

# A Fast Learning Recommender Estimating Preferred Ranges of Features

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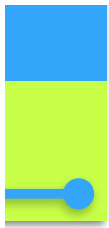
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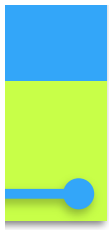
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# Outline

- ☐ recommender basics
- ☐ motivation
- ☐ basic ideas
- ☐ algorithm details
- ☐ experimental evaluation
- ☐ deployment as a web service
- ☐ summary



# What Are Recommenders?

- to recommend items for users
  - inferring items which might be preferable for targeting users
- two types of recommenders
  - content-based recommender
    - based on item features: descriptions, images, prices etc.
  - collaborative filtering
    - based on records of user behaviour
    - e.g. users who bought this item also bought...
- general procedure
  - find a target point in a vector space
  - calculate similarity/proximity of items
    - extensive use of  $k$ -nearest neighbour search
  - create item ranking
    - can be a raw similarity ordered list
    - various re-ranking methods



Click image to open expanded view

### Cryorig Cryorig CR-XTA 140mm Slim Profile PWM System Case Fan

★★★★☆ 21 customer reviews | 8 answered questions

Available from these sellers.

- HPLN (High Precision Low Noise) bearing, offering stable and precision movement eliminating excess vibration and noise.
- Built in Acoustic Vibration Absorbers, every XT140 is ready for low noise operation right out of the box.
- Choose among 3 different colored Acoustic Vibration Absorbers to match your system and case.

Compare with similar items

New (1) from \$25.37 & FREE shipping.

[Report incorrect product information.](#)

...  
With Wraith Prism  
LED Cooler  
> Shop now




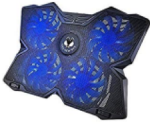





AMD Ryzen 7  
2700X Processor with Wraith Pris...  
★★★★☆ 153  
\$319.99 ✓prime

Ad  
feedback




## Recommendation Example in Amazon.com

### Sponsored products related to this item (What's this?)

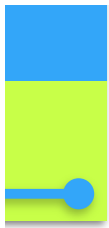
						
Noctua NF-A12x15 PWM Premium-Quality Quiet Slim 120mm Fan ★★★★☆ 18 \$19.95 ✓prime	Noctua NF-S12A PWM chromax.black.swap premium-grade quiet 120mm fan ★★★★☆ 23 \$22.90 ✓prime	Noctua SSO Bearing Fan Retail Cooling NF-P14r redux-1500 PWM ★★★★☆ 44 \$14.95 ✓prime	Tree New Bee 15.6"-17" Laptop Cooling Pad Cooler,Gaming Laptop Cooling Pad with Fou... ★★★★☆ 3601 \$22.99 ✓prime	Gdstime 60x60x10mm 60mm 5V 0.18A Brushless DC Cooling Fan ★★★★☆ 9 \$10.29 ✓prime	Maxone 60GB SSD 3D NAND TLC Cache Performance Boost SATA III 6Gb/s 2.5" 7mm... \$19.99 ✓prime	Desk Personal Fan USB Table Portable Fan(2 Speed, 4 Inch, Quietness) (Black) ★★★★☆ 182 \$12.99 ✓prime

Content-based?

### Customers who bought this item also bought

						
Noctua NH-L12S 70mm Low-Profile CPU Cooler with Quiet 120mm PWM Fan ★★★★☆ 35 \$49.90 ✓prime	Corsair SF Series, SF450, 450 Watt, Fully Modular Power Supply, 80+ Gold Certified ★★★★☆ 203 \$89.50 ✓prime	ASUS ROG Strix Z370-I Gaming LGA1151 (Intel 8th Gen) DDR4 DP HDMI M.2 Z370 Mini ITX... ★★★★☆ 298 \$105.44	Corsair SF Series, SF600, 600 Watt, Fully Modular Power Supply, 80+ Gold Certified ★★★★☆ 203 \$116.56 ✓prime	Corsair LPX 32GB DRAM 3000MHz C15 Memory Kit for DDR4 Systems ★★★★☆ 2,557 \$314.51 ✓prime	Cryorig XF140 CR-XFA 140mm PWM Case Fan 26mm Thick ★★★★☆ 13 \$16.99 ✓prime	Cryorig H5 Universal CR-H5A Mid Tower CPU Heatsink with... ★★★★☆ 43 \$46.99 ✓prime

Collaborative filtering



# Motivation

## □ making a recommender

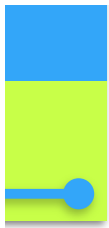
- equipped with web service like interactive user interface
  - to help users recognise their own preferences
- whose users are mostly new or not registered

## □ want to estimate new users' preferences

- *cold-start* problem
  - no user attributes
  - no behavioural history -> collaborative filtering cannot be applied
  - need to know users' preferences to match item features
- estimate feature-wise?
  - needs high degree of user effort
  - what about interaction between features?

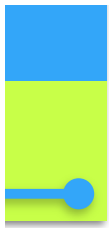
## □ objectives

- infer users' preferable ranges of item features
- reduce number of user interactions as far as possible



# Basic Ideas

- binary search like active learning
  - aggressively cut the search space out
  - change the search area according to user responses
- dimensionality reduction of the item space
  - to make binary search applicable
  - by multidimensional scaling (MDS)



# Binary Search Like Active Learning

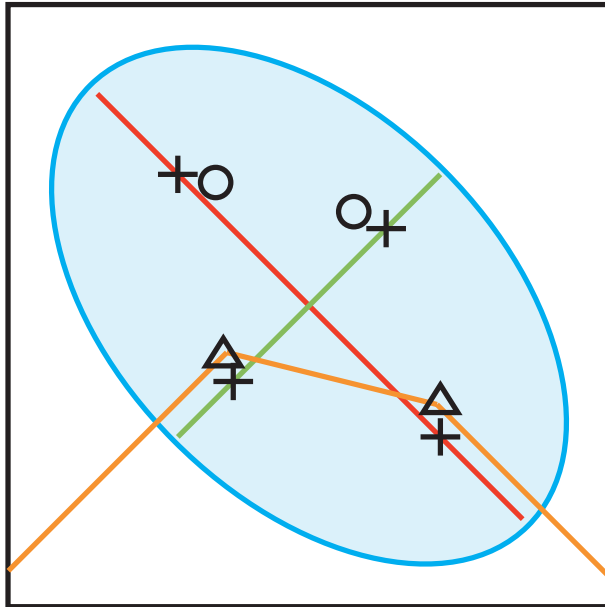
- binary search (actually not exactly)
  - estimate a preferable range within  $[0, 1]$ 
    - present a pair  $(0.25, 0.75)$  to the user
    - discard  $(0.5, 1]$  if she prefers 0.25,  $[0, 0.5)$  otherwise
    - next iteration starts with the remaining range
- can be two-dimensional
  - present a set of pairs along two axes
  - need to determine two axes
    - want to choose the most "effective" axes
    - choose axes spanning the most widely distributed directions
    - by principal component analysis (PCA)
  - discard an area around not preferable ones
  - next iteration starts with the remaining area



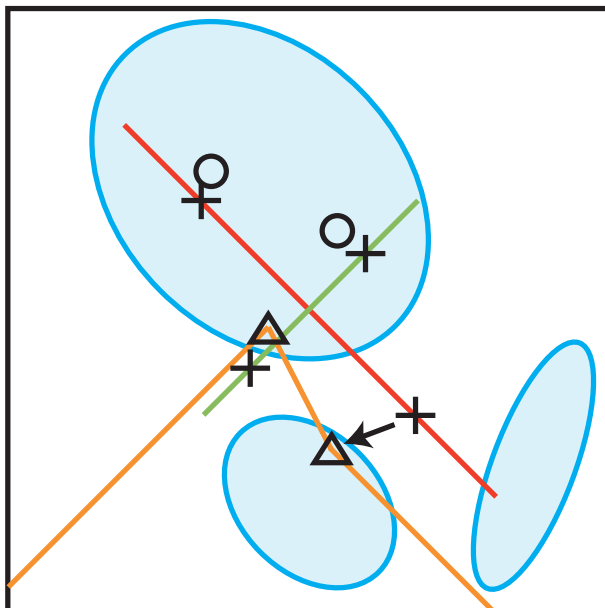
## Geometrical Exclusion

pivot points are on-axis reference points, and items to be presented to the user are nearest items to the pivot points

area to be discarded is determined by line segments through not preferable items



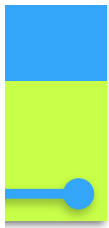
Convex case



Concave case

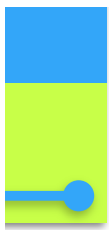
- cyan circle: item distribution
- red and green line: axis
- cross: pivot point
- black circle: preferable item
- triangle: not preferable item
- orange line: to segment the area to be discarded





# Dimensionality Reduction

- how about more than two dimensions?
  - possible, but impractical; needs  $2^{d-1}$  pairs
- reduce dimensionality without loss of information as far as possible
  - by multidimensional scaling (MDS)
  - using classical MDS, which is effectively the same as linear PCA
    - non-linear MDS can be used, but *regularisation* not applicable (next page)
- what is MDS?
  - calculate a low-dimensional representation from a distance matrix
  - preserving between-item distances as well as possible



# Regularisation of the Learning Process

- a problem caused by dimensionality reduction
  - searching is done in a reduced space, pick items to present a user
  - can infer features in the original item space by linear regression
  - but we want to present a user actual item features
  - what if magnitude relations of a feature inferred by linear regression and original items' are different?
- a simple solution
  - select a pair of items near the pivot point
  - check if magnitude relations of features are *coincide*
    - coincide means relations (which is larger, in this case) are the same
  - if not, pick next pair

	Item A	Rel	Item B
inferred	0.25	<	0.75
actual	0.21	<	0.83

coincide!

	Item A	Rel	Item B
inferred	0.25	<	0.75
actual	0.83	>	0.21

not coincide



Initialise search space  $S$

**repeat**

Fill  $S$  by colour  $k_1$

Analyse  $S$  by principal component analysis

$a_{1,2} \leftarrow$  axes corresponding to two eigenvalues

**for**  $i \leftarrow 1, 2$  **do**

Select pivot points  $p_{1,2}$  from axis  $a_i$

**repeat**

Select candidates  $c_{1,2}$  around  $p_{1,2}$  respectively

**until**  $\text{coincide?}(S, c_{1,2})$

Display candidates  $c_{1,2}$  and wait response

$r_i^p \leftarrow$  candidate chosen,  $r_i^n \leftarrow$  candidate not chosen

**end for**

Place line segments  $l_{1,2,3}$  based on the position of  $r_{1,2}^n$

Draw  $l_{1,2,3}$  on  $S$  by colour  $k_3$

Select an arbitrary tile  $t$  not belonging to  $l_{1,2,3}$

Flood-fill  $S$  from  $t$  by colour  $k_2$

$k \leftarrow$  colours of  $r_{1,2}^p$  and the mean

$u \leftarrow$  subscript of the majority of colours in  $k$

Exclude  $k_{3-u}$  and  $k_3$  coloured tiles from  $S$

**until**  $\text{converged?}(S)$

## Algorithm Details

} determine axes

} choose appropriate items

} get a user response

} place line segments

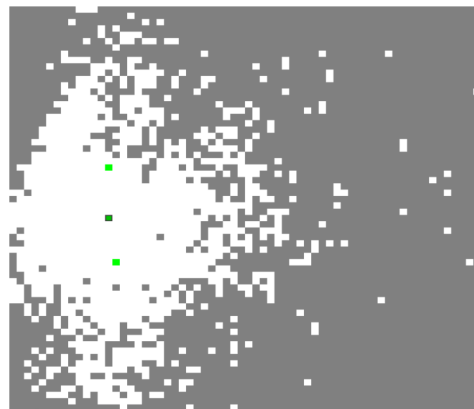
} discard a non-preferable area



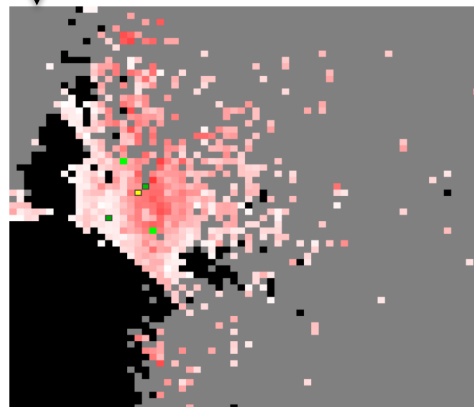
## An Actual Progress of Geometrical Exclusion

- white tile: at least one item exists
- gray tile: no item exists
- black tile: excluded
- green tile: pivot point
- red tile: received positive responses
- blue tile: received negative responses

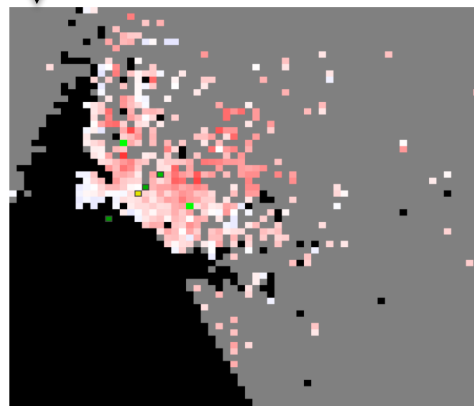
positive/negative judgement is by using a linear classifier (not covered by the paper)



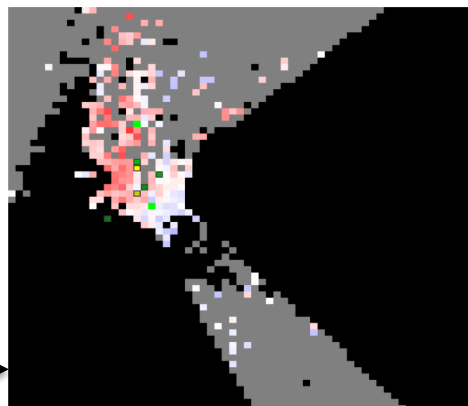
Initial state



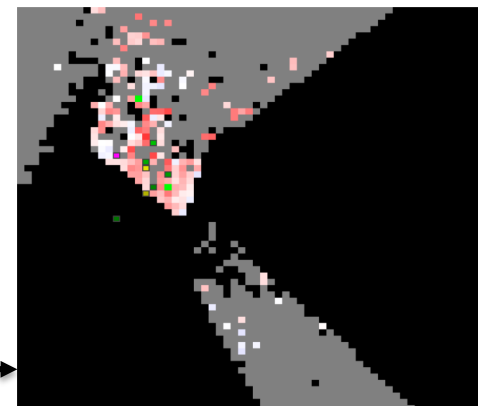
After 2 responses



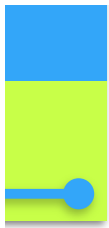
After 4 responses



After 6 responses



After 8 responses



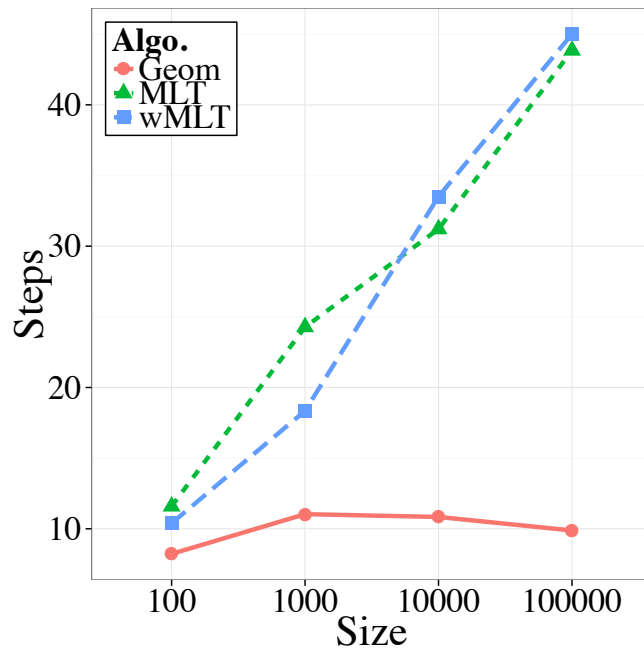
# Experimental Evaluation

## □ compared algorithms

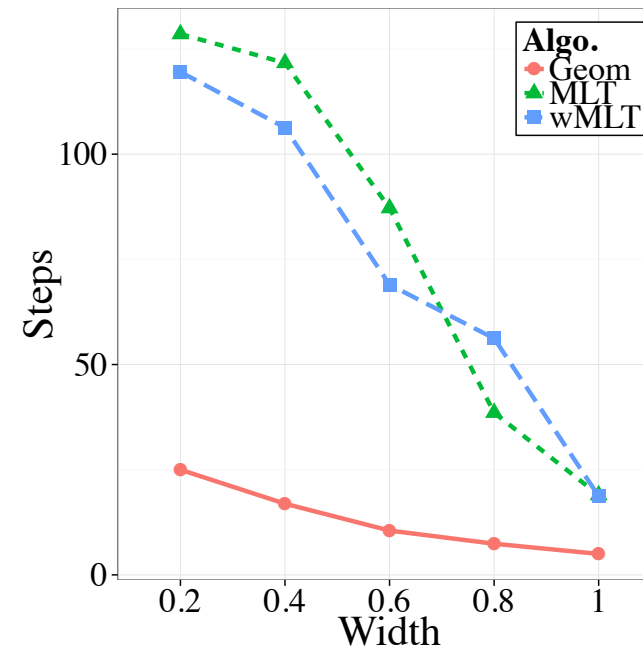
- more like this (MLT) by L. McGinty and B. Smyth
  - has an internal feature-wise query
  - next query is created by incorporating all features of a selected item
  - baseline
- a variant, weighted more like this (wMLT)
  - each feature has its weight
  - weight is a ratio of unique feature values
  - performed best in their experiment

## □ simulated experiments

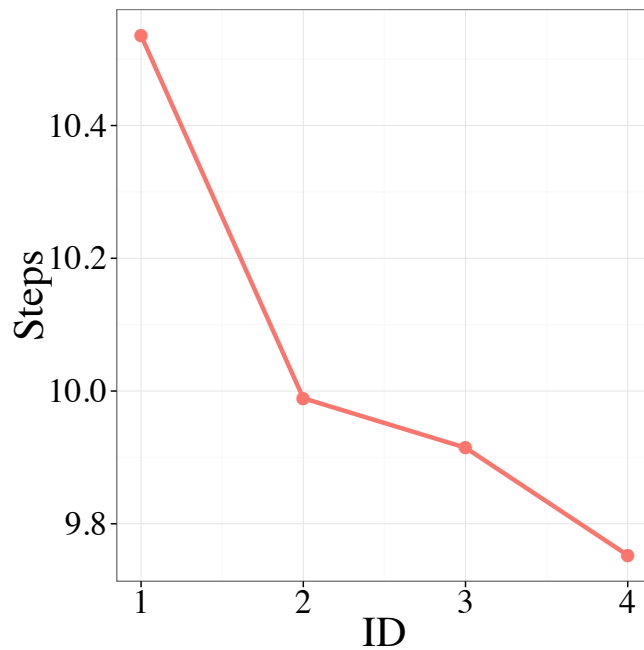
- randomly select a target item (user's most preferable item) at first
  - its surrounding region is an "answer" region
- a "user" knows which item is closer to the target item and will select it
- when reached the "answer" region, simulation stops



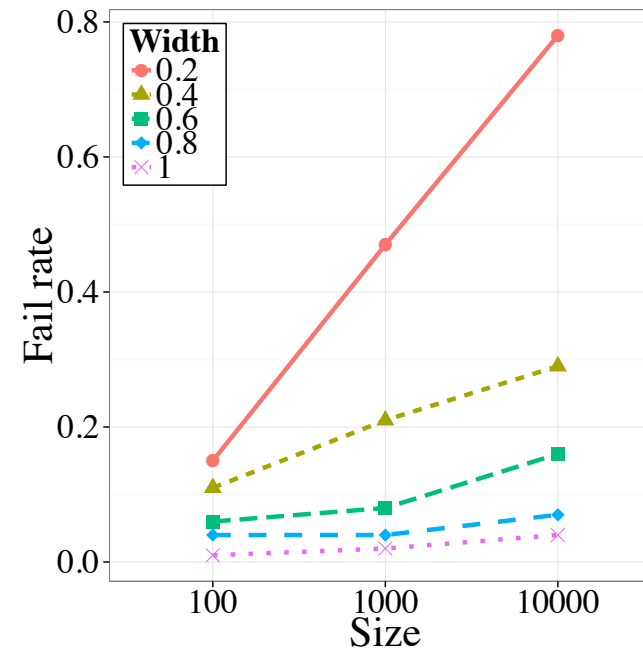
Varying data sizes



Varying "answer" region width (stddev)



Varying correlations between features



Fail rate analysis

# Deployment as a Web Service

- implemented an online recommender system

- for rental residence recommendation
- UI is designed for smartphones

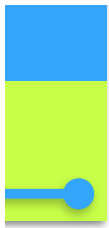
- deployed five weeks

- within a commercial web service
- received favourable responses

- features

- monthly rent
- floor area
- age
- distance from the nearby station





# Summary

- proposed an algorithm to infer preferred ranges of features
  - fast learning inspired by binary search
- showed its effectiveness by simulated experiments
- implemented the algorithm as an online recommender
  - as a part of a commercial web service