HIGH-RESOLUTION IMAGE INPAINTING USING MULTI-SCALE NEURAL PATCH SYNTHESIS

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Adobe

BAD THINGS HAPPEN

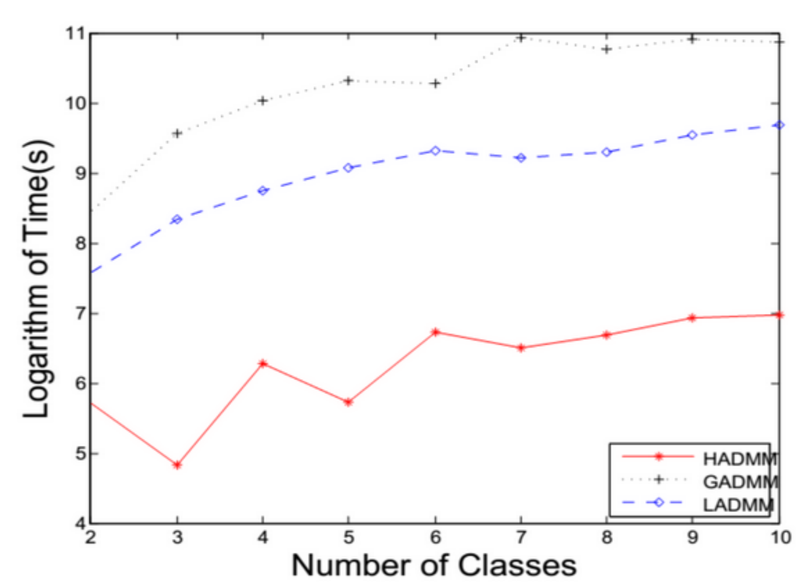
Imaging you would like to edit a photo after breaking up, or restore an old picture from damages, we designed a MULTI-SCALE DEEP LEARNING algorithm to help you! We

- proposed a joint optimization framework that can hallucinates missing image regions by modeling a global content constraint and local texture constraint with convolutional neural networks.
- further introduced a multi-scale neural patch syn- thesis algorithm for high-resolution image in- painting based on the joint optimization framework.

EXPERIMENTS

- Synthetic data

Experiment (Synthetic)

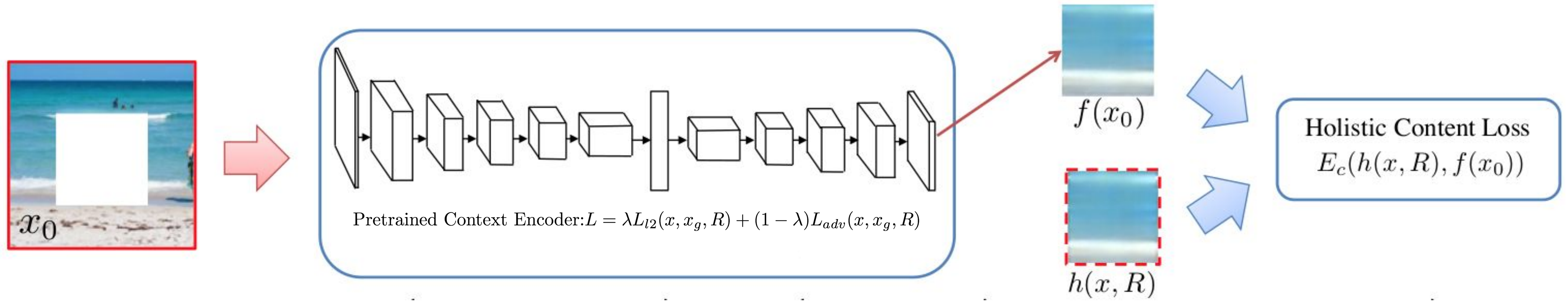


- Real data

Method	Setting 1	Setting 2	Setting 3	Setting 4	Setting 5
HADMM	3.46	8.23	3.9	1.71	1.11
LADMM	> 12	> 12	> 12	3.72	1.98
GADMM	4.2	> 12	> 12	11.04	6.93

THE CONTENT AND TEXTURE NETWORK

From low-res: the content network



To high-res: the texture network A typical joint graphical lasso is formulated as the following optimization problem:

$$\min \sum_{k=1}^{K} L(\mathbf{\Theta}^{(k)}) + P(\mathbf{\Theta}) \tag{1}$$

Where $\mathbf{\Theta}^{(k)} \succ 0$ is the precision matrix $(k = 1, \ldots, K)$ and $\mathbf{\Theta}$ represents the set of $\mathbf{\Theta}^{(k)}$. The negative log-likelihood $L(\mathbf{\Theta}^{(k)})$ and the regularization $P(\mathbf{\Theta})$ are defined as follows.

$$L(\mathbf{\Theta}^{(k)}) = -\log\det(\mathbf{\Theta}^{(k)}) + \mathrm{tr}(\mathcal{S}^{(k)}\mathbf{\Theta}^{(k)}) \tag{2}$$

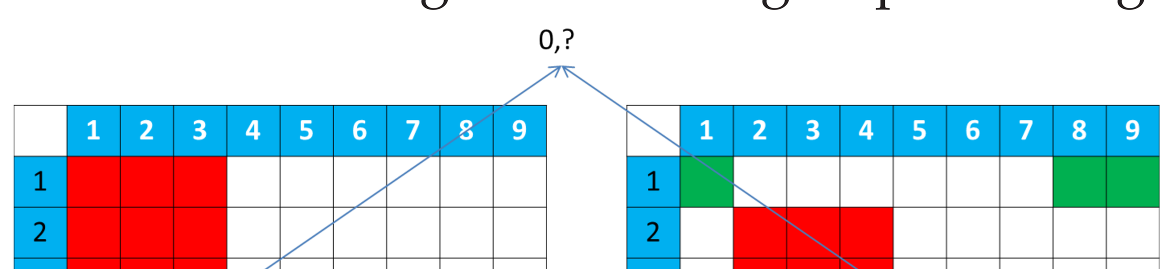
$$P(\mathbf{\Theta}) = \lambda_1 \sum_{k=1}^{K} \|\mathbf{\Theta}^{(k)}\|_1 + \lambda_2 J(\mathbf{\Theta}) \tag{3}$$

Here $\lambda_1 > 0$ and $\lambda_2 > 0$ and $J(\mathbf{\Theta})$ is some penalty function used to encourage similarity (of the structural patterns) among the K classes. In this paper, we focus on group graphical lasso. That is,

$$J(\mathbf{\Theta}) = 2 \sum_{1 \le i < j \le p} \sqrt{\sum_{k=1}^{K} (\mathbf{\Theta}_{i,j}^{(k)})^2} \tag{4}$$

NON-UNIFORM THRESHOLDING

Non-uniform thresholding generates a non-uniform feasible partition by thresholding the K empirical covariance matrices separately. In a non-uniform partition, two variables of the same group in one class may belong to different groups in another class. Figure **??** shows an example of non-uniform partition. In this example, all the matrix elements in white color are set to 0 by non-uniform thresholding. Except the white color, each of the other colors indicates one group. The 7th and 9th variables belong to the same group in the left matrix, but not in the right matrix. Similarly, the 3rd and 4th variables belong to the same group in the right matrix, but not in the left matrix.



Algorithm 1 Hybrid Covariance Screening Algorithm

for $k = 1$ *to* K **do**
  Initialize $\mathbf{I}_{i,j}^{(k)} = \mathbf{I}_{j,i}^{(k)} = 1, \forall 1 \le i < j \le p$
  Set $\mathbf{I}_{i,j}^{(k)} = 0$, if $|\boldsymbol{S}_{i,j}^{(k)}| \le \lambda_1$ and $i \ne j$
  Set $\mathbf{I}_{i,j}^{(k)} = 0$, if $\sum_{k=1}^{K}(|\boldsymbol{S}_{i,j}^{(k)}| - \lambda_1)_+^2 \le \lambda_2^2$ and $i \ne j$
end for
for $k = 1$ *to* K **do**
  Construct a graph $\boldsymbol{G}^{(k)}$ for $\mathcal{V}$ from $\boldsymbol{I}^{(k)}$
  Find connected components of $G^{(k)}$
  for $\forall(i,j)$ *in the same component of* $\boldsymbol{G}^{(k)}$ **do**
    Set $\boldsymbol{I}_{i,j}^{(k)} = \boldsymbol{I}_{j,i}^{(k)} = 1$
  end for
end for
repeat
  Search for triple (x, i, j) satisfying the following condition:
  $\boldsymbol{I}_{i,j}^{k} = 0, |\boldsymbol{S}_{i,j}^{(x)}| > \lambda_1$ and $\exists s$, s.t. $\boldsymbol{I}_{i,j}^{(s)} = 1$
  if $\exists(x, i, j)$ satisfies the condition above **then**