Web Science

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Lecture plan

- Collective Intelligence
- Crowdsourcing

Let’s start with an experiment

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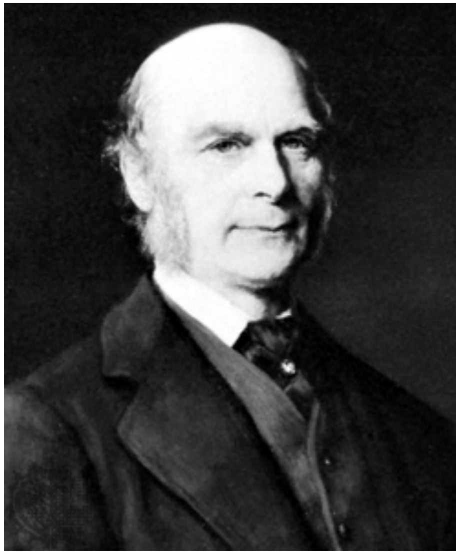
How many M&Ms are in this bag?

https://goo.gl/forms/oWowMNJdOAPD2O6u1

https://goo.gl/forms/Bp71901mX8d9x7vC2

Sir Francis Galton, 1822 − 1911, Victorian polymath



Charles Darwin's half-cousin

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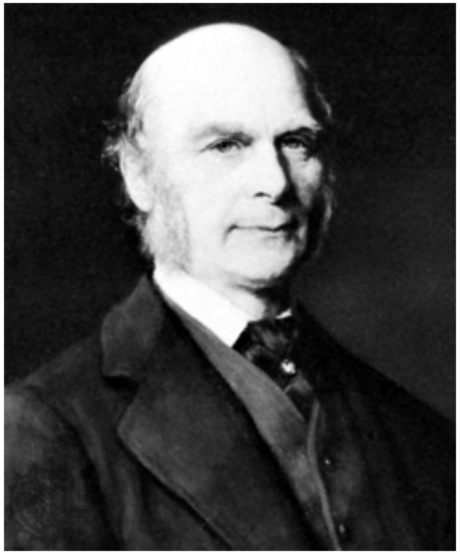
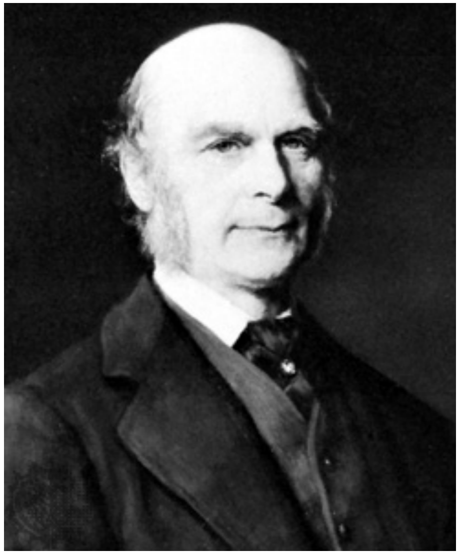
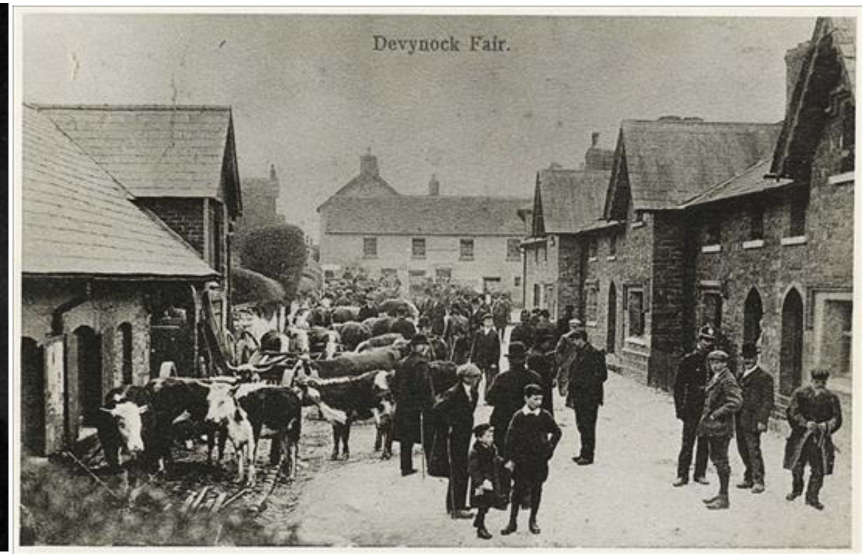


Charles Darwin’s half-cousin

- Created statistical concept of correlation
- Introduced questionnaires & surveys
- Coined terms “eugenics”, “nature versus nurture”
- Founded psychometrics & differential psychology
- Invented fingerprint classification in forensics
- Co-founded scientific meteorology, first weather map

Sir Francis Galton, Cambridge University 1906





Guess the weight of an ox − prize for the best guess

- People placed wagers on the ox’s weight

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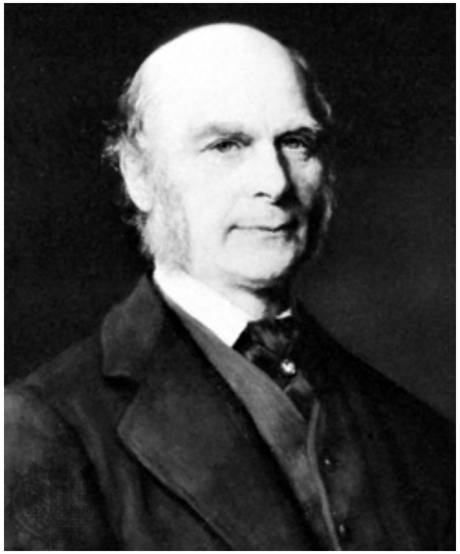

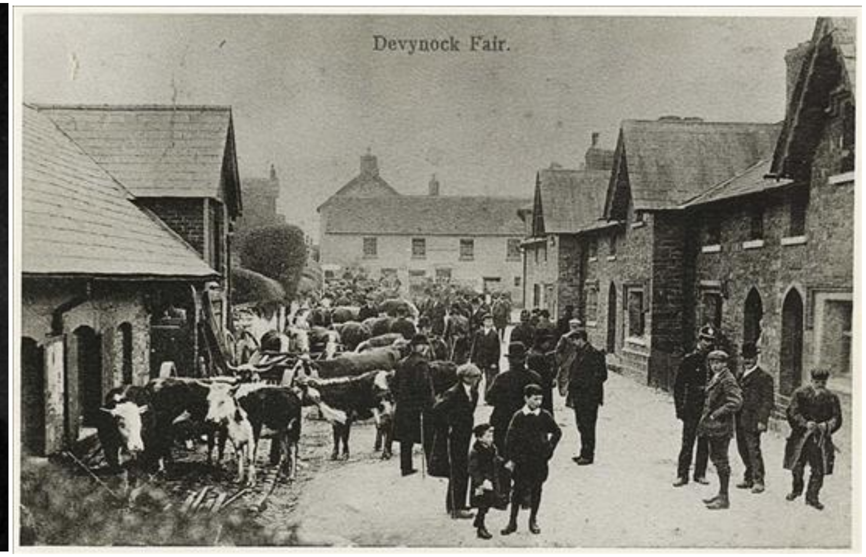

Guess the weight of an ox − prize for the best guess

- People placed wagers on the ox's weight
- Galton analysed 800 guesses
- Crowd's median guess: 542kg
- No one found the exact weight: 543kg

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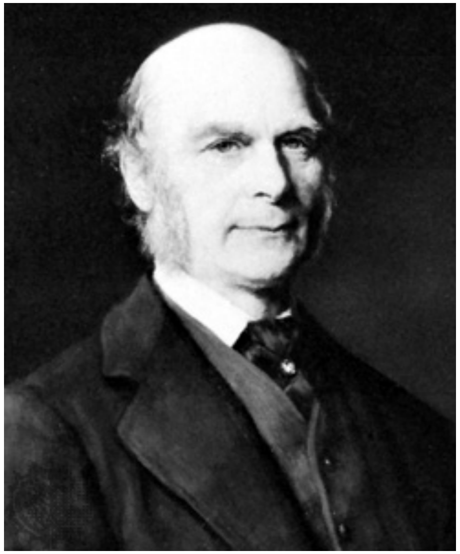

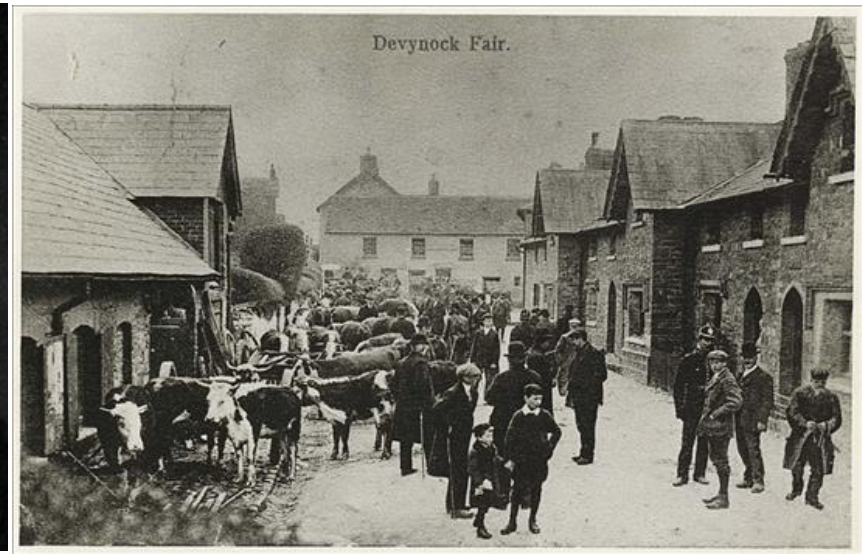

If you put together a big enough and diverse enough group of people and ask them to make a decision, that group's decision will, over time, be intellectually superior to the isolated individual

“Collective intelligence” (CI), Levy (philosopher) 1994

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Intelligence definition: the ability to solve problems

- A system is more intelligent than another system if, in a given time interval, it can:
  - solve more problems, or
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Collective Intelligence: a group can find more or better solutions than the whole of all solutions that would be found by its members working individually

Social insects

Complex & highly intelligent how:

- ants map out their environment
- termites build their mounds

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Self-organising system: very large numbers of simple components interacting locally to produce global organization and adaptation.

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- Columns will grow towards each other until they touch → arch
- Arch will grow until it touches other arches → intricate structure of interlocking arches

Swarm intelligence (in AI)

Emergent collective intelligence of groups of simple agents

The key is that complex behaviour (problem solving) arises out of a composition of simple behaviours

Ant colonies, bird flocking, animal herding, microbial intelligence, etc.

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The World Wide Web

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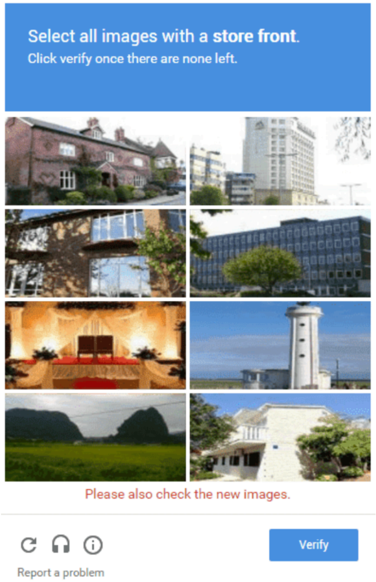
Crowdsourcing (type of Collective Intelligence)

- Taking a job traditionally done by a designated person and outsourcing it to an undefined, large group of people

Crowdsourcing: human-based computation

Use humans as processors in a distributed system

- Wikipedia, Captcha



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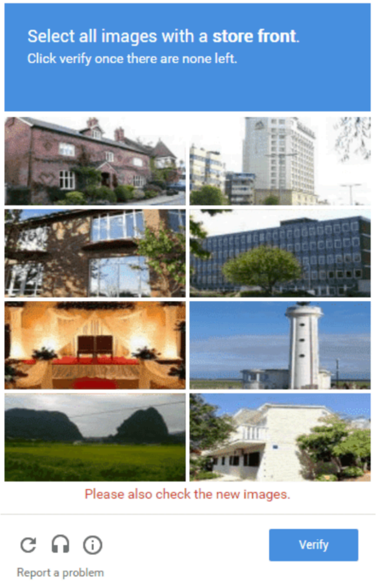

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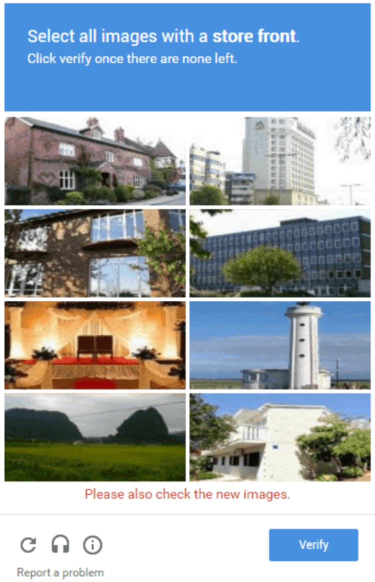
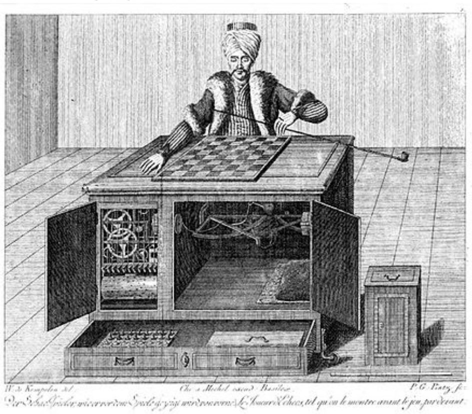
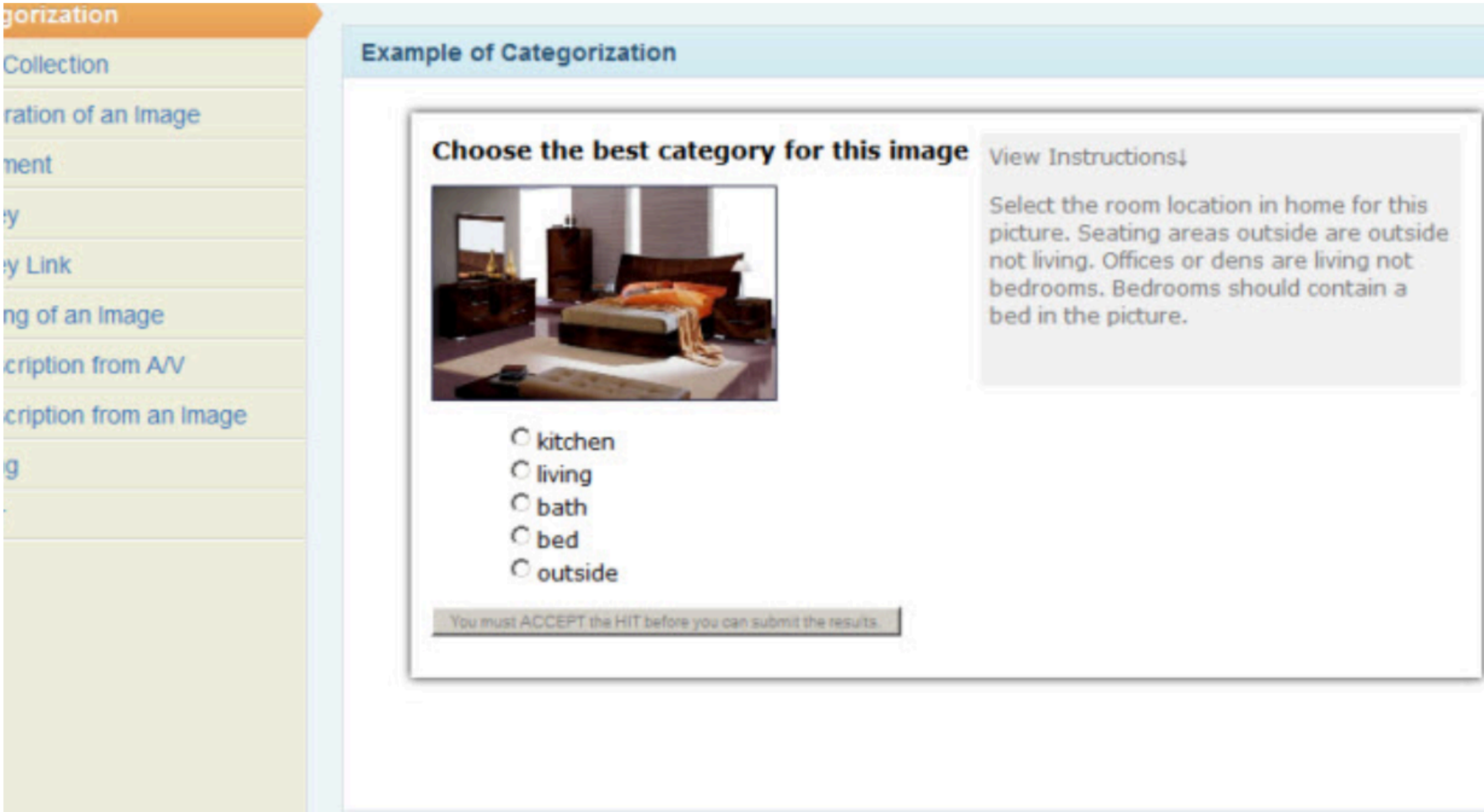


Amazon Mechanical Turk (mturk.com):

- Crowdsourcing platform
- Named after Mechanical Turk, fake chess playing machine in 18C
- Artificial artificial intelligence

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Collection
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cription from an Image
g
Example of Categorization
Choose the best category for this image
View Instructions↓
Select the room location in home for this picture. Seating areas outside are outside not living. Offices or dens are living not bedrooms. Bedrooms should contain a bed in the picture.
kitchen
living
bath
bed
outside
You must ACCEPT the HIT before you can submit the results.

Amazon Mechanical Turk

- <u>Requesters</u>

- <u>Workers</u>

Amazon Mechanical Turk

- Requesters create human intelligence tasks (HITs) via web services API or dashboards
- Workers

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- Currently >200,000 workers from >100 countries; millions of HITs completed

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- a requestor (with some **internal objective**) solicits a group of workers to perform tasks in service of that objective

Requestor's objective → utility function to be maximised

Example: obtain labels for a set of images

Requestor's objective includes:

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Requestor must choose:

- How many workers should be given a labelling task
- How their responses should be aggregated to estimate the best answer

Assumptions:

- workers act independently, interacting only through shared tasks
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Crowdsourcing for AI: use crowdsourcing to label training sets as input for data-hungry supervised algorithms

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Challenges:

- Highly varying skills, abilities, motivation of workers
- Different tasks may be individually easier or more difficult, requiring less or more work (iterations) on them

Methods to address these challenges:

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Crowdsourcing quality: highly dependent on 1-3

Crowdsourcing strategies

- Post hoc response aggregation (after responses have been received)

- Dynamically fit tasks to workers (while responses are being received)

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- set of questions, workers, and their responses (some questions are answered by more than one worker)

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Goal:

1) exploit redundancy
2) learn and track worker skills

1. Exploit redundancy by comparing different workers responses to the same question

- Snow et al 2008: with simple majority voting a crowd of novices outperformed an expert on sentiment analysis and semantic word similarity

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2. Learn and track the skills of workers

- Instead of majority voting, weigh worker responses by using models of workers' abilities. E.g. if a worker is excellent at translating French to English, assume that their English to French translations are of high quality

Improve on majority voting by modelling worker skill

- Supervised learning: give workers questions for which gold standard answers are already known
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Common problem: **gaming behaviour**

- answer the first few questions and then decrease effort and accuracy on remaining questions

Solution: intermix questions with known and unknown answers

Early use of expectation maximisation

David & Skene 1979 (medical diagnosis)

- There is a single question with an unknown correct answer
- $P_w(r|a)$: probability that worker w will give response r when true answer is a
- If $r \neq a$, an expert worker would have $P_w(r|a) = 0$
- Worker responses are conditionally independent of each other, given the true answer
- Expectation maximisation: iterative algorithm to estimate which answers are correct at the same time that the algorithm learns the model of worker accuracies

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- Repeat until quiescence

Expectation Maximisation:

Expectation: given estimates of all the probabilities, compute the probability of each possible answer using Bayes rules and assuming conditional independence

Maximisation: given the posterior probability of each possible answer, compute new parameters than maximise the likelihood of each voter’s response

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- allows for single strong worker to overrule multiple weak workers
- predicted answer may not always be the majority vote

EM extension (Whitehill et al. 2009)

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Idea: use worker errors to update estimate of task difficulty and worker accuracy.

Same idea as in EM, but probability computations include worker expertise and task difficulty.

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Question features need not be specified a priori: the algorithm learns the features.

Excellent performance but low interpretability

Further extensions (I)

Prelec and Seung 2007

Find correct answers missed by the majority by asking workers to predict coworkers mistakes

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Further extensions (I)

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<u>Lin et al. 2012</u>

When requesters cannot enumerate all possible answers for the worker or when the solution space is infinitely large

Further extensions (II)

<u>Raykar et al. 2010</u>

Fully automatic:

- learn worker abilities
- infers correct responses
- learns a logistic regression classifier to predict future crowd responses or the answer (no need to consult human workers in the future)

Instead of only reconciling multiple responses, get the answers themselves

Further extensions (III)

<u>Dekel and Shamir 2009</u>

Limit influence of bad workers.

- use worker responses to train a SVM
- add constrains to the loss function such that no bad worker can overly influence the learned weights
- prune bad workers

Further extensions (III)

Dekel and Shamir 2009

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Wauthier and Jordan 2011

Relax the idea that tasks must contain a correct answer.

- predict each worker’s response to a future subjective question.