Introduction to **Machine Learning** (IML) and **Interactive Machine Learning** (IML)

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Python Notebook

Introduction to

Interactive Machine Learning (IML)

Interactive Machine Learning is about creating **interactions** between **human-users** and the (whole) **machine learning pipeline**

ML & Human(s)

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Who is helping Who?

- **Machine helping the human**

  Amplifying human abilities

- **Humans helping the machine**

  Providing labels, preferences and guidance

- **Towards a collaboration / cooperation / partnership?**

  Crandall et al. (2018). Cooperating with machines. Nature Communications, 9(1), 1-12

  Tschandl et al. (2020). Human–computer collaboration for skin cancer recognition. Nature Medicine, 26(8), 1229-1234

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.

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

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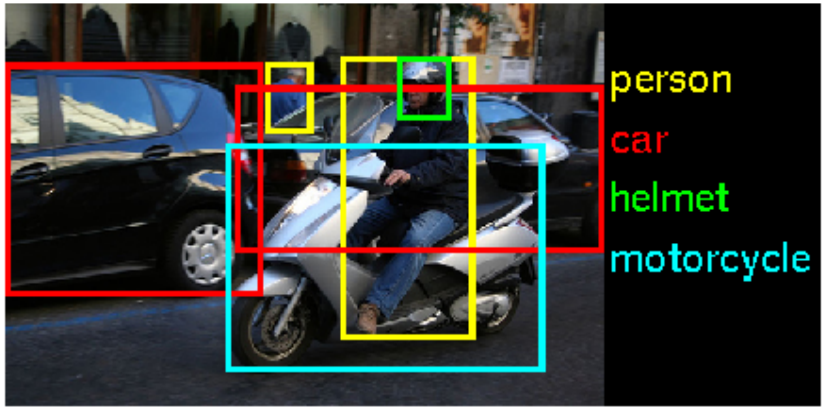
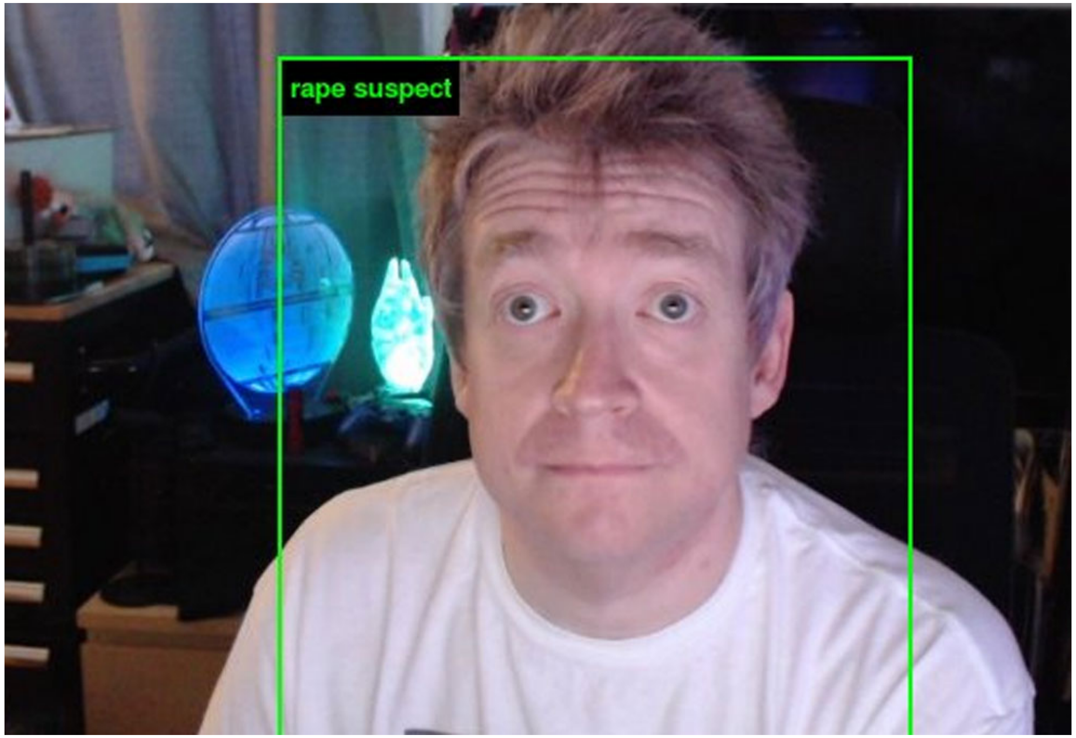
Example: ***ImageNet***

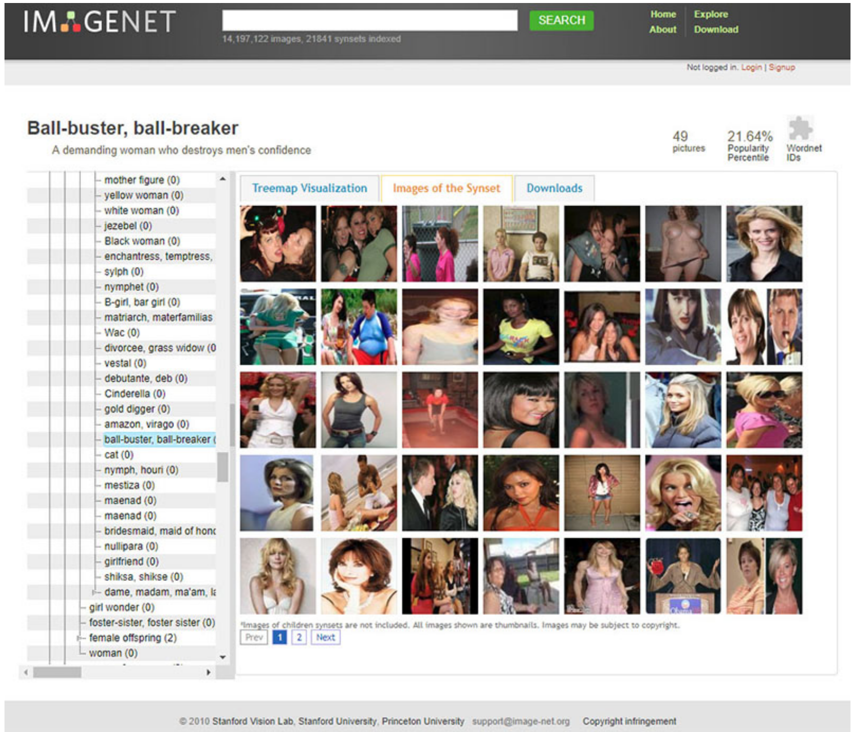


- Large visual database for vision research
- Constructed with crowdsourcing
- Total number of images: 14,197,122
- Number of images with bounding box annotations: 1,034,908

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.

Human biases => machine biases





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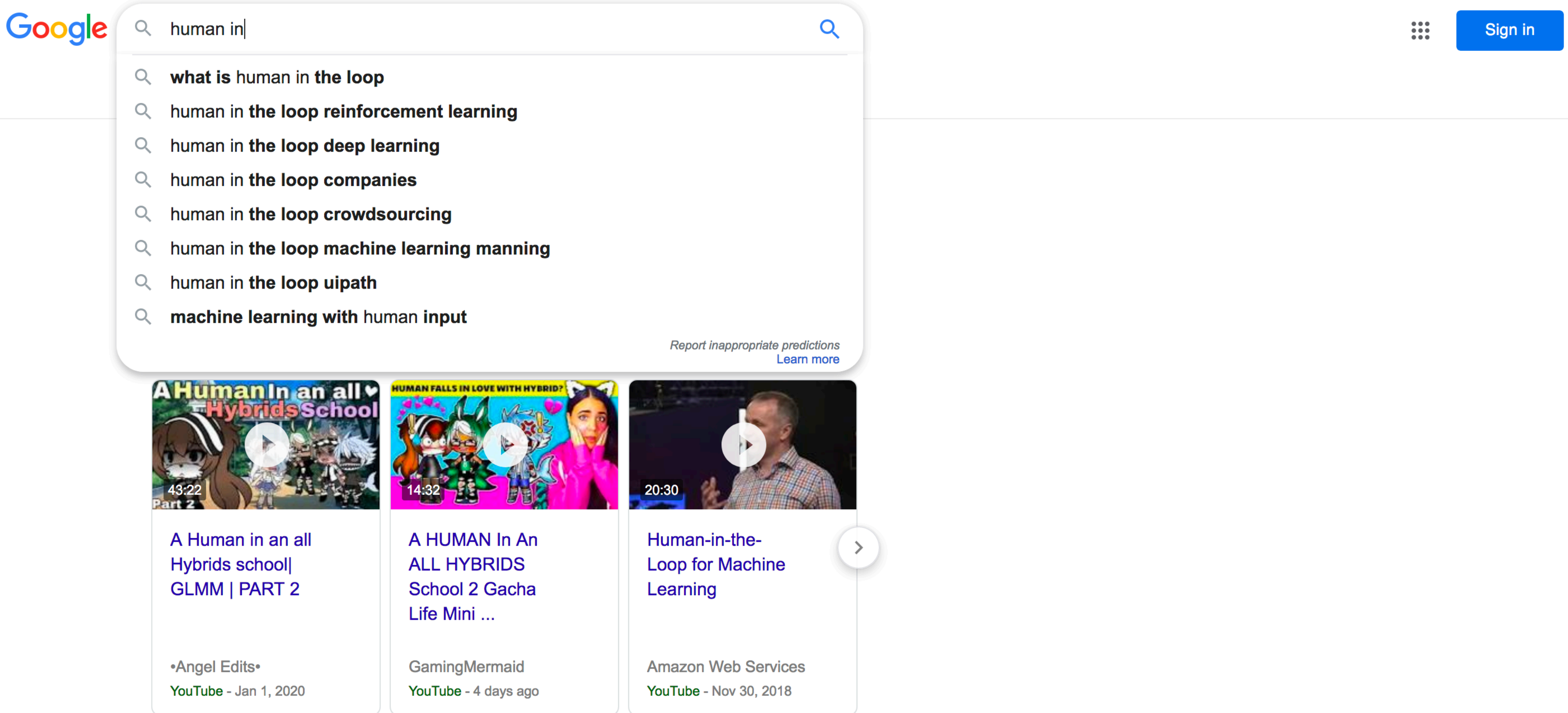
Human-in-the-loop ML

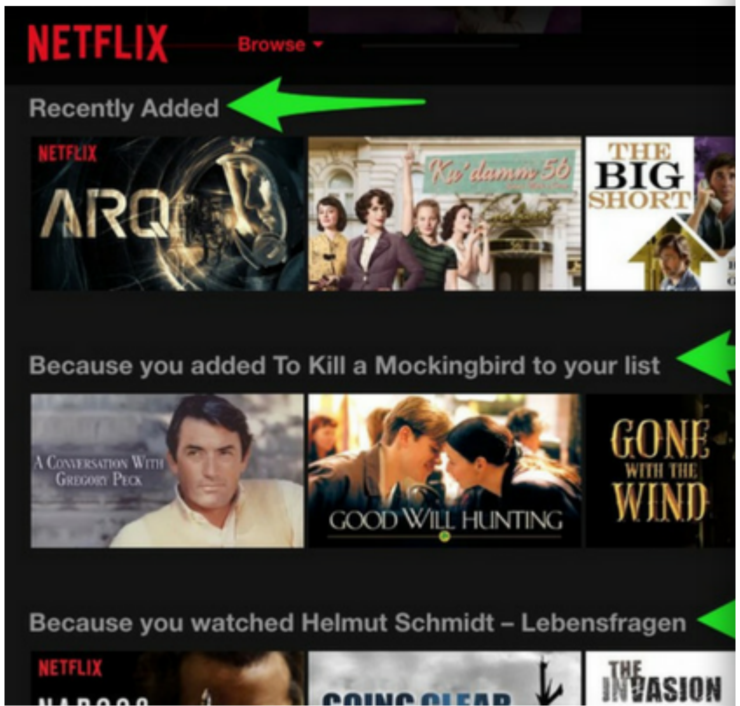
Human-in-the-loop ML

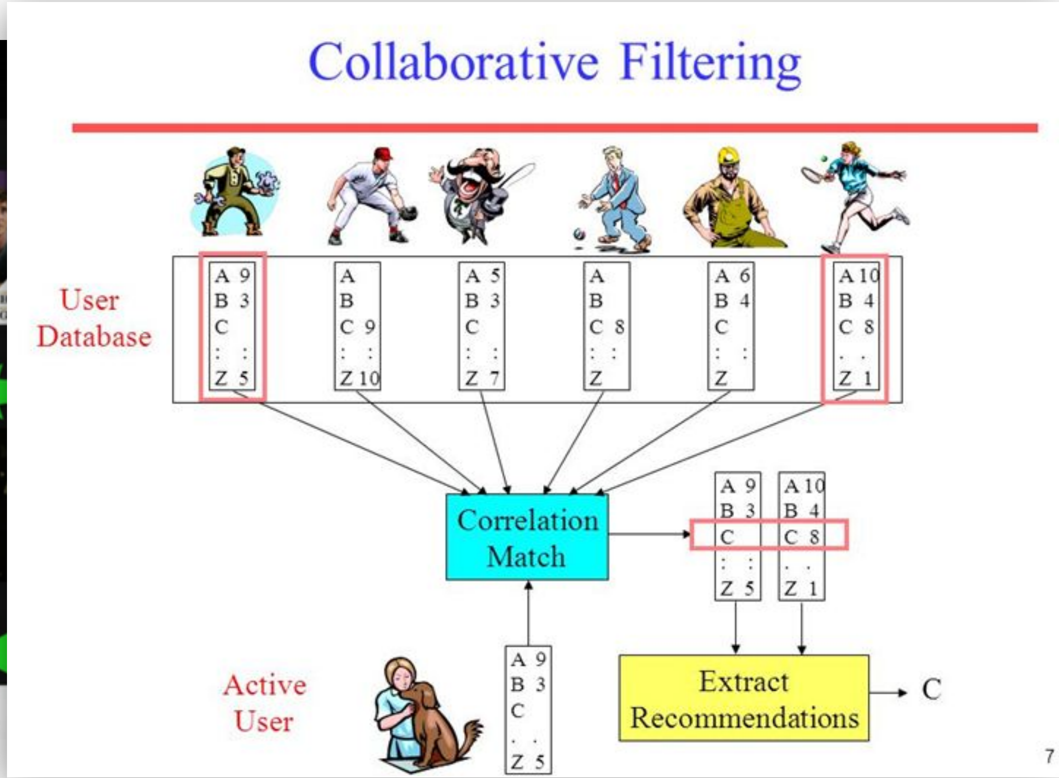
Use human input to **improve the algorithm**



Example: Recommender Systems

Combine human input to ***personalise*** *predictions*



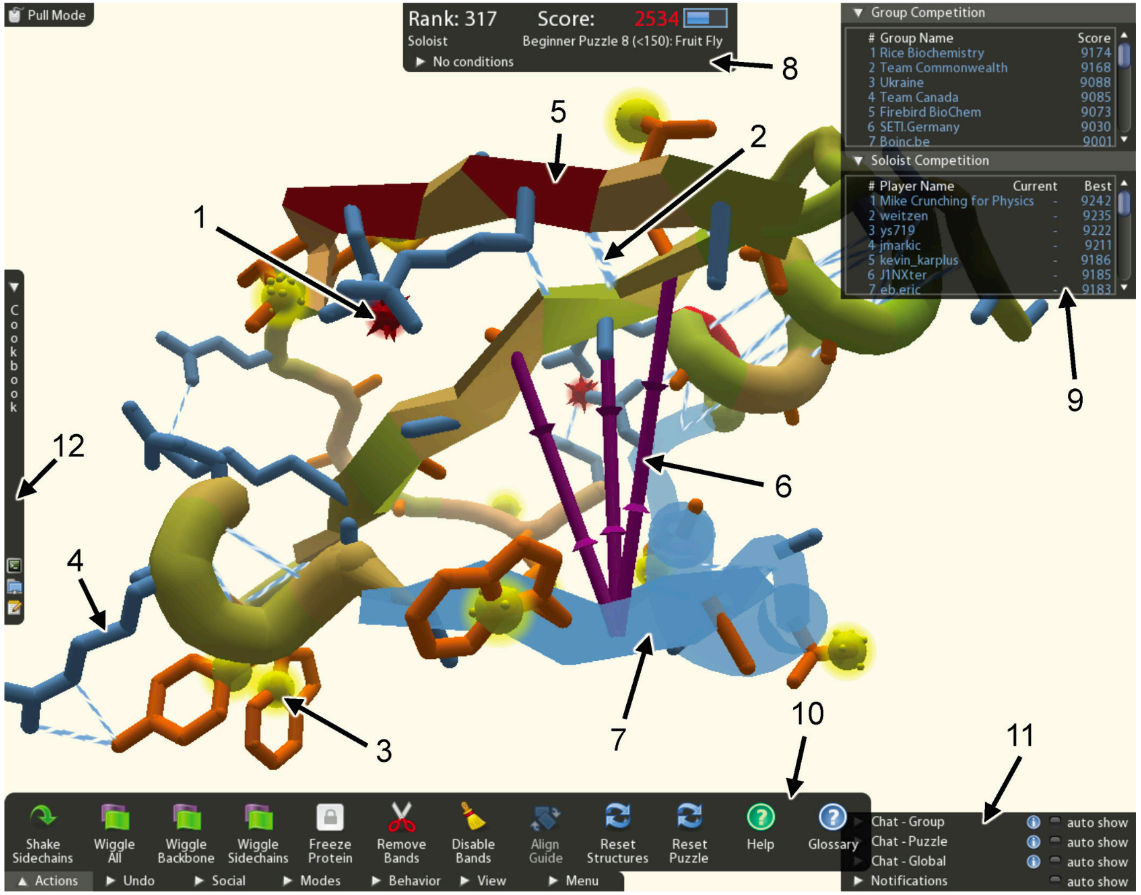


Example: Human-Robot Interaction

Learning from demonstrations: Use human input to *teach new skills*

Example: Expert Domain

Use crowd intelligence to help protein structure discovery:
Foldit



Cooper et al. (2010) Predicting protein structures with a multiplayer online game. *Nature* 466(7307):756–760
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2956414/pdf/nihms218516.pdf

Interactive Machine Learning

demo

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.

What IML is not

- Considering that **people are only useful** for ML

  Using people to label large datasets

  Exploiting user’s choices/preferences to improve an algorithm (blindly)

- Using an interactive system **integrating a ML algorithm**

  Using a computer vision algorithm to track a person’s skeleton

  Integrating speech recognition

Traditional ML workflow

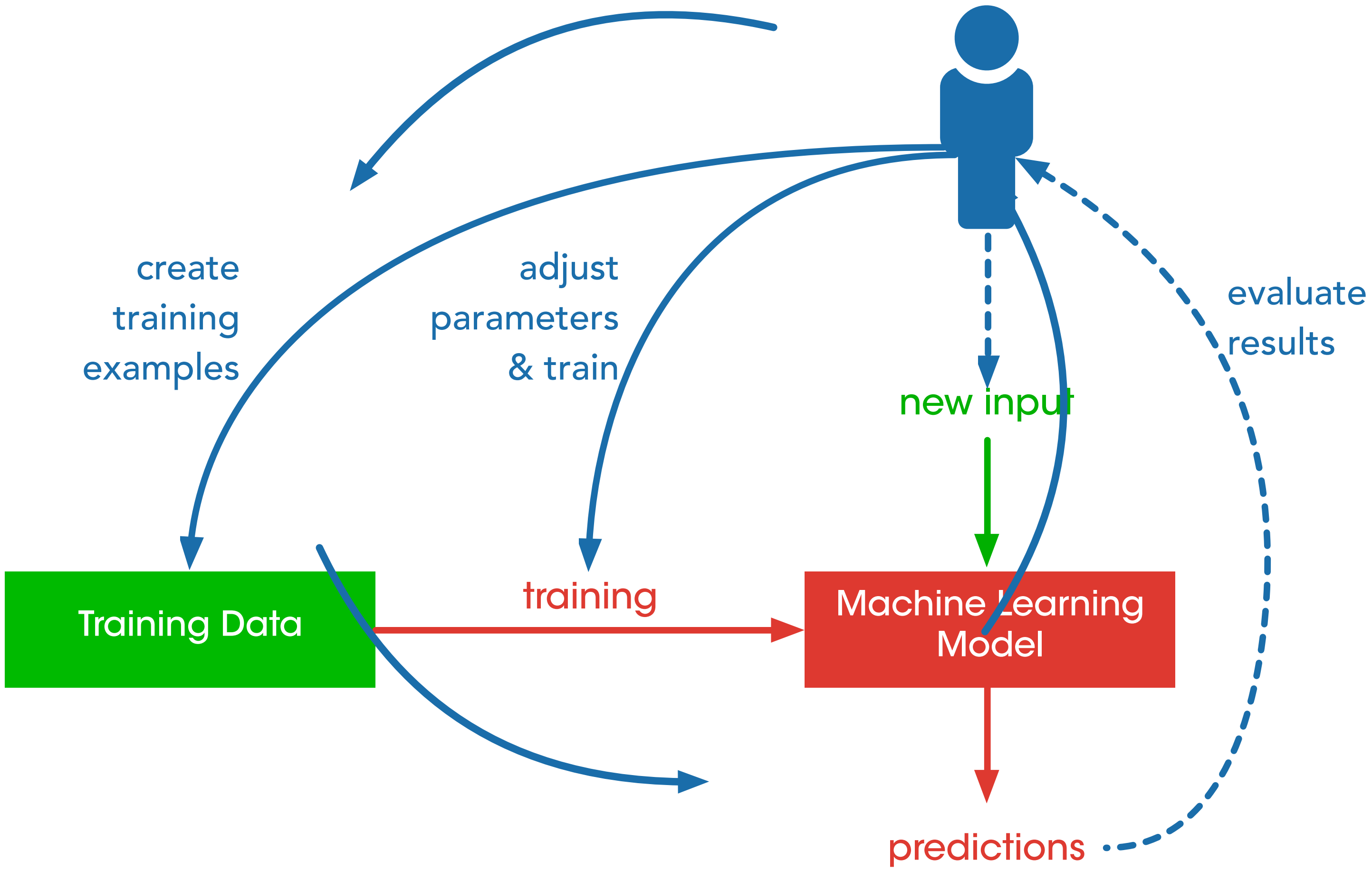
Development (by ML experts):

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

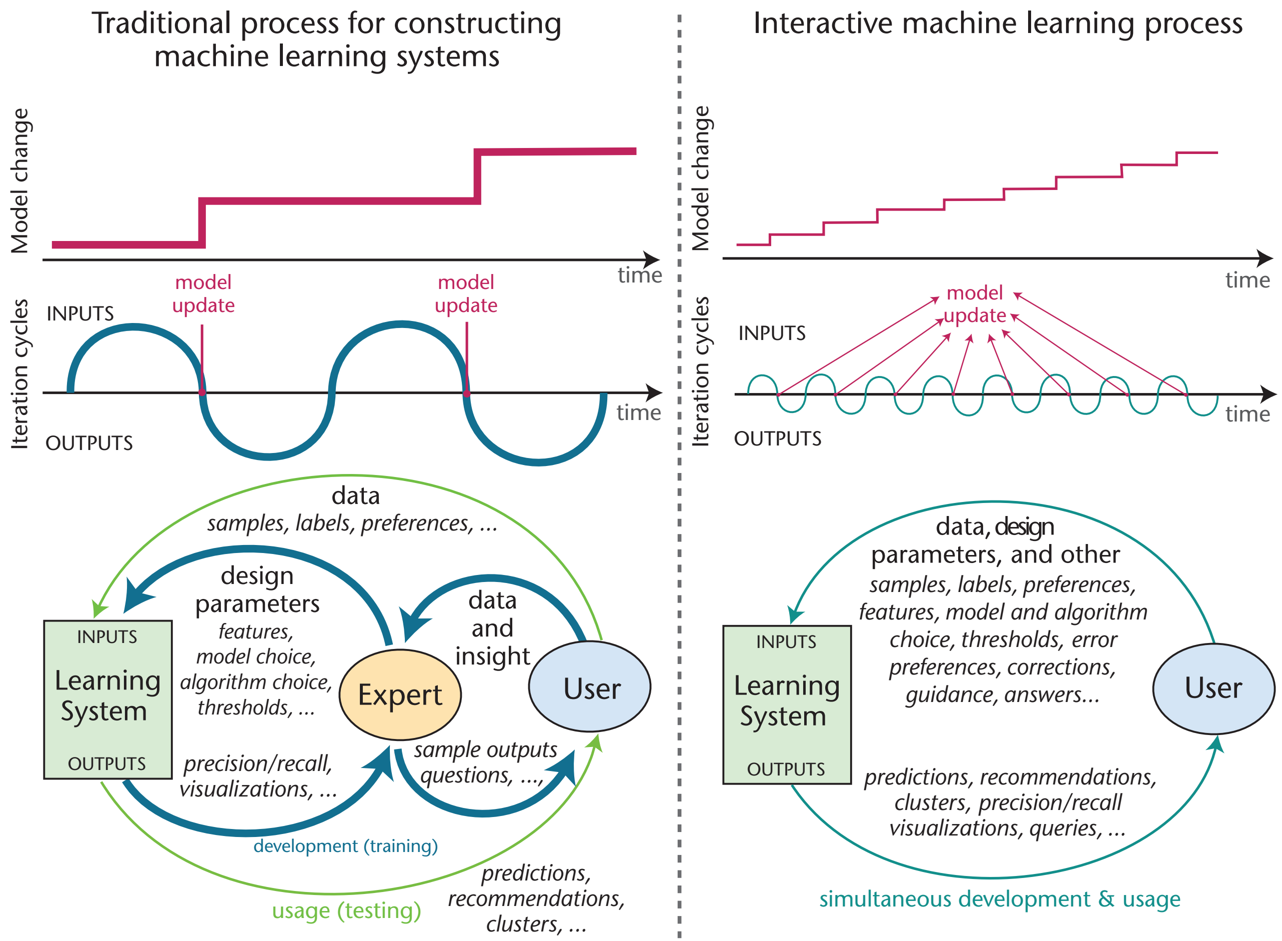
Usage (by end-users): limited to providing data/annotations, answering domain-related questions, or giving feedback about the learned model.

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.

Interactive Machine Learning workflow

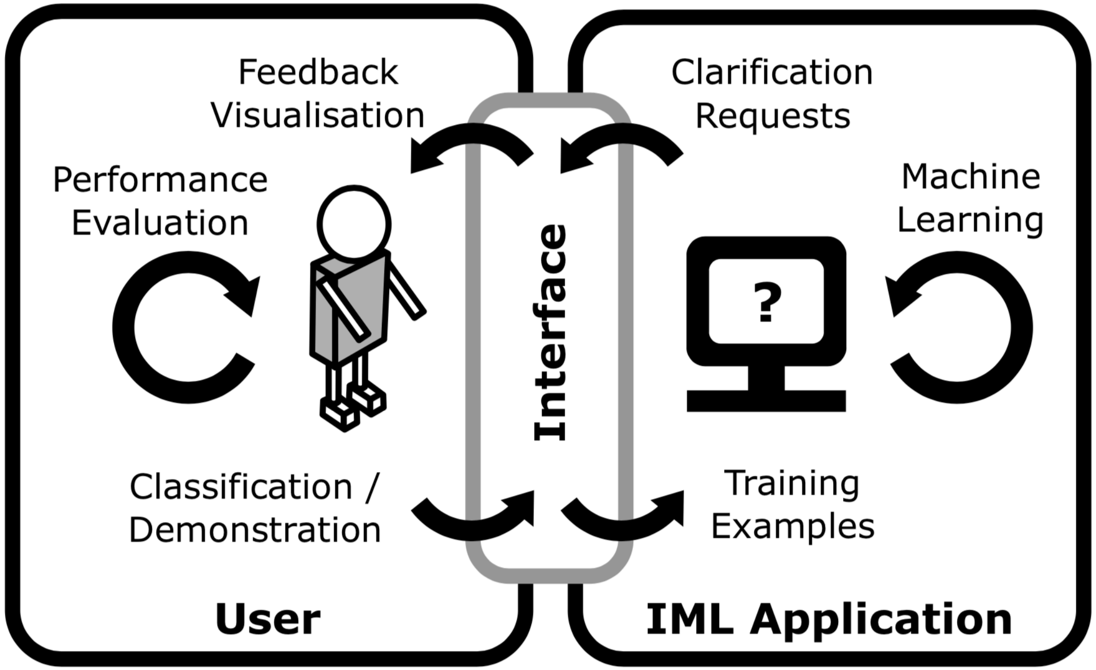


Traditional v. IML workflows



[Amershi et al. 2014]

Overview of an IML System



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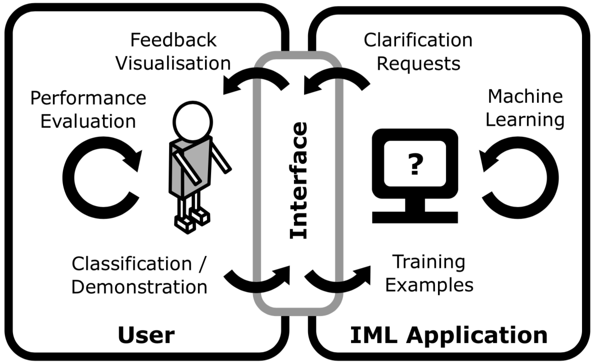

User:

- 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, …)

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.

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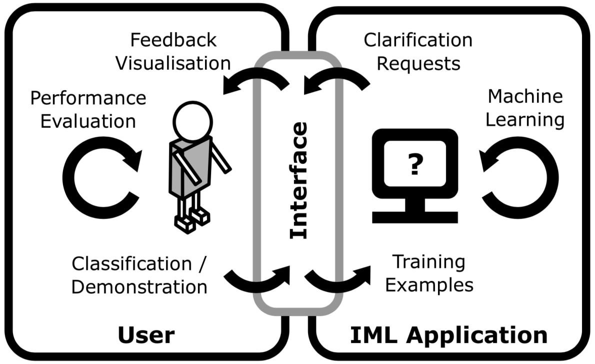


Data:

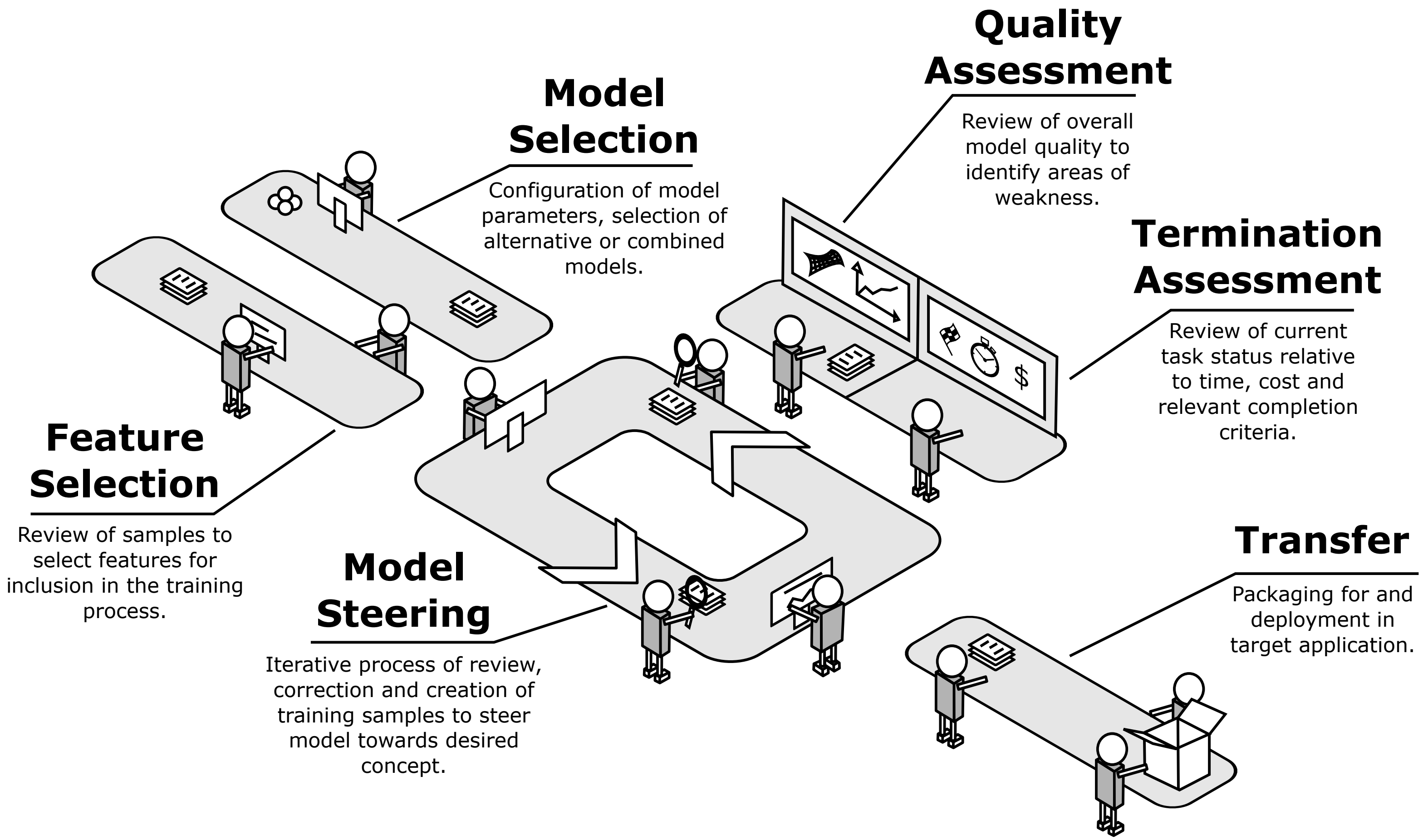
- Provided and labeled by the user
- Should describe the system's desired behavior
- Variable across applications

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

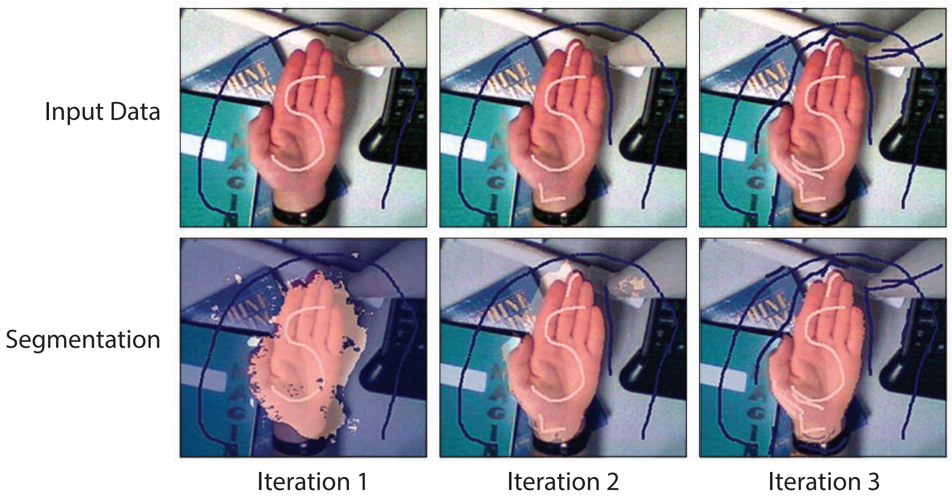


Dudley, J. J., & Kristensson, P. O. (2018). A review of user interface design for interactive machine learning. ACM Transactions on Interactive Intelligent Systems (TiiS), 8(2), 8.

Examples

Crayons

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

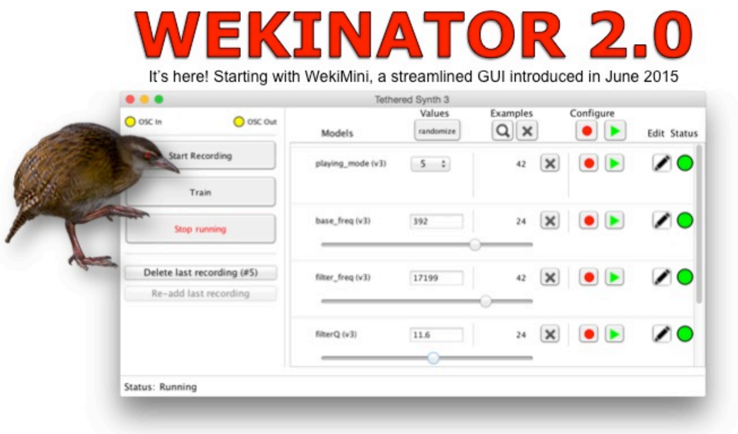


=> Users can easily identify classification errors and provide more annotations to improve the classifier

Fails et al. (2003). Interactive machine learning. In Proceedings of IUI (pp. 39-45). ACM. PDF

Wekinator

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



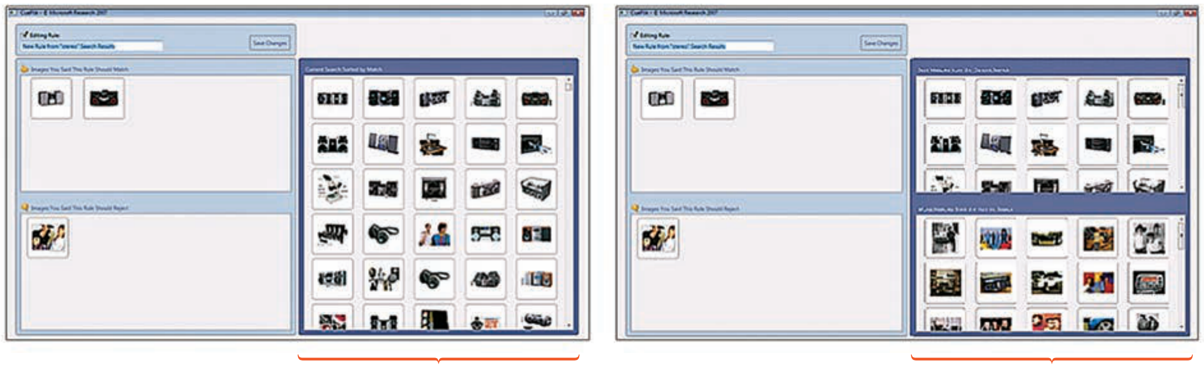
http://www.wekinator.org/example-projects/

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

Fiebrink et al. (2011). Human model evaluation in interactive supervised learning. In Proceedings of CHI (pp. 147-156). ACM. [PDF](#)

CueFlik

- **Task:** image classification
- Goal: improve image-based web search
- Allow end-users to build rules by demonstration of pos/neg exemples



Standard presentation using a ranked list of examples

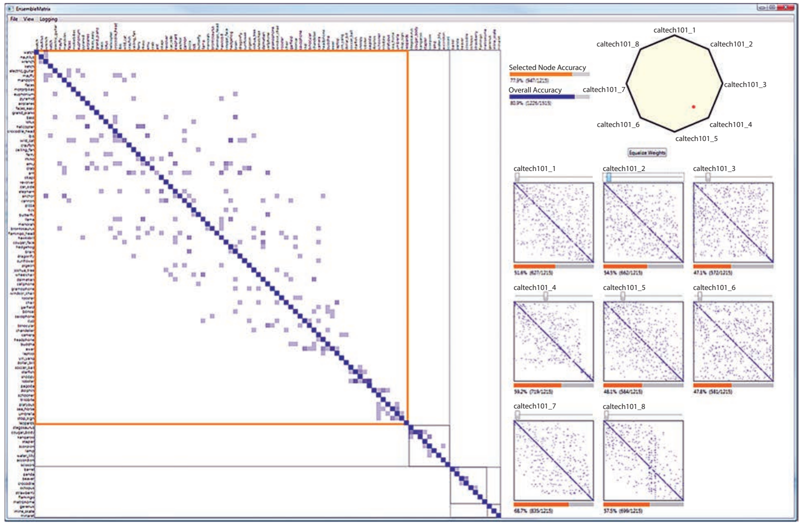
Best and worst matching examples presentation

=> Improved presentation leads to better models

Fogarty et al. (2008). CueFlik: interactive concept learning in image search. In Proceedings of CHI (pp. 29-38). ACM. [PDF]

EnsembleMatrix

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

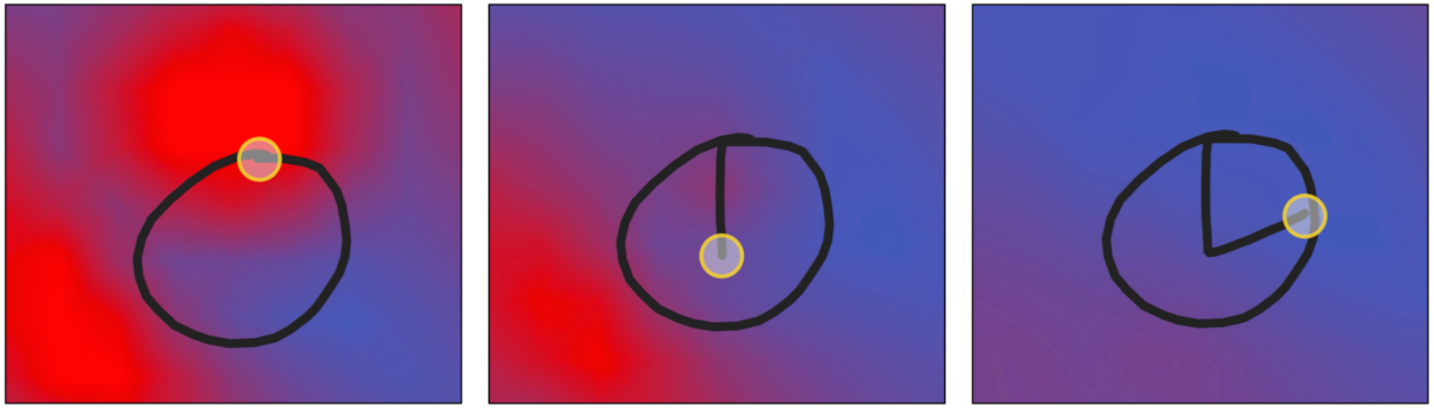


=> Thanks to their intuition and visual processing abilities, users quickly create state of the art ensemble classifiers

Talbot et al. (2009). EnsembleMatrix: interactive visualization to support machine learning with multiple classifiers. In Proceedings of CHI (pp. 1283-1292). ACM. [PDF]

Fieldward

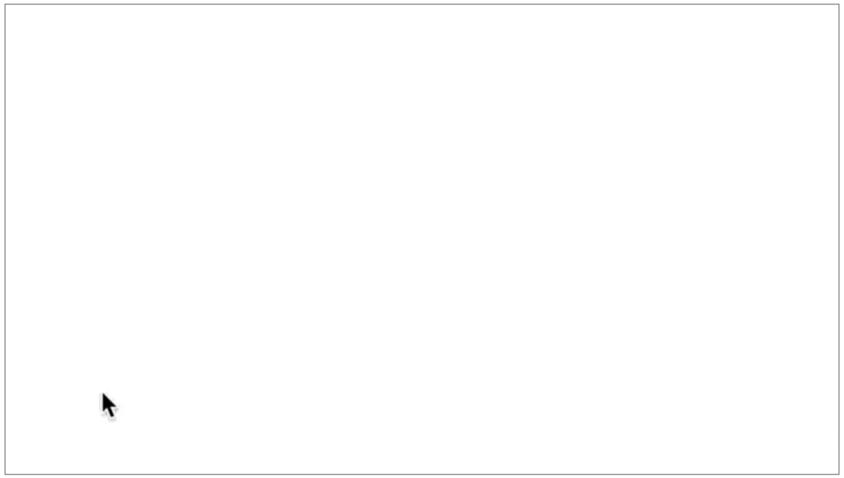
- **Task**: Gesture recognition
- Goal: help user create gestures that will be accurately recognized
- Visualize color gradients to reveal optimal directions for creating recognizable gestures



Malloch et al. (2017). Fieldward and Pathward: Dynamic Guides for Defining Your Own Gestures. In Proceedings of CHI (pp. 4266-4277). ACM. [*PDF*]

Sketch-RNN

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



Ha, D., & Eck, D. (2017). A neural representation of sketch drawings. arXiv preprint arXiv:1704.03477. PDF
https://magenta.tensorflow.org/sketch-rnn-demo

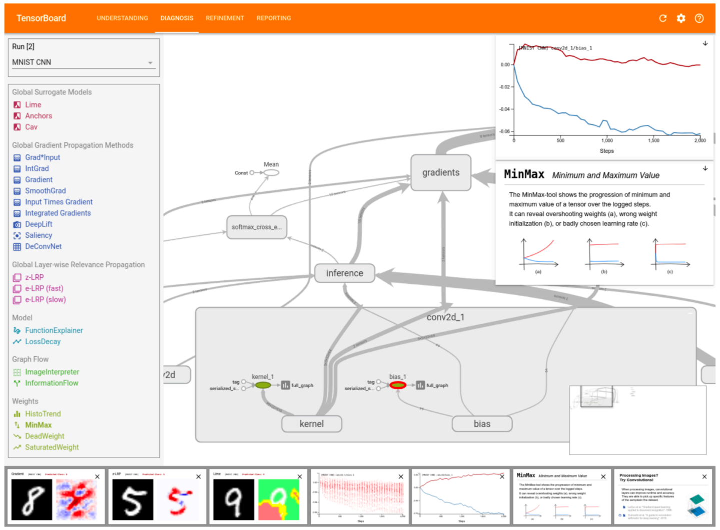
Elucidebug

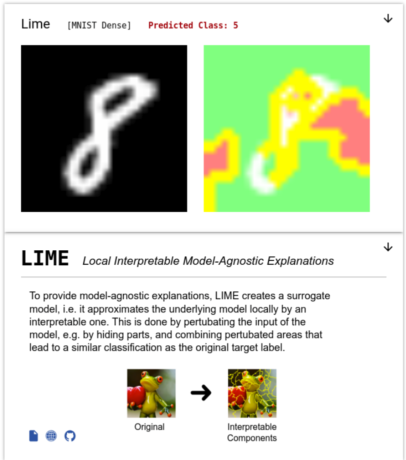
- **Task:** text analysis (spam filtering & classification)
- Goal: give users explanations about the algorithm's decisions
- Allow users to query the system about particular decisions
- Provides feedback about uncertainty

Kulesza et al. (2015). Principles of explanatory debugging to personalize interactive machine learning. ACM IUI. [PDF]

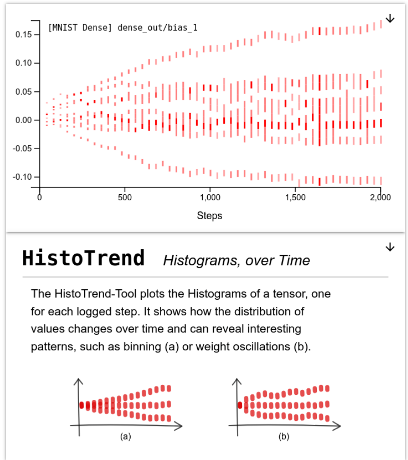
explAIner

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





(a) LIME (high-abstraction explainer)

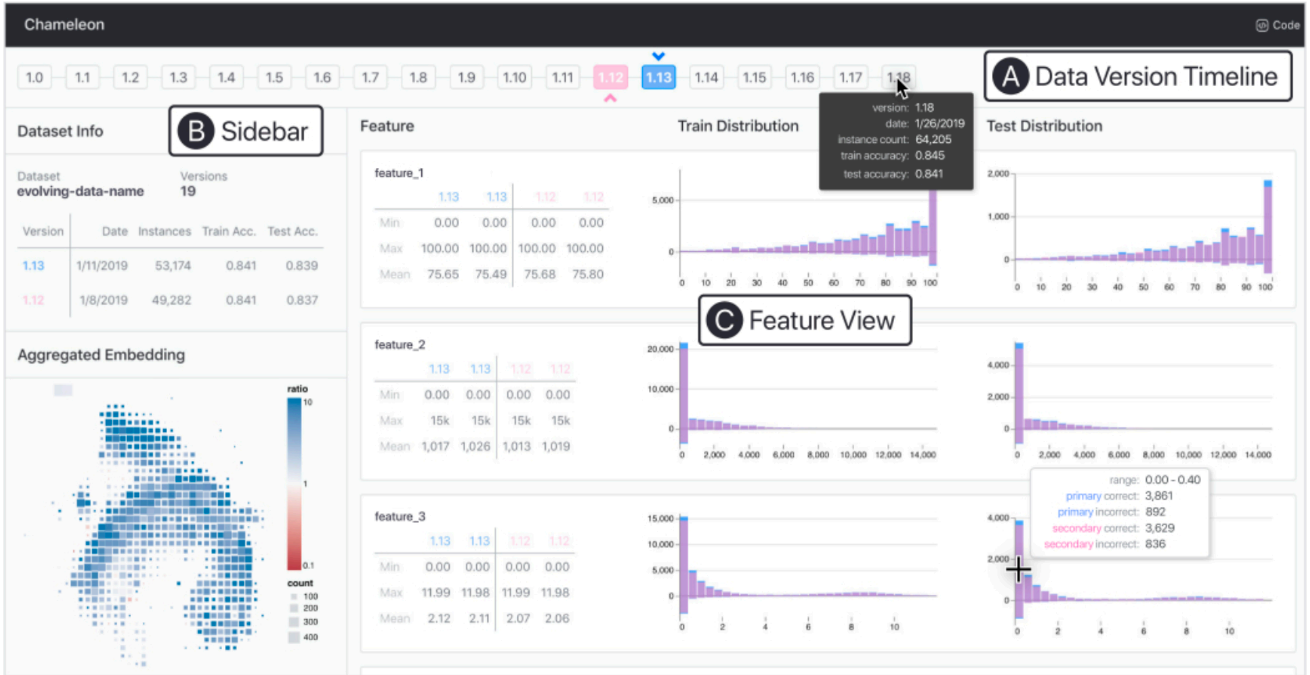


(b) HistoTrend (low-abstraction explainer)

Spinner et al. (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE transactions on visualization and computer graphics, 26(1), 1064-1074. [PDF]

Chameleon

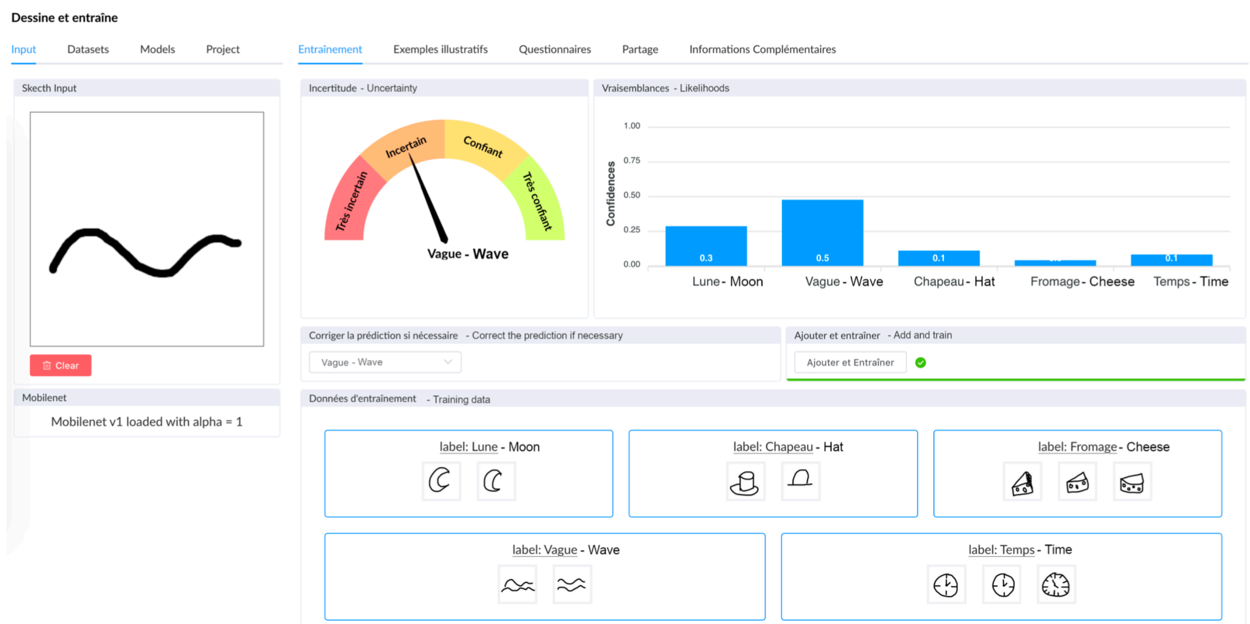
- **Task**: Classification
- Goal: ML experts can build more robust models
- Facilitate data iteration
- Think-aloud protocol



Hohman et al. (2020). Understanding and visualizing data iteration in machine learning. In Proceedings of CHI (pp. 1-13). [PDF](PDF)

Sketch Teaching

- **Task**: Classification
- Goal: Neophytes teach the system
- User's understanding and misunderstanding of DL
- Think-aloud protocol



Sanchez et al. (2021). How do People Train a Machine? Strategies and (Mis)Understandings. In Proceedings of CSCW

Class framework: Marcelle

What is *Marcelle*?

> an interactive machine learning toolkit

https://marcelle.dev

Marcelle

A Toolkit for Composing Interactive Machine Learning Workflows and Interfaces

Marcelle is a modular open source toolkit for programming interactive machine learning applications. Marcelle is built around components embedding computation and interaction that can be composed to form reactive machine learning pipelines and custom user interfaces. This architecture enables rapid prototyping and extension. Marcelle can be used to build interfaces to Python scripts, and it provides flexible data stores to facilitate collaboration between machine learning experts, designers and end users.

Get Started →

Try the Demos

Françoise, J., Caramiaux, B., & Sanchez, T. (2021). **Marcelle: Composing Interactive Machine Learning Workflows and Interfaces**. In *UIST'21*

Marcelle examples

Part 1: Exploring ML concepts

- *supervised learning example*

- *model comparison: MLP vs kNN*

Part 2: Interactive ML workflow

- *machine teaching with sketch*

Examples at: https://demos.marcelle.dev/