Mining Big Data - Assignment 3b

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```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth, association_rules


def frequent_patterns(file_path):
    data = pd.read_csv(file_path)
    # Group the dataset with member number and date, to get the items in sa
    transactions = data.groupby(['Member_number', 'Date'])['itemDescriptior
    trans_encoder = TransactionEncoder()
    arr = trans_encoder.fit(transactions).transform(transactions)
    df = pd.DataFrame(arr, columns = trans_encoder.columns_)

    frequent_itemsets = fpgrowth(df, min_support = 0.001, use_colnames = Tr

    return frequent_itemsets
```

```
# My teammate needs the output includes frequent itemsest, alongside their
def get_martrix(frequent_itemsets):
    output_matrix = [[list(itemsets), support] for itemsets, support in zip
    # Get the sorted list, so that it will be easy to analyze
    output_matrix = sorted(output_matrix, key = lambda x: x[1], reverse = T
    return output_matrix
```

```
def get_rules(frequent_itemsets):
    rules = association_rules(frequent_itemsets, metric="confidence", min_t
    rules['interest'] = rules['confidence'] - rules['consequent support']
    return rules
```

```
def get_conf_supp(frequent_itemsets, rules):
  results = dict()
  for index, rule in rules.iterrows():
    (item1,) = rule['antecedents']
    (item2,) = rule['consequents']
    itemsets = item1 + ', ' + item2
    if (item2 + ', ' + item1) not in results.keys():
      results[itemsets] = [rule['support'], rule['confidence']]
    else:
      if results[((item2 + ', ' + item1))][0] < rule['confidence']:
        results[itemsets] = [rule['support'], rule['confidence']]
        del results[((item2 + ', ' + item1))]
      else:
        continue
  results = sorted(results.items(), key=lambda item: item[1][0], reverse =
  return results
```

```
def get_interest(rules):
    interest = []
    for index, rule in rules.iterrows():
        (item1,) = rule['antecedents']
        (item2,) = rule['consequents']
        itemsets = [item1, item2]
        interest.append([itemsets, rule["interest"]])
    return interest
```

```
# Use this function to print the frequent
def print_frequent(results):
    for item in results:
      print(f'patterns:[{item[0]}], support: {item[1][0]}, confidence: {ite
```

```
file_path = 'Groceries data train.csv'

# Print the results after the fp-growth
frequent_itemsets = frequent_patterns(file_path)
print(frequent_itemsets)

# Print the results
rules = get_rules(frequent_itemsets)
results = get_conf_supp(frequent_itemsets, rules)
print("\nThe results: ")
print_frequent(results)

interest = get_interest(rules)
```

```
patterns:[frozen vegetables, rolls/buns], support: 0.0015106826846989425,
patterns:[waffles, whole milk], support: 0.0015106826846989425, confidence
patterns:[curd, tropical fruit], support: 0.0014387454139989928, confiden
patterns:[curd, rolls/buns], support: 0.0014387454139989928, confidence: (
patterns:[chocolate, rolls/buns], support: 0.0014387454139989928, confide
patterns:[hamburger meat, whole milk], support: 0.0014387454139989928, co
patterns:[domestic eggs, sausage], support: 0.0014387454139989928, confid
patterns:[coffee, rolls/buns], support: 0.0014387454139989928, confidence
patterns:[onions, whole milk], support: 0.0014387454139989928, confidence
patterns:[berries, whole milk], support: 0.0014387454139989928, confidence
patterns:[butter, bottled water], support: 0.0013668081432990432, confide
patterns:[coffee, yogurt], support: 0.0013668081432990432, confidence: 0.
patterns:[oil, whole milk], support: 0.0013668081432990432, confidence: 0
patterns:[sugar, whole milk], support: 0.0012948708725990935, confidence:
patterns:[dessert, whole milk], support: 0.0012948708725990935, confidence
patterns:[coffee, other vegetables], support: 0.0012948708725990935, conf
patterns:[long life bakery product, whole milk], support: 0.001294870872
patterns:[napkins, other vegetables], support: 0.0012948708725990935, con
patterns:[napkins, whole milk], support: 0.0012948708725990935, confidence
patterns:[frozen vegetables, soda], support: 0.0012229336018991439, confi
patterns:[frozen vegetables, sausage], support: 0.0012229336018991439, co
patterns:[UHT-milk, other vegetables], support: 0.0012229336018991439, co
patterns:[candy, whole milk], support: 0.0012229336018991439, confidence:
patterns:[beverages, whole milk], support: 0.0012229336018991439, confide
patterns:[salty snack, rolls/buns], support: 0.0012229336018991439, confi
patterns:[frozen vegetables, root vegetables], support: 0.00115099633119
patterns:[hamburger meat, soda], support: 0.0011509963311991942, confiden
patterns:[grapes, soda], support: 0.0011509963311991942, confidence: 0.10
patterns:[processed cheese, rolls/buns], support: 0.0011509963311991942,
patterns:[meat, other vegetables], support: 0.0011509963311991942, confid
patterns:[napkins, pastry], support: 0.0011509963311991942, confidence: 0
patterns:[salty snack, whole milk], support: 0.0011509963311991942, confi
patterns:[waffles, rolls/buns], support: 0.0011509963311991942, confidence
patterns:[white bread, rolls/buns], support: 0.0010790590604992446, confi
patterns:[chicken, other vegetables], support: 0.0010790590604992446, con
patterns:[hamburger meat, other vegetables], support: 0.00107905906049924
patterns:[hamburger meat, rolls/buns], support: 0.0010790590604992446, co
patterns:[specialty bar, whole milk], support: 0.0010790590604992446, con
patterns:[grapes, whole milk], support: 0.0010790590604992446, confidence
patterns:[frozen meals, soda], support: 0.0010790590604992446, confidence
patterns:[napkins, soda], support: 0.0010790590604992446, confidence: 0.0
patterns:[ham, other vegetables], support: 0.0010790590604992446, confide
patterns:[berries, other vegetables], support: 0.0010790590604992446, con
patterns:[hard cheese, rolls/buns], support: 0.0010790590604992446, confi
patterns:[hygiene articles, whole milk], support: 0.0010071217897992951,
patterns:[chocolate, sausage], support: 0.0010071217897992951, confidence
patterns:[chocolate, yogurt], support: 0.0010071217897992951, confidence:
patterns:[dessert, rolls/buns], support: 0.0010071217897992951, confidence
patterns:[hamburger meat, yogurt], support: 0.0010071217897992951, confid
patterns:[herbs, whole milk], support: 0.0010071217897992951, confidence:
patterns:[UHT-milk, tropical fruit], support: 0.0010071217897992951, conf
patterns:[grapes, other vegetables], support: 0.0010071217897992951, conf
patterns:[frozen meals, whole milk], support: 0.0010071217897992951, conf
```

```
patterns:[frozen meals, other vegetables], support: 0.0010071217897992951,
patterns:[napkins, rolls/buns], support: 0.0010071217897992951, confidence
patterns:[salty snack, other vegetables], support: 0.0010071217897992951,
patterns:[waffles, other vegetables], support: 0.0010071217897992951, con
```

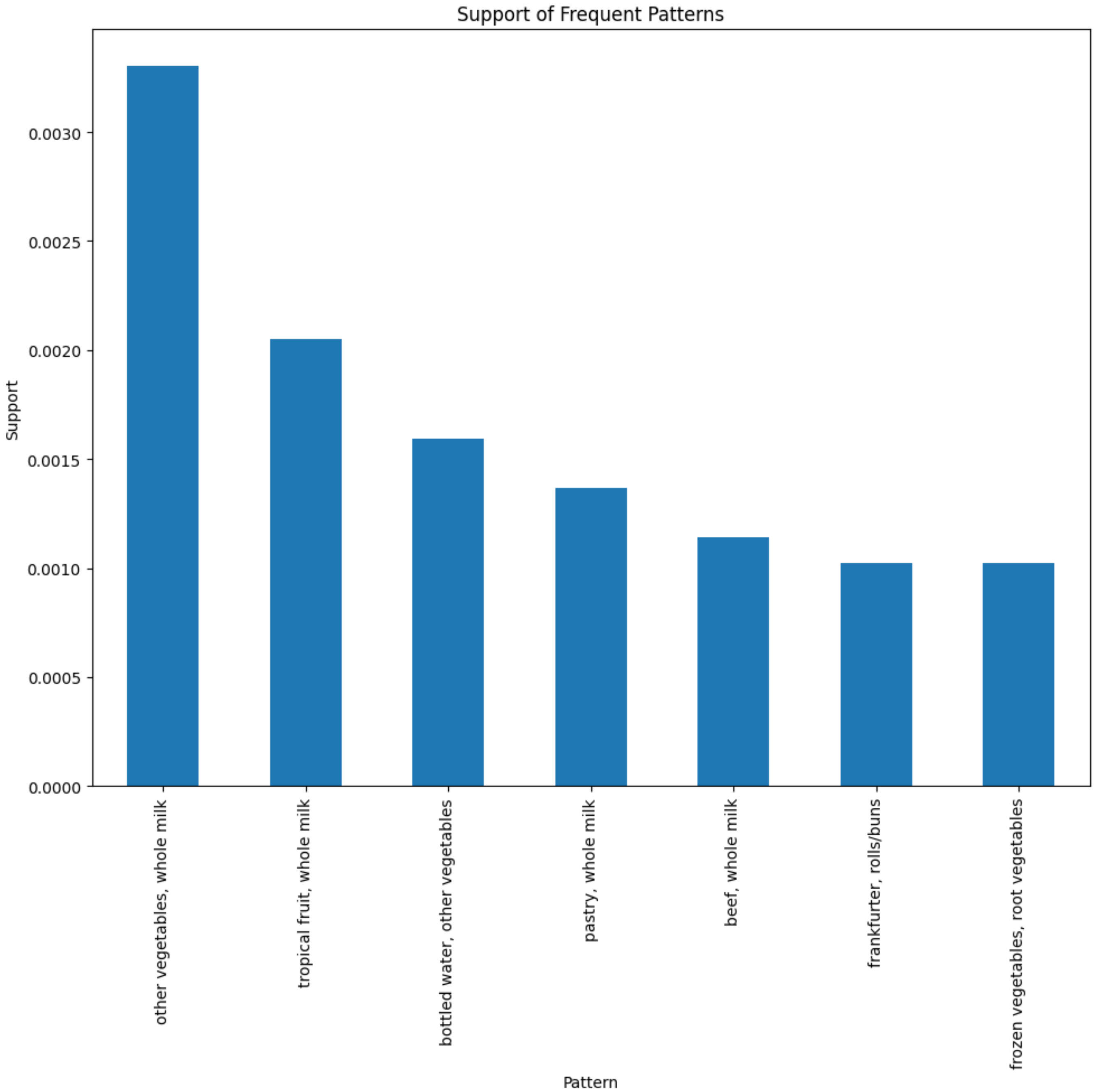
```
def get_5_output(file_path):
  frequent_itemsets = frequent_patterns(file_path)
  rules = get_rules(frequent_itemsets)
  results = get_conf_supp(frequent_itemsets, rules)
  print_frequent(results[:5])
  return results
```

```
# for Trainning dataset
print('5 patterns of train dataset:')
train_results = get_5_output('Groceries data train.csv')


# For test dataset
print('\n5 patterns of test dataset:')
test_results = get_5_output('Groceries data test.csv')
```

```
5 patterns of train dataset:
patterns:[rolls/buns, whole milk], support: 0.007913099776994462, confidenc
patterns:[other vegetables, whole milk], support: 0.006977915257895115, con
patterns:[yogurt, whole milk], support: 0.006546291633695417, confidence: 0
patterns:[whole milk, soda], support: 0.005970793468095820, confidence: 0.05
patterns:[other vegetables, soda], support: 0.005467232573196173, confidenc

5 patterns of test dataset:
patterns:[other vegetables, whole milk], support: 0.0033055967172005017, co
patterns:[tropical fruit, whole milk], support: 0.0020517496865382423, conf
patterns:[bottled water, other vegetables], support: 0.0015958053117519663,
patterns:[pastry, whole milk], support: 0.0013678331243588283, confidence:
patterns:[beef, whole milk], support: 0.0011398609369656903, confidence: 0.
```

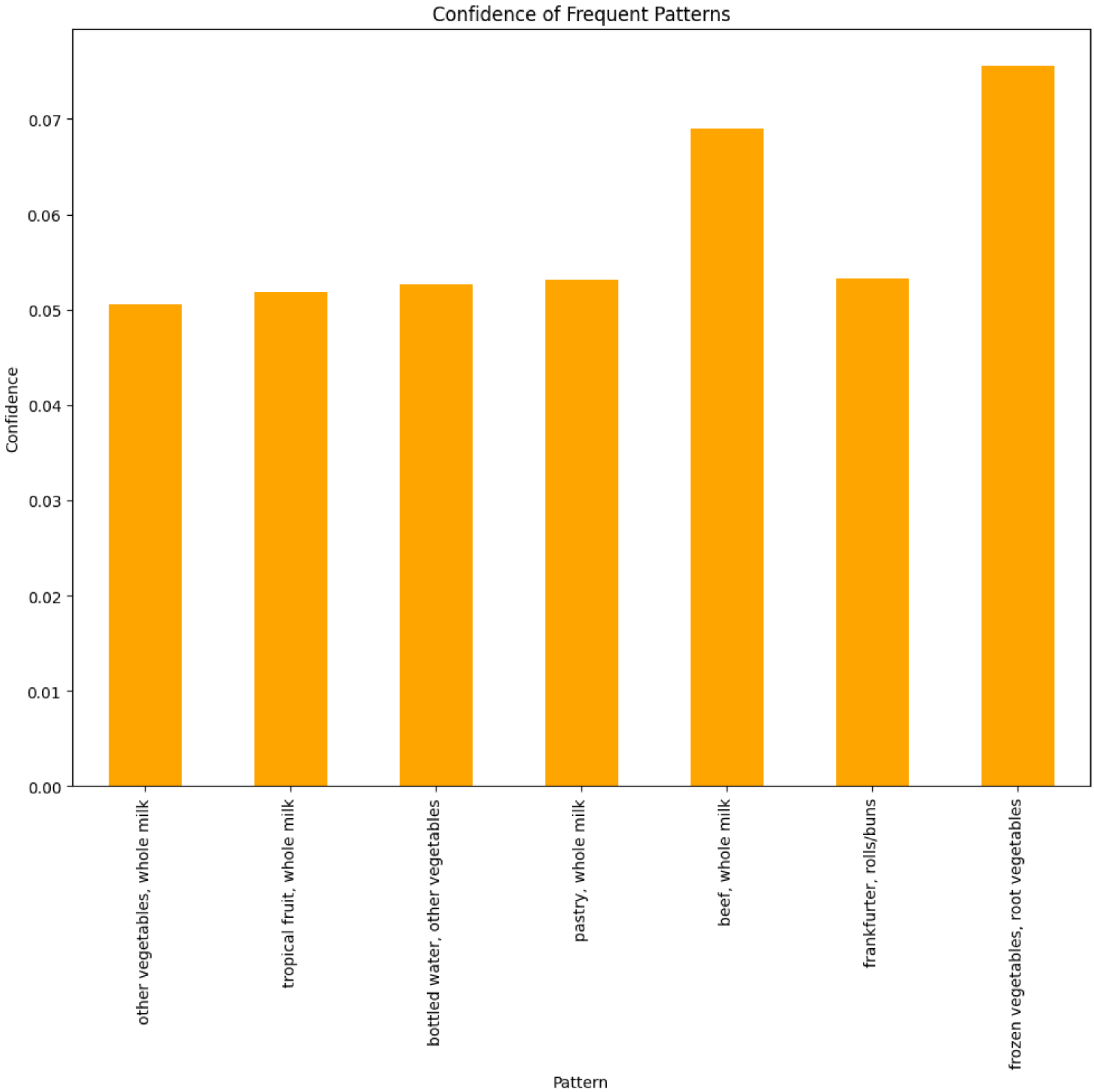
```
df = pd.DataFrame({
    'Pattern': [],
    'Support': [],
    'Confidence': []
})
for item in test_results:
  new_row = pd.DataFrame({
    'Pattern': [item[0]],
    'Support': [item[1][0]],
    'Confidence': [item[1][1]]})
  df = pd.concat([df, new_row], ignore_index=True)
```

```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
df.plot.bar(x='Pattern', y='Support', ax=ax, legend=False)
ax.set_ylabel('Support')
ax.set_title('Support of Frequent Patterns')
plt.tight_layout()
plt.show()
```




```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))

```

```
df.plot.bar(x='Pattern', y='Confidence', ax=ax, color='orange', legend=Fals
ax.set_ylabel('Confidence')
ax.set_title('Confidence of Frequent Patterns')
plt.tight_layout()
plt.show()
```


Confidence of Frequent Patterns
Confidence
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
other vegetables, whole milk
tropical fruit, whole milk
bottled water, other vegetables
pastry, whole milk
beef, whole milk
frankfurter, rolls/buns
frozen vegetables, root vegetables
Pattern

```
# Week 11 Workshop Solutions were used in the development of the code in th
# https://myuni.adelaide.edu.au/courses/91968/files/14319268?wrap=1
```

```
import numpy as np

# Reading in Training and Test Datasets
train_set_df = pd.read_csv('Groceries data train.csv')
test_set_df = pd.read_csv('Groceries data test.csv')

train_rows, test_cols = np.shape(train_set_df)
test_rows, test_cols = np.shape(test_set_df)

print("Train:", np.shape(train_set_df))
print("Test:", np.shape(test_set_df))
```

```
Train: (27000, 7)
Test: (11765, 7)
```

```
train_set = np.array(train_set_df)
test_set = np.array(test_set_df)
```

```
print(train_set[0:3])
```

```
[[3021 '30/01/2015' 'frankfurter' 2015 1 30 4]
 [1292 '24/10/2015' 'pork' 2015 10 24 5]
 [4206 '4/04/2014' 'root vegetables' 2014 4 4 4]]
```

```
print(test_set[0:3])
```

```
[[3481 '8/03/2015' 'candy' 2015 3 8 6]
 [1254 '19/04/2015' 'white wine' 2015 4 19 6]
 [2835 '28/01/2014' 'domestic eggs' 2014 1 28 1]]
```

```
train_set = np.array([[row[0], row[2]] for row in train_set])
test_set = np.array([[row[0], row[2]] for row in test_set])
```

```
train_set = train_set[train_set[:, 0].argsort()]        # this part is (bas
test_set = test_set[test_set[:, 0].argsort()]           # this part is (bas
```

```
ids = []
items = []

for i in range(train_rows):
    if train_set[i][0] not in ids:
        ids.append(train_set[i][0])

    if train_set[i][1] not in items:
        items.append(train_set[i][1])

for i in range(test_rows):
    if test_set[i][0] not in ids:
        ids.append(test_set[i][0])

    if test_set[i][1] not in items:
        items.append(test_set[i][1])

user_count = len(ids)
item_count = len(items)
```

```
new_id_dict = {}
new_id_reverse_dict = {}

for i in range(len(ids)):
    new_id_dict[ids[i]] = i
    new_id_reverse_dict[i] = ids[i]
```

```
item_id_dict = {}
item_id_reverse_dict = {}

for i in range(item_count):
    item_id_dict[items[i]] = i
    item_id_reverse_dict[i] = items[i]
```

```
for i in range(train_rows):
    train_set[i][0] = new_id_dict[train_set[i][0]]
    train_set[i][1] = item_id_dict[train_set[i][1]]

for i in range(test_rows):
    test_set[i][0] = new_id_dict[test_set[i][0]]
    test_set[i][1] = item_id_dict[test_set[i][1]]
```

```
import copy

user_item_matrix = [[0 for i in range(item_count)] for j in range(user_cour
user_item_matrix = np.array(user_item_matrix)

test_user_item_matrix = copy.deepcopy(user_item_matrix)              # t
collab_filter_user_item_matrix = copy.deepcopy(user_item_matrix)       # t
```

```
for i in range(train_rows):
    user = int(train_set[i][0])
    item = int(train_set[i][1])
    user_item_matrix[user][item] += 1
```

```
alt_user_item_matrix = copy.deepcopy(user_item_matrix)      # this part is
```

```
for i in range(user_count):
    row_mean = np.mean(user_item_matrix[i])         # this part is (based c
    for j in range(item_count):
        alt_user_item_matrix[i][j] -= row_mean
```

```
# Method used to calculate cosine similarity in below function based off ir
def cosine_similarity(vec1, vec2):
    len1 = len(vec1)
    len2 = len(vec2)
    cos_sim = (np.dot(vec1, vec2)) / (len1 * len2)      # this part is (bas
    return cos_sim
```

```
# Following function based on [8] (Week 11 Workshop Solutions)
def get_similarity_vec(user, item, user_item_matrix):
    similarity_vec = []
    for i in range(user_count):
        if i != user and user_item_matrix[i][item] != 0:
            cosine_sim = cosine_similarity(alt_user_item_matrix[user], alt_
            similarity_vec.append([cosine_sim, i])

    similarity_vec = sorted(similarity_vec, reverse=True)
    return similarity_vec
```

```
# [8] (Week 11 Workshop Solutions) assisted the development of the followir
def weighted_avg(user, item, n, original_u_i_matrix, modified_u_i_matrix):
    sim_vec = get_similarity_vec(user, item, modified_u_i_matrix)
    neighbours = []
    cos_sims = []

    n = min(n, len(sim_vec))
    for i in range(n):
        neighbours.append(sim_vec[i][1])
        cos_sims.append(sim_vec[i][0])

    if n == 0 or max(cos_sims) == 0:
        return 0

    weighted_sum = 0
    for i in range(n):
        original_item_count = original_u_i_matrix[neighbours[i]][item]
        cos_sim = cos_sims[i]
        weighted_sum += (cos_sim * original_item_count)

    weight_avg = weighted_sum / sum(cos_sims)
    return weight_avg
```

```
# Following function based on [8] (Week 11 Workshop Solutions)
def recommend(user, original_u_i_matrix, modified_u_i_matrix, top_recs=1, t
    recommendation_ratings = []

    for i in range(item_count):
        if original_u_i_matrix[user][i] == 0:
            recommendation_rating = weighted_avg(user, i, top_users, origir
            if recommendation_rating == 0:
                continue
            recommendation_ratings.append([recommendation_rating, i])

    if len(recommendation_ratings) == 0:
        return 0

    recommendation_ratings = sorted(recommendation_ratings, reverse=True)
    return recommendation_ratings[:top_recs]
```

```
for i in range(test_rows):
    user = int(test_set[i][0])
    item = int(test_set[i][1])
    test_user_item_matrix[user][item] += 1
```

```
import math

# Formula for root mean squared error (RMSE) used to develop function belov
def RMSE(errors):
    rmse = 0
    for error in errors:
        error_squared = error * error
        rmse += error_squared

    rmse = rmse / len(errors)
    return math.sqrt(rmse)      # this part is (based on) from [5]
```

```
collab_filter_losses = []

# [8] (Week 11 Workshop Solutions) assisted the development of the code in
for i in range(user_count):
    recommendations = recommend(i, user_item_matrix, alt_user_item_matrix)
    if recommendations == 0:
        continue

    for j in range(len(recommendations)):
        recommended_item = recommendations[j][1]
        if user_item_matrix[i][recommended_item] == 0:
            collab_filter_user_item_matrix[i][recommended_item] = recommenc
            loss = collab_filter_user_item_matrix[i][recommended_item] - te
            collab_filter_losses.append(loss)

print("Root Mean Squared Error (RMSE) for Collaborative Filtering:", RMSE(c
```

```
Root Mean Squared Error (RMSE) for Collaborative Filtering: 2.3536843146554
```

```
freq_itemsets = interest

for i in range(len(freq_itemsets)):
    freq_itemset = freq_itemsets[i][0]
    for j in range(len(freq_itemset)):
        freq_itemset[j] = item_id_dict[freq_itemset[j]]
```

```
def get_itemset_relevance(user, freq_itemset, user_item_matrix):
    item_relevances = []
    items = freq_itemset[0]
    interest = freq_itemset[1]

    for i in range(len(items)):
        item = items[i]
        item_relevances.append(user_item_matrix[user][item] * interest)

    return sum(item_relevances)
```

```
pattern_recs_true = 0
pattern_recs_false = 0

for i in range(user_count):
    relevant_itemsets = []
    for j in range(item_count):
        for k in range(len(freq_itemsets)):
            if user_item_matrix[i][j] == 1 and j in freq_itemsets[k][0]:
                relevant_itemsets.append(freq_itemsets[k])

    if len(relevant_itemsets) == 0:
        continue

    itemset_relevances = []
    for j in range(len(relevant_itemsets)):
        itemset_relevances.append([get_itemset_relevance(i, relevant_itemse

    itemset_relevances = sorted(itemset_relevances, reverse=True)
    top_freq_itemset = relevant_itemsets[itemset_relevances[0][1]][0]

    print("\nRecommendations for User", new_id_reverse_dict[i])
    for j in range(len(top_freq_itemset)):
        if user_item_matrix[user][top_freq_itemset[j]] == 0 and test_user_i
            print(item_id_reverse_dict[top_freq_itemset[j]])
            pattern_recs_true += 1
        elif user_item_matrix[user][top_freq_itemset[j]] == 0:
            print(item_id_reverse_dict[top_freq_itemset[j]])
            pattern_recs_false += 1

pattern_recs_accuracy = pattern_recs_true / (pattern_recs_true + pattern_re
print("\nAccuracy of Recommendations Generated From Frequent Itemsets:", pa
```

```
Recommendations for User 1000
grapes
```

```
Recommendations for User 1001
processed cheese
rolls/buns

Recommendations for User 1002
ham
whole milk

Recommendations for User 1003
processed cheese
rolls/buns

Recommendations for User 1004
processed cheese
rolls/buns

Recommendations for User 1005
margarine

Recommendations for User 1006
processed cheese
rolls/buns

Recommendations for User 1008
UHT-milk
tropical fruit

Recommendations for User 1009
napkins
pastry

Recommendations for User 1010
UHT-milk
tropical fruit

Recommendations for User 1011
processed cheese
rolls/buns

Recommendations for User 1012
processed cheese
rolls/buns

Recommendations for User 1013
ham
whole milk

Recommendations for User 1014
ham
whole milk

Recommendations for User 1015
ham
```

Reference List

1. https://stackoverflow.com/questions/2828059/sorting-arrays-in-numpy-by-column
2. https://stackoverflow.com/questions/2612802/how-do-i-clone-a-list-so-that-it-doesnt-change-unexpectedly-after-assignment
3. https://numpy.org/doc/stable/reference/generated/numpy.mean.html
4. https://numpy.org/doc/stable/reference/generated/numpy.dot.html
5. https://www.w3schools.com/python/ref_math_sqrt.asp
6. https://myuni.adelaide.edu.au/courses/91968/pages/module-8-online-learning?module_item_id=3274637
7. https://en.wikipedia.org/wiki/Cosine_similarity#:~:text=In%20data%20analysis%2C%20cosine%20similarity,the%20product%20of%20their%20lengths.
8. https://myuni.adelaide.edu.au/courses/91968/files/14319268?wrap=1
9. https://docs.oracle.com/en/cloud/saas/planning-budgeting-cloud/pfusu/insights_metrics_RMSE.html

```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

data = pd.read_csv('Groceries data train.csv')
data.head()
```

	Member_number	Date	itemDescription	year	month	day	day_of_week
0	3021	30/01/2015	frankfurter	2015	1	30	4
1	1292	24/10/2015	pork	2015	10	24	5
2	4206	4/04/2014	root vegetables	2014	4	4	4
3	4369	25/08/2015	onions	2015	8	25	1
4	1522	1/07/2014	waffles	2014	7	1	1

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27000 entries, 0 to 26999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Member_number    27000 non-null  int64 
 1   Date             27000 non-null  object
 2   itemDescription  27000 non-null  object
 3   year             27000 non-null  int64 
 4   month            27000 non-null  int64 
 5   day              27000 non-null  int64 
 6   day_of_week      27000 non-null  int64 
dtypes: int64(5), object(2)
memory usage: 1.4+ MB
```

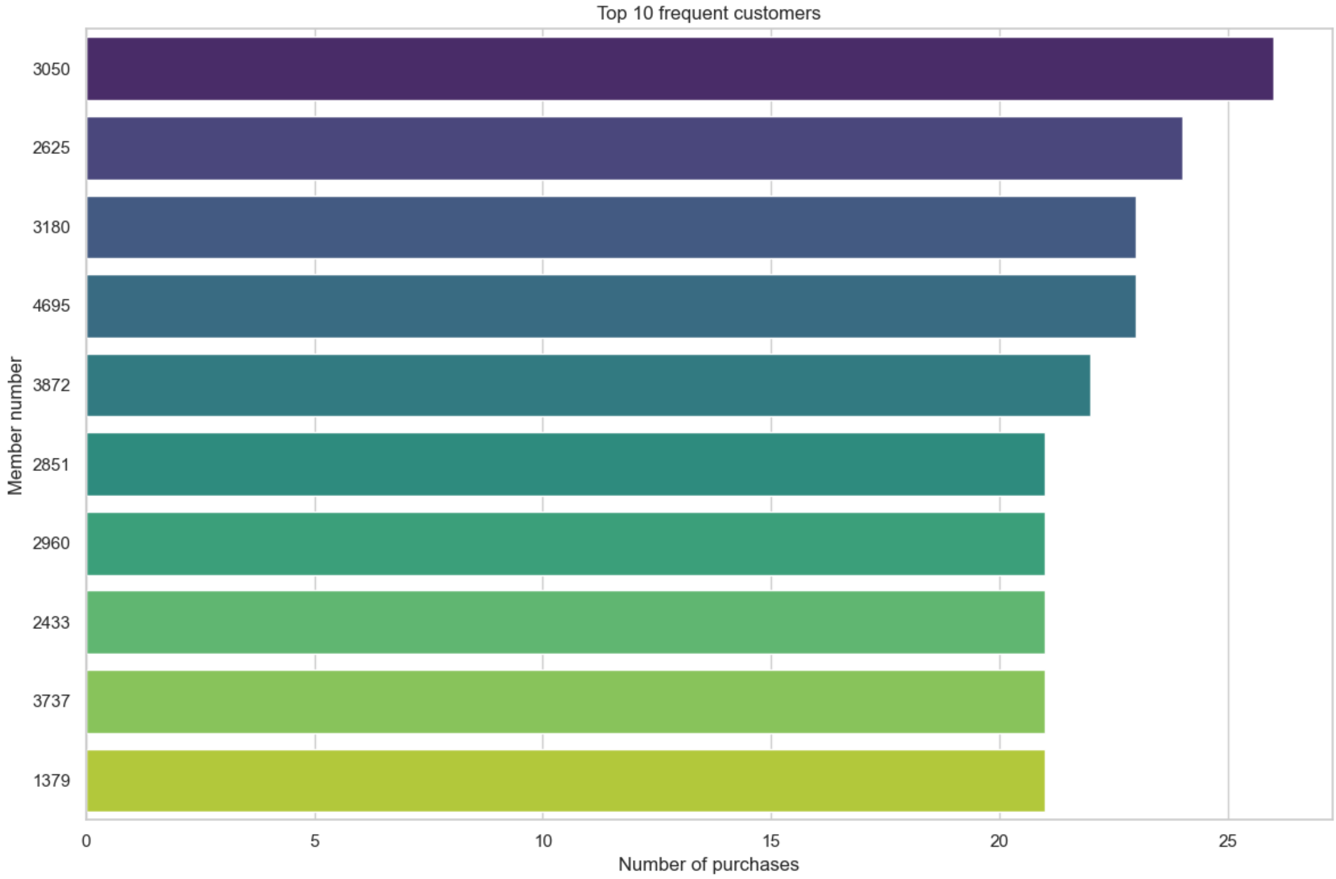
```
data['Date'] = pd.to_datetime(data['Date'],dayfirst=True)
data['year'] = data['Date'].dt.year
data['month'] = data['Date'].dt.month
data['day'] = data['Date'].dt.day
data['day_of_week'] = data['Date'].dt.dayofweek
basket = data.groupby(['Member_number', 'Date'])['itemDescription'].apply(l
basket['itemDescription'] = basket['itemDescription'].apply(lambda x: ', '.
# basket_sets = basket['itemDescription'].str.get_dummies(sep=', ')
basket.head(10)
```

	Member_number	Date	itemDescription
0	1000	2014-06-24	pastry
1	1000	2015-03-15	sausage, yogurt
2	1000	2015-05-27	soda, pickled vegetables
3	1000	2015-07-24	misc. beverages, canned beer
4	1000	2015-11-25	sausage
5	1001	2014-07-02	rolls/buns, whole milk, sausage
6	1001	2014-12-12	soda, whole milk
7	1001	2015-01-20	soda, whipped/sour cream
8	1001	2015-02-05	frankfurter, curd
9	1001	2015-04-14	white bread, beef

```
sales_count = data['Member_number'].apply(lambda x: str(x)).value_counts().
```

```
sales_count.columns = ['Member_number', 'count']

sns.set(style="whitegrid")


plt.figure(figsize=(12,8))
sns.barplot(y='Member_number', x='count', data=sales_count, palette='viridi
plt.title('Top 10 frequent customers')
plt.xlabel('Number of purchases')
plt.ylabel('Member number')
plt.tight_layout()
plt.savefig("top_customer.png")
plt.show()
```

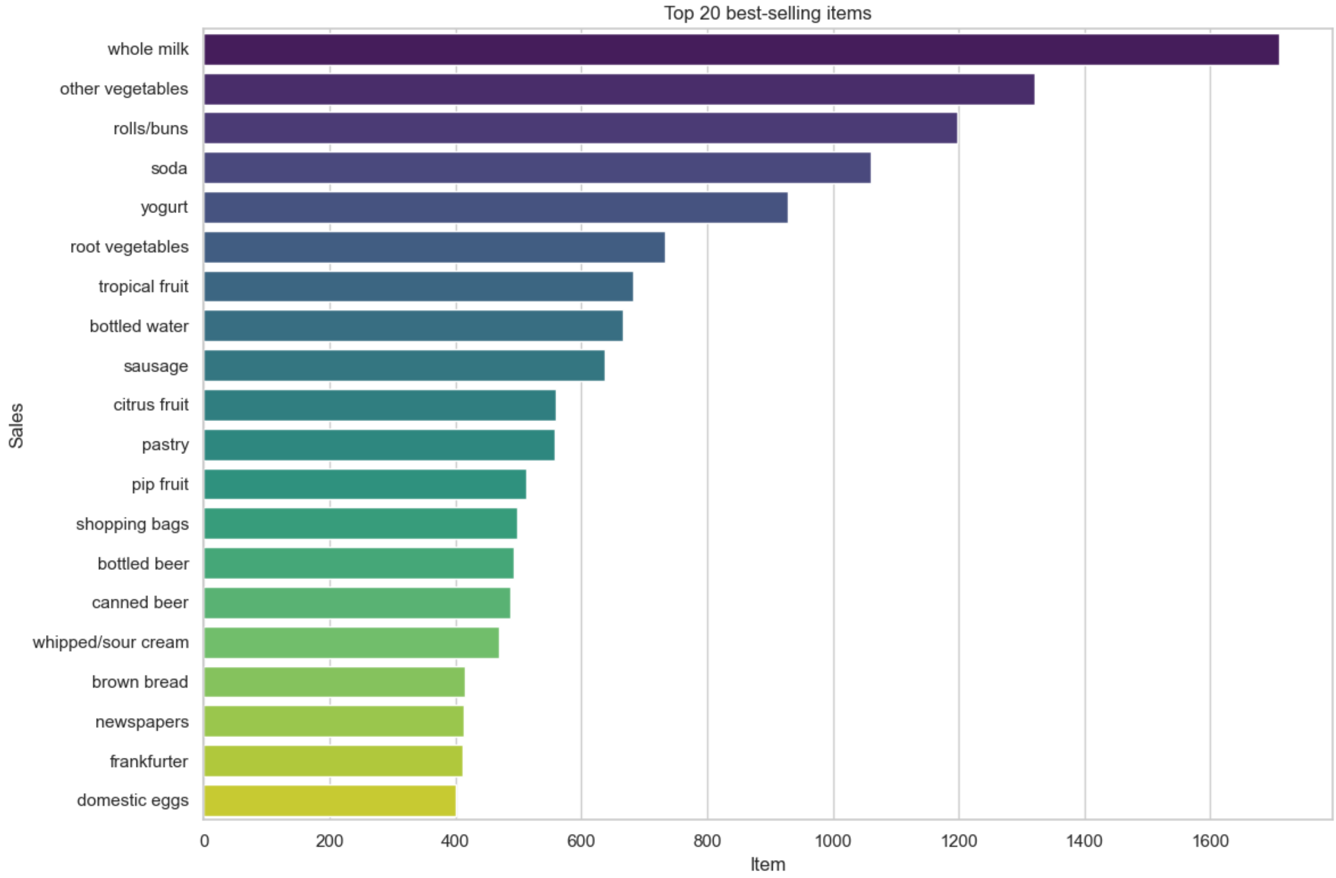
```
C:\Users\ebube\AppData\Local\Temp\ipykernel_8092\419175320.py:8: FutureWarn
Passing `palette` without assigning `hue` is deprecated and will be removed
  sns.barplot(y='Member_number', x='count', data=sales_count, palette='viri
```




```
1 sales_count = data['itemDescription'].value_counts().reset_index()[:20]
```

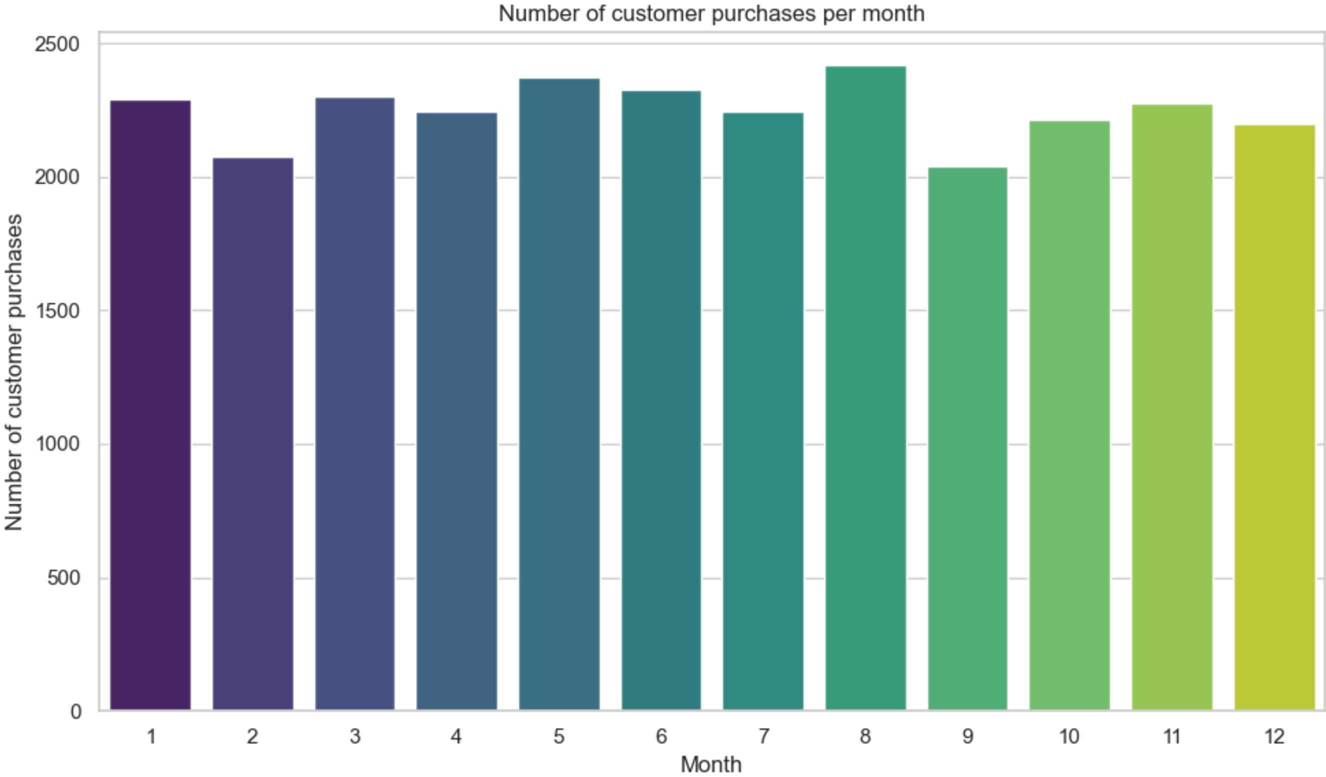
```
sales_count = data['itemDescription'].value_counts().reset_index()[:20]
sales_count.columns = ['itemDescription', 'count']


sns.set(style="whitegrid")

# 绘制直方图
plt.figure(figsize=(12,8))
sns.barplot(y='itemDescription', x='count', data=sales_count, palette='viri
plt.title('Top 20 best-selling items')
plt.xlabel('Item')
plt.ylabel('Sales')
plt.xticks()
plt.tight_layout()
plt.savefig('topsales.png', dpi=300)

plt.show()
```

```
C:\Users\ebube\AppData\Local\Temp\ipykernel_8092\2162360578.py:9: FutureWar
Passing `palette` without assigning `hue` is deprecated and will be removed
  sns.barplot(y='itemDescription', x='count', data=sales_count, palette='vi
```



```
data['month'] = data['month'].astype(int)


monthly_counts = data['month'].value_counts().sort_index()

monthly_counts_df = monthly_counts.reset_index()
monthly_counts_df.columns = ['month', 'count']

sns.set(style="whitegrid")

plt.figure(figsize=(10,6))
sns.barplot(x='month', y='count', data=monthly_counts_df, palette='viridis'
plt.title('Number of customer purchases per month')
plt.xlabel('Month')
plt.ylabel('Number of customer purchases')
plt.xticks(rotation=0)
plt.tight_layout()
plt.savefig("monthly_counts.jpg",dpi=300)
plt.show()
```

```
C:\Users\ebube\AppData\Local\Temp\ipykernel_8092\2750937065.py:12: FutureWa
Passing `palette` without assigning `hue` is deprecated and will be removed
  sns.barplot(x='month', y='count', data=monthly_counts_df, palette='viridi
```




```
basket_sets = basket['itemDescription'].str.get_dummies(sep=', ')
```

```
basket_sets
```

	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner
0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
13896	0	0	0	0	0	0	0	0
13897	0	0	0	0	0	0	0	0
13898	0	0	0	0	0	0	0	0
13899	0	0	0	0	0	0	0	0
13900	0	0	0	0	0	0	0	0

```
data = pd.read_csv('Groceries data test.csv')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11765 entries, 0 to 11764
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Member_number    11765 non-null  int64 
 1   Date             11765 non-null  object
 2   itemDescription  11765 non-null  object
 3   year             11765 non-null  int64 
 4   month            11765 non-null  int64 
 5   day              11765 non-null  int64 
 6   day_of_week      11765 non-null  int64 
dtypes: int64(5), object(2)
memory usage: 643.5+ KB
```