Human-Computer Decision Systems in Cybersecurity

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Collaboration Between Human Experts and ML

Two typical approaches to classification or categorization:

Human analysts and **machine learning (ML) classifiers**.

Different strengths and weaknesses. Why pick one?

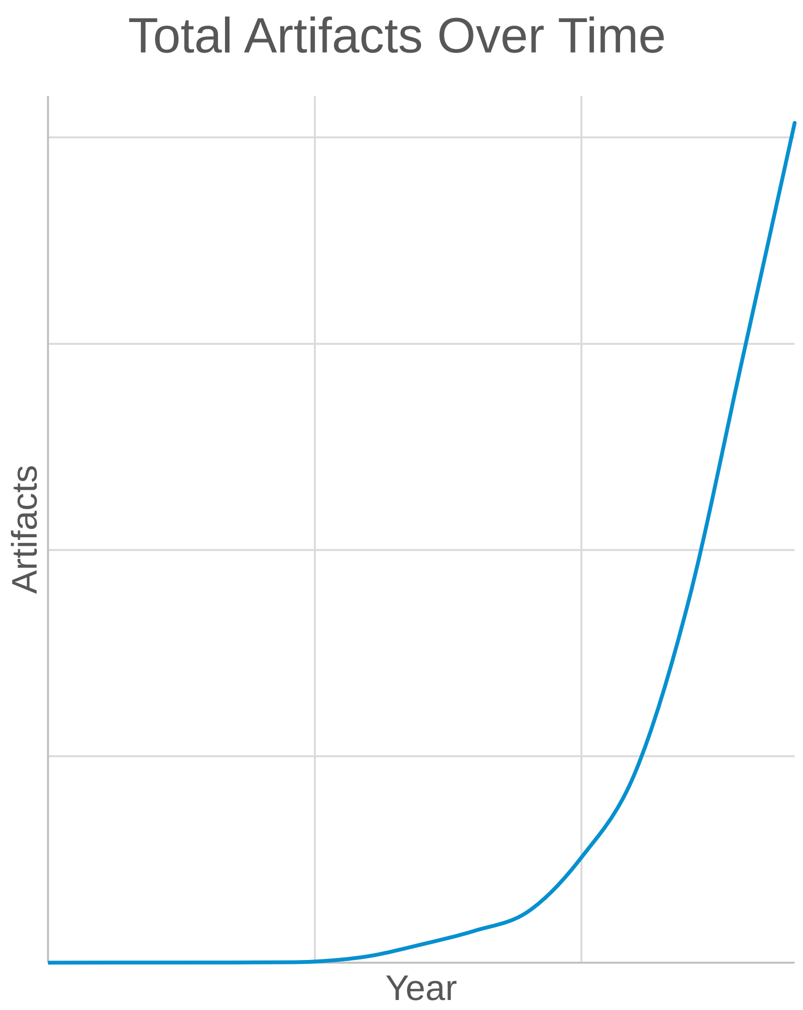
Analysts

- Flexible, adaptable
- Sensitive to context
- Ability to explain

Machine Learning

- Scalable
- High dimensional
- Precisely specified

A Motivating Problem – Malware Classification



- CERT artifact catalog is a valuable resource that depends on expert reverse engineers for labels.
- Sample growth is exponential. Staffing growth is… sub-exponential.
- One-off ML models show promise, but can we do better?
- Other potential domains
  - SOC/CSIRT Triage
  - Insider Threat

Background and goals

Learning theory progress

Experimental progress

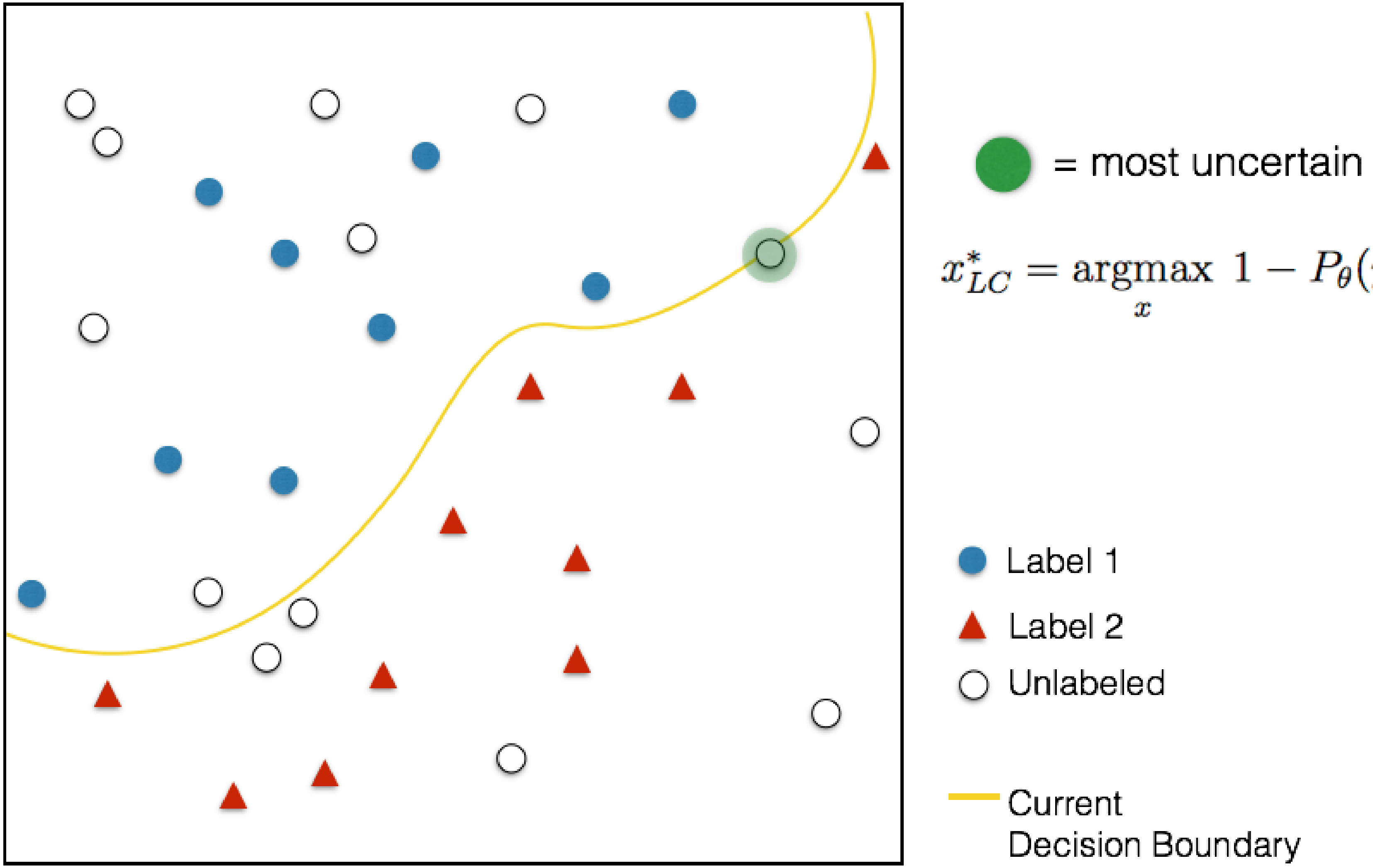
Conclusions and next steps

From Classifiers to Collaboration

Traditional machine learning: select a random sample to label for training data.

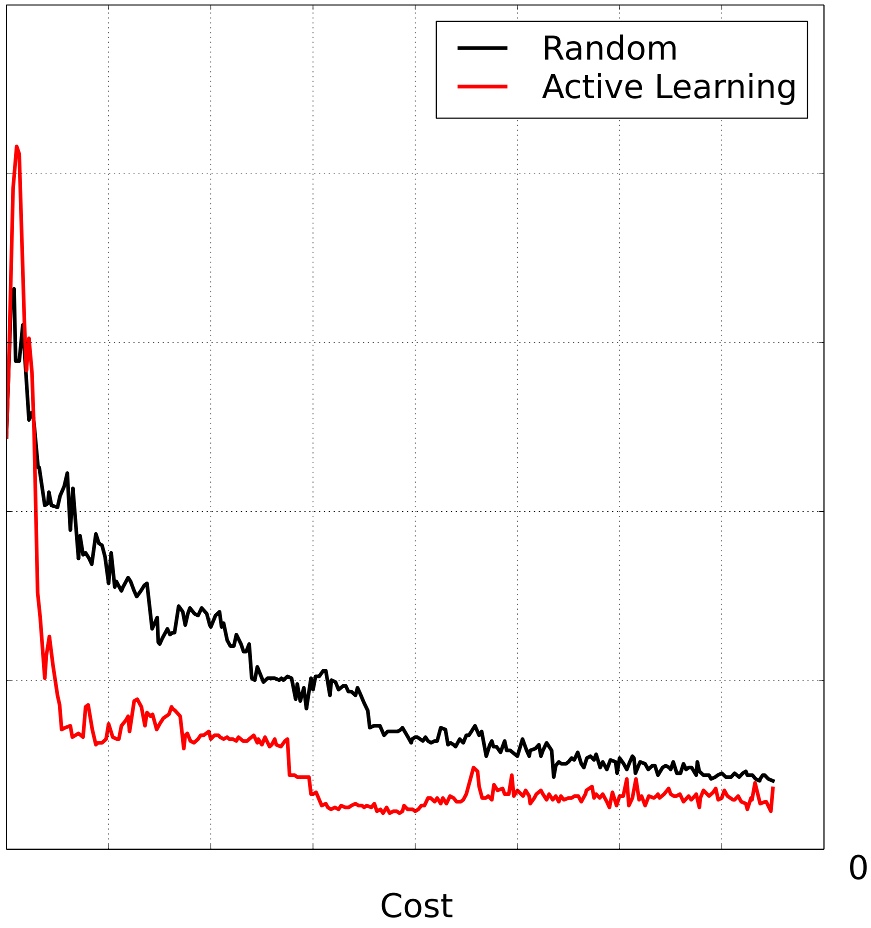
Active learning: the model estimates an ideal sequence of samples and gets labels.

Traditional Active Learning (uncertainty-based)



$$x^*_{LC} = \underset{x}{\operatorname{argmax}} \ 1 - P_\theta(\hat{y}|x)$$

Simulated Active Learning



From Classifiers to Collaboration

Traditional machine learning: select a random sample to label for training data.

Active learning: the model estimates an ideal sequence of samples and gets labels.

Proactive learning: active learning, but don't assume the labels are perfect or perfectly reliable since they come from a human, not an oracle.

Human-computer collaboration:

The human experts are a persistent team. The algorithm estimates the best instances to show to each analyst to improve the long-term performance of both the machine and human learners.

Apparatus for HCDS Research

- How is it done today? Simulations, mostly.

- Why isn't that good enough?
  - Proactive learning and human-computer decision systems model and respond to the behavior of humans annotators.
  - Simulated annotators will not have the same behavior (errors and learning patterns) as actual human experts.

- What would we need to know whether a new approach works?
  - Realistic data: Class and feature distributions that relate to a transition domain.
  - Human participants: Actual errors and learning patterns.
  - Ground truth: Because we know labelers are fallible.

What We are Doing

Track 1: Learning theory advances to account for persistent human expert teams.

Track 2: Human subjects experiments to validate improvement to system.

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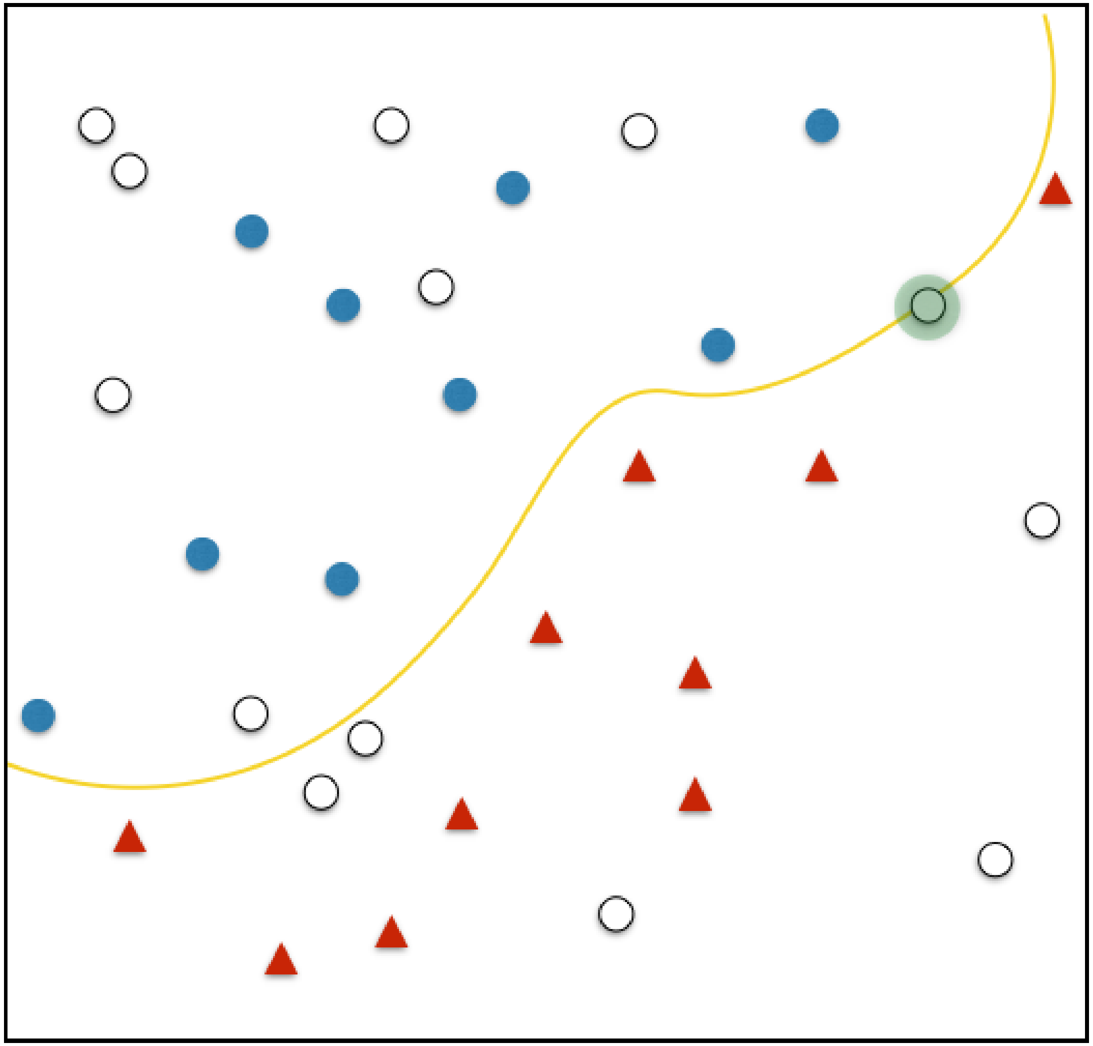


$$x^*_{LC} = \underset{x}{\operatorname{argmax}}\ 1 - P_\theta(\hat{y}|x)$$

Proactive Learning With Multiple Domain Experts

Problem Formulation (Objective)

$$\max_{S \subset UL} E[V(S)] - \lambda(\sum_k t_k \cdot C_k)$$

$$\text{s.t.} \sum_k t_k \cdot C_k \leq B, \sum_k t_k = |S|$$

S : the set of instances to be sampled

$E[V(S)]$: the expected value of information of the sampled data

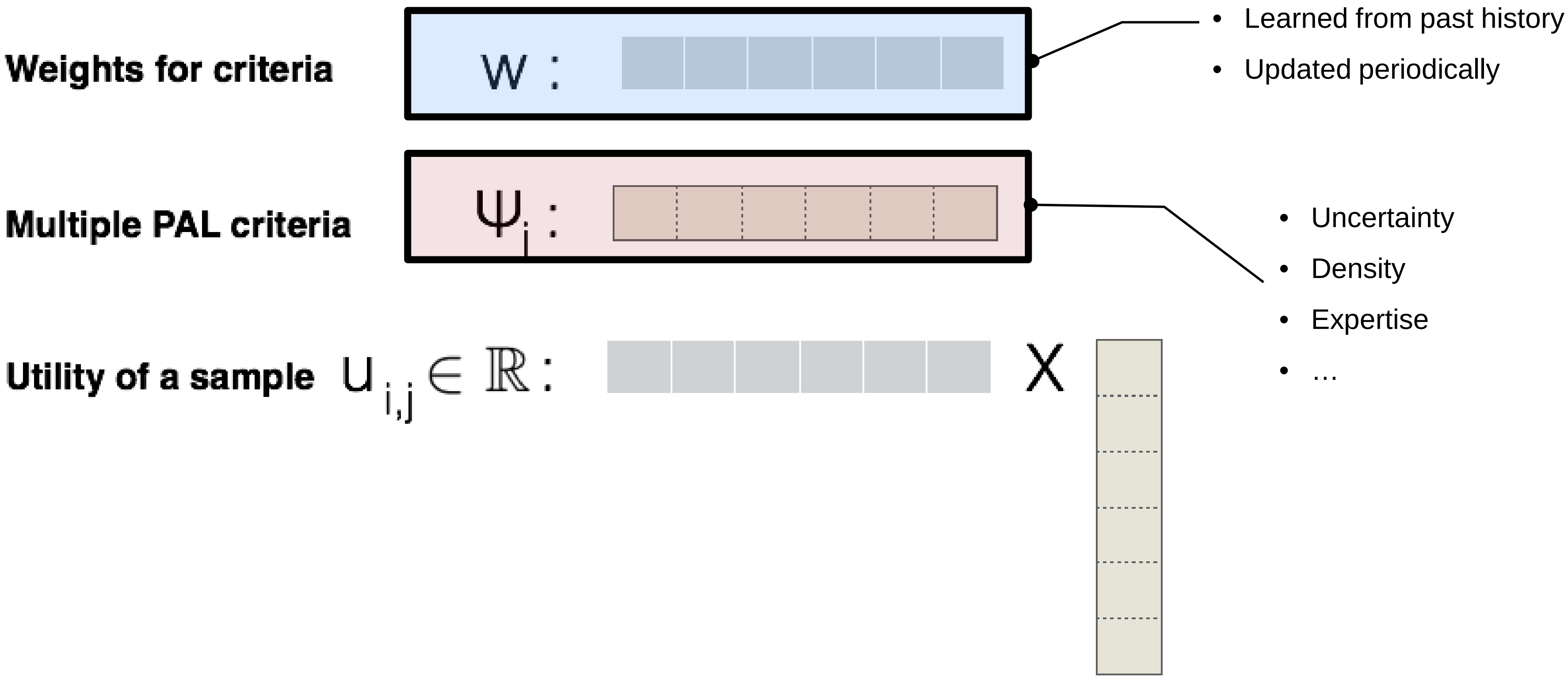
C_k : cost of the chosen expert k

Greedy Approximation

$$(x^*, k^*) = \underset{x \in UL, k \in K}{\operatorname{argmax}} U(x, k)$$

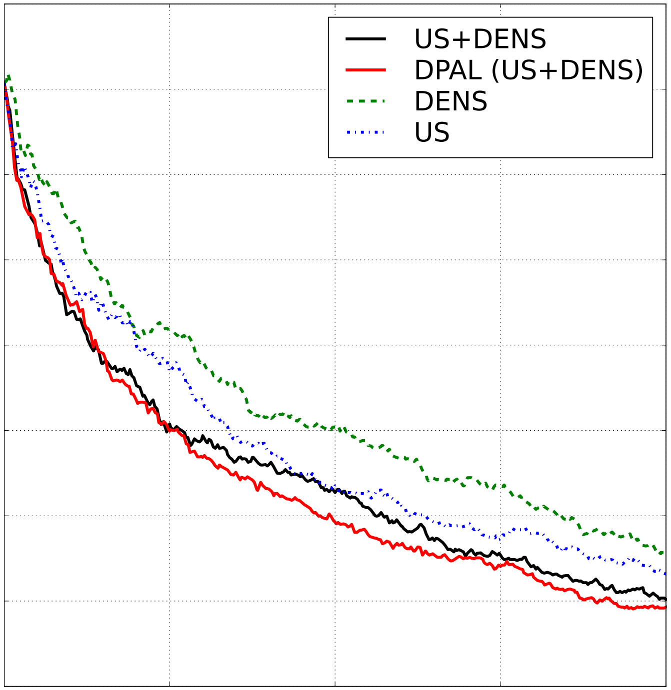
[Moon and Carbonell, 2014]

Dynamic Proactive Learning (DPAL)



DPAL is a mathematical framework to support active learning using many simultaneous criteria.

Preliminary DPAL Results



- In simulation, a simple DPAL configuration outperforms other active learning strategies.
- US = Uncertainty Sampling
- DENS = Density Sampling
- US + DENS = static weighting
- DPAL = dynamic weighting

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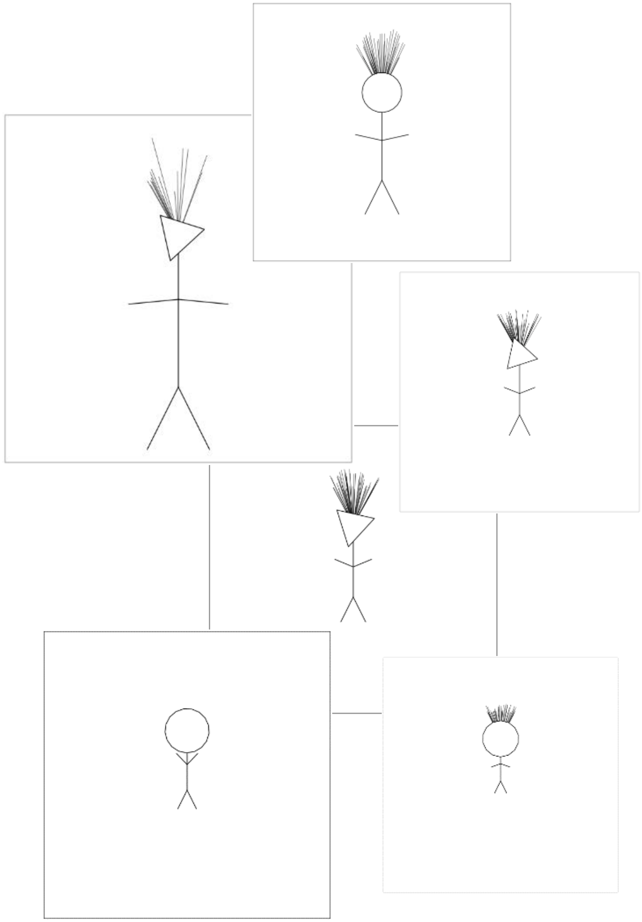
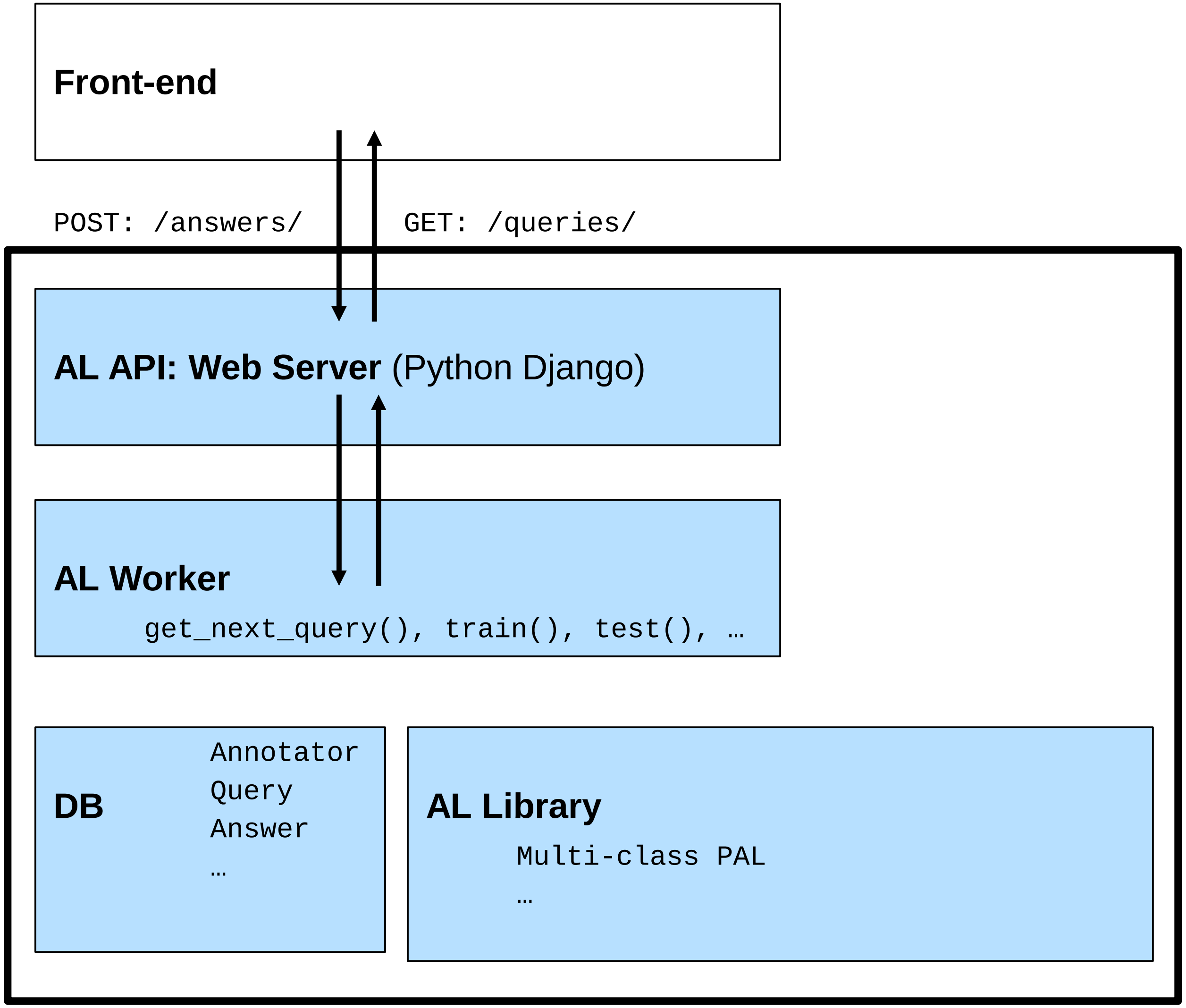
Experiments In the Wild



For research development and validation, we need a **learnable task** and **ground truth**.

To stay close to the real data, we projected the samples into a three dimensional PCA space, and mapped those dimensions onto stick figures to classify.

Proactive Learning API



→ allows for real experiments using the most advanced active learning techniques

Complete Experimentation System

Browser (from Mechanical Turk)

Exp API: Web Server (Python Django)
`GET: newsession, GET: nextstim, …`

`POST: /answers/`
`GET: /queries/`

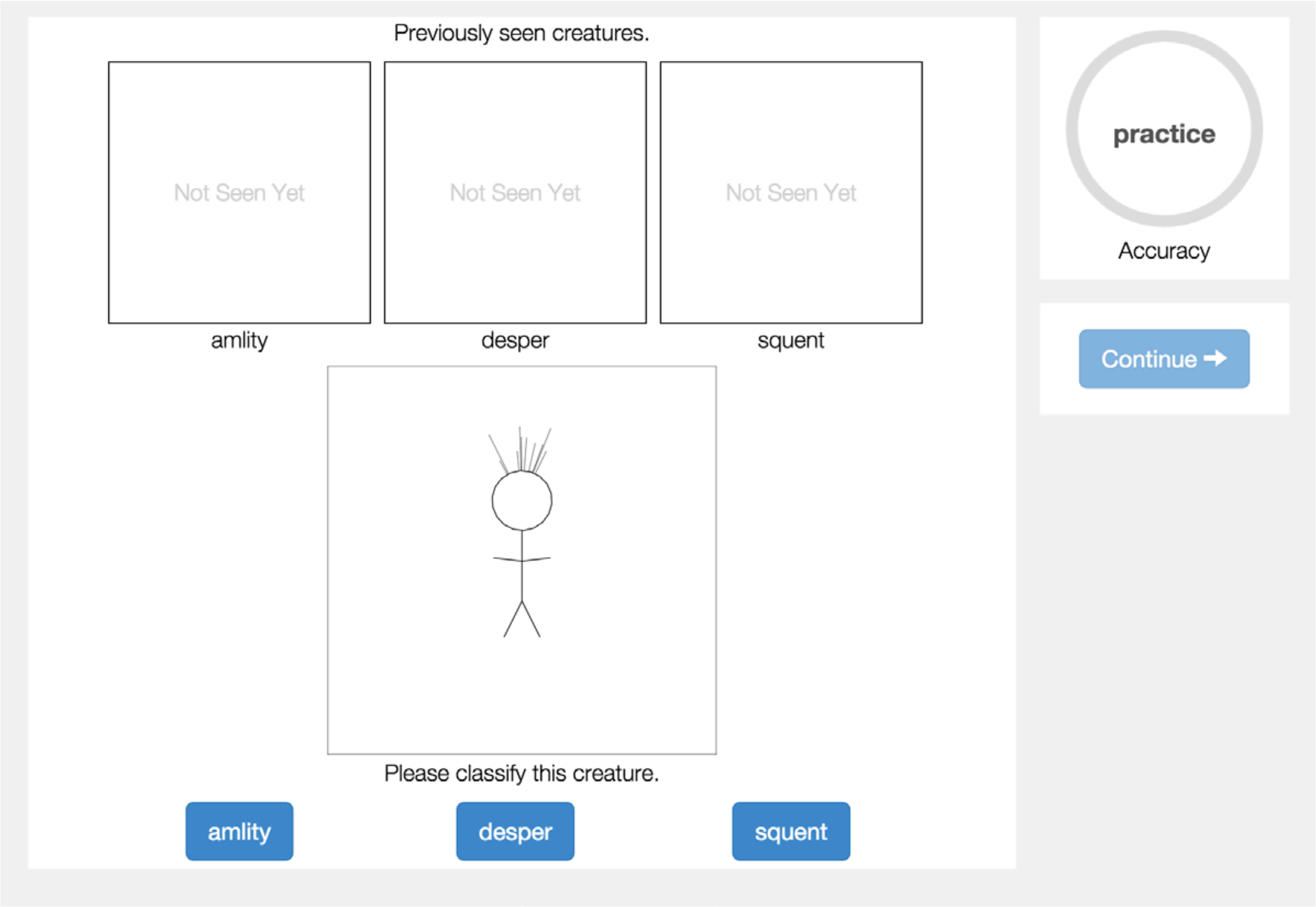
AL API: Web Server (Python Django)

AL Worker
`get_next_query(), train(), test(), …`

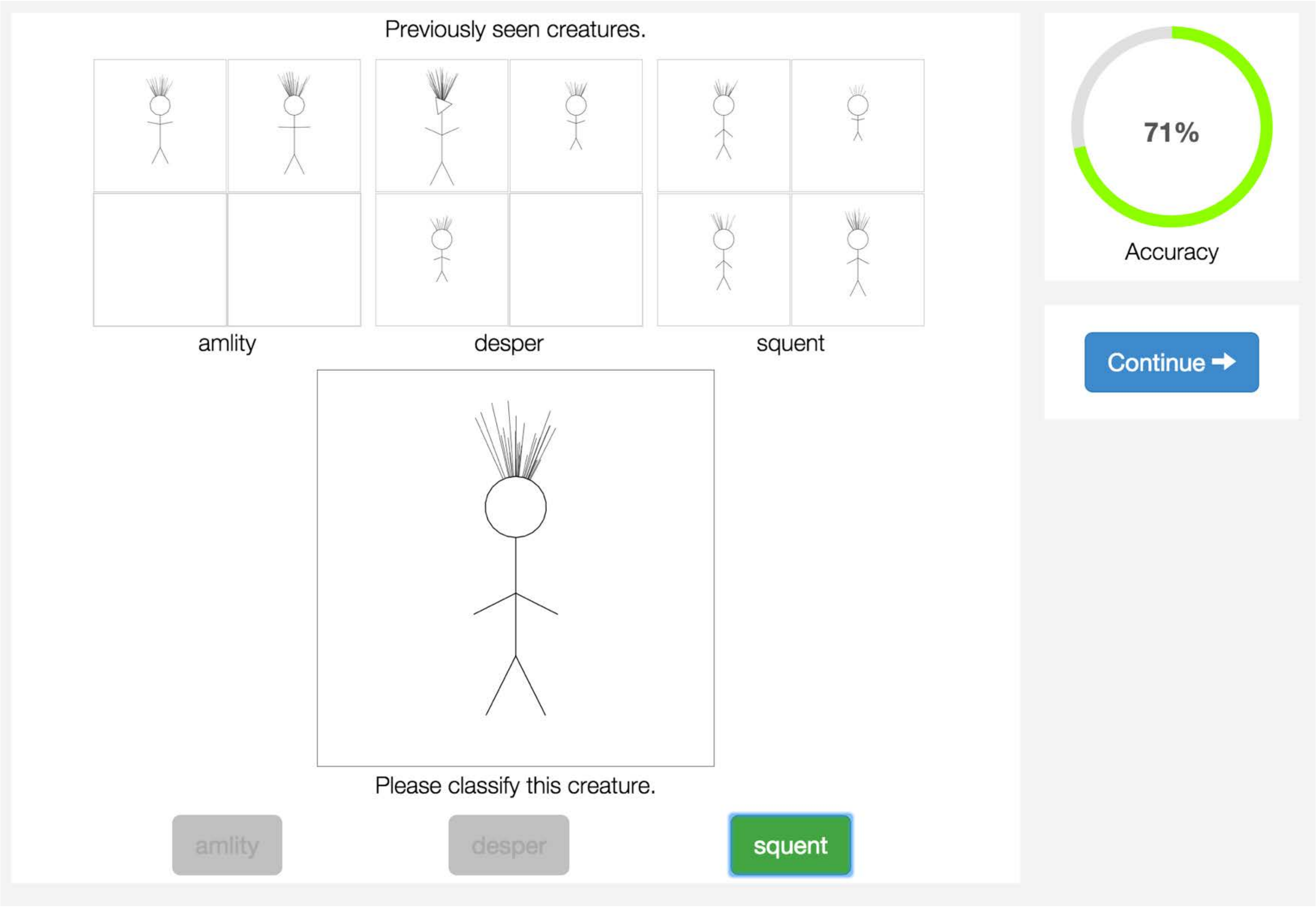
DB
`Annotator`
`Query`
`Answer`
`…`

AL Library
`Multi-class PAL`
`…`

Creature Classification on AMT



Creature Classification on AMT



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Next Steps

- Complete pilot: Is the task learnable?
- DPAL vs. baseline
- Joint optimization of analyst and classifier objectives.
- Extension of experimentation software to allow multi-session experiments and team experiments.
- …
- Test transferability of results to a target task (i.e., malware reverse engineering).

Conclusions

- Including humans makes the system more resilient against adversaries.

- When thinking of machine learning for cybersecurity problems, we should be optimizing for what we really care about – the performance the complete human-computer system.

- Experimentation *with* humans is essential in understanding the true impact of active learning advancements.

- “The ability to accurately represent fully reactionary complex human and group activity in experiments will be instrumental in creating laboratory environments that realistically represent real-world cyber operations.” – Cybersecurity Experimentation of the Future Report