Cross-domain-aware Worker Selection with Training for Crowdsourced Annotation

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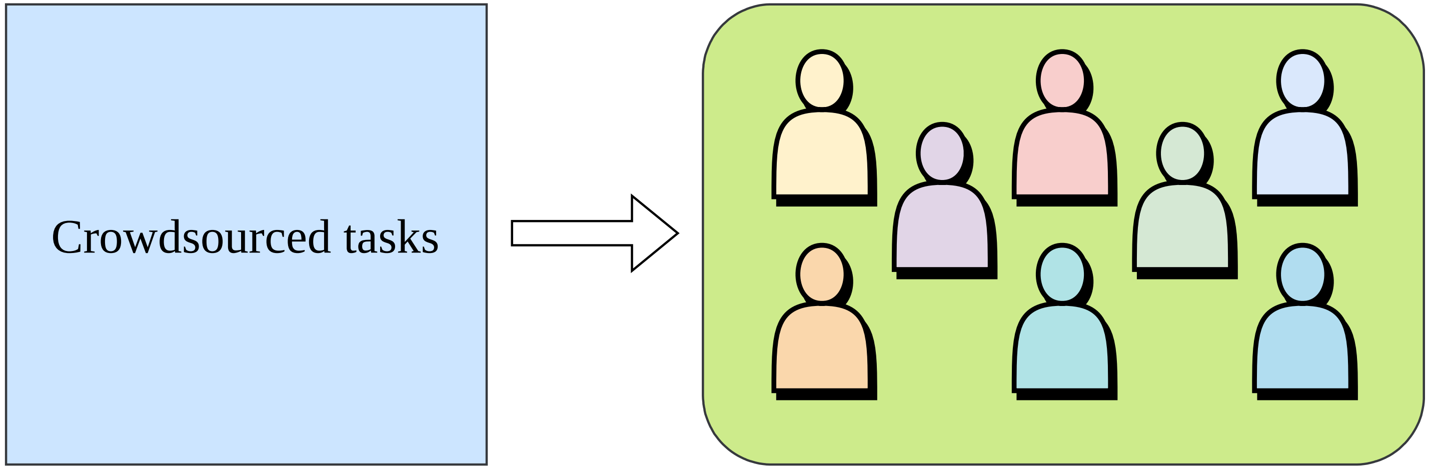
Outline

- Background and Motivation
- Definitions
- Methodology
- Experiments
- Summary

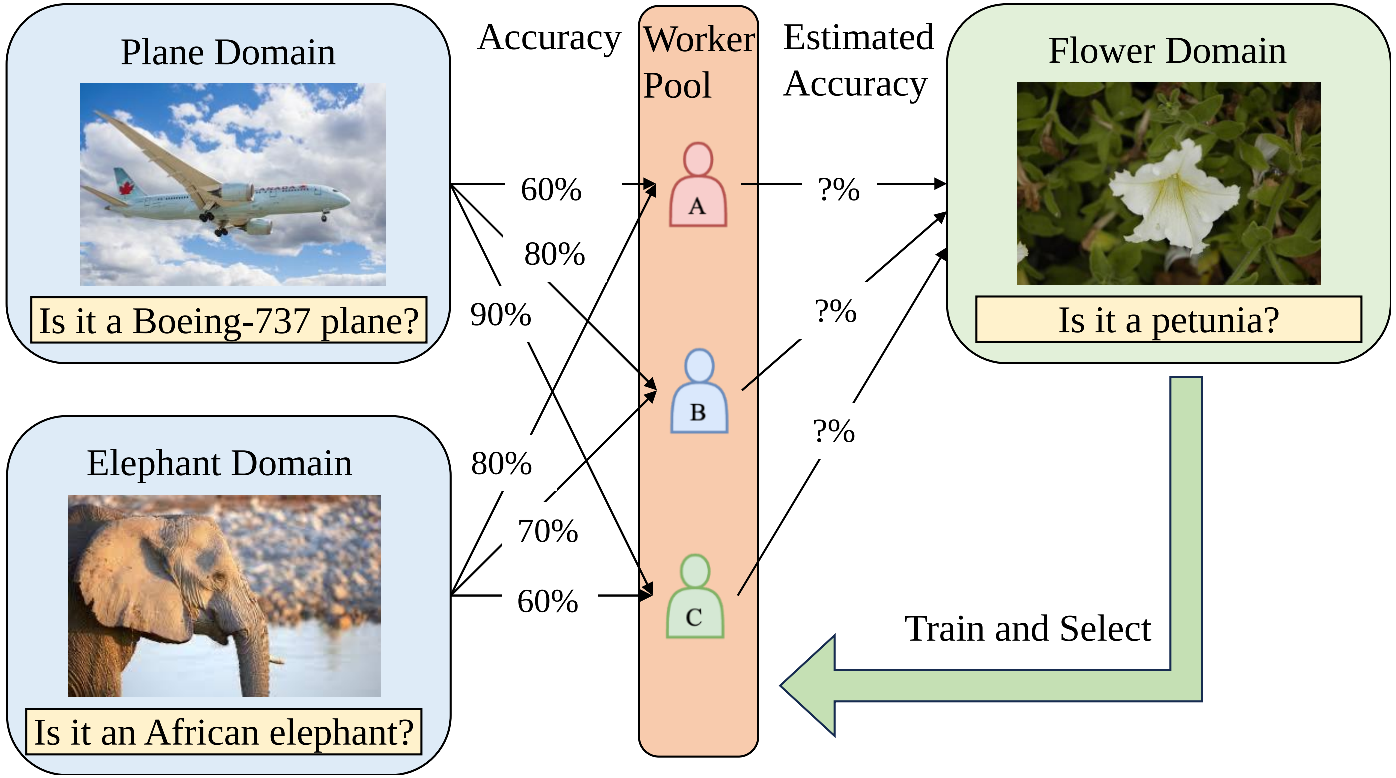
Background and Motivation

- Crowdsourcing is preferable for obtaining **high-quality** annotations for **large-scale** datasets.
- **Worker Selection is important** in Crowdsourcing.
- How to design an allocation scheme to select high-performance crowd workers remains a challenge.



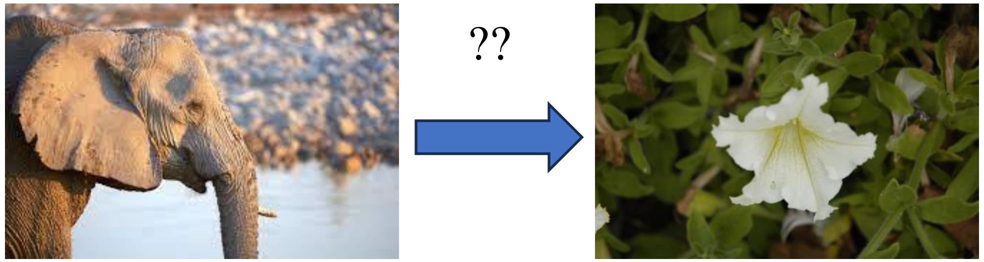
Background and Motivation

- The **answering history of workers** (prior domain knowledge) can help select high-quality workers when **annotating a new domain** (target domain task).



Background and Motivation

- However, there are two challenges:
  - Difficulty in accurately estimating the **correlation between domains** with a limited budget.
  - Difficulty in estimating the **workers' dynamic knowledge change** during the question-answering worker training process.



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Definitions

- Cross-domain-aware worker selection with training:
  - Given target domain tasks $T = \{T_l, T_w\}$, the total budget B, and worker pool W with each worker w_i's historical profile h_i.
  - Cross-domain-aware worker selection with training problem is to 1) assign no more than B tasks to |W| workers **for training** and 2) **select top k workers** with the highest possible annotation accuracy on working tasks T_w.

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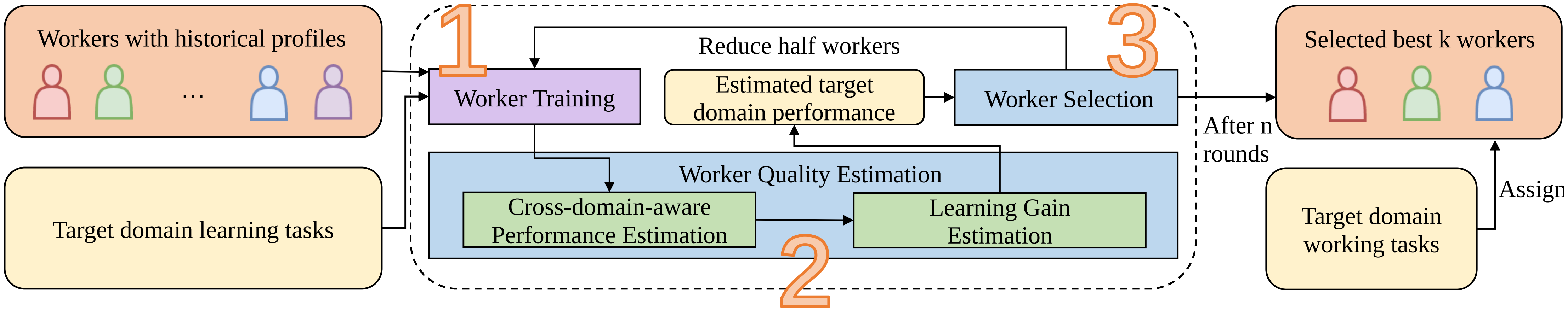
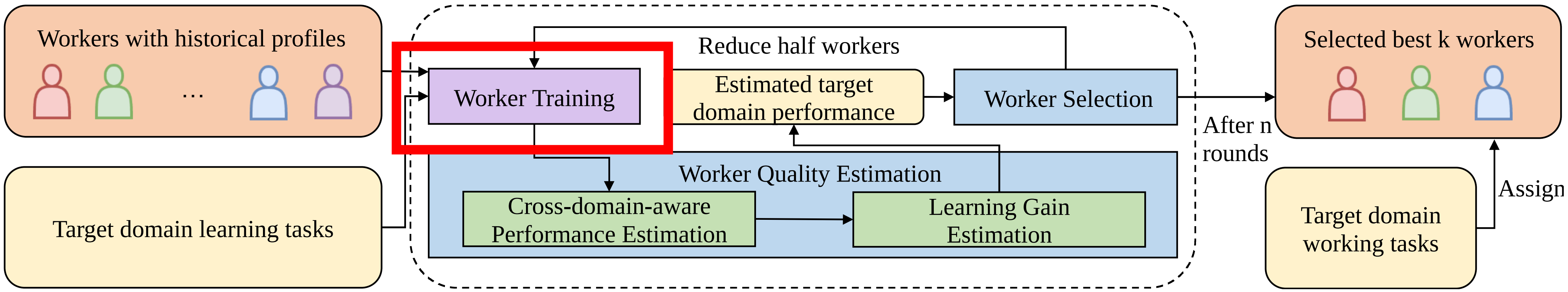
Methodology

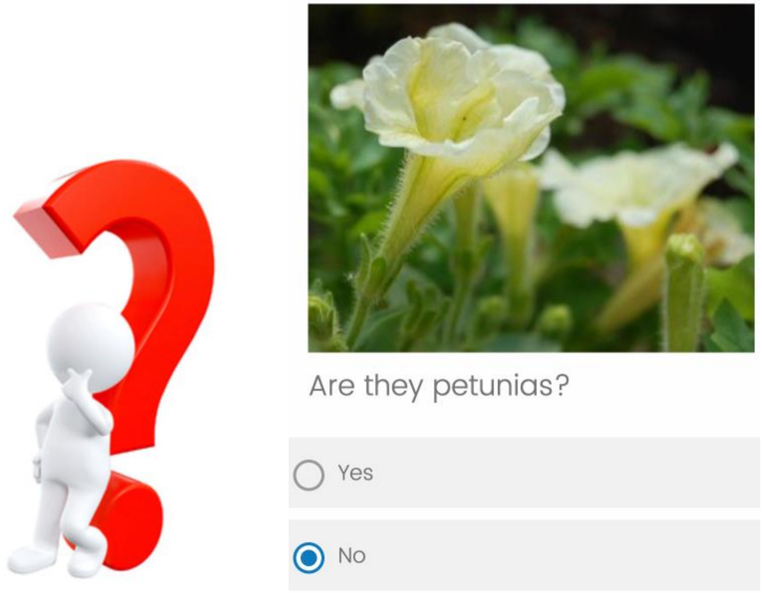


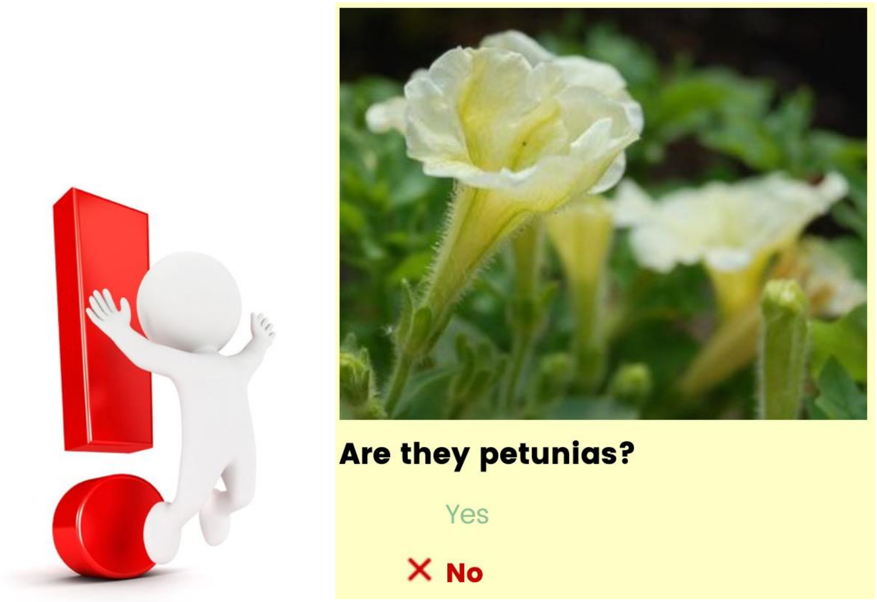
Methodology



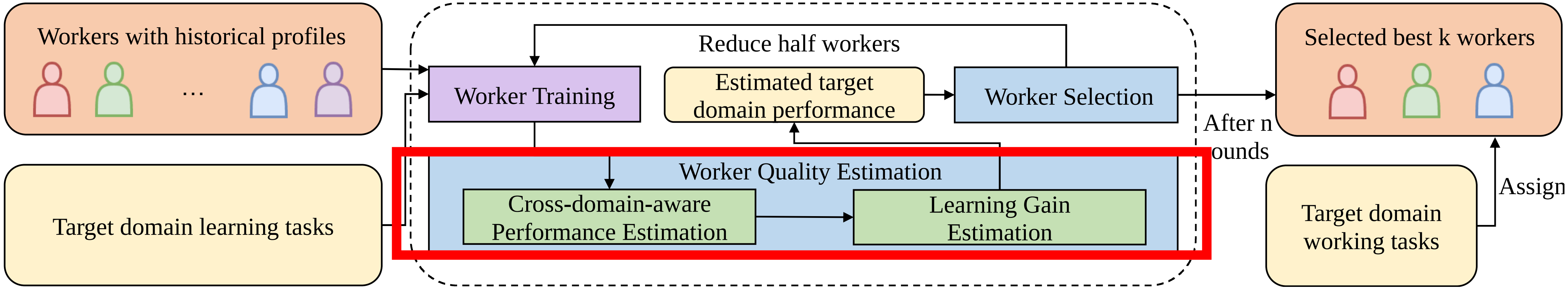
Methodology – Worker Training

- Worker training is treated as an **"Answer and learn"** process for workers.





Methodology

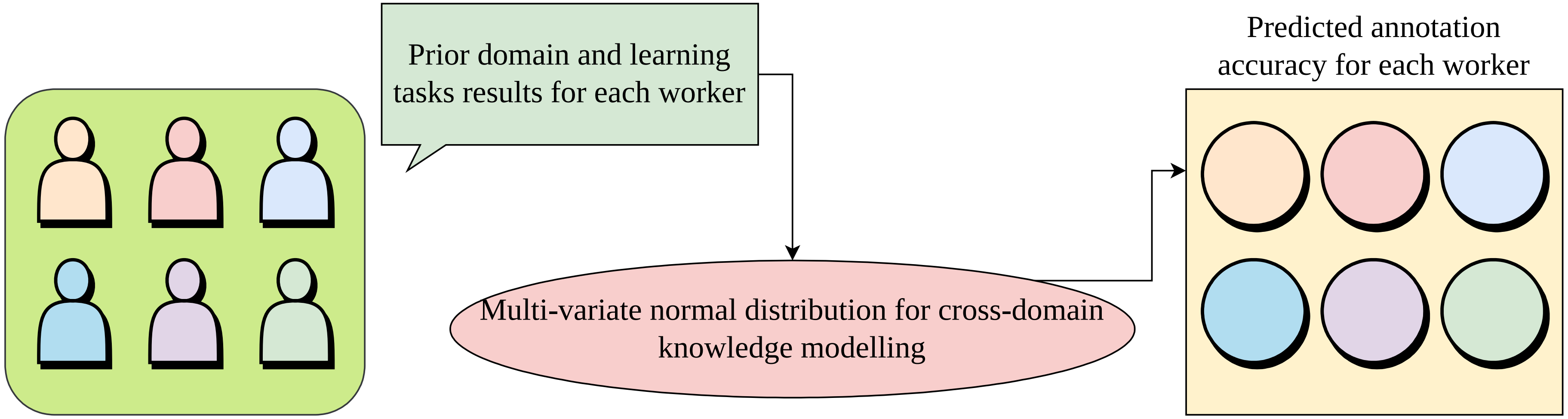


Methodology – Worker Quality Estimation

- We consider two factors in estimating workers' quality:
- **Cross-domain correlation** – Cross-domain-aware Performance Estimation (CPE)
- **Worker learning gain** – Learning Gain Estimation (LGE)

Methodology - CPE

- Model the **correlation** between workers' **prior knowledge and the target domain** knowledge as a **multivariate normal distribution**.
- Record **the correct and wrong number** of learning tasks for each worker.
- Update the distribution with **maximum likelihood estimation**.
- **Predict the annotation accuracy** of each worker.



Methodology - CPE

- Maximum likelihood estimation:

$$\begin{aligned}\log L &= \sum_{i=1}^{|W_c|} \log P(h_{i,T}|h_i) \\ &= \sum_{i=1}^{|W_c|} \log \int_0^1 h_{i,T}^{C_{i,c}} (1-h_{i,T})^{X_{i,c}} \frac{e^{-\Psi}}{\sqrt{2\pi|\bar{\Sigma}|}} \mathrm{d}h_{i,T} \\ &= \sum_{i=1}^{|W_c|} \Big[\log \int_0^1 h_{i,T}^{C_{i,c}} (1-h_{i,T})^{X_{i,c}} e^{-\Psi} \mathrm{d}h_{i,T} \\ &\quad + \log \frac{1}{\sqrt{2\pi}} - \frac{1}{2}\log|\bar{\Sigma}|\Big],\end{aligned}$$

$$\bar{\mu} = \mu_T + \Sigma_{1\times D}\Sigma_{D\times D}^{-1}(h_i - \mu_{1\sim D}),$$
$$\bar{\Sigma} = \Sigma_{1\times 1} - \Sigma_{1\times D}\Sigma_{D\times D}^{-1}\Sigma_{D\times 1},$$

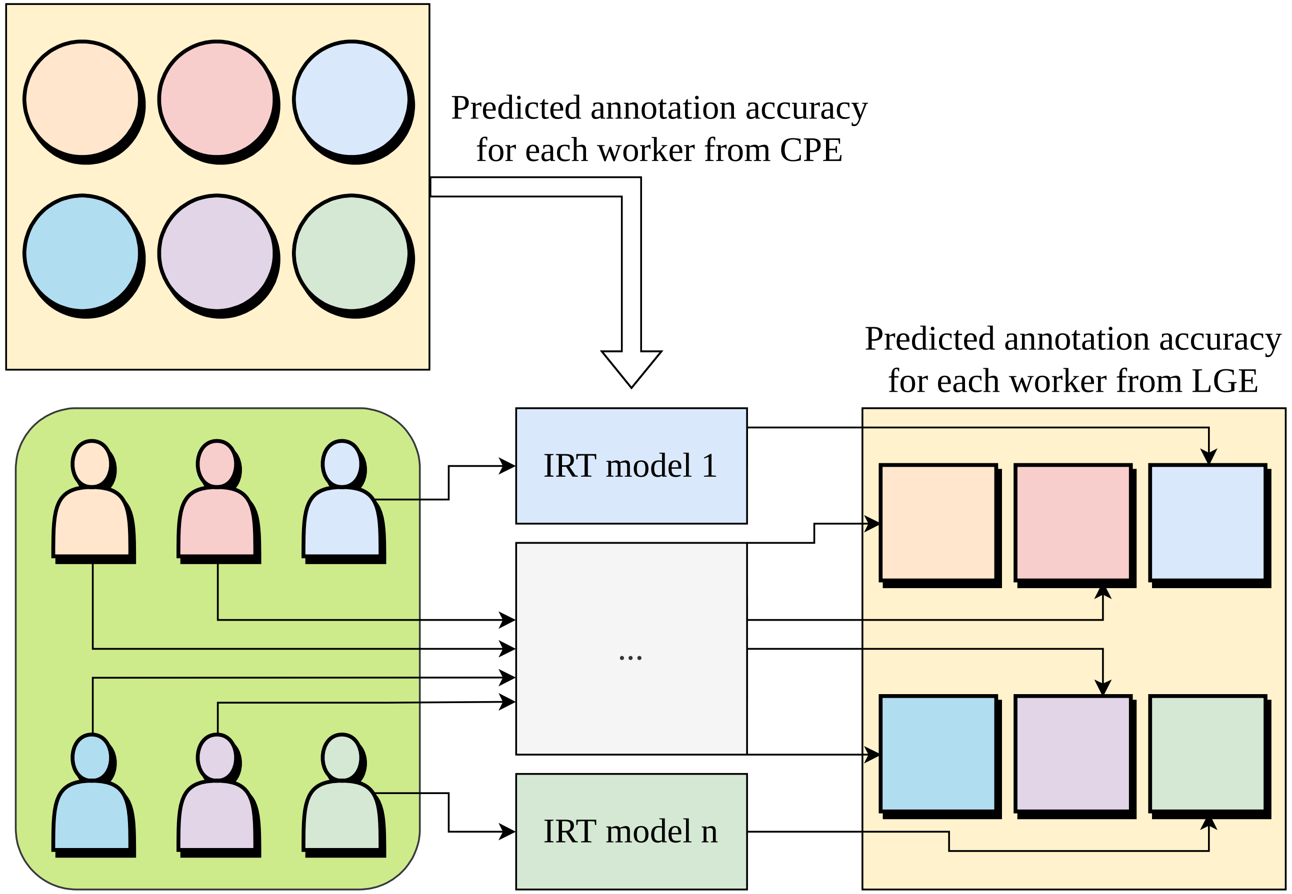
and $\Psi = \frac{(h_{i,T}-\bar{\mu})^{\mathsf{T}}(h_{i,T}-\bar{\mu})}{2\bar{\Sigma}}$.

- Updated annotation accuracy:

$$\begin{aligned}p_{c,i} &= E[h_{i,T}|h_i] \\ &= \int_0^1 h_{i,T} P(h_{i,T}|h_i) \mathrm{d}h_{i,T} \\ &= \int_0^1 h_{i,T} \frac{P(h_i, h_{i,T})}{P(h_i)} \mathrm{d}h_{i,T},\end{aligned}$$

Methodology - LGE

- Adapt the **Item Response Theory (IRT)** model to estimate the learning gain.
  - Compute the IRT scores on the **prior domains**.
  - Compute the IRT scores on the **target domain learning tasks**.
  - Update the learning parameter α_i for each worker based on the **CPE scores and answering history**.
- Predict the estimated scores in the current round.



Methodology - LGE

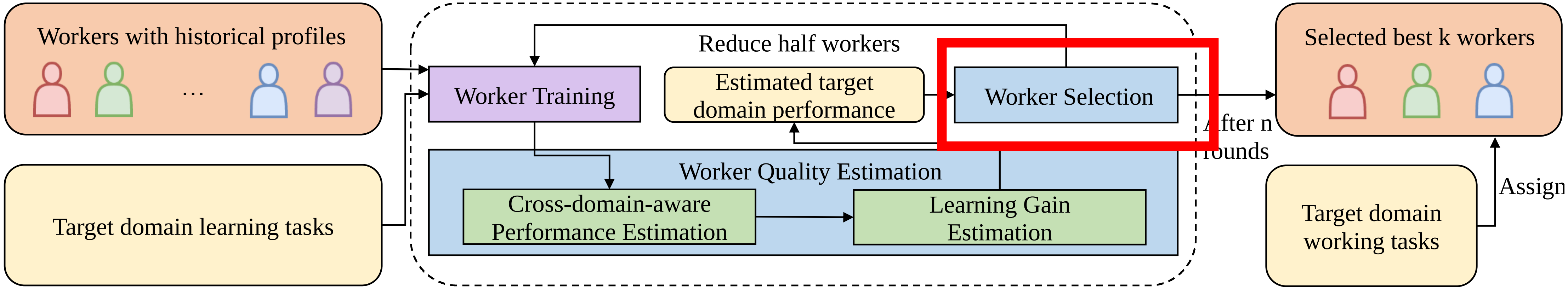
- IRT score:

$$\hat{p}_{j,i,d} = g(\alpha_i, \beta_d, K_j) = \frac{1}{1 + e^{-(\alpha_i \ln(K_j+1) - \beta_d)}}.$$

- Update the learning parameter α_i:

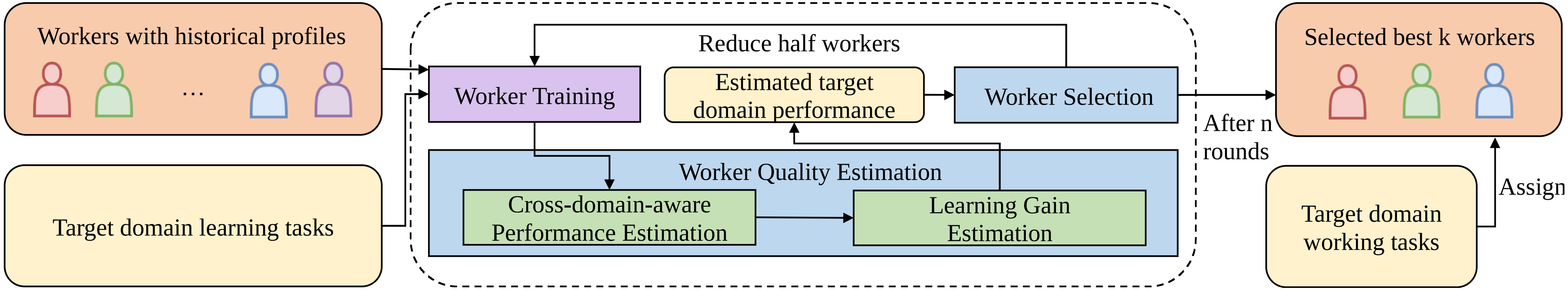
$$\alpha_i = \arg\min_{\alpha_i} \left[\sum_{d=1}^{D} (\hat{p}_{1,i,d} - h_{i,d})^2 + \sum_{j=1}^{c} (\hat{p}_{j-1,i,t} - p_{j,i})^2 \right]$$

Methodology



Methodology – Worker Selection

- Adapt the ME algorithm to select the **top half of the workers** in the current round.
- Error bound: $O(\sqrt{\frac{nk}{B}\ln\frac{1}{\delta_c}})$.



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Experiments

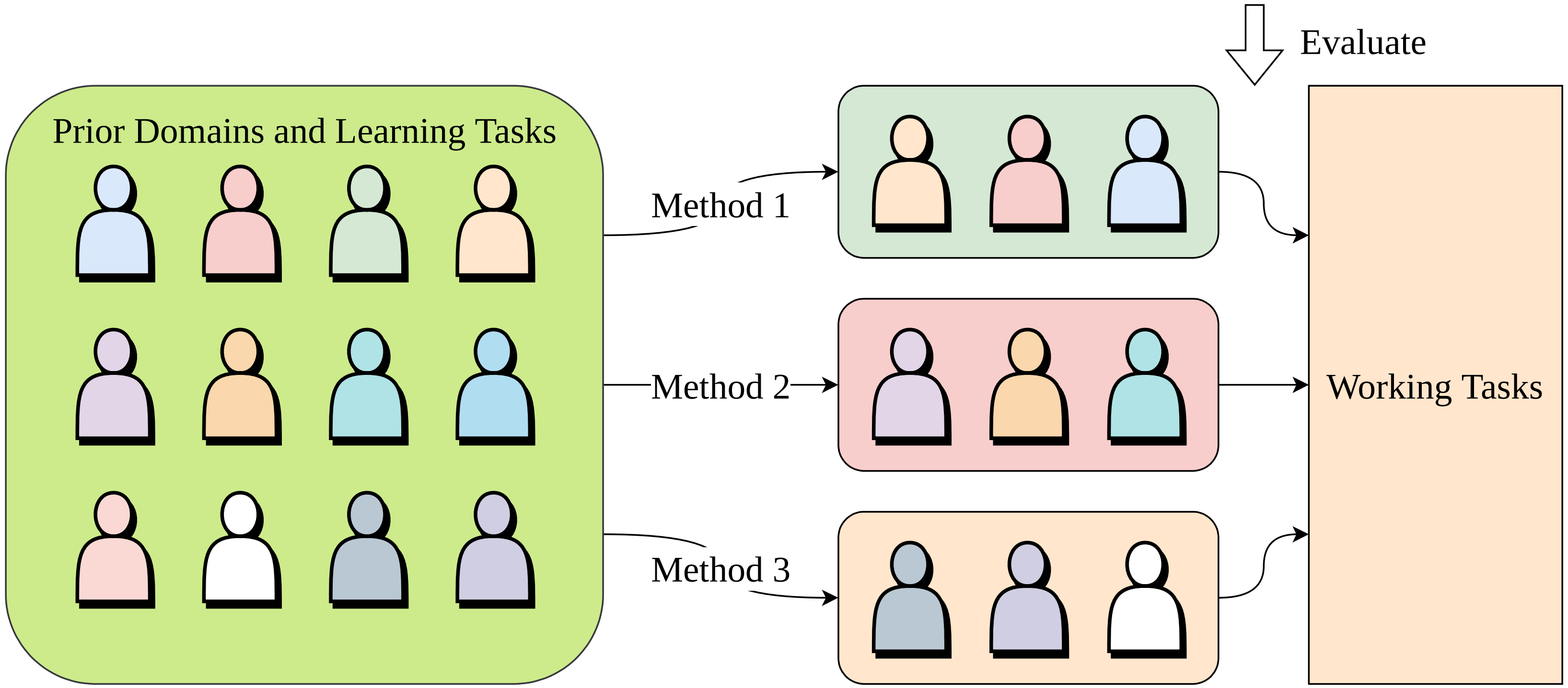
- Datasets:

TABLE II
DATASET STATISTICS

Datasets	$\|W\|$	Q	k	total # of batches	B
RW-1	27	10	7	3	540
RW-2	35	10	9	3	700
S-1	40	20	5	7	2400
S-2	50	20	5	7	3000
S-3	80	20	5	15	6400
S-4	160	20	5	31	16000

Experiments

- Metric: averaged annotation accuracy of the selected top-k workers on the target domain working task.



Experiments

- Baselines: We considered three baselines, Universal Sampling (US), Medium Elimination (ME), and Li et al.
  - US: use the budget for all the workers equally and select the top k workers
  - ME: allocates the budget in rounds and eliminates the workers by half in each round based on the accuracy of the learning tasks
  - Li et al.: compute the correlation between the prior domain historical results with the target domain performance

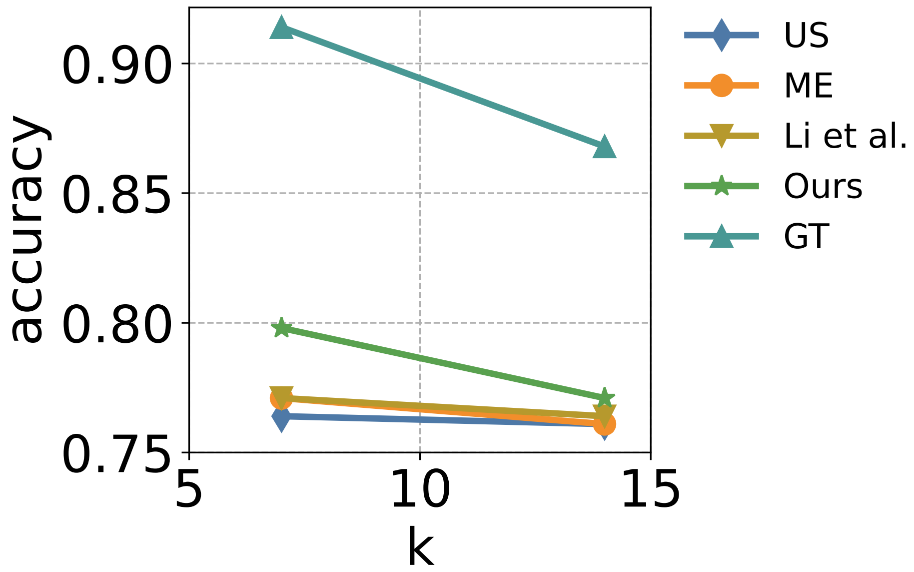
Experiments

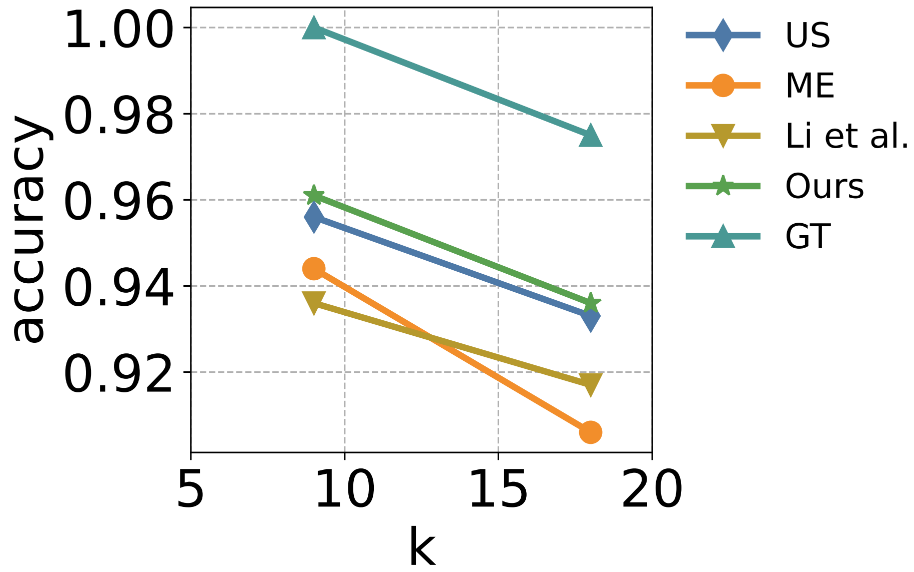
TABLE V
EXPERIMENT RESULTS

	RW-1	RW-2	S-1	S-2	S-3	S-4
US [11], [19]	0.764 (4.5% ↑)	0.956 (0.5% ↑)	0.765 (8.5% ↑)	0.775 (6.8% ↑)	0.815 (4.3% ↑)	0.865 (2.4% ↑)
ME [11], [19]	0.771 (3.5% ↑)	0.944 (1.8% ↑)	0.720 (15.3% ↑)	0.785 (5.5% ↑)	0.795 (6.9% ↑)	0.880 (0.7% ↑)
Li et al. [31]	0.771 (3.5% ↑)	0.936 (2.7% ↑)	0.780 (6.4% ↑)	0.805 (2.9% ↑)	0.845 (0.6% ↑)	0.870 (1.8% ↑)
Ours	**0.798**	**0.961**	**0.830**	**0.828**	**0.850**	**0.886**
Ground Truth	0.914	1.000	0.885	0.875	0.915	0.975

Experiments

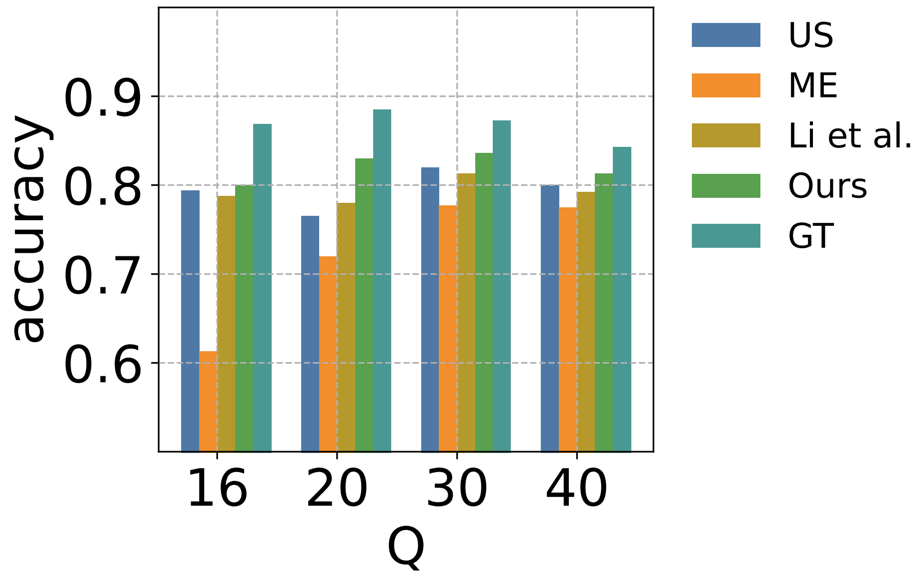
- Stability over the parameter k (number of desired workers)

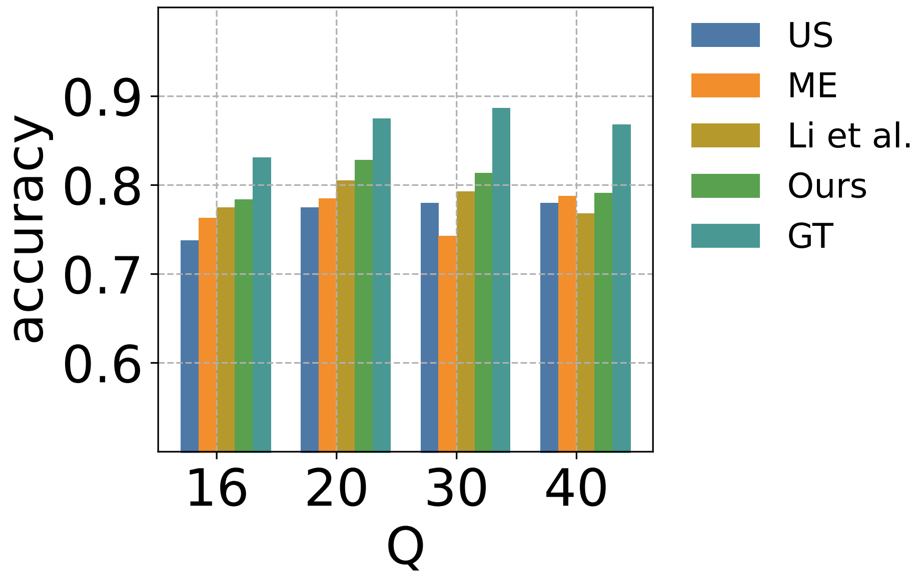




Experiments

- Stability over the parameter Q (number of learning tasks per batch)





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Summary

- We incorporate the **cross-domain knowledge** information and propose a novel **Median Elimination-based** worker selection with training algorithm to find high-quality workers.
- We comprehensively consider the **learning gain** of workers during the learning task worker training process over the new domain to get a better estimate of the **dynamic change** in worker quality.
- We collect **two novel cross-domain worker selection datasets** for the crowdsourcing research community to study the problem of cross-domain worker selection with training.
- We conduct **extensive experiments** on real-world and synthesized datasets to evaluate the performance of our proposed method comprehensively.

Thank you