

# Summarizing Visual Data Using Bidirectional Similarity

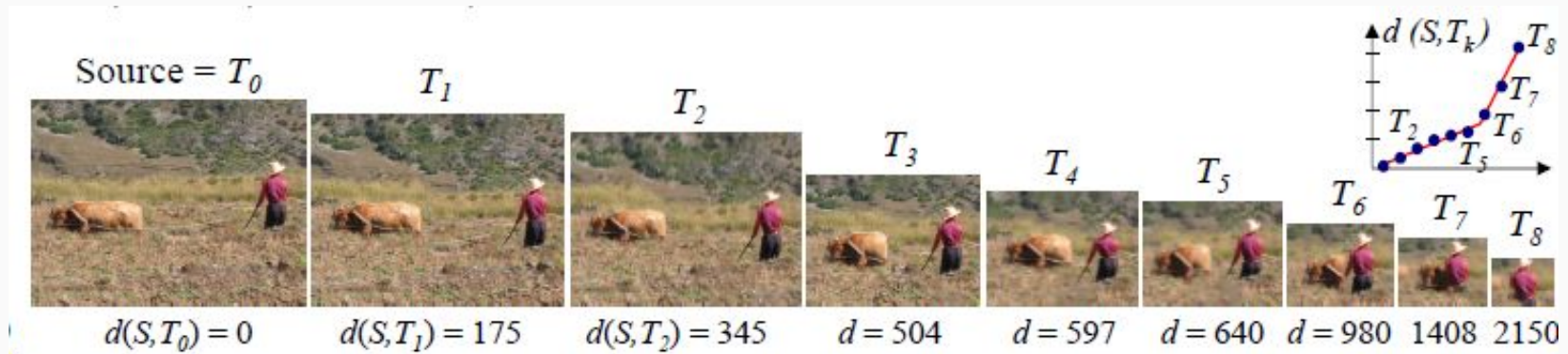
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# Visual Summary

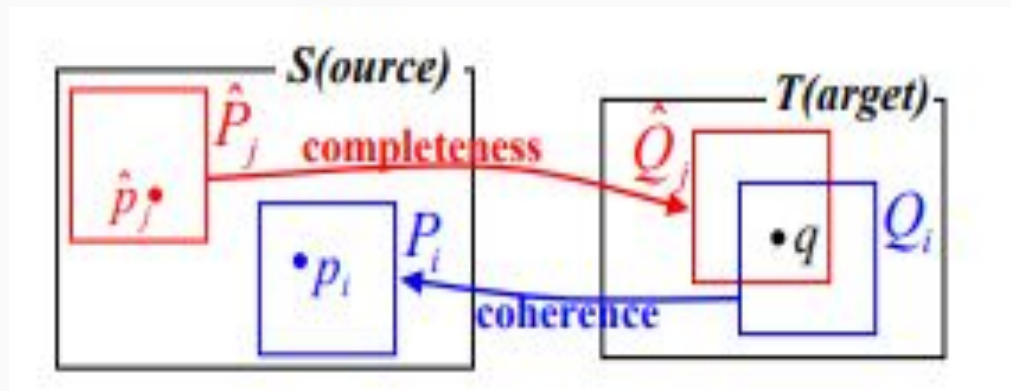
## Goal:

Produce a smaller image that summarizes the content of the larger image



# Comparing two images

- Completeness
- Coherence



# Similarity Distance

Source



(a)

~~complete~~  
coherent



(b)

~~complete~~  
~~coherent~~



(c)

complete  
*and*  
coherent



# Bidirectional similarity measure

- Error or dissimilarity measure

$$d(S, T) = \overbrace{\frac{1}{N_S} \sum_{P \subset S} \min_{Q \subset T} D(P, Q)}^{d_{\text{complete}}(S, T)} + \overbrace{\frac{1}{N_T} \sum_{Q \subset T} \min_{P \subset S} D(Q, P)}^{d_{\text{cohere}}(S, T)}$$

Where,

S and T are the source and Target images, P and Q are the patches of fixed size of S and T.  
D is the Sum of Squared Difference between the patches.

# The Summarization (Retargeting) Algorithm

# The Iterative Update rule: contribution of a pixel to the coherence measure

- Let  $q$  be a pixel of  $T$ ,  $q$  lies inside  $m$  neighboring patches  $Q_1, Q_2, \dots, Q_m$
- These patches are matched to  $P_1, P_2, \dots, P_m$  in source image  $S$
- The positions corresponding to  $q$  in  $P_1, P_2, \dots, P_m$  are  $p_1, p_2, \dots, p_m$

Hence, the contribution is

$$\frac{1}{N_T} \sum_{i=1}^m \|S(p_i) - T(q)\|^2$$

# The Iterative Update rule: contribution of a pixel to the completeness measure

- Let  $q$  be a pixel of  $T$ ,
- $q$  lies inside  $n$  neighboring patches  $\hat{Q}_1, \hat{Q}_2, \dots, \hat{Q}_n$  that are the nearest patch to some patches of  $S$   $\hat{P}_1, \hat{P}_2, \dots, \hat{P}_n$
- The positions corresponding to  $q$  in  $\hat{P}_1, \hat{P}_2, \dots, \hat{P}_m$  are  $\hat{p}_1, \dots, \hat{p}_m$

Hence, the contribution is

$$\frac{1}{N_S} \sum_{i=1}^n \|S(\hat{p}_i) - T(q)\|^2$$



# Color Update

The best  $T(q)$  should minimise

$$\frac{1}{N_S} \sum_{j=1}^n (S(\hat{p}_j) - T(q))^2 + \frac{1}{N_T} \sum_{i=1}^m (S(p_i) - T(q))^2$$

Color Update:

$$T(q) = \frac{\frac{1}{N_S} \sum_{j=1}^n S(\hat{p}_j) + \frac{1}{N_T} \sum_{i=1}^m S(p_i)}{\frac{n}{N_S} + \frac{m}{N_T}}$$

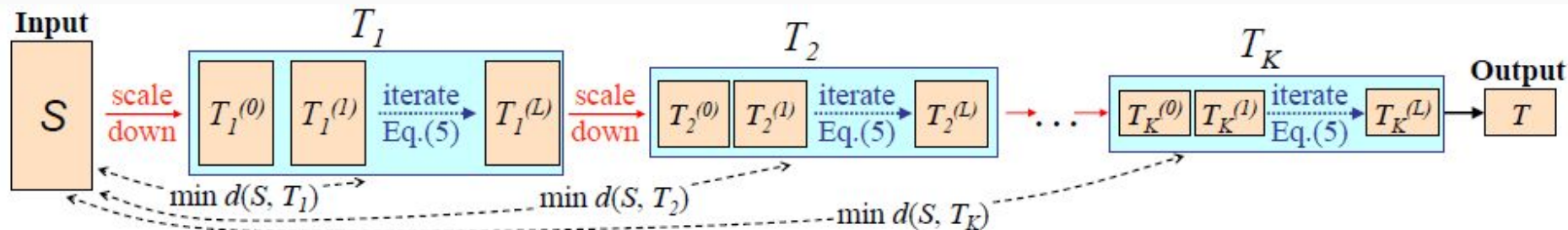
# Iterative Update rule

Given a source signal  $S$ , we want to reconstruct a target signal  $T$  that optimizes the similarity measure



























$$T_{output} = \arg \min_T d(S, T).$$

# Gradual Resizing

- When the target has a very different size from the source: what is a good initial guess?
- Iterative process: downsample the image and apply the reconstruction

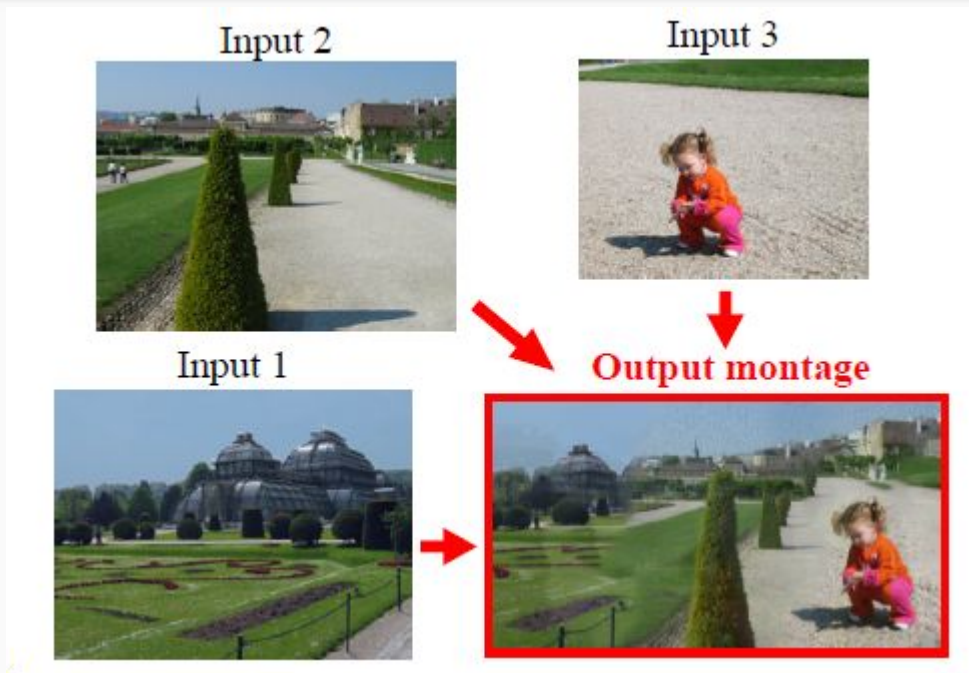


# Visual Summary

Input image	Input image	Input image	Input image	Input image
				
 	 	 	 	 
  	 	 	 	 
pure scaling				
				Wolf et al.

# Applications

# Image Montage



# Image Completion and Synthesis

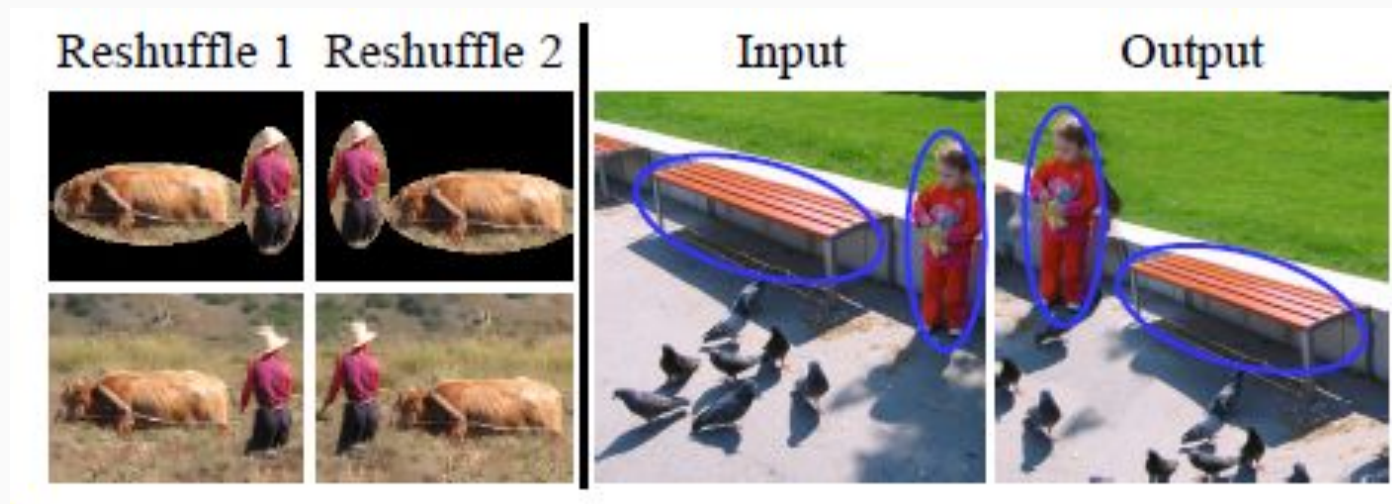
Input



Bigger output (Synthesis)



# Photo Reshuffling



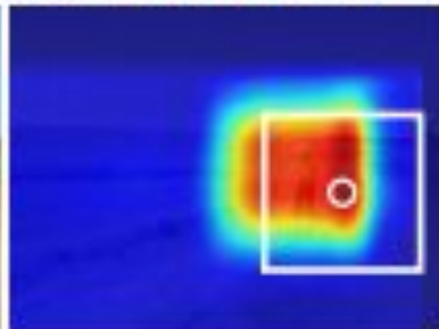


# Automated Optimal Cropping

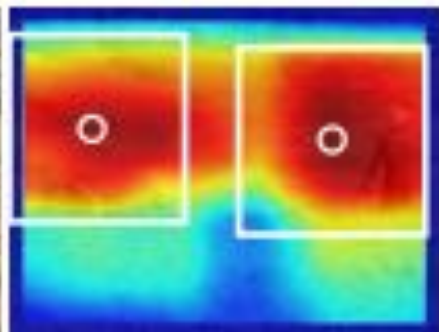
**(a) Input image**



**(b) Bidirectional  
similarity map**



**(c) Detected  
optimal cropping**



## Incorporating Non Uniform Importance

**Input image**



**Importance weights**



**Our summary  
without weights**



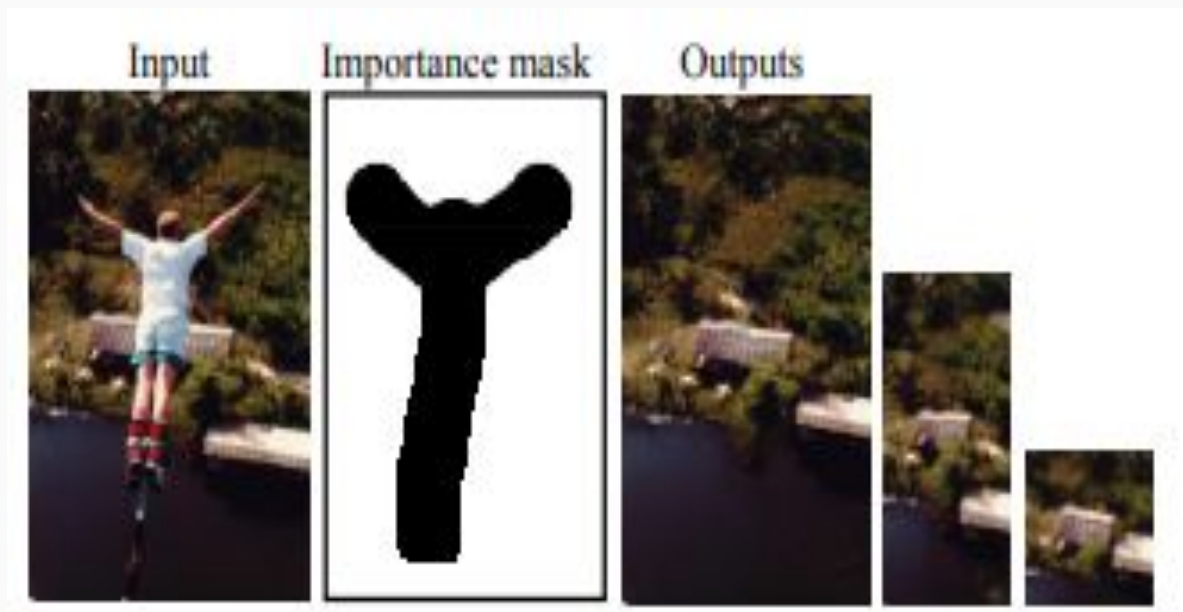
**Our summary  
with weights**



**Wolf et al.  
(with weights)**



# Summarization with object removal constraints



Thank you