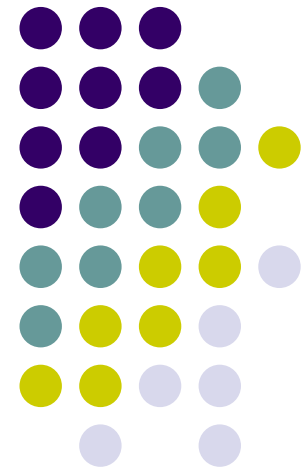


Induction of user preferences

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Outline

- Motivation
- User model
- Learning the model
- Experiments
- Conclusion



Motivation – current state

- Classical e-shop
 - Strict criteria on attributes
 - Price 50-100\$
 - Simple ordering by price, name

Sort by Price: Low to High

- Many or few objects

Showing 1 - 24 of 990 Results

Showing 1 Result

- Same answer for every user

amazon.com

Shop All Departments

Computer & Accessories

Department
< Electronics
< Computers & Accessories
Laptops

Operating System
Any Operating System
Windows 7 (51)

Display Size
 Under 13.9 Inches (17)
 14 to 14.9 Inches (10)
 15 to 15.9 Inches (21)
 16 to 17.9 Inches (4)

Processor Type
Any Processor Type
AMD Athlon (3)
AMD Phenom (3)
AMD Turion (4)
Intel Core 2 (14)
Intel Core i3 (5)
Intel Core i5 (5)
Intel Pentium (14)
> See more...

Installed RAM
 1 GB & Under (1)
 2 GB (6)
 3 GB (12)
 4 GB (34)

Hard Disk Size
 80 GB & Under (2)
 121 to 320 GB (37)
 321 to 500 GB (14)

Shipping Option (What's this?)
Any Shipping Option
Prime Eligible
Free Super Saver Shipping

Brand
 Toshiba (31)
 Asus (9)
 Hewlett-Packard (3)
 Dell (2)
 Lenovo (6)
 Compaq (1)





Motivation – dream state

- Personalization
 - Results reflect the user, not only the query
- More insight for the user
 - Solve „no object“ or „too many objects“ problem
 - *How good is the notebook?*
 - Relaxed criteria
 - More complex ordering

Motivation – preference search



- Ordering
 - Instead of restriction
- Specification of ideal attribute values
 - Rather than acceptable values
- Possible visualization of the result set

Notebook 251	Notebook 188	Notebook 32
 <p>If you're into high-def movies, games, music and photography, this laptop is for you. New Windows gives you more ways than ever of savoring your digital</p>	 <p>Your on-the-go lifestyle might be hectic. But this laptop can smooth out the twists and turns. Powered by new Windows and reliable processing power from Intel</p>	 <p>If you're into high-def movies, games, music and photography, this laptop is for you. New Windows gives you more ways than ever of savoring your digital</p>
<ul style="list-style-type: none">○ Manufacturer: ACER● LCD size: 12 inches● Wifi: Yes● RAM size: 8192 MBProcessor: Core 2 Duo T7500	<ul style="list-style-type: none">○ Manufacturer: ACER● LCD size: 14.1 inches● Wifi: Yes● RAM size: 2048 MBProcessor: Core 2 Duo T7100	<ul style="list-style-type: none">○ Manufacturer: ACER● LCD size: 15.4 inches● Wifi: No● RAM size: 1024 MBProcessor: *
<p>● 38305,- incl. VAT 45582.95,-</p> <p>In Stock </p>	<p>● 28190,- incl. VAT 33546.1,-</p> <p>In Stock </p>	<p>● 17016,- incl. VAT 20249.04,-</p> <p>Out of Stock </p>

Motivation – preference learning



- Let's expect even less from the user
 - Instead of direct specification of ideal values - learning the most preferred values from a less complex user input
 - A few ratings of objects



Toshiba Portege R600

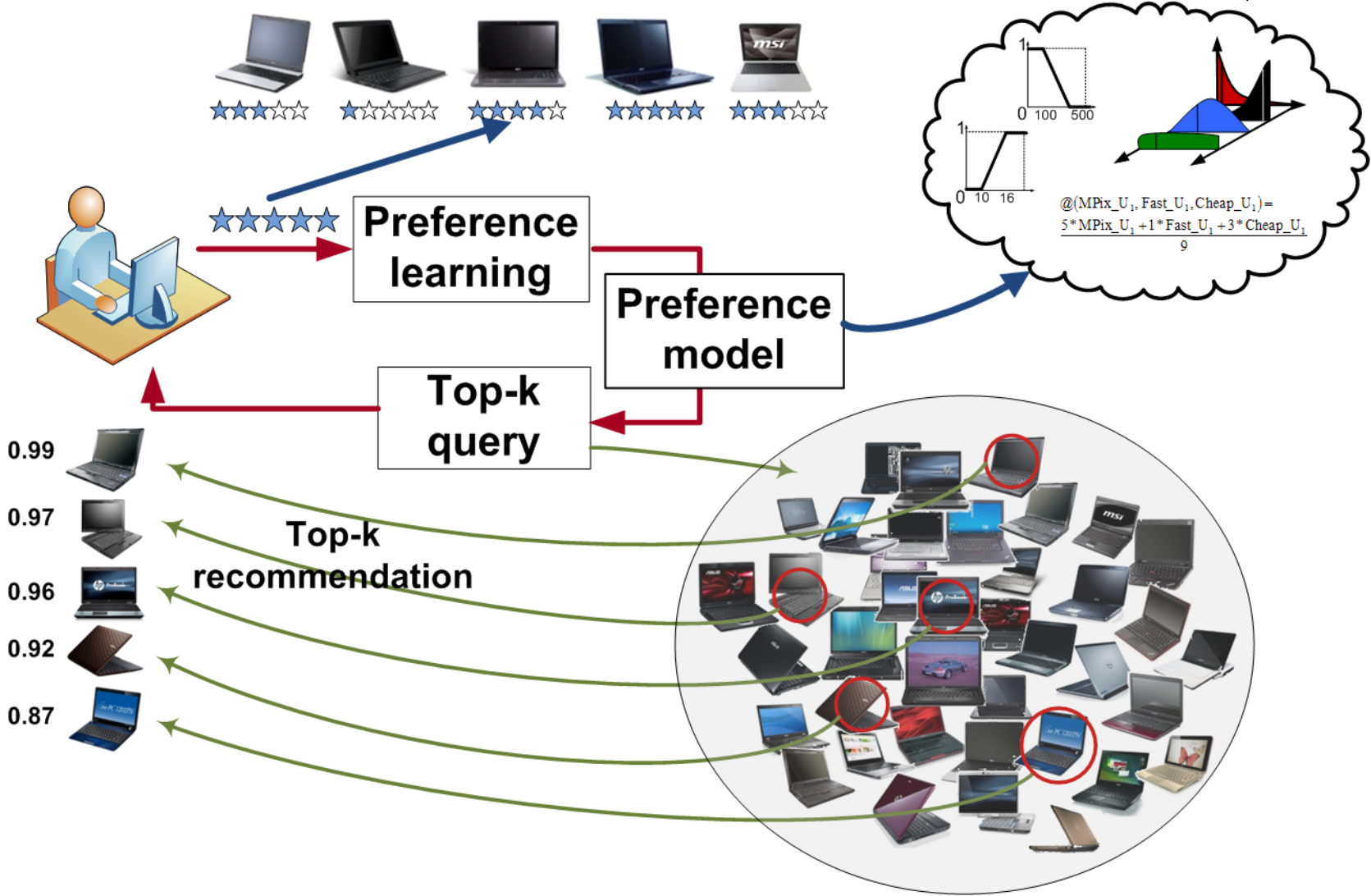
Toshiba's Portege R600 is one of the best ultraportables on the market, if you're willing to pay the price.

Tags: [toshiba](#), [portege](#), [r600](#), [ultraportable](#), [laptop](#)

Your rating: ★★★★★

- Construction of a general user preference model
 - Each user has his/her own preference model
 - Based on his/her ratings

Motivation – preference learning



User model



- User model learning is divided into two steps
 1. **Local preferences** - normalization of the attribute values of notebooks to their preference degrees

$$f_i : D_{A_i} \rightarrow [0,1]$$

Transforms the space ΠD_{A_i} into $[0,1]^N$

- Manufacturer: ACER
- LCD size: 14.1 inches
- Wifi: Yes
- RAM size: 2048 MB
- > Processor: Core 2 Duo T7100

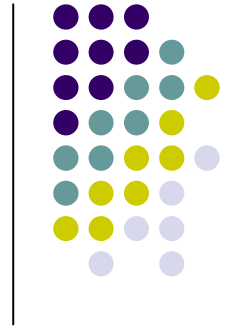
2. **Global preferences** - aggregation of preference degrees of attribute values into the predicted rating

$$@ : [0,1]^N \rightarrow [0,1]$$

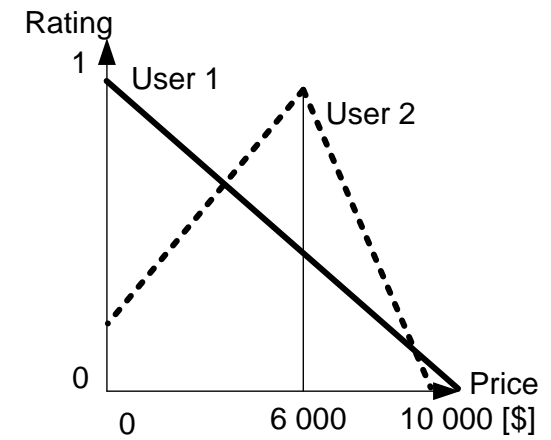
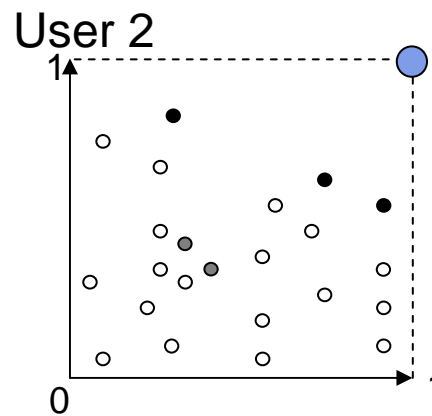
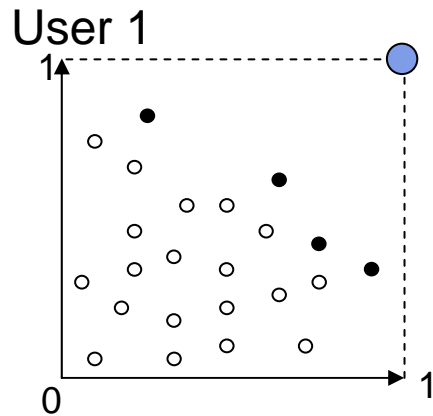
Notebook 188

59%

User model



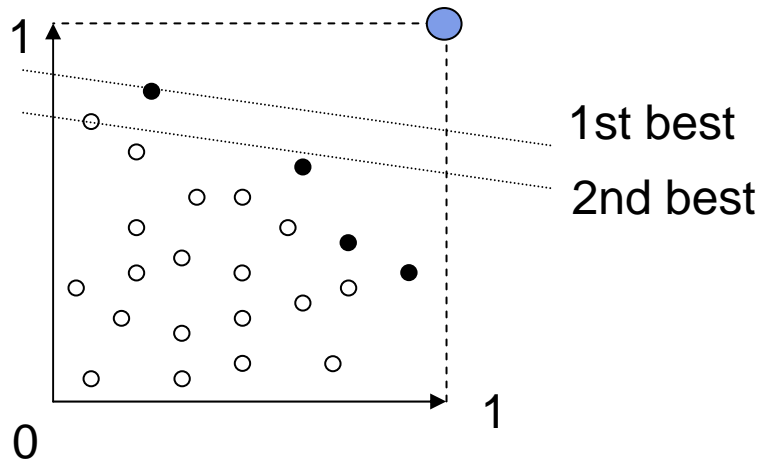
- Local preferences
 - Transform the space ΠD_{A_i} to monotone space $[0, 1]^N$
 - $\bullet = (1, \dots, 1)$ is the best object
 - Allow direct comparison of objects





User model

- Global preferences $@ : [0,1]^N \rightarrow [0,1]$
 - Order all objects according to overall preference
 - Allow recommendation of top-k objects

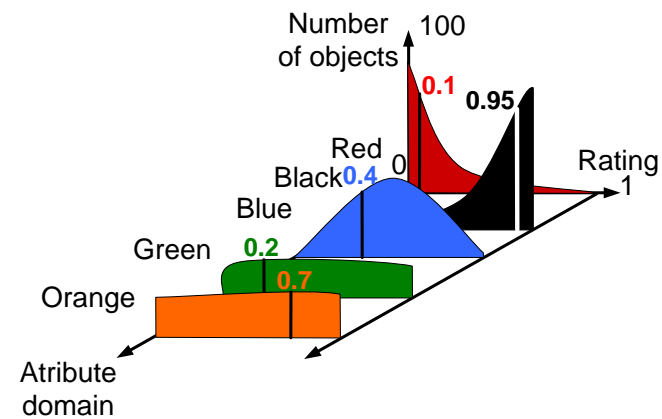
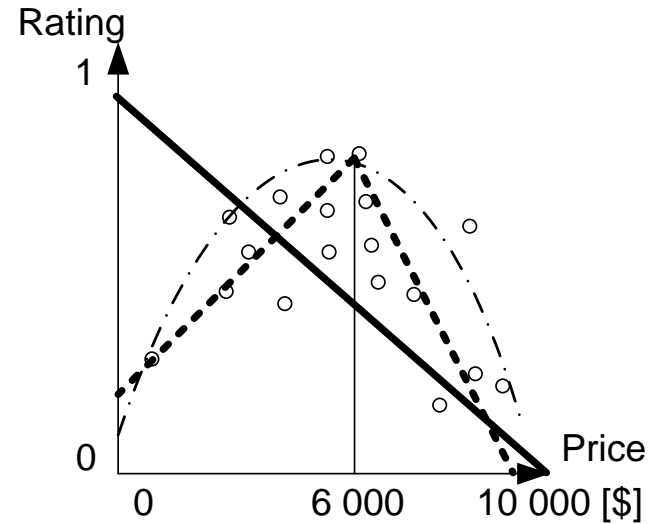


$$@(\text{RAM}_{U_1}, \text{CPU}_{U_1}, \text{Price}_{U_1}) = \frac{5 * \text{RAM}_{U_1} + 1 * \text{CPU}_{U_1} + 3 * \text{Price}_{U_1}}{9}$$



Learning user model

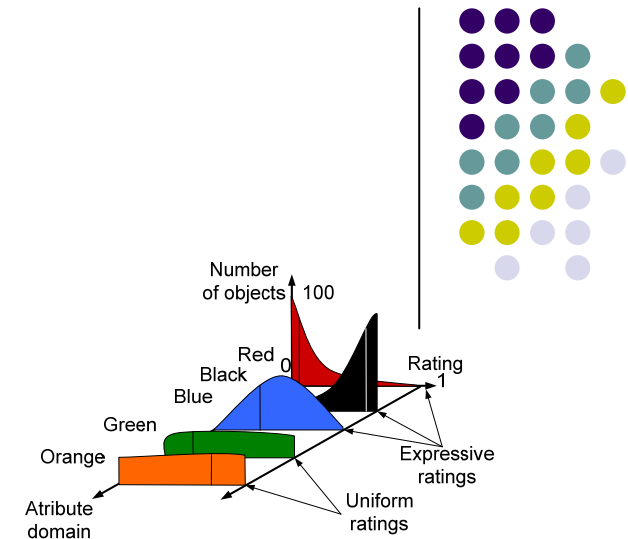
- Regression for numerical attributes
- Average rating for nominal attributes



Learning user model

- *Statistical*

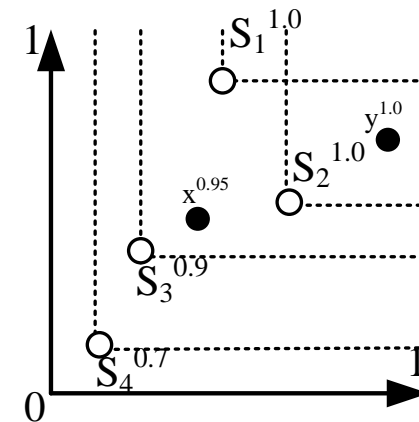
- Learned weights for weighted average
- Using distribution of ratings



$$\text{@}(\text{RAM_}U_1, \text{CPU_}U_1, \text{Price_}U_1) = \frac{5 * \text{RAM_}U_1 + 1 * \text{CPU_}U_1 + 3 * \text{Price_}U_1}{9}$$

- *Instances*

- Uses objects from training set for estimation of rating



Specific problems to preference learning



- Small training set
 - Users do not want to invest too much effort
- Different error measures than “standard” machine learning
 - Correct ordering is important
 - Better rated objects are more important
- Transparent preference model needed
 - For using the information in user interface
 - Why is the object recommended by the system?

Specific problems to preference learning

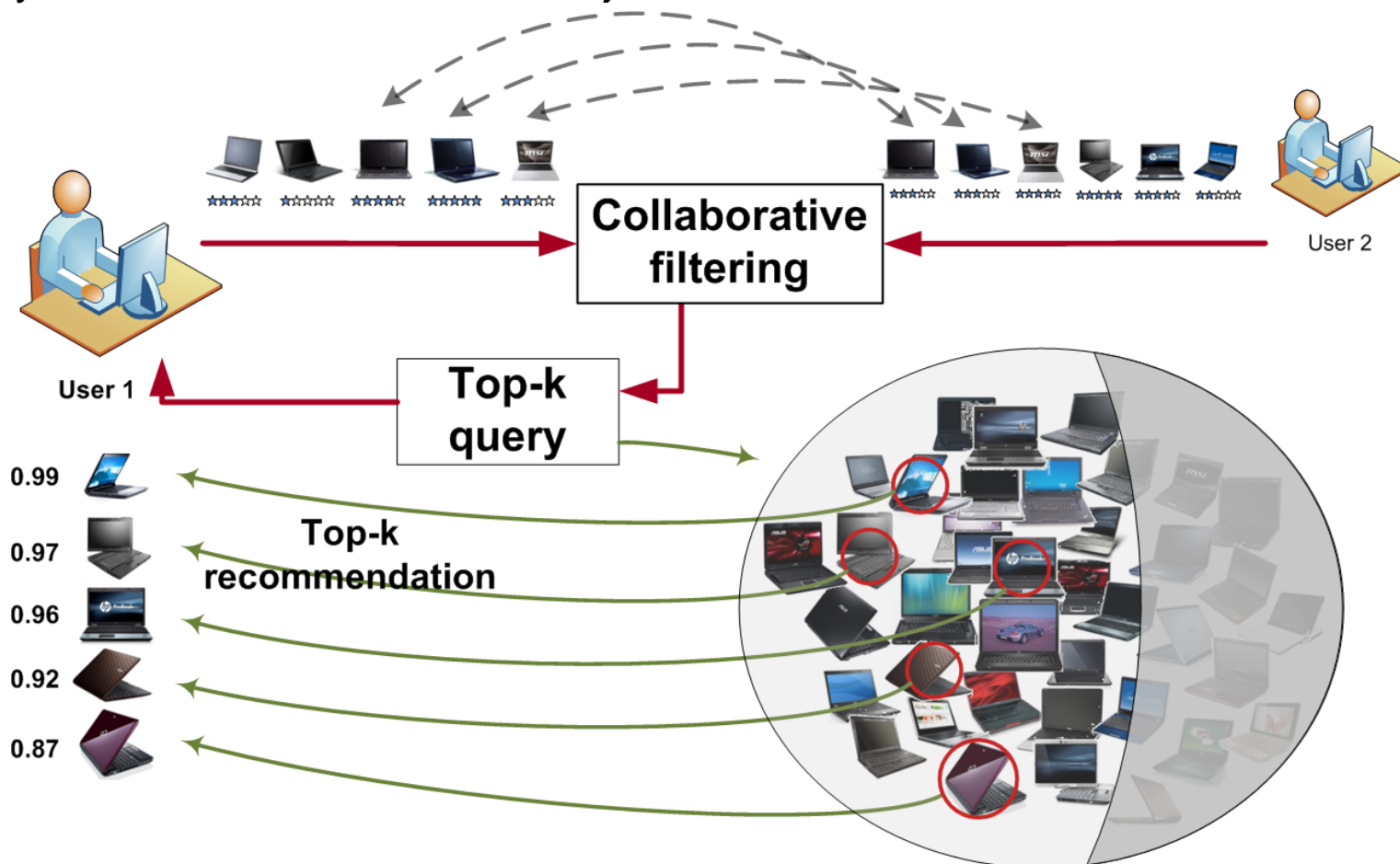


- Error measures
 - WRMSE
 - $\sqrt{\frac{\sum_{o \in X} r(o)(\hat{r}(o) - r(o))^2}{\sum_{o \in X} r(o)}}$
 - WTau coefficient
 - Compares two ordered lists and emphasizes better rated objects
 - Top-k score
 - Percentage of correct objects in top-k (without order)



Collaborative filtering

- Similarity of users based on ratings of common rated objects
 - Only users with common rated objects can be evaluated



Combination with other methods



- Similarity of user preference models for collaborative filtering
 - StatColl
 - Similarity of local and global preferences
 - All users can be evaluated, every user has preference model
 - In normal CF, similarity based on ratings
 - Only users with common rated objects can be evaluated



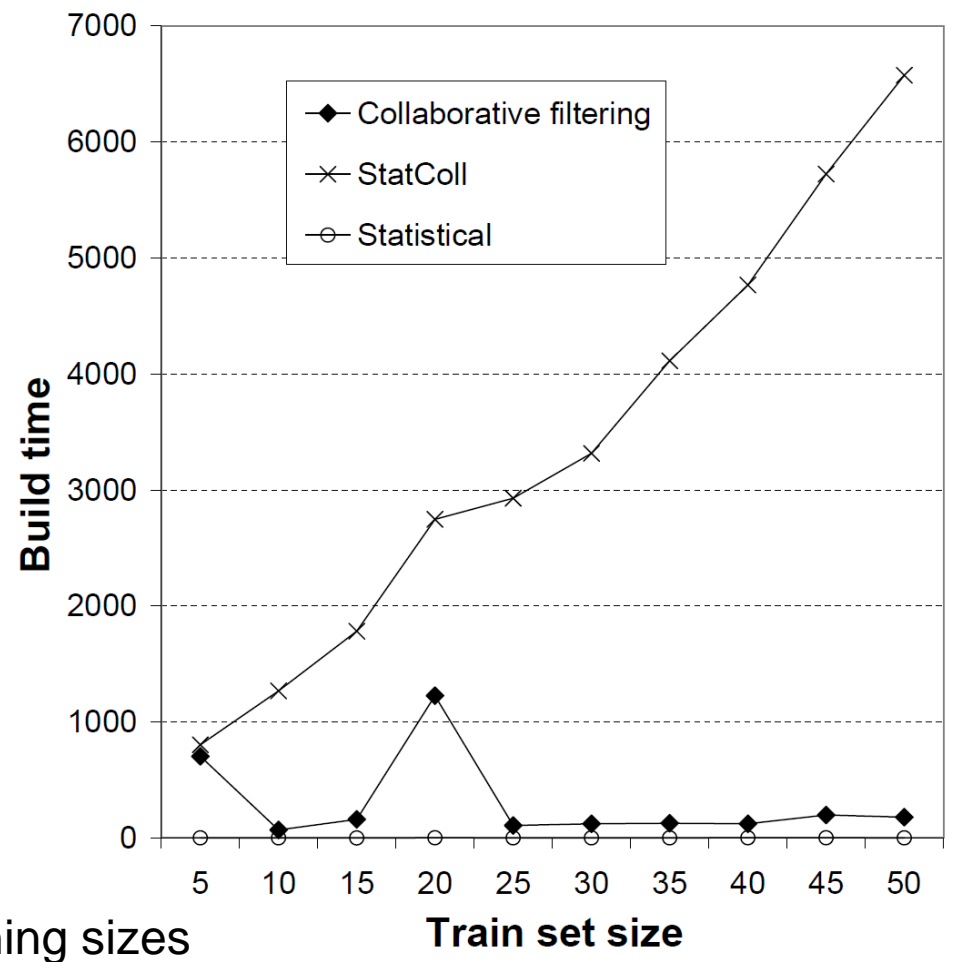
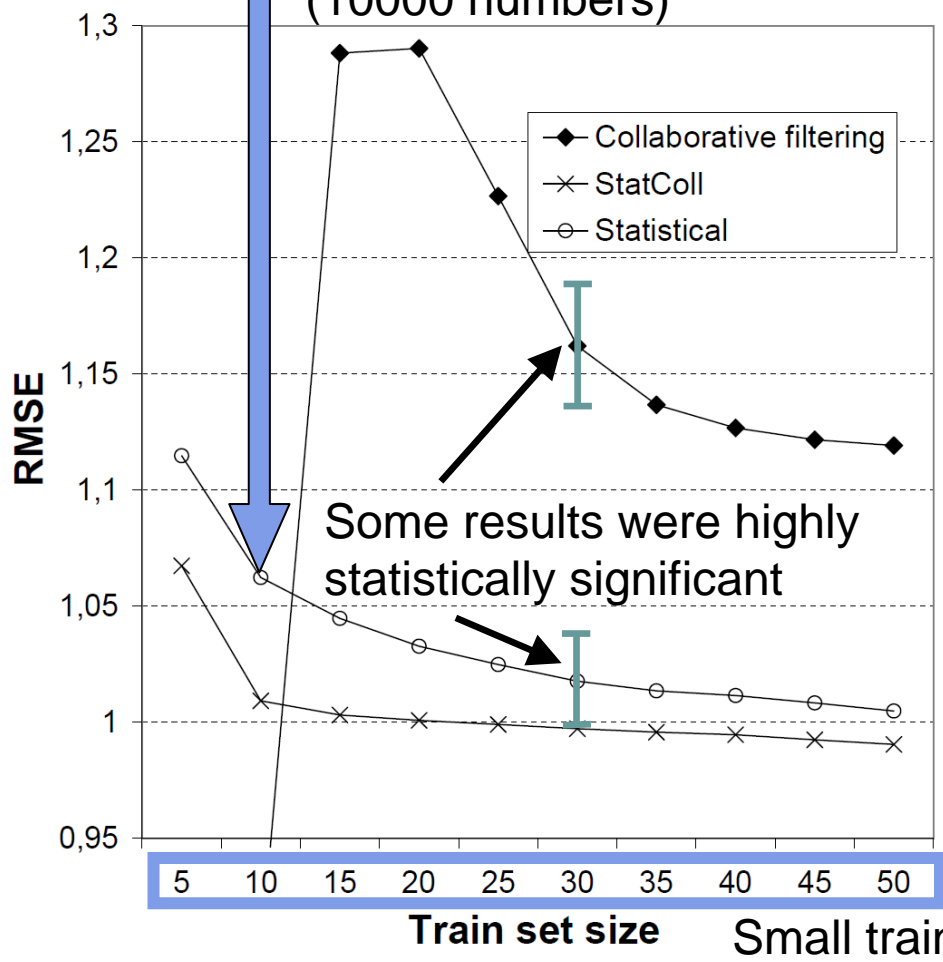
Experiment results

- **Enhancing Collaborative filtering**
 - *StatColl* uses similarity of user models (Statistical)
 - Enables computing the similarity for all users
 - StatColl statistically significantly better
 - Netflix dataset + IMDb dataset

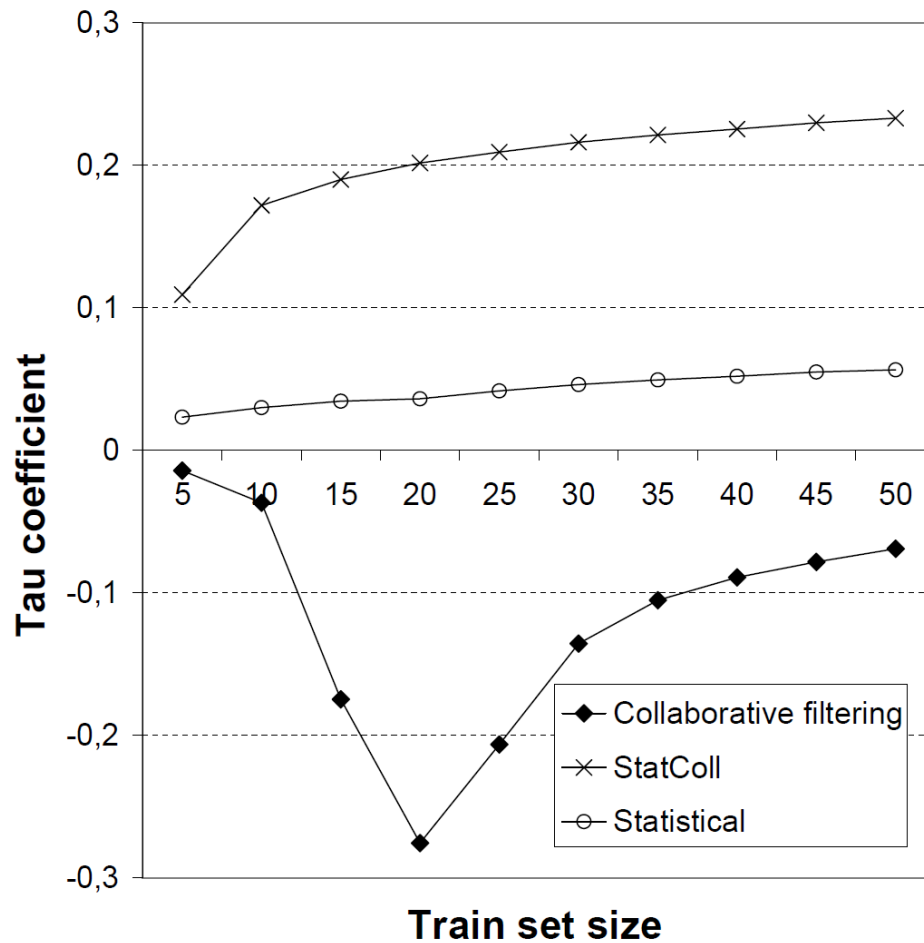
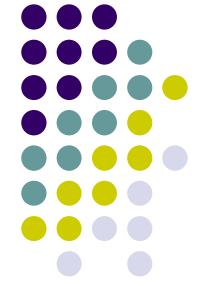


Experiment results

One point in the graph represents the average of all runs and all datasets / users (10000 numbers)



Experiment results



Tau coefficient is negative for CF, because it has a lot of unpredicted objects



Experiment realization

- PrefWork was used for performing the experiments
 - Easy configuration, alteration, repetition of experiments
 - New methods, datasets, error measures, testing setting, integration of other methods

Conclusion



- Proposal of various methods for preference learning
 - New approaches specific for preferences, addressing problems of preference learning, implemented, ready to use in a web shop - a transparent preference model
- Experimental verifications of several new approaches
 - Statistically significant improvement of various methods
 - Enhancement of existing methods
- PrefWork for performing experiments



Future work

- Extending the e-shop with even more preferences
 - Vaclav - Java, Kolomicenko - PHP
 - New user interfaces
 - New paradigm for preference use
- New methods for learning for PrefWork
 - From user behavior
 - Learning of preference relations