

# A closed-loop model of news recommendations

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## User Opinion Model

$$o_{\text{usr}}(t+1) = \alpha o_{\text{usr}}^0 + \beta o_{\text{usr}}(t) + \gamma p_{\text{art}}(t) \quad t \in \mathbb{N}_0$$

$o_{\text{usr}}^0 \in [-1, 1]$  is a **prejudice** (i.e.  $o_{\text{usr}}(0) = o_{\text{usr}}^0$ )  
 $p_{\text{art}}(t) \in \{-1, +1\}$  is the **position of the article** proposed by the recommender at time  $t$

Weights  $\alpha, \beta, \gamma \geq 0$  and  $\alpha + \beta + \gamma = 1$  give relative importance of **prejudice**, **memory**, and **new information**



## User Click Model

The **user** decides whether to read the recommended item or not, following their **confirmation bias**

The **click decision**  $\text{clk} \in \{0, 1\}$  is stochastic:

$$\text{clk}(t) = \begin{cases} 1 & \text{with probability } \frac{1}{2} + \frac{1}{2} o_{\text{usr}}(t) p_{\text{art}}(t) \\ 0 & \text{with probability } \frac{1}{2} - \frac{1}{2} o_{\text{usr}}(t) p_{\text{art}}(t) \end{cases}$$



## Recommender System Model

The **recommender system** wants to **maximize engagement**,

measured by **click-through rate**  $\text{ctr}(t) = \frac{1}{t} \sum_{s=0}^{t-1} \text{clk}(s)$

User is seen as a **“two-armed bandit”**

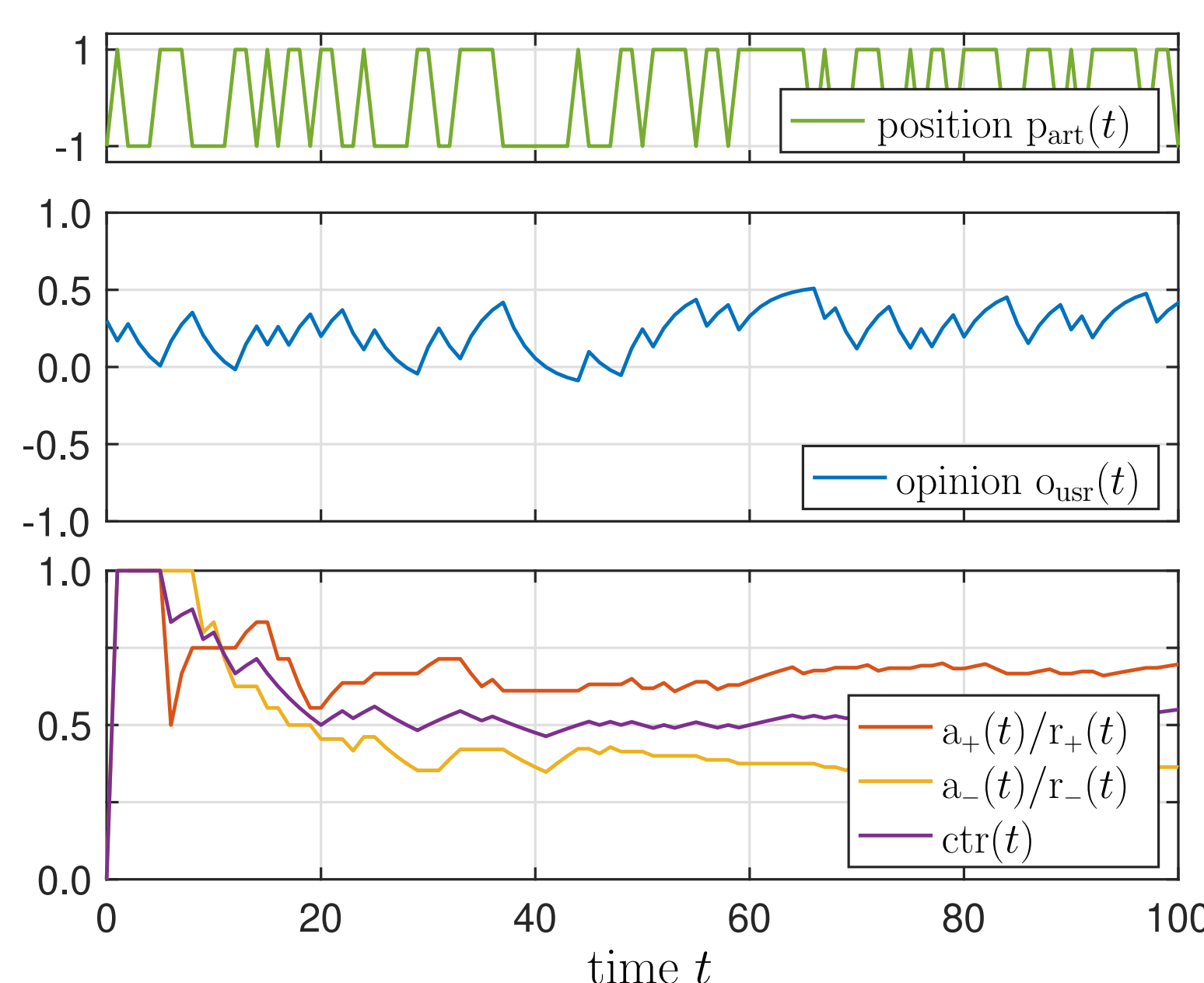
solved by **ε-greedy** algorithm:

$$p_{\text{art}}(t) = \begin{cases} \text{exploitation} & \text{with probability } 1 - \epsilon \\ \text{exploration} & \text{with probability } \epsilon \end{cases}$$

using counters  $r_+, r_-, a_+, a_-$  to track past recommendations and clicks



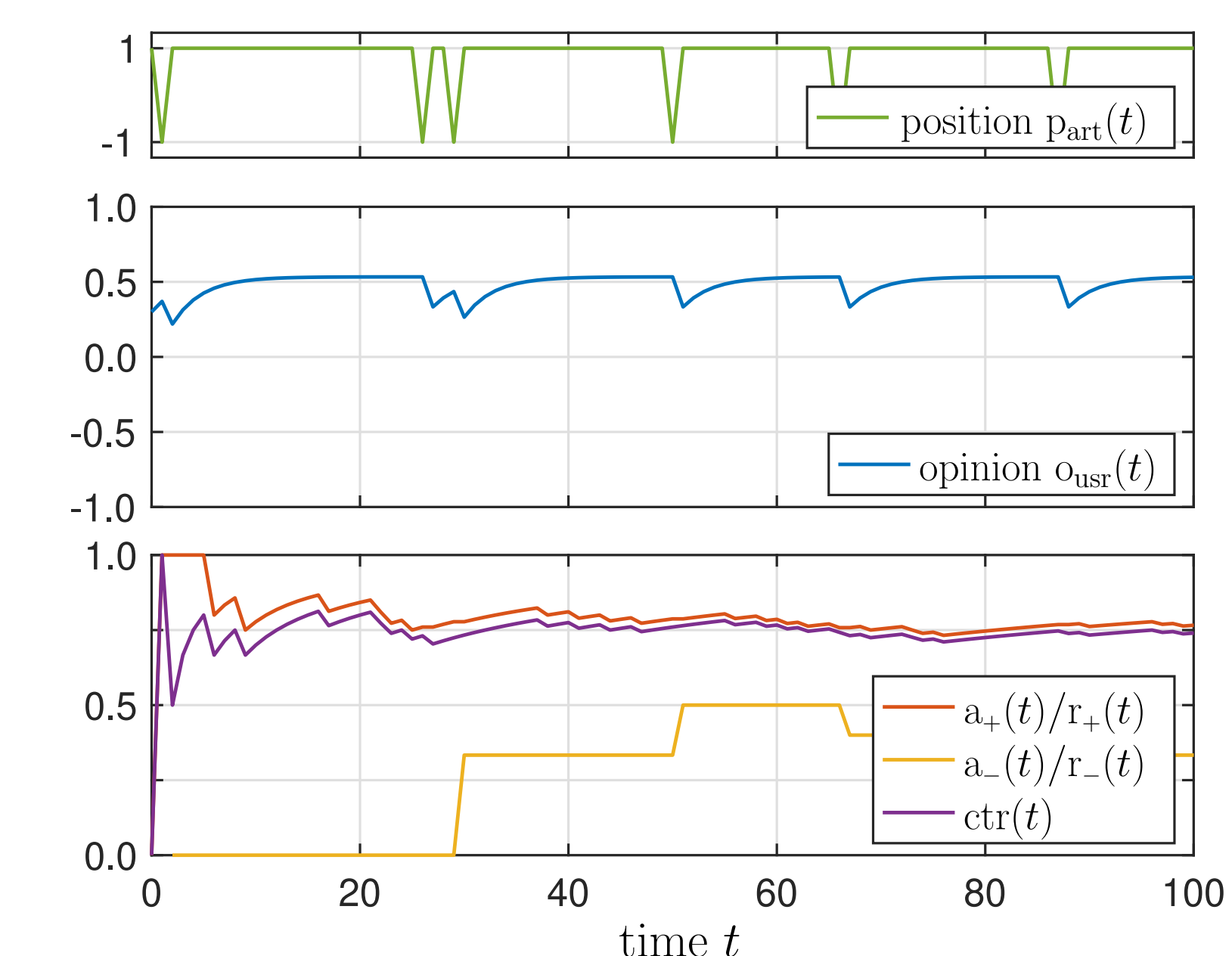
## With Random Recommendations



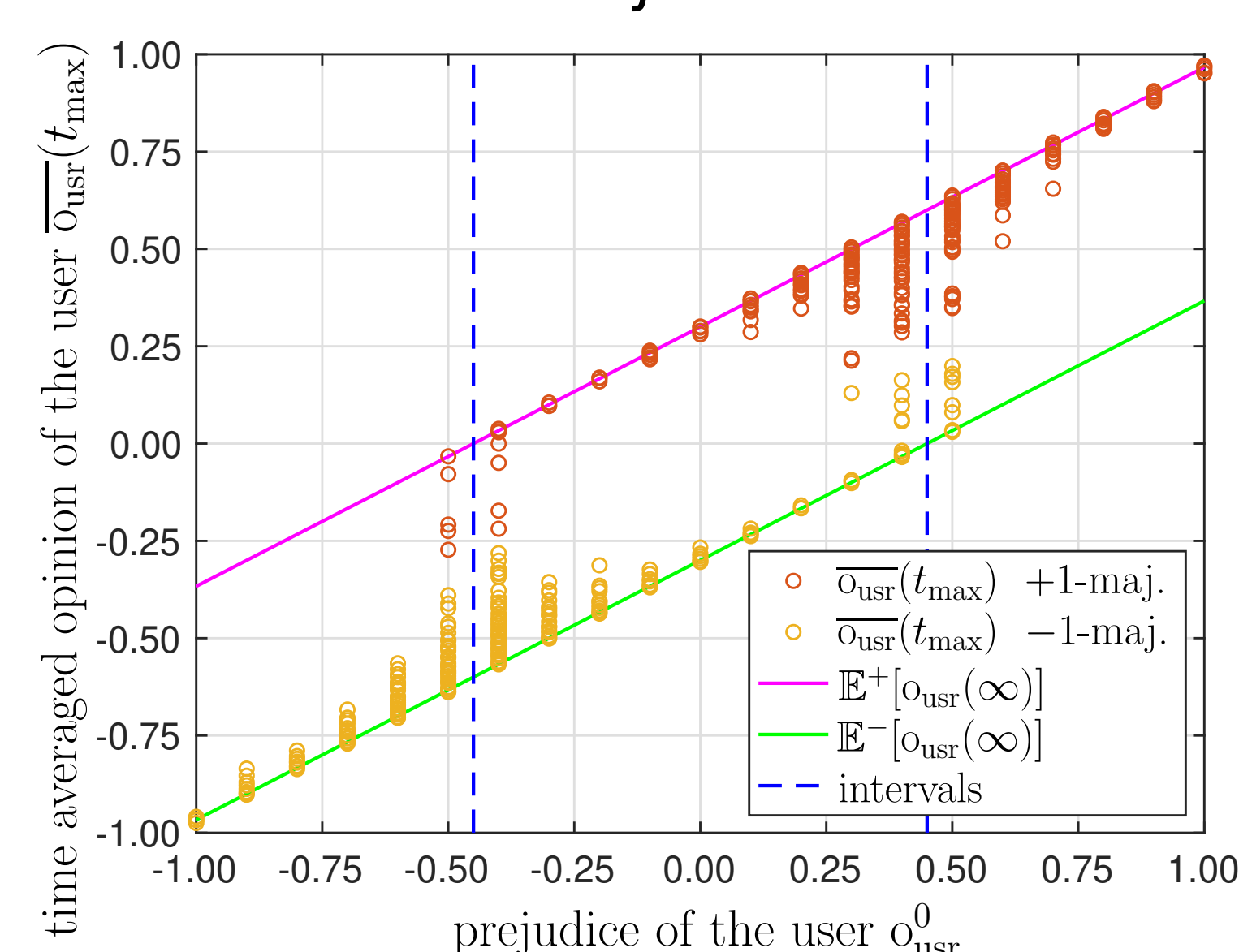
User (Reader)

News Recommender

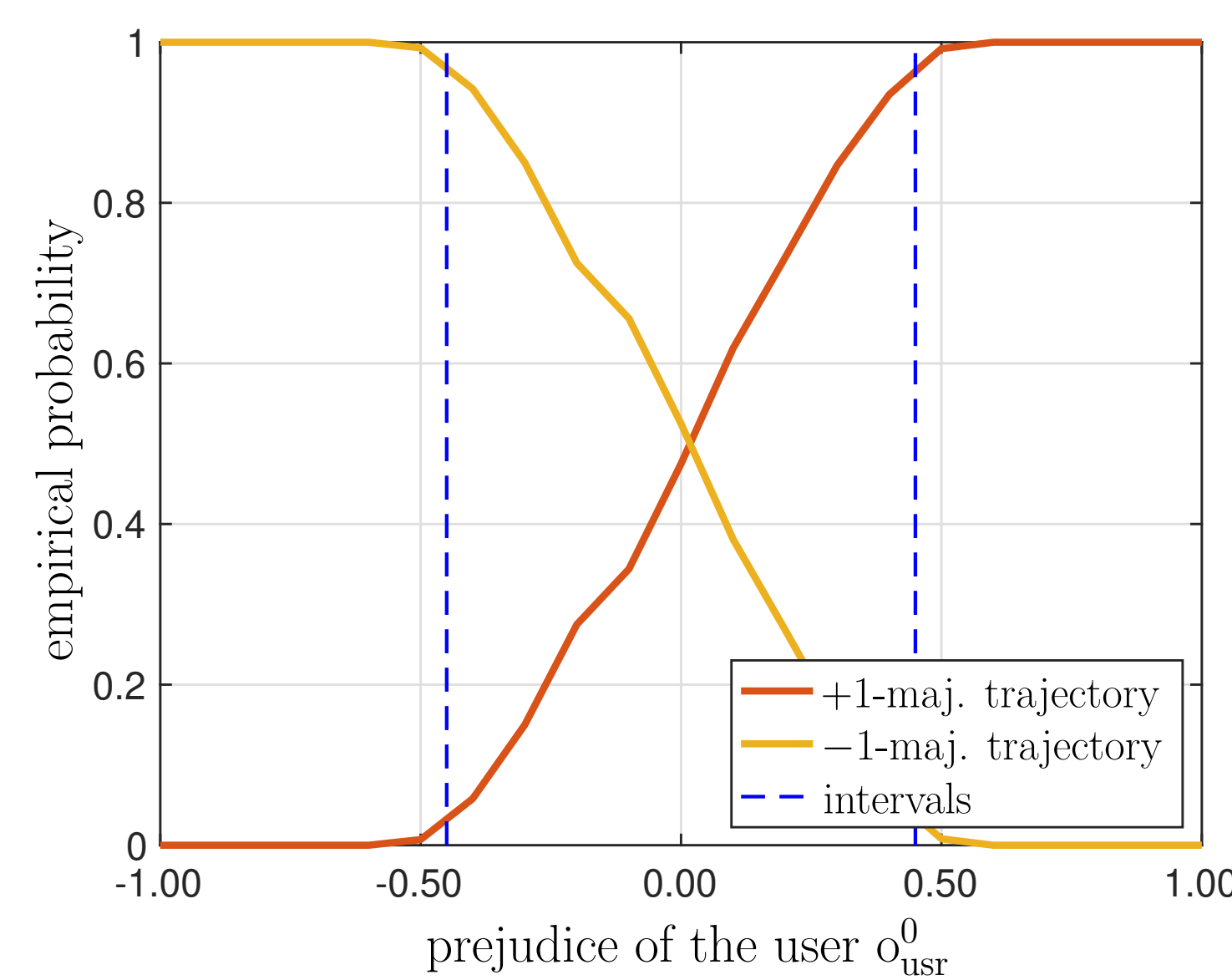
## With Personalised Recommendations



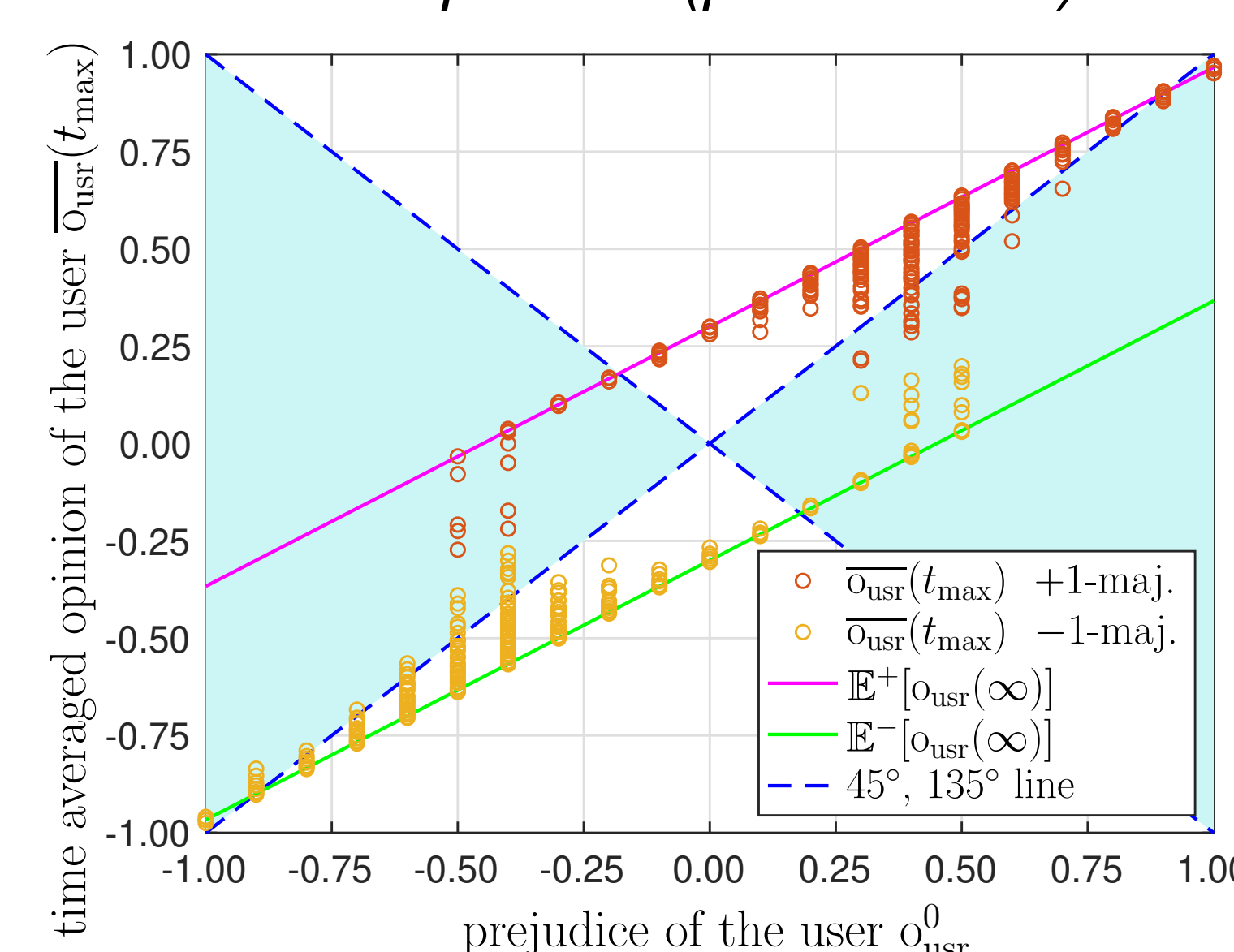
Opinions split between +1-trajectories and -1-trajectories



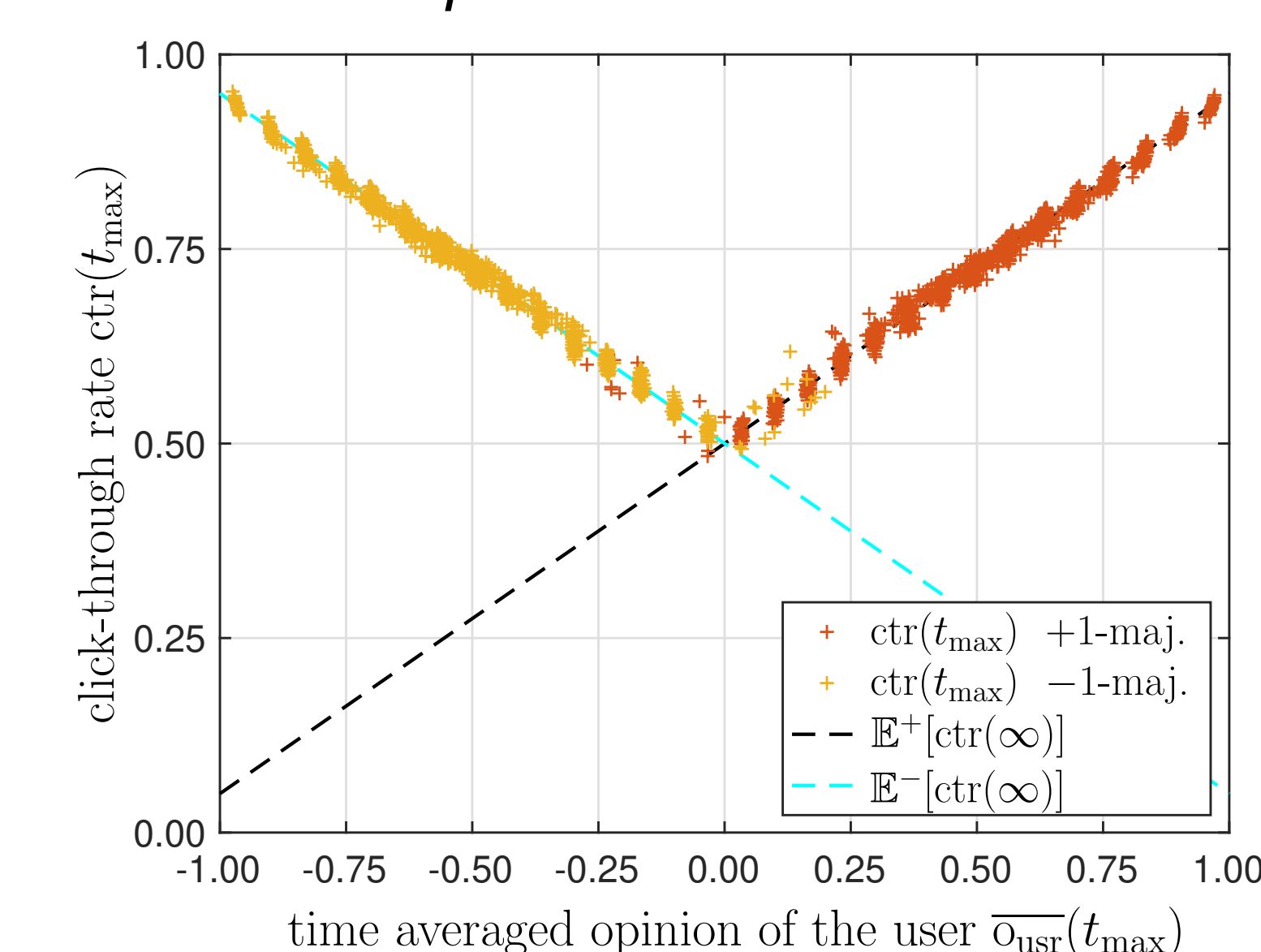
Strong prejudices lead to biased recommendations



Most trajectories produce more extreme opinions (polarization)



Recommendations are more effective when opinions are extreme



Effectiveness of recommendations and impact on opinions are correlated

