

Optimality Bounds and Optimization for Image Partitioning

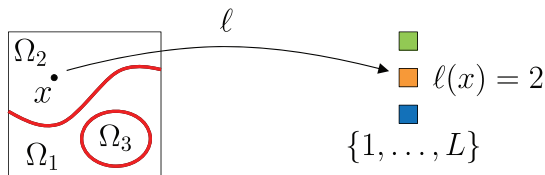
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Universität Heidelberg

Efficient Algorithms for Global Optimisation Methods
Dagstuhl, November 21, 2011

Motivation – Problem

- ▶ Labeling problem:

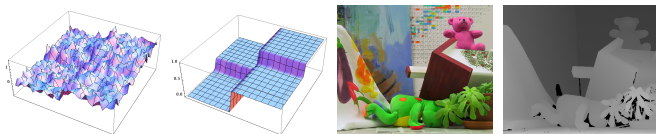


- ▶ Partition image domain Ω into L regions
- ▶ *Discrete* decision at each point in *continuous* domain Ω
- ▶ Variational Approach:

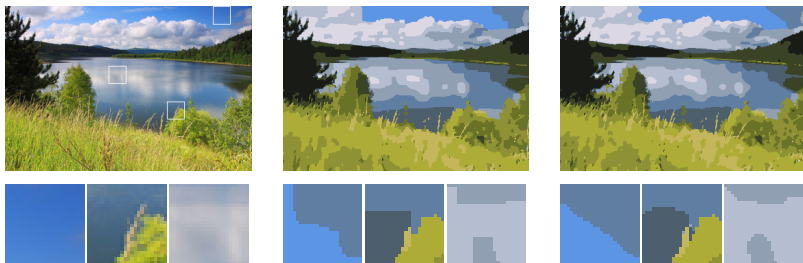
$$\min_{\ell} \underbrace{\int_{\Omega} s(\ell(x), x) dx}_{\text{local data fidelity}} + \underbrace{J(\ell)}_{\text{regularizer}}$$

Motivation – Multiclass Labeling

- ▶ **Applications:** Denoising, segmentation, 3D reconstruction, depth from stereo, inpainting, photo montage, optical flow,...

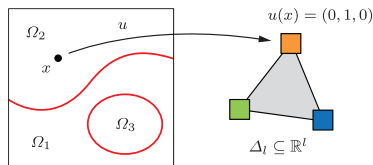


- ▶ Spatially continuous formulation avoids metrication artifacts:



Model – Multi-Class Labeling

- ▶ Multi-class relaxation: [Lie et al. 06, Zach et al. 08, Lellmann et al. 09, Pock et al. 09]



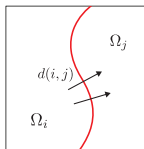
- ▶ Embed labels into \mathbb{R}^L as $\mathcal{E} := \{e^1, \dots, e^L\}$, relax to the unit simplex:

$$\Delta_L := \{x \in \mathbb{R}^L \mid x \geq 0, \sum_i x_i = 1\} = \text{conv } \mathcal{E},$$

$$\min_{u \in \text{BV}(\Omega, \Delta_L)} f(u), \quad f(u) := \int_{\Omega} \langle u(x), s(x) \rangle dx + \int_{\Omega} \Psi(Du)$$

- ▶ Advantages: No explicit parametrization, rotation invariance, *convex*

- ▶ $J(\ell)$: Weight boundary length by *interaction potential* $d(i, j)$



- ▶ $J(u)$ implicitly defined as local envelope for given d

[ChambolleCremersPock08, LellmannSchnoerr10]

$$J(u) := \sup_{v \in \mathcal{D}} \int_{\Omega} \langle Du, v \rangle = \int_{\Omega} \underbrace{\sigma_{\mathcal{D}_{\text{loc}}}(Du)}_{\Psi(Du)},$$

$$\mathcal{D} := \{v \in (C_c^\infty)^{d \times L} \mid v(x) \in \mathcal{D}_{\text{loc}} \forall x \in \Omega\},$$

$$\mathcal{D}_{\text{loc}} := \{(v^1, \dots, v^L) \in \mathbb{R}^{d \times L} \mid \|v^i - v^j\| \leq d(i, j) \forall i, j\}.$$

- ▶ *Fractional* solutions may occur:



- ▶ **Goal:** Find *rounding scheme* $u^* \mapsto \bar{u}^* : \Omega \rightarrow \{e^1, \dots, e^L\}$ such that

$$f\left(\underbrace{\bar{u}^*}_{\text{rounded relaxed solution}}\right) \leq C f\left(\underbrace{u_{\mathcal{E}}^*}_{\text{best integral solution}}\right).$$

for some $C \geq 1$.

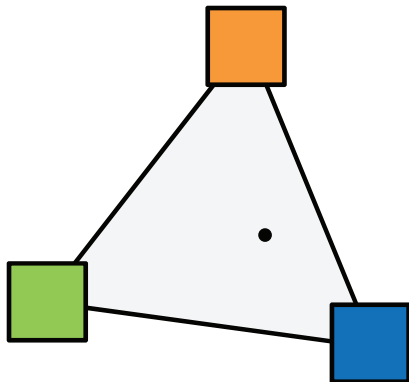
- ▶ Two-class case: Generalized *coarea formula* [Strang83, ChanEsedogluNikolova06, Zach et al. 09, Olsson et al. 09]

$$f(u) = \int_0^1 f(\bar{u}_\alpha) d\alpha, \quad \bar{u}_\alpha := \begin{cases} e^1, & u_1(x) > \alpha, \\ e^2, & u_1(x) \leq \alpha. \end{cases}$$

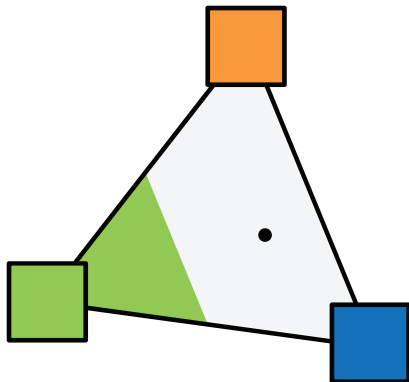
- ▶ Also: *Choquet integral*, *Lovász extension*, *levelable function*,...
- ▶ Consequence: $C = 1$, global *integral* minimizer for a.e. α :
- ▶ Multi-class generalization (*approximate* generalized coarea formula):

$$Cf(u) \geq \int_{\Gamma} f(\bar{u}_\gamma) d\mu(\gamma) = \mathbb{E}_\gamma f(\bar{u}_\gamma)$$

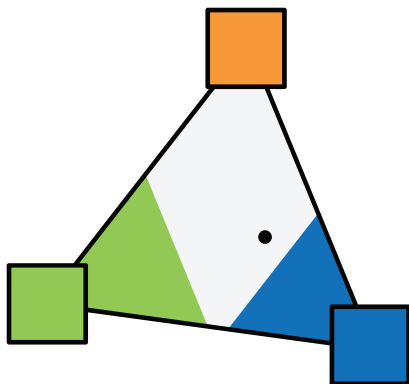
- ▶ Parameter space: *sequences* $\gamma \in \Gamma := (\{1, \dots, L\} \times [0, 1])^{\mathbb{N}}$

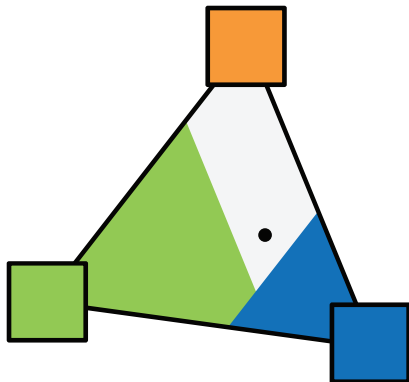


Optimality – Example

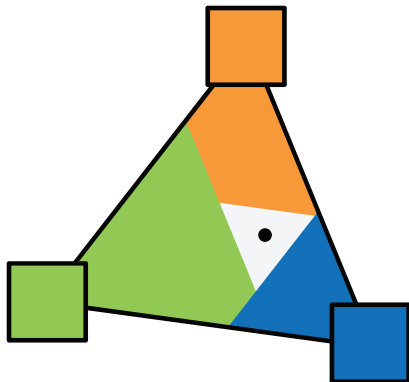


Optimality – Example

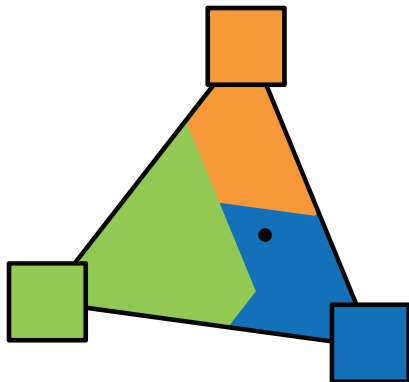




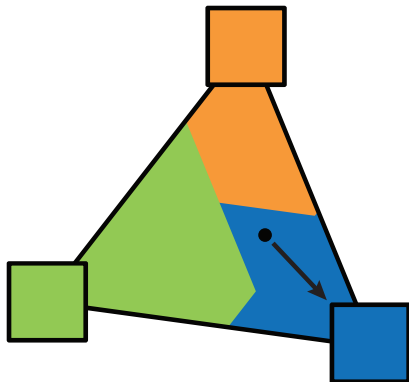
Optimality – Example



Optimality – Example



Optimality – Example



Theorem (Optimality [LellmannLenzenSchnoerr2011])

Let $u \in \text{BV}(\Omega, \Delta_L)$, $s \in L^\infty(\Omega)^L$, $s \geq 0$, d metric. Then

$$\mathbb{E}f(\bar{u}) \leq 2 \frac{\max_{i \neq j} d(i, j)}{\min_{i \neq j} d(i, j)} f(u) \quad \text{and} \quad \mathbb{E}f(\bar{u}^*) \leq 2 \frac{\max_{i \neq j} d(i, j)}{\min_{i \neq j} d(i, j)} f(u_{\mathcal{E}}^*).$$

- ▶ Provides “approximate” generalized coarea formula
- ▶ Compatible with bounds for finite-dimensional multiway cut, α -expansion, LP relaxation [Dahlhaus et al. 94, KleinbergTardos 99, Boykov et al. 01, KomodakisTziritas 07]
- ▶ Formulated in BV, independent of discretization, true *a priori* bound

- ▶ Tight regularizer, but:

$$\mathcal{D}_{\text{loc}} := \{(v^1, \dots, v^L) \in \mathbb{R}^{d \times L} \mid \|v^i - v^j\| \leq d(i, j) \forall i, j\}.$$

- ▶ Many constraints: $O(L^2)$

- ▶ Assume there is (i, j, k) such that $d(i, k) \stackrel{(\leq)}{\geq} d(i, j) + d(j, k)$. Then

$$\|v^i - v^k\| \leq \|v^i - v^j\| + \|v^j - v^k\| \leq d(i, j) + d(j, k) \leq d(i, k).$$

\Rightarrow Removing constraint for (i, k) *does not change* \mathcal{D}_{loc} .

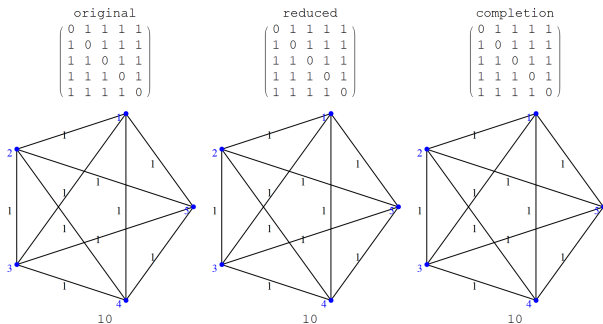
- ▶ How to continue?

- ▶ Can show:
 - ▶ No need for sequential removal
 - ▶ Remaining set of constraints is unique
 - ▶ Does *not* change dual constraint set \mathcal{D}_{loc} /regularizer Ψ

Algorithm 1 (Reducing Metrics)

- ▶ For all $(i, j, k) \in \{1, \dots, L\}^3$:
 - ▶ If $d(i, k) \geq d(i, j) + d(j, k)$: remove constraint $\|v^i - v^k\| \leq d(i, k)$

- ▶ Uniform (Potts) metric: $d(i,j) = 1_{i \neq j}$



- ▶ No reduction possible

Reducing Metrics – Uniform and Linear

- ▶ Linear metric: $d(i, j) = |i - j|$

original

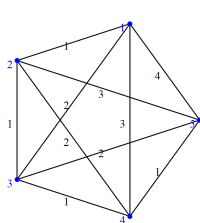
0	1	2	3	4
1	0	1	2	3
2	1	0	1	2
3	2	1	0	1
4	3	2	1	0

reduced

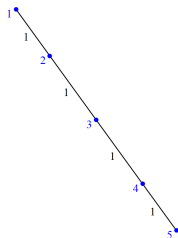
0	1	∞	∞	∞
1	0	1	∞	∞
∞	1	0	1	∞
∞	∞	1	0	1
∞	∞	∞	1	0

completion

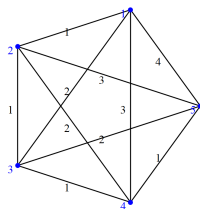
0	1	2	3	4
1	0	1	2	3
2	1	0	1	2
3	2	1	0	1
4	3	2	1	0



10



4



10

- ▶ Full reduction: $O(n^2) \rightarrow O(n)$

Reducing Metrics – Trees

- Tree metric: $d(i, j) = \text{shortest_path}(T, i, j)$

original

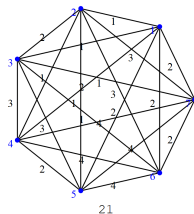
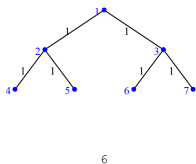
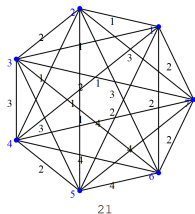
0	1	1	2	2	2	2
1	0	2	1	1	3	3
1	2	0	3	3	1	1
2	1	3	0	2	4	4
2	1	3	2	0	4	4
2	3	1	4	4	0	2
2	3	1	4	4	2	0

reduced

0	1	1	∞	∞	∞	∞
1	0	∞	1	1	∞	∞
1	∞	0	∞	∞	1	1
∞	1	∞	0	∞	∞	∞
∞	1	∞	∞	0	∞	∞
∞	∞	1	∞	∞	0	∞
∞	∞	1	∞	∞	∞	0

completion

0	1	1	2	2	2	2
1	0	2	1	1	3	3
1	2	0	3	3	1	1
2	1	3	0	2	4	4
2	1	3	2	0	4	4
2	3	1	4	4	0	2
2	3	1	4	4	2	0

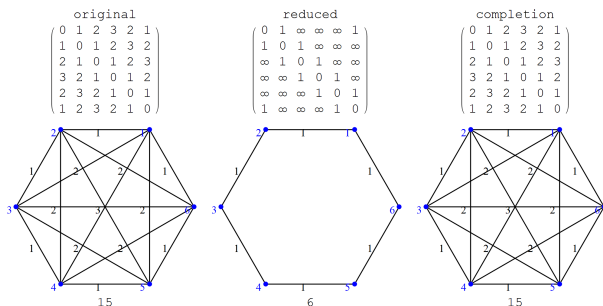


- Full reduction: $O(n^2) \rightarrow O(n)$

Reducing Metrics – Cyclic

- ▶ General graph: $d(i, j) = \text{shortest_path}(G, i, j)$
- ▶ Continuous analogue: TV_{S^1} for angular/orientation data

[StekalovskiyCremers2011]



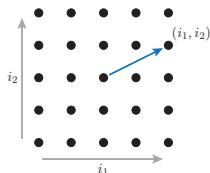
- ▶ Full reduction: $O(n^2) \rightarrow O(n)$

Reducing Metrics – Multiple Components

- ▶ Labels quantize vector-valued quantities, e.g. optical flow
- ▶ n quantization steps per component
⇒ n^2 labels, $O(n^4)$ constraints!
- ▶ Separable metric (*linear*):

$$d((i_1, i_2), (j_1, j_2)) = |i_1 - j_1| + |i_2 - j_2|$$

- ▶ Possible: *two* indicator functions
 - ▶ Nonconvex dataterm, needs relaxation ⇒ less tight [GoldlueckeCremers2010]
 - ▶ or additional dual variables [StekalovskiyGoldlueckeCremers2011]

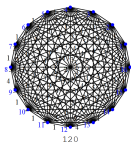
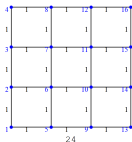
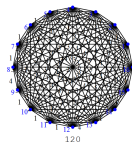


Reducing Metrics – Multiple Components

- ▶ Separable metric (*linear*):

$$d((i_1, i_2), (j_1, j_2)) = |i_1 - j_1| + |i_2 - j_2|$$

original	reduced	completion
<pre>0 1 2 3 1 2 3 4 2 3 4 5 3 4 5 6 1 0 1 2 2 1 2 3 3 2 3 4 4 3 4 5 2 1 0 1 3 2 1 2 4 3 2 3 5 4 3 4 3 2 1 0 4 3 2 1 5 4 3 2 6 5 4 3 1 2 3 4 0 1 2 3 1 2 3 4 2 3 4 5 2 1 2 3 1 0 1 2 2 1 2 3 3 2 3 4 3 2 1 2 2 1 0 1 3 2 1 2 4 3 2 3 4 3 2 1 3 2 1 0 4 3 2 1 5 4 3 2 2 3 4 5 1 2 3 4 0 1 2 3 1 2 3 4 3 2 3 4 2 1 2 3 1 0 1 2 2 1 2 3 4 3 2 3 3 2 1 2 2 1 0 1 3 2 1 2 5 4 3 2 4 3 2 1 3 2 1 0 4 3 2 1 3 4 5 6 2 3 4 5 1 2 3 4 0 1 2 3 4 3 4 5 3 2 3 4 2 1 2 3 1 0 1 2 5 4 3 4 4 3 2 3 3 2 1 2 2 1 0 1 6 5 4 3 5 4 3 2 4 3 2 1 3 2 1 0</pre>	<pre>0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0</pre>	<pre>0 1 2 3 1 2 3 4 2 3 4 5 3 4 5 6 1 0 1 2 2 1 2 3 3 2 3 4 4 3 4 5 2 1 0 1 3 2 1 2 4 3 2 3 5 4 3 4 3 2 1 0 4 3 2 1 5 4 3 2 6 5 4 3 1 2 3 4 0 1 2 3 1 2 3 4 2 3 4 5 2 1 2 3 1 0 1 2 2 1 2 3 3 2 3 4 3 2 1 2 2 1 0 1 3 2 1 2 4 3 2 3 4 3 2 1 3 2 1 0 4 3 2 1 5 4 3 2 2 3 4 5 1 2 3 4 0 1 2 3 1 2 3 4 3 2 3 4 2 1 2 3 1 0 1 2 2 1 2 3 4 3 2 3 3 2 1 2 2 1 0 1 3 2 1 2 5 4 3 2 4 3 2 1 3 2 1 0 4 3 2 1 3 4 5 6 2 3 4 5 1 2 3 4 0 1 2 3 4 3 4 5 3 2 3 4 2 1 2 3 1 0 1 2 5 4 3 4 4 3 2 3 3 2 1 2 2 1 0 1 6 5 4 3 5 4 3 2 4 3 2 1 3 2 1 0</pre>



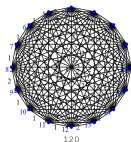
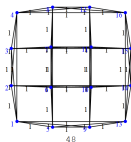
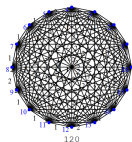
- ▶ Full reduction: $O(n^4) \rightarrow O(n^2)$ (n^2 labels)

Reducing Metrics – Multiple Components

- ▶ Separable metric (*uniform/Potts*):

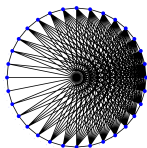
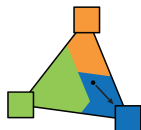
$$d((i_1, i_2), (j_1, j_2)) = \mathbf{1}_{i_1 \neq j_1} + \mathbf{1}_{i_2 \neq j_2}$$

original	reduced	completion
<pre>0 1 1 1 1 2 2 2 1 2 2 2 1 2 2 2 2 1 0 1 1 1 2 1 2 2 2 1 2 2 2 1 2 2 2 1 1 0 1 2 2 1 2 2 2 1 2 2 2 2 1 2 1 1 1 0 2 2 2 1 2 2 2 1 2 2 2 1 2 1 2 2 2 0 1 1 1 1 2 2 2 1 2 2 2 2 2 1 2 2 1 0 1 1 2 1 2 2 2 1 2 2 2 2 2 1 2 1 1 0 1 2 2 2 1 2 2 2 1 2 2 2 2 1 1 1 1 0 2 2 2 1 2 2 2 1 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 1 0 1 1 2 1 2 2 2 2 1 2 2 2 1 2 1 1 0 1 2 2 1 2 2 2 2 1 1 1 1 0 2 2 2 1 2 2 2 1 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 1 0 1 1 2 1 2 2 2 2 1 2 2 2 1 2 1 1 0 1 2 2 1 2 2 2 2 1 2 2 2 1 1 1 1 0 2 2 2 1 2 1 2 2 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 1 2 2 2 1 2 2 2 1 2 2 1 2 1 0 1 1 2 2 1 2 2 2 1 2 2 2 1 2 2 1 1 0 1 1 2 2 1 2 2 2 1 2 2 2 1 2 2 1 1 0 1 1 2 2 2 1 2 2 2 1 2 2 2 1 1 1 1 0 1 1</pre>	<pre>0 1 1 1 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 1 1 1 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 1 1 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 1 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 1 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 1 1 1 1 1 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 1 0 1 1 0 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 1 1 0 1 0 1</pre>	<pre>0 1 1 1 1 1 2 2 2 1 2 2 2 1 2 2 2 2 1 0 1 1 1 2 1 2 2 2 1 2 2 2 1 2 2 2 1 1 0 1 2 2 1 2 2 2 1 2 2 2 2 1 2 2 1 1 1 0 2 2 2 1 2 2 2 1 2 2 2 1 2 2 1 2 2 2 0 1 1 1 1 2 2 2 1 2 2 2 2 2 1 2 2 1 0 1 1 2 1 2 2 2 1 2 2 2 2 2 1 2 1 0 1 1 2 1 2 2 2 1 2 2 2 2 2 2 1 1 1 1 0 2 2 2 1 2 2 2 1 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 1 0 1 1 2 1 2 2 2 2 1 2 2 2 1 2 1 1 0 1 2 2 1 2 2 2 2 2 1 1 1 1 0 2 2 2 1 2 2 2 1 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 1 0 1 1 2 1 2 2 2 2 1 2 2 2 1 2 1 1 0 1 2 2 1 2 2 2 2 2 1 2 2 2 1 1 1 1 0 2 2 2 1 2 1 2 2 2 1 2 2 2 1 2 2 2 0 1 1 1 1 2 1 2 2 2 1 2 2 2 1 2 2 2 1 0 1 1 1 2 2 1 2 2 2 1 2 2 2 1 2 2 1 1 0 1 1 2 2 1 2 2 2 1 2 2 2 1 2 2 1 1 0 1 1 2 2 2 1 2 2 2 1 2 2 2 1 1 1 1 0 1 1</pre>



- ▶ Reduction: $O(n^4) \rightarrow O(n^3)$ (still n^2 labels)

- ▶ **Setting:**
 - ▶ Tight convex relaxation of multiclass image labeling
- ▶ **Bounds:**
 - ▶ *Probabilistic a priori* bound
 - ▶ Approximate generalized coarea formula
 - ▶ Compatible with finite-dimensional results
- ▶ **Reducing Metrics:**
 - ▶ Automatically remove redundant constraints
 - ▶ Reduces complexity for widely used metrics
 - ▶ Easy integration into other approaches



Optimality Bounds and Optimization for Image Partitioning

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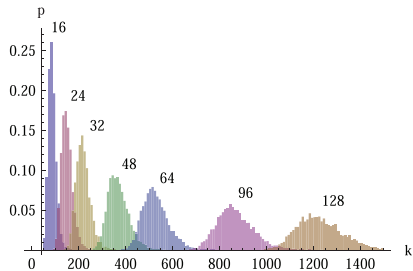
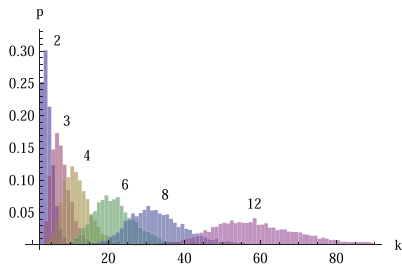
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Dagstuhl, November 21, 2011

Theorem (Termination)

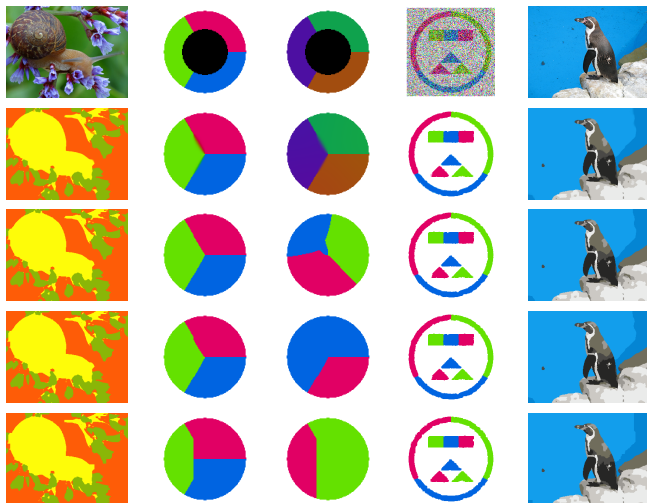
Let $u \in \text{BV}(\Omega, \Delta_L)$. Then (almost surely) Alg. 1 generates a sequence that becomes stationary in some $\bar{u} \in \text{BV}(\Omega, \mathcal{E})$.

- ▶ Result is in BV
- ▶ Independent of data term

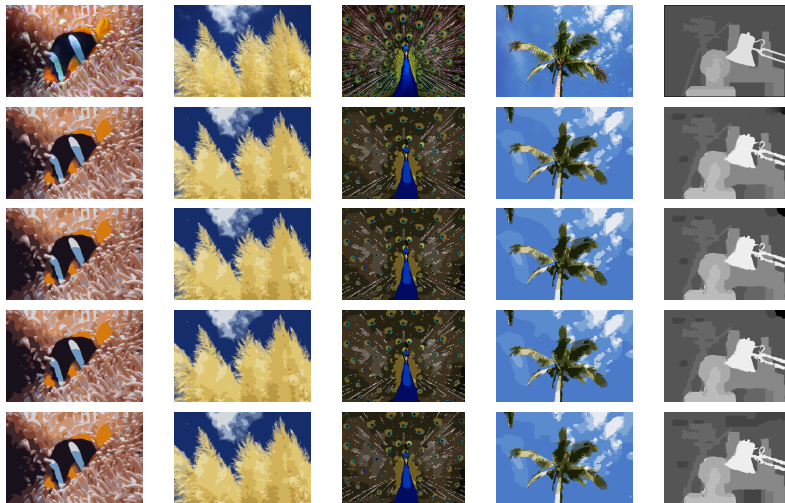
Experiments – Iterations



Experiments I



Experiments II



Experiments – Results

problem	1	2	3	4	5	6	7	8	9	10
# points	76800	14400	14400	129240	76800	86400	86400	76800	86400	110592
# labels	3	4	4	4	8	12	12	12	12	16
mean # iter.	7.27	7.9	8.05	10.79	31.85	49.1	49.4	49.4	49.7	66.1
<i>a priori</i> ε	1.	1.	1.	1.	1.	1.	1.	1.	1.	2.6332
<i>a posteriori</i>										
- first-max	0.0007	0.0231	0.2360	0.0030	0.0099	0.0102	0.0090	0.0101	0.0183	0.0209
- prob. best	0.0010	0.0314	0.1073	0.0045	0.0177	0.0195	0.0174	0.0219	0.0309	0.0487
- prob. mean	0.0007	0.0231	0.0547	0.0029	0.0138	0.0152	0.0134	0.0155	0.0247	0.0292

Algorithm 1 (Randomized Rounding in BV)

1. **Input:** $u^0 \in \text{BV}(\Omega, \Delta_L)$
2. **For** $k = 1, 2, \dots$
3. Sample $\gamma^k = (i^k, \alpha^k) \in \{1, \dots, L\} \times [0, 1]$ uniformly
4. $u^k \leftarrow e^{i^k} 1_{\{u_{i^k}^{k-1} > \alpha^k\}} + u^{k-1} 1_{\{u_{i^k}^{k-1} \leq \alpha^k\}}$
5. **Output:** Limit \bar{u} of (u^k)

▶ Parameter space: *sequences* $\gamma \in \Gamma := (\{1, \dots, L\} \times [0, 1])^{\mathbb{N}}$

Definition

For some sequence (γ^k) , if (u_γ^k) becomes stationary at some $u_\gamma^{k'} \in \mathbb{N}$, denote output $\bar{u}_\gamma := u_\gamma^{k'}$. For some functional $f : \text{BV}(\Omega)^L \rightarrow \mathbb{R}$, define

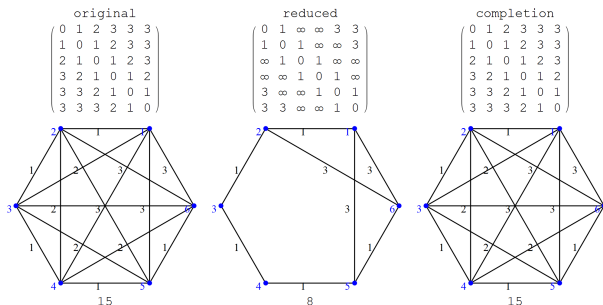
$$f(\bar{u}_\gamma) : \Gamma^{\mathbb{N}} \rightarrow \mathbb{R} \cup \{+\infty\}$$

$$\gamma \in \Gamma^{\mathbb{N}} \mapsto f(\bar{u}_\gamma) := \begin{cases} f(u_\gamma^{k'}), & (u_\gamma^k) \text{ stationary at } u_\gamma^{k'} \in \text{BV}(\Omega)^L, \\ +\infty, & \text{otherwise.} \end{cases} \quad (*)$$

- ▶ Can show: $\mathbb{P}_\gamma(f(\bar{u}_\gamma) < \infty) = 1$.
 - ▶ Generates “output” in finite time almost surely
 - ▶ Output is in $\text{BV}(\Omega)^L$ almost surely

Reducing Metrics – Uniform and Linear

- ▶ Truncated linear metric: $d(i, j) = \min\{3, |i - j|\}$



- ▶ Half the number of constraints