Building Interactive Systems Learning & Prediction **Professor Bilge Mutlu | Spring 2023**



What we will cover today

- \rightarrow Interactive systems that learn
- \rightarrow Reading group discussion
- \rightarrow HACK 3 heads up
- → INTEGRATE Milestone 1 preview

Definitions¹²

Learning: A learning algorithm is a software system that improves its performance in some task domain based on partial experience with that domain.

Adaptive Systems: An adaptive user interface is an interactive software system that improves its ability to interact with a user based on partial experience with that user.

Intelligent User Interfaces: Intelligent user interfaces (IUI) are driven by the goal of improvement in human–computer interaction (HCI), mainly improving user interfaces' user experience (UX) or usability with the help of artificial intelligence.

¹Langley (2005). <u>Machine learning for adaptive user interfaces</u>. *In Proceedings KI-97*.

² Brdnik et al. (2022). Intelligent user interfaces and their evaluation: A systematic mapping study. Sensors.

Scope & Assumptions

- For this lecture, we will adopt the IUI term for systems that learn, predict, and \rightarrow adapt.
- Looking at learning and AI from the perspective of interactive systems. \rightarrow
- Very large, sparse area we will take an empirical approach to mapping it. \rightarrow

Basic Learning Terminology

- → **Timeframe:** Learned and/or learning systems¹
- → **Approaches:** Supervised, unsupervised, semi-supervised, reinforcement learning³
- → **Model tasks:** Classification, clustering, regression/estimation
- → **Priors:** Model-based vs. model-free learning (e.g., RL) or decision-making⁴
- → **Data sources:** Sparse, multimodal, high-cost

¹Langley (2005). <u>Machine learning for adaptive user interfaces</u>. *In Proceedings KI-97*.

³ <u>SuperVize Me</u>

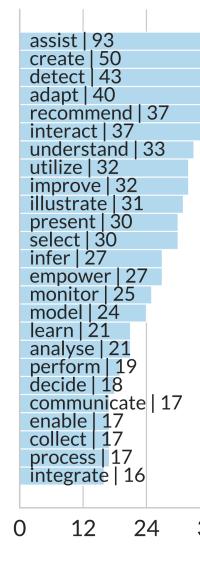
⁴ Lockwood et al. (2020). <u>Model-free decision making is prioritized when learning to avoid harming others.</u> PNAS.

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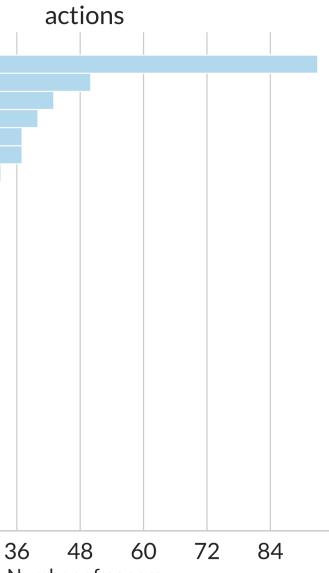
einforcement learning³ on cision-making⁴

What Do IUIs Do?

Meta-analysis of 25 years of IUI research⁵



⁵ Völkel et al. (2020). <u>What is" intelligent" in intelligent user interfaces? a meta-analysis of 25 years of IUI.</u> In *IUI 2020*.



Number of papers

We will focus on the top six (but only cover those marked with " \leftarrow " today):

- Assist aid users in tasks (e.g., increasing task efficiency) « \rightarrow
- **Create** generate content (e.g., generating summaries) \rightarrow
- **Detect** capturing specific information (e.g., detecting emotions) **~** \rightarrow
- **Adapt** matching user characteristics (e.g., generating assistive interfaces) \rightarrow
- **Recommend** filtering information for users (e.g., book recommendations) \rightarrow
- **Interact** enabling interaction with the user (e.g., natural language) \rightarrow

For each category, we will discuss:

Context/task, learning approach, learning input, learning timeframe \rightarrow

Interactive Systems that Assist

Also called **generative interfaces**, which focus on the generation of some useful knowledge structure.¹

Systems that augment human capabilities to perform tasks that might be took complex, too tedious, and/or generally undesirable.

¹Langley (2005). <u>Machine learning for adaptive user interfaces</u>. *In Proceedings KI-97*.

Example Assistive System

Excel Flash Fill⁶

Task: Data cleanup

Learning approach: Interactive ML; Learning from demonstration

Learning input: User examples

Learning timeframe: Interactive, during task

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2	Thomas, Rhonda 8213
3	Emmett, Keara 34231
4	Vogel, James 32493
5	Jelen, Bill 23911
6	Miller, Sylvia 78356
7	Lambert, Bobby 2590
8	Sweet, Julie 65477
9	Williams, Don 43920
10	Spake, Deborah 3348

⁶ Image

	В	С
	First name and last name	ID #
32	Rhonda Thomas	
	Keara Emmett	
	James Vogel	
	Bill Jelen	
	Sylvia Miller	
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	Julie Sweet	
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8	Deborah Spake	

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⁷ YouTube



Detour: Learning Approach

- Learning from Demonstration; Imitation Learning; Apprenticeship Learning; \rightarrow Interactive Machine Learning; One-shot Learning
- **Low-level learning:** trajectory-based learning, supervised, reinforcement learning, \rightarrow policy search
- **High-level learning:** inverse reinforcement learning, graph learning, skill learning \rightarrow
- Active learning: policy learning, interactive learning, dialogue-based methods \rightarrow

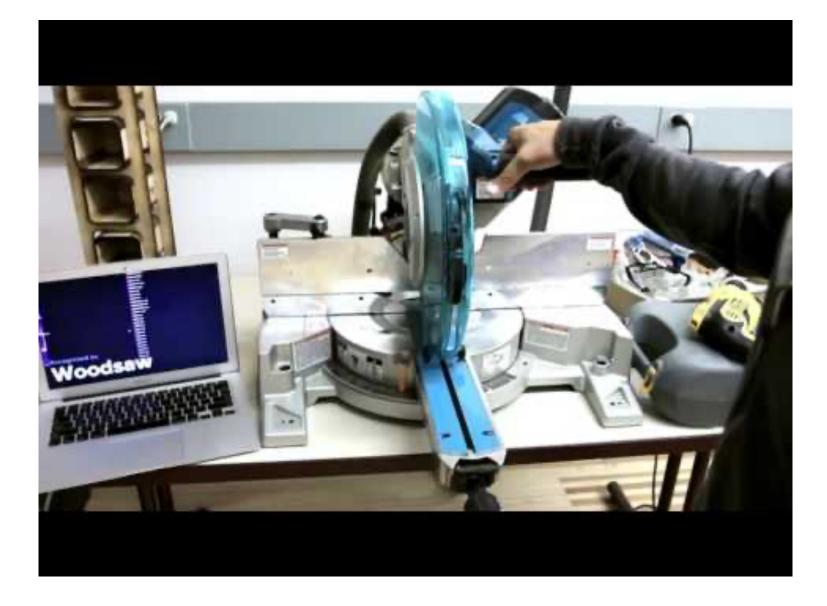
Interactive Systems that Detect

Systems that can detect users, their presence and activities, and distinguish among \rightarrow users and activities using "learned" models from prior data on the users and their activities.

Example Detecting System

Synthetic sensors^{8 9 10}

Task: Detecting and differentiating between user activities



⁸ Laput et al. (2017). <u>Synthetic Sensors: Towards General-Purpose Sensing</u>. In *CHI 2017*. ⁹ <u>Images</u>

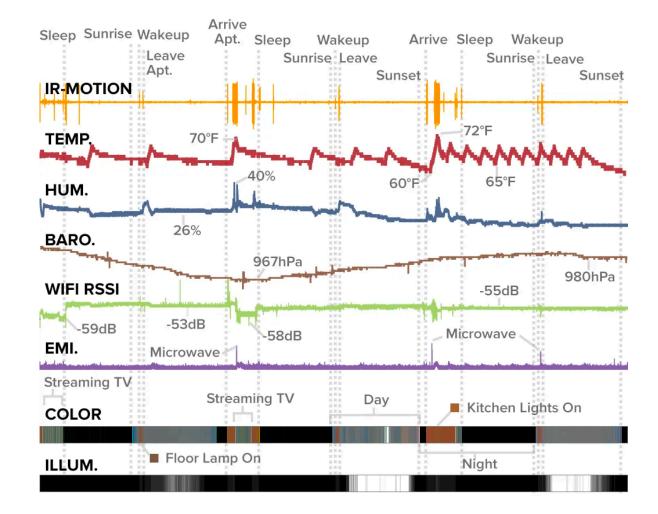
¹⁰ YouTube

Synthetic sensors^{8 9 10}

Learning approach: Batch learning using support vector machines (SVM)

Learning input: Sensor suite data (e.g, motion, temperature, humidity, barometric pressure, WiFi received signal strength indicator (RSSI), electromagnetic interference, color, illumination)

Learning timeframe: Offline, users interact with a "learned" system



⁸ Laput et al. (2017). <u>Synthetic Sensors: Towards General-Purpose Sensing</u>. In CHI 2017.

⁹Images

¹⁰ YouTube

Interactive Systems that Recommend

Also called **informative interfaces**, which attempt to select or filter information for \rightarrow the user, presenting only those items he will find interesting or useful.¹

¹Langley (2005). <u>Machine learning for adaptive user interfaces.</u> In Proceedings KI-97.

Example Recommender System

Amazon Book Recommendation¹¹

Task: Filtering through 33M books.



Customers who bought this item also bought



Hardcover

CDN\$ 49.90

CDN\$ 85.09 vprime

Ian Goodfellow ***** Hardcover CDN\$ 92.40 vprime

¹¹ Images: <u>Top</u>, <u>Bottom</u>

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R for Data Science: Import, Tidy, Transform, Visualize, and Model Data Hadley Wickham ***** Paperback CDN\$ 41.48 vprime



ggplot2: Elegant Graphics for Data Analysis Hadley Wickham ******1** Paperback CDN\$ 55.65 **√prime**



Python Machine Learning Sebastian Raschka Paperback CDN\$ 47.97 vprime



R for Everyone: Advanced Analytics and Graphics Jared P. Lander Paperback CDN\$ 38.43 vprime

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Amazon Book Recommendation¹²

Task: Filtering through 33M books.

Learning approach: Collaborative-filtering — e.g., user-based KNNs, graph-based association rules, matrix factorization (stochastic gradient descent, alternating least squares), deep NN⁶

Learning input: Set of users, set of items, recommendations

Learning timeframe: Offline, constantly updated, users interact with a "learned" system

¹² <u>Machine Learning for Recommender systems</u>

⁶ Image

Interactive Systems that Interact

Systems that use AI methods to enable more effective or novel ways of interacting \rightarrow with users, e.g., through a better understanding of user activities, input, intent.

Example Interactive System

Anticipatory robot control¹³

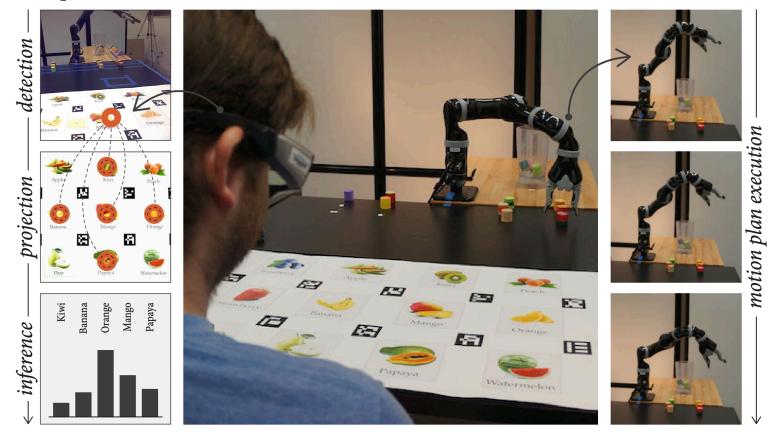
Task: Predicting user intent

Learning approach: Batch learning, SVM

Learning input: Features of the user's gaze

Learning timeframe: A learned system

Intent prediction



¹³ Huang & Mutlu (2016). <u>Anticipatory robot control for efficient human-robot collaboration</u>. In *HRI 2016*.

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Anticipatory action

Reading Groups



- **Huang et al.:** Surprising that people can respond negatively to predictive systems. 1.
- **Horvitz et al.:** Success depends on task complexity. 2.
- **Yang et al.:** Transparency is difficult. Different problems require different amounts 3. of data.
- Meta learning to determine suitability for the use of learning-based system. 4.
- Clean design vs. intelligibility. How much to expose the learning to the user? 5.
- Is there a way to bring the tradeoff into marketing? Medical systems expose the 6. confidence of the model.
- Communicating confidence can help build user trust. 7.

HACK 3 Heads Up

- \rightarrow HACK 3 will be released on Wednesday
- \rightarrow HACK 3 \rightarrow HACK3+ (an *intelligent* version)
- \rightarrow Same teams, same resources
- \rightarrow Due in 2.5 weeks

INTEGRATE Milestone 1 Preview

- Four steps: \rightarrow
 - Literature survey \rightarrow map of the state of the art + opportunities 1.
 - Brainstorming \rightarrow ideas capitalizing on the opportunities 2.
 - Critique \rightarrow narrowing down to good ideas 3.
 - Idea refinement & articulation \rightarrow communicating top-3 ideas 4.
- Due Friday \rightarrow
- **Wednesday**: present where you are (5-10 minute presentation) \rightarrow