Mini project

A regression problem of predicting `reviews_per_month`, as a proxy for the popularity of the listing with New York City Airbnb listings from 2019 dataset.

1. Understand the dataset

Tasks:

1. Understanding the problem and what each feature means.
2. Download the dataset and read it as a pandas dataframe.
3. Carry out any preliminary preprocessing, if needed.

I will start by doing EDA on the dataset and set up a column transformer to preprocess the data, then I will split the data into train and test datasets, and calculate cross validation scores for the potential models on the train set. Lastly, I will report scores with the models and choose the model based on CV scores and scoring metrics.

In [1]:

```
import pandas as pd
import numpy as np
import altair_ally as aly
import altair as alt
import warnings
from sklearn.model_selection import (
    train_test_split,
    cross_val_score,
    cross_validate)
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import (
    OneHotEncoder,
    OrdinalEncoder,
    StandardScaler)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.dummy import DummyRegressor
from sklearn.linear_model import (
    LinearRegression,
    LogisticRegression,
    Ridge,
    RidgeCV,
    LassoCV)
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import (
    RandomForestRegressor,
    GradientBoostingRegressor)
from scipy.stats import loguniform, randint
from sklearn.model_selection import RandomizedSearchCV
```

```python
import shap


warnings.filterwarnings('ignore', category=FutureWarning)
aly.alt.data_transformers.enable('vegafusion')
```

Out[1]: DataTransformerRegistry.enable('vegafusion')

In [2]:
```python
#start code to read the data
#transform last_review from object format to datetime format
NY_airbnb = pd.read_csv('data/AB_NYC_2019.csv')

NY_airbnb = NY_airbnb.dropna()

NY_airbnb.head()
```

Out[2]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	la
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.
5	5099	Large Cozy 1 BR Apartment In Midtown East	7322	Chris	Manhattan	Murray Hill	40.

2. Data splitting

Tasks:

1. Split the data into train and test portions.

In [3]:
```python
train_df, test_df = train_test_split(NY_airbnb, test_size=0.35, random_state
X_train, y_train = train_df.drop(columns=["reviews_per_month"]), train_df["r
X_test, y_test = test_df.drop(columns=["reviews_per_month"]), test_df["revie
train_df.head()
```

Out[3]:

	id	name	host_id	host_name	neighbourhood_group	neighbou
44893	34453822	Quiet Room Next to Times Square and Bryant Park	260191397	Hotel Mela	Manhattan	Theater
25676	20558461	Big Private Room in shared apt in Rego Park, NY	146823994	Abdul	Queens	Reg
44071	34020040	Homey, Friendly Apt Share Next To Subway	253836845	Ollie	Brooklyn	Crown H
31084	24122599	Cozy room in a Victorian house in Central Broo...	14905006	Myriam	Brooklyn	Kens
16991	13506168	Spacious Beautiful 1 bdrm in Gramercy	25912717	Will	Manhattan	Gra

3. EDA

Perform exploratory data analysis on the train set.

Tasks:

1. Include at least two summary statistics and two visualizations that you find useful, and accompany each one with a sentence explaining it.
2. Summarize your initial observations about the data.
3. Pick appropriate metric/metrics for assessment.

Summary of initial observation:

- Numeric features vary widely in scale (e.g., latitude: 40.728990–40.913060, price and number_of_reviews: 0–10,000), highlighting the need for scaling.
- Features like id, host_name, and host_id should be dropped due to their uniqueness and low predictive value.
- Correlation analysis shows weak relationships between numeric features and the target variable (reviews_per_month), with all correlations falling between -0.25 and 0.25.

In [4]:
```
#perform EDA using describe() and info()
train_df.describe()
```

Out[4]:

	id	host_id	latitude	longitude	price	mir
count	2.523300e+04	2.523300e+04	25233.000000	25233.000000	25233.000000	:
mean	1.798131e+07	6.334293e+07	40.728331	-73.951309	142.506123	
std	1.070396e+07	7.535072e+07	0.055107	0.046597	199.325460	
min	2.539000e+03	2.438000e+03	40.506410	-74.244420	0.000000	
25%	8.589668e+06	6.828085e+06	40.688720	-73.982340	69.000000	
50%	1.871953e+07	2.784779e+07	40.721680	-73.955050	100.000000	
75%	2.746639e+07	9.869714e+07	40.763150	-73.935670	170.000000	
max	3.645581e+07	2.738417e+08	40.913060	-73.719280	10000.000000	

In [5]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 25233 entries, 44893 to 18958
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              25233 non-null  int64  
 1   name                            25233 non-null  object 
 2   host_id                         25233 non-null  int64  
 3   host_name                       25233 non-null  object 
 4   neighbourhood_group             25233 non-null  object 
 5   neighbourhood                   25233 non-null  object 
 6   latitude                        25233 non-null  float64
 7   longitude                       25233 non-null  float64
 8   room_type                       25233 non-null  object 
 9   price                           25233 non-null  int64  
 10  minimum_nights                  25233 non-null  int64  
 11  number_of_reviews               25233 non-null  int64  
 12  last_review                     25233 non-null  object 
 13  reviews_per_month               25233 non-null  float64
 14  calculated_host_listings_count  25233 non-null  int64  
 15  availability_365                25233 non-null  int64  
dtypes: float64(3), int64(7), object(6)
memory usage: 3.3+ MB
```

In [6]:
```
#numeric and categorical features that need to be dropped because of their u
print(train_df['id'].nunique())
print(train_df['host_id'].nunique())
print(train_df['host_name'].nunique())
```

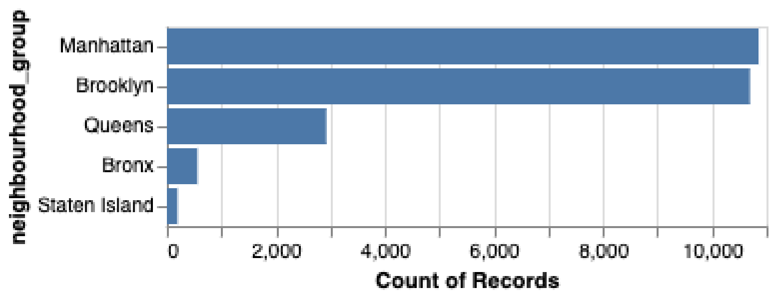
```
25233
20782
7595
```

In [7]:
```
#produce visualizations on categorical features: neighbourhood_group, neighb

#bar plot for neighbourhood_group
bar_neigh_group = alt.Chart(train_df).mark_bar().encode(
    x = 'count()',
    y = alt.Y('neighbourhood_group').sort('-x'),
)

#bar_plot for room_type
bar_room_type = alt.Chart(train_df).mark_bar().encode(
    x = 'count()',
    y = alt.Y('room_type').sort('-x'),
)

#get unique values of neighbourhood
uni_value_count_neighbourhood = train_df['neighbourhood'].value_counts()

print(uni_value_count_neighbourhood)
```

```
neighbourhood
Williamsburg          2092
Bedford-Stuyvesant    2012
Harlem                1453
Bushwick              1257
Upper West Side        994
                      ...
West Farms               1
Holliswood               1
Breezy Point             1
Eltingville              1
Richmondtown             1
Name: count, Length: 214, dtype: int64
```

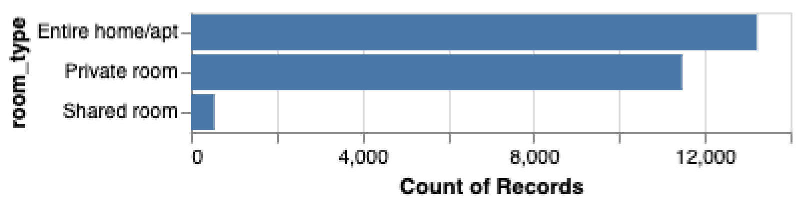
In [8]:
```python
bar_neigh_group
```

Out[8]:



In [9]:
```python
bar_room_type
```

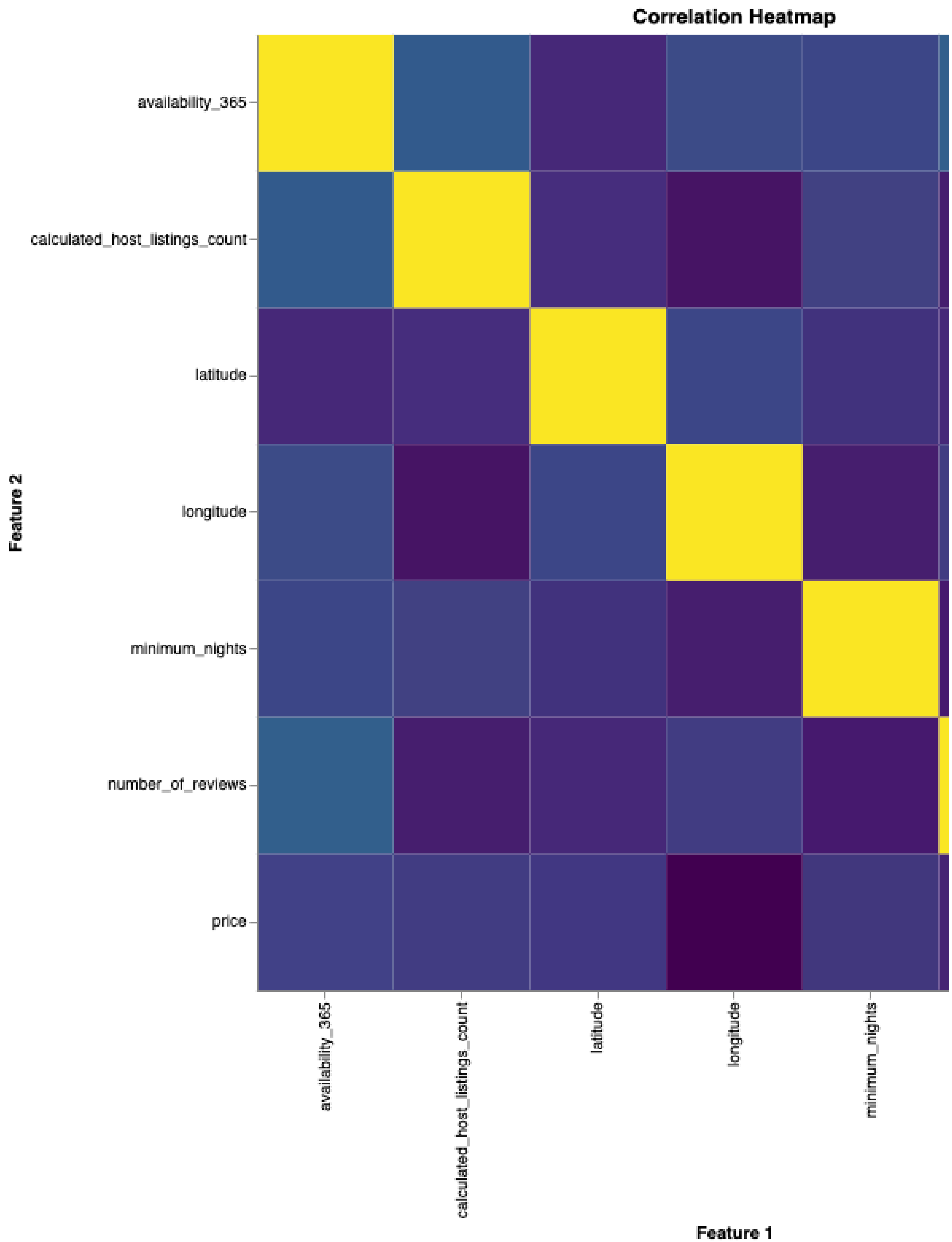
Out[9]:



In [10]:
```python
#checking numeric features' correlations except for id and host_id
numeric_features = ['latitude',
                    'longitude',
                    'price',
                    'minimum_nights',
                    'number_of_reviews',
                    'calculated_host_listings_count',
                    'availability_365']

correlation_matrix = train_df[numeric_features].corr()
correlation_long = correlation_matrix.reset_index().melt(id_vars='index')
correlation_long.columns = ['Feature 1', 'Feature 2', 'Correlation']

alt.Chart(correlation_long, width=80, height=80).mark_rect().encode(
    x='Feature 1:O',
    y='Feature 2:O',
    color=alt.Color('Correlation:Q', scale=alt.Scale(scheme='viridis')),
    tooltip=['Feature 1', 'Feature 2', 'Correlation']
).properties(
    width=600,
    height=600,
```

```
    title="Correlation Heatmap"
)
```

Out[10]:



In [11]:

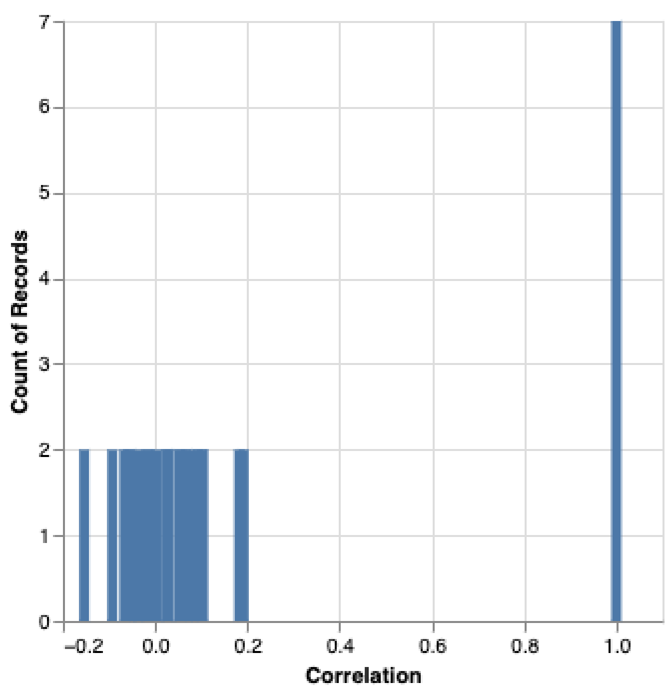
```
aly.corr(train_df)
```

Out[11]:

In [12]:

```
#to check the range of correlations
alt.Chart(correlation_long).mark_bar().encode(
    x = 'Correlation',
    y = 'count()')
```

Out[12]:



4. Preprocessing and transformations

Tasks:

1. Identify different feature types and the transformations you would apply on each feature type.
2. Define a column transformer, if necessary.

In [13]:
```
drop_features = ['id',
                 'host_id',
                 'host_name']

categorical_features = ['neighbourhood_group',
                        'neighbourhood',
                        'room_type',
                        'last_review']
text_features = 'name'
```

In [14]:
```
preprocessor = make_column_transformer(
    (StandardScaler(), numeric_features),
    (OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value = -1),
    (CountVectorizer(stop_words="english"), text_features),
    ("drop", drop_features)
)
```

5. Baseline model

Tasks:

1. Train a baseline model for your task and report its performance.

In [15]:
```
# find the mean and std of the cross validated scores for all metrics as a d
cross_val_results = {}

#try DummyRegressor model and get CV results
dummy = DummyRegressor()

cross_val_results['dummy'] = pd.DataFrame(
        cross_validate(
        dummy,
        X_train,
        y_train,
        return_train_score=True
    )
).agg(['mean', 'std']).round(5).T

#show mean and std of CV results of DummyRegressor model
cross_val_results['dummy']
```

Out[15]:

	mean	std
fit_time	0.00147	0.00035
score_time	0.00030	0.00010
test_score	-0.00027	0.00035
train_score	0.00000	0.00000

In [16]:

```
#fit the model
dummy.fit(X_train, y_train)

#report train score
train_score_dummy = dummy.score(X_train, y_train)
train_score_dummy
```

Out[16]: 0.0

In [17]:

```
#report test score
test_score_dummy = dummy.score(X_test, y_test)
test_score_dummy
```

Out[17]: -0.00017907409091266757

6. Linear models

Tasks:

1. Try a linear model as a first real attempt.
2. Carry out hyperparameter tuning to explore different values for the regularization hyperparameter.
3. Report cross-validation scores along with standard deviation.
4. Summarize the results.

Summary:

- From the CV results below, we can see that both mean test(0.43732) and mean train (0.45279) scores are low, thus this Ridge model underfits the data, which implies that the model doesn't capture the underlying patterns in the data well.
- The mean of fit time is very long, which implies high computational overhead.
- The number of non-zero coefficients is 5385, most of them are originated from Countvectorizer. A large number of redundant coefficients can also increase computational complexity and memory usage without improving model performance.
- The test score is 0.4130877019657089, the train score is 0.45061872757465393, also indicates the model is underfitting the dataset.

- Thus, the model doesn't fit the data well and further improvement is needed.

In [18]:
```
#try a linear model with Ridge and tune alpha
alphas = 10.0 ** np.arange(-5, 5, 1)

ridge = make_pipeline(preprocessor, RidgeCV(alphas=alphas, cv=5))
```

In [19]:
```
#get CV results dataframe for Ridge
cross_val_results['ridge'] = pd.DataFrame(
        cross_validate(
        ridge,
        X_train,
        y_train,
        cv = 5,
        return_train_score=True
    )
).agg(['mean', 'std']).round(5).T

#show mean and std of CV results of Ridge model
cross_val_results['ridge']
```

Out[19]:

	mean	std
fit_time	0.65320	0.03695
score_time	0.02098	0.00119
test_score	0.43732	0.01254
train_score	0.45279	0.00298

In [20]:
```
# fit the model
ridge.fit(X_train, y_train)

#find the best alpha
ridge_alpha = ridge.named_steps['ridgecv'].alpha_

ridge_alpha
```

Out[20]:
```
np.float64(100.0)
```

In [21]:
```
# create a dataframe of the coeffcients
ridge_coef = ridge[:-1].get_feature_names_out()

ridge_coef_df = pd.DataFrame({
    'variable': ridge_coef,
    'coef': ridge.named_steps['ridgecv'].coef_.tolist()
})

ridge_coef_df
```

Out[21]:

	variable	coef
0	standardscaler__latitude	-0.048306
1	standardscaler__longitude	0.114205
2	standardscaler__price	-0.004776
3	standardscaler__minimum_nights	-0.091987
4	standardscaler__number_of_reviews	0.751964
...	...	...
5380	countvectorizer__한성	0.005002
5381	countvectorizer__ｱｸｾｽ抜群	-0.001535
5382	countvectorizer__ｳｨﾘｱﾑｽﾞﾊﾞｰｸﾞのかわいいお部屋です2	-0.000962
5383	countvectorizer__ﾏﾝﾊｯﾀﾝ10分	-0.001535
5384	countvectorizer__ﾐｯﾄﾞﾀｳﾝｳｴｽﾄｻｲﾄﾞ	-0.001321

5385 rows × 2 columns

In [22]:
```
#count non-zero coefficients
n_coefs_nonzero_ridge = ((ridge.named_steps['ridgecv'].coef_) != 0).sum()
n_coefs_nonzero_ridge
```

Out[22]: np.int64(5385)

In [23]:
```
# report the train score
train_score_ridge = ridge.score(X_train, y_train)
train_score_ridge
```

Out[23]: 0.45061872757465393

In [24]:
```
# report the test score
test_score_ridge = ridge.score(X_test, y_test)
test_score_ridge
```

Out[24]: 0.4130877019657089

7. Different models

Tasks:

1. Try out three other models aside from the linear model.
2. Summarize the results in terms of overfitting/underfitting and fit and score times.
3. Can you beat the performance of the linear model?

Summary:

I also used Lasso model, RandomForestRegressor model and GardientBoostingRegressor model.

Comparison between above three model and the linear model (Ridge model):

- Lasso:
    - has the longest mean fit time
    - CV results: mean train score is 0.45080, mean test score is 0.43700
    - train score is 0.4478163165767438, test score is 0.41333833995252334
- RandomForestRegressor:
    - has the second longest mean fit time
    - CV results: mean train score is 0.95026, mean test score is 0.65634
    - train score is 0.9513277342209916, test score is 0.6307274904682476
- GardientBoostingRegressor:
    - has the third longest mean fit time
    - CV results: mean train score is 0.65467, mean test score is 0.63095
    - train score is 0.6525094855132751, test score is 0.6034722669200422
- Linear (Ridge):
    - has the shortest fit time
    - CV results: mean train score is 0.45279, mean test score is 0.43732
    - train score is 0.45061872757465393, test score is 0.4130877019657089

From above results, GradientBoostingRegressor model performs better than the other three models overall.

As the GradientBoostingRegressor model has the highest train and test score, and lower mean fit time and mean score time. Even though, both of the mean train score and mean test score are relatively low, around 0.6, overall, it has the best performance.

First model: Lasso

In [25]:
```
#try lasso model

# setup the pipeline
alphas = 10.0 ** np.arange(-3, 3, 1)
lasso = make_pipeline(preprocessor, LassoCV(alphas=alphas, max_iter=3_000, t
```

In [26]:
```
cross_val_results['lasso'] = pd.DataFrame(
        cross_validate(
        lasso,
        X_train,
        y_train,
```

```
        cv = 5,
        return_train_score=True
    )
).agg(['mean', 'std']).round(5).T

#show mean and std of CV results of Lasso model
cross_val_results['lasso']
```

Out[26]:

	mean	std
fit_time	27.11282	10.15979
score_time	0.02511	0.00098
test_score	0.43700	0.01272
train_score	0.45080	0.00325

In [27]:

```
# fit the lasso model
lasso.fit(X_train, y_train)

#find the best alpha
lasso_alpha = lasso.named_steps['lassocv'].alpha_

lasso_alpha
```

Out[27]:

```
np.float64(0.001)
```

In [28]:

```
# create a dataframe of the lasso coeffcients
lasso_coef = lasso[:-1].get_feature_names_out()

lasso_coef_df = pd.DataFrame({
    'variable': lasso_coef,
    'coef': lasso.named_steps['lassocv'].coef_.tolist()
})

lasso_coef_df
```

Out[28]:

	variable	coef
0	standardscaler__latitude	-0.027210
1	standardscaler__longitude	0.106793
2	standardscaler__price	0.010259
3	standardscaler__minimum_nights	-0.099051
4	standardscaler__number_of_reviews	0.748722
...	...	...
5380	countvectorizer__한성	0.000000
5381	countvectorizer__ｱｸｾｽ抜群	-0.000000
5382	countvectorizer__ｳｨﾘｱﾑｽﾞﾊﾞｰｸﾞ のかわいいお部屋です2	-0.000000
5383	countvectorizer__ﾏﾝﾊｯﾀﾝ10分	-0.000000
5384	countvectorizer__ﾐｯﾄﾞﾀｳﾝｳｴｽﾄｻｲﾄﾞ	-0.000000

5385 rows × 2 columns

In [29]:

```
#report train score
train_score_lasso = lasso.score(X_train, y_train)
train_score_lasso
```

Out[29]: 0.4478163165767438

In [30]:

```
#report test score
test_score_lasso = lasso.score(X_test, y_test)
test_score_lasso
```

Out[30]: 0.41333833995252334

Second model: RandomForestRegressor

In [31]:

```
rf = make_pipeline(
    preprocessor,
    RandomForestRegressor(
        n_jobs=-1,
        n_estimators=50,
        random_state=123))
```

In [32]:

```
cross_val_results['rfregressor'] = pd.DataFrame(
        cross_validate(
        rf,
        X_train,
        y_train,
        cv = 5,
        return_train_score=True
    )
).agg(['mean', 'std']).round(5).T
```

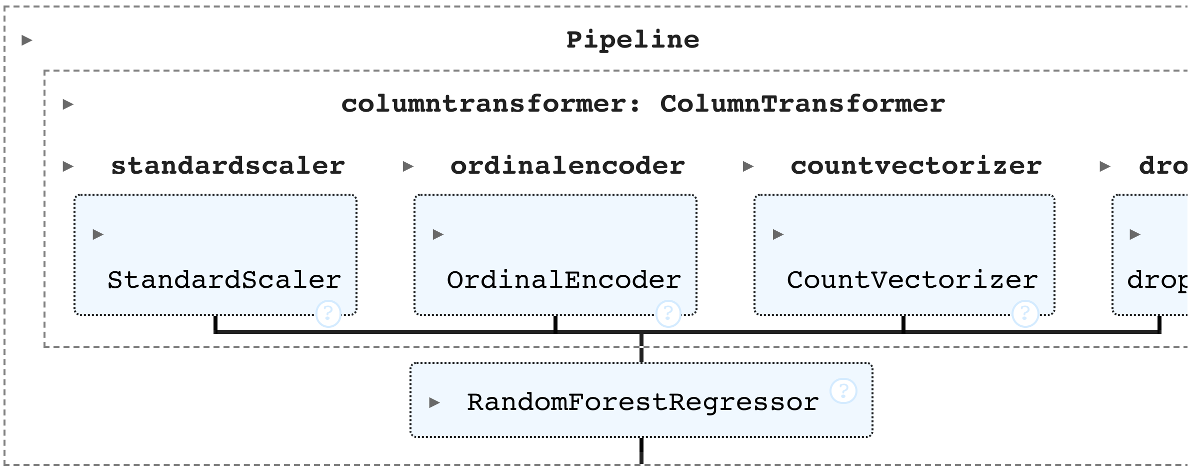
```python
#show mean and std of CV results of Lasso model
cross_val_results['rfregressor']
```

Out[32]:

	mean	std
fit_time	18.97879	23.74302
score_time	0.05528	0.00697
test_score	0.65634	0.01141
train_score	0.95026	0.00029

In [33]:
```python
# fit the RandomForestRegressor model
rf.fit(X_train, y_train)
```

Out[33]:



In [34]:
```python
#report train score
train_score_rf = rf.score(X_train, y_train)
train_score_rf
```

Out[34]: 0.9513277342209916

In [35]:
```python
#report test score
test_score_rf = rf.score(X_test, y_test)
test_score_rf
```

Out[35]: 0.6307274904682476

Third model: GardientBoostingRegressor

In [36]:
```python
gb = make_pipeline(
    preprocessor,
    GradientBoostingRegressor(
        n_estimators=50,
        random_state=123))

cross_val_results['gbregressor'] = pd.DataFrame(
        cross_validate(
        gb,
```

```python
        X_train,
        y_train,
        cv = 5,
        return_train_score=True
    )
).agg(['mean', 'std']).round(5).T

#show mean and std of CV results of Lasso model
cross_val_results['gbregressor']
```

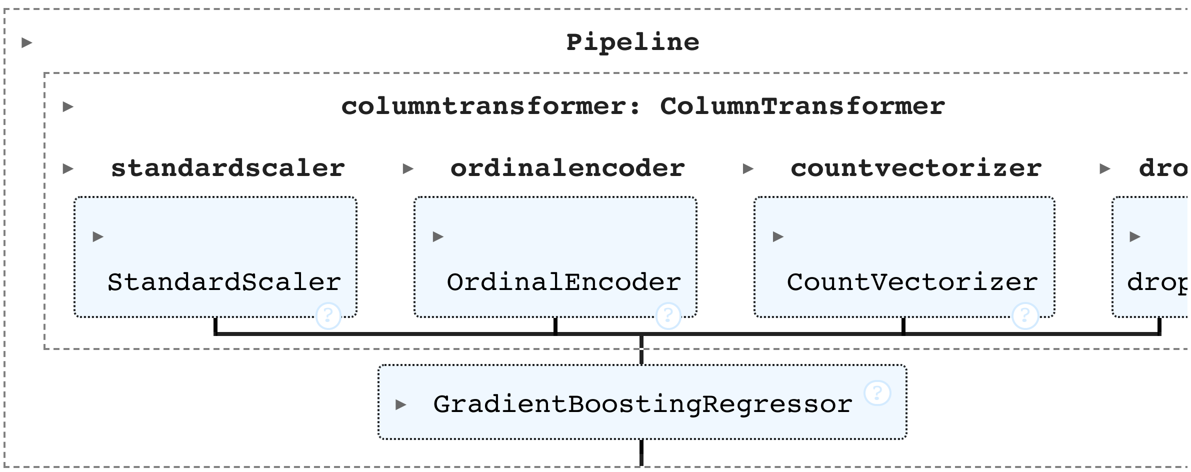
Out[36]:

	mean	std
fit_time	1.61729	0.02872
score_time	0.02319	0.00055
test_score	0.63095	0.01180
train_score	0.65467	0.00296

In [37]:

```python
# fit the GradientBoostingRegressor model
gb.fit(X_train, y_train)
```

Out[37]:



In [38]:

```python
#report train score
train_score_gb = gb.score(X_train, y_train)
train_score_gb
```

Out[38]: `0.6525094855132751`

In [39]:

```python
#report test score
test_score_gb = gb.score(X_test, y_test)
test_score_gb
```

Out[39]: `0.6034722669200422`

8. Hyperparameter optimization

Tasks:

1. Make some attempts to optimize hyperparameters for the models you've tried and summarize your results.
2. Briefly summarize your results.

- GridSearchCV
- RandomizedSearchCV
- scikit-optimize

Summary:

- Based on below results, the best parameters of the RandomForestRegressor model is countvectorizer's max_features: 5106, Randomforestregressor's n_estimators: 100; the best parameters of the GradientBoostingRegressor's n_estimators: 100.
- From the LassoCV in question 8, the best alpha is 0.001.

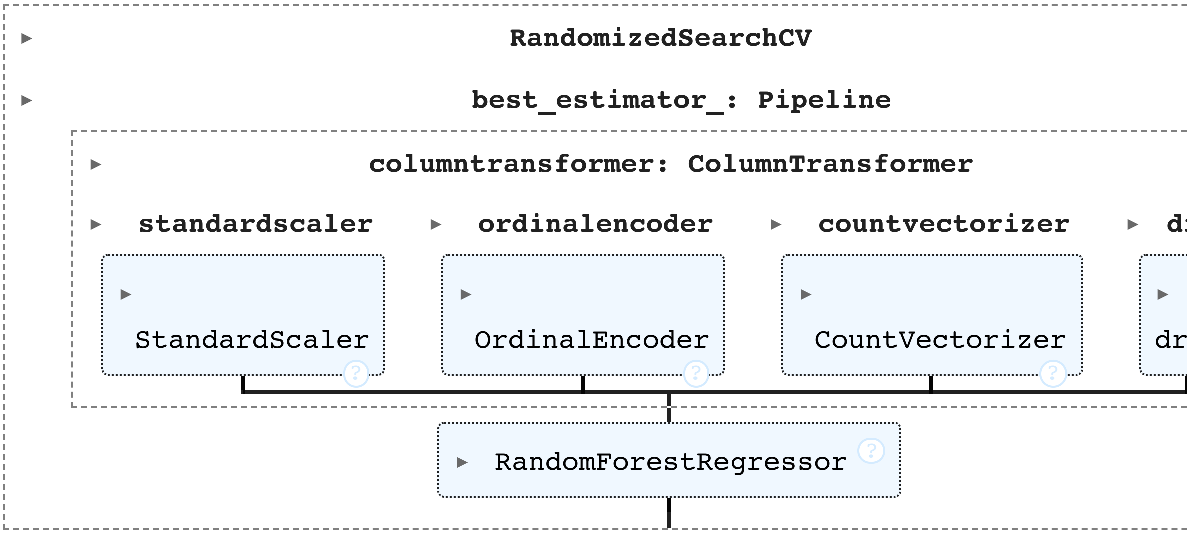
To tune the RanomdForestRegressor model:

In [40]:
```
#start hyperparameter optimization
len_vocab = len(
    rf.named_steps["columntransformer"]
    .named_transformers_["countvectorizer"]
    .get_feature_names_out()
)

param_dist = {
    "columntransformer__countvectorizer__max_features": randint(5_000, len_v
    "randomforestregressor__n_estimators": np.arange(10, 110, step = 10)
}

random_search = RandomizedSearchCV(
    rf,
    param_distributions=param_dist,
    n_iter=10,
    verbose=1,
    n_jobs=-1,
    random_state=123,
)
```

In [41]:
```
random_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

Out[41]:



In [42]:

```
# best hyperparameters
best_parameters = random_search.best_params_
best_parameters
```

Out[42]:

```
{'columntransformer__countvectorizer__max_features': 5106,
 'randomforestregressor__n_estimators': np.int64(100)}
```

To tune the GradientBoostingRegressor model:

In [43]:

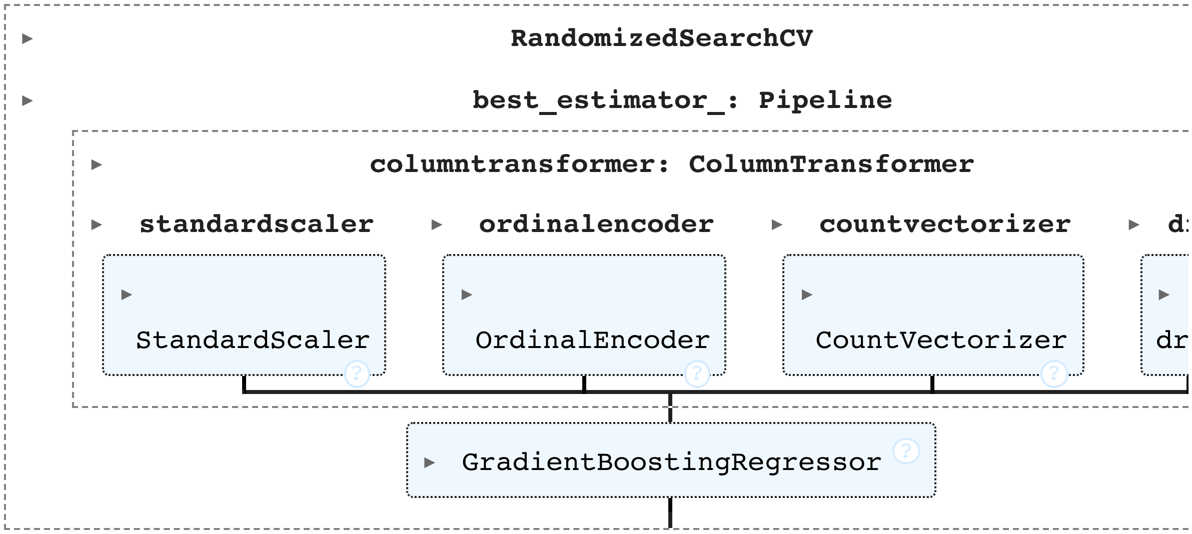
```
#start hyperparameter optimization
param_dist = {
    "gradientboostingregressor__n_estimators": np.arange(10, 110, step = 10)
}

random_search = RandomizedSearchCV(
    gb,
    param_distributions=param_dist,
    n_iter=10,
    verbose=1,
    n_jobs=-1,
    random_state=123,
)
```

In [44]:

```
random_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

Out[44]:



In [45]:
```
# best hyperparameters
best_parameters = random_search.best_params_
best_parameters
```

Out[45]:
```
{'gradientboostingregressor__n_estimators': np.int64(100)}
```

9. Interpretation and feature importances

Tasks:

1. Examine the most important features of one of the non-linear models.
2. Summarize the observations.

I will examine feature importance of GradientBoostingRegressor.

From below gb_imp_df, we can see that globally, feature 'number_of_reviews' has the highest importance value (0.570242) and thus has the most influential feature. The second most influential feature is minimum_nights, the third most influential feature is availability_365.

In [46]:
```
#extract feature names
feature_names = gb[:-1].get_feature_names_out()
```

In [47]:
```
#extract feature importance
data = {
    "Importance": gb.named_steps["gradientboostingregressor"].feature_import
}
```

In [48]:
```
#get the dataframe
gb_imp_df = pd.DataFrame(
    data=data,
    index=feature_names,
```

```python
).sort_values(by="Importance", ascending=False)

gb_imp_df[:15]
```

Out[48]:

	Importance
ordinalencoder__last_review	0.609370
standardscaler__number_of_reviews	0.231849
standardscaler__minimum_nights	0.100696
standardscaler__longitude	0.022983
standardscaler__availability_365	0.006767
countvectorizer__jfk	0.006418
countvectorizer__lga	0.005610
countvectorizer__lou	0.005174
standardscaler__latitude	0.002237
countvectorizer__common	0.001122
standardscaler__calculated_host_listings_count	0.000999
countvectorizer__cakes	0.000774
countvectorizer__comfort	0.000650
countvectorizer__balcony	0.000609
standardscaler__price	0.000601

10. Results on the test set

Tasks:

1. Try your best performing model on the test data and report test scores.
2. Do the test scores agree with the validation scores from before? To what extent do you trust your results? Do you think you've had issues with optimization bias?
3. Take one or two test predictions and explain them with SHAP force plots.

Summary:

- The GradientBoostingRegressor emerged as the best-performing model based on Question 8.
- Its test score is 0.6035, which aligns well with its cross-validation (CV) results: a mean train score of 0.6547 and a mean test score of 0.6310. The consistency between the test and validation scores (~0.6) gives me high confidence in the model's reliability.

- Since a separate test dataset was used for evaluation, optimization bias is likely minimized.
- SHAP force plots reveal that the top three most influential features are 'last_review', 'minimum_nights', and 'number_of_reviews'. Interestingly, 'last_review' has contrasting effects: it positively impacts the prediction in the first plot and negatively impacts it in the second.

In [49]:
```
# report the test score
test_score_ridge = gb.score(X_test, y_test)
test_score_ridge
```

Out[49]: 0.6034722669200422

In [50]:
```
X_train_enc = preprocessor.fit_transform(X_train).todense()
```

In [51]:
```
# We need access to the transformed features and their feature names
X_test_enc = pd.DataFrame(
    data=preprocessor.transform(X_test).toarray(),
    columns=feature_names,
    index=X_test.index,
)
X_test_enc.iloc[[0, 1]]
```

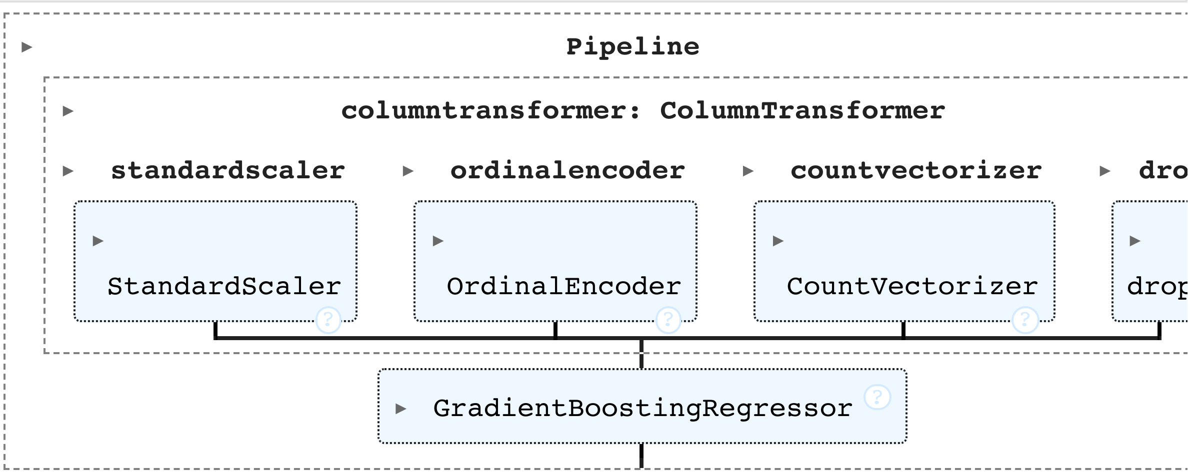
Out[51]:

	standardscaler__latitude	standardscaler__longitude	standardscaler__price	sta
39615	0.653813	-0.782932	-0.112914	
19583	0.184534	-0.783576	0.469061	

2 rows × 5385 columns

In [52]:
```
gb
```

Out[52]:



In [53]:
```
gb_explainer = shap.TreeExplainer(
    gb.named_steps['gradientboostingregressor'],
    X_train_enc
```

```
)

gb_explanation = gb_explainer(X_test_enc)
gb_explanation[:2]
```

```
95%|=================== | 12922/13588 [00:16<00:00]
```

Out[53]:

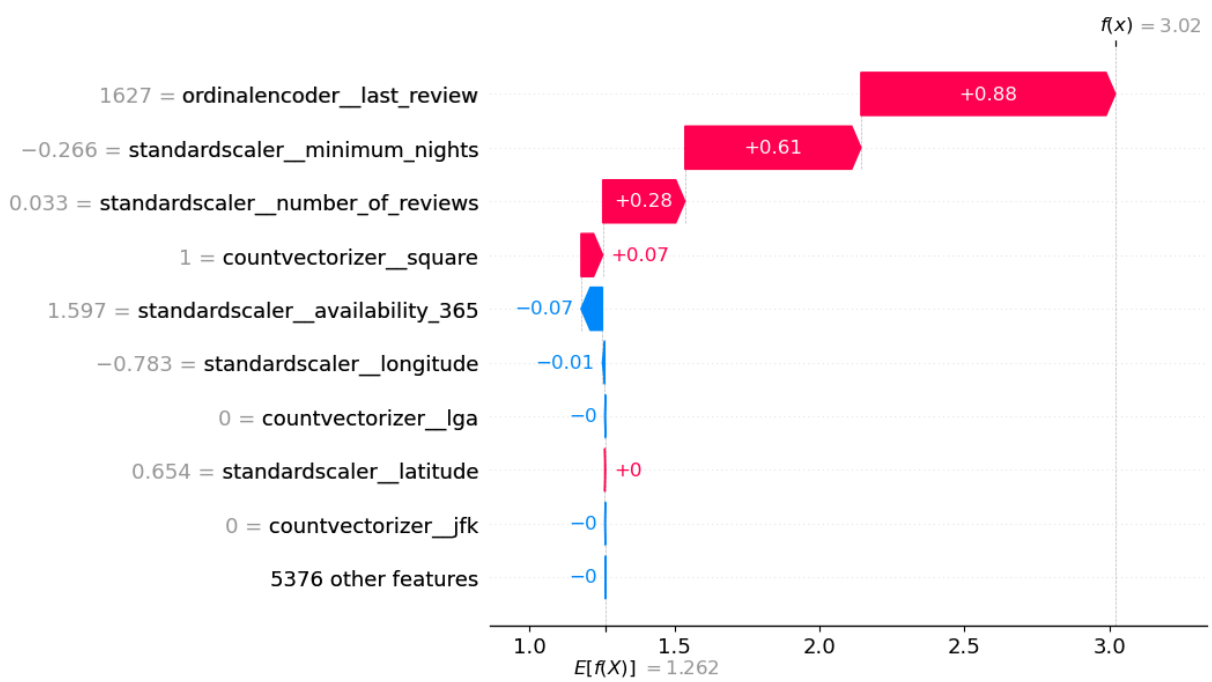
```
.values =
array([[ 0.00205964, -0.00787905, -0.00019984, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.        , -0.01408305, -0.00016343, ...,  0.        ,
         0.        ,  0.        ]])

.base_values =
array([1.26234151, 1.26234151])

.data =
array([[ 0.65381303, -0.78293218, -0.11291367, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.18453411, -0.78357601,  0.46906065, ...,  0.        ,
         0.        ,  0.        ]])
```

In [54]:

```
# load JS visualization code to notebook
shap.initjs()
```

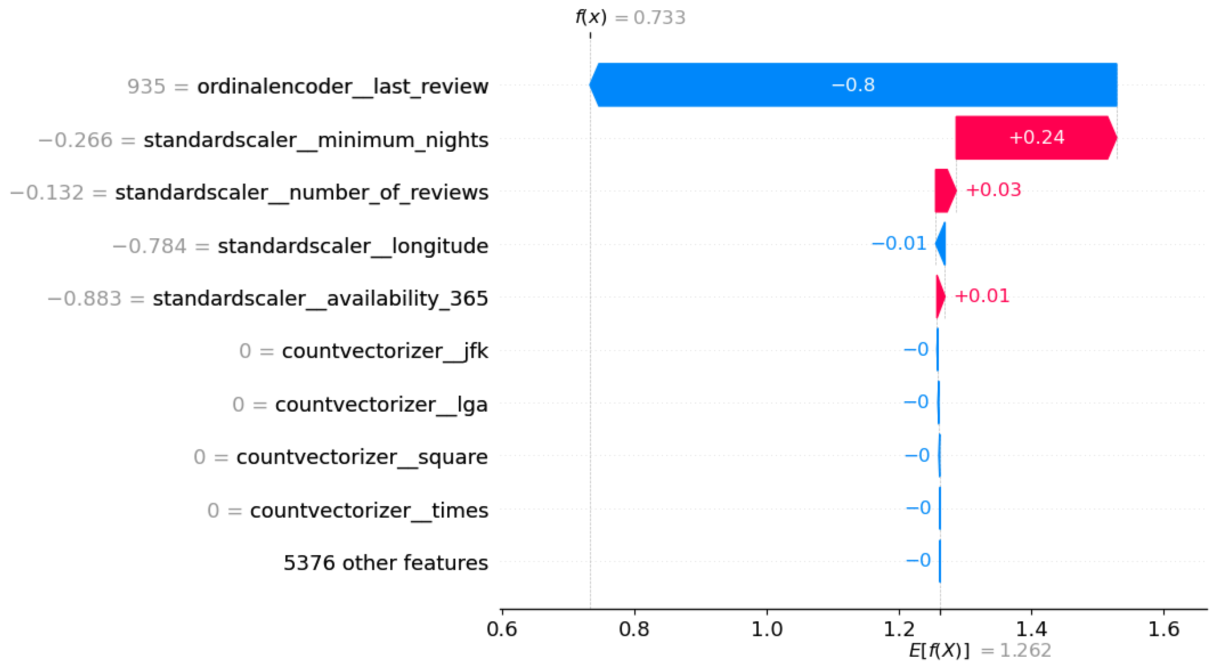
In [55]:

```
#first plot
shap.plots.waterfall(gb_explanation [0, :])
```



In [56]:

```
#second plot
shap.plots.waterfall(gb_explanation [1, :])
```



11. Summary of results

Tasks:

1. Create a table summarizing important results.
2. Write concluding remarks.
3. Discuss other ideas that you did not try but could potentially improve the performance/interpretability .
4. Report your final test score along with the metric you used at the top of this notebook.

Summary:

- The GradientBoostingRegressor model outperformed the other models (DummyRegressor, RandomForestRegressor, Ridge, and Lasso) with the highest cross-validation (CV) mean train and test scores. Additionally, it demonstrated lower mean fit and score times, and its test score of 0.6035 aligns well with the CV results.

- Despite its superior performance, the CV results suggest that the GradientBoostingRegressor is underfitting the dataset. To address this, further improvement through feature engineering is recommended. This could involve creating new features that better represent the dataset and potentially improve both training and test scores.

In [57]:
```
#to show the table
pd.concat(
```

```python
    cross_val_results,
    axis='columns'  # Get the right model names and mean/std as columns
)
```

Out[57]:

	dummy		ridge		lasso		rfregress	
	mean	std	mean	std	mean	std	mean	s
fit_time	0.00147	0.00035	0.65320	0.03695	27.11282	10.15979	18.97879	23.743
score_time	0.00030	0.00010	0.02098	0.00119	0.02511	0.00098	0.05528	0.006
test_score	-0.00027	0.00035	0.43732	0.01254	0.43700	0.01272	0.65634	0.01
train_score	0.00000	0.00000	0.45279	0.00298	0.45080	0.00325	0.95026	0.000