School of Advanced Professional Studies

Convergence and Open Sharing System COSS 인공지능 전남대학교 인공지능혁신융합대학사업단

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AICOSS - AI Special Program

Sample solutions to exercise for data cleaning

In the original Kaggle Competition for this data set, a prediction model was to be developed for the variable `price_doc` (*target*). In order to train such a model, however, some variables must first be adjusted. This is what you will do in this exercise.

Clean up the following variables:

- **`state`**
  `state` indicates the status of the apartment and should contain the values 1-4.
- **`floor` and `max_floor`**
  What is the connection between `floor` and `max_floor`? Find and correct any inconsistencies.
- **`build_year`**
  Check `build_year` for incorrect values and correct them in a meaningful way.
- **`life_sq`**
  Remove outlier from `life_sq` and perform two different types of imputation.

In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
df = pd.read_csv('./data/sberbank.csv')
```

`state`

In [3]:

```
df['state'].unique()
```

Out[3]:

```
array([nan,  3.,  1.,  2.,  4., 33.])
```

The `33rd` could be a typing error. We replace with `3.`:

In [4]:

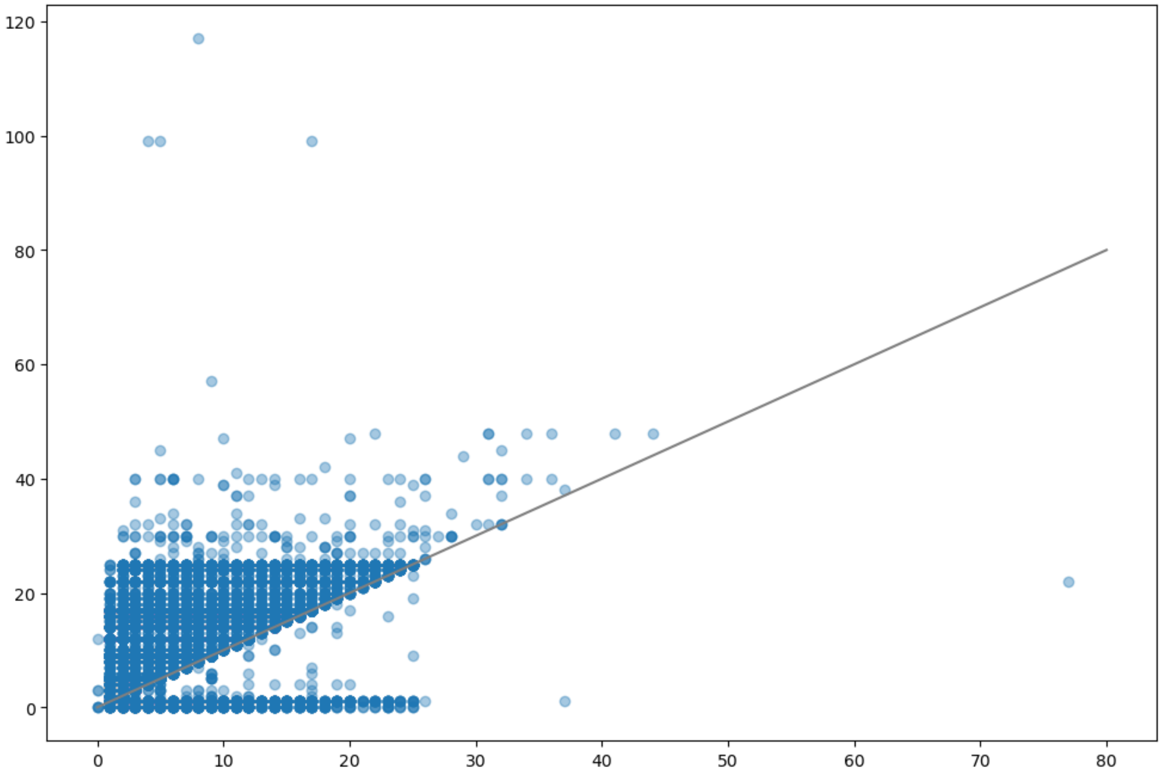
```
df['state'].replace(33., 3., inplace=True)
```

floor und max_floor

Check the value combinations:

In [5]:

```
f, ax = plt.subplots(figsize=(12, 8))
plt.scatter(x=df['floor'], y=df['max_floor'],alpha=0.4)
plt.plot([0, 80], [0, 80], color='.5');
```



Actually, we should not find any values below the diagonal, as the number of maximum storeys is then smaller than the number of existing storeys.

In [6]:

```
df.loc[df['max_floor'] < df['floor'],:].shape
```

Out[6]:

```
(1493, 292)
```

This is the case for 1493 entries! We can replace the incorrect values (as well as the zero values) with `NaN` :

In [7]:

```
mask = (df['max_floor'] < df['floor']) | (df['max_floor']==0.0)
```

In [8]:

```
df.loc[mask,'max_floor'] = np.NaN
```

build_year

The following values are available in `build_year` :

In [9]:

```
df['build_year'].dropna().astype('int64').unique()
```

```
Out[9]: array([    1907,      1980,      2014,      1970,      1982,      2013,
                   2004,      2003,      1957,      1986,      1960,      1995,
                   1979,      1975,      1987,      1962,      1969,      1993,
                   1996,      1972,      2011,      1965,      2010,      1985,
                   2006,      1961,      1971,      1978,      1966,      1967,
                   2000,      1964,      1977,      1983,      1968,      1974,
                   2008,      1959,      2007,      1984,      1976,      1997,
                   1989,      1958,      1988,      2012,      1990,      1946,
                   1917,      2002,      2005,      2001,      1963,      1954,
                   1951,      1981,      1955,      1999,      2009,      1973,
                   1994,      1998,      1992,      1950,      1956,      2015,
                      0,      1932,         1,      1937,      1938,      1939,
                   1991,      1934,      1935,  20052009,      1947,      1953,
                   1933,      2016,      1930,      1912,      1929,         3,
                   1928,      1915,      1936,      1925,      1940,      1943,
                   1927,      1896,      1911,      1924,      1952,      2017,
                   1926,      1931,        20,      1860,      1949,      1914,
                   4965,      1910,      1895,      1948,      1876,      1900,
                   1890,      1920,      1904,      1906,      1941,      1691,
                   1905,      1886,      2018,       215,        71])
```

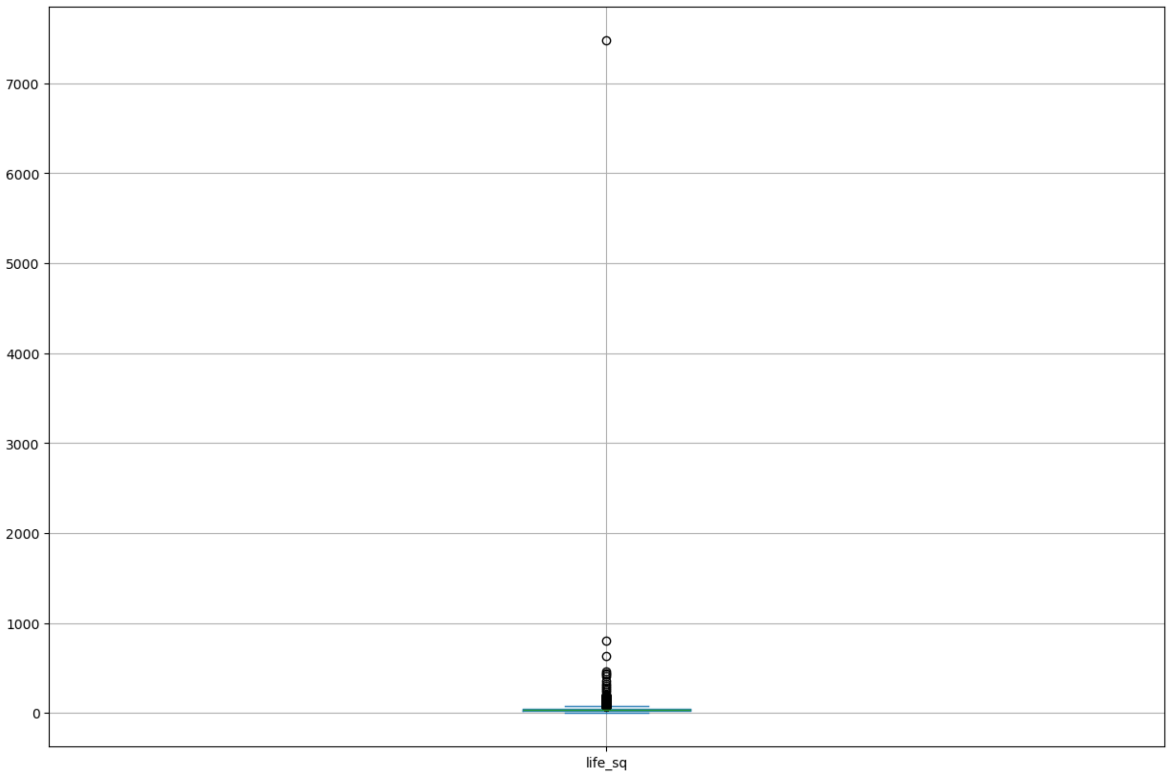
The following values must be replaced:

- `0` with `2000
- `1` with `2001
- `3` with `2003
- `20` with `1920
- `20052009` with `2005
- `215` with `2015
- `71` with `1971
- `4965` with `1965

```
In [10]: df['build_year'].replace(0.0, 2000.0, inplace=True)
         df['build_year'].replace(1.0, 2001.0, inplace=True)
         df['build_year'].replace(3.0, 2003.0, inplace=True)
         df['build_year'].replace(20.0, 1920.0, inplace=True)
         df['build_year'].replace(20052009.0, 2005.0, inplace=True)
         df['build_year'].replace(215.0, 2015.0, inplace=True)
         df['build_year'].replace(71.0, 1971.0, inplace=True)
         df['build_year'].replace(4965.0, 1965.0, inplace=True)
```

`life_sq`

```
In [11]: df['life_sq'].plot.box(figsize=(15,10), grid=True);
```



The boxplot shows a clear outlier with a value above 7000, which we can simply filter (we want to keep 'NaN'):

```
In [12]: mask = (df['life_sq']< 1000) | (df['life_sq'].isnull())
         df = df[mask]
```

Imputation with Mean

```
In [13]: df_mean = df.copy()
```

```
In [14]: mean = df_mean['life_sq'].mean(); mean
```

```
Out[14]: 34.09424170714493
```

```
In [15]: df_mean['life_sq'].fillna(mean, inplace=True)
```

```
In [16]: df_mean['life_sq'].isnull().sum()
```

```
Out[16]: 0
```

KNN-Imputation

Since we cannot use all features for KNN imputation for efficiency reasons, we want to select features that correlate with `life_sq`.

```
In [17]: df_knn = df.select_dtypes(include=[np.number])
```

```
In [18]: df_knn.dtypes.unique()
```

```
Out[18]: array([dtype('int64'), dtype('float64')], dtype=object)
```

In [19]:

```
correlations = {}
for i,feature in enumerate(df_knn.columns):
    correlations[i] = df_knn['life_sq'].corr(df_knn[feature])
```

In [20]:

```
sorted(correlations.items(), key=lambda x: x[1], reverse=True)[:10]
```

Out[20]:

```
[(2, 1.0),
 (7, 0.5513954768950734),
 (275, 0.4148448606438824),
 (1, 0.3951990153935231),
 (6, 0.2198999416737205),
 (125, 0.1508240306510387),
 (10, 0.14751393386330344),
 (261, 0.14549050222571336),
 (259, 0.14541745192012867),
 (260, 0.14533108257930286)]
```

We still need to check how many `NaN` values these features have. At best, these should only be a few...

In [21]:

```
df_knn.iloc[:,[2,7,275,1,6,125,10,261,259,260]].isnull().sum()
```

Out[21]:

```
life_sq                          6383
num_room                         9572
price_doc                           0
full_sq                             0
build_year                      13605
workplaces_km                       0
area_m                              0
cafe_avg_price_5000               297
cafe_sum_5000_min_price_avg       297
cafe_sum_5000_max_price_avg       297
dtype: int64
```

Apart from `build_year`, many values are available, so we can perform the imputation in this way.

In [22]:

```
from sklearn.impute import KNNImputer
```

In [23]:

```
imputer = KNNImputer(n_neighbors=2)
```

In [24]:

```
imputed = imputer.fit_transform(df_knn.iloc[:,[2,7,275,1,6,125,10,261,259
```

We create a new DataFrame with the filled values:

In [25]:

```
df_imputed = pd.DataFrame(imputed, columns=df_knn.iloc[:,[2,7,275,1,6,125
```

Check whether all values have been replaced:

In [26]:

```
df_imputed.head()
```

Out[26]:

	life_sq	num_room	price_doc	full_sq	build_year	workplaces_km	area_m
0	27.0	1.0	5850000.0	43.0	1986.0	0.884350	6.407578e+06
1	19.0	1.5	6000000.0	34.0	1972.5	0.686252	9.589337e+06
2	29.0	1.5	5700000.0	43.0	1963.5	1.510089	4.808270e+06
3	50.0	4.0	13100000.0	89.0	2014.5	0.622272	1.258354e+07
4	77.0	3.5	16331452.0	77.0	1947.5	0.892668	8.398461e+06

In [27]:

```
df_imputed.isnull().sum()
```

Out[27]:

```
life_sq                        0
num_room                       0
price_doc                      0
full_sq                        0
build_year                     0
workplaces_km                  0
area_m                         0
cafe_avg_price_5000            0
cafe_sum_5000_min_price_avg    0
cafe_sum_5000_max_price_avg    0
dtype: int64
```