In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from dataprep.eda import create_report
from pandas_profiling import ProfileReport
from sklearn.compose import (
    ColumnTransformer,
    TransformedTargetRegressor,
    make_column_transformer,
)
from sklearn.dummy import DummyRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.impute import SimpleImputer
from sklearn.linear_model import Ridge, RidgeCV
from sklearn.metrics import make_scorer, mean_squared_error, r2_score
from sklearn.model_selection import (
    GridSearchCV,
    cross_val_score,
    cross_validate,
    train_test_split,
)
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler
from sklearn.tree import DecisionTreeRegressor
%matplotlib inline
```

```
Pandas backend loaded 1.4.3
Numpy backend loaded 1.23.2
Pyspark backend NOT loaded
Python backend loaded
C:\Users\Nandakumar\AppData\Local\Temp\ipykernel_18928\3904670446.py:5: Deprecatio
nWarning: `import pandas_profiling` is going to be deprecated by April 1st. Please
use `import ydata_profiling` instead.
  from pandas_profiling import ProfileReport
```

In [7]:
```
import warnings

warnings.simplefilter(action="ignore", category=FutureWarning)
```

In [8]:
```
data=pd.read_csv('query_result.csv')
```

Exploratory Data Analysis

In [4]:
```
profile = ProfileReport(data, title="Report")
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

Overview

Dataset statistics

Number of variables	24
Number of observations	136119
Missing cells	2948
Missing cells (%)	0.1%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	24.9 MiB
Average record size in memory	192.0 B

Variable types

Categorical	6
Numeric	18

Alerts

`ml_num` has a high cardinality: 136119 distinct values	High cardinality
`date_start` has a high cardinality: 686 distinct values	High cardinality
`date_end` has a high cardinality: 366 distinct values	High cardinality

Out[4]:

Key findings:

- columns named **lp_dol** has high correlation with our target variable
- **yr_built** and **garage type** has some missing values which is less than 1% of the total dataset (missing in random category)
- lat and lon does not have direct correlation between the target column (location might not be a huge factor as of now but lets dig deeper while making them a categorical

feature and checking later.)

- We can see that id_community,id_municipality,ml_num are ids we have to cast it as objects so that they dont add in the Modelling part.
- ml_num should not be considered in the future of modelling because it has all distinct values and hence making model more ambiguous.

The date column can be really helpful in upcoming predictions so converted into the right format

In [9]:
```
data['date_start'] = pd.to_datetime(data['date_start'], format='%Y-%m-%d %H:%M:%S')
data['date_end'] = pd.to_datetime(data['date_end'], format='%Y-%m-%d %H:%M:%S')
data['diff_in_dates'] =pd.to_numeric(data['date_end']-  data ['date_start'])
data['id_municipality'] =data['id_municipality'].astype(object)
data['id_community'] =data['id_community'].astype(object)
```

In [10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 136119 entries, 0 to 136118
Data columns (total 25 columns):
 #   Column                   Non-Null Count   Dtype         
---  ------                   --------------   -----         
 0   ml_num                   136119 non-null  object        
 1   property_type            136119 non-null  object        
 2   br                       134949 non-null  float64       
 3   br_plus                  136119 non-null  int64         
 4   br_final                 136119 non-null  float64       
 5   bath_tot                 136119 non-null  int64         
 6   taxes                    136119 non-null  float64       
 7   lp_dol                   136119 non-null  int64         
 8   yr_built                 136117 non-null  object        
 9   gar_type                 134343 non-null  object        
 10  garage                   136119 non-null  float64       
 11  topHighschoolScore       136119 non-null  float64       
 12  topBelowHighschoolScore  136119 non-null  float64       
 13  geo_latitude             136119 non-null  float64       
 14  geo_longitude            136119 non-null  float64       
 15  lot_frontfeet            136119 non-null  float64       
 16  lot_depthfeet            136119 non-null  float64       
 17  lot_size                 136119 non-null  float64       
 18  sqft_numeric             136119 non-null  int64         
 19  id_community             136119 non-null  object        
 20  id_municipality          136119 non-null  object        
 21  date_start               136119 non-null  datetime64[ns]
 22  date_end                 136119 non-null  datetime64[ns]
 23  price_sold               136119 non-null  int64         
 24  diff_in_dates            136119 non-null  int64         
dtypes: datetime64[ns](2), float64(11), int64(6), object(6)
memory usage: 26.0+ MB
```

In [11]:
```
# splitting the data to maintain the golden rule
from sklearn.model_selection import cross_val_score, cross_validate, train_test_spl
train_df,test_df = train_test_split(data,test_size=0.2 ,random_state=123)
train_df.shape
```

Out[11]:
```
(108895, 25)
```

In [12]:
```
#huge variability in the data these are allshould be moslty closely located area ir
data['geo_latitude'].value_counts(normalize=True)
```

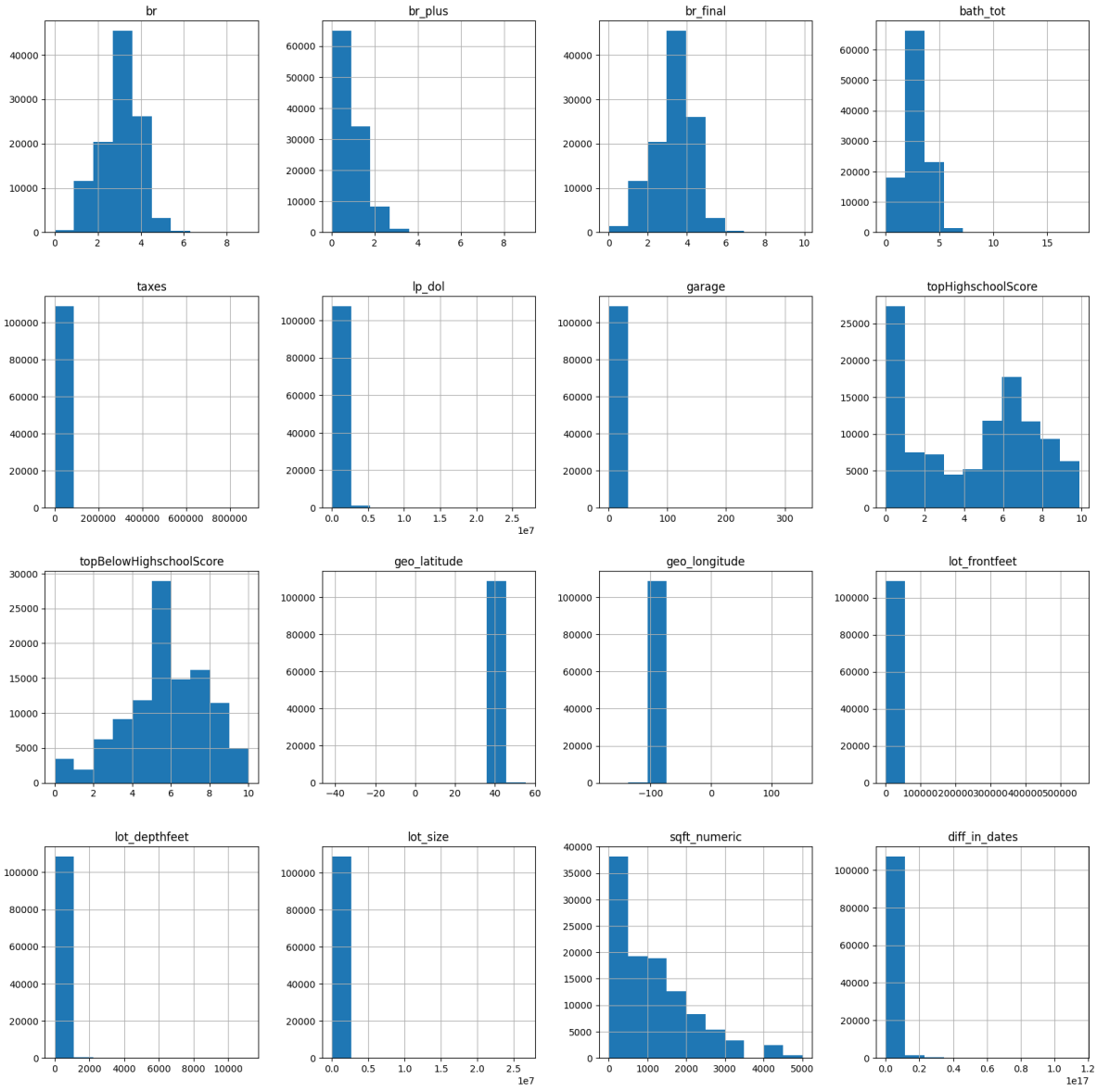
Out[12]:
```
43.777502    0.000984
43.641579    0.000771
43.641596    0.000676
43.659329    0.000669
43.636101    0.000654
               ...
44.403672    0.000007
43.818745    0.000007
43.701665    0.000007
43.396994    0.000007
43.894330    0.000007
Name: geo_latitude, Length: 98896, dtype: float64
```

In [13]:
```
train_df.describe().T
```

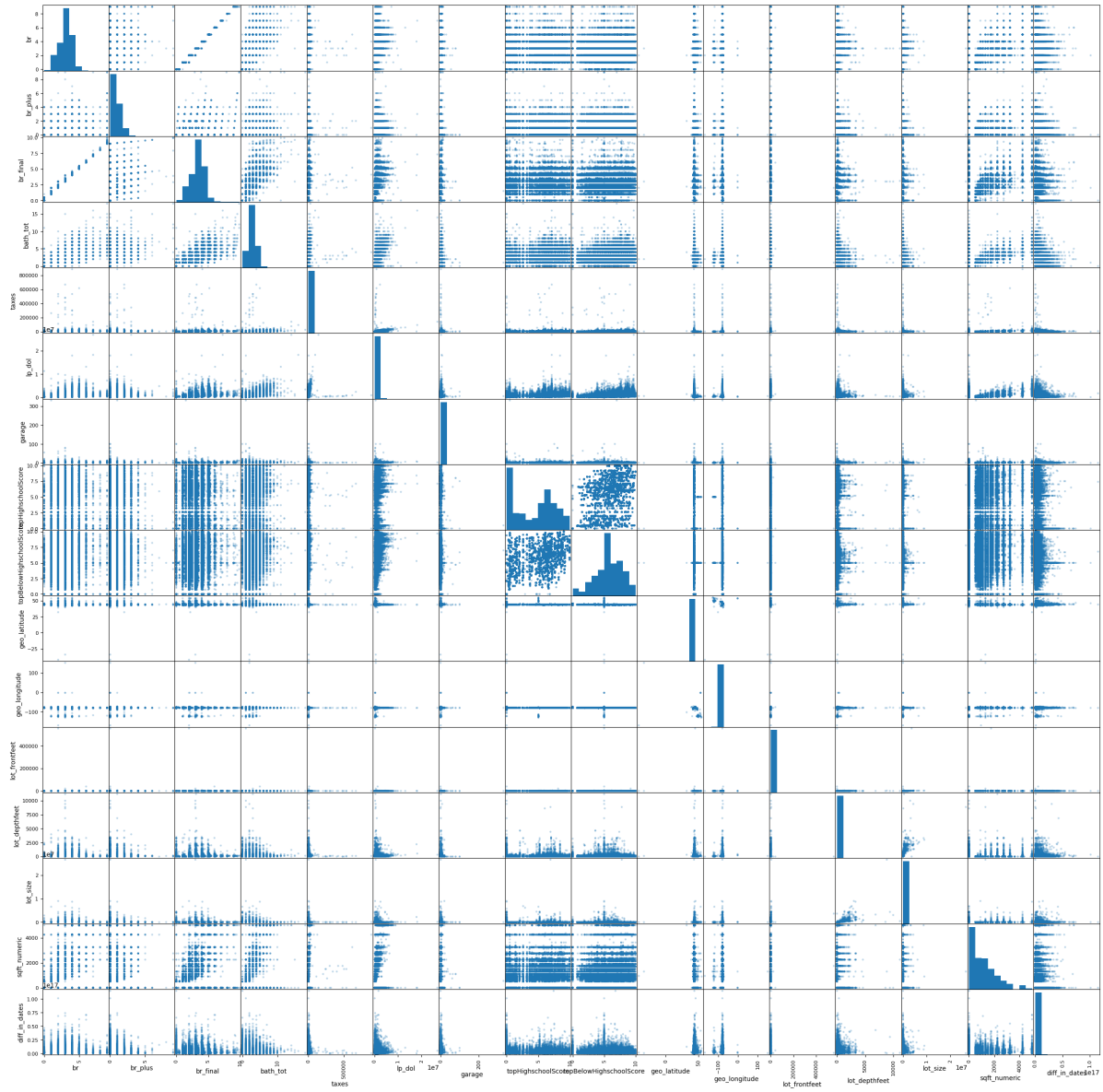
Out[13]:

	count	mean	std	min	25%	
br	107964.0	2.901078e+00	1.048421e+00	0.000000	2.000000e+00	3.0
br_plus	108895.0	5.094816e-01	7.061903e-01	0.000000	0.000000e+00	0.0
br_final	108895.0	2.964327e+00	1.042934e+00	0.000000	2.100000e+00	3.0
bath_tot	108895.0	2.630562e+00	1.207713e+00	0.000000	2.000000e+00	2.0
taxes	108895.0	3.781379e+03	6.478388e+03	0.000000	2.425000e+03	3.3
lp_dol	108895.0	6.735559e+05	5.135342e+05	1.000000	3.890000e+05	5.4
garage	108895.0	1.270563e+00	1.497978e+00	0.000000	1.000000e+00	1.0
topHighschoolScore	108895.0	4.352461e+00	3.189895e+00	0.000000	8.000000e-01	5.2
topBelowHighschoolScore	108895.0	5.651880e+00	2.137176e+00	0.000000	4.400000e+00	5.5
geo_latitude	108895.0	4.379830e+01	5.264347e-01	-41.872312	4.364237e+01	4.3
geo_longitude	108895.0	-7.950593e+01	1.650825e+00	-169.157540	-7.971425e+01	-7.9
lot_frontfeet	108895.0	4.383721e+01	1.688723e+03	0.000000	0.000000e+00	3.0
lot_depthfeet	108895.0	9.012811e+01	1.526978e+02	0.000000	0.000000e+00	1.0
lot_size	108895.0	1.036533e+04	1.357734e+05	0.000000	0.000000e+00	3.0
sqft_numeric	108895.0	1.088336e+03	1.083436e+03	0.000000	0.000000e+00	9.4
price_sold	108895.0	6.889055e+05	5.156448e+05	1.000000	3.899000e+05	5.6
diff_in_dates	108895.0	1.808598e+15	2.964509e+15	0.000000	4.320000e+14	8.6

In [14]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
numeric_data=train_df[['br','br_plus', 'br_final',
                       'bath_tot', 'taxes',
                       'lp_dol', 'garage', 'topHighschoolScore',
                       'topBelowHighschoolScore', 'geo_latitude',
                       'geo_longitude', 'lot_frontfeet', 'lot_depthfeet','lot_size
numeric_data.hist(figsize=(20,20));
```



In [13]:
```
# we can see some correlated and some completely not corelated pattern here.
pd.plotting.scatter_matrix(numeric_data,alpha=.3,figsize=(30,30));
```



In [15]:
```
#getting all the categorical data seperately as they have to be trated diffierently
categorical_df=train_df.select_dtypes(include='object').columns
categorical_df
```

Out[15]:
```
Index(['ml_num', 'property_type', 'yr_built', 'gar_type', 'id_community',
       'id_municipality'],
      dtype='object')
```

In [16]:
```
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler
```

In [17]:
```
# there is one ordinal feature here year built as it has an inherent order to it
list(train_df['yr_built'].unique())
```

Out[17]:
```
['6-15',
 '0',
 '16-30',
 '0-5',
 'New',
 '31-50',
 '11-15',
 '100+',
 '51-99',
 '6-10',
 nan]
```

In [18]:
```
len(train_df['id_community'].unique())+len(train_df['property_type'].unique())+len(
```

Out[18]:
```
1658
```

In [19]:
```
# as we can see below New ,0,0-5,6-15 ... up to 100+ lets create an order to it.
ordinal_feature_ordering =[
     ['New','0','0-5','6-10','6-15','11-15','16-30','31-50','51-99','100+','nan']]
ordinal_features_oth = ['yr_built']
#re-initializing removing year built
categorical_features= ['property_type', 'gar_type', 'id_community',
       'id_municipality']
# as this is id it can be dropped in the preparation step
drop_features = ['ml_num']
numeric_features = ['br','br_plus', 'br_final',
                        'bath_tot', 'taxes',
                        'lp_dol', 'garage', 'topHighschoolScore',
                        'topBelowHighschoolScore', 'geo_latitude',
                        'geo_longitude', 'lot_frontfeet', 'lot_depthfeet','lot_size
# creating pipeline so that the same process is releated in the test and dev as wel
numeric_transformer = make_pipeline(SimpleImputer(strategy="median"), StandardScale
ordinal_transformer_oth = make_pipeline(
    SimpleImputer(strategy="most_frequent"),
    OrdinalEncoder(categories=ordinal_feature_ordering),
)
categorical_transformer = make_pipeline(
    SimpleImputer(strategy="constant", fill_value="missing"),
    OneHotEncoder(handle_unknown="ignore", sparse=False),
)
```

In [20]:
```
X_train = train_df.drop(columns=['price_sold'])
X_test = test_df.drop(columns=['price_sold'])
y_train = train_df['price_sold']
y_test = test_df['price_sold']
```

In [21]:
```
#preprocessor defined to handle all types of data
preprocessor = make_column_transformer(
    ("drop", drop_features),
    (numeric_transformer, numeric_features),
    (ordinal_transformer_oth, ordinal_features_oth),
    (categorical_transformer, categorical_features),
)
```

In [22]:
```
preprocessor
```

Out[22]:
```
ColumnTransformer(transformers=[('drop', 'drop', ['ml_num']),
                                ('pipeline-1',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer(strategy='media
n')),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['br', 'br_plus', 'br_final', 'bath_tot',
                                  'taxes', 'lp_dol', 'garage',
                                  'topHighschoolScore',
                                  'topBelowHighschoolScore', 'geo_latitude',
                                  'geo_longitude', 'lot_frontfeet',
                                  'lot_depthfeet...
                                                  OrdinalEncoder(categories=[['Ne
w',
                                                                              '0',
                                                                              '0-
5',
                                                                              '6-1
0',
                                                                              '6-1
5',
                                                                              '11-
15',
                                                                              '16-
30',
                                                                              '31-
50',
                                                                              '51-
99',
                                                                              '100
+',
                                                                              'na
n']]))]),
                                 ['yr_built']),
                                ('pipeline-3',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer(fill_value='missin
g',
                                                                strategy='constan
t')),
                                                 ('onehotencoder',
                                                  OneHotEncoder(handle_unknown='ig
nore',
                                                                sparse=False))]),
                                 ['property_type', 'gar_type', 'id_community',
                                  'id_municipality'])])
```

In [23]:
```
preprocessor.fit(X_train)  # Calling fit to examine all the transformers.
preprocessor.named_transformers_
```

Out[23]:
```
{'drop': 'drop',
 'pipeline-1': Pipeline(steps=[('simpleimputer', SimpleImputer(strategy='media
n')),
                ('standardscaler', StandardScaler())]),
 'pipeline-2': Pipeline(steps=[('simpleimputer', SimpleImputer(strategy='most_freq
uent')),
                ('ordinalencoder',
                 OrdinalEncoder(categories=[['New', '0', '0-5', '6-10', '6-15',
                                             '11-15', '16-30', '31-50', '51-99',
                                             '100+', 'nan']]))]),
 'pipeline-3': Pipeline(steps=[('simpleimputer',
                 SimpleImputer(fill_value='missing', strategy='constant')),
                ('onehotencoder',
                 OneHotEncoder(handle_unknown='ignore', sparse=False))]),
 'remainder': 'drop'}
```

In [24]:
```
ohe_columns = list(
    preprocessor.named_transformers_["pipeline-3"]
    .named_steps["onehotencoder"]
    .get_feature_names_out(categorical_features)
)
new_columns = (
    numeric_features  + ordinal_features_oth + ohe_columns
)
```

In [25]:
```
X_train_enc = pd.DataFrame(
    preprocessor.transform(X_train), index=X_train.index, columns=new_columns
)
X_train_enc.head()
```

Out[25]:

	br	br_plus	br_final	bath_tot	taxes	lp_dol	garage	topHighschoolS
32534	1.051833	-0.721454	0.993042	1.133916	0.089617	-0.182376	0.486950	-1.36
51293	-0.863941	-0.721454	-0.924633	-0.522115	-0.172718	-0.456751	-0.180620	-1.20
59241	-0.863941	0.694601	-0.445214	0.305901	-0.112186	0.051300	1.822089	0.98
50702	-1.821828	0.694601	-1.404052	-1.350130	-0.210964	-0.591504	-0.180620	0.70
37089	-0.863941	0.694601	-0.828749	-1.350130	-0.027998	-0.454998	-0.180620	-0.11

5 rows × 1675 columns

In [26]:
```
X_train.shape , X_train_enc.shape
# there is jump of 1651 features
```

Out[26]:
```
((108895, 24), (108895, 1675))
```

Model Building

1. Three machine learning models such as,
   - Regression based on k-nearest neighbors.
   - Ridge: Linear least squares with l2 regularization.
   - Random Forest Regressor: To improve score and avoid over-fitting.

In [30]:
```
from sklearn.linear_model import Ridge
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
models = {
    "KNN_reg": KNeighborsRegressor(),
    "Ridge": Ridge(),
    "RandomForest" : RandomForestRegressor()
}
score_types_reg = {
    "neg_mean_squared_error": "neg_mean_squared_error",
    "neg_root_mean_squared_error": "neg_root_mean_squared_error",
    "neg_mape": "neg_mean_absolute_percentage_error",
    "r2": "r2",
}
```

In [32]:
```
cross_val_results={}
for i in models:
    print(models[i])
    pipe=make_pipeline(preprocessor,models[i])
    cross_val_results[i] = pd.DataFrame(
        cross_validate(pipe, X_train, y_train,cv=2,return_train_score=True,
       scoring=score_types_reg)).agg(['mean','std']).round(3).T
pd.concat(
    cross_val_results,
    axis='columns'
).xs(
    'mean',
    axis='columns',
    level=1
).style.format(
    precision=2
).background_gradient(
    axis=None
)
```

```
KNeighborsRegressor()
Ridge()
RandomForestRegressor()
```

Out[32]:

	KNN_reg	Ridge	regr
fit_time	1.60	3.00	432.32
score_time	178.39	0.97	3.75
test_neg_mean_squared_error	-27204765429.02	-11801765631.02	-18768213966.71
train_neg_mean_squared_error	-17184316405.79	-10783325768.32	-937074347.40
test_neg_root_mean_squared_error	-163381.65	-103990.29	-136862.86
train_neg_root_mean_squared_error	-129525.85	-97981.02	-29882.99
test_neg_mape	-6.18	-6.81	-156.94
train_neg_mape	-6.90	-7.43	-2.89
test_r2	0.90	0.96	0.93
train_r2	0.94	0.96	1.00

- Random Forest regressor is Overfitting. Ridge regressor is working well for house prediction usecase based on Test_r2 (r squared)

Hyperparameter Tuning using Random Search Cross validation.

In [28]:
```
from scipy.stats import loguniform
from sklearn.model_selection import RandomizedSearchCV
param_dist = {"ridge__alpha": 10.0 ** np.arange(-5, 5, 1)}
pipe = make_pipeline(preprocessor, Ridge())
search = RandomizedSearchCV(pipe, param_dist, return_train_score=True,cv = 5, n_jo
search.fit(X_train,y_train)
best_parameter = search.best_params_
best_parameter
```

Out[28]:
```
{'ridge__alpha': 100.0}
```

In [39]:
```
# Top 10 Important features
coef=pd.DataFrame(best_model.named_steps.ridge.coef_,X_train_enc.columns,columns=[
coef = coef.sort_values('importance',ascending=False).iloc[:10,:]
coef.style.format(
    precision=2
).background_gradient(
    axis=None
)
```

Out[39]:

	importance
lp_dol	468780.70
id_community_111	141065.02
id_municipality_10343	91293.35
id_community_705	89905.37
id_municipality_10234	79553.05
id_community_22	64720.36
id_community_42	61880.76
property_type_V.	60739.83
id_municipality_10280	52383.73
id_community_45	50727.03

Evaluating best model (Ridge with best parameter) using test dataset

In [31]:
```
best_model=search.best_estimator_
best_model.score(X_test,y_test)
```

Out[31]:
```
0.8129602321005545
```

- Model is achieving **81.3% R-squared value**. Which is a really good fit model for house price prediction data.

In [53]:
```
import pickle
pickle.dump(best_model, open('Random_forest_regressor_model.pkl','wb'))
```

Inference Pipeline: Predict house price prediction for new input

In [56]:
```
# data=pd.read_csv('query_result.csv')
input_house_data = data.iloc[0,:]
new = pd.DataFrame(input_house_data).T
new['date_start'] = pd.to_datetime(new['date_start'], format='%Y-%m-%d %H:%M:%S')
new['date_end'] = pd.to_datetime(new['date_end'], format='%Y-%m-%d %H:%M:%S')
new['diff_in_dates'] =pd.to_numeric(new['date_end']-  new ['date_start'])
new['id_municipality'] =new['id_municipality'].astype(object)
new['id_community'] = new['id_community'].astype(object)
new = new.drop(columns=['price_sold'])
```

In [55]:
```
#predicted value for new input
model=pickle.load(open("Random_forest_regressor_model.pkl", "rb"))
print(model.predict(new))
```

```
[401622.83103571]
```

In [57]:
```
#Actual value for the new input
input_house_data['price_sold']
```

Out[57]:
```
406400
```

Model is able to predict the house price prediction using Ridge Regressor

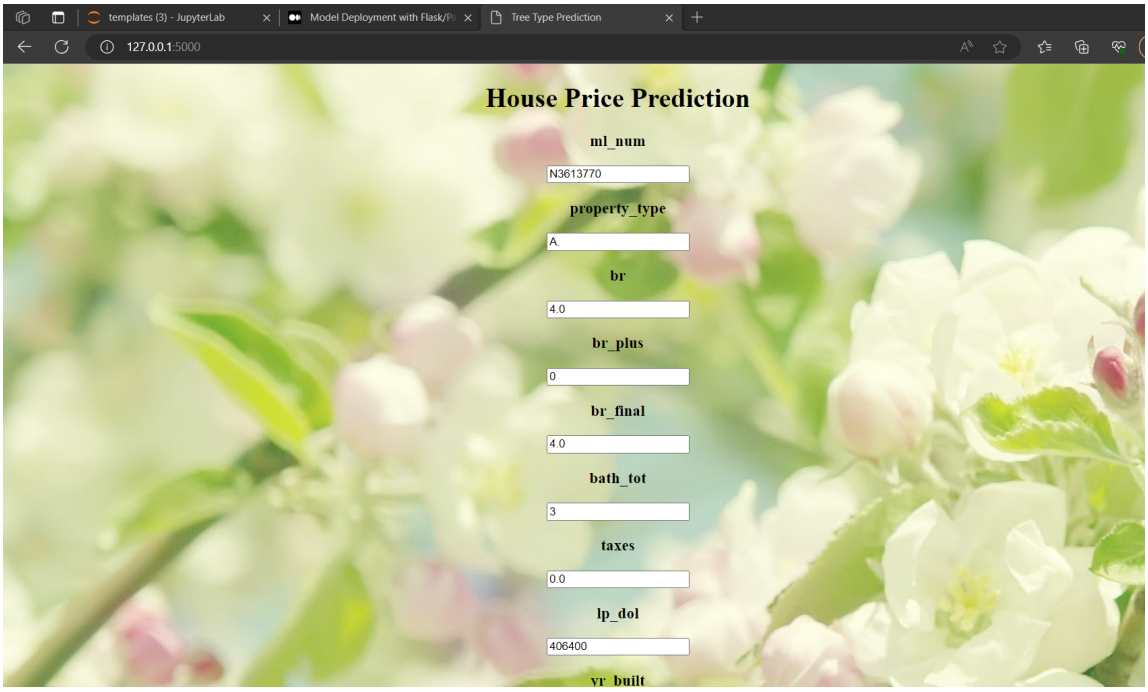
Model deployment in Flast API

1. **app.py**: This is the main file for receiving required information for house price prediction through GUI or API calls and computing the predicted house price and returning it.
2. **index.html** Template folder: This folder contains an HTML template for user input, based on which the model will make house price predictions.
3. **requirements.txt**: This file provides packages to install for your web app to run.

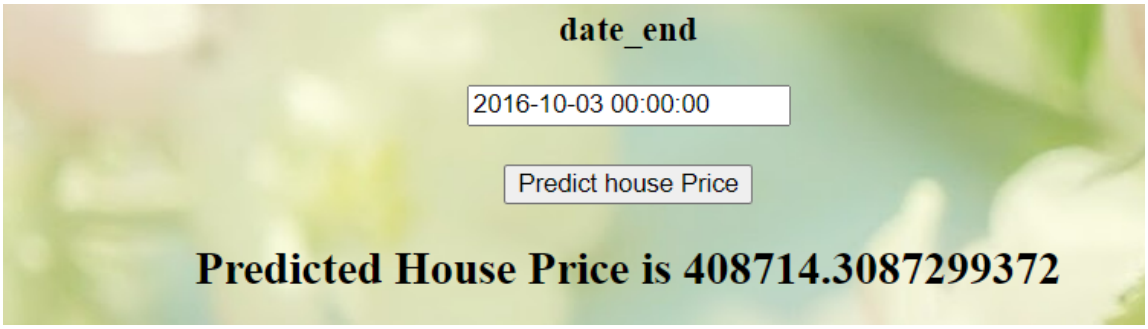
How to Run the model API

1. run the following code in command line. `python app.py`
2. Open the following link in the browser. `127.0.0.1:5000`
3. Provide the Input data for house price prediction and click on **predict house price** button.
4. The button will direct to the following link `127.0.0.1:5000/predict`
5. Predict page will provide the predicted house price at the bottom of the page.

SNIPPETS OF THE MODEL AS API IS SHOWN BELOW


templates (3) - JupyterLab
Model Deployment with Flask/Pa
Tree Type Prediction
127.0.0.1:5000
House Price Prediction
ml_num
N3613770
property_type
A
br
4.0
br_plus
0
br_final
4.0
bath_tot
3
taxes
0.0
lp_dol
406400
yr_built


Model Deployment with Flask/Pa
Tree Type Prediction
-79.857459
lot_frontfeet
30.02
lot_depthfeet
117.29
sqft_numeric
1750
id_community
232
id_municipality
10103
lot_size
3521.0458
date_start
2016-09-25 00:00:00
date_end
2016-10-03 00:00:00
Predict house Price


date_end
2016-10-03 00:00:00
Predict house Price
Predicted House Price is 408714.3087299372