Covert learning and its applications

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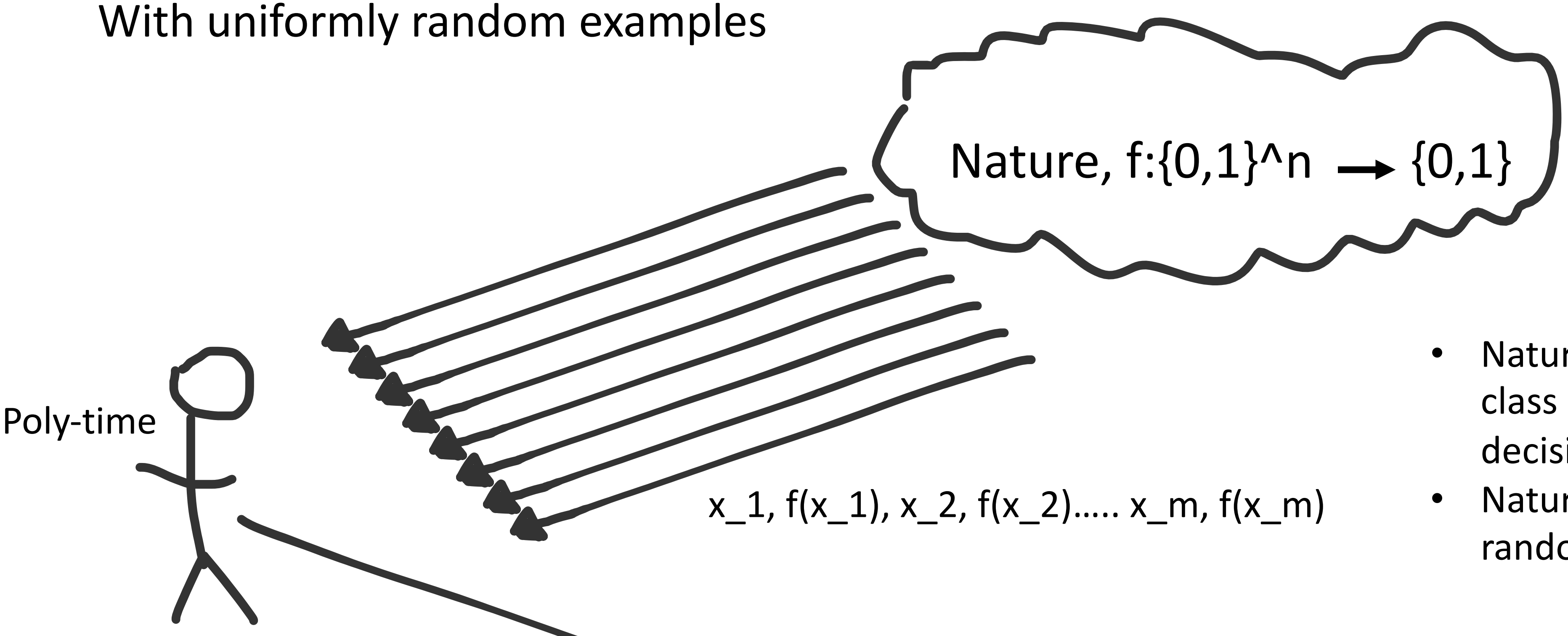
Based on https://ia.cr/2021/764 (Canetti, Karchmer TCC '21)

https://ia.cr/2022/1039 (Karchmer SATML '23)

Learning

With uniformly random examples



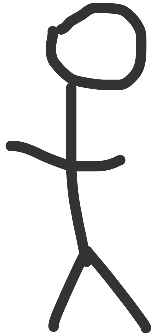
- Nature chooses f from some class C (e.g. bounded depth decision trees)
- Nature samples uniformly random points x_1 … x_m

Uniform over {0,1}^n

$$\Pr_{x}\left[f(x) \neq h(x)\right] \leq \epsilon$$

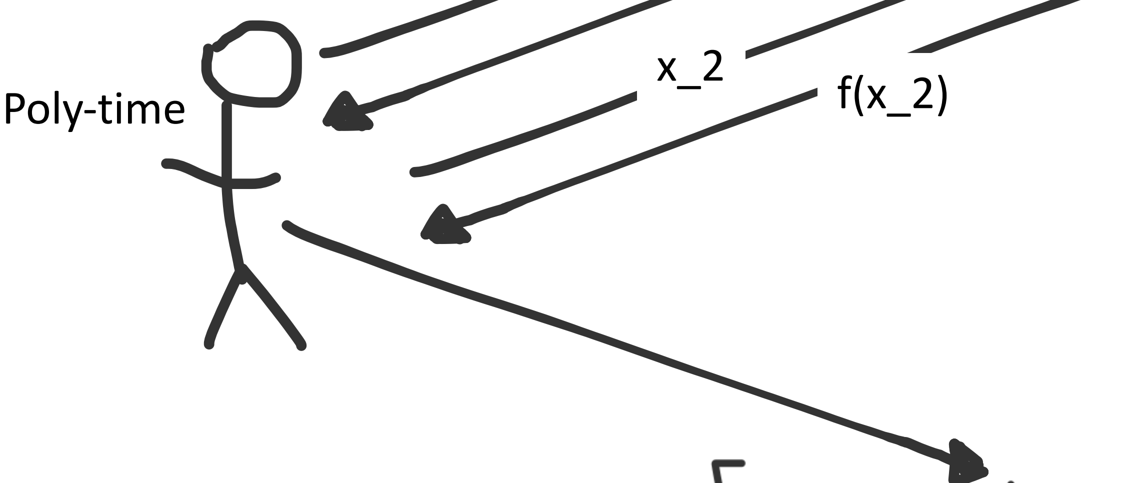
With probability 0.99 over choices of

and set of examples



Learning

With **Queries**



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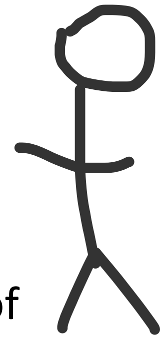
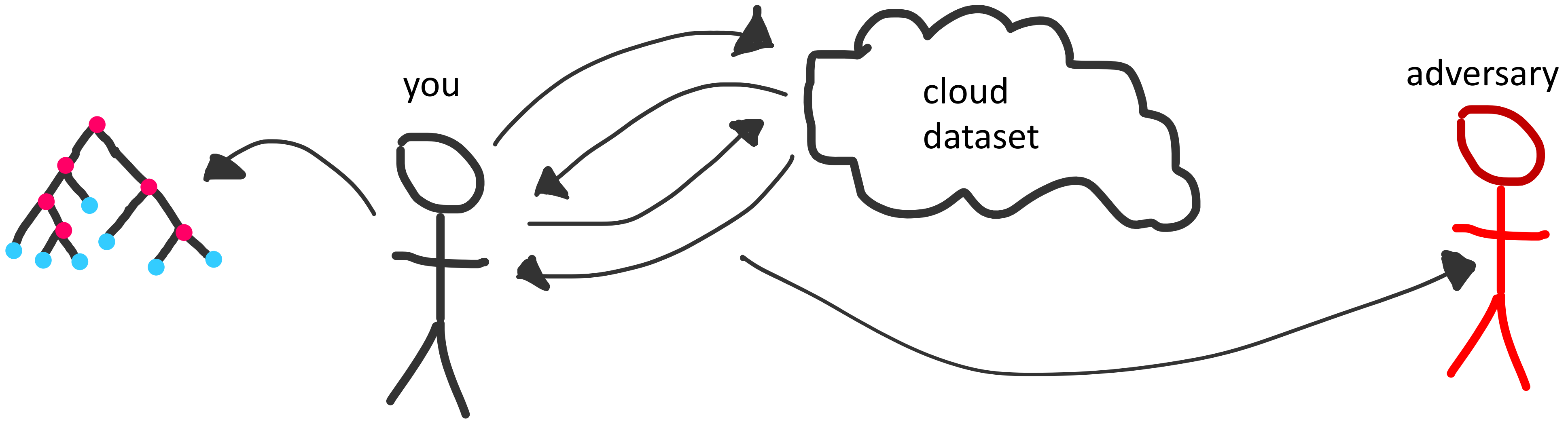


Covert learning

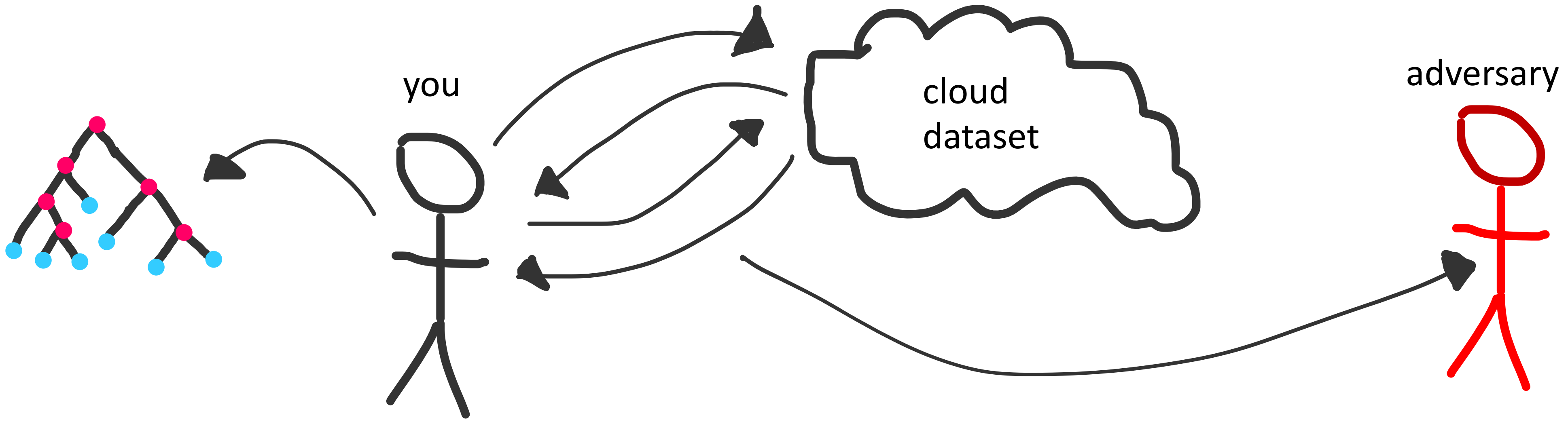
- You have query access to a dataset owned by another party
- Try to conduct some learning algorithm (or analysis, testing, etc.)
- Can you prevent anyone who views your queries -- and the answers -- from understanding what you have learned?



Covert learning

Main caveat: the party who owns data won’t help you

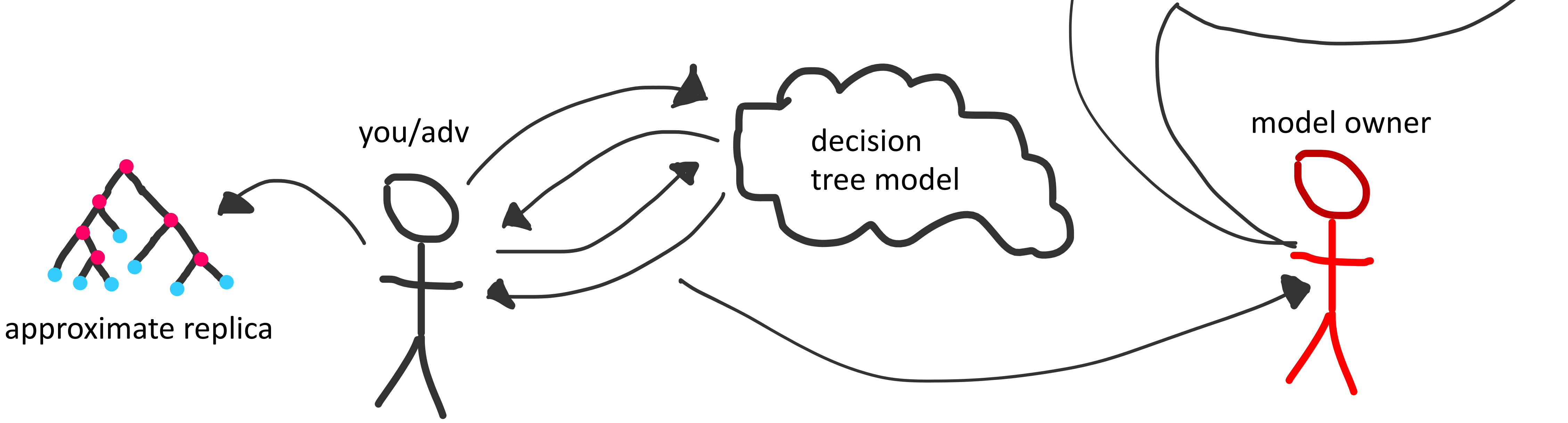
- Maybe they are the adversary, or maybe they don’t know how
- All you can do is choose your queries carefully (and have secret state)



Model extraction

In a model extraction attack, a client maliciously probes an interface to a machine learning model in order to extract the machine learning model itself.

- ✅ Model owner is "adversary's adversary," and won't help
- ✅ You're on your own to steal the model
- ✅ Model owner will try to figure out <u>if/what</u> you are learning



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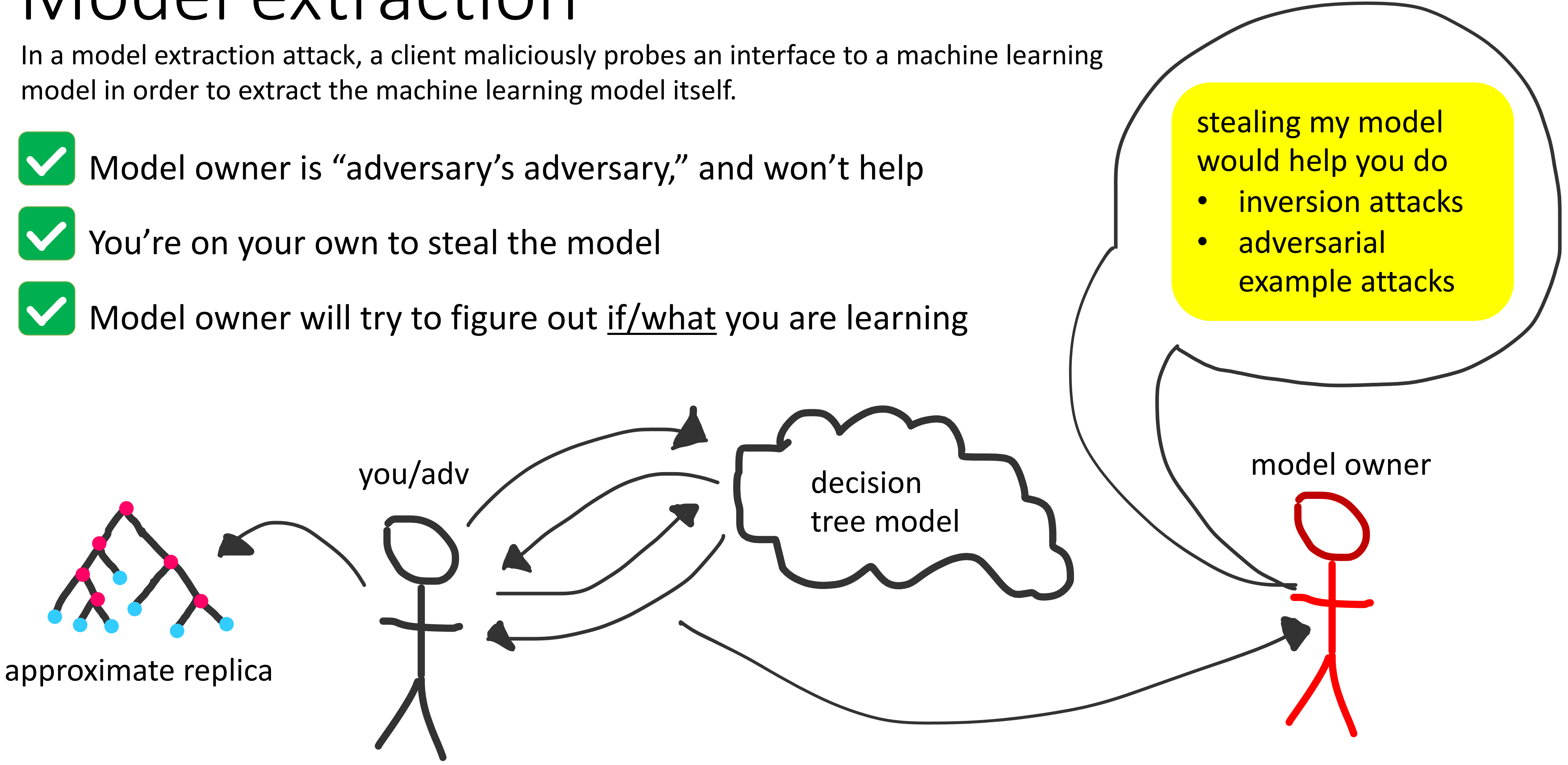


Many defenses observe

*"Security concerns give rise to a strong interest in using cryptographic techniques for protecting data in the cloud. The challenge is to <u>balance</u> **security**, **performance**, and **functionality**."*

-ESSA23 webpage

- Determine if you are adversarial or benign
  - e.g. Extraction Monitor [KMAM18], PRADA [JSMA19], VarDetect [PGKS21]

Estimate information gained by client by training proxy model based on queries. Warn model owner when information gain passes a threshold.

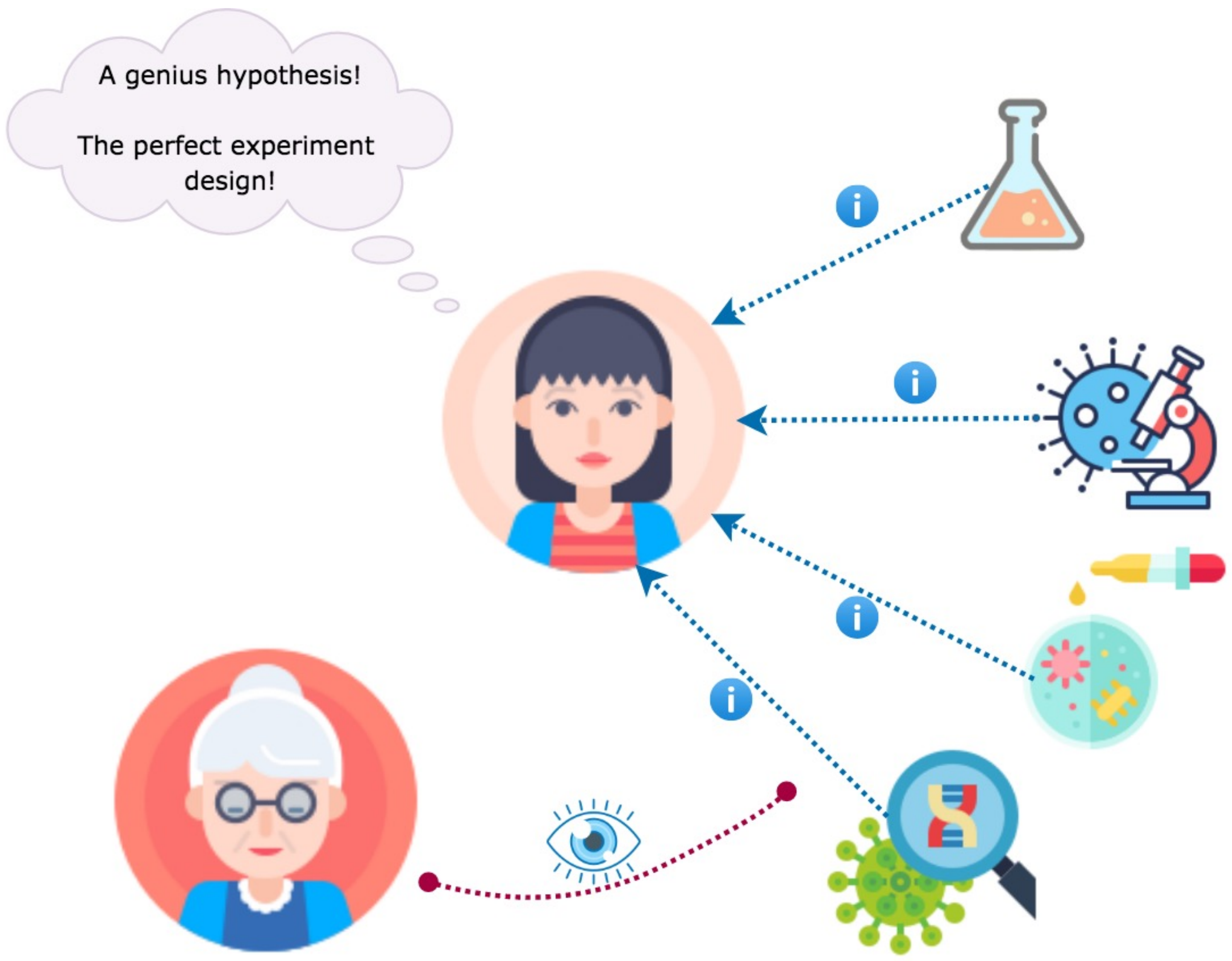
Conduct normality test on Hamming distances between queries, and rejects deviating clients. Assumes honest clients have this "benign" property.

Uses Variational Autoencoder to map "problem domain" queries and "outlier" queries to distinct regions in latent space. Classifies clients as honest or adversarial.

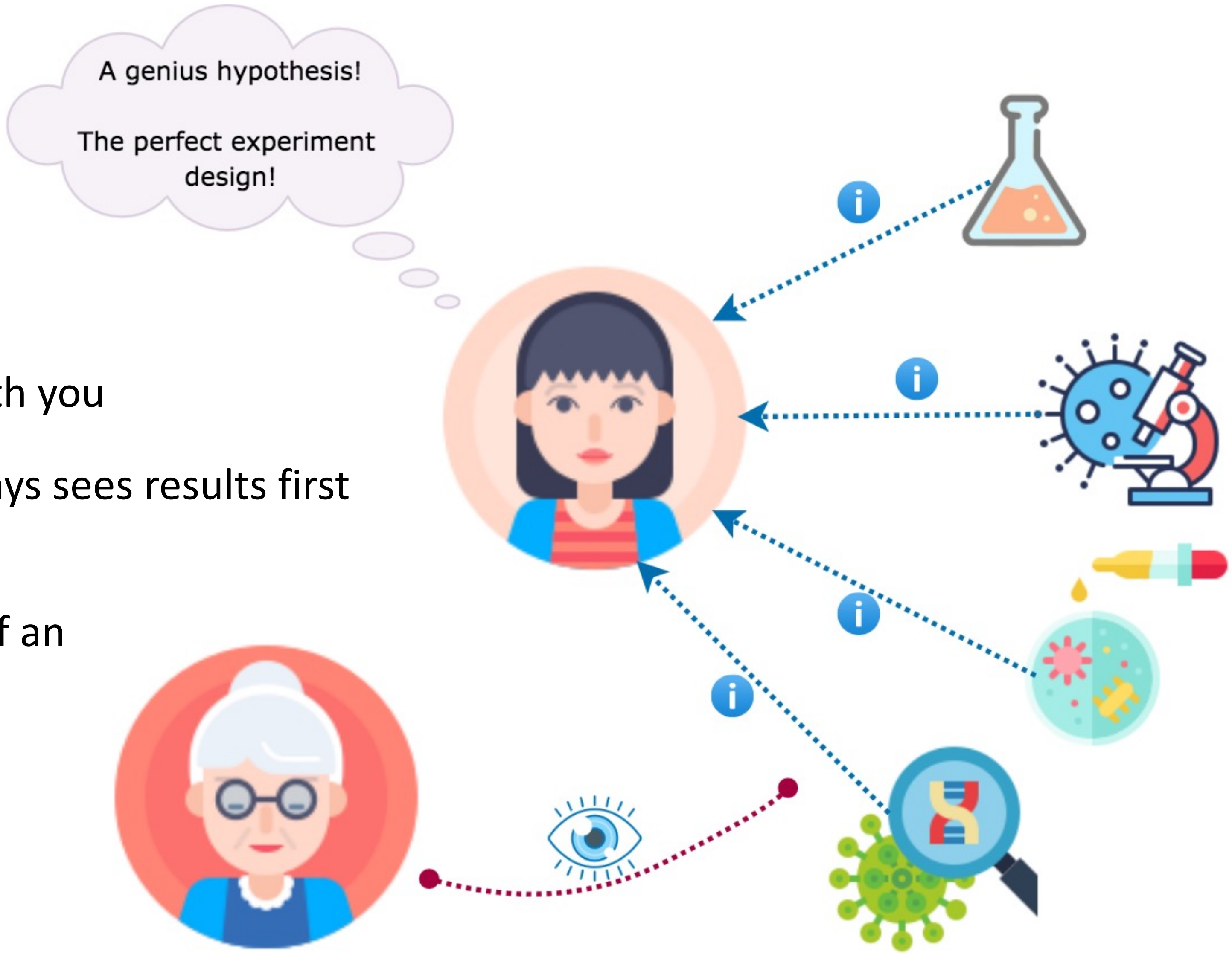
Covert learning will, in theory, defeat any poly-time defense like this [Kar23]

Quantitative Structure-Activity Research (**QSAR**)

- Can think of an experiment as a request to observe whether a reaction occurs between k of n molecules
- Want to build a model/sketch of how **Nature** determines these reactions
- E.g. drug discovery: outsource experiments to a lab



Quantitative Structure-Activity Research (**QSAR**)



- Biological data can’t run a protocol with you
- Outsourced experiments, the Lab always sees results first
- The lab could sell the results of the experiments or intellectual property of an inferred hypothesis to competitors

Covert learning goals

Learning: Alice learns a good model from her experiments

Concept-hiding: No information about the underlying molecular relationship is leaked

Hypothesis-hiding: No information about Alice's hypothesis or domain knowledge used to influence the hypothesis is leaked

Defining covert learning

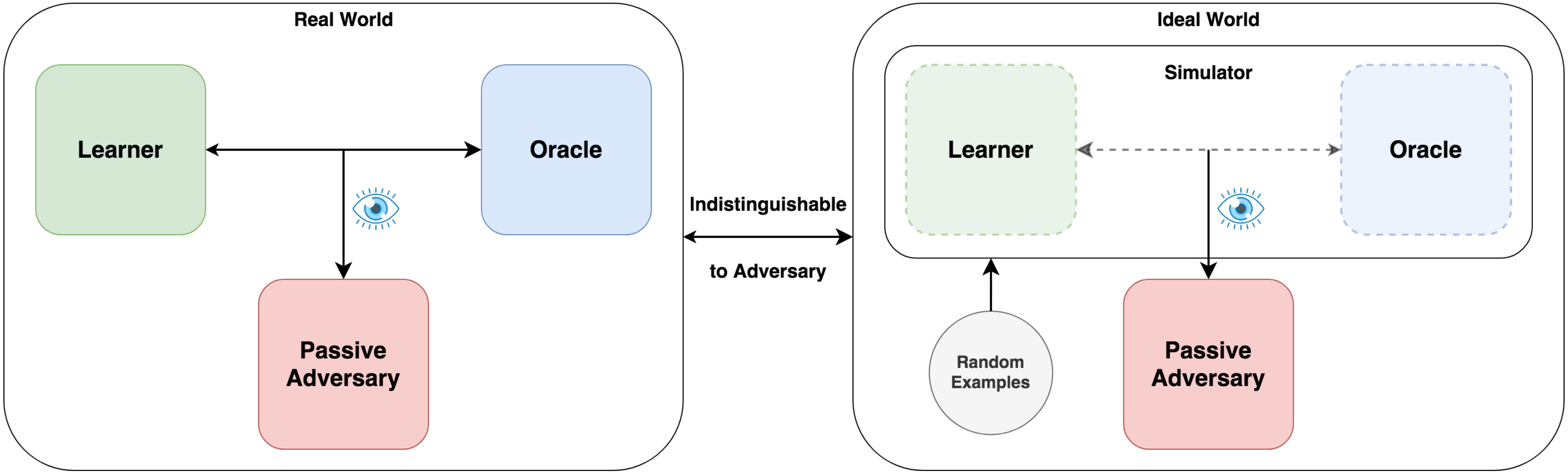
- Experiments are basically queries to “concept” f: {0,1}^n → {0,1}
- Poly-time learning is defined learning-theoretically, for class of concepts **C**

$$\Pr_{A}\left[\Pr_{x}\left[f(x) \neq h(x)\right] \leq \epsilon : h \leftarrow A^{f}\right] \geq 1-\delta$$

- Simulation-based security. Define **View(A^f)** as the random variable given by a transcript of the labelled queries performed by **A**

- Secure if there exists **SIM**(random examples) such that for every **A, f in C, SIM** is indistinguishable from **View(A^f)**

Defining covert learning



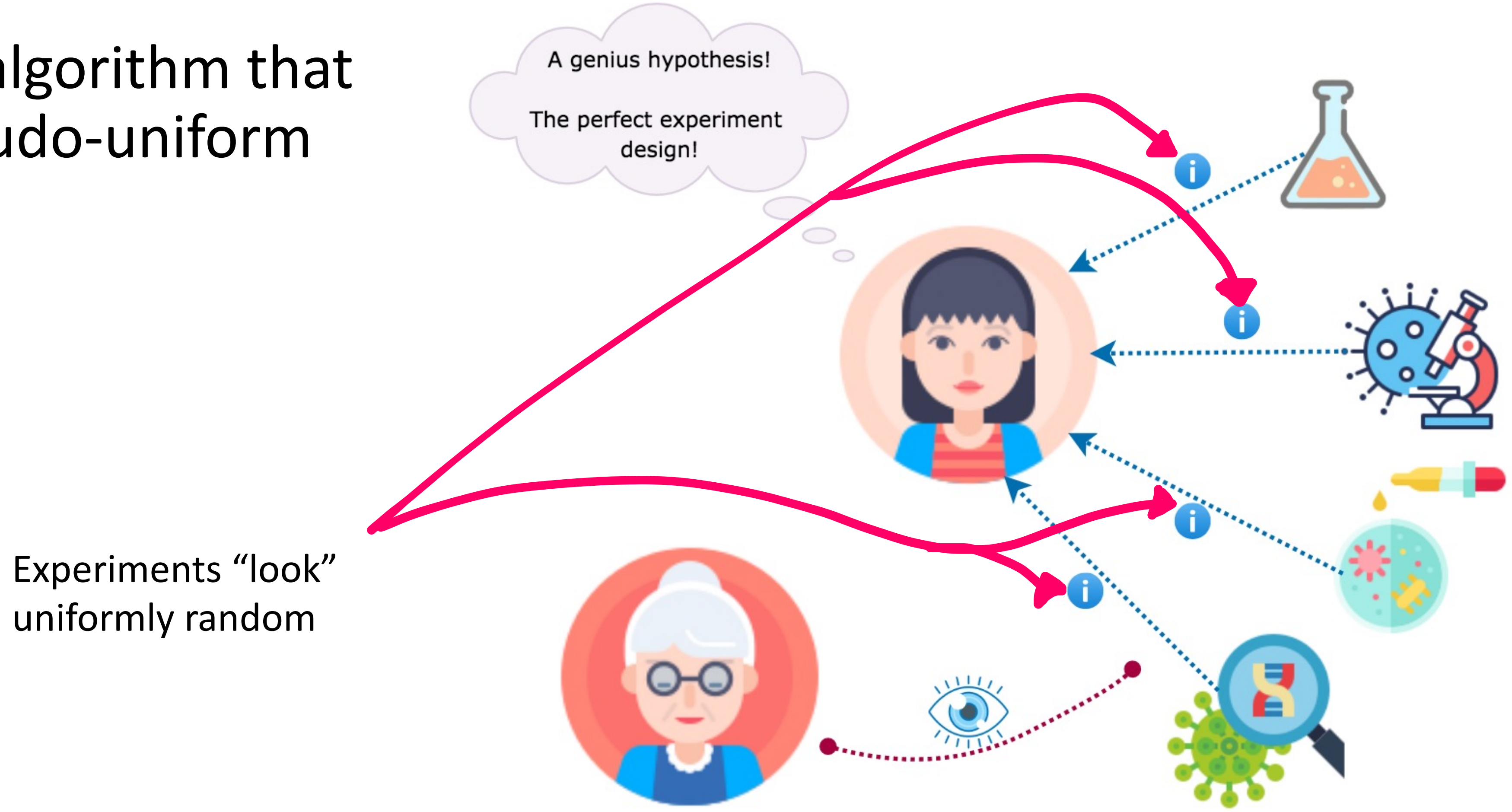
Q: How do you hide the constant function? Noiseless linear function?

A: You don't, we seek to preserve "zero-knowledge" gained over random examples to the concept. Any function that can be learned with random examples is <u>out.</u>

- Backed by learning theory: learning DT/DNF is conjectured hard (from random examples)

”Natural covert learning”

- A query algorithm that uses pseudo-uniform queries



Select covert learning positive results

work	result	setting
[CK21]	Linear functions with little noise	"Single server," computational security
[CK21]	Decision trees (agnostic)	"Single server," computational security
Implicit in [IKOS19]	O(log n)-juntas	"2-server," perfect security
[JH23]	Fourier-sparse functions (agnostic)	"k-server," perfect security

All these in "natural" setting of pseudo-uniform queries. Limited results outside this, great **Open Problems**!

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Very simple, will describe now

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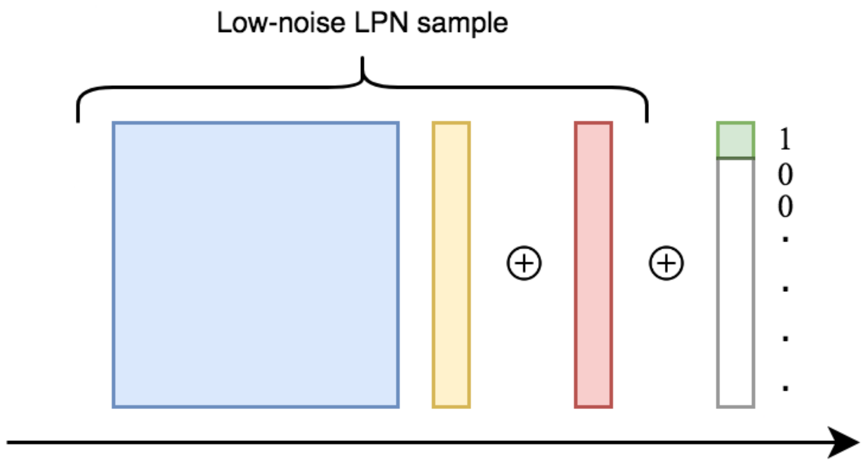
Covert learning for noisy parities

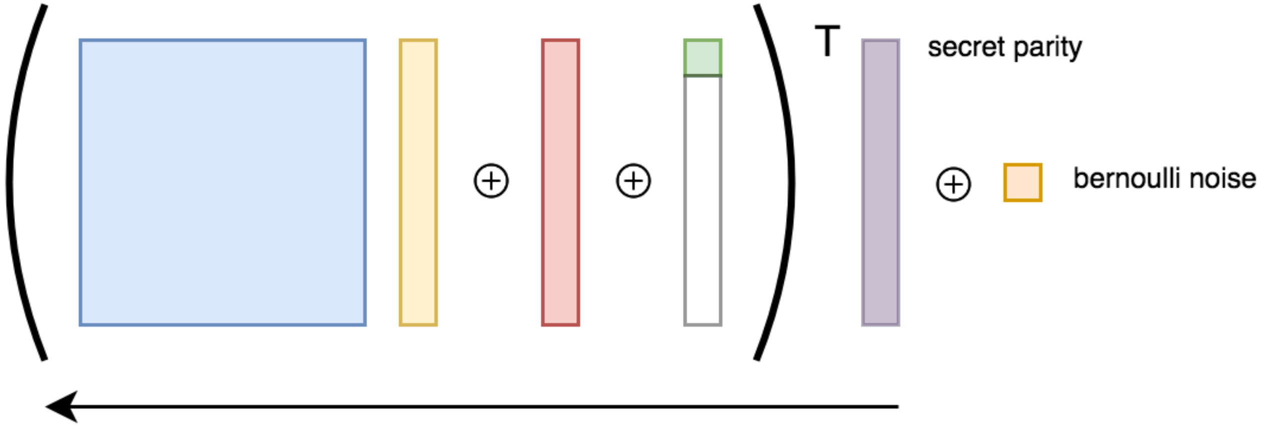
Low-noise LPN

- Low-noise LPN distribution [Ale03]:
  - Sample $s \in \{0,1\}^n, e \in \{0,1\}$ from Bernoulli r.v. with mean $1/\sqrt{n}$
  - Sample $a \in \{0,1\}^n$ uniformly at random
  - Return $a, \langle a, s \rangle \oplus e$ (s is persistent over each example)
- **Search LPN:** find s.
- **Decision LPN:** distinguish $a, \langle a, s \rangle \oplus e$ from uniformly random. Both are thought to be subexponentially-hard
- Is there a covert learning algorithm for learning s?
- Can learn it trivially with queries (exercise left to listeners)

Covert learning for noisy parities



“Masked queries”



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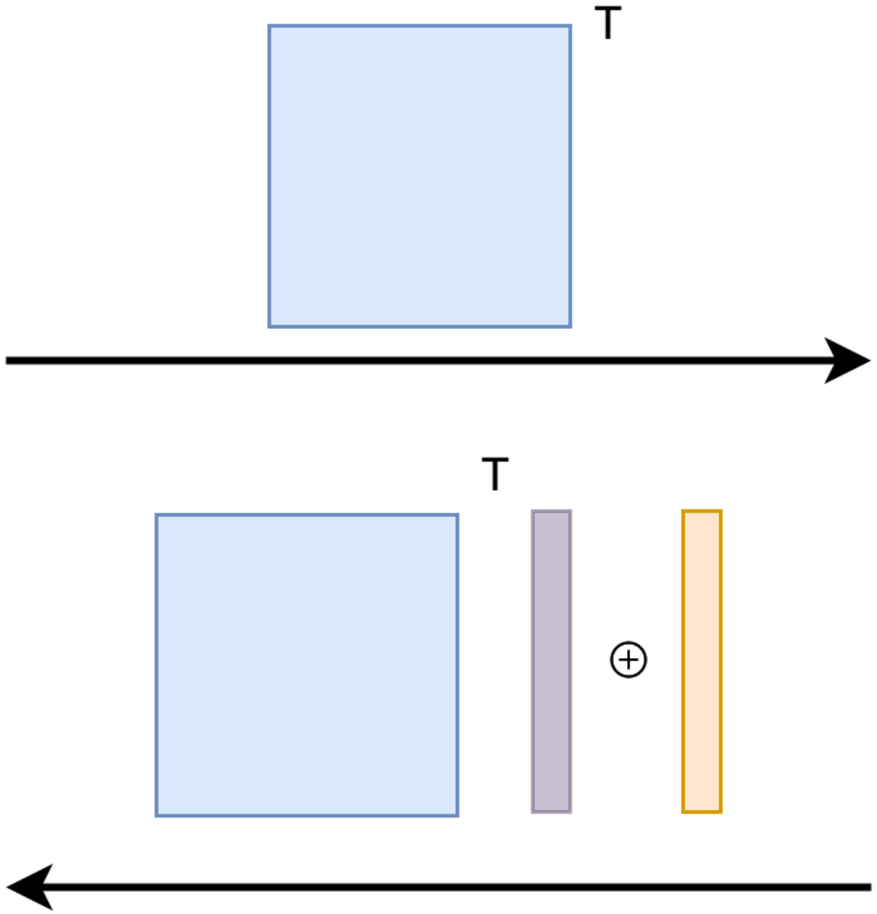

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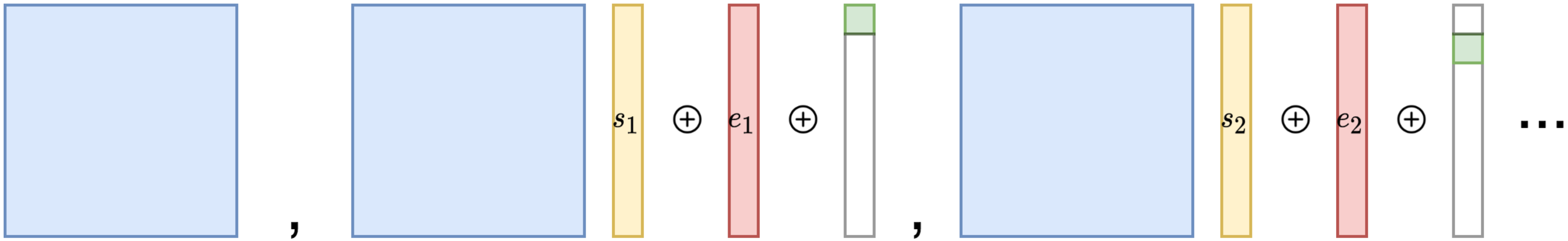


$\approx$

$2n$

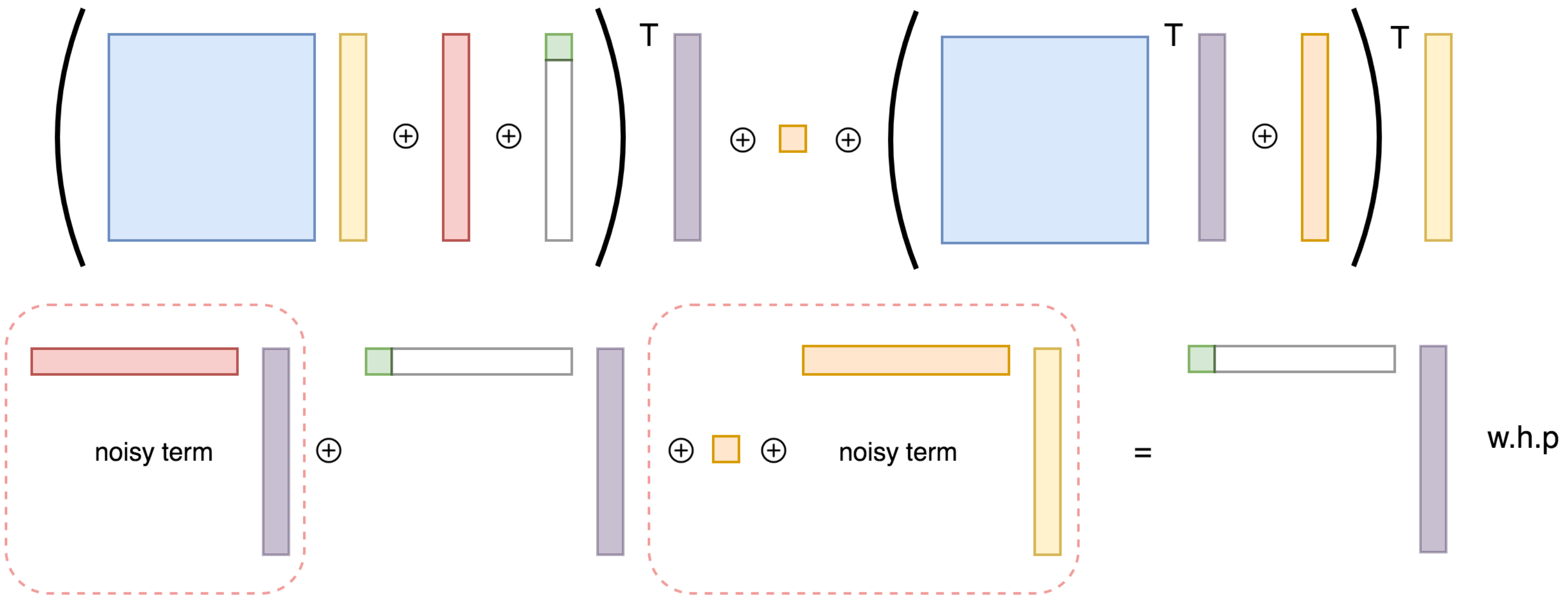
pseudorandom queries

Covert learning for noisy parities

For $\mu \in [0,1/2]$, and random variables $E_1 \cdots E_m$ that are i.i.d. from Bernoulli r.v. with mean μ, we have that

$$Pr[\bigoplus_{i=1}^{m} E_i = 0] = \frac{1}{2} + \frac{1}{2}(1-2\mu)^m$$

Decoding procedure:



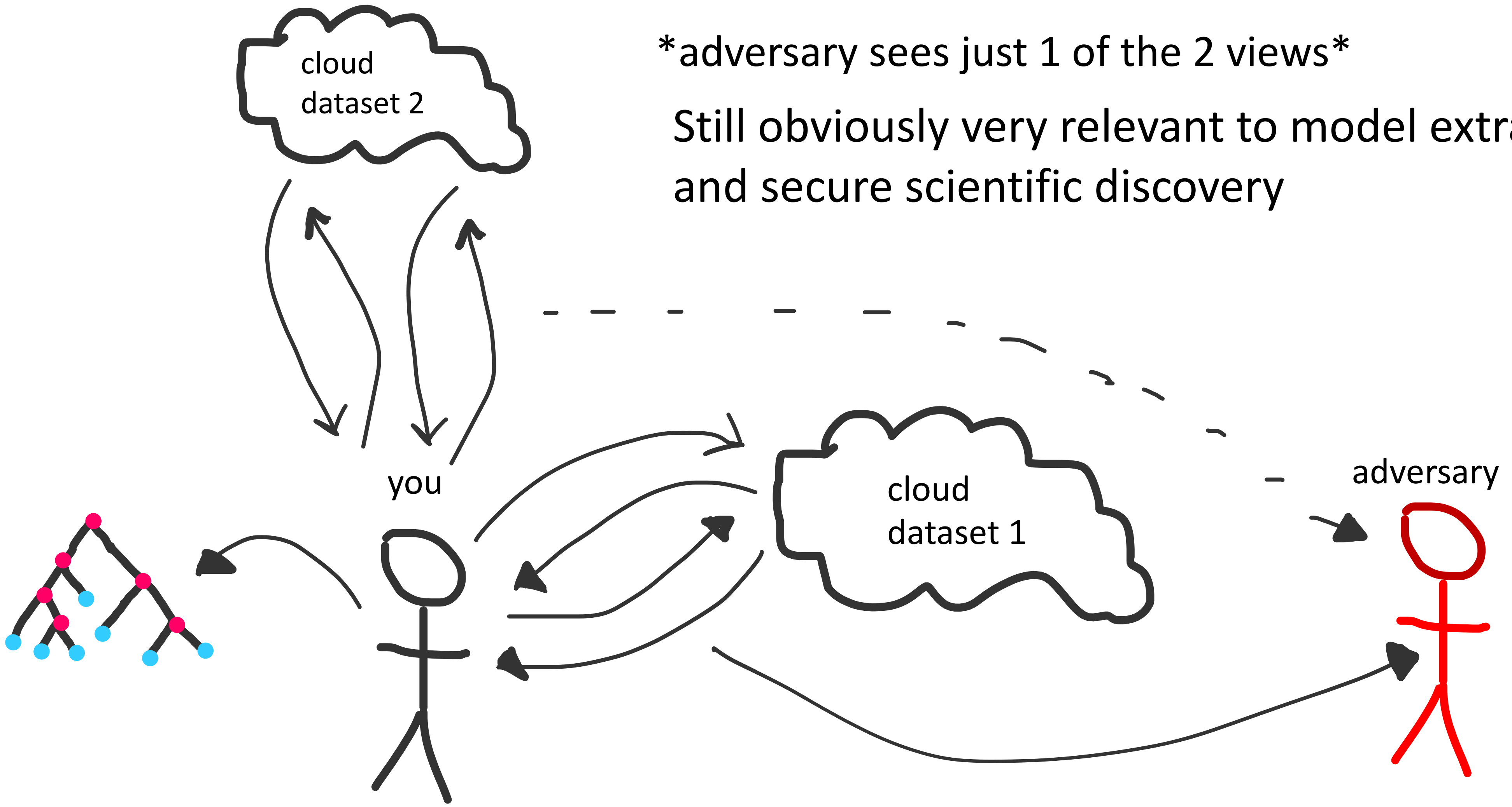
Noisy terms are biased to 0 w.p. $\frac{1}{2} + \Omega(1)$

Repetition and majority voting to decode bit-by-bit

"Multi-server" covert learning

adversary sees just 1 of the 2 views

Still obviously very relevant to model extraction and secure scientific discovery

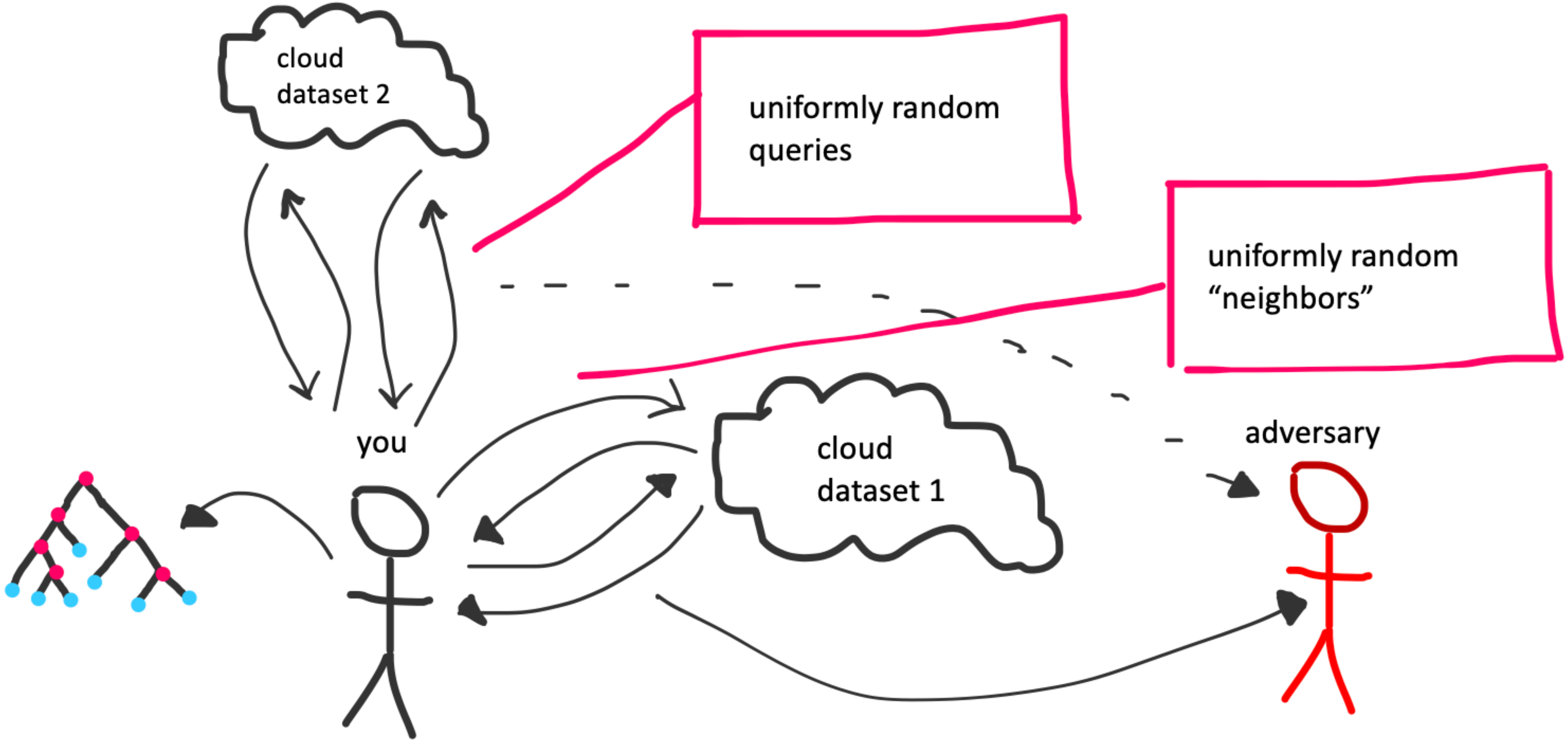


k-Juntas

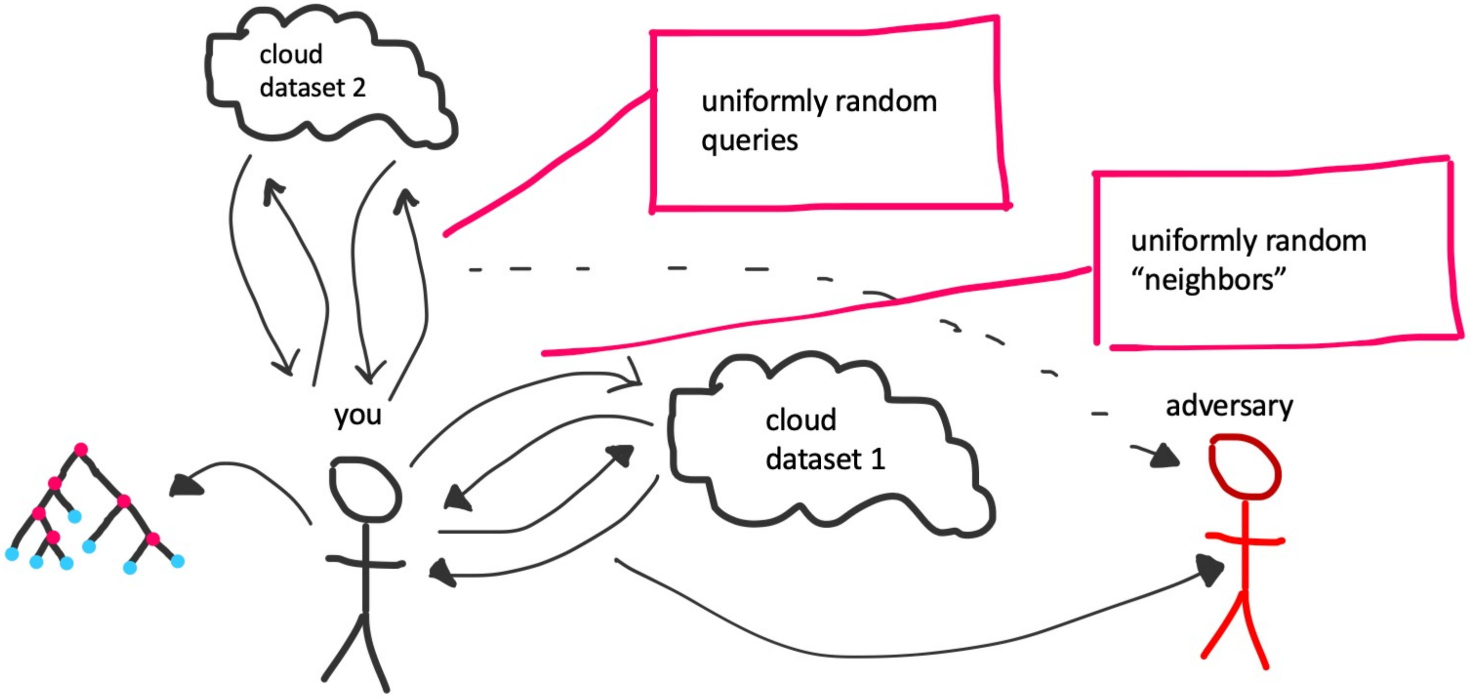
- An input variable x_i of a function f:{0,1}^n $\rightarrow$ {0,1} is <u>irrelevant</u> if for any input x, f(x) = f(y) where y = x except at x_i
- A k-junta has at least n-k irrelevant variables
- Learning O(log n)-juntas with uniform examples is conjectured to require super-polynomial time (best algorithms only slightly better than brute force)
- Easy with queries (exercise)

2-oracle covert learning for juntas

- Implicit in [IKOS19] that studies distributed "cryptographic sensing"
- Motivated by bio data



2-server covert learning for juntas



- Use neighbor queries to find all variables that are relevant to the function
- Once we know these variables, use more random examples to build truth table of all 2^k settings of the variables ✅

Works in polynomial time for k = O(log n)

Open questions

- Make known covert learning algorithms practical! Our model may be much stronger than necessary for practical applications
- Study ”covert property testing” learning is in general stronger than testing so we could possible expect more here
- Is there a general compiler for any learning algorithm that makes it covert? My guess is no, give counter example?

- Grazie