Confidence and lift

MARKET BASKET ANALYSIS IN PYTHON

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When support is misleading

TID	Transaction
1	Coffee, Milk
2	Bread, Milk, Orange
3	Bread, Milk
4	Bread, Milk, Sugar
5	Bread, Jam, Milk
...	...

1. **Milk and bread frequently purchased together.**
   - Support: {Milk} $\rightarrow$ {Bread}
2. **Rule is not informative for marketing.**
   - Milk and bread are both popular items.

The confidence metric

1. Can improve over **support** with additional metrics.
2. Adding **confidence** provides a more complete picture.

$$\frac{Support(X\&Y)}{Support(X)}$$

Interpreting the confidence metric

TID	Transaction
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TID	Transaction
1	Coffee, Milk
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5	Bread, Jam, Milk

$$Support(Milk\&Coffee) = 0.20$$

$$Support(Milk) = 1.00$$

Interpreting the confidence metric

$$\frac{Support(Milk\&Coffee)}{Support(Milk)} = \frac{0.20}{1.00} = 0.20$$

$$\frac{Support(Milk\&Coffee)}{Support(Milk)} = \frac{0.20}{0.80} = 0.25$$

$$\frac{Support(Milk\&Coffee)}{Support(Milk)} = \frac{0.20}{0.20} = 1.00$$

The lift metric

- **Lift provides another metric for evaluating the relationship between items.**
  - **Numerator:** Proportion of transactions that contain X and Y.
  - **Denominator:** Proportion if X and Y assigned randomly and independently.

$$\frac{Support(X\&Y)}{Support(X)Support(Y)}$$

Preparing the data

```
from mlxtend.preprocessing import TransactionEncoder
import pandas as pd

# Split library strings into lists
libraries = data['Library'].apply(lambda t: t.split(','))

# Convert to list of lists
libraries = list(libraries)

# One-hot encode books
books = TransactionEncoder().fit(libraries).transform(libraries)

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

Computing confidence and lift

```
# Print first five items
print(books.head())
```

```
      Hunger     Gatsby
0     False      True
1     False      True
2     False      False
3     False      True
4     False      True
```

Dataset: GoodBooks-10K.

Computing confidence and lift

```
# Computing support.
supportHG = np.logical_and(books['Hunger'],books['Gatsby']).mean()
supportH = books['Hunger'].mean()
supportG = books['Gatsby'].mean()
```

```
# Compute and print confidence and lift.
confidence = supportHG / supportH
lift = supportHG / (supportH * supportG)
```

```
# Print results.
print(supportG, confidence, lift)
```

```
(0.30, 0.16, 0.53)
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON

Leverage and conviction

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Building on simpler metrics

$$Support(X) = \frac{Frequency(X)}{N}$$

$$Support(X \rightarrow Y) = \frac{Frequency(X\&Y)}{N}$$

$$Confidence(X \rightarrow Y) = \frac{Support(X \rightarrow Y)}{Support(X)}$$

$$Lift(X \rightarrow Y) = \frac{Support(X \rightarrow Y)}{Support(X)Support(Y)}$$

The leverage metric

- Leverage also builds on **support**.

$$Leverage(X \rightarrow Y) =$$

$$Support(X\&Y) - Support(X)Support(Y)$$

- Leverage is similar to lift, but **easier to interpret.**
- Leverage **lies in -1 and +1 range**.
  - **Lift** ranges from 0 to infinity.

Computing leverage

```
# Compute support for Twilight and Harry Potter
supportTP = np.logical_and(books['Twilight'], books['Potter']).mean()

# Compute support for Twilight
supportT = books['Twilight'].mean()

# Compute support for Harry Potter
supportP = books['Potter'].mean()
```

```
# Compute and print leverage
leverage = supportTP - supportP * supportT
print(leverage)
```

```
0.018
```

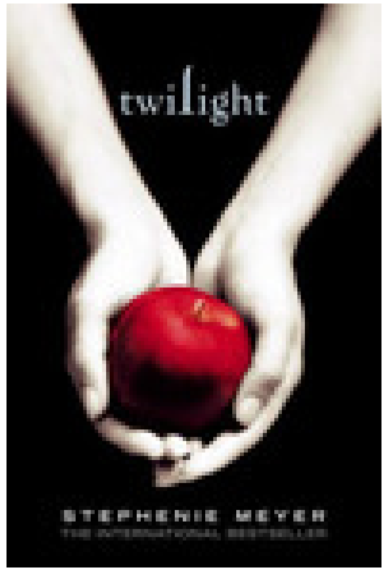
The conviction metric

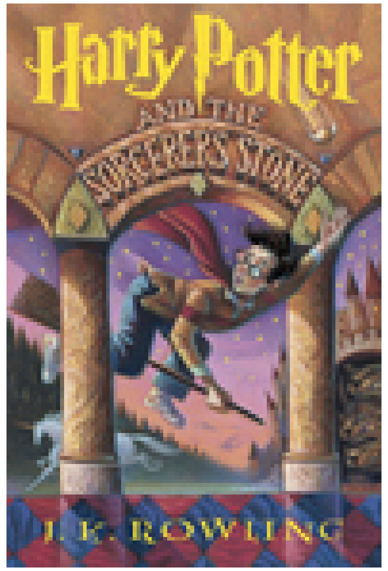
1. **Conviction** is also built using support.
2. More complicated and less intuitive than **leverage**.

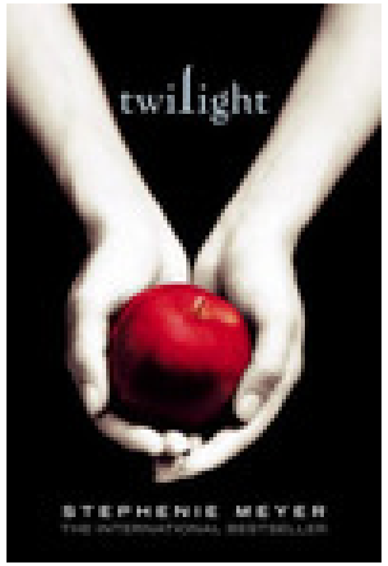
$$Conviction(X \rightarrow Y) =$$

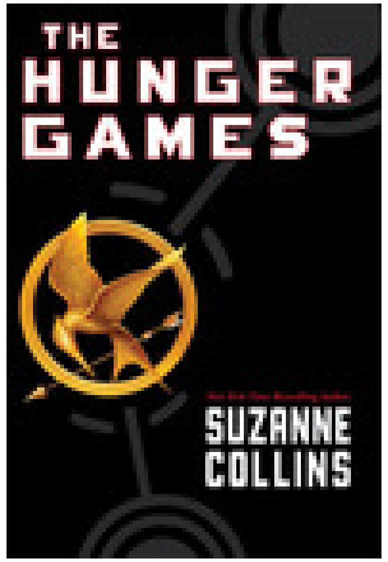
$$\frac{Support(X)Support(\bar{Y})}{Support(X\&\bar{Y})}$$

Interpreting conviction









[1] Images taken from goodreads.com.

Computing conviction

```
# Compute support for Twilight and Harry Potter and Twilight
supportTP = np.logical_and(books['Twilight'], books['Potter']).mean()
supportT = books['Twilight'].mean()
```

```
# Compute support for NOT Harry Potter
supportnP = 1.0 - books['Potter'].mean()
```

```
# Compute support for Twilight and NOT Harry Potter
supportTnP = supportT - supportPT
```

```
# Compute conviction
conviction = supportT*supportnP / supportTnP
print(conviction)
```

```
1.16
```

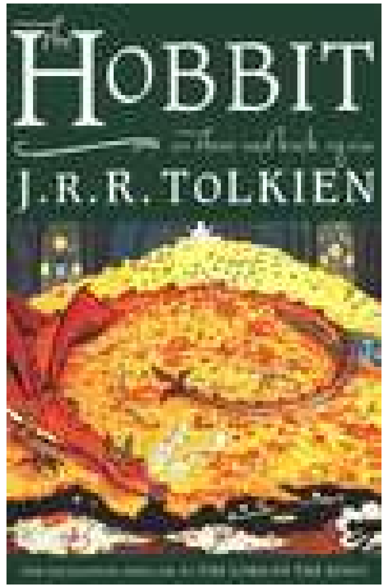
Let's practice!

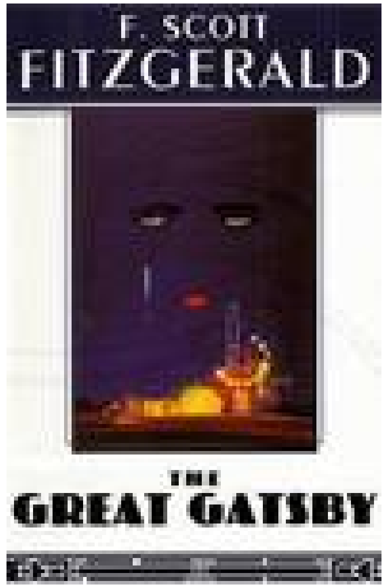
Association and dissociation

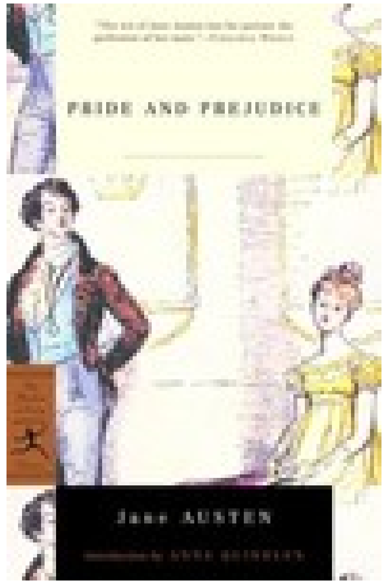
MARKET BASKET ANALYSIS IN PYTHON

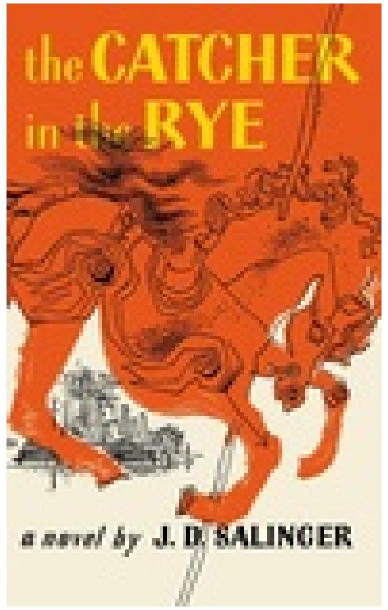
Isaiah Hull
Economist

Using dissociation to pair ebooks









[1] Images taken from goodreads.com.

Introduction to Zhang's metric

1. **Introduced by Zhang (2000)**
   - Takes values between -1 and +1
   - Value of +1 indicates perfect association
   - Value of -1 indicates perfect dissociation
2. **Comprehensive and interpretable**
3. **Constructed using support**

[1] Zhang, T. (2000). Association Rules. Proceedings of the 4th Pacific-Asia conference, PADKK, pp.245-256. Kyoto, Japan.

Defining Zhang's metric

$$Zhang(A \rightarrow B) =$$

$$\frac{Confidence(A \rightarrow B) - Confidence(\bar{A} \rightarrow B)}{Max[Confidence(A \rightarrow B), Confidence(\bar{A} \rightarrow B)]}$$

$$Confidence = \frac{Support(A\&B)}{Support(A)}$$

Constructing Zhang's metric using support

$$Zhang(A \rightarrow B) =$$

$$\frac{Support(A\&B) - Support(A)Support(B)}{Max[Support(AB)(1 - Support(A)), Support(A)(Support(B) - Support(AB))]}$$

Computing Zhang's metric

```
# Compute the support of each book
supportH = hobbit.mean()
supportP = pride.mean()
```

```
# Compute the support of both books
supportHP = np.logical_and(hobbit, pride).mean()
```

Computing Zhang's metric

```
# Compute the numerator
num = supportHP - supportH*supportP
```

```
# Compute the denominator
denom = max(supportHP*(1-supportH), supportH*(supportP-supportHP))
```

```
# Compute Zhang's metric
zhang = num / denom
print(zhang)
```

```
0.08903
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON

Advanced rules

MARKET BASKET ANALYSIS IN PYTHON

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Overview of market basket analysis

- **Standard procedure for market basket analysis.**
  1. Generate large set of rules.
  2. Filter rules using metrics.
  3. Apply intuition and common sense.

Generating rules

- **Number of rules grows exponentially in number of items.**
  - Most rules are not useful.
- **Must apply initial round of filtering.**
  - Covered in chapter 3 using Apriori algorithm

How does filtering work?

ID	antecedents	consequents	support	Lift
1	Harry Potter	The Hunger Games	**0.001**	1.01
2	Hunger Games	Twilight	0.020	1.23
3	Pride and Prejudice	The Hobbit	0.030	1.05
4	The Hobbit	Twilight	0.015	**0.85**
5	Harry Potter	The Hobbit	0.010	1.07

Multi-metric filtering

ID	antecedents	consequents	support	zhang
1	Harry Potter	The Hunger Games	0.001	-0.05
2	Hunger Games	Twilight	0.020	0.17
3	Pride and Prejudice	The Hobbit	0.030	0.06
4	The Hobbit	Twilight	0.015	-0.04
5	Harry Potter	The Hobbit	0.010	0.34

Performing multi-metric filtering

```
print(rules.head())
```

```
  antecedents consequents  antecedent support  ... support  confidence  ... conviction
0 Potter      Hunger       0.48                ...  0.12  ... 0.26      ...  0.92
1 Potter      Hunger       0.32                ...  0.12  ... 0.26      ...  0.92
2 Twilight    Hunger       0.26                ...  0.09  ... 0.35      ...  1.04
3 Hunger      Twilight     0.32                ...  0.09  ... 0.28      ...  1.03
4 Mockingbird Hunger       0.48                ...  0.10  ... 0.20      ...  0.85
```

Performing multi-metric filtering

```
# Select subset of rules with low consequent support.
rules = rules[rules['consequent support'] < 0.05]
print(len(rules))
```

```
12
```

```
# Select subset of rules with lift > 1.5.
rules = rules[rules['lift'] > 1.5]
print(len(rules))
```

```
2
```

Let's practice!

MARKET BASKET ANALYSIS IN PYTHON