04_3_GaussRank

January 28, 2021

[ ]:

1 Tutorial: Feature Engineering for Recommender Systems

2 4. Feature Engineering - Numerical

2.1 4.3. Gauss Rank

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

[4]:
```
for cat in cats:
    df_train, df_valid = target_encode(df_train, df_valid, cat, 'target')
```

[5]:
```
cats = ['brand', 'user_id', 'product_id', 'cat_0', 'cat_1', 'cat_2']
```

[6]:
```
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)
```

[7]:
```
%%time

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

```
CPU times: user 644 ms, sys: 1.27 s, total: 1.92 s
Wall time: 1.92 s
```

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

[8]:
```
                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]
```

2.2 Theory

In the previous notebook, we discussed how important *Normalization* is for neural networks. We learned some basic strategies for normalizing numerical features. In this notebook, we will provide another normalization technique, called *Gauss Rank*.

Gauss Rank transforms any arbitrary distribution to a Gaussian normal distribution by 1. Compute the rank (or sort the values ascending) 2. Scale the values linearly from -1 to +1 3. Apply the erfinv function

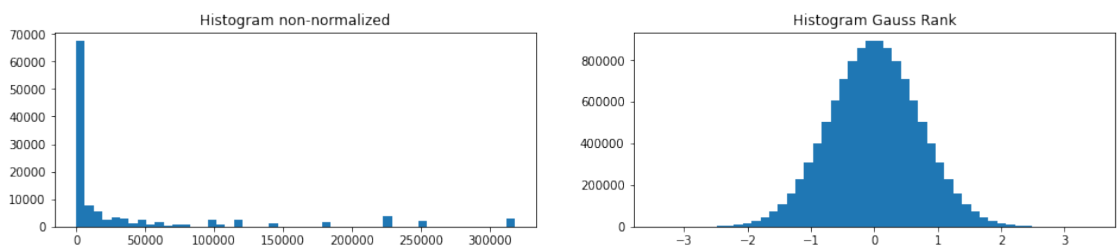
Source: https://medium.com/rapids-ai/gauss-rank-transformation-is-100x-faster-with-rapids-and-cupy-7c947e3397da

[9]:
```
import cupy as cp
from cupyx.scipy.special import erfinv
import cudf as gd

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy.special import erfinv as sp_erfinv
```

[10]:
```
def gaussrank_cpu(data, epsilon = 1e-6):
    r_cpu = data.argsort().argsort()
    r_cpu = (r_cpu/r_cpu.max()-0.5)*2 # scale to (-1,1)
    r_cpu = np.clip(r_cpu,-1+epsilon,1-epsilon)
    r_cpu = sp_erfinv(r_cpu)
    return(r_cpu)

def gaussrank_gpu(data, epsilon = 1e-6):
    r_gpu = data.argsort().argsort()
    r_gpu = (r_gpu/r_gpu.max()-0.5)*2 # scale to (-1,1)
    r_gpu = cp.clip(r_gpu,-1+epsilon,1-epsilon)
    r_gpu = erfinv(r_gpu)
    return(r_gpu)
```

[11]:
```
fig, axs = plt.subplots(1, 2, figsize=(16,3))
col = 'CE_product_id'
data_sample = df_train[col].sample(frac=0.01)
axs[0].hist(data_sample.to_pandas().values, bins=50)
axs[1].hist(cp.asnumpy(gaussrank_gpu(df_train[col].values)), bins=50)
axs[0].set_title('Histogram non-normalized')
axs[1].set_title('Histogram Gauss Rank')
```

[11]:
```
Text(0.5, 1.0, 'Histogram Gauss Rank')
```



2.3 Practice

Now, it is your turn.

ToDo:

Normalize the features price, TE_ts_weekday_ts_hour_cat_2_brand and CE_cat_2 with GaussRank

Plot the non-normalized and normalized values

2.4 Optimization

Let's compare a CPU with the GPU version.

[14]:
```
data_cpu = df_train['TE_ts_weekday_ts_hour_cat_2_brand'].to_pandas().values
data_gpu = df_train['TE_ts_weekday_ts_hour_cat_2_brand'].values
```

[15]:
```
%%time

gaussrank_cpu(data_cpu)
```

```
CPU times: user 3.76 s, sys: 176 ms, total: 3.94 s
Wall time: 3.93 s
```

[15]:
```
array([-0.49958087, -0.31557098, -0.39975219, …, -0.33439334,
        0.06216684, -0.5348664 ])
```

[16]:
```
%%time

gaussrank_gpu(data_gpu)
```

```
CPU times: user 36 ms, sys: 64 ms, total: 100 ms
Wall time: 100 ms
```

[16]:
```
array([-0.50025555, -0.31601779, -0.40005142, …, -0.3343783 ,
        0.06505958, -0.53484046])
```

In our experiments, we achieved a speedup of 80.3x.

We shutdown the kernel.

[17]:
```
app = IPython.Application.instance()
app.kernel.do_shutdown(False)
```

[17]:
```
{'status': 'ok', 'restart': False}
```