04_2_Normalization

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[ ]:
```
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```

1 Tutorial: Feature Engineering for Recommender Systems

2 4. Feature Engineering - Numerical

2.1 4.2. Normalization

[1]:
```
import IPython

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

```python
import matplotlib.pyplot as plt

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

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

df_train['cat_0'] = df_train['cat_0'].fillna('UNKNOWN')
df_valid['cat_0'] = df_valid['cat_0'].fillna('UNKNOWN')
df_test['cat_0'] = df_test['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_test['cat_1'] = df_test['cat_1'].fillna('UNKNOWN')

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

We generate some numerical features with the feature engineering from the previous notebooks.

[2]:
```python
def target_encode(train, valid, col, target, kfold=5, smooth=20, gpu=True):
    """
        train:  train dataset
        valid:  validation dataset
        col:    column which will be encoded (in the example RESOURCE)
        target: target column which will be used to calculate the statistic
    """

    # We assume that the train dataset is shuffled
    train['kfold'] = ((train.index) % kfold)
    # We keep the original order as cudf merge will not preserve the original␣
 ↪order
    if gpu:
        train['org_sorting'] = cupy.arange(len(train), dtype="int32")
    else:
        train['org_sorting'] = np.arange(len(train), dtype="int32")
    # We create the output column, we fill with 0
    col_name = '_'.join(col)
    train['TE_' + col_name] = 0.
    for i in range(kfold):
        ###################################
        # filter for out of fold
        # calculate the mean/counts per group category
```

```
        # calculate the global mean for the oof
        # calculate the smoothed TE
        # merge it to the original dataframe
        ###################################

        df_tmp = train[train['kfold']!=i]
        mn = df_tmp[target].mean()
        df_tmp = df_tmp[col + [target]].groupby(col).agg(['mean', 'count']).
↪reset_index()
        df_tmp.columns = col + ['mean', 'count']
        df_tmp['TE_tmp'] = ((df_tmp['mean']*df_tmp['count'])+(mn*smooth)) /␣
↪(df_tmp['count']+smooth)
        df_tmp_m = train[col + ['kfold', 'org_sorting', 'TE_' + col_name]].
↪merge(df_tmp, how='left', left_on=col, right_on=col).
↪sort_values('org_sorting')
        df_tmp_m.loc[df_tmp_m['kfold']==i, 'TE_' + col_name] = df_tmp_m.
↪loc[df_tmp_m['kfold']==i, 'TE_tmp']
        train['TE_' + col_name] = df_tmp_m['TE_' + col_name].fillna(mn).values


    ###################################
    # calculate the mean/counts per group for the full training dataset
    # calculate the global mean
    # calculate the smoothed TE
    # merge it to the original dataframe
    # drop all temp columns
    ###################################

    df_tmp = train[col + [target]].groupby(col).agg(['mean', 'count']).
↪reset_index()
    mn = train[target].mean()
    df_tmp.columns = col + ['mean', 'count']
    df_tmp['TE_tmp'] = ((df_tmp['mean']*df_tmp['count'])+(mn*smooth)) /␣
↪(df_tmp['count']+smooth)
    if gpu:
        valid['org_sorting'] = cupy.arange(len(valid), dtype="int32")
    else:
        valid['org_sorting'] = np.arange(len(valid), dtype="int32")
    df_tmp_m = valid[col + ['org_sorting']].merge(df_tmp, how='left',␣
↪left_on=col, right_on=col).sort_values('org_sorting')
    valid['TE_' + col_name] = df_tmp_m['TE_tmp'].fillna(mn).values

    valid = valid.drop('org_sorting', axis=1)
    train = train.drop('kfold', axis=1)
    train = train.drop('org_sorting', axis=1)
    return(train, valid)
```

[3]:
```
df_train.columns
```

[3]:
```
Index(['event_time', 'event_type', 'product_id', 'brand', 'price', 'user_id',
       'user_session', 'target', 'cat_0', 'cat_1', 'cat_2', 'cat_3',
       'timestamp', 'ts_hour', 'ts_minute', 'ts_weekday', 'ts_day', 'ts_month',
       'ts_year'],
      dtype='object')
```

[4]:
```
cats = [['cat_0'], ['cat_1'], ['cat_2'], ['cat_0', 'cat_1', 'cat_2'],␣
 ↪['ts_hour'], ['ts_weekday'], ['ts_weekday', 'ts_hour', 'cat_2', 'brand']]
```

[5]:
```
for cat in cats:
    df_train, df_valid = target_encode(df_train, df_valid, cat, 'target')
```

[6]:
```
cats = ['brand', 'user_id', 'product_id', 'cat_0', 'cat_1', 'cat_2']
```

[7]:
```
def count_encode(train, valid, col, gpu=True):
    """
        train:  train dataset
        valid:  validation dataset
        col:    column which will be count encoded (in the example RESOURCE)
    """
    # We keep the original order as cudf merge will not preserve the original␣
 ↪order
    if gpu:
        train['org_sorting'] = cupy.arange(len(train), dtype="int32")
    else:
        train['org_sorting'] = np.arange(len(train), dtype="int32")

    train_tmp = train[col].value_counts().reset_index()
    train_tmp.columns = [col,  'CE_' + col]
    df_tmp = train[[col, 'org_sorting']].merge(train_tmp, how='left',␣
 ↪left_on=col, right_on=col).sort_values('org_sorting')
    train['CE_' + col] = df_tmp['CE_' + col].fillna(0).values

    if gpu:
        valid['org_sorting'] = cupy.arange(len(valid), dtype="int32")
    else:
        valid['org_sorting'] = np.arange(len(valid), dtype="int32")
    df_tmp = valid[[col, 'org_sorting']].merge(train_tmp, how='left',␣
 ↪left_on=col, right_on=col).sort_values('org_sorting')
    valid['CE_' + col] = df_tmp['CE_' + col].fillna(0).values

    valid = valid.drop('org_sorting', axis=1)
    train = train.drop('org_sorting', axis=1)
    return(train, valid)
```

[8]:

```
%%time

for cat in cats:
    df_train, df_valid = count_encode(df_train, df_valid, cat, gpu=True)
```

```
CPU times: user 648 ms, sys: 1.26 s, total: 1.91 s
Wall time: 1.91 s
```

[9]:

```
df_train.head()
```

[9]:

```
                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

   … TE_cat_0_cat_1_cat_2  TE_ts_hour  TE_ts_weekday  \
0  …             0.280155    0.305423       0.410060
1  …             0.350069    0.305249       0.410061
2  …             0.351989    0.305235       0.410059
3  …             0.351410    0.305370       0.410061
4  …             0.460389    0.305449       0.410061

   TE_ts_weekday_ts_hour_cat_2_brand  CE_brand  CE_user_id  CE_product_id  \
0                           0.301241     10859           9            743
1                           0.333539     50273          56             12
2                           0.319065     50273          56             12
3                           0.333539     50273          56             12
4                           0.466269   2323417           9         317711

   CE_cat_0  CE_cat_1  CE_cat_2
0    372964     51652   5058060
1   1527338    287043    213674
2   1527338    287043    213674
3   1527338    287043    213674
4   3363367   3307872   3172781

[5 rows x 32 columns]
```

[10]:
```
df_train.columns
```

[10]:
```
Index(['event_time', 'event_type', 'product_id', 'brand', 'price', 'user_id',
       'user_session', 'target', 'cat_0', 'cat_1', 'cat_2', 'cat_3',
       'timestamp', 'ts_hour', 'ts_minute', 'ts_weekday', 'ts_day', 'ts_month',
       'ts_year', 'TE_cat_0', 'TE_cat_1', 'TE_cat_2', 'TE_cat_0_cat_1_cat_2',
       'TE_ts_hour', 'TE_ts_weekday', 'TE_ts_weekday_ts_hour_cat_2_brand',
       'CE_brand', 'CE_user_id', 'CE_product_id', 'CE_cat_0', 'CE_cat_1',
       'CE_cat_2'],
      dtype='object')
```

2.2 Theory

Normalization is required to enable neural networks to leverage numerical features. Tree-based models do not require normalization as they define the split independent of the scale of a feature. Without normalization, neural networks are difficult to train. The image visualizes the loss surface and the gradient updates for non-normalized input (left) and normalized input (right).

Source: https://www.jeremyjordan.me/batch-normalization/

The reason is that different numerical features have different scales. When we combine the features in a hidden layer, the different scales make it more difficult to extract patterns from it.

2.3 Normalization Techniques

After we outline the importance for normalizing the numerical input feature, we will discuss different strategy to achieve a normal distributed input feature: 1. Normalization with mean/std 2. Log-based normalization 3. Scale to 0-1 4. Gauss Rank (separate notebook) 5. Power transfomer

2.3.1 4.2.1 Normalization with mean/std

The most common approach is to normalize a numerical feature by substracting the mean and divide the feature by the standard derviation:

$$X_{norm} = \frac{X - mean_X}{\sigma_X} \sim \mathcal{N}(0, 1) \tag{1}$$

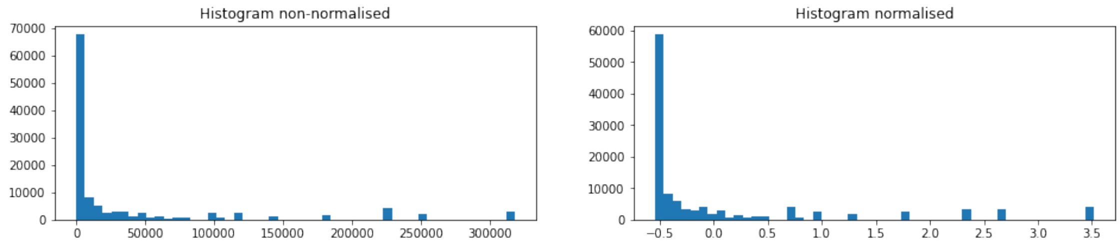
[11]:
```
X = df_train['CE_product_id']
```

[12]:
```
X_norm = (X-X.mean())/X.std()
```

Our features does not follow a normal distribution

[13]:
```
fig, axs = plt.subplots(1, 2, figsize=(16,3))
axs[0].hist(X.sample(frac=0.01).to_pandas(), bins=50)
axs[0].set_title('Histogram non-normalised')
axs[1].hist(X_norm.sample(frac=0.01).to_pandas(), bins=50)
axs[1].set_title('Histogram normalised')
```

[13]: Text(0.5, 1.0, 'Histogram normalised')



2.3.2 4.2.2 Log-based normalization

Some features are not normal distributed in the raw format. If they have a long-tail distribution, we can normalize them by applying the log function, first.

$$X_{log} = log(X+1) X_{log-norm} = \frac{X_{log} - mean_{X_{log}}}{\sigma_{X_{log}}} \sim \mathcal{N}(0, 1) \tag{2}$$

User behavior data have often a long-tail distribution, such as # of clicks or # of purchases.

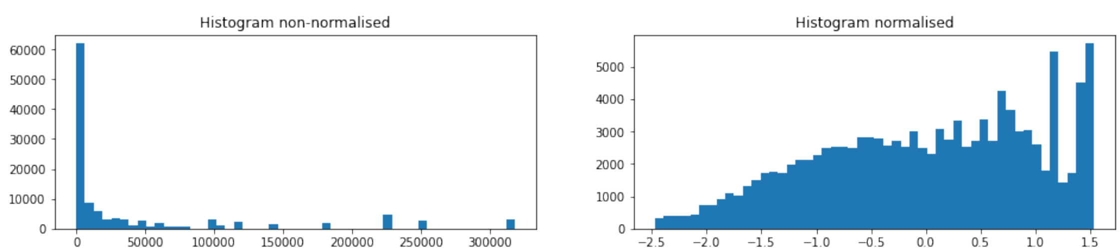
[14]:
```
X = df_train['CE_product_id'].to_pandas()
```

[15]:
```
X_log = np.log(X+1)
```

[16]:
```
X_norm = (X_log-X_log.mean())/X_log.std()
```

[17]:
```
fig, axs = plt.subplots(1, 2, figsize=(16,3))
axs[0].hist(X.sample(frac=0.01), bins=50)
axs[0].set_title('Histogram non-normalised')
axs[1].hist(X_norm.sample(frac=0.01), bins=50)
axs[1].set_title('Histogram normalised')
```

[17]: Text(0.5, 1.0, 'Histogram normalised')



2.3.3 4.2.3 Scale to 0-1

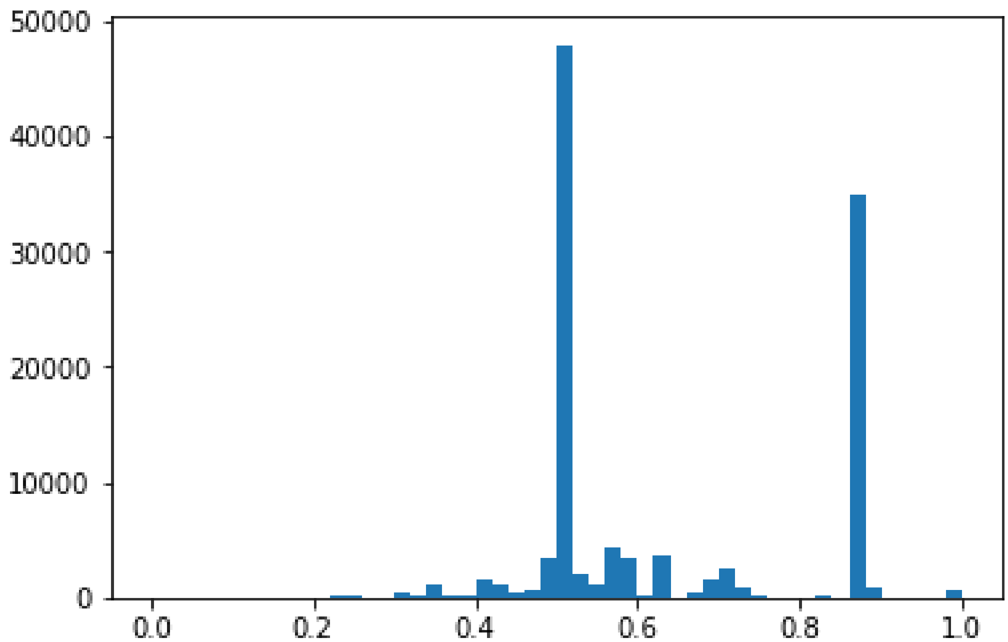
Another technique is to scale the numerical features between 0-1.

$$X_{norm} = \frac{X - min(X)}{max(X) - min(X)} \tag{3}$$

[18]:
```
X = df_train['TE_cat_2']
```

[19]:
```
plt.hist(((X-X.min())/(X.max()-X.min())).sample(frac=0.01).to_pandas(), bins=50)
```

[19]:
```
(array([8.0000e+00, 8.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00,
        0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 1.0000e+00,
        3.2000e+01, 9.2000e+01, 1.5600e+02, 1.4000e+01, 4.9000e+01,
        3.4800e+02, 9.1000e+01, 1.0510e+03, 1.1800e+02, 1.7700e+02,
        1.4710e+03, 1.1560e+03, 3.5200e+02, 7.2900e+02, 3.4340e+03,
        4.7980e+04, 1.9500e+03, 1.0770e+03, 4.4340e+03, 3.4220e+03,
        2.9400e+02, 3.6550e+03, 0.0000e+00, 3.5900e+02, 1.6090e+03,
        2.5380e+03, 9.9100e+02, 2.3800e+02, 0.0000e+00, 0.0000e+00,
        0.0000e+00, 2.7500e+02, 0.0000e+00, 3.4905e+04, 8.4600e+02,
        0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 7.5400e+02]),
 array([0.  , 0.02, 0.04, 0.06, 0.08, 0.1 , 0.12, 0.14, 0.16, 0.18, 0.2 ,
        0.22, 0.24, 0.26, 0.28, 0.3 , 0.32, 0.34, 0.36, 0.38, 0.4 , 0.42,
        0.44, 0.46, 0.48, 0.5 , 0.52, 0.54, 0.56, 0.58, 0.6 , 0.62, 0.64,
        0.66, 0.68, 0.7 , 0.72, 0.74, 0.76, 0.78, 0.8 , 0.82, 0.84, 0.86,
        0.88, 0.9 , 0.92, 0.94, 0.96, 0.98, 1.  ]),
 <BarContainer object of 50 artists>)
```



2.4 Practice

Now, it is your turn.

ToDo:

Normalize the features: price, TE_ts_weekday_ts_hour_cat_2_brand, CE_cat_2

Which normalization technique seems good?

[20]:
```
### ToDo
```

Optimisation is skipped

We shutdown the kernel.

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

[25]:
```
{'status': 'ok', 'restart': False}
```