Collaborative Filtering at Scale

Recommender engines with **Mahout** and **Hadoop**

Berlin Buzzwords

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Mahout is …

- Machine learning …
  - **Collaborative filtering (recommenders)**
  - Clustering
  - Classification
  - Frequent item set mining
  - and more
- … at scale
  - Much implemented on Hadoop
  - Efficient data structures

Collaborative Filtering is …

- Given a **user's preferences** for **items**, guess which other items would be highly preferred
- Only needs preferences; users and items opaque
- Many algorithms!

Collaborative Filtering is …

Sean likes "Scarface" a lot
Robin likes "Scarface" somewhat
Grant likes "The Notebook" not at all
…

(123,654,5.0)
(789,654,3.0)
(345,876,1.0)
…

Magic

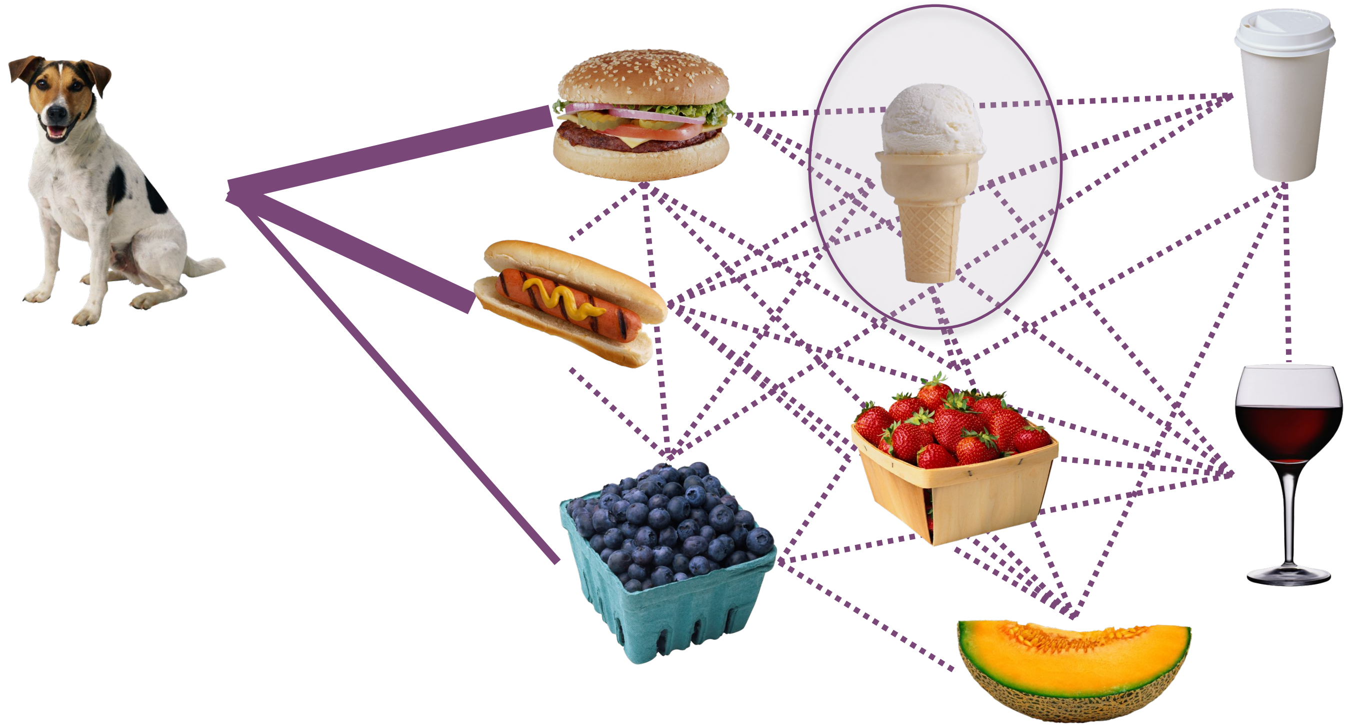
(345,654,4.5)
…

Grant may like "Scarface" quite a bit
…

Recommending people food

Item-Based Algorithm

- Recommend items similar to a user's highly-preferred items



Item-Based Algorithm

- Have user's preference for items
- Know all items and can compute weighted average to *estimate user's preference*
- What is the item – item similarity notion?

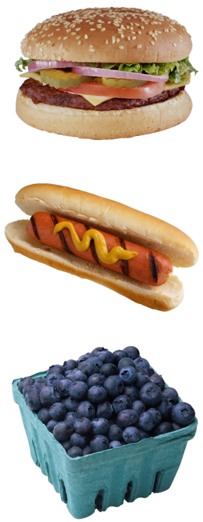
```
for every item i that u has no preference for yet
  for every item j that u has a preference for
    compute a similarity s between i and j
    add u's preference for j, weighted by s,
             to a running average
return the top items, ranked by weighted average
```

Item-Item Similarity

- Could be based on content…
  - Two foods similar if both sweet, both cold
- **BUT** in collaborative filtering, based only on preferences (numbers)
  - Pearson correlation between ratings ?
  - Log-likelihood ratio ?
  - **Simple co-occurrence**:
    Items similar when appearing often in the same user's set of preferences

Estimating preference

Preference



5

5

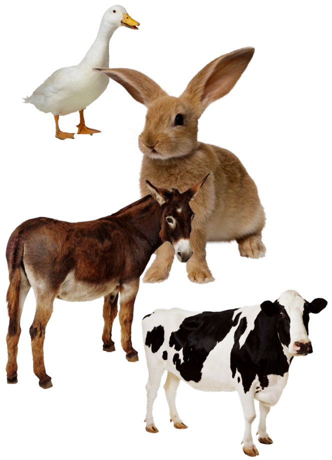
2

9

16

5

Co-occurrence



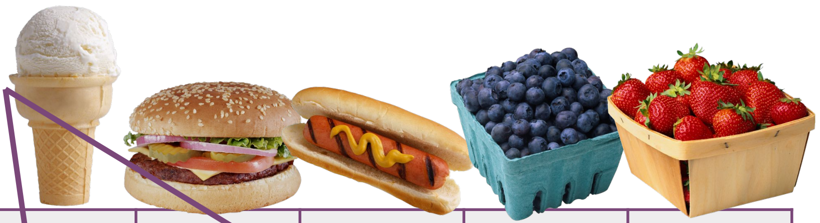
4.5  $= \dfrac{5 \cdot 9 + 5 \cdot 16 + 2 \cdot 5}{9 + 16 + 5} = \dfrac{135}{30}$

As matrix math

- User's **preferences** are a **vector**
  - Each dimension corresponds to one item
  - Dimension value is the preference value
- Item-item **co-occurrences** are a **matrix**
  - Row i / column j is count of item i / j co-occurrence
- Estimating preferences:
  co-occurrence **matrix** × preference (column) **vector**

As matrix math

16 animals ate both hot dogs and ice cream



16	9	16	5	6
9	30	19	3	2
16	19	23	5	4
5	3	5	10	20
6	2	4	20	9

×

0
5
5
2
0

=

135
251
220
60
70

10 animals ate blueberries

A different way to multiply

- **Normal**: for each row of matrix
  - Multiply (dot) row with column vector
  - Yields scalar: one final element of recommendation vector
- **Inside-out**: for each element of column vector
  - Multiply (scalar) with corresponding matrix *column*
  - Yield column vector: parts of final recommendation vector
  - Sum those to get result
  - Can skip for zero vector elements!

As matrix math, again

$$5\begin{bmatrix}9\\30\\19\\3\\2\end{bmatrix} + 5\begin{bmatrix}16\\19\\23\\5\\4\end{bmatrix} + 2\begin{bmatrix}5\\3\\5\\10\\20\end{bmatrix} = \begin{bmatrix}135\\251\\220\\60\\70\end{bmatrix}$$

What is MapReduce?

- **1** Input is a series of key-value pairs: (K1,V1)
- **2** map() function receives these, outputs 0 or more (K2, V2)
- **3** All values for each K2 are collected together
- **4** reduce() function receives these, outputs 0 or more (K3,V3)
- Very distributable and parallelizable
- Most large-scale problems can be chopped into a series of such MapReduce jobs

Build user vectors (mapper)

- Input is text file: `user,item,preference`
- Mapper receives
  - K1 = file position (ignored)
  - V1 = line of text file
- Mapper outputs, for each line
  - K2 = user ID
  - V2 = (item ID, preference)

1

Build user vectors (reducer)

- Reducer receives
  - K2 = user ID
  - V2,… = (item ID, preference), …
- Reducer outputs
  - K3 = user ID
  - V3 = Mahout Vector implementation
- Mahout provides custom Writable implementations for efficient Vector storage

1

Count co-occurrence (mapper)

- Mapper receives
  - K1 = user ID
  - V1 = user Vector
- Mapper outputs, for each pair of items
  - K2 = item ID
  - V2 = other item ID

2

Count co-occurrence (reducer)

- Reducer receives
  - K2 = item ID
  - V2,… = other item ID, …
- Reducer tallies each other item; creates a Vector
- Reducer outputs
  - K3 = item ID
  - V3 = column of co-occurrence matrix as Vector

2

Partial multiply (mapper #1)

- Mapper receives
  - K1 = user ID
  - V1 = user Vector
- Mapper outputs, for each item
  - K2 = item ID
  - V2 = (user ID, preference)

3

Partial multiply (mapper #2)

- Mapper receives
  - K1 = item ID
  - V1 = co-occurrence matrix column Vector
- Mapper outputs
  - K2 = item ID
  - V2 = co-occurrence matrix column Vector

3

Partial multiply (reducer)

- Reducer receives
  - K2 = item ID
  - V2,… = (user ID, preference), …
    and co-occurrence matrix column Vector
- Reducer outputs, for each item ID
  - K3 = item ID
  - V3 = column vector and (user ID, preference) pairs

Aggregate (mapper)

- Mapper receives
  - K1 = item ID
  - V1 = column vector and (user ID, preference) pairs
- Mapper outputs, for each user ID
  - K2 = user ID
  - V2 = column vector times preference

4

Aggregate (reducer)

- Reducer receives
  - K2 = user ID
  - V2,… = partial recommendation vectors
- Reducer sums to make recommendation Vector and finds top n values
- Reducer outputs, for top value
  - K3 = user ID
  - V3 = (item ID, value)

4

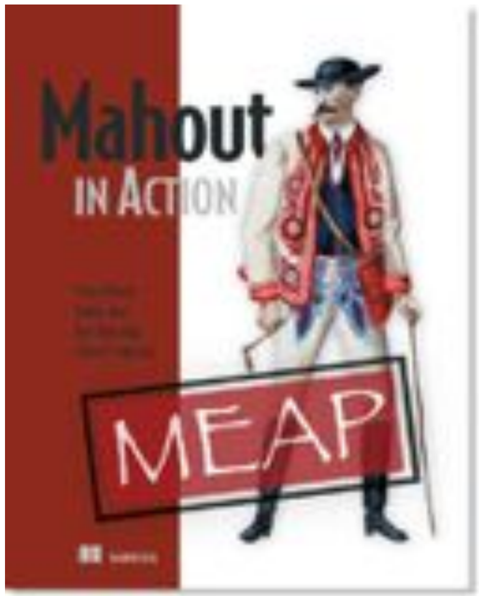
Reality is a bit more complex

Ready to try

- Obtain and build Mahout from Subversion
  http://mahout.apache.org/versioncontrol.html
- Set up, run Hadoop in local pseudo-distributed mode
- Copy input into local HDFS
- ```
  hadoop jar mahout-0.4-SNAPSHOT.job
    org.apache.mahout.cf.taste.hadoop.item.RecommenderJob
    -Dmapred.input.dir=input
    -Dmapred.output.dir=output
  ```
  ```

Mahout in Action

- Recommenders
  - Data representation
  - Non-distributed algorithms
  - Distributed algorithms
- Clustering
  - Available in weeks
- Classification
  - In progress
- http://www.manning.com/owen/



Questions?

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