

Log Grouping and Causality Analysis

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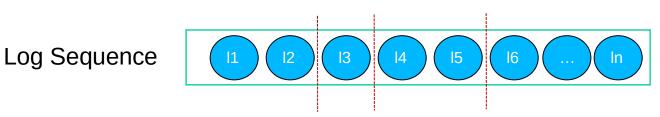
Polytechnique Montréal

DORSAL Laboratory

Agenda

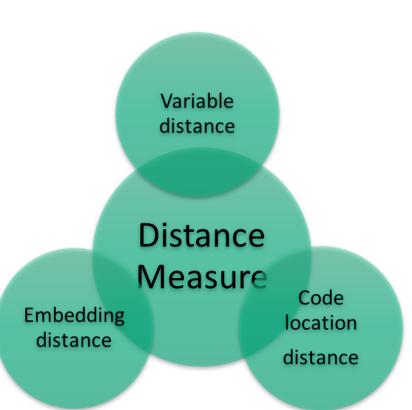
Log grouping
 Incremental Prefix Tree
 Co-occurrence Probability
 Causality Analysis

Log Grouping



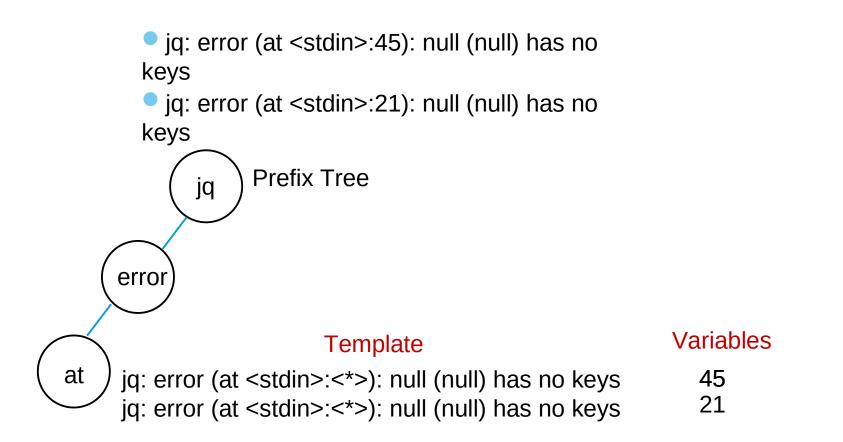
≻ Log

- Template
 - Embedding distance
- Variable
 - Cosine distance

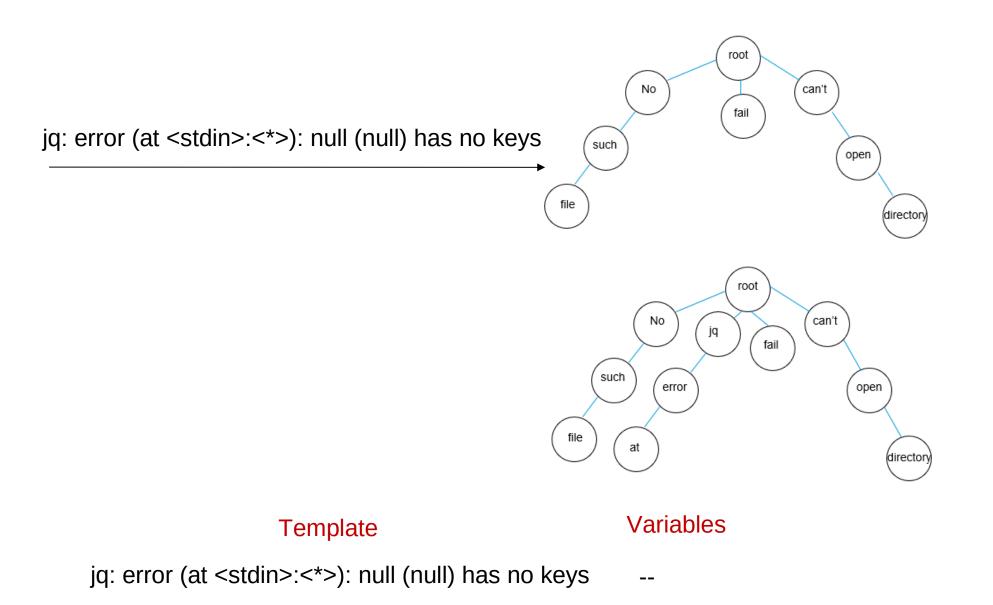


Incremental Prefix Tree

- Parsing logs
 - Drain method
 - Prefix Tree

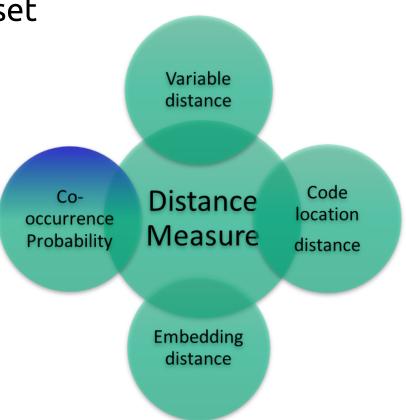


Incremental Prefix Tree



Co-occurrence Probability

- A log file is an ordered sequence of logs
 Sequential information
 Representing logs as sequence set
 Each sequence is a log file
 - Each event is a log



Sequence set

Each log template is mapped to a unique number

2 14 14 14 14 15 14 15 15 15 15 15 14 15 15 15 16 16 17 18 19 15 20 19 14 14 5 26 26 26 26 27 28 26 26 29 30 13 13 13 13 13 13 13 13 13 13 13 13 8 26 26 27 27 27 26 26 26 26 26 51 51 38 39 52 53 38 39 40 41 42 43 13 13 13 13 54 9 26 26 26 26 27 28 26 26 55 56 29 57 30 13 13 13 13 13 13 13 13 13 13 13 13 10 0 58 59 60 61 62 39 59 60 63 64 65 66 40 41 67 11 14 14 68 14 14 69 14 14 14 70 14 14 71 72 14 70 70 70 16 16 73 74 75 25 25 25 25 14 14 14 14 14 14 14 14 14 14 14 14 82 82 79 82 82 79 16 16 79 83 16 16 79 47 48 16 16 79 47 48 16 16 79 47 48 16 16 79 47 48 16 16 79 79 79 79 25 25 25 25 15 14 14 23 14 14 84 14 14 14 14 14 14 14 16 16 79 16 16 79 47 48 16 16 79 16 16 79 47 48 16 16 79 47 48 16 16 79 47 48 79 79 16 85 86 85 86 85 86 85 86 85 86 85 86 85 86 85 86 85 86 85 86 85 86 45 45 45 45 45 45 45 45 45 45 45 45 88 89 90 13 19 14 22 14 22 22 14 14 14 14 14 14 14 14 14 22 22 22 22 22 22 22 22 22 22 28 28 29 16 16 49 98 24 16 16 49 47 48 16 16 49 47 48 16 16 49 47 48 16 16 49 47 48 16 16 49 50 50 25 25 20 99 99 0 100 40 41 13 13 13 13 13 13 13 13 13 13 13 13 14 154 22 26 26 27 27 27 26 26 26 26 105 106 106 104 38 39 52 53 38 39 40 41 42 43 44 24 0 107 114 115 65 40 41 13 13 13 13 13 13 13 13 13 13 13 13 54 26 14 14 14 14 76 14 14 14 14 14 14 16 16 79 130 130 79 16 16 79 136 135 136 135 136 136 103 38 39 52 53 38 39 40 41 42 43 44 28 0 137 138 139 117 63 140 65 141 142 143 144 145 13 13 13 13 13 13 13 13 13 13 13 13 101 54 30 14 14 14 14 14 14 14 14 14 14 45 45 47 48 16 16 79 47 48 16 16 79 47 48 16 16 79 23 146 146 31 14 14 14 14 14 14 14 14 14 14 14 16 16 79 147 16 16 79 148 47 48 16 16 79 47 48 16 16 79 47 48 16 16 79 79 79 79 79 25 25 32 0 149 150 13 13 13 13 13 13 13 13 13 13 13 35 157 39 158 159 40 41 13 13 13 13 13 13 13 13 13 13 13 160 54 37 162 0 107 114 13 13 13 13 13 13 13 13 13 13 13 13 **38** 0 107 114 59 60 117 163 164 163 39 39 39 39 59 60 63 64 65 66 40 41 13 13 13 13 13 13 13 13 13 13 13 13 54 39 14 22 12 12 12 12 12 12 12 12 12 165 14 22 22 14 22 40 14 22 14 22 22 151 14 14 14 14 14 14 14 14 22 22 22 22 22 22 22 22 166 47 48 16 16 49 47 48 16 16 49 146 146 41 14 14 14 14 76 14 14 14 14 14 14 14 42 14 14 14 14 14 14 14 14 14 14 14 82 82 79 82 82 79 167 16 16 79 16 16 79 16 16 79 168 168 47 48 16 16 79 47 48 16 16 79 16 16 79 47 48 79 79 79 79 43 169 169 169 170 44 46 26 26 27 27 27 26 26 26 26 26 136 173 38 39 136 174 38 39 175 175 174 38 39 52 53 38 39 40 41 42 43 44 50 14 14 186 16 16 79 187 14 14 14 14 51 14 14 23 14 14 76 14 14 14 14 14 14 14 18 189 190 191 192 189 190 192 189 190 192 47 48 16 16 79 47 48 16 16 79 47 48 16 16 79 16 79 23 53 194 195 55 197 198

Co-occurrence Probability

- Considering the time window T:
 Linear probability
 - Non linear probability
- Suppose
 - $\succ M_{ij}$: the number of co occurrence time intervals,
 - $> N_i$: the number of time intervals with logj

$$\succ CP[i][i] = 1$$

 $\succ CP[i][j] = CP[j][i] = Max(CP[i][j], CP[j][i])$

Linear:
$$CP[i][j] = \frac{M_{ii}}{N_j}$$
,
Non linear: $CP[i][j] = \frac{1}{1+e^{-X}}$, $x = k\left(M_{ij} - \frac{N_i}{2}\right), k = 1$

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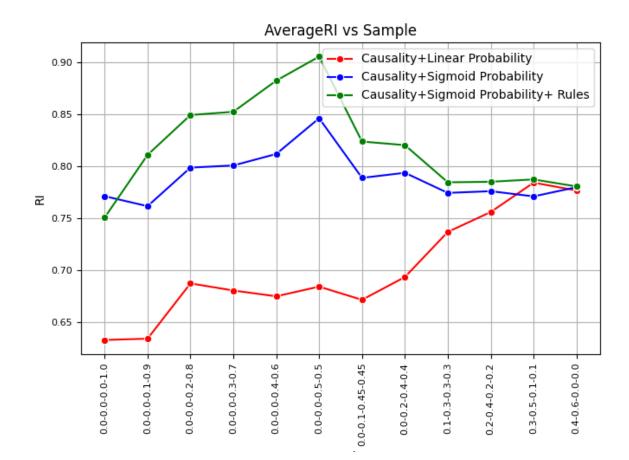
Co-occurrence Probability Matrix

1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	c
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	C (
Q	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0		0.4	0.12	0.84	0	0	0	0	0	0	0	0.24	0	0	0	0	0	0	(
0	0.75	0	0.25	0.75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0.0286	0	0.8	0.0571	0.4286	0	0.0286	0	0	0	0	0	0.2571	0.0286	0	0	0.2	0.1143	0.1425
0	0	0	0	0.8966	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0.0055	0	0.8866	0.0066	0.4262	0.0407	0.0352	0.0286	0.0011	0	0.1828	0.0441	0.011	0.0242	0	0	C
0	0	0	0	0	0.9	0.9	0.8	0.7	0.6	0.6	0.4	0	0	0	0	0	0	0	Ç
0	0	0	0.0032	0	0.0317	0.0032	0.8508	0.1032	0.0921	0.1016	0.0032	0	0.0063	0.0952	0.054	0.1746	0	0	0
0	0	0	0	0	0.1053	0.0263	0.6053	0.5789	0.9474	0.8947	0.0263	0	0	0.1053	0.0263	0	0	0	(
0	0	0	0	0	0.1111	0.0278	0.6667	0.6111	0.5833	0.8889	0.0278	0	0	0.1111	0.0278	0	0	0	0
0	0	0	0	0	0.0652	0.0217	0.6087	0.5217	0.4783	0.6957	0.0217	0	0	0.1957	0.0217	0	0	0	C
0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0.0238	0	0.3095	0	0.4643	0.0417	0.0417	0.0357	0	0	0.869	0.1369	0.25	0.0417	0	0	Ç
0	0	0	0	0.0822	0.3014	0	0.0411	0	0	0	0	0	0.137	0.3014	0	0.1233	0	0	(
0	0	0	0	0	0	0	0.6364	0	0	0	0	0	0	0.0909	0.2273	0.2273	0	0	(
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0988	0	0.8663	_	0	C
0	0	0	0.0294	0.1397	0	0	0	0	0	0	0	0	0	0.0699	0	0	0.8346	0.4007	0.2647
0	0	0	0.0122	0.0854	0	0	0	0	0	0	0	0	0	0.0244	0	0	0.939	0.5122	0.2073
0	0	0	0.0556	8.2718	0	0	0	0	0	0	0	0	0	0.1111	0	0		0	0
0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Ç
0	0	0	0	0.9091	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	-0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	C

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Experimental Results

- Co-occurrence probability
 - ≻ Linear
 - ≻ Non linear
- removing noise



Conditional Independence

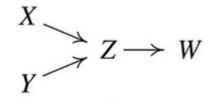
- Co-occurrence does not necessarily mean causality
- Buying cold water
- Buying ice cream
- Hot weather
- Conditional Independency (X⊥Y|Z)
- Statistical test, chi-square

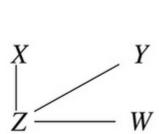
PC Algorithm

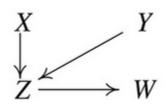
- Suppose we have 4 variable {X,Y,Z,W}
- Initialize a fully connected undirected graph

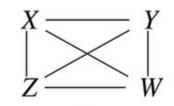
Remove edges based on conditional independence tests
 If X \perp Y | Z, remove the edge between X and Y

Orient Edges to Form a Directed Graph









Chi-square Test

- Step1: create the contingency tables
- Suppose A_BC

Group 1: C = Present

Event A	Event B	Frequency
Present	Present	1
Present	Absent	1
Absent	Present	1
Absent	Absent	1

Group 2: C = Absent

Event A	Event B	Frequency
Present	Present	1
Present	Absent	1
Absent	Present	1
Absent	Absent	2

Chi-square Test

Calculate Expected Frequencies

$$\label{eq:Expected Frequency} \begin{split} \text{Expected Frequency} = \frac{(\text{Marginal Total of A}) \times (\text{Marginal Total of B})}{\text{Total Number of Observations}} = \frac{2 \times 2}{4} = 1 \end{split}$$

Step 3: Compute Chi-Square Statistic

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

If the chi-square statistic exceeds the critical value, we reject the null hypothesis and conclude that A and B are not independent given C. Data Representation

Considering each log template as a variable to form a data frame

Seq	Α	В	С	D
ABC	1	1	1	0
DC	0	0	1	1
ACD	1	0	1	1

- > Time series:
 - ➢ For each log in each log file
 - > The order and time of events are critical
 - > Highly sparse
 - Statistical approaches rely on sufficient overlap and density in the data

Hybrid Representation

The order is considered but not the absolute time



- Pair: (E1,E2) , (E1,E3), (E2,E3), (E1⊥E3|E2)
- Conditional independence test
- \geq 92% accuracy with Ciena log files