Dataset: [Airbnb Listings (https://www.kaggle.com/rudymizrahi/airbnb-listings-in-major-us-cities-deloitte-ml#train.csv)](https://www.kaggle.com/rudymizrahi/airbnb-listings-in-major-us-cities-deloitte-ml#train.csv)

Project Description and Requirements:

Dataset requirements:

For this projects in this class, you will pick your datasets. The datasets should satisfy the following conditions:

- At least 15 features (columns)
- At least 1000 instances (rows)
-
  - Shape of train data:
-
  - Shape of test data:
- At least two categorical/ordinal columns.
- Between 5 to 10 percent missing values across the dataset.

Importing the libraries

In [1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
import seaborn as sns
import sklearn
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import scale
```

In [2]:
```
%matplotlib inline
```

Project Description:

Read data into Jupyter notebook, use pandas to import data into a data frame Preprocess data: Explore data, check for missing data and apply data scaling. Justify the type of scaling used.

Loading the dataset

In [3]:
```
df = pd.read_csv("train.csv")
```

In [4]:
```
print('Shape of train data: ', df.shape)
```

```
Shape of train data:  (74111, 29)
```

29 features and 74111 instances are avalable in this data set

In [5]:
```
df.head()
```

Out[5]:

	id	log_price	property_type	room_type	amenities	accommodates	bathroon
0	6901257	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3	1
1	6304928	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7	1
2	7919400	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5	1
3	13418779	6.620073	House	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4	1
4	3808709	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2	1

5 rows × 29 columns

Few changes in df...

In [6]:
```
df['host_response_rate']= pd.to_numeric(df['host_response_rate'].str.strip('%'
))
df['room_type']= df['room_type'].map({'Entire home/apt':'Entire home/apt','Pri
vate room':'Private room','Shared room':'Private room'})
```

Dataset Description and goal

This dataset has many features that are important in the Airbnb price of a house or Apt or ... and might affect its Price. The aim of this competition was to predict the price of AirBnB listings in major U.S. cities.

Data Description

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74111 entries, 0 to 74110
Data columns (total 29 columns):
id                        74111 non-null int64
log_price                 74111 non-null float64
property_type             74111 non-null object
room_type                 74111 non-null object
amenities                 74111 non-null object
accommodates              74111 non-null int64
bathrooms                 73911 non-null float64
bed_type                  74111 non-null object
cancellation_policy       74111 non-null object
cleaning_fee              74111 non-null bool
city                      74111 non-null object
description               74111 non-null object
first_review              58247 non-null object
host_has_profile_pic      73923 non-null object
host_identity_verified    73923 non-null object
host_response_rate        55812 non-null float64
host_since                73923 non-null object
instant_bookable          74111 non-null object
last_review               58284 non-null object
latitude                  74111 non-null float64
longitude                 74111 non-null float64
name                      74111 non-null object
neighbourhood             67239 non-null object
number_of_reviews         74111 non-null int64
review_scores_rating      57389 non-null float64
thumbnail_url             65895 non-null object
zipcode                   73145 non-null object
bedrooms                  74020 non-null float64
beds                      73980 non-null float64
dtypes: bool(1), float64(8), int64(3), object(17)
memory usage: 15.9+ MB
```

In [8]:
```
df.isnull().sum()
# number of nulls
```

Out[8]:
```
id                            0
log_price                     0
property_type                 0
room_type                     0
amenities                     0
accommodates                  0
bathrooms                   200
bed_type                      0
cancellation_policy           0
cleaning_fee                  0
city                          0
description                   0
first_review              15864
host_has_profile_pic        188
host_identity_verified      188
host_response_rate        18299
host_since                  188
instant_bookable              0
last_review               15827
latitude                      0
longitude                     0
name                          0
neighbourhood              6872
number_of_reviews             0
review_scores_rating      16722
thumbnail_url              8216
zipcode                     966
bedrooms                     91
beds                        131
dtype: int64
```

In [9]:
```
print('missing values across the dataset % {:.2f}'.format(df.isnull().sum().su
m()/(len(df)*29)*100))
```

```
missing values across the dataset % 3.90
```

The number of nulls are didn't meet the requirments, we have to generate them.

In [10]:
```
df.columns
```

Out[10]:
```
Index(['id', 'log_price', 'property_type', 'room_type', 'amenities',
       'accommodates', 'bathrooms', 'bed_type', 'cancellation_policy',
       'cleaning_fee', 'city', 'description', 'first_review',
       'host_has_profile_pic', 'host_identity_verified', 'host_response_rat
e',
       'host_since', 'instant_bookable', 'last_review', 'latitude',
       'longitude', 'name', 'neighbourhood', 'number_of_reviews',
       'review_scores_rating', 'thumbnail_url', 'zipcode', 'bedrooms', 'bed
s'],
      dtype='object')
```

Target variable

- SalePrice: the property's sale price in dollars. This is the target variable that we're trying to predict.

Features

- id: The Property id
- log price: the log price of the property for the night in dollar
- property type: Apartment or House
  - Apartment = 1 and House = 0 **(since the apartment has more instanses)**
- room_type: Entire or Private
  - Entire = 1 and Private = 0
- amenities: list of all amenities
  - because all of them are unique the column will be dropped
- accommodates: Number of guests that a house can accommodate
- bathroom: Number of bathrooms
- bed_type: Airbed, couch, Futon, Pull out sofa, Real bed
  - there is no difference between them so we will use one hot-vector
- cancellation_policy: strict, moderate, flexible
- cleaning fee: True, they have cleaning fee False otherwise
  - we will use True = 1 and False = 0 **(since we have more instances with TRUE values)**
- city: NYC is a new york city and LA is Los Angeles, Boston, Chicago, DC, SF
  - we will use one-hot vector for this feature
- description: Description of the house
  - we will drop this column since all values are unique
- first_review: the date of the first review
  - we have to see the correlation matrix but, even with high numbers in there it is still not believable to find a relation between the date and price, So I'll drop this feature later.
- host_has_profile_pic: True means it has, False otherwise
  - we will use True = 1 and False = 0 **(since we have more instanses with TRUE vlaues)**
- host_identity_verified: True means it has, False otherwise
  - we will use True = 1 and False = 0 **(since we have more instanses with TRUE vlaues)**
- host_response_rate: % of respond rate, between 0 and 1
- host_since: the date of the host account
  - we have to see the correlation matrix but, even with high numbers in there it is still not believable to find a relation between the date and price, So I'll drop this feature later.
- instant_bookable: True means it has, False otherwise
  - we will use True = 1 and False = 0 **(since we have more instanses with TRUE vlaues)**
- last_review: the date of the last review
  - we have to see the correlation matrix but, even with high numbers in there it is still not believable to find a relation between the date and price, So I'll drop this feature later.
- latitude: related to the location of the house, great for the visualization but not useful for regression, however, the location can be scored base on the location, and neighborhood but for simplification, we will ignore this part
- longitude: related to the location of the house, great for the visualization but not useful for regression, however, the location can be scored base on the location and neighborhood but for simplification, we will ignore this part

- name: All unique values for the place
  - since all values are unique we will drop this feature
- neighborhood: related to the location of the house, great for the visualization but not useful for regression, however, the location can be scored base on the location, and neighborhood but for simplification, we will ignore this part
- number_of_reviews: number of views
- review_scores_rating: review score between 0 - 100
- thumbnail_url:
  - not related to the regression
- zipcode: related to the location of the house, great for the visualization but not useful for regression, however, the location can be scored base on the location, and neighborhood but for simplification, we will ignore this part
- bedrooms: number of bedrooms a house has
- beds: number of beds a house have

In [11]:
```
df.drop(columns= ['id', 'amenities', 'description', 'first_review',
       'host_since','last_review', 'latitude',
       'longitude', 'name', 'neighbourhood', 'thumbnail_url', 'zipcode'], inpl
ace= True)
```

so we droped the features with mostly uniuqe instances so the we can draw smaller correlation matrix.

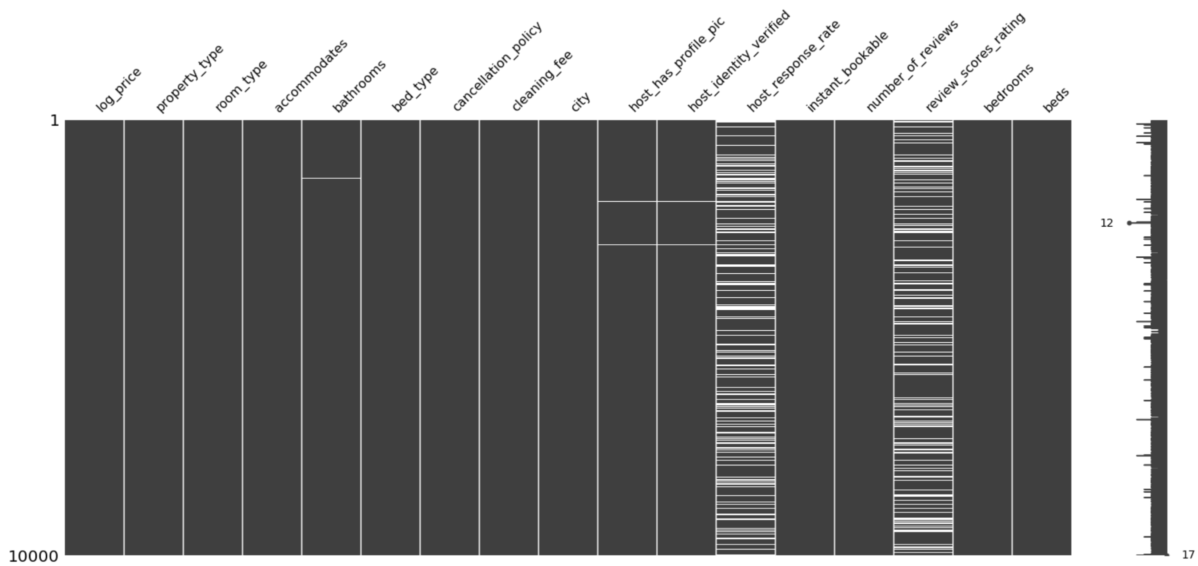
the data set has around 75,000 instanses and it will too long in the ML models to run each model. I will use only 10000 of them.

In [12]:
```
df=df[0:10000]
```

Visualizing the missing portion of the dataset

In [13]:
```
# !pip install missingno
import missingno as msno
msno.matrix(df)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1d4abfeedc8>



In [14]:
```
print('missing values across the dataset % {:.2f}'.format(df.isnull().sum().su
m()/(len(df)*17)*100))
```

```
missing values across the dataset % 2.91
```

So we have to generate missed values so we are going to generate them. now they are only in two columns.

Creating missing data

We will create a mask here that randomly will null out values in our dataset , we will pass p to the mask, which the first element, will determine the % of the missing data we want.

In [15]:
```
df = df.mask(np.random.choice([True, False], size=df.shape, p=[.02,.98]))
```

In [16]:
```
all_data_na = (df.isnull().sum() / len(df)) * 100
all_data_na = all_data_na.drop(all_data_na[all_data_na == 0].index).sort_value
s(ascending=False)[:30]
missing_data = pd.DataFrame({'Missing Ratio' :all_data_na})
missing_data
```

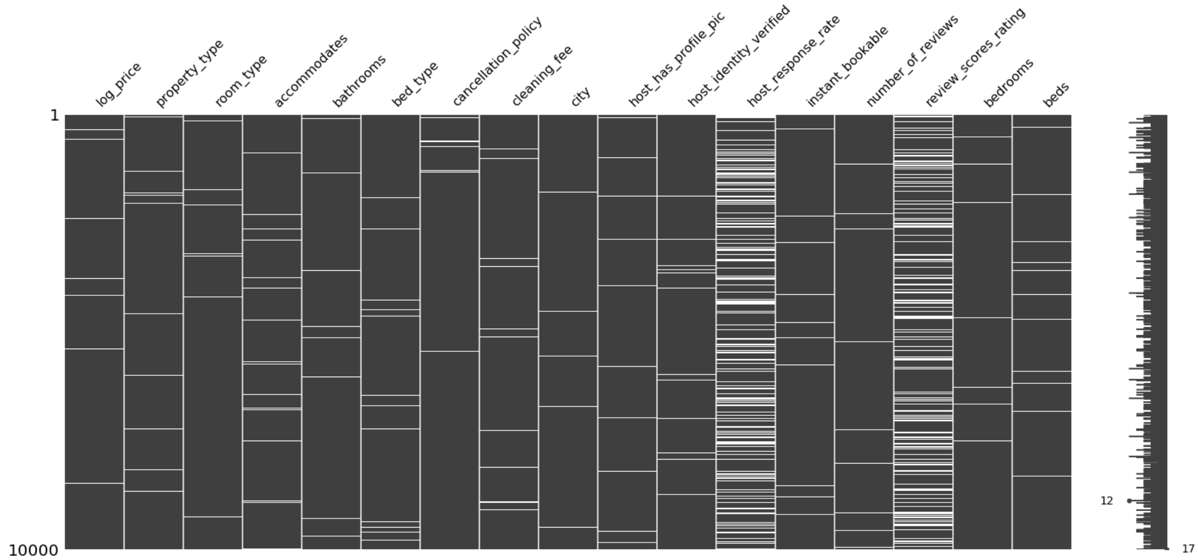
Out[16]:

	Missing Ratio
host_response_rate	26.87
review_scores_rating	24.54
bathrooms	2.39
host_has_profile_pic	2.39
host_identity_verified	2.26
instant_bookable	2.18
beds	2.17
room_type	2.13
log_price	2.09
number_of_reviews	2.09
bedrooms	2.08
accommodates	2.06
property_type	2.04
city	1.94
bed_type	1.92
cleaning_fee	1.91
cancellation_policy	1.56

visualizing the dataset after nulling out values at random

In [17]:
```
import missingno as msno
msno.matrix(df)
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d4abc8db48>
```



In [18]:
```
print('missing values across the dataset % {:.2f}'.format(df.isnull().sum().su
m()/(len(df)/17)))
```

```
missing values across the dataset % 14.05
```

Now it is okay.

In [19]:
```
df.columns
```

Out[19]:
```
Index(['log_price', 'property_type', 'room_type', 'accommodates', 'bathroom
s',
       'bed_type', 'cancellation_policy', 'cleaning_fee', 'city',
       'host_has_profile_pic', 'host_identity_verified', 'host_response_rat
e',
       'instant_bookable', 'number_of_reviews', 'review_scores_rating',
       'bedrooms', 'beds'],
      dtype='object')
```

Dropping and imputing missing data

So we have two general course of action regarding the missing data, either dropping them or replacing them with the mean or the median. Here in this case, most of our variables are catagorical and we will be dropping those because random assignment doesnt make sense.on other features we are going to use mean for normal distribution and median for skewed ones.

Dropping rows:

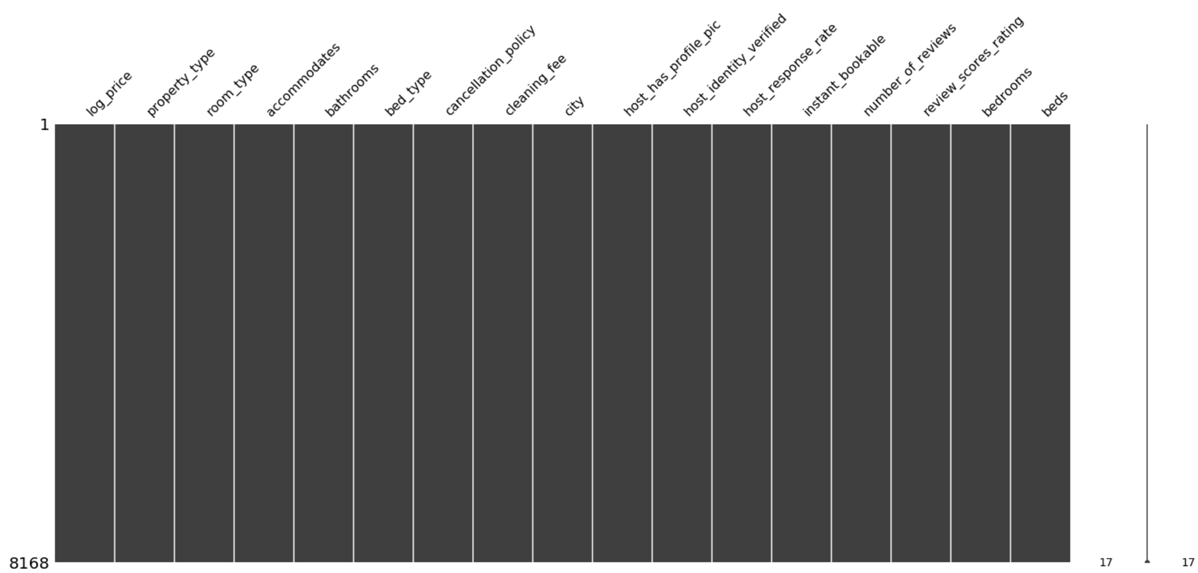
At first you might think it is best to impute the missing data however the features with missing data that remain are mostly categorical and mode isnt a correct representation of the missing values, so I've decided to drop the rows in order notto misrepresent the data. Also we are going to drop instances in target column with missing values\

In [20]:
```
rows_drop=['log_price', 'property_type', 'room_type',
       'bed_type', 'cancellation_policy', 'cleaning_fee', 'city',
       'host_has_profile_pic', 'host_identity_verified',
       'instant_bookable']
for i in rows_drop:
    df=df[df[i].notnull()]
```

In [21]:
```
df['accommodates'].fillna(df['accommodates'].median(),inplace=True)
df['bathrooms'].fillna(df[ 'bathrooms'].median(),inplace=True)
df['host_response_rate'].fillna(df['host_response_rate'].mean(),inplace=True)
df['number_of_reviews'].fillna(round(df['number_of_reviews'].mean(),0),inplace
=True)
df['review_scores_rating'].fillna(round(df[ 'review_scores_rating'].mean()),in
place=True)
df['bedrooms'].fillna(df['bedrooms'].median(),inplace=True)
df['beds'].fillna(df['beds'].median(),inplace=True)
```

In [22]:
```
msno.matrix(df)
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d4abdf5848>
```



In [23]:
```
df.shape
# row and columns after cleaning
```

Out[23]:
```
(8168, 17)
```

Datatypes and Transformations

In [24]:
```
df.dtypes
```

Out[24]:
```
log_price                 float64
property_type              object
room_type                  object
accommodates              float64
bathrooms                 float64
bed_type                   object
cancellation_policy        object
cleaning_fee              float64
city                       object
host_has_profile_pic       object
host_identity_verified     object
host_response_rate        float64
instant_bookable           object
number_of_reviews         float64
review_scores_rating      float64
bedrooms                  float64
beds                      float64
dtype: object
```

In [25]:
```
df.bed_type.unique()
```

Out[25]:
```
array(['Real Bed', 'Futon', 'Couch', 'Pull-out Sofa', 'Airbed'],
      dtype=object)
```

In [26]:
```
df.head(10)
```

Out[26]:

	log_price	property_type	room_type	accommodates	bathrooms	bed_type	cancellation_poli
0	5.010635	Apartment	Entire home/apt	3.0	1.0	Real Bed	str
1	5.129899	Apartment	Entire home/apt	7.0	1.0	Real Bed	str
2	4.976734	Apartment	Entire home/apt	5.0	1.0	Real Bed	modera
5	4.442651	Apartment	Private room	2.0	1.0	Real Bed	str
6	4.418841	Apartment	Entire home/apt	3.0	1.0	Real Bed	modera
7	4.787492	Condominium	Entire home/apt	2.0	1.0	Real Bed	modera
8	4.787492	House	Private room	2.0	1.0	Real Bed	modera
9	3.583519	House	Private room	2.0	1.0	Real Bed	modera
10	4.605170	Apartment	Private room	2.0	1.0	Real Bed	str
12	4.248495	Apartment	Private room	2.0	1.0	Real Bed	flexib

In [27]:
```
df['room_type'] = df['room_type'].map({'Entire home/apt':1,'Private room':0}).
astype(int)
df['host_has_profile_pic'] = df['host_has_profile_pic'].map({'t':1,'f':0}).ast
ype(int)
df['host_identity_verified'] = df['host_identity_verified'].map({'t':1,'f':0})
.astype(int)
df['instant_bookable'] = df['instant_bookable'].map({'t':1,'f':0}).astype(int)
```

Now one hot-vectors

In [28]:
```
emb=pd.get_dummies(df['property_type'],columns='property_type',prefix='propert
y_type ')
df=pd.concat([df, emb], axis=1)
df.drop(['property_type'],axis=1,inplace= True)
```

In [29]:
```
emb=pd.get_dummies(df['bed_type'],columns='bed_type',prefix='bed_type ')
df=pd.concat([df, emb], axis=1)
df.drop(['bed_type'],axis=1,inplace= True)
```

In [30]:
```
emb=pd.get_dummies(df['cancellation_policy'],columns='cancellation_policy',pre
fix='cancellation_policy ')
df=pd.concat([df, emb], axis=1)
df.drop(['cancellation_policy'],axis=1,inplace= True)
```

In [31]:
```
emb=pd.get_dummies(df['city'],columns='city',prefix='city ')
df=pd.concat([df, emb], axis=1)
df.drop(['city'],axis=1,inplace= True)
```

In [32]:
```
df.head()
```

Out[32]:

	log_price	room_type	accommodates	bathrooms	cleaning_fee	host_has_profile_pic	host_ide
0	5.010635	1	3.0	1.0	1.0	1	
1	5.129899	1	7.0	1.0	1.0	1	
2	4.976734	1	5.0	1.0	1.0	1	
5	4.442651	0	2.0	1.0	1.0	1	
6	4.418841	1	3.0	1.0	1.0	1	

5 rows × 51 columns

In [33]:
```
df.describe()
```

Out[33]:

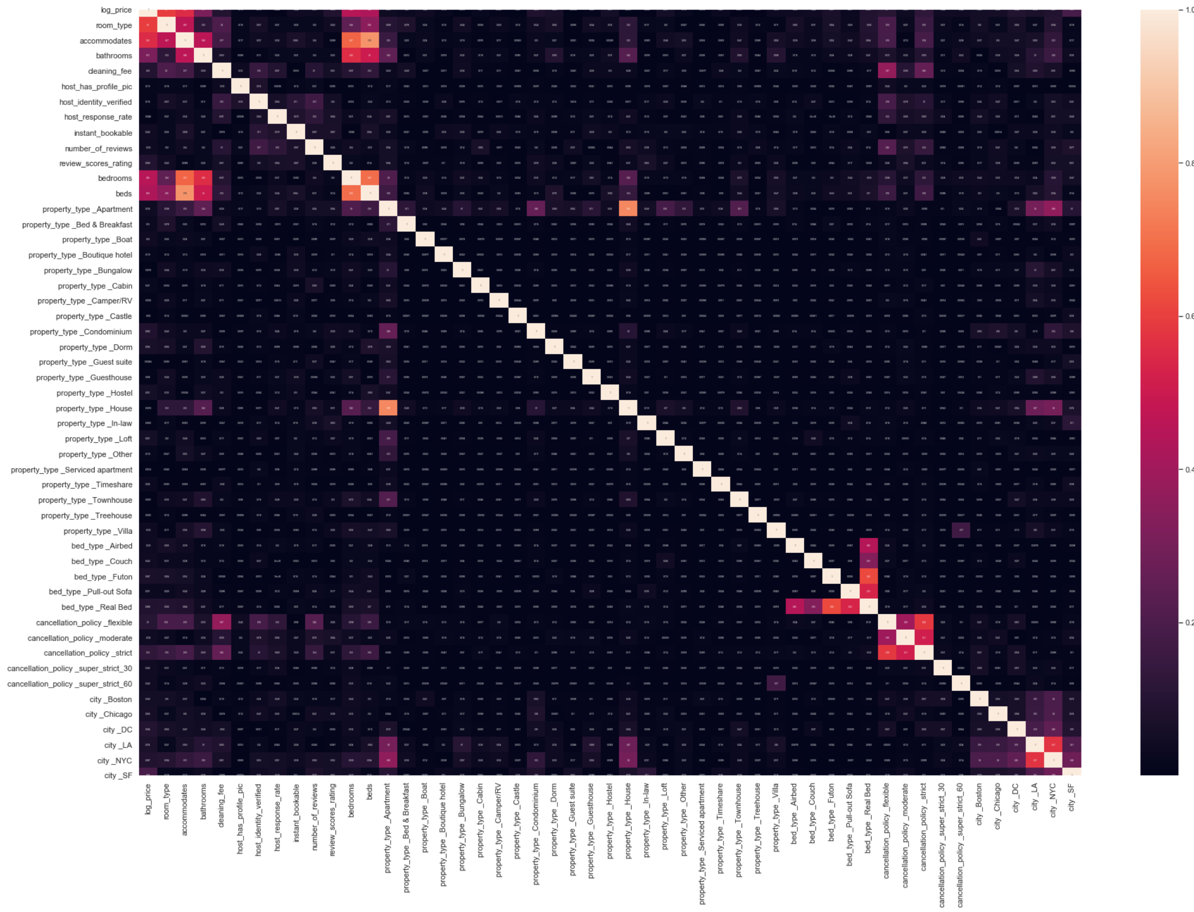
	log_price	room_type	accommodates	bathrooms	cleaning_fee	host_has_profile_pic
count	8168.000000	8168.000000	8168.000000	8168.000000	8168.000000	8168.000000
mean	4.782515	0.558888	3.121939	1.221780	0.734574	0.997307
std	0.711945	0.496550	2.140199	0.560582	0.441587	0.051832
min	2.302585	0.000000	1.000000	0.000000	0.000000	0.000000
25%	4.317488	0.000000	2.000000	1.000000	0.000000	1.000000
50%	4.718499	1.000000	2.000000	1.000000	1.000000	1.000000
75%	5.192957	1.000000	4.000000	1.000000	1.000000	1.000000
max	7.598399	1.000000	16.000000	8.000000	1.000000	1.000000

8 rows × 51 columns

Correlation and highly correlated features

In [34]:
```
# Correlation of all the variables with respect to each other
sns.set(font_scale=1.8)
sns.set(rc={'figure.figsize':(30,20)})
sns.heatmap(df.corr().abs(),annot=True, annot_kws={"size": 3})
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1d4abe182c8>

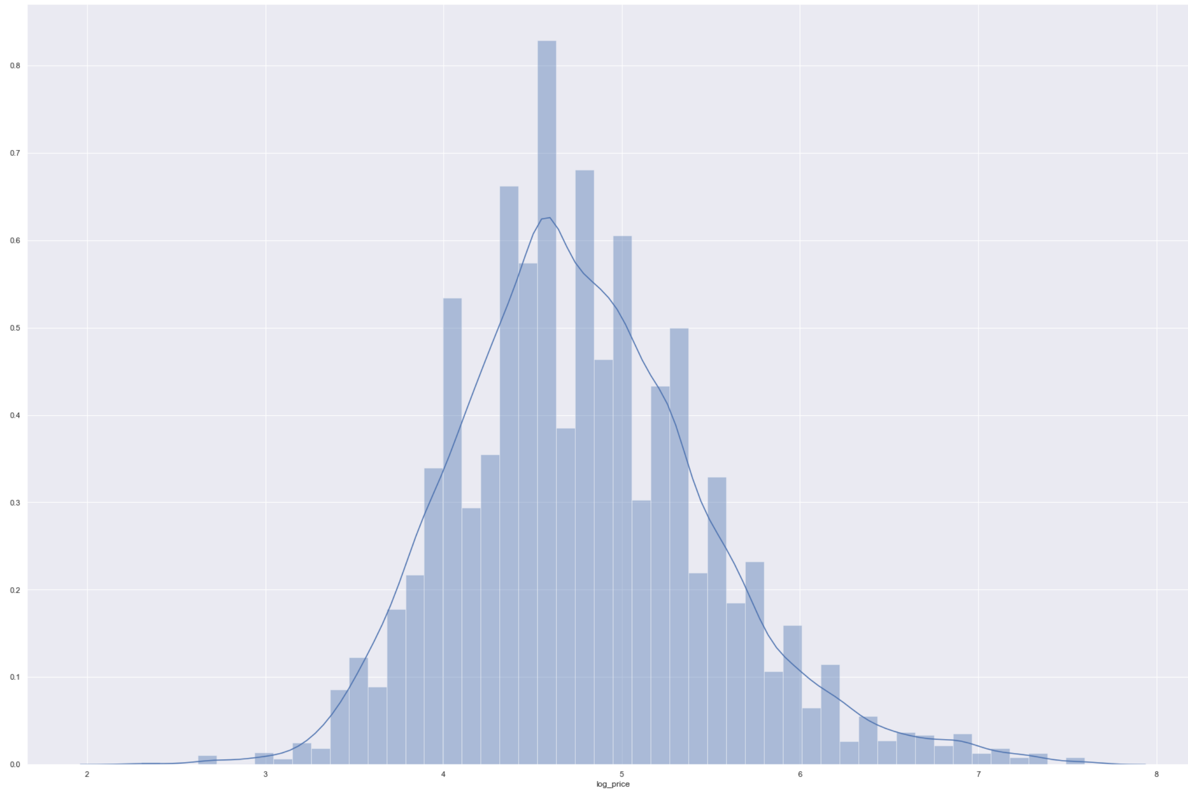


As it shows most of the variables don't have a correlation to each other more than 70% so there is no need to be worried about collinearity. on the other hand, log_price has a relation with bedrooms, beds, room_type, and accommodates.

Scaling and transformation

In [35]:
```
#histogram of target variable :
sns.distplot(df['log_price']);

print(df.log_price.var())
```

```
0.5068655635085126
```



since the data already logged the histogram looks just fine

Dropping index + target features

the data set has around 40,000 instanses and it will too long in the ML models to run each model. I will use only 10,000 of them.

In [36]:
```
df_org = df
y_org = df['log_price']
X_org = df.drop(columns=['log_price'],axis=1)
```

`python MinMaxScaler(feature_range = (0, 1))` will transform each value in the column proportionally within the range [0,1]. Use this as the first scaler choice to transform a feature, as it will preserve the shape of the dataset (no distortion).

`python StandardScaler()` will transform each value in the column to range about the mean 0 and standard deviation 1, ie, each value will be normalised by subtracting the mean and dividing by standard deviation. Use StandardScaler if you know the data distribution is normal.

If there are outliers, use `pyhton RobustScaler()` . Alternatively you could remove the outliers and use either of the above 2 scalers (choice depends on whether data is normally distributed)

based on the explanation above I will use the MinMaxScaler. However, our data are mostly less than 10 and exept for one or two featuers there is no need for scaleing

In [37]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

X_train_org, X_test_org, y_train, y_test = train_test_split(X_org,y_org, test_
size=0.25, random_state=0)
```

In [38]:
```
X_train_org.describe()
```

Out[38]:

	room_type	accommodates	bathrooms	cleaning_fee	host_has_profile_pic	host_identity
count	6126.000000	6126.000000	6126.000000	6126.000000	6126.000000	612
mean	0.559582	3.110839	1.225106	0.729350	0.997225	
std	0.496478	2.102272	0.561424	0.444332	0.052610	
min	0.000000	1.000000	0.000000	0.000000	0.000000	
25%	0.000000	2.000000	1.000000	0.000000	1.000000	
50%	1.000000	2.000000	1.000000	1.000000	1.000000	
75%	1.000000	4.000000	1.000000	1.000000	1.000000	
max	1.000000	16.000000	8.000000	1.000000	1.000000	

8 rows × 50 columns

In [39]:
```
scaler = MinMaxScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train_org),columns=X_train_org.c
olumns)
X_test = pd.DataFrame(scaler.transform(X_test_org),columns=X_test_org.columns)

print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(6126, 50) (6126,) (2042, 50) (2042,)
```

In [40]:
```
X_train.describe()
```

Out[40]:

	room_type	accommodates	bathrooms	cleaning_fee	host_has_profile_pic	host_identity
count	6126.000000	6126.000000	6126.000000	6126.000000	6126.000000	612
mean	0.559582	0.140723	0.153138	0.729350	0.997225	
std	0.496478	0.140151	0.070178	0.444332	0.052610	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.066667	0.125000	0.000000	1.000000	
50%	1.000000	0.066667	0.125000	1.000000	1.000000	
75%	1.000000	0.200000	0.125000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 50 columns

Regression Task:

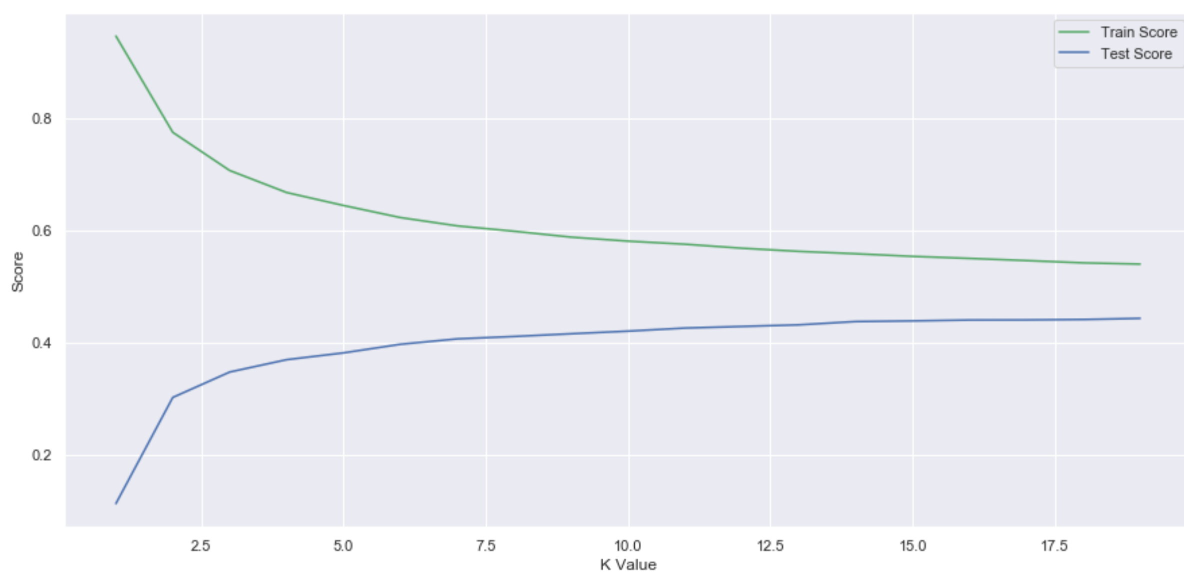
- Apply all the regression models you've learned so far. If your model has a scaling parameter(s) use Grid Search to find the best scaling parameter. Use plots and graphs to help you get a better glimpse of the results.
- Then use cross-validation to find average training and testing score.
- Your submission should have at least the following regression models: KNN regressor, linear regression, Ridge, Lasso, polynomial regression, SVM both simple and with kernels.
- Finally, find the best regressor for this dataset and train your model on the entire dataset using the best parameters and predict the target values for the test_set.

ML models

1. KNN regressor

In [41]:
```
from sklearn.neighbors import KNeighborsRegressor

sns.set(rc={'figure.figsize':(15,7)})

train_score_array = []
test_score_array = []

for k in range(1,20):
    knn_reg = KNeighborsRegressor(k)
    knn_reg.fit(X_train, y_train)
    train_score_array.append(knn_reg.score(X_train, y_train))
    test_score_array.append(knn_reg.score(X_test, y_test))

x_axis = range(1,20)
plt.plot(x_axis, train_score_array, c = 'g', label = 'Train Score')
plt.plot(x_axis, test_score_array, c = 'b', label = 'Test Score')
plt.legend()
plt.xlabel('K Value')
plt.ylabel('Score')
```

Out[41]:
```
Text(0, 0.5, 'Score')
```



In [42]:
```
from sklearn.metrics import mean_squared_error
knn_reg = KNeighborsRegressor(3)
knn_reg.fit(X_train, y_train)
y_pred = knn_reg.predict(X_test)
print('Train score: {:.4f} %'.format(knn_reg.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(knn_reg.score(X_test, y_test)*100))

print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred))))
print('r2_score :', knn_reg.score(X_test,y_test))
```

```
Train score: 70.7158 %
Test score: 34.7600 %
RMSE: 0.5730
r2_score : 0.3475999336885124
```

In [43]:
```
from pprint import pprint
pprint(knn_reg.get_params())
```

```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 3,
 'p': 2,
 'weights': 'uniform'}
```

KNN regressor Gridsearch

In [44]:
```
from sklearn.model_selection import GridSearchCV
param_grid_knn = {
            'n_neighbors' : range(1,25),
            'weights': ['distance','uniform']
            }

CV_knn = GridSearchCV(estimator =knn_reg, param_grid = param_grid_knn ,cv = 10
,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_knn.fit(X_train, y_train)

best_parameters_knn=CV_knn.best_params_
print(best_parameters_knn)
```

```
{'n_neighbors': 19, 'weights': 'uniform'}
```

```
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning
```

Best params for KNN Regressor from GridSearch

In [45]:
```
knn_reg=KNeighborsRegressor(n_neighbors=CV_knn.best_params_.get('n_neighbors'
),weights='uniform')

knn_reg.fit(X_train, y_train)

y_pred_knn=knn_reg.predict(X_test)

print('Train score: {:.4f} %'.format(knn_reg.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(knn_reg.score(X_test, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_knn))))
print('r2_score :', knn_reg.score(X_test,y_test))
knn_reg_S = knn_reg.score(X_test,y_test)
```

```
Train score: 54.0145 %
Test score: 44.3362 %
RMSE: 0.5293
r2_score : 0.4433617832102187
```

It used the r2_score as the goal. and based on what we saw in the correlation matrix, the low test score was predictable.

Cross Validation - KNN Regressor

In [46]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
scores_train = cross_val_score(knn_reg, X_train, y_train,cv=10)
scores_test = cross_val_predict(knn_reg, X_test, y_test,cv=10)
print("Average cross-validation score_train: {:.4f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Average cross-validation score_train: 0.4840
Average cross-validation score_test: 4.79
```

2.linear regression

In [47]:
```
lreg = LinearRegression()
lreg.fit(X_train, y_train)
```

Out[47]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=Fals
e)
```

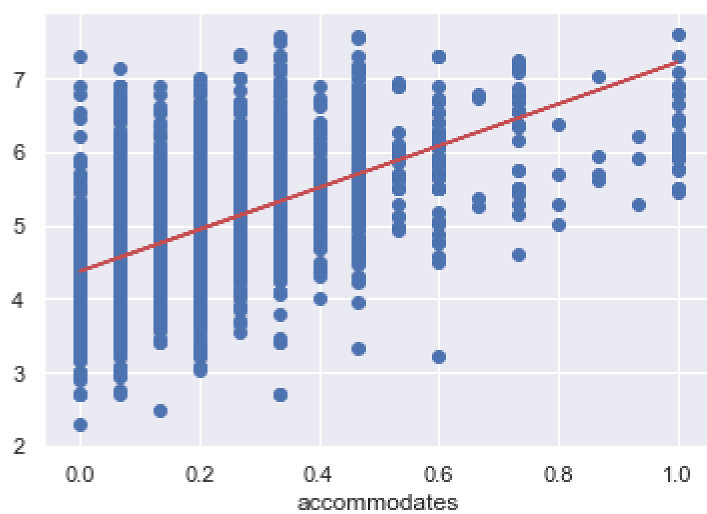
In [48]:
```
from sklearn.metrics import mean_squared_error
pred_linear = lreg.predict(X_test)

print('Train score: {:.4f} %'.format(lreg.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(lreg.score(X_test, y_test)*100))

print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,pred_linear))))
print ("r2_score : ", lreg.score(X_test,y_test))
lreg_S = lreg.score(X_test,y_test)
```

```
Train score: 55.4796 %
Test score: 50.3333 %
RMSE: 0.5000
r2_score :  0.5033334904250996
```

In [49]:
```
%matplotlib inline
import matplotlib.pyplot as plt
# print(X_train)

X_train_ac = X_train.values[:,1].reshape(-1,1)
print(X_train.values[:,1].shape)
print(X_train_ac.shape)
lreg.fit(X_train_ac, y_train)
y_predict = lreg.predict(X_train_ac)

plt.plot(X_train_ac, y_predict, c = 'r')
plt.scatter(X_train_ac,y_train)
plt.xlabel('accommodates')
```

```
(6126,)
(6126, 1)
```

Out[49]: Text(0.5, 0, 'accommodates')



Cross Validation - Linear Regression

In [50]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
lin_reg = LinearRegression()
scores_train = cross_val_score(lin_reg, X_train, y_train,cv=10)
scores_test = cross_val_predict(lin_reg, X_test, y_test,cv=10)
print("Average cross-validation score_train: {:.4f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Average cross-validation score_train: 0.5437
Average cross-validation score_test: 24376671.78
```

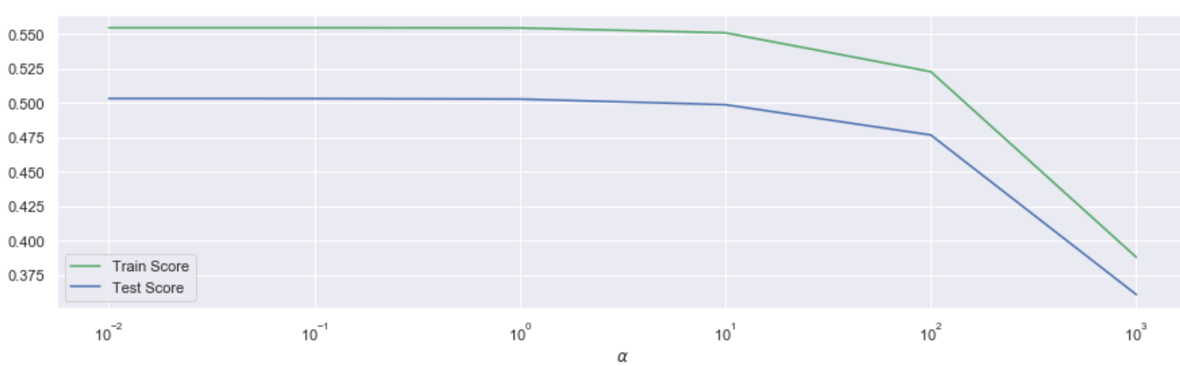
It doesn't have any hyperparameter so there is no need for grid-search

3.Ridge

In [51]:
```
from  sklearn.linear_model import Ridge

x_range = [0.01, 0.1, 1, 10, 100, 1000]
train_score_list = []
test_score_list = []

for alpha in x_range:
    ridge = Ridge(alpha,random_state=0)
    ridge.fit(X_train,y_train)
    train_score_list.append(ridge.score(X_train,y_train))
    test_score_list.append(ridge.score(X_test, y_test))
```

In [52]:
```
%matplotlib inline
import matplotlib.pyplot as plt

sns.set(rc={'figure.figsize':(15,4)})

plt.plot(x_range, train_score_list, c = 'g', label = 'Train Score')
plt.plot(x_range, test_score_list, c = 'b', label = 'Test Score')
plt.xscale('log')
plt.legend(loc = 3)
plt.xlabel(r'$\alpha$')
```

Out[52]:
```
Text(0.5, 0, '$\\alpha$')
```



GridSearch

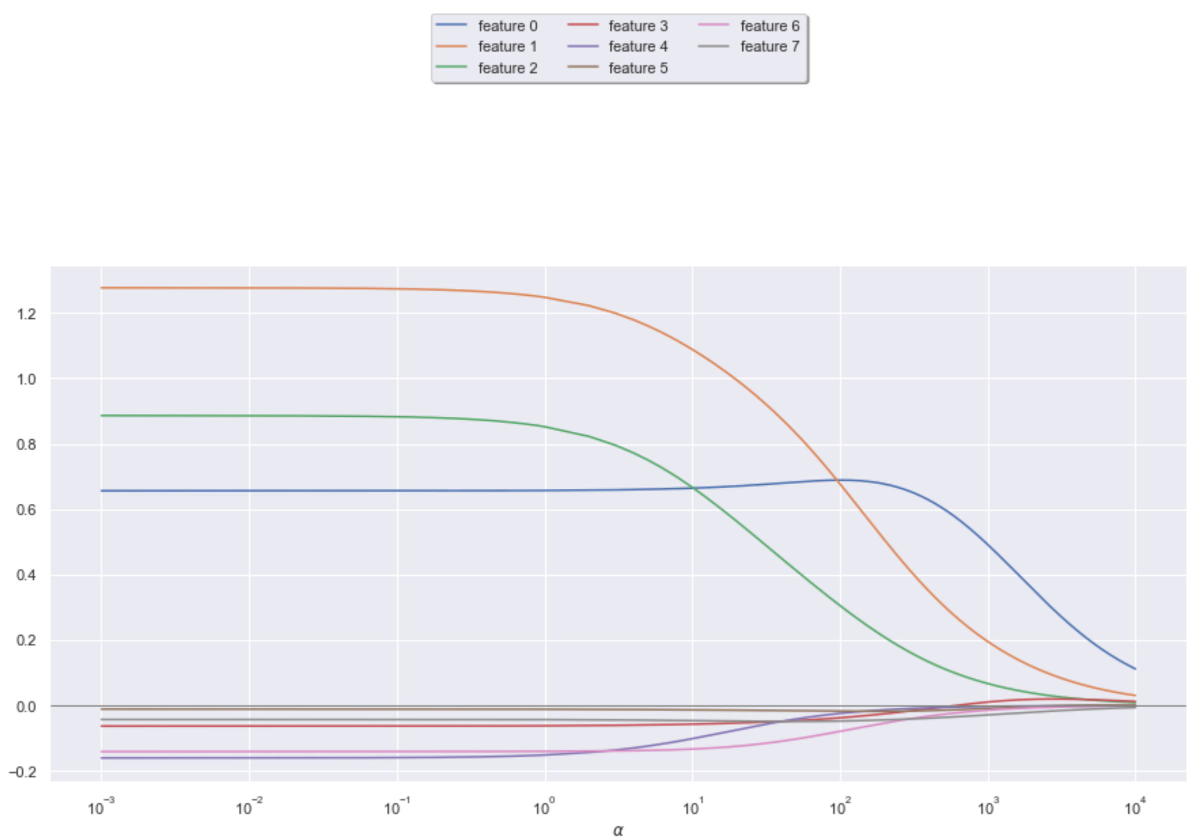
In [53]:
```
from sklearn.model_selection import GridSearchCV
param = {
            'alpha' : [0.01, 0.1, 1, 10, 100, 1000]
            }

CV_ridge = GridSearchCV(estimator =ridge, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_ridge.fit(X_train, y_train)

best_parameters_ridge=CV_ridge.best_params_
print(best_parameters_ridge)
```

```
{'alpha': 1}

C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning
```

Feature selection

I Just show the calculations but I'm not going to use it because it is not the case of over fitting.
Also, we can see the most important features.

In [54]:
```
%matplotlib inline
sns.set(rc={'figure.figsize':(15,7)})

x_range1 = np.linspace(0.001, 1, 100).reshape(-1,1)
x_range2 = np.linspace(1, 10000, 10000).reshape(-1,1)

x_range = np.append(x_range1, x_range2)
coeff = []

for alpha in x_range:
    ridge = Ridge(alpha,random_state=0)
    ridge.fit(X_train,y_train)
    coeff.append(ridge.coef_ )

coeff = np.array(coeff)

for i in range(0,8):
    plt.plot(x_range, coeff[:,i], label = 'feature {:d}'.format(i))

plt.axhline(y=0, xmin=0.001, xmax=9999, linewidth=1, c ='gray')
plt.xlabel(r'$\alpha$')
plt.xscale('log')
plt.legend(loc='upper center', bbox_to_anchor=(0.5, 1.5),
          ncol=3, fancybox=True, shadow=True)
plt.show()
```



the best model

In [55]:
```
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score, cross_val_predict
ridge1 = Ridge(alpha =CV_ridge.best_params_.get('alpha'),random_state=0)
ridge1.fit(X_train, y_train)

pred_ridge1 = ridge1.predict(X_test)

print('Train score: {:.4f} %'.format(ridge1.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(ridge1.score(X_test, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,pred_ridge1))))
print ("r2_score : ", ridge1.score(X_test,y_test))
ridge1_S=ridge1.score(X_test,y_test)
```

```
Train score: 55.4644 %
Test score: 50.2905 %
RMSE: 0.5002
r2_score :  0.5029048723304245
```

CV

In [56]:
```
scores_train = cross_val_score(ridge1, X_train, y_train, cv= 10)
scores_test = cross_val_score(ridge1, X_test, y_test, cv= 10)
print("Cross-validation scores_train: {}".format(scores_train))
print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score_train: {:.4f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

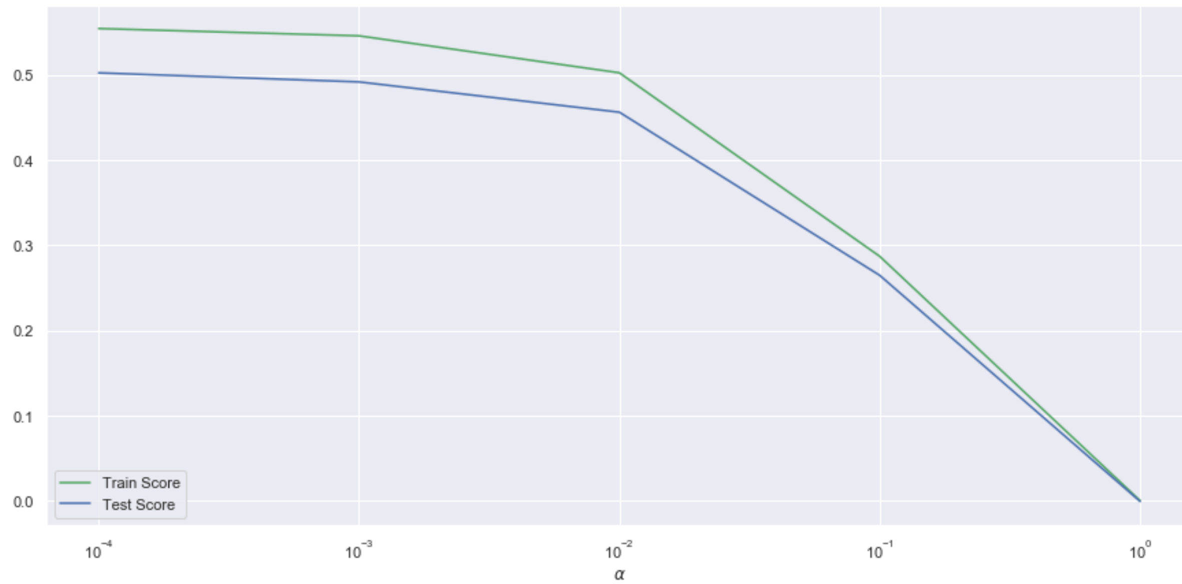
```
Cross-validation scores_train: [0.50048185 0.53937199 0.53170925 0.5775199
0.49534686 0.57320083
 0.59026799 0.5799406  0.49458718 0.56134208]
Cross-validation scores_test: [0.4848092  0.43080499 0.57967649 0.4153975  0.
53084906 0.43497602
 0.4524962  0.49345449 0.53020717 0.55224088]
Average cross-validation score_train: 0.5444
Average cross-validation score_test: 0.49
```

4.Lasso

In [57]:
```
from sklearn.linear_model import Lasso
x_range = [0.0001,0.001,0.01, 0.1, 1]
train_score_list = []
test_score_list = []

for alpha in x_range:
    lasso = Lasso(alpha,random_state=0)
    lasso.fit(X_train,y_train)
    train_score_list.append(lasso.score(X_train,y_train))
    test_score_list.append(lasso.score(X_test, y_test))
```

In [58]:
```
plt.plot(x_range, train_score_list, c = 'g', label = 'Train Score')
plt.plot(x_range, test_score_list, c = 'b', label = 'Test Score')
plt.xscale('log')
plt.legend(loc = 3)
plt.xlabel(r'$\alpha$')
```

Out[58]:
```
Text(0.5, 0, '$\\alpha$')
```



GridSearch

In [59]:
```
param = {
            'alpha' : [0.0001,0.001,0.01, 0.1, 1, 10, 100]
            }

CV_lasso = GridSearchCV(estimator =lasso, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_lasso.fit(X_train, y_train)

best_parameters_lasso=CV_lasso.best_params_
print(best_parameters_lasso)
```

```
{'alpha': 0.0001}

C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning
```

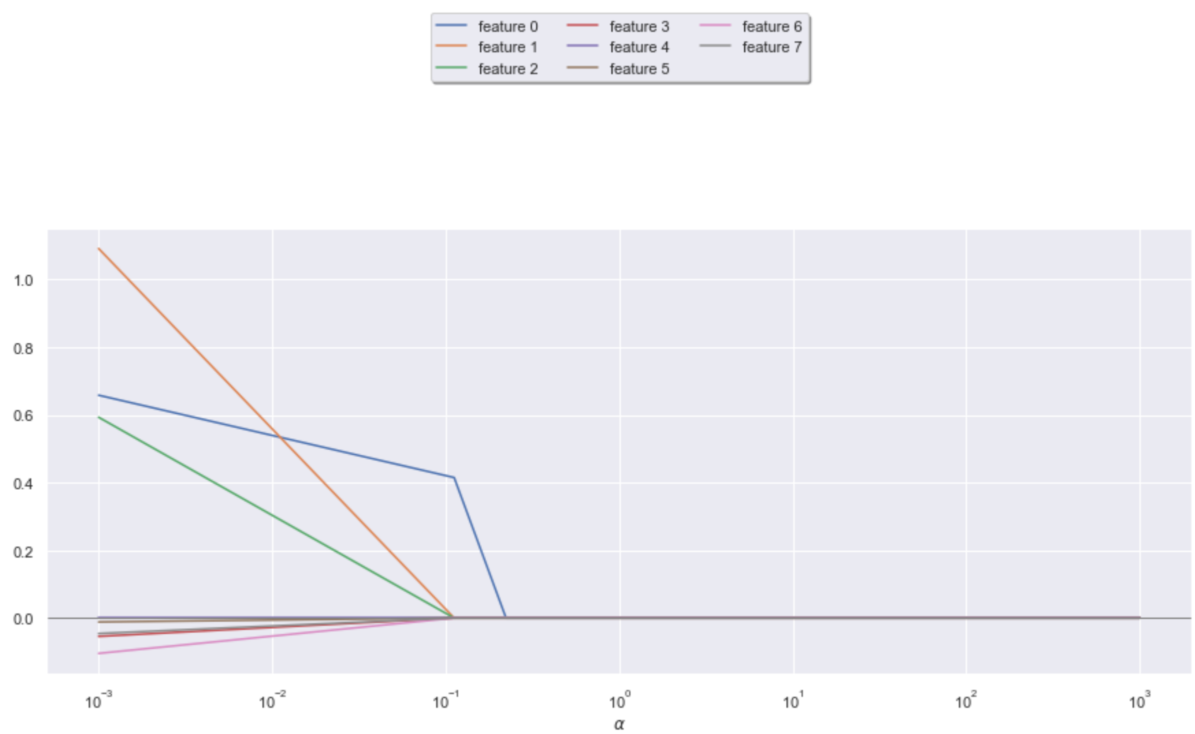
the best model

In [60]:

```
lasso = Lasso(alpha = CV_lasso.best_params_.get('alpha'),random_state=0)
lasso.fit(X_train,y_train)

y_pred_lasso=lasso.predict(X_test)

print('Train score: {:.4f} %'.format(lasso.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(lasso.score(X_test, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_lasso))))
print('r2_score :', lasso.score(X_test,y_test))
lasso_S = lasso.score(X_test,y_test)
```

```
Train score: 55.4394 %
Test score: 50.2367 %
RMSE: 0.5005
r2_score : 0.502367367163491
```

In [61]:
```
%matplotlib inline
sns.set(rc={'figure.figsize':(15,6)})


x_range1 = np.linspace(0.001, 1, 10).reshape(-1,1)
x_range2 = np.linspace(1, 1000, 1000).reshape(-1,1)

x_range = np.append(x_range1, x_range2)
coeff = []

for alpha in x_range:
    lasso = Lasso(alpha,random_state=0)
    lasso.fit(X_train,y_train)
    coeff.append(lasso.coef_ )

coeff = np.array(coeff)

for i in range(0,8):
    plt.plot(x_range, coeff[:,i], label = 'feature {:d}'.format(i))

plt.axhline(y=0, xmin=0.001, xmax=9999, linewidth=1, c ='gray')
plt.xlabel(r'$\alpha$')
plt.xscale('log')
plt.legend(loc='upper center', bbox_to_anchor=(0.5, 1.5),
          ncol=3, fancybox=True, shadow=True)
plt.show()
```



Cross validation -Lasso

In [62]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict

scores_train = cross_val_score(lasso, X_train, y_train,cv=10)
scores_test = cross_val_predict(lasso, X_train, y_train,cv=10)

print("Cross-validation scores_train: {}".format(scores_train))
print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score: {:.4f}".format(scores_train.mean()))
print("Average cross-validation score: {:.2f}".format(scores_test.mean()))
```

```
Cross-validation scores_train: [-3.56007956e-04 -1.76021488e-03 -3.58072349e-
05 -1.11279816e-03
 -7.47058877e-06 -3.32974793e-03 -4.34965549e-04 -3.37734676e-03
 -2.24985125e-05 -2.52893802e-03]
Cross-validation scores_test: [4.7784229 4.7784229 4.7784229 ... 4.7807906 4.
7807906 4.7807906]
Average cross-validation score: -0.0013
Average cross-validation score: 4.78
```

SGD Regressor

In [63]:
```
from sklearn.linear_model import SGDRegressor

sgd_reg = SGDRegressor(random_state= 0, max_iter = 100000, learning_rate = 'op
timal', penalty = 'l2')
sgd_reg.fit(X_train, y_train)
print(sgd_reg.score(X_train, y_train))
print(sgd_reg.score(X_test, y_test))
```

```
-875837439233870.1
-760066675127372.1
```

GridSearch

In [64]:
```
param = {
            'max_iter' : [0.0001,0.001,0.01, 0.1, 1, 10, 100,1000,10000,100000
]
            }

CV_sgd_reg = GridSearchCV(estimator =sgd_reg, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_sgd_reg.fit(X_train, y_train)

best_parameters_sgd_reg=CV_sgd_reg.best_params_
print(best_parameters_sgd_reg)
```

```
{'max_iter': 0.0001}

C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning
```

In [65]:
```
sgd_reg = SGDRegressor(random_state= 0, max_iter = 0.0001, learning_rate = 'op
timal', penalty = 'l2')
sgd_reg.fit(X_train, y_train)

print('Train score: {:.4f} %'.format(lasso.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(lasso.score(X_test, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_lasso))))
print('r2_score :', lasso.score(X_test,y_test))
```

```
Train score: 0.0000 %
Test score: -0.0921 %
RMSE: 0.5005
r2_score : -0.0009214558309931231
```

5.Polynomial regression

In [66]:
```
from sklearn.preprocessing import PolynomialFeatures
train_score_list = []
test_score_list = []
poly = PolynomialFeatures(2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
lreg.fit(X_train_poly, y_train)
y_pred_poly=lreg.predict(X_test_poly)
print('r2_score :', lreg.score(X_test_poly,y_test))
```

```
r2_score : -3.692451576238759e+19
```

visual search for best degree

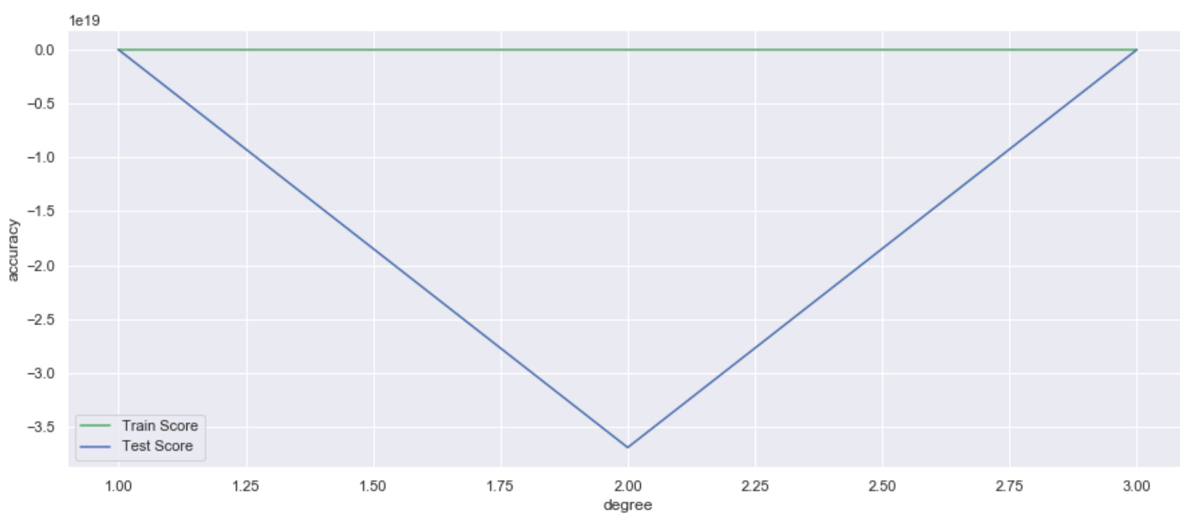
In [67]:
```
train_score_list = []
test_score_list = []

for n in range(1,4):
    poly = PolynomialFeatures(n)
    X_train_poly = poly.fit_transform(X_train)
    X_test_poly = poly.transform(X_test)
    lreg.fit(X_train_poly, y_train)
    train_score_list.append(lreg.score(X_train_poly, y_train))
    test_score_list.append(lreg.score(X_test_poly, y_test))
```

In [68]:
```
print(train_score_list)
print(test_score_list)
```

```
[0.5547858227609721, 0.6317555395761426, 0.7414740902517392]
[0.5033454447466288, -3.692451576238759e+19, -24911983615.244186]
```

In [69]:
```
%matplotlib inline
sns.set(rc={'figure.figsize':(15,6)})


x_axis = range(1,4)
plt.plot(x_axis, train_score_list, c = 'g', label = 'Train Score')
plt.plot(x_axis, test_score_list, c = 'b', label = 'Test Score')
plt.xlabel('degree')
plt.ylabel('accuracy')
plt.legend()
```

Out[69]: <matplotlib.legend.Legend at 0x1d4beb54748>



best poly model

In [70]:
```
poly = PolynomialFeatures(3)
lreg = LinearRegression()
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
lreg.fit(X_train_poly, y_train)

y_pred_poly=lreg.predict(X_test_poly)

print('Train score: {:.4f} %'.format(lreg.score(X_train_poly, y_train)*100))
print('Test score: {:.4f} %'.format(lreg.score(X_test_poly, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_poly))))
print('r2_score :', lreg.score(X_test_poly,y_test))
poly_S = 'negative'
```

```
Train score: 74.1474 %
Test score: -2491198361524.4185 %
RMSE: 111972.8644
r2_score : -24911983615.244186
```

Cross validation poly

In [71]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict

scores_train = cross_val_score(lreg, X_train_poly, y_train,cv=10)
scores_test = cross_val_predict(lreg, X_train_poly, y_train,cv=10)

print("Cross-validation scores_train: {}".format(scores_train))
print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score: {:.4f}".format(scores_train.mean()))
print("Average cross-validation score: {:.2f}".format(scores_test.mean()))
```

```
Cross-validation scores_train: [-3.61363719e+10 -3.74963529e+11 -1.85854507e+
12 -2.23917536e+12
 -1.31305240e+12 -4.34867723e+13 -1.26135644e+17 -4.63816327e+11
 -2.19205497e+19 -2.42869240e+12]
Cross-validation scores_test: [3.77614286e+00 4.09971825e+00 6.03983981e+00
... 1.54287638e+06
 3.88514445e+00 5.61546401e+00]
Average cross-validation score: -2204673751078980096.0000
Average cross-validation score: -3527429.43
```

6. SVMs

Simple SVM

I know the max iteration is not a hyperparamiter for models but I what to see the effect, and with the low max_iter python will give the warning.

In [72]:
```
from sklearn.svm import LinearSVR, SVR

sns.set(rc={'figure.figsize':(15,6)})
linear_svm = LinearSVR(random_state=0)

linear_svm.fit(X_train, y_train)
y_pred=linear_svm.predict(X_test)

train_score_array = []
test_score_array = []

for n in range(1,10):
    linear_svm = LinearSVR(max_iter=n)
    linear_svm.fit(X_train, y_train)
    train_score_array.append(linear_svm.score(X_train, y_train))
    test_score_array.append(linear_svm.score(X_test, y_pred))

x_axis = range(1,10)
plt.plot(x_axis, train_score_array, c = 'g', label = 'Train Score')
plt.plot(x_axis, test_score_array, c = 'b', label = 'Test Score')
plt.legend()
plt.xlabel('Max Iterations')
plt.ylabel('Score')
```

```
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
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  "the number of iterations.", ConvergenceWarning)
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
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  "the number of iterations.", ConvergenceWarning)
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  "the number of iterations.", ConvergenceWarning)
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  "the number of iterations.", ConvergenceWarning)
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```
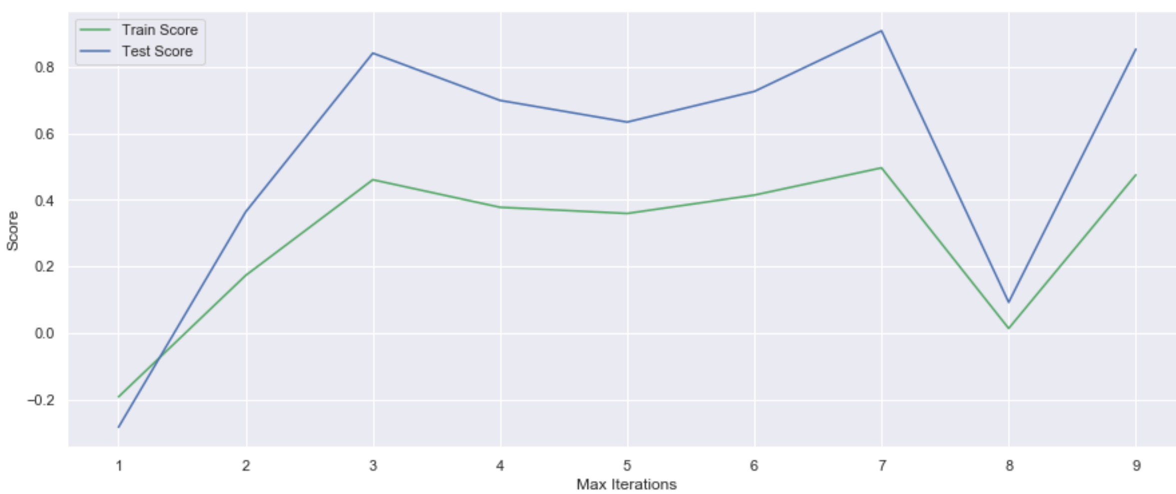

Out[72]: Text(0, 0.5, 'Score')



Grid Search

In [73]:
```
from sklearn import svm
from sklearn.svm import SVR

param = {
            'max_iter':[0.01,0.1,1,10,100,1000,10000,100000]
                }


CV_linear_svm = GridSearchCV(estimator =linear_svm, param_grid = param ,cv = 1
0,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_linear_svm.fit(X_train, y_train)

best_parameters_linear_svm=CV_linear_svm.best_params_
print(best_parameters_linear_svm)
```

```
{'max_iter': 1000}

C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\svm\_base.py:947: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

The best model is:

In [74]:
```
linear_svm = LinearSVR(max_iter=10000,random_state=0)
linear_svm.fit(X_train, y_train)

y_pred_svm=linear_svm.predict(X_test)

print('Train score: {:.4f} %'.format(linear_svm.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(linear_svm.score(X_test, y_test)*100))
print('r2_score :', linear_svm.score(X_test,y_test))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_svm))))
linear_svm_S  = linear_svm.score(X_test,y_test)
```

```
Train score: 54.8847 %
Test score: 49.4550 %
r2_score : 0.49454952737953706
RMSE: 0.5044
```

cross validation -SVM

In [75]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
linear_svr = LinearSVR(max_iter=10000,random_state=0)
scores_train = cross_val_score(linear_svr, X_train, y_train,cv=10)
scores_test = cross_val_predict(linear_svr, X_test, y_test,cv=10)
print("Average cross-validation score_train: {:.2f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Average cross-validation score_train: 0.54
Average cross-validation score_test: 4.77
```

SVR with linear Kernel

In [76]:
```
clf = SVR(kernel='linear', C=1)
clf.fit(X_train,y_train)
y_pred_clf=clf.predict(X_test)
print('Train score: {:.4f} %'.format(clf.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(clf.score(X_test, y_test)*100))
print('r2_score :', clf.score(X_test,y_test))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_clf))))
```

```
Train score: 54.9059 %
Test score: 49.4692 %
r2_score : 0.4946921297164778
RMSE: 0.5043
```

CV for SVR

In [77]:
```
from sklearn import svm
from sklearn.svm import SVR

param = {
            'C':[0.01,1,100], 'kernel' :['linear']
                }


CV_clf = GridSearchCV(estimator =clf, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_clf.fit(X_train, y_train)

best_parameters_clf=CV_clf.best_params_
print(best_parameters_clf)
```

```
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning

{'C': 1, 'kernel': 'linear'}
```

The best model is:

In [78]:
```
clf = SVR(kernel='linear', C=CV_clf.best_params_.get('C'))
clf.fit(X_train, y_train)

y_pred_clf=clf.predict(X_test)

print('Train score: {:.4f} %'.format(clf.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(clf.score(X_test, y_test)*100))
print('r2_score :', clf.score(X_test,y_test))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_clf))))
clf_S =clf.score(X_test,y_test)
```

```
Train score: 54.9059 %
Test score: 49.4692 %
r2_score : 0.4946921297164778
RMSE: 0.5043
```

cross validation -SVM

In [79]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
clf = SVR(kernel='linear', C=10)
scores_train = cross_val_score(clf, X_train, y_train,cv=10)
scores_test = cross_val_predict(clf, X_test, y_test,cv=10)
# print("Cross-validation scores_train: {}".format(scores_train))
# print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score_train: {:.2f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Average cross-validation score_train: 0.54
Average cross-validation score_test: 4.77
```

SVR with Poly Kernel

In [80]:
```
clf_poly = SVR(kernel='poly',degree = 1, C = 1, gamma = 'auto')
clf_poly.fit(X_train,y_train)
clf_poly.score(X_train,y_train)
```

Out[80]:
```
0.537576515760964
```

Grid Search

In [81]:
```
param = {
            'C':[0.1,1, 10], 'degree': [1,2,3], 'kernel' :['poly']
                }
CV_clf_poly = GridSearchCV(estimator =clf_poly, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_clf_poly.fit(X_train, y_train)

best_parameters_clf_poly=CV_clf_poly.best_params_
print(best_parameters_clf_poly)
```

```
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning

{'C': 10, 'degree': 2, 'kernel': 'poly'}
```

Best model will be:

In [82]:
```
clf_poly = SVR(kernel='poly',degree = CV_clf_poly.best_params_.get('degree'),
               C = CV_clf_poly.best_params_.get('C'),gamma='auto')
clf_poly.fit(X_train, y_train)

y_pred_clf_poly=clf_poly.predict(X_test)

print('Train score: {:.4f} %'.format(clf_poly.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(clf_poly.score(X_test, y_test)*100))
print('r2_score :', clf_poly.score(X_test,y_test))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_clf_poly
))))
clf_poly_S = clf_poly.score(X_test,y_test)
```

```
Train score: 56.8345 %
Test score: 51.0000 %
r2_score : 0.5100003641673975
RMSE: 0.4966
```

cross validation -SVM

In [83]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict

scores_train = cross_val_score(clf_poly, X_train, y_train,cv=10)
scores_test = cross_val_predict(clf_poly, X_test, y_test,cv=10)
# print("Cross-validation scores_train: {}".format(scores_train))
# print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score_train: {:.2f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Average cross-validation score_train: 0.55
Average cross-validation score_test: 4.77
```

SVR with rbf Kernel

In [84]:
```
clf_SVR = SVR(kernel='rbf', C=1, gamma = 0.1)
clf_SVR.fit(X_train,y_train)
clf_SVR.score(X_train,y_train)
```

Out[84]:
```
0.593986226372378
```

Grid Search

In [85]:
```
param = {
            'C':[0.1,1, 100], 'gamma': [0.001, 0.01,1,10], 'kernel' :['rbf']
                }
CV_clf_SVR = GridSearchCV(estimator =clf_SVR, param_grid = param ,cv = 10,
                      iid= False, return_train_score = True, n_jobs = -1)
CV_clf_SVR.fit(X_train, y_train)

best_parameters_clf_SVR=CV_clf_SVR.best_params_
print(best_parameters_clf_SVR)
```

```
C:\Users\mahdi\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:823: FutureWarning: The parameter 'iid' is deprecated in 0.22 and will be r
emoved in 0.24.
  "removed in 0.24.", FutureWarning

{'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
```

Best model will be:

In [86]:
```
clf_SVR = SVR(kernel='rbf', C=CV_clf_SVR.best_params_.get('C'), gamma = CV_clf
_SVR.best_params_.get('gamma'))
clf_SVR.fit(X_train, y_train)

y_pred_clf_SVR=clf_SVR.predict(X_test)

print('Train score: {:.4f} %'.format(clf_SVR.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(clf_SVR.score(X_test, y_test)*100))
print('r2_score :', clf_SVR.score(X_test,y_test))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_clf_SVR
))))
clf_SVR_S = clf_SVR.score(X_test,y_test)
```

```
Train score: 59.2149 %
Test score: 51.9203 %
r2_score : 0.5192027736391902
RMSE: 0.4919
```

cross validation -SVM

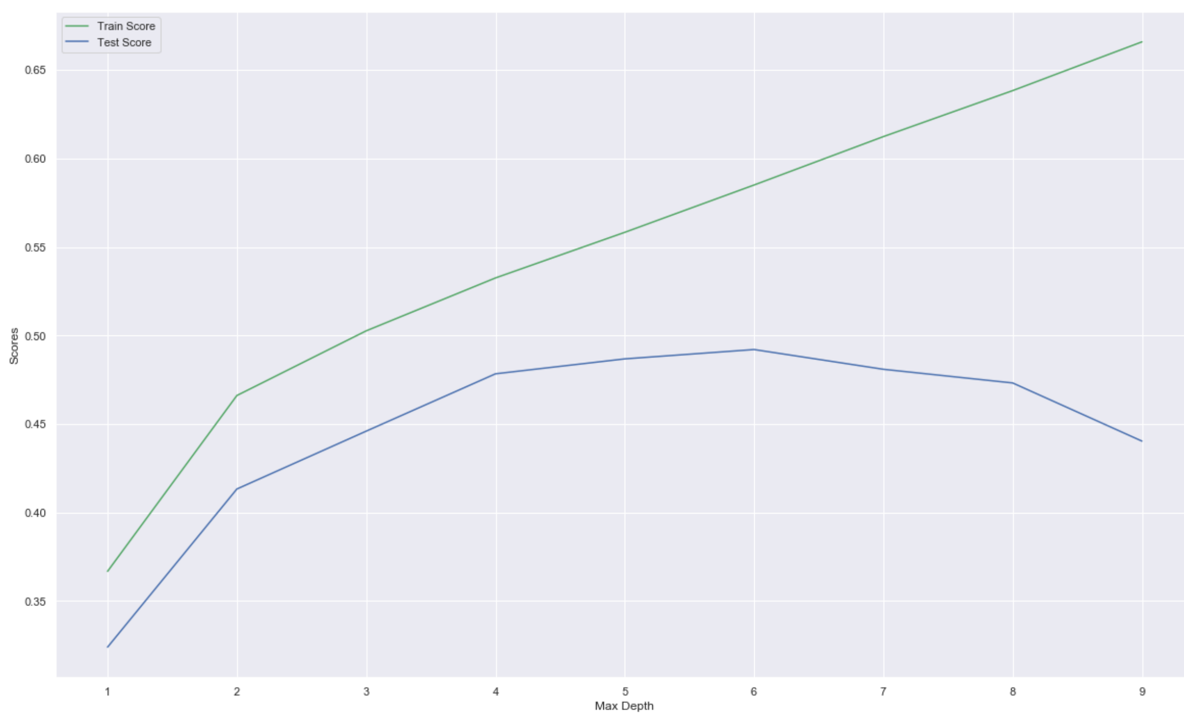
In [87]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict

scores_train = cross_val_score(clf_SVR, X_train, y_train,cv=10)
scores_test = cross_val_predict(clf_SVR, X_test, y_test,cv=10)
print("Cross-validation scores_train: {}".format(scores_train))
print("Cross-validation scores_test: {}".format(scores_test))
print("Average cross-validation score_train: {:.2f}".format(scores_train.mean
()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
```

```
Cross-validation scores_train: [0.50370951 0.55022731 0.57133536 0.58934654
0.5159808  0.58253428
 0.60785101 0.5935815  0.50450988 0.5734037 ]
Cross-validation scores_test: [4.33708253 5.36045905 5.05834637 ... 4.4496842
5 4.30629455 3.92199847]
Average cross-validation score_train: 0.56
Average cross-validation score_test: 4.78
```

7. Decision Tree

In [88]:
```
from sklearn.tree import DecisionTreeRegressor

sns.set(rc={'figure.figsize':(20,12)})


train_score_array = []
test_score_array = []

for n in range(1,10):
    tree = DecisionTreeRegressor(max_depth=n,random_state=0)
    tree.fit(X_train, y_train)
    train_score_array.append(tree.score(X_train, y_train))
    test_score_array.append(tree.score(X_test, y_test))

x_axis = range(1,10)
plt.plot(x_axis, train_score_array, c = 'g', label = 'Train Score')
plt.plot(x_axis, test_score_array, c = 'b', label = 'Test Score')
plt.legend()
plt.xlabel('Max Depth')
plt.ylabel('Scores')
```

Out[88]:
```
Text(0, 0.5, 'Scores')
```



In [89]:
```
tree = DecisionTreeRegressor(max_depth=2)
tree.fit(X_train, y_train)

y_pred=tree.predict(X_test)

print('Train score: {:.4f} %'.format(tree.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(tree.score(X_test, y_test)*100))
```

```
Train score: 46.6090 %
Test score: 41.3260 %
```

Grid Search - Decision Tree Regressor

In [90]:
```
from sklearn.model_selection import GridSearchCV
param_grid_tree = {
            'max_depth' : range(1,10),
            'min_samples_leaf' : range(1,10)
            }

CV_tree = GridSearchCV(estimator =tree, param_grid = param_grid_tree , return_
train_score=True, n_jobs = -1, cv=10)
CV_tree.fit(X_train, y_train)

best_parameters_tree=CV_tree.best_params_
print(best_parameters_tree)
```

```
{'max_depth': 7, 'min_samples_leaf': 6}
```

Best params from gridsearch

In [91]:
```
tree = DecisionTreeRegressor(max_depth=CV_tree.best_params_.get('max_depth'),m
in_samples_leaf=CV_tree.best_params_.get('min_samples_leaf'))
tree.fit(X_train, y_train)

y_pred_tree=tree.predict(X_test)

print('Train score: {:.4f} %'.format(tree.score(X_train, y_train)*100))
print('Test score: {:.4f} %'.format(tree.score(X_test, y_test)*100))
print('RMSE: {:.4f}'.format(np.sqrt(mean_squared_error(y_test,y_pred_tree))))
print('r2_score :', tree.score(X_test,y_test))
tree_S = tree.score(X_test,y_test)
```

```
Train score: 60.2775 %
Test score: 48.7681 %
RMSE: 0.5078
r2_score : 0.4876811310558109
```

CV -decision trees

In [92]:
```
from sklearn.model_selection import cross_val_score, cross_val_predict
tree1 = DecisionTreeRegressor(max_depth=4,min_samples_leaf=3)
scores_train = cross_val_score(tree1, X_train, y_train,cv=10)
scores_test = cross_val_predict(tree1, X_test, y_test,cv=10)
print("Cross-validation scores_train: {}".format(scores_train.mean()))
print("Cross-validation scores_test: {}".format(scores_test.mean()))
print("Average cross-validation score_test: {:.2f}".format(scores_test.mean
()))
print("Average cross-validation score_train: {:.4f}".format(scores_train.mean
()))
```

```
Cross-validation scores_train: 0.521538817728638
Cross-validation scores_test: 4.804867752124089
Average cross-validation score_test: 4.80
Average cross-validation score_train: 0.5215
```

The Best Model

In [93]:
```
# initialize list of lists
data = [['KNN',knn_reg_S],
        ['Linear regression',lreg_S],
        ['Ridge',ridge1_S],
        ['Lasso', lasso_S],
        ['Polynomial',poly_S],
        ['Simple linear SVM ',linear_svm_S],
        ['SVM with linear kernel',clf_S],
        ['SVM with poly kernel',clf_poly_S],
        ['SVM with rbf kernel',clf_SVR_S],
        ['decision tree',tree_S]]

# Create the pandas DataFrame
results = pd.DataFrame(data, columns = ['Model', 'r2 score'])

# print dataframe.
results
```

Out[93]:

	Model	r2 score
0	KNN	0.443362
1	Linear regression	0.503333
2	Ridge	0.502905
3	Lasso	0.502367
4	Polynomial	negative
5	Simple linear SVM	0.49455
6	SVM with linear kernel	0.494692
7	SVM with poly kernel	0.51
8	SVM with rbf kernel	0.519203
9	decision tree	0.487681

As we can see comparing the average score schieved by cross validation on our training dataset SVR with rbf kernel has the best score between the models and therefore is the chosen model.After that lasso would be our second model for best prediction.

In [ ]:
```

```