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Cross-Domain Recommender Systems

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2nd ed. of the RSs Handbook
Cross-Domain Recommender Systems

Iván Cantador

Ignacio Fernández-Tobıas

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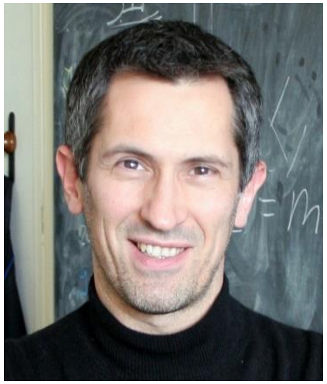
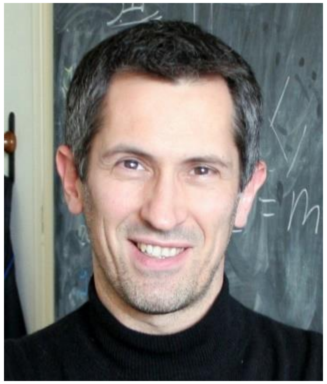
Tutorial
Cross-Domain Recommender Systems

Iván Cantador



Paolo Cremonesi

Today
Cross-Domain Recommender Systems



Paolo Cremonesi

Recommendations for single domains

- Traditional recommender systems suggest items belonging to a single domain
  - movies in Netflix
  - songs in Last.fm
  - …
- This is not perceived as a limitation, but as a focus on a certain market

User profiles in multiple systems

Nowadays, **users**…

- provide feedback for **items of different types**
  - e.g., in Amazon we can rate books, DVDs, …
- express their opinions on **different social media** and **different providers**
  - e.g., Facebook, Twitter, Amazon, Netflix, TripAdvisor

Nowadays **providers** wish to …

- cross-sell products and services
- provide recommendations to new users

Recommendations for multiple domains

Can we leverage all the available personal data provided in distinct **domains** to generate **better recommendations**?

definition of "***domain***"

definition of "***better recommendations***"

Problems related to Cross-Domain RSs

- **Machine Learning**
  - **Multi-Task Learning / Transfer Learning**
- **User Modeling**
  - aggregation user preferences for cross system personalization, targeted adv., security
- **Context Aware** recommender
  - different domains as different context
- **Hybrid** recommender (**Ensemble** learning)
  - AdaBoost → Hybrid
  - Bootstrap / Blending → Cross Domain

History of Cross-Domain RSs

- **2002**: the term "**cross-domain recommenders**" appear for the first time in a patent:
  - Triplehop Technologies (now Oracle)
- **2005**: some papers suggest "**cross-domain**" as an interesting topic
  - Mark van Setten, Sean M. McNee, Joseph A. Konstan. 2005
  - Shlomo Berkovsky, Tsvi Kuflik, Francesco Ricci. 2005
- **2007**: first papers with contributions on "**cross-domain**"
  - Ronald Chung, David Sundaram, Ananth Srinivasan. 2007
  - Shlomo Berkovsky, Tsvi Kuflik, Francesco Ricci. 2007
  - Ronald Chung, David Sundaram, Ananth Srinivasan. 2007

History of Cross-Domain RSs

- First papers trying to classify problems and approaches
  - Antonis Loizou. 2009
  - Sinno Jialin Pan, and Qiang Yang. 2010
  - Bin Li. 2011
  - Paolo Cremonesi, Antonio Tripodi, and Roberto Turrin. 2011
  - Fernández-Tobías, Ignacio, Iván Cantador, Marius Kaminskas, and Francesco Ricci. 2012

Cross-domain recommendations

- **Single-Domain:** Treat each domain independently
- **Collective-Domain:** Merge domains an treat them as a single domain

baseline

- **Cross-Domain:** Transfer knowledge from source to target
  - **assumption**: information overlap between users and/or items across different domains
    - overlaps of users, items, attributes, …

Goal of this tutorial

- **Taxonomy** of problems and techniques
- **Literature overview**: who is doing what
- **Guidelines**, based on consolidated as well as state-of-the-art best practices from the research community

Contents

1. The cross-domain recommendation problem
2. Cross-domain recommendation techniques
3. Evaluation of cross-domain recommenders
4. Open issues in cross-domain recommendation

Definition of the cross-domain problem

- Domains
  - which types of domains exist?
- Goals
  - why do we need cross-domain recommenders?
- Tasks
  - which parts of the datasets are used?
- Scenarios
  - which overlap of information exists between domains?

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1. The cross-domain recommendation problem
   - **Definition of domain**
   - Cross-domain recommendation goals and tasks
   - Cross-domain recommendation scenarios
2. Cross-domain recommendation techniques
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Definition of domain

- A **domain** is a particular field of thought, activity, or interest
- In the literature researchers have considered **distinct notions of domain**:
  - movies vs. books
  - action movies vs. comedy movies
  - ...

Definition of domain

- Domains differ because of
  - different types of items
    - Movies vs. Books
  - different types of users
    - pay-per-view users vs. users with yearly subscription
  - “partition” of users with respect to items
    - e.g., users with ratings on
      - Books only
      - Movies only
      - Books and Movies

Definition of domain

We focus on two domains

source D_S $\leftrightarrow$ **target D_T**

(*auxiliary*)

Domain levels

- **Attribute level** (*Comedy* ↔ *Thriller*)
  - same type of items, different values of certain attribute
- **Type level** (*Movies* ↔ *Books*)
  - similar types, sharing some attributes
- **Item level** (*Movies* ↔ *Restaurants*)
  - distint types, differing in most, if not all attributes
- **System level** (*Netflix* ↔ *Movielens*)
  - almost the same items, collected in different ways and/or from different operators

Domain levels in the literature…

- **Attribute level** (*Comedy* ↔ *Thriller*): **12%**
  - Movie genres (Movielens, Eachmovie)
- **Type level** (*Movies* ↔ *Books*): **9%**
  - Amazon
- **Item level** (*Movies* ↔ *Music*): **55%**
  - Movielens, Last.fm, Delicious, BookCrossing, Facebook
- **System level** (*Netflix* ↔ *Movielens*): **24%**
  - Last.fm, Delicious

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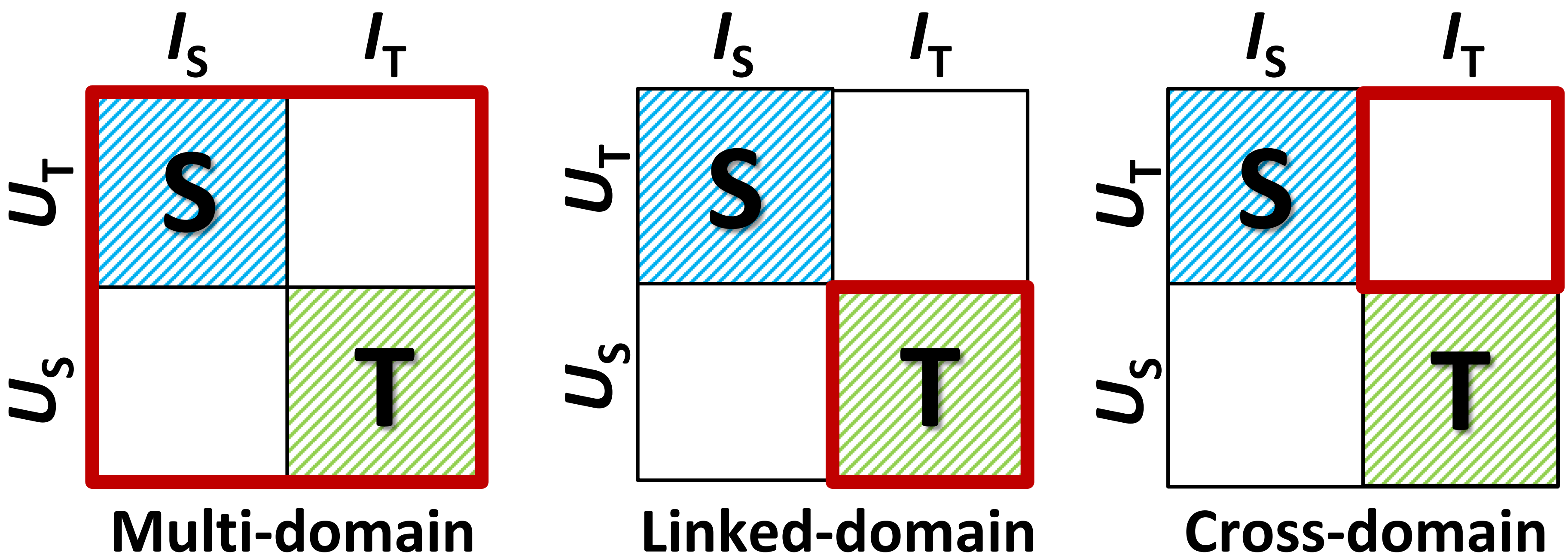
Cross-domain recommendation goals

- Addressing the cold-start problem
  - recommending to new users
  - cross-selling of products
- Improving accuracy
  - e.g., by reducing sparsity
- Offering added value to recommendations
  - diversity, novelty, serendipity
- Enhancing user models
  - discovering new user preferences
  - vulnerability in social networks

Goals in the literature …

Goal	Percentage
Cold start	5%
New user	15%
New item	5%
Accuracy	55%
Diversity	5%
Privacy	5%
User model	10%

Cross-domain recommendation tasks

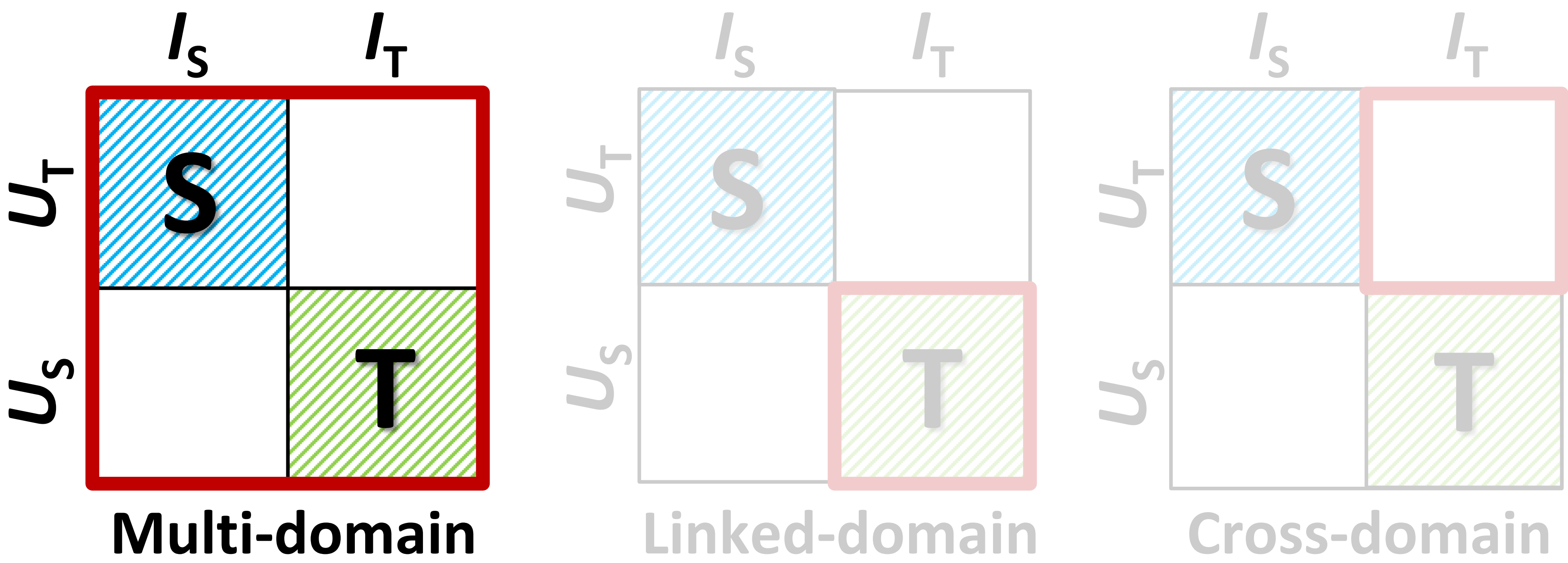


= data from source domain

= data from target domain

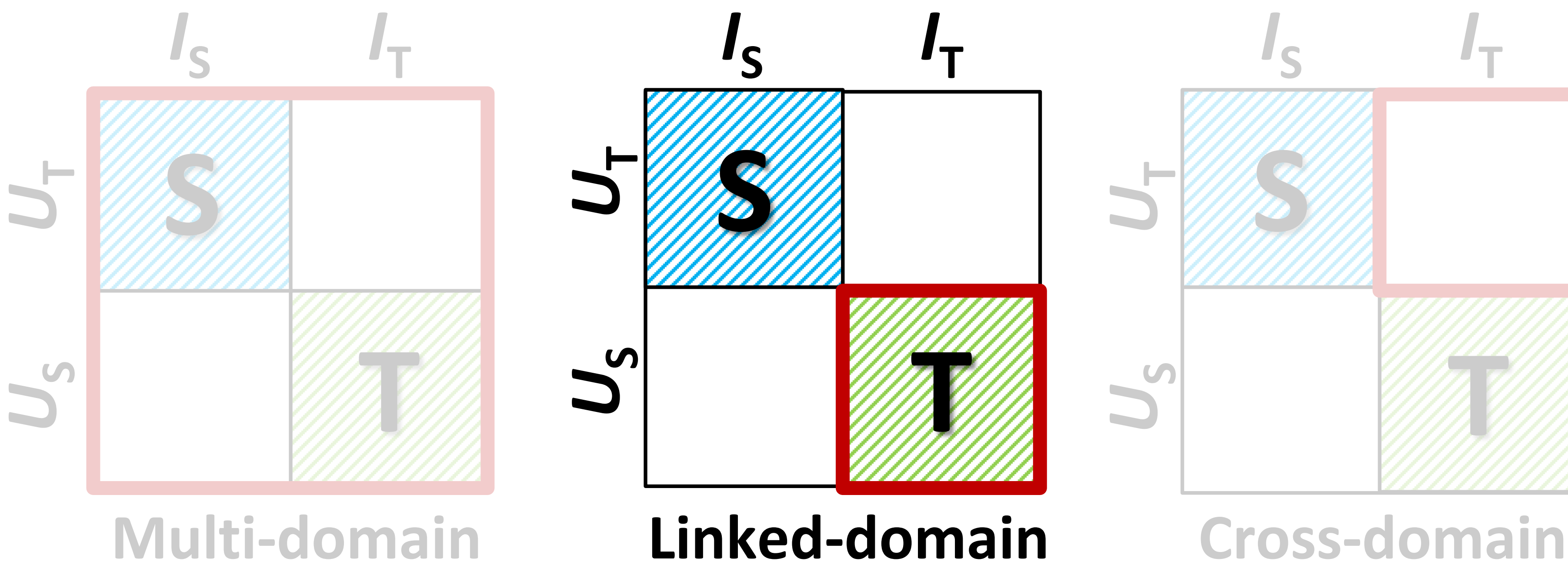
= target of recommendations

Multi-domain recommendation task



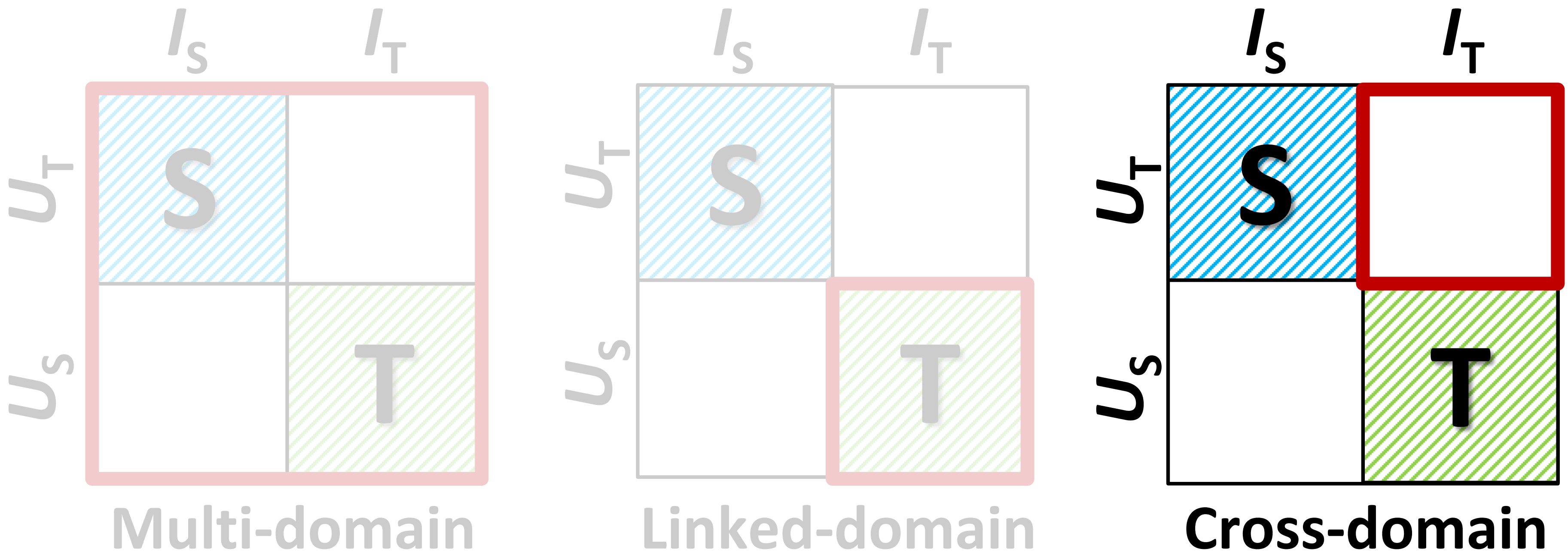
- Recommend items in both source and target domains
- Goal: cross-selling, improve diversity, novelty, serendipity
- Approach: sharing knowledge and linking domains

Linked-domain recommendation task



- Recommend target items to users in the target domains
- Goal: improve accuracy of recommendations in the target domain (e.g., reduce sparsity)
- Approach: all

Cross-domain recommendation task



- Recommend items in the target domain to users in the source domain
- Goal: solve cold-start, new users and new item probl.
- Approach: aggregating knowledge

Tasks in the literature …

Task	Multi-domain
Multi-domain	20%
Linked-domain	55%
Cross-domain	25%

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Notation

$\mathbf{X}_U$ → set of characteristics used to represent users

= $\mathbf{F}_U$ → side information (features) about users
(e.g., demographics, tags, friends, …)

= $\mathbf{I}$ → items rated by users

$\mathbf{X}_I$ → set of characteristics used to represent items

= $\mathbf{F}_I$ → side information (features) about items
(e.g., genres, keywords, …)

= $\mathbf{U}$ → users rating items

Linking domains

Overlapping attributes of …

… users:

- $\mathbf{F}_U(S) \cap \mathbf{F}_U(T) \neq \varnothing$
  - e.g., we have demographics of users in both domains

… items:

- $\mathbf{F}_I(S) \cap \mathbf{F}_I(T) \neq \varnothing$
  - e.g., items share the same set of attributes in both domains

Linking domains

Mapping attributes of …

… users:

- $f : \mathbf{X}_U(S) \rightarrow \mathbf{X}_U(T)$
  - e.g., friends of …

… items:

- $f : \mathbf{X}_I(S) \rightarrow \mathbf{X}_I(T)$
  - e.g., "vampire" in source and "zombie" in target are both "horror"

Linking domains

Overlap of …

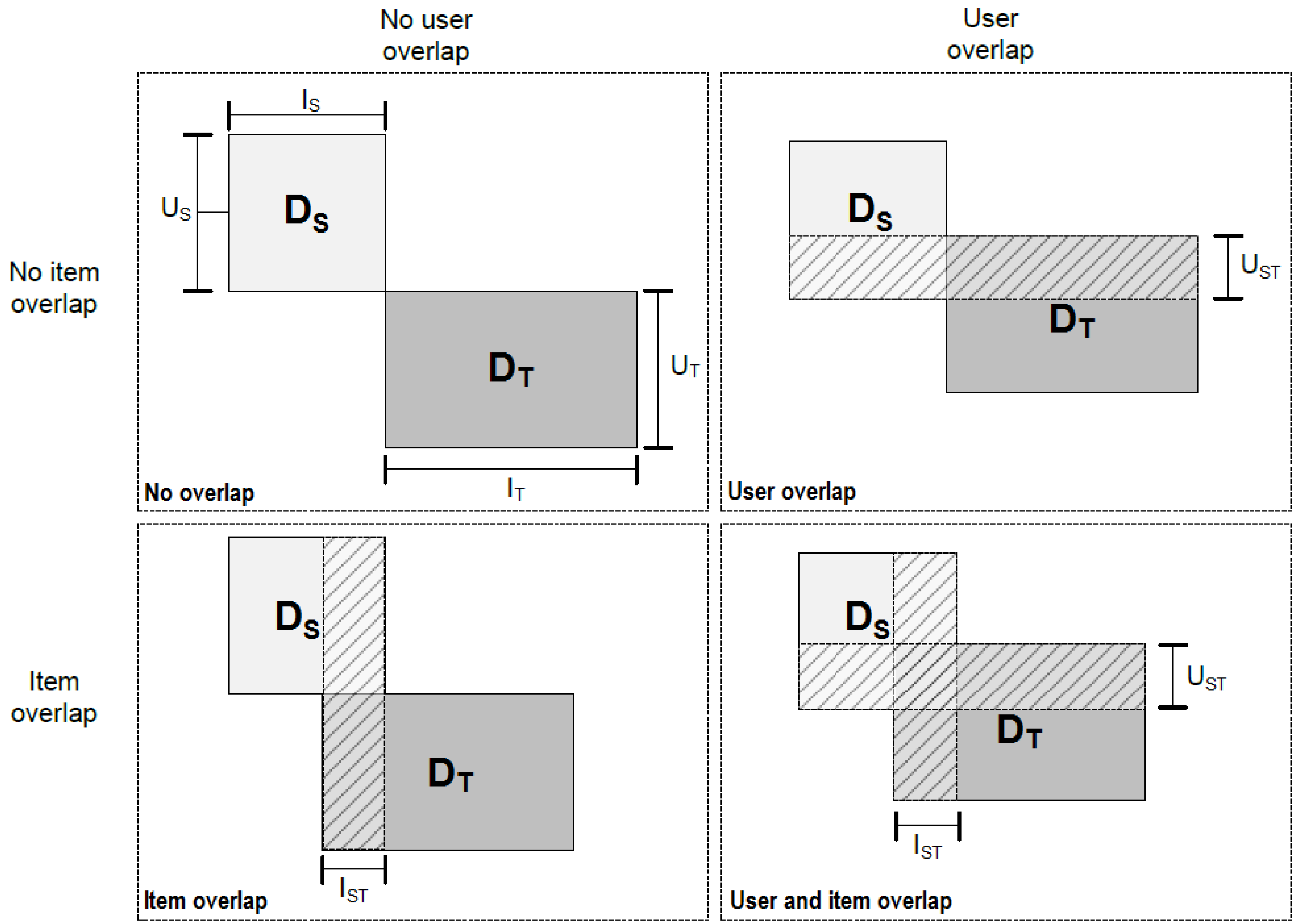
… items:

- $I(S) \cap I(T) \neq \emptyset$
  - e.g., we have same common items between domains

… users:

- $U(S) \cap U(T) \neq \emptyset$
  - e.g., we have same common users between domains

Cross-domain recommendation scenarios (I)



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Cross-Domain: opportunity or problem?

- The source domain is a potential source of bias
  - If the source domain is richer than the target domain, algorithms learn how to recommend items in the source domain and consider the target domain as noise
- The source domain is a potential source of noise
  - If the user models in the two domains differ, the source domain introduce noise in the learning of the target domain

Cross-Domain: opportunity or problem?

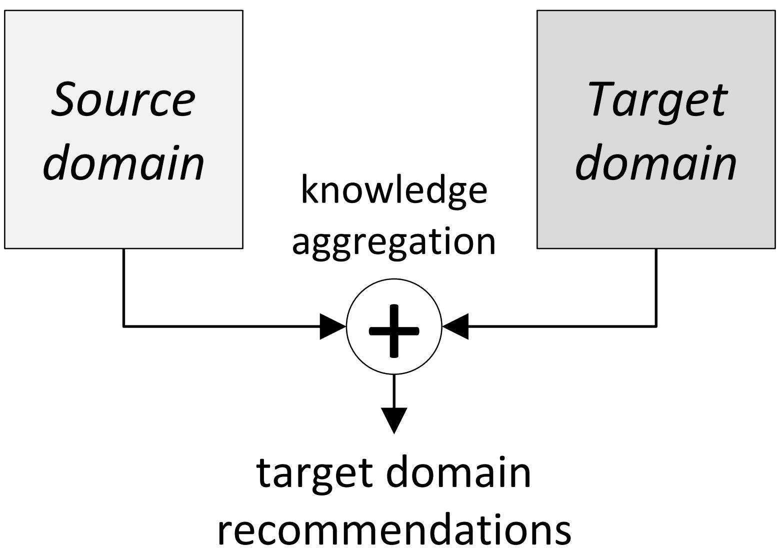
is a matter of **weights**

which is the relative “weight” of the two domains?

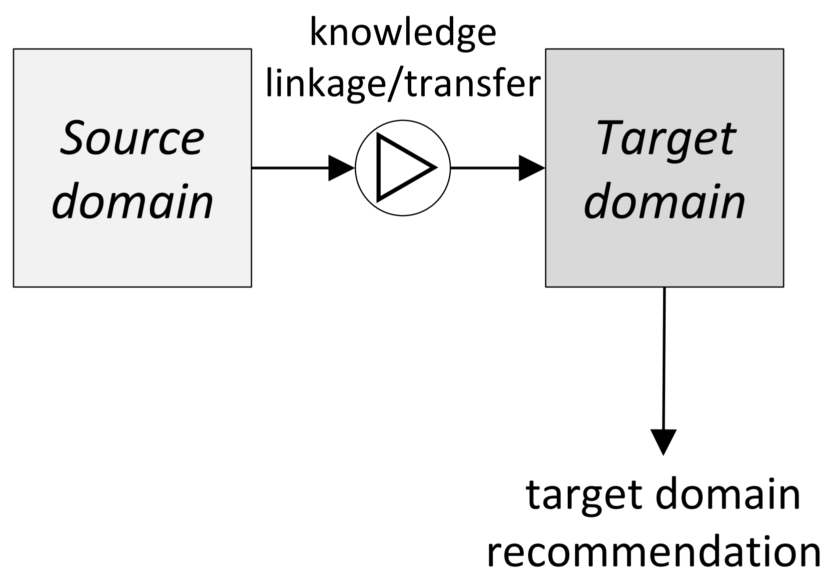
how much do we “weight” the information coming from the source domain?

Different approaches (I)

- Two types of cross-domain approaches, based on how knowledge from the source domain is exploited



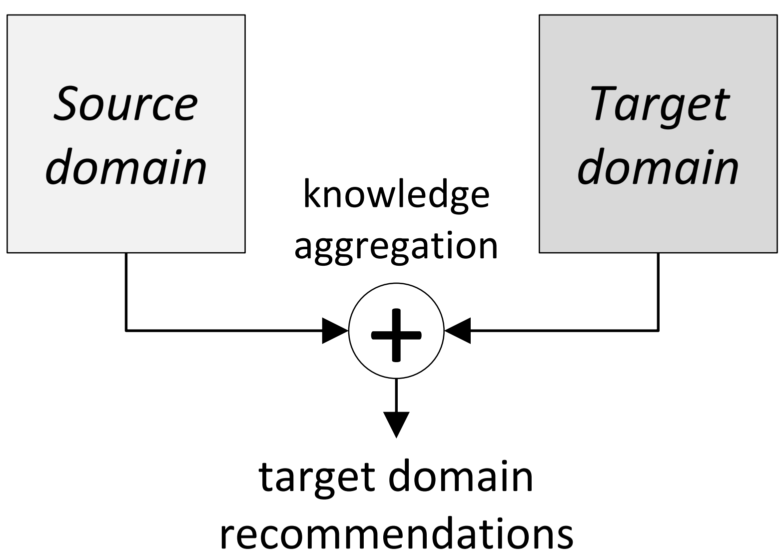
Linking/Aggregating knowledge



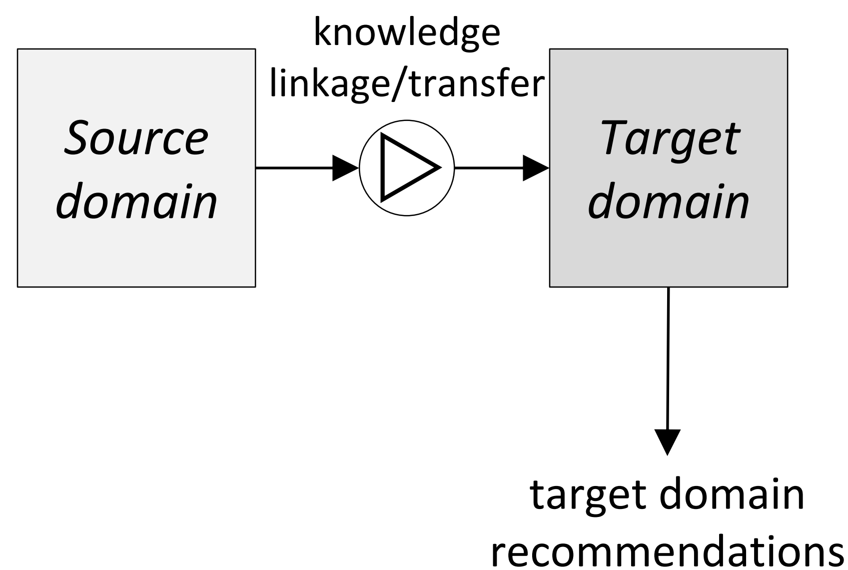
Sharing/Transferring knowledge

Different approaches (I)

- Two types of cross-domain approaches, based on how knowledge from the source domain is exploited



Linking/Aggregating knowledge



Sharing/Transferring knowledge

Fuzzy !!!

Different approaches (II)

- **Linking/Aggregating knowledge**
  - Merging user preferences
  - Mediating user modeling data
  - Combining recommendations
  - Linking domains
- **Sharing/Transferring knowledge**
  - Sharing latent features
  - Transferring rating patterns

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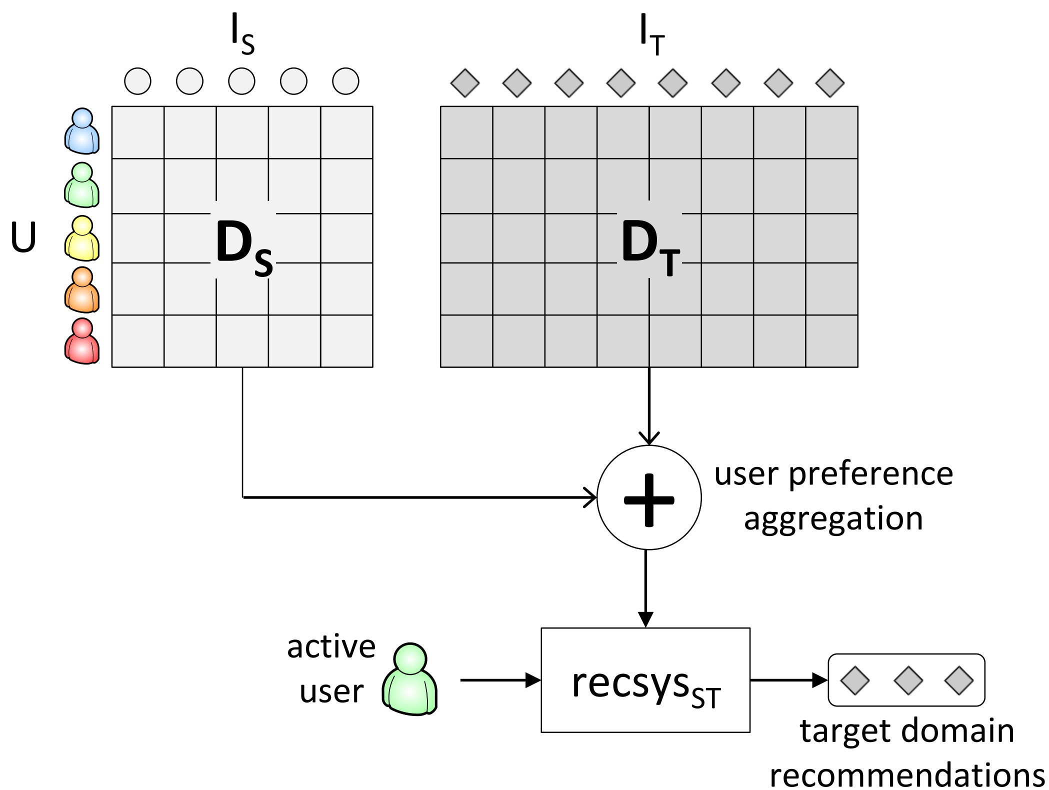
Proposed categorization

- Linking/aggregating knowledge
  - **Merging user preferences**
  - Mediating user modeling data
  - Combining recommendations
  - Linking domains
- **Sharing/transferring knowledge**
  - Sharing latent features
  - Transferring rating patterns

Merging user preferences (I)

- Aggregate user preferences
  - ratings, tags, transaction logs, click-through data



Merging user preferences (II)

- **Pros**:
  - work well for the new-user problem
  - robust (evolution of standard SD techniques)
  - facilitate explanation
- **Cons**:
  - need user-overlap between the source and target domains

Merging user preferences: approaches

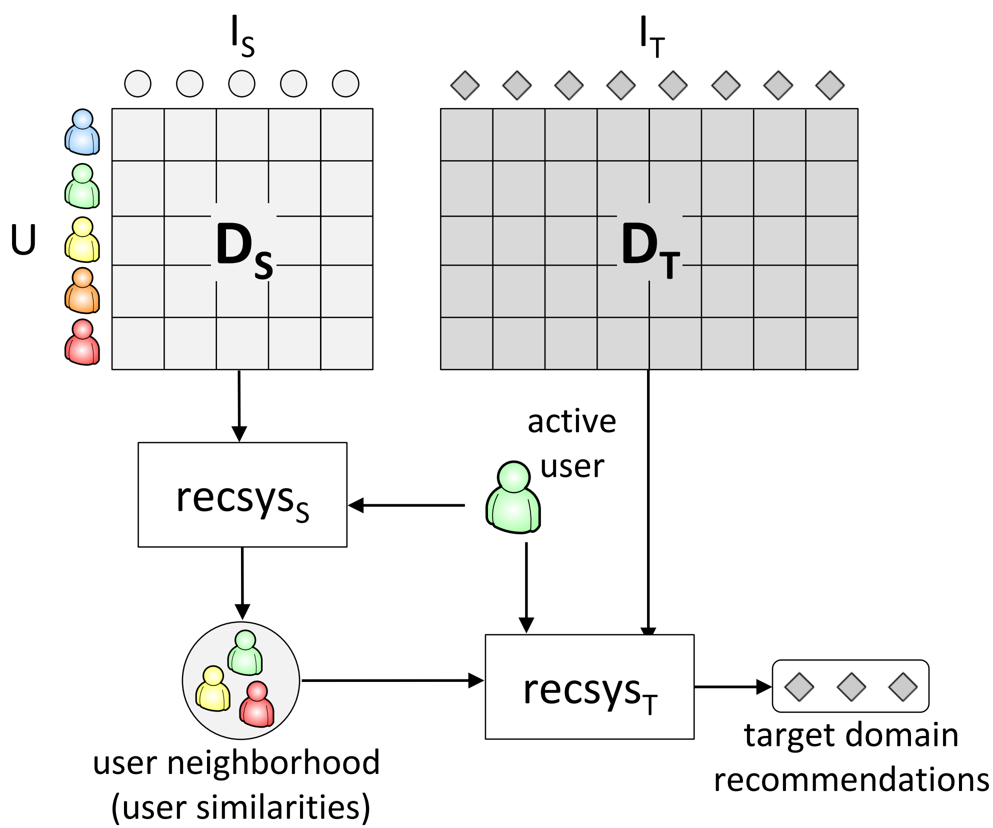
- On the aggregated matrix we can apply "weighted" single-domain techniques
  - User-based kNN
    - Berkovsky et al. 2007; Shapira et al. 2013; Winoto & Tang 2008;
  - Graph-based
    - Nakatsuji et al. 2010; Cremonesi et al. 2011; Tiroshi et al. 2013
  - Matrix Factorization / Factorization Machine
    - Loni et al. 2014

Proposed categorization

- Linking/aggregating knowledge
  - Merging user preferences
  - **Mediating user modeling data**
  - Combining recommendations
  - Linking domains
- **Sharing/transferring knowledge**
  - Sharing latent features
  - Transferring rating patterns

Mediating user modeling data (I)

- Aggregate models (CF, CBF, Hybrid) from different domains
  - user similarities, user neighborhoods



Mediating user modeling data (II)

- Pros:
  - suited to the new-user problem and accuracy goals
  - robust (evolution of standard SD techniques)
- Cons:
  - need of either user- or item-overlap between the source and target domains

Mediating modeling data: approaches

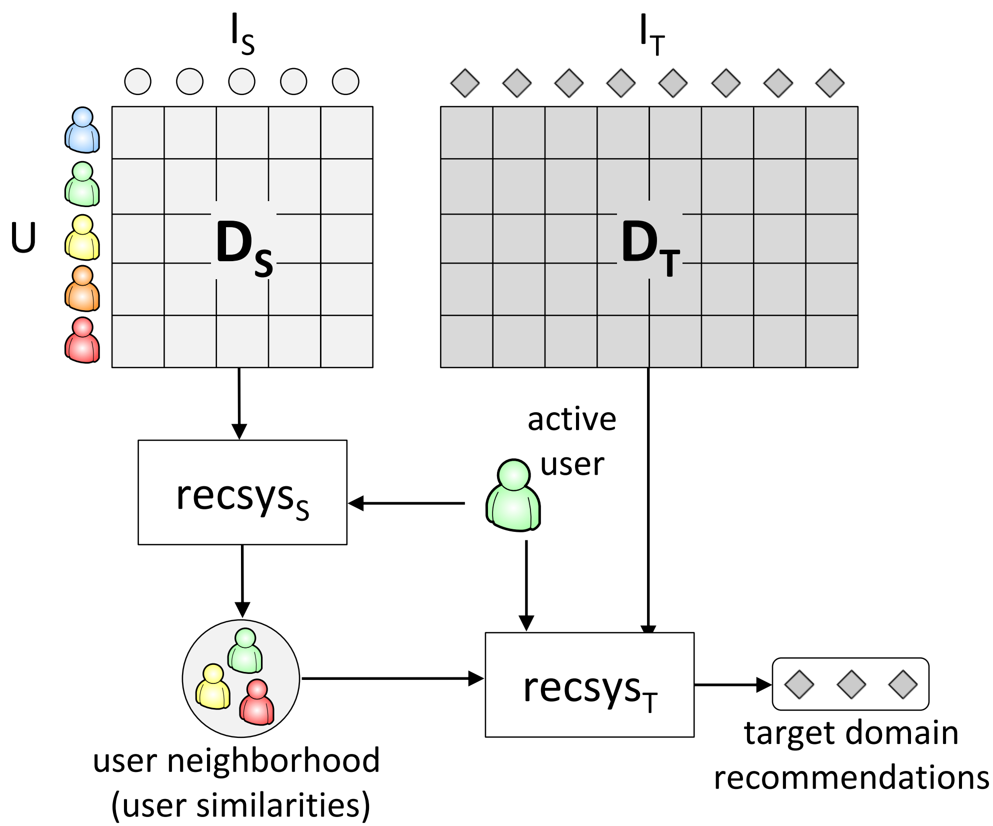
- Aggregating collaborative or content similarities
  - Berkovsky et al. 2007; Shapira et al. 2013; Shlomo Berkovsky, Tsvi Kuflik, and Francesco Ricci. 2008.
- Aggregating user neighborhoods
  - Berkovsky et al. 2007; Tiroshi & Kuflik 2012; Shapira et al. 2013
- Aggregating latent features
  - Low et al. 2011

Proposed categorization

- **Linking/Aggregating knowledge**
  - Merging user preferences
  - Mediating user modeling data
  - **Combining recommendations**
  - Linking domains
- **Sharing/transferring knowledge**
  - Sharing latent features
  - Transferring rating patterns

Combining recommendations (I)

- Aggregate single-domain recommendations
  - ratings, ranking, probability distributions



Combining recommendations (II)

- Pros:
  - easy to implement
  - independent of the stand alone recommenders
  - increase diversity
  - independent of context
- Cons:
  - need overlap of users
  - difficult to tune weights assigned to recommendations coming from different domains

Combining recommendations: approaches

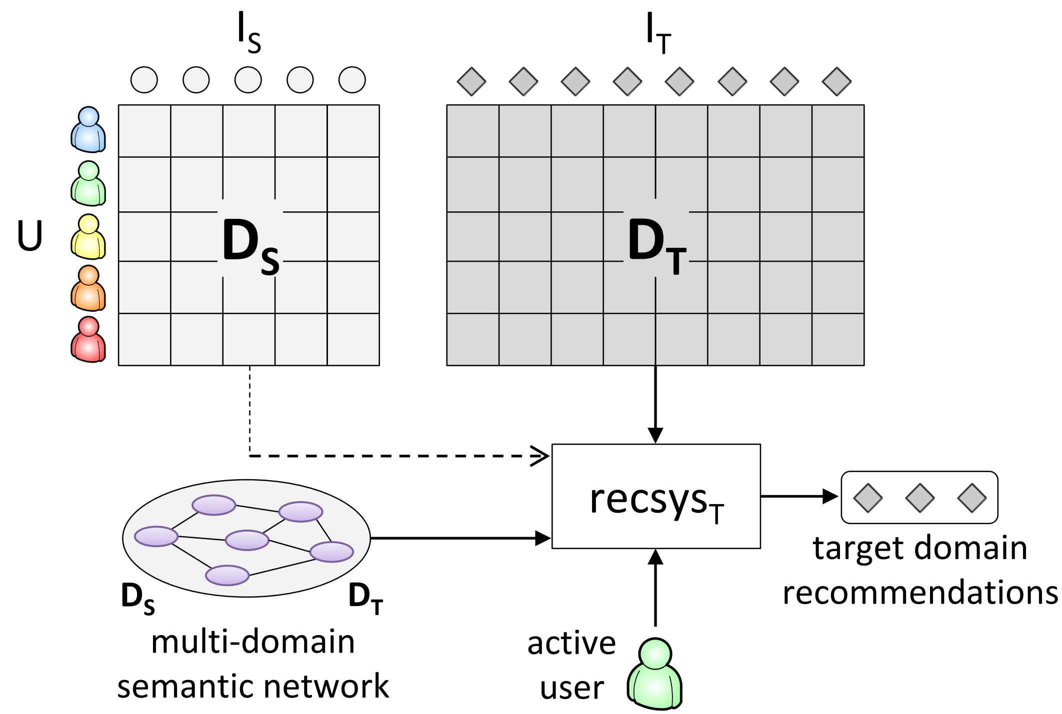
- Aggregating estimated values of ratings (blanding)
  - Berkovsky et al. 2007; Givon & Lavrenko 2009
- Combining estimations of rating distribution
  - Zhuang et al. 2010

Proposed categorization

- **Linking/aggregating knowledge**
  - Merging user preferences
  - Mediating user modeling data
  - Combining recommendations
  - **Linking domains**
- Sharing/transferring knowledge
  - Sharing latent features
  - Transferring rating patterns

Linking domains (I)

- Linking domains by a common knowledge
  - item attributes, user attributes, association rules, semantic networks,



Linking domains (II)

- Pros:
  - no need of user or item overlap
  - bland with other technique
- Cons:
  - difficult to generalize
  - designed for particular cross-domain scenarios

Linking domains: approaches

- Overlap of user/item attributes
  - Chung et al. 2007
- Overlap of social tags
  - Szomszor et al. 2008; Abel et al. 2011; Abel et al. 2013; Fernández-Tobias et al. 2013
- Overlap of text (BoW)
  - Berkovsky et al. 2006
- Semantic networks
  - Loizou 2009; Fernández-Tobias et al. 2011; Kaminskas et al. 2013
- Knowledge-based rules
  - Azak et al. 2010; Cantador et al. 2013

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Proposed categorization

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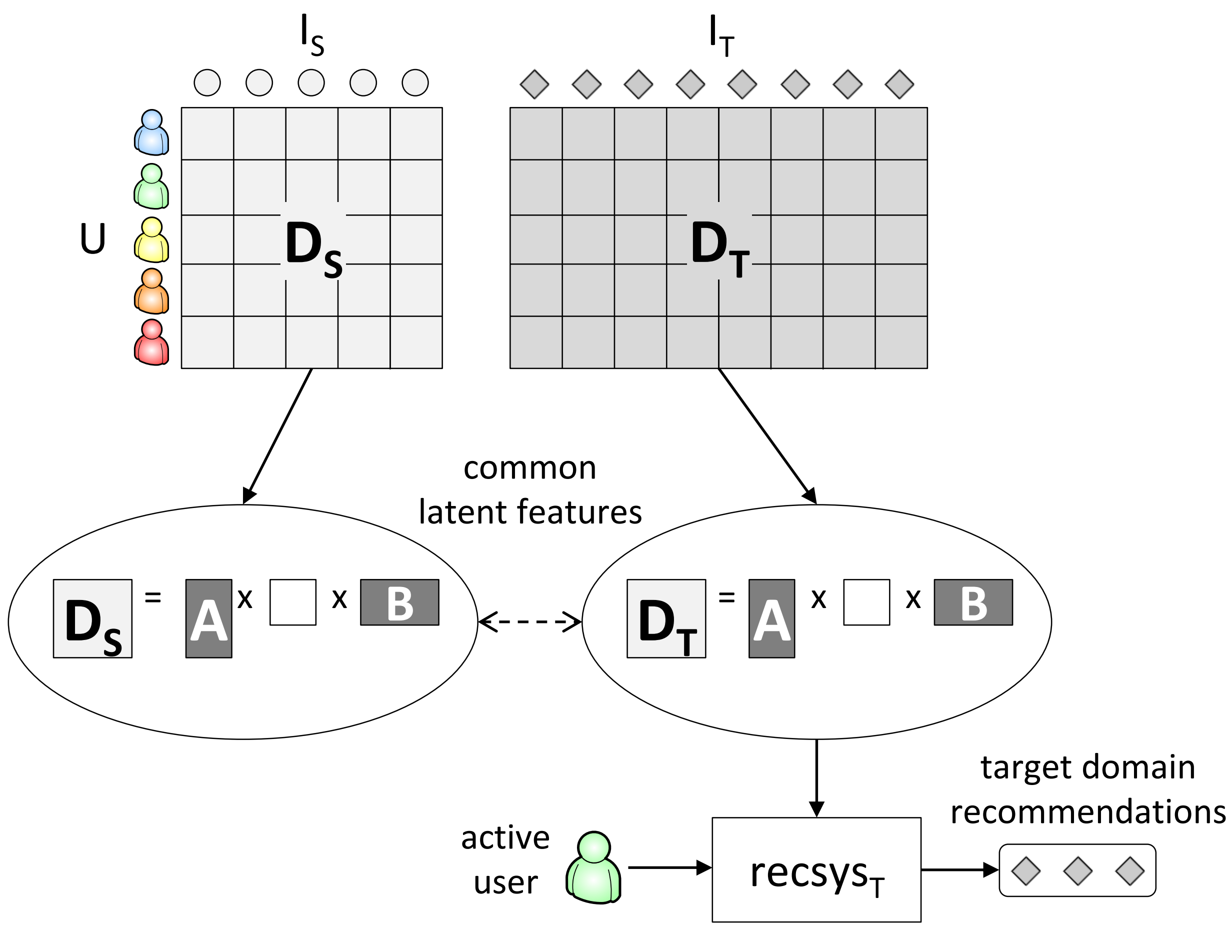
- Sharing/transferring knowledge
  - **Sharing latent features**
  - Transferring rating patterns

Sharing latent features (I)

- source and target domains are related by means of shared latent features



Sharing latent features (II)

- Pros:
  - work well to reduce sparsity and increase accuracy for both source and target domains
- Cons:
  - computationally expensive
  - need overlap of users and/or items

Sharing latent features: approaches (I)

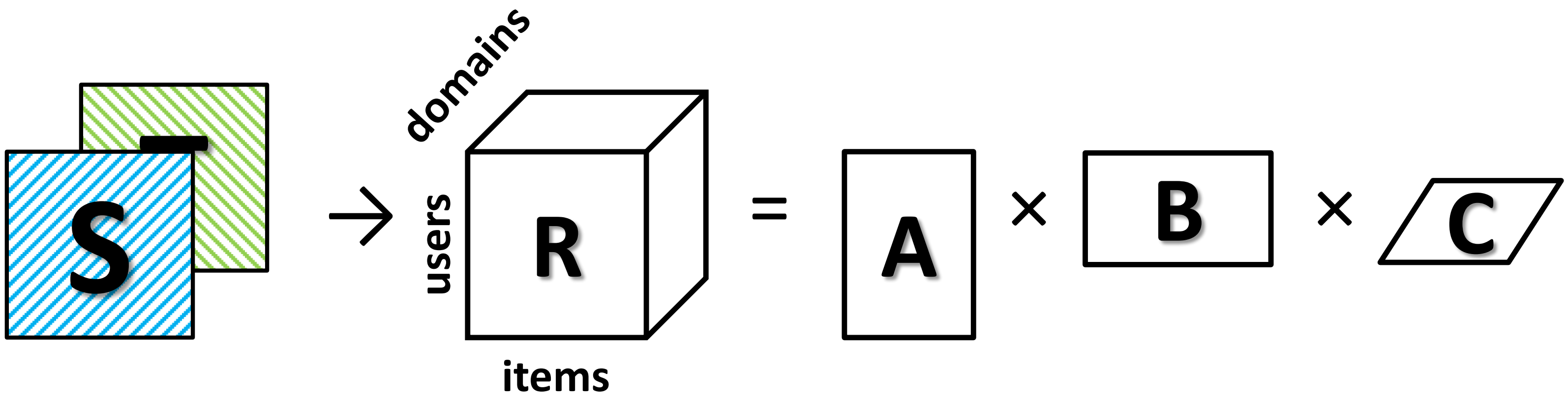
- **Tri-matrix co-factorization**: user and item factors (U and V) are shared between domains; rating patterns (B) are different
  - Pan et al. 2010 and 2011

$\mathbf{R}_S = \mathbf{U}\times\mathbf{B}_S\times\mathbf{V}'$

$\mathbf{R}_T = \mathbf{U}\times\mathbf{B}_T\times\mathbf{V}'$

Sharing latent features: approaches (II)

- Tensor-based factorization (domain as a context)
  - Hu et al. 2013

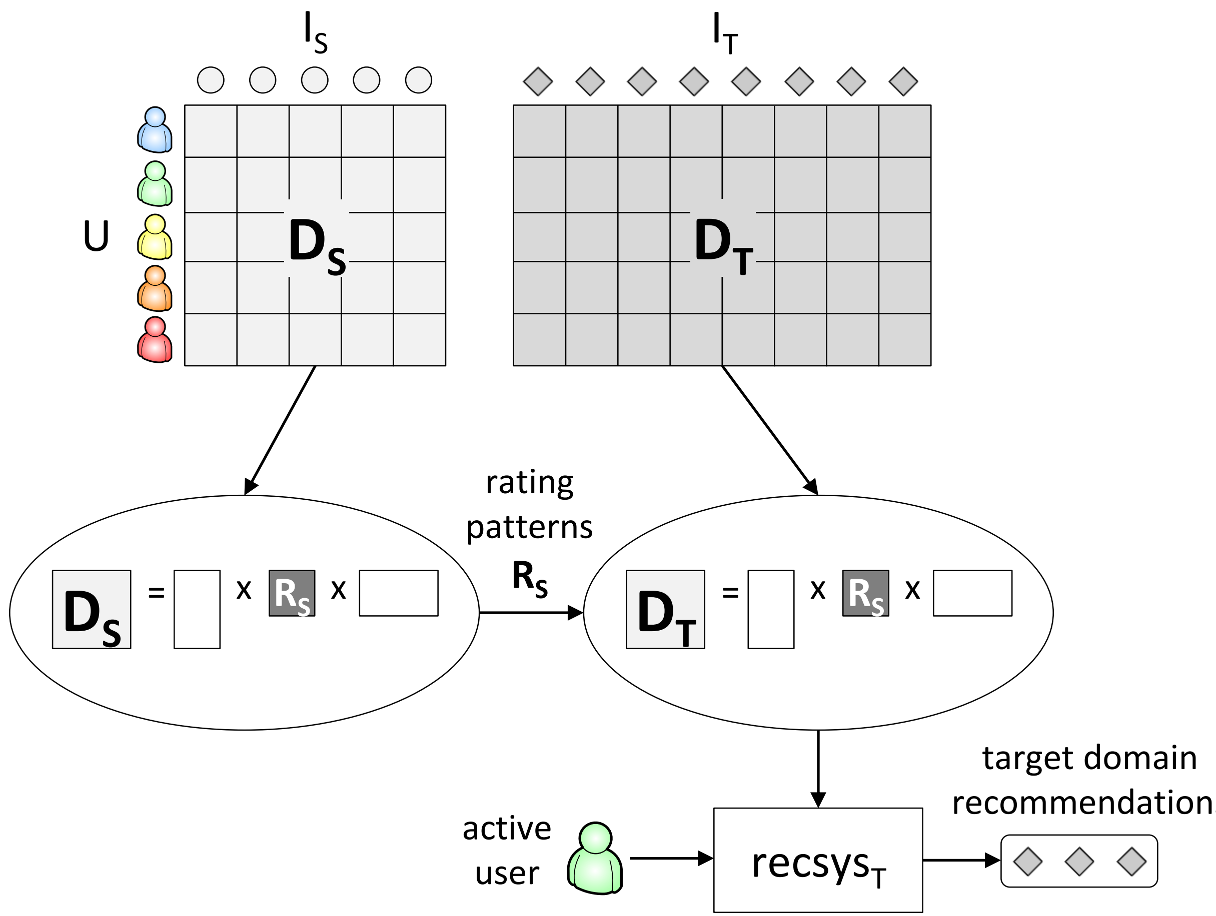


Proposed categorization

- **Linking/aggregating knowledge**
  - Merging user preferences
  - Mediating user modeling data
  - Combining recommendations
  - Linking domains
- Sharing/transferring knowledge
  - Sharing latent features
  - **Transferring rating patterns**

Transferring rating patterns (I)

- rating patterns are transferred between domains



Transferring rating patterns (II)

- **Pros**:
  - apparently, no need of user or item overlap
- **Cons**:
  - computationally expensive

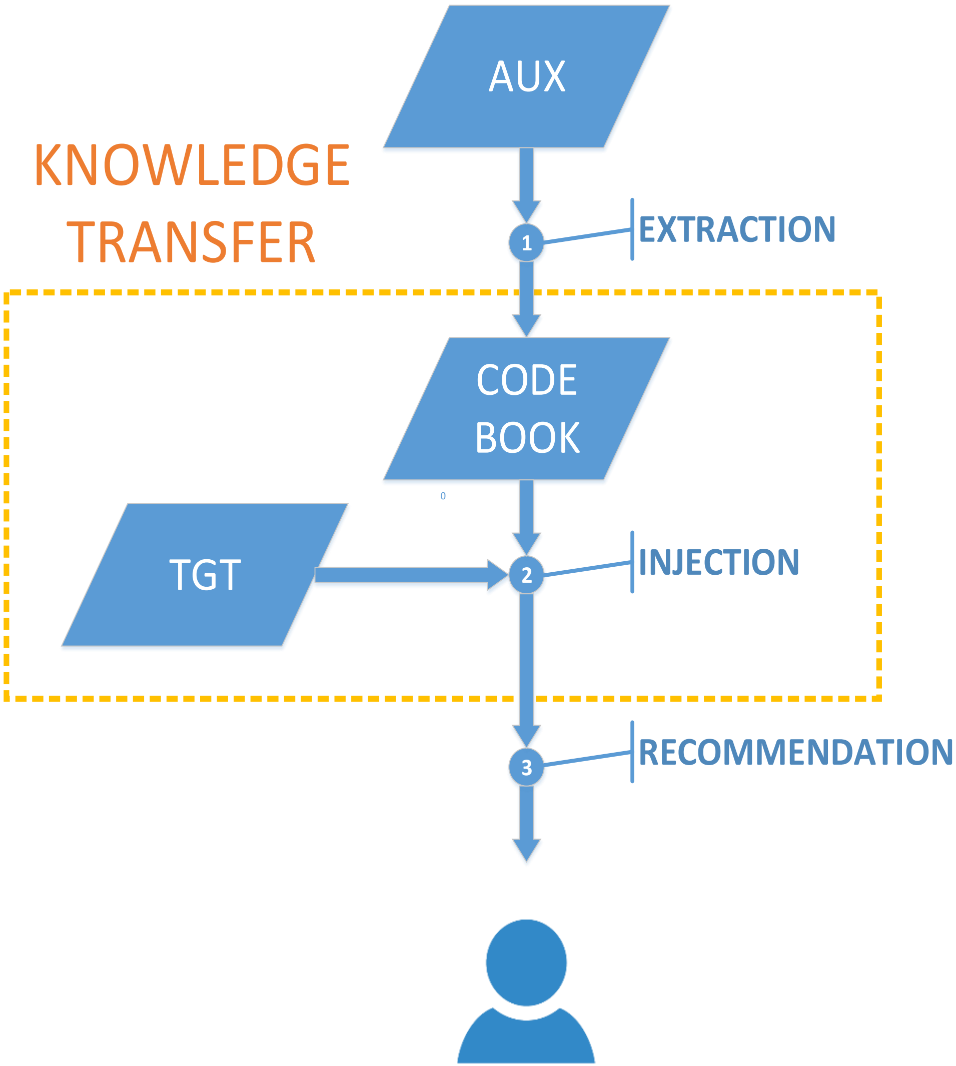
Transferring rating patterns: approaches

- Code-Book-Transfer (CBT): Transferring cluster-level rating patterns
  - Li et al. 2009; Moreno et al. 2012; Gao et al. 2013

$\mathbf{R}_S = \mathbf{U}_S \times \mathbf{B} \times \mathbf{V}_S'$

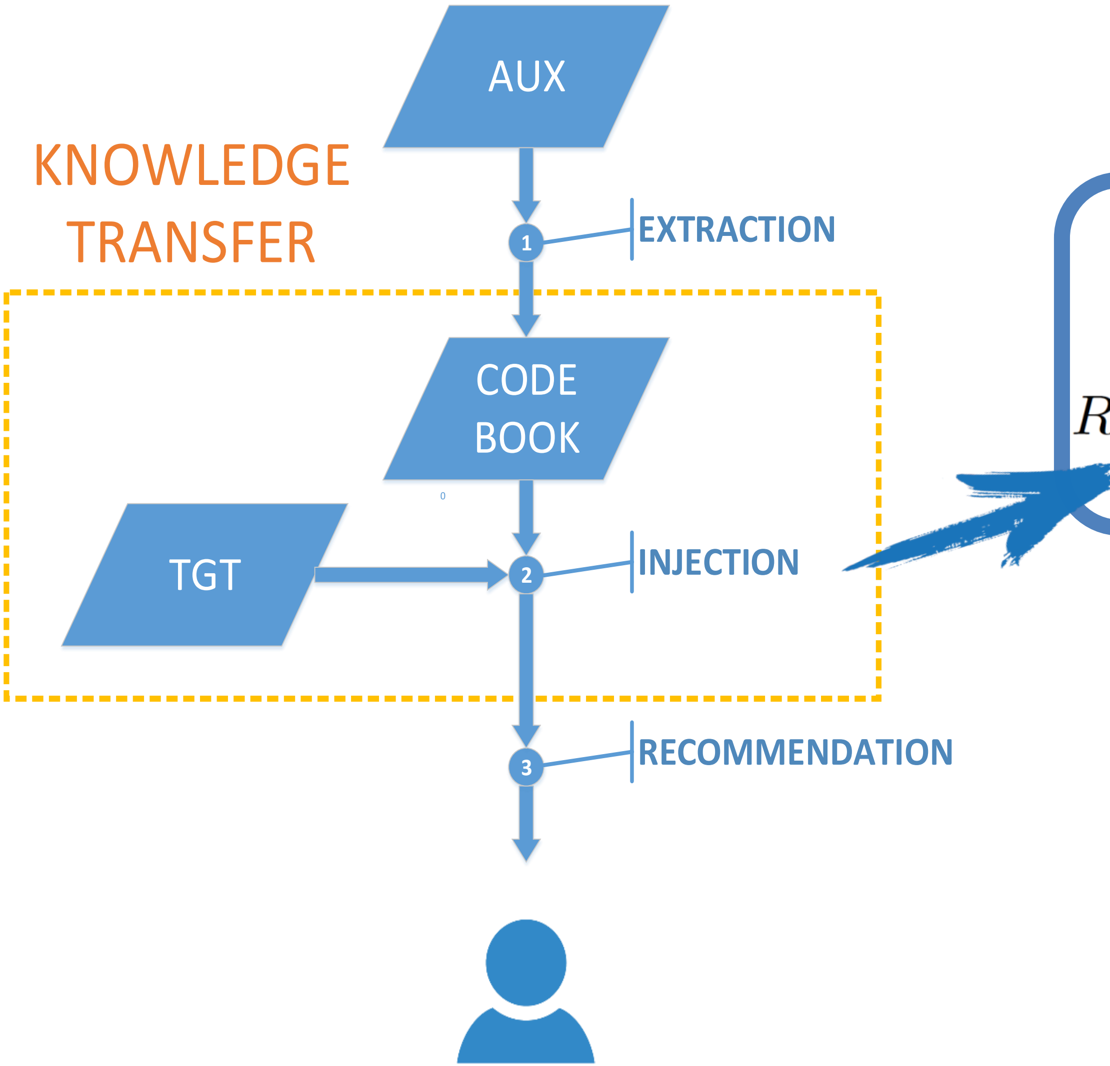
$\mathbf{R}_T = \mathbf{U}_T \times \mathbf{B} \times \mathbf{V}_T'$

Transferring rating patterns: CBT



1. Extraction of knowledge (codebook **B**) from auxiliary domain
2. Injection of knowledge in target domain to reduce sparsity
3. Recommendation in target domain with user-based kNN

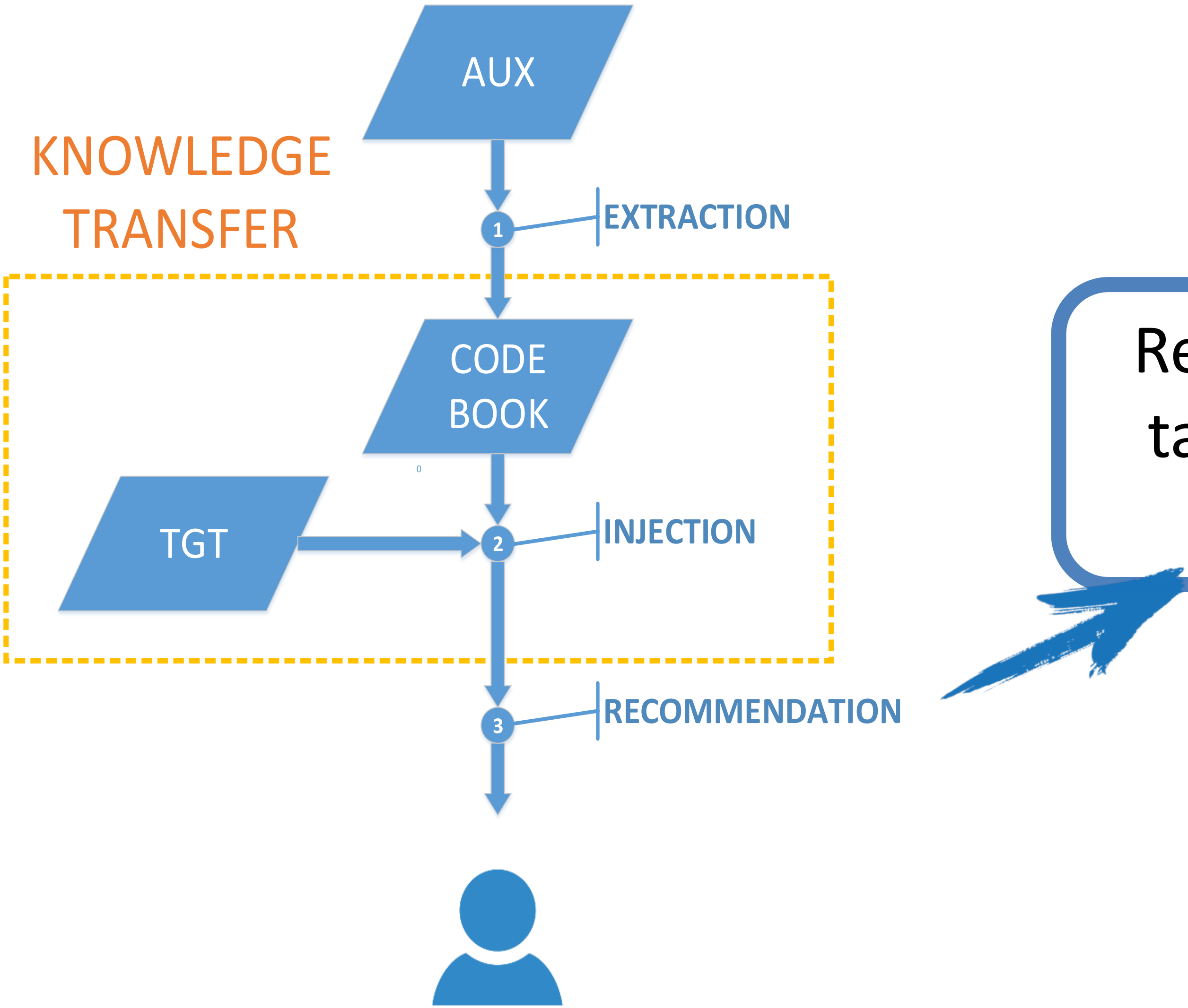
Transferring rating patterns: CBT



$$\min \| R_T - U_T B V_T^\top \|^2$$

$$R_T \leftarrow W \circ R_T + [\mathbf{1} - W] \circ \left[U_T B V_T^\top \right]$$

Transferring rating patterns: CBT



Recommendation in target domain with user-based kNN

Transferring rating patterns: CBT

AUX: MovieLens *TGT: BookCrossing*		
	kNN	**CBT**
MAE	0,5216	**0,5064**
RMSE	0,4736	0,4492

Transferring rating patterns: CBT

AUX: MovieLens *TGT: BookCrossing*			
	kNN	**CBT**	**RND**
MAE	0,5216	**0,5064**	**0,4963**
RMSE	0,4736	0,4492	**0,4380**

Paolo Cremonesi and Massimo Quadrana. 2014.
Cross-domain recommendations without overlapping data: myth or reality?

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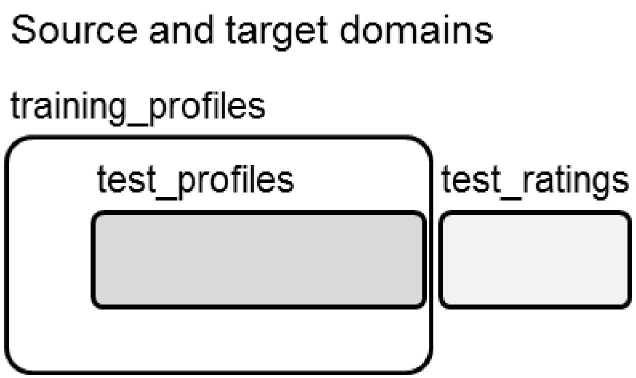
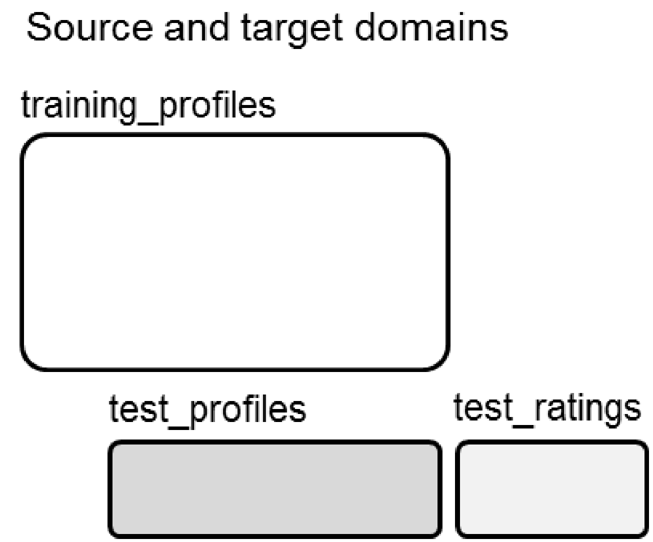
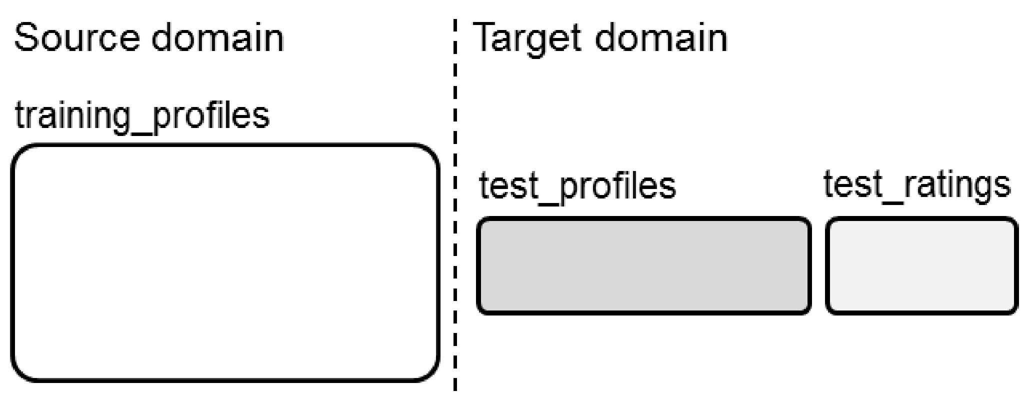
Data partitioning



Hold-out



Leave-some-users-out



Leave-all-users-out

Goal vs. partitioning technique

	Hold-out	Leave-some-users-out	Leave-all-users-out
Cold start			X
New user		X	
New item			X
Accuracy	X		
Diversity	X		

Contents

Research issues (I)

- Synergy between cross-domain and **contextual recommendations**
  - different contexts (e.g., location, time, and mood) can be treated as different domains
  - … and vice versa

Research issues (II)

- Cross-domain recommenders to reduce the **user model elicitation** effort
  - able to build detailed user profiles without the need to collect explicit user preferences

- New, real life cross-domain **datasets**
  - quite scarce and hard to reach in practice;
  - gathered by big industry players, like Amazon, eBay, and Yelp, but rarely available to the broader research community

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Cross-domain Recommender Systems

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