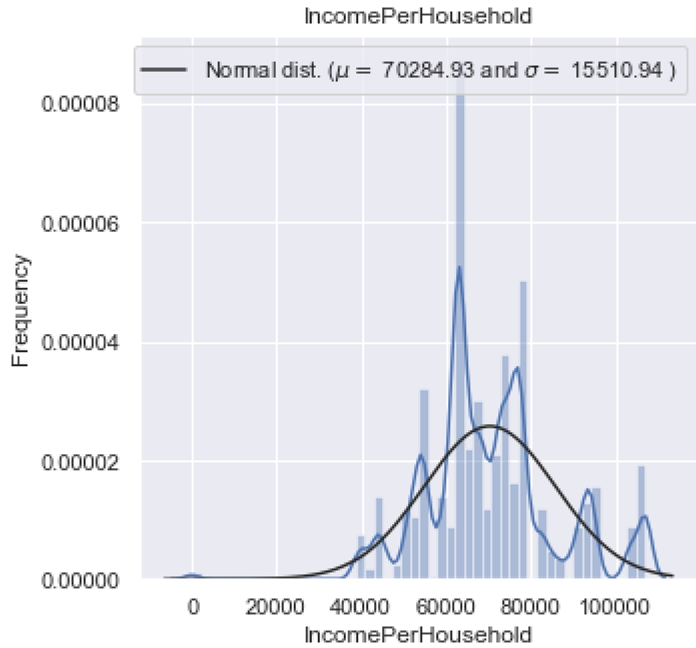
Out[233]: <matplotlib.legend.Legend at 0x1aaa2338d0>

Out[233]: Text(0, 0.5, 'Frequency')

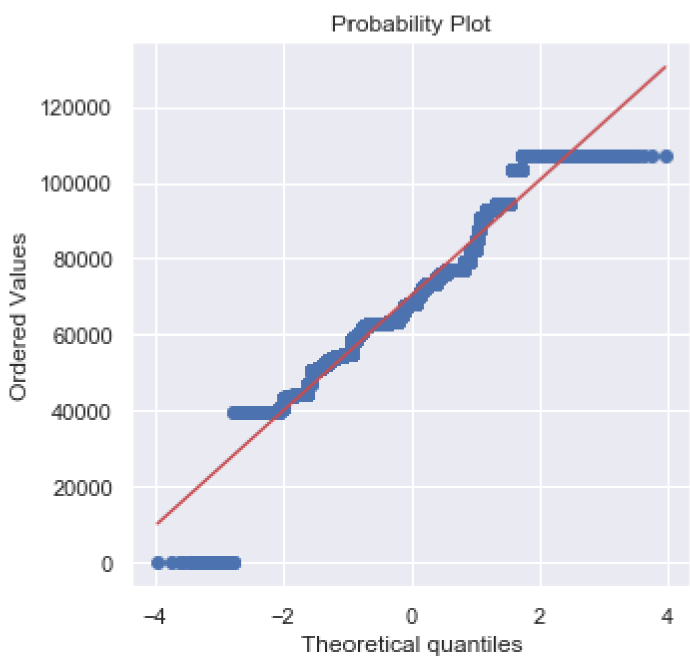
Out[233]: Text(0.5, 1.0, 'IncomePerHousehold')

Out[233]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>



Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1aac01a990>

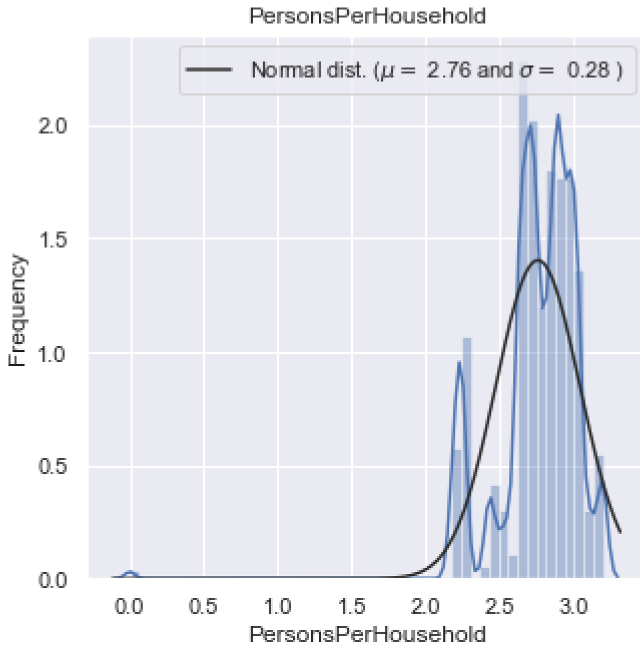
Out[233]: <matplotlib.legend.Legend at 0x1aac3acd10>

Out[233]: Text(0, 0.5, 'Frequency')

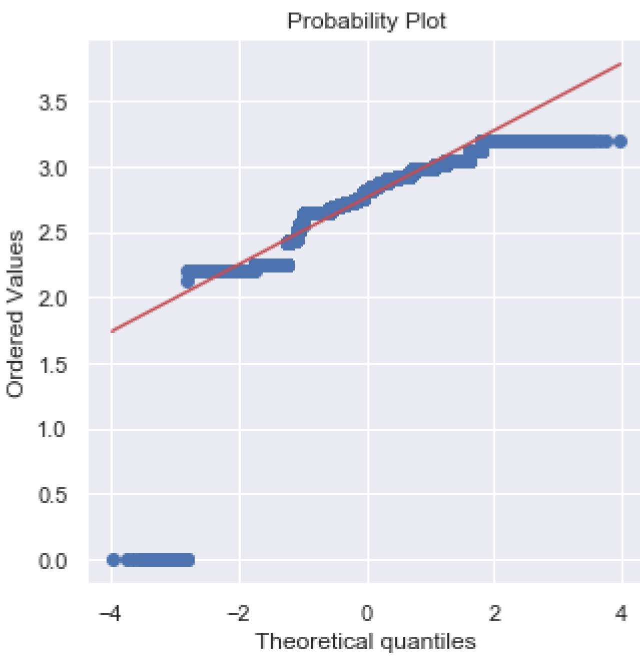
Out[233]: Text(0.5, 1.0, 'PersonsPerHousehold')

Out[233]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
```

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Out[233]: <Figure size 360x360 with 0 Axes>
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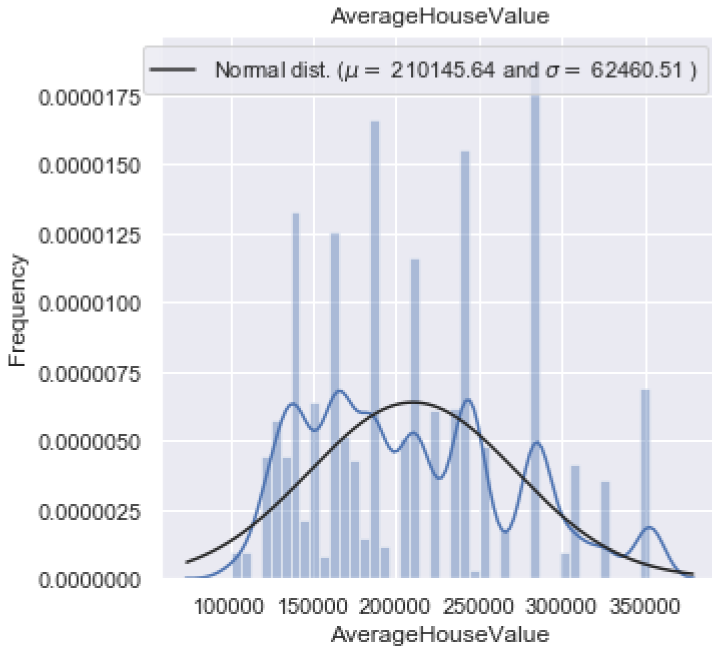
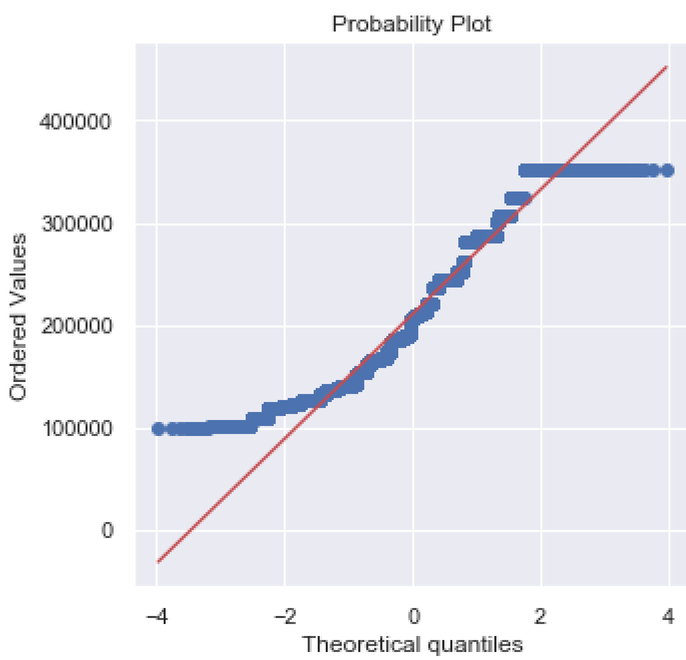
Out[233]: <matplotlib.legend.Legend at 0x1aab68a8d0>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'AverageHouseValue')
Out[233]: <Figure size 360x360 with 0 Axes>
           <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```

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Out[233]: <Figure size 360x360 with 0 Axes>
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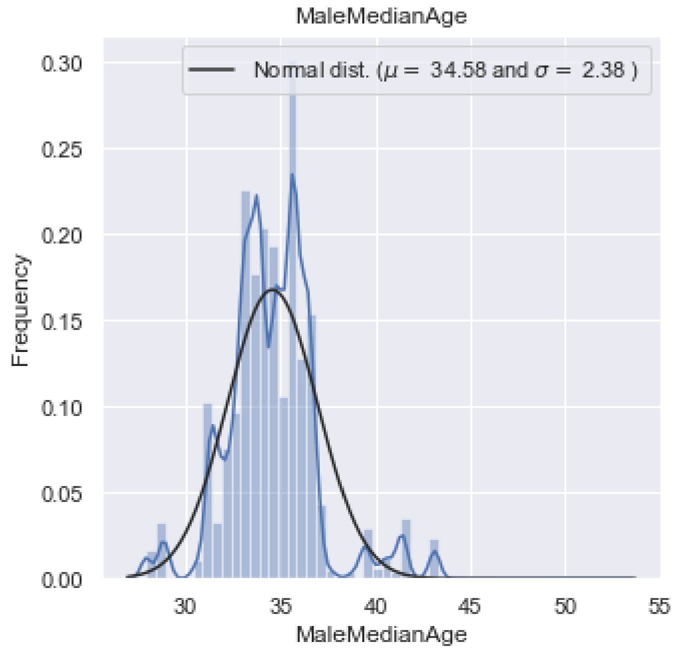
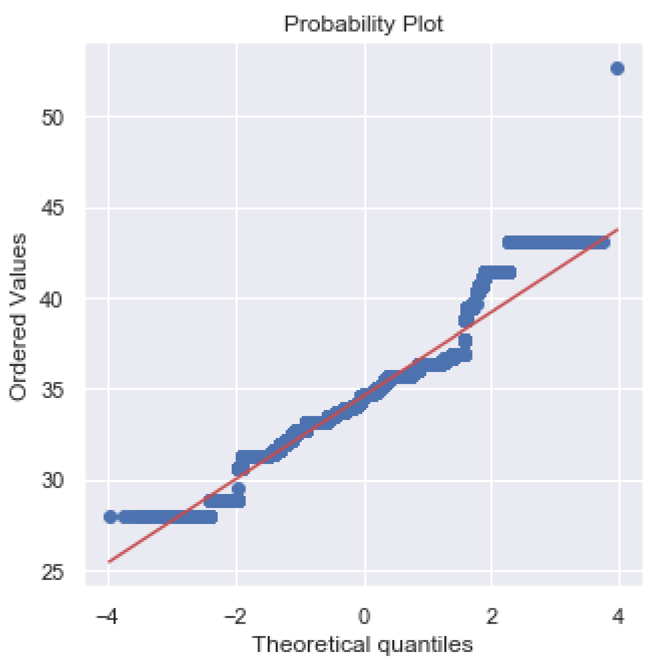
Out[233]: <matplotlib.legend.Legend at 0x1a25accb10>
Out[233]: Text(0, 0.5, 'Frequency')
Out[233]: Text(0.5, 1.0, 'MaleMedianAge')
Out[233]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```

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Out[233]: <Figure size 360x360 with 0 Axes>

Out[233]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23570bd0>

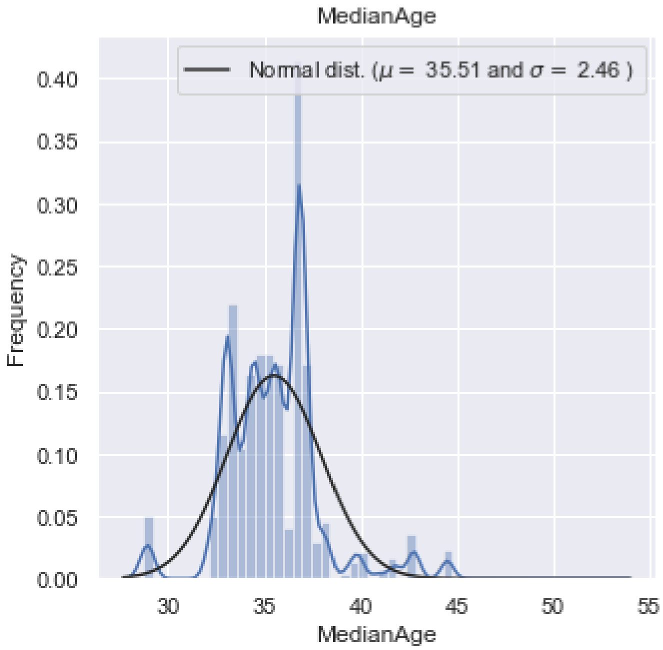
Out[233]: <matplotlib.legend.Legend at 0x1a23967750>

Out[233]: Text(0, 0.5, 'Frequency')

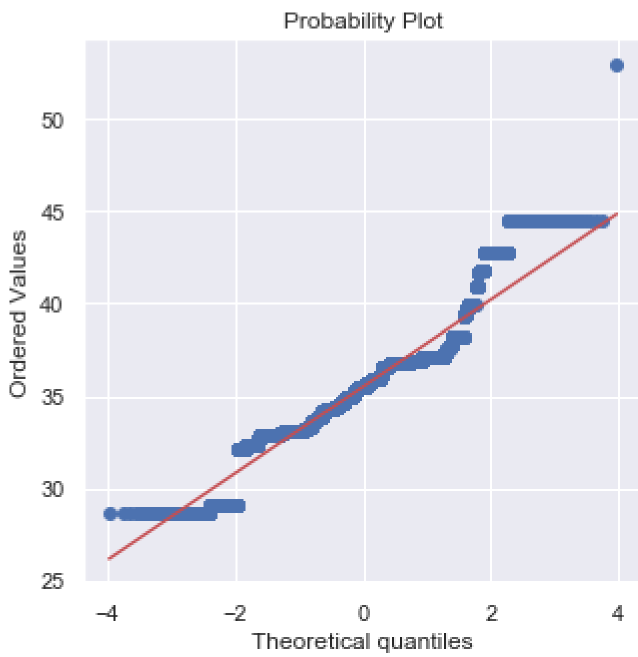
Out[233]: Text(0.5, 1.0, 'MedianAge')

Out[233]: <Figure size 360x360 with 0 Axes>

           <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>



According to the graph of distribution and QQ plot, we find most of the features follow skewed distribution.

4.2 Transfer skewed distribution to normal

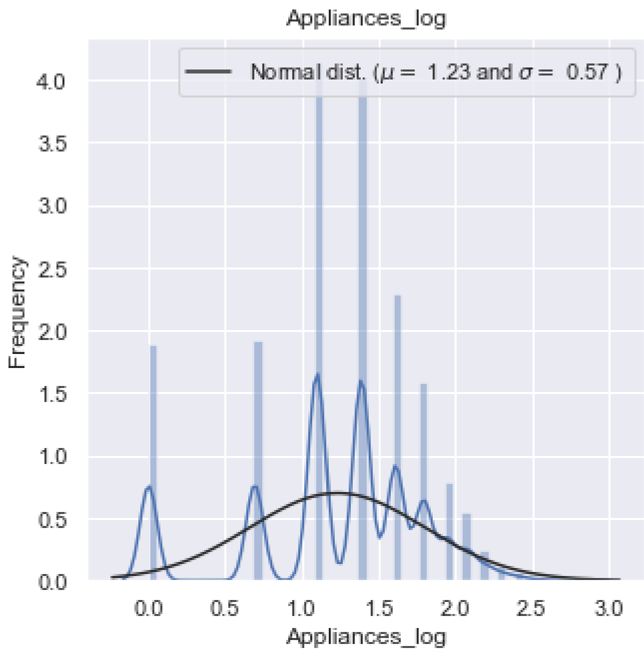
As the transformation we do in the data processing part, we took the log of the value of the features, so we can modify the distribution of the features to normal distribution.

In [234]:
```
for k in ['Appliances_log','Price_log','TaxAssessedValue_log','DaysOnZillow_lo
g',
          'PageViewCount_log', 'FavoriteCount_log','Bedrooms_log', 'Bathrooms_
log', 'Stories_log',
          'LivingArea_log', 'LotSize_log', 'Basement_log','YearBuilt_log', 'Pr
imarySchoolDistance_log', 'PrimarySchoolRating_log',
       'MiddleSchoolDistance_log', 'MiddleSchoolRating_log',
       'HighSchoolDistance_log', 'HighSchoolRating_log',
       'BusinessMailboxes_log', 'ResidentialMailboxes_log',
       'NumberofBusinesses_log', 'NumberofEmployees_log', 'Population2010_log'
,
       'CurrentPopulation_log', 'AmericanIndianPopulation_log',
       'AsianPopulation_log', 'BlackPopulation_log', 'HawaiianPopulation_log',
       'HispanicPopulation_log', 'WhitePopulation_log', 'AnnualPayroll_log',
       'Households_log', 'FemalePopulation_log', 'MalePopulation_log',
       'IncomePerHousehold_log', 'PersonsPerHousehold_log',
       'AverageHouseValue_log', 'MaleMedianAge_log', 'MedianAge_log']:
    df1=num_df_log

    fig = plt.figure()
    plt.figure(figsize=(5,5))
    sns.distplot(df1[k] , fit=norm) #画出数据的分布图
    (mu, sigma) = norm.fit(df1[k])  #求mu，sigma
    plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu
, sigma)], loc='best') #画图例
    plt.ylabel('Frequency')
    plt.title(k)

    fig = plt.figure()
    plt.figure(figsize=(5,5))
    res = stats.probplot(df1[k], plot=plt) #画拟合曲线
    plt.show()
```

```
Out[234]: <Figure size 360x360 with 0 Axes>
Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2439e550>
Out[234]: <matplotlib.legend.Legend at 0x1a24407ed0>
Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'Appliances_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```




```
          <Figure size 432x288 with 0 Axes>
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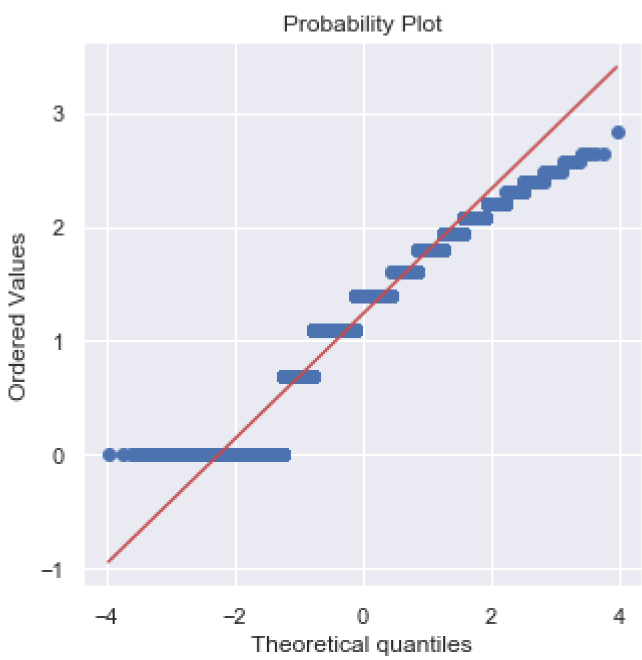



```
Out[234]: <Figure size 360x360 with 0 Axes>
```

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa8971050>

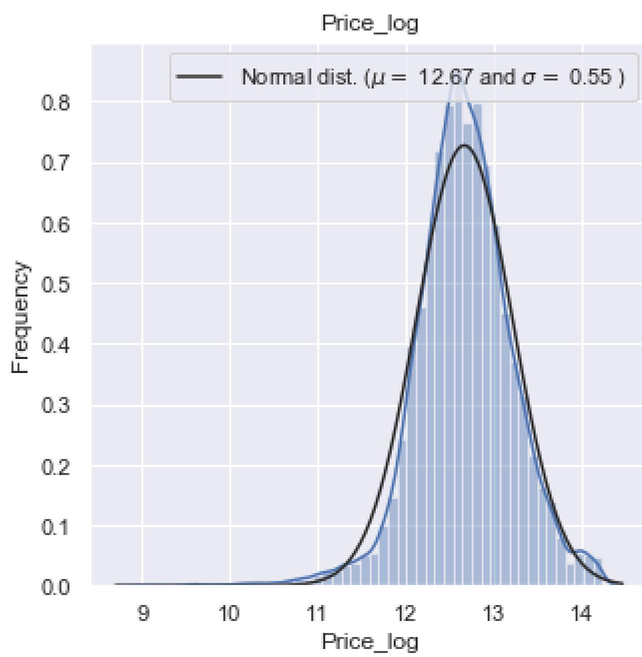
Out[234]: <matplotlib.legend.Legend at 0x1aac819c50>

Out[234]: Text(0, 0.5, 'Frequency')

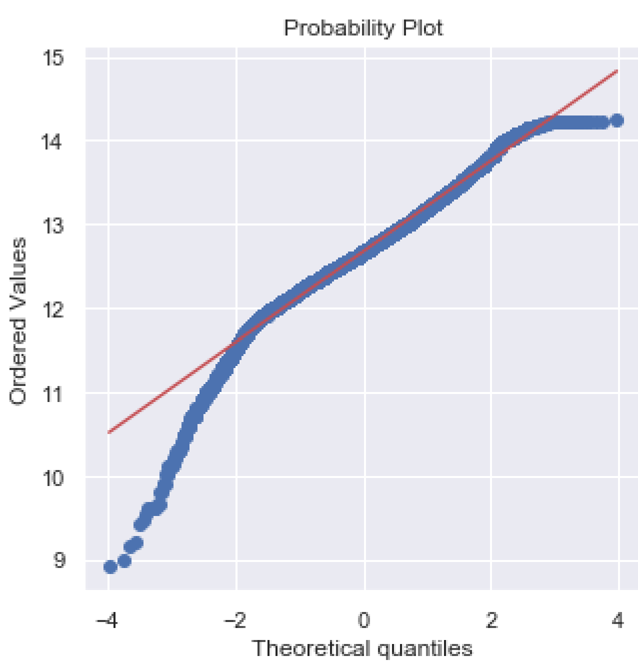
Out[234]: Text(0.5, 1.0, 'Price_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



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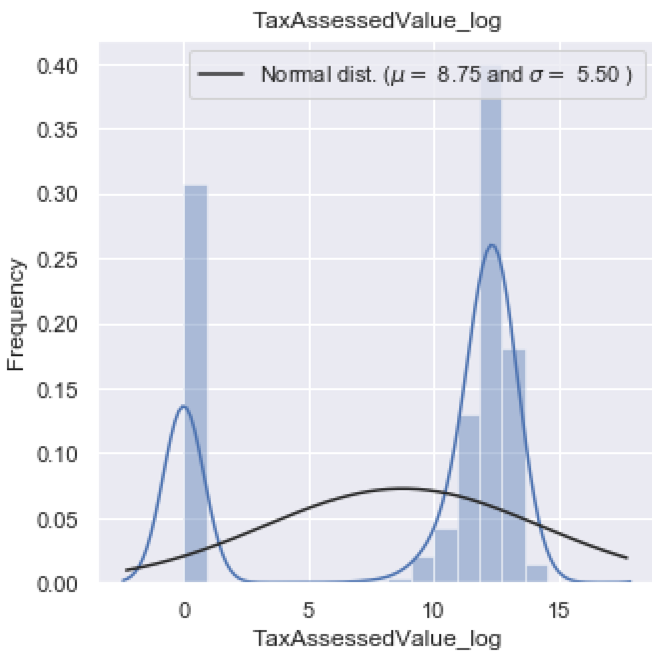
Out[234]: <matplotlib.legend.Legend at 0x1aaa09e650>

Out[234]: Text(0, 0.5, 'Frequency')

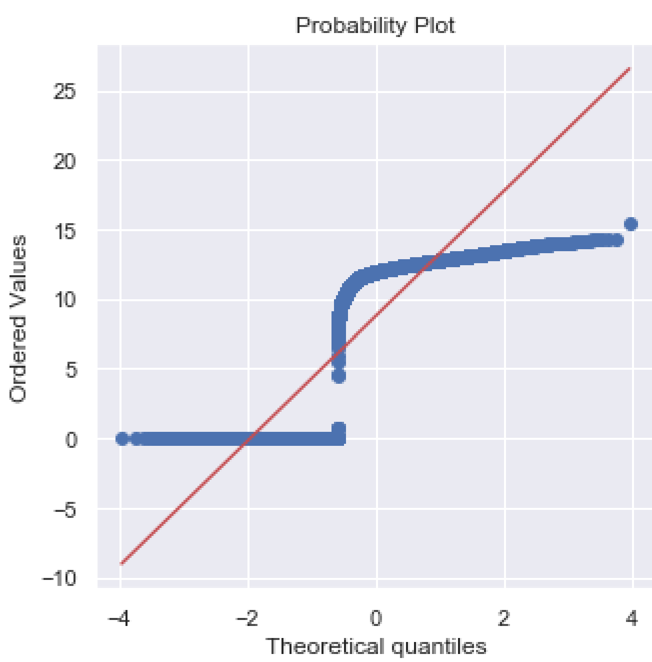
Out[234]: Text(0.5, 1.0, 'TaxAssessedValue_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

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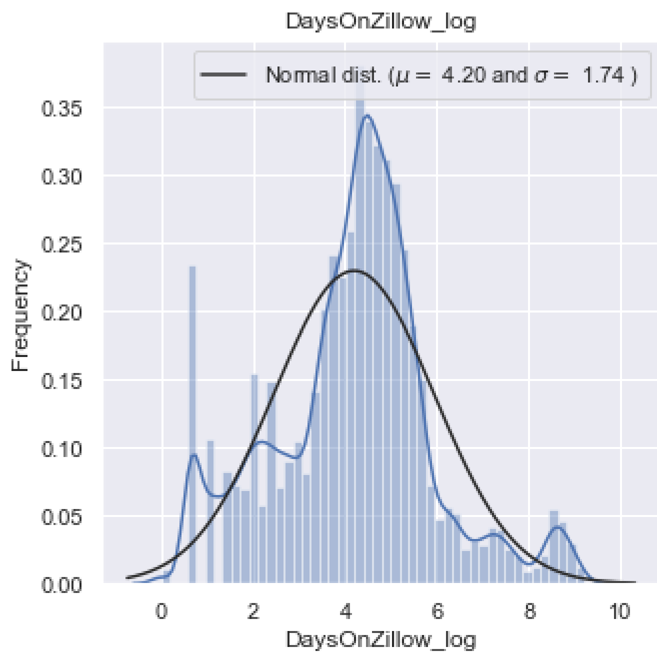
Out[234]: <matplotlib.legend.Legend at 0x1aac9a35d0>

Out[234]: Text(0, 0.5, 'Frequency')

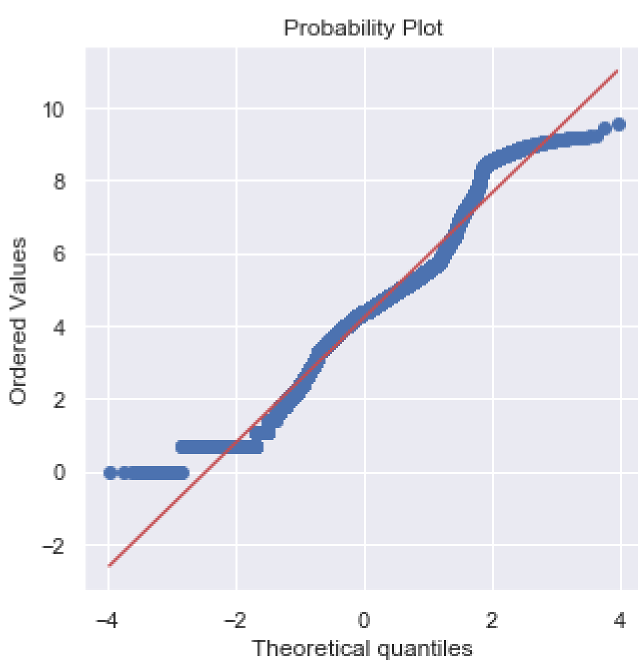
Out[234]: Text(0.5, 1.0, 'DaysOnZillow_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aac84e3d0>

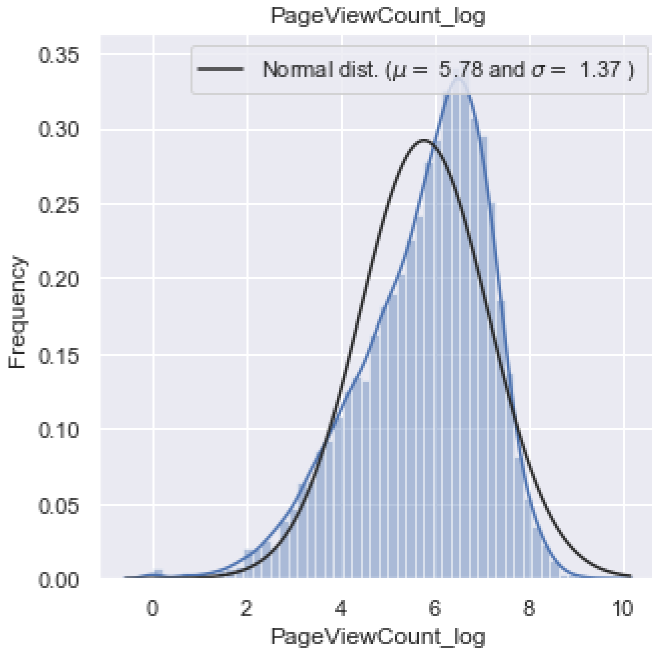
Out[234]: <matplotlib.legend.Legend at 0x1aaa0bea10>

Out[234]: Text(0, 0.5, 'Frequency')

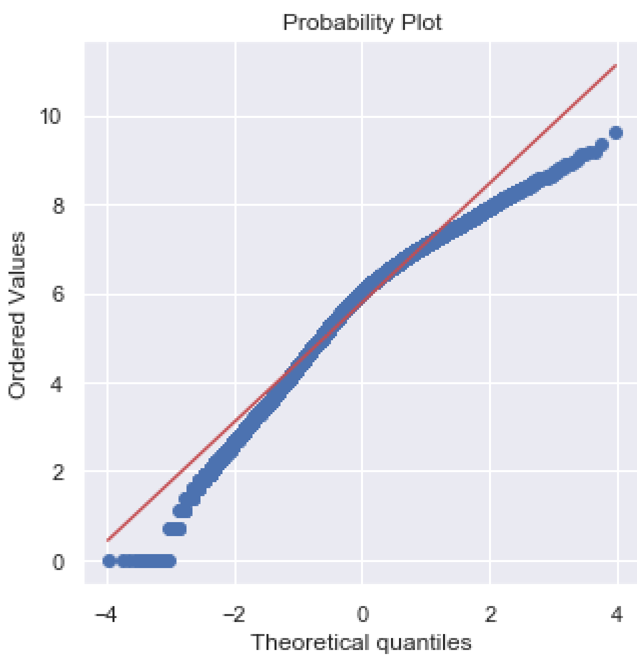
Out[234]: Text(0.5, 1.0, 'PageViewCount_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aacb53590>

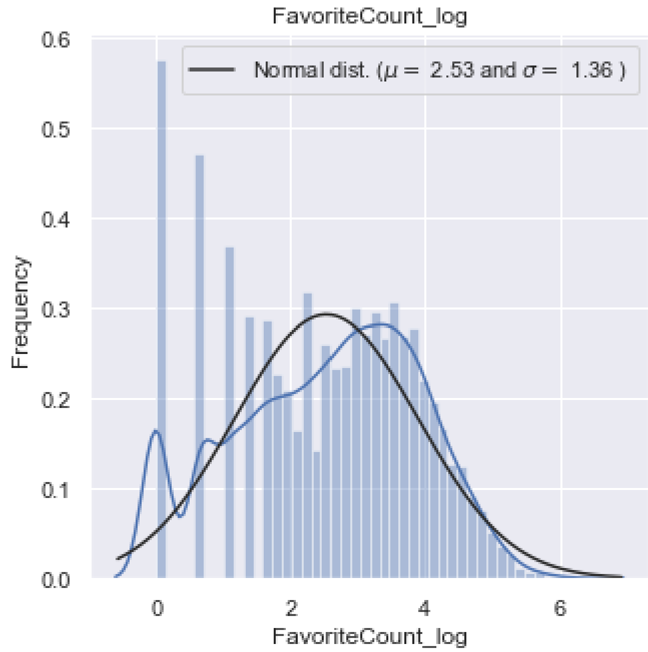
Out[234]: <matplotlib.legend.Legend at 0x1aacd55650>

Out[234]: Text(0, 0.5, 'Frequency')

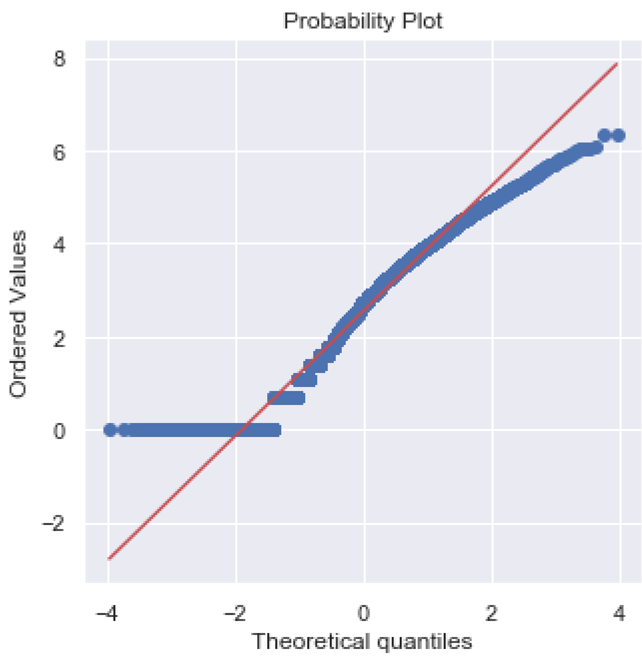
Out[234]: Text(0.5, 1.0, 'FavoriteCount_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa600f490>

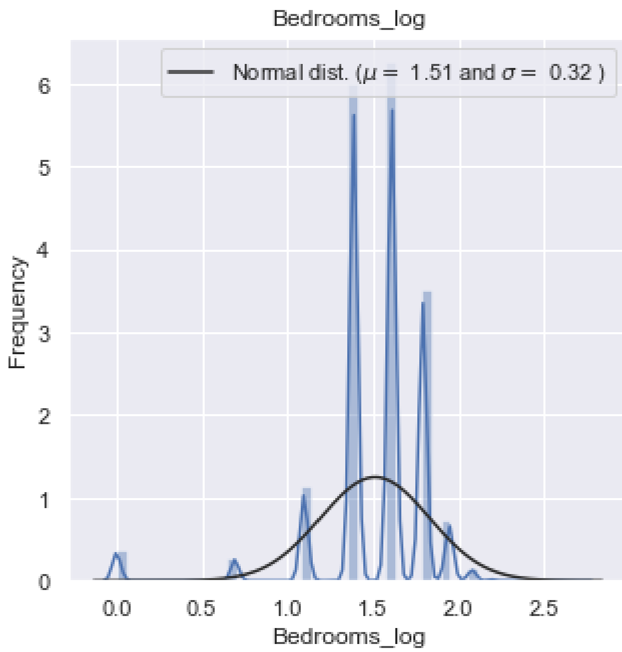
Out[234]: <matplotlib.legend.Legend at 0x1aab68f710>

Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'Bedrooms_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



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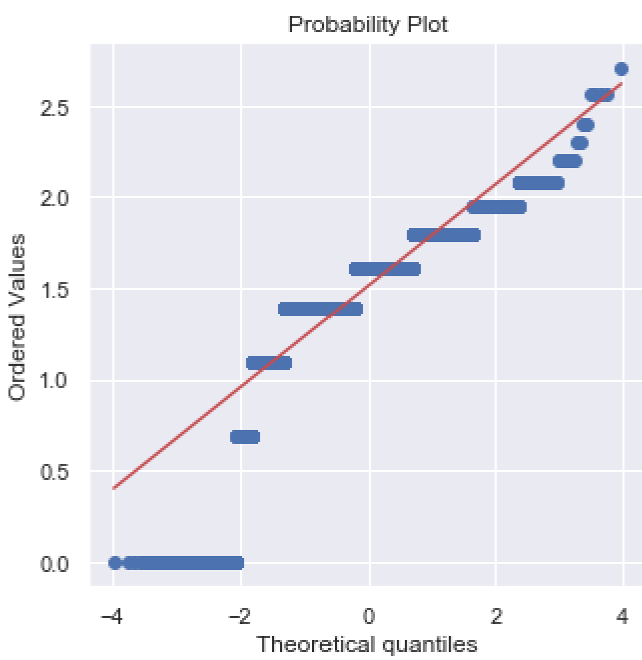


Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaac9ee50>

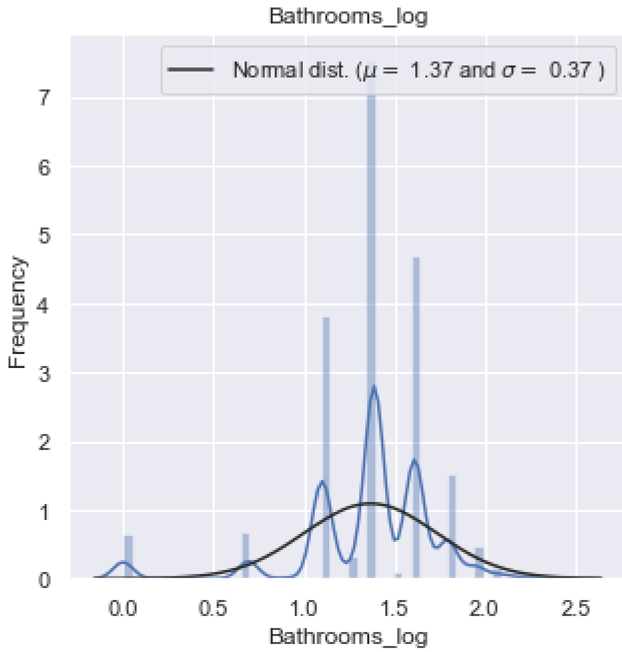
Out[234]: <matplotlib.legend.Legend at 0x1aac819490>

Out[234]: Text(0, 0.5, 'Frequency')

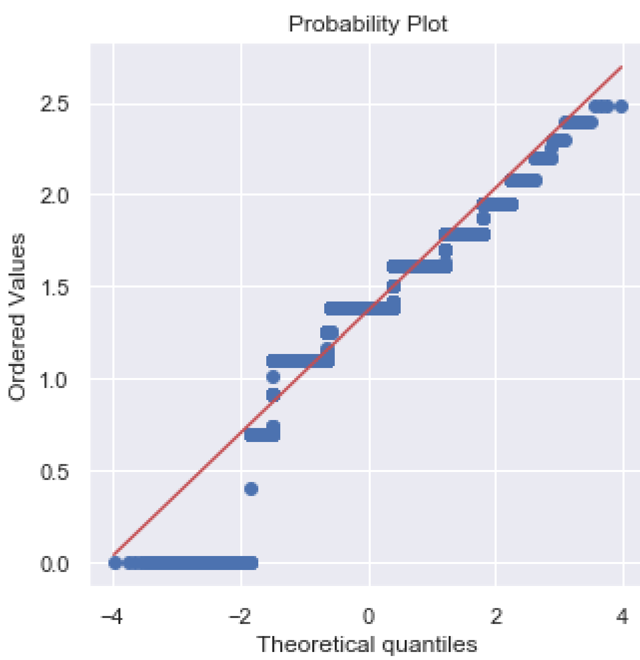
Out[234]: Text(0.5, 1.0, 'Bathrooms_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

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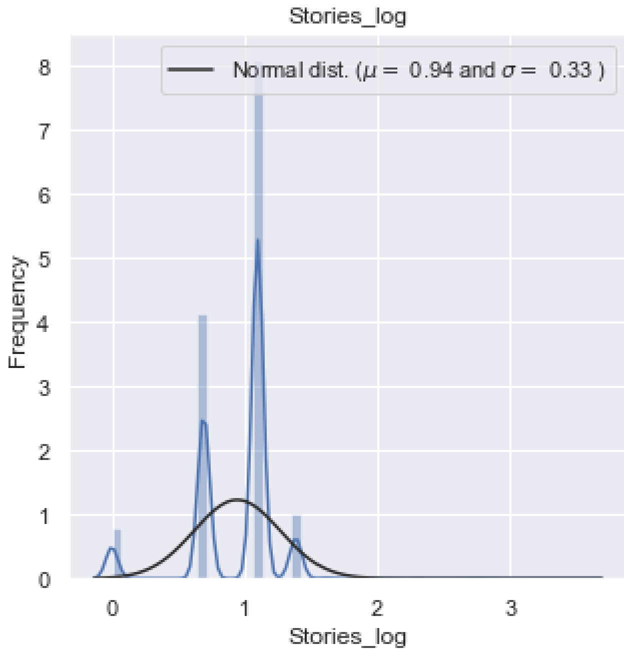
Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'Stories_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
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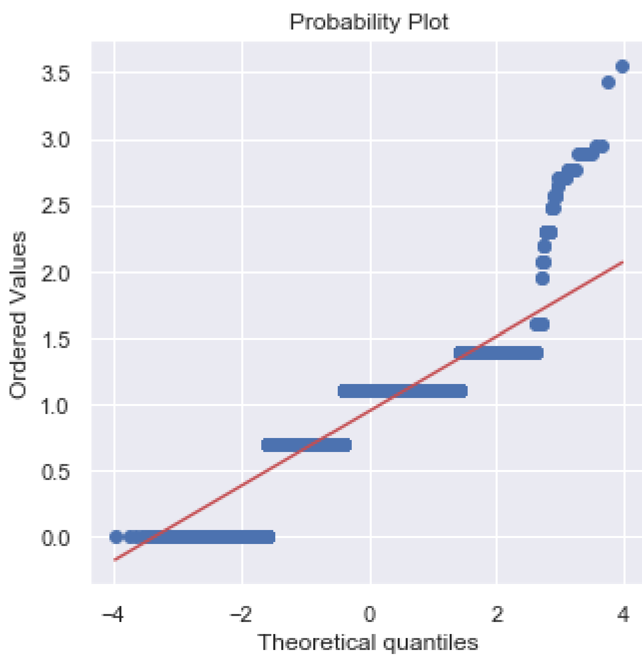


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Out[234]: <Figure size 360x360 with 0 Axes>
Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1a246d5390>
Out[234]: <matplotlib.legend.Legend at 0x1aaae25990>
Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'LivingArea_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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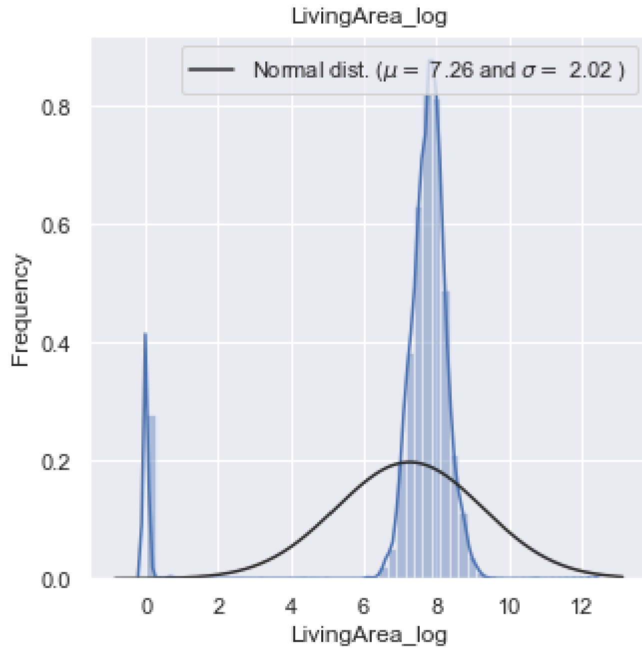


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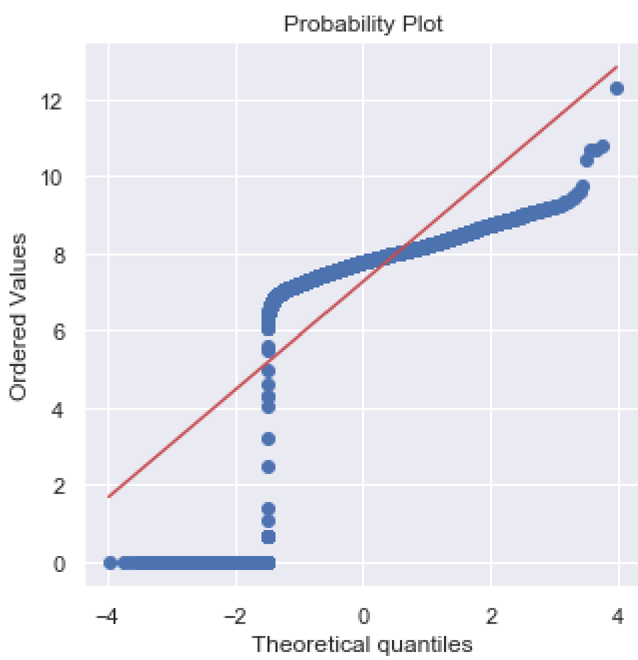


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Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'LotSize_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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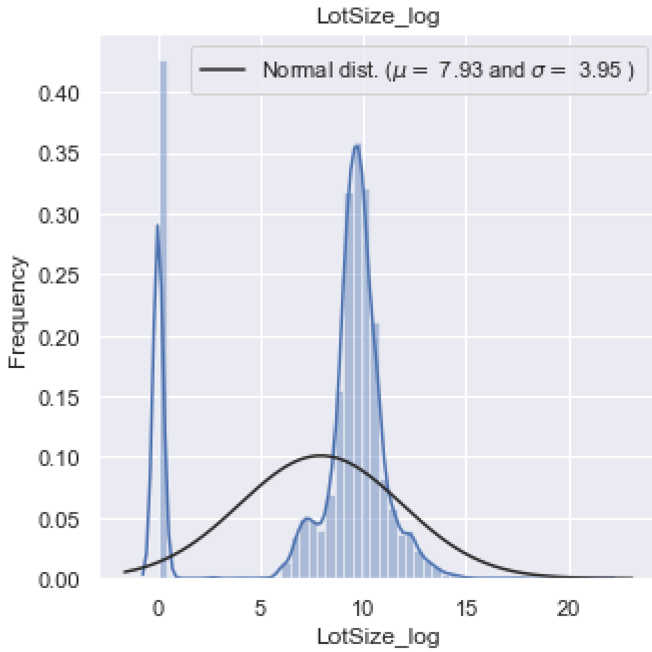

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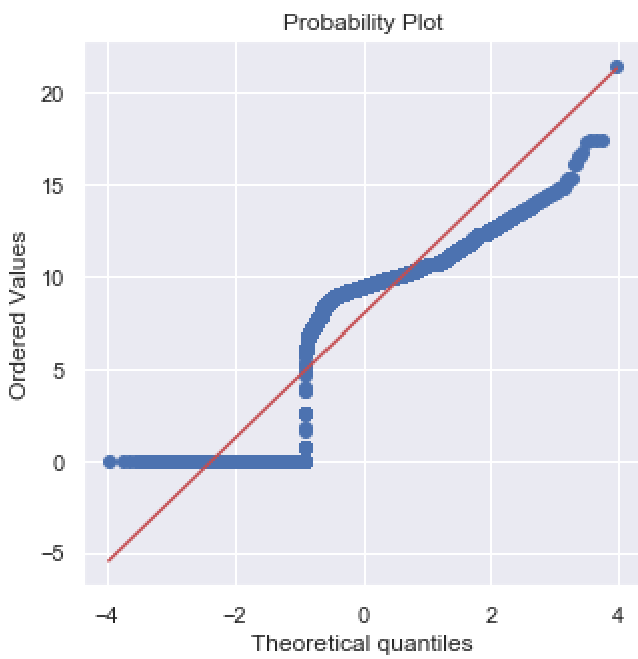

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Out[234]: Text(0.5, 1.0, 'Basement_log')

Out[234]: <Figure size 360x360 with 0 Axes>

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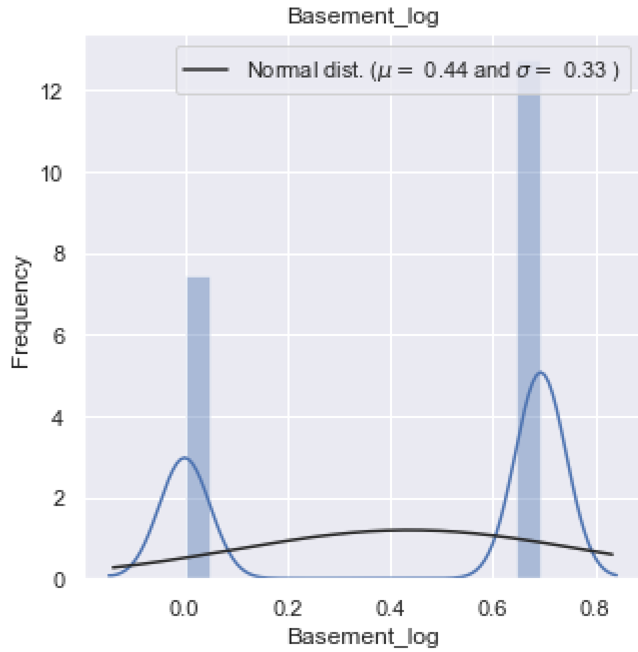


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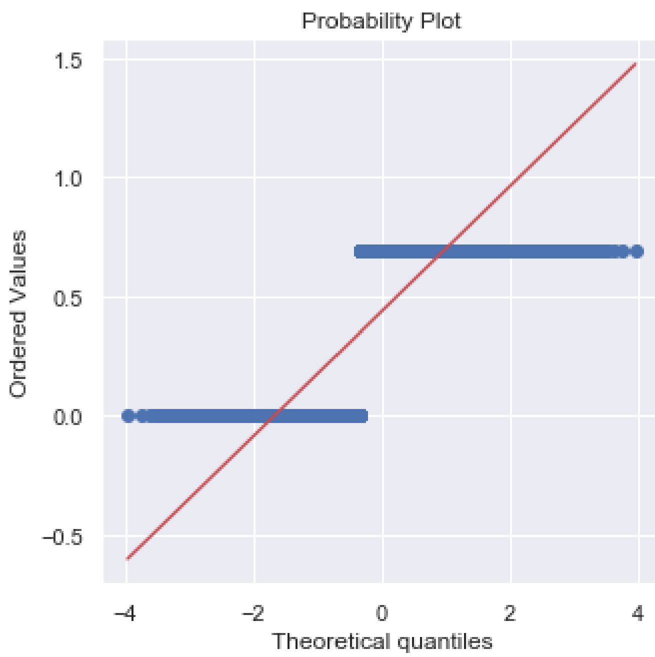


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Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'YearBuilt_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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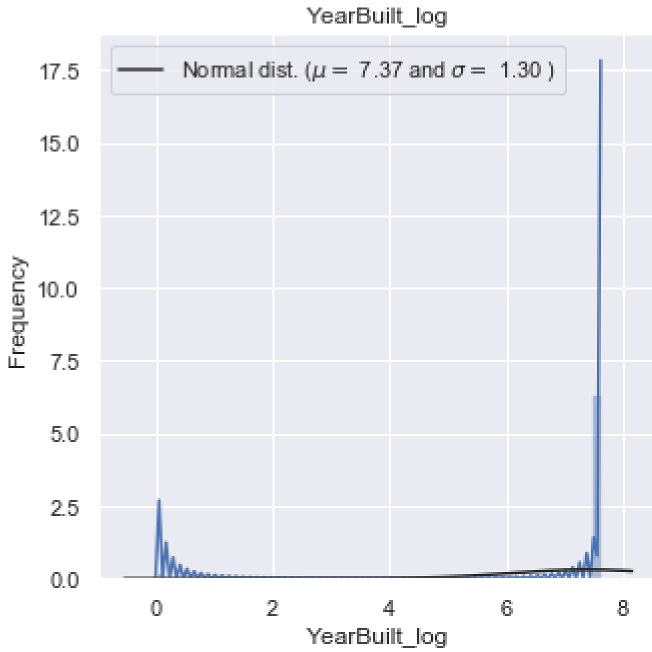

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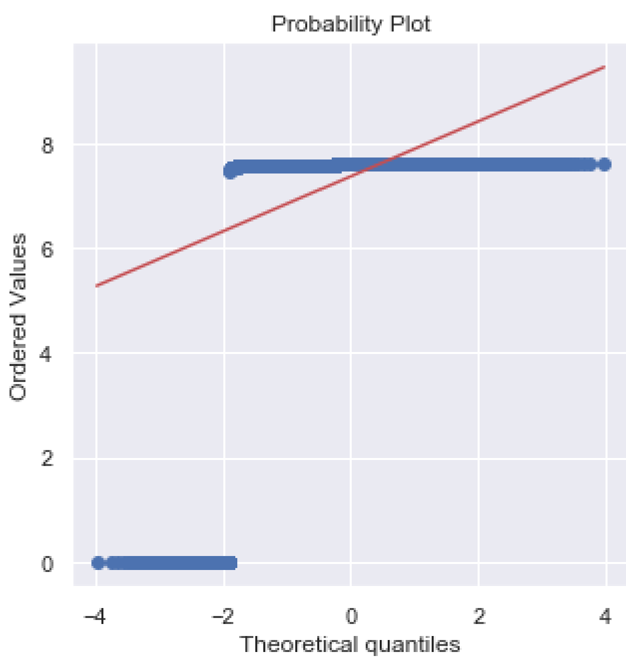

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Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'PrimarySchoolDistance_log')

Out[234]: <Figure size 360x360 with 0 Axes>

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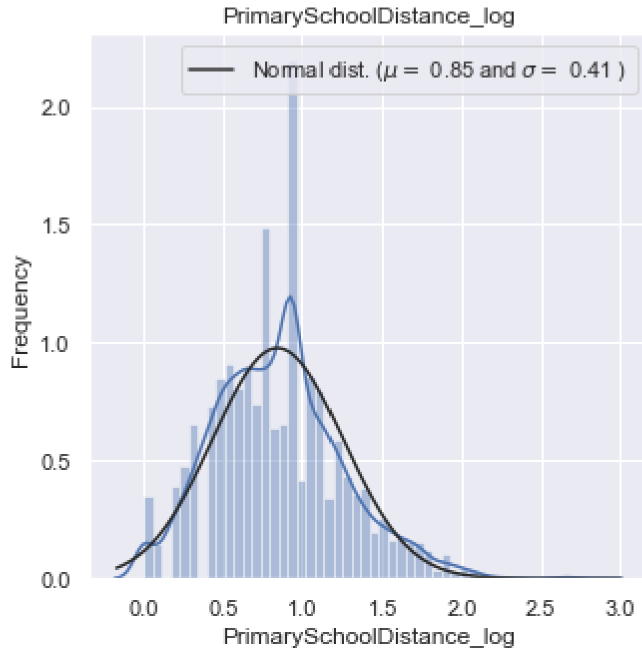

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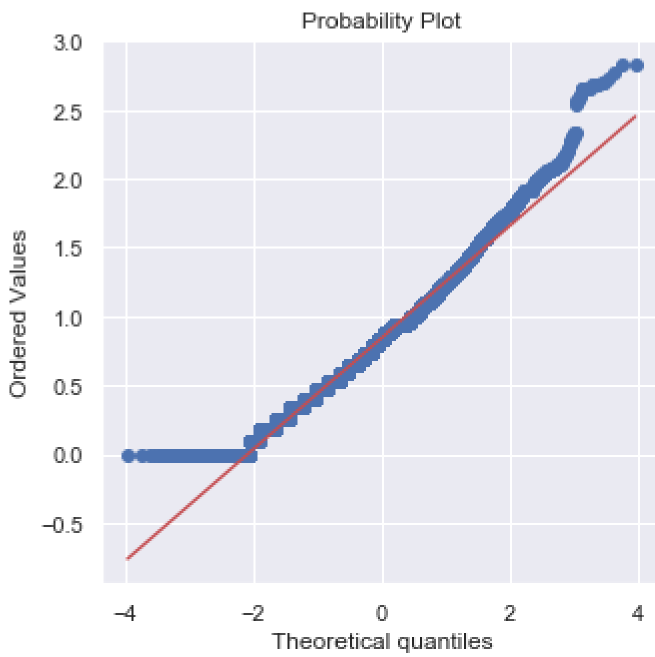

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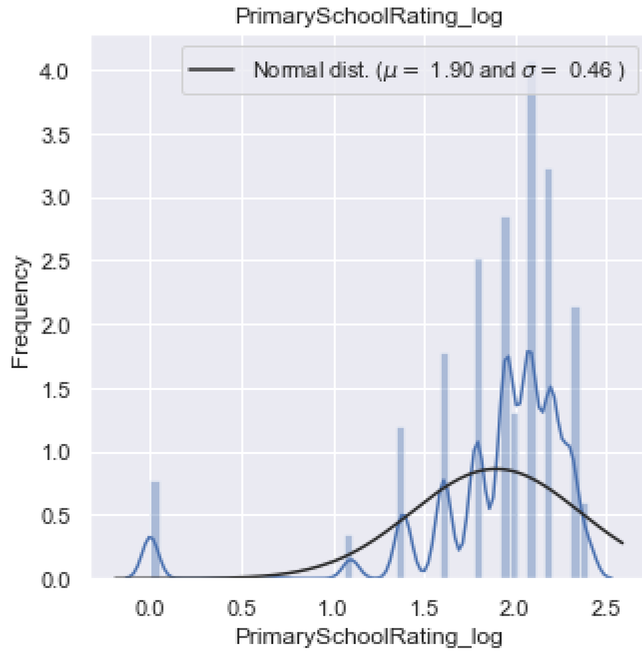
Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'PrimarySchoolRating_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



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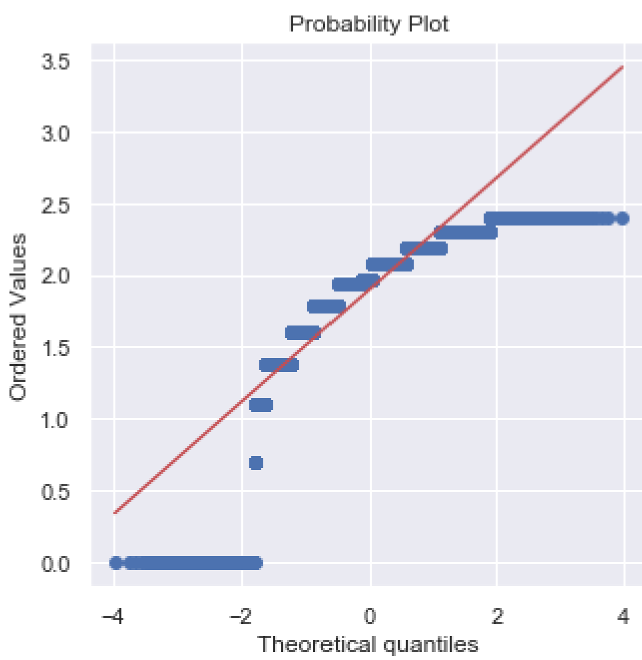

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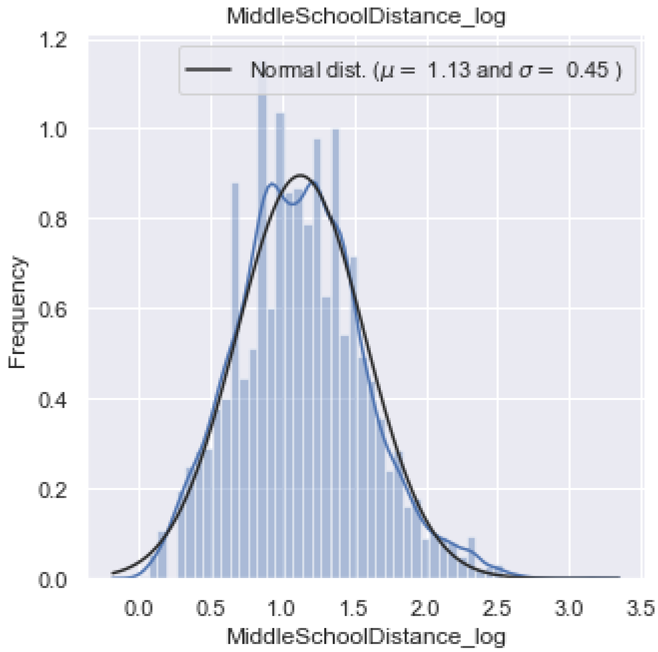
Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'MiddleSchoolDistance_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>

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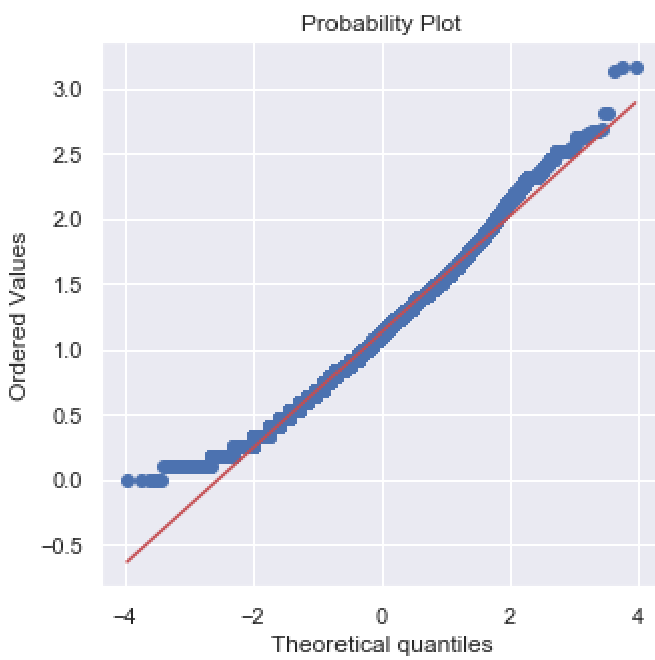


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Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'MiddleSchoolRating_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>
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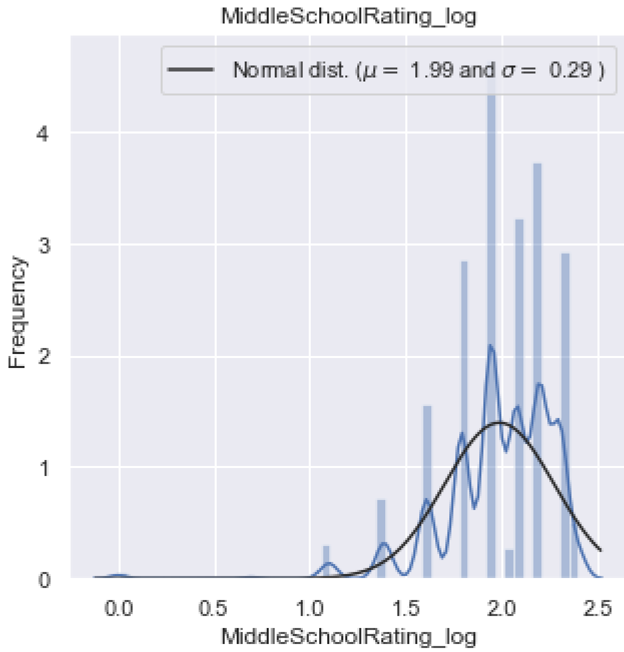


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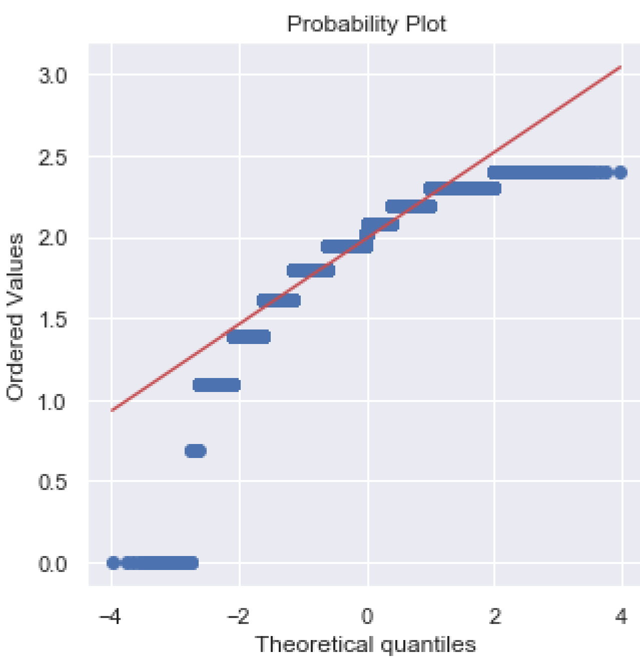


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Out[234]: Text(0, 0.5, 'Frequency')

Out[234]: Text(0.5, 1.0, 'HighSchoolDistance_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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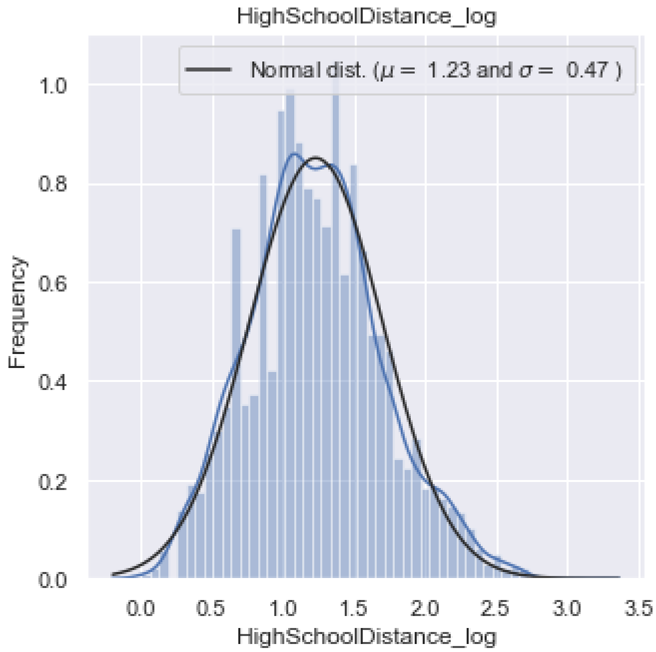


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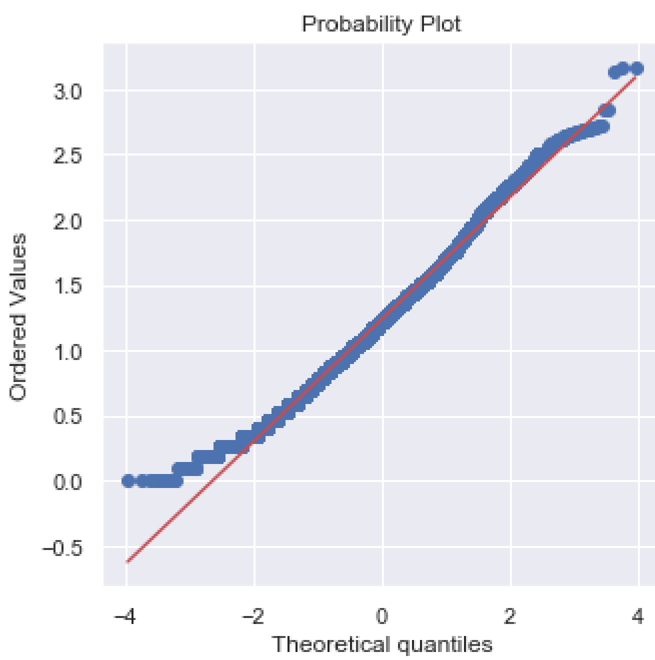


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Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'HighSchoolRating_log')
Out[234]: <Figure size 360x360 with 0 Axes>
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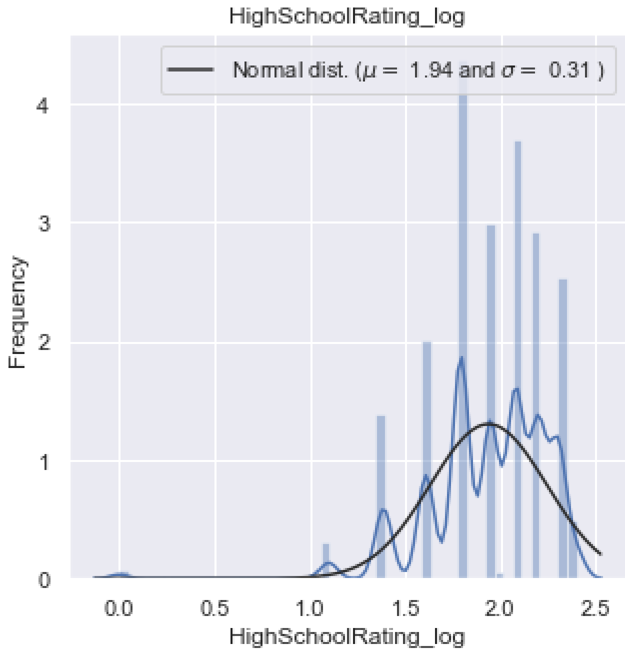


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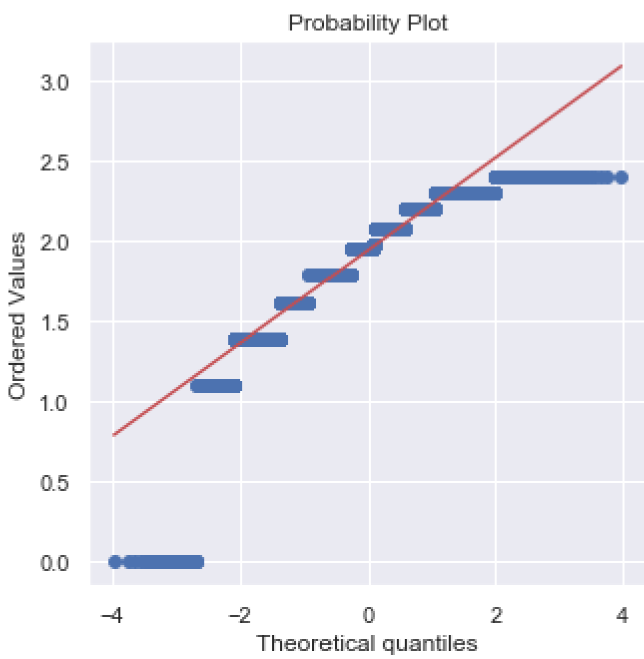


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Out[234]: Text(0.5, 1.0, 'BusinessMailboxes_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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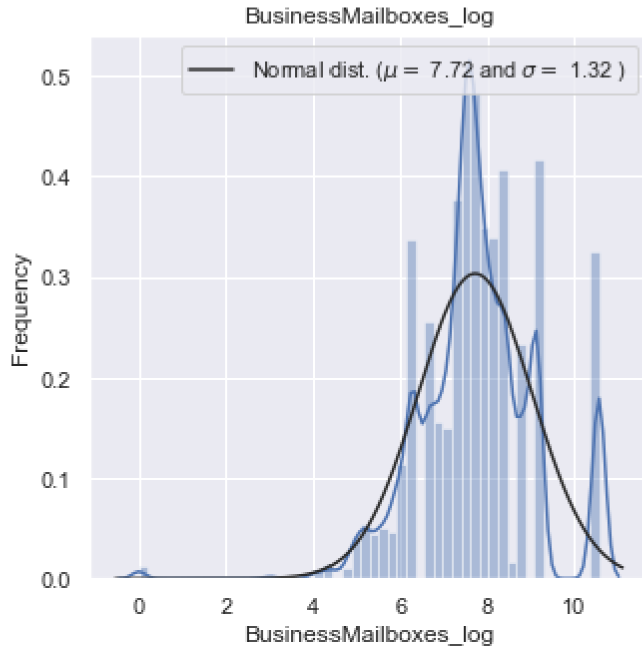


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<Figure size 432x288 with 0 Axes>
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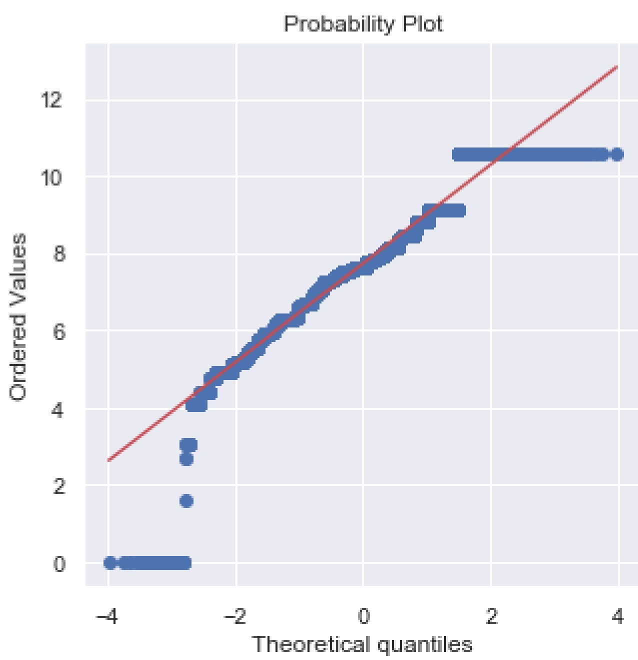


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Out[234]: <Figure size 360x360 with 0 Axes>

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Out[234]: Text(0.5, 1.0, 'ResidentialMailboxes_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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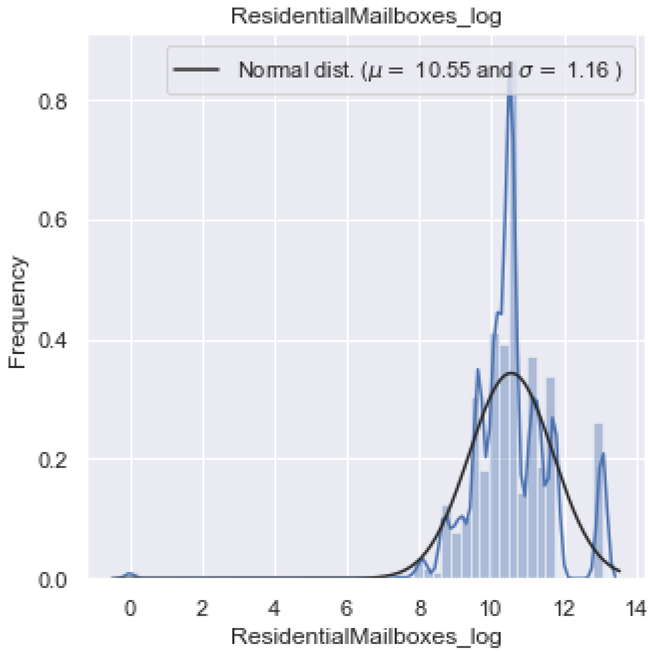


```
<Figure size 432x288 with 0 Axes>
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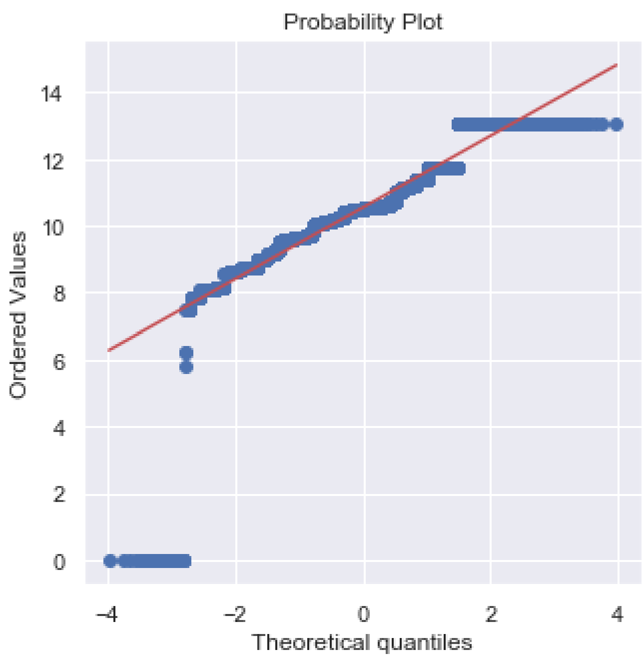


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Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'NumberofBusinesses_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
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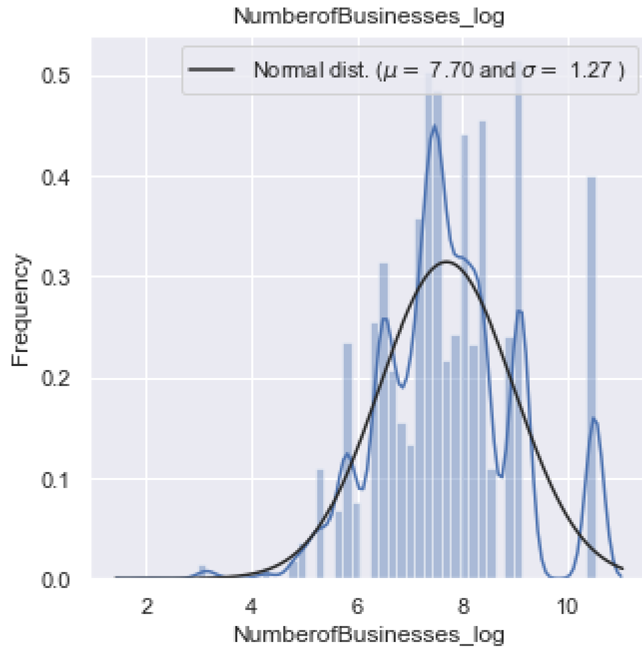


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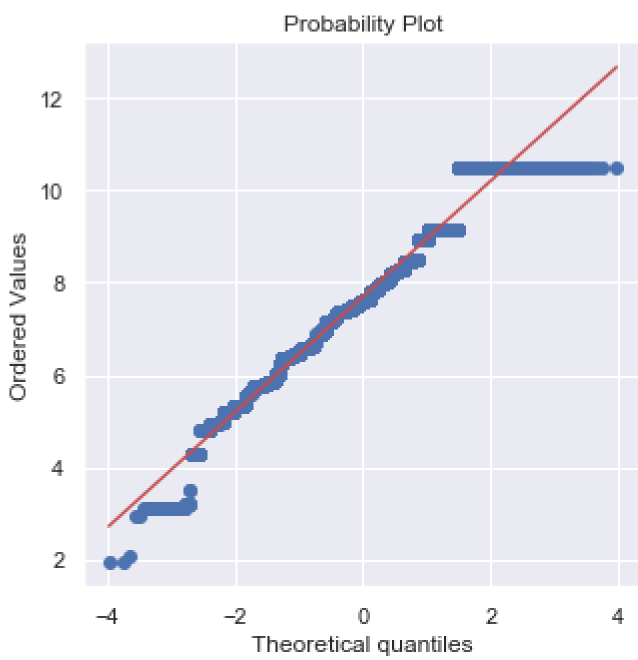


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Out[234]: Text(0.5, 1.0, 'NumberofEmployees_log')
Out[234]: <Figure size 360x360 with 0 Axes>
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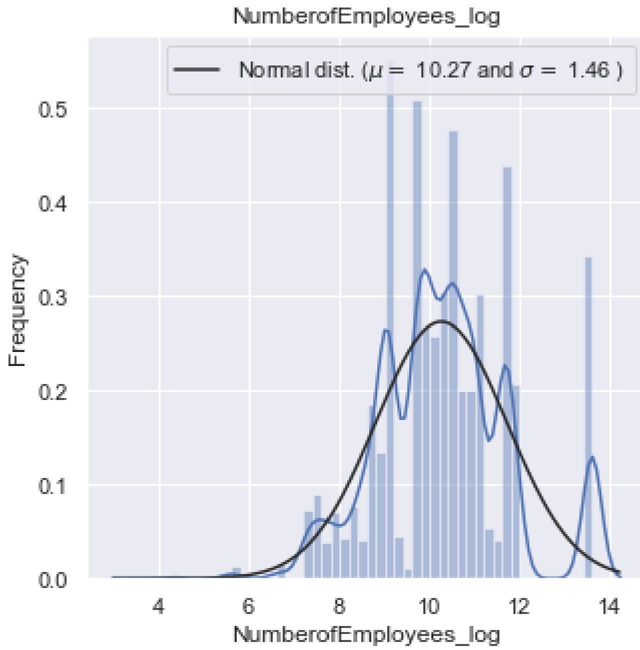


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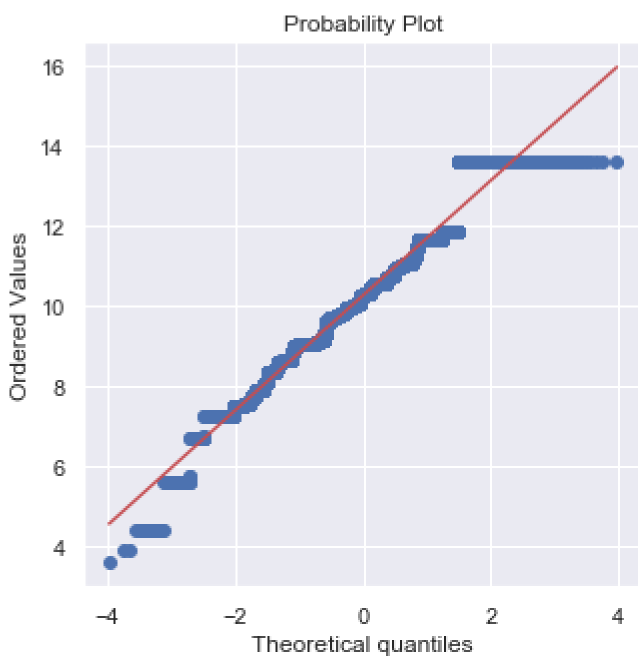


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Out[234]: Text(0.5, 1.0, 'Population2010_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
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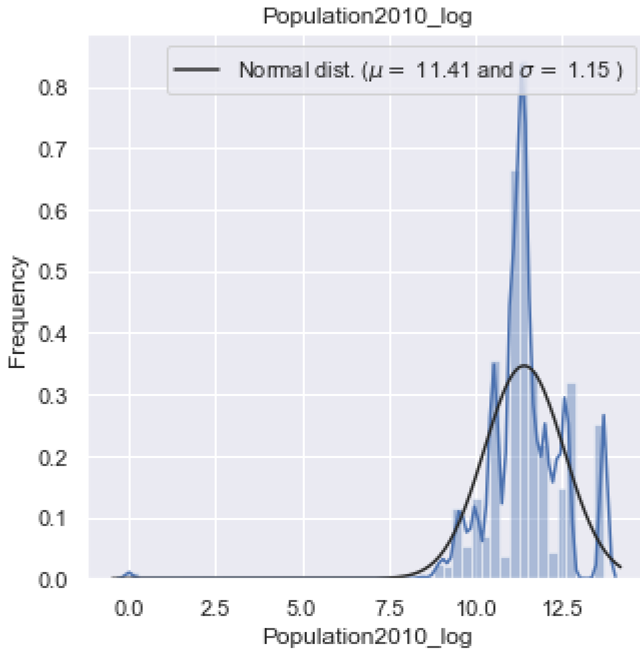

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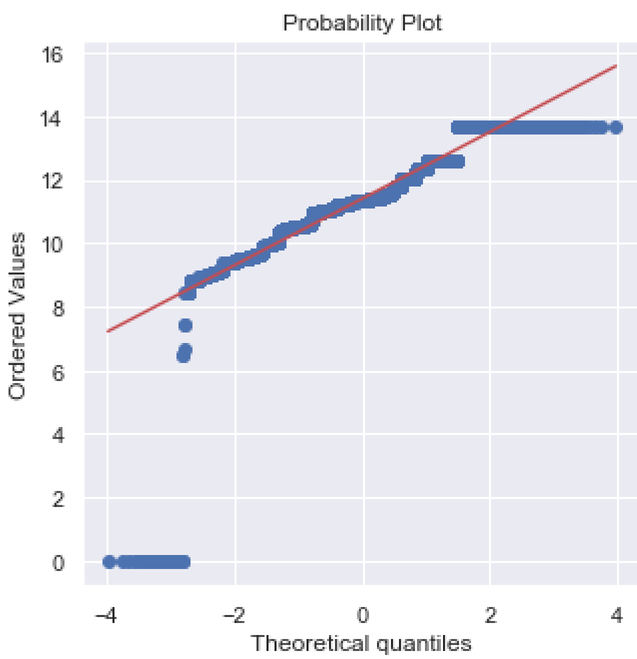

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Out[234]: Text(0.5, 1.0, 'CurrentPopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

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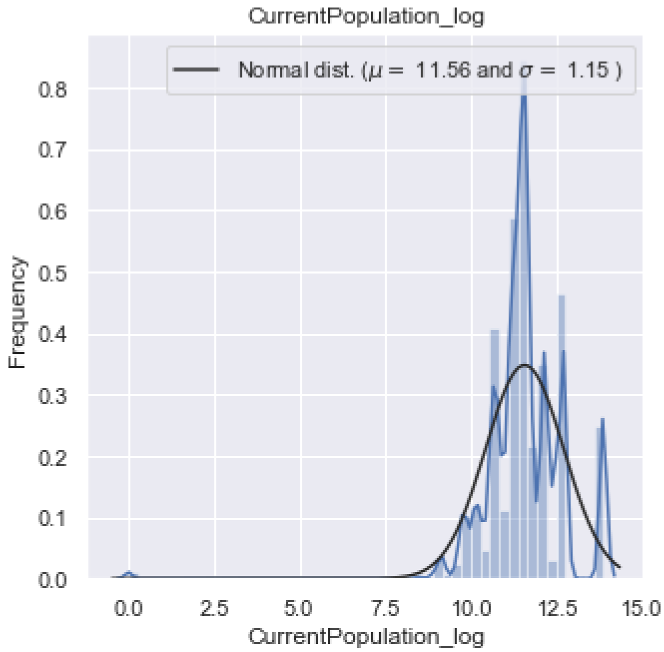

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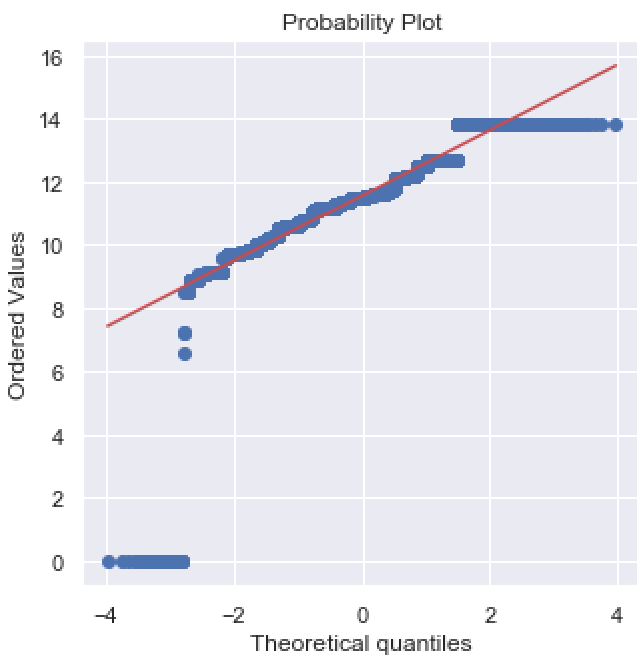

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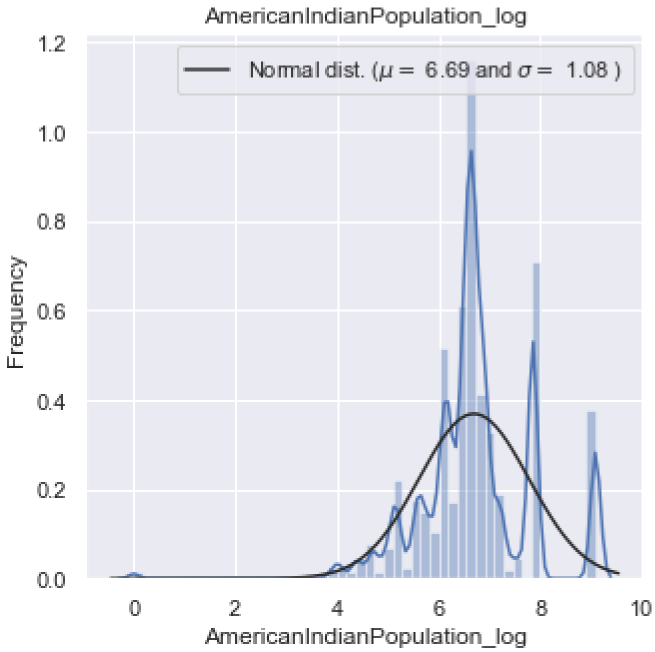
Out[234]: Text(0.5, 1.0, 'AmericanIndianPopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



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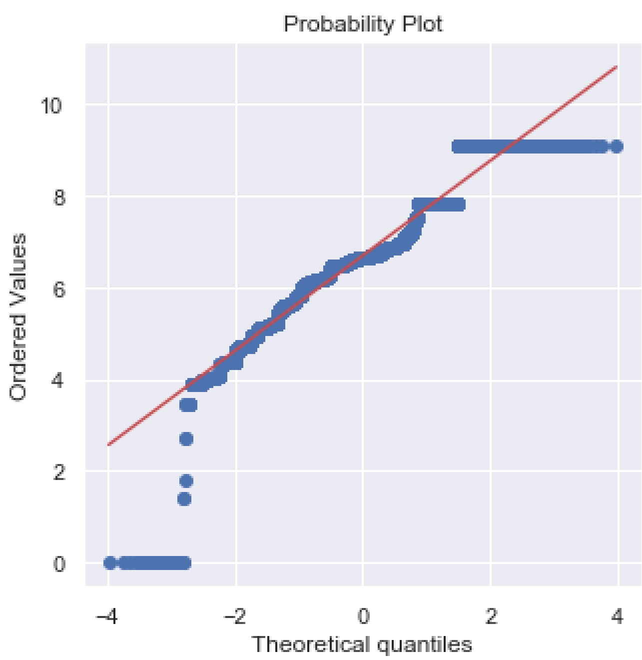

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Out[234]: <Figure size 360x360 with 0 Axes>

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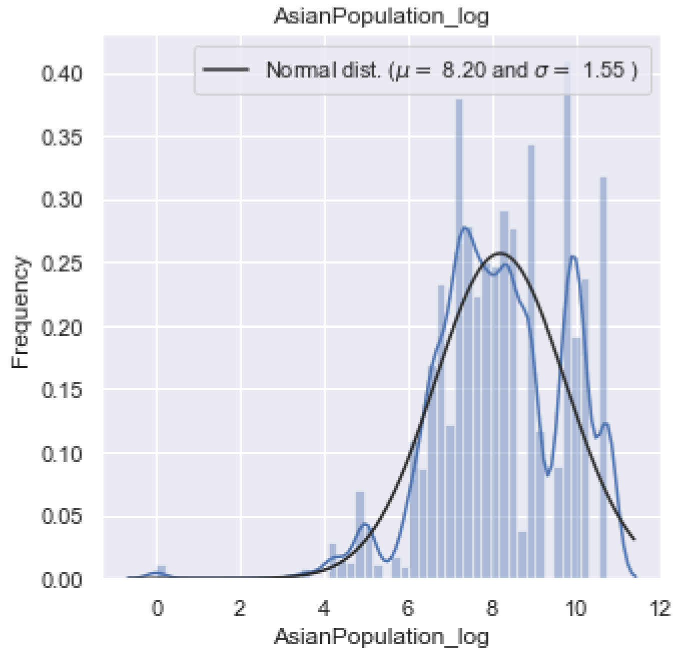

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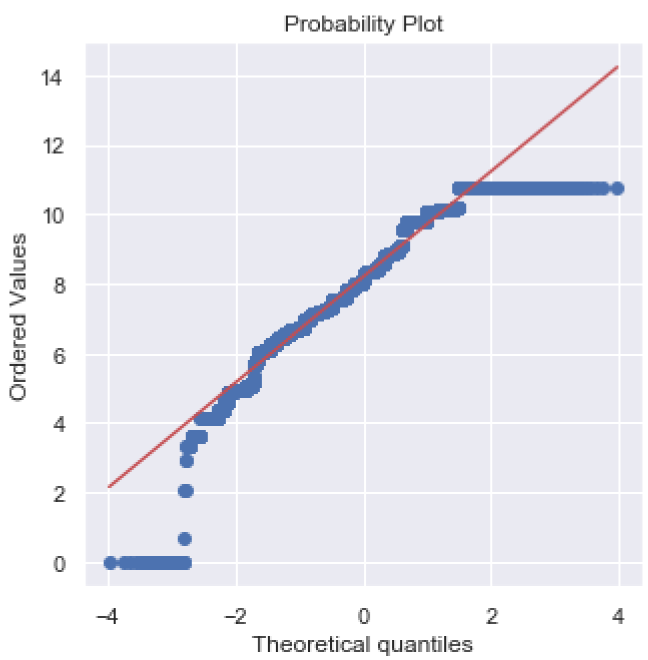

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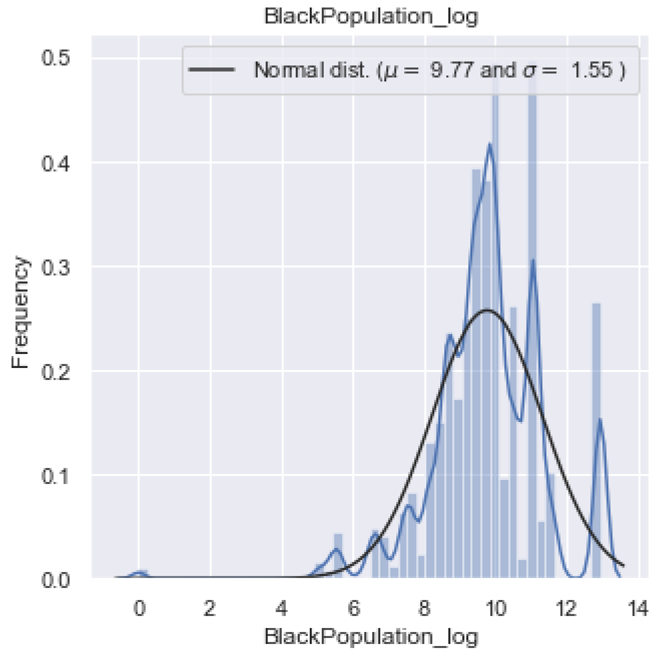
Out[234]: Text(0.5, 1.0, 'BlackPopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>

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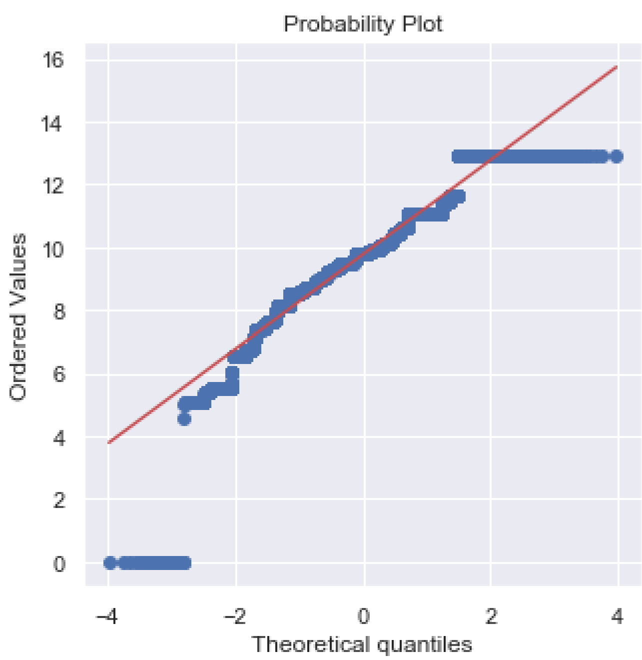


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Out[234]: Text(0.5, 1.0, 'HawaiianPopulation_log')
Out[234]: <Figure size 360x360 with 0 Axes>
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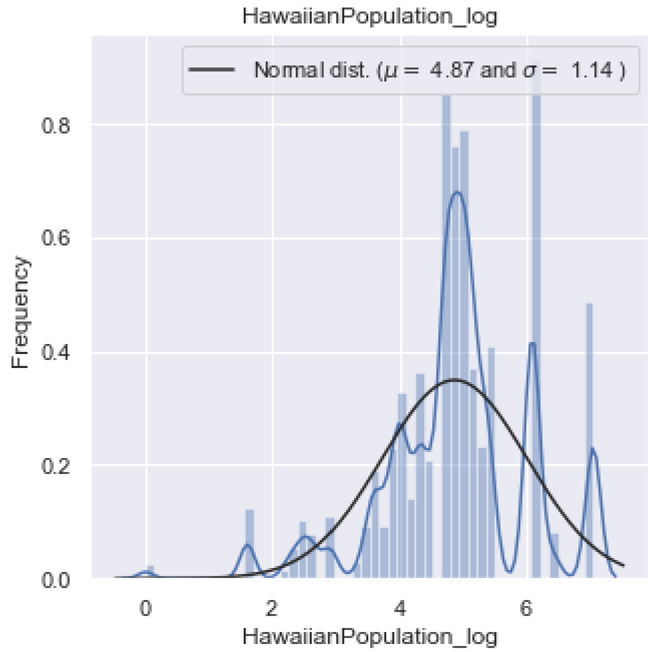

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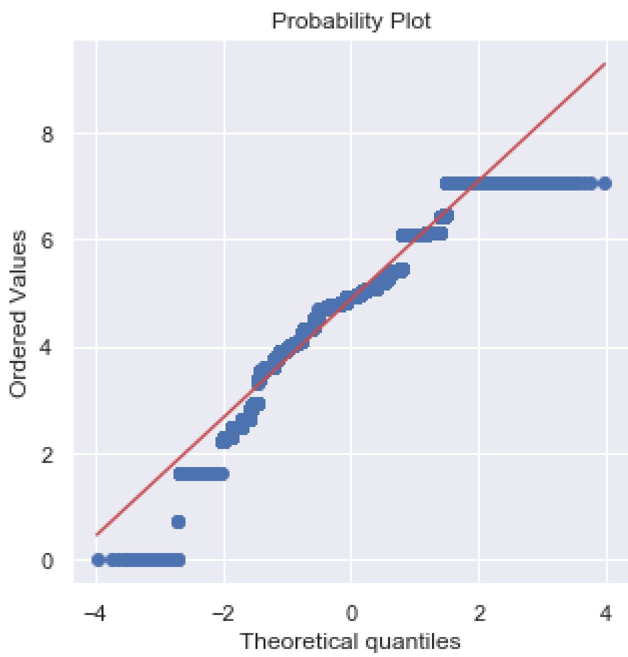

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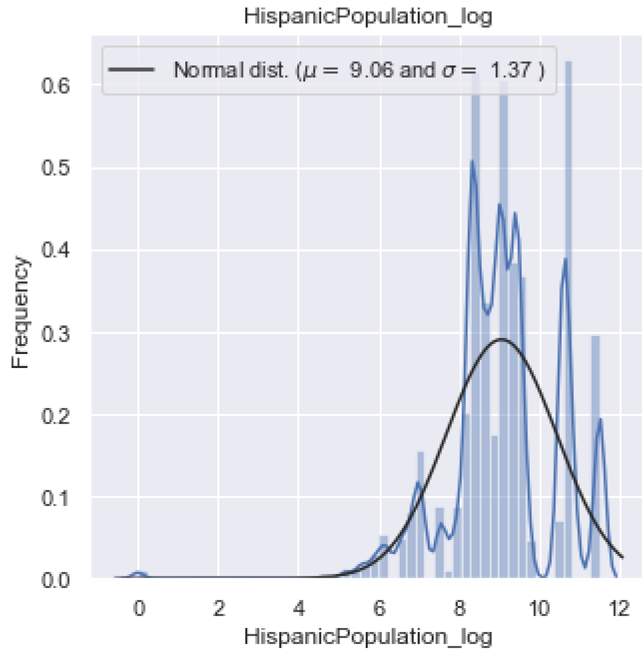

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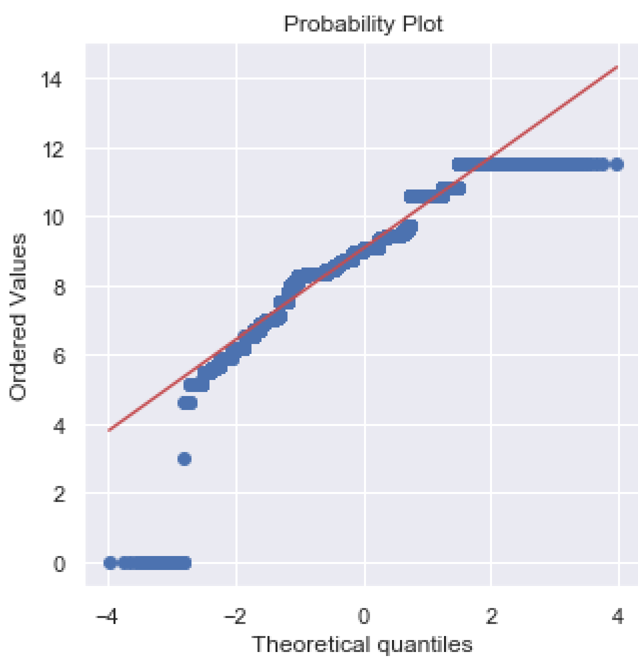

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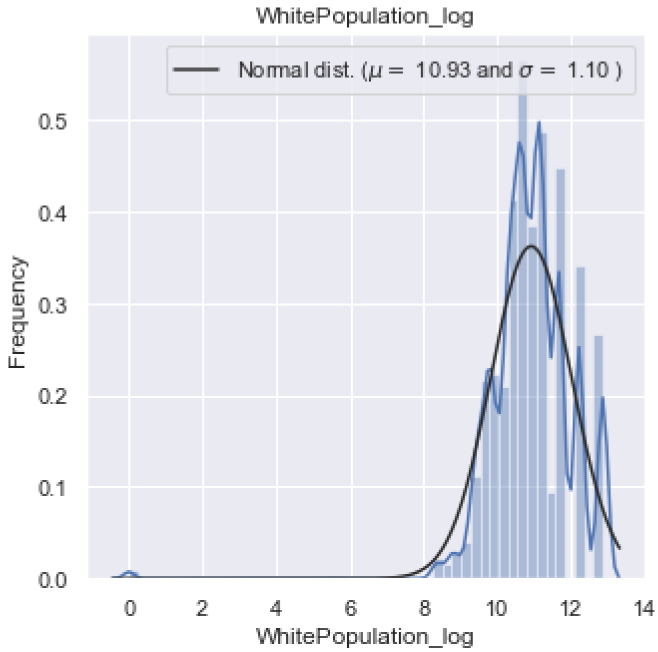
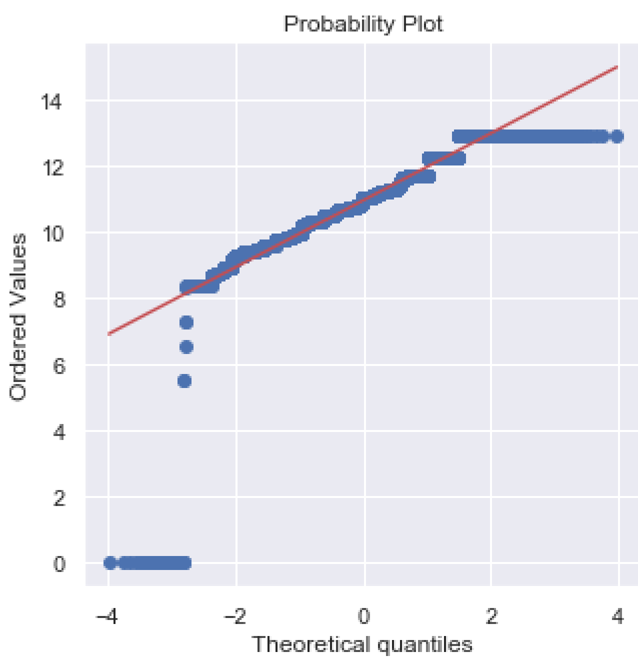
Out[234]: Text(0.5, 1.0, 'WhitePopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

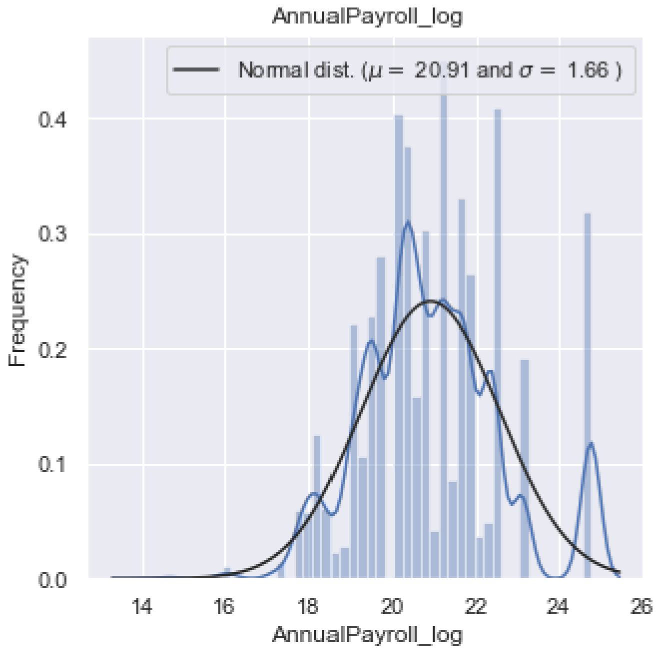
<Figure size 432x288 with 0 Axes>



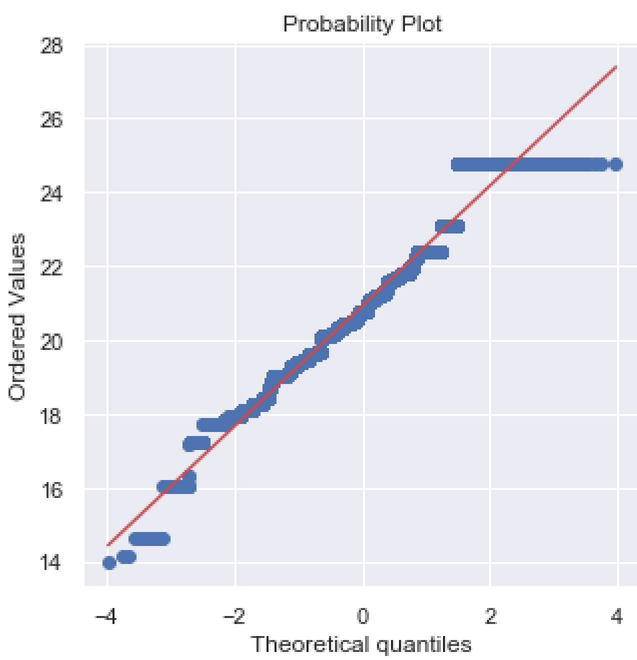
<Figure size 432x288 with 0 Axes>



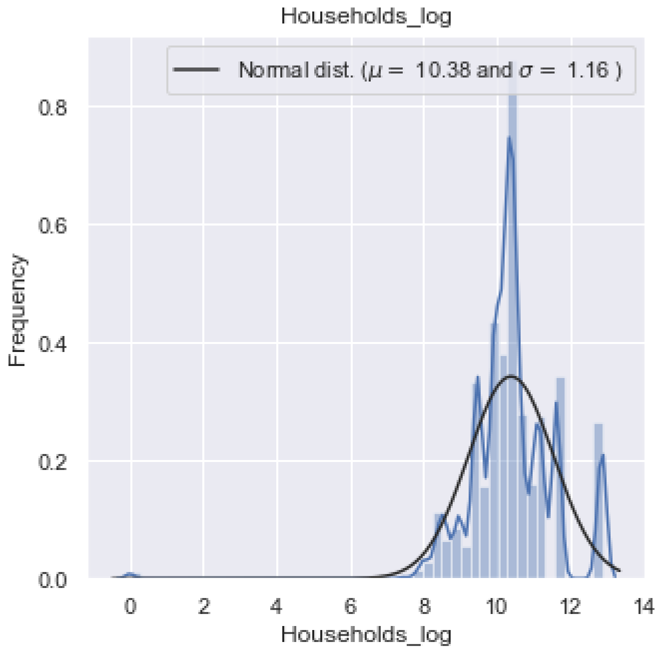

```
Out[234]: <Figure size 360x360 with 0 Axes>
Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaa644650>
Out[234]: <matplotlib.legend.Legend at 0x1aac052610>
Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'AnnualPayroll_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```



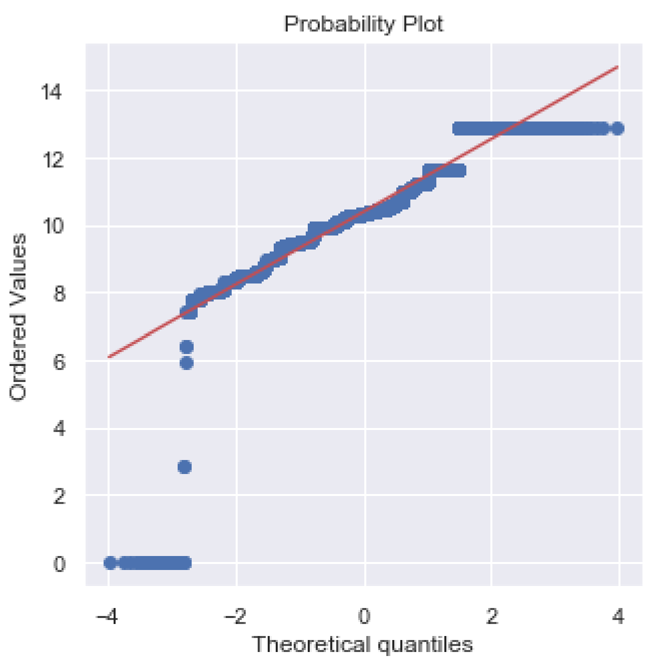

```
<Figure size 432x288 with 0 Axes>
```




```
Out[234]: <Figure size 360x360 with 0 Axes>
Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaa6f58d0>
Out[234]: <matplotlib.legend.Legend at 0x1a250a3750>
Out[234]: Text(0, 0.5, 'Frequency')
Out[234]: Text(0.5, 1.0, 'Households_log')
Out[234]: <Figure size 360x360 with 0 Axes>
          <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aab114d10>

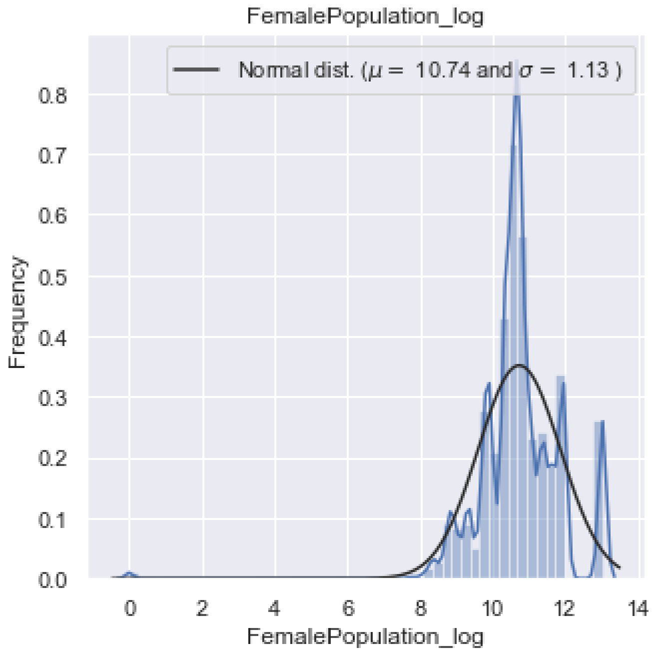
Out[234]: <matplotlib.legend.Legend at 0x1aa8a09710>

Out[234]: Text(0, 0.5, 'Frequency')

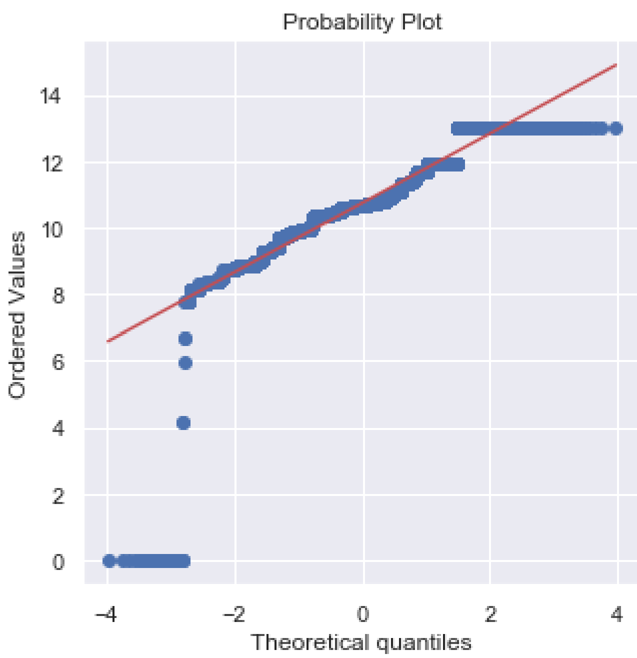
Out[234]: Text(0.5, 1.0, 'FemalePopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1a24e7a810>

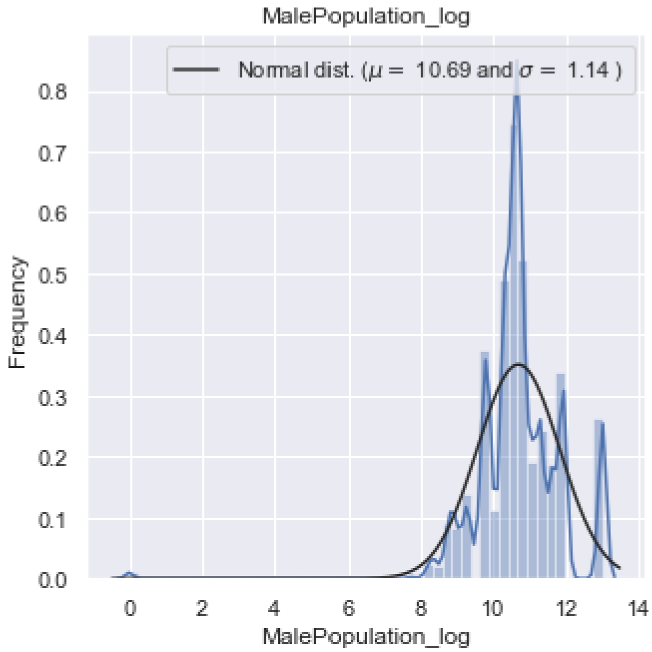
Out[234]: <matplotlib.legend.Legend at 0x1aab1056d0>

Out[234]: Text(0, 0.5, 'Frequency')

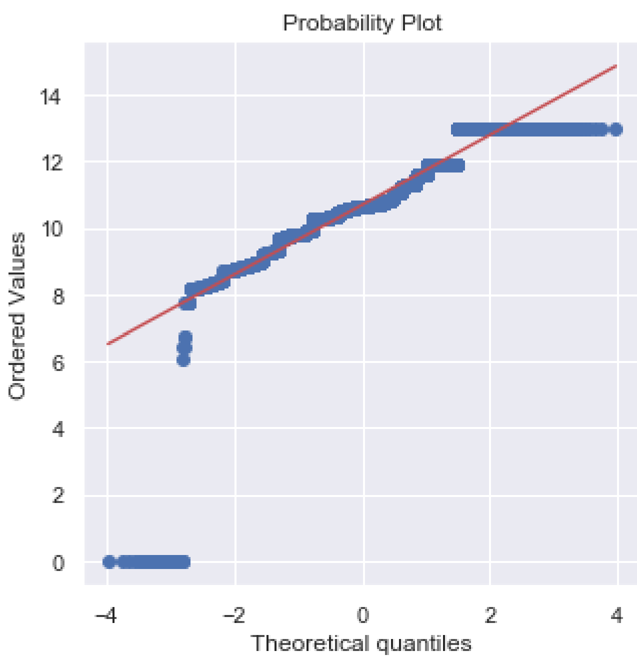
Out[234]: Text(0.5, 1.0, 'MalePopulation_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
```




```
Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaa531210>

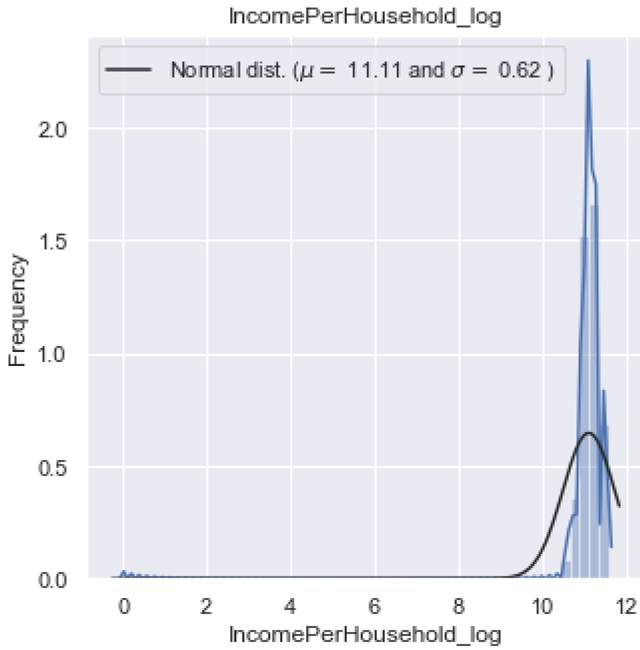
Out[234]: <matplotlib.legend.Legend at 0x1aab03df90>

Out[234]: Text(0, 0.5, 'Frequency')

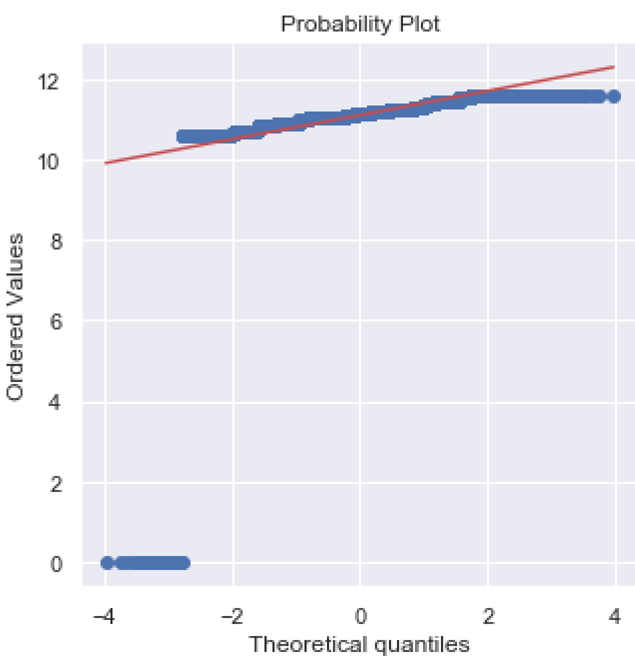
Out[234]: Text(0.5, 1.0, 'IncomePerHousehold_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>




```
Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa8971d50>

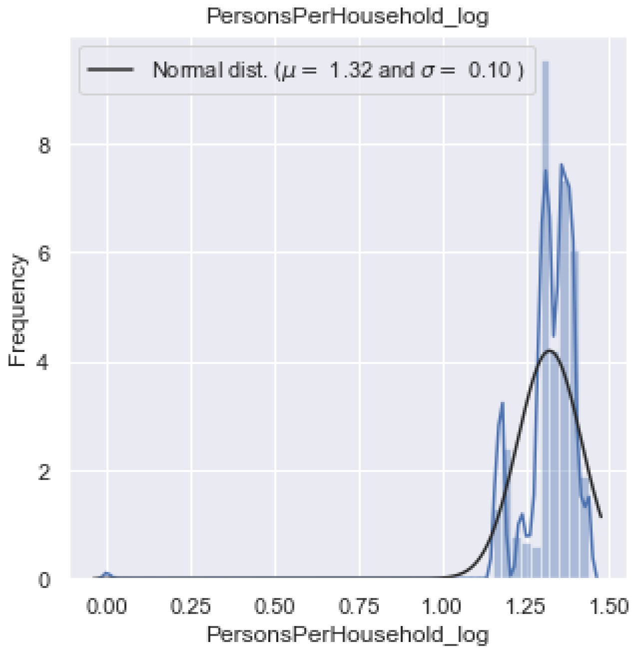
Out[234]: <matplotlib.legend.Legend at 0x1aab059f10>

Out[234]: Text(0, 0.5, 'Frequency')

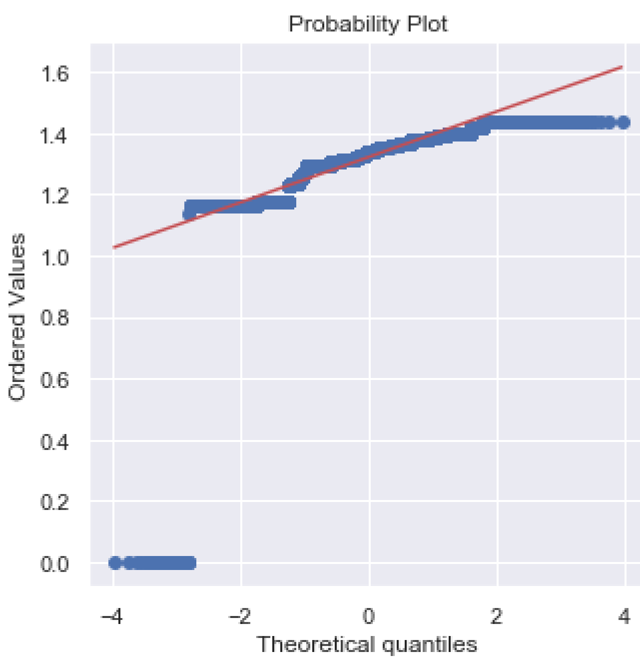
Out[234]: Text(0.5, 1.0, 'PersonsPerHousehold_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>



Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaa9873d0>

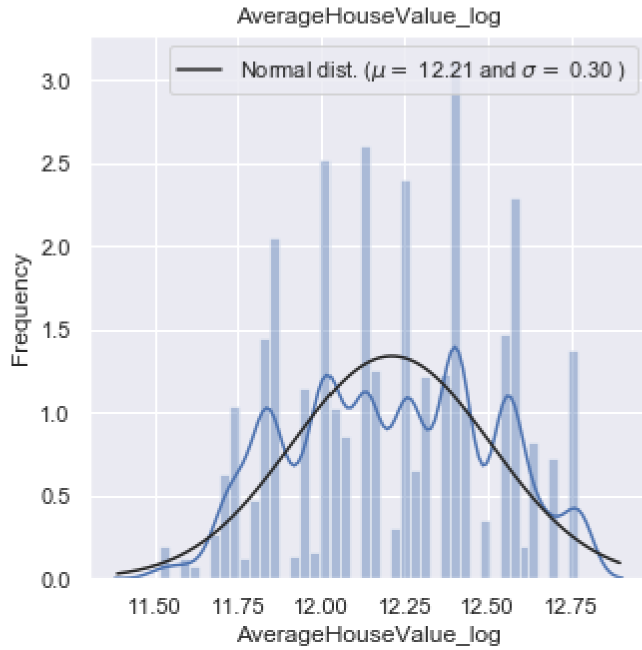
Out[234]: <matplotlib.legend.Legend at 0x1aaaed6850>

Out[234]: Text(0, 0.5, 'Frequency')

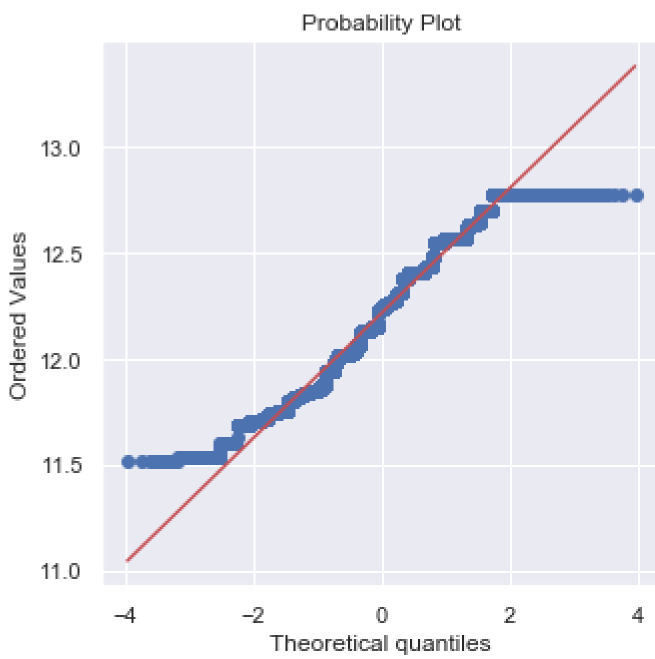
Out[234]: Text(0.5, 1.0, 'AverageHouseValue_log')

Out[234]: <Figure size 360x360 with 0 Axes>

<Figure size 432x288 with 0 Axes>




```
<Figure size 432x288 with 0 Axes>
```




```
Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aaac87e10>

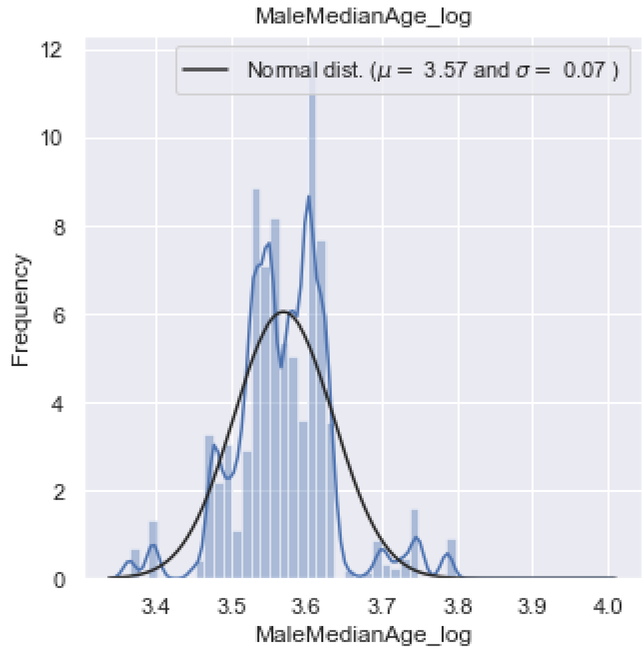
Out[234]: <matplotlib.legend.Legend at 0x1aa609f190>

Out[234]: Text(0, 0.5, 'Frequency')

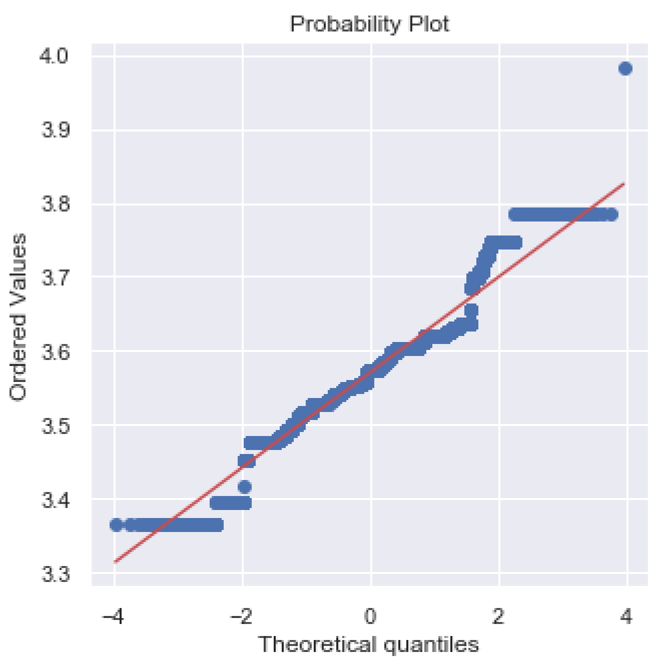
Out[234]: Text(0.5, 1.0, 'MaleMedianAge_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```



<Figure size 432x288 with 0 Axes>




```
Out[234]: <Figure size 360x360 with 0 Axes>

Out[234]: <matplotlib.axes._subplots.AxesSubplot at 0x1aa9ffbc50>

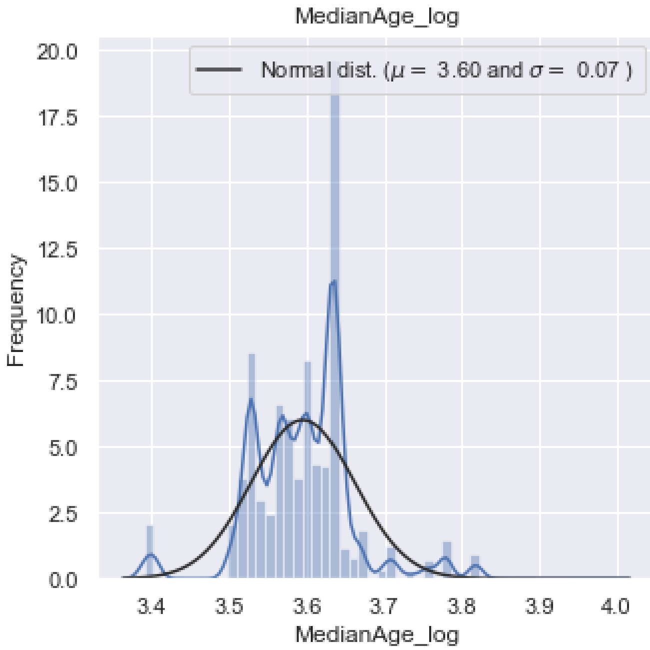
Out[234]: <matplotlib.legend.Legend at 0x1aa9feead0>

Out[234]: Text(0, 0.5, 'Frequency')

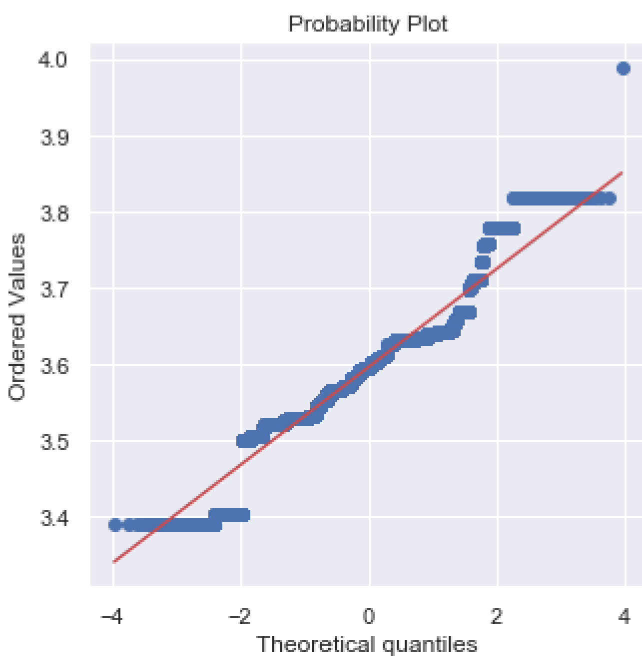
Out[234]: Text(0.5, 1.0, 'MedianAge_log')

Out[234]: <Figure size 360x360 with 0 Axes>

          <Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```



5.Test Hypotheses

5.1 Hypothese

- 1.H0:The numbers of bedrooms/ bathrooms would be important features to affect house price
- 2.H0:The numbers of living areas would be important features to affect house price.
- 3.H0:The Tax Assessed Value would be important features to affect house price.
- 4.H0:The distance of middle school and the rate of middle school would be important features to affect house price.
- 5.H0:The distance of primary school and the rate of primary school would be important features to affect house price.
- 6.H0:The distance of high school and the rate of high school would be important features to affect house price.
- 7.H0:There is no strong correlation between the variables.

5.2 H0(1-4)

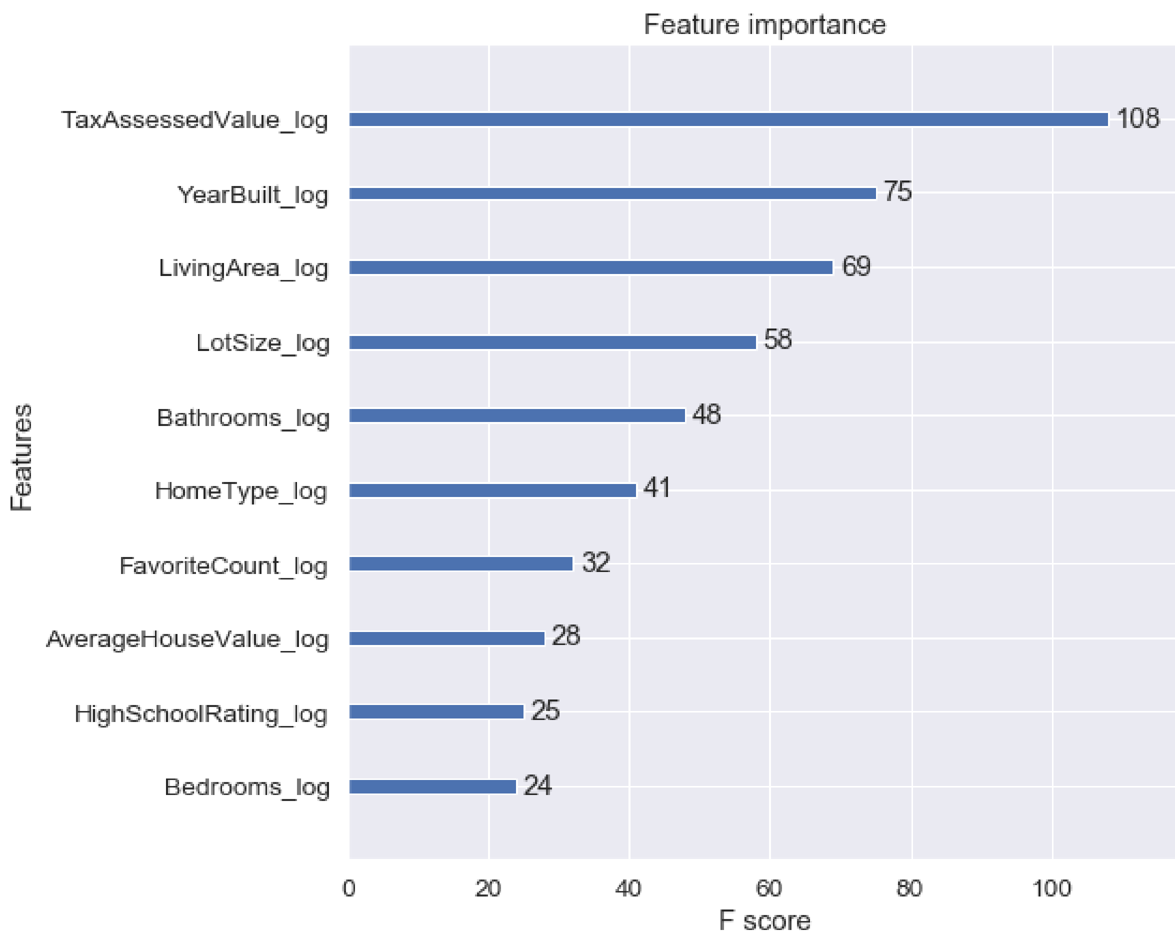
We use XGboost Feature Importance to solve the first four hypotheses.

In [297]:
```
model = XGBRegressor()
model.fit(x_train, y_train)
plot_importance(model, max_num_features=10)
plt.show()
```

```
[15:46:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[297]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

Out[297]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a22226d10>
```



Acccording to the result,

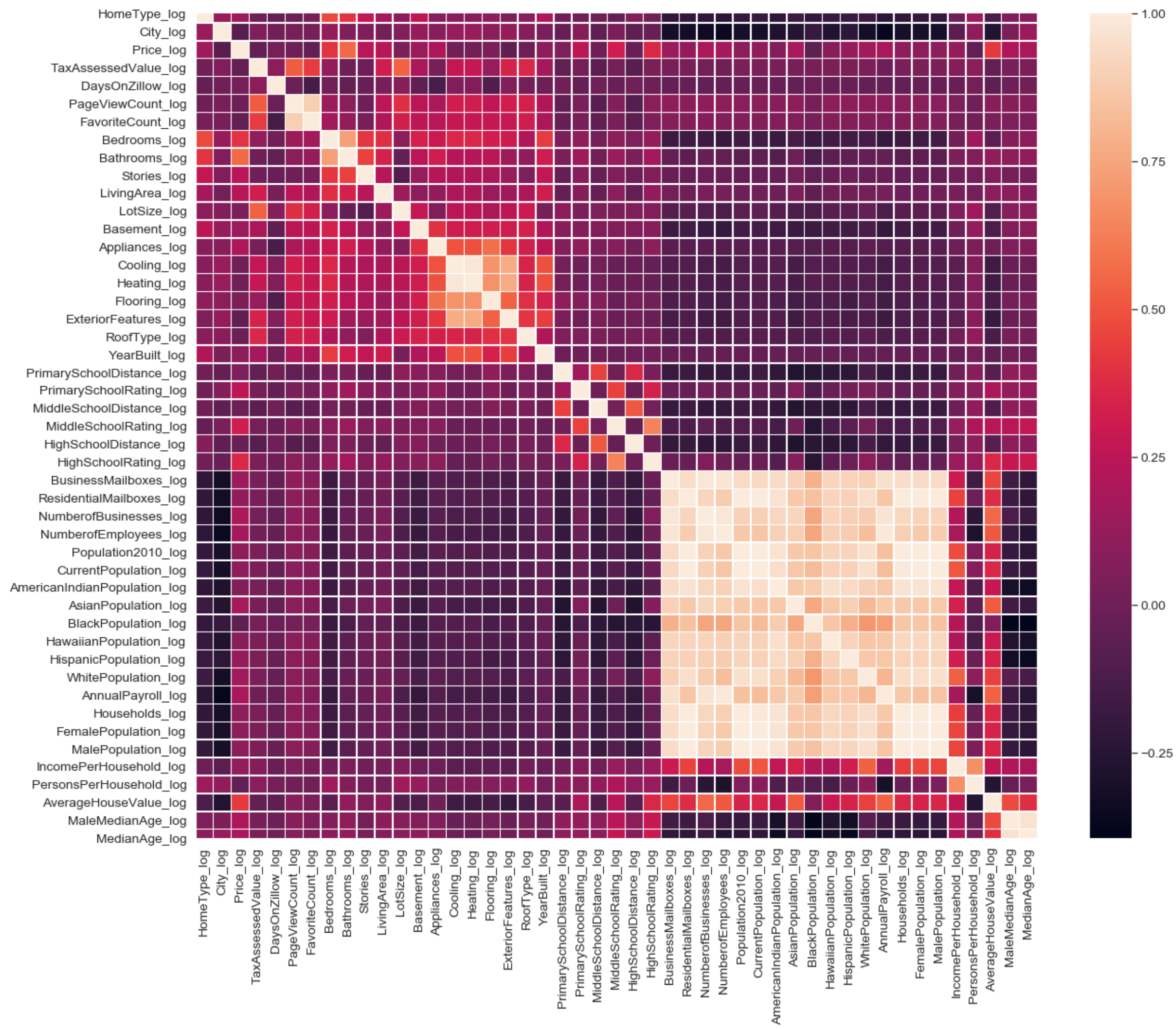
- We can not refuse the first hypothese,
- we can not refuse the second hypothese,
- we can not refuse the third hypothese,
- we refuse the forth hypothese,
- we refuse the fifth hypothese,
- we can not refuse the sixth hypothese.

5.3 H0(5)

We do the Correlation Analysis to test the the fifth hypotheses.

In [298]:
```
#Correlation Analysis
df=num_df_log
cormat = df.corr()
f, ax = plt.subplots(figsize=(20, 16))
#sns.heatmap(cormat, vmax=.8, square=True)
sns.heatmap(cormat, fmt="d", square=True, linewidths=.5)
```

Out[298]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22646290>



In [ ]:

Accord to the Correlation analysis,we find Features('BusinessMailboxes', 'ResidentialMailboxes', 'NumberofBusinesses','NumberofEmployees', 'Population2010', 'CurrentPopulation','AmericanIndianPopulation', 'AsianPopulation', 'BlackPopulation','HawaiianPopulation', 'HispanicPopulation', 'WhitePopulation','AnnualPayroll', 'Households', 'FemalePopulation', 'MalePopulation') have strong correlation.

In [317]:

```
k = 10
cols = corrmat.nlargest(k, 'Price_log')['Price_log'].index
#df[["HighSchoolRating",'MiddleSchoolRating','PrimarySchoolRating']] = df[["HighSchoolRating",'MiddleSchoolRating','PrimarySchoolRating']].astype("float")
cm = df[cols].corr()
sns.set(font_scale=1.25)
f, ax = plt.subplots(figsize=(20, 16))
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 10}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```

Dataset after transformation:num_df_log

In [292]:
```
num_df_log.describe()
```

Out[292]:

	HomeType_log	City_log	Price_log	TaxAssessedValue_log	DaysOnZillow_log	Pa
count	19173.000000	19173.000000	19173.000000	19173.000000	19173.000000	
mean	1.730991	3.152491	12.671136	8.751206	4.199001	
std	0.273359	1.086894	0.548613	5.496046	1.739694	
min	0.000000	0.000000	8.922792	0.000000	0.000000	
25%	1.791759	2.772589	12.345839	0.000000	3.295837	
50%	1.791759	3.610918	12.663469	11.921060	4.356709	
75%	1.791759	3.931826	13.001384	12.534336	5.111988	
max	1.945910	4.276666	14.247294	15.434986	9.584452	

8 rows × 47 columns

PART THREE

Linear Regression Model

In [51]:
```
from sklearn import linear_model
model = linear_model.LinearRegression()
model.fit(x_train, y_train)
```

Out[51]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [52]:
```
pred_train = model.predict(x_train)
pred_train_and_truth_train = pd.DataFrame({'predict_train_price_log':pred_trai
n, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pre
d_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth_train.head(20)
```

Out[52]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.556079	12.238675	283815.0	206628.0
18253	12.636126	12.574185	307468.0	289001.0
4741	13.121579	13.945662	499608.0	1139001.0
8406	12.658403	12.312687	314394.0	222501.0
234	12.865758	13.060277	386837.0	469901.0
11125	12.644936	12.610173	310189.0	299591.0
2813	12.937120	13.060277	415451.0	469901.0
698	12.998240	13.199141	441636.0	539901.0
10623	13.100364	13.384729	489121.0	650001.0
16239	12.542968	12.577636	280119.0	290000.0
15949	12.455405	12.049425	256634.0	171001.0
1668	12.850045	12.911645	380806.0	405001.0
3372	13.104070	13.485618	490936.0	719001.0
10397	12.487891	12.425212	265108.0	249001.0
17489	11.894047	12.383675	146393.0	238870.0
6284	13.204633	12.895553	542875.0	398536.0
9598	12.799507	12.498373	362039.0	267901.0
12770	12.286667	11.774528	216786.0	129901.0
6068	12.806256	12.891669	364490.0	396991.0
8000	13.206723	12.779594	544010.0	354901.0

In [53]:
```
metrics_new(pred_train_and_truth_train['predict_train_price'], pred_train_and_
truth_train['truth_train_price'])
```

```
MSE: 24232630584.36
RMSE: 155668.34
R^2: 0.475
```

In [54]:
```
pred = model.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[54]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.776966	12.672950	353969.0	319001.0
17892	12.134827	12.100718	186247.0	180001.0
12198	12.778883	12.736704	354649.0	340001.0
9774	12.667722	12.594734	317338.0	295001.0
18511	12.309434	11.938200	221778.0	153001.0
18437	12.396334	12.341438	241913.0	228991.0
8661	13.192121	13.038440	536124.0	459751.0
14024	13.053426	12.985170	466693.0	435901.0
12975	12.701386	12.514296	328202.0	272201.0
4385	12.478052	12.257041	262512.0	210458.0
18095	12.740454	12.736410	341279.0	339901.0
13870	12.962142	13.361382	425978.0	635001.0
9663	12.567285	12.429220	287014.0	250001.0
15665	12.205366	11.956976	199859.0	155901.0
6755	13.074740	13.997833	476747.0	1200001.0
2695	12.736137	12.524166	339808.0	274901.0
15953	12.270244	12.205578	213255.0	199901.0
16692	12.416146	12.706821	246754.0	329991.0
14	12.061417	11.660492	173064.0	115901.0
15851	12.430727	12.165256	250378.0	192001.0

In [55]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23692169913.22
RMSE: 153922.61
R^2: 0.494
```

In [56]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LinerRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(linear_model.LinearReg
ression(), X, Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[56]: <Figure size 576x576 with 0 Axes>

Out[56]: Text(0.5, 1.0, 'LinerRegressor')

Out[56]: Text(0.5, 0, 'Training examples')

Out[56]: Text(0, 0.5, 'Score')

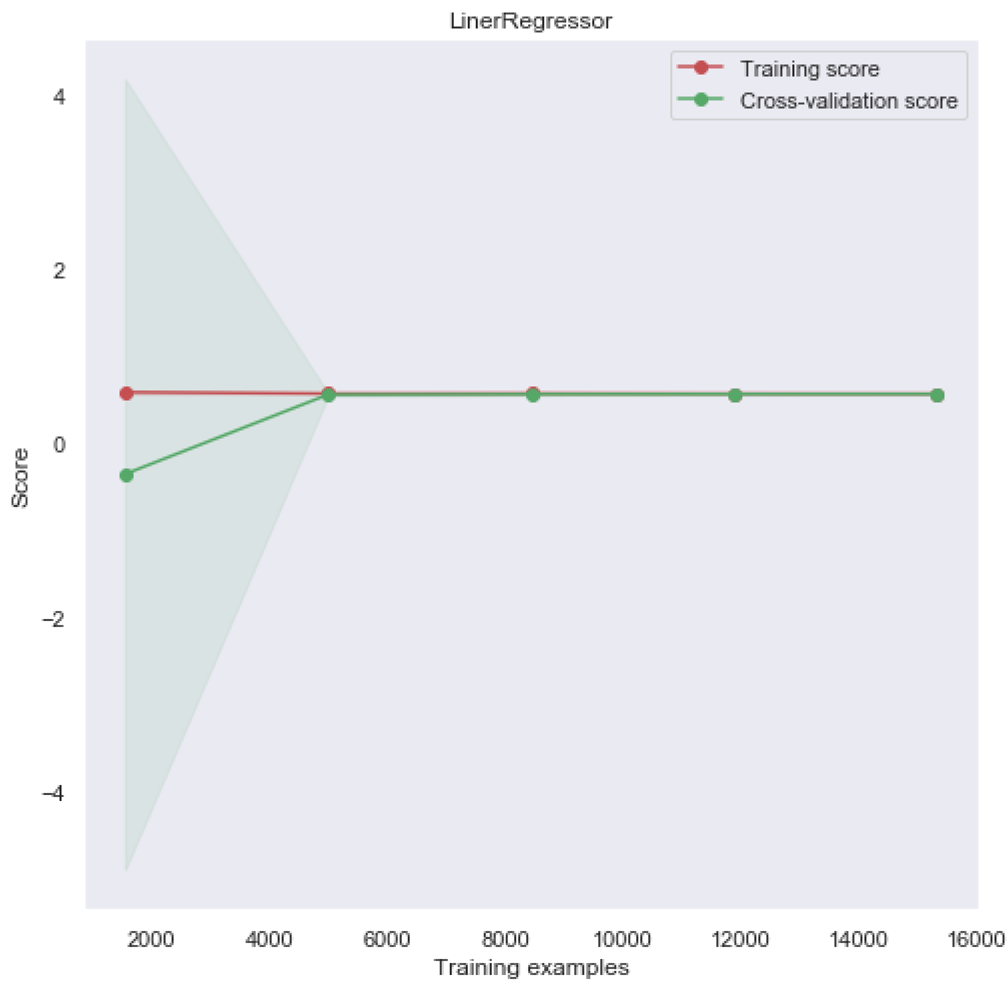
Out[56]: <matplotlib.collections.PolyCollection at 0x1a23154350>

Out[56]: <matplotlib.collections.PolyCollection at 0x1a22d8c910>

Out[56]: [<matplotlib.lines.Line2D at 0x1a23154d90>]

Out[56]: [<matplotlib.lines.Line2D at 0x1a22e1ad90>]

Out[56]: <matplotlib.legend.Legend at 0x1a2550e690>



Suprised Result about Linear Regression

We got suprised result from linear model. The R^2 of linear model in train set is 0.475 and the R^2 of linear model in test set is 0.494. The "accuracy" of linear model in test set is larger than train set. We thought the the problem would caused by under-fitting. Because underfitting of linear regression, and train set has much larger number of data than test set. Therefore, train test's total variation is much bigger than test set's. R^2 caculated by explained variation/ total variation. Therefore, test set's R^2 is higher than train set's. In conclusion, the main reason is underfitting.

Lasso before tunning

In [57]:
```
from sklearn.linear_model import LassoCV

lasso_before_tune = LassoCV(random_state=42)
lasso_before_tune.fit(x_train, y_train)
```

Out[57]:
```
LassoCV(alphas=None, copy_X=True, cv=None, eps=0.001, fit_intercept=True,
        max_iter=1000, n_alphas=100, n_jobs=None, normalize=False,
        positive=False, precompute='auto', random_state=42, selection='cycli
c',
        tol=0.0001, verbose=False)
```

In [58]:
```
pred_train = lasso_before_tune.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[58]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.560945	12.238675	285200.0	206628.0
18253	12.589637	12.574185	293501.0	289001.0
4741	13.092976	13.945662	485520.0	1139001.0
8406	12.715466	12.312687	332856.0	222501.0
234	12.814673	13.060277	367571.0	469901.0
11125	12.659639	12.610173	314783.0	299591.0
2813	12.955898	13.060277	423326.0	469901.0
698	12.969534	13.199141	429138.0	539901.0
10623	13.104674	13.384729	491233.0	650001.0
16239	12.513348	12.577636	271943.0	290000.0
15949	12.448790	12.049425	254942.0	171001.0
1668	12.845361	12.911645	379026.0	405001.0
3372	13.099178	13.485618	488541.0	719001.0
10397	12.489319	12.425212	265486.0	249001.0
17489	11.876379	12.383675	143829.0	238870.0
6284	13.238098	12.895553	561349.0	398536.0
9598	12.801840	12.498373	362885.0	267901.0
12770	12.290086	11.774528	217529.0	129901.0
6068	12.843656	12.891669	378381.0	396991.0
8000	13.190836	12.779594	535436.0	354901.0

In [59]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 24338199207.20
RMSE: 156007.05
R^2: 0.473
```

In [60]:
```
pred = lasso_before_tune.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[60]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.779611	12.672950	354907.0	319001.0
17892	12.124018	12.100718	184244.0	180001.0
12198	12.778795	12.736704	354617.0	340001.0
9774	12.673518	12.594734	319182.0	295001.0
18511	12.250711	11.938200	209130.0	153001.0
18437	12.347855	12.341438	230465.0	228991.0
8661	13.216737	13.038440	549485.0	459751.0
14024	13.088215	12.985170	483214.0	435901.0
12975	12.704250	12.514296	329144.0	272201.0
4385	12.427848	12.257041	249658.0	210458.0
18095	12.721644	12.736410	334919.0	339901.0
13870	12.985262	13.361382	435941.0	635001.0
9663	12.560380	12.429220	285039.0	250001.0
15665	12.241180	11.956976	207146.0	155901.0
6755	13.061725	13.997833	470582.0	1200001.0
2695	12.747466	12.524166	343680.0	274901.0
15953	12.265742	12.205578	212297.0	199901.0
16692	12.433037	12.706821	250957.0	329991.0
14	12.016714	11.660492	165498.0	115901.0
15851	12.454108	12.165256	256301.0	192001.0

In [61]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23786964926.03
RMSE: 154230.23
R^2: 0.492
```

In [62]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Lasso_before_tune_Regressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(lasso_before_tune, X,
Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[62]: <Figure size 576x576 with 0 Axes>

Out[62]: Text(0.5, 1.0, 'Lasso_before_tune_Regressor')

Out[62]: Text(0.5, 0, 'Training examples')

Out[62]: Text(0, 0.5, 'Score')

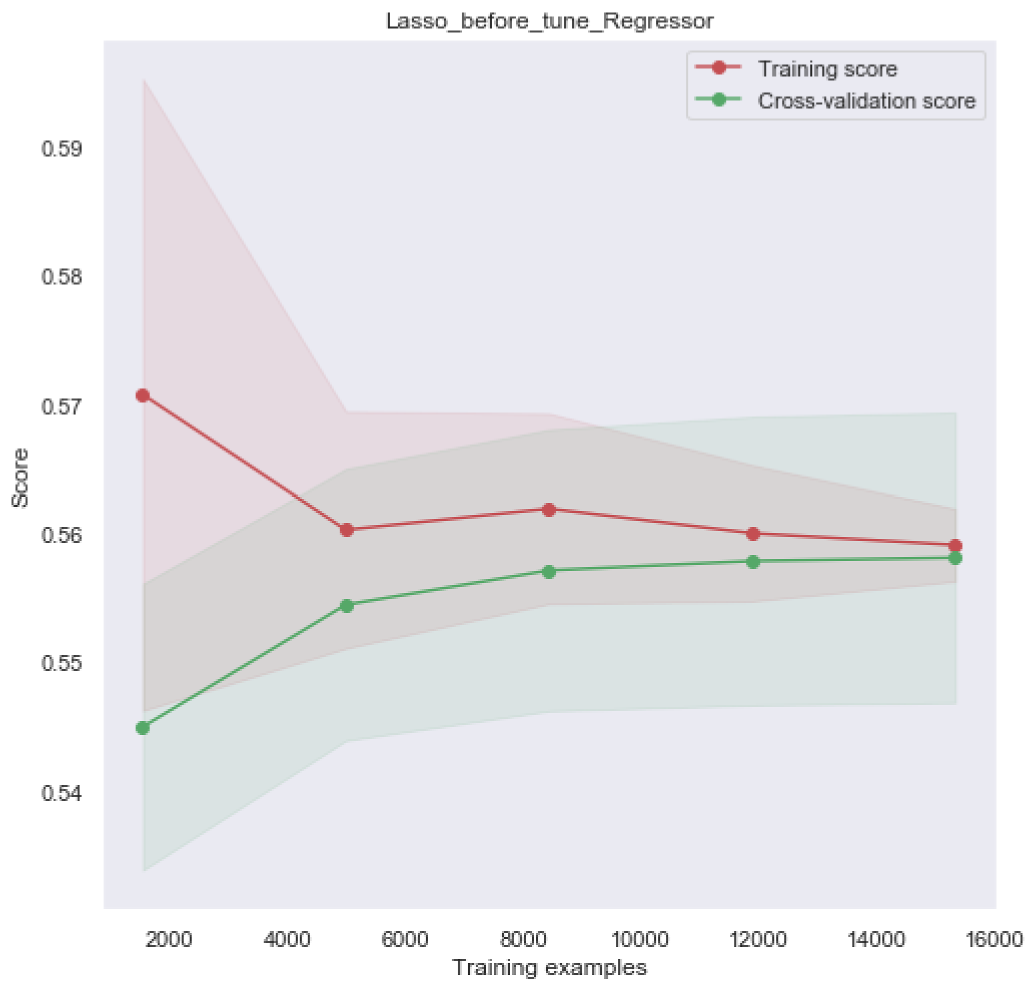
Out[62]: <matplotlib.collections.PolyCollection at 0x1a266ce990>

Out[62]: <matplotlib.collections.PolyCollection at 0x1a266ced90>

Out[62]: [<matplotlib.lines.Line2D at 0x1a266ce810>]

Out[62]: [<matplotlib.lines.Line2D at 0x1a266cea10>]

Out[62]: <matplotlib.legend.Legend at 0x1a266cea90>



Lasso Tunning

In [63]:
```
from sklearn.linear_model import LassoCV
from sklearn.linear_model import Lasso
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

lasso = Lasso()
alphas = np.logspace(-4, -0.5, 30)


tuned_parameters = [{'alpha': alphas}]
n_folds = 10

grid_lasso = GridSearchCV(lasso, tuned_parameters, cv=n_folds, refit=True, sco
ring = 'r2')
grid_lasso.fit(x_train, y_train)
print(grid_lasso.best_params_)
```

Out[63]:
```
GridSearchCV(cv=10, error_score=nan,
             estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=1000, normalize=False, positive=False,
                             precompute=False, random_state=None,
                             selection='cyclic', tol=0.0001, warm_start=Fals
e),
             iid='deprecated', n_jobs=None,
             param_grid=[{'alpha': array([1.00000000e-04, 1.32035178e-04, 1.7
4332882e-04, 2.30180731e-04,
       3.03919538e-0...
       2.80721620e-03, 3.70651291e-03, 4.89390092e-03, 6.46167079e-03,
       8.53167852e-03, 1.12648169e-02, 1.48735211e-02, 1.96382800e-02,
       2.59294380e-02, 3.42359796e-02, 4.52035366e-02, 5.96845700e-02,
       7.88046282e-02, 1.04049831e-01, 1.37382380e-01, 1.81393069e-01,
       2.39502662e-01, 3.16227766e-01])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)

{'alpha': 0.0001}
```

In [64]:
```
best_model_lasso = Lasso().set_params(**grid_lasso.best_params_)
best_model_lasso.fit(x_train,y_train)
pred_train = best_model_lasso.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[64]:
```
Lasso(alpha=0.0001, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
```

Out[64]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.558036	12.238675	284371.0	206628.0
18253	12.580563	12.574185	290850.0	289001.0
4741	13.100440	13.945662	489158.0	1139001.0
8406	12.718950	12.312687	334018.0	222501.0
234	12.818273	13.060277	368897.0	469901.0
11125	12.641743	12.610173	309200.0	299591.0
2813	12.944877	13.060277	418686.0	469901.0
698	12.984651	13.199141	435675.0	539901.0
10623	13.106468	13.384729	492115.0	650001.0
16239	12.527788	12.577636	275898.0	290000.0
15949	12.447808	12.049425	254691.0	171001.0
1668	12.844400	12.911645	378662.0	405001.0
3372	13.100395	13.485618	489136.0	719001.0
10397	12.486900	12.425212	264845.0	249001.0
17489	11.872781	12.383675	143312.0	238870.0
6284	13.251691	12.895553	569031.0	398536.0
9598	12.805580	12.498373	364244.0	267901.0
12770	12.292059	11.774528	217958.0	129901.0
6068	12.847709	12.891669	379917.0	396991.0
8000	13.199623	12.779594	540161.0	354901.0

In [65]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 24297057076.22
RMSE: 155875.13
R^2: 0.474
```

In [66]:
```
pred = best_model_lasso.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[66]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.776502	12.672950	353805.0	319001.0
17892	12.131508	12.100718	185630.0	180001.0
12198	12.784891	12.736704	356786.0	340001.0
9774	12.673216	12.594734	319086.0	295001.0
18511	12.253911	11.938200	209800.0	153001.0
18437	12.350842	12.341438	231155.0	228991.0
8661	13.199654	13.038440	540178.0	459751.0
14024	13.081594	12.985170	480025.0	435901.0
12975	12.703772	12.514296	328987.0	272201.0
4385	12.434745	12.257041	251386.0	210458.0
18095	12.716590	12.736410	333230.0	339901.0
13870	12.980056	13.361382	433677.0	635001.0
9663	12.557013	12.429220	284081.0	250001.0
15665	12.243141	11.956976	207553.0	155901.0
6755	13.062106	13.997833	470761.0	1200001.0
2695	12.741878	12.524166	341765.0	274901.0
15953	12.265984	12.205578	212348.0	199901.0
16692	12.418352	12.706821	247299.0	329991.0
14	12.015480	11.660492	165294.0	115901.0
15851	12.441186	12.165256	253010.0	192001.0

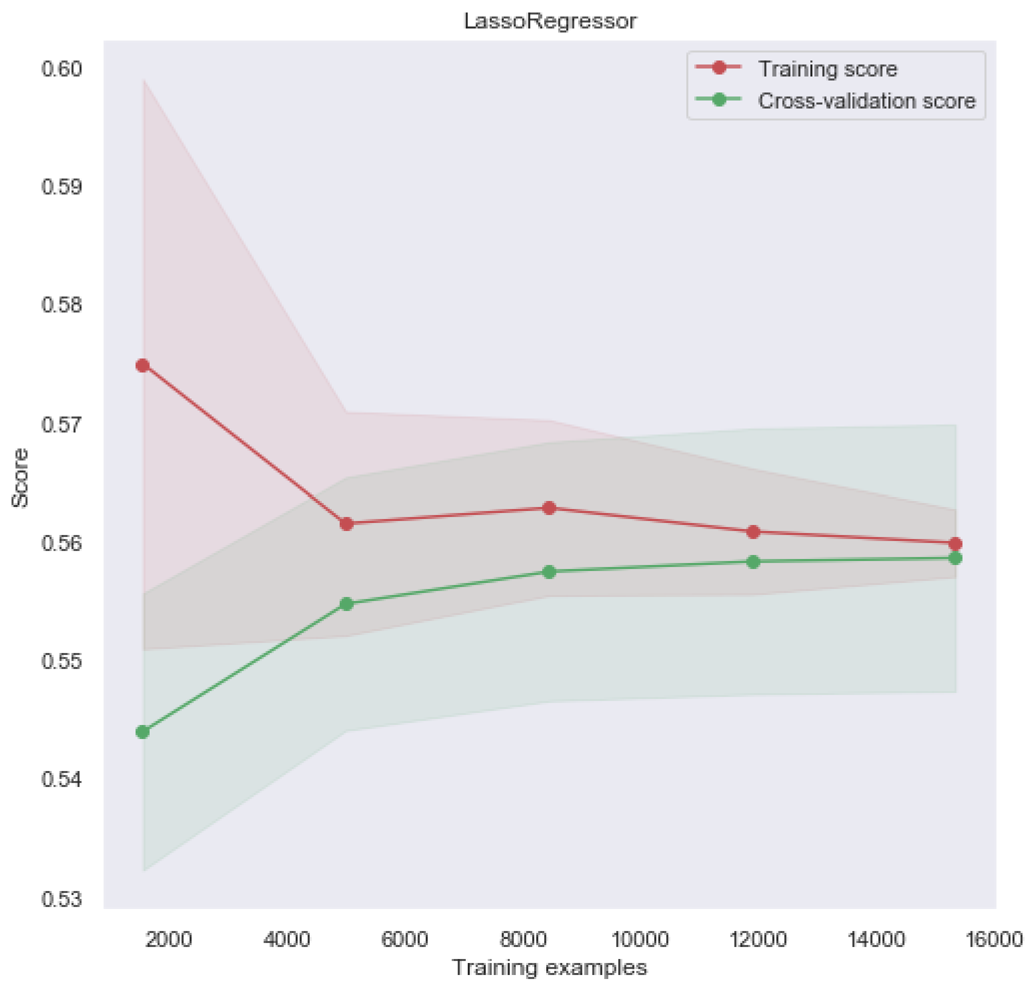
In [67]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23742069014.06
RMSE: 154084.62
R^2: 0.493
```

In [68]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LassoRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model_lasso, X, Y
, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[68]: <Figure size 576x576 with 0 Axes>
Out[68]: Text(0.5, 1.0, 'LassoRegressor')
Out[68]: Text(0.5, 0, 'Training examples')
Out[68]: Text(0, 0.5, 'Score')
Out[68]: <matplotlib.collections.PolyCollection at 0x1a26a87f10>
Out[68]: <matplotlib.collections.PolyCollection at 0x1a26afc110>
Out[68]: [<matplotlib.lines.Line2D at 0x1a266ce890>]
Out[68]: [<matplotlib.lines.Line2D at 0x1a26a9b110>]
Out[68]: <matplotlib.legend.Legend at 0x1a266eca50>
```



Tiny Conclusion for Lasso Linear Regression

The R^2 of Lasso Linear Regression is 0.493. We used one hyperparameter which is alpha (penalty). The default Lasso model and tuned Lass model have similar R^2. It makes sense that tuned lasso regression do not have higher "accuracy", because the hyperparameter (alpha) is used to penlizing (avoid overfitting). Its purpose is increase bias and decrease variance.

Random Forest before tunning

In [69]:
```
from sklearn.ensemble import RandomForestRegressor

rf_before_model= RandomForestRegressor(random_state=42)
rf_before_model.fit(x_train, y_train)
```

Out[69]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=Non
e,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [70]:
```
pred_train = rf_before_model.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[70]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.263242	12.238675	211767.0	206628.0
18253	12.586665	12.574185	292630.0	289001.0
4741	13.879479	13.945662	1066059.0	1139001.0
8406	12.291581	12.312687	217854.0	222501.0
234	13.063931	13.060277	471621.0	469901.0
11125	12.602915	12.610173	297424.0	299591.0
2813	13.010668	13.060277	447158.0	469901.0
698	13.205200	13.199141	543182.0	539901.0
10623	13.391559	13.384729	654455.0	650001.0
16239	12.613209	12.577636	300502.0	290000.0
15949	12.074775	12.049425	175391.0	171001.0
1668	12.917067	12.911645	407203.0	405001.0
3372	13.461799	13.485618	702077.0	719001.0
10397	12.444249	12.425212	253787.0	249001.0
17489	12.371105	12.383675	235886.0	238870.0
6284	12.901373	12.895553	400862.0	398536.0
9598	12.501056	12.498373	268621.0	267901.0
12770	11.765908	11.774528	128786.0	129901.0
6068	12.893123	12.891669	397569.0	396991.0
8000	12.777310	12.779594	354091.0	354901.0

In [71]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 1528574786.11
RMSE: 39096.99
R^2: 0.967
```

In [72]:
```
pred = rf_before_model.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[72]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.684504	12.672950	322708.0	319001.0
17892	11.480072	12.100718	96768.0	180001.0
12198	12.701751	12.736704	328322.0	340001.0
9774	12.494716	12.594734	266923.0	295001.0
18511	12.020730	11.938200	166164.0	153001.0
18437	12.350983	12.341438	231187.0	228991.0
8661	13.173865	13.038440	526425.0	459751.0
14024	12.943309	12.985170	418030.0	435901.0
12975	12.545072	12.514296	280709.0	272201.0
4385	12.252470	12.257041	209498.0	210458.0
18095	12.619474	12.736410	302390.0	339901.0
13870	12.880712	13.361382	392665.0	635001.0
9663	12.391427	12.429220	240729.0	250001.0
15665	11.930781	11.956976	151870.0	155901.0
6755	13.848393	13.997833	1033430.0	1200001.0
2695	12.374204	12.524166	236618.0	274901.0
15953	12.187745	12.205578	196368.0	199901.0
16692	12.433198	12.706821	250997.0	329991.0
14	11.819950	11.660492	135937.0	115901.0
15851	12.153537	12.165256	189764.0	192001.0

In [73]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 9153757256.71
RMSE: 95675.27
R^2: 0.805
```

In [74]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('RandomForest_before_tune_Regressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(rf_before_model, X, Y,
cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[74]: <Figure size 576x576 with 0 Axes>

Out[74]: Text(0.5, 1.0, 'RandomForest_before_tune_Regressor')

Out[74]: Text(0.5, 0, 'Training examples')

Out[74]: Text(0, 0.5, 'Score')

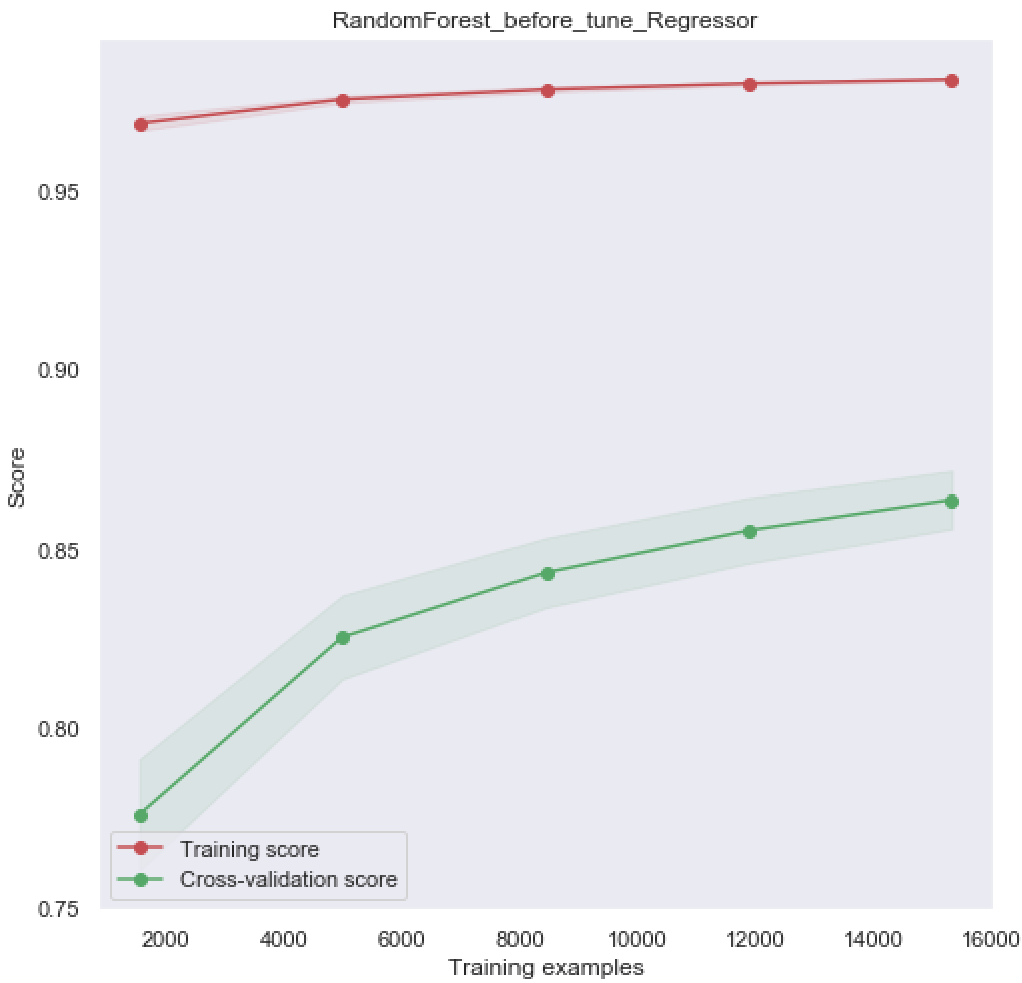
Out[74]: <matplotlib.collections.PolyCollection at 0x1a2656ee10>

Out[74]: <matplotlib.collections.PolyCollection at 0x1a2658dc50>

Out[74]: [<matplotlib.lines.Line2D at 0x1a2658dc90>]

Out[74]: [<matplotlib.lines.Line2D at 0x1a2656eed0>]

Out[74]: <matplotlib.legend.Legend at 0x1a2656ee90>



Random Forest_RandomSearch

In [75]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
from sklearn.model_selection import RandomizedSearchCV

model = RandomForestRegressor(random_state=42)
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 200, num = 10
)]
# Number of features to consider at every split
#max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 50, num = 5)]
#max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 4, 8,10,20,50]
# Method of selecting samples for training each tree
bootstrap = [True]

# Create the random grid
param_grid= {'n_estimators': n_estimators,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

rf_random = RandomizedSearchCV(model,param_grid, n_iter = 1000, cv =5,random_s
tate=42, n_jobs = -1, scoring = 'r2')
# Fit the random search model
rf_random.fit(x_train, y_train)

# examine the best model
print(rf_random.best_params_)
print(rf_random.best_estimator_)
```

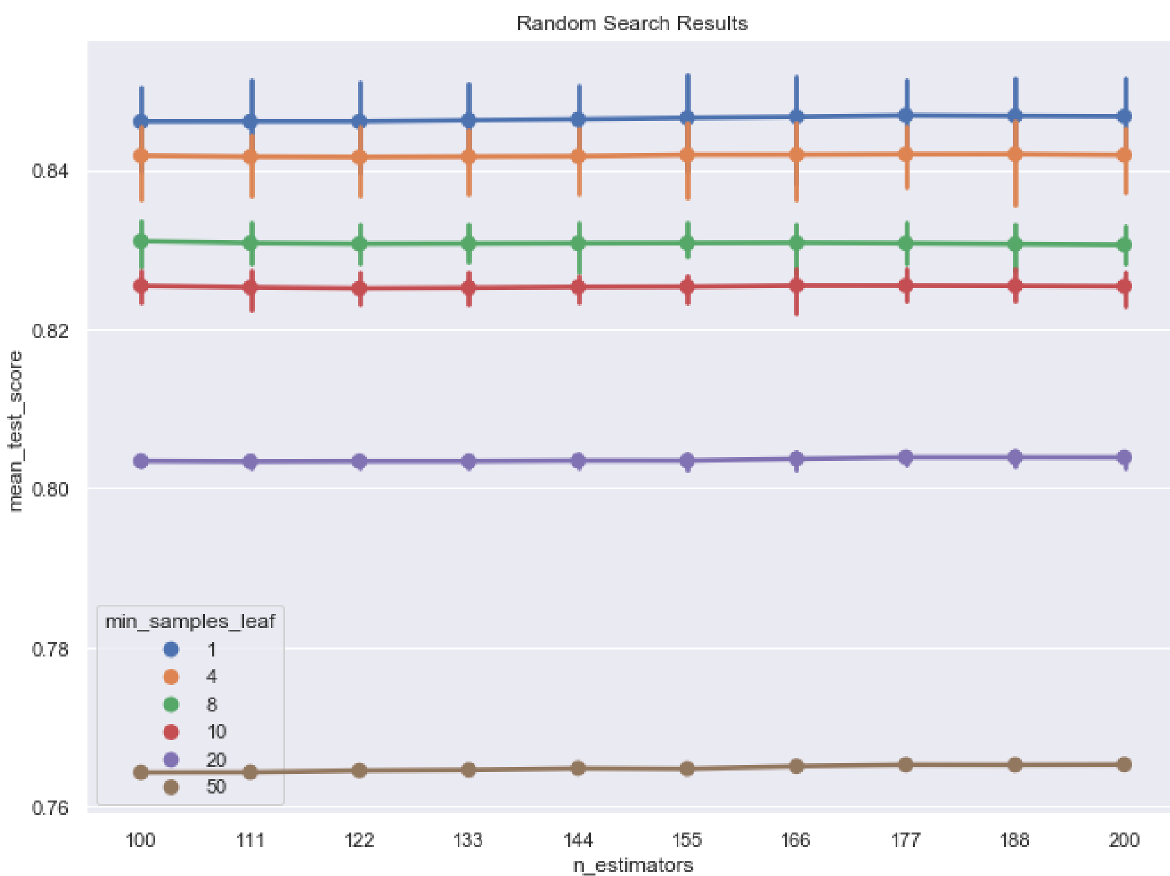
Out[75]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_leaf=
0.0,
                                                   n_estimators=100,
                                                   n_jobs=None, oob_score=Fal
se,
                                                   random_state=42, verbose=
0,
                                                   warm_start=False),
                   iid='deprecated', n_iter=1000, n_jobs=-1,
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [10, 20, 30, 40, 50],
                                        'min_samples_leaf': [1, 4, 8, 10, 20,
                                                             50],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 111, 122, 133,
                                                         144, 155, 166, 177,
                                                         188, 200]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='r2', verbose=0)
```

```
{'n_estimators': 177, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_dep
th': 30, 'bootstrap': True}
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=30, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=177, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [76]:
```
import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Random Search Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(rf_random.cv_results_, 'n_estimators', 'min_samples_lea
f')
```



In [77]:
```
best_rf_model = RandomForestRegressor(random_state=42).set_params(**rf_random.
best_params_)
best_rf_model.fit(x_train,y_train)
```

Out[77]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=30, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=177, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [78]:
```
pred_train = best_rf_model.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[78]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.259371	12.238675	210949.0	206628.0
18253	12.588797	12.574185	293255.0	289001.0
4741	13.880571	13.945662	1067223.0	1139001.0
8406	12.288503	12.312687	217185.0	222501.0
234	13.065233	13.060277	472235.0	469901.0
11125	12.604005	12.610173	297749.0	299591.0
2813	13.007100	13.060277	445566.0	469901.0
698	13.210090	13.199141	545845.0	539901.0
10623	13.408097	13.384729	665369.0	650001.0
16239	12.606796	12.577636	298581.0	290000.0
15949	12.054496	12.049425	171870.0	171001.0
1668	12.920553	12.911645	408625.0	405001.0
3372	13.461680	13.485618	701994.0	719001.0
10397	12.443359	12.425212	253561.0	249001.0
17489	12.388571	12.383675	240042.0	238870.0
6284	12.902052	12.895553	401134.0	398536.0
9598	12.498806	12.498373	268017.0	267901.0
12770	11.735844	11.774528	124972.0	129901.0
6068	12.902608	12.891669	401358.0	396991.0
8000	12.771847	12.779594	352162.0	354901.0

In [79]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 1523391655.95
RMSE: 39030.65
R^2: 0.967
```

In [80]:
```
pred = best_rf_model.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[80]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.680442	12.672950	321400.0	319001.0
17892	11.465357	12.100718	95355.0	180001.0
12198	12.704762	12.736704	329312.0	340001.0
9774	12.494212	12.594734	266789.0	295001.0
18511	12.058968	11.938200	172641.0	153001.0
18437	12.352421	12.341438	231520.0	228991.0
8661	13.156100	13.038440	517156.0	459751.0
14024	12.933460	12.985170	413933.0	435901.0
12975	12.529389	12.514296	276340.0	272201.0
4385	12.256808	12.257041	210409.0	210458.0
18095	12.606308	12.736410	298435.0	339901.0
13870	12.848457	13.361382	380202.0	635001.0
9663	12.376206	12.429220	237092.0	250001.0
15665	11.933989	11.956976	152358.0	155901.0
6755	13.867820	13.997833	1053701.0	1200001.0
2695	12.367563	12.524166	235052.0	274901.0
15953	12.184781	12.205578	195787.0	199901.0
16692	12.414887	12.706821	246443.0	329991.0
14	11.801463	11.660492	133447.0	115901.0
15851	12.165088	12.165256	191969.0	192001.0

In [213]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

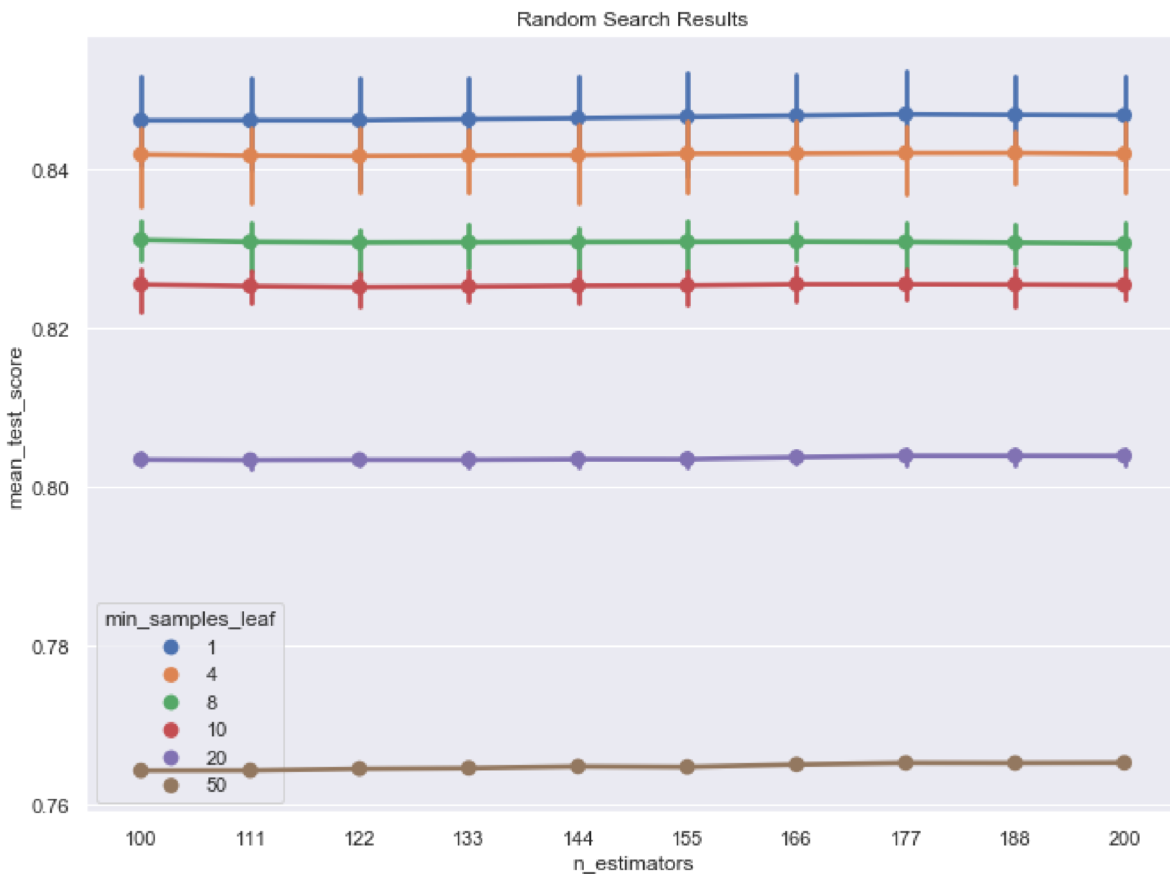
```
MSE: 15874918336.07
RMSE: 125995.71
R^2: 0.661
```

In [82]:
```
# plot the results

import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Random Search Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

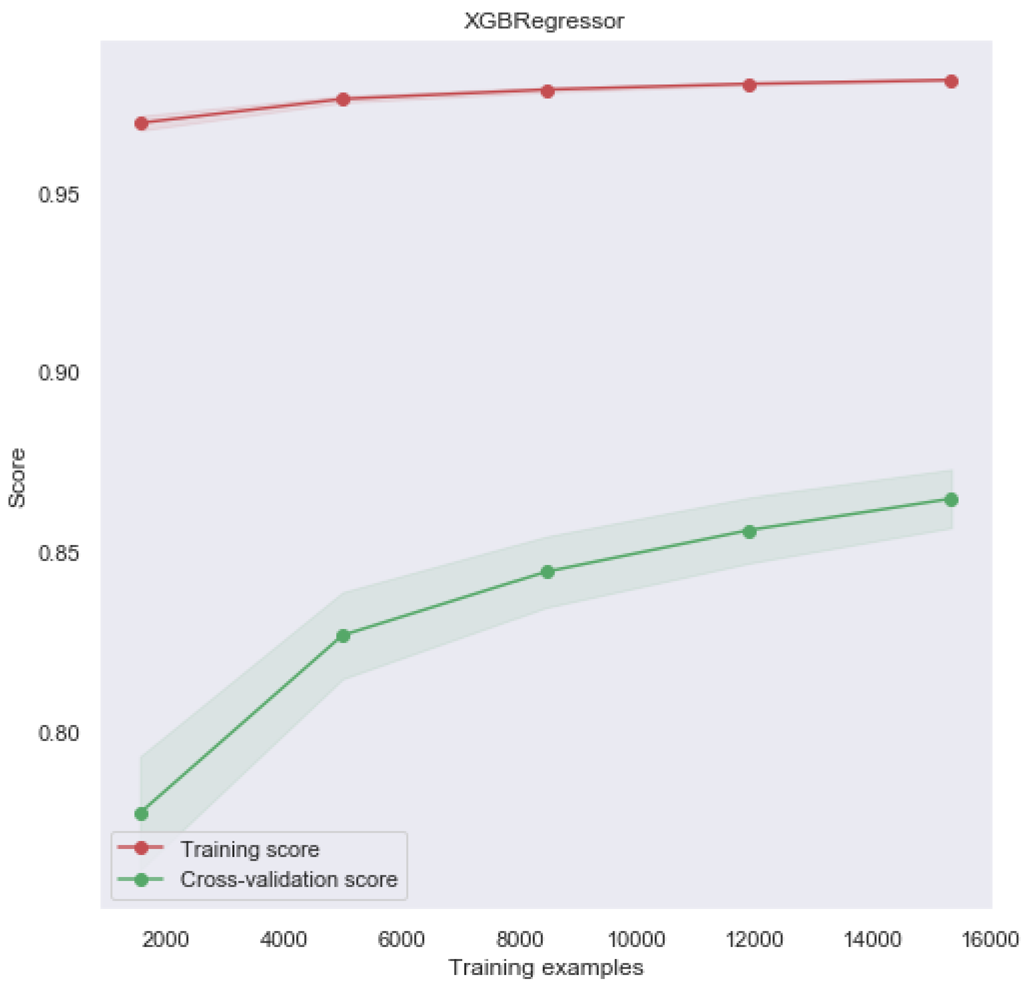
fig = plot_cv_results(rf_random.cv_results_, 'n_estimators', 'min_samples_lea
f')
```



In [83]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('XGBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_rf_model, X, Y, c
v=cv, train_sizes=np.linspace(.1, 1.0, 5), random_state=2020)
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[83]: <Figure size 576x576 with 0 Axes>
Out[83]: Text(0.5, 1.0, 'XGBRegressor')
Out[83]: Text(0.5, 0, 'Training examples')
Out[83]: Text(0, 0.5, 'Score')
Out[83]: <matplotlib.collections.PolyCollection at 0x1a268d3090>
Out[83]: <matplotlib.collections.PolyCollection at 0x1a26405690>
Out[83]: [<matplotlib.lines.Line2D at 0x1a2607e590>]
Out[83]: [<matplotlib.lines.Line2D at 0x1a264b2990>]
Out[83]: <matplotlib.legend.Legend at 0x1a26038250>
```



Tiny Conclusion for Random Forest

The R^2 of default Random Forest Model is 0.805. We used four hyperparameters to tune the Random Forest model.They are number of estimators, max despth, min sample split and min sample leaf. The R^2 of Random Forest Model is 0.661. The tuned Random forest got really bad R^2 in test set but has good R^2 in tran set which is 0.967. It means Tuned Random Forest overfitting. Our assumption is that we set too large of n_estimators too force model to be more complicated. Random Forest tuning really wastes time (half or one day for Random Forest Tuning), so we do not have enough time to revise hyperparameters and tune model again. In the future, we will try revise the range of n_estimators and we have confidence that Random Forest will have much better result in test set.

XGBoost_GridSearch

In [84]:
```
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
%matplotlib inline
from sklearn.model_selection import train_test_split
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

model = XGBRegressor(objective ='reg:squarederror',random_state=42)
model.fit(x_train, y_train)

# Create the random grid
param_grid= {"learning_rate"    : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30 ] ,
 "max_depth"        : [3, 4, 5, 6, 8, 10, 12, 15] }
print(param_grid)

grid = GridSearchCV(model, param_grid, cv=5, scoring = 'r2')
grid.fit(x_train, y_train)
print(grid.best_params_)
print(grid.best_estimator_)
```

Out[84]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

```
{'learning_rate': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3], 'max_depth': [3, 4, 5,
6, 8, 10, 12, 15]}
```

Out[84]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                    colsample_bylevel=1, colsample_bynode=1,
                                    colsample_bytree=1, gamma=0,
                                    importance_type='gain', learning_rate=0.
1,
                                    max_delta_step=0, max_depth=3,
                                    min_child_weight=1, missing=None,
                                    n_estimators=100, n_jobs=1, nthread=None,
                                    objective='reg:squarederror',
                                    random_state=42, reg_alpha=0, reg_lambda=
1,
                                    scale_pos_weight=1, seed=None, silent=Non
e,
                                    subsample=1, verbosity=1),
             iid='deprecated', n_jobs=None,
             param_grid={'learning_rate': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3],
                         'max_depth': [3, 4, 5, 6, 8, 10, 12, 15]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)
```

```
{'learning_rate': 0.15, 'max_depth': 8}
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.15, max_delta_step=0,
             max_depth=8, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

In [85]:
```
best_model_XGBoost = XGBRegressor(random_state=42).set_params(**grid.best_para
ms_)
best_model_XGBoost.fit(x_train,y_train)
```

```
[04:21:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[85]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.15, max_delta_step=0,
             max_depth=8, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [86]:
```
pred_train = best_model_XGBoost.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[86]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.250715	12.238675	209131.0	206628.0
18253	12.607268	12.574185	298722.0	289001.0
4741	13.897685	13.945662	1085645.0	1139001.0
8406	12.286574	12.312687	216766.0	222501.0
234	13.054332	13.060277	467115.0	469901.0
11125	12.608298	12.610173	299030.0	299591.0
2813	13.006720	13.060277	445396.0	469901.0
698	13.190767	13.199141	535399.0	539901.0
10623	13.437185	13.384729	685007.0	650001.0
16239	12.637964	12.577636	308034.0	290000.0
15949	12.043436	12.049425	169980.0	171001.0
1668	12.944077	12.911645	418351.0	405001.0
3372	13.371639	13.485618	641548.0	719001.0
10397	12.492845	12.425212	266424.0	249001.0
17489	12.398043	12.383675	242327.0	238870.0
6284	12.890859	12.895553	396669.0	398536.0
9598	12.555911	12.498373	283768.0	267901.0
12770	11.826969	11.774528	136895.0	129901.0
6068	12.935985	12.891669	414979.0	396991.0
8000	12.777688	12.779594	354225.0	354901.0

In [87]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 1361838390.75
RMSE: 36903.09
R^2: 0.971
```

In [88]:
```
pred = best_model_XGBoost.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[88]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.710608	12.672950	331243.0	319001.0
17892	11.431957	12.100718	92222.0	180001.0
12198	12.656980	12.736704	313947.0	340001.0
9774	12.546282	12.594734	281048.0	295001.0
18511	12.022827	11.938200	166513.0	153001.0
18437	12.372535	12.341438	236224.0	228991.0
8661	13.263519	13.038440	575802.0	459751.0
14024	13.024722	12.985170	453487.0	435901.0
12975	12.479917	12.514296	263002.0	272201.0
4385	12.179930	12.257041	194839.0	210458.0
18095	12.681760	12.736410	321824.0	339901.0
13870	13.182715	13.361382	531105.0	635001.0
9663	12.358023	12.429220	232820.0	250001.0
15665	11.979459	11.956976	159446.0	155901.0
6755	13.842778	13.997833	1027642.0	1200001.0
2695	12.422010	12.524166	248205.0	274901.0
15953	12.080418	12.205578	176384.0	199901.0
16692	12.456396	12.706821	256888.0	329991.0
14	11.704274	11.660492	121088.0	115901.0
15851	12.132890	12.165256	185886.0	192001.0

In [89]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

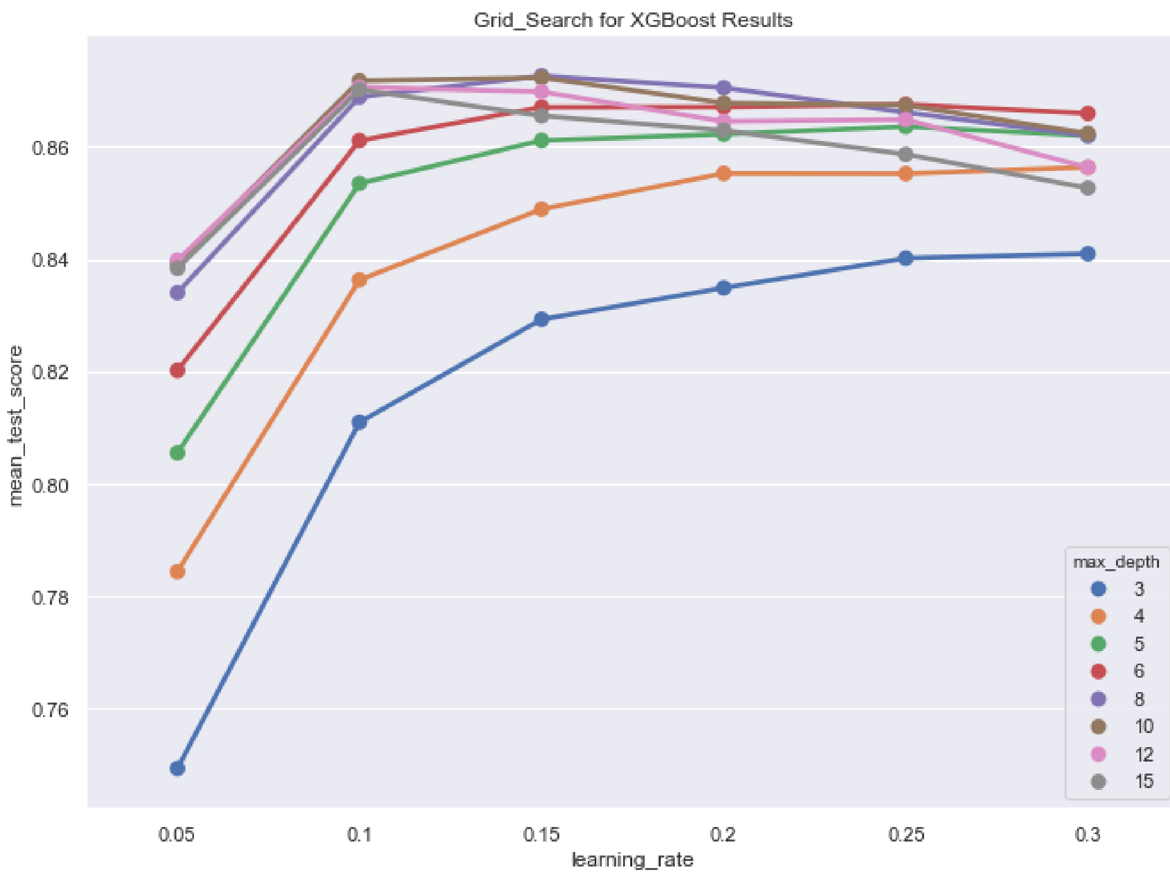
```
MSE: 8167857347.30
RMSE: 90376.20
R^2: 0.826
```

In [90]:
```python
# plot the results

import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Grid_Search for XGBoost Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(grid.cv_results_, 'learning_rate', 'max_depth')
```



In [91]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('XGBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model_XGBoost, X,
Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5), random_state=2020)
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[91]: <Figure size 432x288 with 0 Axes>
Out[91]: Text(0.5, 1.0, 'XGBRegressor')
Out[91]: Text(0.5, 0, 'Training examples')
Out[91]: Text(0, 0.5, 'Score')
```

```
[04:21:31] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:21:32] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:21:35] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:21:40] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:21:46] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:21:55] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:21:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:21:59] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:22:04] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:20] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:21] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:24] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:35] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:44] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:45] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:22:53] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:08] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:09] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:12] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:17] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:24] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:33] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:36] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:41] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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precated in favor of reg:squarederror.
[04:23:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:23:57] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:01] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:13] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:21] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:22] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:25] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:30] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:46] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:24:47] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:24:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:24:54] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:01] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:10] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:25:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:25:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:26] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:25:35] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:43] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:25:59] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:26:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
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[04:26:02] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:07] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:24] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:27] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:31] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:47] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:26:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:03] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:12] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:13] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:16] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:20] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:27] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:36] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:40] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:45] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:27:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:01] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:04] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:09] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:16] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:25] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:26] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:40] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:49] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:53] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:28:58] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:05] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:15] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:18] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:39] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:47] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:29:54] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:02] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:03] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:18] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:27] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:31] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:35] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:52] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:30:55] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:07] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:15] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:16] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:31:41] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:04] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:05] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:08] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:13] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:20] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:32] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:44] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:53] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:32:54] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:32:57] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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precated in favor of reg:squarederror.
[04:33:02] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[04:33:09] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:33:17] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:33:18] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:33:21] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:33:26] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[04:33:33] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[91]: `<matplotlib.collections.PolyCollection at 0x1a27248f50>`

Out[91]: `<matplotlib.collections.PolyCollection at 0x1a2737ce90>`

Out[91]: `[<matplotlib.lines.Line2D at 0x1a27248fd0>]`

Out[91]: `[<matplotlib.lines.Line2D at 0x1a2737cd90>]`

Out[91]: `<matplotlib.legend.Legend at 0x1a2737c090>`

XGBoost before Tunning

In [93]:
```
from xgboost import XGBRegressor
model_XGB = XGBRegressor(objective ='reg:squarederror', random_state=42)
model_XGB.fit(x_train, y_train)
```

Out[93]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

In [94]:
```
pred_train = model_XGB.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[94]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.226754	12.238675	204179.0	206628.0
18253	12.604381	12.574185	297860.0	289001.0
4741	13.730320	13.945662	918337.0	1139001.0
8406	12.357557	12.312687	232712.0	222501.0
234	13.070049	13.060277	474515.0	469901.0
11125	12.569075	12.610173	287528.0	299591.0
2813	12.940280	13.060277	416766.0	469901.0
698	13.224698	13.199141	553877.0	539901.0
10623	13.523803	13.384729	746986.0	650001.0
16239	12.712918	12.577636	332009.0	290000.0
15949	12.139552	12.049425	187129.0	171001.0
1668	12.969047	12.911645	428929.0	405001.0
3372	13.346521	13.485618	625634.0	719001.0
10397	12.429756	12.425212	250135.0	249001.0
17489	12.179892	12.383675	194832.0	238870.0
6284	12.984177	12.895553	435468.0	398536.0
9598	12.527796	12.498373	275900.0	267901.0
12770	11.937084	11.774528	152830.0	129901.0
6068	12.925675	12.891669	410723.0	396991.0
8000	12.833187	12.779594	374440.0	354901.0

In [95]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 9581065388.97
RMSE: 97882.92
R^2: 0.793
```

In [96]:
```
pred = model_XGB.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[96]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.639056	12.672950	308370.0	319001.0
17892	11.471642	12.100718	95956.0	180001.0
12198	12.651381	12.736704	312194.0	340001.0
9774	12.518630	12.594734	273383.0	295001.0
18511	12.224936	11.938200	203808.0	153001.0
18437	12.469892	12.341438	260378.0	228991.0
8661	13.346697	13.038440	625744.0	459751.0
14024	12.955319	12.985170	423081.0	435901.0
12975	12.652393	12.514296	312510.0	272201.0
4385	12.172954	12.257041	193485.0	210458.0
18095	12.673296	12.736410	319111.0	339901.0
13870	12.996673	13.361382	440944.0	635001.0
9663	12.346475	12.429220	230147.0	250001.0
15665	12.115696	11.956976	182717.0	155901.0
6755	13.773303	13.997833	958670.0	1200001.0
2695	12.406693	12.524166	244432.0	274901.0
15953	12.120080	12.205578	183520.0	199901.0
16692	12.420364	12.706821	247797.0	329991.0
14	11.630335	11.660492	112458.0	115901.0
15851	12.216623	12.165256	202121.0	192001.0

In [97]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 11276221962.81
RMSE: 106189.56
R^2: 0.759
```

In [98]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
estimator=XGBRegressor(objective ='reg:squarederror')
plt.figure()
plt.title('XGBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(estimator, X, Y, cv=cv
, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[98]: <Figure size 432x288 with 0 Axes>

Out[98]: Text(0.5, 1.0, 'XGBRegressor')

Out[98]: Text(0.5, 0, 'Training examples')

Out[98]: Text(0, 0.5, 'Score')

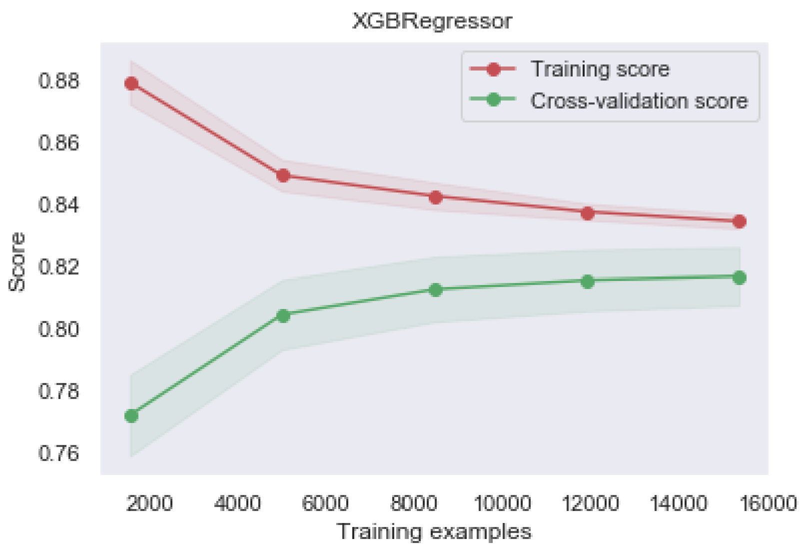
Out[98]: <matplotlib.collections.PolyCollection at 0x1a22538fd0>

Out[98]: <matplotlib.collections.PolyCollection at 0x1a26330f50>

Out[98]: [<matplotlib.lines.Line2D at 0x1a22545d10>]

Out[98]: [<matplotlib.lines.Line2D at 0x1a22545ed0>]

Out[98]: <matplotlib.legend.Legend at 0x1a263306d0>



Tiny Conclusion for XGBoost

The R^2 of default XGBoost model in test set is 0.759. We tuned two hyperparameters (Learning rate and max depth). After tuned, the R^2 of the optimal XGBoost model ('learning_rate': 0.15, 'max_depth': 8) in test set is 0.826. In conclusion, tuned hyperparameters help XGBoost model to have higher "accuracy". According to the XGBoost introduction online, we need to tune learning rate and number of iteration together to get great result (higher R^2 or lower MSE/RMSE). However, number of iterations tunning cost too much time, we did not try it. If we have more time, we will try more useful and important hyperparameters.

LGBM_before_tunning

In [99]:
```
from lightgbm.sklearn import LGBMRegressor

lgbm_model_before_tune= LGBMRegressor(random_state=42)
lgbm_model_before_tune.fit(x_train, y_train)
```

Out[99]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_split_gain=0.
0,
              n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
              random_state=42, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

In [100]:
```
pred_train = lgbm_model_before_tune.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                              columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[100]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.216293	12.238675	202055.0	206628.0
18253	12.563306	12.574185	285874.0	289001.0
4741	13.924917	13.945662	1115616.0	1139001.0
8406	12.314943	12.312687	223004.0	222501.0
234	13.054483	13.060277	467186.0	469901.0
11125	12.615701	12.610173	301252.0	299591.0
2813	12.951652	13.060277	421532.0	469901.0
698	13.230585	13.199141	557147.0	539901.0
10623	13.472658	13.384729	709743.0	650001.0
16239	12.638364	12.577636	308157.0	290000.0
15949	12.066349	12.049425	173920.0	171001.0
1668	12.941940	12.911645	417458.0	405001.0
3372	13.374813	13.485618	643588.0	719001.0
10397	12.499728	12.425212	268264.0	249001.0
17489	12.346002	12.383675	230039.0	238870.0
6284	12.930675	12.895553	412782.0	398536.0
9598	12.547516	12.498373	281395.0	267901.0
12770	11.794248	11.774528	132488.0	129901.0
6068	12.919420	12.891669	408162.0	396991.0
8000	12.793792	12.779594	359976.0	354901.0

In [101]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 4875456830.55
RMSE: 69824.47
R^2: 0.894
```

In [102]:
```
pred = lgbm_model_before_tune.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[102]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.697397	12.672950	326896.0	319001.0
17892	11.301721	12.100718	80961.0	180001.0
12198	12.652824	12.736704	312645.0	340001.0
9774	12.535093	12.594734	277921.0	295001.0
18511	12.125326	11.938200	184485.0	153001.0
18437	12.403332	12.341438	243612.0	228991.0
8661	13.281429	13.038440	586207.0	459751.0
14024	13.011335	12.985170	447457.0	435901.0
12975	12.581651	12.514296	291167.0	272201.0
4385	12.182793	12.257041	195398.0	210458.0
18095	12.681321	12.736410	321683.0	339901.0
13870	13.113408	13.361382	495542.0	635001.0
9663	12.353393	12.429220	231745.0	250001.0
15665	11.876265	11.956976	143812.0	155901.0
6755	13.816665	13.997833	1001155.0	1200001.0
2695	12.333773	12.524166	227243.0	274901.0
15953	12.133921	12.205578	186078.0	199901.0
16692	12.499332	12.706821	268158.0	329991.0
14	11.707227	11.660492	121446.0	115901.0
15851	12.174837	12.165256	193849.0	192001.0

In [103]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 8262161622.80
RMSE: 90896.43
R^2: 0.824
```

In [104]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LassoRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(lgbm_model_before_tune
, X, Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[104]: <Figure size 432x288 with 0 Axes>

Out[104]: Text(0.5, 1.0, 'LassoRegressor')

Out[104]: Text(0.5, 0, 'Training examples')

Out[104]: Text(0, 0.5, 'Score')

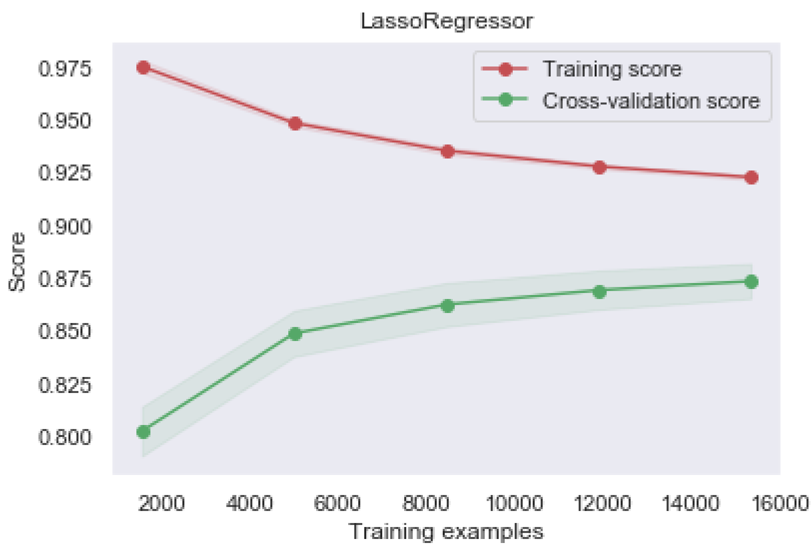
Out[104]: <matplotlib.collections.PolyCollection at 0x1a2717c3d0>

Out[104]: <matplotlib.collections.PolyCollection at 0x1a2717ccd0>

Out[104]: [<matplotlib.lines.Line2D at 0x1a2717c850>]

Out[104]: [<matplotlib.lines.Line2D at 0x1a2717c190>]

Out[104]: <matplotlib.legend.Legend at 0x1a26e5db90>



LGBM_GridSearch

In [105]:
```
from lightgbm.sklearn import LGBMRegressor

model = LGBMRegressor()
model.fit(x_train, y_train)
```

Out[105]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_split_gain=0.
0,
              n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
              random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

In [106]:
```
from sklearn.model_selection import GridSearchCV
%matplotlib inline
from sklearn.model_selection import train_test_split
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

model = LGBMRegressor(random_state=42)
model.fit(x_train, y_train)

# Create the random grid
param_grid= {"num_leaves"    : [20,30,60,70,100,150,200] ,
    "min_data_in_leaf"        : [10,20,50,100,150,200,300]  }
print(param_grid)

grid_LGBM = GridSearchCV(model, param_grid, cv=5, scoring = 'r2')
grid_LGBM.fit(x_train, y_train)
print(grid_LGBM.best_params_)
print(grid_LGBM.best_estimator_)
```

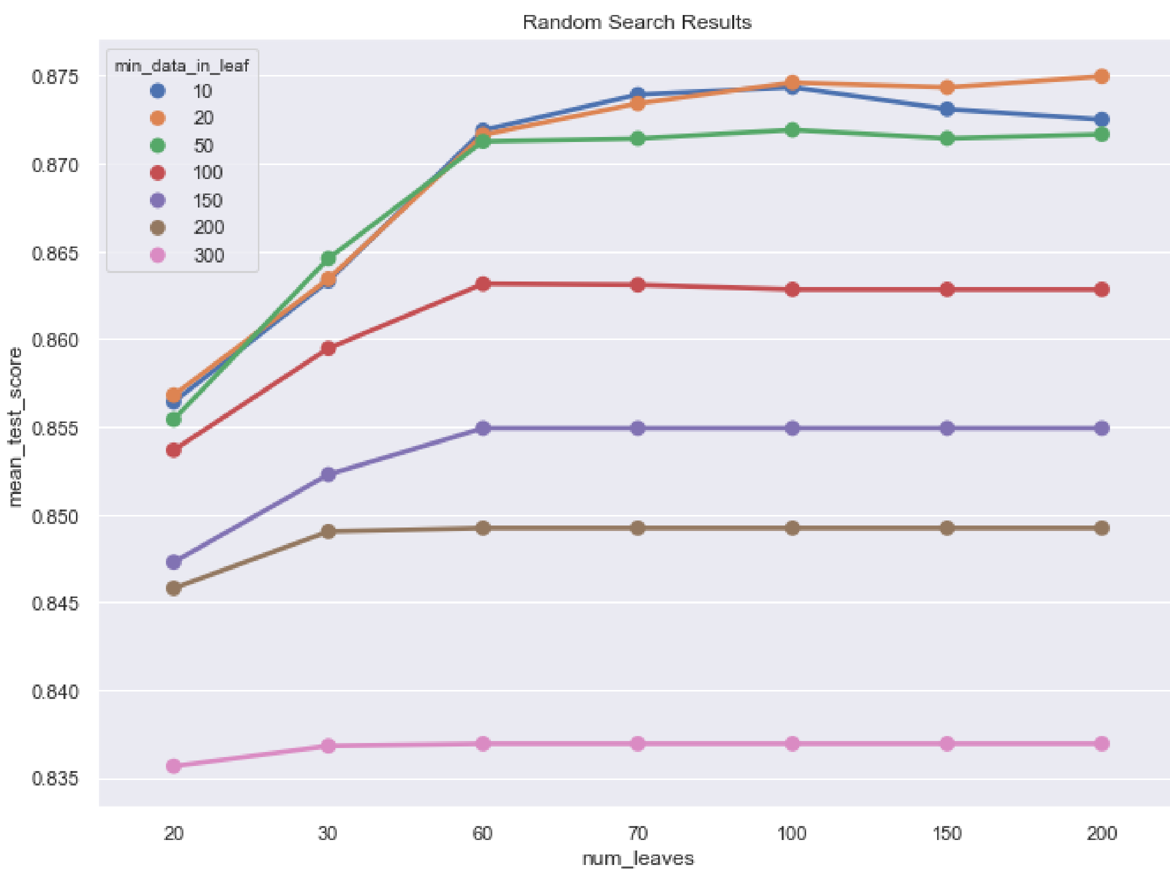
Out[106]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_split_gain=0.
0,
              n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
              random_state=42, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

```
{'num_leaves': [20, 30, 60, 70, 100, 150, 200], 'min_data_in_leaf': [10, 20,
50, 100, 150, 200, 300]}
```

Out[106]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=LGBMRegressor(boosting_type='gbdt', class_weight=None,
                                     colsample_bytree=1.0,
                                     importance_type='split', learning_rate=
0.1,
                                     max_depth=-1, min_child_samples=20,
                                     min_child_weight=0.001, min_split_gain=
0.0,
                                     n_estimators=100, n_jobs=-1, num_leaves=
31,
                                     objective=None, random_state=42,
                                     reg_alpha=0.0, reg_lambda=0.0, silent=Tr
ue,
                                     subsample=1.0, subsample_for_bin=200000,
                                     subsample_freq=0),
             iid='deprecated', n_jobs=None,
             param_grid={'min_data_in_leaf': [10, 20, 50, 100, 150, 200, 30
0],
                         'num_leaves': [20, 30, 60, 70, 100, 150, 200]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)
```

```
{'min_data_in_leaf': 20, 'num_leaves': 200}
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=
20,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=20
0,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
```

In [107]:
```python
import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Random Search Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(grid_LGBM.cv_results_, 'num_leaves', 'min_data_in_leaf')
```



In [108]:
```
best_model_Lgbm = LGBMRegressor(random_state=42).set_params(**grid_LGBM.best_p
arams_)
best_model_Lgbm.fit(x_train,y_train)
```

Out[108]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=
20,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=20
0,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
```

In [109]:
```
pred_train =best_model_Lgbm.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[109]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.256304	12.238675	210303.0	206628.0
18253	12.560228	12.574185	284995.0	289001.0
4741	13.989030	13.945662	1189484.0	1139001.0
8406	12.317927	12.312687	223670.0	222501.0
234	13.057503	13.060277	468599.0	469901.0
11125	12.616866	12.610173	301603.0	299591.0
2813	12.990851	13.060277	438384.0	469901.0
698	13.220418	13.199141	551512.0	539901.0
10623	13.426770	13.384729	677910.0	650001.0
16239	12.633948	12.577636	306799.0	290000.0
15949	12.026002	12.049425	167042.0	171001.0
1668	12.917561	12.911645	407404.0	405001.0
3372	13.425758	13.485618	677224.0	719001.0
10397	12.470274	12.425212	260478.0	249001.0
17489	12.427596	12.383675	249595.0	238870.0
6284	12.889724	12.895553	396219.0	398536.0
9598	12.526541	12.498373	275555.0	267901.0
12770	11.762226	11.774528	128313.0	129901.0
6068	12.923896	12.891669	409993.0	396991.0
8000	12.802093	12.779594	362976.0	354901.0

In [110]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 1035184184.50
RMSE: 32174.28
R^2: 0.978
```

In [111]:
```
pred = best_model_Lgbm.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[111]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.705462	12.672950	329543.0	319001.0
17892	11.502408	12.100718	98954.0	180001.0
12198	12.641831	12.736704	309227.0	340001.0
9774	12.489500	12.594734	265534.0	295001.0
18511	12.146452	11.938200	188424.0	153001.0
18437	12.354230	12.341438	231939.0	228991.0
8661	13.174958	13.038440	527001.0	459751.0
14024	12.921175	12.985170	408879.0	435901.0
12975	12.525407	12.514296	275242.0	272201.0
4385	12.161620	12.257041	191304.0	210458.0
18095	12.692497	12.736410	325298.0	339901.0
13870	13.067452	13.361382	473285.0	635001.0
9663	12.390830	12.429220	240585.0	250001.0
15665	11.970024	11.956976	157948.0	155901.0
6755	13.866594	13.997833	1052410.0	1200001.0
2695	12.449884	12.524166	255221.0	274901.0
15953	12.111594	12.205578	181969.0	199901.0
16692	12.487294	12.706821	264949.0	329991.0
14	11.722908	11.660492	123366.0	115901.0
15851	12.120149	12.165256	183533.0	192001.0

In [112]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 7837783637.59
RMSE: 88531.26
R^2: 0.833
```

In [113]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LGMBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model_Lgbm, X, Y,
cv=cv, train_sizes=np.linspace(.1, 1.0, 5), random_state=2020)
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[113]: <Figure size 432x288 with 0 Axes>
Out[113]: Text(0.5, 1.0, 'LGMBRegressor')
Out[113]: Text(0.5, 0, 'Training examples')
Out[113]: Text(0, 0.5, 'Score')
Out[113]: <matplotlib.collections.PolyCollection at 0x1a25e4c750>
Out[113]: <matplotlib.collections.PolyCollection at 0x1a264b2910>
Out[113]: [<matplotlib.lines.Line2D at 0x1a26038b90>]
Out[113]: [<matplotlib.lines.Line2D at 0x1a272f11d0>]
Out[113]: <matplotlib.legend.Legend at 0x1a26075ad0>
```

Tiny Conclusion for LGBM

The R^2 of default lgbm model in test set is 0.822. We tuned two hyperparameters (min data in leaf and number of leaves). After tuned, the R^2 of the optimal LGBM model ('min_data_in_leaf': 20, 'num_leaves': 200) in test set is 0.833. In conclusion, tuned hyperparameters help LGBM model to have higher R^2.

According to the grid search graph and LGBM introduction online, Setting min_data_in_leaf to smaller value will lead growing deeper a tree, which means will help model to have higher "accuracy" and also will be easier to be overfitting. Online paper mentioned that larger number of leaves means higher "accuracy" (higher R^2 or lower RMSE/MSE), but our grid search showed that it also has possbility that "accuracy" decreased when number of leaves increased. Therefore, the better way is to consider more hyperparameters (If we have enough time, we will try more).

An interesting story: In the beginning, we found that R^2 of tuned LGBM even smaller than R^2 of the default LGBM. After we checked LGBM Introfuction online, we found that the default value of num_leaves is 31. But our first tuning range of num_leaves is (5,30). Our max value in the range of num_leaves still smaller than default value. After revised the range of num_leaves, we got better results.

Ensemble Learning for built in model

In [114]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor()
LCV_model = LassoCV()
lr_model = linear_model.LinearRegression()
XGB_model = XGBRegressor(objective ='reg:squarederror')
LGBM_model = LGBMRegressor()
estimators = [XGB_model, LGBM_model, lr_model, LCV_model, rf_model]
reg_built_in_model = StackingRegressor(regressors=estimators, meta_regressor=G
radientBoostingRegressor(random_state=42))
reg_built_in_model.fit(x_train,y_train)
```

Out[114]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                            ccp_alpha=0.0,
                                                            criterion='friedma
n_mse',
                                                            init=None,
                                                            learning_rate=0.1,
                                                            loss='ls',
                                                            max_depth=3,
                                                            max_features=None,
                                                            max_leaf_nodes=Non
e,
                                                            min_impurity_decre
ase=0.0,
                                                            min_impurity_split
=None,
                                                            min_samples_leaf=
1,
                                                            min_samples_split=
2,
                                                            min_weight_fractio
n_leaf=0.0,
                                                            n_estimators=100,
                                                            n_iter_no_change=N
o...
                                                     max_depth=None,
                                                     max_features='auto',
                                                     max_leaf_nodes=None,
                                                     max_samples=None,
                                                     min_impurity_decrease=0.
0,
                                                     min_impurity_split=None,
                                                     min_samples_leaf=1,
                                                     min_samples_split=2,
                                                     min_weight_fraction_leaf=
0.0,
                                                     n_estimators=100,
                                                     n_jobs=None,
                                                     oob_score=False,
                                                     random_state=None,
                                                     verbose=0,
                                                     warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [115]:
```
pred_train = reg_built_in_model.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[115]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.252118	12.238675	209424.0	206628.0
18253	12.575672	12.574185	289431.0	289001.0
4741	13.893850	13.945662	1081490.0	1139001.0
8406	12.266059	12.312687	212364.0	222501.0
234	13.048036	13.060277	464184.0	469901.0
11125	12.605369	12.610173	298155.0	299591.0
2813	13.027253	13.060277	454636.0	469901.0
698	13.180979	13.199141	530184.0	539901.0
10623	13.419867	13.384729	673246.0	650001.0
16239	12.617255	12.577636	301720.0	290000.0
15949	12.063560	12.049425	173435.0	171001.0
1668	12.915169	12.911645	406431.0	405001.0
3372	13.474555	13.485618	711091.0	719001.0
10397	12.444606	12.425212	253877.0	249001.0
17489	12.387150	12.383675	239701.0	238870.0
6284	12.902923	12.895553	401484.0	398536.0
9598	12.496000	12.498373	267266.0	267901.0
12770	11.725929	11.774528	123739.0	129901.0
6068	12.912723	12.891669	405438.0	396991.0
8000	12.764635	12.779594	349632.0	354901.0

In [116]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 800889354.09
RMSE: 28299.99
R^2: 0.983
```

In [117]:
```
pred = reg_built_in_model.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                               columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[117]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.703892	12.672950	329026.0	319001.0
17892	11.471332	12.100718	95926.0	180001.0
12198	12.718498	12.736704	333867.0	340001.0
9774	12.472514	12.594734	261062.0	295001.0
18511	12.086035	11.938200	177377.0	153001.0
18437	12.344003	12.341438	229579.0	228991.0
8661	13.108398	13.038440	493066.0	459751.0
14024	12.915169	12.985170	406431.0	435901.0
12975	12.517587	12.514296	273098.0	272201.0
4385	12.224459	12.257041	203711.0	210458.0
18095	12.625228	12.736410	304135.0	339901.0
13870	12.829662	13.361382	373122.0	635001.0
9663	12.377097	12.429220	237304.0	250001.0
15665	11.937188	11.956976	152846.0	155901.0
6755	13.900430	13.997833	1088629.0	1200001.0
2695	12.372849	12.524166	236298.0	274901.0
15953	12.189015	12.205578	196617.0	199901.0
16692	12.414247	12.706821	246286.0	329991.0
14	11.855402	11.660492	140843.0	115901.0
15851	12.175923	12.165256	194060.0	192001.0

In [118]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 9273818536.51
RMSE: 96300.67
R^2: 0.802
```

In [119]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg_built_in_model, X,
Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[119]: <Figure size 432x288 with 0 Axes>

Out[119]: Text(0.5, 1.0, 'Ensemble Learning')

Out[119]: Text(0.5, 0, 'Training examples')

Out[119]: Text(0, 0.5, 'Score')

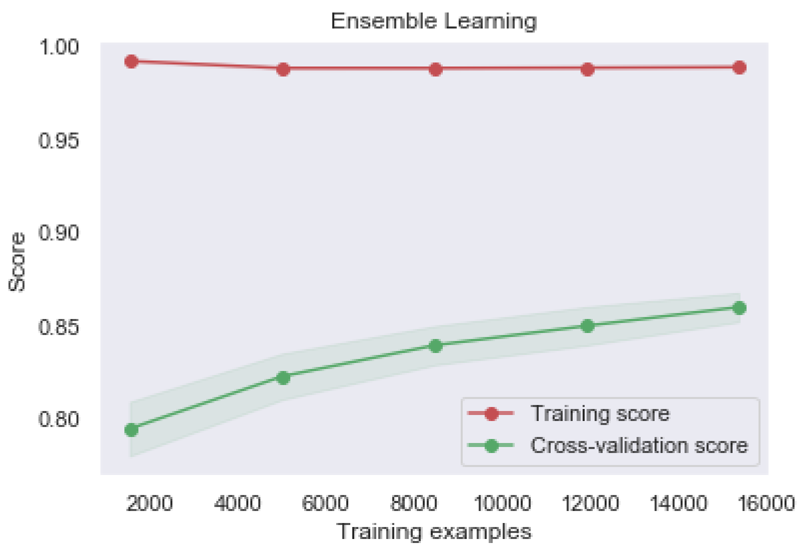
Out[119]: <matplotlib.collections.PolyCollection at 0x1a2713ca90>

Out[119]: <matplotlib.collections.PolyCollection at 0x1a264b7f50>

Out[119]: [<matplotlib.lines.Line2D at 0x1a26abff90>]

Out[119]: [<matplotlib.lines.Line2D at 0x1a264b7310>]

Out[119]: <matplotlib.legend.Legend at 0x1a26ac4390>



Ensemble learning without linear and lasso

In [120]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
XGB_model = XGBRegressor(objective ='reg:squarederror')
LGBM_model = LGBMRegressor()
estimators = [XGB_model, LGBM_model, rf_model]
reg_built_in_model_without_linearlasso = StackingRegressor(regressors=estimato
rs, meta_regressor=GradientBoostingRegressor(random_state=42))
reg_built_in_model_without_linearlasso.fit(x_train,y_train)
```

Out[120]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [121]:
```
pred_train = reg_built_in_model_without_linearlasso.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                                     columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[121]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.254827	12.238675	209993.0	206628.0
18253	12.590112	12.574185	293641.0	289001.0
4741	13.906026	13.945662	1094739.0	1139001.0
8406	12.276252	12.312687	214540.0	222501.0
234	13.063033	13.060277	471198.0	469901.0
11125	12.596836	12.610173	295622.0	299591.0
2813	13.040962	13.060277	460912.0	469901.0
698	13.187536	13.199141	533672.0	539901.0
10623	13.406665	13.384729	664417.0	650001.0
16239	12.591836	12.577636	294147.0	290000.0
15949	12.036338	12.049425	168778.0	171001.0
1668	12.930963	12.911645	412901.0	405001.0
3372	13.472081	13.485618	709334.0	719001.0
10397	12.463106	12.425212	258618.0	249001.0
17489	12.393213	12.383675	241159.0	238870.0
6284	12.889354	12.895553	396073.0	398536.0
9598	12.492748	12.498373	266398.0	267901.0
12770	11.698635	11.774528	120407.0	129901.0
6068	12.929759	12.891669	412404.0	396991.0
8000	12.765815	12.779594	350044.0	354901.0

In [122]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 896157567.52
RMSE: 29935.89
R^2: 0.981
```

In [123]:
```
pred = reg_built_in_model_without_linearlasso.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[123]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.669739	12.672950	317979.0	319001.0
17892	11.365807	12.100718	86319.0	180001.0
12198	12.702112	12.736704	328441.0	340001.0
9774	12.492478	12.594734	266326.0	295001.0
18511	12.141012	11.938200	187402.0	153001.0
18437	12.334361	12.341438	227376.0	228991.0
8661	13.108372	13.038440	493053.0	459751.0
14024	12.946020	12.985170	419165.0	435901.0
12975	12.516335	12.514296	272757.0	272201.0
4385	12.230039	12.257041	204851.0	210458.0
18095	12.611659	12.736410	300036.0	339901.0
13870	12.809540	13.361382	365690.0	635001.0
9663	12.359793	12.429220	233233.0	250001.0
15665	11.962359	11.956976	156742.0	155901.0
6755	13.888551	13.997833	1075774.0	1200001.0
2695	12.344346	12.524166	229658.0	274901.0
15953	12.186400	12.205578	196104.0	199901.0
16692	12.432804	12.706821	250899.0	329991.0
14	11.870431	11.660492	142976.0	115901.0
15851	12.139050	12.165256	187035.0	192001.0

In [124]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 9405134334.19
RMSE: 96980.07
R^2: 0.799
```

In [125]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg_built_in_model_wit
hout_linearlasso, X,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[125]: <Figure size 432x288 with 0 Axes>

Out[125]: Text(0.5, 1.0, 'Ensemble Learning')

Out[125]: Text(0.5, 0, 'Training examples')

Out[125]: Text(0, 0.5, 'Score')

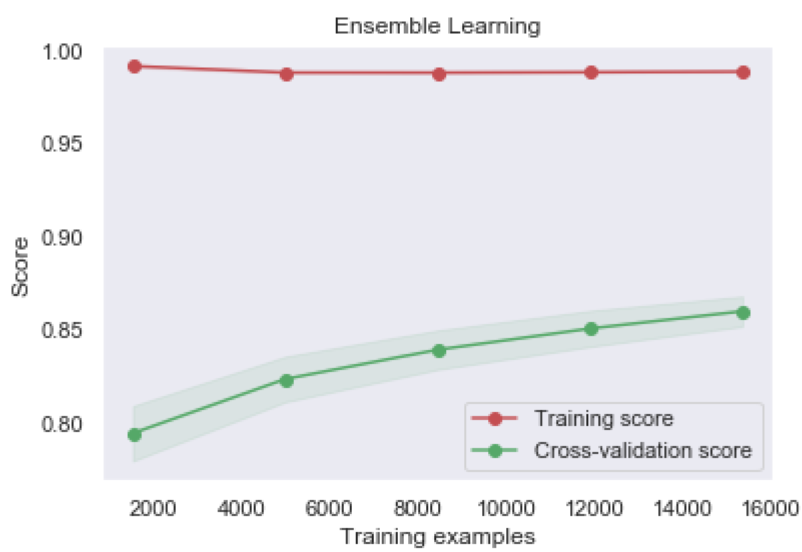
Out[125]: <matplotlib.collections.PolyCollection at 0x1a269cd850>

Out[125]: <matplotlib.collections.PolyCollection at 0x1a263c9f50>

Out[125]: [<matplotlib.lines.Line2D at 0x1a26edb2d0>]

Out[125]: [<matplotlib.lines.Line2D at 0x1a263c1850>]

Out[125]: <matplotlib.legend.Legend at 0x1a27083dd0>



Ensemble Learning with best model

In [126]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor()
LCV_model = LassoCV()
lr_model = linear_model.LinearRegression()
XGB_model = XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1
,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.15, max_delta_step=0,
             max_depth=8, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
LGBM_model = LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_
bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=2
0,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=200,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
estimators = [XGB_model, LGBM_model, lr_model, LCV_model, rf_model]
reg_model = StackingRegressor(regressors=estimators, meta_regressor=GradientBo
ostingRegressor(random_state=42))
reg_model.fit(x_train,y_train)
```

Out[126]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [127]:
```
pred_train = reg_model.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[127]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.239362	12.238675	206770.0	206628.0
18253	12.581536	12.574185	291133.0	289001.0
4741	13.955235	13.945662	1149957.0	1139001.0
8406	12.308868	12.312687	221653.0	222501.0
234	13.077298	13.060277	477967.0	469901.0
11125	12.593354	12.610173	294594.0	299591.0
2813	12.997173	13.060277	441164.0	469901.0
698	13.208977	13.199141	545238.0	539901.0
10623	13.445491	13.384729	690721.0	650001.0
16239	12.606514	12.577636	298497.0	290000.0
15949	12.038252	12.049425	169101.0	171001.0
1668	12.925124	12.911645	410497.0	405001.0
3372	13.448738	13.485618	692967.0	719001.0
10397	12.445397	12.425212	254078.0	249001.0
17489	12.403385	12.383675	243625.0	238870.0
6284	12.886681	12.895553	395016.0	398536.0
9598	12.514139	12.498373	272158.0	267901.0
12770	11.760993	11.774528	128155.0	129901.0
6068	12.920390	12.891669	408559.0	396991.0
8000	12.771602	12.779594	352076.0	354901.0

In [128]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 679834537.60
RMSE: 26073.64
R^2: 0.985
```

In [129]:
```
pred = reg_model.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[129]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.698518	12.672950	327262.0	319001.0
17892	11.484257	12.100718	97174.0	180001.0
12198	12.667002	12.736704	317109.0	340001.0
9774	12.483223	12.594734	263873.0	295001.0
18511	12.130040	11.938200	185357.0	153001.0
18437	12.349281	12.341438	230794.0	228991.0
8661	13.140289	13.038440	509043.0	459751.0
14024	12.926570	12.985170	411091.0	435901.0
12975	12.552530	12.514296	282810.0	272201.0
4385	12.173802	12.257041	193649.0	210458.0
18095	12.672355	12.736410	318812.0	339901.0
13870	13.098249	13.361382	488087.0	635001.0
9663	12.363714	12.429220	234149.0	250001.0
15665	11.970096	11.956976	157960.0	155901.0
6755	13.900067	13.997833	1088234.0	1200001.0
2695	12.386294	12.524166	239496.0	274901.0
15953	12.114935	12.205578	182578.0	199901.0
16692	12.447619	12.706821	254643.0	329991.0
14	11.747873	11.660492	126484.0	115901.0
15851	12.110827	12.165256	181830.0	192001.0

In [130]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 7828995180.93
RMSE: 88481.61
R^2: 0.833
```

Ensemble Learning with best model

In [131]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
XGB_model = XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1
,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.15, max_delta_step=0,
             max_depth=8, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
LGBM_model = LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_
bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=2
0,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=200,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
estimators = [XGB_model, LGBM_model, rf_model]
reg_built_in_model_without_linearlasso_best = StackingRegressor(regressors=est
imators, meta_regressor=GradientBoostingRegressor(random_state=42))
reg_built_in_model_without_linearlasso_best.fit(x_train,y_train)
```

Out[131]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [132]:
```
pred_train = reg_built_in_model_without_linearlasso_best.predict(x_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[132]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.244835	12.238675	207905.0	206628.0
18253	12.593818	12.574185	294731.0	289001.0
4741	13.952725	13.945662	1147074.0	1139001.0
8406	12.315671	12.312687	223166.0	222501.0
234	13.064758	13.060277	472011.0	469901.0
11125	12.596447	12.610173	295507.0	299591.0
2813	12.998764	13.060277	441867.0	469901.0
698	13.213304	13.199141	547602.0	539901.0
10623	13.437662	13.384729	685334.0	650001.0
16239	12.629219	12.577636	305352.0	290000.0
15949	12.040844	12.049425	169540.0	171001.0
1668	12.928074	12.911645	411710.0	405001.0
3372	13.445009	13.485618	690388.0	719001.0
10397	12.452710	12.425212	255943.0	249001.0
17489	12.413146	12.383675	246015.0	238870.0
6284	12.891234	12.895553	396818.0	398536.0
9598	12.507033	12.498373	270231.0	267901.0
12770	11.749452	11.774528	126684.0	129901.0
6068	12.915290	12.891669	406480.0	396991.0
8000	12.788456	12.779594	358060.0	354901.0

In [133]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 706618290.29
RMSE: 26582.29
R^2: 0.985
```

In [134]:
```
pred = reg_built_in_model_without_linearlasso_best.predict(x_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[134]:

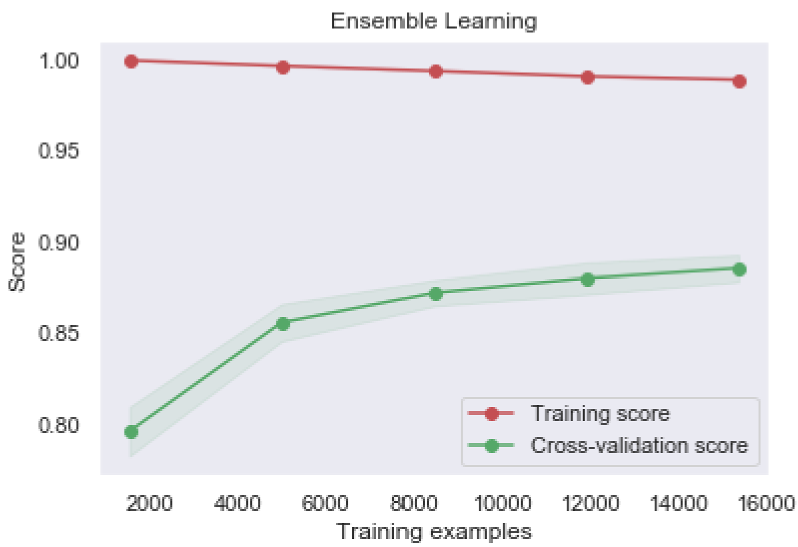
	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.705049	12.672950	329407.0	319001.0
17892	11.492899	12.100718	98017.0	180001.0
12198	12.677317	12.736704	320397.0	340001.0
9774	12.494966	12.594734	266990.0	295001.0
18511	12.130043	11.938200	185358.0	153001.0
18437	12.347009	12.341438	230270.0	228991.0
8661	13.191548	13.038440	535817.0	459751.0
14024	12.915290	12.985170	406480.0	435901.0
12975	12.526269	12.514296	275480.0	272201.0
4385	12.175029	12.257041	193887.0	210458.0
18095	12.635726	12.736410	307345.0	339901.0
13870	13.136932	13.361382	507338.0	635001.0
9663	12.394757	12.429220	241532.0	250001.0
15665	11.966390	11.956976	157375.0	155901.0
6755	13.919076	13.997833	1109119.0	1200001.0
2695	12.422218	12.524166	248256.0	274901.0
15953	12.108187	12.205578	181350.0	199901.0
16692	12.477166	12.706821	262280.0	329991.0
14	11.736769	11.660492	125088.0	115901.0
15851	12.119488	12.165256	183412.0	192001.0

In [135]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 7740236898.29
RMSE: 87978.62
R^2: 0.835
```

In [136]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg_built_in_model_wit
hout_linearlasso_best, X,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[136]: <Figure size 432x288 with 0 Axes>
Out[136]: Text(0.5, 1.0, 'Ensemble Learning')
Out[136]: Text(0.5, 0, 'Training examples')
Out[136]: Text(0, 0.5, 'Score')
Out[136]: <matplotlib.collections.PolyCollection at 0x1a2713cc90>
Out[136]: <matplotlib.collections.PolyCollection at 0x1a2589f750>
Out[136]: [<matplotlib.lines.Line2D at 0x1a25c0fc50>]
Out[136]: [<matplotlib.lines.Line2D at 0x1a26e42290>]
Out[136]: <matplotlib.legend.Legend at 0x1a264bc4d0>
```



Tiny Conclusion for Ensemble Learning

In the beginning, we ensemble all default models (linear, lasso, XGBoost, LGBM, Random Forest) and have R^2 = 0.805. Then we tried ensemble all tuned models and have R^2 = 0.833. We also tried to remove linear and lass models from ensemble learning model (just have tuned XGBoost, LGBM and Random Forest)that have low R^2, and have R^2 = 0.835.

An interesting finding is that the R^2 of default ensemble learning (linear, lasso, XGBoost, LGBM, Random Forest) even smaller than R^2 of default LGBM. It told us that ensemble learning would have worse result if it includes really bad models. (the proof is that R^2 increased a little bit after we removed linear and lasso models from ensemble learning (tuned XGBoost, LGBM and Random Forest)).

3.Dimension Deduction

After trying different models with and without tuning, we get some good result on test dataset but we also found the problem of overfitting in our model. Overfitting means the model would not work in real world. To solve this problem, we applied PCA to perform dimension deduction in our input data. We first standardized the the whole dataset, because the range of each feature vary. So when a small set of variables has a much larger magnitude than others, the components in the PCA analysis are heavily weighted along those variables, while other variables are ignored.We set the threshold of 99% to select the number of features that explain 99% of the total variance, and we found the number is 28.

After feature reduction,we repeat the same process as we did before feature reduction. The models we tried are shown in the following:

1.Linear Regression

2.Default Lasso Model

3.Lasso with GridSearch

4.Default Random Forest Model

5.Random Forest Model with RandomSearch

6.Default XGBoost Model

7.XGBoost Model with GridSearch

8.Ensemble Learning with Default Model

9.Ensemble Learning with Best Models based on R^2 Result

However, based on the results, we found that we do reduce the problem of overfitting in some model but the accuracy also being reduced.One reason might be that some information that seems to be unimportant in train dataset might be very important to test dataset. So one way we can improve it is to feed more training data.

In addition,based on the article written by Lever and Altman in 2017, one limitation that PCA might generate worse performance than single model is becuase its underlying assumption that " the structure of data must be linear". While in our previous data preprocessing, we have some categorical data which might bring nonlinearity to our dataset. And usually, when we have too much feature which is 47 in our case, it is hard to said that they are linear correlated to our target variable.

Data Standarization for PCA

In [137]:
```
import copy
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

df_before_pca=copy.deepcopy(df_before_log)
Y_for_pca = df_before_log['Price']
X_for_pca = df_before_log.drop(['Price'], axis=1)
#Standarization
X_for_pca = (X_for_pca - X_for_pca.mean())/np.std(X_for_pca)
Y_for_pca = (Y_for_pca - Y_for_pca.mean())/np.std(Y_for_pca)
```

Fit PCA model and select the main principle components

In [138]:

```
pca = PCA().fit(X_for_pca)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
print(pca.explained_variance_ratio_)

pca = PCA(.99)

principalComponents = pca.fit_transform(X_for_pca)

# To get how many principal components was chosen
print(pca.n_components_)
#Therefore, we should apply n_components_=28 to conduct dimension reduction
```

Out[138]:

```
[<matplotlib.lines.Line2D at 0x1a264c9690>]
```

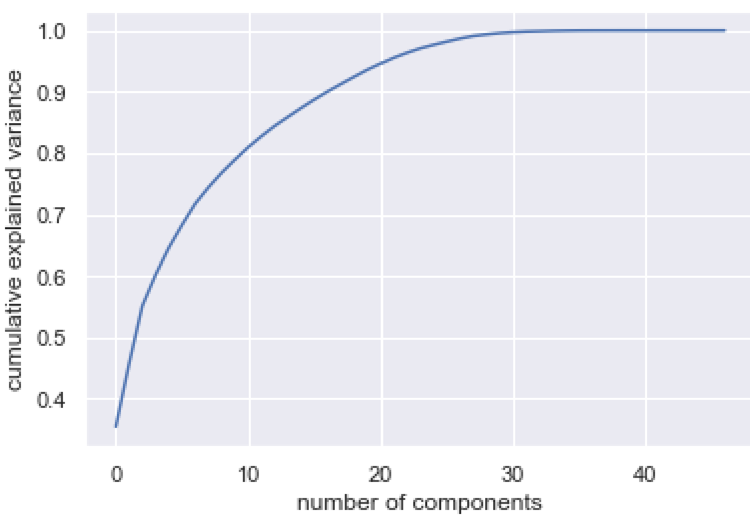
Out[138]:

```
Text(0.5, 0, 'number of components')
```

Out[138]:

```
Text(0, 0.5, 'cumulative explained variance')
```

```
[3.54385344e-01 1.02499953e-01 9.42784774e-02 5.06330534e-02
 4.36100059e-02 3.71611334e-02 3.46999416e-02 2.66388280e-02
 2.38546671e-02 2.12692489e-02 2.02537822e-02 1.79628847e-02
 1.67652350e-02 1.47740835e-02 1.44819878e-02 1.38651078e-02
 1.30664561e-02 1.21289018e-02 1.18388636e-02 1.14976452e-02
 1.02117204e-02 9.73541441e-03 8.08307204e-03 7.19218909e-03
 5.63779885e-03 5.26647732e-03 5.06950661e-03 4.13530592e-03
 2.48610620e-03 2.14802711e-03 1.49369985e-03 1.01612883e-03
 5.55984402e-04 5.39166319e-04 3.76913990e-04 2.53842447e-04
 6.28474268e-05 2.56276476e-05 2.11261173e-05 1.42834305e-05
 5.17562574e-06 2.15407373e-06 1.49050869e-06 1.92238011e-07
 1.08736304e-07 3.98189812e-08 6.98901859e-32]
28
```



In [139]:
```
#x_train, x_test, y_train, y_test = train_test_split(X_for_pca, Y_for_pca, tes
t_size=0.3, random_state=2020)
Y = num_df_log['Price_log']
# Creat PCA model
pca = PCA(n_components=28)
# Fit anf tranform data
X_for_pca= pca.fit_transform(X_for_pca)
# Spliting data into test dataset and train dataset
X_pca_train, X_pca_test, Y_pca_train, Y_pca_test = train_test_split(X_for_pca,
Y,test_size=0.3, random_state=2020)
X_for_pca.shape
```

Out[139]:
```
(19173, 28)
```

Conduct model testing using transformed data

Linear Model

In [140]:
```
# Conduct model testing using transformed data
from sklearn import linear_model
model_after_pca = linear_model.LinearRegression()
model_after_pca.fit(X_pca_train, Y_pca_train)
```

Out[140]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

In [141]:
```
pred_train = model_after_pca.predict(X_pca_train)
pred_train_and_truth_train = pd.DataFrame({'predict_train_price_log':pred_trai
n, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pre
d_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth_train.head(20)
```

Out[141]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.534306	12.238675	277702.0	206628.0
18253	12.693932	12.574185	325765.0	289001.0
4741	13.276656	13.945662	583416.0	1139001.0
8406	12.555688	12.312687	283704.0	222501.0
234	12.825286	13.060277	371493.0	469901.0
11125	12.609099	12.610173	299269.0	299591.0
2813	13.172658	13.060277	525790.0	469901.0
698	13.123423	13.199141	500530.0	539901.0
10623	13.444057	13.384729	689731.0	650001.0
16239	12.648132	12.577636	311182.0	290000.0
15949	12.455330	12.049425	256614.0	171001.0
1668	12.791415	12.911645	359121.0	405001.0
3372	13.288832	13.485618	590563.0	719001.0
10397	12.441041	12.425212	252974.0	249001.0
17489	12.074633	12.383675	175366.0	238870.0
6284	12.924450	12.895553	410220.0	398536.0
9598	12.810024	12.498373	365867.0	267901.0
12770	12.249723	11.774528	208924.0	129901.0
6068	12.885459	12.891669	394533.0	396991.0
8000	13.221733	12.779594	552237.0	354901.0

In [142]:
```
metrics_new(pred_train_and_truth_train['predict_train_price'], pred_train_and_
truth_train['truth_train_price'])
```

```
MSE: 26168545020.24
RMSE: 161766.95
R^2: 0.433
```

In [143]:
```
pred = model_after_pca.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_test, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test},
                             columns=['predict_price_log', 'truth_price_log', 'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[143]:

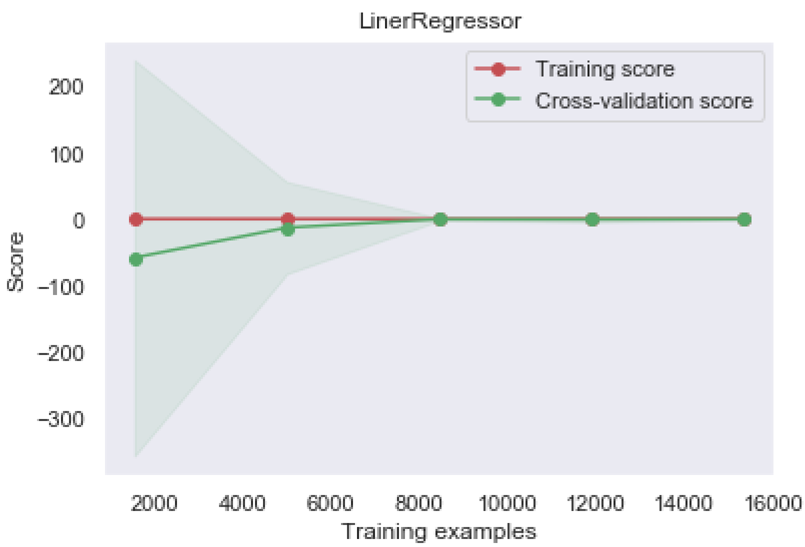
	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.766796	12.672950	350388.0	319001.0
17892	11.859022	12.100718	141354.0	180001.0
12198	12.661800	12.736704	315464.0	340001.0
9774	12.666349	12.594734	316902.0	295001.0
18511	12.270633	11.938200	213338.0	153001.0
18437	12.380942	12.341438	238218.0	228991.0
8661	12.845478	13.038440	379071.0	459751.0
14024	13.064333	12.985170	471811.0	435901.0
12975	12.497887	12.514296	267771.0	272201.0
4385	12.080675	12.257041	176429.0	210458.0
18095	12.528284	12.736410	276035.0	339901.0
13870	12.623508	13.361382	303613.0	635001.0
9663	12.613313	12.429220	300533.0	250001.0
15665	12.355788	11.956976	232301.0	155901.0
6755	13.589443	13.997833	797664.0	1200001.0
2695	12.715497	12.524166	332866.0	274901.0
15953	12.370380	12.205578	235715.0	199901.0
16692	12.385494	12.706821	239305.0	329991.0
14	11.932357	11.660492	152110.0	115901.0
15851	12.317471	12.165256	223568.0	192001.0

In [144]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23677190543.01
RMSE: 153873.94
R^2: 0.495
```

In [145]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LinerRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(model_after_pca, X_for
_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[145]: <Figure size 432x288 with 0 Axes>

Out[145]: Text(0.5, 1.0, 'LinerRegressor')

Out[145]: Text(0.5, 0, 'Training examples')

Out[145]: Text(0, 0.5, 'Score')

Out[145]: <matplotlib.collections.PolyCollection at 0x1a26075410>

Out[145]: <matplotlib.collections.PolyCollection at 0x1a2729c9d0>

Out[145]: [<matplotlib.lines.Line2D at 0x1a2729c310>]

Out[145]: [<matplotlib.lines.Line2D at 0x1a2729c350>]

Out[145]: <matplotlib.legend.Legend at 0x1a26eecf10>
```



Lasso_pca_before_tunning

```python
In [146]: from sklearn.linear_model import LassoCV

lasso_before_tune_pca = LassoCV(random_state=42)
lasso_before_tune_pca.fit(X_pca_train, Y_pca_train)
```

```
Out[146]: LassoCV(alphas=None, copy_X=True, cv=None, eps=0.001, fit_intercept=True,
        max_iter=1000, n_alphas=100, n_jobs=None, normalize=False,
        positive=False, precompute='auto', random_state=42, selection='cycli
c',
        tol=0.0001, verbose=False)
```

In [147]:
```
pred_train =lasso_before_tune_pca.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[147]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.532444	12.238675	277186.0	206628.0
18253	12.696509	12.574185	326606.0	289001.0
4741	13.268599	13.945662	578734.0	1139001.0
8406	12.558673	12.312687	284553.0	222501.0
234	12.822795	13.060277	370569.0	469901.0
11125	12.602662	12.610173	297349.0	299591.0
2813	13.160296	13.060277	519330.0	469901.0
698	13.108141	13.199141	492939.0	539901.0
10623	13.436218	13.384729	684345.0	650001.0
16239	12.653208	12.577636	312765.0	290000.0
15949	12.447811	12.049425	254692.0	171001.0
1668	12.799413	12.911645	362005.0	405001.0
3372	13.286054	13.485618	588925.0	719001.0
10397	12.446775	12.425212	254428.0	249001.0
17489	12.082607	12.383675	176770.0	238870.0
6284	12.911724	12.895553	405033.0	398536.0
9598	12.821982	12.498373	370268.0	267901.0
12770	12.249990	11.774528	208979.0	129901.0
6068	12.880844	12.891669	392717.0	396991.0
8000	13.221367	12.779594	552035.0	354901.0

In [148]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 26782229168.45
RMSE: 163652.77
R^2: 0.420
```

In [149]:
```
pred = lasso_before_tune_pca.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[149]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.773535	12.672950	352757.0	319001.0
17892	11.863863	12.100718	142040.0	180001.0
12198	12.664532	12.736704	316327.0	340001.0
9774	12.678368	12.594734	320734.0	295001.0
18511	12.265855	11.938200	212321.0	153001.0
18437	12.381751	12.341438	238411.0	228991.0
8661	12.852149	13.038440	381608.0	459751.0
14024	13.068902	12.985170	473972.0	435901.0
12975	12.504203	12.514296	269468.0	272201.0
4385	12.083833	12.257041	176987.0	210458.0
18095	12.528150	12.736410	275998.0	339901.0
13870	12.629473	13.361382	305429.0	635001.0
9663	12.625620	12.429220	304255.0	250001.0
15665	12.350137	11.956976	230992.0	155901.0
6755	13.581343	13.997833	791229.0	1200001.0
2695	12.726160	12.524166	336435.0	274901.0
15953	12.362648	12.205578	233900.0	199901.0
16692	12.390817	12.706821	240582.0	329991.0
14	11.932094	11.660492	152070.0	115901.0
15851	12.321491	12.165256	224469.0	192001.0

In [150]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23505846998.14
RMSE: 153316.17
R^2: 0.498
```

In [151]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LassoRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(lasso_before_tune_pca,
X_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[151]: <Figure size 432x288 with 0 Axes>
Out[151]: Text(0.5, 1.0, 'LassoRegressor')
Out[151]: Text(0.5, 0, 'Training examples')
Out[151]: Text(0, 0.5, 'Score')
Out[151]: <matplotlib.collections.PolyCollection at 0x1a270fe6d0>
Out[151]: <matplotlib.collections.PolyCollection at 0x1a270fe990>
Out[151]: [<matplotlib.lines.Line2D at 0x1a270fe5d0>]
Out[151]: [<matplotlib.lines.Line2D at 0x1a270fe710>]
Out[151]: <matplotlib.legend.Legend at 0x1a270fee90>
```

Lasso_GridSearch

In [152]:
```
from sklearn.linear_model import LassoCV
from sklearn.linear_model import Lasso
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

lasso = Lasso()
alphas = np.logspace(-4, -0.5, 30)


tuned_parameters = [{'alpha': alphas}]
n_folds = 5

grid_pca_lasso = GridSearchCV(lasso, tuned_parameters, cv=n_folds, refit=True,
scoring='r2')
grid_pca_lasso.fit(X_pca_train, Y_pca_train)
print(grid_pca_lasso.best_params_)
```

Out[152]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                             max_iter=1000, normalize=False, positive=False,
                             precompute=False, random_state=None,
                             selection='cyclic', tol=0.0001, warm_start=Fals
e),
             iid='deprecated', n_jobs=None,
             param_grid=[{'alpha': array([1.00000000e-04, 1.32035178e-04, 1.7
4332882e-04, 2.30180731e-04,
       3.03919538e-04...
       2.80721620e-03, 3.70651291e-03, 4.89390092e-03, 6.46167079e-03,
       8.53167852e-03, 1.12648169e-02, 1.48735211e-02, 1.96382800e-02,
       2.59294380e-02, 3.42359796e-02, 4.52035366e-02, 5.96845700e-02,
       7.88046282e-02, 1.04049831e-01, 1.37382380e-01, 1.81393069e-01,
       2.39502662e-01, 3.16227766e-01])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)

{'alpha': 0.0021261123338996556}
```

In [153]:
```
best_model_pca_lasso = Lasso().set_params(**grid_pca_lasso.best_params_)
best_model_pca_lasso.fit(X_pca_train, Y_pca_train)
pred_train = best_model_pca_lasso.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[153]:
```
Lasso(alpha=0.0021261123338996556, copy_X=True, fit_intercept=True,
      max_iter=1000, normalize=False, positive=False, precompute=False,
      random_state=None, selection='cyclic', tol=0.0001, warm_start=False)
```

Out[153]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.532515	12.238675	277206.0	206628.0
18253	12.696936	12.574185	326745.0	289001.0
4741	13.265553	13.945662	576975.0	1139001.0
8406	12.561608	12.312687	285389.0	222501.0
234	12.819794	13.060277	369459.0	469901.0
11125	12.595092	12.610173	295106.0	299591.0
2813	13.147382	13.060277	512667.0	469901.0
698	13.093319	13.199141	485687.0	539901.0
10623	13.428664	13.384729	679196.0	650001.0
16239	12.659056	12.577636	314600.0	290000.0
15949	12.443080	12.049425	253490.0	171001.0
1668	12.806666	12.911645	364640.0	405001.0
3372	13.282408	13.485618	586781.0	719001.0
10397	12.451974	12.425212	255755.0	249001.0
17489	12.094031	12.383675	178801.0	238870.0
6284	12.900615	12.895553	400559.0	398536.0
9598	12.831955	12.498373	373979.0	267901.0
12770	12.252781	11.774528	209563.0	129901.0
6068	12.876936	12.891669	391185.0	396991.0
8000	13.219739	12.779594	551137.0	354901.0

In [154]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 27725049001.07
RMSE: 166508.41
R^2: 0.400
```

In [155]:
```
pred = best_model_pca_lasso.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[155]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.780082	12.672950	355074.0	319001.0
17892	11.867837	12.100718	142605.0	180001.0
12198	12.666620	12.736704	316988.0	340001.0
9774	12.686893	12.594734	323480.0	295001.0
18511	12.259814	11.938200	211042.0	153001.0
18437	12.381783	12.341438	238419.0	228991.0
8661	12.856807	13.038440	383390.0	459751.0
14024	13.071236	12.985170	475079.0	435901.0
12975	12.510675	12.514296	271217.0	272201.0
4385	12.088666	12.257041	177845.0	210458.0
18095	12.526868	12.736410	275645.0	339901.0
13870	12.633718	13.361382	306728.0	635001.0
9663	12.637730	12.429220	307961.0	250001.0
15665	12.346666	11.956976	230191.0	155901.0
6755	13.573730	13.997833	785229.0	1200001.0
2695	12.735066	12.524166	339444.0	274901.0
15953	12.357771	12.205578	232762.0	199901.0
16692	12.394497	12.706821	241469.0	329991.0
14	11.930911	11.660492	151890.0	115901.0
15851	12.323787	12.165256	224984.0	192001.0

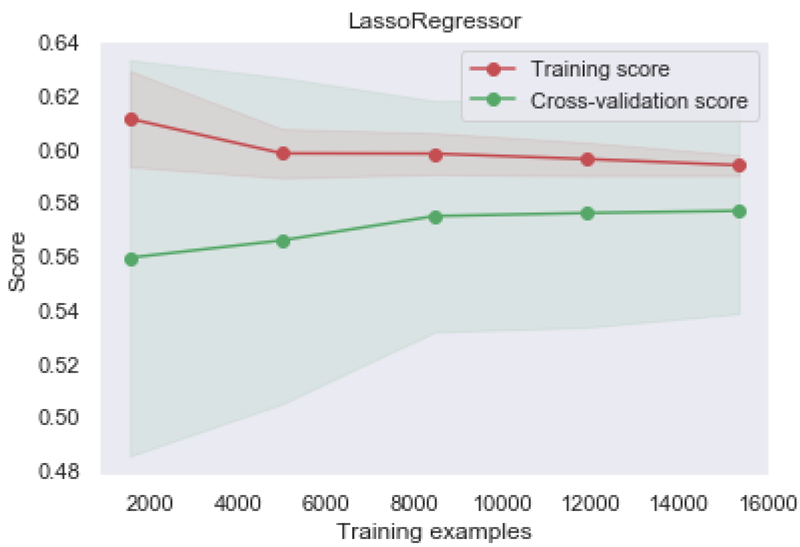
In [156]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 23340697194.79
RMSE: 152776.63
R^2: 0.502
```

In [157]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LassoRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model_pca_lasso,
X_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[157]: <Figure size 432x288 with 0 Axes>
Out[157]: Text(0.5, 1.0, 'LassoRegressor')
Out[157]: Text(0.5, 0, 'Training examples')
Out[157]: Text(0, 0.5, 'Score')
Out[157]: <matplotlib.collections.PolyCollection at 0x1a262376d0>
Out[157]: <matplotlib.collections.PolyCollection at 0x1a26dfdd90>
Out[157]: [<matplotlib.lines.Line2D at 0x1a26dfdd10>]
Out[157]: [<matplotlib.lines.Line2D at 0x1a261a2710>]
Out[157]: <matplotlib.legend.Legend at 0x1a2625bf50>
```



RandomForest_pca_before_tunning

```
In [158]: from sklearn.ensemble import RandomForestRegressor

rf_pca_before_model= RandomForestRegressor(random_state=42)
rf_pca_before_model.fit(X_pca_train, Y_pca_train)
```

```
Out[158]: RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=Non
e,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [159]:
```
pred_train = rf_pca_before_model.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[159]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.324874	12.238675	225229.0	206628.0
18253	12.650269	12.574185	311847.0	289001.0
4741	13.749302	13.945662	935936.0	1139001.0
8406	12.375359	12.312687	236892.0	222501.0
234	13.079601	13.060277	479070.0	469901.0
11125	12.605467	12.610173	298184.0	299591.0
2813	13.005564	13.060277	444882.0	469901.0
698	13.185840	13.199141	532767.0	539901.0
10623	13.413967	13.384729	669286.0	650001.0
16239	12.614677	12.577636	300943.0	290000.0
15949	12.206370	12.049425	200059.0	171001.0
1668	12.894927	12.911645	398287.0	405001.0
3372	13.399981	13.485618	659991.0	719001.0
10397	12.441867	12.425212	253183.0	249001.0
17489	12.307319	12.383675	221310.0	238870.0
6284	12.901607	12.895553	400956.0	398536.0
9598	12.576750	12.498373	289743.0	267901.0
12770	11.952505	11.774528	155205.0	129901.0
6068	12.909630	12.891669	404186.0	396991.0
8000	12.836571	12.779594	375709.0	354901.0

In [160]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 3107429696.93
RMSE: 55744.32
R^2: 0.933
```

In [161]:
```
pred = rf_pca_before_model.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[161]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.644290	12.672950	309988.0	319001.0
17892	11.105340	12.100718	66525.0	180001.0
12198	12.685588	12.736704	323058.0	340001.0
9774	12.668963	12.594734	317732.0	295001.0
18511	12.036049	11.938200	168729.0	153001.0
18437	12.343909	12.341438	229558.0	228991.0
8661	13.062677	13.038440	471030.0	459751.0
14024	12.911544	12.985170	404960.0	435901.0
12975	12.456896	12.514296	257017.0	272201.0
4385	12.307922	12.257041	221443.0	210458.0
18095	12.762453	12.736410	348870.0	339901.0
13870	12.735084	13.361382	339451.0	635001.0
9663	12.554559	12.429220	283384.0	250001.0
15665	12.071314	11.956976	174785.0	155901.0
6755	13.372133	13.997833	641865.0	1200001.0
2695	12.647898	12.524166	311109.0	274901.0
15953	12.317477	12.205578	223569.0	199901.0
16692	12.319033	12.706821	223918.0	329991.0
14	11.849624	11.660492	140032.0	115901.0
15851	12.333341	12.165256	227144.0	192001.0

In [162]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 15987427626.83
RMSE: 126441.40
R^2: 0.659
```

In [163]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Random_Forest_Regressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(rf_pca_before_model,X_
for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[163]: <Figure size 432x288 with 0 Axes>

Out[163]: Text(0.5, 1.0, 'Random_Forest_Regressor')

Out[163]: Text(0.5, 0, 'Training examples')

Out[163]: Text(0, 0.5, 'Score')

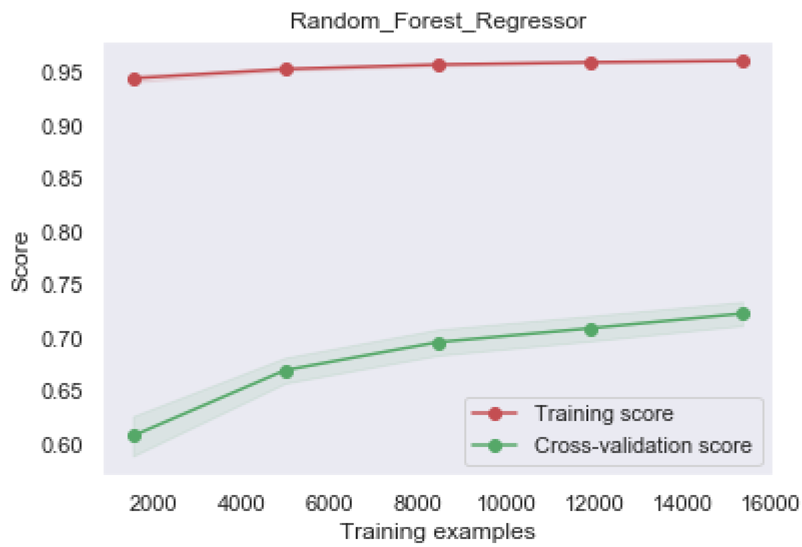
Out[163]: <matplotlib.collections.PolyCollection at 0x1a273576d0>

Out[163]: <matplotlib.collections.PolyCollection at 0x1a27357850>

Out[163]: [<matplotlib.lines.Line2D at 0x1a27328550>]

Out[163]: [<matplotlib.lines.Line2D at 0x1a26e03890>]

Out[163]: <matplotlib.legend.Legend at 0x1a2704d890>
```



Random_Foreast_GridSearch

In [164]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
from sklearn.model_selection import RandomizedSearchCV

model = RandomForestRegressor(random_state=42)
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 200, num = 10
)]
# Number of features to consider at every split
#max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 50, num = 5)]
#max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 4, 8,10,20,50]
# Method of selecting samples for training each tree
bootstrap = [True]

# Create the random grid
param_grid= {'n_estimators': n_estimators,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

rf_pca_random = RandomizedSearchCV(model,param_grid, n_iter = 1000, cv =5,rand
om_state=42, n_jobs = -1, scoring='r2')
# Fit the random search model
rf_pca_random.fit(X_pca_train, Y_pca_train)

# examine the best model
print(rf_pca_random.best_params_)
print(rf_pca_random.best_estimator_)
```

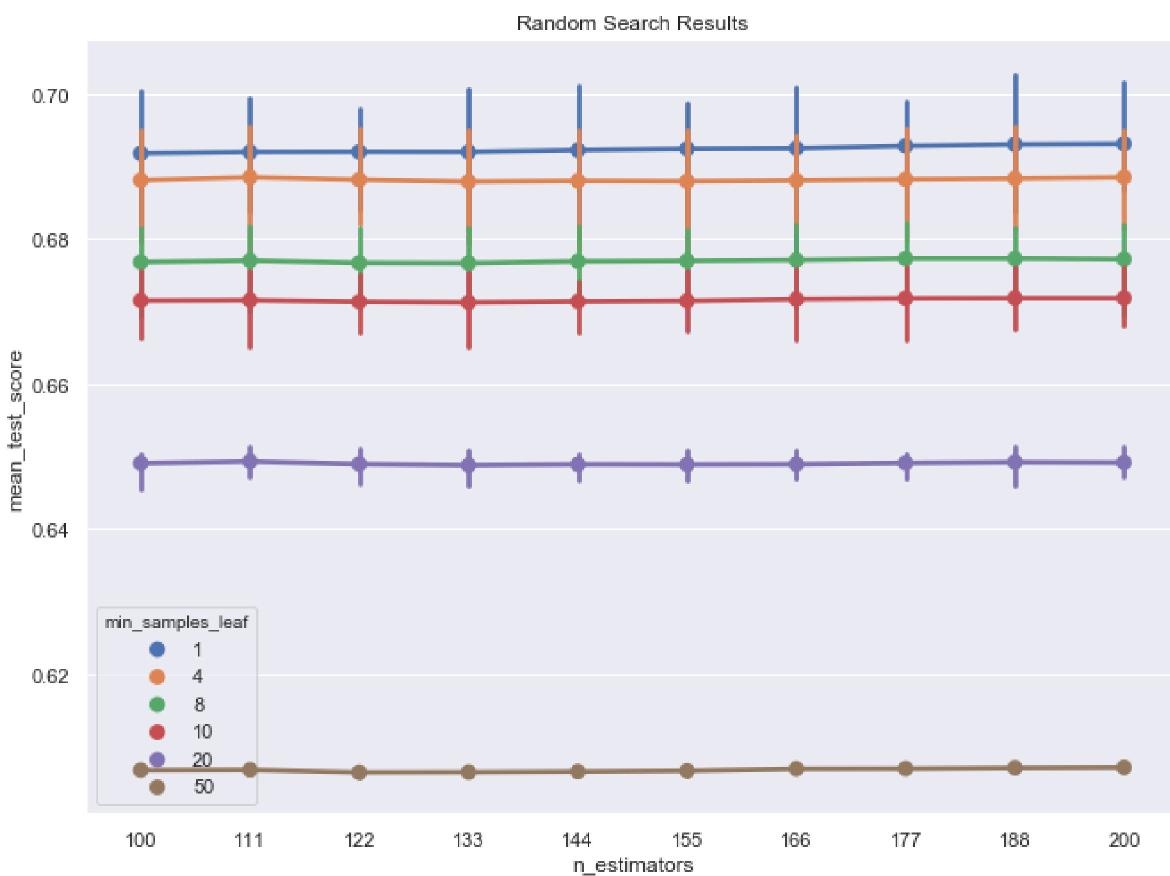
Out[164]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_leaf=
0.0,
                                                   n_estimators=100,
                                                   n_jobs=None, oob_score=Fal
se,
                                                   random_state=42, verbose=
0,
                                                   warm_start=False),
                   iid='deprecated', n_iter=1000, n_jobs=-1,
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [10, 20, 30, 40, 50],
                                        'min_samples_leaf': [1, 4, 8, 10, 20,
                                                             50],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 111, 122, 133,
                                                         144, 155, 166, 177,
                                                         188, 200]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring='r2', verbose=0)
```

```
{'n_estimators': 200, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_dep
th': 40, 'bootstrap': True}
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=40, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=200, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [165]:
```
import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Random Search Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(rf_pca_random.cv_results_, 'n_estimators', 'min_samples_
leaf')
```



In [166]:
```
best_rf_pca_model = RandomForestRegressor(random_state=42).set_params(**rf_pca
_random.best_params_)
best_rf_pca_model.fit(X_pca_train, Y_pca_train)
```

Out[166]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=40, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=200, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

In [167]:
```
pred_train = best_rf_pca_model.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                              columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[167]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.309461	12.238675	221784.0	206628.0
18253	12.648319	12.574185	311240.0	289001.0
4741	13.763490	13.945662	949309.0	1139001.0
8406	12.364788	12.312687	234401.0	222501.0
234	13.075849	13.060277	477275.0	469901.0
11125	12.602992	12.610173	297447.0	299591.0
2813	12.996689	13.060277	440951.0	469901.0
698	13.189173	13.199141	534546.0	539901.0
10623	13.406674	13.384729	664423.0	650001.0
16239	12.613144	12.577636	300482.0	290000.0
15949	12.190131	12.049425	196837.0	171001.0
1668	12.905529	12.911645	402531.0	405001.0
3372	13.392648	13.485618	655169.0	719001.0
10397	12.435242	12.425212	251511.0	249001.0
17489	12.354548	12.383675	232013.0	238870.0
6284	12.901803	12.895553	401035.0	398536.0
9598	12.559147	12.498373	284687.0	267901.0
12770	11.927795	11.774528	151417.0	129901.0
6068	12.909055	12.891669	403954.0	396991.0
8000	12.836448	12.779594	375663.0	354901.0

In [168]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 3077453509.96
RMSE: 55474.80
R^2: 0.933
```

In [169]:
```
pred = best_rf_pca_model.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[169]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.653336	12.672950	312805.0	319001.0
17892	11.116646	12.100718	67282.0	180001.0
12198	12.707628	12.736704	330257.0	340001.0
9774	12.671559	12.594734	318558.0	295001.0
18511	12.048744	11.938200	170885.0	153001.0
18437	12.354117	12.341438	231913.0	228991.0
8661	13.067891	13.038440	473492.0	459751.0
14024	12.915607	12.985170	406609.0	435901.0
12975	12.466955	12.514296	259615.0	272201.0
4385	12.270113	12.257041	213227.0	210458.0
18095	12.768467	12.736410	350974.0	339901.0
13870	12.744648	13.361382	342713.0	635001.0
9663	12.556351	12.429220	283892.0	250001.0
15665	12.053489	11.956976	171697.0	155901.0
6755	13.384614	13.997833	649926.0	1200001.0
2695	12.639107	12.524166	308386.0	274901.0
15953	12.307582	12.205578	221368.0	199901.0
16692	12.296641	12.706821	218959.0	329991.0
14	11.904111	11.660492	147873.0	115901.0
15851	12.321210	12.165256	224405.0	192001.0

In [170]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 15967809345.04
RMSE: 126363.80
R^2: 0.659
```

In [171]:

```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('RandomForest')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_rf_pca_model, X_f
or_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[171]: <Figure size 432x288 with 0 Axes>

Out[171]: Text(0.5, 1.0, 'RandomForest')

Out[171]: Text(0.5, 0, 'Training examples')

Out[171]: Text(0, 0.5, 'Score')

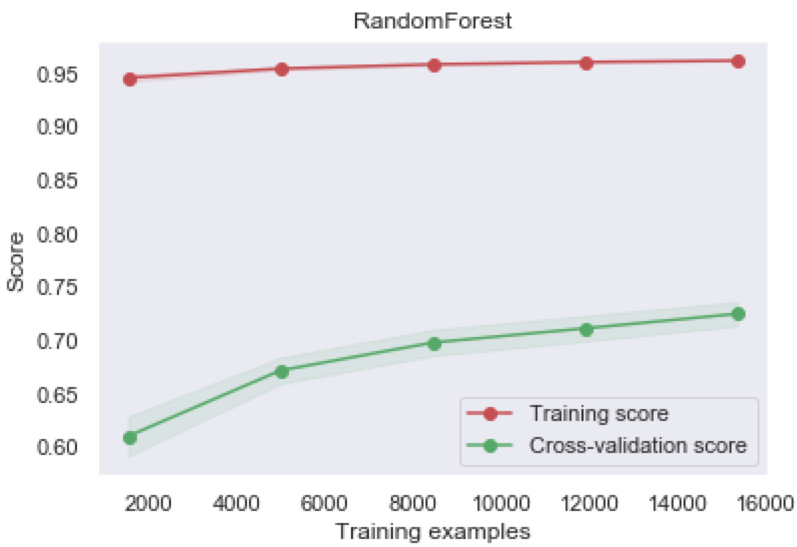
Out[171]: <matplotlib.collections.PolyCollection at 0x1a265d49d0>

Out[171]: <matplotlib.collections.PolyCollection at 0x1a25fc6fd0>

Out[171]: [<matplotlib.lines.Line2D at 0x1a22e3ba90>]

Out[171]: [<matplotlib.lines.Line2D at 0x1a26189e10>]

Out[171]: <matplotlib.legend.Legend at 0x1a26fb80d0>



XGBoost_PCA_before_tunning

In [172]:
```
model_pca_XGB = XGBRegressor(objective ='reg:squarederror', random_state=42)
model_pca_XGB.fit(X_pca_train, Y_pca_train)
```

Out[172]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

In [173]:
```
pred_train = model_pca_XGB.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                            columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[173]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.480698	12.238675	263207.0	206628.0
18253	12.808240	12.574185	365214.0	289001.0
4741	13.400783	13.945662	660520.0	1139001.0
8406	12.463491	12.312687	258717.0	222501.0
234	12.974253	13.060277	431168.0	469901.0
11125	12.515450	12.610173	272515.0	299591.0
2813	12.915627	13.060277	406617.0	469901.0
698	13.120508	13.199141	499073.0	539901.0
10623	13.391962	13.384729	654719.0	650001.0
16239	12.605047	12.577636	298059.0	290000.0
15949	12.393540	12.049425	241238.0	171001.0
1668	12.881688	12.911645	393048.0	405001.0
3372	13.279531	13.485618	585096.0	719001.0
10397	12.465779	12.425212	259310.0	249001.0
17489	12.281021	12.383675	215566.0	238870.0
6284	13.017072	12.895553	450031.0	398536.0
9598	12.760952	12.498373	348346.0	267901.0
12770	12.203931	11.774528	199572.0	129901.0
6068	12.968221	12.891669	428575.0	396991.0
8000	13.082991	12.779594	480696.0	354901.0

In [174]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 16295116517.36
RMSE: 127652.33
R^2: 0.647
```

In [175]:
```
pred = model_pca_XGB.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[175]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.659907	12.672950	314867.0	319001.0
17892	11.454642	12.100718	94338.0	180001.0
12198	12.753218	12.736704	345662.0	340001.0
9774	12.710289	12.594734	331137.0	295001.0
18511	12.146794	11.938200	188489.0	153001.0
18437	12.469183	12.341438	260194.0	228991.0
8661	12.942021	13.038440	417492.0	459751.0
14024	12.853834	12.985170	382251.0	435901.0
12975	12.482648	12.514296	263721.0	272201.0
4385	12.127110	12.257041	184815.0	210458.0
18095	12.688649	12.736410	324049.0	339901.0
13870	12.718350	13.361382	333818.0	635001.0
9663	12.553021	12.429220	282949.0	250001.0
15665	12.437690	11.956976	252127.0	155901.0
6755	13.485560	13.997833	718959.0	1200001.0
2695	12.671740	12.524166	318615.0	274901.0
15953	12.359011	12.205578	233050.0	199901.0
16692	12.340637	12.706821	228808.0	329991.0
14	11.890510	11.660492	145876.0	115901.0
15851	12.407652	12.165256	244667.0	192001.0

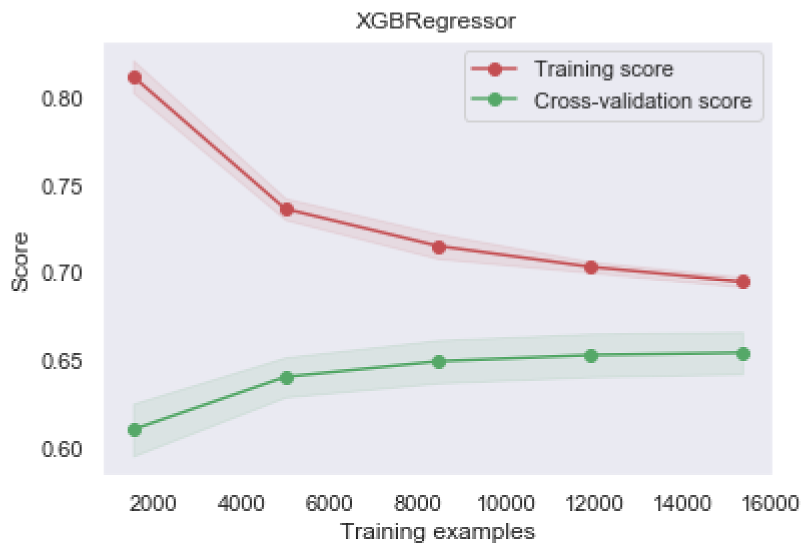
In [176]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 18767434954.58
RMSE: 136994.29
R^2: 0.599
```

In [177]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
estimator=XGBRegressor(objective ='reg:squarederror')
plt.figure()
plt.title('XGBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(estimator, X_for_pca,Y
, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[177]: <Figure size 432x288 with 0 Axes>
Out[177]: Text(0.5, 1.0, 'XGBRegressor')
Out[177]: Text(0.5, 0, 'Training examples')
Out[177]: Text(0, 0.5, 'Score')
Out[177]: <matplotlib.collections.PolyCollection at 0x1a268ca810>
Out[177]: <matplotlib.collections.PolyCollection at 0x1a268ca090>
Out[177]: [<matplotlib.lines.Line2D at 0x11e66dcd0>]
Out[177]: [<matplotlib.lines.Line2D at 0x1a268cac10>]
Out[177]: <matplotlib.legend.Legend at 0x1a268ca4d0>
```



XGBoost_Tunning

In [178]:
```
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
%matplotlib inline
from sklearn.model_selection import train_test_split
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

model = XGBRegressor(objective ='reg:squarederror',random_state=42)

# Create the random grid
param_grid= {"learning_rate"    : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30 ] ,
 "max_depth"        : [3, 4, 5, 6, 8, 10, 12, 15] }
print(param_grid)

grid_pca_XGB = GridSearchCV(model, param_grid, cv=5, scoring='r2')
grid_pca_XGB.fit(X_pca_train, Y_pca_train)
print(grid_pca_XGB.best_params_)
print(grid_pca_XGB.best_estimator_)
```

```
{'learning_rate': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3], 'max_depth': [3, 4, 5,
6, 8, 10, 12, 15]}
```

Out[178]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                    colsample_bylevel=1, colsample_bynode=1,
                                    colsample_bytree=1, gamma=0,
                                    importance_type='gain', learning_rate=0.
1,
                                    max_delta_step=0, max_depth=3,
                                    min_child_weight=1, missing=None,
                                    n_estimators=100, n_jobs=1, nthread=None,
                                    objective='reg:squarederror',
                                    random_state=42, reg_alpha=0, reg_lambda=
1,
                                    scale_pos_weight=1, seed=None, silent=Non
e,
                                    subsample=1, verbosity=1),
             iid='deprecated', n_jobs=None,
             param_grid={'learning_rate': [0.05, 0.1, 0.15, 0.2, 0.25, 0.3],
                         'max_depth': [3, 4, 5, 6, 8, 10, 12, 15]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)
```

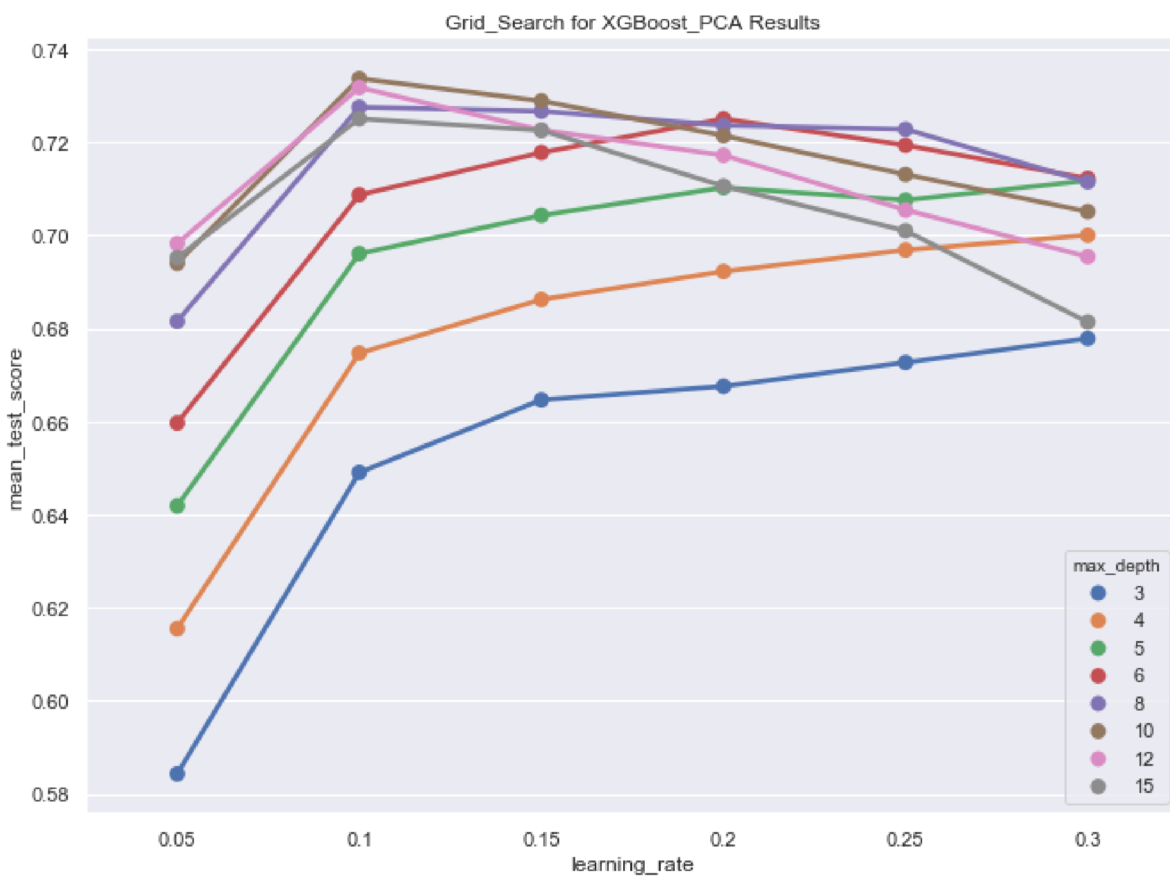
```
{'learning_rate': 0.1, 'max_depth': 10}
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=None, n_estimators=10
0,
             n_jobs=1, nthread=None, objective='reg:squarederror',
             random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
             seed=None, silent=None, subsample=1, verbosity=1)
```

In [179]:
```
# plot the results

import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("Grid_Search for XGBoost_PCA Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(grid_pca_XGB.cv_results_, 'learning_rate', 'max_depth')
```



In [180]:
```
best_model__pca_XGBoost = XGBRegressor(random_state=42).set_params(**grid_pca_
XGB.best_params_)
best_model__pca_XGBoost.fit(X_pca_train, Y_pca_train)
```

```
[23:49:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[180]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=None, n_estimators=10
0,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [181]:

```
pred_train = best_model__pca_XGBoost.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[181]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.286829	12.238675	216821.0	206628.0
18253	12.619142	12.574185	302290.0	289001.0
4741	13.839398	13.945662	1024175.0	1139001.0
8406	12.394897	12.312687	241566.0	222501.0
234	13.037136	13.060277	459152.0	469901.0
11125	12.608179	12.610173	298994.0	299591.0
2813	12.996835	13.060277	441015.0	469901.0
698	13.234846	13.199141	559526.0	539901.0
10623	13.393592	13.384729	655787.0	650001.0
16239	12.602781	12.577636	297384.0	290000.0
15949	12.205249	12.049425	199835.0	171001.0
1668	12.913526	12.911645	405763.0	405001.0
3372	13.431582	13.485618	681180.0	719001.0
10397	12.415743	12.425212	246654.0	249001.0
17489	12.384296	12.383675	239018.0	238870.0
6284	12.911499	12.895553	404942.0	398536.0
9598	12.486477	12.498373	264733.0	267901.0
12770	11.820960	11.774528	136075.0	129901.0
6068	12.927592	12.891669	411511.0	396991.0
8000	12.842742	12.779594	378035.0	354901.0

In [182]:

```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 1705696904.55
RMSE: 41300.08
R^2: 0.963
```

In [183]:
```
pred = best_model__pca_XGBoost.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[183]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.567652	12.672950	287119.0	319001.0
17892	11.434557	12.100718	92462.0	180001.0
12198	12.618391	12.736704	302063.0	340001.0
9774	12.689084	12.594734	324190.0	295001.0
18511	12.130878	11.938200	185513.0	153001.0
18437	12.381063	12.341438	238247.0	228991.0
8661	13.037307	13.038440	459230.0	459751.0
14024	12.931354	12.985170	413062.0	435901.0
12975	12.480871	12.514296	263253.0	272201.0
4385	12.130005	12.257041	185351.0	210458.0
18095	12.861080	12.736410	385031.0	339901.0
13870	12.670679	13.361382	318277.0	635001.0
9663	12.556166	12.429220	283840.0	250001.0
15665	12.010821	11.956976	164526.0	155901.0
6755	13.598380	13.997833	804825.0	1200001.0
2695	12.648769	12.524166	311380.0	274901.0
15953	12.296788	12.205578	218991.0	199901.0
16692	12.367016	12.706821	234924.0	329991.0
14	11.693563	11.660492	119798.0	115901.0
15851	12.290377	12.165256	217592.0	192001.0

In [184]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 13994241344.22
RMSE: 118297.26
R^2: 0.701
```

In [185]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('XGBRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model__pca_XGBoos
t, X_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[185]: <Figure size 432x288 with 0 Axes>

Out[185]: Text(0.5, 1.0, 'XGBRegressor')

Out[185]: Text(0.5, 0, 'Training examples')

Out[185]: Text(0, 0.5, 'Score')

```
[23:49:35] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[23:49:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[23:49:41] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[23:49:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[23:49:59] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:13] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:18] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:26] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:52] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:50:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:04] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:33] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:41] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:51:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:18] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:43] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:52:55] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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```
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[23:53:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:53:20] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:53:33] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:53:43] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:56:33] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[23:59:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:00:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:00:53] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:01:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:01:53] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:02:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:02:08] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:02:12] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:02:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:02:30] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[00:02:44] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:02:45] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:02:49] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:02:57] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:08] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:21] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:27] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

```
[00:03:45] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:03:59] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:05] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:12] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:23] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:36] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:04:49] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:15] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:26] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:37] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:52] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:05:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:04] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:14] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:41] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:06:52] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:06] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:07] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:11] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
```

```
precated in favor of reg:squarederror.
[00:07:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:29] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:43] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:44] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:49] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:07:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[00:08:07] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[185]: `<matplotlib.collections.PolyCollection at 0x1a26cd97d0>`

Out[185]: `<matplotlib.collections.PolyCollection at 0x1a25c0b5d0>`

Out[185]: `[<matplotlib.lines.Line2D at 0x1a26ccdbd0>]`

Out[185]: `[<matplotlib.lines.Line2D at 0x1a25c0b310>]`

Out[185]: `<matplotlib.legend.Legend at 0x1a26cdab50>`

LGBM_PCA_Before_Tunning

In [186]:
```
from lightgbm.sklearn import LGBMRegressor

lgbm_pca_before_tune= LGBMRegressor(random_state=42)
lgbm_pca_before_tune.fit(X_pca_train, Y_pca_train)
```

Out[186]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_split_gain=0.
0,
              n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
              random_state=42, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

In [187]:
```
pred_train = lgbm_pca_before_tune.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                              columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[187]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.371154	12.238675	235898.0	206628.0
18253	12.806156	12.574185	364454.0	289001.0
4741	13.602440	13.945662	808099.0	1139001.0
8406	12.449398	12.312687	255097.0	222501.0
234	13.044085	13.060277	462353.0	469901.0
11125	12.645348	12.610173	310316.0	299591.0
2813	12.979550	13.060277	433458.0	469901.0
698	13.223910	13.199141	553441.0	539901.0
10623	13.392619	13.384729	655149.0	650001.0
16239	12.655055	12.577636	313343.0	290000.0
15949	12.276014	12.049425	214489.0	171001.0
1668	12.859327	12.911645	384357.0	405001.0
3372	13.379424	13.485618	646562.0	719001.0
10397	12.465877	12.425212	259335.0	249001.0
17489	12.219188	12.383675	202640.0	238870.0
6284	12.892307	12.895553	397244.0	398536.0
9598	12.643856	12.498373	309854.0	267901.0
12770	12.009321	11.774528	164279.0	129901.0
6068	12.990600	12.891669	438274.0	396991.0
8000	13.042173	12.779594	461470.0	354901.0

In [188]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 9409083099.47
RMSE: 97000.43
R^2: 0.796
```

In [189]:
```
pred = lgbm_pca_before_tune.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[189]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.535992	12.672950	278171.0	319001.0
17892	11.118954	12.100718	67437.0	180001.0
12198	12.710436	12.736704	331186.0	340001.0
9774	12.582306	12.594734	291357.0	295001.0
18511	12.169762	11.938200	192868.0	153001.0
18437	12.423131	12.341438	248483.0	228991.0
8661	13.005322	13.038440	444774.0	459751.0
14024	12.916607	12.985170	407016.0	435901.0
12975	12.412199	12.514296	245782.0	272201.0
4385	12.106510	12.257041	181047.0	210458.0
18095	12.646162	12.736410	310569.0	339901.0
13870	12.736376	13.361382	339890.0	635001.0
9663	12.457016	12.429220	257047.0	250001.0
15665	12.158204	11.956976	190652.0	155901.0
6755	13.445653	13.997833	690833.0	1200001.0
2695	12.687598	12.524166	323708.0	274901.0
15953	12.222447	12.205578	203302.0	199901.0
16692	12.219061	12.706821	202615.0	329991.0
14	11.714268	11.660492	122304.0	115901.0
15851	12.318382	12.165256	223772.0	192001.0

In [190]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 15078122621.43
RMSE: 122793.01
R^2: 0.678
```

In [191]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
import warnings
warnings.simplefilter(action='ignore')

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LassoRegressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(lgbm_pca_before_tune,X
_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[191]: <Figure size 432x288 with 0 Axes>

Out[191]: Text(0.5, 1.0, 'LassoRegressor')

Out[191]: Text(0.5, 0, 'Training examples')

Out[191]: Text(0, 0.5, 'Score')

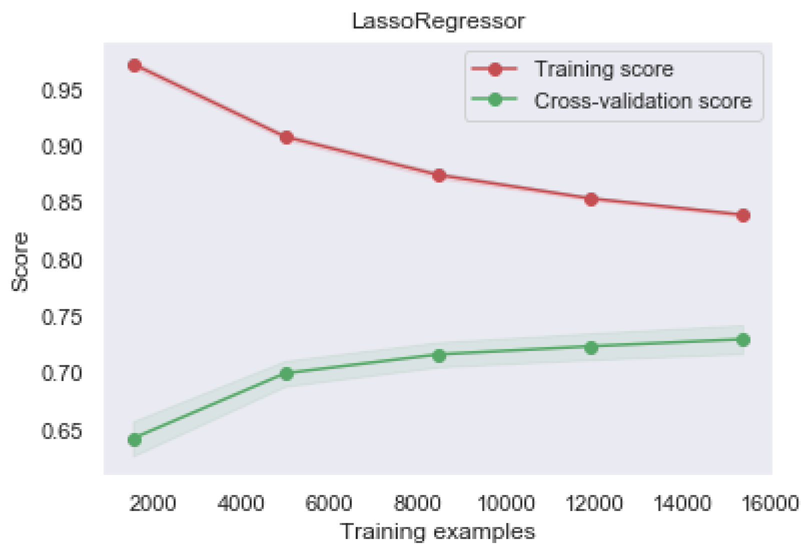
Out[191]: <matplotlib.collections.PolyCollection at 0x1a25a9dfd0>

Out[191]: <matplotlib.collections.PolyCollection at 0x1a25b469d0>

Out[191]: [<matplotlib.lines.Line2D at 0x1a25b31f90>]

Out[191]: [<matplotlib.lines.Line2D at 0x1a25b31e90>]

Out[191]: <matplotlib.legend.Legend at 0x1a25b46b50>



LGBM_GridSearch

In [192]:
```
from lightgbm.sklearn import LGBMRegressor
```

In [193]:
```
from sklearn.model_selection import GridSearchCV
%matplotlib inline
from sklearn.model_selection import train_test_split
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

model = LGBMRegressor(random_state=42)
model.fit(X_pca_train, Y_pca_train)

# Create the random grid
param_grid= {"num_leaves"    : [2,4,8,10,15,20,30] ,
    "min_data_in_leaf"        : [10,20,50,100,150,200,300]  }
print(param_grid)

grid_pca_LGBM = GridSearchCV(model, param_grid, cv=5, scoring='r2')
grid_pca_LGBM.fit(X_pca_train, Y_pca_train)
print(grid_pca_LGBM.best_params_)
print(grid_pca_LGBM.best_estimator_)
```

Out[193]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_split_gain=0.
0,
              n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
              random_state=42, reg_alpha=0.0, reg_lambda=0.0, silent=True,
              subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

```
{'num_leaves': [2, 4, 8, 10, 15, 20, 30], 'min_data_in_leaf': [10, 20, 50, 10
0, 150, 200, 300]}
```

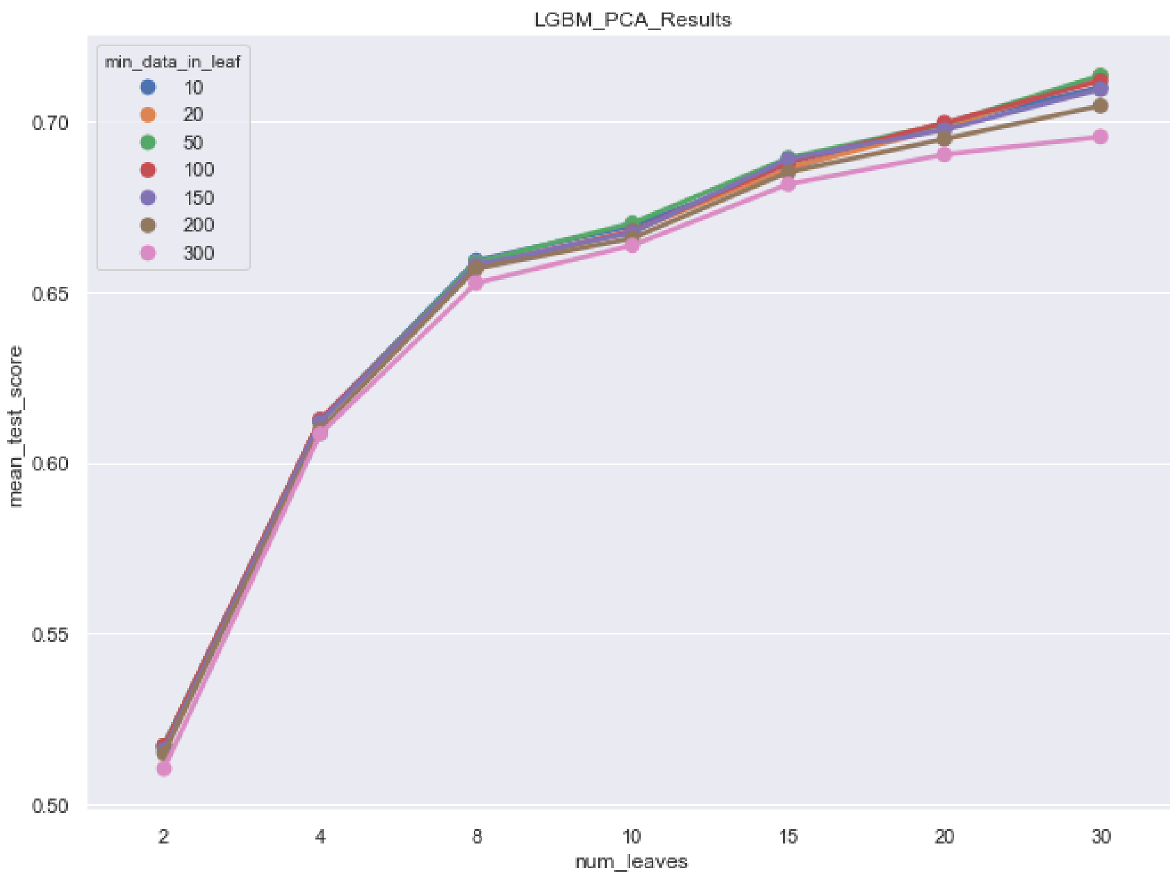
Out[193]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=LGBMRegressor(boosting_type='gbdt', class_weight=None,
                                     colsample_bytree=1.0,
                                     importance_type='split', learning_rate=
0.1,
                                     max_depth=-1, min_child_samples=20,
                                     min_child_weight=0.001, min_split_gain=
0.0,
                                     n_estimators=100, n_jobs=-1, num_leaves=
31,
                                     objective=None, random_state=42,
                                     reg_alpha=0.0, reg_lambda=0.0, silent=Tr
ue,
                                     subsample=1.0, subsample_for_bin=200000,
                                     subsample_freq=0),
             iid='deprecated', n_jobs=None,
             param_grid={'min_data_in_leaf': [10, 20, 50, 100, 150, 200, 30
0],
                         'num_leaves': [2, 4, 8, 10, 15, 20, 30]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='r2', verbose=0)
```

```
{'min_data_in_leaf': 50, 'num_leaves': 30}
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=
50,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=30,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
```

In [194]:
```
import seaborn as sns
import pandas as pd

def plot_cv_results(cv_results, param_x, param_z, metric='mean_test_score'):
    """
    cv_results - cv_results_ attribute of a GridSearchCV instance (or similar)
    param_x - name of grid search parameter to plot on x axis
    param_z - name of grid search parameter to plot by line color
    """
    cv_results = pd.DataFrame(cv_results)
    col_x = 'param_' + param_x
    col_z = 'param_' + param_z
    fig, ax = plt.subplots(1, 1, figsize=(11, 8))
    sns.pointplot(x=col_x, y=metric, hue=col_z, data=cv_results, ci=99, n_boot
=64, ax=ax)
    ax.set_title("LGBM_PCA_Results")
    ax.set_xlabel(param_x)
    ax.set_ylabel(metric)
    ax.legend(title=param_z)
    return fig

fig = plot_cv_results(grid_pca_LGBM.cv_results_, 'num_leaves', 'min_data_in_le
af')
```



In [195]:
```
best_model_pca_Lgbm = LGBMRegressor(random_state=42).set_params(**grid_pca_LGB
M.best_params_)
best_model_pca_Lgbm.fit(X_pca_train, Y_pca_train)
```

Out[195]:
```
LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=
50,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=30,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
```

In [196]:
```
pred_train = best_model_pca_Lgbm.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                                    columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[196]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.390095	12.238675	240409.0	206628.0
18253	12.742177	12.574185	341867.0	289001.0
4741	13.606130	13.945662	811087.0	1139001.0
8406	12.504002	12.312687	269413.0	222501.0
234	13.051815	13.060277	465942.0	469901.0
11125	12.661756	12.610173	315450.0	299591.0
2813	12.920031	13.060277	408412.0	469901.0
698	13.208261	13.199141	544847.0	539901.0
10623	13.368305	13.384729	639412.0	650001.0
16239	12.609576	12.577636	299412.0	290000.0
15949	12.207723	12.049425	200330.0	171001.0
1668	12.852552	12.911645	381762.0	405001.0
3372	13.412133	13.485618	668060.0	719001.0
10397	12.448990	12.425212	254993.0	249001.0
17489	12.339977	12.383675	228657.0	238870.0
6284	12.908437	12.895553	403704.0	398536.0
9598	12.637894	12.498373	308012.0	267901.0
12770	12.034980	11.774528	168549.0	129901.0
6068	13.003978	12.891669	444177.0	396991.0
8000	13.025659	12.779594	453912.0	354901.0

In [214]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 1029509121.69
RMSE: 32085.96
R^2: 0.978
```

In [198]:
```
pred = best_model_pca_Lgbm.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                              columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[198]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.508001	12.672950	270493.0	319001.0
17892	11.141814	12.100718	68997.0	180001.0
12198	12.595140	12.736704	295121.0	340001.0
9774	12.635759	12.594734	307355.0	295001.0
18511	12.223390	11.938200	203494.0	153001.0
18437	12.390809	12.341438	240580.0	228991.0
8661	13.062685	13.038440	471034.0	459751.0
14024	12.966745	12.985170	427943.0	435901.0
12975	12.434096	12.514296	251223.0	272201.0
4385	12.137497	12.257041	186745.0	210458.0
18095	12.671039	12.736410	318392.0	339901.0
13870	12.810494	13.361382	366038.0	635001.0
9663	12.496096	12.429220	267292.0	250001.0
15665	12.248652	11.956976	208700.0	155901.0
6755	13.512407	13.997833	738523.0	1200001.0
2695	12.634588	12.524166	306995.0	274901.0
15953	12.181274	12.205578	195101.0	199901.0
16692	12.277968	12.706821	214909.0	329991.0
14	11.689618	11.660492	119326.0	115901.0
15851	12.340896	12.165256	228867.0	192001.0

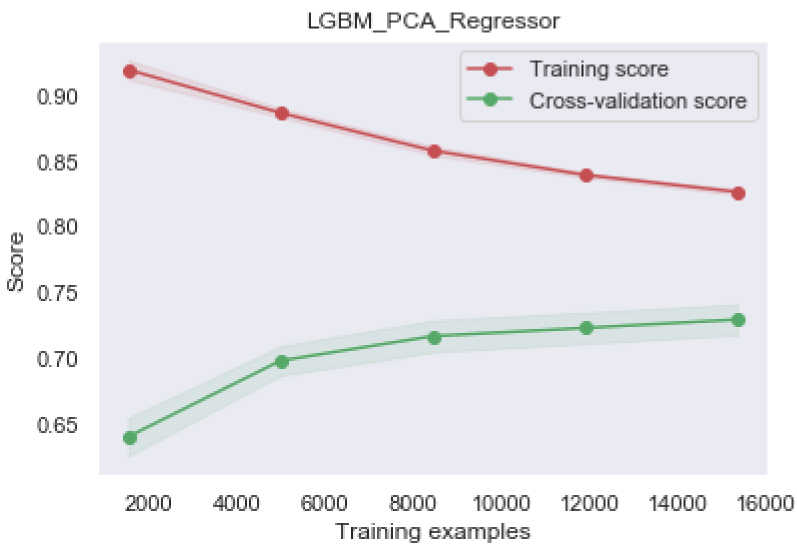
In [199]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 14880559313.26
RMSE: 121985.90
R^2: 0.682
```

In [200]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('LGBM_PCA_Regressor')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(best_model_pca_Lgbm, X
_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[200]: <Figure size 432x288 with 0 Axes>
Out[200]: Text(0.5, 1.0, 'LGBM_PCA_Regressor')
Out[200]: Text(0.5, 0, 'Training examples')
Out[200]: Text(0, 0.5, 'Score')
Out[200]: <matplotlib.collections.PolyCollection at 0x1a25a1d9d0>
Out[200]: <matplotlib.collections.PolyCollection at 0x1a25a1d350>
Out[200]: [<matplotlib.lines.Line2D at 0x1a25a1d490>]
Out[200]: [<matplotlib.lines.Line2D at 0x1a25b31f50>]
Out[200]: <matplotlib.legend.Legend at 0x1a25a9db10>
```



Ensemble Learning_PCA

In [201]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor()
LCV_model = LassoCV()
lr_model = linear_model.LinearRegression()
XGB_model = XGBRegressor(objective ='reg:squarederror')
LGBM_model = LGBMRegressor()
estimators = [XGB_model, LGBM_model, lr_model, LCV_model, rf_model]
reg = StackingRegressor(regressors=estimators, meta_regressor=GradientBoosting
Regressor(random_state=42))
reg.fit(X_pca_train, Y_pca_train)
```

Out[201]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [202]:
```
pred_train = reg.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                            columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[202]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.308802	12.238675	221638.0	206628.0
18253	12.558697	12.574185	284559.0	289001.0
4741	13.781061	13.945662	966137.0	1139001.0
8406	12.378734	12.312687	237693.0	222501.0
234	13.029552	13.060277	455683.0	469901.0
11125	12.580296	12.610173	290772.0	299591.0
2813	13.056137	13.060277	467959.0	469901.0
698	13.197887	13.199141	539225.0	539901.0
10623	13.422947	13.384729	675323.0	650001.0
16239	12.606642	12.577636	298535.0	290000.0
15949	12.138843	12.049425	186996.0	171001.0
1668	12.909543	12.911645	404151.0	405001.0
3372	13.384362	13.485618	649762.0	719001.0
10397	12.428285	12.425212	249767.0	249001.0
17489	12.395307	12.383675	241665.0	238870.0
6284	12.880137	12.895553	392439.0	398536.0
9598	12.492952	12.498373	266453.0	267901.0
12770	11.968507	11.774528	157709.0	129901.0
6068	12.886312	12.891669	394870.0	396991.0
8000	12.826381	12.779594	371900.0	354901.0

In [203]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 1077641375.80
RMSE: 32827.45
R^2: 0.977
```

In [204]:
```
pred = reg.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[204]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.620155	12.672950	302596.0	319001.0
17892	11.103111	12.100718	66377.0	180001.0
12198	12.709389	12.736704	330840.0	340001.0
9774	12.587995	12.594734	293020.0	295001.0
18511	12.001898	11.938200	163064.0	153001.0
18437	12.325568	12.341438	225386.0	228991.0
8661	13.080699	13.038440	479596.0	459751.0
14024	12.888982	12.985170	395926.0	435901.0
12975	12.479553	12.514296	262906.0	272201.0
4385	12.344598	12.257041	229716.0	210458.0
18095	12.845235	12.736410	378979.0	339901.0
13870	12.717650	13.361382	333584.0	635001.0
9663	12.488831	12.429220	265357.0	250001.0
15665	11.954991	11.956976	155592.0	155901.0
6755	13.466128	13.997833	705123.0	1200001.0
2695	12.627350	12.524166	304781.0	274901.0
15953	12.203170	12.205578	199420.0	199901.0
16692	12.252678	12.706821	209542.0	329991.0
14	11.918111	11.660492	149958.0	115901.0
15851	12.298893	12.165256	219453.0	192001.0

In [205]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 15833301638.94
RMSE: 125830.45
R^2: 0.662
```

In [206]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg, X_for_pca,Y, cv=c
v, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

```
Out[206]: <Figure size 432x288 with 0 Axes>

Out[206]: Text(0.5, 1.0, 'Ensemble Learning')

Out[206]: Text(0.5, 0, 'Training examples')

Out[206]: Text(0, 0.5, 'Score')

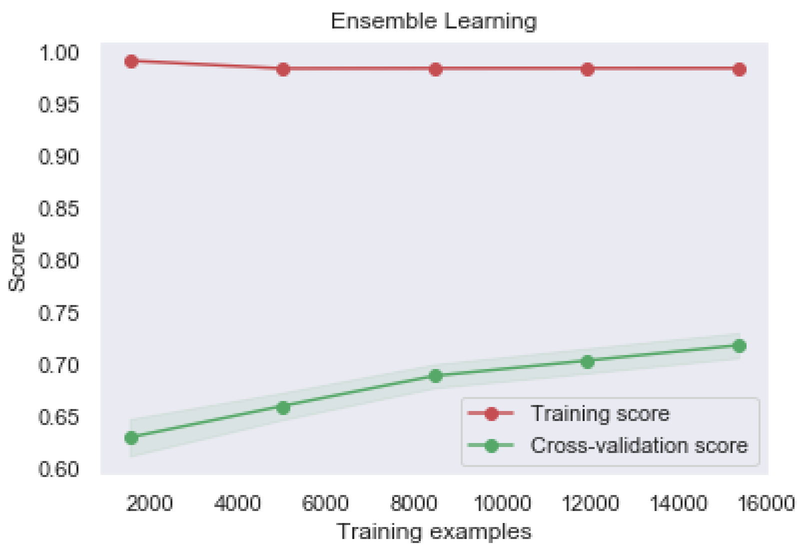
Out[206]: <matplotlib.collections.PolyCollection at 0x1a25bc4610>

Out[206]: <matplotlib.collections.PolyCollection at 0x1a25fea110>

Out[206]: [<matplotlib.lines.Line2D at 0x1a25a43b50>]

Out[206]: [<matplotlib.lines.Line2D at 0x1a25feaad0>]

Out[206]: <matplotlib.legend.Legend at 0x1a25b9bdd0>
```



Ensemble Learning without Linear and Lasso

In [207]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
XGB_model = XGBRegressor(objective ='reg:squarederror')
LGBM_model = LGBMRegressor()
estimators_without_linearlasso = [XGB_model, LGBM_model,rf_model]
reg_without_linearlasso= StackingRegressor(regressors=estimators_without_linea
rlasso, meta_regressor=GradientBoostingRegressor(random_state=42))
reg_without_linearlasso.fit(X_pca_train, Y_pca_train)
```

Out[207]:
```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [208]:
```
pred_train = reg_without_linearlasso.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'tr
uth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_trai
n, 0), 'truth_train_price': np.e ** y_train},
                             columns=['predict_train_price_log', 'truth_train_
price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[208]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.324461	12.238675	225136.0	206628.0
18253	12.618278	12.574185	302029.0	289001.0
4741	13.831056	13.945662	1015667.0	1139001.0
8406	12.337928	12.312687	228189.0	222501.0
234	13.049647	13.060277	464932.0	469901.0
11125	12.608497	12.610173	299089.0	299591.0
2813	13.060167	13.060277	469849.0	469901.0
698	13.188063	13.199141	533953.0	539901.0
10623	13.375882	13.384729	644276.0	650001.0
16239	12.609747	12.577636	299463.0	290000.0
15949	12.082568	12.049425	176763.0	171001.0
1668	12.898998	12.911645	399911.0	405001.0
3372	13.438461	13.485618	685882.0	719001.0
10397	12.433082	12.425212	250968.0	249001.0
17489	12.390369	12.383675	240475.0	238870.0
6284	12.879813	12.895553	392312.0	398536.0
9598	12.518279	12.498373	273287.0	267901.0
12770	11.830617	11.774528	137395.0	129901.0
6068	12.883939	12.891669	393934.0	396991.0
8000	12.842404	12.779594	377907.0	354901.0

In [209]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth[
'truth_train_price'])
```

```
MSE: 1029509121.69
RMSE: 32085.96
R^2: 0.978
```

In [210]:
```
pred = reg_without_linearlasso.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[210]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.663205	12.672950	315908.0	319001.0
17892	10.997386	12.100718	59718.0	180001.0
12198	12.729438	12.736704	337540.0	340001.0
9774	12.640836	12.594734	308919.0	295001.0
18511	11.991954	11.938200	161451.0	153001.0
18437	12.318603	12.341438	223821.0	228991.0
8661	13.104945	13.038440	491366.0	459751.0
14024	12.866247	12.985170	387026.0	435901.0
12975	12.482034	12.514296	263559.0	272201.0
4385	12.335147	12.257041	227555.0	210458.0
18095	12.759154	12.736410	347720.0	339901.0
13870	12.710291	13.361382	331138.0	635001.0
9663	12.564901	12.429220	286330.0	250001.0
15665	11.992466	11.956976	161533.0	155901.0
6755	13.354991	13.997833	630956.0	1200001.0
2695	12.587296	12.524166	292815.0	274901.0
15953	12.234153	12.205578	205696.0	199901.0
16692	12.292591	12.706821	218074.0	329991.0
14	12.001777	11.660492	163044.0	115901.0
15851	12.316517	12.165256	223355.0	192001.0

In [211]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 15874918336.07
RMSE: 125995.71
R^2: 0.661
```

In [212]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg_without_linearlass
o, X_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[212]: <Figure size 432x288 with 0 Axes>

Out[212]: Text(0.5, 1.0, 'Ensemble Learning')

Out[212]: Text(0.5, 0, 'Training examples')

Out[212]: Text(0, 0.5, 'Score')

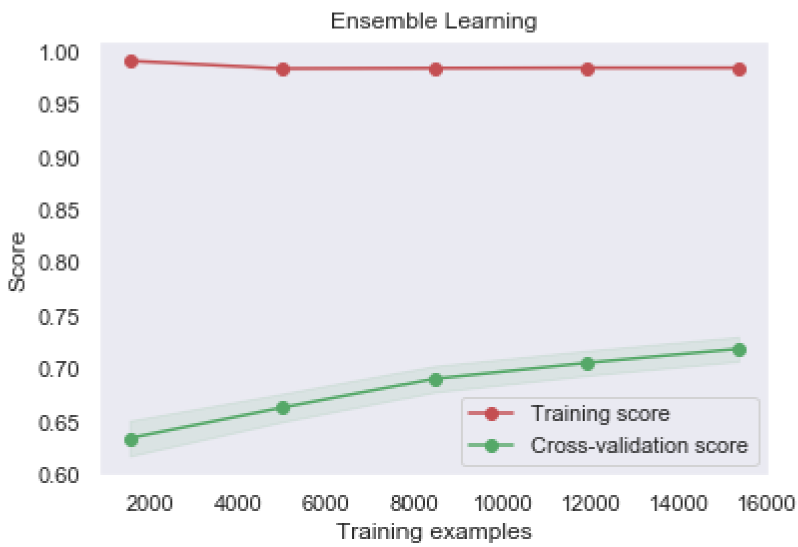
Out[212]: <matplotlib.collections.PolyCollection at 0x1a260206d0>

Out[212]: <matplotlib.collections.PolyCollection at 0x1a2591ab10>

Out[212]: [<matplotlib.lines.Line2D at 0x1a26db7650>]

Out[212]: [<matplotlib.lines.Line2D at 0x1a25bada90>]

Out[212]: <matplotlib.legend.Legend at 0x1a2591b410>



Ensemble Learning after PCA with Best Model

In [215]:
```
from sklearn.ensemble import GradientBoostingRegressor
from mlxtend.regressor import StackingRegressor
from sklearn import linear_model
from sklearn.linear_model import LassoCV
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
XGB_model = XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1
,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=10, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
LGBM_model = LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_
bytree=1.0,
              importance_type='split', learning_rate=0.1, max_depth=-1,
              min_child_samples=20, min_child_weight=0.001, min_data_in_leaf=5
0,
              min_split_gain=0.0, n_estimators=100, n_jobs=-1, num_leaves=30,
              objective=None, random_state=42, reg_alpha=0.0, reg_lambda=0.0,
              silent=True, subsample=1.0, subsample_for_bin=200000,
              subsample_freq=0)
estimators = [XGB_model, LGBM_model, rf_model]
reg_built_in_model_pca_without_linearlasso_best = StackingRegressor(regressors
=estimators, meta_regressor=GradientBoostingRegressor(random_state=42))
reg_built_in_model_pca_without_linearlasso_best.fit(X_pca_train, Y_pca_train)
```

```
[09:11:00] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

Out[215]:

```
StackingRegressor(meta_regressor=GradientBoostingRegressor(alpha=0.9,
                                                           ccp_alpha=0.0,
                                                           criterion='friedma
n_mse',
                                                           init=None,
                                                           learning_rate=0.1,
                                                           loss='ls',
                                                           max_depth=3,
                                                           max_features=None,
                                                           max_leaf_nodes=Non
e,
                                                           min_impurity_decre
ase=0.0,
                                                           min_impurity_split
=None,
                                                           min_samples_leaf=
1,
                                                           min_samples_split=
2,
                                                           min_weight_fractio
n_leaf=0.0,
                                                           n_estimators=100,
                                                           n_iter_no_change=N
o...
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.
0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=
0.0,
                                                    n_estimators=100,
                                                    n_jobs=None,
                                                    oob_score=False,
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False)],
                  store_train_meta_features=False,
                  use_features_in_secondary=False, verbose=0)
```

In [216]:
```
pred_train = reg_built_in_model_pca_without_linearlasso_best.predict(X_pca_train)

pred_train_and_truth = pd.DataFrame({'predict_train_price_log':pred_train, 'truth_train_price_log':y_train, 'predict_train_price':np.round(np.e ** pred_train, 0), 'truth_train_price': np.e ** y_train},
                                     columns=['predict_train_price_log', 'truth_train_price_log', 'predict_train_price', 'truth_train_price'])
pred_train_and_truth.head(20)
```

Out[216]:

	predict_train_price_log	truth_train_price_log	predict_train_price	truth_train_price
10503	12.238352	12.238675	206561.0	206628.0
18253	12.641172	12.574185	309023.0	289001.0
4741	13.933797	13.945662	1125566.0	1139001.0
8406	12.389923	12.312687	240367.0	222501.0
234	13.034490	13.060277	457938.0	469901.0
11125	12.580528	12.610173	290840.0	299591.0
2813	13.065916	13.060277	472558.0	469901.0
698	13.233441	13.199141	558741.0	539901.0
10623	13.409888	13.384729	666561.0	650001.0
16239	12.605763	12.577636	298273.0	290000.0
15949	12.144902	12.049425	188133.0	171001.0
1668	12.895928	12.911645	398685.0	405001.0
3372	13.432793	13.485618	682006.0	719001.0
10397	12.417275	12.425212	247032.0	249001.0
17489	12.344449	12.383675	229681.0	238870.0
6284	12.920614	12.895553	408650.0	398536.0
9598	12.487499	12.498373	265004.0	267901.0
12770	11.782249	11.774528	130908.0	129901.0
6068	12.871963	12.891669	389244.0	396991.0
8000	12.836507	12.779594	375685.0	354901.0

In [217]:
```
metrics_new(pred_train_and_truth['predict_train_price'], pred_train_and_truth['truth_train_price'])
```

```
MSE: 619115690.78
RMSE: 24882.04
R^2: 0.987
```

In [218]:
```
pred = reg_built_in_model_pca_without_linearlasso_best.predict(X_pca_test)
pred_and_truth = pd.DataFrame({'predict_price_log':pred, 'truth_price_log':y_t
est, 'predict_price':np.round(np.e ** pred, 0), 'truth_price': np.e ** y_test
},
                             columns=['predict_price_log', 'truth_price_log',
'predict_price', 'truth_price'])
pred_and_truth.head(20)
```

Out[218]:

	predict_price_log	truth_price_log	predict_price	truth_price
1356	12.672300	12.672950	318794.0	319001.0
17892	11.378668	12.100718	87436.0	180001.0
12198	12.650682	12.736704	311976.0	340001.0
9774	12.649074	12.594734	311475.0	295001.0
18511	12.044588	11.938200	170176.0	153001.0
18437	12.329407	12.341438	226252.0	228991.0
8661	13.048442	13.038440	464372.0	459751.0
14024	12.964777	12.985170	427101.0	435901.0
12975	12.467986	12.514296	259883.0	272201.0
4385	12.201152	12.257041	199018.0	210458.0
18095	12.844277	12.736410	378616.0	339901.0
13870	12.680435	13.361382	321398.0	635001.0
9663	12.584824	12.429220	292092.0	250001.0
15665	11.969101	11.956976	157803.0	155901.0
6755	13.611513	13.997833	815464.0	1200001.0
2695	12.650901	12.524166	312044.0	274901.0
15953	12.296943	12.205578	219025.0	199901.0
16692	12.323730	12.706821	224972.0	329991.0
14	11.630740	11.660492	112504.0	115901.0
15851	12.296092	12.165256	218839.0	192001.0

In [219]:
```
metrics_new(pred_and_truth['predict_price'], pred_and_truth['truth_price'])
```

```
MSE: 14465387200.00
RMSE: 120272.14
R^2: 0.691
```

In [220]:
```
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=30, test_size=0.2, random_state=0)
plt.figure()
plt.title('Ensemble Learning')
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(reg_built_in_model_pca
_without_linearlasso_best, X_for_pca,Y, cv=cv, train_sizes=np.linspace(.1, 1.0
, 5))
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()
plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training scor
e")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",  label="Cross-validat
ion score")
plt.legend(loc="best")
```

Out[220]: <Figure size 432x288 with 0 Axes>

Out[220]: Text(0.5, 1.0, 'Ensemble Learning')

Out[220]: Text(0.5, 0, 'Training examples')

Out[220]: Text(0, 0.5, 'Score')

```
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precated in favor of reg:squarederror.
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[09:26:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
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[10:29:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:29:40] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:29:58] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
```

```
precated in favor of reg:squarederror.
[10:30:31] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:31:19] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:32:22] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:32:28] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:33:03] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:33:39] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
[10:34:51] WARNING: src/objective/regression_obj.cu:152: reg:linear is now de
precated in favor of reg:squarederror.
```

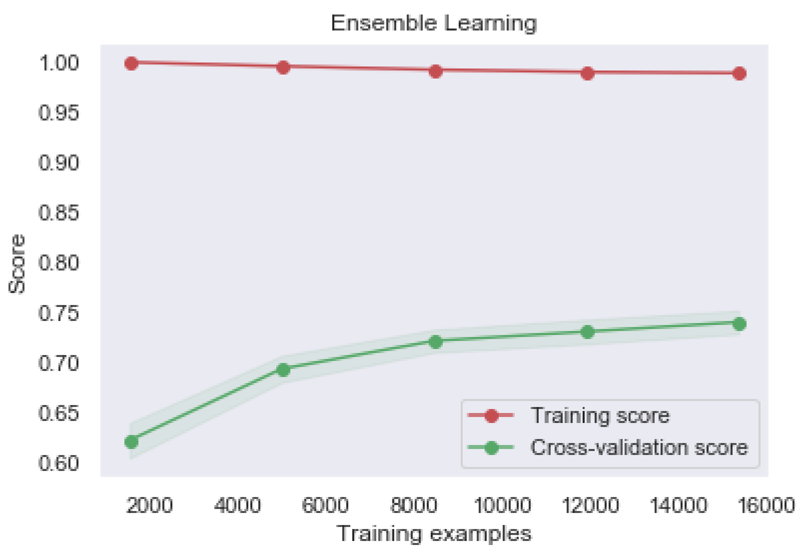
```
Out[220]: <matplotlib.collections.PolyCollection at 0x1a25f2e990>

Out[220]: <matplotlib.collections.PolyCollection at 0x1a26958950>

Out[220]: [<matplotlib.lines.Line2D at 0x1a26958510>]

Out[220]: [<matplotlib.lines.Line2D at 0x1a25b52a10>]

Out[220]: <matplotlib.legend.Legend at 0x1a26958f10>
```



Conclusion

According to our result the top 10 most important of prediction of house price in Georgia state are TaxAssessedValue, YearBuilt, LivingArea, LotSize, Bathrooms, HomeType, FavoriteCount, AverageHouseValue, HighSchoolRating, PageViewCount. Obviously, when people decide to buy the house, they take into account not only the value of the home itself, but also the property tax. Buyers pay much attention to the length of time, because it is closely related to the quality of the house. It is also obvious that living area directly determines the price of a house. For the convenience of daily life, buyers will consider not only the areas of the house where they are active for long periods of time, but also the amount of bathroom. One of the interesting aspects of the results is that buyers tend to prefer homes near high schools, perhaps because of the high security or high traffic around the school.

So, if people want to sale their house at a good price in Georgia state, their house should have low Tax, the age of the house should not be long, for the house situation, living area should around 2000, lost size should be around 20000 and bathrooms should be more than two, they should be single family and if they near good high school will be a plus. Besides, they should show good description and introduction on the website, which may attract more people, for pageviewcount feature are also important.

At the beginning of the project, we decided to use six metrics (RMSE, MAE, MSE, MAPE, MPE and R^2) to evaluate our model results, but as we continued to train the model, we found that some of these metrics were not applicable to our model training and evaluation. Therefore, we finally chose MSE, RMSE and R^2 for evaluation and training.

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