Label Aggregation: Belief Propagation and Others

Chien-Ju (CJ) Ho

Label Aggregation

- Goal:
    - Given a set of labels from a set of workers to tasks
    - Infer the true label of each task

!amt_annotation_ids	!amt_worker_ids	orig_id	response	gold
89KZPYXSTGTJ0CZY2Y1ZB28YQ9GBT88Z2W1KDYTZ	A19IBSKBTABMR3	266	1	1
89KZPYXSTGTJ0CZY2Y1ZYAJC56Z6FBPGXJYVPXM0	AEX5NCH03LWSG	266	1	1
89KZPYXSTGTJ0CZY2Y1ZFWHATWX49Y3ZTPX4FYH0	A17RPF5ZMO75GW	266	1	1
89KZPYXSTGTJ0CZY2Y1ZV89Z3WRZ6R8ZM4ZZZ070	A15L6WGIK3VU7N	266	0	1
89KZPYXSTGTJ0CZY2Y1ZWZHZYZCCYYVYPDZVNRAZ	A3U7T47F498T1P	266	1	1
89KZPYXSTGTJ0CZY2Y1Z09PZYS137RPZT6SY4A20	AXBQF8RALCIGV	266	1	1
89KZPYXSTGTJ0CZY2Y1ZQ30CJXY2EB96XJS543YZ	A1DCEOFAUIDY58	266	1	1
89KZPYXSTGTJ0CZY2Y1ZXZ3ZNYY7VZKZSCY0B94Z	A1Q4VUJBMY78YR	266	0	1
89KZPYXSTGTJ0CZY2Y1ZDZGGWVYY8XDZTKYC9XKZ	A18941IO2ZZWW6	266	1	1
89KZPYXSTGTJ0CZY2Y1Z3Z7ZWY9J4WFMX60VRVXZ	A11GX90QFWDLMM	266	1	1
89KZPYXSTGTJ0CZY2Y1ZB28YQ9GBT88Z2W1KDYTZ	A19IBSKBTABMR3	934	0	0
89KZPYXSTGTJ0CZY2Y1ZYAJC56Z6FBPGXJYVPXM0	AEX5NCH03LWSG	934	0	0
89KZPYXSTGTJ0CZY2Y1ZFWHATWX49Y3ZTPX4FYH0	A17RPF5ZMO75GW	934	0	0
89KZPYXSTGTJ0CZY2Y1ZV89Z3WRZ6R8ZM4ZZZ070	A15L6WGIK3VU7N	934	0	0
89KZPYXSTGTJ0CZY2Y1ZWZHZYZCCYYVYPDZVNRAZ	A3U7T47F498T1P	934	0	0
89KZPYXSTGTJ0CZY2Y1Z09PZYS137RPZT6SY4A20	AXBQF8RALCIGV	934	1	0
89KZPYXSTGTJ0CZY2Y1ZQ30CJXY2EB96XJS543YZ	A1DCEOFAUIDY58	934	0	0
89KZPYXSTGTJ0CZY2Y1ZXZ3ZNYY7VZKZSCY0B94Z	A1Q4VUJBMY78YR	934	0	0

What We Learned So Far

- EM-based methods
  - Empirically performs well
  - Relatively computationally efficient
  - No theoretical guarantee

- Matrix-based methods
  - Comes with theoretical guarantee
  - Computationally expensive
  - Require some “potentially unreasonable” assumptions for the analysis

This Lecture

- More label aggregation methods
  - Iterative message passing
  - Variational inference
  - Minimax entropy
- Discussion on common assumptions and limitations
- Examples on human-in-the-loop learning

Iterative Learning for Reliable Crowdsourcing Systems

Karger, Oh, and Shah. NIPS 2011.

Iterative Message Passing

- One of the more well-cited papers in label aggregation
  - One of the early non-EM-based papers
  - The algorithm is very simple and intuitive
  - Solid theoretical guarantees
  - One of the first to formally address the task assignment question

Setting (Basically the same as the paper in our previous lecture)

- Basic components
  - m tasks $i = 1, \dots, m$
  - n workers $j = 1, \dots, n$
  - $A_{i,j} \in \{+1, -1\}$: label provided by worker j to task i

- Label generation process
  - Each task i has a true label $s_i \in \{+1, -1\}$
  - Each worker j gives correct label with probability p_j

$$\mathbf{A}_{ij} = \begin{cases} s_i & \text{with probability } p_j \,, \\ -s_i & \text{with probability } 1 - p_j \,, \end{cases}$$

Essentially
- Homogeneous tasks
- Unknow worker skills

Key Idea of the Proposed Algorithm

	Task 1	Task 2	Task 3	Task 4	…
Worker 1	1	-1	1	1	
Worker 2	1	-1	-1	-1	
Worker 3	-1	1	-1	1	
Worker 4	1	-1	1	1	
…					

Labels are in $\{1, -1\}$

One-min short discussion:

What do you think is the most likely label for task 3? Why?

(We can apply SVD, but can you come up with more intuitive methods?)

Iterative Updates

	Task 1	Task 2	Task 3	Task 4	…	skill estimates	
Worker 1	1	-1	1	1		0.875	1
Worker 2	1	-1	-1	-1		0.625	0.5
Worker 3	-1	1	-1	1		0.375	0.25
Worker 4	1	-1	1	1		0.875	1
…							
label estimates	1	-1	?	1			
	1	-1	1	1			

Note:
The algorithm in the paper shares similar ideas but is not exactly the same.

Unlikely to Have a Complete Matrix

- In the previous lecture
  - Assume each rater i has a probability p_i to rate a contribution

$$u_{ti} = \begin{cases} q_t & \text{w.p. } p_i\psi_i \\ -q_t & \text{w.p. } p_i(1-\psi_i) \\ 0 & \text{w.p. } 1-p_i. \end{cases}$$

Not an ideal model.
However, it makes the analysis tractable.

- In this work, assume the requester can ***assign tasks*** to workers
  - Want to achieve similar property above (in a more deterministic way)

Task Allocation via Regular Graph

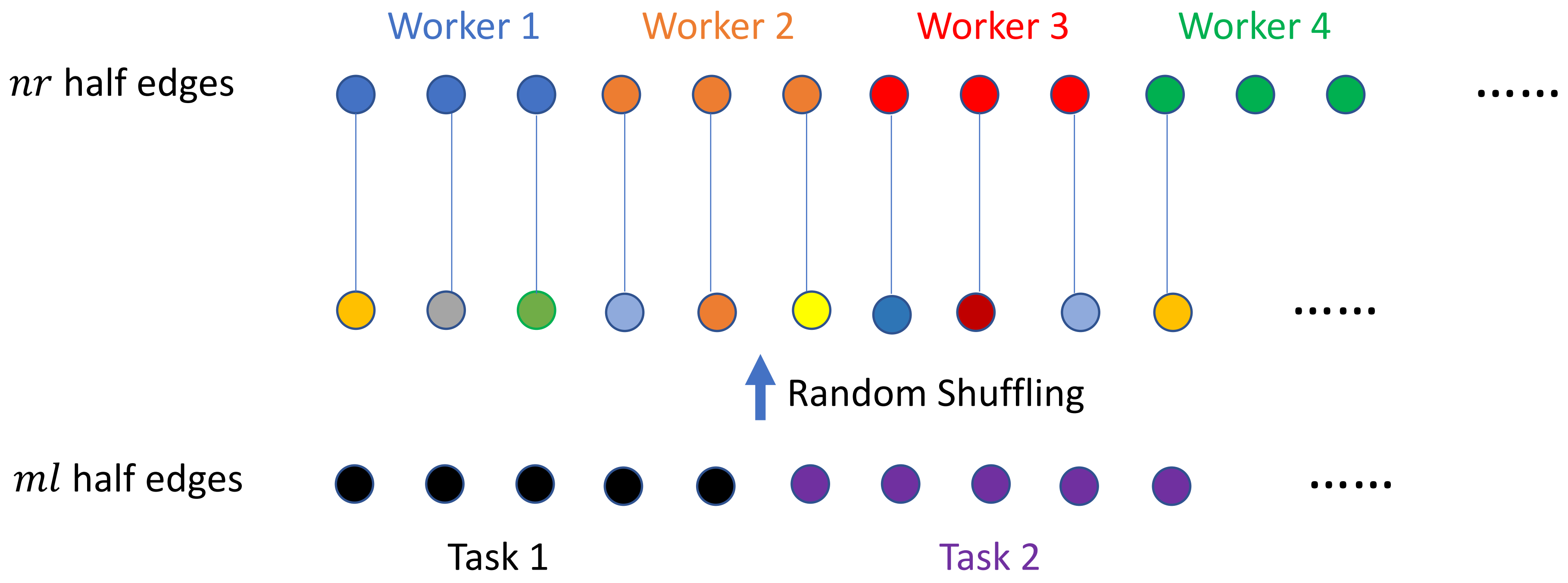
- Requirements:
  - m tasks; n workers
  - Each worker is assigned r tasks
  - Each task is assigned to l workers
  - $ml = nr$

- Assume $m \gg r$ and $n \gg l$

- Goal: Try to make the allocation as "uniform" as possible

(l, r)-Regular Bipartite Graph

- An informal description
  - Each worker is assigned $r = 3$ tasks
  - Each task is assigned to $l = 5$ workers



Inference via Iterative Message Passing

- Notations
  - Task message at round k: $x_{i \to j}^{(k)}$
  - Worker message at round k: $y_{j \to i}^{(k)}$
- Algorithm:
  - Randomly initialize worker message from a normal distribution
  - For $k = 1$ to k_{max}

$$x_{i\to j}^{(k)} = \sum_{j' \in \partial i \backslash j} A_{ij'} y_{j' \to i}^{(k-1)},$$

$$y_{j\to i}^{(k)} = \sum_{i' \in \partial j \backslash i} A_{i'j} x_{i' \to j}^{(k)},$$

  - Prediction according to $sign(\sum_{j \in \partial_i} A_{ij} y_{j \to i}^{(k_{max})})$

Task messages:
How likely the true label is +1

Worker messages:
How likely the worker gives correct labels?

∂_j: the set of tasks assigned to worker j
∂_i : the set of workers who are assigned task i

Key Intuitions in the Analysis

- Using approximated tree structure
  - (l, r)-regular bipartite graph gives a local tree structure in message passing
  - Each leaf is drawn from Gaussian distribution
  - The root is a *weighted sum of Gaussian variables*

- Key techniques used
  - Estimate the mean and variance of the weighted sum of Gaussian variables
  - Using the estimated mean and variance to prove the tail bounds

Main Results (1)

Corollary 2.2. *Under the hypotheses of Theorem 2.1, there exists* $m_0 = 3\ell r e^{\ell q/4\sigma_\infty^2}(\hat{\ell}\hat{r})^{2(k-1)}$ *and* $k_0 = 1 + \big(\log(q/\mu^2)/\log(\hat{\ell}\hat{r}q^2)\big)$ *such that*

$$\frac{1}{m}\sum_{i=1}^{m}\mathbb{P}\big(t_i \neq \hat{t}_i^{(k)}\big) \;\leq\; 2e^{-\ell q/(4\sigma_\infty^2)}\,, \tag{4}$$

for all $m \geq m_0$ *and* $k \geq k_0$.

- Expected error = $O(e^{-lq})$
  - l: number of workers per task
  - $q = E[(2p_j - 1)^2]$ is the expected “quality” of the workers

Main Results (2)

Theorem 2.7. *When $q \leq C$ for any constant $C < 1$, there exists a positive constant C' such that*

$$\min_{\tau \in \widetilde{\mathcal{T}}_\ell, \hat{t}} \quad \max_{t \in \{\pm 1\}^m, \mathcal{F} \in \mathcal{F}_q} \quad \frac{1}{m} \sum_{i \in [m]} \mathbb{P}(t_i \neq \hat{t}_i) \quad \geq \quad \frac{1}{2} e^{-C' \ell q} , \tag{5}$$

for all m where the task assignment scheme τ ranges over all adaptive schemes that use at most $m\ell$ queries and $\hat{t}$ ranges over all estimators that are measurable functions over the responses.

- In this setting, no matter what task assignment algorithm you use (even adaptive ones), the expected error is at least $\Omega(e^{-lq})$

A very strong claim, but what is the claim really saying?

Ben and Ricky will discuss more ontask assignment on Thursday.

Learning from the Wisdom of Crowd by Minimax Entropy

Zhou et al. NIPS 2012.

Entropy (Information Entropy)

- Consider a random variable X with n possible values
- The probability for each value i happening is P_i

- Information entropy (Shannon entropy)

$$H(X) = -\sum_{i=1}^{n} P_i \ln P_i$$

What are the interpretations of entropy?

Higher entropy => More uncertainty => Higher unpredictability

Principle of Maximum Entropy

"the probability distribution which best represents the current state of knowledge is the one with largest entropy"

- Consider a dice with 6 faces
  - Without any knowledge, what's your best bet on the probability of 1~6 happening
  - Assume you are told the probability of 3 happening is ½, what's your best bet on the probability of the rest numbers happening?

Setting

Goal: Infer $\vec{\pi}$ and $\vec{y}$ from $\vec{z}$

Observations

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{z}_{1,1}$	$\vec{z}_{1,2}$	$\vec{z}_{1,3}$	…	$\vec{z}_{1,n}$
Worker 2	$\vec{z}_{2,1}$	$\vec{z}_{2,2}$	$\vec{z}_{2,3}$	…	$\vec{z}_{2,n}$
Worker 3	$\vec{z}_{3,1}$	$\vec{z}_{3,2}$	$\vec{z}_{3,3}$	…	$\vec{z}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{z}_{m,1}$	$\vec{z}_{m,2}$	$\vec{z}_{m,3}$	…	$\vec{z}_{m,n}$

Underlying distribution

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{\pi}_{1,1}$	$\vec{\pi}_{1,2}$	$\vec{\pi}_{1,3}$	…	$\vec{\pi}_{1,n}$
Worker 2	$\vec{\pi}_{2,1}$	$\vec{\pi}_{2,2}$	$\vec{\pi}_{2,3}$	…	$\vec{\pi}_{2,n}$
Worker 3	$\vec{\pi}_{3,1}$	$\vec{\pi}_{3,2}$	$\vec{\pi}_{3,3}$	…	$\vec{\pi}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{\pi}_{m,1}$	$\vec{\pi}_{m,2}$	$\vec{\pi}_{m,3}$	…	$\vec{\pi}_{m,n}$

- Components
  - Workers $i = 1, \dots, m$
  - Tasks $j = 1, \dots, n$
  - Labels $k = 1, \dots, c$
- $\vec{y}_j = (y_{i,1}, \dots, y_{j,c})$
  - $y_{j,l} = 1$ if task j's label is l
  - $y_{j,l} = 0$ otherwise
- $\vec{z}_{i,j} = (z_{i,j,1}, \dots, z_{i,j,c})$
  - $z_{i,j,k} = 1$ if worker i label task j as class k
  - $z_{i,j,k} = 0$ otherwise
- $\vec{\pi}_{i,j} = (\pi_{i,j,1}, \dots, \pi_{i,j,c})$
  - $z_{i,j,k}$: probability for worker i label task j as class k

Apply the Maximum Entropy Principle

- Assume true labels $\vec{y}_j$ are given, how to infer $\vec{\pi}$?

- Choose $\vec{\pi}$ that maximizes entropy subject to the observations of $\vec{z}$

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$$\max_{\pi} \quad \boxed{-\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{c} \pi_{ijk} \ln \pi_{ijk}}$$

Entropy

s.t.

$$\boxed{\sum_{k=1}^{c} \pi_{ijk} = 1, \ \forall i, j, \ \pi_{ijk} \geq 0, \ \forall i, j, k.}$$

Probability constraints

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{z}_{1,1}$	$\vec{z}_{1,2}$	$\vec{z}_{1,3}$	…	$\vec{z}_{1,n}$
Worker 2	$\vec{z}_{2,1}$	$\vec{z}_{2,2}$	$\vec{z}_{2,3}$	…	$\vec{z}_{2,n}$
Worker 3	$\vec{z}_{3,1}$	$\vec{z}_{3,2}$	$\vec{z}_{3,3}$	…	$\vec{z}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{z}_{m,1}$	$\vec{z}_{m,2}$	$\vec{z}_{m,3}$	…	$\vec{z}_{m,n}$

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{\pi}_{1,1}$	$\vec{\pi}_{1,2}$	$\vec{\pi}_{1,3}$	…	$\vec{\pi}_{1,n}$
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Worker 3	$\vec{\pi}_{3,1}$	$\vec{\pi}_{3,2}$	$\vec{\pi}_{3,3}$	…	$\vec{\pi}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{\pi}_{m,1}$	$\vec{\pi}_{m,2}$	$\vec{\pi}_{m,3}$	…	$\vec{\pi}_{m,n}$

- Choose $\vec{\pi}$ that maximizes entropy subject to the observations of $\vec{z}$

$$\max_{\pi} \quad -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{c} \pi_{ijk} \ln \pi_{ijk}$$

$$\text{s.t.} \quad \boxed{\sum_{i=1}^{m} \pi_{ijk} = \sum_{i=1}^{m} z_{ijk}, \ \forall j, k,}$$

$$\sum_{k=1}^{c} \pi_{ijk} = 1, \ \forall i, j, \ \pi_{ijk} \geq 0, \ \forall i, j, k.$$

"expected # labels in each class = empirical # labels
(We can relax them to "approximately equal")

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{z}_{1,1}$	$\vec{z}_{1,2}$	$\vec{z}_{1,3}$	…	$\vec{z}_{1,n}$
Worker 2	$\vec{z}_{2,1}$	$\vec{z}_{2,2}$	$\vec{z}_{2,3}$	…	$\vec{z}_{2,n}$
Worker 3	$\vec{z}_{3,1}$	$\vec{z}_{3,2}$	$\vec{z}_{3,3}$	…	$\vec{z}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{z}_{m,1}$	$\vec{z}_{m,2}$	$\vec{z}_{m,3}$	…	$\vec{z}_{m,n}$

	Task 1	Task 2	Task 3	…	Task n
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…	…	…	…	…	…
Worker m	$\vec{\pi}_{m,1}$	$\vec{\pi}_{m,2}$	$\vec{\pi}_{m,3}$	…	$\vec{\pi}_{m,n}$

- Choose $\vec{\pi}$ that maximizes entropy subject to the observations of $\vec{z}$

$$\max_{\pi} \quad -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{c}\pi_{ijk}\ln\pi_{ijk}$$

$$\text{s.t.} \quad \sum_{i=1}^{m}\pi_{ijk}=\sum_{i=1}^{m}z_{ijk},\ \forall j,k,\ \boxed{\sum_{j=1}^{n}y_{jl}\pi_{ijk}=\sum_{j=1}^{n}y_{jl}z_{ijk},\ \forall i,k,l,}$$

$$\sum_{k=1}^{c}\pi_{ijk}=1,\ \forall i,j,\ \pi_{ijk}\geq 0,\ \forall i,j,k.$$

	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{z}_{1,1}$	$\vec{z}_{1,2}$	$\vec{z}_{1,3}$	…	$\vec{z}_{1,n}$
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…	…	…	…	…	…
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	Task 1	Task 2	Task 3	…	Task n
Worker 1	$\vec{\pi}_{1,1}$	$\vec{\pi}_{1,2}$	$\vec{\pi}_{1,3}$	…	$\vec{\pi}_{1,n}$
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Worker 3	$\vec{\pi}_{3,1}$	$\vec{\pi}_{3,2}$	$\vec{\pi}_{3,3}$	…	$\vec{\pi}_{3,n}$
…	…	…	…	…	…
Worker m	$\vec{\pi}_{m,1}$	$\vec{\pi}_{m,2}$	$\vec{\pi}_{m,3}$	…	$\vec{\pi}_{m,n}$

Solving the Optimization

- Given true labels y, we use maximum entropy to find π

=> For every set of true labels y, we obtain π and the corresponding entropy

- How to decide the true labels y?
  - Higher entropy => higher uncertainty
  - Choosing labels that minimize uncertainty/entropy

- Minimax entropy

$$
\begin{aligned}
\min_{y} \max_{\pi} \quad & -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{c} \pi_{ijk} \ln \pi_{ijk} \\
\text{s.t.} \quad & \sum_{i=1}^{m} \pi_{ijk} = \sum_{i=1}^{m} z_{ijk},\ \forall j, k,\ \sum_{j=1}^{n} y_{jl}\pi_{ijk} = \sum_{j=1}^{n} y_{jl} z_{ijk},\ \forall i, k, l, \\
& \sum_{k=1}^{c} \pi_{ijk} = 1,\ \forall i, j,\ \pi_{ijk} \geq 0,\ \forall i, j, k,\ \sum_{l=1}^{c} y_{jl} = 1,\ \forall j,\ y_{jl} \geq 0,\ \forall j, l.
\end{aligned}
$$

An interesting way of looking at label aggregation

- Finding the labels/distribution with minimax entropy

- Can we incorporate models of label generation?
  - e.g., Tasks are homogeneous
  - e.g., Tasks have different difficulty levels

- Express them as additional constraints

Additional Details on the Technical Insights

- The dual formulation gives nice insights
  - One set of dual variables represent worker skills
  - Another set of dual variable represent task difficulties

- Perform reasonably well in practice

Method	Dogs	Web
Minimax Entropy	84.63	88.05
Dawid & Skene	84.14	83.98
Majority Voting	82.09	73.07
Average Worker	70.60	37.05

A Recap on Label Aggregation

The Approaches We Covered

- EM-Based methods (The mainstream approach)
  - Develop models of label generation
  - Write down the likelihood function
  - Using EM algorithms to optimize likelihood
- Matrix-based method
  - Perform SVD, using the top left singular vector as the prediction
- Others
  - Iterative message passing
    - Be careful about message normalization if you want to use this for assignment 3
  - Minimax entropy

Which one would you like to implement for Assignment 3?

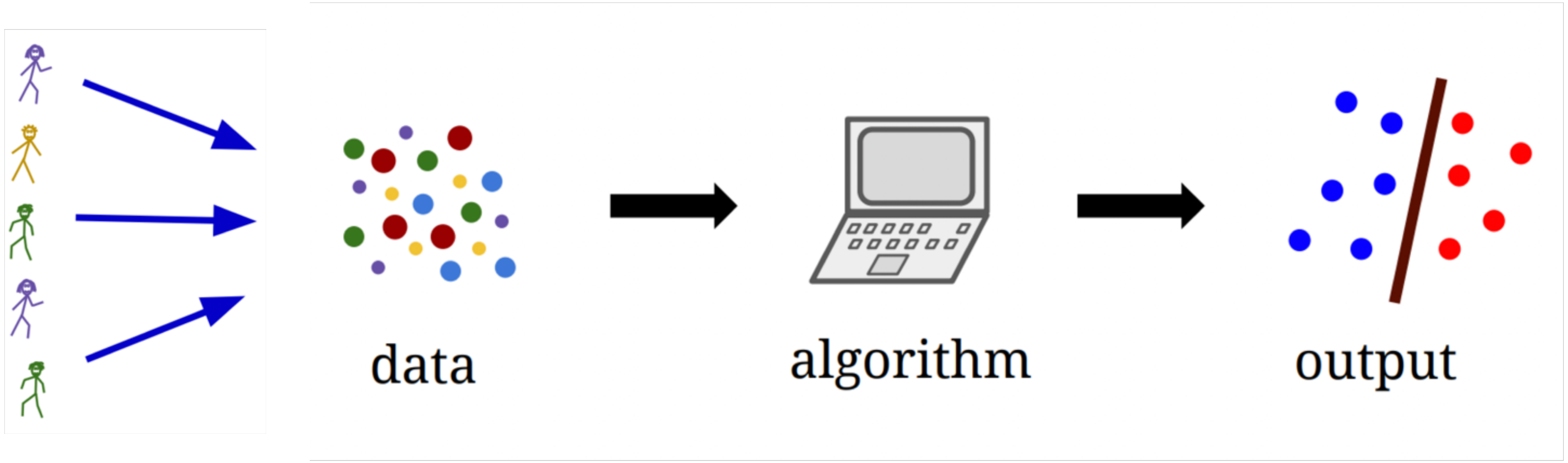
General Discussion on Label Aggregation

- Common assumption: each label is i.i.d. drawn from some distribution
- This assumption enables tons of papers applying statistics/learning techniques in crowdsourcing (low-hanging fruit)

- Discussion
  - What other assumptions have been made in the papers you read?
  - Under what scenarios do you think this (and/or other assumptions) is reasonable?
  - Is there any assumption you think we should try to relax in this line of research.

Beyond Label Aggregation

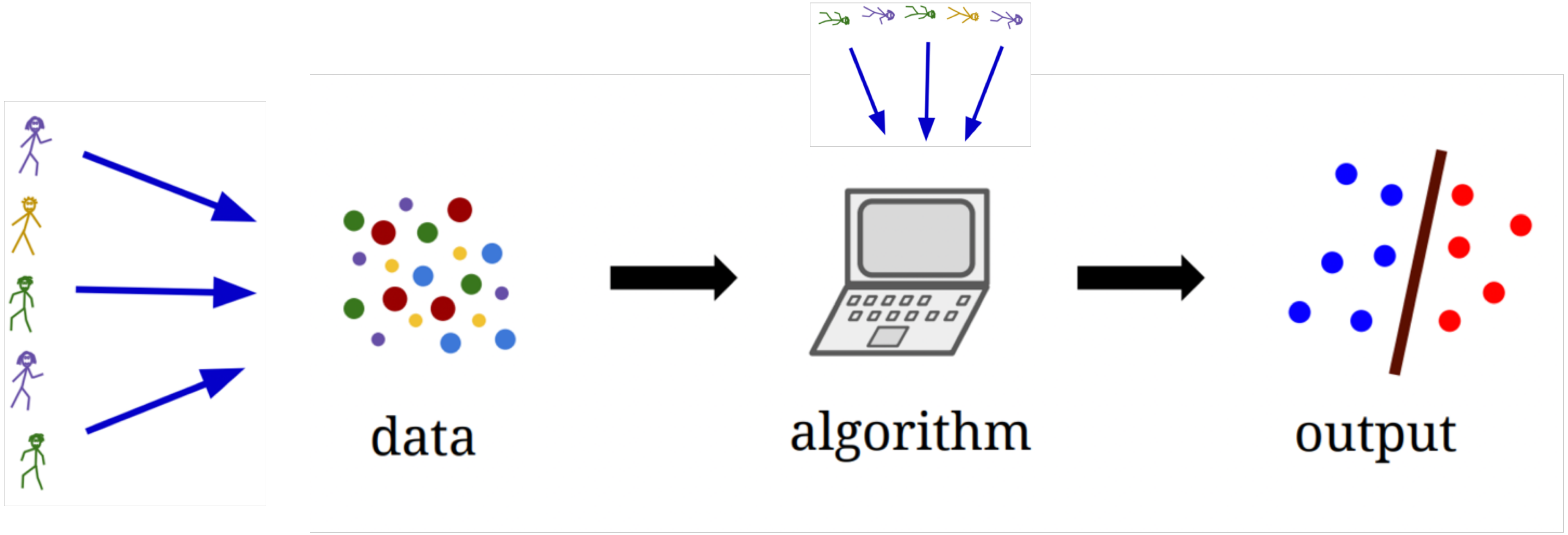
Learning with Humans in the Loop



We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

1. What if data is not i.i.d.?

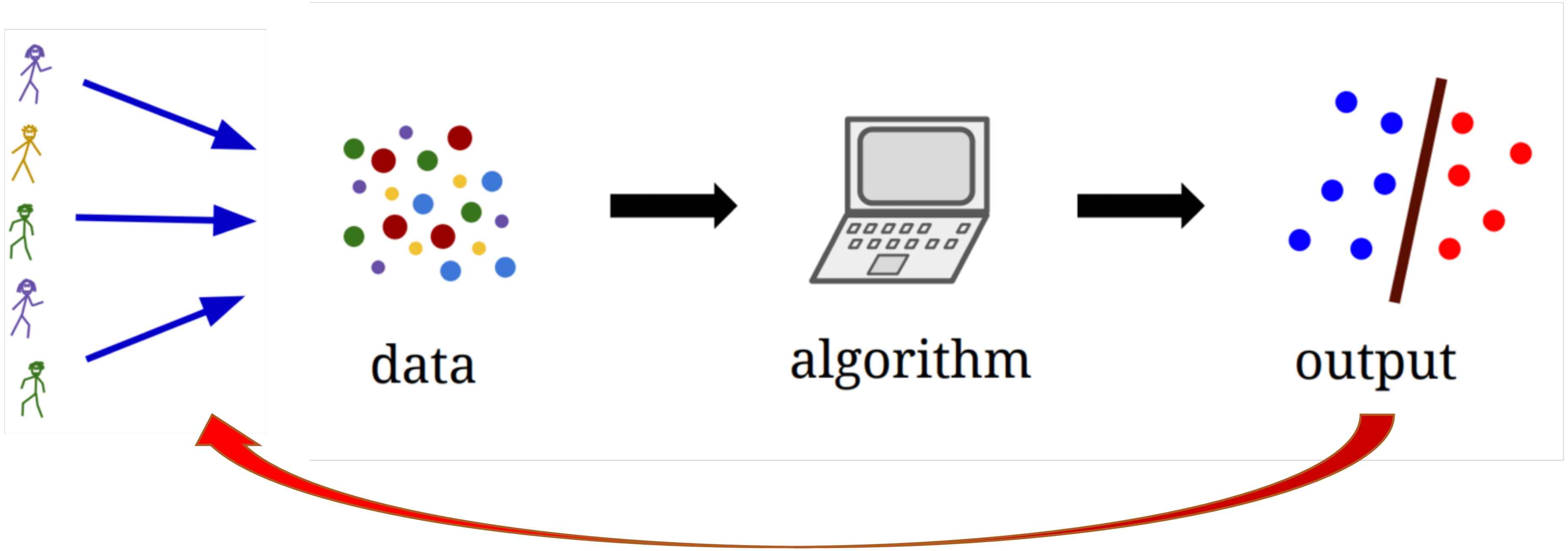
Learning with Humans in the Loop



We have focused on the aspect of “data generated by humans”
Make strong i.i.d. assumptions on the data generation process

2. Can humans be involved in the algorithm as well?

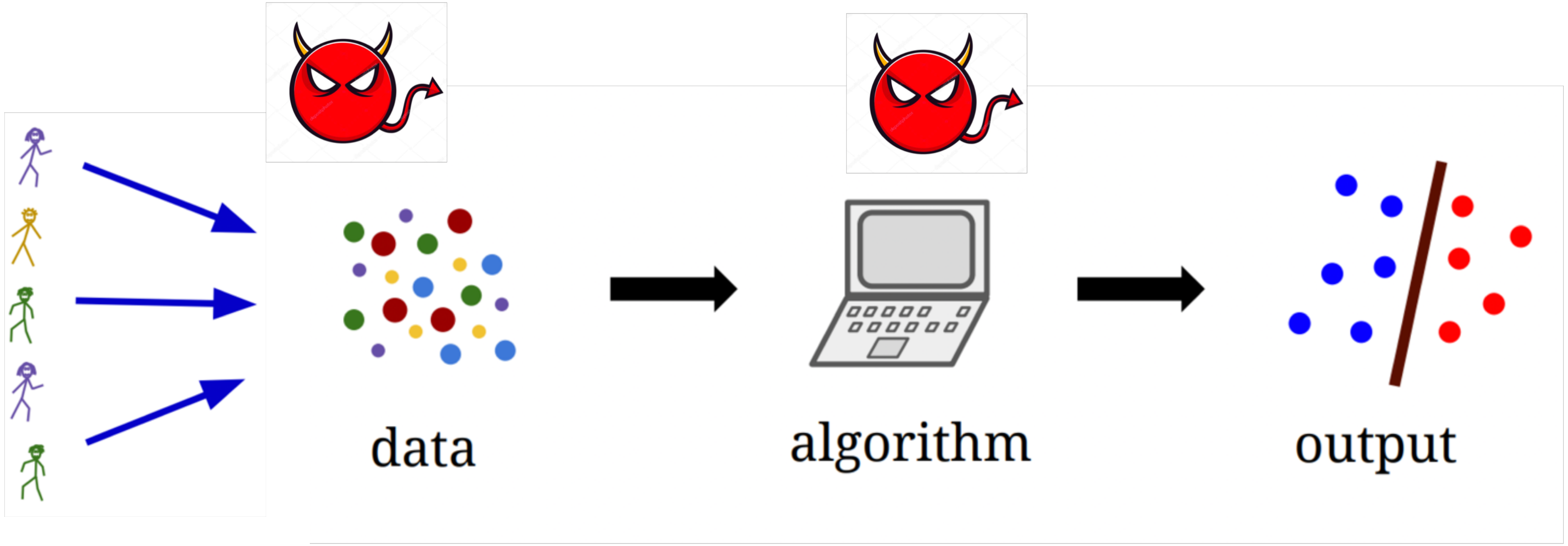
Learning with Humans in the Loop



We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

3. What if the output has impacts to humans?

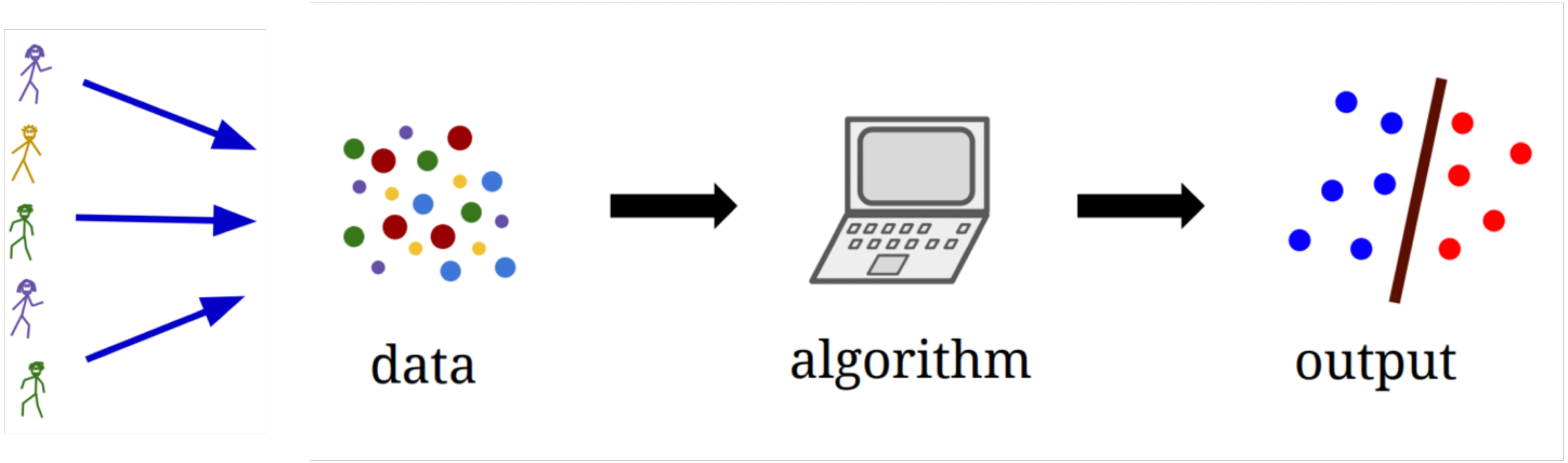
Learning with Humans in the Loop



We have focused on the aspect of “data generated by humans”
Make strong i.i.d. assumptions on the data generation process

4. What if some users try to sabotage the system.

Learning with Humans in the Loop



We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

1. What if data is not i.i.d.?

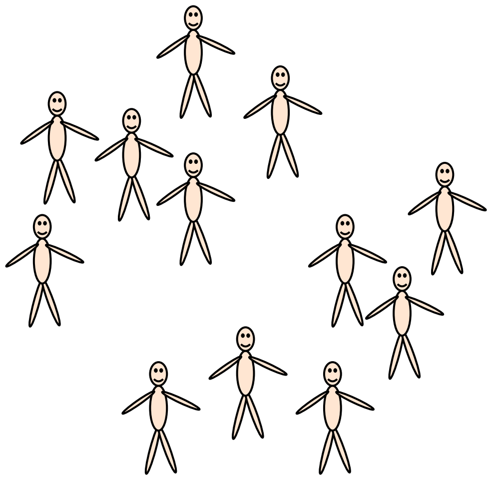
Active Buying Data for Machine Learning

Joint work with
Jake Abernethy, Yiling Chen, and Bo Waggoner

ACM Economics and Computation 2015

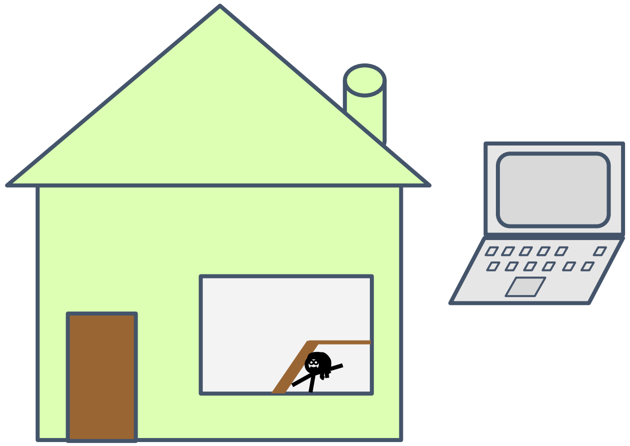
Learning via Buying Data from Humans

data-holders



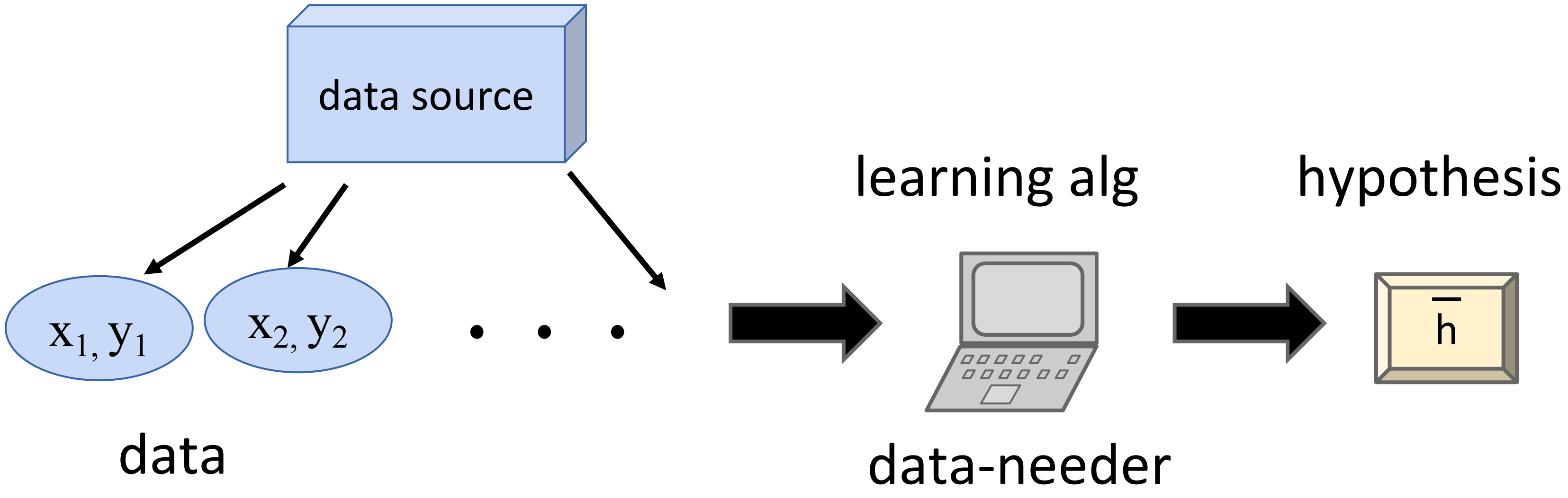
ex: medical data

data-needers

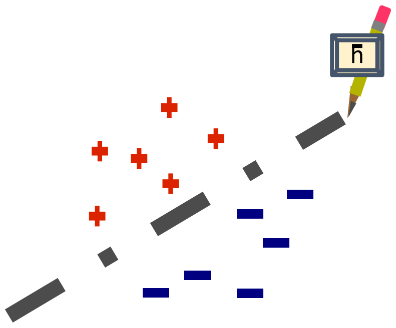


ex: pharmaceutical co.

(Traditional) Learning Problems

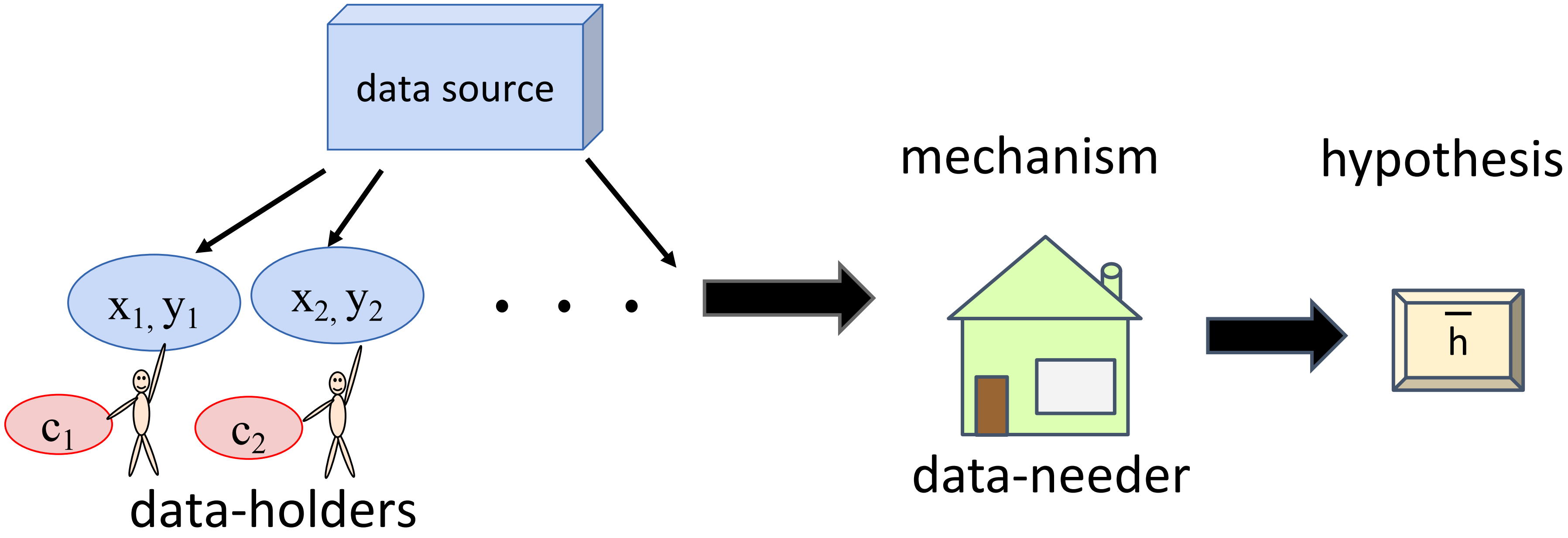


Goal:
Learn a **good** hypothesis *h* with **few** data points



Example: Classification
Data: (point, label) where label is + or −
Hypothesis: hyperplane separating the two types

Our Setting: Data are Held by Humans



Goal:

Learn a **good** hypothesis *h* with **small** budgets

Assumptions:

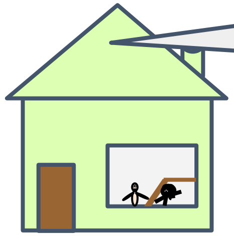
data cannot be fabricated

costs are **unknown** to the data-needer and **bounded**

costs can be arbitrarily **correlated** with data

What can we do?

Want to learn a classifier for HIV
(the maximum cost is $1000)



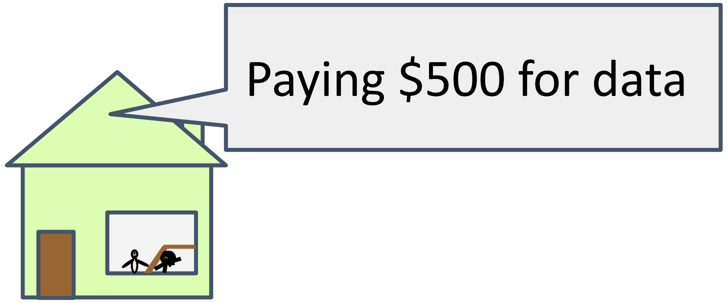
Paying $1000 for everyone
until the budget is exhausted.

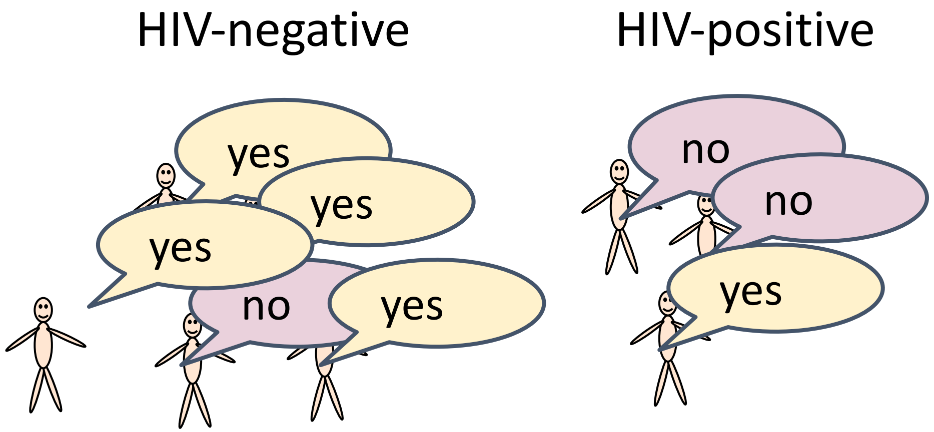
Pro: We can apply standard learning algorithms

Con: Waste a lot of money

What can we do?

Want to learn a classifier for HIV
(the maximum cost is $1000)

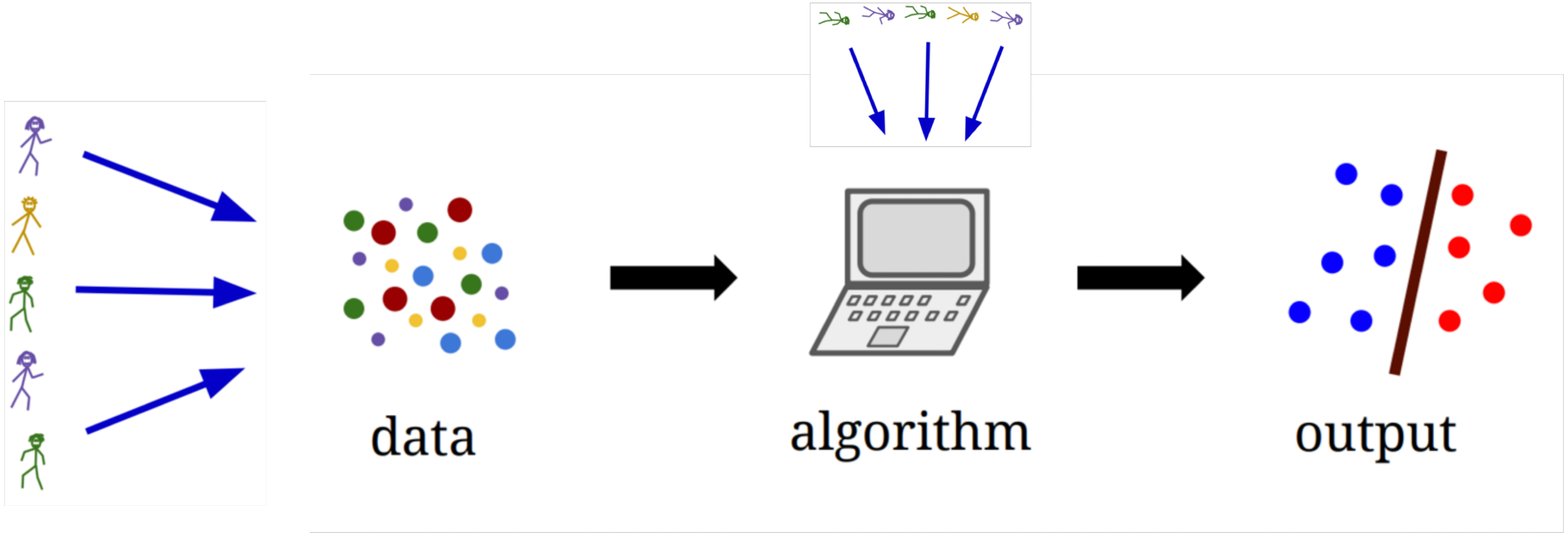




Challenge 1: How to deal with **biases**?

Challenge 2: Which data is more **useful**?

Learning with Humans in the Loop

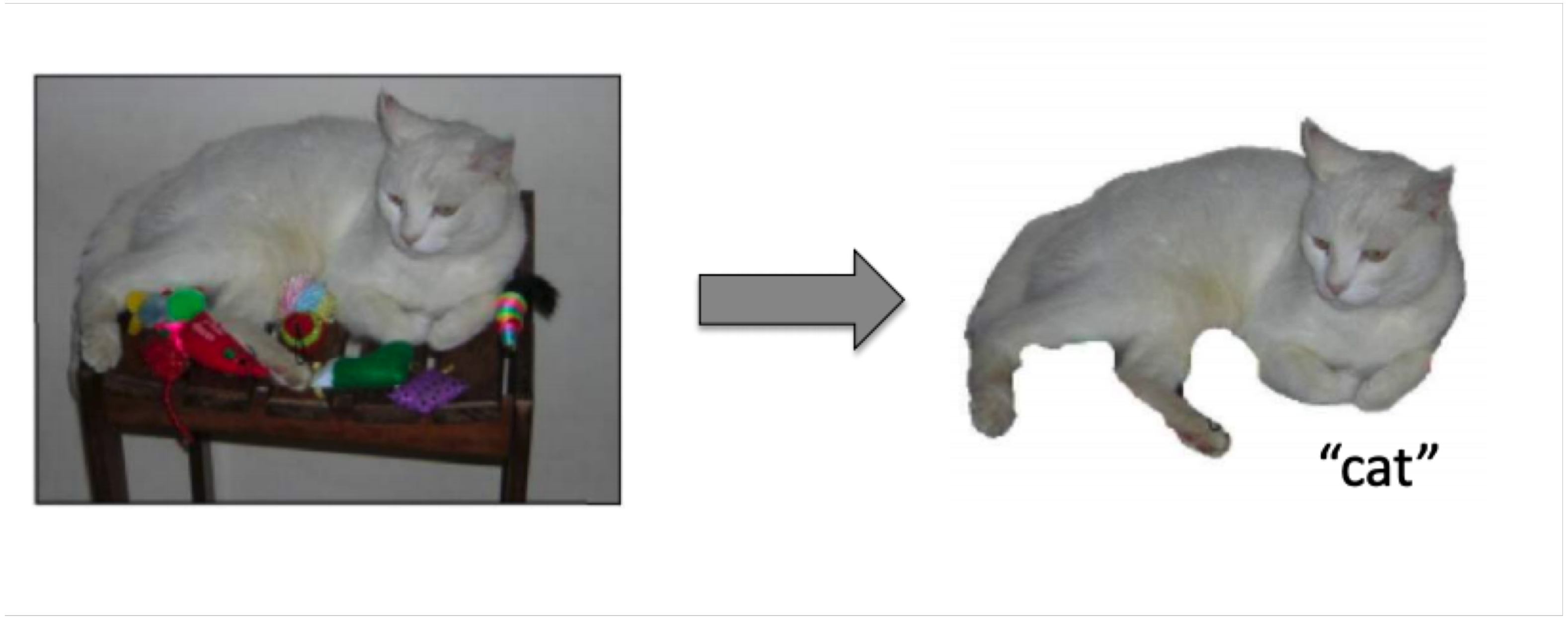


We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

2. Can humans be involved in the algorithm as well?

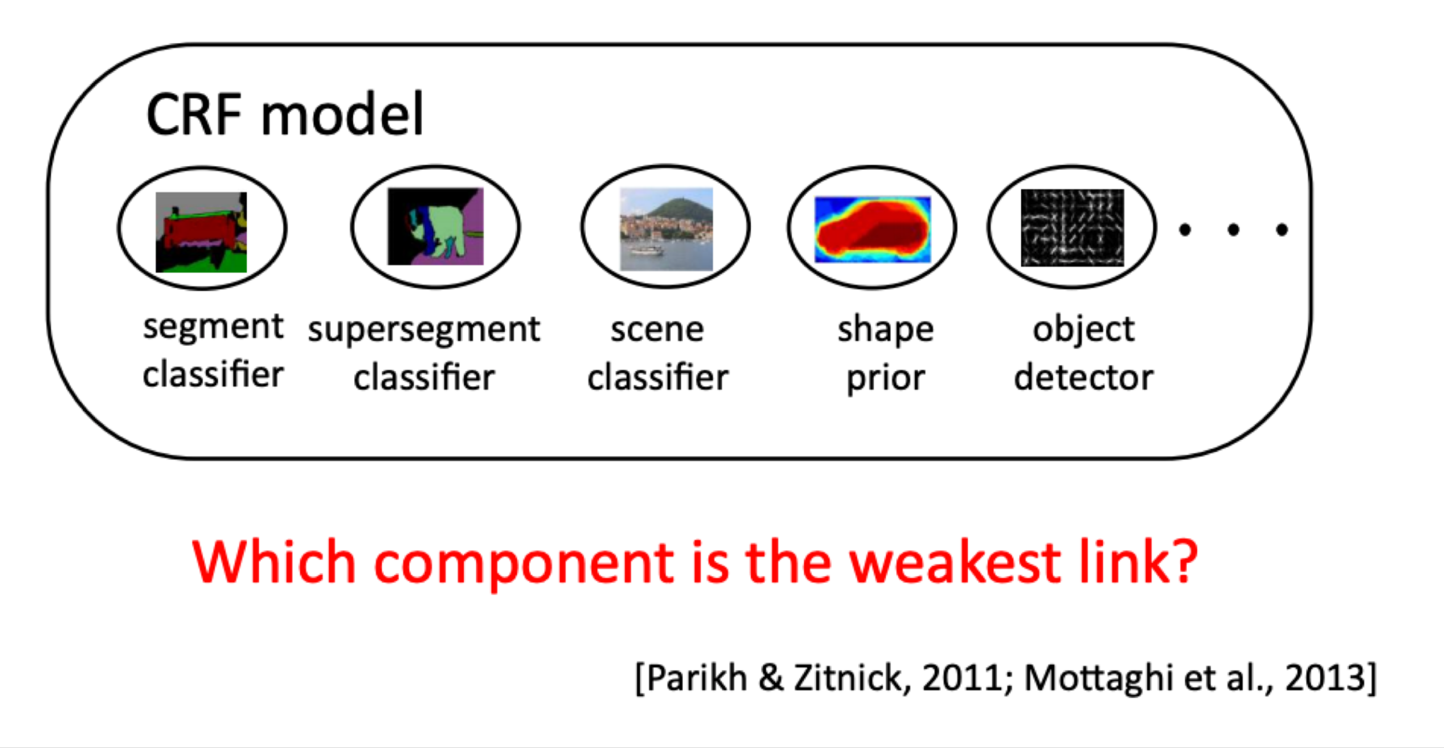
Human Debugging

- Semantic segmentation: partition an image into semantically meaningful parts, and label each part.

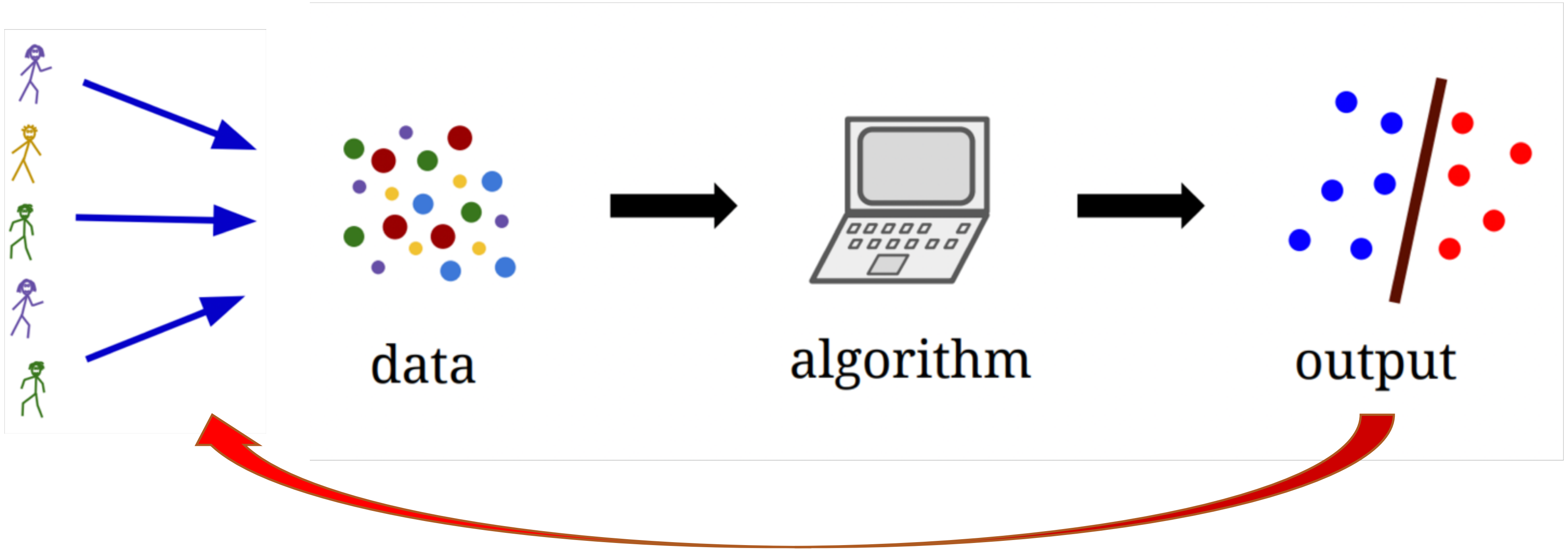


Human Debugging

- Semantic segmentation: partition an image into semantically meaningful parts, and label each part.



Learning with Humans in the Loop



We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

3. What if the output has impacts to humans?

Counterfactual Machine Learning

- Consider you are a search engine
  - You use the click data to estimate how relevant a website is to a search
  - Determine how to rank them based on the estimation
- What's wrong here?
  - The data you collected depends on how you rank
    - Websites ranked higher gets more clicks
  - Need to infer "what if" we use a different policy
- Standard approaches: A/B-Testing => Too many possibilities
- Counterfactual ML => Develop user models to answer the "what if" question

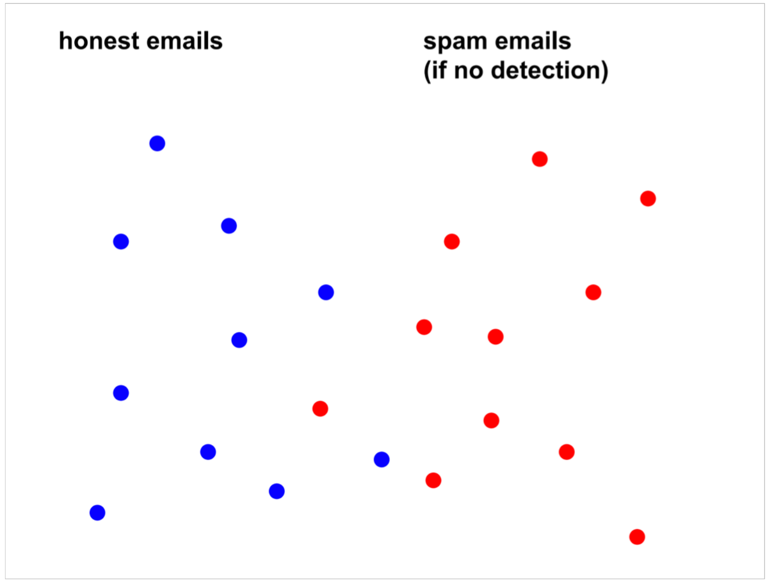
Strategic Machine Learning

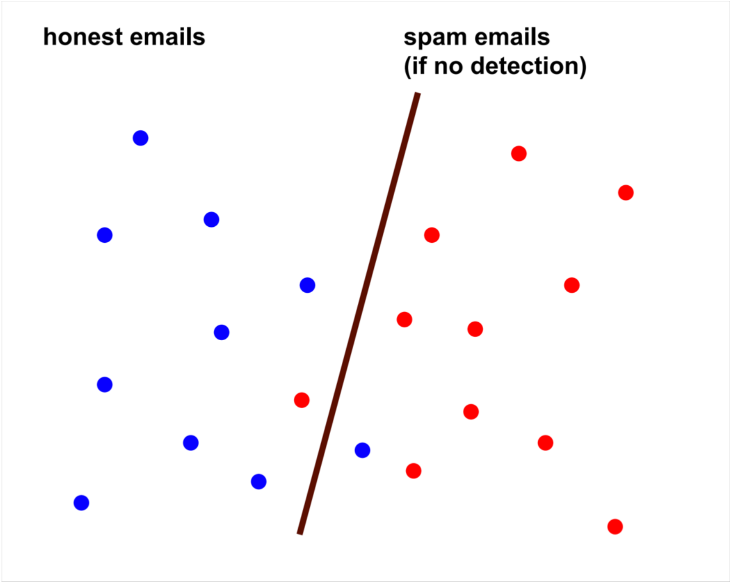
Goodhart’s law:

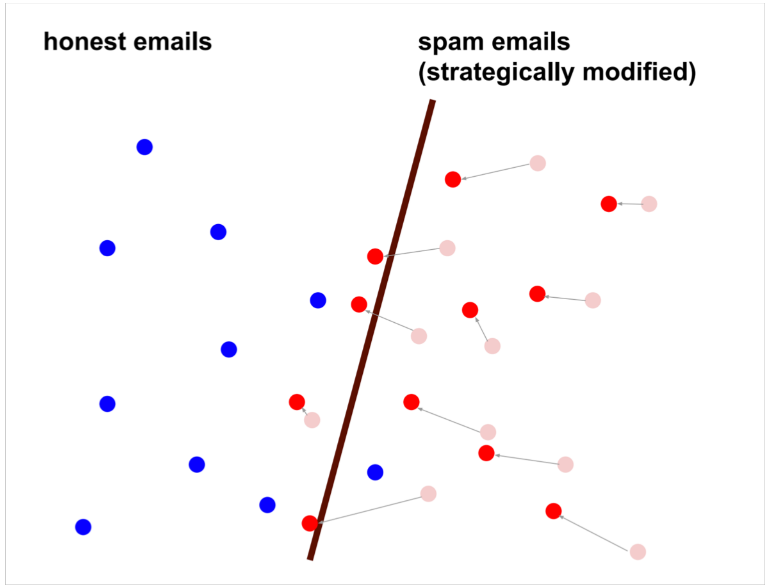
“If a measure becomes the public’s goal,
it is no longer a good measure.”

Strategic Machine Learning

- Spam classification example as in last lecture







- More examples: School admission, Job offer determination, etc

Ethical Issues

- A Game for Collecting User Preferences on Images

Matchin: Eliciting User Preferences with an Online Game. Hacker and von Ahn. CHI 2009.

Ethical Issues

- Which one do you like

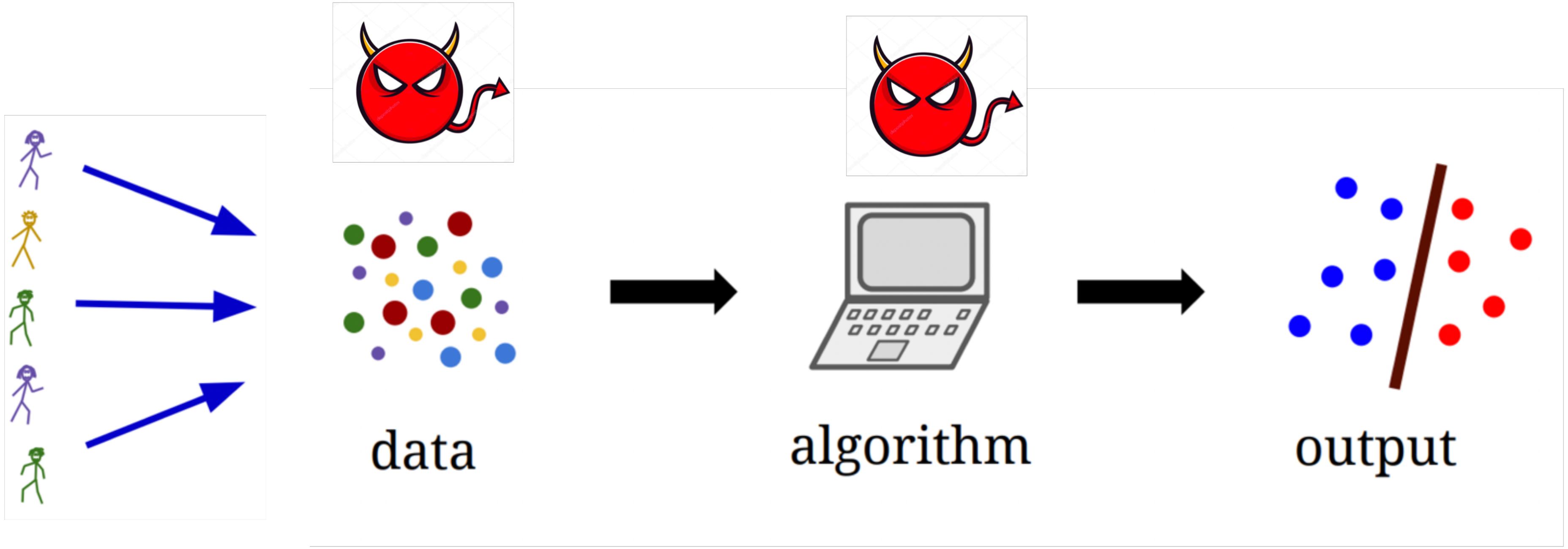
Matchin: Eliciting User Preferences with an Online Game. Hacker and von Ahn. CHI 2009.

Ethical Issues

- Building Gender Models using Images
- Ask MTurk workers to compare 10 pairs of pre-selected images.
  - Accuracy for guessing the gender correctly: 78.3%
- Workers are not contributing data. They might be sacrificing some privacy as well.

Matchin: Eliciting User Preferences with an Online Game. Hacker and von Ahn. CHI 2009.

Learning with Humans in the Loop



We have focused on the aspect of "data generated by humans"
Make strong i.i.d. assumptions on the data generation process

4. What if some users try to sabotage the system.

Adversarial Machine Learning (CSE544T)

(a) (b) (c)

Can an adversary “inject” a small amount of data to break ML algorithms?