The Impact of Differential Privacy on Recommendation Accuracy and Popularity Bias

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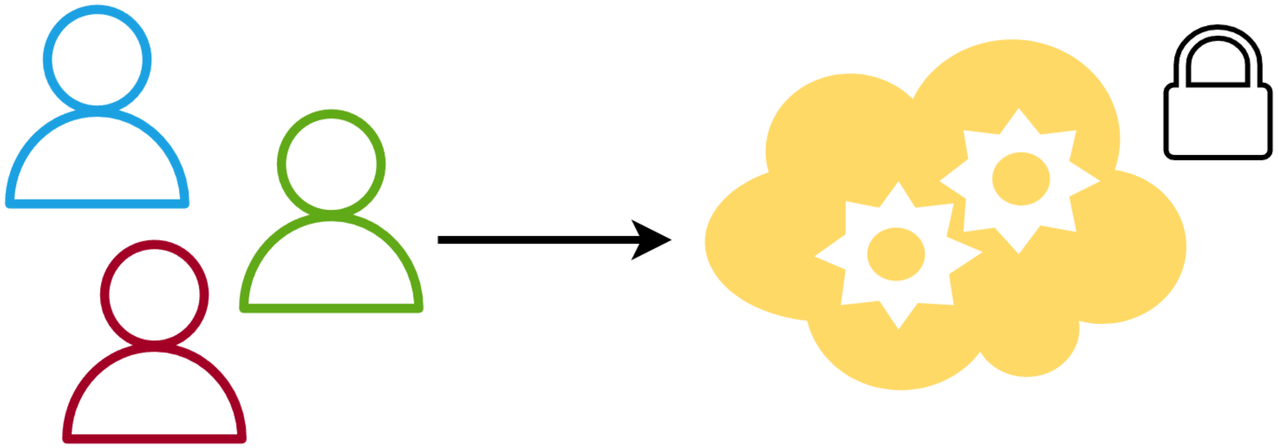
Motivation

- Recommender Sytems exploit user data to generate recommendaions
- Recommendations can **leak user data**! [1, 4, 5]
- Often, **Differential Privacy** used to prohibit this leakage



The Problem with DP

- For DP, random noise is injected into the training process
- Level of noise/privacy regulated by privacy-parameter ϵ
- **How does this random noise impact recommendations?**
  - How many users are impacted?
  - How strong are they impacted?
  - How does privacy-parameter ϵ influence the accuracy?
  - How does DP impact popularity bias?

Our Approach

- Binary DP mechanism[1] for implicit feedback data [2, 3]
- Train model A on data without DP
- Train model B on data with DP
- For each user, compare both models' recommendations

[1] Randomly substitutes positive feedback data with negative or missing feedback data with probability $1 / (e^{\epsilon} + 1)$

Results

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How many users are impacted?

- For each user, we compare recommendations with and without DP
- If at least one recommended item different → "impacted"
- **Nearly all users are impacted!**

ϵ	Model	*MovieLens 1M*	*LastFM User Groups*	*Amazon Grocery & Gourmet*
2	*ENMF*	99.85%	99.64%	**100.00%**
	LightGCN	99.86%	99.92%	99.99%
	MultVAE	99.93%	**100.00%**	**100.00%**
1	*ENMF*	99.99%	99.95%	**100.00%**
	LightGCN	**99.99%**	99.99%	**100.00%**
	MultVAE	**100.00%**	**100.00%**	**100.00%**
0.1	*ENMF*	**100.00%**	**100.00%**	**100.00%**
	LightGCN	**99.99%**	**100.00%**	**100.00%**
	MultVAE	**100.00%**	**100.00%**	**100.00%**

Table: No. of impacted users

How strong are those users impacted?

- Jaccard distance between recommendations with and without DP
- **Recommendations change a lot!**
- Worse for small ϵ values

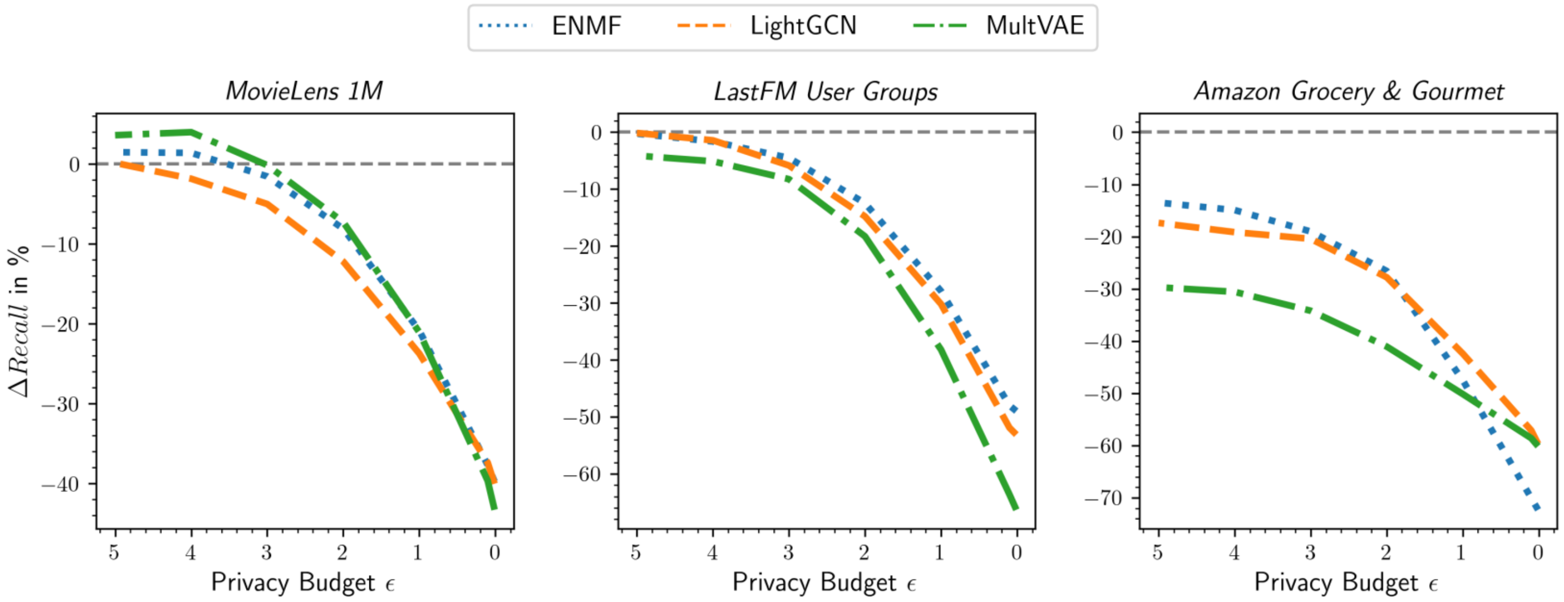
ϵ	Model	*MovieLens 1M*	*LastFM User Groups*	*Amazon Grocery & Gourmet*
2	*ENMF*	0.5974	0.5757	0.8620
	LightGCN	0.6252	0.6518	0.8132
	MultVAE	0.6828	0.7950	0.9447
1	*ENMF*	0.7006	0.6858	0.9253
	LightGCN	0.7352	0.7464	0.8775
	MultVAE	0.7592	0.8408	0.9567
0.1	*ENMF*	**0.8183**	**0.8058**	**0.9743**
	LightGCN	**0.8300**	**0.8490**	**0.9360**
	MultVAE	**0.8447**	**0.9250**	**0.9635**

Table: Average Jaccard distance

How does this affect accuracy and popularity bias?

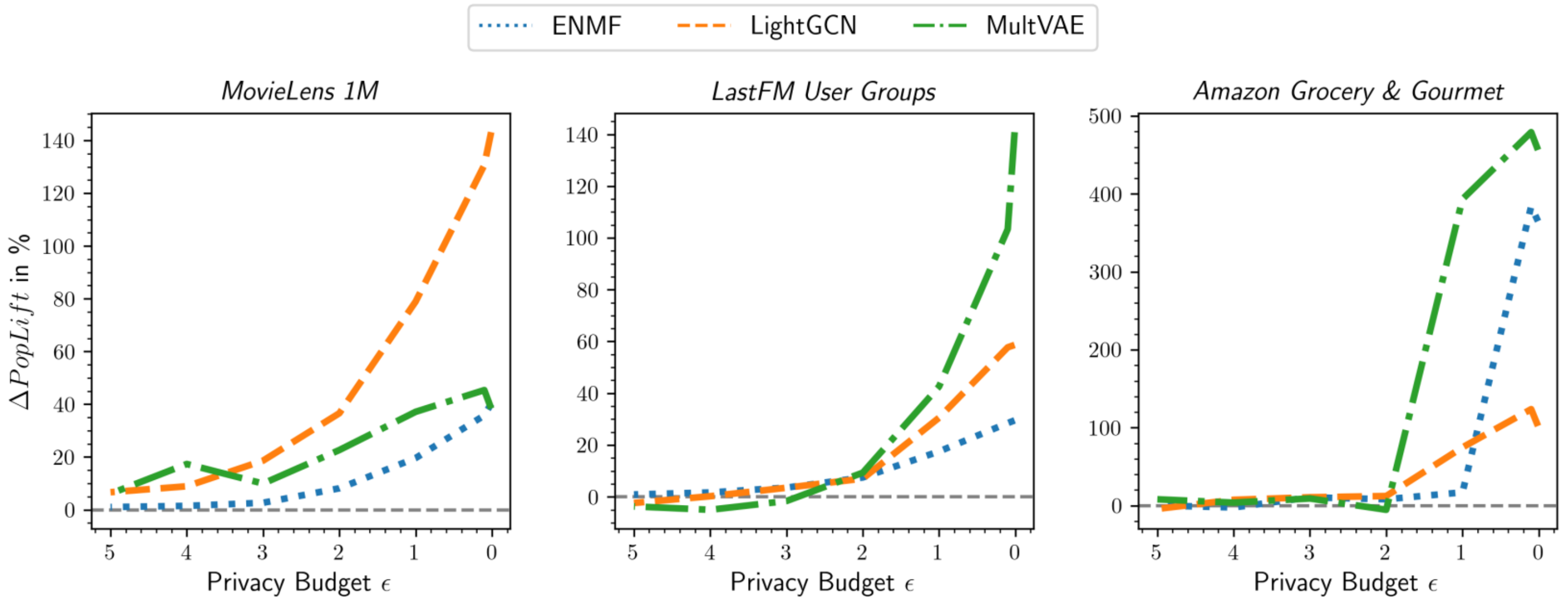
How does ϵ influence the accuracy?

- Measure ΔRecall = (Recall$_{DP}$ − Recall)/Recall
- **Recall drops, especially for small ϵ values!**



How does DP impact popularity bias?

- Measure ΔPopLift = (PopLift$_{DP}$ − PopLift)/PopLift
- **PopLift increases, especially for small ϵ values!**



How does DP impact popularity bias?

- Users that prefer popular (U_{high}) and unpopular items (U_{high})
- Disparate Impact = PopLift(U_{high}) − PopLift(U_{high})
- **Popularity bias for U_{low} tends to be stronger than for U_{high}!**

ϵ	Method	*MovieLens 1M*	*LastFM User Groups*	*Amazon Grocery & Gourmet*
2	*ENMF*	+0.6941	+3.3158	+1.3597
	LightGCN	+0.1241	+1.8623	+1.3215
	MultVAE	+0.2595	-0.8629	+1.2161
1	*ENMF*	+0.8046	+3.9001	+1.4206
	LightGCN	+0.4368	+2.2851	+1.8303
	MultVAE	+0.3811	**-0.9744**	+4.0117
0.1	*ENMF*	**+0.8831**	**+4.2769**	**+3.7277**
	LightGCN	**+0.9352**	**+4.0773**	**+2.9563**
	MultVAE	**+0.5225**	-0.7113	**+5.2092**

Table: Disparate Impact

Conclusion and Future Work

Conclusions and Future Work

- DP has substantial impact on entire user base
  - Different recommendations than without DP
  - Severe accuracy drop
  - Sharp increase of popularity bias
- Users are impacted differently w.r.t. popularity bias
- Choice of ϵ is a major factor
- Increase ϵ to decrease impact? → No privacy!

How to balance recommendation accuracy, popularity bias, and privacy?

(e.g., by applying popularity bias mitigation strategies)

Thank you!

Source code: github.com/pmuellner/ImpactOfDP/

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Binary DP mechanism by Ding et al. [3]

- **Randomize positive feedback data used for model training!**
- For a user feedback $f_{u,i}$ for user u, item i, and training data D^+
- Now, randomly substitute positive feedback D^+ with negative/missing feedback D^-

$$Pr[f_{u,i} \in \mathcal{D}_{DP}^{+}] = \begin{cases} \frac{e^{\epsilon}}{e^{\epsilon}+1} & \text{if } f_{u,i} \in \mathcal{D}^{+} \\ 1 - \frac{e^{\epsilon}}{e^{\epsilon}+1} & \text{if } f_{u,i} \in \mathcal{D}^{-} \end{cases}$$

- Privacy-parameter ϵ regulates how much leakage can be tolerated