UNIVERSITY OF WARSAW

WYDZIAŁ MATEMATYKI, INFORMATYKI I MECHANIKI

MIM

Active Learning - practical considerations and open problems

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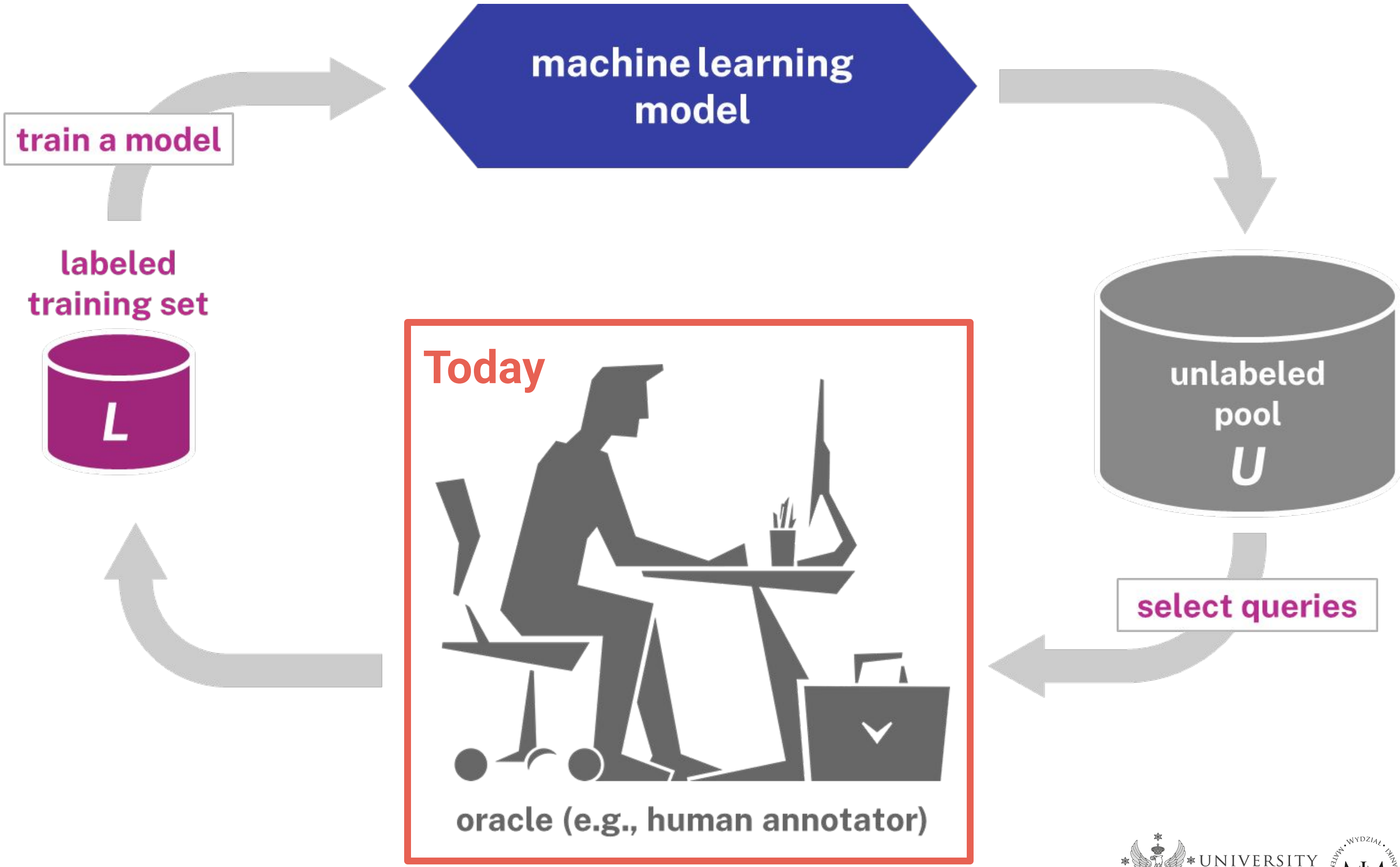
THE PLAN

- A recap of the previous lectures.
- Dealing with a faulty Oracle.
- Estimating usefulness of experts.
- Optimization of query assignments.
- Application examples and experiments.
- Summary.

The active learning cycle - the Oracle



The initial data batch

- The initial batch has huge impact on the active learning performance.
  - Random sampling.
  - Iterative sampling using the representativeness-diversity function.
  - Clustering-based sampling.
- Random samples are always needed for the evaluation!
- <u>We will focus on this problem in a different lecture!</u>

Faulty Oracle

- Some cases might be difficult to label even for domain experts.
  - Imagine a group of medical doctors discussing a difficult case.
  - People get distracted and tired over time.
- Some Oracles might not be "composed" of real experts.
  - Crowdsourcing the labeling task.
- How can we detect and deal with wrong or suspicious data labels?

Image: Freepik.com

What can we do?

- Redundancy in data labeling.
  - Each query is shown to a few <u>independent</u> experts.
  - The ground truth can be decided by voting.
  - It increases the total amount of labeling that needs to be done by experts…
- Data consistency checks.
  - Are there any similar cases from the same/other classes?
- The diagnostic of a trained model.
  - The use of XAI tools can help in flagging cases with “suspicious” labels.

Dealing with noisy data labels

- Strategies for the redundant labeling:
  - There is no “the best” method - the right approach strongly depends on a particular application.
  - Queries need to be selected in batches.
- The “query push” and “query pull” approaches:
  - Sets of queries are created and “pushed” for each expert.
    - It balances the workload.
    - A new iteration of AL cycle starts when all labeling is done.
    - The query sets may overlap.
  - One que of queries is created with duplicated entries.
    - Experts “pull” queries asynchronously from the que.
    - It makes sense to start a new AL cycle before the que depletes.

Reaching a consensus

- Majority voting.
  - The ground truth is decided by voting.
  - Each sample needs to be labeled by at least two (three) experts.
- Hierarchical verification of labels.
  - A part of labels is double-checked by “senior” annotators.
- Weighted voting.
  - Reliability scores are given to experts and used as weights.

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Iterative algorithm for reaching a consensus

- Each expert is characterized by two vectors - true positive rates (TPR_ℓ) and true negative rates (TNR_ℓ) for each possible label ℓ.
  - Initially, all *TPR*s are set to *1/L* and *TNR*s to *(1 - 1/L)*, where *L* is the number of possible labels.

Step 1. *Temporary ground truths* are obtained by weighted voting. The weights are assigned using *TPR*s and *TNR*s.

Step 2. *TPR*s and *TNR*s are updated by comparing labels from each expert to the *temporary ground truths*.

- Steps 1 and 2 are repeated until the algorithm converges.
  - Output: the ground truths and expert reliability estimates

An experiment - reasoning from noisy labels

- Label counts per example: $S_1, \dots, S_N \sim Cat(s)$
- Label probabilities: $P_{i,c} \sim Uniform(0, 1)$
- True labels for each example: $L_{i,c} \mid P_{i,c}, S_i = 1 \text{ if } P_{i,c} \geq P_i^{S_i}$
- Probabilities of assigning a task to experts: $A_1, \dots, A_K \sim Beta(a_1, a_2)$
- Samples assigned to each expert: $U_{i,1}, \dots, U_{i,N} \sim Bernoulli(A_i)$
- Whether an expert is reliable: $G_1, \dots, G_K \sim Bernoulli(p_{good})$
- *TPR* (true positive rate) for each expert: $TP_i \mid G_i = g \sim Beta(\beta^g_{tpr}, \gamma^g_{tpr})$
- *TNR* (true negative rate) for each expert: $TN_i \mid G_i = g \sim Beta(\beta^g_{tnr}, \gamma^g_{tnr})$
- Finally, sample user labelings:

$$UL_{u,i,j} \mid L_{i,j} = 1, TP_u \sim Bernoulli(TP_u)$$

$$UL_{u,i,j} \mid L_{i,j} = 0, TN_u \sim Bernoulli(1 - TN_u)$$

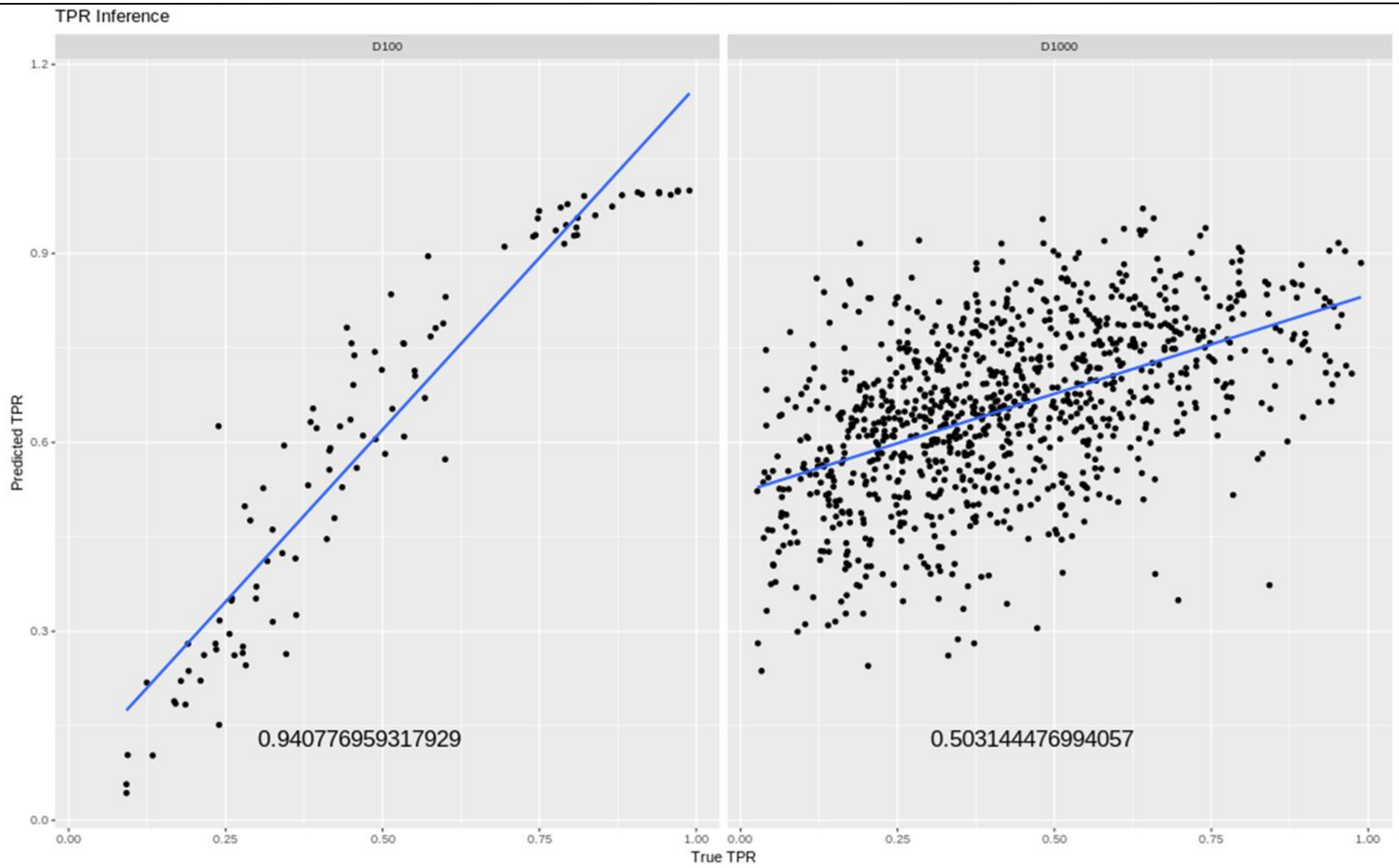
Experimental setup

Data Set	D100	D1000
Difficulty	Moderate	Hard
Number of Samples	10000	10000
Number of Experts	100	1000
Means Samples per User	400	40
Expected Good Users	25 (25%)	50 (5%)
Expected TPR	Good - 0.8 / Bad - 0.4	Good - 0.8 / Bad - 0.4
Expected TNR	Good - 0.9 / Bad - 0.7	Good - 0.9 / Bad - 0.7

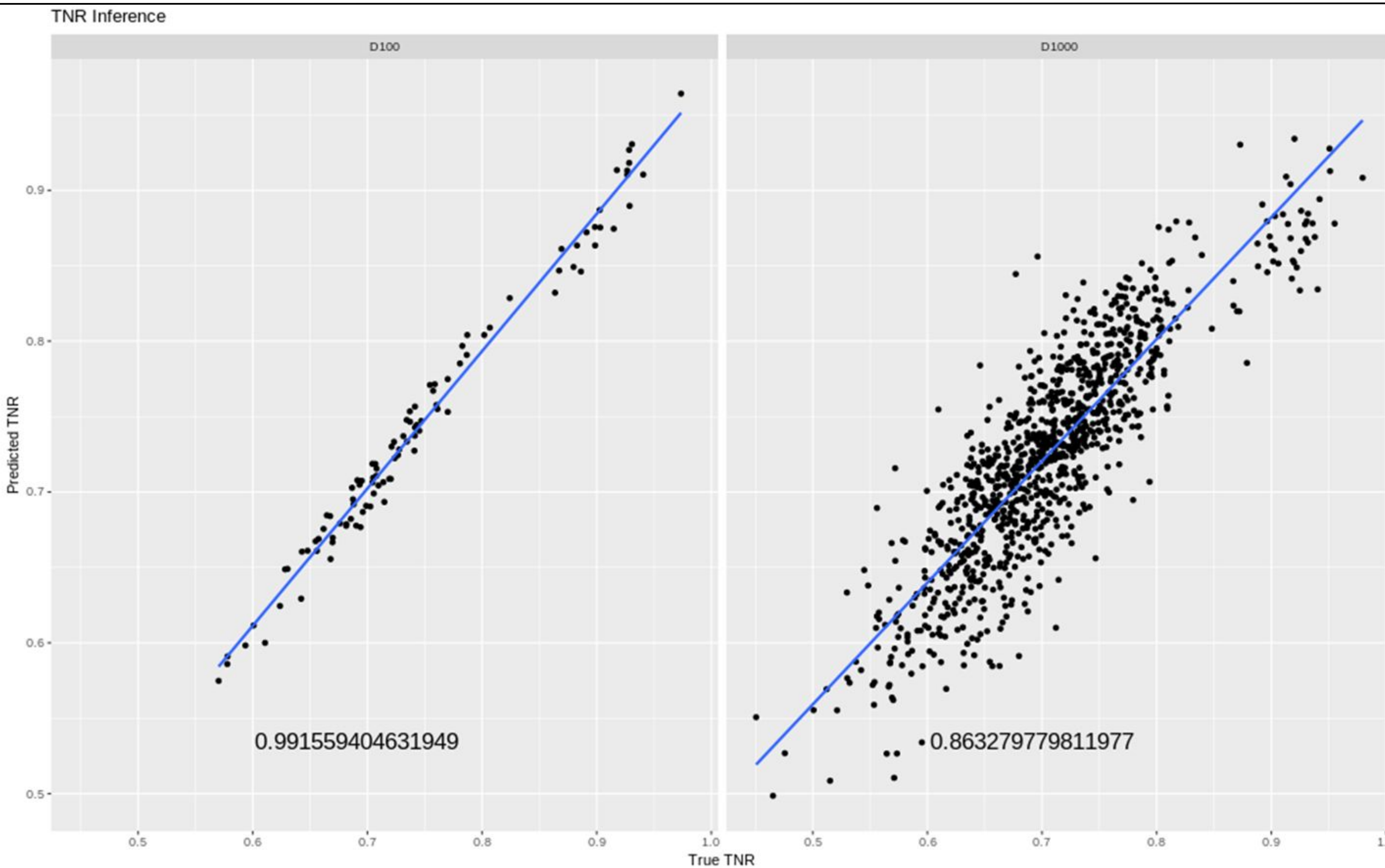
Results - the quality of ground truth estimation

Data set / Method	Accuracy	Precision	Recall	F1 Score
D100 / MV	0.834	0.434	**0.398**	0.415
D100 / EM	**0.889**	**0.731**	0.393	**0.511**
D1000 / MV	0.796	0.307	**0.296**	0.301
D1000 / EM	**0.825**	**0.359**	0.278	**0.313**

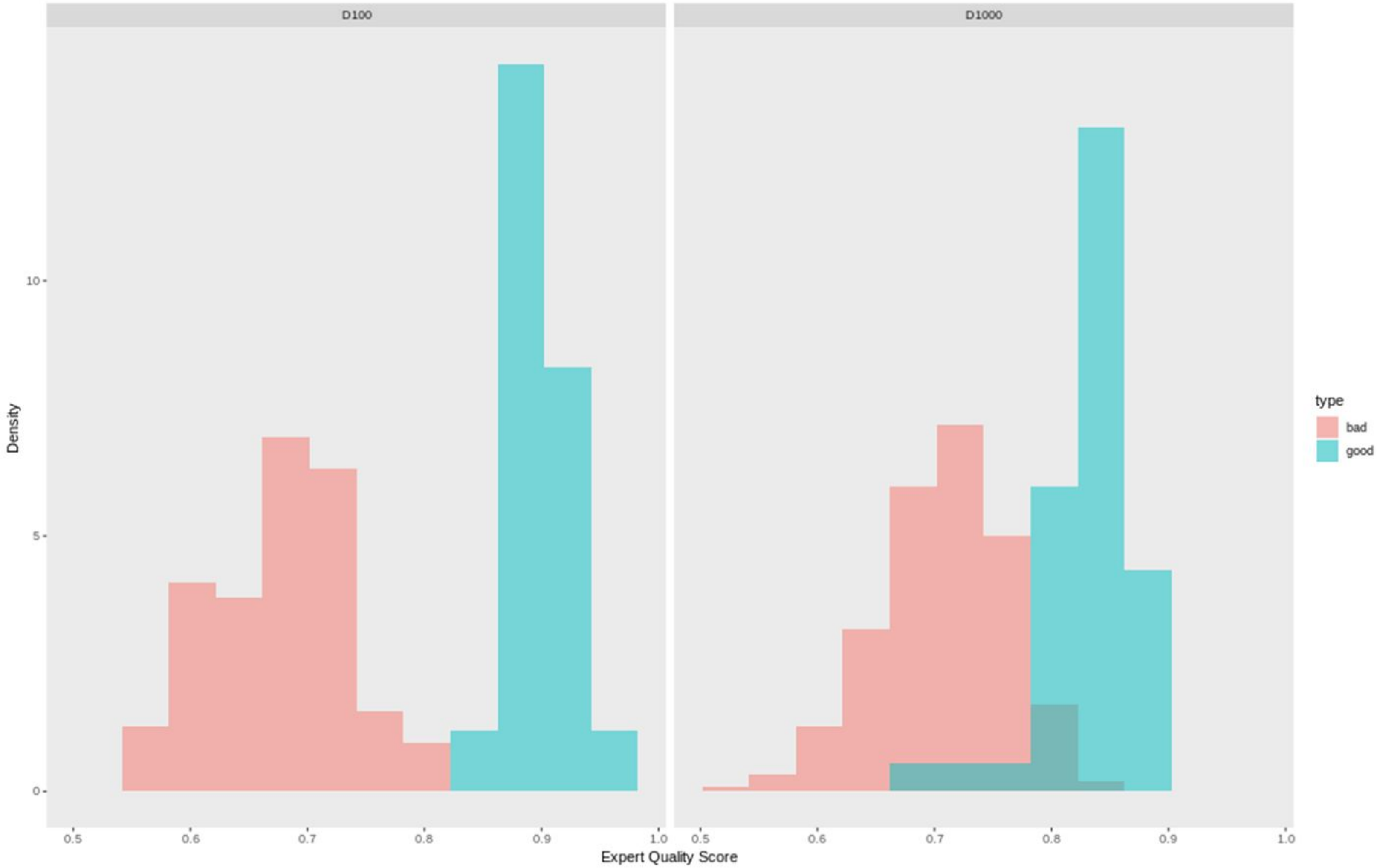
Results - the estimation of *TPRs*



Results - the estimation of *TNR*s



Results - the identification of reliable experts



An alternative approach

- Ideally, we would like to estimate expert's reliability and get the ground truth labels without annotating the same sample more than once.
  - Surrogate ML models approximate votes of each expert.
  - ML voters have to be perfectly consistent with expert annotations and their voting weights should be lower.
- Limitations:
  - The number of annotated samples per each expert and class needs to be large enough.
  - Experts have to be reasonably reliable.

Other ideas for dealing with noisy labels?

- When crowdsourcing the annotation task, we need to closely monitor the reliability of labels.
  - Assigning control queries from a predefined (known) pool.
  - High redundancy of acquired labels is advisable.
  - Means of protection against adversarial labels are necessary.
    - Monitoring of IP addresses.
    - Anti-spam protection (e.g., CAPTCHA).
- Providing a communication platform for the experts.
- Repeating the same queries a few times at different timepoints to check the labeling consistency.

Smart assignment of queries

- The estimation of expert reliability allows to optimize the query assignment:
  - We may assign a query to an expert with the highest expectation of assigning the correct label…
  - or to an expert who we believe assigned correct labels to similar queries in the past.
  - Experts availability - the workload control.

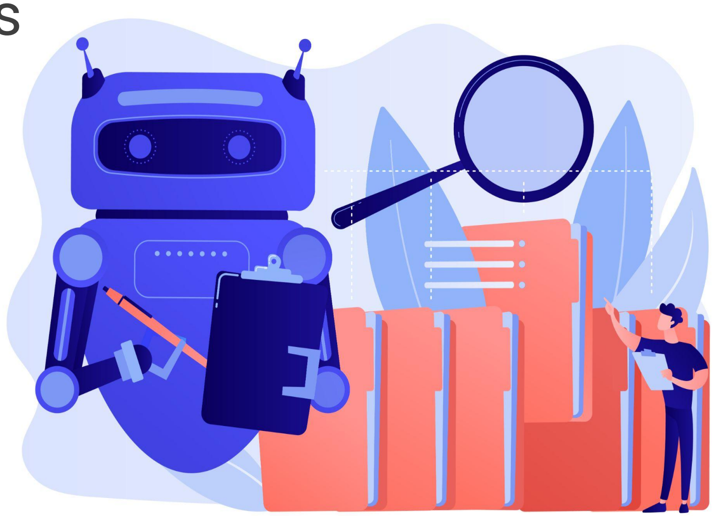


Image: Freepik.com

- Does the optimization of query assignment biases the estimation of expert reliability?
  - It definitely does.
  - <u>The optimization of the labeling process is an open problem!</u>

Design of an experiment

- For the purpose of experiments, we model experts using prediction algorithms:
  - Independent data is used to train the experts models.
  - For each "expert", data is biased in a different way to express various specializations and skills.
  - The expected quality of experts is estimated in advance.
- Queries are assigned to experts with the highest expectation of assigning the correct label (given the prediction of the model used for the query selection).
  - Significant improvement of the label quality.
  - Doesn't work well in combination with the assessment of the reliability of experts…

Variable labeling costs?

- The active learning objective can be modified to minimize the overall labeling cost.
  - Samples have the cost proportional to their “size”, e.g. number of words in a document, length of a recording.
  - The cost of labeling is expressed in the same currency as the cost of misclassification.
- The labeling costs may be predefined or approximated.
  - E.g., we may try to predict the expected labeling time.
- The labeling cost may depend on a particular annotator.
- <u>Many open problems remain!</u>

Unusual query types

- Examples of queries for structured data:
  - Selecting images for the segmentation task.
  - Selecting phrases for the named entity recognition task.
- Active semi-supervised learning.
  - Each query is composed of a pair of samples - we ask if they are similar.
  - Can be more intuitive for experts.
- Active class selection.
- Active feature value acquisition.

Image: Freepik.com

Stopping criteria for active learning

- Active learning usually stops when the labeling costs exceed the gains resulting from the expected model improvements.
  - Our querying budget ends.
  - Model improvement in a few consecutive iterations is lower than a predefined threshold.
- The life-long learning setup:
  - The learning never stops.
  - Suitable for detecting new classes or dealing with the concept drift.

Summary

- We discussed the basic principles of active learning.
- We considered three different active learning application scenarios, with their pros and cons.
- We talked about the informativeness of instances in the context of AL and its relation to the uncertainty of the learner.
- We analyzed a few AL algorithms and application examples for different real-world ML tasks.

Literature:

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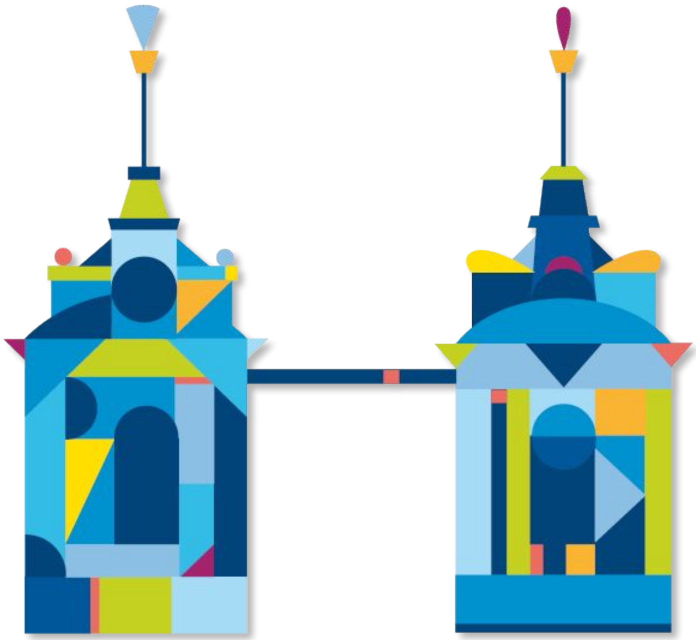

QUESTIONS OR COMMENTS?

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