Low-Energy High-Performance Approximation System via Genetic Programming and Error-Aware Classification Model

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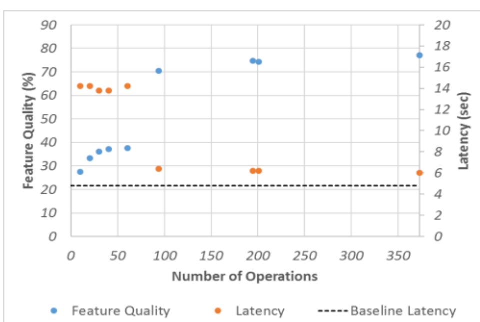
Machine learning has found a host of utilities in the modern world. The ability to learn predictive models from large sets of data can be found in contemporary fraud detection, web advertisements, and even the auto-fill of search engines. The two common components of machine-learning include a feature extraction step followed by classification to generate a model fit for the data. General machine learning can be very useful, but can also be energy intensive. Depending on the application, the feature extraction phase can pose as a large power drain; we aim to reduce this energy usage.

Genetic programming (GP) is a tool that can efficiently model input-output data to optimize a set of objectives in a way that mirrors the effects of natural selection [1]. A potential benefit of using GP is its efficiency in producing features without excessive drain of energy. However, due to the nature of GP, the feature vectors may accrue some amount of approximation error. An error-aware support vector machine (SVM) classifier is thus used to produce a model that may fit the feature vector accordingly even if it contains does errors [2]. We demonstrate this through a case study with EEG based seizure detection data [3], in the hopes that we can produce low complexity GP models that can still perform at a high level.

To evaluate the efficiency of this method, we took an approximation of the energy required to produce the GP model based on the number of calculations required to produce a feature. A baseline feature extraction and classification performance was measured using signal filtration methods (band-pass filter and decimation in the time or frequency domain) to compare against the GP models. The average number of baseline operations per feature is 57472 in the time-domain and 8576 from the frequency-domain. From Fig. 1, we see that the GP models reach an almost baseline performance both in terms of latency and the number of false alarms while still maintaining a reduced number of operations. More work can still be done to reduce the complexity of the GP models.

A



B

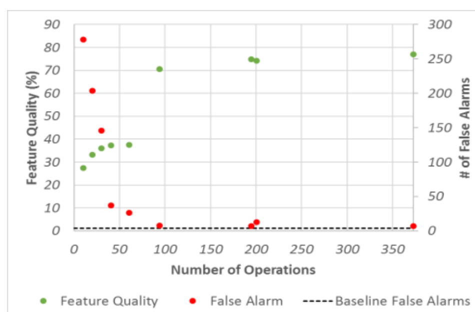


Fig. 1 **(A)** Comparison of model efficiency to feature quality and classification latency (baseline = 4.81). **(B)** Comparison of model efficiency to feature quality and the number of false alarms (baseline = 4).

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