# Chopping stuff up... To decide things fast! 

Benjamin Merlin Bumpus - University of Florida 2

Based on:

1. arXiv-2302.05575
(w/ Ernst Althaus, James Fairbanks \& Daniel Rosiak)
2. arXiv-2207.06091v2 (w/ Jade Master \& Zoltan Kocsis)
3. blog posts at bmbumpus.com

## This talk

## Compositionality

Structural
Representational
Algorithmic

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## Compositionality

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Sheaves

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## Algorithmic



Dynamic Programming

## MR TR Use category theory to amalgamate these 3 perspectives

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## This talk

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Dynamic Programming


Sheaves

## This talk <br> Use category theory to amalgamate these 3 perspectives



Obtain Algorithmic meta-theorem:
Deciding Sheaves in linear time
on "nicely" decomposable classes of inputs

## Why am I giving this talk?

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Structural Graph theory \&
Complexity theory
(Graph minors, Tree-
Decompositions, algorithms ...)

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Category Theory


## Lots of deep graph theory is about much more than graphs!

## Why am I talking to you?

1. To get you excited about decompositions \& algorithms
2. To get friendly feedback
3. I'm looking for collaborators!

## The Nitty-Gritty PT1: Background

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(Graph minors, TreeDecompositions, algorithms ...)


## The Nitty-Gritty PT1: Background



3 perspectives on graph decompositions:

1. Completions
2. Decompositions
3. Width measures


## The Nitty-Gritty PT1: Background



## Df/ Thm [Dirac]:

The class of chordal graphs is defined recursively as follows:

1. Every complete graph $K_{n}$ is chordal
2. If $H_{1}$ and $H_{2}$ are chordal, then the pushout of any span $H_{1} \hookleftarrow K_{n} \hookrightarrow H_{2}$ is a chordal graph.

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3. Width


## The Nitty-Gritty PT2: compositional data.

 Structured decompositions
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For any category C, a C-valued structured decomposition of shape $G$ is a diagram

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d: \int G \rightarrow C
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where $G$ is a graph

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\begin{aligned}
G: \text { GrSch } \rightarrow \text { FinSet } \\
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Objects: $d: \int G \rightarrow C$ with $G \in \mathscr{G}$
Morphisms: $(F, \eta):\left(d: \int G \rightarrow C\right) \rightarrow\left(d^{\prime}: \int G^{\prime} \rightarrow C\right)$
where $F: \int G \rightarrow \int G^{\prime}$ and $\eta: d \Rightarrow d^{\prime} \circ F$

## Structured decompositions (of graphs)

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d: \int T \rightarrow \mathrm{Gr}
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A graph $G$.

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Recall "completions vs decompositions"

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monos into chordal graphs

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Construct "maximally dense" compositional structures

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Def: a $(\mathscr{G}, \Omega)$-completion of some $c \in \mathrm{C}$ is a mono

$$
c \hookrightarrow(\operatorname{colim} \circ \mathfrak{D} \Omega) d .
$$

Say that $c \in \mathrm{C}$ has $(\mathscr{G}, \Omega)$-width at most K if it admits a $(\mathscr{G}, \Omega)$-completion

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Lemma 5.10. Let $\mathbf{C}$ be an adhesive category, $\mathbf{J}$ be a non-empty category with finitely-many objects and whose arrows are monic, $\mathbf{D}: \mathbf{J} \rightarrow \mathbf{C}$ be a diagram in $\mathbf{C}$ which preserves monomorphisms, $\Lambda$ be a colimit conone over $D$ and $\delta: X \rightarrow$ colim $D$ be an arrow. Then $X$ is the colimit of the diagram $D_{X}: J \rightarrow \mathbf{C}$ obtained by pullback of $\Lambda$ along $\delta$ as in the following diagram.

[Bumpus, Kocsis, Master]

## Defining Width Measures

## Summary:

- Pick out "atomic" objects to be viewed as "complex"
- This, together with completions $\rightarrow$ define structural complexity
- From any completion we can recover a genuine decomposition

The Nitty-Gritty PT2.
Compositional algorithms: deciding sheaves on presheaves

## Algorithms

$\mathrm{C} \longrightarrow \mathcal{F} \longrightarrow$ finset $^{o p} \longrightarrow \operatorname{dec}^{o p} \longrightarrow \mathbf{2}^{o p}$

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Dynamic
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Theorem 3.5. If C is a small adhesively cocomplete category, then the functor Dcmp (defined below) is a subfunctor of subMon.

$$
\begin{aligned}
& \text { Dcmp : } \mathrm{C}^{o p} \rightarrow \text { Set } \\
& \text { Dcmp : } c \mapsto\{d \mid \operatorname{colim} d=c \text { and } d \in \mathfrak{D C \}} \\
& \text { Dcmp : }(f: a \rightarrow b) \mapsto\left(f^{*}:(d \in \operatorname{subMon} b) \mapsto\left(d_{f} \in \operatorname{subMon} a\right)\right) .
\end{aligned}
$$

Furthermore, for any such C , we have that $(\mathrm{C}, \mathrm{Dcmp})$ and $\left(\mathrm{C}_{\text {mono }}, \mathrm{Dcmp}_{\mathrm{C}_{\text {mono }}}\right)$ are sites.

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Structured decomps. yield Grothendieck topologies on adhesive categories w/ sufficiently many colimits...
... we can speak of sheaves with respect to the decomposition topology

## Algorithms



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## Structured decompositions represent compositional data. <br> $$
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$\begin{aligned} & \text { Structured decompositions represent } \\ & \text { compositional data. }\end{aligned} \quad d: \int G \rightarrow \mathrm{C}$ \& yield Grothendieck topologies

Shaves represent compositional problems<br>$\mathrm{C} \xrightarrow{\mathscr{F}} \mathrm{FinSet}^{o p} \xrightarrow{\text { dec } o p} \mathbf{2}^{o p}$



## Recap

Structured decompositions represent compositional data.

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d: \int G \rightarrow \mathrm{C}
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 \& yield Grothendieck topologies

Shaves represent compositional problems
$\mathrm{C} \xrightarrow{\mathscr{F}} \mathrm{FinSet}^{o p} \xrightarrow{\text { dec }}{ }^{o p} \mathbf{2}^{o p}$


We obtain a fast dynamic programming algorithm for problems encoded as sheaves w.r.t. decomposition topology


## What next?

1. Structured decomps $d: \int G \rightarrow C$, but with $G$ another kind of $C$-set?
2. Obstructions to categorial decompositions (tangles, brambles, etc.)
3. Applications of decompositions to other areas of math / CS?
4. How does this relate to your work?
5. Get in touch to get involved!

## Thanks!

Blog: bmbumpus.com
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