

Heuristics and Really Hard Instances for Subgraph Isomorphism Problems

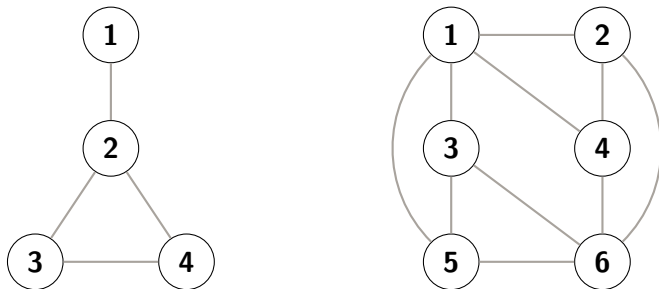
Ciaran McCreesh, Patrick Prosser and
James Trimble



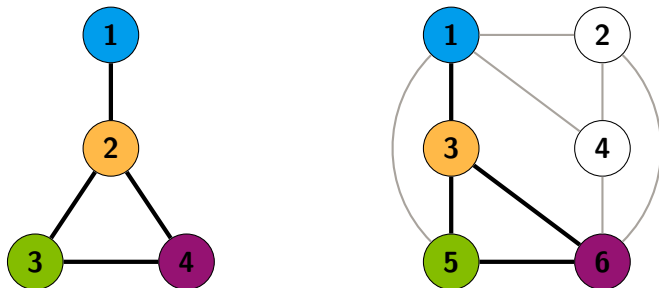
University
of Glasgow



Non-Induced Subgraph Isomorphism



Non-Induced Subgraph Isomorphism



Benchmarking

- Based upon chemical and computer vision datasets, we can handle patterns with 1,000 vertices and targets with 10,000 vertices.
- Do these results reflect the worst case, or are they too optimistic?
- Can we create “hard” benchmark instances?

Randomly Selected Subgraphs

- Start with a random target graph.
- Pick vertices at random to make a pattern.
- Shuffle the numbering.

Randomly Selected Subgraphs

- Start with a random target graph.
- Pick vertices at random to make a pattern.
- Shuffle the numbering.
- These instances will always be satisfiable!

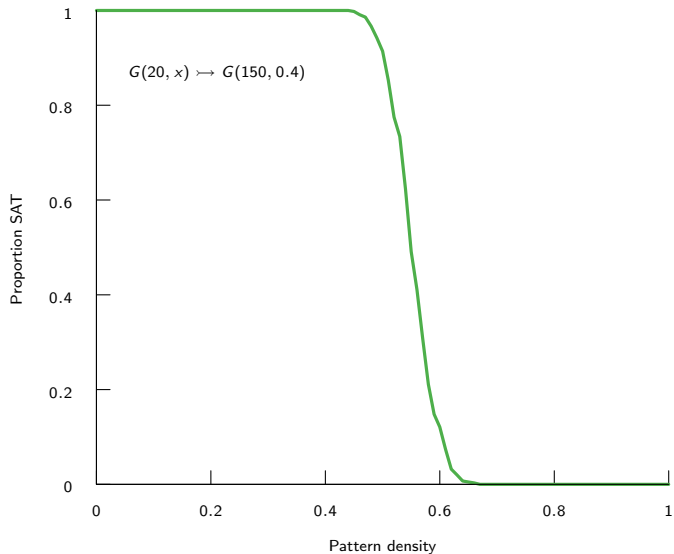
Independently Random Subgraphs

- Make a random target graph.
- Independently, make a random pattern graph.

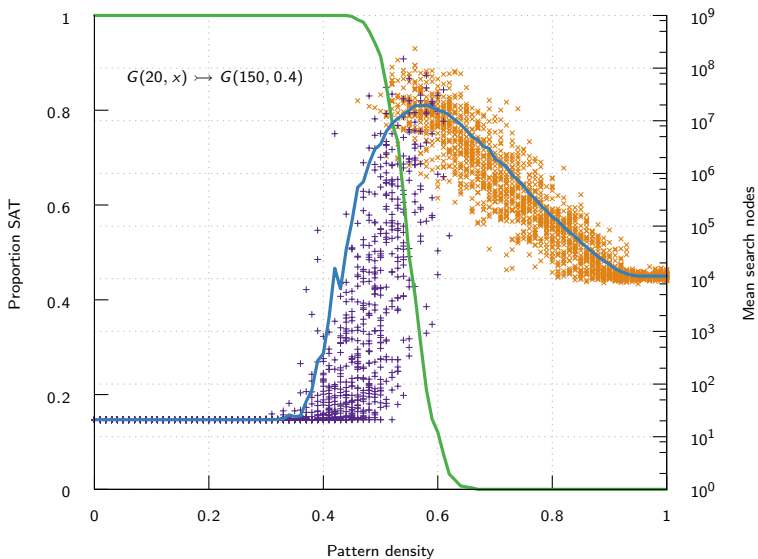
Independently Random Subgraphs

- Make a random target graph.
- Independently, make a random pattern graph.
- Will these instances ever be satisfiable?

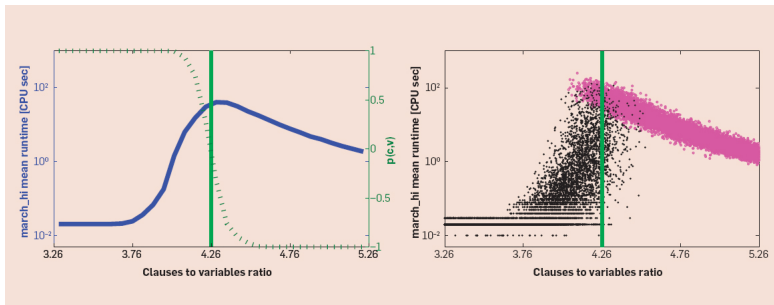
A Phase Transition



A Phase Transition



This Looks Familiar...



Understanding the Empirical Hardness of NP-Complete Problems.
Kevin Leyton-Brown, Holger H. Hoos, Frank Hutter, Lin Xu.
Communications of the ACM, Vol. 57 No. 5, Pages 98-107

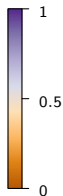
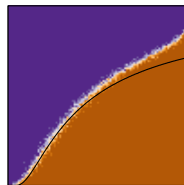
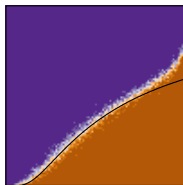
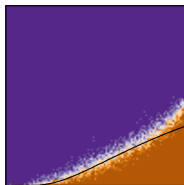
In Two Dimensions?

$$G(10, x) \rightarrow G(150, y)$$

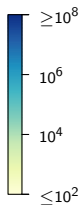
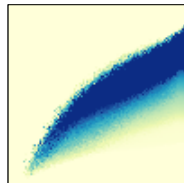
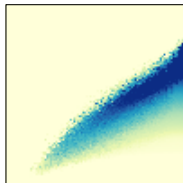
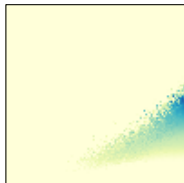
$$G(20, x) \rightarrow G(150, y)$$

$$G(30, x) \rightarrow G(150, y)$$

Satisfiable?



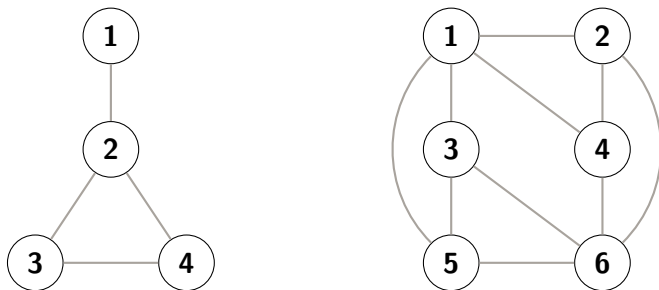
Difficulty (Glasgow)



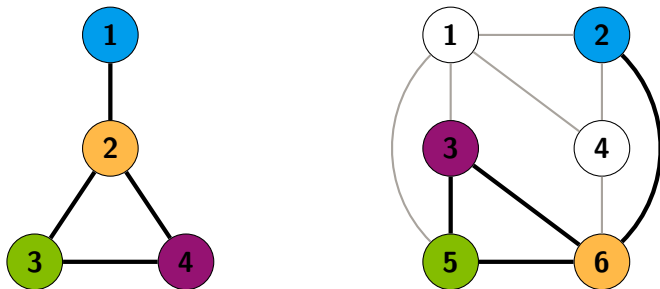
See The Paper For...

- Is this behaviour solver-independent?
- Estimating the phase transition location.
- Using this to rediscover variable and value ordering heuristics.

Induced Subgraph Isomorphism



Induced Subgraph Isomorphism



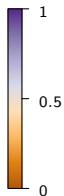
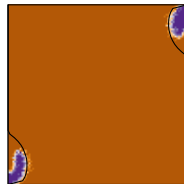
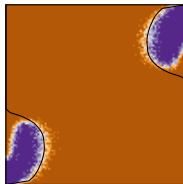
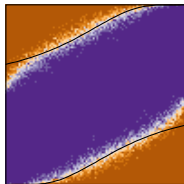
Induced in 2D

$$G(10, x) \hookrightarrow G(150, y)$$

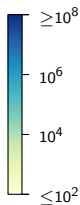
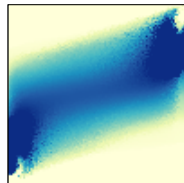
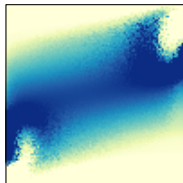
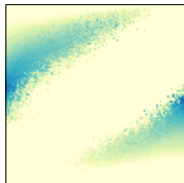
$$G(20, x) \hookrightarrow G(150, y)$$

$$G(30, x) \hookrightarrow G(150, y)$$

Satisfiable?



Difficulty (Glasgow)



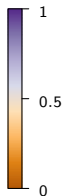
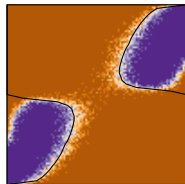
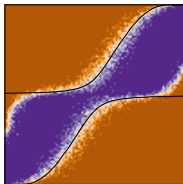
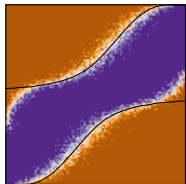
What Changes Between 10 and 20?

$$G(14, x) \hookrightarrow G(150, y)$$

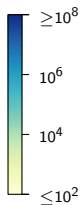
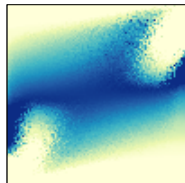
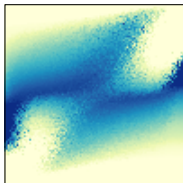
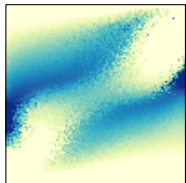
$$G(15, x) \hookrightarrow G(150, y)$$

$$G(16, x) \hookrightarrow G(150, y)$$

Satisfiable?

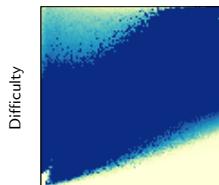
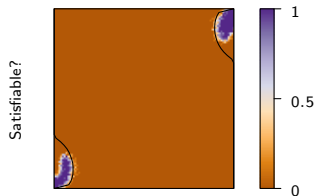


Difficulty (Glasgow)

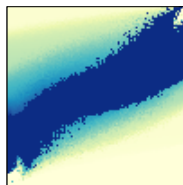


Is The Central Region Really Hard?

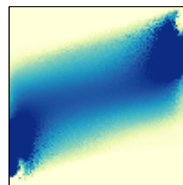
$$G(30, x) \hookrightarrow G(150, y)$$



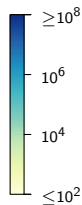
VF2



LAD

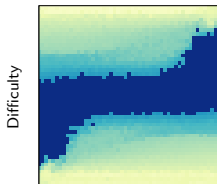
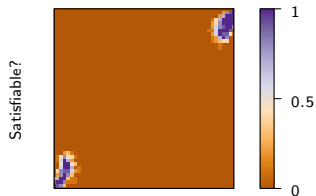


Glasgow

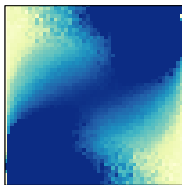


What About Encodings or Reductions?

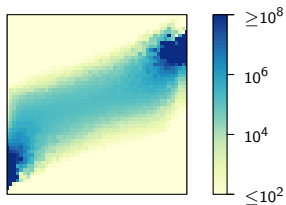
$$G(25, x) \hookrightarrow G(75, y)$$



Clasp (PB)



BBMC (Clique)

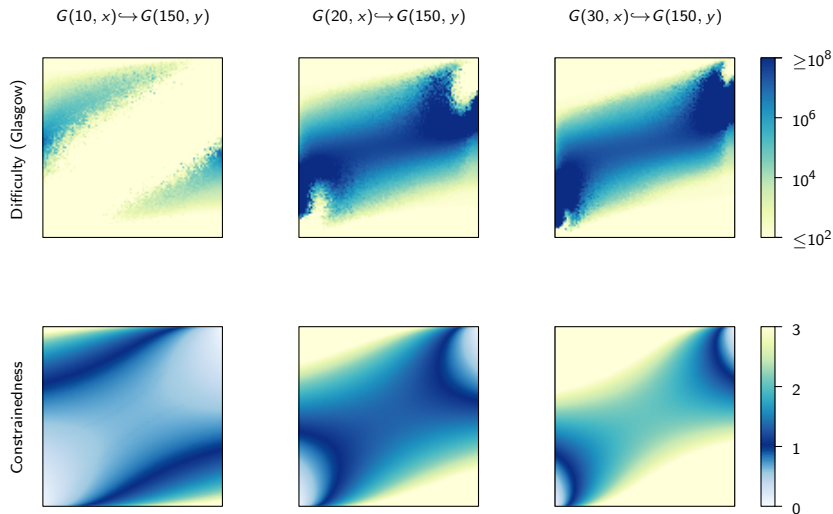


Glasgow

Constrainedness

$$\kappa = 1 - \frac{\log \left(t^p \cdot d_t^{d_p \cdot \binom{p}{2}} \cdot (1 - d_t)^{(1-d_p) \cdot \binom{p}{2}} \right)}{\log t^p}$$

Constrainedness versus Difficulty



See The Paper For...

- More on solver-independence and reductions.
- Estimating the phase transition location.
- Using this to invent new variable and value ordering heuristics.
 - But something unexpected happens this time!

Future Work

- Other randomness models (bounded degree, regular, scale-free).
- Better estimates of the phase transition location for very sparse or very dense patterns.
 - This needs a horrible variance calculation. Please get in touch if you like doing this sort of thing.
- Dynamic heuristics?



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