

Fig4PM: A Library for Calculating Event Log Measures (Extended Abstract)

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Abstract—Calculating event log measures (also known as features, metrics, and characteristics) is a common task required by many process mining applications. Process mining research studies and industrial applications often need to generate measures depending on their requirements. This has resulted in a plethora of event log measures being (re-)invented and (re-)implemented on different platforms. Fig4PM is an attempt toward building a standard, comprehensive, and reusable library for calculating event log measures. The current version of this open-source program offers 73 distinct control-flow measures either directly extracted from the literature (48 measures) or derived from the existing measures (25 measures). Eventually, our objective is to build a standard public Python library to facilitate feature generation in process mining applications.

I. INTRODUCTION

Process mining projects typically start with extracting data from a process-aware information system and transforming them into an event log [1]. These event logs serve as input for virtually all process mining applications. In order to characterize the event logs and assess the specific differences (and similarities) among the traces, process analysts often employ event log measures, i.e., “numeric representations of raw data” [2]. These measures can provide a priori insights about a log, which can then be used to draw conclusions about their properties. Typically, a measure is calculated at trace level and then aggregated to represent the event log characteristics. For example, calculating the length of each trace helps building the *average trace length* at event log level.

A wide range of process mining applications utilize such measures. We conducted a literature review to collect the studies that considered implementing new measures based on an event log’s control-flow and found 21 scientific papers¹ ranging from 2001 to 2020. Interestingly, we noticed a certain level of overlap among these studies, i.e., different studies do not refer to fully-distinct and exclusive measures. According to the results of our literature review, many approaches require implementing measures, including (but not limited to) data preprocessing [3], data quality [4], predictive process mining [5], approaches that use deep learning techniques [6], business process simulation [7], process complexity analysis [8], and trace clustering [9].

To avoid the repeated (re-)invention and (re-)implemented of the same event log measures on different platforms, we

introduce the Fig4PM library.² It provides researchers and practitioners with a basic library to access previously implemented event log measures and is specifically set out to be a starting point for ongoing development efforts. Prospective users may contribute to this project by developing new measures, improving the existing functions, add more data connectors, and improve its overall performance³.

II. MEASURES

In Fig4PM, we distinguish two types of measures based on the underlying data structure. Linear measures perceive a trace as an array, matrix, or sequence of letters (a string), whereas non-linear measures perceive a trace as a directed graph, i.e., nodes represent activities while sequences determine edges [9].

A. Measures Derived From Linear Structures

Table I lists the measures derived from linear structures that were identified in the literature. For each measure, we list its abbreviation, description, and literature source. The measures are separated into groups based on their literature source and intended purpose.

The first two groups provide a brief overview of the log size and variability. The large third group measures structuredness and variance, i.e., risk of producing a Spaghetti model [13]. To quantify these properties, we can measure reoccurring behavior in terms of self-loops and repetitions as well as the number of start and end events which concern variability in initialization or termination. As more elaborate measures for structuredness, we measure the *number of distinct traces per 100 traces (tcpht)*, *absolute trace coverage (tco)* and the *relative trace coverage (rtco)*. The lower *tcpht*, the more structured the underlying event log. *tco* represents the minimum number of distinct traces required to cover 80% of all traces in the log hence, evaluating the variants’ frequencies. Relating *tco* to *ntc* yields the relative trace coverage, which is better suited for comparison across different (sub-)logs.

The fourth group consists of several measures based on density, similarity (diversity), and complexity. The fifth group measures event log entropy using 3 different methods.

²Code is available at <https://github.com/f-zand/fig4pm>.

³Demo video available at <https://bit.ly/3iTi5MR>.

¹Material is available at <https://doi.org/10.6084/m9.figshare.14912313.v2>.

TABLE I
LITERATURE-BASED MEASURES - LINEAR STRUCTURE

Abbreviation	Measure
<i>ne</i>	Total number of events [10]–[12]
<i>nec</i>	Total number of event classes [10]–[12]
<i>nt</i>	Total number of traces [10]–[12]
<i>ntc</i>	Total number of trace classes [10], [11]
<i>atl</i>	Average trace length [13], [14]
<i>mitl</i>	Minimum trace length [13], [14]
<i>matl</i>	Maximum trace length [13], [14]
<i>ats</i>	Avg. trace size (level of detail) [11], [12], [15]
<i>nsec</i>	Number of distinct start events [10], [13]
<i>nec</i>	Number of distinct end events [10], [13]
<i>ntsl</i>	Abs. # traces with a self-loop [13]
<i>ntr</i>	Abs. # traces with a repetition [13]
<i>rnsec</i>	Rel.# distinct start events [13]
<i>rntec</i>	Rel. # distinct end events [13]
<i>rntsl</i>	Rel. # traces with a self-loop [13]
<i>rntnr</i>	Rel. # traces with a repetition [13]
<i>anslt</i>	Avg. # self-loops per trace [13]
<i>manslt</i>	Max. # self-loops per trace [13]
<i>asslt</i>	Avg. size of self-loops per trace [13]
<i>masslt</i>	Max. size of self-loops per trace [13]
<i>tcpht</i>	# distinct traces per hundred traces [13]
<i>tco</i>	Absolute trace coverage [13]
<i>rtco</i>	Relative trace coverage [13]
<i>edn</i>	Event density [11], [15]
<i>thr</i>	Traces heterogeneity rate [11]
<i>tsr</i>	Trace similarity rate [11]
<i>cf</i>	Complexity factor [11]
<i>std</i>	Simple trace diversity [15]
<i>atd</i>	Advanced trace diversity [15]
<i>tentr</i>	Trace entropy [16]
<i>prentnr</i>	Prefix entropy [16]
<i>abentr</i>	All-block entropy [16]

B. Measures Derived From Non-Linear Structure

Table II lists the literature-based measures derived from non-linear structures. In comparison to the linear measures, their number is rather limited. Many measures from the literature require post-discovery knowledge which is out of scope for this study. The remaining measures mainly focus on the directly-follows-graph (DFG) of the event log, quantifying the relationship between its nodes N and edges A .

TABLE II
LITERATURE-BASED MEASURES - NON-LINEAR STRUCTURE

Abbreviation	Measure
N	Number of nodes / vertices
A	Number of arcs / edges
<i>gcnc</i>	Coefficient of network connectivity [17], [18]
<i>gand</i>	Average node degree [17]
<i>gmnd</i>	Maximum node degree [17]
<i>gdn</i>	Density [17]
<i>gst</i>	Structure [12]
<i>gcn</i>	Cyclomatic number [18]
<i>gdm</i>	Graph diameter [17]
<i>gcv</i>	Number of cut vertices [14]
<i>gsepr</i>	Separability ratio [17]
<i>gseqr</i>	Sequentiality ratio [17]
<i>gcy</i>	Cyclicity [17]
<i>gaf</i>	Affinity [12]
<i>gspc</i>	Simple path complexity [19]

C. Self-Developed Measures

Inspired by the initial set of measures, we created 25 new measures to improve comprehensiveness and cover more topics. Linear structure includes measures focusing on frequency, connectedness, trace length, trace profile, and spatial proximity. Non-linear structure measures include measures based on modularity, cut-vertices, and activity labeling. In the additional material to this work, we provide a summary of the literature review and a list of all measures plus their respective formulas.

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