Harvard John A. Paulson
School of Engineering
and Applied Sciences

ICML
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A Model of Place Field Reorganization During Reward Maximization

M Ganesh (“guh-nay-sh”) Kumar

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Blake Bordelon


Jacob Veth-Zavatone


Cengiz Pehlevan

mganeshkumar@seas.harvard.edu M Ganesh Kumar mgkumar138

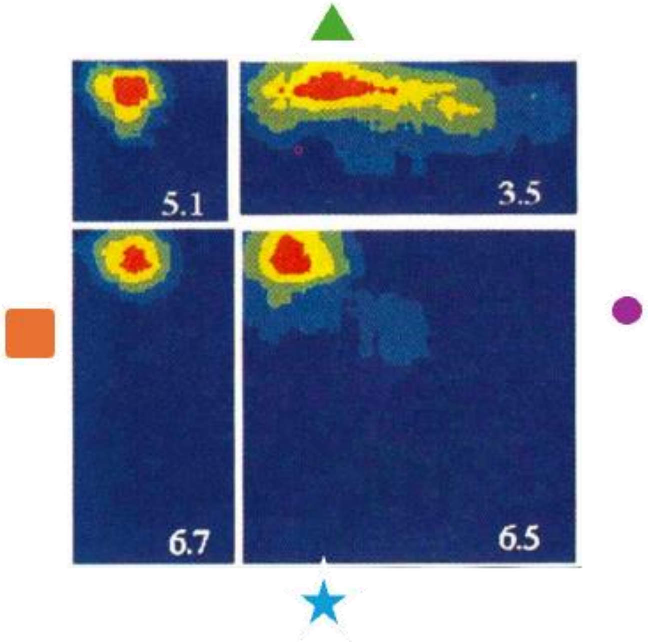
First, some terminologies…

- Place *cell*: A neuron in the hippocampus that exhibits place fields
- Place *field*: A **localized region** where a place cell robustly fires with a Gaussian distribution
- *Population* of place fields: State space representation for localization (i.e. biological "GPS")
- Place field *dynamics*: How individual place field's spatial representation changes over time

Key phenomena:

1) High density at rewards ("Reward Over-representation")
2) Elongation against trajectory ("Predictive Coding")
3) Drift with stable behavior ("Representational Drift")

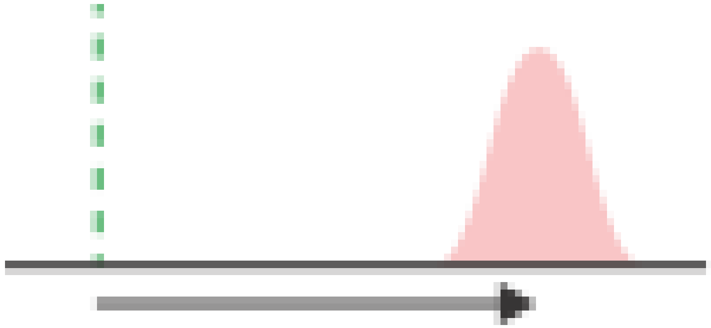
*Question: **Why** do place fields **reorganize** during learning?*



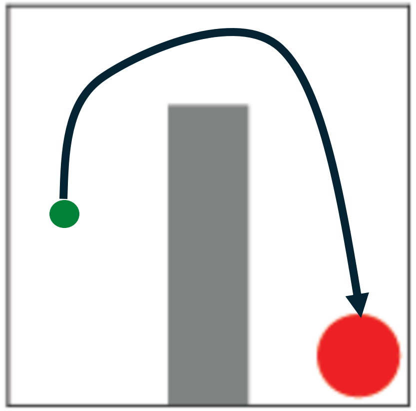
O'Keefe, Burgess 1996 Nature

Navigation task:
Choose actions to move from Start to Target

1D



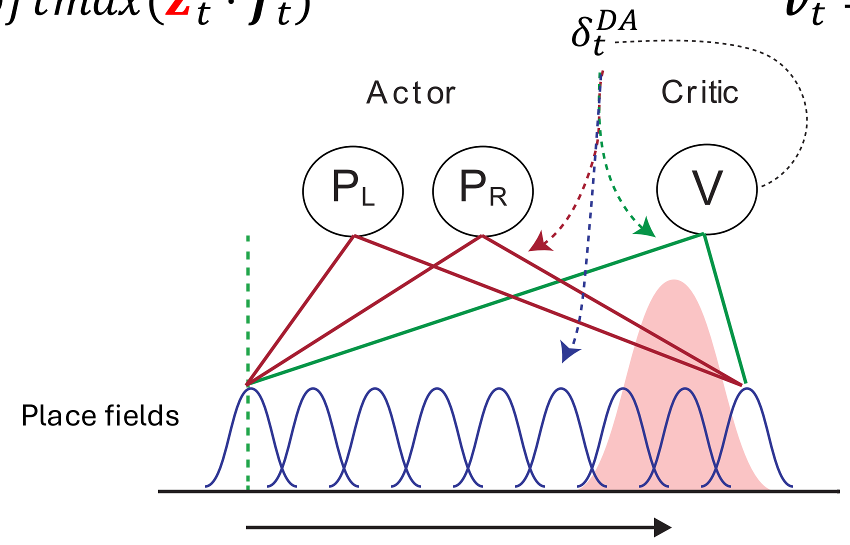
2D



Foster et al., 2000; Kumar et al., 2022; 2024

Simple HPC-BG agent with tunable place fields

$$\tilde{\boldsymbol{a}}_t = softmax(\boldsymbol{Z}_t \cdot \boldsymbol{f}_t) \qquad \boldsymbol{v}_t = \boldsymbol{w}_t \cdot \boldsymbol{f}_t$$



$$\boldsymbol{f}_t(\boldsymbol{\theta}) = \boldsymbol{\alpha}_t^2 \exp\left(-\frac{\left|\left|x_t - \boldsymbol{\lambda}_t\right|\right|^2}{2\boldsymbol{\sigma}_t^2}\right)$$

Temporal Difference error modulated learning

$$\delta_t^{DA} = r_t + \gamma v_{t+1} - v_t$$

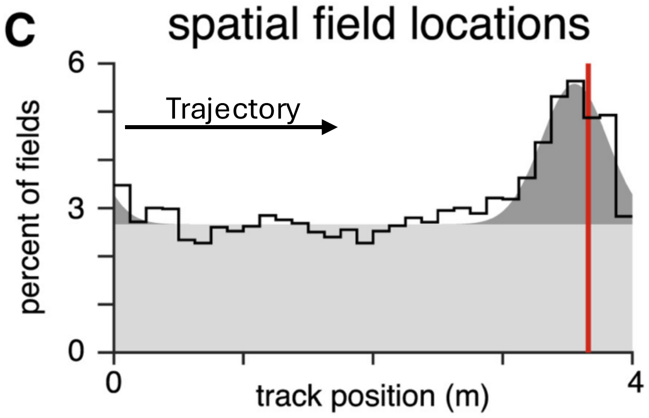
$$\Delta \boldsymbol{w}_t \propto \boldsymbol{f}_t \cdot \delta_t^{DA}$$

$$\Delta \boldsymbol{Z}_t \propto \boldsymbol{f}_t \cdot \boldsymbol{a}_t \cdot \delta_t^{DA}$$

$$\Delta \boldsymbol{\theta}_t \propto \boldsymbol{f}'_t(\boldsymbol{\theta}) \cdot (\boldsymbol{w}_t + \boldsymbol{Z}_t \cdot \hat{\boldsymbol{a}}_t) \cdot \delta_t^{DA}$$

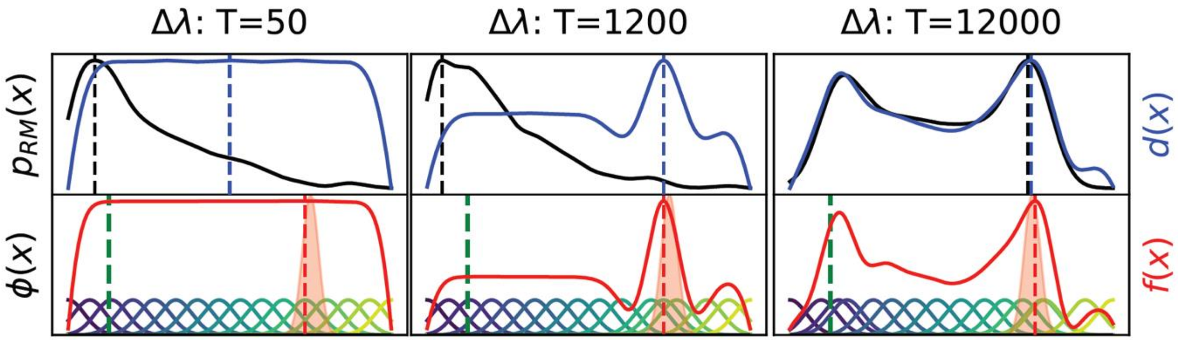
High place field density emerges at reward and start

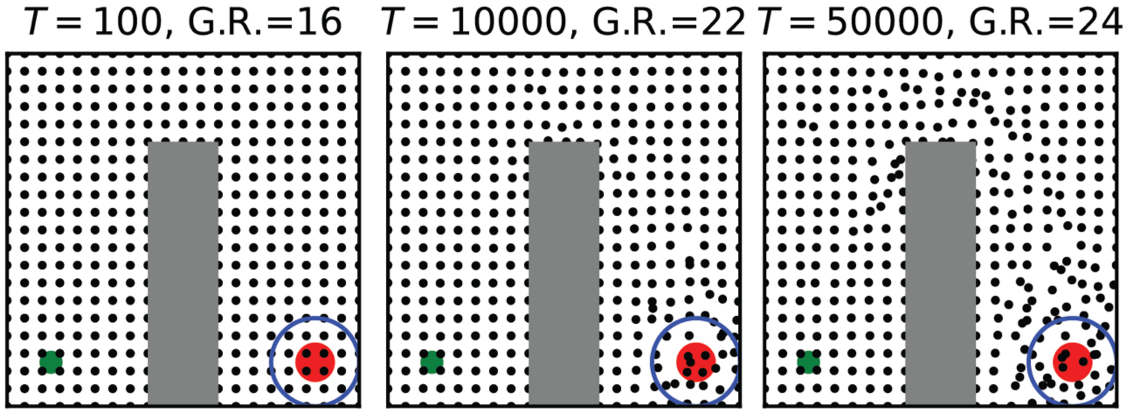
Experiment



Gauthier et al. 2018 Neuron

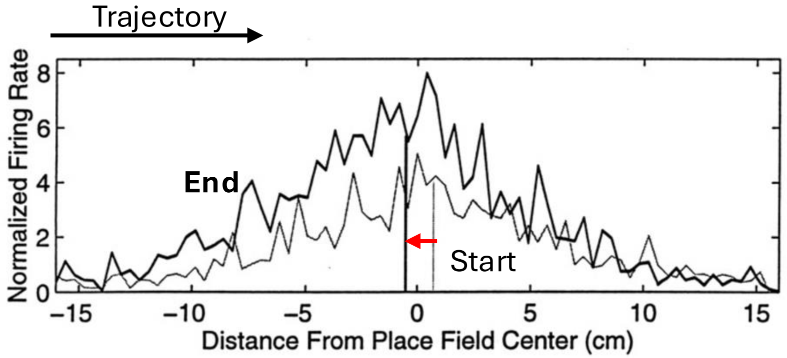
Model

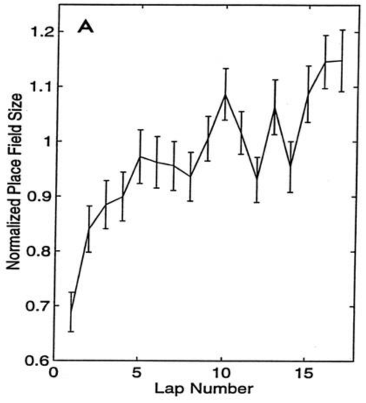


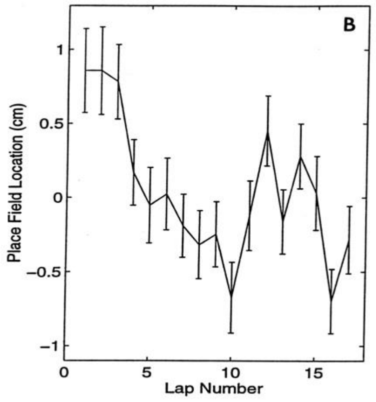


Place fields elongate against the trajectory

Experiment

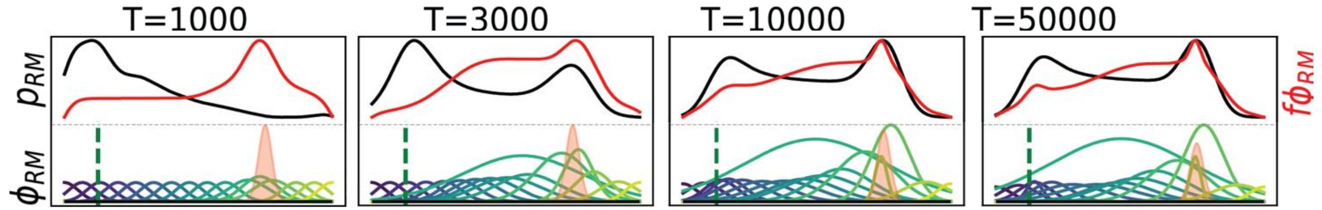


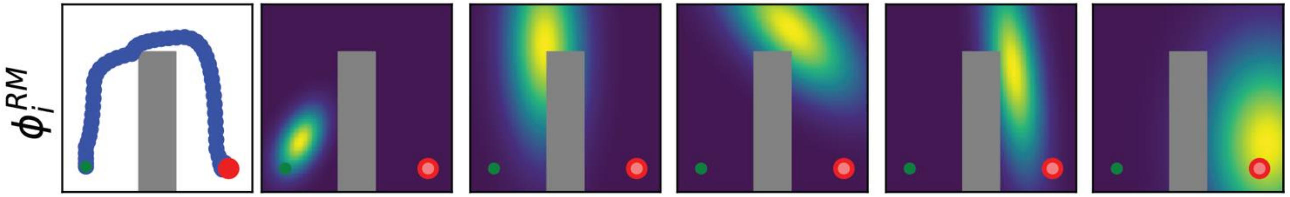


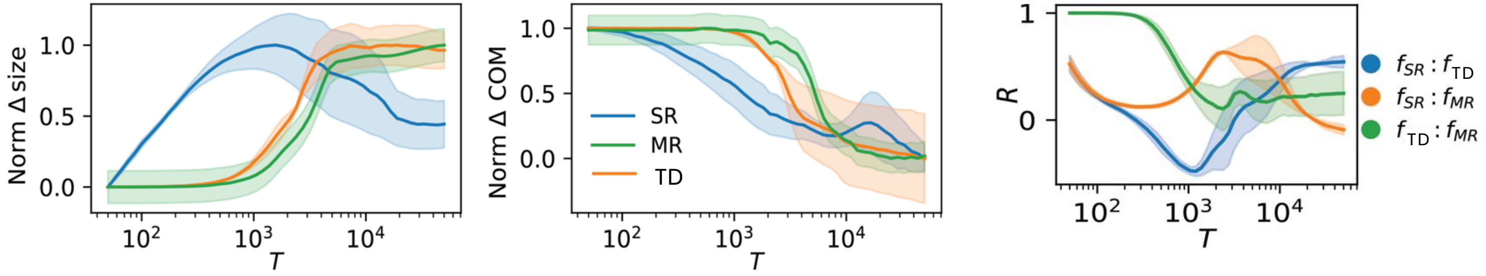


Mehta et al. 1997 PNAS

Model

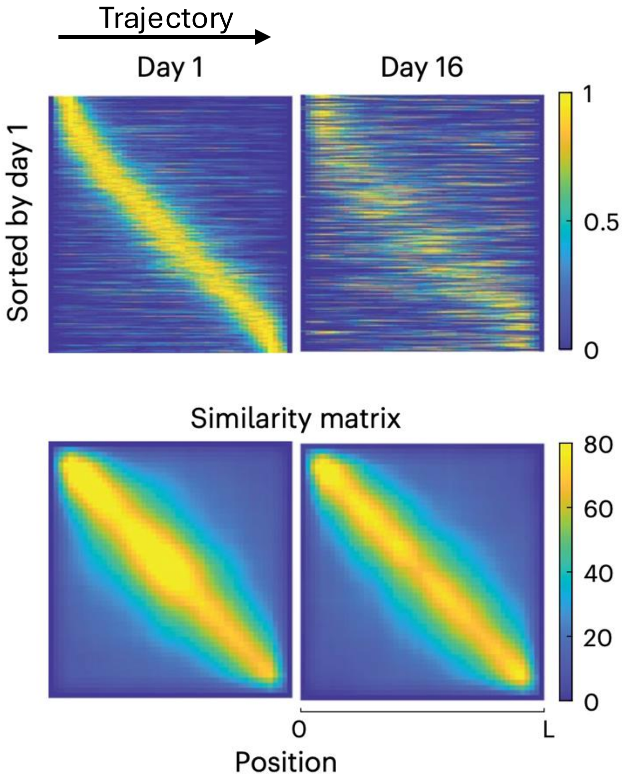






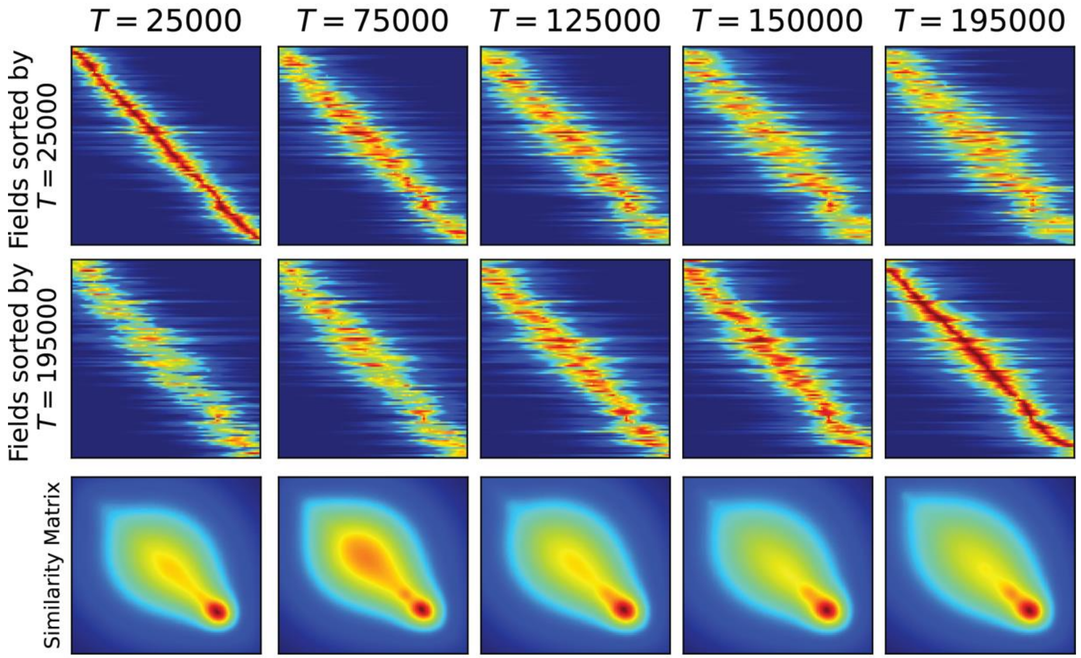
Noisy fields drift while stable navigation behavior

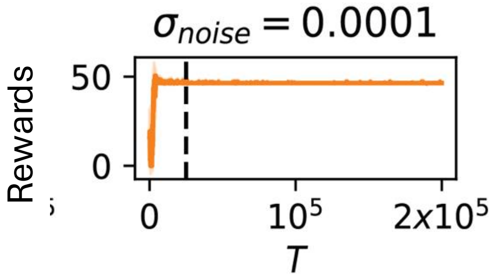
Experiment

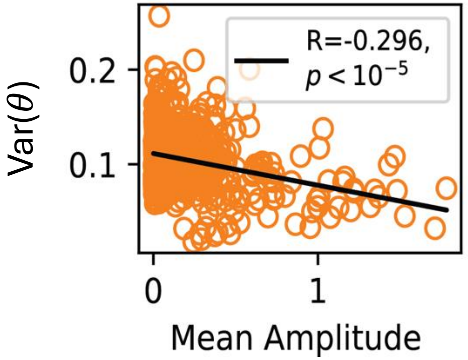


Qin et al. 2023 Nat. Neuro.

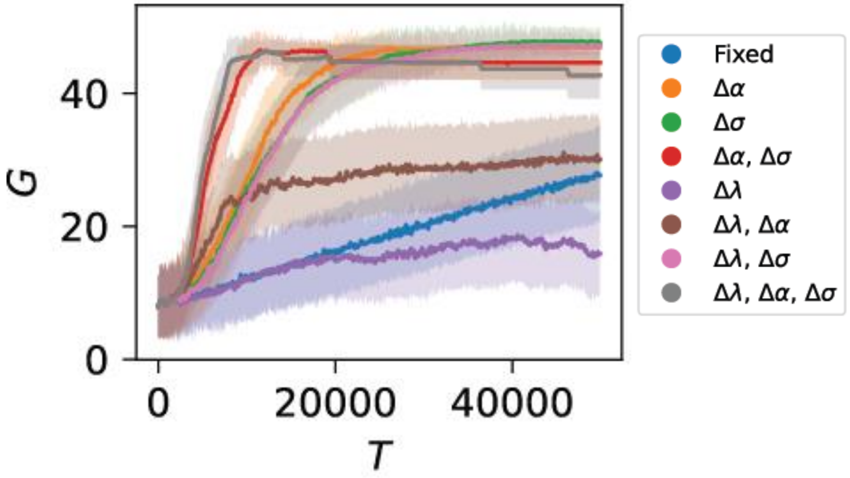
Model

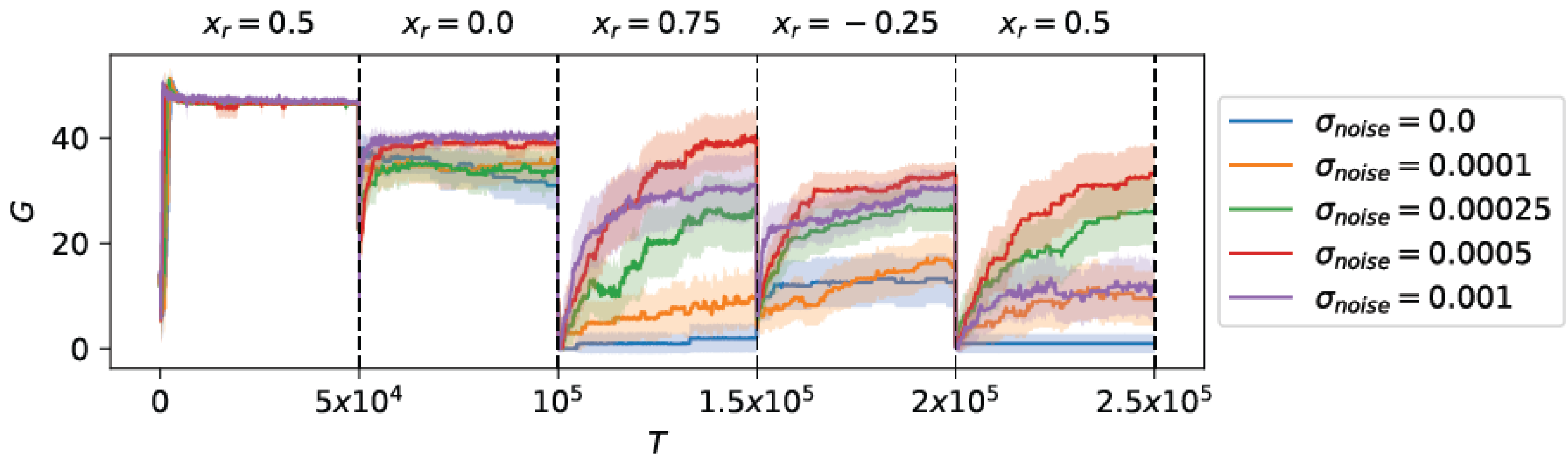






Place field representation learning improves policy convergence and flexibility





Parameter importance: $\sigma > \alpha > \lambda$

Conclusion

- Simple model is **biologically grounded** to neuroanatomy and computation.
- **Gaussian basis functions** trained using the reward prediction error to **maximize rewards**.
- Model recapitulates **three key** place field phenomena.
- Show place field reorganization **improves policy convergence** and **new target learning**.
- Model can be used to make **testable predictions** and **improve learning algorithms**.

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mganeshkumar@seas.harvard.edu M Ganesh Kumar mgkumar138