Interaction-Grounded Learning for Recommender Systems

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Implicit user feedback is not the true satisfaction signal!

Premise: learner optimizes for latent rewards by interacting with the environment and associating observed feedback with the unobservable true reward

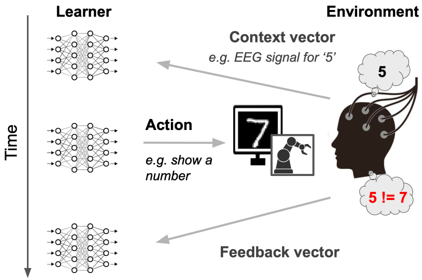


Figure 1: Original motivation for IGL [8]

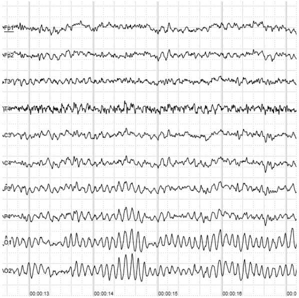
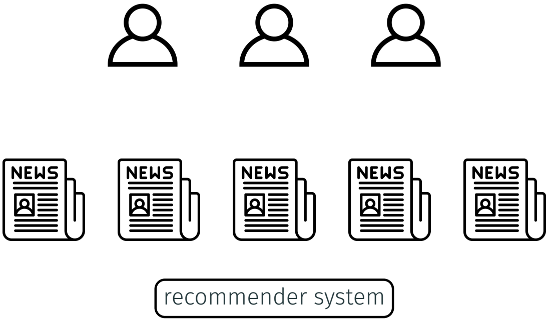


Figure 2: EEG signals[1]

[1]https://team.inria.fr/potioc/old-research-topics/eeg-signal-processing/

IGL FOR RECOMMENDER SYSTEMS



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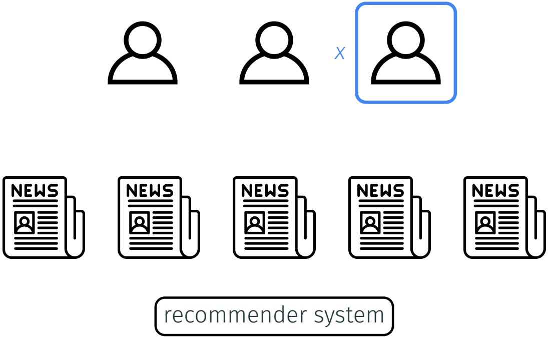

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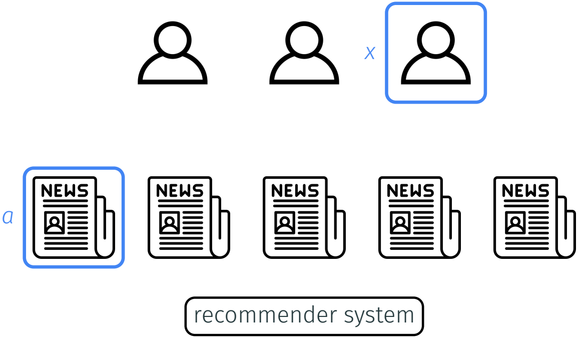

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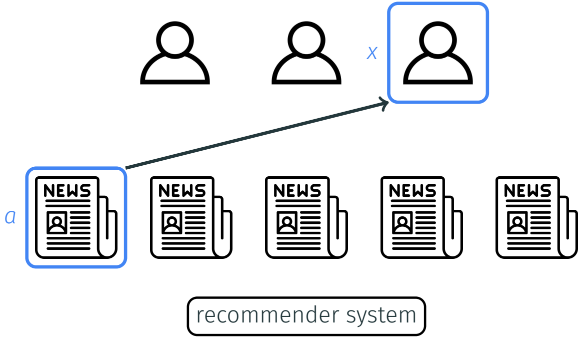

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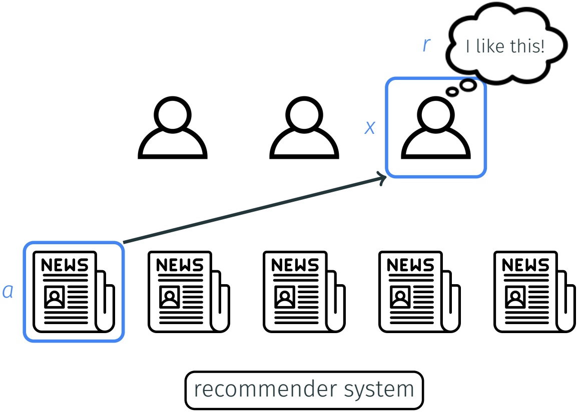

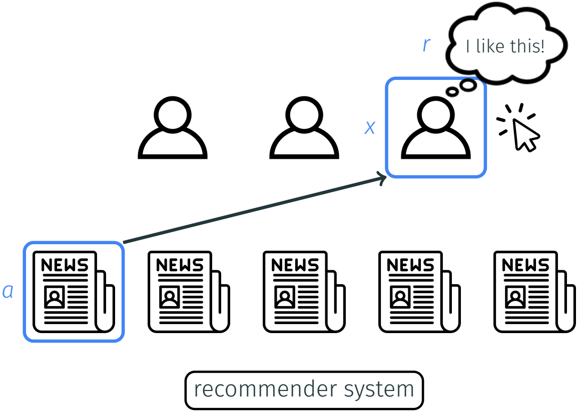
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I like this!
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NEWS
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a
recommender system

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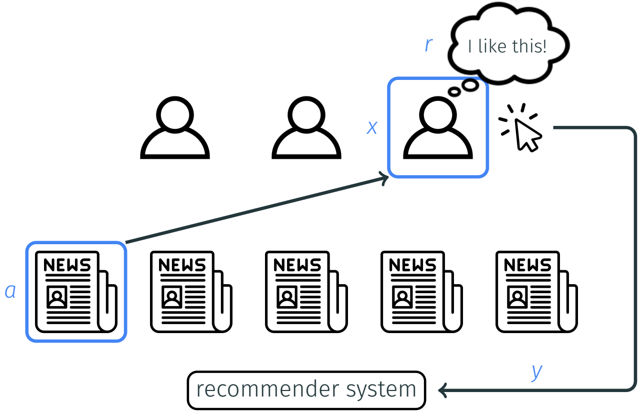

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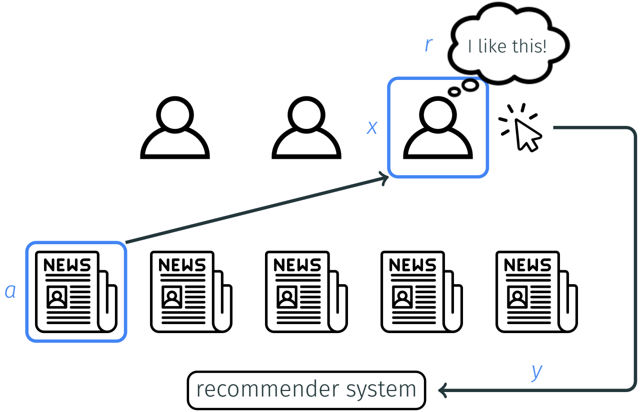
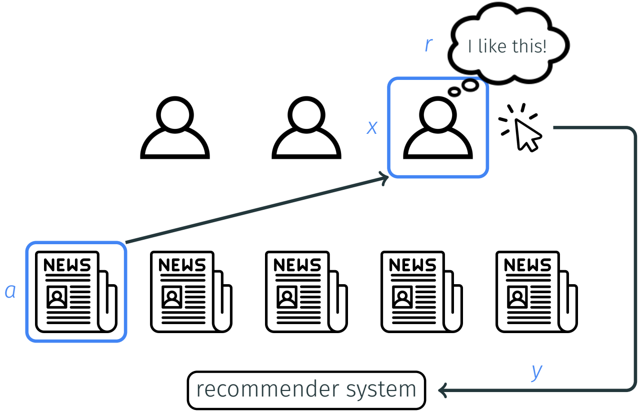


It is information theoretically impossible to solve IGL without assumptions about the relation between x, y and a [9].



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Consistent communication assumption: $y \perp a | x, r$

ARE 2 LATENT STATES SUFFICIENT FOR RECOMMENDER SYSTEMS?

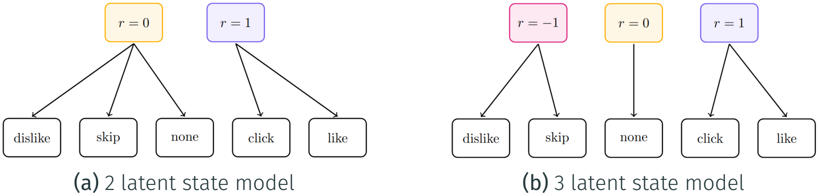

Figure 3: Example of the latent reward structure for a music recommendation system. In Fig. 1a, $r = 0$ corresponds to anything other than the user actively enjoying the content, whereas in Fig. 1b, lack of user enjoyment is split into indifference and active dissatisfaction.

Algorithm idea: anytime the posterior probability of an action is predicted to be more than twice the prior probability, we deduce $r \neq 0$.

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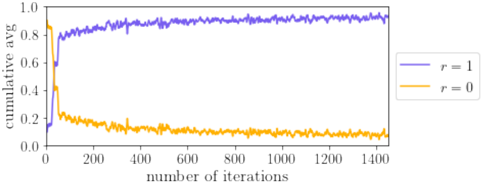

Figure 4: Performance of *IGL-P(2)* when there are two latent states.

IGL-P(2): AN ALGORITHM FOR TWO LATENT STATES

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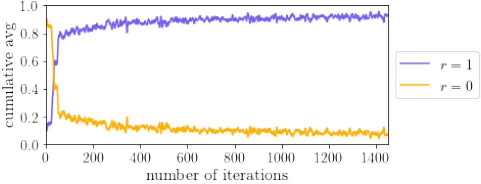

Figure 4: Performance of *IGL-P(2)* when there are two latent states.

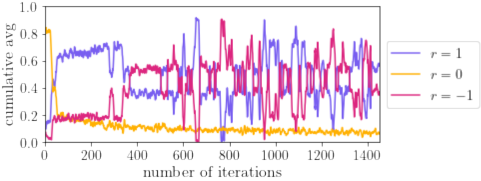

Figure 5: Performance of *IGL-P(2)* when there are three latent states.

IGL-P(3): AN ALGORITHM FOR THREE LATENT STATES

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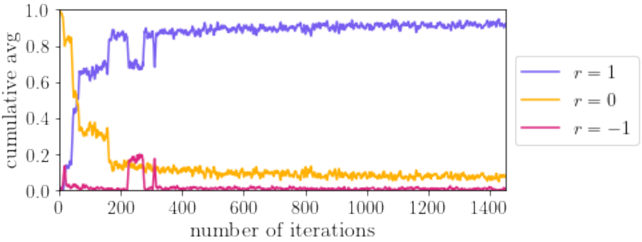

Figure 6: *IGL-P(3)* successfully maximizes user satisfaction while minimizing dissatisfaction.

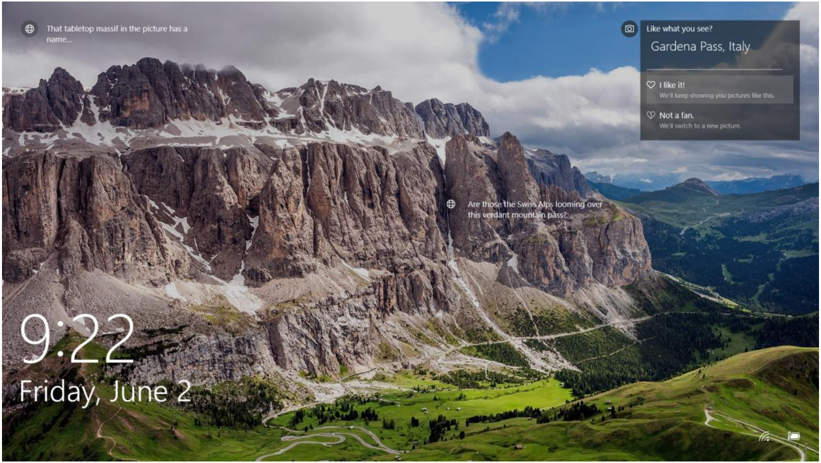

Figure 7: An example of a Windows Spotlight lock screen. Users can interact with the interface using 'click', 'like' or 'dislike' feedback.

Production setting: Windows Spotlight

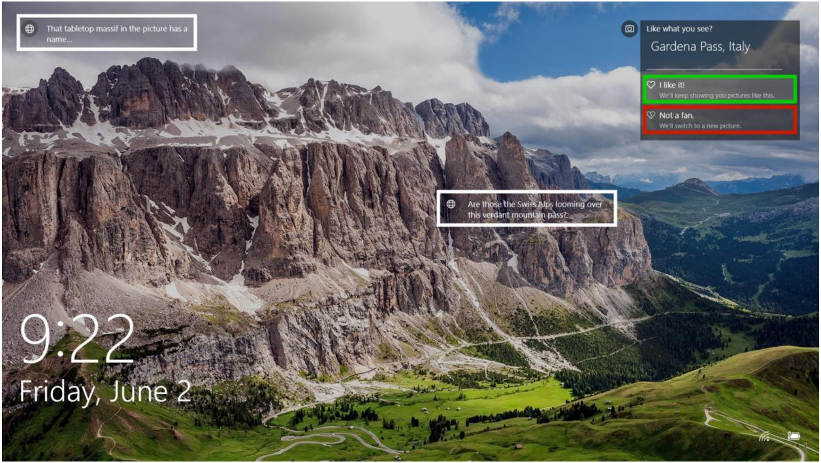

Figure 7: An example of a Windows Spotlight lock screen. Users can interact with the interface using 'click', 'like' or 'dislike' feedback.

Algorithm	*IGL-P(2)*	*IGL-P(3)*
Clicks	[0.926, 1.005, 1.091]	[0.999, 1.067, 1.152]
Likes	[0.914, 0.949, 0.988]	[0.985, 1.029, 1.054]
Dislikes	[1.141, 1.337, 1.557]	[0.751, 1.072, 1.274]

Table 1: Relative metrics lift over a production baseline. The production baseline uses a hand-engineered reward function which is not available to IGL algorithms. Shown are point estimates and associated bootstrap 95% confidence regions. *IGL-P(2)* erroneously increases dislikes to the detriment of other metrics. *IGL-P(3)* directionally improves over the hand-engineered reward function.

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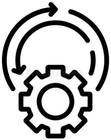

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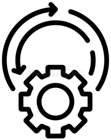

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Improved fairness for diverse users

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1. Despite its popularity as a reward objective, implicit user feedback is ***not*** the true satisfaction signal.

2. The Interaction-Grounded Learning (IGL) framework directly targets the underlying user satisfaction.

3. IGL outperforms state-of-the-art real world systems by learning personalized reward functions for users.

Thank you! Any questions?

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