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NAACL-HLT 2021 hands-on tutorial

Crowdsourcing Natural Language Data at Scale: A Hands-On Tutorial

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Part III:

Advanced Techniques

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Analyst/Software Developer
Crowdsourcing Research Group

Tutorial Schedule

Introduction: 15 min

Part I: 30 min
Key Components for Data Collection

Part II: 60 min
Practice Session I

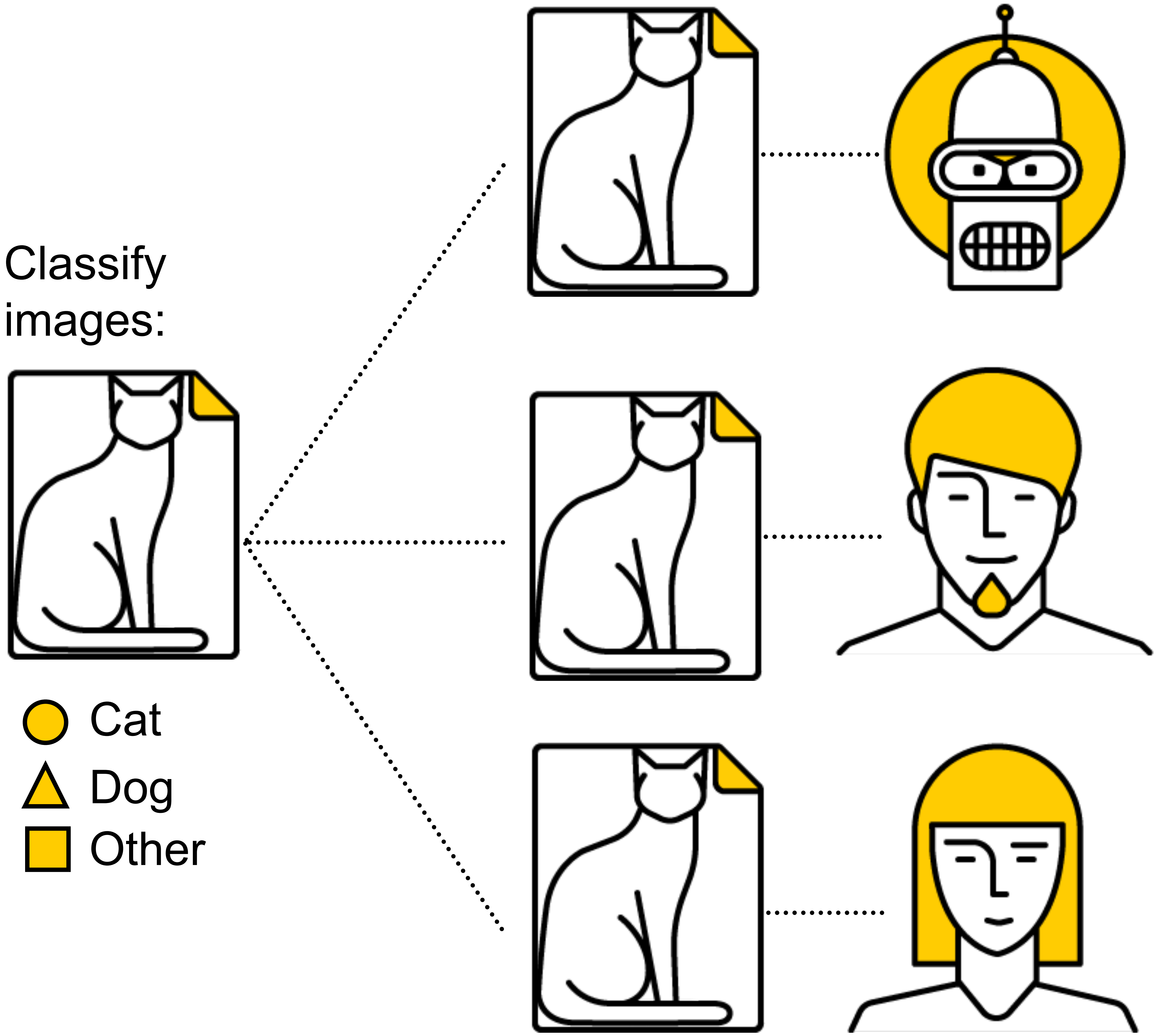
Lunch Break: 45 min

Part III: 45 min
Advanced Techniques

Part IV: 30 min
Practice Session II

Part V: 15 min
Conclusion

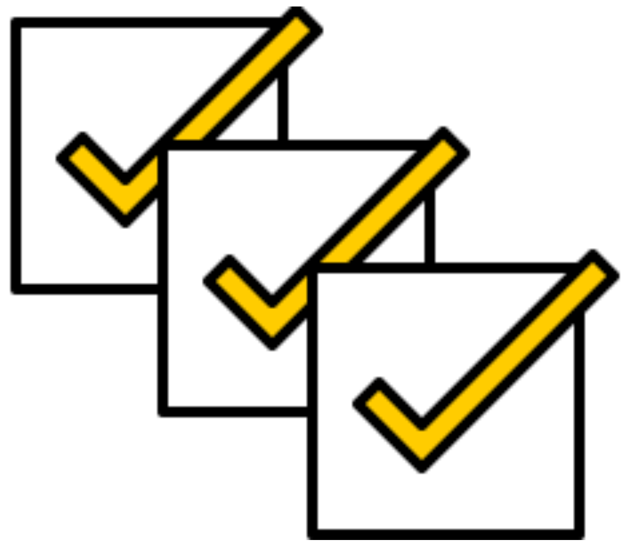
Labeling data with crowdsourcing



- How to choose a reliable label?
- How many labels per object?
- How much to pay for labels?
- …

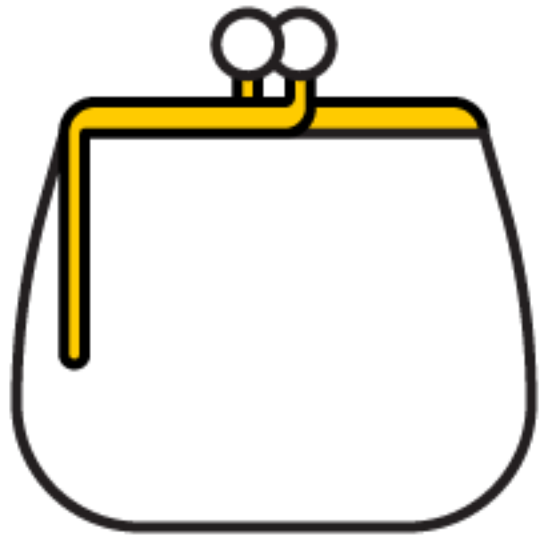
Evaluation of labeling approaches

Accuracy



vs

Cost

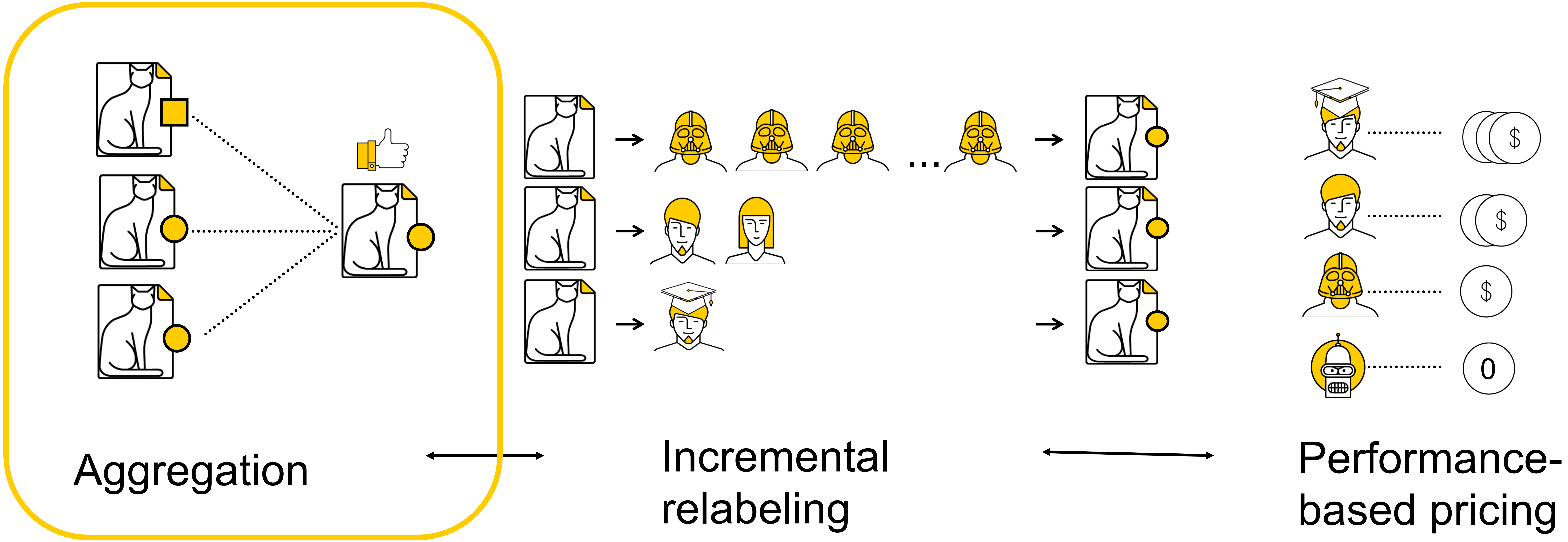


Labels with a maximal level of accuracy for a given budget

or

Labels of a chosen accuracy level for a minimal budget

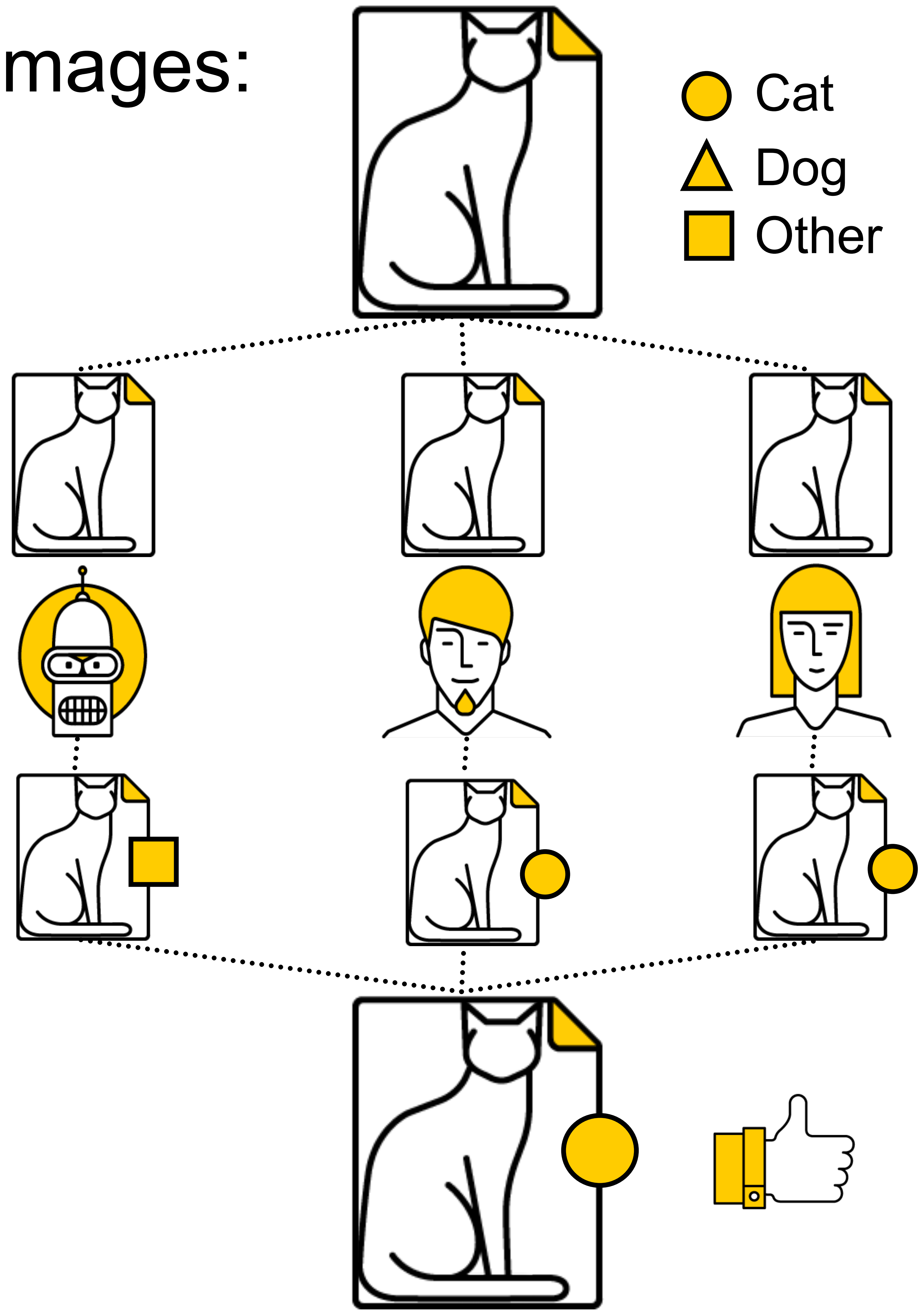
Key components of labeling with crowds



Aggregation

Labeling data with crowds

Classify images:

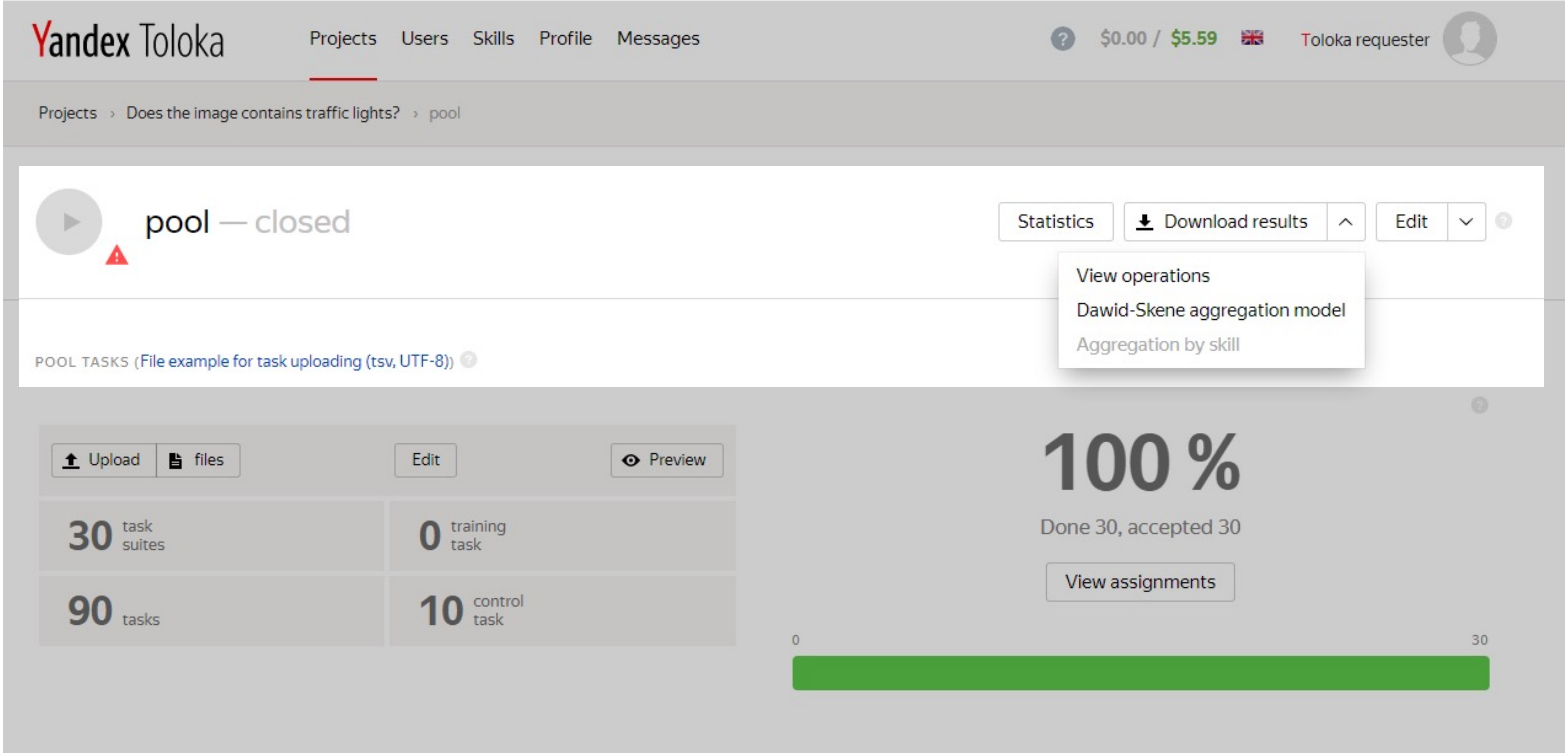


Upload multiple copies of each object to label

Performers assign noisy labels to objects

Aggregate multiple labels for each object into a more reliable one

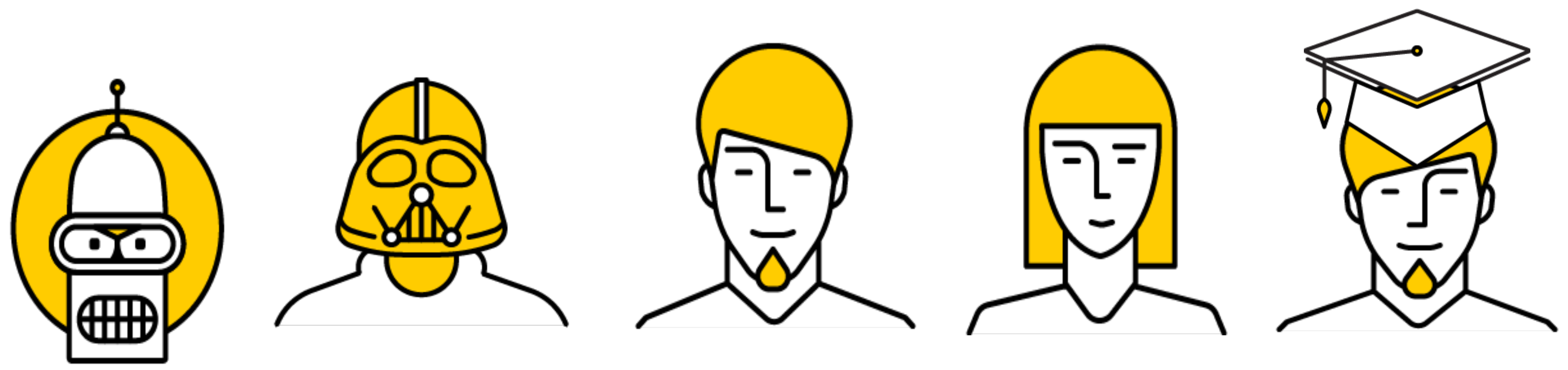
Process results



Multiclass labels

Multiclassification

Notation

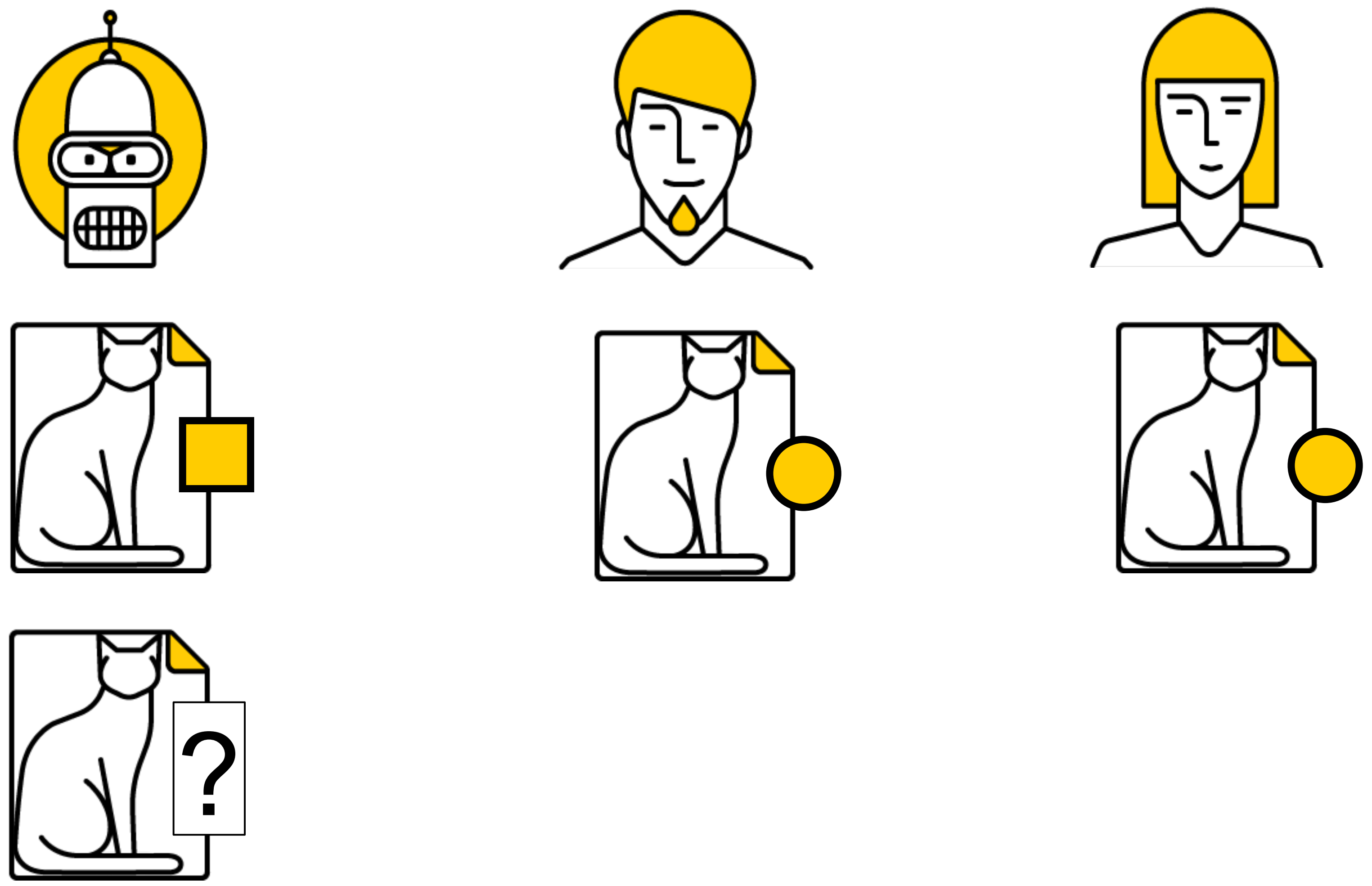
- Categories $k \in \{1, \dots, K\}$. E.g.: Cat Dog Other
- Objects $j \in \{1, \dots, J\}$. E.g.: 
- Performers: $w \in \{1, \dots, W\}$. E.g.: 
  - $W_j \subseteq \{1, \dots, W\}$ - performers labeled object j

The simplest aggregation: Majority Vote (MV)

The problem of aggregation:

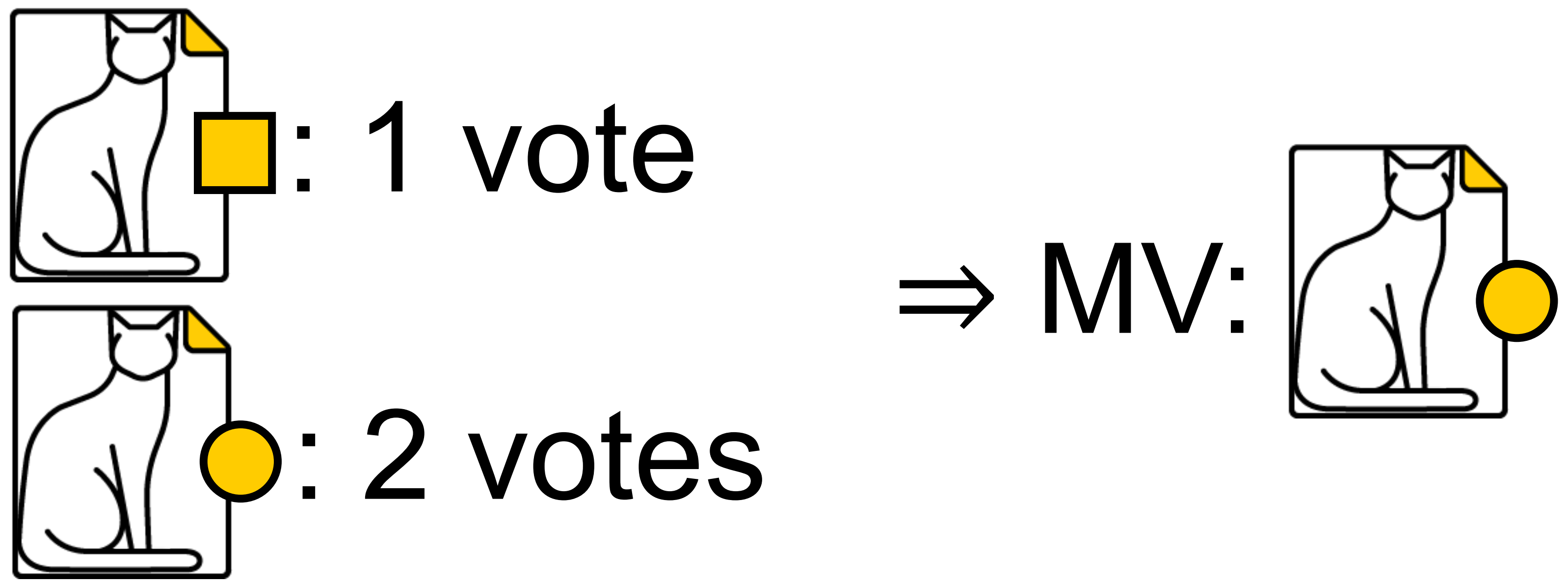
- Observe noisy labels

$$\mathbf{y} = \{y_j^w \mid j = 1, \ldots, J \text{ and } w = 1, \ldots, W\}$$



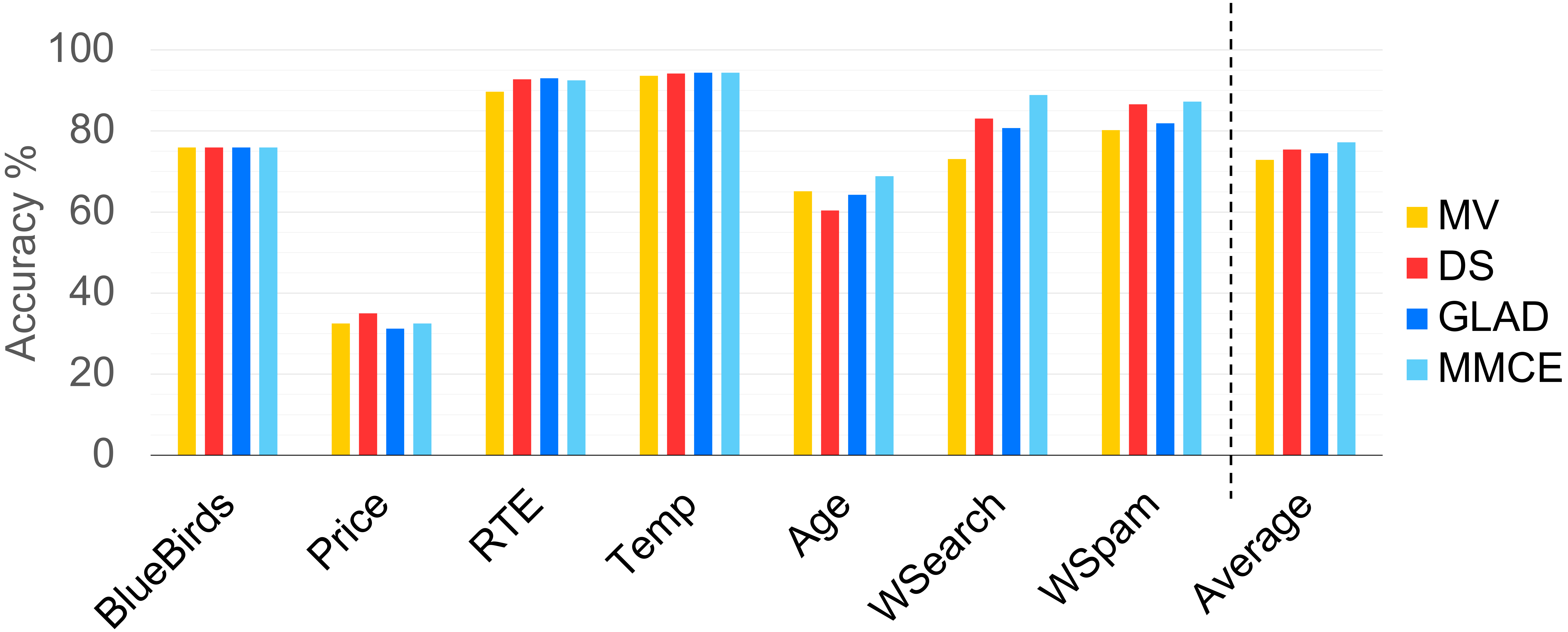
- Recover true labels $\mathbf{z} = \{z_j \mid j = 1, \ldots, J\}$

A straightforward solution:



$\hat{z}_j^{MV} = \arg\max_{y=1,\ldots,K} \sum_{w \in W_j} \delta(y = y_j^w)$, where $\delta(A) = 1$ if A is true and 0 otherwise

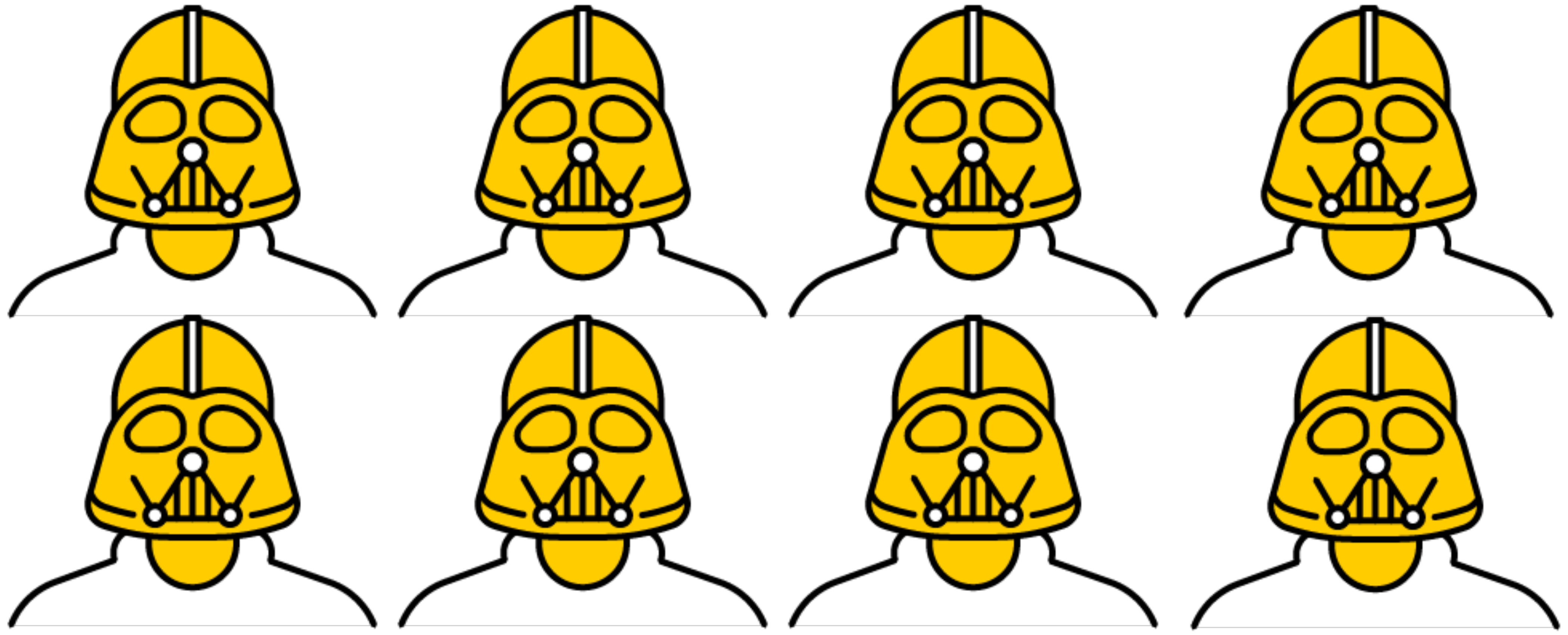
Performance of MV vs other methods



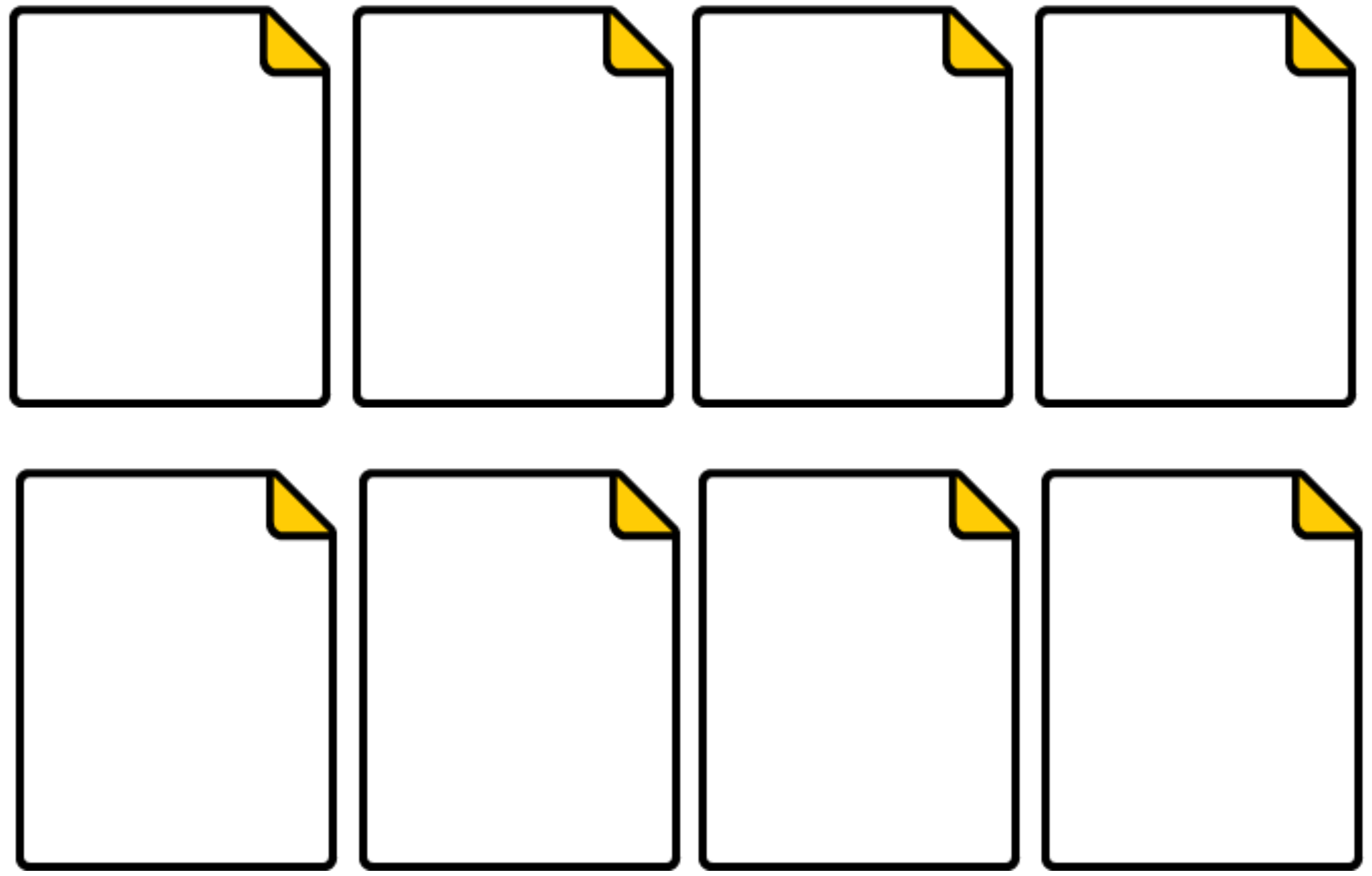
Zhou D. et al. Regularized minimax conditional entropy for crowdsourcing. 2015

Properties of MV

- All performers are treated similarly

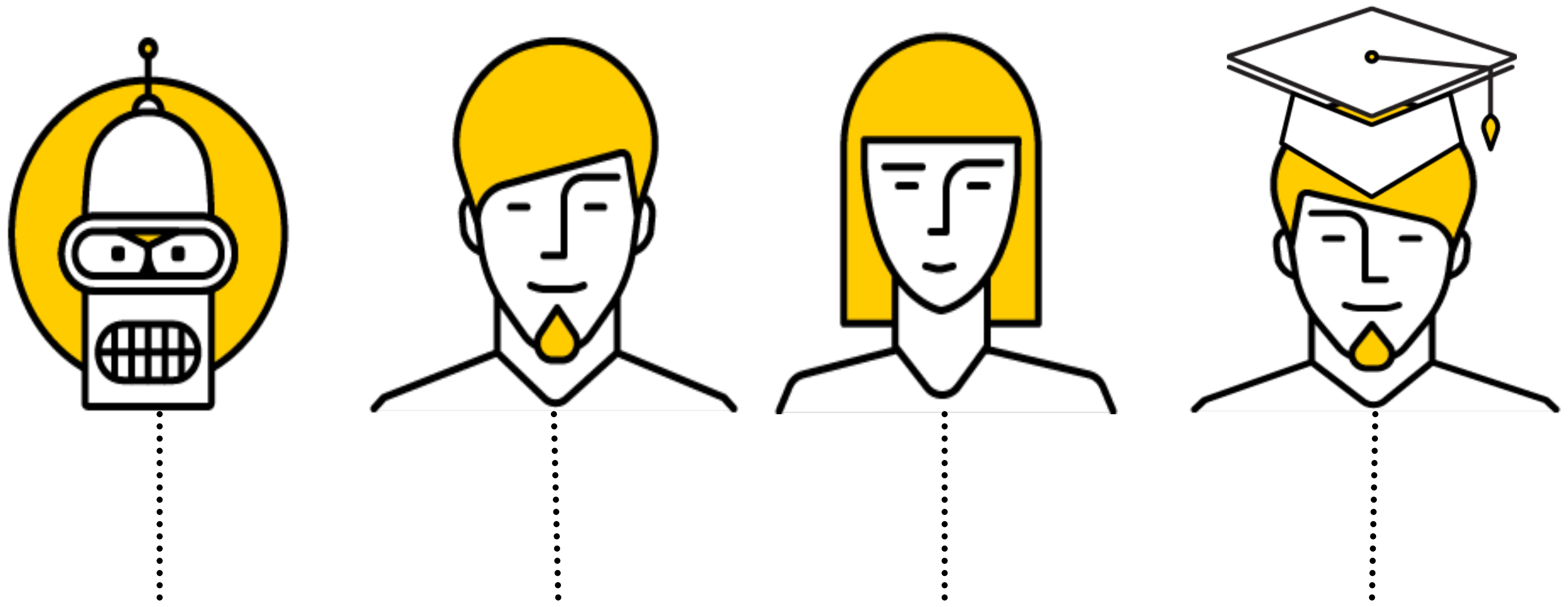


- All objects are treated similarly



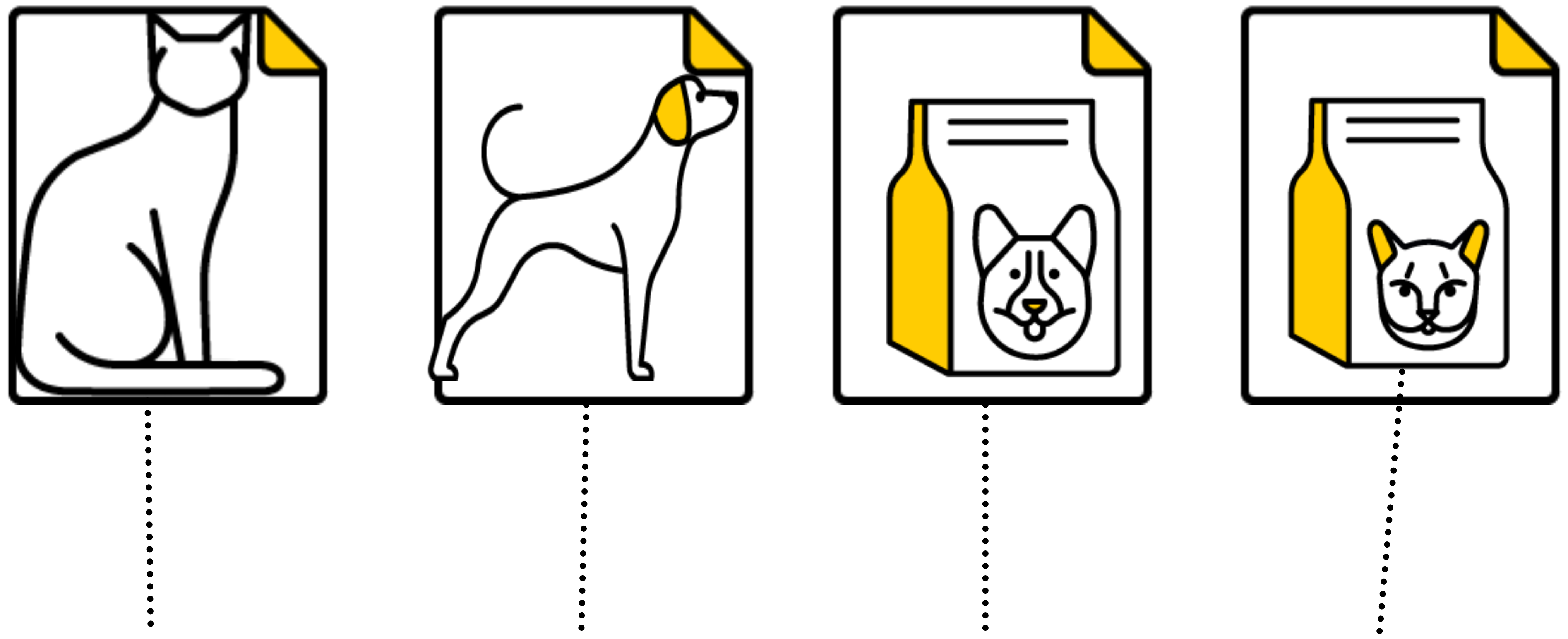
Advanced aggregation: performers and objects

- Parameterize expertise of performers by e^{w}



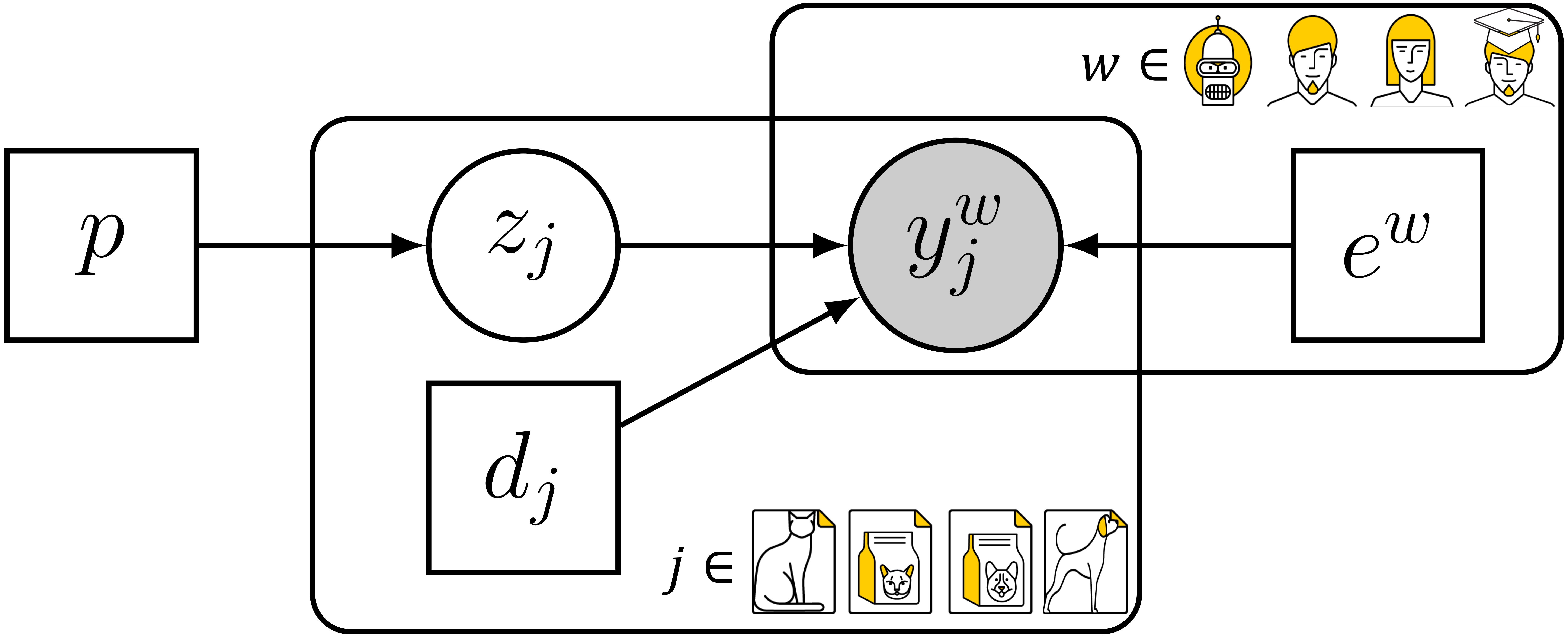
e^{w_1} e^{w_2} e^{w_3} e^{w_4}

- Parameterize difficulty of objects by d_j

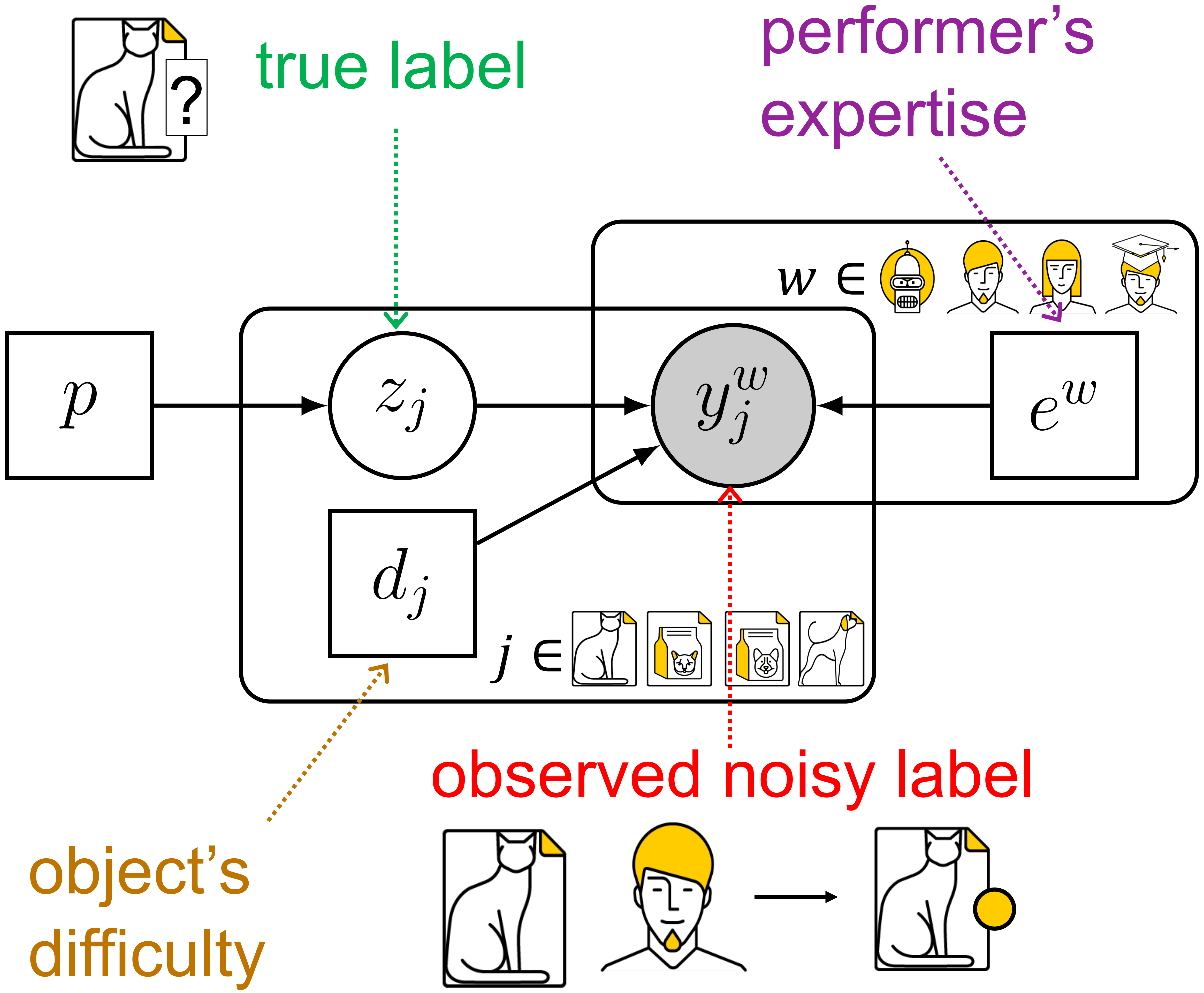


d_{j_1} d_{j_1} d_{j_1} d_{j_1}

Advanced aggregation: latent label models

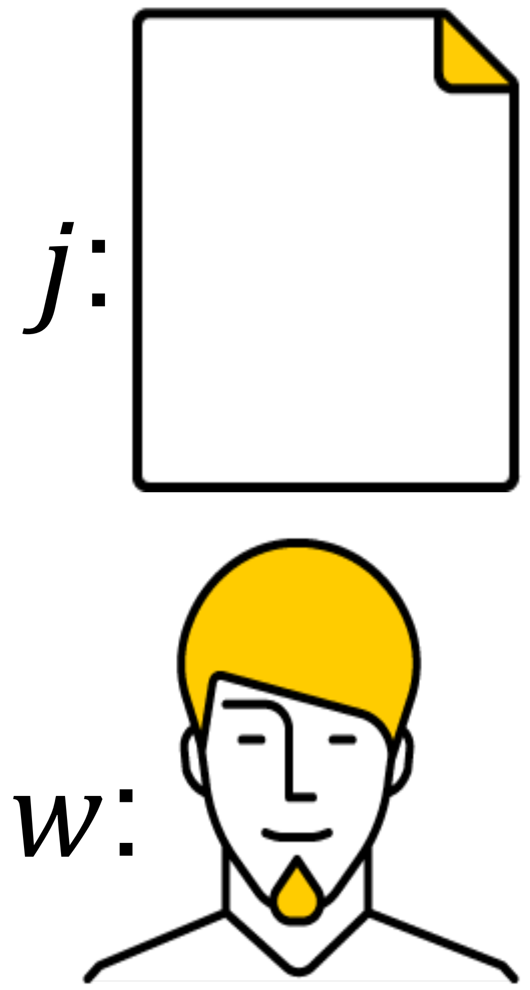


Latent label models: noisy label model



- A noisy label model $M_j^w = M(e^w, d_j)$ is a matrix of size $K \times K$ with elements

$$M_j^w[c, k] = Pr\left(Y_j^w = k \mid Z_j = c\right)$$

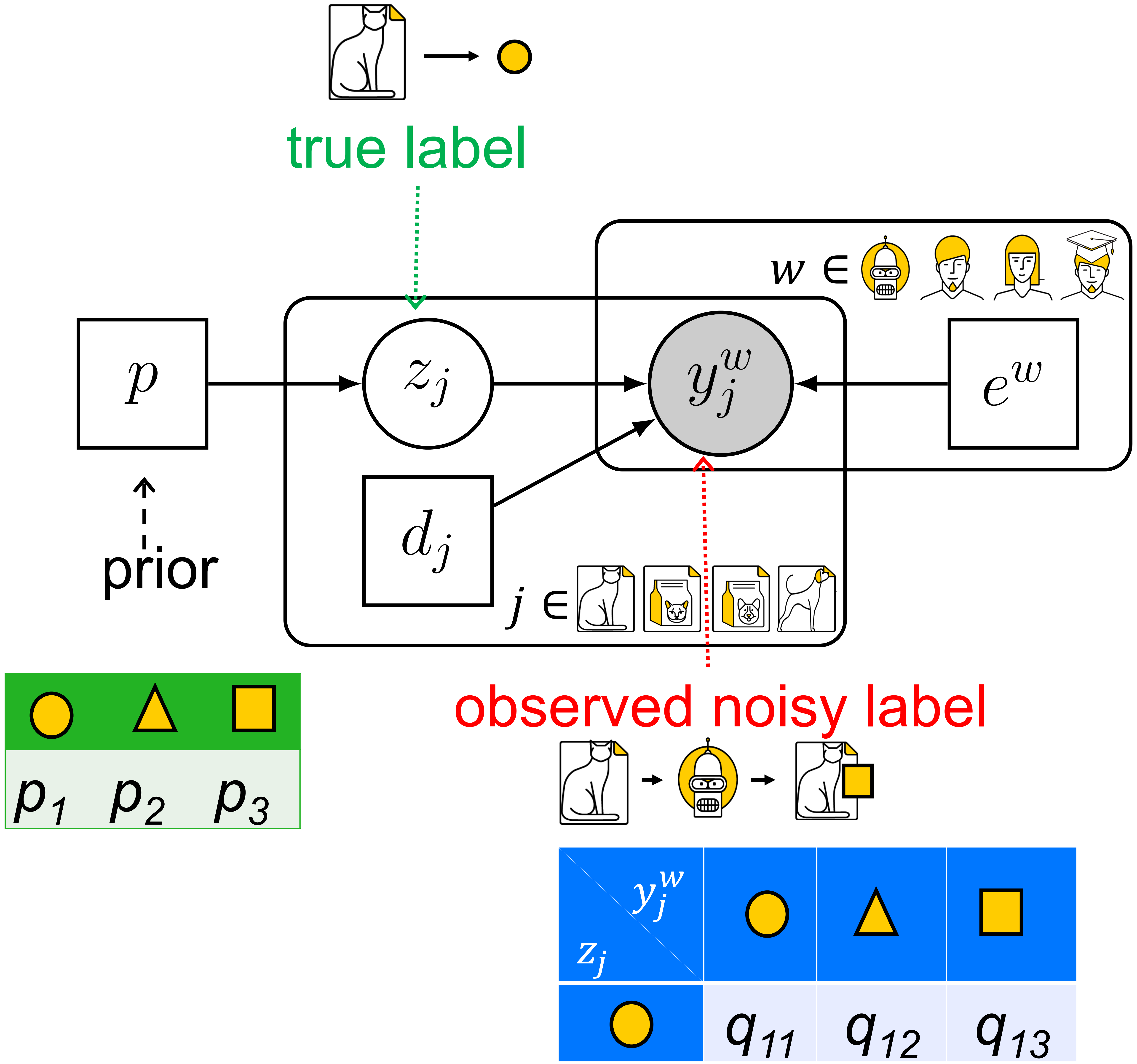


M_j^w:

True \ Noisy	●	▲	■
●	q_{11}	q_{12}	q_{13}
▲	q_{21}	q_{22}	q_{23}
■	q_{31}	q_{32}	q_{33}

$q_{c1} + q_{c2} + q_{c3} = 1$ for each c

Latent label models: generative process



- Noisy labels generation:

1. Sample z_j from a distribution $P_Z(p)$
2. Sample y_j^w from a distribution $P_Y\left(M_j^w[z_j,\cdot]\right)$

In multiclassification, a standard choice for $P_Z(\cdot)$ and $P_Y(\cdot)$ is a Multinomial distribution $\mathrm{Mult}(\cdot)$

Latent label models: parameters optimization

- Assumption: y_j^w is cond. independent of everything else given z_j, d_j, e^w
- The likelihood of $\mathbf{y}$ and $\mathbf{z}$ under the latent label model:

observed noisy label

$$L\left(\{z_j\}_{j=1}^{J}, p, \{d_j\}_{j=1}^{J}, \{e^w\}_{w=1}^{W}\right) = \prod_{j \in J} \underbrace{\sum_{z_j \in \{1,\ldots,K\}} \Pr(z_j | p) \prod_{w \in W_j} \Pr(y_j^w | z_j, d_j, e^w)}_{\text{likelihood of noisy and true labels for object } j}$$

latent true label

latent parameters

- Estimate parameters and true labels by maximizing $L(\ldots)$

Latent label models: EM algorithm

- Maximization of the expectation of log-likelihood (LL), a lower bound on LL of **y** and **z**

$$\mathbb{E}_{\mathbf{z}} \log \Pr(\mathbf{y}, \mathbf{z}) = \sum_{j \in \mathrm{J}} \sum_{z_j \in \{1,\ldots,K\}} \Pr(z_j | p) \log \prod_{w \in W_j} \Pr(z_j | p) \Pr(y_j^w | z_j, d_j, e^w)$$

- **E-step**: Use Bayes' theorem for posterior distribution of $\hat{\mathbf{z}}$ given p, $\mathbf{d}$, $\mathbf{e}$:

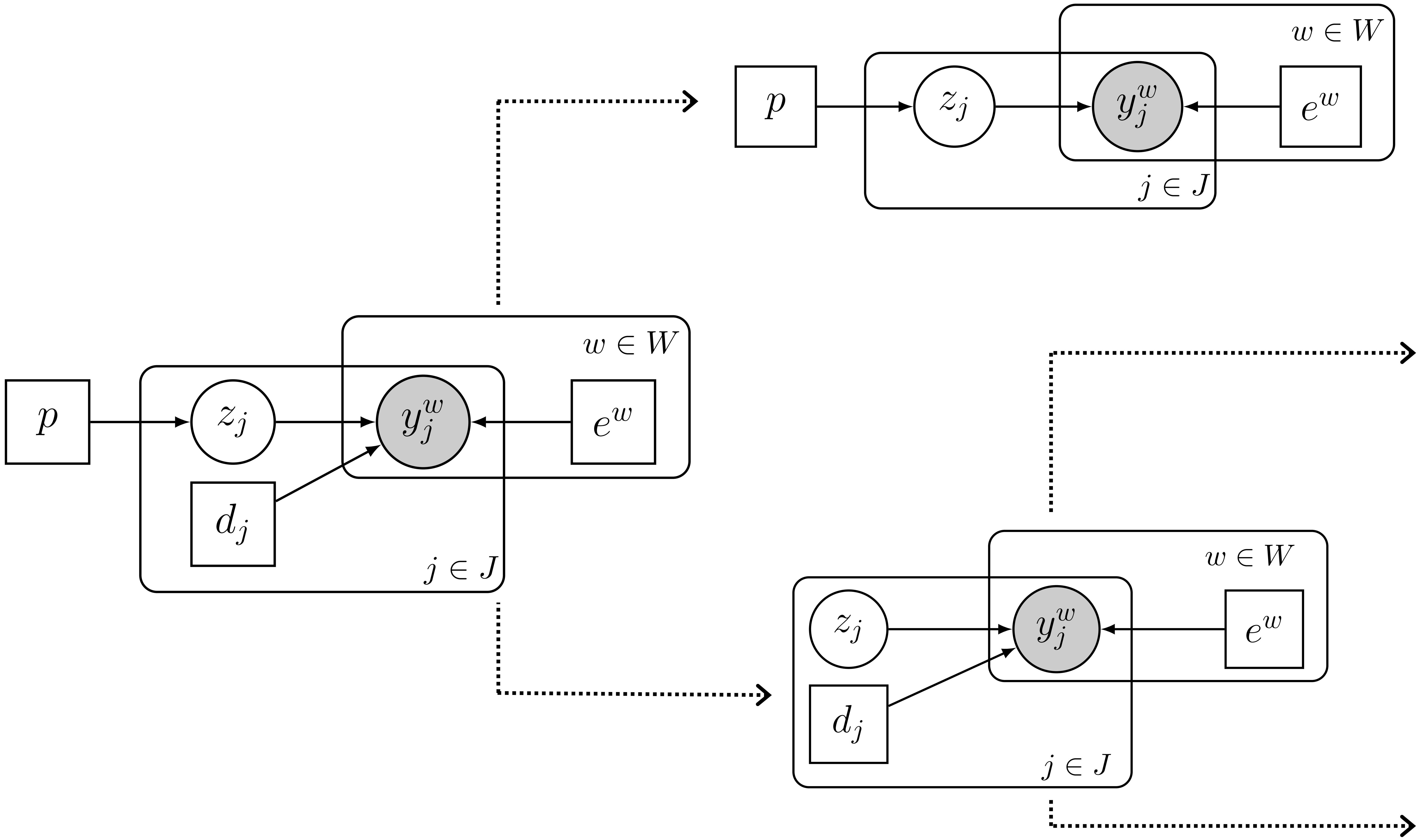
$$\hat{z}_j[c] = \Pr(Z_j = c | \mathbf{y}, p, \mathbf{d}, \mathbf{e}) \propto \Pr(Z_j = c | p) \prod_{w \in W_j} \Pr(y_j^w | Z_j = c, d_j, e^w)$$

- **M-step**: Maximize the expectation of LL with respect to the posterior distribution of $\hat{\mathbf{z}}$:

$$(p, \mathbf{d}, \mathbf{e}) = \operatorname{argmax} \mathbb{E}_{\hat{\mathbf{z}}} \log \Pr(z_j | p) \prod_{w \in W_j} \Pr(y_j^w | z_j, d_j, e^w)$$

  - Analytical solutions
  - Gradient descent

Latent label model (LLM): special cases



Dawid and Skene model (DS):

- categories are different
- objects are similar
- performers are different

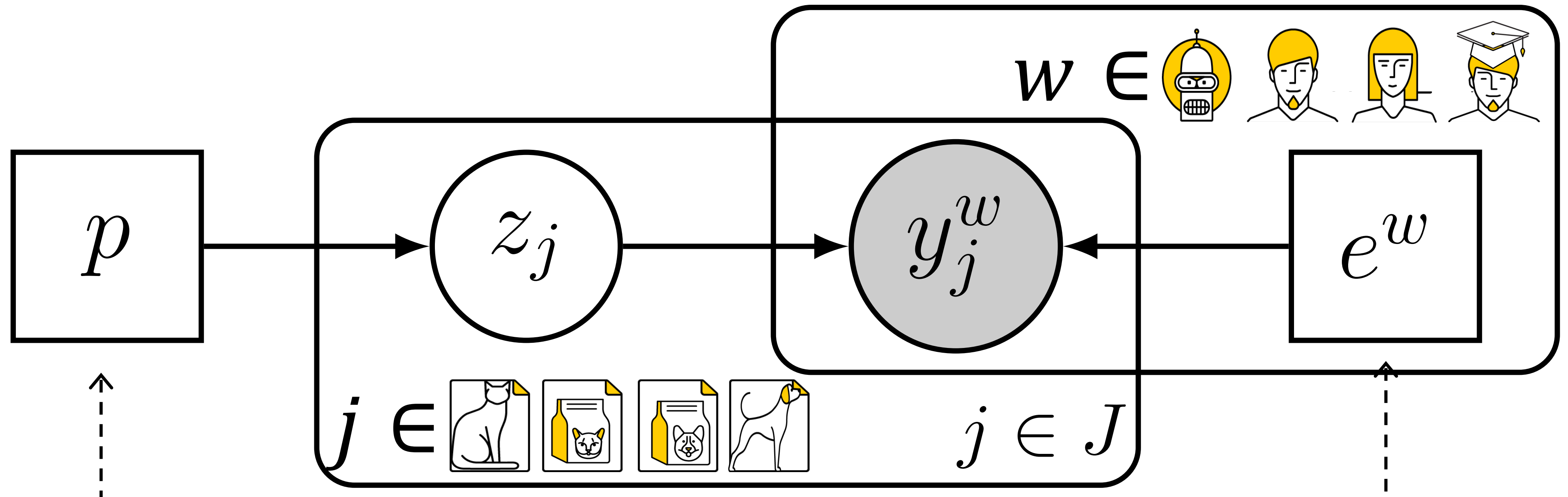
Generative model of labels, abilities, and difficulties (GLAD):

- categories are similar
- objects are different
- performers are different

Minimax conditional entropy model (MMCE):

- categories are different
- objects are different
- performers are different

Dawid and Skene model (DS)

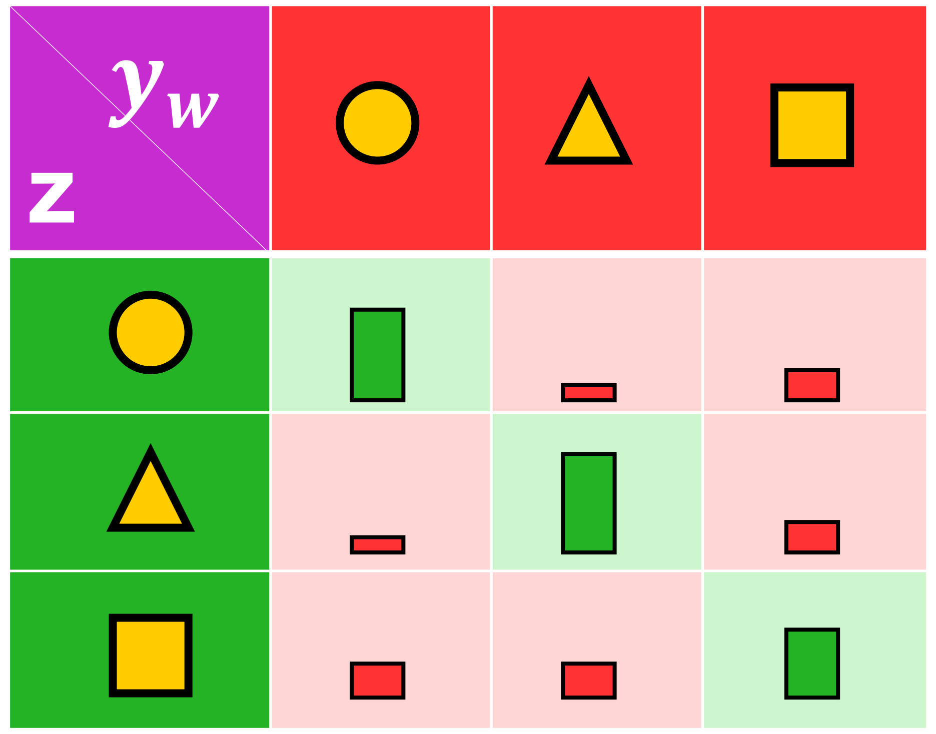


class prior

performer's confusion matrix

LLM with parameters:

- p – vector of length K: $p[i] = \Pr(Z = c)$
- e^w– matrix of size $K \times K$:
  $e^w[c, k] = \Pr(Y^w = k | Z = c)$



Dawid and Skene, Maximum Likelihood Estimation of Observer Error-Rates Using the *EM* Algorithm,1979

DS: parameters optimization

- **E-step**:

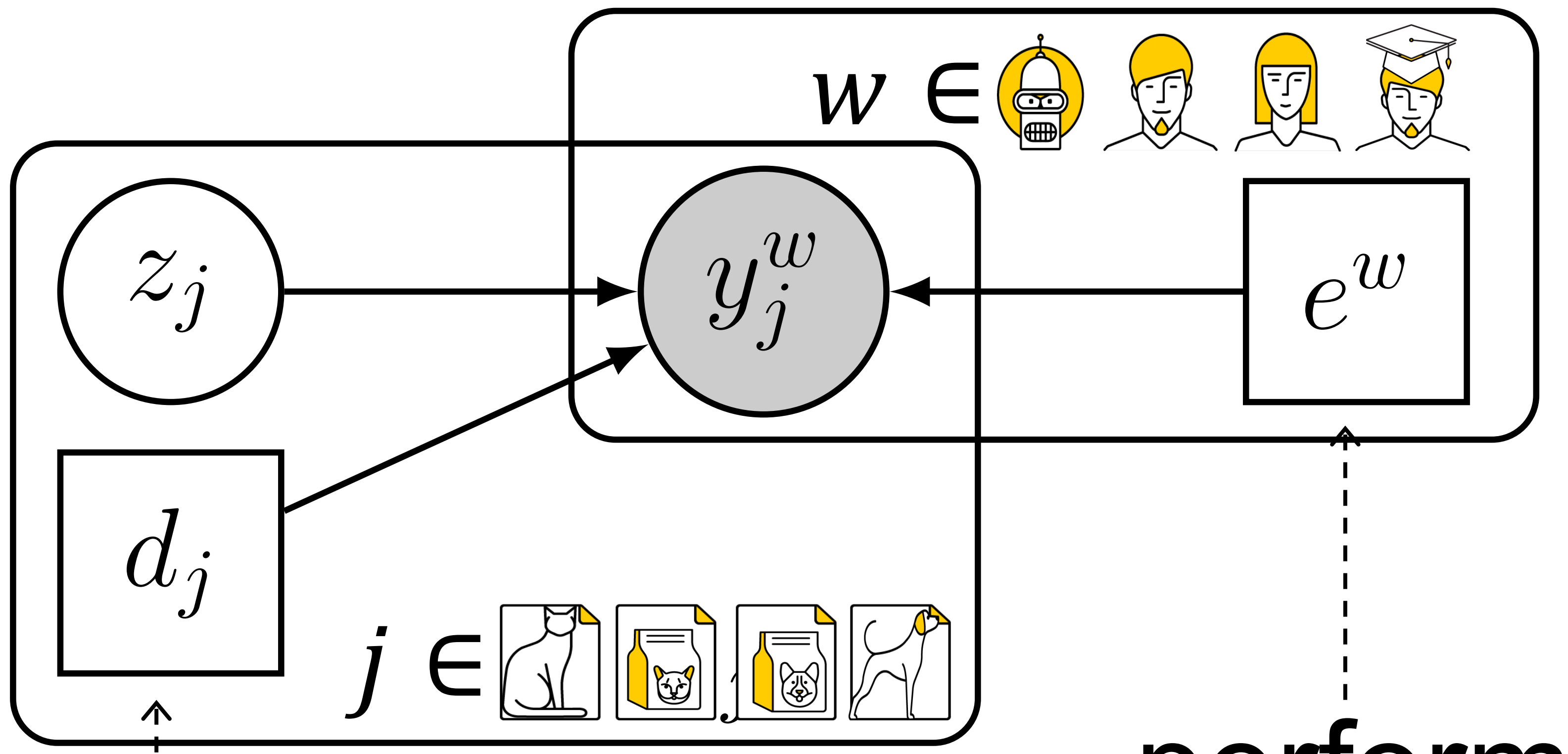
$$\hat{z}_j[c] = \frac{p[c] \prod_{w \in W_j} e^w[c, y_j^w]}{\sum_k p[k] \prod_{w \in W_j} e^w[k, y_j^w]}, \qquad c = 1, \dots, K$$

- **M-step**: Analytical solution

$$e^w[c,k] = \frac{\sum_{j \in J} \hat{z}_j[c] \delta(y_j^w = k)}{\sum_{q=1}^K \sum_{j \in J} \hat{z}_j[c] \delta(y_j^w = q)}, \qquad k, c = 1, \dots, K$$

$$p[c] = \frac{\sum_{j \in J} \hat{z}_j[c]}{J}, \qquad c = 1, \dots, K$$

Generative model of Labels, Abilities, and Difficulties (GLAD)



performer's ability

object's inverse difficulty

LLM with parameters:

- scalar $d_j \in (0, \infty)$
- scalar $e^w \in (-\infty, \infty)$
- Model:

$$\Pr\left(Y_j^w = k \mid Z_j = c\right) = \begin{cases} a(w,j), & c = k \\ \dfrac{1 - a(w,j)}{K-1}, & c \neq k \end{cases}$$

$$\text{where } a(w,j) = \frac{1}{1 + \exp(-e^w d_j)}$$

Whitehill et al., Whose vote should count more: Optimal integration of labels from labelers of unknown expertise, 2009

GLAD: parameters optimization

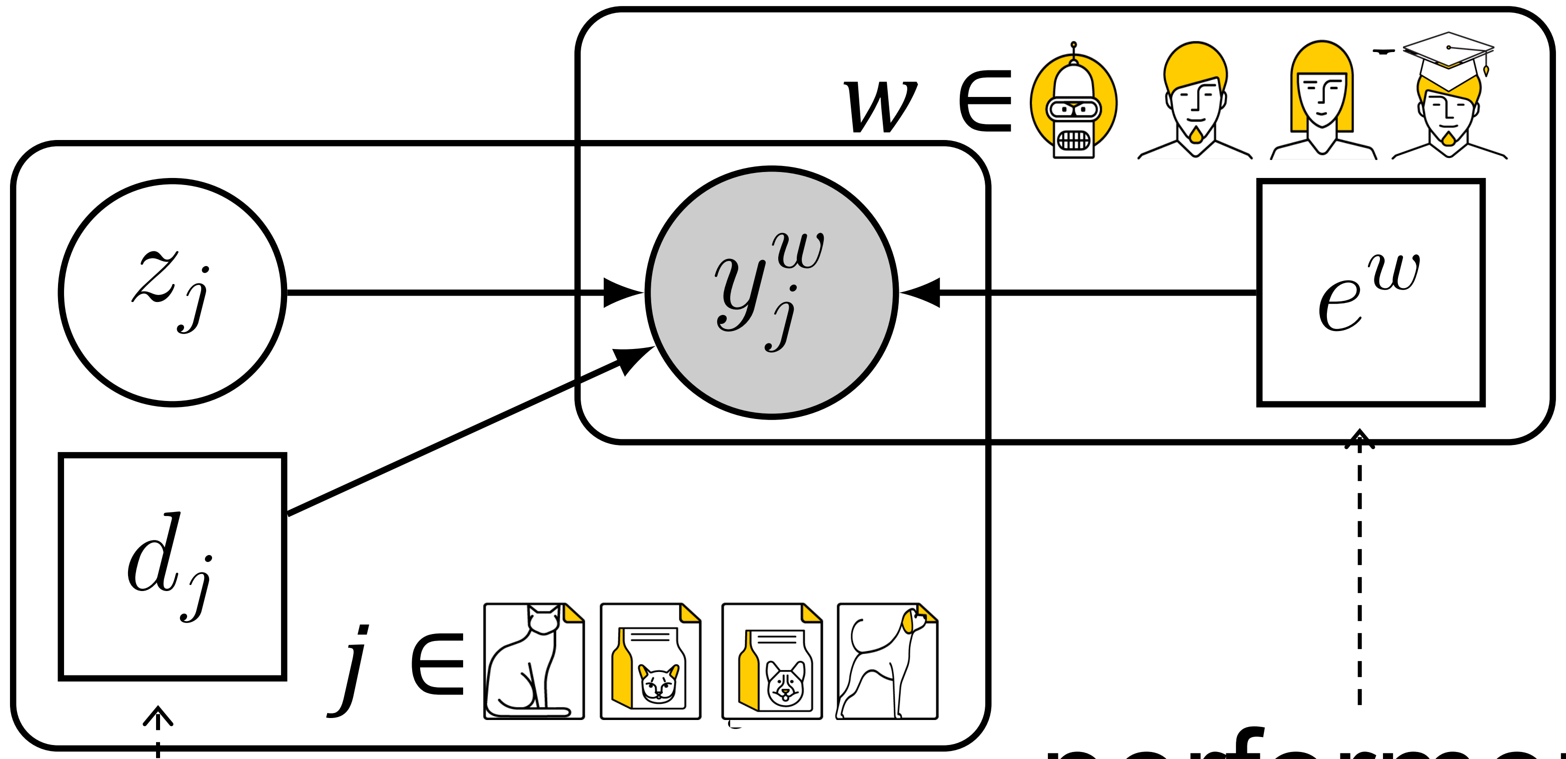
- Let $a(w,j) = \frac{1}{1+\exp(-e^w d_j)}$ and $\mathrm{P}(z_j)$ be a predefined prior (e.g., $\mathrm{P}(z_j) = {}^{1}/_{K}$)
- **E-step**:

$$\widehat{z_j}\,[c] \propto \mathrm{P}(Z_j = c) \prod_{w \in W_j} a(w,j)^{\delta(y_j^w = c)} \left(\frac{1 - a(w,j)}{K-1}\right)^{\delta(y_j^w \neq c)}, \quad c = 1, \dots, K$$

- **M-step**: estimate $(\mathbf{d}, \mathbf{e})$ for given $\hat{\mathbf{z}}$ using gradient descent

$$(\mathbf{d}^{\mathrm{t}}, \mathbf{e}^{\mathrm{t}}) = \operatorname{argmax} \sum_{j \in J} \left[\mathbb{E}_{\widehat{z_j}} \log \mathrm{P}(z_j) + \sum_{w \in W_j} \mathbb{E}_{\widehat{z_j}} \log \Pr(y_j^w | z_j) \right]$$

MiniMax Conditional Entropy model (MMCE)



object's confusability matrix

performer's expertise matrix

- Find parameters that minimize the maximum conditional entropy of observed labels:

$$\min_Q \max_P - \sum_{\substack{j \in J \\ c \in \{1,\dots,K\}}} Q(Z_j = c) \sum_{\substack{w \in W \\ k \in \{1,\dots,K\}}} P(Y_j^w = k | Z_j = c) \log P(Y_j^w = k | Z_j = c)$$

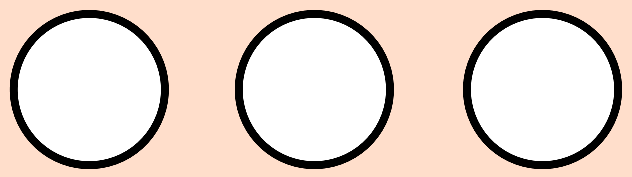
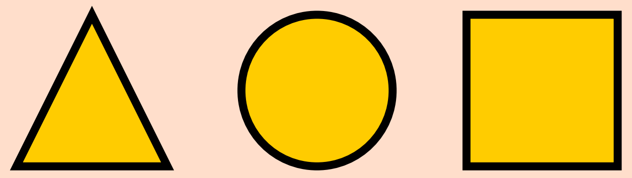
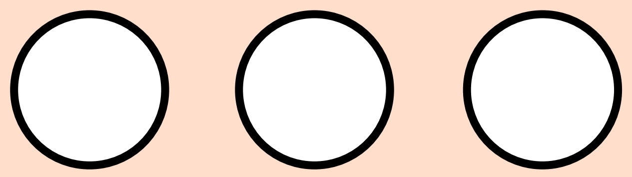
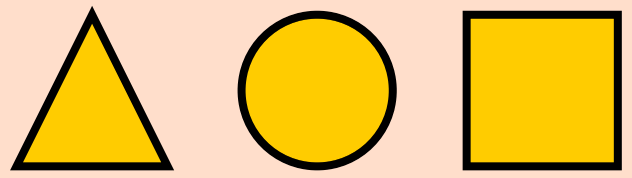
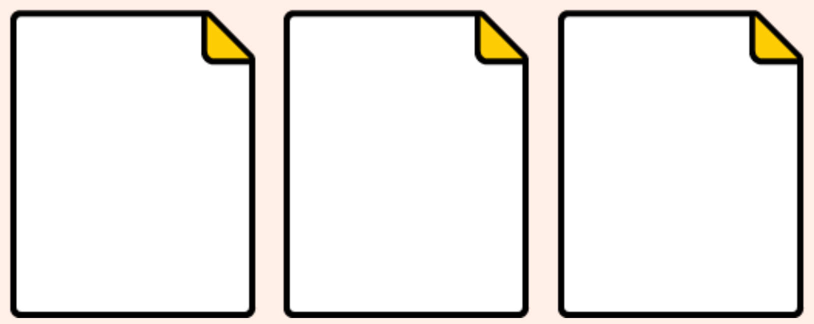
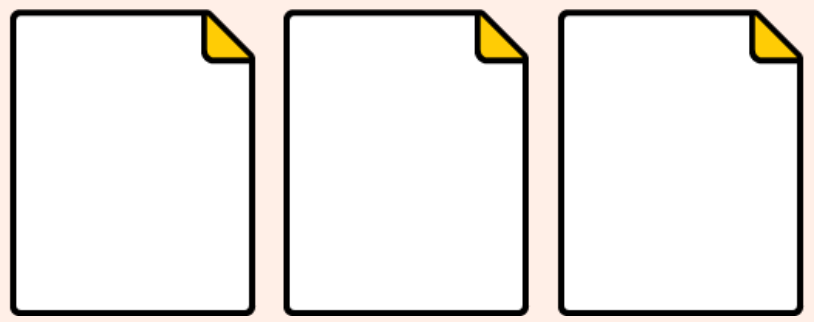
LLM with parameters:

- d_j – matrix of size $K \times K$
- e^w – matrix of size $K \times K$
- Noisy label model:

$$\Pr(Y_j^w = k | Z_j = c) = \exp(d_j[c,k] + e^w[c,k])$$

Zhou et al., Learning from the Wisdom of Crowds by Minimax Entropy, 2012

Summary of aggregation methods

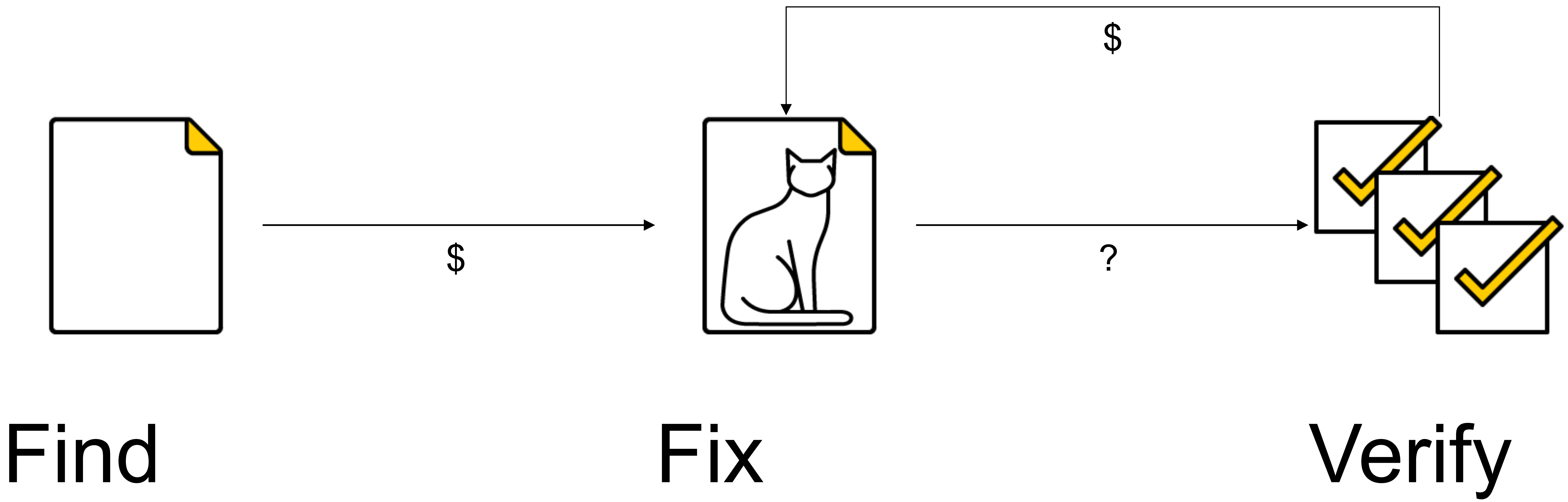
	MV	DS	GLAD	MMCE
Categories (K)				
Objects (J)				
Performers (W)				
Number of parameters	0	$WK^2 + K$	$W + J$	$(W + J)K^2$

Text Aggregation

Text Aggregation

- So far we discussed how to aggregate *categorical* responses
- In NLP we often work with **textual data**, i.e., with *sequences*
- How can we solve tasks with ”unknown” responses?

Crowdsourced Copy-Editing: Soylent



Bernstein et al. (UIST '10), https://doi.org/10.1145/1866029.1866078

Automatic Text Aggregation

- Post-acceptance is a universal technique for open-ended tasks
- However, it adds additional (slight) complexity to the pipeline
- Can we aggregate texts without human intervention?
- We would like to minimize **Word Error Rate** (WER) computed as a function of the number of **C**orrect, **S**ubstitution, **D**eletion, **I**nsertion items:

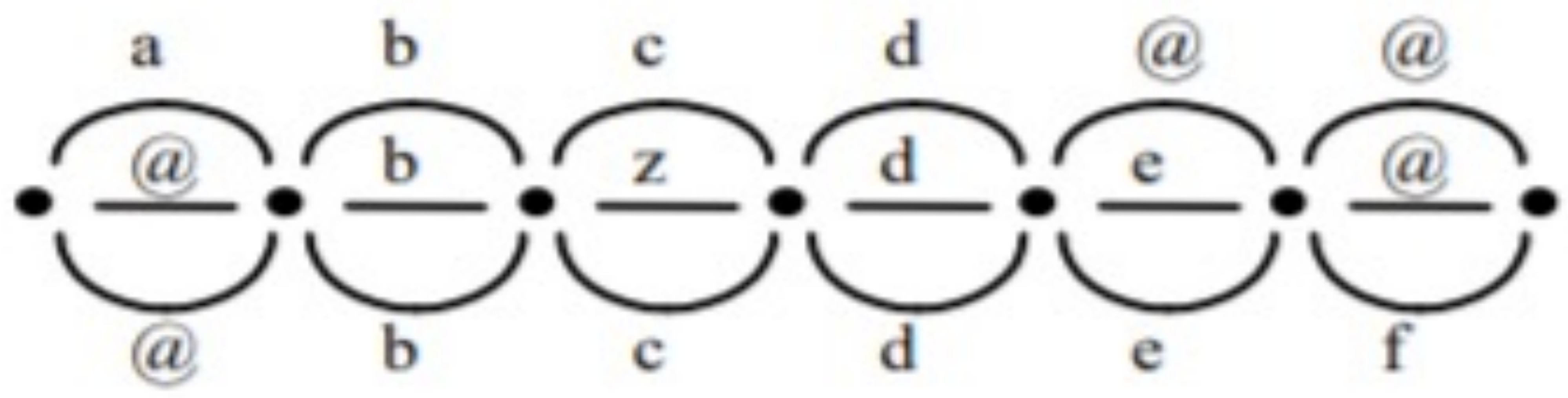
$$\mathrm{WER} = \frac{S + D + I}{C + S + D}$$

Automatic Text Aggregation: ROVER

An efficient method for long sequences:

- **Input:** `a b c d`; `b z d e`; `b c d e f`

- **Word Transition Network:**
(words with highest scores are chosen)



- **Result:** `b c d e`

Marge, M. et al. (ICASSP '10), https://doi.org/10.1109/ICASSP.2010.5494979

Automatic Text Aggregation: HRRASA

- Obtain the sequence embeddings with BERT, RoBERTa, etc.

- Choose the response that is the closes to the embedding $e()$ of the estimated response (a_j^w) provided by performer w for task j

$$\beta_w = \frac{\chi^2_{\left(\frac{\alpha}{2}, |V_w|\right)}}{\sum\left(e\left(a_j^w\right) - \hat{e}_j\right)^2} \qquad \hat{e}_j = \frac{\sum \beta_w e(a_j^w)}{\sum \beta_w}$$

$$s_j^w = \beta_w \cdot \exp\left(-\frac{\left\|e_j^w - \hat{e}_j\right\|^2}{\left\|e_j^w\right\|^2 \left\|\hat{e}_j\right\|^2}\right) + \gamma_j^w$$

- Parameters are estimated step-by-step

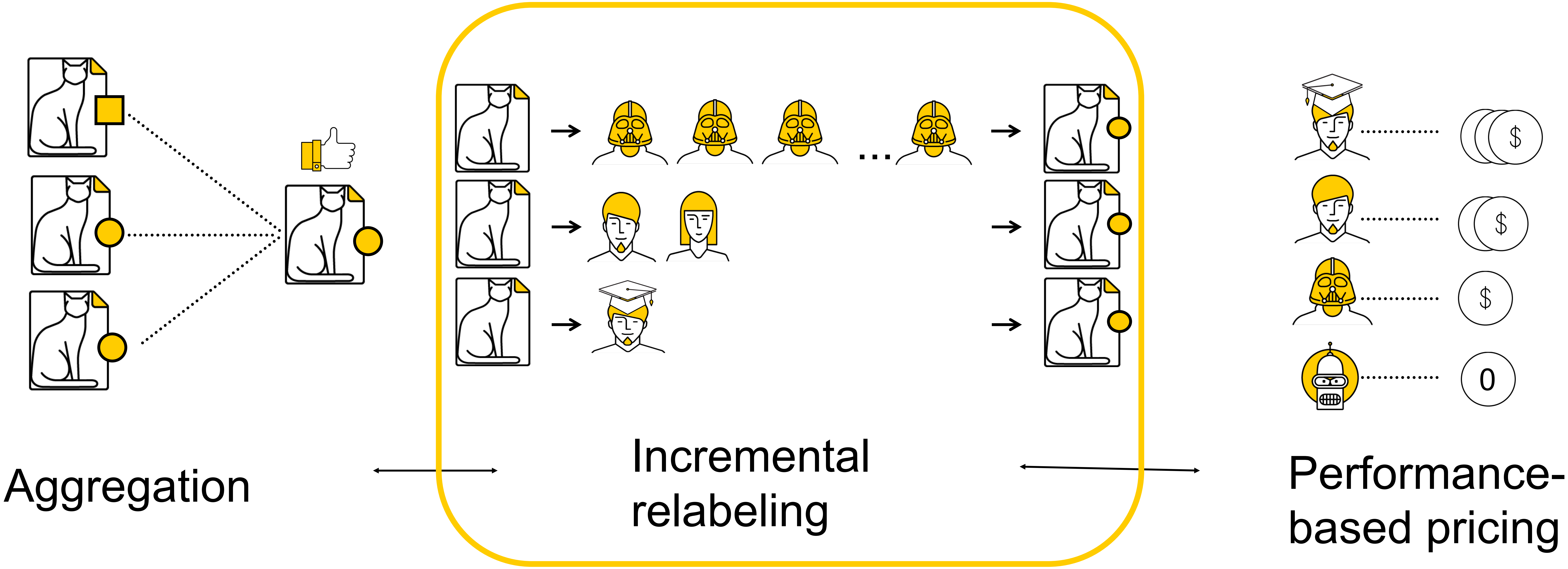
Li, J. (SIGIR '20), https://doi.org/10.1145/3397271.3401239

Crowd-Kit, a General-Purpose Toolkit

https://pypi.org/project/crowd-kit/

Crowd-Kit allows aggregating answers of many kinds,
including categorial, sequential, and graphical,
using the same API.

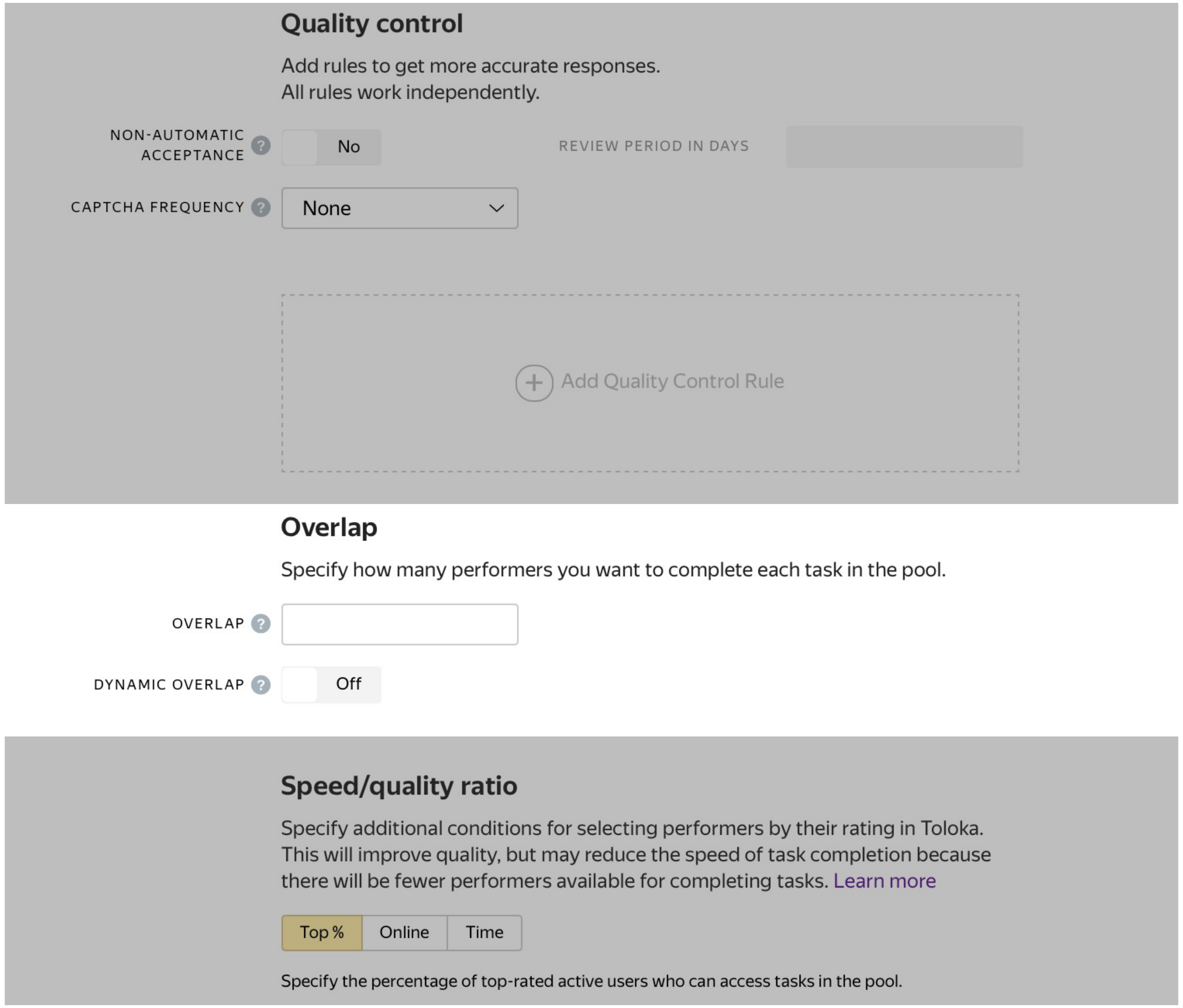
Key components of labeling with crowds



Incremental relabeling

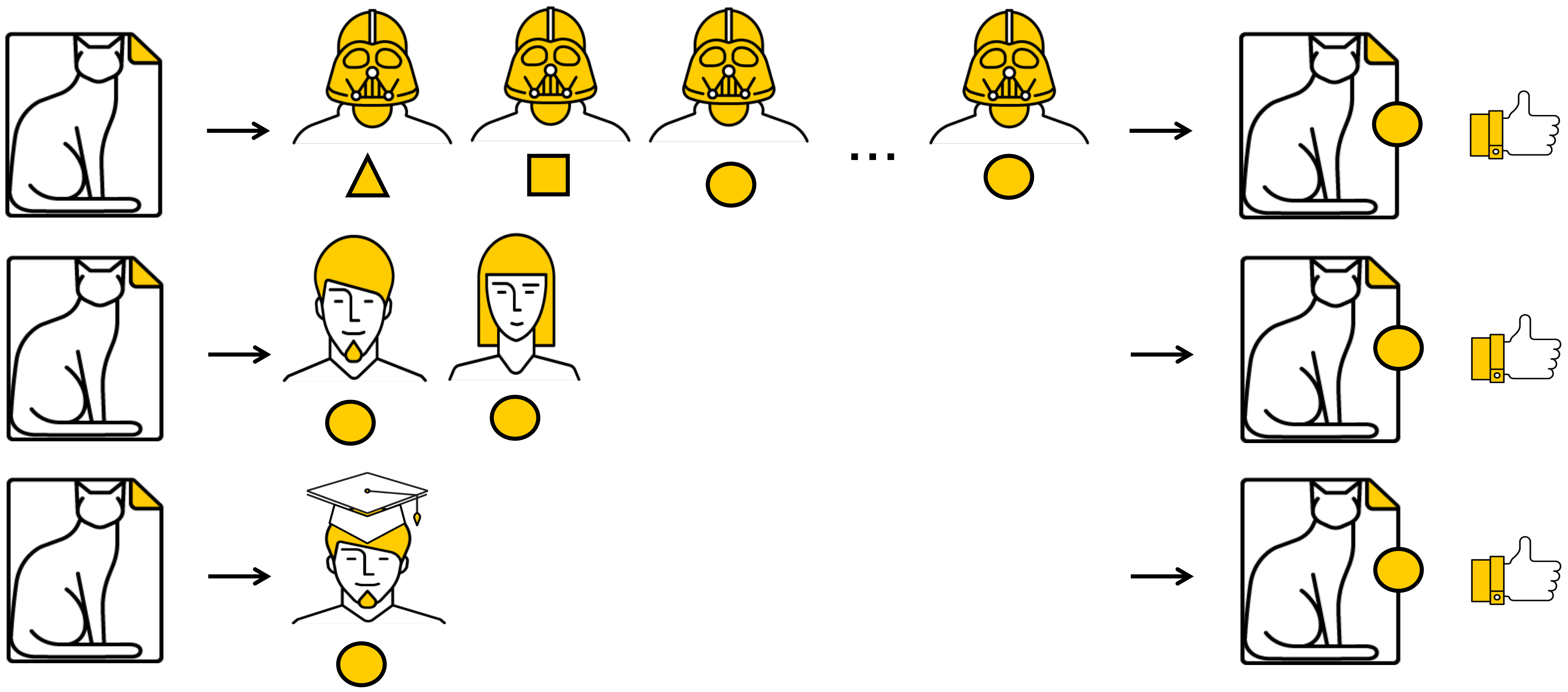
aka dynamic overlap

Pool settings: dynamic overlap



Incremental relabeling problem

Obtain aggregated labels of a desired level of quality using a fewer number of noisy labels



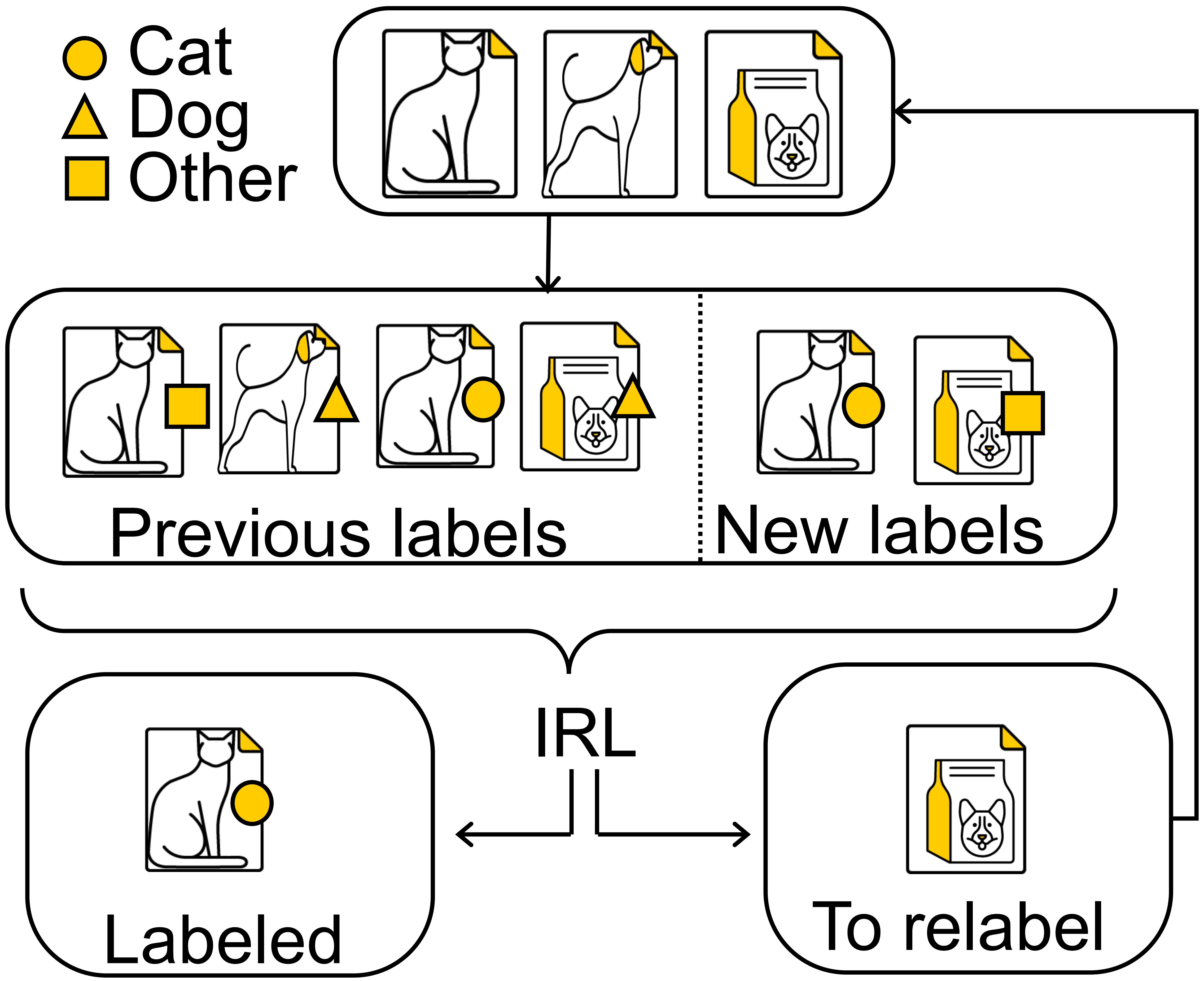
Incremental relabeling scheme (IRL)

Request a label for each object

In real time IRL algorithm receives:
(1) previously accumulated labels
(2) new labels

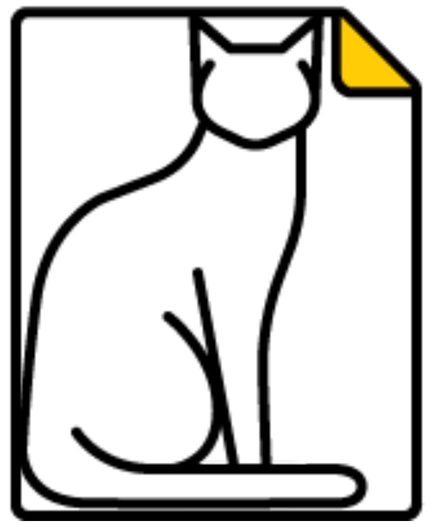
Decides:
(1) which objects are labeled
(2) which objects to relabel

Repeat until all tasks are labeled



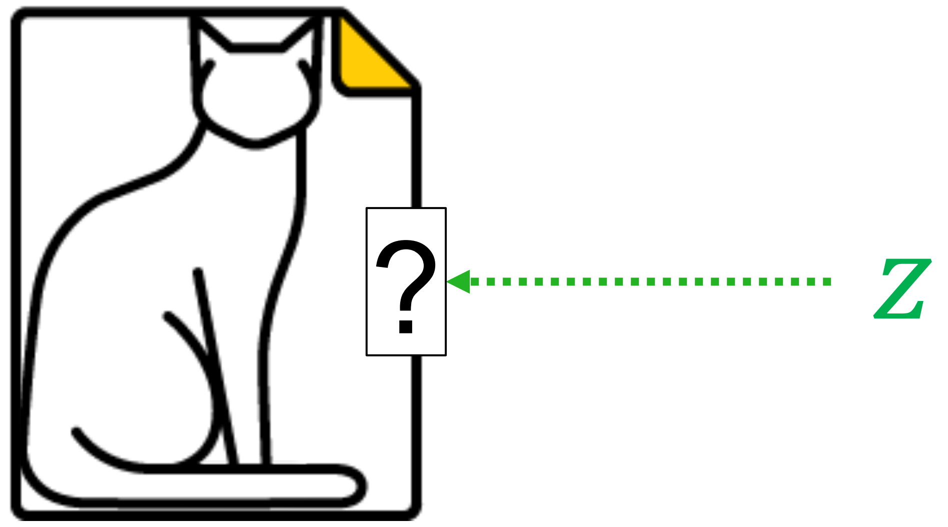
Notations

- Consider one object

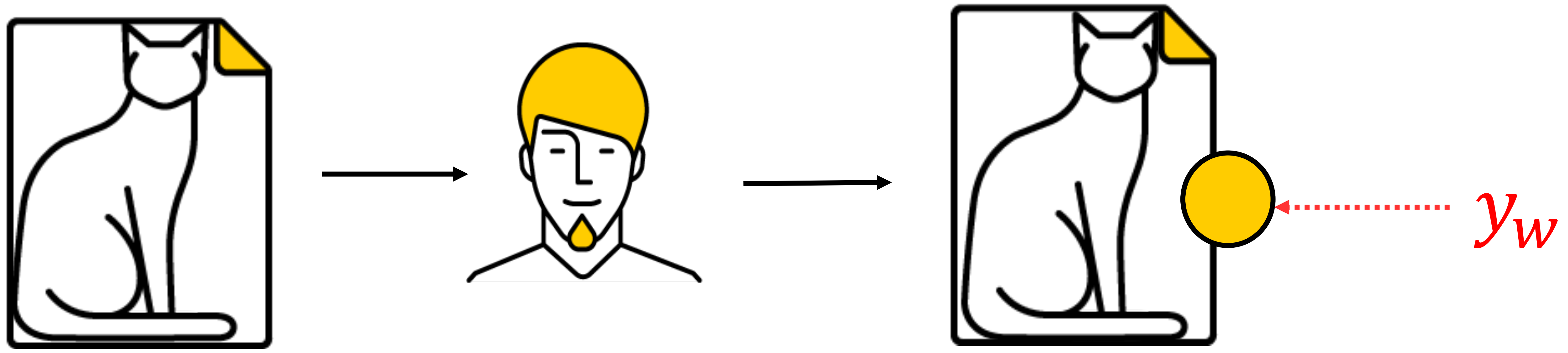


Classify images:
- Cat
- Dog
- Other

- $z \in \{1, \dots, K\}$ - latent true label



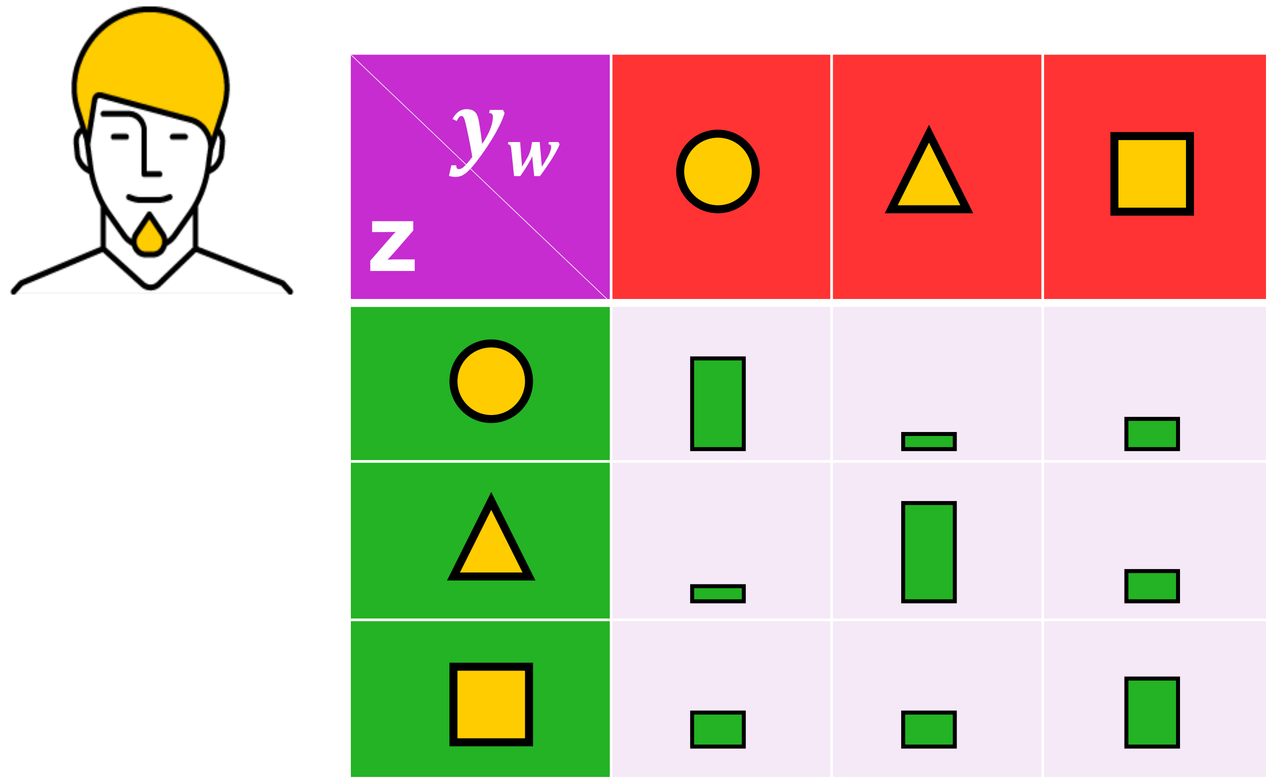
- $y_w \in \{1, \dots, K\}$ - observed noisy label from performer w:

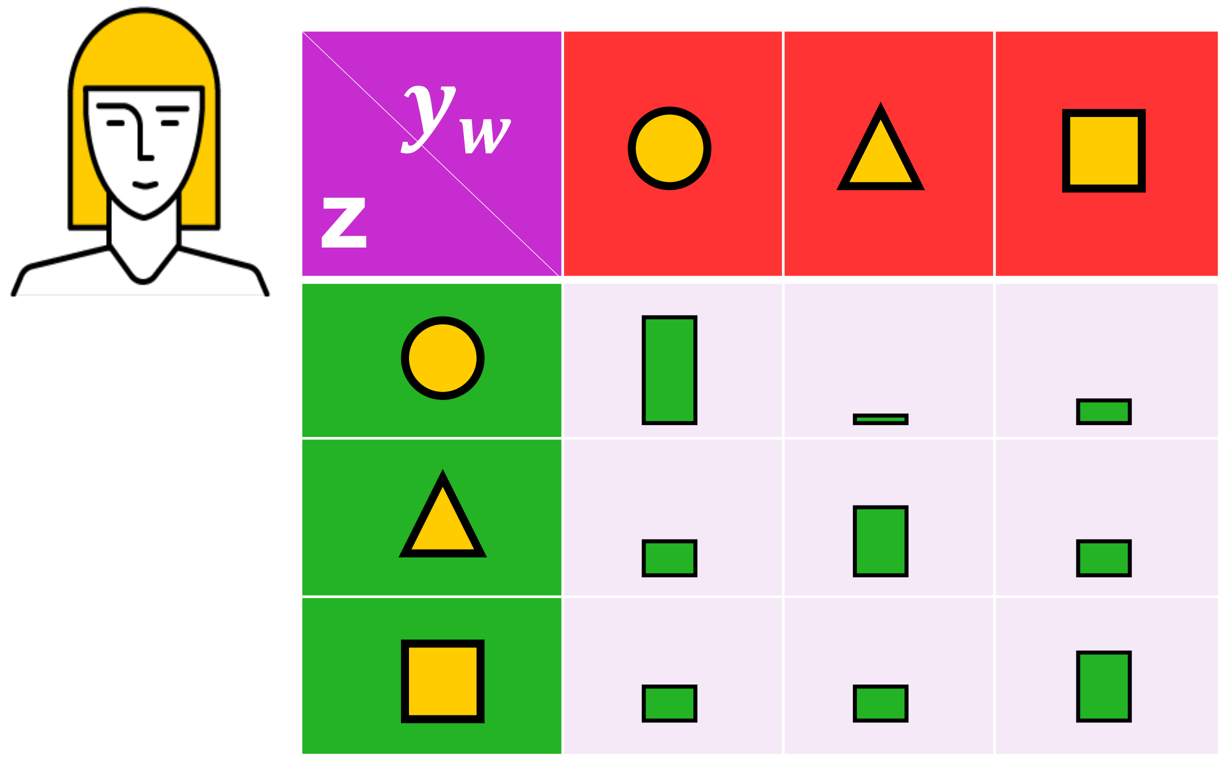


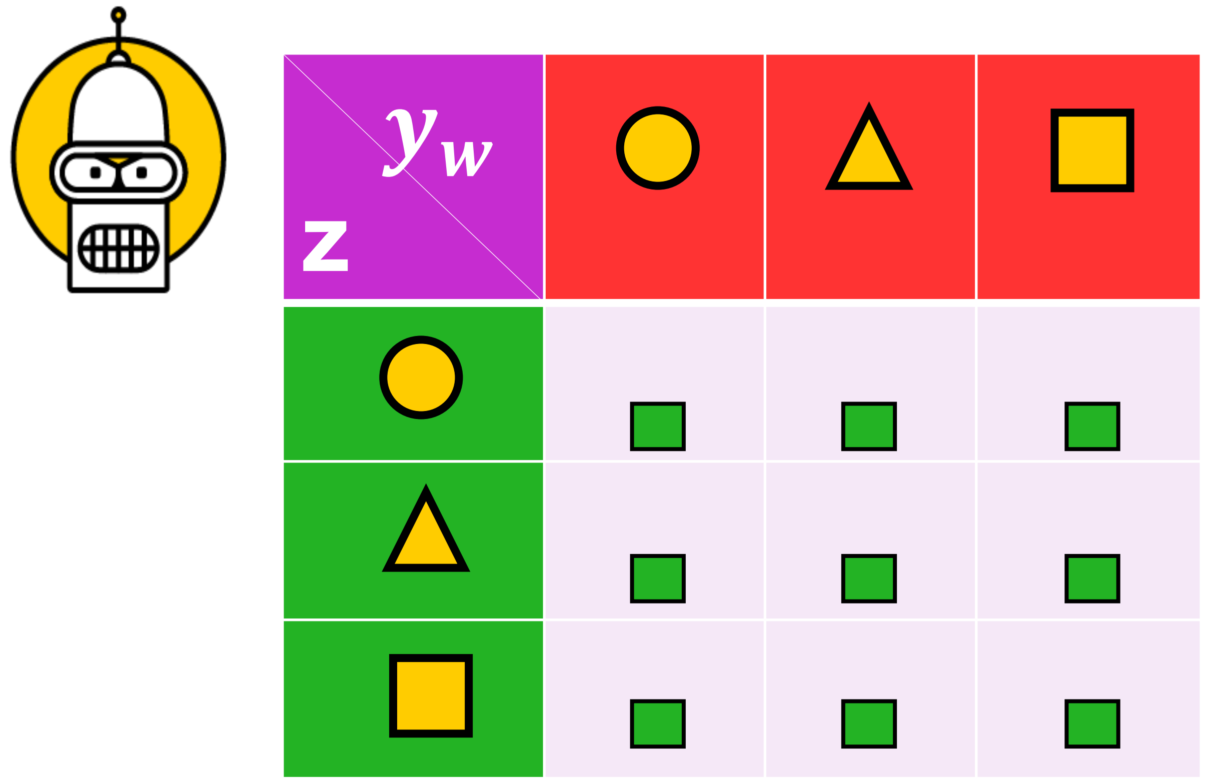
Notations

- Noisy label model for performer w:

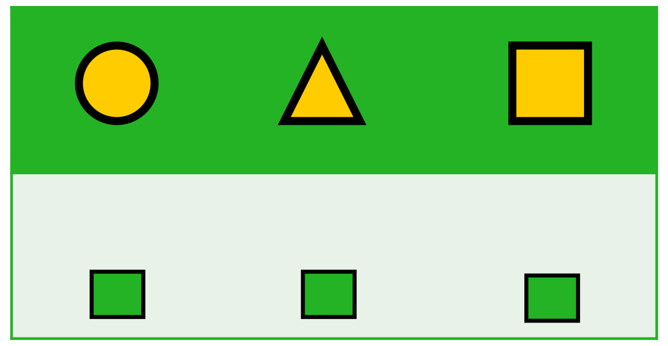
  $M_w \in [0,1]^{K \times K}: \Pr(Y_w = k | Z = c) = M_w[c, k]$







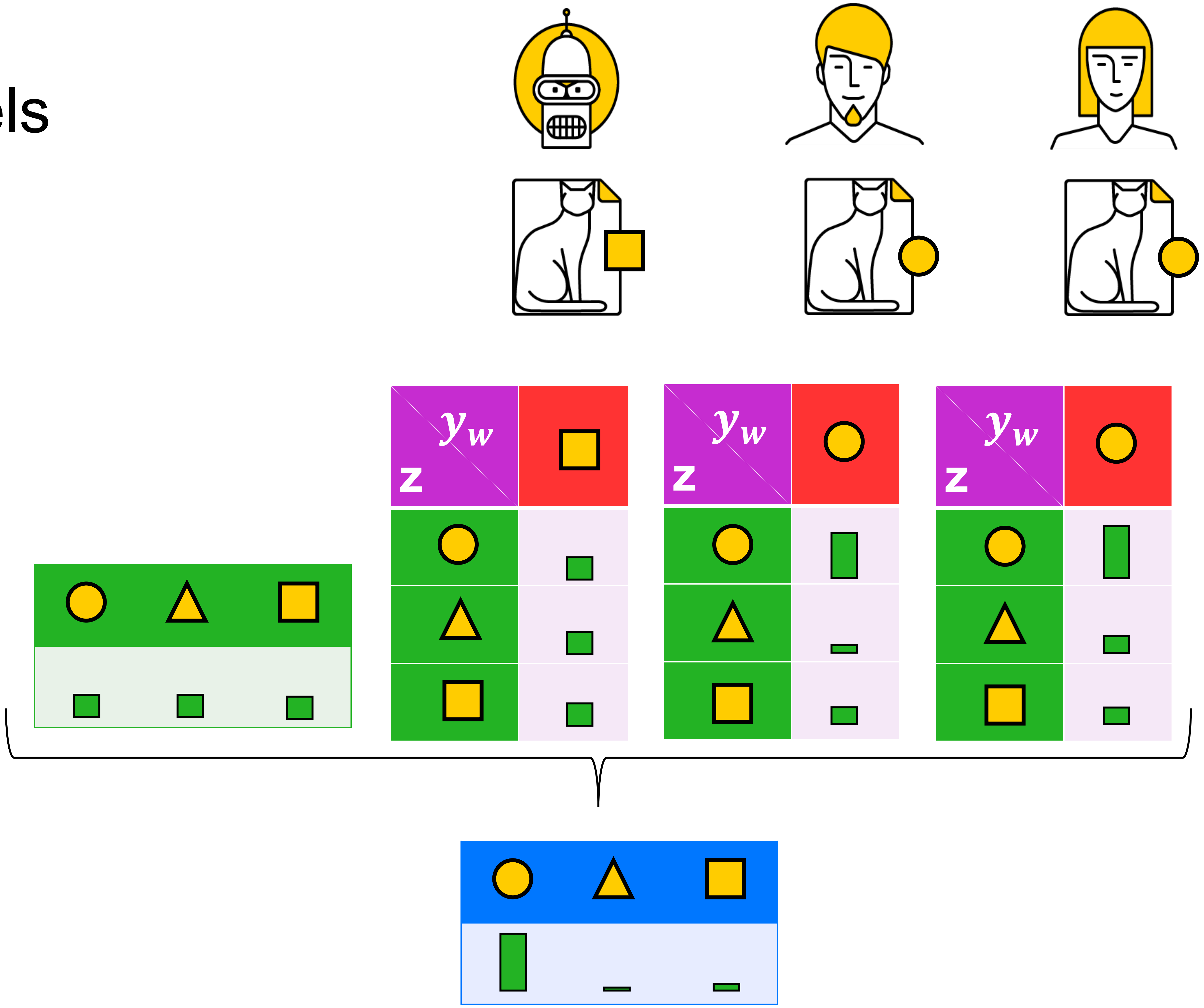
- Prior distribution: $\Pr(Z = k) = p_k$



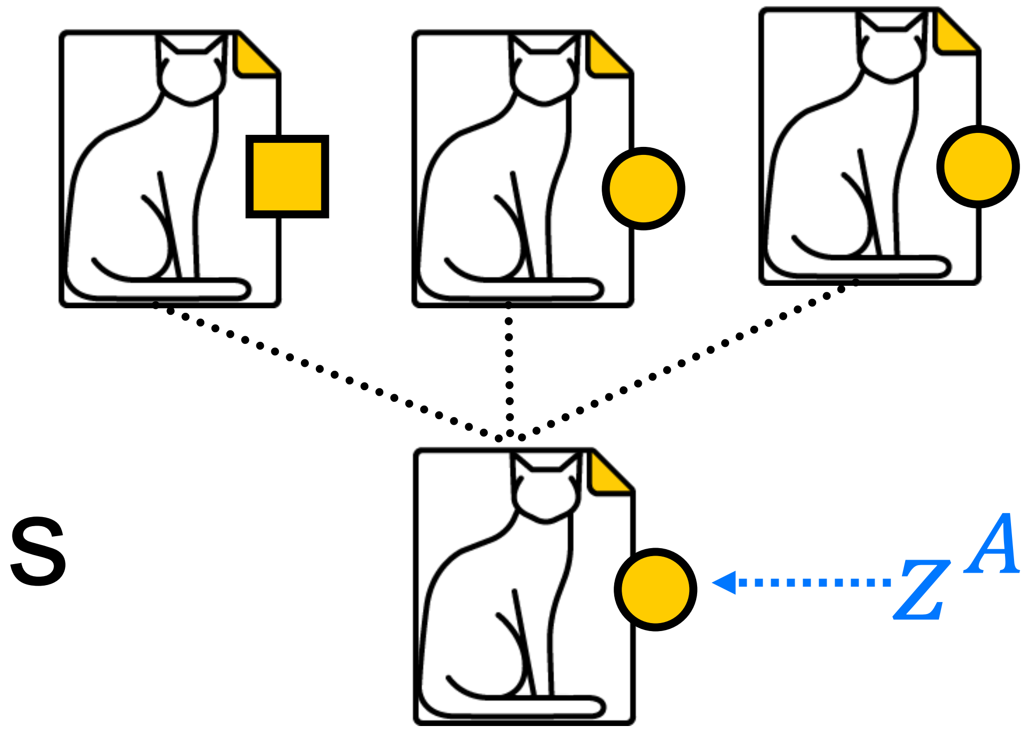
Posterior distribution

- $\{y_{w_1}, \ldots, y_{w_n}\}$ - accumulated noisy labels for the object
- Using Bayes rule:

$$\Pr\left(Z = k \middle| \{y_{w_1}, \ldots, y_{w_n}\}\right) = \frac{\Pr(Z = k)\Pr\left(\{y_{w_1}, \ldots, y_{w_n}\} | Z = k\right)}{\Pr\left(\{y_{w_1}, \ldots, y_{w_n}\}\right)} = \frac{p_k \prod_{i=1}^{n} M_{w_i}\left[k, y_{w_i}\right]}{\sum_{t=1}^{K} p_t \prod_{i=1}^{n} M_{w_i}\left[t, y_{w_i}\right]}$$



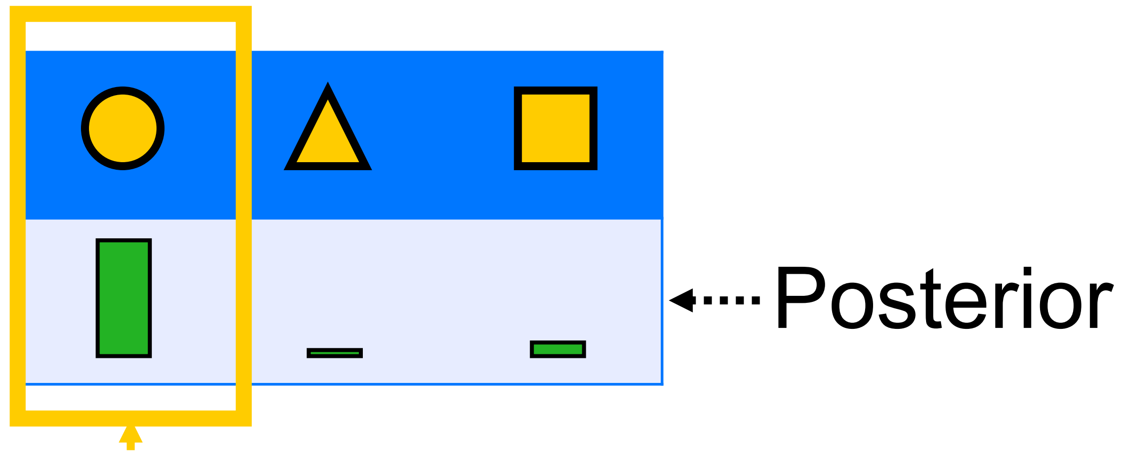
Expected accuracy of aggregated labels



- Let A be an aggregation model, e.g. MV, DS, GLAD,…
- Denote aggregated label $z^A = A(\{y_{w_1}, \dots, y_{w_n}\})$
- Expected accuracy of aggregated labels given noisy labels is

$$E\left(\delta(z = z^A) \middle| \{y_{w_1}, \dots, y_{w_n}\}\right) = \Pr\left(z = z^A \middle| \{y_{w_1}, \dots, y_{w_n}\}\right)$$

- Stop labeling if $E\left(\delta(z = z^A) \middle| \{y_{w_1}, \dots, y_{w_n}\}\right) \geq C$

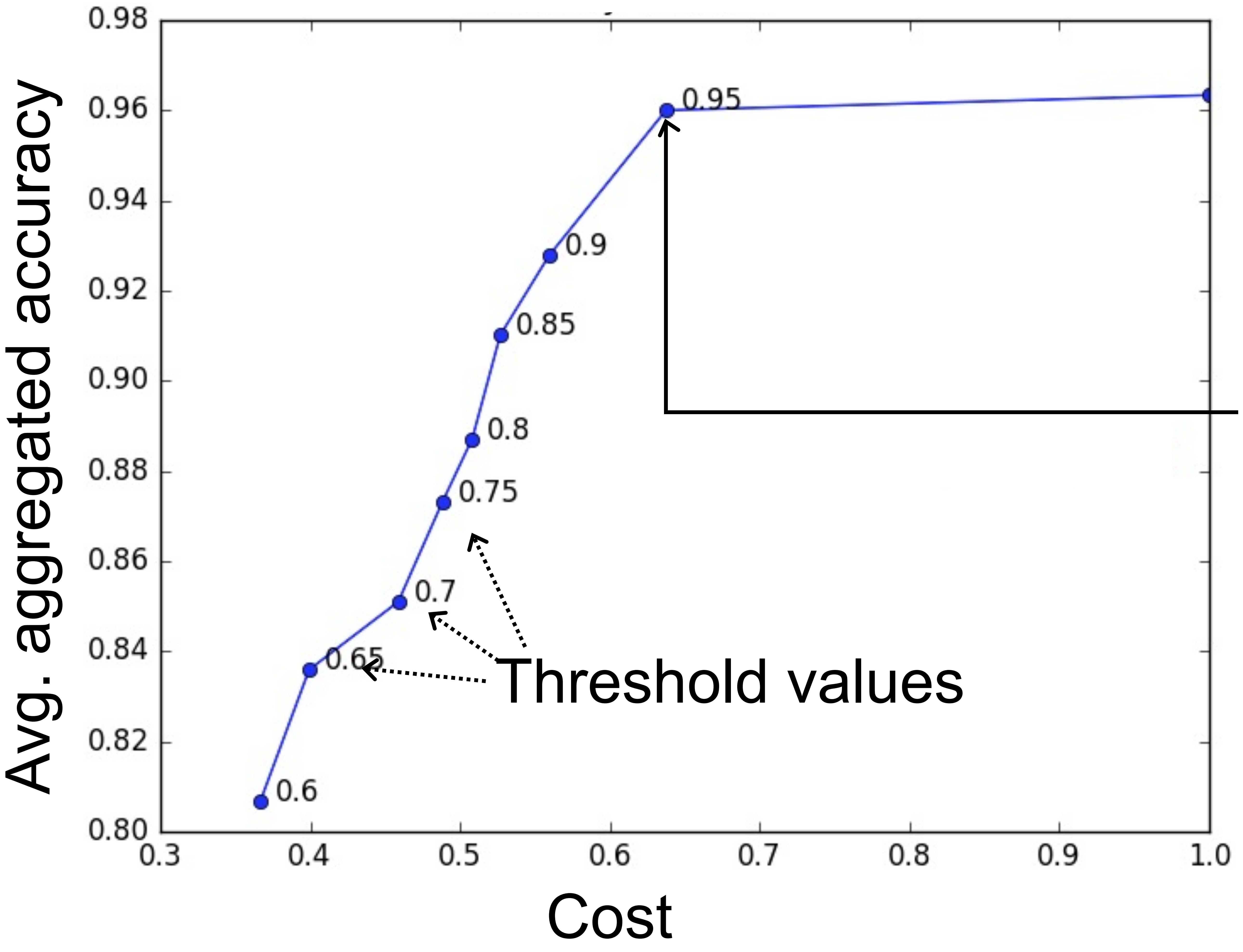


parameter

Expected accuracy of z^A

Sheng VS, Provost F, Ipeirotis PG. Get another label? improving data quality and data mining using multiple, noisy labelers. KDD 2008

Threshold in IRL: cost – accuracy trade-off

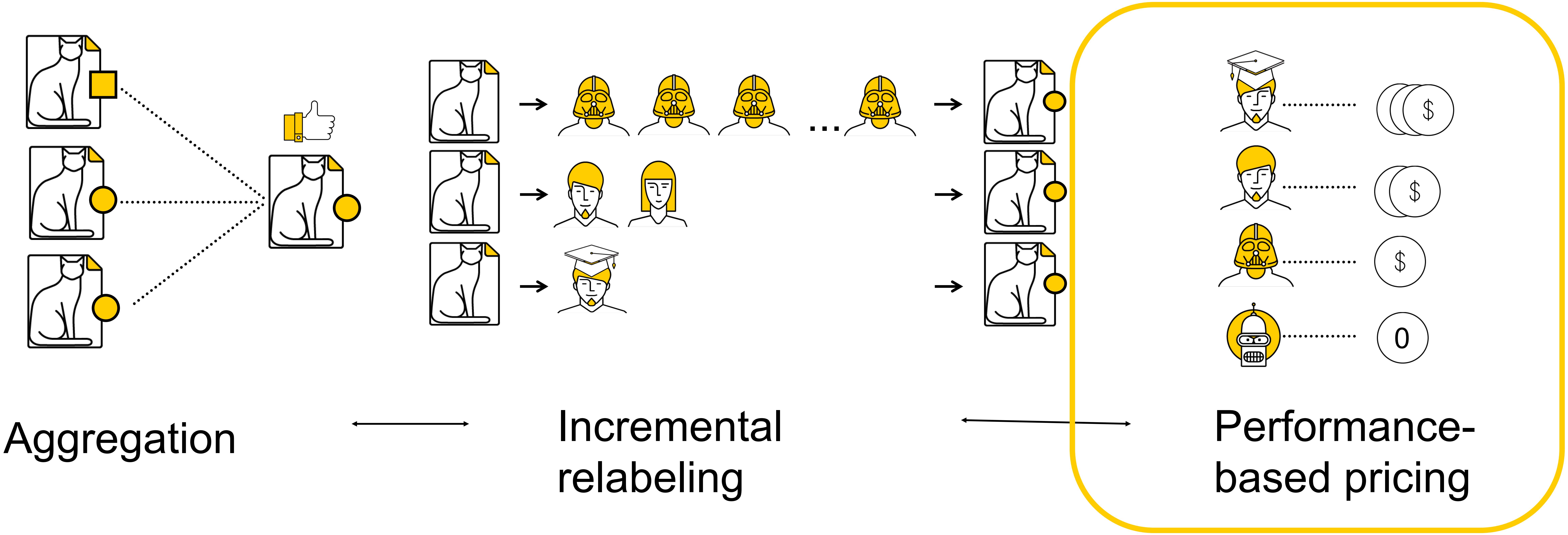


A higher c does not increase accuracy

Optimal threshold $c = 0.95$

Saving ≈ 35% of noisy labels

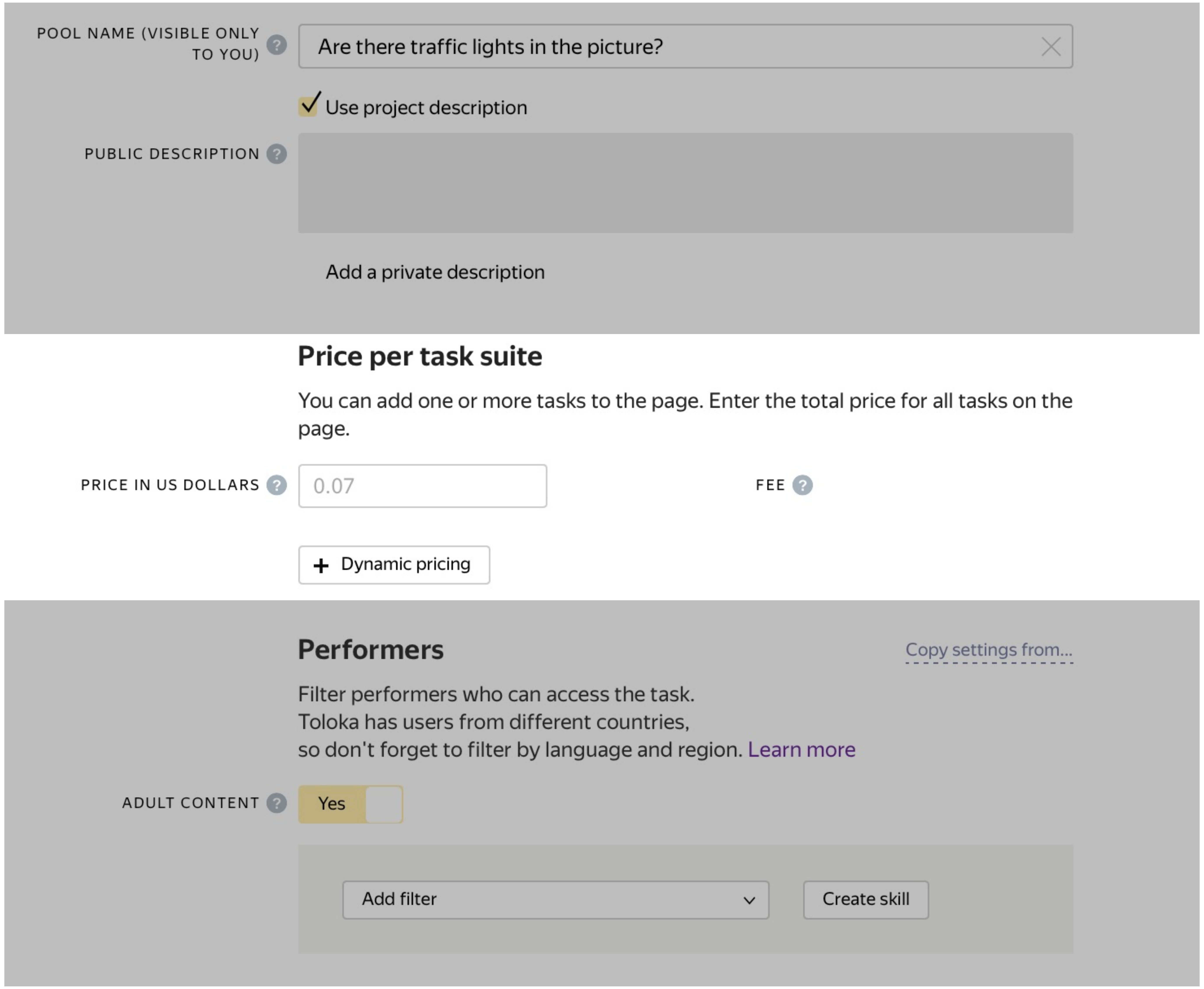
Key components of labeling with crowds



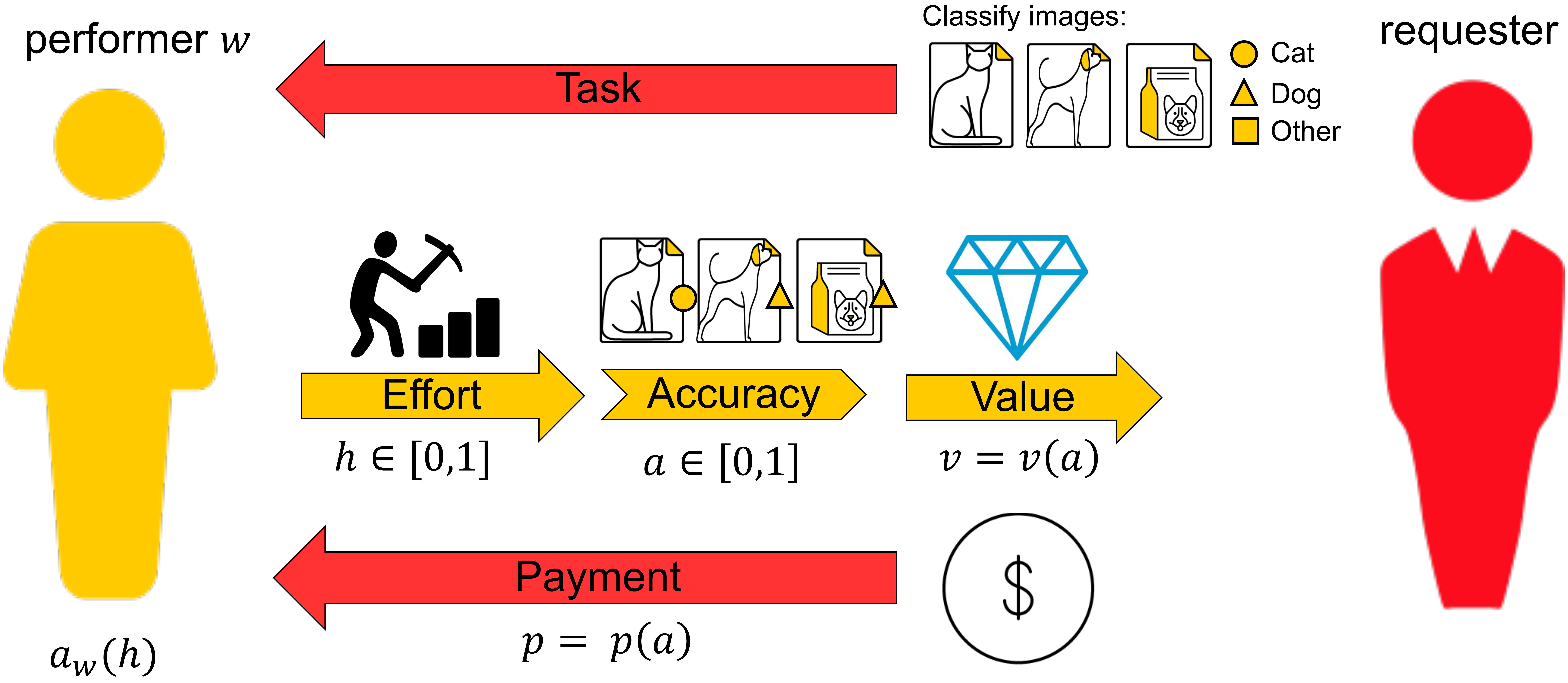
Performance-based pricing

aka dynamic pricing

Pool settings: dynamic pricing

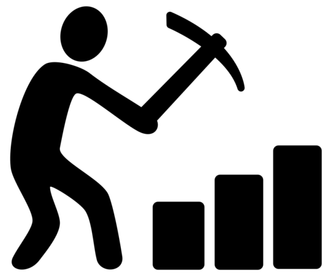


Labeling as a game: notation



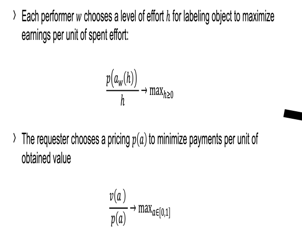
Labeling as a game: formalization

- Each performer w chooses a level of effort h for labeling object to maximize earnings per unit of spent effort:



$$\frac{p\big(a_w(h)\big)}{h} \rightarrow \max_{h \geq 0}$$

- The requester chooses a pricing $p(a)$ to minimize payments per unit of obtained value



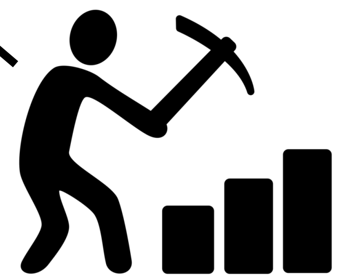
$$\frac{v(a\ )}{p(a)} \rightarrow \max_{a \in [0,1]}$$

Labeling as a game: incentive compatible pricing

- Assume $a_w(h)$ is a linear function of h:

$$a_w(h) = c_1 h + c_0$$

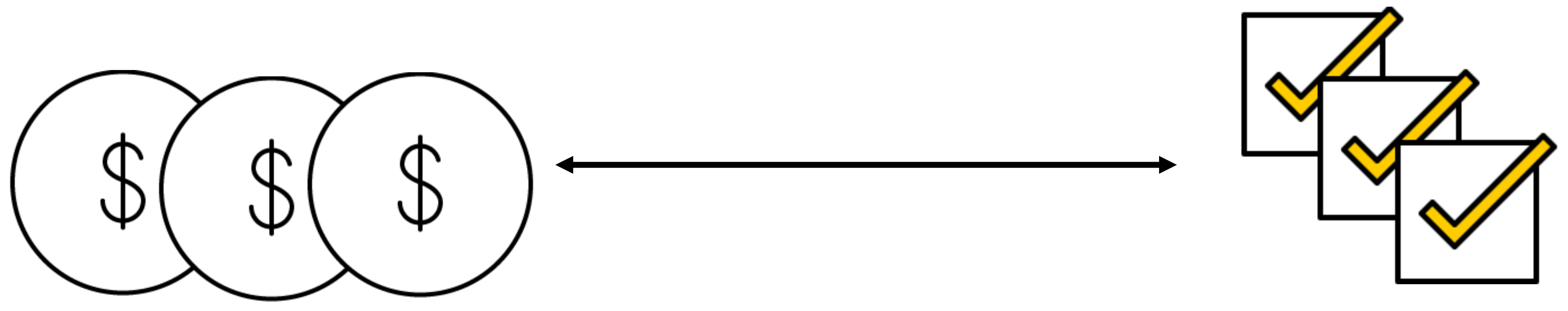
Accuracy



The requester and performers maximize their utility simultaneously if the pricing $p(a)$ for each label is proportional to its accuracy a.

Performance-based pricing in practice: settings

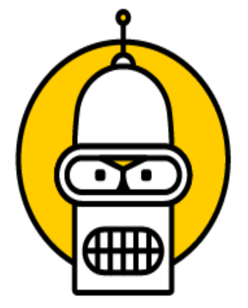
- Price p for the level of accuracy a_0 : $\Pr(\hat{z} = z) \geq a_0$ E.g.:



p = 0.3$ a_0 = 0.99

- $\hat{q}_w = \Pr(y^w = z)$ - estimated quality level of performer w,

  e.g. the fraction of correct labels for golden set (GS):



5 correct GS among 10 $\hat{q}_w = 0.5$

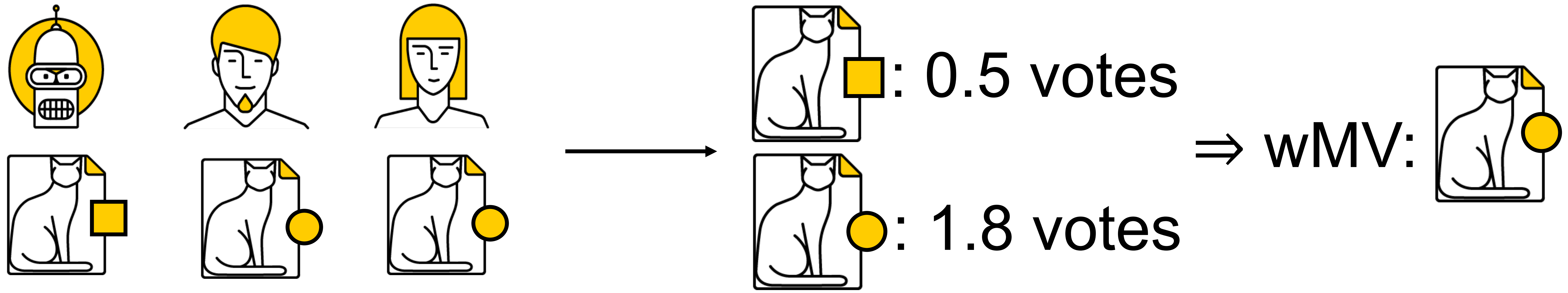
16 correct GS among 20 $\hat{q}_w = 0.8$

100 correct GS among 100 $\hat{q}_w = 1$

Wang, Ipeirotis, and Provost, Quality-Based Pricing for Crowdsourced Workers, 2013

Performance-based pricing in practice: settings

- Aggregation $\hat{z}_j^{\mathrm{wMV}} = \arg\max_{y=1,\dots,K} \sum_{w \in W_j} \hat{q}_w \delta(y = y_j^w)$



- IRL algorithm is based on the expected accuracy of $\hat{z}_j^{\mathrm{wMV}}$

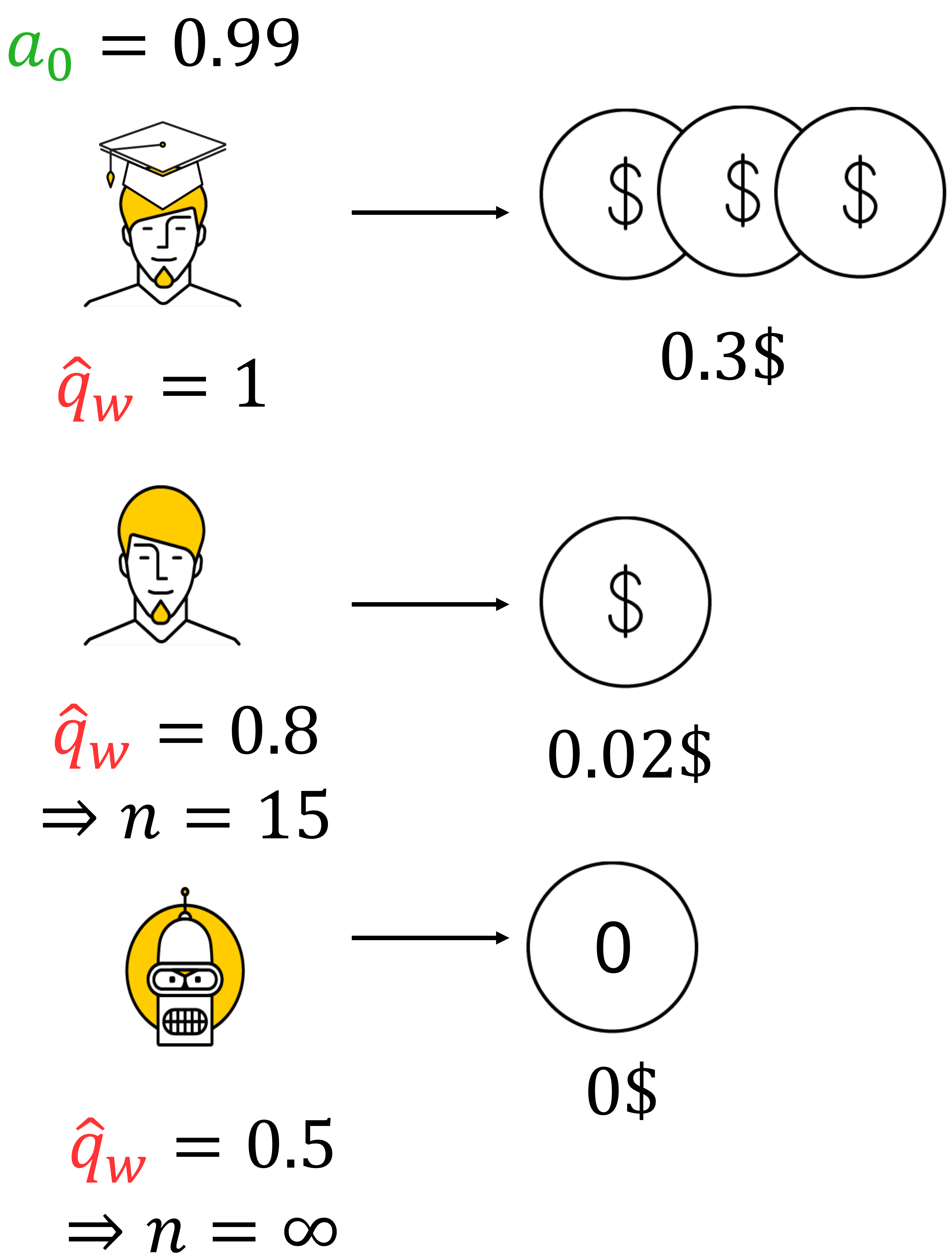
Performance-based pricing in practice

Pricing rules

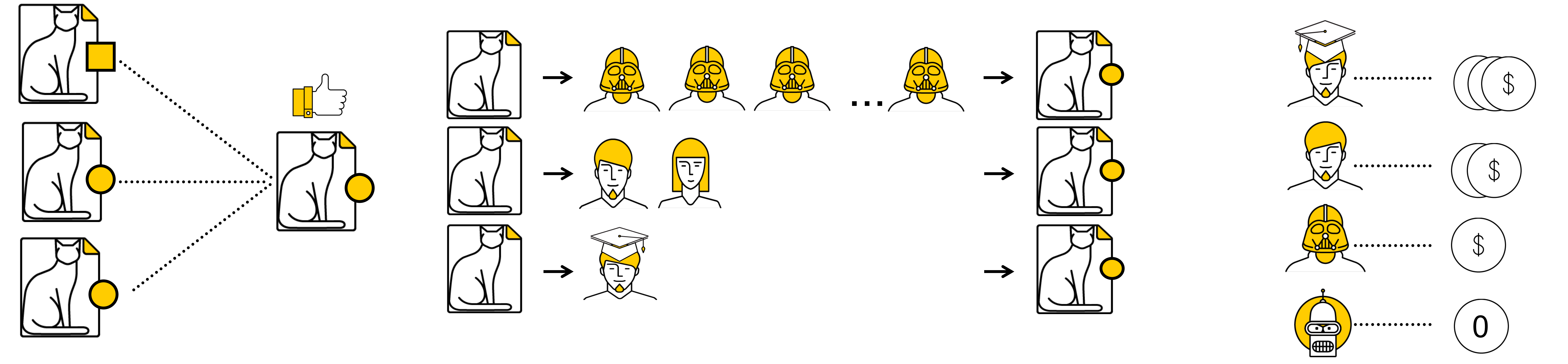
1. If $\hat{q}_w \geq a_0$, then the price is p
2. Else find n:

$$\underbrace{\sum_{k=0}^{n/2}\binom{n}{k}\hat{q}_w^{\,n-k}(1-\hat{q}_w)^k}_{\text{Expected accuracy for MV}} \geq a_0$$

The price is p/n



Key components of labeling with crowds



Aggregation

Incremental relabeling

Performance-based pricing

Tutorial Schedule

Introduction: 15 min

Part I: 30 min
Key Components for Data Collection

Part II: 60 min
Practice Session I

Lunch Break: 45 min

Part III: 45 min
Advanced Techniques

Part IV: 30 min
Practice Session II

Part V: 15 min
Conclusion

Yandex

Thank you!
Questions?

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https://research.yandex.com/tutorials/crowd/naacl-2021