TRUST AWARE RECOMMENDER SYSTEMS

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OPENING QUESTION

- Do you ever get lost in 5-10 videos you never expected to watch?

- I do…

INTRODUCTION

- What are recommender systems?
  - Recommender systems is a type of information filtering system that looks to predict the rating or preference a user would give on an item.
    - Food, movies, sport items, etc…

- What is the importance of recommender systems?
  - Improve retention
  - Increase sales
  - Form habits
  - Accelerate work

PRESENTATION OUTLINE

- Introduction ✓
- Background information
- Trust-Aware Collaborative Filtering using Ant-Colony Optimization (TCFACO)
- Tests and results
- Conclusion

BACKGROUND

- Recommender systems (RS)
- Trust
- Metaheuristic algorithms

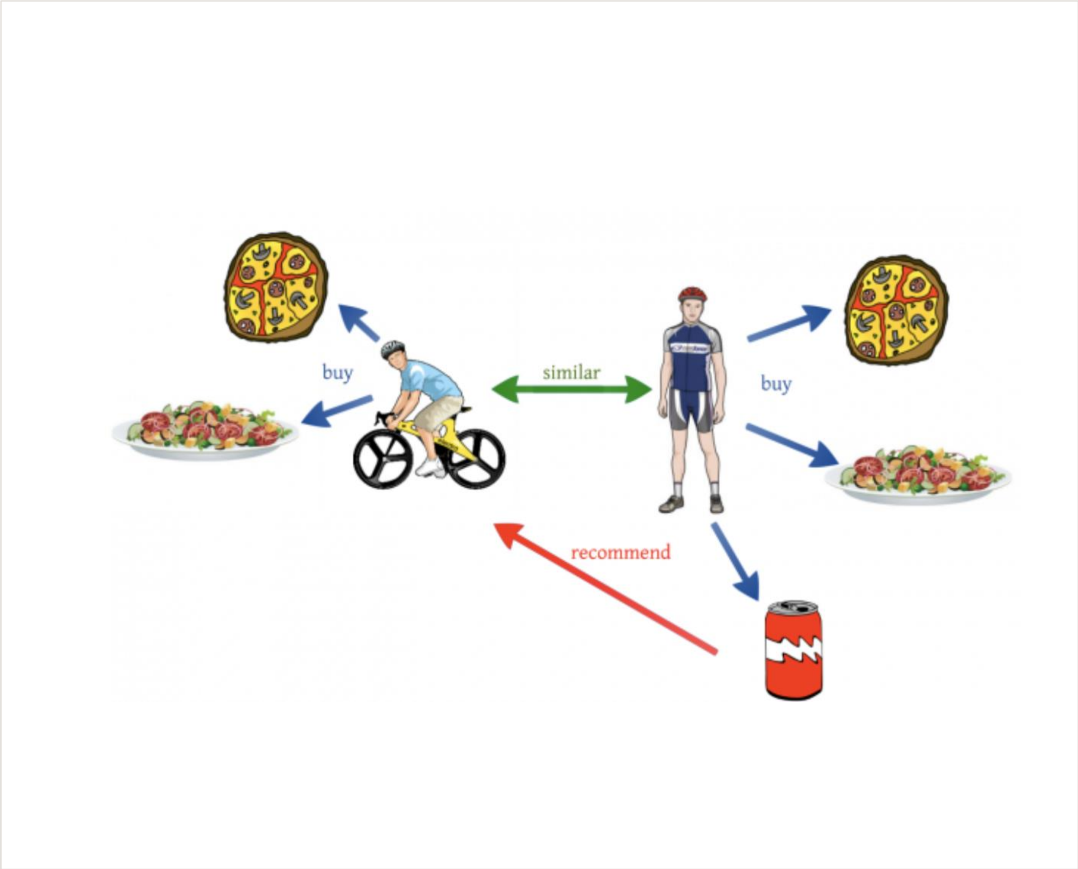
TYPES OF RECOMMENDER SYSTEMS

- Recommender system
  - A recommender system is a filtering system that helps recommend ratings and preferences for future items

- Types of recommender systems
  - Collaborative filtering
  - Content based
  - Demographic based
  - Utility based

COLLABORATIVE FILTERING RS

- User to user recommendation
- Compares users



COLLABORATIVE FILTERING RS

- Item to item recommendation
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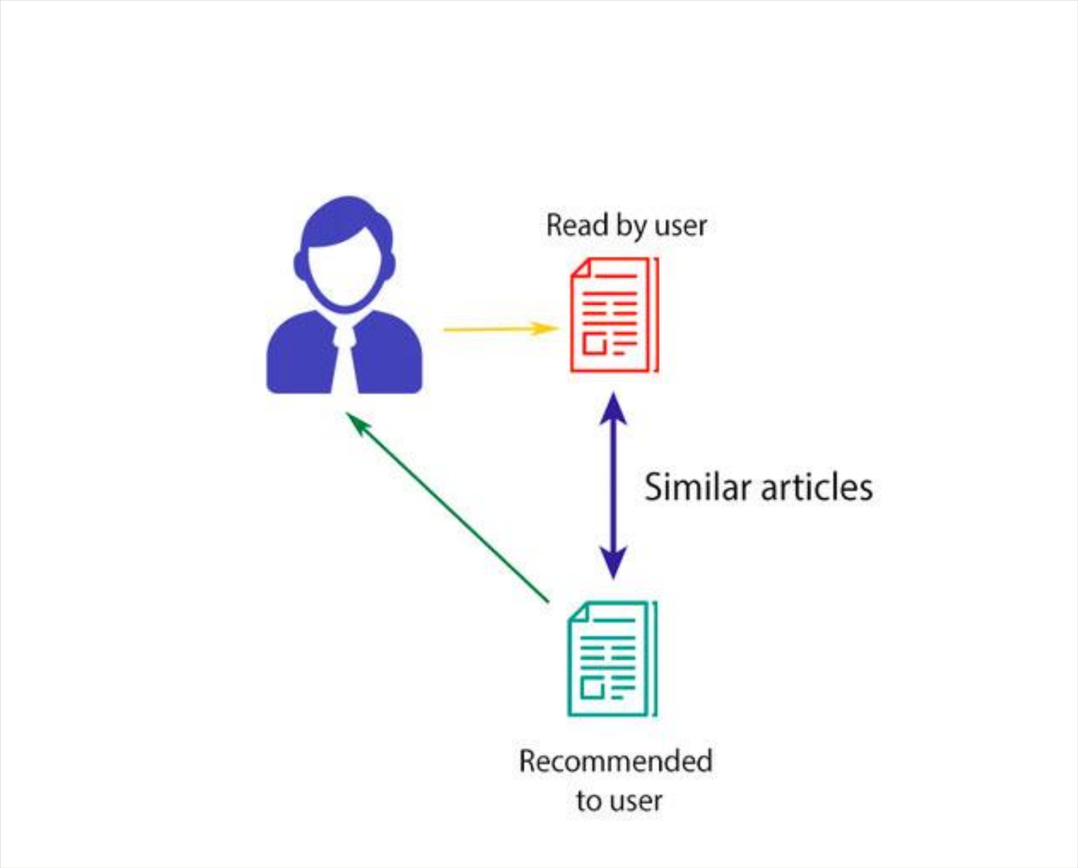

TRUST

- What is trust?
- How is trust made?
- What is the importance of trust?

WHAT IS TRUST?

- Formal definition
  - Firm belief in the reliability, truth, ability, or strength of someone or something.
- Trust in Recommender System
  - Similar to the formal definition, trust in recommender systems is a layer added to filtering methods that checks how trustworthy and sufficient a user and their data is.

IMPORTANCE OF TRUST IN RS

- Key benefits of trust
  - Rich side information for data review
  - Eliminate malicious attacks
  - Helps with sparsity problems
  - Strengthens recommendations for cold start users

HOW IS TRUST GATHERED?

- Explicit trust
  - Known trust
  - User provided data that shows who the user does and does not trust.
- Implicit trust
  - Implied trust
  - Implicit trust is trust that can be calculated using already present information in the database.

METAHEURISTIC ALGORITHMS

- What is a metaheuristic algorithm
- Ant Colony Optimization (ACO)

WHAT IS METAHEURISTIC ALGORITHM

- What is a metaheuristic algorithm in RS
  - An algorithm that aims to find a possible solution for complex and optimization tasks
  - The algorithm searches through a set of possible solutions to find the optimal region of the search space and discover a near optimal solution in reasonable time

BACKGROUND OF ANT COLONY OPTIMIZATION

- Introduced in the early 1990's
  - Marco Dorigo
  - ACO was created to mimic ant colonies and use their searching method for approximate solutions to discrete optimization problems.
  - ACO is used in this presentation to help provide more accurate information in a recommender system.

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INTRODUCTION TCFACO PAPER

- One big problem in collaborative filtering is **choosing the appropriate set of users** for the recommendation process and using them to **predict ratings**.
- Key steps/roles
  - Collaborative filtering with known ratings and trust
  - Use Ant Colony Optimization to assign proper weightings
  - Prediction Process

GOALS

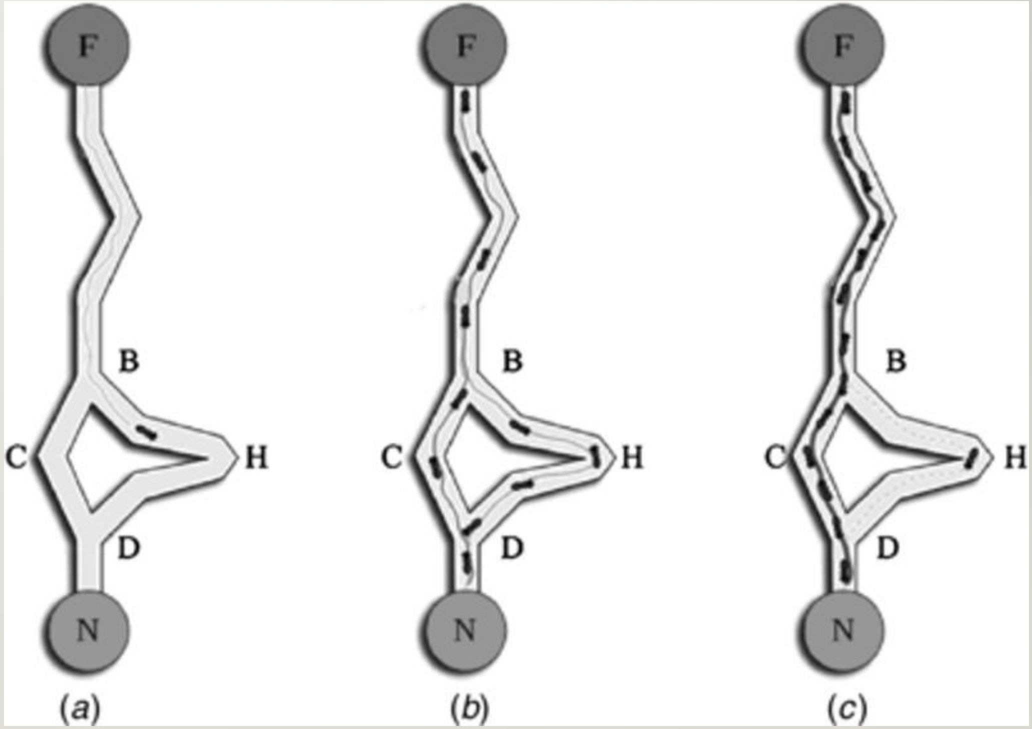
1. Generate more predictions using trust and ACO
2. Generate more accurate predictions
3. Better recommendations for different genres of users
    1. Cold-start
    2. Opinionated users
    3. Etc…

SOCIAL TRUST

- What is Social Trust?
    - Social trust is using the users account to create implicit or explicit trust statements.
- What is a trust statement?
    - A declaration of trust in a user or item.
- How is a trust statement declared?
    - **Explicitly** is compared by information the user states, such as creating friendships within the social network
    - **Implicitly** is when the user's information such as user's profile or the reviews made is used to calculate a trust statement.

ANT COLONIES

- ACO is based directly off of the technique of Ant Colonies
- Ants Communicate through pheromones (lines on figure)
  - The stronger the pheromone level, the more optimized the path is to the food.
- Ants are then constantly exploring to find food until they are attracted to the optimized path. (figure (c))
- Pheromones evaporate over time



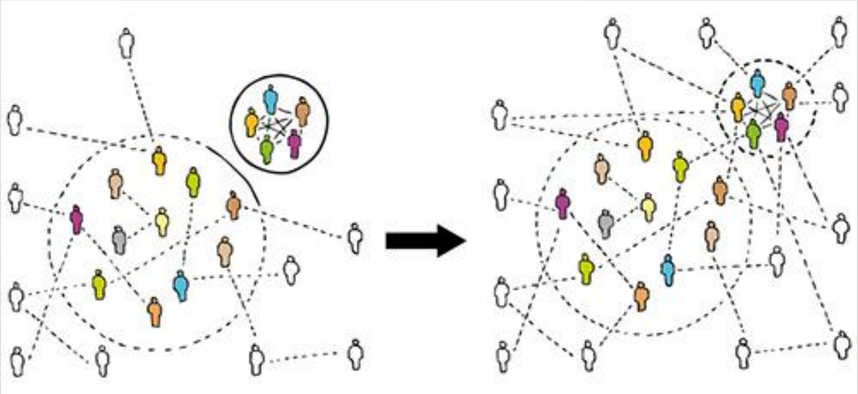
DESCRIBE THE PROCESS OF TCFACO

- Inputs
- Ranking users process
- Weighting process
- Prediction process

INPUTS

- Target User
- Rating Matrix
  - Ratings made previously by the user and others in the database
- Trust network
  - Trust statements created or provided by the user

	Movie 1	Movie 2	Movie 3
Ted	4	5	5
Carol		5	5
Bob		5	?



RANKING PROCESS

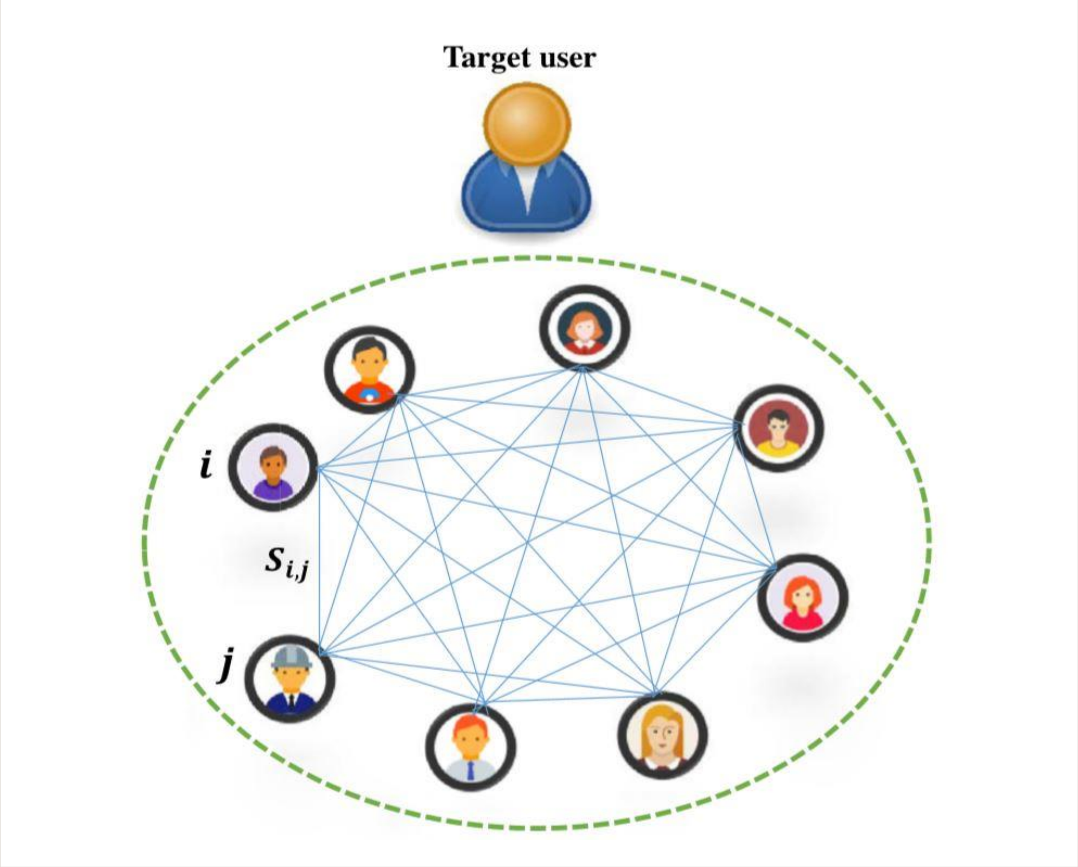
- Description of step
  - Trust based similarity metric is used to rank users based on their similarities to the target user and then select the top ranked users to be used in further steps.
- How is similarities gathered?
  - Pearson Correlation Coefficient (PCC) is used on the trust network and rating matrix between users to find the top ranked similar users.

WEIGHTING PROCESS

1. Create graph
2. Place ants/movement
3. Evaporation of pheromones

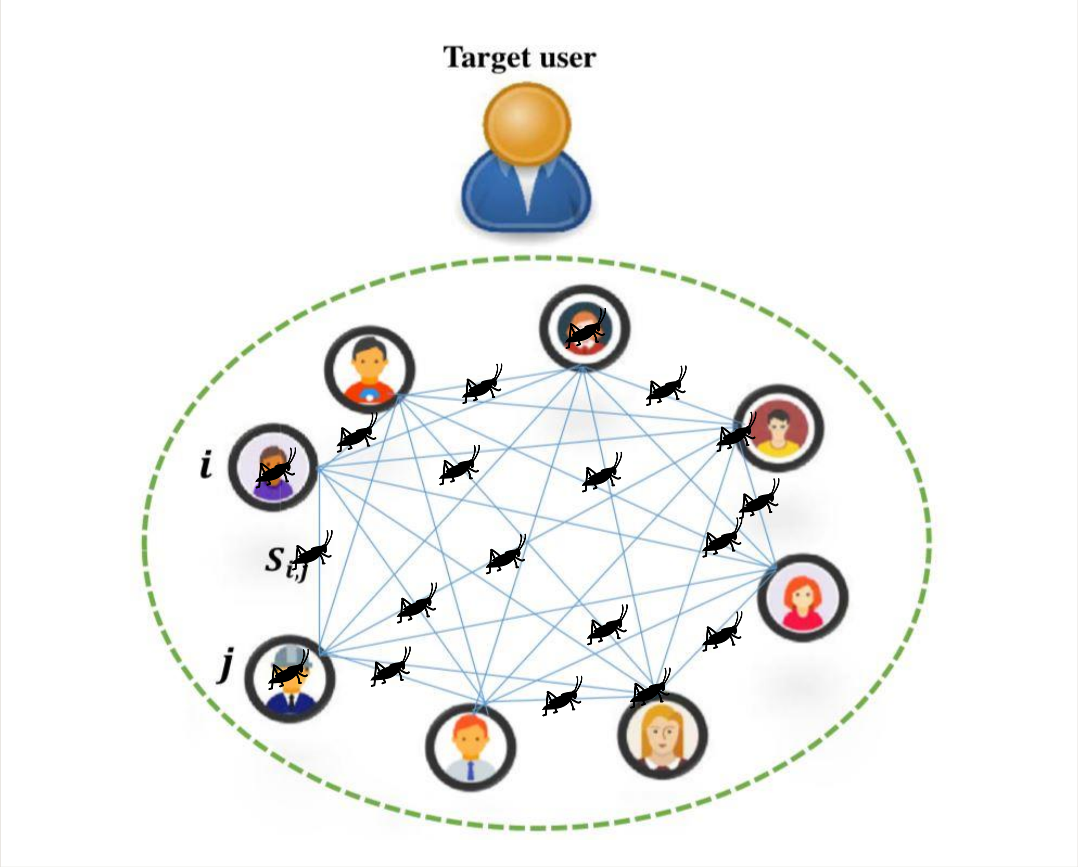
CREATE AN UNDIRECTED GRAPH

- Graph consists of the top ranked users in previous step
- Nodes represent users
- Weights represent similarity between users



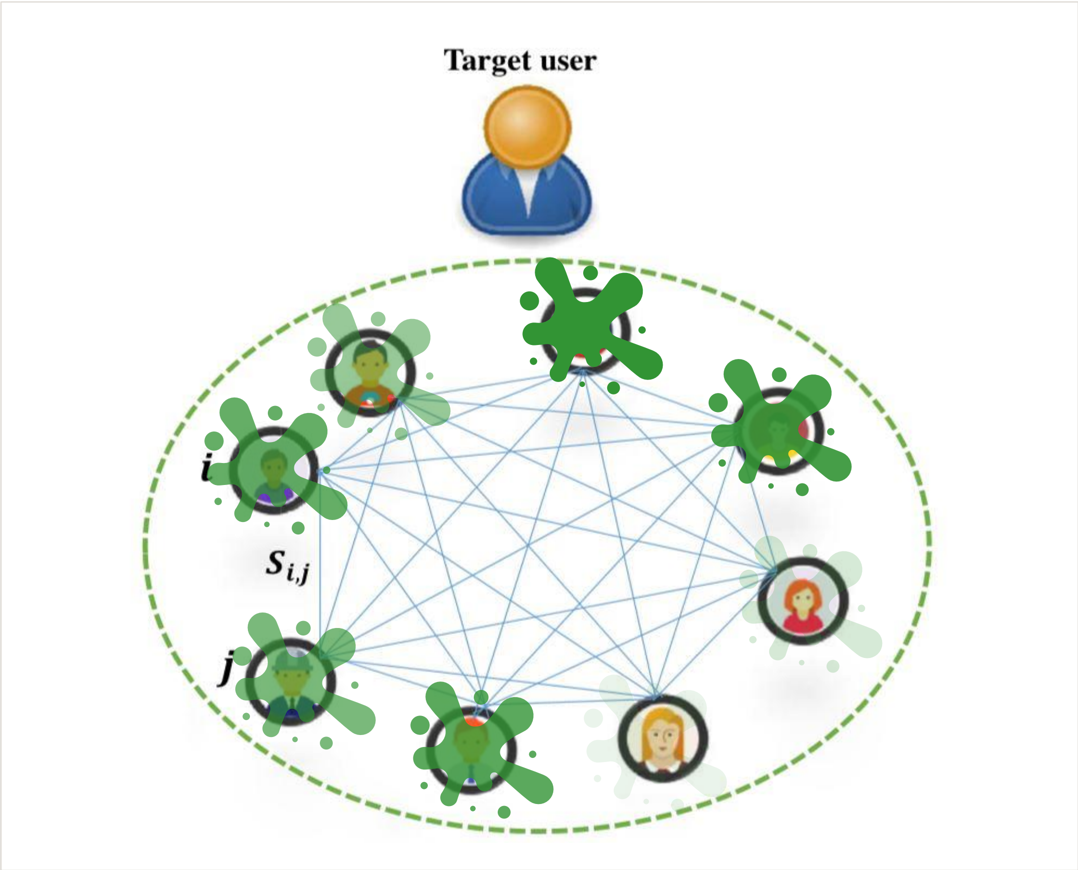
ANT PLACEMENT/MOVEMENT

1. Ants are placed randomly throughout the graph
2. Ants move throughout the graph depending on the similarities of the ranked users.
3. Weights are updated with pheromone based on the level of similarities.



WEIGHTING PROCESS

- Pheromones evaporate
  - Pheromone levels evaporate over time on nodes to eliminate connection of bad solutions.
- Repeat
  - Multiple iterations are done with pheromone levels updated each round.



PREDICTING PROCESS

- The nodes are evaluated for pheromone values
- Then the top K users are selected based on their pheromone values and they are used in the prediction process.
- Prediction Example

Target User	Target Prediction
Jill	????

Top K Users	Similarity to Target User	Rating on Target Item
Bob	.96	4
Joe	.95	4
Bill	.94	5

$$\text{Target Item Prediction} = \frac{Sum\ of\ Similarity\ * rating}{\text{Sum of similarities}}$$

$$Target\ Item\ Prediction = \frac{(.96 * 4) + (.95 * 4) + (.94 * 5)}{.96 + .95 + .94} = 4.29$$

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Jill	4.29

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DATASETS

	Epinions	FilmTrust	Ciao
Users	40,163	1,508	30,444
Items	139,783	2,071	72,665

User Types	Descriptions
Cold-start Users	User has made less than 5 ratings
Heavy Raters	Users has made more than 10 ratings
Opinion Users	More than 4 ratings, standard deviation higher than 1.5
Niche Items	Items fewer than 5 ratings
Controversial items	Items with standard deviation of their ratings higher than 1.5

TESTS

- Employed Tests
  - Mean Average Error (MAE)
    - Computed by comparing predicted ratings with the true ratings
  - Root Mean Square Error (RMSE)
    - Demonstrates the contributions of the absolute errors among true and predicted rating values
  - Rate Coverage (RC)
    - Used to measure the number of items predicted by the method

Compared to Metaheuristics RS's

FilmTrust

Methods	Error metrics	Datasets: All data	Cold users	Heavy users	Opin. users	Contr. items	Niche items
Bobadilla	MAE	0.771	0.784	0.823	1.492	1.502	**0.795**
	RMSE	0.982	0.998	1.032	1.834	1.673	**1.042**
Yilmaz	MAE	0.685	0.722	0.754	**1.395**	1.514	0.841
	RMSE	0.912	0.931	0.971	**1.731**	1.663	1.084
TARS	MAE	0.662	0.693	**0.615**	1.451	1.483	0.862
	RMSE	0.872	0.923	**0.814**	1.772	1.651	1.092
TCFACO	MAE	**0.561**	**0.597**	0.634	1.405	**1.438**	0.801
	RMSE	**0.764**	**0.774**	0.823	1.752	**1.622**	1.050
	(Improve)	%14.5	13.6%	9.6%	4.1%	6.1%	3.2%

Epinion

Methods	Error metrics	Datasets: All data	Cold users	Heavy users	Opin. users	Contr. items	Niche items
Bobadilla	MAE	0.862	0.881	1.543	0.921	1.576	**0.793**
	RMSE	1.124	1.126	1.855	1.193	1.859	**1.061**
Yilmaz	MAE	0.852	0.871	1.525	0.901	1.562	0.824
	RMSE	1.101	1.124	1.855	1.171	1.853	1.082
TARS	MAE	0.830	0.853	1.530	**0.890**	**1.536**	0.833
	RMSE	1.092	1.105	1.862	**1.142**	**1.821**	1.092
TCFACO	MAE	**0.795**	**0.837**	**1.510**	0.903	1.545	0.815
	RMSE	**1.043**	**1.072**	**1.852**	1.161	1.832	1.071
	(Improve)	5.3%	3.1%	2.2%	0.11%	1.3%	0.16%

Ciao

Methods	Error metrics	Datasets: All data	Cold users	Heavy users	Opin. users	Contr. items	Niche items
Bobadilla	MAE	0.526	0.752	0.602	1.176	1.462	**0.632**
	RMSE	0.712	0.952	0.807	1.556	1.899	**0.491**
Yilmaz	MAE	**0.491**	0.747	**0.563**	1.172	1.452	0.532
	RMSE	**0.670**	0.932	**0.782**	1.554	1.897	0.675
TARS	MAE	0.522	0.723	0.591	1.169	1.432	0.512
	RMSE	0.702	0.928	0.804	1.541	1.882	0.664
TCFACO	MAE	0.509	**0.701**	0.571	**1.165**	**1.401**	0.502
	RMSE	0.690	**0.914**	0.791	**1.545**	**1.860**	0.657
	(Improve)	0.40%	3.9%	1.4%	0.73%	4.7%	5.6%

Compared to other Trust aware RS's

FilmTrust

Datasets	Error metrics	TrustSVD	TrustMF	Social MF	RSTE	Social Rec	TCFACO	Improve
All data	MAE	0.607	0.721	0.698	0.680	0.712	0.561	12.26%
	RMSE	0.787	0.919	0.852	0.851	0.916	0.764	10.10%
Cold users	MAE	0.650	0.619	0.589	0.618	0.757	**0.597**	4.96%
	RMSE	0.845	0.882	0.818	0.775	0.939	**0.774**	7.78%
Heavy users	MAE	0.665	0.729	0.669	0.679	0.637	**0.634**	4.18%
	RMSE	0.852	0.933	0.848	0.853	0.828	**0.823**	3.98%
Opin. users	MAE	1.515	1.584	**1.402**	1.419	1.518	1.405	8.26%
	RMSE	**1.607**	2.115	1.801	1.764	1.698	1.752	4.50%
Contr. items	MAE	1.488	1.529	1.452	1.490	1.442	**1.438**	4.22%
	RMSE	**1.616**	2.019	1.881	1.835	1.637	1.622	17.56%
Niche items	MAE	0.829	0.907	0.815	0.884	0.913	**0.801**	6.86%
	RMSE	1.059	1.249	1.100	1.067	1.150	**1.050**	7.50%

Epinions

Datasets	Error metrics	TrustSVD	TrustMF	Social MF	RSTE	Social Rec	TCFACO	Improve
All data	MAE	0.834	0.877	0.862	0.873	0.862	**0.795**	6.66%
	RMSE	1.094	1.184	1.104	1.100	1.104	**1.043**	7.42%
Cold users	MAE	0.861	0.934	0.919	0.930	0.919	**0.837**	7.56%
	RMSE	1.117	1.373	1.312	1.269	1.312	**1.072**	20.46%
Heavy users	MAE	1.712	1.605	1.539	1.526	1.530	**1.510**	7.24%
	RMSE	1.978	2.040	1.886	**1.839**	1.886	1.852	7.38%
Opin. users	MAE	0.941	0.926	0.914	0.924	0.914	**0.903**	2.08%
	RMSE	1.230	1.299	1.203	1.188	1.203	**1.161**	6.36%
Contr. items	MAE	**1.492**	1.605	1.539	1.526	1.539	1.545	0.48%
	RMSE	**1.808**	2.040	1.886	1.839	1.886	1.832	5.98%
Niche items	MAE	0.829	0.856	0.837	0.840	0.837	**0.815**	2.48%
	RMSE	1.096	1.190	1.131	1.107	1.131	**1.071**	6.00%

Ciao

Datasets	Error metrics	TrustSVD	TrustMF	Social MF	RSTE	Social Rec	TCFACO	Improve
All data	MAE	0.723	**0.505**	0.637	0.560	0.571	0.509	9.02%
	RMSE	0.955	**0.710**	0.905	0.773	0.803	0.690	13.92%
Cold users	MAE	0.725	1.073	1.014	0.878	1.014	**0.701**	23.98%
	RMSE	0.939	1.311	1.266	1.150	1.266	**0.914**	27.24%
Heavy users	MAE	0.589	**0.497**	0.586	0.559	0.584	0.571	0.80%
	RMSE	0.792	**0.684**	0.812	0.782	0.808	**0.791**	1.54%
Opin. users	MAE	1.192	1.301	1.189	1.178	1.189	**1.165**	4.48%
	RMSE	1.556	1.702	1.590	**1.543**	1.590	1.545	5.12%
Contr. items	MAE	1.426	1.719	1.528	1.413	1.528	**1.401**	12.18%
	RMSE	**1.402**	2.197	1.989	1.885	1.989	1.860	3.24%
Niche items	MAE	0.503	1.209	0.935	0.880	0.935	**0.502**	39.04%
	RMSE	**0.659**	1.493	1.232	1.140	1.232	0.657	49.42

Compared to rating based recommender systems

Datasets	measures	Methods							
		UserAvg	ItemAvg	PMF	SVD++	BpoissMf	LLorma	ANLF	TCFACO
FilmTrust	RMSE	0.943	0.925	1.02	0.891	1.35	1.14	1.00	**0.764**
	MAE	0.729	0.696	0.753	0.699	0.991	0.848	0.751	**0.561**
Epinions	RMSE	1.19	1.09	1.81	1.20	1.38	2.03	1.31	**1.043**
	MAE	0.925	0.823	1.35	0.912	0.973	1.62	1.15	**0.795**
Ciao	RMSE	0.678	0.480	0.42	1.00	1.38	1.014	0.841	**0.690**
	MAE	0.456	0.255	0.24	0.74	1.21	0.803	0.659	**0.509**

RC Results

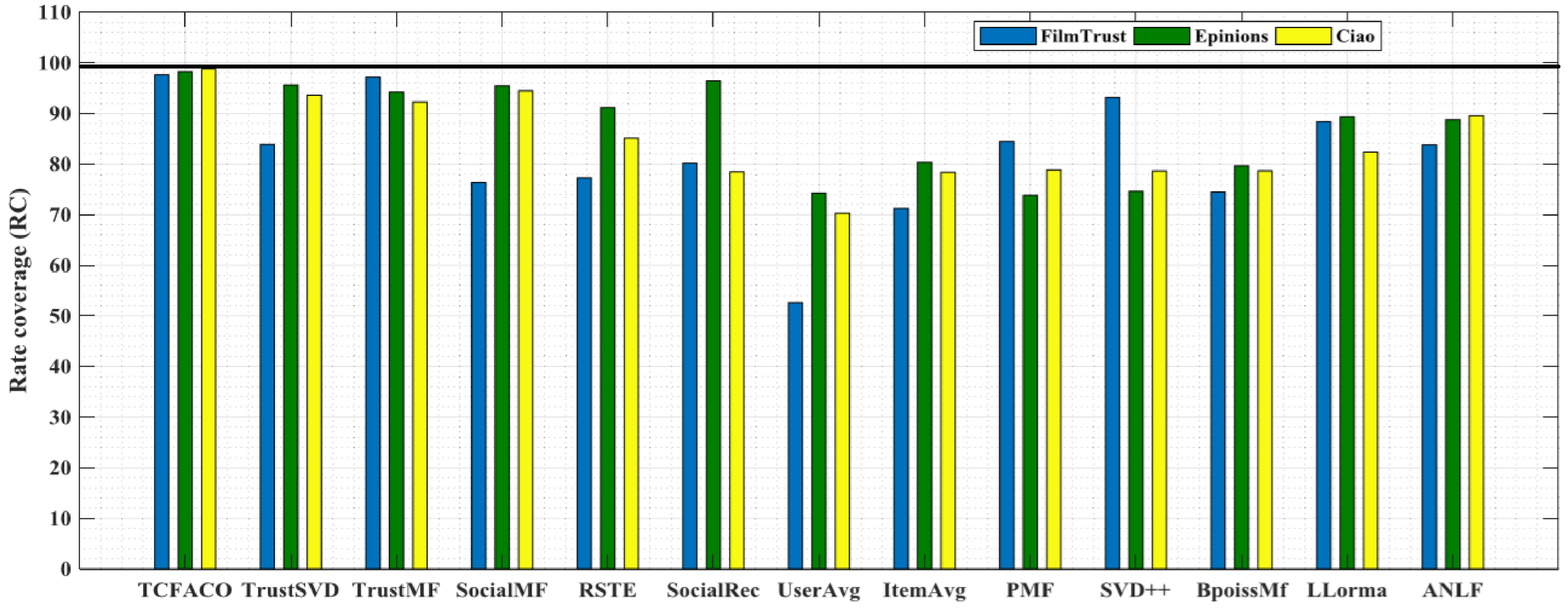

Fig 6. Rate coverage (RC) over the datasets.

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CONCLUSION

- The more side information in a recommender system the better
- ACO applied to a trust aware recommender system produces a more accurate set of users for the prediction process
- Cold start is the largest problem in collaborative filtering and TCFACO improved it in every dataset compared to every other state of the art recommender systems.

QUESTIONS?

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