Probabilistic Machine Learning Against Disinformation

Uncertainty, Robustness, and Trust

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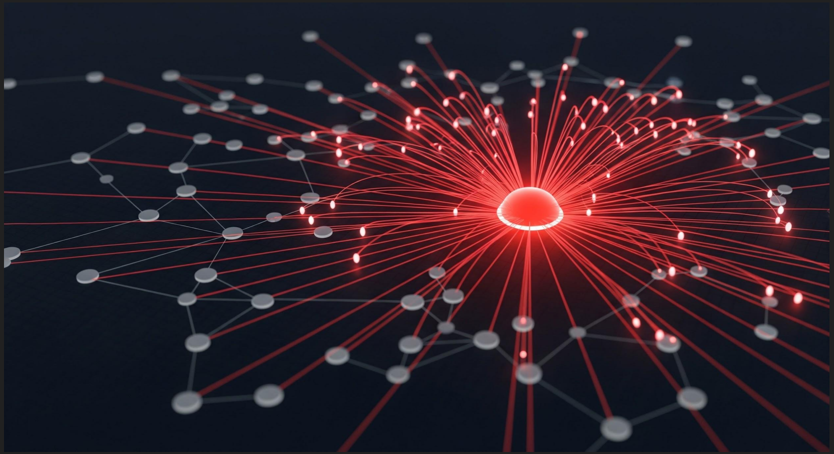
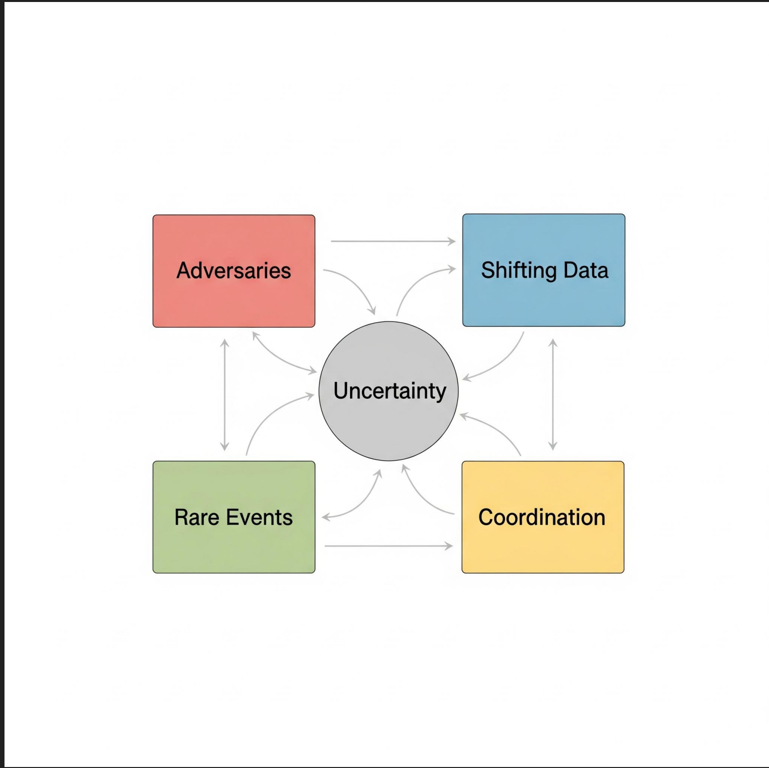
The Disinformation Problem



- AI now allows *cheap, scalable, highly convincing* synthetic content
- Disinformation spreads faster than verification
- Tactics evolve constantly → yesterday's data ≠ today's threats
- Consequences span **crime**, **security**, and **societal trust**

Why Disinformation Is Hard

- **Adaptive adversaries**: attackers change style, tone, and patterns
- **Fast-evolving data**: models trained last month already lag
- **Low signal-to-noise**: harmful content is rare but impactful
- **Coordinated behaviour**: networks of bots amplify narratives
- **High uncertainty**: ground truth is ambiguous or delayed



Why Probabilistic Machine Learning?

- Traditional ML gives **a single answer**
- Probabilistic ML gives **a distribution over answers**
- It quantifies **how uncertain** the model is
- Uncertainty spikes when data **shift** or inputs are **manipulated**
- Helps decide **when not to trust** a prediction

Uncertainty Quantification

- Models should **know what they don’t know**
- Useful for detecting **ambiguous**, **manipulated**, or **out-of-distribution** content
- Uncertainty is a **signal**, not a weakness
- Enables safer decisions: *flag*, *abstain*, *prioritise for human review*

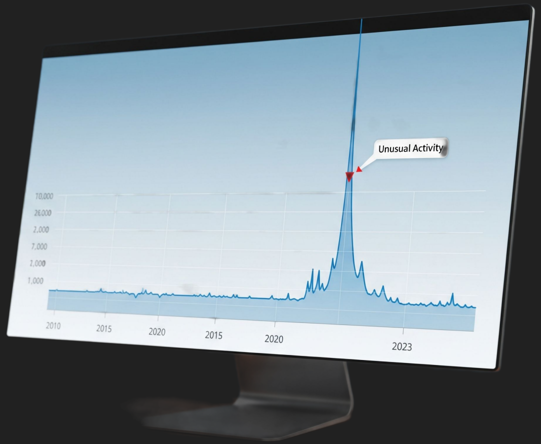
Distribution Shift: Why It Breaks Models

- Attackers constantly change style, structure, and timing
- Models trained on “yesterday’s data” quickly become obsolete
- Theory helps: PAC-Bayes links **training error**, **model complexity**, and **future performance**
- Key idea: we need models that **generalise under uncertainty**, not just fit past data
- This is a key area in theoretical machine learning

$$\mathbb{E}_Q[L] \leq \hat{L} + \sqrt{\frac{\mathrm{KL}(Q\|P) + \log(1/\delta)}{2n}}$$

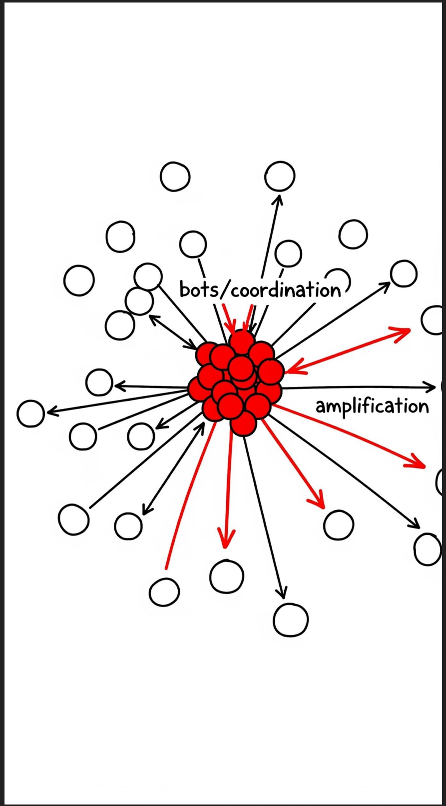
Anomaly Detection

- Disinformation often leaves **subtle statistical fingerprints**
- Detect rare patterns in:
  - writing style
  - metadata (timing, device, IP clusters)
  - propagation dynamics
- Useful for spotting **synthetic**, **manipulated**, or **out-of-distribution** content
- Works even when attackers try to mimic normal behaviour



Network Modelling

- Disinformation spreads through **relationships**, not isolated messages
- Graph models reveal **coordinated clusters** and amplification patterns
- Key signals of manipulation:
  - synchronous posting
  - repeated resharing within tight communities
  - identical message templates across accounts
- Early detection often comes from **network structure**, not content

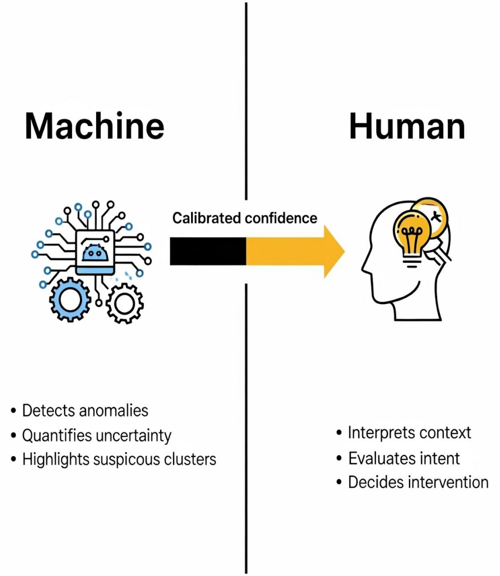


Counterfactual Reasoning

- Understand *how* content could influence different groups
- Explore “what if?” scenarios:
    - What if the message were phrased differently?
    - What if it targeted another demographic?
    - What if it spread earlier/later?
- Helps estimate **potential harm**, not just detect anomalies
- Supports smarter **intervention strategies** (timing, prioritisation)

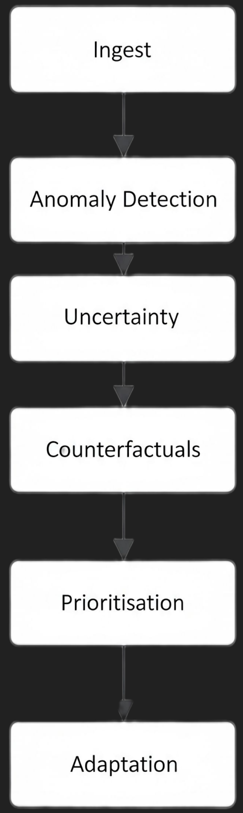
Human + Machine: Calibration & Prioritisation

- Disinformation requires **context and judgement**
- Probabilistic models guide humans by signalling:
  - *high uncertainty*
  - *high potential harm*
  - *unusual activity patterns*
- Calibrated models ensure confidence that what we get is close to reality
- Goal: **prioritise analyst attention**, not replace it



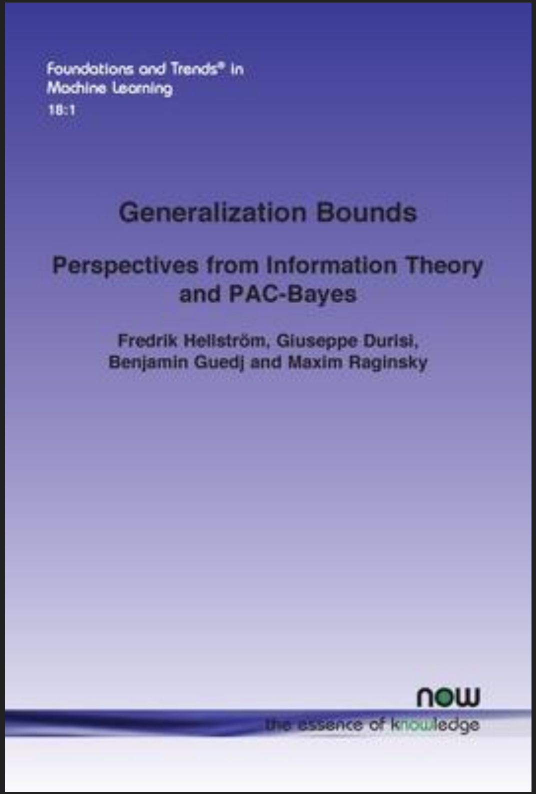
A Practical Probabilistic Pipeline

- **1. Ingest**
  Collect content + metadata + network signals
- **2. Detect anomalies**
  Spot rare or unusual patterns (text, propagation, timing)
- **3. Quantify uncertainty**
  Identify cases where the model is unsure
- **4. Assess impact (counterfactuals)**
  Estimate who could be influenced and how
- **5. Prioritise**
  Send the highest-risk items to analysts
- **6. Learn & adapt**
  Update models as attackers evolve



Takeaways

- Disinformation is **adaptive**, **fast**, and **adversarial**
- Traditional ML fails under **shift**, **manipulation**, and **coordination**
- Probabilistic ML provides:
    - **uncertainty quantification**
    - **robustness under drift**
    - **anomaly & network detection**
    - **risk-aware prioritisation**
- Goal: support **trust**, **safety**, and **effective investigation**



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