Automating the junior analyst

Cyber security report generation with classic AI

by Sergey Polzunov
Effective reporting is difficult
Requirements

- **Efficiency**: there is a demand for extensive communication towards both internal and external stakeholders, placing a significant burden on the security teams to produce a wide range of reports.

- **Quality**: inconsistent quality hinders understanding within an organization. With reports varying in accuracy and clarity, it is difficult for stakeholders to make informed decisions promptly.

- **Customisation**: crafting reports to meet the specific needs of various stakeholders manually requires time and effort.
The problem with efficiency

- **Efficiency**: it is difficult to scale up the report production:
  - while creative in-depth research work enjoys a dedicated time budget, simpler reports are often neglected and left to junior analysts to do
  - the reporting features in the security platforms are simplistic: mostly multi-page text-area forms or WYSIWYG editors (*bonus points if you can insert pictures or tables!*
The problem with quality

- **Quality**: the teams develop internal guidelines and templates but there are associated costs:
  - template management is painful – the templates are treated as artifacts and are stored in Google Docs, OneDrive, Confluence, or in endless email threads with Word documents *(bonus points if you use git!)*
  - there are no built-in control checks to make sure all required data is included in the final text
  - stylistic and formatting constraints are not applied automatically, leaving space for inconsistencies.
The problem with customisation

- **Customisation**: the final form of the report depends on the target audience and on the input data available:
  - the multiple variants of the same report are either produced from a clean slate or require some creative frankenstein-ing of various other templates into one
  - writer’s block is still an issue when starting from scratch
  - the templates are rigid and must be adjusted manually if the shape of input data changes
Let’s automate it!

- **Efficiency**: using code to generate the reports
- **Quality** and **Customisation**: introducing “reports-as-code” templating:
  - A template is specification tree written in a custom declarative DSL
  - A template defines the document structure and the data needed to populate the document, without prescribing the exact words / phrases to be used
  - The same template can be used to produce multiple variants of the report or produce the report from different shapes of input data:
    - the “compilation” step of combining the **template**, the **configuration**, and the **input data** defines the final form of the document.
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❗ Full automation is unachievable – somebody always needs to perform the last editing step and sign off on the final product
Where is AI here?
Classic and modern AI from a bird’s-eye view

- **Symbolic AI**
  - Rule-based systems that relied on predefined rules and logic, making them suitable for deterministic well-defined tasks and problems.
  - Excels in the domains where the knowledge can be structured and codified into a clean input data. No learning ability.

- **ML models**
  - Utilise machine learning algorithms to enable systems to learn complex patterns, relationships, and behaviours from data. Training requires vast amounts of training data.
Why not just throw a LLM at it?

Using LLMs as end-to-end solution relies on LLM as both a knowledge base and a comprehension engine:

- there are issues with the embedded knowledge base:
  - limited domain expertise
  - over-reliance on training data, with all its built-in biases
- there are issues with the comprehension engine:
  - limited context understanding ability
  - absence of transparency, explainability and auditability (cyber security becoming more regulated!) that hinders QA efforts and erodes trust
Natural Language Generation pipeline

Data → Document planner → Micro planner → Surface realiser → Text
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- selects the template and the relevant input data
- defines the document structure based on configuration and available data
- selects properties and data points from the input data
- defines the aggregations of the data points to be expressed together
- generates the final text from a spec
- performs syntactical, morphological and orthographic realisation (SimpleNLG, Grammatical Framework, etc)
Natural Language Generation pipeline

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**Threat actor X**
- associated TTPs
- associated campaigns
- associated victims

Threat actor X was described by **Vendor V**. The actor is also known as “**Alias1**” and “**Alias2**”.
The actor is associated with **Campaign A**, first observed on Oct 2, 2023.
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Threat actor X
- created by: Vendor V
- aliases: Alias1, Alias2
  Associated Campaign A
  - first seen: Oct 2, 2023

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Natural Language Generation pipeline with ML

Narrow scope allows for specialised ML models:

- Custom RNN data-to-text / graph-to-text models
- BART language model (2018): converting a partial set of unordered non-inflected tokens into a full set of ordered inflected tokens

- Yao Zhou, Cong Liu, and Yan Pan. 2016. “Modelling sentence pairs with tree-structured attentive encoder”

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or a **constrained** use of LLMs (GPT, LLaMA, etc).

The model just needs to know English language.
The final editing step is the smallest.

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Wider scope requires the model to “understand”:
- summarisation
- rephrasing

Less control:
- it is difficult to impose restrictions on the output
- the result text is less predictable
- larger editing step

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The right amount of ML in NLG

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- Scope
- Control
- Risks
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Scope

Control

Risks
Conclusions

- **Re-evaluate existing tech:**
  - classic rule-based systems have a lot to offer and can be nicely combined with the creativity of the modern ML models

- **Define how much ML is right for you:**
  - be mindful of the risks that come with deploying ML models (and LLMs) in production in mission critical workflows

- **Sometimes less is more:**
  - LLMs are powerful and easy to integrate with, but there are smaller ML models that might fit your use cases better, are easier to manage and can be run on-prem

- **Be on top of your reporting game!**
  - NIS2 brings additional pressure to have the communications streamlined
Thank you!

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