Reinforcement Learning Based Online Active Learning for Human Activity Recognition

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Human Activity Recognition

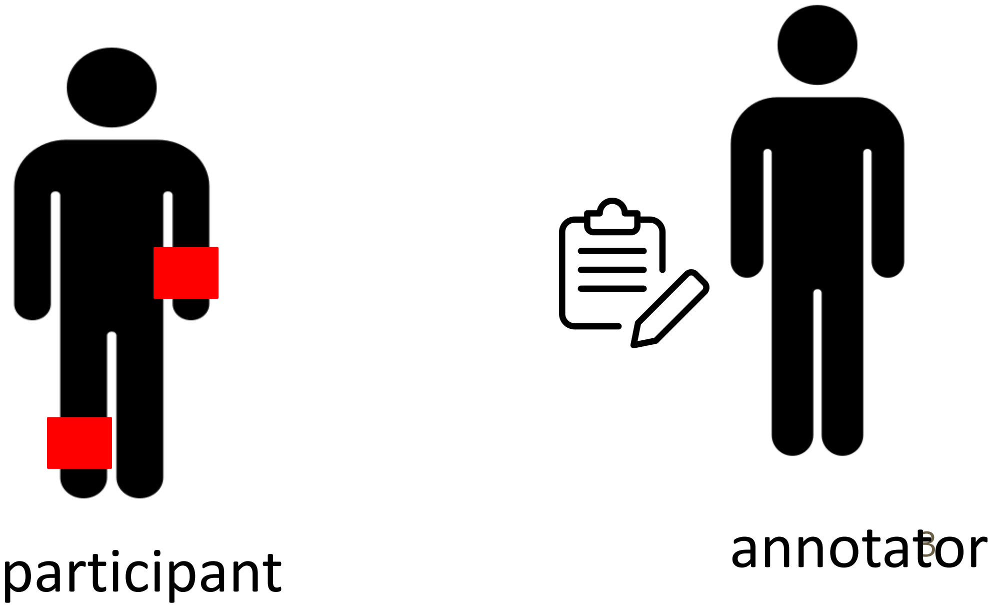
- Human Activity Recognition is at the core of ubiquitous computing
  - Health monitoring
  - Daily Living
  - Sports monitoring

- Predominantly supervised learning of HAR models

Annotation challenges for HAR

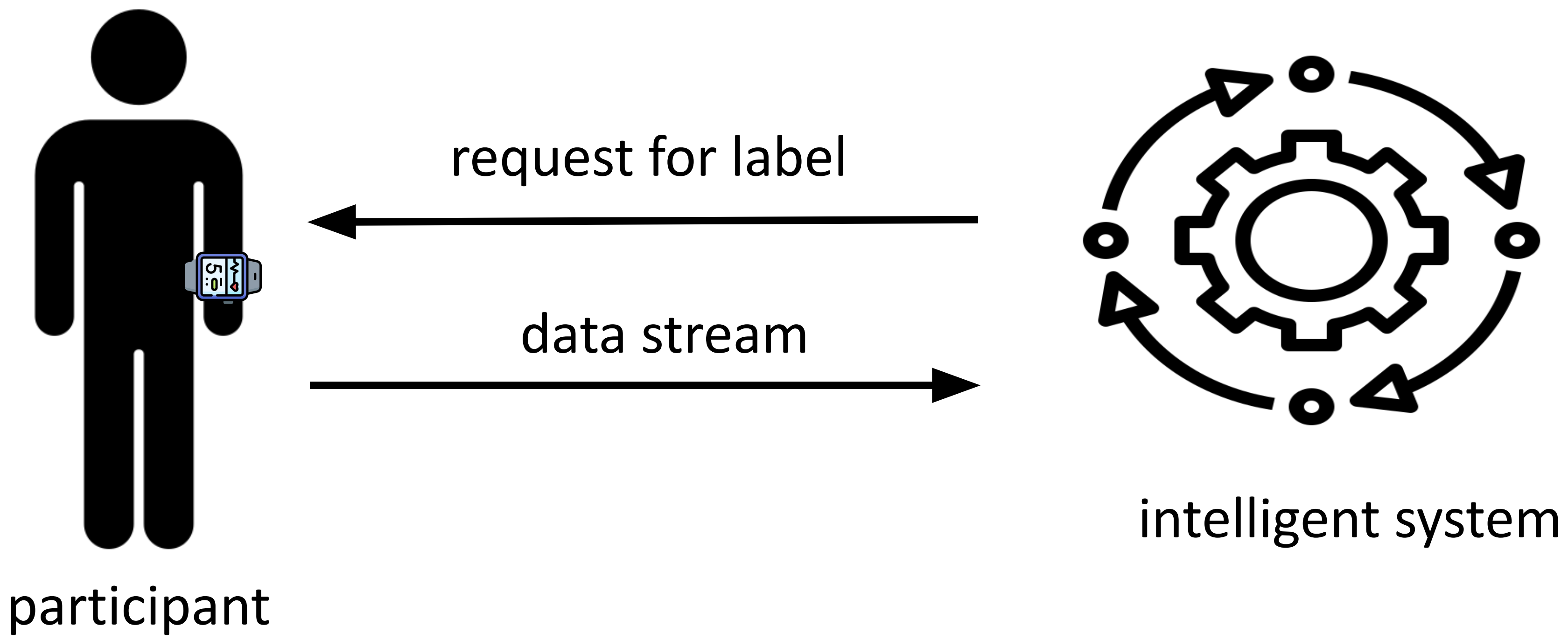
- Predominantly supervised learning of HAR models

- Challenging to acquire annotations
  - Traditional methods include manual labelling by experts / researchers
  - Resource Intensive
    - expensive, time-consuming



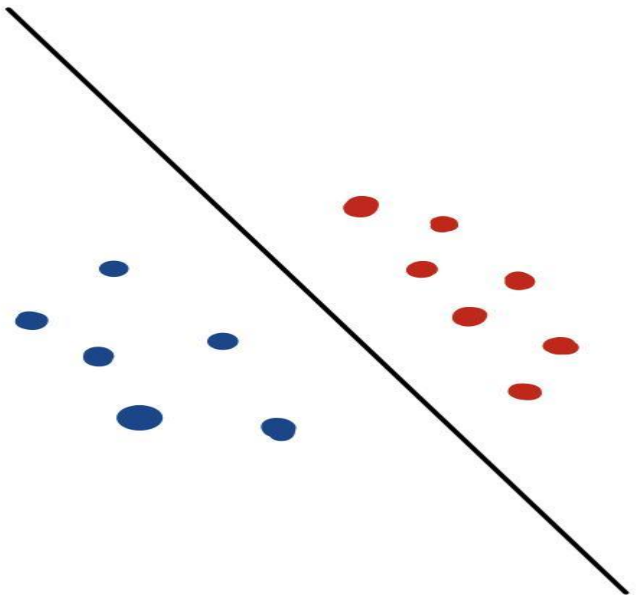
Active Learning

- Can participants provide activity labels?



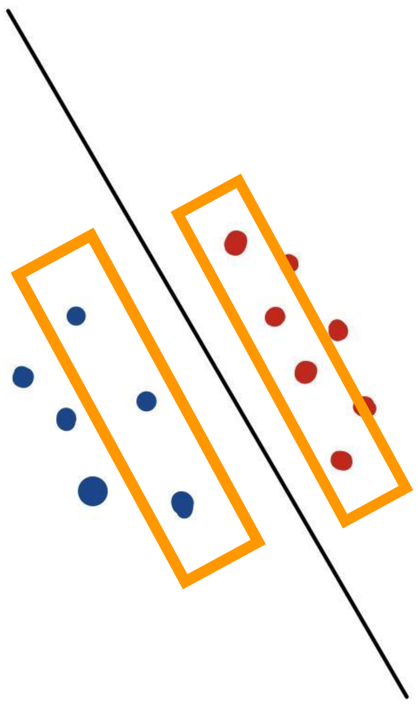
Active Learning

- Active Learning - a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns.



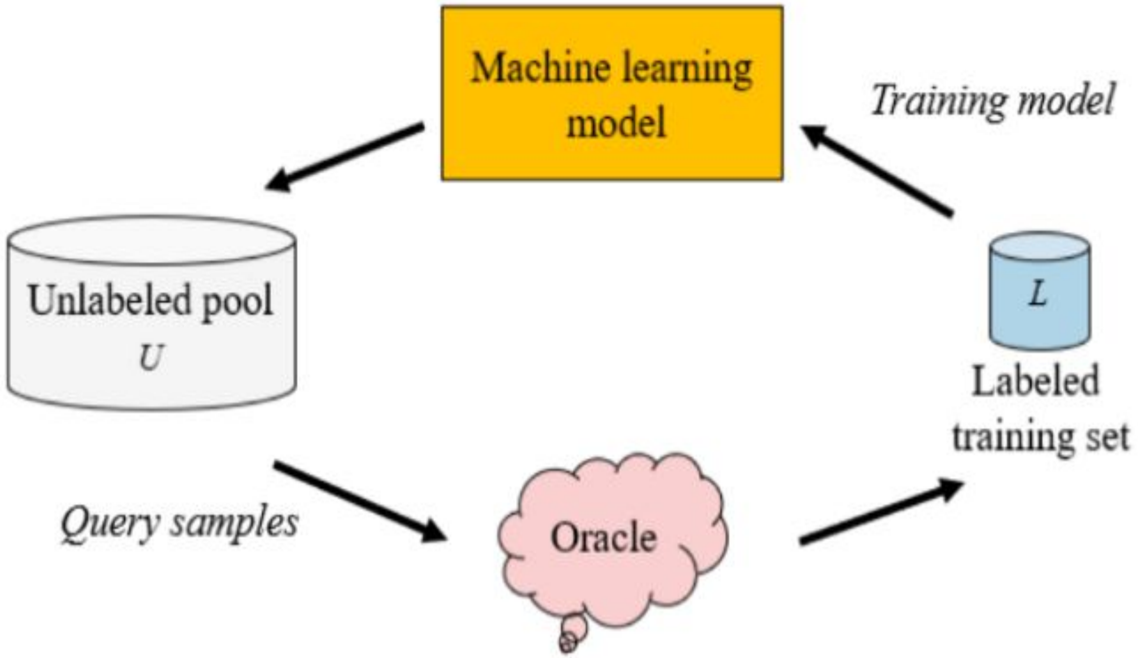
Active Learning

- Active learning: the most informative data points are important for model-training



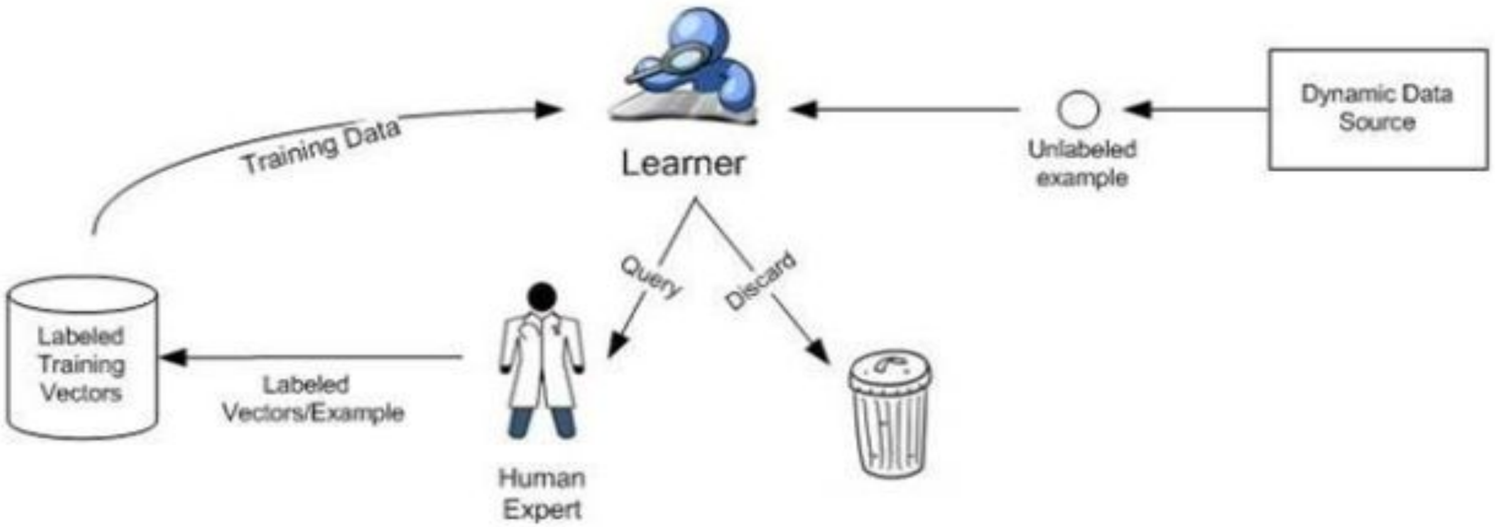
Active Learning - Pool-based

- Pool-based Active Learning
  - all unlabeled data is available to be choose from during training



Active Learning - Stream-based

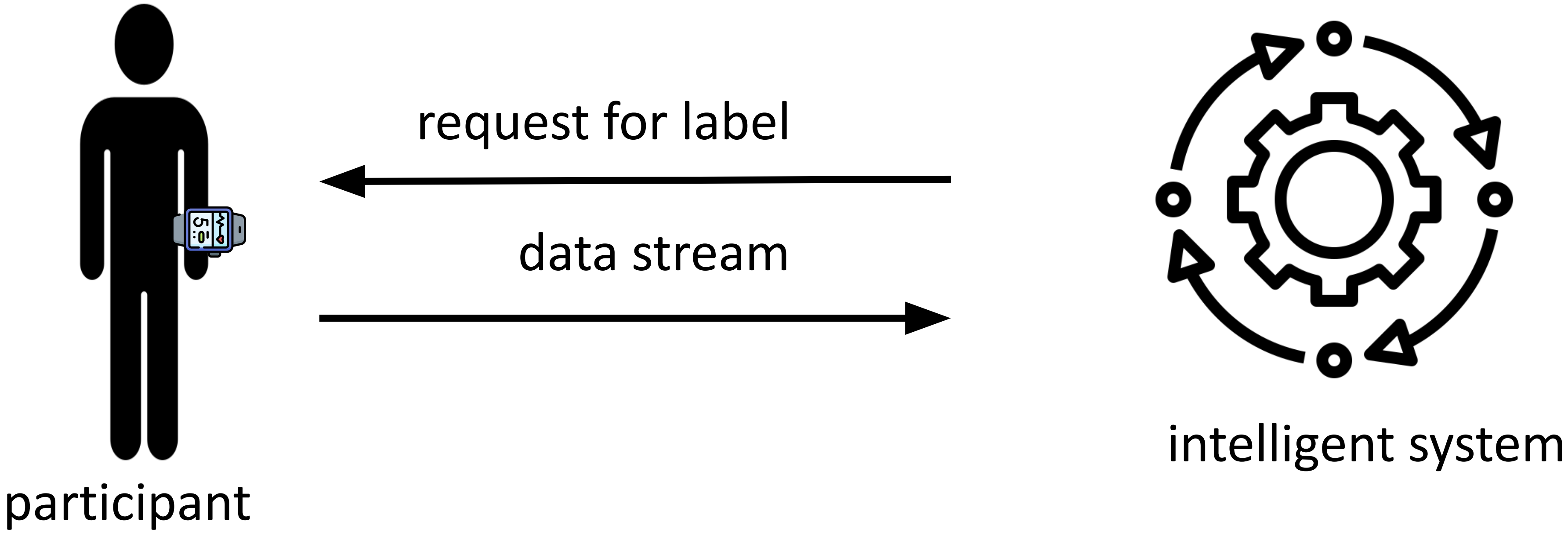
- Stream-based or Online Active Learning
  - data arrives in a sequential fashion



Budget-based Active Learning

- Budget
  - how many annotations ?

- Budget-spending strategies
  - when do we ask the participant for annotations?

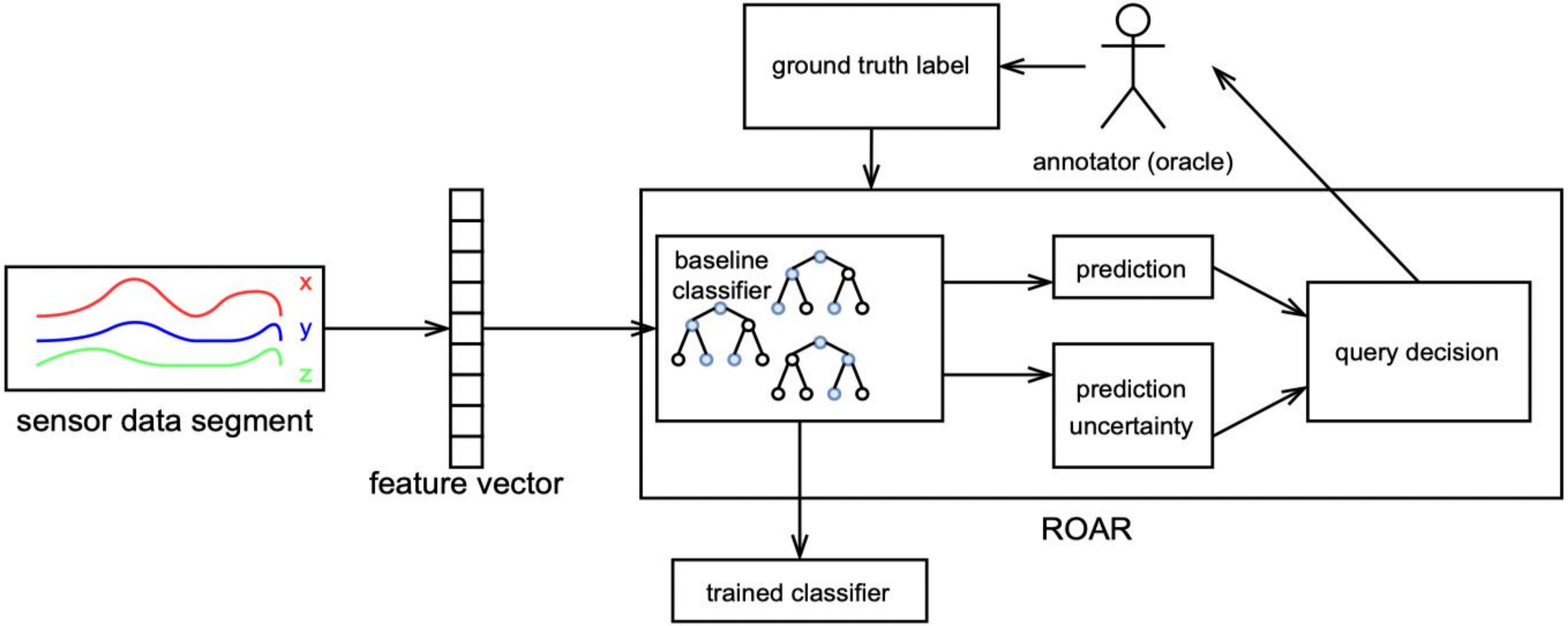


Existing Online Active Learning Approaches

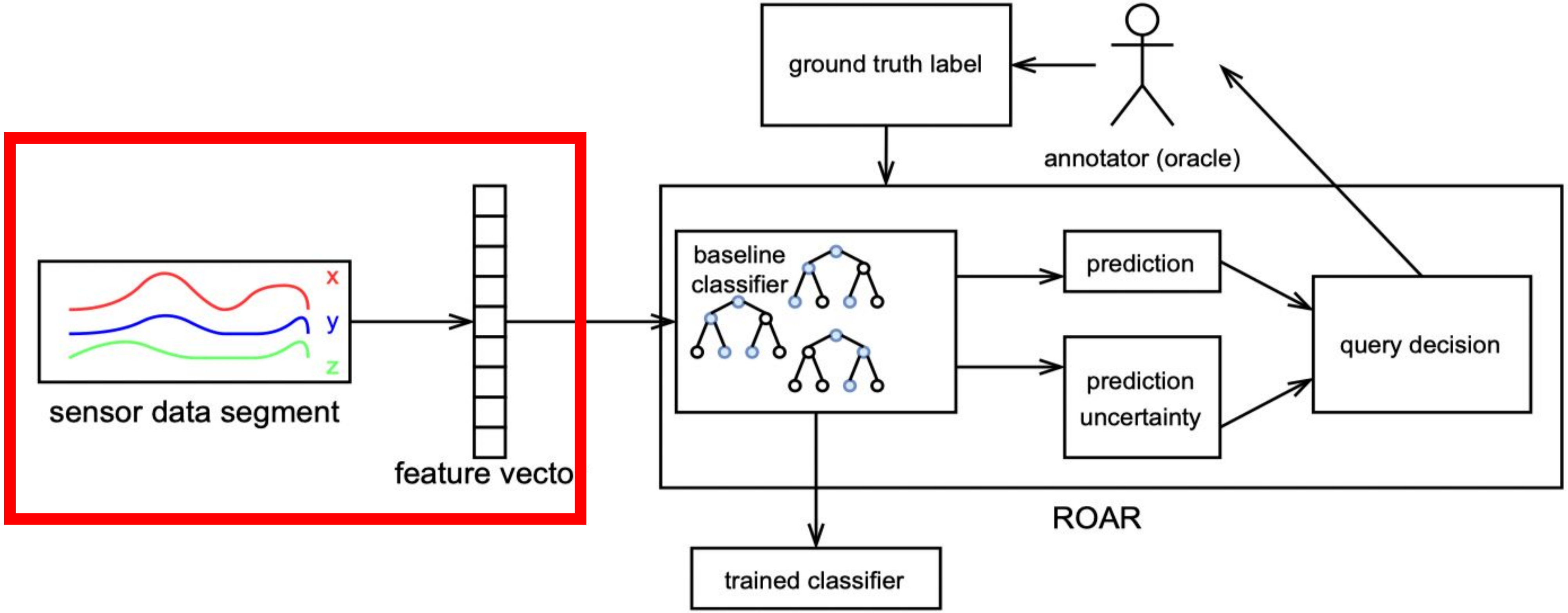
- Measure of Uncertainty - classification confidence

- Pre-train models with data from all classes

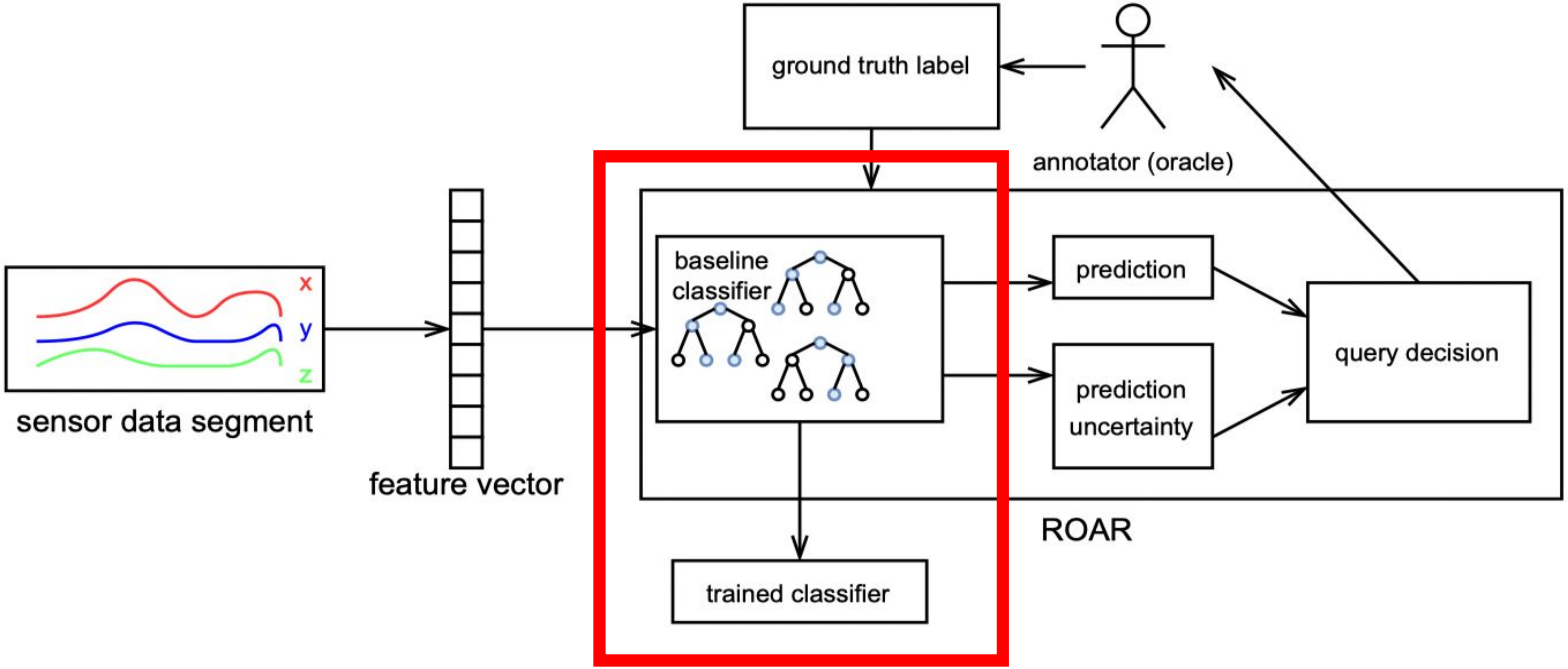
ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION



ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION

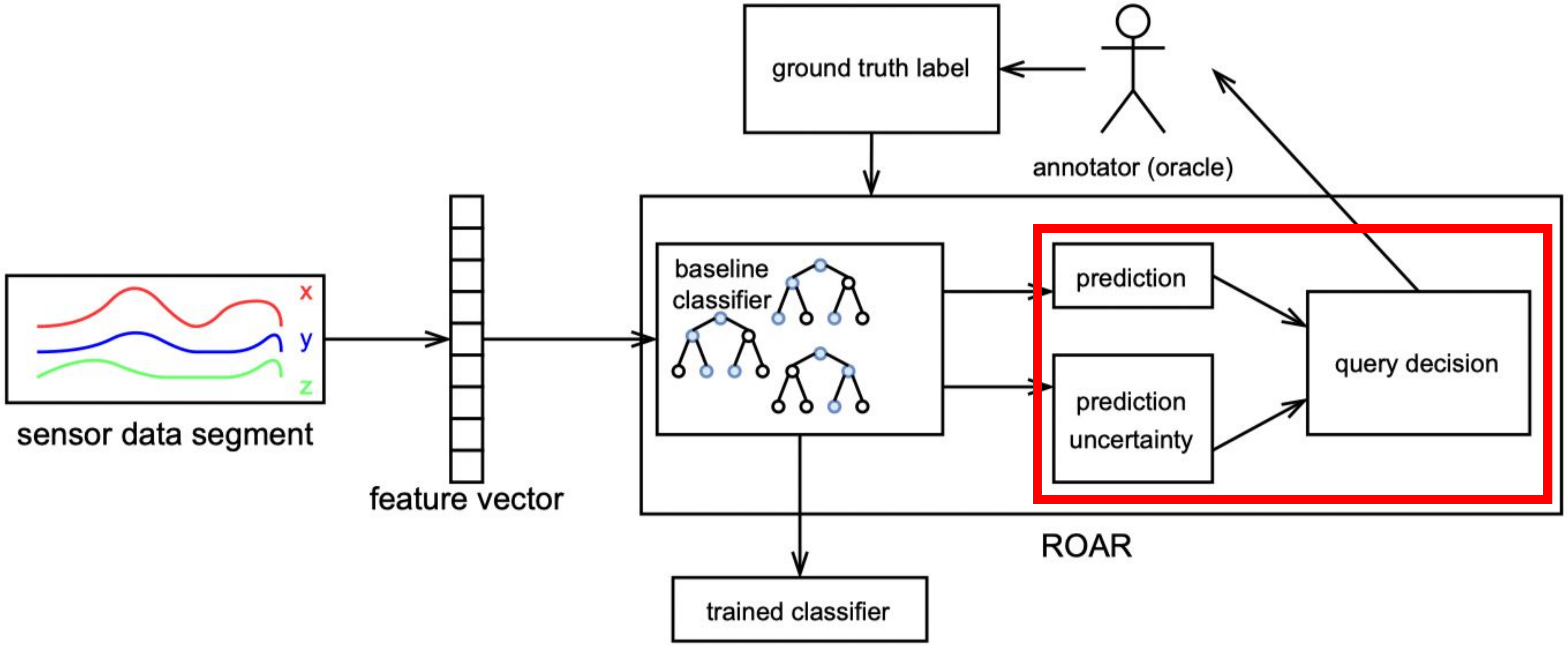


ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION



ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION

- Query decision
  - Decide whether to ask annotator (oracle) for the label of an incoming data



ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION

Query Decision (Policy):

$$\textbf{if } p < \epsilon \text{ or } y_{conf} < \theta \textbf{ then}$$
$$\quad y \leftarrow askOracle(\mathbf{x})$$

ROAR: RL-BASED ONLINE ACTIVE LEARNING FOR ACTIVITY RECOGNITION

Policy Update:

$$\theta \leftarrow \min(\theta(1 + \eta \times (1 - 2^{\frac{r}{p^-}})), 1)$$

- policy (θ): a threshold for decision confidence
- reward (r): updates the probability(p) for policy
- η: learning rate
- p-: negative absolute value of the reward

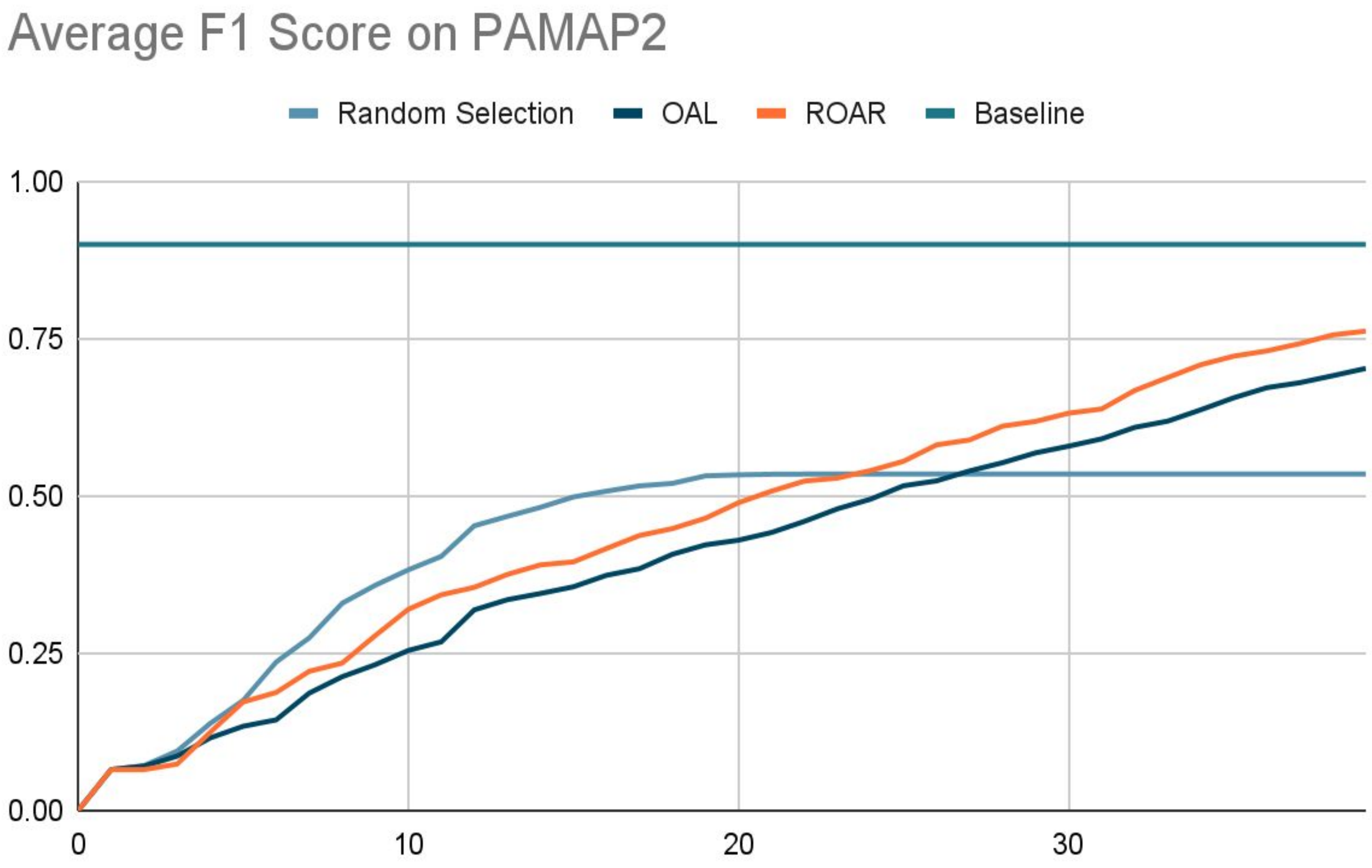
EXPERIMENTAL EVALUATION

- Experimental Simulation
  - Employ 80 / 20 for the train-test split
    - user specific analysis
    - dataset is unshuffled
    - activities are present in both train and test set

  - Budget - 40 samples from train set

  - Evaluation - test set

EXPERIMENTAL EVALUATION



Miu, T., Missier, P., & Plötz, T. (2015, October). Bootstrapping personalised human activity recognition models using online active learning. In *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing* (pp. 1138-1147). IEEE.

EXPERIMENTAL EVALUATION

Dataset	Random	OAL	ROAR	Baseline
USC-HAD	0.52±0.17	0.62±0.13	0.69±0.12	0.87±0.10
Daphnet	0.60±0.21	0.66±0.22	0.73±0.20	0.78±0.17
PAMAP2	0.54±0.11	0.70±0.12	0.76±0.07	0.90±0.05
Opportunity	0.34±0.11	0.33±0.06	0.37±0.10	0.40±0.11
Skoda	0.61±0.05	0.65±0.01	0.76±0.01	0.98±0.01
MHealth	0.74±0.07	0.51±0.04	0.87±0.08	0.90±0.06
WARD	0.53±0.11	0.67±0.13	0.68±0.12	0.88±0.11

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CONCLUSION

- Obtaining ground truth annotations is hard
- We employ an online active learning procedure for HAR using a RL approach
- For a given budget size
    - ROAR intelligently queries data points
    - In half the cases, we get close to fully supervised baselines