

Tractability of Interpretability via Selection of Group-Sparse Models

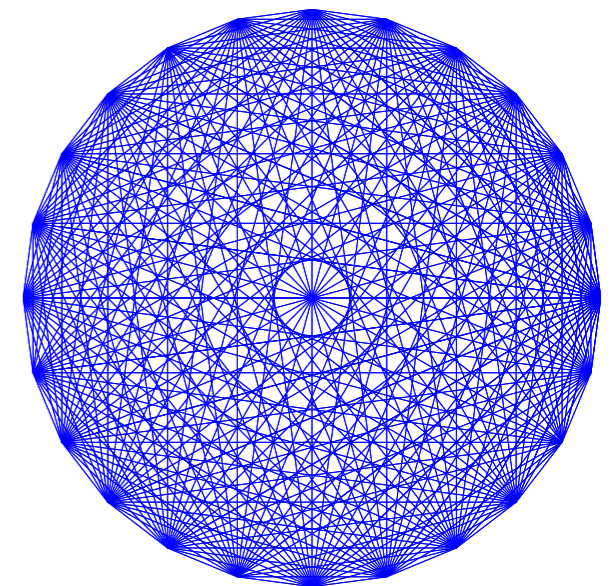
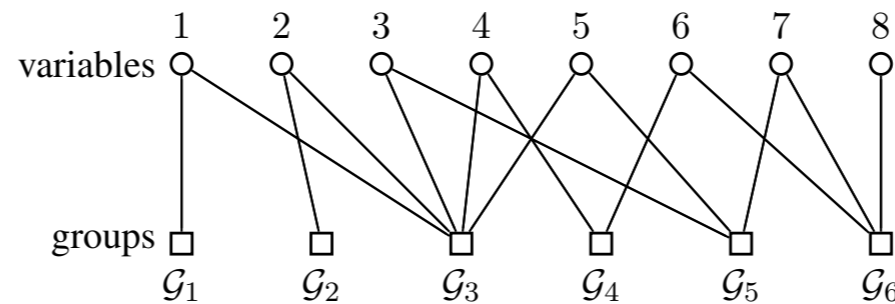
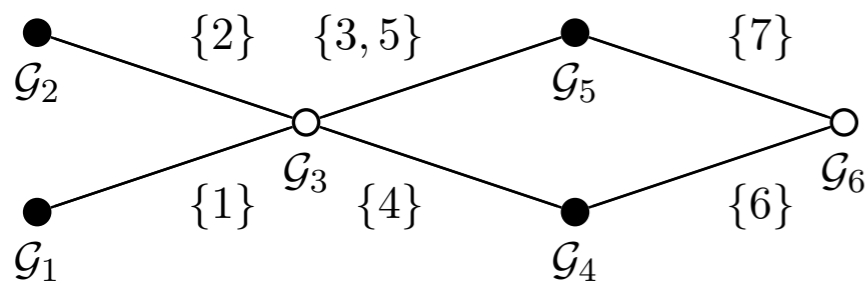
A tale of NP-hard problems claimed to be solved by convex relaxations...

Nirav Bhan, Luca Baldassarre, Volkan Cevher

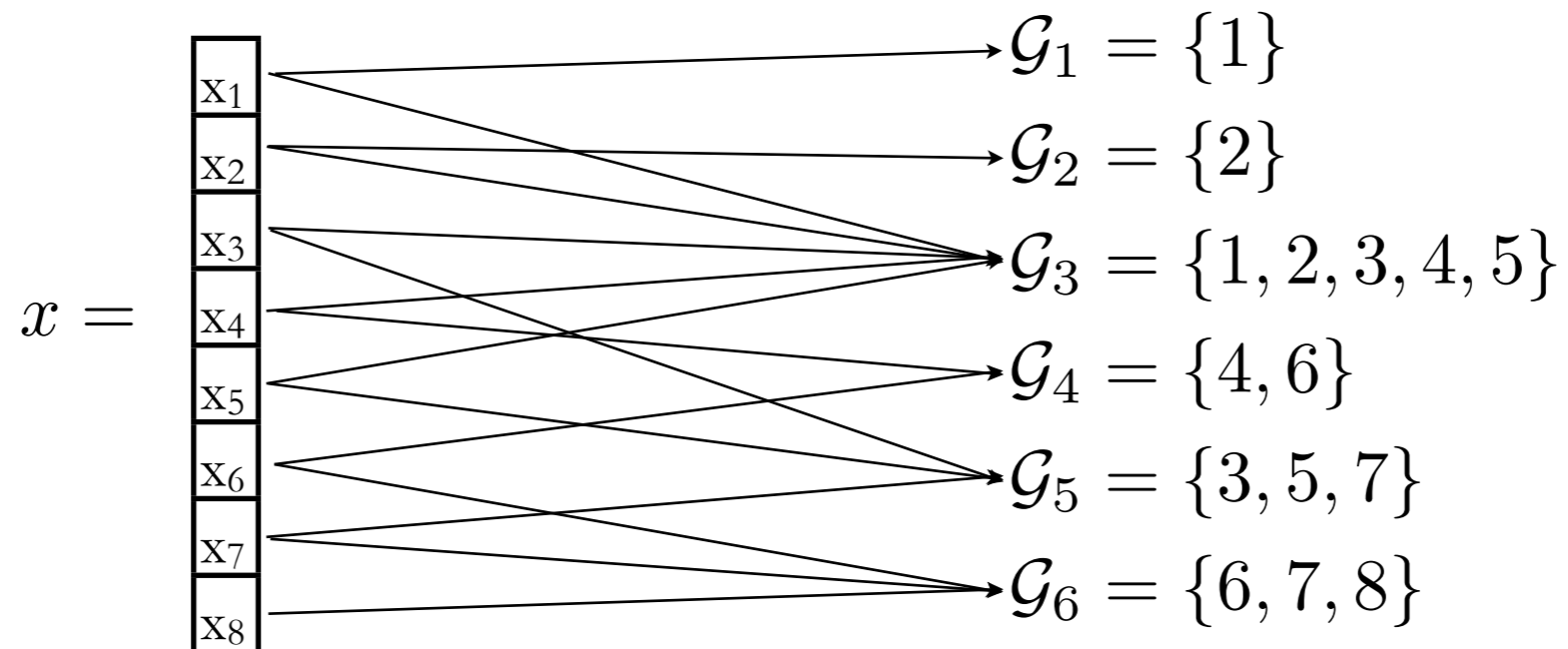
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A generalization of sparsity



Group-structure: a collection of groups of variables

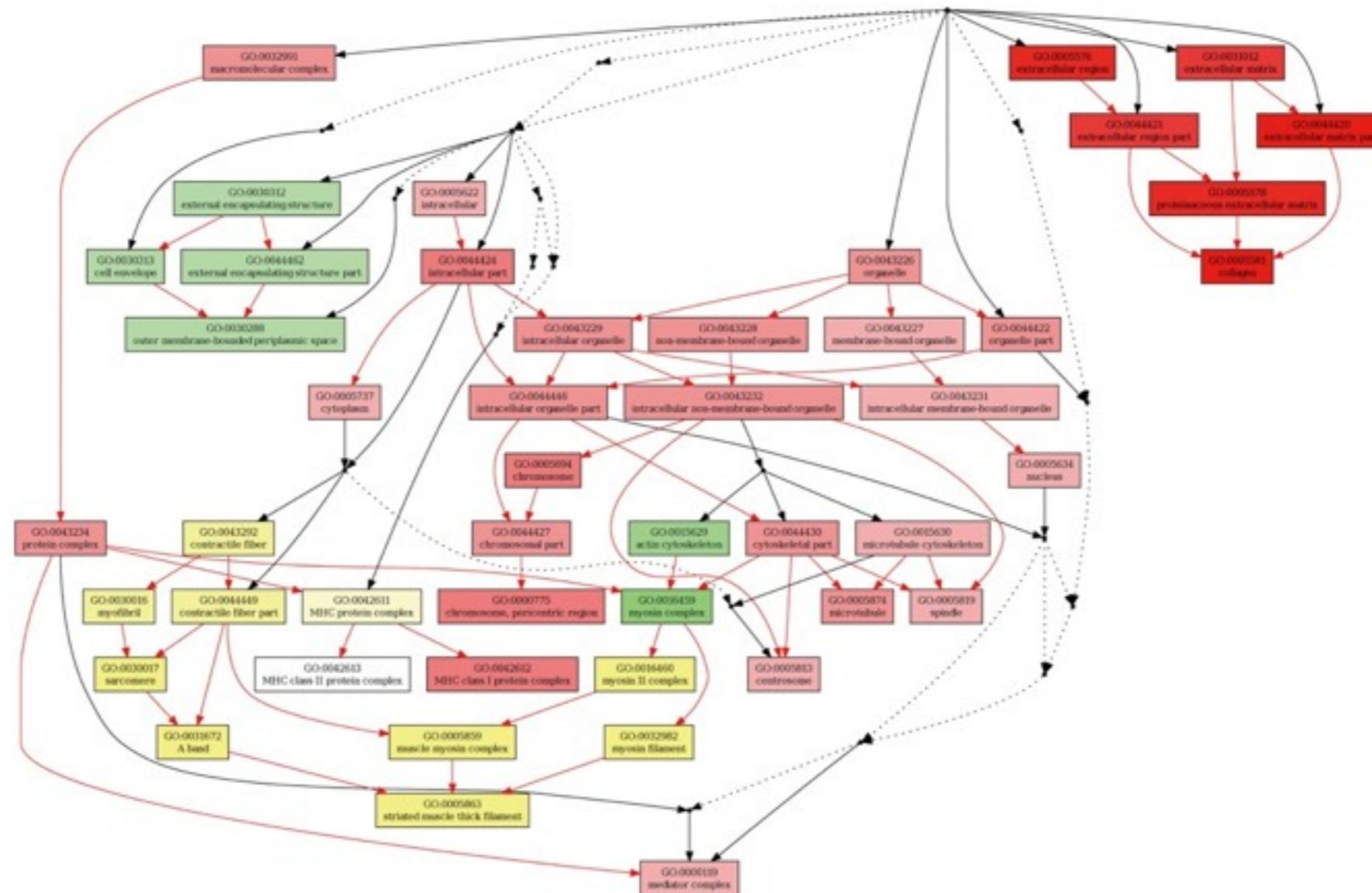
Given a signal $x \in \mathbb{R}^N$, we want to find an approximation \hat{x} whose support is contained in the union of few **active** groups from the group-structure

Group-based interpretations

Group models are ubiquitous.

Examples:

- Genetic Pathways in Microarray data analysis

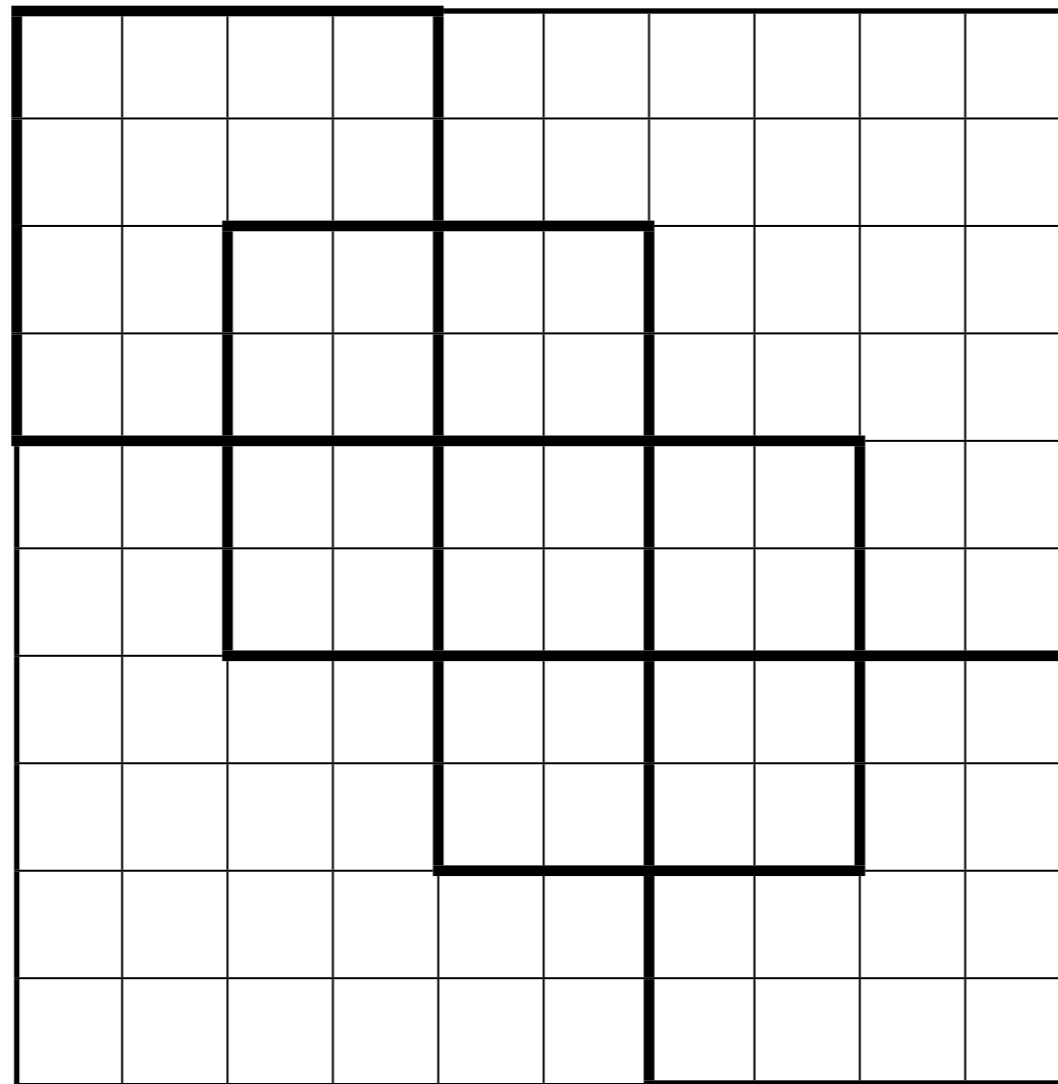


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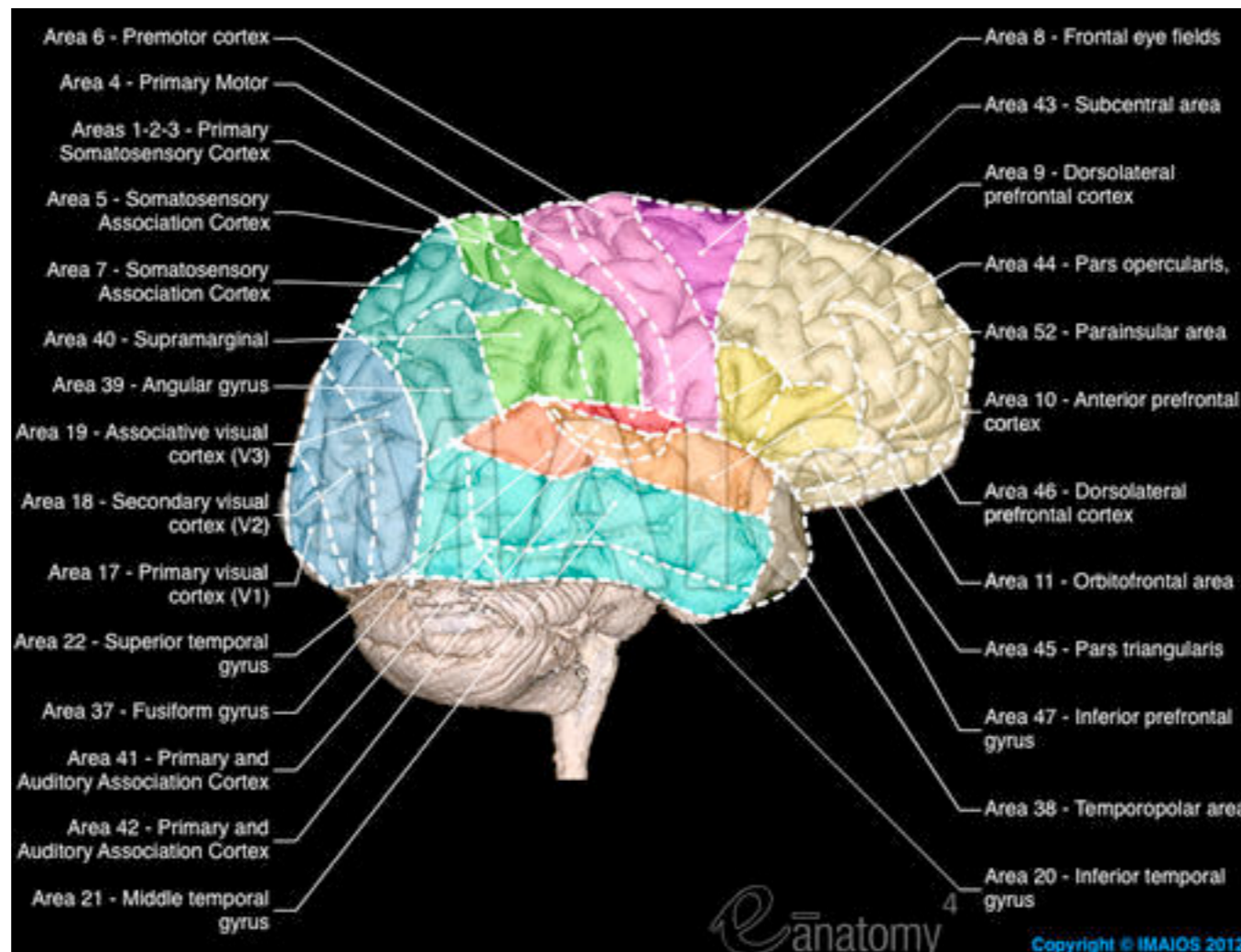
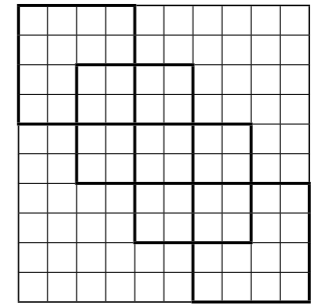
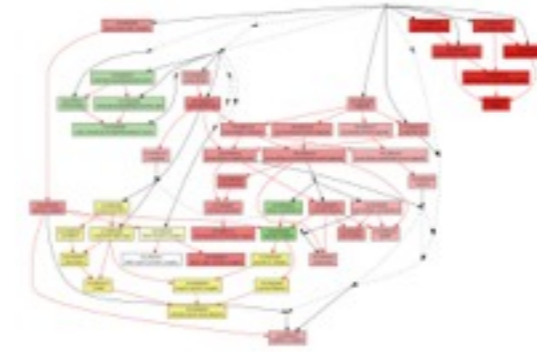


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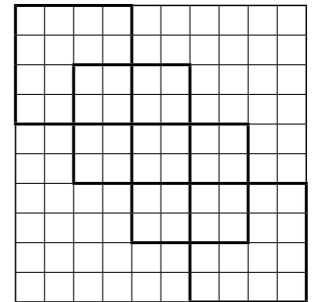


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Group models are motivated by **interpretability**.

- **Which** are the pathways that lead to correct diagnosis of cancer?
- **Which** patches contain foreground objects?
- **Which** brain regions decode external stimuli?

Outline

1. Definitions and graph-based representation of group structures.
2. **NP-hardness** of the group-sparse decompositions.
3. Special group-structures that allow tractable decompositions.
4. Relaxations:
 - I. *Discrete relaxations* & **totally unimodular** constraints.
 - II. Convex relaxations & their deficiencies.
5. Generalizations: group model + sparsity
6. Conclusions

Definitions I $x \in \mathbb{R}^N$

Ground set: $\mathcal{N} = \{1, \dots, N\}$

Group structure: a collection of subsets of the ground set

$$\mathfrak{G} = \{\mathcal{G}_1, \dots, \mathcal{G}_M\} \quad \mathcal{G}_j \subseteq \mathcal{N}, \quad \forall j = 1, \dots, M$$

Binary matrix encoding the group structure

$$\mathbf{A}_{ij}^{\mathfrak{G}} = \begin{cases} 1 & \text{if } i \in \mathcal{G}_j \\ 0 & \text{otherwise} \end{cases}$$

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Example:

$$\mathcal{G}_1 = \{1\}$$

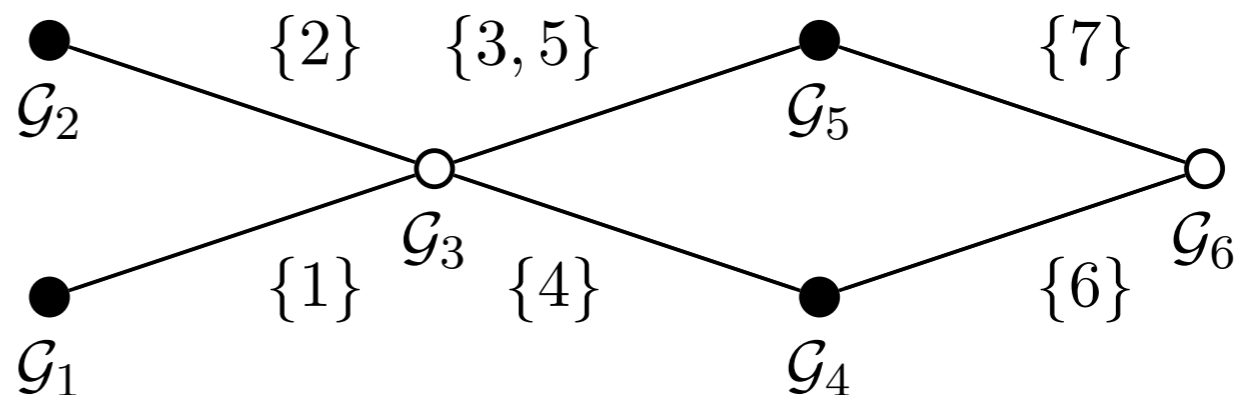
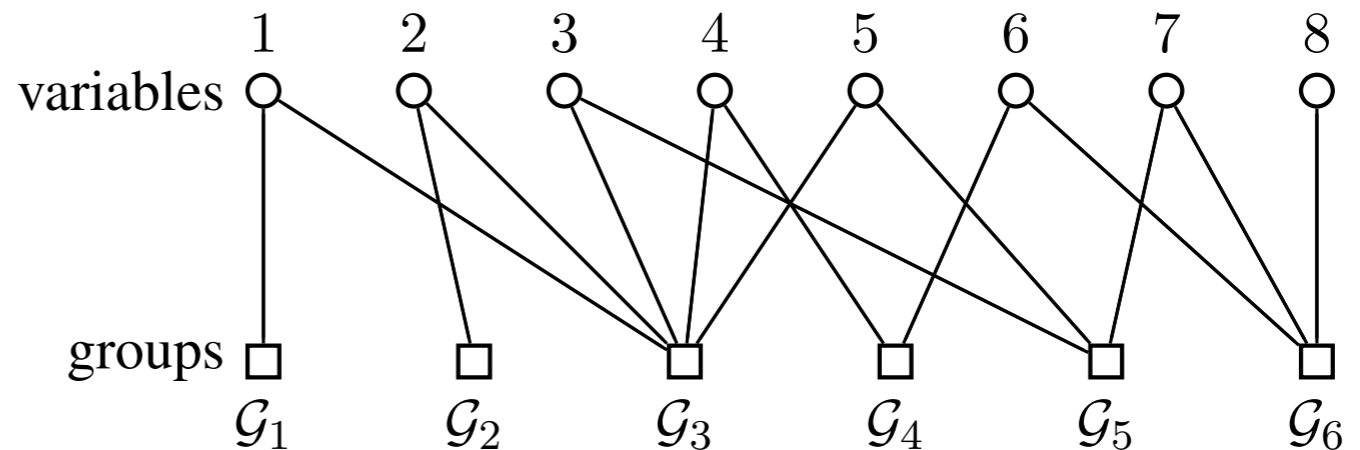
$$\mathcal{G}_2 = \{2\}$$

$$\mathcal{G}_3 = \{1, 2, 3, 4, 5\}$$

$$\mathcal{G}_4 = \{4, 6\}$$

$$\mathcal{G}_5 = \{3, 5, 7\}$$

$$\mathcal{G}_6 = \{6, 7, 8\}$$



Definitions II

Group cover: $S(x) \subseteq \mathfrak{G}$ s.t. $\text{supp}(x) \subseteq \bigcup_{\mathcal{G} \in S} \mathcal{G}$

G-group cover: $S^G(x) \subseteq \mathfrak{G}$ s.t. $|S| \leq G$, $\text{supp}(x) \subseteq \bigcup_{\mathcal{G} \in S} \mathcal{G}$ **Might not exist!**

Minimal group-cover: $\mathcal{M}(x)$ smallest group cover **Might not be unique!**

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$$\iota(x)_i = \begin{cases} 1 & \text{if } x_i \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

ω is a M-dimensional binary variable

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$$\hat{\omega} \in \underset{\omega}{\text{argmin}} \left\{ \sum \omega_j : \mathbf{A}^{\mathfrak{G}} \omega \geq \iota(x) \right\}$$

Group ℓ_0 "norm" and approximations

$$\|x\|_{\mathfrak{G},0} := \min_{\omega \in \mathbb{B}^M} \left\{ \sum_{j=1}^M \omega_j : A^{\mathfrak{G}} \omega \geq \iota(x) \right\}$$

x is **G-group sparse** if $\|x\|_{\mathfrak{G},0} \leq G$

G-group sparse approximation of a signal $\hat{x} \in \operatorname{argmin}_{z \in \mathbb{R}^N} \{ \|x - z\|_2^2 : \|z\|_{\mathfrak{G},0} \leq G \}$

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NP-HARD!

Tractability of Interpretability I

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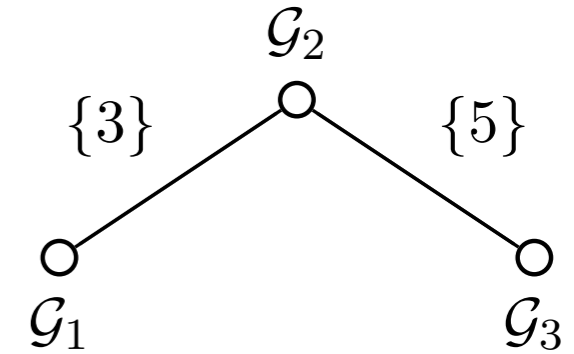
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- Only pairwise overlaps
- No loops

$$\mathcal{G}_1 = \{1, 2, 3\}$$

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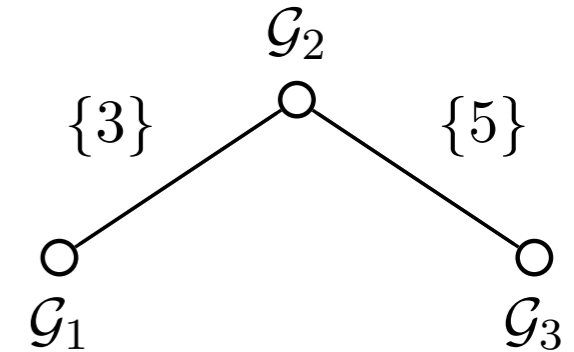
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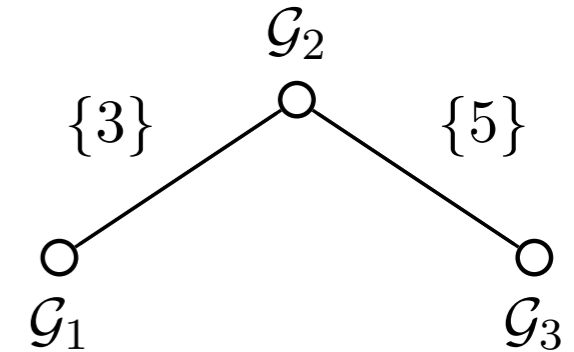
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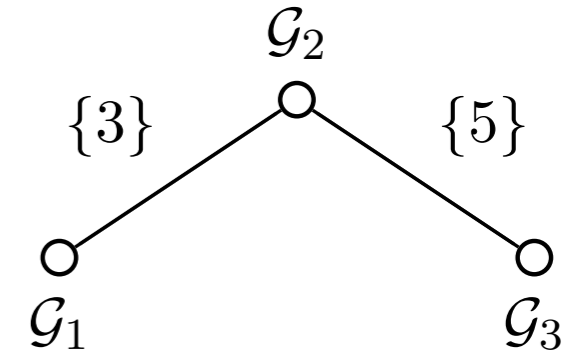
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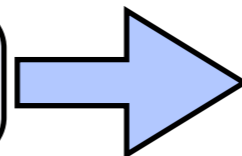


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$A^{\mathcal{G}}$ is Totally Unimodular for LPOG



Polynomial-time solvers

Tractability of Interpretability II

Pareto frontier of **WMC**:

set of optimal values as parameter G is varied

$$\mathcal{P} = \left\{ G, \sum_i x_i^2 y_i \right\}_{G=1}^M$$

Theorem: The discrete relaxation finds only the solutions in the intersection between \mathcal{P} and the **boundary of the convex hull** of \mathcal{P}

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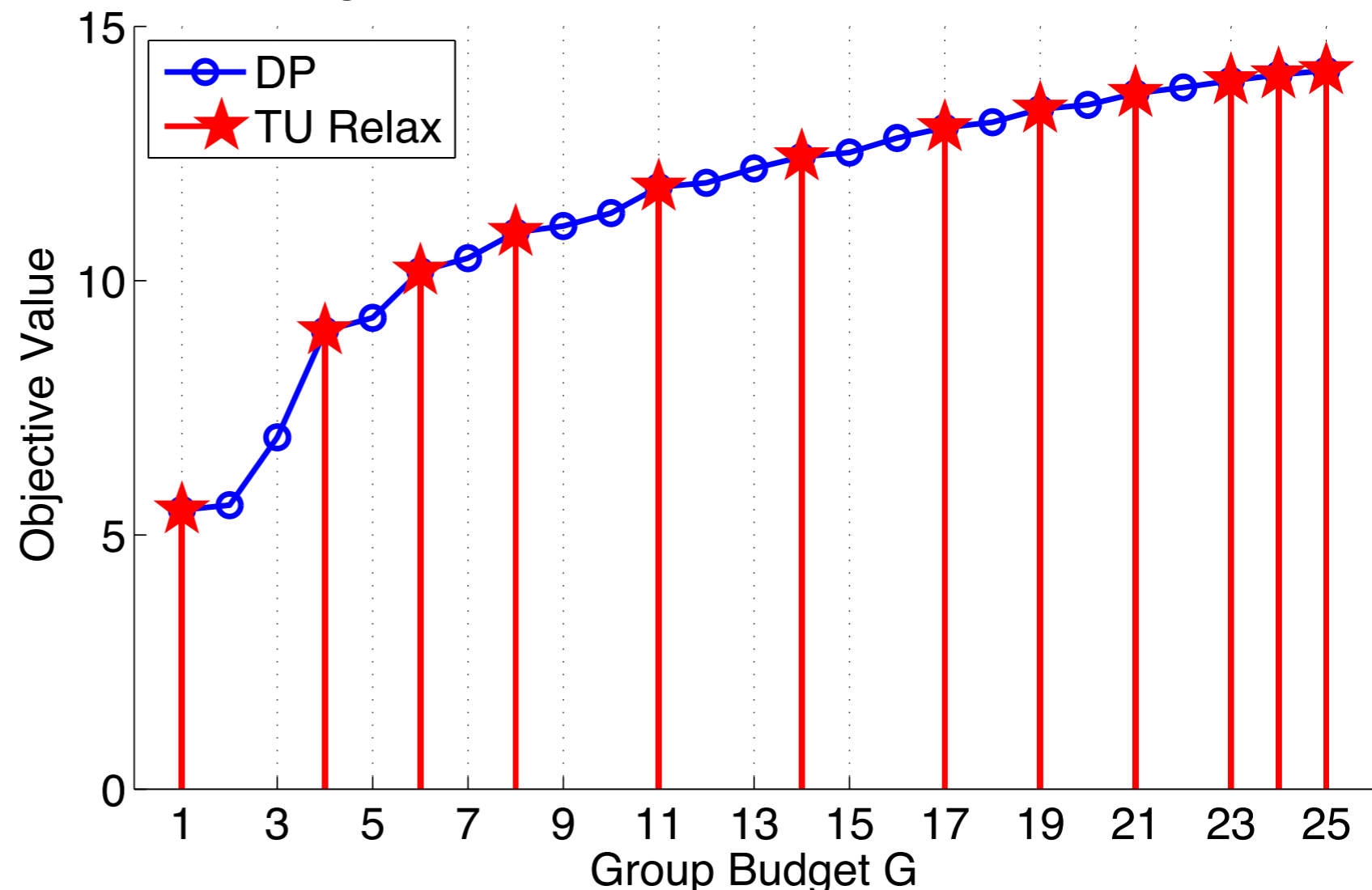
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Example

- **ID block signals** have a sparse representation via the Haar wavelet coefficients.
- The coefficients are arranged **hierarchically**.
- This hierarchy is a **special group structure**, that we can handle **exactly**.

If TU-relax obtains a G-group solution, it solves the original problem

Signal Approximation on Wavelet Tree



Convex relaxations

Latent Group Lasso Norm:

promotes sparsity at the group level [Obozinski et al., 2011]

$$\|x\|_{\mathfrak{G}, \{1,2\}} := \inf_{\substack{\mathbf{v}^1, \dots, \mathbf{v}^M \in \mathbb{R}^N \\ \forall j, \text{supp}(\mathbf{v}^j) = \mathcal{G}_j}} \left\{ \sum_{j=1}^M d_j \|\mathbf{v}^j\|_2 : \sum_{j=1}^M \mathbf{v}^j = x \right\} \quad (*)$$

The group cover is defined by the non-zero terms in the **optimal decomposition**.

$\check{\mathcal{S}}(x) := \{ \mathcal{G}_j \in \mathfrak{G} : \exists \mathbf{v} \in \mathcal{V}(x) \text{ s.t. } \mathbf{v}_j \neq 0 \}$ $\mathcal{V}(x)$ is the set of solutions of (*)

$\check{\mathcal{S}}(x)$ **might not** contain the minimal group cover for x

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Group-sparse approximation: $\hat{x} = \underset{z \in \mathbb{R}^N}{\text{argmin}} \{ \|x - z\|_2^2 : \|z\|_{\mathfrak{G},\{1,2\}} \leq \lambda \}$

Group-support recovery guarantees are given with respect to $\check{\mathcal{S}}(x)$ and not to the underlying discrete problem (WMC).

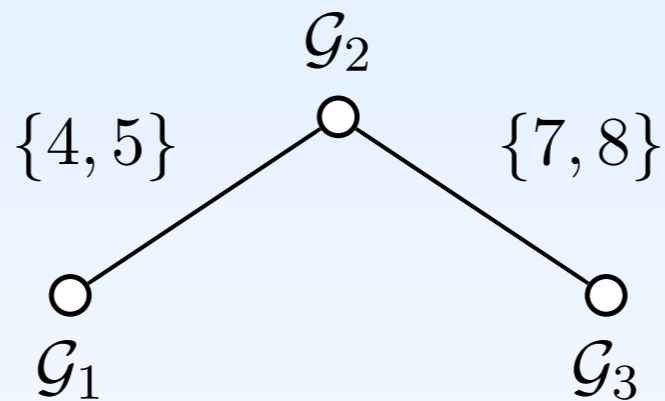
Example

$$\mathcal{N} = \{1, \dots, 11\}$$

$$\mathcal{G}_1 = \{1, \dots, 5\}$$

$$\mathcal{G}_2 = \{4, \dots, 8\}$$

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Loopless pairwise overlapping groups

$$x = [0 \ 0 \ \overbrace{1 \ 1 \ 1}^{\mathcal{G}_1} \ 0 \ \overbrace{1 \ 1 \ 1}^{\mathcal{G}_3} \ 0 \ 0]^\top$$

$\underbrace{\hspace{10em}}_{\mathcal{G}_2}$

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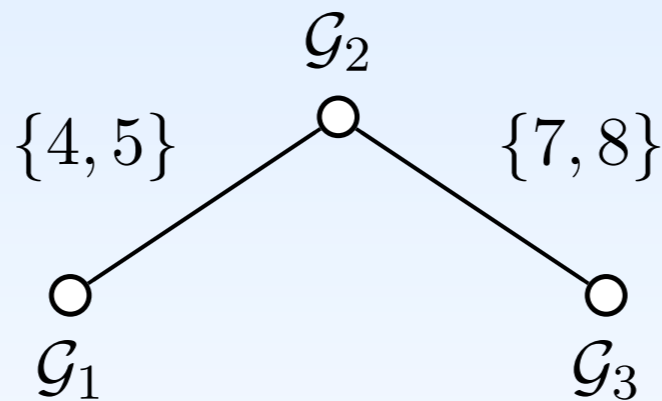
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Discrete relaxation solution: $S^\lambda(\hat{x}) = \{\mathcal{G}_1, \mathcal{G}_3\}$ for $0 < \lambda \leq 2$

Convex relaxation solution: $\check{S}(x) = \emptyset$ with $d_j = \text{constant}$

$\check{S}(x) = \{\mathcal{G}_1, \mathcal{G}_3\}$ with $d_1 = d_3 = 1$ and $d_2 > \frac{2}{\sqrt{3}}$

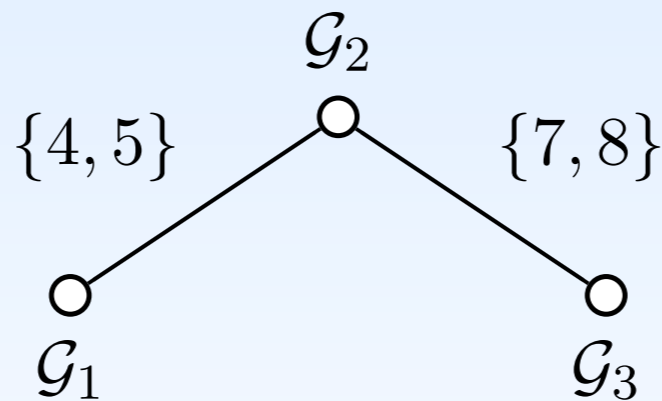
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Need to know **beforehand** which groups are irrelevant!

Generalization

- Introduce **sparsity budget** K .
- Allow **individual element** within a group to be selected.
- Discrete problem still **NP-HARD**.

Generalized Weighted Maximum Coverage

$$\begin{aligned} & \text{maximize}_{\omega \in \mathbb{B}^M, y \in \mathbb{B}^N} && \sum_{i=1}^N y_i x_i^2 \\ & \text{subject to} && A^{\mathcal{G}} \omega \geq y \\ & && \sum_{j=1}^M \omega_j \leq G \\ & && \sum_{i=1}^N y_i \leq K \end{aligned}$$

- **Hierarchical constraints** can be encoded in the Generalized WMC.
- We developed a **polynomial-time** Dynamic Program to solve the GWMC for hierarchical constraints.
- **Hierarchical constraints are TU**: the discrete relaxation (in both group and sparsity budget) allows polynomial solvers.

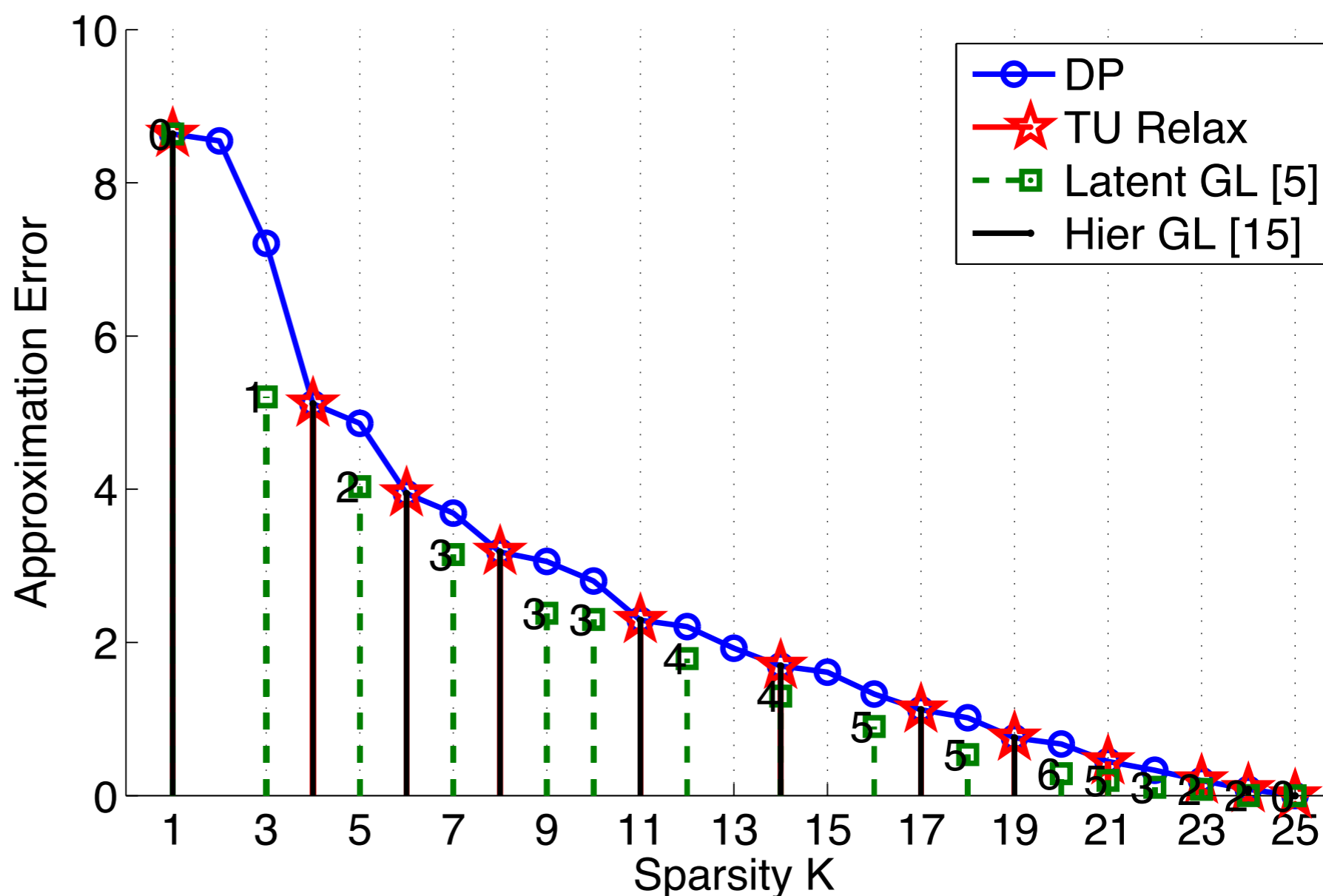
$$\max_{\omega \in \mathbb{B}^M, y \in \mathbb{B}^N} \left\{ \sum_{i=1}^N y_i x_i^2 - \lambda_G \sum_{j=1}^M \omega_j - \lambda_K \sum_{i=1}^N y_i : A^{\mathcal{G}} \omega \geq y \right\}$$

Example: Approximation using wavelet tree

- Block signal of size $N = 64$
- Sparse representation in Haar wavelet coefficients that satisfy hierarchical constraints

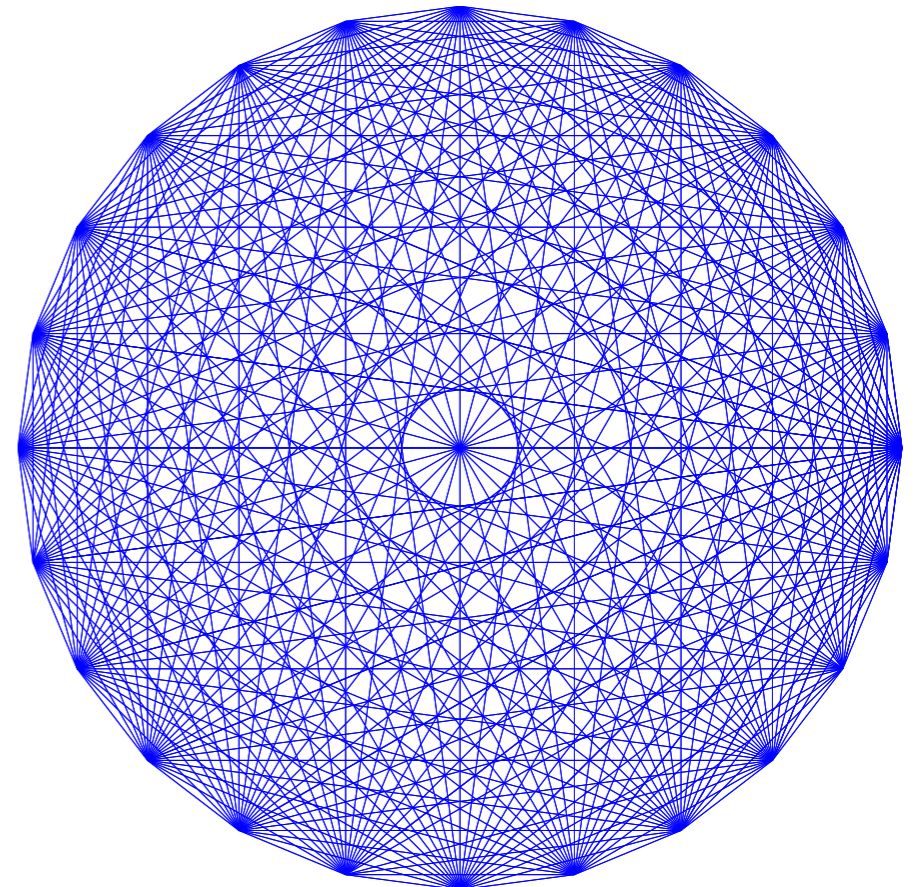
Methods:

1. Dynamic Programming (DP)
2. Discrete relaxation with TU constraints (TU)
3. Latent Group Lasso with groups given as all father-child pairs: **not all constraints are satisfied** [Rao et al., 2012]
4. Hierarchical group lasso [Jenatton et al., 2009]



Conclusions

- Convex relaxations **cannot solve** the original discrete NP-hard problem and give only a subset of the solutions.
- We identified group structures that lead to **tractable group-based interpretations.**
- Totally Unimodular group structures allow **efficient relaxations.**
- However, some relevant application do not have tractable group structures:
 - ➔ e.g. Breast cancer dataset:
group-graph of the top 25 pathways from
the Molecular Signature Database
[Subramanian et al., 2005]



References

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