EMBEDDED MACHINE LEARNING

Exercise 1

Group 6
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Contents

1 Reading

The paper MLPerf Tiny Benchmark presents the MLPerf Tiny Benchmark, the first industry-standard suite specifically designed to evaluate the performance of ultra-low-power machine learning systems. Recognising the unique challenges of TinyML implementation, the benchmark focuses on four critical workloads: keyword spotting, anomaly detection, visual wake words, and person detection. The paper details a well-defined set of metrics (accuracy, latency, and energy consumption), along with comprehensive guidelines aimed at establishing fair and reproducible TinyML performance comparisons.

The authors highlight that the lack of standardisation to date has been a significant barrier to objective evaluation of TinyML systems, and has consequently hindered progress in the field. MLPerf Tiny directly addresses the complexities of measuring performance on resource-constrained devices, with a strong emphasis on energy consumption as a critical metric. In addition, by selecting specific workloads, the paper highlights the unique capabilities and limitations of TinyML applications for real-world scenarios.

The paper is well written and conveys the motivation behind the benchmark and the rationale for its design. The emphasis on energy efficiency as a core metric is crucial and accurately reflects the real-world considerations for deploying TinyML solutions.

Assuming the target venue for the paper is benchmarking methodologies or machine learning systems, this paper makes a valuable and substantive contribution and we would therefore recommend it for acceptance.

2 Polynomial curve fitting

Figure 1 shows the training data together with the test data. It also shows the ideal target results or the ground truth. Figure 2 and 3 show polynomial curve fitting with a third degree polynomial and an eleventh degree polynomial. Since the test and training data correspond to the ground truth, a sine with noise, an eleventh degree polynomial is too high, as expected, which overfits the data. This can also be seen in the last figure 4, which shows the RMS error against the degree of the polynomials. As can be seen, the best results, i.e. the smallest error, are achieved with a polynomial between degree three and five.

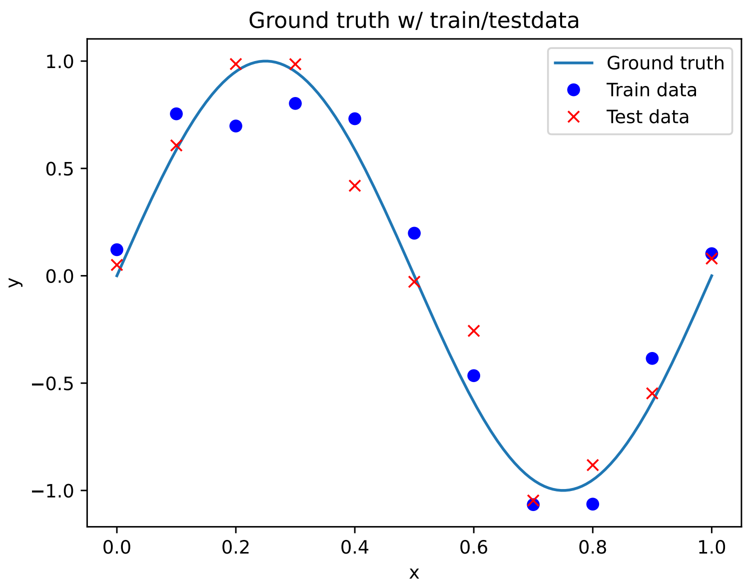

Figure 1: Ground truth with test data and training data

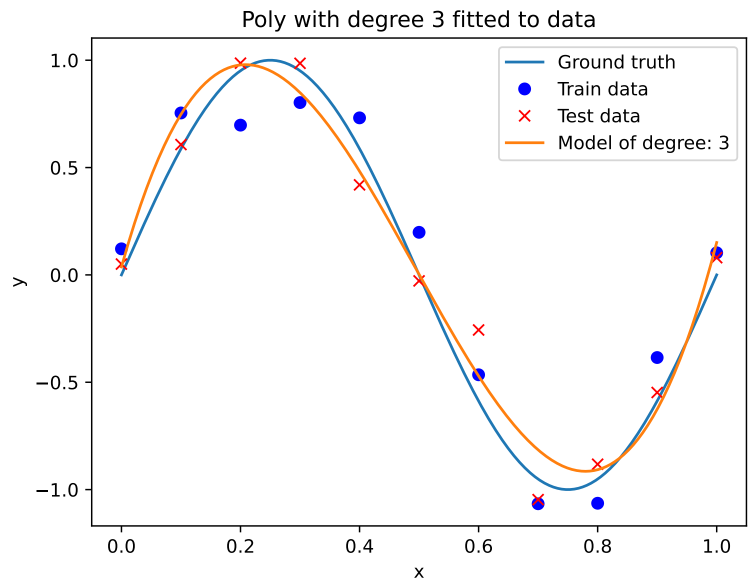

Figure 2: Ground truth with the result of a third degree polynomial fitted to the train data

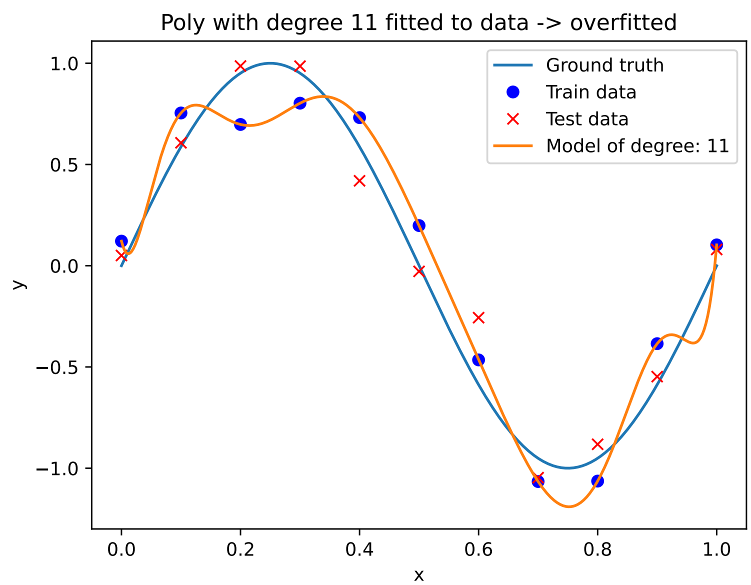

Figure 3: Ground truth with the result of an eleventh degree polynomial fitted to the train data

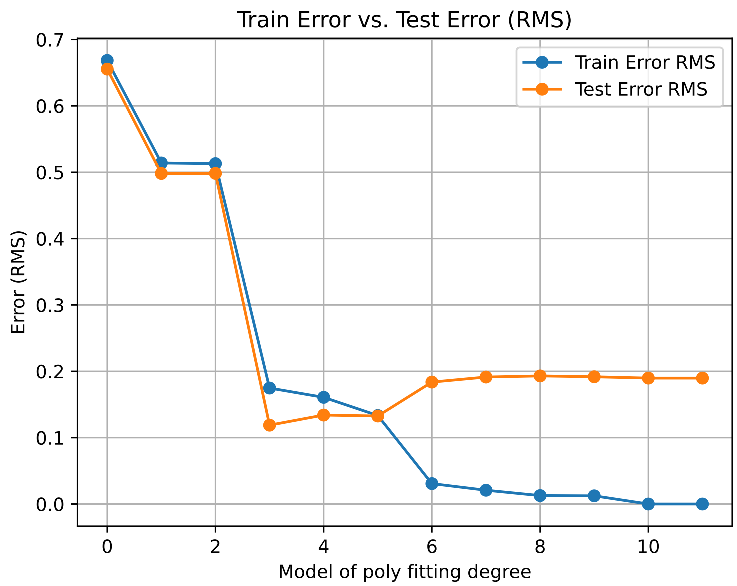

Figure 4: Error of the training data against error of the test data via polynomial degrees 0 - 12

3 Willingness to present

Exercise 1	Yes
Exercise 2	Yes