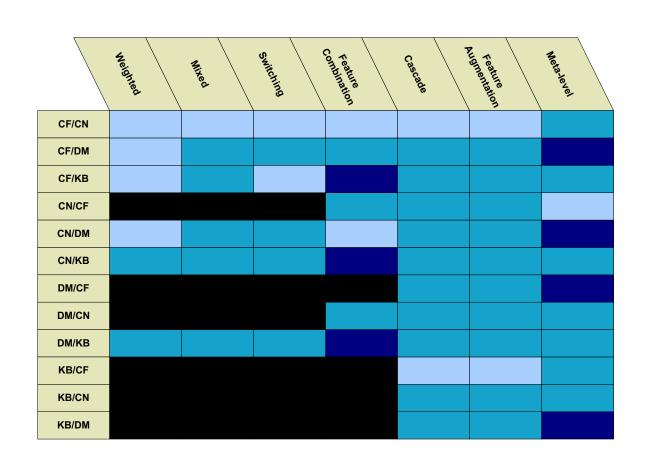


Recommender Systems Hybrid Experiments

Professor Robin Burke Spring 2019



Hybrid design space



Previously implemented

New hybrids

Not possible

Redundant

Oops

Comparative Study

- 41 hybrid designs
 - 24 / 53 spots in matrix
- Entree Chicago data
 - trace of critiquing interactions
 - 50,000 sessions
 - also 20,000 multi-visit sessions
 - about 280k total "ratings"
- 5x 50% partition of sessions
 - 6 conditions
 - 5, 10, 15 ratings in single session
 - 10, 20, 30 ratings in multi-visit sessions

+ Algorithms

■ CFP

■ kNN Collaborative filtering k=50, Pearson's r correlation

■ CFH

■ kNN Collaborative filtering k=50, semantic metric

■ CN

Content-based recommendation, naive Bayes

Take critique similarity into account

■ KB

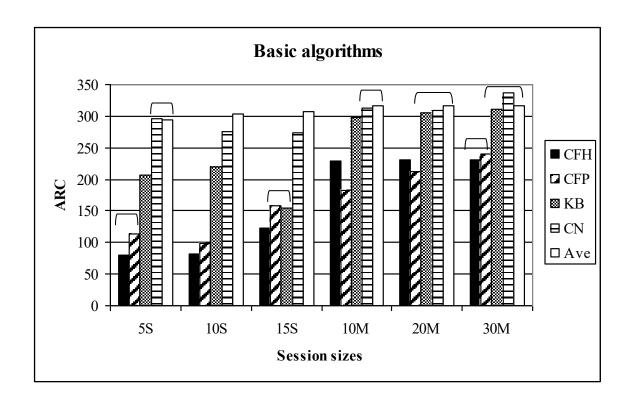
- Knowledge-based recommendation using Entree engine
- Use a similarity-based query from the last item in the session
 - not the endpoint

How to evaluate?

- Convert user actions to ratings
 - critiques = negative ratings
 - start / end points = positive ratings
- Many more negative than positive
- Task
 - make a good recommendation based on available data
 - standard metrics not a good fit (prec/recall, MAE)
 - average rank of correct recommendation (ARC)
 - MRR would have been better



Baseline results

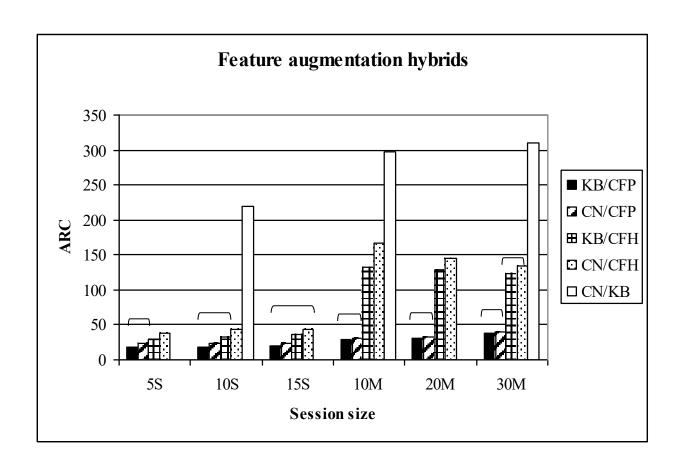


+ Analysis

- Difficult recommendation task
 - classic cold-start situation
- Stronger recommenders
 - CFH, CFP
- Weaker
 - CN, KB

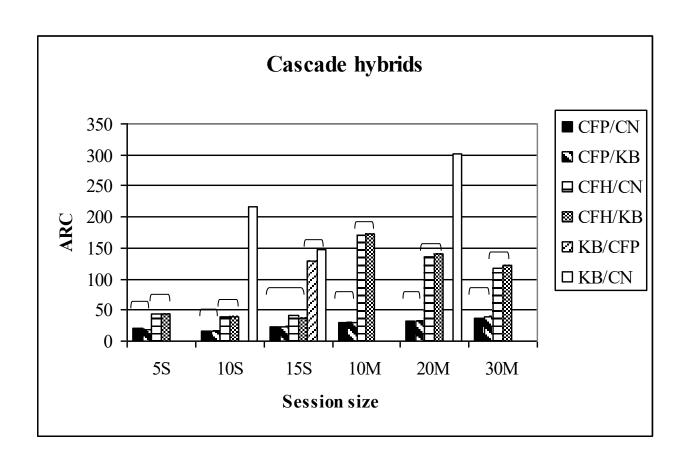
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Feature Augmentation



+

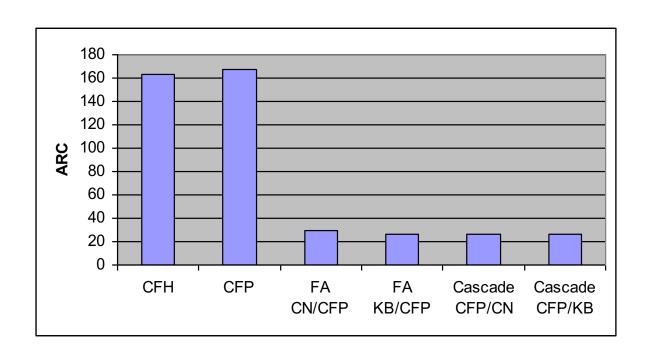
Cascade results



+ Summary

- **■** Effective
 - Feature Augmentation
 - Cascade
- Ineffective
 - Weighted, Switching, Feature Combination, and Meta

Do Hybrids Work?



Best hybrids?

- Feature augmentation/Cascade
- Why?
 - priority relationship between recommenders
 - makes the most of weak/strong combinations
- Other hybrids?
 - not compatible with this domain/data set

+ Criteria

- Uniformity of performance
 - across item / user space
- Relative accuracy
 - over training data

	Uniform	~Uniform
Equally accurate	Weighted, Mixed, Meta- level	Switching
Unequal	Weighted, Augmentation, Cascade	Switching, Combination, Augmentation, Cascade