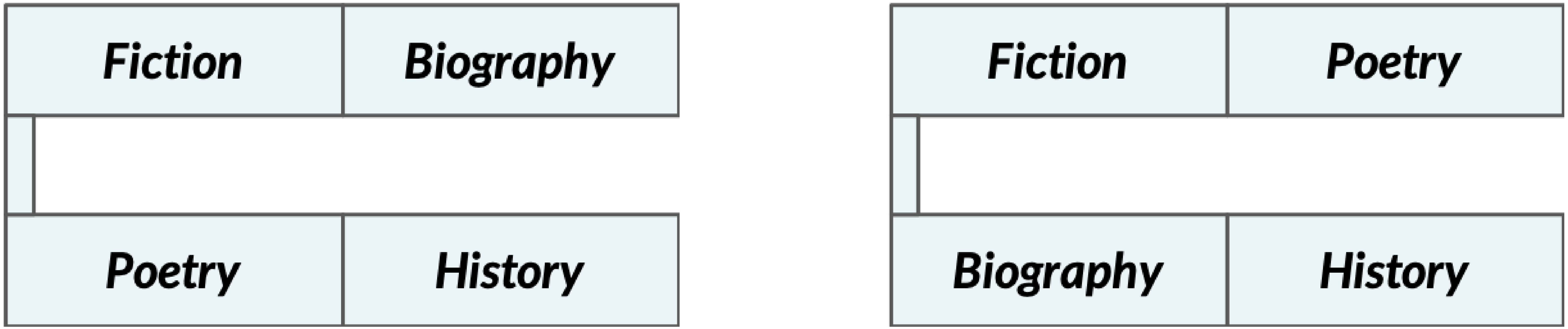
What is market basket analysis?

MARKET BASKET ANALYSIS IN PYTHON

Isaiah Hull
Economist

Selecting a bookstore layout



Exploring transaction data

TID	Transaction
1	biography, history
2	fiction
3	biography, poetry
4	fiction, history
5	biography
...	...
75000	fiction, poetry

- **TID** = unique ID associated with each transaction.
- **Transaction** = set of unique items purchased together.

What is market basket analysis?

1. **Identify products frequently purchased together.**
   - Biography and history
   - Fiction and poetry
2. **Construct recommendations based on these findings.**
   - Place biography and history sections together.
   - Keep fiction and history apart.

The use cases of market basket analysis

1. Build Netflix-style recommendations engine.
2. Improve product recommendations on an e-commerce store.
3. Cross-sell products in a retail setting.
4. Improve inventory management.
5. Upsell products.

Using market basket analysis

TID	Transaction
11	**fiction, biography**
12	**fiction, biography**
13	history, biography
...	...
19	**fiction, biography**
20	**fiction, biography**
...	...

- **Market basket analysis**
  - Construct association rules
  - Identify items frequently purchased together
- **Association rules**
  - {antecedent} $\rightarrow$ {consequent}
    - {fiction} $\rightarrow$ {biography}

Loading the data

```python
import pandas as pd

# Load transactions from pandas.
books = pd.read_csv("datasets/bookstore.csv")

# Print the header
print(books.head(2))
```

```
TID           Transaction
0    biography, history
1               fiction
```

For a refresher, see the Pandas Cheat Sheet.

Building transactions

```
# Split transaction strings into lists.
transactions = books['Transaction'].apply(lambda t: t.split(','))

# Convert DataFrame into list of strings.
transactions = list(transactions)
```

Counting the itemsets

```
# Print the first transaction.
print(transactions[0])
```

```
['biography', 'history']
```

```
# Count the number of transactions that contain biography and fiction.
transactions.count(['biography', 'fiction'])
```

```
218
```

Making a recommendation

```
# Count the number of transactions that contain fiction and poetry.
transactions.count(['fiction', 'poetry'])
```

```
5357
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON

Identifying association rules

MARKET BASKET ANALYSIS IN PYTHON

Isaiah Hull
Economist

Loading and preparing data

```
import pandas as pd

# Load transactions from pandas.
books = pd.read_csv("datasets/bookstore.csv")
```

```
# Split transaction strings into lists.
transactions = books['Transaction'].apply(lambda t: t.split(','))
```

```
# Convert DataFrame into list of strings.
transactions = list(transactions)
```

Exploring the data

```
print(transactions[:5])
```

```
[['language', 'travel', 'humor', 'fiction'],
 ['humor', 'language'],
 ['humor', 'biography', 'cooking'],
 ['cooking', 'language'],
 ['travel']]
```

Association rules

- **Association rule**
  - Contains antecedent and consequent
    - $\{health\} \rightarrow \{cooking\}$
- **Multi-antecedent rule**
  - $\{humor, travel\} \rightarrow \{language\}$
- **Multi-consequent rule**
  - $\{biography\} \rightarrow \{history, language\}$

Difficulty of selecting rules

- **Finding useful rules is difficult.**
    - Set of all possible rules is large.
    - Most rules are not useful.
    - Must discard most rules.
- **What if we restrict ourselves to simple rules?**
    - One antecedent and one consequent.
    - Still challenging, even for small dataset.

Generating the rules

- fiction
- poetry
- history
- biography
- cooking
- health
- travel
- language
- humor

Generating the rules

Fiction Rules	Poetry Rules	...	Humor Rules
fiction->poetry	poetry->fiction	...	humor->fiction
fiction->history	poetry->history	...	humor->history
fiction->biography	poetry->biography	...	humor->biography
fiction->cooking	poetry->cooking	...	humor->cooking
...	...	...	...
fiction->humor	poetry->humor	...	

Generating rules with itertools

```
from itertools import permutations

# Extract unique items.
flattened = [item for transaction in transactions for item in transaction]
items = list(set(flattened))
```

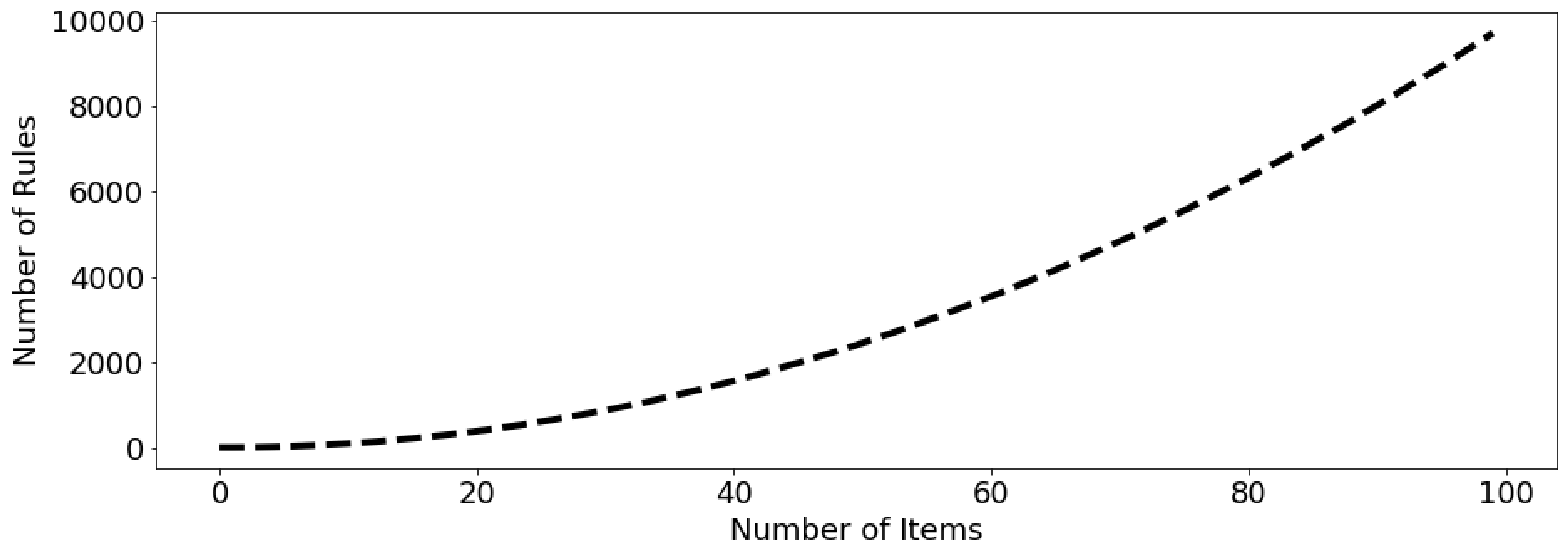
```
# Compute and print rules.
rules = list(permutations(items, 2))
print(rules)
```

```
[('fiction', 'poetry'),
 ('fiction', 'history'),
 ...
 ('humor', 'travel'),
 ('humor', 'language')]
```

Counting the rules

```
# Print the number of rules
print(len(rules))
```

```
72
```



Looking ahead

```python
# Import the association rules function
from mlxtend.frequent_patterns import association_rules
from mlxtend.frequent_patterns import apriori

# Compute frequent itemsets using the Apriori algorithm
frequent_itemsets = apriori(onehot, min_support = 0.001,
                            max_len = 2, use_colnames = True)

# Compute all association rules for frequent_itemsets
rules = association_rules(frequent_itemsets,
                            metric = "lift",
                             min_threshold = 1.0)
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON

The simplest metric

MARKET BASKET ANALYSIS IN PYTHON

Isaiah Hull
Economist

Metrics and pruning

- A **metric** is a measure of performance for rules.
  - $\{\text{humor}\} \rightarrow \{\text{poetry}\}$
    - 0.81
  - $\{\text{fiction}\} \rightarrow \{\text{travel}\}$
    - 0.23
- **Pruning** is the use of metrics to discard rules.
  - Retain: $\{\text{humor}\} \rightarrow \{\text{poetry}\}$
  - Discard: $\{\text{fiction}\} \rightarrow \{\text{travel}\}$

The simplest metric

- The **support metric** measures the share of transactions that contain an itemset.

$$\frac{\text{number of transactions with items(s)}}{\text{number of transactions}}$$

$$\frac{\text{number of transactions with milk}}{\text{total transactions}}$$

Support for language

TID	Transaction
0	travel, humor, fiction
1	**humor, language**
2	humor, biography, cooking
3	**cooking, language**
4	travel

TID	Transaction
5	poetry, health, travel, history
6	humor
7	travel
8	poetry, fiction, humor
9	fiction, biography

Support for *{language}* = 2 / 10 = 0.2

Support for {Humor} $\rightarrow$ {Language}

TID	Transaction
0	travel,humor,fiction
1	**humor,language**
2	humor,biography,cooking
3	cooking,language
4	travel

TID	Transaction
5	poetry,health,travel,history
6	humor
7	travel
8	poetry,fiction,humor
9	fiction,biography

SUPPORT for *{language}* $\rightarrow$ *{humor}* = 0.1

Preparing the data

```
print(transactions)
```

```
[['travel', 'humor', 'fiction'],
...
['fiction', 'biography']]
```

```
from mlxtend.preprocessing import TransactionEncoder
```

```
# Instantiate transaction encoder
encoder = TransactionEncoder().fit(transactions)
```

Preparing the data

```
# One-hot encode itemsets by applying fit and transform
onehot = encoder.transform(transactions)
```

```
# Convert one-hot encoded data to DataFrame
onehot = pd.DataFrame(onehot, columns = encoder.columns_)
print(onehot)
```

```
   biography  cooking  ...  poetry  travel
0  False      False   ...  False    True
...
9  True       False   ...  False    False
```

Computing support for single items

```
print(onehot.mean())
```

```
biography     0.2
cooking       0.2
fiction       0.3
health        0.1
history       0.1
humor         0.5
language      0.2
poetry        0.2
travel        0.4
dtype: float64
```

Computing support for multiple items

```python
import numpy as np

# Define itemset that contains fiction and poetry
onehot['fiction+poetry'] = np.logical_and(onehot['fiction'],onehot['poetry'])

print(onehot.mean())
```

```
biography         0.2
cooking           0.2
...               ...
travel            0.4
fiction+poetry    0.1
dtype: float64
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON