

Deep Learning for Anomaly Detection and Cause Identification Quentin Fournier quentin.fournier@polymtl.ca

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How to leverage the event fields?

Why Use the Event Fields?

- The information is already available...
- ...or it can be made available at a low cost.
- The more information is considered, the better will be the model¹.
- In particular neural networks strive with more data.

¹There are some caveats, for example, models may be subject to the curse of dimensionality.

Which Event Field to Consider?

- Let us focus on the system calls.
- Some fields are in virtually every event:
 - system call name
 - timestamp
 - entry/exit
 - return value

- process name
- process id (pid)
- thread id (tid)

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How to Use the Event Fields?

- Models take as input a vectorial representation of the event.
- This representation should take into account the fields.
- The simplest representation is one-hot encoding:
 - event a ightarrow $\{1,0,0,...,0\}$
 - event $\texttt{b} \rightarrow \{0,1,0,...,0\}$

• Not practical... The representation must be learned.



How to Use the Event Fields?



LM Objective

- Let us consider the task of Language Modelling (LM).
- Predict the next event based on the previous ones.
- Do not require labels.
- Allow computing the likelihood of a sequence.
- Sequences with a low probability may be anomalies.



LM Objective - Example



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Experiments

- The model is a neural network.
- Sequences correspond to web requests.
- Inputs x_i are the vectorial representation of system calls.

Results - LSTM

Model	Cross-entropy		Accuracy		Testates stars
	Train	Test	Train	Test	training time
2-gram			31.5	31.5	0h29
3-gram			43.1	43.2	0h29
4-gram			46.7	46.8	0h31
{system call name}	0.074	0.073	97.3	97.4	0h44
Previous + {timestamp}	0.076	0.074	97.3	97.3	0h41
<pre>Previous + {entry/exit, success/failure}</pre>	0.066	0.065	97.6	97.7	0h38
Previous + {process name, pid, tid}	0.061	0.059	97.8	97.9	0h52

Results - Transformer

Model	Cross-entropy		Accuracy		Training time
	Train	Test	Train	Test	training time
2-gram			31.5	31.5	0h29
3-gram			43.1	43.2	0h29
4-gram			46.7	46.8	0h31
{system call name}	0.100	0.084	96.6	97.1	0h53
Previous + {timestamp}	0.165	0.117	94.1	96.0	1h24
Previous + {entry/exit, success/failure}	0.097	0.081	96.7	97.2	0h50
Previous + {process name, pid, tid}	0.076	0.065	97.3	97.7	1h08

• Timestamps degrade the model... their representation is inappropriate.

How to leverage the huge amount of data available?



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Available Data

- Huge amount of data available, or easily obtainable.
- Unlabelled and boring...
- Yet there is the data underlying structure².
- Some models benefit from learning this structure.
- How to learn this structure from many unlabelled examples?

 2 Underlying structure may be understood as the data distribution, or the set of syntactic and semantic rules.

MLM Objective

- Language Model is one approach...
- But it is directional, only the previous events are considered.
- Masked Language Model (MLM) address this limitation.
- Mask some of the input and learn to predict them.
- Learn to reconstruct the data, hence its underlying structure.

MLM Objective - Example





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- As an unsupervised pre-training step
- Learn the structure of the data, then use the model for another task



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Create an encoder which takes as input the vectorial representation of events:

Encoder

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2 Add the classifier for the Mask Language Modelling (MLM):





3 Train the encoder and the classifier using MLM:



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A Now both the encoder and the classifier are trained on MLM:





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6 The classifier is removed since we only need the encoder. It is said the encoder has been pre-trained.

Encoder

6 Add the classifier or the predictor for the final task:





7 Train only the classifier or decoder:



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8 Fine-tune the whole model to get the best performance:



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Preliminary Results - Transformer

- No preliminary results for the impact of pre-training.
- Ciena is collecting labelled data.
- Early results indicate that event fields seem to have a large impact on the pre-training.

Future Works

- Evaluate the impact of pre-training with MLM.
- Better quantify the impact of event fields.
- Compute the sequence likelihood to detect anomalies.
- Reduce the complexity of the models used.

Thank You



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