Counterfactual Evaluation for Recommender Systems

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RecSys Lab.

Counterfactual Evaluation

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    - Medicine

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  - RecSys/Computational advertisement
  - Medicine
  - Economics (2021 Nobel prize)
  - etc.

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- Intersection between Machine Learning and Causal Inference
- The theory can be applied in a lot of domains:
    - RecSys/Computational advertisement
    - Medicine
    - Economics (2021 Nobel prize)
    - etc.
- Today we focus on RecSys Evaluation

Evaluation in RecSys

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Evaluation in RecSys

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- A recommender is already up and running (**baseline**)
- The R&D team develops a new recommender
- We would like to assess its quality (in terms of some metric)

Online Evaluation

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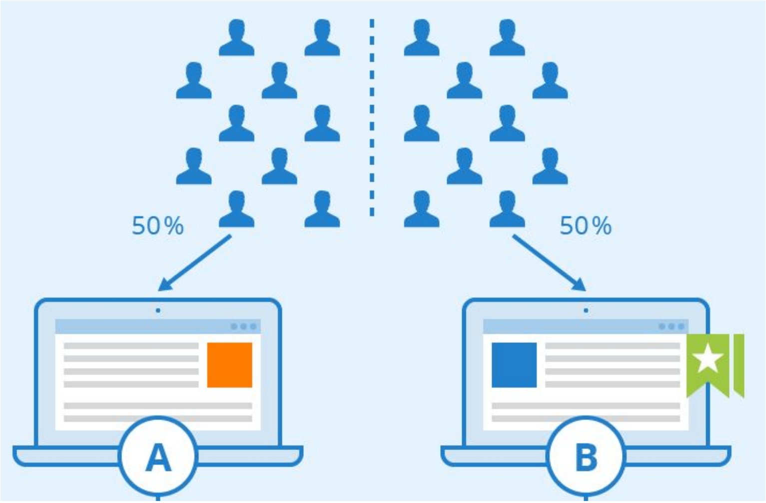
- Main way to do it: A/B testing



Online Evaluation

Online Evaluation

✅ Statistically sound procedure

Online Evaluation

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❌ High risk

- Providing bad recommendations to real user can harm the platform!
- We would like to evaluate the recommender <u>*offline*</u> first

Offline Evaluation

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- Then, evaluate the new recommender on the offline logged dataset

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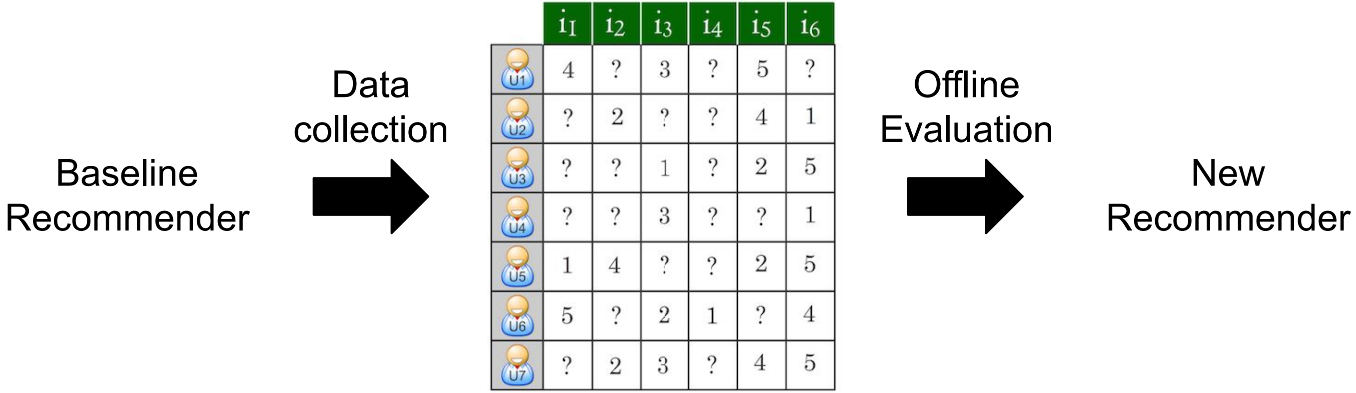

	i_1	i_2	i_3	i_4	i_5	i_6
U1	4	?	3	?	5	?
U2	?	2	?	?	4	1
U3	?	?	1	?	2	5
U4	?	?	3	?	?	1
U5	1	4	?	?	2	5
U6	5	?	2	1	?	4
U7	?	2	3	?	4	5

Offline Evaluation

Offline Evaluation

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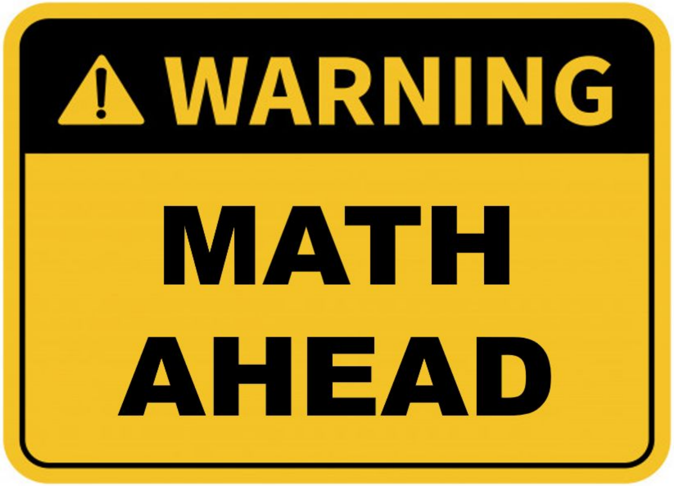
Offline Evaluation

- ✅ A lot cheaper
- ❌ Potentially high bias
    - The matrix may be heavily influenced by the baseline recommender!
    - Furthermore, ratings are not Missing-at-Random

A realistic example


WARNING
MATH
AHEAD

Example

- We run a movie streaming platform

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G	Action	Romance	Drama
Action Lovers	5	1	3
Romance Lovers	1	5	3

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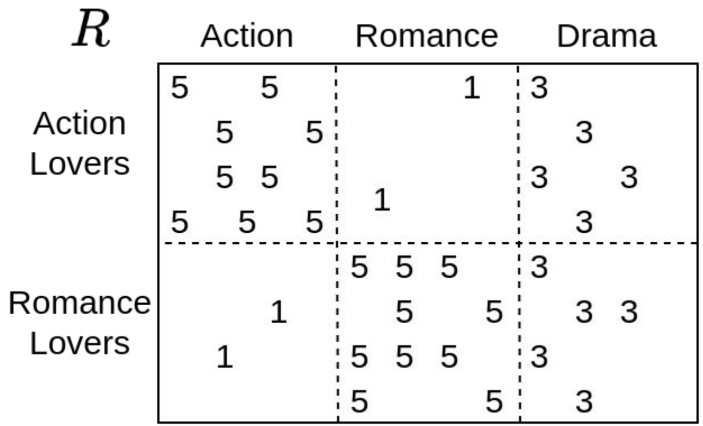
- We collect the URM from the baseline recommender:



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- We would like to compare two recommenders (Mean Absolute Error)

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Action Lovers	5	5	3
Romance Lovers	5	5	3

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- We would like to compare two recommenders (Mean Absolute Error)

G	Action	Romance	Drama
Action Lovers	5	1	3
Romance Lovers	1	5	3

$\lvert G - \hat{R}_1 \rvert$	Action	Romance	Drama
Action Lovers	0	0	2
Romance Lovers	0	0	2

$\lvert G - \hat{R}_2 \rvert$	Action	Romance	Drama
Action Lovers	0	4	0
Romance Lovers	4	0	0

Example

- But we don't know G, we can only use the **URM**

R	Action							Romance							Drama						
Action Lovers	5				5								1		3						
			5				5										3				
			5		5										3				3		
	5			5			5		1								3				
Romance Lovers								5		5		5			3						
					1					5				5			3		3		
			1					5		5		5			3						
								5						5			3				

$\hat{R}_1$	Action	Romance	Drama
Action Lovers	5	1	5
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$\hat{R}_2$	Action	Romance	Drama
Action Lovers	5	5	3
Romance Lovers	5	5	3

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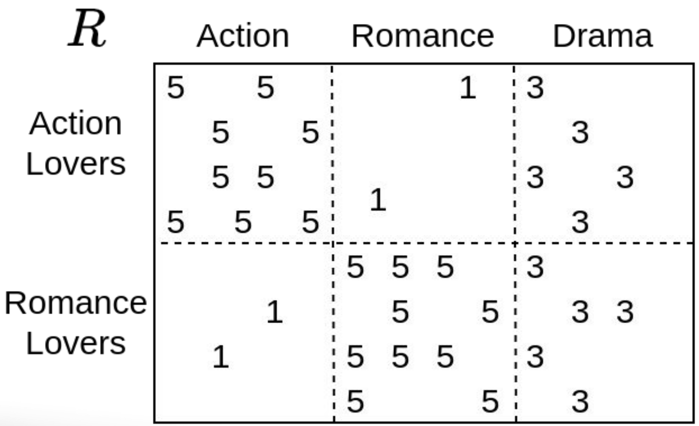

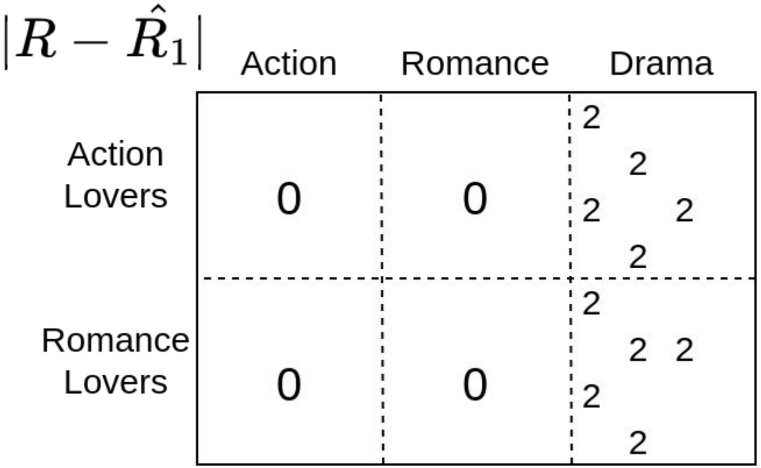

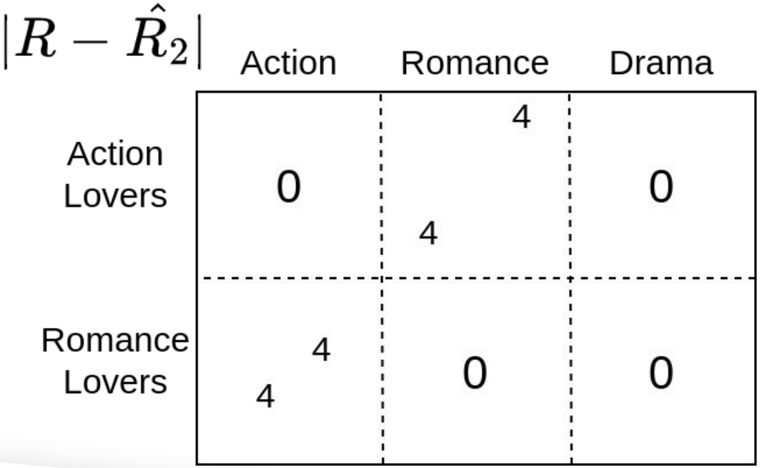

Example

- But we don't know G, we can only use the **URM**

R

	Action	Romance	Drama
Action Lovers	5 5 5 5 5 5 5 5 5	1 1	3 3 3 3 3
Romance Lovers	1 1	5 5 5 5 5 5 5 5 5 5	3 3 3 3 3

$|R - \hat{R}_1|$

	Action	Romance	Drama
Action Lovers	0	0	2 2 2 2 2
Romance Lovers	0	0	2 2 2 2 2

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$|R - \hat{R}_2|$

	Action	Romance	Drama
Action Lovers	0	4 4	0
Romance Lovers	4 4	0	0

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What is the problem?

Why do we obtain wrong results with offline evaluation with the observed URM?

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Why do we obtain wrong results with offline evaluation with the observed URM?

- Missing values are not Missing-at-Random!
- The baseline recommender may have biased the data collection
- Users tend to rate items they like

How to debias the results?

If we knew the probability of observing a rating:

P	Action	Romance	Drama
Action Lovers	0.8	0.1	0.5
Romance Lovers	0.1	0.8	0.5

We could de-bias the results

Counterfactual Evaluation

- What would have happened if the users had observed all the items?

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- We answer this counterfactual question with the **Inverse Propensity Scoring** (IPS) technique
- If a rating has a probability p of being observed, we balance this by re-weighting the corresponding error by 1/p

Counterfactual Evaluation

- What would have happened if the users had observed all the items?

- We answer this counterfactual question with the **Inverse Propensity Scoring** (IPS) technique

- If a rating has a probability p of being observed, we balance this by re-weighting the corresponding error by 1/p
    - If a rating has a probability 0.1 of being observed, we multiply the corresponding error by 10

R	Action				Romance				Drama			
Action Lovers	5		5					1	3			
		5		5						3		
		5	5						3		3	
	5	5		5	1					3		
Romance Lovers					5	5	5		3			
			1			5		5		3	3	
		1			5	5	5		3			
					5			5		3		

P	Action	Romance	Drama
Action Lovers	0.8	0.1	0.5
Romance Lovers	0.1	0.8	0.5

$\hat{R}_1$	Action	Romance	Drama
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$\hat{R}_2$	Action	Romance	Drama
Action Lovers	5	5	3
Romance Lovers	5	5	3

R

	Action	Romance	Drama
Action Lovers	5 5 5 5 5 5 5 5 5	1 1	3 3 3 3 3
Romance Lovers	1 1	5 5 5 5 5 5 5 5 5 5	3 3 3 3 3

P

	Action	Romance	Drama
Action Lovers	0.8	0.1	0.5
Romance Lovers	0.1	0.8	0.5

$|R - \hat{R}_1|$

	Action	Romance	Drama
Action Lovers	0	0	2 2 2 2 2
Romance Lovers	0	0	2 2 2 2 2

$|R - \hat{R}_2|$

	Action	Romance	Drama
Action Lovers	0	4 4	0
Romance Lovers	4 4	0	0

R	Action	Romance	Drama
Action Lovers	5 5 5 5 5 5 5 5 5	1 1	3 3 3 3 3
Romance Lovers	1 1	5 5 5 5 5 5 5 5 5 5	3 3 3 3 3

P	Action	Romance	Drama
Action Lovers	0.8	0.1	0.5
Romance Lovers	0.1	0.8	0.5

$\lvert R - \hat{R}_1 \rvert_{IPS}$	Action	Romance	Drama
Action Lovers	0	0	4 4 4 4 4
Romance Lovers	0	0	4 4 4 4 4

$\lvert R - \hat{R}_2 \rvert_{IPS}$	Action	Romance	Drama
Action Lovers	0	40 40	0
Romance Lovers	40 40	0	0

R

	Action	Romance	Drama
Action Lovers	5 5 5 5 5 5 5 5 5	1 1	3 3 3 3 3
Romance Lovers	1 1	5 5 5 5 5 5 5 5 5 5	3 3 3 3 3

P

	Action	Romance	Drama
Action Lovers	0.8	0.1	0.5
Romance Lovers	0.1	0.8	0.5

$|R - \hat{R}_1|_{IPS}$

	Action	Romance	Drama
Action Lovers	0	0	4 4 4 4 4
Romance Lovers	0	0	4 4 4 4 4

40

$|R - \hat{R}_2|_{IPS}$

	Action	Romance	Drama
Action Lovers	0	40 40	0
Romance Lovers	40 40	0	0

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    - Missing: what to do when P is not known, theoretical guarantees (bias, variance, convergence), other types of estimators, etc.

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- Offline Evaluation: can be unreliable if used naively
- Counterfactual Evaluation: could improve reliability of offline evaluation in RecSys
  - Missing: what to do when P is not known, theoretical guarantees (bias, variance, convergence), other types of estimators, etc.
- Interesting lecture on the topic: https://www.youtube.com/watch?v=HMo9fQMVB4w

Thanks for the attention

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