ProVe - finding item replacements during inventory shortages

Experimental Protocol for XCS224U Spring 2020

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1 The Hypothesis

In past years we have seen a lot of cross-domain applications from various deep learning areas to particular real-life cases with apparently little connection. One of those areas is that of applying deep representation learning based on neural language processing to business analytics systems and recommender systems in particular. The intuition behind our proposed deep learning pipeline is that we could, at least in theory, generate, through multiple modeling iterations, powerful-enough semantic vector space embeddings for each individual item (product) so that we can infer replacements items and propose them in the case on original product shortages – all of these in a self-supervised setting. Employing the same self-supervised approach and proposed experiment setting we are proposing a secondary generative model. This secondary objective is aiming at providing a cold-start for new products that are introduced in the inventory and, as such, do not have a transactional history and thus any kind of patterns.

The hypothesis is that we can apply post-processing fine-tuning after trained product embeddings - *ProVe* - that have been generated with GloVe [1] in a similary way as Grbovic et al [2] use word2vec [3] in their *prod2-vec* [2] work. The fine tuning process will be either based on retrofitting or on actual re-construction of the vector space with new co-occurrence matrices in order to generate a product vector space model able to generate both item-replacement information as well as new embeddings for cold-start-ing items in inventories.

More precisely the hypothesis is that our proposed approach will reduce the distance between products that can actually replace each other in real life, while "pushing" apart dissimilar products in a similar manner as presented in the work of Faruqui et al[4], Mrkšić et al [5] and in the more recent work of Dingwall et al [6] and Lengerich et al [7] . Although the before mentioned work addresses natural language processing & understanding, we will assimilate product/items with words as well as other NLP/NLU objects with retail/business concepts.

2 The Data

For our experiment we decided to use a real-life transactional dataset that contains more than 2M transactions of a retailer with various locations over a period of more than 3 years. Although the dataset contains more than 15,000 different products in order to speed-up experiment time using full in-GPU training we reduced the number of products to a maximum of 13,000 top sold products.

Further information on the data can be observed in the data loading, preparation and minimal visualization of the experiment.

We load the required packages and setup the notebook environment

```
In [1]: import numpy as np
        from scipy import sparse
        import itertools
        import os
        import pandas as pd
        from datetime import datetime as dt
        from time import time
        import textwrap
        from itertools import combinations
        import matplotlib.pyplot as plt
        %matplotlib inline
```

We prepare the majority of our global variables

```
In [2]: print_df = False

        DEBUG = True # in-development flag

        MODEL_NAME = 'exp_v1'

        DATA_HOME = 'exp_data'
        MODEL_HOME = 'exp_models'
        DATA_FILE = os.path.join(DATA_HOME, 'df_tran_proc_top_13.5k.csv')
        DATA_SLICE_FILE = os.path.join(DATA_HOME, 'df_tran_proc_top_13.5k_slice.csv')
        META_FILE = os.path.join(DATA_HOME, 'df_items_top_13.5k.csv')
        META_INFO = os.path.join(DATA_HOME, 'obfuscated_keys.txt')

        MCO_OUT_FILE = os.path.join(MODEL_HOME, 'exp_mco.npz')

        EMB_OUT_FILE = os.path.join(MODEL_HOME, MODEL_NAME + '_embeds.npy')

        CHUNK_SIZE = 100 * 1024 ** 2 # read 100MB chunks

        MAX_N_TOP_PRODUCTS = 13000  # top sold products

        _MCO_FILE  = os.path.join(MODEL_HOME, 'mco_top_13.5k.npz') # debug pre-prepared mco
```

2.1 Data processing approach

Due to the size of transactional databases that often have billions of transactions each with many individual items we generate the proposed matric o co-occurence (MCO) with efficient batch reading of the transactional data.

For the purpose of efficiently processing the transactional records we have `generate_sparse_mco(file_name)` *function with its* `add_to_mco` *helper method*

We load our ProVe framework as well as other utility functions and pretty-prints settings for `Pandas` *and* `NumPy`*. In order to ensure experiment replicability for all iterations we have setup a simple logging process*

```
In [3]: from prove import Log
        from prove import load_categs_from_json
        from prove import generate_sparse_mco
        from prove import show_neighbors
        from prove import filter_categs
        from prove import show_categs

In [4]: pd.set_option('display.max_rows', 500)
        pd.set_option('display.max_columns', 500)
        pd.set_option('display.max_colwidth', 500)
        pd.set_option('display.width', 1000)
        pd.set_option('precision', 4)
        pd.set_option('display.notebook_repr_html', True)

        def _repr_latex_(self):
            str_latex = ''
            str_latex += '\scriptsize\n'
            str_latex += self.to_latex(
                bold_rows=True,
                index_names=False,
            )
            return str_latex

        pd.DataFrame._repr_latex_ = _repr_latex_  # monkey patch pandas DataFrame


        np.set_printoptions(precision=3)
        np.set_printoptions(suppress=True)
        np.set_printoptions(linewidth=500)

        plt.style.use('ggplot')

        log = Log()
```

2.2 Understanding the data

The proposed experimental real-life data comes within a few files generated by SQL commands and exports from an existing ERP system of our retailer. The most notable data files are the transactional database file and the metadata file. The metadata information taken directly from a real-life production system (ERP) contains raw information minimally describing each product-SKU `IdemId` with product name (`ItemName`) and other information such as number of item sales in observed in the selected period, a unique sequential item identificator (`IDE`) as well as as hierarchy information in two fields `Ierarhie1` and `Ierarhie2` that will be further used as a knowledge graph similar to WordNet [8]. There is also a secondary de-obfuscation data-source that contains for each hierarchy identified the actual name of that category. This information can also be used as a source for self-supervision in the process of creating the knowledge graph for the fine-tuning of our semantic vector space model.

The real-life transactional dataset, as previously mentioned, contains over 6M observations for over 2M different transactions. Each observation in the transactional database contains a `BasketId` identifier of the transaction as well as individual transaction detail information such as `ItemId` (and its counterpart `IDE`), a `SiteId` field that identifies the location of that particular transaction, a `TimeStamp` time-identification that is basically the same for all items of the same transaction, a quantity field, a customer identifier field and a product availability indicator.

For the metadata we load the whole file and analyse its content while for the transactional database we take a quick look at the first chunk of 15 rows

```
In [5]: def show_product(IDE, df):
            rec = df[df.IDE==IDE].iloc[0]
```

```
        log.P("   Name:  {}".format(rec.ItemName))
        log.P("   Id:    {}".format(rec.ItemId))
        log.P("   Freq:  {}".format(rec.Freq))
        log.P("   Hrchy: {}/{}".format(rec.Ierarhie1, rec.Ierarhie2))
        return

    log.P("Metatada information:")
    df_meta = pd.read_csv(META_FILE)
    df_meta = df_meta[df_meta.IDE < MAX_N_TOP_PRODUCTS]
    log.P("  Total no of products: {}".format(df_meta.ItemId.unique().shape[0]))
    log.P("  Total no of level 1 hierarchies:
    {}".format(df_meta.Ierarhie1.unique().shape[0]))
    log.P("  Total no of level 2 hierarchies:
    {}".format(df_meta.Ierarhie2.unique().shape[0]))
    log.P("  Most sold individual product over period:")
    show_product(df_meta[df_meta.Freq == df_meta.Freq.max()].iloc[0]['IDE'], df_meta)
    log.P("  Least sold individual product over period:")
    show_product(df_meta[df_meta.Freq == df_meta.Freq.min()].iloc[0]['IDE'], df_meta)
    df_meta[df_meta.ItemName.str.len()<30].iloc[:15,:-1]
```

```
            Metatada information:
Total no of products: 13000
Total no of level 1 hierarchies: 24
Total no of level 2 hierarchies: 181
Most sold individual product over period:
 Name:  YUVAL NOAH HARARI / SAPIENS. SCURTA ISTORIE A OMENIRII
 Id:    545535
 Freq:  21248
 Hrchy: 1/17
Least sold individual product over period:
 Name:  DAVID GROSSMAN / UN CAL INTRA ÎNTR-UN BAR
 Id:    442552
 Freq:  156
 Hrchy: 1/0
```

	ItemId	IDE	Freq	ItemName	Ierarhie1	Ierarhie2
2	406083	2	13371	FELICITARI A 7331335123458	11	107
6	258901	6	8341	TURTA DULCE TIP INIMIOARE	20	269
13	527499	13	7676	TIBI USERIU / 27 DE PASI	1	9
15	493855	15	7354	IRINA BINDER / FLUTURI VOL. 3	1	0
23	651356	23	6718	SACOSA BIO CARTURESTI	11	100
24	522568	24	6531	IRINA BINDER / INSOMNII	1	9
30	599979	30	6006	MICHELLE OBAMA / POVESTEA MEA	1	9
34	439986	34	5434	PAULA HAWKINS / FATA DIN TREN	1	0
40	258895	40	5143	TURTA DULCE POM DE CRACIUN	20	269
41	258898	41	5122	TURTA DULCE MOS CRACIUN MIC	20	269
46	355291	46	5061	SABOTEUR / 8+ / 747496	4	181
48	258361	48	4998	M35 WINTER COCKTAIL 50G	13	79
50	258270	50	4953	M161 MULTI FRUIT 50G	13	79
58	406255	58	4806	SENECA / ALT TIMP NU AM	1	43
59	258417	59	4765	M85 REDBUSH BAKED APPLE 50G	13	79

As we are working with a real-life normed relational database the hyerarchi fields do not tell much information other than a simple `int` identifier. Now we can deobfuscate the `Ierarhie1` and `Ierarhie2` fields

```
In [6]: df_meta, dct_categories = load_categs_from_json(df_meta, META_INFO)
        df_meta[df_meta.ItemName.str.len()<30].iloc[:15,[3,7,8]]
```

	ItemName	Ierarhie1_name	Ierarhie2_name
2	FELICITARI A 7331335123458	PAPETARIE	Giftware
6	TURTA DULCE TIP INIMIOARE	GASTRONOMIE	Bakery
13	TIBI USERIU / 27 DE PASI	CARTE ROM	BIOGRAFII / MEMORII
15	IRINA BINDER / FLUTURI VOL. 3	CARTE ROM	FICTIUNE
23	SACOSA BIO CARTURESTI	PAPETARIE	TEMPORAR 1
24	IRINA BINDER / INSOMNII	CARTE ROM	BIOGRAFII / MEMORII
30	MICHELLE OBAMA / POVESTEA MEA	CARTE ROM	BIOGRAFII / MEMORII
34	PAULA HAWKINS / FATA DIN TREN	CARTE ROM	FICTIUNE
40	TURTA DULCE POM DE CRACIUN	GASTRONOMIE	Bakery
41	TURTA DULCE MOS CRACIUN MIC	GASTRONOMIE	Bakery
46	SABOTEUR / 8+ / 747496	JUCARII	CARD GAMES
48	M35 WINTER COCKTAIL 50G	GASTRONOMIE AA	Ceai
50	M161 MULTI FRUIT 50G	GASTRONOMIE AA	Ceai
58	SENECA / ALT TIMP NU AM	CARTE ROM	FILOSOFIE
59	M85 REDBUSH BAKED APPLE 50G	GASTRONOMIE AA	Ceai

```
In [7]: chunk_reader = pd.read_csv(DATA_SLICE_FILE, iterator=True)
        chunk_reader.get_chunk(15).iloc[:,:-2]
```

	BasketId	ItemId	SiteId	TimeStamp	Qtty	ClientId
0	7130756	441093	26	2016-01-01 14:49:02.403	1.0	-103
1	7130756	464012	26	2016-01-01 14:49:02.403	1.0	-103
2	7130756	464013	26	2016-01-01 14:49:02.403	1.0	-103
3	7130802	377742	20	2016-01-01 15:49:03.860	1.0	-103
4	7130802	405083	20	2016-01-01 15:49:03.860	1.0	-103
5	7130802	405084	20	2016-01-01 15:49:03.860	1.0	-103
6	7130803	365473	26	2016-01-01 15:49:42.567	1.0	-103
7	7130803	381249	26	2016-01-01 15:49:42.567	1.0	-103
8	7130809	344274	26	2016-01-01 15:53:19.953	1.0	-103
9	7130809	393877	26	2016-01-01 15:53:19.953	1.0	-103
10	7130810	165748	20	2016-01-01 15:54:17.053	1.0	-103
11	7130810	363903	20	2016-01-01 15:54:17.053	1.0	-103
12	7130822	350149	20	2016-01-01 16:05:18.960	1.0	-103
13	7130822	447921	20	2016-01-01 16:05:18.960	1.0	-103
14	7130822	464013	20	2016-01-01 16:05:18.960	1.0	-103

```
In [8]: chunk_reader.close()
```

2.3 NLU meets BPA

In terms of natural language models analogy to Business Predictive Analytics systems, we consider each individual basket as a "sentence" and consider each individual product id as a "word". Referring to our proposed method of constructing matrix of co-occurrence counts and applying GloVe approach for the vector space representation modeling we have two options:

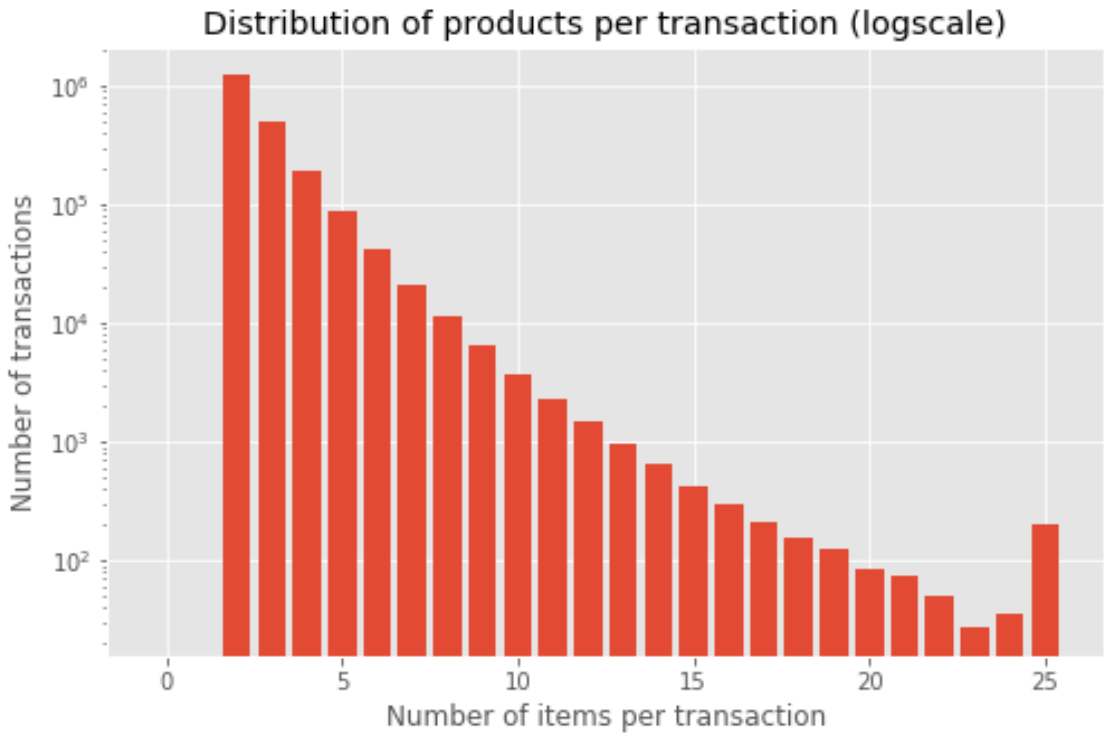
- using a specific context window size controlled as a model hyperparameter with or without weighting between focal and each individual item;
- considering each transaction as the overall context with no distance weighting between the focal word and the context word;

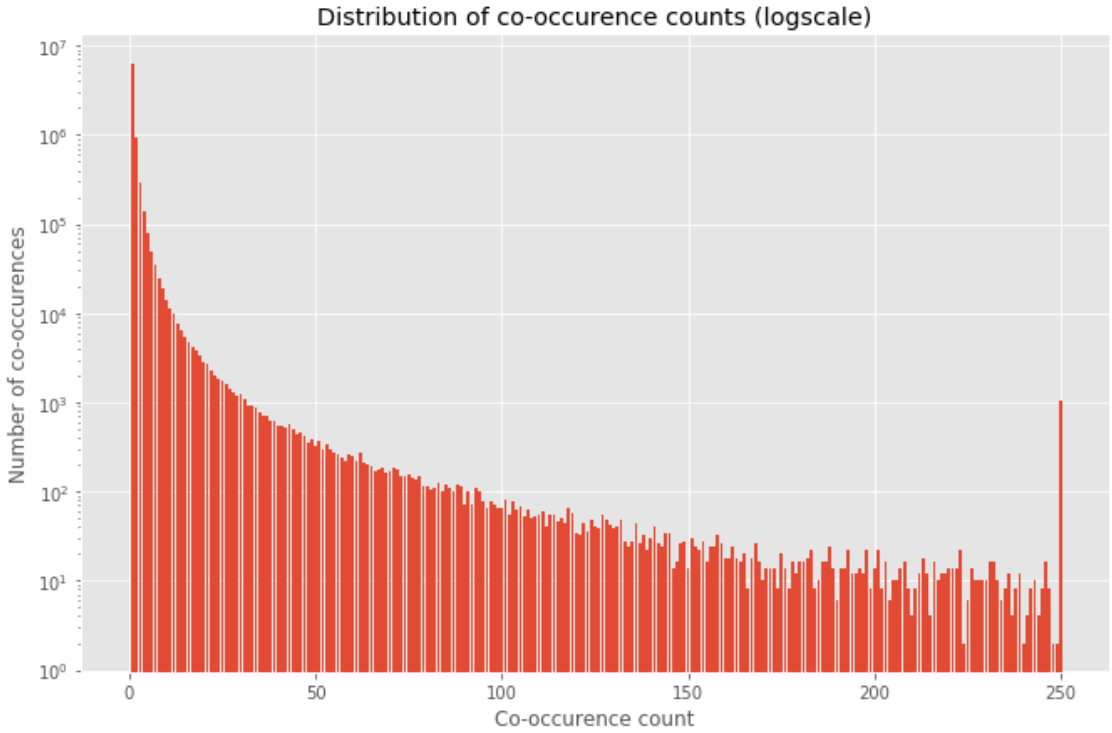
Regarding the context window it is important to note that for online shopping systems the items ordering, in each individual transaction, is quite important as it is directly correlated to the user journey in the website. As such for the particular case the definition of a hyperparameter that will control the context window size is important. For classic brick-and-mortar retailers the order of each product in the receipt is not important as it is unlikely that it reflects the actual user sequence of actions. In our particular case of the real-life dataset we have a retailer that has over 30 locations and a website that seems to generate less than 10% of the revenue. As a result we decided to consider each transaction as a single-context for the computing of item co-counts.

Now the next logical step is to generate the matrix of item co-occurrence counts

```
In [9]: csr_mco, tran_sizes = generate_sparse_mco(
            DATA_FILE, mco_out_file=MCO_OUT_FILE,
            plot=True, return_counts=True, log=log,
            DEBUG=DEBUG, mco_file=_MCO_FILE)

                Loading MCO...
Loading raw data...
  MCO Processing done in 0.08 min (sparse mat creation: 0.08 min):
  Start date: None
```

```
End date:   None
Max co-occ: 5998.0

Co-occurence distribution:
  Counts:   00 6382178 913964 293414 138452 77970 49730 34124 24904 18758
  Nr items:  0       1      2      3      4     5     6     7     8     9

Transactions size distrib:
  Counts:   00 00 1210270 484388 194496 86254 41847 21134 11616 6430
  Nr items:  0  1       2      3      4     5     6     7     8    9

Transactional data:
     BasketId  ItemId  SiteId               TimeStamp  Qtty  ClientId
  0   7130756  441093      26  2016-01-01 14:49:02.403   1.0      -103
  1   7130756  464012      26  2016-01-01 14:49:02.403   1.0      -103
  2   7130756  464013      26  2016-01-01 14:49:02.403   1.0      -103
  3   7130802  377742      20  2016-01-01 15:49:03.860   1.0      -103
  4   7130802  405083      20  2016-01-01 15:49:03.860   1.0      -103

MCO data: (only 7x7 values displayed)
  [[   0.   25.   49. 5998.  297.   85.   28.]
   [  25.    0.   32.   19.    6.    9.   15.]
   [  49.   32.    0.   22.    8.   15.   28.]
   [5998.   19.   22.    0.  165.   42.   13.]
   [ 297.    6.    8.  165.    0.  141.   11.]
   [  85.    9.   15.   42.  141.    0.   11.]
   [  28.   15.   28.   13.   11.   11.    0.]]
```






```
Saving 'exp_models\exp_mco.npz'
```

2.3.1 Meta-information & categories

With regard to the meta-data that can generate important knowledge graph information for our self-supervised approach we found out that the *detail category* - or the so called "level 2 hierarchy" - has a finer granularity than the first level hierarchical information.

```
In [10]: dct_i2n = {k:v for k,v in zip(df_meta.IDE, df_meta.ItemName)}

         # we slice and convert the sparse matrix
         np_mco = csr_mco.toarray()[:MAX_N_TOP_PRODUCTS,:MAX_N_TOP_PRODUCTS]
         df_meta = df_meta.iloc[:MAX_N_TOP_PRODUCTS]
         # raw sanity-check
         for i in range(np_mco.shape[0]):
             assert i in df_meta.IDE

         show_categs(df_meta, dct_categories, k=5, log=log)
```

```
                Hierarchy level 1 'Ierarhie1' contains 32 categories
  Category name: ACCESORII GASTRO AA  Id:   9  Prods:  523
  Category name: ALTELE               Id:  26  Prods:    9
  Category name: CARTE ROM            Id:   1  Prods: 7202
  Category name: CARTE STRAINA        Id:   0  Prods:  736
  ...
Hierarchy level 2 'Ierarhie2' contains 356 categories
  Category name: ACCESORII              Id: 116  Prods:    3
  Category name: ACCESORII FASHION      Id: 274  Prods:   21
  Category name: ACCESORII MASA         Id: 249  Prods:   26
  Category name: ALTELE                 Id:  60  Prods:   60
  ...
```

2.3.2 Analogy with word-vectors

As previously mentioned, the proposed ProVe model is expected to generate similar results with those of GloVe applied to word-vectors. Just as we load a pre-trained GloVe-100 embeddings matrix with the 400,000 words vector space representations and run a neighbourhood analysis for a word such as "beatles" and obtain "lennon"b, "mccartney" we expect to have similar outputs from our product semantic vector space model.

```
In [11]: if 'wemb' not in globals():
             log.P("Loading GloVe word embeddings")
             glove_words = os.path.join(DATA_HOME, 'glove_words_and_embeds_100d.npz')
             data = np.load(glove_words)
             np_words = data['arr_0']
             wemb = data['arr_1']

         def show_word(word):
             show_neighbors(word, wemb, np_words, log=log)

         show_word('beatles')
```

```
                Loading GloVe word embeddings
Top neighbors for 'beatles'
  beatles:    0.000
  lennon:     0.246
  mccartney:  0.276
  dylan:      0.304
  songs:      0.305
  recordings: 0.325
  albums:     0.326
  elvis:      0.326
  motown:     0.327
  presley:    0.333
```

2.4 Self-supervised training and supervised testing

Although the training process is entirely self-supervised, one particular challenge that was faced was the preparation of test cases and actual evaluation metrics. For the development of the evaluation dataset a classic "supervised" approach has been adopted based on manual data exploration. After manual selection of a limited list of categories based on the available meta information a sample of products has been extracted and analysed. For each of the target selected categories - `MUSIC`, `VYNIL`, `DVD`, `Board-games` - multiple products have been manually selected. Following the manual selection of product candidates for evaluation data, for each individual chosen item the top neighbors items have been prepared using cosine distance.

```
In [12]: proposed_test_categs = {
           'Ierarhie1': {
               'COMICS&MANGA': 21, 'GASTRONOMIE': 20, 'HOME&DECO AA': 10,
               'LIFESTYLE': 12, 'MULTIMEDIA': 8,'MUZICA': 2, 'NOVELTY': 23,
               'VINURI': 14,
           },
           'Ierarhie2': {
               'AUDIO & VIDEOBOOK': 259, 'Accesorii apple': 193, 'Activity': 294,
               'Audiobook CD': 111,'BLU-RAY': 36, 'BLU-RAY 3D': 224, 'BOARD GAMES': 140,
               'Backtoschool': 108, 'Bakery': 269, 'Bath': 262, 'Blu-Ray Audio': 165,
               'Blu-Ray Video': 65, 'Body Care': 330, 'CD Clasica/Opera': 83, 'COMICS': 87,
               'Comics': 120, 'DRAW MANGA/COMICS/VIDEOGAMES': 72, 'FILOSOFIE': 43,
               'Film Blu-Ray': 136, 'Film DVD': 52, 'Film VHS': 343, 'GASTRO/BAKERY': 314,
               'Giftware': 107, 'Gourmet': 192, 'Jazz': 308, 'Kitchen': 118, 'LIFESTYLE': 283,
               'MANGA': 63, 'ROBOTICA': 300, 'SelfHelp': 198, 'TRAVELING COLLECTION': 139,
               'Travel': 243, 'Travel Mug': 144, 'Travelling collection': 75, 'UHD': 183,
               'Vinyl': 10,
            }
         }
         dct_cat = filter_categs(
             proposed_test_categs, df_meta, dct_categories,
             max_n_top_products=MAX_N_TOP_PRODUCTS)


         show_categs(df_meta, dct_cat, k=1000, log=log)
```

```
df_tpr = df_meta[
      df_meta.Ierarhie1.isin(list(dct_cat['Ierarhie1'].values())) |
      df_meta.Ierarhie2.isin(list(dct_cat['Ierarhie2'].values()))
      ]
```

```
   Hierarchy level 1 'Ierarhie1' contains 8 categories
  Category name: COMICS&MANGA  Id:  21  Prods:  135
  Category name: GASTRONOMIE   Id:  20  Prods:  196
  Category name: HOME&DECO AA  Id:  10  Prods:  174
  Category name: LIFESTYLE     Id:  12  Prods:  239
  Category name: MULTIMEDIA    Id:   8  Prods:  411
  Category name: MUZICA        Id:   2  Prods:  219
  Category name: NOVELTY       Id:  23  Prods:  103
  Category name: VINURI        Id:  14  Prods:   23
Hierarchy level 2 'Ierarhie2' contains 14 categories
  Category name: Audiobook CD           Id: 111  Prods:    7
  Category name: BLU-RAY                Id:  36  Prods:   16
  Category name: BOARD GAMES            Id: 140  Prods:  165
  Category name: Backtoschool           Id: 108  Prods:   16
  Category name: Bakery                 Id: 269  Prods:   10
  Category name: COMICS                 Id:  87  Prods:    3
  Category name: Comics                 Id: 120  Prods:   23
  Category name: FILOSOFIE              Id:  43  Prods:  144
  Category name: Giftware               Id: 107  Prods:   95
  Category name: LIFESTYLE              Id: 283  Prods:   11
  Category name: MANGA                  Id:  63  Prods:   87
  Category name: Travel Mug             Id: 144  Prods:   66
  Category name: Travelling collection  Id:  75  Prods:   19
  Category name: Vinyl                  Id:  10  Prods:   52
```

3 Metrics and overall evaluation

With regard to metrics and evaluation of this particular experiment it is important to decide how we view the model - as a classic classification or as a ranking problem. As a result the possible metrics that can be applied to our experiment are varied and the options range from the classification metrics such as accuracy, precision, recall, F-score up to recommender systems domain-specific metrics. The initially proposed metrics were _Recall@K_ that measures the ability of our system to recommend viable items within the first K proposed candidates as well as the more importantly the _MRR@k_ (Mean Reciprocal Rank) applied only for the first K candidates (if the target is ranked lower than the K then the score is 0).

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{r_i}$$

In the above formula Q represents all the tests performed while r_i represents the rank of the positive candidate (`inf` if no candidate matches the gold value). Finally we decided to use only MRR as evaluation metric with various small number of candidates (K=1 and K=5).

In [13]:
```
def mrr_k(np_cands_batch, np_gold_batch, k=5):
    """
    will compute Mean Reciprocal Rank for a batch of predictions
    inputs:
      np_cands_batch: [batch, no_products] - the candidates for each experiment in batch
      np_gold_batch: [batch,] or [batch, 1] - the actual gold target product replacement
      k: int (default 5) the max number of candidates evaluated
    """
    assert len(np_cands_batch.shape) == 2
    np_gold_batch  = np_gold_batch.reshape(-1,1)
    np_cands_batch = np_cands_batch[:,:k]
    n_obs, n_cands = np_cands_batch.shape
    matches = np_cands_batch == np_gold_batch
    _x = np.repeat(np.arange(1,n_cands+1).reshape(1,-1),n_obs, axis=0)
    _y = np.ones((n_obs,n_cands)) * np.inf
    np_res = 1 / np.where(matches, _x, _y).min(axis=1)
    return np_res.mean()
```

4 The Models

For this work we decided to take the most straightforward approach at "classifying" viable replacement candidates: that of using cosine distance and take the first 5 candidates (or just the first one) as potential replacement items for a target item. Two main models form the base of our experiment - GloVe [1] in its new *ProVe* form as well as retrofitting techniques derived from the work of Faruqui et al [4], Mrkšić et al [5] and Dingwall et al [6].

4.1 Hyperparameters

The hyper-parameter selection is entirely based on the results of our exploratory data analysis on the real-life dataset combined with the know-how resulted from the natural language counterparts. For the vector space dimensionality we chosed 128. We chosed a maximum frequency of co-occurrences of 250 although as it can be observed from the distribution of counts we have a maximum of over 5000. The number of iterations is on-purpose set to a large number (250,000) as during our experimentation we concluded that after 1000 iterations the optimization begins to decrease slowly and we have decided a good-enough products vector representation is obtained when the loss starts to decrease at a rate of 0.1 per iteration. We save during our ProVe optimization after each 1000 iterations.

In [14]:
```
EMBED_SIZE = 128
MAX_FREQ = 250
MAX_ITERS = 250000
SAVE_ITERS = 1000
```

4.2 ProVe implementation

For the training of the *product* embeddings we are using the Mittens (https://github.com/roamanalytics/mittens) framework by Dingwall et al [6] on the prepared co-occurences. As prviously mentioned in order to speed-up model experimentation time we decided to drop the number of products down to 13,000 different items and gain optimization speed. The entire optimization procedure based on the Mittens [6] was modified so that it allows a finer control of the iterations as well as full in-GPU training without any RAM-to-VRAM transfer.

In [15]:
```
## ProVe implementation

if os.path.isfile(EMB_OUT_FILE):
    embeds = np.load(EMB_OUT_FILE)
else:
    np_data = csr_mco.toarray()
    glove_model = GloVe(
        n=EMBED_SIZE,
        xmax=MAX_FREQ,
        max_iter=MAX_ITERS,
        save_folder=MODEL_HOME,
        save_iters=SAVE_ITERS,
        name='exp_v1',
    )
    embeds = glove_model.fit(np_data)
log.P("ProVe embeds {} loaded.".format(embeds.shape))

def show_prod(pid ,k=10):
    show_neighbors(pid, embeds, dct_i2n, k=k, log=log)

def show_prod_df(pid,k=10):
    df = show_neighbors(pid, embeds, dct_i2n, df=df_meta, k=k, log=log)
    if print_df:
      log.P(df)
    else:
      return df
```

```
ProVe embeds (13000, 128) loaded.
```

4.3 Refining evaluation data using trained ProVe

Following the full generation of the ProVe vector space model for product embeddings we can run few neighbors tests of our items expecting similar results as with the word embeddings. As previously mentioned we selected manually each individual evaluation item in order to find those that would clearly fail at proposing a good replacement candidate with just a cosine distance neighbor search within the products vector space.

In [16]:
```
test_items = [
    12071, 10088, 9251,
```

```
        9845, 8956, 6020,
        129, 1150, 3852
    ]
    show_prod_df(12071)
```

```
Top neighbors for 'CD / DAVID BOWIE / BLACKSTAR (2016)'
```

	ID	DIST	NAME	H1	H2
0	12071	0.0000	CD / DAVID BOWIE / BLACKSTAR (2016)	MUZICA	CD International
1	5312	0.6531	IAN MCDERMOTT / NLP PENTRU CARIERA SI VI	CARTE ROM	DEZVOLTARE PERSONALA
2	9997	0.6543	HOLLY SMALE / TOCILARA	CARTE ROM	FICTIUNE ADOLESCENTI
3	1115	0.6829	DAN LUNGU / SUNT O BABA COMUNISTA (TOP10	CARTE ROM	FICTIUNE
4	10047	0.6899	MAGNET METAL - BATMAN (JOKER)	COMICS&MANGA	Comics
5	2883	0.6930	HARRIET MUNCASTER / ISADORA MOON MERGE C	CARTE ROM	CARTI PENTRU COPII
6	12399	0.7012	YOU GIVE ME A REASON MINI CARD / KELLY H	PAPETARIE AA	Cadouri
7	7132	0.7027	SALLY GARDNER / ARIPI SI CO 3: MISTERIOA	CARTE ROM	CARTI PENTRU COPII
8	6443	0.7119	DVD / DUNKIRK (2017)	MULTIMEDIA	DVD
9	9334	0.7229	SET 6 COASTERS PARIS MONUMENTS	ACCESORII GASTR	Accesorii servit mas

5 The full Pipeline

There are two main pipelines, one for each of our two individual objectives : that of finding product replacements and the second one of cold-start-ing new products in inventories:

Algorithm #1 - Product Replacement Modelling

```
1. Create MCO
2. Apply ProVe and obtain item embeddings
3. Extract knowledge graph information from meta-data
4. For each individual product
    4.1. Find connected products
    4.2. Retrofit the product using connected products
```

Algorithm #2 - Cold-start new products

```
1. Setup embeddings of existing products and extract knowledge graph information from meta-data
2. Input new product hierarchy information
3. Input similar products from proposed similar products
4. Create new product embedding based on proposed similar with simple mean over embeddings
5. Add all hierarchy-based products to the list of similar products
6. Retrofit the new product embedding to all similar products
```

In [ ]:

6 Progress history

At this point in our research and development process we managed to obtain generate the product embeddings based starting from the real-life transactional database. A more important finding is that we have experimental proof that our *ProVe* model shows clear signs of capturing "semantic" information regarding product similarities as well as product complementarity, albeit without a clear cut between the two distinct categories. Similar findings can be discerned from the early work of Grbovic et al [2] who use the k-means based clusters in order to separate potential similarities from complementarities.

```
In [17]: print("Experiment end")
```

```
Experiment end
```

References

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