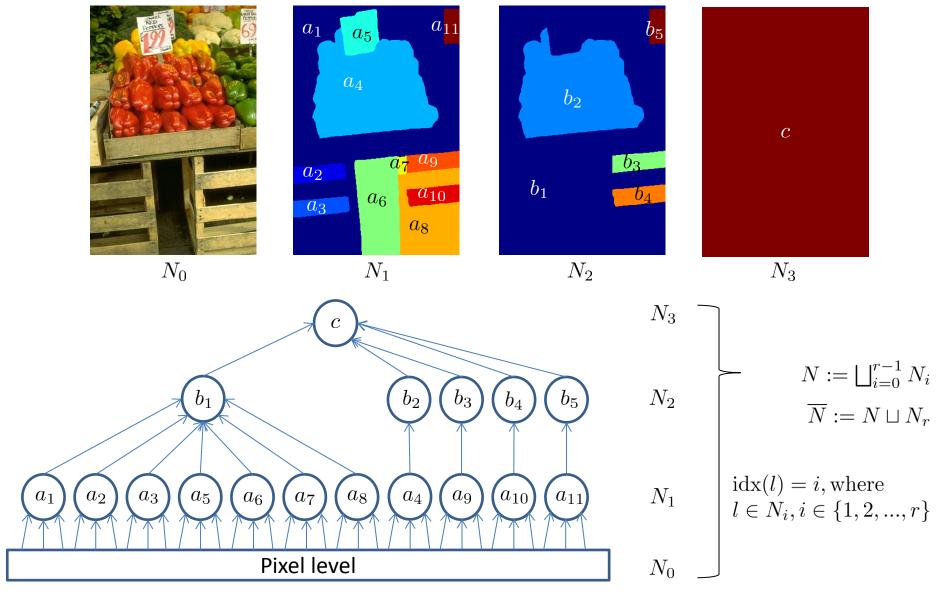
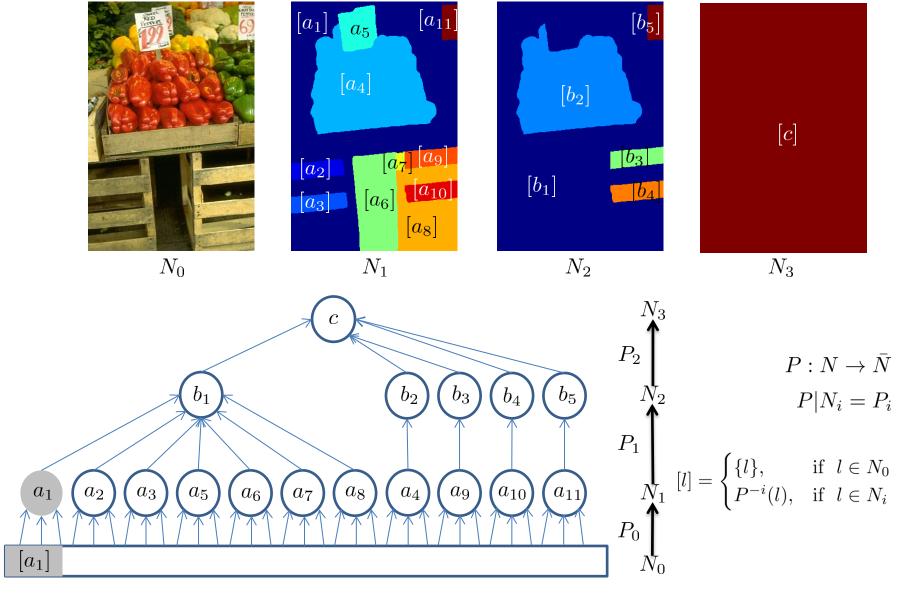
# Multi-labeling Optimization on Hierarchies of Partitions

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Results

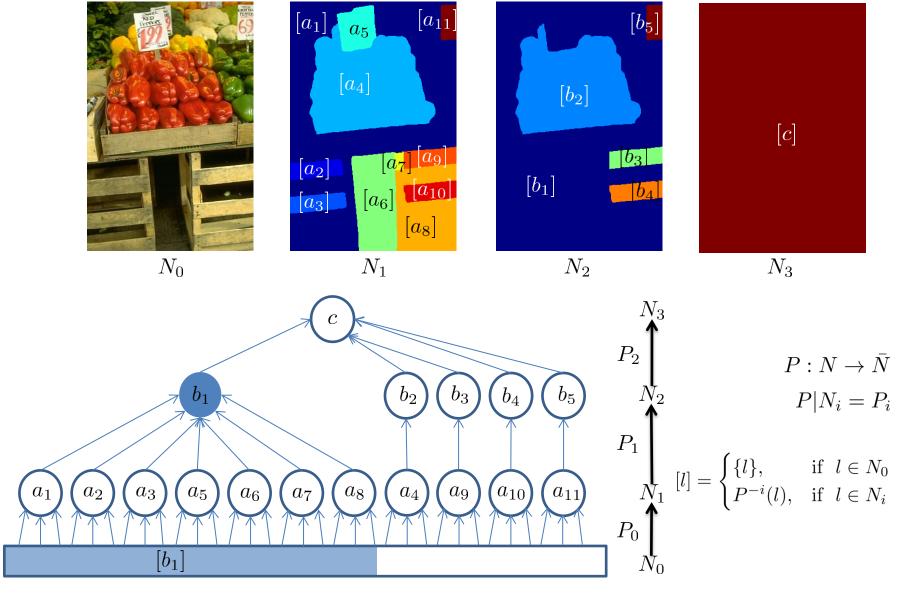
# Hierarchy of Labels



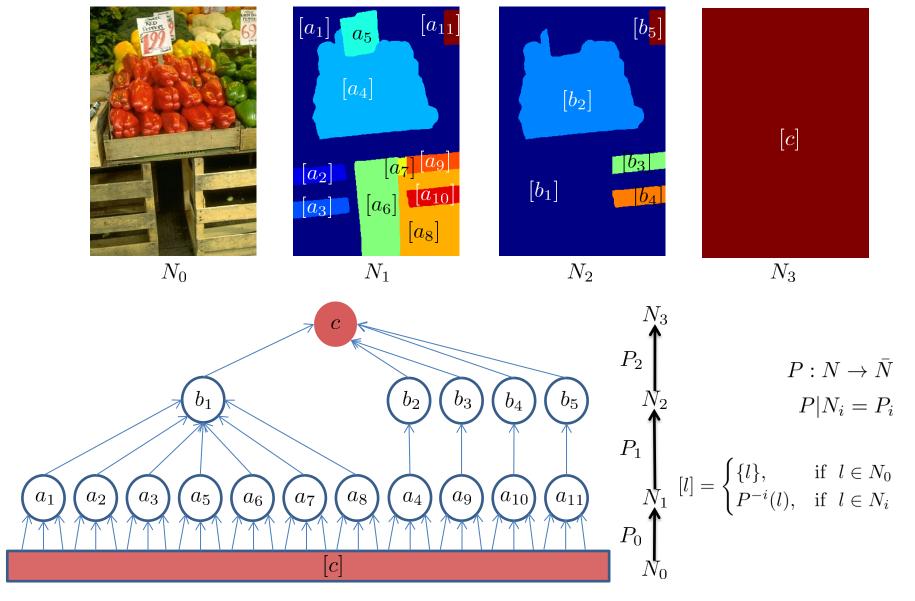
Class [a<sub>1</sub>] of Label a<sub>1</sub>



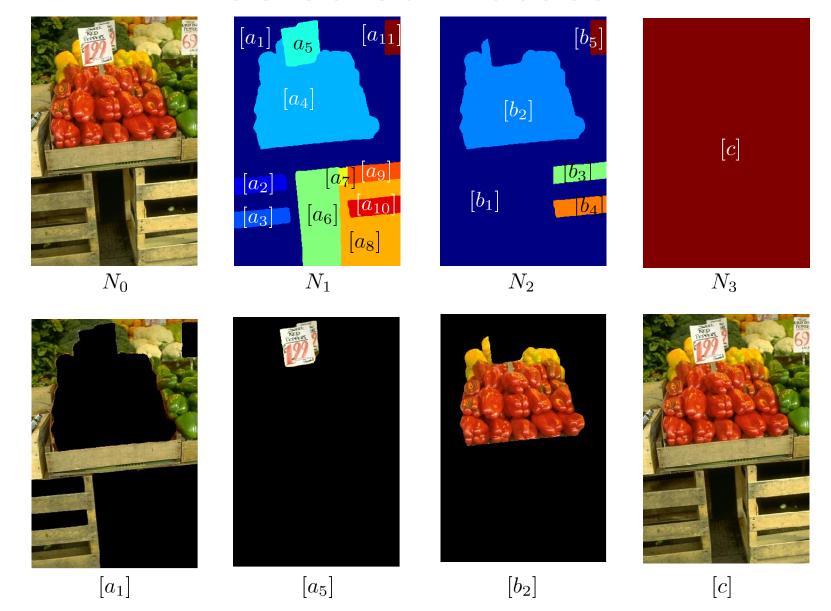
Class [b<sub>1</sub>] of Label b<sub>1</sub>



# Class [c] of Label c



#### Selected Classes



$$E(P) = \sum_{i=1}^r \left[ \sum_{l \in N_i} \int_{[l]} f_l(x) \mathrm{d}x + \lambda_i \sum_{l < m \in N_i} d(l,m) \cdot \mathrm{Length}(\partial[l] \cap \partial[m]) \right]$$

- $f_l$  is the negative log-likelihood of a probabilistic model
- $d(l, m) := idx(l \vee m) idx(l) = d(m, l)$
- Length is weighted by d(l, m) the distance to their maximum.

$$E(P) = \sum_{i=1}^{r} \left[ \sum_{l \in N_i} \int_{[l]} f_l(x) dx + \lambda_i \sum_{l < m \in N_i} d(l, m) \cdot \text{Length}(\partial[l] \cap \partial[m]) \right]$$
Data term

Length term

$$E(P) = \sum_{i=1}^{r} \left[ \sum_{l \in N_i} \int_{[l]} f_l(x) dx + \lambda_i \sum_{l < m \in N_i} d(l, m) \cdot \text{Length}(\partial[l] \cap \partial[m]) \right]$$
Data term

Length term

Geodesic Length: Len<sub>l,m</sub> $(s) = d(l,m) \cdot g_{l,m}(s)$ 

$$E(P) = \sum_{i=0}^{r-1} \sum_{u \in N_i} \int_{[u]} f_{P_i(u)}(x) dx + \sum_{i=1}^r \lambda_i \cdot \sum_{l < m \in N_i} \int_{\partial[l] \cap \partial[m]} \operatorname{Len}_{l,m}(s) ds$$

$$E(P) = \sum_{i=1}^{r} \left[ \sum_{l \in N_i} \int_{[l]} f_l(x) dx + \lambda_i \sum_{l < m \in N_i} d(l, m) \cdot \text{Length}(\partial[l] \cap \partial[m]) \right]$$
Data term

Length term

Geodesic Length: Len<sub>l,m</sub> $(s) = d(l,m) \cdot g_{l,m}(s)$ 

$$E(P) = \sum_{i=0}^{r-1} \sum_{u \in N_i} \int_{[u]} f_{P_i(u)}(x) dx + \sum_{i=1}^r \lambda_i \cdot \sum_{l < m \in N_i} \int_{\partial[l] \cap \partial[m]} \operatorname{Len}_{l,m}(s) ds$$

$$D_u(l) = \int_{[u]} f_l(x) \mathrm{d}x$$

Neighbourhoods  $\mathcal{N}_i \subset N_i \times N_i$ 

$$E(P) = \sum_{i=0}^{r-1} \left[ \sum_{u \in N_i} D_u(P_i(u)) + \lambda_i \sum_{u,v \in \mathcal{N}_i} V_{u,v}(P_i(u), P_i(v)) \right]$$

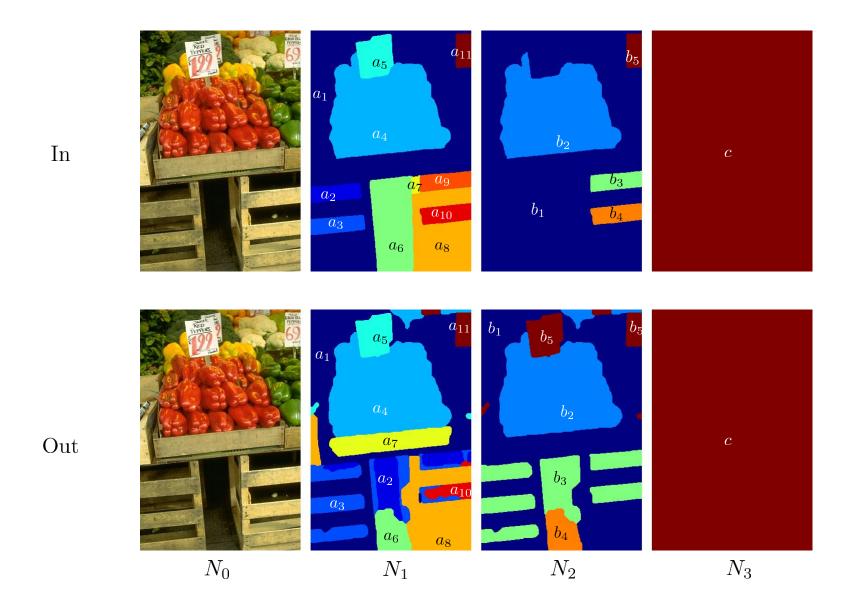
$$E(P) = \sum_{i=0}^{r-1} \left[ \sum_{u \in N_i} D_u(P_i(u)) + \lambda_i \sum_{u,v \in \mathcal{N}_i} V_{u,v}(P_i(u), P_i(v)) \right]$$

$$= \sum_{i=0}^{r-1} E_i(P_i)$$

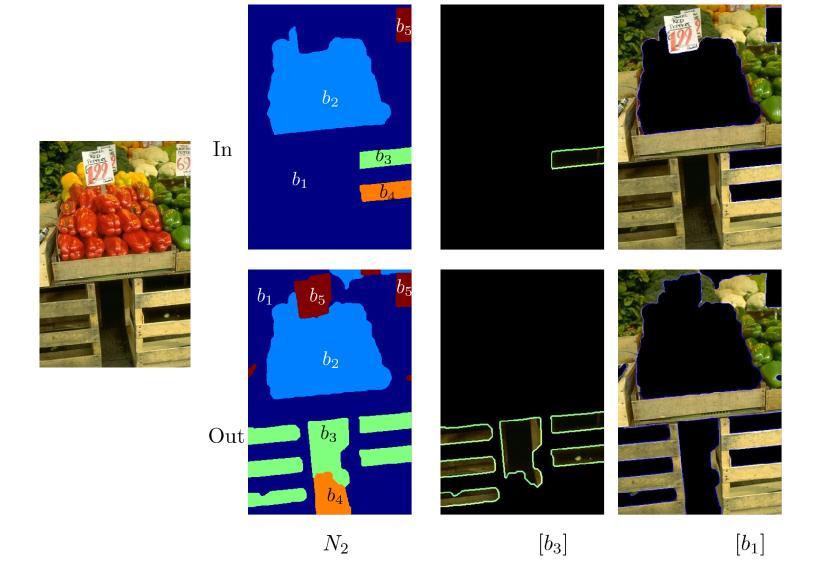
$$E_i(P_i) = \left[ \sum_{u \in N_i} D_u(P_i(u)) + \lambda_i \sum_{u,v \in \mathcal{N}_i} V_{u,v}(P_i(u), P_i(v)) \right]$$

 $E_i$  can be optimized via  $\alpha$ -expansion.

This results in a new hierarchy  $\hat{P}$  with  $E(\hat{P}) \leq E(P)$ .



# Before and After Optimization: Selected Classes

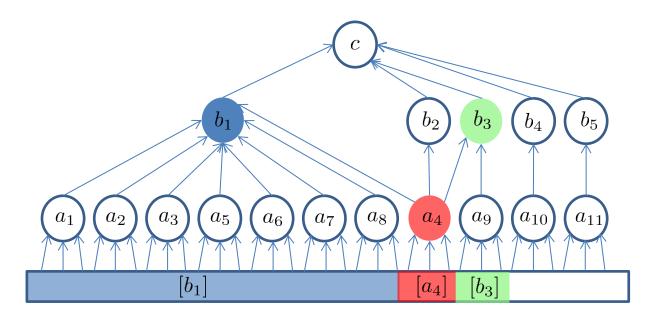


#### Parent Label Costs

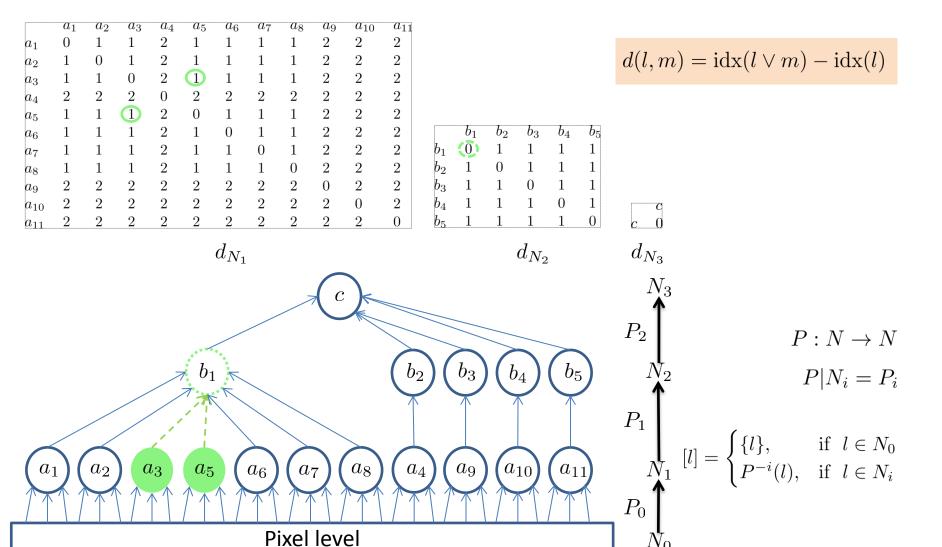
$$D_u(l) = \int_{[u]} f_l(x) \mathrm{d}x$$

$$D_{a_4}(b_1) = \int_{[a_4]} -\log f_{b_1}(x) dx \qquad D_{a_4}(b_3) = \int_{[a_4]} -\log f_{b_3}(x) dx,$$

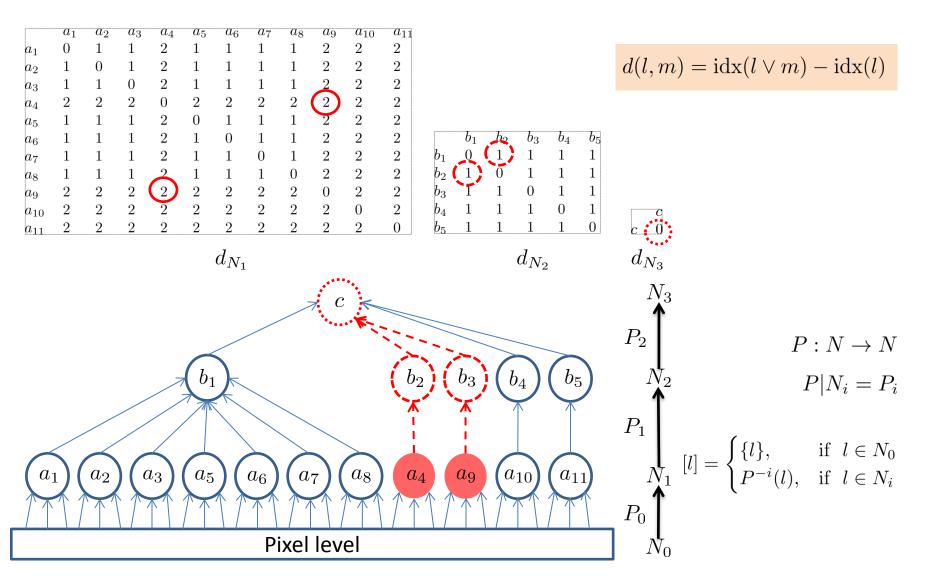
$$D_{a_4}(b_3) = \int_{[a_4]} -\log f_{b_3}(x) dx,$$



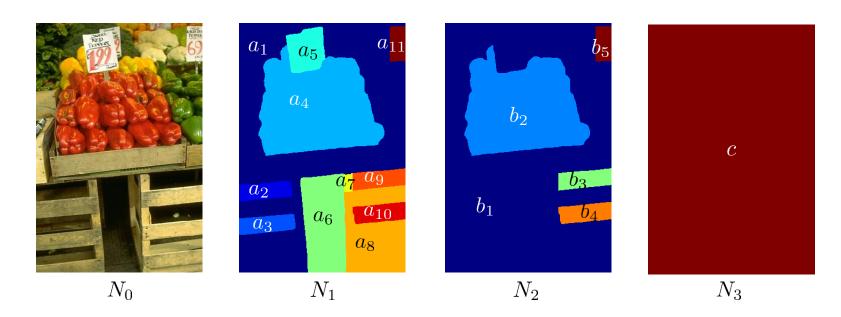
#### **Hierarchical Structure Costs**



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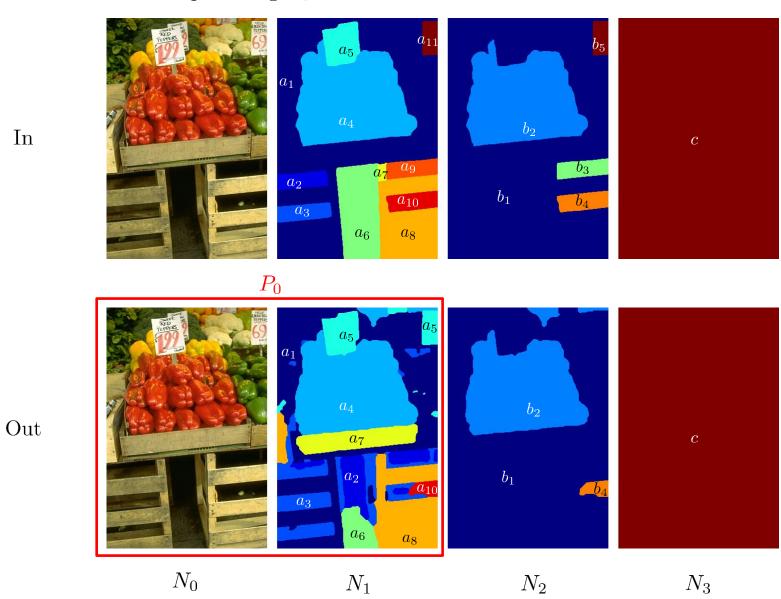
# Inputs: Hierarchy 4 Levels



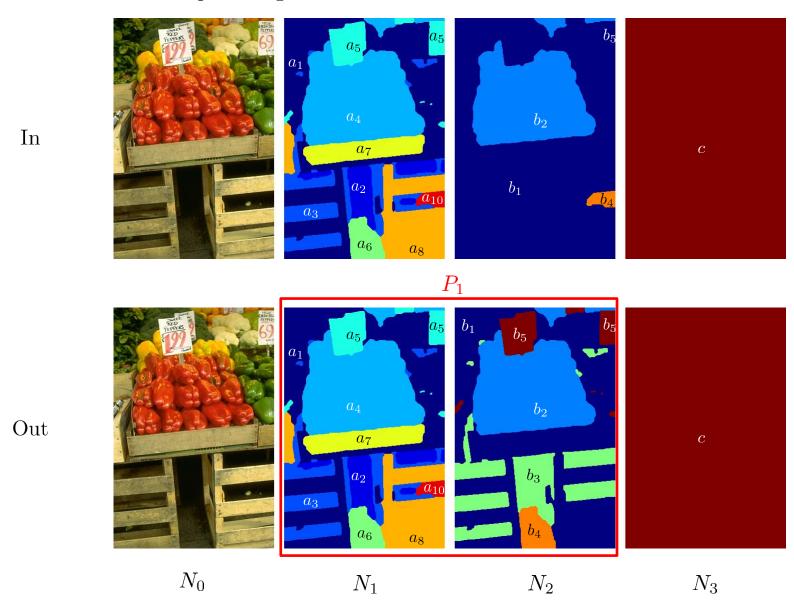
#### Iterate until convergence:

- 1. Optimizing  $E_0(\alpha$ -Expansion, EM)
- 2. Optimizing  $E_1(\alpha$ -Expansion, EM)
- 3. Optimizing  $E_2$  (Trivial solution)

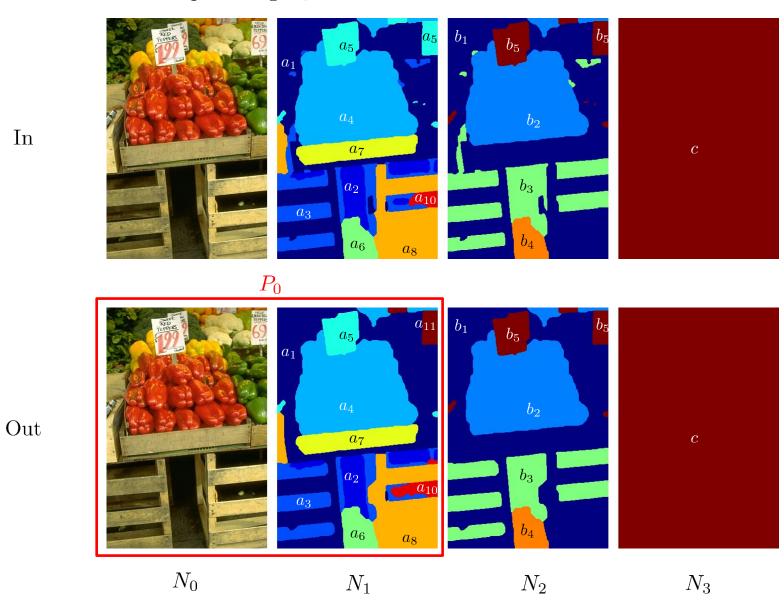
Iteration 1: Optimizing  $E_0$ 



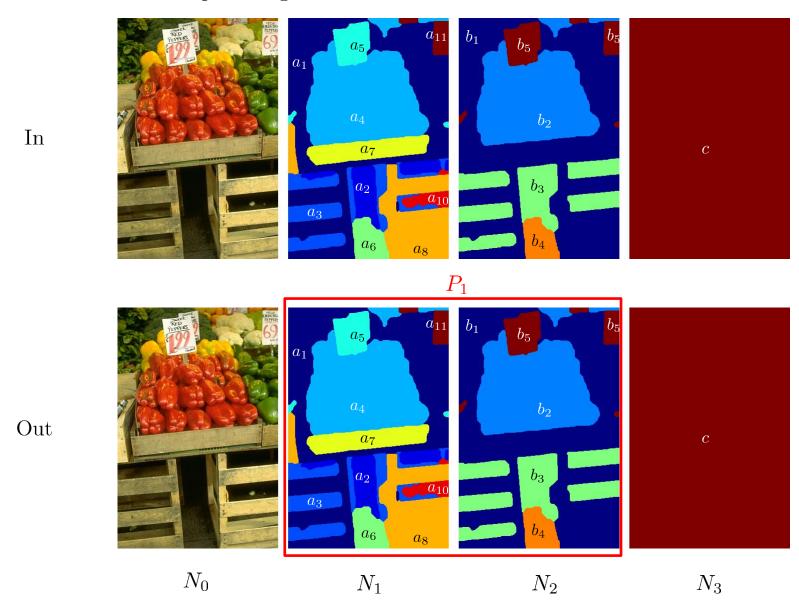
Iteration 1: Optimizing  $E_1$ 



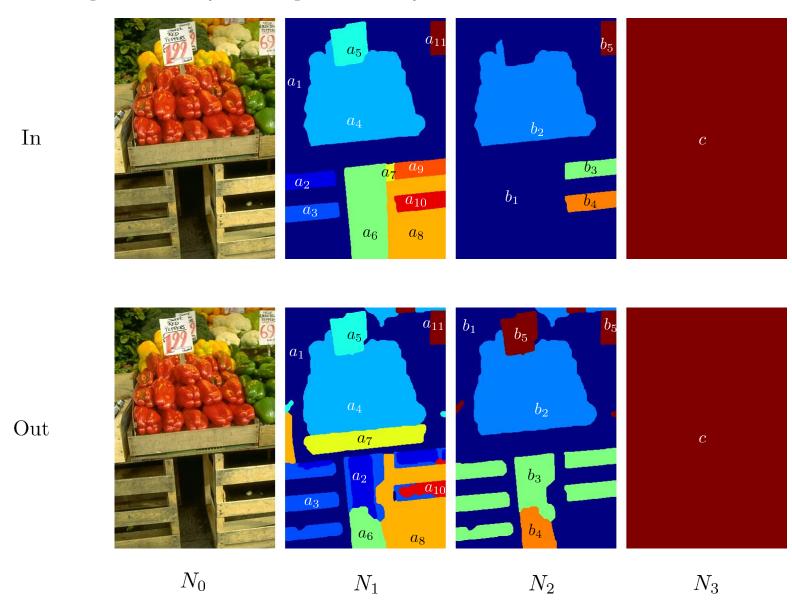
Iteration 2: Optimizing  $E_0$ 



Iteration 2: Optimizing  $E_1$ 



Input Hierarchy Vs Output Hierarchy



Topological Watershed

