

# **Dependency Graph Topology and Classical Compressibility Diagnostics for AI Value in Systems Engineering Models**

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# Bio



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Dr. Robert Hill is an adjunct professor for the Online Engineering Programs at The George Washington University in Washington, DC. He has two decades of experience in quantitative finance, algorithmic trading, and data science. He has designed financial systems across an array of products and markets in the floor exchange, proprietary trading, and hedge fund industries.

He holds undergraduate and graduate degrees from Princeton, Oxford, and Cambridge, in history, politics, and economics. He also holds an M.B.A. from NYU, specializing in quantitative finance and data science, and an M.S. in operations research, from Columbia SEAS. His Ph.D. in systems engineering from George Washington University focused on applying graph theory to managing stakeholders in technical and complex organizations. His research interests include network science, machine learning for graphs, resilience, strategic management, stakeholder theory, and portfolio optimization.

# Agenda

- I. Motivation: When is AI worth using (i.e. an 'AI-first' approach to system design)?
- II. Classical compressibility and dependency topology
- III. Preliminary / characteristic empirical cases
- IV. Implications for interpretability, DSMs, and generative AI

Goal: a practical AI-readiness screen for systems engineering models on a spectrum:

Human-specified -> Interpretable -> Explainable -> Black-box

# Motivation: AI Value Is a Systems Engineering Question

AI models in SE and DoD contexts value must be weighed against practical constraints:

Interpretability: can engineers understand the model's structure?

Explainability: can the model justify its recommendations?

Trust: can stakeholders rely on outputs for consequential decisions?

Validation burden: can the model be tested, bounded, and certified?

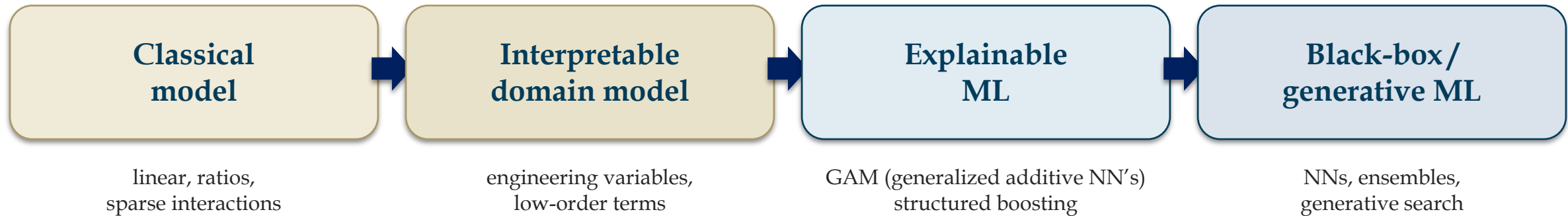
Context limits: can generative AI 'see' enough of the architecture, requirements, interfaces, and constraints?

Token / compute cost: is the workflow economical enough for repeated design iterations?

**Diagnostic question: which systems justify AI, and which remain 'classically compressible'?**

# Classical Compressibility

A system is 'classically compressible' when most input-output behavior can be captured using expert-specifiable structure, with 'black-box' models at the other end of a spectrum of 'explainability'



**What matters is not linearity, but whether linearity is expert-specifiable.  
For this, sparsity and hierarchy in dependencies are often key.**

# From DSM to Dependency Graph

A Design Structure Matrix represents system elements and dependencies.

Treated as an adjacency matrix, it becomes a graph. DSM topology may help diagnose when expert models are enough — and when AI-assisted exploration is justified.

**Design Structure Matrix (DSM)**

|   | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| A |   | • | • | • |   |   |   |
| B | • |   | • |   |   |   |   |
| C | • | • |   | • |   | • |   |
| D |   |   |   |   | • |   |   |
| E |   |   |   | • |   | • |   |
| F |   |   |   |   |   |   | • |
| G |   |   |   |   |   | • |   |

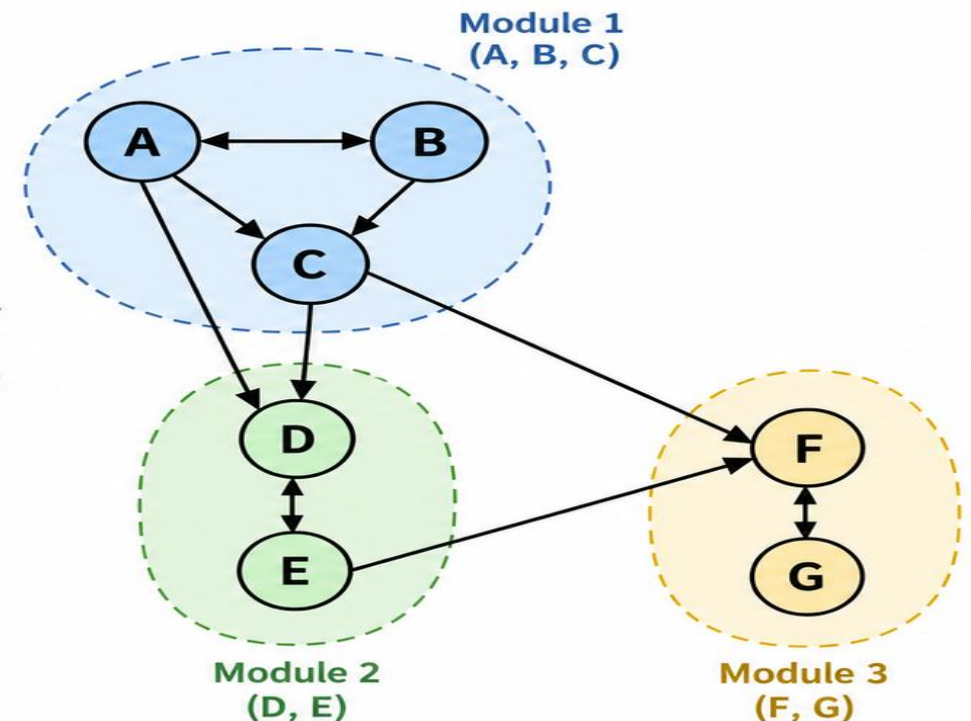
Module 1  
(A, B, C)

Module 2  
(D, E)

Module 3  
(F, G)

Derived from  
DSM

**Graph Representation**

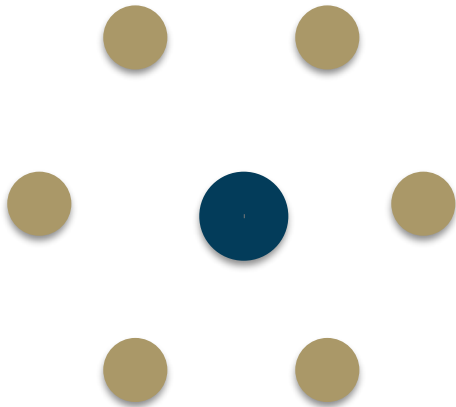


Nodes = system elements; edges = dependencies

# Degree Assortativity as an Early-Warning Signal

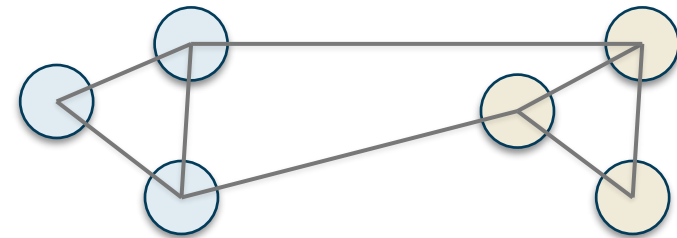
## Low / negative assortativity (low node degree correlation)

more hub-like, hierarchical or decomposable  
dependencies may concentrate around key variables  
expert models may be more competitive  
interpretability may be recoverable



## High positive assortativity (high node degree correlation)

clustered, mutually dependent variables  
distributed interaction structure  
harder to compress manually  
learned models may retain more advantage



**Caveat: topology is a heuristic, not a final decision rule; it must be paired with a compressibility test.**

# Methodology: The Compressibility Test

- 1 Build feature-dependency graph (using correlations between main effects)
- 2 Measure topology: degree assortativity as heuristic
- 3 Compare model ladder: linear → quadratic → domain model → ML
- 4 Measure residual ML advantage

$$\text{Residual ML advantage} = (\text{Classical RMSE} - \text{ML RMSE}) / \text{Classical RMSE}$$

**Q: Does AI add sufficient value after an expert-specified model has been tried?**

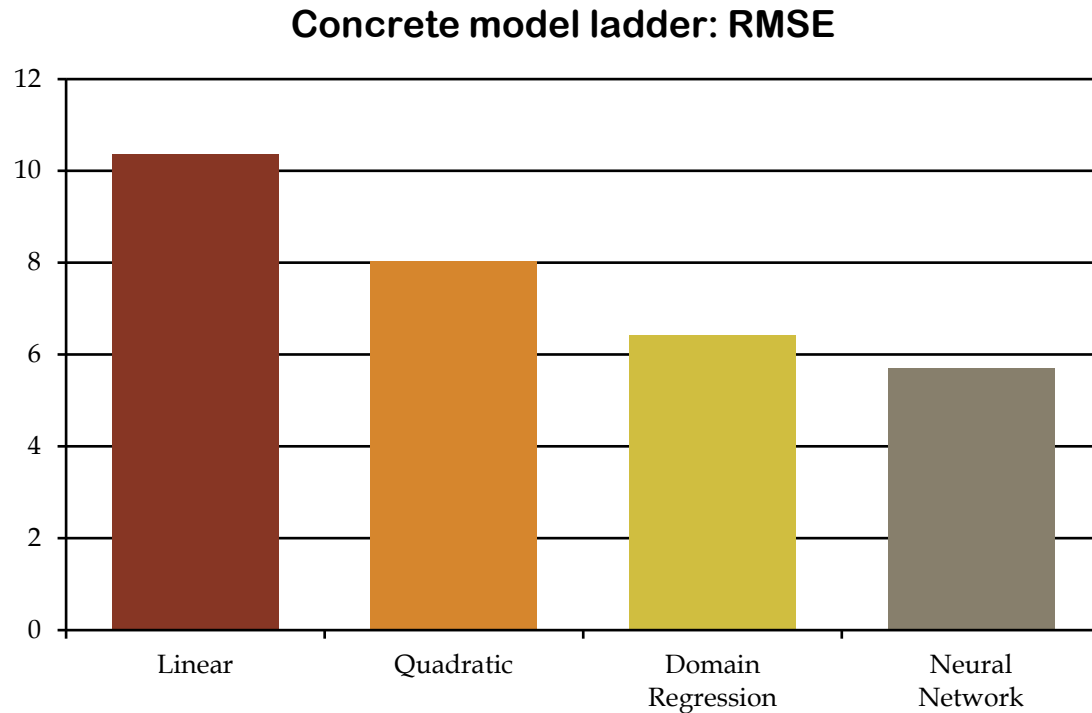
# Characteristic Results and Patterns

| Dataset                  | Topology / structure            | Result                                               | Interpretation                                    |
|--------------------------|---------------------------------|------------------------------------------------------|---------------------------------------------------|
| <b>Superconductivity</b> | High assortativity; 81 features | ~39% ML advantage                                    | AI-favorable                                      |
| <b>Bike Sharing</b>      | Assortative / interaction-heavy | ~53% ML advantage                                    | AI captures context                               |
| <b>Auto MPG</b>          | Low / negative                  | Quadratic closes gap                                 | Classically compressible                          |
| <b>Power Plant</b>       | Somewhat low / hierarchical     | ~15% ML advantage                                    | Mostly compressible / interpretable               |
| <b>Concrete</b>          | Low / negative assortativity    | ML initially outperforms but domain model closes gap | Interpretability partly recoverable / explainable |

Preliminary results: useful patterns, not a universal law. Topology must be paired with the compressibility test.

# Concrete: The 'Explainability Exception'

Concrete shows how ML can reveal that the first human/classical specification was underspecified.



Raw graph: low / negative assortativity

Generic classical terms helped, but left a large ML gap

Domain variables: binder, water/binder, water/cement, composition shares, log age, targeted interactions

Domain regression closed much of the gap, but NN retained residual advantage

**Interpretation: ML can be a diagnostic tool — not just a replacement for expert modeling.**

# Practical Takeaways

1

## **DSM topology can inform AI readiness**

Sparse, decomposable systems may be more classically compressible; assortative systems may justify an AI-first approach. Intermediate 'compressibility' may allow interpretability or explainability.

2

## **Pair classical compressibility tests with graph topology**

If topology and compressibility diagnostics agree, we are likely to either 'need' AI (assortative/not compressible) or be unlikely to benefit from an AI-first approach (disassortative/compressible).

3

## **Interpretable and Explainable AI are the interesting middle categories**

When assortativity is low but initial human-specified regressions lag ML, yet black-box AI is problematic, try structured interpretable (harder) or explainable (easier) ML.

4

## **Generative AI may be most valuable in highly coupled, complex design spaces**

DSM topology analysis often shows that architectural properties such as resilience, flexibility, adaptability, or innovation-orientation often produce assortative DSM's where ML seems to strictly dominate. Modularity, maintainability & repairability may be associated with lower assortativity; thus better designed by humans.

**Goal: identify when the dependency structure of the system justifies AI — and when human expert models remain the better engineering choice.**