Inference by Learning: Speeding-up Graphical Model Optimization via a Coarse-to-Fine Cascade of Pruning Classifiers
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Supplemental materials

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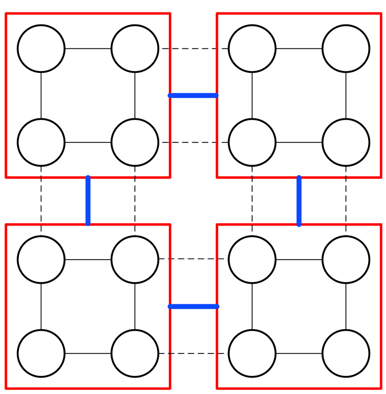
A Toy example for model coarsening



Given $\mathcal{M} = \big(\mathcal{V}, \mathcal{E}, \mathcal{L}, \{\phi_i\}_{i\in\mathcal{V}}, \{\phi_{ij}\}_{(i,j)\in\mathcal{E}}\big)$, a graphical model, we create the coarsened graphical model $\mathcal{M}' = \big(\mathcal{V}', \mathcal{E}', \mathcal{L}, \{\phi'_i\}_{i\in\mathcal{V}'}, \{\phi'_{ij}\}_{(i,j)\in\mathcal{E}'}\big)$.
The vertices of $\mathcal{V}$ are the black circles and the the black thin solid and dashed lines are the edges $\mathcal{E}$. In this toy example, we consider a grouping function g that merges vertices of $\mathcal{V}$ of 2×2 subgrids together.
The grouping function g creates the coarsened graphical model $\mathcal{M}'$ where the red squares are the new induced vertices $\mathcal{V}'$ and the solid thick blue lines are the new induced edges $\mathcal{E}'$.

Figure 1: Toy example for model coarsening

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B Results

B.1 Stereo

B.1.1 Tsukuba

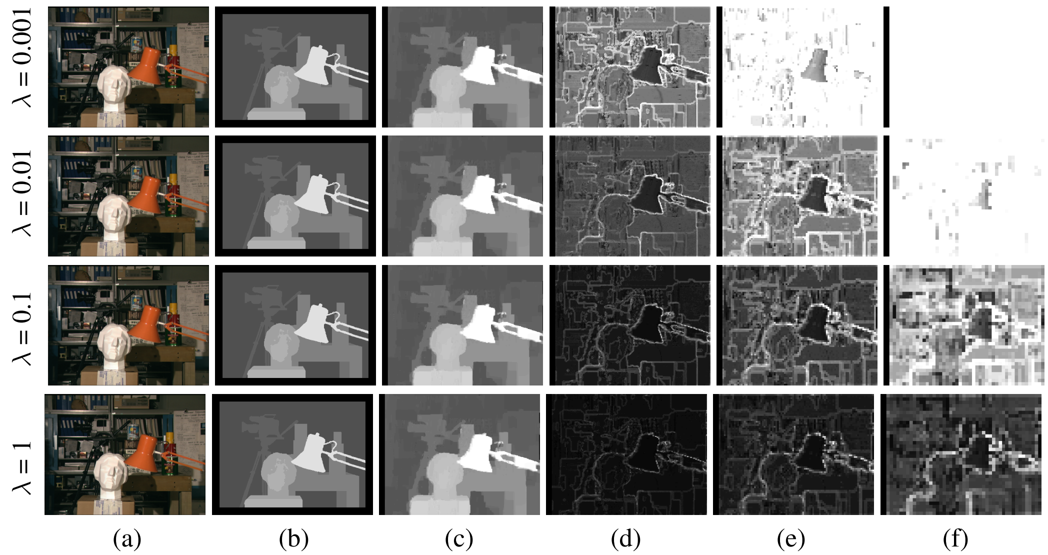

Figure 2: Results of our Inference by Learning framework for Tsukuba. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.1.2 Venus

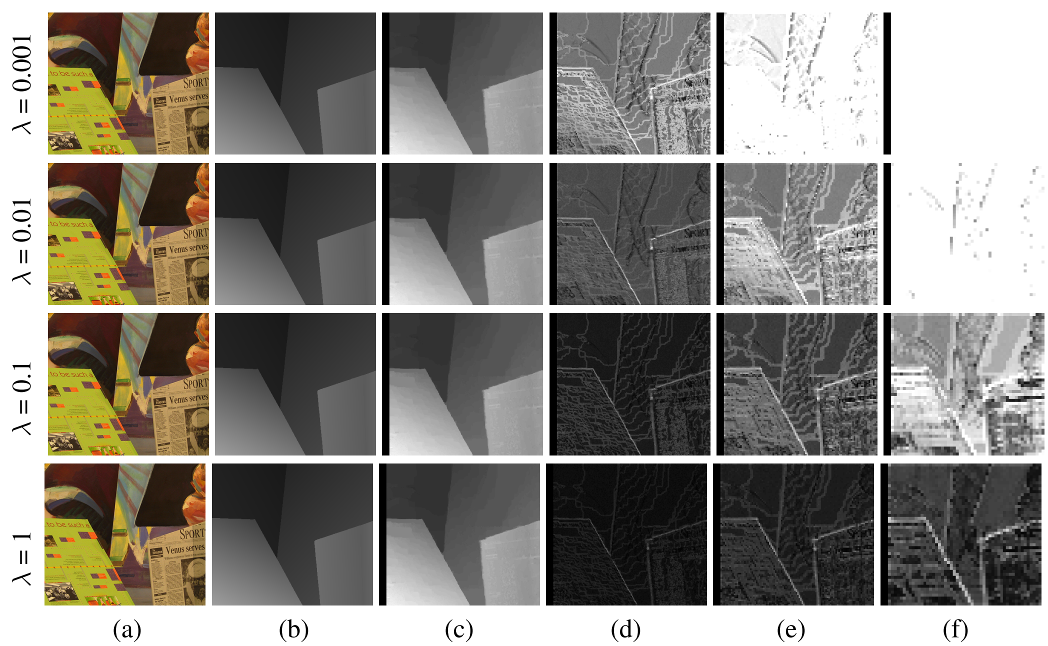

Figure 3: Results of our Inference by Learning framework for Venus. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.1.3 Teddy

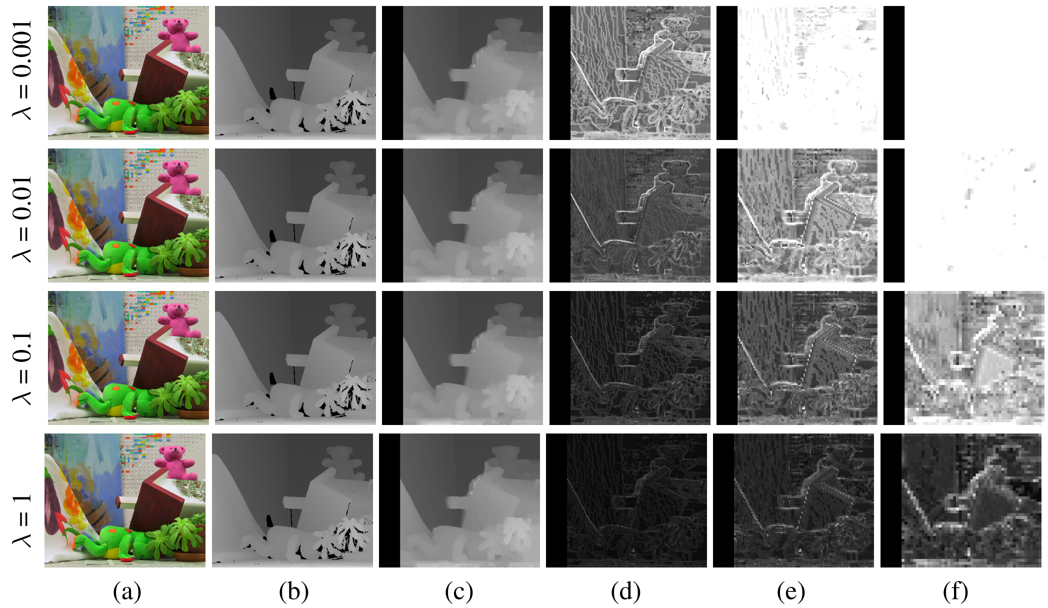

Figure 4: Results of our Inference by Learning framework for Teddy. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.2 Optical-Flow

B.2.1 Army

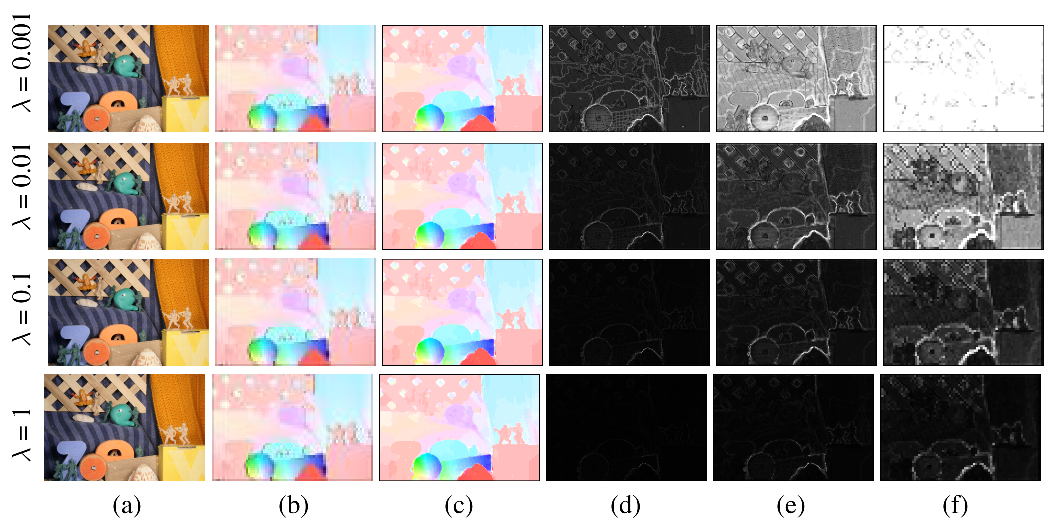

Figure 5: Results of our Inference by Learning framework for Army. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.2.2 Dimetrodon

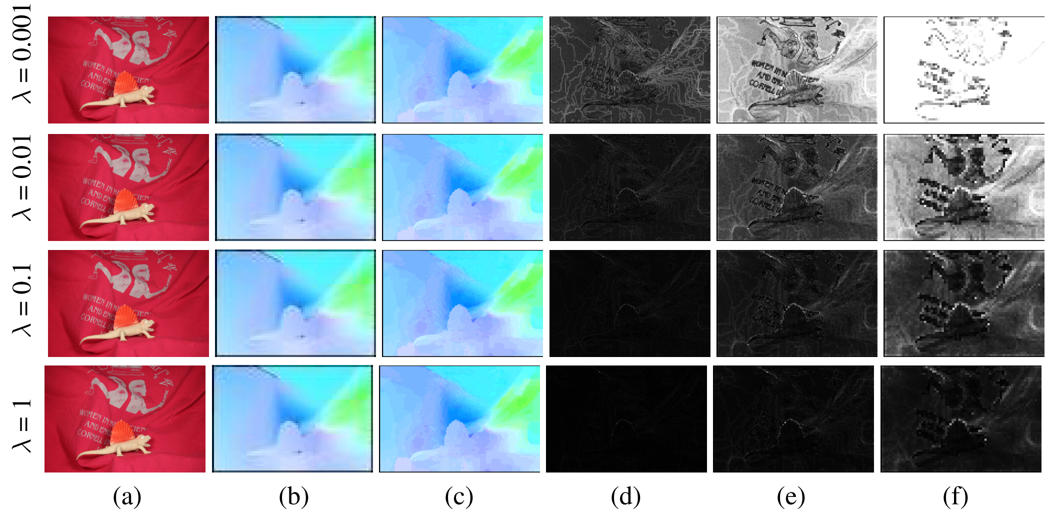

Figure 6: Results of our Inference by Learning framework for Dimetrodon. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.2.3 Rubberwhale

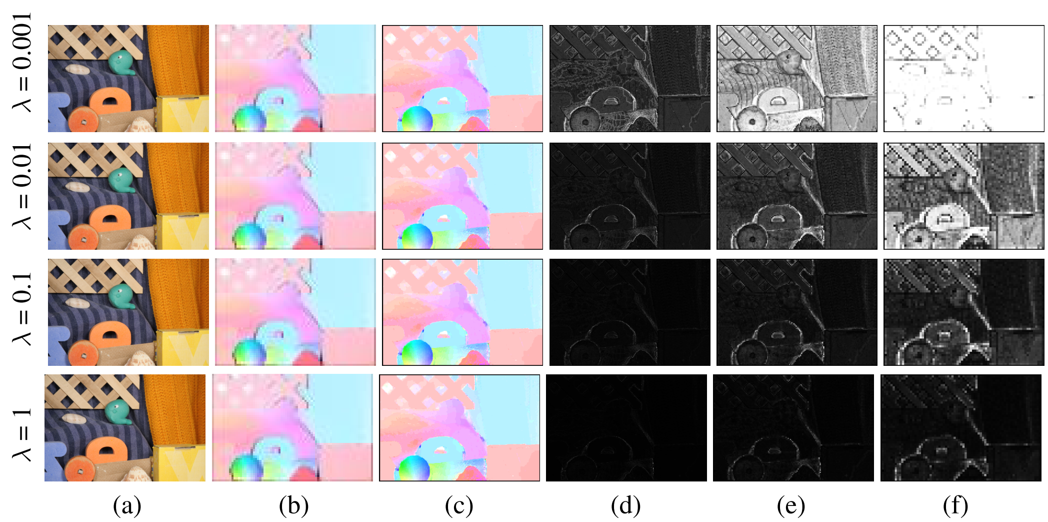

Figure 7: Results of our Inference by Learning framework for Rubberwhale. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.3 Denoising

B.3.1 Penguin

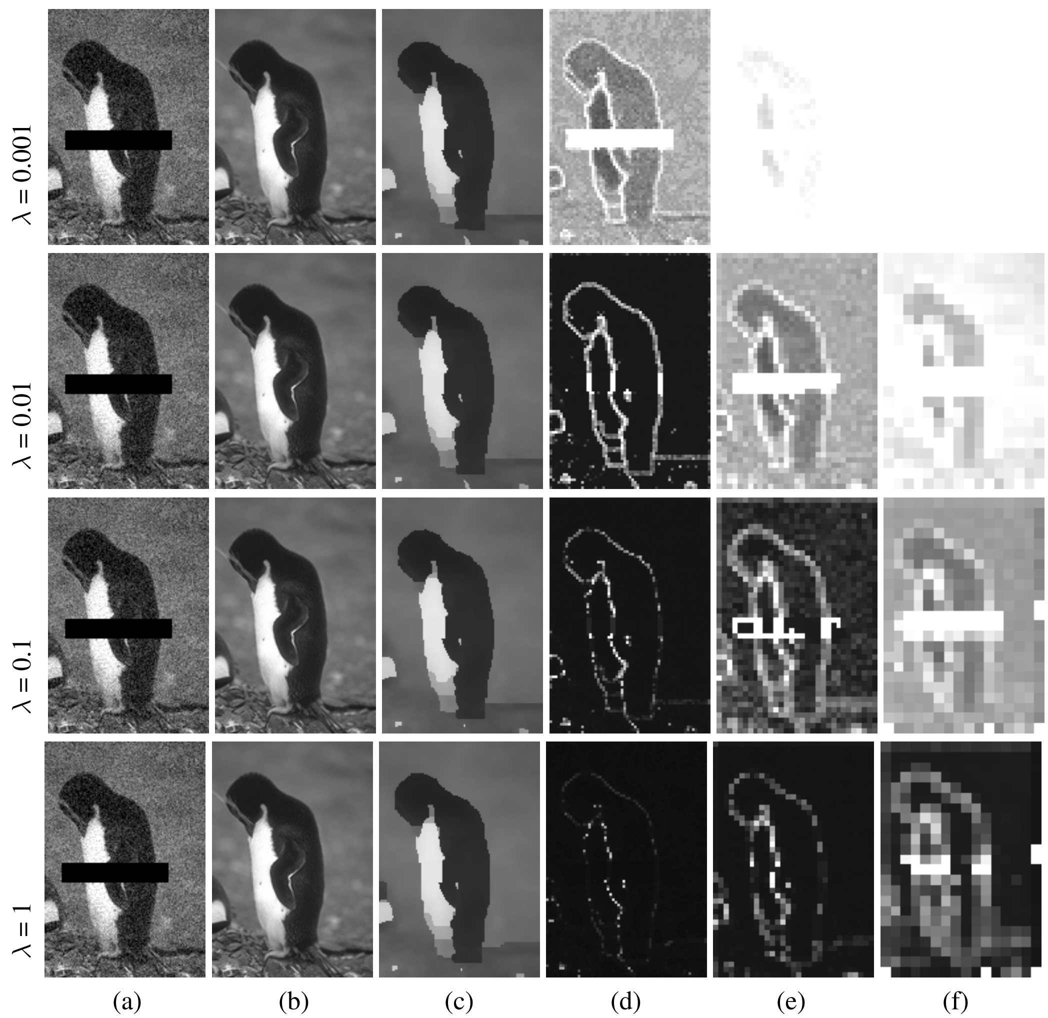

Figure 8: Results of our Inference by Learning framework for Penguin. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).

B.3.2 House

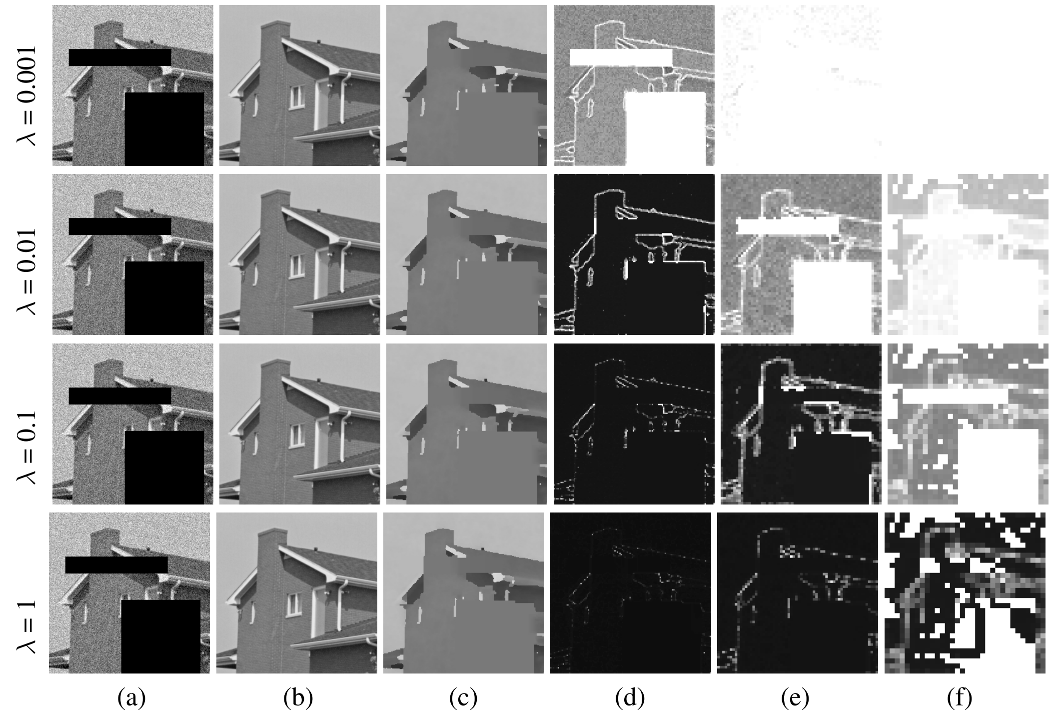

Figure 9: Results of our Inference by Learning framework for House. Each row is a different pruning aggressiveness value (λ). (a) original image, (b) ground truth, (c) solution of the pruning framework, (d,e,f) percentage of active labels per vertex for scale 0, 1 and 2 (black 0%, white 100%).