Segmentation by Weighted Aggregation for Video

CVPR 2014 Tutorial Slides

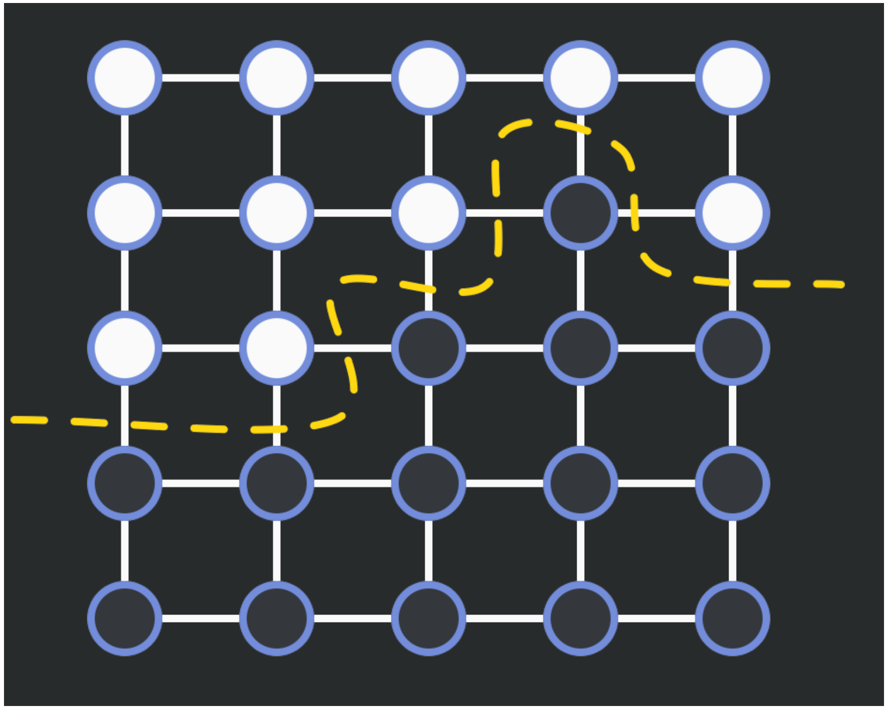
Jason Corso

Segmentation by Weighted Aggregation Set-Up

- Define the problem on a graph: $G = \{\mathcal{V}, \mathcal{E}\}$
  - Edges are sparse, to neighbors.
  - Each pixel / voxel is a node.
- Augment nodes, for $v \in \mathcal{V}$
  - statistics: s_v
  - class label: c_v
- Define affinity between $u, v \in \mathcal{V}$

$$w_{uv} \in \exp\left(-D(s_u, s_v; \theta)\right)$$

  - where D is some non-negative distance function and θ are some predetermined values.
- Regions are defined by cuts.



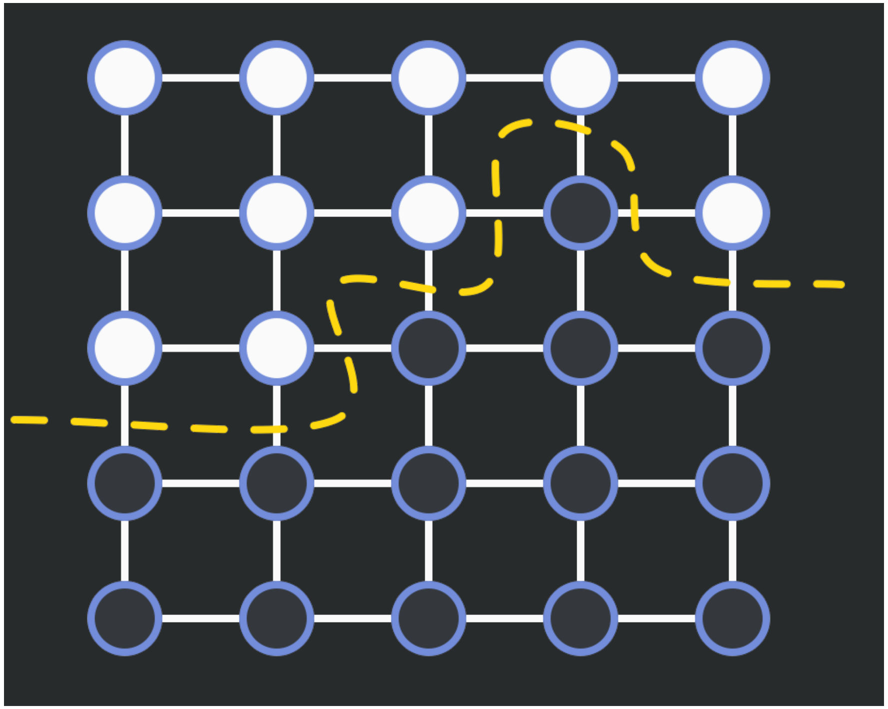
[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

SWA Region Saliency

- Define a region saliency measure.

$$\Gamma(R) = \frac{\sum_{u \in R, v \notin R} w_{uv}}{\sum_{u,v \in R} w_{uv}}$$

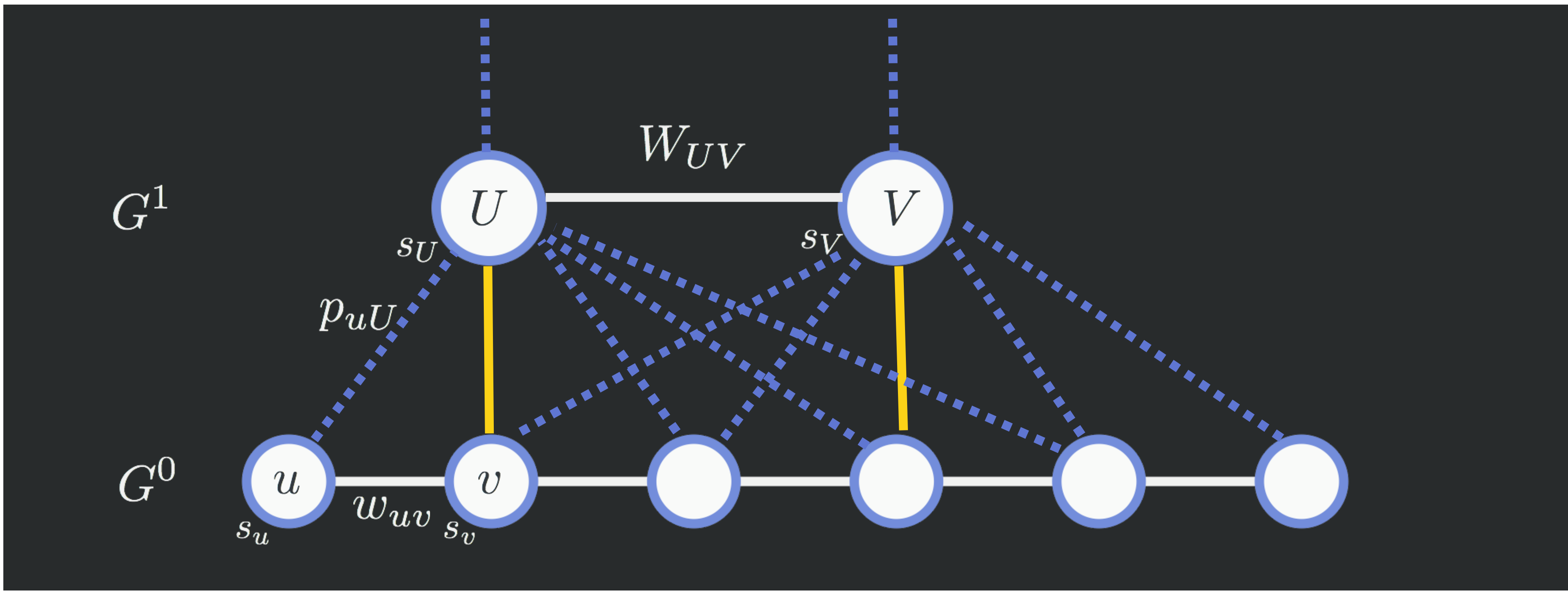
- Low $\Gamma(R)$ means good saliency:
  - Low affinity on boundary.
  - High affinity in interior.
- Criterion is based on the normalized cut criterion (Shi & Malik)
  - Affinities at the pixel scale only.



[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

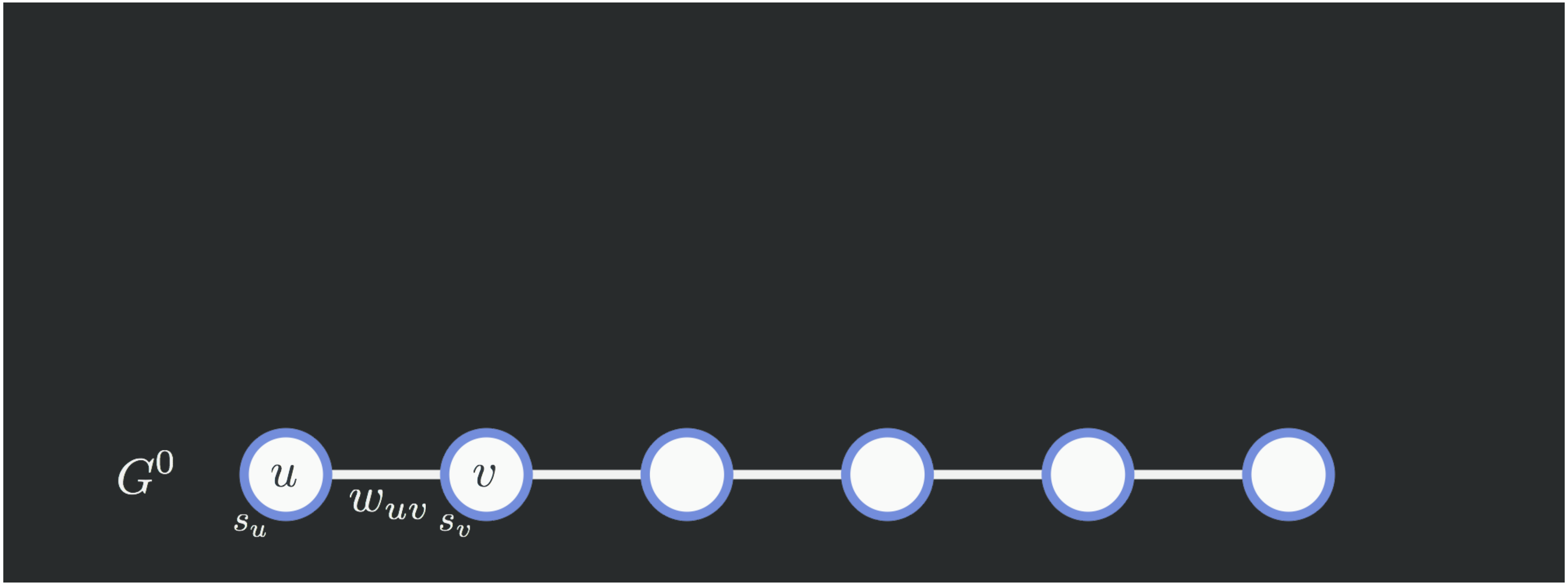
- Invented in natural image domain by Sharon et al. (CVPR 2000, 2001, Nature 2006).
- Used in medical imaging Akselrod-Ballrin (CVPR 2006), Corso et al. (MICCAI 2006, TMI 2008)
- Extended to videos Xu and Corso (CVPR 2012, ECCV 2012)
- Efficient, multiscale process inspired by Algebraic Multigrid optimization.
- Results in a pyramid of recursively coarsened graphs that capture multiscale properties of the data.
- Affinities are calculated at each level of the graph.
- Statistics in each graph node are agglomerated up the hierarchy.



[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Finest layer induced by pixel/voxel lattice
  - 4/6-neighbor connectivity
  - Node properties s_u set according to multimodal image intensities.
  - Affinities initialized by L1-distance: $w_{uv} = \exp\left(-\theta |s_u - s_v|_1\right)$
- Superscripts on graph denotes level in a pyramid of graphs. $\mathcal{G} = \{G^t : t = 0, \ldots, T\}$



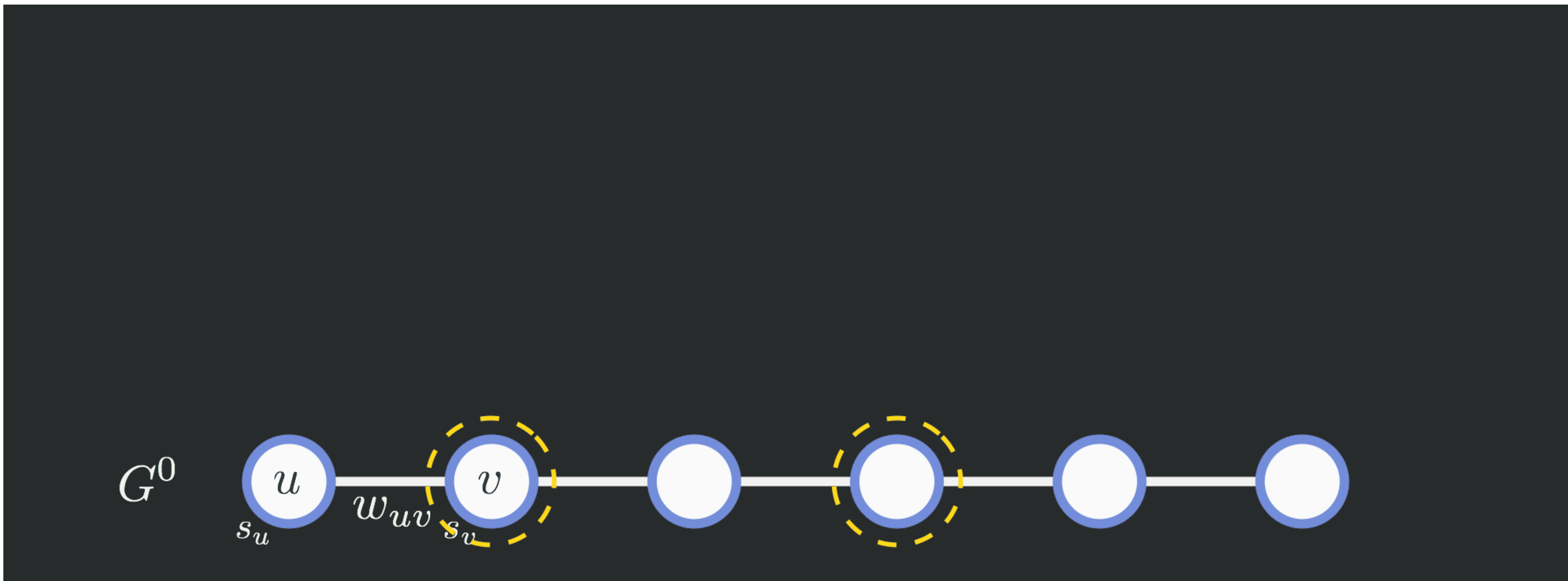
[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Select a representative set of nodes satisfying

$$\sum_{v \in \mathcal{R}^t} w_{uv} \geq \beta \sum_{v \in \mathcal{V}^t} w_{uv}$$

  - i.e., all nodes in finer level have strong affinity to nodes in coarser.



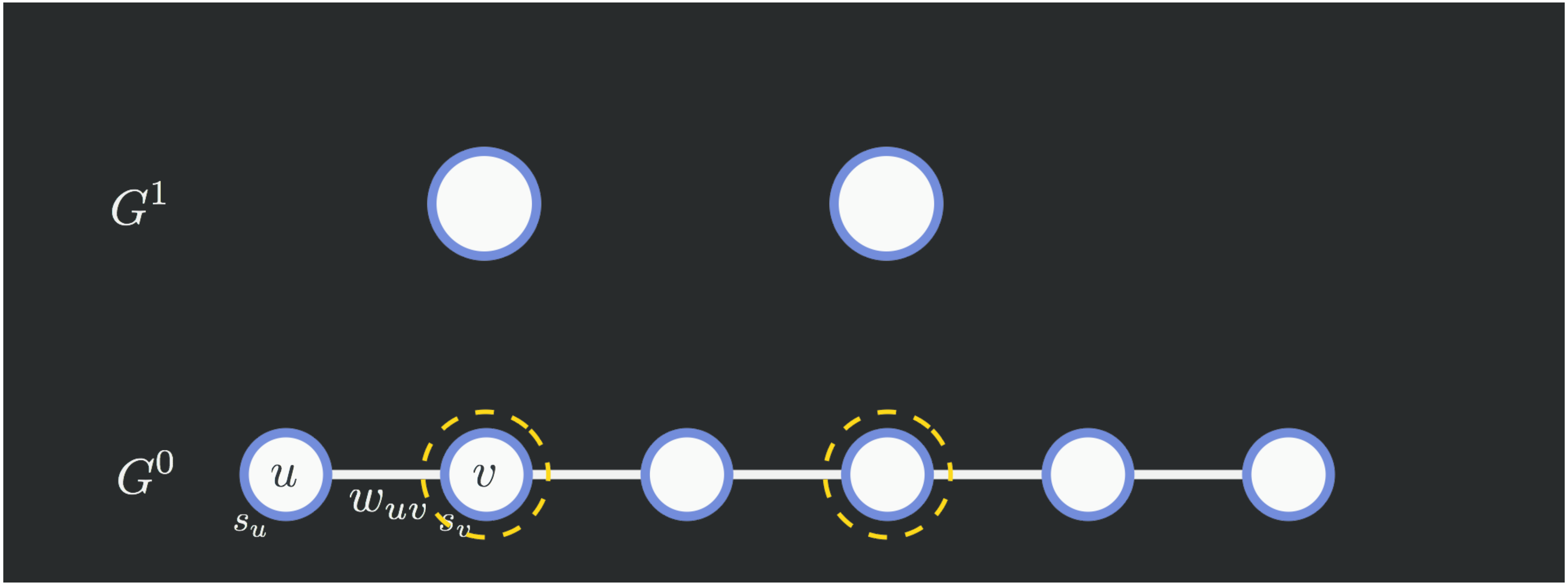
[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Select a representative set of nodes satisfying

$$\sum_{v \in \mathcal{R}^t} w_{uv} \geq \beta \sum_{v \in \mathcal{V}^t} w_{uv}$$

  - i.e., all nodes in finer level have strong affinity to nodes in coarser.
- Begin to define the graph $G^1 = \{\mathcal{V}^1, \mathcal{E}^1\}$

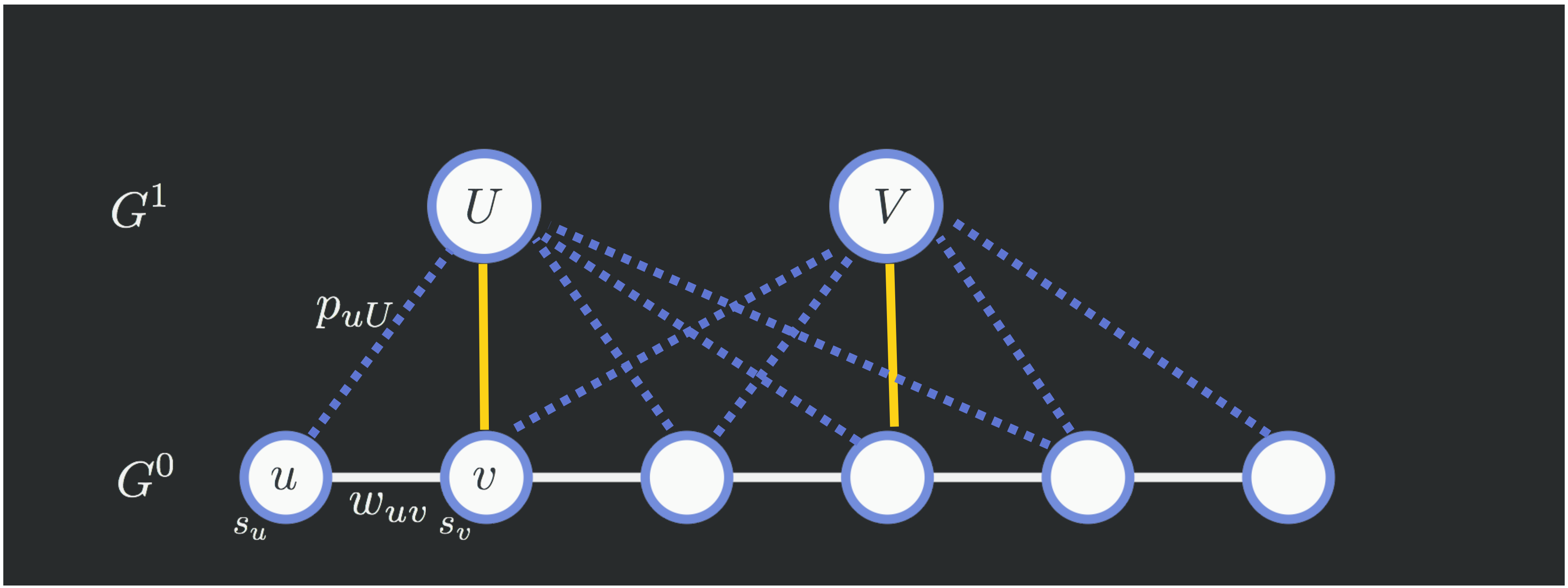


[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Compute interpolation weights between coarse and fine levels

$$p_{uU} = \frac{w_{uU}}{\sum_{V \in \mathcal{V}^{t+1}} w_{uV}}$$



[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

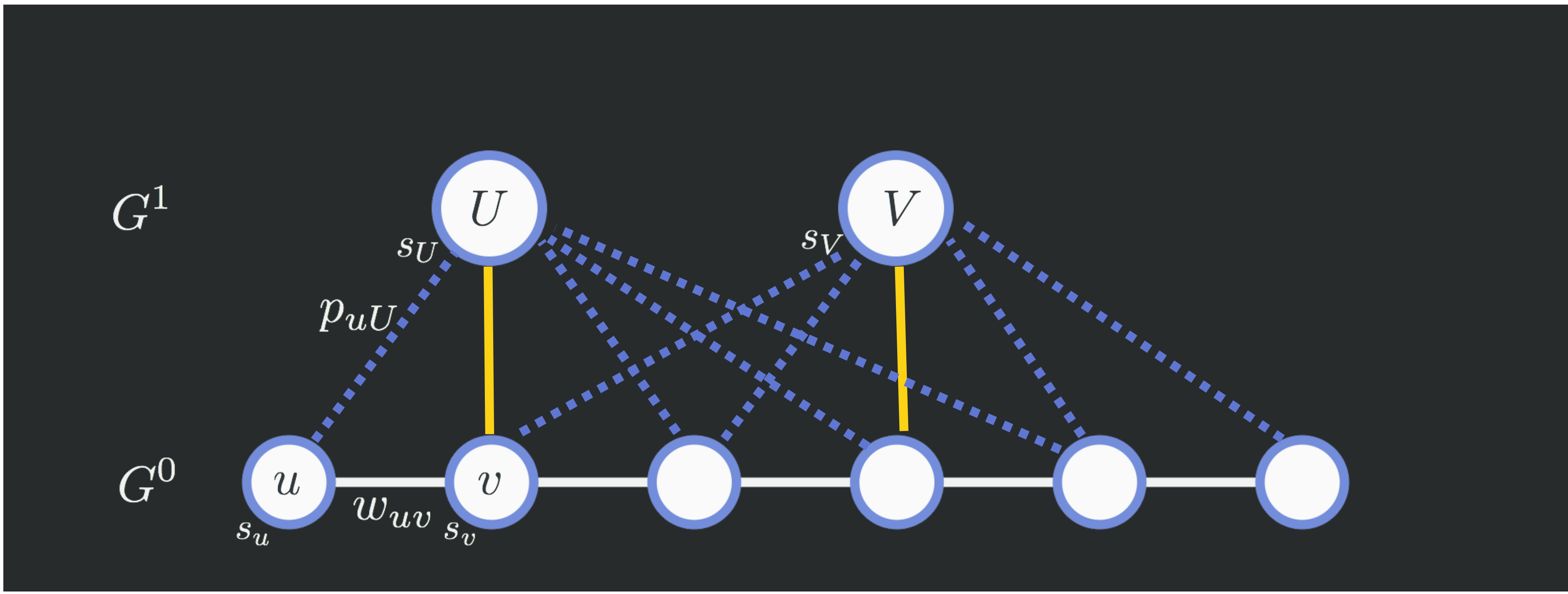
Segmentation by Weighted Aggregation

- Compute interpolation weights between coarse and fine levels

$$p_{uU} = \frac{w_{uU}}{\sum_{V \in \mathcal{V}^{t+1}} w_{uV}}$$

- Accumulate statistics at the coarse level

$$s_U = \sum_{u \in \mathcal{V}^t} \frac{p_{uU}\, s_u}{\sum_{v \in \mathcal{V}^t} p_{vU}}$$

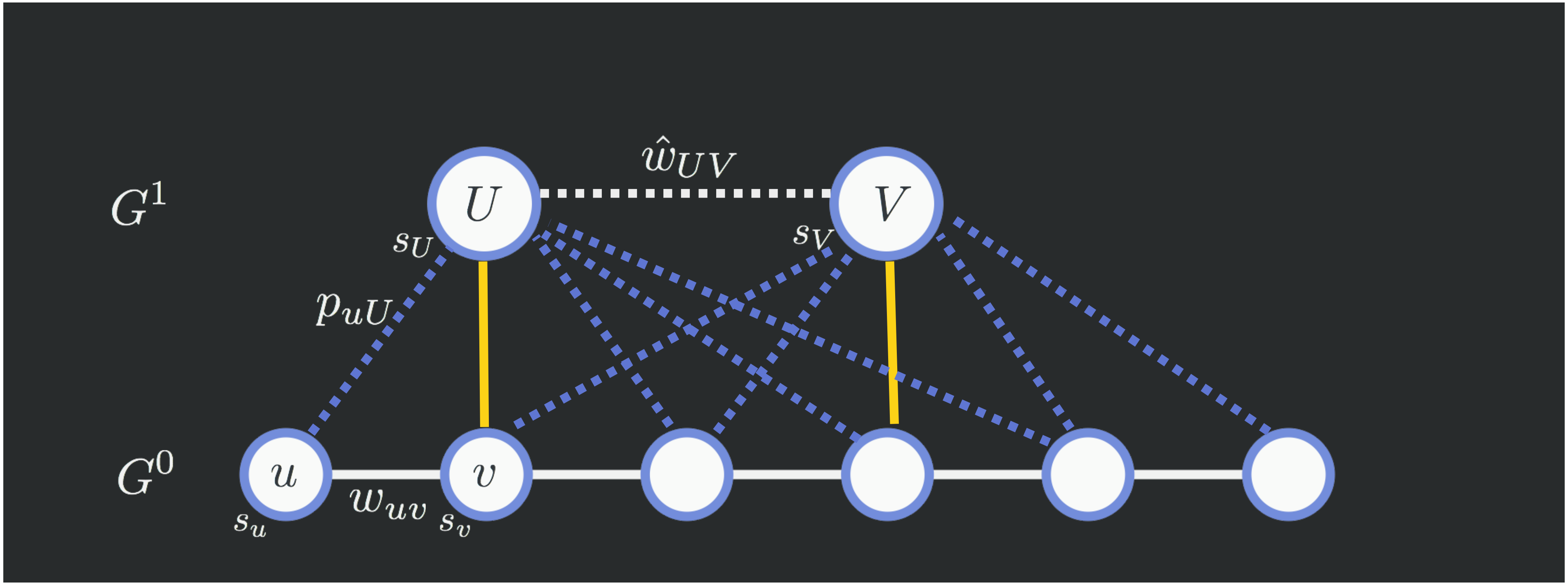


[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Interpolate affinity from finer levels

$$\hat{w}_{UV} = \sum_{(u \neq v) \in \mathcal{V}^t} p_{uU} w_{uv} p_{uV}$$



[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

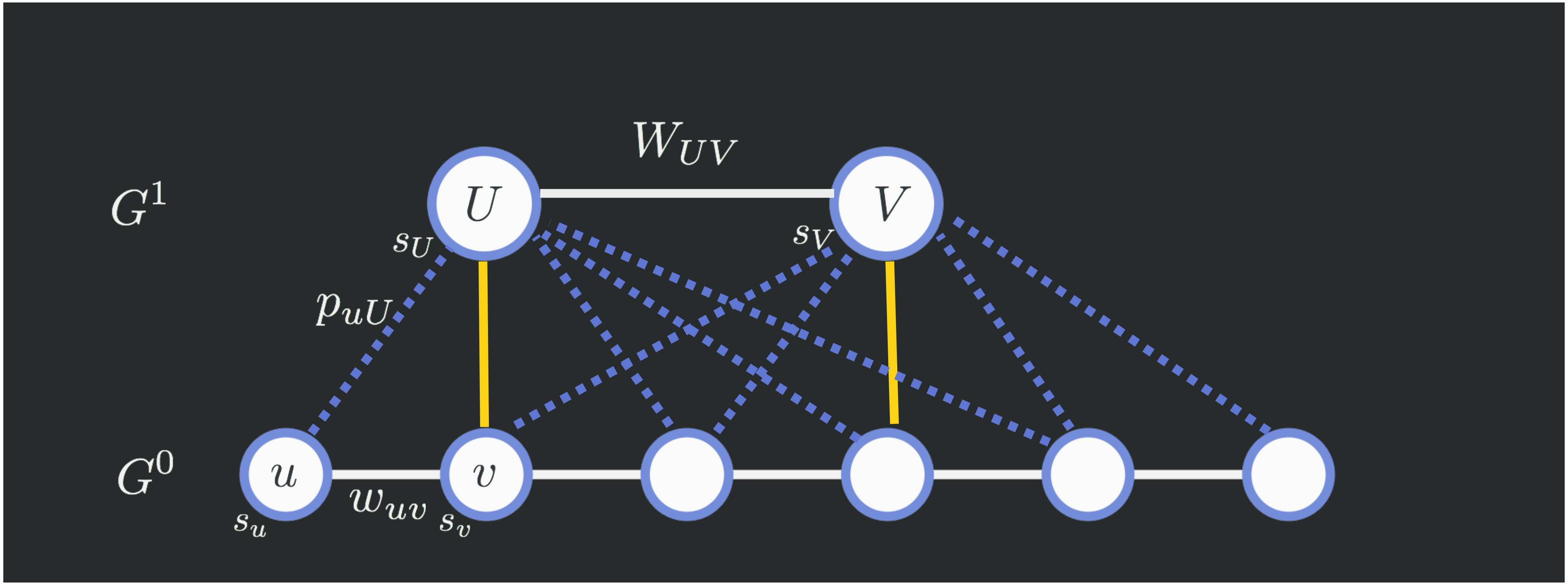
Segmentation by Weighted Aggregation

- Interpolate affinity from finer levels.

$$\hat{w}_{UV} = \sum_{(u \neq v) \in \mathcal{V}^t} p_{uU} w_{uv} p_{uV}$$

- Use coarse affinity to modulate the interpolated affinity.

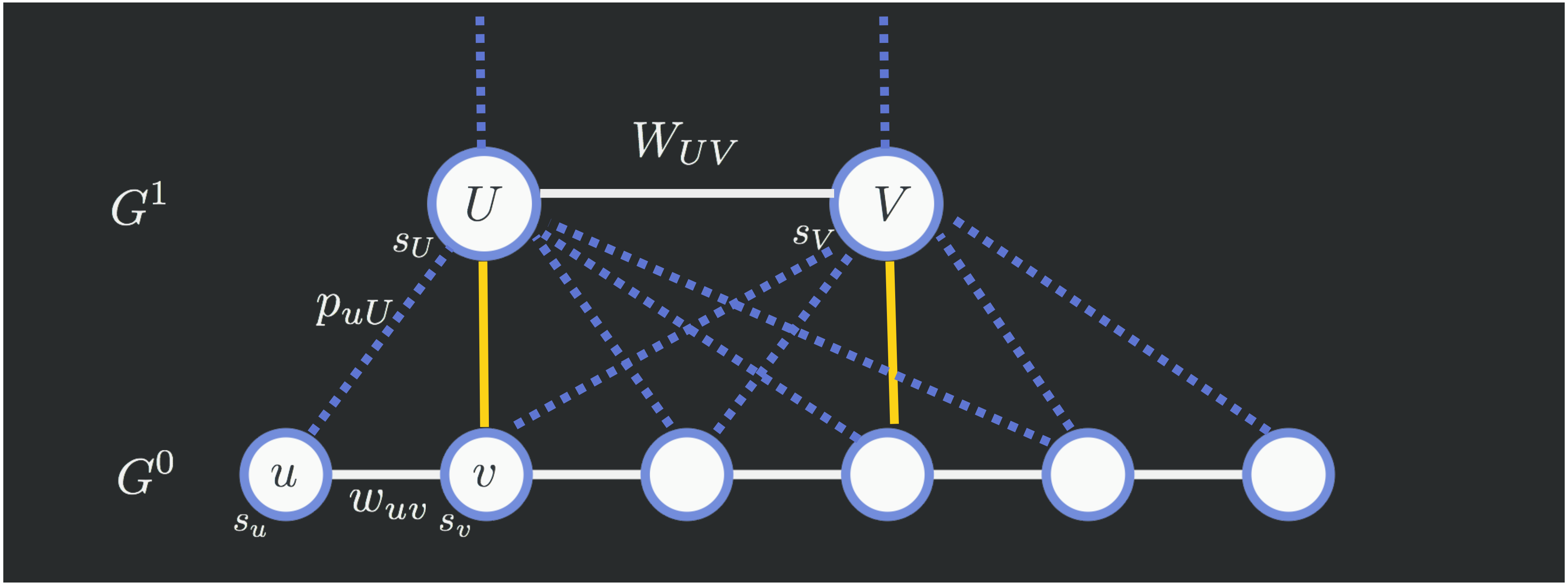
$$W_{UV} = \hat{w}_{UV} \exp\left(-D(s_U, s_V; \theta)\right)$$



[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Segmentation by Weighted Aggregation

- Repeat ...



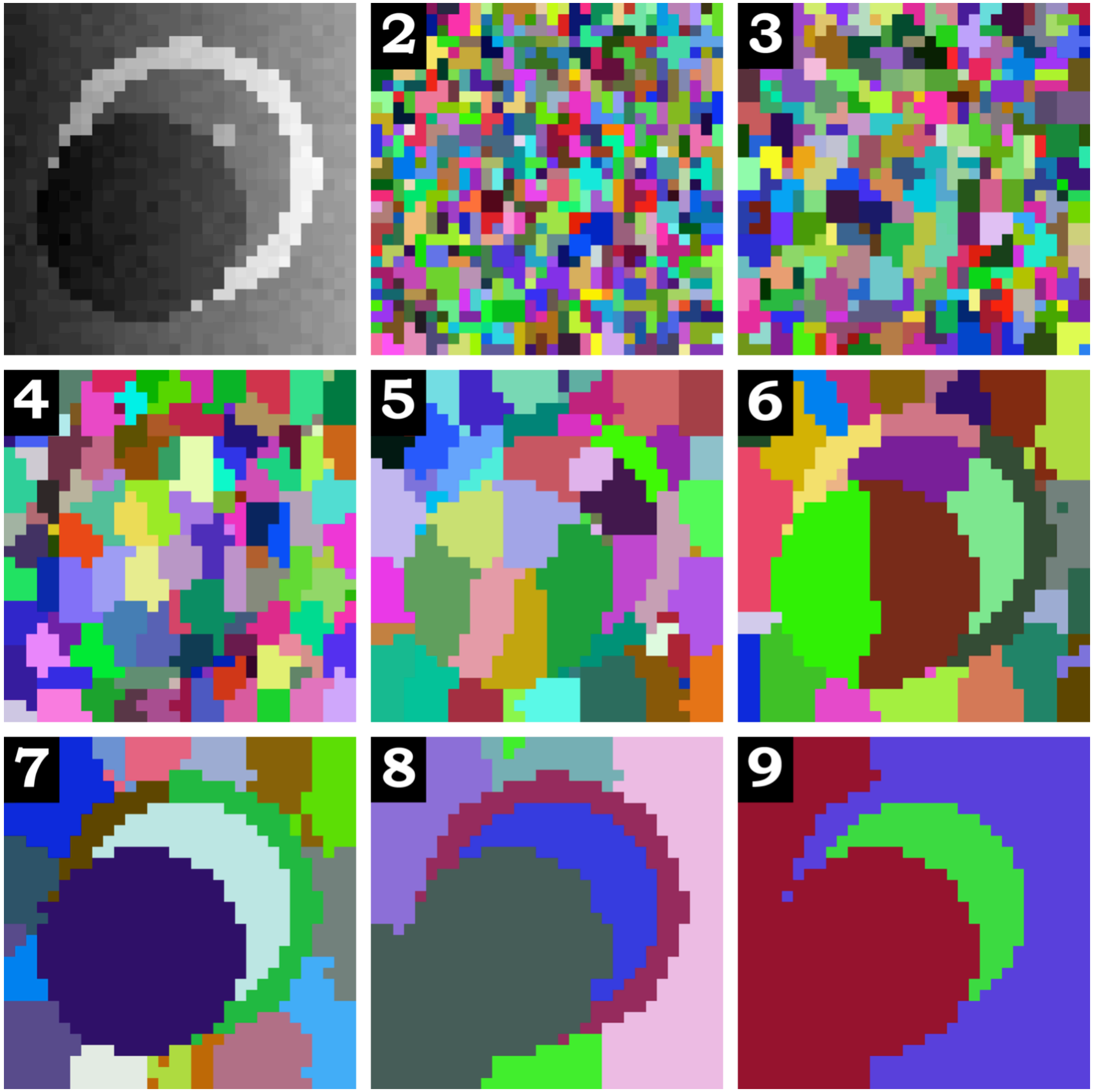
[Sharon et al. CVPR 2001, NATURE 2006. Corso TMI 2008]

Bayesian Affinities

- Standard affinity calculation is based on simple features, such as the L1-distance of intensities as in the example.
- Affinity can be extended using metric learning
  - LMNN [Weinberger et al. NIPS05], ITML [Davis et al. ICML07], RFD [Xiong et al. KDD12]
- Or Bayesian view of affinity [Corso, Yuille TMI 2008]
  - Introduce a binary grouping random variable X_{uv} .

$$
\begin{aligned}
P(X_{uv}|s_u, s_v) &= \sum_{m_u}\sum_{m_v} P(X_{uv}|s_u, s_v, m_u, m_v) P(m_u, m_v|s_u, s_v) \quad , \\
&\propto \sum_{m_u}\sum_{m_v} P(X_{uv}|s_u, s_v, m_u, m_v) P(s_u, s_v|m_u, m_v) P(m_u, m_v) \quad , \\
&= \sum_{m_u}\sum_{m_v} \underbrace{P(X_{uv}|s_u, s_v, m_u, m_v)}_{\text{Model Specific Measurement}} \underbrace{P(s_u|m_u) P(s_v|m_v)}_{\text{Node Likelihoods}} \underbrace{P(m_u, m_v)}_{\text{Class Prior}}
\end{aligned}
$$

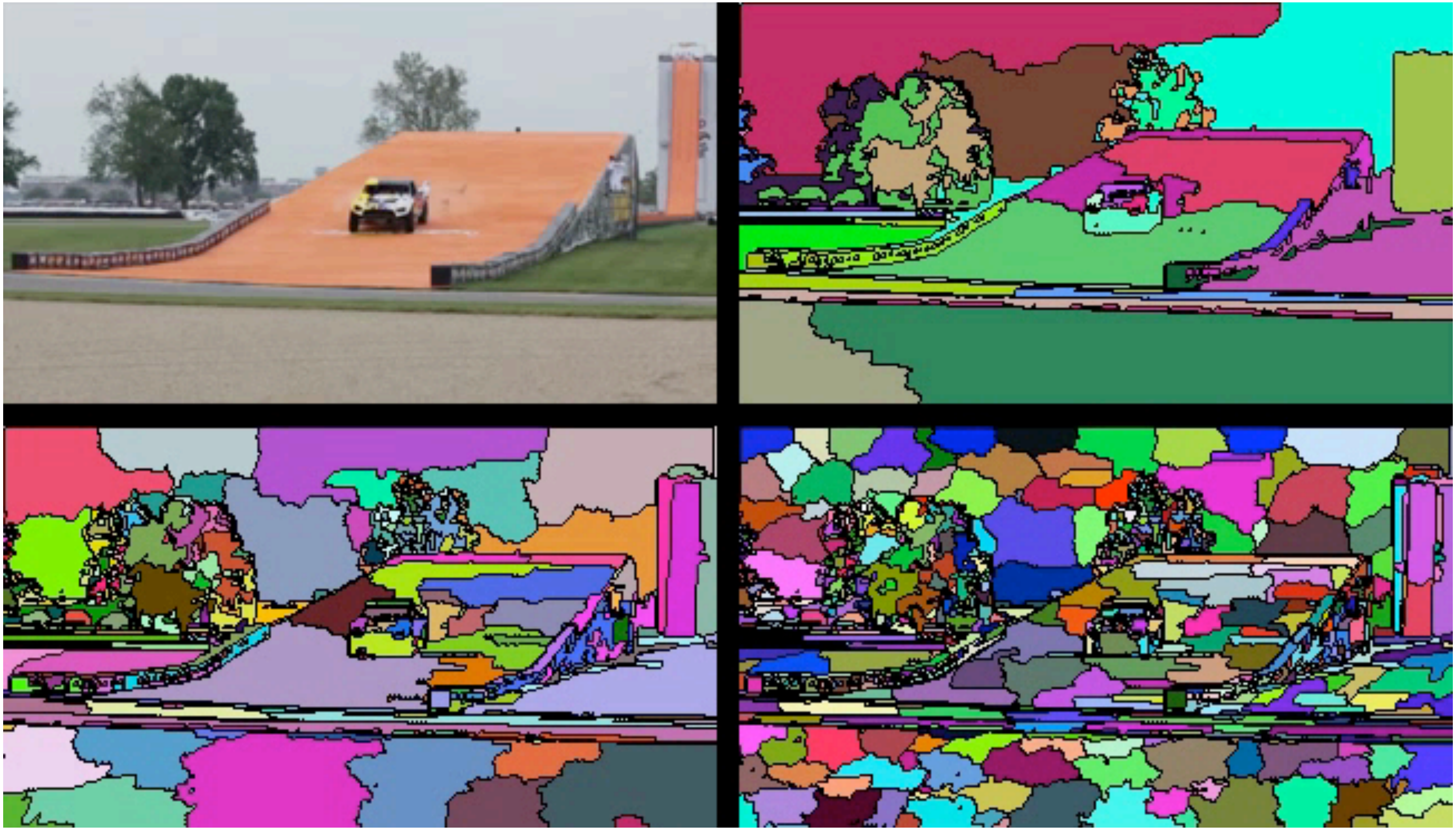
Example on Synthetic Grayscale Image



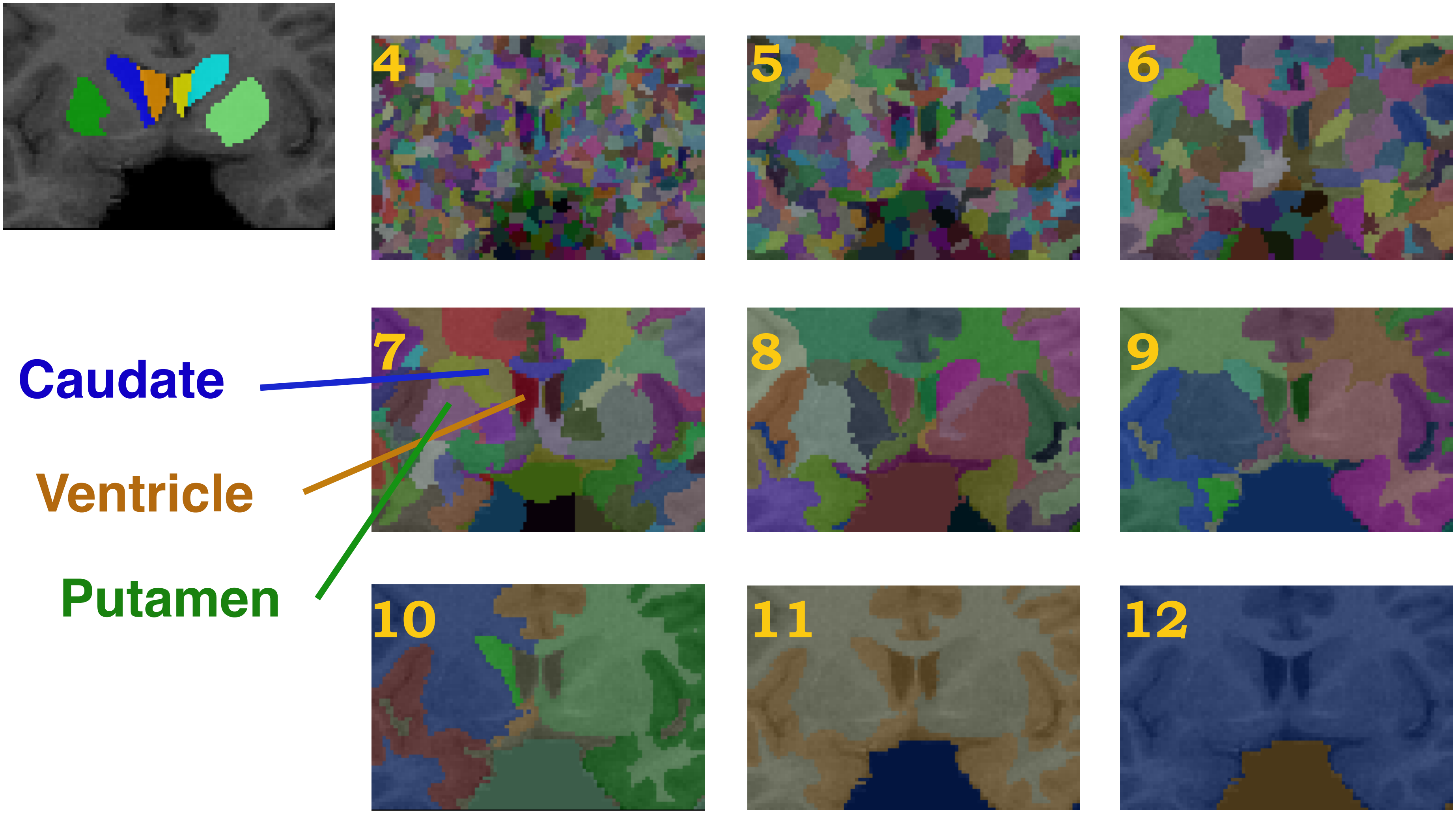
SWA Video Examples

SWA Video Examples

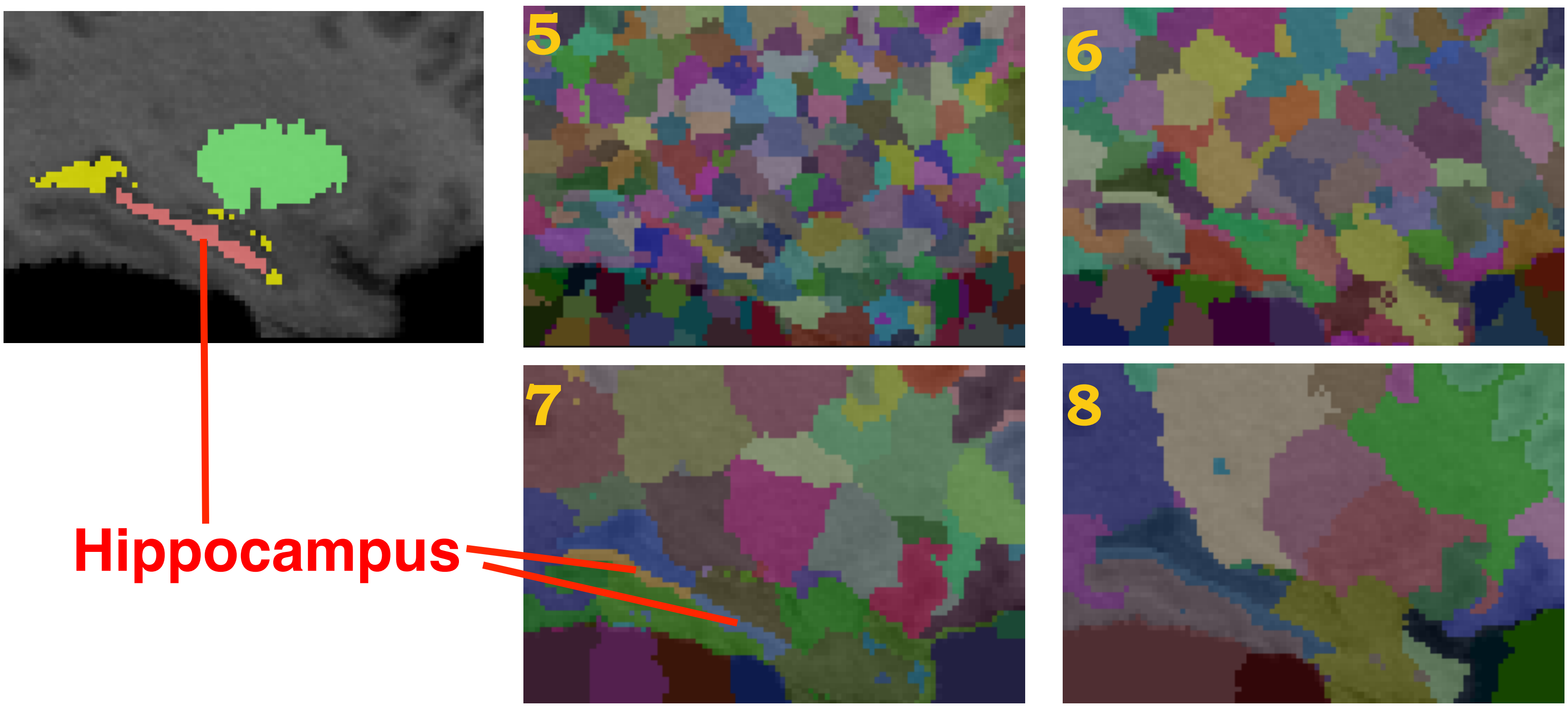
SWA Video Examples



Example of the Segmentation Pyramid



Example of the Segmentation Pyramid



Streaming Hierarchical Video Segmentation

A Framework and Implementation

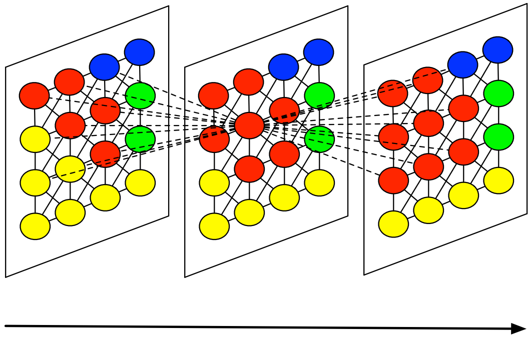
Streaming Hierarchical Video Segmentation

- An approximation framework for Streaming Hierarchical Video Segmentation.
- We'll discuss the minimum spanning forest method within the framework: **StreamGBH**.
- Incorporates ideas from the data streams literature to allow
  - a constant (and small) memory requirement,
  - a method to handle arbitrarily long (or streaming) video,
  - a balance between subsequence length and overall performance.

[Xu, Xiong and Corso, ECCV 2012]

Why Streaming?

- Practical use of video segmentation presents two problems
  - **Memory**—Videos are an order of magnitude larger than images.
  - **Duration**—how much of the video to process at once.
    - Indeed some videos are *endless.*

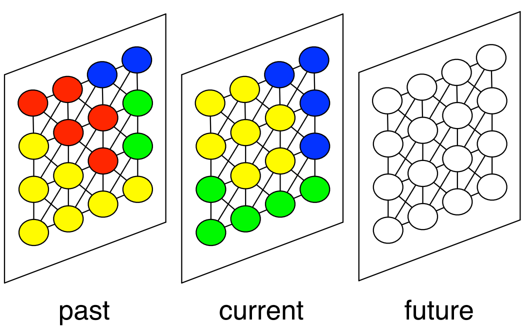


Full Video

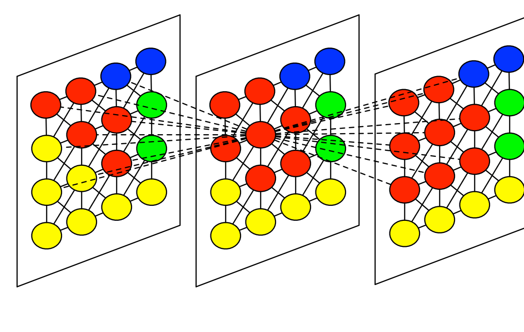
[Paris and Durand CVPR 2007]
[Grundmann et al. CVPR 2010]
[Lezama et al. CVPR 2011]

Why Streaming?

- Works have resorted to a frame-by-frame segmentation followed by a correspondence.
  - Temporal coherence is problematic.



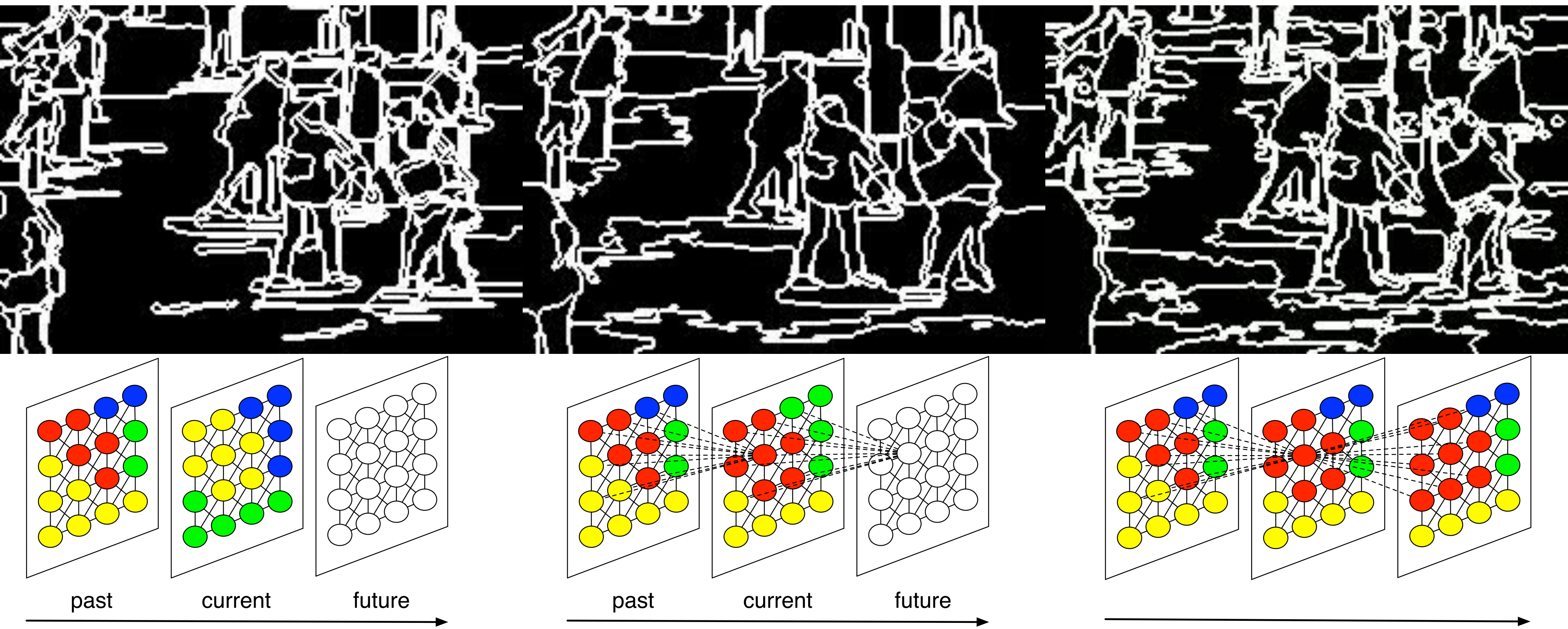
Frame-by-Frame
[Brendel and Todorovic ICCV 2009]
[Lee et al. CVPR 2011]



Full Video
[Paris and Durand CVPR 2007]
[Grundmann et al. CVPR 2010]
[Lezama et al. CVPR 2011]

Why Streaming?

- Streaming is needed.
  - Can we **bound memory needs** and **handle arbitrarily long** videos **without sacrificing quality** of segmentation?



Frame-by-Frame
[Brendel and Todorovic ICCV 2009]
[Lee et al. CVPR 2011]

Streaming
[Paris ECCV 2008]
[Grundmann et al. CVPR 2010]
(Clip-based)

Full Video
[Paris and Durand CVPR 2007]
[Grundmann et al. CVPR 2010]
[Lezama et al. CVPR 2011]

Streaming Hierarchical Video Segmentation

- Basic problem statement:

Segmentation   Video Input

$$\boxed{\mathcal{S}^*} = \operatorname*{argmin}_{\mathcal{S}} E(\mathcal{S}\boxed{|\mathcal{V})}$$

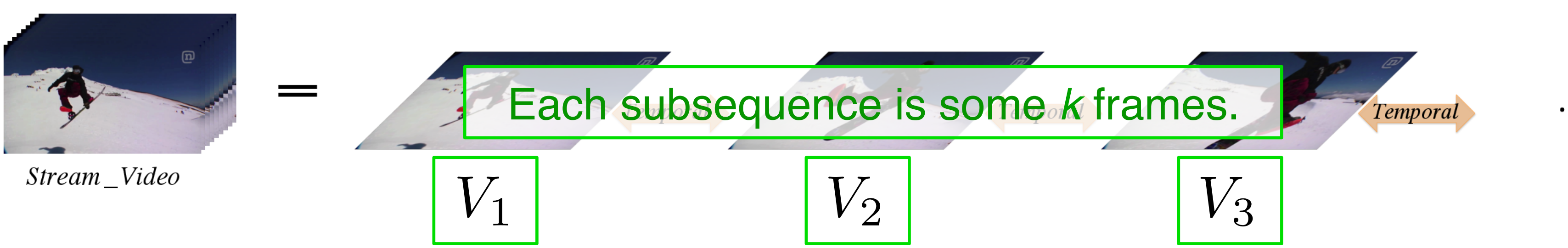
- Segmentation hierarchy

$$\mathcal{S} \doteq \{S^1, S^2, \ldots, S^h\}$$

$S^i \doteq \{s_1, s_2, \ldots\}$ such that $s_j \subset \Gamma$, $\cup_j s_j = \Gamma$, and $s_i \cap s_j = \varnothing$ for pairs i, j

- Consider a stream pointer t that indexes into the video; the streaming method may not alter any prior result $\hat{t} < t$.
  - Analogous to treating the video as a set of sequential subsequences. $\mathcal{V} = \{V_1, V_2, \cdots, V_m\}$
  - Framework generalizes a spectrum of methods.

Process a streaming video as a set of non-overlapping subsequences

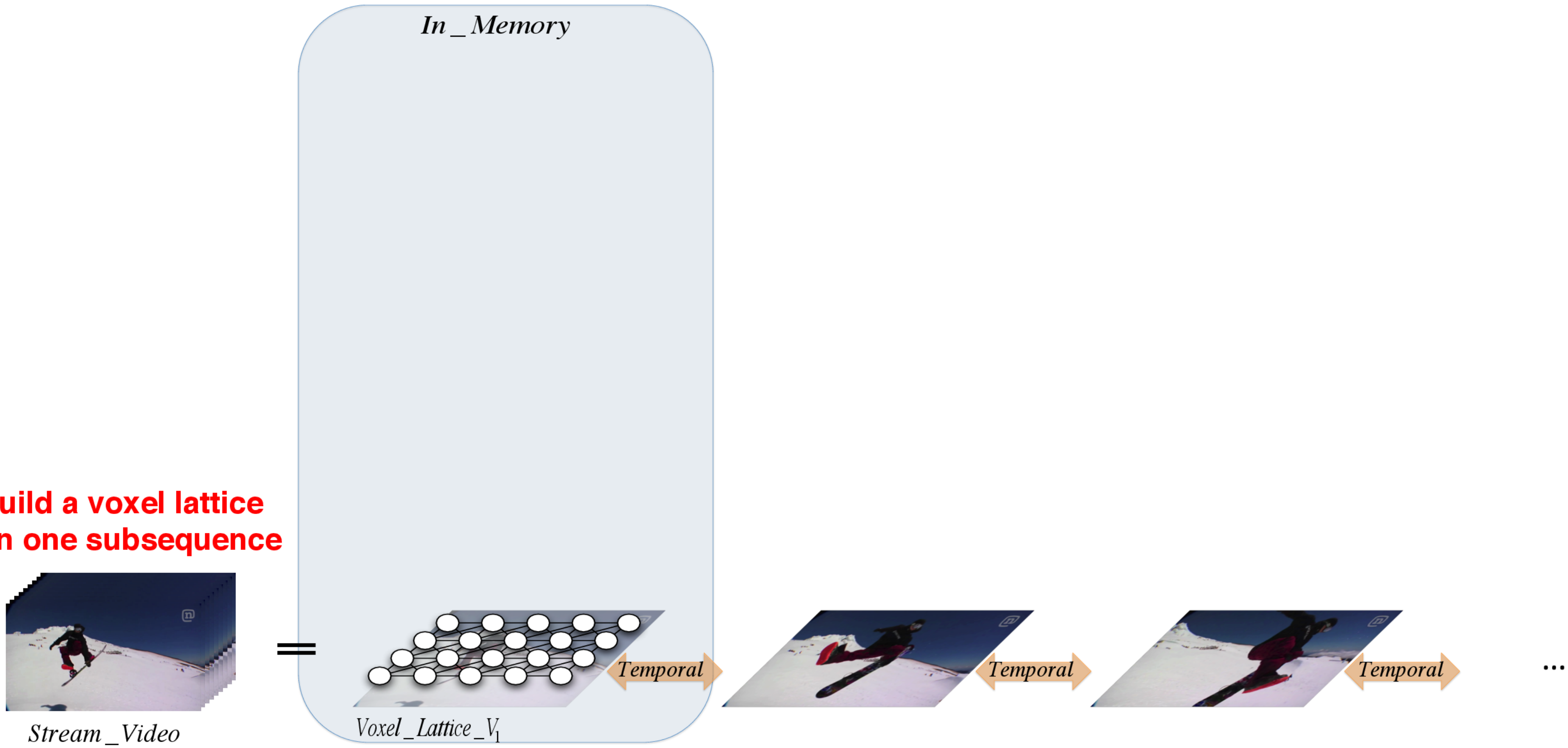


Streaming Hierarchical Video Segmentation

- Can apply to various hierarchical methods, such as the minimum spanning tree method of Felzenszwalb et al. IJCV 2004.

$$E(S^1|\mathcal{V}) = \tau \sum_{s \in S^1} \sum_{e \in \mathrm{MST(s)}} w(e) + \sum_{s,t \in S^1} \min_{e \in \langle s,t \rangle} w(e)$$

Build a voxel lattice on one subsequence

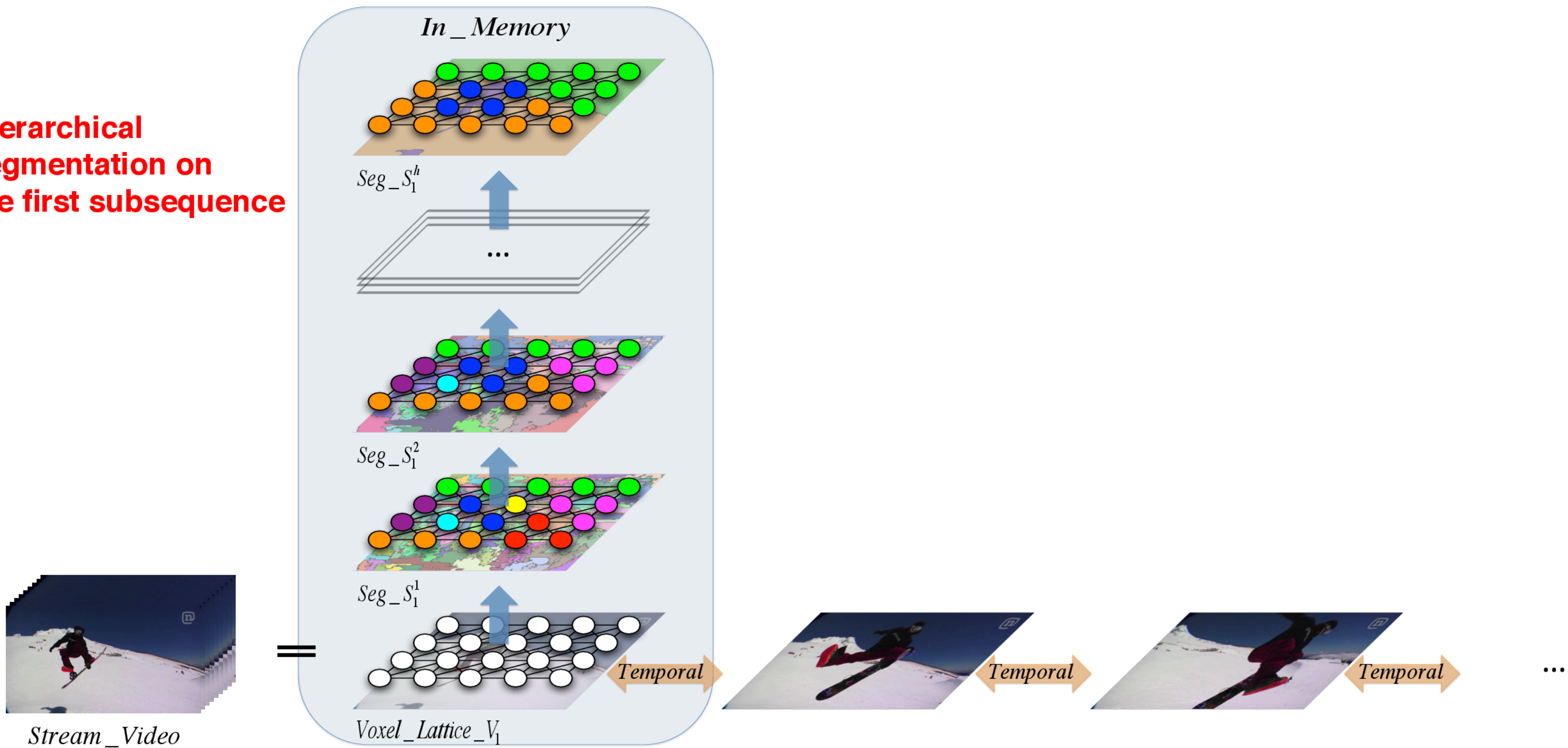


[Xu, Xiong and Corso, ECCV 2012]

Streaming Hierarchical Video Segmentation

- Similarity between regions in the hierarchy is reevaluated with multiscale features.
- Hierarchical grouping strategies must maintain segmentations that were computed for prior subsequence.

Hierarchical segmentation on the first subsequence



[Xu, Xiong and Corso, ECCV 2012]

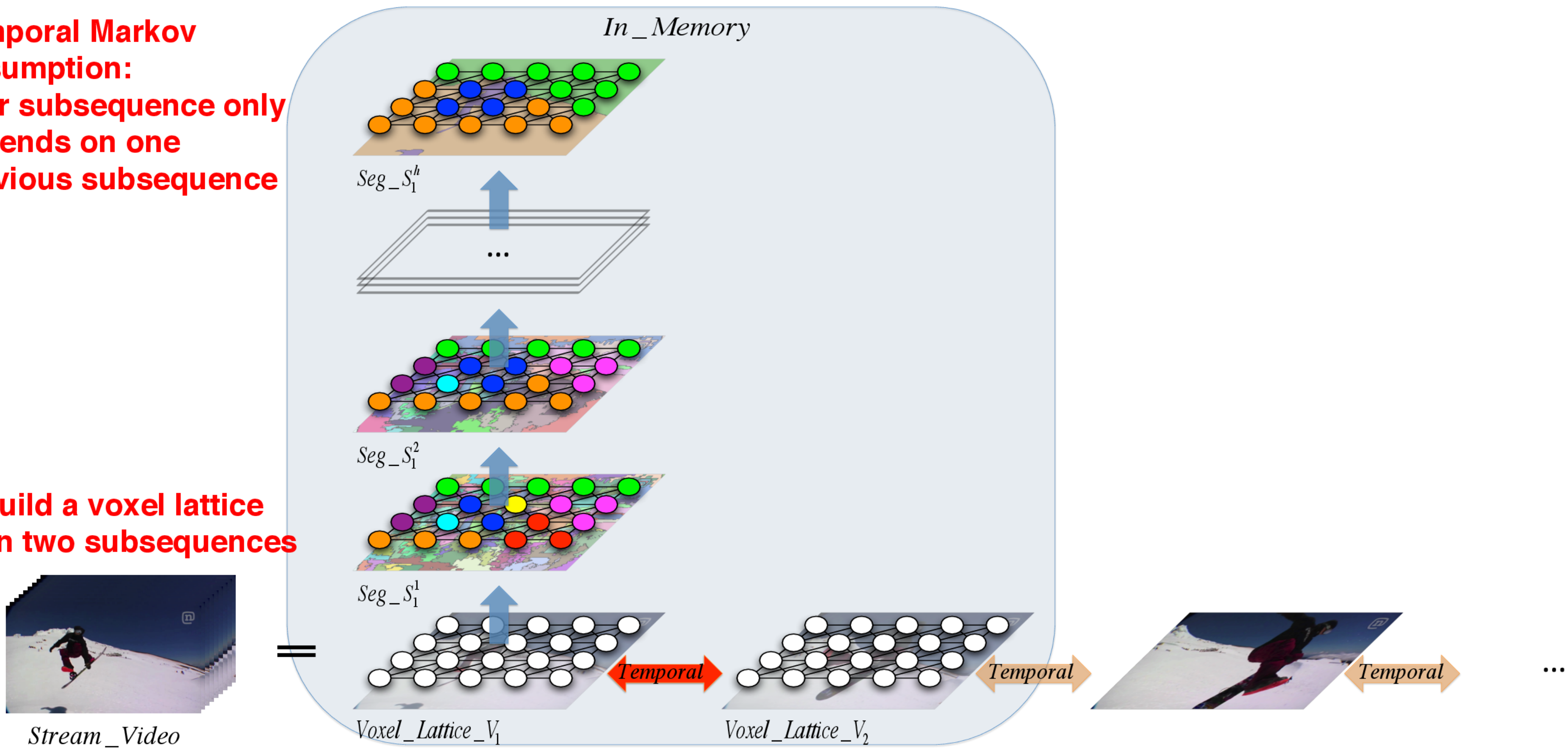
Streaming Hierarchical Video Segmentation

- Streaming Markovianity assumption.

$$\mathcal{S} = \{S_1, \cdots, S_m\} = \underset{S_1, S_2, \cdots, S_m}{\operatorname{argmin}} \left[E^1(S_1|V_1) + \sum_{i=2}^{m} E^1(S_i|V_i, S_{i-1}, V_{i-1}) \right]$$

Temporal Markov Assumption: later subsequence only depends on one previous subsequence

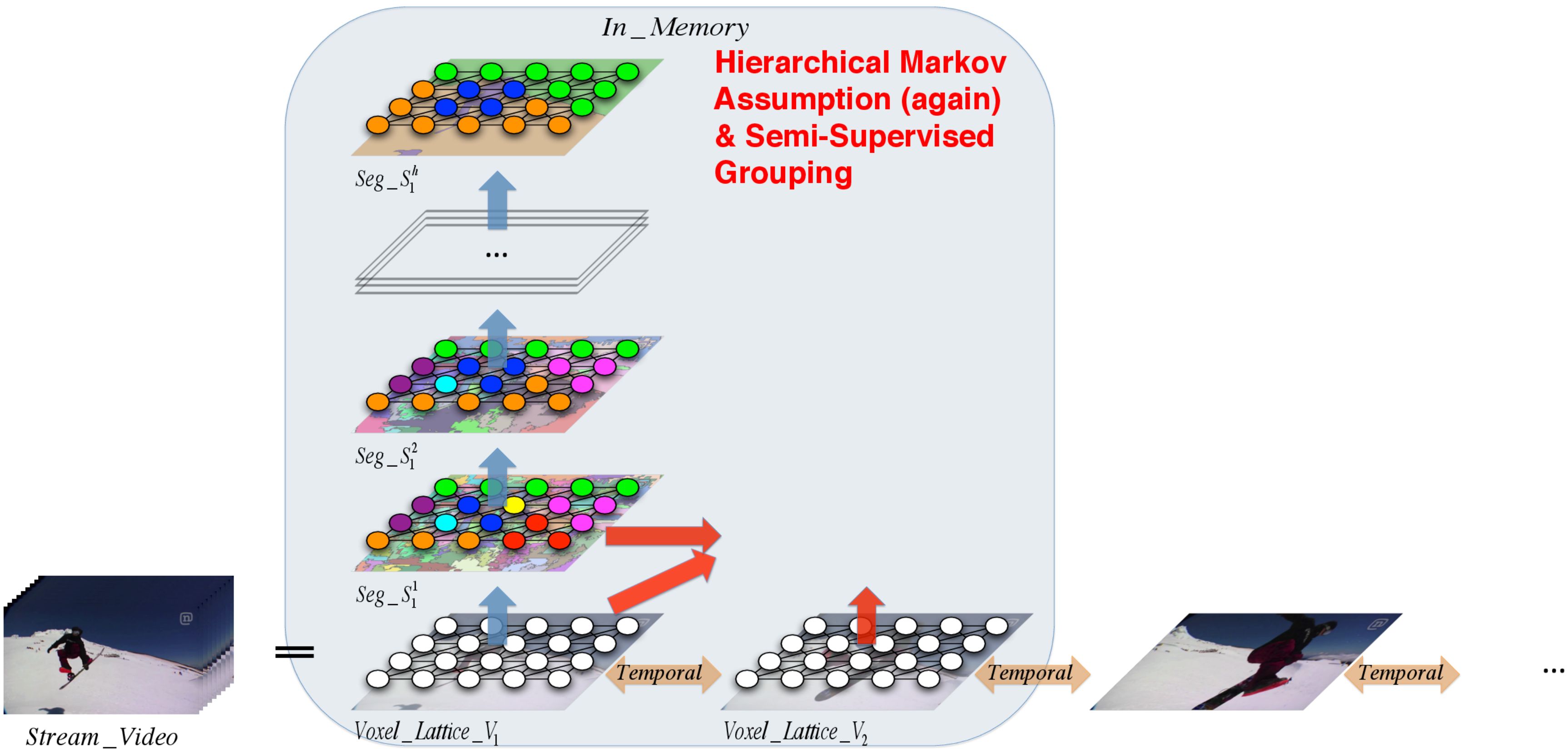
Build a voxel lattice on two subsequences



[Xu, Xiong and Corso, ECCV 2012]

Streaming Hierarchical Video Segmentation

$$S_i = \underset{S_i}{\operatorname{argmin}} E^1(S_i|V_i, S_{i-1}, V_{i-1}) = \Big\{ \underset{S_i^2}{\operatorname{argmin}} E^2(S_i^2|V_i, S_i^1, S_{i-1}^1, S_{i-1}^2, V_{i-1}), \cdots,$$
$$\underset{S_i^h}{\operatorname{argmin}} E^2(S_i^h|V_i, S_i^{h-1}, S_{i-1}^{h-1}, S_{i-1}^h, V_{i-1}) \Big\}$$

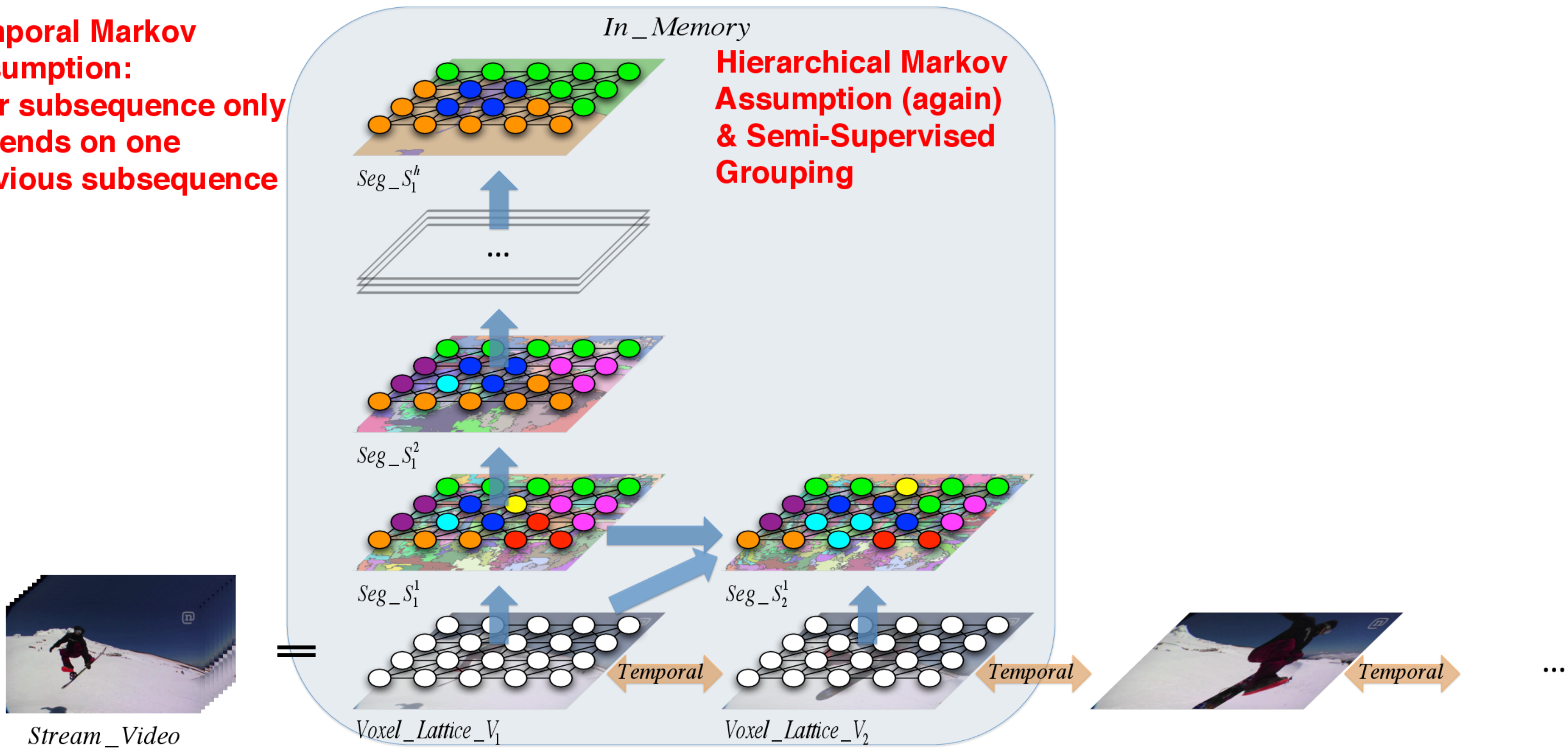


[Xu, Xiong and Corso, ECCV 2012]

Streaming Hierarchical Video Segmentation

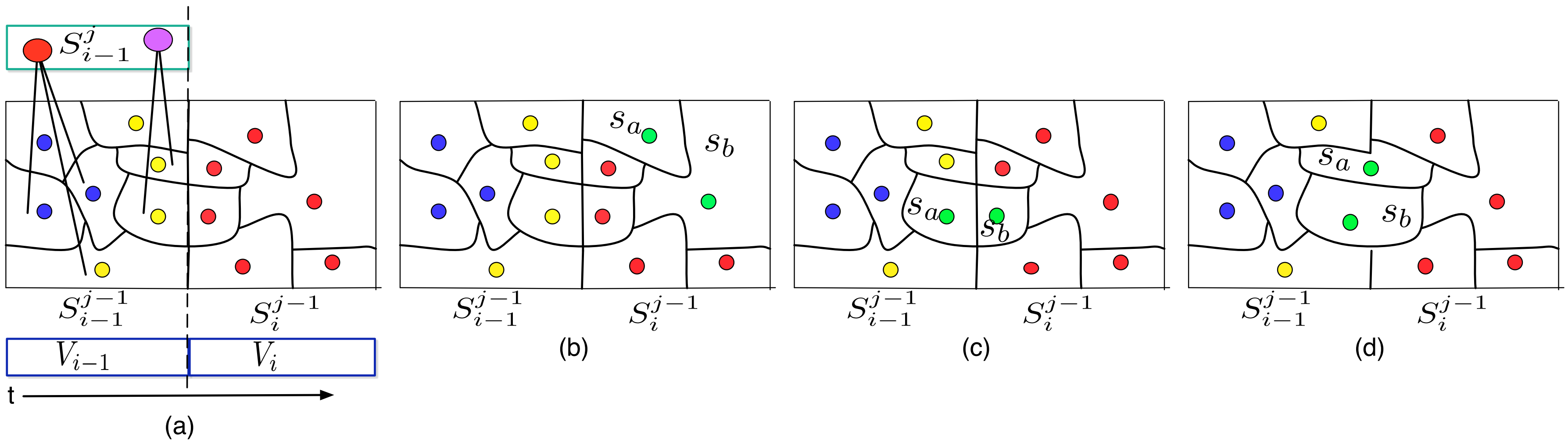
- Estimating a single sub-sequence/level segmentation can be considered a **semi-supervised problem**.
- **Additional merging criteria** at upper levels to avoid changing previously computed hierarchy before current stream point.

Temporal Markov Assumption:
later subsequence only depends on one previous subsequence



[Xu, Xiong and Corso, ECCV 2012]

Additional Merging Criteria



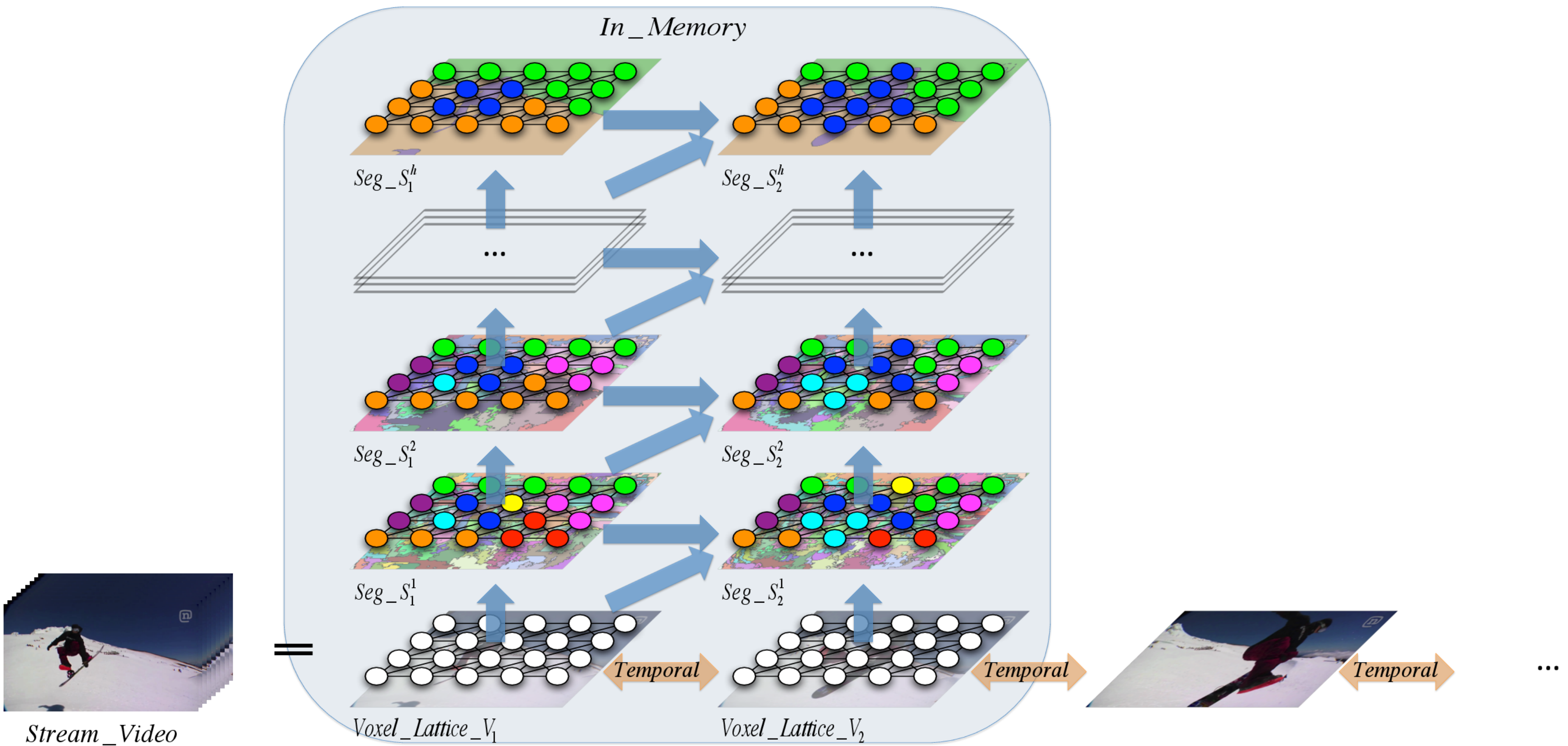
1. If s_a and s_b both are unsupervised segments, as in (b), then s_a and s_b can be merged.

2. If s_a is an unsupervised segment and s_b contains some supervised segments, as in (c), then s_a and s_b also can be merged, vice versa.

3. If s_a and s_b both contain some supervised segments, as in (d), if they have the same parent, then they are merged, otherwise they are not merged.

Streaming Hierarchical Video Segmentation

- Finish the hierarchical segmentation at the current stream pointer time.

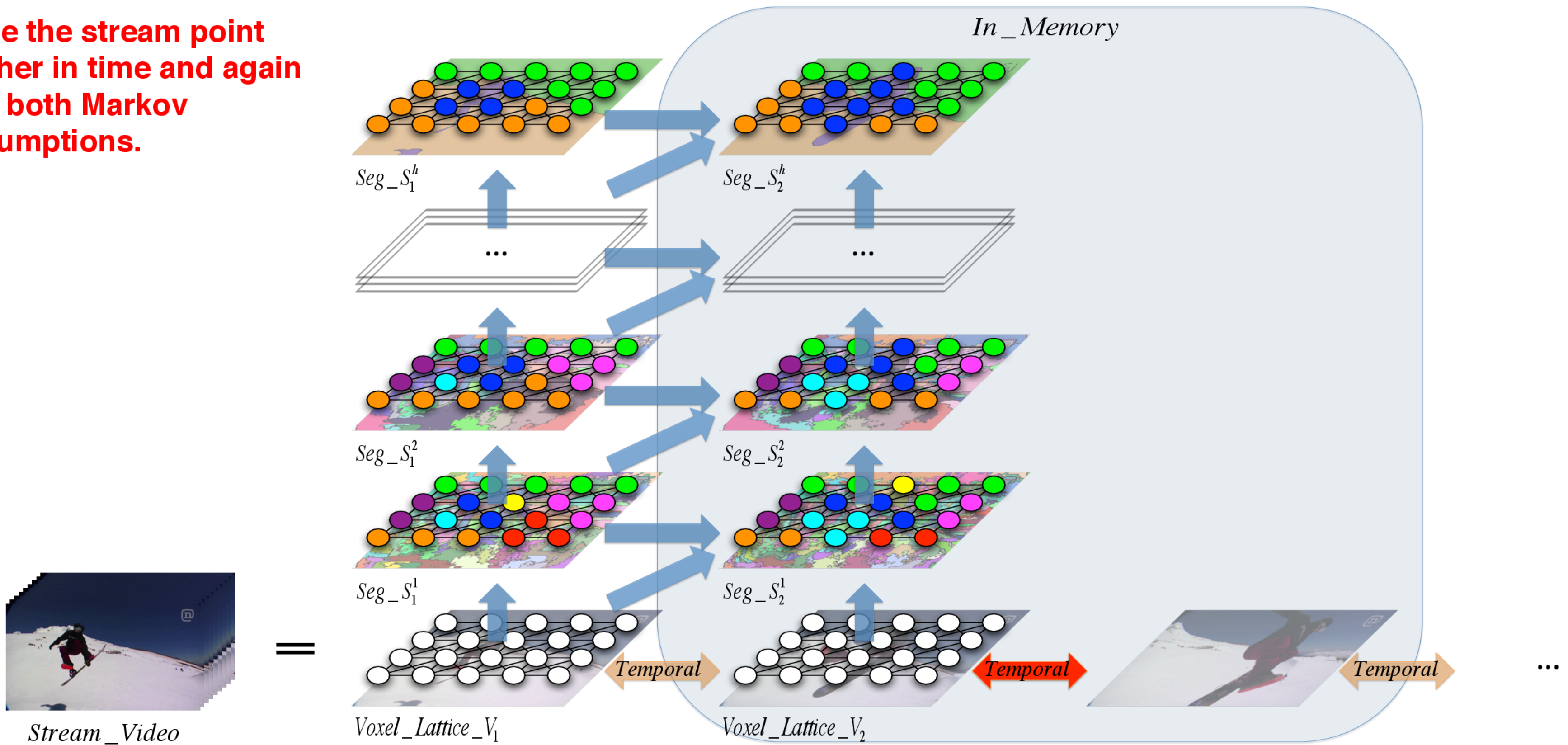


[Xu, Xiong and Corso, ECCV 2012]

Streaming Hierarchical Video Segmentation

- Once finished with two subsequences, move the stream pointer forward.
- Offload the earlier subsequence from memory and load the next.

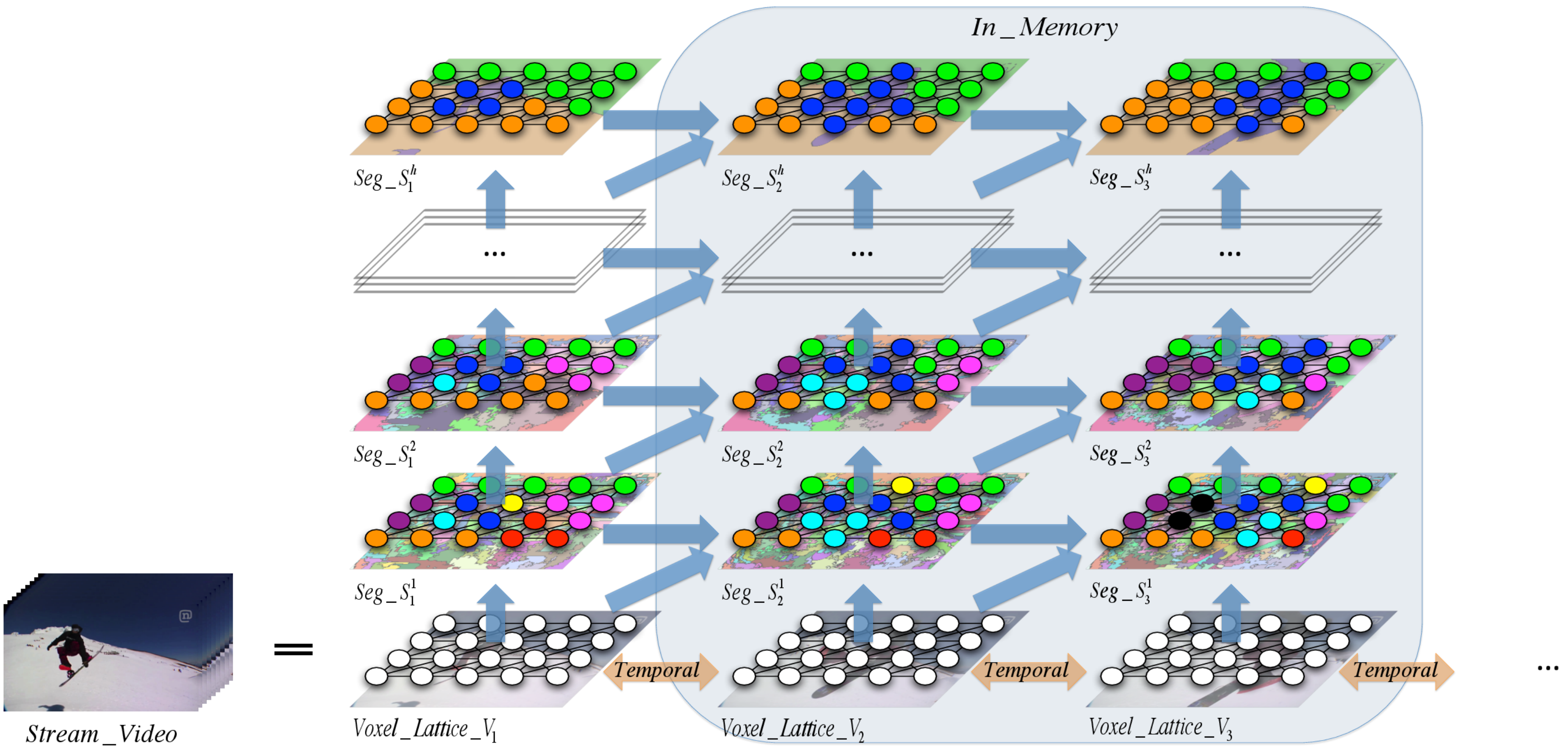
Slide the stream point further in time and again use both Markov assumptions.



[Xu, Xiong and Corso, ECCV 2012]

Streaming Hierarchical Video Segmentation

- Segment again…



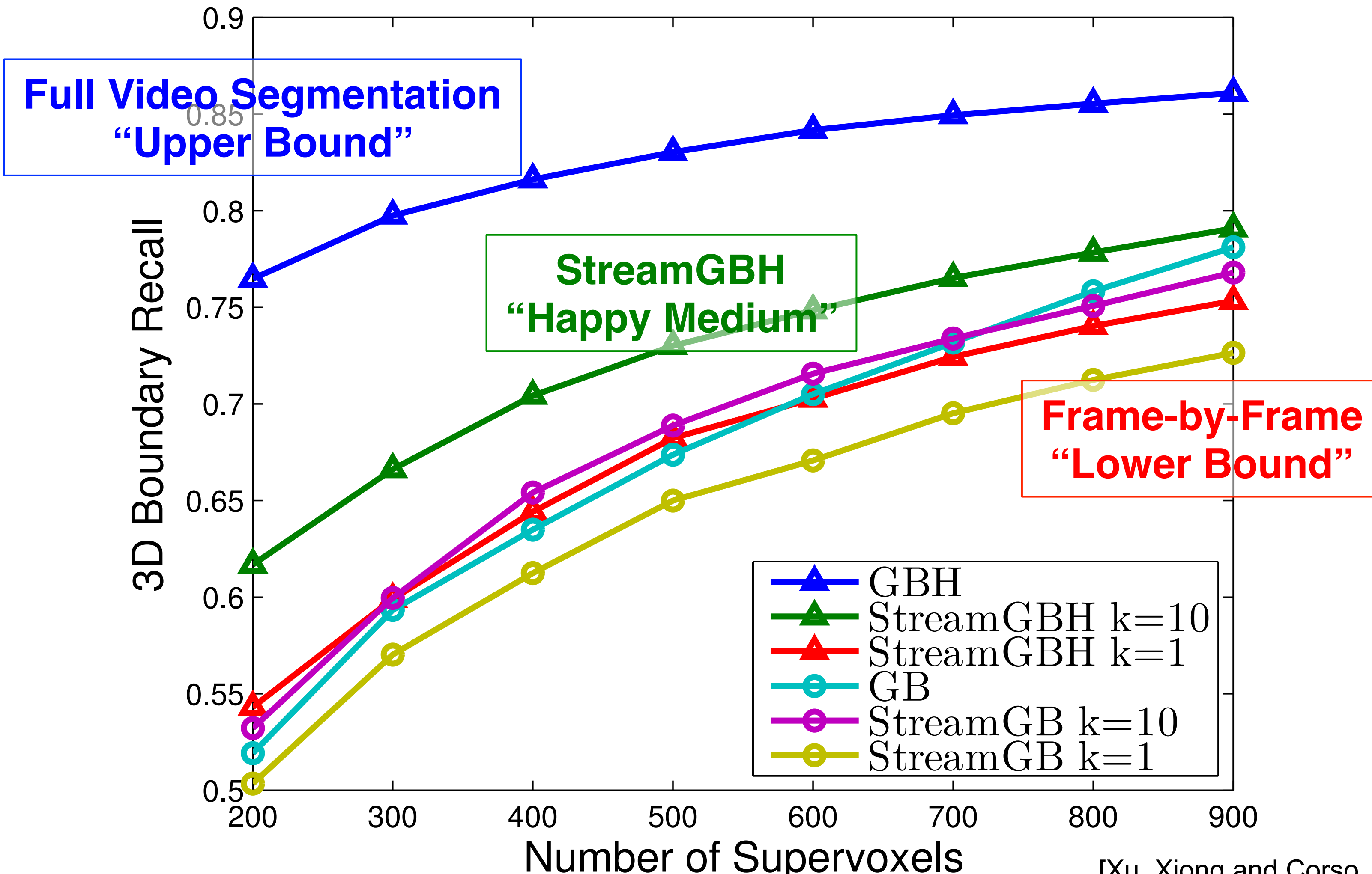
[Xu, Xiong and Corso, ECCV 2012]

StreamGBH Example Results

[Xu, Xiong and Corso, ECCV 2012]

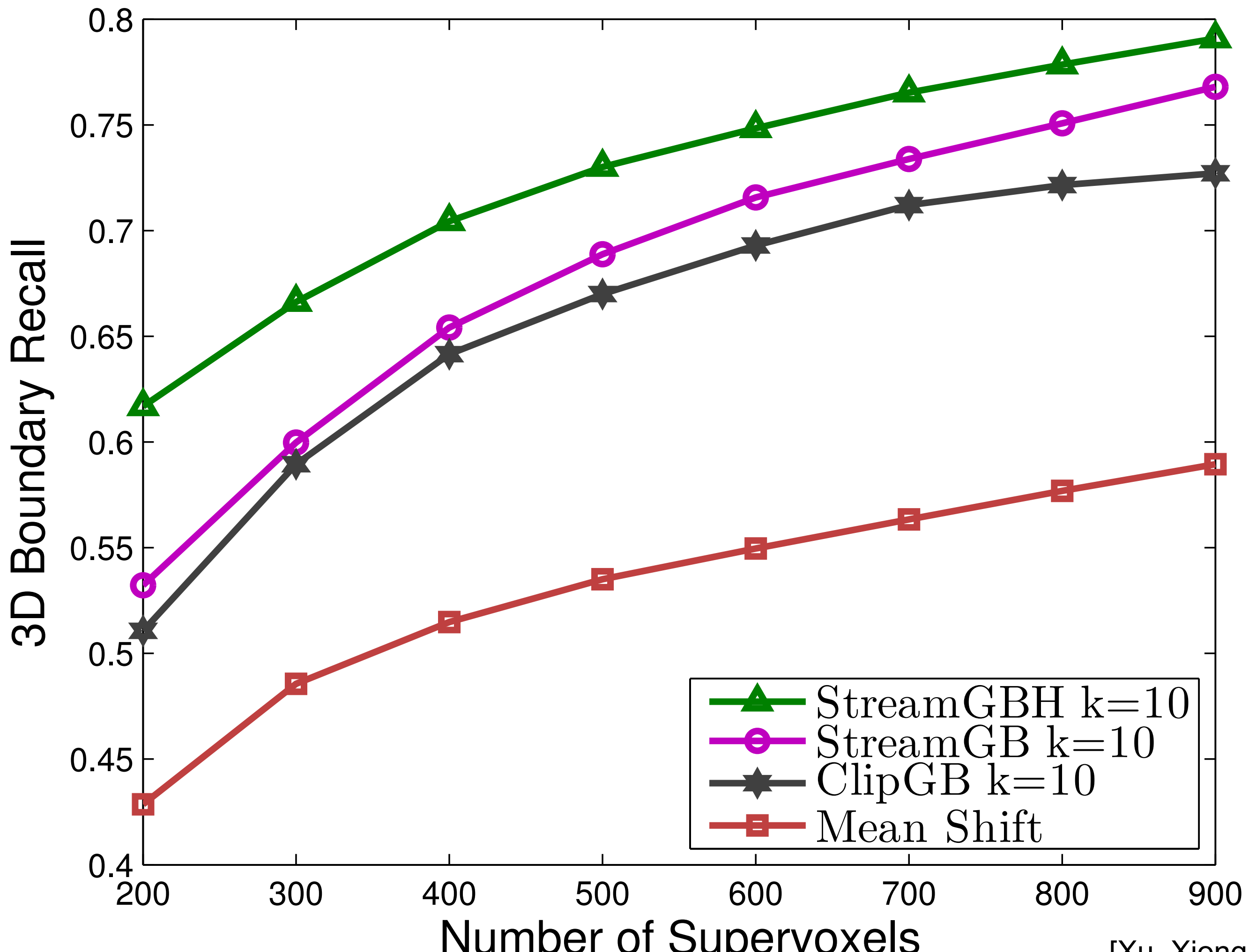
StreamGBH Quantitative Comparisons

- Does StreamGBH balance between frame-to-frame methods and full-video methods?



[Xu, Xiong and Corso, ECCV 2012]

- How does StreamGBH compare to existing streaming video segmentation methods.
  - ClipGB is our implementation of Grundmann et al. CVPR 2010.
  - MeanShift is Paris et al. ECCV 2008 implementation.

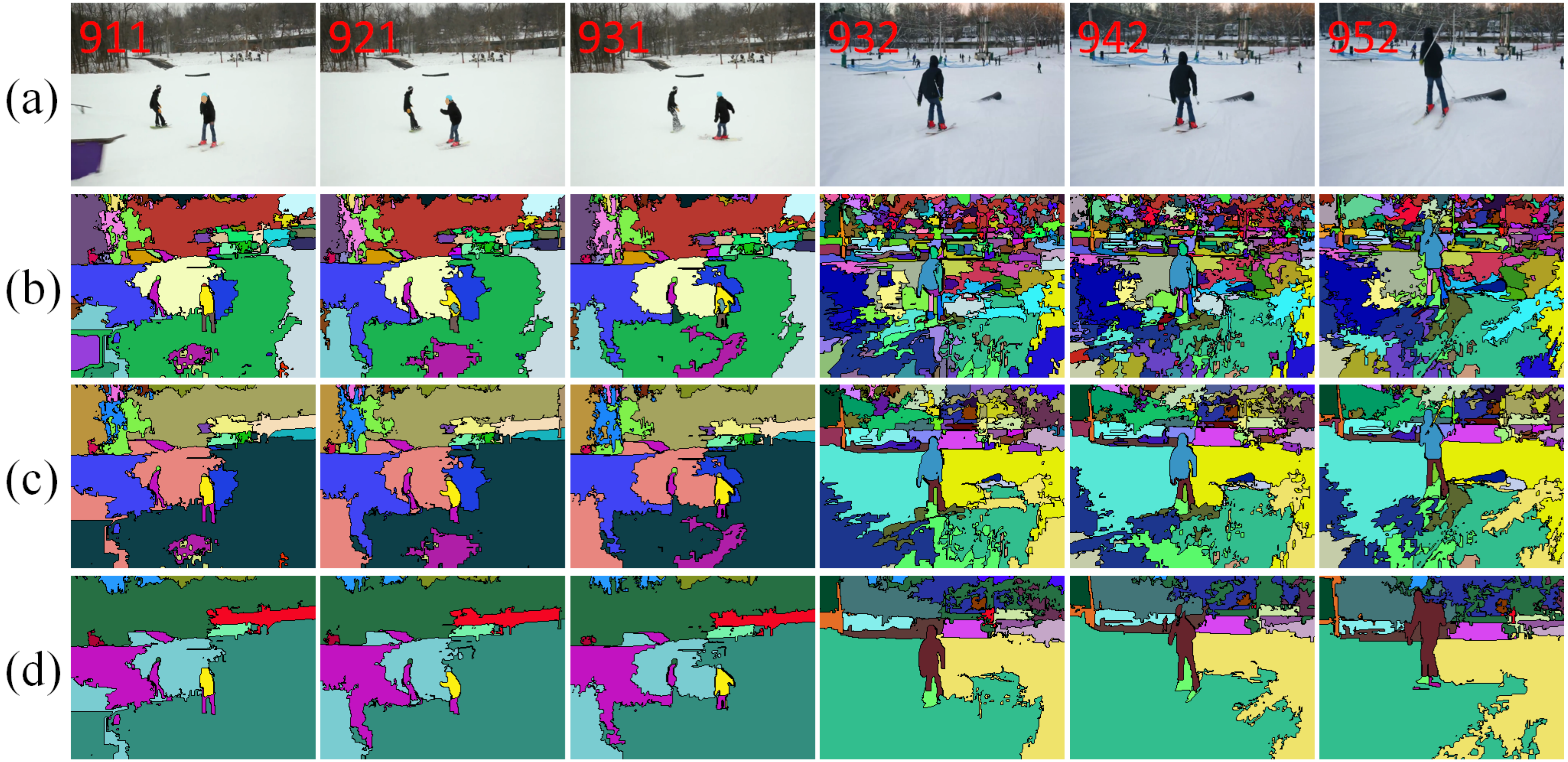


[Xu, Xiong and Corso, ECCV 2012]

StreamGBH Example Results

[Xu, Xiong and Corso, ECCV 2012]

StreamGBH Example Result: Shot-Detection



[Xu, Xiong and Corso, ECCV 2012]

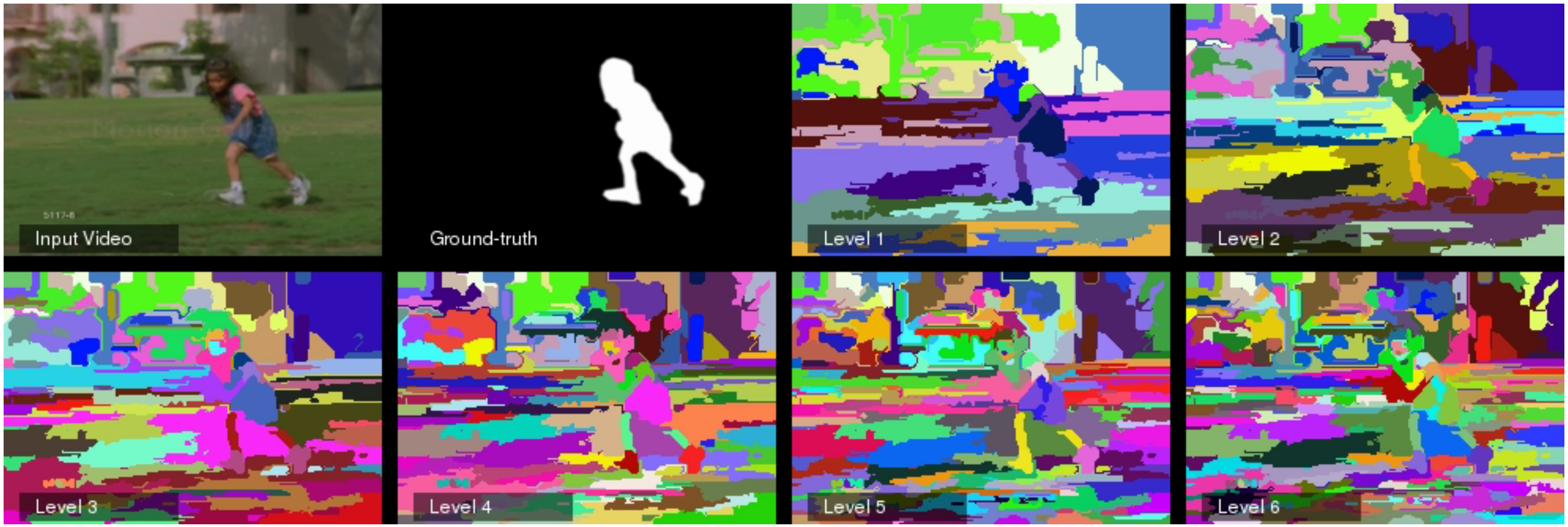
Summary of StreamGBH

- The first method for **streaming hierarchical** video segmentation.
  - Memory need is independent of video length.
  - Can handle streaming / arbitrarily long video.
  - A general approximation framework for other methods.

- **StreamGBH** smoothly varies between frame-based segmentation and whole-video segmentation, based on k.
- **StreamGBH** performance approaches whole-video segmentation as k increases, and degrades gracefully as k decreases.

Supervoxel Hierarchical Flattening with the Uniform Entropy Slice

Why Flatten the Hierarchy?

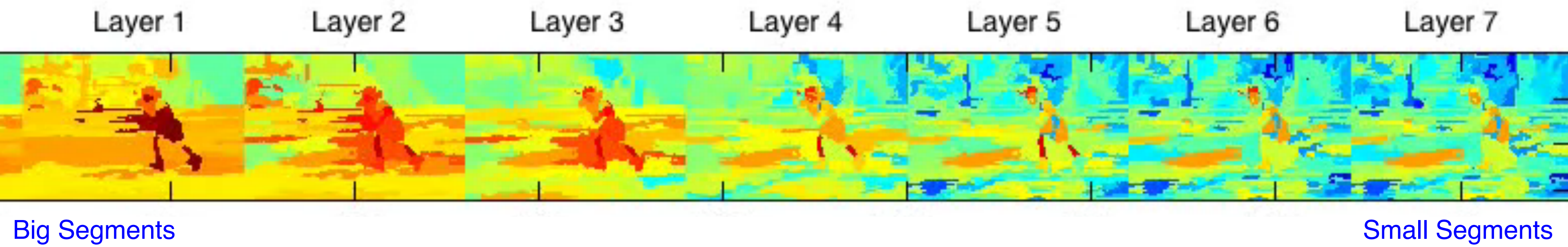


- Over-segmentation on a budget…
- A single layer slice may give too much detail near the semantics you care about and too little detail in other places.
- Combining regions from different levels, can overcome this.

Need supervised guidance on the unsupervised hierarchy!

Uniform Entropy Slice on Motion

- The entropy of the motion at each supervoxel hints at where the **high information segments** are.



$$E(s_i^l) \doteq -\sum_m \sum_\alpha P_{\mathcal{O}(s_i^l)}(m,\alpha) \log P_{\mathcal{O}(s_i^l)}(m,\alpha)$$

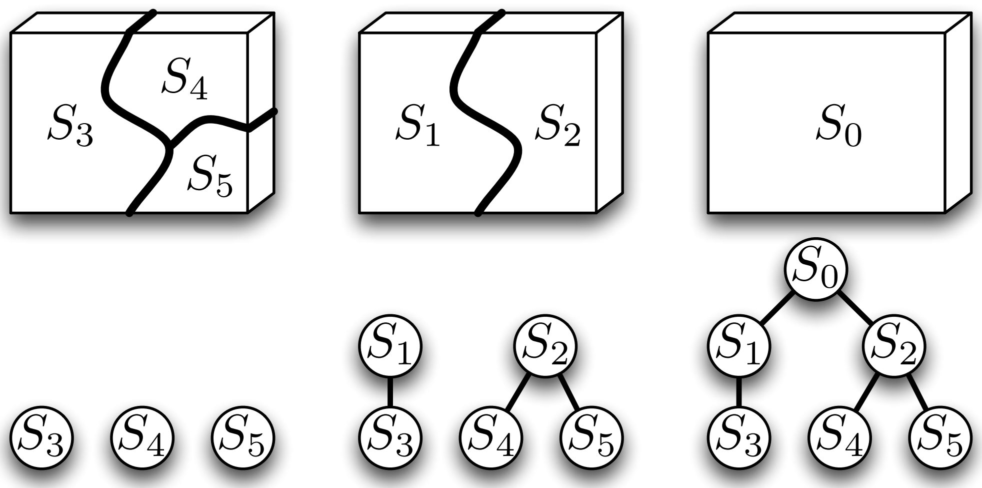
- Seek a flat segmentation that balances the amount of motion entropy across the selects segments.
  – Segments with less motion (low entropy) choose high level.
  – Segments with more motion (high entropy) choose low level.

$$\mathcal{F}^* = \arg\min_{\mathcal{F}} \sum_{s_i, s_j \in \mathcal{F}} \left| E(s_i) - E(s_j) \right|$$

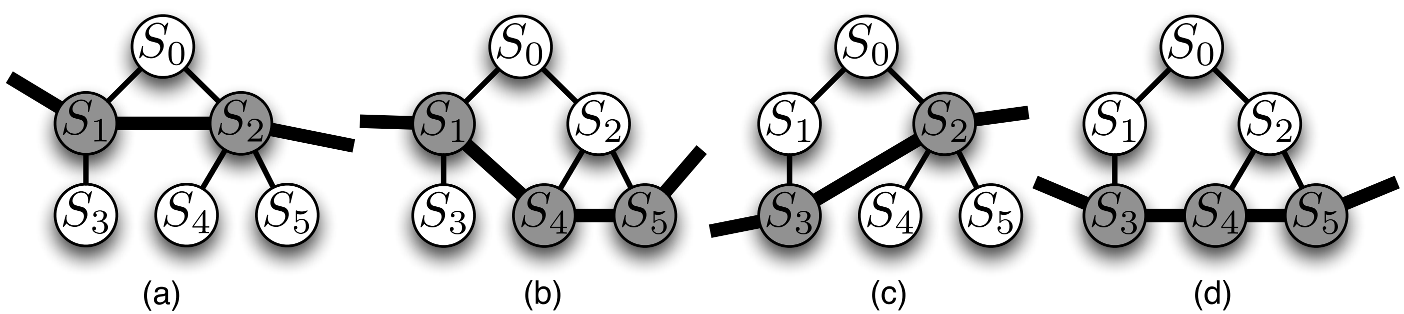
[Xu, Whitt and Corso ICCV2013]

Segmentation Tree Slice

An Example Segmentation Tree



Possible Segmentation Tree Slices



[Xu, Whitt and Corso ICCV2013]

Uniform Motion Entropy as a Segmentation Tree Slice

- We can formulate the uniform motion entropy as a segmentation tree slice via the following binary QP.

$$\begin{aligned} \text{minimize} \quad & \sum_i \alpha_i x_i + \sigma \sum_{i,j} \beta_{i,j} x_i x_j \\ \text{subject to} \quad & \mathcal{P}\mathbf{x} = \mathbf{1}_p \\ & \mathbf{x} = \{0,1\}^N \end{aligned}$$

Segmentation Tree Slice Constraint

- Linear term pushes the cut up the hierarchy.

$$\alpha_i = |S^l| \quad \text{if } s_i \in S^l$$

- Quadratic term balances entropy across neighbors.

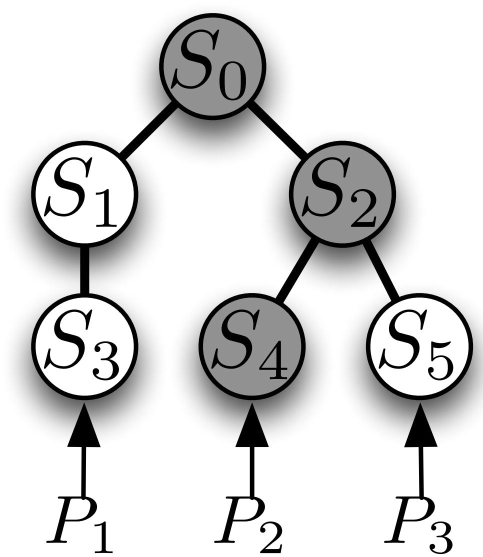
$$\beta_{i,j} = |E(s_i) - E(s_j)||\mathcal{R}(s_i)||\mathcal{R}(s_j)|$$

[Xu, Whitt and Corso ICCV2013]

Segmentation Tree Slice as a Linear Constraint

$$\mathcal{P}\mathbf{x} = \mathbf{1}_p$$

A Segmentation Tree



Corresponding Path Matrix $\mathcal{P}$

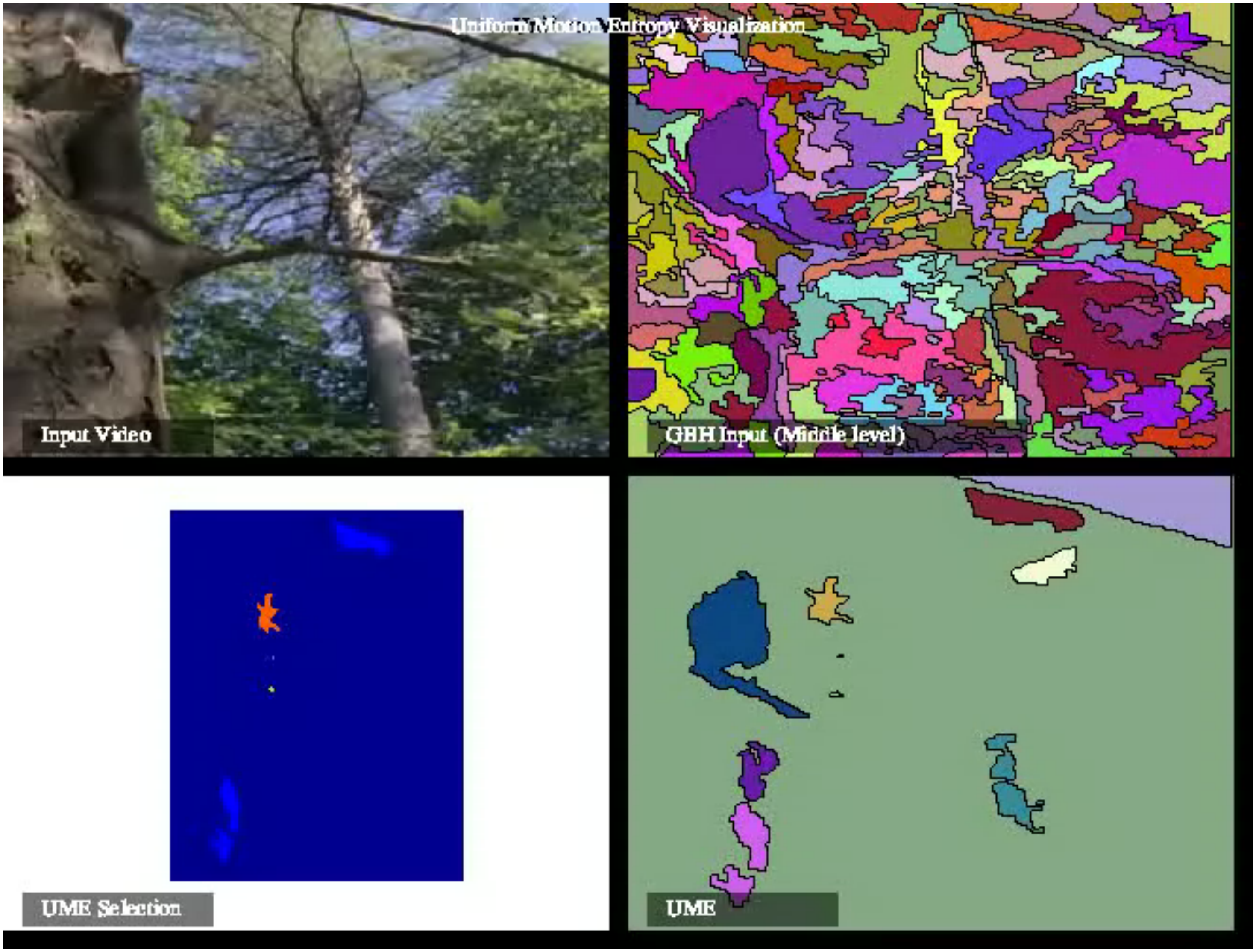
	S_0	S_1	S_2	S_3	S_4	S_5
P_1	1	1	0	1	0	0
P_2	1	0	1	0	1	0
P_3	1	0	1	0	0	1

[Xu, Whitt and Corso ICCV2013]

Visual Comparisons

[Xu, Whitt and Corso ICCV2013]

Visual Comparisons



Quantitative Comparisons

- LIBSVX benchmark: 3D ACCU, 3D UE, 3D BR. We add 3D BP.
- Data set: SegTrack has six videos, an average of 41 frames-per-video (fpv), a minimum of 21 fpv and a maximum of 71 fpv.

Video	3D ACCU			3D UE			3D BR			3D BP		
	GBH	SAS	UME	GBH	SAS	UME	GBH	SAS	UME	GBH	SAS	UME
birdfall2	0.0	0.0	**62.9**	46.1	44.9	**42.4**	78.8	81.3	**88.0**	0.67	0.73	**0.86**
cheetah	**43.2**	41.5	41.5	19.2	19.0	**18.6**	84.5	84.1	**88.9**	1.10	1.09	**1.16**
girl	60.5	59.7	**81.9**	**10.2**	**10.2**	10.8	89.3	89.2	**91.7**	3.43	3.43	**3.86**
monkeydog	81.5	81.3	**81.6**	14.2	**14.0**	15.1	93.6	**94.1**	93.6	1.36	1.37	**1.39**
parachute	**85.4**	**85.4**	**85.4**	21.1	**19.7**	21.1	**94.9**	**94.9**	94.6	1.06	1.05	**1.07**
penguin	**71.1**	**71.0**	45.2	1.7	**1.6**	2.0	78.8	**79.0**	75.2	0.95	0.95	**0.96**
AVERAGE	57.0	56.5	**66.4**	18.7	**18.2**	18.3	86.7	87.1	**88.7**	1.43	1.44	**1.55**

Table 1. Quantitative comparison of GBH, SAS and UME on all 6 videos in SegTrack [16].

Generalizing the Feature Criterion

- The post-hoc guidance function is arbitrary.
- Have shown: unsupervised motion
- Can apply:
  - Supervised, Class-Specific
    - Human-ness
    - Car-ness
  - Supervised, Class-Agnostic
    - Object-ness

[Xu, Whitt and Corso ICCV2013]

Generalizing the Feature Criterion

[Xu, Whitt and Corso ICCV2013]

Summary and Thanks!

- Segmentation hierarchies generate rich decompositions of the image/video/what-have-you content.
- But in many situations **the hierarchy is too much data.**

- Propose a physically plausible model based on **balancing feature entropy** to drive the selection of segments at different levels through the hierarchy.
- Formulate the model as a **binary QP** with a segmentation tree-cut constraint via a simple path matrix.

- Code available in LIBSVX 3.0
  - http://www.supervoxel.com/

COFFEE BREAK!