An overview of Interactive Machine Learning

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HCID - IML Lecture 3 — 13/01/2020

How do we interact with computers?

Computer as tool

=> *Empower users*

Human-Computer Interaction

Computer as servant

=> *Delegate tasks*

Artificial Intelligence

Computer as medium

=> *Communicate*

Mediated Communication

Human interaction with Machine Learning

ML & Human(s)

There is no ML or AI without massive human input!

A.I. Is Learning From Humans. Many Humans.

Artificial intelligence is being taught by thousands of office workers around the world. It is not exactly futuristic work.

ML & Human(s)

There is no ML or AI without massive human input!

Who is helping who?

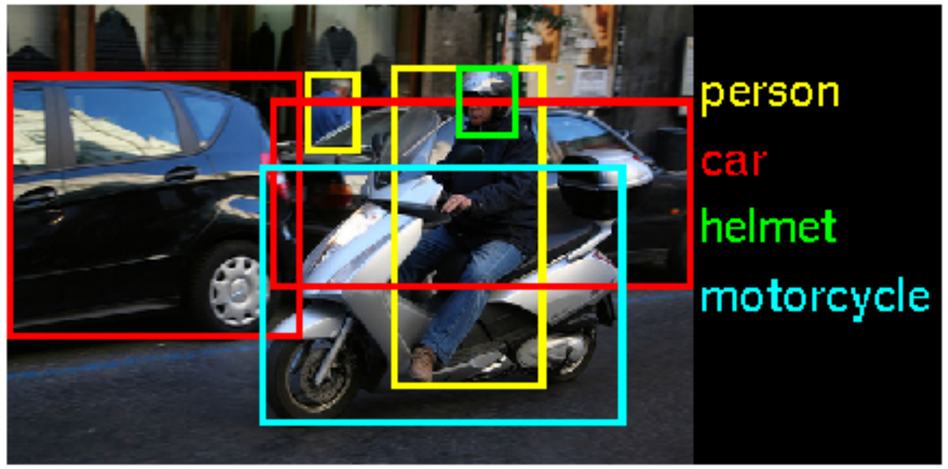
- **Machine helping the human**
  - Amplifying human abilities
- **Humans helping the machine**
  - Providing labels, preferences and guidance
- **Partnership?**

Crowd for Supervised Learning

Human Computation: On-demand and scalable access to human intelligence for tasks that computers cannot yet do alone.

=> user crowds to annotate (label) massive dataset

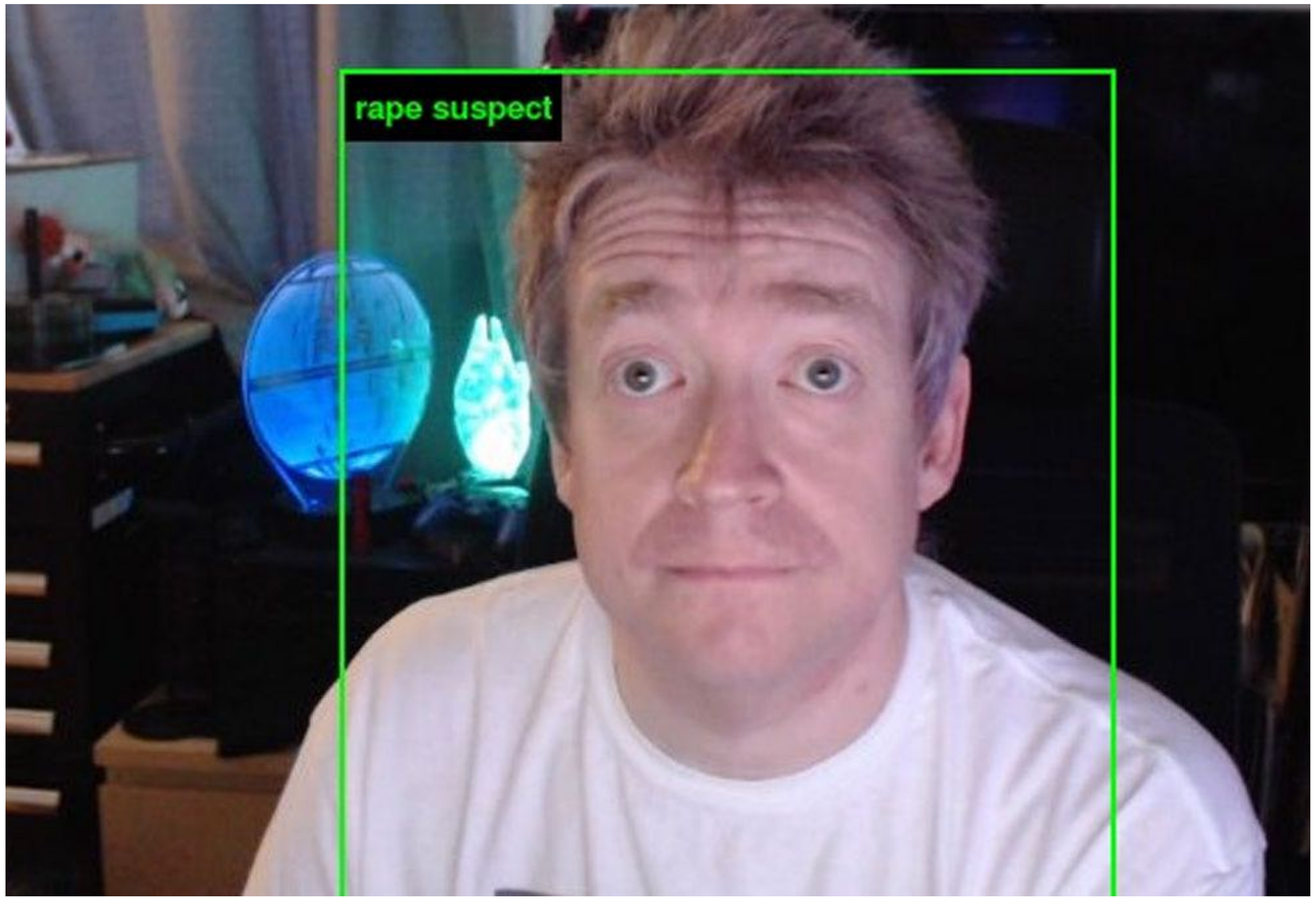
Example: ***ImageNet***

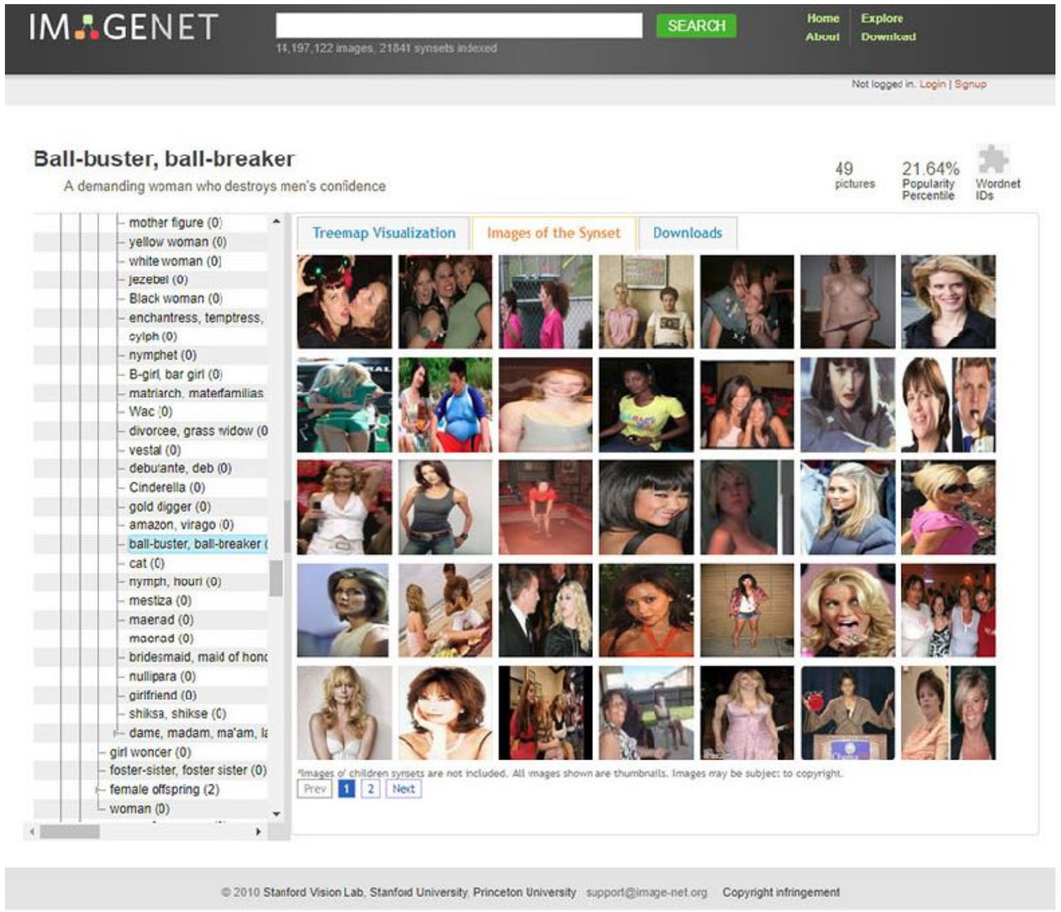


- Large visual database for vision research
- Constructed with crowdsourcing
- Total number of images: 14,197,122
- Number of images with bounding box annotations: 1,034,908

Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009, June). Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition (pp. 248-255). IEEE.

Crowd for Supervised Learning





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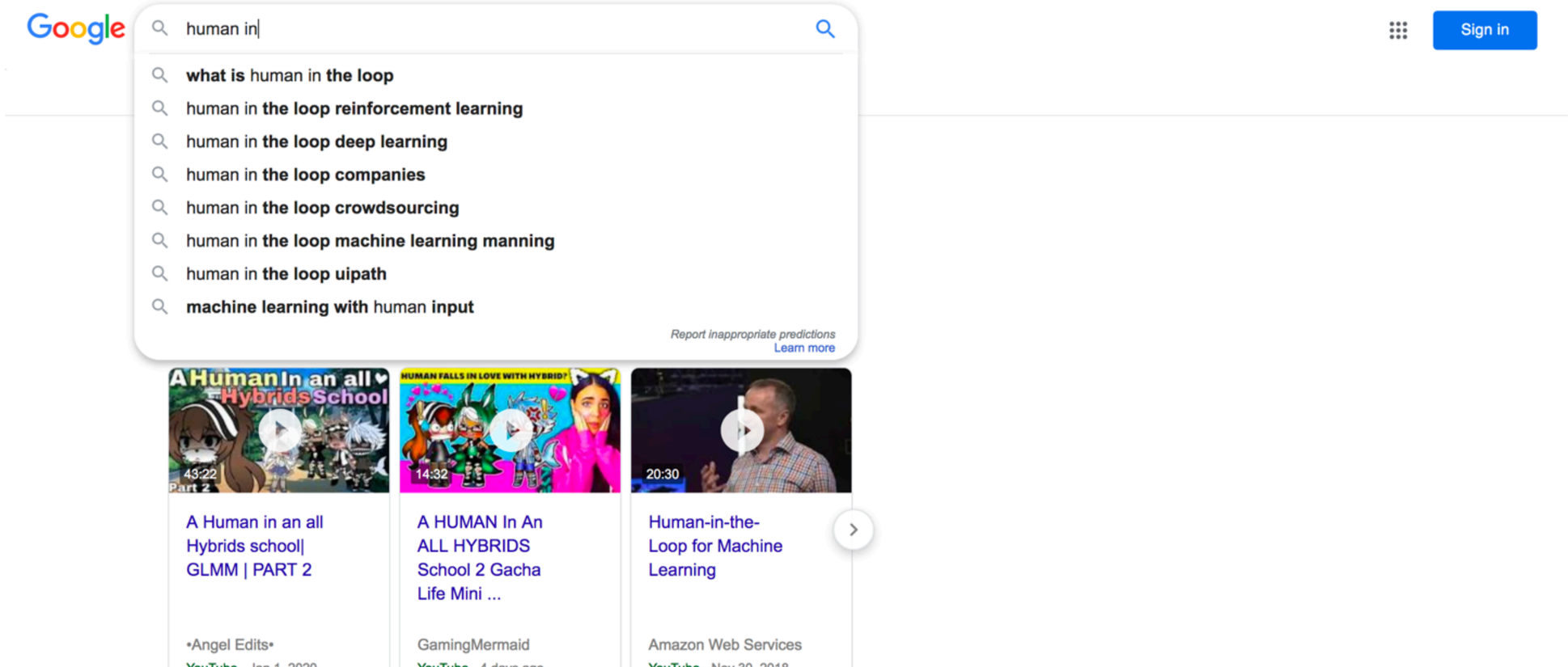
Human-in-the-loop ML & AI

Human-in-the-Loop:

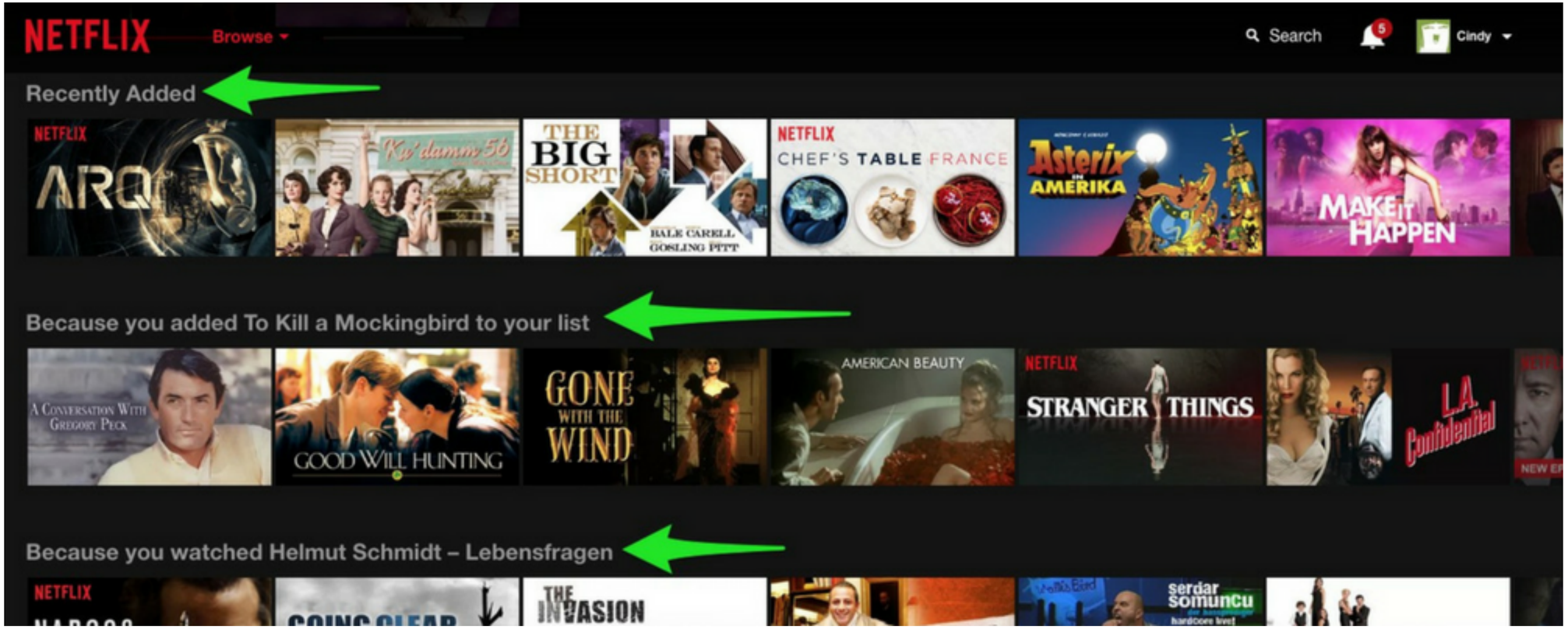
Use human input to *improve the algorithm*



Human-in-the-loop ML & AI

Recommender systems:

Combine human input to *personalise predictions*



Human-in-the-loop ML & AI

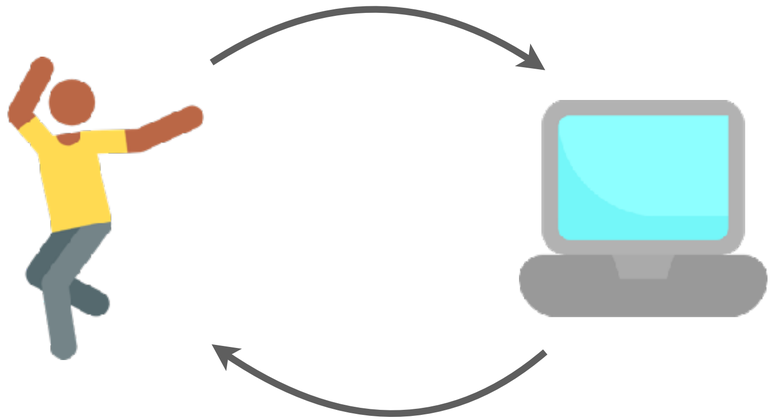
Robot Learning from demonstrations:

Use human input to *teach new skills*

Interactions with ML algorithms

Human as a labeller

Human as an information processor



Human as a designer

Human as an explorer

From Ashish Kapoor @ Microsoft Research

Interactive Machine Learning

What IML is not

- Considering that people are useful for ML
    - Using people to label large datasets
    - Exploiting user's choices/preferences to improve an algorithm (blindly)
- Using machine learning as a tool in an interactive system
    - Using a computer vision algorithm to track a person's skeleton
    - Integrating speech recognition

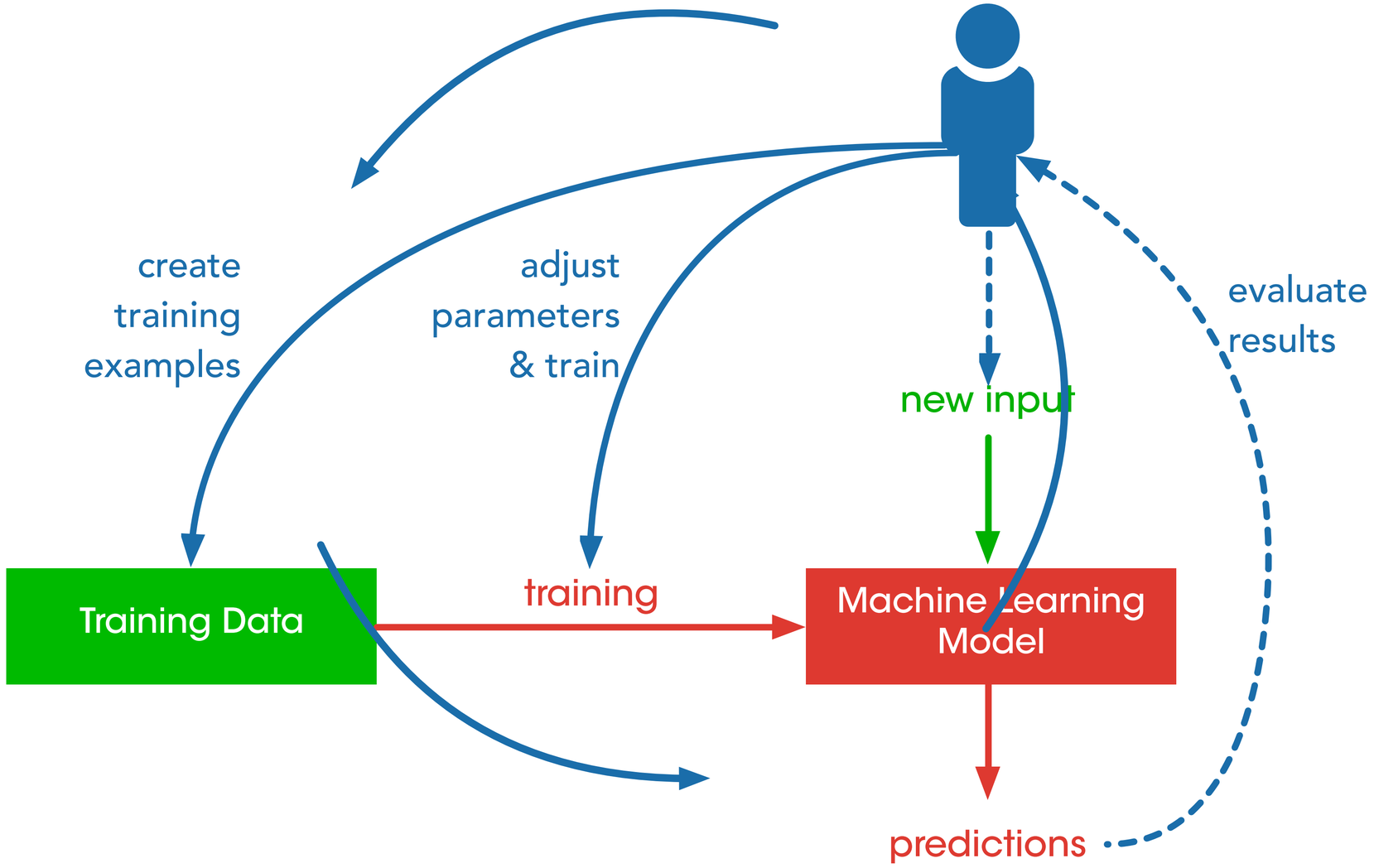
Interactive Machine Learning

End-user Interaction with the Machine Learning process

« Interactive Machine Learning is an interaction paradigm in which a user or user group iteratively builds and refines a mathematical model to describe a concept through iterative cycles of input and review »

Dudley, J. J., & Kristensson, P. O. (2018). A review of user interface design for interactive machine learning. ACM Transactions on Interactive Intelligent Systems (TiiS), 8(2), 8.

Interactive Machine Learning



Traditional ML workflow

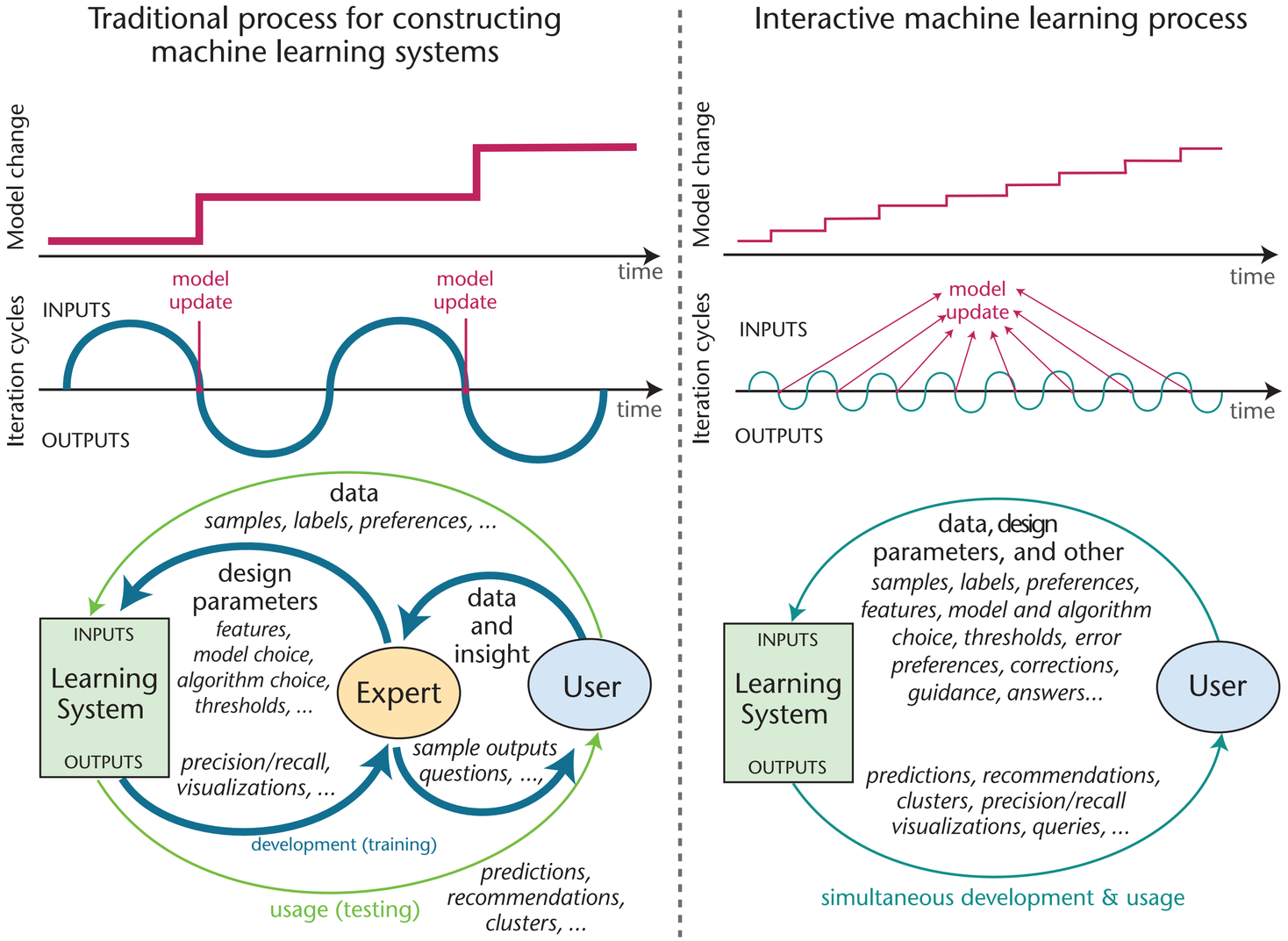
Practitioners:

1. Collect data
2. Select features to represent the data
3. Preprocess and transform the data
4. Choose a representation and learning algorithm to construct the model
5. Tune parameters of the algorithm
6. Assess the quality of the resulting model.

End-users: limited to providing data, answering domain-related questions, or giving feedback about the learned model.

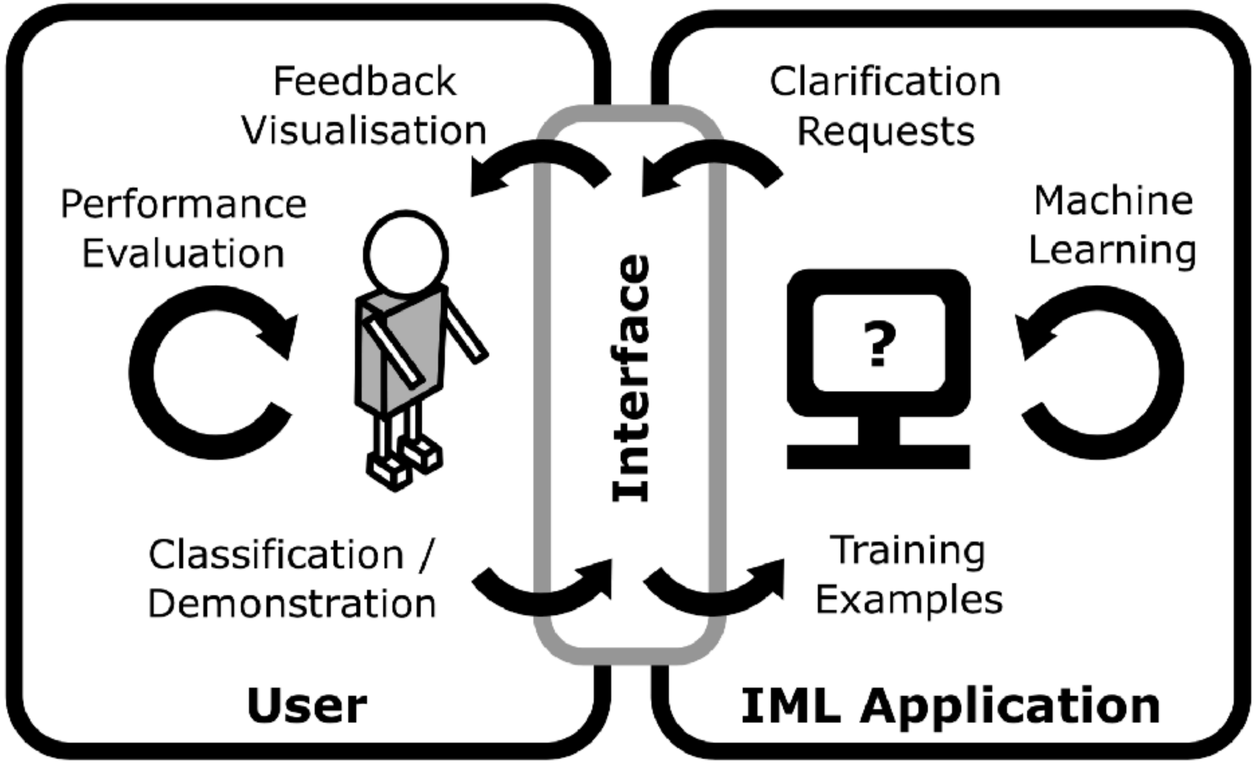
Amershi, S., Cakmak, M., Knox, W. B., & Kulesza, T. (2014). Power to the People: The Role of Humans in Interactive Machine Learning. AI Magazine, 35(4), 105-120.

Traditional v. IML workflows



[Amershi et al. 2014]

Overview of an IML System



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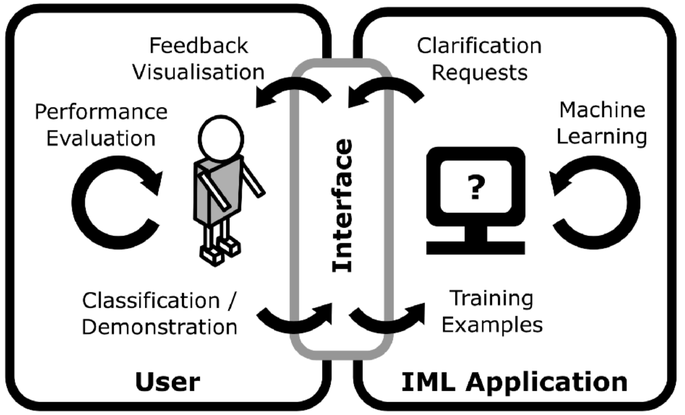

User:

- Main driver of the interaction
- Usually, not a ML expert
- Potentially unreliable (concept drift, variability, …)

Model:

- The component that makes predictions from input
- Can be parametrised and retrained
- Need to be appropriate for IML (fast training, few examples, …)

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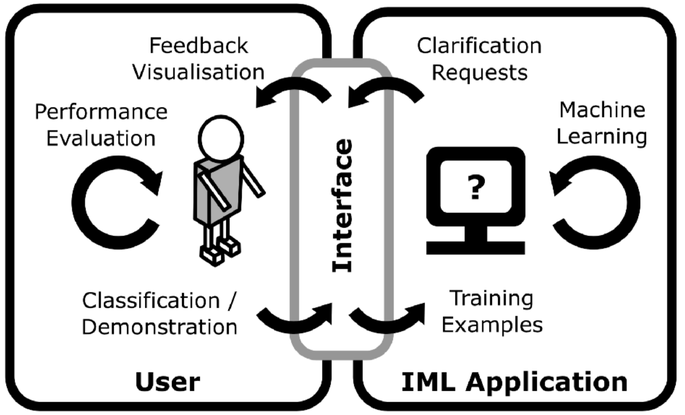


Data:

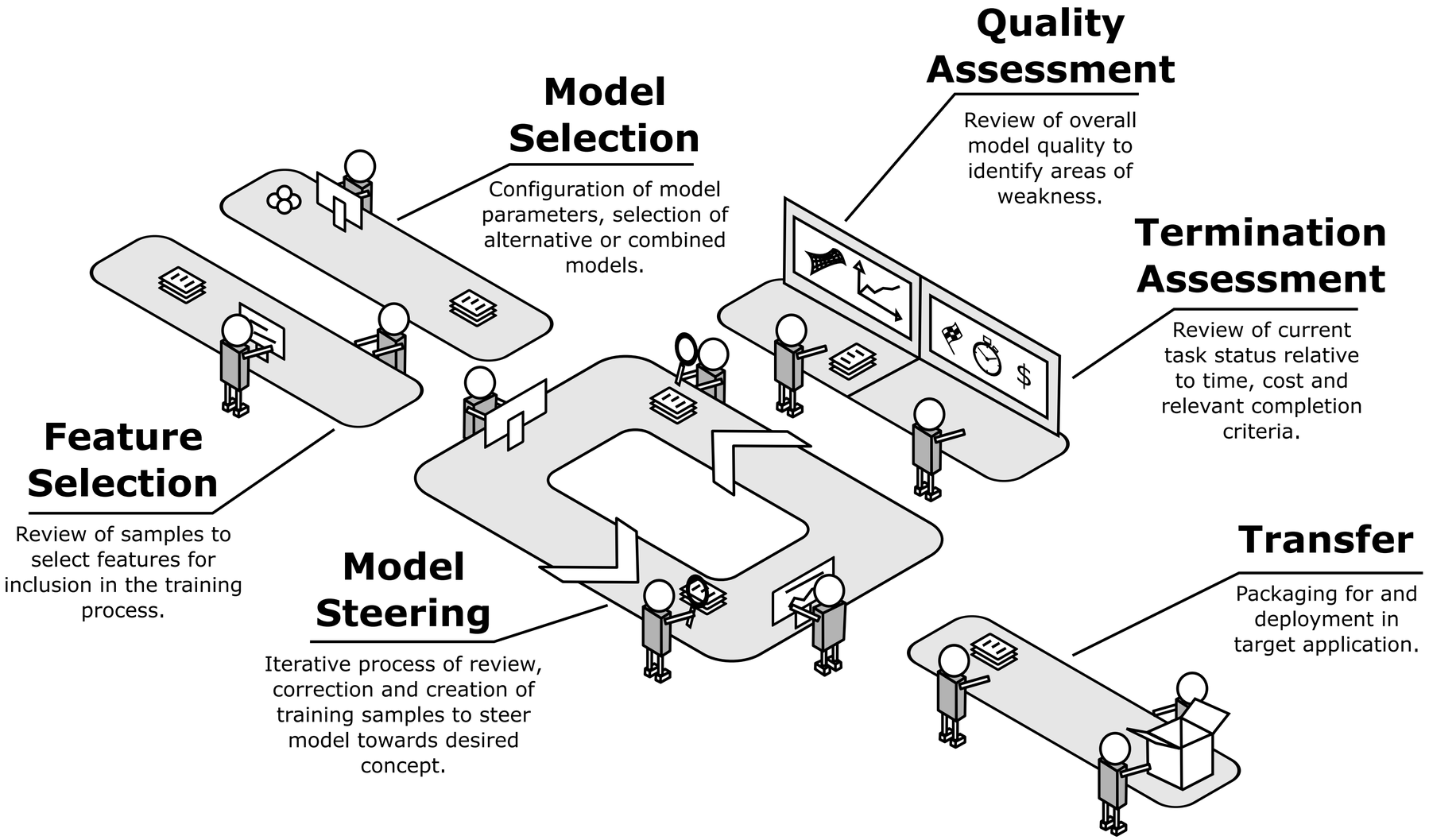
- Provided and labeled by the user
- Should describe the system's desired behavior (with annotations)
- Variable across applications

Interface:

- bidirectional feedback between the user and the model/data.
- Support input+output
- Critical for user's understanding and expressivity

Dudley, J. J., & Kristensson, P. O. (2018). A review of user interface design for interactive machine learning. ACM Transactions on Interactive Intelligent Systems (TiiS), 8(2), 8.

IML Workflow

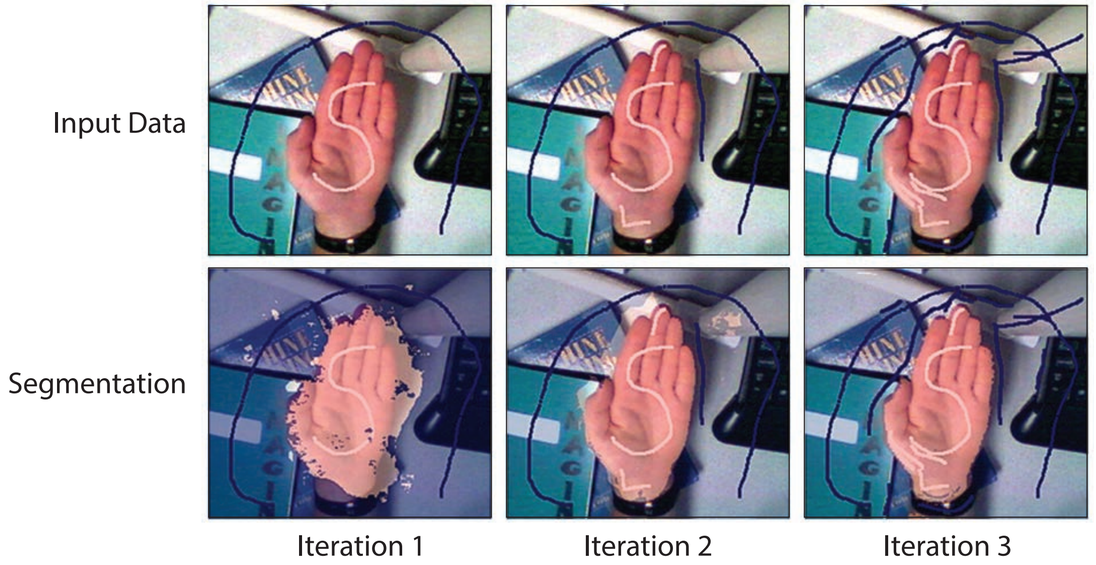


Dudley, J. J., & Kristensson, P. O. (2018). A review of user interface design for interactive machine learning. ACM Transactions on Interactive Intelligent Systems (TiiS), 8(2), 8.

Examples

Crayons

- **Task:** image segmentation
- Goal: identify foreground/background in images
- Users can draw to mark specify if pixels are foreground or background



=> Users can easily identify classification errors and provide more annotations to improve the classifier

Fails, J. A., & Olsen Jr, D. R. (2003, January). Interactive machine learning. In Proceedings of the 8th international conference on Intelligent user interfaces (pp. 39-45). ACM.

Wekinator

- **Task:** Music performance
- Goal: create novel gesture-based instruments
- Regression to learn movement-sound mapping

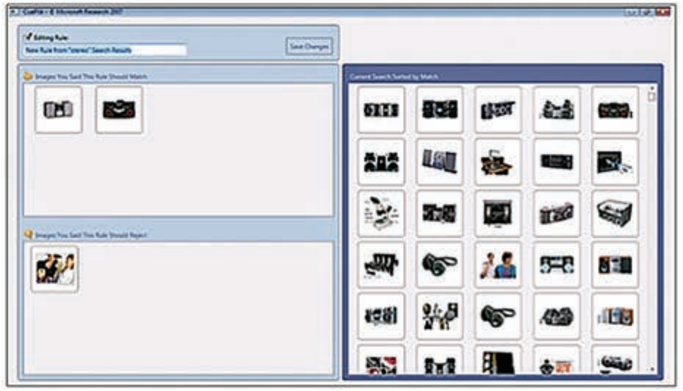
http://www.wekinator.org/example-projects/

=> Users learn how to give examples and update their expectations along the process

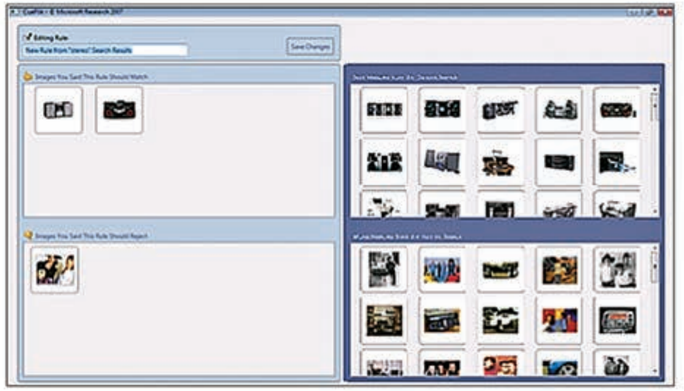
Fiebrink, R., Cook, P. R., & Trueman, D. (2011, May). Human model evaluation in interactive supervised learning. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 147-156). ACM.

CueFlik

- **Task:** image classification
- Goal: assess model quality
- Show best and worst matching examples for a class



Standard presentation using
a ranked list of examples



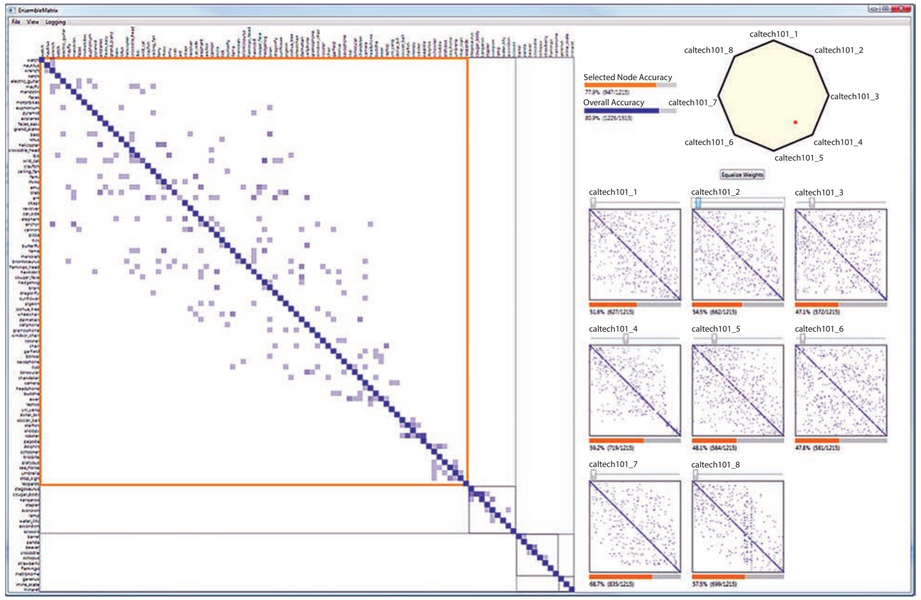
Best and worst matching
examples presentation

=> Improved presentation leads to better models

Fogarty, J., Tan, D., Kapoor, A., & Winder, S. (2008, April). CueFlik: interactive concept learning in image search. In Proceedings of the sigchi conference on human factors in computing systems (pp. 29-38). ACM.

EnsembleMatrix

- **Task:** classification
- Goal: create ensemble classifiers
- Show confusion matrix resulting from linear combination of classifiers

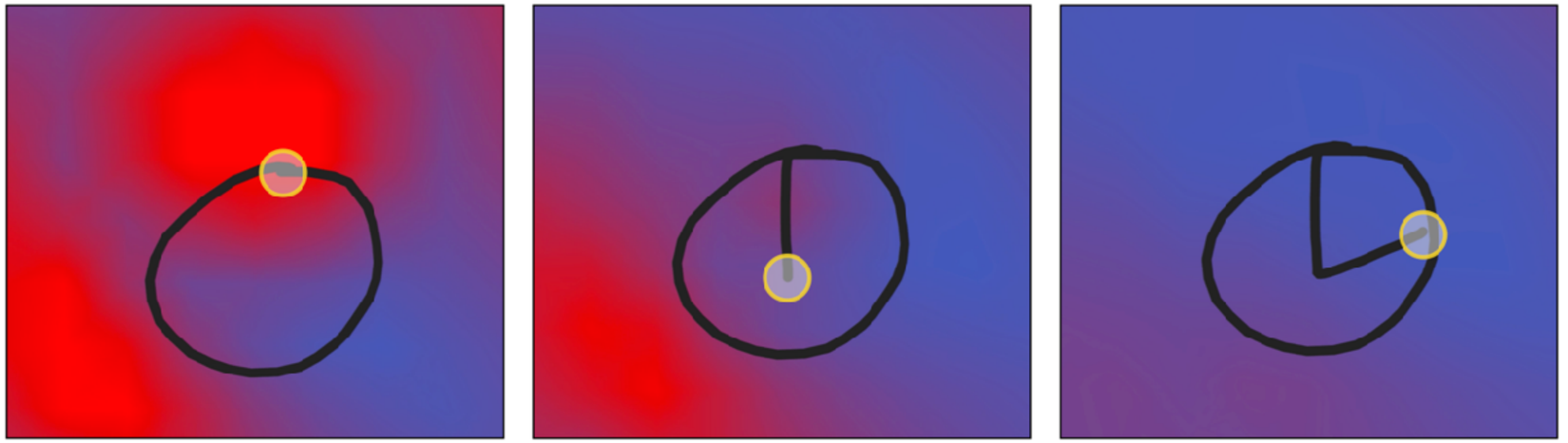


=> Thanks to their intuition and visual processing abilities, users quickly create state of the art ensemble classifiers

Talbot, J., Lee, B., Kapoor, A., & Tan, D. S. (2009, April). EnsembleMatrix: interactive visualization to support machine learning with multiple classifiers. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 1283-1292). ACM.

Fieldward

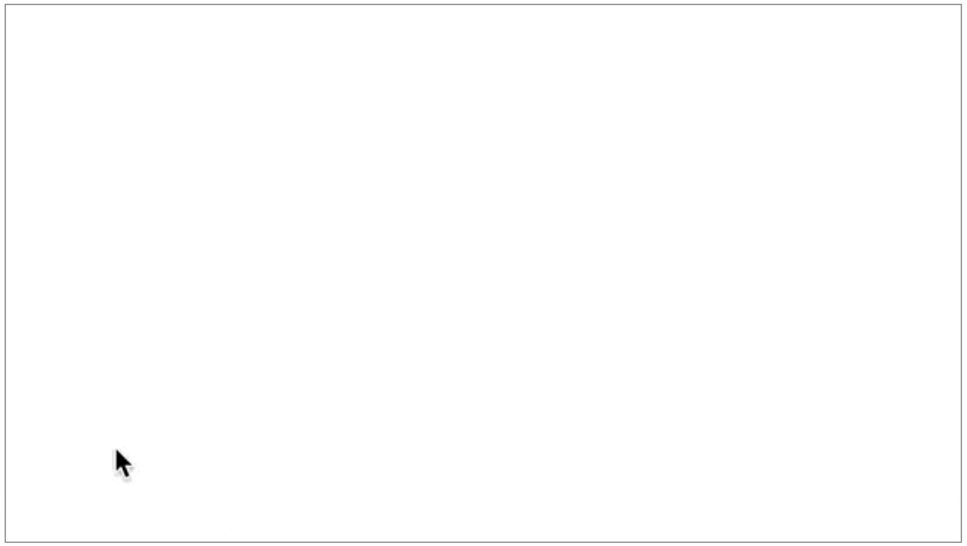
- **Task**: Gesture recognition
- Goal: help user create gestures that will be accurately recognized
- Visualize color gradients to reveal optimal directions for creating recognizable gestures

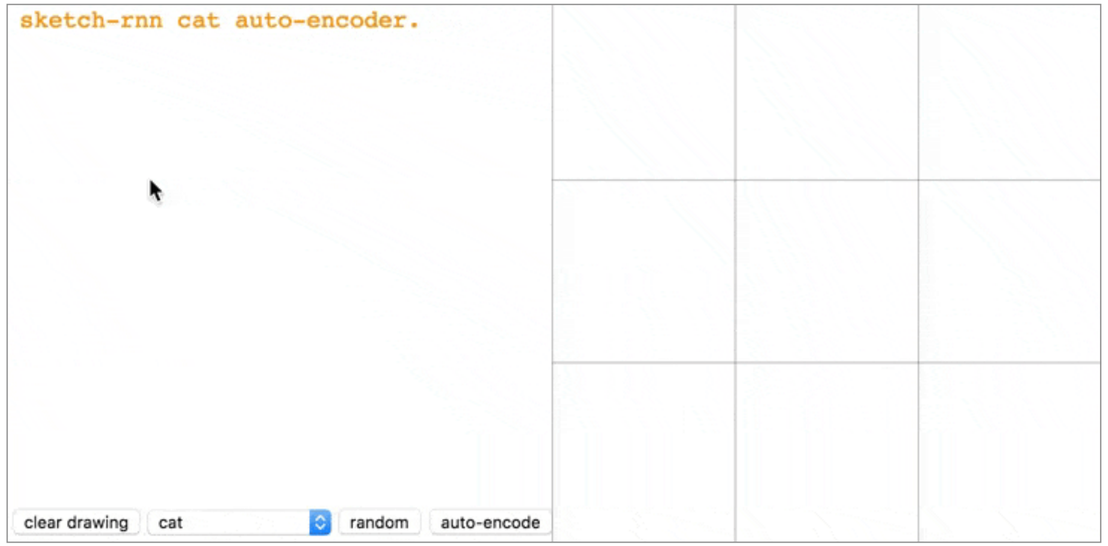


Malloch, J., Griggio, C. F., McGrenere, J., & Mackay, W. E. (2017, May). Fieldward and Pathward: Dynamic Guides for Defining Your Own Gestures. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (pp. 4266-4277). ACM.

Sketch-RNN

- **Task**: Sketch generation
- Goal: Exploring and steering model predictions
- Recurrent network trained from QuickDraw

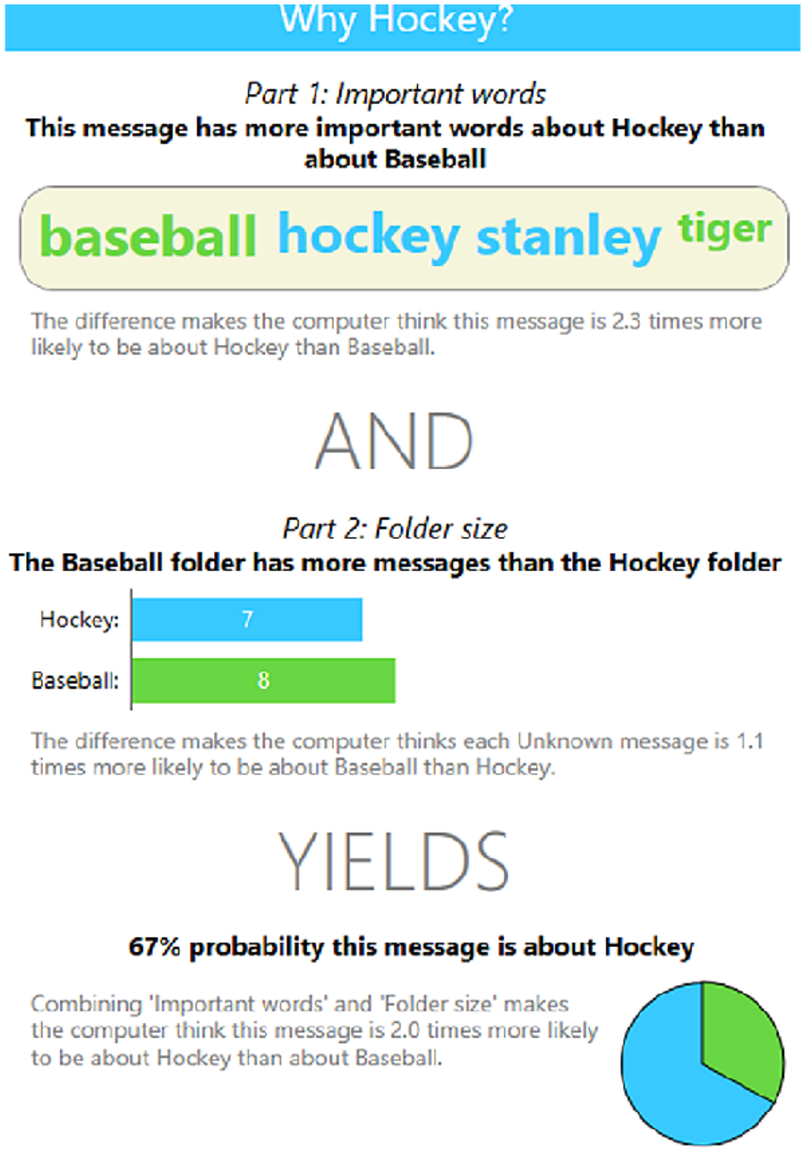




https://magenta.tensorflow.org/sketch-rnn-demo
https://magic-sketchpad.glitch.me/

Elucidebug

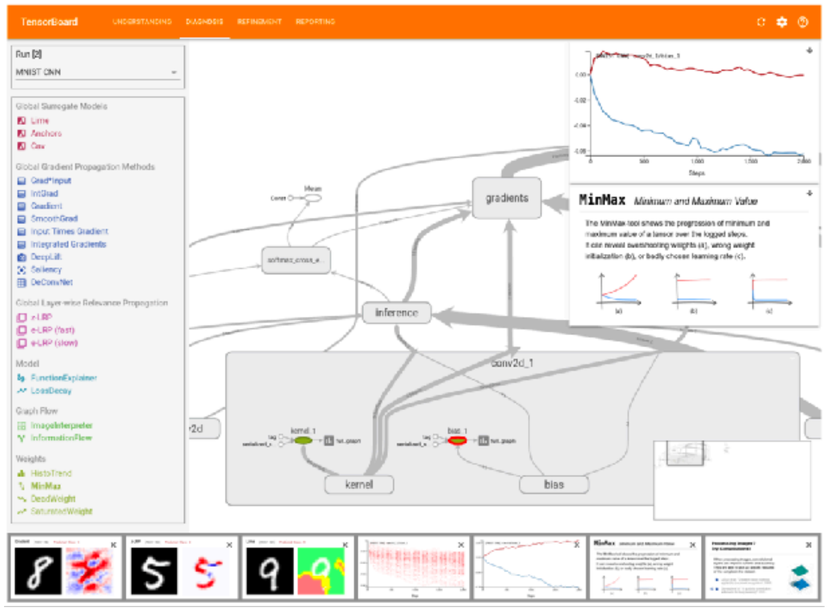
- **Task:** text analysis (spam filtering & classification)
- Goal: give users explanations about the algorithm's decisions
- Allow users to query the system about particular decisions
- Provides feedback about uncertainty

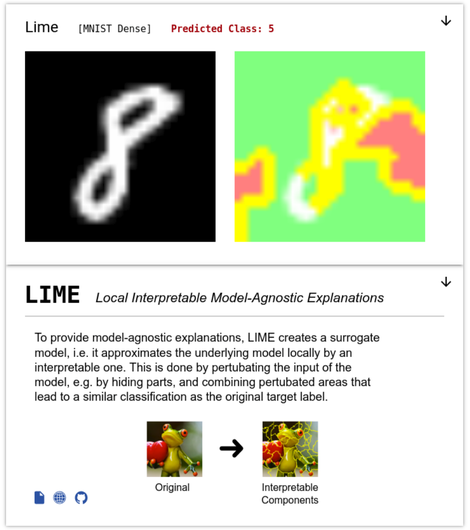


Kulesza, T., Burnett, M., Wong, W. K., & Stumpf, S. Principles of explanatory debugging to personalize interactive machine learning. ACM IUI 2015

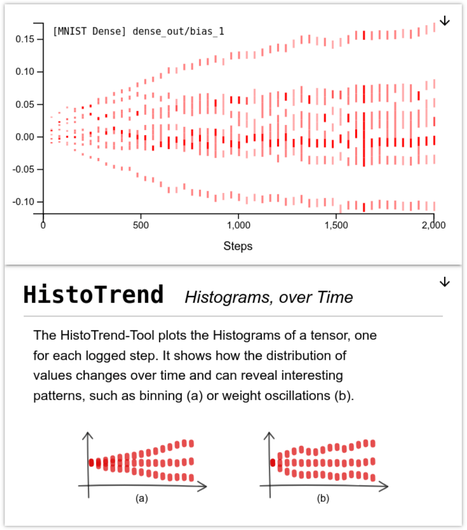
explAIner

- **Task:** Generic
- Goal: give users explanations about the algorithm's decisions
- Combine various model-specific and model-agnostic explainers





(a) LIME (high-abstraction explainer)



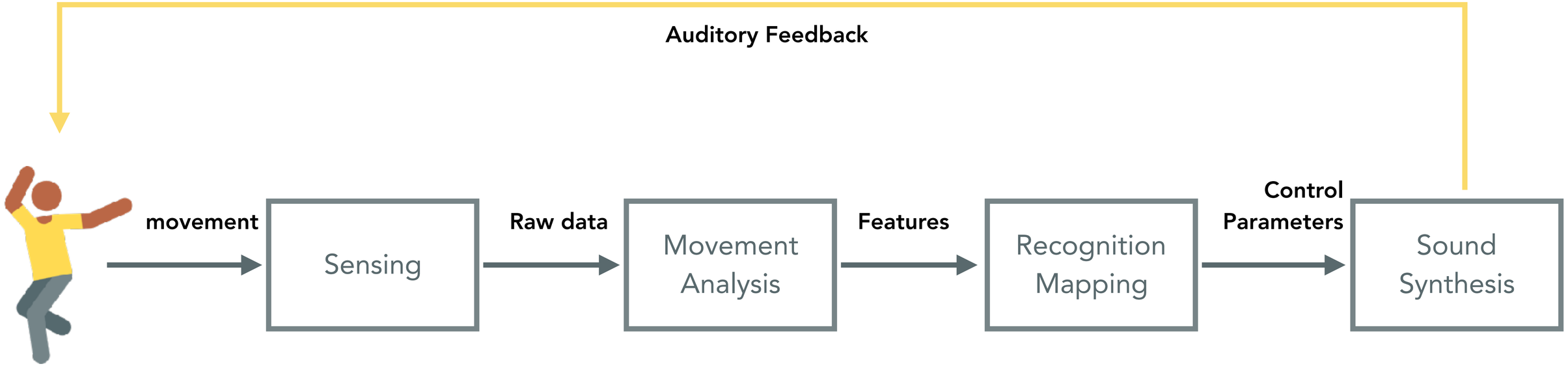
(b) HistoTrend (low-abstraction explainer)

Spinner, T., Schlegel, U., Schäfer, H., & El-Assady, M. (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE transactions on visualization and computer graphics, 26(1), 1064-1074.

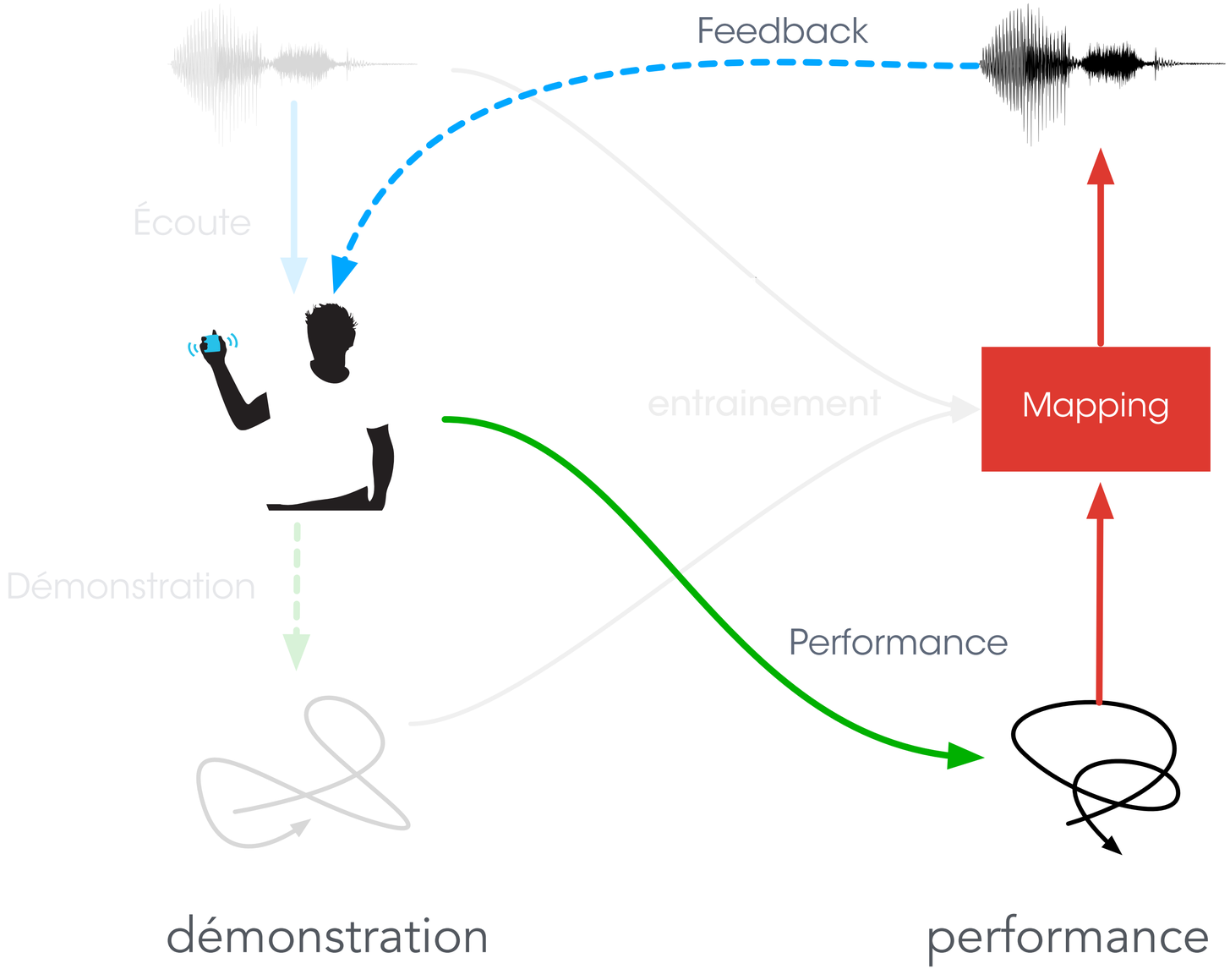
Case study: IML for Movement Sonification

Mapping by Demonstration

How to design movement sonification systems by demonstration?



Mapping by Demonstration



Modular Musical Objects

IRCAM, NoDesign, Da Fact 2011

Designing with machine learning

- **Advantages**
  - No need for a formal (mathematical) description of the problem
  - Design using bodily knowledge
  - Specification of (possibly complex) target gestures for sonification
  - Individualised adaptation

- **But…**
  - How do we make it work?

Specific Constraints

- User-centred approach in creating the database

- Small data
    - linked to specific styles and approach
    - Possibly idiosyncratic to the user
    - unlabelled or inconsistent labelling

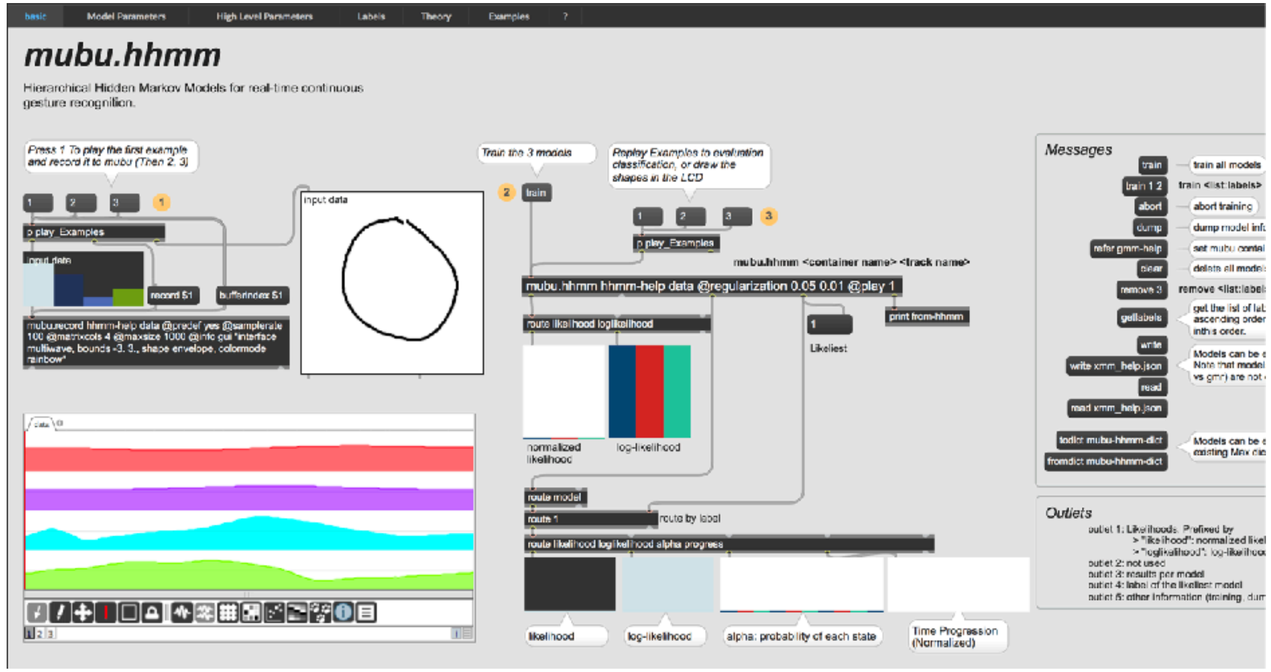
- Data evolving with time
    - learning processes from rehearsal to performance
    - Specific tasks and use cases

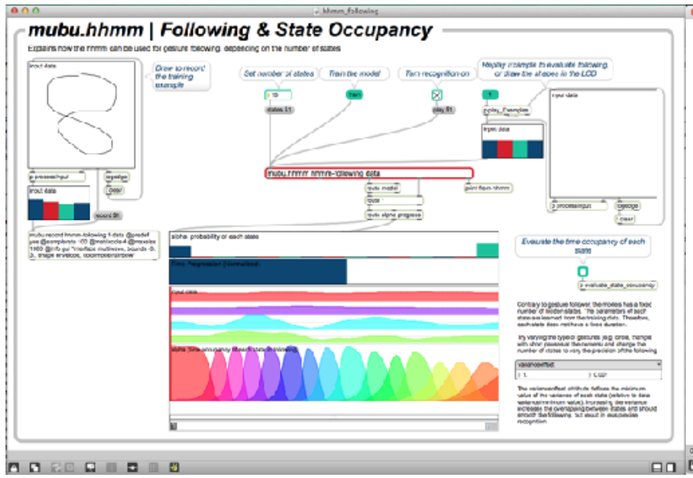
Understanding Models

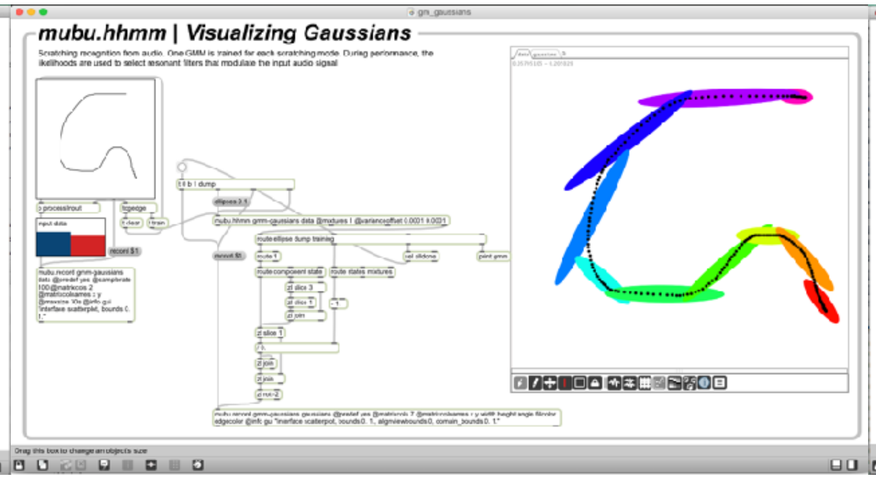
	Recognition	Generation
Instantaneous	Gaussian Mixture Models gmm	Gaussian Mixture Regression gmr
Temporal	Hierarchical Hidden Markov Models & others gf, gvf, hhmm	Hierarchical Hidden Markov Regression hhmr

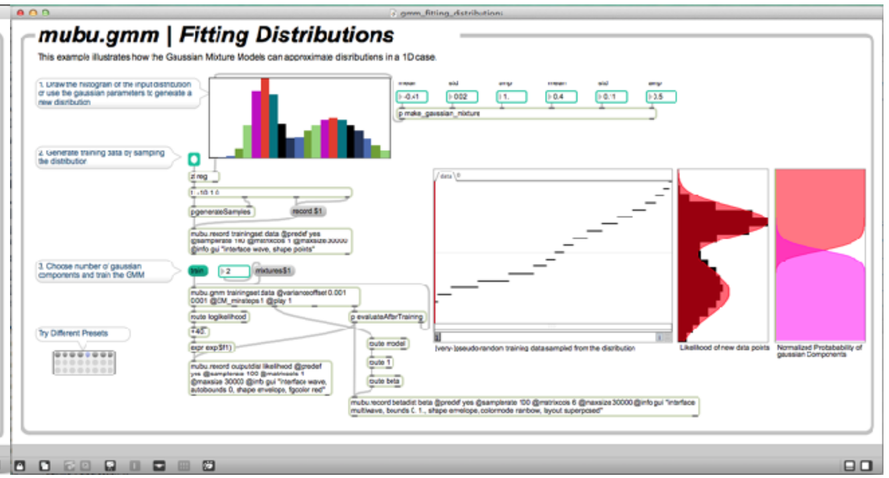
Supporting Tools

- XMM => Real-time HMM library
- Mubu => IML interfaces in Max









https://forum.ircam.fr/projects/detail/mubu/

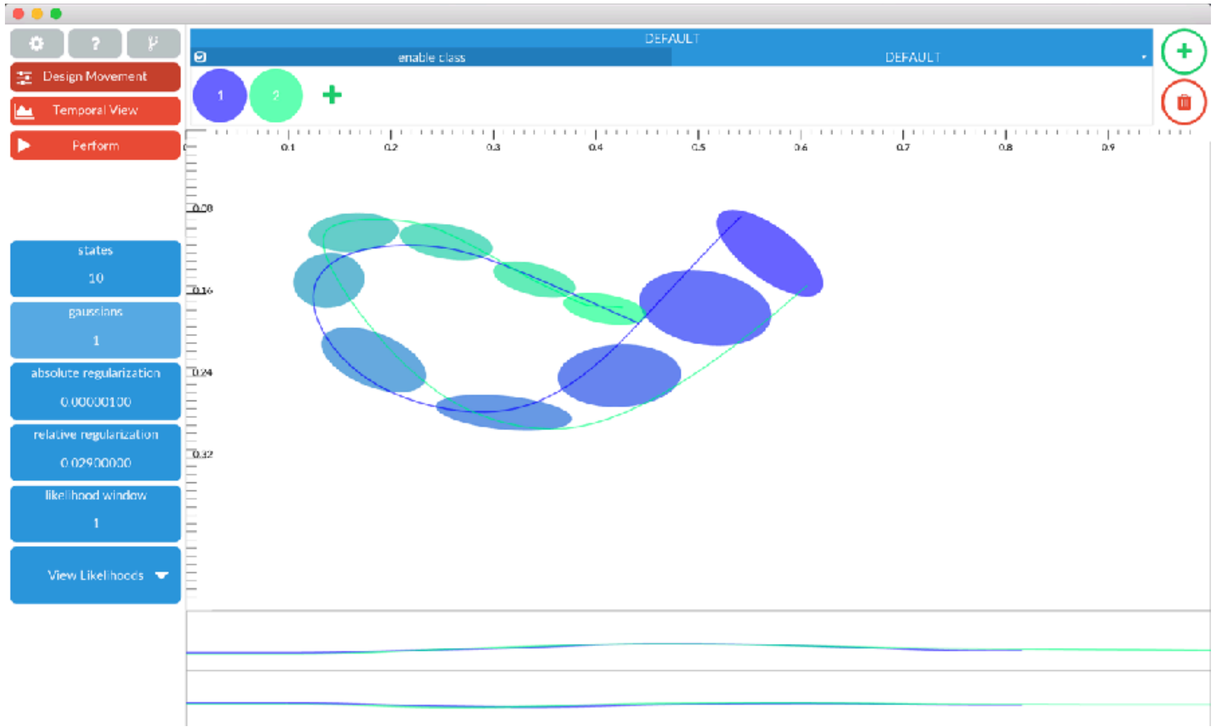
Design Process

- **Process**
  - The user imagines a vocabulary of gestures (+ sounds)
  - The user records demonstrations
  - The ML algorithm learns the mapping/classifier
  - It does **not** work.
- **Reasons for Failure**
  - *Technical factors*
    - Appropriate choice of sensor, features, model, and parameters
    - High-quality examples
  - *Cognitive and sensori-motor factors*
    - Gesture design + Execution

An iterative process

- **Co-adaptive perspective**
  - The human and the machine iteratively learn from each other
  - Users adapt their gesture design by iterating over demonstration & performance

- **How to make it work?**
  - Improve the transparency
  - Support practice & exploration



Discussion

Goals of IML

- Improve usability
    - Facilitate interaction with the ML process for users with low expertise
    - Provide new avenues for exploration of ML (ex: art)
- Increase performance
    - Provide mechanisms to assist practitioners in optimising ML algorithms
- Improve transparency
    - Provide explanations on ML/AI decisions
    - Help assessing fairness (discrimination, …)

Opportunities

- Supporting Assessment of Model Quality
- Supporting Experimentation with Model Inputs
- Appropriately Timing Queries to the User
- Enabling Users to Query the Learner
- Enabling Users to Critique Learner Output
- Allowing Users to Specify Preferences on Errors
- Combining Models
- …

User Interaction with ML

Tight coupling between the user and the system
=> impossible to study the system in isolation from the user.

- People don’t want to be oracles (ex: active learning)
- People tend to give more positive rewards (ex : reinforcement learning)
- People give hints for future actions rather than evaluate past actions
- People want to give more input than just labels
- People value transparency (~~black box~~)
- Transparency can help people provide better labels

IML Design Principles

1. Make task goals and constraints explicit
2. Support user understanding of model uncertainty and confidence
3. Capture intent rather than input
4. Provide effective data representations
5. Exploit interactivity and promote rich interactions
6. Engage the user

Dudley, J. J., & Kristensson, P. O. (2018). A review of user interface design for interactive machine learning. ACM Transactions on Interactive Intelligent Systems (TiiS), 8(2), 8.

Challenges: from a ML perspective

- Small datasets (when data is provided by users)
- Inconsistent annotations, concept drift
- Standard success criteria (ex: scores) can be irrelevant for users
    - ex: decision boundary on a classifier
- Not all models are suitable for IML
    - Need for rapid, incremental iterations
    - Speed-accuracy tradeoff
        - Simple models (HMM, GMM) vs Large networks

Challenges: from a HCI perspective

- ML systems are often difficult to understand
- ML systems are inherently uncertain
- Notions of safety and trust
- Mixed-initiative systems
  - Balancing AI/ML with direct manipulation (Horvitz)
  - How to manage system adaptation (timing, scope, …)

Hands-on session

Hands-on Session

- Exploration of the Marcelle API
- Follow the getting started guide in the documentation:

marcelle.netlify.com

Projects

Projects

Propose the design of an Interactive Machine Learning system

- By groups of 2
  - Mixed skills (design/CS if possible)
- Goal:
  - Identify a research question within the field of IML and propose a design
  - Implement a prototype based on the Marcelle framework:
    => **extension**, for instance a new Marcelle Component
    => **integration** of Marcelle in another application

Projects

- Possible contributions:
  - New scenario with different input or output modality
  - New interface facilitating interaction with ML
  - New visualization tool for machine learning
  - New technique for explaining ML predictions, etc.…
- Evaluation : **Presentations on February 28**
  - **Slides**
    - State of the art (situating the problem within the field)
    - Research Question
    - Proposed design with motivations & Implementation
  - **Demo**