SDSC3001 Tutorial 1

Frequent Pattern Mining

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About TAs

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Review of Frequent Pattern Mining (FPM)

Find all the frequent item sets that appear at least minimum support times

- Data Mining: extracting patterns from massive data
  - Pattern: a set of items, subsequences, or substructures that occur together frequently in a data set
- Motivation: uncovering inherent regularities in data

Frequently bought together

Total price: CDN$ 42.90

Add both to Cart

☑ **This item:** Huggies Natural Care Fragrance-Free Baby Wipes, Refill Pack, 1056 Count CDN$ 19.97 (CDN$ 0.02 / count)

☑ Playtex Diaper Genie Diaper Pail System Refills, 3 pack CDN$ 22.93 (CDN$ 7.64 / ring)

Tid	Items bought
10	Beer, Nuts, Diaper
20	Beer, Coffee, Diaper
30	Beer, Diaper, Eggs
40	Nuts, Eggs, Milk
50	Nuts, Coffee, Diaper, Eggs, Milk

- Frequent Pattern/Itemset Mining
  - Input: a transaction DB, *min_sup*
  - Output: all frequent itemsets

Review of Frequent Pattern Mining (FPM)

Algorithm 1 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

1: $L_1 \leftarrow \{frequent\ items\}$
2: **for** $k = 2$; $L_{k-1} \neq \emptyset$; $k \leftarrow k + 1$ **do**
3: $C_k \leftarrow$ candidates generated based on L_{k-1} **(Candidate Generation)**
4: Scan Transaction DB to count supports of itemsets in C_k **(Counting Supports)**
5: $L_k \leftarrow$ candidates in C_k with *min_sup*
6: **end for**
7: **return** $\cup_k L_k$

Review of Frequent Pattern Mining (FPM)

Algorithm 2 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

1: $L_1 \leftarrow \{frequent\ items\}$
2: **for** $k = 2$; $L_{k-1} \neq \emptyset$; $k \leftarrow k+1$ **do**
3: $\quad C_k \leftarrow$ candidates generated based on L_{k-1} (Candidate Generation)
4: $\quad$ Scan Transaction DB to count supports of itemsets in C_k (Counting Supports)
5: $\quad L_k \leftarrow$ candidates in C_k with *min_sup*
6: **end for**
7: **return** $\cup_k L_k$

Candidate Generation in Apriori

- C_k is generated based on L_{k-1}
  - Candidates should be extensions of itemsets in L_{k-1}
- Step 1: Self-joining L_{k-1}
  - Idea: use two $(k-1)$-itemsets in L_{k-1} to make a possibly frequent k-itemset
  - Every itemset is a string in alphabetical order (e.g. items are $a < b < ... < z$, $\{a, d, c, b\} = abcd$)
  - If $l_1[1 : k-2] = l_2[1 : k-2]$, and $l_1[k-1] < l_2[k-1]$, add $l_3 = l_1 \cup l_2$ to C_k (Prove the completeness by yourself)
- Step 2: Pruning candidates that are supersets of infrequent $(k-1)$-itemsets
  - The anti-monotonicity property of itemsets
  - Check every $(k-1)$-subset of a candidate

L: Frequent Pattern Set
C_k: Candidates

Input

min_sup=2

Database TDB

Tid	Items
10	A, C, D
20	B, C, E
30	A, B, C, E
40	B, E

1[st] scan

C_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{D}	1
{E}	3

L_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{E}	3

$C_k \leftarrow$ candidates generated based on L_{k-1}

1. Self-Joining: All possible combination $C_4^2 = 6$
2. Pruning candidates

Step 2: Pruning candidates that are supersets of infrequent $(k-1)$-itemsets

- The anti-monotonicity property of itemsets
- Check every $(k-1)$-subset of a candidate

C_2

Itemset
{A, B}
{A, C}
{A, E}
{B, C}
{B, E}
{C, E}

2[nd] scan

C_2

Itemset	sup
{A, B}	1
{A, C}	2
{A, E}	1
{B, C}	2
{B, E}	3
{C, E}	2

L_2

Itemset	sup
{A, C}	2
{B, C}	2
{B, E}	3
{C, E}	2

C_3

Itemset
{B, C, E}

3[rd] scan

L_3

Itemset	sup
{B, C, E}	2

Q: ? NO {A,B,C}{A,B,E}

A: {A,B} does not show up in L_2<- {A,B} Infrequent

- Any superset of an infrequent itemset must also be infrequent
  - {beer,diaper} is infrequent $\Rightarrow$ {beer,diaper,nuts} is infrequent
  - No superset of infrequent itemset should be generated
  - **Many item combinations can be pruned!**

Algorithm 2 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

```
L_1 ← {frequent items}
for k = 2; L_{k-1} ≠ ∅; k ← k + 1 do
    C_k ← candidates generated based on L_{k-1} (Candidate Generation)
    Scan Transaction DB to count supports of itemsets in C_k (Counting Supports)
    L_k ← candidates in C_k with min_sup
end for
return ∪_k L_k
```

Code implementation of FPM

- Jupyter Notebook
- Python
- C, Java, …

Download Data

https://archive.ics.uci.edu/dataset/352/online+retail

Online Retail

Donated on 11/5/2015

This is a transnational data set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail.

Dataset Characteristics
Multivariate, Sequential, Time-Series

Subject Area
Business

Associated Tasks
Classification, Clustering

Attribute Type
Integer, Real

 # Instances
541909

 # Attributes
8

Information

Additional Information

This is a transnational data set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail.The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers.

Data processing

First 10 rows of the dataset

1	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
2	536365	85123A	WHITE HANGING HEART	6	2010/12/1 8:26	2.55	17850	United Kingdom
3	536365	71053	WHITE METAL LANTERN	6	2010/12/1 8:26	3.39	17850	United Kingdom
4	536365	84406B	CREAM CUPID HEARTS (	8	2010/12/1 8:26	2.75	17850	United Kingdom
5	536365	84029G	KNITTED UNION FLAG I	6	2010/12/1 8:26	3.39	17850	United Kingdom
6	536365	84029E	RED WOOLLY HOTTIE WI	6	2010/12/1 8:26	3.39	17850	United Kingdom
7	536365	22752	SET 7 BABUSHKA NEST	2	2010/12/1 8:26	7.65	17850	United Kingdom
8	536365	21730	GLASS STAR FROSTED '	6	2010/12/1 8:26	4.25	17850	United Kingdom
9	536366	22633	HAND WARMER UNION J.	6	2010/12/1 8:28	1.85	17850	United Kingdom
10	536366	22632	HAND WARMER RED POL	6	2010/12/1 8:28	1.85	17850	United Kingdom

Data processing

1	InvoiceNo	StockCode
2	536365	85123A
3	536365	71053
4	536365	84406B
5	536365	84029G
6	536365	84029E
7	536365	22752
8	536365	21730
9	536366	22633
10	536366	22632

Itemset1:
{85123A, 71053, 84406B, 84029G, 84029E, 22752, 21730}

Itemset2:
{22633, 22632}

Data processing

In [11]:
```
import pandas as pd
import pickle

data = pd.read_excel("Online Retail.xlsx") # read excel by pandas
print(data)
data = data.values
data = data[:, 0:2] # we only need first two columns print(data)
order_list = list() # empty list, list of our final data
order_set = set() # empty orderSet
InvoiceNo = data[0, 0] # the current InvoiceNo
```

```
       InvoiceNo StockCode                          Description  Quantity  \
0         536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1         536365     71053                  WHITE METAL LANTERN         6
2         536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3         536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4         536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
...          ...       ...                                  ...       ...
541904    581587     22613          PACK OF 20 SPACEBOY NAPKINS        12
541905    581587     22899         CHILDREN'S APRON DOLLY GIRL          6
541906    581587     23254        CHILDRENS CUTLERY DOLLY GIRL          4
541907    581587     23255      CHILDRENS CUTLERY CIRCUS PARADE         4
541908    581587     22138        BAKING SET 9 PIECE RETROSPOT          3

               InvoiceDate  UnitPrice  CustomerID         Country
0      2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1      2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2      2010-12-01 08:26:00       2.75     17850.0  United Kingdom


[541909 rows x 8 columns]
```

Data processing

```
for i in range(len(data)):
    if data[i, 0] == InvoiceNo:
        # add a new item in orderSet
        order_set.add(str(data[i, 1]))
    else:
        # this orderSet is end
        order_list.append(order_set)
        InvoiceNo = data[i, 0]  # next InvoiceNo
        order_set = set()
        order_set.add(data[i, 1])
print(order_list[0:10])
```

```
[{'85123A', '22752', '84406B', '21730', '71053', '84029G', '84029E'}, {22633, '22632'}, {'21755', '22748', '22623', '22622', '22310', 84879, '22745', '21754', '21777', '84969', '48187', '22749'}, {22960, '22912', '22914', '22913'}, {21756}, {'22659', '21883', '21035', '21724', '22727', '21913', '21731', '22726', '21791', 'POST', '22544', '22492', 22728, '10002', '22631', '22900', '22629', '22661', '22540', '22326'}, {22086}, {22632, '22633'}, {'85123A', '82482', '21730', '22752', '37370', '82483', '21068', '21871', '84406B', '20679', '82486', '71053', '21071', '82494L', '84029G', '84029E'}, {21258}]
```

Review of Frequent Pattern Mining (FPM)

Algorithm 1 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

1: $\boxed{L_1 \leftarrow \{frequent\ \ items\}}$ → Initialization
2: **for** $k = 2$; $L_{k-1} \neq \emptyset$; $k \leftarrow k + 1$ **do**
3: $C_k \leftarrow$ candidates generated based on L_{k-1} **(Candidate Generation)**
4: Scan Transaction DB to count supports of itemsets in C_k **(Counting Supports)**
5: $L_k \leftarrow$ candidates in C_k with *min_sup*
6: **end for**
7: **return** $\cup_k L_k$

Apriori Algorithm

In [20]:
```
# the initial candidates_dict are all single item
candidates_dict = dict()
for order in order_list:
    for item in order:
        item = tuple([item])
        if item not in candidates_dict:
            candidates_dict[item] = 0    # add an item in candidates_dict with count 0

print("initial candidates_dict")
print(candidates_dict)
print("length of initial candidates_dict")
print(len(candidates_dict))
```

```
initial candidates_dict
{('85123A',): 0, ('22752',): 0, ('84406B',): 0, ('21730',): 0, ('71053',): 0, ('84029G',): 0, ('84029E',): 0, (22633,): 0, ('22632',): 0,
('21755',): 0, ('22748',): 0, ('22623',): 0, ('22622',): 0, ('22310',): 0, (84879,): 0, ('22745',): 0, ('21777',): 0, ('21754',): 0, ('481
87',): 0, ('22749',): 0, ('84969',): 0, (22960,): 0, ('22912',): 0, ('22914',): 0, ('22913',): 0, (21756,): 0, ('22659',): 0, ('21883',):
0, ('22326',): 0, ('21035',): 0, ('21724',): 0, ('22727',): 0, ('21913',): 0, ('21731',): 0, ('22726',): 0, ('21791',): 0, ('22544',): 0,
('22492',): 0, (22728,): 0, ('10002',): 0, ('22631',): 0, ('22900',): 0, ('22629',): 0, ('22661',): 0, ('22540',): 0, ('POST',): 0, (2208
6,): 0, (22632,): 0, ('22633',): 0, ('82482',): 0, ('37370',): 0, ('82483',): 0, ('21068',): 0, ('21871',): 0, ('20679',): 0, ('82486',):
0, ('21071',): 0, ('82494L',): 0, (21258,): 0, ('21733',): 0, (22114,): 0, ('84519A',): 0, ('20723',): 0, ('21977',): 0, ('85183B',): 0,
```

Review of Frequent Pattern Mining (FPM)

Algorithm 1 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

```
L_1 ← {frequent items}
for k = 2; L_{k-1} ≠ ∅; k ← k + 1 do
    C_k ← candidates generated based on L_{k-1} (Candidate Generation)
    Scan Transaction DB to count supports of itemsets in C_k (Counting Supports)
    L_k ← candidates in C_k with min_sup
end for
return ∪_k L_k
```

Use a function

Candidates Generation

In [19]:

```
def update_candidates_dict(frequent_list):
    old_candidates_list = list()
    for candidate in frequent_list:
        candidate = list(candidate)
        candidate.sort()
        old_candidates_list.append(candidate)

    # the size of old candidate
    size = len(old_candidates_list[0])

    new_candidates_list = list()
    # i = 0, j = 1, 2, 3, ..., m-1
    # i = 1, j = 2, ..., m-1
    # i = 2, j = 3, ..., m-1
    # ...
    # i = m-2, j = m-1
    for i in range(len(old_candidates_list) - 1):
        for j in range(i+1, len(old_candidates_list)):
            candidateA = list(old_candidates_list[i])
            candidateB = list(old_candidates_list[j])
            agree = True    # they have a possible father candidate
            for k in range(size-1):
                if candidateA[k] != candidateB[k]:
                    agree = False
                    break
            if agree:
                candidateC = candidateA.copy()
                candidateC.extend(candidateB)
                new_candidates_list.append(candidateC)

    candidates_dict = dict()
    for candidate in new_candidates_list:
        candidates_dict[tuple(candidate)] = 0    # add a candidate in candidates_dict with count 0
    return candidates_dict
```

K-1

l_1 (candidateA), l_2 (candidateB)

K-2

$l_1[1:k-2] = l_2[1:k-2]$,

K items

- C_k is generated based on L_{k-1}
  - Candidates should be extensions of itemsets in L_{k-1}
- Step 1: Self-joining L_{k-1}
  - Idea: use two $(k-1)$-itemsets in L_{k-1} to make a possibly frequent k-itemset
  - Every itemset is a string in alphabetical order (e.g. items are $a < b < ... < z$, $\{a, d, c, b\} = abcd$)
  - If $l_1[1:k-2] = l_2[1:k-2]$, and $l_1[k-1] < l_2[k-1]$, add $l_3 = l_1 \cup l_2$ to C_k (Prove the completeness by yourself)
- Step 2: Pruning candidates that are supersets of infrequent $(k-1)$-itemsets
  - The anti-monotonicity property of itemsets
  - Check every $(k-1)$-subset of a candidate

sort:

$l_1[k-1] < l_2[k-1]$,

- Every itemset is a string in alphabetical order (e.g. items are $a < b < ... < z$, $\{a, d, c, b\} = abcd$)

Candidates Generation

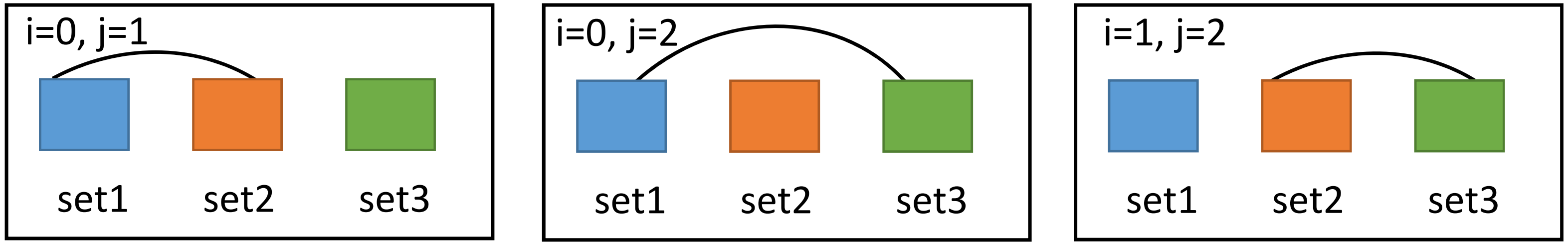
```python
old_candidates_list = list()
for candidate in frequent_list:
    candidate = list(candidate)
    candidate.sort()
    old_candidates_list.append(candidate)

# the size of old candidate
size = len(old_candidates_list[0])

new_candidates_list = list()
```

Candidates Generation

```python
for i in range(len(old_candidates_list) - 1):
    for j in range(i+1, len(old_candidates_list)):
        candidateA = list(old_candidates_list[i])
        candidateB = list(old_candidates_list[j])
        agree = True    # they have a possible father candidate
        for k in range(size-1):
            if candidateA[k] != candidateB[k]:
                agree = False
                break
        if agree:
            candidateC = candidateA.copy()
            candidateC.extend(candidateB)
            new_candidates_list.append(candidateC)
```



Candidates Generation: An Example

L4: [{abcd}, {abcg}, {abef}]

C5: ?

Here k=5, k-2=3

Candidates Generation: An Example

L4: [{abcd}, {abcg}, {abef}]

{<u>abc</u>d}, {<u>abc</u>g} -> “abc” = “abc”

{abcdg}

Candidates Generation: An Example

L4: [{abcd}, {abcg}, {abef}]

{<u>abc</u>d}, {<u>abe</u>f} -> "abc" $\neq$ "abe"

{<u>abc</u>g}, {<u>abe</u>f} -> "abc" $\neq$ "abe"

Candidates Generation: An Example

L4: [{abcd}, {abcg}, {abef}]

C5: [{abcdg}]

(Only 1 candidate)

Apriori Algorithm

```python
# core code
print()
while True:
    print()
    print("Start Scan the data set...")
    # go though the order_list
    for order in order_list:
        for candidate in candidates_dict:
            temp_set = set()
            for item in candidate:
                temp_set.add(item)
            if temp_set.issubset(order):      # check issubset
                candidates_dict[candidate] += 1   # count

    # check frequency
    frequent_list = list()
    for candidate in candidates_dict:
        if candidates_dict[candidate] >= min_sup:
            frequent_list.append(candidate)
    print("frequent_list:")
    print(frequent_list)
    print("length of frequent_list:")
    print(len(frequent_list))
    if len(frequent_list) == 0:
        break

    final_output_list.extend(frequent_list)

    # update candidates_dict
    candidates_dict = update_candidates_dict(frequent_list)
    print("lenght of new candidates_dict")
    print(len(candidates_dict))
```

Algorithm 1 Apriori

Input: a transaction DB and *min_sup*
Output: all frequent itemsets

1: $L_1 \leftarrow \{frequent\ items\}$
2: **for** $k = 2$; $L_{k-1} \neq \emptyset$; $k \leftarrow k+1$ **do**
3: $C_k \leftarrow$ candidates generated based on L_{k-1} **(Candidate Generation)**
4: Scan Transaction DB to count supports of itemsets in C_k **(Counting Supports)**
5: $L_k \leftarrow$ candidates in C_k with *min_sup*
6: **end for**
7: **return** $\cup_k L_k$

Apriori Algorithm

1-itemset

```
frequent_list:
[('85123A',), ('22752',), ('84406B',), ('71053',), ('84029G',), ('84029E',), ('22632',), ('21755',), ('22748',), ('22622',), ('22745',),
('21754',), ('48187',), ('22749',), ('22659',), ('22326',), ('21035',), ('22727',), ('21731',), ('22726',), ('21791',), ('22492',), ('2263
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('21733',), ('20723',), ('21977',), ('21094',), ('84991',), ('21033',), ('22352',), ('21975',), ('85099C',), ('84997C',), ('84997B',), ('2
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('22467',), ('22549',), ('82580',), ('22851',), ('22435',), ('85049E',), ('21122',), ('85150',), ('82578',), ('22413',), ('22804',), ('219
07',), ('20992',), ('22768',), ('21328',), ('20749',), ('21213',), ('22296',), ('20728',), ('84380',), ('22383',), ('84992',), ('22417',),

length of frequent_list:
590
```

2-itemset

```
frequent_list:
[('85123A', '82482'), ('85123A', '82494L'), ('85123A', '21733'), ('85123A', '20725'), ('85123A', '21212'), ('85123A', '22469'), ('85123A',
'22457'), ('85123A', '22470'), ('85123A', '85099B'), ('85123A', '22197'), ('85123A', '84879'), ('85123A', '22384'), ('85123A', '22804'),
('85123A', '22383'), ('85123A', '20727'), ('85123A', '22178'), ('85123A', '22423'), ('85123A', '22666'), ('85123A', '47566'), ('85123A',
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1', '22355'), ('21931', '20711'), ('21931', '21928'), ('21931', 'DOT'), ('21931', '20724'), ('21931', '22385'), ('21931', '23201'), ('2193
1', '23199'), ('21931', '23202'), ('21931', '23203'), ('20725', '21212'), ('20725', '22411'), ('20725', '22662'), ('20725', '85099B'), ('2

length of frequent_list:
408
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8-itemset

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frequent_list:
[('21931', '21931', '22386', '22411', '21931', '21931', '22386', '85099B')]
length of frequent_list:
1
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Thank you!