Attribution Improvement by User Path & Behavior Clustering

August 31, 2020

1 Package Dependency

Data Preprocessing: **Pandas, Numpy, Proprocess**
Data Transformation: **Utils, Train-Test-Split**
Data Visualization: **Pyplot, Seaborn, Axes3D, TQDM**
User Vector Model based on Path: **TaggedDocument, Doc2Vec**
User Cluster Model based on User Path Vector Model: **KMeans**
Path Attribution Verification & Explanability: **Scipy.stats, NGrams, Counter, Utils**
User Cluster Model application on Base Model: **PCA, XGBoost**
User Cluster Model Verification: **Classification Report, Confusion Matrix, MAE, MSE, Explained Variance**

Please note that some modules are not listed in the the cell below, including **Counter, NGrams, and TaggedDocument**. They were Util's dependency.

[1]:
```
# common package
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# miscellaneous
from tqdm import tqdm
import scipy.stats
from mpl_toolkits.mplot3d import Axes3D

# helper functions
from utils import *
from preprocess import Preprocess

# models
from gensim.models.doc2vec import Doc2Vec
from xgboost import XGBClassifier
from xgboost import XGBRegressor
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

# evaluation
```

```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import explained_variance_score
from sklearn.metrics import classification_report
```

2 Data Preprocessing

Using user_behavior (log) as the bridge, merge three datasheets together.

Add an arbitrary new_session column based on a user's time difference between two logs to indicate if the latter log is the beginning of a new session.

Create two labels based on user's age for later use.

label_unbalanced (Each bin has significantly different counts but each age interval is roughly the same):

Age 11 - 20: 0

Age 21 - 30: 1

Age 31 - 40: 2

Age 41 - 50: 3

Age 51 - 90: 4

```
    </li>
    <li> label_balanced (Each bin has roughly the same count but each age interval is differen
        <ul>
            <li> Age 18 - 23: 0 </li>
            <li> Age 24 - 27: 1 </li>
            <li> Age 28 - 31: 2 </li>
            <li> Age 32 - 38: 3 </li>
            <li> Age 39 - 90: 4 </li>
        </ul>
    </li>
</ul>
```

[2]:
```python
prep = Preprocess('item.csv', 'user.csv', 'user_behavior.csv')
df = prep.init_process()
sc = SessionClassifier()
timeframe = df['time'].to_numpy()
userframe = df['user_id'].to_numpy()
df['new_session'] = sc.stamp_to_signal(userframe, timeframe)
df['label_unbalanced'] = df['age'].apply(lambda x: str(x)).str[0].replace(['9',␣
↪'8', '7', '6'], '5').apply(lambda x: int(x) - 1)
df['label_balanced'] = df['age'].apply(lambda x: group_age(x))
```

3 Visualization [Optional]

Global
user_id: a numeric representation of a user unit

Basic Information
time: the time that the log is created; representation of sequence
gender: gender corresponding to that user_id. Male = 0 | Female = 1
age: age corresponding to that user_id
label_balanced: balanced age group
label_unbalanced: unbalanced age group
power: buying power corresponding to that user_id

Path Information
time: the time that the log is created; representation of sequence
new_session: if new_session in a log is 1, it means that the log is the first path that a user takes in a new session
item_id: page_id_item-wise
cat_id: page_id_catagory-wise
shop_id: page_id_shop-wise
brand_id: page_id_brand-wise
type: behavior corresponding to a page_id

b = buy

p = preview

f = favorite

c = cart

[3]:
```
df.head(5)
```

[3]:
```
        user_id   item_id type    time  cat_id  shop_id  brand_id  gender  \
940626      279  40410079    b  221239    5296   948294     28570       1
940686      279  22830135    p  221258   12973   962246    216567       1
940667      279  26991039    p  221369   11072  2432702    216567       1
940668      279  26991039    p  221412   11072  2432702    216567       1
940669      279  26991039    p  221416   11072  2432702    216567       1

        age  power  new_session  label_unbalanced  label_balanced
940626   30      1            1                 2               2
940686   30      1            0                 2               2
940667   30      1            0                 2               2
940668   30      1            0                 2               2
940669   30      1            0                 2               2
```

4 Data Transformation

Here, we are going to construct four types of paths for each user: path on user_id, path on cat_id, path on shop_id, path on brand_id. We stored the paths in dictionaries. The key of one dictionary is the user_id, with its value corresponding to the user path, separated by different sessions. For instance:

lst_dics[0][279] == [[a,b,c],[d,e,f]] means user 279 has two sessions, in the first session the path is a–>b–>c, and in the second session the path is d–>e–>f. Each element within the path is a combination of type and item_id given this path is constructed upon item_id

A single element within a path follows the format: behavior_type + page_id + "x" if it's the same combination over more than two (including two) times. For instance, considering category path, row five on the above visualization will be written as **p11072x**

Our next step is to build sentences and documents based on these path dictionaries for each user while make sure these sentences and documents correspond to the right fornat for document vectorization.

Since gensim has a bug that tags must be continuous (i.e. we can't use user_id as tags for these documents), we need to map each user_id to a tag, that's what we did with map_dic. We also built inverse dictionaries that map each tag to a user_id, that's what we did with inv_map.

[4]:
```
# initiate the encoder class
pe = PathEncoder()
lst = df.to_numpy()

# corresponding columns to be encoded as path
path_col_index = [1,4,5,6]
title_col = [df.columns[i] for i in path_col_index]

# encode viewing history as path
lst_result = []
lst_dics = []
lst_actions_sum = []
for index in path_col_index:
    pe.set_cat(index)
    result, dic, actions_sum = pe.get_path(lst, mode = 'full_modified')
    lst_result.append(result)
    lst_dics.append(dic)
    lst_actions_sum.append(actions_sum)

# transform path as the input for tagged documents and mapping dictionary
sentences_docs_lst = []
map_dic_lst = []
for dic in lst_dics:
    sentences_doc, map_dic = get_sentences_doc(dic)
    sentences_docs_lst.append(sentences_doc)
```

```
    map_dic_lst.append(map_dic)

# build tagged documents from transformed path
documents_lst = []
for sentences_docs in sentences_docs_lst:
    documents = get_documents(sentences_docs)
    documents_lst.append(documents)

# build the inverse of map_dic
inv_map_lst = [{v: k for k, v in map_dic.items()} for map_dic in map_dic_lst]
```

5 Visualzation [Optional]

An example of tagged document is shown below:

Here, documents_lst[0][0] represents the tagged document for tag 0 based on item_id path (first [0] determines the type of path, second [0] determines the tag, which can be mapped back to a user_id)

Since gensim's doc2vec needs to take tagged document as input, so we have to transform the path in this way. In this example, the sequence of the words means the sequence of the path that user_id 279 (which corresponds to tag 0) has taken based on item_id. The list of the words represents that user 279 goes from b40410079 to p22830135 to p26991039 to p26991039x …

Here, we lost information on the length of each session and if one single point on a path is the start or end of a session. However, that's how Doc2Vec works - gensim's model ignored such relationships

[5]:
```
documents_lst[0][0]
```

[5]:
```
TaggedDocument(words=['b40410079', 'p22830135', 'p26991039', 'p26991039x',
'p14027124', 'f28270315', 'p35691221', 'p40291124', 'p29238588', 'p28270315',
'p6440229', 'f35829863', 'p11949954', 'p39046777', 'p18821181', 'p33094004',
'p16577496', 'p24903693', 'p12579266', 'p19563589', 'b12579266', 'p26991039',
'p32551586', 'p12619624', 'p35691221', 'p9016213', 'p28447881', 'p6209524',
'p6233634', 'p31957385', 'p20675979', 'p6233634', 'p18821181', 'f11429680',
'p8563896', 'p35691221', 'p32475263', 'p25645133', 'p29706693', 'p20210657',
'p31386755', 'p31386755x', 'p3321291', 'p7488085', 'b3321291', 'f16663644',
'p40626877', 'p33828756', 'p3321291', 'p28019828', 'p20210657', 'p20210657x',
'b20210657', 'p23326995', 'p11349276', 'p10715952', 'f40559724', 'p28529301',
'p40559724', 'p40559724x', 'p40410079', 'p28756126', 'f10754411', 'p852621',
'p10754411', 'p8713690', 'p10754411', 'p10164893', 'p15952244', 'p410467',
'p10754411', 'p4827584', 'p6735395', 'p23349698', 'p10754411', 'p26211487',
'p156722', 'p41801718', 'p7421474', 'p11214731', 'f4172507', 'p30256882',
'p3806371', 'p13030925', 'p3235052', 'p37114807', 'p25019049', 'p37114807',
'p4712708', 'p16105282', 'p24047785', 'p37114807', 'p39176282', 'f37114807',
'p39176282', 'p37114807', 'p11214731', 'f11214731', 'p42120790', 'p4827584',
'p37114807', 'p25019049', 'p37114807', 'p10164893', 'p984553', 'p40567412',
'p31947929', 'p36009711', 'p30465914', 'p40931208', 'p30367974', 'p36925984',
```

```
'p37114807', 'p3443232', 'p35210153', 'p26211487', 'p9047144', 'p19930117',
'p9047144', 'p9047144x', 'p38238422', 'p9047144', 'p9047144x', 'p26211487',
'p42120790', 'p15287475', 'p11781051', 'p39006518', 'p6898903', 'p19195609',
'f28605354', 'p10066101', 'f21524880', 'p37038644', 'p13548540', 'p15287475',
'p17168812', 'p17985835', 'p22537341', 'p5965267', 'p36353803', 'p71113',
'p13776689', 'p6317804', 'p23148509', 'p206573', 'f10521021', 'p39297658',
'p3530388', 'p3632376', 'p5965267', 'p30256882', 'p14804991', 'p25402990',
'p36968945', 'f3443232', 'p34512294', 'p39006518', 'p10974839', 'p31342998',
'p39628773', 'p28019828', 'p37114807', 'b3321291', 'p39176282', 'p30262604',
'p3321291', 'p17985835', 'p33055710', 'p18623111', 'p32741209'], tags=[0])
```

6 Data Vectorization (Modeling - Slow)

This part of the code will build four doc2vec models using the above tagged documents. Each model represents a type of path, i.e. item_id, cat_id, etc. The model itself doesn't filter out rare words because the path distribution is scarce, and it's important that we consider rare words into the vocabulary.

This modeling process can be relatively slow (~10 minutes on my computer), so the latter part of the below cell save the model into my local drive.

[6]:
```
# # build Doc2Vec Models for each kind of path
# d2v_models_lst = []
# for documents in documents_lst:
#     model = Doc2Vec(documents)
#     model.train(documents, total_examples=model.corpus_count, epochs=30)
#     d2v_models_lst.append(model)

# # save the models
# for i in range(len(d2v_models_lst)):
#     d2v_models_lst[i].save("d2v{}.model".format(path_col_index[i]))
```

7 Data Clustering (Modeling - Fast)

After we built four doc2vec models, we extract all users' path information into vectors, where each vector represents some path features of a user. Here, based on some verification models later, we believe that these features include the similarity in path preference and some latent variables reflected from the path such as age, gender, buying power.

I used KMeans to cluster different users into different user groups based on user vectors constructed from each user's paths. Here, K is equal to 8 - but I believe that a larger K brings out a better in-group path similarity as well as better inference on each user's age, gender and buying power.

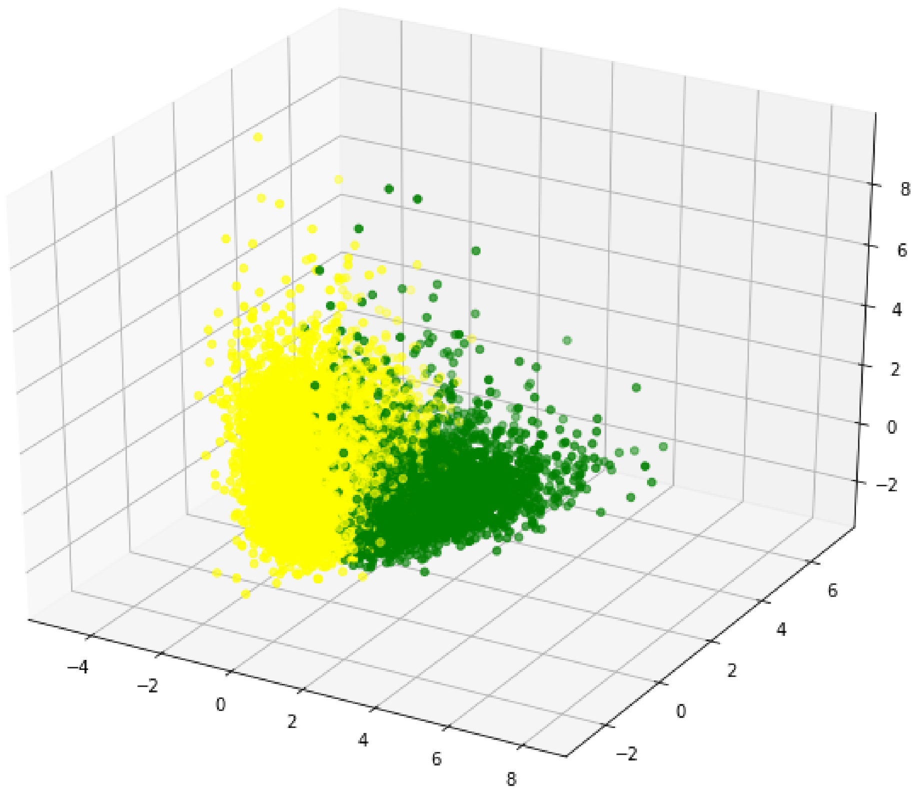
[7]:
```
# load the models
d2v_models_lst = []
```

```
for i in range(len(path_col_index)):
    model= Doc2Vec.load("d2v{}.model".format(path_col_index[i]))
    d2v_models_lst.append(model)

# build KMeans clusters for each user vector within each Doc2Vec models
K = 8
group_lst = []
for model in d2v_models_lst:
    group = KMeans(n_clusters=K, max_iter=100).fit_predict(model.docvecs.
 ↪vectors_docs)
    group_lst.append(group)
```

8 Visualization [Optional]

Here, the visualization represents the result of clustering when taking different K value (here from 2-9). We can find that although user vectors are not "technically" clustered, the algorithm is still possible to make some partitions based on their relative distance

[8]:
```
for i in range(2, 10):
    kmeans_model = KMeans(n_clusters=i, init='k-means++', max_iter=100)
    X = kmeans_model.fit(d2v_models_lst[0].docvecs.vectors_docs)
    labels=kmeans_model.labels_.tolist()
    l = kmeans_model.fit_predict(d2v_models_lst[0].docvecs.vectors_docs)
    pca = PCA(n_components=3).fit(d2v_models_lst[0].docvecs.vectors_docs)
    datapoint = pca.transform(d2v_models_lst[0].docvecs.vectors_docs)
    fig = plt.figure(figsize=(9, 7))
    ax = Axes3D(fig)
    label1 = ['#FFFF00', '#008000', '#0000FF', '#800080', '#15e6df', '#e067c4',␣
 ↪'#e62222', '#e69b22', '#40ffb3', '#44d2f2']
    color = [label1[i] for i in labels]
    ax.scatter(datapoint[:, 0], datapoint[:, 1], datapoint[:, 2], c=color)
    centroids = kmeans_model.cluster_centers_
    centroidpoint = pca.transform(centroids)
    ax.scatter(centroidpoint[:, 0], centroidpoint[:, 1], centroidpoint[:, 2],␣
 ↪marker='^', c='#000000')
    plt.show()

# plot_sil_sse(sil, sse)
```



8
6
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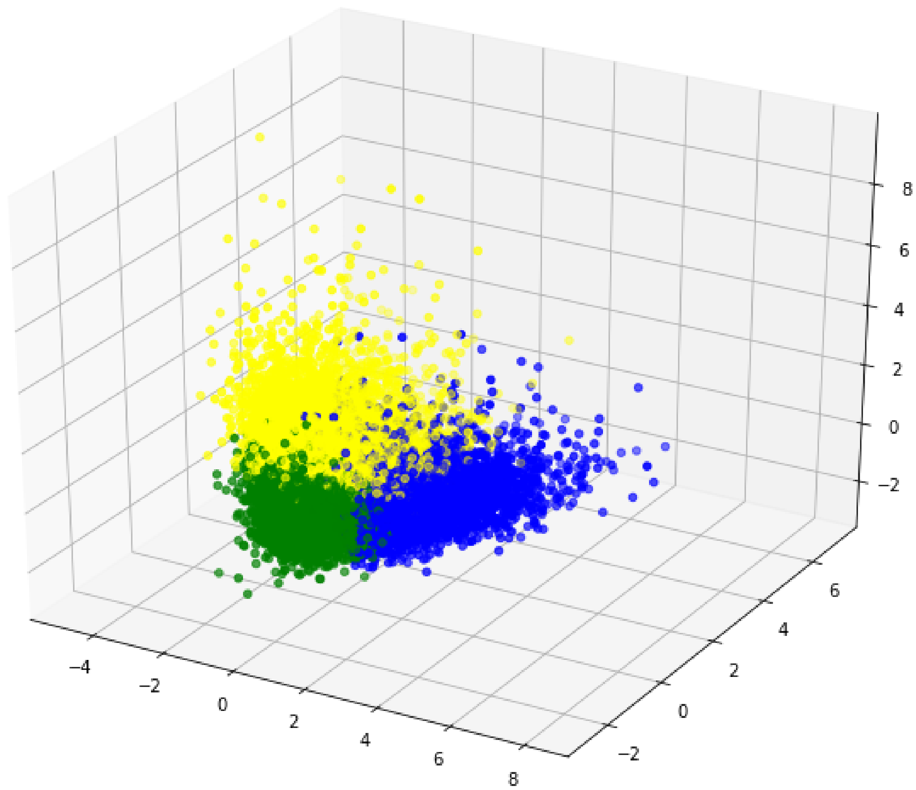

−4
−2
0
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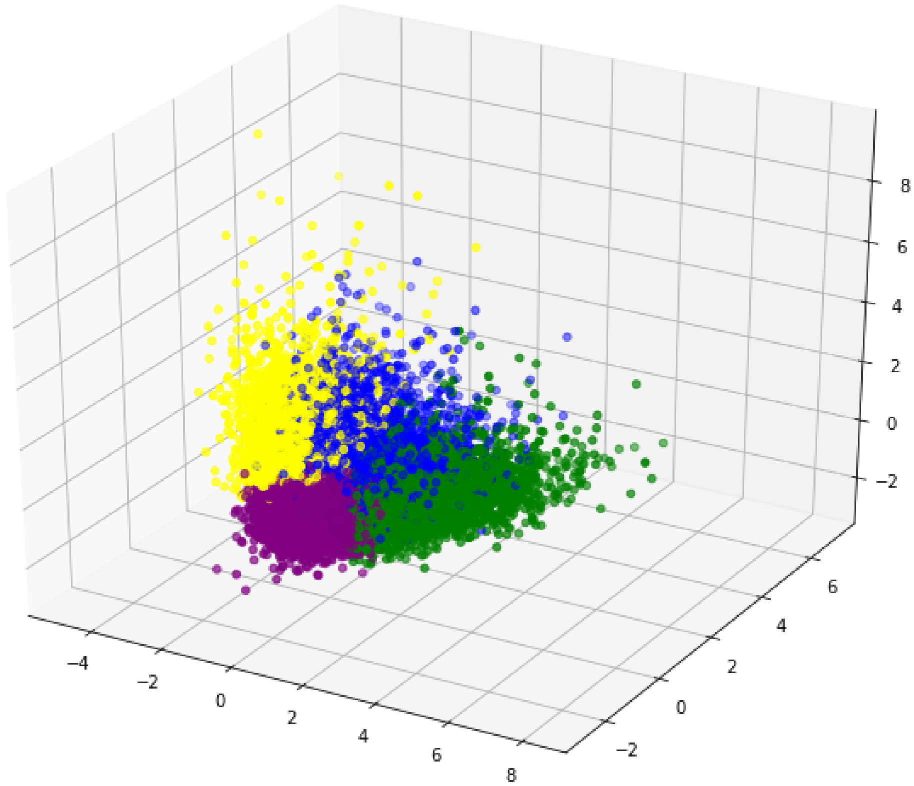

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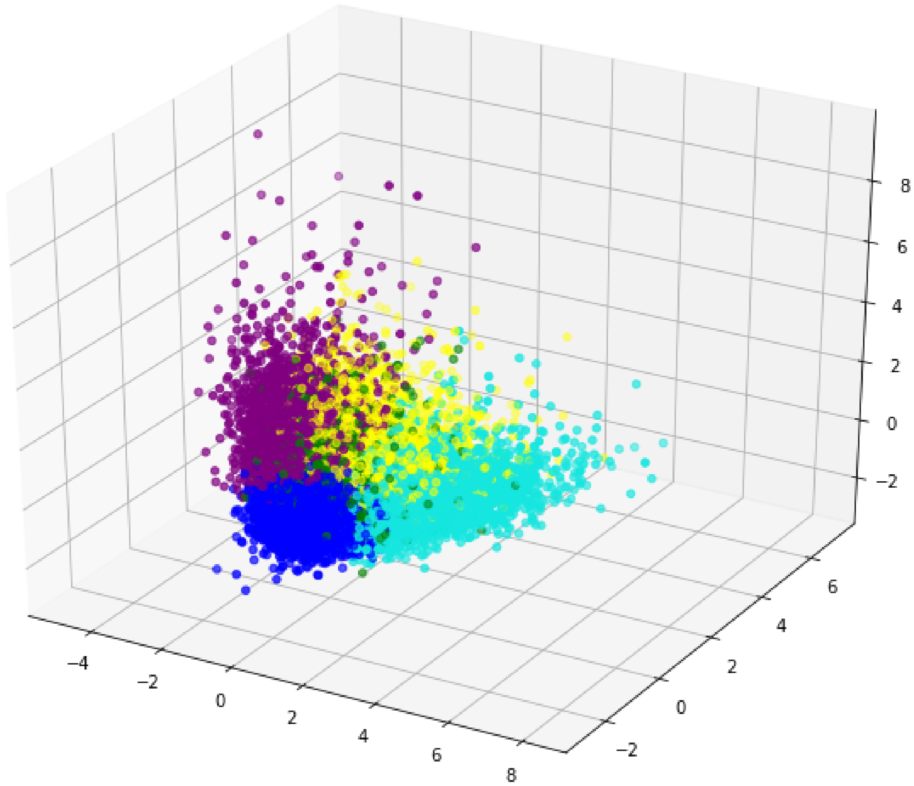

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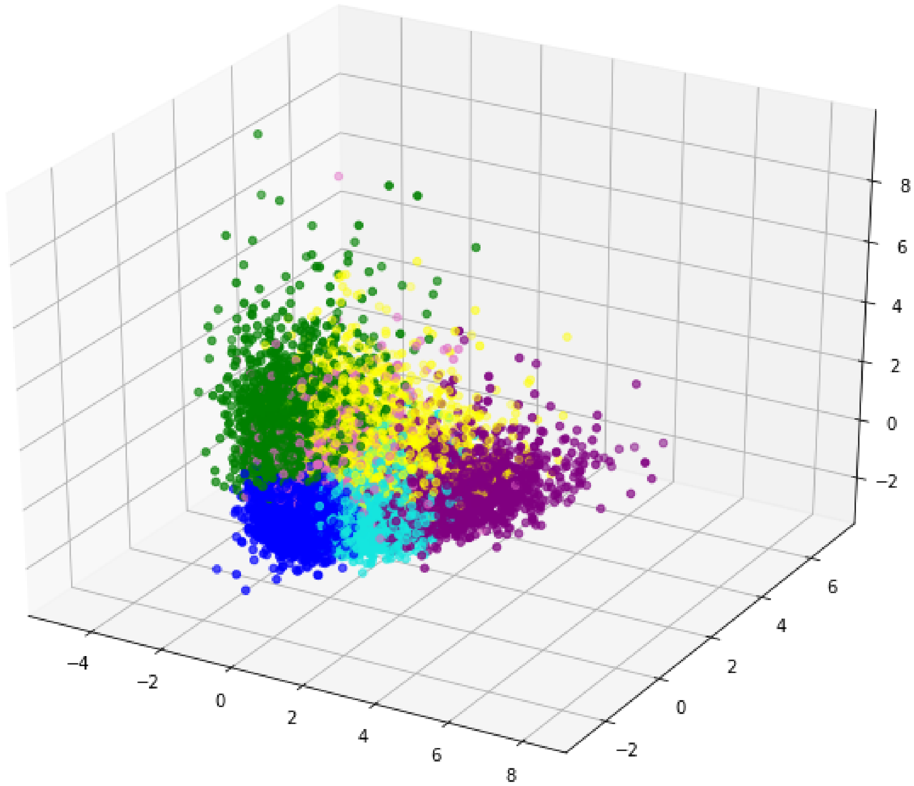

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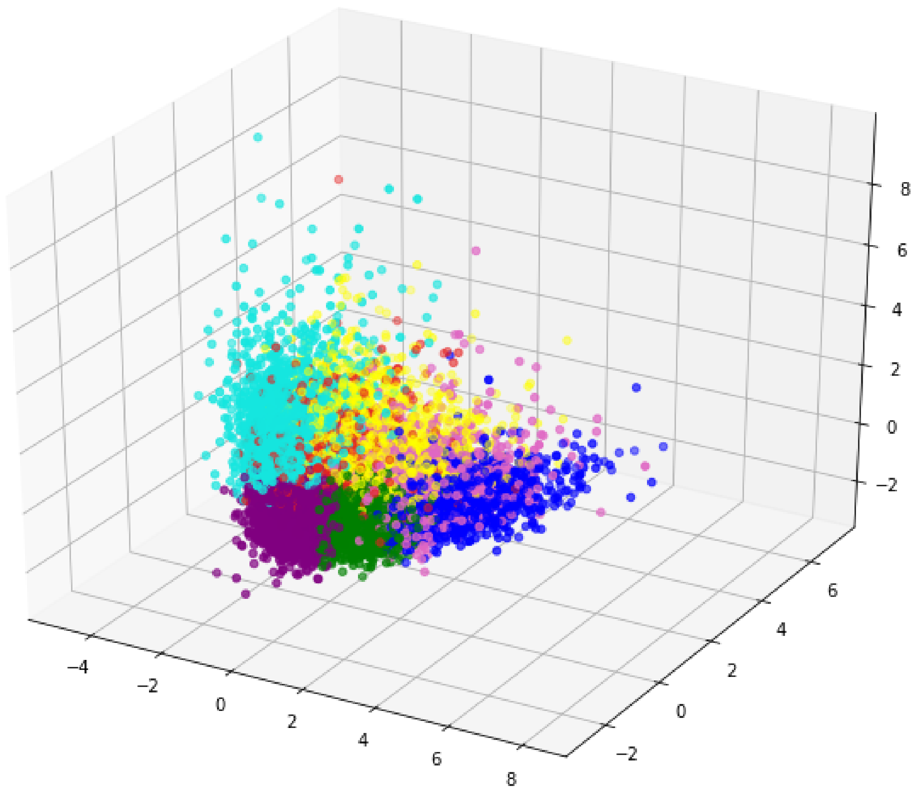
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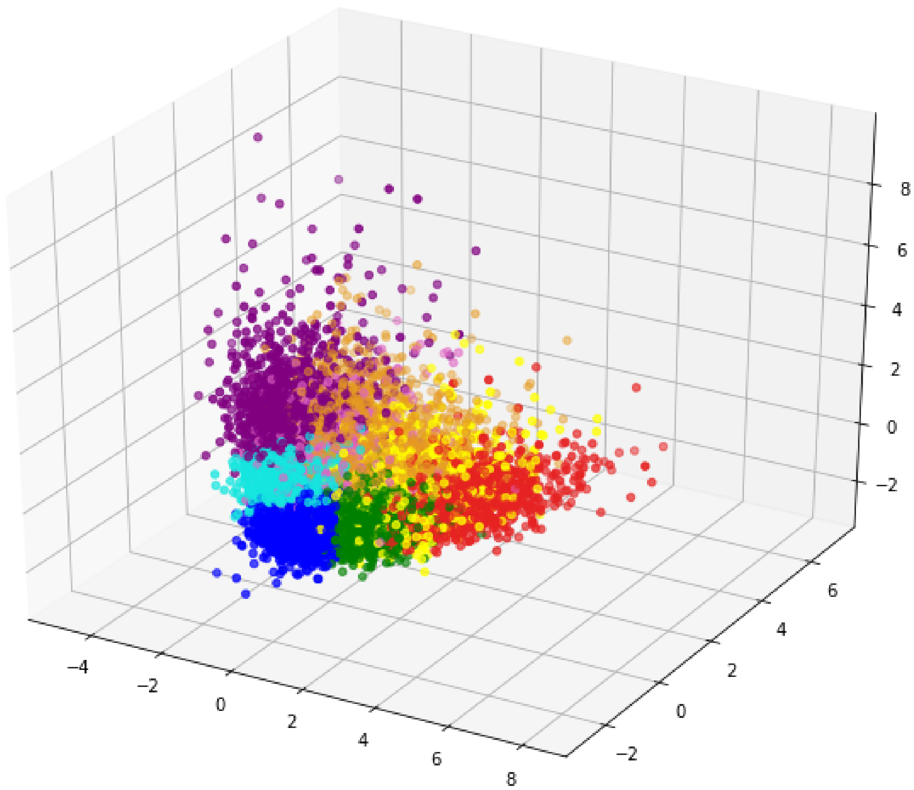

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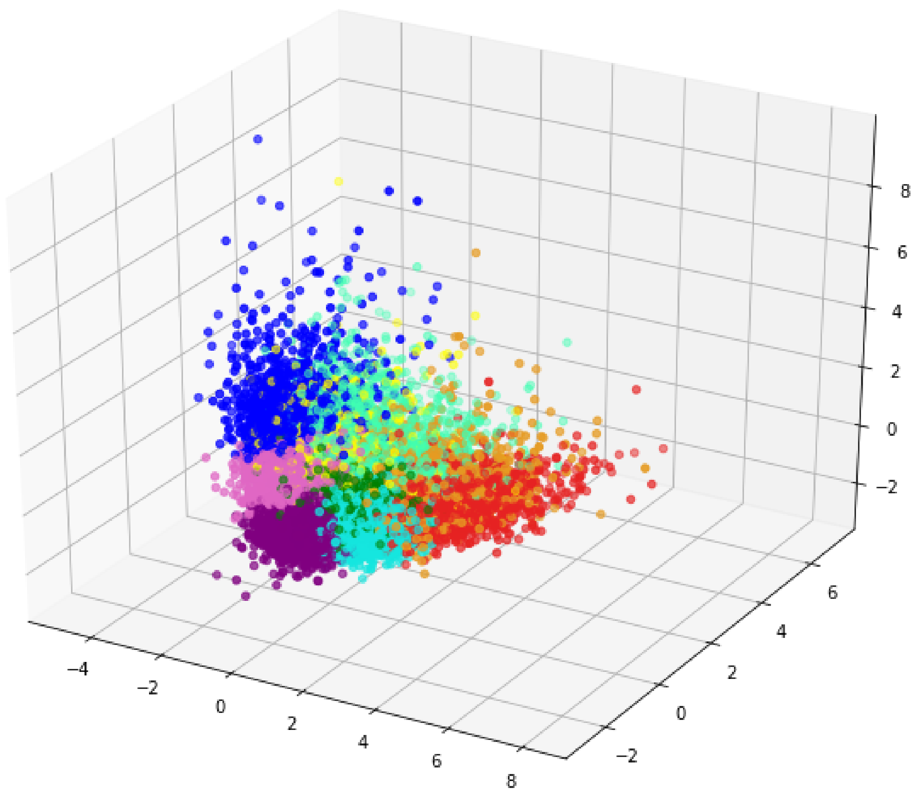


9 Statistical Verification for Frequent Paths [Optional]

Here, we are building some statictical verification data to verify if clustering works. That is, within the same type of path, does each group have its unique frequent paths? By using ngrams we'll be able to calculate the frequency. Since many times there were cases where a frequent page sequence is the same but its behaviors are different, ngrams will treat them as two different paths. For a better visualization, I seperated page path and behavior path for demonstrations.

The first part of the cell builds group_user list of dictionary. The outer lists specify the type of path. The inner elements are dictionaries, where each dictionary represents all users and their corresponding paths within the same group

The second part of the cell builds aggregated sentence for each group. The outer lists specify the type of path. The inner elements are concatenated paths of all users regardless of markers in new user, new session, etc because Doc2Vec model didn't use session information as well.

The third part of the cell builds n-gram (most frequent full path with length of n) information for the top 10 frequent paths over each user group over each type of path. Here we use n = 4 and built frequent paths that are sensitive to both page & behavior information

The last part of the cell differntiates frequent page path and frequent behavior path over each user group over each type of path. Here, visualizing such information over many groups will be complicated. As a demonstration, we'll only differentiates frequent page path and frequent behavior path over the first two user groups over each type of path.

[9]:
```
print("Build grouped_user list of dictionary", end = " ... ")

# build grouped user
partition_lst = []
for i in range(len(group_lst)):
    partition = partition_user_group(map_dic_lst[i], group_lst[i], lst_dics[i])
    partition_lst.append(partition)

print("finished")
print("Build aggregated sentence for each group", end = " ... ")

# build aggregated sentence for each group
ls_lst = []
for partition in partition_lst:
    lst_sentence = ld_to_ls(partition)
    ls_lst.append(lst_sentence)

print("finished")
print("Build n-gram for each type of path with specific user group", end = " ...
 ↪ ")

# build n-gram for each type of path with specific user group
# eg. ngram_lst[0][0] means the path n-gram for user_group 0 for their item_id␣
 ↪data
# eg. ngram_lst[1][2] means the path n-gram for user_group 2 for their cat_id␣
 ↪data
n_grams_lst = []
for ls in ls_lst:
    temp = [build_ngram_from_string(ls[i], length = 10) for i in range(K)]
    n_grams_lst.append(temp)

print("finished")
print("Build sample stats for each group's frequent path/behavior", end = " ...␣
 ↪")

# build sample stats for each group's frequent path/behavior
COMPARISON_GROUP = 2
sample_stat_lst = []
for path_type in range(len(path_col_index)):
    sample_stat_lst.append([])
    for i, _type in enumerate(['page', 'behavior']):
```

```
        sample_stat_lst[path_type].append([])
        for group_label in range(COMPARISON_GROUP):
            sample_stat_lst[path_type][i].append\
            (calculate_stat(n_grams_lst[path_type][group_label], normalization␣
 ↪= True, mode = _type))

print("finished")
```

```
Build grouped_user list of dictionary … finished
Build aggregated sentence for each group … finished
Build n-gram for each type of path with specific user group … finished
Build sample stats for each group's frequent path/behavior … finished
```

10 Visualization [Optional]

The below cell shows information from the last part in the above cell. Here, for instance, path type = 0 represents paths based on item_id. group = 0 represents that the first user group's path is being visualized. Page represents page path information whereas behavior represents behavior path information.

In each piece of information, the first four markers mean the specific path. The float over four markers mean the frequency of the path that appeared within the entire user_group. For instance, in [('24884366', '27354353', '10335776', '13482763'), 0.15819209039548024], it means that 0.15819209039548024 of all page paths within this user group follows the sequence ('24884366', '27354353', '10335776', '13482763'). For instance, in [('p', 'p', 'p', 'p'), 1.0], it means that 1.0 (all) of all behavior paths within this user group follows the sequence ('p', 'p', 'p', 'p').

[10]:
```
DISPLAY_NUM = 5
for path_type in range(len(path_col_index)):
    print("Path Type = {}".format(path_type), end = "\n")
    for group_label in range(COMPARISON_GROUP):
        print("Group = {}".format(group_label))
        for _type in range(len(['page', 'behavior'])):
            print(['Page', 'Behavior'][_type], end = "\n")
            for i in range(DISPLAY_NUM):
                if (i < len(sample_stat_lst[path_type][group_label][_type])):
                    print(sample_stat_lst[path_type][group_label][_type][i])
```

```
Path Type = 0
Page
Group = 0
[('24884366', '27354353', '10335776', '13482763'), 0.15819209039548024]
[('31775392', '27507619', '31775392', '27507619'), 0.11864406779661017]
[('7180901', '10366372', '7180901', '10366372'), 0.11864406779661017]
[('10366372', '7180901', '10366372', '7180901'), 0.11299435028248588]
[('27507619', '31775392', '27507619', '31775392'), 0.096045197740113]
Group = 1
```

```
[('p', 'p', 'p', 'p'), 1.0]
Behavior
Group = 0
[('37940136', '14808276', '37940136', '14808276'), 0.15053763440860216]
[('14808276', '37940136', '14808276', '37940136'), 0.15053763440860216]
[('5264777', '28470380', '5264777', '28470380'), 0.11827956989247312]
[('28470380', '5264777', '28470380', '5264777'), 0.10752688172043011]
[('2437626', '9264728', '2437626', '9264728'), 0.08602150537634409]
Group = 1
[('p', 'p', 'p', 'p'), 1.0]
Path Type = 1
Page
Group = 0
[('7441', '7441', '7441', '7441'), 0.39925373134328357]
[('8913', '8913', '8913', '8913'), 0.1044776119402985]
[('12475', '12475', '12475', '12475'), 0.09328358208955224]
[('7441', '7441', '8677', '7441'), 0.08582089552238806]
[('5480', '5480', '5480', '5480'), 0.08208955223880597]
Group = 1
[('p', 'px', 'c', 'p'), 0.5597014925373134]
[('p', 'px', 'p', 'p'), 0.2462686567164179]
[('px', 'c', 'p', 'px'), 0.12686567164179105]
[('p', 'px', 'p', 'px'), 0.06716417910447761]
Behavior
Group = 0
[('7441', '7441', '7441', '7441'), 0.45817490494296575]
[('7442', '7442', '7442', '7442'), 0.1850443599493029]
[('7441', '7441', '8677', '7441'), 0.12737642585551331]
[('7441', '7441', '7442', '7441'), 0.08238276299112801]
[('7441', '7441', '6305', '7441'), 0.07541191381495564]
Group = 1
[('p', 'px', 'c', 'p'), 0.3669201520912547]
[('p', 'px', 'p', 'p'), 0.28517110266159695]
[('px', 'c', 'p', 'px'), 0.18694550063371357]
[('p', 'px', 'f', 'p'), 0.09569074778200254]
[('p', 'px', 'p', 'px'), 0.06527249683143219]
Path Type = 2
Page
Group = 0
[('2997236', '2997236', '2997236', '2997236'), 0.2761904761904762]
[('1600933', '1600933', '1600933', '1600933'), 0.2523809523809524]
[('2375564', '2375564', '2375564', '2375564'), 0.1]
[('2997236', '2997236', '2375564', '2375564'), 0.08571428571428572]
[('451197', '451197', '451197', '451197'), 0.0761904761904762]
Group = 1
[('p', 'px', 'c', 'p'), 0.5476190476190477]
[('p', 'px', 'b', 'bx'), 0.18095238095238095]
[('p', 'px', 'p', 'px'), 0.1523809523809524]
```

```
[('px', 'c', 'p', 'px'), 0.11904761904761904]
Behavior
Group = 0
[('622485', '622485', '622485', '622485'), 0.43209876543209874]
[('2027734', '2027734', '2027734', '2027734'), 0.4279835390946502]
[('1600933', '1600933', '1600933', '1600933'), 0.13991769547325103]
Group = 1
[('p', 'px', 'c', 'p'), 0.42386831275720166]
[('px', 'c', 'p', 'px'), 0.205761316872428]
[('c', 'p', 'px', 'c'), 0.16049382716049382]
[('p', 'c', 'p', 'px'), 0.13991769547325103]
[('p', 'px', 'b', 'bx'), 0.06995884773662552]
Path Type = 3
Page
Group = 0
[('-1', '-1', '-1', '-1'), 0.8320987654320988]
[('-1', '-1', '167611', '-1'), 0.10452674897119342]
[('-1', '167611', '-1', '-1'), 0.06337448559670782]
Group = 1
[('p', 'px', 'c', 'p'), 0.1925925925925926]
[('p', 'px', 'p', 'px'), 0.1794238683127572]
[('p', 'c', 'p', 'px'), 0.1094650205761317]
[('p', 'px', 'p', 'p'), 0.10452674897119342]
[('px', 'c', 'p', 'px'), 0.0962962962962963]
Behavior
Group = 0
[('-1', '-1', '-1', '-1'), 0.7326839826839827]
[('-1', '-1', '167611', '-1'), 0.13636363636363635]
[('-1', '167611', '-1', '-1'), 0.13095238095238096]
Group = 1
[('p', 'px', 'c', 'p'), 0.23484848484848486]
[('p', 'px', 'p', 'p'), 0.13636363636363635]
[('px', 'c', 'p', 'px'), 0.12445887445887446]
[('p', 'c', 'p', 'px'), 0.10822510822510822]
[('p', 'px', 'p', 'px'), 0.08658008658008658]
```

11 Generate User Info Distribution for Each Group [Optional]

Here, we are trying to verify the validity of user clustering based over their path preference over different type of paths by extracting user information from each clustered user group. Note that each user's age, gender and buying power are not fed into the doc2vec model, so if each group's information distribution is different, it means that the doc2vec model has successfully clustered users into different groups.

[11]:
```
dftemp = pd.read_csv('user.csv')
dftemp.columns = ['user_id', 'gender', 'age', 'power']
```

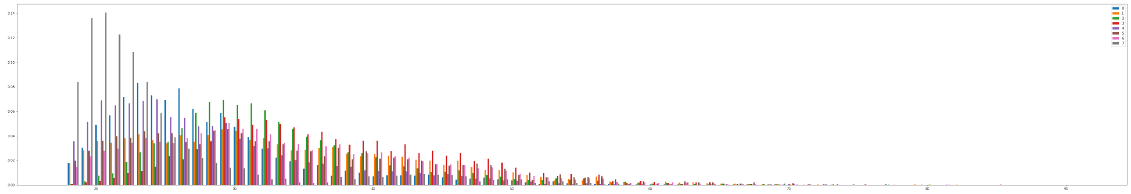
```
age_groups_lst = []
gender_groups_lst = []
for i in range(len(inv_map_lst)):
    age_groups, gender_groups = generate_user_info_distribution(df, dftemp,␣
↪inv_map_lst[i], group_lst[i], K = K)
    age_groups_lst.append(age_groups)
    gender_groups_lst.append(gender_groups)

del dftemp
```

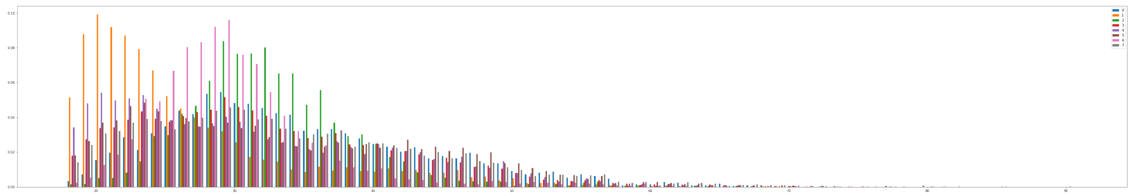
12 Visualization [Optional]

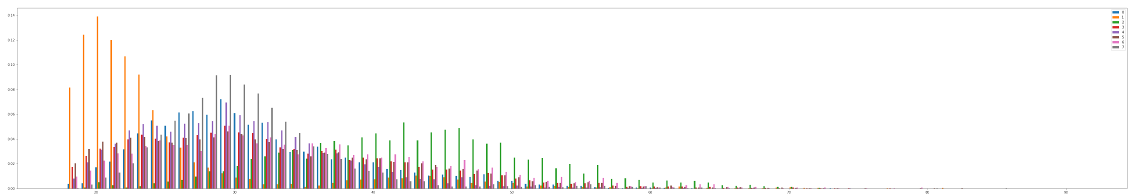
Here, the visualization verified the statement in the above cell's explanation. The first four figures represent age distribution over each user group, with each figure representing each type of paths analyzed (each group has one color in the barplot). The last four figures represent user information distribution over gender distribution over each user group, with each figure representing each type of paths analyzed (each group has one color in the barplot).

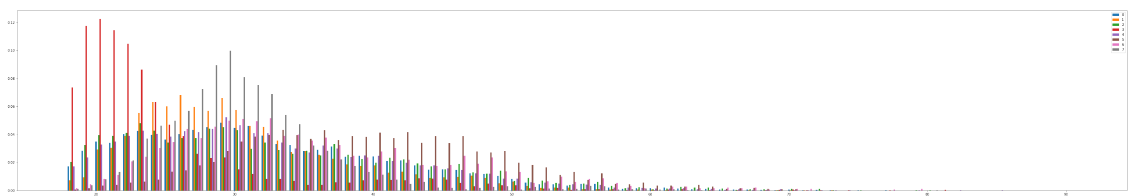
[12]:
```
def plot_age_distribution(age_groups_lst):
    for age_groups in age_groups_lst:
        indices = np.array(df['age'].unique().tolist())
        width = 0.1
        fig = plt.gcf()
        fig.set_size_inches(60, 10)
        for i in range(K - 1):
            plt.bar(indices + width*i, np.array(list(age_groups[i].values()))/
↪sum(list(age_groups[i].values())), width, label='{}'.format(i))
        plt.bar(indices + width*(i+1), np.array(list(age_groups[K - 1].
↪values()))/sum(list(age_groups[K - 1].values())), width, label='{}'.format(K␣
↪- 1))
        plt.legend(loc='best')
        plt.show()

def plot_gender_distribution(gender_groups_lst):
    for gender_groups in gender_groups_lst:
        indices = np.array(df['gender'].unique().tolist())
        width = 0.1
        fig = plt.gcf()
        fig.set_size_inches(16, 10)
        for i in range(K - 1):
            plt.bar(indices + width*i, np.array(list(gender_groups[i].
↪values()))/sum(list(gender_groups[i].values())), width, label='{}'.format(i))
        plt.bar(indices + width*(i+1), np.array(list(gender_groups[K - 1].
↪values()))/sum(list(gender_groups[K - 1].values())), width, label='{}'.
↪format(K - 1))
        plt.xticks(indices + width*3, ('Female', 'Male'))
```

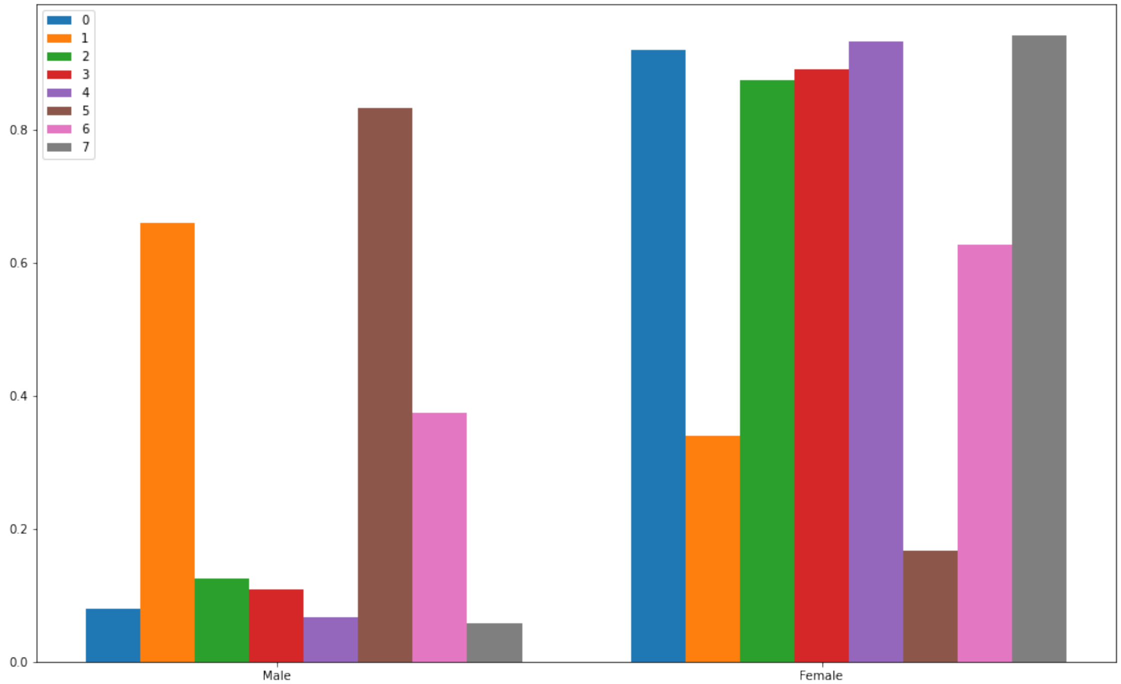
```
        plt.legend(loc='best')
        plt.show()

plot_age_distribution(age_groups_lst)
plot_gender_distribution(gender_groups_lst)
```

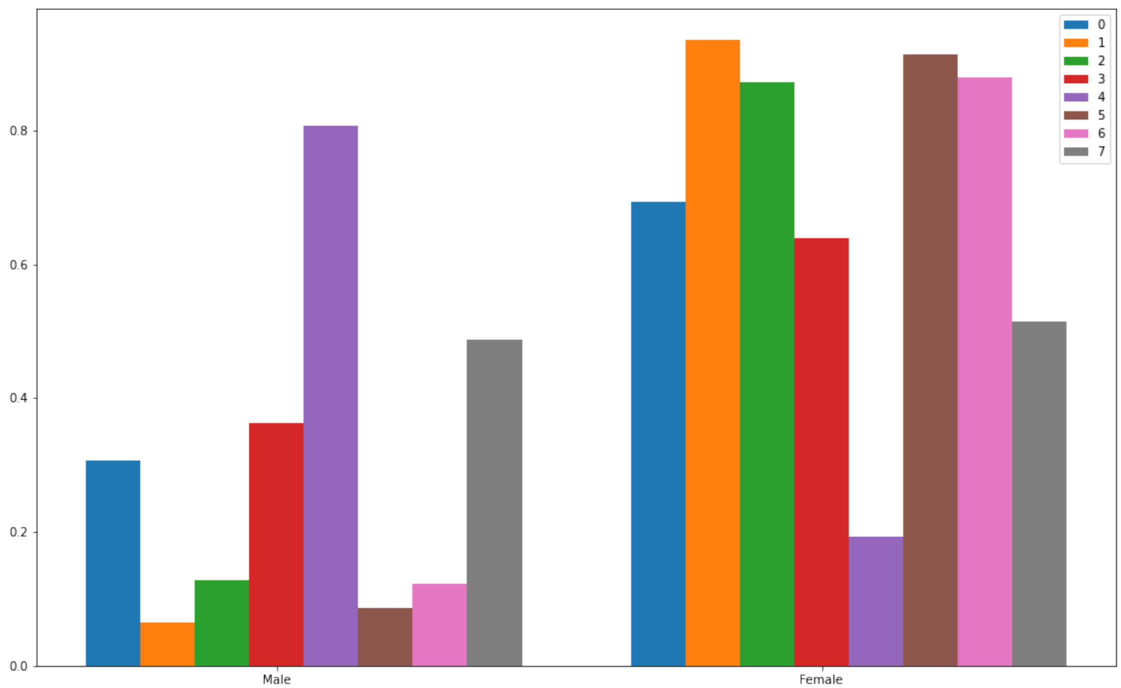


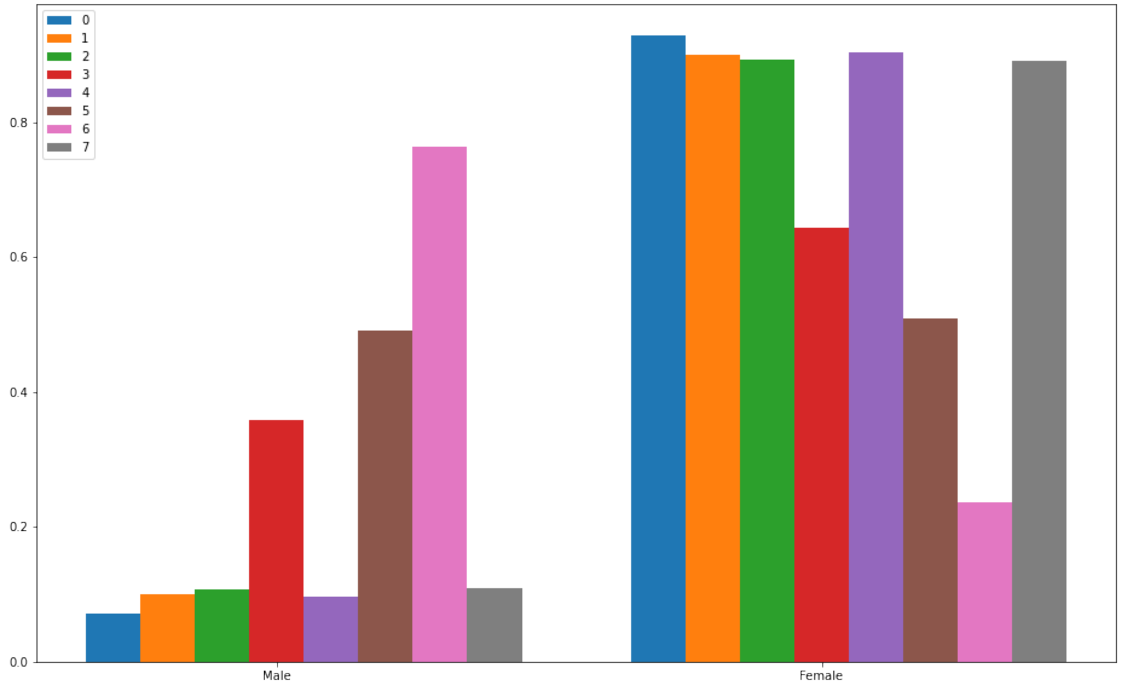


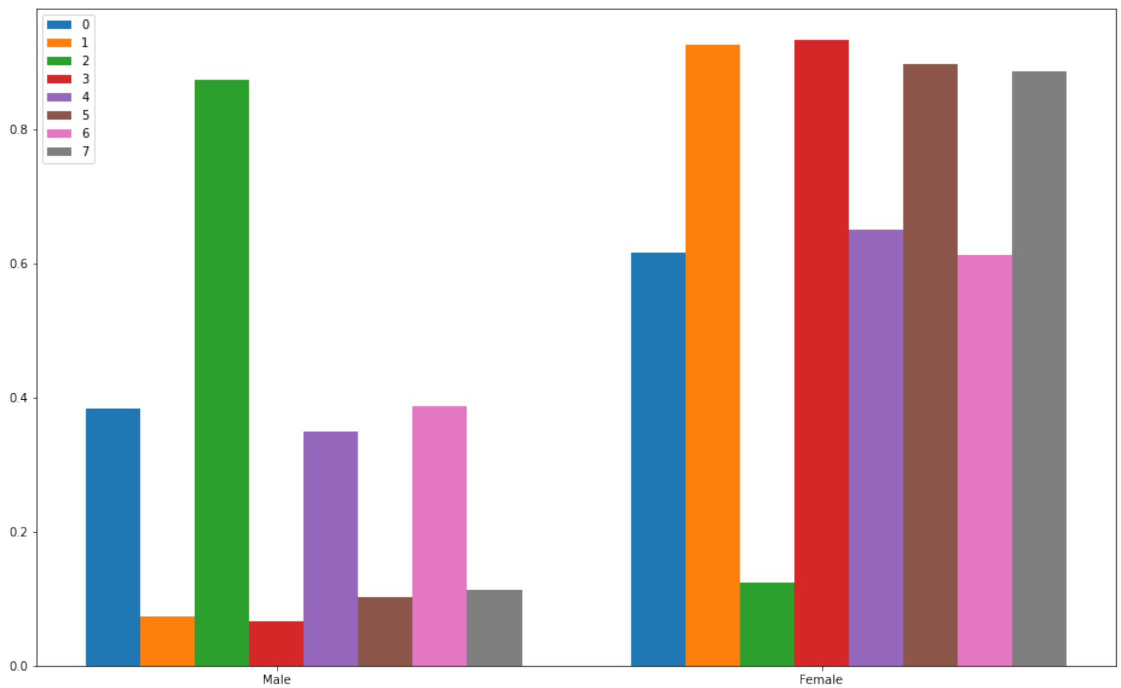





0
1
2
3
4
5
6
7
0.0
0.2
0.4
0.6
0.8
Male
Female


0
1
2
3
4
5
6
7
0.0
0.2
0.4
0.6
0.8
Male
Female


0
1
2
3
4
5
6
7
0.0
0.2
0.4
0.6
0.8
Male
Female


0
1
2
3
4
5
6
7
0.0
0.2
0.4
0.6
0.8
Male
Female

13 Attribution Analysis

Here, we are building an explainable model for path attribution over each user group over each type of path. In the first part of the cell, we concatenate each user group's data together that contains session information. In the second part of the cell, we build attribution dictionary over each user group over each type of path. The outer list specifies types of path, and the inner list specified which user group. The key of any attribution dictionary is a single point on a path, and the values are the attribution coefficient of paths that lead to the key path. Please refer to https://www.jianshu.com/p/a1fa42c5cc42 on how the coefficient was computed.

In the below example, we are using last click as our analysis mode. I'll use p1101 as our target to explain some details. We don't discard the same page, which means that it is okay that p1101 leads to p1101. We count blank into our analysis, which means that it is okay that we count None as the last click before p1101 when it comes as the first point of path in a new session.

[13]:
```
path_data_lst = []
for i in range(len(group_lst)):
    for j in tqdm(range(0, K+1)):
        path_data_lst.append([])
        path_data = aggregate_group_path_data(lst_dics[i], map_dic_lst[i],␣
 ↪group_lst[i], group = j-1)
        path_data_lst[i].append(path_data)

# dic cannot be built upon brand_id because it contains to many unknow brands␣
 ↪as -1
reason_dic_lst = []
for i in range(len(group_lst) - 1):
    for j in tqdm(range(0, K+1)):
        reason_dic_lst.append([])
        reason_dic = analyze_sequence_by_prior_sequence\
                   (path_data_lst[i][j], mode = 'last', discard_same_page =␣
 ↪False, count_blank = True)
        reason_dic_lst[i].append(reason_dic)
```

```
100%|      | 9/9 [00:00<00:00, 20.30it/s]
100%|      | 9/9 [00:00<00:00, 21.24it/s]
100%|      | 9/9 [00:00<00:00, 20.53it/s]
100%|      | 9/9 [00:00<00:00, 20.96it/s]
100%|      | 9/9 [00:37<00:00,  4.11s/it]
100%|      | 9/9 [00:22<00:00,  2.50s/it]
100%|      | 9/9 [00:27<00:00,  3.01s/it]
```

14 Attribution Analysis Report with Partitioned Group [Optional]

Here we have two parts. Before we start, I will define several terms:

Reasoning Coefficient: the number of a target's attributors' successors that lead to the target itself

/ the total number of a target's attributors' successors.

Macro Accuracy: the average of reasoning coefficients over all targets within a user group regardless of each target's importance (number of appearances)

Weighted Accuracy: the average of reasoning coefficients over all targets within a user group weighted by each target's importance (number of appearances)

In the first part one can query a single target's reasoning coefficient, and in the second part the reasoning coefficient of each group is shown, with group -1 representing the an aggregated path without user clustering/grouping. From the result, we can see that such user clustering gives better results in attribution analysis, which yields a higher reasoning coefficient and accuracy within each group compared to the same metrics without user clustering. This result means that the doc2vec models successfully clustered users that have different path preferences.

[14]:
```python
# Query single reasoning coefficient
# for key in reason_dic_lst[0]:
#     validate_reason_last(key, path_data_lst[0], reason_dic_lst[0], amount =␣
↪10)

for k in range(int(len(reason_dic_lst)/len(reason_dic_lst[0]))):
    validation_report(path_data_lst[k], reason_dic_lst[k], title = "Path␣
↪Constructed by: {}".format(title_col[k]), K = K)
```

```
----------------------------------------------------------------------
Path Constructed by: item_id
Group -1 | Macro Accuracy: 0.7534601252081541 | Weighted Accuracy:
0.3347449684876893
Group 0 | Macro Accuracy: 0.8226142608967039 | Weighted Accuracy:
0.4966169922730122
Group 1 | Macro Accuracy: 0.8476923766791497 | Weighted Accuracy:
0.5210717839918043
Group 2 | Macro Accuracy: 0.825083102087142 | Weighted Accuracy:
0.4864820252728828
Group 3 | Macro Accuracy: 0.8036253733470817 | Weighted Accuracy:
0.46764433474793965
Group 4 | Macro Accuracy: 0.8323921172677644 | Weighted Accuracy:
0.49471483715401954
Group 5 | Macro Accuracy: 0.8277411311628649 | Weighted Accuracy:
0.5153664512452513
Group 6 | Macro Accuracy: 0.8699514055948352 | Weighted Accuracy:
0.5067350569089156
Group 7 | Macro Accuracy: 0.8047645664440346 | Weighted Accuracy:
0.46781037359962624

Without Clustering:
Macro Accuracy: 0.7534601252081541 | Weighted Accuracy: 0.3347449684876893

With Clstering:
```

```
Macro Accuracy: 0.8292330416849469 | Weighted Accuracy: 0.4945552318991815

--------------------------------------------------------------------
Path Constructed by: cat_id
Group -1 | Macro Accuracy: 0.4297398944307159 | Weighted Accuracy:
0.09291808537639822
Group 0 | Macro Accuracy: 0.5408626841869046 | Weighted Accuracy:
0.12282202468892463
Group 1 | Macro Accuracy: 0.5373758436326971 | Weighted Accuracy:
0.10395427568553854
Group 2 | Macro Accuracy: 0.5337643113479934 | Weighted Accuracy:
0.10195655071470924
Group 3 | Macro Accuracy: 0.5340739883987731 | Weighted Accuracy:
0.11033771195832041
Group 4 | Macro Accuracy: 0.5420066592743142 | Weighted Accuracy:
0.12150391809818893
Group 5 | Macro Accuracy: 0.5377642359793369 | Weighted Accuracy:
0.11441378918706029
Group 6 | Macro Accuracy: 0.5431215966395315 | Weighted Accuracy:
0.11887210944051033
Group 7 | Macro Accuracy: 0.5239892182421946 | Weighted Accuracy:
0.16311305100593643

Without Clustering:
Macro Accuracy: 0.4297398944307159 | Weighted Accuracy: 0.09291808537639822

With Clstering:
Macro Accuracy: 0.5366198172127181 | Weighted Accuracy: 0.11962167884739859

--------------------------------------------------------------------
Path Constructed by: shop_id
Group -1 | Macro Accuracy: 0.6694670206828178 | Weighted Accuracy:
0.1882293251715604
Group 0 | Macro Accuracy: 0.7627591540162199 | Weighted Accuracy:
0.33689216817232304
Group 1 | Macro Accuracy: 0.7349415614762211 | Weighted Accuracy:
0.2708128021718966
Group 2 | Macro Accuracy: 0.7509069568719786 | Weighted Accuracy:
0.32864807335171786
Group 3 | Macro Accuracy: 0.8026075561472468 | Weighted Accuracy:
0.34869194102700907
Group 4 | Macro Accuracy: 0.7460869086004316 | Weighted Accuracy:
0.3121073848885428
Group 5 | Macro Accuracy: 0.7764544208358356 | Weighted Accuracy:
0.34929260020397157
Group 6 | Macro Accuracy: 0.7669623292004877 | Weighted Accuracy:
0.3867215594068267
Group 7 | Macro Accuracy: 0.7555165207823971 | Weighted Accuracy:
```

```
0.3338690487359667

Without Clustering:
Macro Accuracy: 0.6694670206828178 | Weighted Accuracy: 0.1882293251715604

With Clstering:
Macro Accuracy: 0.7620294259913523 | Weighted Accuracy: 0.33337944724478175
```

15 Clustering Verification by Embedding

We can further examine this attribution improvement by user path and behavior clustering by adding clustering information as user features to classify users' age group, gender, and buying power.

Here, user labeling across different types of paths can be similar, and we will use one-hot encodings to utilize these user group embeddings. In an 8-group setting with 4 types of paths, we'll have 32 additional features. We'll use PCA to transform this 32 dimension features into 8 dimension features to reduce memory use and solve the sparsity of our features.

We also turn each log's user behavior into one-hot encodings, and add them to the dataframe.

[15]:
```
N = 8

# generate embeddings for each kind of path
embed_lst = []
for i in range(len(group_lst)):
    group = group_lst[i]
    inv_map = inv_map_lst[i]
    embed_lst.append(generate_embed(group, inv_map, df))
embeds = np.transpose(np.array(embed_lst))

# create a temporary dataframe for embeddings
embed_col = ['embed_{}'.format(name) for name in title_col]
df_embed = pd.DataFrame(data = embeds, index = df.index, columns = embed_col)
to_reduce = []

# transform embeddings dataframe to one-hot encoding
for col_name in embed_col:
    embed_dum = pd.get_dummies(df_embed[col_name])
    for i in range(K): to_reduce.append(embed_dum[i].tolist())

# reduce embedding data to N dimensions
to_reduce = np.transpose(np.array(to_reduce))
pca = PCA(n_components = N)
reduced_embeds = pca.fit_transform(to_reduce)

# add reduced embedding data to dataframe
```

```
embed_col = ["embed_dim_{}".format(i) for i in range(1, N + 1)]
df_reduced_embeds = pd.DataFrame(data = reduced_embeds, index = df.index,
    columns = embed_col)
df = df.join(df_reduced_embeds)

# add behavior data as one-hot encoding to dataframe
df_type = pd.get_dummies(df['type'])
df_type_col = ['beh_b', 'beh_c', 'beh_f', 'beh_p']
df_type.columns = df_type_col
df = df.join(df_type)
```

16 Visualization [Optional]

This visualization can be compared to the visualization in the third part of this report. Things that are additional in this dataframe are:

8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.
4 user behavior one-hot encodings.

[16]:
```
df.head(5)
```

[16]:
```
        user_id   item_id type    time  cat_id  shop_id  brand_id  gender  \
940626      279  40410079    b  221239    5296   948294     28570       1
940686      279  22830135    p  221258   12973   962246    216567       1
940667      279  26991039    p  221369   11072  2432702    216567       1
940668      279  26991039    p  221412   11072  2432702    216567       1
940669      279  26991039    p  221416   11072  2432702    216567       1

        age  power  …  embed_dim_3  embed_dim_4  embed_dim_5  embed_dim_6  \
940626   30      1  …     0.948022    -0.140931    -0.429757    -0.013779
940686   30      1  …     0.948022    -0.140931    -0.429757    -0.013779
940667   30      1  …     0.948022    -0.140931    -0.429757    -0.013779
940668   30      1  …     0.948022    -0.140931    -0.429757    -0.013779
940669   30      1  …     0.948022    -0.140931    -0.429757    -0.013779

        embed_dim_7  embed_dim_8  beh_b  beh_c  beh_f  beh_p
940626     0.110143     0.851477      1      0      0      0
940686     0.110143     0.851477      0      0      0      1
940667     0.110143     0.851477      0      0      0      1
940668     0.110143     0.851477      0      0      0      1
940669     0.110143     0.851477      0      0      0      1

[5 rows x 25 columns]
```

17 Multiclass Classification Model over Unbalanced Age Group(XGBoost)

Here, we are examining the effectiveness of user clustering based on user path over differnet types of paths by classifying unbalanced user age group (definition of "unbalanced" is in the second part of this report).

The base information including: new session signal (1 or 0), behaviors as one-hot encodings, and time as a continuous value.

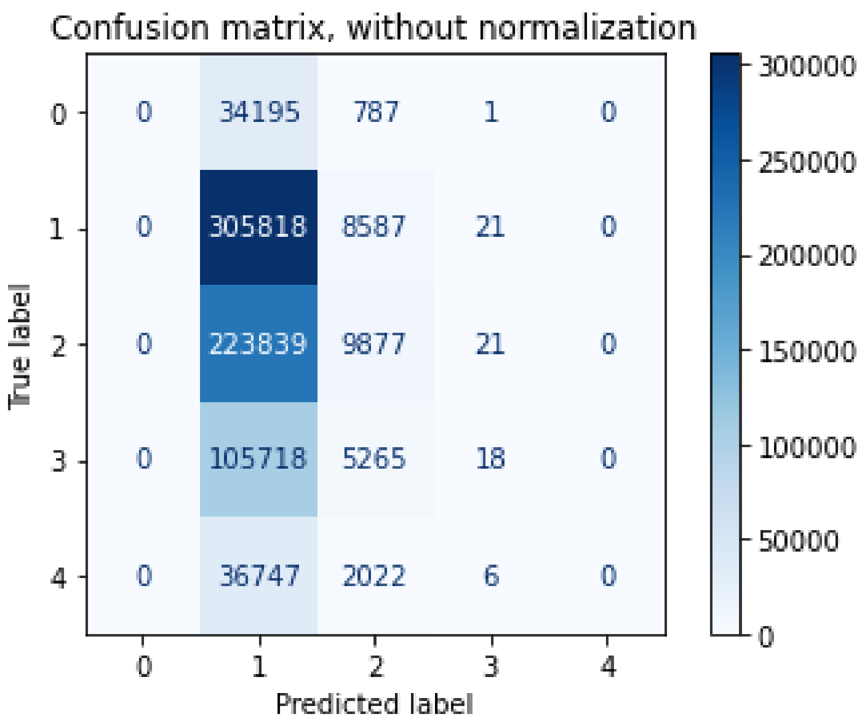
Verification information including: 8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.

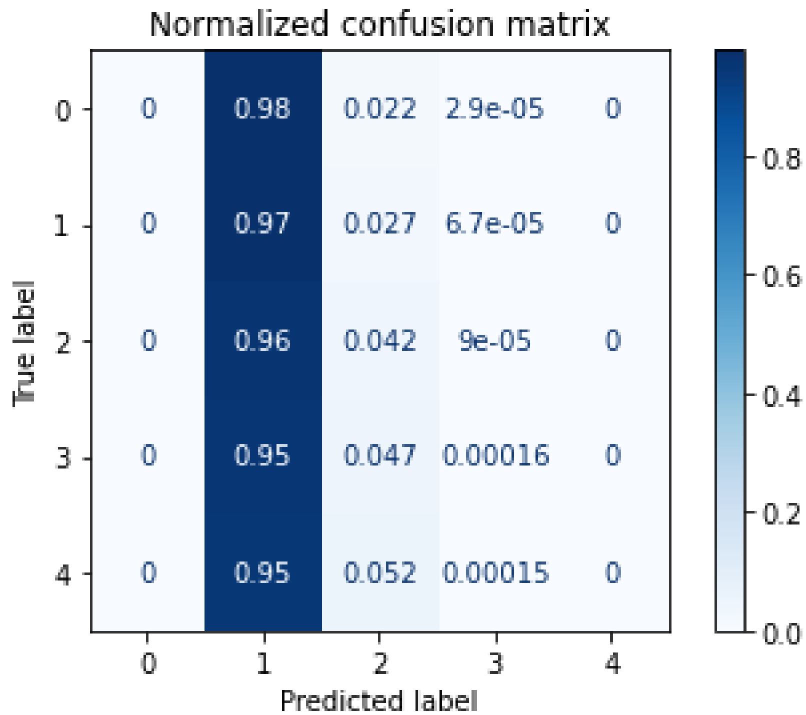
[17]:
```python
# Classification without Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time']
X = df[X_col]
y = df['label_unbalanced']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Age Classification without Path Clustering")
print(classification_report(y_test, result))
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(clf, X_test, y_test,
                                 # display_labels=class_names1,
                                   cmap=plt.cm.Blues,
                                   normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
plt.show()

# Classification with Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time'] + embed_col
X = df[X_col]
y = df['label_unbalanced']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
```

```python
print("Age Classification with Path Clustering")
print(classification_report(y_test, result))
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(clf, X_test, y_test,
                                 # display_labels=class_names1,
                                   cmap=plt.cm.Blues,
                                   normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
plt.show()

# Path Clustering Feature Contribution to Model Weights
temp = list(zip(X_col, clf.feature_importances_))
for i in range(len(temp)):
    print(temp[i])
_sum = 0
for i in range(6, len(temp)):
    _sum += temp[i][1]
print("Path Clustering Feature Relative Importance {}".format(_sum))
```

```
Age Classification without Path Clustering

C:\Users\Colin\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

              precision    recall  f1-score   support

           0       0.00      0.00      0.00     34983
           1       0.43      0.97      0.60    314426
           2       0.37      0.04      0.08    233737
           3       0.27      0.00      0.00    111001
           4       0.00      0.00      0.00     38775

    accuracy                           0.43    732922
   macro avg       0.21      0.20      0.14    732922
weighted avg       0.35      0.43      0.28    732922

Confusion matrix, without normalization
[[     0  34195    787      1      0]
 [     0 305818   8587     21      0]
 [     0 223839   9877     21      0]
```

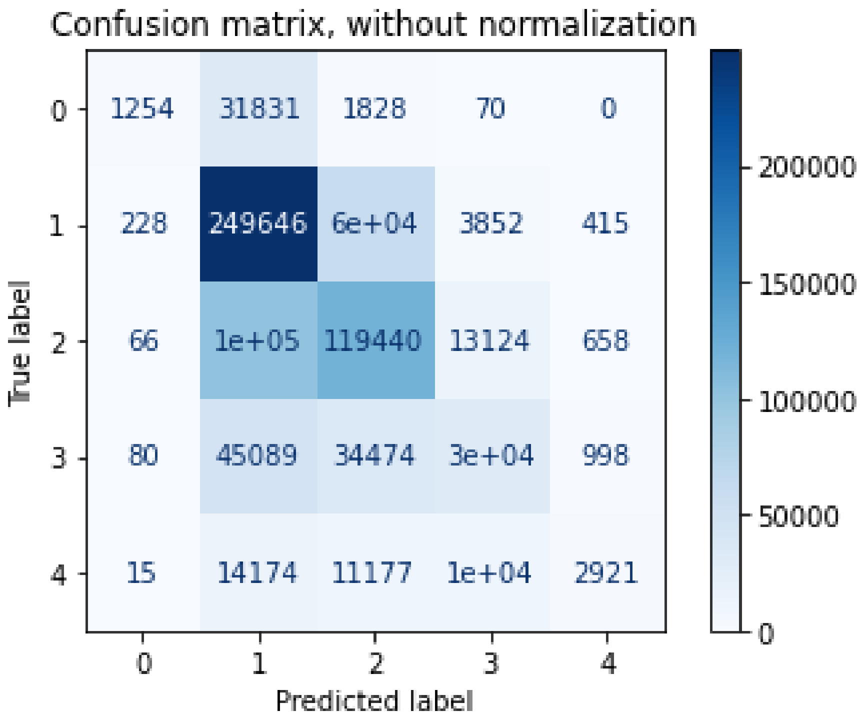
```
 [     0 105718   5265     18      0]
 [     0  36747   2022      6      0]]
Normalized confusion matrix
[[0.00000000e+00 9.77474773e-01 2.24966412e-02 2.85853129e-05
  0.00000000e+00]
 [0.00000000e+00 9.72623129e-01 2.73100825e-02 6.67883699e-05
  0.00000000e+00]
 [0.00000000e+00 9.57653260e-01 4.22568956e-02 8.98445689e-05
  0.00000000e+00]
 [0.00000000e+00 9.52405834e-01 4.74320051e-02 1.62160701e-04
  0.00000000e+00]
 [0.00000000e+00 9.47698259e-01 5.21470019e-02 1.54738878e-04
  0.00000000e+00]]
```

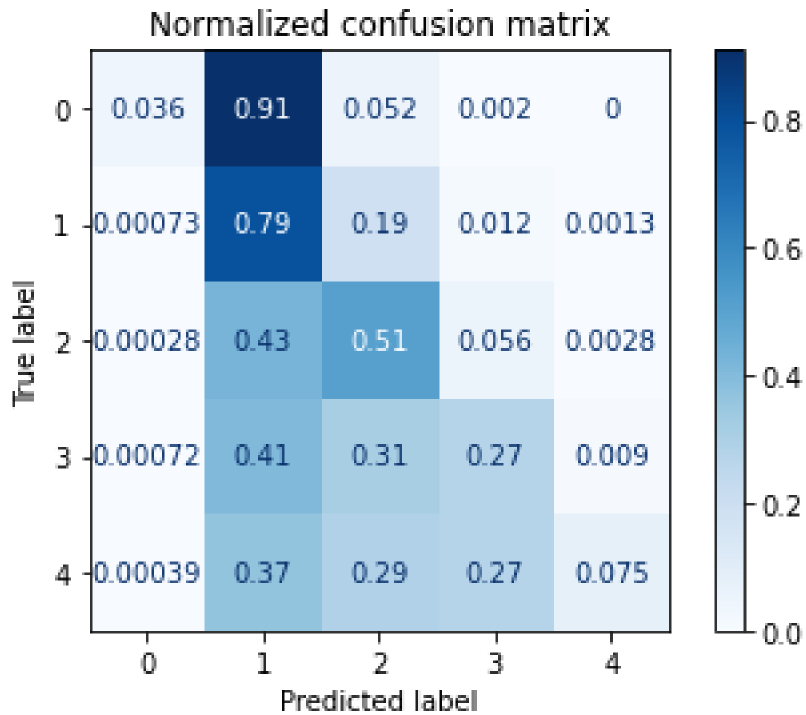





```
Age Classification with Path Clustering
              precision    recall  f1-score   support

           0       0.76      0.04      0.07     34983
           1       0.57      0.79      0.66    314426
           2       0.53      0.51      0.52    233737
           3       0.52      0.27      0.36    111001
           4       0.59      0.08      0.13     38775

    accuracy                           0.55    732922
   macro avg       0.59      0.34      0.35    732922
weighted avg       0.56      0.55      0.51    732922

Confusion matrix, without normalization
[[  1254  31831   1828     70      0]
 [   228 249646  60285   3852    415]
 [    66 100449 119440  13124    658]
 [    80  45089  34474  30360    998]
 [    15  14174  11177  10488   2921]]
Normalized confusion matrix
[[3.58459823e-02 9.09899094e-01 5.22539519e-02 2.00097190e-03
  0.00000000e+00]
 [7.25130873e-04 7.93973781e-01 1.91730328e-01 1.22508953e-02
  1.31986541e-03]
```

```
[2.82368645e-04 4.29752243e-01 5.11001681e-01 5.61485772e-02
 2.81512983e-03]
[7.20714228e-04 4.06203548e-01 3.10573779e-01 2.73511049e-01
 8.99090999e-03]
[3.86847195e-04 3.65544810e-01 2.88252740e-01 2.70483559e-01
 7.53320438e-02]]
```






```
('new_session', 0.002392162)
('beh_b', 0.0065037357)
('beh_c', 0.006366512)
('beh_f', 0.009621514)
('beh_p', 0.004681309)
('time', 0.012955252)
('embed_dim_1', 0.07437169)
('embed_dim_2', 0.07596885)
('embed_dim_3', 0.28262696)
('embed_dim_4', 0.24713342)
('embed_dim_5', 0.0795425)
('embed_dim_6', 0.071293145)
('embed_dim_7', 0.04892026)
('embed_dim_8', 0.077622734)
Path Clustering Feature Relative Importance 0.9574795514345169
```

18 Multiclass Classification Model over Balanced Age Group(XGBoost)

Here, we are examining the effectiveness of user clustering based on user path over differnet types of paths by classifying balanced user age group (definition of "balanced" is in the second part of this report).

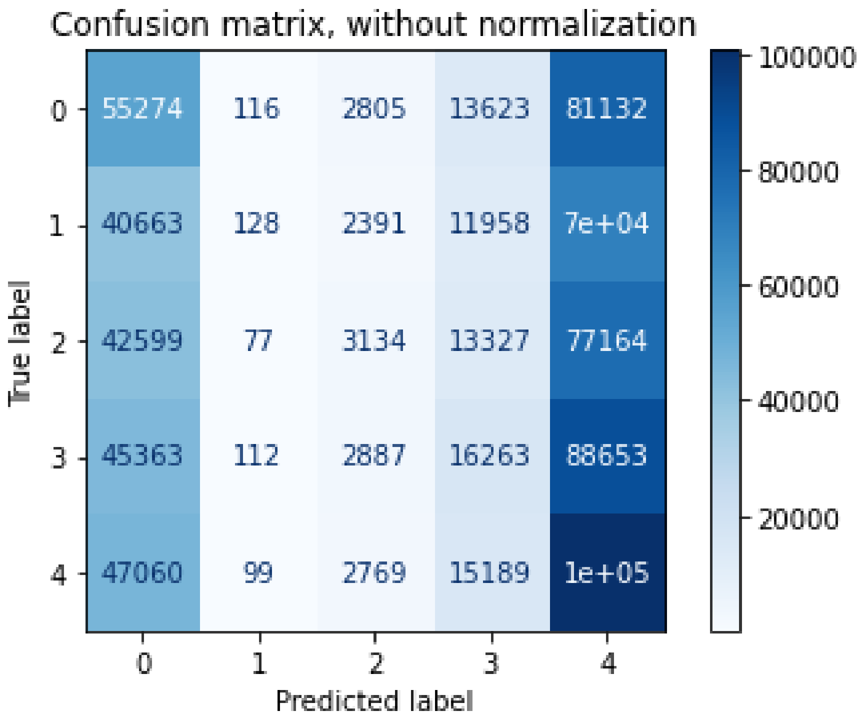
The base information including: new session signal (1 or 0), behaviors as one-hot encodings, and time as a continuous value.

Verification information including: 8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.

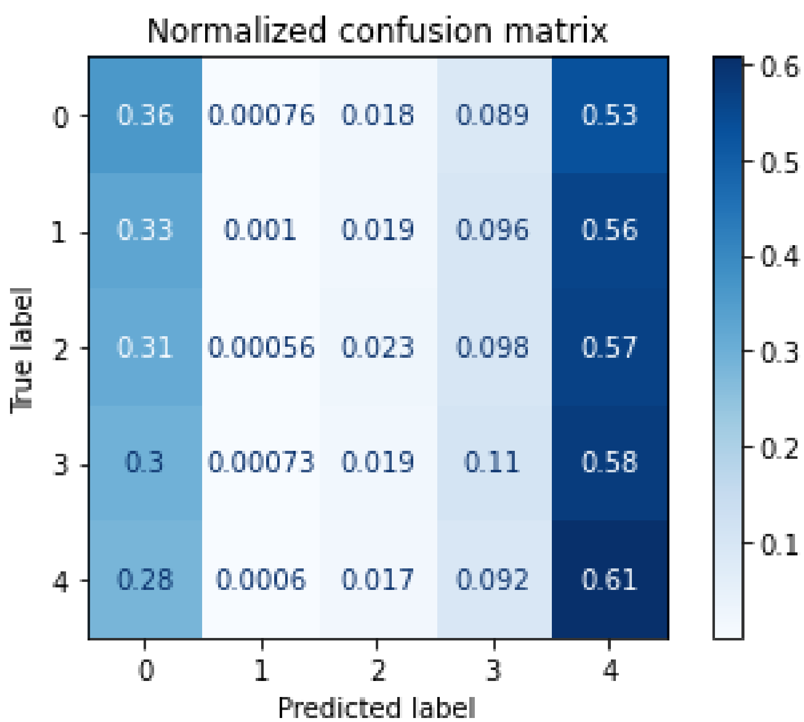
[18]:
```
# Classification without Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time']
X = df[X_col]
y = df['label_balanced']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Age Classification without Path Clustering")
print(classification_report(y_test, result))
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(clf, X_test, y_test,
                               # display_labels=class_names1,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
plt.show()

# Classification with Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time'] + embed_col
X = df[X_col]
y = df['label_balanced']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Age Classification with Path Clustering")
print(classification_report(y_test, result))
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(clf, X_test, y_test,
                               # display_labels=class_names1,
```

```
                                    cmap=plt.cm.Blues,
                                    normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)
plt.show()

# Path Clustering Feature Contribution to Model Weights
temp = list(zip(X_col, clf.feature_importances_))
for i in range(len(temp)):
    print(temp[i])
_sum = 0
for i in range(6, len(temp)):
    _sum += temp[i][1]
print("Path Clustering Feature Relative Importance {}".format(_sum))
```

```
Age Classification without Path Clustering
              precision    recall  f1-score   support

           0       0.24      0.36      0.29    152950
           1       0.24      0.00      0.00    124646
           2       0.22      0.02      0.04    136301
           3       0.23      0.11      0.15    153278
           4       0.24      0.61      0.35    165747

    accuracy                           0.24    732922
   macro avg       0.24      0.22      0.16    732922
weighted avg       0.24      0.24      0.18    732922

Confusion matrix, without normalization
[[ 55274    116   2805  13623  81132]
 [ 40663    128   2391  11958  69506]
 [ 42599     77   3134  13327  77164]
 [ 45363    112   2887  16263  88653]
 [ 47060     99   2769  15189 100630]]
Normalized confusion matrix
[[3.61386074e-01 7.58417784e-04 1.83393266e-02 8.90683230e-02
  5.30447859e-01]
 [3.26227877e-01 1.02690820e-03 1.91823243e-02 9.59356899e-02
  5.57627200e-01]
 [3.12536225e-01 5.64926156e-04 2.29932282e-02 9.77762452e-02
  5.66129375e-01]
 [2.95952452e-01 7.30698469e-04 1.88350579e-02 1.06101332e-01
  5.78380459e-01]
 [2.83926708e-01 5.97295879e-04 1.67061847e-02 9.16396677e-02
  6.07130144e-01]]
```

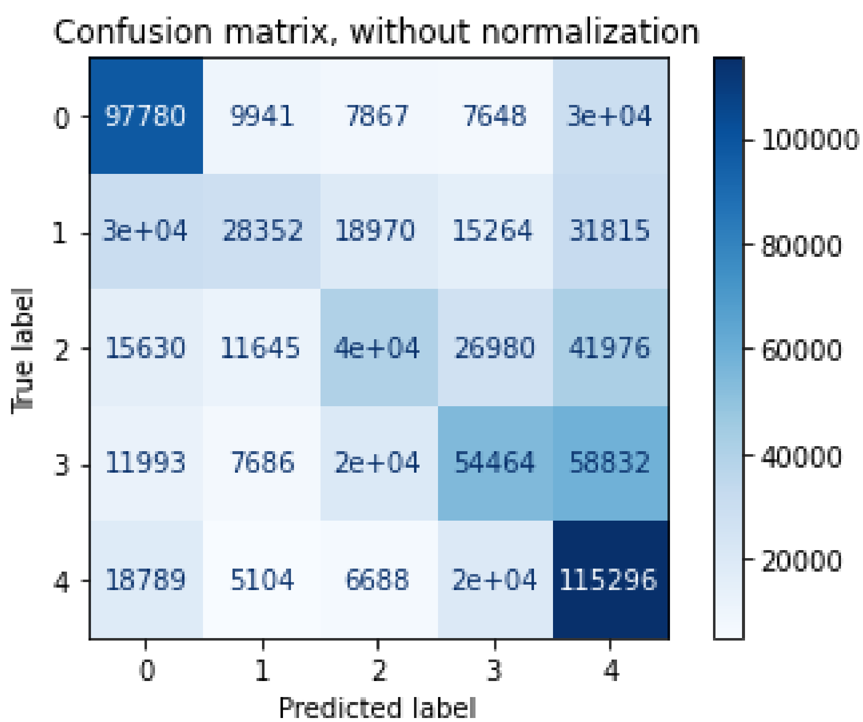


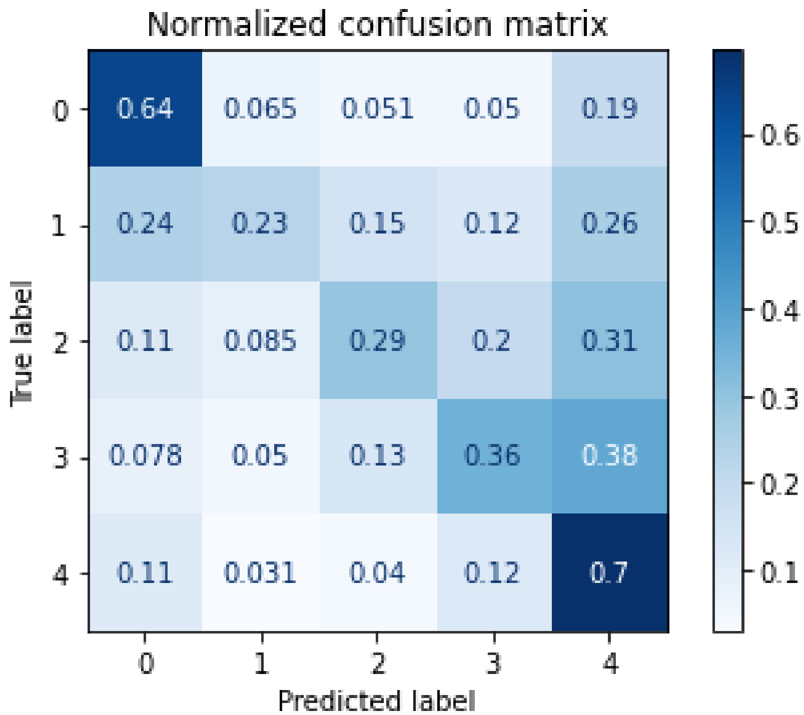
Confusion matrix, without normalization
55274
116
2805
13623
81132
40663
128
2391
11958
7e+04
42599
77
3134
13327
77164
45363
112
2887
16263
88653
47060
99
2769
15189
1e+05
True label
Predicted label
100000
80000
60000
40000
20000



Normalized confusion matrix
0.36
0.00076
0.018
0.089
0.53
0.33
0.001
0.019
0.096
0.56
0.31
0.00056
0.023
0.098
0.57
0.3
0.00073
0.019
0.11
0.58
0.28
0.0006
0.017
0.092
0.61
True label
Predicted label
0.6
0.5
0.4
0.3
0.2
0.1

```
Age Classification with Path Clustering
              precision    recall  f1-score   support

           0       0.56      0.64      0.60    152950
           1       0.45      0.23      0.30    124646
           2       0.43      0.29      0.35    136301
           3       0.44      0.36      0.39    153278
           4       0.42      0.70      0.52    165747

    accuracy                           0.46    732922
   macro avg       0.46      0.44      0.43    732922
weighted avg       0.46      0.46      0.44    732922

Confusion matrix, without normalization
[[ 97780   9941   7867   7648  29714]
 [ 30245  28352  18970  15264  31815]
 [ 15630  11645  40070  26980  41976]
 [ 11993   7686  20303  54464  58832]
 [ 18789   5104   6688  19870 115296]]
Normalized confusion matrix
[[0.63929389 0.0649951  0.05143511 0.05000327 0.19427264]
 [0.24264718 0.22746017 0.152191   0.1224588  0.25524285]
 [0.11467267 0.08543591 0.2939817  0.19794426 0.30796546]
 [0.07824345 0.05014418 0.13245867 0.35532823 0.38382547]
 [0.11335952 0.03079392 0.04035065 0.11988151 0.6956144 ]]
```






```
('new_session', 0.0023009244)
('beh_b', 0.0037570342)
('beh_c', 0.005786406)
('beh_f', 0.007597619)
('beh_p', 0.0039792764)
('time', 0.011652075)
('embed_dim_1', 0.05700931)
('embed_dim_2', 0.09245034)
('embed_dim_3', 0.34842554)
('embed_dim_4', 0.21034999)
('embed_dim_5', 0.07934962)
('embed_dim_6', 0.0674926)
('embed_dim_7', 0.04081827)
('embed_dim_8', 0.06903106)
Path Clustering Feature Relative Importance 0.9649267308413982
```

19 Regression Model over Age (XGBoost)

Here, we are examining the effectiveness of user clustering based on user path over differnet types of paths by predicting the exact user age.

The base information including: new session signal (1 or 0), behaviors as one-hot encodings, and time as a continuous value.

Verification information including: 8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.

[19]:
```
# Regression without Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time']
X = df[X_col]
y = df['age']
X_train, X_test, y_train, y_test_without_embeddings = train_test_split(X, y,␣
↪test_size=0.2, random_state=42)
clf = XGBRegressor(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result_without_embeddings = clf.predict(X_test)

# Regression with Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p', 'time'] + embed_col
X = df[X_col]
y = df['age']
X_train, X_test, y_train, y_test_with_embeddings = train_test_split(X, y,␣
↪test_size=0.2, random_state=42)
clf = XGBRegressor(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result_with_embeddings = clf.predict(X_test)

print("Explained Varience Score without Path Clustering Features: {}".format\
      (explained_variance_score(y_test_without_embeddings,␣
↪result_without_embeddings)))
print("Explained Varience Score with Path Clustering Features: {}".format\
      (explained_variance_score(y_test_with_embeddings,␣
↪result_with_embeddings)))
print()

print("Mean Squared Error without Path Clustering Features: {}".format\
      (mean_squared_error(y_test_without_embeddings,␣
↪result_without_embeddings)))
print("Mean Squared Error with Path Clustering Features: {}".format\
      (mean_squared_error(y_test_with_embeddings, result_with_embeddings)))
print()

print("Mean Absolute Error without Path Clustering Features: {}".format\
      (mean_absolute_error(y_test_without_embeddings,␣
↪result_without_embeddings)))
print("Mean Absolute Error with Path Clustering Features: {}".format\
      (mean_absolute_error(y_test_with_embeddings, result_with_embeddings)))
print()
```

```
Explained Varience Score without Path Clustering Features: 0.006841957627061412
Explained Varience Score with Path Clustering Features: 0.3130052552489362

Mean Squared Error without Path Clustering Features: 91.49775937351009
Mean Squared Error with Path Clustering Features: 63.291537825644966

Mean Absolute Error without Path Clustering Features: 7.595422869264912
Mean Absolute Error with Path Clustering Features: 5.90505474569291
```

20 Classification Model over Gender (XGBoost)

Here, we are examining the effectiveness of user clustering based on user path over differnet types of paths by classifying user's gender.

The base information including: new session signal (1 or 0), behaviors as one-hot encodings, and time as a continuous value.

Verification information including: 8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.

[20]:
```python
# Classification without Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p']
X = df[X_col]
y = df['gender']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Gender Classification without Path Clustering")
print(classification_report(y_test, result))

# Classification with Path Clustering
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p'] + embed_col
X = df[X_col]
y = df['gender']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Gender Classification with Path Clustering")
print(classification_report(y_test, result))
```

```
Gender Classification without Path Clustering
```

```
C:\Users\Colin\anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           0       0.00      0.00      0.00    189281
           1       0.74      1.00      0.85    543641

    accuracy                           0.74    732922
   macro avg       0.37      0.50      0.43    732922
weighted avg       0.55      0.74      0.63    732922

Gender Classification with Path Clustering
              precision    recall  f1-score   support

           0       0.80      0.60      0.68    189281
           1       0.87      0.95      0.91    543641

    accuracy                           0.86    732922
   macro avg       0.83      0.77      0.80    732922
weighted avg       0.85      0.86      0.85    732922
```

21 Multiclass Classification Model over Power Group (XGBoost)

Here, we are examining the effectiveness of user clustering based on user path over differnet types of paths by classifying user's buying power.

The base information including: new session signal (1 or 0), behaviors as one-hot encodings, and time as a continuous value.

Verification information including: 8 new user embeddings based on labelings over different user groups over different type of paths, as mentioned above.

[21]:
```python
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p']
X = df[X_col]
y = df['power']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Power Classification without Path Clustering")
print(classification_report(y_test, result))
```

```python
X_col = ['new_session', 'beh_b', 'beh_c', 'beh_f', 'beh_p'] + embed_col
X = df[X_col]
y = df['power']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
clf = XGBClassifier(random_state = 42, tree_method='gpu_hist', gpu_id=0)
clf.fit(X_train, y_train)
result = clf.predict(X_test)
print("Power Classification with Path Clustering")
print(classification_report(y_test, result))
```

```
Power Classification without Path Clustering
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     37818
           2       0.00      0.00      0.00     47450
           3       0.00      0.00      0.00     50790
           4       0.00      0.00      0.00     50809
           5       0.00      0.00      0.00     50966
           6       0.30      1.00      0.46    221459
           7       0.00      0.00      0.00    139826
           8       0.00      0.00      0.00     85306
           9       0.00      0.00      0.00     48498

    accuracy                           0.30    732922
   macro avg       0.03      0.11      0.05    732922
weighted avg       0.09      0.30      0.14    732922

Power Classification with Path Clustering
              precision    recall  f1-score   support

           1       0.52      0.05      0.10     37818
           2       0.37      0.07      0.12     47450
           3       0.48      0.05      0.09     50790
           4       0.59      0.05      0.09     50809
           5       0.59      0.04      0.08     50966
           6       0.34      0.89      0.49    221459
           7       0.41      0.19      0.26    139826
           8       0.39      0.18      0.24     85306
           9       0.37      0.19      0.25     48498

    accuracy                           0.35    732922
   macro avg       0.45      0.19      0.19    732922
weighted avg       0.42      0.35      0.27    732922
```