Continuous Monitoring of Pareto Frontiers over Partially Ordered Attributes for Many Users

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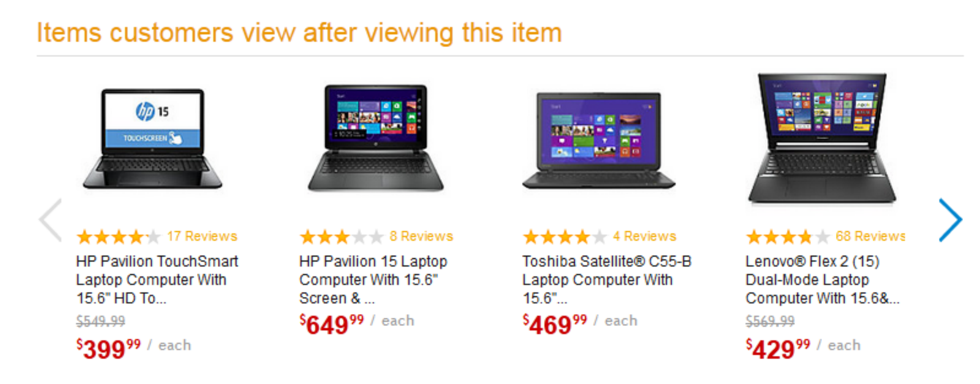
Motivation

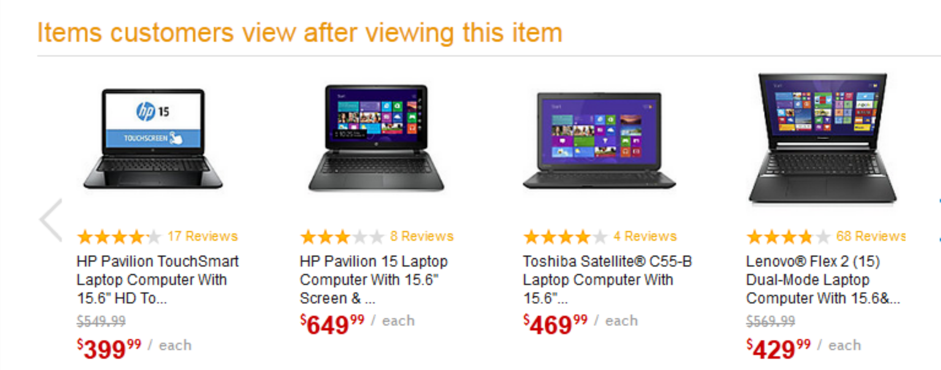
- Recommendation based on users' preferences



Motivation

- Recommendation based on users' preferences
- Preferences with multiple attributes

I prefer 16" to 14" display.

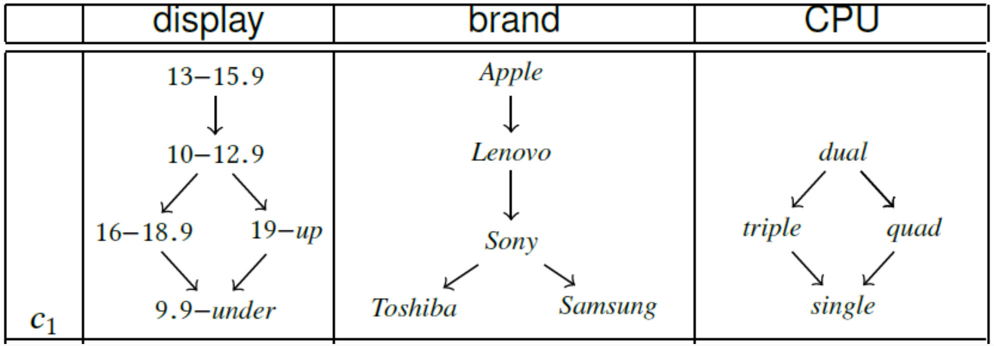


Motivation

- Recommendation based on users' preferences
- Preferences with multiple attributes
- ➢ Goal: objects that "stand out"

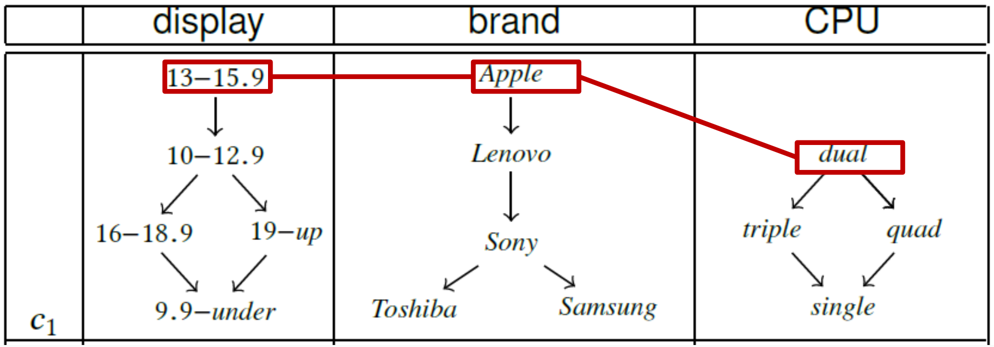
I prefer 16" to 14" display.

An Example



	display	brand	CPU
o_1	12	*Apple*	*single*
o_2	14	*Apple*	*dual*
…	…	…	…
o_7	16.5	*Lenovo*	*quad*

An Example



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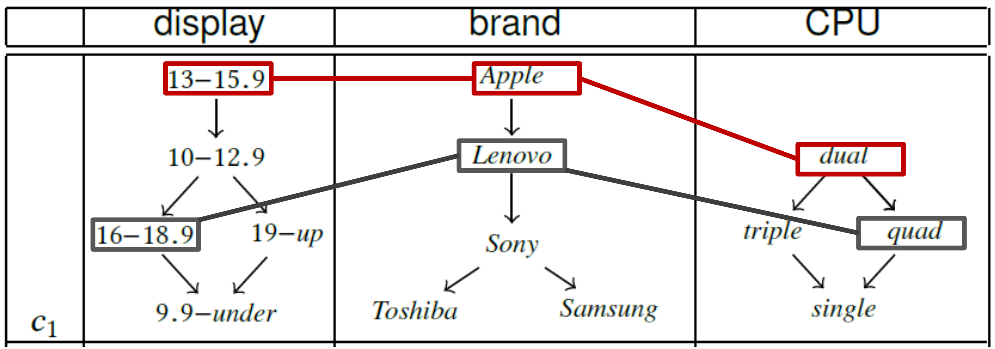

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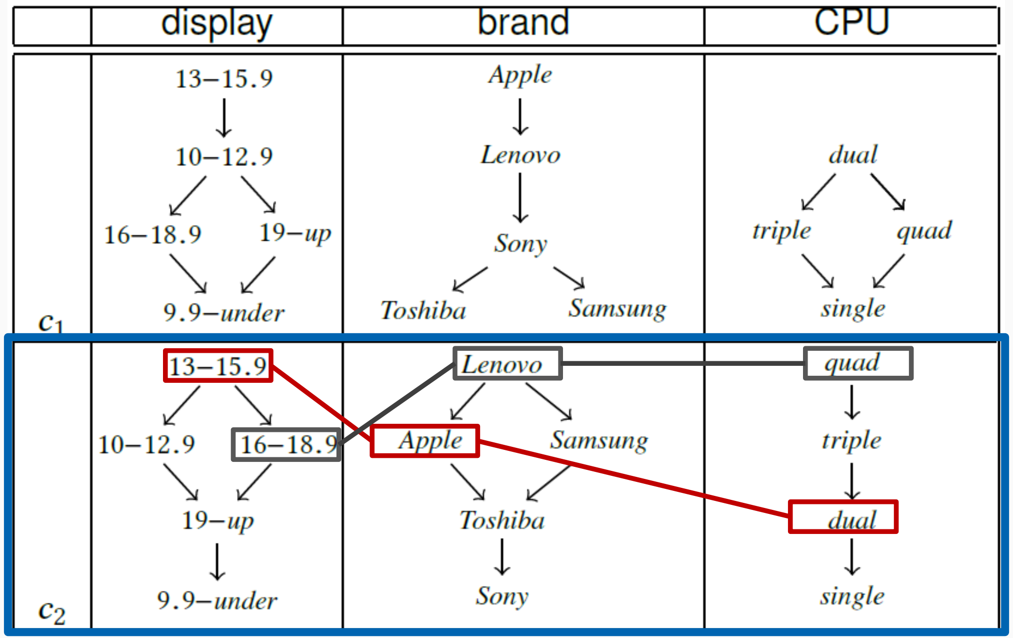

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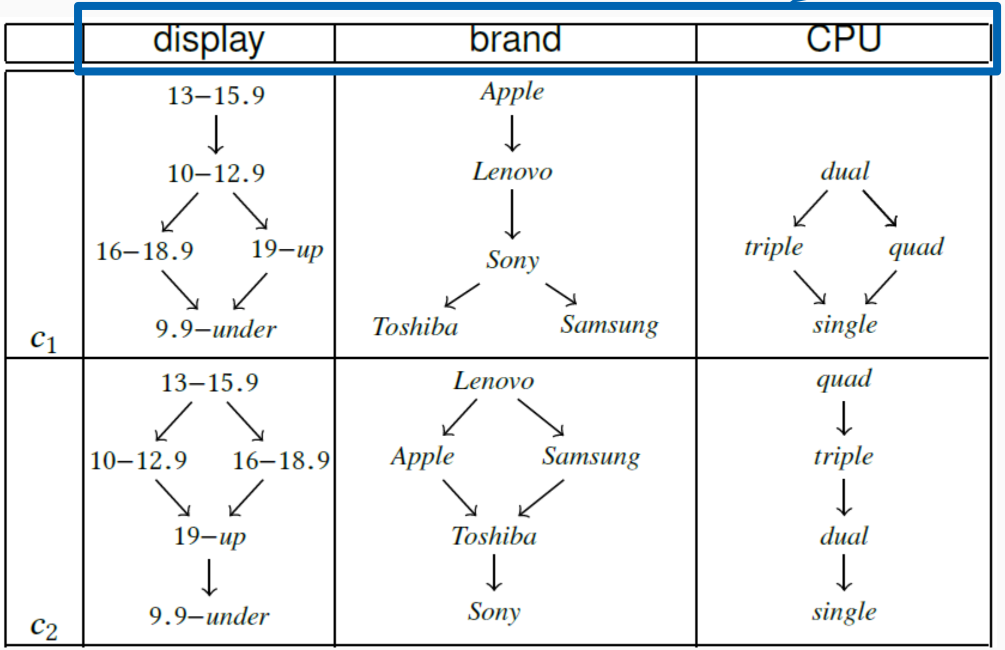
…	…	…	…
o_7	16.5	*Lenovo*	*quad*

Problem Formulation

Set of attributes $\mathcal{D}$



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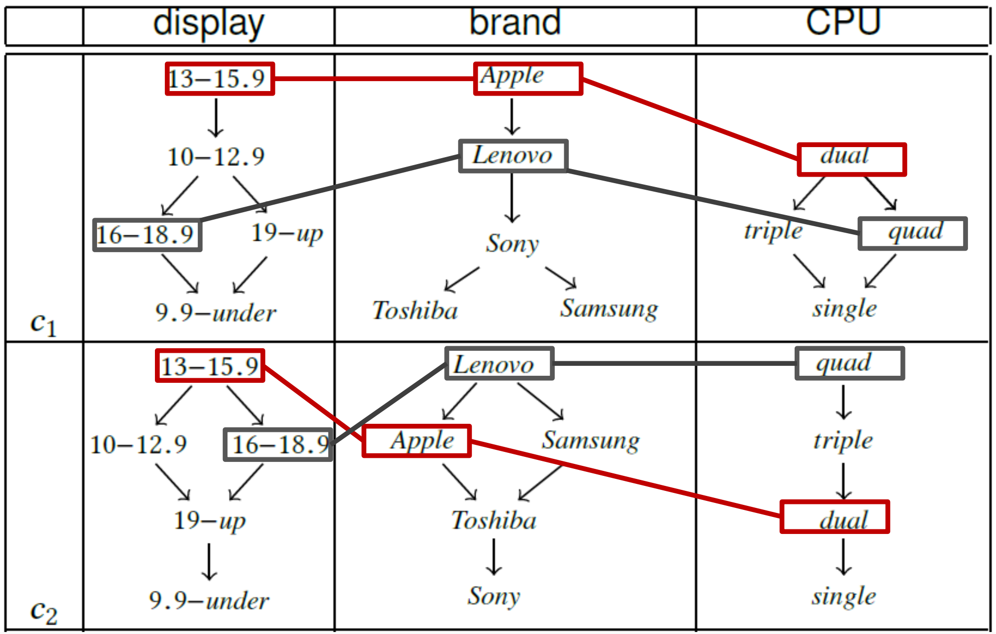
…	…	…	…
o_7	16.5	*Lenovo*	*quad*

Append-only object table O

Users' preferences

Problem Formulation



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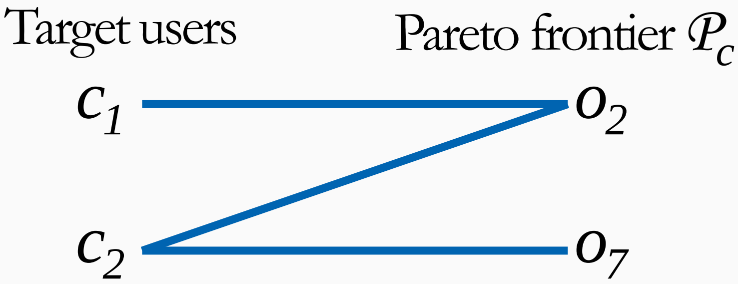
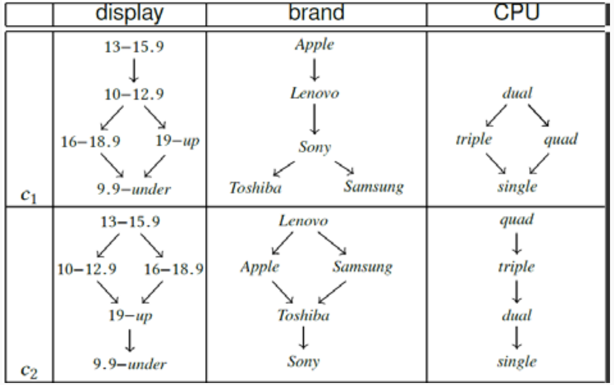


Problem Formulation; Continuous Object Dissemination



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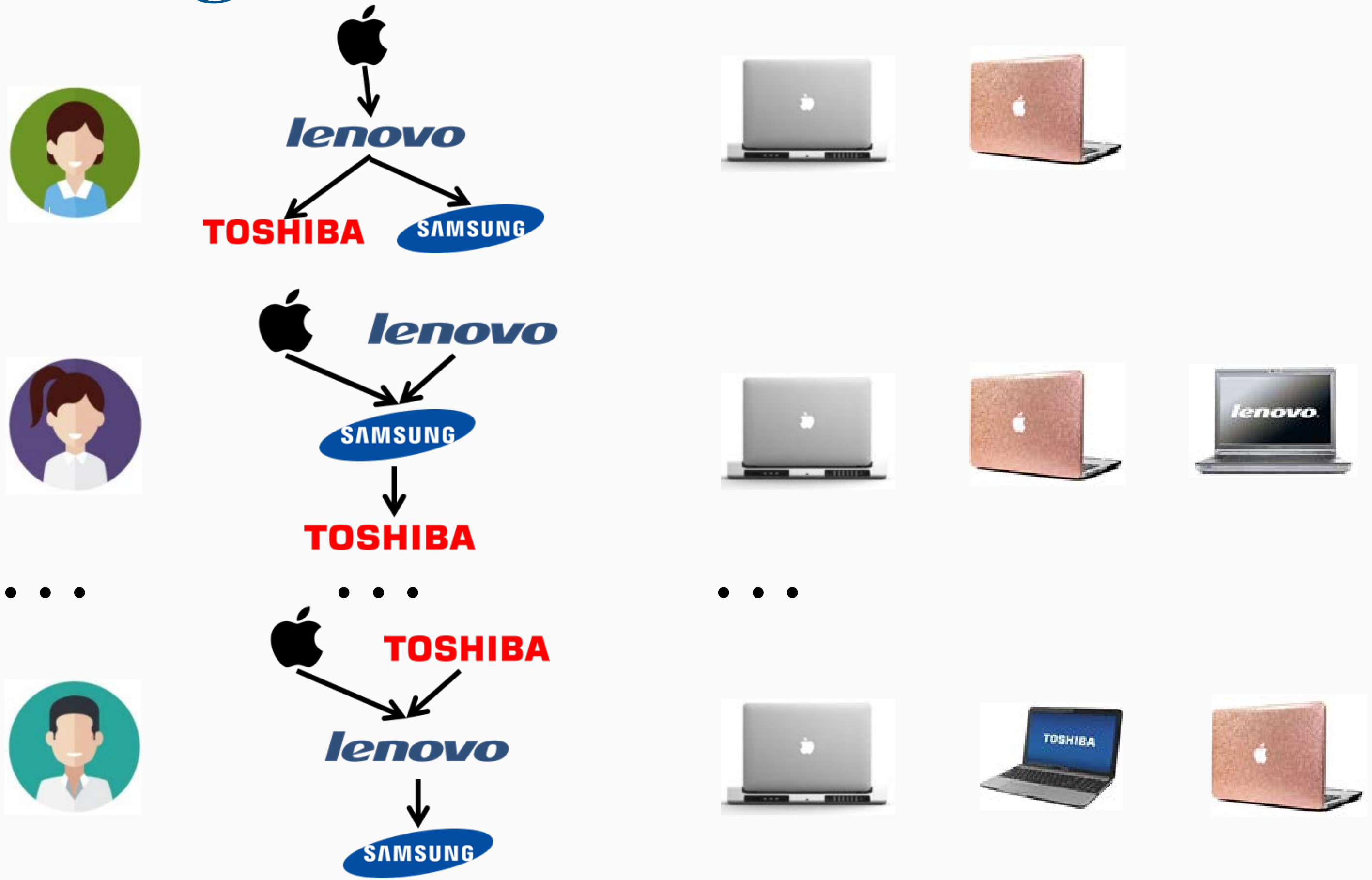
Find target users such that o_7 is in the Pareto frontier.

$\boxed{c_2}$

Challenges & Ideas



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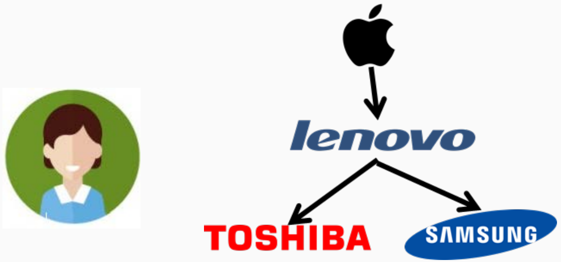

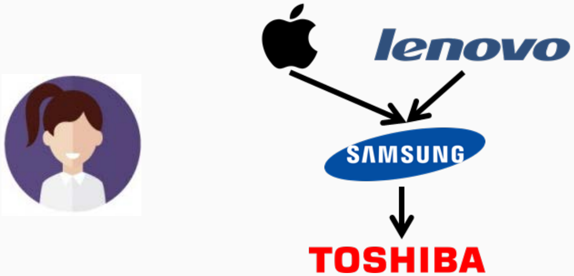

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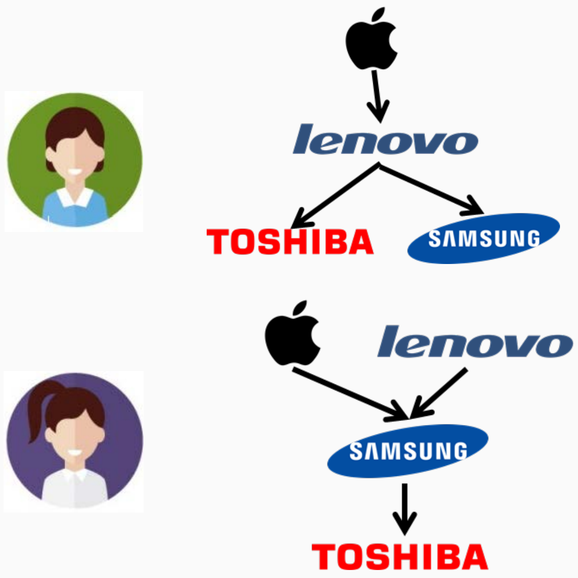
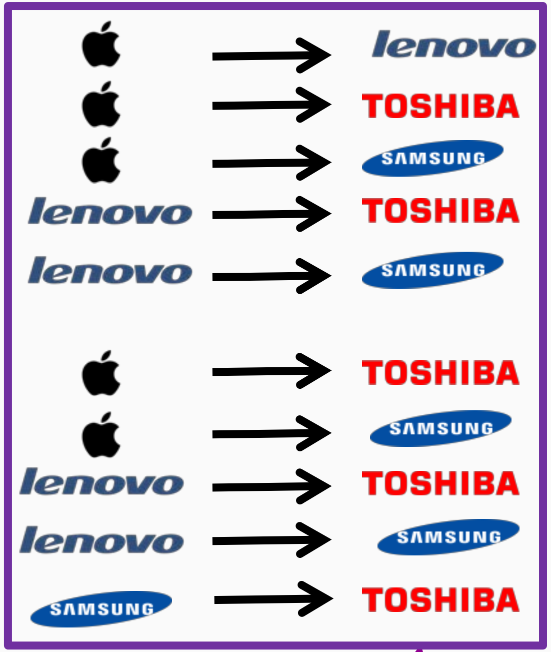
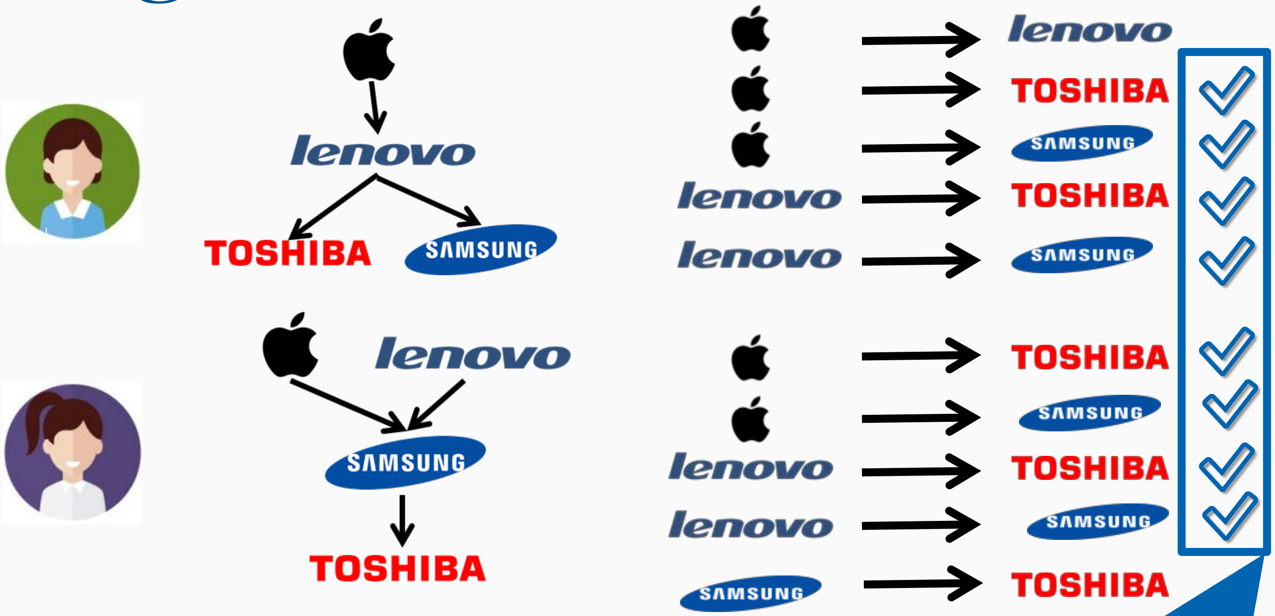




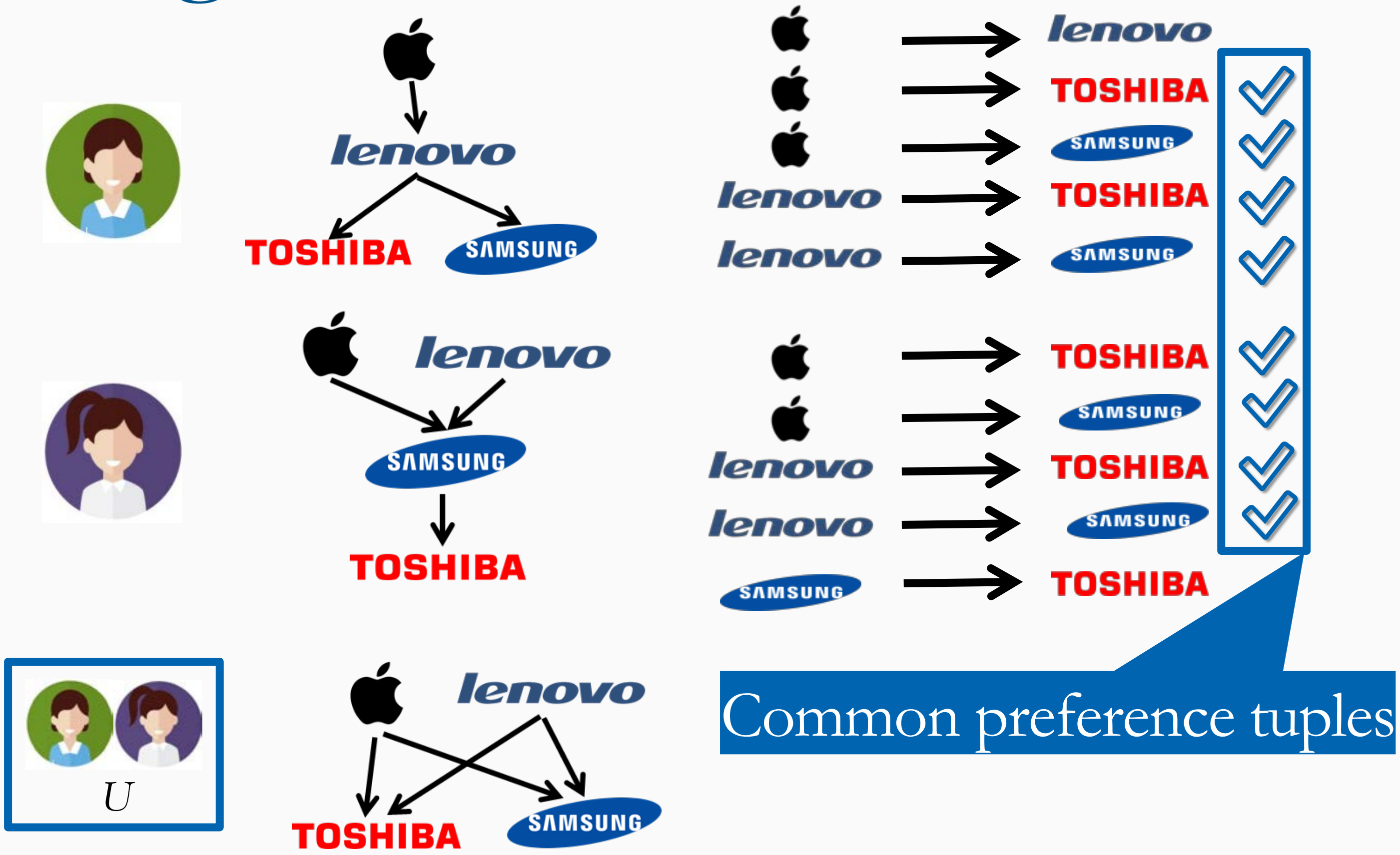
Preference tuples

Challenges & Ideas



Common preference tuples

Challenges & Ideas



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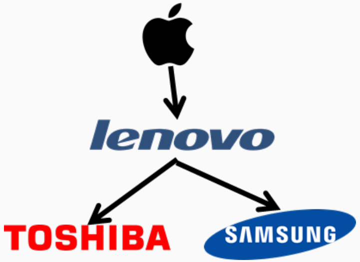
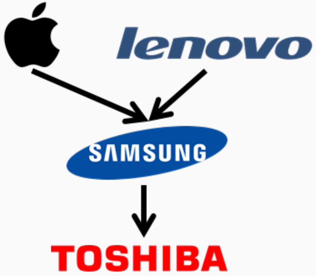
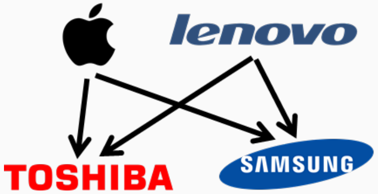
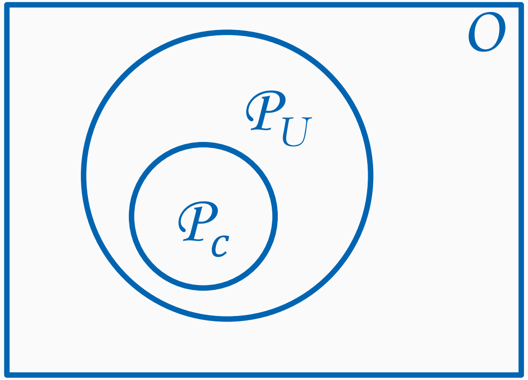






Challenges & Ideas

- Theorem 1: $\mathcal{P}_U \supseteq \mathcal{P}_c$
- Lemma 1: $\mathcal{P}_c$ w.r.t. $O = \mathcal{P}_c$ w.r.t. $\mathcal{P}_U$
- Recall & precision: 100%

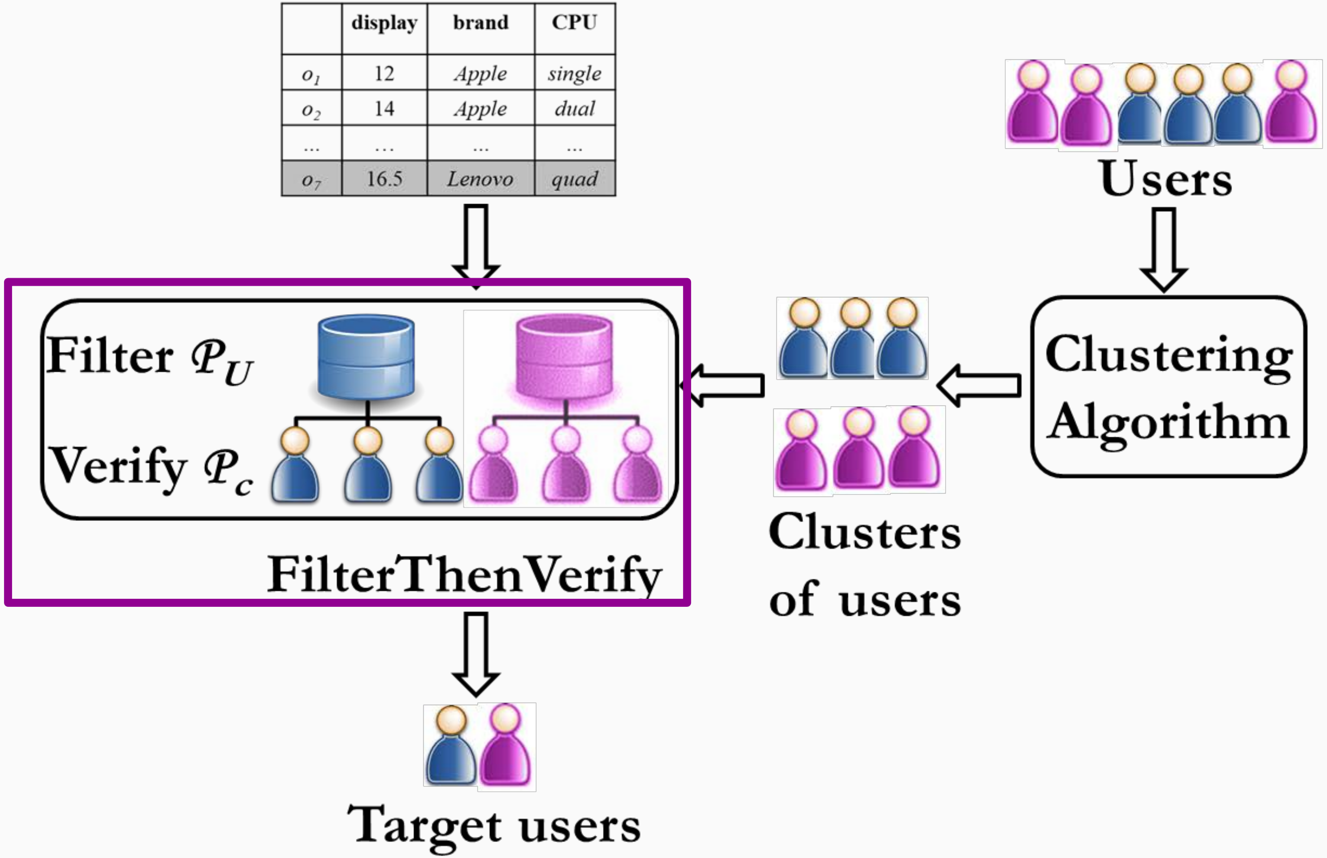


Sharing computation across users

Challenge and Ideas

- ❑ Which users share preferences?
  - ✓ Cluster users based on preferences
- ❑ No prior study on clustering for partial orders
  - ✓ Study clustering partial orders

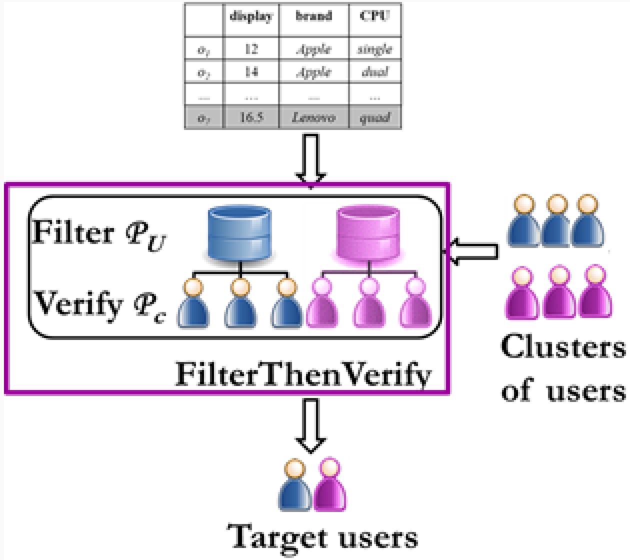
System Architecture



FilterThenVerify

For each cluster in C

- **Filter:** if U approve o in Pareto-optimality, stores o in $\mathcal{P}_U$
  - **Verify:** for each c, determines whether o belongs to $\mathcal{P}_c$



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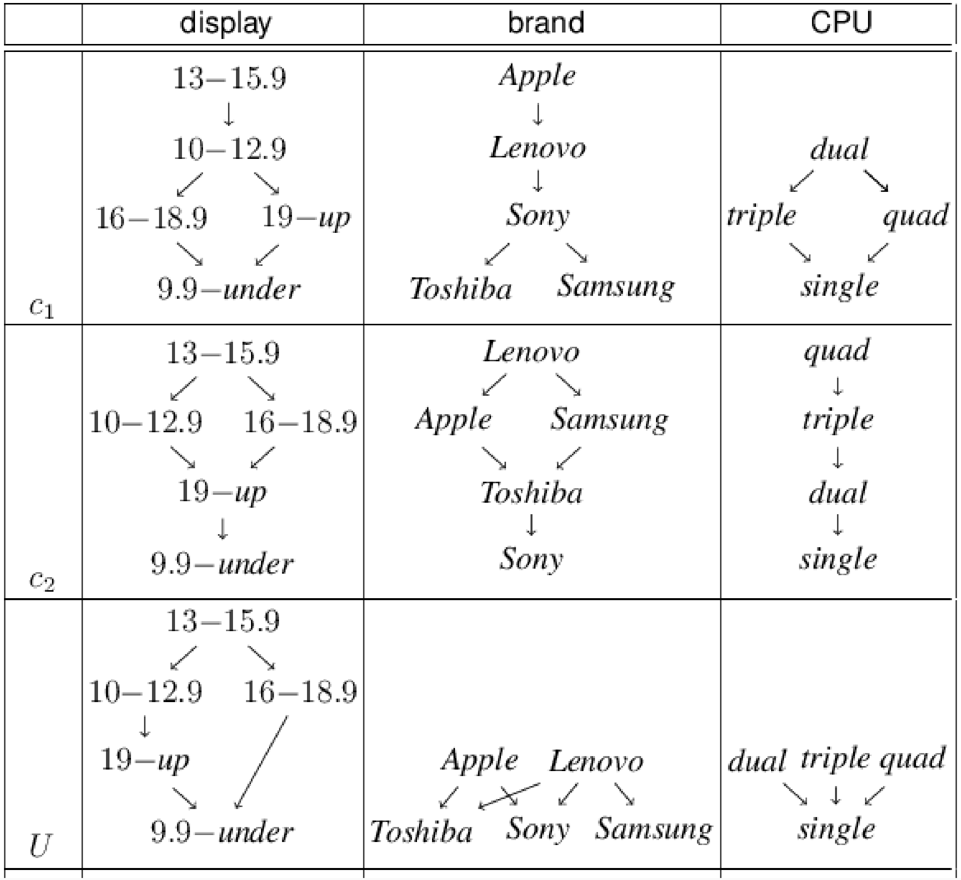

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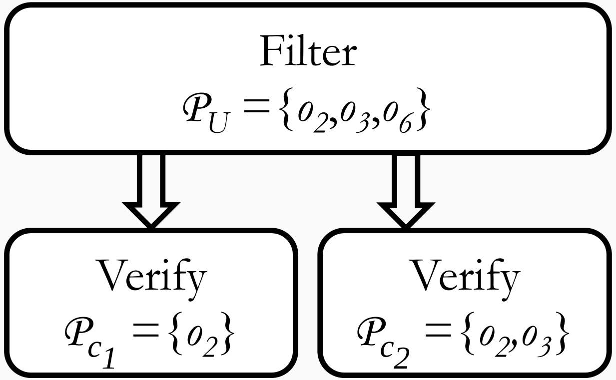

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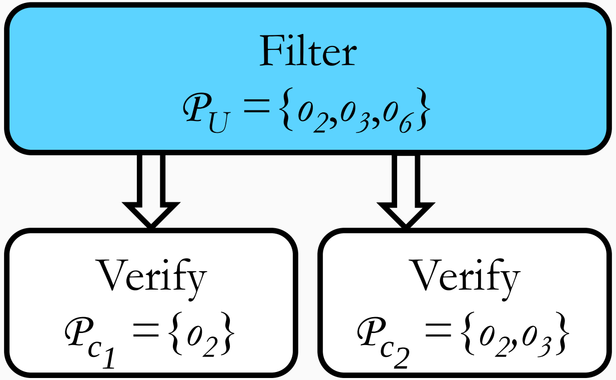

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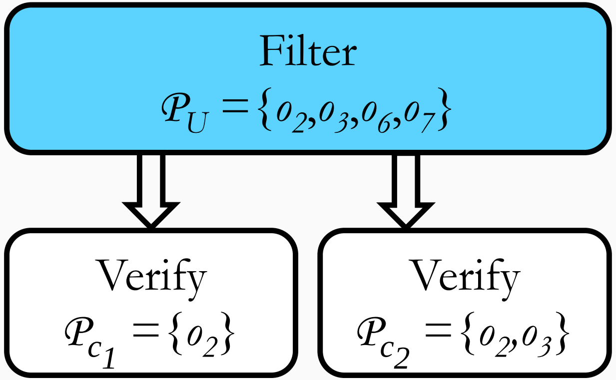

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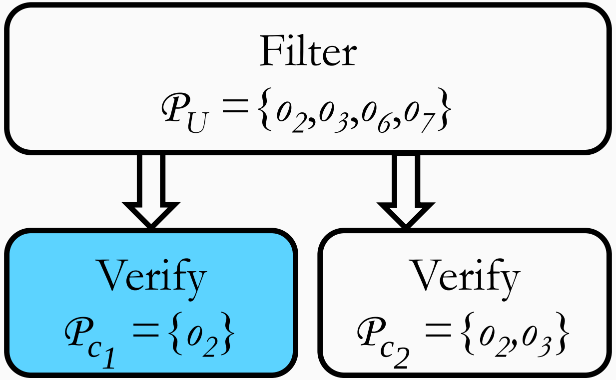

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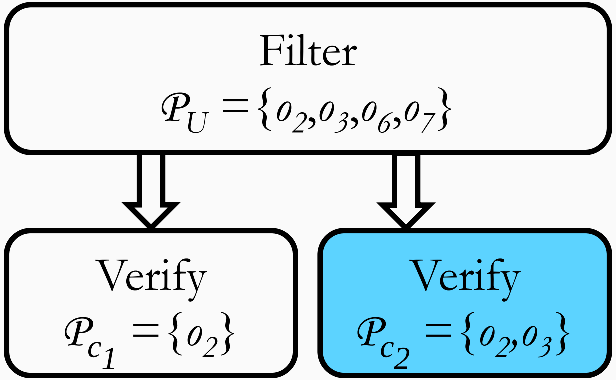

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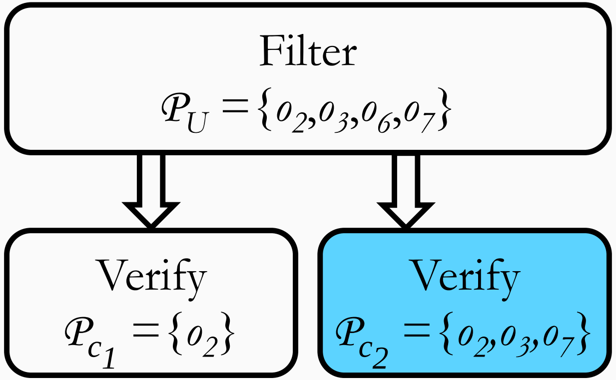

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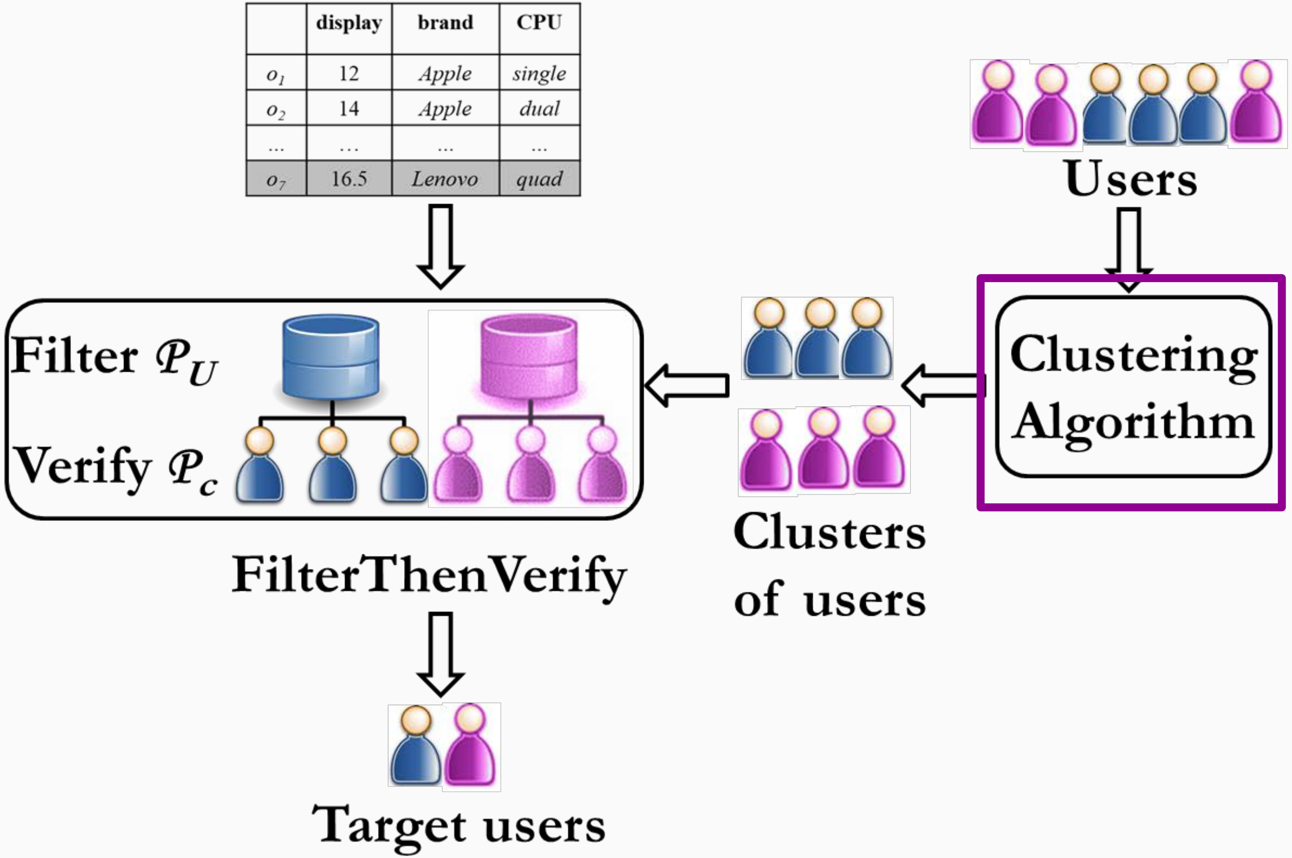
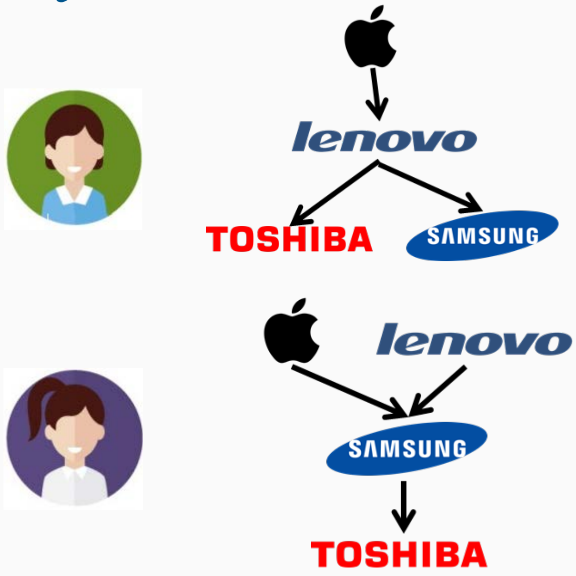
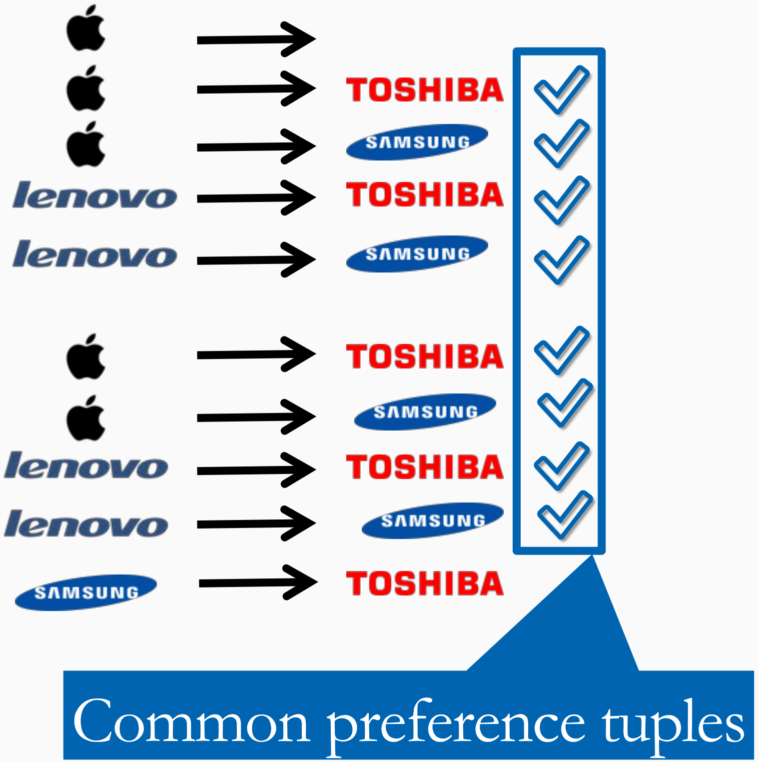


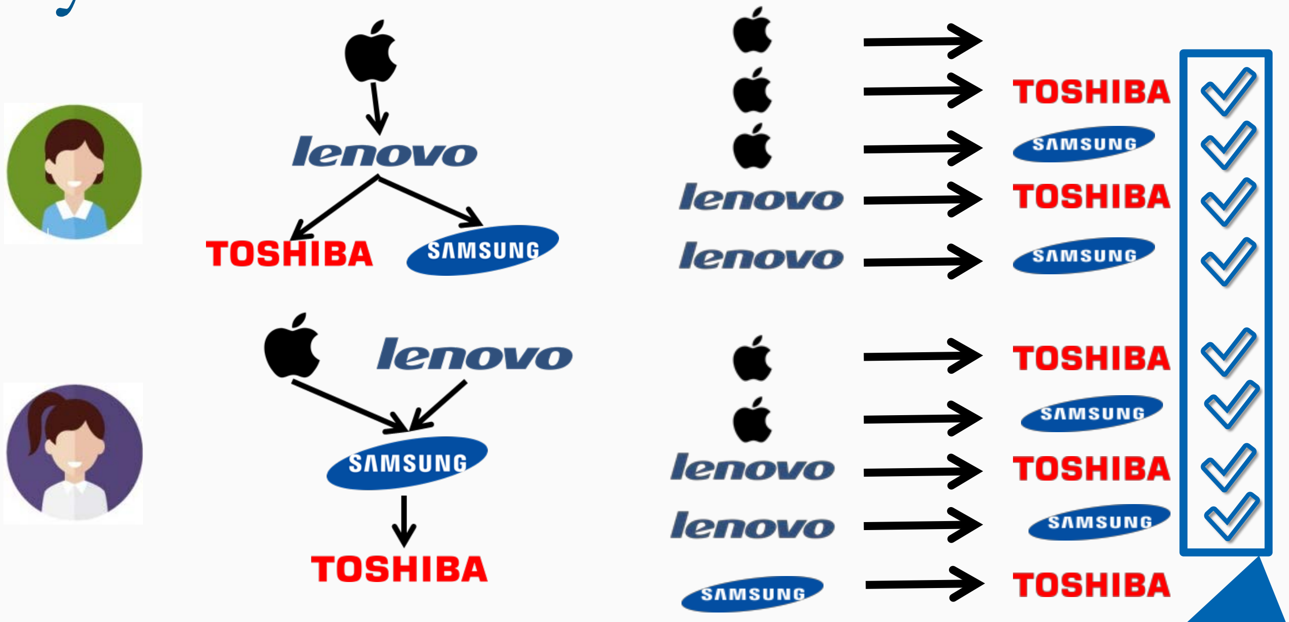
Similarity Function





- Jaccard similarity
  - $\frac{|Common\ preference\ tuples|}{|All\ preference\ tuples|}$

Similarity Function



Common preference tuples

- ❑ Weighted Jaccard similarity
  - ▪Locations of preference tuples

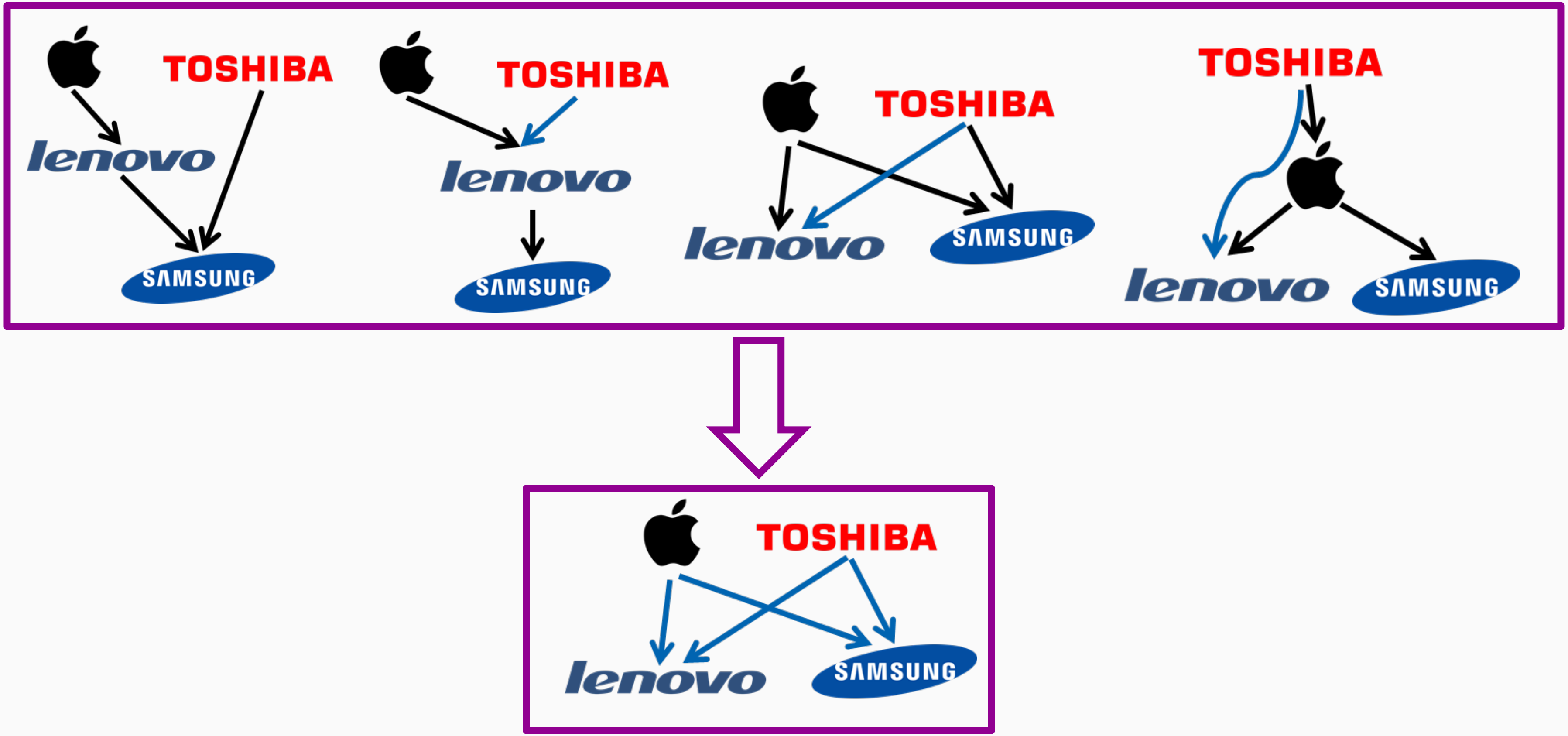
Approx. Common Preference Tuples

- Preferences can be diverse
  - Tiny clusters

Approx. Common Preference Tuples

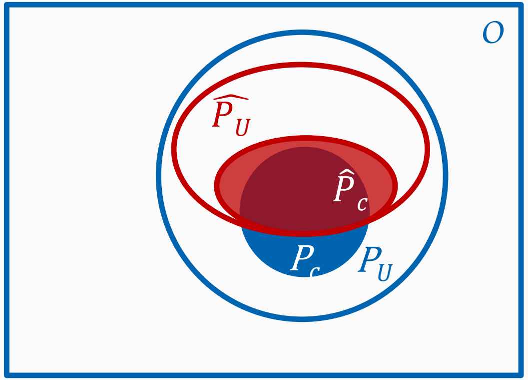
- Preferences can be diverse
  - Tiny clusters
- Relax idea of common preference tuple
  - ✓ Preference polling

GetApproxCommonPreferenceTuples



Properties of Approx. Common Preference Tuples

- Pareto frontier w.r.t. approx. common preference tuples: $\widehat{P_U}$
- Pareto frontier w.r.t. user upon approximation: $\widehat{P}_c$
- Lemma 2:
  - Approx. common preference tuples $\supseteq$ Common preference tuples
- Theorem 2
  - $\widehat{P_U} \subseteq P_U$
- Lemma 3
  - $\widehat{P_U} \supseteq \widehat{P}_c$
- Theorem 3
  - $\widehat{P_U} \cap P_c \subseteq \widehat{P}_c$



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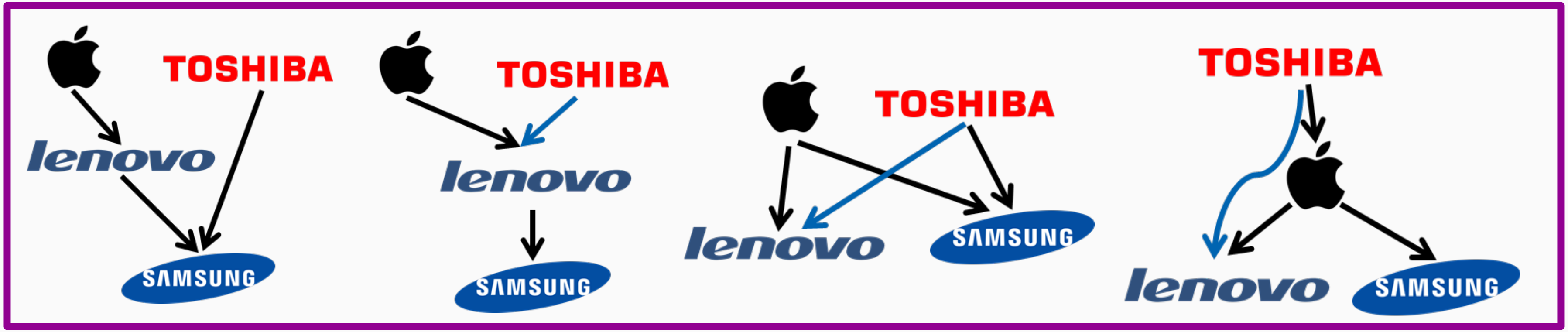


- ❑Percentage of preference tuples

Related Works

- ➢Conventional preference query (Kießling VLDB 2002)
  - Pareto frontier w.r.t. individual users, separately
- ✓Our solution---
  - Share computation across multiple users

Related Works

- Mining favorable facets (Wong et al. SIGKDD 2007)
  - Minimum disqualifying condition

	brand	CPU
o_1	*Apple*	*single*
o_2	*Samsung*	*dual*
o_3	*Toshiba*	*quad*

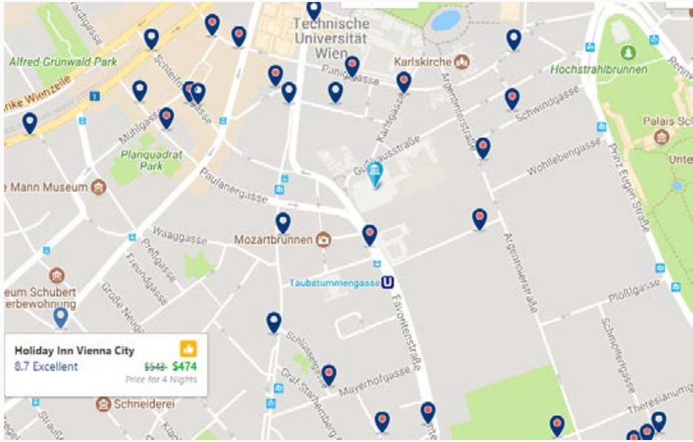
	Minimum set of preferences to disqualify
o_1	((*Samsung*,*Apple*) ∧ (*dual*,*single*)) ∨ ((*Toshiba*,*Apple*) ∧ (*quad*,*single*))
o_2	((*Apple*,*Samsung*) ∧ (*single*,*dual*)) ∨ ((*Toshiba*,*Samsung*) ∧ (*quad*,*dual*))
o_3	((*Apple*,*Toshiba*) ∧ (*single*,*quad*)) ∨ ((*Samsung*,*Toshiba*) ∧ (*dual*,*quad*))

✓ Our solution---

- Compatible with continuously arriving objects

Related Works

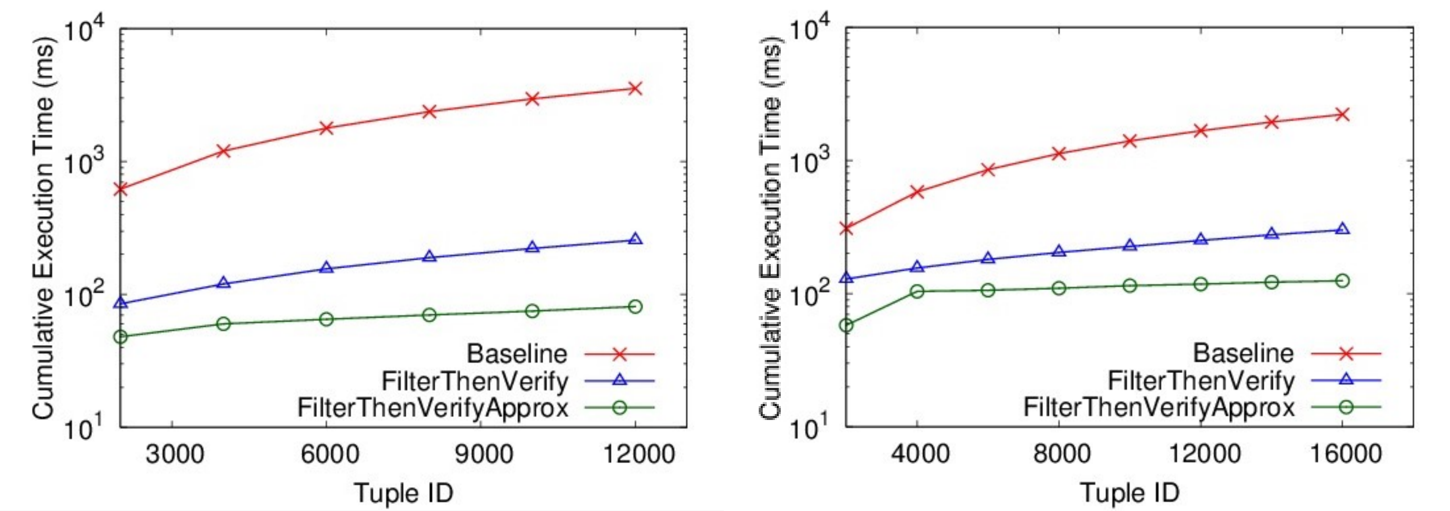
	Attribute	Order
Reverse skyline query (Dellis et al. VLDB 2007)	Numerical: price, distance	Total
Our solution	Categorical/numerical: brand, hotel/suite	Partial



Experiment by Simulation

- Movie Dataset
  - 12,749 movies: joined Netflix dataset with data from IMDB
  - 1000 users
  - 4 attributes: *actor*, *director*, *genre*, *writer*
- Publication Dataset
  - 17,598 publications: ACM Digital Library
  - 1000 users
  - 4 attributes: *affiliation*, *author*, *conference*, and *keyword*

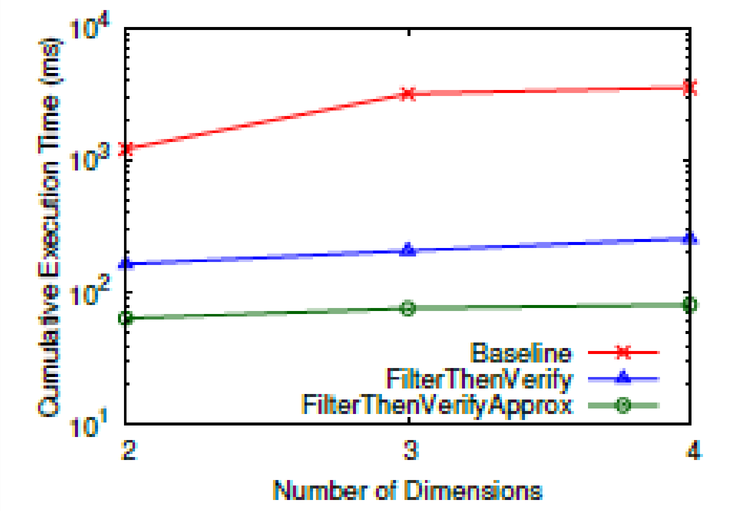
Performance of FilterThenVerify/FilterThenVerifyApprox



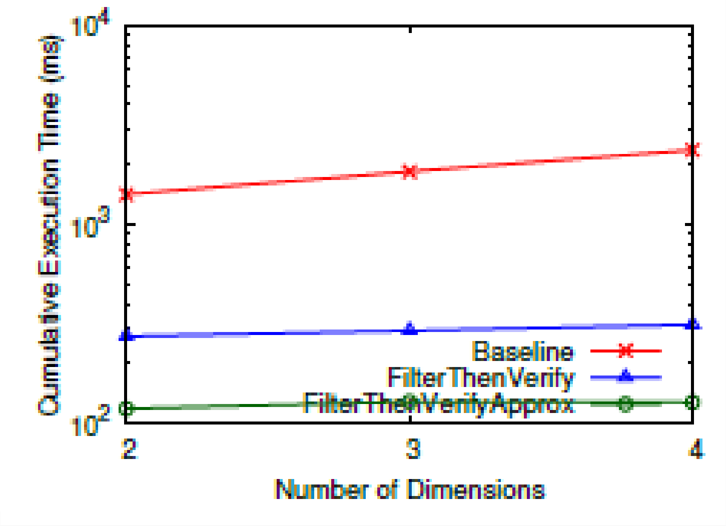
Movie Dataset **Publication Dataset**

- Baseline < FilterThenVerify/FilterThenVerifyApprox
  - Fewer comparisons due to filtering
- FilterThenVerify < FilterThenVerifyApprox
  - Approx. allows more sharing

Performance of FilterThenVerify/FilterThenVerifyApprox



Movie Dataset



Publication Dataset

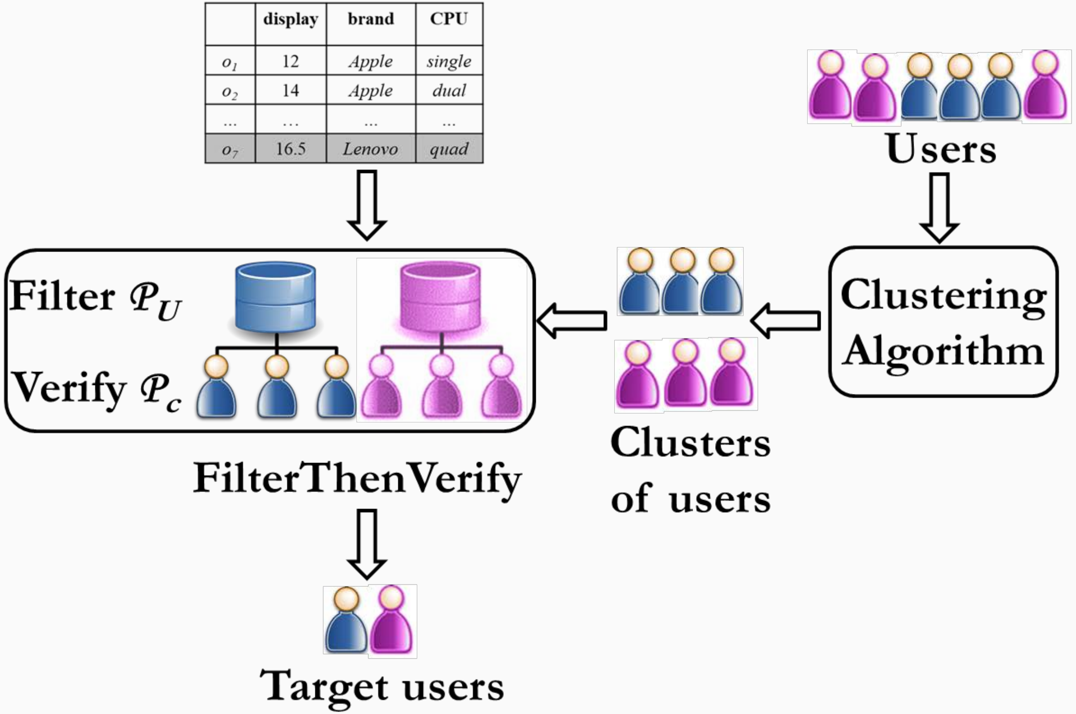
- Execution time increases with *d*
  - High *d*=>large Pareto frontiers=>more comparisons

Efficacy of FilterThenVerifyApprox

Dataset	h = 0.70			h = 0.55		
	Precision	Recall	F-measure	Precision	Recall	F-measure
Movie	100	95.43	97.67	99.99	90.46	94.99
Publication	100	96.59	98.27	100	95.13	97.51

- Recall decreases with h
  - Small h=>large clusters=>high false negatives
- Stable precision
  - Few false negatives=>fewer false positives

Conclusion



- ✓ Efficient algorithm to find target users
- ✓ Novel problem of clustering partial orders

THANK YOU!