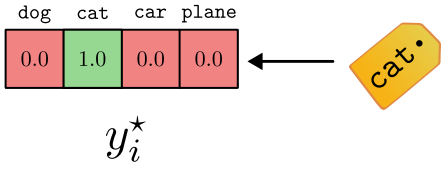
Label ambiguity in crowdsourcing for classification and expert feedback

Tanguy Lefort
IMAG, Univ Montpellier, CNRS
INRIA, LIRMM,

Supervised by
Benjamin Charlier
Alexis Joly
and **Joseph Salmon**

How to train your classifier

x_i



$y_i^\star$

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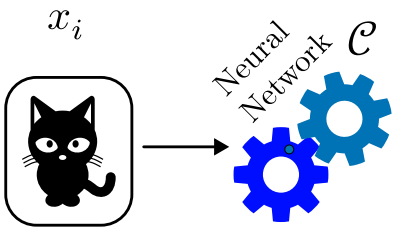

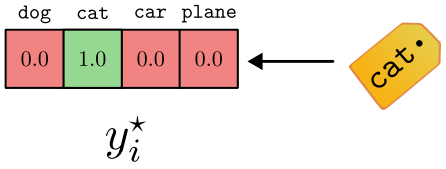

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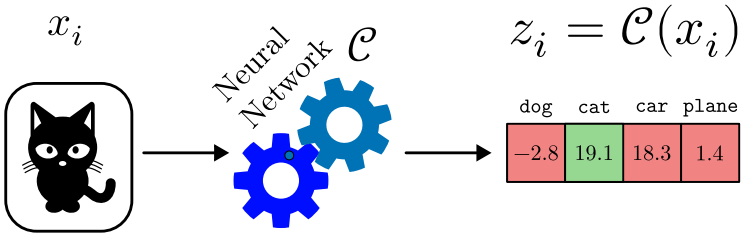

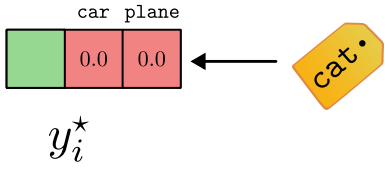

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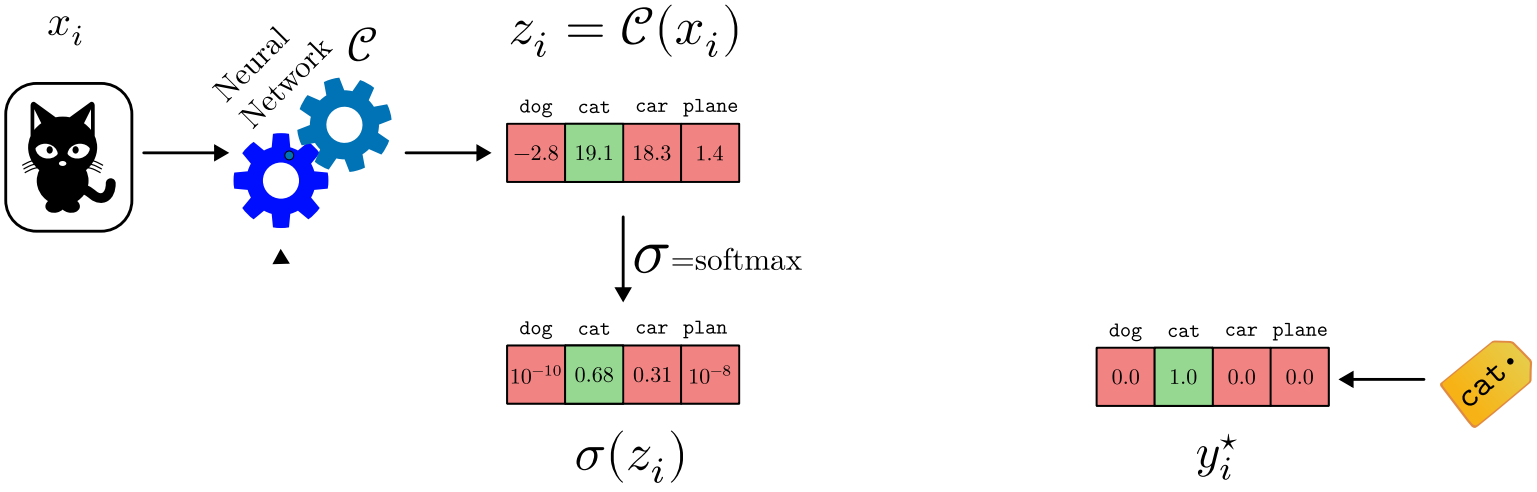

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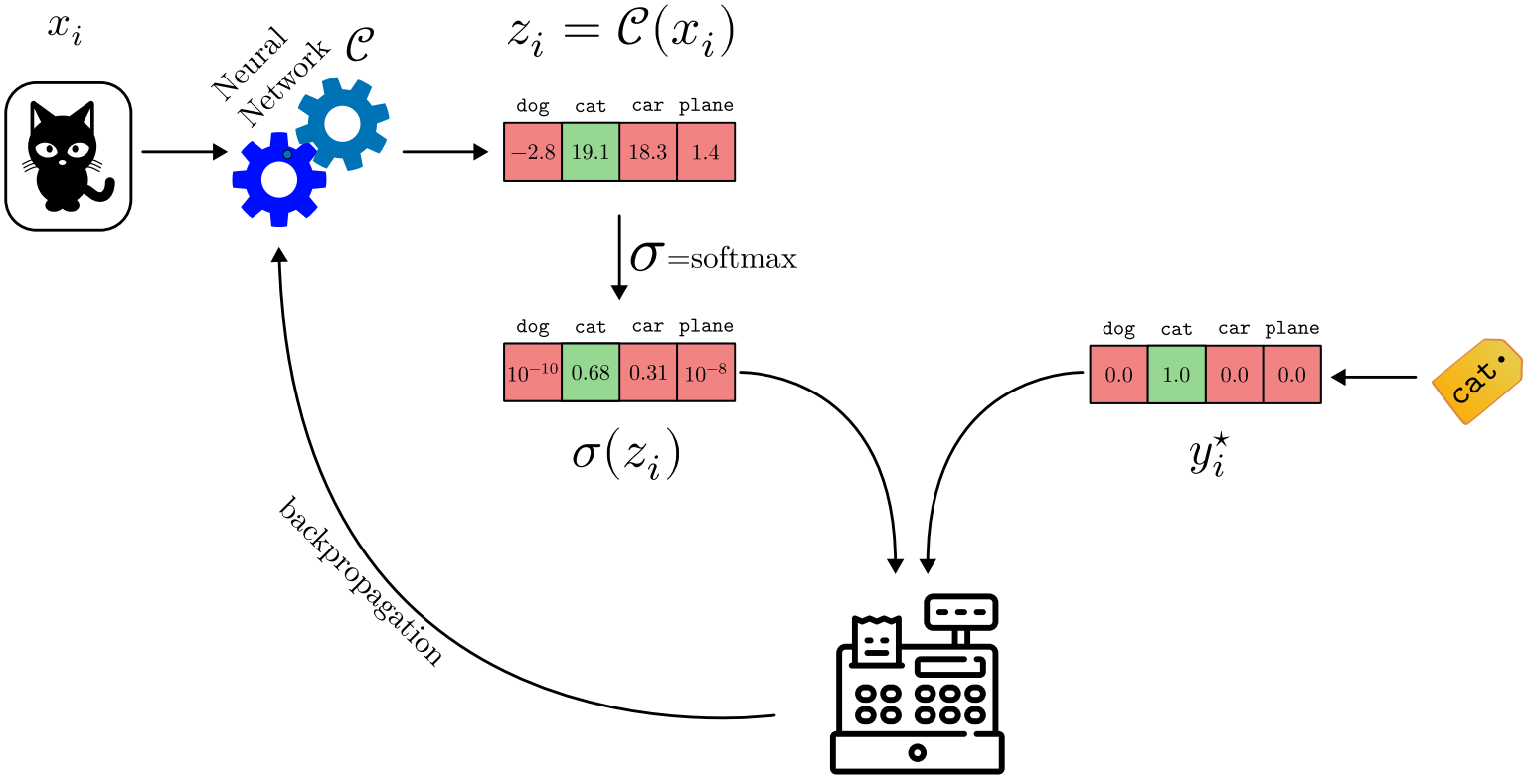

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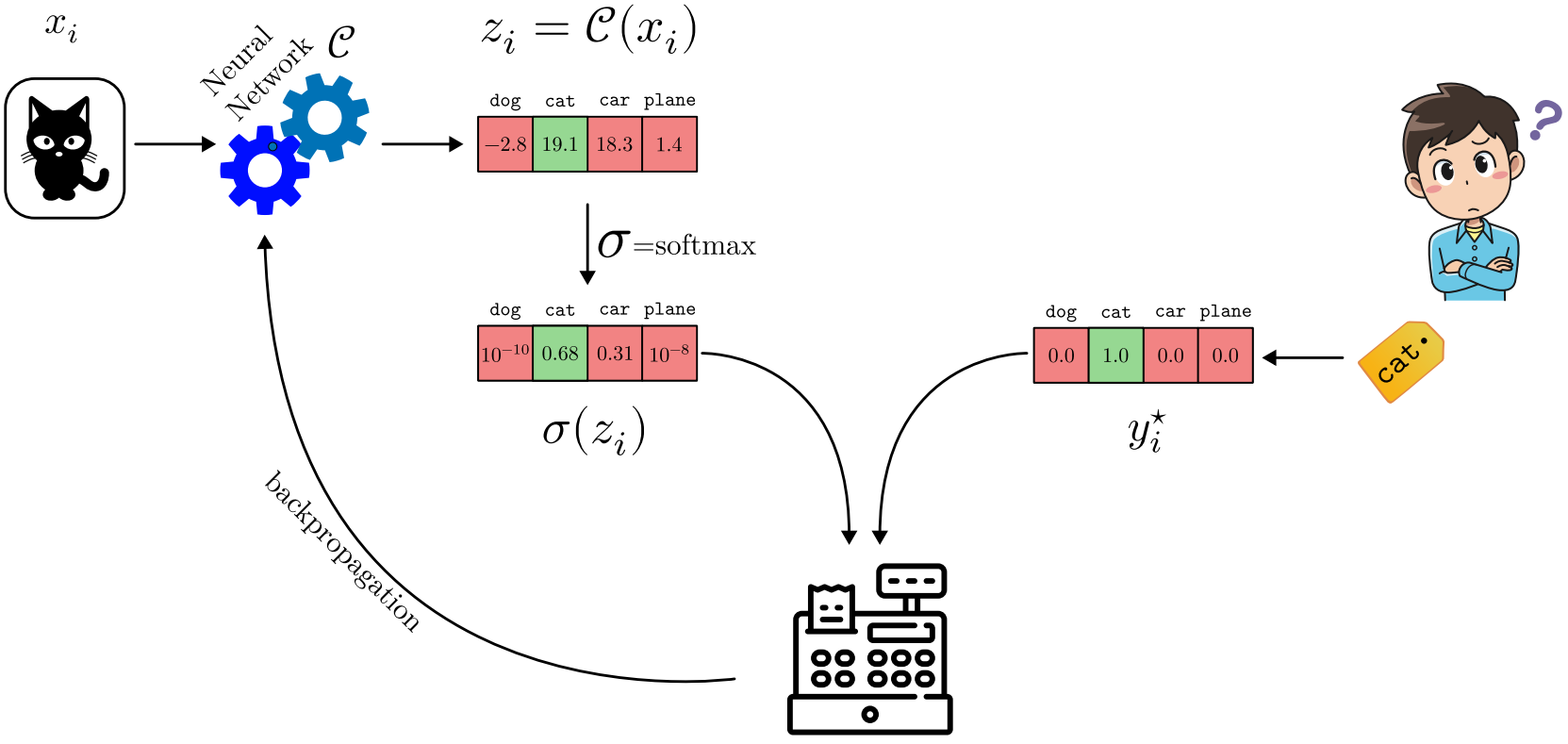
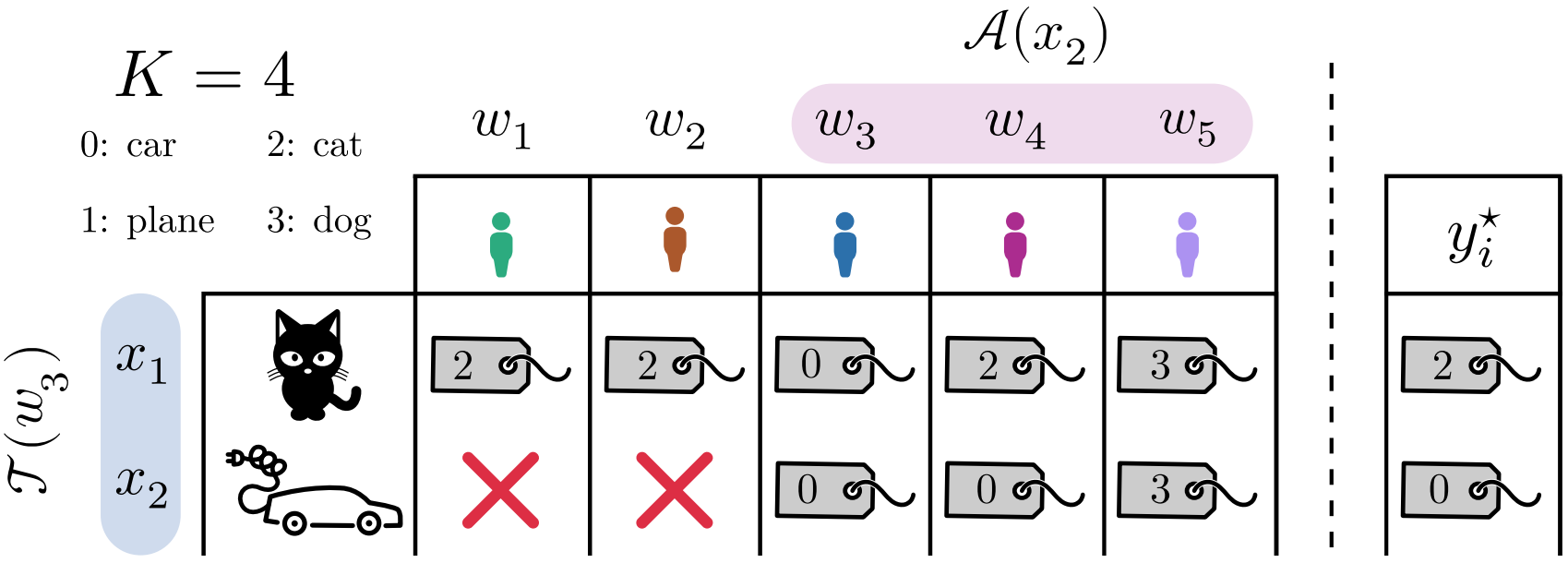


Ask citizens to label our data

Framework and notations

- Workers sort a given task into one of the K classes



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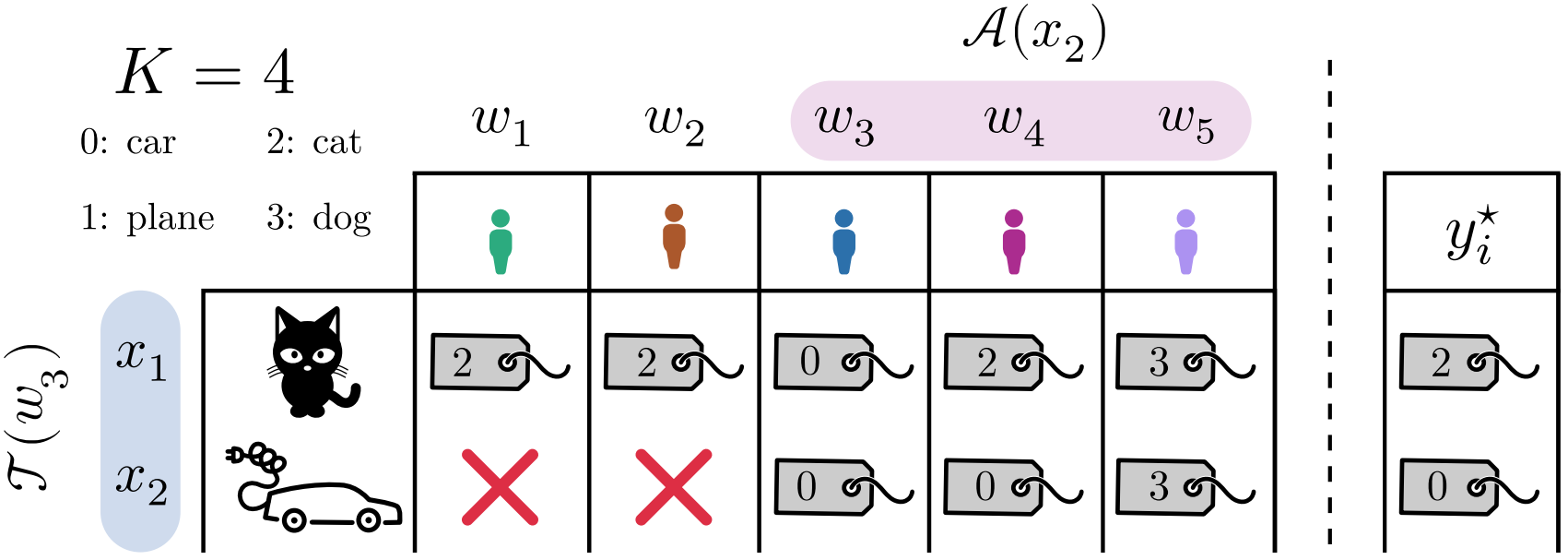
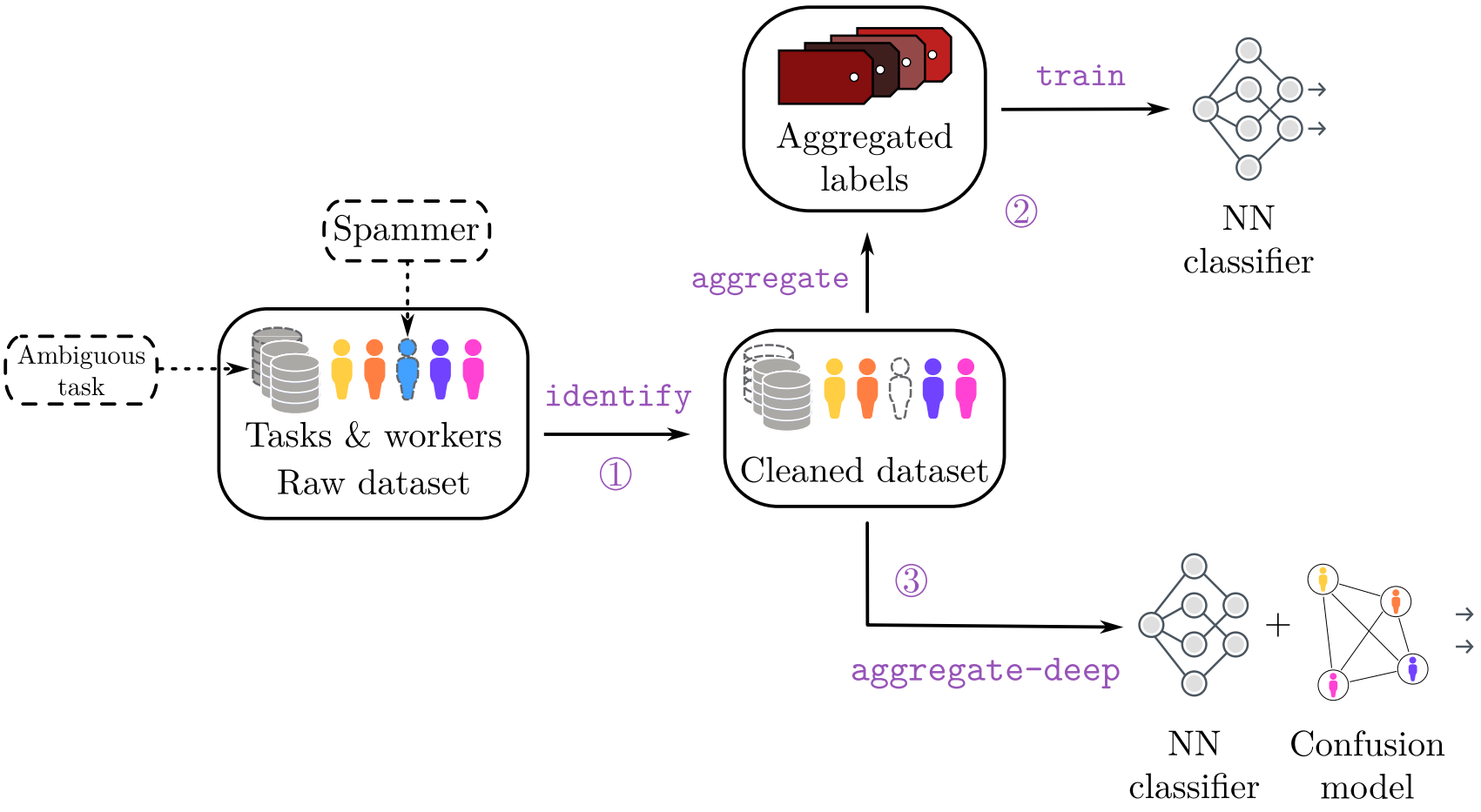


- $y_i^{(j)} \in [K] :=$ answer of worker j to task i

From the data to the classifier

The pipeline



Main contributions

- Can we improve performance by leveraging better-quality data

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- Release a real, large-scaled dataset with `Pl@ntNet`
  - Creation and evaluation of a **new benchmark dataset**

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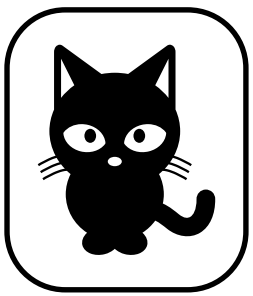
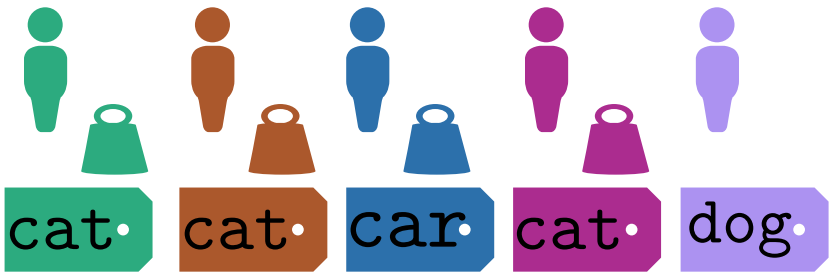
Classical aggregation strategy
(Weighted) Majority Votes

$$\hat{y}_i^{\text{WMV}} = \underset{k \in [K]}{\text{argmax}} \sum_{j \in \mathcal{A}(x_i)} \text{⚖}_j \, \mathbb{1}(y_i^{(j)} = k)$$

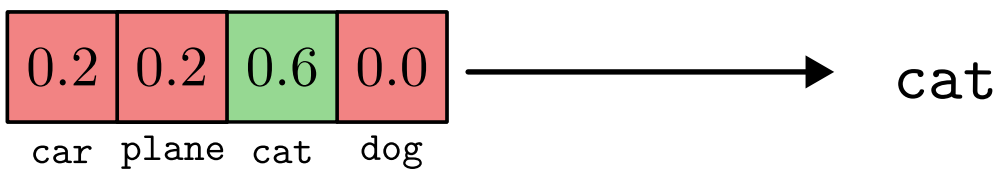
For example with equal weights:





0: car 2: cat

1: plane 3: dog



Classical aggregation strategy
(Weighted) Majority Votes

Many existing weight choices:

- WAWA[3]:

$$\text{weight}(w_j) = \text{Accuracy}(\{y_i^{(j)}\}_i, \{\hat{y}_i{}^{\text{MV}}\}_i)$$

- Shapley based[4]

- Matrix completion (MACE)[5] ...

Pros: "simple" weight can scale to large datasets and be easy to interpret
Cons: Can not capture worker skills in detail

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[3] `https://success.appen.com/hc/en-us/articles/202703205-Calculating-Worker-Agreement-with-Aggregate-Wawa`

[4] T. Lefort et al. (July 2024b). "Weighted majority vote using Shapley values in crowdsourcing". In: *CAp 2024 - Conférence sur l'Apprentissage Automatique*. Lille, France.

[5] D. Hovy et al. (2013). "Learning whom to trust with MACE". In: *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 1120–1130.

Classical aggregation strategy

Dawid and Skene[6]

- Represent workers from their pairwise confusions matrix $\pi^{(j)} \in \mathbb{R}^{K \times K}$
- Probabilistic model on their answers:

$$y^{(j)} | y^\star \sim \text{Multinomial}(\pi^{(j)}_{y^\star, \bullet})$$

with $\pi^{(j)}_{k,\ell} = \mathbb{P}(\text{worker } j \text{ answers } \ell \text{ with unknown truth} k)$

Pros:

- Finer modelisation
- Can use adversarial workers

Cons:

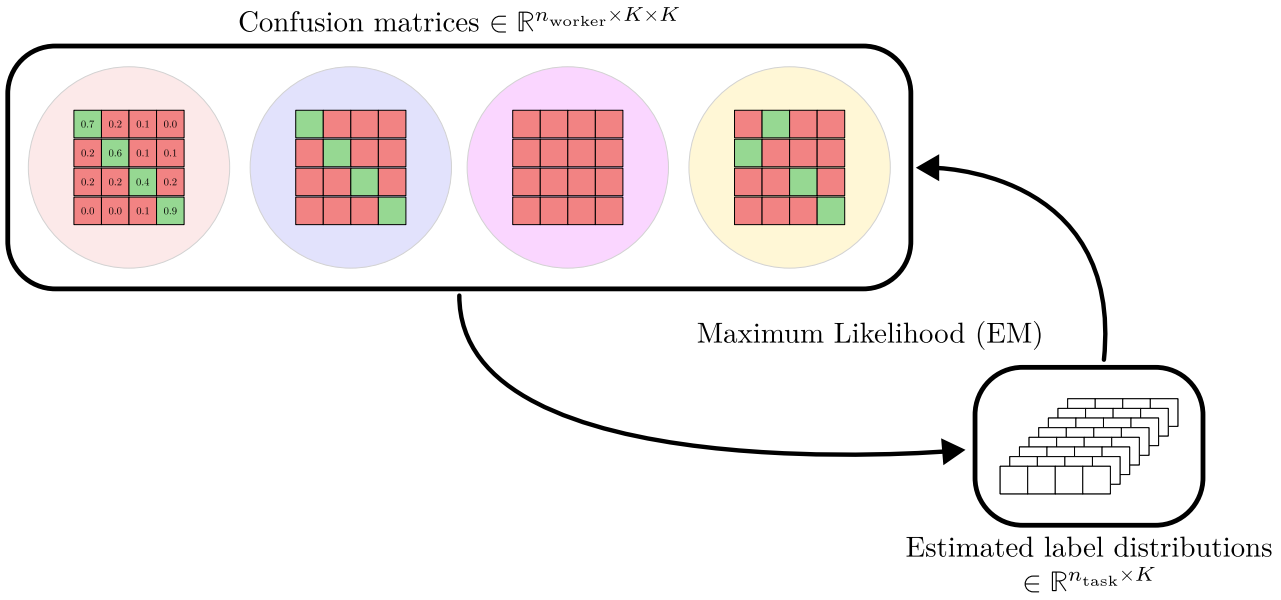
- Memory issue: $n_{\texttt{worker}} \times K^2$ parameters to estimate only the confusion matrices

[6] A. Dawid and A. Skene (1979). "Maximum Likelihood Estimation of Observer Error-Rates Using the EM Algorithm". In: *J. R. Stat. Soc. Ser. C. Appl. Stat.* 28.1, pp. 20–28.

Classical aggregation strategy

Dawid and Skene – Model

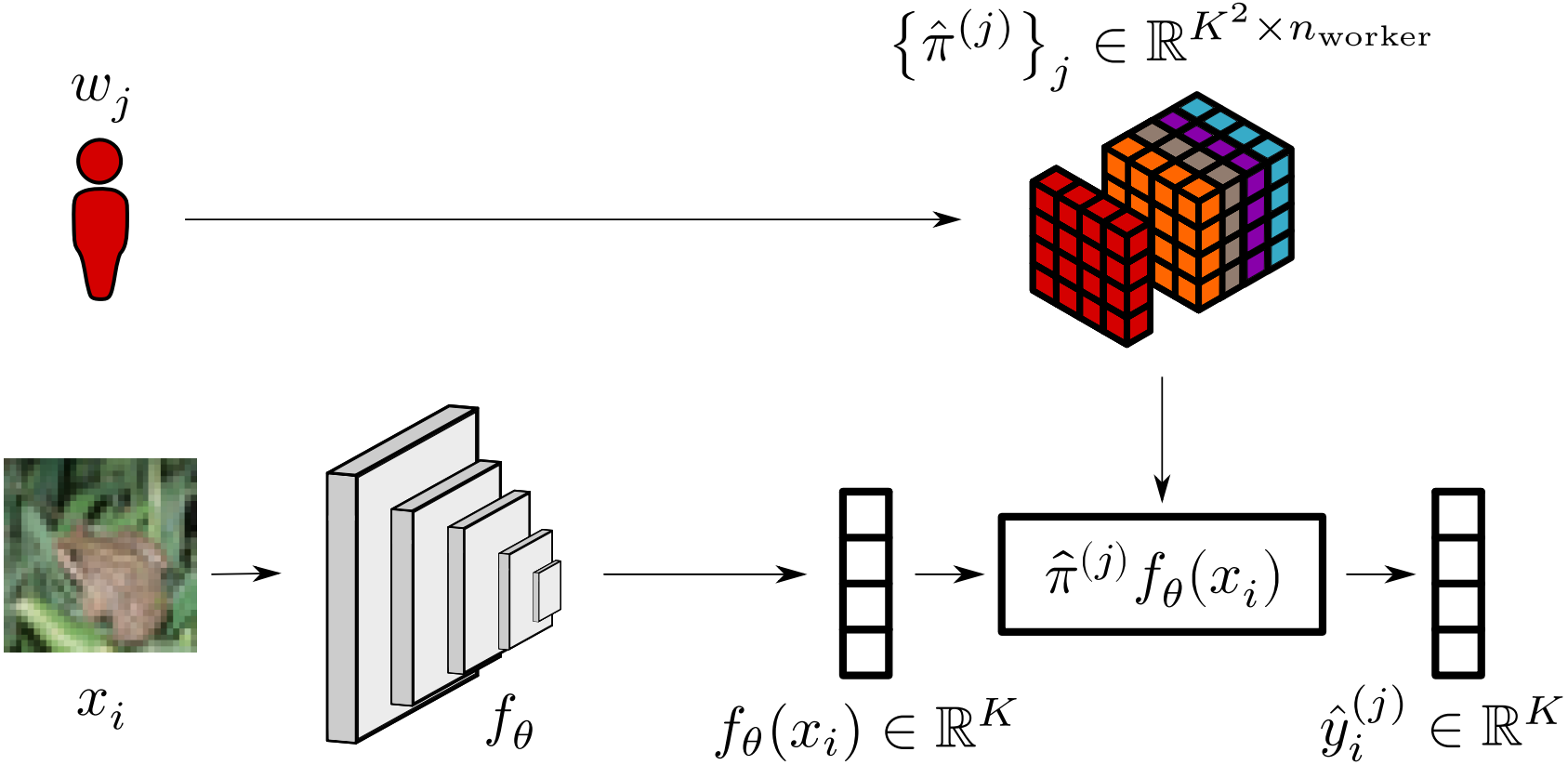
Probabilistic model $\longrightarrow$ Likelihood (to maximize)



Classical deep-learning strategy

CrowdLayer[7]

- Idea: put the DS confusion matrix in a neural network as a new layer

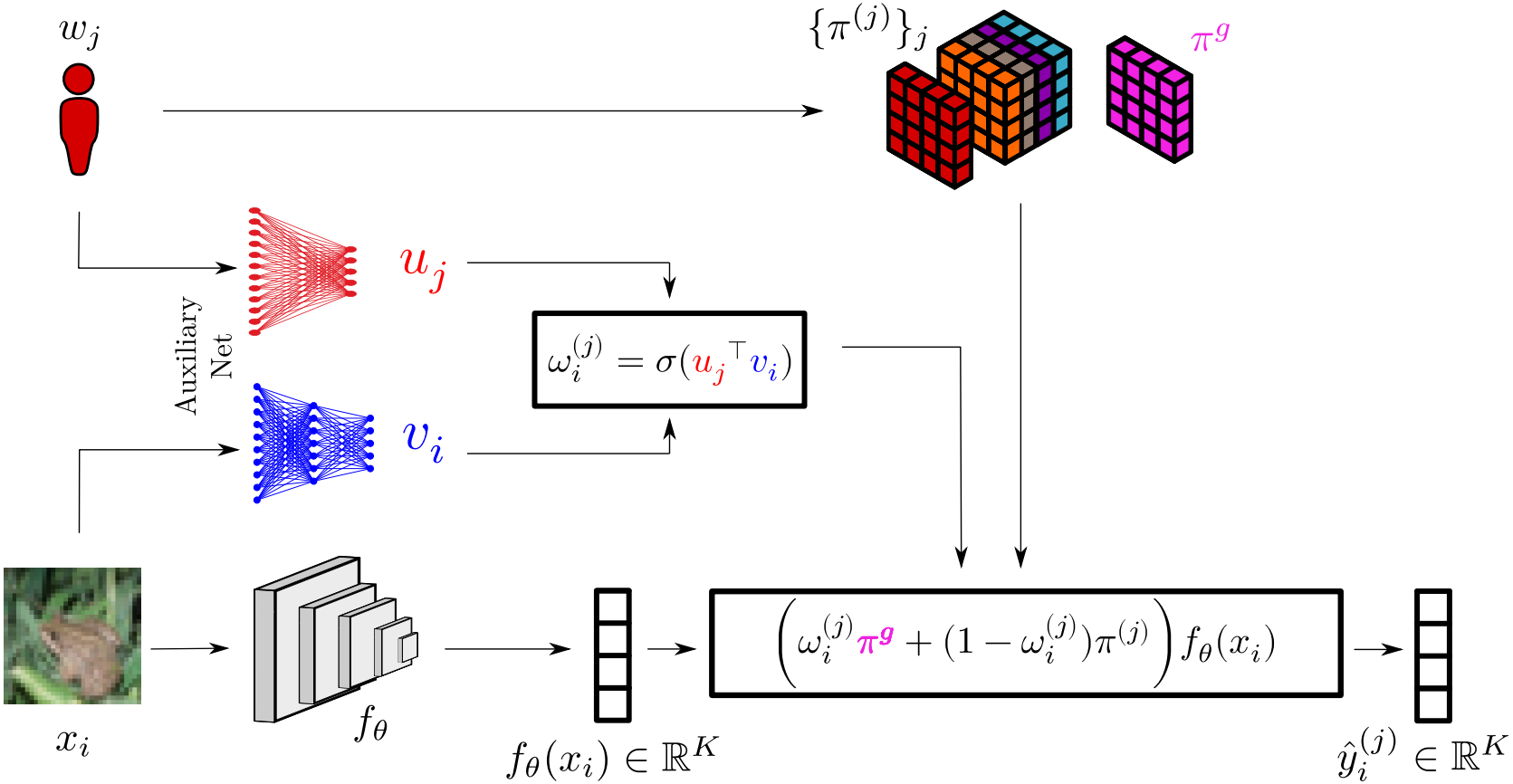


[7] F. Rodrigues and F. Pereira (2018). "Deep learning from crowds". In: *AAAI*. vol. 32.

Classical deep-learning strategy

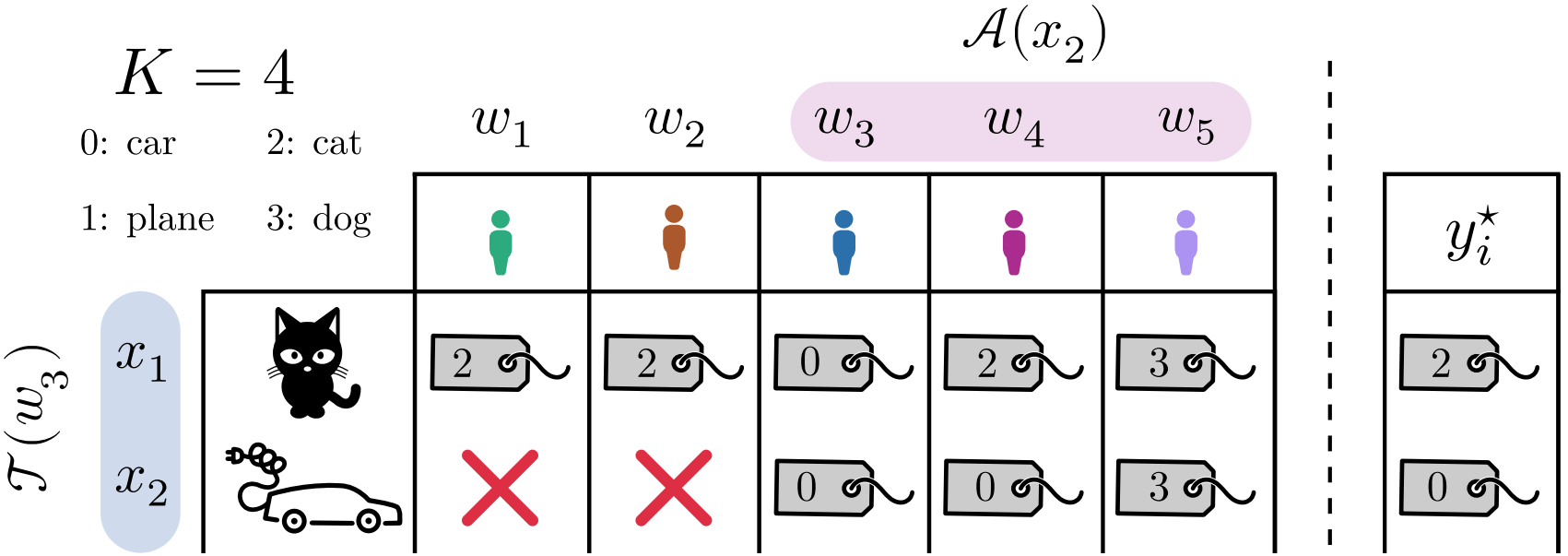
CoNAL[8]

- Idea: CrowdLayer + global and local confusions



[8] Z. Chu, J. Ma, and H. Wang (2021). "Learning from Crowds by Modeling Common Confusions.". In: *AAAI*, pp. 5832–5840.

When images have underlying ambiguity



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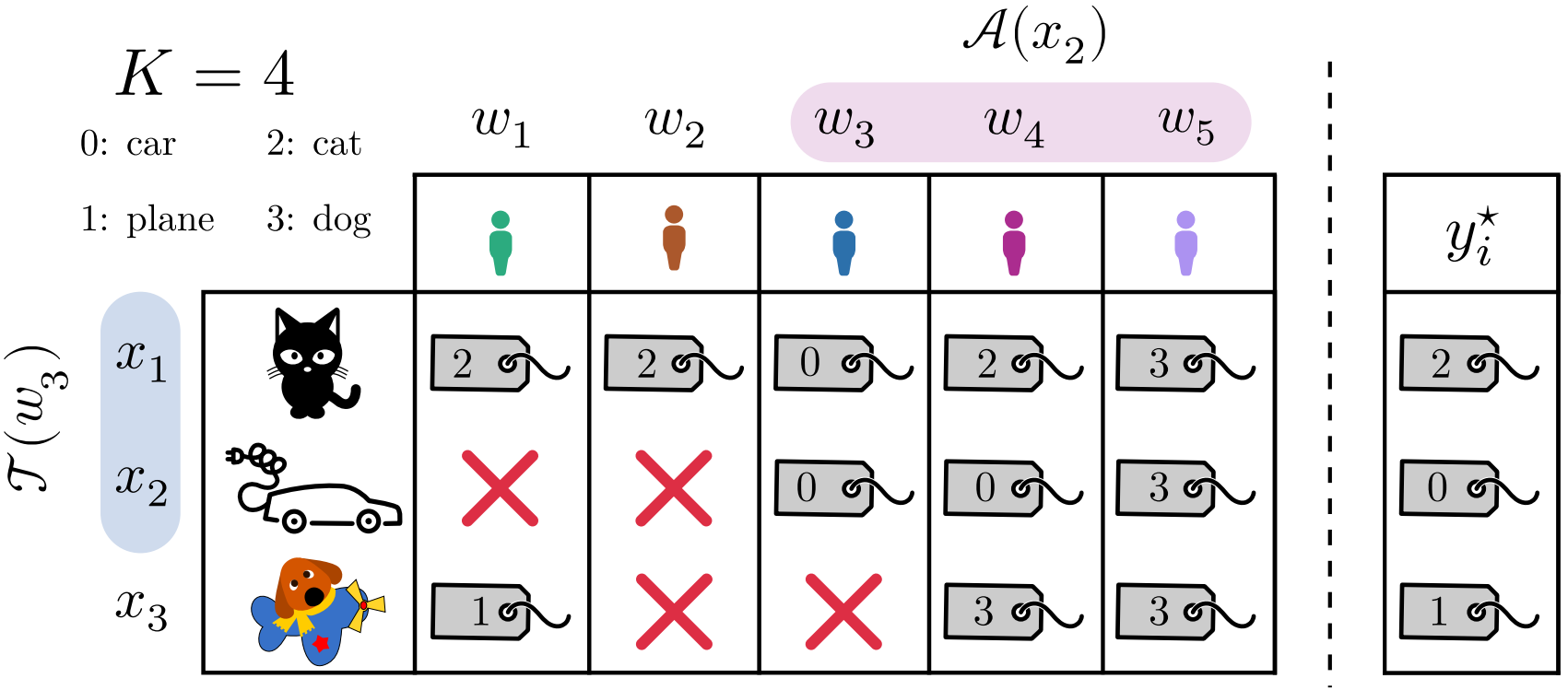

Ambiguity in classical supervised setting
Area Under the Margin (AUM)

Goal: identify issues in classical datasets $(x_1, y_1), \ldots, (x_n, y_n) \in \mathcal{X} \times [K]$

- AUM[9]: monitor margin during training
- Classifier: at epoch $t \in [T]$, $\mathcal{C}^{(t)}(x_i) \in \mathbb{R}^K$ a vector of scores (logits)

Average = Stability

Margin between scores: content of Hinge loss

$$\mathrm{AUM}(x_i, y_i) = \frac{1}{T} \sum_{t=1}^{T} \left[\mathcal{C}^{(t)}(x_i)_{y_i} - \max_{\ell \neq y_i} \mathcal{C}^{(t)}(x_i)_\ell \right]$$

Score of assigned label

Other maximum score

[9] G. Pleiss et al. (2020). "Identifying mislabeled data using the area under the margin ranking". In: *NeurIPS*.

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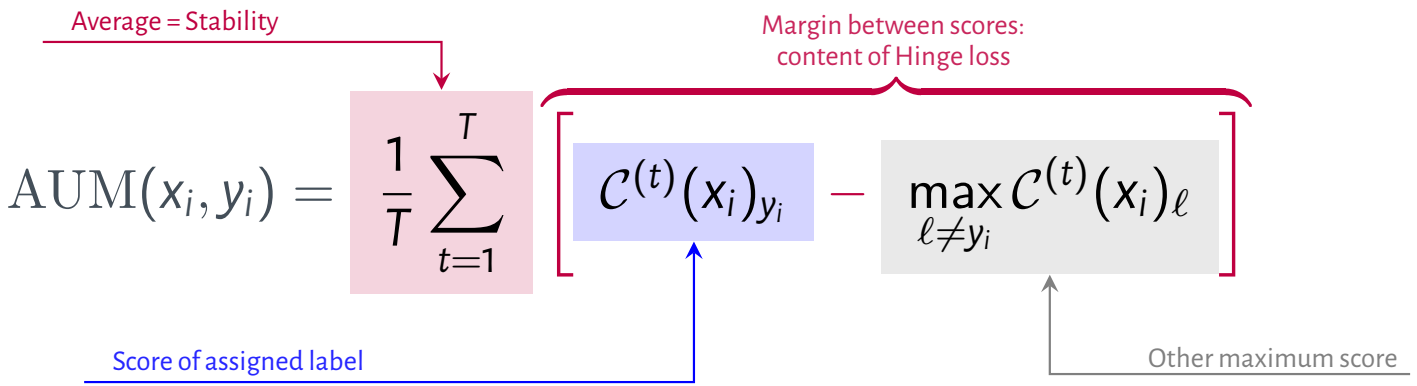

Challenging for crowdsourcing:

- No single y_i, multiple $y_i^{(j)}$: one for each worker w_j answering task x_i

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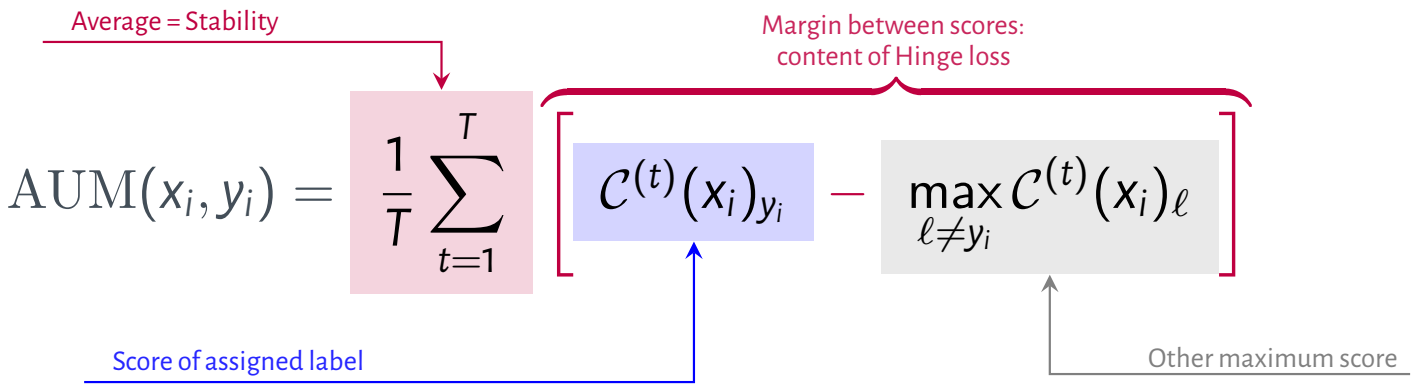

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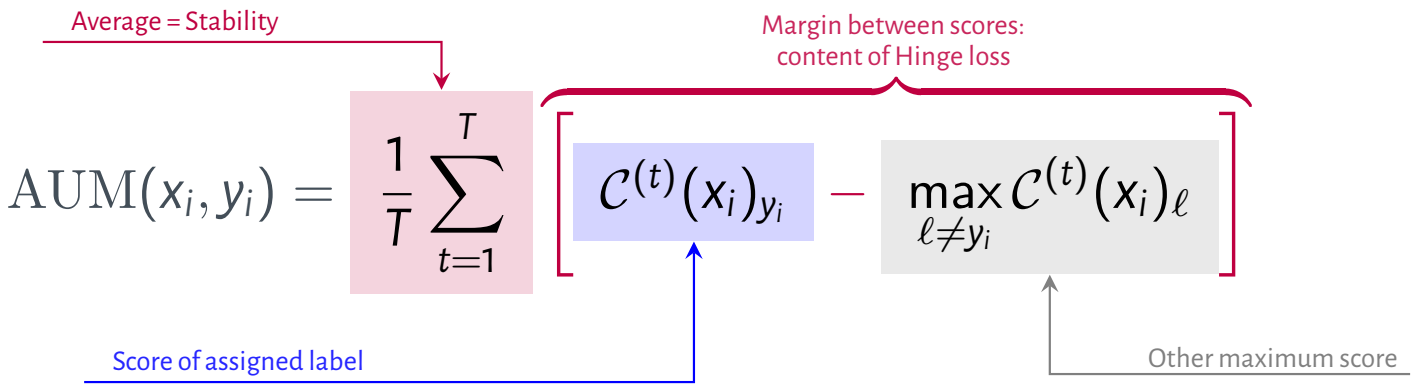

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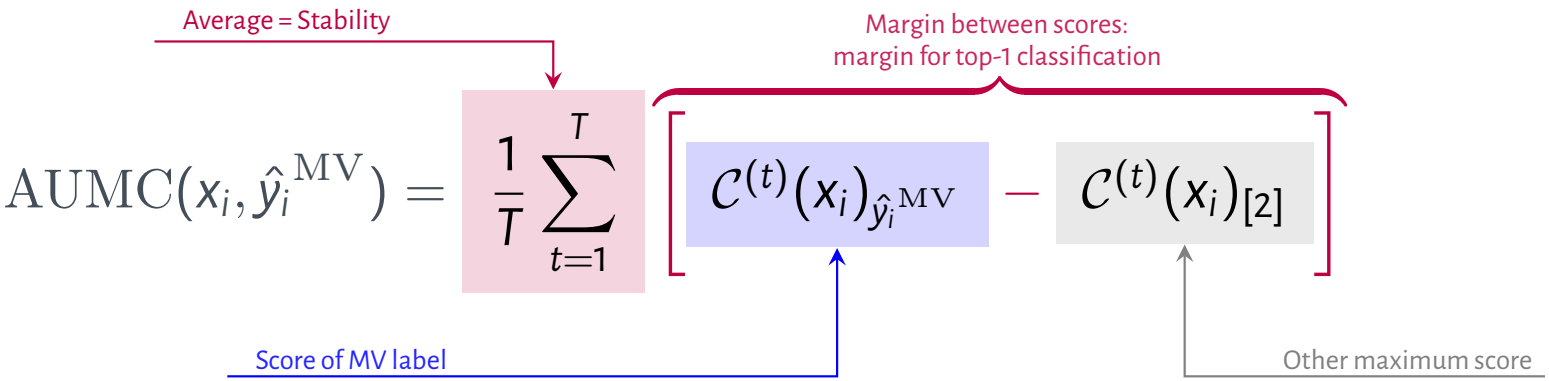
Going to the crowdsourcing setting
AUMC

Naive extension: Use the MV label $\hat{y}_i^{\mathrm{MV}}$ instead of the unknown y_i + use previous work of margins' properties [10]



Issue:

- Lose all worker-related information
- Sensitive to poorly performing workers

[10] M. Lapin, M. Hein, and B. Schiele (2016). "Loss functions for top-k error: Analysis and insights". In: *CVPR*, pp. 1468–1477.

Going to the crowdsourcing setting
WAUM

Weighted Areas Under the Margins:

- Scale effects in the scores discarded, need normalization [11]

[11] C. Ju, A. Bibaut, and M. van der Laan (2018). "The relative performance of ensemble methods with deep convolutional neural networks for image classification". In: *J. Appl. Stat.* 45.15, pp. 2800–2818.

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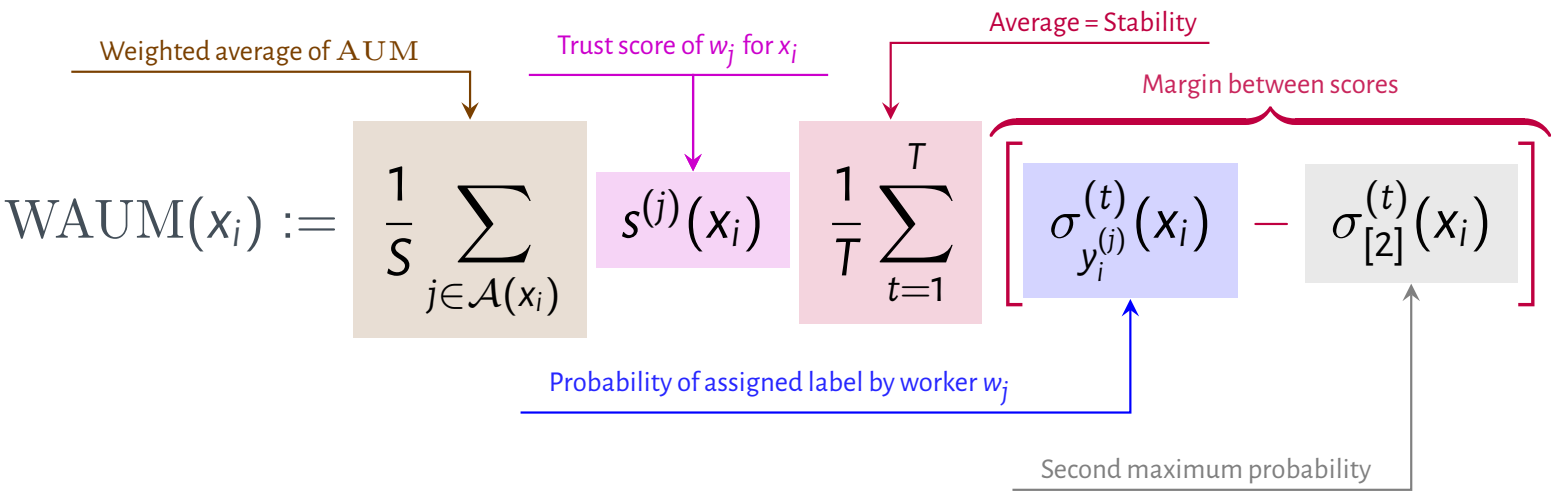
With:

- $\sigma(x_i) = \sigma(\mathcal{C}(x_i)) \in \Delta_{K-1}$ (simplex of dim $K-1$)
- Softmax ordered: $\sigma_{[1]}(x_i) \geq \cdots \geq \sigma_{[K]}(x_i) > 0$



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Weights in the WAUM

Leverage both tasks and labels

Our chosen worker/task score:

- Consider a score of the form: worker term $\times$ task term (similar to GLAD[12])
- Use multidimensionality of DS confusion matrices
- Use a neural network as a control agent to measure task difficulty[13]

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[13] M. Servajean et al. (2017). "Crowdsourcing thousands of specialized labels: A Bayesian active training approach". In: *IEEE Transactions on Multimedia* 19.6, pp. 1376–1391.

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$$s^{(j)}(x_i) = \left\langle \operatorname{diag}(\hat{\pi}^{(j)}) \mid \sigma^{(T)}(x_i) \right\rangle \in [0,1]$$

Worker j overall ability

Difficulty of task i

[12] J. Whitehill et al. (2009). "Whose Vote Should Count More: Optimal Integration of Labels from Labelers of Unknown Expertise". In: *NeurIPS*. vol. 22.

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Computing the WAUM

The pipeline summarized

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- For each task compute $\mathrm{WAUM}(x_i) = \dfrac{\sum_{j \in \mathcal{A}(x_i)} s^{(j)}(x_i) \mathrm{AUM}(x_i, y_i^{(j)})}{\sum_{j' \in \mathcal{A}(x_i)} s^{(j')}(x_i)}$

Usage (for learning):

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Usage (for learning):

- **Prune** x_i's with $\mathrm{WAUM}(x_i)$ below quantile q_α (say $\alpha = 0.01$)
- **Estimate confusion matrices** $\hat{\pi}^{(j)}$ on pruned training dataset

Computing the WAUM

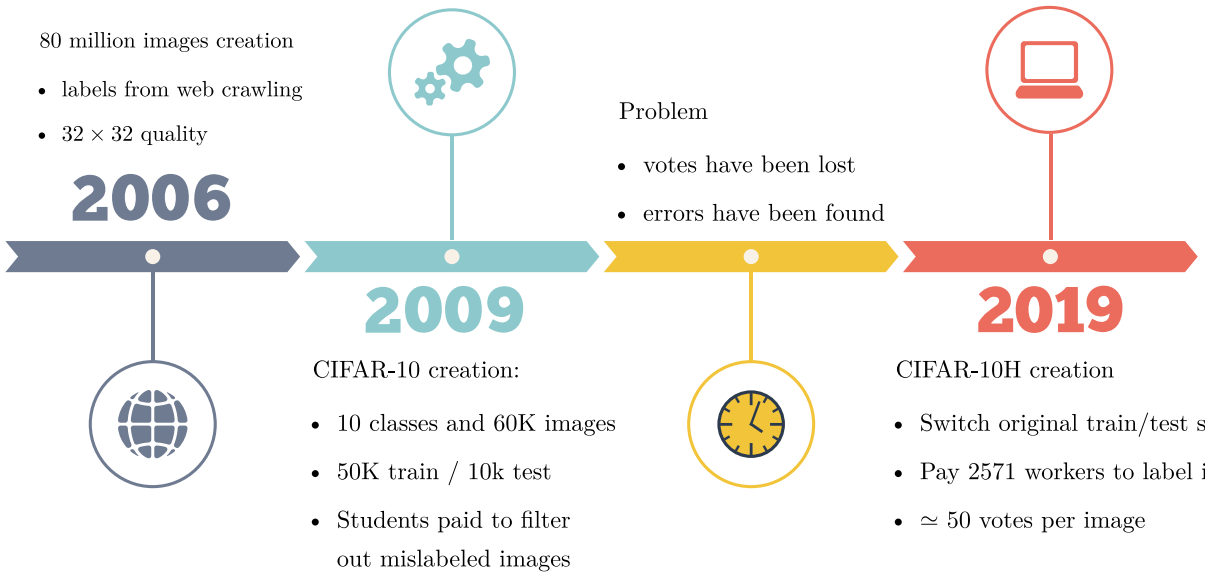
The pipeline summarized

- Estimate confusion matrices $\pi^{(j)} \in \mathbb{R}^{K \times K}$, for all $j \in [n_{\texttt{worker}}]$
- Train a network on all crowdsourced task/label pairs: $(x_i, y_i^{(j)})$
- Compute all $\mathrm{AUM}(x_i, y_i^{(j)})$
- Compute trust scores $s^{(j)}(x_i)$
- For each task compute $\mathrm{WAUM}(x_i) = \dfrac{\sum_{j \in \mathcal{A}(x_i)} s^{(j)}(x_i) \mathrm{AUM}(x_i, y_i^{(j)})}{\sum_{j' \in \mathcal{A}(x_i)} s^{(j')}(x_i)}$

Usage (for learning):

- **Prune** x_i's with $\mathrm{WAUM}(x_i)$ below quantile q_α (say $\alpha = 0.01$)
- **Estimate confusion matrices** $\hat{\pi}^{(j)}$ on pruned training dataset
- **Aggregate** labels and **Train** a classifier on the newly pruned dataset

Presenting CIFAR-10H[14] dataset



Labels: cat, dog, car, plane, bird, horse, frog, deer, ship, truck

[14] J. C. Peterson et al. (2019). "Human Uncertainty Makes Classification More Robust". In: *ICCV*, pp. 9617–9626.

Presenting CIFAR-10H[14] dataset

2006

80 million images creation

- labels from web crawling
- 32×32 quality

2009

CIFAR-10 creation:

- 10 classes and 60K images
- 50K train / 10k test
- Students paid to filter out mislabeled images

Problem

- votes have been lost
- errors have been found

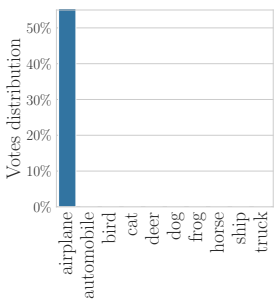
2019

CIFAR-10H creation

- Switch original train/test sets
- Pay 2571 workers to label images
- $\simeq$ 50 votes per image

Labels: cat, dog, car, plane, bird, horse, frog, deer, ship, truck

Image #7681
CIFAR-10 label: airplane



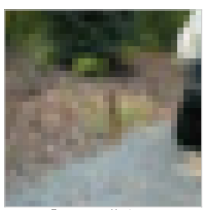
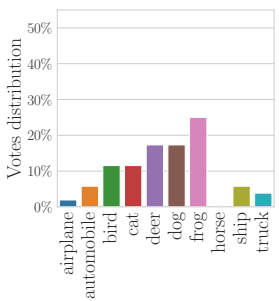


Image #6750
CIFAR-10 label: deer



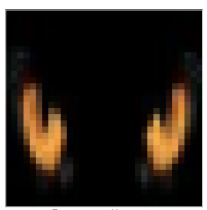
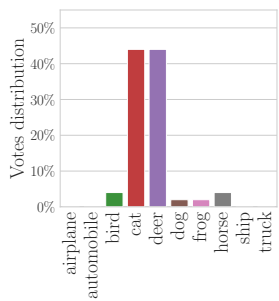


Image #9246
CIFAR-10 label: cat



[14] J. C. Peterson et al. (2019). "Human Uncertainty Makes Classification More Robust". In: *ICCV*, pp. 9617–9626.

Presenting LabelMe dataset[15]

- 1000 training / 500 validation / 1188 test images
- 59 workers: each task has up to 3 votes
- 8 classes: highway, insidecity, tallbuilding, street, forest, coast, mountain, opencountry

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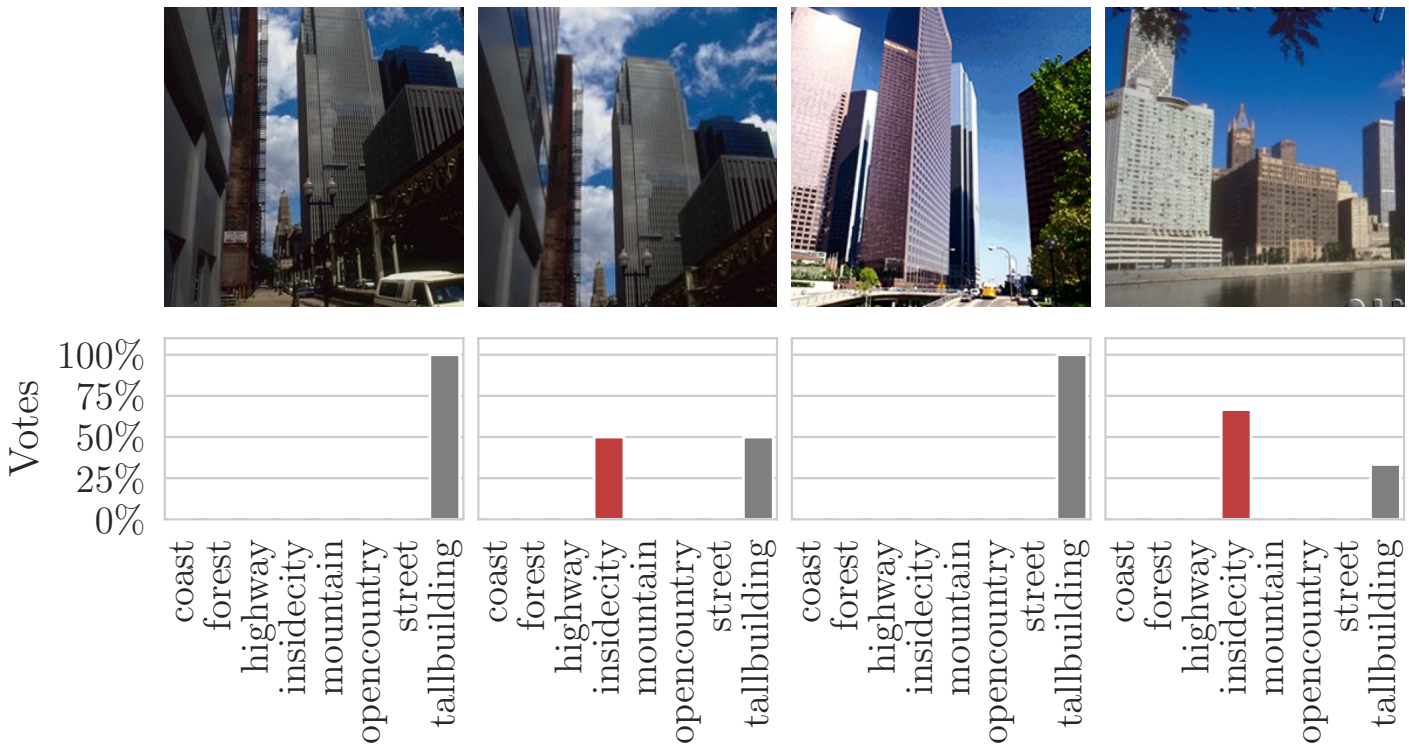

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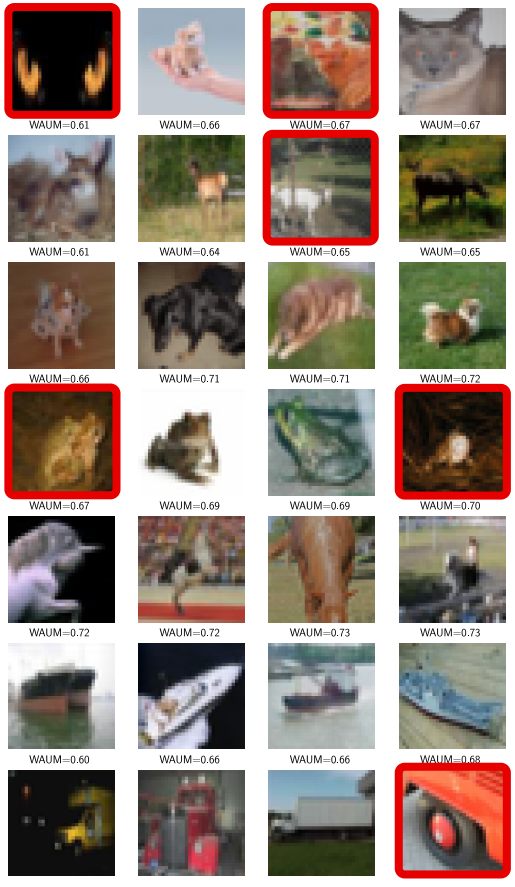
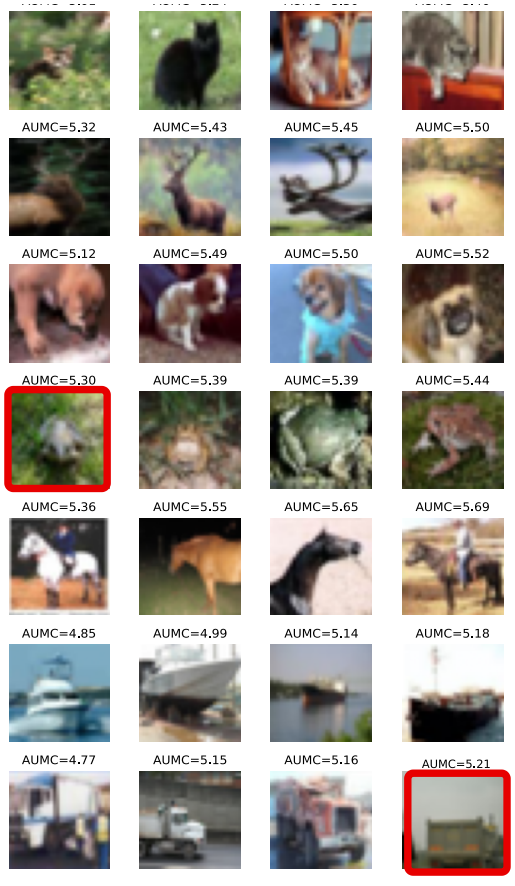
Qualitative results

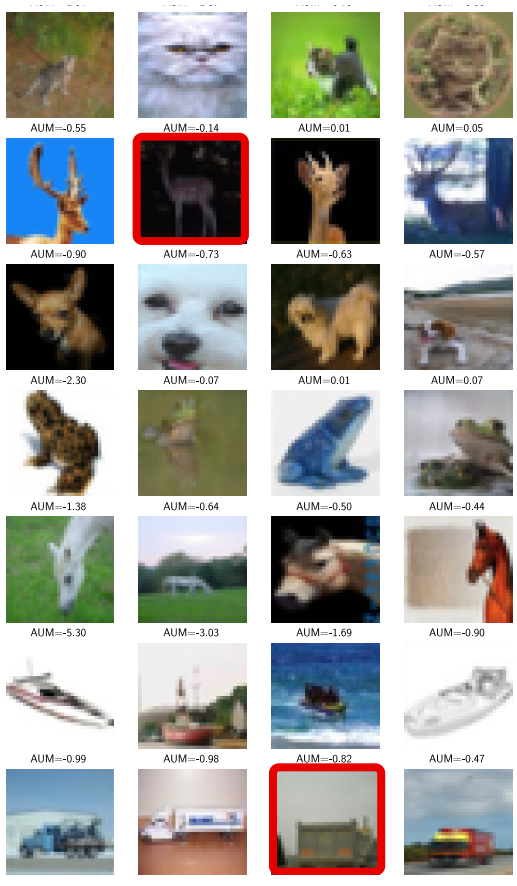
WAUM



AUMC

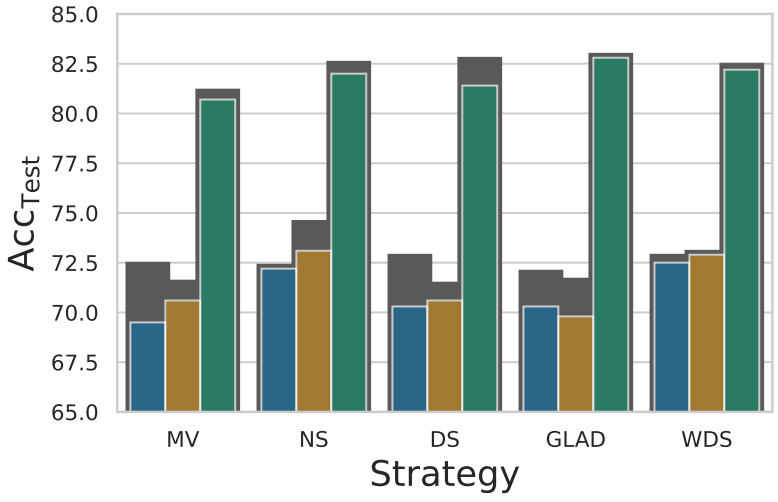


AUM

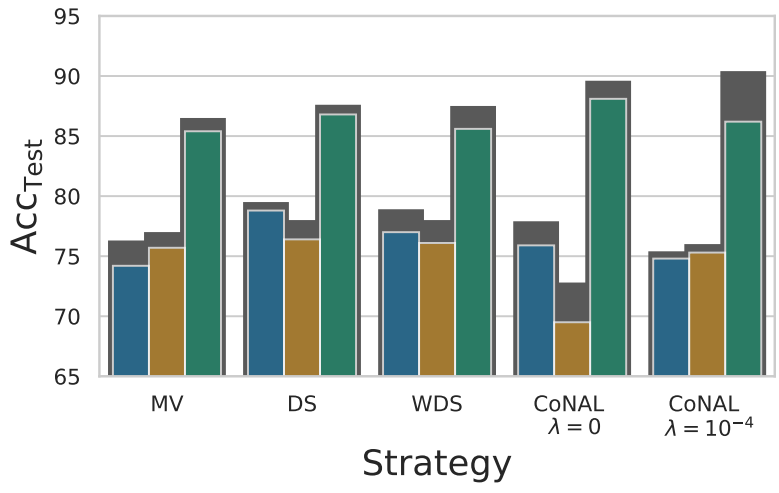


Ablation study

CIFAR-10H



LabelMe



In short

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- Better quality data can improve performance

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- Can we evaluate their performance?

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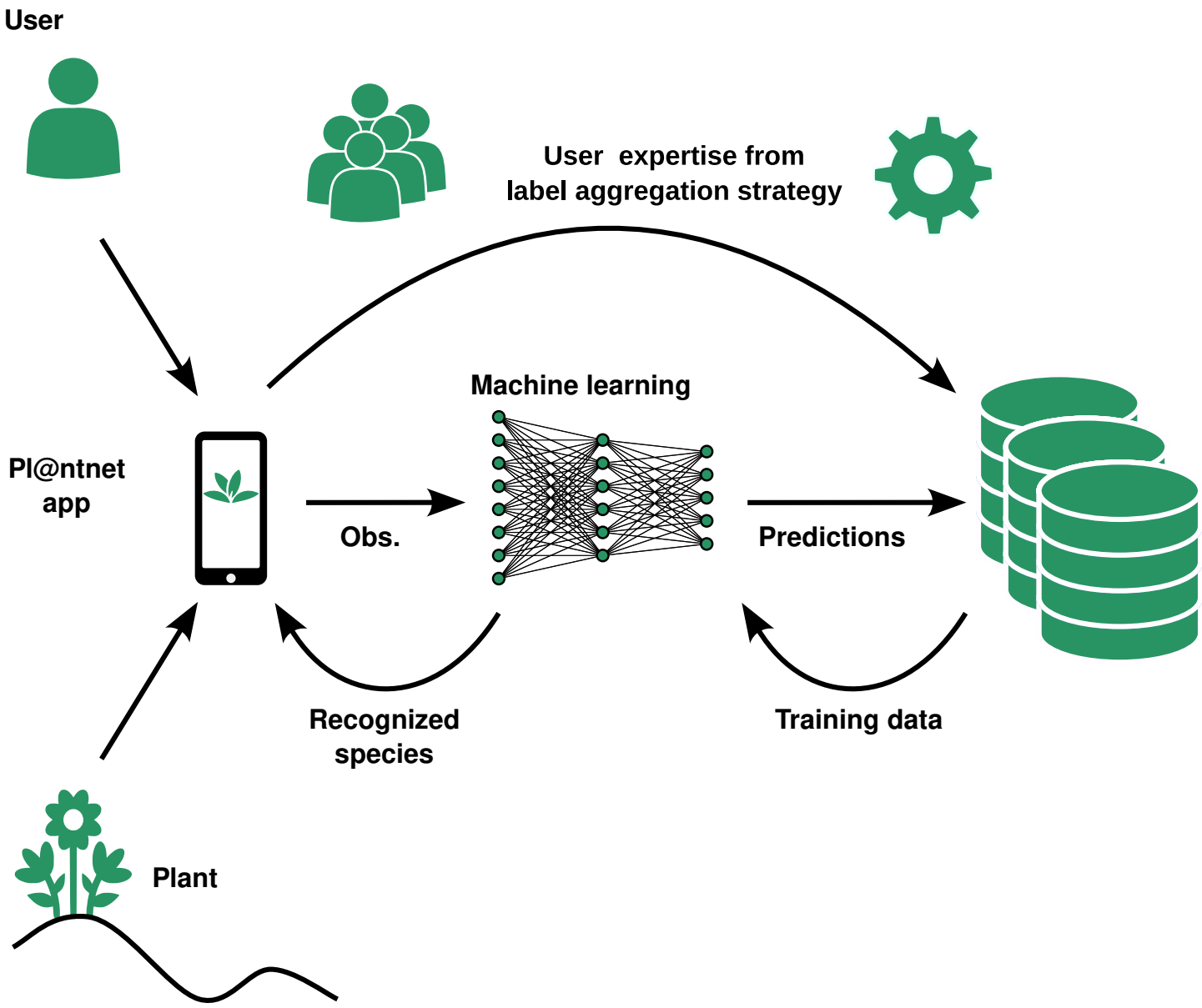
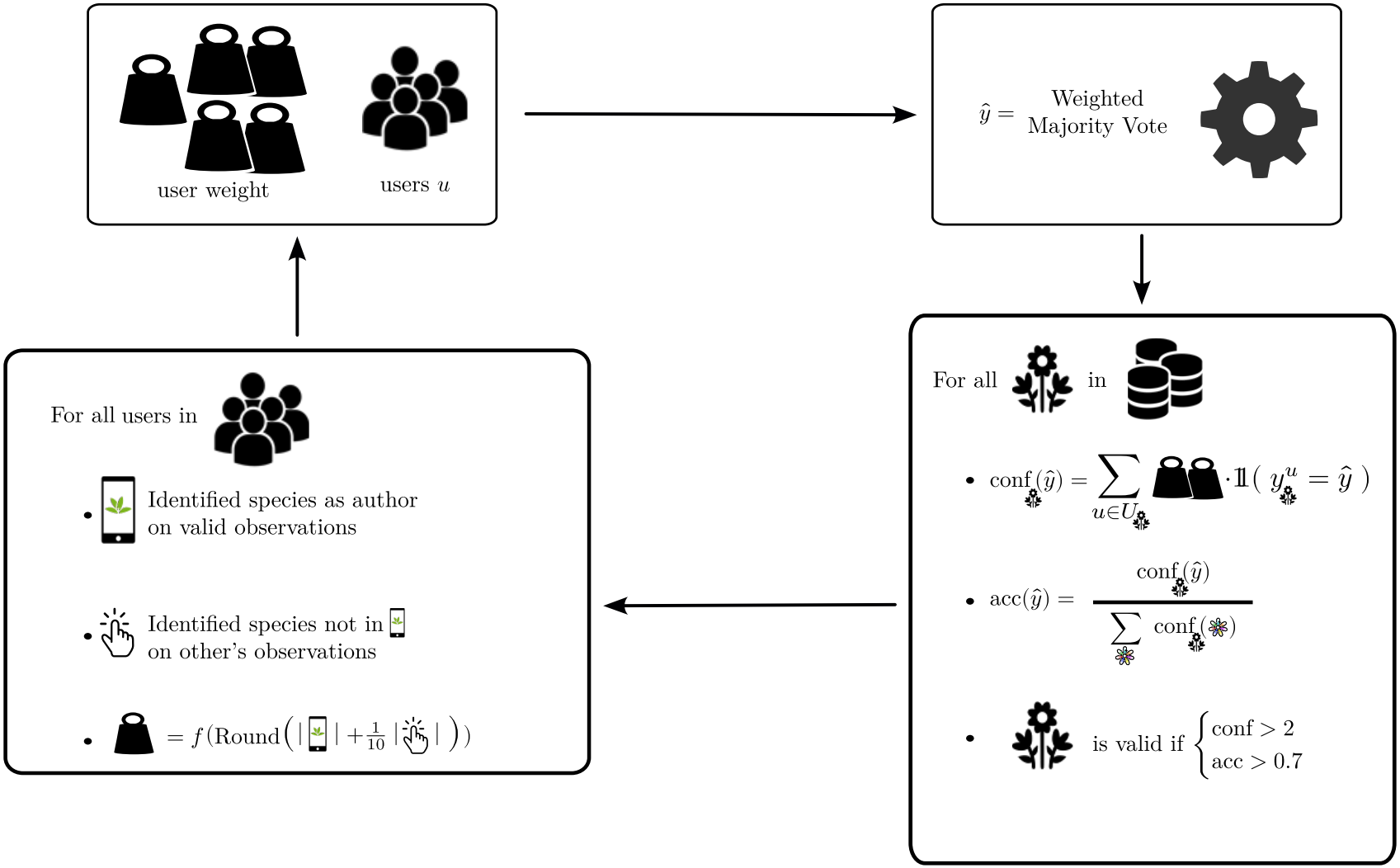
Towards large-scale problems

- DS model and confusion matrices do not scale
- What is currently done in large-scale settings?
- Can we evaluate their performance?
  - To evaluate we need the dataset!

Presenting Pl@ntNet pipeline



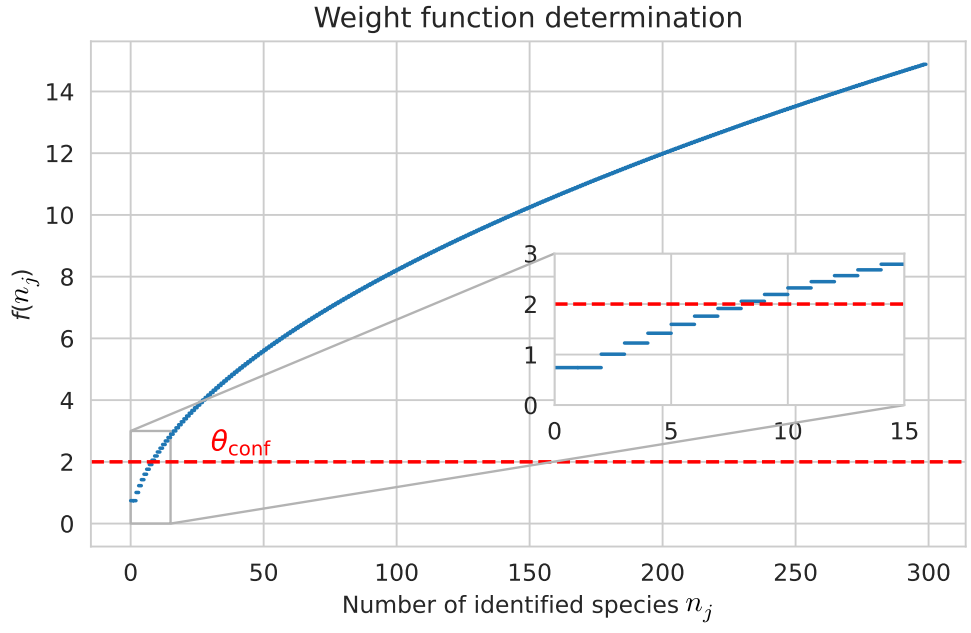
Pl@ntNet aggregation strategy



Pl@ntNet aggregation strategy

Weight function

$$f(n_j) = n_j^{\alpha} - n_j^{\beta} + \gamma \text{ with } \begin{cases} \alpha & = 0.5 \\ \beta & = 0.2 \\ \gamma & \simeq 0.74 \end{cases}$$



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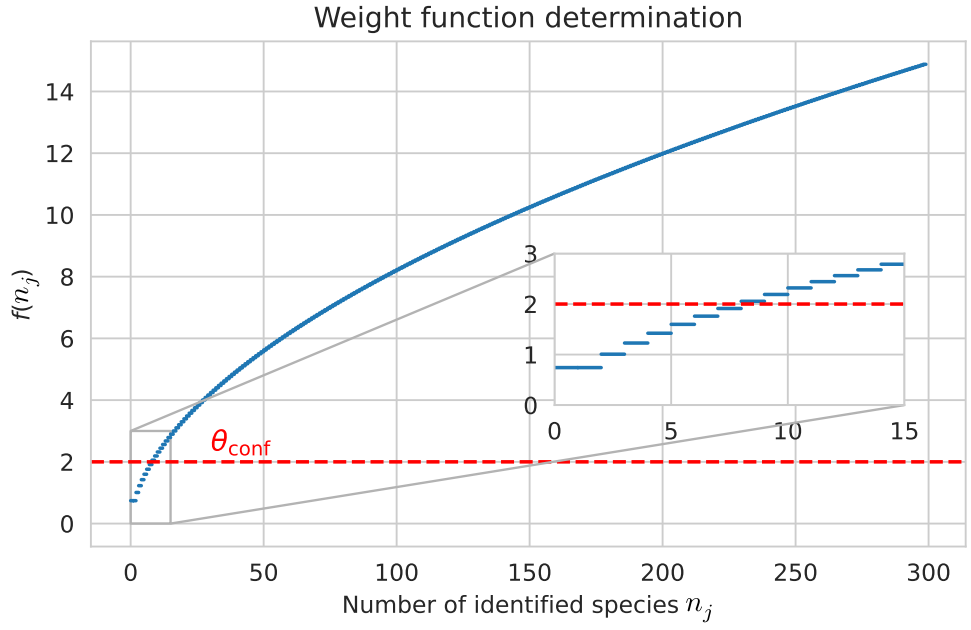
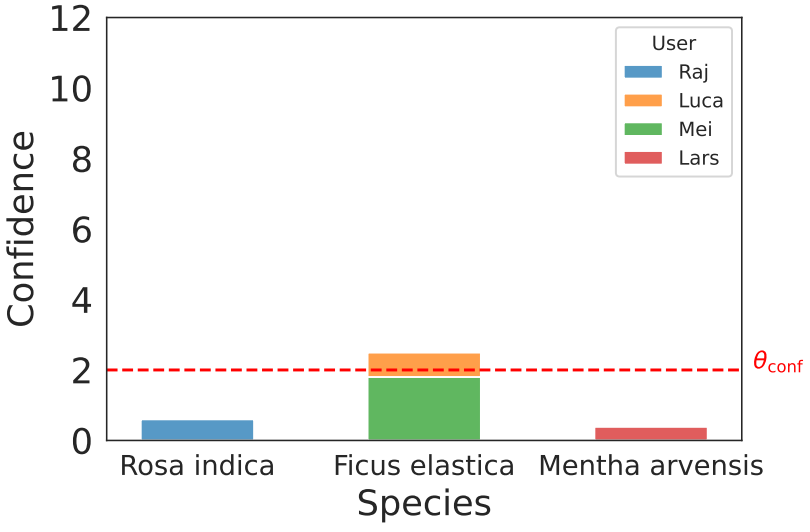


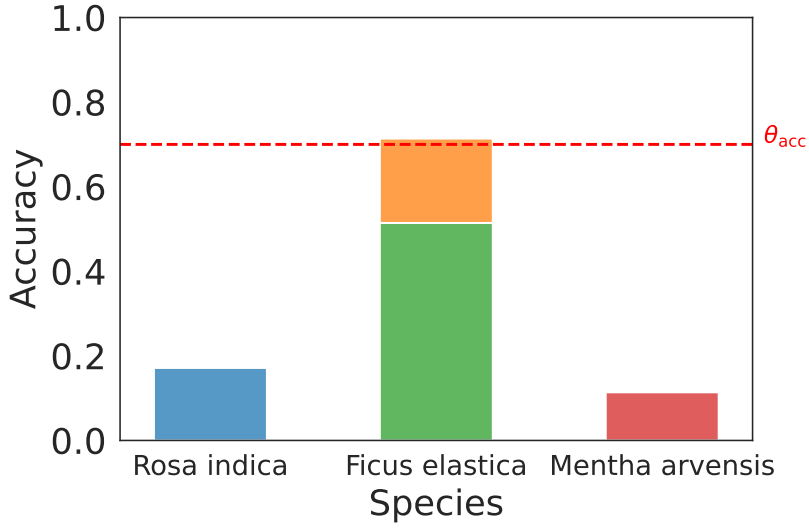
- With 8 identified species one becomes self-validating
- But observations can be invalidated at any time in the future

Pl@ntNet aggregation strategy

Examples

Initial setting

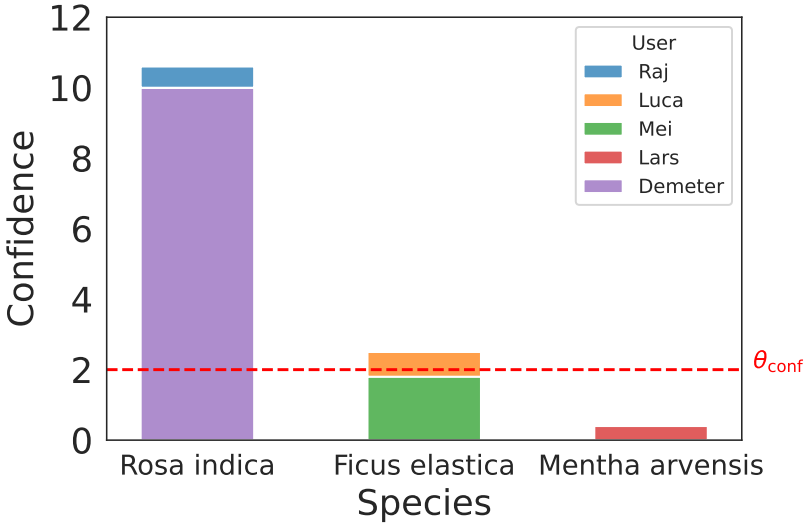


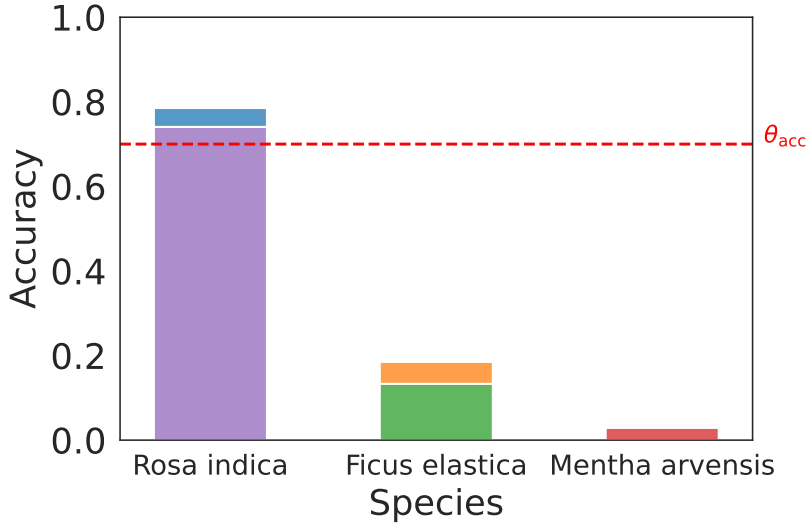


Pl@ntNet aggregation strategy

Examples

Label switch

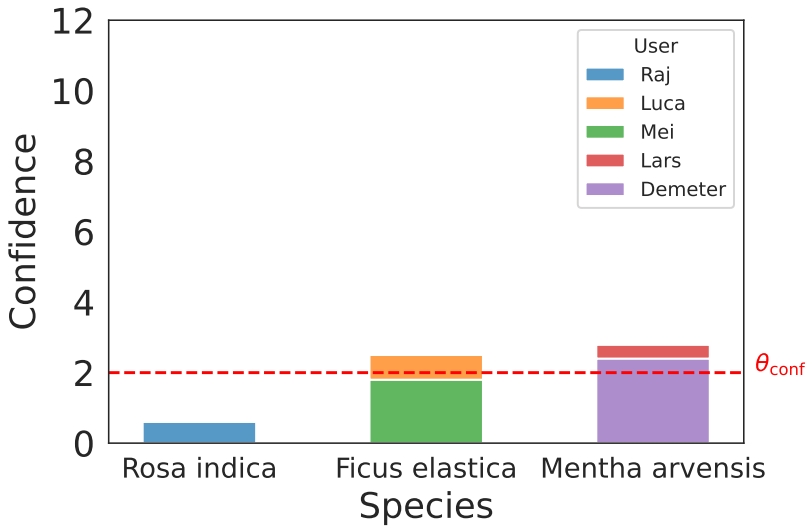


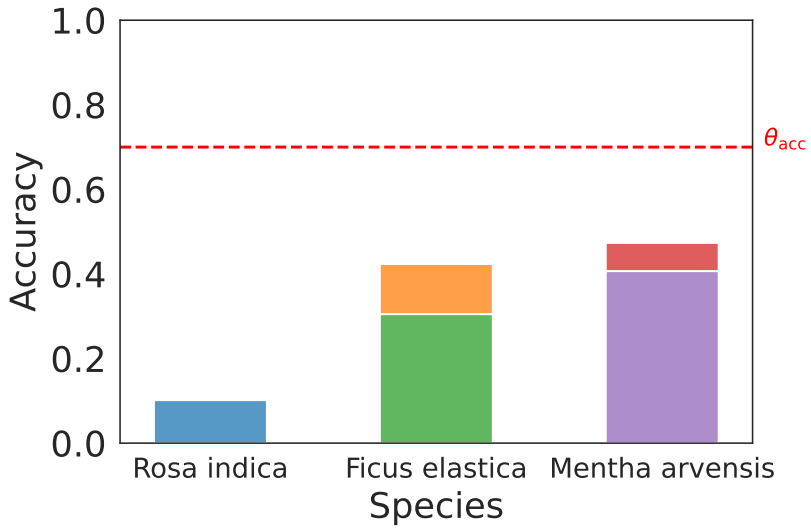


Pl@ntNet aggregation strategy

Examples

Invalidate





Realeasing a new dataset

- South Western European flora obs since 2017
- 823 000 users answered more than 11000 species
- 6 700 000 observations
- 9 000 000 votes casted
- **Imbalance**: 80% of observations are represented by 10% of total votes

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- Extraction of 98 experts (TelaBotanic + prior knowledge – thanks to Pierre Bonnet)

Compared strategies

- **Majority Vote** (MV)

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- **Worker agreement with aggregate (WAWA)** (**appen**)
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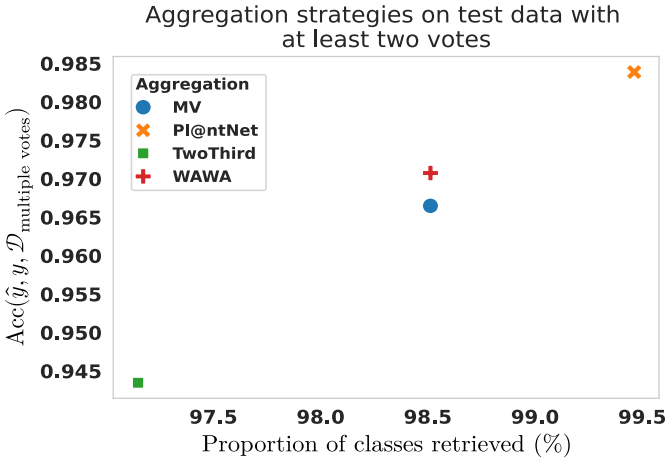
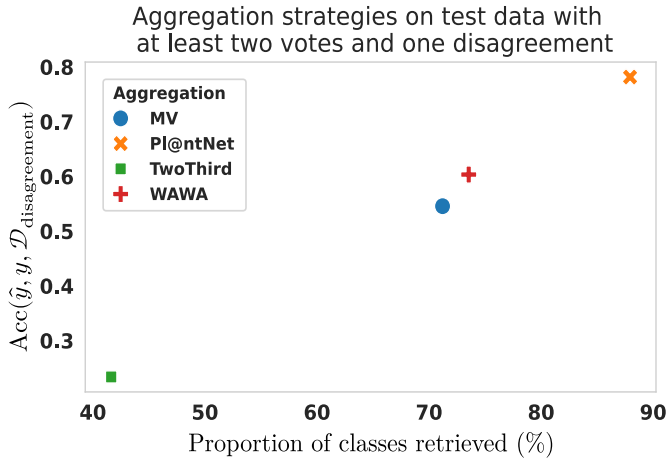
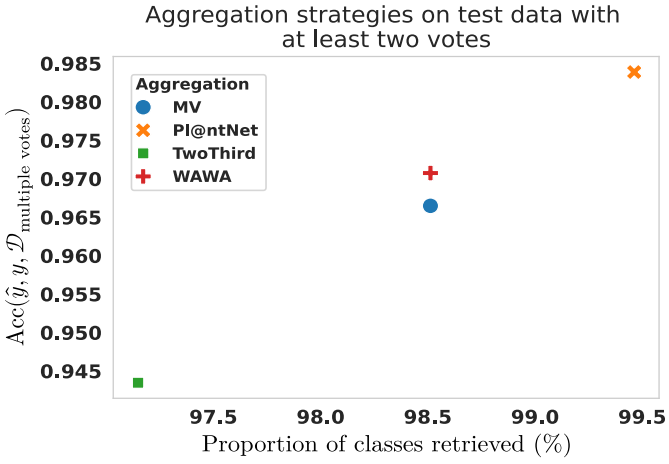
- **iNaturalist**
  - Need 2 votes
  - 2/3 of agreements

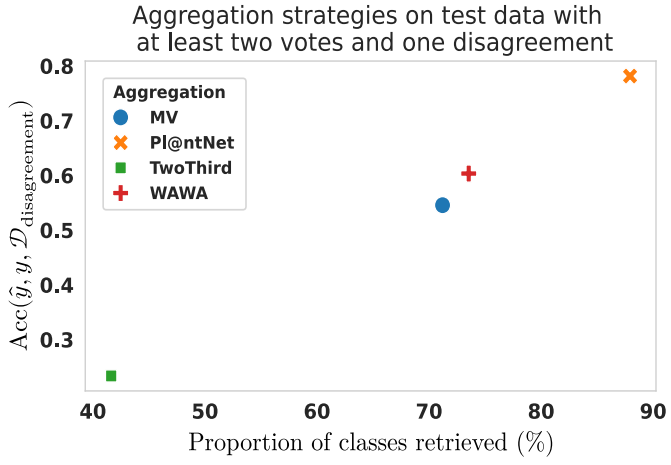
Results


Aggregation strategies on test data with at least two votes
Aggregation
MV
Pl@ntNet
TwoThird
WAWA
0.985
0.980
0.975
0.970
0.965
0.960
0.955
0.950
0.945
97.5
98.0
98.5
99.0
99.5
Proportion of classes retrieved (%)
$\mathrm{Acc}(\hat{y}, y, \mathcal{D}_{\text{multiple votes}})$


Aggregation strategies on test data with at least two votes and one disagreement
Aggregation
MV
Pl@ntNet
TwoThird
WAWA
0.8
0.7
0.6
0.5
0.4
0.3
40
50
60
70
80
90
Proportion of classes retrieved (%)
$\mathrm{Acc}(\hat{y}, y, \mathcal{D}_{\text{disagreement}})$

Results





In short

- Pl@ntNet aggregation performs better overall
- TwoThird is highly impacted by their reject threshold
- In ambiguous settings (right), strategies weighting users are better

More experiments

- AI vote's integration

- Penalizing user's mistakes

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- AI vote's integration
  - include AI's vote in the aggregation
  - Risks of model collapse
  - Results suggest using AI's vote if the score is above a threhsold $\theta_{\text{score}} = 0.7$ can improve performance
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- AI vote's integration
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  - Results suggest using AI's vote if the score is above a threhsold $\theta_{\text{score}} = 0.7$ can improve performance
- Penalizing user's mistakes
  - users with large number of erroneous votes would be penalized in weight
  - Currently this does not improve performance
  - Taking the Accuracy of each user in the weight function shows however close performance from the current strategy

Conclusion and perspectives
Key points

- We released a new dataset for large-scale crowdsourced data: `https://zenodo.org/records/10782465`
- We evaluated the current label aggregation in Pl@ntNet against other scaling ones and show better performance overall

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- We evaluated the current label aggregation in Pl@ntNet against other scaling ones and show better performance overall

- There is a need to *better collect votes* and not *waste* expert knowledge $\rightarrow$ recommendation system
- We worked on the aggregation of species determination, users can enter other information – the observation is a flower/organ/*etc.*

Thank you

Peerannot library

`https://peerannot.github.io`

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