Slovak University of Technology in Bratislava
Faculty of Informatics and Information Technologies

Bc. Ľudovít Popelka

RECOMMENDER SYSTEM

Project 2

Field of study: Intelligent software systems
Year: 1st
Course: Information retrieval
Class: Thursday 11:00
Lab lecturer: Ing. Peter Gašpar
Acad. year: 2018/2019

ASSIGNMMENT BRIEFLY

Code recommender system for customers of unknown e-shop. Utilize provided dataset to recommend top K products and calculate standard evaluation metrics. Use of recommender frameworks is not allowed. Optionally participate in Kaggle challenge.

TOOLS

Used standard python data science toolkit (**pandas, matplotlib**, …). Here only conceptual decision process is discussed. For implementation details, see Appendix A with a single jupyter notebook. Contains also setup for running code at Google Colaboratory.

Additional tools (python libs):

- **dpath**: category tree construction
- **BeautifulSoap**: HTML parsing
- **elasticsearch** & **elasticsearch_**dsl: python ElasticSearch client & query language

DATA

2 dataset files from clothing vendor:

PRODUCT CATALOG

product ID, category ID and path, brand, gender, description (HTML), price

EVENTS LOG

customer ID, product ID, type (view, cart, purchase), timestamp

PRE-PROCESSING

Exploration is markdown commented within Appendix A.

Summary:

- Descriptive statistics

Both global for each dataset, and on per attribute basis.

- Visualization

bar charts – discrete attribute value counts, missing values

continuous attributes - histogram, scatter plot, QQplot, violin plot

- Category tree

Reverse construction of full eshop category tree. For this dpath library was used. Saved in *categories.npy* file.

- Missing attributes

Not identified to be problem considering key attributes (for example, no missing product and customer IDs).

- Attribute extraction

New attributes were discovered and extracted. Namely:

  - name: h2 tag or first strong tag
  - strong: strong tags – not used later due to rare occurrence
  - features: bullet points
  - desc: polished description
  - product code –used to detect duplicates

All identified within description. However, not contained within all products. For this BeautifulSoup was used.

- Duplicate products removal

Discovered by same product code value. Confirmed by all same: brand, gender, description, price. Thus, we deal with same products within more categories.

- Reflect duplicates to events

Events log product IDs were unified for each duplicate. In this way we increased customer+product unit size in events log (= information of previous activity per customer).

Key output: **duplicates removal reduced catalog** from 28 368 to 17 423 products **(by 38.58%)**.

IMPLEMENTATION IDEA

Dump ElasticSearch (later “elastic”) with reduced product catalog and try to recommend based on similarity score for different attribute combinations. Values passed to search for each attribute are suggested from customer’s previous activity, per test customer.

The point is to measure how much elastic can improve a base recommender. Base recommender here will be recommending products solely by previous activity of customer.

To get to objective implications, elastic will be compared to trivial approach. The most trivial would be random recommender. We use here not random but best sellers for this purpose (global statistics), since overcoming random does not say anything about recommender quality – random is not realistic to be deployed (fully random, not few random recommendations of all).

RECOMMENDER FUNCIONALITY

Selected recommender options:

- K-most-viewed

For each recommended K, we can choose how big max. portion (another K-most-viewed <= K) will be selected from customers' previous activity. Here **view means all 3 event types** contained within train set, not only view product event.

- best sellers

Global best sellers.

- best sellers by gender/price

Global best sellers from filtered catalog. Gender/brand value is determined as the most frequent value in the past customer activity.

- elastic

Query elastic for selected attributes. Attribute values are determined by

  - most viewed: a product that has been the most common in customer's previous activity.
  - ideal product: combination of previously seen products (max on keywords, join on lists etc., see Appendix A)

Sort by options:

  - _score
  - purchases: purchase count

Supported fields: **brand, gender, name, features, desc** (see elastic index for types, Appendix A for queries). The later three utilize more_like_this query. Work with elastic powered by curl and python elastic client/DSL.

TESTING

Events log dataset train-test split is different for each K, where K is the number of recommended products. For each K, test set is the last K purchases (by timestamp) per customer (for customers having at least K purchases). Train set is then all activity that occurred at least 12 hours before the first test set purchase, per customer.

Estimation-validation split was skipped because:

- Number of customers with at least 10 purchases is only 100+.
- Test set here is quasi the first validation only. The second is public part of Kaggle challenge. Real, final testing of solution will be private+public part of Kaggle challenge.

EXPERIMETS & THOUGHTS

All runs filled up to K (for example if strategy provides 8 of 10 only, other 2 are considered to be wrong). This was necessary to compare consistently among different approaches.

1st series of runs (exploration, Tab. 1):

- global best sellers
- global best sellers by customer's most viewed gender
- global best sellers by customer's most viewed brand
- most viewed by customer
- most viewed by customer + global best sellers
- most viewed by customer + global best sellers by customer's most viewed gender
- most viewed by customer + global best sellers by customer's most viewed brand
- elastic match attribute of most viewed, sort by _score
- elastic match attribute of most viewed, sort by purchases match
- elastic match 2 attributes of most viewed, sort by _score
- elastic match 2 attributes of most viewed, sort by purchases
- elastic match 3 attributes of most viewed, sort by _score
- elastic match 3 attributes of most viewed, sort by purchases
- …
- elastic match all attributes of most viewed, sort by _score
- elastic match all attributes of most viewed, sort by purchases
- elastic match attribute of ideal product, sort by _score
- elastic match attribute of ideal product, sort by purchases match
- elastic match 2 attributes of ideal product, sort by _score
- elastic match 2 attributes of ideal product, sort by purchases
- elastic match 3 attributes of ideal product, sort by _score
- elastic match 3 attributes of ideal product, sort by purchases

- …
- elastic match all attributes of ideal product, sort by _score
- elastic match all attributes of ideal product, sort by purchases

Implications from the 1st series of runs:

- We choose best sellers to be elastic's rival for further comparison.
- Best sellers by gender or brand are not effective.
- Brand and gender are poor indicators alone (logical).
- desc is the best indicator alone.
- Attribute combinations increase precision in general compared to attributes alone.
- Sort by purchases decreases precision for low K but increases for high K compared to sort by _score. An interpretation can be that a more specialized query (_score) hits, but customer, understandably, does not buy more of too similar products. Next, we focus on sort by _score.
- Not all attributes are necessary to be matched separately, a best-chosen combination should be enough.
- Search by attributes combined from more products (ideal product) fails compared to search by single most viewed product. With features (list-like attribute) we observe improvement which, however, vanish when we combine with another attribute.

2nd series of runs (optimization, Tab. 2):

- selected cross field runs

Based on results from the 1st run, we decided to search cross fields. Meaning not only search 1 attribute in 1 another, but also 1:N, N:1 and N:M. Recommender was designed to support such combined queries.

- selected cross field combined with selected match runs

The combination of both query approaches, even sometimes with the same attribute in both.

Implications from the 2nd series of runs:

Now we optimized elastic recommender to approximately highest % but we still need to evaluate how well it recommends not previously seen products. The reason is that the optimized algorithm can with increasing percentage just converge to recommending previously seen products.

3rd series of runs (comparison, Tab. 3):

For each k we recommended maximum 1-k most viewed products. First without any secondary strategy – we call this a base recommender. Then we tried to improve the base recommender by different secondary strategies.

Implications from the 3rd series of runs:

Check colours at Tab. 3 before reading further. We see that the very most from recommender success was created by previously seen products. The actual recommendation value of the proposed elastic recommender is ~0.2%, which not bad considering relations exclusively among products, no previous activity. Random product selection from the catalog is ~0,00588% (1:~17000). Our approach might be an option when we strictly want to recommend based to product similarity. On the other hand, if the vendor wants just to boost volume of products sold, no matter what, a trivial approach (such as the best sellers used here) overcomes elastic significantly.

RESULTS

Not all runs are documented here, only meaningful ones. For all full outputs including total number of hits see Appendix A.

Precision tables follow:

default sort by _score

default search by most viewed

Legend:

ES = elastic

B = brand

G = gender

N = name

F = features

D = desc

MV = most viewed

BS = best sellers

k	**1**	**3**	**5**	**10**
BS	2.705%	10.784%	14.092%	17.630%
BS by G	0.986%	2.609%	3.467%	5.111%
BS by B	2.319%	2.891%	3.245%	4.074%
ES match N	3.478%	3.755%	3.218%	3.852%
ES match F	3.440%	3.057%	2.275%	2.148%
ES match D	6.493%	5.999%	5.049%	5.407%
ES match B, G	0.271%	0.681%	0.472%	1.481%
ES match B, D	6.841%	6.314%	5.326%	5.630%
ES match G, D	7.014%	5.683%	4.743%	5.259%
ES match N, D	6.493%	5.999%	5.076%	4.963%
ES match F, D	6.512%	5.982%	5.076%	5.037%
ES match B, G, sort by purchases	4.116%	5.533%	5.548%	7.926%
ES match B, D, sort by purchases	4.213%	5.550%	5.770%	6.667%
ES match G, D, sort by purchases	2.261%	4.088%	4.688%	6.444%
ES match N, D, sort by purchases	1.913%	4.104%	5.243%	5.852%
ES match F, D, sort by purchases	1.778%	3.971%	5.437%	6.444%
ES match B, F, D	6.860%	6.314%	5.381%	5.185%
ES match G, F, D	7.092%	5.666%	4.660%	4.815%
ES match B, G, D	7.382%	6.015%	4.993%	5.407%
ES match B, G, D, sort by purch.	4.947%	5.733%	5.298%	7.259%
ES match all except G	6.841%	6.331%	5.381%	5.259%
ES match all except N	7.459%	6.015%	4.910%	4.963%
ES match all except F	7.324%	5.999%	4.910%	5.481%
ES match all except F, sort by purch.	5.063%	5.749%	5.270%	7.259%
ES match all	7.440%	6.015%	4.910%	5.037%
ES match all, sort by purch.	5.159%	5.749%	5.409%	6.889%
ES match F, search by ideal product	3.246%	4.271%	4.133%	3.037%
ES match F, D, search by ideal prod.	5.121%	5.351%	4.383%	3.778%

Tab. 1: 1st series of runs

k	**1**	**3**	**5**	**10**
ES F in F	3.440%	3.057%	2.275%	2.148%
ES F in N	0.329%	0.648%	0.527%	0.296%
ES F in D	3.150%	2.941%	2.441%	2.593%
ES N in D	2.783%	3.473%	3.107%	4.074%
ES G in G, D, match D	7.014%	5.683%	4.743%	5.259%
ES G, B in G, B, D, match D	7.227%	6.281%	5.354%	7.285%
ES G, B in G, B, D, match F, D	7.285%	6.298	5.381%	5.185%
ES G, B, F in G, B, D, match D	7.227%	6.281%	5.354%	5.630%

Tab. 2: 2nd series of runs

k	1	3	5	10
max. 1 MV, worst scenario	8.986%	5.849%	4.660%	4.815%
max. 3 MV, worst scenario	-	10.917%	9.570%	7.778%
max. 5 MV, worst scenario	-	-	11.789%	11.407%
max. 10 MV, worst scenario	-	-	-	14.074%
max. 1 MV, rest BS	10.647%	14.789%	16.865%	19.926%
max. 3 MV, rest BS	-	17.930%	19.723%	22.000%
max. 5 MV, rest BS	-	-	21.110%	24.519%
max. 10 MV, rest BS	-	-	-	25.852%
max. 1 MV, rest BS by G	8.986%	7.328%	7.074%	8.593%
max. 3 MV, rest BS by G	-	11.283%	10.846%	11.481%
max. 5 MV, rest BS by G	-	-	12.594%	14.741%
max. 10 MV, rest BS by G	-	-	-	14.741%
max. 1 MV, rest BS by B	8.986%	7.262%	6.574%	7.037%
max. 3 MV, rest BS by B	-	11.333%	10.541%	9.852%
max. 5 MV, rest BS by B	-	-	12.261%	13.037%
max. 10 MV, rest BS by B	-	-	-	14.963%
max. 1 MV, rest ES match D	8.986%	6.530%	5.326%	5.630%
max. 3 MV, rest ES match D	-	11.050%	9.931%	8.593%
max. 5 MV, rest ES match D	-	-	11.928%	11.778%
max. 10 MV, rest ES match D	-	-	-	14.074%
max. 1 MV, rest ES match B, G, D	8.986%	6.198%	4.993%	5.481%
max. 3 MV, rest ES match B, G, D	-	10.950%	9.736%	8.444%
max. 5 MV, rest ES match B, G, D	-	-	11.845%	11.630%
max. 10 MV, rest ES match B, G, D	-	-	-	14.074%
max. 1 MV, rest ES G, B in G, B, D, match D	8.986%	6.481%	5.354%	5.704%
max. 3 MV, rest ES G, B in G, B, D, match D	-	11.034%	9.931%	8.593%
max. 5 MV, rest ES G, B in G, B, D, match D	-	-	11.928%	11.778%
max. 10 MV, rest ES G, B in G, B, D, match D	-	-	-	14.074%

Tab. 3: 3rd series of runs (green is improvement from red)

nDCG

The recommender supports also normalized discounted cumulative gain calculation. Implemented based on Fig. 1.

Discounted Cumulative Gain

- *DCG* is the total gain accumulated at a particular rank *p*:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}$$

- Alternative formulation:

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log(1+i)}$$

Fig. 1: DCG formula (source: Stanford Intro to IR course)

We calculated nDCG just on some best elastic configurations (Tab. 4) and did not go to deeper exploration.

Customers do not rank products, so we come up with a following ranking function.

2 for the first product (the earliest timestamp) from the test set that customer really bought

1 for the last product (the latest timestamp) from the test set that customer really bought

1-2 for the rest of products from the test set that customer really bought (proportionally in time)

0 for recommended but not actually bought product

k=10	**precision**	**nDCG**
ES match D	5.407%	3.512%
max. 5 MV, rest ES match D	11.778%	7.094%
ES G, B in G, B, D, match D	5.630%	3.812%

Tab. 4: nDCG of selected runs

RECOMMENDER CATEGORIZATION

elastic similarity is purely content-based approach. So is analysing previous product activity per customer. However, we also rely on best sellers which is global statistics. That is why the proposed recommender is hybrid.

CONCLUSION

ElasticSearch is a great tool providing fast search but not universal similarity score for all kinds of our problems. The effective product-based recommender system should be based on in-depth, data driven, statistically supported decisions. In this manner, ElasticSearch can provide us with an additional help, however, cannot to serve as core of recommendations.

Surprisingly and ultimately, a basic more_like_this query on product description, cleaned from HTML elements, achieved the highest recommendation power, leaving super-complicated cross-field plus extracted attribute combinations behind.

KAGGLE CHALLENGE

We submitted several configurations from above. The generating scripts are archived in Appendix A.

Observed an inconsistent behaviour. Consider following example (2 recommended, ordered lists):

1. red socks, 2. blue shirt, 3. yellow T-shirt
2. red socks, 2. red socks, 3. blue shirt

The former should score higher even if red socks are preferred by customer. After submission, the latter (of course a bigger volume) scores more than double. Thus, we believe proposed Kaggle tester does not pay attention to duplicates.

Finally, we do not understand the necessity to achieve highest score in the challenge, since both collaborative and content-based recommenders have different, own qualities. Moreover, the challenge evaluation probably does not recognize duplicates.

BIBLIOGRAPHY

elastic.co. Elasticsearch Reference [online]. Available from: https://www.elastic.co/guide/en/elasticsearch/reference/current/index.html

Maher Malaeb. Recall and Precision at k for Recommender Systems. In Medium [online]. 2017. Available from: https://medium.com/@m_n_malaeb/recall-and-precision-at-k-for-recommender-systems-618483226c54

elasticsearch-py.readthedocs.io. Python Elasticsearch Client [online]. Available from: https://elasticsearch-py.readthedocs.io/en/master/

elasticsearch-dsl.readthedocs.io. Elasticsearch DSL [online]. Available from: https://elasticsearch-dsl.readthedocs.io/en/latest/

kaggle. VI Challenge [online]. Available from: https://www.kaggle.com/c/vi-challenge-2018

PyPI. dpath [online]. Available from: https://pypi.org/project/dpath/

Leonard Richardson. Beautiful Soup Documentation. In crummy.com [online]. Available from: https://www.crummy.com/software/BeautifulSoup/bs4/doc/

Google Research. Google Colaboratory [online]. Available from: https://colab.research.google.com

Stanford. Evaluation [online] In: Introduction to Information Retrieval. Available from: https://web.stanford.edu/class/cs276/handouts/EvaluationNew-handout-6-per.pdf

APPENDIX

A. jupyter notebook

Setup env

For Google Colaboratory only

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')
```

In [2]:

```
import os
os.chdir('/content/drive/My Drive/Colab Notebooks/vi2')
```

In [3]:

```
!pip install dpath
!pip install beautifulsoup4
!pip install elasticsearch
!pip install elasticsearch-dsl
#!pip install dill
!pip install pypandoc
```

```
Requirement already satisfied: dpath in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (1.4.2)
```

```
You are using pip version 10.0.1, however version 18.1 is available.
You should consider upgrading via the 'python -m pip install --upgrade pip' command.
```

```
Requirement already satisfied: beautifulsoup4 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (4.6.3)
```

```
You are using pip version 10.0.1, however version 18.1 is available.
You should consider upgrading via the 'python -m pip install --upgrade pip' command.
```

```
Requirement already satisfied: elasticsearch in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (6.3.1)
Requirement already satisfied: urllib3>=1.21.1 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from elasticsearch) (1.21.1)
```

```
You are using pip version 10.0.1, however version 18.1 is available.
You should consider upgrading via the 'python -m pip install --upgrade pip' command.
```

```
Requirement already satisfied: elasticsearch-dsl in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (6.3.0)
Requirement already satisfied: python-dateutil in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from elasticsearch-dsl)
(2.7.3)
Requirement already satisfied: elasticsearch<7.0.0,>=6.0.0 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from elasticsearch-dsl)
(6.3.1)
Requirement already satisfied: six in c:\users\pc\appdata\local\programs\python\python36\lib\site-
packages (from elasticsearch-dsl) (1.11.0)
Requirement already satisfied: urllib3>=1.21.1 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from
elasticsearch<7.0.0,>=6.0.0->elasticsearch-dsl) (1.21.1)
```

```
You are using pip version 10.0.1, however version 18.1 is available.
You should consider upgrading via the 'python -m pip install --upgrade pip' command.
```

```
Requirement already satisfied: pypandoc in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (1.4)
Requirement already satisfied: setuptools in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from pypandoc) (39.0.1)
```

```
Requirement already satisfied: pip>=8.1.0 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from pypandoc) (10.0.1)
Requirement already satisfied: wheel>=0.25.0 in
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages (from pypandoc) (0.32.3)
```

```
You are using pip version 10.0.1, however version 18.1 is available.
You should consider upgrading via the 'python -m pip install --upgrade pip' command.
```

Preprocess

Import

In [4]:

```
import itertools
import json
import pprint
from xml.sax import saxutils

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns

from IPython.display import display, IFrame, HTML

import dpath.util
from bs4 import BeautifulSoup
from elasticsearch import Elasticsearch
from elasticsearch_dsl import Search, MultiSearch, Q
from elasticsearch_dsl.query import Match, MoreLikeThis
```

In [5]:

```
# display HTML within notebook
def phtml(s):
  display(HTML(s))

# pretty print dictionary as JSON
#
# None key changes to "null"
# does not handle python sets!!
def pdict(d):
  print(json.dumps(d, indent=4))
```

In [6]:

```
def bs(s):
  return BeautifulSoup(s, 'html.parser')

pretty_printer = pprint.PrettyPrinter(indent=4)
def pp(o):
  pretty_printer.pprint(o)
```

In [7]:

```
ELASTIC_INDEX = 'rec'
ELASTIC_HOST = 'localhost:9200'
es = Elasticsearch(ELASTIC_HOST)
```

Plotting toolbox

In [8]:

```
# histogram
def hist(series, title=None, bins=20):
    plt.figure()
    series.plot(kind='hist', bins=bins, title=title)
    plt.show()
    plt.close()

# box plot
def box(series, title=None):
    plt.figure()
    sns.boxplot(series).set_title(title)
    plt.show()
    plt.close()

# violin plot
def violin(series):
    plt.figure()
    sns.violinplot(series)
    plt.show()
    plt.close()

# q-q plot
def qqplot(series, title=None):
    plt.figure(figsize=[5,5])
    stats.probplot(series, plot=plt); # default is normal distribution
    plt.title(title)
    plt.show()
    plt.close()

# series of plots for continuous variables
def contplot(series, bins=20):
    hist(series, title=series.name, bins=bins)
    box(series)
    violin(series)
    qqplot(series)

# bar chart
def bar(series, title=None, orientation='vertical'):
    plt.figure()
    kind = 'barh' if orientation is 'horizontal' else 'bar'
    ax = series.value_counts().plot(kind=kind, title=title)
    # Annotate each bar with value count
    # https://stackoverflow.com/questions/25447700/annotate-bars-with-values-on-pandas-bar-plots
    for p in ax.patches:
        ax.annotate(str(p.get_height()), (p.get_x() * 1.005, p.get_height() * 1.005))
    plt.tight_layout()
    plt.show()
    plt.close()

# scatter plot
def scatter(series_x, series_y, color_series=None):
    plt.figure(figsize=[8,8])
    plt.scatter(series_x, series_y, s=7, alpha=.5, label=None, c=color_series)
    plt.xlabel(series_x.name)
    plt.ylabel(series_y.name)
    plt.show()
    plt.close()
```

Dataset

In [9]:

```
df_events = pd.read_csv('data/vi_dataset_events.csv')
df_catalog = pd.read_csv('data/vi_dataset_catalog.csv')
for dframe in [df_events, df_catalog]:
  display(dframe.head())
  dframe.info()
  print(dframe.describe(include='all'))
```

	customer_id	product_id	type	timestamp
0	1	19685	view_product	1527812004
1	1	19685	view_product	1527812041

	customer_id	product_id	type	timestamp
2	1	19685	add_to_cart	1527812046
3	1	19685	view_product	1527812048
4	1	19685	view_product	1527812050

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 653125 entries, 0 to 653124
Data columns (total 4 columns):
customer_id    653125 non-null int64
product_id     653125 non-null int64
type           653125 non-null object
timestamp      653125 non-null int64
dtypes: int64(3), object(1)
memory usage: 19.9+ MB
          customer_id     product_id          type     timestamp
count   653125.000000  653125.000000        653125  6.531250e+05
unique            NaN            NaN             3           NaN
top               NaN            NaN  view_product           NaN
freq              NaN            NaN        592299           NaN
mean     35238.833857   16286.328308           NaN  1.529080e+09
std      24765.642265    8352.079466           NaN  7.379100e+05
min          1.000000       1.000000           NaN  1.527812e+09
25%      13555.000000    8634.000000           NaN  1.528441e+09
50%      31609.000000   18780.000000           NaN  1.529045e+09
75%      55352.000000   23626.000000           NaN  1.529738e+09
max      86016.000000   28369.000000           NaN  1.530403e+09
```

	product_id	category_id	category_path	brand	gender	description	price
0	1	1	Sports|Outdoor|Outdoor Shoes|Children's Outdoo...	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
1	2	1	Sports|Outdoor|Outdoor Shoes|Children's Outdoo...	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
2	3	2	Clothes	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
3	4	1	Sports|Outdoor|Outdoor Shoes|Children's Outdoo...	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
4	5	3	Children|Children's Footwear|Children's Sport ...	Nike	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	23.73

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28369 entries, 0 to 28368
Data columns (total 7 columns):
product_id       28369 non-null int64
category_id      28369 non-null int64
category_path    28369 non-null object
brand            28369 non-null object
gender           28369 non-null object
description      26927 non-null object
price            28369 non-null float64
dtypes: float64(1), int64(2), object(4)
memory usage: 1.5+ MB
         product_id   category_id     category_path   brand gender  \
count   28369.00000  28369.000000             28369   28369  28369
unique          NaN           NaN               322     517      5
top             NaN           NaN  Men|Men Clothing  Adidas    Man
freq            NaN           NaN              5078    1799   9566
mean    14185.00000     74.630230               NaN     NaN    NaN
std      8189.56923     62.568572               NaN     NaN    NaN
min         1.00000      1.000000               NaN     NaN    NaN
25%      7093.00000     35.000000               NaN     NaN    NaN
50%     14185.00000     56.000000               NaN     NaN    NaN
75%     21277.00000     83.000000               NaN     NaN    NaN
max     28369.00000    329.000000               NaN     NaN    NaN

                                             description         price
count                                              26927  28369.000000
unique                                             13293           NaN
top     <!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...           NaN
freq                                                1437           NaN
mean                                                 NaN     28.471033
std                                                  NaN     28.122249
```

```
min                                                        NaN       0.000000
25%                                                        NaN      12.530000
50%                                                        NaN      19.530000
75%                                                        NaN      34.740000
max                                                        NaN    1039.430000
```

Category tree

Construct full category tree - **list** is product **count**

In [10]:

```
PATH_CATEGORIES_COUNT = 'categories_count.npy'
categories_count = {}
try:
  categories_count = np.load(PATH_CATEGORIES_COUNT).item()
except FileNotFoundError:
  sep = '|'
  for path in df_catalog['category_path']:
    if dpath.util.search(categories_count, path, separator=sep):
      v = dpath.util.get(categories_count, path, separator=sep)
      v[None] = v[None] + 1 if None in v else 1
      dpath.util.set(categories_count, path, v, separator=sep)
    else:
      dpath.util.new(categories_count, path, {None: 1}, separator=sep)
  np.save(PATH_CATEGORIES_COUNT, categories_count)
pdict(categories_count)
```


```
{
    "Sports": {
        "Outdoor": {
            "Outdoor Shoes": {
                "Children's Outdoor Shoes": {
                    "null": 29,
                    "Children's Outdoor Sandals": {
                        "null": 14
                    }
                },
                "Men's Outdoor Shoes": {
                    "null": 120,
                    "Men's Outdoor Sandals": {
                        "null": 13
                    }
                },
                "Women's Outdoor Shoes": {
                    "null": 101,
                    "Women's Outdoor Sandals": {
                        "null": 20
                    }
                }
            },
            "Outdoor Clothing": {
                "Women's Outdoor Clothing": {
                    "Women's Outdoor T-Shirts": {
                        "null": 31
                    },
                    "Women's Outdoor Pants": {
                        "null": 24
                    },
                    "Women's Outdoor Jackets": {
                        "null": 32
                    },
                    "Women's Outdoor Sweatshirts": {
                        "null": 30
                    },
                    "Women's Functional Clothing": {
                        "null": 26
                    },
                    "Women's Outdoor Shorts": {
                        "null": 4
                    }
                },
                "Men's Outdoor Clothing": {
```

```
                    "Men's Outdoor Shorts": {
                        "null": 23
                    },
                    "Men's Outdoor T-Shirts": {
                        "null": 30
                    },
                    "Men's Functional Clothing": {
                        "null": 37
                    },
                    "Men's Outdoor Sweatshirts": {
                        "null": 27
                    },
                    "Men's Outdoor Jackets": {
                        "null": 31
                    },
                    "Men's Outdoor Pants": {
                        "null": 21
                    },
                    "null": 1
                }
            },
            "Outdoor Accessories": {
                "null": 90,
                "Mats": {
                    "null": 4
                }
            }
        },
        "Running": {
            "Running Shoes": {
                "Men's Running  Shoes": {
                    "null": 293
                },
                "Women's Running Shoes": {
                    "null": 200
                },
                "Children's Running Shoes": {
                    "null": 34
                }
            },
            "Running Clothing": {
                "Women's Running Clothing": {
                    "Women's Running Accessories": {
                        "null": 58
                    },
                    "Women's Running Shorts": {
                        "null": 41
                    },
                    "Women's Running T-Shirts": {
                        "null": 87
                    },
                    "Women's Running Jackets": {
                        "null": 16
                    }
                },
                "null": 6,
                "Men's Running  Clothing": {
                    "Men's Running Shorts": {
                        "null": 44
                    },
                    "Men's Running T-Shirts": {
                        "null": 72
                    },
                    "Men's Running Jackets": {
                        "null": 27
                    },
                    "Men's Running  Accessories": {
                        "null": 16
                    }
                },
                "Children's Running Clothing": {
                    "Children's Running Shorts": {
                        "null": 16
                    },
                    "Children's Running T-Shirts": {
                        "null": 14
                    },
```

```
            "Children's Running Jackets": {
                "null": 8
            }
        }
    },
    "Running Accessories": {
        "null": 26
    }
},
"Football": {
    "null": 770
},
"Boxing": {
    "Boxing Clothing": {
        "Women's Boxing Clothing": {
            "Women's Boxing Tops": {
                "null": 486
            },
            "Women's Boxing Leggings": {
                "null": 101
            }
        },
        "Men's Boxing Clothing": {
            "Men's Boxing Tracksuits and Shorts": {
                "null": 348
            },
            "Men's Boxings Tops": {
                "null": 121
            }
        }
    },
    "Boxing Shoes": {
        "null": 3
    },
    "Boxing Gloves": {
        "null": 3
    },
    "Boxing Accessories": {
        "null": 2
    }
},
"Water Sports": {
    "Men's Shorts and Swimwear": {
        "null": 128
    },
    "Women's Swimwear": {
        "One-piece Swimsuit": {
            "null": 283
        },
        "Bikinis": {
            "null": 475
        }
    },
    "Children's Swimwear": {
        "Girl's Swimwear": {
            "null": 51
        },
        "Boy's Swimwear": {
            "null": 27
        },
        "null": 2
    },
    "Water Footwear": {
        "null": 21
    },
    "Swimsuit Accessories": {
        "null": 17
    }
},
"Golf": {
    "Golf Clothing": {
        "Men's Golf Clothing": {
            "Men's Golf Tops": {
                "null": 544
            },
            "Men's Golf Pants": {
                "null": 31
```

```
                },
                "null": 2
            },
            "Children's Golf Clothing": {
                "null": 43
            },
            "Women's Golf Clothing": {
                "Women's Golf Tops": {
                    "null": 121
                },
                "Women's Golf Pants": {
                    "null": 62
                }
            }
        },
        "Golf Accessories": {
            "Golf Caps": {
                "null": 64
            },
            "null": 4,
            "Golf Gloves": {
                "null": 1
            }
        },
        "Golf shoes": {
            "Women's Golf shoes": {
                "null": 6
            },
            "Men's Golf Shoes": {
                "null": 8
            }
        }
    },
    "Tennis": {
        "Tennis Clothing": {
            "Children's Tennis Clothing": {
                "null": 26
            },
            "Men's Tennis Clothing": {
                "null": 47
            },
            "Women's Tennis Clothing": {
                "null": 70
            }
        },
        "Tennis Accessories": {
            "null": 30
        },
        "Tennis Shoes": {
            "Men's Tennis Shoes": {
                "null": 22
            },
            "Women's Tennis Shoes": {
                "null": 12
            },
            "Children's Tennis Shoes": {
                "null": 7
            }
        }
    },
    "Fitness": {
        "Fitness Clothing": {
            "Women's Fitness Clothing": {
                "Women's Fitness Tops": {
                    "null": 13
                },
                "Women's Fintess Leggings": {
                    "null": 12
                },
                "Fintess Accessories": {
                    "null": 16
                }
            },
            "Men's Fitness Clothing": {
                "Men's Fitness Tracksuits": {
                    "null": 4
                },
```

```
                "Men's Fitness Shorts": {
                    "null": 4
                },
                "Men's Fitness Tops": {
                    "null": 9
                }
            }
        },
        "Fitness Accessories": {
            "null": 49
        }
    },
    "Cycling": {
        "Cycling Clothing": {
            "Men's Cycling Clothing": {
                "Men's Cycling Jackets": {
                    "null": 3
                },
                "Men's Cycling Pants": {
                    "null": 4
                },
                "null": 1,
                "Men's Cycling Jerseys": {
                    "null": 2
                }
            },
            "Women's Cycling Clothing": {
                "Women's Cycling Jerseys": {
                    "null": 4
                },
                "Women's Cycling Pants and Shorts": {
                    "null": 4
                }
            },
            "Children's Cycling Clothing": {
                "Children's Cycling pants": {
                    "null": 1
                }
            }
        },
        "Cycling Accessories": {
            "null": 7
        }
    }
},
"Clothes": {
    "null": 306,
    "Bestseller": {
        "null": 8,
        "Star Wars": {
            "null": 44
        }
    }
},
"Children": {
    "Children's Footwear": {
        "Children's Sport Footwear": {
            "null": 53,
            "Children's Football boots": {
                "null": 25
            },
            "Children's Sports sneakers": {
                "null": 47
            },
            "Children's Indoor Football Shoes": {
                "null": 13
            },
            "Children's Running Shoes": {
                "null": 4
            }
        },
        "Sandshoes": {
            "null": 21
        },
        "For the Little Ones": {
            "null": 28
        },
```

```
            "Girls Ballerinas": {
                "null": 9
            },
            "null": 594,
            "Indoor Football Shoes": {
                "null": 15
            },
            "Children's Shoes": {
                "null": 14
            },
            "Children's sandals and Flip-Flops": {
                "null": 3,
                "Children's Sandals": {
                    "null": 140
                },
                "Children's Slippers": {
                    "null": 41
                },
                "Children's Flip Flops": {
                    "null": 8
                }
            },
            "Children's Ankle Boots": {
                "null": 17
            },
            "Children's Sneakers": {
                "Children's Low Top Sneakers": {
                    "null": 188
                },
                "Children's High Top Sneakers": {
                    "null": 25
                }
            },
            "Children's Footwear for home": {
                "null": 4
            },
            "Children's Winter Footwear": {
                "null": 2
            },
            "Children's Wellington Boots": {
                "null": 9
            },
            "Flip-Flops": {
                "null": 1
            }
        },
        "Girl's Clothing": {
            "Skirts, Dresses and Overalls": {
                "null": 63
            },
            "Girl's T-Shirts": {
                "T-Shirts": {
                    "null": 125
                },
                "Tank tops": {
                    "null": 23
                },
                "Sports T-Shirts": {
                    "null": 1
                }
            },
            "Girl's Shorts": {
                "null": 47
            },
            "Girl's Jackets": {
                "Winter Jackets": {
                    "null": 48
                },
                "null": 5,
                "Autumn Jackets": {
                    "null": 25
                },
                "Sports Jackets": {
                    "null": 1
                }
            },
            "null": 75,
```

```
            "Girl's Sweatshirts": {
                "Hooded Sweatshirts": {
                    "null": 53
                },
                "Sweatshirts": {
                    "null": 33
                },
                "Sports Sweatshirts": {
                    "null": 5
                }
            },
            "Girl's Sets": {
                "null": 123
            },
            "Girl's Sweaters": {
                "null": 10
            },
            "Girl's Trousers": {
                "null": 12
            },
            "Girl's Tracksuits": {
                "null": 3
            }
        },
        "Boy's Clothing": {
            "Boy's Shorts": {
                "null": 145
            },
            "Boy's Jackets": {
                "Sport Jackets": {
                    "null": 6
                },
                "Winter Jackets": {
                    "null": 33
                },
                "Autumn Jackets": {
                    "null": 28
                },
                "null": 7
            },
            "Boy's Tracksuits": {
                "null": 76
            },
            "Boy's T-Shirts": {
                "Polo Shirts": {
                    "null": 9
                },
                "null": 5,
                "Sports T-Shirts": {
                    "null": 52
                },
                "T-Shirts": {
                    "null": 204
                },
                "Tank Tops": {
                    "null": 11
                }
            },
            "Boy's Shirts": {
                "null": 31
            },
            "Boy's Sweaters": {
                "null": 20
            },
            "Boy's Sets": {
                "null": 193
            },
            "Boy's Sweatshirts": {
                "Hooded Sweatshirts": {
                    "null": 135
                },
                "Sports Sweatshirts": {
                    "null": 16
                },
                "Sweatshirts": {
                    "null": 27
                },
```

```
                "null": 3
            },
            "Boy's Trousers": {
                "null": 34
            }
        },
        "Children's Accessories": {
            "Baseball Caps": {
                "null": 9
            },
            "Caps": {
                "null": 13
            },
            "Socks": {
                "null": 31
            },
            "null": 210,
            "Bra": {
                "null": 3
            },
            "Payamas": {
                "null": 11
            },
            "Boxer Shorts": {
                "null": 7
            },
            "Gloves": {
                "null": 1
            },
            "Children's Underwear": {
                "Girl's Underwear": {
                    "null": 5
                },
                "Boy's Underwear": {
                    "null": 21
                }
            }
        }
    },
    "Men": {
        "null": 41,
        "Men Footwear": {
            "Men's Ankle Boots": {
                "null": 1
            },
            "null": 1260,
            "Men's Sneakers": {
                "Men's High Top Sneakers": {
                    "null": 71
                },
                "null": 23,
                "Men's Low Top Sneakers": {
                    "null": 532
                }
            },
            "Men's Sports Footwear": {
                "Men's Sports Sneakers": {
                    "null": 49
                },
                "Men's running shoes": {
                    "null": 4
                },
                "Men's Football Boots": {
                    "null": 2
                },
                "Men's Indoor Football Shoes": {
                    "null": 31
                },
                "null": 3
            },
            "Men's Work Shoes": {
                "null": 23
            },
            "Men's Hiking Shoes": {
                "null": 4
            },
            "Men's sandals and Flip-Flops": {
```

```
            "null": 9,
            "Men's Slippers": {
                "null": 71
            },
            "Men's Sandals": {
                "null": 17
            },
            "Men's Flip Flops": {
                "null": 64
            },
            "Men's Trekking sandals": {
                "null": 2
            }
        },
        "Winter Shoes": {
            "null": 11
        },
        "Men's Wellington Boots": {
            "null": 7
        },
        "Men's Workers": {
            "null": 2
        }
    },
    "Men Accessories": {
        "Swimwear": {
            "null": 5
        },
        "Men's Baseball caps": {
            "null": 44
        },
        "null": 394,
        "Men's socks": {
            "null": 34
        },
        "Men's underwear": {
            "null": 1,
            "Men's Boxers": {
                "null": 252
            },
            "Men's Briefs": {
                "null": 20
            },
            "Men's Shorts": {
                "null": 27
            }
        },
        "Men's Wallets": {
            "null": 68
        },
        "Men's Watches": {
            "null": 48
        },
        "Men's caps": {
            "null": 17
        },
        "Men's gloves": {
            "null": 5
        },
        "Men's Sunglasses": {
            "null": 59
        },
        "Men's belts": {
            "null": 57
        },
        "Men's shawls": {
            "null": 3
        },
        "Underpants": {
            "null": 1
        }
    },
    "Men Clothing": {
        "Men's Shorts": {
            "Men swimming shorts": {
                "null": 245
            },
```

```
                "null": 29
            },
            "null": 5078,
            "Men's T-Shirts": {
                "Short Sleeve T-Shirts": {
                    "null": 4
                },
                "Long Sleeve T-Shirts": {
                    "null": 1
                },
                "null": 6,
                "Tank Tops": {
                    "null": 1
                },
                "Sports T-Shirts": {
                    "null": 2
                }
            },
            "Men's jackets": {
                "Winter jackets": {
                    "Ski Jackets": {
                        "null": 26
                    },
                    "null": 2
                },
                "null": 2
            },
            "Men's Tracksuits": {
                "Tracksuits": {
                    "null": 128
                },
                "Three Quarter Tracksuit Bottoms": {
                    "null": 23
                }
            },
            "Men's Shirts": {
                "null": 13
            },
            "Men's Thermal underwear": {
                "null": 10
            },
            "Men's sweatshirts": {
                "null": 24,
                "Hooded sweatshirts": {
                    "null": 6
                },
                "Fleece Sweatshirts": {
                    "null": 26
                },
                "Sports sweatshirts": {
                    "null": 3
                }
            },
            "Vests": {
                "null": 1
            },
            "Men's Trousers": {
                "Ski Trousers": {
                    "null": 17
                }
            }
        }
    },
    "Women": {
        "Women's Footwear": {
            "Women's Hiking shoes": {
                "null": 2
            },
            "Women's Sport footwear": {
                "Women's Sports Sneakers": {
                    "null": 346
                },
                "Women's Running Shoes": {
                    "null": 6
                },
                "null": 5
            },
```

```
            },
            "Women's Sandals and Flip-Flops": {
                "Women's Slippers": {
                    "null": 171
                },
                "Women's Sandals": {
                    "null": 511
                },
                "null": 4,
                "Women's Flip Flops": {
                    "null": 123
                },
                "Women's Trekking sandals": {
                    "null": 17
                }
            },
            "Women's Ankle Footwear": {
                "With no heel": {
                    "null": 78
                },
                "Women's Workers": {
                    "null": 40
                },
                "Platform": {
                    "null": 19
                },
                "High Heels": {
                    "null": 51
                }
            },
            "Women's Sneakers": {
                "null": 10,
                "Women's Low Top sneakers": {
                    "null": 915
                },
                "Women's High Top sneakers": {
                    "null": 123
                }
            },
            "null": 1165,
            "Women's Ballerinas": {
                "Slip on": {
                    "null": 240
                },
                "null": 6
            },
            "Wellington Boots": {
                "null": 4
            },
            "Women's High Heel shoes": {
                "null": 283
            },
            "Women's Platform Shoes": {
                "null": 229
            },
            "Women's Pumps": {
                "null": 44
            },
            "Women's Winter Shoes": {
                "Women's Snow Boots": {
                    "null": 61
                }
            },
            "Women's Ankle boots": {
                "Loafers": {
                    "null": 245
                }
            },
            "Women's Boots": {
                "null": 2
            }
        },
        "Women's Clothing": {
            "null": 3014,
            "Women's Shorts": {
                "null": 1
            },
            "Women's Trousers": {
```

```
            "Women's Trousers": {
                "null": 13,
                "Ski Trousers": {
                    "null": 23
                }
            },
            "Women's Sweatshirts": {
                "Fleece Sweatshirts": {
                    "null": 19
                },
                "Sports Sweatshirts": {
                    "null": 26
                },
                "Hooded Sweatshirts": {
                    "null": 1
                }
            },
            "Thermal Underwear": {
                "null": 6
            },
            "Women's Jackets": {
                "Winter Jacket": {
                    "Ski Jackets": {
                        "null": 34
                    }
                },
                "null": 1
            },
            "Sweaters, Pullovers": {
                "null": 5
            },
            "T-Shirts": {
                "Tank Tops": {
                    "null": 1
                }
            },
            "Dresses, Skirts, Overalls": {
                "null": 1,
                "Skirts": {
                    "null": 4
                }
            }
        },
        "Women's  Accessories": {
            "Women's Swimwear and Bikinis": {
                "null": 5
            },
            "Women's Caps": {
                "null": 50
            },
            "Women's Socks": {
                "null": 56
            },
            "Women's bras": {
                "null": 16
            },
            "null": 319,
            "Women's panties": {
                "null": 28
            },
            "Women's belts": {
                "null": 9
            },
            "Women's Watches": {
                "null": 69
            },
            "Women's caps": {
                "null": 5
            },
            "Women's Gloves": {
                "null": 6
            },
            "Women's Payamas": {
                "null": 3
            },
            "Women's Shawls and Scarves": {
                "null": 5
            }
```

```
            }
        },
        "April Fashion": {
            "null": 222
        },
        "Accessories": {
            "Backpacks and Bags": {
                "Shoulder Bag": {
                    "null": 76
                },
                "Sports Bags": {
                    "null": 53
                },
                "Suitcases": {
                    "null": 65
                },
                "Handbags": {
                    "null": 66
                },
                "Sport Bags": {
                    "null": 44
                },
                "School and City Backpacks": {
                    "null": 284,
                    "Urban Backpacks": {
                        "null": 11
                    }
                },
                "Children's Backpacks": {
                    "null": 28
                },
                "null": 3,
                "Travel Backpacks": {
                    "null": 38
                },
                "Waist Bags": {
                    "null": 20
                },
                "Cycling Backpacks": {
                    "null": 1
                }
            },
            "Accessories": {
                "null": 72,
                "Accessories": {
                    "null": 13
                },
                "Gift Things": {
                    "null": 1
                }
            },
            "Jewellery": {
                "null": 49,
                "Bracelets": {
                    "null": 22
                },
                "Hair Accessories": {
                    "null": 15
                },
                "Earrings": {
                    "null": 4
                }
            },
            "Ski Accessories": {
                "Ski Goggles": {
                    "null": 3
                },
                "Ski Helmets": {
                    "null": 5
                }
            },
            "Outdoor": {
                "Water Bottles": {
                    "null": 2
                }
            }
```

```
        },
        "Sale - Women": {
            "Sale - Women's Clothing": {
                "Sale - Women's Jackets": {
                    "null": 127
                },
                "Sale - Women's Pants": {
                    "null": 24
                },
                "Sale - Women's Tracksuits": {
                    "null": 4
                },
                "Sale - Women's T-Shirts": {
                    "null": 34
                },
                "Sale - Women's Sweatshirts": {
                    "null": 35
                },
                "Sale - Dresses, Skirts, Overalls": {
                    "null": 13
                },
                "Sale - Women's Shorts": {
                    "null": 10
                },
                "null": 1
            },
            "Sale - Women's Footwear": {
                "null": 11
            },
            "Sale - Women's Accessories": {
                "null": 2
            }
        },
        "Sale - Men": {
            "Sale - Men's clothing": {
                "Sale - Men's Jackets": {
                    "null": 93
                },
                "Sale - Men's Trousers": {
                    "null": 10
                },
                "Sale - Men's Shorts": {
                    "null": 10
                },
                "Sale - Men's T-Shirts": {
                    "null": 40
                },
                "Sale - Men's Sweatshirts": {
                    "null": 21
                },
                "Sale - Men\u00b4s Sweatpants": {
                    "null": 14
                },
                "Sale - men's Shirts": {
                    "null": 6
                },
                "Sale - Men's Sweaters": {
                    "null": 2
                }
            },
            "Sale - Men's footwear": {
                "null": 4
            },
            "Sale - Men's accessories": {
                "null": 14
            }
        },
        "Test Categories": {
            "null": 4
        },
        "Children's Outdoor Clothing": {
            "Children's Functional Clothing": {
                "null": 8
            },
            "Children's Outdoor Pants": {
                "null": 2
            },
            "Children's Outdoor Jackets": {
```

```
        "Children's Outdoor Jackets": {
            "null": 34
        },
        "Children's Outdoor Sweatshirts": {
            "null": 12
        },
        "Children's Outdoor T-Shirts": {
            "null": 1
        }
    },
    "Sale - Children": {
        "Sale - Children's Clothing": {
            "Sale - Children's T-Shirts": {
                "null": 4
            },
            "Sale - Children\u00b4s Sweatshirts": {
                "null": 20
            },
            "Sale - Children's Jackets": {
                "null": 19
            },
            "Sale - Children\u00b4s Trousers": {
                "null": 4
            },
            "Sale - Children\u00b4s Shorts": {
                "null": 3
            }
        },
        "Sale - Children's Footwear": {
            "null": 3
        }
    }
}
```


Construct full category tree - **list** is product **id**

In [11]:

```
PATH_CATEGORIES = 'categories.npy'
categories = {}
try:
  categories = np.load(PATH_CATEGORIES).item()
except FileNotFoundError:
  sep = '|'
  for index,path in df_catalog['category_path'].iteritems():
    if dpath.util.search(categories, path, separator=sep):
      v = dpath.util.get(categories, path, separator=sep)
      if None in v:
        #v[None].append(index)
        v[None].add(index) # faster set version not supported by JSON for printing
      else:
        #v[None] = [index]
        v[None] = {index}
      dpath.util.set(categories, path, v, separator=sep)
    else:
      #dpath.util.new(categories, path, {None: [index]}, separator=sep)
      dpath.util.new(categories, path, {None: {index}}, separator=sep)
  np.save('categories.npy', categories)
# TODO propose set-to-JSON method
#pdict(categories)
```

In [12]:

```
df_catalog.drop(['category_id','category_path'], axis=1, inplace=True)
display(df_catalog.head())
df_catalog.info()
```

	product_id	brand	gender	description	price
0	1	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
1	2	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64
2	3	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64

	product_id	brand	gender	description	price
3	4	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5...	41.64
4	5	Nike	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	23.73

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28369 entries, 0 to 28368
Data columns (total 5 columns):
product_id     28369 non-null int64
brand          28369 non-null object
gender         28369 non-null object
description    26927 non-null object
price          28369 non-null float64
dtypes: float64(1), int64(1), object(3)
memory usage: 1.1+ MB
```

Description

In [13]:

```
phtml(df_catalog.iloc[7]['description'])
print(df_catalog.iloc[7]['description'])
```

<h2><!-- mp_trans_rt_start id="1" args="as" 5 -->Slazenger Canvas Infants Pump <!-- mp_trans_rt_end 5 --></h2> <!-- mp_trans_remove_start="DE,FR,AT" -->
The Slazenger Canvas Infants Pump are perfect for everyday wear, featuring a lightweight upper with stitched detail and the Slazenger logo to the heel. These Slazenger canvas shoes also benefit from a textured outsole along with elasticated laces up front for a secure and comfortable fit.
 <!-- mp_trans_remove_end="DE,FR,AT" --><!-- mp_trans_add="DE,FR,AT" <!-- mp_trans_ost_start --]> -->
> Kids canvas shoes
> Elasticated laces
> Textured outsole
> Stitched detail
> Slazenger branding
> Upper- textile
> Lining - textile
> Sole - synthetic
> Textile upper and inner, synthetic sole

<!-- mp_trans_add="DE,FR,AT" <!-- mp_trans_ost_end --]> -->For our full range of <u>Kids Canvas Shoes</u> visit
 <p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_ucProductCode_lblProductCode" class="productCode">Product code: 028170</p>

```
&lt;h2&gt;&lt;!-- mp_trans_rt_start id=&quot;1&quot; args=&quot;as&quot; 5 --&gt;Slazenger Canvas
Infants Pump &lt;!-- mp_trans_rt_end 5 --&gt;&lt;/h2&gt; &lt;!--
mp_trans_remove_start=&quot;DE,FR,AT&quot; --&gt;&lt;br&gt;The Slazenger Canvas Infants Pump  are
perfect for everyday wear, featuring a lightweight upper with stitched detail and the Slazenger lo
go to the heel. These Slazenger canvas shoes also benefit from a textured outsole along with
elasticated laces up front for a secure and comfortable fit.  &lt;br&gt; &lt;!--
mp_trans_remove_end=&quot;DE,FR,AT&quot; --&gt;&lt;!-- mp_trans_add=&quot;DE,FR,AT&quot; &lt;!-- m
p_trans_ost_start --]&gt; --&gt;&lt;br&gt;&gt; Kids canvas shoes  &lt;br&gt;&gt; Elasticated laces
&lt;br&gt;&gt; Textured outsole  &lt;br&gt;&gt; Stitched detail  &lt;br&gt;&gt; Slazenger branding
&lt;br&gt;&gt; Upper- textile &lt;br&gt;&gt; Lining - textile &lt;br&gt;&gt; Sole - synthetic &lt;
br&gt;&gt; Textile upper and inner, synthetic sole &lt;br&gt;&lt;br&gt;&lt;!--
mp_trans_add=&quot;DE,FR,AT&quot; &lt;!-- mp_trans_ost_end --]&gt; --&gt;For our full range of &lt
;a href=&quot;/kids/kids-canvas-shoes&quot;&gt;&lt;u&gt;Kids Canvas Shoes&lt;/u&gt;&lt;/a&gt; visi
t &lt;br&gt;                              &lt;p
id=&quot;dnn_ctr103511_ViewTemplate_ctl00_ctl21_ucProductCode_lblProductCode&quot;
class=&quot;productCode&quot;&gt;Product code: 028170&lt;/p&gt;
```

In [14]:

```
# correct &lt; &gt;
df_catalog['description'] = df_catalog['description'].apply(lambda x: saxutils.unescape(x, {'&quot;
': '"'}) if pd.notnull(x) else '?')
```

In [15]:

```
# unite break lines
df_catalog['description'] = df_catalog['description'].apply(lambda x: x.replace('<br/>','<br>').rep
lace('<br />','<br>'))
```

In [16]:

```
phtml(df_catalog.iloc[7]['description'])
print(df_catalog.iloc[7]['description'])
```

Slazenger Canvas Infants Pump

Slazenger Canvas Infants Pump

The Slazenger Canvas Infants Pump are perfect for everyday wear, featuring a lightweight upper with stitched detail and the Slazenger logo to the heel. These Slazenger canvas shoes also benefit from a textured outsole along with elasticated laces up front for a secure and comfortable fit.

> Kids canvas shoes
> Elasticated laces
> Textured outsole
> Stitched detail
> Slazenger branding
> Upper- textile
> Lining - textile
> Sole - synthetic
> Textile upper and inner, synthetic sole

For our full range of Kids Canvas Shoes visit

Product code: 028170

```
<h2><!-- mp_trans_rt_start id="1" args="as" 5 -->Slazenger Canvas Infants Pump <!--
mp_trans_rt_end 5 --></h2> <!-- mp_trans_remove_start="DE,FR,AT" --><br>The Slazenger Canvas
Infants Pump  are perfect for everyday wear, featuring a lightweight upper with stitched detail an
d the Slazenger logo to the heel. These Slazenger canvas shoes also benefit from a textured
outsole along with elasticated laces up front for a secure and comfortable fit.  <br> <!--
mp_trans_remove_end="DE,FR,AT" --><!-- mp_trans_add="DE,FR,AT" <!-- mp_trans_ost_start --]> -->
<br>> Kids canvas shoes  <br>> Elasticated laces <br>> Textured outsole  <br>> Stitched detail
<br>> Slazenger branding <br>> Upper- textile <br>> Lining - textile <br>> Sole - synthetic <br>>
Textile upper and inner, synthetic sole <br><br><!-- mp_trans_add="DE,FR,AT" <!-- mp_trans_ost_end
--]> -->For our full range of <a href="/kids/kids-canvas-shoes"><u>Kids Canvas Shoes</u></a> visit
<br>                              <p
id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_ucProductCode_lblProductCode"
class="productCode">Product code: 028170</p>
```

Product code

In [17]:

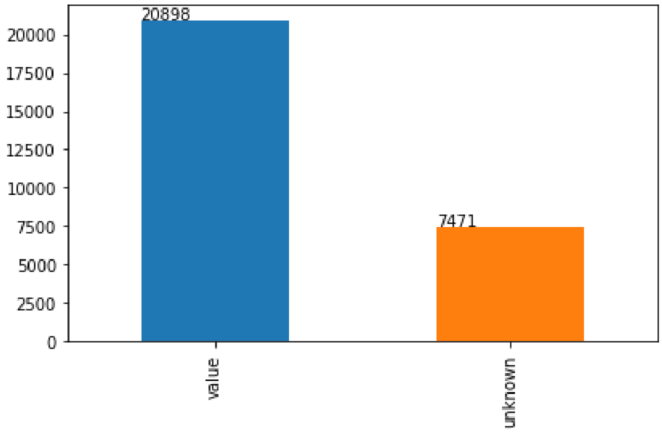
```python
def extract_product_code(html):
  product_code = '?'
  if pd.notnull(html):
    try:
      product_code = html.split('"productCode">')[1].split('</p>')[0].replace('Product code: ', '')
    except:
      if 'productcode' in html.lower().replace('_',''):
        print(html)
  return product_code

df_catalog['product_code'] = pd.Series(df_catalog['description'].apply(extract_product_code), index
=df_catalog.index)
display(df_catalog.head())
```

	product_id	brand	gender	description	price	product_code
0	1	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64	020014
1	2	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64	020014
2	3	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64	020014
3	4	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64	020014
4	5	Nike	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	23.73	021316

By product code, we identified duplicates. Many products are exactly same, just in more categories

In [18]:

```python
bar(df_catalog['product_code'].apply(lambda x: 'unknown' if x == '?' else 'value'))
```



In [19]:

```
df_catalog[df_catalog['product_code']=='?']
```

Out[19]:

	product_id	brand	gender	description	price	product_code
378	379	BELLE WOMEN	Other	<table style="border: 0pt solid #000000; heigh...	17.43	?
379	380	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	18.83	?
380	381	NEW TLCK	Other	<!-- TABELA 2 -->\n<table style="width: 330px;...	8.33	?
381	382	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	10.43	?
382	383	SERGIO TODZI	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	13.23	?
383	384	AMERICAN CLUB	Other	<!-- TABELA 2 -->\n<table style="width: 330px;...	14.63	?
384	385	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	19.53	?
385	386	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	15.33	?
386	387	TORNA	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	10.43	?
387	388	COMER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	31.43	?
388	389	COMER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	17.43	?
389	390	Adidas	Other	<!-- TABELA ADIDAS MĘSKIE CZ -->\n<table style...	83.23	?
390	391	Adidas	Other	<!-- TABELA ADIDAS DAMSKIE CZ -->\n<table styl...	52.43	?
391	392	Nike	Other	<!-- TABELA NIKE DAMSKIE CZ -->\n<table style=...	48.93	?
392	393	CINK ME	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
393	394	QUEEN BEE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	19.53	?
394	395	WILADY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	16.03	?
395	396	WILADY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	11.83	?
396	397	QUEEN BEE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	19.53	?
397	398	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	19.53	?
398	399	L. DAY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	11.83	?
399	400	HAKER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	16.03	?
400	401	Adidas	Other	<!-- TABELA ADIDAS MĘSKIE CZ -->\n<table style...	74.13	?
401	402	VICES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
424	425	WIND	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	9.03	?
425	426	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	17.43	?
426	427	YES MILE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	22.33	?
427	428	YES MILE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	22.33	?
428	429	COMER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	31.43	?
429	430	Nike	Other	<!-- TABELA NIKE DAMSKIE CZ -->\n<table style=...	48.93	?
...	...	...	...	...	...	...
28310	28311	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28311	28312	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?

	product_id	brand	gender	description	price	product_code
28311	28312	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28312	28313	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28313	28314	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28314	28315	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28315	28316	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28316	28317	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28317	28318	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28318	28319	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28319	28320	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	?
28320	28321	VIA GIULIA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28321	28322	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	14.63	?
28322	28323	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	14.63	?
28323	28324	CZASNABUTY	Other	<!-- TABELA CZASNABUTY MĘSKIE CZ -->\n<table s...	12.53	?
28324	28325	CZASNABUTY	Other	<!-- TABELA CZASNABUTY MĘSKIE CZ -->\n<table s...	12.53	?
28325	28326	CZASNABUTY	Other	<!-- TABELA CZASNABUTY MĘSKIE CZ -->\n<table s...	12.53	?
28326	28327	Firetrap	Other	?	14.63	?
28328	28329	Miso	Other	Product code: 425460	14.63	?
28338	28339	Trendyol	Other	Model Measurements: Height: 1.77, Che...	65.03	?
28339	28340	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	17.43	?
28340	28341	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	14.63	?
28341	28342	SEASTAR	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	9.73	?
28342	28343	SMALL SWAN	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28343	28344	MELISA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28344	28345	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28345	28346	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28346	28347	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28347	28348	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	?
28348	28349	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	11.83	?
28349	28350	LICEAN	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	9.73	?

7471 rows × 6 columns

In [20]:

```
phtml(df_catalog.iloc[378]['description'])
print(df_catalog.iloc[378]['description'])
```

The SIZE of the	36	37	38	39	40	41
LENGTH (CM)	23.5	24	25	25.5	26	26.5

State of the art boating this season.

Elegant and distinctive shape.

High heel needle.

The shoes fit.

Heel: 11 cm

Material: lacquered eco leather

```
<table style="border: 0pt solid #000000; height: 54px;" dir="ltr" border="0" cellspacing="2"
cellpadding="2" width="277" frame="border" rules="none" align="center">
<tbody style="text-align: left;">
<tr style="text-align: left;">
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle"><span style="font-family: arial black,avant garde;"><strong>The SIZE of
the</strong></span></td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">36</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">37</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">38</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">39</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">40</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">41</td>
</tr>
<tr class="t5" style="text-align: left;" valign="middle">
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle"><span style="font-family: arial black,avant garde;"><strong>LENGTH (CM)</strong></
span></td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">23.5</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">24</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">
<p>25</p>
</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">25.5</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">26</td>
<td style="width: 20px; height: 20px; border: 1px solid #000000; text-align: center;"
valign="middle">26.5</td>
</tr>
</tbody>
</table>
<p>State of the art boating this season.</p>
<p>Elegant and distinctive shape.</p>
<p>High heel needle.</p>
<p><span style="font-size: 9pt;">The shoes fit.</span></p>
<p><strong>Heel: </strong>11 cm</p>
<p><strong>Material:</strong> lacquered eco leather</p>
<p><strong><br></strong></p>
```

We have seen that product code is missing especially for shoes.

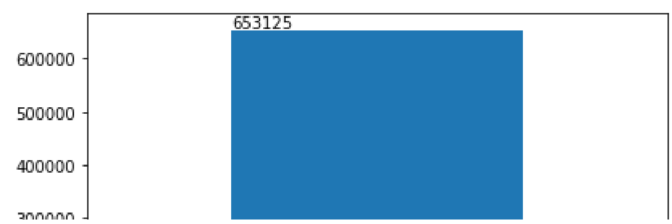
Let's unite duplicates by single id per unique product. We reflect it also to events log.

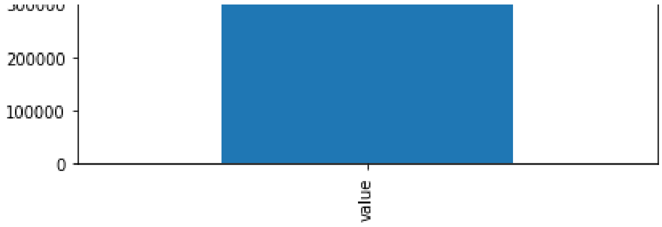
In [21]:

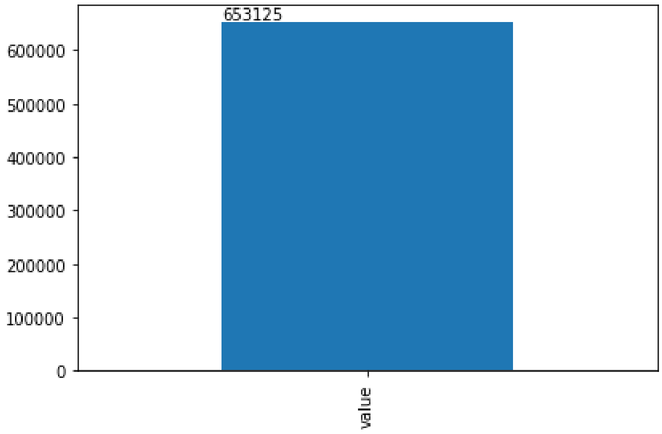
```
for index, product_code, product_id in df_catalog.filter(['product_code',
'product_id']).itertuples(name=None):
  if product_code == '?':
    df_catalog.at[index, 'product_code'] = 'x{}'.format(product_id)
```

In [22]:

```
for col in ['product_id', 'customer_id']:
  bar(df_events[col].apply(lambda x: 'unknown' if pd.isnull(x) else 'value'))
```







In [23]:

```
df_events = df_events.merge(df_catalog, on='product_id', how='left', copy=False)
display(df_events.head())
```

	customer_id	product_id	type	timestamp	brand	gender	description	price	product_cod
0	1	19685	view_product	1527812004	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	35437
1	1	19685	view_product	1527812041	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	35437
2	1	19685	add_to_cart	1527812046	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	35437
3	1	19685	view_product	1527812048	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	35437
4	1	19685	view_product	1527812050	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	35437

Duplicates are not supported only by same product code. In fact, all 4 main attributes are totally equal.

In [24]:

```
DUPLICATE_COLS = ['brand','gender','description','price']
df_catalog.drop_duplicates(DUPLICATE_COLS, inplace=True)
display(df_catalog.head())
```

	product_id	brand	gender	description	price	product_code
0	1	Firetrap	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	41.64	020014
4	5	Nike	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	23.73	021316
5	6	Lonsdale	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	12.53	023060
6	7	Dunlop	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	9.03	028027
7	8	Slazenger	Child	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	4.20	028170

In [25]:

```
display(df_events.loc[69])
```

```
customer_id                7
```

```
product_id              13690
type              view_product
timestamp           1527865432
brand                     2117
gender                   Other
description                  ?
price                    23.87
product_code            x13690
Name: 69, dtype: object
```

In [26]:

```
df_events.rename(index=str, columns={"product_id": "product_id_original"}, inplace=True)
```

In [27]:

```
df_events = df_events.merge(df_catalog.filter((DUPLICATE_COLS + ['product_id'])),
on=DUPLICATE_COLS, how='left', copy=False)
display(df_events.head())
```

	customer_id	product_id_original	type	timestamp	brand	gender	description	price	proc
0	1	19685	view_product	1527812004	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	
1	1	19685	view_product	1527812041	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	
2	1	19685	add_to_cart	1527812046	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	
3	1	19685	view_product	1527812048	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	
4	1	19685	view_product	1527812050	Full Circle	Woman	<p id="dnn_ctr103511_ViewTemplate_ctl00_ctl21_...	18.13	

In [28]:

```
display(df_events.loc[69])
```

```
customer_id                      7
product_id_original          13690
type                  view_product
timestamp               1527865432
brand                         2117
gender                       Other
description                      ?
price                        23.87
product_code                x13690
product_id                   13688
Name: 69, dtype: object
```

In [29]:

```
df_events.drop(DUPLICATE_COLS, axis=1, inplace=True)
display(df_events.head())
```

	customer_id	product_id_original	type	timestamp	product_code	product_id
0	1	19685	view_product	1527812004	354370	19685
1	1	19685	view_product	1527812041	354370	19685
2	1	19685	add_to_cart	1527812046	354370	19685
3	1	19685	view_product	1527812048	354370	19685
4	1	19685	view_product	1527812050	354370	19685

We both significantly reduced product catalog size and increased number of events per pair product and customer.

Extract attributes: name

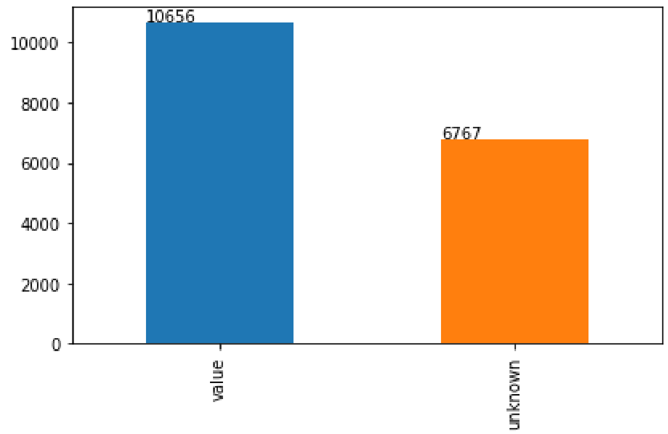
In [30]:

```
def extract_name(html):
  name = '?'
  if html != '?':
    # normally observed name "h2", occasionally 1st "strong"
    for tag in ['h2', 'strong']:
      element = bs(html).find(tag)
      if element:
        name = element.get_text() # BeautifulSoap already ignores HTML comments!
        break
  return name

df_catalog['name'] = pd.Series(df_catalog['description'].apply(extract_name), index=df_catalog.inde
x)
display(df_catalog.filter(['name']).head())
```

	name
0	Firetrap Rhino Infant Boots
4	Nike Air Max Ivo Infant Girl Trainers
5	Lonsdale Camden Infant Boys Trainers
6	Dunlop Infant Canvas High Top Trainers
7	Slazenger Canvas Infants Pump

In [31]:

```
bar(df_catalog['name'].apply(lambda x: 'unknown' if x == '?' else 'value'))
```



Extract attributes: desc

Description text

In [32]:

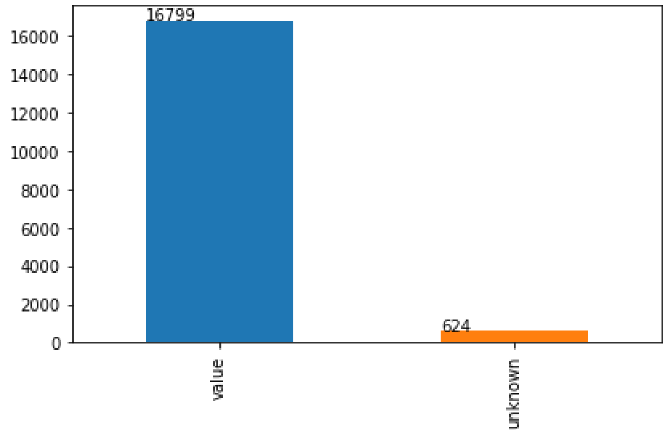
```
def extract_desc(html):
  if html == '?':
    return '?'
  return ''.join(c for c in bs(html).get_text() if c.isalnum() or c == ' ')

df_catalog['desc'] = pd.Series(df_catalog['description'].apply(extract_desc), index=df_catalog.inde
x)
display(df_catalog.filter(['desc']).head())
```

	desc
0	Firetrap Rhino Infant Boots These Firetrap Rhi...

	desc
4	Nike Air Max Ivo Infant Girl Trainers Get a...
5	Lonsdale Camden Infant Boys Trainers These Lon...
6	Dunlop Infant Canvas High Top Trainers The Dun...
7	Slazenger Canvas Infants Pump The Slazenger C...

In [33]:

```
bar(df_catalog['desc'].apply(lambda x: 'unknown' if x == '?' else 'value'))
```



Extract attributes: strong

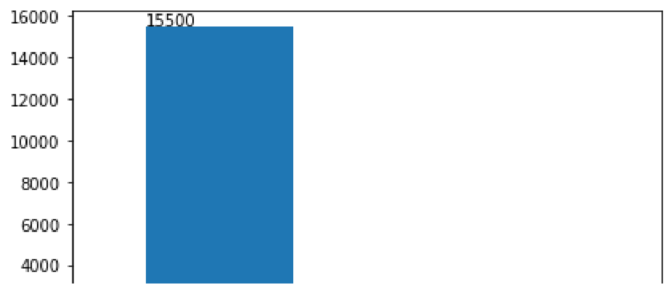
In [34]:

```
def extract_strong(html):
  arr = []
  if pd.notnull(html):
    for element in bs(html).find_all('strong'):
      arr.append(element.get_text())
  return arr

df_catalog['strong'] = pd.Series(df_catalog['description'].apply(extract_strong), index=df_catalog.
index)
display(df_catalog.filter(['strong']).head())
```

	strong
0	[Firetrap Rhino Infant Boots, Firetrap boots, ...
4	[]
5	[]
6	[Dunlop Canvas High Top Trainers, Infant Train...
7	[]

In [35]:

```
bar(df_catalog['strong'].apply(lambda x: 'value' if x else 'unknown'))
```



Extract attributes: features

Bullet points with product properties.

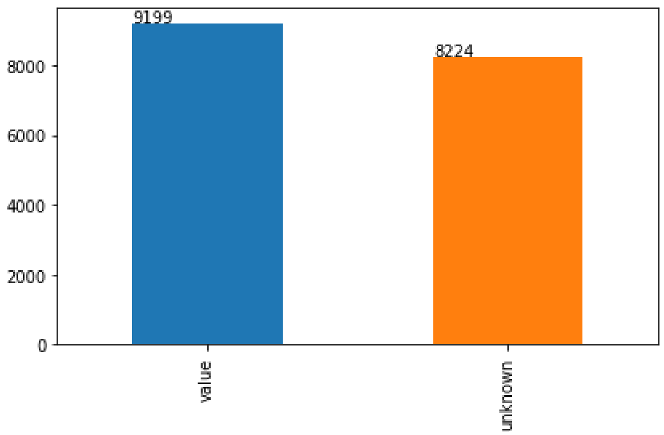
In [36]:

```
def extract_features(html):
  arr = []
  if pd.notnull(html):
    # starts with "break line"
    for x in html.split('<br>'):
      # followed by "greater than"
      if x.startswith('>'):
        # can contain more, comma separated
        for feature in x.replace('<strong>','').replace('</strong>','').replace('>','').strip().spl
it(', '):
          arr.append(feature)
  return arr

df_catalog['features'] = pd.Series(df_catalog['description'].apply(extract_features), index=df_cata
log.index)
display(df_catalog.filter(['features']).head())
```

	features
0	[Boys boots, Firetrap branding, Ankle height, ...
4	[Infant Girls, Full lace up, Air Max technolog...
5	[Lonsdale Camden Infant Boys Trainers, Lonsdal...
6	[Canvas Trainers, Lace up, Herringbone pattern...
7	[Kids canvas shoes, Elasticated laces, Texture...

In [37]:

```
bar(df_catalog['features'].apply(lambda x: 'value' if x else 'unknown'))
```



Brand

In [38]:

```
[print(brand) for brand in np.sort(df_catalog['brand'].unique())];
```

2117
4F
883 Police
ABLOOM
ALPINE PRO
AMERICAN CLUB
ANDY Z
ANESIA PARIS
ANNALISA
ARRIGO BELLO
AV
AX BOXING
AX Paris
Accessories
Adidas
Airwalk
Alesha Dixson
Amy Childs
Animal
Aqua Sphere
Arena
Ashworth
Asics
Atak
Azzurri
B&C
BALADA
BBB
BEAUTY GIRL'S
BELLA PARIS
BELLA STAR
BELLE WOMEN
BELLO STAR
BEST SHOES
BESTELLE
BETLER
BIGBRANDSALE
BONA
Babolat
Back To School
Bafiz
Banana Moon
Beach Athletics
Ben Sherman
Beppi
Berghaus
Bernie Mev
Betty
Big Brand Sale
Bjorn Borg
Black Diamond
Blink
Blowfish
Briers
British Knights
Brogini
Bronx
Burton
CH. CREATION
CINK ME
CM PARIS
COCO PERLA
COMER
CONS
CORINA
COURA
CZASNABUTY
Callaway
Calvin Klein
Calvin Klein Underwear
Camelbak
Camping
Campri
Canterbury
Carlton
Casall

Case Scenario
Cayler and Sons
Champion
Character
Chervo
Chillaz
Christmas
Chub
Claudia
Colmar
Columbia
Converse
Cortica
Cosmic
Cote De Moi
Craft
Crafted
Crafted Essentials
Crafted Mini
Craghoppers
Creative Recreation
Crocs
Cruyff
Cupcake Cult
D555
DANIC
DC
DC Comics
DIAMANTIQUE
DIMAR
DOKE
DOLI-BERRY
Dainese
David And Goliath
David Barry
Deadly Denim
Diadora
Diem
Disney
Disturbia
Dolcis
Donnay
Dropshot
Dublin
Duck and Cover
Dunlop
Dynafit
EMAKS
ENCOR
ERCO
ERYNN
EVENTO
Ellesse
Emoji
England
Equestrian
Erima
Eskadron
Esprit
Eurostar
Everlast
Extremities
FA
FAMA
FASHION
FGM PARIS
FIFA
FILIPPO
FLYFOR
FOREVER FOLIE
FUNSTORM
Fabric
Falke
Fearless Illustration
Festival Shop
Fila
Firetrap

Five
Flash Sale Eight
Flash Sale Four
Flossy
Fly London
Flyer
Football
Football Boot Launches
Football Kit Launches
Football Shirts
Footjoy
Forever Unique
Fox
Franklin and Marshall
Fred Perry
French Connection
Fruit of the Loom
Full Blue
Full Circle
Funkita
Funky Trunks
G Star
GEOX
GIRLHOOD
GOGO
GROTO GOGO
Galoppo
Garmont
Gelert
Get The Look
Get The Look 2
Get The Look Mens 02
Get The Look Mens 03
Get The Look Womens
Get The Look Womens 02
Get The Look Womens 03
Gilbert
Giorgio
Giro
Glamorous
Glitzy
Golddigga
Goodie Two Sleeves
Gore
Guess
Gul
HAKER
HANNAH
HASBY
HUSKY
HV Polo
Hac Tac
Harry Hall
Havaianas
Head
Heartless Clothing
Heatons
Helly Hansen
Henri Lloyd
Hi Tec
Hilly
Holiday Shop
Horseware
Hot Tuna
Hudson Jeans
Hummel
Hunter
IDEAL SHOES
INVITO
J Lindeberg
J. STAR
JDY
JULIET
Jack Murphy
Jack and Jones
Jako
Jeffrey Campbell

Jilted Generation
Joma
JuJu Jellies
Julbo
Just Togs
K Swiss
K100 Karrimor
KAYLA
KEEN
KJUS
KYLIE
Kangol
Kappa
Karl Lagerfeld
Karrimor
Keds
Keen
Kelme
Kickers
Kids
Kiefer
Kilpi
Kookaburra
L&H
L. DAY
L. LUX. SHOES
LA Gear
LAURA MODE
LGM
LICEAN
LOAP
LOVERY
LOVIT
LUCCA
LUCKY SHOES
La Sportiva
Lacoste
Ladies
Le Breve
Lee Cooper
Lego Wear
Levis
Limited Sports
Linens and Lace
Lipsy
Lonsdale
Lorus
Lotto
Lowa
Luke Sport
M Collection
MANNIKA
MARIO BOSCHETTI
MARQUIZ
MAZARO
MCKEY
MELISA
MILAYA
MORIMIA
MUTO
Mac
Marc Aurel
Marmot
Marshall Artist
Maru
Marvel
Matt Hayes
McKeylor
Mega Value
Mega Value Store
Mens
Merrell
Millet
Minnetonka
Misc
Miso
Miss Fiori

Mitre
Mizuno
Mountain Horse
Moving Comfort
Muddyfox
Mueller
Mystify
Mystify Collection
NCAA
NEW AGE
NEW TLCK
NIKE
NIO NIO
NORDBLANC
NORTHFINDER
NUFC
NUMOCO
Nevica
New Balance
New Era
New York
Nike
No Fear
Noisy May
Noric
ONeill
ONeills
OUTHORN
Ocean Pacific
Odlo
Official
Ombre
Only
Only and Sons
Original Penguin
Ortovox
Osaka Laundry
Osprey
Outdoor Equipment
Outdoor Footwear
POD
POLBUT
PRIMAVERA
PTPT
Pantone
Patrick
Peaked Apparel
Penguin
Pepe Jeans
Pieces
Pierre Cardin
Platinum
Poivre blanc
Police
Pre Order
Precision Training
Prince
Puffa
Pulp
Puma
Pumpkin Patch
QINBA
QUEEN BEE
QUEEN VIVI
QUEENTINA
Quiksilver
R'S
RAPTER
RAWEKS
RENDA
REPRESENT
REWEKS
RFU
Racktime
Rafiki
Reebok
Regatta

Rehall
Replay
Requisite
Reusch
Rip Curl
Rock and Rags
Rocket Dog
Rockport
Ron Hill
Rossignol
Roxy
Russell Athletic
S Oliver
SAXX
SCHWARZWOLF
SDS
SEASTAR
SERGIO TODZI
SHOW IT
SMALL SWAN
SORRENTO
SPORT
SUN COLOR
SUPER ME
SUPER MODE
SWEET SHOES
Saddler
Salewa
Salming
Salomon
Scarpa
Schneider
Search
Sergio Tacchini
Seven Summits
Shires
Shock Absorber
Sistema
Sixth Sense
Skechers
Skins
Slazenger
Slydes
Smartwool
Sondico
SoulCal
Source Lab
Soviet
Speedo
Sport Zone
SportFX
Sportline
Spyder
Stanford Home
Star
Star Wars
Steve Madden
Storm
Summer Sale
Superga
Susino
Swiss Cross by Strellson
TINA&CO
TLCK SHOES
TOM WINS
TOP SHOES
TORNA
TRIMM
TULLO
Tagg
Take Off
Tapout
TaylorMade
Team
Tefal
Teva
The North Face

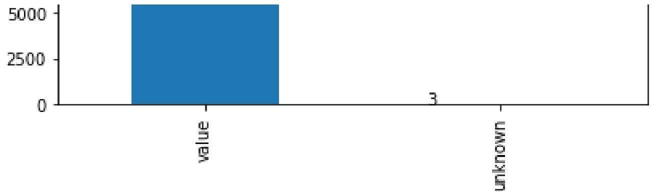
```
Timberland
Timex
Tom Tailor
Tommy Hilfiger
Tony Hawk
Too Fast
Toxic Threads
Trendyol
Trespass
True Denim
Tyr
US Polo
USA Pro
Uglies
Umbro
Unbranded
Uncut
Under Armour
Unknown
VCS new collection
VESUVIO
VIA GIULIA
VICES
VICES NEW COLLECTION
VINCEZA
VOI
Vandanel
Vans
Vaude
Vero Moda
Vespa
View All Footballs
Vixxsin
W. POTOCKI
WEIDE
WILADY
WIN
WIND
WOLSKI
WOOX
WaiKoa
Weekend Offender
Weird Fish
Wilson
Windsor Smith
Workwear and Safety Wear
Xmas
Y&L
YAS
YES MILE
ZEEPACK
Zaxy
Zoggs
Zukie
adidas energy cloud
producent niezdefiniowany
```

In [39]:

```
df_catalog['brand'].replace(to_replace='producent niezdefiniowany', value='?', inplace=True)
```

In [40]:

```
bar(df_catalog['brand'].apply(lambda x: 'unknown' if x == '?' else 'value'))
```



Gender

In [41]:

```
df_catalog['gender'].unique()
```

Out[41]:

```
array(['Child', 'Man', 'Woman', 'Unisex', 'Other'], dtype=object)
```

In [42]:

```
df_catalog[df_catalog['gender']=='Other']
```

Out[42]:

	product_id	brand	gender	description	price	product_code	name	desc	strong	f
378	379	BELLE WOMEN	Other	<table style="border: 0pt solid #000000; heigh...	17.43	x379	The SIZE of the	The SIZE of the363738394041LENGTH CM2352425255...	[The SIZE of the, LENGTH (CM), Heel: , Materia...	
379	380	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	18.83	x380	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41,]	
380	381	NEW TLCK	Other	<!-- TABELA 2 -->\n<table style="width: 330px;...	8.33	x381	18	RozmiaryDł wkładkiRozmiaryDł wkładki1811 cm281...	[18, 28, 19, 29, 20, 30, 21, 31, 22, 32, 23, 3...	
381	382	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	10.43	x382	35	The size of theThe length of the Insert35225 c...	[35, 36, 37, 38, 39, 40, 41, , Material:]	
382	383	SERGIO TODZI	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	13.23	x383	35	The size of theThe length of the Insert35225 c...	[35, 36, 37, 38, 39, 40, 41,]	
383	384	AMERICAN CLUB	Other	<!-- TABELA 2 -->\n<table style="width: 330px;...	14.63	x384	18	RozmiaryDł wkładkiRozmiaryDł wkładki1811 cm281...	[18, 28, 19, 29, 20, 30, 21, 31, 22, 32, 23, 3...	
384	385	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	19.53	x385	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41,]	
385	386	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	15.33	x386	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
386	387	TORNA	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	10.43	x387	35	The size of theInsert the DL3522 cm36225 cm372...	[35, 36, 37, 38, 39, 40, 41]	
387	388	COMER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	31.43	x388	35	The size of theThe length of the Insert35225 c...	[35, 36, 37, 38, 39, 40, 41]	

	product_id	brand	gender	description	price	product_code	name	desc	strong	f
388	389	COMER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	17.43	x389	35	VelikostDl vložky35225 cm3623 cm3724 cm38245 c...	[35, 36, 37, 38, 39, 40, 41,]	
389	390	Adidas	Other	<!-- TABELA ADIDAS MĘSKIE CZ -->\n<table style...	83.23	x390	25.2	The Size Of The TradeAdidas SizeInsert the DL2...	[25.2, 40 2/3, 41, 41 1/3, 42, 42, 26.4, 42 2/...	
390	391	Adidas	Other	<!-- TABELA ADIDAS DAMSKIE CZ -->\n<table styl...	52.43	x391	36	The Size Of The TradeAdidas SizeInsert the DL3...	[36, 36, 22.7, 36 2/3, 37, 37 1/3, 38, 38, 23....	
391	392	Nike	Other	<!-- TABELA NIKE DAMSKIE CZ -->\n<table style=...	48.93	x392	36	The size of theInsert the DL36225 cm22723 cm23...	[36, 22.7, 23.3, 38, 23.9, 39, 40, 25.2, 41]	
392	393	CINK ME	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x393	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
393	394	QUEEN BEE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	19.53	x394	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
394	395	WILADY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	16.03	x395	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
395	396	WILADY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	11.83	x396	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
398	399	L. DAY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	11.83	x399	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
399	400	HAKER	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	16.03	x400	35	The size of theThe length of the Insert35225 c...	[35, 36, 37, 38, 39, 40, 41]	
400	401	Adidas	Other	<!-- TABELA ADIDAS MĘSKIE CZ -->\n<table style...	74.13	x401	25.2	The Size Of The TradeAdidas SizeInsert the DL2...	[25.2, 40 2/3, 41, 41 1/3, 42, 42, 26.4, 42 2/...	
401	402	VICES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	x402	35	VelikostDl vložky35225 cm36235 cm3724 cm38245 ...	[35, 36, 37, 38, 39, 40, 41]	
424	425	WIND	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	9.03	x425	35	The size of theThe length of the Insert35225 c...	[35, 36, 37, 38, 39, 40, 41, Material:]	
425	426	VICES	Other	<!-- TABELA 1 -->\n<table style="width: 330px;...	17.43	x426	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41,]	
426	427	YES MILE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	22.33	x427	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
430	431	SEASTAR	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x431	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
431	432	SEASTAR	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	19.53	x432	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
442	443	LUCCA	Other	<!-- TABELA CZASNABUTY	41.23	x443	40	The size of theInsert the	[40, 41, 42, 43,	

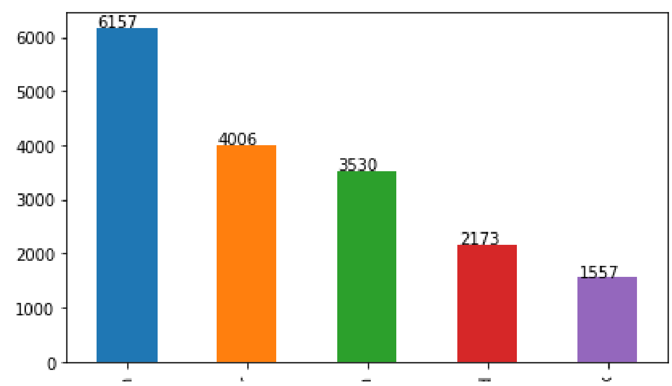
	product_id	brand	gender	description	price	product_code	name	desc	strong	fe
				MESKIE CZ -- >\n<table s...				DL4028 cm41285 cm422...	44, 45, 46]	
450	451	COMER	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	24.43	x451	35	The size of theInsert the DL3522 cm36225 cm372...	[35, 36, 37, 38, 39, 40, 41]	
455	456	BALADA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	13.93	x456	35	The size of theInsert the DL35225 cm3623 cm372...	[35, 36, 37, 38, 39, 40, 41]	
...	...	...	...	...	...	...	...	...	...	
28065	28066	Adidas	Other	Dual-density Boost cushioning on the medial si...	82.94	212097	?	Dualdensity Boost cushioning on the medial sid...	[]	
28066	28067	SoulCal	Other	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	21.63	542062	SoulCal Signature Polo Shirt Mens	SoulCal Signature Polo Shirt MensThis mens pol...	[]	[Mer po s Fol
28067	28068	Gul	Other	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	9.73	659744	Gul Logo T Shirt Ladies	Gul Logo T Shirt LadiesRefine your tshirt coll...	[]	[L shi nec s
28068	28069	Get The Look	Other	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	16.03	599712	Hot Tuna Sublimation Print T Shirt Mens	Hot Tuna Sublimation Print T Shirt Mens The Ho...	[]	shi s Cre
28069	28070	Nike	Other	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	104.23	121313	Nike Air Max Axis Trainers Mens	Nike Air Max Axis Trainers MensThe Nike Air Ma...	[]	[Mer t I fa
28105	28106	Pierre Cardin	Other	Product code: 642009	14.63	x28106	?	Product code 642009	[]	
28161	28162	CZASNABUTY	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	12.53	x28162	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28170	28171	MARQUIZ	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	12.53	x28171	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28171	28172	TINA&CO	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	13.93	x28172	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28174	28175	SPORT	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	13.93	x28175	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
28219	28220	?	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	12.53	x28220	35	The size of theInsert the DL3522 cm36225 cm372...	[35, 36, 37, 38, 39, 40, 41]	
28233	28234	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	14.63	x28234	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
28234	28235	LAURA MODE	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	13.93	x28235	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28240	28241	PRIMAVERA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	17.43	x28241	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28246	28247	SUN COLOR	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	12.53	x28247	35	The size of theInsert the DL3522 cm36225 cm372...	[35, 36, 37, 38, 39, 40, 41]	
28247	28248	PRIMAVERA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -- >\n<table ...	12.53	x28248	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
				<!-- TABELA					[35, 36	

	product_id	brand	gender	description	price	product_code	name	desc	strong	f
28262	28263	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x28263	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28265	28266	VIA GIULIA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	x28266	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
28266	28267	VIA GIULIA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	x28267	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28279	28280	ANESIA PARIS	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x28280	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28300	28301	QUEENTINA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	x28301	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28310	28311	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x28311	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28314	28315	ABLOOM	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x28315	35	The size of theInsert the DL3522 cm36225 cm372...	[35, 36, 37, 38, 39, 40, 41]	
28317	28318	TOP SHOES	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	13.93	x28318	35	The size of theInsert the DL3523 cm3624 cm3724...	[35, 36, 37, 38, 39, 40, 41]	
28323	28324	CZASNABUTY	Other	<!-- TABELA CZASNABUTY MĘSKIE CZ -->\n<table s...	12.53	x28324	40	The size of theInsert the DL4026 cm41265 cm422...	[40, 41, 42, 43, 44, 45, 46]	
28327	28328	Kappa	Other	<h2><!-- mp_trans_rt_start id="1" args="as" 5 ...	13.64	629088	Kappa Santos Short Sleeve T Shirt Mens	Kappa Santos Short Sleeve T Shirt Mens This K...	[]	Ligh F
28328	28329	Miso	Other	Product code: 425460	14.63	x28329	?	Product code 425460	[]	
28338	28339	Trendyol	Other	Model Measurements: Height: 1.77, Che...	65.03	x28339	?	Model Measurements Height 177 Chest 80 Waist ...	[]	
28343	28344	MELISA	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	12.53	x28344	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	
28349	28350	LICEAN	Other	<!-- TABELA CZASNABUTY DAMSKIE CZ -->\n<table ...	9.73	x28350	35	The size of theInsert the DL35225 cm36235 cm37...	[35, 36, 37, 38, 39, 40, 41]	

4006 rows × 10 columns

In [43]:

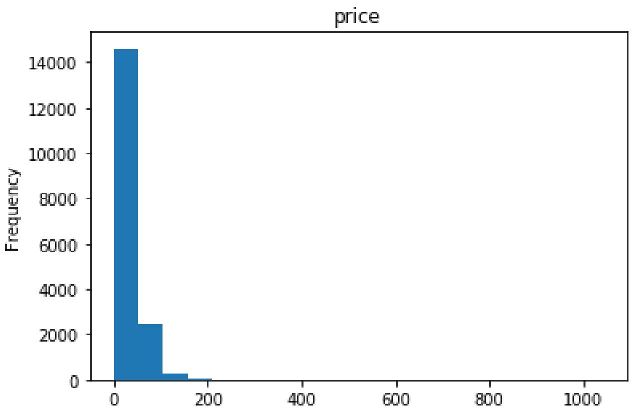
```
bar(df_catalog['gender'])
```

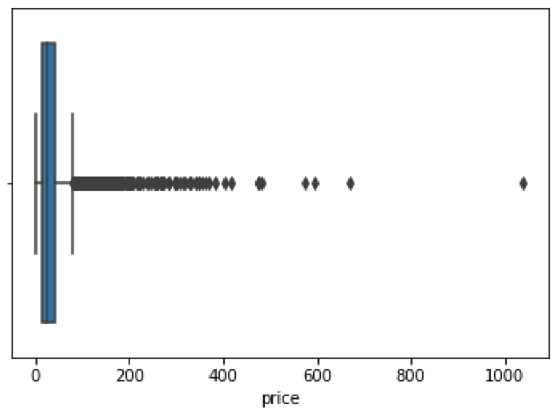


Price

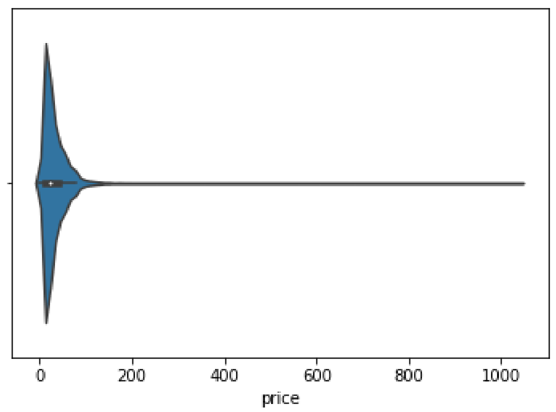
In [44]:

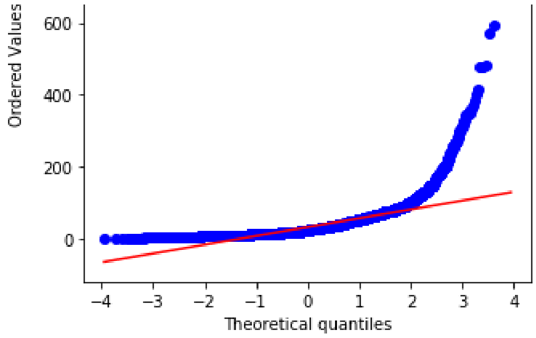
```
contplot(df_catalog['price'])
```





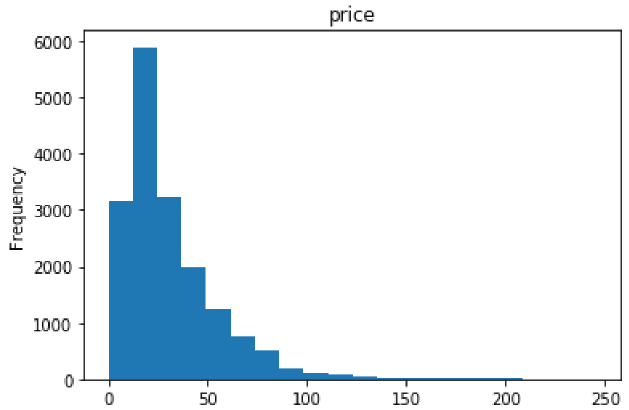

```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

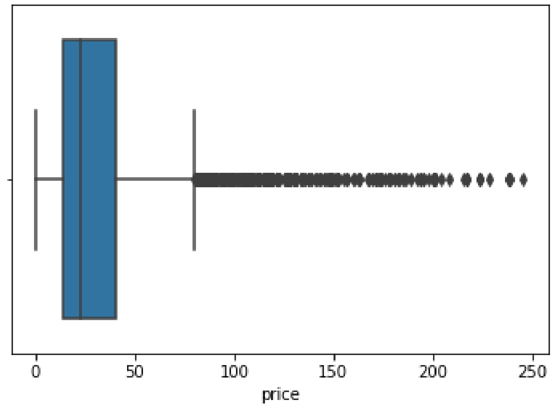




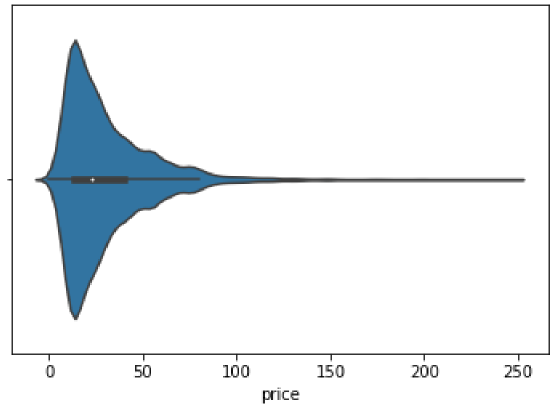
In [45]:

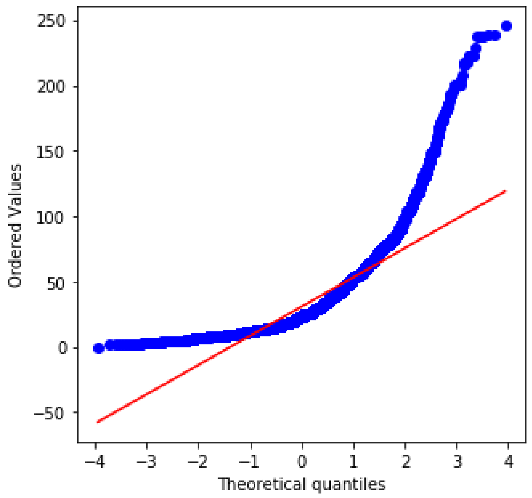
```
contplot(df_catalog[df_catalog['price']<250]['price'])
```





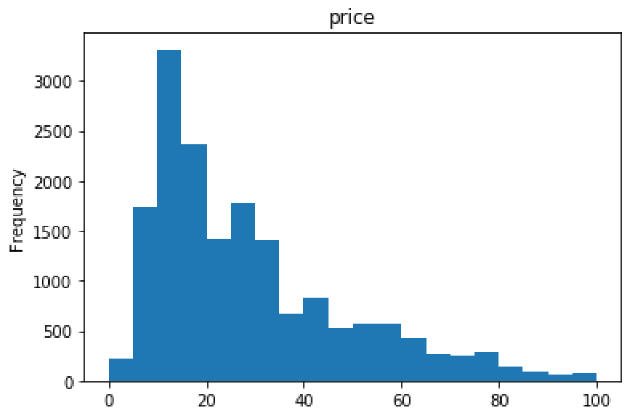

```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\scipy\stats\stats.py:1713: Fu
tureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tupl
e(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index,
`arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

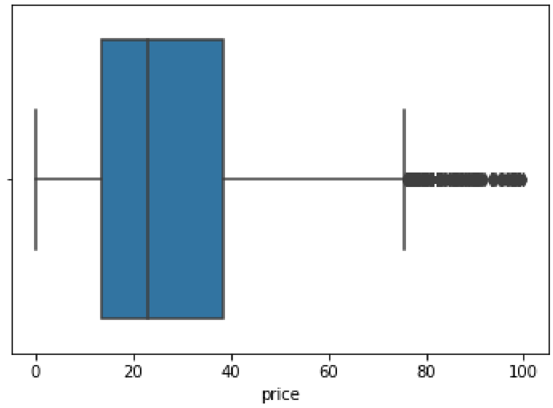




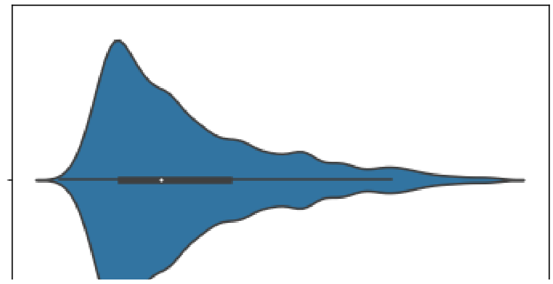

```
In [46]:
```

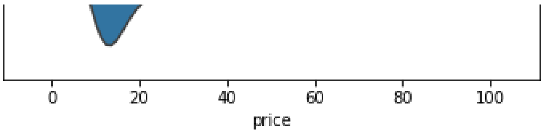
```
contplot(df_catalog[df_catalog['price']<100]['price'])
```

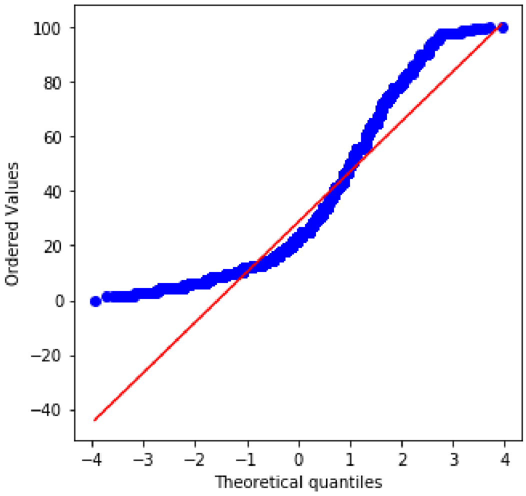





```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



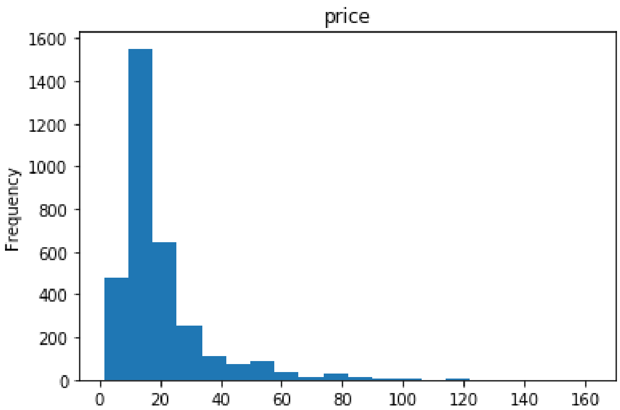


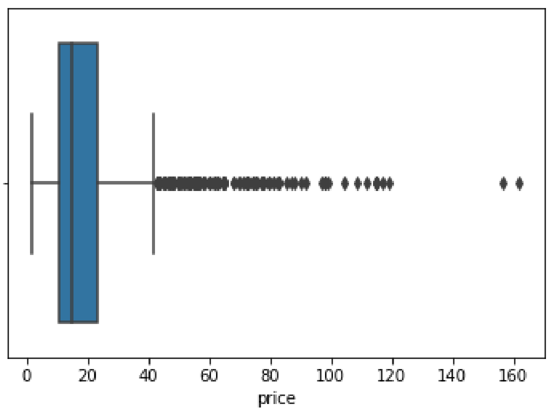


Now only sold products

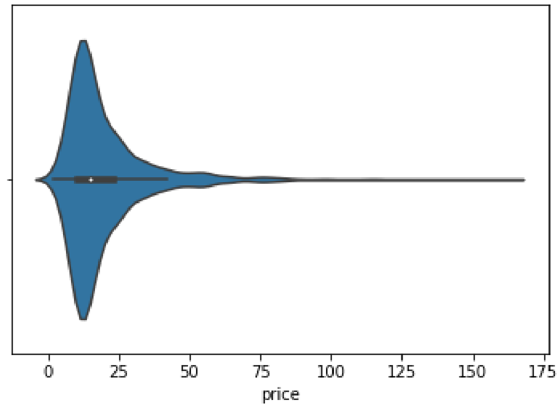
In [47]:

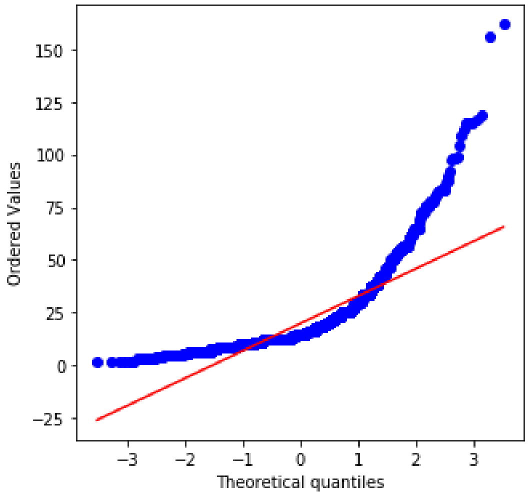
```
contplot(df_catalog[df_catalog['product_id'].isin(df_events[df_events['type']=='purchase_item']['p
roduct_id'])]['price'])
```






```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\scipy\stats\stats.py:1713: Fu
tureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tupl
e(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index,
`arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

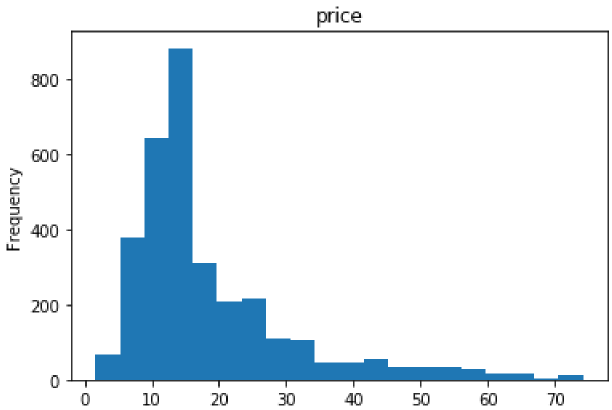


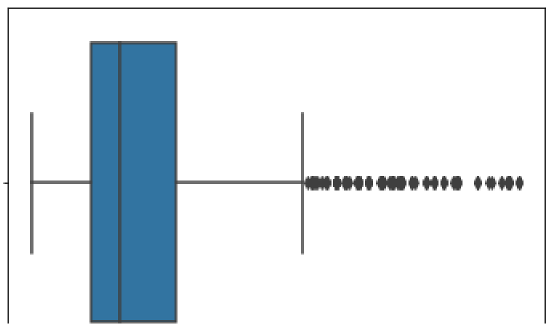


In [48]:

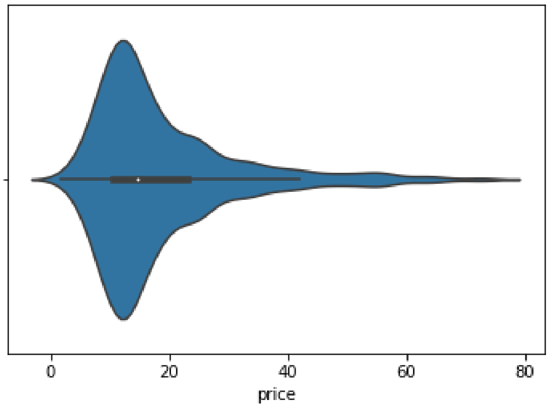
```
contplot(df_catalog[df_catalog['product_id'].isin(df_events[df_events['type']=='purchase_item']['p
roduct_id'])][df_catalog['price']<75]['price'])
```

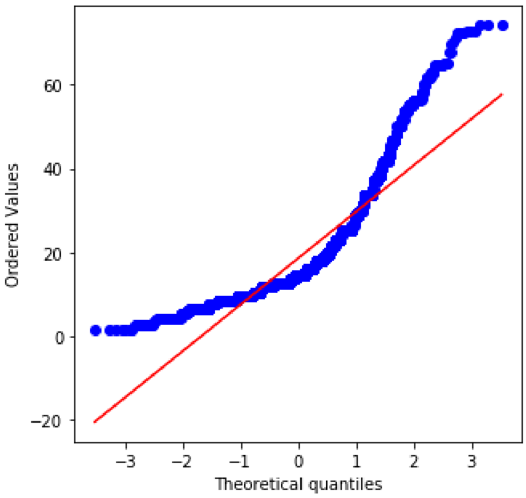
```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:1:
UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  """Entry point for launching an IPython kernel.
```






```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\scipy\stats\stats.py:1713: Fu
tureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tupl
e(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index,
`arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```





Most products are cheap. Purchases per price category are proportional to its volume.

Purchases

In [49]:

```
df_events['type'].value_counts()
```

Out[49]:

```
view_product     592299
add_to_cart       46121
purchase_item     14705
Name: type, dtype: int64
```

In [50]:

```
print(df_events[df_events['type']=='purchase_item']['customer_id'].nunique(), end="")
print(' customers with a purchase')
```

```
5175 customers with a purchase
```

In [51]:

```
df_purchased = df_events[df_events['type']=='purchase_item'].merge(df_catalog, on='product_id',
how='left', copy=False)
```

In [52]:

```
purchase_counts = df_purchased.groupby('product_id').size()
df_catalog['purchased'] = df_catalog['product_id'].apply(lambda x: purchase_counts[x] if x in purch
ase_counts.index else 0)
```

In [53]:

```
purchase_counts.sort_values(ascending=False).head(20)
```

Out[53]:

```
product_id
3662     601
11219    372
26717    366
22030    311
3524     272
20581    247
20589    196
4230     195
23887    173
1027     167
16959    132
21410    129
3617     118
2934     113
22257    102
3477      93
24372     91
21926     90
23450     82
5930      80
dtype: int64
```

In [54]:

```
def best_sellers(n, filter_by=None, filter_value=None, exclude=[]):
    if filter_by is None:
        best_sellers = df_purchased[~df_purchased['product_id'].isin(exclude)].groupby('product_id'
).size().sort_values(ascending=False)
    else:
        best_sellers = df_purchased[~df_purchased['product_id'].isin(exclude)][df_purchased[filter_
by]==filter_value].groupby('product_id').size().sort_values(ascending=False)
    return best_sellers[:n].keys().tolist()
```

Elastic index

We propose and prepare following ElasticSearch index.

In [55]:

```
with open('index.txt') as f:
    print(f.read())
```

```
# create index
PUT rec
{
  "mappings": {
    "_doc": {
      "properties": {
        "brand": {
          "type": "keyword"
        },
        "gender": {
```

```
          "type": "keyword"
        },
        "price": {
          "type": "float"
        },
        "name": {
          "type": "text"
        },
        "desc": {
          "type": "text"
        },
        "strong": {
          "type": "text"
        },
        "features": {
          "type": "text"
        },
        "purchased": {
          "type": "integer",
          "null_value": 0
        }
      }
    }
  }
}
```

Dump Elastic with product catalog

In [56]:

```
NULL_CONSTANT = 'null'

def elastify_product(product):
    product_es = pd.Series.copy(product)

    product_es['product_id'] = str(product_es['product_id'])
    if product_es['brand'] == '?':
      product_es['brand'] = NULL_CONSTANT
    if product_es['name'] in ['?', '']:
      product_es['name'] = NULL_CONSTANT # .name leads to disgusting bug
    if product_es['desc'] in ['?', '']:
      product_es['desc'] = NULL_CONSTANT
    product_es['strong'] = ' '.join(product['strong']).strip()
    if product_es['strong'] == '':
      product_es['strong'] = NULL_CONSTANT
    product_es['features'] = ' '.join(product_es['features']).replace('"','').strip()
    if product_es['features'] == '':
      product_es['features'] = NULL_CONSTANT
    return product_es
```

In [57]:

```
FILE_PATH_BULK = 'bulk.json'
def prepare_bulk(df, file_path=FILE_PATH_BULK):
    with open(file_path, 'wb') as f:
      for _,row in df.iterrows():
        product = elastify_product(row)

        f.write('{{"index":{{"_index":"{}","_type":"_doc","_id":{}}}}}\n'
          .format(ELASTIC_INDEX, product['product_id'])
          .encode('utf8'))
        f.write('{{"brand":"{}","gender":"{}","price":{},"name":"{}","desc":"{}","strong":"{}","fe
atures":"{}","purchased":{}}}\n'
          .format(product['brand'], product['gender'], product['price'], product['name'], product['
desc'], product['strong'], product['features'], product['purchased'])
          .replace("\"null\"", NULL_CONSTANT)
          .encode('utf8'))
```

In [58]:

```
# prepare_bulk(df_catalog)
```

In [59]:

```
with open(FILE_PATH_BULK) as f:
    for _ in range(6):
        print(f.readline())
```


```
{"index":{"_index":"rec","_type":"_doc","_id":1}}

{"brand":"Firetrap","gender":"Child","price":41.64,"name":"Firetrap Rhino Infant
Boots","desc":"Firetrap Rhino Infant Boots These Firetrap Rhino Infant Boots provide excellent
comfort thanks to a  padded ankle collar and tongue coupled with a lace up design for a secure fit
The Firetrap boots benefit from Firetrap branding to outside and tongue of the boot and are finish
ed off with a moulded outsole which provides a great level of grip and makes them great on any sur
face   Boys boots  Firetrap branding  Ankle height  Metallic eyelets  Stripy laces  Moulded
outsole  Leather Upper Synthetic Sole Textile InnerFor our full range of Kids Trainers visit
Product code 020014","strong":"Firetrap Rhino Infant Boots Firetrap boots Boys
boots","features":"Boys boots Firetrap branding Ankle height Metallic eyelets Stripy laces Moulded
outsole Leather Upper Synthetic Sole Textile Inner","purchased":0}

{"index":{"_index":"rec","_type":"_doc","_id":5}}

{"brand":"Nike","gender":"Child","price":23.73,"name":"Nike Air Max Ivo Infant Girl
Trainers","desc":"Nike Air Max Ivo Infant Girl Trainers Get a great look with these Nike Air Max I
vo Infant Girl Trainers which have a full lace up padded ankle collar cushioned insole and the Air
Max technology offers wonderful and comfy cushioning    Infant Girls    Full lace up    Air Max techn
ology   Meshed panelling  Rugged sole for grip  Upper SyntheticTextile Lining Textile Sole
Synthetic    For our full range of Kids Trainers visit  Product code
021316","strong":null,"features":"Infant Girls Full lace up Air Max technology Meshed panelling Ru
gged sole for grip Upper: Synthetic/Textile Lining: Textile Sole: Synthetic","purchased":0}

{"index":{"_index":"rec","_type":"_doc","_id":6}}

{"brand":"Lonsdale","gender":"Child","price":12.53,"name":"Lonsdale Camden Infant Boys
Trainers","desc":"Lonsdale Camden Infant Boys Trainers These Lonsdale Camden Infant Boys Trainers
are perfect for delivering that last bit of fashion and style to your outfit with every wear The l
ow profile design of the Lonsdale Camden Infant Boys Trainers is perfect for giving you exceptiona
l fashion looks as the colour accenting and stitch detailing adds a final touch to the eye
catching look Complete with a hook and loop tape closure that aids the padded collar and tongue in
providing a comfortable and firm fit   Lonsdale Camden Infant Boys Trainers  Lonsdale branding  Li
ghtweight  Stylish look  High quality   Padded collar and tongue  Hook and loop tape closure  Low
profile design  Colour accenting  Effective grip patterning   Stitch detailingFor our full range o
f Lonsdale Footwear visit  Product code 023060","strong":null,"features":"Lonsdale Camden Infant B
oys Trainers Lonsdale branding Lightweight Stylish look High quality Padded collar and tongue Hook
and loop tape closure Low profile design Colour accenting Effective grip patterning Stitch
detailing","purchased":0}
```


Windows users

In [60]:

```
# %%cmd
# curl -X POST http://localhost:9200/rec/_delete_by_query -H "Content-Type: application/json" -d "
{"""query""":{"""match_all""":{}}}"
```

In [61]:

```
# %%cmd
# curl -X POST http://localhost:9200/rec/_bulk -H "Content-Type: application/json" --data-binary @
bulk.json
```

Linux users

In [62]:

```
# %%bash
# curl -X POST 'localhost:9200/rec/_delete_by_query' -H 'Content-Type: application/json' -d '{"que
ry":{"match_all":{}}}'
```

In [63]:

In [63]:

```
# %%bash
# curl -X POST 'localhost:9200/rec/_bulk' -H 'Content-Type: application/json' --data-binary @bulk.
json
```

In [64]:

```
def es_q(product, match=[], fields_like=[], fields_in=[], exclude=[]):
    product_es = elastify_product(product)
    q = ~Q() # MatchNone()
    q2 = Q()
    # & is must
    # | is should
    if match:
        for col in match:
            if product_es[col] != NULL_CONSTANT:
                if col in ['brand', 'gender']:
                    # keyword
                    q2 = q2 & Q({"match": {col: product_es[col]}})
                else:
                    # text
                    q2 = q2 & MoreLikeThis(like=[product_es[col]],
                                             fields=[col],
                                             min_term_freq=1,
                                             min_doc_freq=1)
    if fields_like and fields_in:
        like = []
        for col in fields_like:
            if product_es[col] != NULL_CONSTANT:
                if col in ['brand', 'gender', 'name', 'desc']:
                    # string
                    like.append(product_es[col])
                elif col in ['features']:
                    # list of strings
                    like += product[col]
        if like:
            q2 = q2 & MoreLikeThis(like=like,
                                   fields=fields_in,
                                   min_term_freq=1,
                                   min_doc_freq=1)
    q = q | q2
    if exclude:
        for product_id in exclude:
            q = q & ~Q('match', _id=product_id)
    ### DEBUG
    if debug_on:
        print(product_es)
        print(q)
    ###
    return q
```

In [65]:

```
def es_recommend(products, sizes, match=[], fields_like=[], fields_in=[], exclude=[], sort_by_purch
ase=False):
    ms = MultiSearch(using=es, index=ELASTIC_INDEX)
    s = Search().sort({"purchased":{"order" : "desc"}}) if sort_by_purchase else Search()
    for product,size in zip(products,sizes):
        ms = ms.add(s[:size].query(es_q(product, match, fields_like, fields_in, exclude)))
    responses = ms.execute()
    ### DEBUG
    if debug_on:
        for hit in ms.execute()[0].hits:
            print(hit.meta.id)
            print(hit.to_dict())
    ###
    return [[int(hit.meta.id) for hit in response.hits] for response in responses] # make sure to c
onvert to int!
```

Recommender

In [66]:

```
# Change to True to see elastic request and hits example
debug_on = False
```

In [67]:

```
ks = [1,3,5,10]
```

In [68]:

```
def split_df(test='last_n', test_n=1):
    # choose from purchases only
    if test == 'last':
        # same as last_n with test_n=1
        df_test = df_purchased.sort_values(by='timestamp', ascending=False).drop_duplicates('custom
er_id')
    elif test == 'random':
        # test 1 random per customer
        df_test = df_purchased.iloc[randomState.permutation(np.arange(df_purchased.shape[0]))].drop
_duplicates('customer_id')
    elif test == 'last_n':
        # test n last per customer
        df_test = df_purchased.sort_values(by='timestamp', ascending=False).groupby('customer_id').
filter(lambda x: len(x) >= test_n).groupby('customer_id').head(test_n)
    df_train = df_events[~df_events.index.isin(df_test.index)].sort_values(by='timestamp')
    return df_train, df_test
```

In [69]:

```
def dcg(rankings):
    dcg = 0
    for i,r in enumerate(rankings, start=1):
        if i==1:
            dcg += r
        else:
            dcg += r / np.log2(i)
    return dcg
```

In [70]:

```
DAY = 86400
MAX_RANKING = 2
def recommend(df_train, df_test, k=1, k_most_viewed=0, strategy='elastic',
                   match=[], fields_like=[], fields_in=[], sort_by_purchase=False, ndcg=False):
    print('k = {}'.format(k))
    if k_most_viewed > 0:
        print('include {} most viewed'.format(k_most_viewed))

    hits = 0
    recommended = 0
    tested = 0#df_test['customer_id'].nunique()
    ndcg_count = 0.

    for customer_id,purchased in df_test.groupby('customer_id'):
        saw_before = df_train[(df_train['timestamp'] < np.min(purchased['timestamp']) - DAY / 2) &
(df_train['customer_id']==customer_id)]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:k_most_viewed].tolist()
        if len(rec_products) < k:
            if strategy == 'skip':
                # warning: this does NOT test users without previous activity!
                continue
            elif strategy == 'best_seller':
                rec_products += best_sellers(k - len(rec_products), exclude=rec_products)
            elif len(saw_products)>0: # next startegies are based on previously seen
                if strategy == 'best_seller_by_gender':
                    saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.in
dex)]
                    rec_products += best_sellers(k - len(rec_products), filter_by='gender',

filter_value=np.max(saw_products_catalog['gender']), exclude=rec_products)
                elif strategy == 'best_seller_by_brand':
                    saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.in
```

```
dex)]
                    rec_products += best_sellers(k - len(rec_products), filter_by='brand',
                                                 filter_value=np.max(saw_products_catalog['brand'])
exclude=rec_products)
                elif strategy == 'elastic':
                    saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.in
dex)]
                    ideal_product = saw_products_catalog[saw_products_catalog['product_id']==saw_pr
oducts.index[0]].iloc[0].copy()
                    rec_products += es_recommend([ideal_product], [k - len(rec_products)],
                                                 match=match, fields_like=fields_like, fields_in=fi
ds_in,
                                                 exclude=rec_products,
sort_by_purchase=sort_by_purchase)[0]
                    # TODO change to multi request - method already prepared, see
es_recommend([product]...
                    # TODO but it will increase memory requirements.
                elif strategy == 'elastic_combined':
                    saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.in
dex)]
                    ideal_product = saw_products_catalog[saw_products_catalog['product_id']==saw_pr
oducts.index[0]].iloc[0].copy()
                    ideal_product['gender'] = np.max(saw_products_catalog['gender'])
                    ideal_product['brand'] = np.max(saw_products_catalog['brand'])
                    saw_products_catalog = saw_products_catalog[saw_products_catalog['product_id'].
isin(saw_products.index[:3])]
                    ideal_product['features'] = list(set(saw_products_catalog['features'].sum()))
                    rec_products += es_recommend([ideal_product], [k - len(rec_products)],
                                                 match=match, fields_like=fields_like, fields_in=fi
ds_in,
                                                 exclude=rec_products,
sort_by_purchase=sort_by_purchase)[0]
#          if not rec_products: continue
        rec_products += [-1] * (k - len(rec_products))
        assert(len(rec_products)==k), 'Less than {} products recommended'.format(k)
        hits += sum(product in rec_products for product in purchased['product_id'].tolist()) # make
sure comparing same types!
        recommended += len(rec_products)
        tested += 1

        if ndcg:
            documents = purchased.sort_values('timestamp').drop_duplicates('timestamp')
            timestamps = documents['timestamp'].tolist()
            purchased_ids = documents['product_id'].tolist()
            timerange = timestamps[-1] - timestamps[0]
            max_rankings = [MAX_RANKING - (ts - timestamps[0]) / timerange if ts!=timestamps[0]
else MAX_RANKING for ts in timestamps]
            max_ndcg = dcg(max_rankings)
            rankings = []

            for product_id in rec_products:
                try:
                    rankings.append(max_rankings[purchased_ids.index(product_id)])
                except ValueError:
                    rankings.append(0)
            ndcg_count += dcg(rankings) / max_ndcg
    print('{} customers tested'.format(tested))
    print('hits: {} / {}'.format(hits, recommended))
    precision = hits / recommended
    print('{:.3%}'.format(precision))
    if ndcg:
        print('average nDCG {:.3%}'.format(ndcg_count / tested))
    print()
```

In [68]:

```
assert(0), 'End of definition, only runs follow further'
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-68-8a07de0ced1b> in <module>()
----> 1 assert(0), 'End of definition, only runs follow further'

AssertionError: End of definition, only runs follow further
```

test last vs. random

In [74]:

```
last_train, last_test = split_df(test='last')
randomState = np.random.RandomState(seed=42)
random_train, random_test = split_df(test='random')
print('Overlap {:.3%}'.format(2 * len(last_test.index.intersection(random_test.index)) / (len(last_
test.index) + len(random_test.index))))
```

```
Overlap 57.720%
```

In [75]:

```
recommend(last_train, last_test, k_most_viewed=1, strategy='skip')
```

```
k = 1
include 1 most viewed
1938 customers tested
hits: 465 / 1938
23.994%
```

In [76]:

```
recommend(random_train, random_test, k_most_viewed=1, strategy='skip')
```

```
k = 1
include 1 most viewed
1838 customers tested
hits: 448 / 1838
24.374%
```

Roughly same so we continue with last as test set, so training set size is maximized.

Experiments

Best sellers

We talk about **global** best sellers, not only products seen by customer

In [77]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, strategy='best_seller') # this one is not personalized
```

```
k = 1
5175 customers tested
hits: 140 / 5175
2.705%

k = 3
2006 customers tested
hits: 649 / 6018
10.784%

k = 5
721 customers tested
hits: 508 / 3605
14.092%

k = 10
```

```
135 customers tested
hits: 238 / 1350
17.630%
```

In [78]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, strategy='best_seller_by_gender')
```

```
k = 1
5175 customers tested
hits: 51 / 5175
0.986%

k = 3
2006 customers tested
hits: 157 / 6018
2.609%

k = 5
721 customers tested
hits: 125 / 3605
3.467%

k = 10
135 customers tested
hits: 69 / 1350
5.111%
```

In [79]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, strategy='best_seller_by_brand')
```

```
k = 1
5175 customers tested
hits: 120 / 5175
2.319%

k = 3
2006 customers tested
hits: 174 / 6018
2.891%

k = 5
721 customers tested
hits: 117 / 3605
3.245%

k = 10
135 customers tested
hits: 55 / 1350
4.074%
```

Most viewed

We talk about the most viewed **by customer**, not from the whole catalog

In [80]:

```
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed, strategy='worst_scenario')
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%

k = 3
include 1 most viewed
2006 customers tested
hits: 352 / 6018
5.849%

k = 3
include 3 most viewed
2006 customers tested
hits: 657 / 6018
10.917%

k = 5
include 1 most viewed
721 customers tested
hits: 168 / 3605
4.660%

k = 5
include 3 most viewed
721 customers tested
hits: 345 / 3605
9.570%

k = 5
include 5 most viewed
721 customers tested
hits: 425 / 3605
11.789%

k = 10
include 1 most viewed
135 customers tested
hits: 65 / 1350
4.815%

k = 10
include 3 most viewed
135 customers tested
hits: 105 / 1350
7.778%

k = 10
include 5 most viewed
135 customers tested
hits: 154 / 1350
11.407%

k = 10
include 10 most viewed
135 customers tested
hits: 190 / 1350
14.074%
```

Most viewed + Best sellers

In [81]:

```
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed, strategy='best_seller')
```

```
k = 1
include 1 most viewed
```

```
include 1 most viewed
5175 customers tested
hits: 551 / 5175
10.647%

k = 3
include 1 most viewed
2006 customers tested
hits: 890 / 6018
14.789%

k = 3
include 3 most viewed
2006 customers tested
hits: 1079 / 6018
17.930%

k = 5
include 1 most viewed
721 customers tested
hits: 608 / 3605
16.865%

k = 5
include 3 most viewed
721 customers tested
hits: 711 / 3605
19.723%

k = 5
include 5 most viewed
721 customers tested
hits: 761 / 3605
21.110%

k = 10
include 1 most viewed
135 customers tested
hits: 269 / 1350
19.926%

k = 10
include 3 most viewed
135 customers tested
hits: 297 / 1350
22.000%

k = 10
include 5 most viewed
135 customers tested
hits: 331 / 1350
24.519%

k = 10
include 10 most viewed
135 customers tested
hits: 349 / 1350
25.852%
```

In [82]:

```python
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed,
strategy='best_seller_by_gender')
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%

k = 3
```

```
include 1 most viewed
```

```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:5:
UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  """
```

```
2006 customers tested
hits: 441 / 6018
7.328%

k = 3
include 3 most viewed
2006 customers tested
hits: 679 / 6018
11.283%

k = 5
include 1 most viewed
721 customers tested
hits: 255 / 3605
7.074%

k = 5
include 3 most viewed
721 customers tested
hits: 391 / 3605
10.846%

k = 5
include 5 most viewed
721 customers tested
hits: 454 / 3605
12.594%

k = 10
include 1 most viewed
135 customers tested
hits: 116 / 1350
8.593%

k = 10
include 3 most viewed
135 customers tested
hits: 155 / 1350
11.481%

k = 10
include 5 most viewed
135 customers tested
hits: 199 / 1350
14.741%

k = 10
include 10 most viewed
135 customers tested
hits: 224 / 1350
16.593%
```

In [83]:

```
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed,
strategy='best_seller_by_brand')
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%
```

```
k = 3
include 1 most viewed
```

```
c:\users\pc\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:5: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  """
```

```
2006 customers tested
hits: 437 / 6018
7.262%

k = 3
include 3 most viewed
2006 customers tested
hits: 682 / 6018
11.333%

k = 5
include 1 most viewed
721 customers tested
hits: 237 / 3605
6.574%

k = 5
include 3 most viewed
721 customers tested
hits: 380 / 3605
10.541%

k = 5
include 5 most viewed
721 customers tested
hits: 442 / 3605
12.261%

k = 10
include 1 most viewed
135 customers tested
hits: 95 / 1350
7.037%

k = 10
include 3 most viewed
135 customers tested
hits: 133 / 1350
9.852%

k = 10
include 5 most viewed
135 customers tested
hits: 176 / 1350
13.037%

k = 10
include 10 most viewed
135 customers tested
hits: 202 / 1350
14.963%
```

Elastic: match, combinations, search by most viewed

Brute force index properties exploration follows. Sort either by _score or purchase count

In [84]:

```
INDEX_ATTRS = ['brand', 'gender', 'name', 'features', 'desc']
```

In [85]:

```
for col in INDEX_ATTRS:
```

```
    print('\t', col)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col])
```

```
	 brand
k = 1
5175 customers tested
hits: 12 / 5175
0.232%

k = 3
2006 customers tested
hits: 12 / 6018
0.199%

k = 5
721 customers tested
hits: 9 / 3605
0.250%

k = 10
135 customers tested
hits: 10 / 1350
0.741%

	 gender
k = 1
5175 customers tested
hits: 0 / 5175
0.000%

k = 3
2006 customers tested
hits: 0 / 6018
0.000%

k = 5
721 customers tested
hits: 0 / 3605
0.000%

k = 10
135 customers tested
hits: 0 / 1350
0.000%

	 name
k = 1
5175 customers tested
hits: 180 / 5175
3.478%

k = 3
2006 customers tested
hits: 226 / 6018
3.755%

k = 5
721 customers tested
hits: 116 / 3605
3.218%

k = 10
135 customers tested
hits: 52 / 1350
3.852%

	 features
k = 1
5175 customers tested
hits: 178 / 5175
3.440%

k = 3
2006 customers tested
hits: 184 / 6018
```

```
hits: 184 / 6018
3.057%

k = 5
721 customers tested
hits: 82 / 3605
2.275%

k = 10
135 customers tested
hits: 29 / 1350
2.148%

	desc
k = 1
5175 customers tested
hits: 336 / 5175
6.493%

k = 3
2006 customers tested
hits: 361 / 6018
5.999%

k = 5
721 customers tested
hits: 182 / 3605
5.049%

k = 10
135 customers tested
hits: 73 / 1350
5.407%
```

In [86]:

```
for col in INDEX_ATTRS:
    print('\t', col)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col], sort_by_purchase=True)
```

```
	brand
k = 1
5175 customers tested
hits: 173 / 5175
3.343%

k = 3
2006 customers tested
hits: 326 / 6018
5.417%

k = 5
721 customers tested
hits: 213 / 3605
5.908%

k = 10
135 customers tested
hits: 104 / 1350
7.704%

	gender
k = 1
5175 customers tested
hits: 78 / 5175
1.507%

k = 3
2006 customers tested
hits: 251 / 6018
4.171%

k = 5
```

```
721 customers tested
hits: 192 / 3605
5.326%

k = 10
135 customers tested
hits: 105 / 1350
7.778%

  name
k = 1
5175 customers tested
hits: 60 / 5175
1.159%

k = 3
2006 customers tested
hits: 251 / 6018
4.171%

k = 5
721 customers tested
hits: 217 / 3605
6.019%

k = 10
135 customers tested
hits: 84 / 1350
6.222%

  features
k = 1
5175 customers tested
hits: 66 / 5175
1.275%

k = 3
2006 customers tested
hits: 217 / 6018
3.606%

k = 5
721 customers tested
hits: 181 / 3605
5.021%

k = 10
135 customers tested
hits: 94 / 1350
6.963%

  desc
k = 1
5175 customers tested
hits: 90 / 5175
1.739%

k = 3
2006 customers tested
hits: 233 / 6018
3.872%

k = 5
721 customers tested
hits: 193 / 3605
5.354%

k = 10
135 customers tested
hits: 77 / 1350
5.704%
```

In [87]:

```
for col, col2 in itertools.combinations(INDEX_ATTRS, 2):
```

```python
    print('\t', col, '\t', col2)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col, col2])
```

```
	brand	gender
k = 1
5175 customers tested
hits: 14 / 5175
0.271%

k = 3
2006 customers tested
hits: 41 / 6018
0.681%

k = 5
721 customers tested
hits: 17 / 3605
0.472%

k = 10
135 customers tested
hits: 20 / 1350
1.481%

	brand	name
k = 1
5175 customers tested
hits: 187 / 5175
3.614%

k = 3
2006 customers tested
hits: 236 / 6018
3.922%

k = 5
721 customers tested
hits: 119 / 3605
3.301%

k = 10
135 customers tested
hits: 57 / 1350
4.222%

	brand	features
k = 1
5175 customers tested
hits: 183 / 5175
3.536%

k = 3
2006 customers tested
hits: 191 / 6018
3.174%

k = 5
721 customers tested
hits: 90 / 3605
2.497%

k = 10
135 customers tested
hits: 33 / 1350
2.444%

	brand	desc
k = 1
5175 customers tested
hits: 354 / 5175
6.841%

k = 3
2006 customers tested
```

```
hits: 380 / 6018
6.314%

k = 5
721 customers tested
hits: 192 / 3605
5.326%

k = 10
135 customers tested
hits: 76 / 1350
5.630%

  gender   name
k = 1
5175 customers tested
hits: 205 / 5175
3.961%

k = 3
2006 customers tested
hits: 206 / 6018
3.423%

k = 5
721 customers tested
hits: 109 / 3605
3.024%

k = 10
135 customers tested
hits: 51 / 1350
3.778%

  gender   features
k = 1
5175 customers tested
hits: 206 / 5175
3.981%

k = 3
2006 customers tested
hits: 170 / 6018
2.825%

k = 5
721 customers tested
hits: 69 / 3605
1.914%

k = 10
135 customers tested
hits: 26 / 1350
1.926%

  gender   desc
k = 1
5175 customers tested
hits: 363 / 5175
7.014%

k = 3
2006 customers tested
hits: 342 / 6018
5.683%

k = 5
721 customers tested
hits: 171 / 3605
4.743%

k = 10
135 customers tested
hits: 71 / 1350
5.259%

  name   features
```

```
k = 1
5175 customers tested
hits: 201 / 5175
3.884%

k = 3
2006 customers tested
hits: 229 / 6018
3.805%

k = 5
721 customers tested
hits: 116 / 3605
3.218%

k = 10
135 customers tested
hits: 51 / 1350
3.778%

	name	desc
k = 1
5175 customers tested
hits: 336 / 5175
6.493%

k = 3
2006 customers tested
hits: 361 / 6018
5.999%

k = 5
721 customers tested
hits: 183 / 3605
5.076%

k = 10
135 customers tested
hits: 67 / 1350
4.963%

	features	desc
k = 1
5175 customers tested
hits: 337 / 5175
6.512%

k = 3
2006 customers tested
hits: 360 / 6018
5.982%

k = 5
721 customers tested
hits: 183 / 3605
5.076%

k = 10
135 customers tested
hits: 68 / 1350
5.037%
```

In [88]:

```
for col, col2 in itertools.combinations(INDEX_ATTRS, 2):
    print('\t', col, '\t', col2)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col, col2], sort_by_purchase=True)
```

```
	brand	gender
k = 1
5175 customers tested
hits: 213 / 5175
```

```
4.116%

k = 3
2006 customers tested
hits: 333 / 6018
5.533%

k = 5
721 customers tested
hits: 200 / 3605
5.548%

k = 10
135 customers tested
hits: 107 / 1350
7.926%

  brand   name
k = 1
5175 customers tested
hits: 191 / 5175
3.691%

k = 3
2006 customers tested
hits: 335 / 6018
5.567%

k = 5
721 customers tested
hits: 222 / 3605
6.158%

k = 10
135 customers tested
hits: 97 / 1350
7.185%

  brand   features
k = 1
5175 customers tested
hits: 206 / 5175
3.981%

k = 3
2006 customers tested
hits: 320 / 6018
5.317%

k = 5
721 customers tested
hits: 220 / 3605
6.103%

k = 10
135 customers tested
hits: 104 / 1350
7.704%

  brand   desc
k = 1
5175 customers tested
hits: 218 / 5175
4.213%

k = 3
2006 customers tested
hits: 334 / 6018
5.550%

k = 5
721 customers tested
hits: 208 / 3605
5.770%

k = 10
135 customers tested
```

```
hits: 90 / 1350
6.667%

  gender   name
k = 1
5175 customers tested
hits: 89 / 5175
1.720%

k = 3
2006 customers tested
hits: 252 / 6018
4.187%

k = 5
721 customers tested
hits: 187 / 3605
5.187%

k = 10
135 customers tested
hits: 84 / 1350
6.222%

  gender   features
k = 1
5175 customers tested
hits: 90 / 5175
1.739%

k = 3
2006 customers tested
hits: 234 / 6018
3.888%

k = 5
721 customers tested
hits: 172 / 3605
4.771%

k = 10
135 customers tested
hits: 96 / 1350
7.111%

  gender   desc
k = 1
5175 customers tested
hits: 117 / 5175
2.261%

k = 3
2006 customers tested
hits: 246 / 6018
4.088%

k = 5
721 customers tested
hits: 169 / 3605
4.688%

k = 10
135 customers tested
hits: 87 / 1350
6.444%

  name   features
k = 1
5175 customers tested
hits: 83 / 5175
1.604%

k = 3
2006 customers tested
hits: 221 / 6018
3.672%
```

```
k = 5
721 customers tested
hits: 203 / 3605
5.631%

k = 10
135 customers tested
hits: 89 / 1350
6.593%

  name   desc
k = 1
5175 customers tested
hits: 99 / 5175
1.913%

k = 3
2006 customers tested
hits: 247 / 6018
4.104%

k = 5
721 customers tested
hits: 189 / 3605
5.243%

k = 10
135 customers tested
hits: 79 / 1350
5.852%

  features   desc
k = 1
5175 customers tested
hits: 92 / 5175
1.778%

k = 3
2006 customers tested
hits: 239 / 6018
3.971%

k = 5
721 customers tested
hits: 196 / 3605
5.437%

k = 10
135 customers tested
hits: 87 / 1350
6.444%
```

In [89]:

```
for cols in itertools.combinations(INDEX_ATTRS, 3):
    print('\t', cols)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=list(cols))
```

```
  ('brand', 'gender', 'name')
k = 1
5175 customers tested
hits: 211 / 5175
4.077%

k = 3
2006 customers tested
hits: 230 / 6018
3.822%

k = 5
721 customers tested
hits: 118 / 3605
```

```
3.273%

k = 10
135 customers tested
hits: 60 / 1350
4.444%

  ('brand', 'gender', 'features')
k = 1
5175 customers tested
hits: 211 / 5175
4.077%

k = 3
2006 customers tested
hits: 192 / 6018
3.190%

k = 5
721 customers tested
hits: 83 / 3605
2.302%

k = 10
135 customers tested
hits: 34 / 1350
2.519%

  ('brand', 'gender', 'desc')
k = 1
5175 customers tested
hits: 382 / 5175
7.382%

k = 3
2006 customers tested
hits: 362 / 6018
6.015%

k = 5
721 customers tested
hits: 180 / 3605
4.993%

k = 10
135 customers tested
hits: 73 / 1350
5.407%

  ('brand', 'name', 'features')
k = 1
5175 customers tested
hits: 204 / 5175
3.942%

k = 3
2006 customers tested
hits: 238 / 6018
3.955%

k = 5
721 customers tested
hits: 118 / 3605
3.273%

k = 10
135 customers tested
hits: 55 / 1350
4.074%

  ('brand', 'name', 'desc')
k = 1
5175 customers tested
hits: 349 / 5175
6.744%

k = 3
2006 customers tested
```

```
2006 customers tested
hits: 380 / 6018
6.314%

k = 5
721 customers tested
hits: 192 / 3605
5.326%

k = 10
135 customers tested
hits: 71 / 1350
5.259%

  ('brand', 'features', 'desc')
k = 1
5175 customers tested
hits: 355 / 5175
6.860%

k = 3
2006 customers tested
hits: 380 / 6018
6.314%

k = 5
721 customers tested
hits: 194 / 3605
5.381%

k = 10
135 customers tested
hits: 70 / 1350
5.185%

  ('gender', 'name', 'features')
k = 1
5175 customers tested
hits: 229 / 5175
4.425%

k = 3
2006 customers tested
hits: 211 / 6018
3.506%

k = 5
721 customers tested
hits: 101 / 3605
2.802%

k = 10
135 customers tested
hits: 48 / 1350
3.556%

  ('gender', 'name', 'desc')
k = 1
5175 customers tested
hits: 360 / 5175
6.957%

k = 3
2006 customers tested
hits: 342 / 6018
5.683%

k = 5
721 customers tested
hits: 168 / 3605
4.660%

k = 10
135 customers tested
hits: 71 / 1350
5.259%
```

```
  ('gender', 'features', 'desc')
k = 1
5175 customers tested
hits: 367 / 5175
7.092%

k = 3
2006 customers tested
hits: 341 / 6018
5.666%

k = 5
721 customers tested
hits: 168 / 3605
4.660%

k = 10
135 customers tested
hits: 65 / 1350
4.815%

  ('name', 'features', 'desc')
k = 1
5175 customers tested
hits: 336 / 5175
6.493%

k = 3
2006 customers tested
hits: 362 / 6018
6.015%

k = 5
721 customers tested
hits: 185 / 3605
5.132%

k = 10
135 customers tested
hits: 68 / 1350
5.037%
```

In [90]:

```
for cols in itertools.combinations(INDEX_ATTRS, 3):
    print('\t', cols)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=list(cols), sort_by_purchase=True)
```

```
  ('brand', 'gender', 'name')
k = 1
5175 customers tested
hits: 229 / 5175
4.425%

k = 3
2006 customers tested
hits: 337 / 6018
5.600%

k = 5
721 customers tested
hits: 198 / 3605
5.492%

k = 10
135 customers tested
hits: 101 / 1350
7.481%

  ('brand', 'gender', 'features')
k = 1
5175 customers tested
hits: 244 / 5175
```

```
4.715%

k = 3
2006 customers tested
hits: 336 / 6018
5.583%

k = 5
721 customers tested
hits: 198 / 3605
5.492%

k = 10
135 customers tested
hits: 105 / 1350
7.778%

  ('brand', 'gender', 'desc')
k = 1
5175 customers tested
hits: 256 / 5175
4.947%

k = 3
2006 customers tested
hits: 345 / 6018
5.733%

k = 5
721 customers tested
hits: 191 / 3605
5.298%

k = 10
135 customers tested
hits: 98 / 1350
7.259%

  ('brand', 'name', 'features')
k = 1
5175 customers tested
hits: 214 / 5175
4.135%

k = 3
2006 customers tested
hits: 327 / 6018
5.434%

k = 5
721 customers tested
hits: 216 / 3605
5.992%

k = 10
135 customers tested
hits: 96 / 1350
7.111%

  ('brand', 'name', 'desc')
k = 1
5175 customers tested
hits: 222 / 5175
4.290%

k = 3
2006 customers tested
hits: 336 / 6018
5.583%

k = 5
721 customers tested
hits: 207 / 3605
5.742%

k = 10
135 customers tested
```

```
135 customers tested
hits: 90 / 1350
6.667%

  ('brand', 'features', 'desc')
k = 1
5175 customers tested
hits: 226 / 5175
4.367%

k = 3
2006 customers tested
hits: 341 / 6018
5.666%

k = 5
721 customers tested
hits: 209 / 3605
5.798%

k = 10
135 customers tested
hits: 92 / 1350
6.815%

  ('gender', 'name', 'features')
k = 1
5175 customers tested
hits: 114 / 5175
2.203%

k = 3
2006 customers tested
hits: 240 / 6018
3.988%

k = 5
721 customers tested
hits: 171 / 3605
4.743%

k = 10
135 customers tested
hits: 86 / 1350
6.370%

  ('gender', 'name', 'desc')
k = 1
5175 customers tested
hits: 132 / 5175
2.551%

k = 3
2006 customers tested
hits: 260 / 6018
4.320%

k = 5
721 customers tested
hits: 167 / 3605
4.632%

k = 10
135 customers tested
hits: 83 / 1350
6.148%

  ('gender', 'features', 'desc')
k = 1
5175 customers tested
hits: 125 / 5175
2.415%

k = 3
2006 customers tested
hits: 258 / 6018
4.287%
```

```
k = 5
721 customers tested
hits: 178 / 3605
4.938%

k = 10
135 customers tested
hits: 94 / 1350
6.963%

	 ('name', 'features', 'desc')
k = 1
5175 customers tested
hits: 104 / 5175
2.010%

k = 3
2006 customers tested
hits: 243 / 6018
4.038%

k = 5
721 customers tested
hits: 199 / 3605
5.520%

k = 10
135 customers tested
hits: 89 / 1350
6.593%
```

In [91]:

```
for cols in itertools.combinations(INDEX_ATTRS, 4):
    print('\t', cols)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=list(cols))
```

```
	 ('brand', 'gender', 'name', 'features')
k = 1
5175 customers tested
hits: 233 / 5175
4.502%

k = 3
2006 customers tested
hits: 235 / 6018
3.905%

k = 5
721 customers tested
hits: 110 / 3605
3.051%

k = 10
135 customers tested
hits: 57 / 1350
4.222%

	 ('brand', 'gender', 'name', 'desc')
k = 1
5175 customers tested
hits: 379 / 5175
7.324%

k = 3
2006 customers tested
hits: 361 / 6018
5.999%

k = 5
721 customers tested
hits: 177 / 3605
```

```
4.910%

k = 10
135 customers tested
hits: 74 / 1350
5.481%

	('brand', 'gender', 'features', 'desc')
k = 1
5175 customers tested
hits: 386 / 5175
7.459%

k = 3
2006 customers tested
hits: 362 / 6018
6.015%

k = 5
721 customers tested
hits: 177 / 3605
4.910%

k = 10
135 customers tested
hits: 67 / 1350
4.963%

	('brand', 'name', 'features', 'desc')
k = 1
5175 customers tested
hits: 354 / 5175
6.841%

k = 3
2006 customers tested
hits: 381 / 6018
6.331%

k = 5
721 customers tested
hits: 194 / 3605
5.381%

k = 10
135 customers tested
hits: 71 / 1350
5.259%

	('gender', 'name', 'features', 'desc')
k = 1
5175 customers tested
hits: 366 / 5175
7.072%

k = 3
2006 customers tested
hits: 342 / 6018
5.683%

k = 5
721 customers tested
hits: 168 / 3605
4.660%

k = 10
135 customers tested
hits: 65 / 1350
4.815%
```

In [92]:

```
for cols in itertools.combinations(INDEX_ATTRS, 4):
    print('\t', cols)
    for k in ks:
```

```
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=list(cols), sort_by_purchase=True)
```

```
  ('brand', 'gender', 'name', 'features')
k = 1
5175 customers tested
hits: 253 / 5175
4.889%

k = 3
2006 customers tested
hits: 334 / 6018
5.550%

k = 5
721 customers tested
hits: 192 / 3605
5.326%

k = 10
135 customers tested
hits: 97 / 1350
7.185%

  ('brand', 'gender', 'name', 'desc')
k = 1
5175 customers tested
hits: 262 / 5175
5.063%

k = 3
2006 customers tested
hits: 346 / 6018
5.749%

k = 5
721 customers tested
hits: 190 / 3605
5.270%

k = 10
135 customers tested
hits: 98 / 1350
7.259%

  ('brand', 'gender', 'features', 'desc')
k = 1
5175 customers tested
hits: 262 / 5175
5.063%

k = 3
2006 customers tested
hits: 345 / 6018
5.733%

k = 5
721 customers tested
hits: 195 / 3605
5.409%

k = 10
135 customers tested
hits: 93 / 1350
6.889%

  ('brand', 'name', 'features', 'desc')
k = 1
5175 customers tested
hits: 230 / 5175
4.444%

k = 3
2006 customers tested
hits: 342 / 6018
5.683%
```

```
k = 5
721 customers tested
hits: 209 / 3605
5.798%

k = 10
135 customers tested
hits: 92 / 1350
6.815%

  ('gender', 'name', 'features', 'desc')
k = 1
5175 customers tested
hits: 137 / 5175
2.647%

k = 3
2006 customers tested
hits: 262 / 6018
4.354%

k = 5
721 customers tested
hits: 172 / 3605
4.771%

k = 10
135 customers tested
hits: 90 / 1350
6.667%
```

In [93]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=INDEX_ATTRS)
```

```
k = 1
5175 customers tested
hits: 385 / 5175
7.440%

k = 3
2006 customers tested
hits: 362 / 6018
6.015%

k = 5
721 customers tested
hits: 177 / 3605
4.910%

k = 10
135 customers tested
hits: 68 / 1350
5.037%
```

In [94]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=INDEX_ATTRS, sort_by_purchase=True)
```

```
k = 1
5175 customers tested
hits: 267 / 5175
5.159%

k = 3
2006 customers tested
hits: 346 / 6018
```

```
5.749%

k = 5
721 customers tested
hits: 195 / 3605
5.409%

k = 10
135 customers tested
hits: 93 / 1350
6.889%
```

Elastic: match, combinations, search by ideal product

In [95]:

```
IDEAL_ATTRS = [a for a in INDEX_ATTRS if a not in ['name', 'desc']]
IDEAL_ATTRS
```

Out[95]:

```
['brand', 'gender', 'features']
```

In [96]:

```
for col in IDEAL_ATTRS:
    print('\t', col)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col], strategy='elastic_combined')
```

```
	 brand
k = 1
5175 customers tested
hits: 4 / 5175
0.077%

k = 3
2006 customers tested
hits: 4 / 6018
0.066%

k = 5
721 customers tested
hits: 1 / 3605
0.028%

k = 10
135 customers tested
hits: 0 / 1350
0.000%

	 gender
k = 1
5175 customers tested
hits: 0 / 5175
0.000%

k = 3
2006 customers tested
hits: 0 / 6018
0.000%

k = 5
721 customers tested
hits: 1 / 3605
0.028%

k = 10
135 customers tested
hits: 1 / 1350
```

```
0.074%

  features
k = 1
5175 customers tested
hits: 167 / 5175
3.227%

k = 3
2006 customers tested
hits: 257 / 6018
4.271%

k = 5
721 customers tested
hits: 149 / 3605
4.133%

k = 10
135 customers tested
hits: 41 / 1350
3.037%
```

In [97]:

```
for col in IDEAL_ATTRS:
    print('\t', col)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col], sort_by_purchase=True, strategy='elastic_combined'
)
```

```
  brand
k = 1
5175 customers tested
hits: 121 / 5175
2.338%

k = 3
2006 customers tested
hits: 179 / 6018
2.974%

k = 5
721 customers tested
hits: 115 / 3605
3.190%

k = 10
135 customers tested
hits: 54 / 1350
4.000%

  gender
k = 1
5175 customers tested
hits: 51 / 5175
0.986%

k = 3
2006 customers tested
hits: 157 / 6018
2.609%

k = 5
721 customers tested
hits: 125 / 3605
3.467%

k = 10
135 customers tested
hits: 69 / 1350
5.111%
```

```
  features
k = 1
5175 customers tested
hits: 63 / 5175
1.217%

k = 3
2006 customers tested
hits: 196 / 6018
3.257%

k = 5
721 customers tested
hits: 149 / 3605
4.133%

k = 10
135 customers tested
hits: 59 / 1350
4.370%
```

In [98]:

```
for col, col2 in itertools.combinations(INDEX_ATTRS, 2):
    print('\t', col, '\t', col2)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col, col2], strategy='elastic_combined')
```

```
  brand   gender
k = 1
5175 customers tested
hits: 5 / 5175
0.097%

k = 3
2006 customers tested
hits: 17 / 6018
0.282%

k = 5
721 customers tested
hits: 6 / 3605
0.166%

k = 10
135 customers tested
hits: 6 / 1350
0.444%

  brand   name
k = 1
5175 customers tested
hits: 91 / 5175
1.758%

k = 3
2006 customers tested
hits: 92 / 6018
1.529%

k = 5
721 customers tested
hits: 46 / 3605
1.276%

k = 10
135 customers tested
hits: 27 / 1350
2.000%

  brand   features
k = 1
5175 customers tested
hits: 96 / 5175
```

```
1.855%

k = 3
2006 customers tested
hits: 92 / 6018
1.529%

k = 5
721 customers tested
hits: 49 / 3605
1.359%

k = 10
135 customers tested
hits: 9 / 1350
0.667%

  brand   desc
k = 1
5175 customers tested
hits: 195 / 5175
3.768%

k = 3
2006 customers tested
hits: 167 / 6018
2.775%

k = 5
721 customers tested
hits: 71 / 3605
1.969%

k = 10
135 customers tested
hits: 24 / 1350
1.778%

  gender   name
k = 1
5175 customers tested
hits: 142 / 5175
2.744%

k = 3
2006 customers tested
hits: 118 / 6018
1.961%

k = 5
721 customers tested
hits: 63 / 3605
1.748%

k = 10
135 customers tested
hits: 29 / 1350
2.148%

  gender   features
k = 1
5175 customers tested
hits: 146 / 5175
2.821%

k = 3
2006 customers tested
hits: 168 / 6018
2.792%

k = 5
721 customers tested
hits: 90 / 3605
2.497%

k = 10
135 customers tested
```

```
hits: 22 / 1350
1.630%

  gender   desc
k = 1
5175 customers tested
hits: 240 / 5175
4.638%

k = 3
2006 customers tested
hits: 197 / 6018
3.274%

k = 5
721 customers tested
hits: 84 / 3605
2.330%

k = 10
135 customers tested
hits: 29 / 1350
2.148%

  name   features
k = 1
5175 customers tested
hits: 189 / 5175
3.652%

k = 3
2006 customers tested
hits: 267 / 6018
4.437%

k = 5
721 customers tested
hits: 149 / 3605
4.133%

k = 10
135 customers tested
hits: 50 / 1350
3.704%

  name   desc
k = 1
5175 customers tested
hits: 336 / 5175
6.493%

k = 3
2006 customers tested
hits: 361 / 6018
5.999%

k = 5
721 customers tested
hits: 183 / 3605
5.076%

k = 10
135 customers tested
hits: 67 / 1350
4.963%

  features   desc
k = 1
5175 customers tested
hits: 265 / 5175
5.121%

k = 3
2006 customers tested
hits: 322 / 6018
5.351%
```

```
k = 5
721 customers tested
hits: 158 / 3605
4.383%

k = 10
135 customers tested
hits: 51 / 1350
3.778%
```

In [99]:

```
for col, col2 in itertools.combinations(INDEX_ATTRS, 2):
    print('\t', col, '\t', col2)
    for k in ks:
        train, test = split_df(test_n=k)
        recommend(train, test, k=k, match=[col, col2], sort_by_purchase=True,
strategy='elastic_combined')
```

```
	 brand 	 gender
k = 1
5175 customers tested
hits: 110 / 5175
2.126%

k = 3
2006 customers tested
hits: 125 / 6018
2.077%

k = 5
721 customers tested
hits: 63 / 3605
1.748%

k = 10
135 customers tested
hits: 21 / 1350
1.556%

	 brand 	 name
k = 1
5175 customers tested
hits: 125 / 5175
2.415%

k = 3
2006 customers tested
hits: 173 / 6018
2.875%

k = 5
721 customers tested
hits: 105 / 3605
2.913%

k = 10
135 customers tested
hits: 43 / 1350
3.185%

	 brand 	 features
k = 1
5175 customers tested
hits: 121 / 5175
2.338%

k = 3
2006 customers tested
hits: 136 / 6018
2.260%

k = 5
721 customers tested
```

```
hits: 74 / 3605
2.053%

k = 10
135 customers tested
hits: 25 / 1350
1.852%

  brand   desc
k = 1
5175 customers tested
hits: 135 / 5175
2.609%

k = 3
2006 customers tested
hits: 174 / 6018
2.891%

k = 5
721 customers tested
hits: 100 / 3605
2.774%

k = 10
135 customers tested
hits: 42 / 1350
3.111%

  gender   name
k = 1
5175 customers tested
hits: 56 / 5175
1.082%

k = 3
2006 customers tested
hits: 139 / 6018
2.310%

k = 5
721 customers tested
hits: 109 / 3605
3.024%

k = 10
135 customers tested
hits: 42 / 1350
3.111%

  gender   features
k = 1
5175 customers tested
hits: 75 / 5175
1.449%

k = 3
2006 customers tested
hits: 162 / 6018
2.692%

k = 5
721 customers tested
hits: 117 / 3605
3.245%

k = 10
135 customers tested
hits: 53 / 1350
3.926%

  gender   desc
k = 1
5175 customers tested
hits: 81 / 5175
1.565%
```

```
k = 3
2006 customers tested
hits: 152 / 6018
2.526%

k = 5
721 customers tested
hits: 104 / 3605
2.885%

k = 10
135 customers tested
hits: 44 / 1350
3.259%

  name   features
k = 1
5175 customers tested
hits: 79 / 5175
1.527%

k = 3
2006 customers tested
hits: 192 / 6018
3.190%

k = 5
721 customers tested
hits: 153 / 3605
4.244%

k = 10
135 customers tested
hits: 59 / 1350
4.370%

  name   desc
k = 1
5175 customers tested
hits: 99 / 5175
1.913%

k = 3
2006 customers tested
hits: 247 / 6018
4.104%

k = 5
721 customers tested
hits: 189 / 3605
5.243%

k = 10
135 customers tested
hits: 79 / 1350
5.852%

  features   desc
k = 1
5175 customers tested
hits: 85 / 5175
1.643%

k = 3
2006 customers tested
hits: 202 / 6018
3.357%

k = 5
721 customers tested
hits: 143 / 3605
3.967%

k = 10
135 customers tested
hits: 58 / 1350
4.296%
```

This approach is blind path.

Elastic: cross fields

In [100]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, fields_like=['features'], fields_in=['features']) # this is differe
nt from match features
```

```
k = 1
5175 customers tested
hits: 178 / 5175
3.440%

k = 3
2006 customers tested
hits: 184 / 6018
3.057%

k = 5
721 customers tested
hits: 82 / 3605
2.275%

k = 10
135 customers tested
hits: 29 / 1350
2.148%
```

In [101]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, fields_like=['features'], fields_in=['name'])
```

```
k = 1
5175 customers tested
hits: 17 / 5175
0.329%

k = 3
2006 customers tested
hits: 39 / 6018
0.648%

k = 5
721 customers tested
hits: 19 / 3605
0.527%

k = 10
135 customers tested
hits: 4 / 1350
0.296%
```

In [102]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, fields_like=['features'], fields_in=['desc'])
```

```
k = 1
5175 customers tested
hits: 163 / 5175
```

```
hits: 163 / 5175
3.150%

k = 3
2006 customers tested
hits: 177 / 6018
2.941%

k = 5
721 customers tested
hits: 88 / 3605
2.441%

k = 10
135 customers tested
hits: 35 / 1350
2.593%
```

In [103]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, fields_like=['name'], fields_in=['desc'])
```

```
k = 1
5175 customers tested
hits: 144 / 5175
2.783%

k = 3
2006 customers tested
hits: 209 / 6018
3.473%

k = 5
721 customers tested
hits: 112 / 3605
3.107%

k = 10
135 customers tested
hits: 55 / 1350
4.074%
```

In [104]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=['desc'], fields_like=['gender'], fields_in=['gender','desc']
)
```

```
k = 1
5175 customers tested
hits: 363 / 5175
7.014%

k = 3
2006 customers tested
hits: 342 / 6018
5.683%

k = 5
721 customers tested
hits: 171 / 3605
4.743%

k = 10
135 customers tested
hits: 71 / 1350
5.259%
```

In [105]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=['desc'], fields_like=['gender','brand'], fields_in=['gender'
,'brand','desc'])
```

```
k = 1
5175 customers tested
hits: 374 / 5175
7.227%

k = 3
2006 customers tested
hits: 378 / 6018
6.281%

k = 5
721 customers tested
hits: 193 / 3605
5.354%

k = 10
135 customers tested
hits: 76 / 1350
5.630%
```

In [106]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=['features','desc'],
                   fields_like=['gender','brand'], fields_in=['gender','brand','desc'])
```

```
k = 1
5175 customers tested
hits: 377 / 5175
7.285%

k = 3
2006 customers tested
hits: 379 / 6018
6.298%

k = 5
721 customers tested
hits: 194 / 3605
5.381%

k = 10
135 customers tested
hits: 70 / 1350
5.185%
```

In [107]:

```
for k in ks:
    train, test = split_df(test_n=k)
    recommend(train, test, k=k, match=['desc'],
                   fields_like=['gender','brand','features'], fields_in=['gender','brand','desc'])
```

```
k = 1
5175 customers tested
hits: 374 / 5175
7.227%

k = 3
2006 customers tested
hits: 378 / 6018
6.281%
```

```
k = 5
721 customers tested
hits: 193 / 3605
5.354%

k = 10
135 customers tested
hits: 76 / 1350
5.630%
```

Most viewed + Elastic

In [108]:

```python
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed, match=['desc'])
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%

k = 3
include 1 most viewed
2006 customers tested
hits: 393 / 6018
6.530%

k = 3
include 3 most viewed
2006 customers tested
hits: 665 / 6018
11.050%

k = 5
include 1 most viewed
721 customers tested
hits: 192 / 3605
5.326%

k = 5
include 3 most viewed
721 customers tested
hits: 358 / 3605
9.931%

k = 5
include 5 most viewed
721 customers tested
hits: 430 / 3605
11.928%

k = 10
include 1 most viewed
135 customers tested
hits: 76 / 1350
5.630%

k = 10
include 3 most viewed
135 customers tested
hits: 116 / 1350
8.593%

k = 10
include 5 most viewed
135 customers tested
hits: 159 / 1350
```

```
11.778%

k = 10
include 10 most viewed
135 customers tested
hits: 190 / 1350
14.074%
```

In [109]:

```
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed, match=['brand', 'gender',
'desc'])
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%

k = 3
include 1 most viewed
2006 customers tested
hits: 373 / 6018
6.198%

k = 3
include 3 most viewed
2006 customers tested
hits: 659 / 6018
10.950%

k = 5
include 1 most viewed
721 customers tested
hits: 180 / 3605
4.993%

k = 5
include 3 most viewed
721 customers tested
hits: 351 / 3605
9.736%

k = 5
include 5 most viewed
721 customers tested
hits: 427 / 3605
11.845%

k = 10
include 1 most viewed
135 customers tested
hits: 74 / 1350
5.481%

k = 10
include 3 most viewed
135 customers tested
hits: 114 / 1350
8.444%

k = 10
include 5 most viewed
135 customers tested
hits: 157 / 1350
11.630%

k = 10
include 10 most viewed
135 customers tested
```

```
hits: 190 / 1350
14.074%
```

In [110]:

```
for k in ks:
    for k_most_viewed in ks:
        train, test = split_df(test_n=k)
        if k >= k_most_viewed:
            recommend(train, test, k=k, k_most_viewed=k_most_viewed, match=['desc'], fields_like=['
gender','brand'], fields_in=['gender','brand','desc'])
```

```
k = 1
include 1 most viewed
5175 customers tested
hits: 465 / 5175
8.986%

k = 3
include 1 most viewed
2006 customers tested
hits: 390 / 6018
6.481%

k = 3
include 3 most viewed
2006 customers tested
hits: 664 / 6018
11.034%

k = 5
include 1 most viewed
721 customers tested
hits: 193 / 3605
5.354%

k = 5
include 3 most viewed
721 customers tested
hits: 358 / 3605
9.931%

k = 5
include 5 most viewed
721 customers tested
hits: 430 / 3605
11.928%

k = 10
include 1 most viewed
135 customers tested
hits: 77 / 1350
5.704%

k = 10
include 3 most viewed
135 customers tested
hits: 116 / 1350
8.593%

k = 10
include 5 most viewed
135 customers tested
hits: 159 / 1350
11.778%

k = 10
include 10 most viewed
135 customers tested
hits: 190 / 1350
14.074%
```

nDCG

In [111]:

```
recommend(train, test, k=10, match=['desc'], ndcg=True)
```

```
k = 10
135 customers tested
hits: 73 / 1350
5.407%
average nDCG 3.512%
```

In [112]:

```
recommend(train, test, k=10, k_most_viewed=5, match=['desc'], ndcg=True)
```

```
k = 10
include 5 most viewed
135 customers tested
hits: 159 / 1350
11.778%
average nDCG 7.094%
```

In [113]:

```
recommend(train, test, k=10, match=['desc'], fields_like=['gender','brand'], fields_in=['gender','b
rand','desc'], ndcg=True)
```

```
k = 10
135 customers tested
hits: 76 / 1350
5.630%
average nDCG 3.812%
```

In [ ]:

```

```

In [ ]:

```

```

In [114]:

```
assert(0), 'You reached the end. Congratulation!!'
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-114-daad5706ad2b> in <module>()
----> 1 assert(0), 'You reached the end. Congratulation!!'

AssertionError: You reached the end. Congratulation!!
```

Challenge

Comments on challenge are in documentation, here only scripts archived.

In [71]:

```
K = 10
```

In [72]:

```
customer_ids = pd.read_csv('challenge/vi_challenge_uID.csv', dtype=int).iloc[:,0]
print(len(customer_ids))
print(customer_ids.nunique())
```

```
138
138
```

In [ ]:

```
with open('challenge/submit_es1.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
            ideal_product = saw_products_catalog[saw_products_catalog['product_id']==saw_products.i
ndex[0]].iloc[0].copy()
            rec_products += es_recommend([ideal_product], [K - len(rec_products)],
                                         match=['desc'],
                                         exclude=rec_products)[0]
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [77]:

```
with open('challenge/submit_es2.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        saw_products_catalog = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
        ideal_product = saw_products_catalog[saw_products_catalog['product_id']==saw_products.index
[0]].iloc[0].copy()
        rec_products = es_recommend([ideal_product], [K],
                                     match=['desc'],
                                     exclude=rec_products)[0]
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit2.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    rec_products = best_sellers(K)
    assert(len(rec_products) == K)
    assert(pd.Series(rec_products).nunique()==K)
    for customer_id in customer_ids:
```

```
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
K_limit = int(K/2)
with open('challenge/submit3.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K_limit].tolist()
        assert(len(rec_products) <= K/2)
        rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
K_limit = int(K/2)
with open('challenge/submit4.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K_limit].tolist()
        assert(len(rec_products) <= K/2)
        purchased_products = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
        rec_products += best_sellers(K - len(rec_products), filter_by='gender', filter_value=np.max
(purchased_products['gender']), exclude=rec_products)
        if len(rec_products) < k:
            rec_products += best_sellers(k - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
K_limit = int(K/2)
with open('challenge/submit5.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K_limit].tolist()
        assert(len(rec_products) <= K/2)
        purchased_products = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
        rec_products += best_sellers(K - len(rec_products), filter_by='brand', filter_value=np.max(
purchased_products['brand']), exclude=rec_products)
        if len(rec_products) < k:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit6.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        rec_products = df_catalog[df_catalog['product_id'].isin(rec_products)].sort_values('purchas
ed', ascending=False)['product_id'].tolist()
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
```

```
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit7.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        rec_products = df_catalog[df_catalog['product_id'].isin(rec_products)].sort_values('purchas
ed', ascending=False)['product_id'].tolist()
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit8.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            purchased_products = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
            rec_products += best_sellers(K - len(rec_products), filter_by='brand', filter_value=np.
max(purchased_products['brand']), exclude=rec_products)
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
with open('challenge/submit9.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = df_events[df_events['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            purchased_products = df_catalog[df_catalog['product_id'].isin(saw_products.index)]
            rec_products += best_sellers(K - len(rec_products), filter_by='gender', filter_value=np
.max(purchased_products['gender']), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
dfe = pd.read_csv('data/vi_dataset_events.csv')
with open('challenge/submit10.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = dfe[dfe['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += best_sellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
dfp = dfe[dfe['type']=='purchase_item']

def bsellers(n, filter_by=None, filter_value=None, exclude=[]):
    if filter_by is None:
        best_sellers = dfp[~dfp['product_id'].isin(exclude)].groupby('product_id').size().sort_valu
es(ascending=False)
    else:
        best_sellers = dfp[~dfp['product_id'].isin(exclude)][dfp[filter_by]==filter_value].groupby(
'product_id').size().sort_values(ascending=False)
    return best_sellers[:n].keys().tolist()

with open('challenge/submit11.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = dfe[dfe['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += bsellers(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
def mcommon(n, filter_by=None, filter_value=None, exclude=[]):
    if filter_by is None:
        mcommon = dfe[~dfe['product_id'].isin(exclude)].groupby('product_id').size().sort_values(as
cending=False)
    else:
        mcommon = dfe[~dfe['product_id'].isin(exclude)][dfe[filter_by]==filter_value].groupby('prod
uct_id').size().sort_values(ascending=False)
    return mcommon[:n].keys().tolist()

with open('challenge/submit12.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = dfe[dfe['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += mcommon(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
dfv = dfe[dfe['type']=='view_product']

def mviewed(n, filter_by=None, filter_value=None, exclude=[]):
    if filter_by is None:
        mviewed = dfv[~dfv['product_id'].isin(exclude)].groupby('product_id').size().sort_values(as
cending=False)
    else:
        mviewed = dfv[~dfv['product_id'].isin(exclude)][dfv[filter_by]==filter_value].groupby('prod
uct_id').size().sort_values(ascending=False)
    return mviewed[:n].keys().tolist()

with open('challenge/submit13.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = dfe[dfe['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += mviewed(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
```

```
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]:

```
dfc = dfe[dfe['type']=='add_to_cart']

def mcart(n, filter_by=None, filter_value=None, exclude=[]):
    if filter_by is None:
        mcart = dfc[~dfc['product_id'].isin(exclude)].groupby('product_id').size().sort_values(asce
nding=False)
    else:
        mcart = dfc[~dfc['product_id'].isin(exclude)][dfc[filter_by]==filter_value].groupby('produc
t_id').size().sort_values(ascending=False)
    return mcart[:n].keys().tolist()

with open('challenge/submit14.csv', 'wb') as f:
    f.write('customer_id,product_id\n'.encode('utf8'))
    for customer_id in customer_ids:
        saw_before = dfe[dfe['customer_id']==customer_id]
        saw_products = saw_before['product_id'].value_counts()
        rec_products = saw_products.index[:K].tolist()
        if len(rec_products) < K:
            rec_products += mcart(K - len(rec_products), exclude=rec_products)
        assert(len(rec_products) == K)
        assert(pd.Series(rec_products).nunique()==K)
        for product_id in rec_products:
            f.write('{},{}\n'.format(customer_id, product_id).encode('utf8'))
```

In [ ]: