IUI 2018 Two Tools are Better Than One: Tool Diversity as a Means of Improving Aggregate Crowd Performance

Jean Y. Song, Raymond Fok, Alan Lundgard, Fan Yang, Juho Kim, Walter S. Lasecki





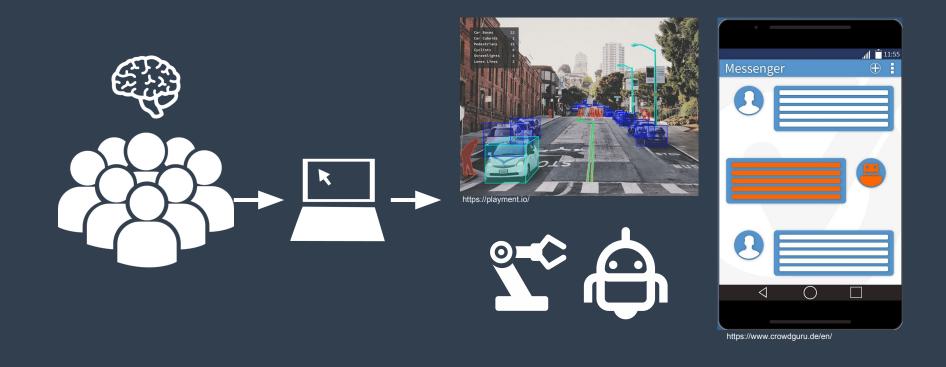




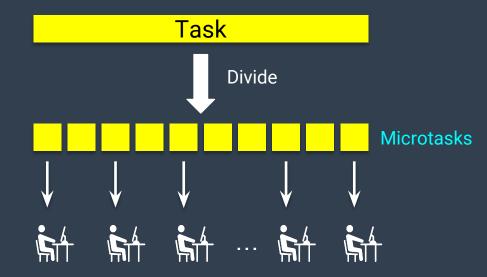
Crowdsourcing Platforms



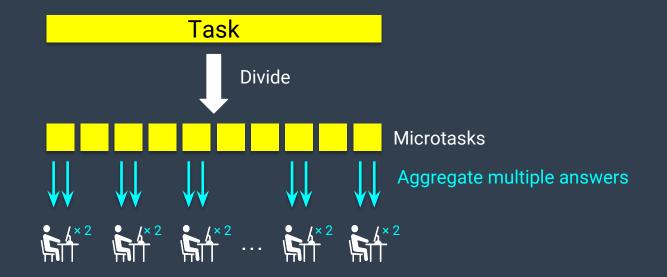
Crowdsourcing for Human Computation



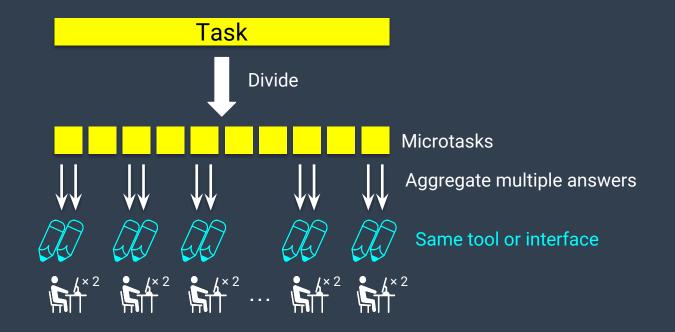
Crowdsourcing Strategy: Microtasking



Crowdsourcing Strategy: Aggregation



Crowdsourcing Strategy: Using Single Tool

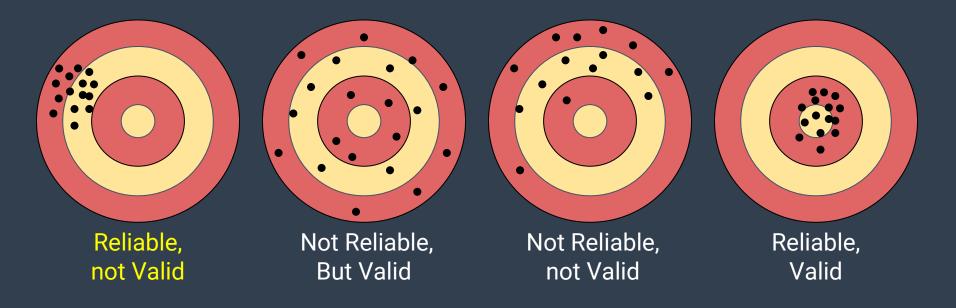


Problem with using a single tool:

Systematic bias can be accumulated, resulting in inaccurate aggregated result.

Q. What is Systematic Bias?

A. Reliable, but not valid performance



Example of Systematic (Error) Bias

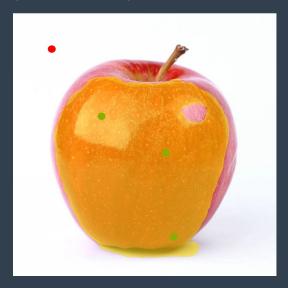
Tool 1: Opensurfaces (TOG 2013)

Bell, Sean, et al. "**Opensurfaces**: A richly annotated catalog of surface appearance." *ACM Transactions on Graphics (TOG)*32.4 (2013): 111.



Tool 2: Click'n'Cut (CrowdMM 2014)

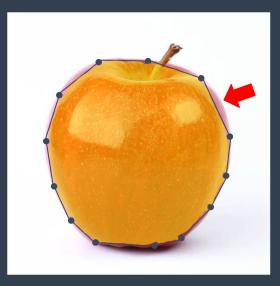
Carlier, Axel, et al. "**Click'n'Cut**: Crowdsourced interactive segmentation with object candidates." *International ACM Workshop on Crowdsourcing for Multimedia*. 2014.



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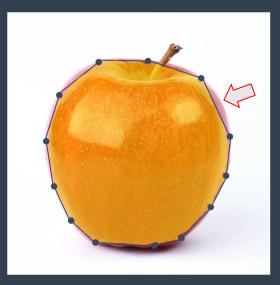
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Proposed Approach:

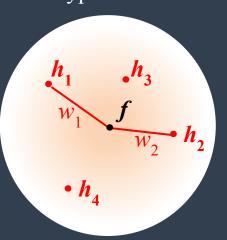
Use tool diversity as a means of improving aggregate crowd performance

What is **Tool Diversity**?

A property that measures how different tools can be built in terms of their induced biases.

Analogy to Ensemble Learning

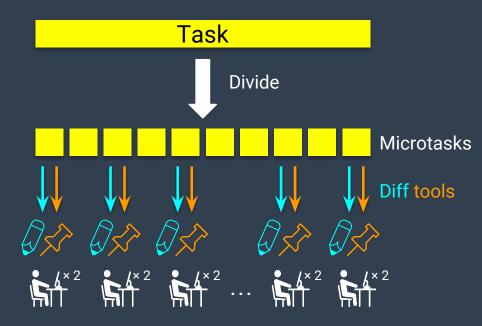
Space of hypotheses



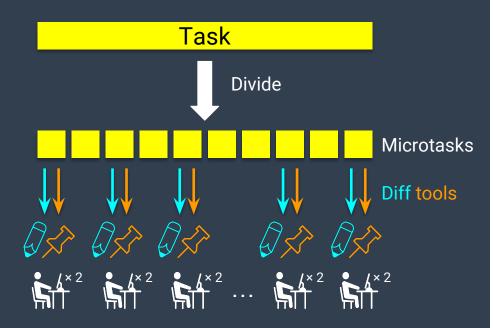
f: best performing hypothesis h_i : other hypotheses w_i : weights

Ensemble learning constructs a combination of two alternative hypotheses h_1 and h_2 with proper weights (w_1 and w_2), and approximates the best hypothesis *f* by averaging the two.

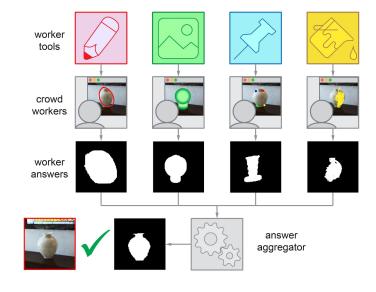
Proposed Method: Leverage Tool Diversity



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Semantic image segmentation task



Choosing the Tools

Q. How to diversify errors produced by different tool types?

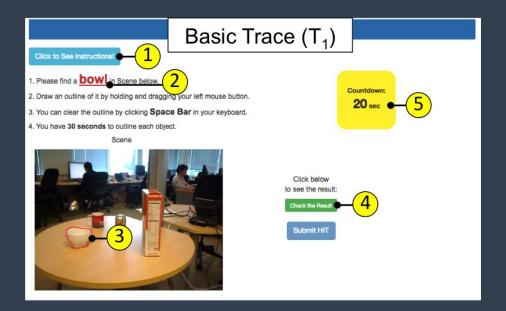
Q. How to diversify errors produced by different tool types?

Q. What are different types of objects?

A. General objects, Fuzzy materials, plants, furry objects, $T_{3} \longrightarrow T_{4}$ transparent objects, reflective surfaces (intuitive, deformability)

Instructions and Worker Interface

Worker Interface :



Instructions and Worker Interface

Instructions :

ATTENTION! Please carefully read the instructions before you ACCEPT HIT

(Please don't accept HIT if you've previously worked on this task. You will not be paid more than onece even though you complete the HIT multiple times.)

Welcome to our object aligning system!

The task is to align all objects in the list with icon images. You'll have 30 seconds to align each object.

bject Highlighting - mode 3 Instruction		<u> </u>
See Instructional		
Plasse find a Flashlight in Scene below and find the most similar icon image from the icon List. (Only shape material Cations do not have to match.) Draglocale/rotate the icon to best align the size and position of a Flashlight in Scene.	Fleehlight Stapler Bowl Mug	
Boane Ison List	Cleaning brush	
	Salar	

Good example of aligning a flashlight



Bad examples of aligning a flashlight





Payments and Expected time:

- · Task: (< 5 minutes) task; \$0.35 for successful completion.
- · IMPORTANT: You must finish(Submit HIT) to get paid.

Please ACCEPT HIT to start task!

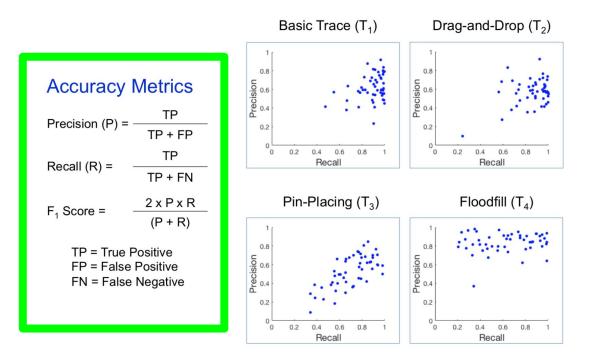
Experiment Settings

- 12 different visual scenes
- Total 51 objects
- Six unique workers for each tool-scene pair (total 288+ workers)
- Total 1224 object segmentations
- Platform: Amazon Mechanical Turk

Each worker was paid between \$0.35 and \$0.60 per task, depending on the number of objects they had to segment or on the level of difficulty of given tool (a pay rate of \sim \$10/hr).

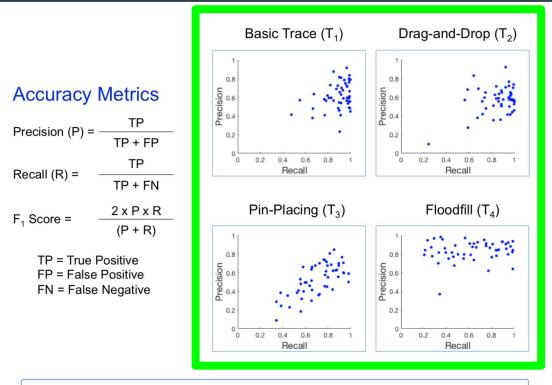
Results & Discussion

Performance of Individual Tools



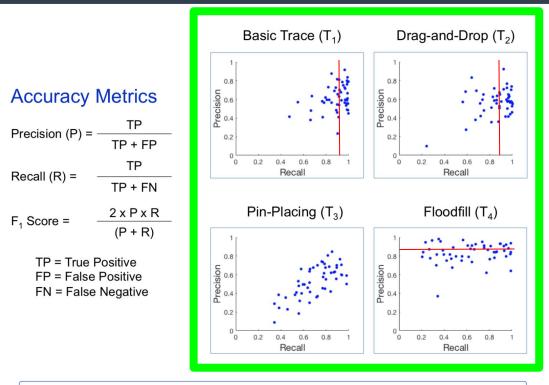
Different tools have different error patterns

Performance of Individual Tools



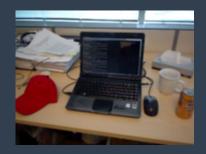
Different tools have different error patterns

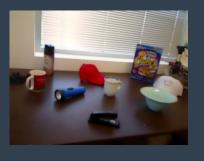
What we observed



Different tools have different error patterns

Some of the Answers from Workers







How can we see the effect of leveraging tool diversity?

Method 1. Single tool aggregation (Uniform majority voting): Baseline

 $T_1 W W W W$

 \rightarrow Aggregate

 T_2 T_2 T_2 T_2 T_2 T_2

 \rightarrow Aggregate

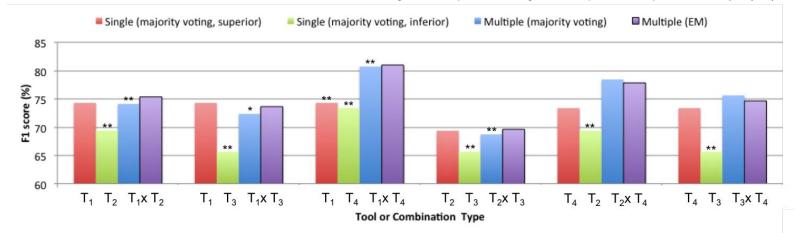
Method 2. Multiple tool aggregation (Uniform majority voting)

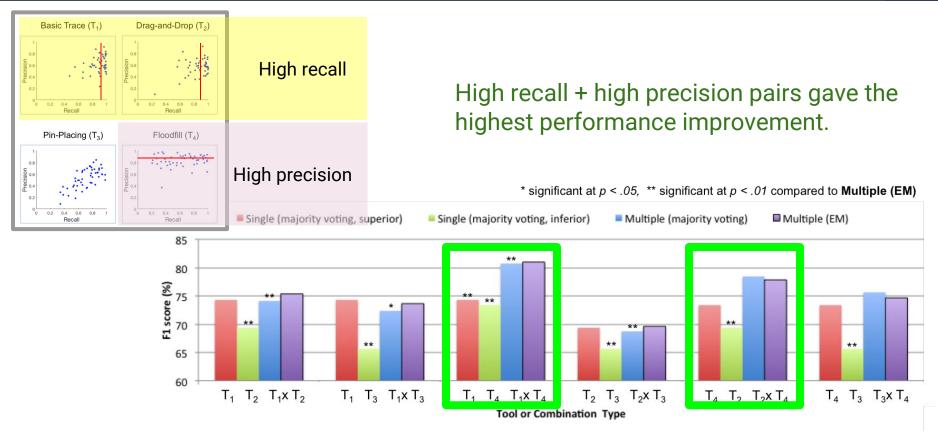


Method 3. Multiple tool aggregation (Expectation maximization)

 \rightarrow Aggregate

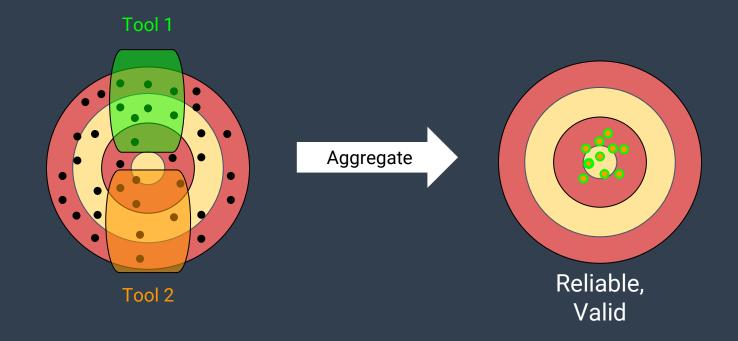
* significant at p < .05, ** significant at p < .01 compared to Multiple (EM)





Generalization

Generalizability: Expected Human Error is Diverse



Generalizability: Aggregation Improves Quality



Generalizability: Objective Correct Answer Exists

Tasks with objective answers:

Image segmentation

Live captioning

Text annotation

Handwriting recognition

Task with subjective answers:

Creative writing

This paper presents Soylent, a word processing interface that uses crowd workers to help with proofreading, document shortening, editing and commenting tasks. Soylent is an example of a new kind of interactive user interface in which the end user has direct access to a crowd of workers for assistance with tasks that require human attention and common sense. Implementing these kinds of interfaces requires new software programming patterns for interface software, since crowds behave differently than computer systems. We have introduced one important pattern, Find-Fix-Verify, which splits complex editing tasks into a series of identification, generation, and verification stages that use independent agreement and voting to produce reliable results. We evaluated Soylent with a range of editing tasks, finding and correcting 82% of grammar errors when combined with automatic checking, shortening text to approximately 85% of original length per iteration, and executing a variety of human macros successfully.

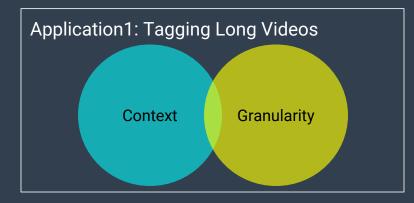
Generalizability: Tolerates Imperfections

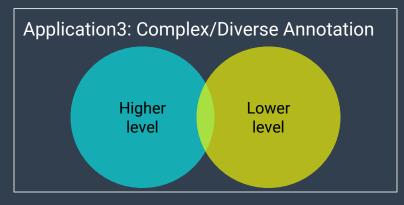
Example: Scribe (UIST 2012)

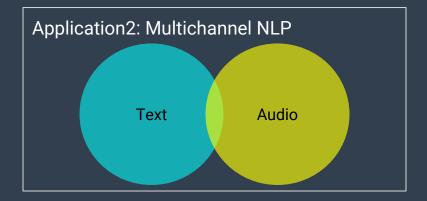
W.S. Lasecki, C.D. Miller, A. Sadilek, A. Abumoussa, D. Borrello, R. Kushalnagar, J.P. Bigham. Real-time Captioning by Groups of Non-Experts. UIST 2012.

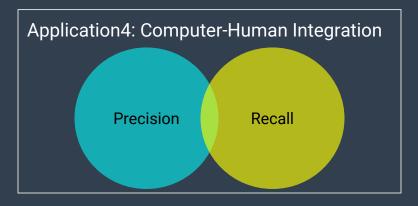
		learn g learning			a	suitcase	word	though	right	SO		has	a lot		there there			
		learning			a	suitcase	word	though			learning	has						
4:		lea ning	is	su h	a				right-	SO	learning						a	lot
5:	SO	learning	is	such	a	suitcase		though			learning	has						lot
6:		learning	is	such	a	suitcfse	word	though	right						this	i	a	lot
F:	SO	learning	is	such	a	suitcase	word	though	right	SO	learning	has	a lot	of	there	i	a	lot

Possible Future Applications









Thank you!

Authors:

Jean Y. Song (jyskwon@umich.edu / jyskwon.github.io), Raymond Fok, Alan Lundgard, Fan Yang, Juho Kim, Walter S. Lasecki

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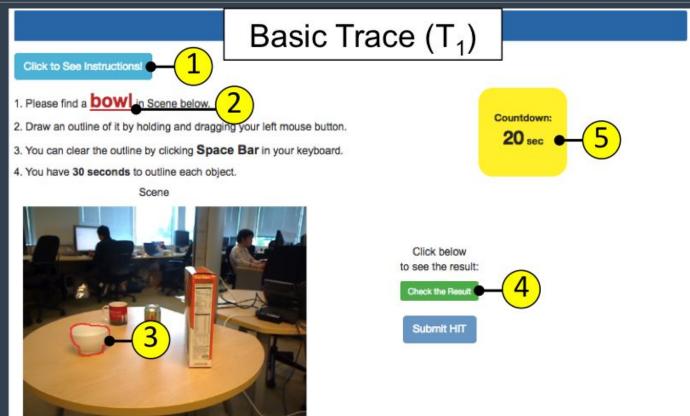


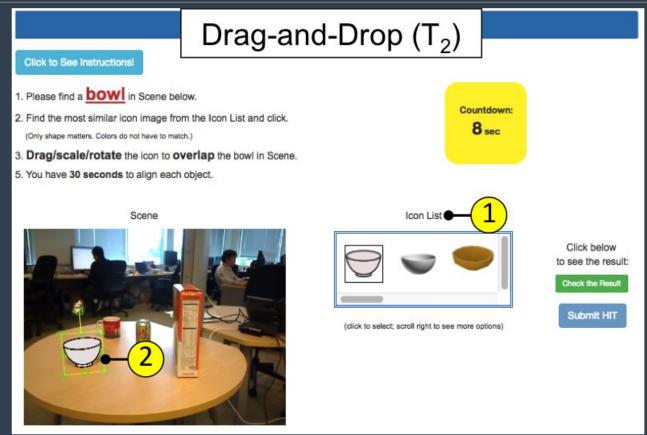


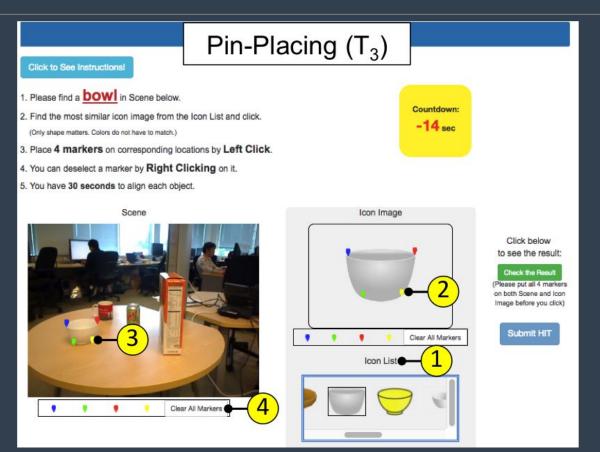


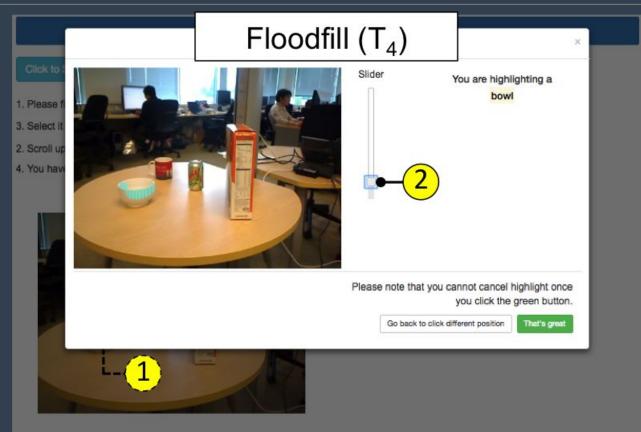


Backup Slides

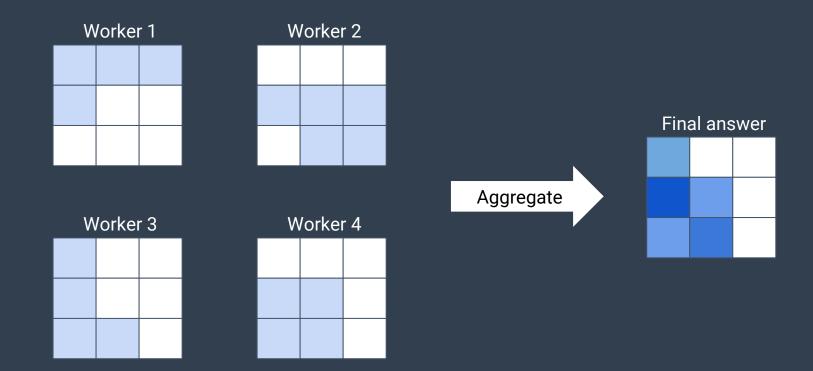








Pixel-Level Majority Voting (50% agreement)



Expectation Maximization (Dawid-Skene Algorithm)

In an image, label a pixel as 1 if it belongs to a target object, and 0 if background.

Assume:

- image *A* having *N* total pixels
- *M* crowd workers
- The label a worker *m* assigns to each pixel is denoted as z_{mn}
- all labels from worker m as a vector Z_m
- the true labels of A to be estimated are denoted as a vector Y
- θ is the confusion matrices set to be estimated.

We can estimate the true labels *Y* by maximizing the marginal likelihood of the observed worker labels:

$$l(\boldsymbol{\theta}) := \log \left(\sum_{Y \in \{0,1\}^n} L(\boldsymbol{\theta}; Y, Z) \right)$$

The EM algorithm works iteratively by applying the 1) expectation step and the 2) maximization step.