Mindful Active Learning

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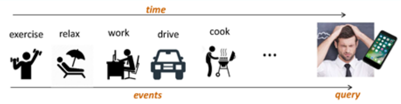
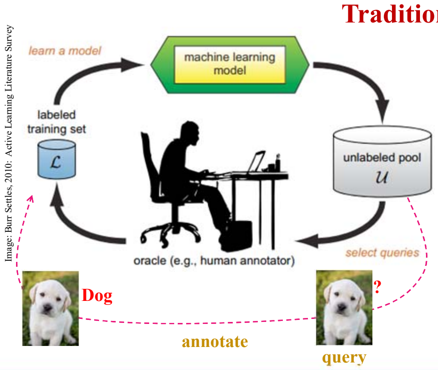
Highlights

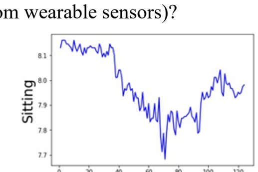


- A novel active learning approach, Mindful Active Learning.
- Motivated by active learning with mobile/wearable devices.
- Taking cognitive and compliance limitations of the oracle into account when querying for labels.
- Limiting the number of queries so that the oracle (i.e., end-user of the mobile system) is not overloaded.
- Incorporating the lag between the event time and the query time.
- Entropy Memory Maximization (EMMA):
  - Optimization problem to maximize the active learning performance while accounting for human constraints.
  - A combinatorial optimization approach.
  - Takes informativeness of sensor data, query budget, and human memory into account.
  - Evaluated EMMA for activity recognition using wearable sensors.
- Accuracy ranges from 21% to 97% depending on memory strength, query budget, and difficulty of the learning task.
- Accuracy 13.5% greater than other methods; at most 20% less than upper-bound; up to 80% higher than lower-bound.
- Mindful active learning is most beneficial when the query budget is small and/or oracle's memory is weak.

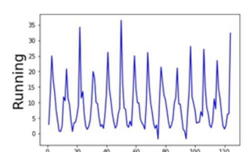
Traditional Active Learning



- Iteratively query oracle for correct label.
- Assumes labels/annotations are perfect/accurate.
- Raw data (e.g. images) are strong cues about correct labels.
- What if unlabeled raw data are different (e.g., time-series signals from wearable sensors)?

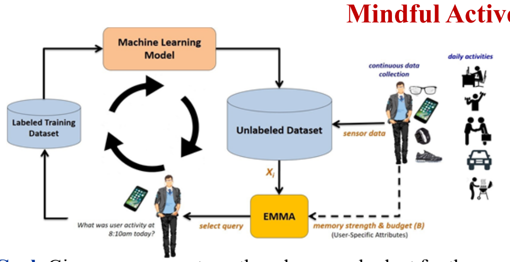


Accelerometer signal for 'sitting' activity



Accelerometer signal for 'running' activity

Mindful Active Learning



- Time-series signals do not provide strong visual cues for highly accurate labeling.
- Mindful active learning assumes that labels are not perfect.
- Humans can forget past events.
- The amounts of queries that one can respond to is limited.

Goal: Given a memory strength and a query budget for the user, iteratively choose sensor observations to query such that the accuracy of the model learned using labeled data is maximized.

Problem Formulation

- Given a pool of sensor observations, select at most B observations s.t. expected gain due to memory and informativeness is maximized.
- **Entropy-Memory Maximization (EMMA)**

$$\text{Maximize} \quad \sum_{i=1}^{m} a_i \mathcal{E}(I_i, M_i) \qquad (1)$$

Subject to:

$$X_i \in \mathcal{X} \qquad (2)$$

$$\sum_i a_i \leq B \qquad (3)$$

$$a_i \in \{0, 1\} \qquad (4)$$

- Assuming informativeness and memory are independent, write expected gain as multiplicative of the two:

$$\mathcal{E}(I_i, M_i) = \mathcal{E}(I_i)\mathcal{E}(M_i)$$

- **Informativeness of Sensor Data**

$$\mathcal{E}(I_i) = E_i = -\sum_{j=1}^{n} P_{ij} \log P_{ij}$$

  - Used entropy to quantify informativeness
  - Because classifier is less certain to classify observations that carry a higher entropy, such observations will be more informative if labeled and used for classifier retraining.
- **Human Memory**

$$\mathcal{E}(M_i) = R_i = e^{-\Delta t_i / s}$$

  - Used Ebbinghaus forgetting curve
  - Memory retention for a sensor observation is probability of a human subject with a memory strength of s being able to remember the event correctly after certain time has elapsed.
- **Brute force solution**
  - Having time complexity of $O(m^B)$, with m as the size of unlabeled set and B as the query budget.

Greedy Solution

- Iteratively chooses the best candidate observation (i.e., one with the highest expected gain) from the set of unlabeled observations.
- After moving an observation from unlabeled dataset (X) to labeled dataset (Z), model M is retrained using the labeled data in Z. The procedure is repeated until the entire budget, B, is consumed.

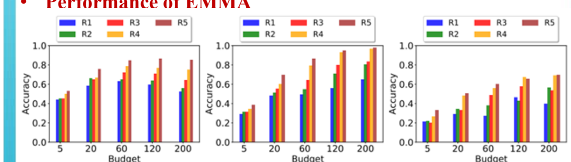
Algorithm 1 Greedy algorithm for EMMA

Input: $\mathcal{X}$ (unlabeled observations), B (budget)
Output: $\mathcal{Z}$ (labeled observations)
for $b = 1$ to B **do**
  Compute $\mathcal{E}(I_i, M_i)$ for all $X_i \in \mathcal{X}$ using (5)–(7)
  Find $X_i \in \mathcal{X}$ with highest value of $\mathcal{E}(I_i, M_i)$
  Remove X_i from $\mathcal{X}$
  Query oracle to annotate X_i, and add labeled X_i to $\mathcal{Z}$
  Retrain model $\mathcal{M}$ using labeled items in $\mathcal{Z}$
end for

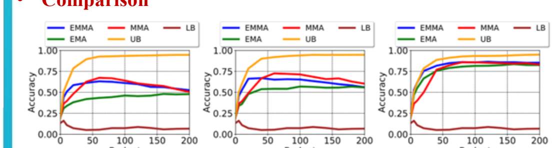
Time complexity: $O(m.B)$
- 'm' : size of X
- 'B' : query budget

Results

- **Performance of EMMA**



  - Memory retention levels: R1 (10%–99%), R2 (20%–99%), R3(30%–99%), R4 (50%–99%), R5 (70%–99%)
  - Min accuracy: (achieved with least budget and weakest memory) 44%, 29% and 21% for HART, DAS and AReM datasets, respectively.
  - Max accuracy: 85.3%, 97.5% and 70% with greatest budget and strongest memory.
  - There is a chance of drop in performance as increasing the budget, when memory is weak.
- **Comparison**



(a) R_1 (b) R_2 (c) R_3

  - Figure shows results on HART dataset for three memory retention levels.
  - EMA (Entropy Maximization): optimize for informativeness only; thus, $E(M_i) = 1$.
  - MMA (Memory Maximization): optimize for memory retention only; thus, $E(I_i) = 1$.
  - Upper-Bound (UB): no erroneous labels exist as a result of memory weakness. That is, assume that the oracle's memory is perfect, as a result of which the optimization problem aims to maximize for entropy only.
  - Lower-Bound (LB): oracle's memory is low and the observations are chosen randomly. Informativeness of the queried observation is not considered as a parameter.
- **Summary of Findings**
  - EMMA performs 13.5% better than EMA and 14% better than MMA with weaker memory and smaller budget (averaged over three datasets).
  - EMMA's accuracy is at most 20% less than UB and up to 80% higher than LB, on average.
  - As memory becomes stronger, EMMA and EMA converge and achieve accuracy values closer to UB.
  - Improvement due to using EMMA over EMA and MMA is most notable when budget is small and memory is weak.
  - EMMA being more consistent over different datasets and tasks.

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