

Predicting Crowd Work Quality under Monetary Interventions

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School of Engineering
and Applied Sciences

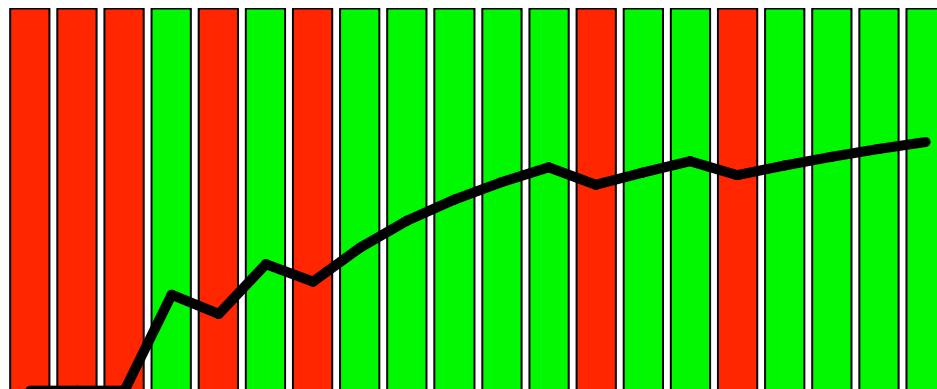
Modeling Worker Performance in Crowdsourcing



Correct in 50% of
the tasks!

Accuracy / Error Rate

(e.g. Whitehill et. al. 2009)

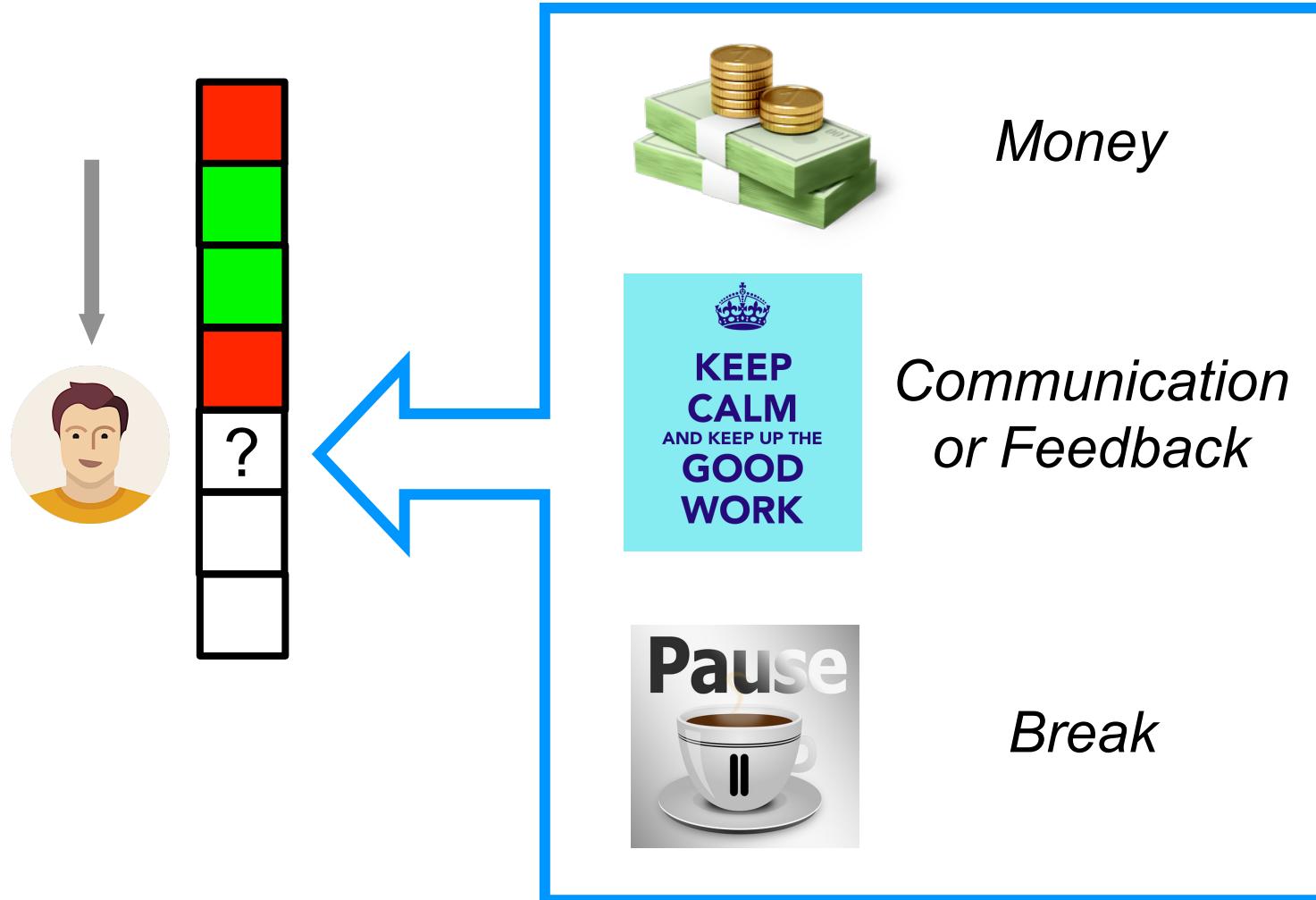


More and more
accurate over time!

Temporal Pattern

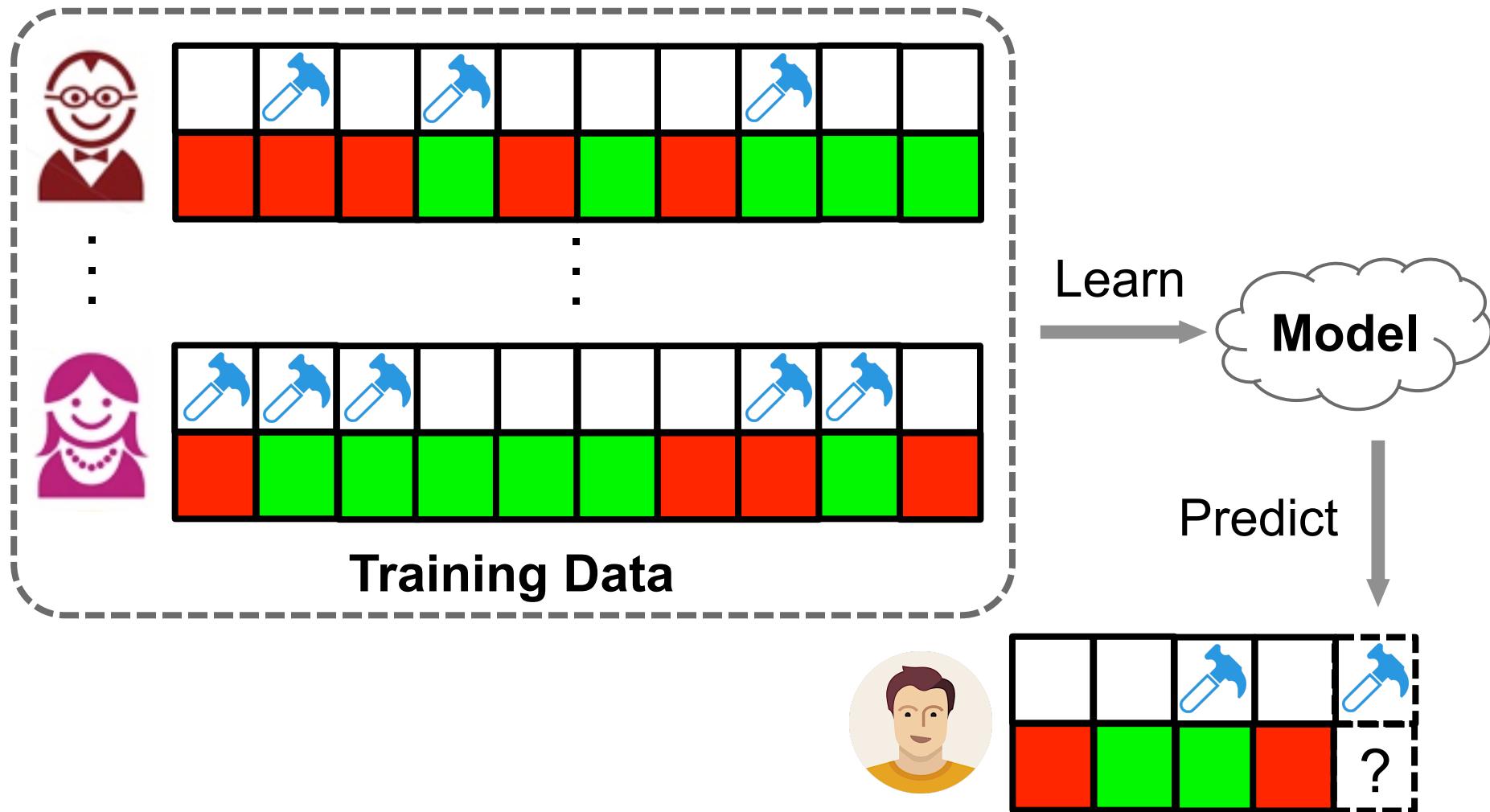
(e.g. Jung, Park & Lease. 2014)

Modeling Worker Performance under Interventions



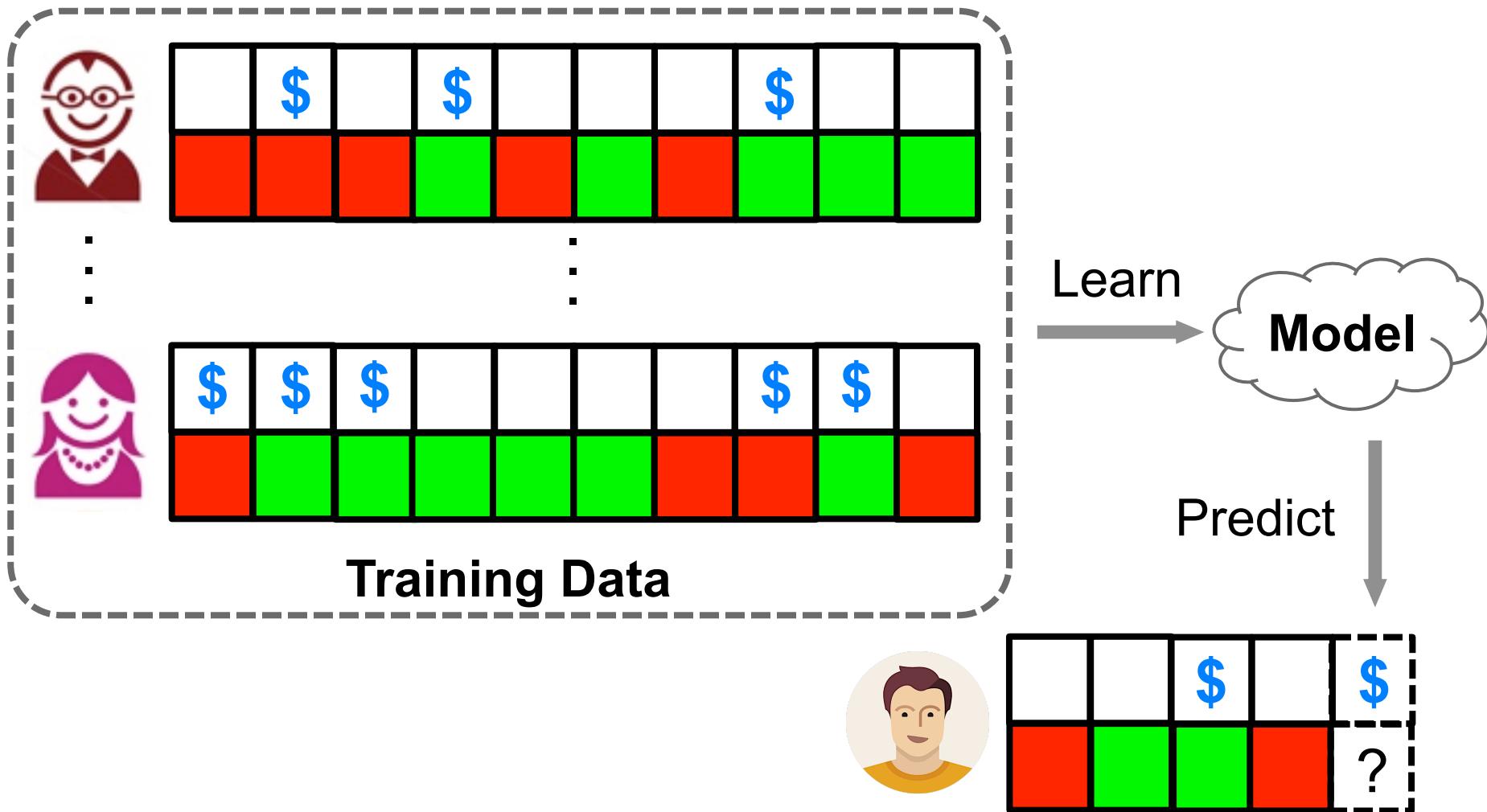
How to capture worker performance under interventions?

A Prediction Perspective



Categorical time series prediction ***with exogenous inputs!***

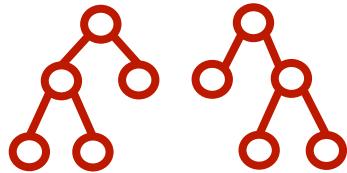
A Prediction Perspective



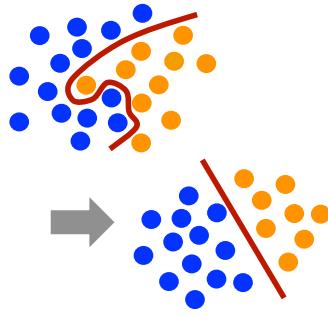
Focus on *monetary intervention* in this talk!

An Empirical Comparison

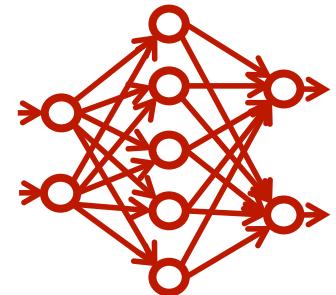
Supervised Learning Models



Random Forests



SVM



Neural Network

Autoregressive Models

$$y_i^t = I_t y_i^{t-D_t} + (1 - I_t) e_t$$

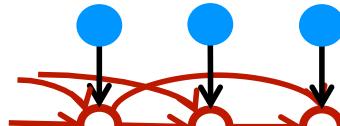
DARX

$$z_i^t = c + \sum_{j=1}^p \phi_j z_i^{t-j} + \sum_{j=0}^{q-1} \theta_j a_i^{t-j} + \epsilon_i^t$$

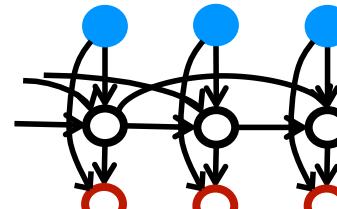
$$Pr(y_i^t = 1) = \frac{1}{1 + e^{-z_i^t}}$$

LARX

Markov Models

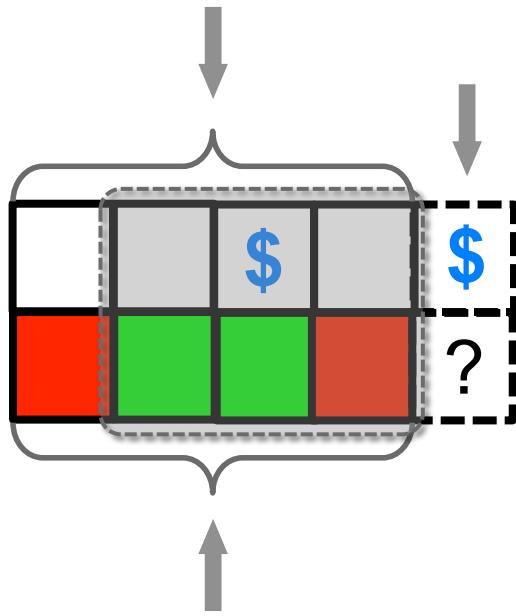


Controlled MC



IOHMM

Supervised Learning Models: Features



Current Intervention Level

Average Intervention Level

Average Performance

Within a history window of size L :

Historical Intervention Levels

Historical Performance

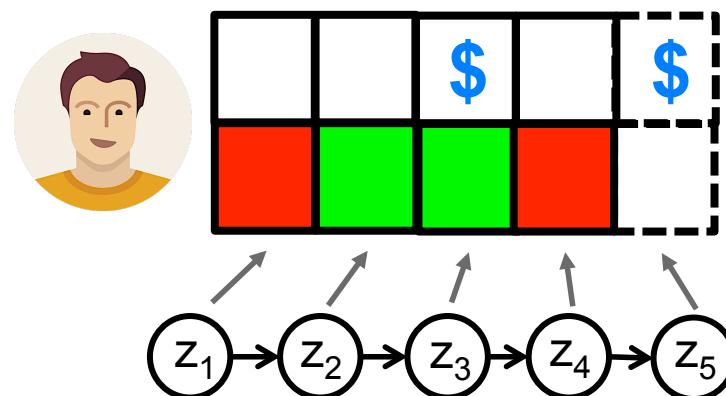
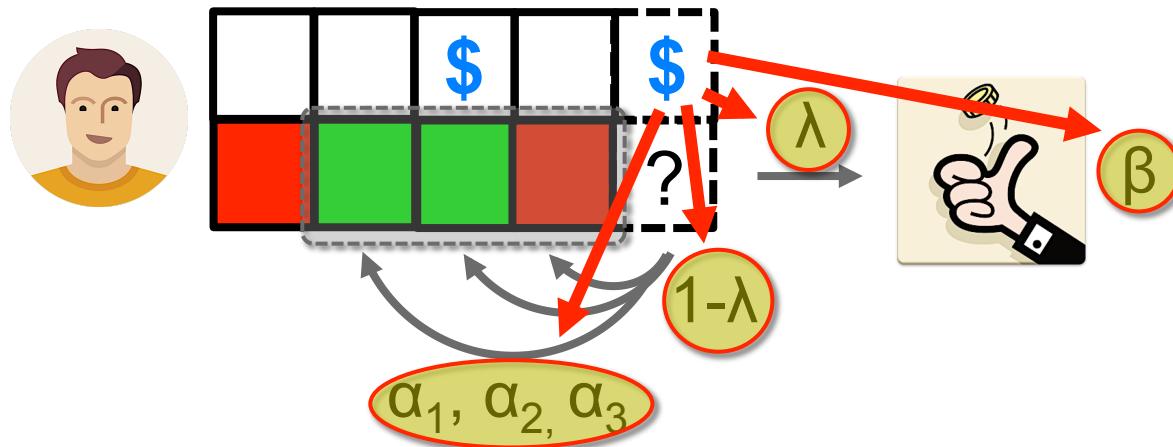
Historical Intervention Changes

Historical Performance Changes

Random Forests, SVM, Neural Network

Autoregressive Models: Incorporating Exogenous Inputs

DARX: Extended from DAR [Jacobs and Lewis 1983]

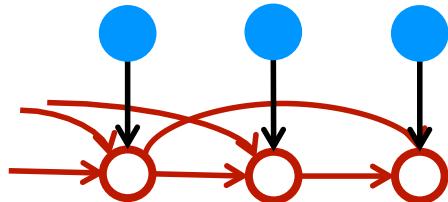


$$z_t = c + \phi z_{t-1} + \varepsilon_t + \theta a_t$$

LARX: Extended from LAR [Jung, Park and Lease 2014]

Markov Models: Application

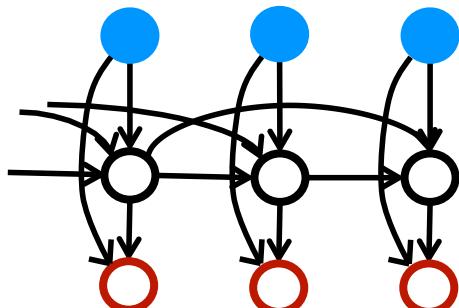
Controlled Markov Chain



Action: Intervention

State: Worker Performance

Input-Output Hidden Markov Model



Inputs: Intervention

Outputs: Worker Performance

Evaluation Datasets



Word Puzzle

300 workers

9 tasks in a session

37% bonus tasks

76.8% high-quality



Butterfly Classification

220 workers

10 tasks in a session

29% bonus tasks

55.5% high-quality



Proofreading

80 workers

10 tasks in a session

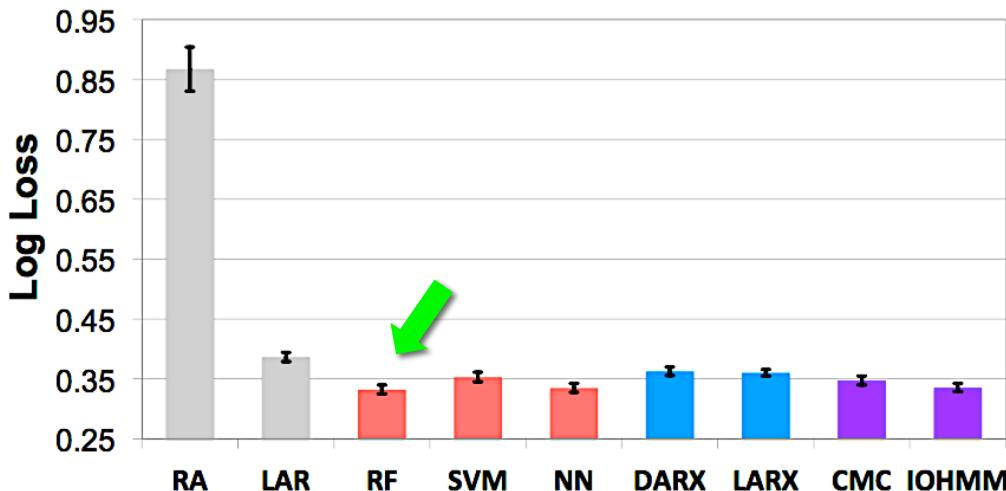
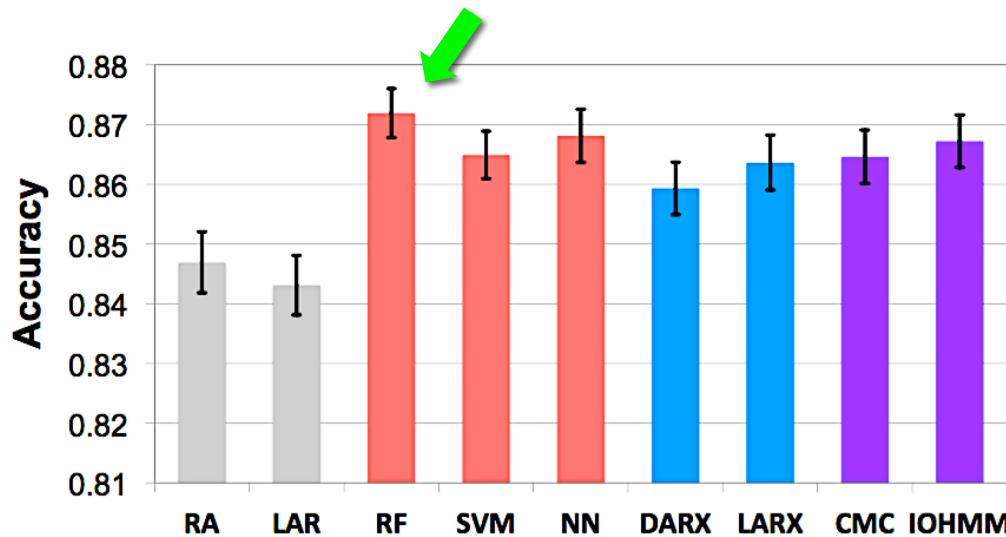
49% bonus tasks

63.4% high-quality

80% Training

20% Testing

Baselines: Running Accuracy, LAR



It is **necessary** to model the impact of monetary interventions on worker performance.

The **random forest** model outperform other prediction models!
(Best model for 7 out of 9 comparisons!)

Predictive features:
average performance;
average intervention level.

More Realistic Scenarios



	\$		\$				\$		
	Red	Red	Red	Green	Red	Red	Green	Green	Green

:



\$	\$	\$					\$	\$	
Red	Green	Green	Green	Green	Red	Red	Green	Red	Red

:

Training Data

Learn

Model

Predict



vs.

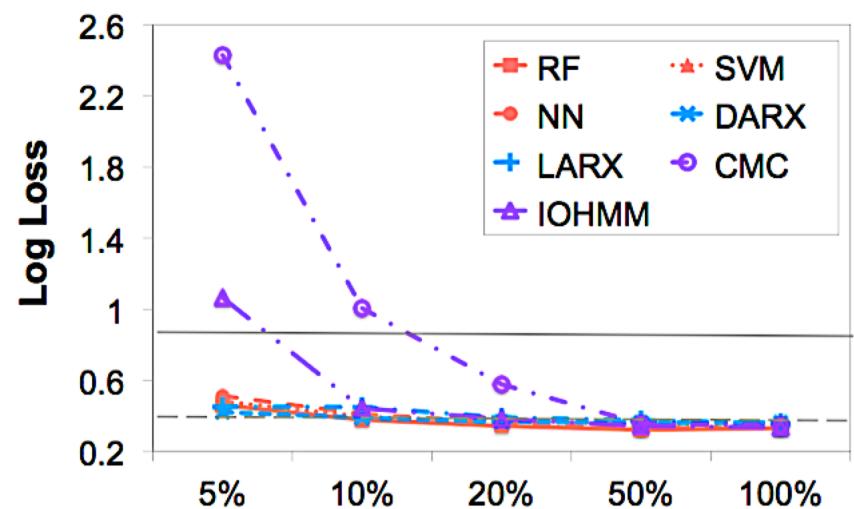
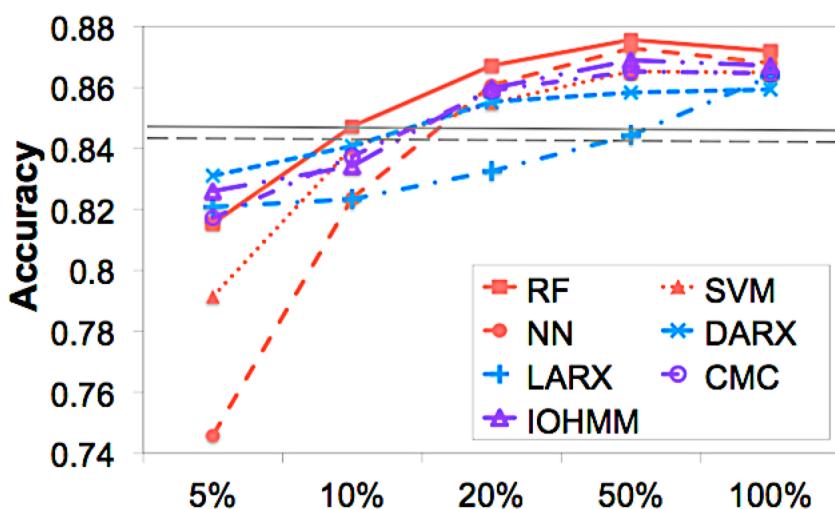


Limited
Training Data



		\$		\$
Red	n/a	Green	n/a	?

Limited Ground Truth



The random forest model is *relatively robust against limited training data*.

80% Training

20% Testing

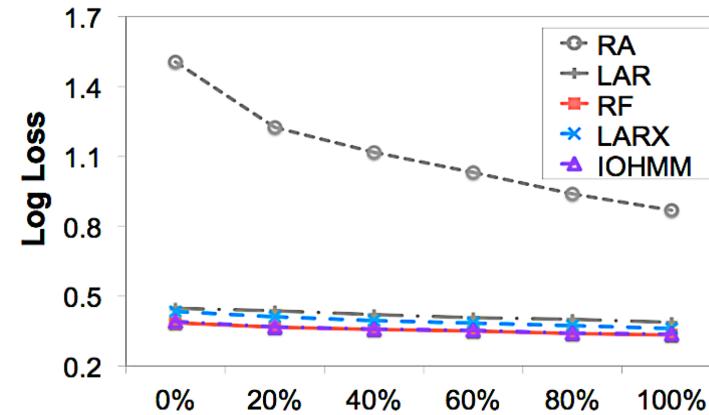
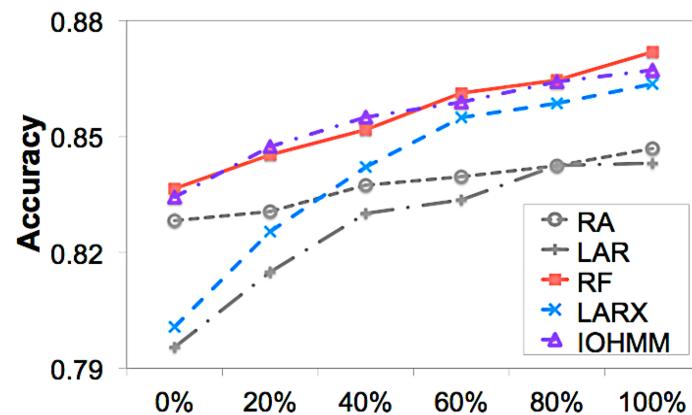
0% Verification

			\$		\$					\$	
				n/a	?						

20% Verification

			\$		\$					\$	
				n/a	n/a	n/a	n/a	green	n/a	n/a	?

40%, 60%, 80%...



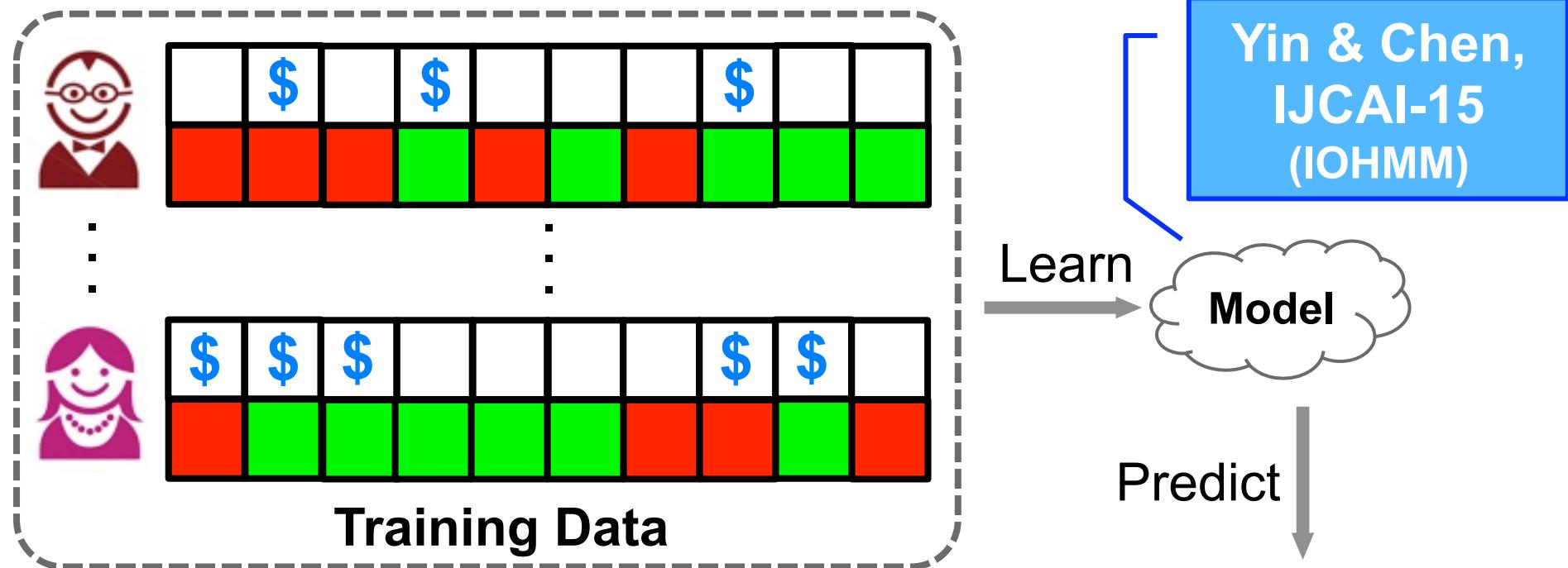
The random forest model (and the IOHMM model) is **relatively robust against limited access to ground truth**.

Summary

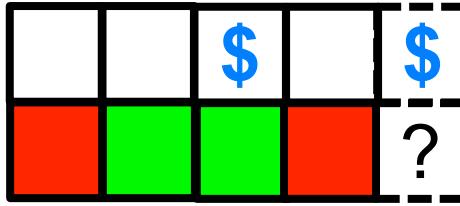
The *random forest model* can be a good model to use in practice to predict crowd work quality under monetary interventions, because of its:

- Accurate predictions with high confidence across different types of tasks
- Robustness against limited training data
- Robustness against limited ground truth

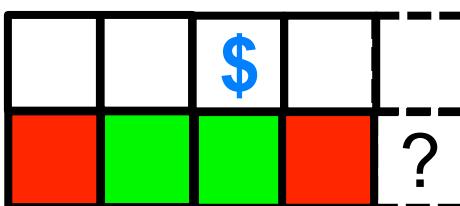
Future Directions



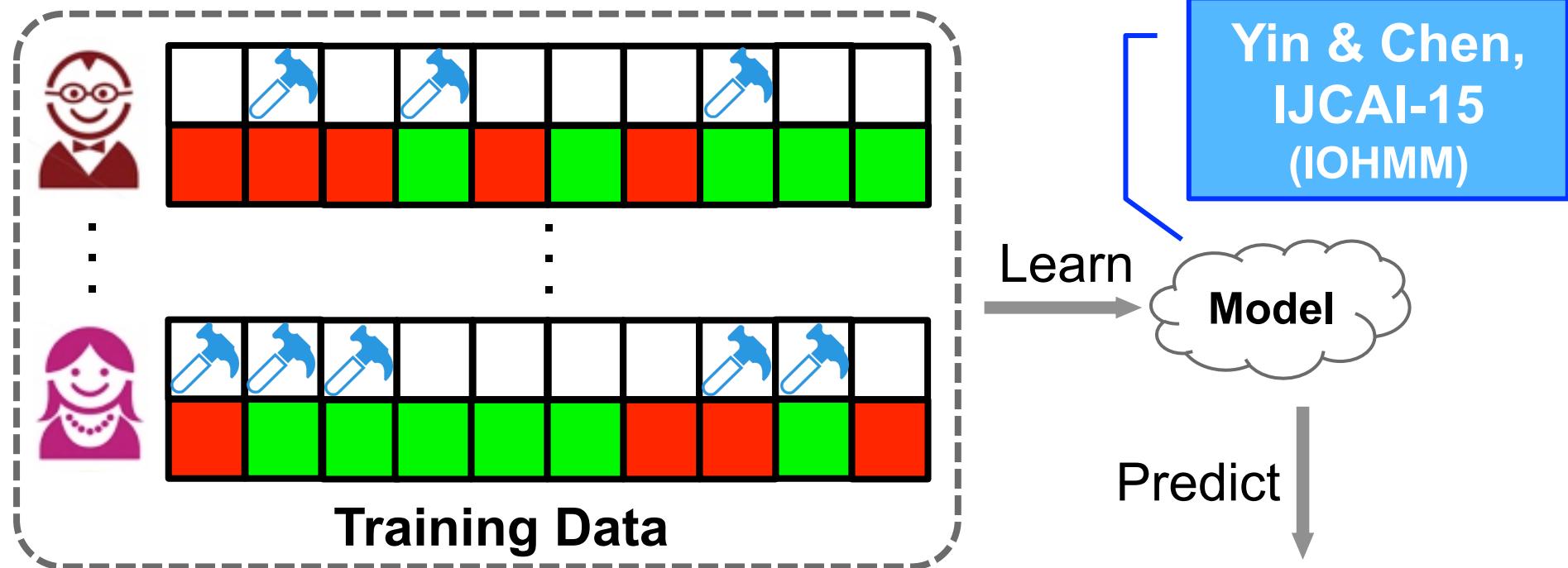
Dynamic Placement of Monetary Intervention



Maximize Utility



Future Directions



Dynamic Placement of Monetary Intervention

Performance Modeling under Other Interventions

Thank you!