Bad Apples and Good Labels: Learning in Real-time Fault Detection

James A Grant
Lancaster University

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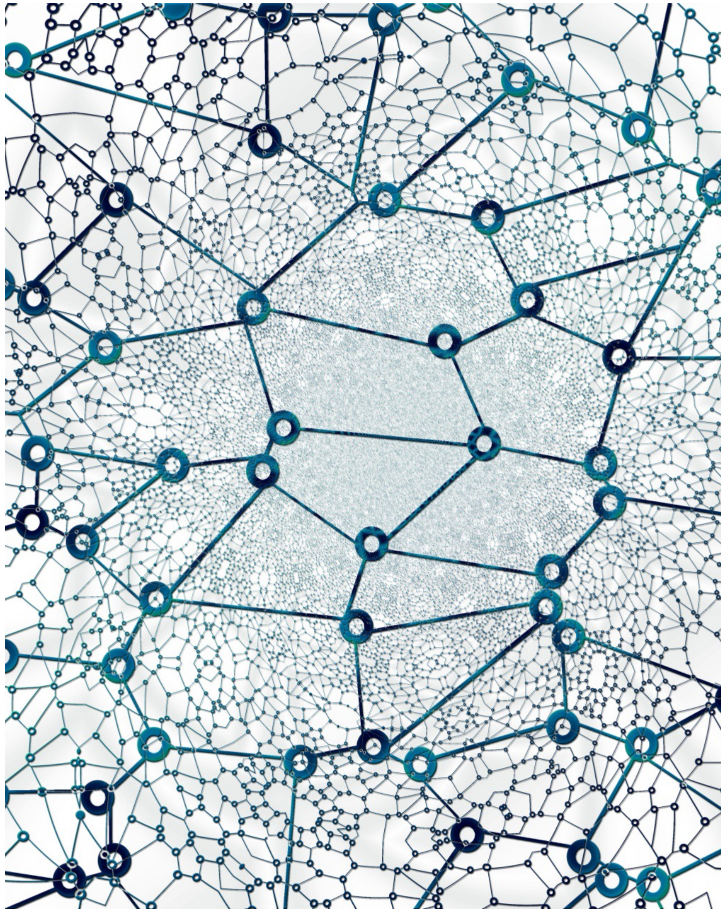
j.grant@lancaster.ac.uk - @james_a_grant

Example: Telecoms Network Control



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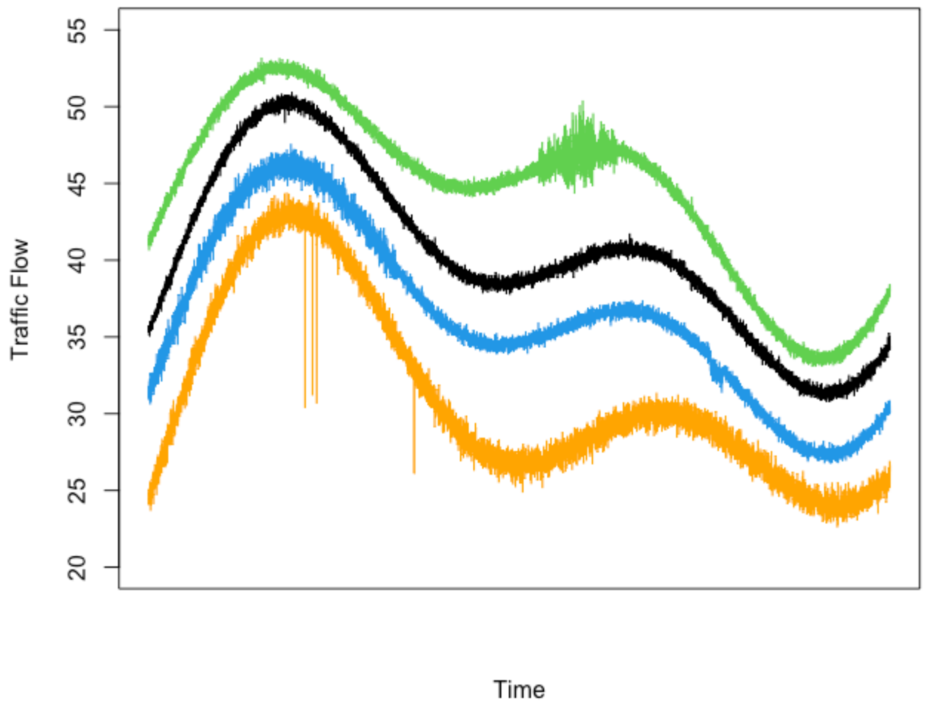

Network traffic data takes the form of multivariate time series.

Engineers monitor these series for outages, faults, etc. and reroute traffic or schedule maintenance accordingly.

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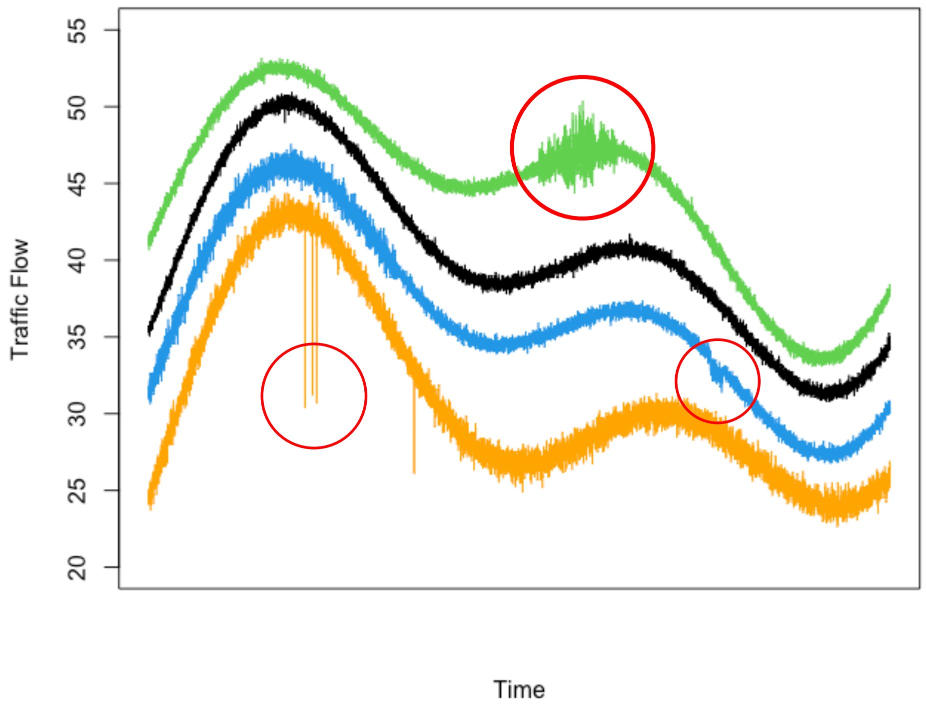

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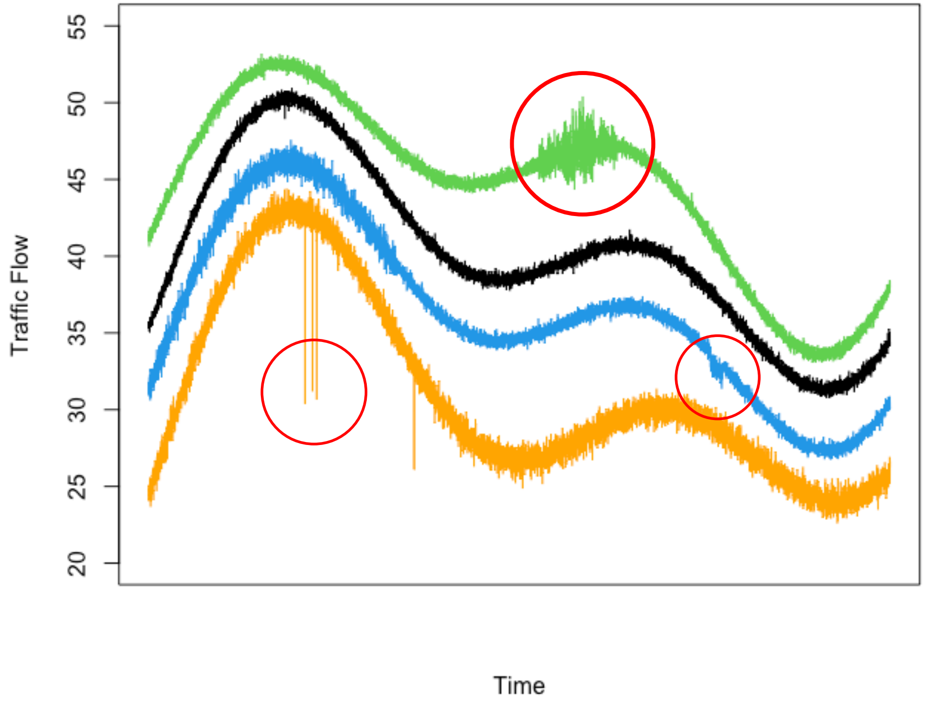

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Can machine learning replicate this?

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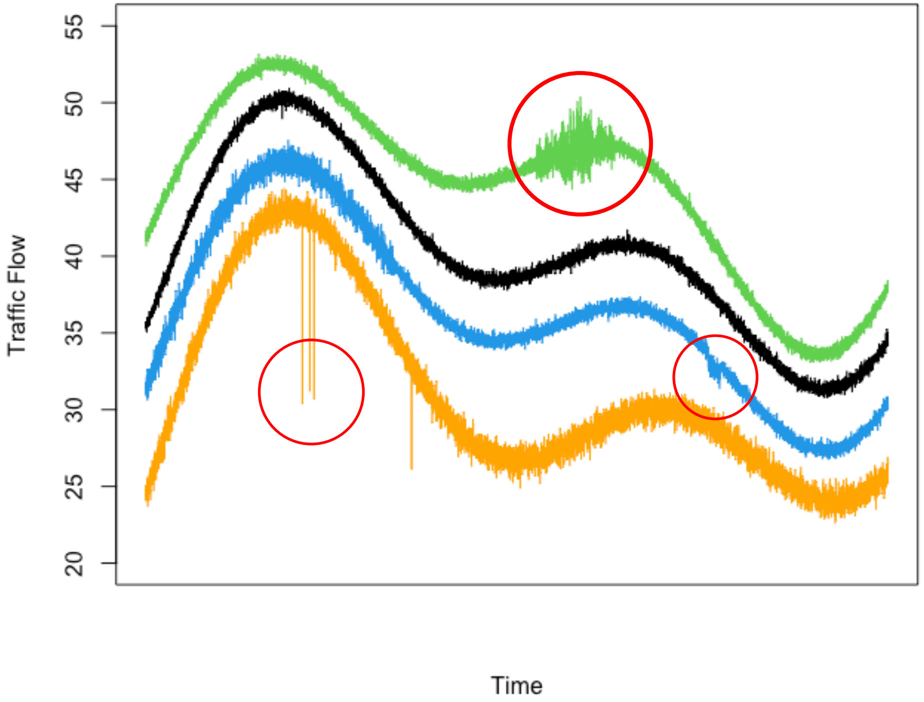

Automating this process is **hard**

- Combining different knowledge
- Domain expertise
- Actions taken are complex
- Unseen examples and changing 'normal' behaviour

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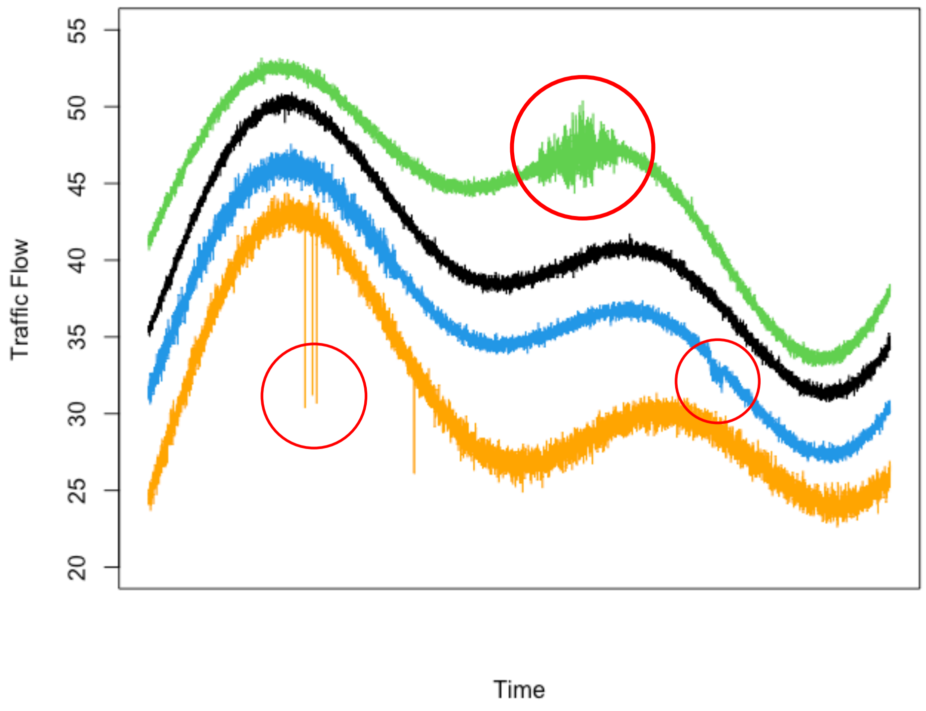
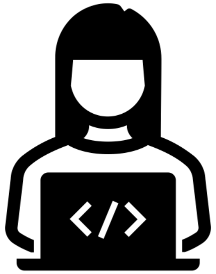


A complete replacement with autonomous decision-making is unrealistic.

A semi-autonomous approach

We instead consider not trying to **make** decisions (per se), but flagging **when** a non-trivial decision needs to be made.

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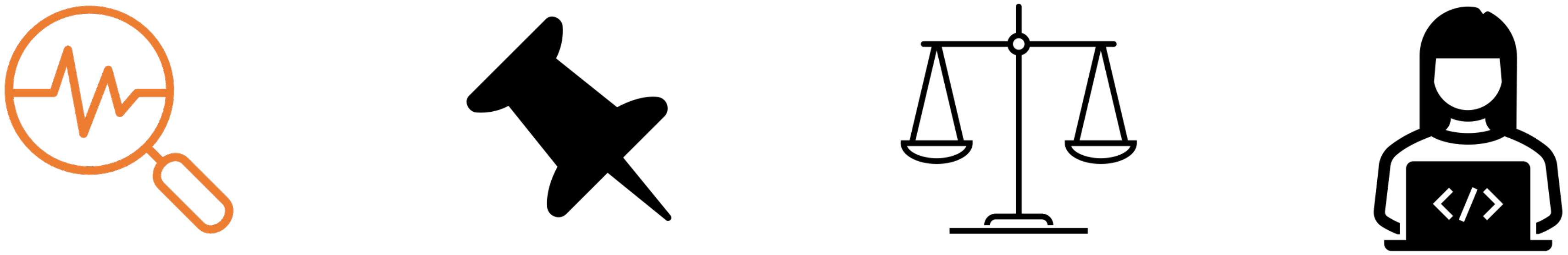

Monitor the data

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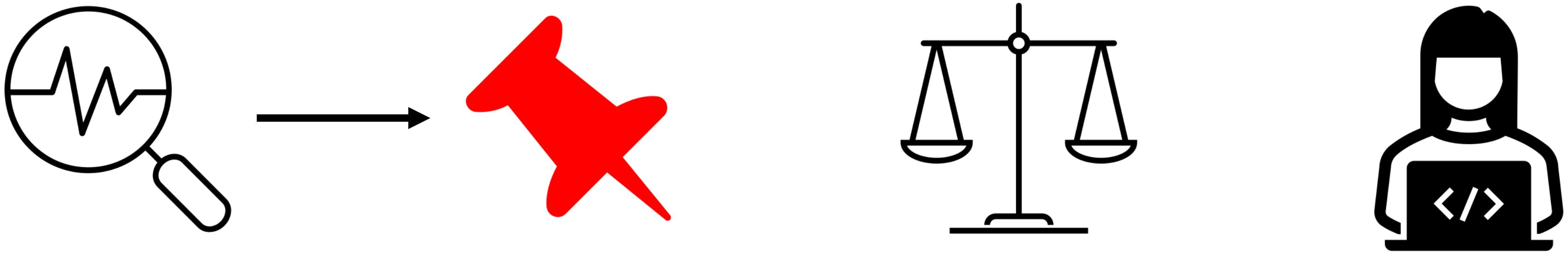

Pin-point interesting regions

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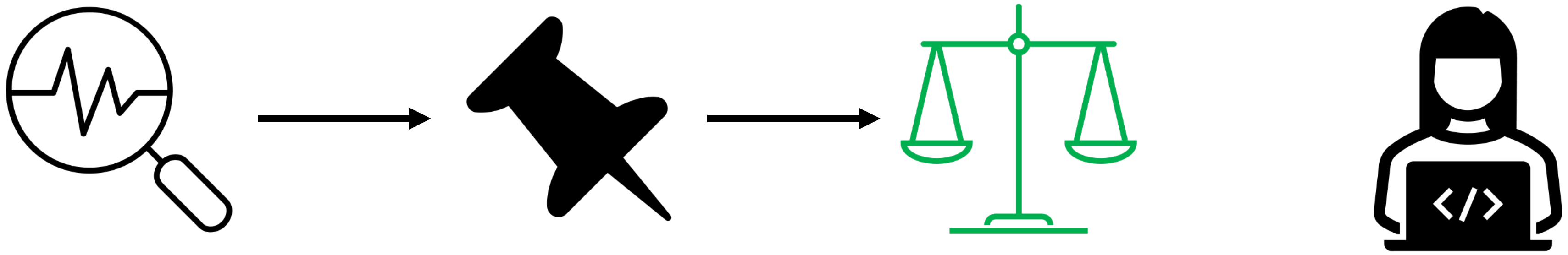

Weigh up whether they are important

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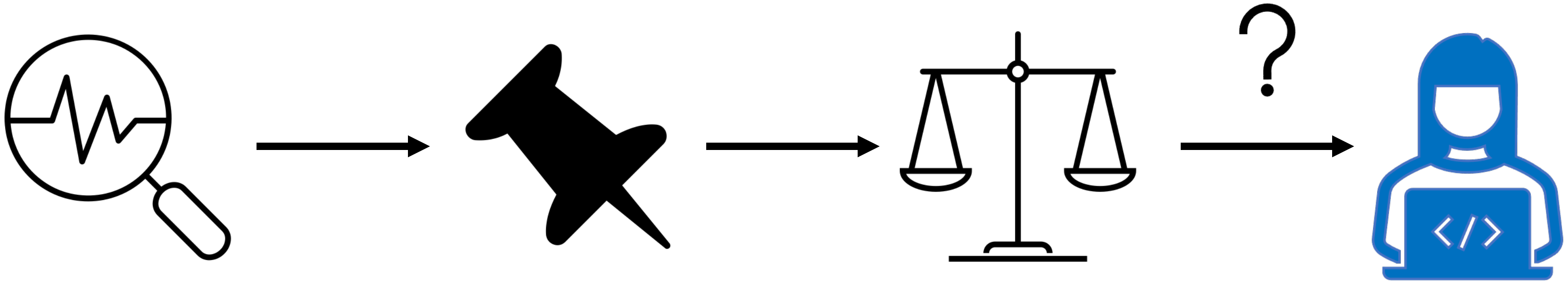

Potentially pass to a human

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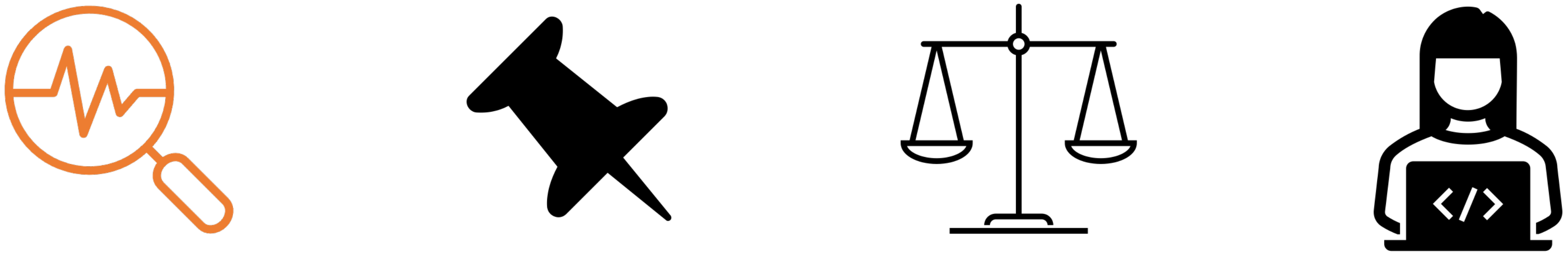

Return to the monitoring phase

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Part 1 – Anomaly Detection

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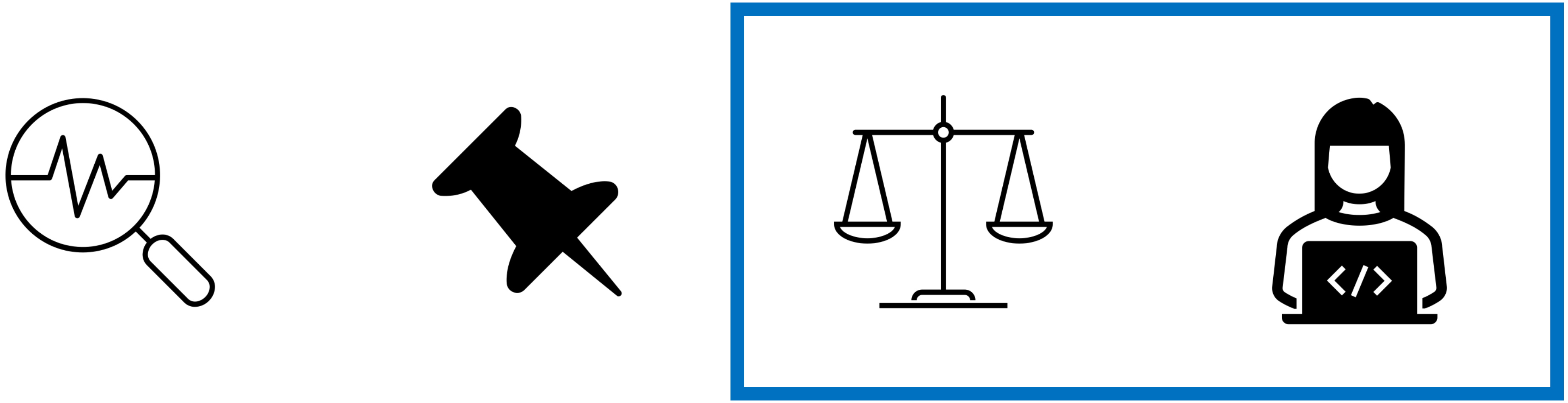

Part 2 – Classification

Learning to Classify

We pose the decision to flag or not as a binary classification task.

Each potentially interesting anomaly ($t = 1,2, \ldots$) has

- Associated feature vector $x_t \in \mathbb{R}^d$ - size of deviation/extraneous variables/baseline deviated from/etc.
- True (latent) class $C_t \in \{0,1\}$ – not interesting/interesting

To some extent x_t's can predict C_t's – e.g. logistic regression-like relationship mediated by parameter $\theta \in \mathbb{R}^d$.

Learning to Classify

Binary classification/logistic regression is really well studied.

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Offline Binary Classification: Have a history of $x_1, \ldots x_n$ and $C_1, \ldots, C_n$ and produce estimate $\hat{\theta}_n$. Predict any future $\hat{C}_t$ based on x_t and $\hat{\theta}_n$.

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Online Binary Classification: Little or no historic data. Iteratively observe x_t, predict $\hat{C}_t$, observe **true** C_t, and update estimate $\hat{\theta}_t$.

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Online Binary Classification: Little or no historic data. Iteratively observe x_t, predict $\hat{C}_t$, observe **true** C_t, and update estimate $\hat{\theta}_t$.

Online Binary Classification with Partial Feedback: Same setting as online – but only observe true C_t if $\hat{C}_t = 1$.

Online Binary Classification with Partial Feedback, or ‘**Apple Tasting**’.

Apple Tasting

- Learning to identify good and bad apples *(Helmbold et al. 1992, 2000)*.
- **Aim**: let all good apples through, remove all bad apples.
- Class only revealed by taste – which destroys the apple:
  - Desirable for bad apples. Wasteful for good apples.

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- **Aim**: let all good apples through, remove all bad apples.
- Class only revealed by taste – which destroys the apple:
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- Challenge is that to maximise accuracy, some good apples must be removed for sake of learning – **but which ones and how many**?

Balancing Exploration and Exploitation

- Repeatedly face the following question:
  - Given observed features x_t, and a guess of the class $\mathrm{P}(C_t = 1)$ (based on a $\hat{\theta}_t$) do we choose treat as a good or bad apple?
  - **NB:** doesn't have to be treat as bad if $P(C_t = 1) > 0.5$ – can have more conservative view of trade-off.
  - For ease in what follows: assume parity between false positive and false negative.

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- Why not just use best guess all the time?
    - Could work brilliantly - if x_i sequence is sufficiently variable, if you start with good data
    - Could also fail catastrophically – initialise $\hat{\theta}$ poorly and only observe data which confirms bias.

Balancing Exploration and Exploitation

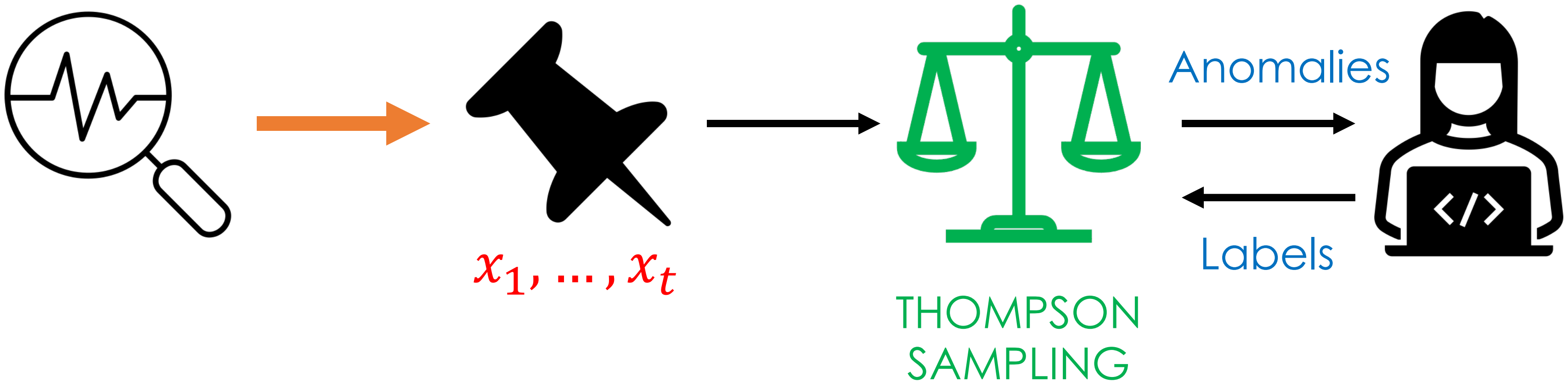
- Superior methods ensure we have enough data to maintain a good estimate of $\hat{\theta}_t$.
- Two main techniques:
  - **Confidence bounds** - only treat as a good apple if we're very certain it's good (effectively shift $\hat{\theta}_t$ to the limit of some region Θ_t such that $P(\theta \in \Theta_t) > 1 - \delta$)
  - **Randomisation** – add (appropriate) noise to $\hat{\theta}_t$, so that sometimes an estimated label $\hat{C}_t$ will be flipped (encouraging exploration)
- Both converge to using $\hat{C}_t$ once $\hat{\theta}_t$ is well estimated.

Randomised Decision Making via Thompson Sampling

- Initialise with a prior distribution $\pi_0(\theta)$
- At time $t = 1, 2, \ldots$
  - Draw a sample $\tilde{\theta}_t$ from the current posterior $\pi_{t-1}(\theta)$
  - Treat $\tilde{\theta}_t$ as the true parameter and estimate $\hat{C}(\tilde{\theta}_t)$ based on x_t.
  - If $\hat{C}(\tilde{\theta}_t) = 1$
    - Remove the apple/show anomaly to human
    - Observe C_t and update the belief distribution to $\pi_t(\theta)$.
  - If $\hat{C}(\tilde{\theta}_t) = 0$
    - Let apple/anomaly pass
    - Observe nothing and set $\pi_t(\theta) = \pi_{t-1}(\theta)$.

Summing up

We've put anomaly detection and online classification (Apple Tasting via Thompson Sampling) together to produce a semi-autonomous algorithm.



Summing up

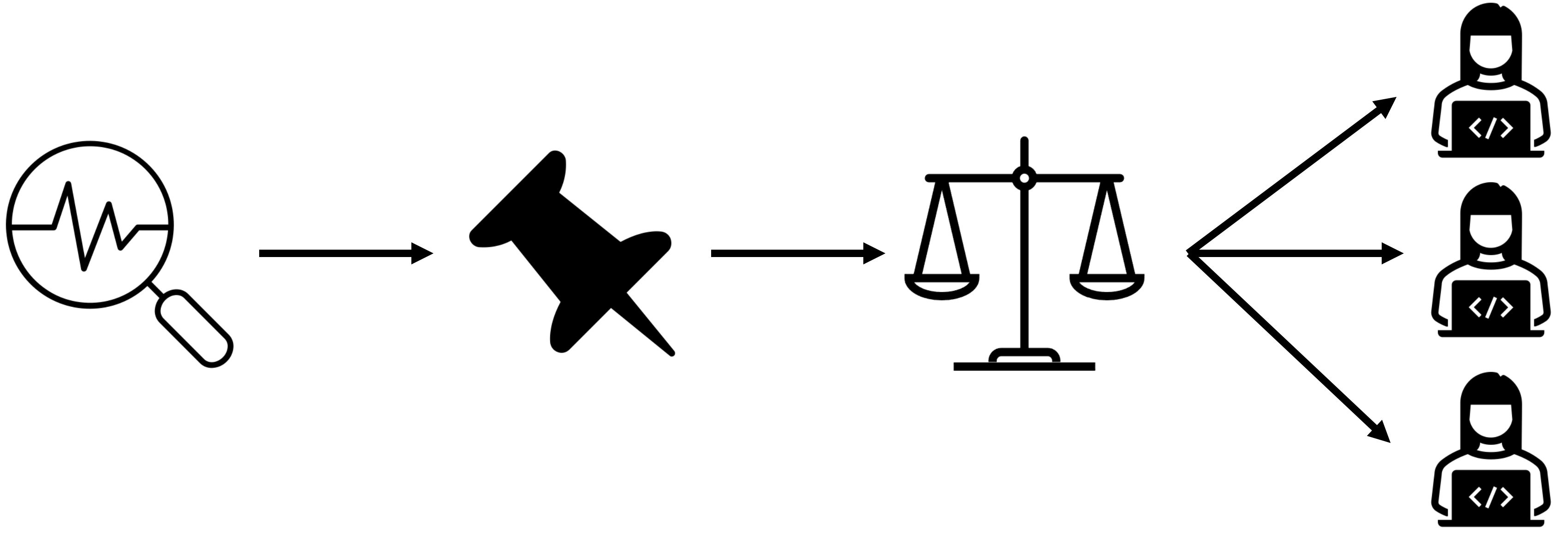
We’ve put anomaly detection and online classification (Apple Tasting via Thompson Sampling) together to produce a semi-autonomous algorithm.

The approach allows us to **automate where possible**, without large amounts of initial labelled data, and continues to **learn as it proceeds**.

The principle is simple but widely applicable/extendable.

Summing up

Going forward in this space we want to explore more complex decision-making setups:



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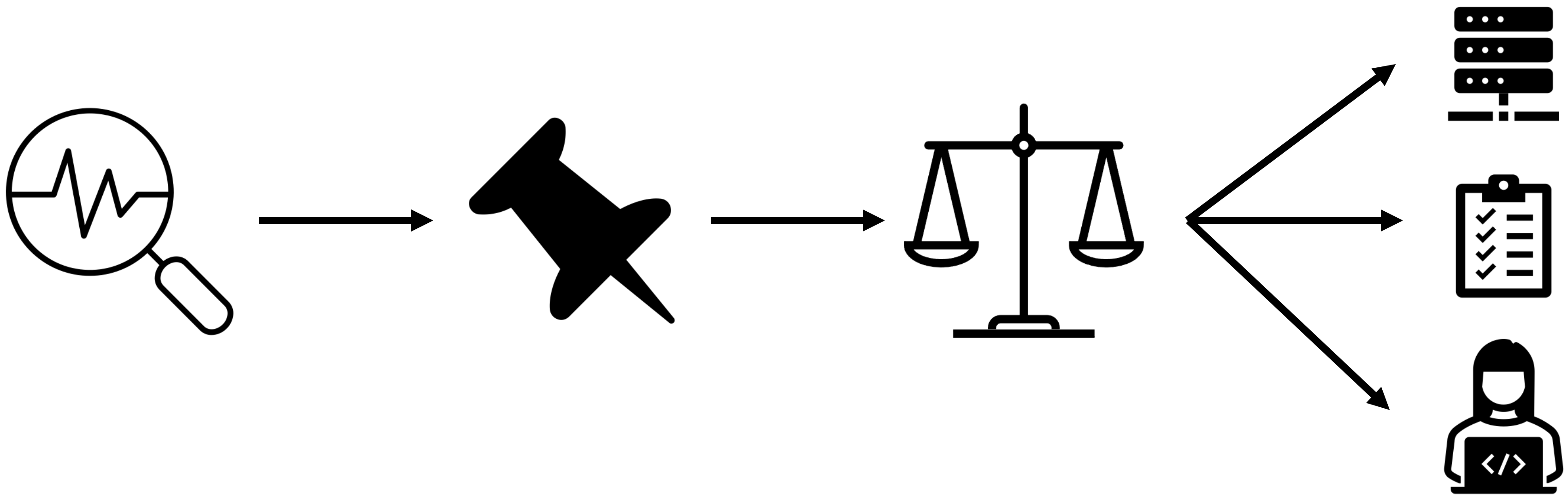

References & Contact

- Grant, J.A., Leslie D.S. (2021). *Apple Tasting Revisited: Partially Monitored Online Binary Classification*. In Submission, arXiv:2109.14412.

- Helmbold, D.P., Littlestone, M., and Long, P.M. (2000). *Apple Tasting*. Information and Computation.

j.grant@lancaster.ac.uk @james_a_grant