

# Detection Under Complexity: Classical Scaling vs Quantum Framing

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## **Abstract**

Modern malware detection systems are increasingly evaluated as classification engines operating over high-dimensional feature spaces. While this framing has proven operationally useful, it masks a deeper issue: detection under realistic system complexity exhibits exponential scaling that fundamentally limits robustness, regardless of data volume or model sophistication. In this paper, we formalize detection as a complexity-driven inference problem, derive classical scaling bounds for behavior enumeration and boundary-based classification, and contrast these with a quantum-inspired reframing based on state representation and distinguishability. This work makes no claim of quantum speedup or near-term deployment advantage. Instead, it demonstrates how quantum framing changes the structure of the detection problem itself, clarifying why detection often fails first in complex systems.

## **1 Detection as a Scaling Problem**

Consider a program or system whose execution can be modeled as a sequence of discrete steps. At each step, the system may branch into multiple valid behaviors due to configuration, input variability, timing, or environmental interaction.

Let:

$$n = \text{number of execution steps}$$

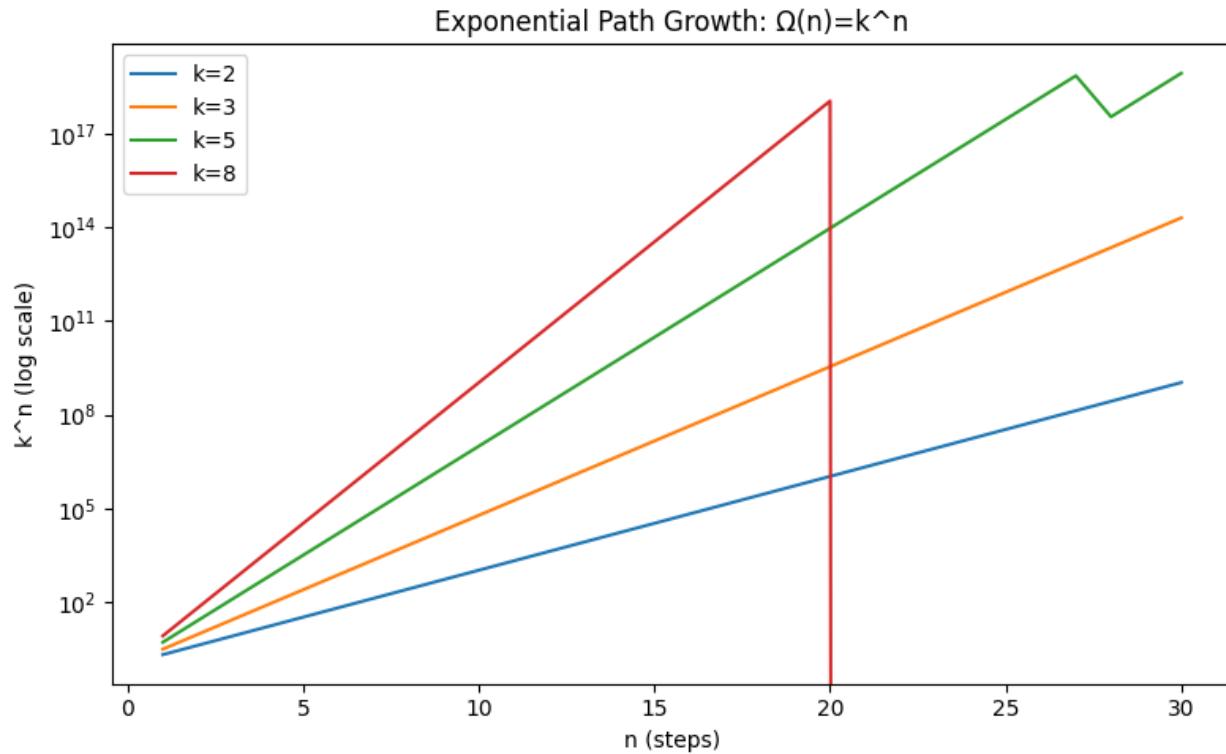
$$k = \text{average branching factor per step}$$

The total number of possible execution paths is then:

$$\Omega(n) = k^n$$

Even for modest values of  $k$ , the state space grows exponentially in  $n$ . Detection systems are therefore not observing a single behavior, but sampling from an exponentially large behavioral manifold.

## Scaling Log, Notebook Cell 4.



## 2 Classical Detection and Feature Projection

Classical detection pipelines typically project execution behavior into a feature space:

$$\phi: \mathcal{E} \rightarrow \mathbb{R}^d$$

where  $\mathcal{E}$  denotes execution traces and  $d$  is the feature dimensionality.

Classification then proceeds via a decision function:

$$f(\phi(x)) \in \{0, 1\}$$

This implicitly assumes that malicious and benign behaviors are separable under some metric in  $\mathbb{R}^d$ . However, as  $n$  increases, distinct execution paths increasingly map to overlapping feature representations:

$$\exists x_1 \neq x_2 \text{ such that } \phi(x_1) \approx \phi(x_2)$$

This overlap is not noise; it is a structural consequence of compressing exponential behavior into polynomial feature space.

## 3 Boundary-Based Classification Under Complexity

Boundary-based detection attempts to partition feature space using a surface:

$$\mathcal{B} = x|g(x) = 0$$

As the number of overlapping behaviors increases, the boundary must contort to separate increasingly fine distinctions. The effective curvature of the boundary grows, increasing sensitivity to perturbation:

$$\delta x \Rightarrow g(x + \delta x) \cdot g(x) < 0$$

This explains why small, behavior-preserving transformations can flip classification outcomes. Importantly, adding data does not resolve this instability, as the underlying overlap persists.

#### 4 Detection Failure as an Inevitable Phase Transition

We can model detection reliability as a function of complexity:

$$R(n) = \Pr(\text{correct classification}|n)$$

Empirically and theoretically,  $R(n)$  exhibits a sharp decline beyond a critical complexity threshold  $n_c$ :

$$\lim_{n \rightarrow n_c^+} \frac{dR}{dn} \ll 0$$

This resembles a phase transition: below  $n_c$ , detection appears reliable; above it, false positives and false negatives dominate.

#### 5 Quantum Framing: State Representation

Instead of enumerating or projecting behaviors, we may represent execution as a quantum state:

$$\psi = \sum_{i=1}^{k^n} \alpha_i i$$

where each basis state corresponds to a possible execution path.

This representation does not remove complexity, but it preserves superposition rather than collapsing it prematurely into features.

#### 6 Detection as State Discrimination

Under this framing, detection becomes a problem of distinguishing between two classes of

states:

$$\psi_B, \psi_M$$

The optimal minimum-error discrimination is bounded by the Helstrom limit:

$$P_e = \frac{1}{2} \left( 1 - \sqrt{1 - |\langle \psi_B | \psi_M \rangle|^2} \right)$$

This bound is independent of model choice, training data, or optimization technique. It represents a fundamental limit on distinguishability imposed by overlap.

## 7 Why This Changes the Question

Classical detection asks:

“Can we learn a better boundary?”

Quantum framing asks:

“How distinguishable are these behaviors in principle?”

This shift reframes detection failure not as an engineering defect, but as an information-theoretic constraint.

## 8 Illustrative Computational Example

**Toy Enumeration Runtime. Notebook cell 6.**

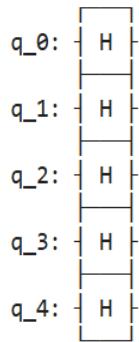
Toy enumeration runtime (extrapolated):						
k	n	paths	sampled	sample_sec	est_total_sec	est_total_min
-----						
3	10	59,049	59,049	0.0236	0.02	0.00
3	12	531,441	200,000	0.0845	0.22	0.00
3	14	4,782,969	200,000	0.0838	2.00	0.03
3	16	43,046,721	200,000	0.0810	17.43	0.29
3	18	387,420,489	200,000	0.0821	159.06	2.65

At this point, we introduce a toy execution model implemented in Python. A classical routine enumerates behavior paths and projects them into a reduced feature space, demonstrating exponential growth in candidate evaluations.

A corresponding Qiskit-based construction encodes paths as amplitudes in a simulated quantum circuit. While slower in wall-clock time, the quantum formulation preserves structural relationships that are lost under classical projection.

## Qiskit toy circuit output (n\_qubits=5; 32 basis states). Notebook, Cell 15.

```
Qiskit toy circuit created:
```



```
Number of basis states: 32
```

```
First 8 probabilities: [0.03125 0.03125 0.03125 0.03125 0.03125 0.03125 0.03125 0.03125]
```

```
Sum of probabilities: 1.000000
```

```
Saved figure: fig_qiskit_circuit.png
```

*Note: This example is not intended to demonstrate speedup. It exists solely to illustrate problem framing.*

## 9 Limits and Non-Claims

This work explicitly does not claim:

- Near-term quantum advantage
- Replacement of classical detection systems
- Hardware feasibility at scale

Its purpose is explanatory, not prescriptive.

## 10 Conclusion

Detection fails first not because defenders lack tools or data, but because complexity imposes unavoidable limits on inference. Classical systems obscure these limits by collapsing behavior into brittle representations. Quantum framing does not eliminate complexity, but it exposes its consequences clearly. Understanding these limits is a prerequisite for designing resilient security systems in an increasingly complex world.