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
sv)
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
coo matrix format as input.
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
sponds the historical order of events.

df_events = pd.read_csv("events.csv")
df_events = df_events.sort_values(by=['timestamp'], ascending=True)
.reset_index(drop=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_
original*qty_all_items_original)

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
inal)
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
red as rating (explicit feedback).
# This information is implicit feedback and lightFM library was des
igned to deal with it.
# Transform events from categorical to numerical format for further
processing.

weight_view = 1
weight_addtocart = 2
weight_transaction = 3

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

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

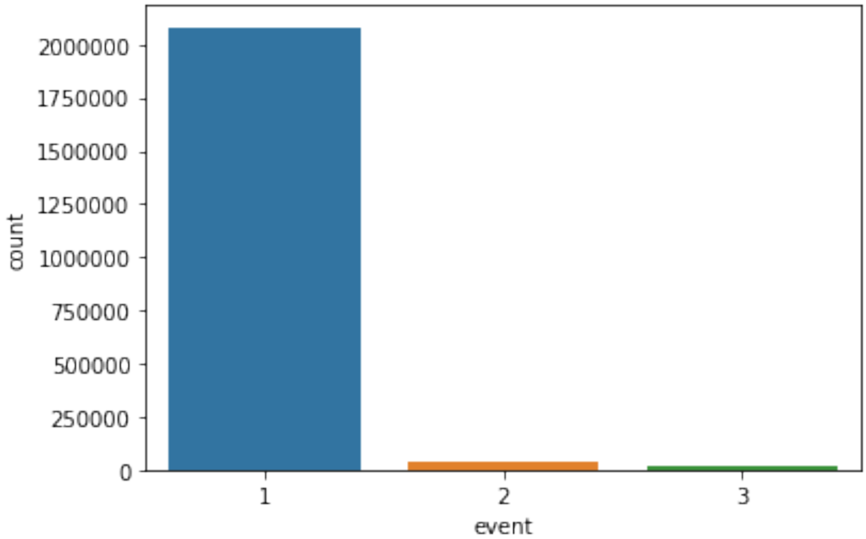
In [11]:
```
# The user may have interacted with item multiple times which is no
w stored in dataframe.
# For current purpose of recommendation we're interested in the hig
hest level of user interest to the item.
# Therefore, the data can be further cleaned.

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

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
o_frame(name='activity_count')
users_activity.head()
```

Out[14]:

	activity_count
visitorid	
0	3
1	1
2	4
3	1
4	1

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

Out[15]:

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

In [16]:
```python
# 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
e likely addtocart/purchase was made.
# Based on this hypothesys the users can be divided into two groups
.

# First group is 'low activity' users - this group is mostly browsi
ng and not making many purchases.
# The ratio of addtocart/purchase is low so it is harder to underst
and what they really like.
# These users will create a noise for the pool of more active users
having higher conversion.
# All types of interactions (view/addtocart/purchase) can be counte
d as positive for 'low activity' users.
# This will lead at least to improvement of customer experience and
users are more likely to find the needed item.
# For the purposes of this project 'low activity' group will be lef
t aside as the goal is basket value, not UX.
# This will allow to get rid of noise.

# Second group is 'high activity' users - this group has higher rat
io of purchases.
# Addtocart interaction type is considered to be positive as purcha
se.
# The item can be added to cart and purchased later, or customer pu
rchased similar item somewhere else.
# All in all, the fact of adding to cart means high interest to the
item.
# Ratio of addtocart and purchase to view is relatively similar whi
ch proves this assumption.
# So, interactions types addtocart/purchase can be considered as po
sitive, and predictions be made on them.
# View interactions are not considered since the user has not proce
eded so this means there's low interest.
# For the purposes of this project 'high activity' group will be us
ed.

# To summarize, using this split resolves several issues:
# 1. The low activity users represent the noise which will affect t
he model performance. So they are not considered.
# 2. The size of dataframe used for the further steps will be signi
ficantly smaller saving computational cost.
```

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

def activity_counter(data, max_interaction_threshold):

    df_events = data
    users_activity = df_events.groupby('visitorid').visitorid.count
().to_frame(name='activity_count')
    count_aggregated = pd.DataFrame(columns = ['interaction_thresho
ld',
                                                'view', 'addtocart',
'purchase',
                                                'conversion',
                                                'total_interactions'
])

    for interaction_threshold in range(max_interaction_threshold):
        users_activity_low = users_activity.loc[users_activity['act
ivity_count'] <= interaction_threshold]
        users_to_remove = users_activity_low.index.tolist()
        df_events = df_events[~df_events.visitorid.isin(users_to_re
move)].reset_index(drop=True)

        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
ransaction])/len(df_events),
            'total_interactions': len(df_events)
        },
            ignore_index=True)

    return(count_aggregated)
```

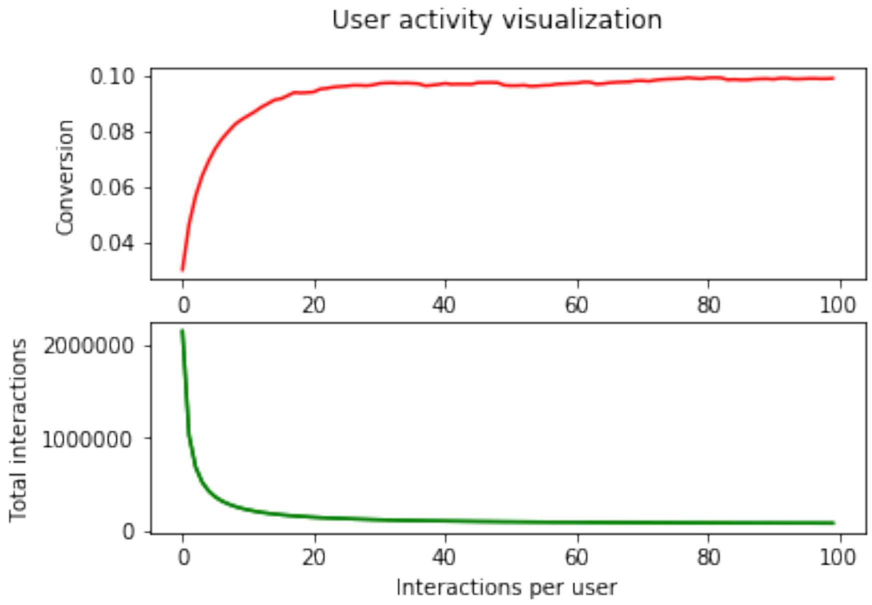
In [19]:
```
# Run fuction.
activities = activity_counter(df_events, 100)
activities.head(10)
```

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
sion'], 'r')
axis_1.set_ylabel('Conversion')

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

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

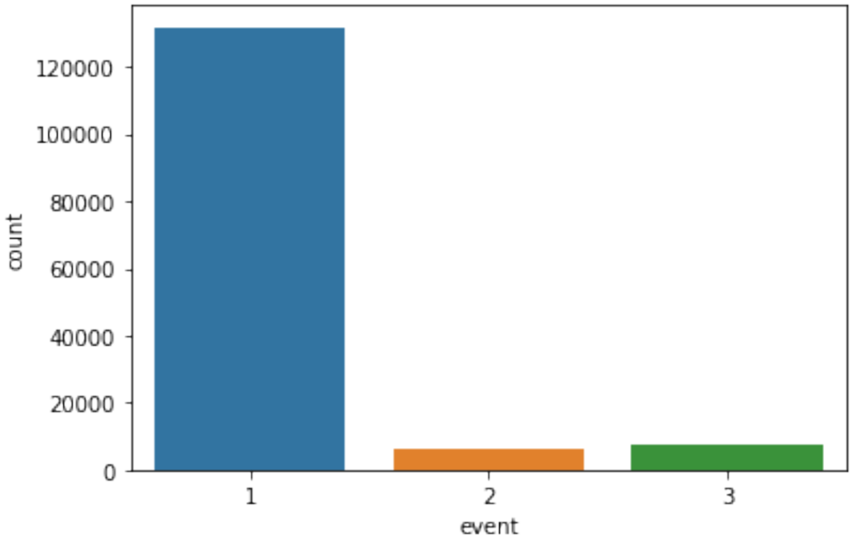


In [21]:
```
# The plot above shows that positive ratio improvement slows down s
ignificantly at 20 interactions threshold.
# Plateau is at conversion rate ~0.1 (10%) which is good in compari
son to eCommerce industry standard 3%.
# It makes sense since the part of less active users was removed.

# 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
unt'] <= interaction_threshold]
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
eset_index(drop=True)
```

In [23]:
```
# View on the ratio between different types of events after cleanin
g.
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
t_addtocart / weight_transaction.
# View interactions are not considered since the user has not proce
eded so this means there's low interest.

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 testing.

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_original,2), '%')
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_original,2), '%')
print()

qty_all_interactions = len(df_events)
print('Original number of interactions:', qty_all_interactions_original)
print('Cleaned dataset number of interactions: ', qty_all_interactions)
print('Cleaned portion:', round(100*qty_all_interactions/qty_all_interactions_original,2), '%')
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
e events.
# In order to achieve the generalization, the train and test split
will be done randomly.

df_events_train, df_events_test = train_test_split(df_events,
                                                    test_size=0.2,
                                                    random_state=np.
random.RandomState(2020))
```

In [27]:
```
# The dataset used for this project does not have any user informat
ion (features) available.
# Therefore, on the evaluation phase there should be only those use
rs, that used to train the model.
# Otherwise the user cold start problem will be faced which will im
pact the evaluation results.
# Meanwhile, this is not the case for items since there's the item
features data available.

df_events_test = df_events_test[(df_events_test['visitorid'].isin(d
f_events_train['visitorid'])) &
                                (df_events_test['itemid'].isin(df_e
vents_train['itemid']))]
```

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
vents_train),2),'% of Train set.')
print('Total number of interactions participating in train:',len(df
_events_train),'/ test: ', len(df_events_test))
```

```
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
at allows to fill in the interactions matrix.
# As the input for this method need to pass the list of tuples (vis
itorid, itemid, weight).

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
(row['itemid']), int(row['event'])))

# 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(
row['itemid']), int(row['event'])))

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

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

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

# data to be sorted by timestamp to reflect the historical change l
og.
df_properties = df_properties.sort_values(by=['timestamp'], ascendi
ng=True).reset_index(drop=True)

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
yid" and "available".

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
ed to trim the properties data.
# The latest properties data is considered to be the best to descri
be items.
# Assumption: the ecommerce team was constantly improving the catal
ogue.
# This action should lead to decrease of the dataframe size.

df_properties = df_properties.sort_values(by=['timestamp'], ascendi
ng=True).drop_duplicates(
    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
ly.
# It won't make sense to consider any value as fixed (in stock or n
ot in stock) for trainig purposes.
# In production this property can be used in real time to filter ou
t unavailable items from prediction.

df_properties = df_properties[~df_properties.property.isin(['availa
ble'])].reset_index(drop=True)

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
ataframe can also be removed.

df_properties = df_properties[df_properties.itemid.isin(df_events['
itemid'])].reset_index(drop=True)

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=
True).reset_index(drop=True)
```

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
rties))
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
el in a format of csr matrix.
# This matrix must have mapping of all items related to the train/t
est process and
# 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
ector for each item.
```

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
ill in the properties data using created mapping.
# Add feature mapping to the existing dataset using fit_partial met
hod.
# 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
ass:
# ['property:value']

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

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

```
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
r of features,
# but is equal to the number of combinations ['property:value'] ava
ilable in the dataframe.
# There's no need to "create" all possible combinations mapping as
this is redundant info.
# Just need to create mapping for existing combinations.
# Additionally, the LightFM package allows to add weight to this co
mbination if needed.

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

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

In [50]:
```
# Transform item features values to the format required by Dataset
class:
# [ (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
tr(row['value']))
    else:
        item_features_values.append((current_item, current_item_fea
tures))
        current_item = row['itemid']
        current_item_features = [str(row['property']) + ':' + str(r
ow['value'])]
item_features_values.append((current_item, current_item_features))

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

```
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
/test interaction matrices should be the same.
# In order to achieve this, need to create mapping for all users an
d all items.
# Then separately for train and test - the interactions will be fil
led in.
```

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

# The fit method of class Dataset takes the list of all the visitor
s and items.
# 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
ations.
```

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
ons(df_events_train_interactions)
(interactions_test, weights_test) = dataset_test.build_interactions
(df_events_test_interactions)
(interactions_all, weights_all) = dataset_all.build_interactions(df
_events_all_interactions)


# Choose interactions to be used at next stages.
# The use of weights did not lead to improvement of model performan
ce even after changing the scale to 1/700/1000.
# Reason for that is that the LightFM model does not count in any e
xplicit feedback which the weights can represent.
# The idea behind the implementation is to count in the implicit fe
edback as binary problem, with either
# positive or negative interactions. As decided above, addtocart an
d purchase are considered as positive.
# The weights table wil not be needed for the purpose of this proje
ct.

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

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

```
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
utes")
```

```
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_
items, ',',
      qty_all_items+len(item_features_mapping), ')')
# Reason for this size is that there's a space for latent vector re
presentation of each item plus all features.
print('Actual size is:', dataset.item_features_shape())
print()

print('Item features matrix number of values is expected to be:', l
en(df_properties)+qty_all_items)
# Reason for this size is that there's a space for latent vector re
presentation of each item plus all features.
print('Actual number of values is:', item_features.getnnz())
print()

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

print('Interactions matrix number of values is expected to be:', le
n(df_events_train) + len(df_events_test))
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
orative filtering.

start_time = time.time()

model_collab = LightFM(no_components=100, loss='warp', random_state
=2020)

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

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

```
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
cision at K will be used for evaluation.
# Both of them are measuring the ranking quality, which means for e
ach particular user the items can be sorted
# in the order of their fit/interest to the user.


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

# AUC (area under the curve) shows how well the items are ranked. P
erfect ranking means that any random positive
# example will be ranked higher than any random negative example. H
ighest metric's value is 1.0 (100%)

# Precision at 'k' shows the ratio of known positive examples in to
p 'k' ranked items.
# 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
ions (bundles) to offer with discount
# 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
ask and can be implemented on all pages if there
# is a business need for that. This will lead to better user experi
ence and avoid recommending too much which
# can cause FOMO (fear of missing out) when the user gets stuck in
front of too wide range of choices.


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
inutes")
```

```
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
ding items to users.
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
inutes")
```

```
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
inutes")
```

```
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
inutes")
```

```
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
ing. This will mean hybrid predictions.
# Hybrid model is benefiting from collaborative and content based f
iltering.

start_time = time.time()

model_hybrid = LightFM(no_components=100, loss='warp', random_state
=2020)

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),
" minutes")
```

```
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
inutes")
```

```
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
ding items to users.
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
inutes")
```

```
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
inutes")
```

```
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
inutes")
```

```
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
o the model improves both metrics.
```

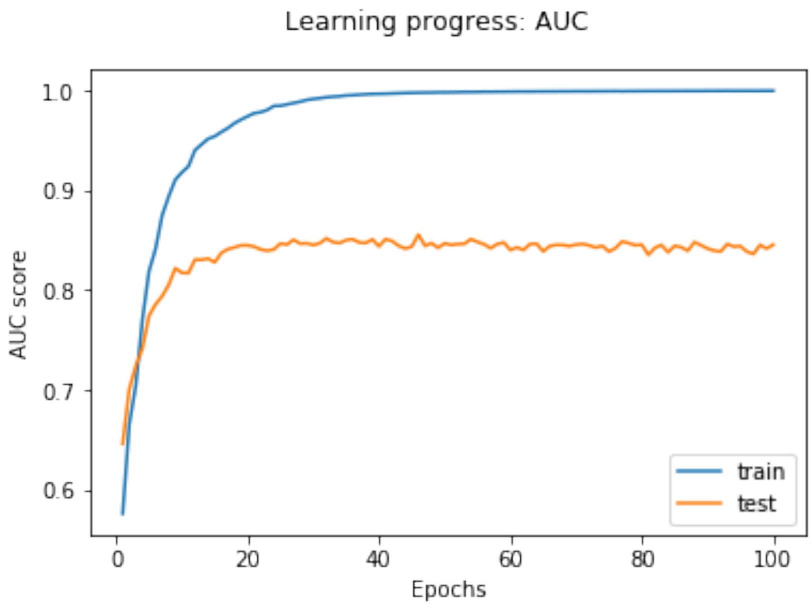
Visualize learning process

In [75]:
```
# Visualization of the learning process will show how quickly the m
odel as learning during epochs.
# Identifying the point of slowing down or termination of learning
will help to improve efficiency by
# limiting the number of epochs needed to achieve the result that s
ufficies.
```

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

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

    stats = pd.DataFrame(columns = ['epochs', 'train_auc', 'test_au
c', 'runtime_min'])

    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
t, item_features, epochs=NUM_EPOCHS)

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

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
```

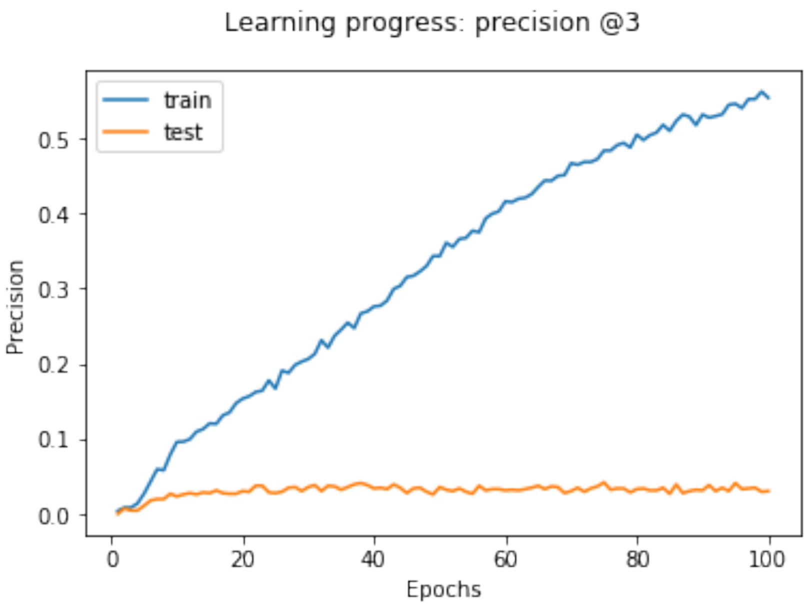
In [80]:
```
# Precision visualization.

def learning_vis_precision(model, train, test, item_features, k, ep
ochs):

    stats = pd.DataFrame(columns = ['epochs', 'train_precision', 't
est_precision', '@k' 'runtime_min'])

    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
s,
                                         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
in')
    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_
features, k=3, epochs=NUM_EPOCHS)

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

```
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 significantly after 30 epochs.
# In order to save the computational costs and optimize the process, set new value for NUM_EPOCHS:

NUM_EPOCHS = 30
```

Hyperparameter tuning

In [85]:
```
# Attempting to regularize model and achieve better results on test
set by hyperparameter tuning.

# The author of the LightFM package Maciej Kula has also developed
the algorythm for hyperparameter tuning.
# Original algorythm was posted on GitHub 23 Apr 2018.
# Code is available via url https://gist.github.com/maciejkula/29aa
f2db2efee5775a7f14dc387f0c0f

# For the purposes of this project the original code was modified t
o meet the needs.

# There will be two attempts:
# AUC focused tuning - when the best model will be chosen based on
the best AUC result.
# Precision focused - when the measure of success to chose the best
model is precision at 'k'
```

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

(train_train, validate) = random_train_test_split(train,
                                                   test_percentage=0
.2)
```

In [87]:
```
# The range of hyperparameters needs to be set up manually.
# Then function will randomly try various combinations to find the
best model depending on goal (AUC/precision).


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
elta']),
            '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
reads=4):

    # 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
eads=num_threads)

        ranking_score = auc_score(model_tuned_auc,
                                  validate, train_interactions=trai
n_train,
                                  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
tted model)





start_time = time.time()

if __name__ == '__main__':

    (ranking_score, hyperparams, model_tuned_auc) = max(random_sear
ch_auc(train_train, validate),
                                                         key=lambda
x: x[0])

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

```
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),
" minutes")
```

```
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
inutes")
```

```
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
ding items to users.
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
inutes")
```

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

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

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

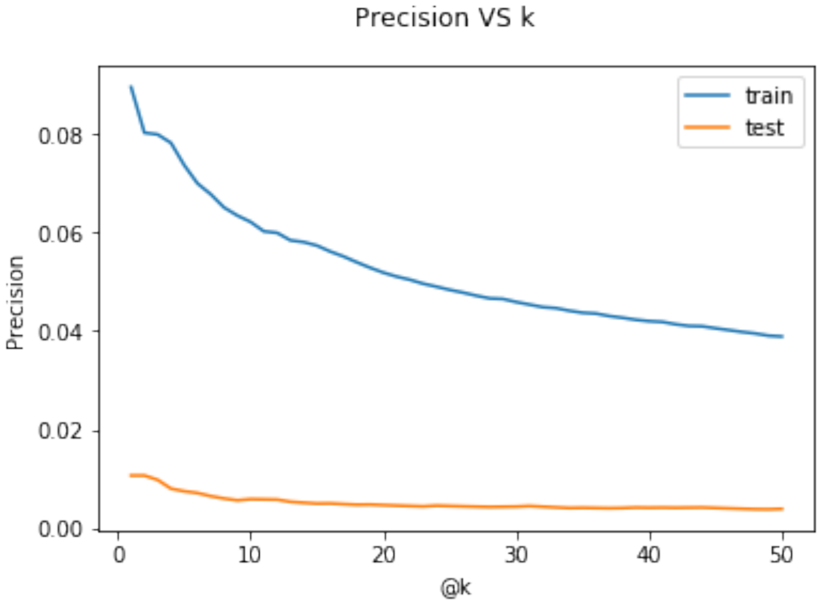
```
Hybrid filtering results:  {'AUC train': 0.99953717, 'AUC test': 0
.84518975, 'Precision @3 train': 0.5577252, 'Precision @3 test': 0
.030222224}
```

In [93]:
```
# Visualize how the precision changes depending on parameter 'k'.
# Since the hyperparameters tuning was not optimized for parameter
'k', the model can be checked at a range of 'k'.

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

    stats = pd.DataFrame(columns = ['@k', 'train_precision', 'test_
precision', 'runtime_min'])

    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
s,
```

```
                                                         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)
```

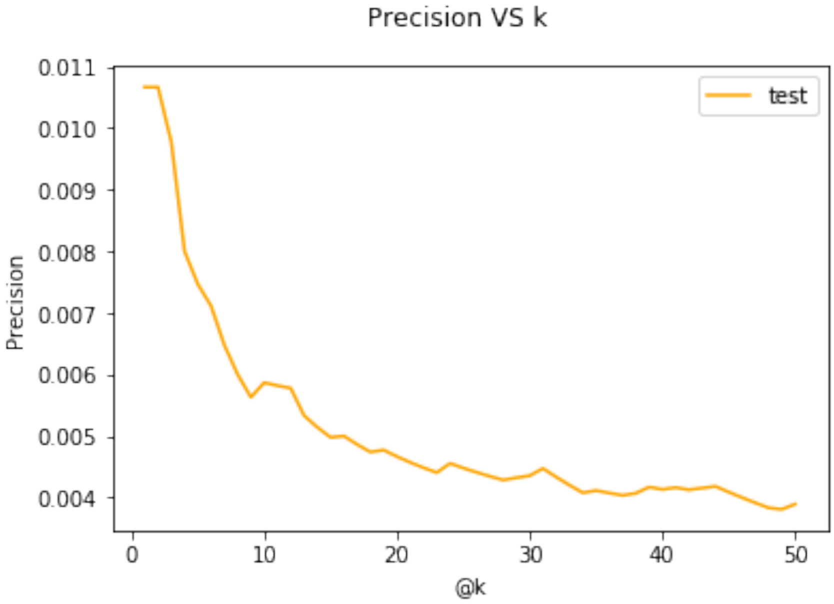
In [94]:
```
start_time = time.time()

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

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

```
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
]['test_precision'], label='test',color='orange')
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
ybrid filtering model result.

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
ce improvement.
```

Precision focused model - Tuning

In [100]:

```
# Improving precision_at_k metric.

def random_search_precision(train_train, validate, num_samples=10,
k=k, num_threads=4):

    # 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_
threads=num_threads)

        ranking_score = precision_at_k(model_tuned_precis, validate
, train_interactions=train_train,
                                      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
t, fitted model)





start_time = time.time()

if __name__ == '__main__':

    (ranking_score, hyperparams, model_tuned_precis) = max(random_s
earch_precision(train_train, validate),
                                                            key=lamb
da x: x[0])

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

```
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),
" minutes")
```

```
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
inutes")
```

```
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
ding items to users.
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
inutes")
```

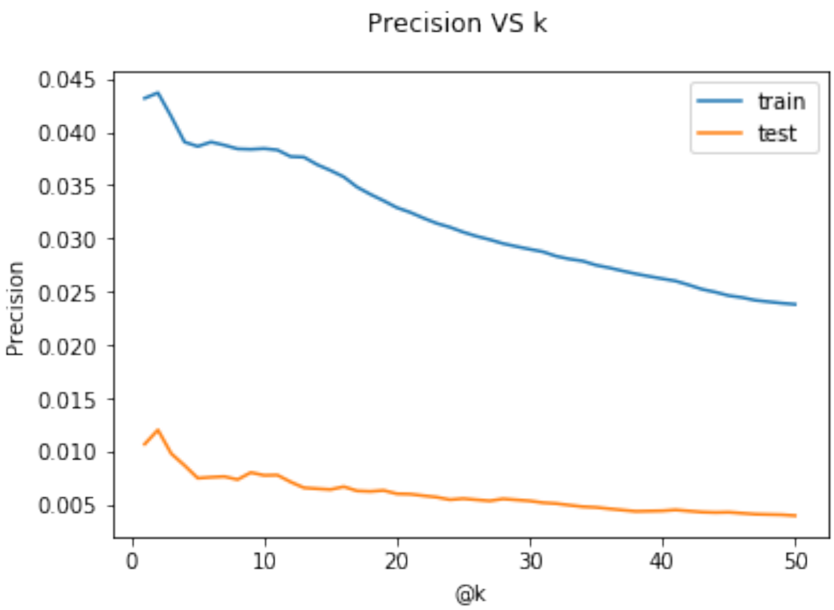
```
Test AUC score:  0.83780867
Calculated in:  0.05  minutes
```

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

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}
```

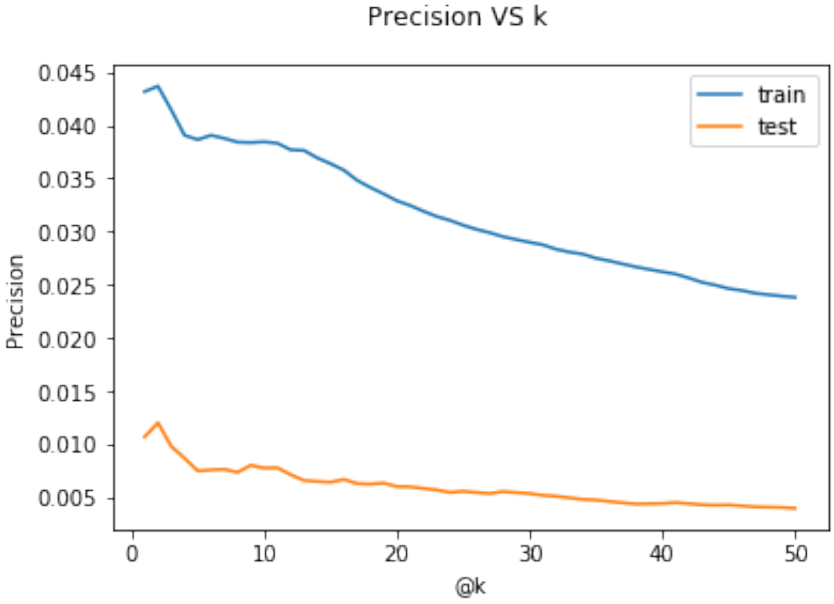
In [106]:
```
# Visualize how the precision changes depending on parameter 'k'.

start_time = time.time()

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

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

```
Calculated in:  8.8  minutes
```



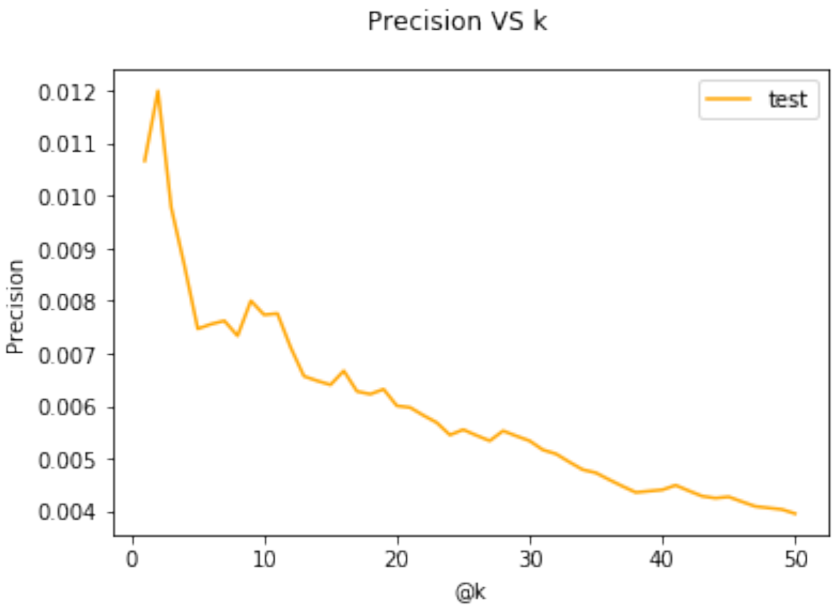
In [107]:
```
k_vis_precision_output[0]
```

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
]['test_precision'], label='test',color='orange')
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
an original hybrid filtering model result (k=3).

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
formance improvement.
```

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
ackage, it is modified for current project.
# 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
```

```
s.
    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
re map, item id map, item feature map).
    # 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
ively interacted in train set.
        positive_items_internal = train.tocsr()[user_internal].indi
ces

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

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

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

        # Convert internal item indecies to item ids and return top
10 recommendations.
        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,
item_3], user_2:[item_4, item_5, item_6], ...}
```

```
    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
ctions.
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
n(selected_users)].sort_values(
    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
ing interactions data.
# This proves the sufficient quality of recommendations.

# The recommendations include items with which user had positive in
teractions.
# Since the item features names and values are hashed, there's no p
roof whether the items can be considered
# for the next purchase or not. If the item is refillable (paper to
wels, toothpaste) it can be the case they may
# be recommended one more time, while the same sofa or carpet are u
nlikely to be recommended second time.
# If the information is provided, the pool of potentially recommend
ed items may be reviewed for better UX.
```

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
from cleaned set.
# This mimics the production recommendations based on the all avail
able data after cleaning.

start_time = time.time()

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

# Number of epochs matches the optimum for hybrid model, selected a
s best.
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
utes')
```

```
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
on,
                                       dataset=dataset,
                                       interactions=production,
                                       userids=selected_users,
                                       N=3)

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

```
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
ta.
# Quality of recommendations is sufficient.
```

Increased basket value - Bundling

In [124]:
```
# Since the item prices are hashed in original dataseta and total n
umber of bundles is 4,
# all bundles will be recommended to user with no negative impact o
n user experience.


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
hybrid approach and
# recommend the discounted bundle of products the user is likely to
be interested in
# which may lead to an increase of the basket value.
# The size of the discount is a subject to setting by the eCommerce
website team,
# for the purposes of this project 10% was aimed to be offered.

# However, since the item prices are hashed, and the number of reco
mmended bundles isn't high (only 4),
# the user may be recommended all 4 bundles on the same page with 1
0% discount each.
# This will lead to improved user experience as all bundles are off
ered at once and the user is able to choose.
```

Conclusion

In [126]:
```
# The developped technical solution can now be implemented into the
website UI or considered for email campaigns.
# In production it is important to measure the success of recommend
ations based on the basket value and rearrange.
```

Future work

In [127]:
```
# Having the item features data unhashed may help to explore deper
the dependencies between items/users.
# Also, the feature selection and feature engineering techniques ma
y be considered for the item features datset.

# Another point to look at is use of timestamps to predict consumer
behavior/interest based on the
# latest interactions. There can be several approaches, including a
ssigning higher 'weight' to recent interactions.

# Evaluating results in production and revisiting the approaches is
the normal cadance of any recommender system
# lifecycle which is broadly used in the industry.
```