Part IV

Setting up and running label collection projects

Olga Megorskaya,
CEO

What you need for the practice session

We are starting the practice session

We give you a card with information and links to:

- A step-by-step instruction to configure and run our crowd projects
- A video version of this instruction
- A dataset of photos that should be labeled
- Login+Password to sign in Toloka as a requester

We also provide several copies of a printed version of the instruction

Did everybody receive this card?

Requester account that you received

You have Login+Password to sign in Toloka as a requester

The same account is given for several participants (a group)

- So, you can divide work on the project configuration within this group
- Or, each member of a group may work individually and create the whole pipeline by her/himself

Sign into Toloka as a requester

1. Go to https://toloka.ai

2. Click on “Sign in” in the top-right corner

3. Use received Login+Password to sign in

Requester account that you received

You have Login+Password to sign in Toloka as a requester

The account of this requester has money

► So, you will run your tasks on real crowd performers!

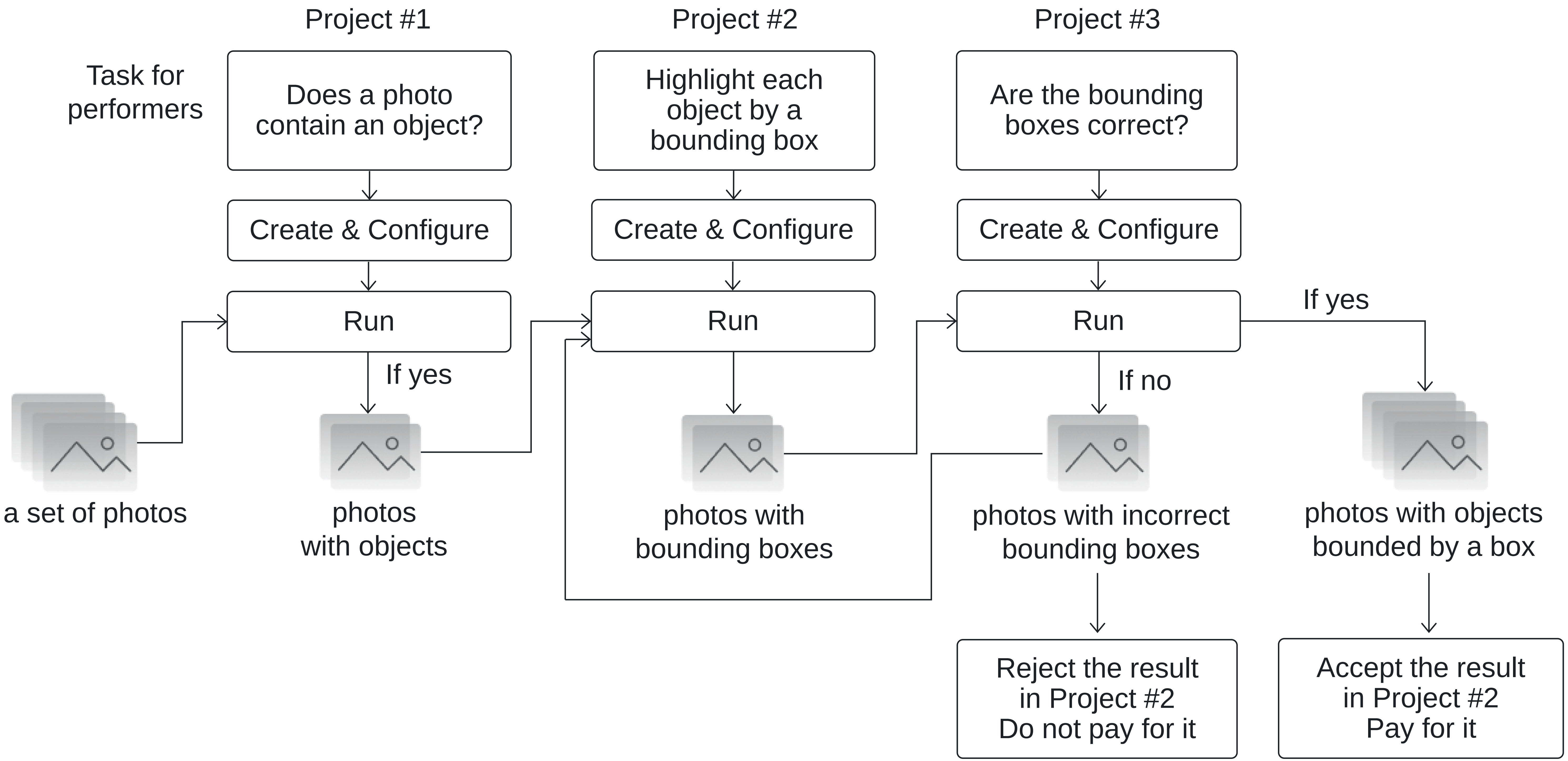
Practice: creating a real crowdsourcing pipeline

Now we will create a real simplified crowdsourcing pipeline

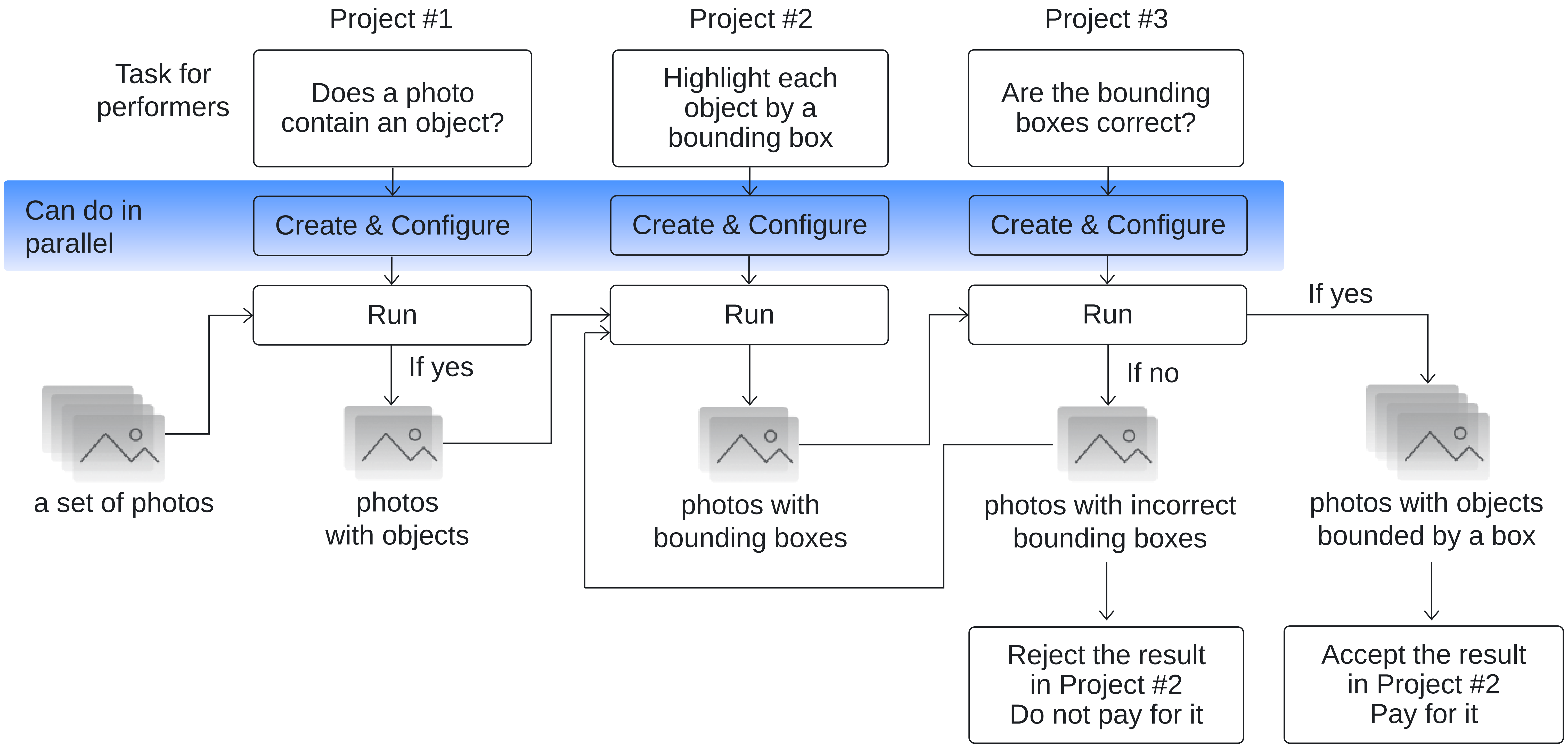
To simplify the task, we ask you to:

- Highlight **one type** of objects
- Choose any type of object you want to highlight. For example, **Traffic signs**
- Use **Bounding Boxes**

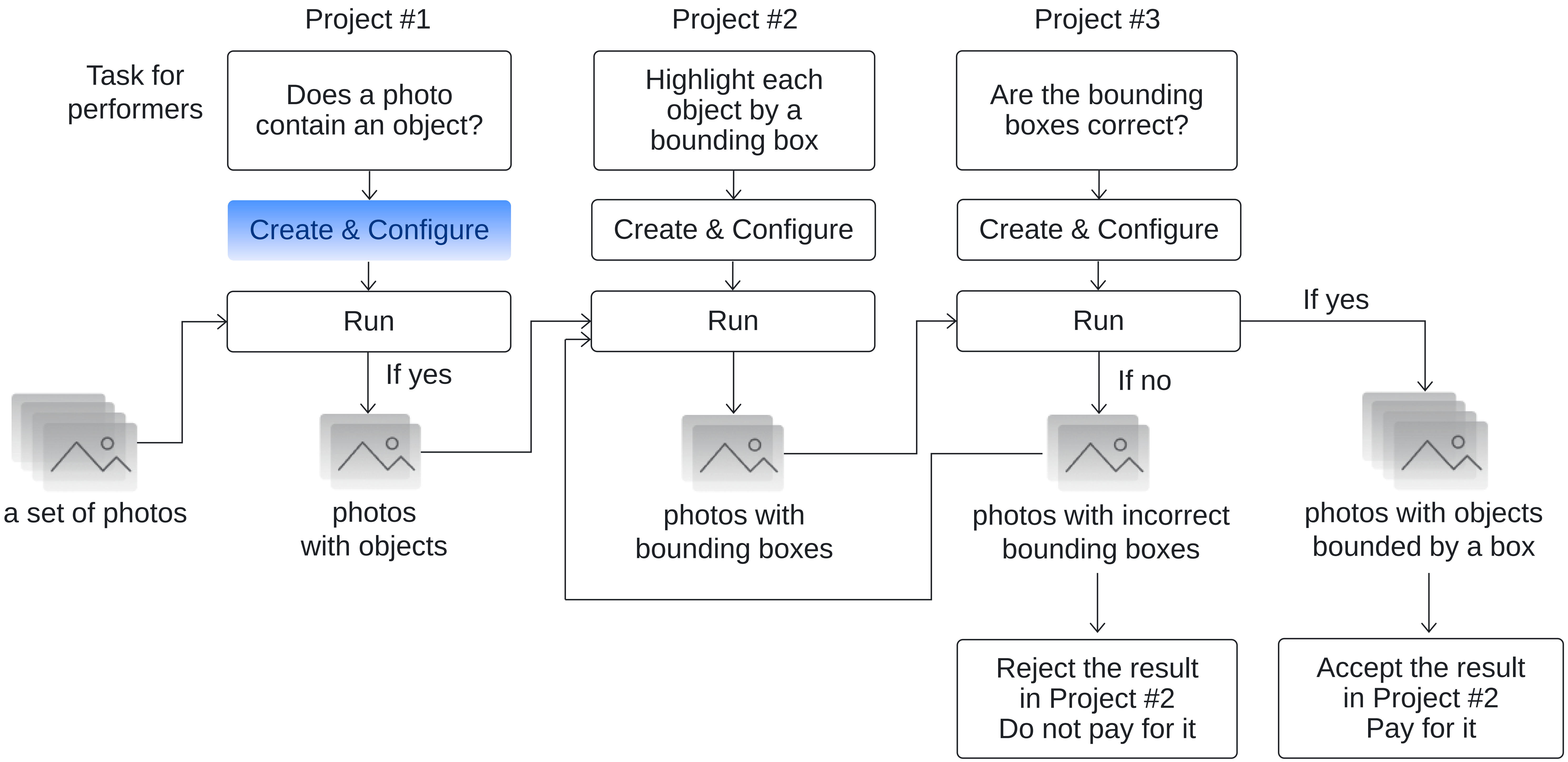
Reminder: we implement and run our pipeline



You can divide work within a participant group

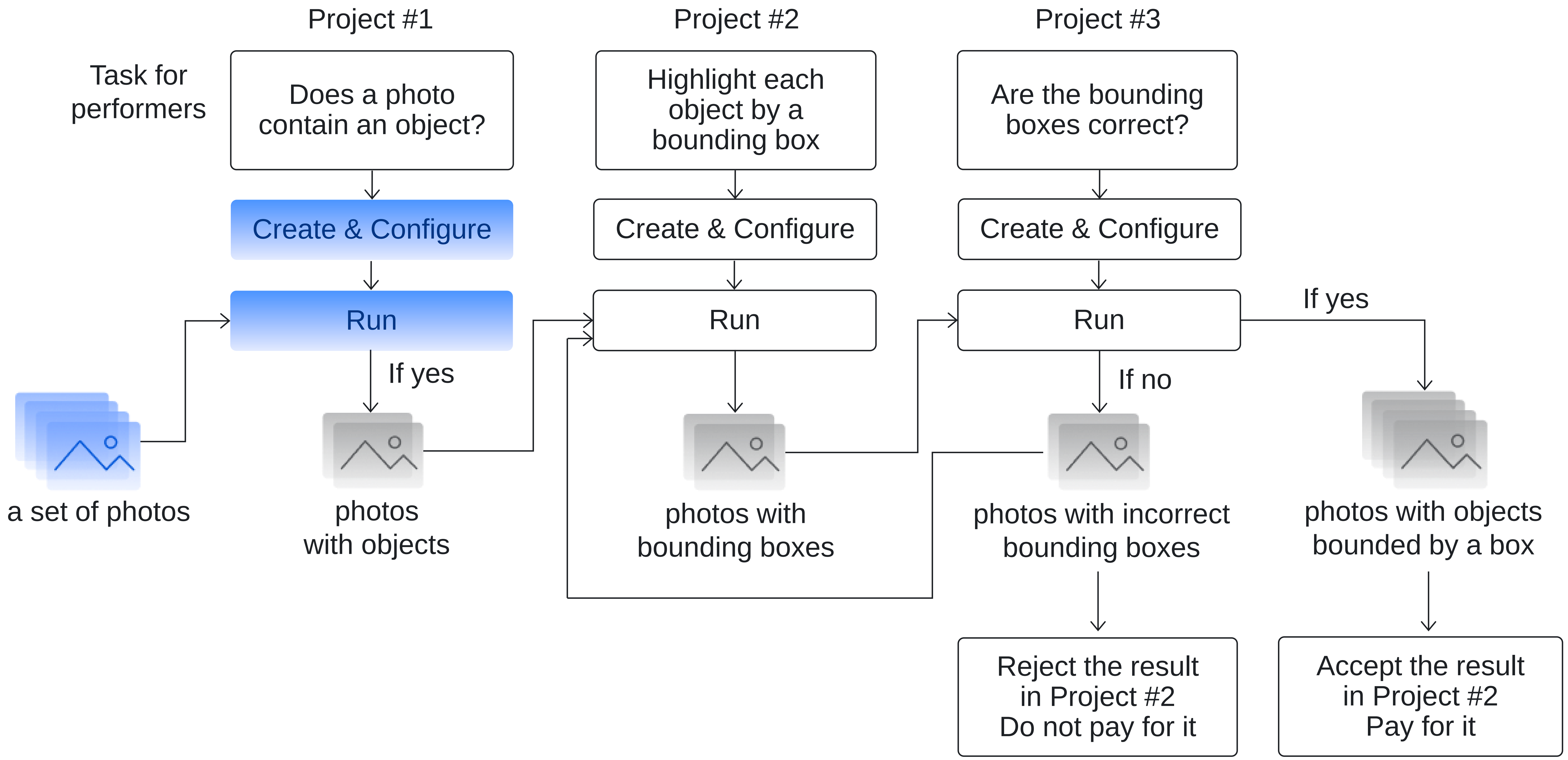


Step #1



Project #1
Project #2
Project #3
Task for performers
Does a photo contain an object?
Highlight each object by a bounding box
Are the bounding boxes correct?
Create & Configure
Create & Configure
Create & Configure
Run
Run
Run
If yes
If no
If yes
a set of photos
photos with objects
photos with bounding boxes
photos with incorrect bounding boxes
photos with objects bounded by a box
Reject the result in Project #2 Do not pay for it
Accept the result in Project #2 Pay for it

Step #2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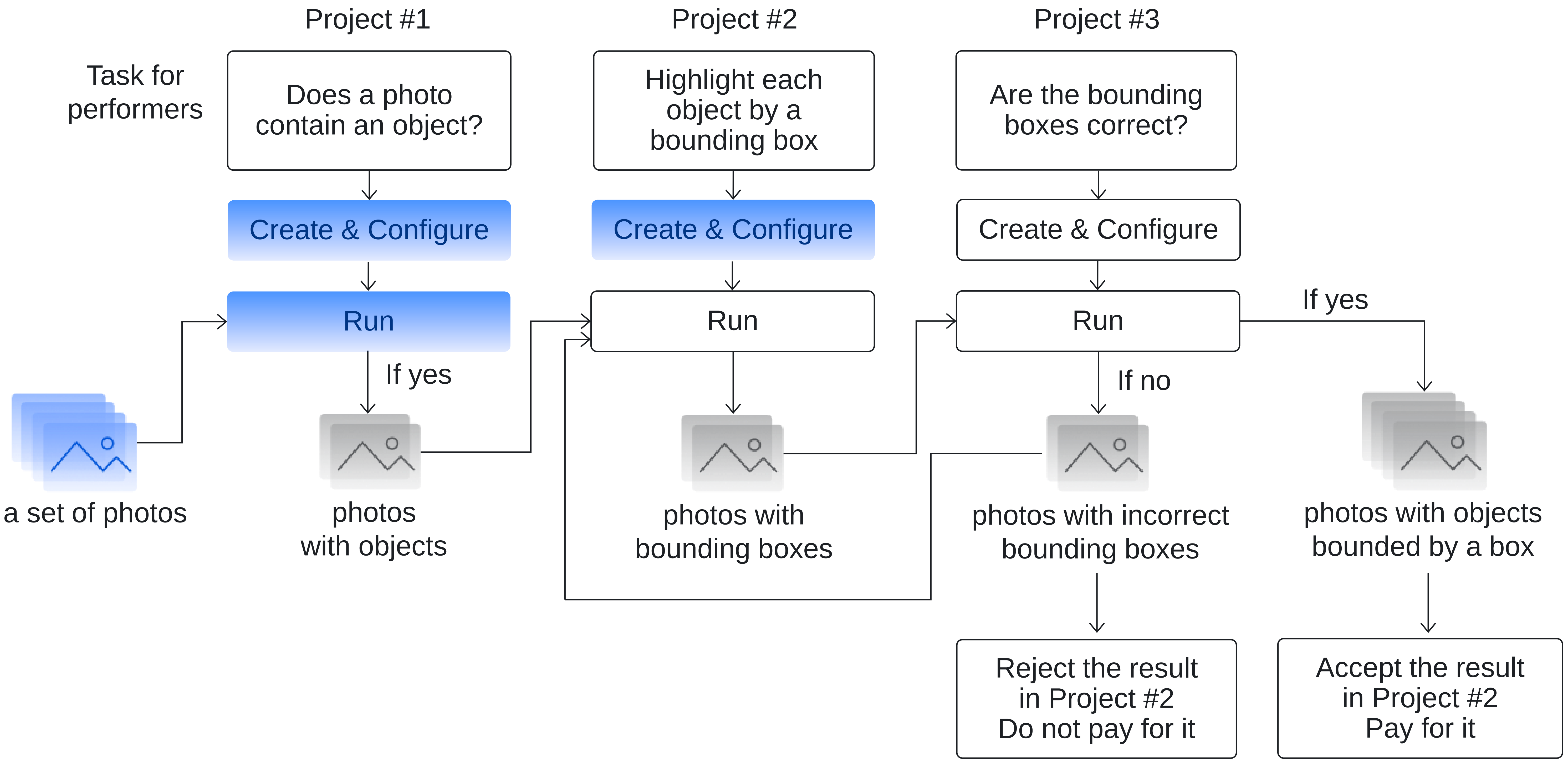
Step #3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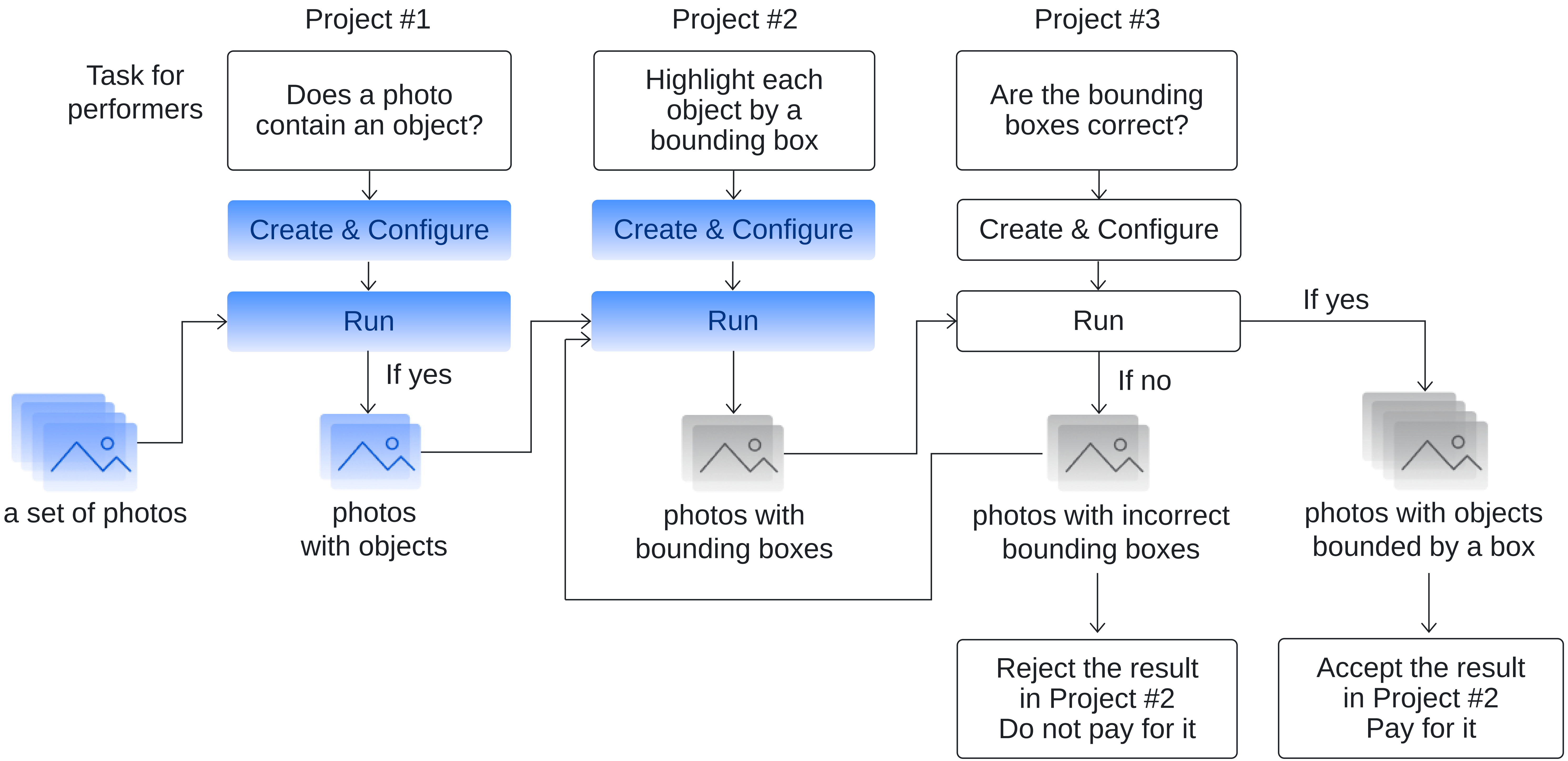
Step #4



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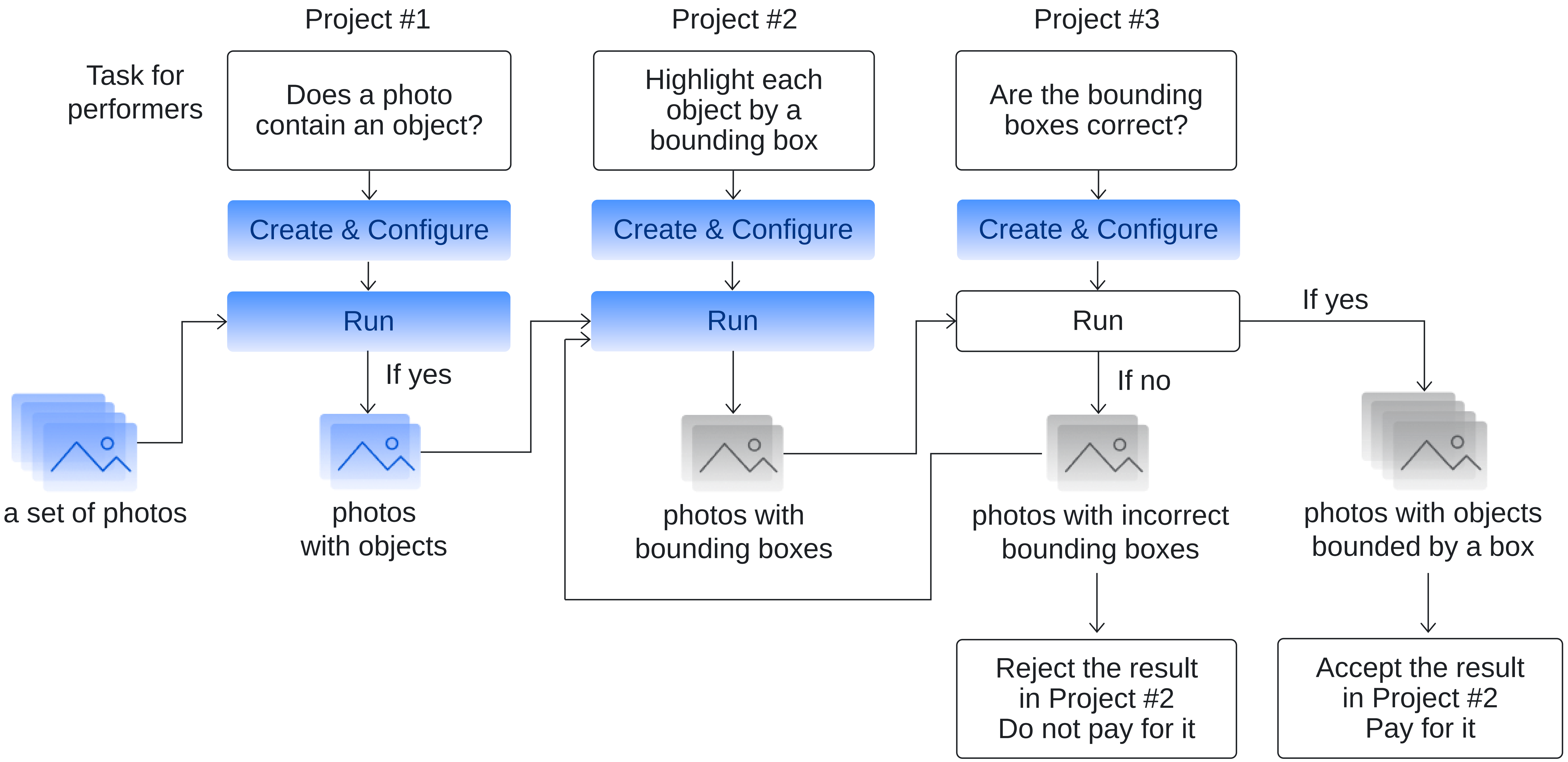
Step #5



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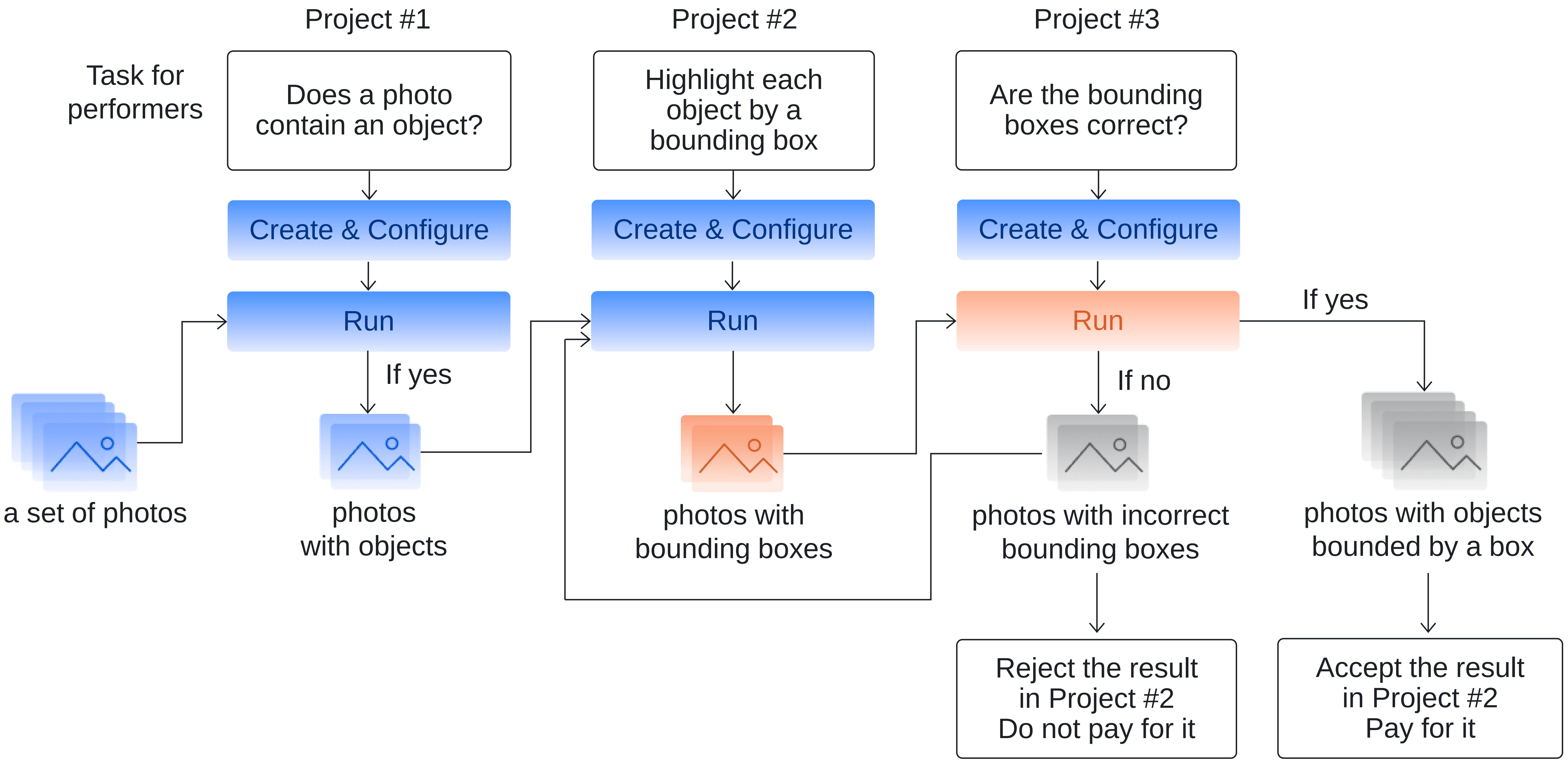
Step #6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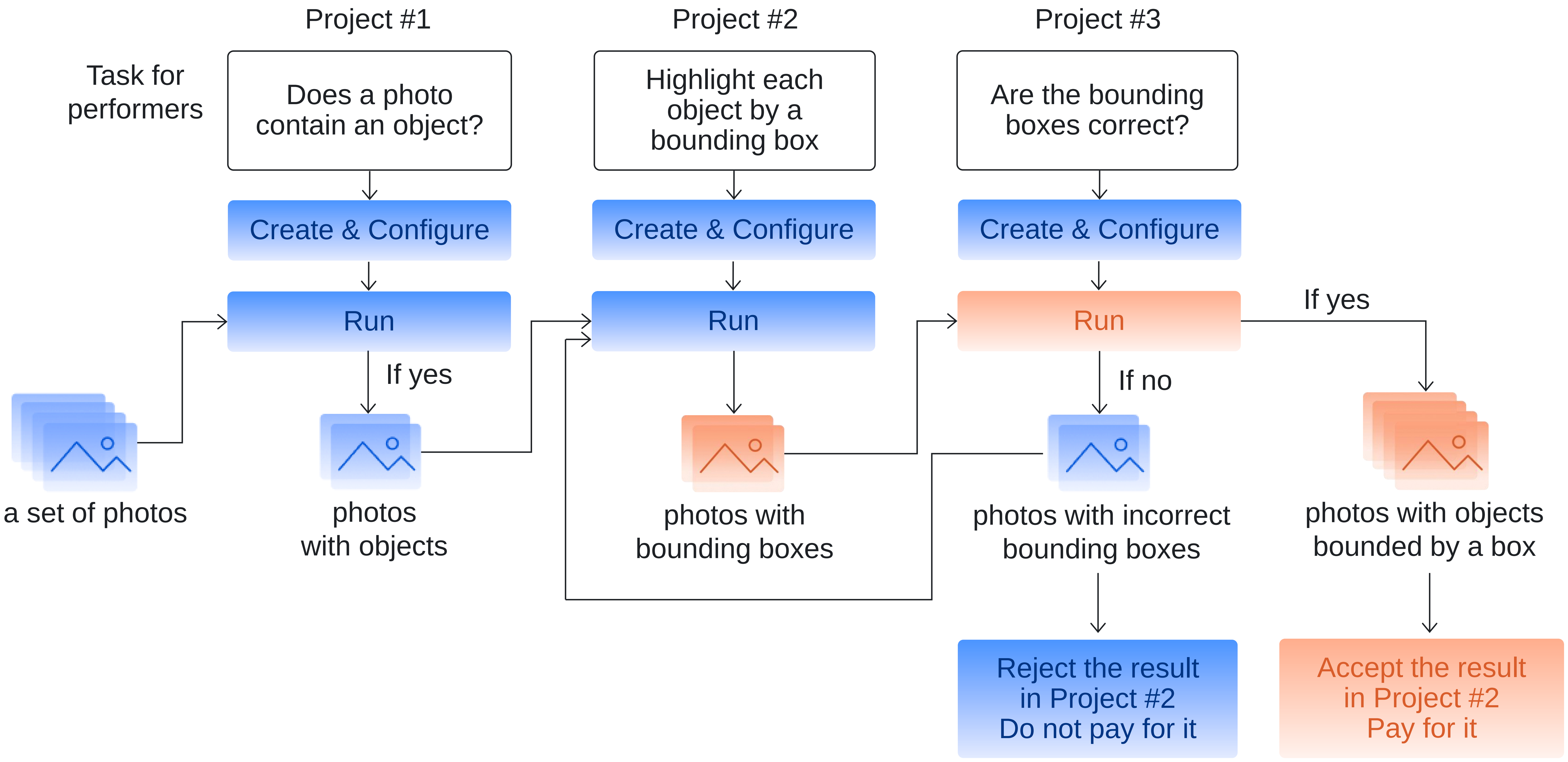
Step #7



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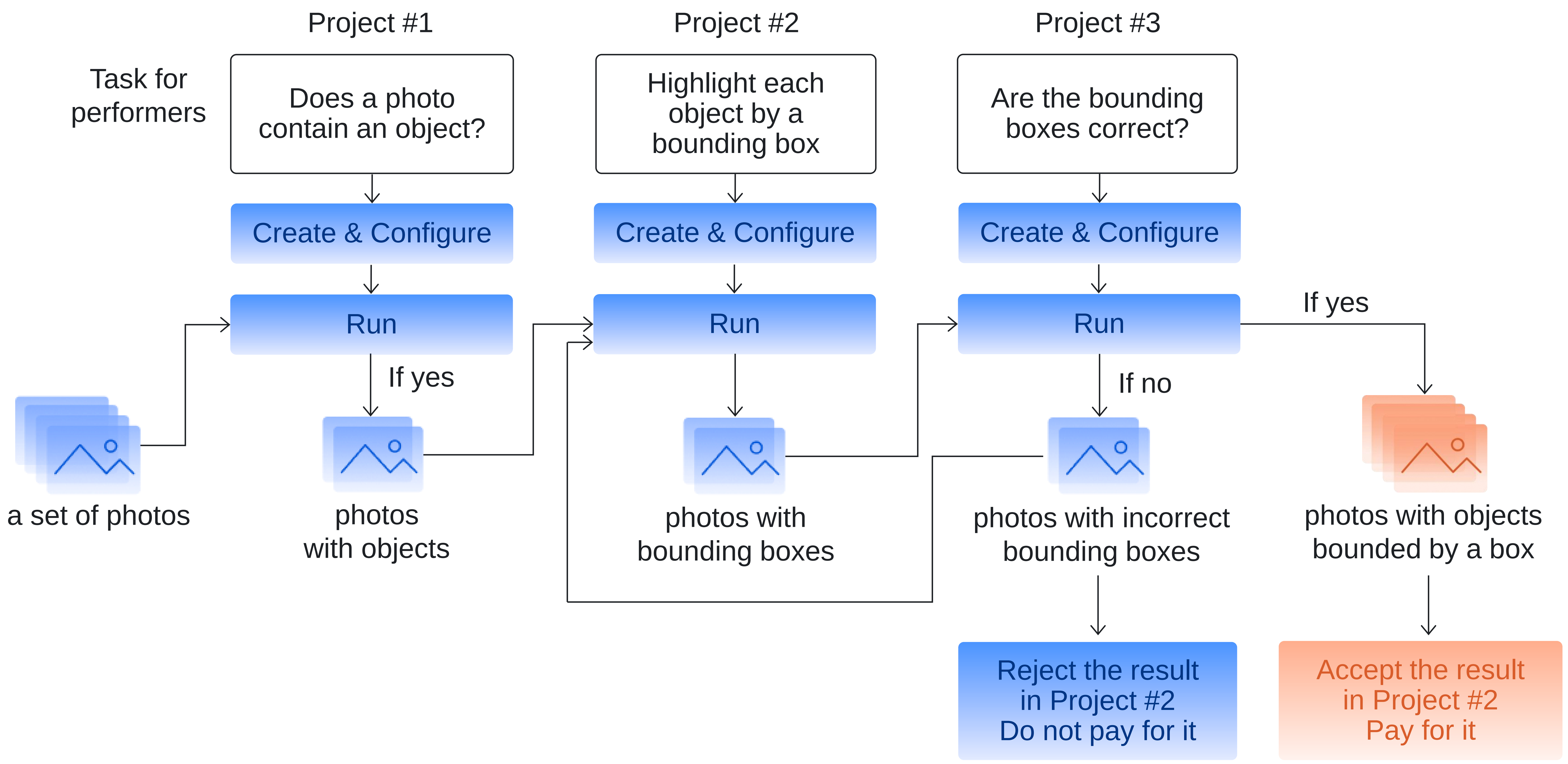
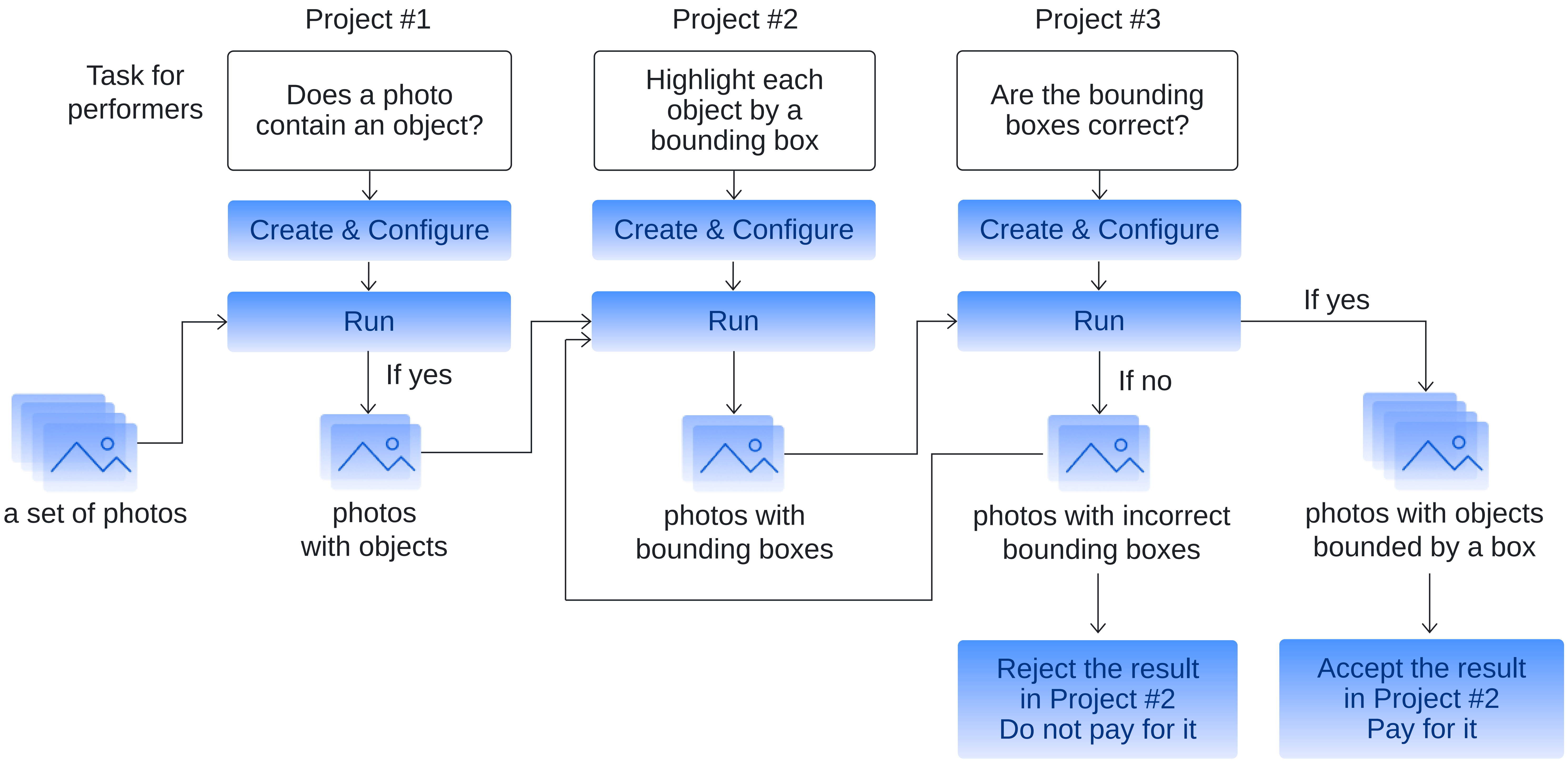
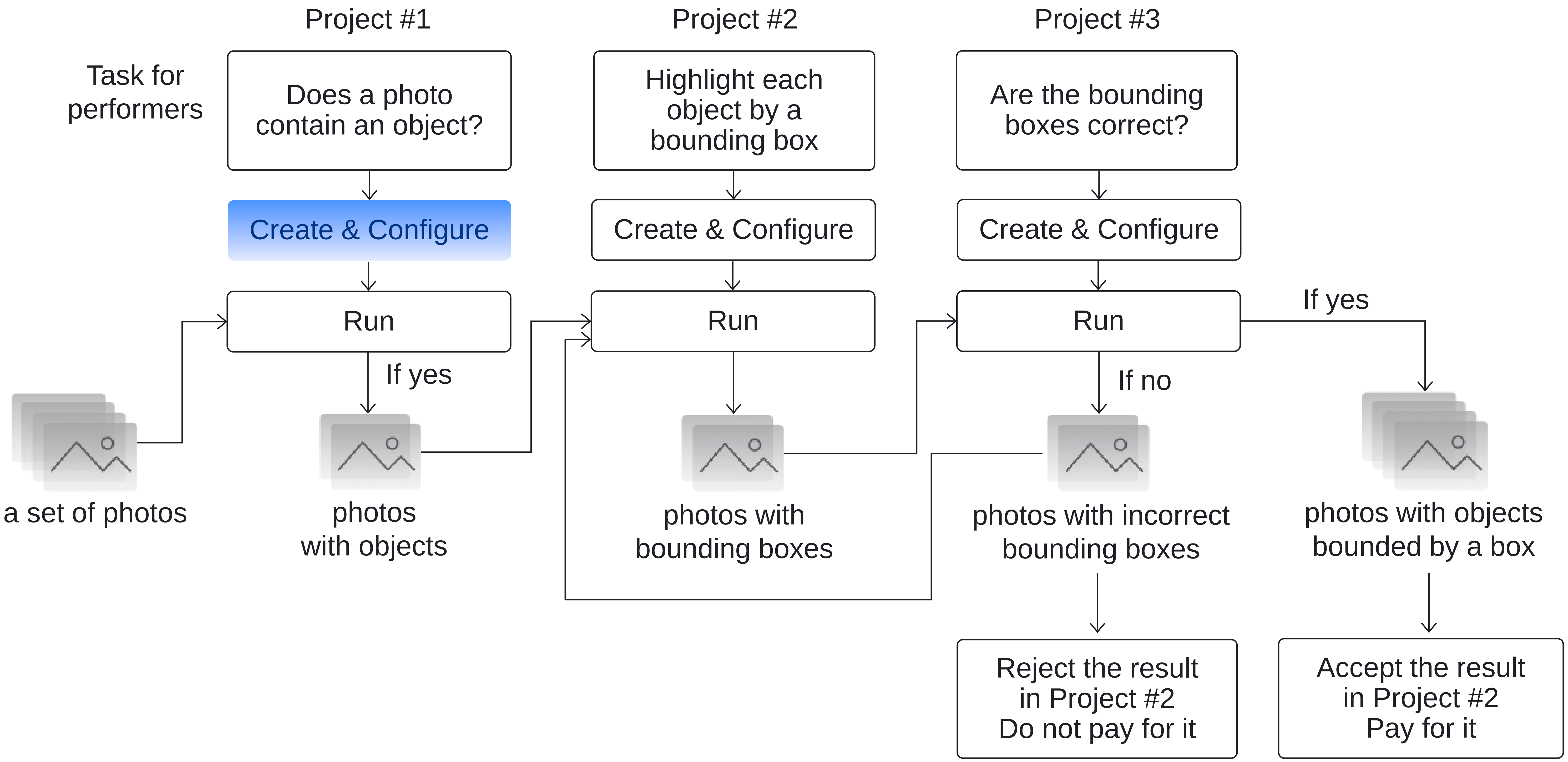
Step #6 (repeat until none rejected in Project #2)



Step #7 (repeat until none rejected in Project #2)



Most of us are at this step



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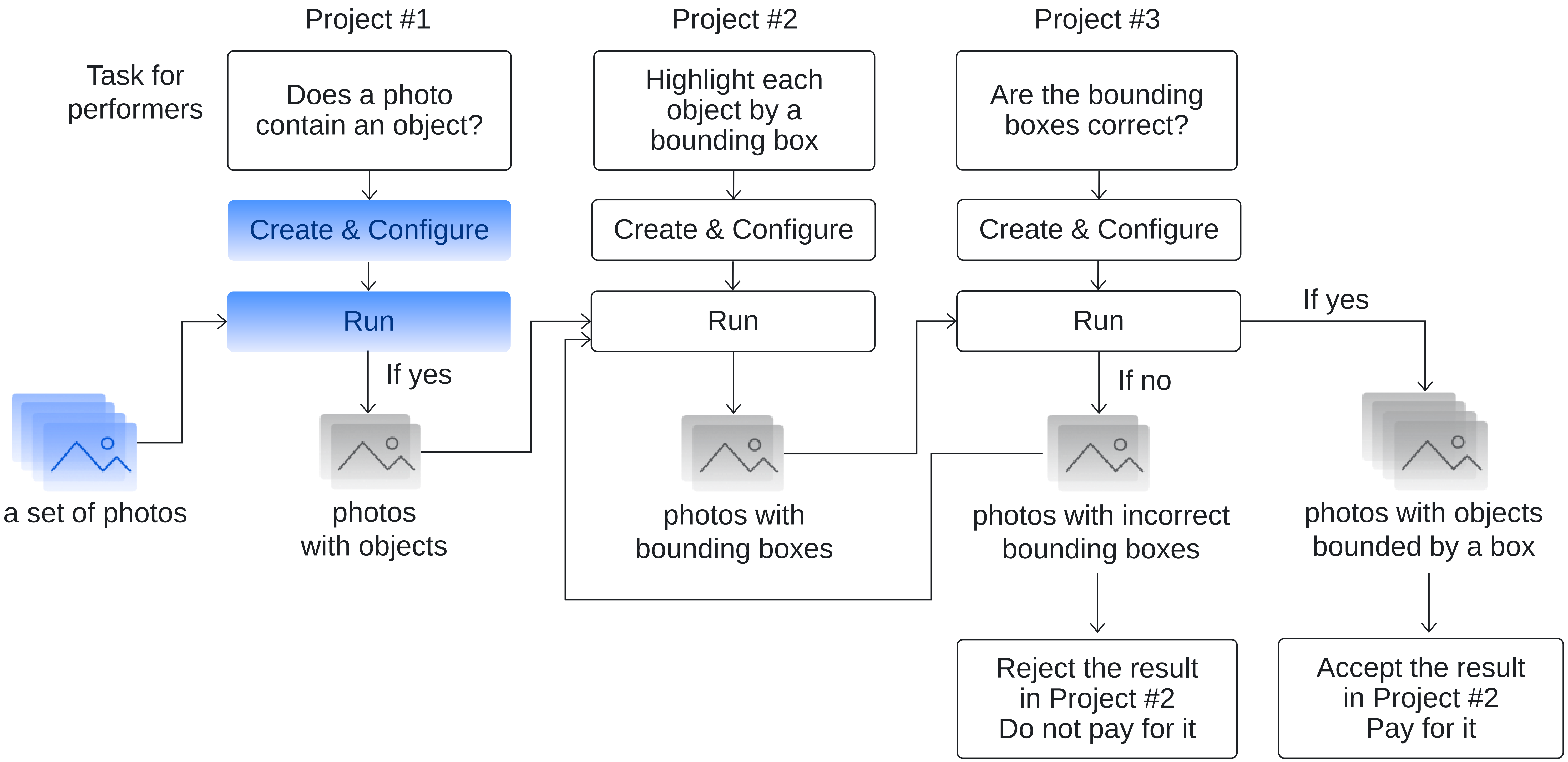

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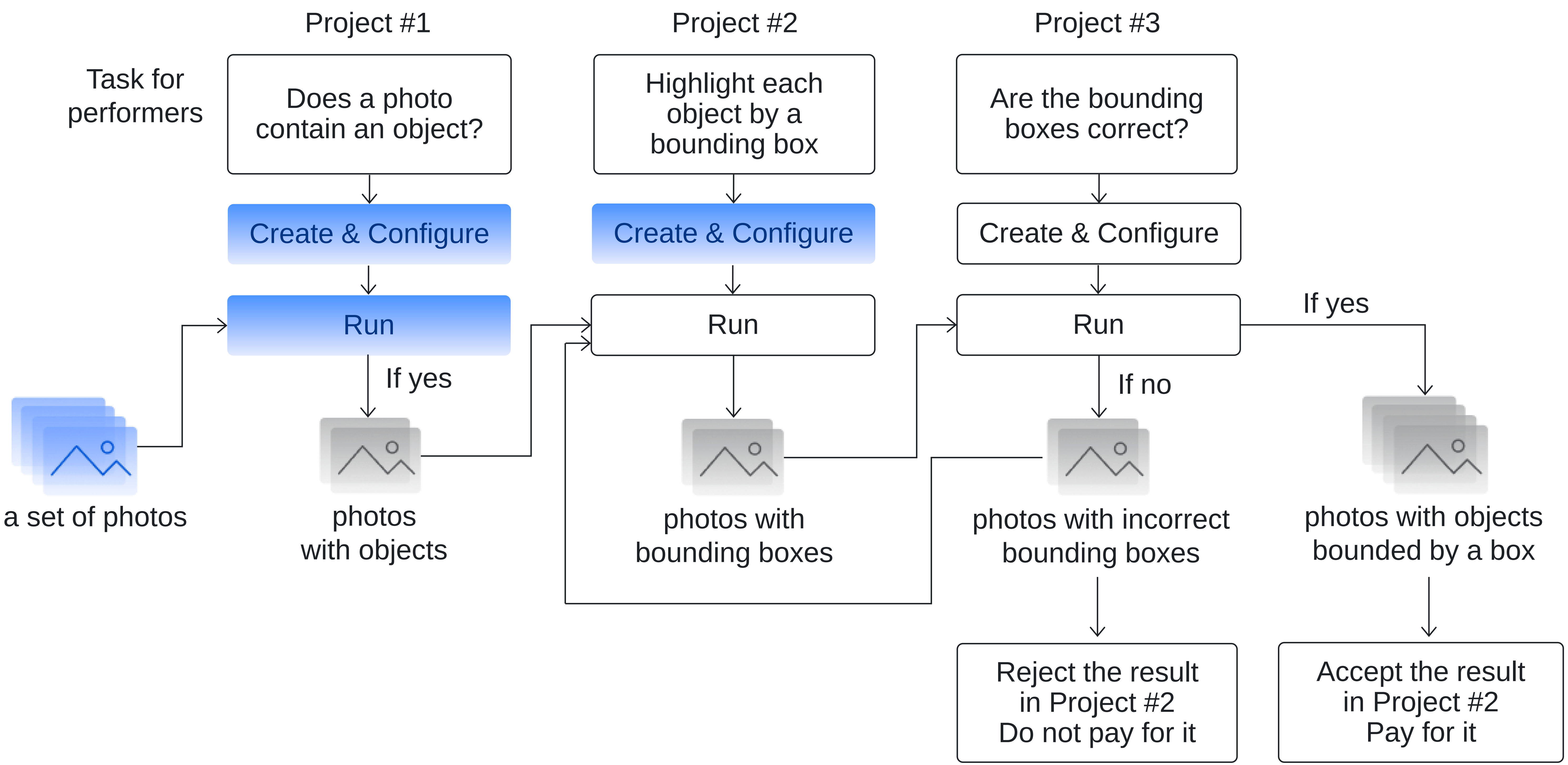

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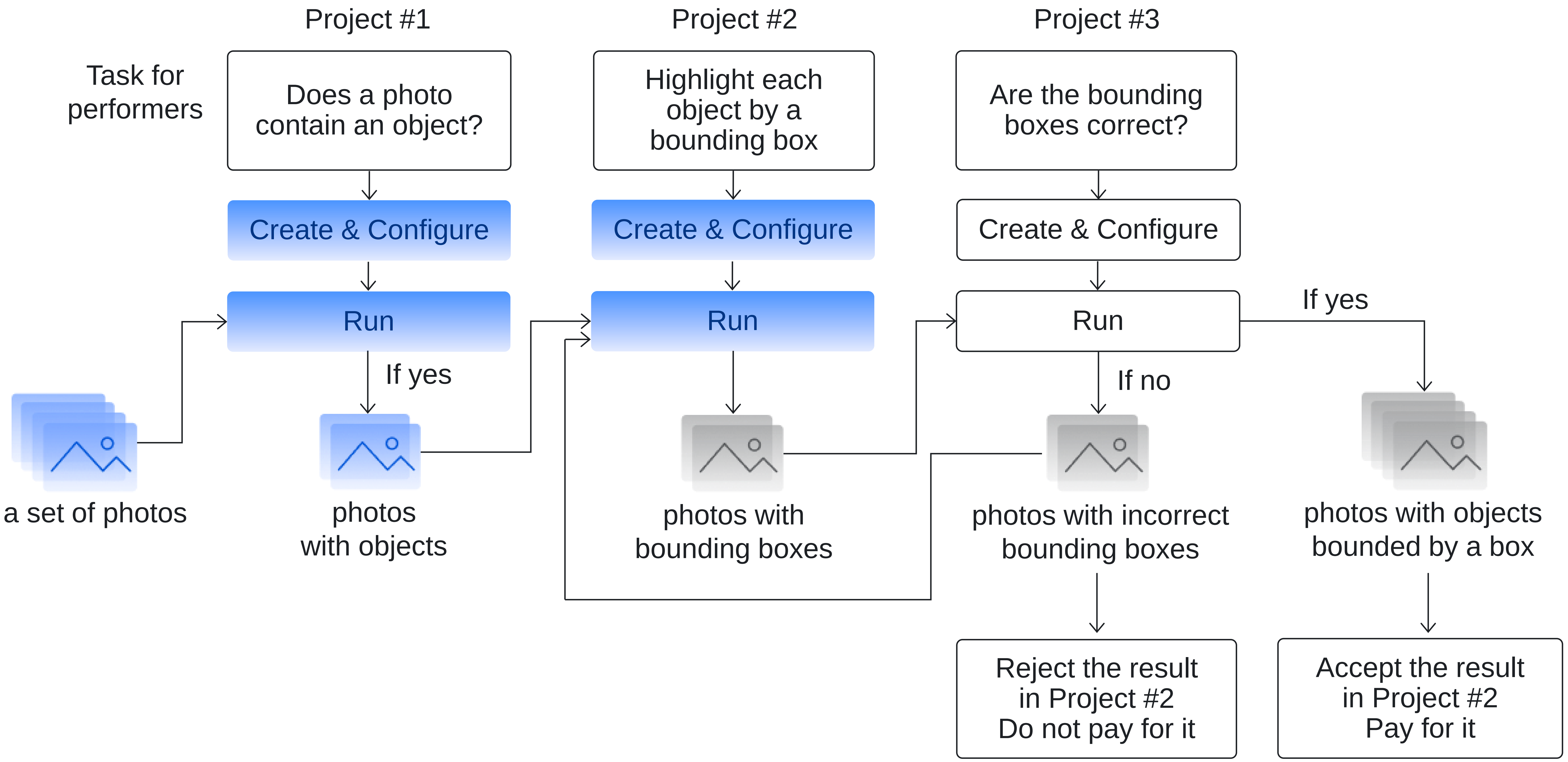

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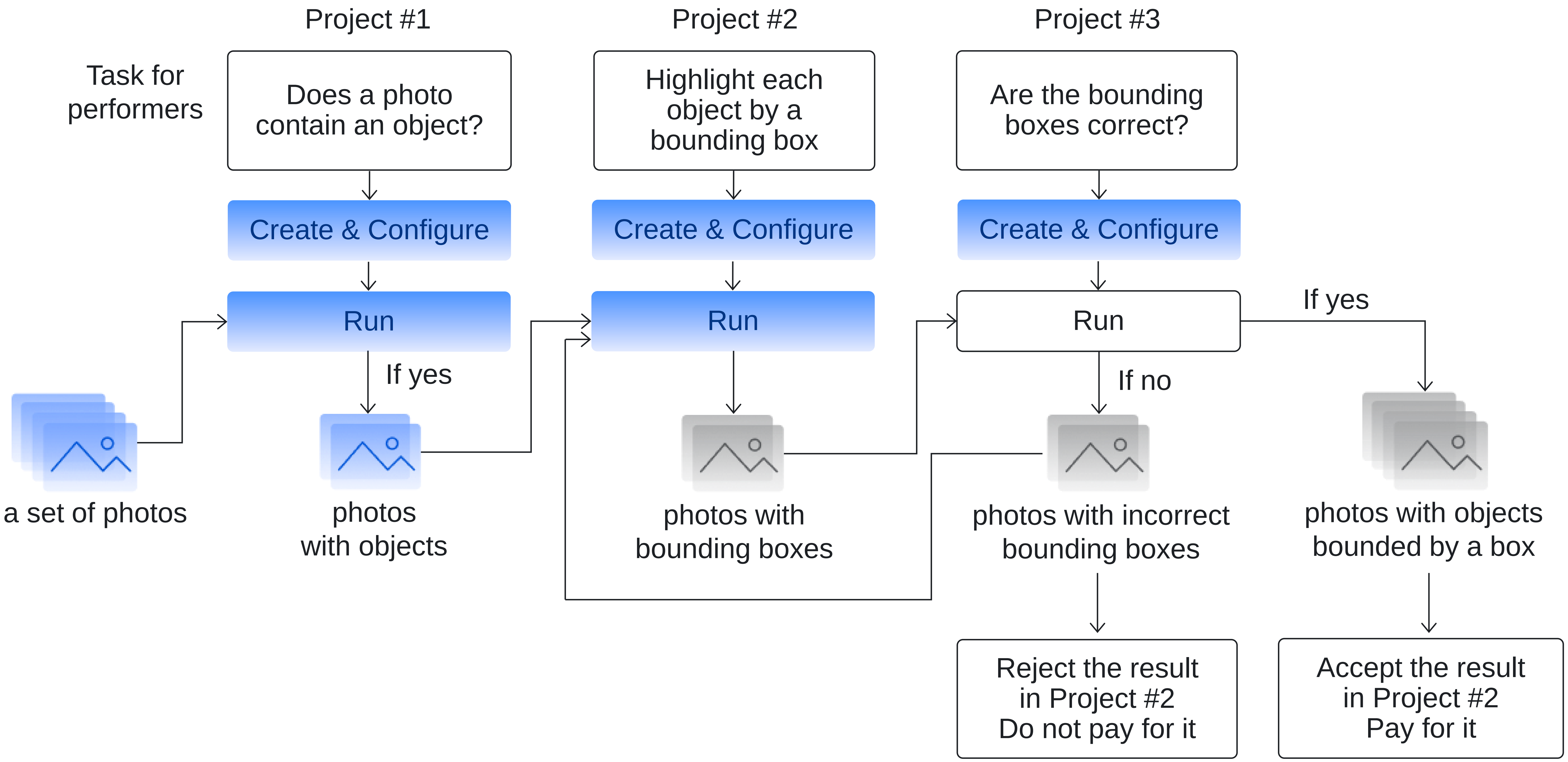

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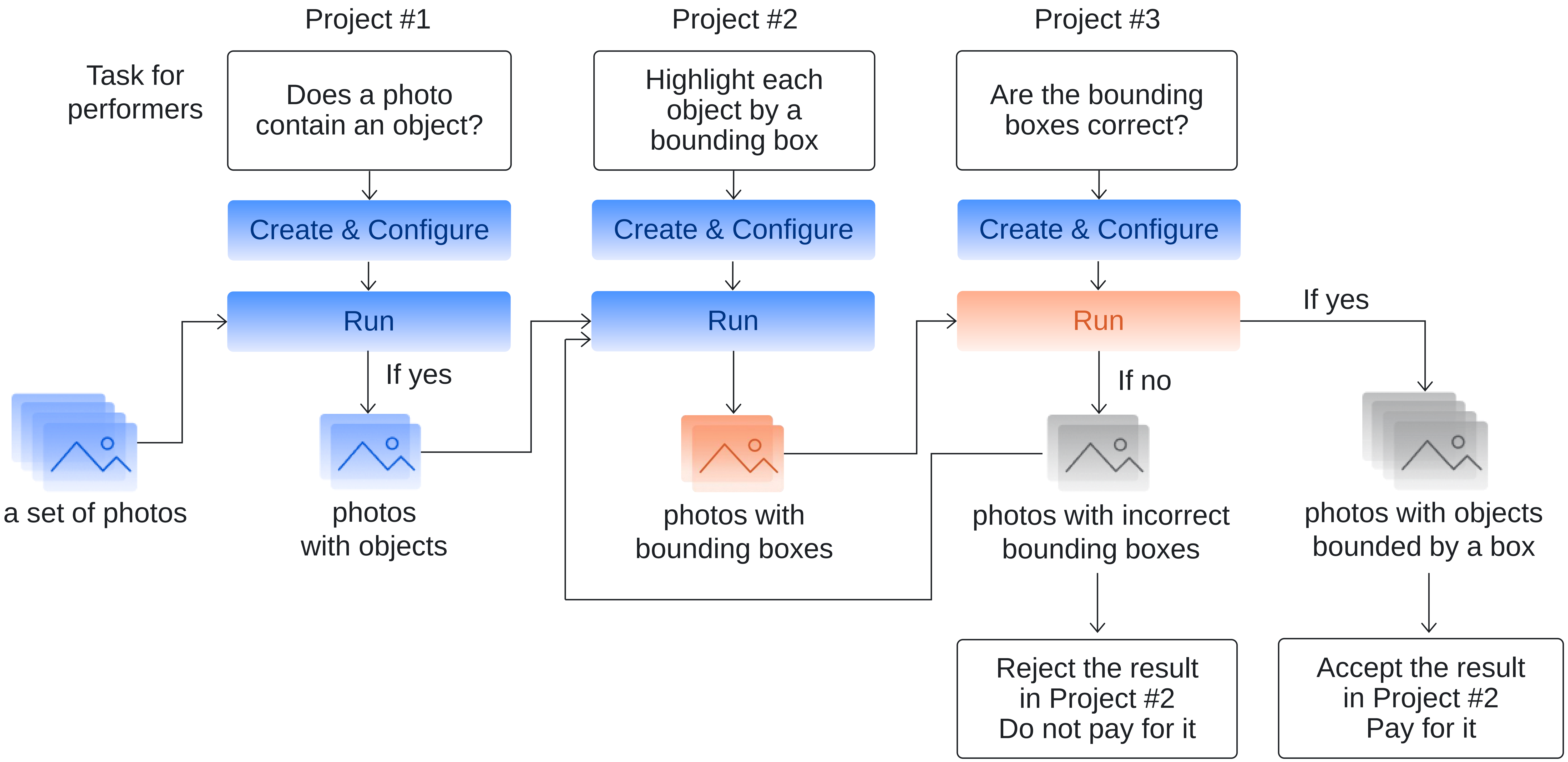

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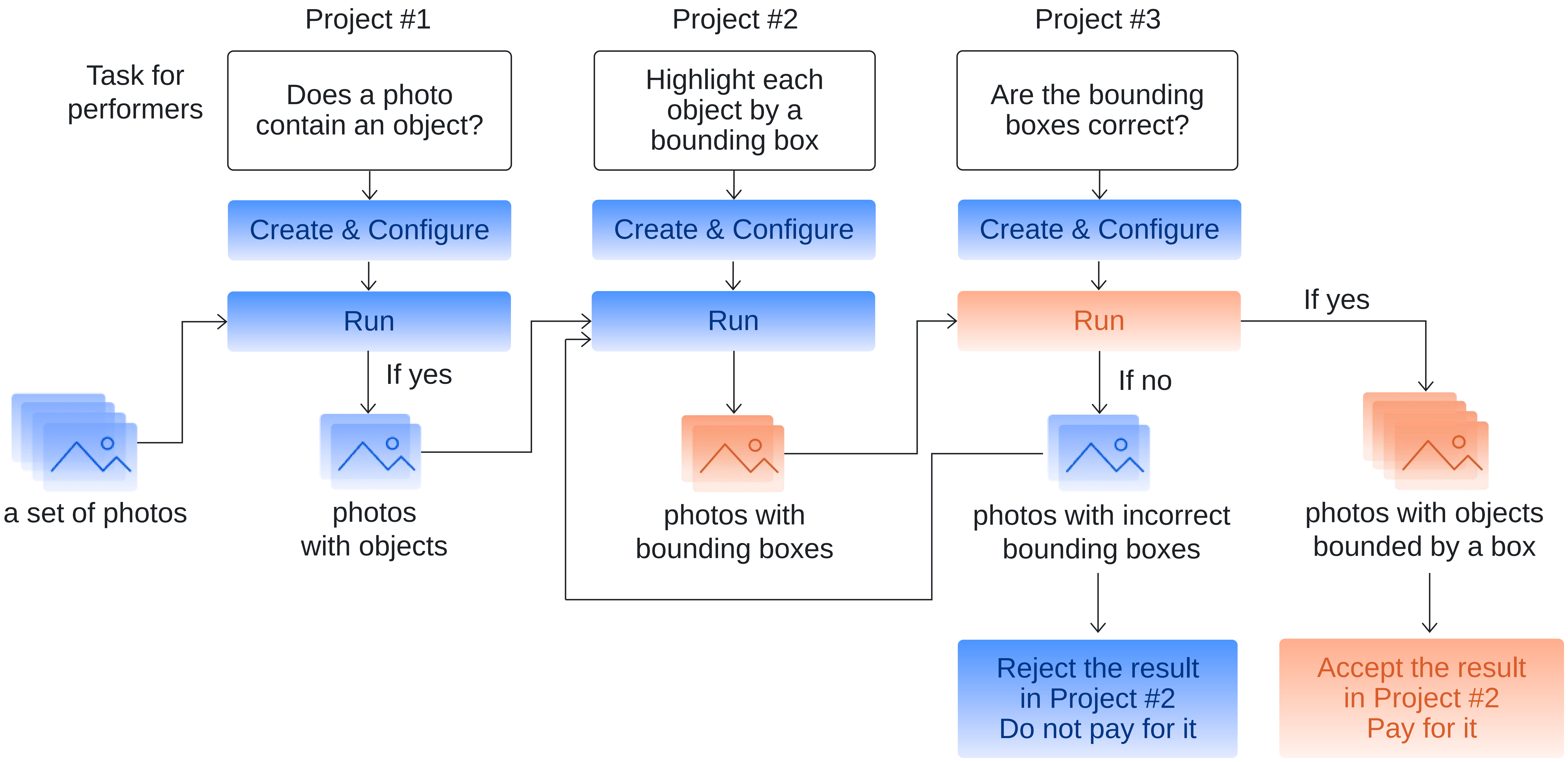

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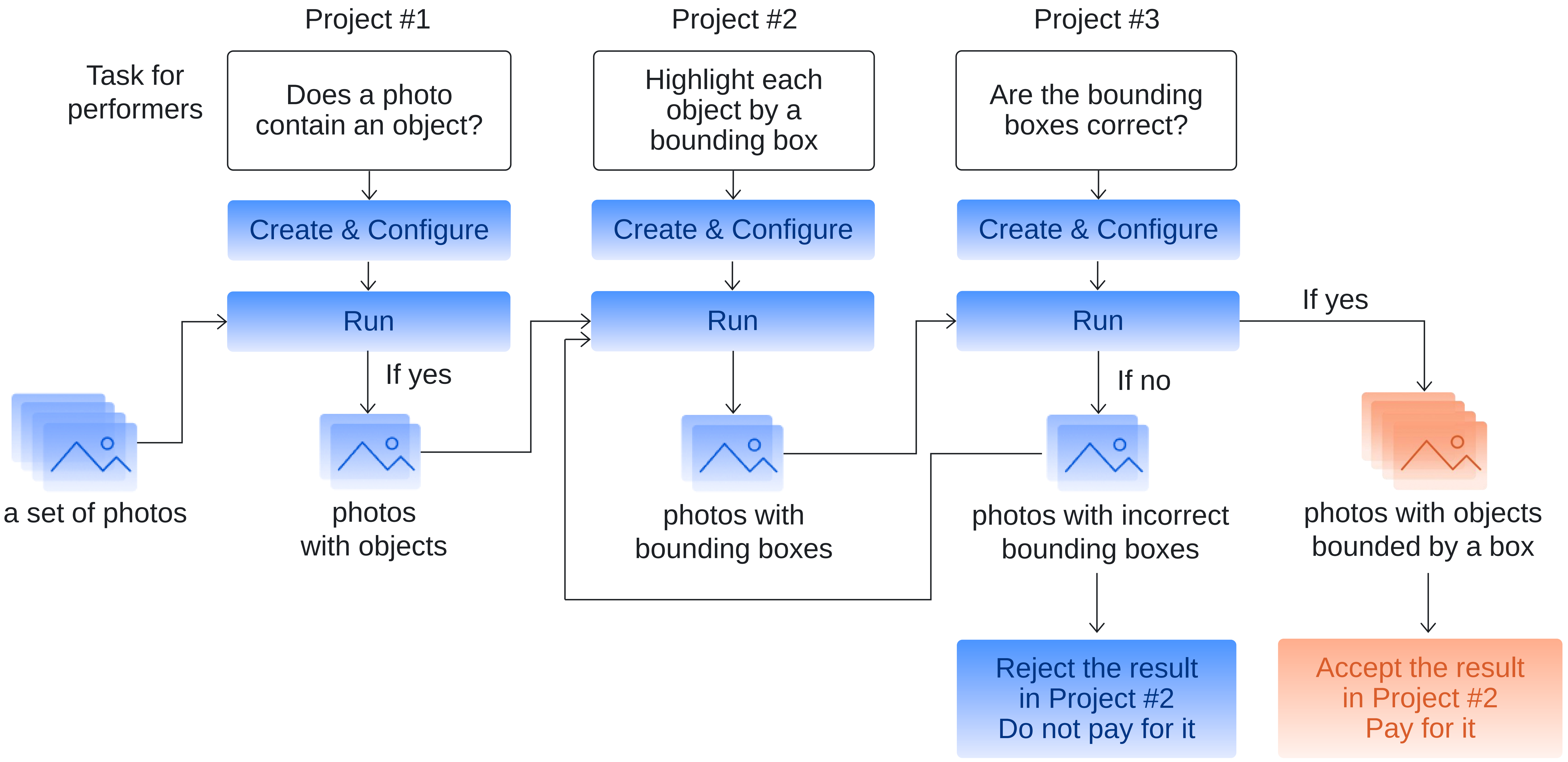

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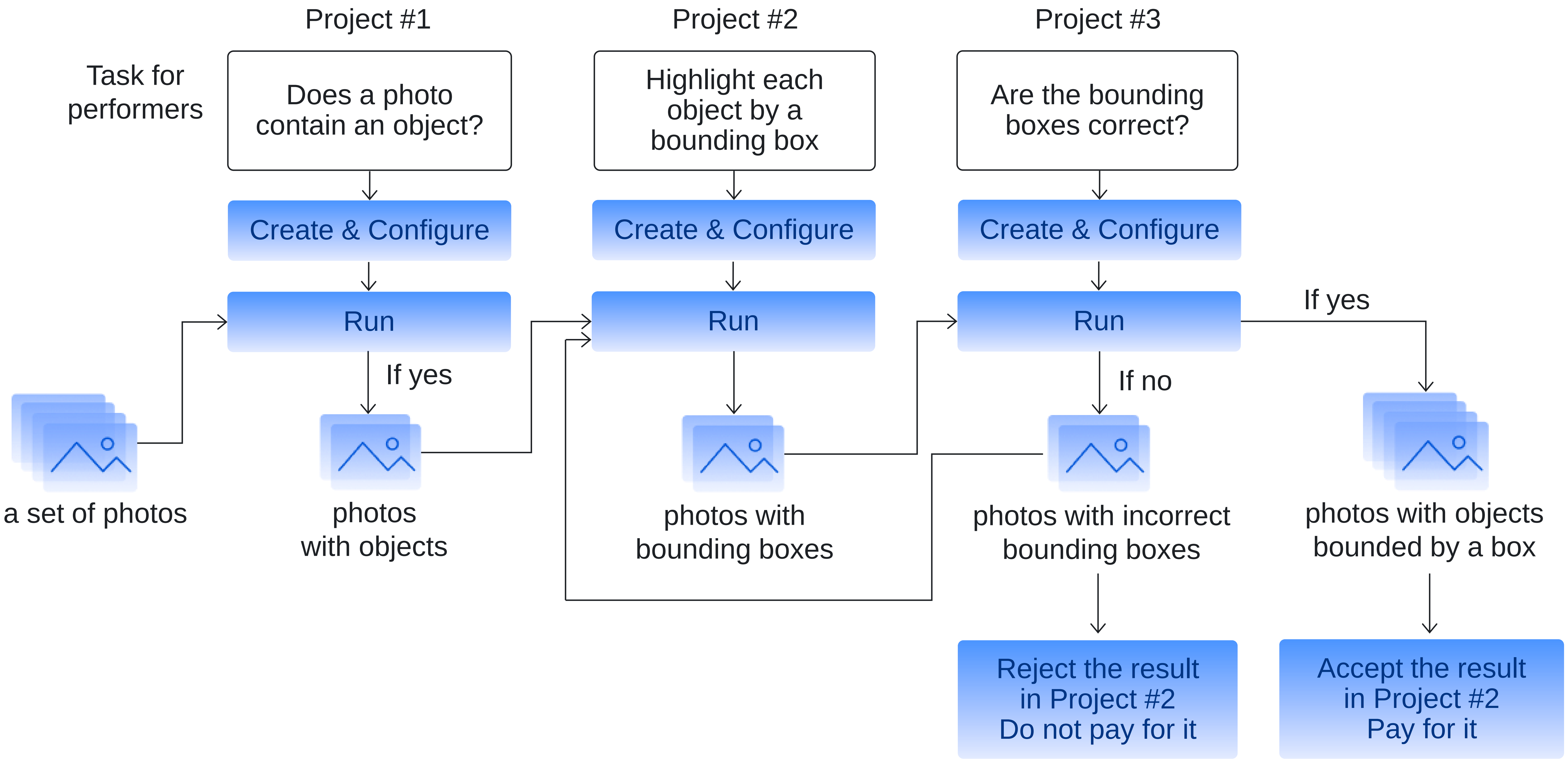


Part V

Theory on efficient aggregation, incremental relabeling, and pricing

Valentina Fedorova,
Researcher

Project 1: Filter images

Does the image contain traffic signs?

Yes

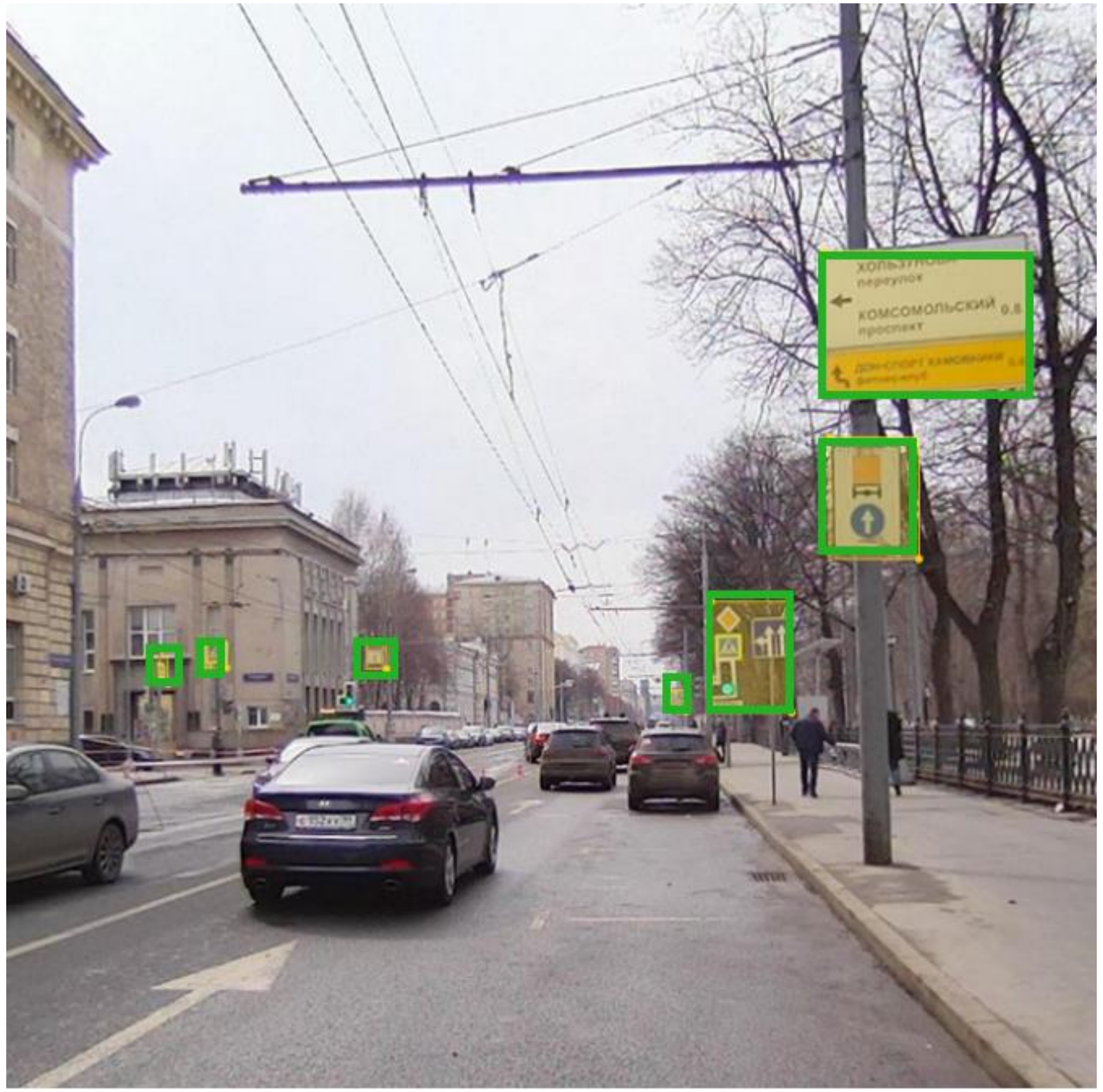
No

Project 3: Verification

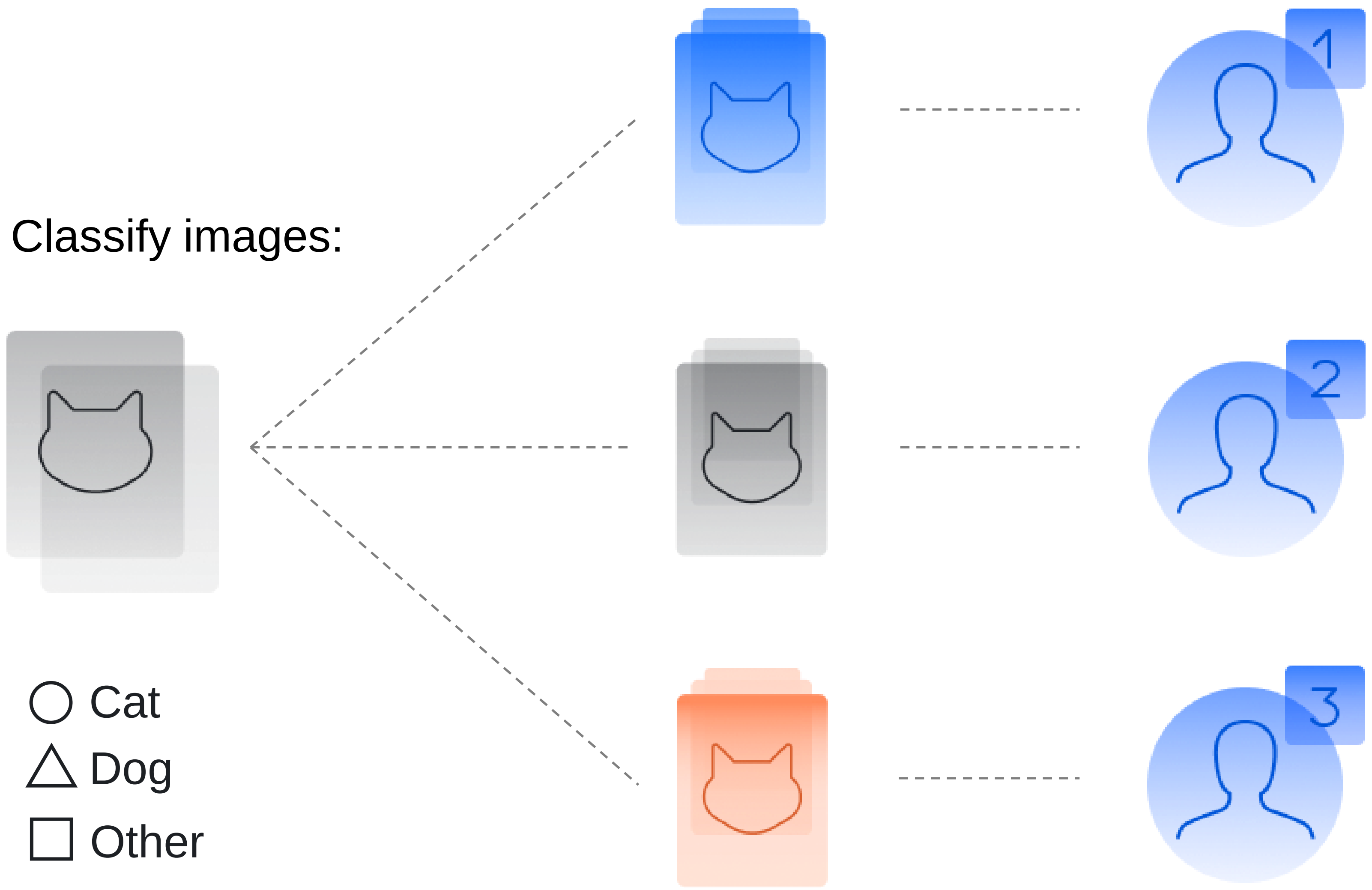
Are the bounding boxes correct?

Yes

No



Labeling data with crowdsourcing



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

Evaluation of labeling approaches

vs

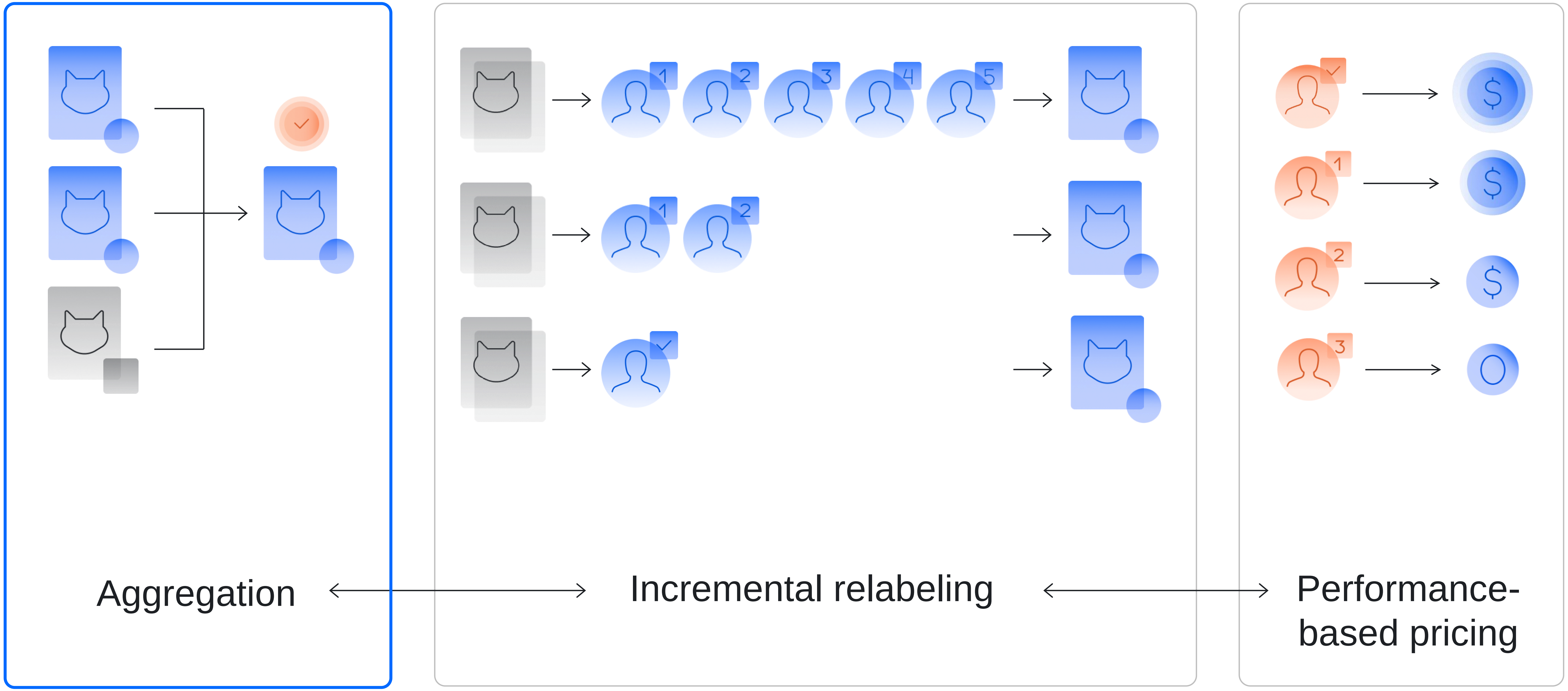
Accuracy

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



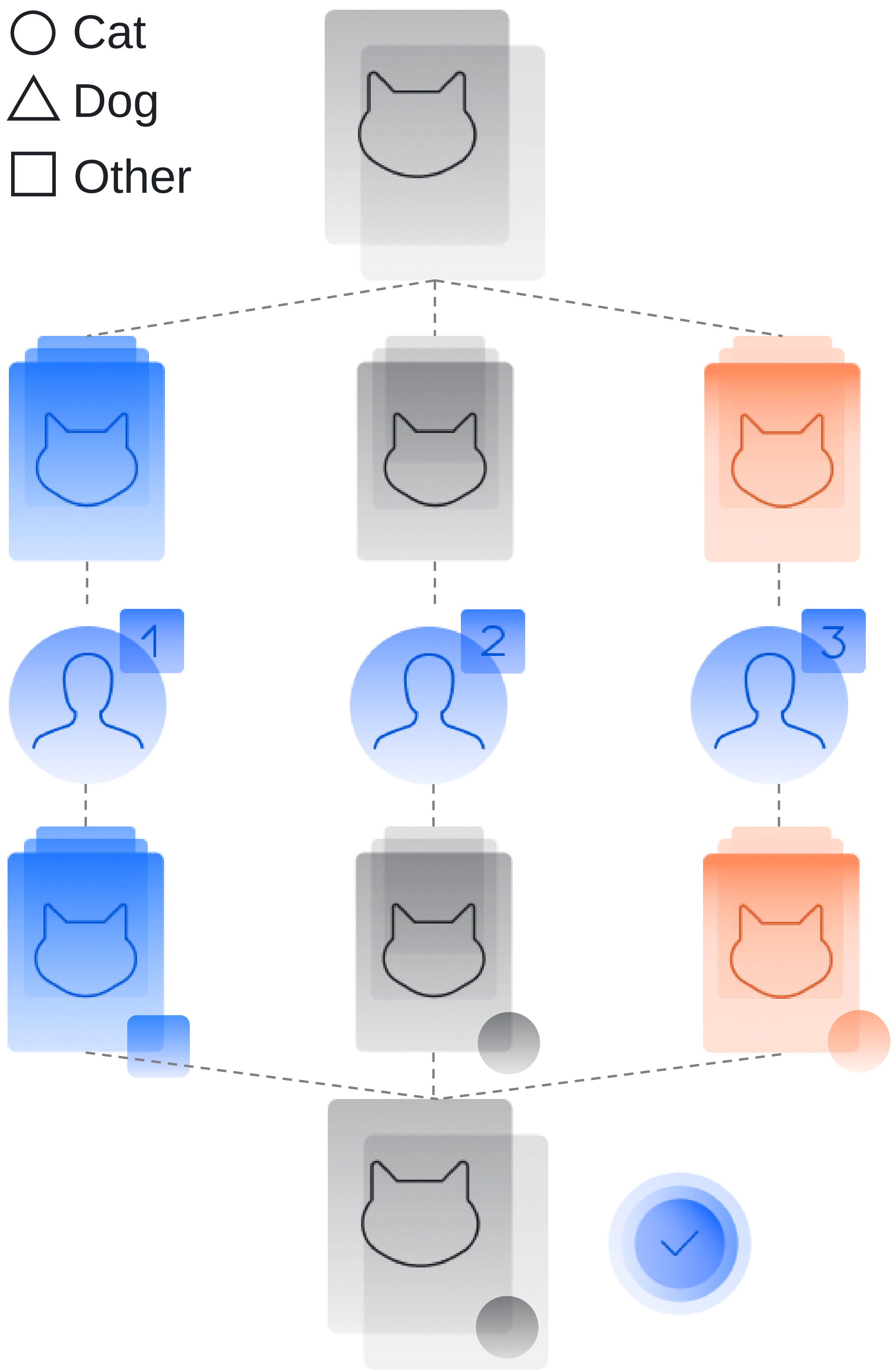
Aggregation

Incremental relabeling

Performance-based pricing

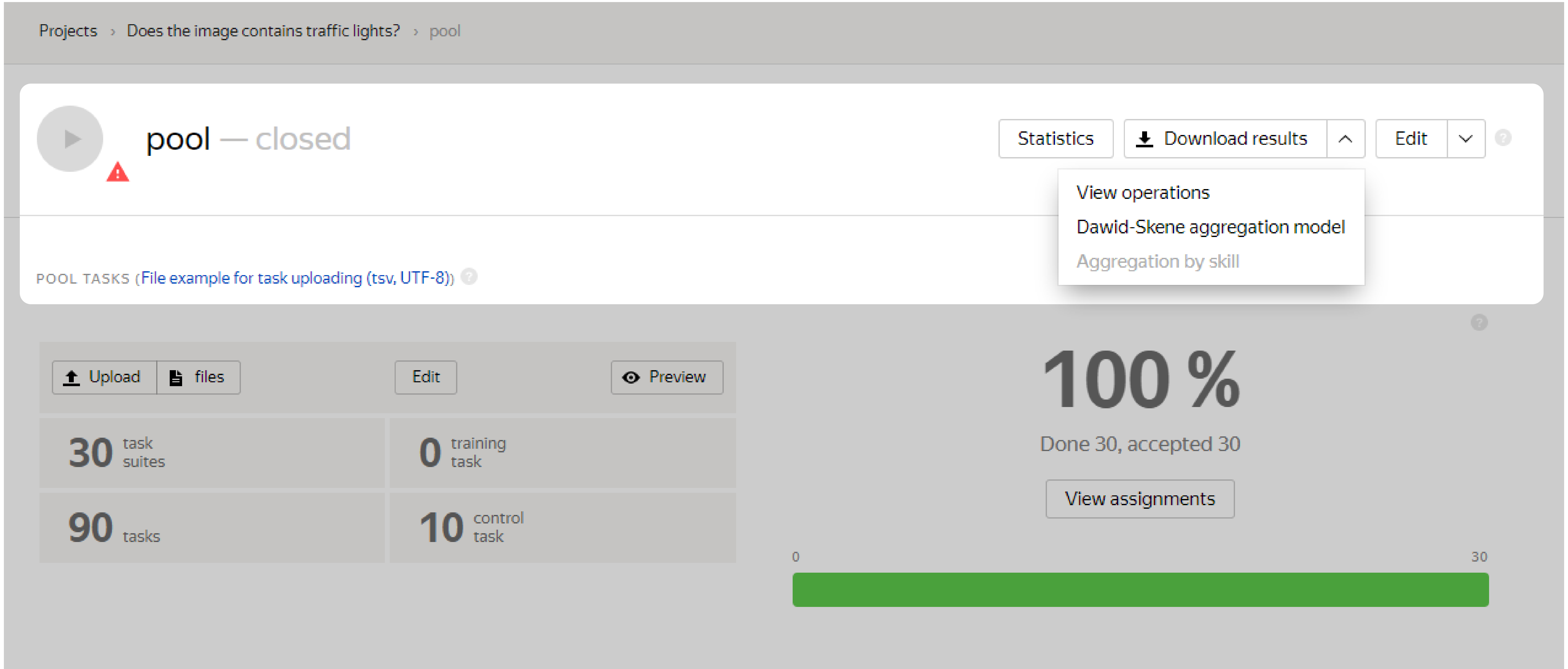
Aggregation

Labeling data with crowds



- ► Classify images
- ► Upload multiple copies of each object to label
- ► Workers assign noisy labels to objects
- ► Aggregate multiple labels for each object into a more reliable one

Process results

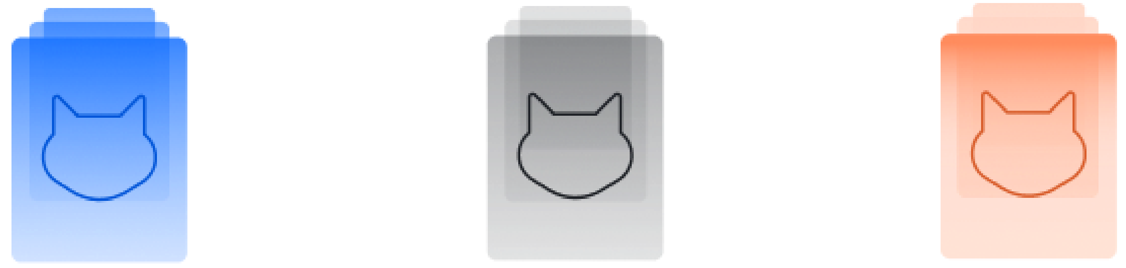


Notation

- Categories $k \in \{1,\dots,K\}$. E.g.:

○ Cat △ Dog □ Other

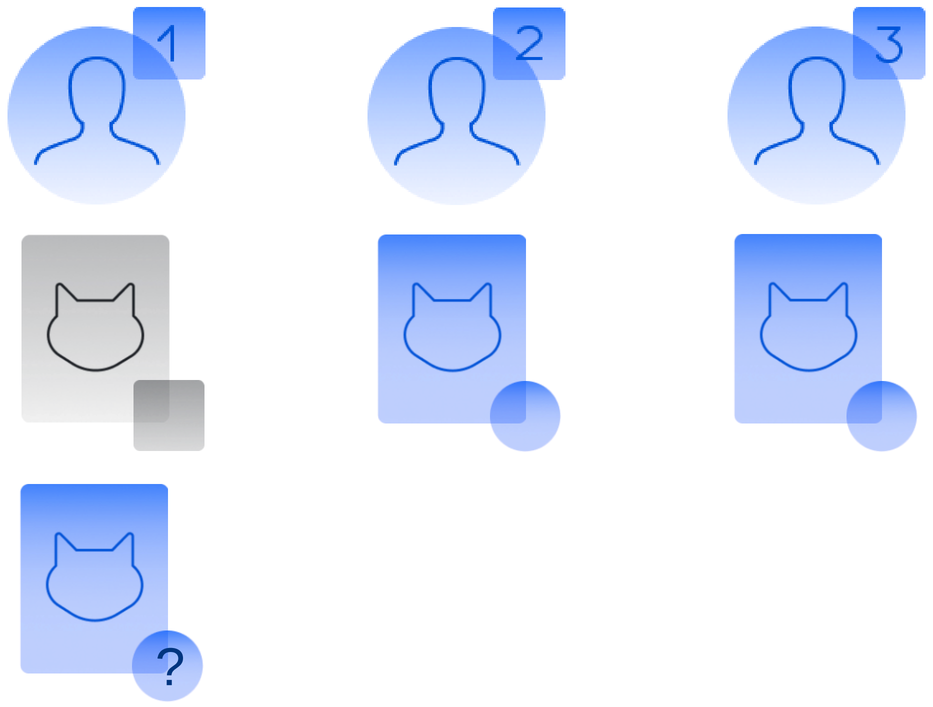
- Objects $j \in \{1,\dots,J\}$. E.g.:



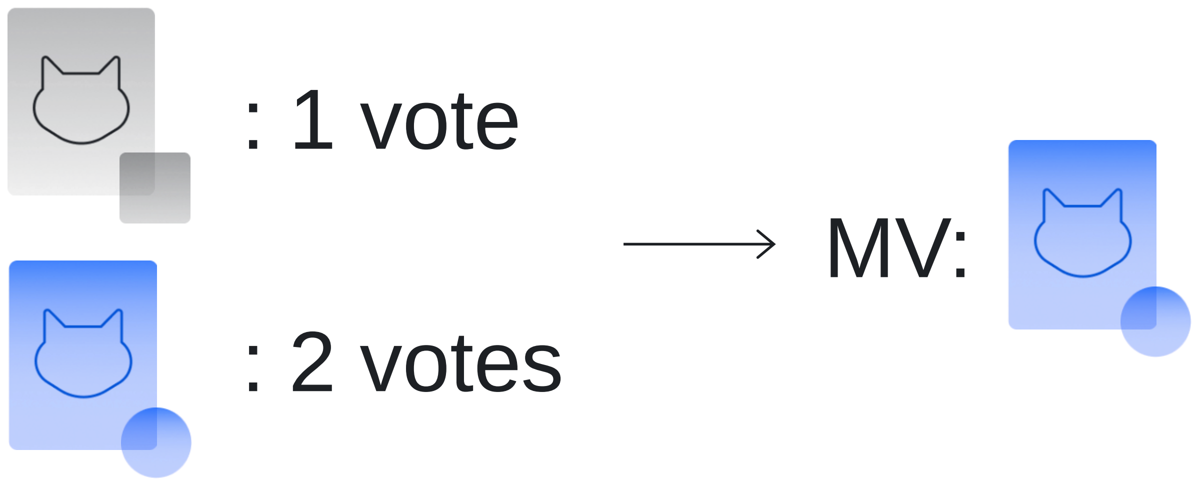
- Workers: $w \in \{1,\dots,W\}$. E.g.:
  - $W\_j \subseteq \{1,\dots,W\}$ — workers labeled object j

The simplest aggregation: Majority Vote (MV)

- The problem of aggregation:
  - Observe noisy labels
    $y = \{y_j^w \mid j = 1, \dots, J \text{ and } w = 1, \dots, W\}$
  - Recover true labels $z = \{z_j \mid j = 1, \dots, J\}$

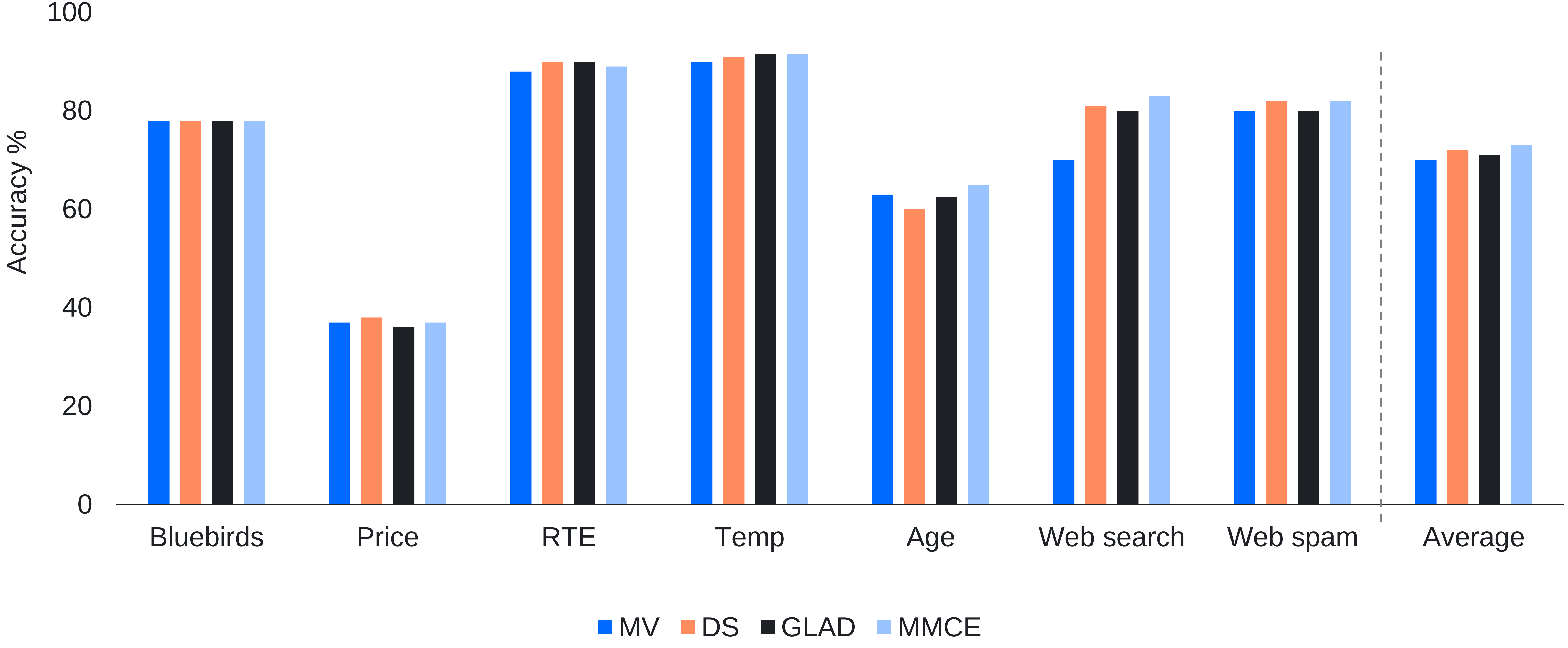


- A straightforward solution:



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

Performance of MV vs other methods

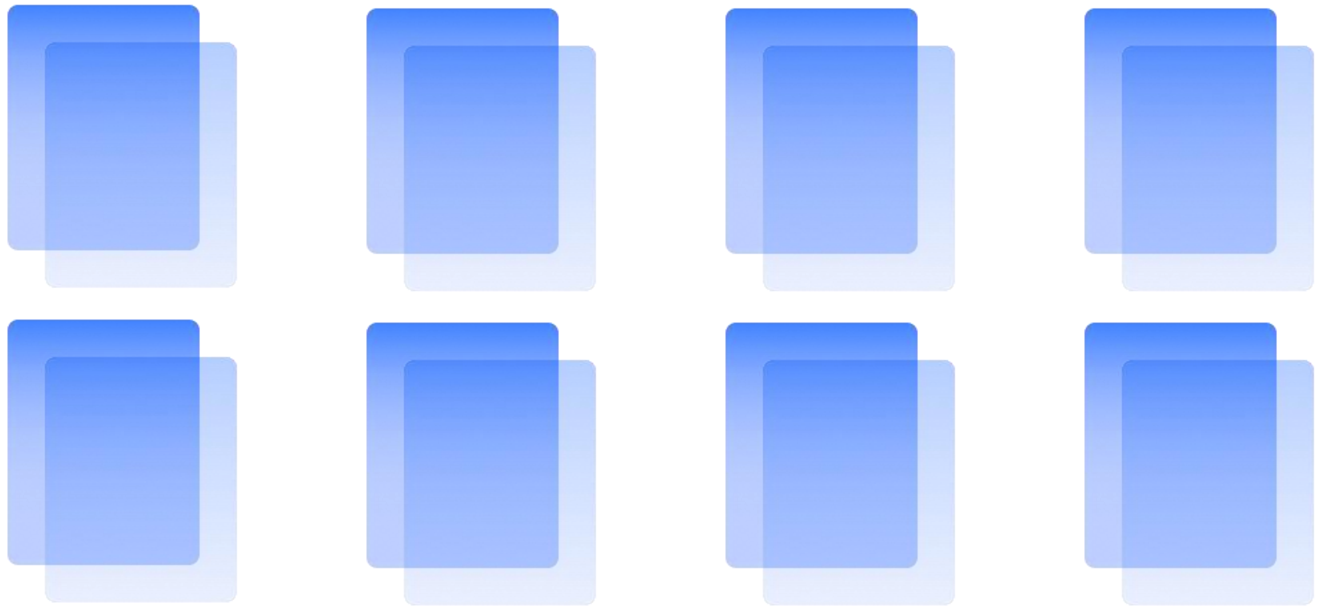


Zhou D. et al. Regularized minimax conditional entropy for crowdsourcing. 2015

Properties of MV

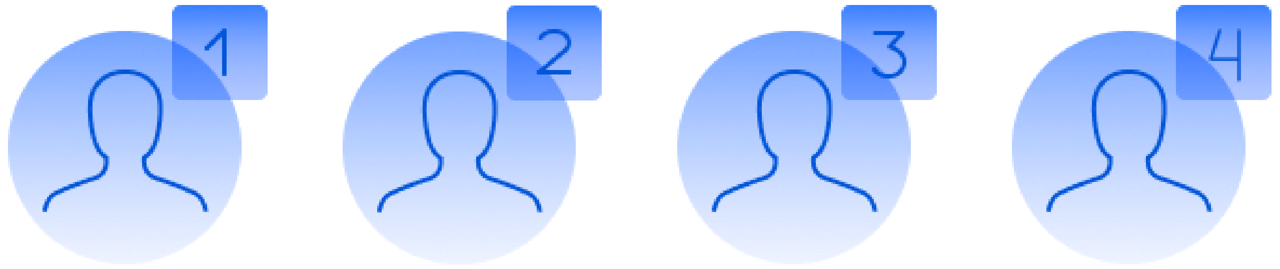
All workers are treated similarly

All objects are treated similarly



Advanced aggregation: workers and objects

Parameterize expertise
of workers by e^w

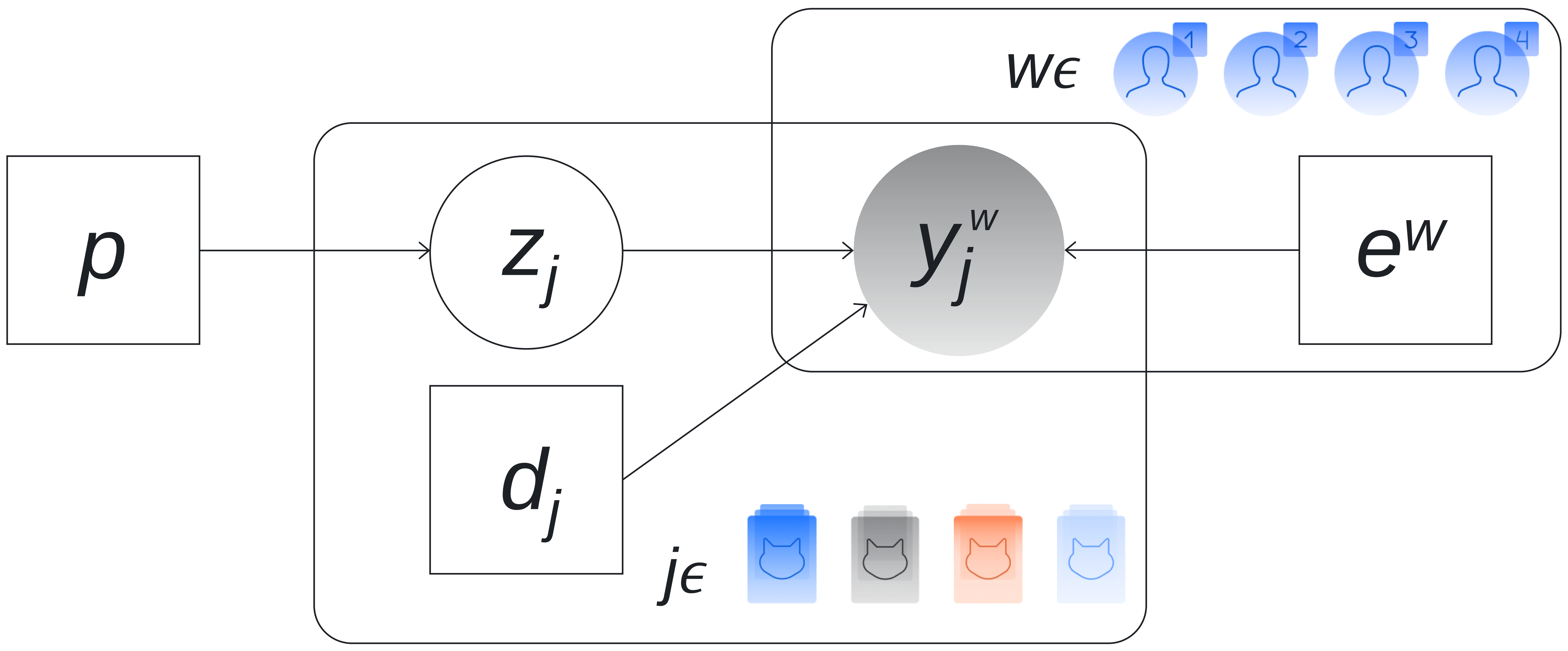


e^{w_1} e^{w_2} e^{w_3} e^{w_4}

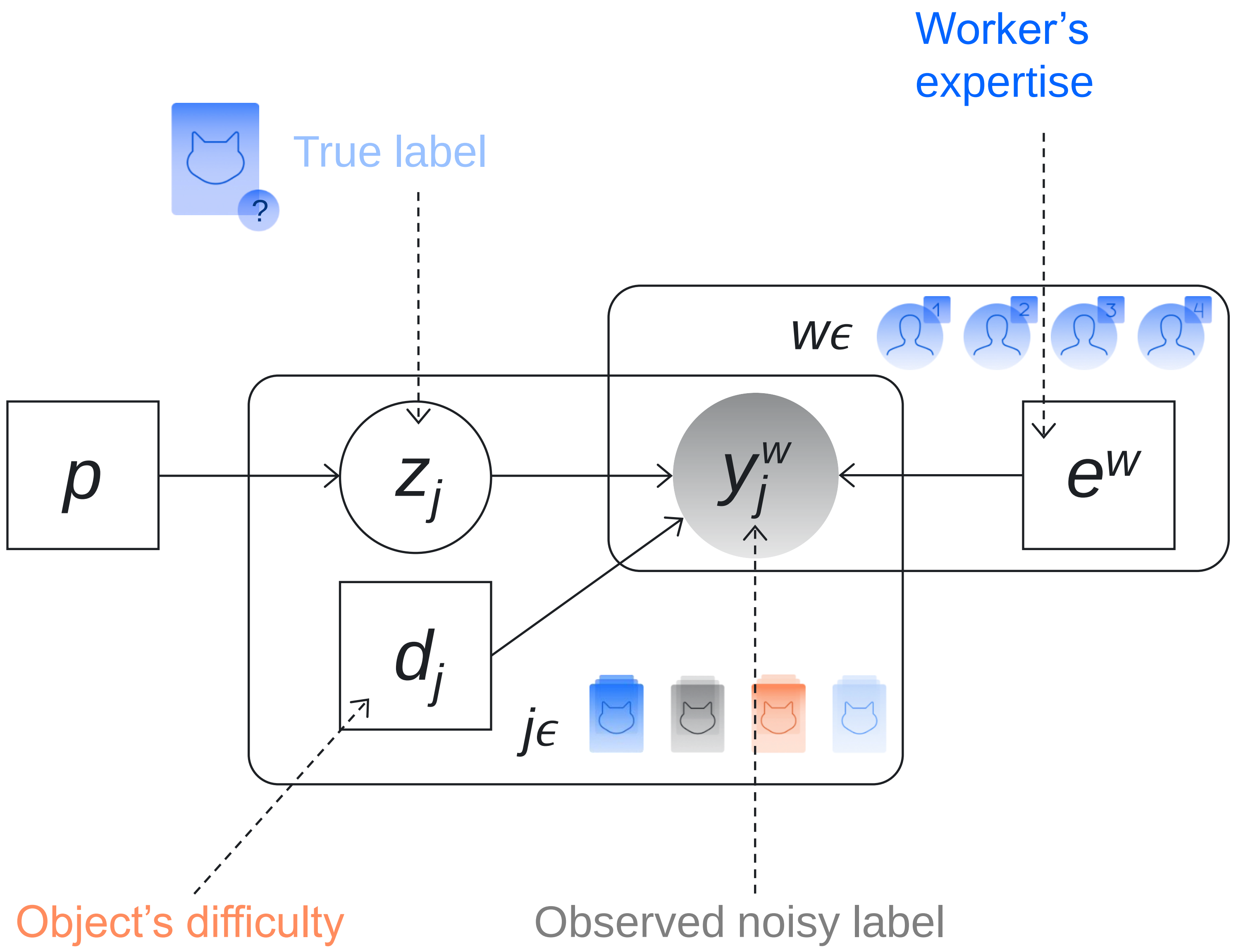
Parameterize difficulty
of objects by d_j

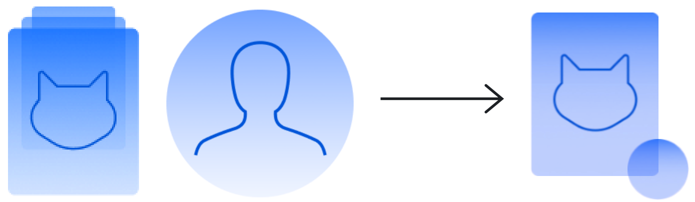
d_{j_1} d_{j_1} d_{j_1} d_{j_1}

Advanced aggregation: latent label models



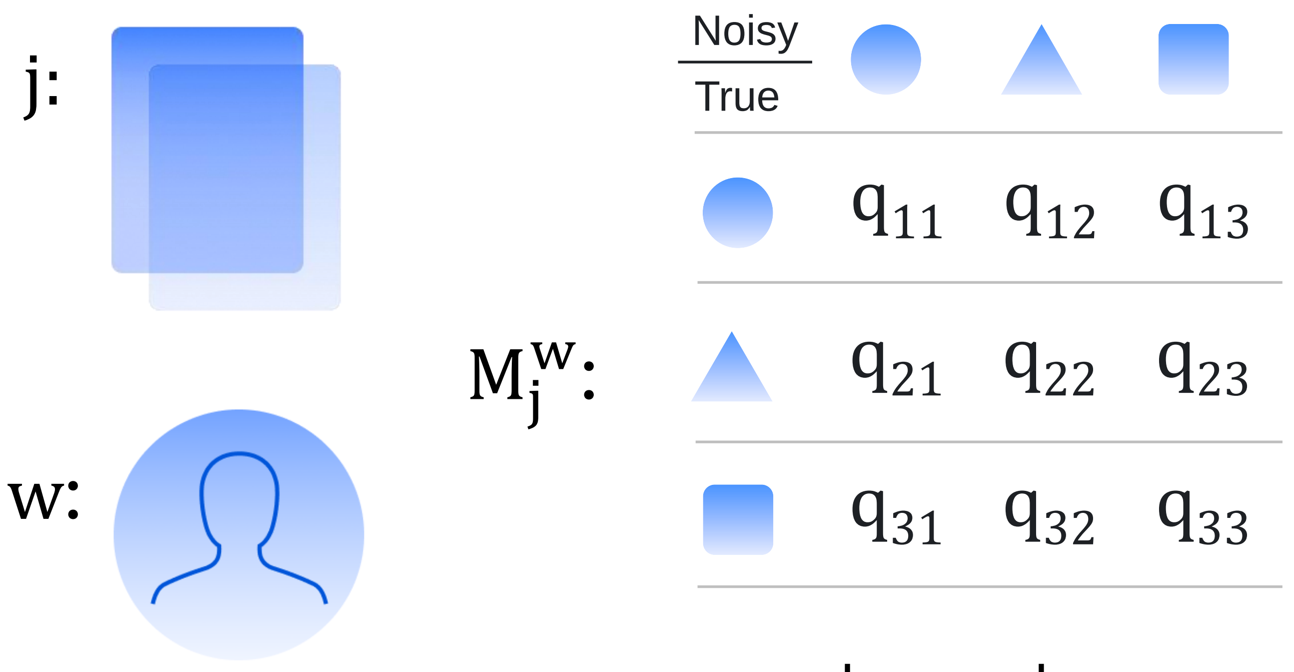
Latent label models: noisy label model





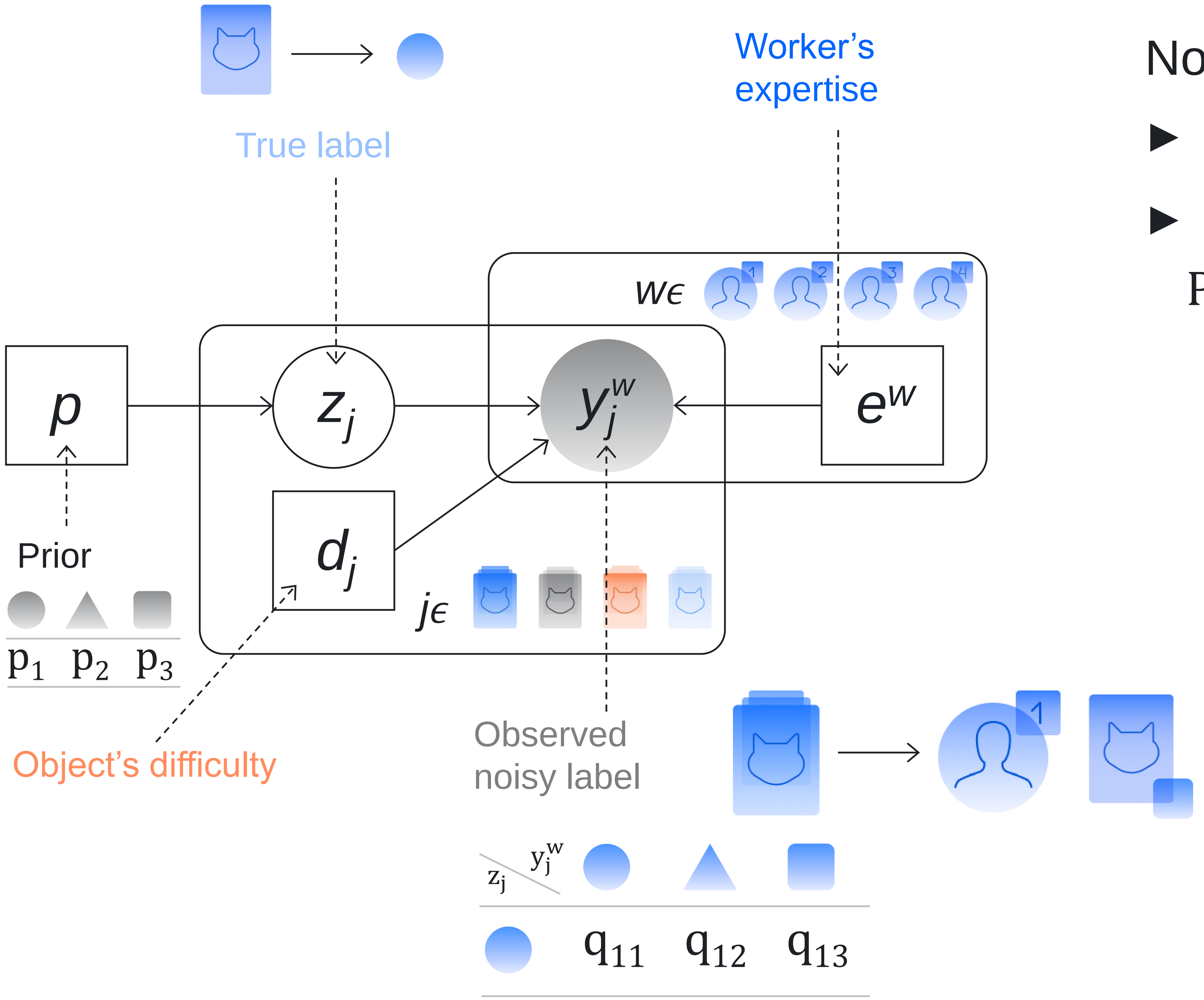
A noisy label model $M_j^w = M(e^w, d_j)$ is a matrix of size $K \times K$ with elements

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



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

Latent label models: generative process



Noisy labels generation:

- Sample z_j from a distribution $P_Z\,(p)$
- 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 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 y and z under the latent label model:

Observed noisy label

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

Latent true label

Latent parameters

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

Latent label models: EM algorithm

- Maximization of the expectation of log-likelihood (LL)*

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

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

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

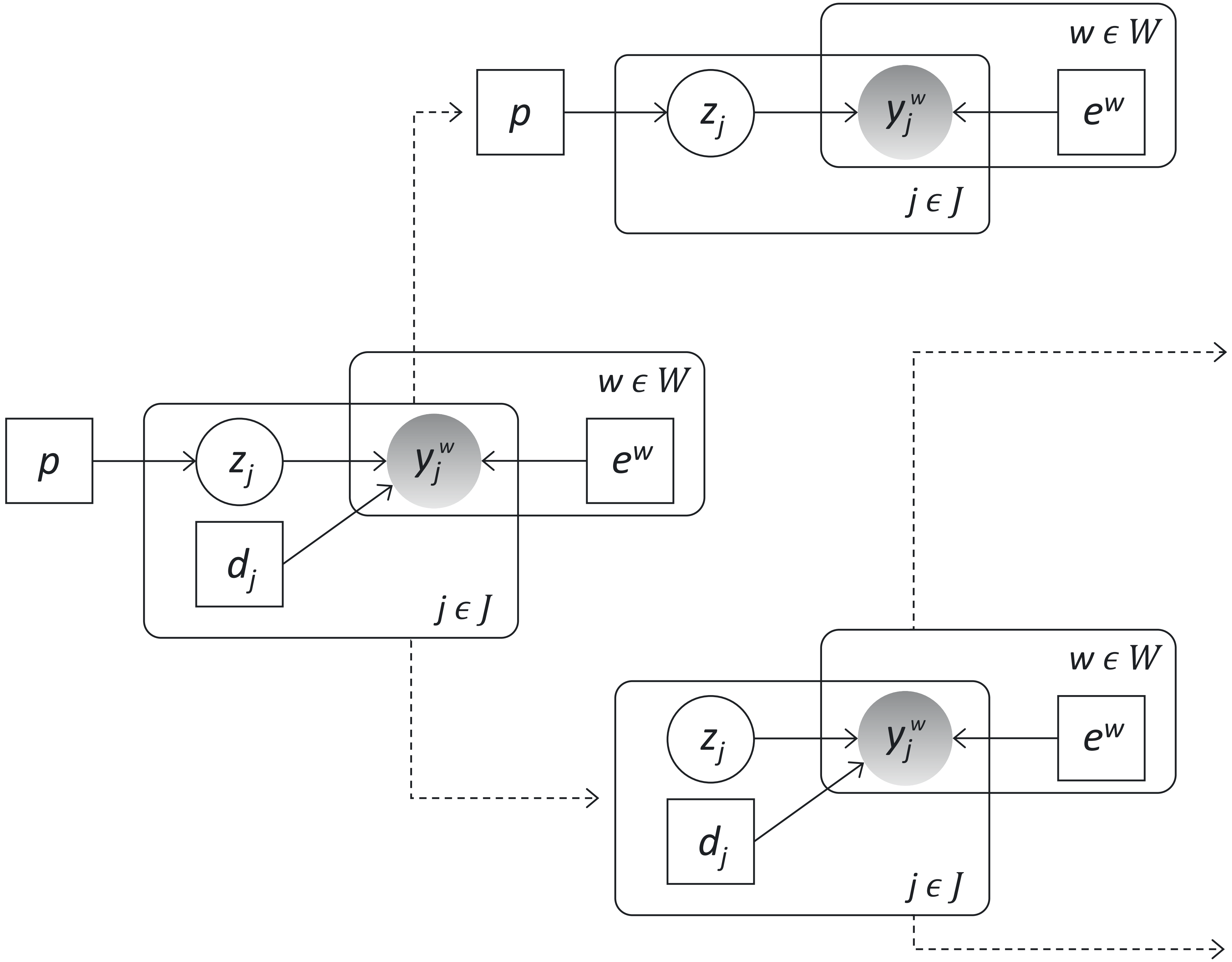
- **M-step:** Maximize the expectation of LL with respect to the posterior distribution of $\hat{z}$:

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

  - Analytical solutions
  - Gradient descent

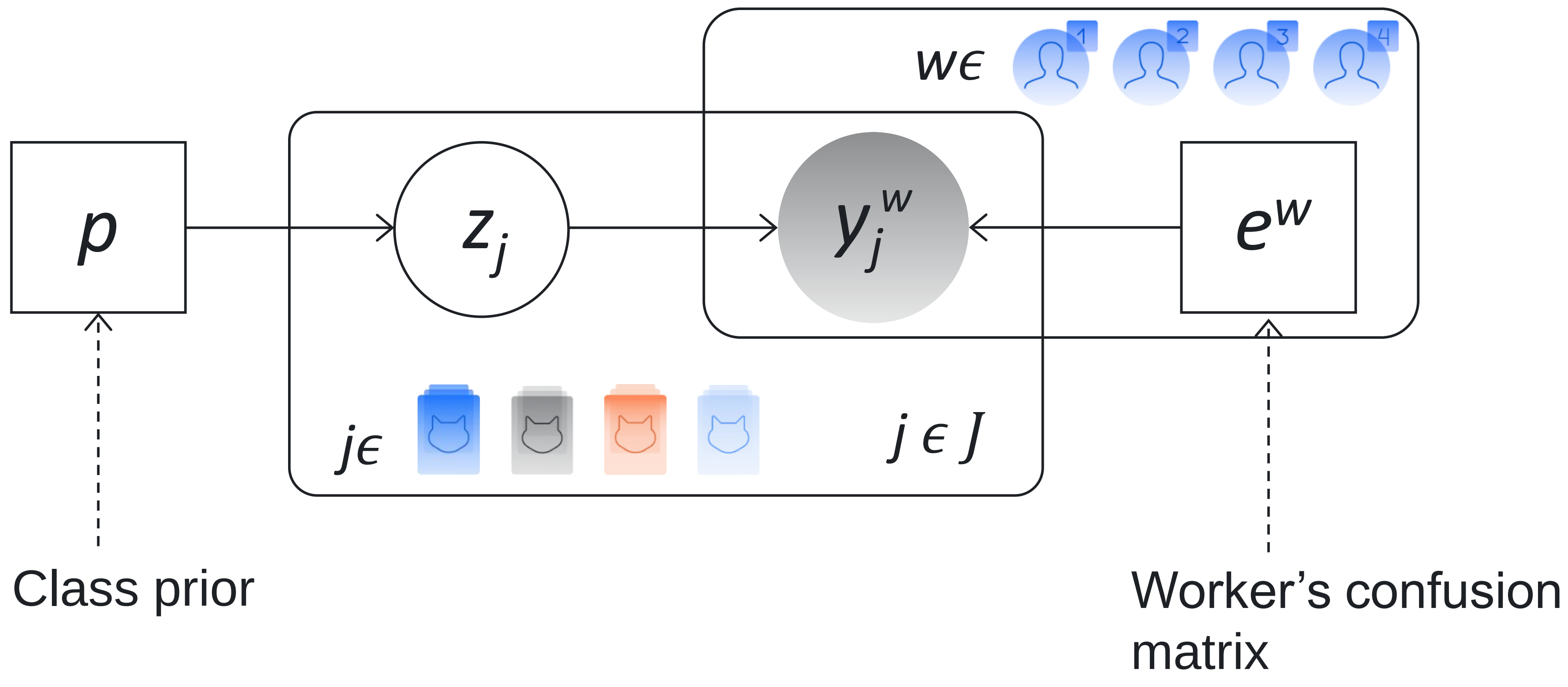
* it is a lower bound on LL of $\mathbf{y}$ and $\mathbf{z}$

Latent label model (LLM): special cases



- Dawid and Skene model (DS):
  - Categories are different
  - Objects are **similar**
  - Workers are different
- Generative model of labels, abilities, and difficulties (GLAD):
  - Categories are **similar**
  - Objects are different
  - Workers are different
- Minimax conditional entropy model (MMCE):
  - Categories are different
  - Objects are different
  - Workers are different

Dawid and Skene model (DS)



LLM with parameters:

- p — vector of length K: $p[i] = \Pr(Z = c)$
- e^w — matrix of size $K \times K$: $e^w[c, k] = \Pr(Y^w = k | Z = c)$
- Model:
  - $Z_j \sim \mathrm{Mult}(p)$
  - $y_j^w \sim \mathrm{Mult}\left(e^w\left[z_j, \cdot\right]\right)$

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

DS: parameters optimization

- **E-step:**

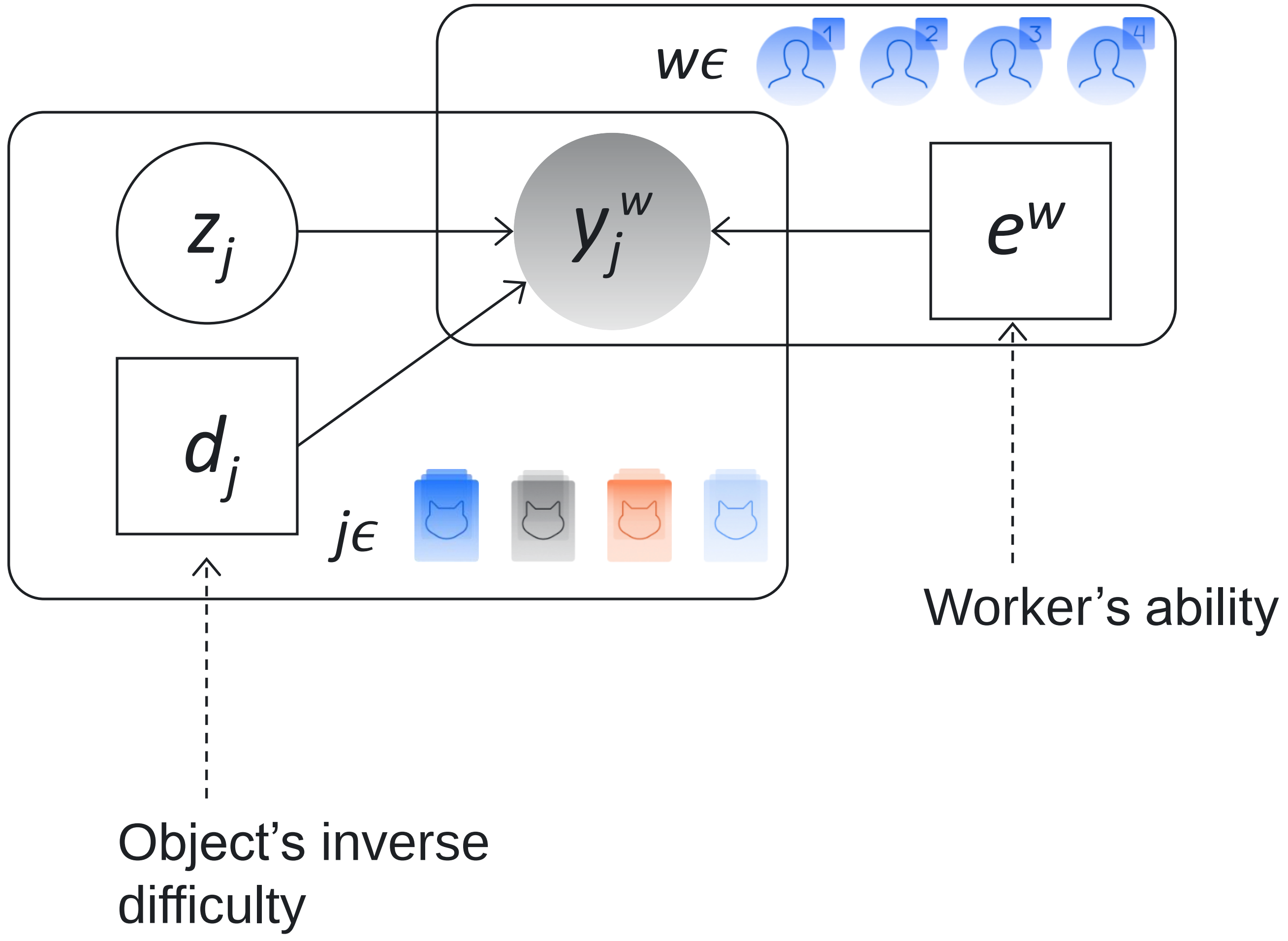
$$\hat{z}_j[c] = \frac{p[c]\ \prod_{w \in W_j} e^w\left[c, y_j^w\right]}{\sum_k p[k]\ \prod_{w \in W_j} e^w\left[k, y_j^w\right]}, \qquad c = 1, \dots, K$$

- **M-step:** Analytical solution

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

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

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



LLM with parameters:

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

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

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

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 $P(z_j)$ be a predefined prior (e.g., $P(z_j) = {}^1/_K$)

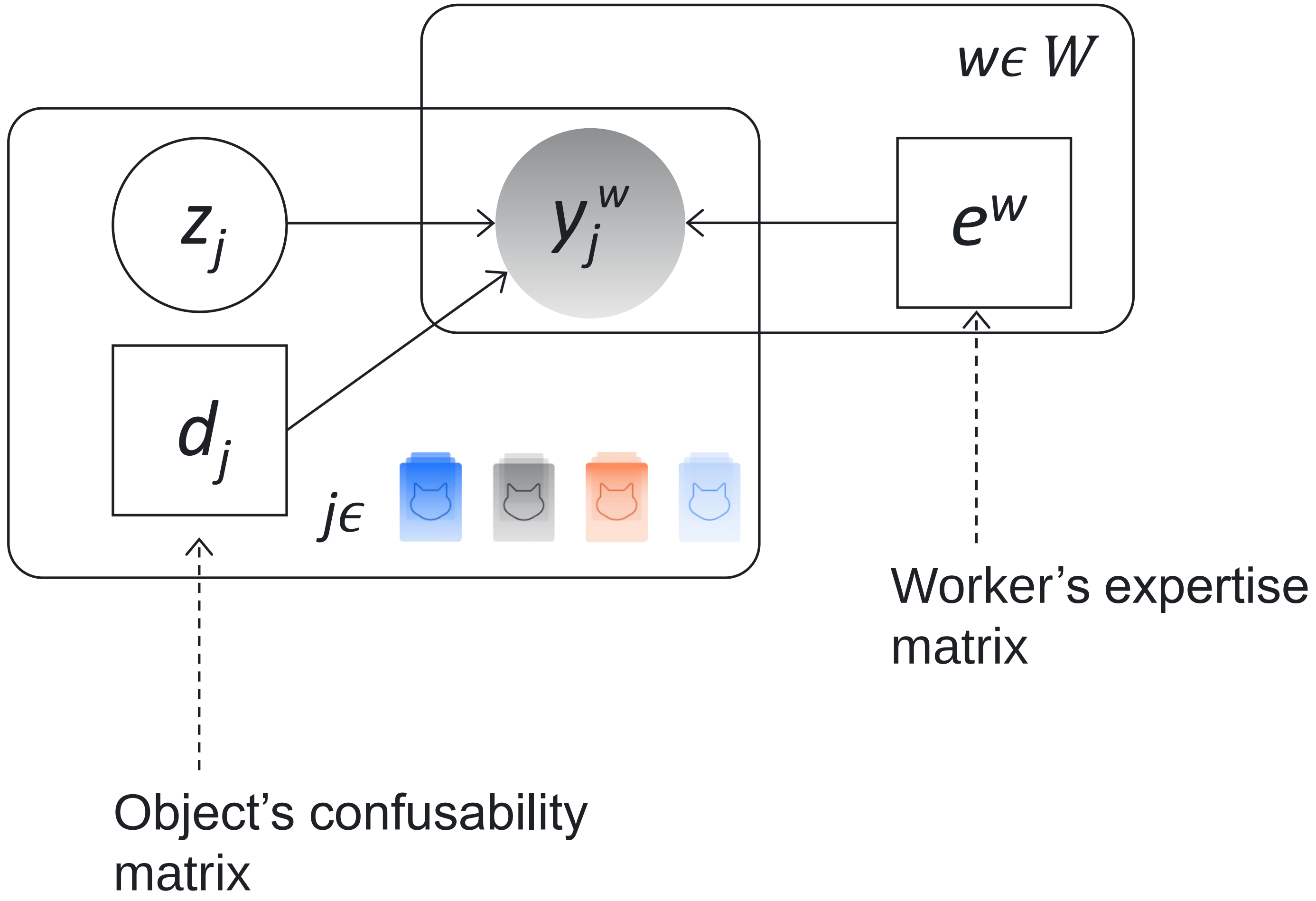
- **E-step:**

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

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

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

MiniMax Conditional Entropy model (MMCE)



- LLM with parameters:
  - d_j — matrix of size $K \times K$
  - e^w — matrix of size $K \times K$
  - Noisy label model*

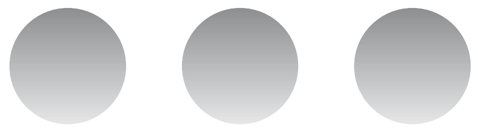
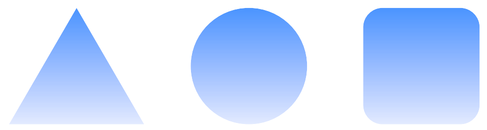
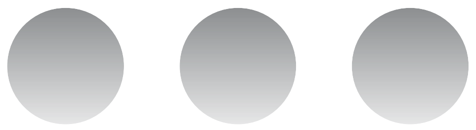
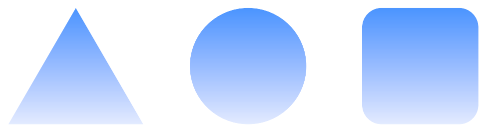
$$\Pr\left(Y_j^w = k | Z_j = c\right) = \exp\left(d_j[c,k] + e^w[c,k]\right)$$

*The model was derived by minimizing the maximum conditional entropy of observed labels

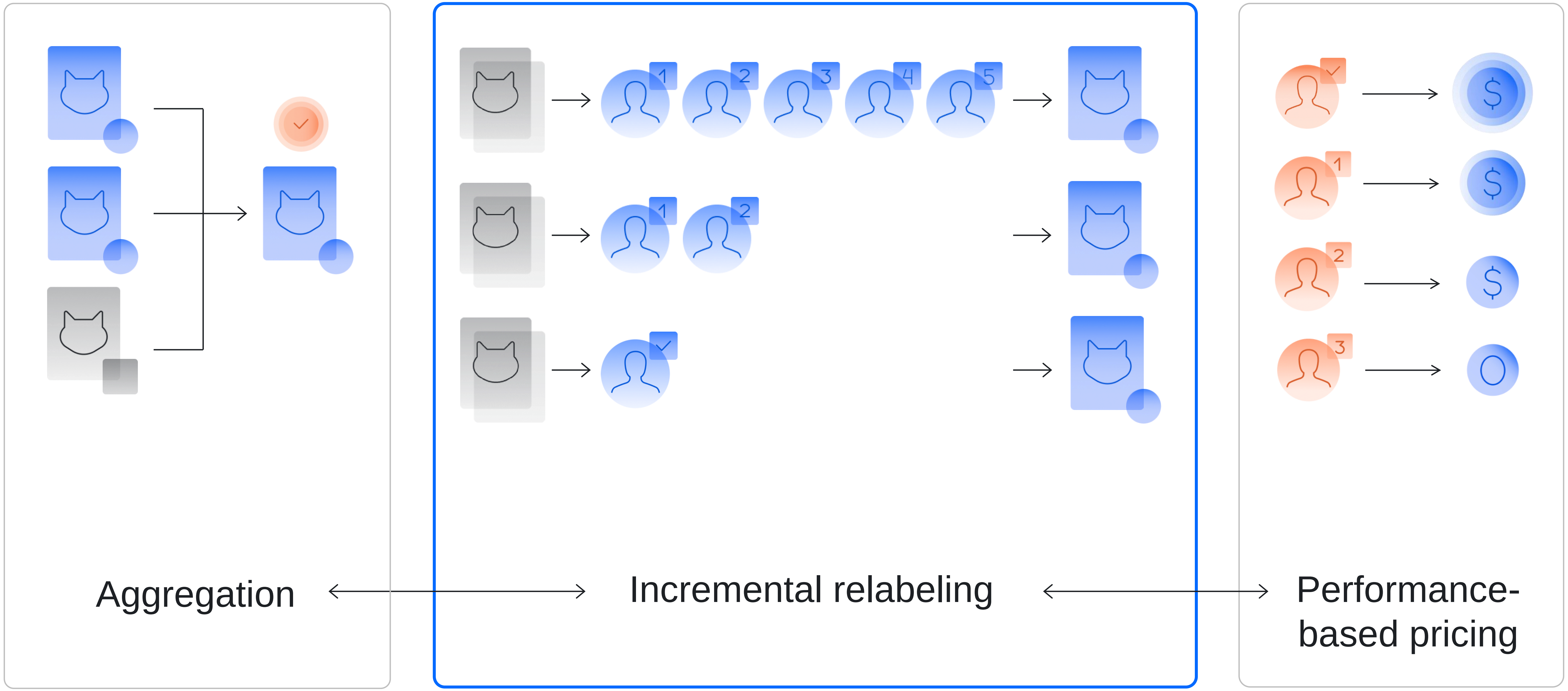
$$\min_Q \max_P - \sum_{\substack{j\in J \\ c\in\{1,\dots,K\}}} Q\left(Z_j = c\right) \sum_{\substack{w\in W \\ k\in\{1,\dots,K\}}} P\left(Y_j^w = k | Z_j = c\right) \log P\left(Y_j^w = k | Z_j = c\right)$$

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

Summary of aggregation methods

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

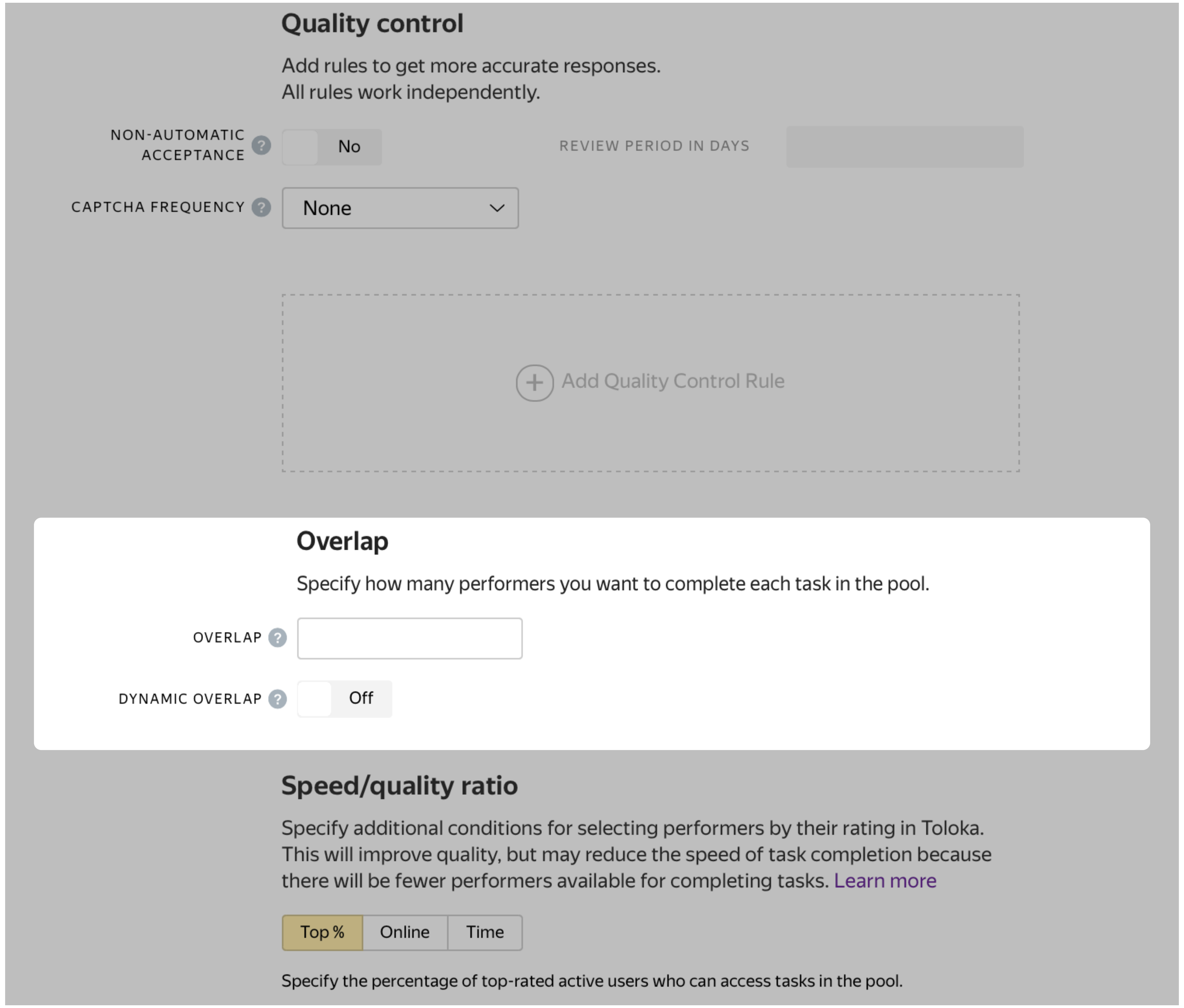
Key components of labeling with crowds



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

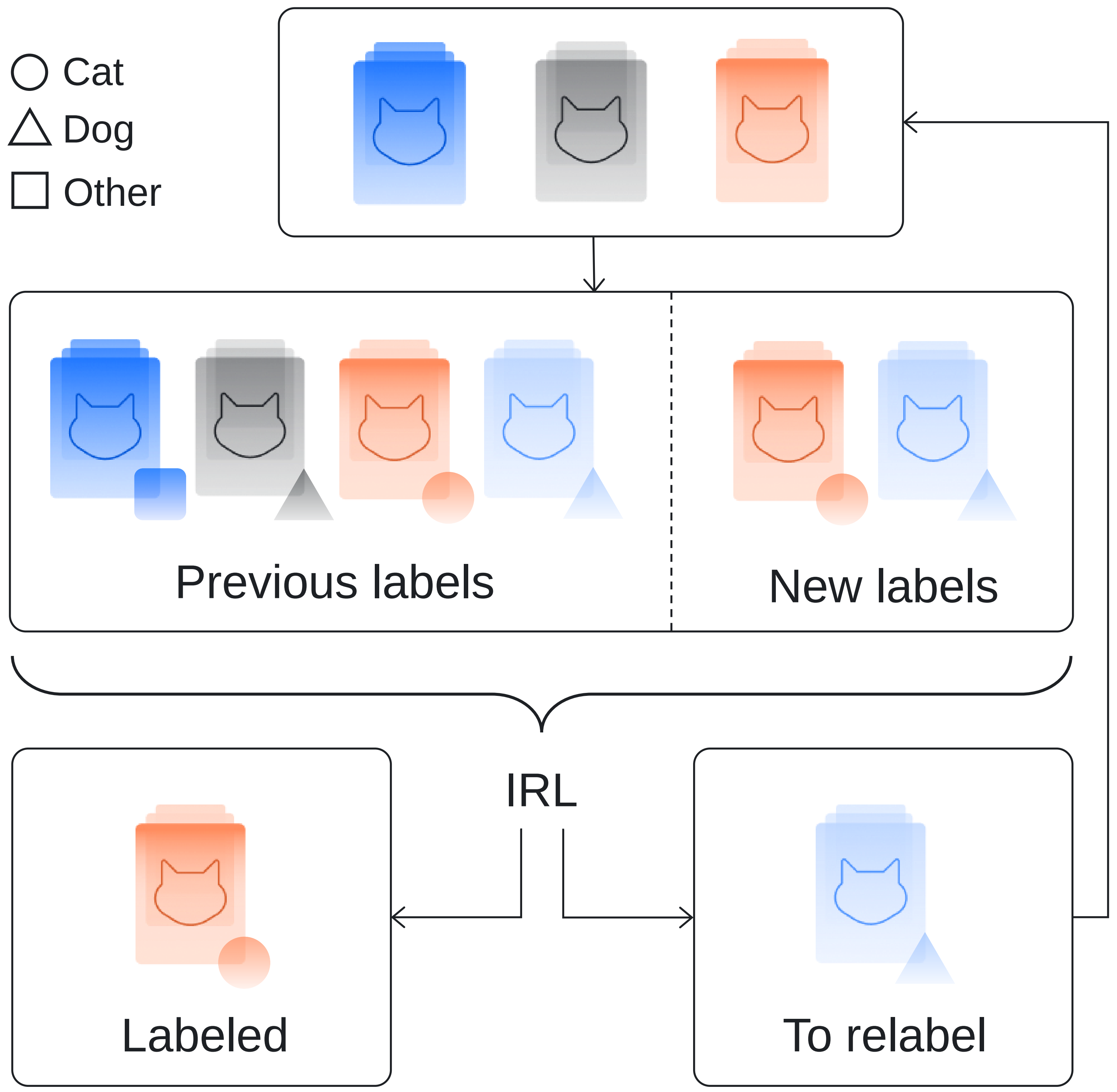
Incremental relabeling scheme (IRL)

Request 1 label for each object

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

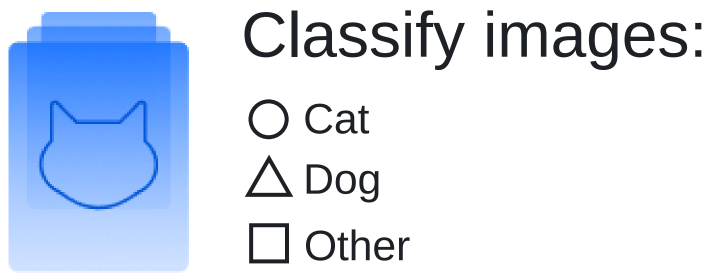
Decides:
(1) which objects are labeled
(2) which objects to relabel

Repeat until all tasks are labeled

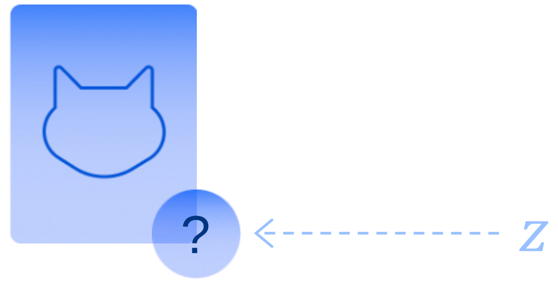


Notations

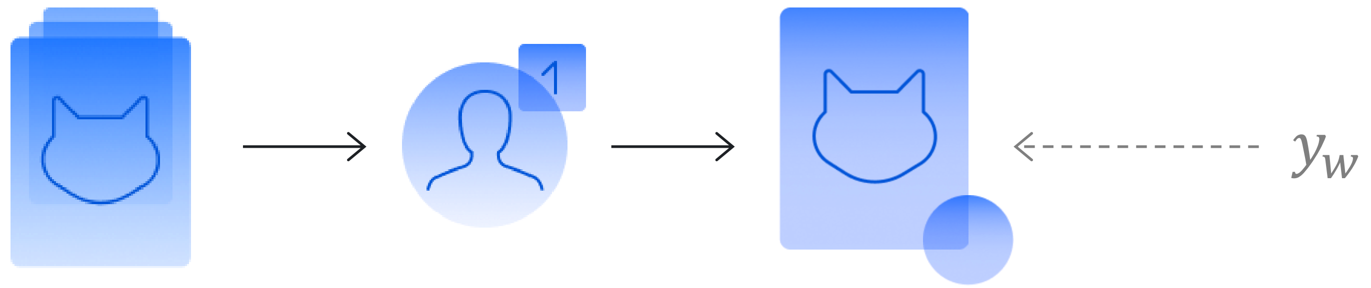
- Consider one object



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



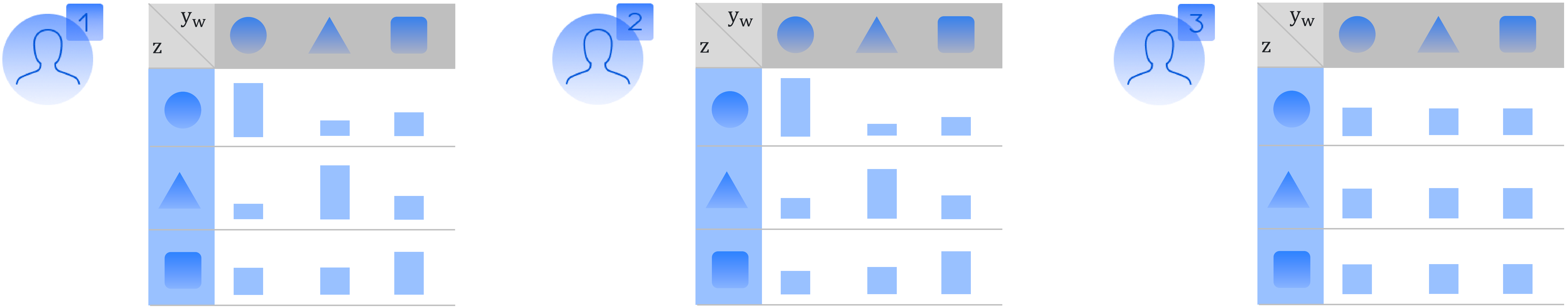
- $y_w \in \{1, \dots, K\}$ — observed noisy label from worker w:



Notations

- Noisy label model for worker w:

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



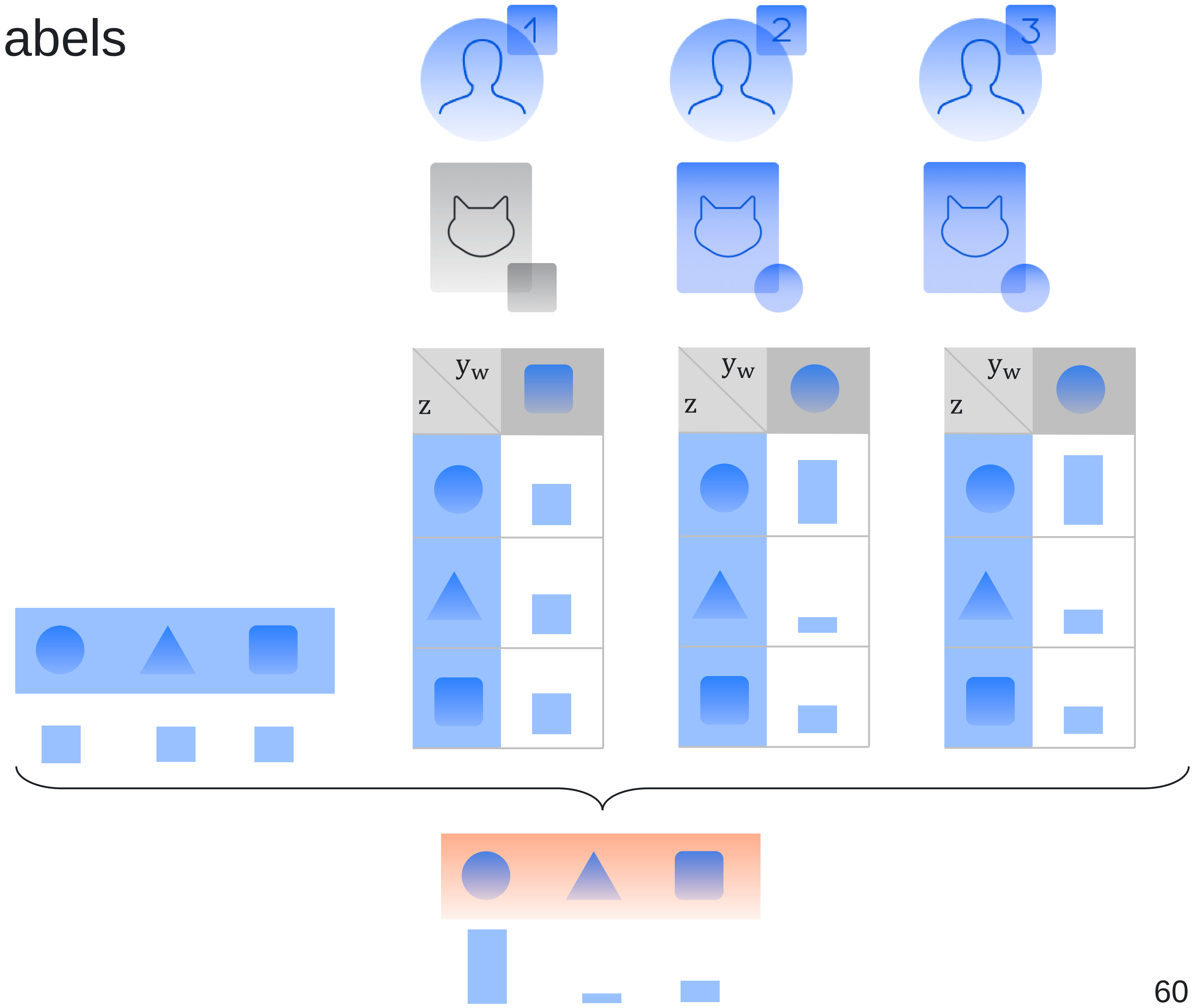
- Prior distribution: $\Pr(Z = k) = p_k$

Posterior distribution

- $\{y_{w_1}, \dots, y_{w_n}\}$ — accumulated noisy labels for the object

- Using Bayes rule:

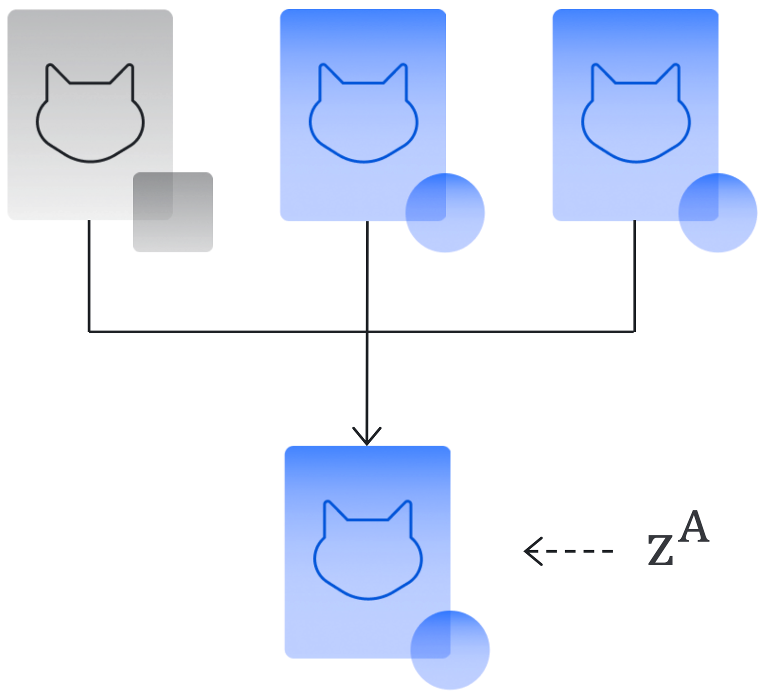
$$\Pr\left(Z = k \middle| \{y_{w_1}, \dots, y_{w_n}\}\right) = \frac{\Pr(Z = k)\Pr\left(\{y_{w_1}, \dots, y_{w_n}\} \middle| Z = k\right)}{\Pr\left(\{y_{w_1}, \dots, y_{w_n}\}\right)} = \frac{p_k \prod_{i=1}^{n} M_{w_i}\left[k, y_{w_i}\right]}{\sum_{t=1}^{K} p_t \prod_{i=1}^{n} M_{w_i}\left[t, y_{w_i}\right]}$$



Expected accuracy of aggregated labels

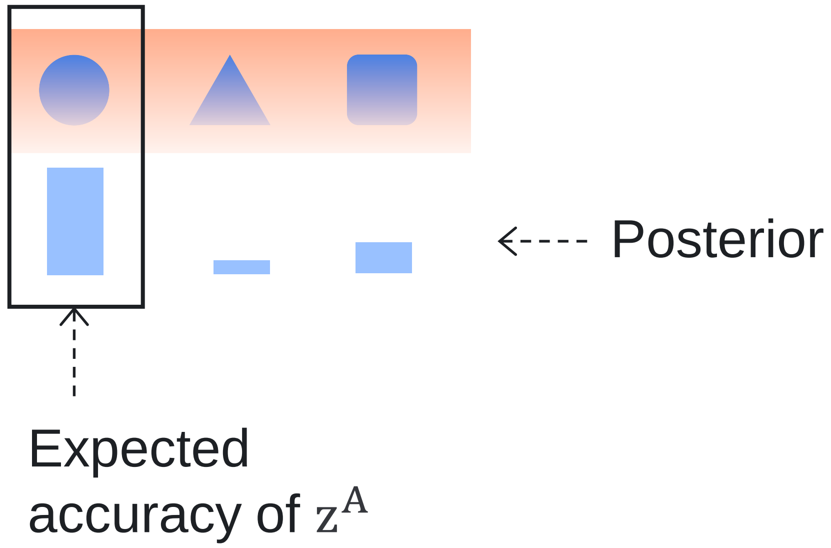
- Let A be an aggregation model, e.g. MV, DS, GLAD,…
- Denote aggregated label $z^A = A(\{y_{w_1}, \ldots, y_{w_n}\})$
- Expected accuracy of aggregated labels given noisy labels is

$$E(\delta(z = z^A) | \{y_{w_1}, \ldots, y_{w_n}\}) = \Pr(z = z^A | \{y_{w_1}, \ldots, y_{w_n}\})$$



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

Parameter



Incremental relabelling algorithm

Input: $\cup_{t=1}^{T-1} Y^t$ — previous labels till step T

Y^T — new labels

Output: R — objects to relabel

For each object j with a label in Y^T: ← Object with a new label

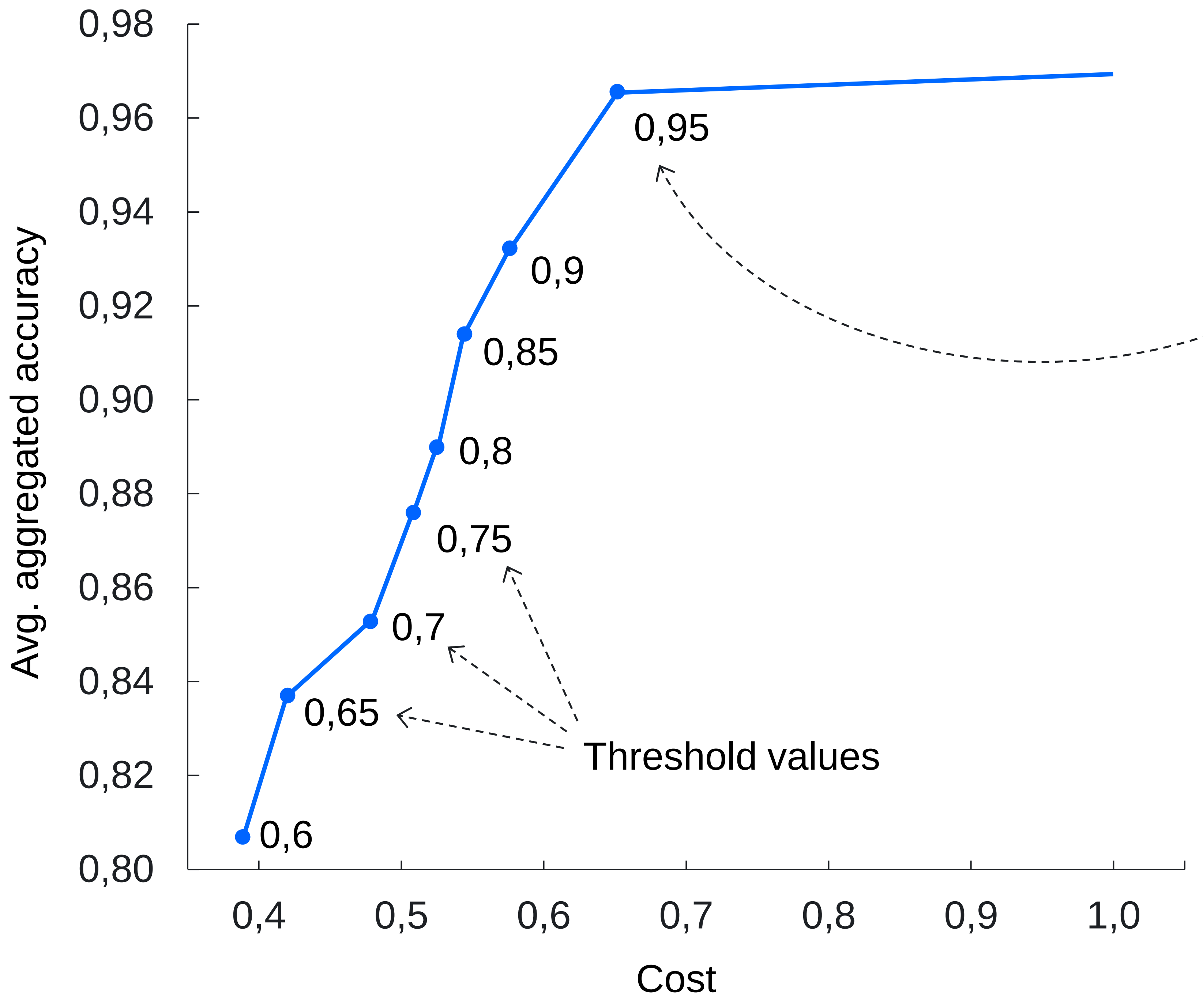
$z_j^M = M(\cup_{t=1}^{T} Y^t)$ ← Current aggregated label

$c_j = E(z_j = z_j^M \mid \cup_{t=1}^{T} Y^t)$ ← Expected accuracy for the current aggregated label

If $c_j < c$, then $R = R \cup j$

Parameter: c — threshold for expected accuracy

Threshold in IRL: cost – accuracy trade-off



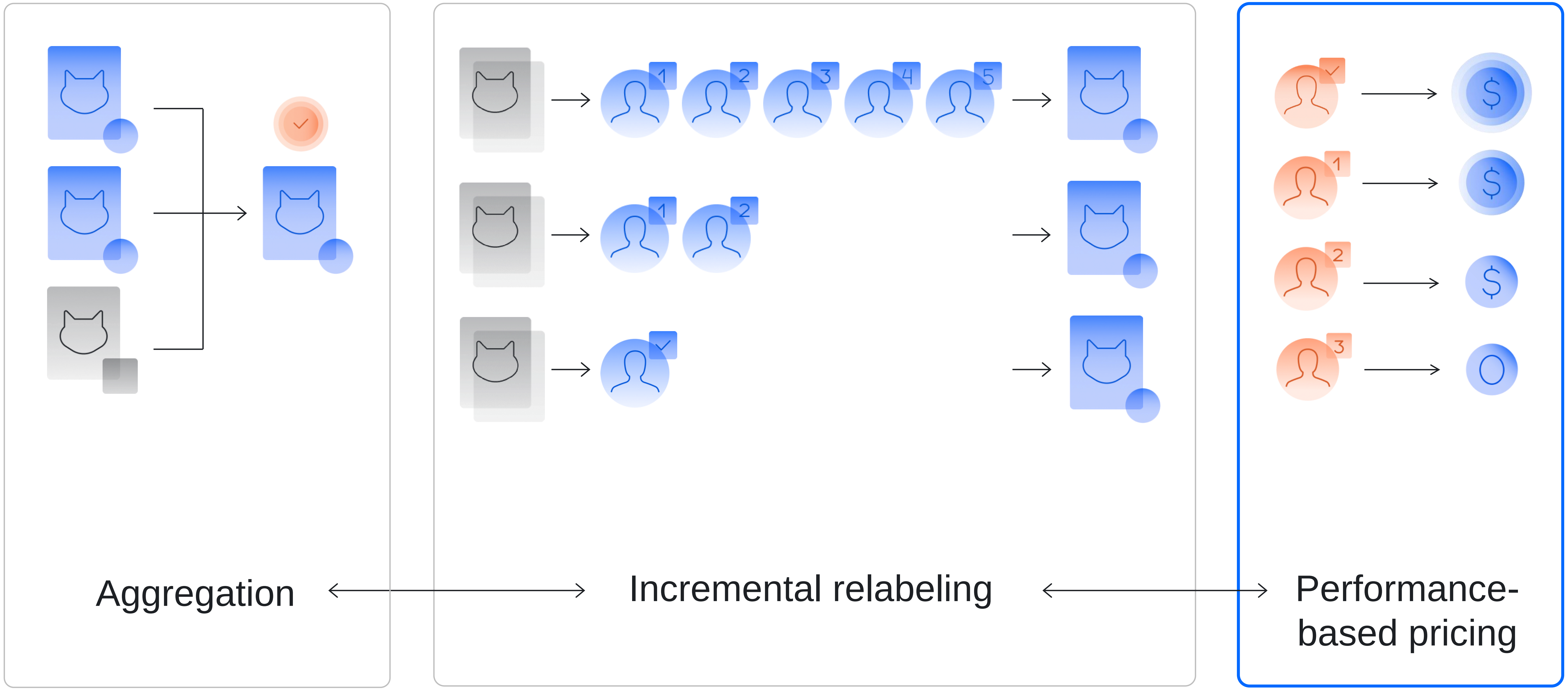
- Optimal threshold $c = 0.95$
- A higher c does not increase accuracy
- Saving ≈ 35% of noisy labels

How to obtain a cost-accuracy plot

Data for the plot:
- ► Label a pool of objects with a redundant overlap (e.g., 10)
- ► Obtain ground truth labels for the objects (e.g., expert labels or MV labels)

Simulate IRL with different thresholds using the data:
- ► For each threshold c from a grid $0 < c_0 < \ldots < c_m \leq 1$
- ► Repeat N times:
  1. Shuffle noisy labels and fix the order of labels
  2. Draw labels sequentially and test the IRL condition after each label
  3. Once the IRL condition for an object is met, discard unused labels for the object
  4. When all objects are labelled calculate
     - accuracy of aggregated labels
     - cost as the fraction of used noisy labels
- ► Average N values of aggregated accuracy and N values of cost for each value of threshold c

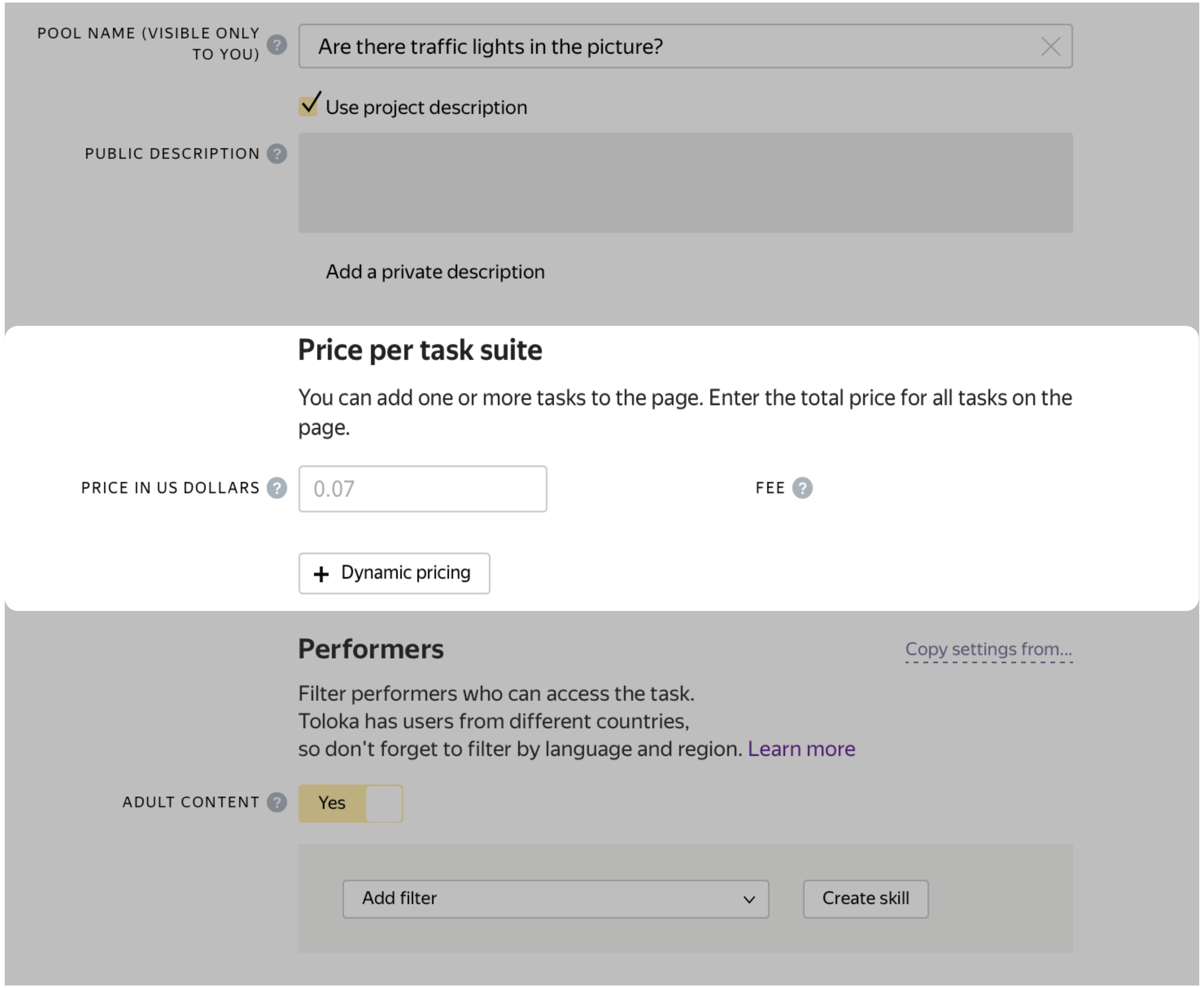
Key components of labeling with crowds



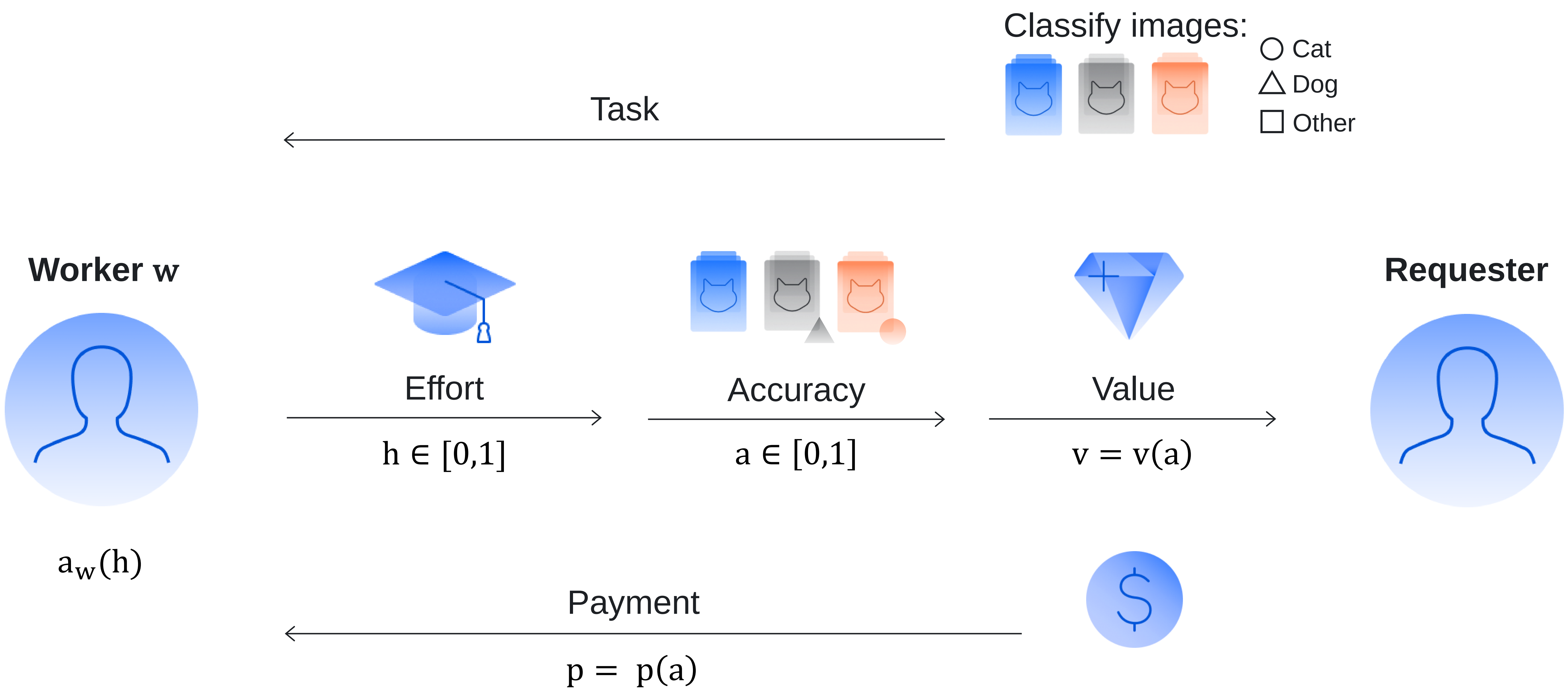
Performance-based pricing

aka dynamic pricing

Pool settings: dynamic pricing



Labeling as a game: notation



Labeling as a game: formalization

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

$$\frac{p\left(a_w(h)\right)}{h} \to \max_{h \geq 0}$$

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

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

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

Theorem: the requester and workers 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 worker 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 $\hat{z}_j^{\mathrm{wMV}} = \arg\max_{y=1,\ldots,K} \sum_{w \in W_j} \hat{q}_w \delta(y = y_j^w)$

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

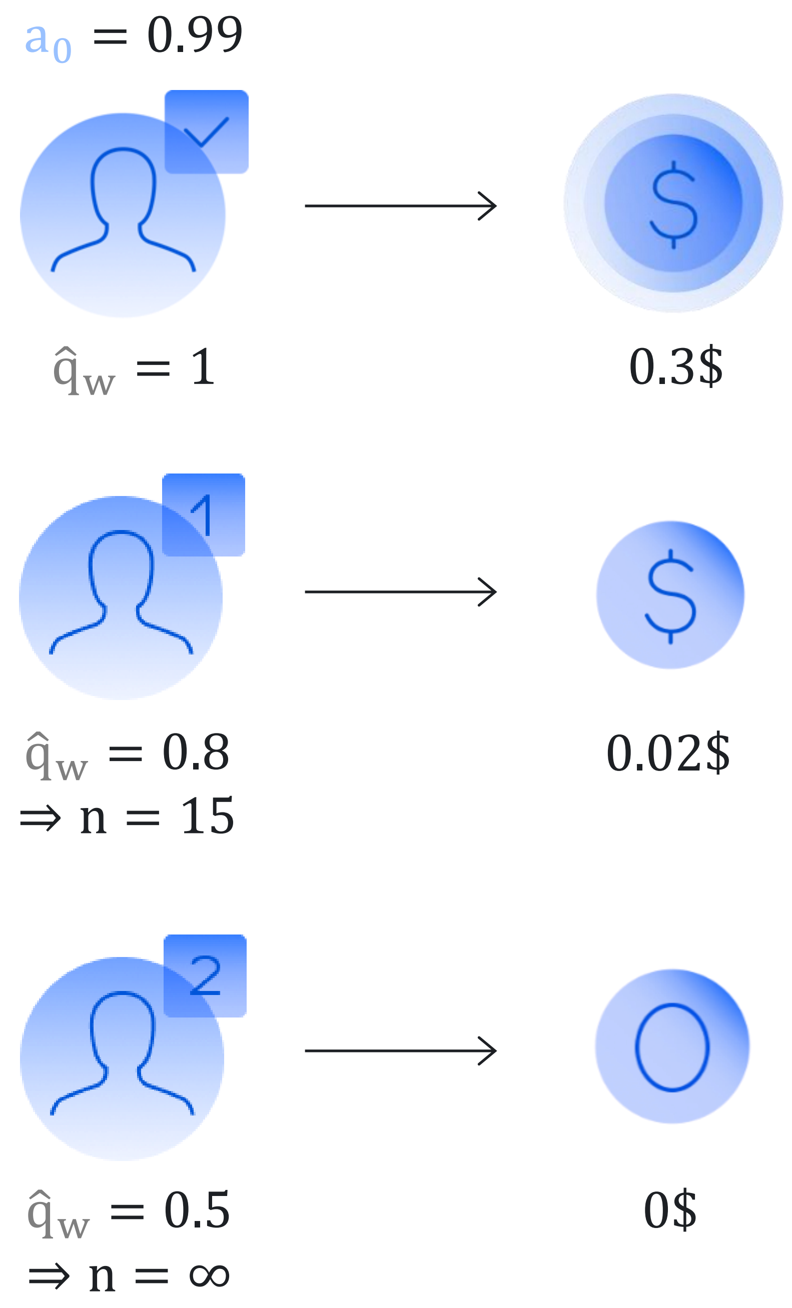
Performance-based pricing in practice

- Pricing rules

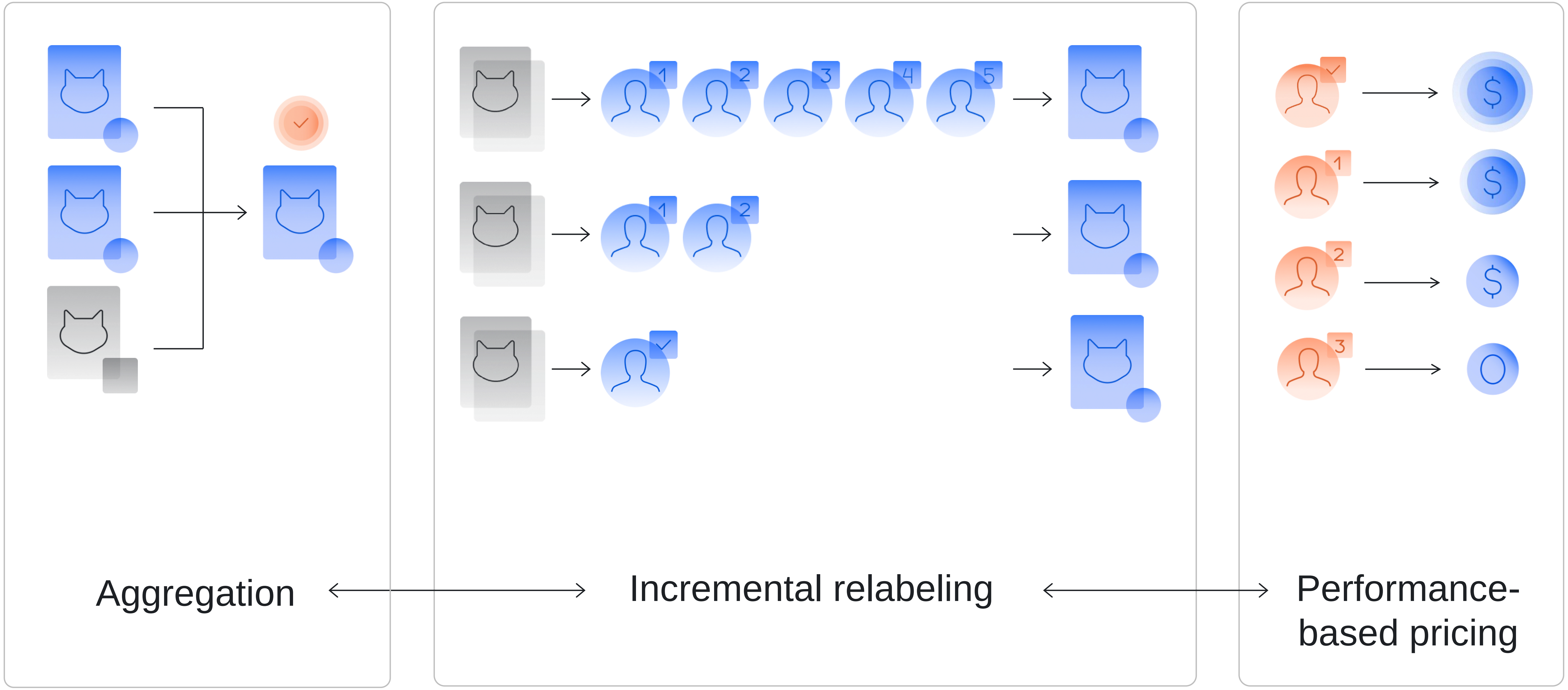
1. If $\hat{q}_w \geq a_0$, then the price is p
2. Else find n:

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

The price is p/n



Key components of labeling with crowds

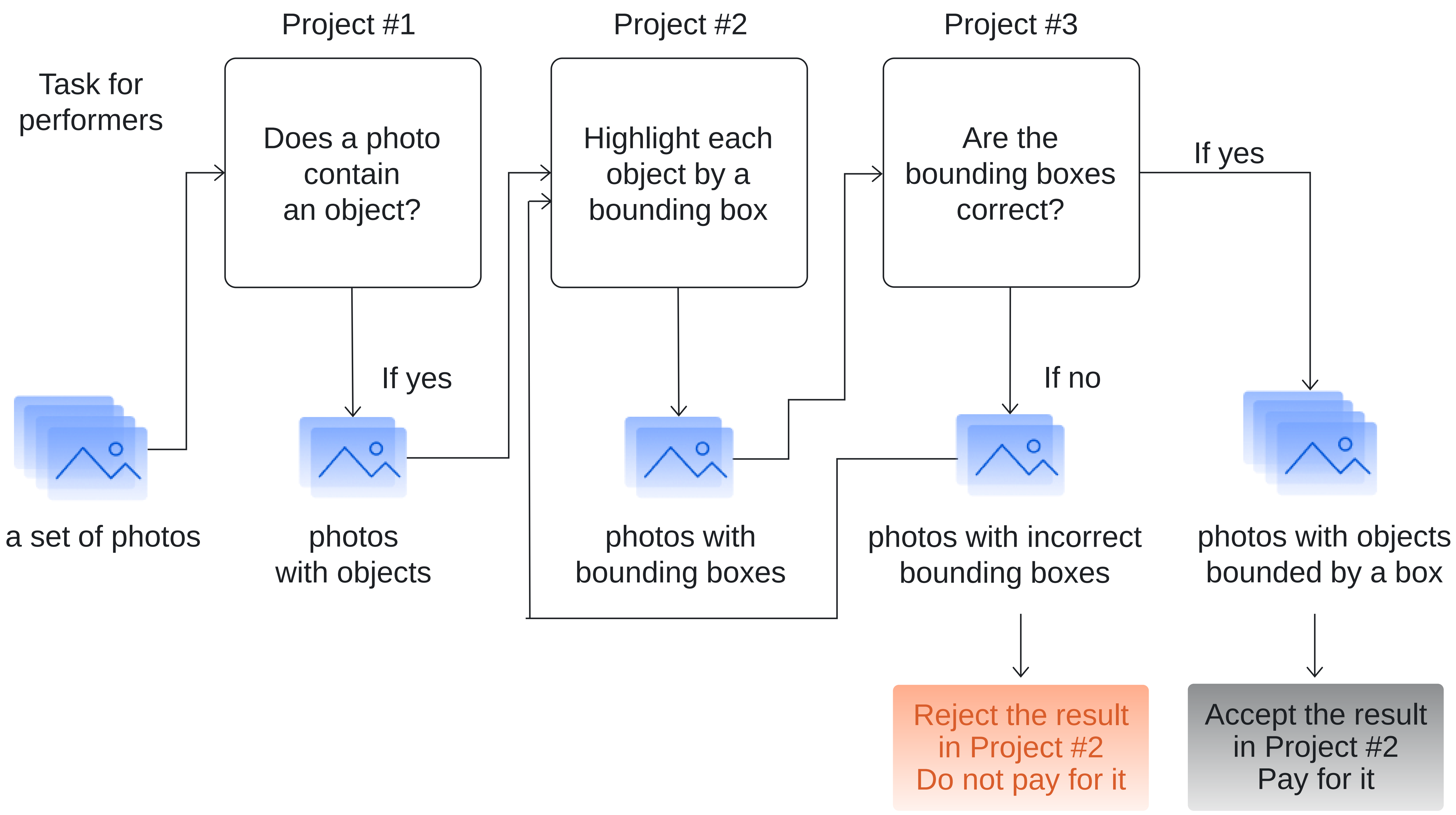


Part VI

Discussion of results from the projects. Conclusions

Olga Megorskaya,
CEO

Reminder: we implemented the pipeline



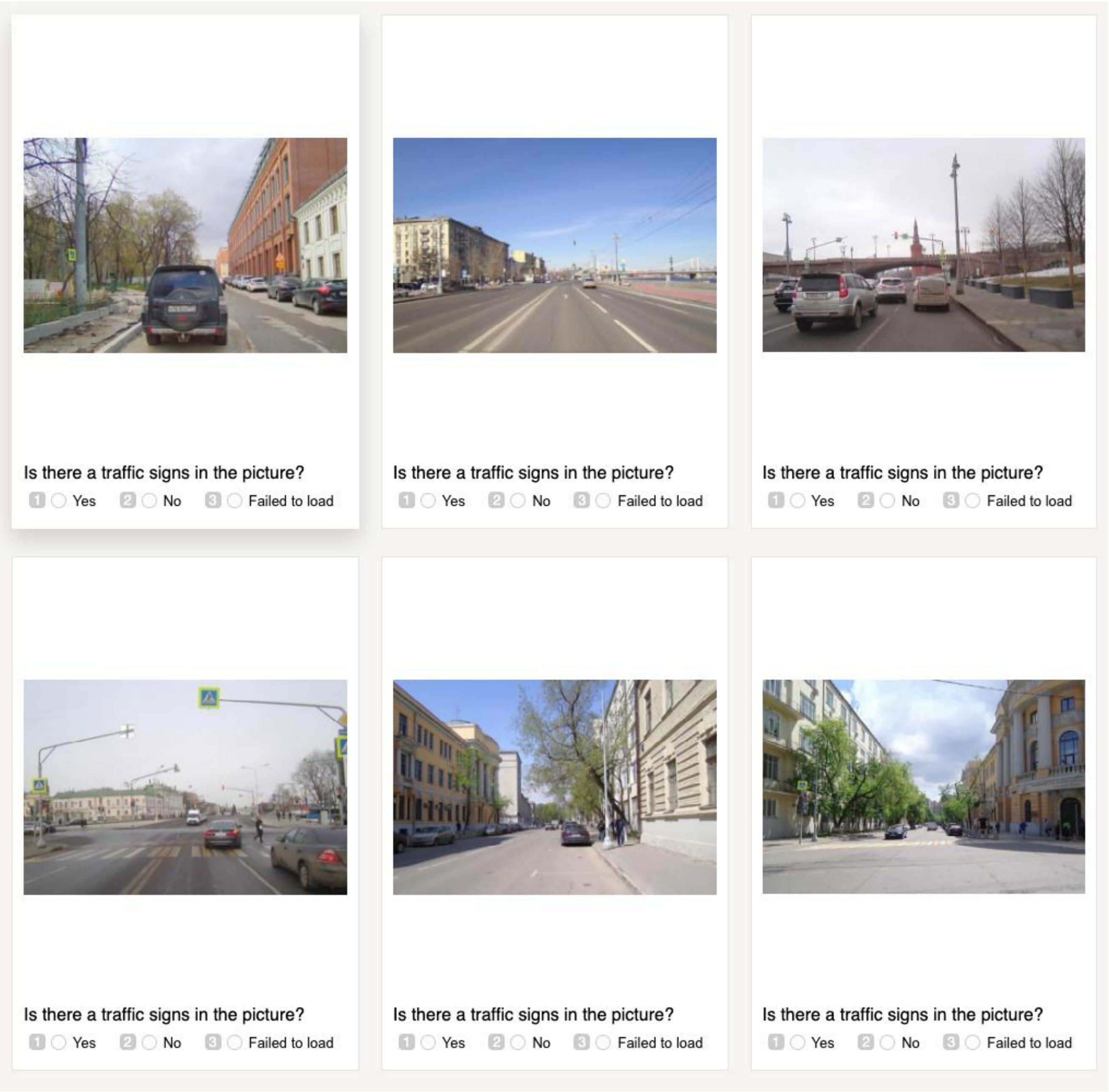
Project #1: Filter out photos without objects

Task

- Does a photo contain objects of desired type?

Our results:

- 100 photos evaluated
- Within 4 min on real performers
- Cost: $0.3 + Toloka fee



Project #2: Highlighting objects by rectangles

Task

- ► Highlight each object of desired type by a bounding box

Our results:

- ► 67 photos processed
- ► Within 5.5 min on real performers
- ► Cost: $0.67 + Toloka fee

Project #3: Accept correct bounding boxes

Task

- Are the objects of desired type highlighted by the bounding boxes correctly?

Our results:

- 90 photos evaluated
- Within 5 min on real performers
- Cost: $0.36 + Toloka fee

Statistics over the whole pipeline

- 100 photos processed to highlight desired objects
- Within 14.5 min on real performers
- Total cost: $1.33 + Toloka fee
- Quality of the final result (via manual assessment):
  - Recall: 90% (measured on results of Project #1)
  - Precision: 86% (measured on results of Project #2)

Afterparty: upgrade your pipeline

To obtain more comprehensive data

- ► Use Polygons instead of Bounding boxes
- ► Highlight more object types

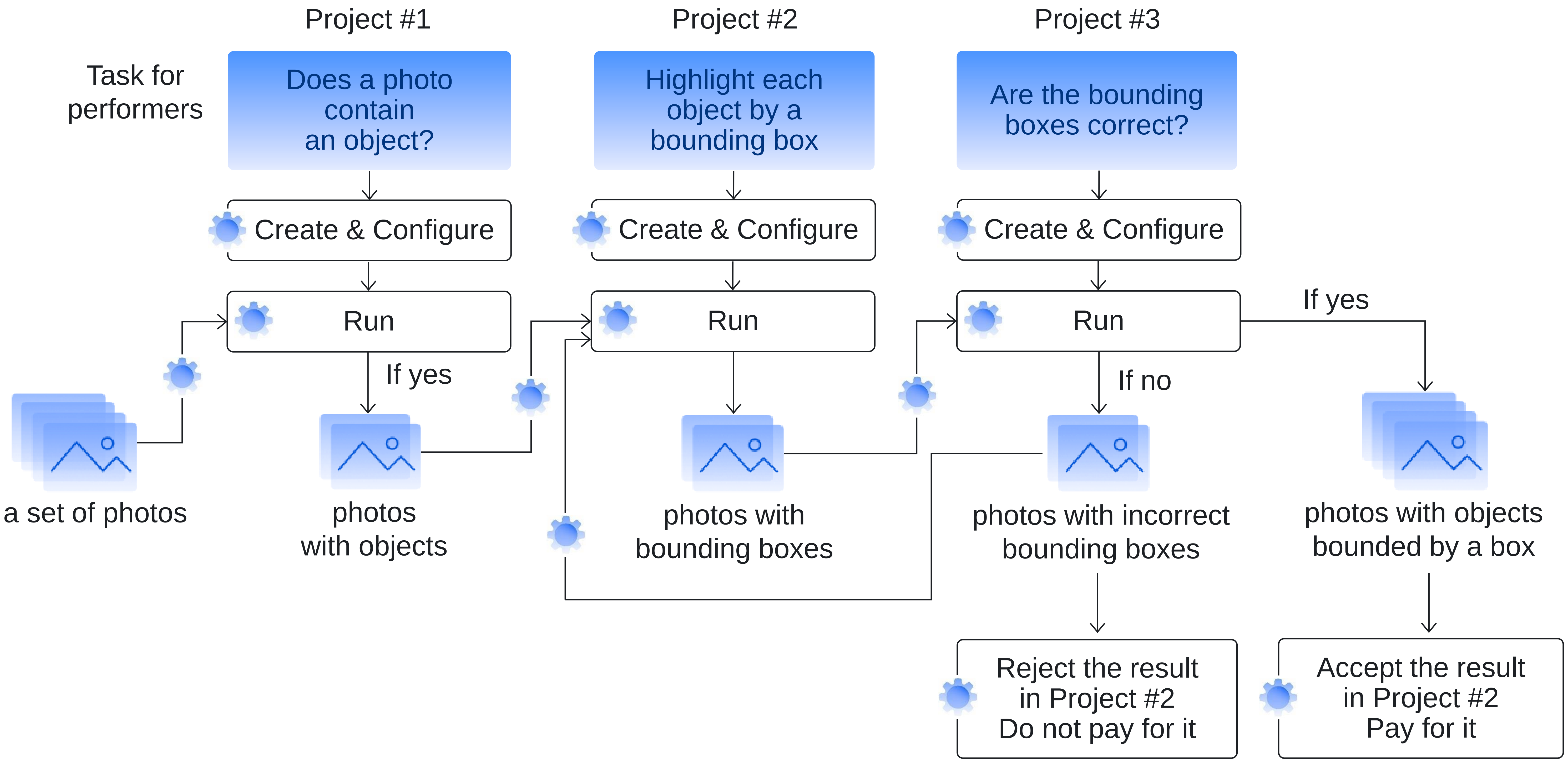
To reduce costs

- ► Use incremental relabeling aka Dynamic overlap

To improve quality

- ► Use dynamic pricing
- ► Add more Golden Sets and hints
- ► Experiment with aggregation methods
- ► Add training for workers

API of Toloka



API of Toloka

Allows you to automate all steps of our pipeline

- Discover at: https://yandex.com/dev/toloka/

Crowdsource all types of data

Search Relevance

Moderation

Generation of content

Computer vision

Speech Technologies

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