Russian Housing Data Imputation

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Paul Adams, Stuart Miller, and Justin Howard

1 Introduction

Strategies for dealing with missing data are a necessary component of the analysis of any new dataset. In most cases, rather than removing records containing missing values, the preferred method is making an educated guess as to what the missing value might be and imputing the datapoint with a best guess estimate. Imputation is a method that preserves the useful data present within a dataset, while providing machine learning algorithms with the complete data they demand.

Like any other phenomena, missing data follows predictable patterns. The imputation strategy that the analyst applies should take into account why the data is missing. To accurately identify the latent patterns causing missing data, the analyst must carefully observe the data that is present for patterns. Data can be missing at random, missing not at random, and missing completely at random. While these categories appear to be very similar, knowing the differences in the patterns they describe can make the difference that leads to a high performing model.

2 Types of Missing Data

A commonly occuring kind of "missingness" is data that is missing at random. When missing data occur randomly, without a noticeable pattern, but the missing data can be modeled, then they are considered missing at random. The existing data can be used to fit a model that predicts what these values may be.

Data that is missing not at random means that the probability of "missingness" is not random, but is not known. An example of this phenomenon is missing data due to a sensor wearing out over time. We may not have a model that accurately predicts when missing data will occur, but we do know that it will occur.

Data that is missing completely at random is a less common occurance. All data points have an equal probability of "missingness", which cannot be predicted, and the cause of the missingness is unknown. An example of data that is missing completely at random are data not inlcuded in the random sample of a population.

3 The Dataset

The dataset is composed of over 30,471 Russian home prices with 292 continuous and categorical features to inform home price predictions. Approximately 47% of the entire dataset is missing data, distributed over 51 columns. Missing datapoints are either missing at random or missing not at random.

4 Imputation Methods

Given that the focus of this study is on imputation methods, we will not delete records from the dataset. Instead, we will explore the dataset for patterns that allow us to interpolate the missing data we observe. The primary means of imputing the data will be univariate inference and Scikit-Learn implementations of a KNN imputation approach and the Iterative Imputation[1].

4.1 Comparing Multiple Imputation Strategies

There are many multiple imputation strategies available and this case study focuses on two in particular, Iterative Imputation and KNN Imputation. The primary difference between the two methods is that iterative imputation uses multiple linear regression as the primary imputation technique while KNN imputation uses a K Nearest Neighbor approach with a euclidean distance metric.

To perform the comparisons, we selected features to impute, trained Sci-kit Learn's IterativeImputer and KNNImputer using the same training sets and random states, fit linear models to both training sets, and used the Root Mean Squared Error as the evaluation metric.

While the performance of KNNImputer is consistently better, the RMSE of both methods is almost identical as shown in Fig. 1. The primary difference between the two is computation time. The computational time of IterativeImputer, while not visualized, is faster than KNNImputer. The computational advantage of the IterativeImputer is mostly due to the ability to parallelize the computations that it does, while KNNImpute relies on building an adjacency matrix, which cannot be parallelized. IterativeImputer will perform much better on large datasets while KNNImputer, with a time complexity of O(N^2), may not be practical.

We will leverage the small size of the given dataset and extract a small amount of accuracy by using the KNNImputer, but we do not advise using this tool on signficantly larger datasets.

[1] https://scikit-learn.org/stable/modules/impute.html

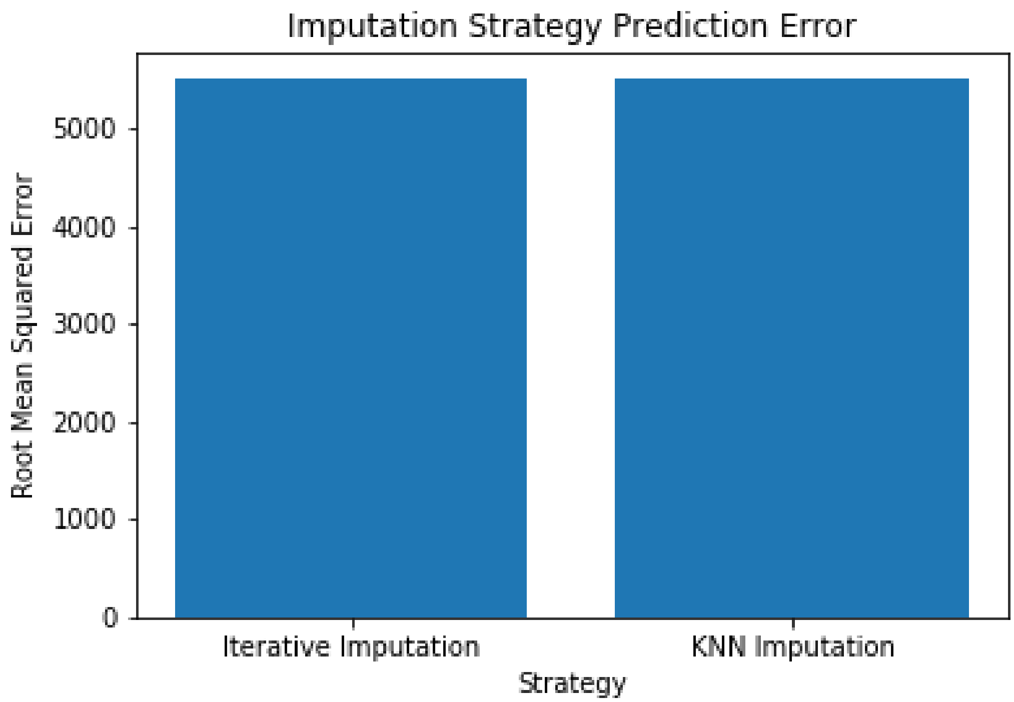


Figure 1: A Comparison of the RMSE of Iterative and KNN Imputation Strategies

4.2 Cafe Variables

A set of variables related to cafe prices are missing values. The variables, `cafe_sum_X_min_price_avg`, `cafe_sum_X_max_price_avg`, and `cafe_avg_price_X`, represent the minimum, maximum, and average cafe bills in a given `X` radius. As shown in Fig. 2, these variables are highly correlated for any given radius. Since these variables are highly correlated, we will drop the minimum and maximum columns and keep only the average price column, namely `cafe_avg_price_X`.

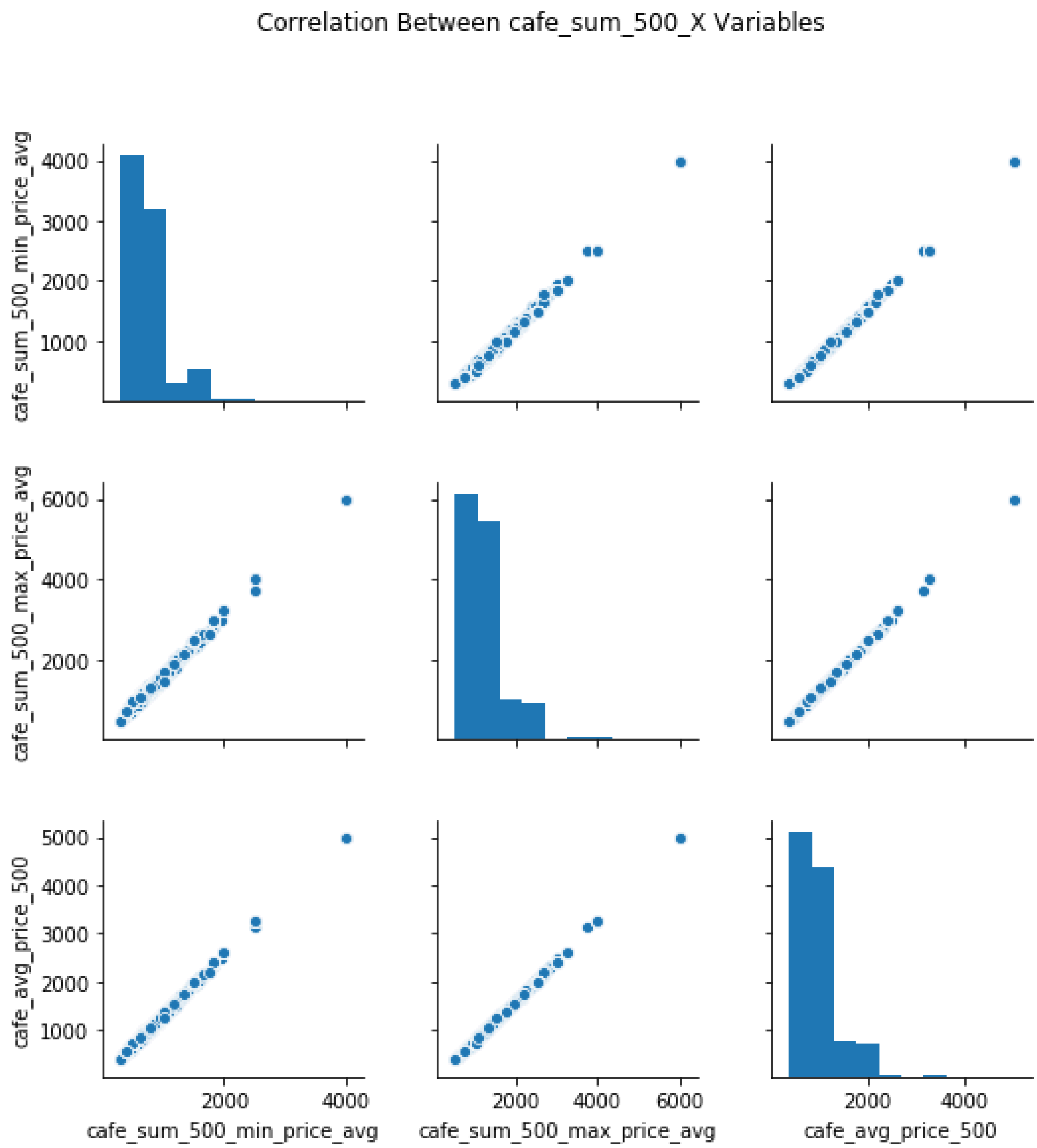


Figure 2: Pair plot of cafe_sum_500_min_price_avg, cafe_sum_500_max_price_avg, and cafe_avg_price_500. These variables are strongly correlated. The other similar cafe variables exhibit similar behavior.

There is also a set related complete columns `cafe_count_X`, which provide a count of the cafes in the given radius `X`. Most of the `cafe_avg_price_X` values are missing when `cafe_count_X==0`, which is sensible. We will set `cafe_avg_price_X` to `-1` when `cafe_count_X==0` as a numeric indication that `cafe_avg_price_X` is missing. However, there are missing values present when `cafe_count_X` is not equal to `0`. The missingness of `cafe_count_X` appears to be related to `sub area` and `cafe_count_X`. Fig. 3 shows that the missingness of `cafe_avg_price_500` is related to `sub_area` and `cafe_count_500`. The other similar variables exhibit similar behavior. There does not appear to be a pattern beyond this relationship. Thus, the missingness of these variable appears to be not at random.

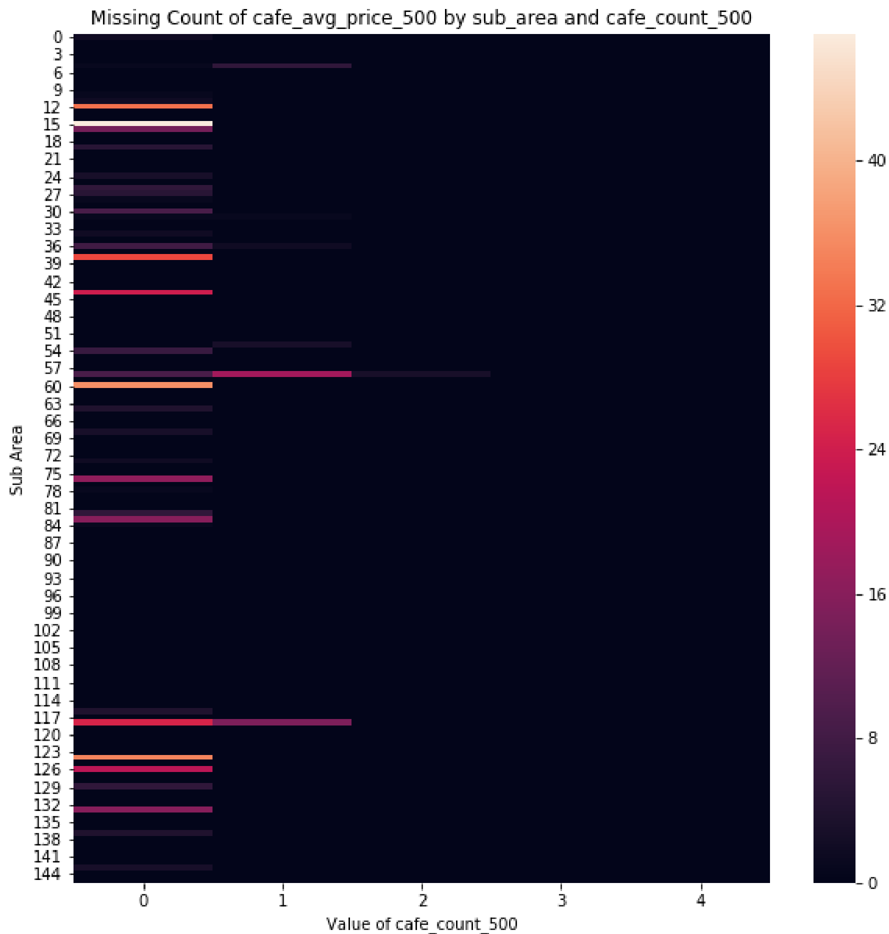


Figure 3: Heatmap of missing count of cafe_avg_price_500 by sub_area and cafe_count_500 (sub_area is indexed). The missingness of cafe_avg_price_500 appears to depend on both sub_area and cafe_count_500.

We used the median value to impute these values. The distributions of `cafe_avg_price_X` variables appear to be irregular as shown in Fig. 4. The imputation strategy was as follows:

- For each `cafe_count_X`:
  - If `cafe_count_X==0`, set `cafe_avg_price_X` to -1 to indicate a null value
  - If `cafe_count_X > 0` and all values of `cafe_avg_price_X` are missing, set `cafe_avg_price_X` to `-1` to indicate null values
  - Else, use median of `cafe_avg_price_X` values corresponding to the levels of `cafe_count_X` and levels of `sub_area`

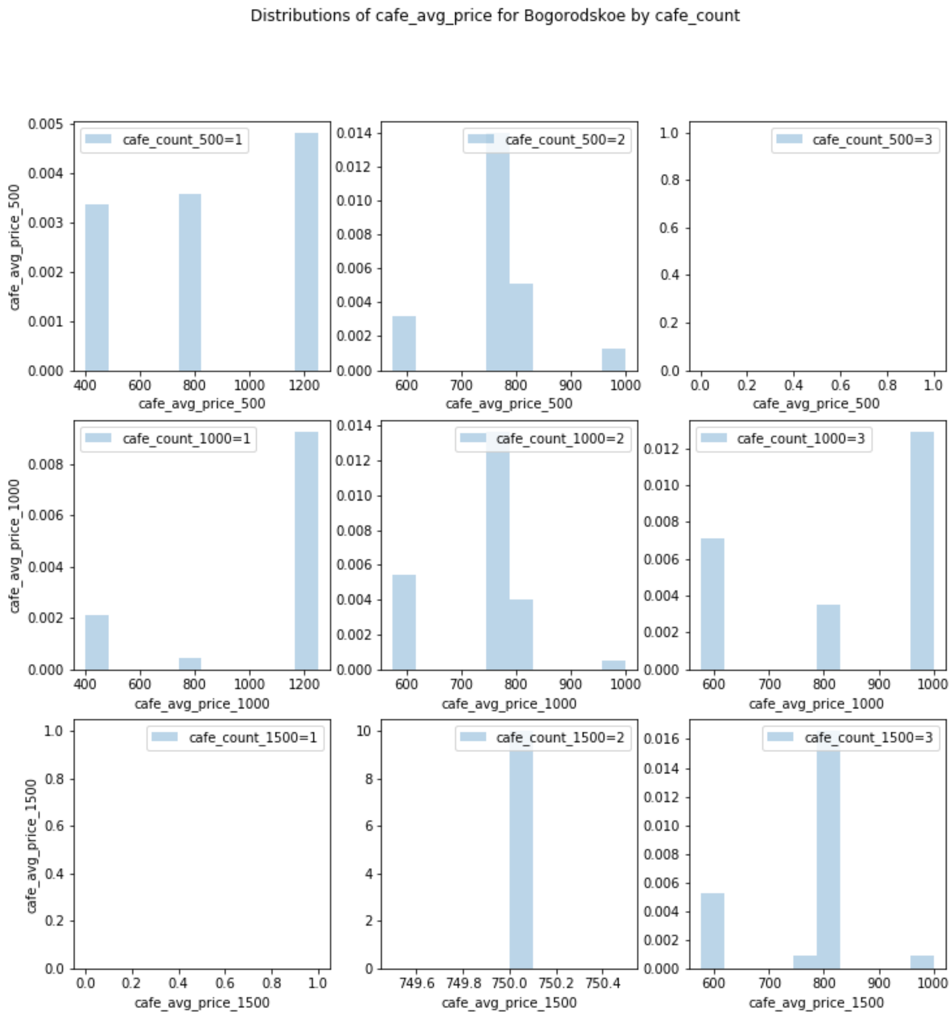


Figure 4: Distributions of several cafe_avg_price_X variables by cafe_count_X

4.3 Walking Distance Features

Five walking distance features each have 25 missing data points that we judge to be missing at random. A Pearson's R correlation matrix (Fig. 5) reveals multicollinearity between features that account for walking distance and those that account for the time it takes to walk from one point to another. We will remove the walking time measurements, `metro_min_walk` and `railroad_station_walk_min` because they are the more subjective of the two. The remaining feature will be imputed using the KNNImputer tool.

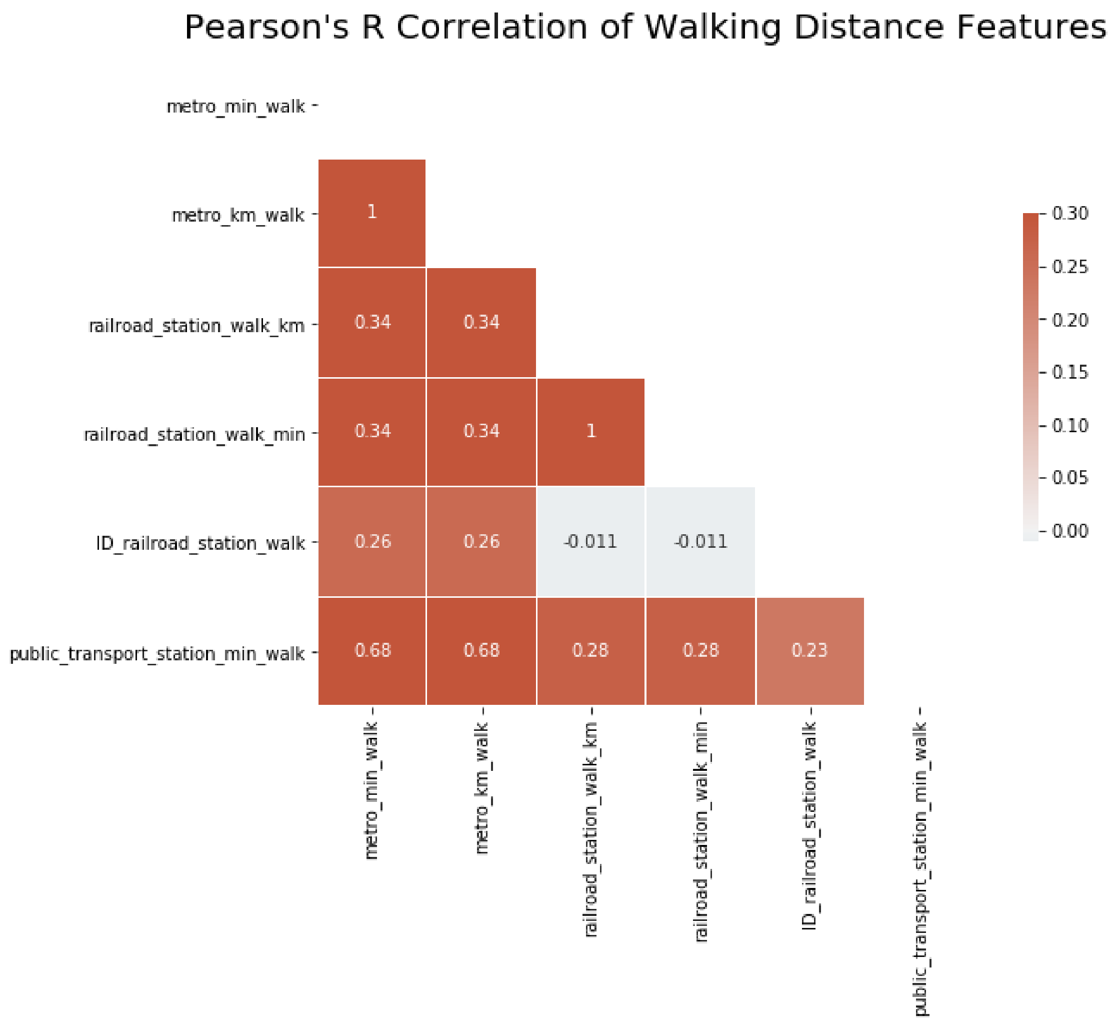


Figure 5: Pearson's R Correlations of Walking Distance Features

4.4 Build_Count Features

The dataset also contains a large number of features that represent counts of homes with specific building materials. These features are counts of homes with materials, and are judged to be missing not at random.

Each of these features contain 4,991 missing values. The sub_area feature was appended to the build_count dataframe, revealing that sub-areas with the Polesenskie prefix contain all of the missing values across all of the build_count features. Of the subset of features having at least 1 missing value, a majority of the missing values were found to be in the `build_count_foam` and `build_count_panel`. We will assume that missing values means that those materials are absent and we will impute them with 0 values.

Additionally, a correlation matrix revealed that `raion_build_count_with_builddate_info` and `raion_build_count_with_material_info` are almost perfectly correlated, so we chose to remove `raion_build_count_with_builddate_info` from the dataset.

4.5 School Seat Count Features

4.5.1 preschool_quota

`preschool_quota` values were missing for all Poselenie sub_areas (neighborhoods) in addition to Molzhaninovskoe and Troickij okrug. Further analysis showed there are preschool-aged children in these sub_areas, but the corresponding `preschool_education_centers_raion` - a feature for the number of pre-school institutions - is 0. Therefore, we assume these values are not missing at random and are intentionally left empty because there are no seats available in pre-school organizations. Thus, we impute all missing values for these `preschool_quota` with 0.

4.5.2 school_quota

As with preschool_quota, missing values for school_quota appear to be missing not at random; the values missing correspond to the Poselenie and Troickij okrug `sub_area` values. In these districts, `school_education_centers_raion` and `school_education_centeres_top_20_raion` all have values of 0 where `school_quota` values are missing. Therefore, we interpret this as there being no school seats available and impute them with 0.

4.6 State Feature

We identified that `state` – a feature representing the quality of the location - is a feature that is not missing at random random. The missing values were not associated with any other feature, such as a particular `timestamp` range, `sub_area` value, or `product_type`. We imputed missing `state` values with a K-NN classifier, which produced reasonable accuracy (61%) on internal cross-validation when using features that appeared in the top 95th percentile of correlation to the `state` values, by Pearson's Coefficient of Correlation, as the predictors.

5 Modeling

After imputing the missing values, we used ElasticNet regession to model is data. ElasticNet is a linear modeling method that makes of use of both L1 and L2 regularization. The implementation of ElasticNet in Scikit-Learn provides inputs for controlling the regularization strength and the ratio of regularization between L1 and L2. The implementation of ElasticNet also auto selects values a range of values to search for regularization strength. In this case study, we search these hyperparameters for good values with a grid search utilizing 5-fold cross-validation (5-CV). The searched range of hyperparameters are shown in table 1. The best parameters chosen by 5-CV and the model performance on the test set are reported in the Results section.

Table 1. Hyperparamers

Parameter	Search Range	Description
`l1_ratio`	`0.1, 0.5, 0.7, 0.9, 0.95, 0.99, 1`	The ratio between L1 and L2 regularization
`alpha`	auto-selected by implementation	The regularization strength of the model

We noted that the target variable was highly skewed. To improve the model performance, we log transformed the target variable, which normalized the target value.

6 Results

The ElasticNet model selected by 5-CV search was entirely weighted towards L1 regularization with a relatively high alpha (high regularization). The hyperparameters selected by 5-CV search ElasticNet are shown in table 2.

Table 2. Tuned Hyperparameters

Parameter	Value
`l1_ratio`	1.0
`alpha`	1998.58

The residuals of the model appear to be approximately normally distributed as shown in Fig. 6.

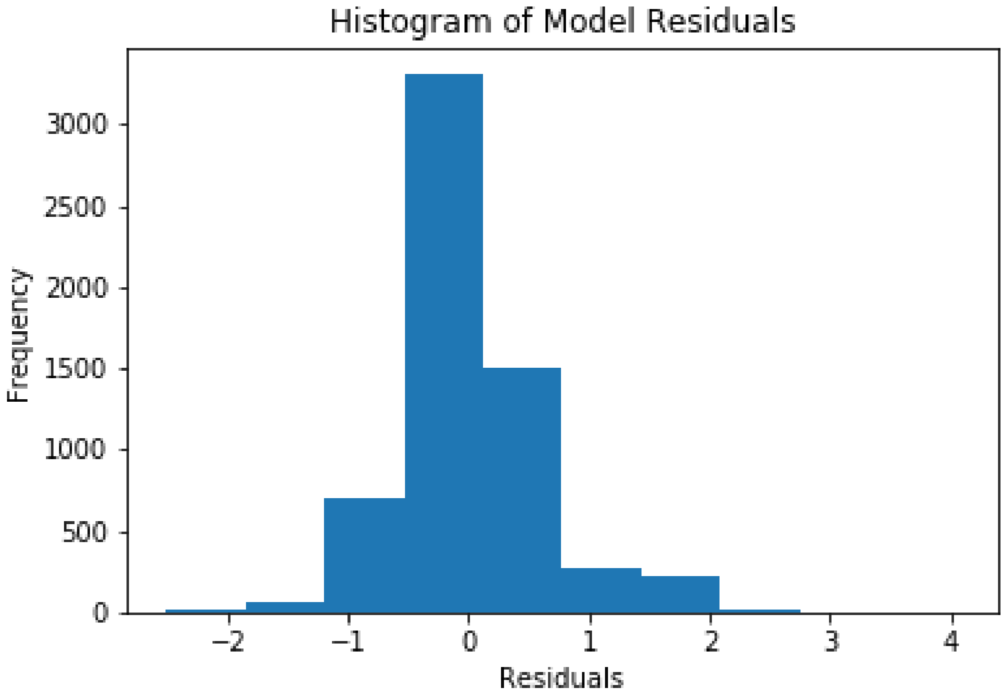


Figure 6: Histogram of fit model residuals on test set.

We estimated the error of this model with 5-CV and holdout validation on a test set using root mean squared error (RMSE) as the scoring metric. There is little different between the RMSE scores produced by both methods.

Table 3. Model Scores

Method	RMSE
Hold-out Test Set	0.584
5-fold Cross Validation	0.585

7 Conclusions

Imputation is a means of extracting value from data with modern machine learning algortihms that require complete datasets. The process of imputation begins with a process of identifying whether missing data is missing at random, not at random or missing completely at random. A careful identification of the types of missing data must take place in order to best apply an imputation strategy. Many of these decisions are judgement calls that can be supported by domain expertise. Once the root causes of missingness for each feature are determined, then a statistical analysis of the distributions of each feature can be conducted. An imputation strategy that is practical for the size of the dataset can then be chosen to impart meaningful predictive substitutions for each missing datapoint.

A Imputations

[2]:
```python
import time
from collections import defaultdict

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import normalize
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, KNNImputer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import ElasticNetCV
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score

random_state = 42
```

[3]:
```python
df = pd.read_csv('./data/train.csv')
df.shape
```

[3]:
```
(30471, 292)
```

A.0.1 Performing train/test split to avoid data leakage

[4]:
```python
y = df.pop('price_doc')
X = df
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
 ↪random_state=random_state)
dfs = {'X_train: ': X_train,
       'X_test: ': X_test,
       'y_train: ': y_train,
       'y_test: ': y_test}
for i,j in dfs.items():
    print(i, j.shape)
```

```
X_train:  (24376, 291)
X_test:  (6095, 291)
y_train:  (24376,)
y_test:  (6095,)
```

A.1 Imputation Code

[34]:
```
#see appendix B for KNN classification model imputations
X_train.loc[:,'school_quota'] = X_train.loc[:,'school_quota'].fillna(0)
X_train.loc[:,'preschool_quota'] = X_train.loc[:,'preschool_quota'].fillna(0)

X_test.loc[:,'school_quota'] = X_test.loc[:,'school_quota'].fillna(0)
X_test.loc[:,'preschool_quota'] = X_test.loc[:,'preschool_quota'].fillna(0)
```

[35]:
```
# KNN imputation helper functions
def KNN_train_impute(correlation_matrix, colname, data, n_neighbors=3):
    """given a pandas correlation matrix, the function fits a
       KNNimputer object using the two most correlated features to the
       given column, then returns an imputed pandas Dataframe
    """
    sorted_corr = correlation_matrix[colname].sort_values(ascending=False)
    top_corr = sorted_corr.index[:2]
    KNNimp = KNNImputer(n_neighbors=n_neighbors)
    KNNimputed = KNNimp.fit_transform(data[top_corr])
    return KNNimputed[:,0], KNNimp

def KNN_test_impute(correlation_matrix, colname, data, fitted_imputer):
    """ given a pandas correlation matrix and a fitted KNN imputer object,
       the function transforms the given columns
    """
    sorted_corr = correlation_matrix[colname].sort_values(ascending=False)
    top_corr = sorted_corr.index[:2]
    KNNimputed = fitted_imputer.transform(data[top_corr])
    return KNNimputed[:,0]

names = X_train.columns
# imputing build_count features
string = ['build_count']
build_cols = [i for i in names if any(sub in i for sub in string)]
for i in build_cols:
    X_train[i].fillna(0, inplace=True)
X_train = X_train.drop('raion_build_count_with_builddate_info', axis = 1)
X_test = X_test.drop('raion_build_count_with_builddate_info', axis = 1)

# imputing sq_ft features
sq_ft_features = ['life_sq', 'full_sq', 'num_room', 'kitch_sq', 'floor',␣
 ↪'max_floor']
full_sq_data = X_train[sq_ft_features]

KNNimp = KNNImputer(n_neighbors = 3)
KNNimp.fit(full_sq_data)
```

```
KNNimp_train = KNNimp.transform(full_sq_data)
X_train['life_sq'] = KNNimp_train[:,0]
X_train['full_sq'] = KNNimp_train[:,1]
X_train['num_room'] = KNNimp_train[:,2]
X_train['kitch_sq'] = KNNimp_train[:,3]
X_train['floor'] = KNNimp_train[:,4]
X_train['max_floor'] = KNNimp_train[:,5]
KNNimp_test = KNNimp.transform(X_test[sq_ft_features])
X_test['life_sq'] = KNNimp_test[:,0]
X_test['full_sq'] = KNNimp_test[:,1]
X_test['num_room'] = KNNimp_test[:,2]
X_test['kitch_sq'] = KNNimp_test[:,3]
X_test['floor'] = KNNimp_test[:,4]
X_test['max_floor'] = KNNimp_test[:,5]

# walking features
walking = [i for i in X_train.columns if any(sub in i for sub in ['walk'])]
walking.append('sub_area')
droppers = ['metro_min_walk','railroad_station_walk_min']
X_train = X_train.drop(droppers, axis = 1)
X_test = X_test.drop(droppers, axis = 1)
walking = [ 'metro_km_walk',
            'railroad_station_walk_km',
            'ID_railroad_station_walk']
corr = X_train.corr()

imputer_dict = dict()
for i in walking:
    X_train[i], imputer_dict[i] = KNN_train_impute(corr, colname = i, data =␣
 ↪X_train)
    X_test[i] = KNN_test_impute(corr, colname = i, data= X_test, fitted_imputer␣
 ↪= imputer_dict[i])

# prom feature
correlation_matrix = X_train.corr()
n_neighbors = 3
sorted_corr = correlation_matrix['prom_part_5000'].sort_values(ascending=False)
top_corr = sorted_corr.index[:2]
KNNimp = KNNImputer(n_neighbors=n_neighbors)
KNNimputed = KNNimp.fit_transform(X_train[top_corr])

X_train['prom_part_5000'] = KNNimputed[:,0]
KNN_test_imputed = KNNimp.transform(X_test[top_corr])
X_test['prom_part_5000'] = KNN_test_imputed[:,0]
```

[188]:
```
# impute the training data
```

```
caf_avg_price_cols = ['cafe_avg_price_500', 'cafe_avg_price_1000',␣
↪'cafe_avg_price_1500',
                  'cafe_avg_price_2000', 'cafe_avg_price_3000',␣
↪'cafe_avg_price_5000']
caf_count_cols = ['cafe_count_500', 'cafe_count_1000', 'cafe_count_1500',
                      'cafe_count_2000', 'cafe_count_3000', 'cafe_count_5000']
# find levels with missing values
missing_levels = dict()
for count_col in caf_count_cols:
    missing_levels[count_col] = np.unique(X_train[X_train[caf_avg_price_cols +␣
↪caf_count_cols].isna().any(axis=1)][caf_count_cols][count_col])
# find levels with missing values
sub_areas = dict()
for price_col in caf_avg_price_cols:
    sub_areas[price_col] = np.unique(X_train[X_train[[price_col] + ['sub_area']].
↪isna().any(axis=1)].sub_area)
# save imputed values
imputes = defaultdict(lambda: -1)
# loop over training data to impute training data and save impute values
for caf_avg_price_col, caf_count_col in zip(caf_avg_price_cols, caf_count_cols):
    for i in missing_levels[caf_count_col]:
        for sub_area in sub_areas[caf_avg_price_col]:
            idxes = X_train.query('sub_area == ' + '"' + sub_area +␣
↪'"')[X_train[caf_avg_price_col].isna() &␣
↪(X_train[caf_count_col]==i)][caf_avg_price_col].index
            # when value of count col is 0 set avg col to -1
            if i == 0:
                X_train.loc[idxes, caf_avg_price_col] = -1
                imputes[caf_avg_price_col + str(i) + sub_area] = -1
            else: # else use the median ignoring the nans
                if np.all(np.
↪isnan(X_train[X_train[caf_count_col]==i][caf_avg_price_col])):
                    X_train.loc[idxes, caf_avg_price_col] = -1
                    imputes[caf_avg_price_col + str(i) + sub_area] = -1
                else:
                    X_train.loc[idxes, caf_avg_price_col] = np.
↪nanmedian(X_train[X_train[caf_count_col]==i][caf_avg_price_col])
                    imputes[caf_avg_price_col + str(i) + sub_area] = np.
↪nanmedian(X_train[X_train[caf_count_col]==i][caf_avg_price_col])

# impute the test data
missing_levels = dict()
for count_col in caf_count_cols:
    missing_levels[count_col] = np.unique(X_test[X_test[caf_avg_price_cols +␣
↪caf_count_cols].isna().any(axis=1)][caf_count_cols][count_col])
```

```
sub_areas = dict()
for price_col in caf_avg_price_cols:
    sub_areas[price_col] = np.unique(X_test[X_test[[price_col] + ['sub_area']].
↪isna().any(axis=1)].sub_area)

for caf_avg_price_col, caf_count_col in zip(caf_avg_price_cols, caf_count_cols):
    for i in missing_levels[caf_count_col]:
        for sub_area in sub_areas[caf_avg_price_col]:
            idxes = X_test.query('sub_area == ' + '"' + sub_area +␣
↪'"')[X_test[caf_avg_price_col].isna() &␣
↪(X_test[caf_count_col]==i)][caf_avg_price_col].index
            X_test.loc[idxes, caf_avg_price_col] = imputes[caf_avg_price_col +␣
↪str(i) + sub_area]
```

[36]:
```
# drop the collinear columns
cafe_min_max_cols = ['cafe_sum_500_min_price_avg', 'cafe_sum_500_max_price_avg',
                     'cafe_sum_1000_min_price_avg',␣
↪'cafe_sum_1000_max_price_avg',
                     'cafe_sum_1500_min_price_avg',␣
↪'cafe_sum_1500_max_price_avg',
                     'cafe_sum_2000_min_price_avg',␣
↪'cafe_sum_2000_max_price_avg',
                     'cafe_sum_3000_min_price_avg',␣
↪'cafe_sum_3000_max_price_avg',
                     'cafe_sum_5000_min_price_avg',␣
↪'cafe_sum_5000_max_price_avg',]

X_train = X_train.drop(cafe_min_max_cols, axis=1)
X_test = X_test.drop(cafe_min_max_cols, axis=1)
```

B Analysis

First, get list of all records with missing values. See if we can drop them all

Recognized there are no records without missing information

Next, if we can drop them all, we can run random forest to see which features are most important.

Finally, we can impute in order of importance; for most important features, we will impute them first, then work downward.

B.1 A count of all missing values

[5]:
```
# Take a copy of X_train and y_train to mimick the real 'df'
df = pd.concat([X_train, y_train], axis=1)
df_test = pd.concat([X_test, y_test], axis=1)
X_train_copy = X_train.copy()
```

[6]:
```
nullList = df.isnull().sum()
na_list=nullList[nullList>0].sort_values(ascending=False)
```

[107]:
```
print('Count of columns with missing values: {}\nCount of columns without␣
 ↪missing values: {}'.format(nullList[nullList>0].sort_values(ascending=False).
 ↪count(), nullList[nullList==0].sort_values(ascending=False).count()))
```

```
Count of columns with missing values: 49
Count of columns without missing values: 243
```

[108]:
```
print('Percent of dataset records with null values: {}%'.
 ↪format(round(nullList[nullList>0].max()/df.shape[0]*100, 2)))
```

```
Percent of dataset records with null values: 47.41%
```

B.1.1 A dataframe of missing values and their data types for selecting imputation algorithm

B.1.2 We're assuming not every neighborhood in Moscow has a hospital, just as not every neighborhood in Dallas has a hospital.

[109]:
```
df_missing = pd.DataFrame(list(zip(na_list.index, na_list.values)),␣
 ↪columns=['feature','na_count'])
df_dtypes = pd.DataFrame(list(zip(df.dtypes.index, X_train.dtypes)),␣
 ↪columns=['feature','type'])
df_missing.merge(df_dtypes, how='inner', on='feature')
```

[109]:

	feature	na_count	type
0	hospital_beds_raion	11557	float64
1	build_year	10881	float64
2	state	10843	float64
3	cafe_sum_500_min_price_avg	10584	float64
4	cafe_sum_500_max_price_avg	10584	float64
5	cafe_avg_price_500	10584	float64
6	max_floor	7661	float64
7	material	7661	float64
8	num_room	7661	float64
9	kitch_sq	7661	float64
10	cafe_avg_price_1000	5189	float64
11	cafe_sum_1000_max_price_avg	5189	float64

```
12            cafe_sum_1000_min_price_avg      5189   float64
13                                life_sq      5108   float64
14                   build_count_1921-1945      4003   float64
15                       build_count_frame      4003   float64
16                        build_count_wood      4003   float64
17                       build_count_block      4003   float64
18    raion_build_count_with_material_info      4003   float64
19                       build_count_brick      4003   float64
20                    build_count_monolith      4003   float64
21                       build_count_panel      4003   float64
22                        build_count_foam      4003   float64
23                        build_count_slag      4003   float64
24                         build_count_mix      4003   float64
25   raion_build_count_with_builddate_info      4003   float64
26                  build_count_before_1920      4003   float64
27                   build_count_after_1995      4003   float64
28                   build_count_1946-1970      4003   float64
29                   build_count_1971-1995      4003   float64
30             cafe_sum_1500_min_price_avg      3321   float64
31             cafe_sum_1500_max_price_avg      3321   float64
32                     cafe_avg_price_1500      3321   float64
33             cafe_sum_2000_min_price_avg      1346   float64
34             cafe_sum_2000_max_price_avg      1346   float64
35                     cafe_avg_price_2000      1346   float64
36             cafe_sum_3000_min_price_avg       784   float64
37             cafe_sum_3000_max_price_avg       784   float64
38                     cafe_avg_price_3000       784   float64
39             cafe_sum_5000_max_price_avg       245   float64
40             cafe_sum_5000_min_price_avg       245   float64
41                     cafe_avg_price_5000       245   float64
42                         prom_part_5000       150   float64
43                                  floor       126   float64
44                railroad_station_walk_km        19   float64
45               railroad_station_walk_min        19   float64
46                ID_railroad_station_walk        19   float64
47                          metro_km_walk        19   float64
48                         metro_min_walk        19   float64
```

[110]:
```
df.dtypes.unique()
```

[110]:
```
array([dtype('int64'), dtype('O'), dtype('float64')], dtype=object)
```

[7]:
```
df_cats = df.select_dtypes(include=['O'])
df_cats_test = df_test.select_dtypes(include=['O'])
```

[8]:
```
df_cats2 = df_cats.drop('timestamp',axis=1)
df_cats2_test = df_cats_test.drop('timestamp',axis=1)
```

[113]:
```python
print('Categorical cardinality:\n\nFeature product_type:\n{}\n\nFeature ecology:
↪\n{}\n\nFeature sub_area:\n{}'.format(df_cats['product_type'].unique(),␣
↪df_cats['ecology'].unique(), df_cats['sub_area'].unique()))
```

```
Categorical cardinality:

Feature product_type:
['OwnerOccupier' 'Investment']

Feature ecology:
['good' 'no data' 'satisfactory' 'poor' 'excellent']

Feature sub_area:
['Nekrasovka' 'Poselenie Rogovskoe' 'Zjuzino' 'Chertanovo Juzhnoe'
 'Juzhnoe Butovo' 'Pokrovskoe Streshnevo' "Tekstil'shhiki" 'Otradnoe'
 'Zjablikovo' 'Jaroslavskoe' 'Tverskoe' 'Poselenie Sosenskoe'
 'Poselenie Shherbinka' "Kon'kovo" 'Poselenie Vnukovskoe' 'Ljublino'
 'Poselenie Moskovskij' 'Golovinskoe' 'Poselenie Voskresenskoe' 'Solncevo'
 'Jakimanka' 'Jasenevo' 'Ramenki' 'Akademicheskoe' 'Matushkino' 'Shhukino'
 'Fili Davydkovo' 'Preobrazhenskoe' 'Sviblovo' 'Caricyno' 'Brateevo'
 'Meshhanskoe' "Mar'ina Roshha" 'Perovo' "Kuz'minki" 'Kotlovka'
 'Orehovo-Borisovo Juzhnoe' 'Begovoe' 'Bogorodskoe' 'Ochakovo-Matveevskoe'
 'Pechatniki' 'Severnoe Tushino' 'Birjulevo Vostochnoe' 'Mitino'
 'Prospekt Vernadskogo' 'Severnoe Butovo' 'Poselenie Filimonkovskoe'
 'Zapadnoe Degunino' "Mar'ino" 'Poselenie Desjonovskoe' 'Bibirevo'
 'Taganskoe' 'Vostochnoe Degunino' 'Novokosino' 'Levoberezhnoe' 'Savelki'
 'Nagatino-Sadovniki' 'Mozhajskoe' "Moskvorech'e-Saburovo"
 'Kosino-Uhtomskoe' 'Juzhnoportovoe' 'Horoshevo-Mnevniki' 'Izmajlovo'
 'Metrogorodok' 'Krylatskoe' 'Obruchevskoe' 'Koptevo'
 'Orehovo-Borisovo Severnoe' 'Sokolinaja Gora' 'Veshnjaki'
 'Vyhino-Zhulebino' 'Hovrino' 'Strogino' 'Lianozovo' 'Troparevo-Nikulino'
 'Lomonosovskoe' "Krasnosel'skoe" "Gol'janovo" 'Dorogomilovo' 'Silino'
 'Sokol' 'Beskudnikovskoe' 'Krjukovo' 'Presnenskoe'
 'Poselenie Rjazanovskoe' 'Vojkovskoe' 'Troickij okrug' 'Rjazanskij'
 'Losinoostrovskoe' 'Nagornoe' "Chertanovo Central'noe" 'Danilovskoe'
 'Filevskij Park' 'Teplyj Stan' 'Chertanovo Severnoe' 'Lefortovo'
 'Kuncevo' 'Novo-Peredelkino' 'Nagatinskij Zaton' 'Severnoe Medvedkovo'
 'Dmitrovskoe' 'Hamovniki' 'Donskoe' 'Ajeroport' 'Juzhnoe Tushino'
 'Cheremushki' 'Severnoe Izmajlovo' "Altuf'evskoe" 'Marfino'
 'Horoshevskoe' 'Novogireevo' 'Poselenie Novofedorovskoe' 'Alekseevskoe'
 'Vostochnoe' 'Poselenie Pervomajskoe' "Sokol'niki" 'Juzhnoe Medvedkovo'
 'Birjulevo Zapadnoe' 'Babushkinskoe' 'Ostankinskoe' 'Timirjazevskoe'
 'Ivanovskoe' 'Vostochnoe Izmajlovo' 'Nizhegorodskoe' 'Severnoe'
 'Basmannoe' 'Savelovskoe' 'Butyrskoe' 'Kurkino' 'Molzhaninovskoe'
 'Staroe Krjukovo' 'Kapotnja' 'Poselenie Shhapovskoe' 'Rostokino'
 'Gagarinskoe' "Zamoskvorech'e" 'Poselenie Marushkinskoe'
 'Poselenie Mosrentgen' 'Poselenie Kokoshkino' 'Arbat'
```

```
'Poselenie Krasnopahorskoe' 'Vnukovo' 'Poselenie Voronovskoe'
'Poselenie Kievskij' 'Poselenie Mihajlovo-Jarcevskoe']
```

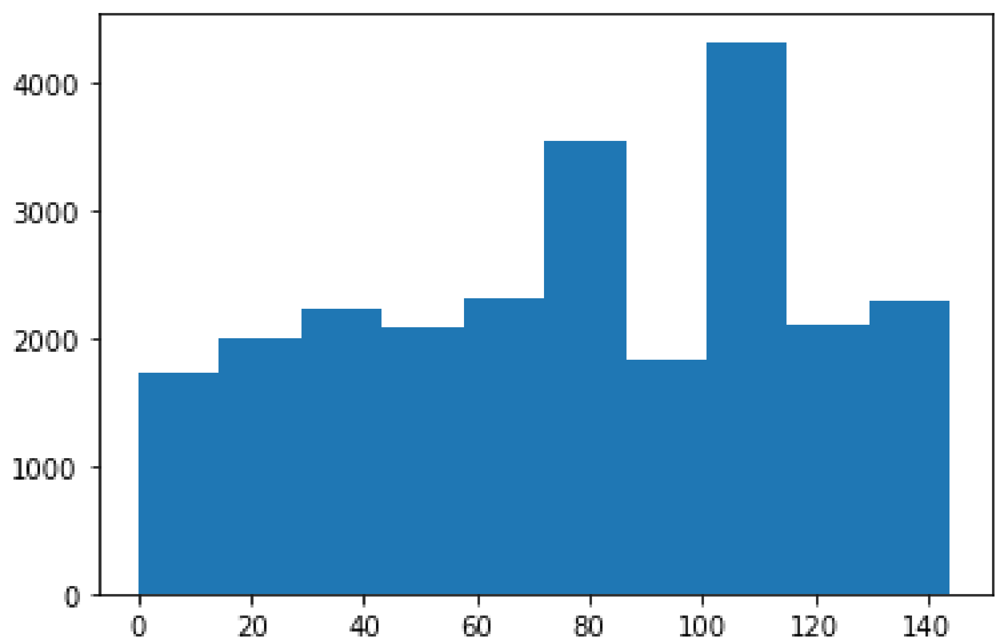
[9]:
```python
df_cats2['sub_area'].isnull().sum()
```

[9]: 0

C One-hot and label encode

[10]:
```python
sub_area = df_cats2['sub_area'].astype('category')
sub_area_final = sub_area.cat.codes
sub_area_test = df_cats2_test['sub_area'].astype('category')
sub_area_final_test = sub_area_test.cat.codes

one_hots = df_cats2.drop('sub_area',axis=1)
one_hots_final = pd.get_dummies(one_hots)
one_hots_test = df_cats2_test.drop('sub_area',axis=1)
one_hots_final_test = pd.get_dummies(one_hots_test)
```

[116]:
```python
import matplotlib.pyplot as plt
plt.hist(sub_area.cat.codes);
```



[117]:
```python
sub_area.isna().sum()
```

[117]: 0

[11]:
```
encodes = pd.concat([sub_area_final,one_hots_final], axis=1).astype('int64')
encodes_test = pd.concat([sub_area_final_test,one_hots_final_test], axis=1).
  ↪astype('int64')
```

D Get a list of the non-null values and run a model to predict price_doc

D.1 Concatenate with encoded variables

[119]:
```
print('time range: [{}, {}]'.format(df['timestamp'].min(),df['timestamp'].max()))
```

```
time range: [2011-08-20, 2015-06-30]
```

[12]:
```
nullList = df.isnull().sum()
non_naList=nullList[nullList==0].sort_values(ascending=False)
non_null_features = list(non_naList.index)
```

[13]:
```
df[non_null_features].dtypes.unique()
```

[13]:
```
array([dtype('int64'), dtype('float64'), dtype('O')], dtype=object)
```

[14]:
```
no_null_df = df[non_null_features].drop(['id','timestamp'], axis=1).
  ↪select_dtypes(include=['int64','float64'])
no_null_df_test = df_test[non_null_features].drop(['id','timestamp'], axis=1).
  ↪select_dtypes(include=['int64','float64'])
```

[15]:
```
df_no_null = pd.concat([no_null_df, encodes], axis=1)
df_no_null_test = pd.concat([no_null_df_test, encodes_test], axis=1)
```

[124]:
```
df_no_null.head()
```

[124]:
```
       price_doc  metro_min_avto  railroad_km  ID_big_road2  big_road2_km  \
12761    4740002        4.721045     1.214861            55      2.657336
27371    6193847       60.941737     8.708224             2     11.745219
19862    7280000        2.157751     2.331635            16      4.035698
4157     8100000        1.240248     0.552915            40      1.849306
2559      990000        2.085207     0.083946            39      3.779375

       ID_big_road1  big_road1_km  kremlin_km  bulvar_ring_km  sadovoe_km  \
12761            11      1.905125   20.549464       19.272537   18.418929
27371            38      0.034646   70.738769       69.984874   68.853047
19862             2      2.155430   10.164680        9.491357    8.146895
4157              2      0.390289   17.158963       16.541632   15.096007
2559              2      2.453278   22.783267       22.103475   20.765428
```

```
       ...  water_1line_yes  big_road1_1line_no  big_road1_1line_yes  \
12761  ...                0                   1                    0
27371  ...                0                   0                    1
19862  ...                0                   1                    0
4157   ...                0                   1                    0
2559   ...                0                   1                    0

       railroad_1line_no  railroad_1line_yes  ecology_excellent  ecology_good  \
12761                  1                   0                  0             1
27371                  1                   0                  0             0
19862                  1                   0                  0             0
4157                   1                   0                  0             0
2559                   0                   1                  0             1

       ecology_no data  ecology_poor  ecology_satisfactory
12761                0             0                     0
27371                1             0                     0
19862                0             0                     1
4157                 0             1                     0
2559                 0             0                     0

[5 rows x 258 columns]
```

D.2 Correlation matrix including encoded categorical data

[125]:
```
# Compute the correlation matrix
corr = df_no_null.corr()
```

D.3 Correlation matrix excluding categorical data

E There is no strong correlation in the dataset when there are only columns that do not contain NA

[ ]:
```
#pd.set_option('display.max_columns', None)
#corr
```

F Running a linear regression on price_doc to assess model performance without variables having missing values. This will be compared again after imputing

[16]:
```
from sklearn import linear_model
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

y = df_no_null['price_doc']
X = df_no_null.drop(['price_doc'], axis=1)
normalized_X = preprocessing.normalize(X)
X_normalized = pd.DataFrame(normalized_X, columns=X.columns)
X_train, X_test, y_train, y_test = train_test_split(X_normalized, y, test_size=0.
 ↪33, random_state=42)
```

[17]:
```
regress = linear_model.LinearRegression()
regress.fit(X_train, y_train)
y_preds = regress.predict(X_test)
print('Mean Squared Error: {}'.format(mean_squared_error(y_test, y_preds)))
```

```
Mean Squared Error: 13895601104806.533
```

F.1 Modeling Price_doc

[128]:
```
from sklearn.feature_selection import RFECV
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

# define the estimator
linearRegress = LinearRegression()
# provide the parameters of the feature selection process
feature_selector = RFECV(linearRegress,
          step = 1,
          min_features_to_select= 1,
          cv = 5,
          n_jobs = -1)
```

[ ]:
```
# fit the selector to the training set
feature_selector = feature_selector.fit(X_train, y_train)
```

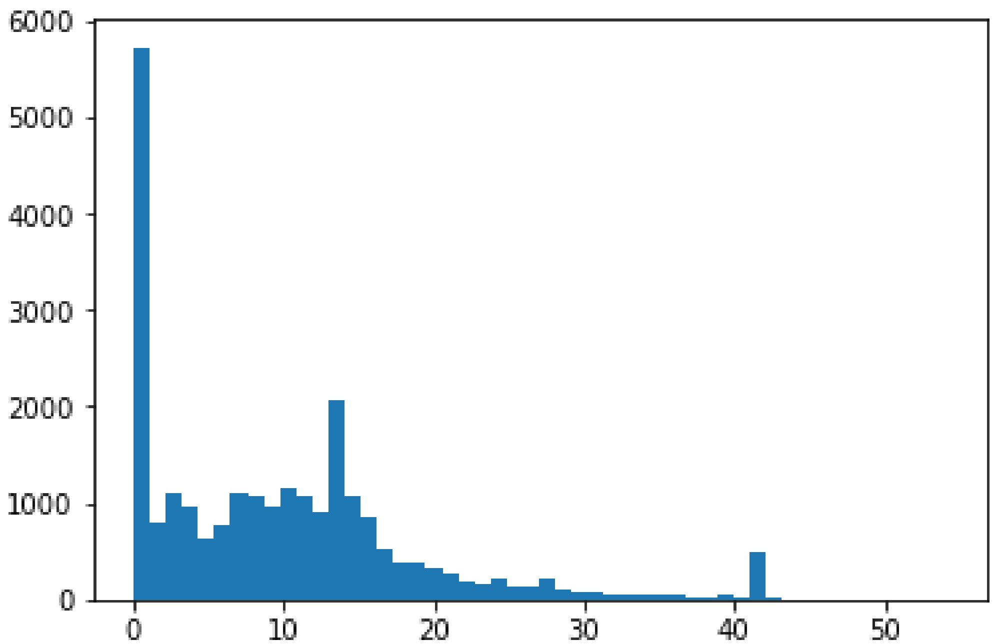
[ ]:
```
# visualize the results
print('Optimal number of features : %d' % feature_selector.n_features_)
plt.figure()
plt.xlabel('Number of features Selected')
```

```
plt.ylabel('Cross validation score')
plt.plot(range(1,len(feature_selector.grid_scores_) +1), feature_selector.
 ↪grid_scores_)
plt.show()
```

[74]:
```
df_no_null.columns[116]
```

[74]: 'male_f'

[75]:
```
plt.hist(df_no_null['sport_count_2000'], bins = 50);
```



[ ]:
```
df_no_sport = df_no_null.drop('sport_count_2000', axis = 1)
feature_selector = feature_selector.fit(X_train, y_train)
# visualize the results
print('Optimal number of features : %d' % feature_selector.n_features_)
plt.figure()
plt.xlabel('Number of features Selected')
plt.ylabel('Cross validation score')
plt.plot(range(1,len(feature_selector.grid_scores_) +1), feature_selector.
 ↪grid_scores_)
plt.show()
```

F.1.1 Using Ordinary Least Squares to check out serial correlation and feature importance relative to price_doc (y)

[18]:
```
import statsmodels.api as sm

y = df_no_null['price_doc']
X = df_no_null.drop(['price_doc'], axis=1)
normalized_X = preprocessing.normalize(X)


X2 = sm.add_constant(X_normalized)
est = sm.OLS(y.values.reshape(-1,1) , X2)
est2 = est.fit()
#est2.summary(alpha=0.05)
```

F.1.2 Durbin-Watson test statistic using lag-1 horizons indicate - with a value converging to 2 - that there is a very minimal risk of serial correlation. Therefore, a time series model is not required.

*****Need to move this up top since this needs to consider timestamp.**

[19]:
```
import statsmodels
resids = y_test-y_preds
print('Durbin-Watson test for serial correlation (lag-1 auto-correlation): {}'.
 ↪format(round(statsmodels.stats.stattools.durbin_watson(resids, axis=0),3)))
```

```
Durbin-Watson test for serial correlation (lag-1 auto-correlation): 2.019
```

F.1.3 A low adjusted r-squared indicates there is too much multi-collinearity in the data and the right features may not be included. Therefore, imputation is necessary.

[131]:
```
print('Adjusted R-Square: {}'.format(round(est2.rsquared_adj, 3)))
```

```
Adjusted R-Square: 0.362
```

F.1.4 The very low value of the smallest eigenvalue also indicates strong multi-collinearity by suggesting the matrix is close to singular

[136]:
```
est2.eigenvals.min()
```

[136]:
```
2.433704917934708e-28
```

[20]:
```
```

```
print('Percent of features that are statistically significant: {}%'.
 ↪format(round(est2.pvalues[est2.pvalues < 0.05].count() / est2.pvalues.
 ↪count()*100, 2)))
```

```
Percent of features that are statistically significant: 51.16%
```

[138]:
```
pval_names = list(est2.pvalues[est2.pvalues < 0.05].index)
pvals = list(est2.pvalues[est2.pvalues < 0.05].values)
```

[139]:
```
stat_sig = pd.DataFrame(list(zip(pval_names, pvals)),␣
 ↪columns=['feature','p-value'])
stat_sig.sort_values(by='p-value').reset_index(drop=True).head()
```

[139]:

	feature	p-value
0	full_sq	0.000000e+00
1	cafe_count_2000_price_4000	1.424464e-12
2	culture_objects_top_25_no	8.620725e-11
3	culture_objects_top_25_yes	1.200802e-10
4	leisure_count_3000	3.930004e-10

After running a linear regression on the data without imputing any values and only using columns that do not have missing information, we have high error and cannot use this method to impute. Because of the high cardinality, we cannot treat the feature as categorical and apply a classification algorithm. Therefore, we impute with zero under the assumption not all sub_areas (neighborhoods) have hospitals. Furthermore, there are no splits on sub_areas; all sub_areas either have hospital bed counts or they do not, but there are no sub_areas that have randomly missing values.

F.2 Hospital_bed_raion

[140]:
```
print('Percent of hospital_beds_raion with missing values: {}%'.
 ↪format(round(100*df['hospital_beds_raion'].isna().sum()/df.shape[0],2)))
```

```
Percent of hospital_beds_raion with missing values: 47.41%
```

[21]:
```
neighborhoods = pd.concat([df['sub_area'],df['hospital_beds_raion']], axis=1)
s = neighborhoods.groupby(neighborhoods['sub_area']).sum()

#pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
s.sort_values(by='sub_area', ascending=True).head() # Missing values appear as 0
```

[21]:

	hospital_beds_raion
sub_area	
Ajeroport	108120.0
Akademicheskoe	141930.0
Alekseevskoe	67760.0

```
Altuf'evskoe                    0.0
Arbat                        5620.0
```

F.2.1 Hospital bed imputation

Because missing values for hospital_beds_raion are missing not at random - meaning neighborhoods that have values have values across all records whereas neighborhoods that do not have values have no values across all records - we will impute missing values for hospital_beds_raion with value zero.

```
[22]: df.loc[df['hospital_beds_raion'].isna(),'hospital_beds_raion'] = 0
      df_test.loc[df_test['hospital_beds_raion'].isna(),'hospital_beds_raion'] = 0
```

```
[23]: df1 = pd.concat([df_no_null, df['hospital_beds_raion']], axis=1)
      df1_test = pd.concat([df_no_null_test, df_test['hospital_beds_raion']], axis=1)
```

F.3 Build Year

For this, we used an ensemble of a linear regression using all numeric features not containing NA and the median by sub_area for imputing build year. Mean squared error outperformed model baseline used to predict price_doc so using linear regression to impute for an input variable will not likely make the model worse.

F.3.1 Median Imputation

To impute with median build_year, we needed to first eliminate the NA and outlier values. For this, we identified that years 0 and 20052009 existed in the dataset. We considered those to be the same as missing as well and dropped them from the dataset. We considered taking the average of 2005 and 2009 for the points with 20052009, but we decided it would be simpler to just impute over this value.

```
[24]: df2 = pd.concat([df_no_null.select_dtypes(include=['int64','float64']),␣
       ↪df['hospital_beds_raion'], df['build_year'], df['sub_area']], axis=1)
      df2_test = pd.concat([df_no_null_test.
       ↪select_dtypes(include=['int64','float64']), df_test['hospital_beds_raion'],␣
       ↪df_test['build_year'], df_test['sub_area']], axis=1)
```

F.3.2 Apply build_year median-stratified imputation:

Treat future or ancient years as NaN so they will be imputed with the other NaNs

```
[27]: # df2 contains all original data and imputed hospital beds
      df2.loc[(df2['build_year'] < 1500),'build_year'] = np.nan
      df2.loc[(df2['build_year'] > 2020),'build_year'] = np.nan
```

```
df2_test.loc[(df2_test['build_year'] < 1500),'build_year'] = np.nan
df2_test.loc[(df2_test['build_year'] > 2020),'build_year'] = np.nan
```

Imputing each sub_area's missing build_year values by the median years. We selected the mean because of housing planning under a command-type economy where market demands don't exist to smooth construction over a duration of time. Instead, with command economies, housing construction is more likely to occurr in spurts, with no growth for many years. To prevent mitigating outliers in that scenario, we selected to impute build_year with the mean of each sub_area.

[28]:
```
df2['build_year'] = df2['build_year'].fillna(df2.
 ↪groupby('sub_area')['build_year'].transform('median'))
df2_test['build_year'] = df2_test['build_year'].fillna(df2_test.
 ↪groupby('sub_area')['build_year'].transform('median'))

df2_test.loc[df2_test['sub_area']=='Poselenie Shhapovskoe', 'build_year'] = 2011
df2_test.loc[df2_test['sub_area']=='Poselenie Rogovskoe', 'build_year'] = 2015
```

Imputations appear well placed and follow the original distributions:

Summary statistics for all non-Poselenie Neighborhoods:

[229]:
```
print('After stratify-imputing build_year values by sub_area:\n')
print('Non-Poselenie Mean build year: {}\nNon-Poselenie Median build year: {}'.
 ↪format(floor(df2['build_year'].mean()), floor(df2['build_year'].median())))
print('\nNon-Poselenie Minimum build year: {}\nNon-Poselenie Maximum build year:␣
 ↪{}'.format(floor(df2['build_year'].min()), floor(df2['build_year'].max())))
```

```
After stratify-imputing build_year values by sub_area:

Non-Poselenie Mean build year: 1990
Non-Poselenie Median build year: 1992

Non-Poselenie Minimum build year: 1860
Non-Poselenie Maximum build year: 2018
```

G Imputing state

State is the condition of an apartment. We impute this column by predicting state based on age, sub_area, and priori values of states for the region.

[29]:
```
df3 = pd.concat([df2, df['state']], axis=1)
df3_test = pd.concat([df2_test, df_test['state']], axis=1)
```

[30]:
```
df3neigh = df3.copy()
df3lr = df3.copy() # categorical encodings for logistic regression
```

```
df3neigh_test = df3_test.copy()
df3lr_test = df3_test.copy() # categorical encodings for logistic regression
```

[31]:
```
df3lr['sub_area'] = df3lr['sub_area'].astype('category').cat.codes
df3lr_test['sub_area'] = df3lr_test['sub_area'].astype('category').cat.codes
```

[32]:
```
sub_area_onehots = pd.get_dummies(df3neigh['sub_area'].astype('category'))
sub_area_onehots_test = pd.get_dummies(df3neigh_test['sub_area'].
 ↪astype('category'))
```

[33]:
```
list(set(sub_area_onehots.columns) - set(sub_area_onehots_test.columns))
```

[33]:
```
['Poselenie Kievskij',
 'Molzhaninovskoe',
 'Poselenie Mihajlovo-Jarcevskoe',
 'Poselenie Voronovskoe']
```

[34]:
```
list(set(sub_area_onehots_test.columns) - set(sub_area_onehots.columns))
```

[34]:
```
['Poselenie Klenovskoe']
```

[35]:
```
sub_area_onehots_test = sub_area_onehots_test.reindex(columns =␣
 ↪sub_area_onehots_test.columns.tolist() + ['Molzhaninovskoe','Poselenie␣
 ↪Voronovskoe','Poselenie Kievskij','Poselenie Mihajlovo-Jarcevskoe'])
sub_area_onehots = sub_area_onehots.reindex(columns = sub_area_onehots.columns.
 ↪tolist() + ['Poselenie Klenovskoe'])

sub_area_onehots_test['Molzhaninovskoe'] = 0
sub_area_onehots_test['Poselenie Voronovskoe'] = 0
sub_area_onehots_test['Poselenie Kievskij'] = 0
sub_area_onehots_test['Poselenie Mihajlovo-Jarcevskoe'] = 0
sub_area_onehots['Poselenie Klenovskoe'] = 0

print('Missing from sub_area_onehots_test: {}'.format(list(set(sub_area_onehots.
 ↪columns) - set(sub_area_onehots_test.columns))))
print('Missing from sub_area_onehots: {}'.format(list(set(sub_area_onehots_test.
 ↪columns) - set(sub_area_onehots.columns))))
```

```
Missing from sub_area_onehots_test: []
Missing from sub_area_onehots: []
```

[36]:
```
df3neigh = pd.concat([df3neigh.drop('sub_area',axis=1), sub_area_onehots],␣
 ↪axis=1) # drop sub_area because it's one-hot encoded
df3neigh_test = pd.concat([df3neigh_test.drop('sub_area',axis=1),␣
 ↪sub_area_onehots_test], axis=1) # drop sub_area because it's one-hot encoded
```

[37]:
```python
corrcats = df3lr.corr()
corrhots = df3neigh.corr()
```

[38]:
```python
corrcats = pd.DataFrame(corrcats['state'])
corrcats['state'] = abs(corrcats['state'])

corrhots = pd.DataFrame(corrhots['state'])
corrhots['state'] = abs(corrhots['state'])
```

Below are the top 10 features correlating to state. We selected from this list the two features with an absolute value of correlation greater than 0.5 in addition to build_year, which was close to 0.5, but we felt is important to consider by virtue of it representing the age of a building.

[39]:
```python
print(corrcats.sort_values(by='state', ascending=False).head(11))
print(corrhots.sort_values(by='state', ascending=False).head(11))
```

```
                               state
state                       1.000000
product_type_Investment     0.700166
product_type_OwnerOccupier  0.700166
build_year                  0.439903
ekder_female                0.376200
ekder_all                   0.373505
raion_popul                 0.372106
work_all                    0.369557
work_male                   0.369380
work_female                 0.367467
ecology_no data             0.363921
                               state
state                       1.000000
product_type_OwnerOccupier  0.700166
product_type_Investment     0.700166
build_year                  0.439903
ekder_female                0.376200
ekder_all                   0.373505
raion_popul                 0.372106
work_all                    0.369557
work_male                   0.369380
work_female                 0.367467
ecology_no data             0.363921
```

[40]:
```python
gt_95 = corrhots.index[corrhots['state'] >= np.percentile(corrhots[corrhots.
 ↪columns][~np.isnan(corrhots[corrhots.columns].values)], 95)].tolist()
```

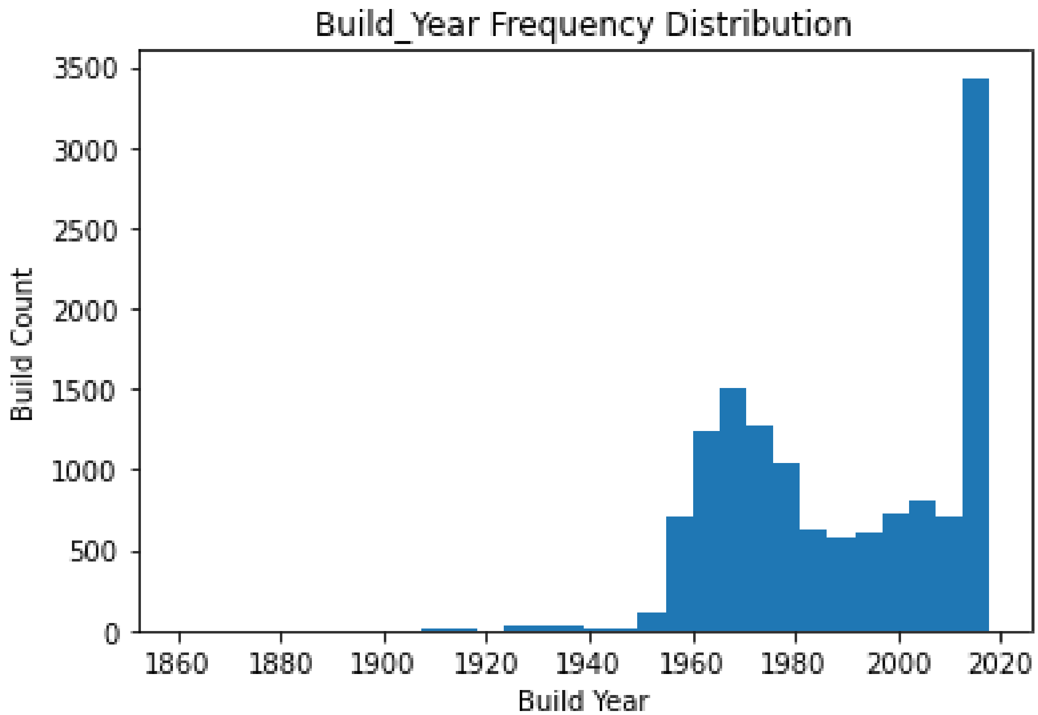
[41]:
```python
gt_95.remove('state')
```

G.0.1 K-Nearest Neighbors

[46]:
```
from sklearn.neighbors import KNeighborsClassifier

df3neigh_train = df3neigh[~df3neigh['state'].isna()]
#model_X = pd.DataFrame(df3neigh_train, columns =␣
↪['product_type_Investment','product_type_OwnerOccupier','build_year'],␣
↪dtype='int32')
model_X = pd.DataFrame(df3neigh_train.loc[:,gt_95], dtype='int32')
model_y = pd.DataFrame(df3neigh_train, columns = ['state'], dtype='int32')

X_train, X_test, y_train, y_test = train_test_split(model_X, model_y,␣
↪shuffle=True)
y_train_ravel = y_train.values.ravel()

neigh = KNeighborsClassifier(n_neighbors=3)
neigh.fit(X_train, y_train_ravel)

neigh.predict(X_train)

print('K-NN accuracy: {}'.format(neigh.score(X_test, y_test,␣
↪sample_weight=None)))
```

```
K-NN accuracy: 0.6152482269503546
```

[47]:
```
import matplotlib.pyplot as plt

plt.hist(df3lr['build_year'], bins=30)
plt.title('Build_Year Frequency Distribution')
plt.xlabel('Build Year')
plt.ylabel('Build Count');
```



G.0.2 Predict the missing 'state' data

```
[48]: # Null State dataset
df3_null = df3neigh.loc[df3neigh['state'].isna(), :]
# Input features of the Null State dataset
df3_input = df3_null.loc[:,gt_95].astype('int64')#␣
 ↪['product_type_Investment','product_type_OwnerOccupier','build_year']].
 ↪astype('int64')
# The No-Null dataset has no NULL values for state. Null dataset will be␣
 ↪appended to this after imputing state
df3_nonull = df3neigh.loc[~df3neigh['state'].isna(),:]


# Null State dataset
df3_null_test = df3neigh_test.loc[df3neigh_test['state'].isna(), :]
# Input features of the Null State dataset
df3_input_test = df3_null_test.loc[:,gt_95].astype('int64')#␣
 ↪['product_type_Investment','product_type_OwnerOccupier','build_year']].
 ↪astype('int64')
# The No-Null dataset has no NULL values for state. Null dataset will be␣
 ↪appended to this after imputing state
df3_nonull_test = df3neigh_test.loc[~df3neigh_test['state'].isna(),:]
```

```
[49]: # Predict 'state'
missing_state_vals = neigh.predict(df3_input)
missing_state_vals_test = neigh.predict(df3_input_test)
```

```
[51]: np.unique(np.array(missing_state_vals))
```

```
[51]: array([1, 2, 3, 4])
```

```
[50]: np.unique(np.array(missing_state_vals_test))
```

```
[50]: array([1, 2, 3, 4])
```

```
[ ]: df3_null['state'] = missing_state_vals
df3_null_test['state'] = missing_state_vals_test
```

```
[53]: print('original values: {}'.format(df.state.unique()))
print('imputed values: {}'.format(np.unique(missing_state_vals)))
```

```
original values: [ 1.  2. nan  3.  4. 33.]
imputed values: [1 2 3 4]
```

G.1 Final imputation of state

[54]:
```
df3_final = df3_null.append(df3_nonull)
df3_final_test = df3_null_test.append(df3_nonull_test)
```

H Max floor

[56]:
```
df4 = pd.concat([df['max_floor'],df3_final], axis=1).copy()
df4_test = pd.concat([df_test['max_floor'],df3_final_test], axis=1).copy()
```

[402]:
```
df4.shape
```

[402]:
```
(24376, 407)
```

[403]:
```
df.shape
```

[403]:
```
(24376, 292)
```

[57]:
```
df4_null = df4.loc[df4['max_floor'].isna(),:]
df4_nonull = df4.loc[~df4['max_floor'].isna(),:]

df4_null_test = df4_test.loc[df4_test['max_floor'].isna(),:]
df4_nonull_test = df4_test.loc[~df4_test['max_floor'].isna(),:]
```

[59]:
```
corr = df4_nonull.corr()
```

[60]:
```
corrfloor = pd.DataFrame(corr['max_floor'])
corrfloor['max_floor'] = abs(corrfloor['max_floor'])

#print(corrfloor.sort_values(by='max_floor', ascending=False).head(26))
```

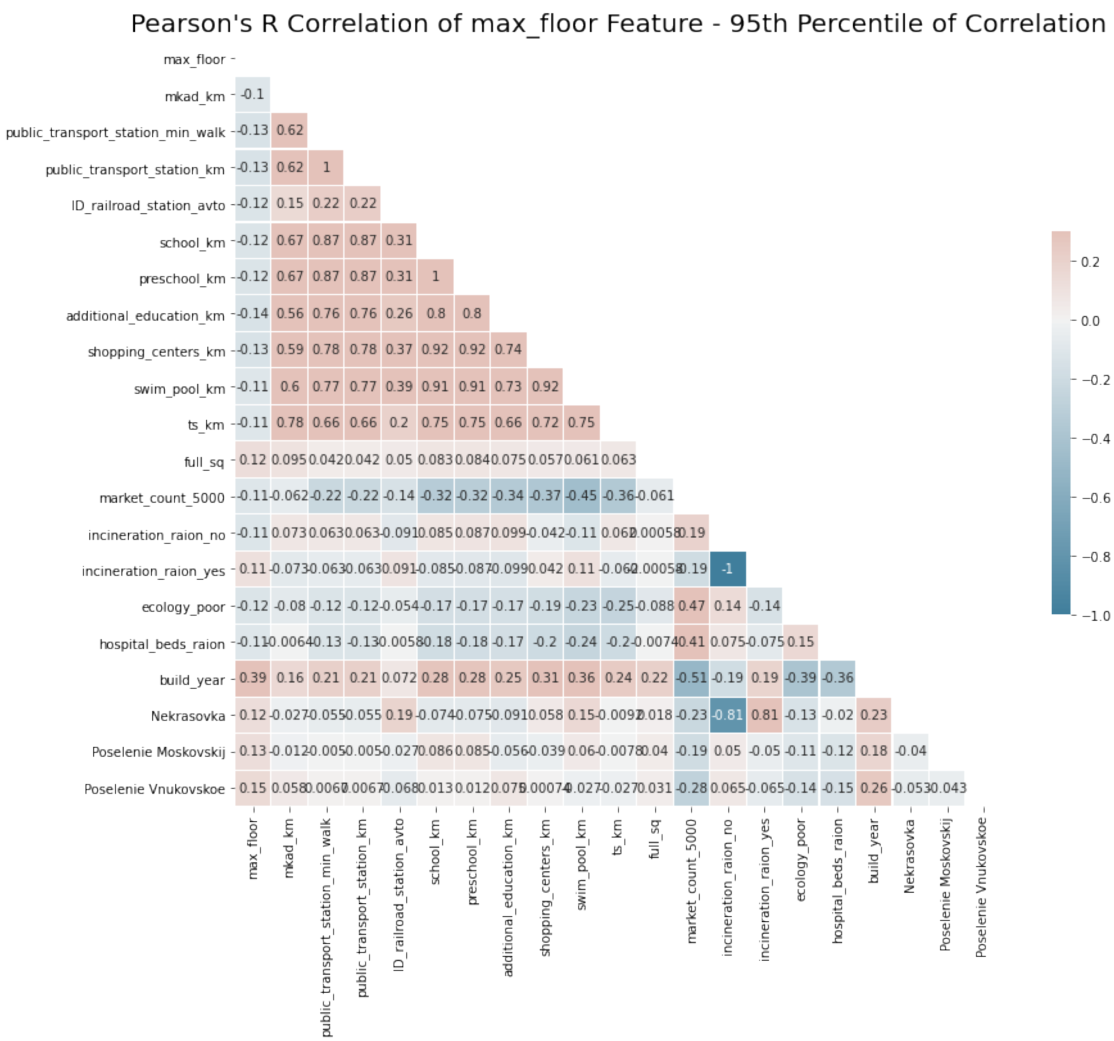
[61]:
```
gt_95 = corrfloor.index[corrfloor['max_floor'] >= np.
↪percentile(corrfloor[corrfloor.columns][~np.isnan(corrfloor[corrfloor.columns].
↪values)], 95)].tolist()
```

H.0.1 Building a model using the 95th percentile of features most correlated with max_floor.

H.1 Impute max_floor

[62]:
```
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr.loc[gt_95,gt_95], dtype=bool))

# Set up the matplotlib figure
```

```python
f, ax = plt.subplots(figsize=(14,11))
plt.title("Pearson's R Correlation of max_floor Feature - 95th Percentile of␣
↪Correlation", fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr.loc[gt_95,gt_95], mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5});
```



K-NN model for max_floor predicted on internal cross-validation with an accuracy of 49.57%. Because there are 48 floors (classes), this is a reasonable imputation method.

[63]:
```
gt_95 = gt_95.remove('max_floor')
```

[64]:
```
model_X = pd.DataFrame(df4_nonull, columns = gt_95, dtype='int64').
↪drop('price_doc',axis=1)
model_y = pd.DataFrame(df4_nonull, columns = ['max_floor'], dtype='int32')

X_train, X_test, y_train, y_test = train_test_split(model_X, model_y,␣
↪test_size=0.33, random_state=42)
```

[65]:
```
y_train_ravel = y_train.values.ravel()

neigh = KNeighborsClassifier(n_neighbors=5)
neigh.fit(X_train, y_train.values.ravel())

neigh.predict(X_train)

print('K-NN accuracy: {}'.format(neigh.score(X_test, y_test.values.ravel(),␣
↪sample_weight=None)))
```

```
K-NN accuracy: 0.49202320522117476
```

[66]:
```
df4_null = df4_null.drop('max_floor',axis=1)
df4_null_test = df4_null_test.drop('max_floor',axis=1)
```

[67]:
```
df4_null_test.loc[df4_null_test['preschool_quota'].isna(),'preschool_quota'] = 0
df4_null_test.loc[df4_null_test['school_quota'].isna(),'school_quota'] = 0
```

[68]:
```
df4_input = pd.DataFrame(df4_null, columns = gt_95, dtype='float64')

missing_max_floor_vals = neigh.predict(df4_input)

df4_input_test = pd.DataFrame(df4_null_test, columns = gt_95, dtype='float64')

missing_max_floor_vals_test = neigh.predict(df4_input_test)
```

[69]:
```
df4_null['max_floor'] = missing_max_floor_vals.copy()
df4_null_test['max_floor'] = missing_max_floor_vals_test.copy()
```

[70]:
```
df4_final = df4_null.append(df4_nonull)
df4_final_test = df4_null_test.append(df4_nonull_test)
```

H.2 Material

[500]:
```
df4_final.shape
```

[500]:
```
(24376, 407)
```

[71]:
```
df5 = pd.concat([df['material'], df4_final], axis=1).copy()
df5_test = pd.concat([df_test['material'], df4_final_test], axis=1).copy()
```

[72]:
```
df5_null = df5.loc[df5['material'].isna(),:]
df5_nonull = df5.loc[~df5['material'].isna(),:]

df5_null_test = df5_test.loc[df5_test['material'].isna(),:]
df5_nonull_test = df5_test.loc[~df5_test['material'].isna(),:]
```

[74]:
```
corr = df5_nonull.corr()
```

[75]:
```
corrmat = pd.DataFrame(corr['material'])
corrmat['material'] = abs(corrmat['material'])

print(corrmat.sort_values(by='material', ascending=False).head(14))
```

```
                                   material
material                           1.000000
incineration_raion_no              0.112190
incineration_raion_yes             0.112190
preschool_quota                    0.110566
ecology_good                       0.110456
school_quota                       0.096572
Poselenie Filimonkovskoe           0.096375
sport_count_5000                   0.096212
ID_big_road2                       0.095217
Nekrasovka                         0.091901
ID_railroad_terminal               0.089944
ecology_poor                       0.089529
office_sqm_5000                    0.089161
preschool_education_centers_raion  0.080061
```

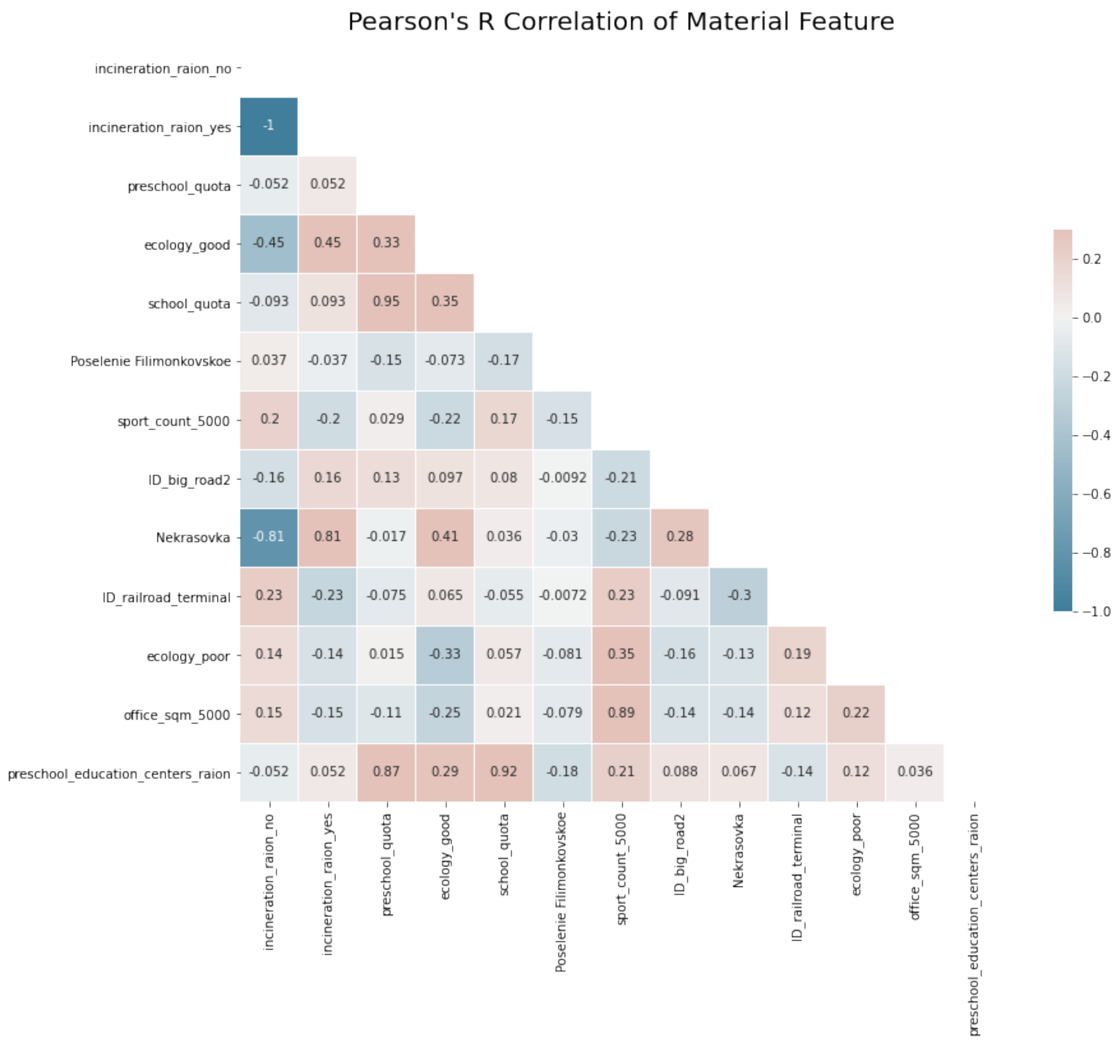
H.2.1 There are not a lot of strong correlators for material so we use everything with a coefficient correlation greater than 0.075

[76]:
```
top_14 = corrmat.sort_values(by='material', ascending=False).head(14)
```

[78]:
```
gt_75 = list(top_14[1:].index)
```

[79]:

```
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr.loc[gt_75,gt_75], dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(14,11))
plt.title("Pearson's R Correlation of Material Feature", fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr.loc[gt_75,gt_75], mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5});
```




```
[80]: model_X = pd.DataFrame(df5_nonull, columns = gt_75, dtype='int64')
model_y = pd.DataFrame(df5_nonull, columns = ['material'], dtype='int32')

X_train, X_test, y_train, y_test = train_test_split(model_X, model_y,␣
 ↪test_size=0.33, random_state=42)
```

H.3 K-Nearest Neighbors

Based on the high cardinality in the floor counts we used K-NN to impute the missing material values. There are three one-hot encoded neighborhoods (sub_area) we used for this - Poselenie Filimonkovskoe, Nekrasovka, and Nagatinskij Zaton - which seem to have some correlation beyond complete randomness. We used additional features such as railroad terminal proximity, ecology, and inceneration raion to predict missing material values. This produced a reasonable accuracy.

[81]:
```
y_train_ravel = y_train.values.ravel()

neigh = KNeighborsClassifier(n_neighbors=5)
neigh.fit(X_train, y_train.values.ravel())

neigh.predict(X_train)

print('K-NN accuracy: {}'.format(neigh.score(X_test, y_test.values.ravel(),␣
↪sample_weight=None)))
```

```
K-NN accuracy: 0.6820159535895577
```

[82]:
```
df5_input = pd.DataFrame(df5_null, columns = gt_75, dtype='int64')
df5_input_test = pd.DataFrame(df5_null_test, columns = gt_75, dtype='int64')
missing_material_vals = neigh.predict(df5_input)
missing_material_vals_test = neigh.predict(df5_input_test)
```

[83]:
```
missing_material_vals_test.shape
```

[83]:
```
(1911,)
```

H.4 Impute Material

[ ]:
```
df5_null['material'] = missing_material_vals
df5_null_test['material'] = missing_material_vals_test
```

[85]:
```
df5_final = df5_null.append(df5_nonull)
df5_final_test = df5_null_test.append(df5_nonull_test)
```

H.5 Num_Room

[86]:
```
df6_test = pd.concat([df_test['num_room'], df5_final_test], axis=1).copy()
df6_null_test = df6_test.loc[df6_test['num_room'].isna(),:]
df6_nonull_test = df6_test.loc[~df6_test['num_room'].isna(),:]

df6 = pd.concat([df['num_room'], df5_final], axis=1).copy()
df6_null = df6.loc[df6['num_room'].isna(),:]
df6_nonull = df6.loc[~df6['num_room'].isna(),:]

corr = df6_nonull.corr()
```

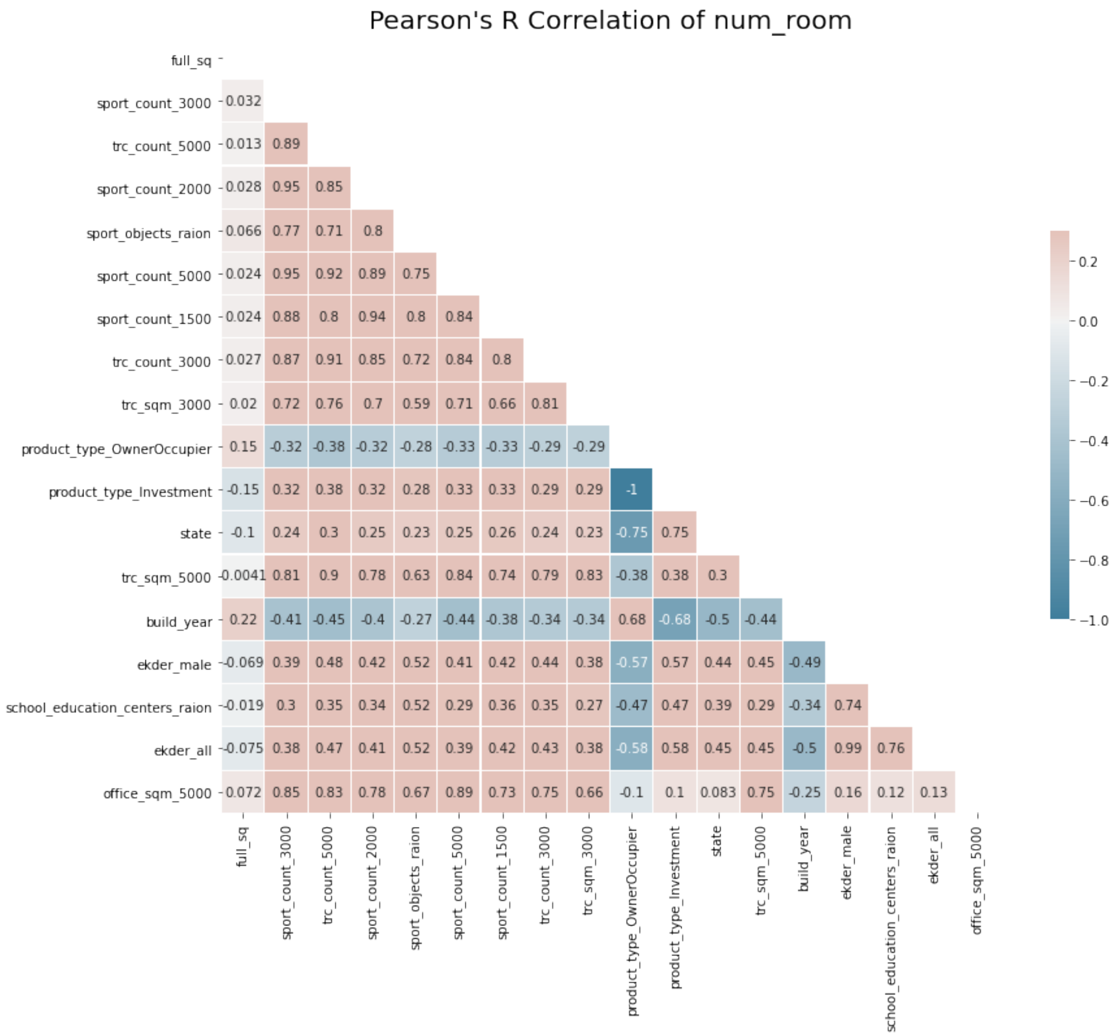
[87]:
```
corrnum = pd.DataFrame(corr['num_room'])
corrnum['num_room'] = abs(corrnum['num_room'])
```

```
#print(corrnum.sort_values(by='num_room', ascending=False).head(20))
```

[88]:
```
top_80 = corrnum.sort_values(by='num_room', ascending=False).head(20).
↪drop('price_doc')
```

[89]:
```
gt_80 = list(top_80[1:].index)
```

[90]:
```
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr.loc[gt_80,gt_80], dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(14,11))
plt.title("Pearson's R Correlation of num_room", fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr.loc[gt_80,gt_80], mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5});
```



[91]:
```
model_X = pd.DataFrame(df6_nonull, columns = gt_80, dtype='int64')
model_y = pd.DataFrame(df6_nonull, columns = ['num_room'], dtype='int32')

X_train, X_test, y_train, y_test = train_test_split(model_X, model_y,␣
↪test_size=0.33, random_state=42)
```

[92]:
```
y_train_ravel = y_train.values.ravel()

neigh = KNeighborsClassifier(n_neighbors=5)
neigh.fit(X_train, y_train.values.ravel())

neigh.predict(X_train)

print('K-NN accuracy: {}'.format(neigh.score(X_test, y_test.values.ravel(),␣
↪sample_weight=None)))
```

```
K-NN accuracy: 0.5830311820159536
```

[93]:
```
df6_input = pd.DataFrame(df6_null, columns = gt_80, dtype='int64')
df6_input_test = pd.DataFrame(df6_null_test, columns = gt_80, dtype='int64')

missing_num_room_vals = neigh.predict(df6_input)
missing_num_room_vals_test = neigh.predict(df6_input_test)
```

[ ]:
```
df6_null['num_room'] = missing_num_room_vals
df6_null_test['num_room'] = missing_num_room_vals_test
```

[95]:
```
print(df6_null['num_room'].isna().sum())
print(df6_null_test['num_room'].isna().sum())
```

```
0
0
```

H.6 Impute Num_Room

[96]:
```
df6_final = df6_null.append(df6_nonull)
df6_final_test = df6_null_test.append(df6_nonull_test)
```

[97]:
```
df6_final_test.loc[df6_final_test['preschool_quota'].isna(),'preschool_quota'] =␣
↪0
df6_final_test.loc[df6_final_test['school_quota'].isna(),'school_quota'] = 0
```

H.7 Floor

[98]:
```
df7_test = pd.concat([df_test['floor'], df6_final_test], axis=1)
df7_null_test = df7_test.loc[df7_test['floor'].isna(),:]
df7_nonull_test = df7_test.loc[~df7_test['floor'].isna(),:]

df7 = pd.concat([df['floor'], df6_final], axis=1).copy()
df7_null = df7.loc[df7['floor'].isna(),:]
df7_nonull = df7.loc[~df7['floor'].isna(),:]
```

[99]:
```
corr = df7_nonull.corr()
```

[100]:
```
df7_nonull_test.shape
```

[100]:
```
(6054, 411)
```

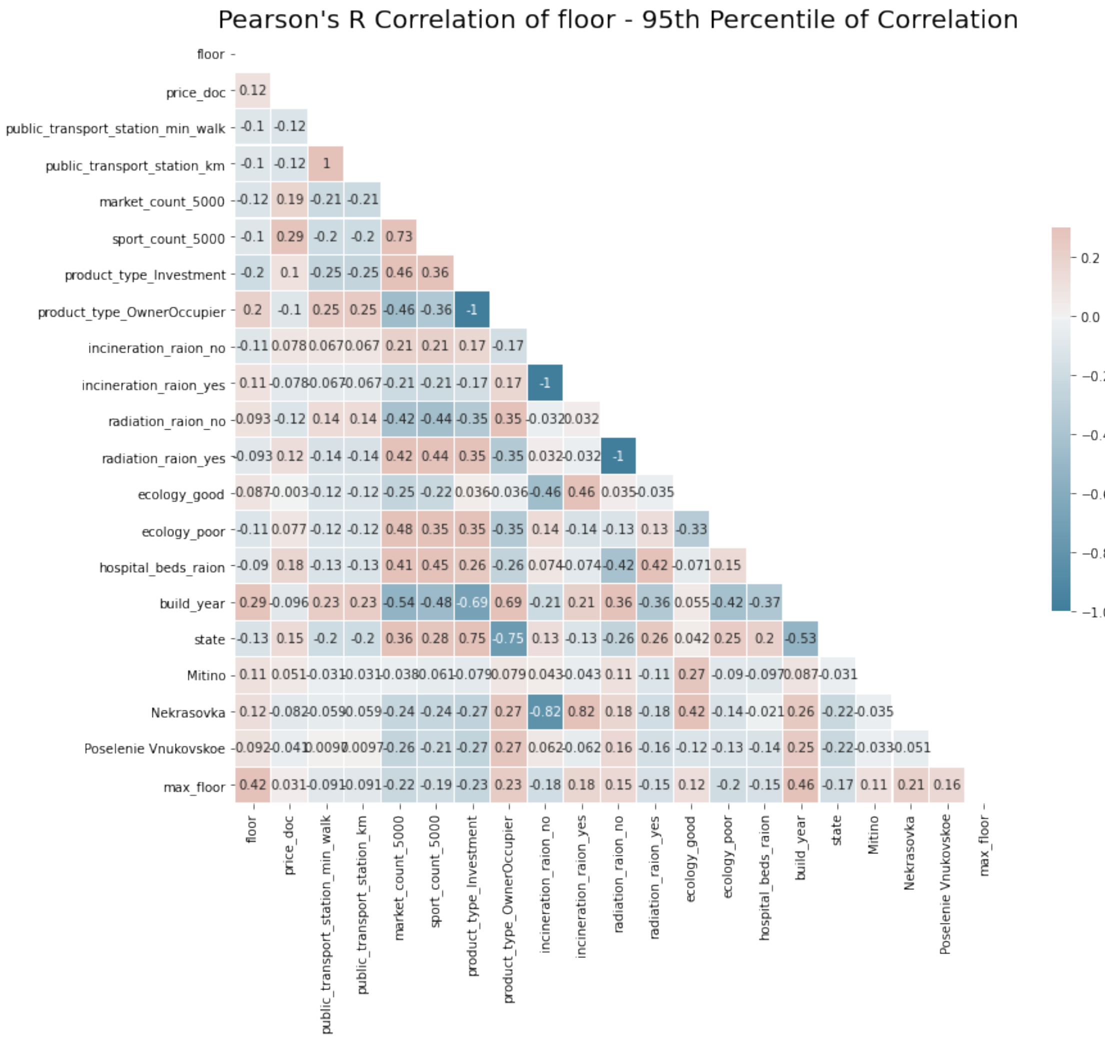
[101]:
```
df7_nonull.shape
```

[101]:
```
(24250, 411)
```

[102]:
```
corrfloor2 = pd.DataFrame(corr['floor'])
corrfloor2['floor'] = abs(corrfloor2['floor'])

#print(corrfloor2.sort_values(by='floor', ascending=False).head(16))
```

[103]:
```
gt_95 = corrfloor2.index[corrfloor2['floor'] >= np.
 ↪percentile(corrfloor2[corrfloor2.columns][~np.isnan(corrfloor2[corrfloor2.
 ↪columns].values)], 95)].tolist()
```

[104]:
```
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr.loc[gt_95,gt_95], dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(14,11))
plt.title("Pearson's R Correlation of floor - 95th Percentile of Correlation",␣
 ↪fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr.loc[gt_95,gt_95], mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5});
```



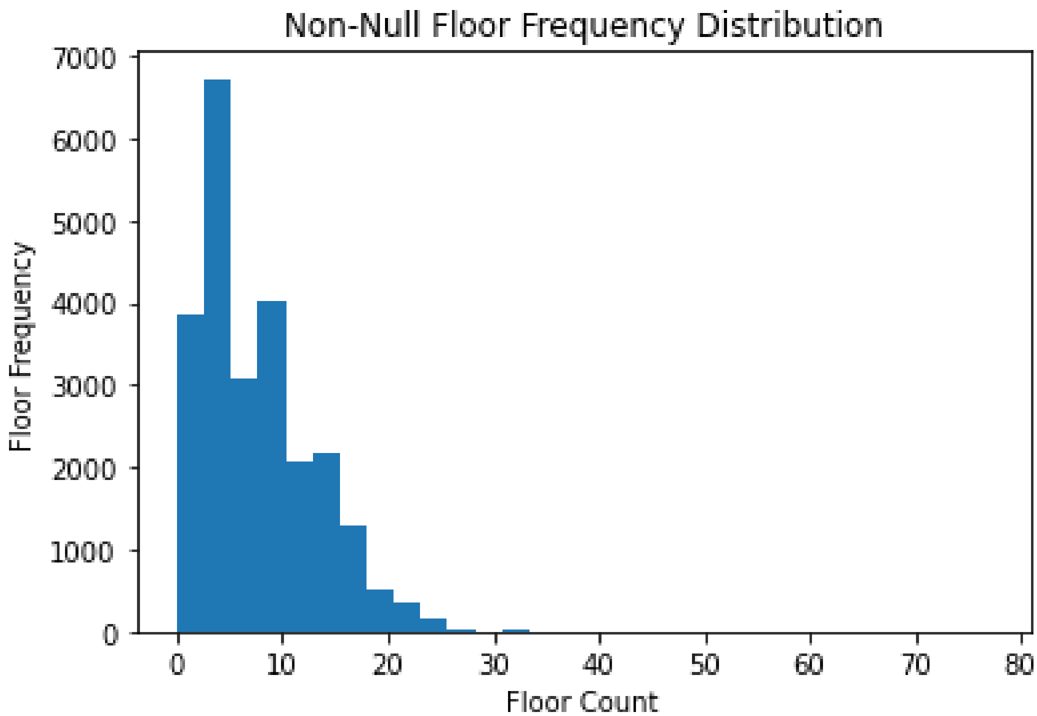
We removed features that had strong correlation with other input features. We gave preference to features that had not previously been imputed. While this may have resulted in less explanation of overall variation for the target (floor), we felt this conservative approach to be more appropriate and risk averse. We considered strong correlation to be greater than 0.5.

Where possible, we minimized re-using features used in imputing other features when there was reasonable correlation. We did this in an effort to preserve original, "intended" variation ("intended" in reference to the assumption missing values should not have been missing). One example of this was selecting sport_count_5000, which had been used to impute num_room. sport_count_5000 shares a Pearson's correlation coefficient greater than 0.733 with market_count_5000, but was used to impute num_room. Therefore, we used market_count_5000 to impute floor.

```
[105]: gt_95.remove('floor')
```

[106]:
```
model_X = pd.DataFrame(df7_nonull, columns = gt_95, dtype='int64')
model_y = pd.DataFrame(df7_nonull, columns = ['floor'], dtype='int32')

X_train, X_test, y_train, y_test = train_test_split(model_X, model_y,␣
 ↪test_size=0.33, random_state=42)
```

[107]:
```
plt.hist(df7_nonull['floor'], bins=30);
plt.title('Non-Null Floor Frequency Distribution')
plt.xlabel('Floor Count')
plt.ylabel('Floor Frequency');
```



[108]:
```
y_train_ravel = y_train.values.ravel()

neigh = KNeighborsClassifier(n_neighbors=2)
neigh.fit(X_train, y_train.values.ravel())

neigh.predict(X_train)

print('K-NN accuracy: {}'.format(neigh.score(X_test, y_test.values.ravel(),␣
 ↪sample_weight=None)))
```

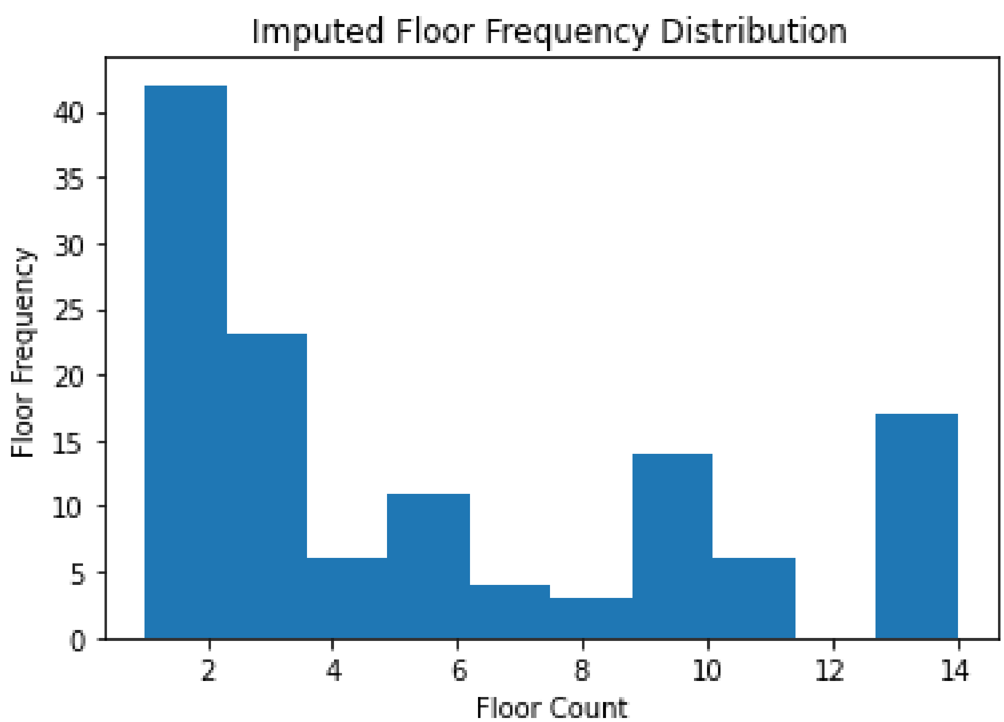
```
K-NN accuracy: 0.10071223291265775
```

[109]:
```
df7_input = pd.DataFrame(df7_null, columns = gt_95, dtype='int64')
df7_input_test = pd.DataFrame(df7_null_test, columns = gt_95, dtype='int64')
```

[110]:
```
missing_floor2_vals = neigh.predict(df7_input)
missing_floor2_vals_test = neigh.predict(df7_input_test)
```

H.7.1 The distribution of the K-NN model appears to provide a reasonable approximation to the Floor feature's non-missing distribution, despite having a poor accuracy (less than 10%). Therefore, we selected this approach over an alternative imputation method.

[545]:
```
plt.hist(missing_floor2_vals)
plt.title('Imputed Floor Frequency Distribution')
plt.xlabel('Floor Count')
plt.ylabel('Floor Frequency');
```



H.8 Impute Floor

[ ]:
```
df7_null['floor'] = missing_floor2_vals
df7_null_test['floor'] = missing_floor2_vals_test
```

[112]:
```
print(df7_null['floor'].isna().sum())
print(df7_null_test['floor'].isna().sum())
```

```
0
0
```

[113]:
```
df7_final = df7_null.append(df7_nonull)
df7_final_test = df7_null_test.append(df7_nonull_test)
```

H.9 Preschool_quota

Preschool_quota values were missing for all Poselenie sub_areas in addition to Molzhaninovskoe and Troickij okrug. Further analysis indicated there are preschool-aged children in these sub_areas, but preschool_education_centers_raion - a feature for the number of pre-school institutions - is 0. Therefore, we assume these values are not missing at random and are left empty because there are not seats available in pre-school organizations, which is what preschool_quota represents. Therefore, we impute all missing values for these sub_areas (account for all missing preschool_quota values total) with 0.

H.10 School_quota

As with preschool_quota, missing values for school_quota appear to be missing not at random; the values missing correspond to the Poselenie districts and Troickij okrug. In these sub_areas, school_education_centers_raion and school_education_centeres_top_20_raion all have values of 0 where school quota is missing. Therefore, we interpret this as there being no seats (school_quota) available for children and impute with 0

Commenting out school_quota and preschool_quota because this is imputed upstream. Below was the original process below during EDA only.

[566]:
```
# df8 = pd.concat([df7_final, df['school_quota'],df['preschool_quota']], axis=1)
# df8_test = pd.concat([df7_final_test,␣
↪df_test['school_quota'],df_test['preschool_quota']], axis=1)
```

[ ]:
```
# df8.loc[df8['school_quota'].isna(),'school_quota'] = 0
# df8.loc[df8['preschool_quota'].isna(),'preschool_quota'] = 0

# df8_test.loc[df8_test['school_quota'].isna(),'school_quota'] = 0
# df8_test.loc[df8_test['preschool_quota'].isna(),'preschool_quota'] = 0
```

[114]:
```
df8 = df7_final.copy()
df8_test = df7_final_test.copy()
```

[116]:
```
print(df8.preschool_quota.isna().sum())
print(df8.school_quota.isna().sum())
```

```
0
0
```

H.11 Kitch_SQ

All missing values for kitch_sq are also missing alongside max_floor, material, build_year, num_room, and state. The values for the previous features were determined to be missing at random since they were not restricted to any particular value ranges and follow no distinctive patterns. Therefore, as with the aforementioned features, we impute kitch_sq using K-NN. Prior to K-NN, we use a correlation analysis to identify features most strongly associated with outcomes in kitch_sq.

H.11.1 Impute Kitch_SQ

[117]:
```
df9 = pd.concat([df.kitch_sq, df8], axis=1)
df9_test = pd.concat([df_test.kitch_sq, df8_test], axis=1)
```

[118]:
```
print(df9.shape)
print(df.shape)
```

```
(24376, 412)
(24376, 292)
```

[119]:
```
print(df9_test.shape)
print(df_test.shape)
```

```
(6095, 412)
(6095, 292)
```

[120]:
```
df9_null_test = df9_test.loc[df9_test['max_floor'].isna(),:]
df9_nonull_test = df9_test.loc[~df9_test['max_floor'].isna(),:]

df9_null = df9.loc[df9['max_floor'].isna(),:]
df9_nonull = df9.loc[~df9['max_floor'].isna(),:]
```

[121]:
```
corr = df9_nonull.corr()
```

[122]:
```
corrkitch = pd.DataFrame(corr['kitch_sq'])
corrkitch['kitch_sq'] = abs(corrkitch['kitch_sq'])

#print(corrkitch.sort_values(by='kitch_sq', ascending=False).head(35))
```

There were no strong correlated values associated with non-missing values of kitch_sq. Therefore, we opted to predict kitch_sq using features with correlation in the top 95th percentile.

[123]:
```
import numpy as np
from sklearn.impute import KNNImputer

imputer = KNNImputer(n_neighbors=2)
df9_final = imputer.fit_transform(df9)
df9_final_test = imputer.fit_transform(df9_test)
```

[124]:
```
df9_final = pd.DataFrame(df9_final)
df9_final.columns = df9.columns

df9_final_test = pd.DataFrame(df9_final_test)
df9_final_test.columns = df9_test.columns
```

[125]:
```
df9_final.kitch_sq.isna().sum()
df9_final_test.kitch_sq.isna().sum()
```

[125]:
```
0
```

[126]:
```
pauls_imputes_train = df9_final.loc[:
 ↪,['kitch_sq','material','state','max_floor','school_quota','preschool_quota','floor','num_roo
pauls_imputes_test = df9_final_test.loc[:
 ↪,['kitch_sq','material','state','max_floor','school_quota','preschool_quota','floor','num_roo
```

[127]:
```
pauls_imputes_train.head(2)
```

[127]:
```
   kitch_sq  material  state  max_floor  school_quota  preschool_quota  floor  \
0       8.0       1.0    2.0        9.0       11065.0           5001.0    4.0
1       4.5       2.0    1.0        9.0        6237.0           3119.0    3.0

   num_room  hospital_beds_raion  build_year
0       2.0                240.0      1977.0
1       1.0                229.0      2014.0
```

[128]:
```
pauls_imputes_test.head(2)
```

[128]:
```
   kitch_sq  material  state  max_floor  school_quota  preschool_quota  floor  \
0       5.5       1.0    2.0        5.0        5050.0            933.0   10.0
1       6.0       1.0    3.0       12.0       11065.0           5001.0    5.0

   num_room  hospital_beds_raion  build_year
0       1.0               4849.0      1957.0
1       2.0                240.0      1976.0
```

H.12 Build_Count Features

The dataset also contains a large number of features that represent counts of homes with specific building materials. These features are counts of homes with materials, we will assume that missing values means that those materials are absent and we will impute them with 0 values. A more detailed justification of this decision is provided below.

Each of these features contain 4,991 missing values. The sub_area feature was appended to the build_count dataframe, revealing that sub-areas with the Polesenskie prefix contain all of the missing values across all of the build_count features. Of the subset of features having at least 1 missing value, a majority of the missing values were found to be in the `build_count_foam` and `build_count_panel`. Additionally, a correlation matrix revealed that `raion_build_count_with_builddate_info` and `raion_build_count_with_material_info` are almost perfectly correlated, so we chose to remove `raion_build_count_with_builddate_info` from the dataset.

[602]:
```
X_train = X_train_copy
names = X_train.columns
# filtering column names for the build_count features
string = ['build_count']
build_cols = [i for i in names if any(sub in i for sub in string)]
# sub_area is appended to the list to find spatial correlations
build_cols.append('sub_area')
```

[603]:
```
# creating a subset of the build_count features
build_count_df = X_train[build_cols]
build_count_df.describe()
```

[603]:
```
       raion_build_count_with_material_info  build_count_block  \
count                          20373.000000       20373.000000
mean                             328.214745          50.196829
std                              275.999953          46.654955
min                                1.000000           0.000000
25%                              180.000000          13.000000
50%                              273.000000          42.000000
75%                              400.000000          72.000000
max                             1681.000000         223.000000

       build_count_wood  build_count_frame  build_count_brick  \
count      20373.000000       20373.000000        20373.00000
mean          40.590536           4.947234          108.27988
std          125.998235          14.867324          129.24004
min            0.000000           0.000000            0.00000
25%            0.000000           0.000000           10.00000
50%            0.000000           0.000000           67.00000
75%            7.000000           1.000000          156.00000
max          793.000000          97.000000          664.00000
```

```
       build_count_monolith  build_count_panel  build_count_foam  \
count          20373.000000       20373.000000      20373.000000   
mean              11.977372         107.042900          0.165759   
std               19.060468          88.060836          1.134687   
min                0.000000           0.000000          0.000000   
25%                2.000000          35.000000          0.000000   
50%                6.000000          92.000000          0.000000   
75%               13.000000         157.000000          0.000000   
max              127.000000         431.000000         11.000000   

       build_count_slag  build_count_mix  \
count      20373.000000     20373.000000   
mean           4.441859         0.572375   
std           13.090118         1.529097   
min            0.000000         0.000000   
25%            0.000000         0.000000   
50%            0.000000         0.000000   
75%            2.000000         0.000000   
max           84.000000         9.000000   

       raion_build_count_with_builddate_info  build_count_before_1920  \
count                           20373.000000             20373.000000   
mean                              327.877534                18.888136   
std                               276.009649                60.771431   
min                                 1.000000                 0.000000   
25%                               178.000000                 0.000000   
50%                               271.000000                 0.000000   
75%                               400.000000                 3.000000   
max                              1680.000000               371.000000   

       build_count_1921-1945  build_count_1946-1970  build_count_1971-1995  \
count           20373.000000           20373.000000           20373.000000   
mean               26.717126             141.552987              80.058656   
std                62.347671             125.290615              57.874105   
min                 0.000000               0.000000               0.000000   
25%                 0.000000              14.000000              37.000000   
50%                 2.000000             135.000000              71.000000   
75%                20.000000             216.000000             111.000000   
max               382.000000             845.000000             246.000000   

       build_count_after_1995  
count            20373.000000  
mean                60.660629  
std                112.529055  
min                  0.000000  
25%                 14.000000  
50%                 24.000000  
```

```
75%                    57.000000
max                   799.000000
```

[604]:

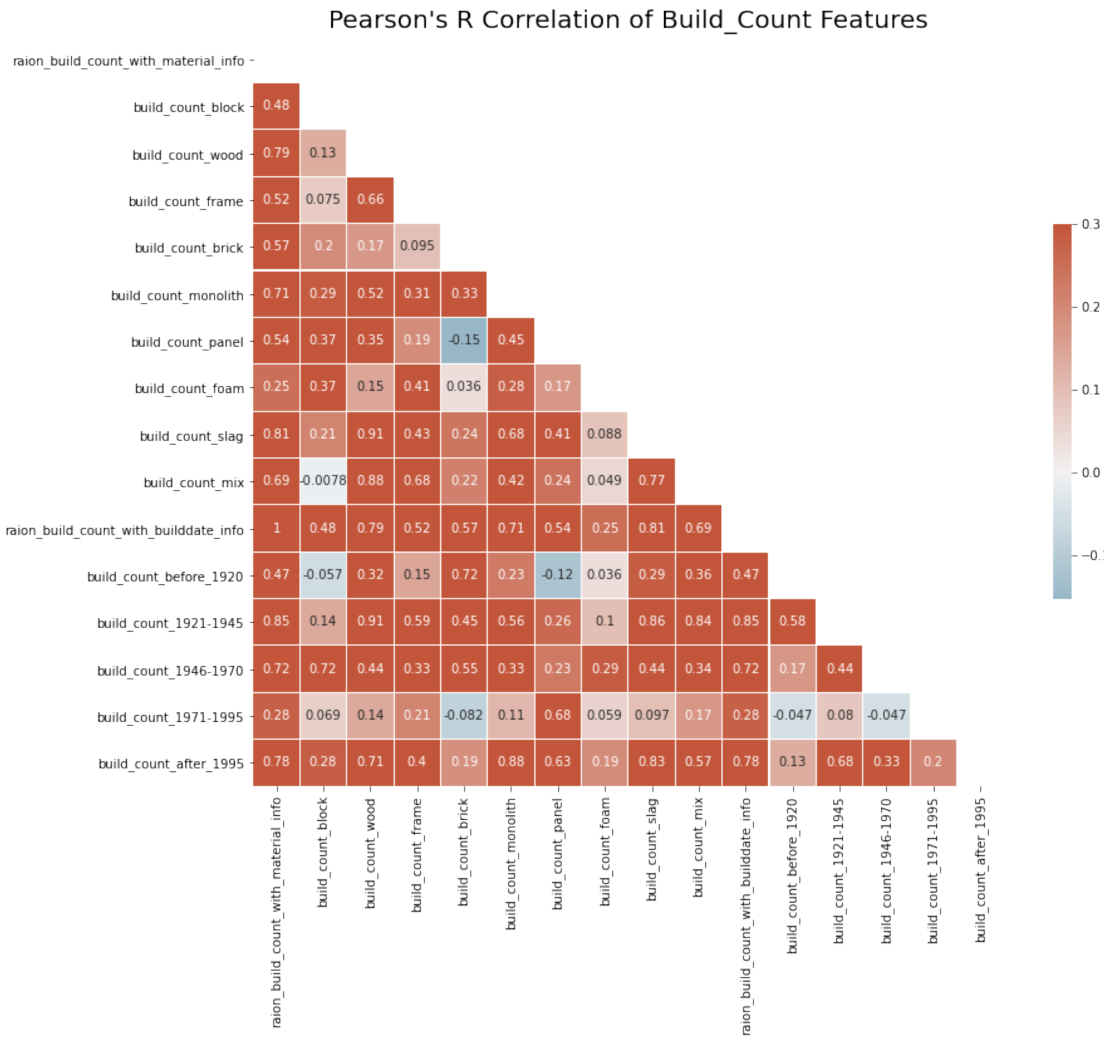
```
build_count_df.isnull().sum()
```

[604]:

```
raion_build_count_with_material_info     4003
build_count_block                        4003
build_count_wood                         4003
build_count_frame                        4003
build_count_brick                        4003
build_count_monolith                     4003
build_count_panel                        4003
build_count_foam                         4003
build_count_slag                         4003
build_count_mix                          4003
raion_build_count_with_builddate_info    4003
build_count_before_1920                  4003
build_count_1921-1945                    4003
build_count_1946-1970                    4003
build_count_1971-1995                    4003
build_count_after_1995                   4003
sub_area                                    0
dtype: int64
```

[605]:

```
materials_corr = build_count_df.corr()
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(materials_corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(14,11))
plt.title("Pearson's R Correlation of Build_Count Features", fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(materials_corr, mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5});
```




```
[606]: p_regions = list(np.unique(build_count_df['sub_area']))
       poselenie_areas = [i for i in p_regions if any(sub in i for sub in ['Pos'])]
       poselenie_areas
```

```
[606]: ['Poselenie Desjonovskoe',
        'Poselenie Filimonkovskoe',
        'Poselenie Kievskij',
        'Poselenie Kokoshkino',
        'Poselenie Krasnopahorskoe',
        'Poselenie Marushkinskoe',
        'Poselenie Mihajlovo-Jarcevskoe',
        'Poselenie Moskovskij',
        'Poselenie Mosrentgen',
        'Poselenie Novofedorovskoe',
        'Poselenie Pervomajskoe',
```

```
 'Poselenie Rjazanovskoe',
 'Poselenie Rogovskoe',
 'Poselenie Shhapovskoe',
 'Poselenie Shherbinka',
 'Poselenie Sosenskoe',
 'Poselenie Vnukovskoe',
 'Poselenie Voronovskoe',
 'Poselenie Voskresenskoe']
```

[607]:
```python
poselenie_df = build_count_df[build_count_df.sub_area.isin(poselenie_areas)]

poselenie_df.describe()
```

[607]:
```
       raion_build_count_with_material_info  build_count_block  \
count                           1231.000000        1231.000000
mean                               2.016247           0.096669
std                               11.379974           0.295627
min                                1.000000           0.000000
25%                                1.000000           0.000000
50%                                1.000000           0.000000
75%                                2.000000           0.000000
max                              180.000000           1.000000

       build_count_wood  build_count_frame  build_count_brick  \
count       1231.000000        1231.000000        1231.000000
mean           1.394801           0.190902           0.036556
std            7.646782           2.990519           0.572653
min            0.000000           0.000000           0.000000
25%            1.000000           0.000000           0.000000
50%            1.000000           0.000000           0.000000
75%            1.000000           0.000000           0.000000
max          121.000000          47.000000           9.000000

       build_count_monolith  build_count_panel  build_count_foam  \
count           1231.000000             1231.0            1231.0
mean               0.004062                0.0               0.0
std                0.063628                0.0               0.0
min                0.000000                0.0               0.0
25%                0.000000                0.0               0.0
50%                0.000000                0.0               0.0
75%                0.000000                0.0               0.0
max                1.000000                0.0               0.0

       build_count_slag  build_count_mix  \
count       1231.000000           1231.0
mean           0.293258              0.0
std            0.455440              0.0
```

```
min           0.000000           0.0
25%           0.000000           0.0
50%           0.000000           0.0
75%           1.000000           0.0
max           1.000000           0.0

       raion_build_count_with_builddate_info  build_count_before_1920  \
count                            1231.000000              1231.000000
mean                                2.016247                 0.004062
std                                11.379974                 0.063628
min                                 1.000000                 0.000000
25%                                 1.000000                 0.000000
50%                                 1.000000                 0.000000
75%                                 2.000000                 0.000000
max                               180.000000                 1.000000

       build_count_1921-1945  build_count_1946-1970  build_count_1971-1995  \
count            1231.000000            1231.000000            1231.000000
mean                0.004062               1.865963               0.048741
std                 0.063628               9.028090               0.763537
min                 0.000000               1.000000               0.000000
25%                 0.000000               1.000000               0.000000
50%                 0.000000               1.000000               0.000000
75%                 0.000000               2.000000               0.000000
max                 1.000000             143.000000              12.000000

       build_count_after_1995
count             1231.000000
mean                 0.093420
std                  1.463445
min                  0.000000
25%                  0.000000
50%                  0.000000
75%                  0.000000
max                 23.000000
```

[560]:
```
nulls = build_count_df[build_count_df.isnull().any(axis=1)]
nulls['sub_area'].value_counts()
```

[560]:
```
Poselenie Sosenskoe           1430
Poselenie Vnukovskoe          1090
Poselenie Voskresenskoe        581
Poselenie Filimonkovskoe       379
Poselenie Desjonovskoe         294
Poselenie Novofedorovskoe      126
Poselenie Rjazanovskoe          28
Poselenie Rogovskoe             25
```

```
Poselenie Krasnopahorskoe          22
Poselenie Mosrentgen               17
Poselenie Voronovskoe               7
Poselenie Kievskij                  2
Poselenie Shhapovskoe               1
Poselenie Mihajlovo-Jarcevskoe      1
Name: sub_area, dtype: int64
```

[561]:
```
for i in build_cols:
    X_train[i].fillna(0, inplace=True)
```

[40]:
```
no_na = X_train.dropna()
no_na.shape
```

[40]:
```
(4860, 291)
```

[41]:
```
no_null_corr = no_na.corr()
```

[564]:
```
life_corr = no_null_corr['life_sq'].sort_values(ascending=False)
life_corr.head(10)
```

[564]:
```
life_sq                        1.000000
full_sq                        0.828458
num_room                       0.579404
price_doc                      0.498951
cafe_count_1000_price_2500     0.199475
cafe_count_1500_price_2500     0.199224
cafe_count_2000_price_high     0.198316
cafe_count_3000_price_4000     0.196827
cafe_count_2000_price_2500     0.196131
cafe_count_2000_price_4000     0.195775
Name: life_sq, dtype: float64
```

[5]:
```
sq_ft_features = ['life_sq', 'full_sq', 'num_room']
full_sq_data = X_train[sq_ft_features]
```

H.13 Multiple Imputation Strategies (Multiple Linear Regression and KNN)

H.13.1 Multiple Linear Regression

[6]:
```
imp = IterativeImputer(max_iter= 10000, random_state = random_state)

imp_train = imp.fit_transform(full_sq_data)
imp_test = imp.transform(X_test[sq_ft_features])
```

[7]:
```
dfs = {'train--':imp_train, 'test--':imp_test}
for i, j in dfs.items():
    print(i, 'nan count: ', sum(np.isnan(j)), 'infinites: ', sum(np.isinf(j)),␣
 ↪'\n')
```

```
train-- nan count:  [0 0 0] infinites:  [0 0 0]

test-- nan count:  [0 0 0] infinites:  [0 0 0]
```

H.13.2 KNN Imputer

[8]:
```
KNNimp = KNNImputer(n_neighbors = 3)

KNNimp_train = KNNimp.fit_transform(full_sq_data)
KNNimp_test = KNNimp.transform(X_test[sq_ft_features])
```

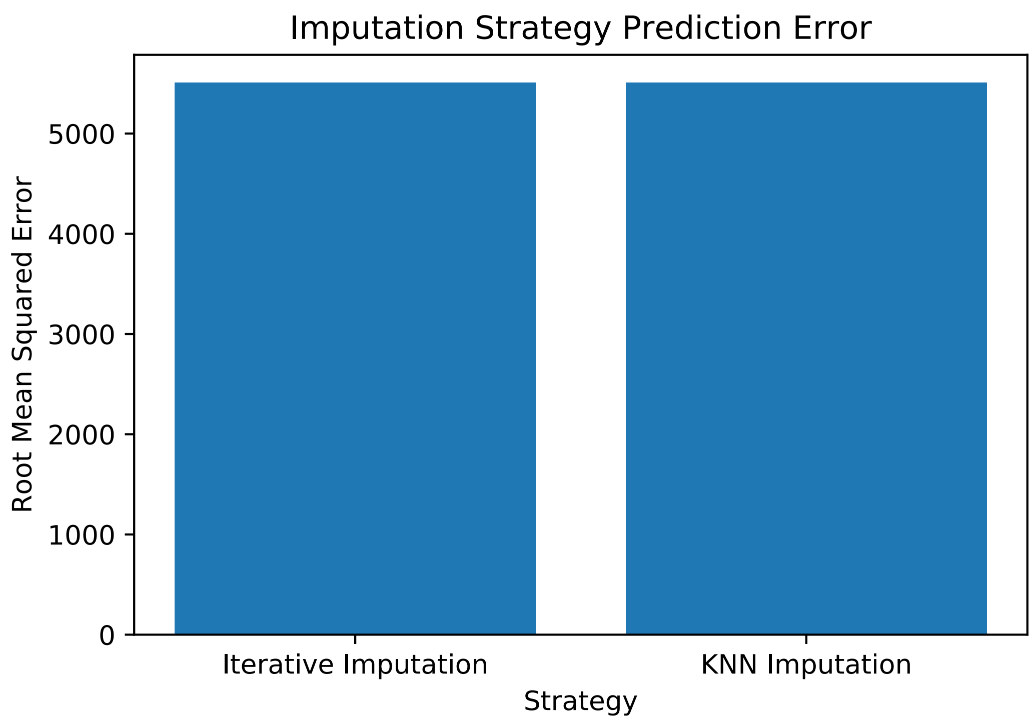
H.14 Comparing the performance of Multiple Imputation Strategies

[11]:
```
from sklearn.linear_model import ElasticNetCV
# instantiate the elastic net regularizer
EN = ElasticNetCV(l1_ratio = .5,
                  cv = 5,
                  n_jobs = -1,
                  random_state = random_state)
# fit a model to the Iteratively Imputed training data
IIimputed_model = EN.fit(imp_train, y_train)
# fit the same model to the KNN Imputed training data
KNNimputed_model = EN.fit(KNNimp_train, y_train)
# predict the target using Iteratively Imputed test data
II_preds = IIimputed_model.predict(imp_test)
# predict the target using KNN imputed test data
KNN_preds = KNNimputed_model.predict(KNNimp_test)

II_RMSE = np.sqrt(np.mean((II_preds - y_test)**2))
KNN_RMSE = np.sqrt(np.mean((KNN_preds - y_test)**2))
print('Iterative Imputed model error: ', II_MSE,
      '\nKNN Imputed model error: ', KNN_MSE)
```

```
Iterative Imputed model error:  4610419.12013875
KNN Imputed model error:  4609582.3854771955
```

[21]:
```
labels = ['Iterative Imputation', 'KNN Imputation']
errors = [II_RMSE, KNN_RMSE]
plt.bar(range(2), errors)
```

```
plt.title('Imputation Strategy Prediction Error')
plt.xlabel('Strategy')
plt.ylabel('Root Mean Squared Error')
#plt.ylim(bottom = 4000000)
plt.xticks(range(2), labels)
plt.savefig('./images/imputation_strategies.png')
plt.show()
```



[19]:
```
np.log(II_RMSE) - np.log(KNN_RMSE)
```

[19]: 0.000181504235836627

[23]:
```
walking = [i for i in X_train.columns if any(sub in i for sub in ['walk'])]
walking
```

[23]:
```
['metro_min_walk',
 'metro_km_walk',
 'railroad_station_walk_km',
 'railroad_station_walk_min',
 'ID_railroad_station_walk',
 'public_transport_station_min_walk']
```

[24]:
```
for i in walking:
    print(i, pd.isna(df[i]).sum())
```

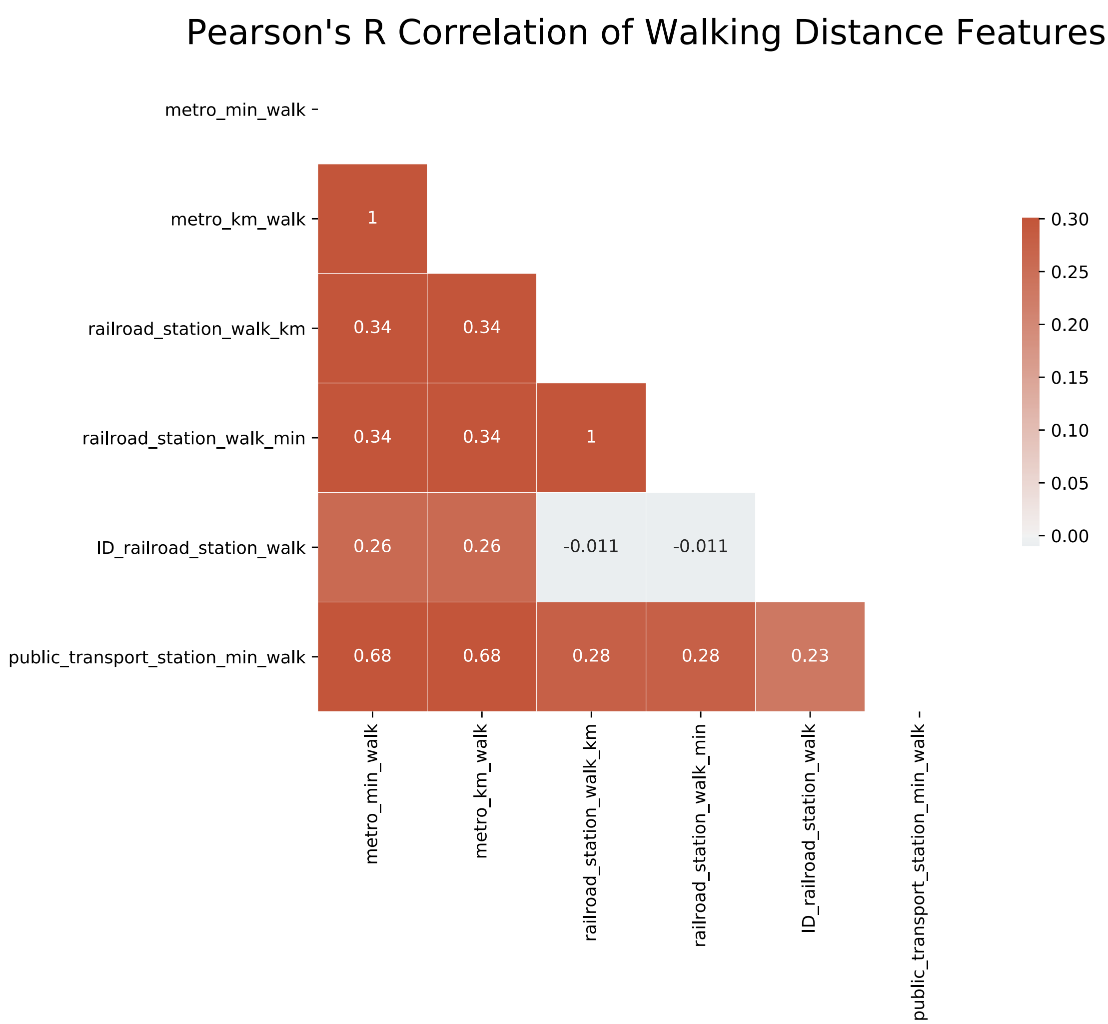
```
metro_min_walk 25
metro_km_walk 25
railroad_station_walk_km 25
railroad_station_walk_min 25
ID_railroad_station_walk 25
public_transport_station_min_walk 0
```

[25]:
```
walking_df = X_train[walking]
walking_corr = walking_df.corr()
```

H.14.1 Walking Distance Features

Five walking distance features each have 25 missing data points. A Pearson's R correlation matrix reveals multicollinearity between features that account for walking distance and those that account for the time it takes to walk from one point to another. We will remove the walking time measurements, `metro_min_walk` and `railroad_station_walk_min` because they are the more subjective of the two.

[28]:
```
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(walking_corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(10,7))
plt.title("Pearson's R Correlation of Walking Distance Features", fontsize = 20)
# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(walking_corr, mask=mask,
                            cmap=cmap,
                            vmax=.3,
                            center=0,
                            square=True,
                            linewidths=.1,
                            annot= True,
                            cbar_kws={"shrink": .5})
plt.savefig('./images/corr_walking_dist.png', bbox_inches = 'tight');
```



[14]:
```
droppers = ['metro_min_walk','railroad_station_walk_min']
X_train = X_train.drop(droppers, axis = 1)
```

[17]:
```
walking = ['metro_km_walk', 'railroad_station_walk_km',␣
↪'ID_railroad_station_walk', 'sub_area']
df_walking = X_train[walking]
```

[30]:
```
pd.options.display.max_rows = 25
walking_nulls = df_walking[df_walking.isnull().any(axis=1)]
walking_nulls
```

[30]:
```
       metro_km_walk  railroad_station_walk_km  ID_railroad_station_walk  \
10709            NaN                       NaN                       NaN
13259            NaN                       NaN                       NaN
13699            NaN                       NaN                       NaN
```

14796	NaN	NaN	NaN
15790	NaN	NaN	NaN
17358	NaN	NaN	NaN
18255	NaN	NaN	NaN
19344	NaN	NaN	NaN
19370	NaN	NaN	NaN
19477	NaN	NaN	NaN
21593	NaN	NaN	NaN
21717	NaN	NaN	NaN
24553	NaN	NaN	NaN
26944	NaN	NaN	NaN
27004	NaN	NaN	NaN
27199	NaN	NaN	NaN
27875	NaN	NaN	NaN
28213	NaN	NaN	NaN
28669	NaN	NaN	NaN
28933	NaN	NaN	NaN
29494	NaN	NaN	NaN
29763	NaN	NaN	NaN
29830	NaN	NaN	NaN
29946	NaN	NaN	NaN
30037	NaN	NaN	NaN

	sub_area
10709	Timirjazevskoe
13259	Timirjazevskoe
13699	Begovoe
14796	Timirjazevskoe
15790	Vojkovskoe
17358	Timirjazevskoe
18255	Begovoe
19344	Timirjazevskoe
19370	Timirjazevskoe
19477	Timirjazevskoe
21593	Vojkovskoe
21717	Timirjazevskoe
24553	Ochakovo-Matveevskoe
26944	Poselenie Vnukovskoe
27004	Timirjazevskoe
27199	Ochakovo-Matveevskoe
27875	Poselenie Vnukovskoe
28213	Timirjazevskoe
28669	Poselenie Vnukovskoe
28933	Krylatskoe
29494	Timirjazevskoe
29763	Krylatskoe
29830	Krylatskoe

```
29946             Krylatskoe
30037             Krylatskoe
```

[32]:
```
walking_subs = np.unique(walking_nulls['sub_area'])
walking_subs
```

[32]:
```
array(['Begovoe', 'Krylatskoe', 'Ochakovo-Matveevskoe',
       'Poselenie Vnukovskoe', 'Timirjazevskoe', 'Vojkovskoe'],
      dtype=object)
```

H.14.2 Imputing Walking Features

The missing walking data appear to be missing at random. Since there are only 25 of these missing values, we decided to use the median values for each feature as the imputed value rather than using a predictive technique. We rounded the walking distance features with a single digit of precision and the ID_railroad_station_walk feauture was imputed without any digits of precision because it is simply an identifier.

[39]:
```
walking_sub_df = X_train[X_train.sub_area.isin(walking_subs)]
walking_sub_df = walking_sub_df[walking]
walking_sub_df.describe()
```

[39]:

	metro_km_walk	railroad_station_walk_km	ID_railroad_station_walk
count	2050.000000	2050.000000	2050.000000
mean	2.676132	3.173610	47.477073
std	1.728267	1.403900	33.614089
min	0.115775	0.091549	10.000000
25%	1.722233	2.096932	24.000000
50%	2.200402	3.735666	24.000000
75%	3.220435	4.299245	63.000000
max	8.038429	7.816257	118.000000

[ ]:

[52]:
```
X_train[X_train['metro_km_walk'].isnull()] =␣
 ↪int(round(walking_sub_df['metro_km_walk'].median(),1))
X_train[X_train['railroad_station_walk_km'].isnull()] =␣
 ↪int(round(walking_sub_df['railroad_station_walk_km'].median(),1))
X_train[X_train['ID_railroad_station_walk'].isnull()] =␣
 ↪int(round(walking_sub_df['ID_railroad_station_walk'].median(),0))
```

[53]:
```
for i in walking_sub_df.columns:
    print(i, sum(pd.isna(df[i])))
```

```
metro_km_walk 0
railroad_station_walk_km 0
```

```
ID_railroad_station_walk 0
sub_area 0
```

H.14.3 Prom Features

[63]:
```python
prom = [i for i in X_train.columns if any(sub in i for sub in ['prom'])]
prom
```

[63]:
```
['prom_part_500',
 'prom_part_1000',
 'prom_part_1500',
 'prom_part_2000',
 'prom_part_3000',
 'prom_part_5000']
```

[55]:
```python
for i in prom:
    print(i, sum(pd.isna(df[i])))
```

```
prom_part_500 0
prom_part_1000 0
prom_part_1500 0
prom_part_2000 0
prom_part_3000 0
prom_part_5000 178
```

[64]:
```python
prom.append('sub_area')
prom_df = df[prom]
prom_na = prom_df[prom_df.isna()]
prom_df.describe()
```

[64]:
```
       prom_part_500  prom_part_1000  prom_part_1500  prom_part_2000  \
count   30471.000000    30471.000000    30471.000000    30471.000000
mean        5.708097        8.771085       10.585864       11.212062
std        11.535957       11.510945       10.972875        9.638425
min         0.000000        0.000000        0.000000        0.000000
25%         0.000000        0.000000        1.520000        3.120000
50%         0.000000        3.990000        7.810000        8.800000
75%         5.760000       12.620000       15.310000       16.210000
max        98.770000       72.200000       63.000000       56.100000

       prom_part_3000  prom_part_5000
count    30471.000000    30293.000000
mean        10.968362       10.341906
std          7.939677        5.672063
min          0.000000        0.210000
25%          4.220000        6.050000
50%          9.650000        8.960000
```

```
75%          15.730000       14.000000
max          45.100000       28.560000
```

[67]:
```
corr = X_train.corr()
prom_5000_corr = corr['prom_part_5000'].sort_values(ascending =False)
prom_5000_corr.head(10)
```

[67]:
```
prom_part_5000       1.000000
prom_part_3000       0.797736
market_count_5000    0.639495
prom_part_2000       0.508599
market_count_3000    0.500044
trc_count_5000       0.496383
trc_sqm_5000         0.461879
sport_count_5000     0.411527
market_count_2000    0.373343
prom_part_1500       0.365271
Name: prom_part_5000, dtype: float64
```

[70]:
```
imp = IterativeImputer(max_iter= 10000, random_state = random_state)
KNNimp = KNNImputer(n_neighbors = 3)

prom_imputes =␣
 ↪['prom_part_5000','prom_part_3000','market_count_5000','prom_part_2000',␣
 ↪'price_doc']
prom_imputed = X_train[prom_imputes]

y = prom_imputed['price_doc']
X = prom_imputed.drop('price_doc', axis = 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .2,␣
 ↪random_state = random_state)
```

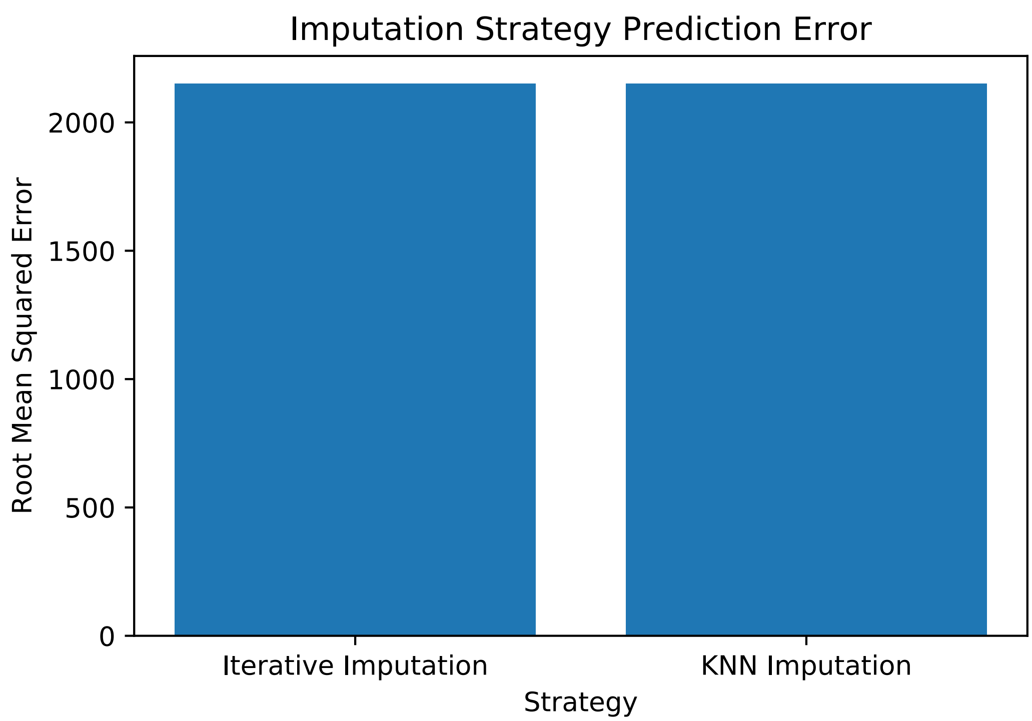
[72]:
```
II_imp_train = imp.fit_transform(X_train)
KNN_imp_train = KNNimp.fit_transform(X_train)

II_imp_test = imp.transform(X_test)
KNN_imp_test = KNNimp.transform(X_test)
```

[74]:
```
from sklearn.linear_model import ElasticNetCV
# instantiate the elastic net regularizer
EN = ElasticNetCV(l1_ratio = .5,
                  cv = 5,
                  n_jobs = -1,
                  random_state = random_state)
# fit a model to the Iteratively Imputed training data
IIimputed_model = EN.fit(II_imp_train, y_train)
```

```
# fit the same model to the KNN Imputed training data
KNNimputed_model = EN.fit(KNN_imp_train, y_train)
# predict the target using Iteratively Imputed test data
II_preds = IIimputed_model.predict(II_imp_test)
# predict the target using KNN imputed test data
KNN_preds = KNNimputed_model.predict(KNN_imp_test)

II_RMSE = np.sqrt(np.mean((II_preds - y_test)**2))
KNN_RMSE = np.sqrt(np.mean((KNN_preds - y_test)**2))
print('Iterative Imputed model error: ', II_RMSE,
      '\nKNN Imputed model error: ', KNN_RMSE)
```

```
Iterative Imputed model error:  4627826.959935145
KNN Imputed model error:  4627823.174102521
```

[75]:
```
labels = ['Iterative Imputation', 'KNN Imputation']
errors = [np.sqrt(II_RMSE), np.sqrt(KNN_RMSE)]
plt.bar(range(2), errors)
plt.title('Imputation Strategy Prediction Error')
plt.xlabel('Strategy')
plt.ylabel('Root Mean Squared Error')
plt.xticks(range(2), labels)
plt.show()
```



```
[80]: prom_imputes.remove('price_doc')
X_train[prom_imputes] = KNNimp.transform(X_train[prom_imputes])
```

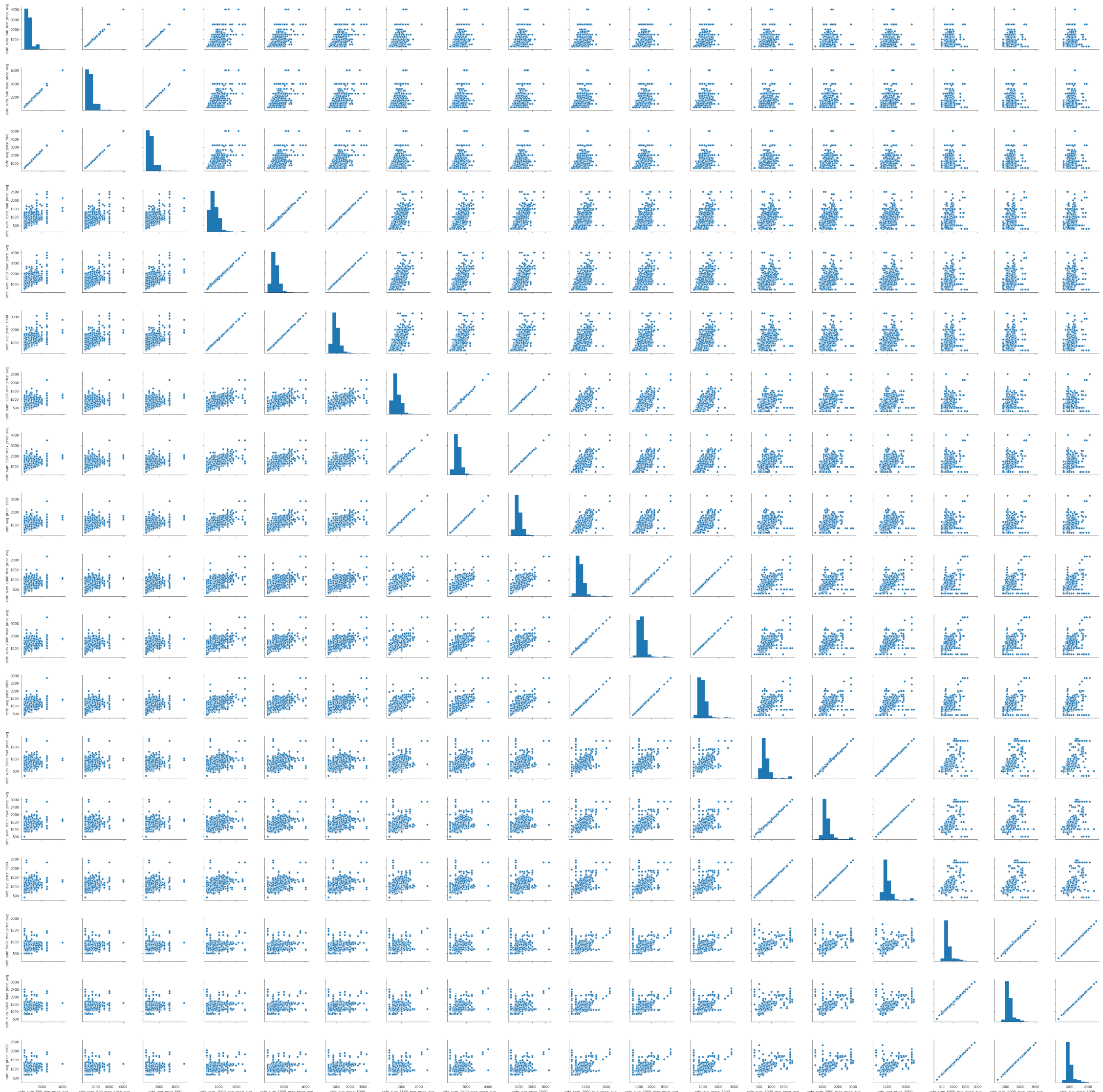
H.15 Cafe Columns Imputation

The `min`/`max` columns are strongly correlated with the `avg price` column for each catgory (500, 1000, etc). So we can drop the min/max variables.

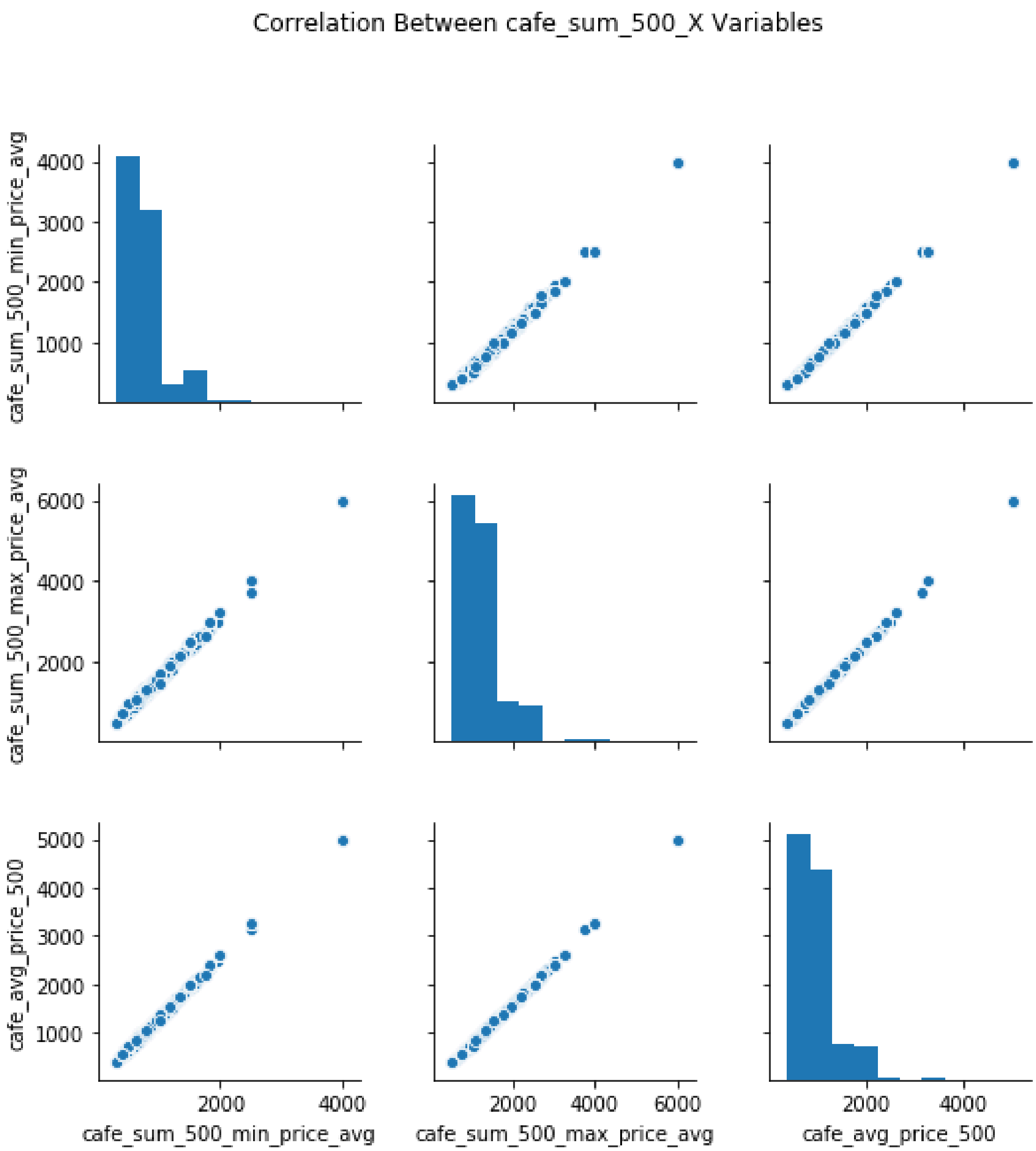
```
[5]: # the min/max columns are strongly correlated with
# the avg_price column for each catgory (500, 1000, etc)
sns.pairplot(df[['cafe_sum_500_min_price_avg', 'cafe_sum_500_max_price_avg',␣
 ↪'cafe_avg_price_500',
                'cafe_sum_1000_min_price_avg', 'cafe_sum_1000_max_price_avg',␣
 ↪'cafe_avg_price_1000',
                'cafe_sum_1500_min_price_avg', 'cafe_sum_1500_max_price_avg',␣
 ↪'cafe_avg_price_1500',
                'cafe_sum_2000_min_price_avg', 'cafe_sum_2000_max_price_avg',␣
 ↪'cafe_avg_price_2000',
                'cafe_sum_3000_min_price_avg', 'cafe_sum_3000_max_price_avg',␣
 ↪'cafe_avg_price_3000',
                'cafe_sum_5000_min_price_avg', 'cafe_sum_5000_max_price_avg',␣
 ↪'cafe_avg_price_5000']])
```

```
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/numpy/lib/histograms.py:839: RuntimeWarning: invalid value encountered
in greater_equal
  keep = (tmp_a >= first_edge)
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/numpy/lib/histograms.py:840: RuntimeWarning: invalid value encountered
in less_equal
  keep &= (tmp_a <= last_edge)
```

```
[5]: <seaborn.axisgrid.PairGrid at 0x7f211488de10>
```



[6]:
```
# the min/max columns are strongly correlated with
# the avg_price column for each catgory (500, 1000, etc)
g = sns.pairplot(df[['cafe_sum_500_min_price_avg', 'cafe_sum_500_max_price_avg', 'cafe_avg_price_500']])
g.fig.suptitle('Correlation Between cafe_sum_500_X Variables', y=1.08);
g.savefig('./images/cafe_sum_500_X_pairplot.png')
```




```
[7]: # get all the compete columns
clean_columns = list((df.isna().sum() == 0)[(df.isna().sum() == 0)].index)
# compare a average price column to the complete columns (correlation)
print('Strongest Positive Correlations\n')
print(df[clean_columns + ['cafe_avg_price_500']].corr()['cafe_avg_price_500'].
 ↪sort_values(ascending=False)[:5])
print('\nStrongest Negative Correlations\n')
print(df[clean_columns + ['cafe_avg_price_500']].corr()['cafe_avg_price_500'].
 ↪sort_values(ascending=False)[-5:])
```

```
Strongest Positive Correlations

cafe_avg_price_500           1.000000
cafe_count_500_price_2500    0.229900
cafe_count_500_price_4000    0.229842
workplaces_km                0.210524
cafe_count_500_price_high    0.197076
Name: cafe_avg_price_500, dtype: float64

Strongest Negative Correlations

work_female    -0.241938
work_male      -0.242593
work_all       -0.243273
ekder_female   -0.244014
raion_popul    -0.245757
Name: cafe_avg_price_500, dtype: float64
```

[8]:

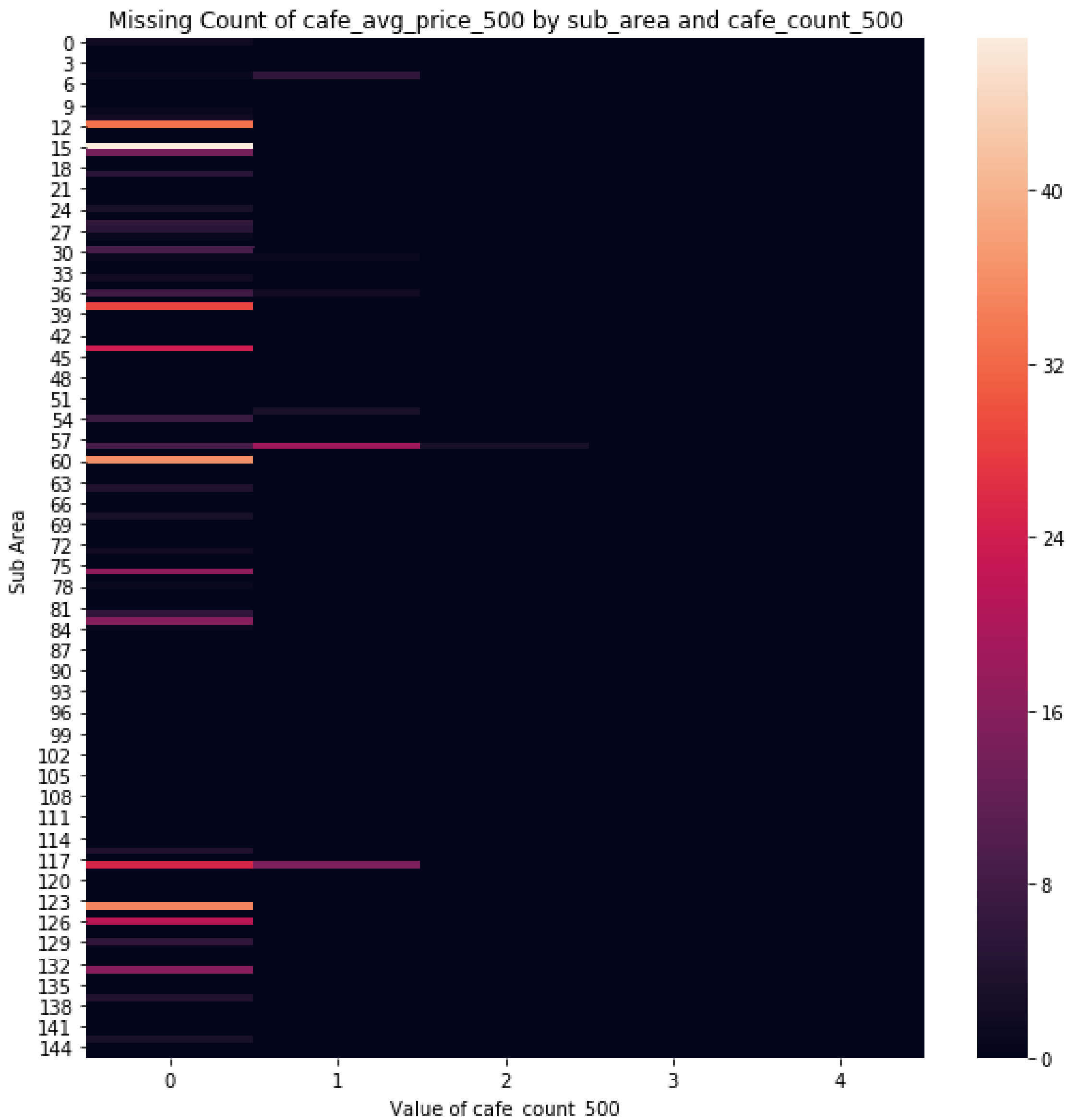
```
caf_avg_price_cols = ['cafe_avg_price_500', 'cafe_avg_price_1000',␣
 ↪'cafe_avg_price_1500',
                      'cafe_avg_price_2000', 'cafe_avg_price_3000',␣
 ↪'cafe_avg_price_5000']
caf_count_cols = ['cafe_count_500', 'cafe_count_1000', 'cafe_count_1500',
                      'cafe_count_2000', 'cafe_count_3000', 'cafe_count_5000']

cafe_count = defaultdict(list)
missing_percent = defaultdict(list)

# get missing percent of cafe_avg_price_X by value of cafe_count_X
for caf_avg_price_col, caf_count_cal in zip(caf_avg_price_cols, caf_count_cols):
    for i in np.unique(df[caf_count_cal])[0:5]:
        missing_count = df[[caf_avg_price_col, caf_count_cal]].
 ↪query(caf_count_cal + ' == ' + str(i)).isna().sum()[caf_avg_price_col]
        total_count = df[[caf_avg_price_col, caf_count_cal]].query(caf_count_cal␣
 ↪+ ' == '  + str(i)).shape[0]
        cafe_count[caf_count_cal].append(i)
        missing_percent[caf_avg_price_col].append(missing_count / total_count)
```

[9]:

```
# get the counts of missing values for cafe_avg_price_500 by cafe_count_500 and␣
 ↪sub_area
missing_freq = np.empty((np.unique(df.sub_area).size, 5))
for i, area in enumerate(np.unique(df.sub_area)):
    for j in range(1, 6):
        missing_freq[i,j-1] = df[['cafe_avg_price_500', 'cafe_count_500',␣
 ↪'sub_area']].query("sub_area == " + '"' + area + '"').query("cafe_count_500 ==␣
 ↪" + str(j)).isna().sum()['cafe_avg_price_500']
```

The heatmap below shows there is a missingness relationship between cafe count 500 and sub area

[10]:
```
plt.subplots(figsize=(10,10))
g = sns.heatmap(missing_freq)
g.set_title('Missing Count of cafe_avg_price_500 by sub_area and␣
 ↪cafe_count_500', y=1.08);
g.set_ylabel('Sub Area')
g.set_xlabel('Value of cafe_count_500');
#plt.savefig('./images/cafe_500_heatmap.png')
```



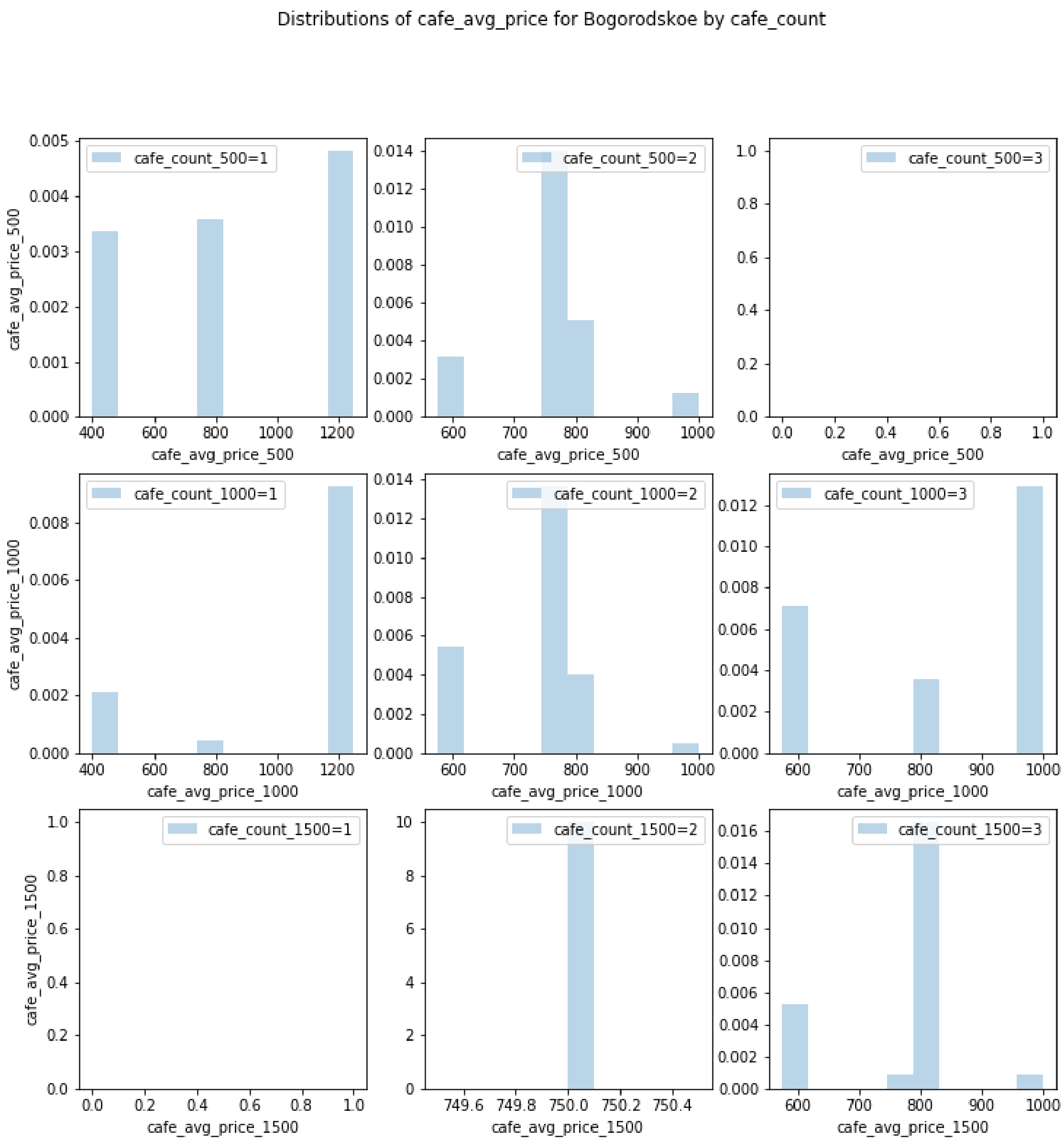
For each `cafe_avg_price` variable, there is a corresponding `cafe_count` variable. When `cafe_count` is 0, the value for `cafe_avg_price` is missing. Except for when `cafe_count` = 0, the missingness of `cafe_avg_price` appears to be random. When `cafe_count` is greater than zero, the missingness of `cafe_avg_price` is low, but related to the value of `cafe_count`. Additionally, the missingness of `cafe_avg_price` appears to be related to `sub_area`

```
values = list()
print("|", "Sub Area", "|", "Missing Count", "|")
print("|", "-" * 27, "|", "-" * 3, "|", sep='')
for sub_area in np.unique(df.sub_area):
    missing = df.query('sub_area == "' + sub_area + '"')
    missing_count = missing.query('cafe_count_500 != 0')['cafe_avg_price_500'].isna().sum()
    if missing_count > 0:
        values.append(missing.query('cafe_count_500 != 0')['cafe_avg_price_500'].values)
    print("|", f"{sub_area:25s}", "|", f"{missing_count}", "|")
```

The distributions of cafe_avg_price_X appear to be irregular with outlier. We will use the median for imputation.

[11]:
```
fig, ax = plt.subplots(nrows=len(caf_avg_price_cols[:3]), ncols=3,␣
↪figsize=(12,12))
fig.suptitle('Distributions of cafe_avg_price for Bogorodskoe by cafe_count')
for i, caf_avg_price_col, caf_count_cal in zip([k for k in␣
↪range(len(caf_avg_price_cols))][:3], caf_avg_price_cols[:3], caf_count_cols[:
↪3]):

    #ax[i].set_title('Distribution of ' + caf_avg_price_col + ' Conditioned on '␣
↪+ caf_count_cal)
    for j in np.unique(df[caf_count_cal])[1:4]:
        ax[i,j-1].hist(df.query(caf_count_cal + ' == ' + str(j)).query('sub_area␣
↪== "Bogorodskoe"')[caf_avg_price_col],
                       label=caf_count_cal + '=' + str(j), alpha=0.3, density=True)
        ax[i,j-1].legend();
        ax[i,j-1].set_xlabel(caf_avg_price_col)
        if j-1 == 0:
            ax[i,j-1].set_ylabel(caf_avg_price_col)
fig.savefig('./images/distributions_of_caf_avg_price_col.png')
```

```
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/numpy/lib/histograms.py:908: RuntimeWarning: invalid value encountered
in true_divide
  return n/db/n.sum(), bin_edges
```



[23]:

```
start_time = time.time()

missing_levels = dict()
for count_col in caf_count_cols:
    missing_levels[count_col] = np.unique(df[df[caf_avg_price_cols +␣
 ↪caf_count_cols].isna().any(axis=1)][caf_count_cols][count_col])

sub_areas = dict()
for price_col in caf_avg_price_cols:
    sub_areas[price_col] = np.unique(df[df[[price_col] + ['sub_area']].isna().
 ↪any(axis=1)].sub_area)
```

```
imputes = defaultdict(lambda: -1)

for caf_avg_price_col, caf_count_col in zip(caf_avg_price_cols, caf_count_cols):
    # print just to see it running
    print(caf_avg_price_col)
    for i in missing_levels[caf_count_col]:
        for sub_area in sub_areas[caf_avg_price_col]:
            idxes = df.query('sub_area == ' + '"' + sub_area +␣
 ↪'"')[df[caf_avg_price_col].isna() & (df[caf_count_col]==i)][caf_avg_price_col].
 ↪index
            # when value of count col is 0 set avg col to -1
            if i == 0:
                df.loc[idxes, caf_avg_price_col] = -1
                imputes[caf_avg_price_col + str(i) + sub_area] = -1
            else: # else use the median ignoring the nans
                if np.all(np.isnan(df[df[caf_count_col]==i][caf_avg_price_col])):
                    df.loc[idxes, caf_avg_price_col] = -1
                    imputes[caf_avg_price_col + str(i) + sub_area] = -1
                else:
                    df.loc[idxes, caf_avg_price_col] = np.
 ↪nanmedian(df[df[caf_count_col]==i][caf_avg_price_col])
                    imputes[caf_avg_price_col + str(i) + sub_area] = np.
 ↪nanmedian(df[df[caf_count_col]==i][caf_avg_price_col])


# drop the collinear columns
cafe_min_max_cols = ['cafe_sum_500_min_price_avg', 'cafe_sum_500_max_price_avg',
                     'cafe_sum_1000_min_price_avg',␣
 ↪'cafe_sum_1000_max_price_avg',
                     'cafe_sum_1500_min_price_avg',␣
 ↪'cafe_sum_1500_max_price_avg',
                     'cafe_sum_2000_min_price_avg',␣
 ↪'cafe_sum_2000_max_price_avg',
                     'cafe_sum_3000_min_price_avg',␣
 ↪'cafe_sum_3000_max_price_avg',
                     'cafe_sum_5000_min_price_avg',␣
 ↪'cafe_sum_5000_max_price_avg',]

df = df.drop(cafe_min_max_cols, axis=1)


end_time = time.time()
duration = end_time - start_time
print(f'Run time:  {int(duration // 3600):02d}::{int((duration % 3600) // 60):
 ↪02d}::{int((duration % 3600) % 60):02d}')
```

```
cafe_avg_price_500
```

```
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/ipykernel_launcher.py:18: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
```

```
cafe_avg_price_1000
cafe_avg_price_1500
cafe_avg_price_2000
cafe_avg_price_3000
cafe_avg_price_5000
Run time:  00::07::15
```

[25]:

```
caf_avg_price_cols = ['cafe_avg_price_500', 'cafe_avg_price_1000',␣
 ↪'cafe_avg_price_1500',
                  'cafe_avg_price_2000', 'cafe_avg_price_3000',␣
 ↪'cafe_avg_price_5000']
caf_count_cols = ['cafe_count_500', 'cafe_count_1000', 'cafe_count_1500',
                      'cafe_count_2000', 'cafe_count_3000', 'cafe_count_5000']
# find levels with missing values
missing_levels = dict()
for count_col in caf_count_cols:
    missing_levels[count_col] = np.unique(X_train[X_train[caf_avg_price_cols +␣
 ↪caf_count_cols].isna().any(axis=1)][caf_count_cols][count_col])
# find levels with missing values
sub_areas = dict()
for price_col in caf_avg_price_cols:
    sub_areas[price_col] = np.unique(X_train[X_train[[price_col] + ['sub_area']].
 ↪isna().any(axis=1)].sub_area)
# save imputed values
imputes = defaultdict(lambda: -1)
# loop over training data to impute training data and save impute values
for caf_avg_price_col, caf_count_col in zip(caf_avg_price_cols, caf_count_cols):
    for i in missing_levels[caf_count_col]:
        for sub_area in sub_areas[caf_avg_price_col]:
            idxes = X_train.query('sub_area == ' + '"' + sub_area +␣
 ↪'"')[X_train[caf_avg_price_col].isna() &␣
 ↪(X_train[caf_count_col]==i)][caf_avg_price_col].index
            # when value of count col is 0 set avg col to -1
            if i == 0:
                X_train.loc[idxes, caf_avg_price_col] = -1
                imputes[caf_avg_price_col + str(i) + sub_area] = -1
            else: # else use the median ignoring the nans
                if np.all(np.
 ↪isnan(X_train[X_train[caf_count_col]==i][caf_avg_price_col])):
                    X_train.loc[idxes, caf_avg_price_col] = -1
                    imputes[caf_avg_price_col + str(i) + sub_area] = -1
                else:
```

```
                    X_train.loc[idxes, caf_avg_price_col] = np.
↪nanmedian(X_train[X_train[caf_count_col]==i][caf_avg_price_col])
                    imputes[caf_avg_price_col + str(i) + sub_area] = np.
↪nanmedian(X_train[X_train[caf_count_col]==i][caf_avg_price_col])
```

```
cafe_avg_price_500
```

```
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/ipykernel_launcher.py:21: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
/home/stuart/anaconda3/envs/tf2/lib/python3.6/site-
packages/pandas/core/indexing.py:966: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[item] = s
```

```
cafe_avg_price_1000
cafe_avg_price_1500
cafe_avg_price_2000
cafe_avg_price_3000
cafe_avg_price_5000
```

```
pauls_imputes_train = pd.read_csv('./paul_imputes/pauls_imputes_train.csv')
pauls_imputes_test = pd.read_csv('./paul_imputes/pauls_imputes_test.csv')

transfer_cols = list(pauls_imputes_train)[1:]

X_train = X_train.drop(transfer_cols, axis=1).reset_index()
X_test = X_test.drop(transfer_cols, axis=1).reset_index()

for col in transfer_cols:
    X_train[col] = pauls_imputes_train[col]
    X_test[col] = pauls_imputes_test[col]

X_train = X_train.drop(['timestamp','id'], axis=1)
X_test = X_test.drop(['timestamp','id'], axis=1)

o_train = X_train.select_dtypes(include='object')
o_test = X_test.select_dtypes(include='object')
object_cols = list(o_test)
object_transformers = dict()
for col in object_cols:
    object_transformers[col] = LabelEncoder()
    object_transformers[col].fit(list(o_train[col]) + list(o_test[col]))
    o_train[col] = object_transformers[col].transform(o_train[col])
    o_test[col] = object_transformers[col].transform(o_test[col])
```

```
X_train = X_train.drop(object_cols, axis=1)
X_test = X_test.drop(object_cols, axis=1)
for col in object_cols:
    X_train[col] = o_train[col]
    X_test[col] = o_test[col]
```

I Modeling

```
en = ElasticNetCV(l1_ratio = [.1, .3, .5, .7, .9, .93, .95, .99, 1],
                  cv = 5,
                  n_jobs = 6,
                  random_state = random_state)

en.fit(X_train, np.log(y_train))
preds = en.predict(X_test)
rmse = np.sqrt(mean_squared_error(preds, np.log(y_test)))
print(rmse)

print(f"Best alpha value: {en.alpha_:0.2f}\nBest l1 ratio: {en.l1_ratio_}")

cv_scores = cross_val_score(en, X_train, np.log(y_train), cv=5, scoring='neg_mean_squared_error'

cv_scores = -cv_scores
print(np.mean(np.sqrt(cv_scores)))

plt.hist(preds-np.log(y_test))
plt.title('Histogram of Model Residuals');
plt.ylabel('Frequency')
plt.xlabel('Residuals')
plt.savefig('./images/model_residuals.png')
```

```
0.5836119057848108

Best alpha value: 1998.58
Best l1 ratio:    1.0

0.5848707337524031
```