# Technical part of MSc project solution

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# Import libraries

In [1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_c
import time
import seaborn as sns
import matplotlib.pyplot as plt
import csv
import json

from itertools import islice
from itertools import combinations

from scipy.sparse import coo_matrix  # LightFM fit method requires
from scipy.sparse import csr_matrix

from lightfm import LightFM
from lightfm.evaluation import auc_score
from lightfm.evaluation import precision_at_k
from lightfm.cross_validation import random_train_test_split
from sklearn.model_selection import train_test_split
from lightfm.data import Dataset
```

```
/Users/konstantinorlovskiy/opt/anaconda3/lib/python3.7/site-packag
es/lightfm/_lightfm_fast.py:9: UserWarning: LightFM was compiled w
ithout OpenMP support. Only a single thread will be used.
  warnings.warn('LightFM was compiled without OpenMP support. '
```

In [2]:
```
# Save start point to calculate the full code run time.

full_cycle_time_start = time.time()
```

# Data

In [3]:
```
# Source of data for this project is available via url:
# https://www.kaggle.com/retailrocket/ecommerce-dataset
```

# Preprocessing

## Data Import and Cleaning - Events

In [4]:
```
# Importing Events data and sorting by timestamp column which corre

df_events = pd.read_csv("events.csv")
df_events = df_events.sort_values(by=['timestamp'], ascending=True)
```

In [5]:
```
df_events.head()
```

Out[5]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 0 | 1430622004384 | 693516 | addtocart | 297662 | NaN |
| 1 | 1430622011289 | 829044 | view | 60987 | NaN |
| 2 | 1430622013048 | 652699 | view | 252860 | NaN |
| 3 | 1430622024154 | 1125936 | view | 33661 | NaN |
| 4 | 1430622026228 | 693516 | view | 297662 | NaN |

In [6]:
```
df_events.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2756101 entries, 0 to 2756100
Data columns (total 5 columns):
timestamp        int64
visitorid        int64
event            object
itemid           int64
transactionid    float64
dtypes: float64(1), int64(3), object(1)
memory usage: 105.1+ MB
```

In [7]:
```
# Save original dataframe count of users, items, interactions.
# Calculate the sparsity of original dataframe.

qty_all_users_original = len(df_events.visitorid.unique())
qty_all_items_original = len(df_events.itemid.unique())
qty_all_interactions_original = len(df_events)
sparsity_original = 1-qty_all_interactions_original/(qty_all_users_

print('Original number of users:', qty_all_users_original)
print('Original number of items:', qty_all_items_original)
print('Original number of interactions:', qty_all_interactions_orig
print('Original sparsity:', round(sparsity_original*100,6), '%')
```

```
Original number of users: 1407580
Original number of items: 235061
Original number of interactions: 2756101
Original sparsity: 99.999167 %
```

In [8]:
```
# Events types “view”, “addtocart”, “transaction” cannot be conside
# This information is implicit feedback and lightFM library was des
# Transform events from categorical to numerical format for further

weight_view = 1
weight_addtocart = 2
weight_transaction = 3

df_events.event.replace(to_replace=dict(
    view=weight_view, addtocart=weight_addtocart, transaction=weigh
```

In [9]:
```
# Now the events replaced with corresponding weights.
df_events.event.unique()
```

Out[9]:
```
array([2, 1, 3])
```

In [10]:
```
df_events.head()
```

Out[10]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 0 | 1430622004384 | 693516 | 2 | 297662 | NaN |
| 1 | 1430622011289 | 829044 | 1 | 60987 | NaN |
| 2 | 1430622013048 | 652699 | 1 | 252860 | NaN |
| 3 | 1430622024154 | 1125936 | 1 | 33661 | NaN |
| 4 | 1430622026228 | 693516 | 1 | 297662 | NaN |

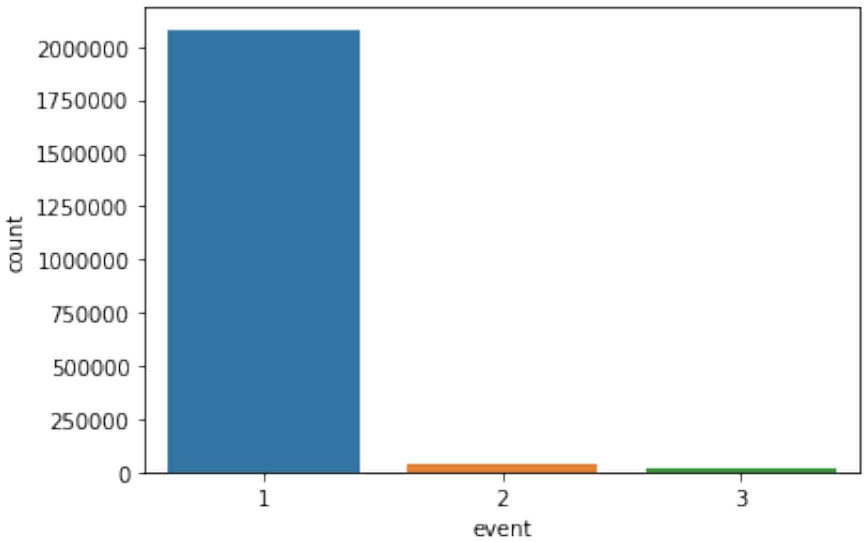
In [11]:
```
# The user may have interacted with item multiple times which is no
# For current purpose of recommendation we're interested in the hig
# Therefore, the data can be further cleaned.

df_events = df_events.sort_values('event').drop_duplicates(
    subset=['visitorid', 'itemid'],
    keep='last').sort_values(by=['timestamp'], ascending=True).rese
```

In [12]:
```
df_events.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2145179 entries, 0 to 2145178
Data columns (total 5 columns):
timestamp        int64
visitorid        int64
event            int64
itemid           int64
transactionid    float64
dtypes: float64(1), int64(4)
memory usage: 81.8 MB
```

In [13]:
```
# View on the ratio between different types of events.
sns.countplot(x='event', data=df_events)
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa483d04290>
```



In [14]:
```
# Count activities by user.
users_activity = df_events.groupby('visitorid').visitorid.count().t
users_activity.head()
```

Out[14]:

| visitorid | activity_count |
|---|---|
| 0 | 3 |
| 1 | 1 |
| 2 | 4 |
| 3 | 1 |
| 4 | 1 |

In [15]:
```
# View on the most active users
users_activity.loc[users_activity['activity_count'] > 1000].sort_va
    by='activity_count', ascending=False).head(10)
```

Out[15]:

| visitorid | activity_count |
|---|---|
| 1150086 | 3814 |
| 530559 | 2209 |
| 892013 | 1738 |
| 895999 | 1641 |
| 152963 | 1622 |
| 371606 | 1399 |
| 163561 | 1314 |
| 79627 | 1257 |
| 286616 | 1230 |
| 684514 | 1187 |

In [16]:
```
# View on historical behaviour of one user 1150086.

df_events.loc[df_events['visitorid'] == 1150086].head(10)
```

Out[16]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 628771 | 1434034517389 | 1150086 | 1 | 133542 | NaN |
| 629008 | 1434035735608 | 1150086 | 1 | 167873 | NaN |
| 629054 | 1434036006651 | 1150086 | 1 | 231726 | NaN |
| 629104 | 1434036288806 | 1150086 | 1 | 427777 | NaN |
| 629170 | 1434036525614 | 1150086 | 3 | 398115 | 7510.0 |
| 629208 | 1434036727711 | 1150086 | 1 | 203425 | NaN |
| 629246 | 1434036891672 | 1150086 | 1 | 458489 | NaN |
| 629369 | 1434037348016 | 1150086 | 3 | 375955 | 6495.0 |
| 629421 | 1434037596453 | 1150086 | 3 | 357133 | 5235.0 |
| 629625 | 1434038553908 | 1150086 | 2 | 368244 | NaN |

In [17]:
```
# Check the hypothesys: the more interactions the user had, the mor
# Based on this hypothesys the users can be divided into two groups

# First group is 'low activity' users - this group is mostly browsi
# The ratio of addtocart/purchase is low so it is harder to underst
# These users will create a noise for the pool of more active users
# All types of interactions (view/addtocart/purchase) can be counte
# This will lead at least to improvement of customer experience and
# For the purposes of this project 'low activity' group will be lef
# This will allow to get rid of noise.

# Second group is 'high activity' users - this group has higher rat
# Addtocart interaction type is considered to be positive as purcha
# The item can be added to cart and purchased later, or customer pu
# All in all, the fact of adding to cart means high interest to the
# Ratio of addtocart and purchase to view is relatively similar whi
# So, interactions types addtocart/purchase can be considered as po
# View interactions are not considered since the user has not proce
# For the purposes of this project 'high activity' group will be us

# To summarize, using this split resolves several issues:
# 1. The low activity users represent the noise which will affect t
# 2. The size of dataframe used for the further steps will be signi
```

In [18]:
```
# Develop the function to see how the number of interactions impact
# Conversion is a ratio of positive interactions(cart, purchase) to

def activity_counter(data, max_interaction_threshold):

    df_events = data
    users_activity = df_events.groupby('visitorid').visitorid.count
    count_aggregated = pd.DataFrame(columns = ['interaction_thresho
                                             'view', 'addtocart',
                                             'conversion',
                                             'total_interactions'

    for interaction_threshold in range(max_interaction_threshold):
        users_activity_low = users_activity.loc[users_activity['act
        users_to_remove = users_activity_low.index.tolist()
        df_events = df_events[~df_events.visitorid.isin(users_to_re

        count = df_events['event'].value_counts()
        count_aggregated = count_aggregated.append({
            'interaction_threshold': int(interaction_threshold),
            'view': int(count[weight_view]),
            'addtocart': int(count[weight_addtocart]),
            'purchase': int(count[weight_transaction]),
            'conversion': (count[weight_addtocart] + count[weight_t
            'total_interactions': len(df_events)
        },
            ignore_index=True)

    return(count_aggregated)
```

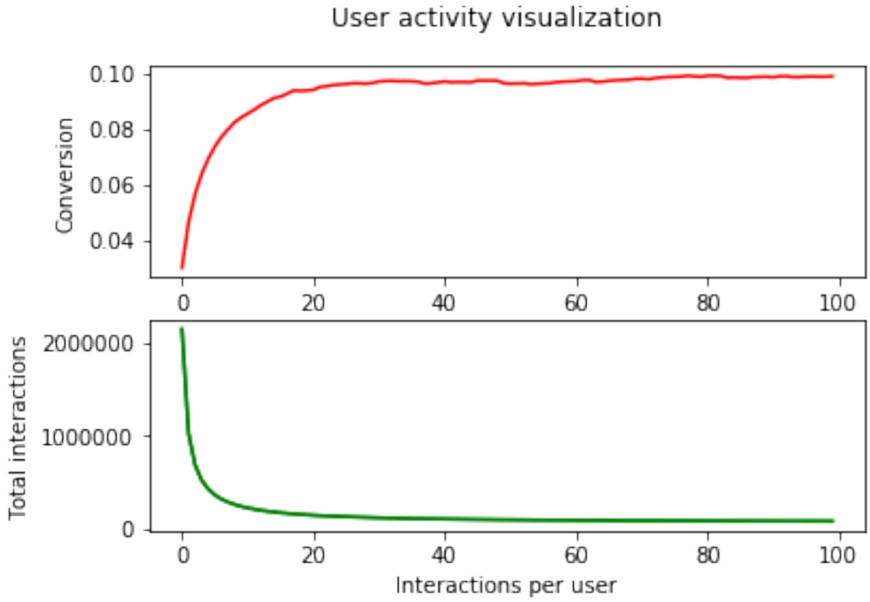
In [19]:
```
# Run fuction.
activities = activity_counter(df_events, 100)
activities.head(10)
```

Out[19]:

| | interaction_threshold | view | addtocart | purchase | conversion | total_interactions |
|---|---|---|---|---|---|---|
| 0 | 0.0 | 2080929.0 | 42980.0 | 21270.0 | 0.029951 | 2145179.0 |
| 1 | 1.0 | 978187.0 | 30775.0 | 16717.0 | 0.046303 | 1025679.0 |
| 2 | 2.0 | 645875.0 | 24367.0 | 14335.0 | 0.056534 | 684577.0 |
| 3 | 3.0 | 488582.0 | 20490.0 | 12800.0 | 0.063790 | 521872.0 |
| 4 | 4.0 | 397669.0 | 17758.0 | 11809.0 | 0.069205 | 427236.0 |
| 5 | 5.0 | 337186.0 | 15840.0 | 10960.0 | 0.073629 | 363986.0 |
| 6 | 6.0 | 294957.0 | 14365.0 | 10264.0 | 0.077065 | 319586.0 |
| 7 | 7.0 | 264109.0 | 13083.0 | 9809.0 | 0.079763 | 287001.0 |
| 8 | 8.0 | 239898.0 | 12078.0 | 9441.0 | 0.082317 | 261417.0 |
| 9 | 9.0 | 220596.0 | 11162.0 | 9085.0 | 0.084067 | 240843.0 |

In [20]:
```
figure, (axis_1, axis_2) = plt.subplots(2)
figure.suptitle('User activity visualization')

axis_1.plot(activities['interaction_threshold'], activities['conver
axis_1.set_ylabel('Conversion')

axis_2.plot(activities['interaction_threshold'], activities['total_
axis_2.plot(activities['interaction_threshold'], activities['total_
axis_2.set_ylabel('Total interactions')
axis_2.set_xlabel('Interactions per user')
```

Out[20]:
```
Text(0.5, 0, 'Interactions per user')
```

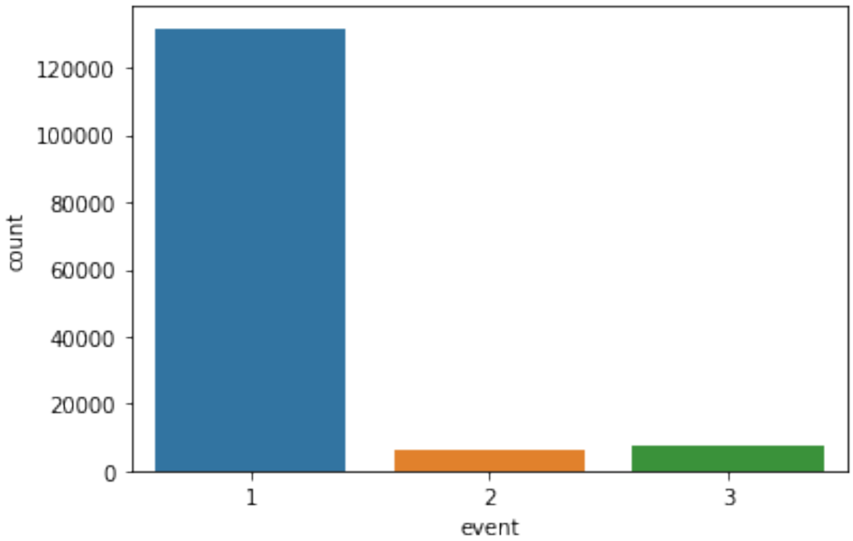



In [21]:
```
# The plot above shows that positive ratio improvement slows down s
# Plateau is at conversion rate ~0.1 (10%) which is good in compari
# It makes sense since the part of less active users was removed.

# Hypothesis is now proved.

# Split point to divide users into two groups:
# 'low activity' users with 20 and less interactions.
# 'high activity' users with more than 20 interactions.
```

In [22]:
```
# Set interactions threshold and remove 'low activity' users.

interaction_threshold = 20

# Create list of users that need to be removed from events data.
users_activity_low = users_activity.loc[users_activity['activity_co
users_to_remove = users_activity_low.index.tolist()

# Remove low activity users from dataframe.
df_events = df_events[~df_events.visitorid.isin(users_to_remove)].r
```

In [23]:
```
# View on the ratio between different types of events after cleanin
sns.countplot(x='event', data=df_events)
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa483d4f290>




In [24]:
```
# Select which types of interaction to be used: weight_view / weigh
# View interactions are not considered since the user has not proce

df_events = df_events.loc[df_events['event'].isin(
    [weight_addtocart,
     weight_transaction])].reset_index(drop=True)

df_events.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13675 entries, 0 to 13674
Data columns (total 5 columns):
timestamp        13675 non-null int64
visitorid        13675 non-null int64
event            13675 non-null int64
itemid           13675 non-null int64
transactionid    7271 non-null float64
dtypes: float64(1), int64(4)
memory usage: 534.3 KB
```

In [25]:
```
# Final view on users and items participating in model training and

qty_all_users = len(df_events['visitorid'].unique())
print('Original number of users:', qty_all_users_original)
print('Cleaned dataset number of users: ', qty_all_users)
print('Cleaned portion:', round(100*qty_all_users/qty_all_users_ori
print()

qty_all_items = len(df_events['itemid'].unique())
print('Original number of items:', qty_all_items_original)
print('Cleaned dataset number of items: ', qty_all_items)
print('Cleaned portion:', round(100*qty_all_items/qty_all_items_ori
print()

qty_all_interactions = len(df_events)
print('Original number of interactions:', qty_all_interactions_orig
print('Cleaned dataset number of interactions: ', qty_all_interacti
print('Cleaned portion:', round(100*qty_all_interactions/qty_all_in
print()

sparsity = 1-qty_all_interactions/(qty_all_users*qty_all_items)
print('Original sparsity: ', round(sparsity_original*100,6), '%')
print('Cleaned sparsity: ', round(100*sparsity,6), '%')
```

```
Original number of users: 1407580
Cleaned dataset number of users:  1015
Cleaned portion: 0.07 %

Original number of items: 235061
Cleaned dataset number of items:  9490
Cleaned portion: 4.04 %

Original number of interactions: 2756101
Cleaned dataset number of interactions:  13675
Cleaned portion: 0.5 %

Original sparsity:  99.999167 %
Cleaned sparsity:  99.85803 %
```

## Train / Test split

In [26]:
```
# Interactions data may depend on seasonality and specific eCommerc
# In order to achieve the generalization, the train and test split

df_events_train, df_events_test = train_test_split(df_events,
                                                    test_size=0.2,
                                                    random_state=np.
```

In [27]:
```
# The dataset used for this project does not have any user informat
# Therefore, on the evaluation phase there should be only those use
# Otherwise the user cold start problem will be faced which will im
# Meanwhile, this is not the case for items since there's the item

df_events_test = df_events_test[(df_events_test['visitorid'].isin(d
                                (df_events_test['itemid'].isin(df_e
```

In [28]:
```
df_events_train.head()
```

Out[28]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 5051 | 1434737258535 | 76757 | 2 | 338427 | NaN |
| 10544 | 1439321239415 | 152963 | 3 | 55955 | 180.0 |
| 8837 | 1437780903046 | 861299 | 3 | 131034 | 7162.0 |
| 8628 | 1437674156662 | 883745 | 3 | 352742 | 11316.0 |
| 11268 | 1440017757081 | 303381 | 3 | 162046 | 13787.0 |

In [29]:
```
df_events_test.head()
```

Out[29]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 10711 | 1439484590277 | 1150086 | 3 | 253615 | 9457.0 |
| 1906 | 1432165517784 | 138131 | 3 | 176995 | 6308.0 |
| 5733 | 1435276573581 | 706387 | 2 | 283492 | NaN |
| 10068 | 1438827382136 | 478537 | 2 | 207430 | NaN |
| 7711 | 1436984362651 | 152693 | 2 | 64026 | NaN |

In [30]:
```
print('Test set represents', round(100*len(df_events_test)/len(df_e
print('Total number of interactions participating in train:',len(df
```

```
Test set represents 10.39 % of Train set.
Total number of interactions participating in train: 10940 / test:
1137
```

## Transforming interactions data into the format acceptable by lightFM model

In [31]:
```
# Dataset class of LightFM package has method build_interactions th
# As the input for this method need to pass the list of tuples (vis

start_time = time.time()

# Train set interactions transformed.
df_events_train_interactions = []
for index, row in df_events_train.iterrows():
    df_events_train_interactions.append((int(row['visitorid']), int

# Test set interactions transformed.
df_events_test_interactions = []
for index, row in df_events_test.iterrows():
    df_events_test_interactions.append((int(row['visitorid']), int(

# Full set of interactions transformed. This will be used for produ
df_events_all_interactions = []
for index, row in df_events.iterrows():
    df_events_all_interactions.append((int(row['visitorid']), int(r

print('Finished in: ', round((time.time()-start_time)/60, 2), " min
```

```
Finished in:  0.02  minutes
```

In [32]:
```
# Check original VS transformed length, should be equal.

print('Check original VS transformed length TRAIN: ',
     len(df_events_train),
     '/',
     len(df_events_train_interactions))

print('Check original VS transformed length TEST: ',
     len(df_events_test),
     '/',
     len(df_events_test_interactions))

print('Check original VS transformed length ALL: ',
     len(df_events),
     '/',
     len(df_events_all_interactions))
```

```
Check original VS transformed length TRAIN:  10940 / 10940
Check original VS transformed length TEST:  1137 / 1137
Check original VS transformed length ALL:  13675 / 13675
```

In [33]:
```
# Cross check successful.
```

# Preprocessing

## Data Import and Cleaning - Item Properties

In [34]:
```
# Import Properties

df_properties1 = pd.DataFrame(pd.read_csv("item_properties_part1.cs
df_properties2 = pd.DataFrame(pd.read_csv("item_properties_part2.cs
df_properties = pd.concat([df_properties1, df_properties2])

# data to be sorted by timestamp to reflect the historical change l
df_properties = df_properties.sort_values(by=['timestamp'], ascendi

df_properties.head(10)
```

Out[34]:

| | timestamp | itemid | property | value |
|---|---|---|---|---|
| 0 | 1431226800000 | 317951 | 790 | n32880.000 |
| 1 | 1431226800000 | 422842 | 480 | 1133979 |
| 2 | 1431226800000 | 310185 | 776 | 103591 |
| 3 | 1431226800000 | 110973 | 112 | 679677 |
| 4 | 1431226800000 | 179597 | available | 0 |
| 5 | 1431226800000 | 260136 | available | 1 |
| 6 | 1431226800000 | 138592 | 764 | 1285872 |
| 7 | 1431226800000 | 216269 | 364 | 336749 |
| 8 | 1431226800000 | 299944 | 764 | 1285872 |
| 9 | 1431226800000 | 146103 | 112 | 679677 |

In [35]:
```
df_properties.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20275902 entries, 0 to 20275901
Data columns (total 4 columns):
timestamp    int64
itemid       int64
property     object
value        object
dtypes: int64(2), object(2)
memory usage: 618.8+ MB
```

In [36]:
```
# Store the original size of item features dataframe.

df_properties_len_orig = len(df_properties)
```

In [37]:

```
# All the categories names and values are hashed excepting "categor

df_properties.loc[df_properties['itemid'] == 216269].head()
```

Out[37]:

| | timestamp | itemid | property | value |
|---|---|---|---|---|
| 7 | 1431226800000 | 216269 | 364 | 336749 |
| 517912 | 1431226800000 | 216269 | categoryid | 1029 |
| 820516 | 1431226800000 | 216269 | 917 | 378110 n18720.000 |
| 873983 | 1431226800000 | 216269 | available | 0 |
| 928887 | 1431226800000 | 216269 | 790 | n51900.000 |

In [38]:

```
# The model is unable to process the historical log so there's a ne
# The latest properties data is considered to be the best to descri
# Assumption: the ecommerce team was constantly improving the catal
# This action should lead to decrease of the dataframe size.

df_properties = df_properties.sort_values(by=['timestamp'], ascendi
    subset=['itemid', 'property'],
    keep='last').reset_index(drop=True)

df_properties.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12003814 entries, 0 to 12003813
Data columns (total 4 columns):
timestamp    int64
itemid       int64
property     object
value        object
dtypes: int64(2), object(2)
memory usage: 366.3+ MB
```

In [39]:
```
# Additionally, we can get rid of the 'available' property complete
# It won't make sense to consider any value as fixed (in stock or n
# In production this property can be used in real time to filter ou

df_properties = df_properties[~df_properties.property.isin(['availa

df_properties.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11586761 entries, 0 to 11586760
Data columns (total 4 columns):
timestamp    int64
itemid       int64
property     object
value        object
dtypes: int64(2), object(2)
memory usage: 353.6+ MB
```

In [40]:
```
# As the next step the items which are not present in the cleaned d

df_properties = df_properties[df_properties.itemid.isin(df_events['

df_properties.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 255722 entries, 0 to 255721
Data columns (total 4 columns):
timestamp    255722 non-null int64
itemid       255722 non-null int64
property     255722 non-null object
value        255722 non-null object
dtypes: int64(2), object(2)
memory usage: 7.8+ MB
```

In [41]:
```
# Timestamp column can also be removed as it is redundant.

df_properties = df_properties.drop(['timestamp'], axis=1)
```

In [42]:
```
# Sort dataframe by itemid.

df_properties = df_properties.sort_values(by=['itemid'], ascending=
```

In [43]:
```
print('Cleaned properties dataframe represents ',
      round(100*len(df_properties)/df_properties_len_orig,2),
     ' % of original dataframe.')
```

```
Cleaned properties dataframe represents  1.26  % of original dataf
rame.
```

In [44]:
```
qty_all_properties = len(df_properties['property'].unique())
print('Cleaned dataset number of properties: ', qty_all_properties)
print('Cleaned dataset number of properties values: ', len(df_prope
print()
print('Cleaned dataset number of items: ', qty_all_items)
print('Cleaned dataset number of users: ', qty_all_users)
print('Cleaned dataset number of interactions: ', len(df_events))
```

```
Cleaned dataset number of properties:  907
Cleaned dataset number of properties values:  255722

Cleaned dataset number of items:  9490
Cleaned dataset number of users:  1015
Cleaned dataset number of interactions:  13675
```

In [45]:
```
df_properties.head(10)
```

Out[45]:

| | itemid | property | value |
|---|---|---|---|
| 0 | 15 | 678 | 245772 |
| 1 | 15 | 915 | 769062 |
| 2 | 15 | 112 | 679677 |
| 3 | 15 | 812 | 769062 |
| 4 | 15 | 764 | 1285872 |
| 5 | 15 | 839 | 245772 |
| 6 | 15 | 616 | 769062 |
| 7 | 15 | 888 | 789221 |
| 8 | 15 | 776 | 604754 |
| 9 | 15 | 917 | 789221 |

## Transforming item features data into the format acceptable by lightFM model.

In [46]:
```
# The item features information should be passed to the lightFM mod
# This matrix must have mapping of all items related to the train/t
# all features available in cleaned properties dataframe.
# Then the matrix is to be filled in with the properties values.
# LightFM model would be then capable to create a latent features v
```

In [47]:
```
df_properties.loc[df_properties['itemid'] == 15].head()
```

Out[47]:

| | itemid | property | value |
|---|---|---|---|
| 0 | 15 | 678 | 245772 |
| 1 | 15 | 915 | 769062 |
| 2 | 15 | 112 | 679677 |
| 3 | 15 | 812 | 769062 |
| 4 | 15 | 764 | 1285872 |

In [48]:
```
# Dataset class has the method build_item_features that allows to f
# Add feature mapping to the existing dataset using fit_partial met
# Data needs to be transformed to the acceptable format.
# https://github.com/lyst/lightfm/issues/393#issuecomment-438237971


# Transform item features list to the format required by Dataset cl
# ['property:value']

item_features_mapping = []
for index, row in df_properties.iterrows():
    item_features_mapping.append(str(row['property']) + ':' + str(r

print('Properties mapping has:', len(item_features_mapping), 'recor
```

```
Properties mapping has: 255722 records
```

In [49]:
```
# As the next step need to remove duplicates in this list.
# So basically the feature mapping length is not equal to the numbe
# but is equal to the number of combinations ['property:value'] ava
# There's no need to "create" all possible combinations mapping as
# Just need to create mapping for existing combinations.
# Additionally, the LightFM package allows to add weight to this co

item_features_mapping = list( dict.fromkeys(item_features_mapping)
print('Properties mapping has:', len(item_features_mapping), 'uniqu
```

```
Properties mapping has: 71436 unique records
```

In [50]:
```
# Transform item features values to the format required by Dataset
# [ (itemid_1, ['property_1:value_1', 'property_2:value_2']) ]

start_time = time.time()

item_features_values = []
current_item = df_properties.itemid[0]
current_item_features = []
for index, row in df_properties.iterrows():
    if row['itemid'] == current_item:
        current_item_features.append(str(row['property']) + ':' + s
    else:
        item_features_values.append((current_item, current_item_fea
        current_item = row['itemid']
        current_item_features = [str(row['property']) + ':' + str(r
item_features_values.append((current_item, current_item_features))

print('Finished in: ', round((time.time()-start_time)/60, 2), " min
```

```
Finished in:  0.37  minutes
```

In [51]:
```
item_features_values[0]
```

Out[51]:
```
(15,
 ['678:245772',
  '915:769062',
  '112:679677',
  '812:769062',
  '764:1285872',
  '839:245772',
  '616:769062',
  '888:789221',
  '776:604754',
  '917:789221',
  '159:519769',
  '364:1047026',
  '698:433564',
  '283:433564 245772 789221 809278 245772 1213953 429140 1322984 7
92235 79212 237874 654986 809278 1215254 249416 646928 750061 9618
77 1152409 780700 1128577 269926 754848 703408 469750 581854 10289
19 1124417 484436 1256252 790607',
  'categoryid:722',
  '790:n8400.000',
  '202:789221',
  '227:433564',
  '591:1116693',
  '693:769062'])
```

# Preprocessing

## Create LightFM dataset mapping

In [52]:
```
# For model evaluation purposes (auc_score) dimensionality of train
# In order to achieve this, need to create mapping for all users an
# Then separately for train and test - the interactions will be fil
```

In [53]:
```
# Create mapping for users, items and item features.

# The fit method of class Dataset takes the list of all the visitor
# The implementation allows to ignore duplicates.

# Train set mapping.
dataset = Dataset()
dataset.fit(
    users = (x for x in df_events['visitorid']),
    items = (x for x in df_events['itemid']),
    user_features=None,
    item_features=item_features_mapping
)

dataset_train = dataset
dataset_test = dataset
dataset_all = dataset  # This will be used for production recommend
```

## Populate LightFM dataset with data

In [54]:
```
# Populate interactions matrix for train and test sets.

start_time = time.time()

(interactions_train, weights_train) = dataset_train.build_interacti
(interactions_test, weights_test) = dataset_test.build_interactions
(interactions_all, weights_all) = dataset_all.build_interactions(df


# Choose interactions to be used at next stages.
# The use of weights did not lead to improvement of model performan
# Reason for that is that the LightFM model does not count in any e
# The idea behind the implementation is to count in the implicit fe
# positive or negative interactions. As decided above, addtocart an
# The weights table wil not be needed for the purpose of this proje

train = interactions_train
test = interactions_test
production = interactions_all  # This will be used for production r

print('Finished in: ', round((time.time()-start_time)/60, 2), " min
```

```
Finished in:  0.0  minutes
```

In [55]:
```
# Populate item features matrix with values.

start_time = time.time()

item_features = dataset.build_item_features(item_features_values)

print('Finished in: ', round((time.time()-start_time)/60, 2), " min
```

```
Finished in:  0.01  minutes
```

In [56]:
```
print('Dataset class cross-check.')
print()

num_users, num_items = dataset.interactions_shape()
print('All users expected:', qty_all_users)
print('Actual number of users:', num_users)
print()
print('All items expected:', qty_all_items)
print('Actual number of items:', num_items)
print()

print('Item features matrix is expected to be of size: (', qty_all_
      qty_all_items+len(item_features_mapping), ')')
# Reason for this size is that there's a space for latent vector re
print('Actual size is:', dataset.item_features_shape())
print()

print('Item features matrix number of values is expected to be:', l
# Reason for this size is that there's a space for latent vector re
print('Actual number of values is:', item_features.getnnz())
print()

print('Interactions matrix is expected to be of the size: (', qty_a
print('Actual size is:', dataset.interactions_shape())
print()

print('Interactions matrix number of values is expected to be:', le
print('Actual number of values is:', train.getnnz() + test.getnnz()
print()
```

```
Dataset class cross-check.

All users expected: 1015
Actual number of users: 1015

All items expected: 9490
Actual number of items: 9490

Item features matrix is expected to be of size: ( 9490 , 80926 )
Actual size is: (9490, 80926)

Item features matrix number of values is expected to be: 265212
Actual number of values is: 265212

Interactions matrix is expected to be of the size: ( 1015 , 9490 )
Actual size is: (1015, 9490)

Interactions matrix number of values is expected to be: 12077
Actual number of values is: 12077
```

# Collaborative LightFM model training

In [57]:
```
# Item features are not passed to the model. This means pure collab

start_time = time.time()

model_collab = LightFM(no_components=100, loss='warp', random_state

model_collab.fit(train,
                 item_features=None,
                 epochs=100,
                 num_threads=4)

print('Model trained in: ', round((time.time()-start_time)/60, 2),
```

```
Model trained in:  0.03  minutes
```

In [58]:
```
model_collab.get_params()
```

Out[58]:
```
{'loss': 'warp',
 'learning_schedule': 'adagrad',
 'no_components': 100,
 'learning_rate': 0.05,
 'k': 5,
 'n': 10,
 'rho': 0.95,
 'epsilon': 1e-06,
 'max_sampled': 10,
 'item_alpha': 0.0,
 'user_alpha': 0.0,
 'random_state': RandomState(MT19937) at 0x7FA2F1DB6160}
```

# Collaborative LightFM model evaluation

In [59]:
```
# Since the recommendation engine is a ranking problem, AUC and Pre
# Both of them are measuring the ranking quality, which means for e
# in the order of their fit/interest to the user.


# [source: https://making.lyst.com/lightfm/docs/lightfm.evaluation.

# AUC (area under the curve) shows how well the items are ranked. P
# example will be ranked higher than any random negative example. H

# Precision at 'k' shows the ratio of known positive examples in to
# Highest metric's value is 1.0 (100%)



# Set parameter "k" value to check precision at "k".
# Initially select k=3 as it will allow to have 4 possible combinat
# to the user and achieve the goal of increasing the basket value.

# User won't be offered set of 2 for each item as this is simpler t
# is a business need for that. This will lead to better user experi
# can cause FOMO (fear of missing out) when the user gets stuck in


k = 3
```

In [60]:
```
start_time = time.time()

train_auc = auc_score(model_collab,
                      train,
                      item_features=None,
                      num_threads=4).mean()

print('Train AUC score: ', train_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train AUC score:  0.9999983
Calculated in:  0.01  minutes
```

In [61]:
```
start_time = time.time()

# Train interactions will be also passed to avoid model re-recommen
test_auc = auc_score(model_collab,
                     test,
                     item_features=None,
                     train_interactions = train,
                     num_threads=4).mean()

print('Test AUC score: ', test_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Test AUC score:  0.65434647
Calculated in:  0.0  minutes
```

In [62]:
```
start_time = time.time()

train_precision = precision_at_k(model_collab,
                                 train,
                                 item_features=None,
                                 num_threads=4,
                                 k=k).mean()

print('Train precision at k: ', train_precision)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train precision at k:  0.7899966
Calculated in:  0.01  minutes
```

In [63]:
```
start_time = time.time()

test_precision = precision_at_k(model_collab,
                                test,
                                item_features=None,
                                train_interactions = train,
                                num_threads=4,
                                k=k).mean()

print('Test precision at k: ', test_precision)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Test precision at k:  0.012444445
Calculated in:  0.0  minutes
```

In [64]:
```
model_collab_results = {}
model_collab_results['AUC train'] = train_auc
model_collab_results['AUC test'] = test_auc
model_collab_results['Precision @3 train'] = train_precision
model_collab_results['Precision @3 test'] = test_precision
```

In [65]:
```
model_collab_results
```

Out[65]:
```
{'AUC train': 0.9999983,
 'AUC test': 0.65434647,
 'Precision @3 train': 0.7899966,
 'Precision @3 test': 0.012444445}
```

# Hybrid LightFM model training

In [66]:
```
# Update the model with item features to drive content based filter
# Hybrid model is benefiting from collaborative and content based f

start_time = time.time()

model_hybrid = LightFM(no_components=100, loss='warp', random_state

NUM_EPOCHS = 100  # Initial number of epochs to be set.

model_hybrid.fit(train,
                 item_features=item_features,
                 epochs=NUM_EPOCHS,
                 num_threads=4)

print('Model trained in: ', round((time.time()-start_time)/60, 2),
```

```
Model trained in:  0.44  minutes
```

In [67]:
```
model_hybrid.get_params()
```

Out[67]:
```
{'loss': 'warp',
 'learning_schedule': 'adagrad',
 'no_components': 100,
 'learning_rate': 0.05,
 'k': 5,
 'n': 10,
 'rho': 0.95,
 'epsilon': 1e-06,
 'max_sampled': 10,
 'item_alpha': 0.0,
 'user_alpha': 0.0,
 'random_state': RandomState(MT19937) at 0x7FA2F1DB65A0}
```

# Hybrid LightFM model evaluation

In [68]:
```
start_time = time.time()

train_auc = auc_score(model_hybrid,
                      train,
                      item_features=item_features,
                      num_threads=4).mean()

print('Train AUC score: ', train_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train AUC score:  0.99953717
Calculated in:  0.12  minutes
```

In [69]:
```
start_time = time.time()

# Train interactions will be also passed to avoid model re-recommen
test_auc = auc_score(model_hybrid,
                     test,
                     item_features=item_features,
                     train_interactions = train,
                     num_threads=4).mean()

print('Test AUC score: ', test_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Test AUC score:  0.84518975
Calculated in:  0.05  minutes
```

In [70]:
```
start_time = time.time()

train_precision = precision_at_k(model_hybrid,
                                 train,
                                 item_features=item_features,
                                 num_threads=4,
                                 k=k).mean()

print('Train precision at k: ', train_precision)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train precision at k:  0.5577252
Calculated in:  0.12  minutes
```

In [71]:
```
start_time = time.time()

test_precision = precision_at_k(model_hybrid,
                                test,
                                item_features=item_features,
                                train_interactions = train,
                                num_threads=4,
                                k=k).mean()

print('Test precision at k: ', test_precision)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Test precision at k:  0.030222224
Calculated in:  0.05  minutes
```

In [72]:
```
model_hybrid_results = {}
model_hybrid_results['AUC train'] = train_auc
model_hybrid_results['AUC test'] = test_auc
model_hybrid_results['Precision @3 train'] = train_precision
model_hybrid_results['Precision @3 test'] = test_precision
```

In [73]:
```
# Compare results of collaborative and hybrid models
print('Collaborative filtering results: ', model_collab_results)
print()
print('Hybrid filtering results: ', model_hybrid_results)
```

```
Collaborative filtering results:  {'AUC train': 0.9999983, 'AUC te
st': 0.65434647, 'Precision @3 train': 0.7899966, 'Precision @3 te
st': 0.012444445}

Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

In [74]:
```
# From the above comparison it's clear that passing item features t
```

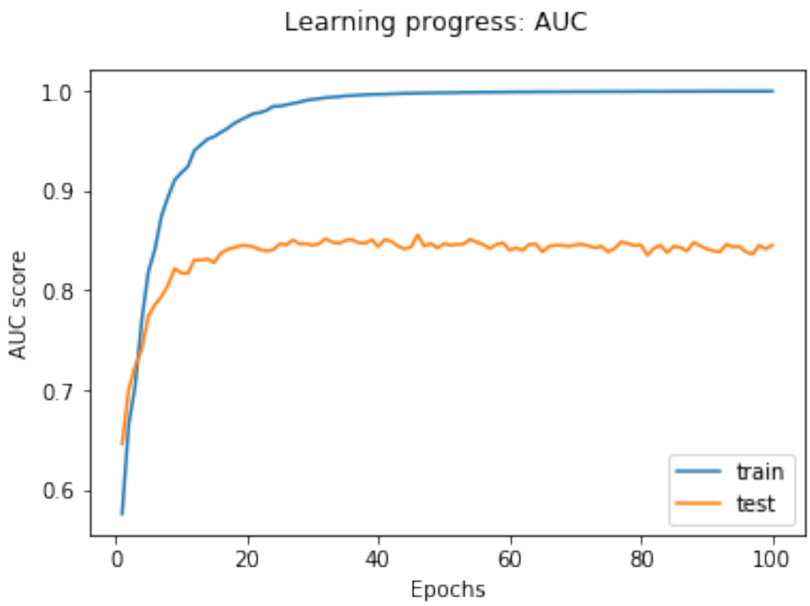
# Visualize learning process

In [75]:
```
# Visualization of the learning process will show how quickly the m
# Identifying the point of slowing down or termination of learning
# limiting the number of epochs needed to achieve the result that s
```

In [76]:
```
# AUC visualization function.

def learning_vis_auc(model, train, test, item_features, epochs):

    stats = pd.DataFrame(columns = ['epochs', 'train_auc', 'test_au

    total_runtime_min = 0

    for epoch in range(1,epochs+1):

        start_time = time.time()

        model.fit(train,
                  item_features=item_features,
                  epochs=epoch,
                  num_threads=4)

        train_auc = auc_score(model,
                              train,
                              item_features=item_features,
                              num_threads=4).mean()

        test_auc = auc_score(model,
                             test,
                             item_features=item_features,
                             train_interactions = train,
                             num_threads=4).mean()

        runtime_min = round((time.time()-start_time)/60, 6)
        total_runtime_min += runtime_min

        stats = stats.append({
            'epochs': int(epoch),
            'train_auc': float(train_auc),
            'test_auc': float(test_auc),
            'runtime_min': float(runtime_min)},
            ignore_index=True)


    import matplotlib.pyplot as plt
    figure, axis = plt.subplots()
    figure.suptitle('Learning progress: AUC')
    axis.plot(stats['epochs'], stats['train_auc'], label='train')
    axis.plot(stats['epochs'], stats['test_auc'], label='test')
    axis.set_xlabel('Epochs')
    axis.set_ylabel('AUC score')
    axis.legend()

    return(figure, stats, total_runtime_min)
```

In [77]:
```
start_time = time.time()

learning_vis_auc_output = learning_vis_auc(model_hybrid, train, tes

print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Calculated in:  42.84  minutes
```




In [78]:
```
learning_vis_auc_output[1]
```

Out[78]:

| | epochs | train_auc | test_auc | runtime_min |
|---|---|---|---|---|
| 0 | 1.0 | 0.575920 | 0.645920 | 0.193750 |
| 1 | 2.0 | 0.665595 | 0.700700 | 0.202326 |
| 2 | 3.0 | 0.704638 | 0.723904 | 0.211005 |
| 3 | 4.0 | 0.770477 | 0.741530 | 0.218210 |
| 4 | 5.0 | 0.818777 | 0.774045 | 0.228176 |
| ... | ... | ... | ... | ... |
| 95 | 96.0 | 0.999500 | 0.838356 | 0.571935 |
| 96 | 97.0 | 0.999470 | 0.836078 | 0.575037 |
| 97 | 98.0 | 0.999505 | 0.845081 | 0.575051 |
| 98 | 99.0 | 0.999561 | 0.841411 | 0.581202 |
| 99 | 100.0 | 0.999536 | 0.845265 | 0.602118 |

100 rows × 4 columns

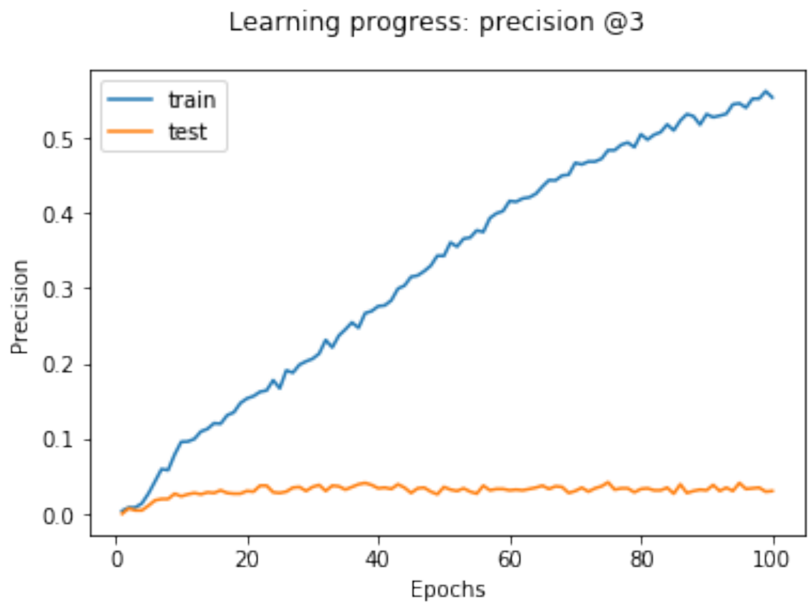
In [79]:
```
learning_vis_auc_output[2]
```

Out[79]: 42.836369000000005

In [80]:
```
# Precision visualization.

def learning_vis_precision(model, train, test, item_features, k, ep

    stats = pd.DataFrame(columns = ['epochs', 'train_precision', 't

    total_runtime_min = 0

    for epoch in range(1,epochs+1):

        start_time = time.time()

        model.fit(train,
                  item_features=item_features,
                  epochs=epoch,
                  num_threads=4)

        train_precision = precision_at_k(model,
                                         train,
                                         item_features=item_feature
                                         num_threads=4,
                                         k=k).mean()

        test_precision = precision_at_k(model,
                                        test,
                                        item_features=item_features
                                        train_interactions=train,
                                        num_threads=4,
                                        k=k).mean()

        runtime_min = round((time.time()-start_time)/60, 6)
        total_runtime_min += runtime_min

        stats = stats.append({
            'epochs': int(epoch),
            'train_precision': float(train_precision),
            'test_precision': float(test_precision),
            '@k': int(k),
            'runtime_min': float(runtime_min)},
            ignore_index=True)


    import matplotlib.pyplot as plt
    figure, axis = plt.subplots()
    figure.suptitle('Learning progress: precision @%s' %k)
    axis.plot(stats['epochs'], stats['train_precision'], label='tra
    axis.plot(stats['epochs'], stats['test_precision'], label='test
    axis.set_xlabel('Epochs')
    axis.set_ylabel('Precision')
    axis.legend()

    return(figure, stats, total_runtime_min)
```

In [81]:
```
start_time = time.time()

prec_at_3 = learning_vis_precision(model_hybrid, train, test, item_

print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

Calculated in:  42.6  minutes




In [82]:
```
prec_at_3[1]
```

Out[82]:

| | epochs | train_precision | test_precision | @kruntime_min | @k | runtime_min |
|---|---|---|---|---|---|---|
| 0 | 1.0 | 0.003768 | 0.000000 | NaN | 3.0 | 0.188984 |
| 1 | 2.0 | 0.008222 | 0.007111 | NaN | 3.0 | 0.195940 |
| 2 | 3.0 | 0.008222 | 0.004444 | NaN | 3.0 | 0.201109 |
| 3 | 4.0 | 0.013703 | 0.004444 | NaN | 3.0 | 0.208089 |
| 4 | 5.0 | 0.026721 | 0.010667 | NaN | 3.0 | 0.215104 |
| ... | ... | ... | ... | ... | ... | ... |
| 95 | 96.0 | 0.539568 | 0.032889 | NaN | 3.0 | 0.574232 |
| 96 | 97.0 | 0.551559 | 0.033778 | NaN | 3.0 | 0.574788 |
| 97 | 98.0 | 0.551559 | 0.034667 | NaN | 3.0 | 0.574860 |
| 98 | 99.0 | 0.561494 | 0.029333 | NaN | 3.0 | 0.579589 |
| 99 | 100.0 | 0.553272 | 0.030222 | NaN | 3.0 | 0.580510 |

100 rows × 6 columns

In [83]:
```
prec_at_3[2]
```

Out[83]: 42.59934299999999

In [84]:
```
# Conclusion on learning process visualization.

# From the plots above it is clear the learning process slows down
# In order to save the computational costs and optimize the process

NUM_EPOCHS = 30
```

# Hyperparameter tuning

In [85]:
```
# Attempting to regularize model and achieve better results on test

# The author of the LightFM package Maciej Kula has also developed
# Original algorythm was posted on GitHub 23 Apr 2018.
# Code is available via url https://gist.github.com/maciejkula/29aa

# For the purposes of this project the original code was modified t

# There will be two attempts:
# AUC focused tuning - when the best model will be chosen based on
# Precision focused - when the measure of success to chose the best
```

In [86]:
```
# Split train set into train_train and validate subsets.

(train_train, validate) = random_train_test_split(train,
                                                  test_percentage=0
```

In [87]:
```
# The range of hyperparameters needs to be set up manually.
# Then function will randomly try various combinations to find the


def sample_hyperparameters():

    # Choose the hyperparameters to tune and the range of values.

    while True:
        yield {
            'no_components': np.random.randint(10, 100),
            'learning_schedule': np.random.choice(['adagrad', 'adad
            'loss': np.random.choice(['bpr', 'warp', 'warp-kos']),
            'k': np.random.randint(1, 10),
            'n': np.random.randint(1, 20),
            'learning_rate': np.random.exponential(0.005),
            'item_alpha': np.random.exponential(1e-10),
            'max_sampled': np.random.randint(5, 30),
            'num_epochs': np.random.randint(10, 100)
        }
```

# AUC focused model - Tuning

In [88]:
```
# Improving AUC metric.


def random_search_auc(train_train, validate, num_samples=50, num_th

    # Randomly search for various combinations of hyperparameters.


    for hyperparams in islice(sample_hyperparameters(), num_samples
        num_epochs = hyperparams.pop('num_epochs')

        model_tuned_auc = LightFM(**hyperparams)
        model_tuned_auc.fit(train_train, epochs=num_epochs, num_thr

        ranking_score = auc_score(model_tuned_auc,
                                  validate, train_interactions=trai
                                  num_threads=num_threads).mean()

        hyperparams['num_epochs'] = num_epochs

        yield (ranking_score, hyperparams, model_tuned_auc)
        # Returns: generator of (auc score, hyperparameter dict, fi





start_time = time.time()

if __name__ == '__main__':

    (ranking_score, hyperparams, model_tuned_auc) = max(random_sear
                                                        key=lambda

    print('Best ranking score {} at {}'.format(ranking_score, hyper
    print('Calculated in: ', round((time.time()-start_time)/60, 2),
```

```
Best ranking score 0.5364086031913757 at {'no_components': 63, 'le
arning_schedule': 'adadelta', 'loss': 'bpr', 'k': 8, 'n': 17, 'lea
rning_rate': 0.0032541544211442037, 'item_alpha': 7.96139580516944
9e-11, 'max_sampled': 25, 'num_epochs': 33}
Calculated in:  1.07  minutes
```

# AUC focused model - Training

In [89]:
```
# Use the tuned model.

start_time = time.time()

model_tuned_auc.fit(train,
                    item_features=item_features,
                    epochs=hyperparams['num_epochs'],
                    num_threads=4)

print('Model trained in: ', round((time.time()-start_time)/60, 2),
```

```
Model trained in:  0.25  minutes
```

# AUC focused model - Evaluation

In [90]:
```
start_time = time.time()

train_auc = auc_score(model_tuned_auc,
                      train,
                      item_features=item_features,
                      num_threads=4).mean()

print('Train AUC score: ', train_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train AUC score:  0.9620935
Calculated in:  0.14  minutes
```

In [91]:
```
start_time = time.time()

# Train interactions will be also passed to avoid model re-recommen
test_auc = auc_score(model_tuned_auc,
                     test,
                     item_features=item_features,
                     train_interactions = train,
                     num_threads=4).mean()

print('Test AUC score: ', test_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Test AUC score:  0.8172267
Calculated in:  0.06  minutes
```

In [92]:
```
# Conclusion:
# Achieved test AUC is lower than original hybrid filtering model r

print('Hybrid filtering results: ', model_hybrid_results)
```

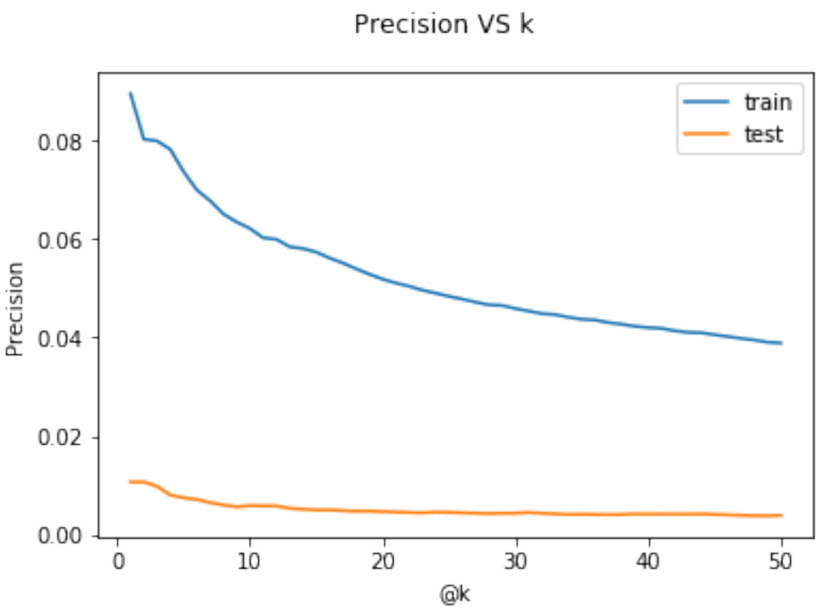
```
Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

In [93]:
```
# Visualize how the precision changes depending on parameter 'k'.
# Since the hyperparameters tuning was not optimized for parameter

def k_vis_precision(model, train, test, item_features, epochs):

    stats = pd.DataFrame(columns = ['@k', 'train_precision', 'test_

    model.fit(train,
              item_features=item_features,
              epochs=epochs,
              num_threads=4)

    total_runtime_min = 0

    for k in range(1,51):

        start_time = time.time()


        train_precision = precision_at_k(model,
                                         train,
                                         item_features=item_feature
                                         num_threads=4,
                                         k=k).mean()

        test_precision = precision_at_k(model,
                                        test,
                                        item_features=item_features
                                        train_interactions = train,
                                        num_threads=4,
                                        k=k).mean()

        runtime_min = round((time.time()-start_time)/60, 6)
        total_runtime_min += runtime_min

        stats = stats.append({
            '@k': int(k),
            'train_precision': float(train_precision),
            'test_precision': float(test_precision),
            'runtime_min': float(runtime_min)},
            ignore_index=True)


    import matplotlib.pyplot as plt
```

```
    figure, axis = plt.subplots()
    figure.suptitle('Precision VS k')
    axis.plot(stats['@k'], stats['train_precision'], label='train')
    axis.plot(stats['@k'], stats['test_precision'], label='test')
    axis.set_xlabel('@k')
    axis.set_ylabel('Precision')
    axis.legend()

    return(figure, stats, total_runtime_min)
```

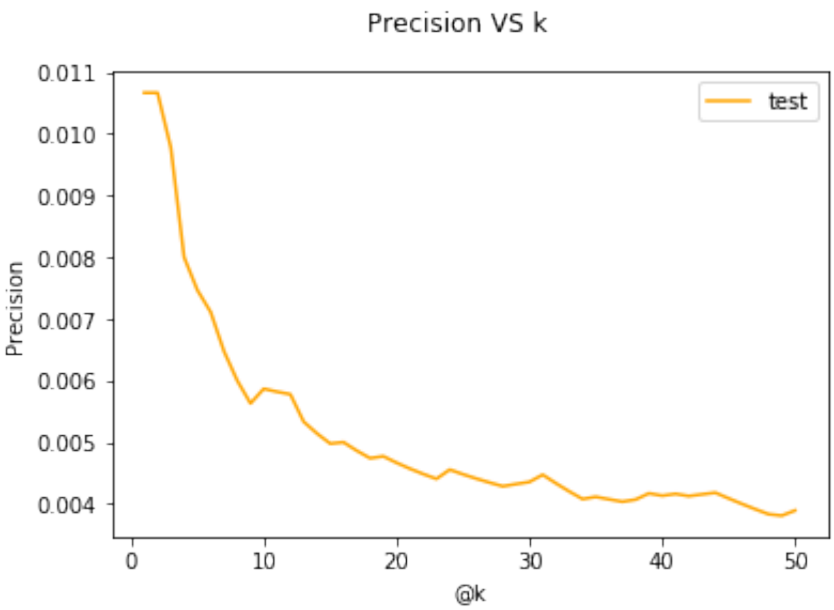
In [94]:
```
start_time = time.time()

k_vis_precision_output = k_vis_precision(model_tuned_auc,
                                         train, test,
                                         item_features,
                                         epochs=hyperparams['num_ep

print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Calculated in:  10.39  minutes
```



In [95]:
```
# Plot test precision separately to have a closer look at behaviour

figure, axis = plt.subplots()
figure.suptitle('Precision VS k')
axis.plot(k_vis_precision_output[1]['@k'], k_vis_precision_output[1
axis.set_xlabel('@k')
axis.set_ylabel('Precision')
axis.legend()
```

Out[95]: <matplotlib.legend.Legend at 0x7fa2ee575990>




In [96]:
```
k_vis_precision_output[1]
```

Out[96]:

| | @k | train_precision | test_precision | runtime_min |
|---|---|---|---|---|
| 0 | 1.0 | 0.089414 | 0.010667 | 0.199227 |
| 1 | 2.0 | 0.080164 | 0.010667 | 0.202507 |
| 2 | 3.0 | 0.079822 | 0.009778 | 0.202348 |
| 3 | 4.0 | 0.078109 | 0.008000 | 0.201115 |
| 4 | 5.0 | 0.073587 | 0.007467 | 0.201835 |
| 5 | 6.0 | 0.069887 | 0.007111 | 0.202830 |
| 6 | 7.0 | 0.067685 | 0.006476 | 0.201747 |
| 7 | 8.0 | 0.065005 | 0.006000 | 0.202387 |
| 8 | 9.0 | 0.063378 | 0.005630 | 0.202498 |
| 9 | 10.0 | 0.062076 | 0.005867 | 0.198151 |
| 10 | 11.0 | 0.060170 | 0.005818 | 0.202942 |
| 11 | 12.0 | 0.059866 | 0.005778 | 0.203475 |
| 12 | 13.0 | 0.058345 | 0.005333 | 0.201572 |

| | | | | |
|---|---|---|---|---|
| 13 | 14.0 | 0.057994 | 0.005143 | 0.202606 |
| 14 | 15.0 | 0.057280 | 0.004978 | 0.200253 |
| 15 | 16.0 | 0.056077 | 0.005000 | 0.202140 |
| 16 | 17.0 | 0.055075 | 0.004863 | 0.201620 |
| 17 | 18.0 | 0.053900 | 0.004741 | 0.203219 |
| 18 | 19.0 | 0.052794 | 0.004772 | 0.201456 |
| 19 | 20.0 | 0.051799 | 0.004667 | 0.202926 |
| 20 | 21.0 | 0.050996 | 0.004571 | 0.201963 |
| 21 | 22.0 | 0.050360 | 0.004485 | 0.201758 |
| 22 | 23.0 | 0.049555 | 0.004406 | 0.201885 |
| 23 | 24.0 | 0.048947 | 0.004556 | 0.202330 |
| 24 | 25.0 | 0.048304 | 0.004480 | 0.201633 |
| 25 | 26.0 | 0.047751 | 0.004410 | 0.202597 |
| 26 | 27.0 | 0.047124 | 0.004346 | 0.203662 |
| 27 | 28.0 | 0.046579 | 0.004286 | 0.202262 |
| 28 | 29.0 | 0.046461 | 0.004322 | 0.202591 |
| 29 | 30.0 | 0.045838 | 0.004356 | 0.201814 |
| 30 | 31.0 | 0.045320 | 0.004473 | 0.204907 |
| 31 | 32.0 | 0.044803 | 0.004333 | 0.201849 |
| 32 | 33.0 | 0.044598 | 0.004202 | 0.202836 |
| 33 | 34.0 | 0.044072 | 0.004078 | 0.203053 |
| 34 | 35.0 | 0.043665 | 0.004114 | 0.201952 |
| 35 | 36.0 | 0.043508 | 0.004074 | 0.204195 |
| 36 | 37.0 | 0.042999 | 0.004036 | 0.204652 |
| 37 | 38.0 | 0.042652 | 0.004070 | 0.205020 |
| 38 | 39.0 | 0.042243 | 0.004171 | 0.208454 |
| 39 | 40.0 | 0.041958 | 0.004133 | 0.203547 |
| 40 | 41.0 | 0.041812 | 0.004163 | 0.208502 |
| 41 | 42.0 | 0.041330 | 0.004127 | 0.206964 |
| 42 | 43.0 | 0.040990 | 0.004155 | 0.203005 |
| 43 | 44.0 | 0.040923 | 0.004182 | 0.201838 |
| 44 | 45.0 | 0.040516 | 0.004089 | 0.201760 |
| 45 | 46.0 | 0.040149 | 0.004000 | 0.198699 |
| 46 | 47.0 | 0.039776 | 0.003915 | 0.201345 |
| 47 | 48.0 | 0.039461 | 0.003833 | 0.206166 |

| | | | | |
|---|---|---|---|---|
| 48 | 49.0 | 0.039013 | 0.003810 | 0.205286 |
| 49 | 50.0 | 0.038849 | 0.003893 | 0.203198 |

In [97]:
```
k_vis_precision_output[2]
```

Out[97]: 10.136576999999997

In [98]:
```
# Conclusion:
# The highest test precision is significantly lower than original h

print('Hybrid filtering results: ', model_hybrid_results)
```

```
Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

In [99]:
```
# Summary:
# AUC focused hyperparameter tuning did not lead to model performan
```

# Precision focused model - Tuning

In [100]:
```
# Improving precision_at_k metric.

def random_search_precision(train_train, validate, num_samples=10,

    # Randomly search for various combinations of hyperparameters.


    for hyperparams in islice(sample_hyperparameters(), num_samples
        num_epochs = hyperparams.pop('num_epochs')

        model_tuned_precis = LightFM(**hyperparams)
        model_tuned_precis.fit(train_train, epochs=num_epochs, num_

        ranking_score = precision_at_k(model_tuned_precis, validate
                                       num_threads=num_threads,
                                       k=k).mean()

        hyperparams['num_epochs'] = num_epochs

        yield (ranking_score, hyperparams, model_tuned_precis)
        # Returns: generator of (precision_at_k, hyperparameter dic




start_time = time.time()

if __name__ == '__main__':

    (ranking_score, hyperparams, model_tuned_precis) = max(random_s
                                                           key=lamb

    print('Best presicion ranking score {} at {}'.format(ranking_sc
    print('Calculated in: ', round((time.time()-start_time)/60, 2),
```

```
Best presicion ranking score 0.009803921915590763 at {'no_componen
ts': 75, 'learning_schedule': 'adagrad', 'loss': 'warp-kos', 'k':
5, 'n': 5, 'learning_rate': 0.007417186569917661, 'item_alpha': 5.
626895454036104e-13, 'max_sampled': 21, 'num_epochs': 98}
Calculated in:  0.25  minutes
```

# Precision focused model - Training

In [101]:
```
# Use the tuned model.

start_time = time.time()

model_tuned_precis.fit(train,
                       item_features=item_features,
                       epochs=hyperparams['num_epochs'],
                       num_threads=4)

print('Model trained in: ', round((time.time()-start_time)/60, 2),
```

```
Model trained in:  0.61  minutes
```

In [102]:
```
# Tuned model evaluation (auc_score, precision_at_k)
```

In [103]:
```
start_time = time.time()

train_auc = auc_score(model_tuned_precis,
                      train,
                      item_features=item_features,
                      num_threads=4).mean()

print('Train AUC score: ', train_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

```
Train AUC score:  0.95148015
Calculated in:  0.12  minutes
```

In [104]:
```
start_time = time.time()

# Train interactions fill be also passed to avoid model re-recommen
test_auc = auc_score(model_tuned_precis,
                     test,
                     item_features=item_features,
                     train_interactions = train,
                     num_threads=4).mean()

print('Test AUC score: ', test_auc)
print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

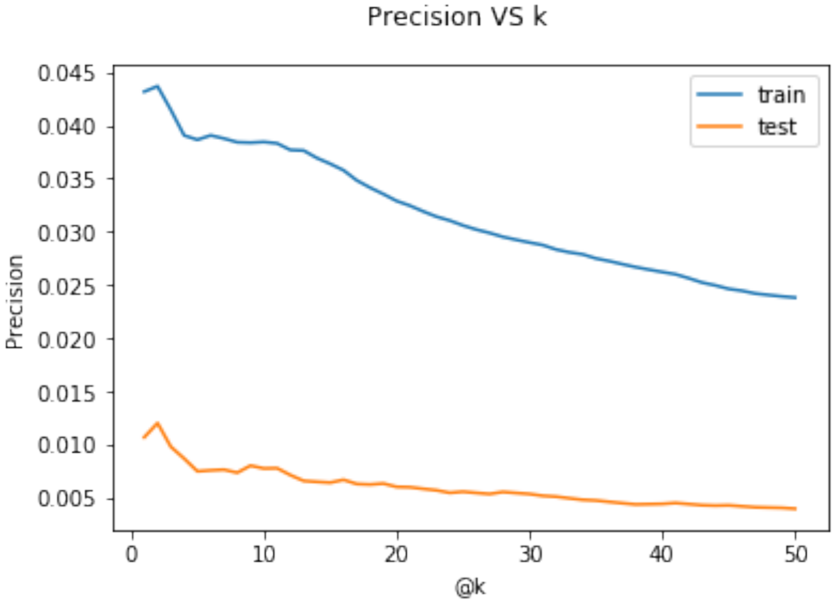
```
Test AUC score:  0.83780867
Calculated in:  0.05  minutes
```

In [105]:
```
# Conclusion:
# Achieved test AUC is lower than original hybrid filtering model r

print('Hybrid filtering results: ', model_hybrid_results)
```

```
Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

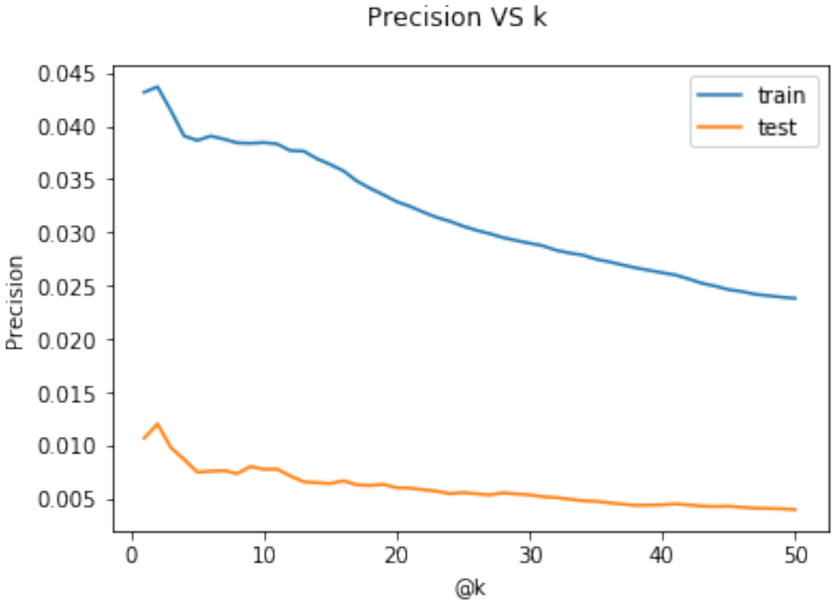
In [106]:
```
# Visualize how the precision changes depending on parameter 'k'.

start_time = time.time()

k_vis_precision_output = k_vis_precision(model_tuned_precis,
                                         train, test, item_features
                                         epochs=hyperparams['num_ep

print('Calculated in: ', round((time.time()-start_time)/60, 2), " m
```

Calculated in:  8.8  minutes



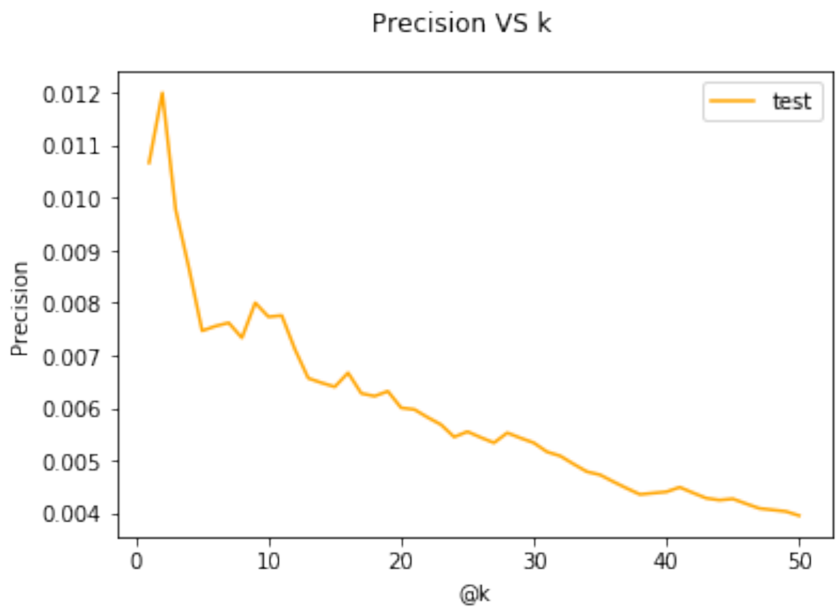

In [107]:
```
k_vis_precision_output[0]
```

Out[107]:



In [108]:
```
# Plot test precision separately to have a closer look at behaviour

figure, axis = plt.subplots()
figure.suptitle('Precision VS k')
axis.plot(k_vis_precision_output[1]['@k'], k_vis_precision_output[1
axis.set_xlabel('@k')
axis.set_ylabel('Precision')
axis.legend()
```

Out[108]: <matplotlib.legend.Legend at 0x7fa2f25c1290>




In [109]:
```
k_vis_precision_output[1]
```

Out[109]:

| | @k | train_precision | test_precision | runtime_min |
|---|---|---|---|---|
| 0 | 1.0 | 0.043165 | 0.010667 | 0.167324 |
| 1 | 2.0 | 0.043679 | 0.012000 | 0.158995 |
| 2 | 3.0 | 0.041453 | 0.009778 | 0.167088 |
| 3 | 4.0 | 0.039054 | 0.008667 | 0.167690 |
| 4 | 5.0 | 0.038643 | 0.007467 | 0.165195 |
| 5 | 6.0 | 0.039054 | 0.007556 | 0.165602 |
| 6 | 7.0 | 0.038761 | 0.007619 | 0.167225 |
| 7 | 8.0 | 0.038412 | 0.007333 | 0.169147 |
| 8 | 9.0 | 0.038369 | 0.008000 | 0.167507 |
| 9 | 10.0 | 0.038438 | 0.007733 | 0.166355 |
| 10 | 11.0 | 0.038307 | 0.007758 | 0.166029 |
| 11 | 12.0 | 0.037684 | 0.007111 | 0.168814 |
| 12 | 13.0 | 0.037631 | 0.006564 | 0.167218 |

| | | | | |
|---|---|---|---|---|
| 13 | 14.0 | 0.036926 | 0.006476 | 0.168310 |
| 14 | 15.0 | 0.036382 | 0.006400 | 0.171864 |
| 15 | 16.0 | 0.035779 | 0.006667 | 0.166642 |
| 16 | 17.0 | 0.034823 | 0.006275 | 0.168910 |
| 17 | 18.0 | 0.034144 | 0.006222 | 0.166894 |
| 18 | 19.0 | 0.033537 | 0.006316 | 0.166359 |
| 19 | 20.0 | 0.032888 | 0.006000 | 0.166807 |
| 20 | 21.0 | 0.032448 | 0.005968 | 0.164949 |
| 21 | 22.0 | 0.031907 | 0.005818 | 0.169869 |
| 22 | 23.0 | 0.031413 | 0.005681 | 0.166557 |
| 23 | 24.0 | 0.031047 | 0.005444 | 0.165879 |
| 24 | 25.0 | 0.030586 | 0.005547 | 0.163540 |
| 25 | 26.0 | 0.030200 | 0.005436 | 0.158399 |
| 26 | 27.0 | 0.029881 | 0.005333 | 0.157166 |
| 27 | 28.0 | 0.029511 | 0.005524 | 0.156121 |
| 28 | 29.0 | 0.029238 | 0.005425 | 0.161352 |
| 29 | 30.0 | 0.028983 | 0.005333 | 0.158430 |
| 30 | 31.0 | 0.028744 | 0.005161 | 0.160629 |
| 31 | 32.0 | 0.028327 | 0.005083 | 0.155505 |
| 32 | 33.0 | 0.028061 | 0.004929 | 0.158485 |
| 33 | 34.0 | 0.027870 | 0.004784 | 0.158016 |
| 34 | 35.0 | 0.027485 | 0.004724 | 0.158691 |
| 35 | 36.0 | 0.027235 | 0.004593 | 0.163349 |
| 36 | 37.0 | 0.026944 | 0.004468 | 0.155753 |
| 37 | 38.0 | 0.026667 | 0.004351 | 0.159396 |
| 38 | 39.0 | 0.026432 | 0.004376 | 0.167959 |
| 39 | 40.0 | 0.026208 | 0.004400 | 0.167179 |
| 40 | 41.0 | 0.025995 | 0.004488 | 0.167082 |
| 41 | 42.0 | 0.025620 | 0.004381 | 0.165094 |
| 42 | 43.0 | 0.025216 | 0.004279 | 0.167039 |
| 43 | 44.0 | 0.024946 | 0.004242 | 0.166080 |
| 44 | 45.0 | 0.024620 | 0.004267 | 0.161133 |
| 45 | 46.0 | 0.024443 | 0.004174 | 0.158594 |
| 46 | 47.0 | 0.024185 | 0.004085 | 0.159618 |
| 47 | 48.0 | 0.024045 | 0.004056 | 0.158333 |

| | | | | |
|---|---|---|---|---|
| 48 | 49.0 | 0.023911 | 0.004027 | 0.157509 |
| 49 | 50.0 | 0.023803 | 0.003947 | 0.161368 |

In [110]:
```
# Conclusion:
# Test precision at k=1 (highest) and k=3 is significantly lower th

print('Hybrid filtering results: ', model_hybrid_results)
```

```
Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

In [111]:
```
# Summary:
# Precision focused hyperparameter tuning did not lead to model per
```

# Conclusion on the Model

In production the model should can be evaluated on the recommendations conversion rate and basket value. The big difference is that in production the users will be given the recommendations and will possibly interact with them.

Since this project is done in isolated environment, where the test set of users isn't actually getting recommendations, the best possible way to evaluate the model is to see the AUC and precision at k metrics.

Item features were successfully used to improve the model performance.

The best achieved test AUC is ~0.84, which means that in 84% of the cases randomly selected positive interaction is ranked higher than any randomly selected negative interaction. This metrics determines how well the products are ranked for each particular user.

The best achieved test precision is 0.03 at k=3, which means in 3% of the cases the positive interaction is in the top 3 recommended items.

Both achieved AUC and precision are comparable to the available web results.

Hyperparameter tuning has not led to improvement of both metrics.

In [112]:
```
model_best = model_hybrid
```

In [113]:
```
full_cycle_time_end = time.time()


print('Full code has been run in: ',
      round((full_cycle_time_end-full_cycle_time_start)/60, 2),
      ' minutes')
```

```
Full code has been run in:  109.71  minutes
```

# Recommendations

### Develop recommender function returning the list of top items for each user, no bundles.

In [114]:
```
# Recommedations algorythm was developed by the author of LightFM p
# https://making.lyst.com/lightfm/docs/quickstart.html

def recommend(model_trained, dataset, interactions, userids, N):

    '''
    model_trained - the trained model to be used for recommendation
    dataset - LightFM Dataset class used to create mapping.
    interactions - coo matrix of known positive interactions.
    users - list of users for recommendations.
    N - top N recommendations to return.
    '''

    model = model_trained
    # Extract user and item mapping from created Dataset class.
    # Mapping is stored as tuple of arrays (user id map, user featu
    # Need to extract arrays with  index 0 and 2.
    mapping_users = dataset.mapping()[0]
    mapping_items = dataset.mapping()[2]

    output = {}

    for user in userids:

        # Convert user to internal index.
        user_internal = mapping_users[user]

        # Extract internal indecies of items whith which user posit
        positive_items_internal = train.tocsr()[user_internal].indi

        # Convert internal item indecies to itemids.
        positive_items = [key for key, val in mapping_items.items()

        # Make prediction.
        scores = model.predict(user_internal, np.arange(len(mapping

        # Sort the recommended items by descending order of their i
        # Array has the internal indecies of the items.
        recommended_items_internal = np.argsort(-scores)

        # Convert internal item indecies to item ids and return top
        recommended_items = []
        for id_internal in recommended_items_internal[:N]:
            for key, value in mapping_items.items():
                if id_internal == value:
                    recommended_items.append(key)

        # Add user and recommended items to output.
        output[user] = recommended_items

    # Returns the recommendation in format{user_1:[item_1, item_2,
    return(output)
```

## See how the top of recommended items compares to the full range of user positive interactions.

In [115]:
```
# Make recommendation to the set of users based on the train intera
selected_users = [566009, 170470, 64931]

recommend_items = recommend(model_trained=model_best,
                            dataset=dataset,
                            interactions=train,
                            userids=selected_users,
                            N=3)

recommend_items
```

Out[115]:
```
{566009: [130371, 247842, 234603],
 170470: [134525, 339517, 369447],
 64931: [119433, 240755, 120262]}
```

In [116]:
```
selected_users_all_inter = df_events.loc[df_events['visitorid'].isi
    by=['visitorid'], ascending=True).reset_index(drop=True)

selected_users_all_inter
```

Out[116]:

| | timestamp | visitorid | event | itemid | transactionid |
|---|---|---|---|---|---|
| 0 | 1431563636311 | 64931 | 3 | 352082 | 17109.0 |
| 1 | 1431542858006 | 64931 | 2 | 66405 | NaN |
| 2 | 1431563636264 | 64931 | 3 | 120262 | 17109.0 |
| 3 | 1431563636295 | 64931 | 3 | 409425 | 17109.0 |
| 4 | 1437351779459 | 64931 | 2 | 134368 | NaN |
| 5 | 1431563636326 | 64931 | 3 | 390824 | 17109.0 |
| 6 | 1437864475709 | 64931 | 2 | 298754 | NaN |
| 7 | 1430782877123 | 64931 | 2 | 35477 | NaN |
| 8 | 1430777820619 | 64931 | 2 | 82125 | NaN |
| 9 | 1430776984572 | 64931 | 2 | 348881 | NaN |
| 10 | 1430776433701 | 64931 | 2 | 94570 | NaN |
| 11 | 1433017038331 | 64931 | 2 | 37521 | NaN |
| 12 | 1431563636342 | 64931 | 3 | 313810 | 17109.0 |
| 13 | 1431054035395 | 170470 | 3 | 103030 | 9705.0 |
| 14 | 1431054035395 | 170470 | 3 | 369447 | 9705.0 |
| 15 | 1431054035379 | 170470 | 3 | 75790 | 9705.0 |
| 16 | 1431054035364 | 170470 | 3 | 329334 | 9705.0 |

| | | | | | |
|---|---|---|---|---|---|
| 17 | 1431054035364 | 170470 | 3 | 420549 | 9705.0 |
| 18 | 1431054035348 | 170470 | 3 | 329467 | 9705.0 |
| 19 | 1431054035348 | 170470 | 3 | 430057 | 9705.0 |
| 20 | 1431054035299 | 170470 | 3 | 431853 | 9705.0 |
| 21 | 1431053917405 | 170470 | 2 | 226258 | NaN |
| 22 | 1431053449701 | 170470 | 2 | 433004 | NaN |
| 23 | 1430872427982 | 170470 | 3 | 76831 | 13759.0 |
| 24 | 1430872427967 | 170470 | 3 | 158666 | 13759.0 |
| 25 | 1430872427967 | 170470 | 3 | 104468 | 13759.0 |
| 26 | 1430870043969 | 170470 | 3 | 452077 | 14666.0 |
| 27 | 1430870043969 | 170470 | 3 | 71443 | 14666.0 |
| 28 | 1430869675493 | 170470 | 2 | 250988 | NaN |
| 29 | 1430869203820 | 170470 | 2 | 134525 | NaN |
| 30 | 1431054035348 | 170470 | 3 | 102136 | 9705.0 |
| 31 | 1438041149396 | 566009 | 3 | 247842 | 1346.0 |
| 32 | 1434416899511 | 566009 | 2 | 11986 | NaN |
| 33 | 1430627485604 | 566009 | 2 | 11249 | NaN |
| 34 | 1434402463336 | 566009 | 2 | 315769 | NaN |
| 35 | 1433365411517 | 566009 | 3 | 187719 | 14366.0 |
| 36 | 1438041149412 | 566009 | 3 | 234603 | 1346.0 |
| 37 | 1430628121182 | 566009 | 2 | 79544 | NaN |
| 38 | 1434404625804 | 566009 | 2 | 180763 | NaN |
| 39 | 1438041149771 | 566009 | 3 | 397602 | 1346.0 |

In [117]:

```
# Conclusion:
# For each user there're items matching in recommendation and exist
# This proves the sufficient quality of recommendations.

# The recommendations include items with which user had positive in
# Since the item features names and values are hashed, there's no p
# for the next purchase or not. If the item is refillable (paper to
# be recommended one more time, while the same sofa or carpet are u
# If the information is provided, the pool of potentially recommend
```

# Production use

Before making recommendations for production the selected model should be trained on the whole cleaned dataset.

In [118]:
```
# Make recommendation to the set of users based on all interactions
# This mimics the production recommendations based on the all avail

start_time = time.time()

# Firstly, train/retrain model on the full data.
model_production = model_best  # Copy the hyperparameters of the be

# Number of epochs matches the optimum for hybrid model, selected a
model_production.fit(production,
                     item_features=item_features,
                     epochs=NUM_EPOCHS,
                     num_threads=4)


print('Trained in : ', round((time.time()-start_time)/60, 2), ' min
```

```
Trained in :  0.24  minutes
```

In [119]:
```
start_time = time.time()

# Select users for to give recommendations.
selected_users = [566009, 170470, 64931]

# Create recommendations.
recommend_items_production = recommend(model_trained=model_producti
                                       dataset=dataset,
                                       interactions=production,
                                       userids=selected_users,
                                       N=3)

print('Recommendations made in : ', round((time.time()-start_time)/
```

```
Recommendations made in :  0.001495  minutes
```

In [120]:
```
recommend_items_production
```

Out[120]:
```
{566009: [164884, 308510, 396575],
 170470: [352230, 7732, 374599],
 64931: [119433, 438885, 369000]}
```

In [121]:
```
# Compare to the recommendations based on train set.

recommend_items
```

Out[121]:
```
{566009: [130371, 247842, 234603],
 170470: [134525, 339517, 369447],
 64931: [119433, 240755, 120262]}
```

In [122]:
```
# The results are slightly different but close.
# This makes sense since the models were trained not on the same da
# Quality of recommendations is sufficient.
```

# Increased basket value - Bundling

In [124]:
```
# Since the item prices are hashed in original dataseta and total n
# all bundles will be recommended to user with no negative impact o


recommend_products_bundles = {}

for user, item in recommend_items.items():
    combos = [tuple(recommend_items[user])]
    for bundle in combinations(recommend_items[user], 2):
        combos.append(bundle)
    recommend_products_bundles[user] = combos

recommend_products_bundles
# Fromat is {user_1: [(bundle_1), (bundle_2), ...],
#            user_2: [(bundle_1), ...], ...}
```

Out[124]:
```
{566009: [(130371, 247842, 234603),
  (130371, 247842),
  (130371, 234603),
  (247842, 234603)],
 170470: [(134525, 339517, 369447),
  (134525, 339517),
  (134525, 369447),
  (339517, 369447)],
 64931: [(119433, 240755, 120262),
  (119433, 240755),
  (119433, 120262),
  (240755, 120262)]}
```

In [125]:
```
# The project is aiming to develop the recommendation system using
# recommend the discounted bundle of products the user is likely to
# which may lead to an increase of the basket value.
# The size of the discount is a subject to setting by the eCommerce
# for the purposes of this project 10% was aimed to be offered.

# However, since the item prices are hashed, and the number of reco
# the user may be recommended all 4 bundles on the same page with 1
# This will lead to improved user experience as all bundles are off
```

# Conclusion

In [126]:
```
# The developped technical solution can now be implemented into the
# In production it is important to measure the success of recommend
```

# Future work

In [127]:
```
# Having the item features data unhashed may help to explore deper
# Also, the feature selection and feature engineering techniques ma

# Another point to look at is use of timestamps to predict consumer
# latest interactions. There can be several approaches, including a

# Evaluating results in production and revisiting the approaches is
# lifecycle which is broadly used in the industry.
```