Introduction to Recommender Systems

Today's Learning Objectives

- Understand what a recommender system is
- Some history and background
- NOT: course or specialization details
  - – next lecture

A Bit of History

- Ants, Cavemen, and Early Recommender Systems
  - The emergence of critics
- Information Retrieval and Filtering
- Manual Collaborative Filtering
- Automated Collaborative Filtering
- The Commercial Era

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Information Retrieval

- Static content base
  - Invest time in indexing content
- Dynamic information need
  - Queries presented in “real time”

- Common approach: TFIDF
  - Rank documents by term overlap
  - Rank terms by frequency

Information Filtering

- Reverse assumptions from IR
  - Static information need
  - Dynamic content base
- Invest effort in modeling user need
  - Hand-created “profile”
  - Machine learned profile
  - Feedback/updates
- Pass new content through filters

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Collaborative Filtering

- Premise
  - Information needs more complex than keywords or topics: quality and taste
- Small Community: Manual
  - Tapestry – database of content & comments
  - Active CF – easy mechanisms for forwarding content to relevant readers

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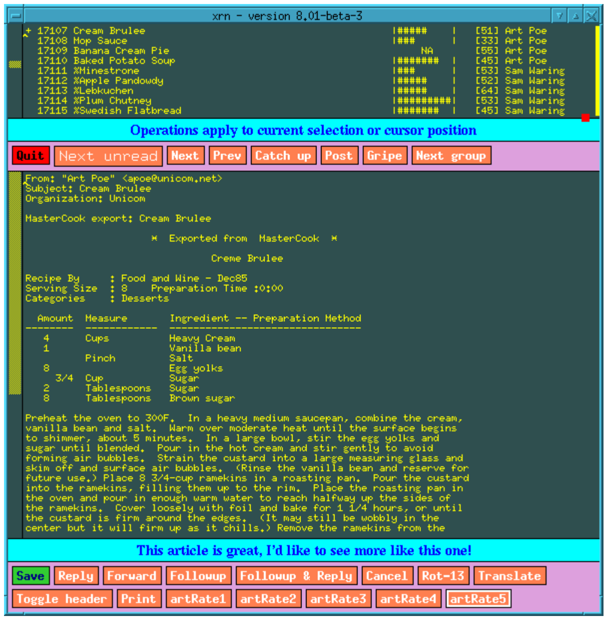
Automated CF

- The GroupLens Project (CSCW '94)
  – ACF for Usenet News
    - users rate items
    - users are correlated with other users
    - personal predictions for unrated items
  – Nearest-Neighbor Approach
    - find people with history of agreement
    - assume stable tastes



Does it Work?

- Yes: The numbers don't lie!
  - Usenet trial: rating/prediction correlation
    - rec.humor: 0.62 (personalized) vs. 0.49 (avg.)
    - comp.os.linux.system: 0.55 (pers.) vs. 0.41 (avg.)
    - rec.food.recipes: 0.33 (pers.) vs. 0.05 (avg.)
  - Significantly more accurate than predicting average or modal rating.
  - Higher accuracy when partitioned by newsgroup

It Works Meaningfully Well!

- Relationship with User Behavior
  - Twice as likely to read 4/5 than 1/2/3
- Users *Like* GroupLens
  - Some users stayed 12 months after the trial!

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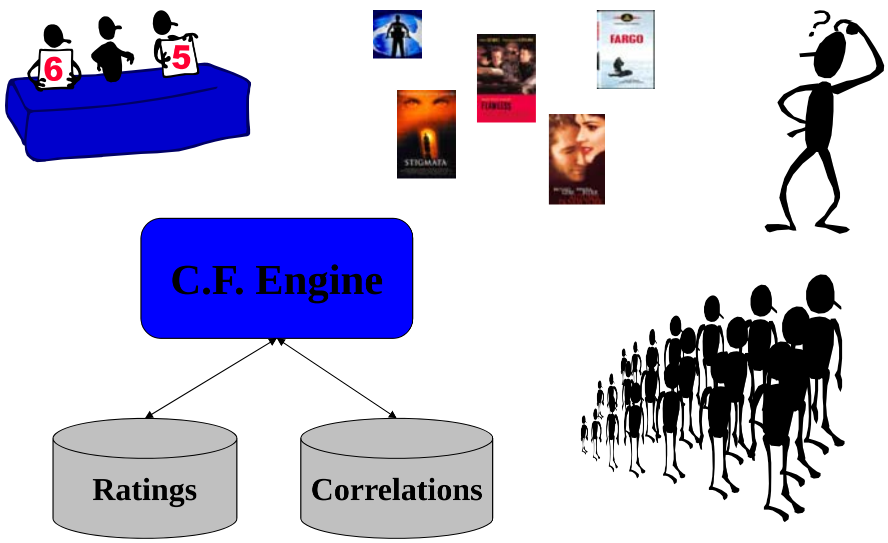
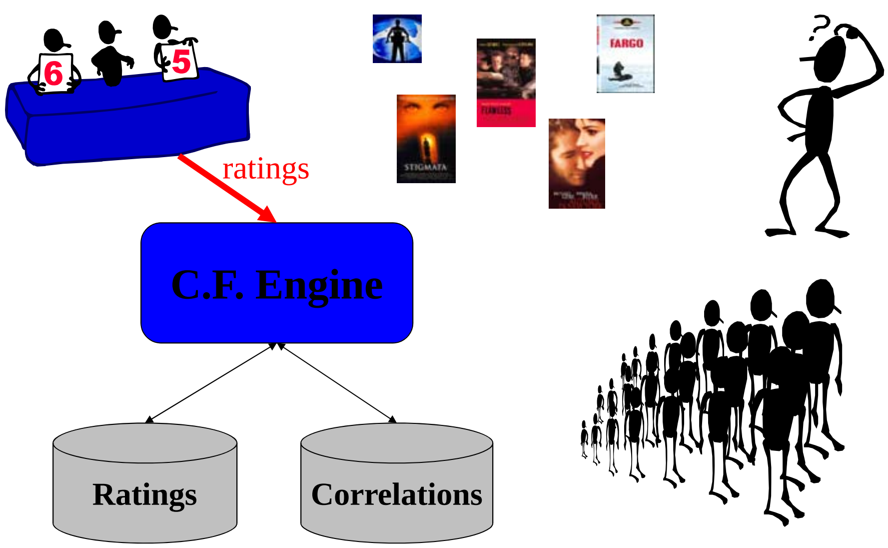
CLASSIC COLLABORATIVE FILTERING

(A MOVIE RECOMMENDER EXAMPLE)

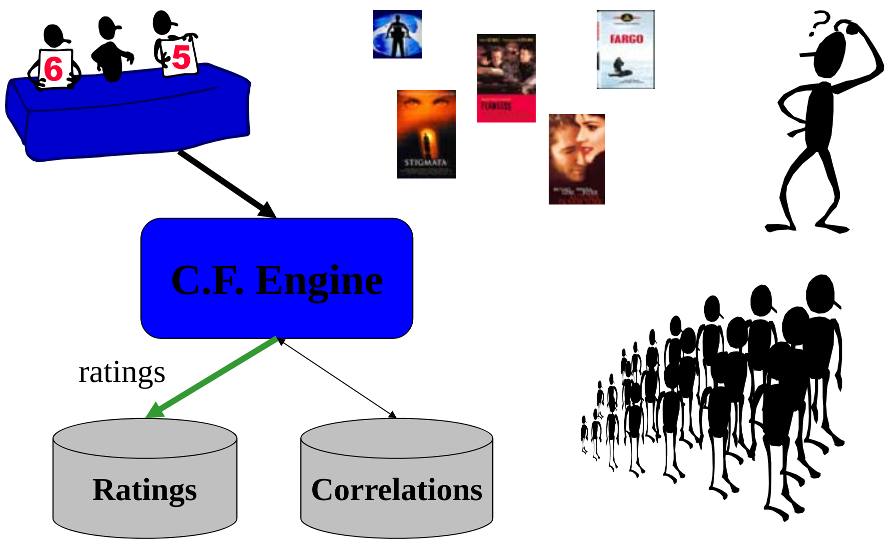
K-Nearest Neighbor User-User



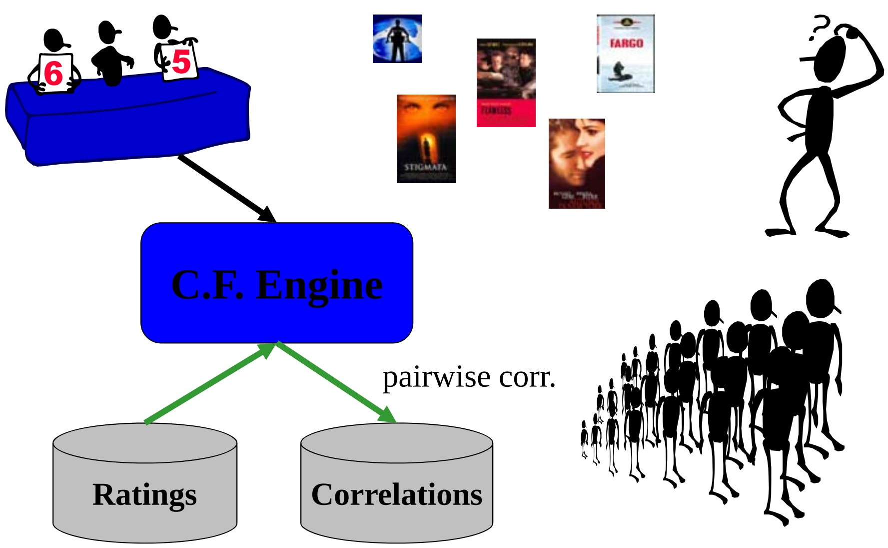
CF Classic: Submit Ratings



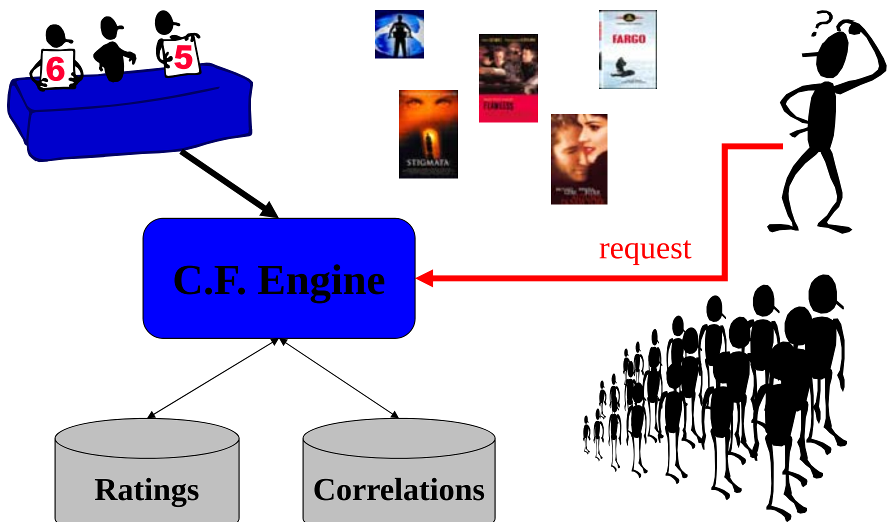
CF Classic: Store Ratings



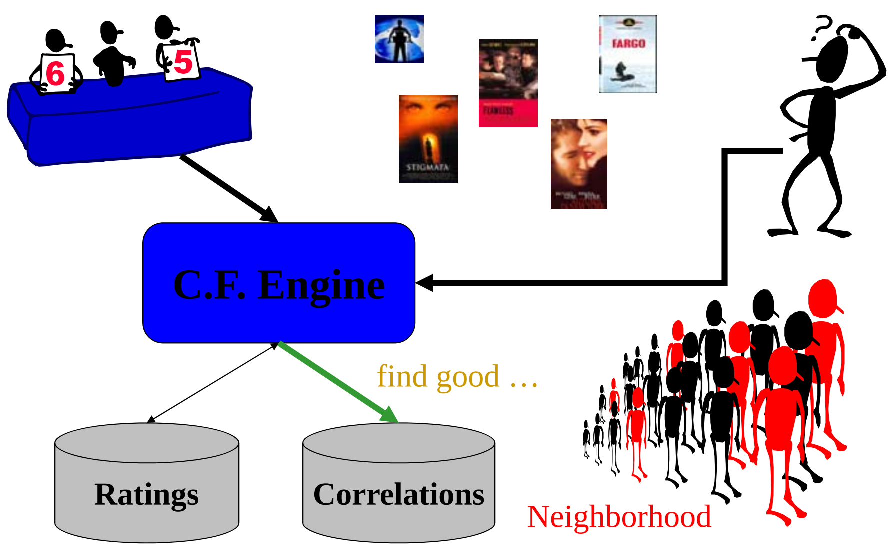
CF Classic: Compute Correlations



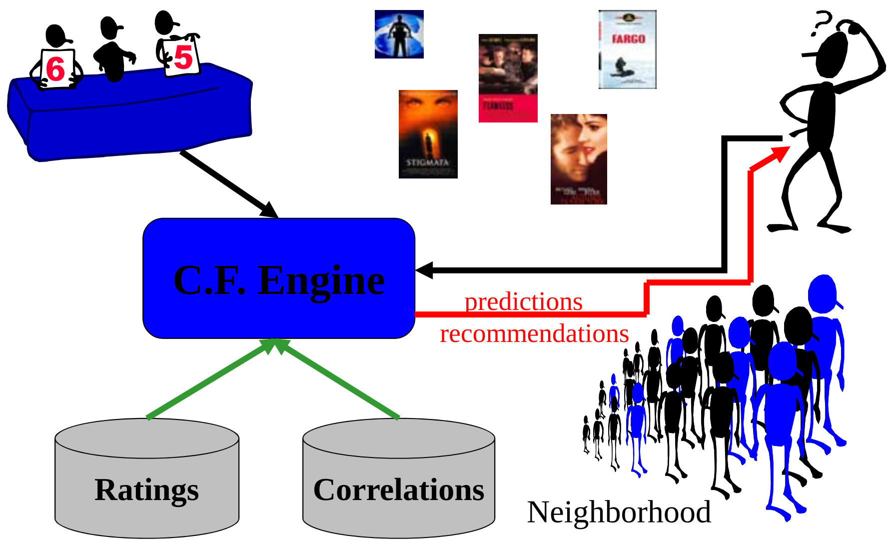
CF Classic: Request Recommendations



CF Classic: Identify Neighbors



CF Classic: Select Items; Predict Ratings



Understanding the Computation

	Hoop Dreams	Star Wars	Pretty Woman	Titanic	Blimp	Rocky XV
M.E.	D	A	B	D	?	?
J.K.	A	F	D		F	
Susan	A	A	A	A	A	A
Pat	D	A		C		
Jean	A	C	A	C		A
Ben	F	A				F
Nathan	D		A		A	

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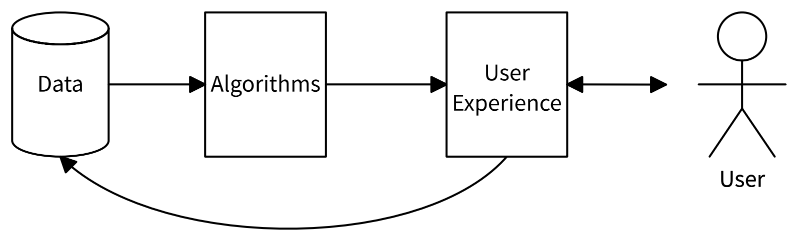
The Bigger Picture



Recommenders

- Tools to help identify worthwhile stuff
  - Filtering interfaces
    - E-mail filters, clipping services
  - Recommendation interfaces
    - Suggestion lists, “top-n,” offers and promotions
  - Prediction interfaces
    - Evaluate candidates, predicted ratings

A Little Vocabulary

- Rating – expression of preference
  - Explicit rating (direct from the user)
  - Implicit rating (inferred from user activity)
- Prediction – estimate of preference
- Recommendation – selected items for user
- Content – attributes, text, etc.
- Collaborative – using data from other users

Recommendation Approaches

- Non-Personalized and Stereotyped
  - Popularity, Group Preference
- Product Association
  - People who liked/bought X, also like Y
- Content-Based
  - Learn what I like (in terms of attributes)
- Collaborative
  - Learn what I like; use others' experience to recommend (many different ways to implement)

Designing a Recommender

- Collecting Opinion and Experience Data
- Finding the Relevant Data for a Purpose
- Computing the Recommendations
- Presenting the Data in a Useful Way

Recommenders as Big Data

- Heavy Emphasis on Analysis and Evaluation
  - Exploring Data to Determine Best Recommendation Approaches
  - Algorithms Optimize Performance Against Metrics
  - Metrics Designed to Improve User Experience and Business Goals
- Continuing Adoption of New Machine Learning Techniques

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