



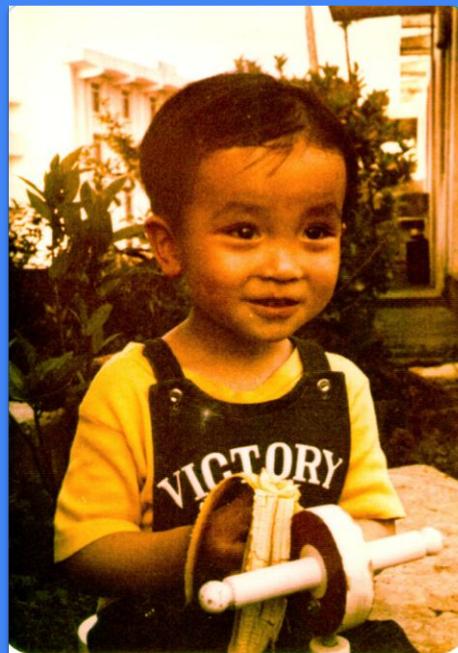
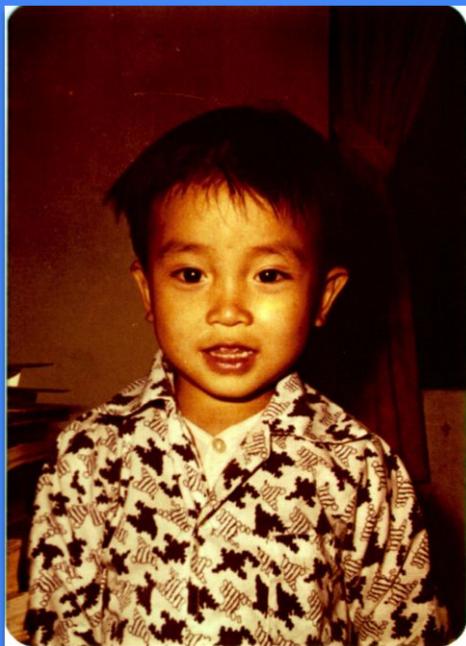
Serving Under-Represented Users in Recommenders with Focused Learning

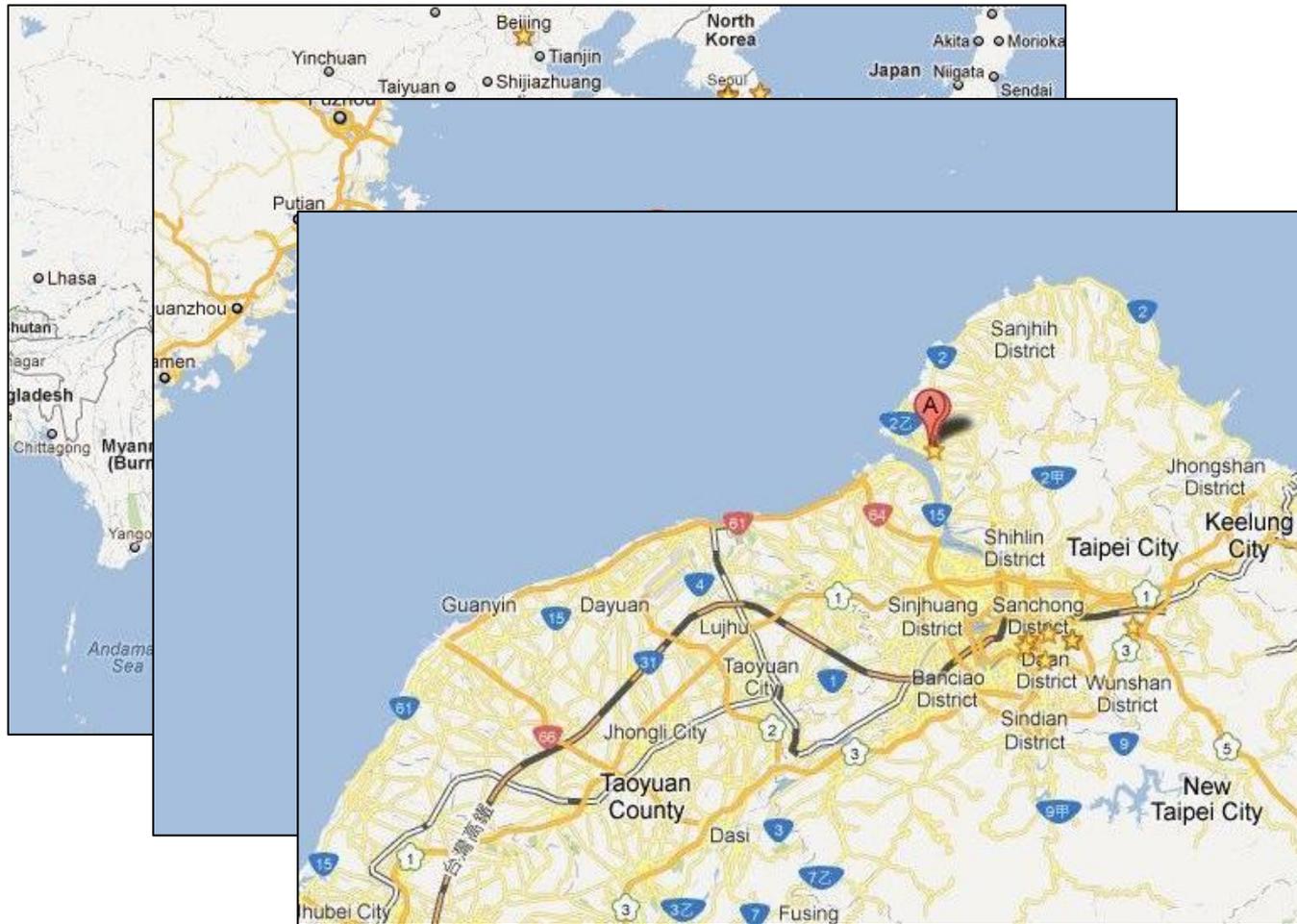
Ed H. Chi

With Alex Beutel, Zhiyuan Cheng, Hubert Pham, John Anderson

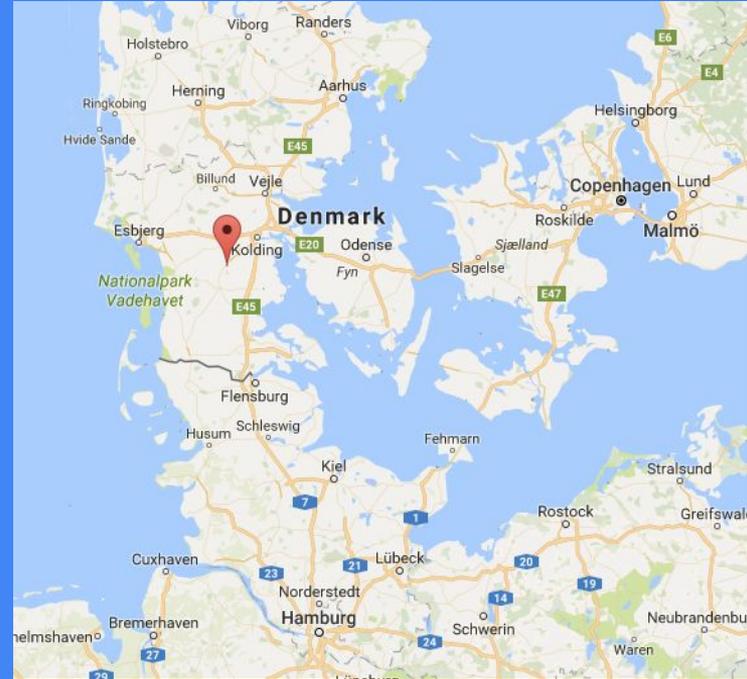
SIR research & Laser team

This is me ...





This is Rasmus...



Rasmus noticed lack of resolution on Danish music...

Poor regional recommendations:

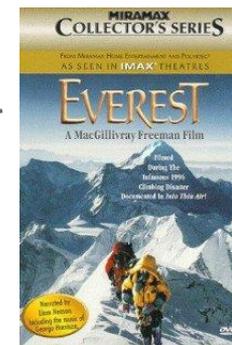
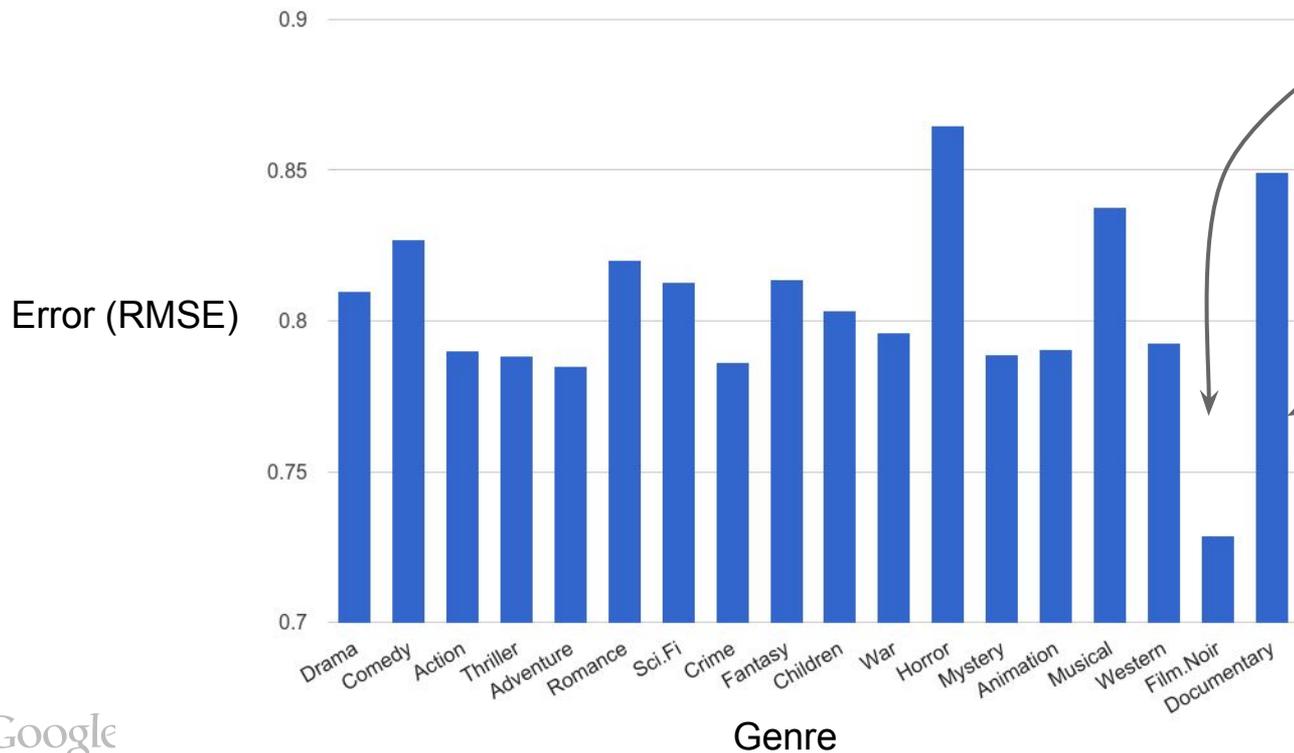
- **L.O.C.** Danish rapper band
- **D.A.D.** Danish rock band
- Recommendations: dominated by generic Danish head artists

Similar phenomenon in many other regions.

Seeds		recommended_entity	Entity	Score
Rap	 L.O.C.			
Rap	0		Suspekt	1.12
Rap/pop	1		Nik & Jay	1.11
Rock	2		Nephew	1.10
Pop	3		Kim Larsen	1.10
Pop	4		Kim Larsen & Kjukken	1.09
Rock	5		Dizzy Mizz Lizzy	1.09
Rock	6		TV-2	1.09
Pop	7		Thomas Helmig	1.09
Pop	8		Shu-bi-dua	1.09
Rock	9		Magtens Korridorer	1.08
Rap	10		Clemens	1.08

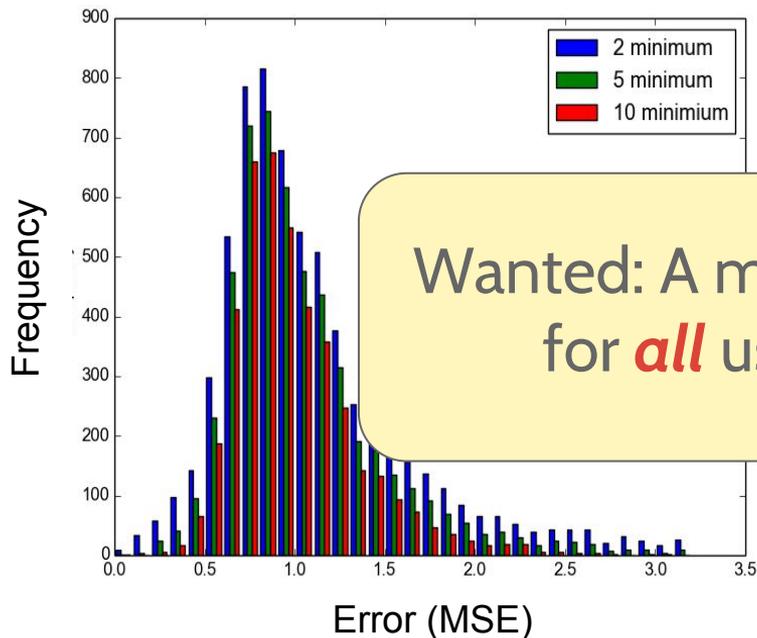
Seeds		recommended_entity	Entity	Score
Rock	 D.A.D.			
Rock	0		Dizzy Mizz Lizzy	1.03
Rock	1		Gasolin	0.89
Pop	2		Shu-bi-dua	0.87
Pop/Rock	3		TV-2	0.86
Pop	4		Kim Larsen	0.86
Rock	5		D-A-D	0.85
Pop	6		Kim Larsen & Kjukken	0.85
Rock	7		Sort Sol	0.84
Pop	8		John Mogensen	0.83
Pop	9		Thomas Helmig	0.83
Rock	10		Magtens Korridorer	0.83

Known: Recommender quality inconsistent across movies

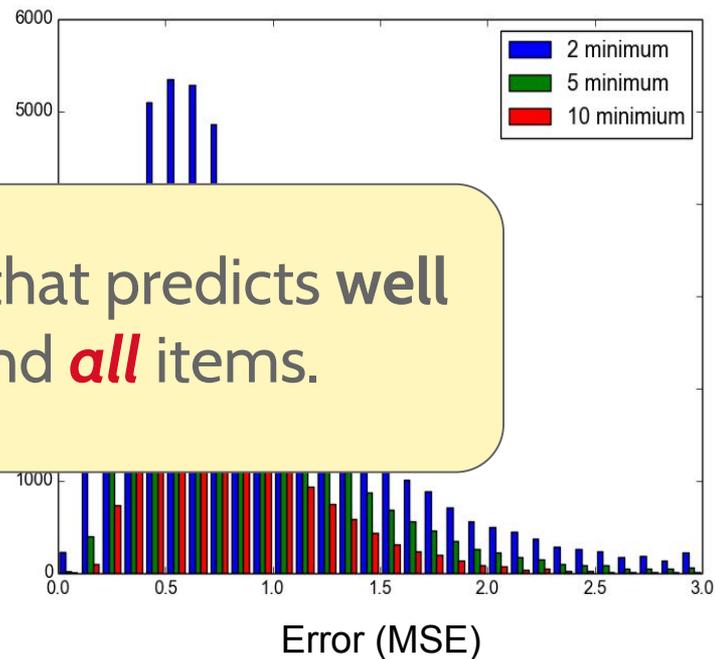


We don't represent users/items equally!

Per-Movie Prediction Accuracy



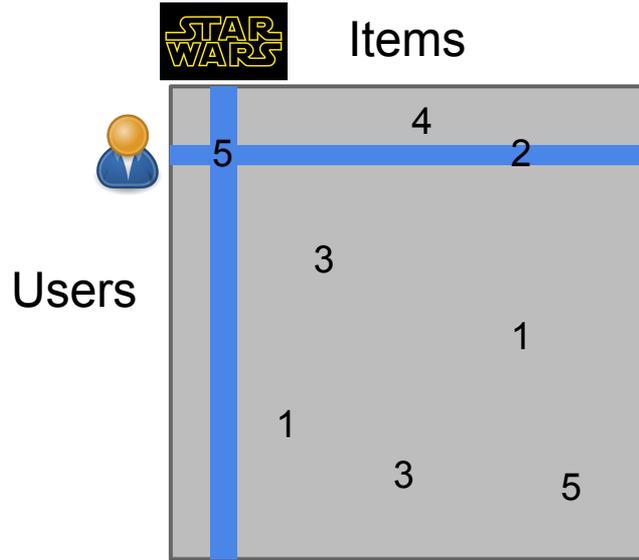
Per-User Prediction Accuracy



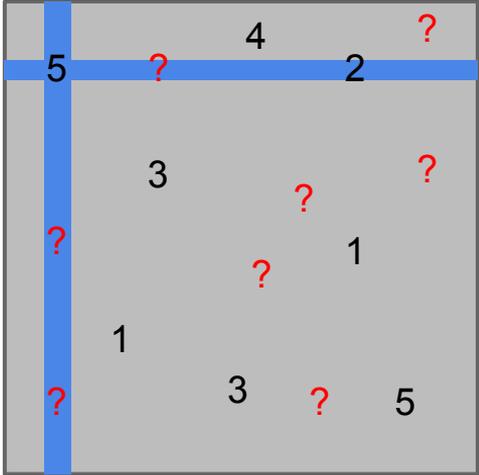
Wanted: A model that predicts well
for *all* users and *all* items.

Why does this happen?

The Recommendation Problem



The Recommendation Problem



	STAR WARS	Items			
Users	5	?	4	2	?
	?	3	?	?	?
	?	1	?	1	
	?	3	?	5	

Given: Observed (user, item) ratings

Find: A model that predicts the missing ratings well

Used throughout Google:



Power Law of Observations

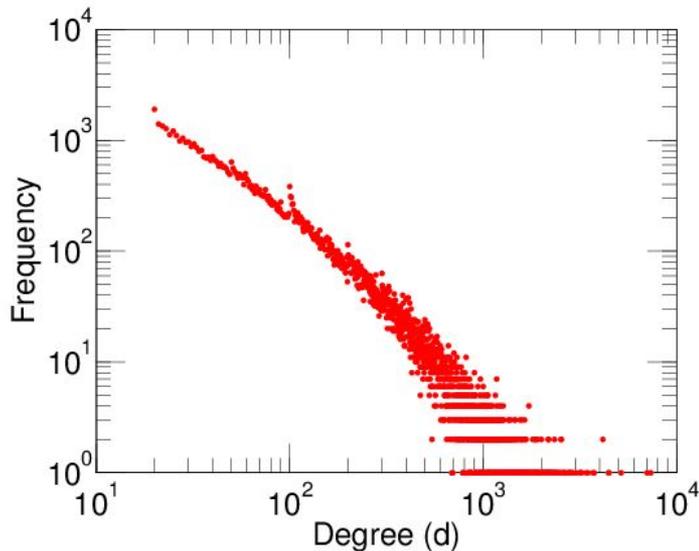
RMSE considers **all** observations equally:

$$\sqrt{\frac{1}{|\mathcal{X}|} \sum_{(i,j) \in \mathcal{X}} (\mathcal{X}_{i,j} - \langle u_i, v_j \rangle)^2}$$

Therefore it values users and movies with more ratings far more than others with less ratings.

That is, “Globally optimal” is more focused on popular, mainstream movies than niche ones.

User Degree Distribution

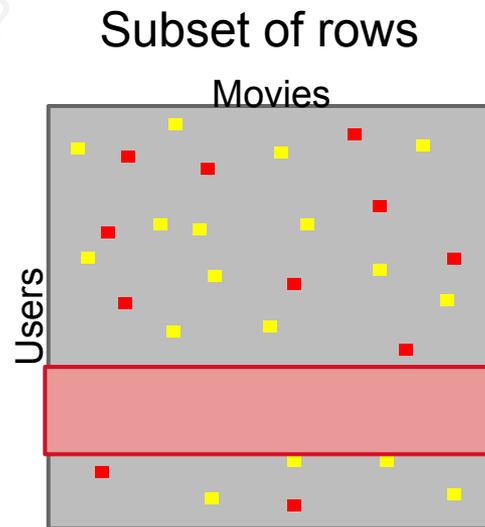
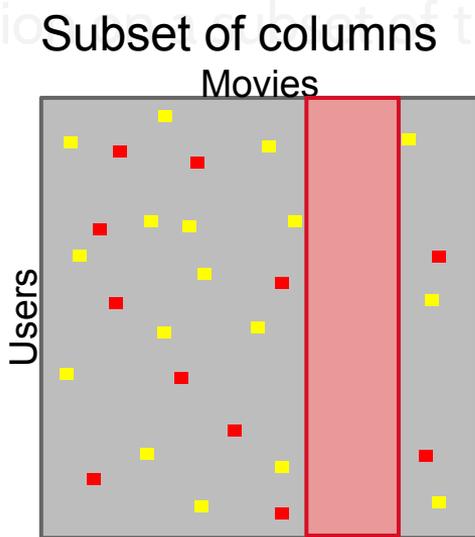


Approach

1. **Focus Selection** - Where should the additional models focus?
2. **Focused Learning** - How can learn a new model to improve prediction on a subset of the data?

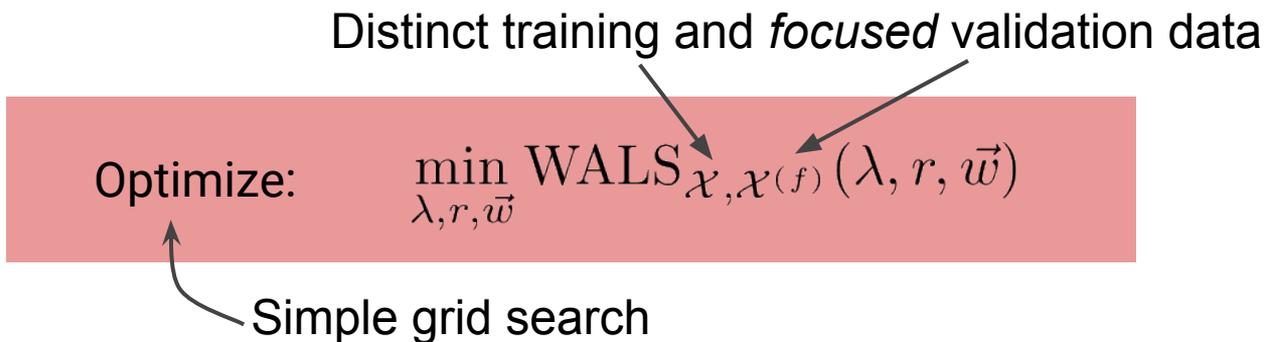
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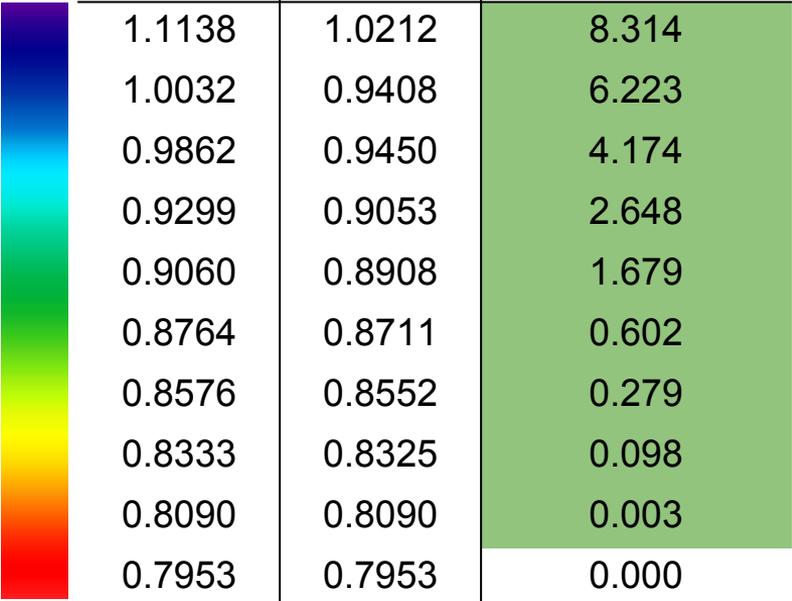


Approach

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Results: Focused by Movie Spectra



	Global	Focused	% Improvement	Focused λ	Unfocused λ
	1.1138	1.0212	8.314	15	150
	1.0032	0.9408	6.223	15	150
	0.9862	0.9450	4.174	15	60
	0.9299	0.9053	2.648	15	60
	0.9060	0.8908	1.679	15	60
	0.8764	0.8711	0.602	30	60
	0.8576	0.8552	0.279	30	60
	0.8333	0.8325	0.098	30	60
	0.8090	0.8090	0.003	30	60
	0.7953	0.7953	0.000	30	30

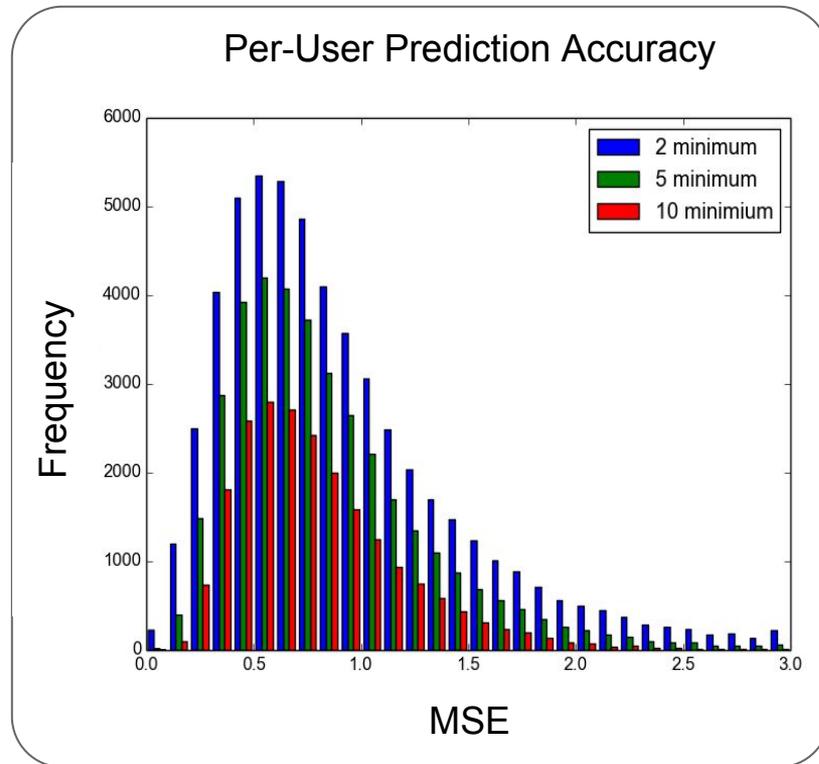
Results: Focused by User

Percentile	Global	Focused	% Improvement
0%-1%	1.9989	1.9664	1.629
0%-10%	1.4192	1.4107	0.596
10%-20%	1.1177	1.1112	0.581
20%-30%	0.9824	0.9769	0.553
30%-40%	0.8834	0.8782	0.587

Conclusion

1. “Globally optimal” is not best for everybody.
2. Learn additional models focused on problematic regions.

“Myth of the average user!”



Contact me:

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go/sir

Fight the long-tail with
different representations!

