01_1_Exploring_DataSet

January 28, 2021

[1]:
```
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```

1 Tutorial: Feature Engineering for Recommender Systems

2 Infrastructure

In our tutorial, we are using RAPIDS.AI cudf, an GPU accelerated dataframe. The API is similar to pandas, but the calculations are executed on the GPU.

[1]:
```
import cudf
```

We are using a NVIDIA Tesla T4 GPU with 16 GB memory.

[2]:
```
!nvidia-smi
```

```
Mon Sep 21 13:27:24 2020
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 440.64.00    Driver Version: 440.64.00    CUDA Version: 10.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla T4            Off  | 00000000:00:1E.0 Off |                    0 |
| N/A   47C    P0    27W /  70W |     11MiB / 15109MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

3 1. Exploring Dataset

In our tutorial, we want to explain and show the value of preprocessing and feature engineering on a real-world dataset. Therefore, we use the eCommerce behavior data from multi category store from REES46 Marketing Platform as our dataset. In a few cases, we will use synthetic data to show the calculations in order to explain the theory.

eCommerce behavior data from multi category store is a dataset containing the user behavior (view/add to cart/ purchase) of an ecommerce shop over 7 months. * Events: View, AddToCart, Purchase * Timeframe: Oct-2019 - April 2020 As the dataset contains only interactions (positive samples), we need to define a goal / target to predict. There is a lot of literature about how to construct negative samples from the dataset in order to make the goal easier or harder to predict. For our tutorial, we decided that our goal is to predict if a user purchased an item:

Positive: User purchased an item

Negative: User added an item to the cart, but did not purchase it (in the same session)

We split the dataset in train, validation and testset by the timestamp:

Training: October 2019 - February 2020

Validation: March 2020

Test: April 2020

Let's have a short look on the dataset

[3]:
```python
import warnings
warnings.filterwarnings("ignore")
```

[4]:
```python
import IPython
```

```python
import cudf
import pandas as pd
import matplotlib.pyplot as plt
```

[5]:
```python
df_train = pd.read_parquet('./data/train.parquet')
df_valid = pd.read_parquet('./data/valid.parquet')
df_test = pd.read_parquet('./data/test.parquet')
```

[6]:
```python
df_train.shape, df_valid.shape, df_test.shape
```

[6]:
```
((11461357, 19), (2461719, 19), (2772486, 19))
```

[7]:
```python
df = pd.concat([df_train, df_valid, df_test],ignore_index=True)
```

[8]:
```python
df.shape
```

[8]:
```
(16695562, 19)
```

[9]:
```python
df['timestamp'] = pd.to_datetime(df['timestamp'])
```

[10]:
```python
df.head()
```

[10]:
```
                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    None  None 2019-12-01 00:00:28        0          0           6       1
1  vacuum  None 2019-12-01 00:00:39        0          0           6       1
2  vacuum  None 2019-12-01 00:00:40        0          0           6       1
3  vacuum  None 2019-12-01 00:00:41        0          0           6       1
4   light  None 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
```

We have the following features: * timestamp * user_id * user_session * product_id * brand * price * category level 0-4 * time features: hour, minute, weekday, day, month, year

[11]:
```
df.target.mean()
```

[11]:
```
0.37005540753884175
```

[12]:
```
df['event_type'].value_counts(normalize=True)
```

[12]:
```
cart        0.629945
purchase    0.370055
Name: event_type, dtype: float64
```

Around 37.0% of datapoints are purchases. Lets take a look on the sparsity of the data.

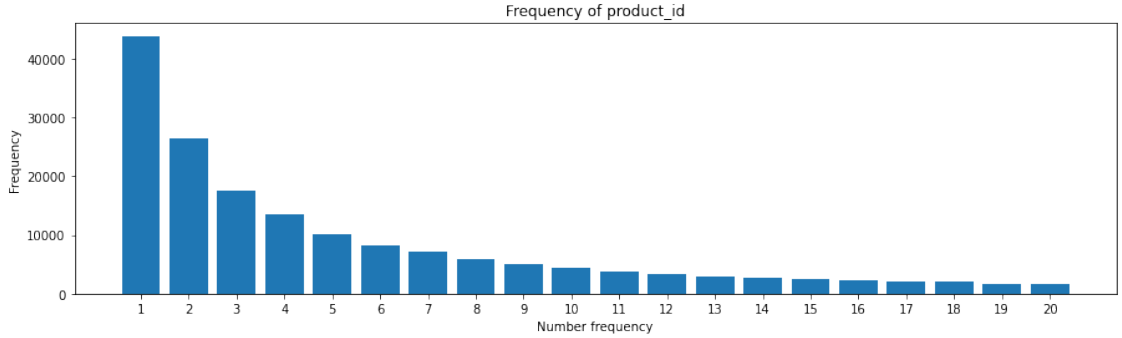
[13]:
```
print('# of datapoints:' + str(df.shape))
print('# of unique users:' + str(df['user_id'].drop_duplicates().shape))
print('# of unique products:' + str(df['product_id'].drop_duplicates().shape))
print('# of unique sessions:' + str(df['user_session'].drop_duplicates().shape))
```

```
# of datapoints:(16695562, 19)
# of unique users:(3584800,)
# of unique products:(214907,)
# of unique sessions:(10715053,)
```

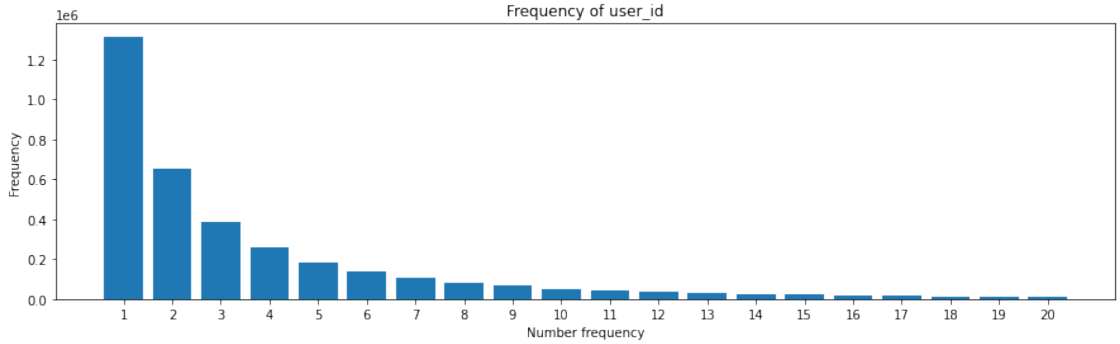
In the beginning, we should do some Exploratory Data Analysis (EDA) to get some understanding and feeling for the data.

[14]:
```
def plot_sparse(df, col):
    stats = df[[col, 'target']].groupby(col).agg(['count', 'mean', 'sum'])
    stats = stats.reset_index()
    stats.columns = [col, 'count', 'mean', 'sum']
    stats_sort = stats['count'].value_counts().reset_index()
    stats_sort = stats_sort.sort_values('index')
    plt.figure(figsize=(15,4))
    plt.bar(stats_sort['index'].astype(str).values[0:20], stats_sort['count'].
 ↪values[0:20])
    plt.title('Frequency of ' + str(col))
    plt.xlabel('Number frequency')
    plt.ylabel('Frequency')
```

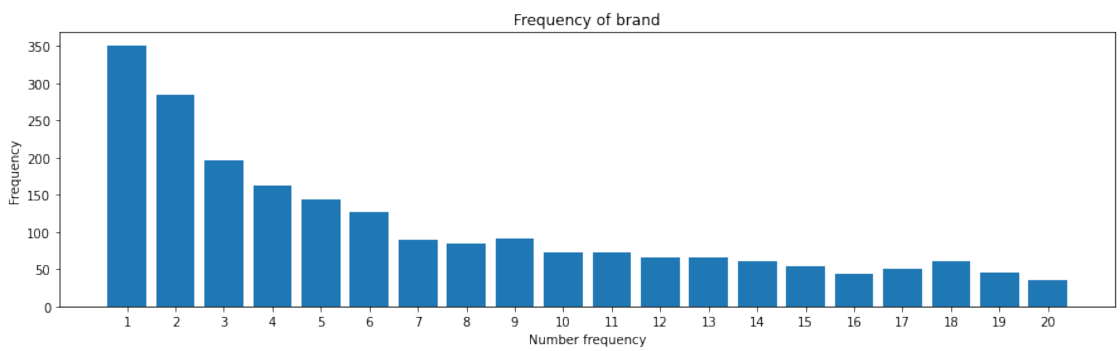
[15]:
```
plot_sparse(df, 'product_id')
```



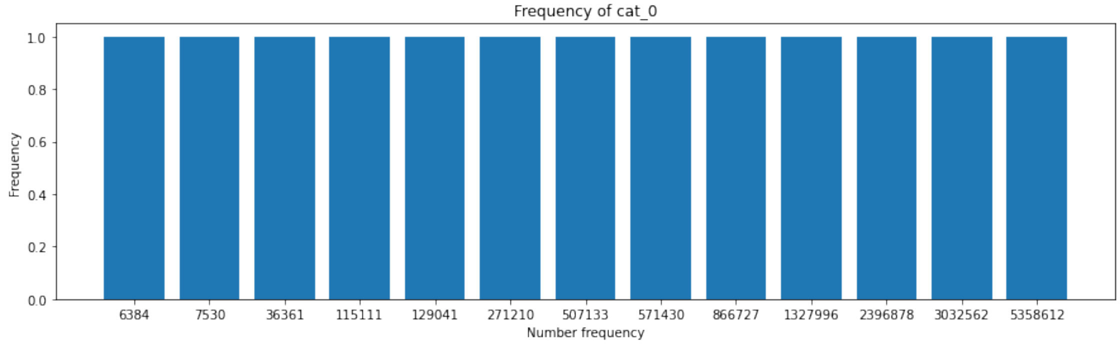

```
[16]: plot_sparse(df, 'user_id')
```



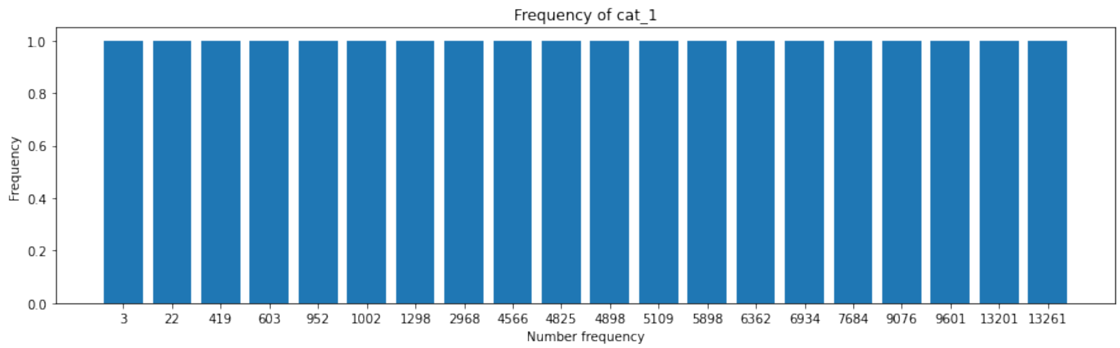

```
[17]: plot_sparse(df, 'brand')
```



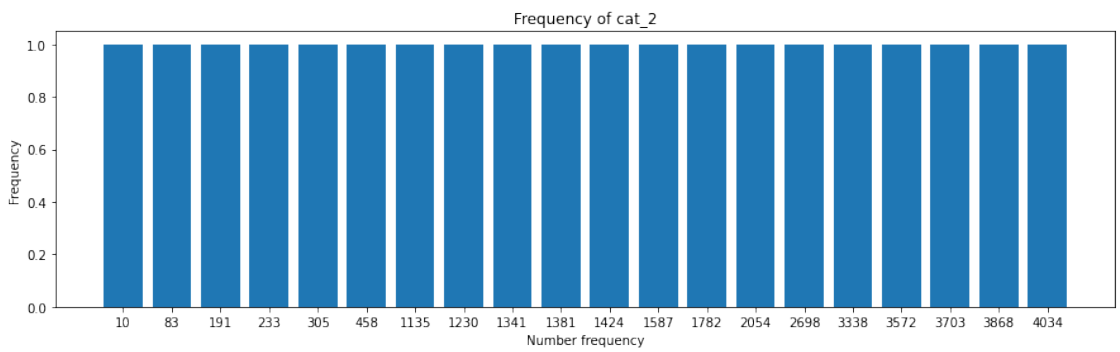

```
[18]: plot_sparse(df, 'cat_0')
```




```
[19]: plot_sparse(df, 'cat_1')
```




```
[20]: plot_sparse(df, 'cat_2')
```



We can observe following pattern:

There are ~45000 products which appear only once in the dataset

There are 1200000 users which appear only once in the dataset

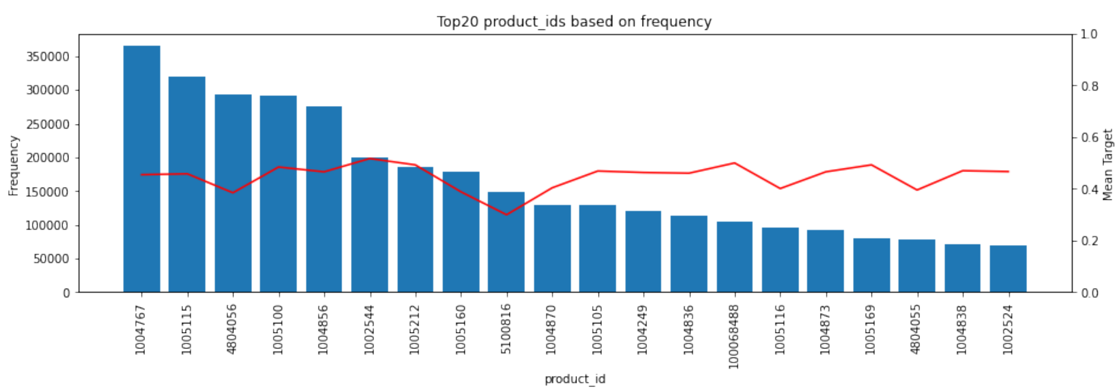
There are 350 brands which appears only once in the dataset

There are 0 cat0, 0 cat1 and 0 cat2 which appear only once in the dataset

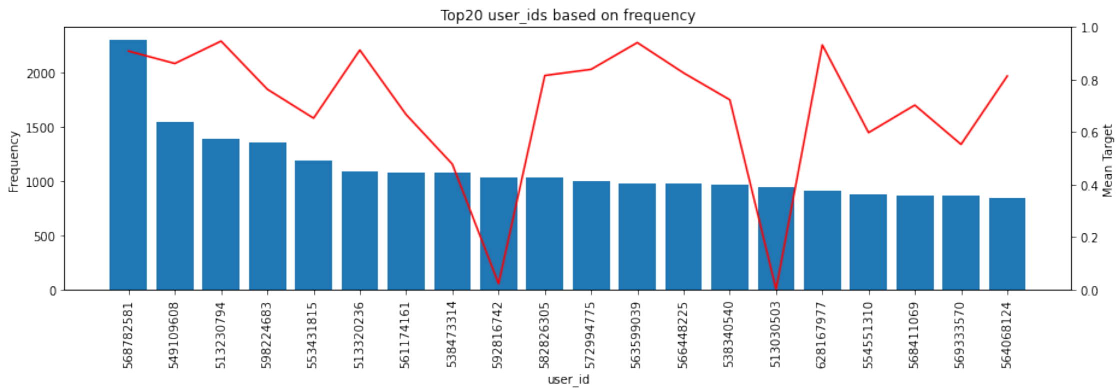
The sparsity is important for understanding which features can be better used in a model. Product_id and User_id have many values which appear only once and the model is less able to learn a good patterns from them. On the other hand, brands, cat1, cat2 and cat3 have many observations and can be leveraged for prediction.

[21]:
```
def plot_top20(df, col):
    stats = df[[col, 'target']].groupby(col).agg(['count', 'mean', 'sum'])
    stats = stats.reset_index()
    stats.columns = [col, 'count', 'mean', 'sum']
    stats = stats.sort_values('count', ascending=False)
    fig, ax1 = plt.subplots(figsize=(15,4))
    ax2 = ax1.twinx()
    ax1.bar(stats[col].astype(str).values[0:20], stats['count'].values[0:20])
    ax1.set_xticklabels(stats[col].astype(str).values[0:20],␣
 ↪rotation='vertical')
    ax2.plot(stats['mean'].values[0:20], color='red')
    ax2.set_ylim(0,1)
    ax2.set_ylabel('Mean Target')
    ax1.set_ylabel('Frequency')
    ax1.set_xlabel(col)
    ax1.set_title('Top20 ' + col + 's based on frequency')
```

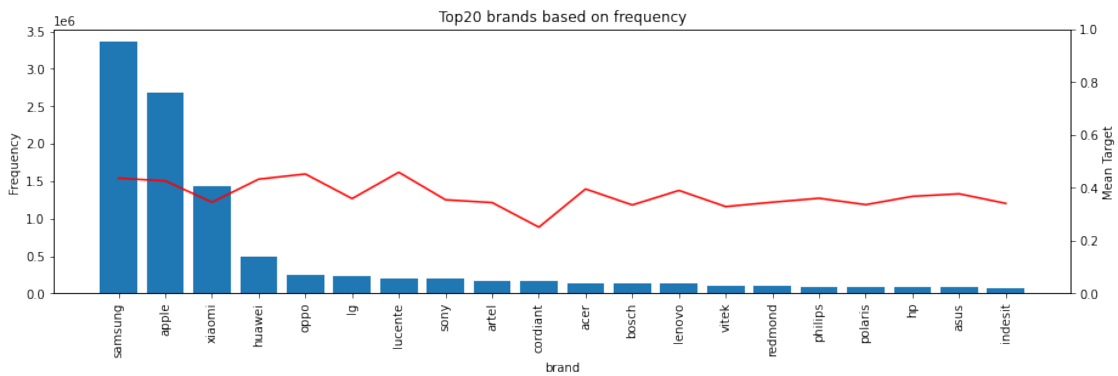
[22]:
```
plot_top20(df, 'product_id')
```



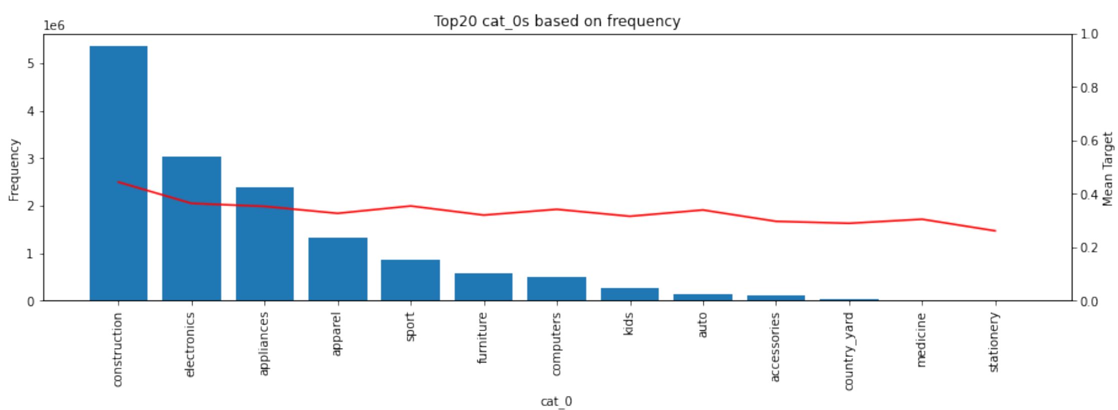
[23]:
```
plot_top20(df, 'user_id')
```



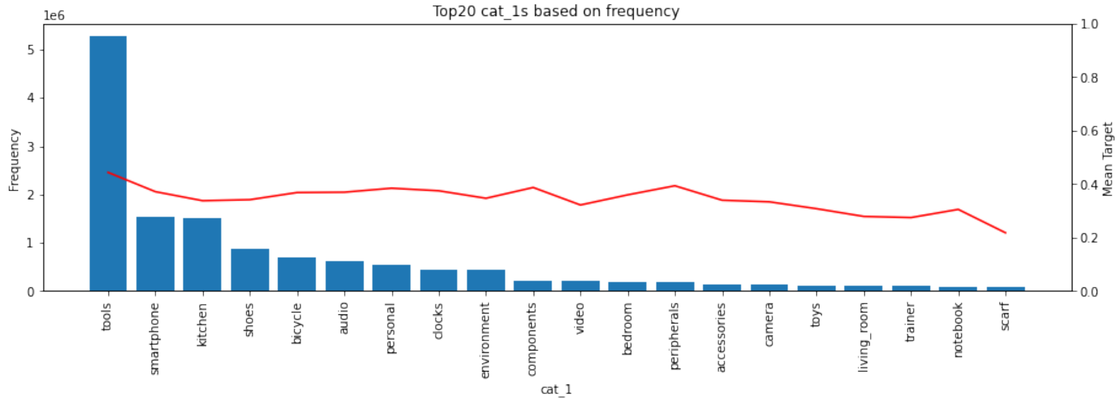

```
[24]: plot_top20(df, 'brand')
```



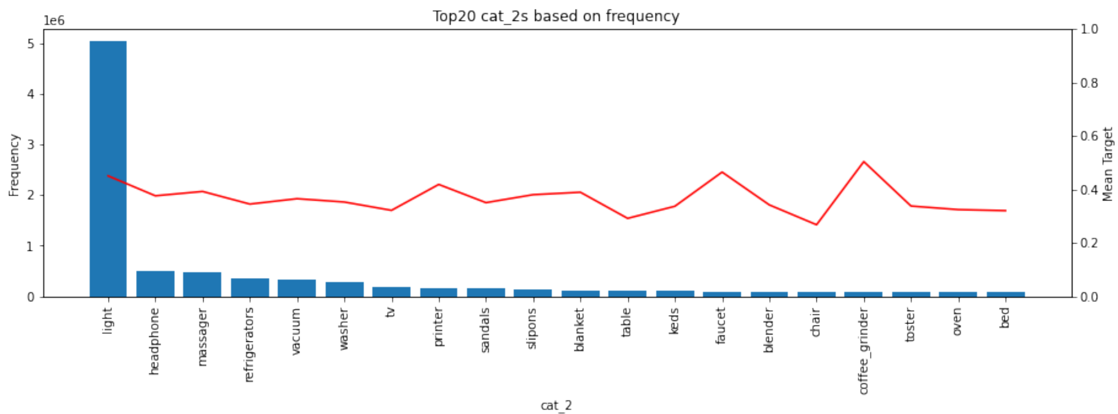

```
[25]: plot_top20(df, 'cat_0')
```




```
[26]: plot_top20(df, 'cat_1')
```



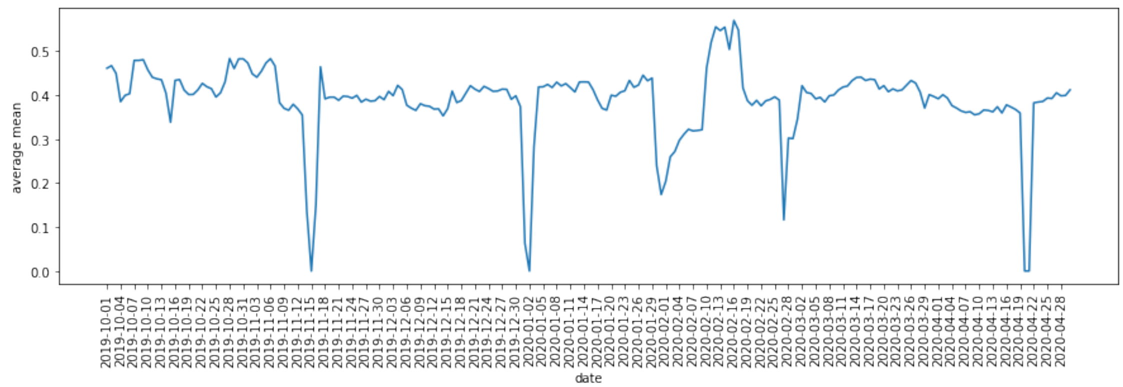
[27]:
```
plot_top20(df, 'cat_2')
```



We can see for the different categorical features, that the top values have many observations and some variance in the target. That is good to train models on top of these features. Finally, we can take a look on the target over time.

[28]:
```
df['date'] = pd.to_datetime(df['timestamp']).dt.date
```

[29]:
```
plt.figure(figsize=(15,4))
plt.plot(df[['date', 'target']].groupby('date').target.mean())
plt.ylabel('average mean')
plt.xlabel('date')
plt.xticks(df[['date', 'target']].groupby('date').target.mean().index[::3],␣
 ↪rotation='vertical')
print('')
```



[30]:
```
df[['date', 'target']].groupby('date').target.mean().sort_values().head(20)
```

[30]:
```
date
2020-01-02    0.000000
2019-11-15    0.000000
2020-04-20    0.000105
2020-04-21    0.000155
2020-01-01    0.063080
2020-02-27    0.116180
2019-11-14    0.136121
2019-11-16    0.150579
2020-01-31    0.173862
2020-02-01    0.203927
2020-01-30    0.239515
2020-02-02    0.259636
2020-02-03    0.271740
2020-01-03    0.283342
2020-02-04    0.297116
2020-02-29    0.300999
2020-02-28    0.302230
2020-02-05    0.310806
2020-02-07    0.318525
2020-02-08    0.319560
Name: target, dtype: float64
```

3.1 Summary:

We explored the data and saw the different raw features available in the dataset.

We analzyed basic statistics of the raw features and saw long-tail distribution for categorical features (user, item, brand)

Some categorical features (categories) have high occurances

In general, we see that categorical features have variance in the target, which we can leverage to engineer more powerful features

We shutdown the kernel.

[31]:
```python
app = IPython.Application.instance()
app.kernel.do_shutdown(False)
```

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