

# UseCase\_AssociationRulesMining

December 17, 2024

## 1 Module 11: Association Rules Mining and Recommendation Systems

### 1.1 Case Study – 1

```
[1]: # 1. Import Libraries and Load Data
# Install mlxtend if not already installed

try:
    from mlxtend.frequent_patterns import apriori, association_rules
except ImportError:
    import sys
    !{sys.executable} -m pip install mlxtend
    # !{sys.executable} -m pip install --force-reinstall --upgrade mlxtend

# 1. Import Libraries
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
import warnings
warnings.filterwarnings('ignore')

# Load datasets
df_ratings = pd.read_csv('BX-Book-Ratings.csv', encoding='ISO-8859-1')
df_books = pd.read_csv('BX-Books.csv', encoding='ISO-8859-1')
df_users = pd.read_csv('BX-Users.csv', encoding='ISO-8859-1')

# Check data
print("Ratings Data:\n", df_ratings.head())
print("Books Data:\n", df_books.head())
print("Users Data:\n", df_users.head())

# Check the null values
print(df_ratings.isnull().sum(), '\n')
print(df_books.isnull().sum(), '\n')
print(df_users.isnull().sum(), '\n')
```

```
print(df_ratings.info(), '\n')
print(df_books.info(), '\n')
print(df_users.info(), '\n')
```

```
Collecting mlxtend
  Using cached mlxtend-0.23.3-py3-none-any.whl.metadata (7.3 kB)
Collecting scipy>=1.2.1 (from mlxtend)
  Using cached scipy-1.14.1-cp310-cp310-win_amd64.whl.metadata (60 kB)
Collecting numpy>=1.16.2 (from mlxtend)
  Using cached numpy-2.2.0-cp310-cp310-win_amd64.whl.metadata (60 kB)
Collecting pandas>=0.24.2 (from mlxtend)
  Using cached pandas-2.2.3-cp310-cp310-win_amd64.whl.metadata (19 kB)
Collecting scikit-learn>=1.3.1 (from mlxtend)
  Using cached scikit_learn-1.6.0-cp310-cp310-win_amd64.whl.metadata (15 kB)
Collecting matplotlib>=3.0.0 (from mlxtend)
  Using cached matplotlib-3.10.0-cp310-cp310-win_amd64.whl.metadata (11 kB)
Collecting joblib>=0.13.2 (from mlxtend)
  Using cached joblib-1.4.2-py3-none-any.whl.metadata (5.4 kB)
Collecting contourpy>=1.0.1 (from matplotlib>=3.0.0->mlxtend)
  Using cached contourpy-1.3.1-cp310-cp310-win_amd64.whl.metadata (5.4 kB)
Collecting cycler>=0.10 (from matplotlib>=3.0.0->mlxtend)
  Using cached cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib>=3.0.0->mlxtend)
  Using cached fonttools-4.55.3-cp310-cp310-win_amd64.whl.metadata (168 kB)
Collecting kiwisolver>=1.3.1 (from matplotlib>=3.0.0->mlxtend)
  Using cached kiwisolver-1.4.7-cp310-cp310-win_amd64.whl.metadata (6.4 kB)
Collecting packaging>=20.0 (from matplotlib>=3.0.0->mlxtend)
  Using cached packaging-24.2-py3-none-any.whl.metadata (3.2 kB)
Collecting pillow>=8 (from matplotlib>=3.0.0->mlxtend)
  Using cached pillow-11.0.0-cp310-cp310-win_amd64.whl.metadata (9.3 kB)
Collecting pyparsing>=2.3.1 (from matplotlib>=3.0.0->mlxtend)
  Using cached pyparsing-3.2.0-py3-none-any.whl.metadata (5.0 kB)
Collecting python-dateutil>=2.7 (from matplotlib>=3.0.0->mlxtend)
  Using cached python_dateutil-2.9.0.post0-py2.py3-none-any.whl.metadata (8.4 kB)
Collecting pytz>=2020.1 (from pandas>=0.24.2->mlxtend)
  Using cached pytz-2024.2-py2.py3-none-any.whl.metadata (22 kB)
Collecting tzdata>=2022.7 (from pandas>=0.24.2->mlxtend)
  Using cached tzdata-2024.2-py2.py3-none-any.whl.metadata (1.4 kB)
Collecting threadpoolctl>=3.1.0 (from scikit-learn>=1.3.1->mlxtend)
  Using cached threadpoolctl-3.5.0-py3-none-any.whl.metadata (13 kB)
Collecting six>=1.5 (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend)
  Using cached six-1.17.0-py2.py3-none-any.whl.metadata (1.7 kB)
Using cached mlxtend-0.23.3-py3-none-any.whl (1.4 MB)
Using cached joblib-1.4.2-py3-none-any.whl (301 kB)
Using cached matplotlib-3.10.0-cp310-cp310-win_amd64.whl (8.0 MB)
Using cached numpy-2.2.0-cp310-cp310-win_amd64.whl (12.9 MB)
Using cached pandas-2.2.3-cp310-cp310-win_amd64.whl (11.6 MB)
```

```

Using cached scikit_learn-1.6.0-cp310-cp310-win_amd64.whl (11.1 MB)
Using cached scipy-1.14.1-cp310-cp310-win_amd64.whl (44.8 MB)
Using cached contourpy-1.3.1-cp310-cp310-win_amd64.whl (218 kB)
Using cached cycler-0.12.1-py3-none-any.whl (8.3 kB)
Using cached fonttools-4.55.3-cp310-cp310-win_amd64.whl (2.2 MB)
Using cached kiwisolver-1.4.7-cp310-cp310-win_amd64.whl (55 kB)
Using cached packaging-24.2-py3-none-any.whl (65 kB)
Using cached pillow-11.0.0-cp310-cp310-win_amd64.whl (2.6 MB)
Using cached pyparsing-3.2.0-py3-none-any.whl (106 kB)
Using cached python_dateutil-2.9.0.post0-py2.py3-none-any.whl (229 kB)
Using cached pytz-2024.2-py2.py3-none-any.whl (508 kB)
Using cached threadpoolctl-3.5.0-py3-none-any.whl (18 kB)
Using cached tzdata-2024.2-py2.py3-none-any.whl (346 kB)
Using cached six-1.17.0-py2.py3-none-any.whl (11 kB)
Installing collected packages: pytz, tzdata, threadpoolctl, six, pyparsing,
pillow, packaging, numpy, kiwisolver, joblib, fonttools, cycler, scipy, python-
dateutil, contourpy, scikit-learn, pandas, matplotlib, mlxtend
  Attempting uninstall: pytz
    Found existing installation: pytz 2024.2
    Uninstalling pytz-2024.2:
      Successfully uninstalled pytz-2024.2
  Attempting uninstall: tzdata
    Found existing installation: tzdata 2024.2
    Uninstalling tzdata-2024.2:
      Successfully uninstalled tzdata-2024.2
  Attempting uninstall: threadpoolctl
    Found existing installation: threadpoolctl 3.5.0
    Uninstalling threadpoolctl-3.5.0:
      Successfully uninstalled threadpoolctl-3.5.0
  Attempting uninstall: six
    Found existing installation: six 1.17.0
    Uninstalling six-1.17.0:
      Successfully uninstalled six-1.17.0
  Attempting uninstall: pyparsing
    Found existing installation: pyparsing 3.2.0
    Uninstalling pyparsing-3.2.0:
      Successfully uninstalled pyparsing-3.2.0
  Attempting uninstall: pillow
    Found existing installation: pillow 11.0.0
    Uninstalling pillow-11.0.0:
      Successfully uninstalled pillow-11.0.0
  Attempting uninstall: packaging
    Found existing installation: packaging 24.2
    Uninstalling packaging-24.2:
      Successfully uninstalled packaging-24.2
  Attempting uninstall: numpy
    Found existing installation: numpy 2.2.0
    Uninstalling numpy-2.2.0:

```

```

    Successfully uninstalled numpy-2.2.0
Attempting uninstall: kiwisolver
    Found existing installation: kiwisolver 1.4.7
    Uninstalling kiwisolver-1.4.7:
        Successfully uninstalled kiwisolver-1.4.7
Attempting uninstall: joblib
    Found existing installation: joblib 1.4.2
    Uninstalling joblib-1.4.2:
        Successfully uninstalled joblib-1.4.2
Attempting uninstall: fonttools
    Found existing installation: fonttools 4.55.3
    Uninstalling fonttools-4.55.3:
        Successfully uninstalled fonttools-4.55.3
Attempting uninstall: cycler
    Found existing installation: cycler 0.12.1
    Uninstalling cycler-0.12.1:
        Successfully uninstalled cycler-0.12.1
Attempting uninstall: scipy
    Found existing installation: scipy 1.14.1
    Uninstalling scipy-1.14.1:
        Successfully uninstalled scipy-1.14.1
Attempting uninstall: python-dateutil
    Found existing installation: python-dateutil 2.9.0.post0
    Uninstalling python-dateutil-2.9.0.post0:
        Successfully uninstalled python-dateutil-2.9.0.post0
Attempting uninstall: contourpy
    Found existing installation: contourpy 1.3.1
    Uninstalling contourpy-1.3.1:
        Successfully uninstalled contourpy-1.3.1
Attempting uninstall: scikit-learn
    Found existing installation: scikit-learn 1.6.0
    Uninstalling scikit-learn-1.6.0:
        Successfully uninstalled scikit-learn-1.6.0
Attempting uninstall: pandas
    Found existing installation: pandas 2.2.3
    Uninstalling pandas-2.2.3:
        Successfully uninstalled pandas-2.2.3
Attempting uninstall: matplotlib
    Found existing installation: matplotlib 3.10.0
    Uninstalling matplotlib-3.10.0:
        Successfully uninstalled matplotlib-3.10.0
Attempting uninstall: mlxtend
    Found existing installation: mlxtend 0.23.3
    Uninstalling mlxtend-0.23.3:
        Successfully uninstalled mlxtend-0.23.3
Successfully installed contourpy-1.3.1 cycler-0.12.1 fonttools-4.55.3
joblib-1.4.2 kiwisolver-1.4.7 matplotlib-3.10.0 mlxtend-0.23.3 numpy-2.2.0
packaging-24.2 pandas-2.2.3 pillow-11.0.0 pyparsing-3.2.0 python-

```

dateutil-2.9.0.post0 pytz-2024.2 scikit-learn-1.6.0 scipy-1.14.1 six-1.17.0  
threadpoolctl-3.5.0 tzdata-2024.2

Ratings Data:

	user_id	isbn	rating
0	276725	034545104X	0
1	276726	155061224	5
2	276727	446520802	0
3	276729	052165615X	3
4	276729	521795028	6

Books Data:

	isbn	book_title \
0	195153448	Classical Mythology
1	2005018	Clara Callan
2	60973129	Decision in Normandy
3	374157065	Flu: The Story of the Great Influenza Pandemic...
4	393045218	The Mummies of Urumchi

	book_author	year_of_publication	publisher
0	Mark P. O. Morford	2002	Oxford University Press
1	Richard Bruce Wright	2001	HarperFlamingo Canada
2	Carlo D'Este	1991	HarperPerennial
3	Gina Bari Kolata	1999	Farrar Straus Giroux
4	E. J. W. Barber	1999	W. W. Norton & Company

Users Data:

	user_id	Location	Age
0	1	nyc, new york, usa	NaN
1	2	stockton, california, usa	18.0
2	3	moscow, yukon territory, russia	NaN
3	4	porto, v.n.gaia, portugal	17.0
4	5	farnborough, hants, united kingdom	NaN

user\_id 0  
isbn 0  
rating 0  
dtype: int64

isbn 0  
book\_title 0  
book\_author 2  
year\_of\_publication 0  
publisher 2  
dtype: int64

user\_id 0  
Location 1  
Age 110763  
dtype: int64

<class 'pandas.core.frame.DataFrame'>

```

RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 3 columns):
#   Column      Non-Null Count  Dtype
---  -
0   user_id     1048575 non-null  int64
1   isbn        1048575 non-null  object
2   rating      1048575 non-null  int64
dtypes: int64(2), object(1)
memory usage: 24.0+ MB
None

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271379 entries, 0 to 271378
Data columns (total 5 columns):
#   Column              Non-Null Count  Dtype
---  -
0   isbn                271379 non-null  object
1   book_title         271379 non-null  object
2   book_author        271377 non-null  object
3   year_of_publication 271379 non-null  object
4   publisher           271377 non-null  object
dtypes: object(5)
memory usage: 10.4+ MB
None

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 278859 entries, 0 to 278858
Data columns (total 3 columns):
#   Column      Non-Null Count  Dtype
---  -
0   user_id     278859 non-null  object
1   Location    278858 non-null  object
2   Age         168096 non-null  float64
dtypes: float64(1), object(2)
memory usage: 6.4+ MB
None

```

```

[2]: # Cleaning the Data:

# Replace missing Location values with 'Unknown Location'
df_users['Location'].fillna('Unknown Location', inplace=True)

# Replace missing Age values with the median age
df_users['Age'].fillna(df_users['Age'].median(), inplace=True)

# Replace missing values in df_books

```

```
df_books['book_author'].fillna('Unknown Author', inplace=True)
df_books['publisher'].fillna('Unknown Publisher', inplace=True)

# Verify updated null values
print("Updated Null Values in df_books:\n", df_books.isnull().sum(), '\n')
print("Updated Null Values in df_users:\n", df_users.isnull().sum(), '\n')
```

Updated Null Values in df\_books:

```
isbn          0
book_title    0
book_author   0
year_of_publication  0
publisher     0
dtype: int64
```

Updated Null Values in df\_users:

```
user_id      0
Location     0
Age          0
dtype: int64
```

```
[3]: # The MemoryError occurs because the pivot operation generates a massive matrix
# (61K rows × 128K columns), which consumes too much memory.
# Focusing on a smaller subset of the data will address this.

# To reduce memory usage and focus on meaningful data, you can filter users
# who have interacted with a significant number of books
# (e.g., users who have rated or rented a certain threshold of books).
# This helps limit the size of the user-book matrix while keeping high-quality
↳ data.

# Step 1: Filter ratings (remove 0 ratings)
df_ratings_filtered = df_ratings[df_ratings['rating'] > 0]

# Step 2: Count the number of books each user interacted with
user_book_counts = df_ratings_filtered['user_id'].value_counts()

# Step 3: Filter users who interacted with significant books (threshold = 5)
threshold = 20
users_significant = user_book_counts[user_book_counts >= threshold].index

# Filter the ratings data for these users
df_ratings_filtered = df_ratings_filtered[df_ratings_filtered['user_id'].
↳ isin(users_significant)]

# Step 4: Merge with books data
```

```

df_merged = pd.merge(df_ratings_filtered, df_books, on='isbn', how='left')

# Keep only necessary columns
df_merged = df_merged[['user_id', 'book_title']]

# Step 5: Build the User-Book Matrix
user_book_matrix = df_merged.pivot_table(index='user_id',
                                           columns='book_title',
                                           aggfunc='size',
                                           fill_value=0)

# Convert to binary format (1 if user interacted with a book)
user_book_matrix = user_book_matrix.applymap(lambda x: 1 if x > 0 else 0)

print("User-Book Matrix (Filtered):\n", user_book_matrix.head())
print(f"Shape of the User-Book Matrix: {user_book_matrix.shape}")

```

User-Book Matrix (Filtered):

book\_title    A Light in the Storm: The Civil War Diary of Amelia Martin,  
Fenwick Island, Delaware, 1861 (Dear America)    \

user_id	
183	0
242	0
254	0
392	0
507	0

book\_title    Dark Justice    \

user_id	
183	0
242	0
254	0
392	0
507	0

book\_title    Earth Prayers From around the World: 365 Prayers, Poems, and  
Invocations for Honoring the Earth    \

user_id	
183	0
242	0
254	0
392	0
507	0

book\_title    Final Fantasy Anthology: Official Strategy Guide (Brady Games)    \

user_id	
183	0
242	0



254	0
392	0
507	0

book_title	Flight of Fancy: American Heiresses (Zebra Ballad Romance)	\
user_id		
183	0	
242	0	
254	0	
392	0	
507	0	

book_title	Garfield Bigger and Better (Garfield (Numbered Paperback))	\
user_id		
183	0	
242	0	
254	0	
392	0	
507	0	

book_title	God's Little Promise Book	\
user_id		
183	0	
242	0	
254	0	
392	0	
507	0	

book_title	Good Wives: Image and Reality in the Lives of Women in Northern New England, 1650-1750	\
user_id		
183	0	
242	0	
254	0	
392	0	
507	0	

book_title	Goosebumps Monster Edition 1: Welcome to Dead House, Stay Out of the Basement, and Say Cheese and Die!	\
user_id		
183	0	
242	0	
254	0	
392	0	
507	0	

book_title	Highland Desire (Zebra Splendor Historical Romances)	... \
user_id		...

183	0	...
242	0	...
254	0	...
392	0	...
507	0	...

book_title	Ängeles fugaces (Falling Angels)	ÄÄ. Kolumnen.	ÄÄa \
user_id			
183	0	0	0
242	0	0	0
254	0	0	0
392	0	0	0
507	0	0	0

book_title	Äber das Fernsehen.	Äber den ProzeÄ der Zivilisation 1.	\
user_id			
183	0		0
242	0		0
254	0		0
392	0		0
507	0		0

book_title	Äber den ProzeÄ der Zivilisation 2.	Äber die Freiheit.	\
user_id			
183	0		0
242	0		0
254	0		0
392	0		0
507	0		0

book_title	Ärger mit Produkt X. Roman.	Ästlich der Berge.	\
user_id			
183	0		0
242	0		0
254	0		0
392	0		0
507	0		0

book_title	Äthique en toc
user_id	
183	0
242	0
254	0
392	0
507	0

[5 rows x 96073 columns]  
Shape of the User-Book Matrix: (3359, 96073)

```
[12]: user_book_matrix
```

```
[12]: book_title    A Light in the Storm: The Civil War Diary of Amelia Martin, Fenwick  
      Island, Delaware, 1861 (Dear America) \
```

```
      user_id  
      183                                0  
      242                                0  
      254                                0  
      392                                0  
      507                                0  
      ...                                ...  
      278356                             0  
      278418                             0  
      278582                             0  
      278633                             0  
      278843                             0
```

```
      book_title    Dark Justice \
```

```
      user_id  
      183                0  
      242                0  
      254                0  
      392                0  
      507                0  
      ...                ...  
      278356              0  
      278418              0  
      278582              0  
      278633              0  
      278843              0
```

```
      book_title    Earth Prayers From around the World: 365 Prayers, Poems, and  
      Invocations for Honoring the Earth \
```

```
      user_id  
      183                                0  
      242                                0  
      254                                0  
      392                                0  
      507                                0  
      ...                                ...  
      278356                             0  
      278418                             0  
      278582                             0  
      278633                             0  
      278843                             0
```

```
      book_title    Final Fantasy Anthology: Official Strategy Guide (Brady Games) \
```

user_id		
183		0
242		0
254		0
392		0
507		0
...	...	
278356		0
278418		0
278582		0
278633		0
278843		0
book_title	Flight of Fancy: American Heiresses (Zebra Ballad Romance)	\
user_id		
183		0
242		0
254		0
392		0
507		0
...	...	
278356		0
278418		0
278582		0
278633		0
278843		0
book_title	Garfield Bigger and Better (Garfield (Numbered Paperback))	\
user_id		
183		0
242		0
254		0
392		0
507		0
...	...	
278356		0
278418		0
278582		0
278633		0
278843		0
book_title	God's Little Promise Book	\
user_id		
183	0	
242	0	
254	0	
392	0	

507	0
...	...
278356	0
278418	0
278582	0
278633	0
278843	0

book\_title Good Wives: Image and Reality in the Lives of Women in Northern New England, 1650-1750 \

user_id	
183	0
242	0
254	0
392	0
507	0
...	...
278356	0
278418	0
278582	0
278633	0
278843	0

book\_title Goosebumps Monster Edition 1: Welcome to Dead House, Stay Out of the Basement, and Say Cheese and Die! \

user_id	
183	0
242	0
254	0
392	0
507	0
...	...
278356	0
278418	0
278582	0
278633	0
278843	0

book\_title Highland Desire (Zebra Splendor Historical Romances) ... \

user_id		
183	0	...
242	0	...
254	0	...
392	0	...
507	0	...
...	...	...
278356	0	...

278418	0	...
278582	0	...
278633	0	...
278843	0	...

book_title	Ängeles fugaces (Falling Angels)	ÄÄ. Kolumnen.	ÄÄa \
user_id			
183	0	0	0
242	0	0	0
254	0	0	0
392	0	0	0
507	0	0	0
...	...	...	...
278356	0	0	0
278418	0	0	0
278582	0	0	0
278633	0	0	0
278843	0	0	0

book_title	ÄÄber das Fernsehen.	ÄÄber den ProzeÄ der Zivilisation 1.	\
user_id			
183	0		0
242	0		0
254	0		0
392	0		0
507	0		0
...	...	...	...
278356	0		0
278418	0		0
278582	0		0
278633	0		0
278843	0		0

book_title	ÄÄber den ProzeÄ der Zivilisation 2.	ÄÄber die Freiheit.	\
user_id			
183	0		0
242	0		0
254	0		0
392	0		0
507	0		0
...	...	...	...
278356	0		0
278418	0		0
278582	0		0
278633	0		0
278843	0		0

book_title	Ã?Ã?rger mit Produkt X. Roman.	Ã?Ã?stlich der Berge.	\
user_id			
183	0	0	
242	0	0	
254	0	0	
392	0	0	
507	0	0	
...	...	...	
278356	0	0	
278418	0	0	
278582	0	0	
278633	0	0	
278843	0	0	

book_title	Ã?Ã?thique en toc
user_id	
183	0
242	0
254	0
392	0
507	0
...	...
278356	0
278418	0
278582	0
278633	0
278843	0

[3359 rows x 96073 columns]

```
[6]: # Apply Association Rule Mining
# We will use the Apriori algorithm to find frequently rented books and
# generate association rules.

import mlxtend
print(mlxtend.__version__)

# Step 1: Apply the Apriori algorithm
min_support = 0.01 # min_support stands for minimum support: threshold that
# determines how frequently an item or itemset must appear in the dataset to
# be considered "frequent".
frequent_itemsets = apriori(user_book_matrix, min_support=min_support,
# use_colnames=True)

print("\nFrequent Itemsets:")
print(frequent_itemsets)
```

```

# Step 2: Generate association rules with a dummy 'num_itemsets'
#rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.0)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.0,
    ↳num_itemsets=len(frequent_itemsets))

# Step 3: Sort and display the rules
rules = rules.sort_values(by="confidence", ascending=False)
print("\nTop Association Rules:")
print(rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']].
    ↳head())

```

0.23.3

Frequent Itemsets:

	support	itemsets
0	0.021137	(1984)
1	0.028580	(1st to Die: A Novel)
2	0.021137	(2nd Chance)
3	0.010717	(84 Charing Cross Road)
4	0.015779	(A Bend in the Road)
..	...	...
376	0.014290	(Harry Potter and the Sorcerer's Stone (Book 1...
377	0.011015	(Harry Potter and the Sorcerer's Stone (Harry ...
378	0.010420	(Harry Potter and the Order of the Phoenix (Bo...
379	0.014290	(Harry Potter and the Chamber of Secrets (Book...
380	0.013397	(Harry Potter and the Chamber of Secrets (Book...

[381 rows x 2 columns]

Top Association Rules:

	antecedents \	consequents	support	confidence \	lift
125	(Harry Potter and the Chamber of Secrets (Book...	(Harry Potter and the Prisoner of Azkaban (Boo...	0.013397	0.978261	21.337521
104	(Harry Potter and the Order of the Phoenix (Bo...	(Harry Potter and the Prisoner of Azkaban (Boo...	0.010420	0.972222	21.205808
93	(Harry Potter and the Sorcerer's Stone (Book 1...	(Harry Potter and the Prisoner of Azkaban (Boo...	0.014290	0.960000	20.939221
127	(Harry Potter and the Sorcerer's Stone (Book 1...	(Harry Potter and the Chamber of Secrets (Book...	0.013397	0.937500	
58	(Harry Potter and the Sorcerer's Stone (Book 1...	(Harry Potter and the Chamber of Secrets (Book...	0.013695	0.920000	



```
127 17.398135
58 17.073370
```

```
[8]: rules[ (rules['lift'] >= 10) &
           (rules['confidence'] >= 0.8) ]
```

```
[8]: antecedents \
125 (Harry Potter and the Chamber of Secrets (Book...
104 (Harry Potter and the Order of the Phoenix (Bo...
93 (Harry Potter and the Sorcerer's Stone (Book 1...
127 (Harry Potter and the Sorcerer's Stone (Book 1...
58 (Harry Potter and the Sorcerer's Stone (Book 1...
76 (Harry Potter and the Sorcerer's Stone (Book 1...
110 (Harry Potter and the Chamber of Secrets (Book...
132 (Harry Potter and the Sorcerer's Stone (Book 1...
111 (Harry Potter and the Chamber of Secrets (Book...
124 (Harry Potter and the Chamber of Secrets (Book...
68 (Harry Potter and the Chamber of Secrets (Book...
50 (Harry Potter and the Chamber of Secrets (Book...
87 (Harry Potter and the Order of the Phoenix (Bo...
92 (Harry Potter and the Sorcerer's Stone (Book 1...
86 (Harry Potter and the Order of the Phoenix (Bo...
44 (Harry Potter and the Chamber of Secrets (Book...
113 (Harry Potter and the Order of the Phoenix (Bo...
74 (Harry Potter and the Chamber of Secrets (Book...
63 (Harry Potter and the Sorcerer's Stone (Harry ...
98 (Harry Potter and the Sorcerer's Stone (Harry ...
52 (Harry Potter and the Goblet of Fire (Book 4),...
70 (Harry Potter and the Order of the Phoenix (Bo...
```

```
consequents antecedent support \
125 (Harry Potter and the Prisoner of Azkaban (Boo... 0.013695
104 (Harry Potter and the Prisoner of Azkaban (Boo... 0.010717
93 (Harry Potter and the Prisoner of Azkaban (Boo... 0.014885
127 (Harry Potter and the Chamber of Secrets (Book... 0.014290
58 (Harry Potter and the Chamber of Secrets (Book... 0.014885
76 (Harry Potter and the Chamber of Secrets (Book... 0.016969
110 (Harry Potter and the Prisoner of Azkaban (Boo... 0.015779
132 (Harry Potter and the Chamber of Secrets (Book... 0.014885
111 (Harry Potter and the Goblet of Fire (Book 4)) 0.016374
124 (Harry Potter and the Goblet of Fire (Book 4)) 0.015481
68 (Harry Potter and the Prisoner of Azkaban (Boo... 0.019053
50 (Harry Potter and the Prisoner of Azkaban (Boo... 0.028878
87 (Harry Potter and the Goblet of Fire (Book 4)) 0.020244
92 (Harry Potter and the Goblet of Fire (Book 4)) 0.016969
86 (Harry Potter and the Prisoner of Azkaban (Boo... 0.020542
44 (Harry Potter and the Goblet of Fire (Book 4)) 0.019053
```

113	(Harry Potter and the Chamber of Secrets (Book...	0.017267
74	(Harry Potter and the Prisoner of Azkaban (Boo...	0.018756
63	(Harry Potter and the Chamber of Secrets (Book...	0.013397
98	(Harry Potter and the Prisoner of Azkaban (Boo...	0.013397
52	(Harry Potter and the Chamber of Secrets (Book...	0.030068
70	(Harry Potter and the Chamber of Secrets (Book...	0.020244

	consequent	support	confidence	lift	representativity	\
125	0.045847	0.013397	0.978261	21.337521	1.0	
104	0.045847	0.010420	0.972222	21.205808	1.0	
93	0.045847	0.014290	0.960000	20.939221	1.0	
127	0.053885	0.013397	0.937500	17.398135	1.0	
58	0.053885	0.013695	0.920000	17.073370	1.0	
76	0.053885	0.015481	0.912281	16.930115	1.0	
110	0.045847	0.014290	0.905660	19.753982	1.0	
132	0.031557	0.013397	0.900000	28.519811	1.0	
111	0.042274	0.014290	0.872727	20.644302	1.0	
124	0.042274	0.013397	0.865385	20.470612	1.0	
68	0.045847	0.016374	0.859375	18.744420	1.0	
50	0.045847	0.024710	0.855670	18.663610	1.0	
87	0.042274	0.017267	0.852941	20.176263	1.0	
92	0.042274	0.014290	0.842105	19.919941	1.0	
86	0.045847	0.017267	0.840580	18.334463	1.0	
44	0.042274	0.015779	0.828125	19.589239	1.0	
113	0.053885	0.014290	0.827586	15.358354	1.0	
74	0.045847	0.015481	0.825397	18.003298	1.0	
63	0.053885	0.011015	0.822222	15.258809	1.0	
98	0.045847	0.011015	0.822222	17.934055	1.0	
52	0.053885	0.024710	0.821782	15.250643	1.0	
70	0.053885	0.016374	0.808824	15.010156	1.0	

	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
125	0.012769	43.891039	0.966368	0.290323	0.977216	0.635234
104	0.009928	34.349509	0.963166	0.225806	0.970888	0.599747
93	0.013608	23.853826	0.966631	0.307692	0.958078	0.635844
127	0.012627	15.137839	0.956186	0.244565	0.933940	0.593059
58	0.012892	11.826436	0.955655	0.248649	0.915444	0.587072
76	0.014566	10.785710	0.957176	0.279570	0.907285	0.599787
110	0.013567	10.114022	0.964597	0.301887	0.901127	0.608674
132	0.012927	9.684430	0.979517	0.405405	0.896741	0.662264
111	0.013598	7.524986	0.967401	0.322148	0.867109	0.605378
124	0.012742	7.114532	0.966106	0.302013	0.859443	0.591143
68	0.015500	6.785088	0.965038	0.337423	0.852618	0.608259
50	0.023386	6.610917	0.974563	0.494048	0.848735	0.697316
87	0.016411	6.512533	0.970075	0.381579	0.846450	0.630696
92	0.013573	6.065595	0.966195	0.317881	0.835136	0.590067
86	0.016325	5.985142	0.965287	0.351515	0.832920	0.608602

44	0.014973	5.572221	0.967383	0.346405	0.820538	0.600682
113	0.013360	5.487467	0.951315	0.251309	0.817767	0.546390
74	0.014621	5.464695	0.962507	0.315152	0.817007	0.581530
63	0.010293	5.321896	0.947153	0.195767	0.812097	0.513321
98	0.010401	5.367111	0.957062	0.228395	0.813680	0.531241
52	0.023089	5.308756	0.963397	0.417085	0.811632	0.640173
70	0.015283	4.948909	0.952664	0.283505	0.797935	0.556345

[ ]: