Bayesian Active Learning for Wearable Stress and Affect Detection

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NEURAL INFORMATION PROCESSING SYSTEMS

Motivation

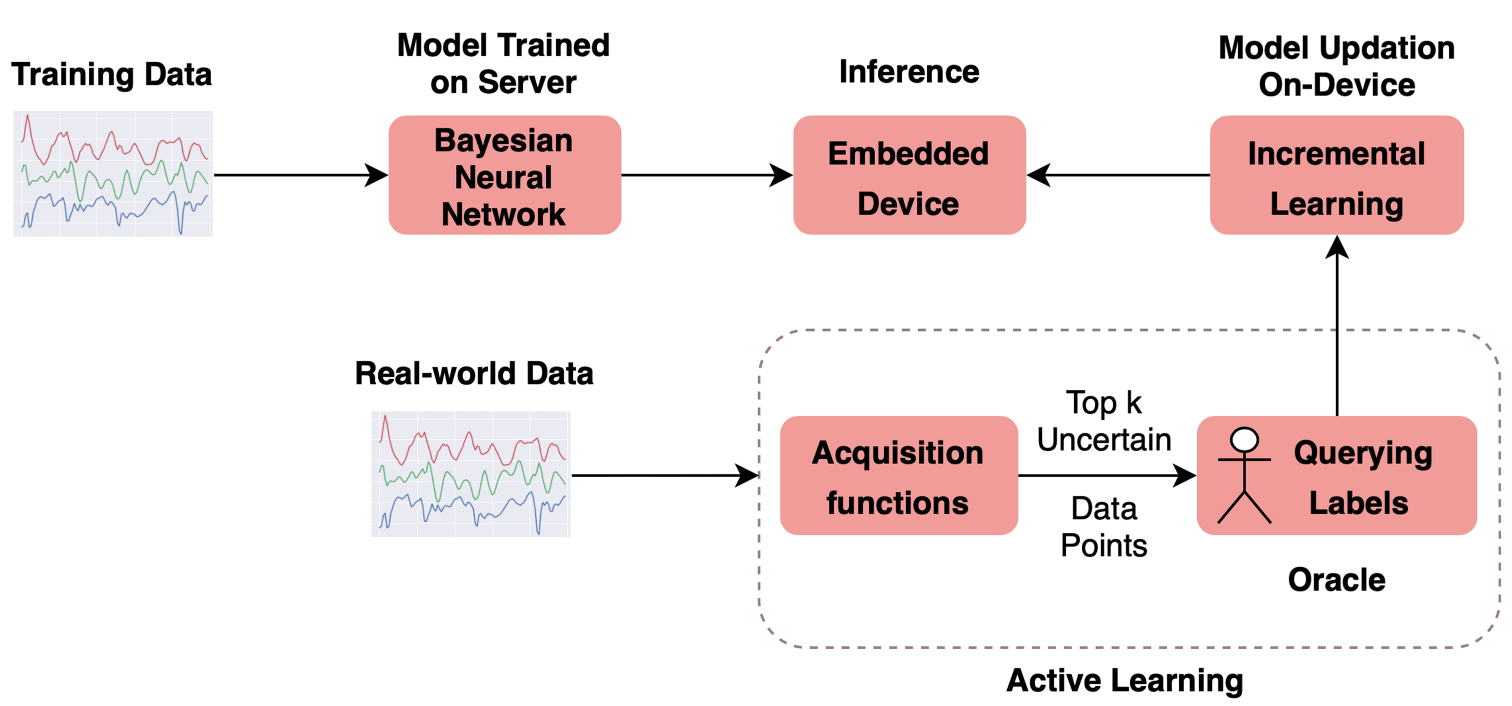
- Psychological stress has been increasingly observed in humans, and early detection is crucial to prevent health risks.
- **Active Learning** – the ability to learn from real-world unlabeled data by querying an oracle – reduce labeling load.
- Unexplored area for such tasks and helps alleviate concept drift.
- **Bayesian Neural Networks (BNNs)** – *Monte Carlo Dropout* with NNs to estimate predictive uncertainties [1].
- Predictive distribution for a new data point can be obtained by,

$$p(y^*|x^*, D_{train}) = \int p(y^*|x^*, \omega)p(\omega|D_{train})d\omega$$

where $p(\omega|D_{train}) = q_\theta^*(\omega)$ and $q_\theta^*(\omega)$ is the dropout distribution approximated using Variational Inference.

- *Dropout,* a light-weight operation enables easier and faster approximation of posterior uncertainties.
- Coupled with active learning *acquisition functions* for querying the most uncertain data points from the oracle.

Overall System Architecture



Dataset

SWELL-KW Dataset

- Participants performed knowledge work tasks
- Perturbed by environmental stressors
- Measures Heart Rate Variability and Skin Conductance
- Affective states – Neutral (N), Interruption (I), Time Pressure (T)
- Binary Classification on N vs I&T (stress)
- Conventional data split into D_{train}, D_{pool} and D_{test} at random

Acquisition Functions for Active Learning

Given a classification model *M*, real-world pool data D_{pool}, and inputs $x \in D_{pool}$, an acquisition function *a(x, M)* is a function of *x* that the active learning system uses to infer the next query point:

$$x^* = argmax_{x \in D_{pool}} a(x, M)$$

Acquisition functions are used in active learning for approximations in Bayesian CNNs, thereby arriving at the most efficient set of data points to query from D_{pool}.

Max Entropy: Pool points are chosen that maximize the predictive entropy.

$$\mathbb{H}[y|x, D_{train}] := -\sum_c p(y = c|x, D_{train}) \log p(y = c|x, D_{train})$$

Bayesian Active Learning by Disagreement (BALD): Pool points that maximize the mutual information between predictions and model posterior, that disagree the most about the outcome.

$$\mathbb{I}[y, \omega|x, D_{train}] = \mathbb{H}[y|x, D_{train}] - E_{p(\omega|D_{train})}[\mathbb{H}[y|x, \omega]]$$

where $[\mathbb{H}[y|x, \omega]]$ is the entropy of y, given model weights ω.

Variation Ratios (VR): The LC (Least Confident) method for uncertainty-based pool sampling.

$$variation - ratio[x] := 1 - \max_y p(y|x, D_{train})$$

Random Sampling: Select a point from the pool points uniformly at random.

Experiments

- We use a four-layer Convolutional 1D network (4, 8, 16, 32).
- Two Fully-Connected (FC) layers (32, 16) after the Conv-1D blocks.
- *MC-Dropout* layer of probability 0.3 between FC-layers making them ***Bayesian Convolutional Neural Networks (B-CNNs).***
- To perform approximate inference using B-CNNs,
  – Dropout is performed at train and test times
  – Using multiple stochastic forward passes (*T*)
  – Optimal Dropout iterations (*T* = 10)
- **Acquisition adaptation factor (η) ∈ [0, 1]**
  – Represents number of acquisition windows used for active learning from D_{pool}

Results

η	Max Entropy	BALD	Variation Ratios	Random Sampling
0.0	79.12	79.12	79.12	79.12
0.2	82.66	81.21	83.11	81.91
0.4	86.43	86.58	88.29	86.76
0.6	89.40	90.22	90.38	88.19
0.8	89.98	90.63	90.82	88.95
1.0	91.92	91.92	91.92	91.92

Acquisition Adaptation Factor vs Accuracy across all acquisition functions

- Baseline Accuracy – **79.12%**, without active learning and trained on D_{train} alone
- Maximum accuracy achieved when trained on all D_{train} and D_{pool}
- Ideal – **η = 0.6**, **Variation Ratios** acquisition function – 90.38% accuracy

On-Device Performance

- Raspberry Pi 2 is used for evaluating our proposed framework
  – has similar hardware & software specifications as predominant contemporary mobile/wearable devices.
- Practical to threshold number of D_{pool} points collected in a single acquisition iteration. Can be quantified in two ways
  – Number of windows (w_a)
  – Time taken (in seconds)

Process	SWELL-KW
Baseline before AL	79.12%
Inference time	9 ms
Stochastic Forward Pass (T)	0.5 sec
Time taken per epoch	0.6 sec
Model size	115 kB

On-Device Performance Metrics

References

[1] Yarin Gal and Zoubin Ghahramani, (2016), "Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning," In: 33rd International Conference on Machine Learning (ICML).

[2] A. Ragav, N. H. Krishna, N. Narayanan, K. Thelly and V. Vijayaraghavan, (2019), "Scalable Deep Learning for Stress and Affect Detection on Resource-Constrained Devices," In:18th IEEE International Conference on Machine Learning and Applications (ICMLA).

[3] Gautham Krishna Gudur, Prahalathan Sundaramoorthy and Venkatesh Umaashankar, (2019), "ActiveHARNet: Towards On-device Deep Bayesian Active Learning for Human Activity Recognition," In: The 3rd International Workshop on Deep Learning for Mobile Systems and Applications (EMDL).