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IMPROVED PRINTER FAILURE PREDICTION

HP INC

Improved Printer Failure Prediction

Abstract: This disclosure describes a more accurate and data efficient failure prediction mechanism for printer components. Better failure prediction leads to improved service efficiencies and cost savings for channel partners.

A technique is disclosed that constructs extremely simple summaries of printer telemetry streams. These summaries are used to construct very data-efficient failure predictors for printer components.

A printer's stream of telemetry data consists of events such as paper jams and thermal spikes. The events are marked 0 or 1 depending on whether we are in a healthy printer state or not. We learn to predict part failures from such annotated printer event streams using machine learning (ML). In non-sequential machine learning, each event is studied as a stand-alone observation. This ignores the context present in a stream of events and gives poor accuracy. In sequential ML, each event is processed within the context provided by the event stream. But this approach is very data hungry. We present a data-efficient sequential ML solution.

In our technique, the event stream is split into the healthy and unhealthy regions. We construct regionwise summaries. Each region (healthy or unhealthy) can be summarized by taking the max of event count over the region. This algorithm is given in detail next.

1) For each type of event (e.g., paper jam)
2) Each region (healthy or unhealthy) is summarized by taking the max of daily counts in that region.
3) This results in a two number summary for each event type. Namely, the max-count-healthy and max-count-unhealthy.

These summaries are sequential in nature. The summarization is illustrated in Fig 1. When the data is well-behaved, these summaries contain all the failure patterns present in the original stream, with very little loss of failure related information. This claim is formalized in Figs 2 and 3.

The current technique is a more compressed version of the event stream summary disclosed in Technical Disclosure 'Printer Operating Characteristics Chart' [1]. The advantage of the current technique over [1], is that we get exactly two features for each event type. Whereas the previous technique was a variable length summary and could result in a variable number of features. This fixed number of features enables standard ML techniques to be used, as described next.

These regionwise features are fed into a simple tree-based ML learner. For each event type, we have a single tree. Such trees are ensembled using the max-ensembling rule (maximum of all individual tree predictions). The combination of regionwise features and simple tree learners, enables us to construct failure prediction models from small amounts of data and increases our prediction accuracy.

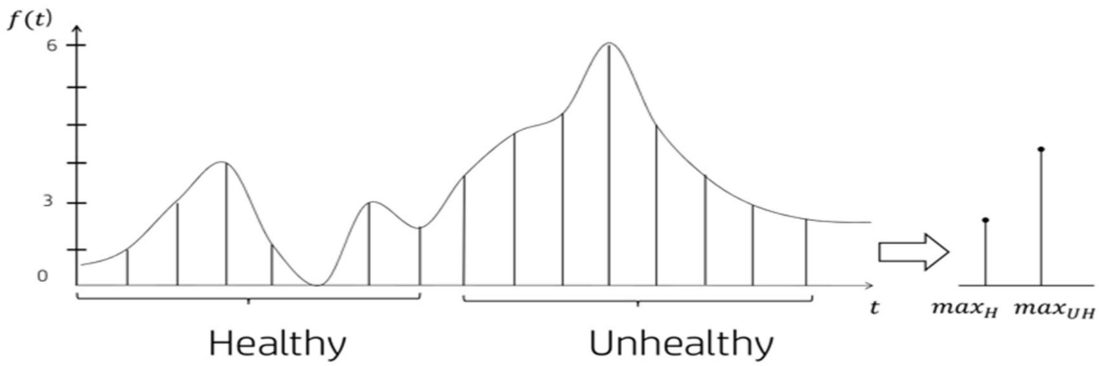

Figure 1: Example summary of paper jam counts. f(t) is daily paper jam count. The whole numeric sequence is compressed into a two number region-wise summary: max-healthy (maxH) and max-unhealthy (maxUH)

Theorem: Let f(t) be Lipschitz continuous with p < 1. Let f(t) start at 0 (WLOG). Let B be a decision boundary for stateless classifier. Then the cost simplifies to:

$$\mathrm{Cost}(B) = \begin{cases} C_{FP} & max_H > B_{min} \\ 0 & max_H < B_{min} < max_{UH} \\ C_{FN} & max_{UH} < B_{min} \end{cases}$$

Figure 2: Formal theorem demonstrating zero information loss in our sequential summarization. C(B) is the loss function of a ML decision boundary B on an input event count sequence f(t). C(B) depends solely on the maxH & maxUH numbers. The rest of the sequence f(t) is irrelevant (fig 1). Conversely, C(B) only depends on Bmin, the least number above which a failure can be predicted, the rest of the boundary B is irrelevant (fig 3). C_FP is cost of False Positive. C_FN is cost of False negative.

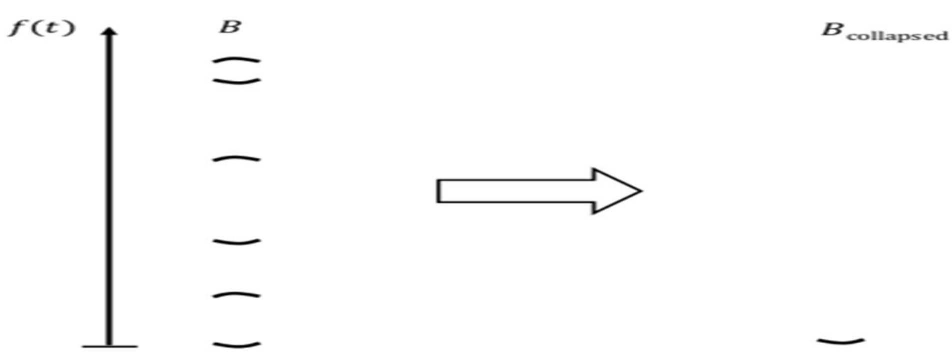

Figure 3: A decision boundary B, is collapsed to the minimum threshold above which it can call a positive (Bmin), as explained in Fig 2.

The disclosed technique enables us to build accurate failure predictors from small amounts of data. This particularly advantageous, when there is a scarcity of failure data, for instance due to the high cost of manually labelling the data. This technique enables accurate part failures prediction, enabling service optimization via better inventory planning, fleet scheduling, and preventative maintenance. This technique delivers valuable savings in both time and cost.

Disclosed by Aravindakshan Babu, Niranjan Damera-Venkata, Prasad Hegde, Md Imbesat Hassan Rizvi, HP Inc.

[1] PRINTER OPERATING CHARACTERISTICS CHART, HP Inc, Aug 2020, Technical Disclosure Commons, https://www.tdcommons.org/cgi/viewcontent.cgi?article=4568&context=dpubs_series