

# Solving relaxations of MAP-MRF problems: Combinatorial in-face Frank-Wolfe directions

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# MAP-MRF problem

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- Goal: minimize function of discrete variables

$$f(\mathbf{x}) = \sum_p f_p(x_p) + \sum_{p,q} f_{pq}(x_p, x_q)$$

- Popular approach: solve LP relaxation
- Extensive literature on specialized LP solvers
  - Block-coordinate ascent on the dual (may get stuck...)
    - TRW-S [K 06] / SRMP [K '15], MPLP [Globerson-Jaakkola'08], DMM [Shekhovtsov'16], MPLP++ [Tourani et al.'18], SPAM [Tourani et al.'20], ..
  - Converge to LP optimum
    - [Ravikumar et al.'10], [Jojic et al.'10], [Savchynskyy et al.'11,'12], [Schmidt et al.'11], [Komodakis et al.11], [Martins et al.'11], [Luong et al.'12], [Schwing et al.'12], ...
  - Frank-Wolfe based approach [Swoboda-K.'19], [K.-Pock'21]
    - this work: efficient FW implementation
    - (*combinatorial*) *in-face* FW directions
    - state-of-the-art LP solver for some applications

# MAP-MRF via Frank-Wolfe (FW)

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- More generally: minimize

$$f(\mathbf{x}) = \sum_{A \subseteq [n]} f_A(x_A)$$

- assumption: can solve

$$\arg \min_{x_A} [f_A(x_A) + \langle x_A, y_A \rangle] \quad \forall y_A \quad \text{“min-oracle”}$$

- e.g. tree-structured MAP-MRF
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- goal: solve certain Lagrangian relaxation

- [Swoboda-K.'19]: proximal point method + FW algorithm

- [K.-Pock'21]: accelerated version, convergence analysis

- $O(1/n^2)$  dual gap after  $O(n \log n)$  oracle calls

(\* *under technical assumptions*)

- best known rate for iterative algorithms

# This work: efficient implementation of FW

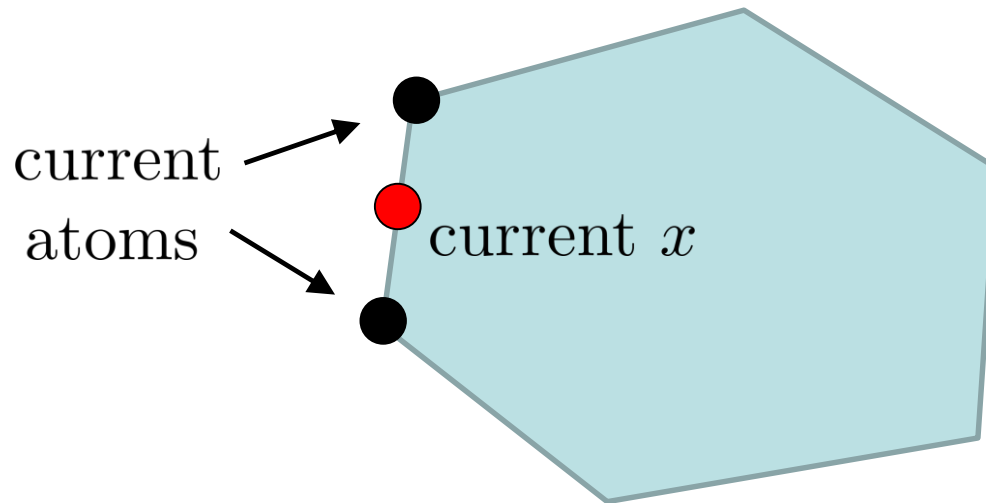
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- Block-coordinate FW [Lacoste-Julien et al.'13]
- Cache atoms [Joachims et al.'09], [Shah et al.'15], [Osokin et al.16]
- Main improvement: *in-face FW directions* [Freund et al.'17]
  - implementation for combinatorial oracles
  - which data structures are needed?

# FW overview

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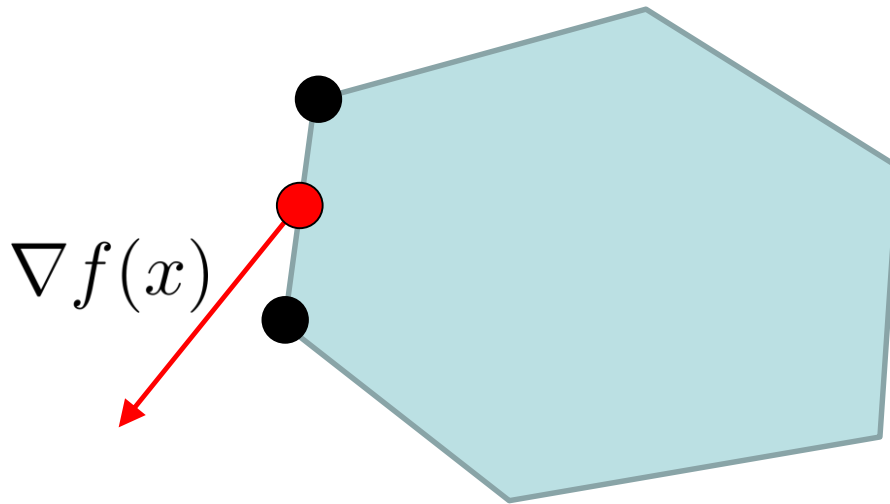
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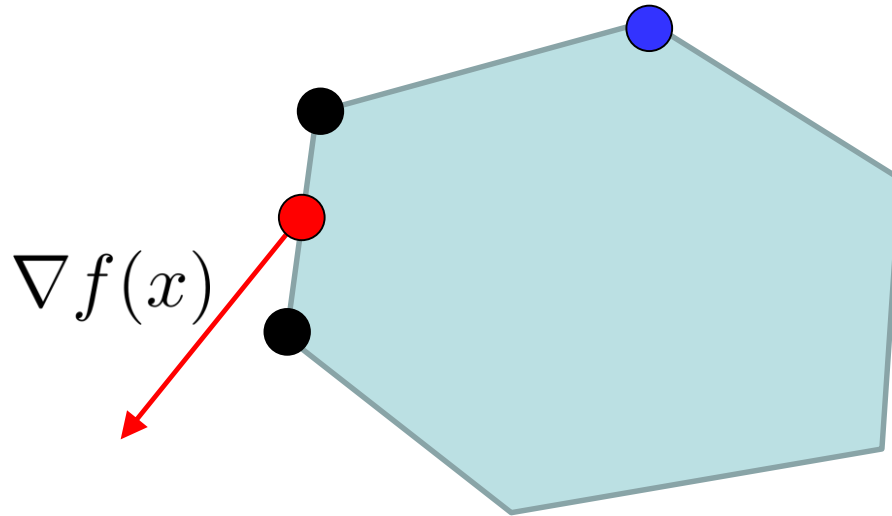
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  - linearize objective at  $x$



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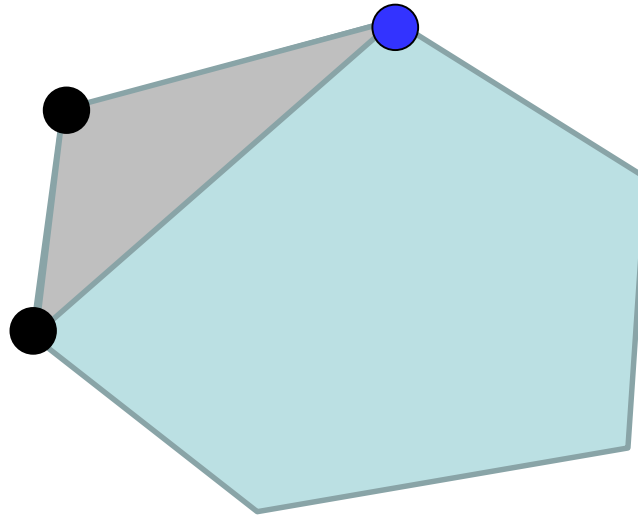


- FW step:
  - linearize objective at  $x$
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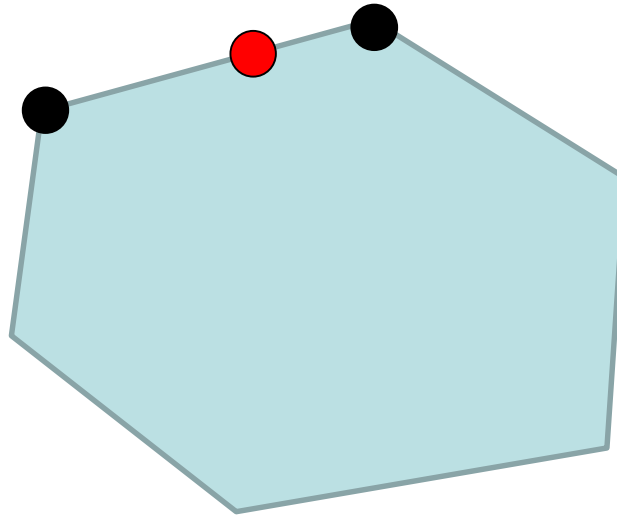


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  - re-optimize  $f$  over atoms

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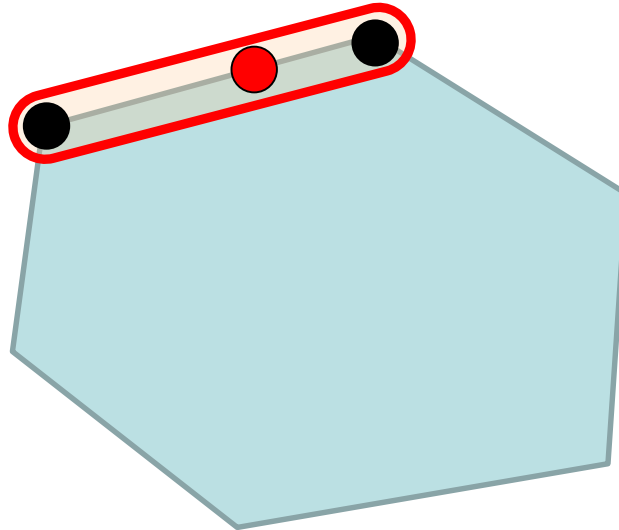


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# In-face FW directions [Freund et al.'17]

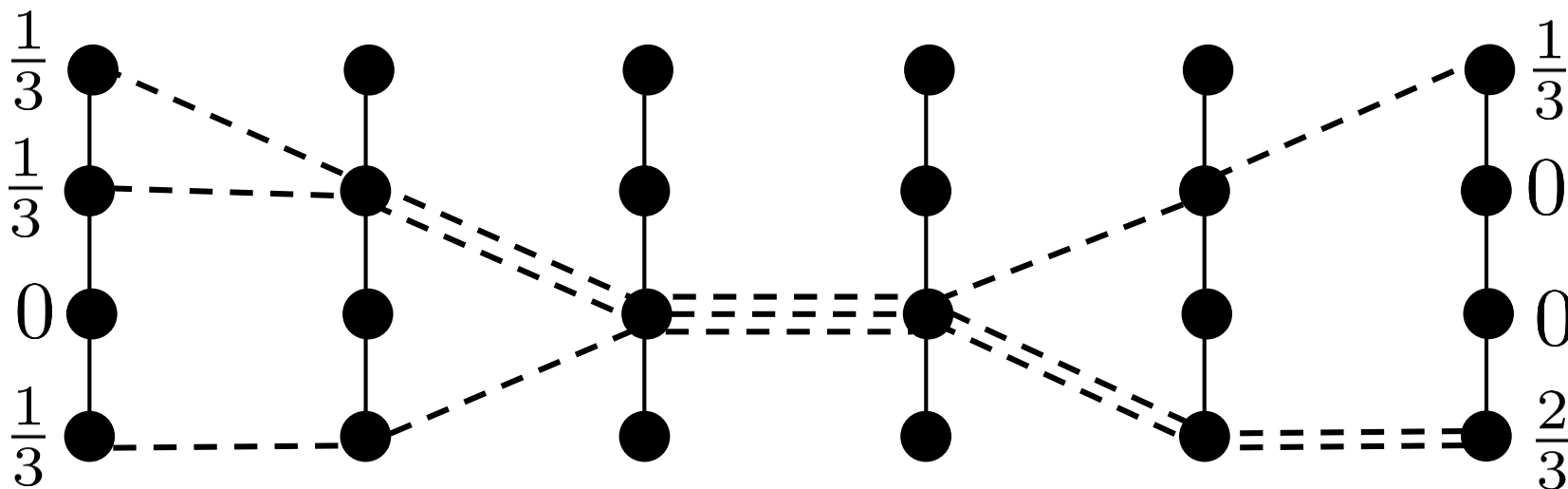
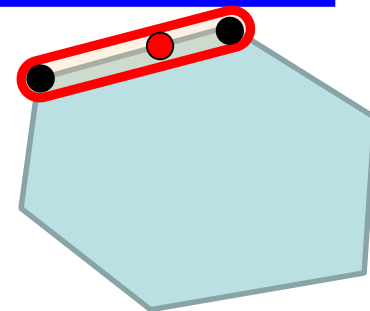
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- Take (minimal) face of the polytope containing  $x$
- Run several FW steps for smaller polytope



# Implementation for tree-structured MAP-MRF

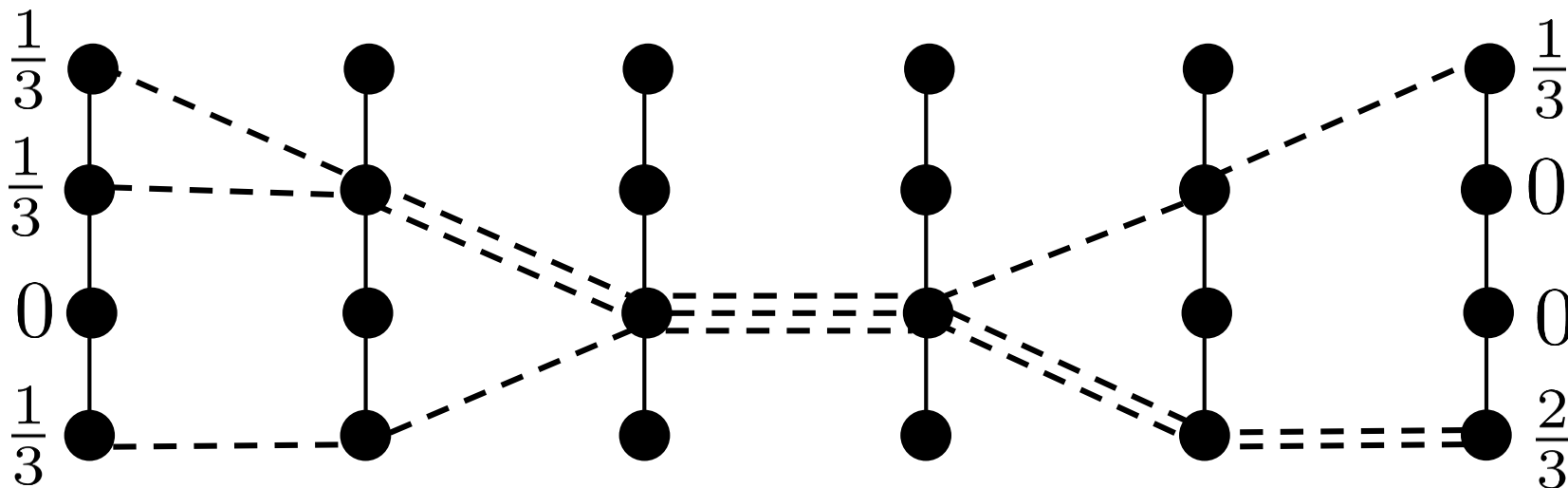
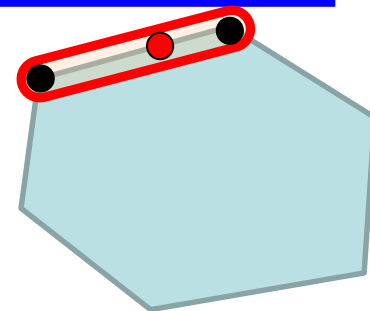
$$f(x) = \sum_{p;a} f_{p;a}(x_{pa}) + x_{\text{edge cost}}$$



# Implementation for tree-structured MAP-MRF

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node  
variables

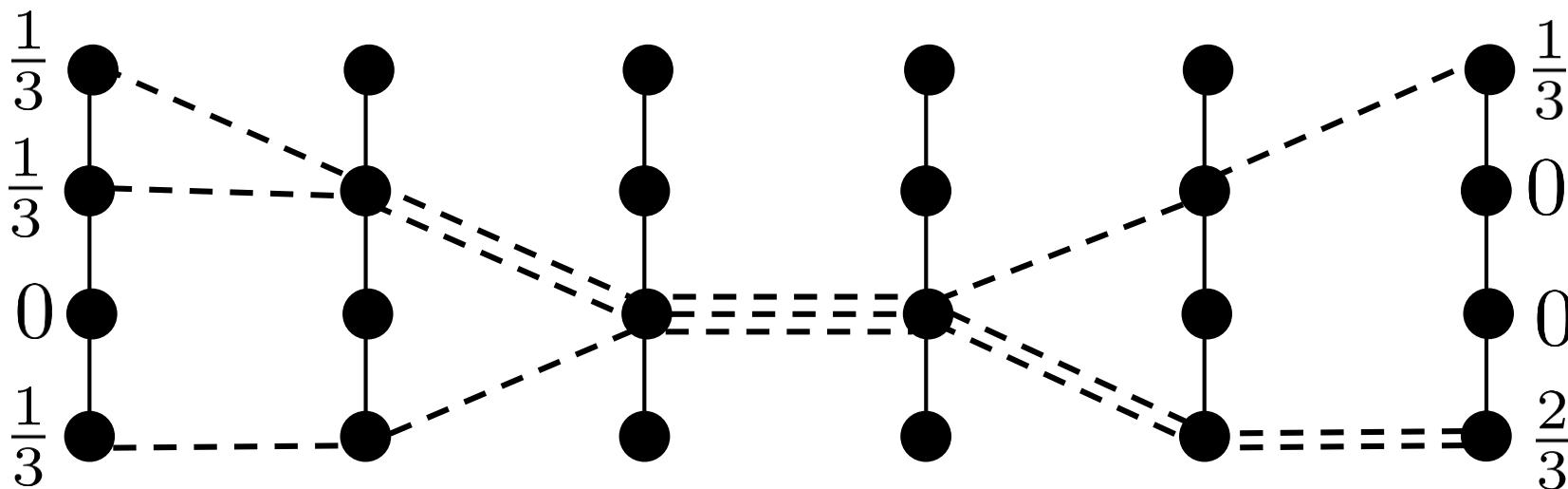
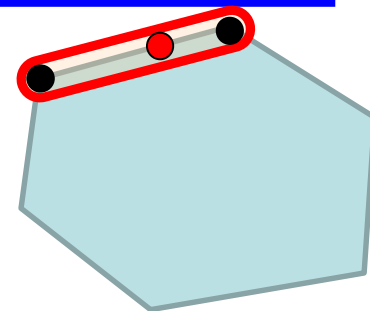


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$$f(x) = \sum_{p;a} f_{p;a}(x_{pa}) + x_{\text{edge cost}}$$

quadratic

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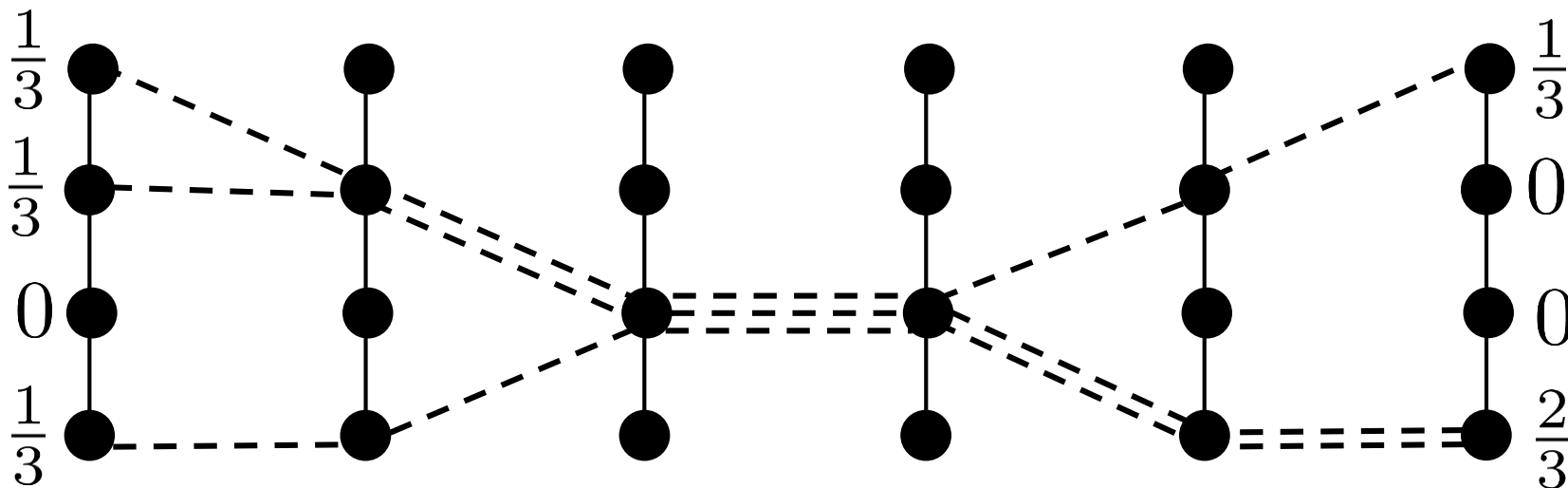
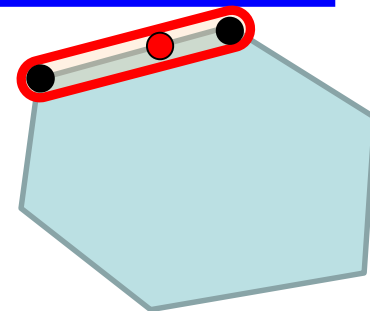
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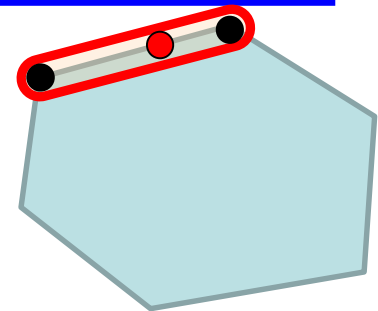
total cost of pairwise terms



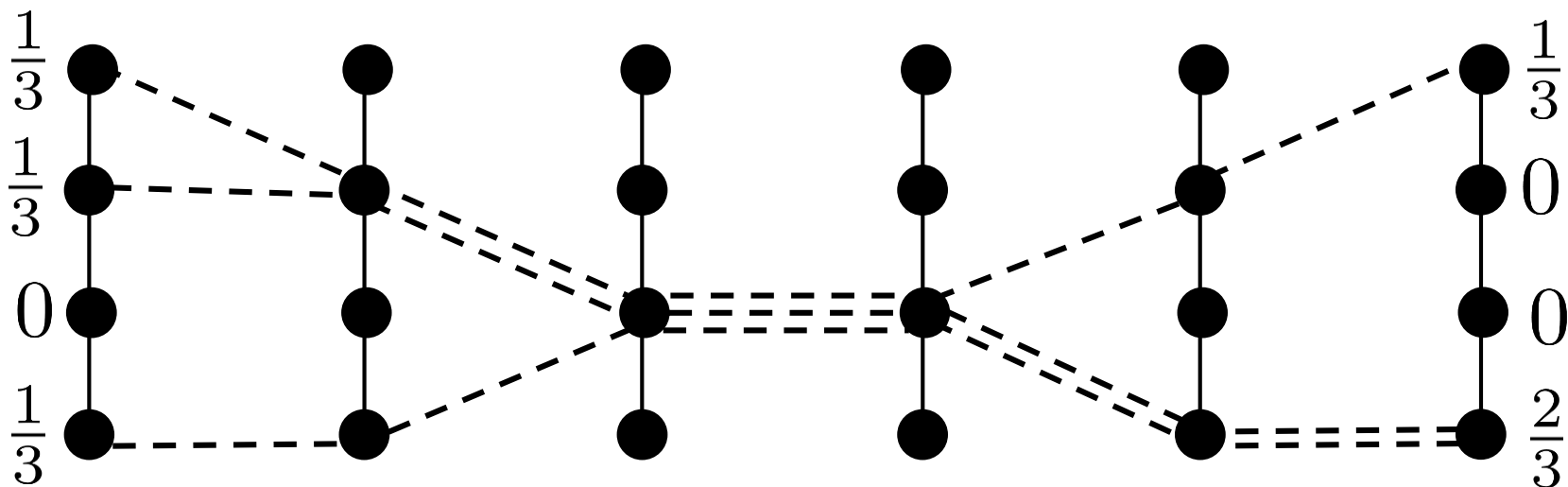


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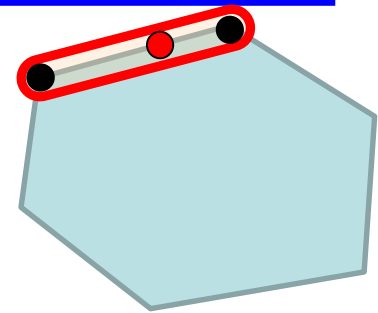


- Face: fix some vars to zero ( $x_{p;a} = 0$ )

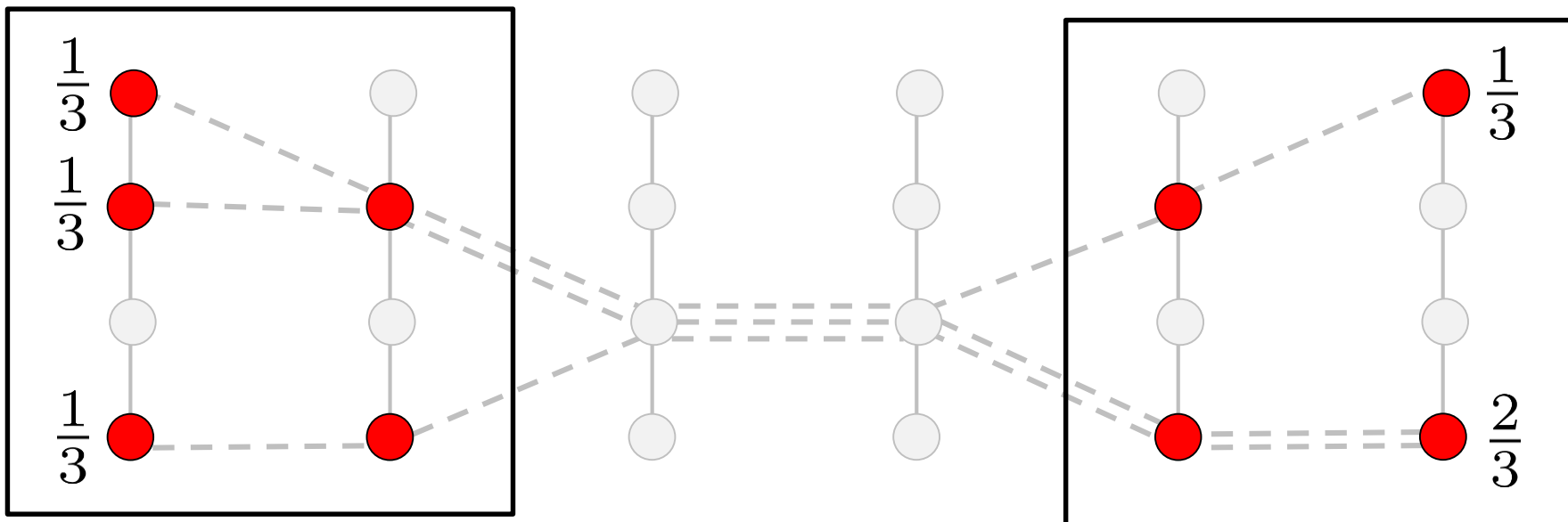


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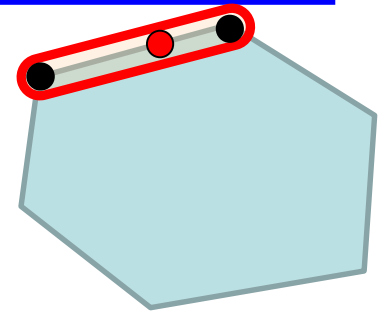


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- May split problem into independent subproblems

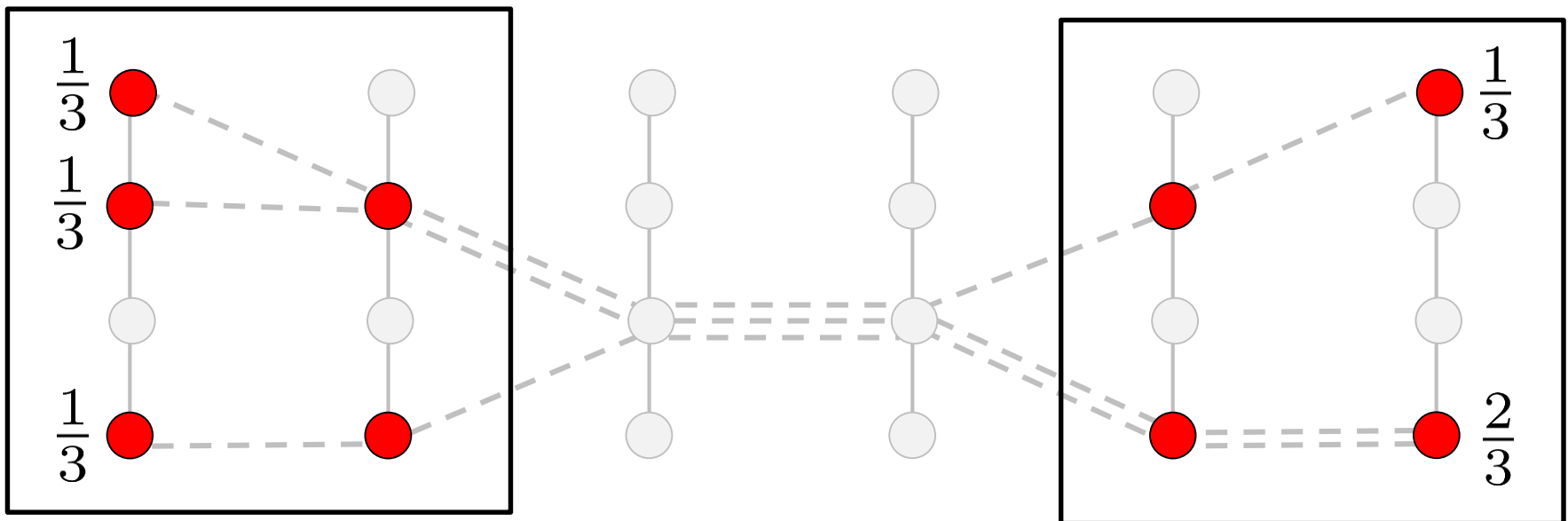


# Implementation for tree-structured MAP-MRF

$$f(x) = \sum_{p;a} f_{p;a}(x_{pa}) + x_{\text{edge cost}}$$



- Face: fix some vars to zero ( $x_{p;a} = 0$ )
- May split problem into independent subproblems
  - use block-coordinate FW for each new subproblem





# “Subproblem” data structure

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- “Parent” and “child” subproblems
- Functions:

AtomToVector( $a$ )

DotProduct( $a, g$ )

...

MinOracle( $a, g$ )

...

Contract( $x, s$ )

for parent subproblems

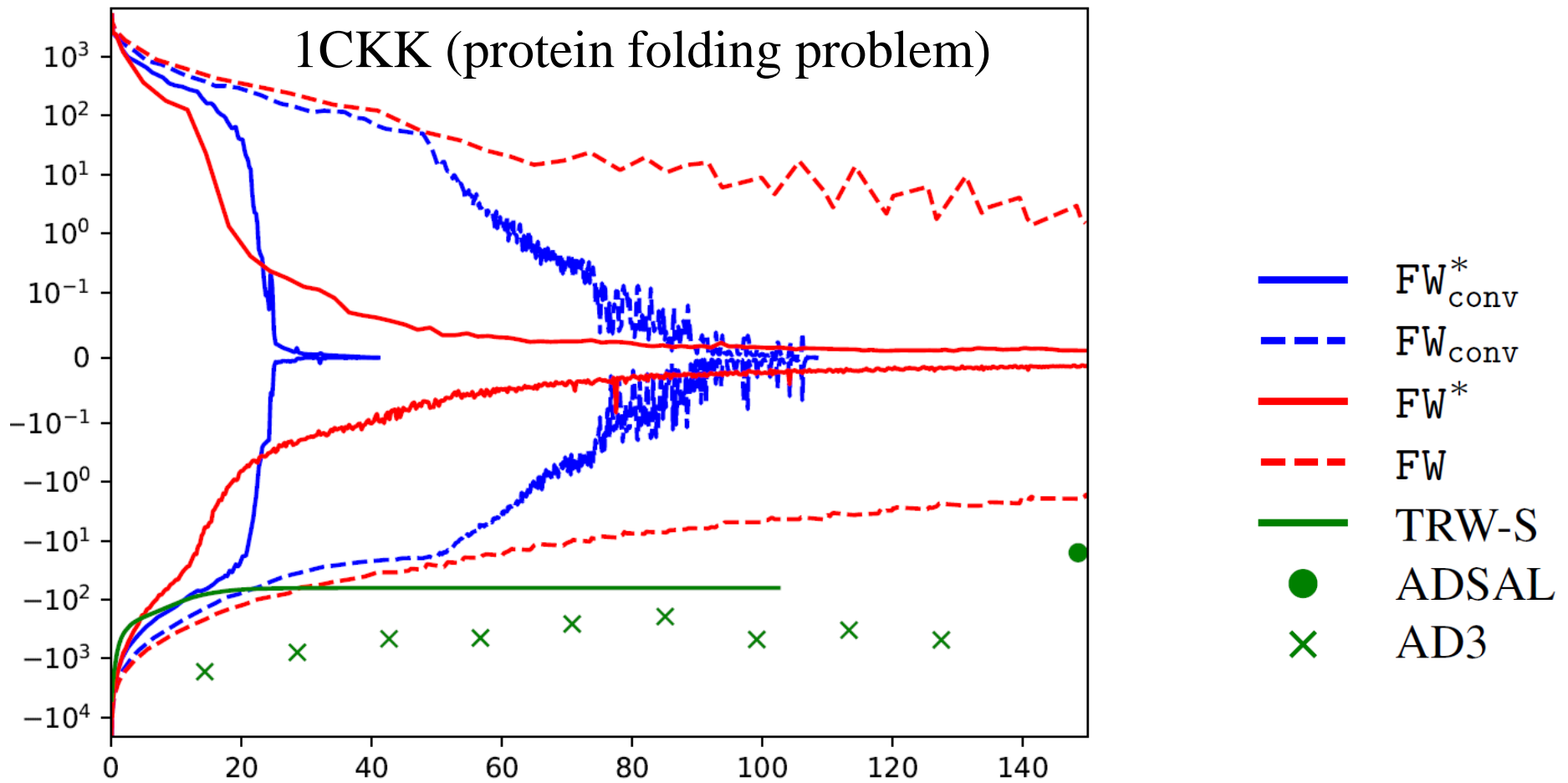
SetAtom( $a$ )

GetAtom( $a$ )

for parent & child subproblems

...

# Results



# Summary

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Goal: solve Lagrangian relaxation of  $\min_{\mathbf{x}} \sum_{A \subseteq [n]} f_A(x_A)$

- Added in-face directions to FW-based approach
  - specified abstract data structure for combinatorial subproblems
  - implementation for tree-structured MAP-MRF problems
  - current state-of-the-art LP solver for some classes of problems
  - C++ code publicly available