2.3_teranet_nonan_new_cols

August 11, 2019

1 GTHA housing market database

2 OSEMN methodology Step 2: Scrub

3 Step 2.3 addition of new attributes to the Teranet dataset

4 (excluding records with `consideration_amt` < 10'000)

This notebook describes Step 2.3 (part of *Step 2: Scrub* of OSEMN methodology) performed on the Teranet dataset.

It is identical to the notebook `notebooks/2.scrub/2.3_teranet_new_cols.ipynb`, with the only difference being that prior to the addition of new attributes, **all records with missing `consideration_amt` are removed from the dataset.** In addition, **all values of `consideration_amt` less than 10'000 CAD are reset to NaN,** to exclude transactions with unreasonably low `consideration_amt`.

Surrogate key `transaction_id` is added prior to the removal of any records, so that the keys match between both versions of the Teranet dataset – the one with unmodified `consideration_amt` and the one where records with `consideration_amt` < 10'000 CAD have been dropped.

Step 2.3 focuses on the addition of several new attributes to the Teranet dataset. Plan for the addition of the new attributes is presented below.

Previous steps included:

- **Step 2.1:** spatial join between the Teranet points and the polygons of GTHA Dissemination Areas (DAs)
  - During step 2.1, Teranet records whose coordinates fall outside of the GTHA boundary (as defined by the DA geometry) have been filtered out (6,803,691 of the original 9,039,241 Teranet records remain in the dataset)
  - In addition to that, three new columns (`OBJECTID`, `DAUID`, and `CSDNAME`) derived from DA attributes have been added to each Teranet transaction
  - for details, see `notebooks/2.scrub/2.1_teranet_gtha_spatial_join.ipynb`
- **Step 2.2:** correction for consistency of the Teranet records

  - column names were converted to lower case
  - inconsistent capitalizations were fixed for columns
    * `municipality`
    * `street_name`
    * `street_designation`
    * `postal_code` (did not show problems, converted as a preventive measure)
  - columns `province` and `street_suffix` were removed from the dataset
  - new column `street_name_raw` was created: reserve copy of unmodified `street_name`
  - column `street_name` was parsed and cleaned for:
    * `postal_code`
    * `unitno`
    * `street_number`
    * `street_direction`
    * `street_designation`
  - plots of the count and percentage of missing values per column were produced
  - inconsistent entries were fixed in the following columns:
    * `street_direction`
    * `street_designation`
    * `municipality`
    * `street_name`
    * `unitno`
  - for details, see `notebooks/2.scrub/2.2_teranet_consistency.ipynb`

For description of OSEMN methodology, see `methodology/0.osemn/osemn.pdf`.

For background information, description of the Teranet dataset, and its attributes, see `methodology/1.obtain/obtain.pdf`.

For description of *Step 2: Scrub* of OSEMN methodology, see `methodology/2.scrub/scrub.pdf`.

For description of the cleanup plan for the Teranet dataset, see `methodology/2.scrub/teranet_cleanup_plan.pdf`.

For description of Step 2.1 of the cleanup process, see `notebooks/2.scrub/2.1_teranet_gtha_spatial_join.ipynb`.

For description of Step 2.2 of the cleanup process, see `notebooks/2.scrub/2.2_teranet_consistency.ipynb`.

4.1 Plan for the addition of the new attributes

All Teranet records with missing `consideration_amt` are removed from the dataset. The rest of this notebook is identical to the notebook `notebooks/2.scrub/2.3_teranet_new_cols`. ***Surrogate key*** `transaction_id` is added prior to the removal of any records, so that the keys match between both versions of the Teranet dataset – the one with unmodified `consideration_amt` and the one where records with `consideration_amt` < 10'000 CAD have been dropped.

4.1.1 Previously added attributes

Previously, the following new attributes were created in the Teranet dataset:

- attributes produced from the spatial join with DA geometry:
  - `objectid`: an identifier for Dissemination Areas (DAs), added as a backup identifier for DAs
  - `dauid`: another identifier for Dissemination Areas, indented to be used as the ***foreign key*** linking Teranet records with DAs (will become the ***primary key*** of DA-level datasets (*e.g.,* DA-level Census data)
  - `csdname`: municipality name according to Census data (DA-level)

These attributes were added to each Teranet record via a spatial join of Teranet points with the polygons of Dissemination Areas (DAs) during Step 2.1 of the cleanup process

- attributes produced during the correction of Teranet records for consistency:
  - `street_name_raw`: unmodified reserve copy of the original `street_name` from the Teranet dataset

4.1.2 Attributes to be added in this step

In this step, the following attributes will be added to the Teranet dataset:

- surrogate key:
  - `transaction_id`: unique identifier for each Teranet transaction

Essentially, a simple range index, which represents the row number of a record in the full Teranet dataset (filtered to include only GTHA records), ordered by date (from earliest to latest) and `pin`

- attributes for display
  - `date_disp`: `registration_date` converted to `datetime.date` data type to exclude the timestamp (original `registration_date` is stored in NumPy's `datetime64` format to allow more efficient datetime operations)
  - `price_disp`: `consideration_amt` formatted to include thousands separator (*e.g.,* '3,455,122') and stored as a string, for display purposes
- attributes for record grouping
  - `year`: year parsed from `registration_date`, to simplify record grouping
  - `year_month`: year and month parsed from `registration_date`, to simplify record grouping
  - `year3`: `registration_date` parsed for 3-year intervals (*e.g.,* '2014-2016'), to simplify record grouping

    - year5: registration_date parsed for 5-year intervals (*e.g.*, '2012-2016'), to simplify record grouping
    - year10: registration_date parsed for 3-year intervals (*e.g.*, '2007-2017'), to simplify record grouping
    - xy: x and y coordinates concatenated together (*e.g.*, '43.098324_-79.234235'), can be used to identify and group records by their coordinate pairs

- correction of consideration_amt for inflation
    - price_infl: consideration_amt corrected for inflation

- exploratory attributes
    - pin/xy_total_sales: total records for this pin/xy
    - pin/xy_prev_sales: previous records from this pin/xy (not counting current transaction)
    - pin/xy_price_cum_sum: cumulative price of all records to date from this pin/xy
    - pin/xy_price_pct_change: price percentage change compared to previous record from this pin/xy
    - price_da_pct_change: price percentage change compared to previous record from this DA (by da_id)
    - pin/xy_years_since_last_sale: years since last sale from this pin/xy
    - da_days_since_last_sale, da_years_since_last_sale: days or years since last sale from this DA (by da_id)
    - sale_next_6m/1y/3y: "looks into the future" to see whether there is another transaction from this pin/xy within the given time horizon (6 months, 1 year, 3 years)

4.2 Import dependencies

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
import pandas as pd
import os
from time import time

sns.set()
```

[2]:
```
data_path = '../../data/teranet/'
os.listdir(data_path)
```

[2]:
```
['Teranet_consistent.csv',
 'Teranet_with_DA_cols.csv',
 'Teranet_new_cols.csv',
 'Teranet_nonan_new_cols.csv',
 'HHSaleHistory.csv']
```

4.3 Load Teranet data

[3]:
```
t = time()

df = pd.read_csv(data_path + 'Teranet_consistent.csv',
                 parse_dates=['registration_date'], low_memory=False)
elapsed = time() - t
print("----- DataFrame loaded"
      "\nin {0:,.2f} seconds ({1:.2f} minutes)".format(elapsed, elapsed / 60) +
      "\nwith {0:,} rows\nand {1:,} columns"
      .format(df.shape[0], df.shape[1]) +
      "\n-- Column names:\n", df.columns)
```

```
----- DataFrame loaded
in 24.97 seconds (0.42 minutes)
with 6,803,691 rows
and 17 columns
-- Column names:
 Index(['lro_num', 'pin', 'consideration_amt', 'registration_date',
       'postal_code', 'unitno', 'street_name', 'street_designation',
       'street_direction', 'municipality', 'street_number', 'x', 'y',
       'objectid', 'dauid', 'csdname', 'street_name_raw'],
      dtype='object')
```

[4]:
```
df.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6803691 entries, 0 to 6803690
Data columns (total 17 columns):
lro_num               6803691 non-null int64
pin                   6803691 non-null int64
consideration_amt     6803691 non-null float64
registration_date     6803691 non-null datetime64[ns]
postal_code           6233365 non-null object
unitno                1572959 non-null object
street_name           6598317 non-null object
street_designation    6522418 non-null object
street_direction      683462 non-null object
municipality          6799681 non-null object
street_number         6594324 non-null object
x                     6803691 non-null float64
y                     6803691 non-null float64
objectid              6803691 non-null int64
dauid                 6803691 non-null int64
csdname               6803691 non-null object
street_name_raw       6598317 non-null object
dtypes: datetime64[ns](1), float64(3), int64(4), object(9)
memory usage: 882.4+ MB
```

4.4 Surrogate key

4.4.1 Add attribute `transaction_id`

Attribute `transaction_id` is intended as a unique identifier for each record in the Teranet dataset. It will be used as the ***primary key*** for records in Teranet table in the proposed GTHA housing market database. It is produced as a surrogate key, as no other attribute or combination of attributes in the Teranet dataset allows the records to be uniquely identified.

`transaction_id` is essentially a simple range index, which represents the row number of a record in the full Teranet dataset (filtered to include only GTHA records), ordered by date (from earliest to latest) and `pin`

Surrogate key `transaction_id` is added prior to the removal of any records, so that the keys match between both versions of the Teranet dataset – the one with unmodified `consideration_amt` and the one where records with `consideration_amt` < 10'000 CAD have been dropped.

Order Teranet records by `registration_date` and `pin`

[5]:
```
df = df.sort_values(['registration_date', 'pin'])
print("DataFrame was resorted by 'registration_date' and 'pin'.")
```

```
DataFrame was resorted by 'registration_date' and 'pin'.
```

Insert the new column `transaction_id`

[6]:
```
df.insert(0, "transaction_id", np.arange(len(df)))
print("New column 'transaction_id' was added to the DataFrame.")
```

```
New column 'transaction_id' was added to the DataFrame.
```

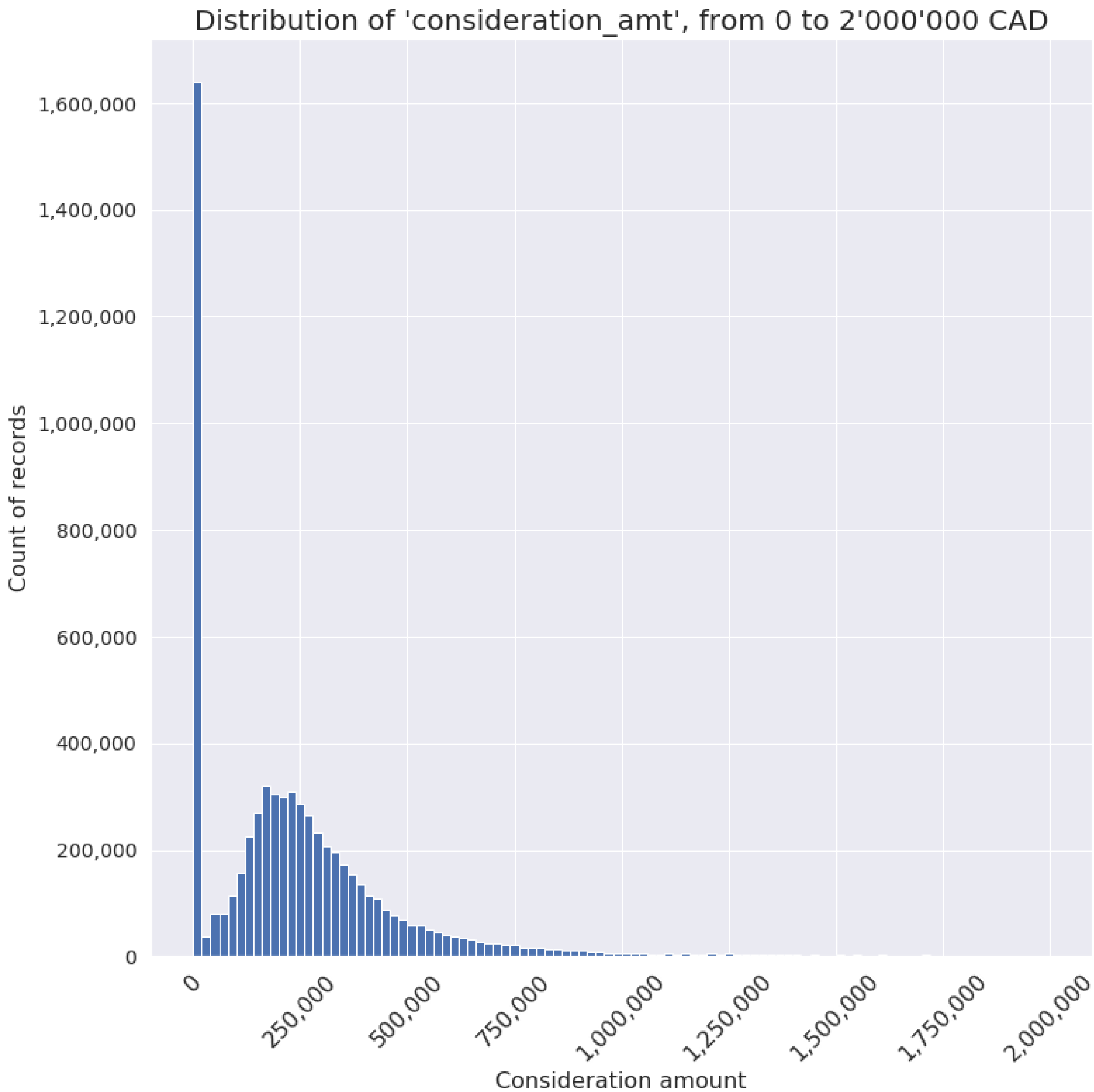
4.5 Reset all values of `consideration_amt` < 10'000 CAD to NaN

All values of `consideration_amt` less than 10'000 CAD are reset to NaN. The boundary of 10'000 CAD has been selected fairly arbitrary, to cut off the spike of records with low values from the distribution of `consideration_amt` (presented below). On the charts below, values of `consideration_amt` greater than 1'000'000 are not displayed, but they are left in the Teranet dataset, only the values with low `consideration_amt` are removed.

Distribution of `consideration_amt`, from 0 to 2'000'000 CAD

[7]:
```
%matplotlib inline
ax = df.query('consideration_amt < 2000000')['consideration_amt']\
    .hist(bins=100, figsize=(12,12))
ax.get_xaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.set_xlabel("Consideration amount", fontsize=16)
ax.set_ylabel("Count of records", fontsize=16)
```

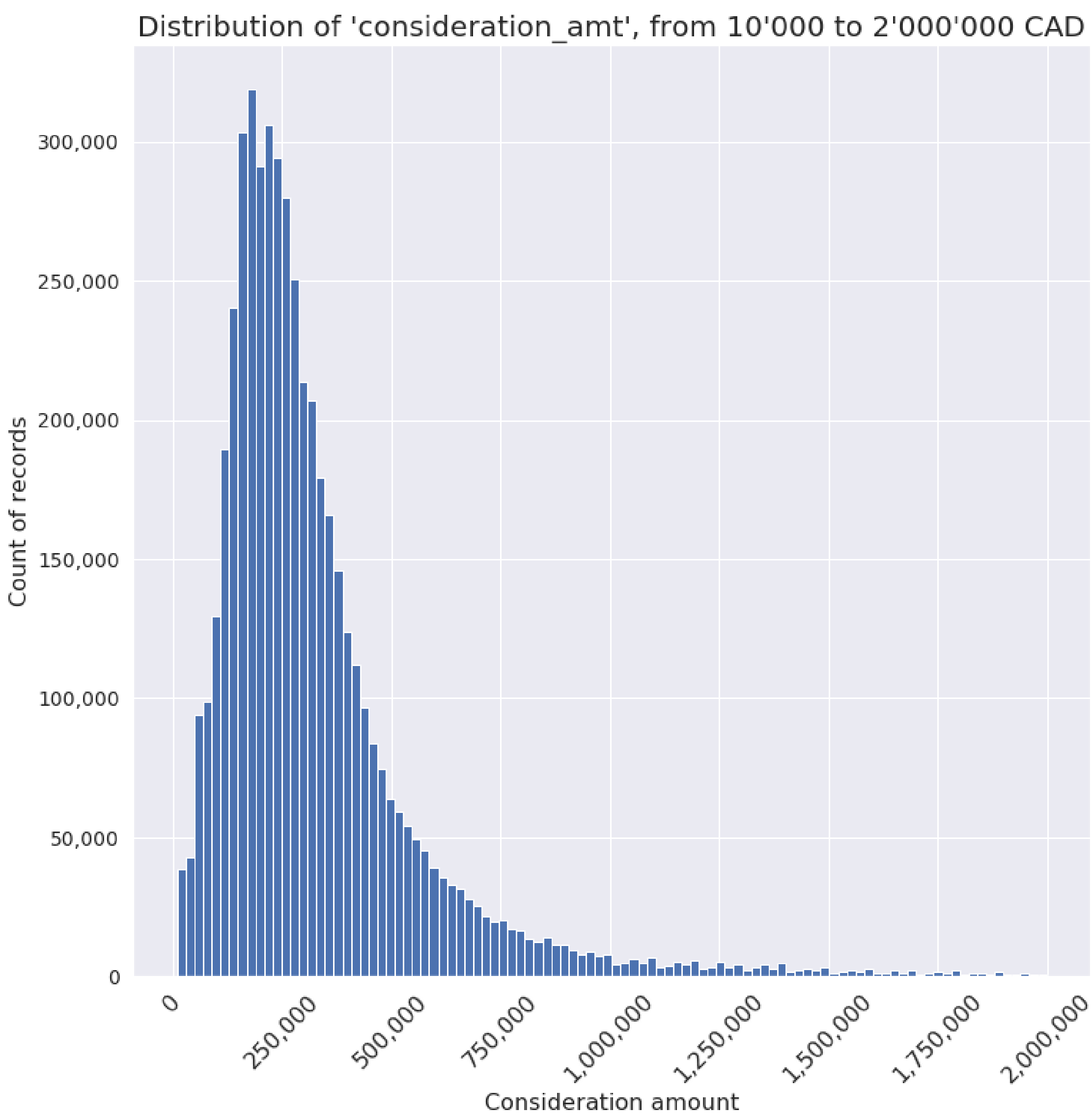
```
ax.set_title("Distribution of 'consideration_amt', from 0 to 2'000'000 CAD",␣
↪fontsize=20)
plt.xticks(rotation=45, fontsize=16)
plt.yticks(fontsize=14)
plt.savefig('results/teranet_price_dist.png', dpi=300, bbox_inches='tight')
```



Distribution of `consideration_amt`, from 10'000 to 2'000'000 CAD

[8]:
```
ax = df.query('consideration_amt < 2000000 & consideration_amt >␣
↪10000')['consideration_amt']\
    .hist(bins=100, figsize=(12,12))
ax.get_xaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
```

```python
ax.get_yaxis().set_major_formatter(
    matplotlib.ticker.FuncFormatter(lambda x, p: format(int(x), ',')))
ax.set_xlabel("Consideration amount", fontsize=16)
ax.set_ylabel("Count of records", fontsize=16)
ax.set_title("Distribution of 'consideration_amt', from 10'000 to 2'000'000␣
 ↪CAD", fontsize=20)
plt.xticks(rotation=45, fontsize=16)
plt.yticks(fontsize=14)
plt.savefig('results/teranet_10000_price_dist.png', dpi=300,␣
 ↪bbox_inches='tight')
```



Reset all values of `consideration_amt` < 10’000 to NaN To eliminate the spike on the distribution of `consideration_amt` corresponding to records with unreasonably low values, all values of `consideration_amt` < 10’000 are reset to NaN. Records with `consideration_amt` > 2’000’000 are left in the Teranet dataset.

[9]:
```
min_price = 10000
mask = df['consideration_amt'] < min_price
df.loc[mask, 'consideration_amt'] = np.nan
print("Values of 'consideration_amt' of all records with price under {0:,} CAD␣
 ↪were set to NaN!"
      .format(min_price) +
       "\n{0:,} values ({1:.2f}% of the total) have been reset to NaN."
       .format(len(df) - df['consideration_amt'].count(),
               (len(df) - df['consideration_amt'].count()) / len(df) * 100) +
       "\n'consideration_amt' now has {0:,} non-null entries."
        .format(df['consideration_amt'].count()))
```

```
Values of 'consideration_amt' of all records with price under 10,000 CAD were
set to NaN!
1,615,178 values (23.74% of the total) have been reset to NaN.
'consideration_amt' now has 5,188,513 non-null entries.
```

4.6 Drop all records with missing `consideration_amt`

All records with missing `consideration_amt` are removed from the Teranet dataset.

[10]:
```
old_len = len(df)
df = df.dropna(subset=['consideration_amt'])
print("{0:,} records ({1:,.2f}% of the total) with missing 'consideration_amt'"
       .format(old_len - len(df), (old_len - len(df)) / old_len * 100) +
       " have been removed from the dataset.\n{0:,} records remaining."
       .format(len(df)))
```

```
1,615,178 records (23.74% of the total) with missing 'consideration_amt' have
been removed from the dataset.
5,188,513 records remaining.
```

[11]:
```
df.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5188513 entries, 793498 to 1218620
Data columns (total 18 columns):
transaction_id        5188513 non-null int64
lro_num               5188513 non-null int64
pin                   5188513 non-null int64
consideration_amt     5188513 non-null float64
registration_date     5188513 non-null datetime64[ns]
postal_code           4881914 non-null object
```

```
unitno                  1332614 non-null object
street_name             5144061 non-null object
street_designation      5090453 non-null object
street_direction        550657 non-null object
municipality            5187161 non-null object
street_number           5142790 non-null object
x                       5188513 non-null float64
y                       5188513 non-null float64
objectid                5188513 non-null int64
dauid                   5188513 non-null int64
csdname                 5188513 non-null object
street_name_raw         5144061 non-null object
dtypes: datetime64[ns](1), float64(3), int64(5), object(9)
memory usage: 752.1+ MB
```

4.7 Attributes for display

4.7.1 Add attribute `date_disp`

Since Teranet records do not carry any actual timestamp (each record has a timestamp of '00:00:00'), a new column `date_disp` is created from `registration_date` to show only dates. The new column `date_disp` has a data type of `datetime.date`, while the original column `registration_date` is stored in NumPy's `datetime64` data type, which allows more efficient date-time operations.

[12]:
```
df['date_disp'] = df['registration_date'].dt.date
print("New column 'date_disp' was added to the DataFrame.")
```

```
New column 'date_disp' was added to the DataFrame.
```

4.7.2 Add attribute `price_disp`

A new column `price_disp` is created from values of `consideration_amt` formatted to include thousands separator (*e.g.*, '3,455,122') and stored as a string, for display purposes.

[13]:
```
df['price_disp'] = df['consideration_amt'].apply(lambda x: '{:,}'.format(x))
print("New column 'price_disp' was added to the DataFrame.")
```

```
New column 'price_disp' was added to the DataFrame.
```

4.8 Add attribute `year`

The new attribute `year` is parsed from `registration_date` and stored as a string, to simplify record grouping.

[14]:
```
df['year'] = df['date_disp'].astype('str').apply(lambda x: x[:4])
print("New column 'year' was added to the DataFrame.")
```

```
New column 'year' was added to the DataFrame.
```

4.9 Add attribute `year_month`

The new attribute `year_month` is parsed from `date_disp` and stored as a string, to simplify record grouping.

[15]:
```
df['year_month'] = df['date_disp'].astype('str').apply(lambda x: x[:7])
print("New column 'year_month' was added to the DataFrame.")
```

```
New column 'year_month' was added to the DataFrame.
```

4.10 Add attribute `year3`

The new attribute `year3` is created from the column `year` parsed for 3-year intervals (*e.g.*, '2014-2016') and stored as a string, to simplify record grouping.

[16]:
```
t = time()

df['year3'] = df['year']

year_list = df['year'].unique()

i = 0
ylist = []
for year in year_list:
    ylist.append(year)
    i += 1
    if i == 3:
        df['year3'] = df['year3'].str.replace('^' + ylist[0] + '$|^' + ylist[1]␣
 ↪+ '$|^' + ylist[2] + '$',
                                               ylist[0] + '-' + ylist[2])
        ylist = []
        i = 0

elapsed = time() - t

print("New column 'year3' was added to the DataFrame. Took {0:,.2f} seconds ({1:
 ↪.2f} minutes)."
      .format(elapsed, elapsed / 60))
df['year3'].value_counts().sort_index()
```

```
New column 'year3' was added to the DataFrame. Took 261.93 seconds (4.37
minutes).
```

[16]:
```
1865-1872     6
1873-1876     7
1877-1880     6
1882-1884     8
1885-1887     8
1888-1890    27
```

```
1891-1895        10
1897-1900        20
1901-1903        14
1904-1906        10
1907-1909        28
1910-1912        63
1913-1915        56
1916-1918        44
1919-1921        65
1922-1924        85
1925-1927        76
1928-1930        95
1931-1933        56
1934-1936        82
1937-1939        78
1940-1942        60
1943-1945        67
1946-1948       129
1949-1951       407
1952-1954       731
1955-1957       927
1958-1960       894
1961-1963       963
1964-1966      1148
1967-1969      1001
1970-1972      1024
1973-1975       807
1976-1978      1154
1979-1981      1507
1982-1984      1042
1985-1987     91732
1988-1990    213380
1991-1993    249801
1994-1996    330847
1997-1999    466378
2000-2002    562066
2003-2005    656825
2006-2008    655581
2009-2011    629141
2012-2014    638766
2015-2017    681291
Name: year3, dtype: int64
```

4.11 Add attribute `year5`

The new attribute `year5` is created from the column `year` parsed for 5-year intervals (*e.g.,* '2012-2016') and stored as a string, to simplify record grouping.

[17]:
```
t = time()

df['year5'] = df['year']

year_list = df['year'].unique()[1:] # skipping first year (1805) to match the␣
↪length of a 5-year window

i = 0
ylist = []
for year in year_list:
    ylist.append(year)
    i += 1
    if i == 5:
        df['year5'] = df['year5'].str.replace('^' + ylist[0] + '$|^' + ylist[1]␣
↪+ '$|^' + ylist[2] + '$|^' + ylist[3] + '$|^' + ylist[4] + '$',
                                                ylist[0] + '-' + ylist[4])
        ylist = []
        i = 0

elapsed = time() - t

print("New column 'year5' was added to the DataFrame. Took {0:,.2f} seconds ({1:
↪.2f} minutes)."
      .format(elapsed, elapsed / 60))
df['year5'].value_counts().sort_index()
```

```
New column 'year5' was added to the DataFrame. Took 158.65 seconds (2.64
minutes).
```

[17]:
```
1865            1
1871-1876      12
1877-1883      10
1884-1888      18
1889-1895      31
1897-1902      29
1903-1907      25
1908-1912      81
1913-1917      93
1918-1922     101
1923-1927     132
1928-1932     140
1933-1937     136
1938-1942      95
1943-1947     152
1948-1952     650
1953-1957    1459
```

```
1958-1962       1502
1963-1967       1855
1968-1972       1673
1973-1977       1692
1978-1982       2224
1983-1987      92326
1988-1992     382245
1993-1997     565972
1998-2002     874255
2003-2007    1110606
2008-2012    1036282
2013-2017    1114716
Name: year5, dtype: int64
```

4.12 Add attribute year10

The new attribute `year10` is created from the column `year` parsed for 5-year intervals (*e.g.*, '2014-2017') and stored as a string, to simplify record grouping.

[18]:
```
t = time()

df['year10'] = df['year']

year_list = df['year'].unique()[1:] # skipping first year (1805) to match the␣
 ↪length of a 10-year window

i = 0
ylist = []
for year in year_list:
    ylist.append(year)
    i += 1
    if i == 10:
        df['year10'] = df['year10'].str.replace('^' + ylist[0] + '$|^' +␣
 ↪ylist[1] + '$|^' + ylist[2] + '$|^' +
                                                ylist[3] + '$|^' + ylist[4] +␣
 ↪'$|^' + ylist[5] + '$|^' + ylist[6] +
                                                '$|^' + ylist[7] + '$|^' +␣
 ↪ylist[8] + '$|^' + ylist[9] + '$',
                                                ylist[0] + '-' + ylist[9])
        ylist = []
        i = 0

elapsed = time() - t

print("New column 'year10' was added to the DataFrame. Took {0:,.2f} seconds␣
 ↪({1:.2f} minutes)."
      .format(elapsed, elapsed / 60))
```

```
df['year10'].value_counts().sort_index()
```

```
New column 'year10' was added to the DataFrame. Took 80.83 seconds (1.35
minutes).
```

[18]:
```
1865              1
1871-1883        22
1884-1895        49
1897-1907        54
1908-1917       174
1918-1927       233
1928-1937       276
1938-1947       247
1948-1957      2109
1958-1967      3357
1968-1977      3365
1978-1987     94550
1988-1997    948217
1998-2007   1984861
2008-2017   2150998
Name: year10, dtype: int64
```

4.12.1 Add attribute xy

The new attribute xy is produced by concatenating x and y together (*e.g.*, '-79.9774202446447_43.203290987723'), it can be used to identify and group records by their coordinate pairs.

[19]:
```
df['xy'] = df['x'].astype('str') + '_' + df['y'].astype('str')
print("New column 'xy' was added to the DataFrame.")
```

```
New column 'xy' was added to the DataFrame.
```

4.13 Correction of consideration_amt for inflation

4.14 Exploratory attributes

4.14.1 Add column total_sales

Total records for each pin, generated as a separate DataFrame df_pin which represents Teranet records grouped and indexed by pin.

total_sales_pin is added as a new column for Teranet records via a merge operation on pin.

[20]:
```
# group records by `pin`
t = time()
pin_counts = \
    df.groupby('pin')['consideration_amt'].count()
pin_counts.name = 'pin_total_sales'
df = pd.merge(df, pin_counts, on='pin')
```

```
elapsed = time() - t
print("\nNew column 'pin_total_sales' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))

# group records by `xy` coordinate pairs
t = time()
xy_counts = \
    df.groupby('xy')['consideration_amt'].count()
xy_counts.name = 'xy_total_sales'
df = pd.merge(df, xy_counts, on='xy')
elapsed = time() - t
print("\nNew column 'xy_total_sales' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
```

```
New column 'pin_total_sales' added to the DataFrame!
took 19.02 seconds.

New column 'xy_total_sales' added to the DataFrame!
took 18.53 seconds.
```

4.14.2 Add column prev_sales

New columns are added to Teranet records capturing, for each transaction, a rolling count of previous records from this pin or xy coordinate pair.

[21]:
```
df['count'] = 1 # used to produce rolling counts per `pin` and `xy`

# group by `pin`
t = time()
df['pin_prev_sales'] = \
    df.sort_values(['pin', 'registration_date'])\
    .groupby('pin')['count'].cumsum() - 1
elapsed = time() - t
print("\nNew column 'pin_prev_sales' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))

# group by xy pairs
t = time()
df['xy_prev_sales'] = \
    df.sort_values(['xy', 'registration_date'])\
    .groupby('xy')['count'].cumsum() - 1
elapsed = time() - t
print("\nNew column 'xy_prev_sales' "
      "added to the DataFrame!"
```

```
       "\ntook {0:.2f} seconds.".format(elapsed))

df = df.drop('count', axis=1)
```

```
New column 'pin_prev_sales' added to the DataFrame!
took 12.75 seconds.

New column 'xy_prev_sales' added to the DataFrame!
took 17.93 seconds.
```

4.14.3 Add columns `price_cum_sum` and `price_pct_change`

New columns are added to Teranet records capturing, for each transaction, a rolling sum of price from previous records from this `pin` or `xy` coordinate pair, and `pct_change` compared to previous transaction from this `pin` or `xy` pair.

[22]:
```
# `price_cum_sum`
# group records by `pin`
t = time()
df['pin_price_cum_sum'] = \
    df.sort_values(['pin', 'registration_date'])\
    .groupby('pin')['consideration_amt'].cumsum()
elapsed = time() - t
print("\nNew column 'pin_price_cum_sum' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
# group records by `xy` pairs
t = time()
df['xy_price_cum_sum'] = \
    df.sort_values(['xy', 'registration_date'])\
    .groupby('xy')['consideration_amt'].cumsum()
elapsed = time() - t
print("\nNew column 'xy_price_cum_sum' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))

# `price_pct_change`
# group records by `pin`
t = time()
df['pin_price_pct_change'] = \
    df.sort_values(['pin', 'registration_date'])\
    .groupby('pin')['consideration_amt'].pct_change()
elapsed = time() - t
print("\nNew column 'pin_price_pct_change' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
# group records by `xy`
```

```
t = time()
df['xy_price_pct_change'] = \
    df.sort_values(['xy', 'registration_date'])\
    .groupby('xy')['consideration_amt'].pct_change()
elapsed = time() - t
print("\nNew column 'xy_price_pct_change' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
```

```
New column 'pin_price_cum_sum' added to the DataFrame!
took 9.17 seconds.

New column 'xy_price_cum_sum' added to the DataFrame!
took 17.82 seconds.

New column 'pin_price_pct_change' added to the DataFrame!
took 10.08 seconds.

New column 'xy_price_pct_change' added to the DataFrame!
took 18.31 seconds.
```

4.15 Add column `price_da_pct_change`

New column is added to Teranet records capturing, for each transaction, percentage change in price compared to the previous record from this `da_id`.

[23]:
```
# add column 'price_da_pct_change' to Teranet records DataFrame
t = time()
df['price_da_pct_change'] = \
    df.sort_values(['dauid', 'registration_date'])\
    .groupby('dauid')['consideration_amt'].pct_change()
elapsed = time() - t
print("\nNew column 'price_da_pct_change' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
```

```
New column 'price_da_pct_change' added to the DataFrame!
took 8.00 seconds.
```

4.16 Add columns `years_since_last_sale`

New columns are added to Teranet records capturing, for each transaction, years passed since the previous record from this `pin` or `xy` coordinate pair.

[24]:
```
t = time()
df['pin_years_since_last_sale'] = \
    df.sort_values(['pin', 'registration_date'])\
```

```
      .groupby('pin')['registration_date']\
        .diff().dt.days / 365
elapsed = time() - t
print("New column 'pin_years_since_last_sale' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds ({1:.2f} minutes).".format(elapsed, elapsed / 60))
```

```
New column 'pin_years_since_last_sale' added to the DataFrame!
took 1118.44 seconds (18.64 minutes).
```

[25]:
```
t = time()
df['xy_years_since_last_sale'] = \
    df.sort_values(['xy', 'registration_date'])\
      .groupby('xy')['registration_date']\
        .diff().dt.days / 365
elapsed = time() - t
print("New column 'xy_years_since_last_sale' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds ({1:.2f} minutes).".format(elapsed, elapsed / 60))
```

```
New column 'xy_years_since_last_sale' added to the DataFrame!
took 653.98 seconds (10.90 minutes).
```

4.17 Add columns da_days_since_last_sale and da_years_since_last_sale

New columns are added to Teranet records capturing, for each transaction, years passed since the previous record from this pin or xy coordinate pair.

[26]:
```
# add column 'da_days_since_last_sale' to Teranet records DataFrame
t = time()
df['da_days_since_last_sale'] = \
    df.sort_values(['dauid', 'registration_date'])\
      .groupby('dauid')['registration_date']\
        .diff().dt.days
elapsed = time() - t
print("New column 'da_days_since_last_sale' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
# add column 'da_years_since_last_sale' to Teranet records DataFrame
t = time()
df['da_years_since_last_sale'] = \
    df.sort_values(['dauid', 'registration_date'])\
      .groupby('dauid')['registration_date']\
        .diff().dt.days / 365
elapsed = time() - t
print("New column 'da_years_since_last_sale' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
```

```
New column 'da_days_since_last_sale' added to the DataFrame!
took 13.73 seconds.
New column 'da_years_since_last_sale' added to the DataFrame!
took 13.54 seconds.
```

4.18 Add columns `sale_next_6m/1y/3y` per `pin` and `xy`

New columns are added to Teranet records capturing, for each transaction, whether there would be another transaction in the future from this `pin`, `xy`, or `da_id`

Time horizons used: 6 months, 1 year, 3 years.

[27]:
```python
# create a new column, marks True if next 'day_diff' <= 5
# group records by `pin`
t = time()
df = df.sort_values(['pin', 'registration_date'])
df['pin_sale_next_6m'] = \
    df['pin_years_since_last_sale'].shift(-1) <= 0.5
df['pin_sale_next_1y'] = \
    df['pin_years_since_last_sale'].shift(-1) <= 1
df['pin_sale_next_3y'] = \
    df['pin_years_since_last_sale'].shift(-1) <= 3
elapsed = time() - t
print("New columns 'pin_sale_next_..' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))

# group records by `xy`
t = time()
df = df.sort_values(['xy', 'registration_date'])
df['xy_sale_next_6m'] = \
    df['xy_years_since_last_sale'].shift(-1) <= 0.5
df['xy_sale_next_1y'] = \
    df['xy_years_since_last_sale'].shift(-1) <= 1
df['xy_sale_next_3y'] = \
    df['xy_years_since_last_sale'].shift(-1) <= 3
elapsed = time() - t
print("New columns 'xy_sale_next_..' "
      "added to the DataFrame!"
      "\ntook {0:.2f} seconds.".format(elapsed))
```

```
New columns 'pin_sale_next_..' added to the DataFrame!
took 8.29 seconds.
New columns 'xy_sale_next_..' added to the DataFrame!
took 10.69 seconds.
```

4.19 Save results to a new .csv file

Teranet dataset without NaN records and with new columns is saved as: `data/HHSaleHistory_cleaned_v0.9_GTHA_DA_with_cols_v0.9.csv`

[28]:
```
df.columns
```

[28]:
```
Index(['transaction_id', 'lro_num', 'pin', 'consideration_amt',
       'registration_date', 'postal_code', 'unitno', 'street_name',
       'street_designation', 'street_direction', 'municipality',
       'street_number', 'x', 'y', 'objectid', 'dauid', 'csdname',
       'street_name_raw', 'date_disp', 'price_disp', 'year', 'year_month',
       'year3', 'year5', 'year10', 'xy', 'pin_total_sales', 'xy_total_sales',
       'pin_prev_sales', 'xy_prev_sales', 'pin_price_cum_sum',
       'xy_price_cum_sum', 'pin_price_pct_change', 'xy_price_pct_change',
       'price_da_pct_change', 'pin_years_since_last_sale',
       'xy_years_since_last_sale', 'da_days_since_last_sale',
       'da_years_since_last_sale', 'pin_sale_next_6m', 'pin_sale_next_1y',
       'pin_sale_next_3y', 'xy_sale_next_6m', 'xy_sale_next_1y',
       'xy_sale_next_3y'],
      dtype='object')
```

[29]:
```
save_path = data_path + 'Teranet_nonan_new_cols.csv'
t = time()
df.to_csv(save_path, index=False)
elapsed = time() - t
print("DataFrame saved to file:\n", save_path,
      "\ntook {0:.2f} seconds ({1:.2f} minutes).".format(elapsed, elapsed / 60))
```

```
DataFrame saved to file:
 ../../data/teranet/Teranet_nonan_new_cols.csv
took 514.03 seconds (8.57 minutes).
```