

# Complexity of Discrete Energy Minimization Problems



Mengtian (Martin) Li  
Carnegie Mellon  
University



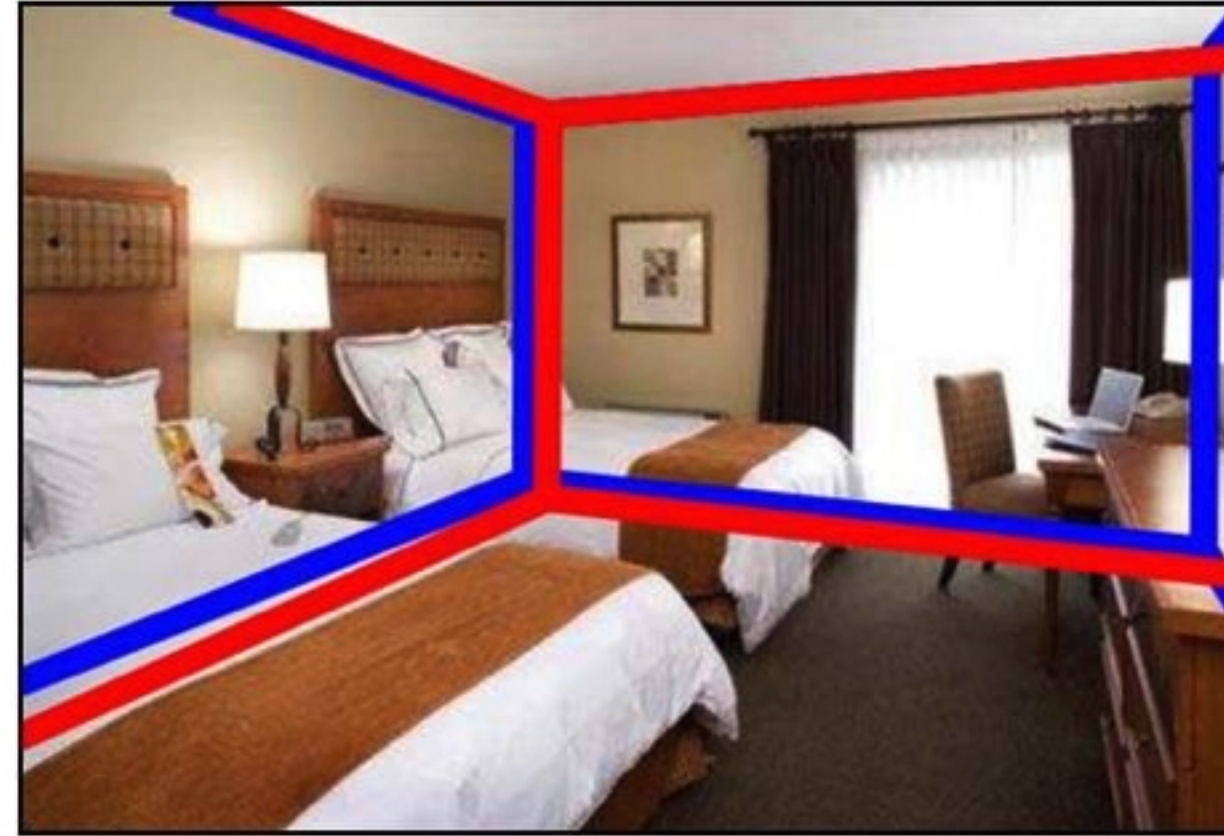
Alexander Shekhovtsov  
Graz University of  
Technology



Daniel Huber  
Carnegie Mellon  
University

# Energy Minimization

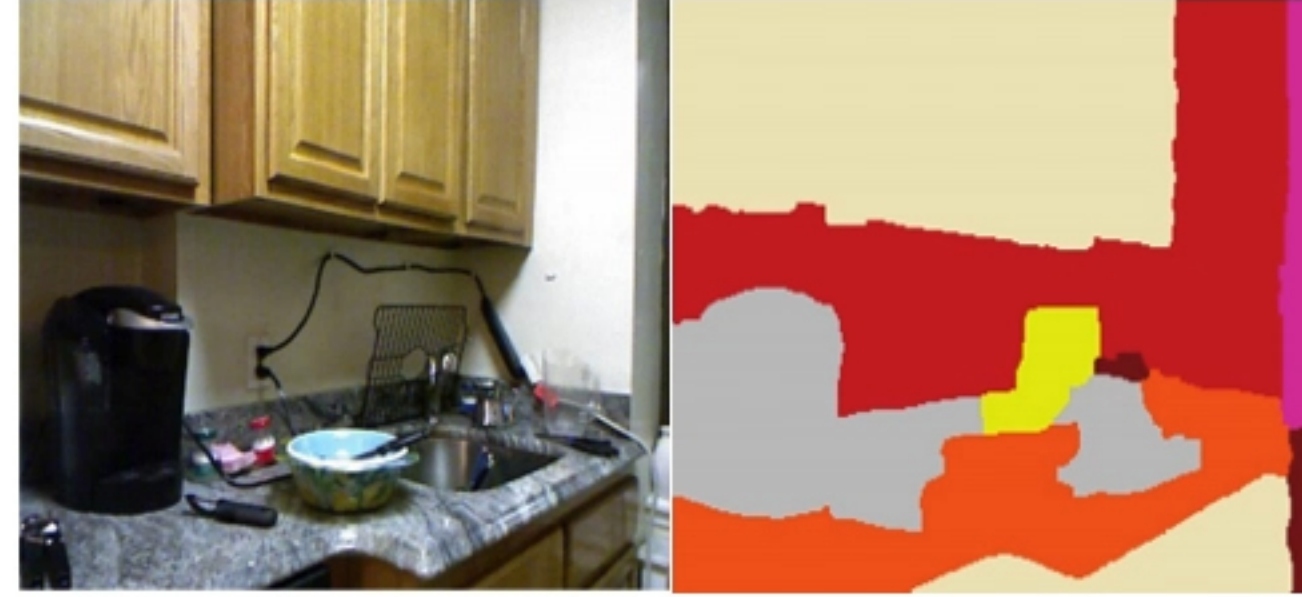
- Used in many CV applications



3D Room Layout  
[Schwing and Urtasun, 2012]

# Energy Minimization

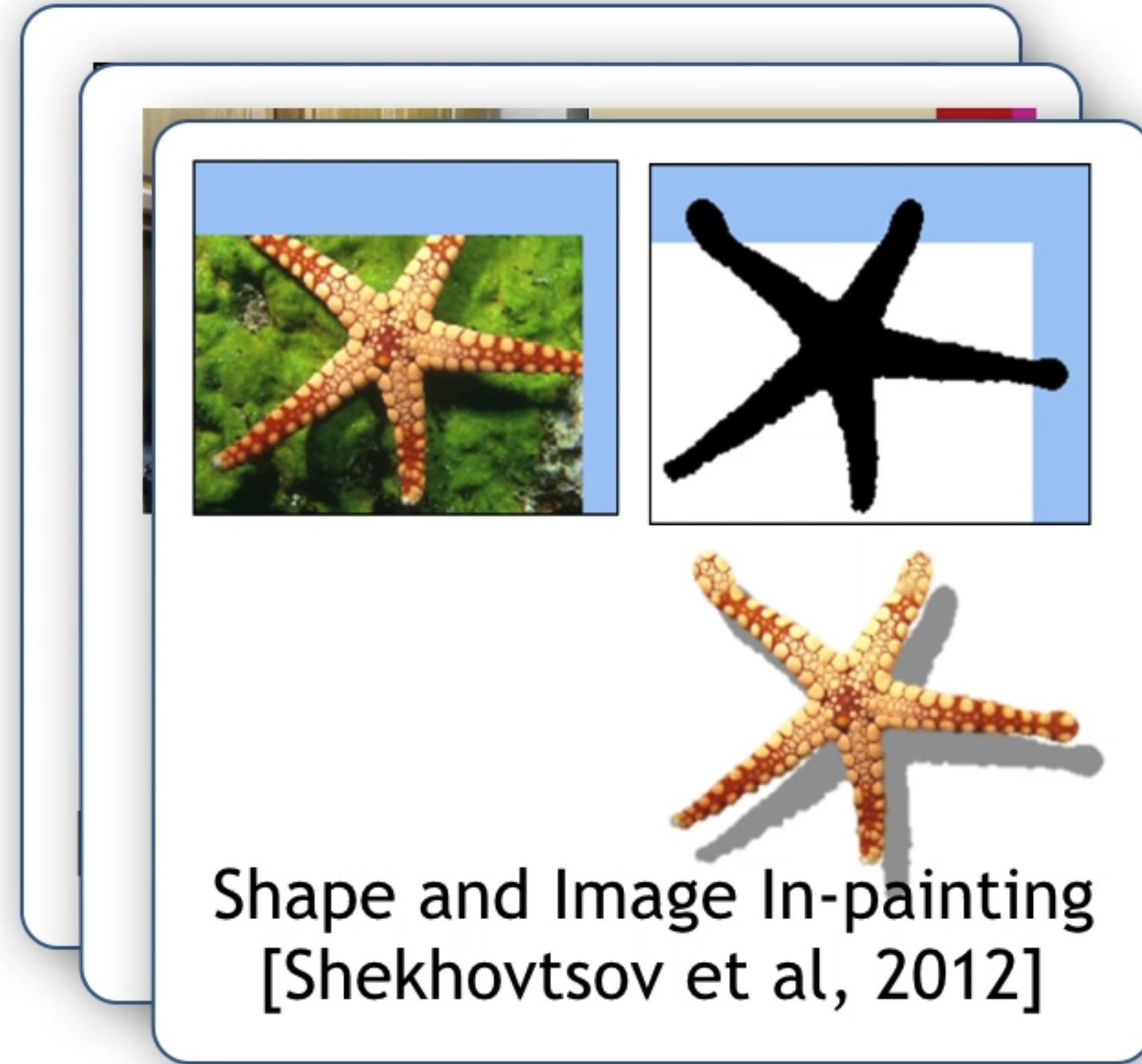
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Semantic Segmentation  
[Ren et al, 2012]

# Energy Minimization

- Used in many CV applications

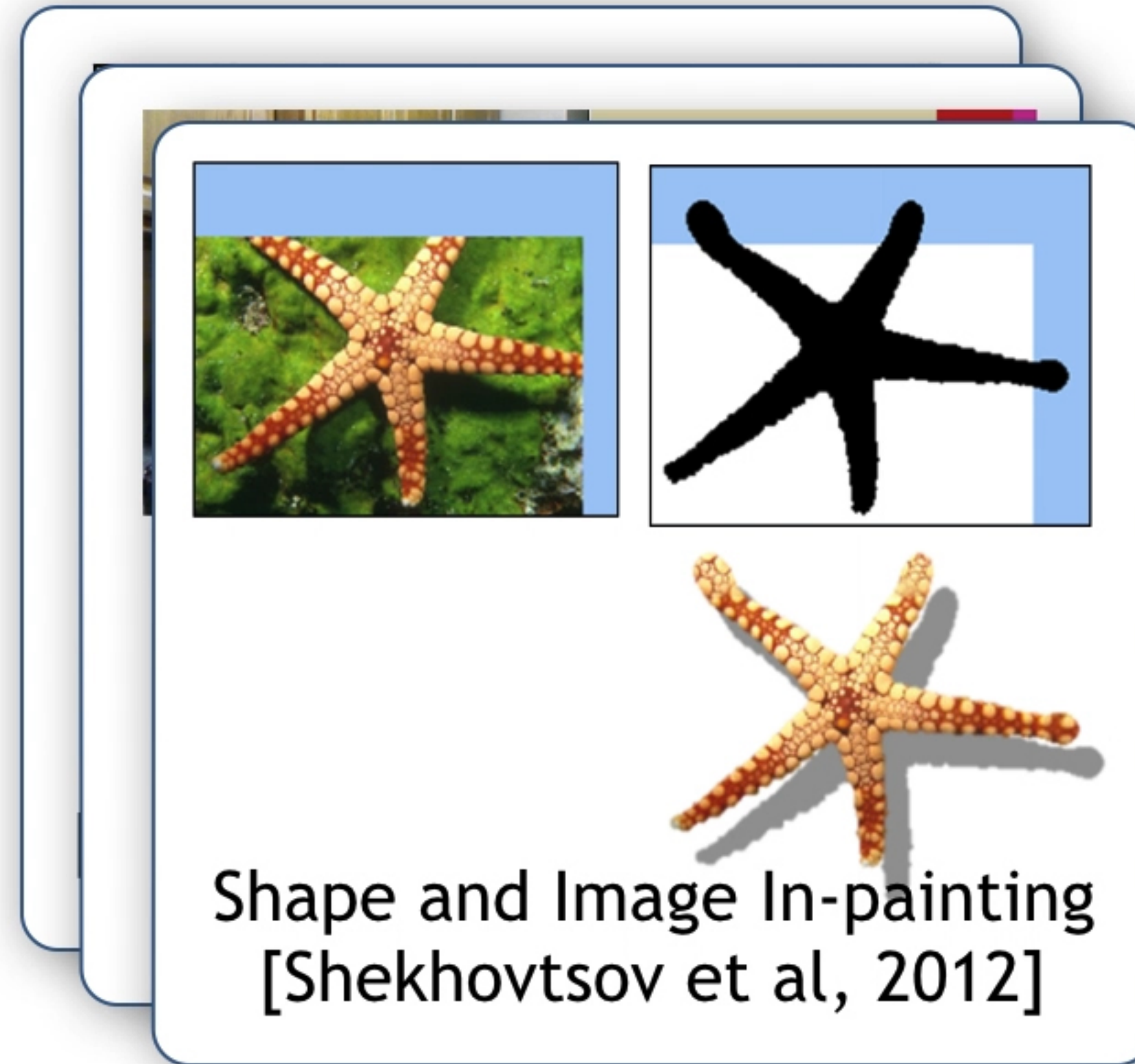


# Energy Minimization

- Used in many CV applications
- Pairwise and higher order

$$\min_{x \in \mathcal{L}^{\mathcal{V}}} \sum_{u \in \mathcal{V}} f_u(x_u) + \sum_{(u,v) \in \mathcal{E}} f_{uv}(x_u, x_v)$$

- But is it efficient?

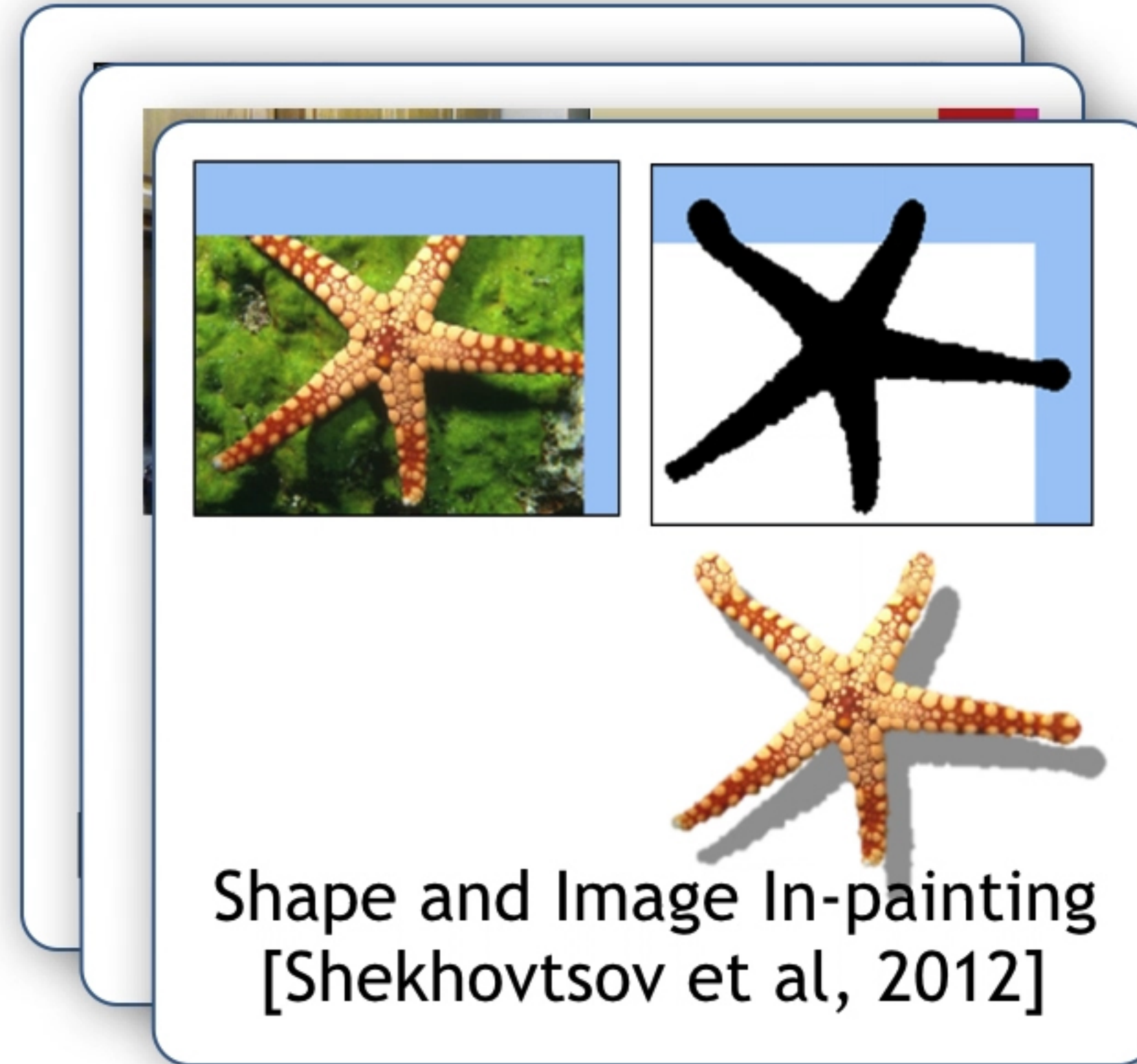


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- But is it efficient?
- In general, NP-hard
- There are tractable classes



NP-hard

Bounded Treewidth

Binary Outerplanar

Convex Interaction

Submodular

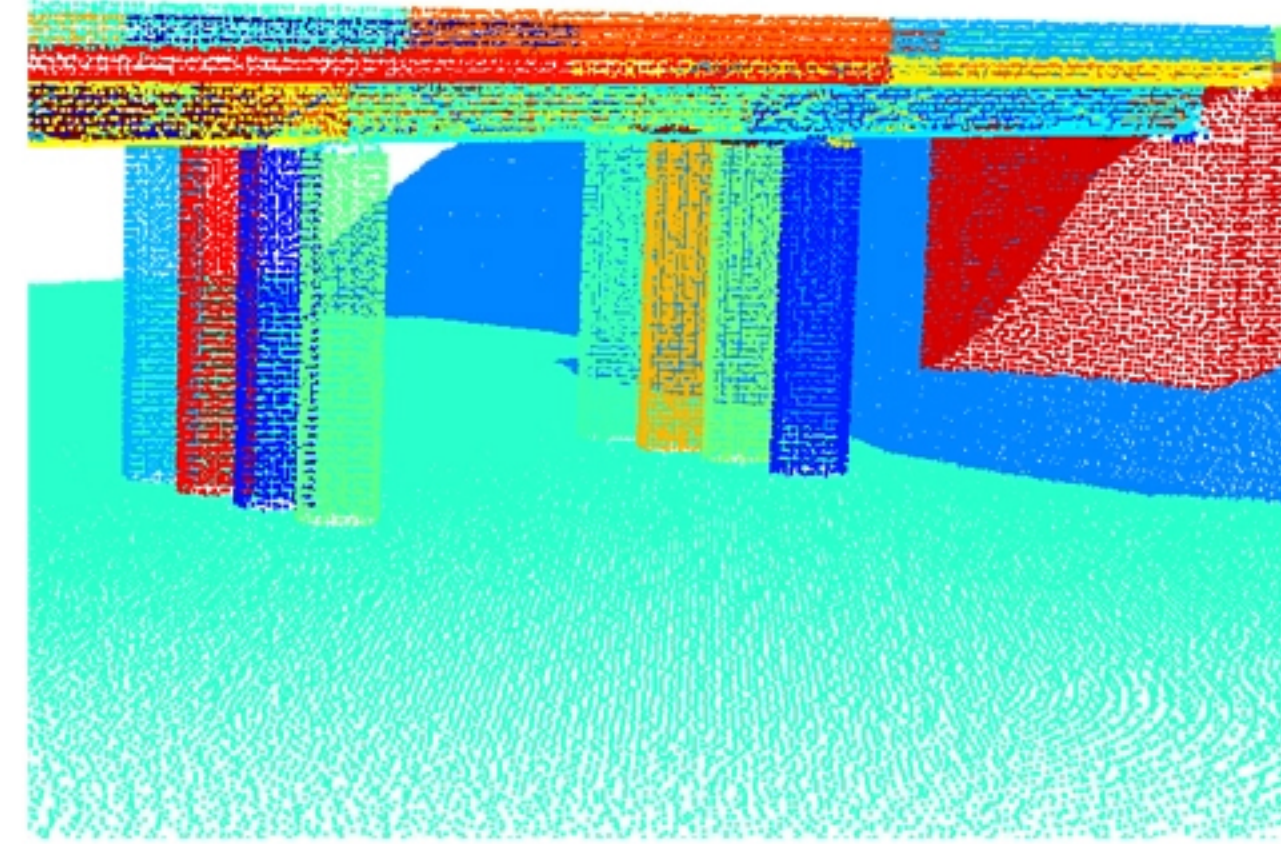
P Optimization

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- Growing corpus of general “approximate” inference methods
- Learning Project with QPBO



3D scene labeling

NP-hard

Bounded Treewidth

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# Energy Minimization

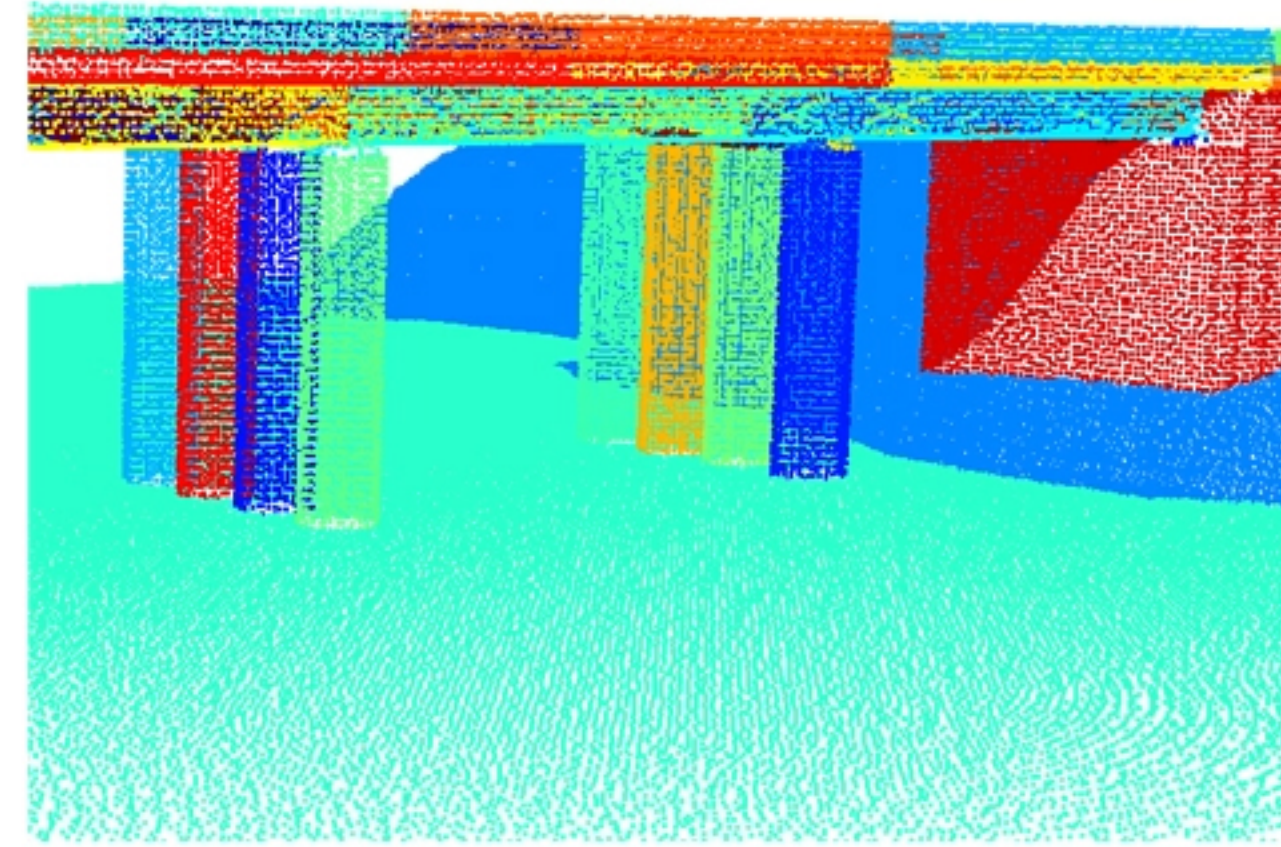
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$$\min_{x \in \mathcal{L}^{\mathcal{V}}} \sum_{u \in \mathcal{V}} f_u(x_u) + \sum_{(u,v) \in \mathcal{E}} f_{uv}(x_u, x_v)$$

Quadratic Pseudo-Boolean Optimization (QPBO):

$$\min_{x \in \{0,1\}^{\mathcal{V}}} \sum_{u \in \mathcal{V}} a_u x_u + \sum_{(u,v) \in \mathcal{E}} a_{uv} x_u x_v$$

- Learning Project with QPBO
  - Difficult instances during learning



3D scene labeling

reference methods

NP-hard

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$$\min_{x \in \mathcal{L}^{\mathcal{V}}} \sum_{u \in \mathcal{V}} f_u(x_u) + \sum_{(u,v) \in \mathcal{E}} f_{uv}(x_u, x_v)$$

- But is it efficient?
- In general, NP-hard
- There are tractable classes
- Growing corpus of general “approximate” inference methods
- Learning Project with QPBO
  - Difficult instances during learning
  - Could benefit from approximation guarantees
- **We find QPBO and general energy minimization to be inapproximable**

Bounded Treewidth

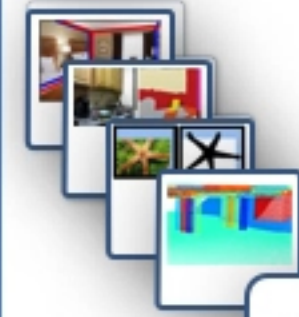
Binary Outerplanar

Convex Interaction

Submodular

P Optimization

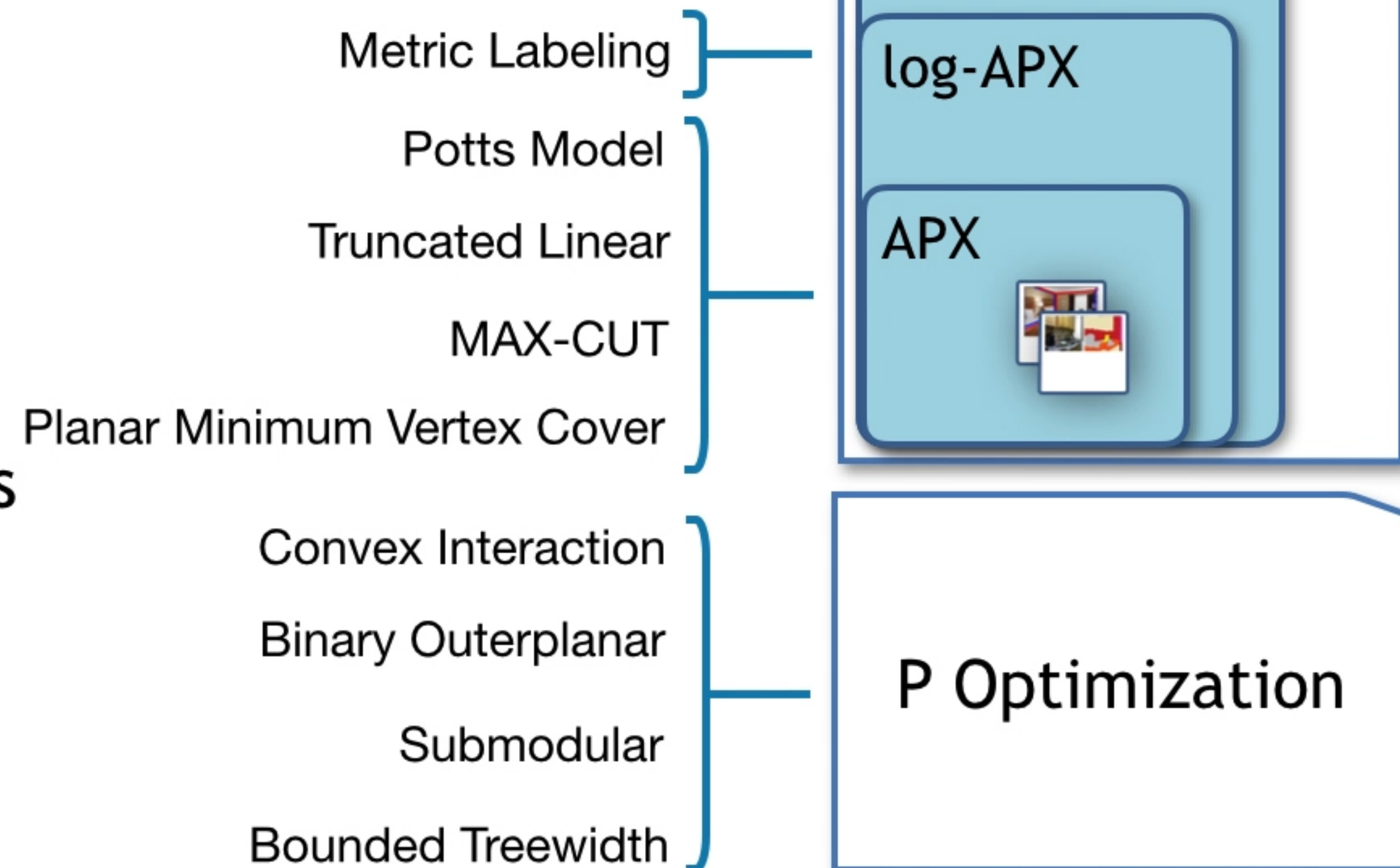
NP-hard



QPBO

# NP-hard Problems Vary Greatly in Approximability

- Approximation Ratio:  $f(x)/f(x^*)$ ,  $f(x^*) > 0$
- Classes of approximation:
  - PTAS - ratio  $1+\epsilon$  in polynomial time (knapsak, Eucledian TSP)
  - APX - constant approximation ratio
  - log-APX - logarithmic in bit-length
  - poly-APX - polynomial
- APX / log-APX indicate more practical clases
  - Algorithms can build on achieving guarantees
  - Much better ratios per instance
- APX-hard is not too bad! How hard is QPBO?



# Which Energy Problems are not in APX?

- class **exp-APX**:
  - Approximation ratio exponential in bit length
  - Suffices to find **any** feasible solution

Theorem:  
QPBO (energy with 2 labels) is **complete** in exp-APX

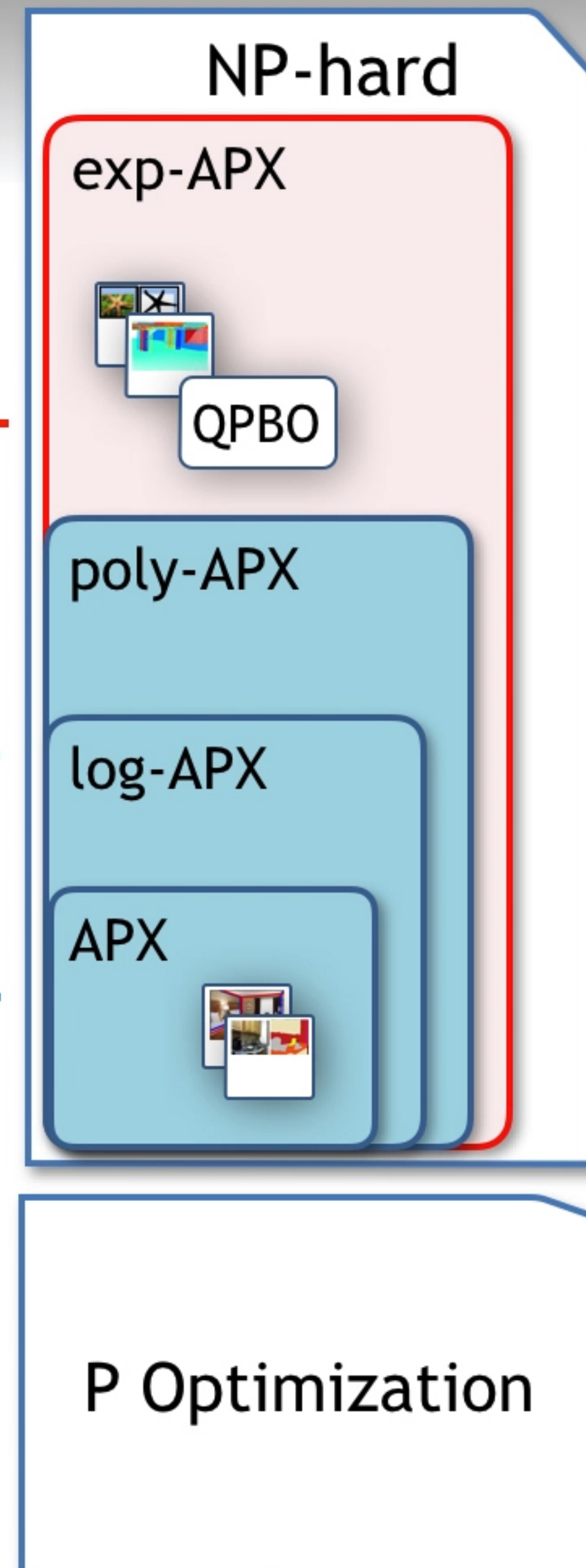
- Any problem from exp-APX can be reduced to QPBO
- In polynomial time
- While preserving approximation ratio

Theorem:  
Planar energy with 3+ labels is **complete** in exp-APX

QPBO  
General Energy Minimization  
Planar with 3+ labels

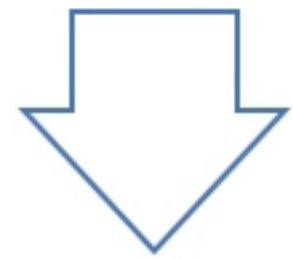
Metric Labeling  
Potts Model  
Truncated Linear  
MAX-CUT  
(Planar) Vertex Cover

Convex Interaction  
Binary Outerplanar  
Submodular  
Bounded Treewidth



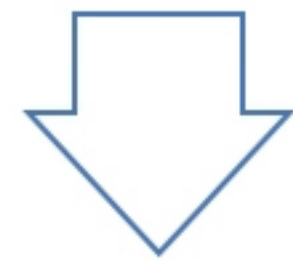
# Proof Scheme

Turing Machine



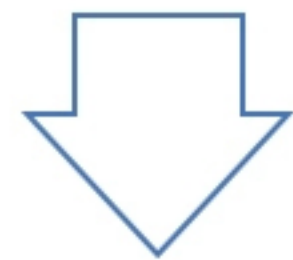
AP-reduction  
[Opronen & Mannila 09]

Weighted 3-SAT



AP-reduction (using Ishikawa's reduction)

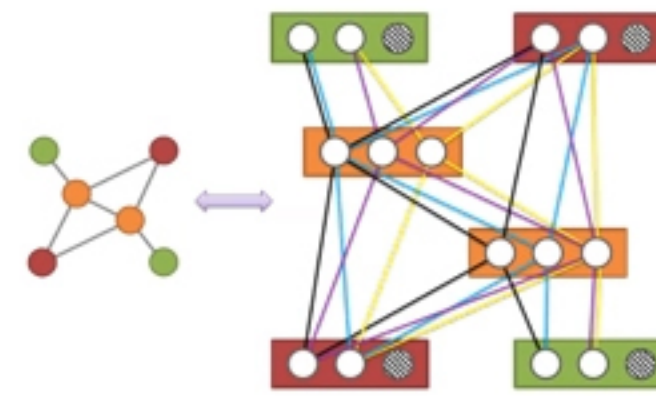
QPBO



AP-reduction

Planar Energy with 3 labels

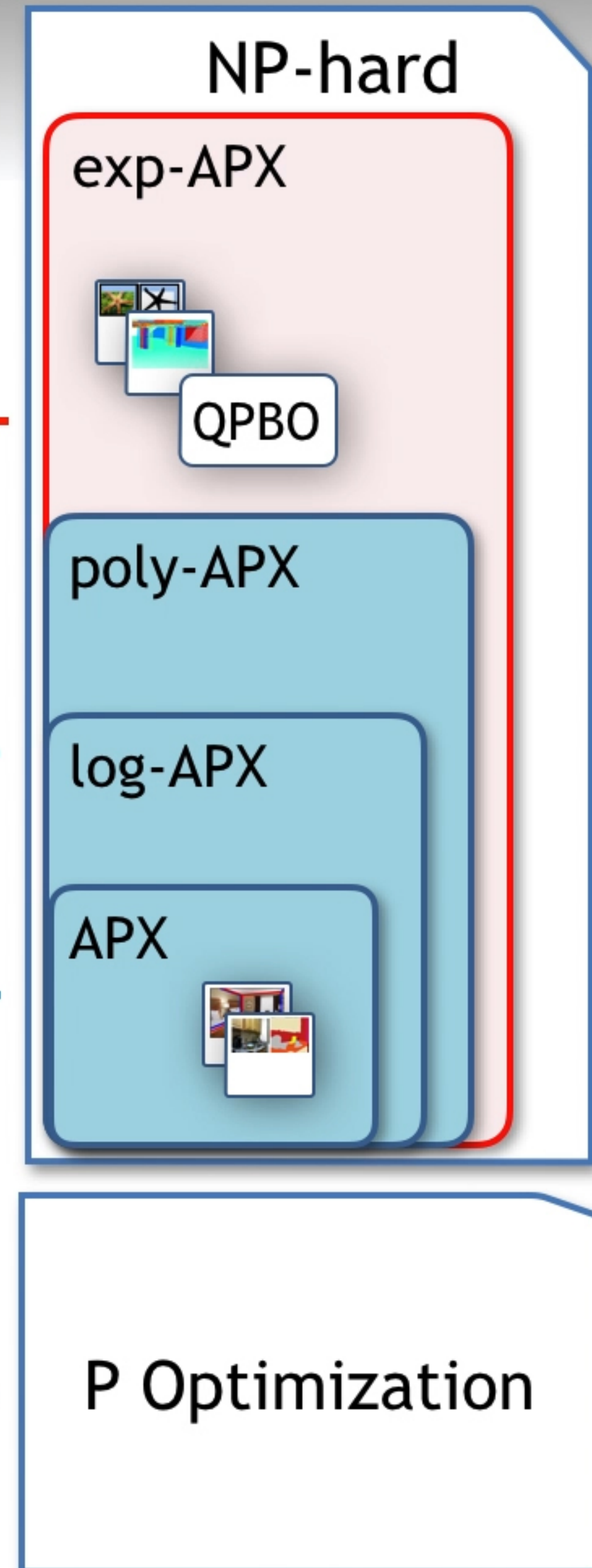
(reduction gadgets)



Weighted 3-SAT  
**QPBO**  
**General Energy Minimization**  
**Planar with 3+ labels**

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# Take Away Message

- Energy minimization problems vary in approximation ratio
- Bounded approximation ratio
  - Indicates a class of practical interest
  - Useful for algorithm design (Primal-Dual)
- Do not try to prove approximation guarantee if
  - Model includes QPBO/ planar 3-label / general energy minimization
  - Or you can build AP-reduction from them

Weighted 3-SAT  
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