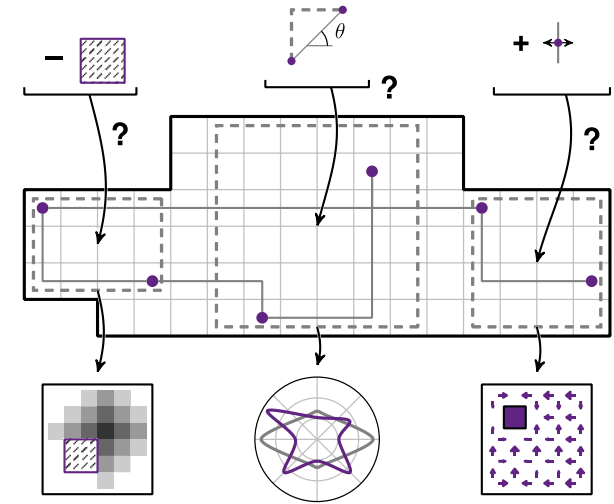


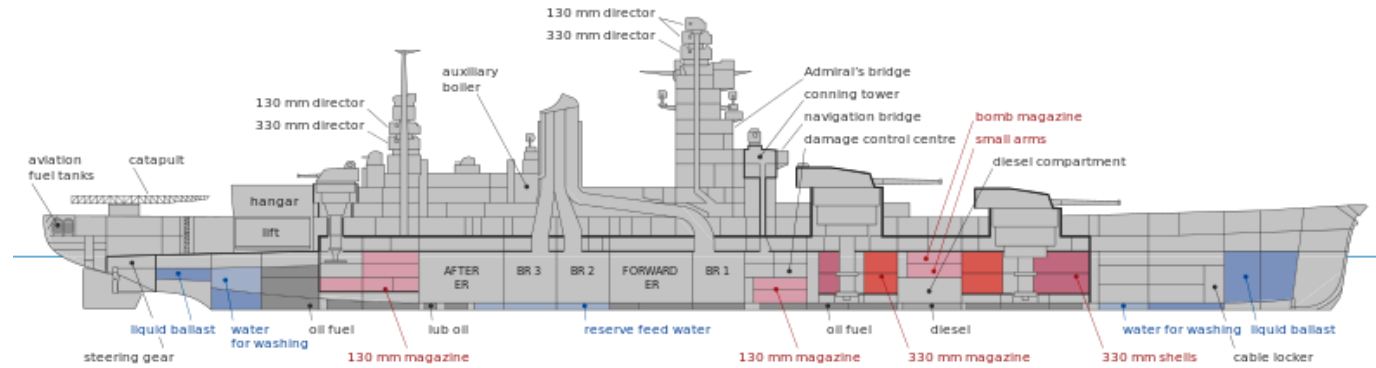
Industrial design process as scientific discovery

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AAAI Spring Symposium on
Computational Approaches to Scientific Discovery
March 29, 2023



Design problems



Maxrossomachin
for Wikipedia

- Needs to be as cheap as possible.
- Needs to float, even after being shot at.
- Needs to support our best current-gen weapons,
as well as next-gen and next-next gen.
- Have redistributable power.
- Have mission flexibility.
- And be fixable when it breaks.
- And ...

...

...

Nouns, verbs, questions

- **Design (noun)**: solution or plan for an object or system that fulfils the desired function.
- **Design (verb)**: the process that sometimes somehow results in **design (noun)**.

- **What** solution should we choose?
- **Why** is that solution preferable?

Design as optimization

The objective function is sometimes called a “cost” function since minimum cost often is taken to characterize the “best” design.

Principles of optimal design: modeling and computation,
PY Papalambros and DJ Wilde.
Cambridge University Press, 2000.

$$f(\alpha) = \sum_m \lambda_m O_m(\alpha) \quad \xrightarrow{\text{Optimization}} \quad \alpha^* = \arg \min_{\alpha} f(\alpha)$$

Why would I want to take a *suboptimal* solution?

How do solutions change with choice of λ_m ?
How many solutions of same cost are there?

Design is not optimization: Wicked Problems

- Never completely defined
- Many stakeholders
- Can't tell when solved
- Can't have a prototype

CW Churchman, *Management Science* (1967)
HW Rittel and MM Webber, *Policy Sciences* (1973)
DJ Andrews, *Proc. Roy. Soc. A* (2012)
R Farrell and C Hooker, *Design studies* (2013)

Operational definition of design

~ computation

~ information

Design is the act of generating knowledge
for decision-making through time.

~ ???

~ non-equilibrium

Maximal entropy statistical mechanics

How do you make the **least informative** random choice of design α ?

Pick at random with p_α that maximizes Shannon entropy S .

$$S = - \sum_{\alpha} p_{\alpha} \ln p_{\alpha} - \sum_m \lambda_m \left(\sum_{\alpha} p_{\alpha} \mathcal{O}_m(\alpha) - \langle \mathcal{O}_m \rangle \right) \rightarrow \max$$

Design pressure m (with arrow pointing to λ_m)
Objective m in design α (with arrow pointing to $\mathcal{O}_m(\alpha)$)
Design objectives $\langle \mathcal{O}_m \rangle$ are reached on average (with arrow pointing to the difference term)

Boltzmann distribution in statistical physics:

$$p(\alpha) = \frac{1}{Z} \exp \left(- \sum_m \lambda_m \mathcal{O}_m(\alpha) \right)$$

Maximum of $p(\alpha)$
is minimum of $f(\alpha) = \sum_m \lambda_m \mathcal{O}_m(\alpha)$

ET Jaynes, *Phys. Rev.* (1957)

AAK, CPF Shields, DJ Singer, G van Anders, *New J. Phys.* (2018)

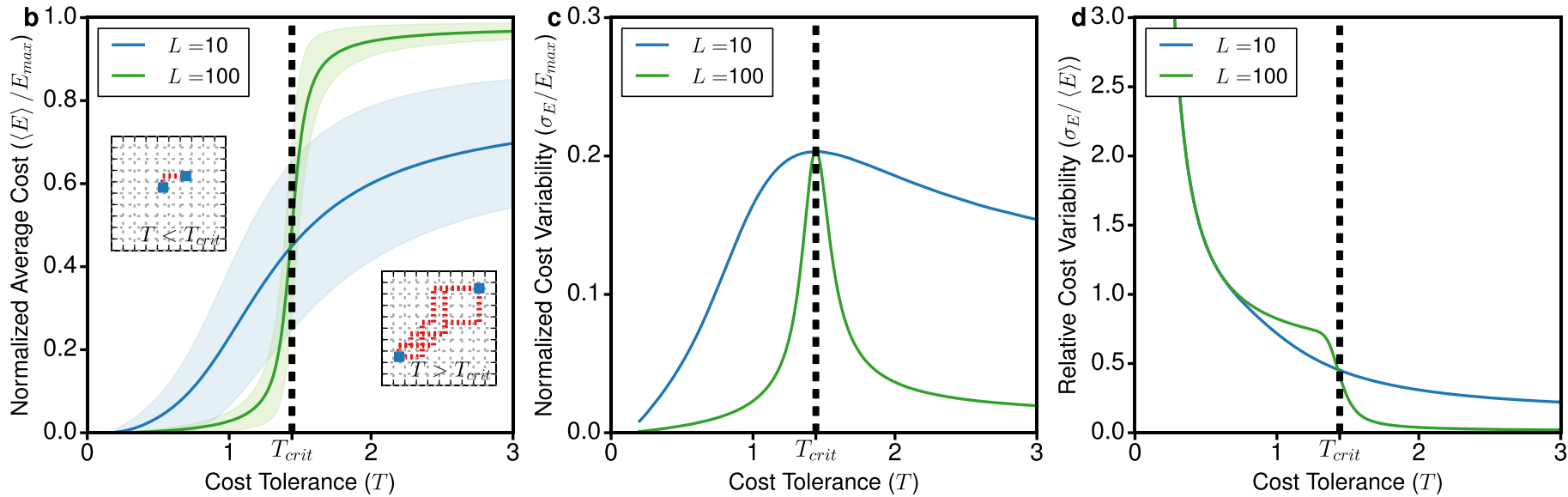


Q: Does solution entropy change anything?

How many solutions of cost $f(\alpha)$ are there?
How does entropy affect average solutions?
Is entropy / flexibility **a virtue**?

Cf. **density of states** in physics

Entropy-driven phase transition



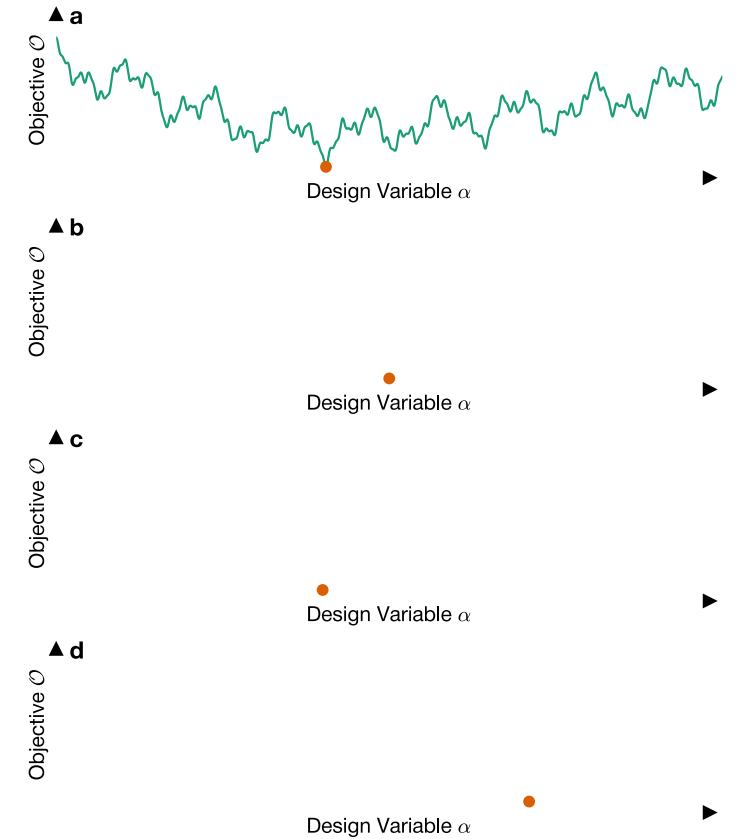
$$E_{max} = 2CL$$

$$T_{crit} = \frac{C}{\ln 2} \approx \boxed{1.44} C$$

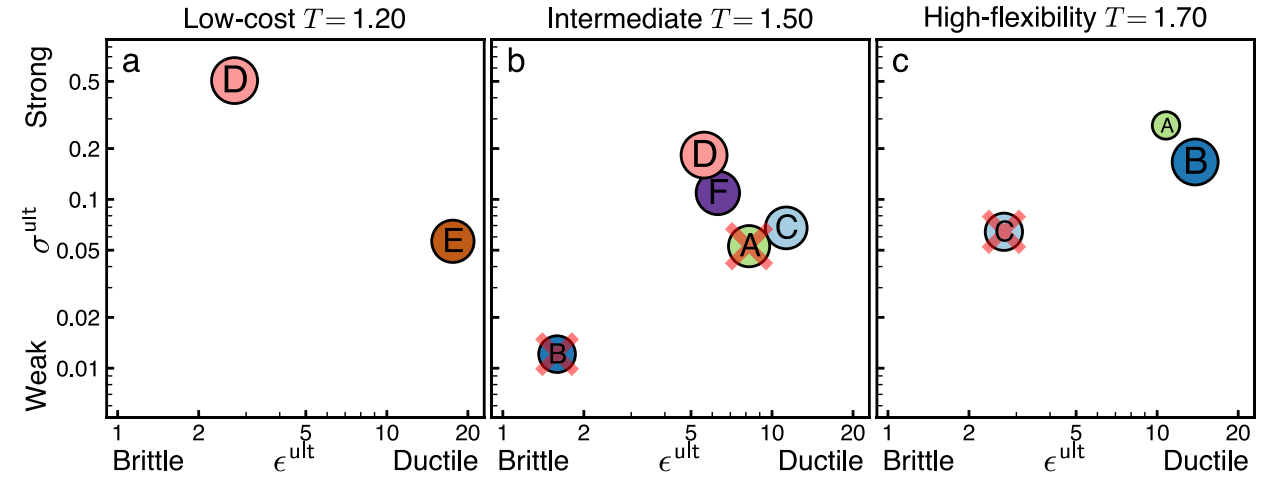
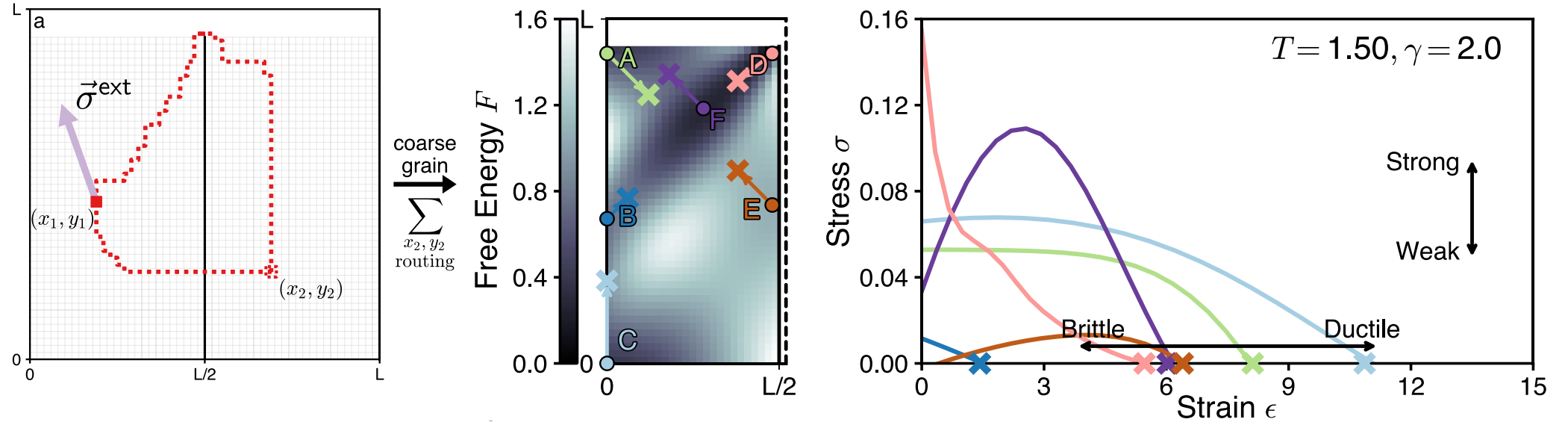
Q: Are solutions robust to problems?

Over-constrained / rough problem
→ hard to find the “best” solution

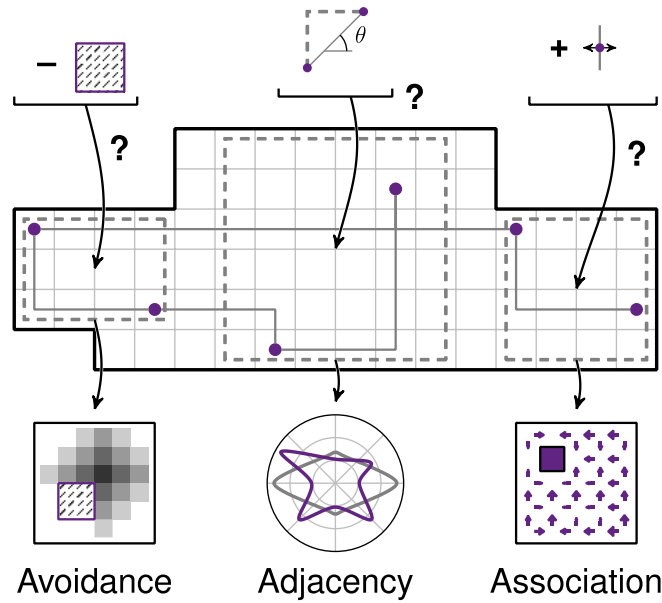
Under-constrained / flat problem
→ “best” solution is useless



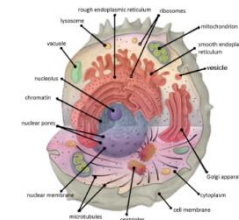
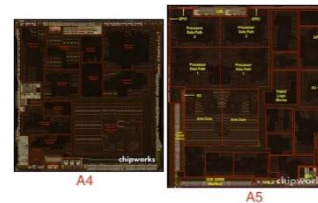
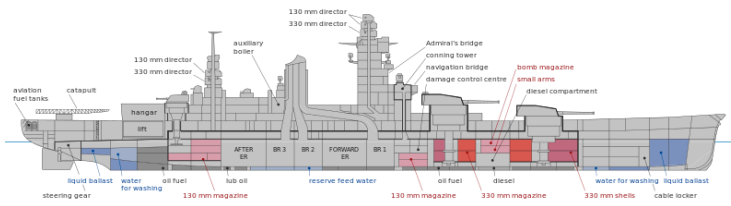
Two-factor robust design



Q: What is the structure of design space?



Avoidance: Where do we pay high space premium?
Adjacency: How does indirect coupling emerge?
Association: How do early design decisions constrain design freedom?



Equipment in a warship?
 Transistors on a chip?
 Organelles in a cell?

Maxrossomachin for Wikipedia

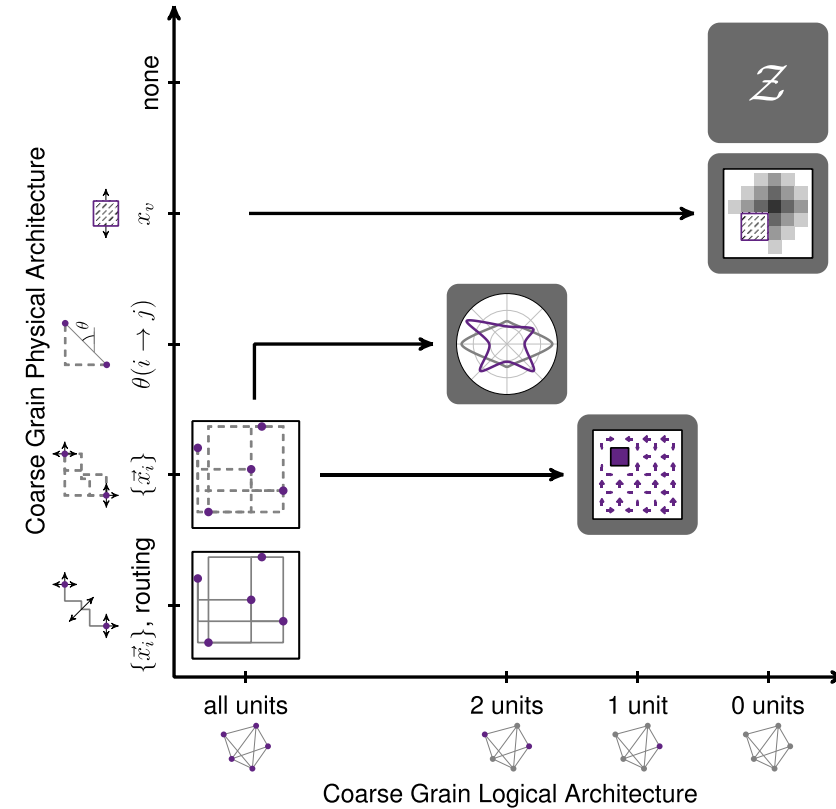
<http://techztalk.com/>

Koswac for Wikipedia



Two directions of coarse graining

- Arrangement patterns span *two dimensions* of architectural detail
- Arrangement patterns ~ physical phenomena:
 - Avoidance ~ symmetry breaking
 - Adjacency ~ emergent correlation
 - Association ~ emergent localization



Q: How to make a posteriori value statements?

$\mathcal{O}_m(\alpha)$ is **what** objective we care about.
 λ_m is **how much** we care about it.

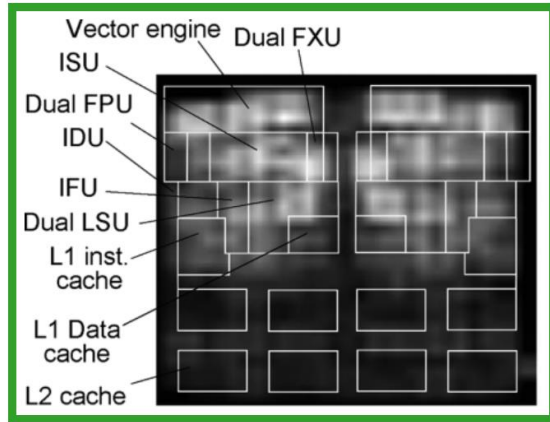
$$\{\lambda_m\} \xrightarrow{\text{Math}} \alpha^*, \{\langle \mathcal{O}_m \rangle\}$$

Choosing λ_m is a value statement.

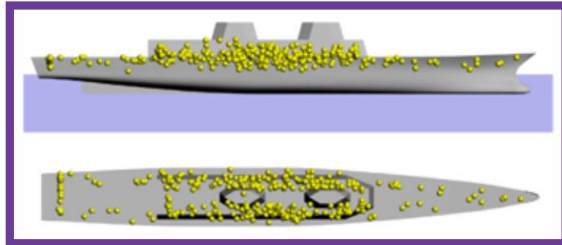
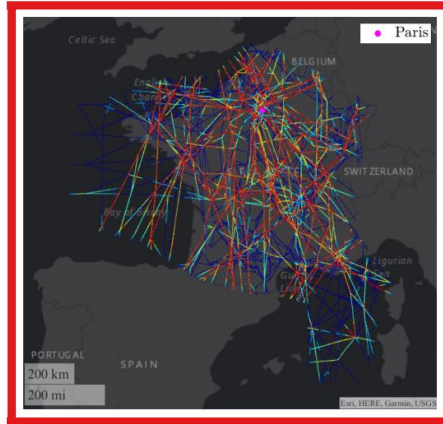
Do we make an **a priori** or a **posteriori** choice?

No Free Lunch for clustering vulnerabilities

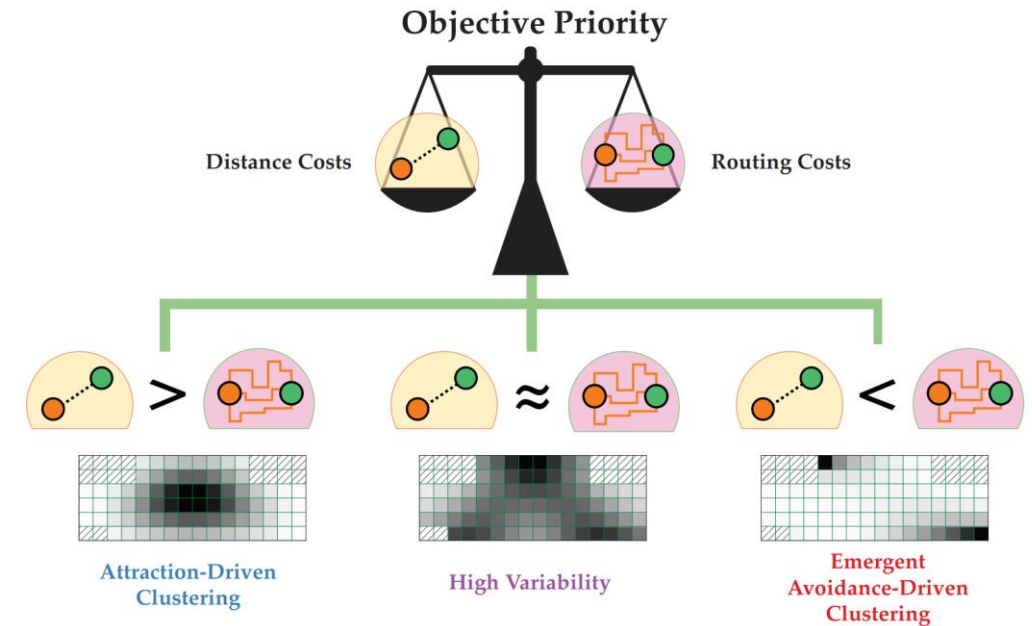
Hot spots in microprocessors¹



Airline congestion²



Weak points in warship design³



P Chitnelawong, **AAK**, et al., *in preparation* (2023)

Slide by P Chitnelawong;

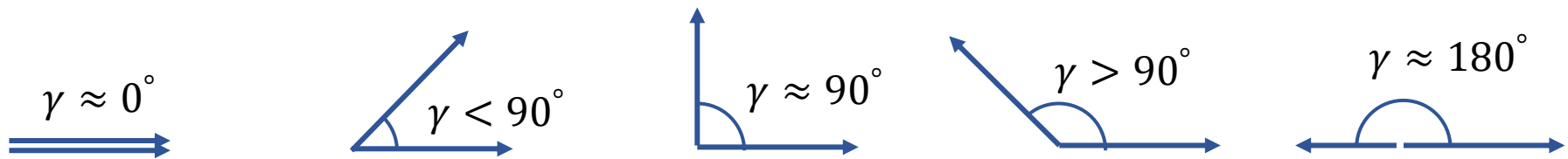
1. HF Hamann et al., *IEEE J. Solid-State Circuits* (2007)
2. J Lavandier et al., *Aerospace* (2021)
3. N Doerry, *Naval Eng. J.* (2007)

Q: Are the objectives compatible?

Road users in a transit system:

- Walking
- Biking
- Public transit
- Driving

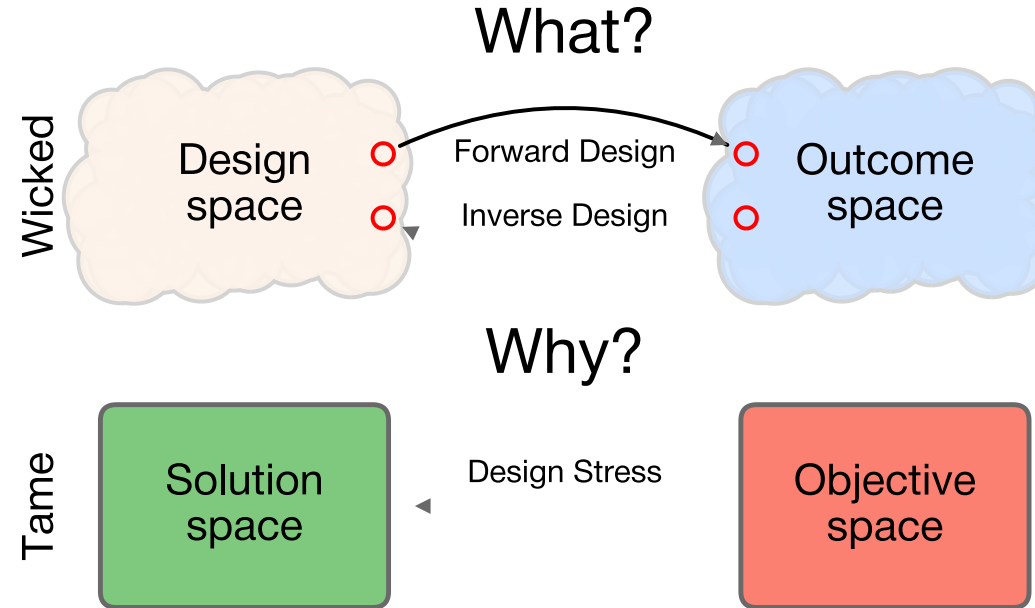
Does helping one objective help another?



Objective angle idea from:
O Braganza, *R. Soc. Open Science* (2022)



Inverse problems in design



Desired material properties → optimal synthesis pathway
Target flow structure → geometry and boundary conditions
Focal distance / aberration → optical lens system

Not just a one-off solution, but a **design rule**

Outlook

- Real life design problems require an analysis frame **broader than optimization**
- We discover **new design phenomena** in an example naval engineering problem
- What is the “**experiment**” for these phenomena?
- What happens in a **different problem space**?
- What if the **operational metaphor** was not physics?

Acknowledgements

Collaboration:

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- Colin PF Shields
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- Pheerawich Chitnelawong



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- Mark EJ Newman
- Bob Ames
- Lynn Conway

Funding:



Code:

- Adam S Jermyn
- Norman Mackay

Computational data management:

- Signac framework

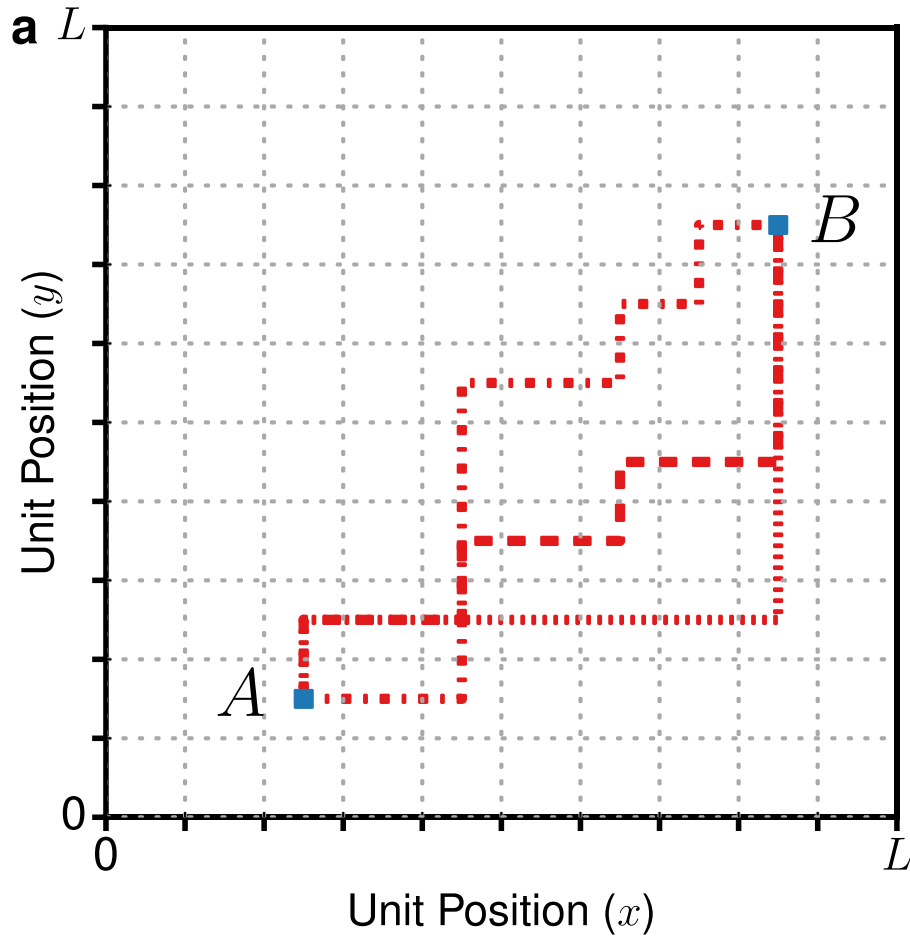


Font "Arsenal" by:

- Andriy Shevchenko (Berdiansk, Ukraine)



Cost vs entropy



Design objective: Cost

$$\mathcal{O}_1 = E = C(\Delta x + \Delta y)$$

Design pressure: Cost Tolerance

$$\lambda_1 = \frac{1}{T}$$

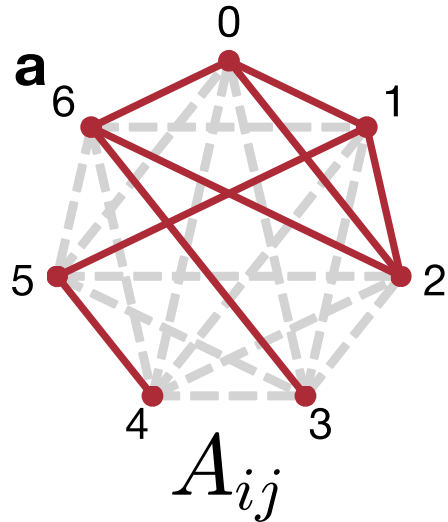
Free energy

$$T \cdot F(\Delta x, \Delta y) \approx E - T \ln n(\Delta x, \Delta y)$$

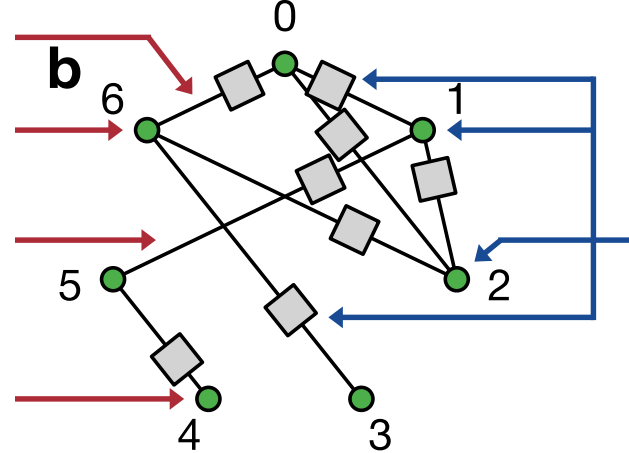


Tensor network as information structure

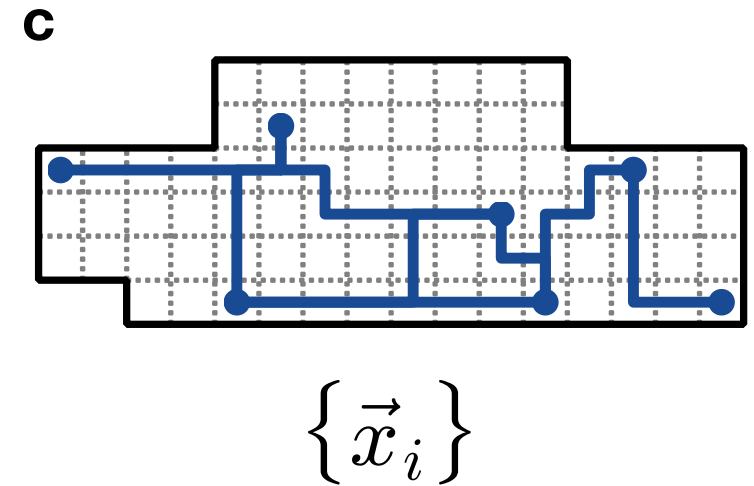
Logical Architecture



Tensor Network



Physical Architecture



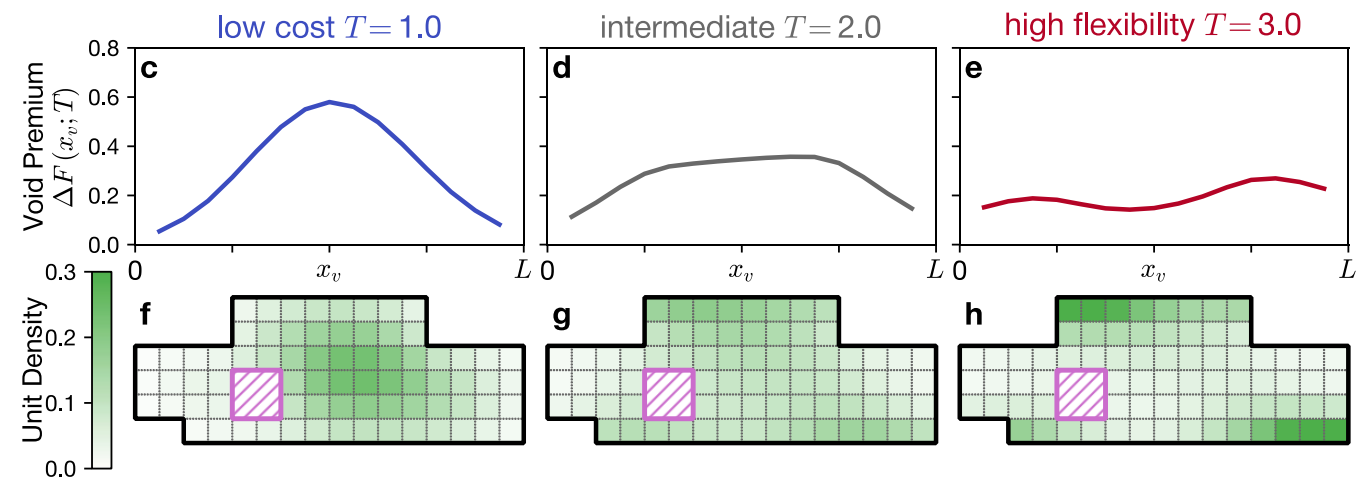
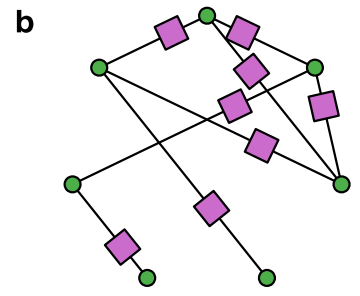
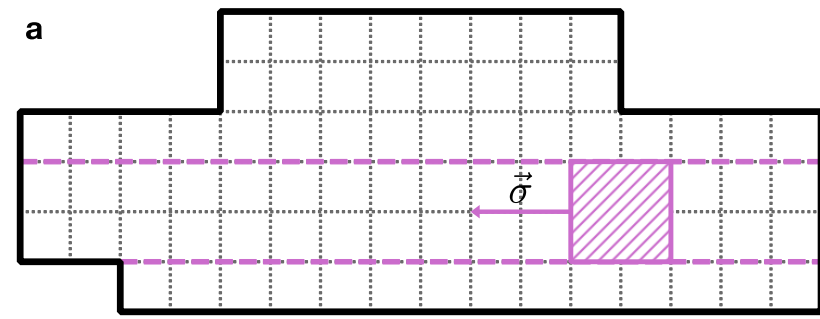
Avoidance: void premium

Void premium

$$\Delta F = -\ln \frac{Z(x_v; T)}{Z(T)}$$

Unit density

$$\rho(\vec{x}) \approx \sum_i p_i(\vec{x})$$



Adjacency: bond diagrams

Bond diagram (with KDE smoothing)

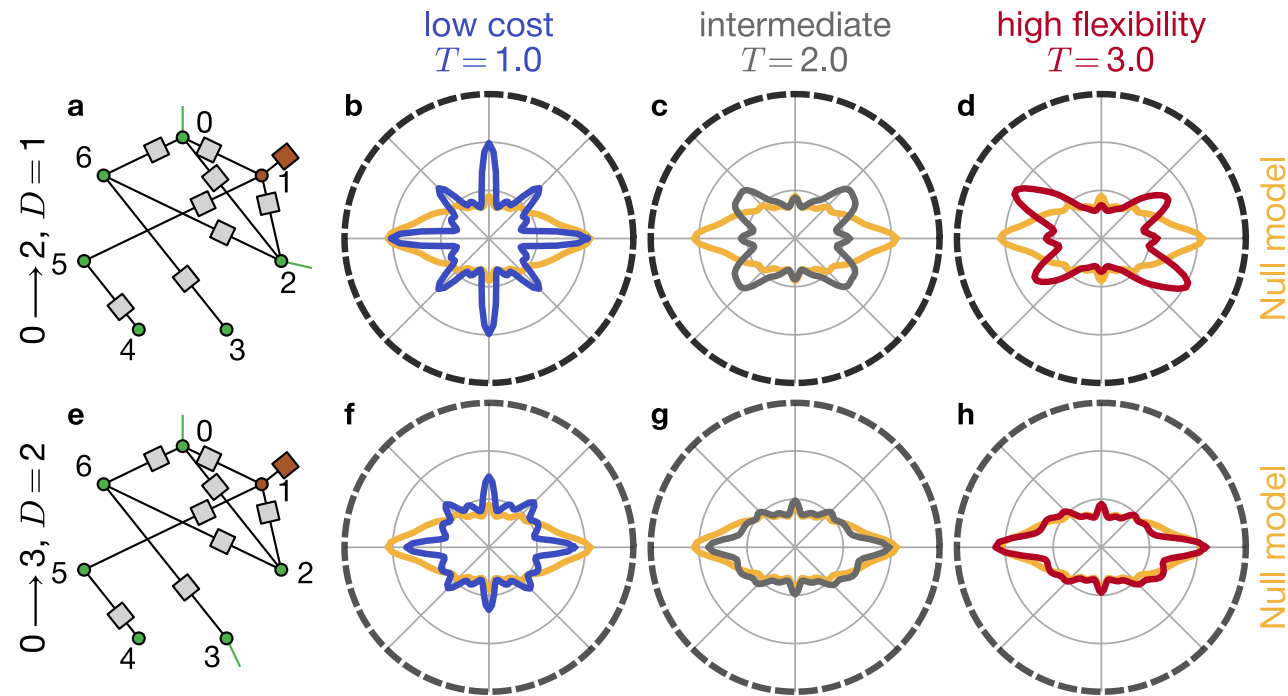
$$p_{i \rightarrow j}(\theta) = \frac{1}{\mathcal{N}} \sum_k \sum_{\vec{x}_i \neq \vec{x}_j} p(\vec{x}_i, \vec{x}_j) e^{-\frac{1}{2}(hk)^2} \cos\left(k\left(\theta - \theta(\vec{x}_i, \vec{x}_j)\right)\right)$$

PJ Steinhardt, DR Nelson, M Ronchetti, *PRB* (1983)

J Roth, AR Denton, *PRE* (2000)

Null model

$$p(\vec{x}_i, \vec{x}_j) = \text{const}$$



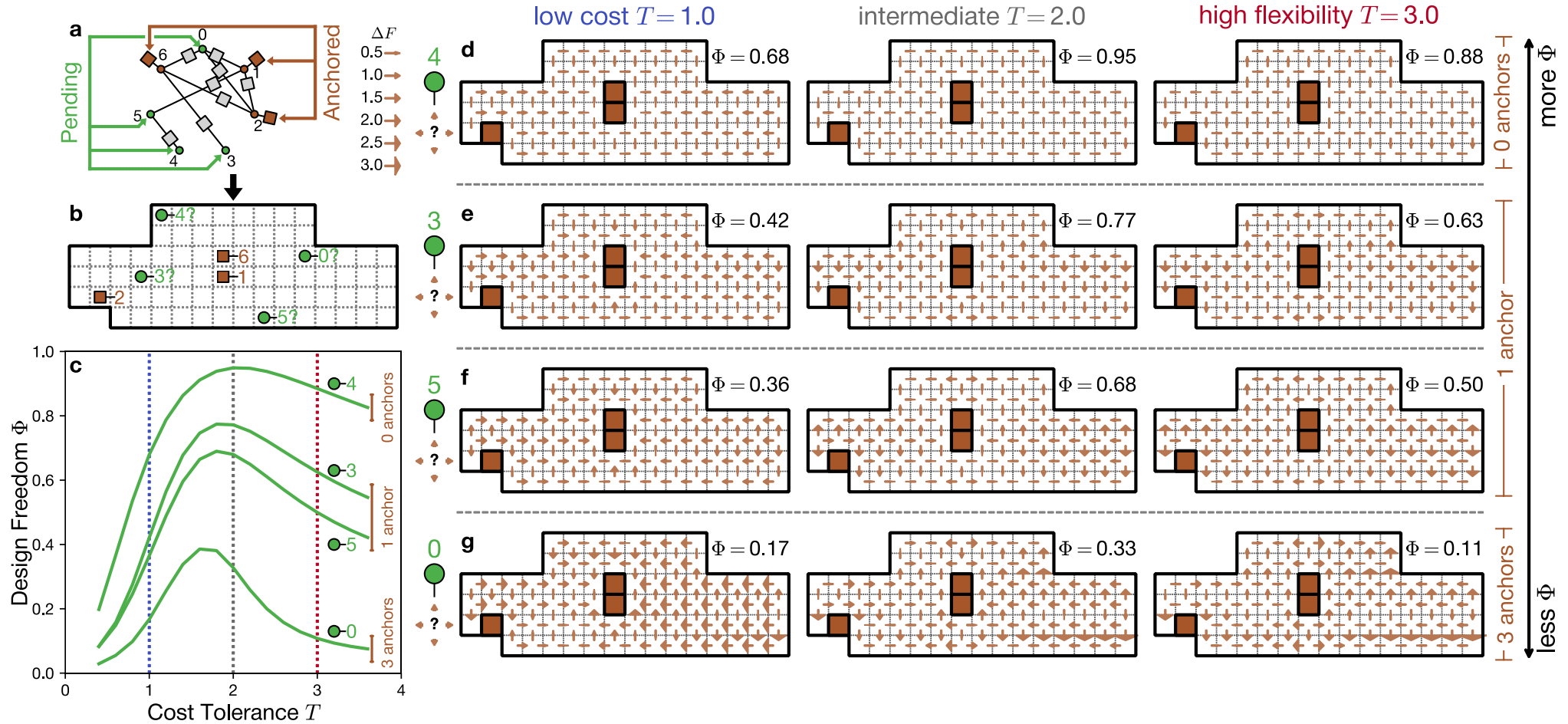
Association

Design freedom

$$\Phi = \frac{1}{Y_0} \frac{(\sum_{\vec{x}} p(\vec{x}))^2}{\sum_{\vec{x}} p(\vec{x})^2}$$

Free energy
 $F(\vec{x}) = -\ln p(\vec{x})$

Design stress
 $\Delta F = -\nabla F$



DJ Thouless, *Physics Reports* (1974)

M Filoche, S Mayboroda, *PRL* (2009)

AAK, DJ Singer, G van Anders, *J. Phys. Complexity* (2021)

Coarse-graining

- Introduce a design feature / order parameter \vec{x}_α s.t. $\alpha \rightarrow \vec{x}$ is surjective (compressing).

- Landau (effective) free energy:

$$e^{-F(\vec{x})} = \sum_{\alpha} \delta(\vec{x} - \vec{x}_\alpha) e^{-\sum_m \lambda_m \mathcal{O}_m(\alpha)}$$

- Defines effective landscapes on a smaller space.

Systems Physics computations

Objective function with only 2-point couplings (aka 2-body Hamiltonian) along a network

$$\lambda O_{eff}(\{x\}) = \sum_{i < j} A_{ij} f(x_i, x_j; T)$$

T = cost tolerance

$T < 1.44$ attract

$T > 1.44$ repel

Partition function

$$Z = \sum_{\{x_i\}} \prod_{ij: A_{ij} \neq 0} e^{-f(x_i, x_j; T)} = ???$$

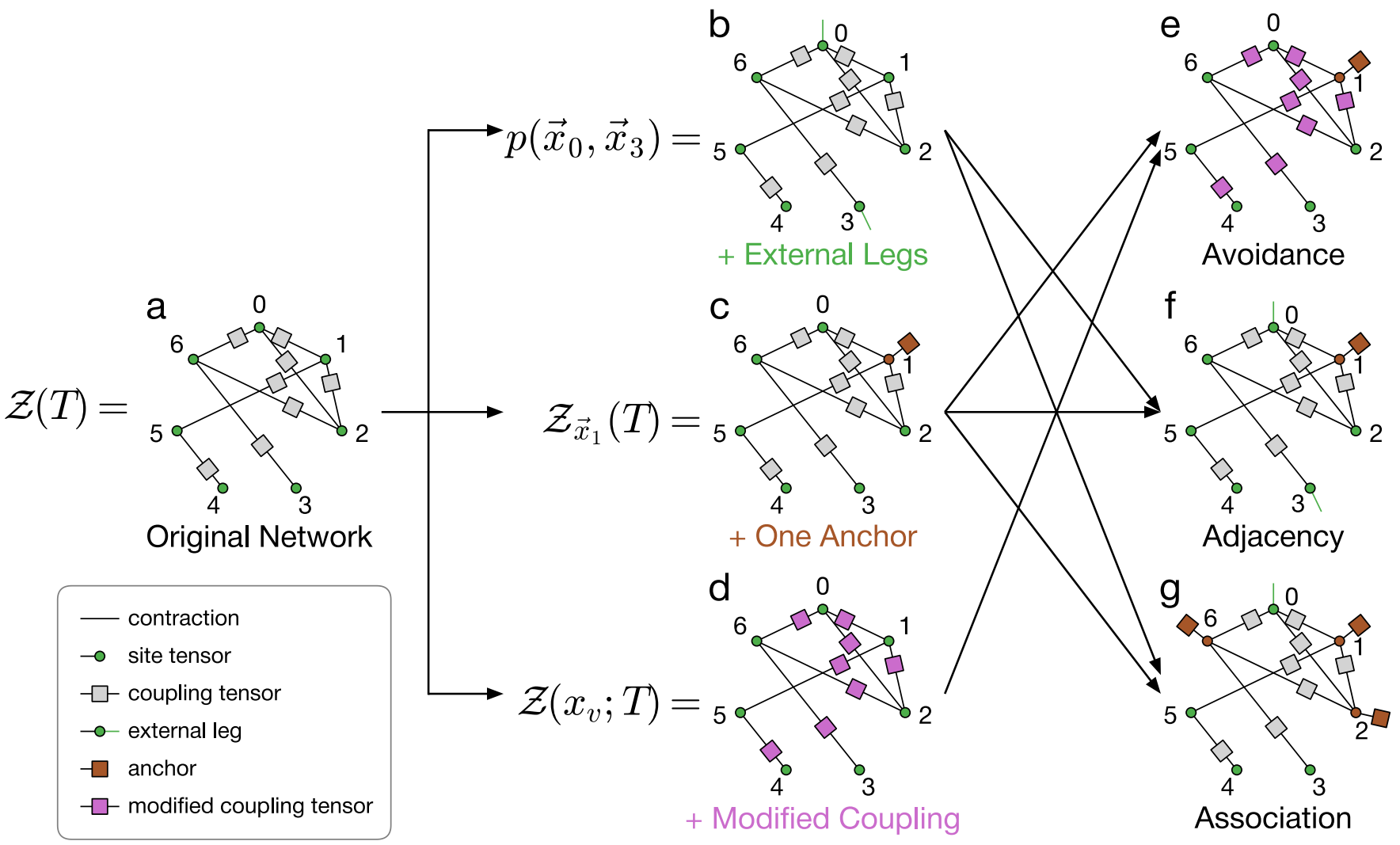
Sum over **all** sites $\sim 10^{13}$ terms

One-unit marginal distribution

$$p(x_k) = \frac{1}{Z} \sum_{\{x_{i \neq k}\}} \prod_{ij: A_{ij} \neq 0} e^{-f(x_i, x_j; T)} = ???$$

Sum over **all but one** sites

Tensor network query language



Adjacency: add and remove links

