04_1_Binning

January 28, 2021

[ ]:
```
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```

1 Tutorial: Feature Engineering for Recommender Systems

2 4. Feature Engineering - Numerical

2.1 4.1. Binning

[1]:
```
import IPython

import pandas as pd
import cudf
import numpy as np
```

```python
import cupy
import matplotlib.pyplot as plt

df_train = cudf.read_parquet('./data/train.parquet')
df_valid = cudf.read_parquet('./data/valid.parquet')

df_train['brand'] = df_train['brand'].fillna('UNKNOWN')
df_valid['brand'] = df_valid['brand'].fillna('UNKNOWN')

df_train['cat_0'] = df_train['cat_0'].fillna('UNKNOWN')
df_valid['cat_0'] = df_valid['cat_0'].fillna('UNKNOWN')

df_train['cat_1'] = df_train['cat_1'].fillna('UNKNOWN')
df_valid['cat_1'] = df_valid['cat_1'].fillna('UNKNOWN')

df_train['cat_2'] = df_train['cat_2'].fillna('UNKNOWN')
df_valid['cat_2'] = df_valid['cat_2'].fillna('UNKNOWN')
```

[2]:
```python
df_train.head()
```

[2]:
```
                event_time event_type  product_id    brand   price    user_id  \
0  2019-12-01 00:00:28 UTC       cart    17800342     zeta   66.90  550465671
1  2019-12-01 00:00:39 UTC       cart     3701309  polaris   89.32  543733099
2  2019-12-01 00:00:40 UTC       cart     3701309  polaris   89.32  543733099
3  2019-12-01 00:00:41 UTC       cart     3701309  polaris   89.32  543733099
4  2019-12-01 00:01:56 UTC       cart     1004767  samsung  235.60  579970209

                           user_session  target         cat_0        cat_1  \
0  22650a62-2d9c-4151-9f41-2674ec6d32d5       0     computers      desktop
1  a65116f4-ac53-4a41-ad68-6606788e674c       0    appliances  environment
2  a65116f4-ac53-4a41-ad68-6606788e674c       0    appliances  environment
3  a65116f4-ac53-4a41-ad68-6606788e674c       0    appliances  environment
4  c6946211-ce70-4228-95ce-fd7fccdde63c       0  construction        tools

     cat_2 cat_3            timestamp  ts_hour  ts_minute  ts_weekday  ts_day  \
0  UNKNOWN  <NA>  2019-12-01 00:00:28        0          0           6       1
1   vacuum  <NA>  2019-12-01 00:00:39        0          0           6       1
2   vacuum  <NA>  2019-12-01 00:00:40        0          0           6       1
3   vacuum  <NA>  2019-12-01 00:00:41        0          0           6       1
4    light  <NA>  2019-12-01 00:01:56        0          1           6       1

   ts_month  ts_year
0        12     2019
1        12     2019
2        12     2019
3        12     2019
4        12     2019
```

2.2 Theory

Binning maps multiple ordinal categorical or numerical features into groups. It is mainly applied to numerical features:

prevent overfitting by grouping values together

enables us to add some expert knowledge into the model

most simple case: binary flags, e.g. features is greater than 0 Examples:

binning weekdays into weekday and weekend

binning hours into morning, early afternoon, late afternoon, evening and night

binning age into child, adlult and retired

We can take a look on the hour of the day. We can see multiple patterns:

0-3 Night: Low purchase probability

4-7 Early morning: Mid purchase probability

8-14 Morning/Lunch: Higher purchase probability

15-20 Afternoon: Low purchase probability

21-23: Evening: High purchase probability

[3]:
```
df_train[['ts_hour', 'target']].groupby('ts_hour').agg(['count', 'mean']).
↪head(10)
```

[3]:
```
          target
           count      mean
ts_hour
0          58470  0.305319
1          99086  0.252377
2         206718  0.282888
3         386098  0.340300
4         554952  0.372178
5         665547  0.375789
6         729542  0.377133
7         758404  0.383824
8         779388  0.393012
9         779987  0.397358
```

[4]:
```
hour = list(range(0,24))
hour_bin = [0]*4 + [1]*4 + [2]*7 + [3]*6 + [4]*3

data = cudf.DataFrame({
    'hour': hour,
    'hour_bin': hour_bin,
})
```

[5]:
```
data.head(10)
```

[5]:

	hour	hour_bin
0	0	0
1	1	0
2	2	0
3	3	0
4	4	1
5	5	1
6	6	1
7	7	1
8	8	2
9	9	2

[6]:
```
df_train = df_train.merge(data, how='left', right_on='hour', left_on='ts_hour')
```

[7]:
```
df_train[['hour_bin', 'target']].groupby('hour_bin').agg(['count', 'mean'])
```

[7]:

	target	
	count	mean
hour_bin		
0	750372	0.310148
1	2708445	0.377661
2	4979563	0.385930
3	2781837	0.337329
4	241140	0.371942

Binning the numerical features reduces the cardinality (# of unique values). Therefore, a model can easier learn the relationship to the target variables, as there are more observation per category. In addition, binning prevents overfitting.

Another reason to apply binning is to standardize numeric variables per category group. The datasets provides information about the product category (cat_1) and price information.

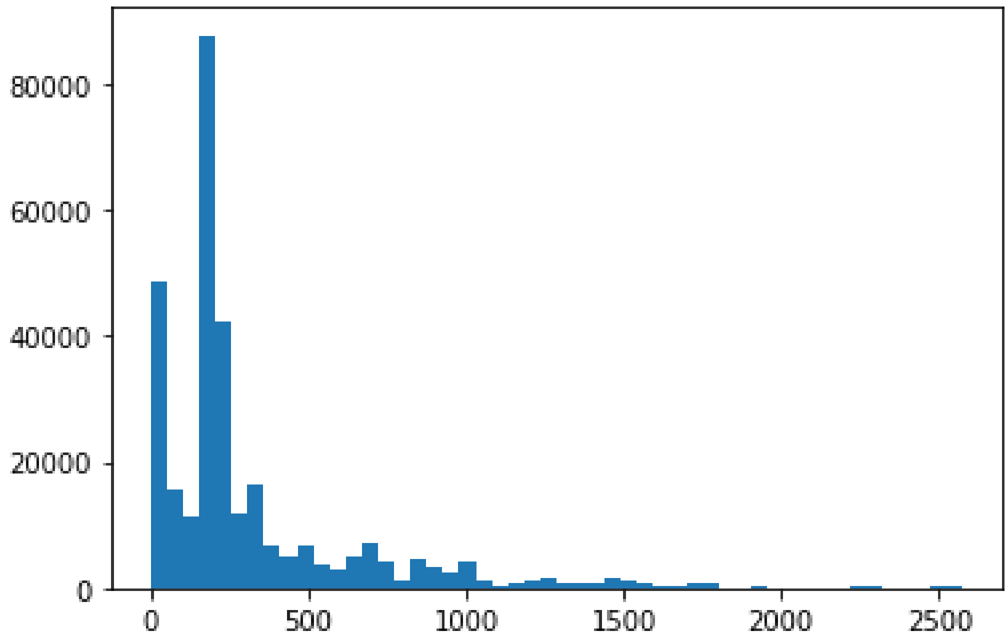
For example, the headphones and smartphones have a different price distribution.

We can probably buy good headphones between $100-$200

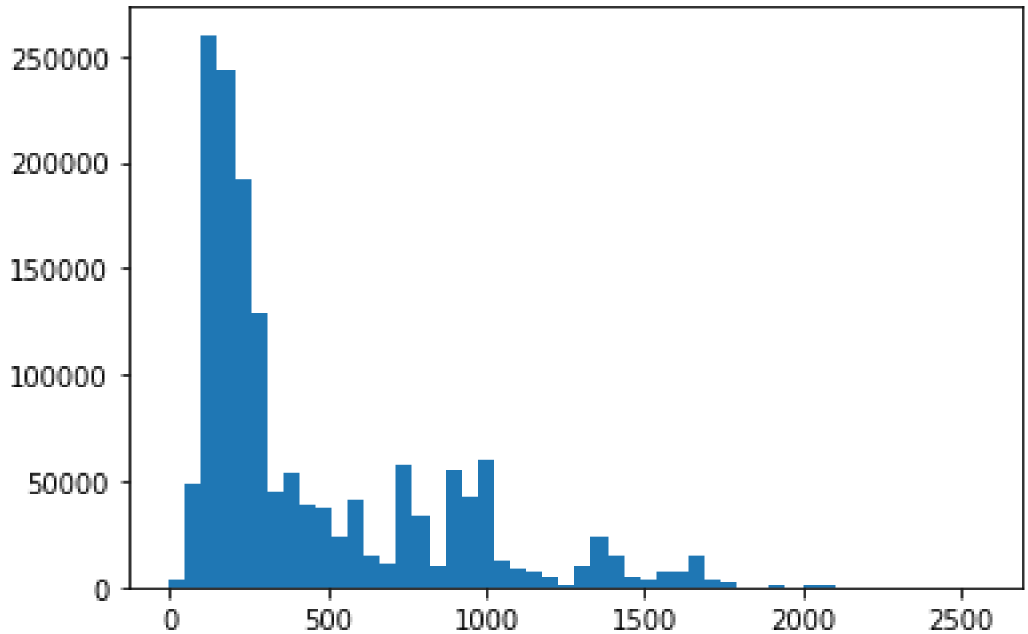
For a good smartphone, prices are probably in the range of $400-$1200

Therefore, the buying behavior should be different depending on the price per category (what is a good deal).

[8]:
```
plt.hist(df_train[df_train['cat_2']=='headphone'].price.to_pandas(), bins=50)
plt.show()
```



[9]:
```
plt.hist(df_train[df_train['cat_1']=='smartphone'].price.to_pandas(), bins=50)
plt.show()
```



```
[10]: print('Headphones mean price: ' + str(df_train[df_train['cat_2']=='headphone'].
       ↪price.mean()) + ' median price: ' +␣
       ↪str(df_train[df_train['cat_2']=='headphone'].price.median()))
      print('Smartphones mean price: ' +␣
       ↪str(df_train[df_train['cat_1']=='smartphone'].price.mean()) + ' median price:
       ↪ ' + str(df_train[df_train['cat_1']=='smartphone'].price.median()))
```

```
Headphones mean price: 316.9701128768166 median price: 189.82
Smartphones mean price: 456.3495716886366 median price: 263.84
```

Based on the category tree, we want to bin the prices as a combination of cat_0, cat_1 and cat_2.

```
[11]: df_train['cat_012'] = df_train['cat_0'].astype(str) + '_' + df_train['cat_1'].
       ↪astype(str) + '_' + df_train['cat_2'].astype(str)
```

```
[12]: q_list = [0.1, 0.25, 0.5, 0.75, 0.9]
```

We calculate the quantiles per category group and then merge the quantile to the original dataframe.

```
[13]: for q_value in q_list:
          q = df_train[['cat_012', 'price']].groupby(['cat_012']).quantile(q_value)
          q = q.reset_index()
          q.columns = ['cat_012', 'price' + str(q_value)]
          df_train = df_train.merge(q, how='left', on='cat_012')
```

Afterwards, we loop through the columns and update the price_bin depending, if the price is between quantiles.

```
[14]: df_train['price_bin'] = -1

      for i, q_value in enumerate(q_list):
          if i == 0:
              df_train.loc[df_train['price']<=df_train['price' + str(q_value)],␣
       ↪'price_bin'] = i
          else:
              df_train.loc[(df_train['price']>df_train['price' + str(q_list[i-1])]) &␣
       ↪(df_train['price']<=df_train['price' + str(q_value)]), 'price_bin'] = i

      df_train.loc[df_train['price']>df_train['price' + str(q_value)], 'price_bin'] =␣
       ↪i+1
```

Example output

```
[15]: df_train[df_train['price_bin']==3][['price', 'price0.1', 'price0.25', 'price0.
       ↪5', 'price0.75', 'price0.9', 'price_bin']].drop_duplicates()
```

[15]:

	price	price0.1	price0.25	price0.5	price0.75	price0.9	price_bin
1427700	7.61	4.12	5.56	7.60	11.58	16.99	3
4858449	7.63	4.12	5.56	7.60	11.58	16.99	3

```
449626     7.68      4.12      5.56      7.60     11.58     16.99          3
138237     7.70      4.12      5.56      7.60     11.58     16.99          3
117511     7.72      3.06      6.15      7.70     12.87     25.71          3
…          …         …         …         …        …         …
8098903  766.73    254.81    308.63    514.56    767.81   1283.73          3
5180578  766.82    254.81    308.63    514.56    767.81   1283.73          3
9155543  767.05    254.81    308.63    514.56    767.81   1283.73          3
941982   767.79    254.81    308.63    514.56    767.81   1283.73          3
629787   767.81    254.81    308.63    514.56    767.81   1283.73          3

[52076 rows x 7 columns]
```

[16]:
```
df_train = df_train.drop(['price' + str(x) for x in q_list])
```

We can see the pattern, that products in a lower quantile 0-10% and 10-25% have lower purchase probabilities.

[17]:
```
df_train[['price_bin', 'target']].groupby('price_bin').agg(['count', 'mean'])
```

[17]:
```
             target
              count      mean
price_bin
0           1190744  0.336958
1           1724067  0.359324
2           2844590  0.369048
3           2874795  0.376165
4           1691338  0.375745
5           1135823  0.368033
```

2.3 Practice

Now, it is your turn. Let's take a look on ts_weekday.

ToDo:

Analyze ts_weekday and find a good mapping

[18]:
```
### ToDo
```

2.4 Optimization

cuDF has no native binning function (per groupby) implemented, yet. However, cuDF is constantly developing and new features get implemented. Stay tuned to get the latest updates. We can improve our above implementation. Currently, we calculate all binnings and merge them to the original dataframe. That requires more memory. We need only consecutive quantile columns.

We restart the kernel.

[25]:
```python
app = IPython.Application.instance()
app.kernel.do_shutdown(True)
```

[25]: {'status': 'ok', 'restart': True}

[2]:
```python
import IPython

import pandas as pd
import cudf
import numpy as np
import cupy
import matplotlib.pyplot as plt

df_train = cudf.read_parquet('./data/train.parquet')

df_train['brand'] = df_train['brand'].fillna('UNKNOWN')
df_train['cat_0'] = df_train['cat_0'].fillna('UNKNOWN')
df_train['cat_1'] = df_train['cat_1'].fillna('UNKNOWN')
df_train['cat_2'] = df_train['cat_2'].fillna('UNKNOWN')
```

[3]:
```python
df_train['cat_012'] = df_train['cat_0'].astype(str) + '_' + df_train['cat_1'].
↪astype(str) + '_' + df_train['cat_2'].astype(str)
```

[4]:
```python
def group_binning(df, q_list = [0.1, 0.25, 0.5, 0.75, 0.9]):
    df['price_bin'] = -1

    for i, q_value in enumerate(q_list):
        print(q_value)
        q = df[['cat_012', 'price']].groupby(['cat_012']).quantile(q_value)
        q = q.reset_index()
        q.columns = ['cat_012', 'price' + str(q_value)]
        df = df.merge(q, how='left', on='cat_012')
        if i == 0:
            df.loc[df['price']<=df['price' + str(q_value)], 'price_bin'] = i
        else:
            df.loc[(df['price']>df['price' + str(q_list[i-1])]) &␣
↪(df['price']<=df['price' + str(q_value)]), 'price_bin'] = i
        if i>=2:
            df.drop(['price' + str(q_list[i-2])], axis=1, inplace=True)

    df.loc[df['price']>df['price' + str(q_value)], 'price_bin'] = i+1
    df.drop(['price' + str(q_list[i-1])], axis=1, inplace=True)
    df.drop(['price' + str(q_list[i])], axis=1, inplace=True)
    return(df)
```

[5]:
```python
df_train_pd = df_train.to_pandas()
```

[6]:
```
%%time

df_train_pd = group_binning(df_train_pd)
```

```
0.1
0.25
0.5
0.75
0.9
CPU times: user 1min 26s, sys: 41.5 s, total: 2min 8s
Wall time: 2min 8s
```

[7]:
```
%%time

df_train = group_binning(df_train)
```

```
0.1
0.25
0.5
0.75
0.9
CPU times: user 3.61 s, sys: 3.32 s, total: 6.93 s
Wall time: 6.62 s
```

[8]:
```
df_train.head()
```

[8]:
```
                event_time event_type  product_id    brand   price    user_id  \
0  2019-12-01 07:51:27 UTC       cart     1004781   huawei  247.27  569317987
1  2019-12-01 07:51:34 UTC       cart     2401055    turbo   47.88  517451347
2  2019-12-01 07:51:36 UTC       cart     1004856  samsung  124.10  580108461
3  2019-12-01 07:51:36 UTC       cart     1004751  samsung  192.77  545521992
4  2019-12-01 07:51:37 UTC       cart     1801906      tcl  231.13  552287591

                           user_session  target         cat_0     cat_1  …  \
0  3c378a32-dd69-4e1b-8251-2cfa0f831cd6       0  construction     tools  …
1  d3b2e38b-5d13-4b60-857c-f79f5674686b       0    appliances   kitchen  …
2  f272b88b-0dcf-48b8-a466-7398dcda9d3b       0  construction     tools  …
3  686fc0f9-193e-4f81-95ec-02552cd596fe       0  construction     tools  …
4  681fbfd6-d352-4f3e-8ba6-5219bc0d3071       0    appliances  personal  …

  cat_3           timestamp ts_hour  ts_minute  ts_weekday  ts_day  ts_month  \
0  <NA> 2019-12-01 07:51:27       7         51           6       1        12
1  <NA> 2019-12-01 07:51:34       7         51           6       1        12
2  <NA> 2019-12-01 07:51:36       7         51           6       1        12
3  <NA> 2019-12-01 07:51:36       7         51           6       1        12
4  <NA> 2019-12-01 07:51:37       7         51           6       1        12
```

```
   ts_year                        cat_012 price_bin
0     2019      construction_tools_light         3
1     2019       appliances_kitchen_hood         2
2     2019      construction_tools_light         0
3     2019      construction_tools_light         2
4     2019  appliances_personal_massager         2

[5 rows x 21 columns]
```

In our experiments, we achieve a speed up of 28.2x.

We shutdown the kernel.

[9]:
```
app = IPython.Application.instance()
app.kernel.do_shutdown(False)
```

[9]:
```
{'status': 'ok', 'restart': False}
```