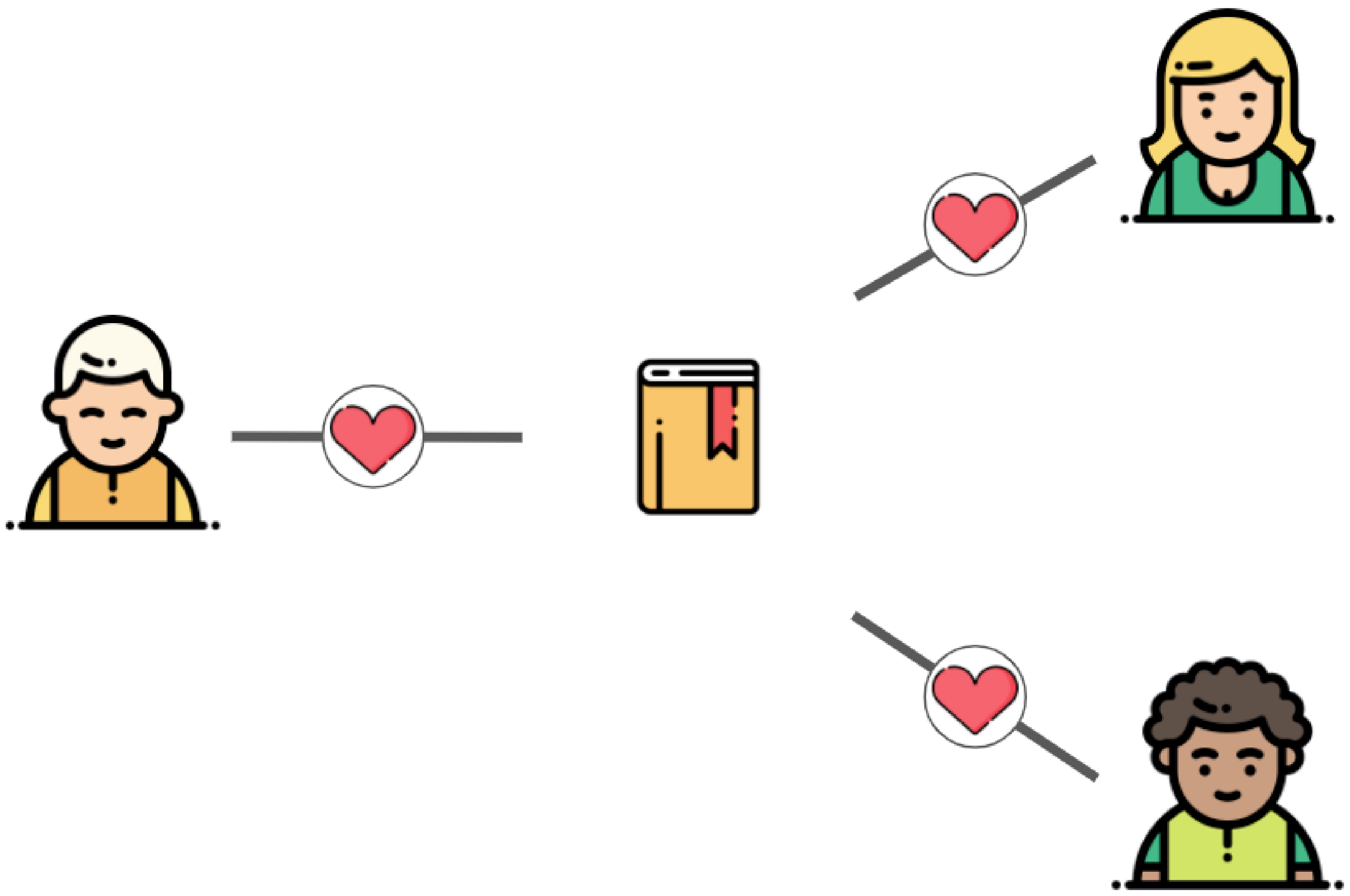
Collaborative filtering

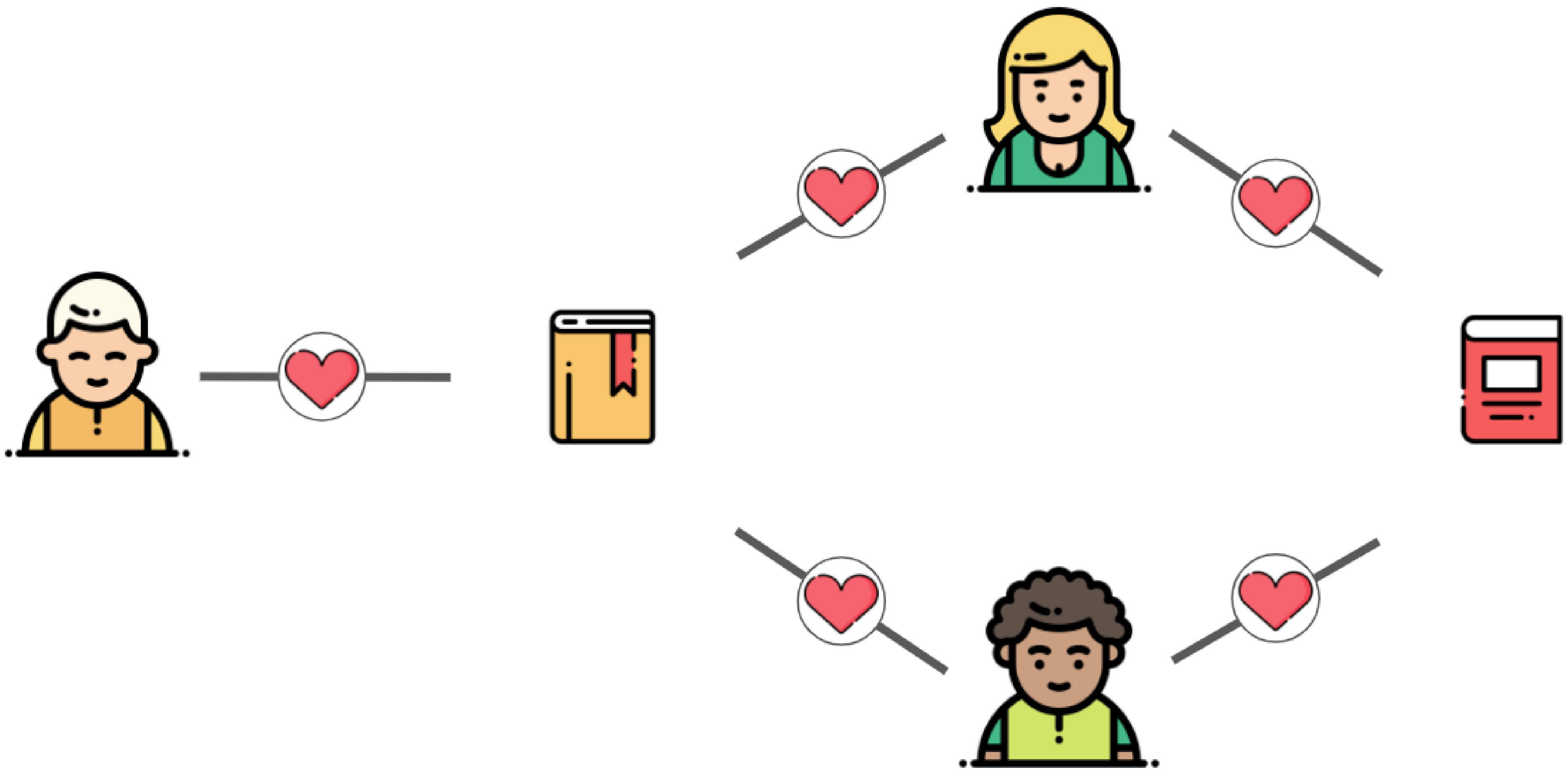
BUILDING RECOMMENDATION ENGINES IN PYTHON

Rob O'Callaghan
Director of Data

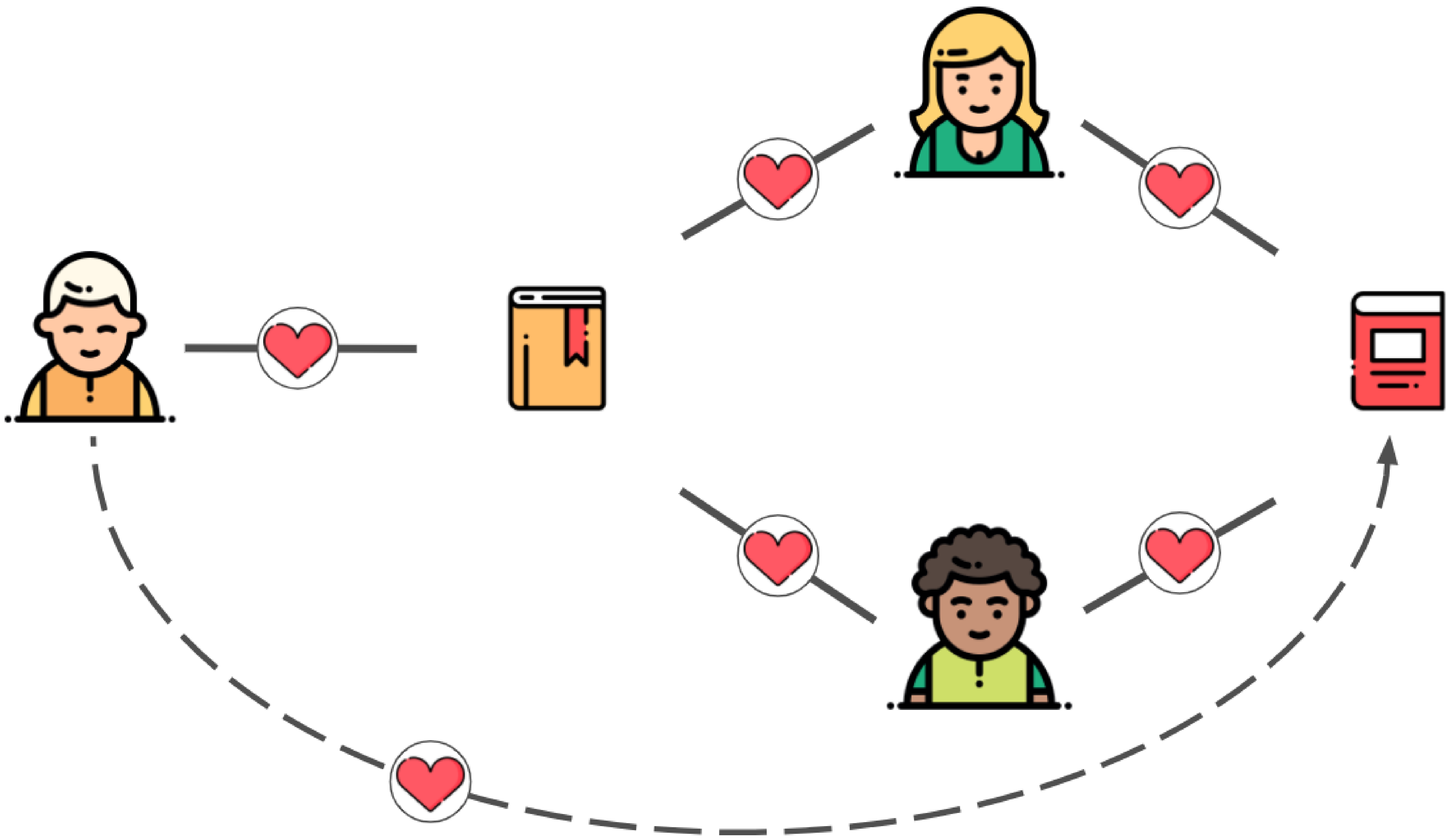
Collaborative filtering



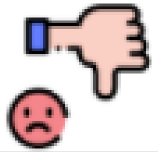
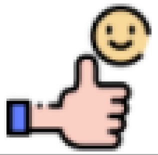
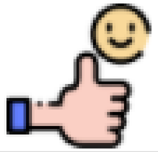
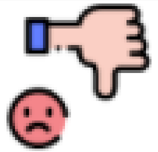
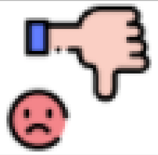
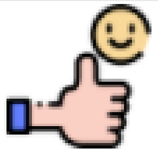
Collaborative filtering



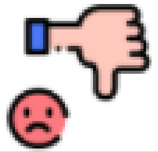
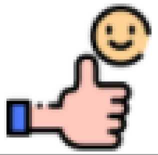
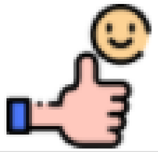
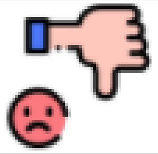
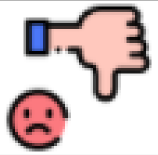
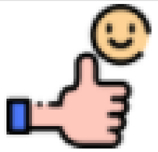
Collaborative filtering

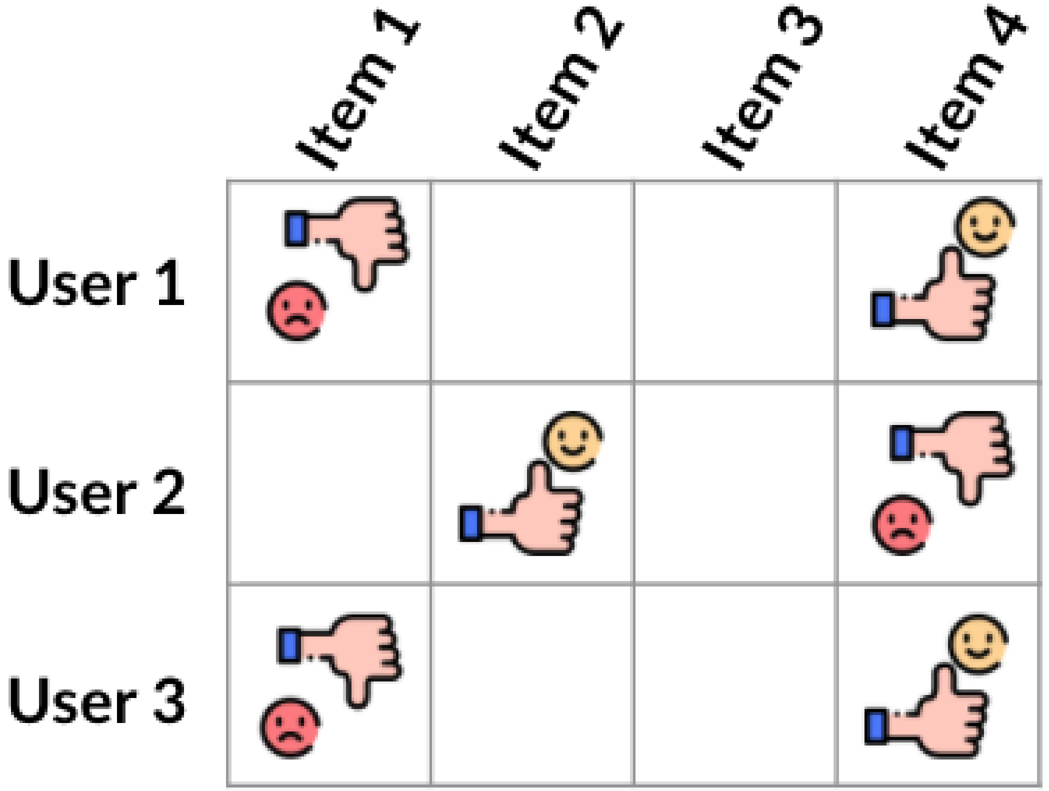


Finding similar users

User ID	Item ID	Review
User 1	Item 1	
User 1	Item 4	
User 2	Item 2	
User 2	Item 4	
User 3	Item 1	
User 3	Item 4	

Finding similar users

User ID	Item ID	Review
User 1	Item 1	
User 1	Item 4	
User 2	Item 2	
User 2	Item 4	
User 3	Item 1	
User 3	Item 4	



Working with real data

`user_ratings` DataFrame:

User	Book	Rating
User_233	The Great Gatsby	3.0
User_651	The Catcher in the Rye	5.0
User_131	The Lord of the Rings	3.0
User_965	The Great Gatsby	4.0
User_651	Fifty Shades of Grey	4.0
...	...	...

Pivoting our data

```
user_ratings_pivot = user_ratings.pivot(index='User',
                                        columns='Book',
                                        values='Rating')
print(user_ratings_pivot)
```

```
title       The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User
User_233                 3.0                       NaN                     NaN
User_651                 NaN                       5.0                     4.0
User_965                 4.0                       3.0                     NaN
     ...                 ...                       ...                     ...
```

Data sparsity

```
title      The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User
User_233                3.0                       NaN                     NaN
User_651                NaN                       5.0                     4.0
User_965                4.0                       3.0                     NaN
     ...                ...                       ...                     ...
```

```
print(user_ratings_pivot.dropna())
```

```
Empty DataFrame
Columns: ["The Great Gatsby", "The Catcher in the Rye", "Fifty Shades of Grey"]
Index: []
```

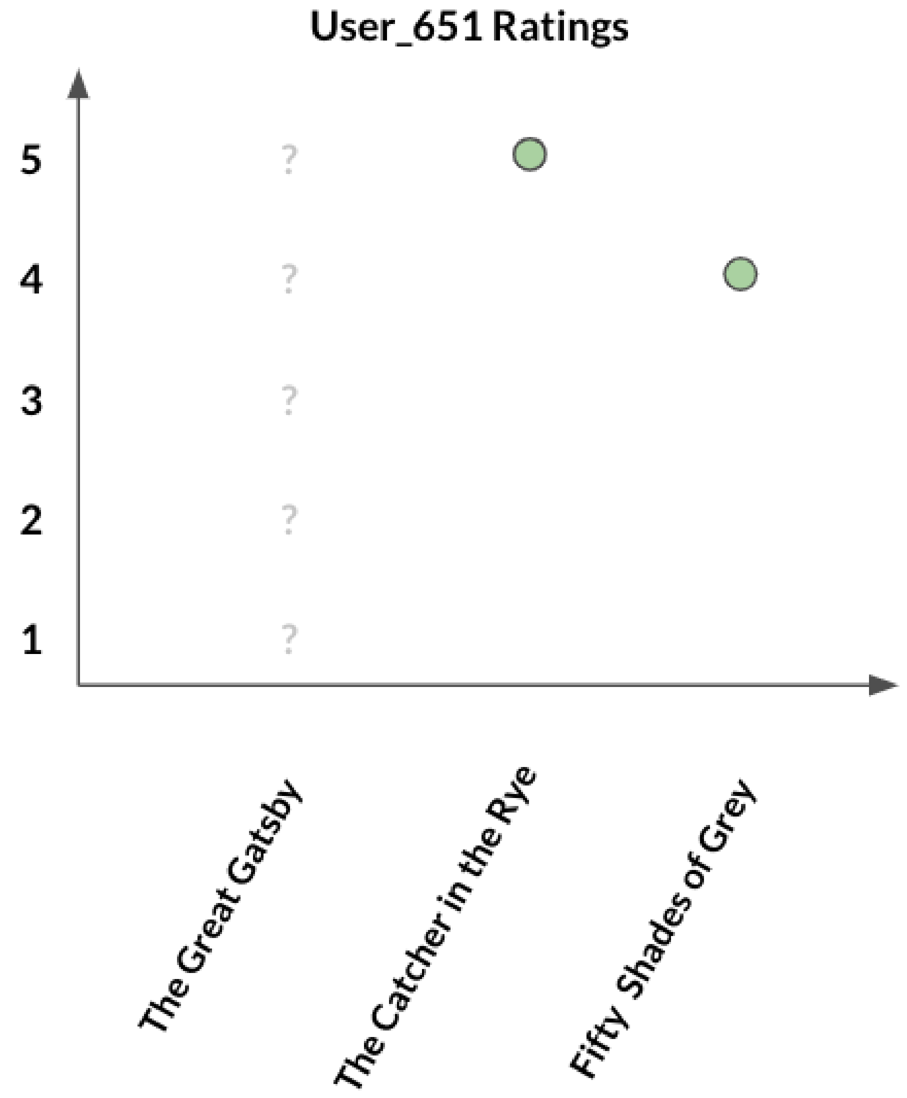
Filling the missing values

```
title      The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User
User_233                3.0                       NaN                     NaN
User_651                NaN                       5.0                     4.0
User_965                4.0                       3.0                     NaN
     ...                ...                       ...                     ...
```

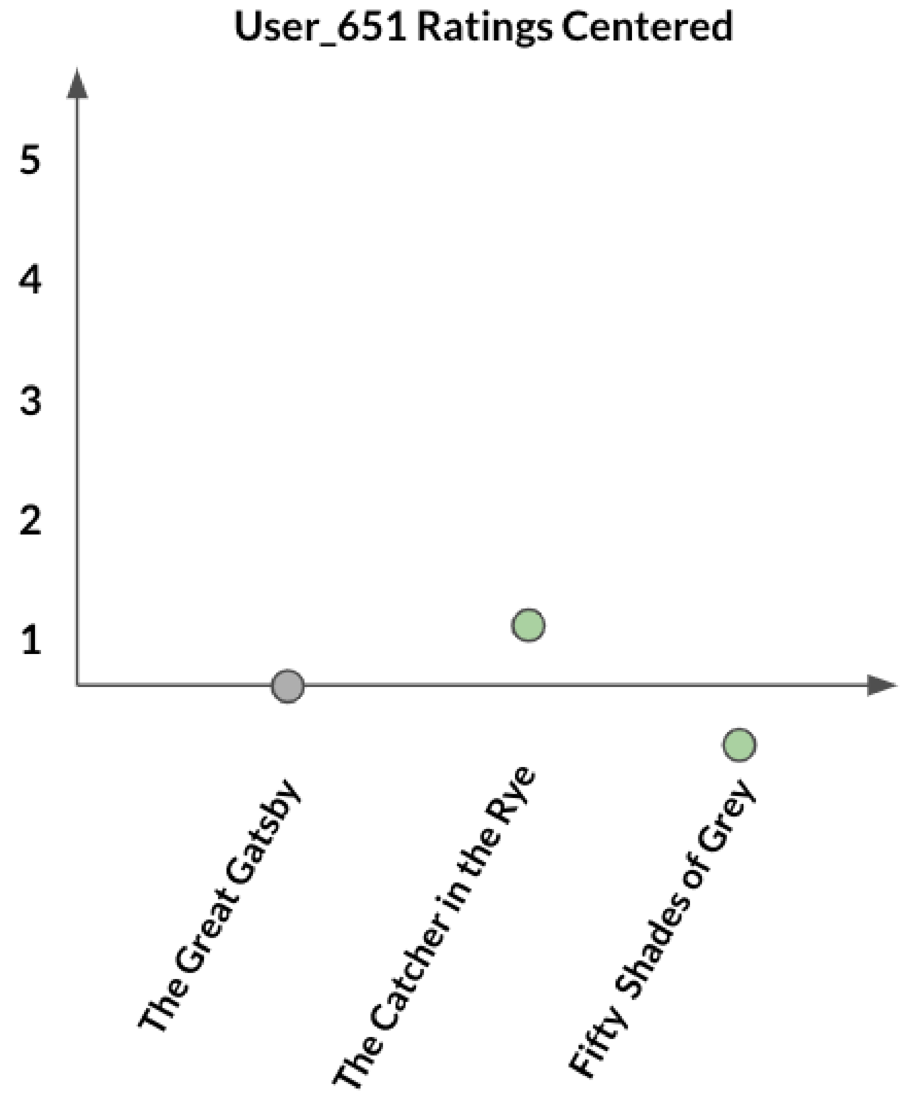
```
print(user_ratings_pivot["User_651"].fillna(0))
```

```
User_651                0.0                       5.0                     4.0
```

Filling the missing values



Center around 0



Filling the missing values

```
avg_ratings = user_ratings_pivot.mean(axis=1)
user_ratings_pivot = user_ratings_pivot.sub(avg_ratings, axis=0)
print(user_ratings_pivot)
```

```
title     The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User
User_233               0.0                       NaN                     NaN
User_651               NaN                       0.5                    -0.5
User_965               0.5                      -0.5                     NaN
     ...               ...                       ...                     ...
```

Filling the missing values

```
user_ratings_pivot.fillna(0)
```

```
title      The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User
User_233                0.0                       0.0                     0.0
User_651                0.0                       0.5                    -0.5
User_965                0.5                      -0.5                     0.0
     ...                ...                       ...                     ...
```

Let's practice!

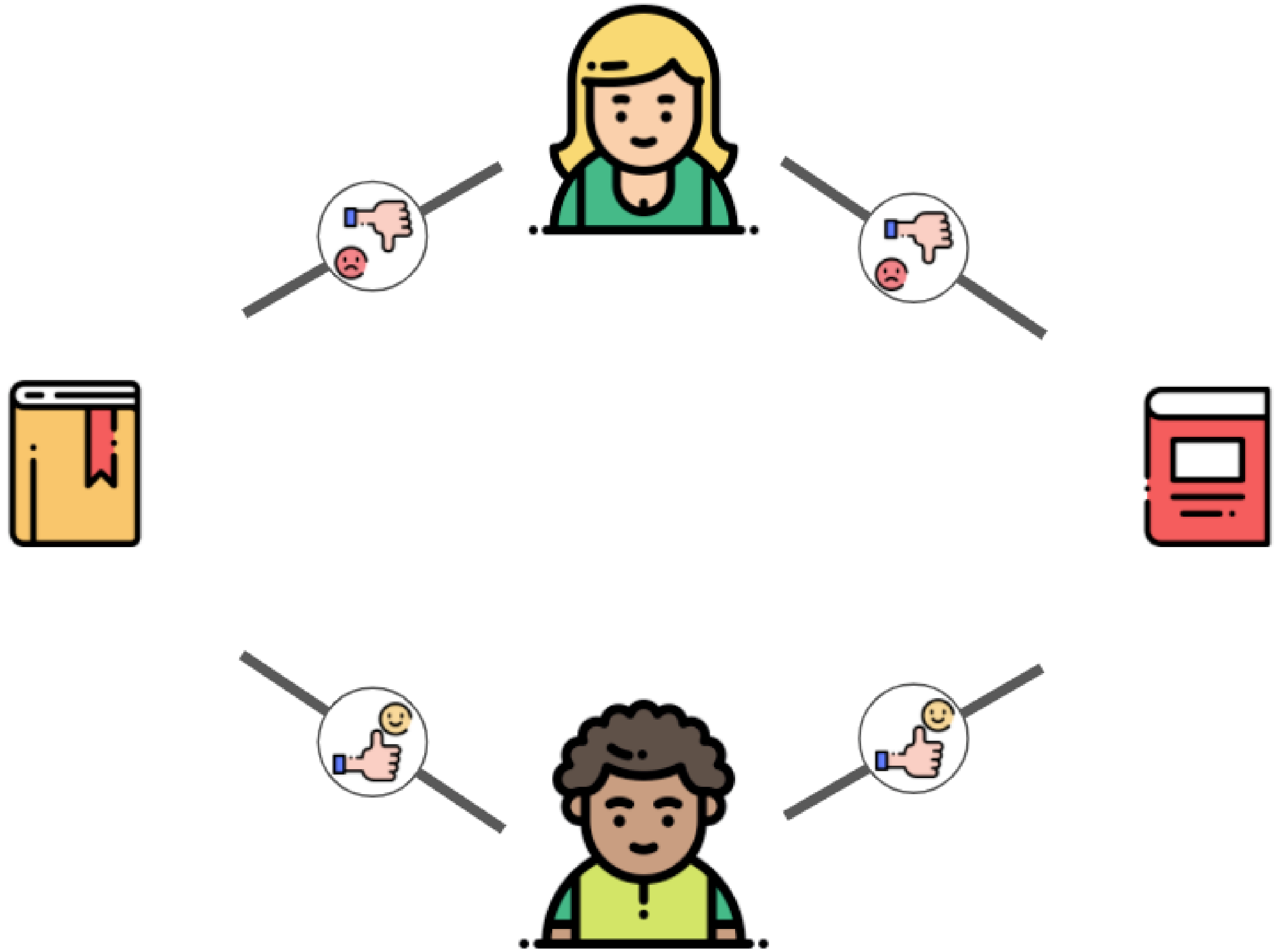
BUILDING RECOMMENDATION ENGINES IN PYTHON

Finding similarities

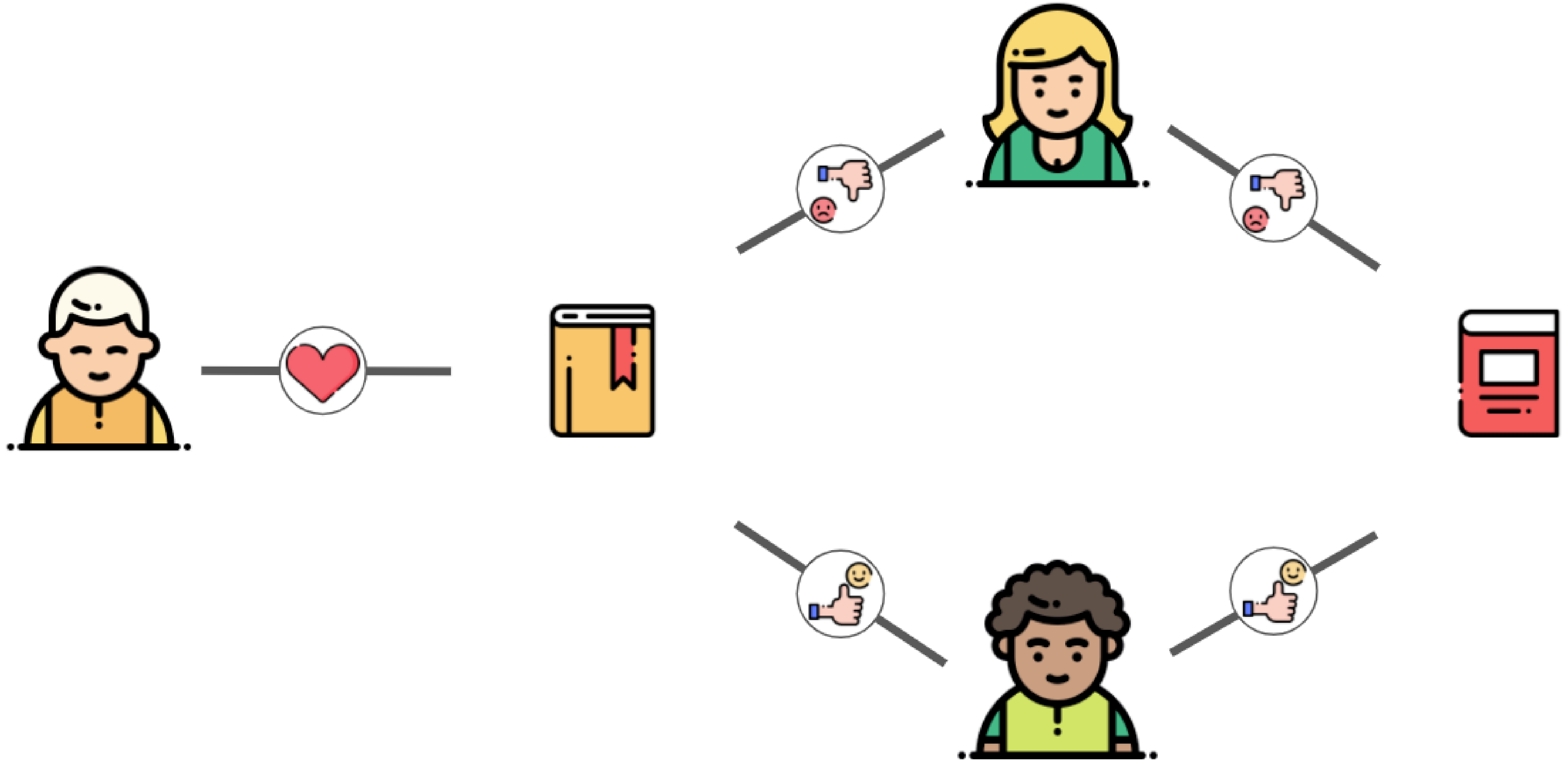
BUILDING RECOMMENDATION ENGINES IN PYTHON

Rob O'Callaghan
Director of Data

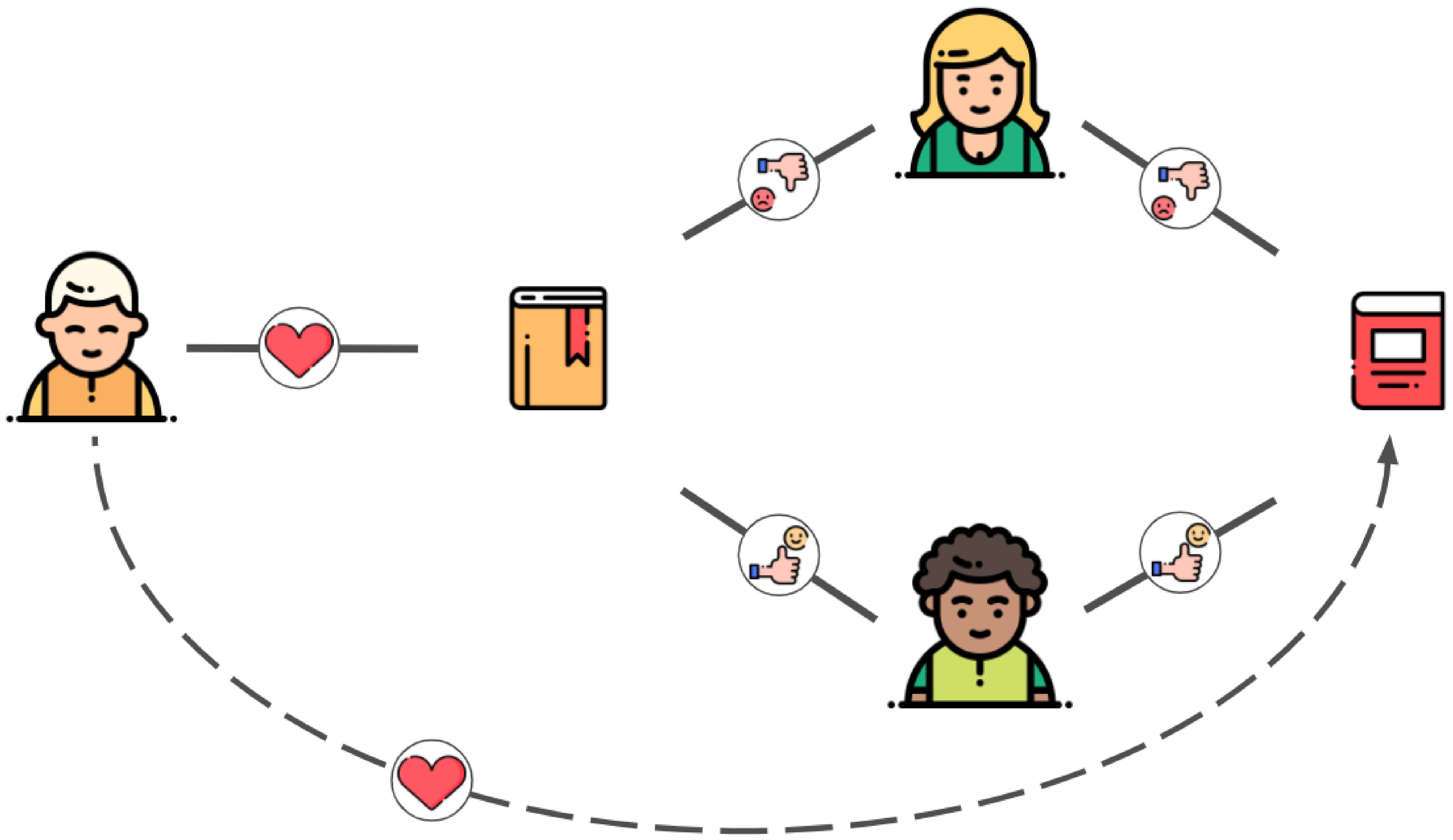
Item-based recommendations



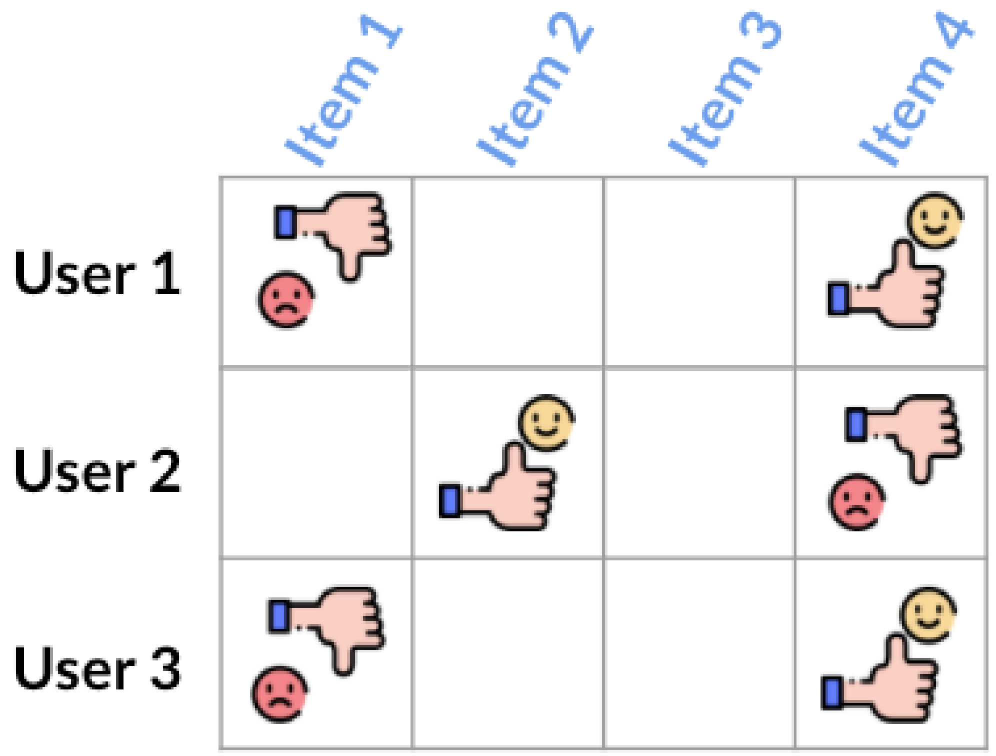
Item-based recommendations



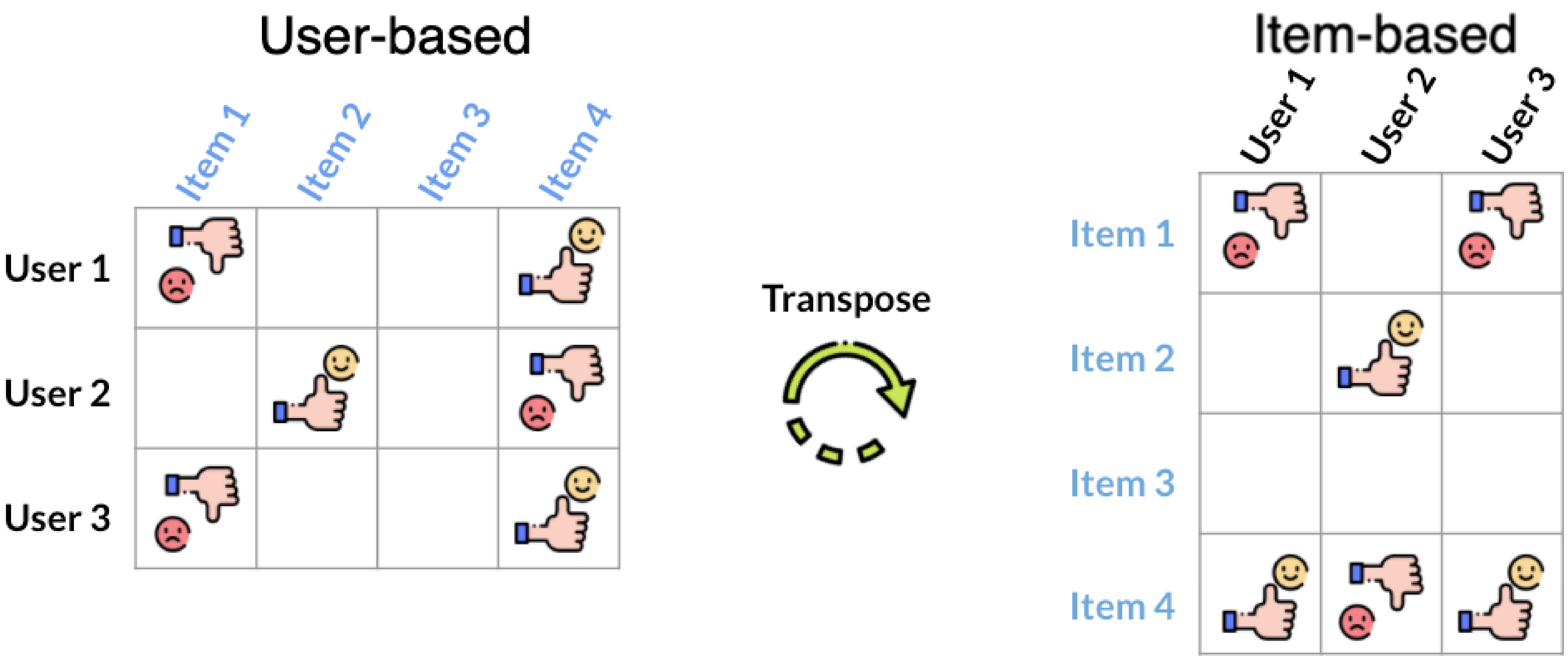
Item-based recommendations



User-based to item-based



User-based to item-based



User-based to item-based

```
print(user_ratings_pivot):
```

```
          The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
User_233               0.0                       0.0                     0.0
User_651               0.0                       0.5                    -0.5
User_965               0.5                      -0.5                     0.0
     ...               ...                       ...                     ...
```

```
book_ratings_pivot = user_ratings_pivot.T
print(book_ratings_pivot)
```

```
                  User_233                  User_651                User_965
The Great Gatsby       0.0                       0.0                     0.5
The Catcher in the Rye 0.0                       0.5                    -0.5
Fifty Shades of Grey   0.0                      -0.5                     0.0
                  ...  ...                       ...                     ...
```

Cosine similarities

`book_ratings_pivot`:

```
                       User_233                 User_651                 User_965
The Great Gatsby            0.0                      0.0                      0.5
The Catcher in the Rye 0.0                           0.5                     -0.5
Fifty Shades of Grey        0.0                     -0.5                      0.0
                  ...       ...                      ...                      ...
```

Cosine similarities

```
cosine_similarity(                                                     ,
                                                              )
```

Cosine similarities

```
cosine_similarity(book_ratings_pivot.loc['Lord of the Rings', :]                         ,
                  book_ratings_pivot.loc['The Hobbit', :]                     )
```

Cosine similarities

```
cosine_similarity(book_ratings_pivot.loc['Lord of the Rings', :].values                      ,
                  book_ratings_pivot.loc['The Hobbit', :].values                     )
```

Cosine similarities

```
cosine_similarity(book_ratings_pivot.loc['Lord of the Rings', :].values.reshape(1, -1),
                  book_ratings_pivot.loc['The Hobbit', :].values.reshape(1, -1))
```

```
0.43
```

```
cosine_similarity(book_ratngs.loc['Lord of the Rings', :].values.reshape(1, -1),
                  book_ratngs.loc['Twilight', :].values.reshape(1, -1))
```

```
-0.64
```

Cosine similarities

```
similarities = cosine_similarity(book_ratings_pivot)
cosine_similarity_df = pd.DataFrame(book_ratings_pivot,
                                    index=book_ratings_pivot.index,
                                    columns=book_ratings_pivot.index)
cosine_similarity_df.head()
```

```
          The Great Gatsby    The Catcher in the Rye    Fifty Shades of Grey
The Great Gatsby       1.0                       0.0                    -0.3
The Catcher in the Rye 0.0                       1.0                    -0.5
Fifty Shades of Grey  -0.3                      -0.5                     1.0
                ...   ...                       ...                      ...
```

Cosine similarities

```
cosine_similarity_series = cosine_similarity_df.loc['The Hobbit']
ordered_similarities = cosine_similarity_series.sort_values(ascending=False)
print(ordered_similarities)
```

```
The Hobbit          1.00
Lord of the Rings   0.43
The Silmarillion    0.37
...
```

Let's practice!

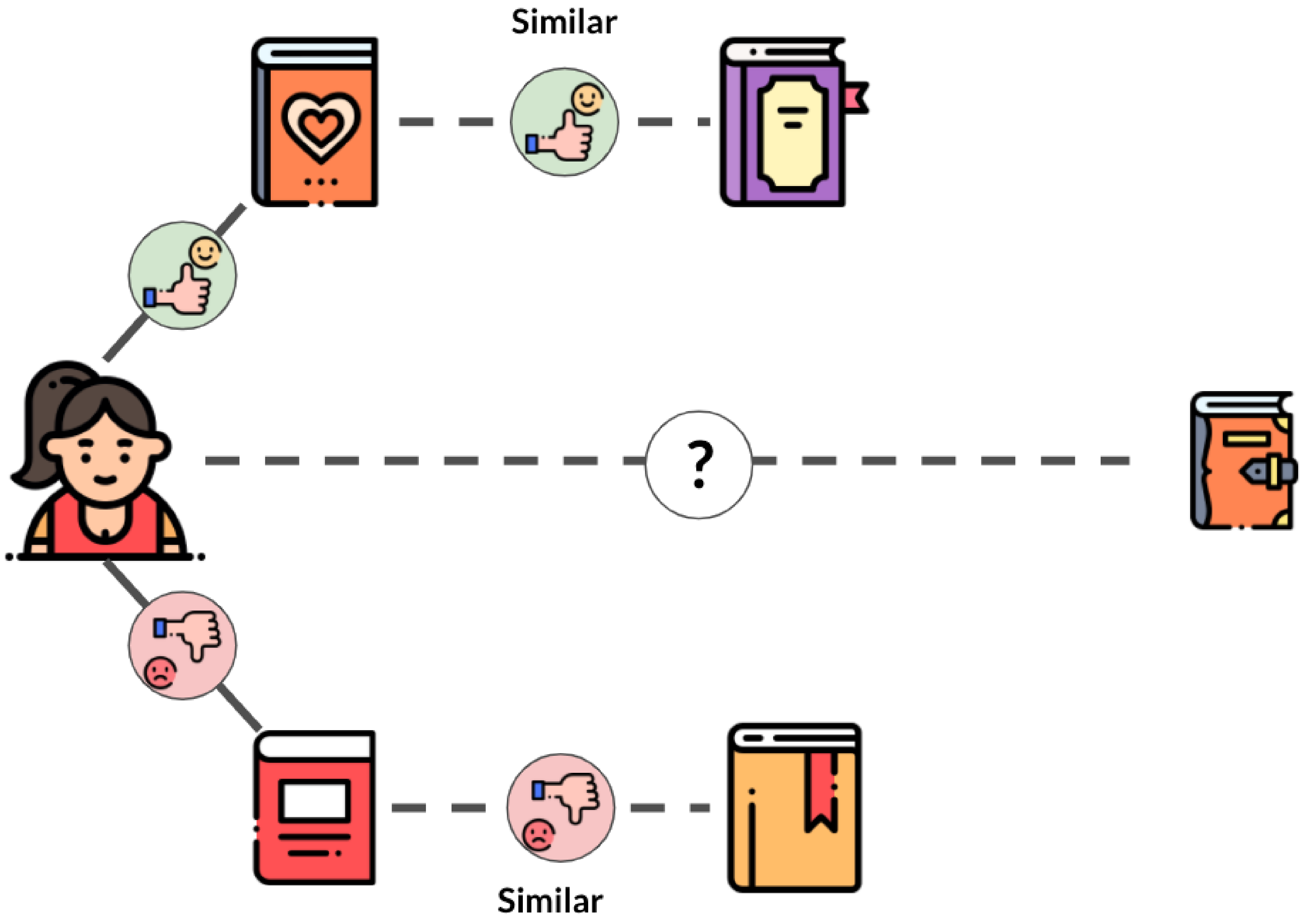
BUILDING RECOMMENDATION ENGINES IN PYTHON

Using K-nearest neighbors

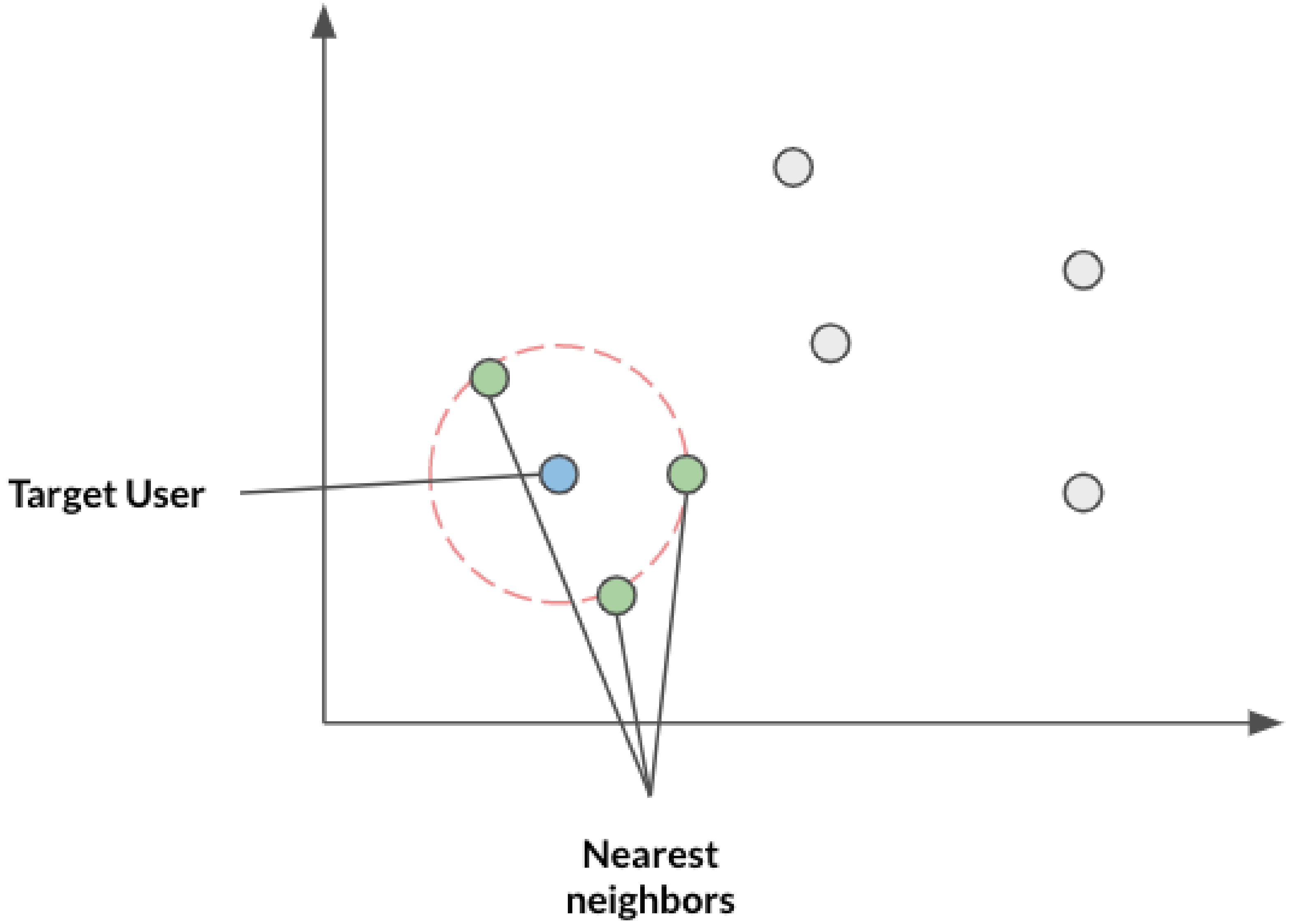
BUILDING RECOMMENDATION ENGINES IN PYTHON

Rob O'Callaghan
Director of Data

Beyond similar items



K-nearest neighbors



User-user similarity

```
similarities = cosine_similarity(user_ratings_pivot)
cosine_similarity_df = pd.DataFrame(user_ratings_pivot,
                                    index=user_ratings_pivot.index,
                                    columns=user_ratings_pivot.index)
cosine_similarity_df.head()
```

```
                  User 001                 User 002                 User 003
User 001               1.0                     -0.4                      0.3
User 002              -0.4                      1.0                     -0.5
User 003               0.3                     -0.5                      1.0
                 ...   ...                      ...                      ...
```

Understanding the similarity matrix

```
                User 001        User 002      User 003

User 001             1.0            -0.4           0.3

User 002            -0.4             1.0          -0.5

User 003             0.3            -0.5           1.0
     ...             ...             ...           ...
```

Understanding the similarity matrix

```
                                                       v
                User 001         User 002      |User 003|
 ---------------------------------------------------------
User 001             1.0             -0.4      |     0.3| <-
 ---------------------------------------------------------
User 002            -0.4              1.0           -0.5


User 003             0.3             -0.5            1.0
     ...             ...              ...            ...
```

Understanding the similarity matrix

```
                                        v
                User 001        |User 002 |     User 003
 ----------------------------------------
User 001             1.0        |    -0.4 |    <-    0.3
 -----------------------------------------
User 002            -0.4              1.0           -0.5


User 003             0.3             -0.5            1.0
     ...             ...              ...            ...
```

Step by step KNN

```
user_similarity_series = user_similarities.loc['user_001']
ordered_similarities = user_similarity_series.sort_values(ascending=False)
nearest_neighbors = ordered_similarities[1:4].index
print(nearest_neighbors)
```

```
user_007
user_042
user_003
```

Step by step KNN

```
neighbor_ratings = user_ratings_table.reindex(nearest_neighbors)
neighbor_ratings['Catch-22'].mean()
```

```
3.2
```

Using scikit-learn's KNN

```
print(user_ratings_pivot)
```

```
          The Great Gatsby              Catch-22    Fifty Shades of Grey
User_233               0.0                   0.0                     0.0
User_651               0.0                   0.5                    -0.5
     ...               ...                   ...                     ...
```

```
print(user_ratings_table)
```

```
          The Great Gatsby              Catch-22    Fifty Shades of Grey
User_233               NaN                   NaN                     NaN
User_651               NaN                   5.0                     4.0
     ...               ...                   ...                     ...v
```

Using scikit-learn's KNN

```
user_ratings_pivot.drop("Catch-22", axis=1, inplace=True)
target_user_x = user_ratings_pivot.loc[["user_001"]]
print(target_user_x)
```

```
          The Great Gatsby   Fifty Shades of Grey                  Iliad
User_001               4.0                    2.0                    3.0
```

```
other_users_y = user_ratings_table["Catch-22"]
print(other_users_y)
```

```
[NaN, '5.0', '3.0', '4.0', '5.0' ...]
```

Using scikit-learn's KNN

```
other_users_x = user_ratings_pivot[other_users_y.notnull()]
print(other_users_x)
```

```
           The Great Gatsby   Fifty Shades of Grey                   Iliad
User_651                0.0                   -0.5                    -0.5
User_442                1.0                    0.0                     1.0
     ...                ...                    ...                     ...
```

```
other_users_y.dropna(inplace=True)
print(other_users_y)
```

```
['5.0', '3.0', '4.0','5.0' ...]
```

Using scikit-learn's KNN

```
from sklearn.neighbors import KNeighborsRegressor
user_knn = KNeighborsRegressor(metric='cosine', n_neighbors=3)
user_knn.fit(other_users_x, other_users_y)
user_user_pred = user_knn.predict(target_user_x)
print(user_user_pred)
```

```
3.3
```

Using scikit-learn's KNN

```python
from sklearn.neighbors import KNeighborsClassifier
user_knn = KNeighborsClassifier(metric='cosine', n_neighbors=3)
user_knn.fit(other_users_x, other_users_y)
user_user_pred = user_knn.predict(target_user_x)
print(user_user_pred)
```

```
3
```

Let's practice!

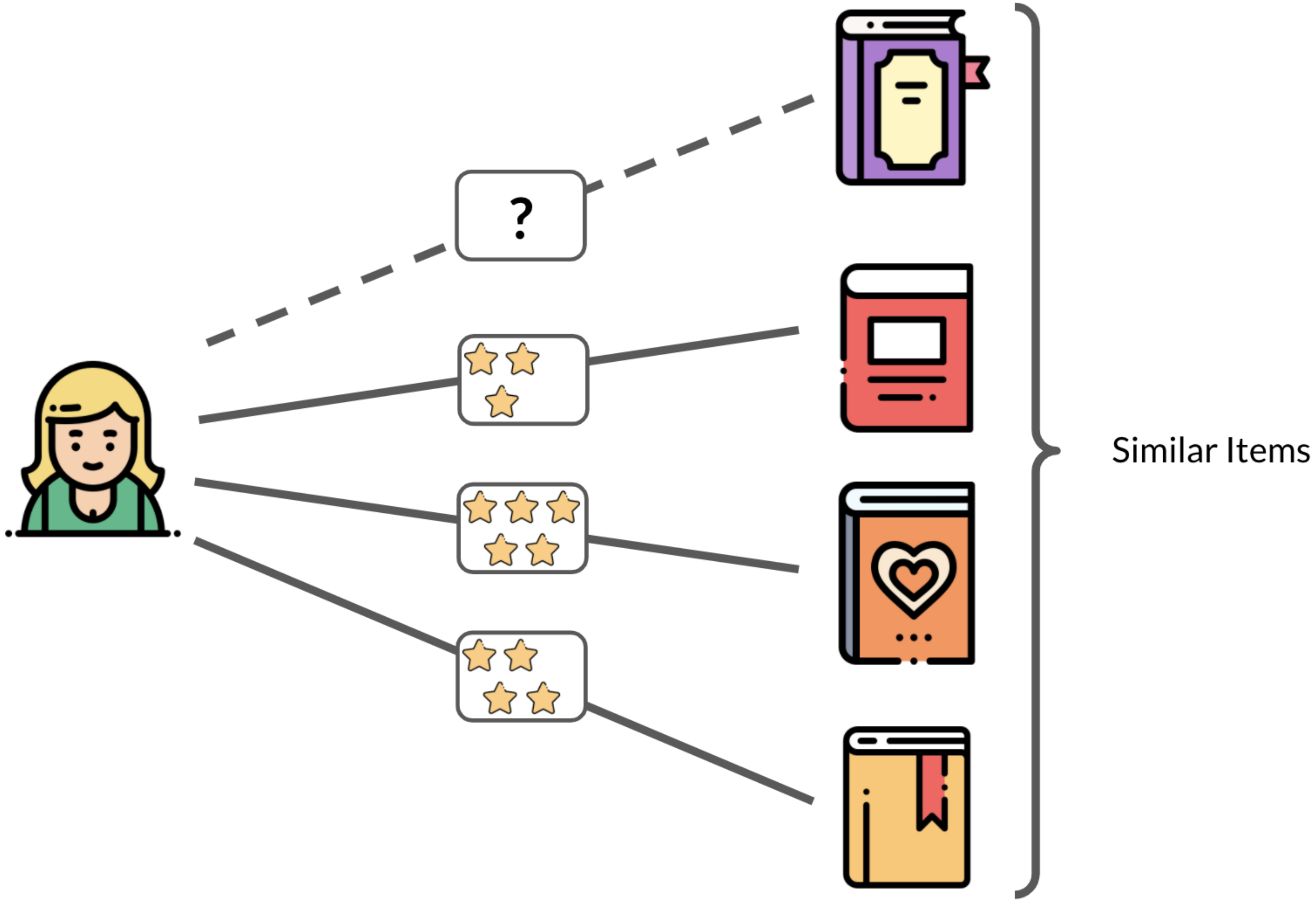
BUILDING RECOMMENDATION ENGINES IN PYTHON

Item-based or user-based

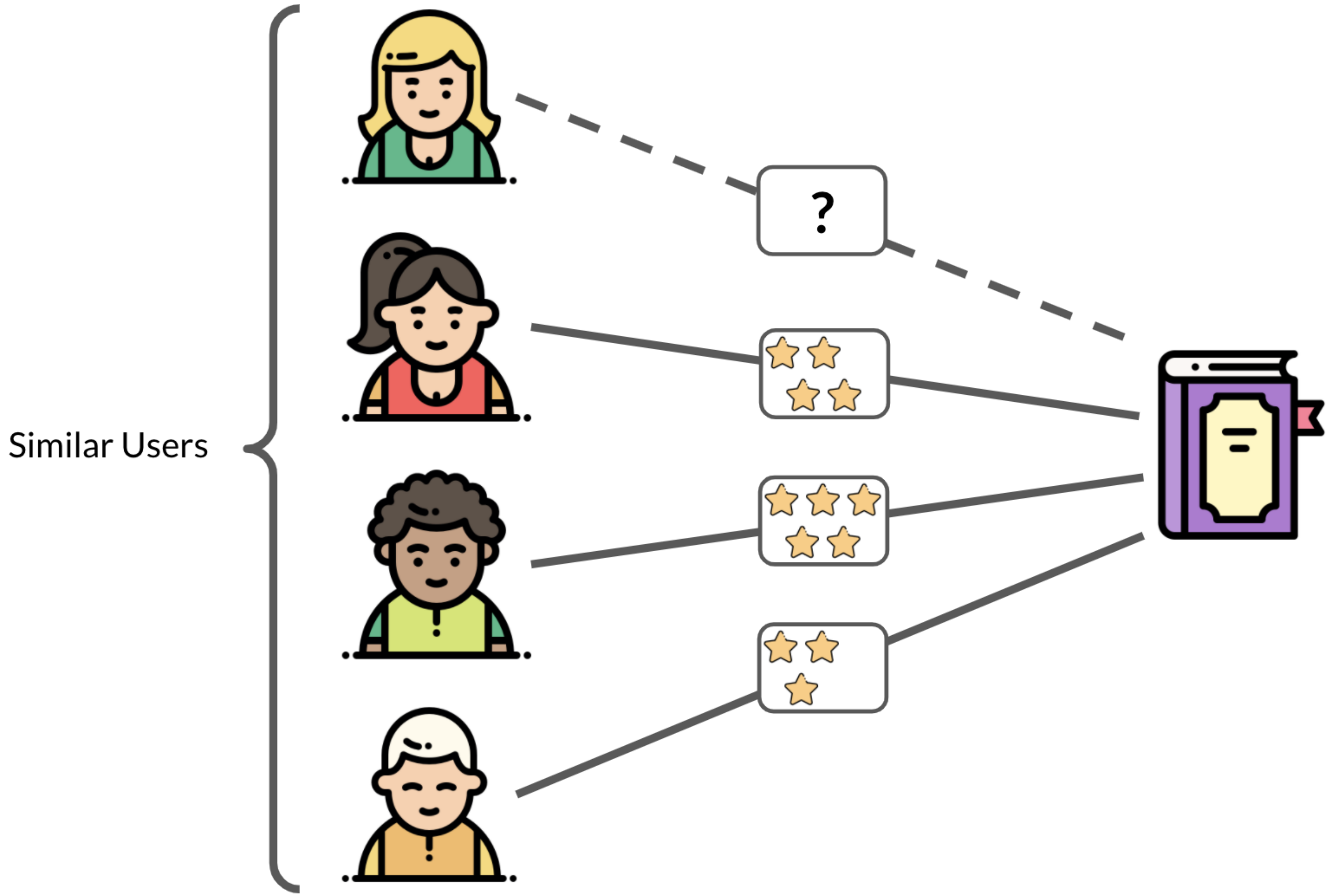
BUILDING RECOMMENDATION ENGINES IN PYTHON

Rob O'Callaghan
Director of Data

Item-based filtering



User-based filtering



Why use item-based filtering?

Pros:

- Item-based recommendations are more consistent over time
- Item-based recommendations can be easier to explain
- Item-based recommendations can be pre-calculated

Cons:

- Item-based recommendations result in very obvious suggestions

Why use user-based filtering?

Pros:

- User-based recommendations can create a lot more interesting suggestions

Cons:

- Generally beaten by item-based recommendations using standard metrics

Let's practice!

BUILDING RECOMMENDATION ENGINES IN PYTHON