and human computation!

Crowdsourcing and Its Application in Cultural Heritage

Andrew Huynh

August 20, 2013

the BIG picture

Who cares?

Why Crowdsourcing?

mechanical turk
Artificial Artificial Intelligence

$30k in rewards per day

150k tasks completed per day

http://mturk.com

fold it BETA
Solve Puzzles for Science

Over 240,000 players

Millions of folded proteins

http://fold.it

Field Expedition:
Mongolia

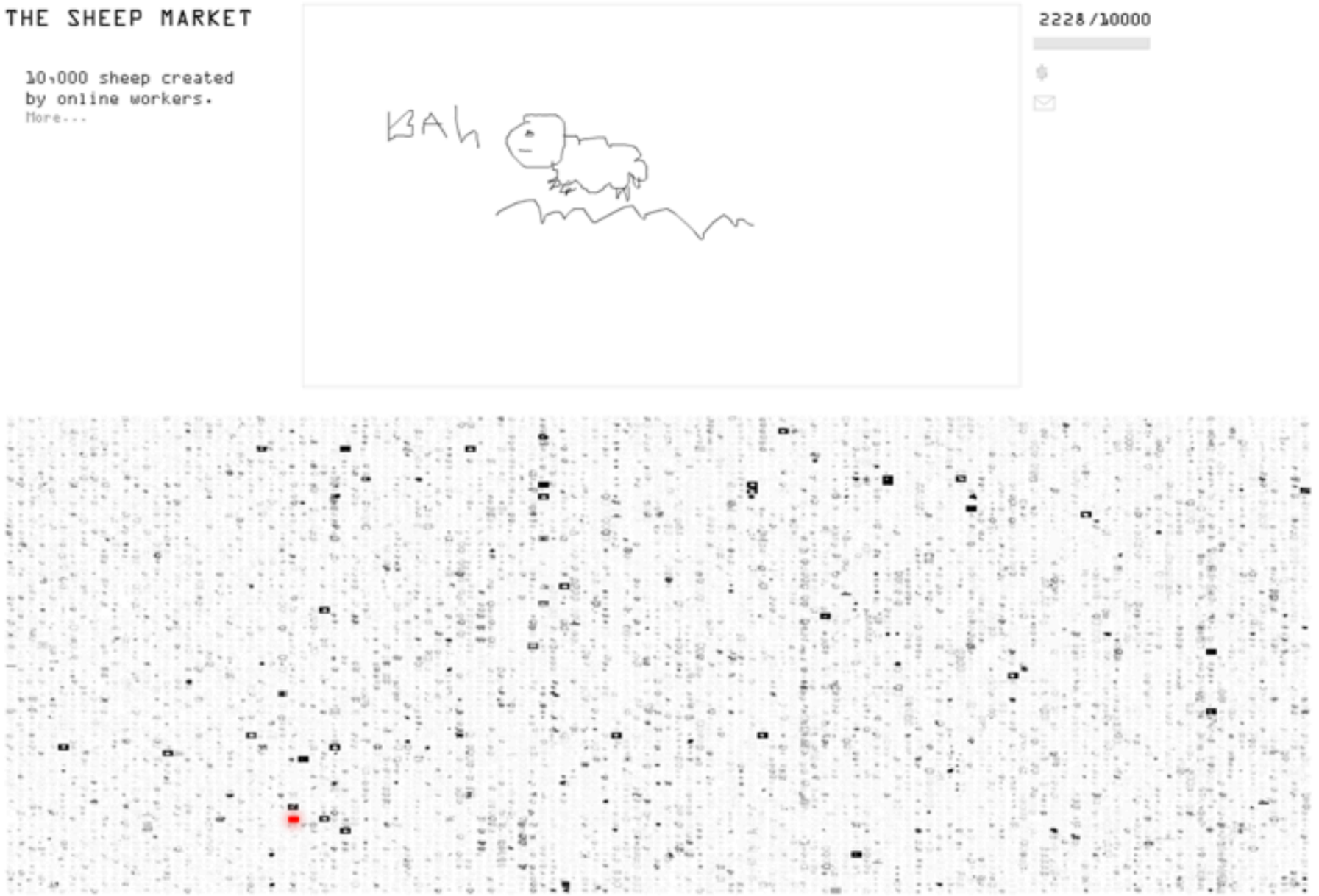
Over 10,000 players

2.4+ million annotations

3.4 man years of exploration.

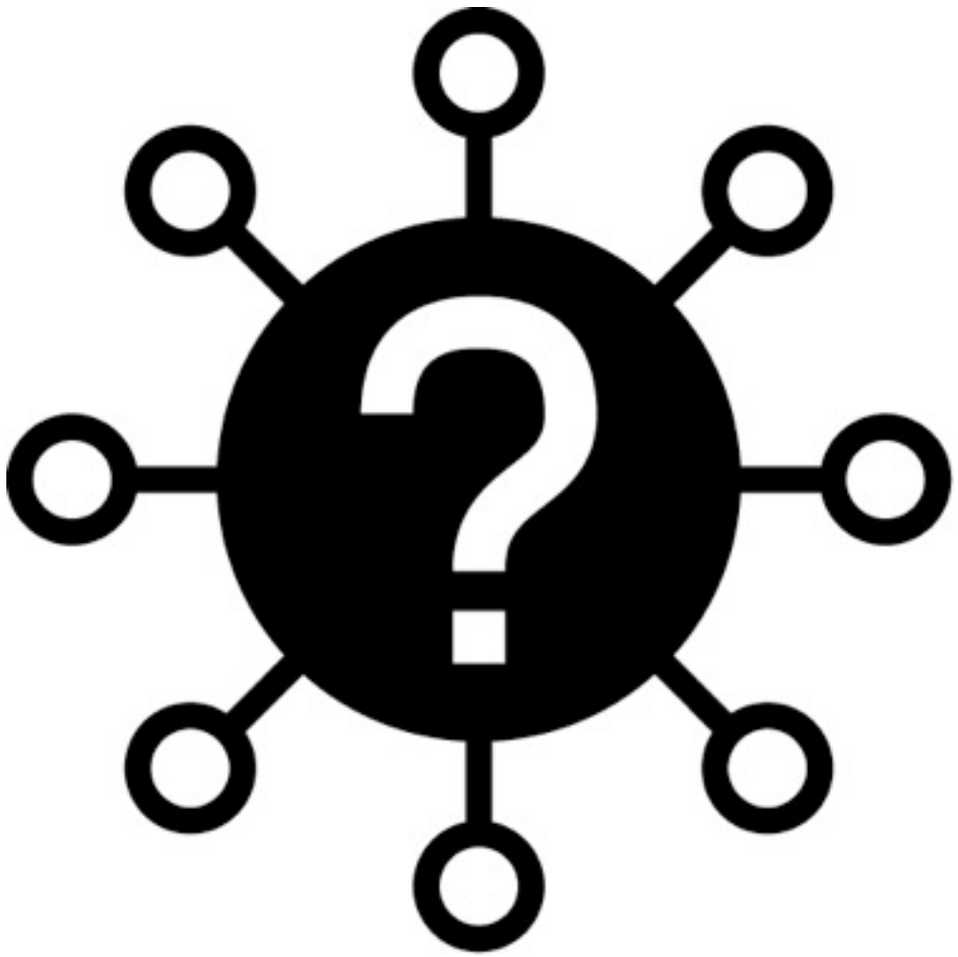
http://exploration.nationalgeographic.com

My personal favorite



40 days. 10,000 sheep. 11 sheep/hour.

What is crowdsourcing?



Outsourcing + crowd

Distribution of tasks

Harness human computation

What is human computation?

Intuition

Creativity

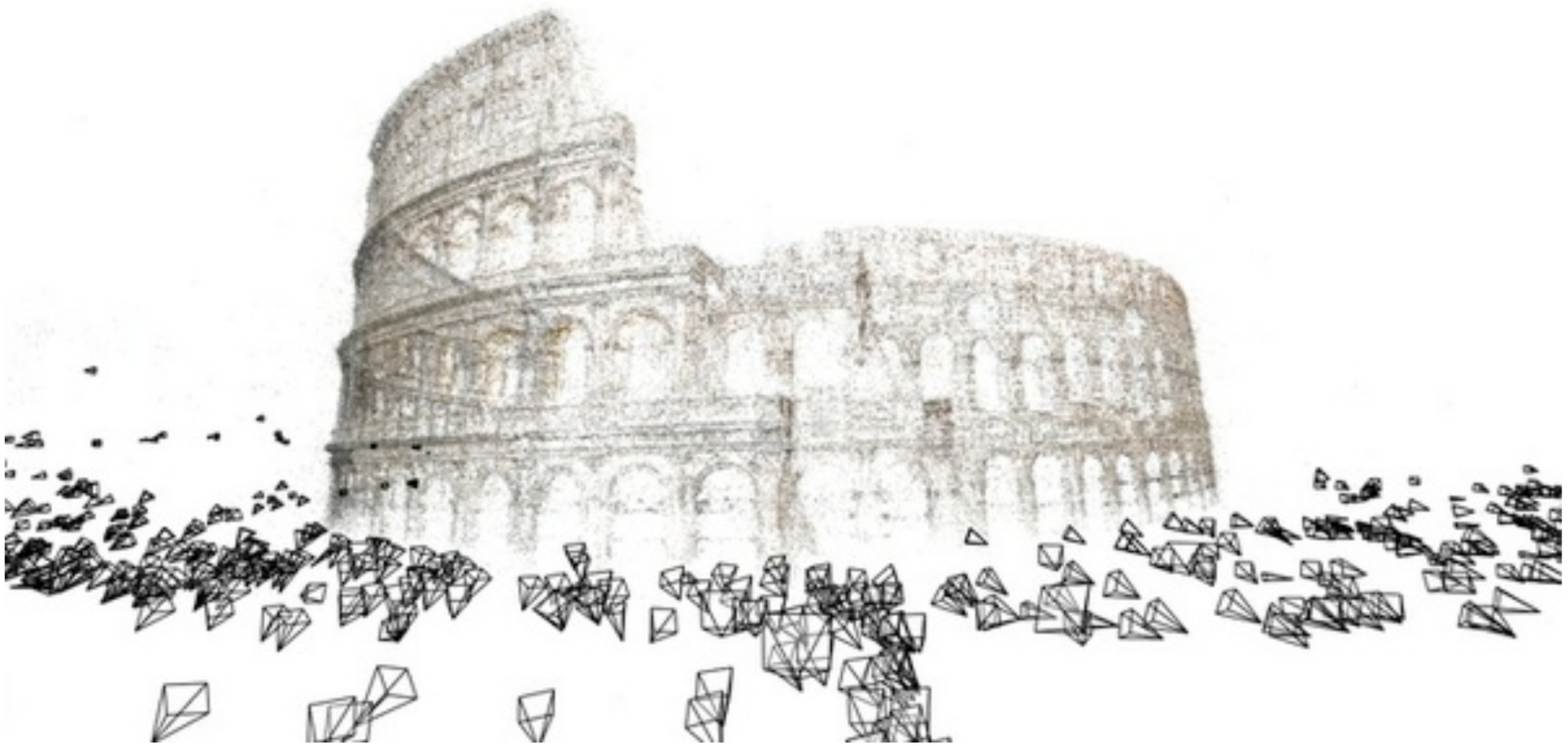
Symbolic Reasoning

Why Cultural Heritage?

Digitization & Preservation

http://ancientlives.org

Digitization & Preservation

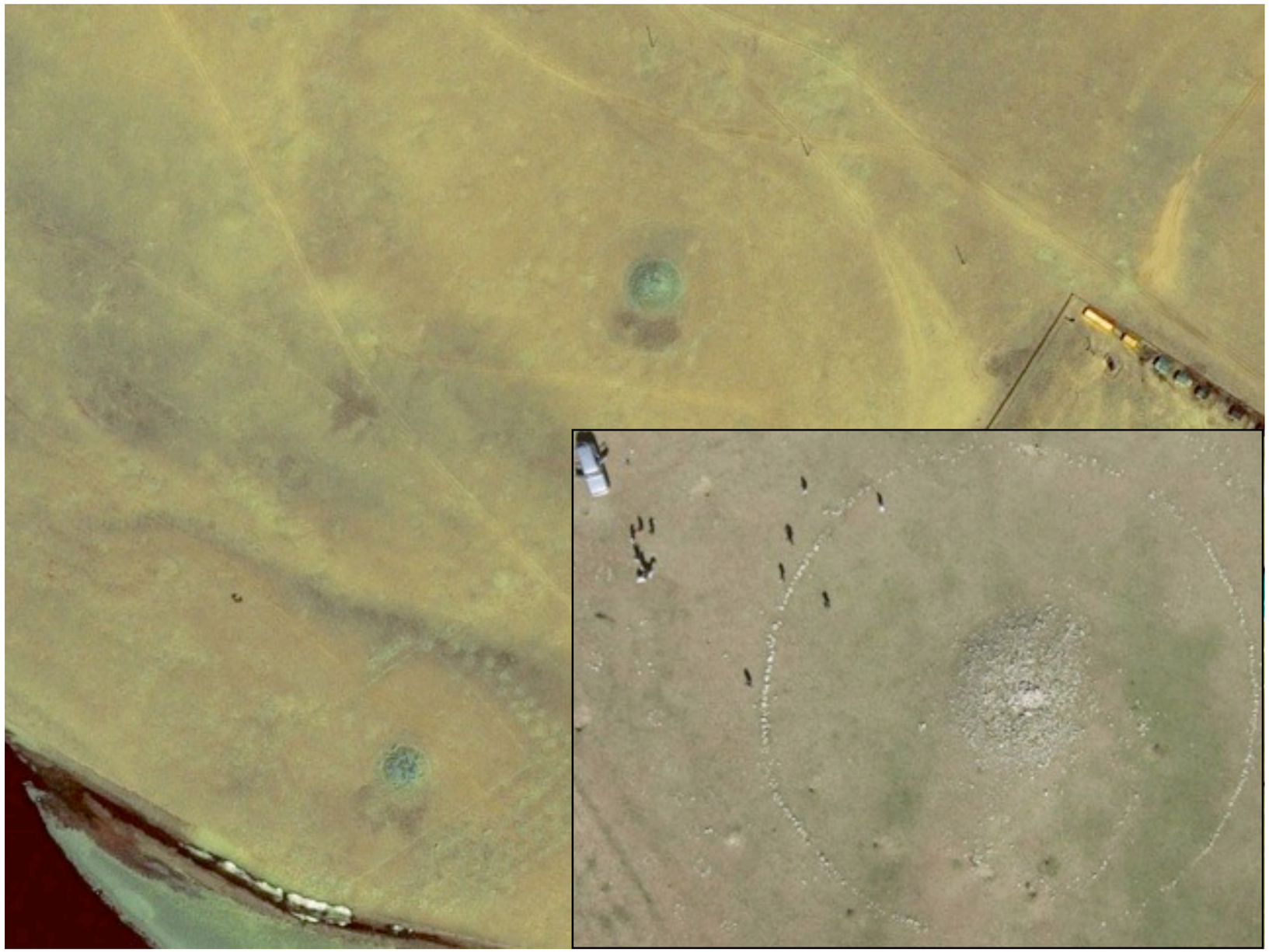


Agarwal, S., Snavely, N., Simon, I., Seitz, S. M., & Szeliski, R.
Building Rome in a day. ICCV (2009)

Exploration & Discovery

Corrie, Robert K.
Detection of ancient Egyptian archaeological sites using satellite remote sensing and digital image processing. Proc. of SPIE Vol. Vol. 8181. (2011)

Exploration & Discovery



Lin, A., Huynh, A., Lanckriet, G., Barrington, L.
Crowdsourcing the Unknown: The Search for Genghis Khan. 2013 (In review).

Active Crowdsourcing

Crowd Engagement

Data Quality Control

Passive Crowdsourcing

Parasitic Computing

Crowdsensing

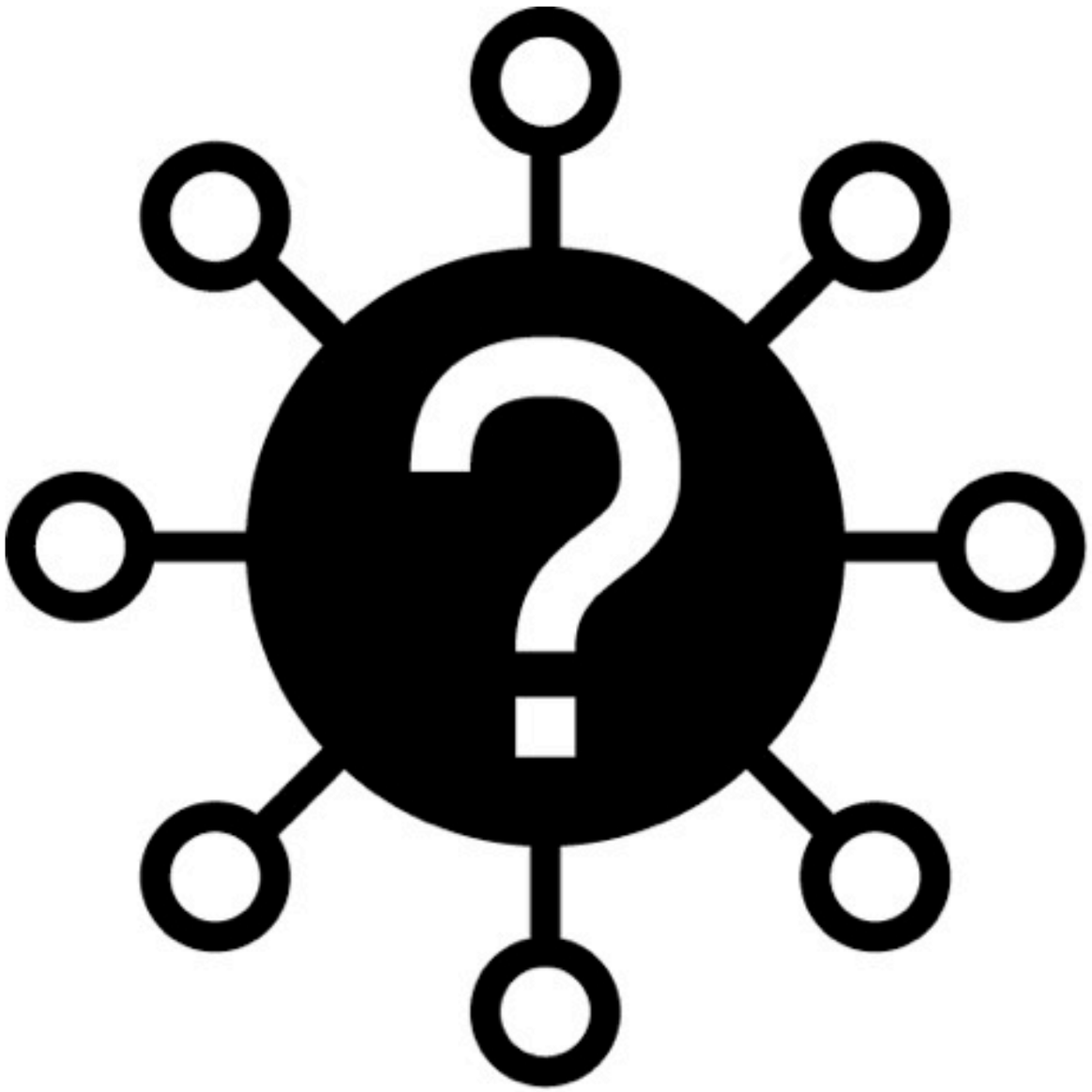
Learning from the Crowd

Active Learning

Closing the Loop

Applications in Cultural Heritage

Active Crowdsourcing

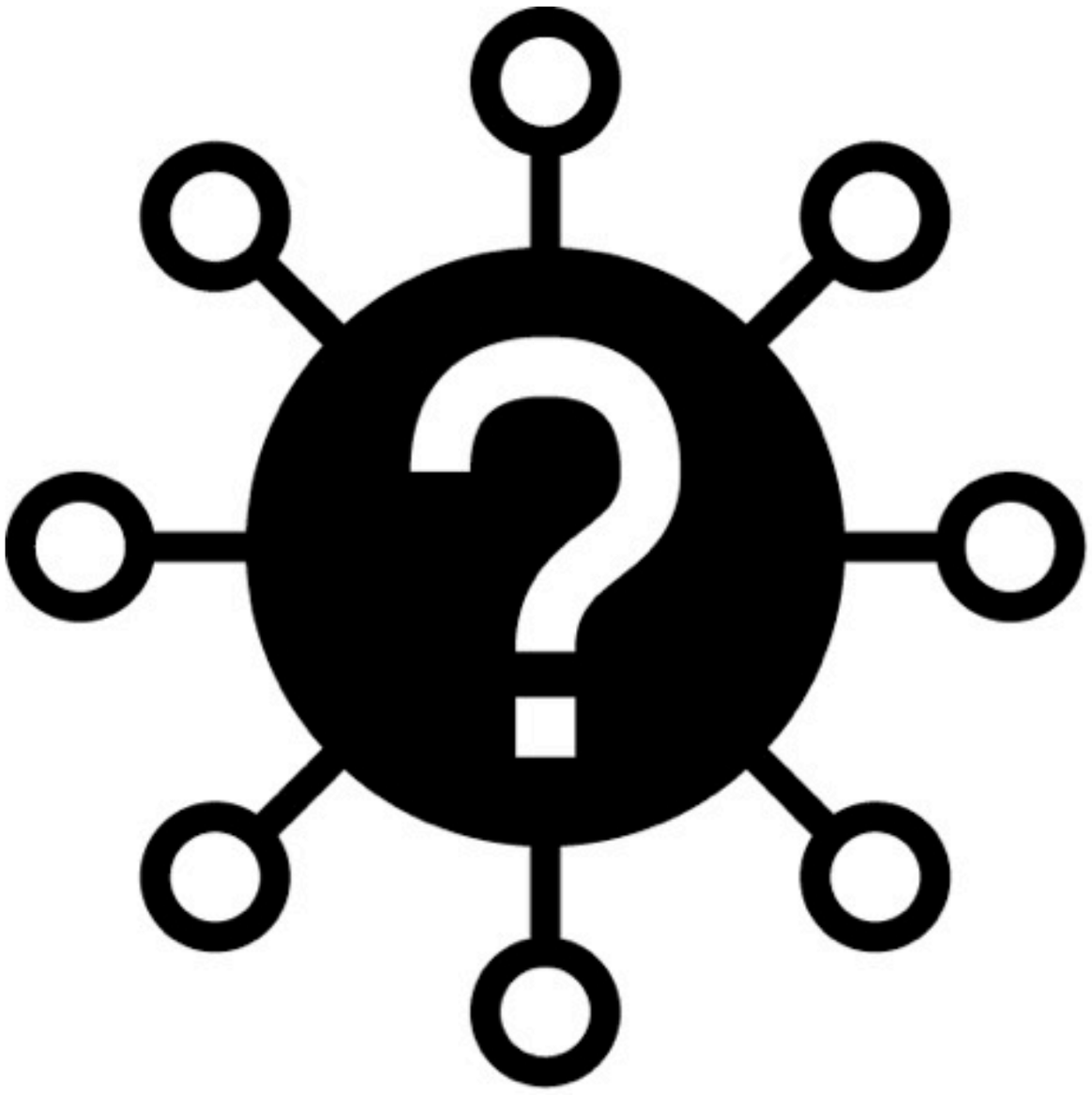


Distributed tasks

Crowd = Pool of labor

Aggregate solutions

Active Crowdsourcing



Distributed tasks

Creating engaging tasks

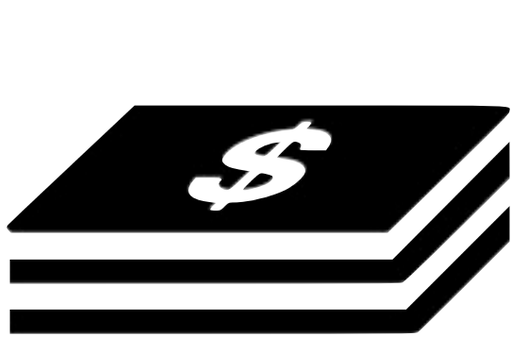
Crowd = Pool of labor

Keeping the crowd motivated

Aggregate solutions

Data quality control

Crowd Engagement & Motivation

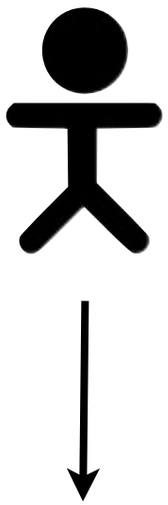


Value

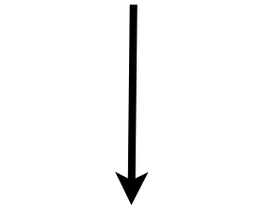
Greater Good

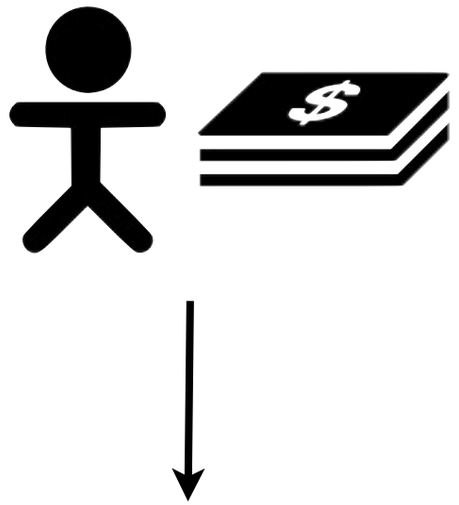
Games

Value Incentives

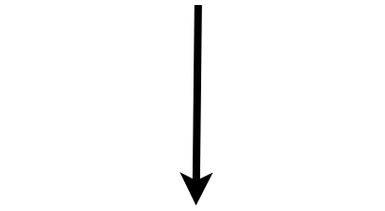


mechanical turk
Artificial Artificial Intelligence





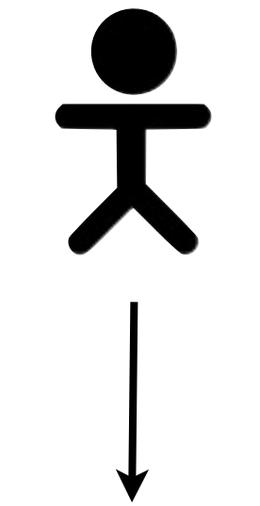
KICKSTARTER



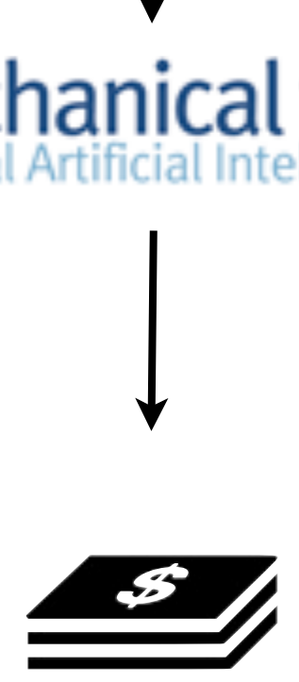
Receiving

Giving

Value Incentives



mechanical turk
Artificial Artificial Intelligence



Can be a great motivator [1]

Quality does not increase with additional money [2]

[1] Tang, J. C., Cebrian, M., Giacobe, N. a., Kim, H.-W., Kim, T., & Wickert, D. “Beaker.” Reflecting on the DARPA Red Balloon Challenge. Communications of the ACM. 2011

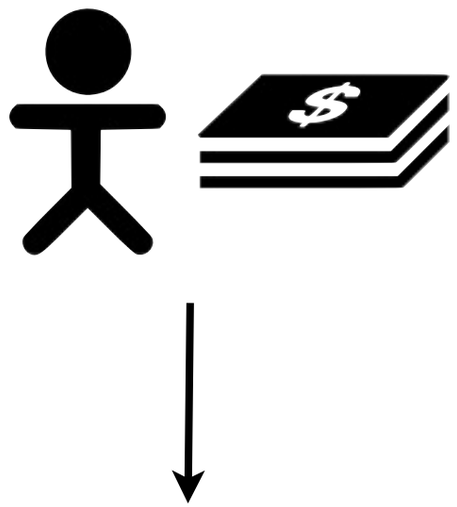
[2] Mason, W., & Watts, D. J. Financial incentives and the performance of crowds. ACM SIGKDD. 2010

Value Incentives

Fund products, projects, services, anything!

Collective pocketbook [1]

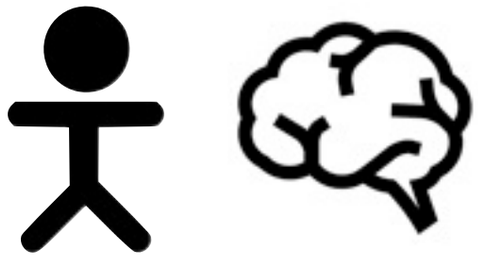
Enhanced customer experience [2]



[1] Howe, J. Crowdsourcing: How the power of the crowd is driving the future of business. 2008

[2] Belleflamme, P. Crowdfunding: Tapping the right crowd. AFFI. 2011

The Greater Good



"Citizen Scientists"

OpenStreetMap

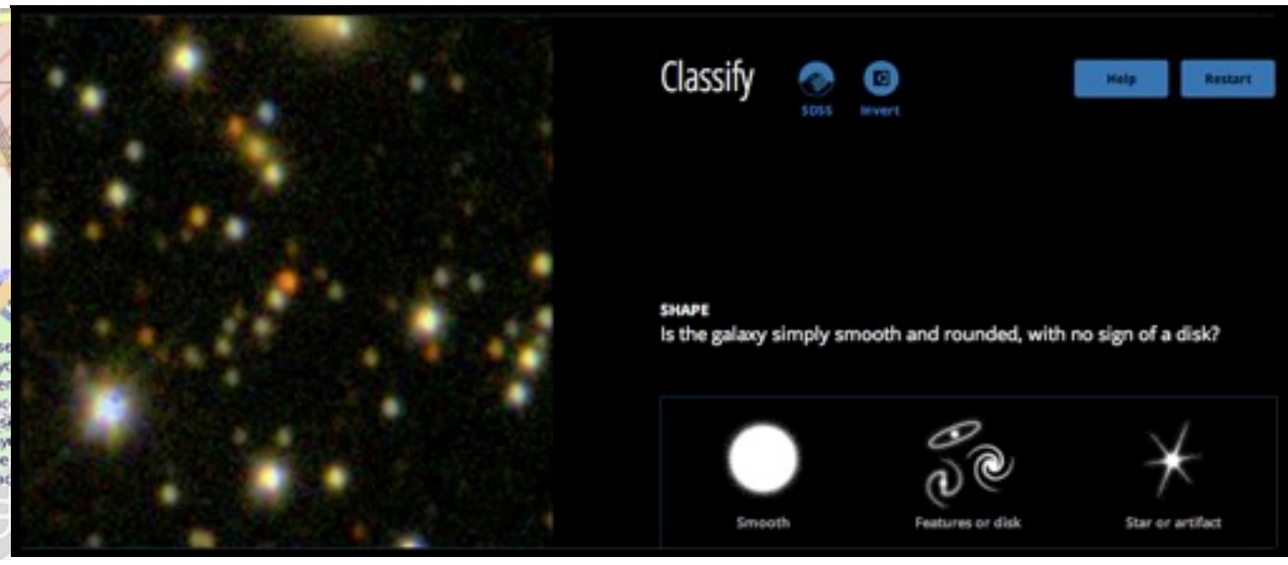
GALAXY ZOO

tomnod
Disaster Mapper

Christchurch GEOCAN

Crowd Engagement & Motivation

The Greater Good



Improved data collection [1]

Analyzing and interpreting data [1]

[1] Newman, G., Wiggins, A., Crall, A., Graham, E., Newman, S., & Crowston, K. (2012). The future of citizen science: emerging technologies and shifting paradigms. Frontiers in Ecology and the Environment.

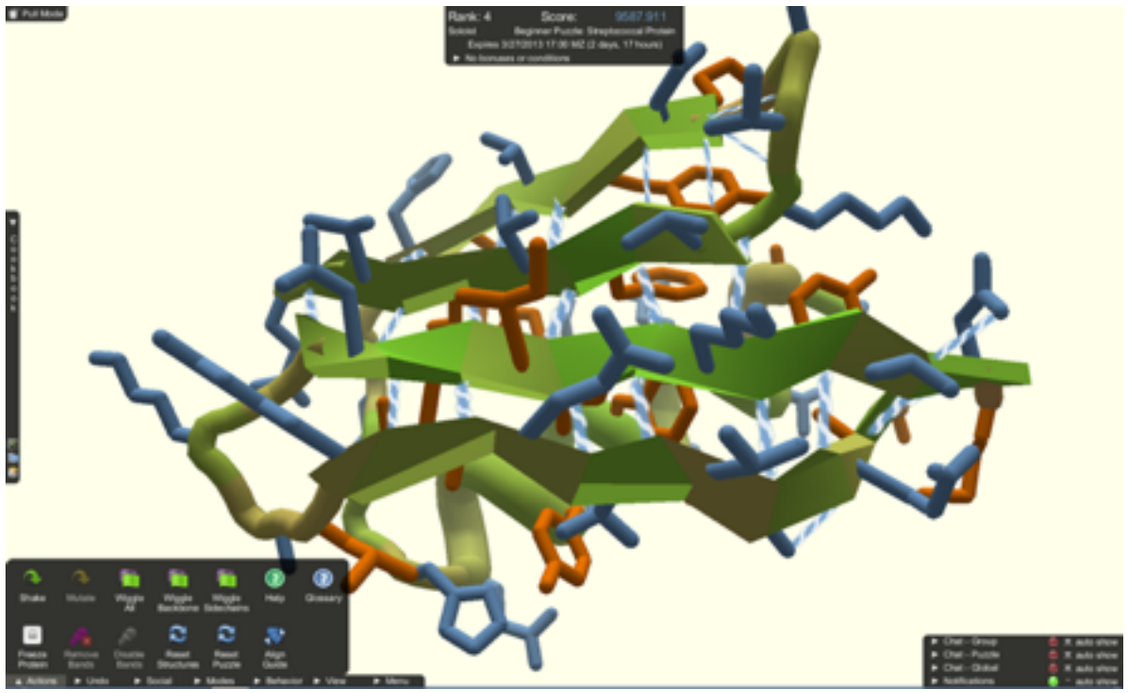
Games With A Purpose [1]

Engagement using a game

[1] Ahn, L. von, & Dabbish, L. (2008). Designing games with a purpose. Communications of the ACM.

Discussion: Engagement & Motivation

Increase quantity and quality of participants



GWAP +
Greater Good

Combine different engagement methods

Discussion: Engagement & Motivation

Increase quantity and quality of participants

Real Fake Fake

Financial incentives increase **quantity** not **quality** [1]

[1] Mason, W., & Watts, D. J.
Financial incentives and the performance of crowds. 2010

Discussion: Engagement & Motivation

Value

Greater Good

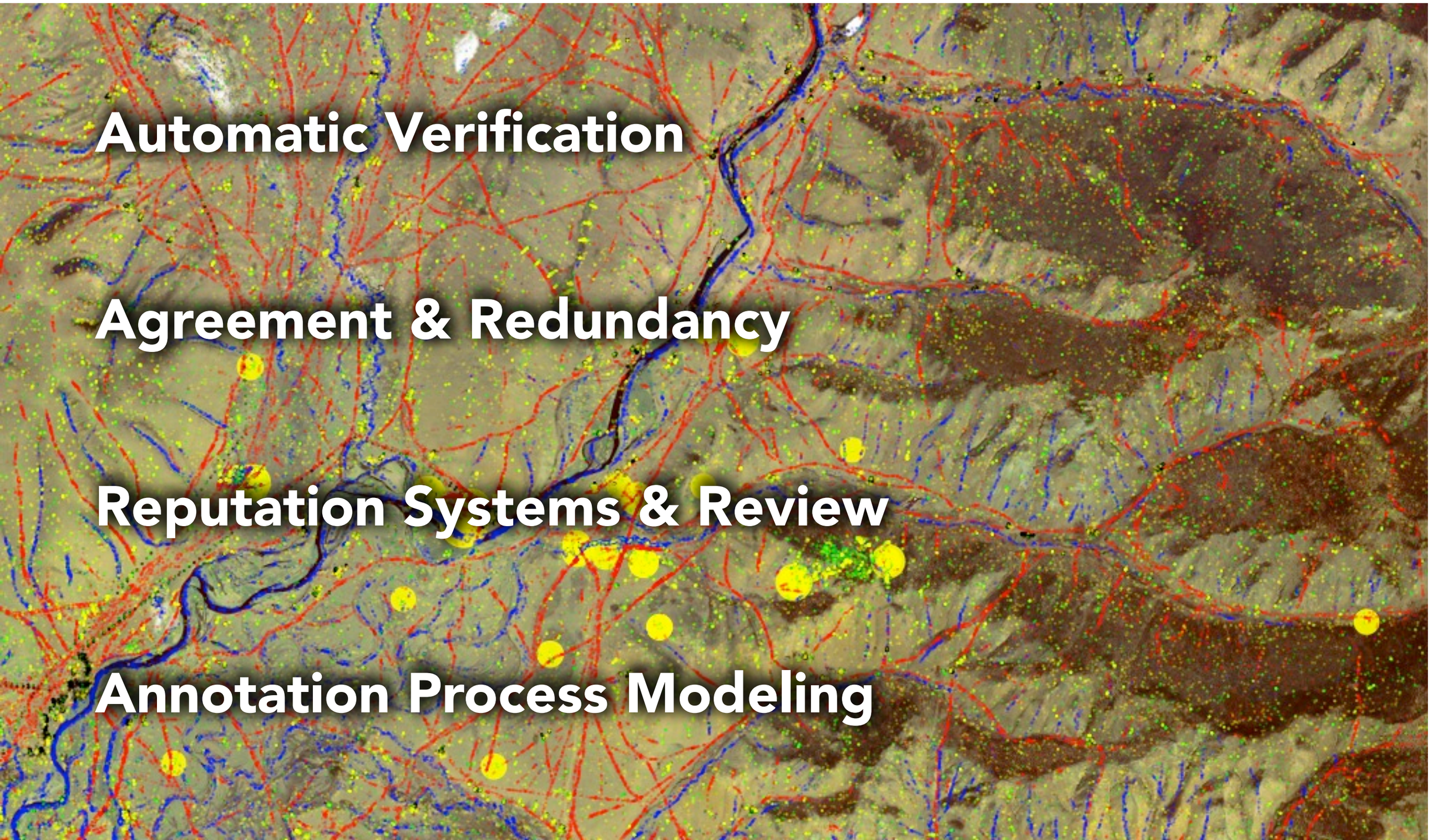
Games

Crowd is engaged and motivated

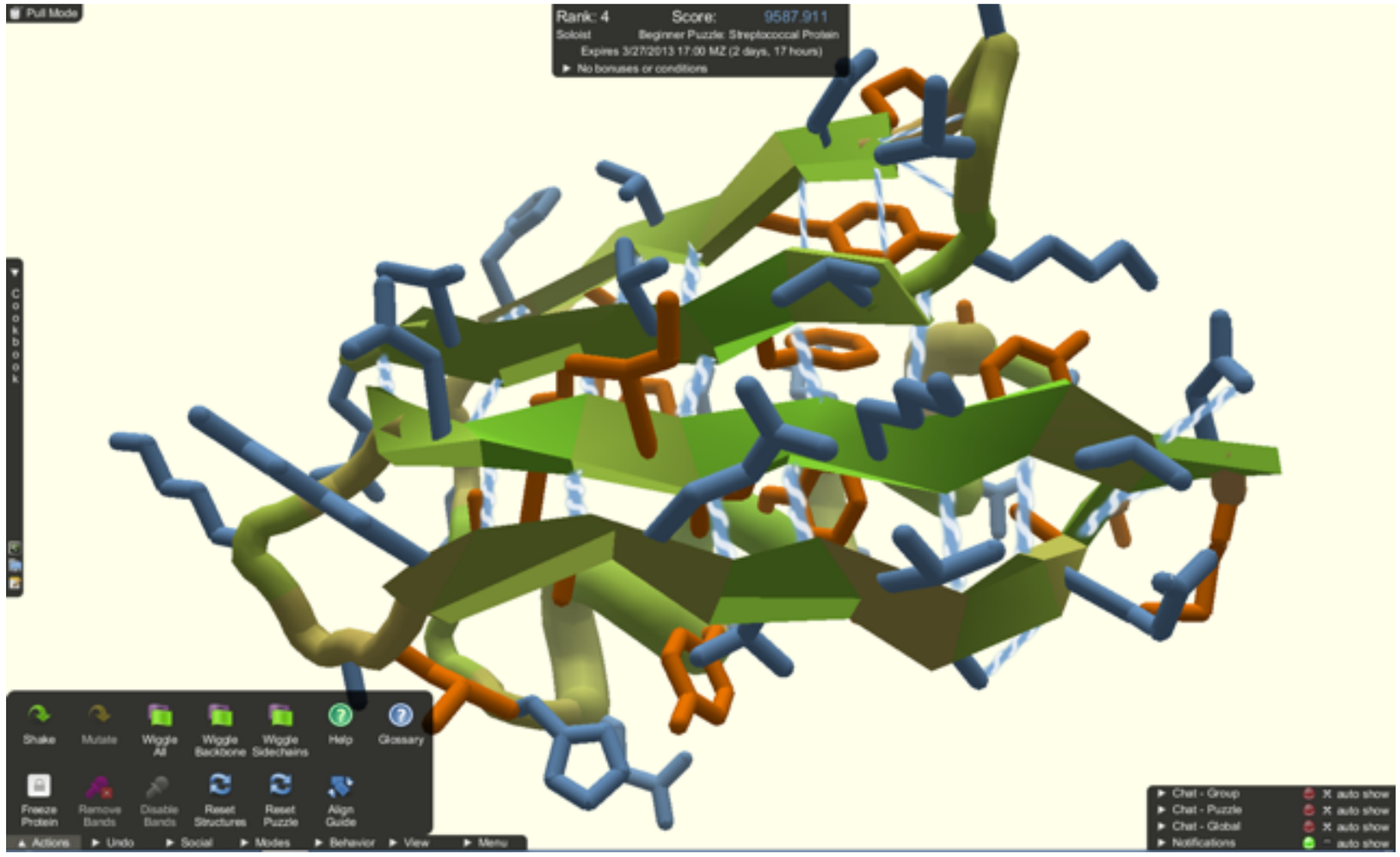
How do we make sure that the data coming in is good?

Active Crowdsourcing

Quality Control



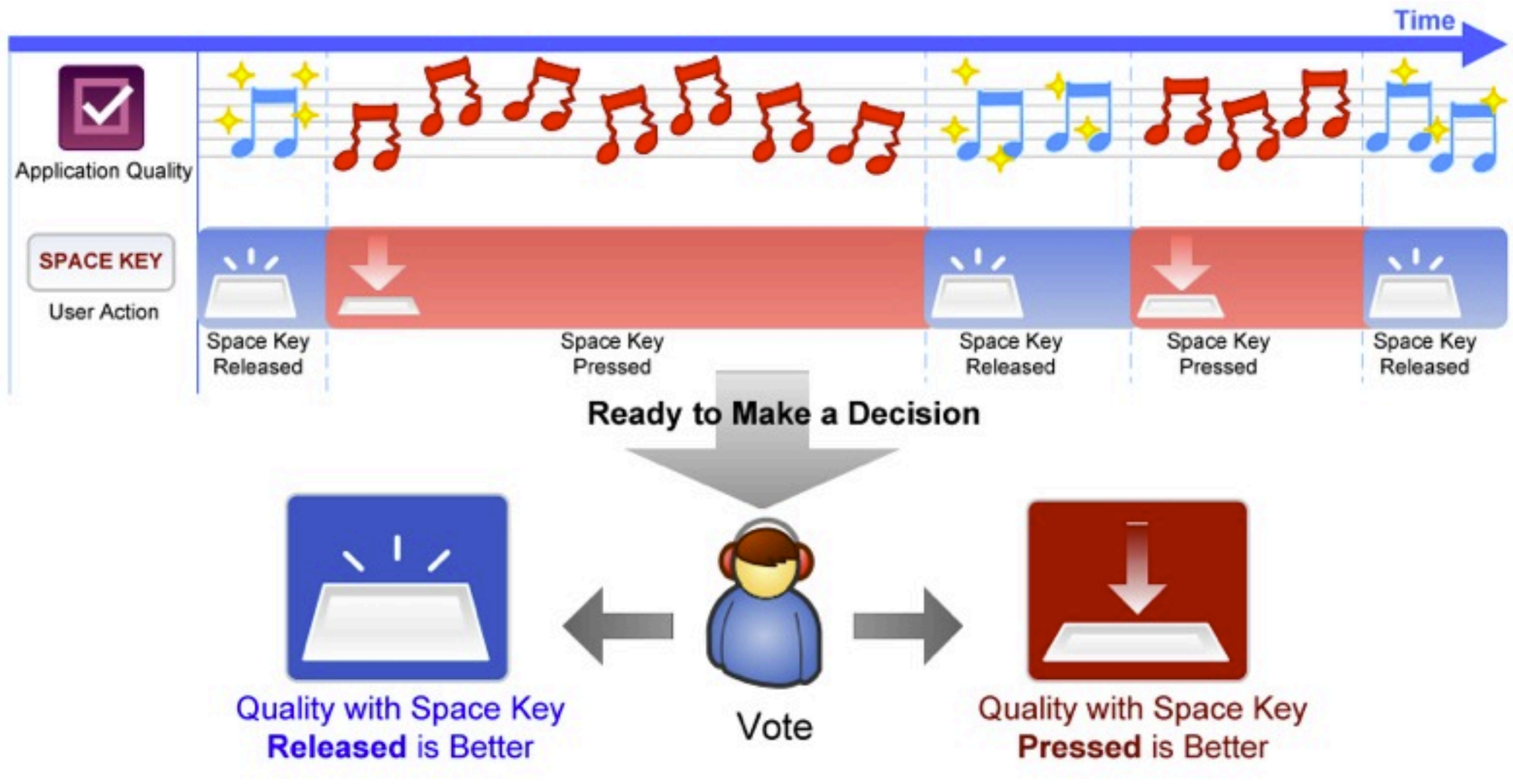
Automatic Verification



Automatic

http://fold.it

Statistical Filtering



QoE can be filtered using the known distribution [1]

[1] Chen, K.-T., Wu, C.-C., Chang, Y.-C., & Lei, C.-L.
A crowdsourceable QoE evaluation framework for multimedia content. 2009

Agreement & Redundancy

Agreement [1]

All participants agree

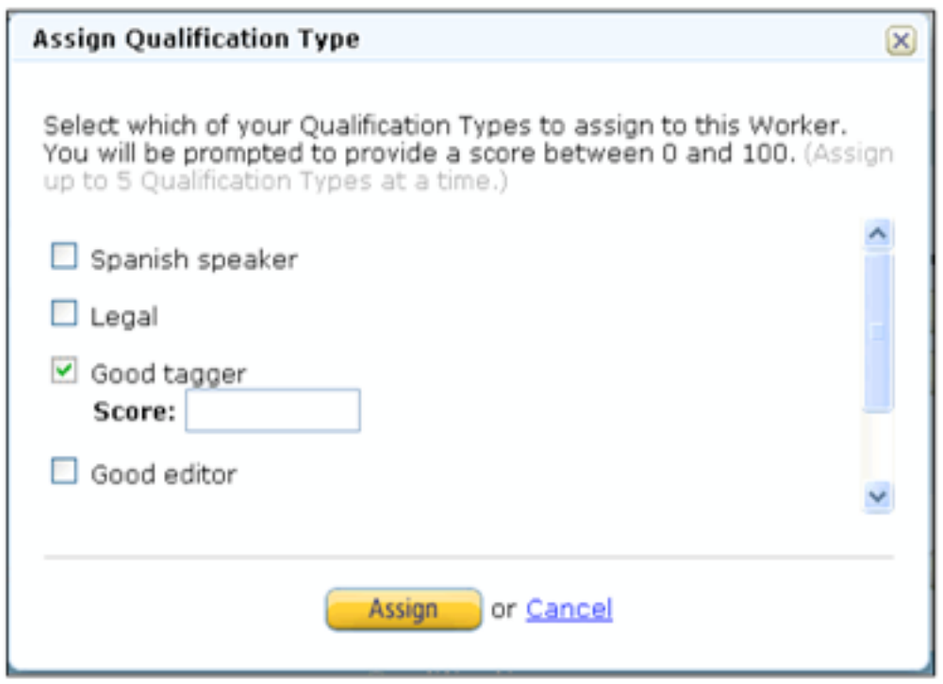
Redundancy [2]

Majority voting or averaging

[1] Ahn, L. von, & Dabbish, L. Labeling images with a computer game. 2004

[2] Ahn, L. von, Maurer, B., McMillen, C., Abraham, D., & Blum, M. reCAPTCHA: human-based character recognition via Web security measures. 2008

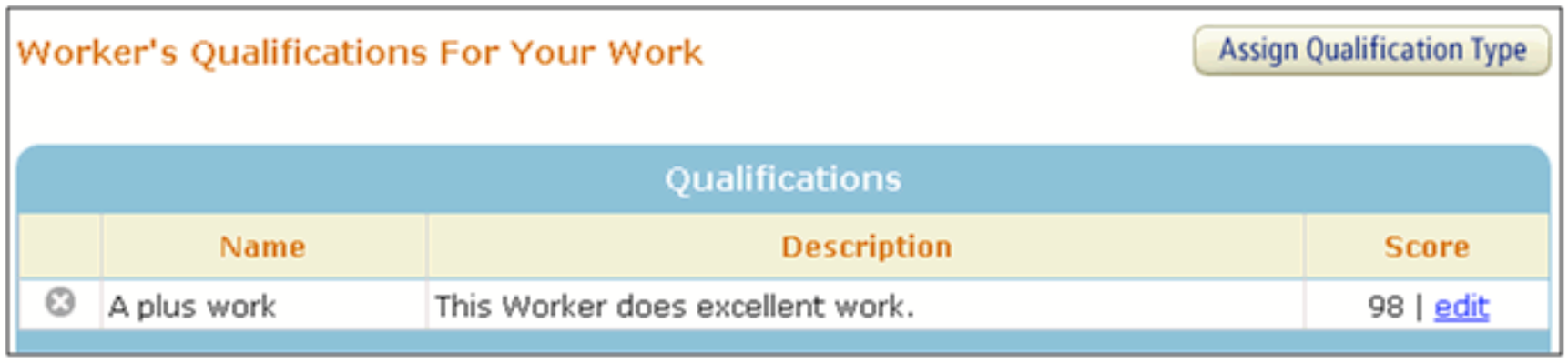
Reputation Systems



Based on previous input

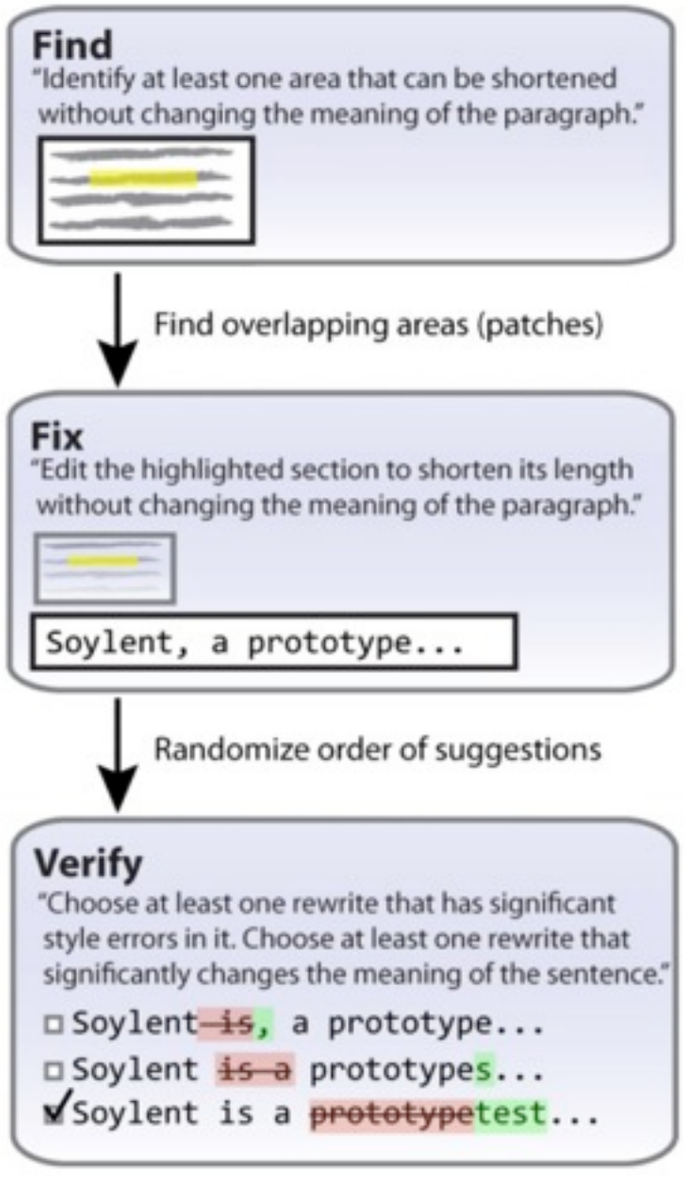
Set a minimum qualification limit

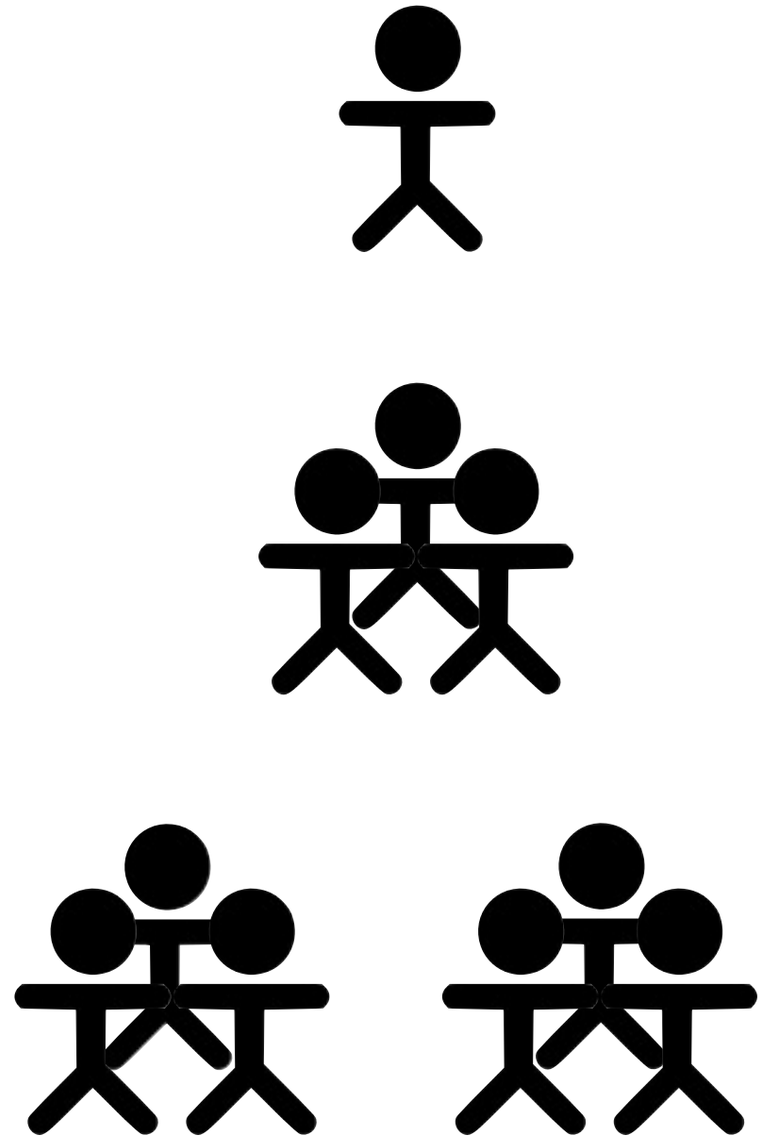
Filter participants by “qualifications”



Expert/Crowdsourced Review

[1]





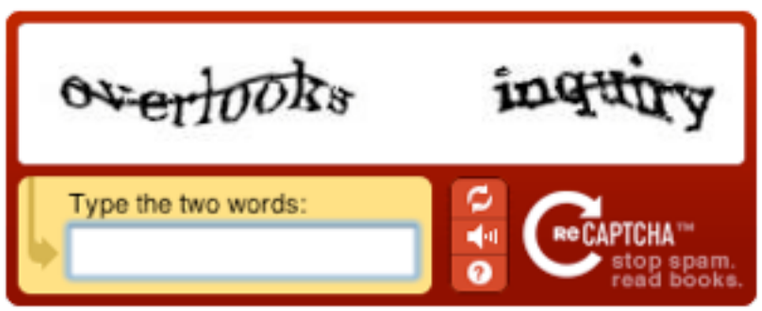
# of vetted solutions

Bernstein, M., Little, G., & Miller, R.
[1] Soylent: a word processor with a crowd inside. Proceedings of the 23nd annual ACM symposium on User interface software and technology. 2010

Annotation Modeling

VS

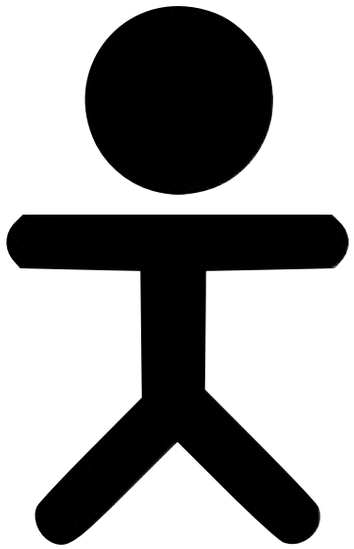
Varying degrees of competence



VS

Some tasks are easier than others

Representing the annotation process [1]



Bias

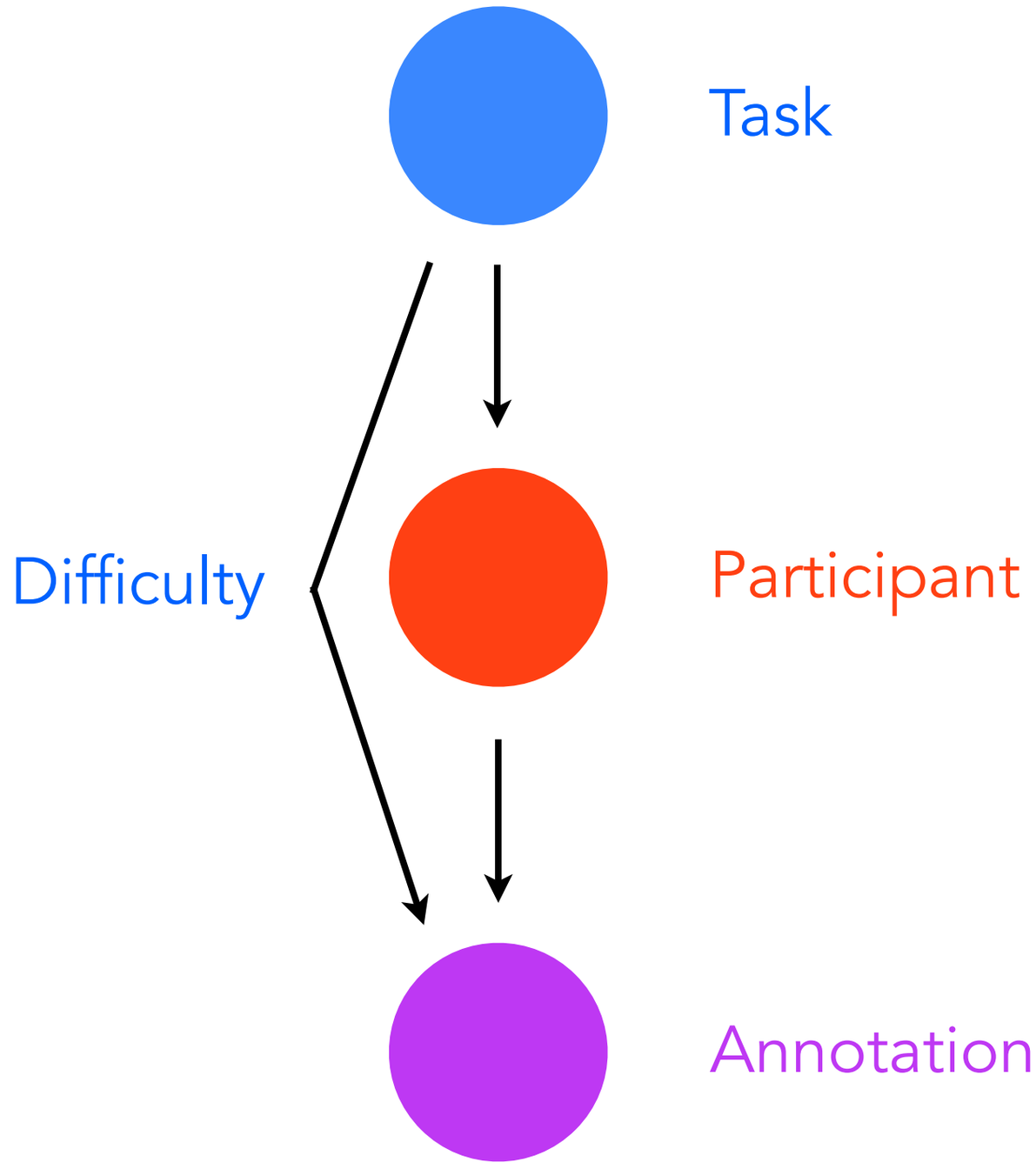
Expertise

Competency

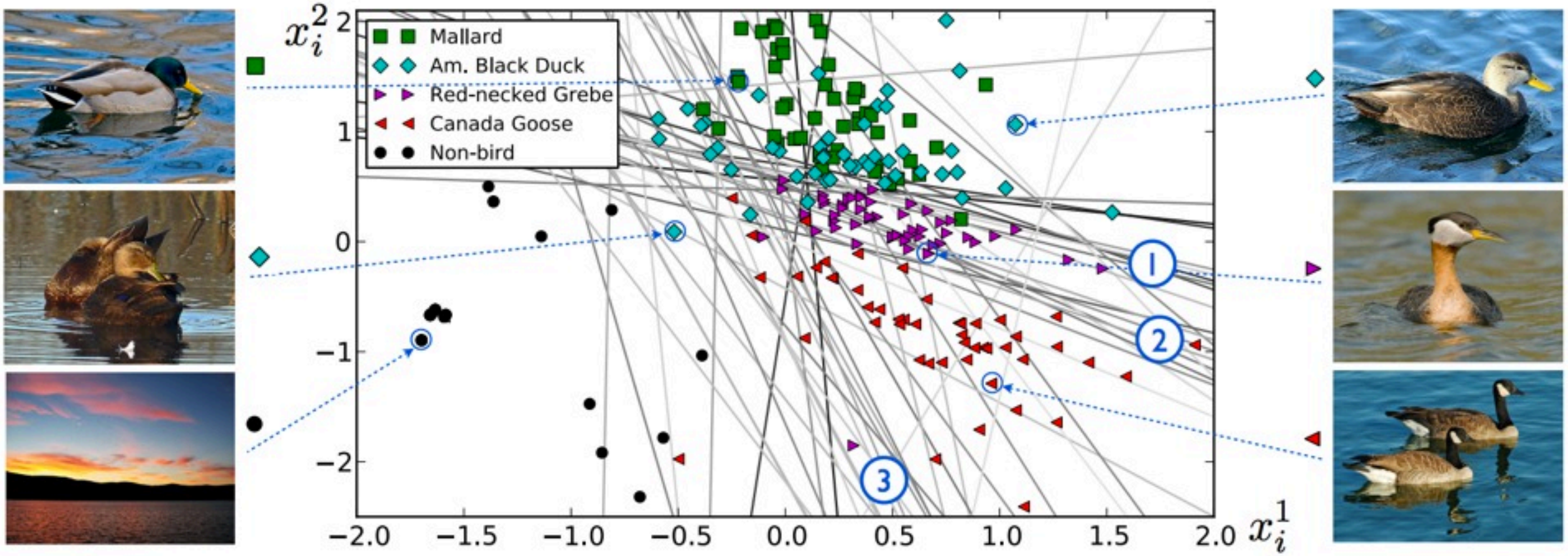
Task Difficulty

[1] Welinder, P., Branson, S., Belongie, S., & Perona, P. The Multidimensional Wisdom of Crowds. 2010

Representing the annotation process



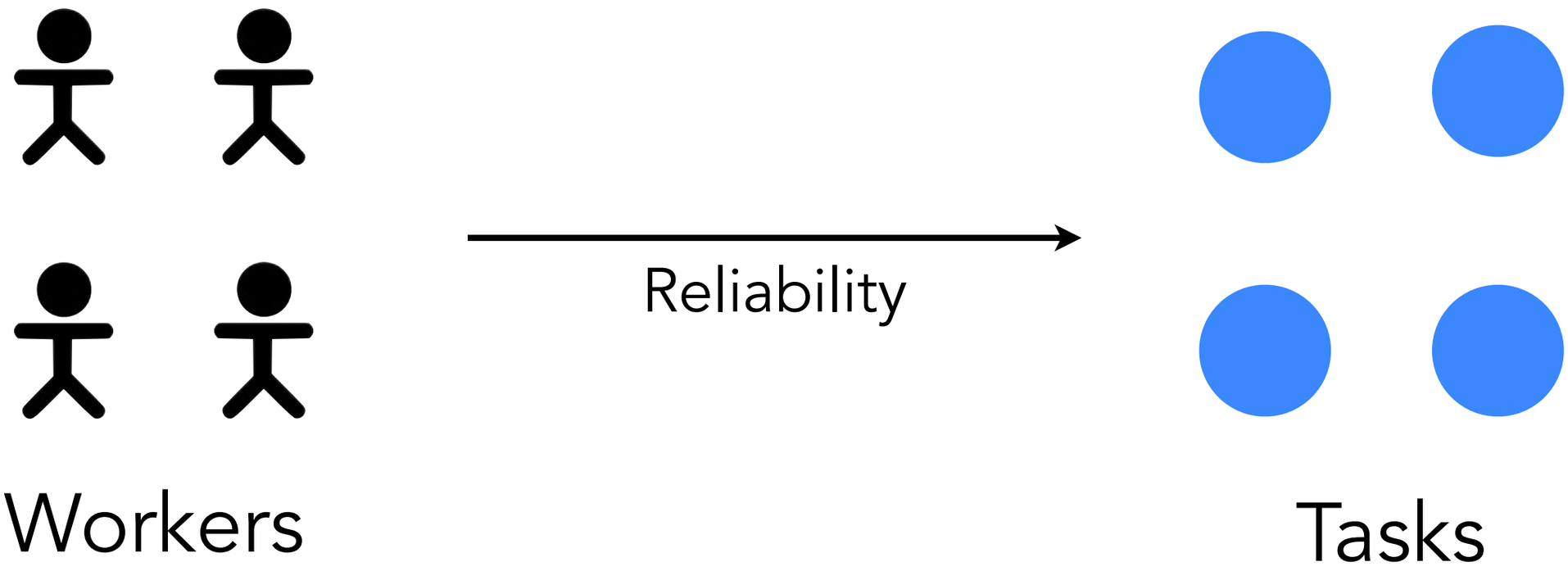
Representing the annotation process



Users (and the data they contribute) can be understood.

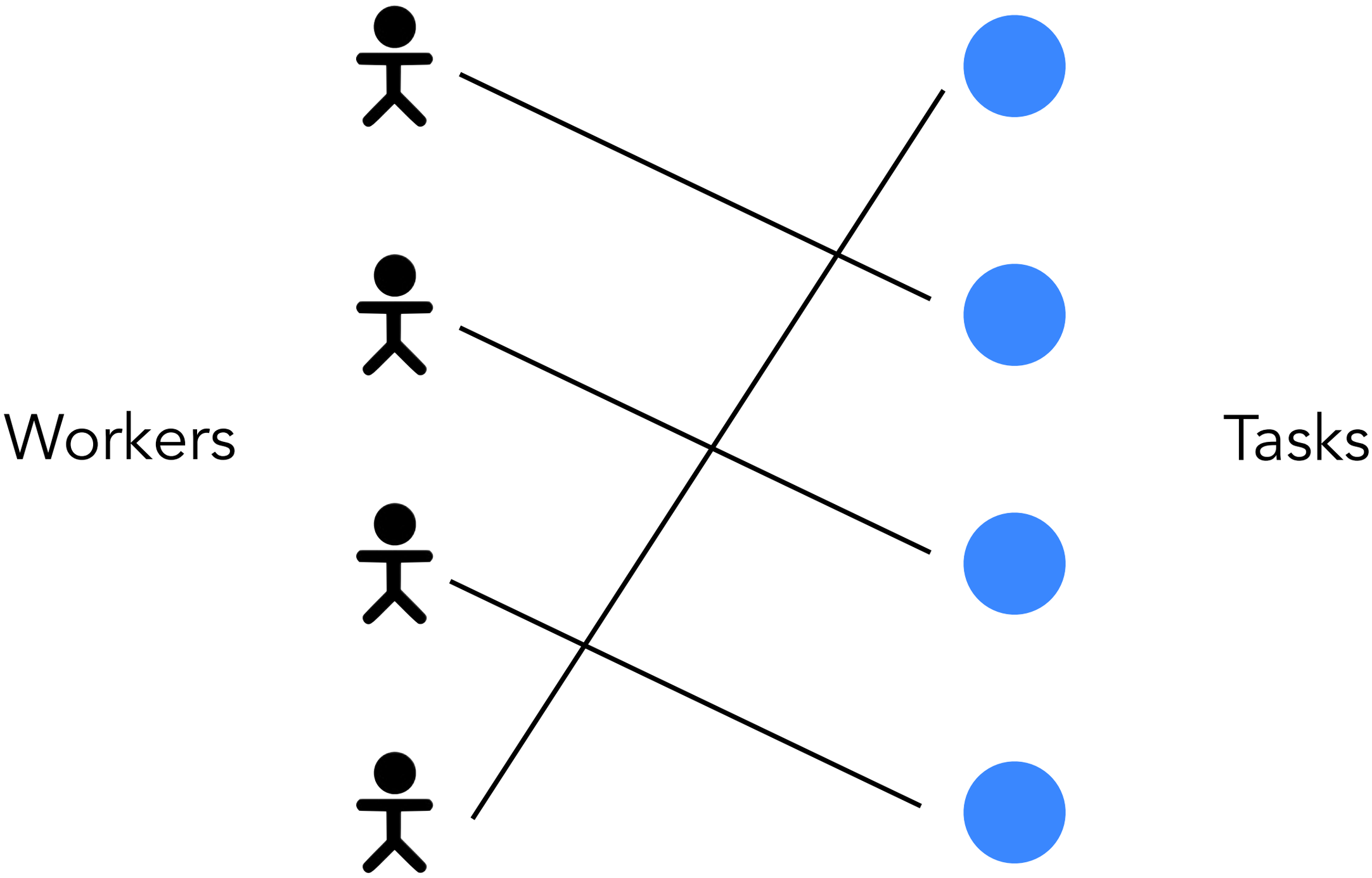
These different “schools of thoughts” can be used to weight the data to retrieve a more accurate classification.

Modeling task assignment [1]



[1] Karger, D., Oh, S., & Shah, D. Iterative learning for reliable crowdsourcing systems. Advances in neural information processing systems, 1–9.2011

Modeling task assignment



Discussion: Quality Control

Increase the quality of data from participants

morning

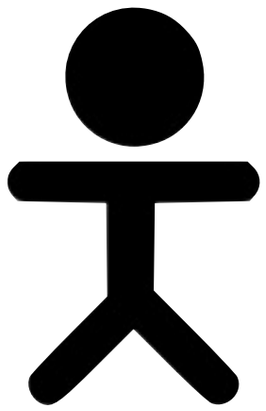
~~moming~~

morning

Depending on task, simple voting may suffice

Discussion: Quality Control

Increase the quality of data from participants



- Bias
- Expertise
- Competency

Task Difficulty

Annotation process modeling improves accuracy with additional computational cost

Passive Crowdsourcing

Active	**Passive**
Distributed tasks	Distributed sensors Idle computers, mobile devices.
Crowd = Pool of labor	Crowd = Source of data Harness existing behavior.
Aggregate solutions	“Work for nothing” [1] No need for motivation/ engagement

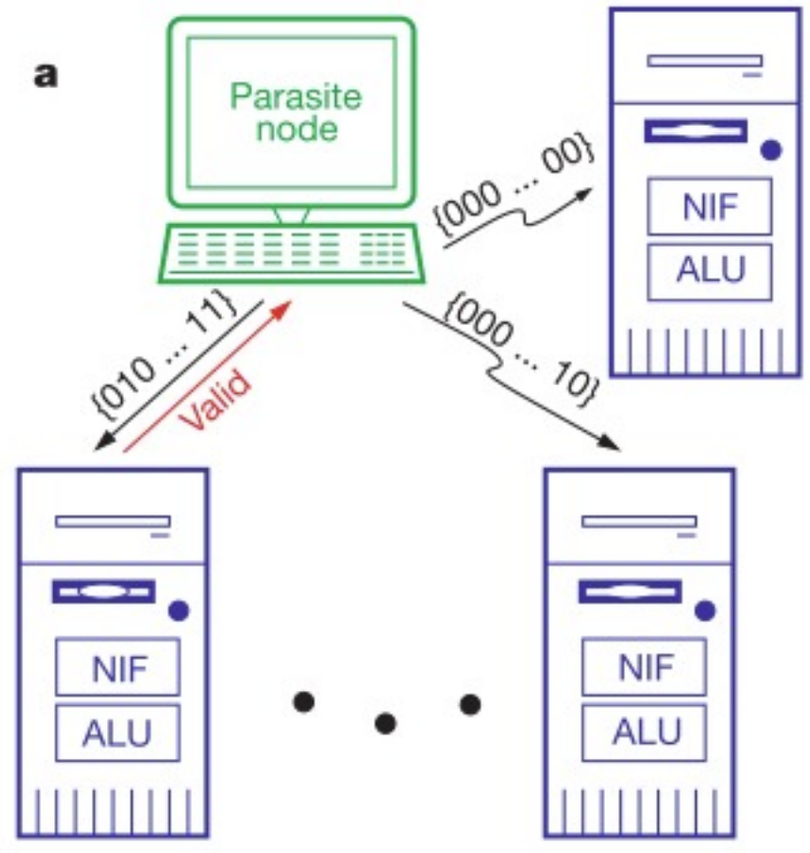
[1] Adar, E.
Why I hate Mechanical Turk research (and workshops). 2011

Parasitic Computing [1]

Computations using TCP checksums.

Failures are dropped.
Success have responses.

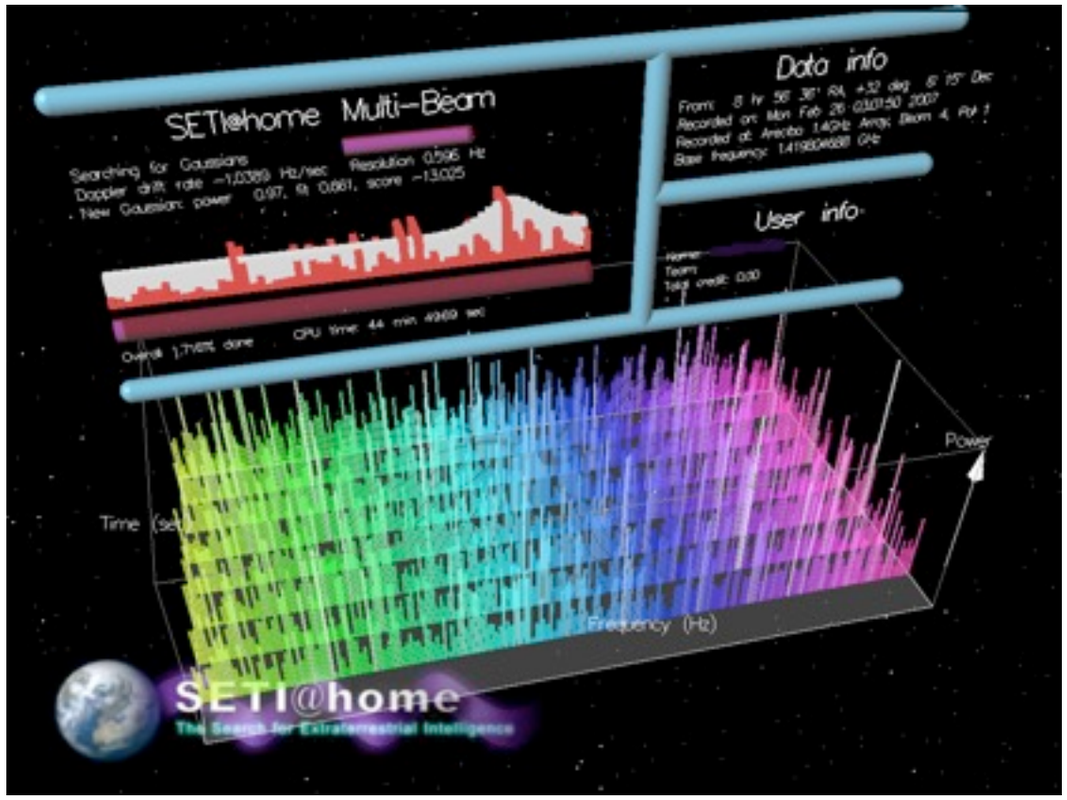
Distributed the computation of a satisfiability problem.



[1] Barabási, a L., Freeh, V. W., Jeong, H., & Brockman, J. B. Parasitic computing. 2001

Passive Crowdsourcing

SETI@Home



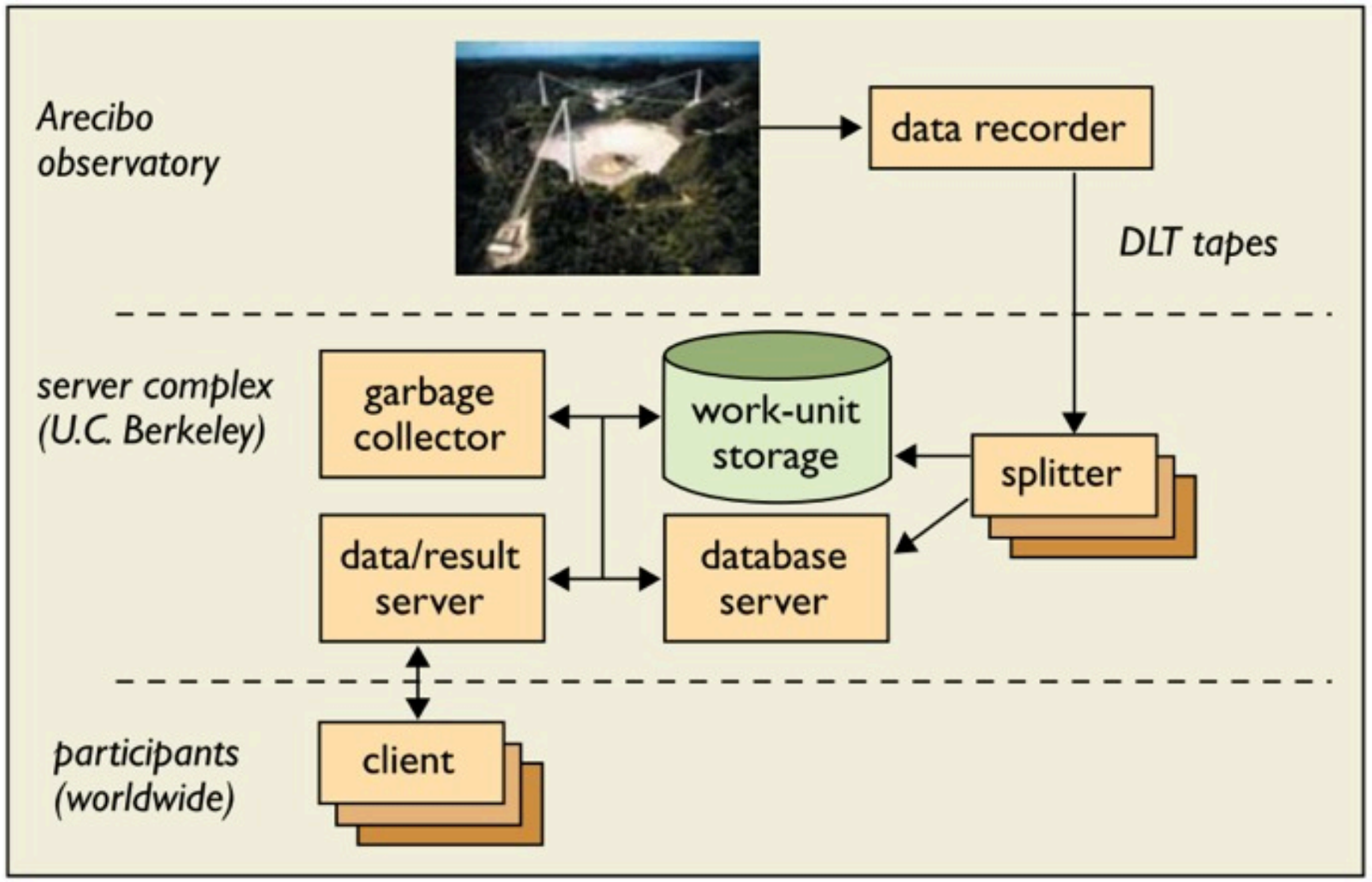
Problems with high computing to data ratio.

Computers often idle.

Idle computing time harnessed [1].

[1] Anderson, D., Cobb, J., & Korpela, E.
SETI@ home: an experiment in public-resource computing. 2002

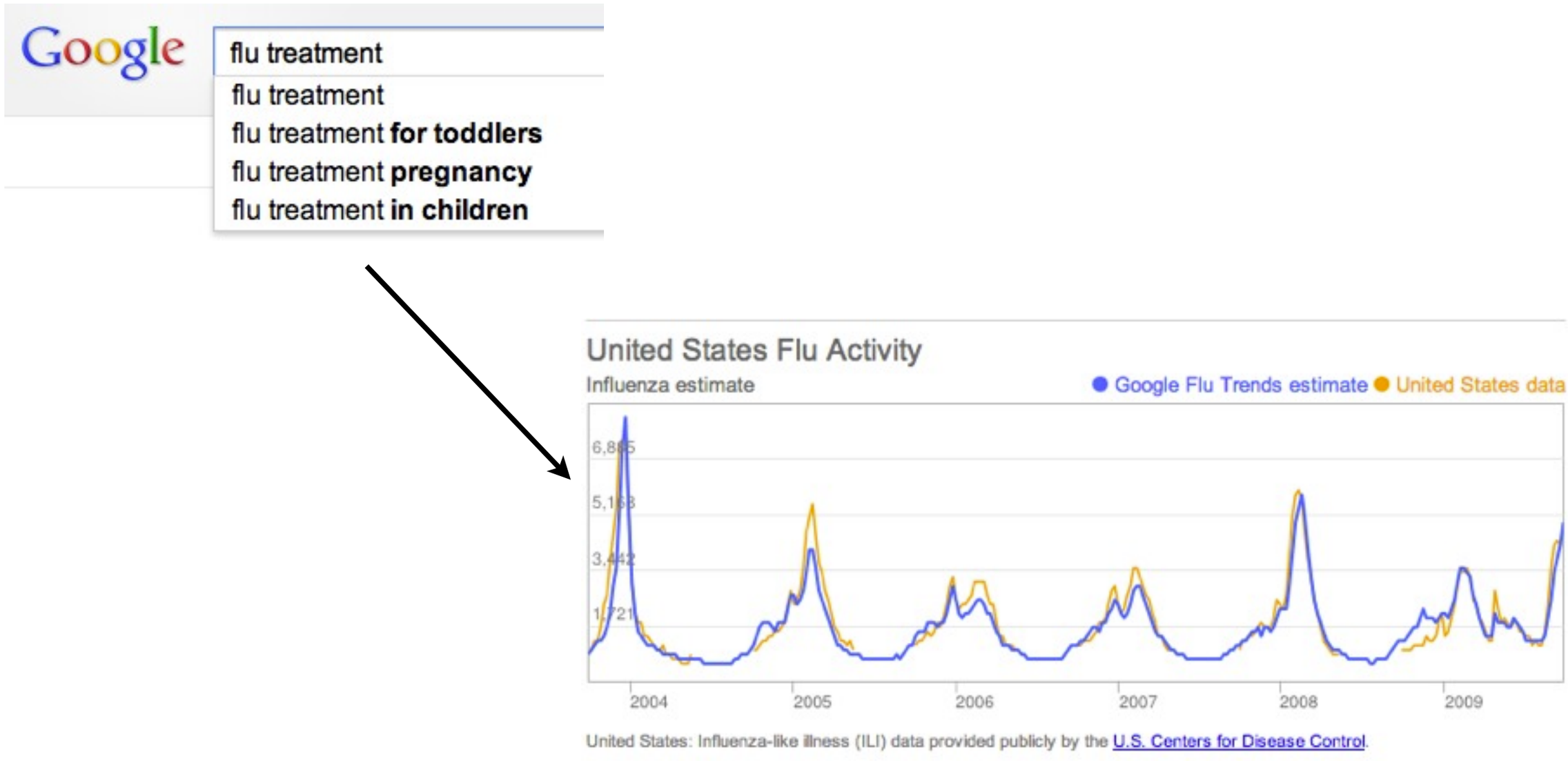
SETI@Home



145,000 active computers. 668 TeraFLOPS

Around 40th on TOP500 supercomputers

Crowdsensing

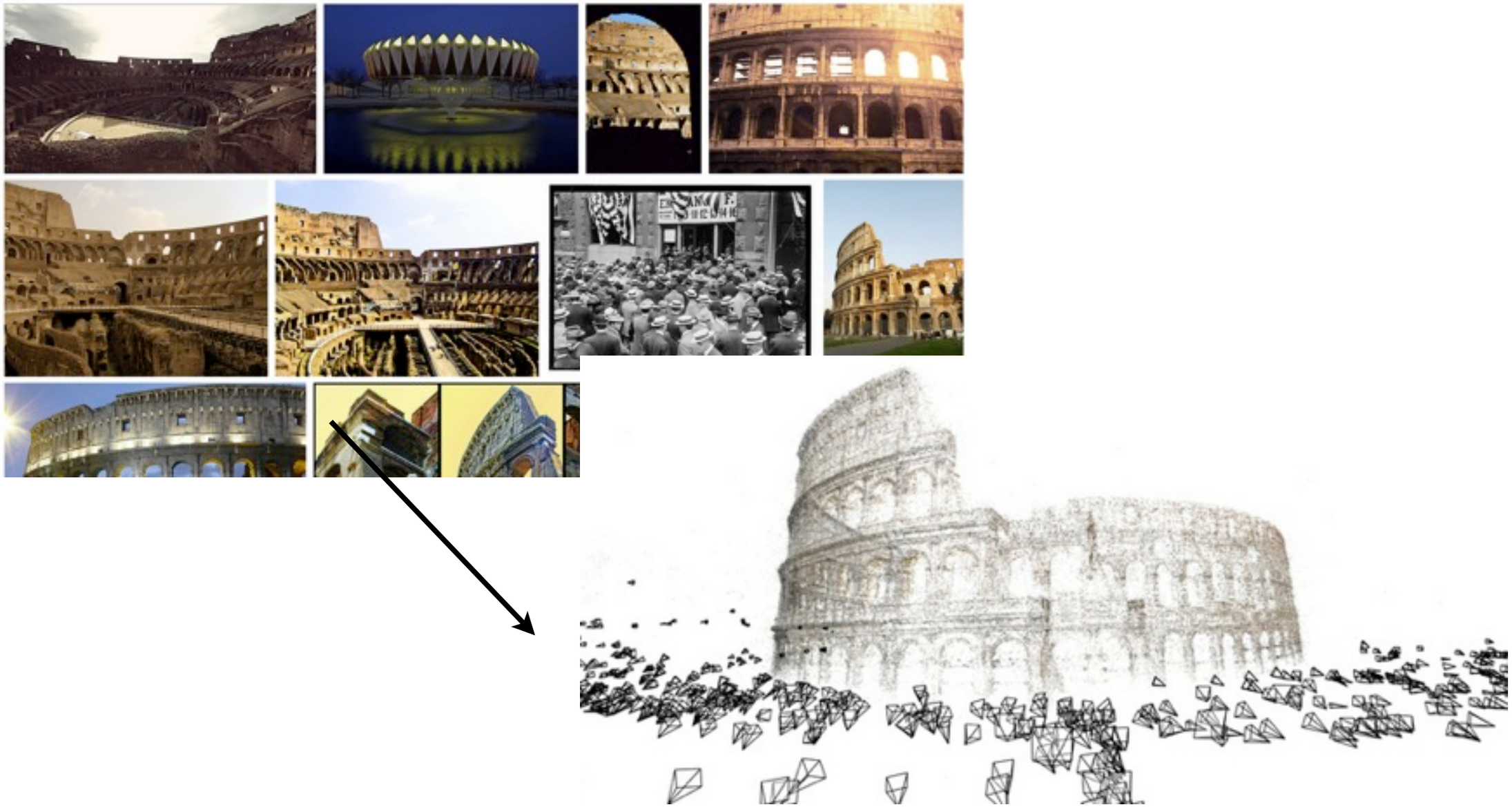


Based on everyday search queries, clear correlations with influenza activity.

Crowdsensing

Gather data from Google Maps app as people sit in traffic

Crowdsensing



Public tourist pictures translated into a 3D model [1]

[1] Agarwal, S., Snavely, N., Simon, I., Seitz, S. M., & Szeliski, R. Building Rome in a day. ICCV, 72–79. 2009

Discussion: Passive Crowdsourcing

Tap into existing behavior to collect data/run computations

Motivation/engagement is no longer a major problem

Untapped source of behavioral data.

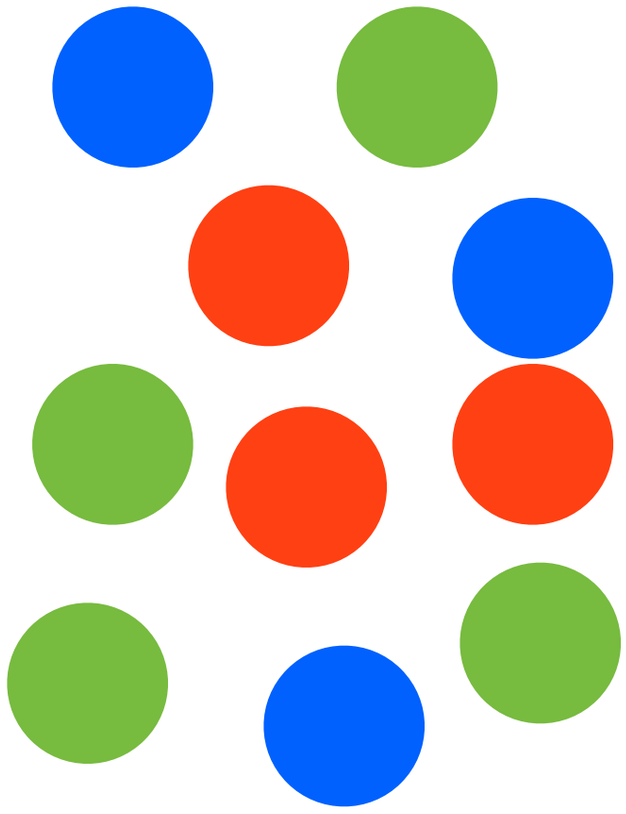
Medical diagnostics, detecting activities such as running, walking, etc.

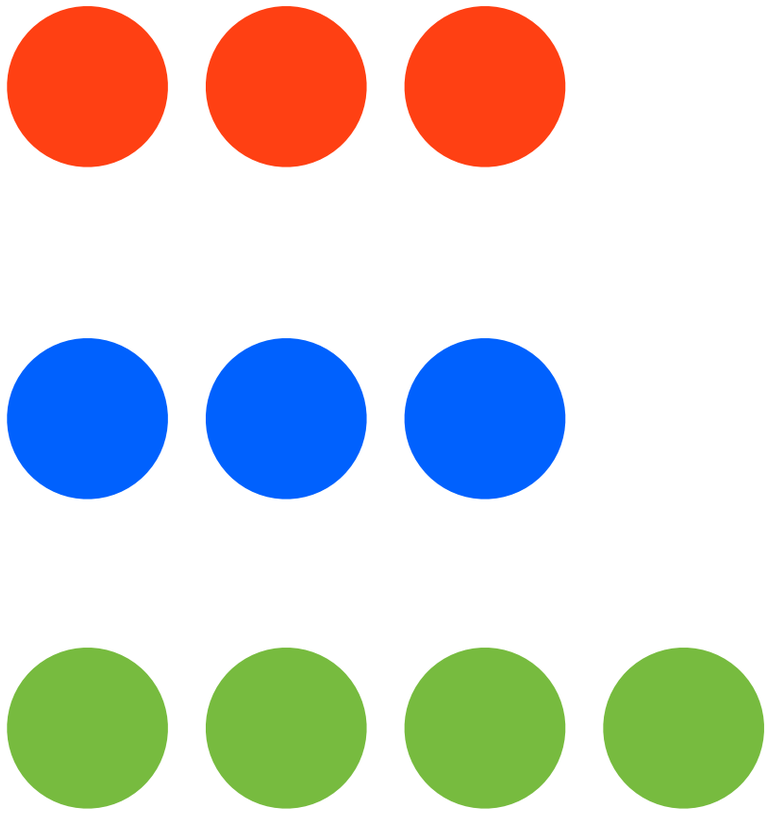
Security?

Privacy?


the
BIG
data

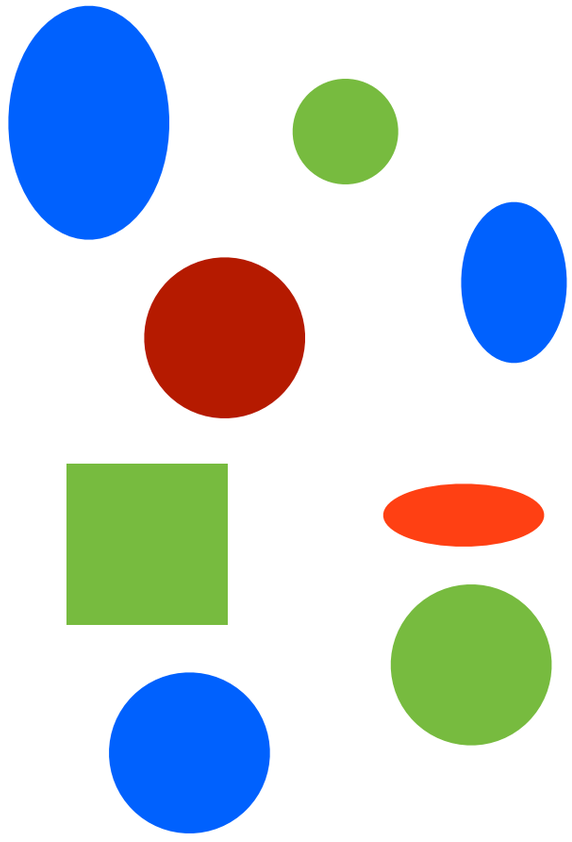
Learning from the Crowd

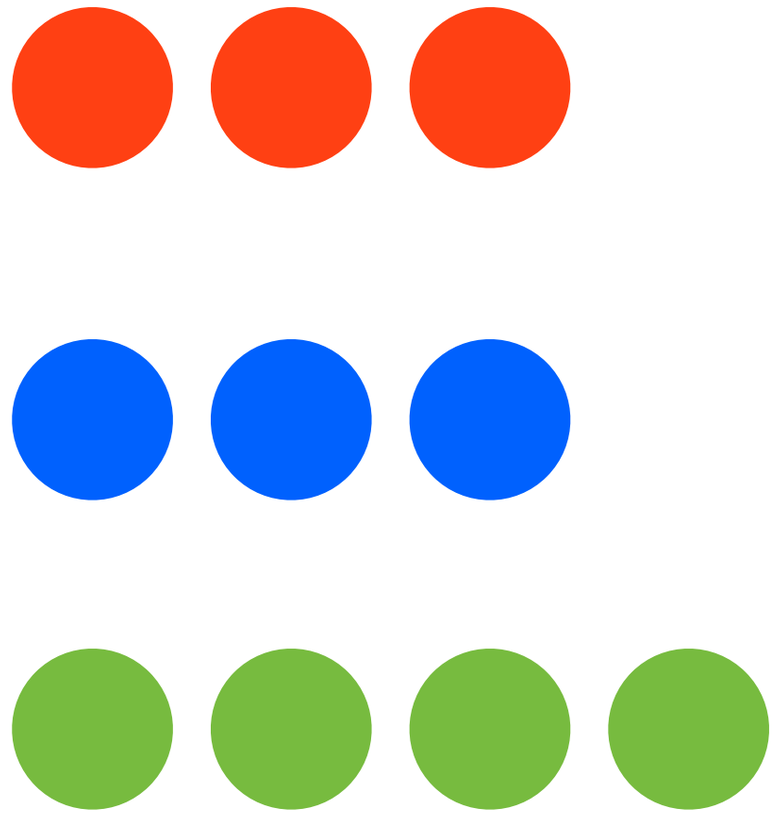




Training Set ⟶ Machine Learning ⟶ Classification

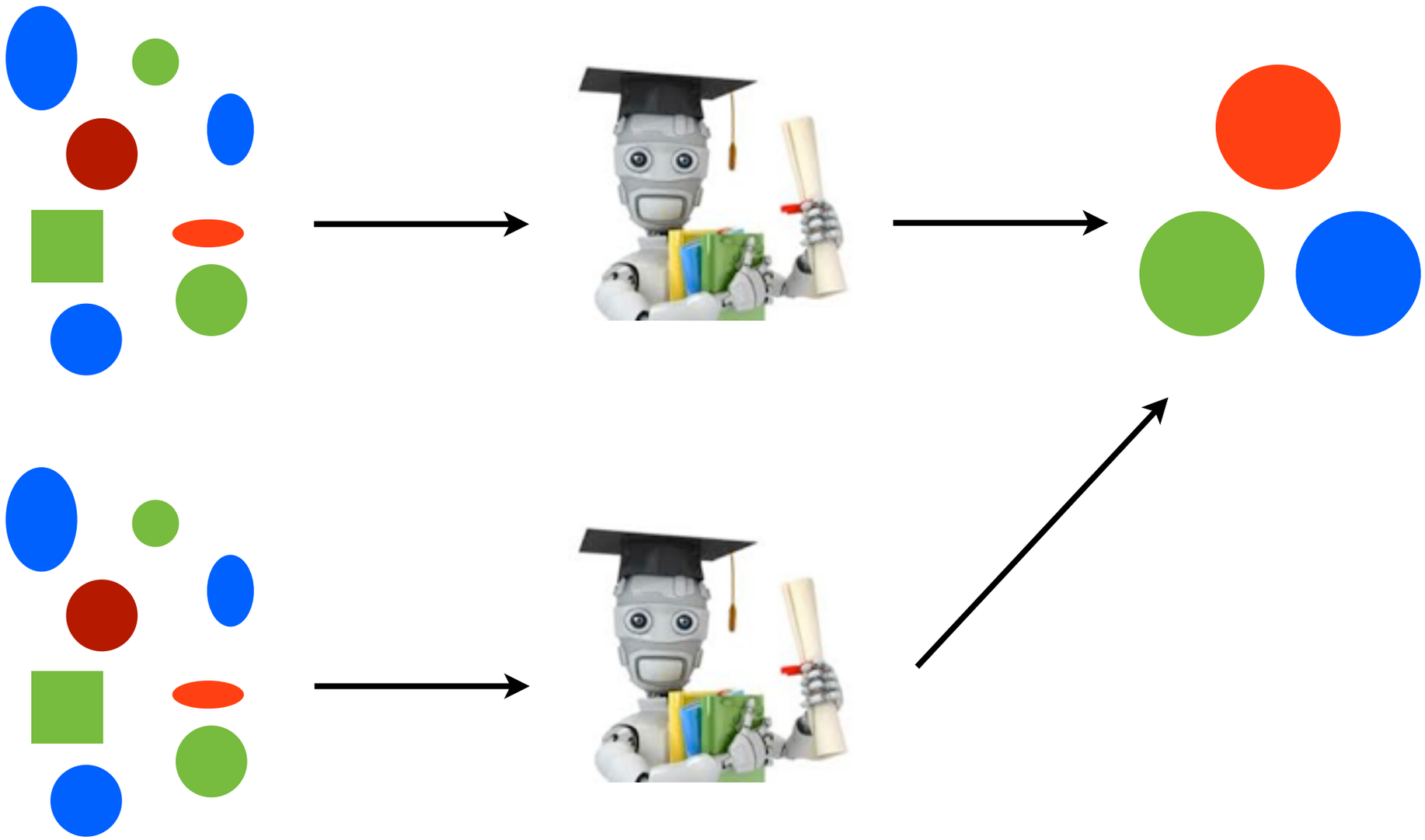
Learning from the Crowd





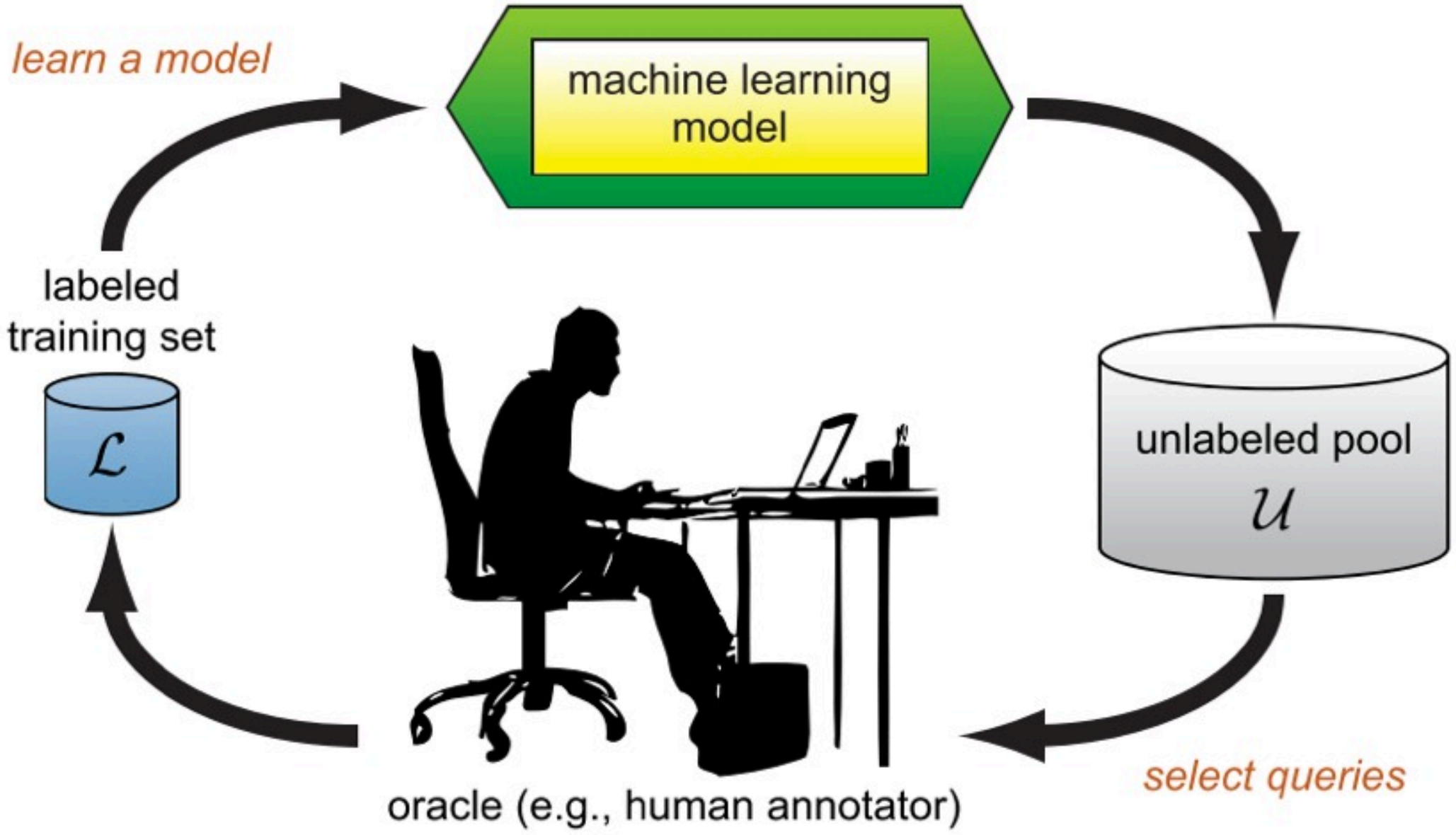
Crowd Data → Machine Learning → Classification

Active Learning



Continually improve model with additional training data

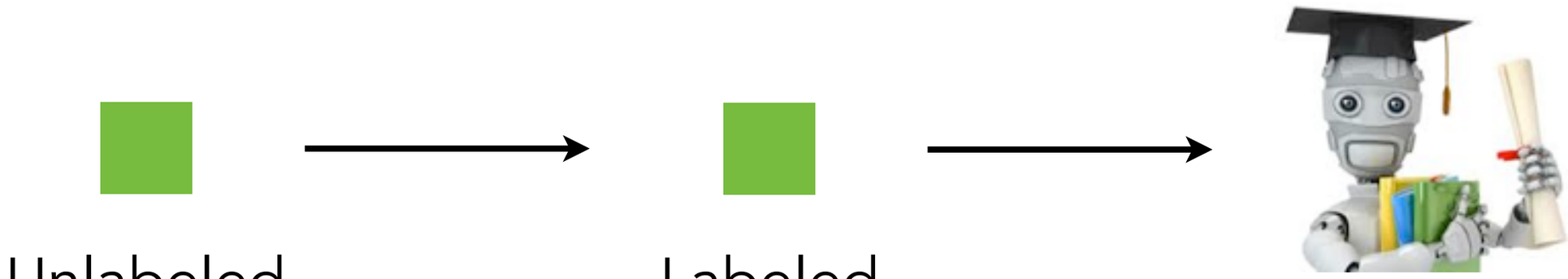
Active Learning

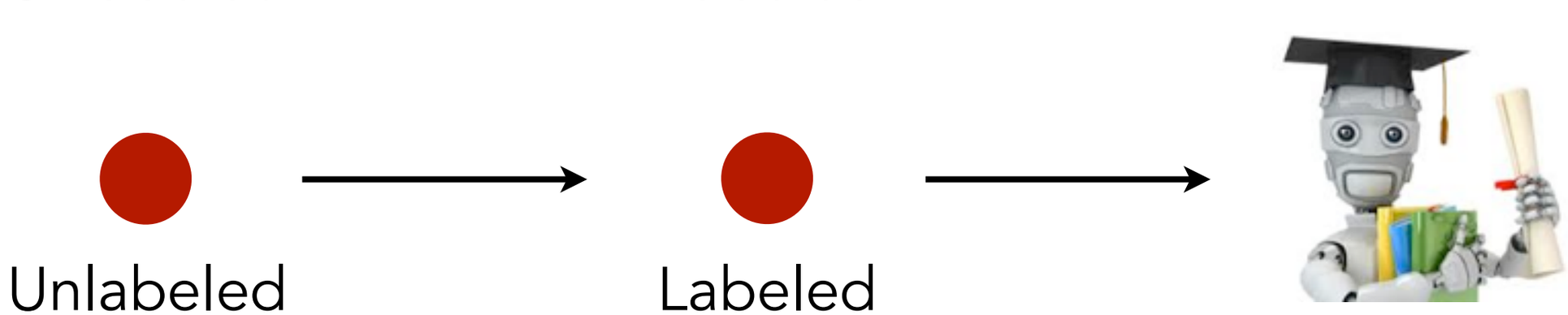


Settles, B. Active learning literature survey. 2010

Sequential/Online approaches

Ask for a single unlabeled data at each iteration





Instances where we have a stream of unlabeled data.

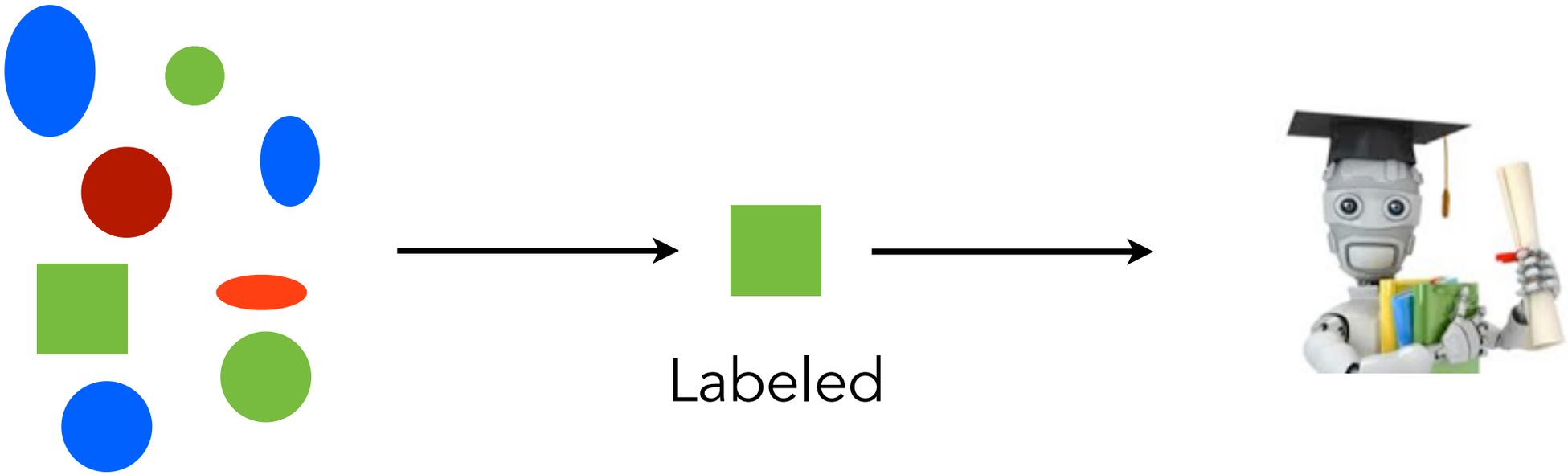
Each instance is drawn one at a time, query for it's label or discard.

Select instances that will be more informative to the model.

Pool-based approaches

Large collections of unlabeled data

Small collection of labeled data

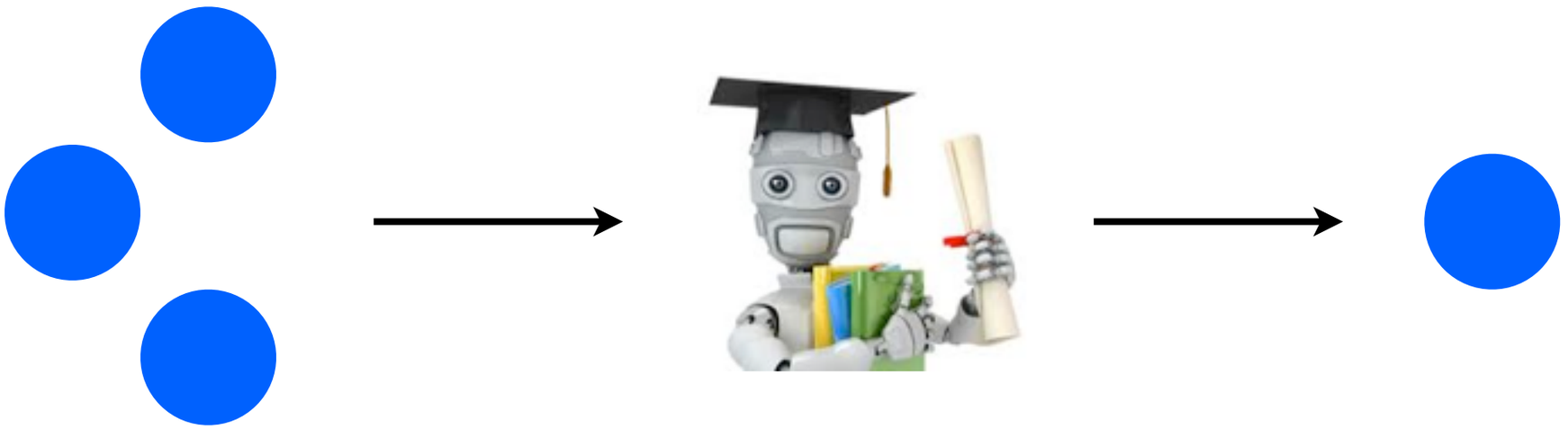


Queries from the pool using some informativeness measure

More computational expensive than online approach. Ranks the entire pool before making decisions.

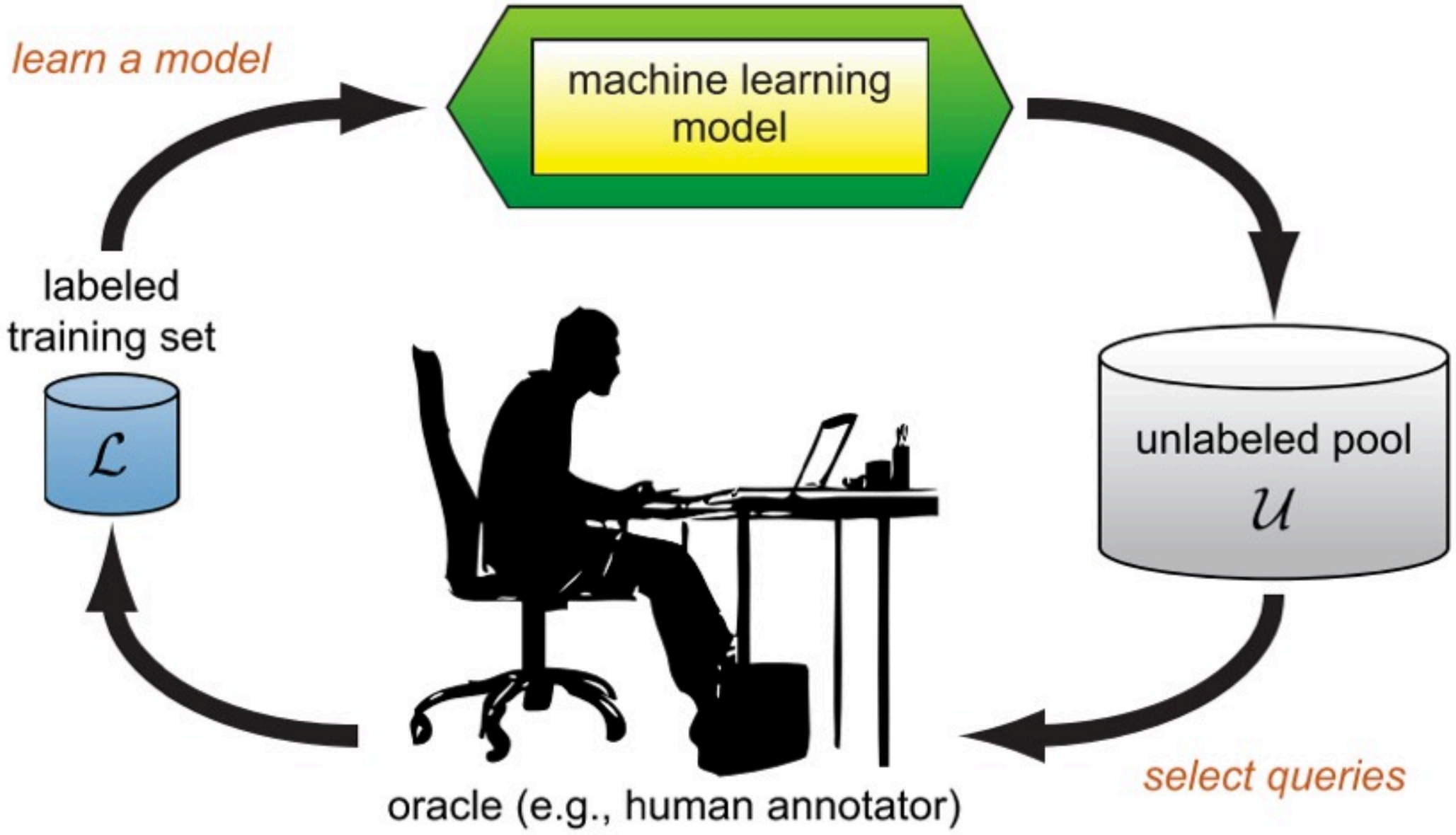
Discriminative vs. Generative

Discriminative uses positive and negative examples for training



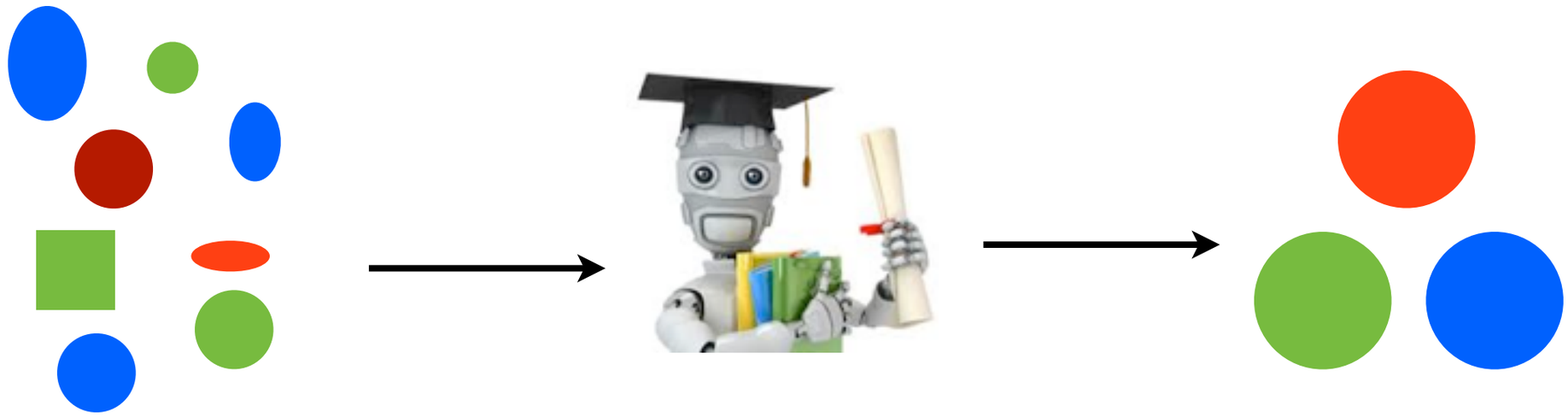
Generative require only positively labeled examples

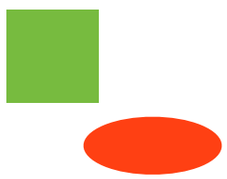
Closing the Loop



Settles, B. Active learning literature survey. 2010

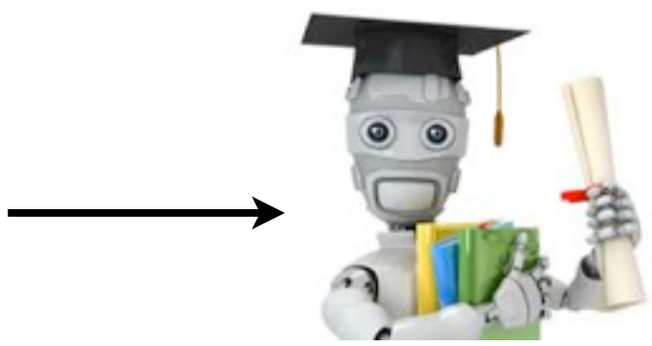
Closing the Loop





Relabel existing

New label

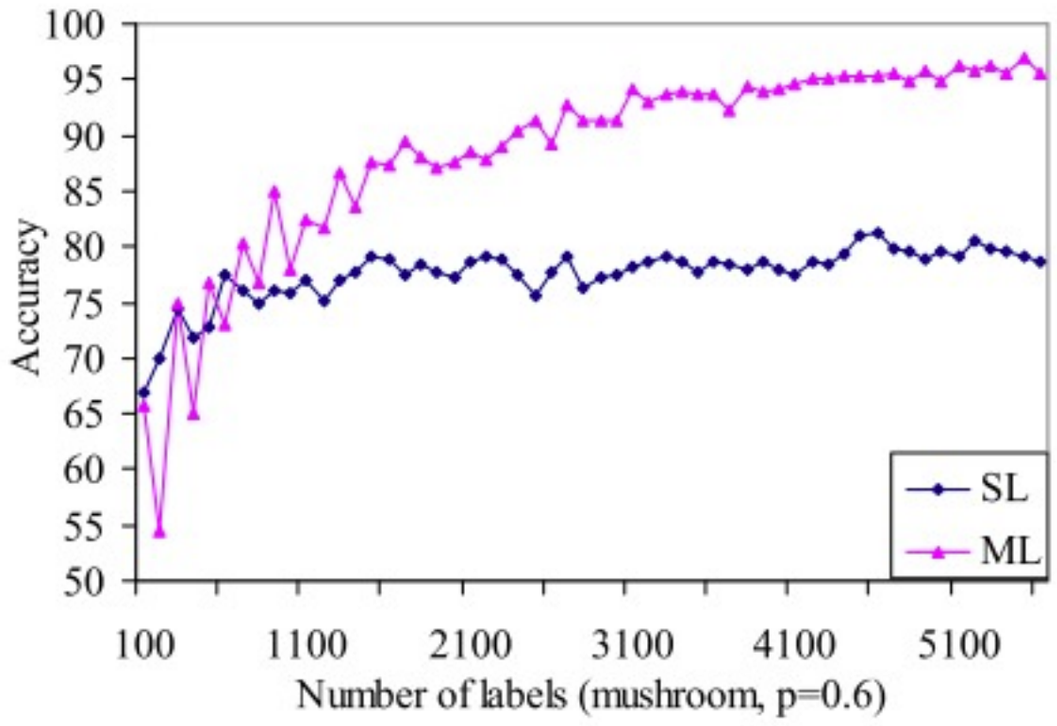


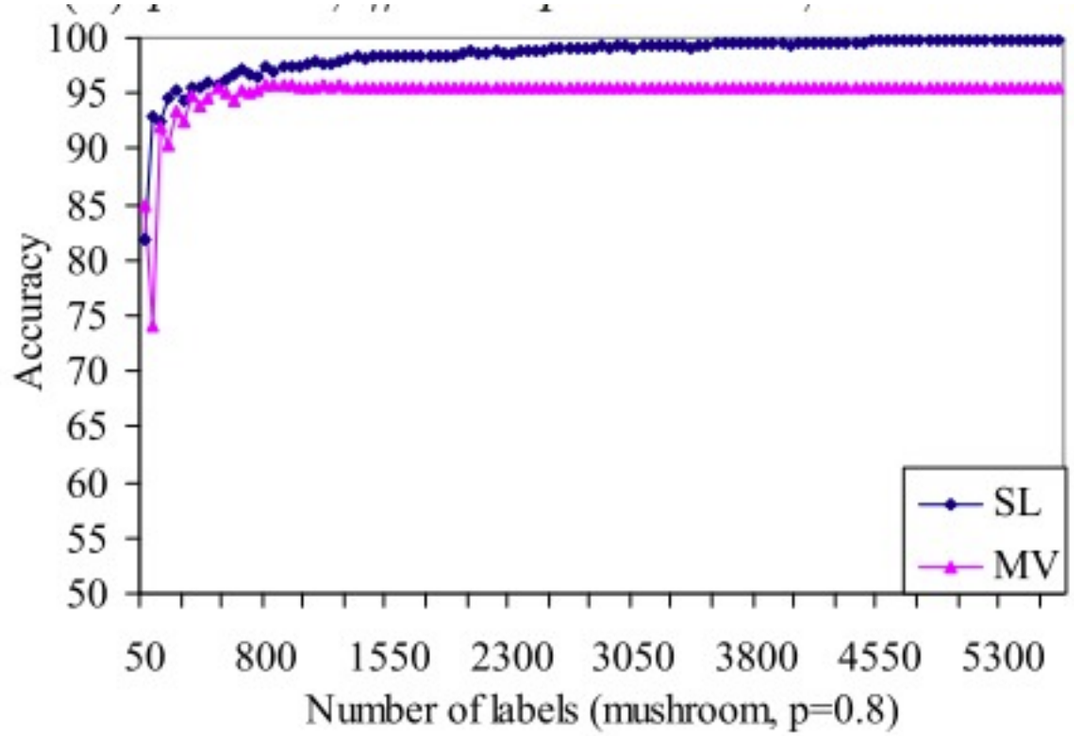
Should we relabel or get new label? [1]

[1] Settles, B. Active learning literature survey. 2010

Closing the Loop

Repeated labeling improves the overall data collected. [1]





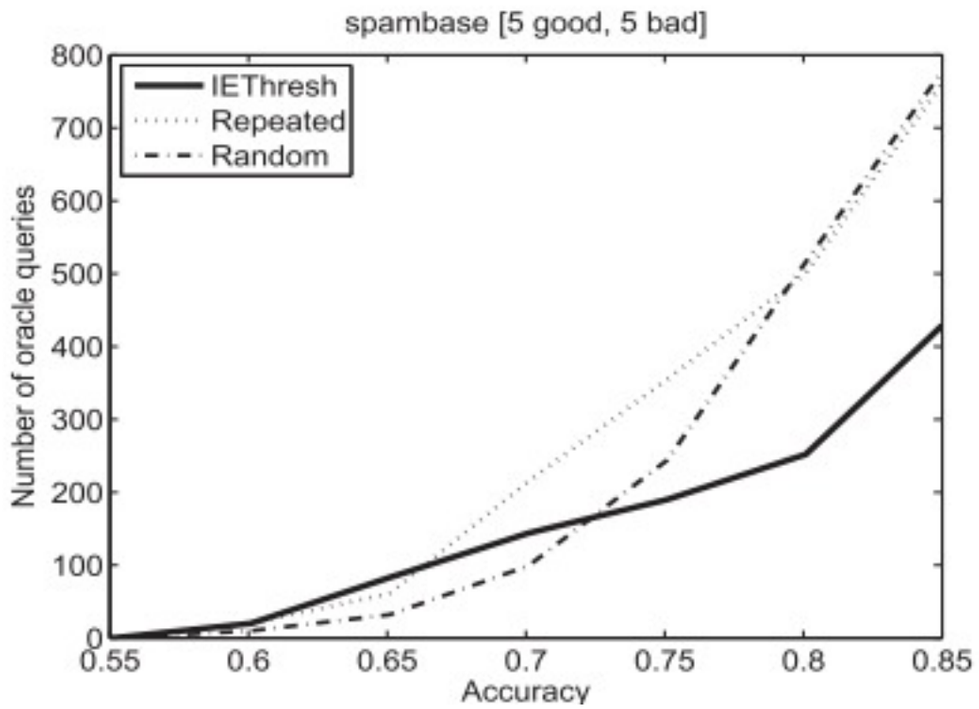
Repeated labeling when labeling is noisy

Must take into account model and label uncertainty

[1] Sheng, V., Provost, F., & Ipeirotis, P.
Get another label? improving data quality and data mining using multiple, noisy labelers. 2008

Closing the Loop

Can further improve accuracy by choosing expert labelers [1]



Compute a confidence level for each participant

On next iteration, pick a better participant for a unlabeled instance

[1] Donmez, P., Carbonell, J. G., & Schneider, J.
Efficiently learning the accuracy of labeling sources for selective sampling. 2009

Discussion

Active learning gives a methodology to iteratively improve models with humans in the loop.

Inexpensive

Crowdsourcing gives us access to inexpensive pools of unlabeled data and noisy labelers.

Improving Uncertainty

We can begin to answer questions that normally had no clear model through uncertainty sampling and repeated labeling.

Scalable

As soon as we have a model we can apply that model to find solutions where before we had to use human labelers

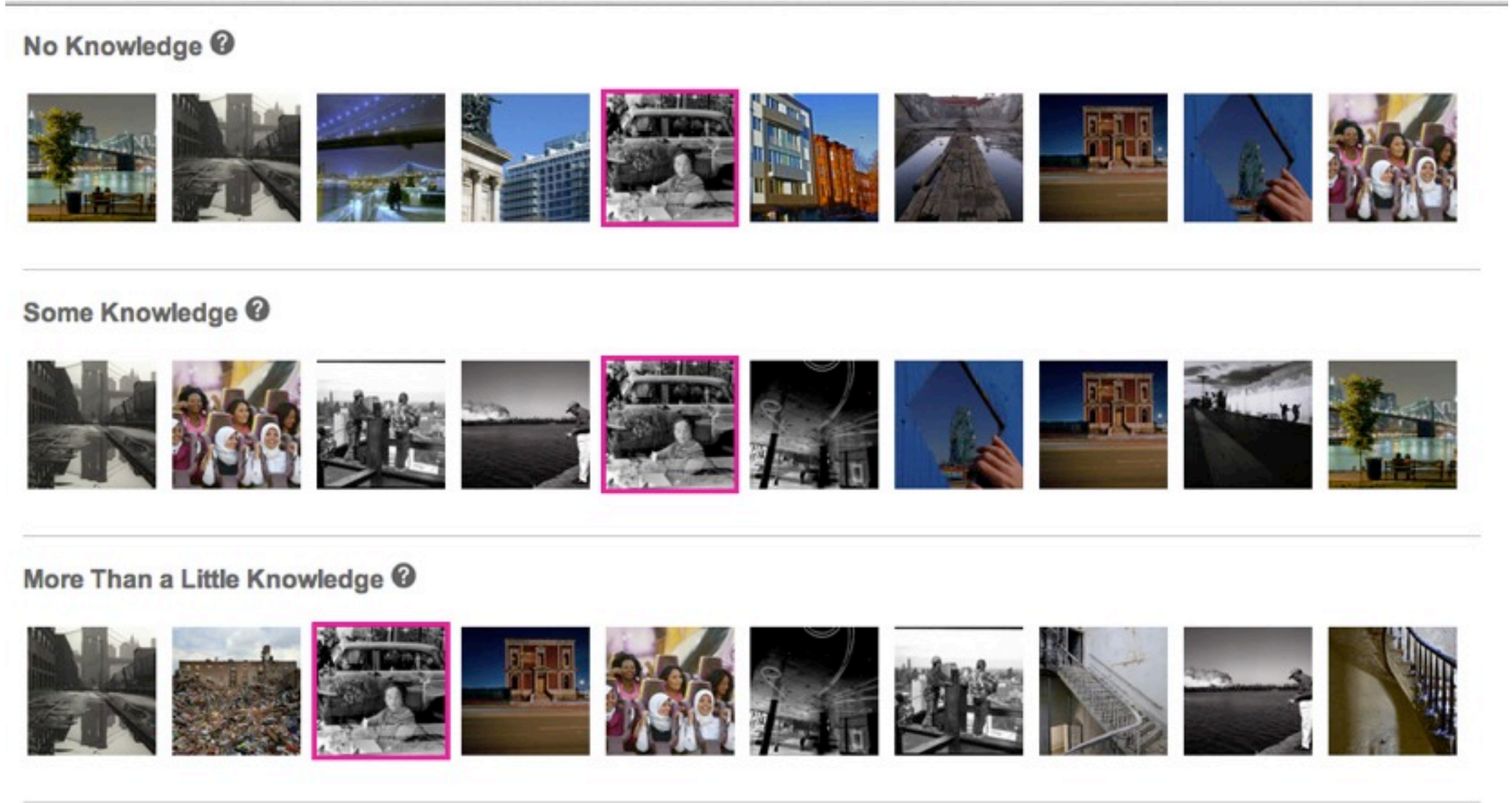
Applications in Cultural Heritage

Increased digitization

Increasing digitization, preservation, exploration efforts

Engage participants with the reason why the digital collections exists

Interpretation



Brooklyn Museum: Click! Crowd curation of photography [1]

[1] Proctor, N. (2010).
Digital: Museum as Platform, Curator as Champion, in the Age of Social Media.

Preservation - Transcription

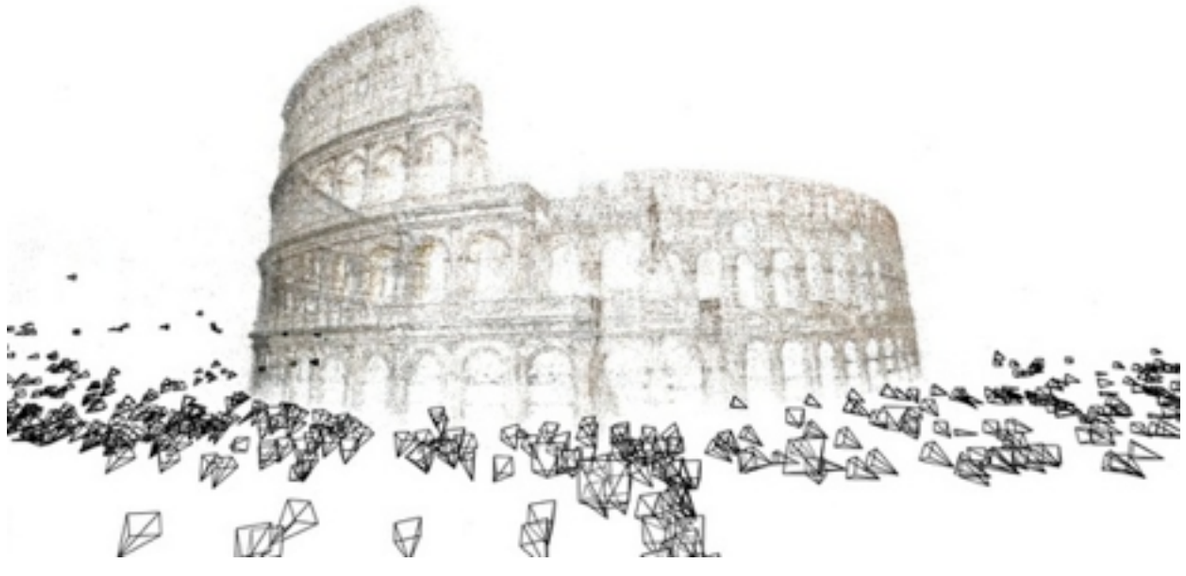
Using symbolic reasoning to transcribe ancient greek texts

CAPTCHAs uses to digitize old texts

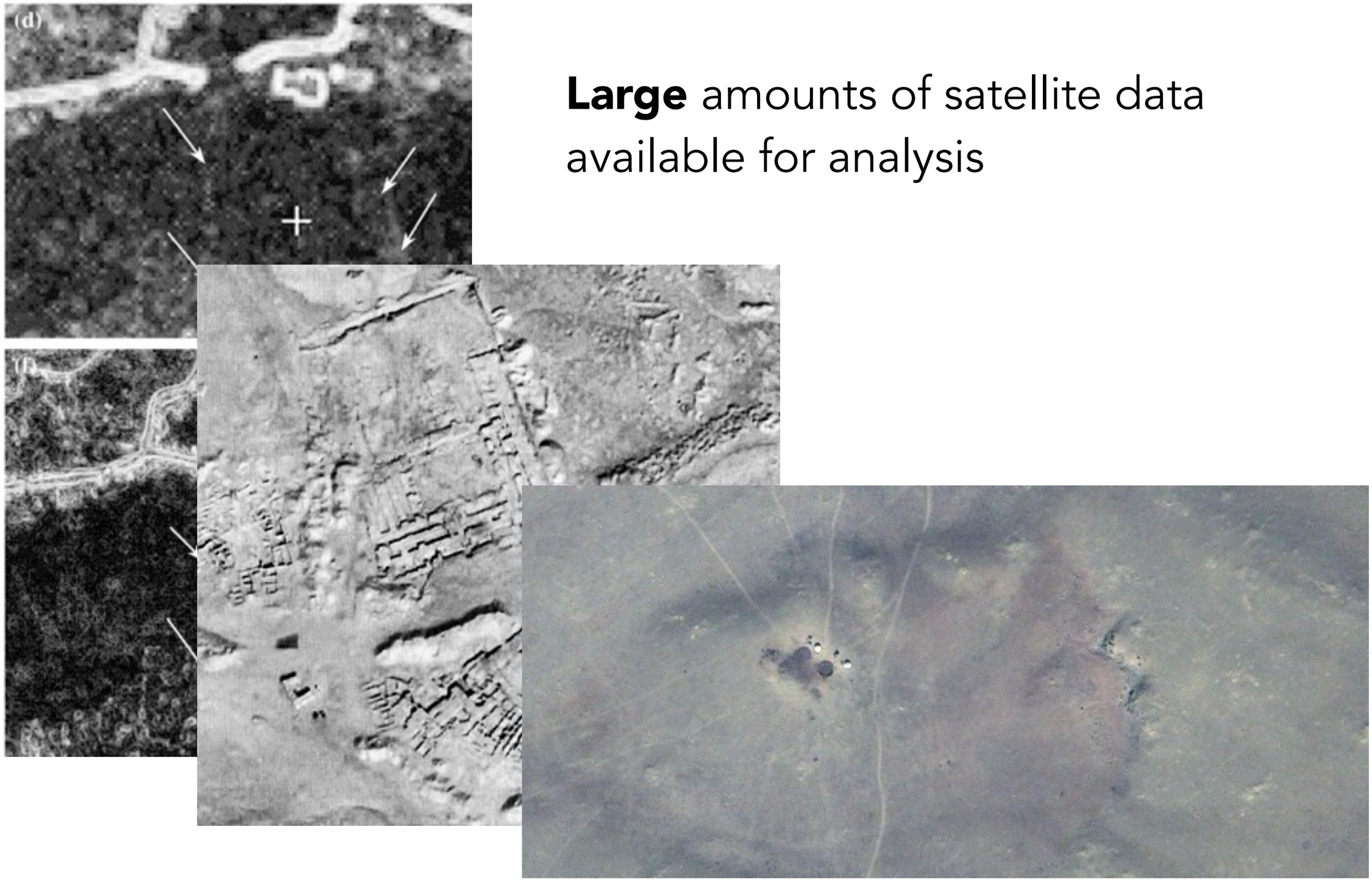
Preservation - Modeling

Traditional methods expensive and time consuming.

Structure from motion utilizing crowdsourced images has great potential.

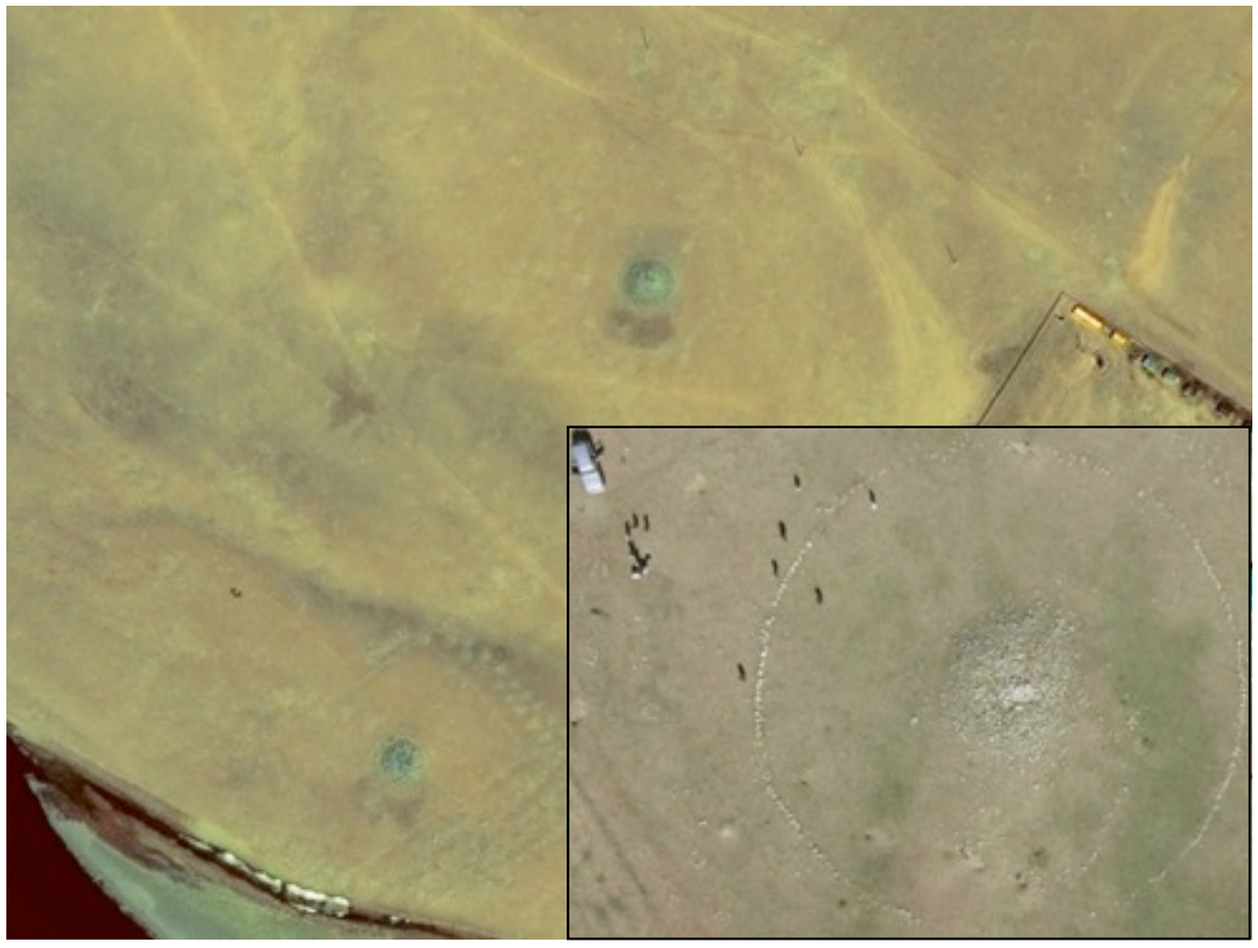


Exploration & Discovery



Large amounts of satellite data available for analysis

Valley of the Khans



100 sites visited.

55 archaeological sites.

3.4 man years of exploration.

Active Crowdsourcing

Crowd Engagement

Data Quality Control

Passive Crowdsourcing

Parasitic Computing

Crowdsensing

Learning from the Crowd

Active Learning

Closing the Loop

Applications in Cultural Heritage

Towards the Future

Numerous success over the years

Crowdsourcing gives us a platform to collect data

POTENTIAL FOR

Increasing use of passive crowdsourcing

More integration between humans and machine learning

Increased use of human cognition to solve problems

Towards the Future

Increased digitization of cultural heritage

More involvement from beneficiaries

POTENTIAL FOR

Crowd-curation of digital collections

Passive digitization of cultural heritage

Discovering new sites of interest

Thank you for listening!

Questions, comments, concerns.

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Proctor, N.
Digital: Museum as Platform, Curator as Champion, in the Age of Social Media. 2010

Image Credits

Pac Man designed by Paulo Volkova from The Noun Project

Brain designed by Arjun Adamson from The Noun Project

Parasitic Computing

a

$$P = (x_1 \oplus x_2) \wedge (x_3 \oplus x_4) \wedge (x_5 \oplus x_6) \wedge (x_7 \oplus x_8) \wedge (x_9 \wedge x_{10}) \wedge (x_{11} \oplus x_{12}) \wedge (x_{13} \wedge x_{14}) \wedge (x_{15} \oplus x_{16})$$

2SAT variables

b

X	Y	$X \oplus Y$	$X \wedge Y$	$X + Y$
0	0	0	0	0 0
0	1	1	0	0 1
1	0	1	0	0 1
1	1	0	1	1 0

c

$M = 0x_1\ 0x_3\ 0x_5\ 0x_7\ 0x_9\ 0x_{11}\ 0x_{13}\ 0x_{15}$ | $0x_2\ 0x_4\ 0x_6\ 0x_8\ 0x_{10}\ 0x_{12}\ 0x_{14}\ 0x_{16}$

$E = 01\ 00\ 01\ 01\ 00\ 01\ 01\ 01$ | $00\ 00\ 01\ 00\ 01\ 01\ 01\ 00$

S_1 S_2

d

$0x_1\ 0x_3\ 0x_5\ 0x_7\ 0x_9\ 0x_{11}\ 0x_{13}\ 0x_{15}$

$0x_2\ 0x_4\ 0x_6\ 0x_8\ 0x_{10}\ 0x_{12}\ 0x_{14}\ 0x_{16}$

⊕ ∧ ⊕ ⊕ ∧ ⊕ ∧ ⊕

01 10 01 01 10 01 10 01

e

S_1 01 00 01 01 00 01 01 01

S_2 00 00 01 00 01 01 01 00

SUM 01 00 10 01 01 10 10 01

$\overline{\text{SUM}}$ 10 11 01 10 10 01 01 10

(Real checksum)

10 01 10 10 01 10 01 10

T_c

Construct message

f

Transmitted message

1001101001100110 | 0100010100010101 | 0000010001010100

T_c S_1 S_2