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Graph-Based Hierarchical Video Segmentation

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Video Segmentation

- Spatio-temporal regions: Group appearance and motion in space and time
- Application: Selecting regions ⇒ rapid annotation

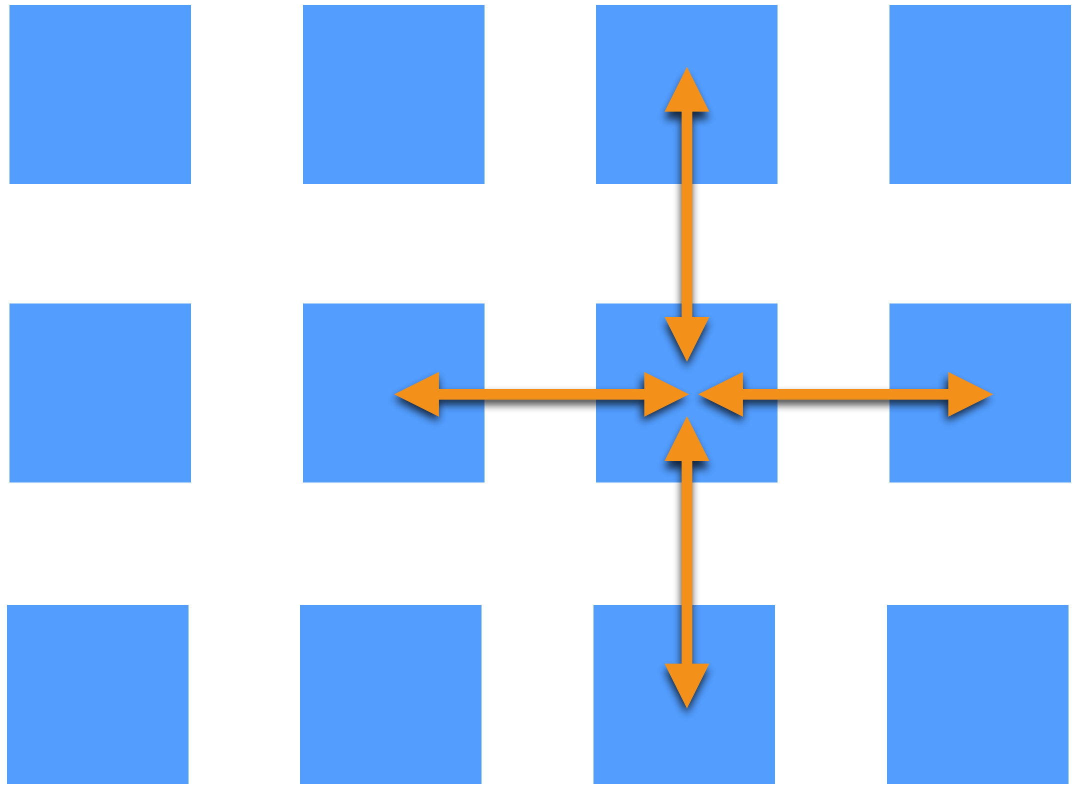
region color indicates region identity

Talk outline

- Graph-based segmentation in the video domain
- Segmentation approaches / agglomerative clustering
- Over-segmentation
- Hierarchical segmentation
- Based on [Grundmann et al. 2010]: Efficient graph-based hierarchical video segmentation
  with many improvements
- Streaming segmentation (next talk)

Graph-based segmentation

- Grid graph over image domain
- Connectedness: N4 or N8
- Affinity between pixels:
  - Color distance
  - Weighted with gradients
  - Take into account optical flow
  - From per pixel classifiers, etc.



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Extending to Video Domain

- Direct application of image-based algorithm per frame
- Lacking temporal coherence
- Unstable boundaries in time
    - Associating 2D regions will yield noisy outcome

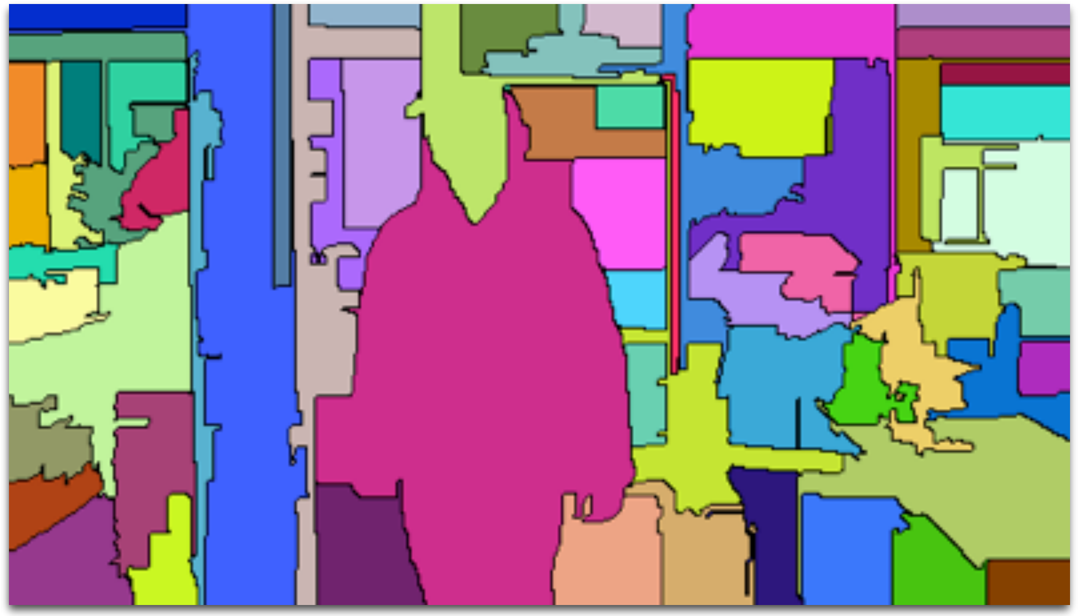
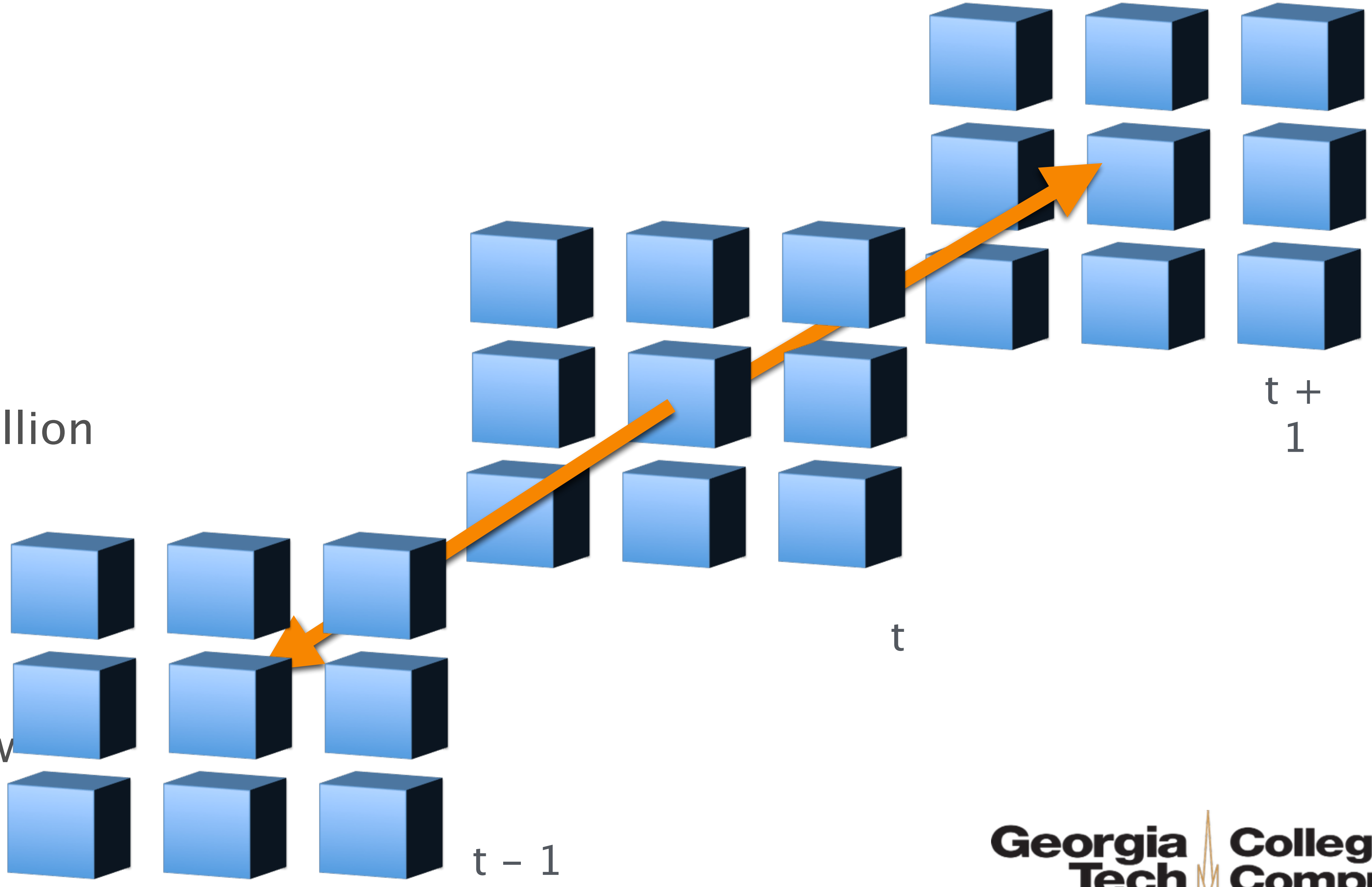


image segmentation
applied to each frame

Extending to Video Domain

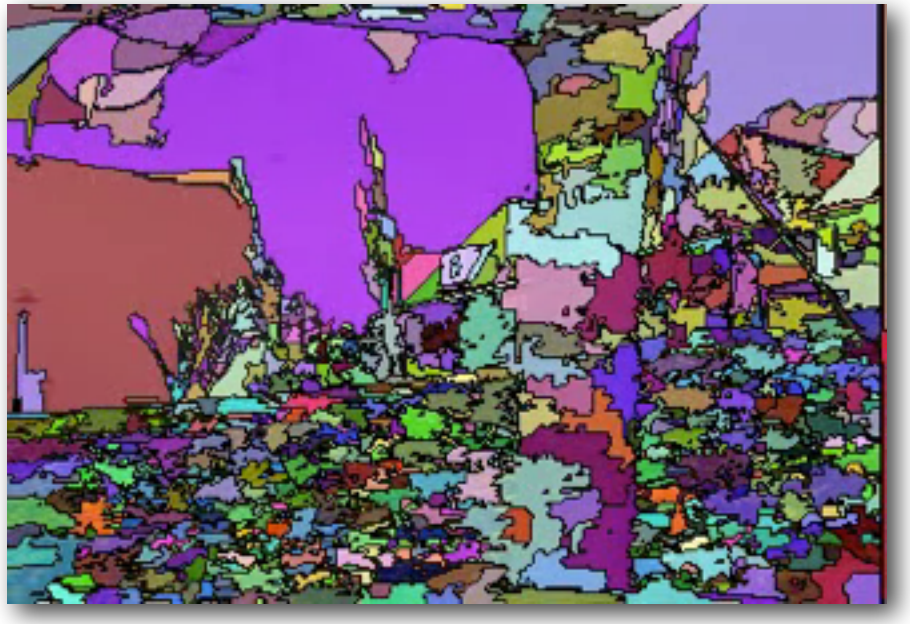
- Extend N8 graph in time: Spatio-Temporal volume
- Connect each pixel to also to its 9 neighbors in time (forward / backward)
- Connectedness: N26
  - 1 sec of 360p video: 90 million edges
  - vs. 1 million for image case
- How to connect?
  - Direct predecessor
  - Displaced along optical flow



Connection in time

- Direct predecessor can't model movements > 1 pixel
- Displace connection in time along dense optical flow

dense flow, hue encodes angle



oversegmentation using
direct
predecessor in volume

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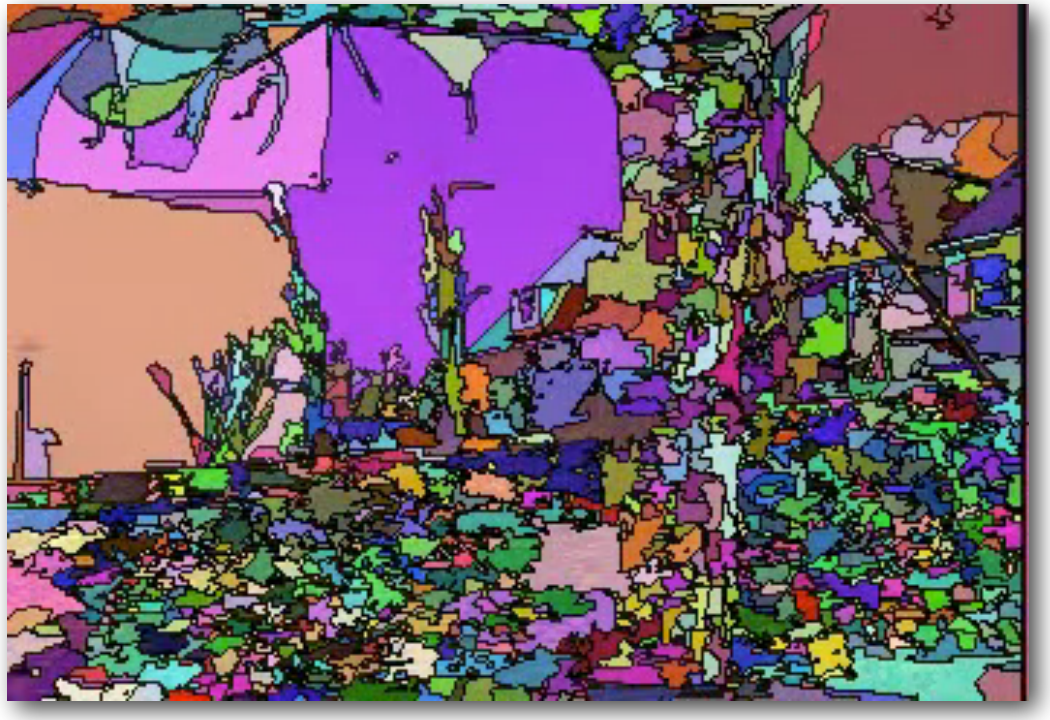
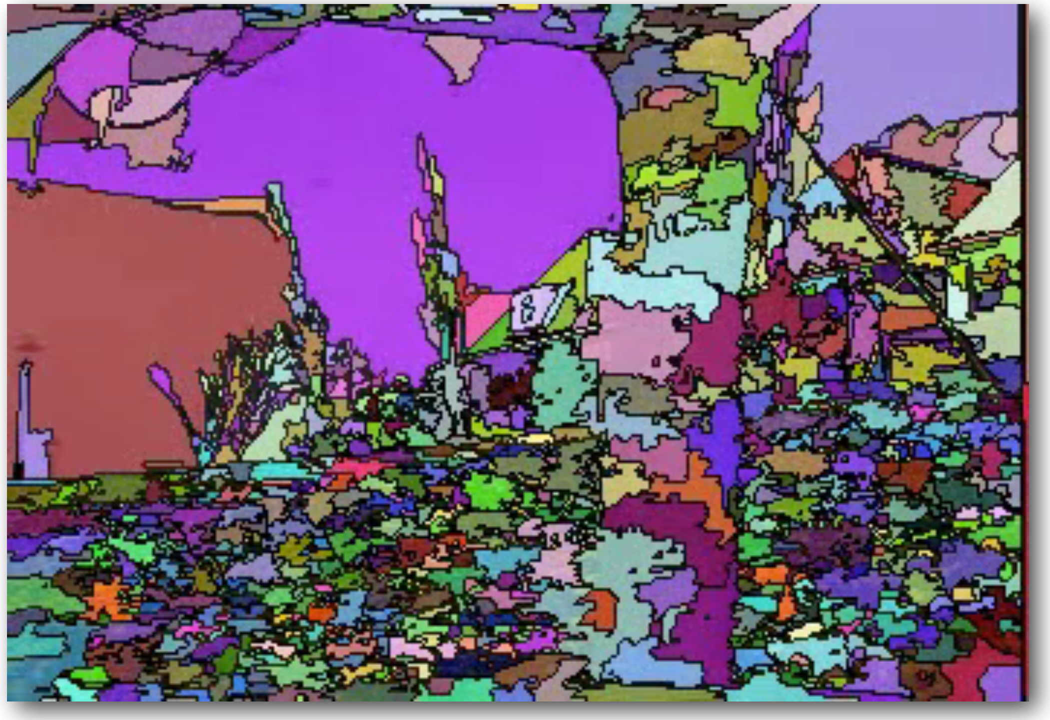
Connection using dense optical flow

- Displace temporal connection along dense optical flow



oversegmentation using predecessor along dense flow



oversegmentation using direct predecessor in volume

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Connection using dense optical flow

- Displace temporal connection along dense optical flow

oversegmentation using predecessor along dense flow

oversegmentation using direct predecessor in volume

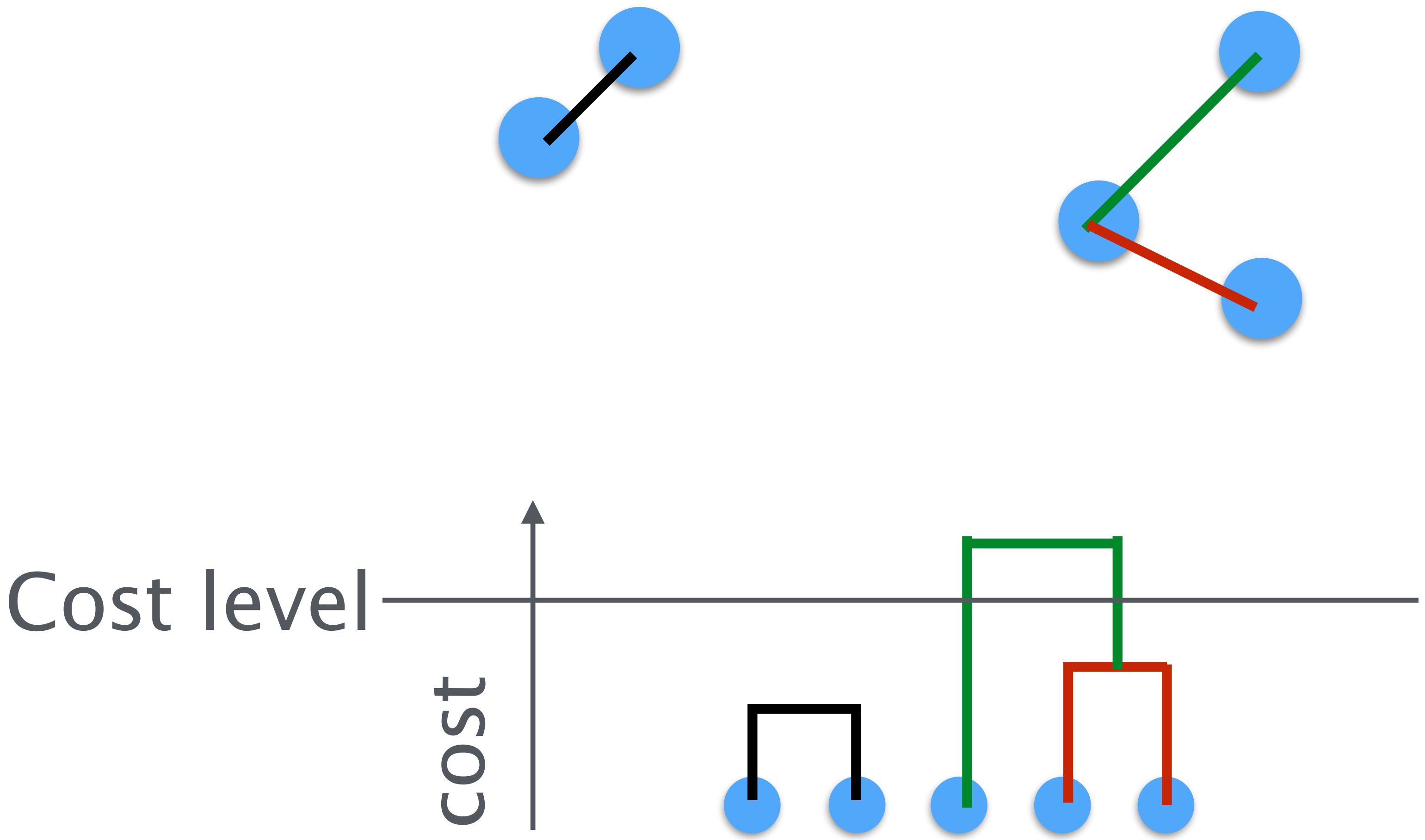
Why Graph-based segmentation

- Need:
  - Low-complexity segmentation algorithm
  - Algorithm that we can constrain (later: for streaming segmentation)
  - Initialization free (i.e. no prior user interaction or parameters, e.g. Snakes, GrabCut)

  - Mean-Shift [Comaniciu and Meer, 2002]
  - Normalized cuts [Shi and Malik, 1997]
  - k-Means, EM / Mixture of Gaussians [Bishop 2006]
  - SLIC [Achanta et al. 2012]
  - Watersheds
  - Turbo Pixels [Levinshtein et al. 2009]
  - Greedy Graph-Based [Felzenszwalb and Huttenlocher 2004]

Agglomerative clustering

- Simplest type of clustering:
- Put every item in a single cluster
- Define distance between clusters
- Iteratively merge the two closest one
- Merge sequence represented by dendrogram
- Segmentation result: Threshold at cost level (not necessarily uniform) or number of regions



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Agglomerative clustering

- How to define the cluster distance between cluster C_1 and C_2?
- Basically 3 types:
  - Single-link

$$\min_{a \in C_1, b \in C_2} ||d(a) - d(b)||$$

  - Complete-link

$$\max_{a \in C_1, b \in C_2} ||d(a) - d(b)||$$

  - Average-link
    (N = total number of summands)

$$\frac{1}{N} \sum_{a \in C_1 \cup C_2} \sum_{b \neq a \in C_1 \cup C_2, b} ||d(a) - d(b)||$$

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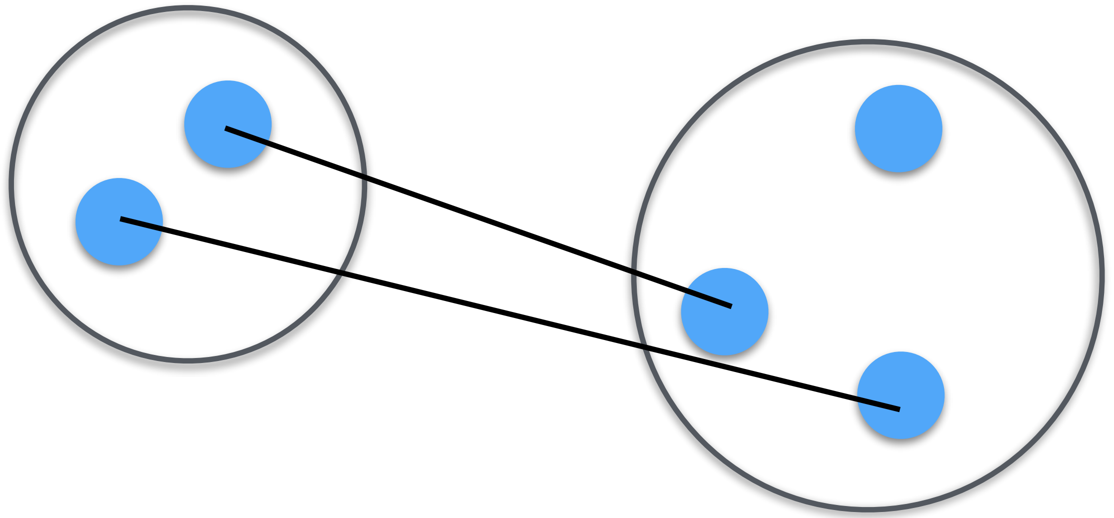
Agglomerative clustering

- Single link:
  - Distance between closest two elements
- Complete link:
  - Distance between two furthest elements
- Average link:
  - Average distance between all elements (not drawn)
- Conclusion:
  - Only single link merges do not alter cluster distance!
  - 1 sec of 360p video: 90 million edges



Single link agglomerative clustering

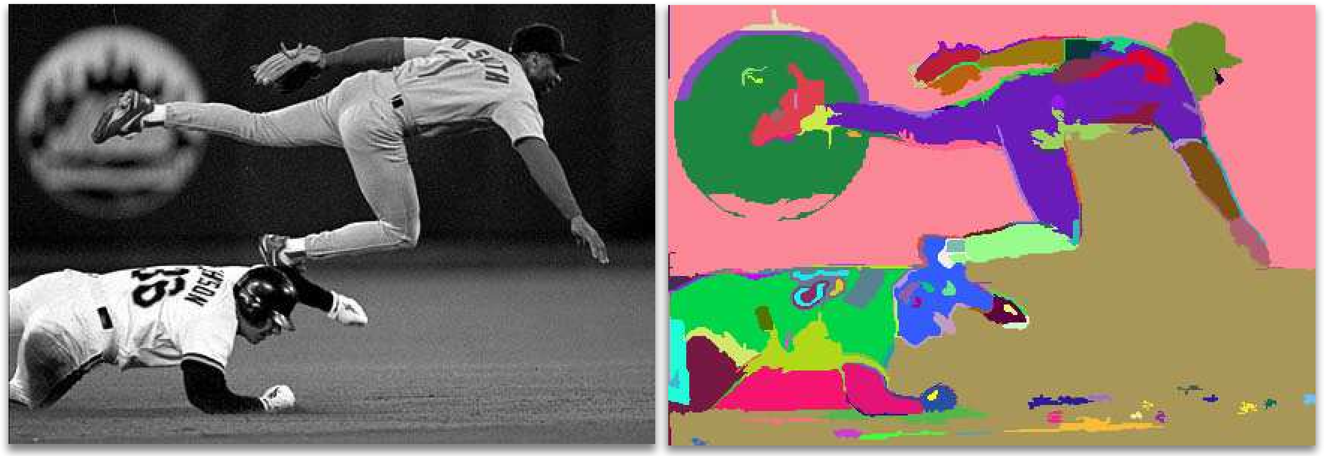
- Complexity:
  - Sort the edges between original nodes O(n log n)
  - Traverse in order O(n)
  - Merges via union–find / disjoint forest
    - Union by rank
    - Path compression
    - Total complexity: O(n α(n)), α : inv. Ackermann, α <= 5 in practice
  - Read result: O(n α(n))
- Total complexity: O(n log n)   Dominated by sort

Efficient graph based image segmentation

- [Felzenszwalb and Huttenlocher 2004]
- Single link agglomerative clustering
  - Cluster distance: Diff. pixel appearance
  - $\mathrm{Int}(C_i)$: last edge weight for each cluster (height from dendrogram)
  - Termination criteria:

$$\min_{a \in C_1, b \in C_2} ||d(a) - d(b)|| = \mathrm{Int}(C_1 \cup C_2) > \min(\mathrm{Int}(C_1) + \tau(C_1), \mathrm{Int}(C_2) + \tau(C_2))$$

  - $\tau(C)$ = constant / |C|



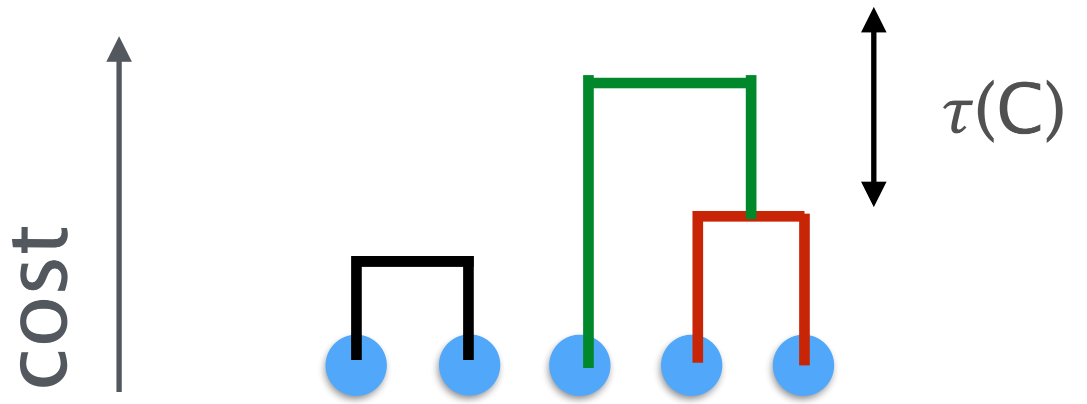
from [Felzenszwalb and Huttenlocher 2004]

Efficient graph based image segmentation

- Termination criteria

$$\mathrm{Int}(C_1 \cup C_2) >$$
$$\min(\mathrm{Int}(C_1) + \tau(C_1), \mathrm{Int}(C_2) + \tau(C_2))$$

- Int(C) : dendrogram height, τ(C) = constant / |C|
- Relative test, space decreases with region size



Efficient graph based image segmentation

- What to take away:
  - [Felzenszwalb and Huttenlocher 2004] is single link agglomerative clustering
  - “Local” termination criteria w.r.t. dendrogram spacing
  - Monotonic criteria: Once violated, the two clusters won’t be merged
  - **Also:** Any other monotonic criteria will do

Efficient graph based video segmentation

- Applying the "Local" termination criteria to video is problematic
  - τ(C) = constant / |C| decreases with region size
- For video:
  - In video region volume >> region area for images
  - Either increase constant (more segmentation errors)
  - Or: Have many small regions
- For practical implementations:
  - For large homogenous regions: $\tau(C) \rightarrow 0$
    ⇒ Regions are broken into small pieces
  - For textured regions: Additional merges required to achieve minimum region size

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Homogenous regions

$$\tau(C) \rightarrow 0$$

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Introducing additional merges

- Forced merges: Merge everything with edge weight < 1 intensity / compression level
- Regular merges: [Felzenszwalb and Huttenlocher 2004] local criteria
- Small region merges: also [Felzenszwalb and Huttenlocher 2004]

with forced merges

without forced merges

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Results use new merge criteria, not [Felzenszwalb and Huttenlocher 2004]

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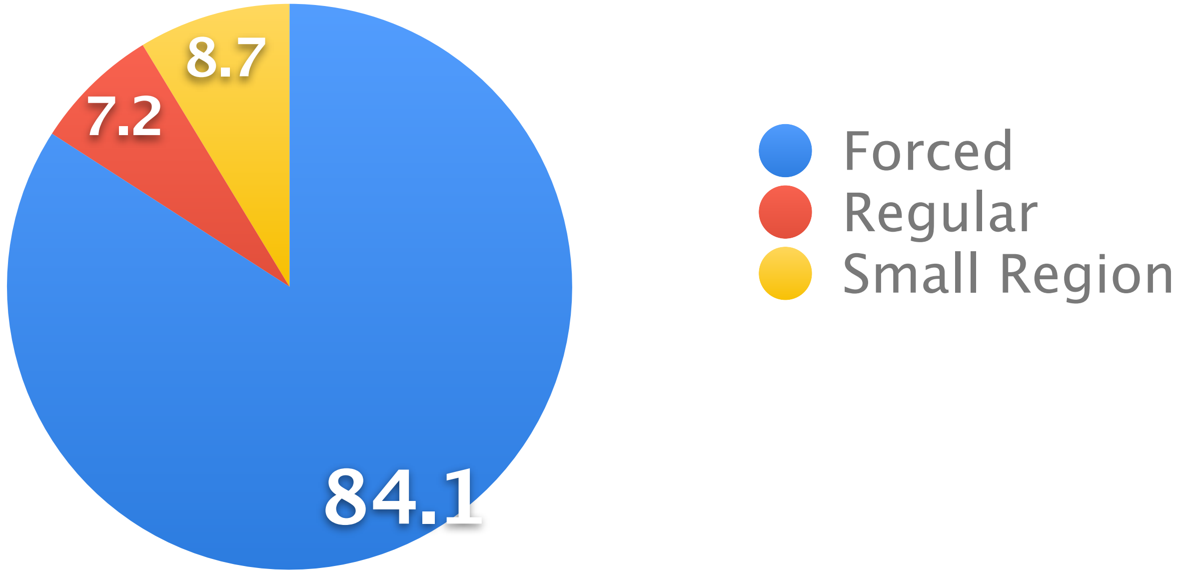
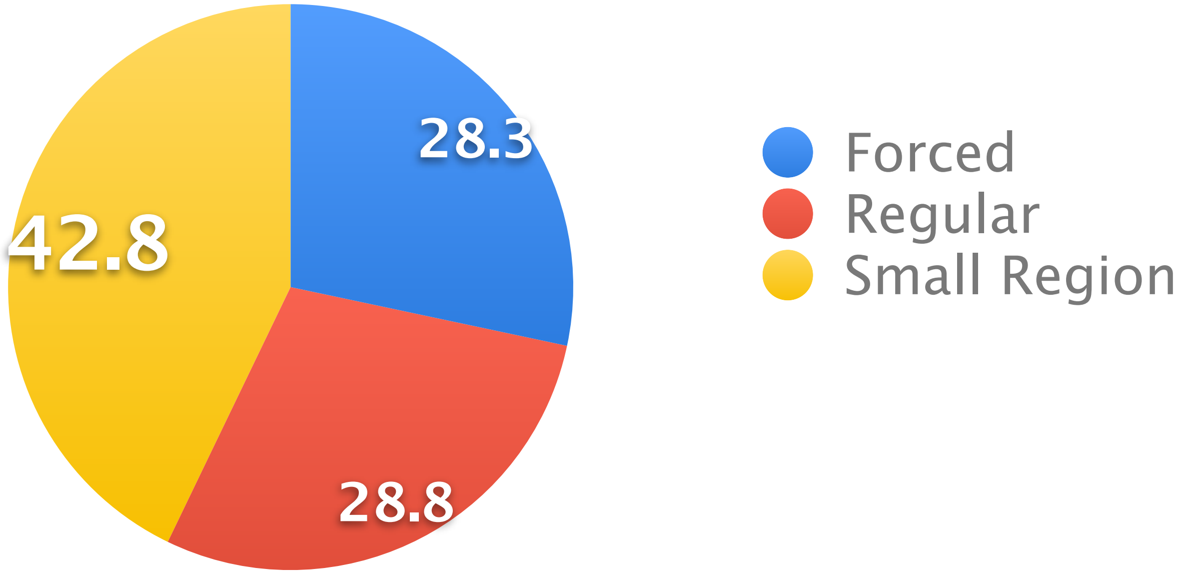
Merge percentages

- [Felzenszwalb and Huttenlocher 2004] with forced merges
- Regular merges account for less than 1/3 of all merges

Truck
(homogenous)



Flowergarden
(textured)



forced includes merges due to constraints

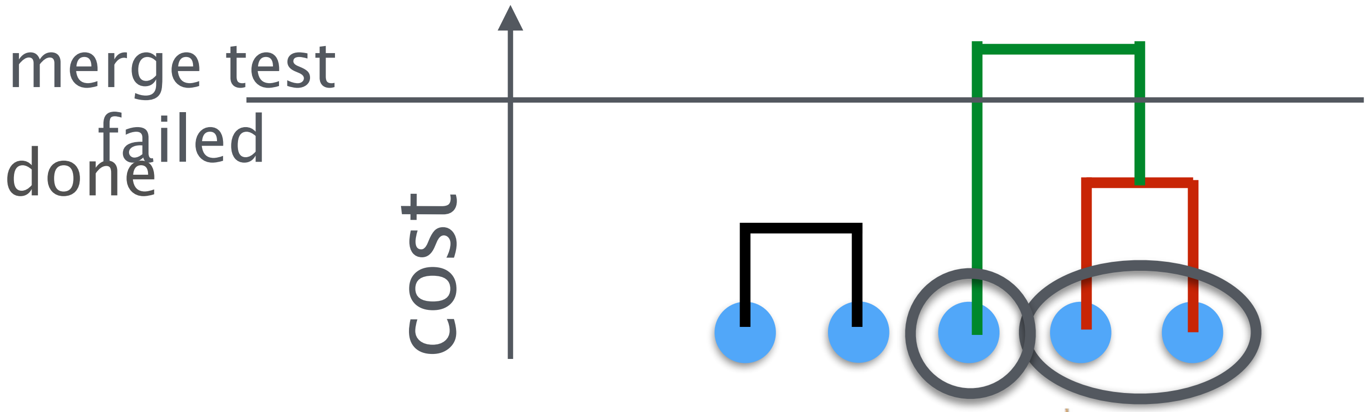
Talk outline

- Graph-based segmentation in the video domain
- Segmentation approaches / agglomerative clustering
- Over-segmentation
- Hierarchical segmentation

A new merge criteria

- Recall: **Any** monotonic criteria will do
- Need more regular merges, distance that accounts for compression levels
- Avoid “chaining” for single link clustering (small local edge weights can accumulate)

- Idea:
  - Build up local descriptors during merge process
  - Use edge and descriptor distance to determine if a merge should be performed
  - Incorporate small region merges
  - Monotonicity: If merge test fails, label regions as done



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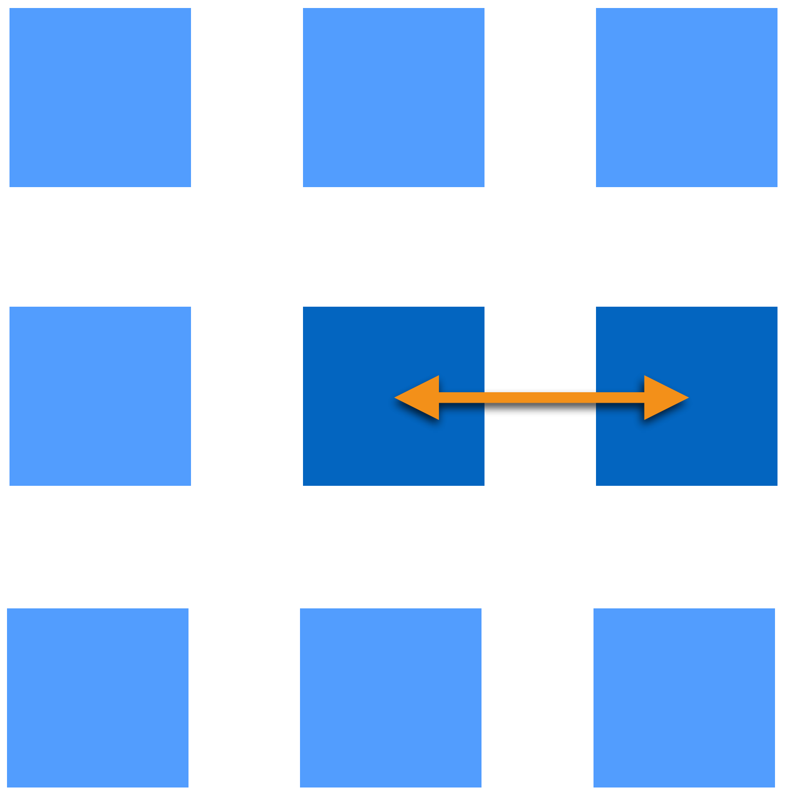
Our new merge criteria

- Descriptor during merges:
  Mean color / Mean flow (any other possible)
- Merge regions if:
  - Edge weight < 1 intensity level and
    descriptor distance < 20%
    (allow for variability but control cutoff)
  - Edge weight >= 1 intensity level and
    descriptor distance < 5% intensity range
  - One of them is too small
- If violated: Flag as done (monotonicity!)



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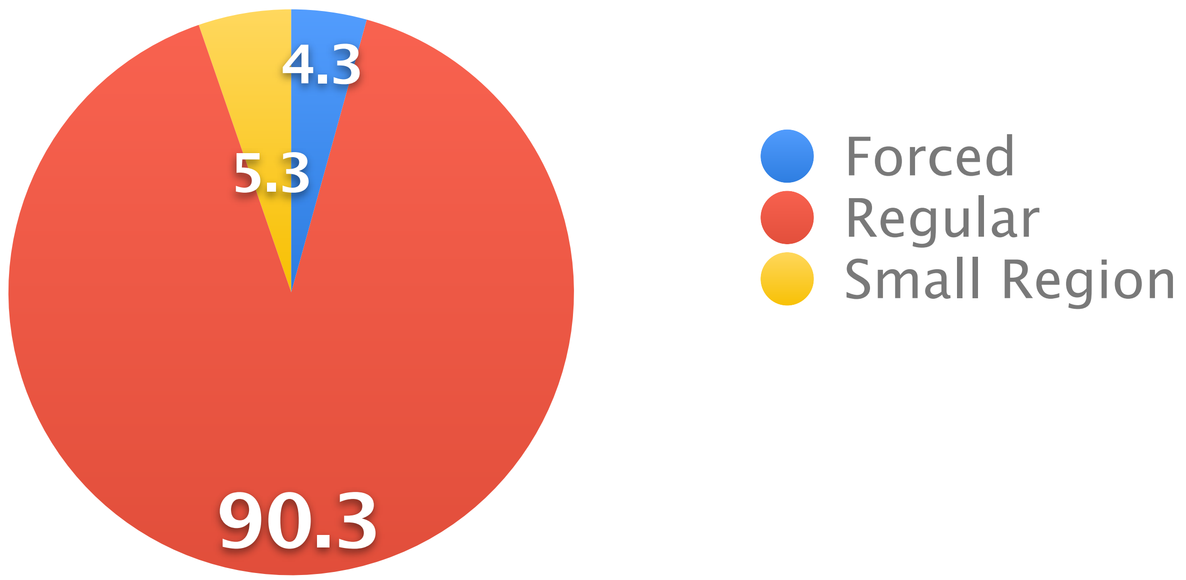
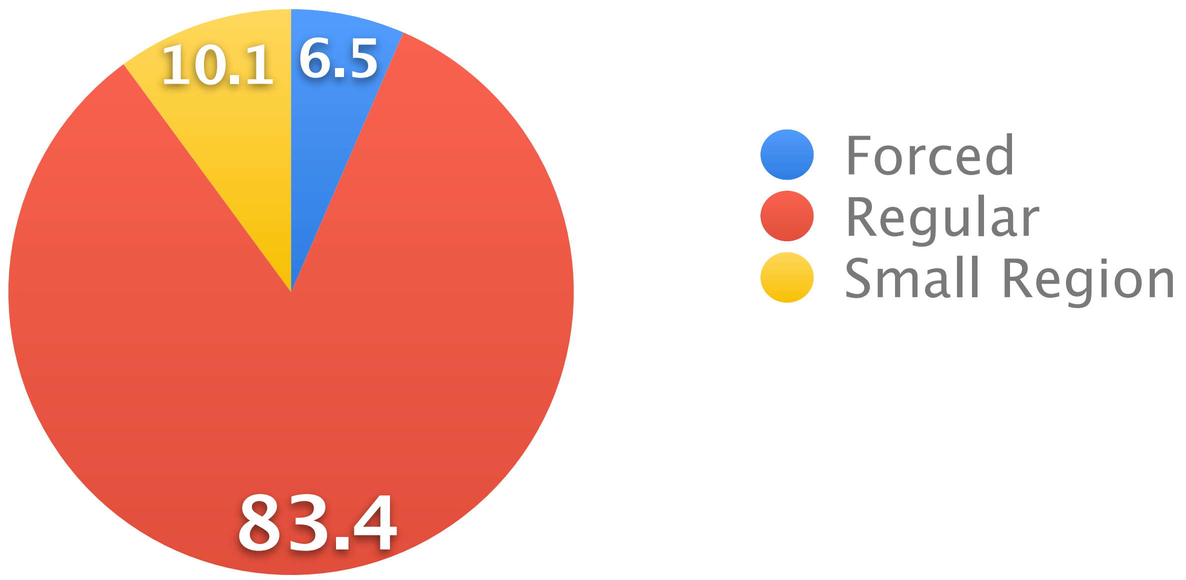
Merge percentages for new criteria

- Regular merges account for more than 80% of all merges!

Truck
(homogenous)



Flowergarden
(textured)



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forced includes merges due to constraints

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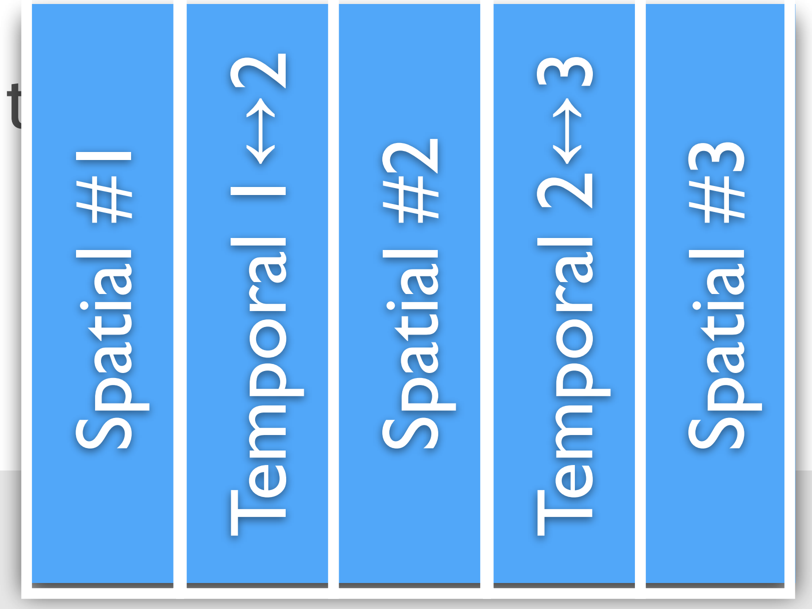
Fast O(n) segmentation

- Single link agglomerative clustering: Total complexity: O(n log n)   Dominated by sort
- Idea: Skip the sort
    - Discretize edge weight domain into 2-4K buckets (bucket sort)
      L1 RGB color distance: 768 values
- **Complexity: O(n)** [no large multipliers, $\alpha(n) < 5$ for all practical values of N]
- Can we do better?
    - Observation: Edge evaluation is costly / Spatial and temporal edges are disjoint
- Bucket lists
    - For N frames use 2 * N – 1 list of 2K buckets
    - Create in parallel via on-demand threads!

31% faster!!



Parallel construction

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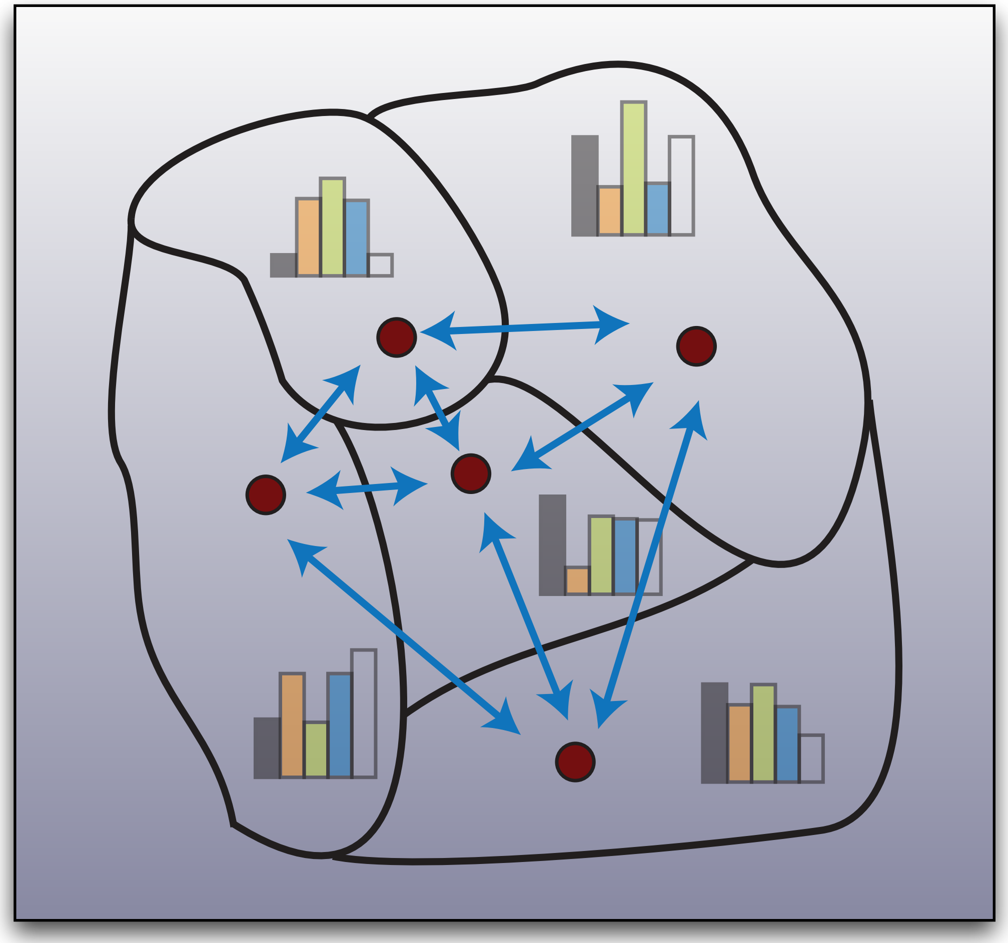
Talk outline

- Graph-based segmentation in the video domain
- Segmentation approaches / agglomerative clustering
- Over-segmentation
- Hierarchical segmentation

Hierarchical graph-based segmentation

- Size of regions: Controlled by merge threshold between descriptors (earlier: τ(C))
- **Hierarchical segmentation**: Instead of tweaking thresholds
- Build spatio-temporal adjacency graph of regions from over-segmentation
- Edge weights based on similarity of region descriptors (Appearance, texture, motion)
- Segment regions in super-regions
- Repeat until: Minimum region number reached



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Hierarchical segmentation

- Descriptors (3):
  - LAB histogram (10 * 16 * 16) w/ interpolation
  - Flow histogram (20 angles)
  - Compare each via χ_2 distance
  - Region Size Penalizer (truncated ratio w.r.t. average region size)
  - Combine via Soft-OR distance times region penalizer γ :

$$\gamma[1 - \prod_i (1 - d_i)]$$

- Merge:
  - Merge each descriptor / histogram
- Important: Merge alters edge weights between clusters (like average-link clustering)

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Hierarchical segmentation

- Which algorithm to use?
- First version: Uses single link [Felzenszwalb and Huttenlocher 2004]
  - Note: Merges alter edge weights!
  - Only allows for one merge per region per hierarchy level
  - Bad control for number of merges per hierarchy level
- Current version: True average-link agglomerative clustering + specify percentage of merges
- Fast: O(n) bucket sort for edges
- At every merge (< n) : Update neighboring edges in parallel
- Total complexity: O(n * k), k < 100 for our purposes

Spatio-Temporal Over-Segmentation

original video

over-segmentation

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Hierarchical Segmentation

Over-segmentation

Hierarchy at 20%

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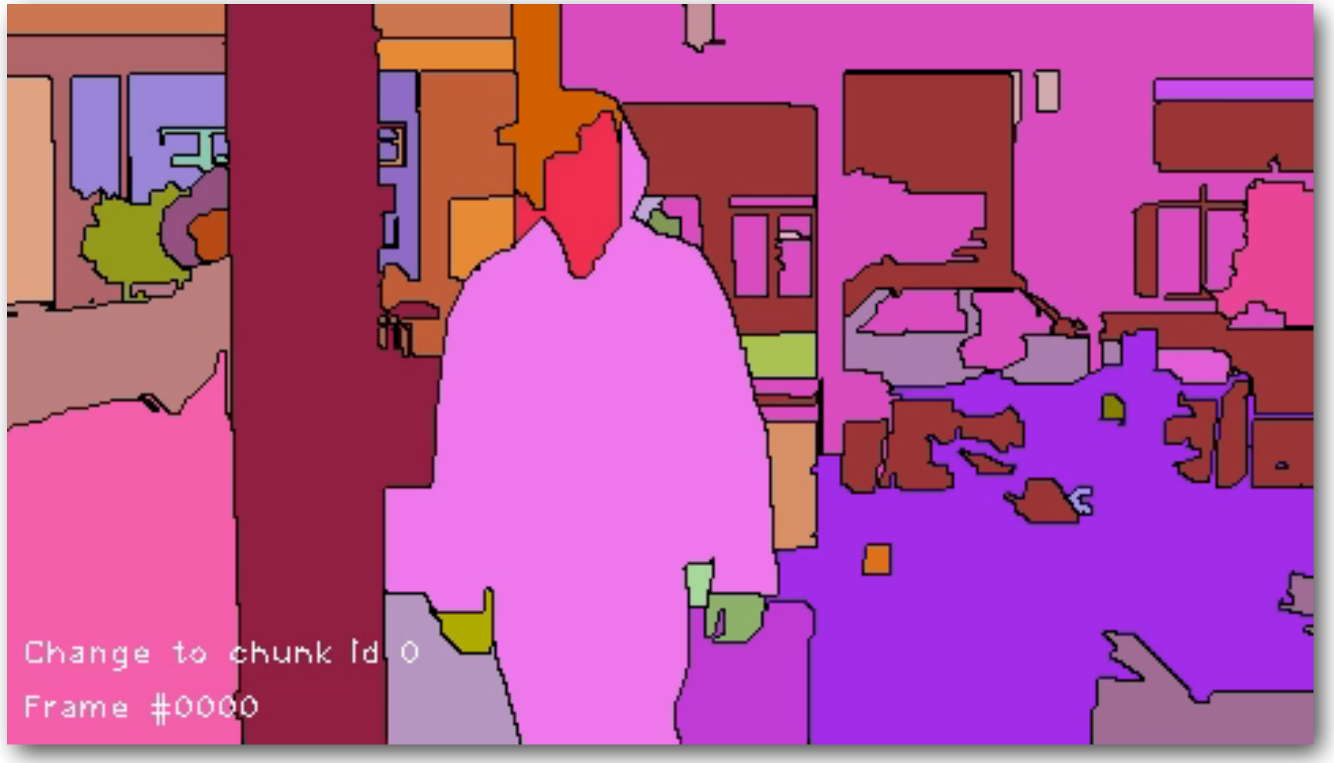
Hierarchical Segmentation

Hierarchy at 20%



Hierarchy at 50%

Benefits of hierarchical segmentation

Note: instability in over-segmentation (identities of region change [lights, window], boundaries are more unstable)

Hierarchical segmentation (shown at 50% of height of segmentation tree)

Over-segmentation only (manually tuned to give similar sized regions)

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Benefits of hierarchical segmentation

Hierarchical segmentation

Over-segmentation only
(manually tuned to give similar
sized regions)

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Effect of flow as feature

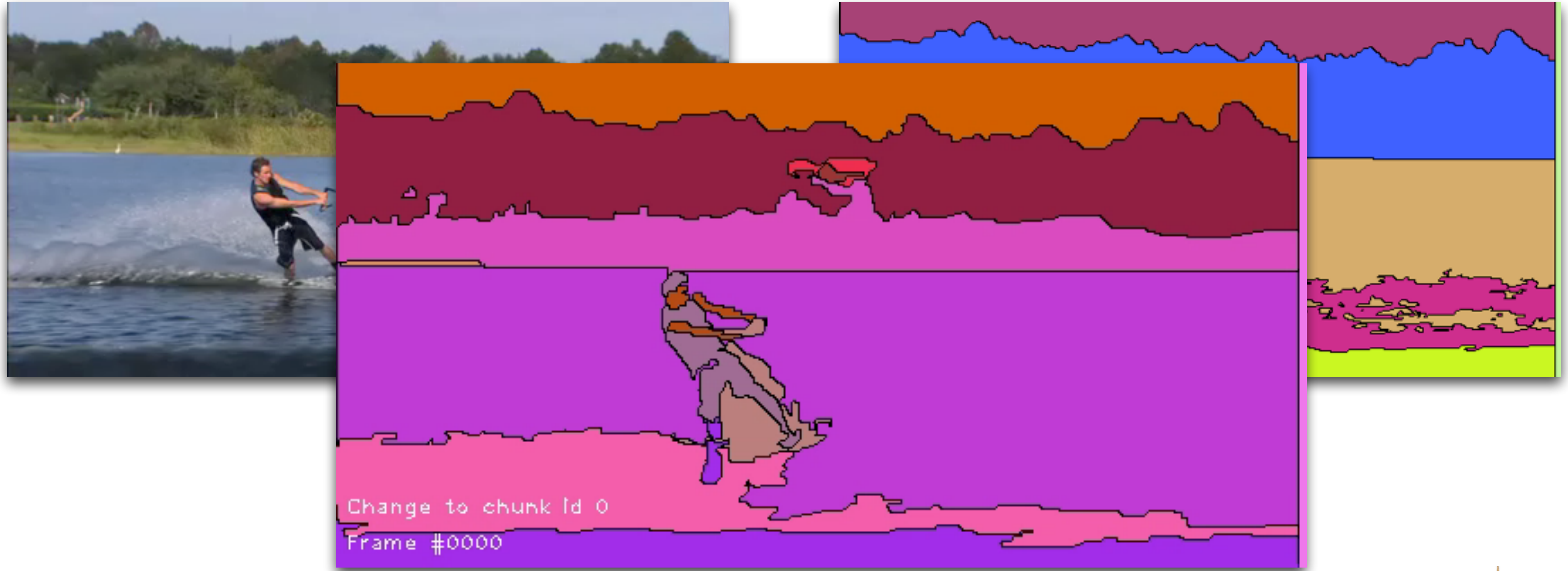
original

no flow

flow in hierarchical segmentation

flow in over-segmentation & flow in hierarchical segmentation

Results



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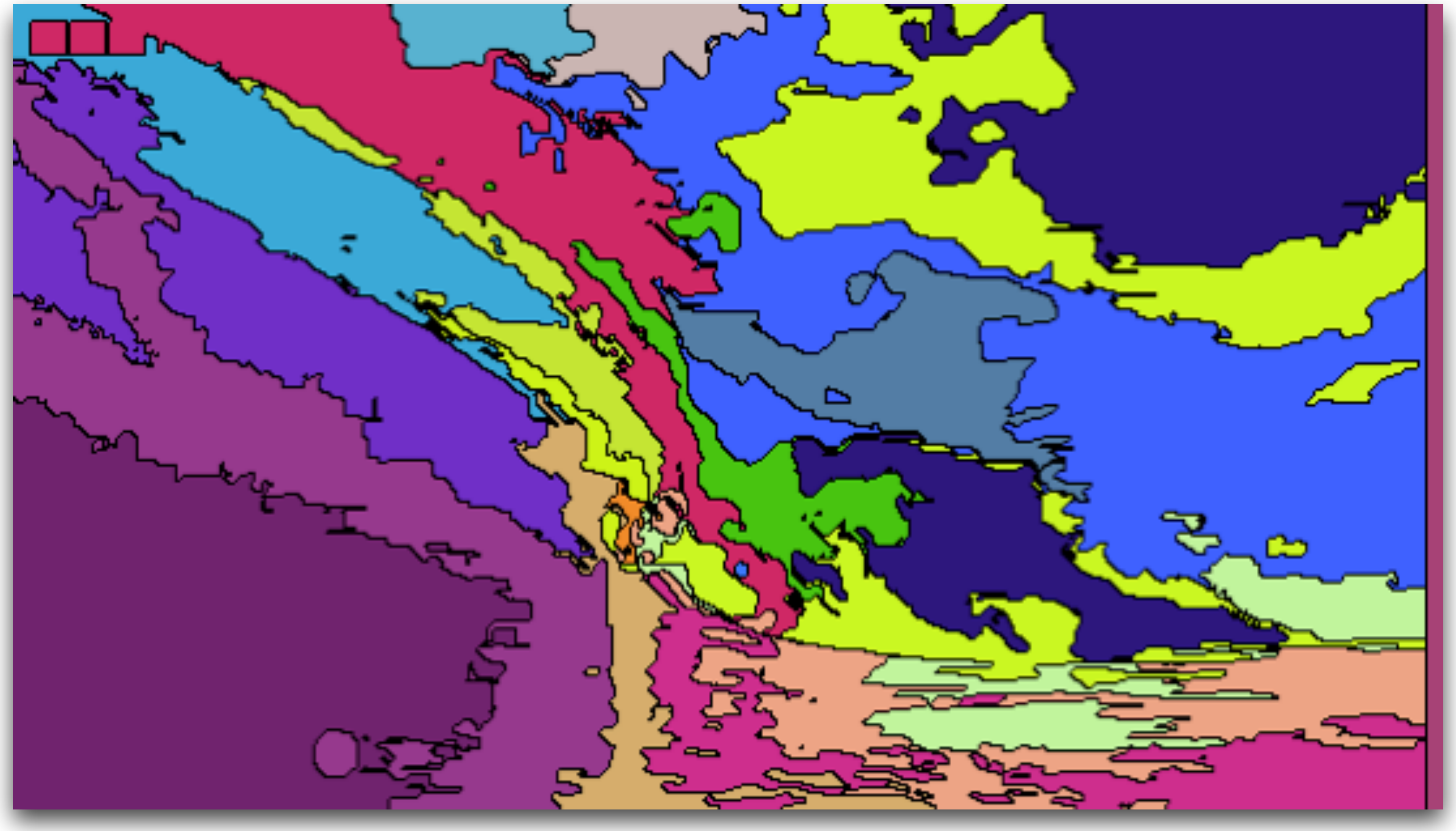
Results



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Applications of Video Segmentation

Matthias Grundmann, Vivek Kwatra, Mei Han

Daniel Castro, Irfan Essa

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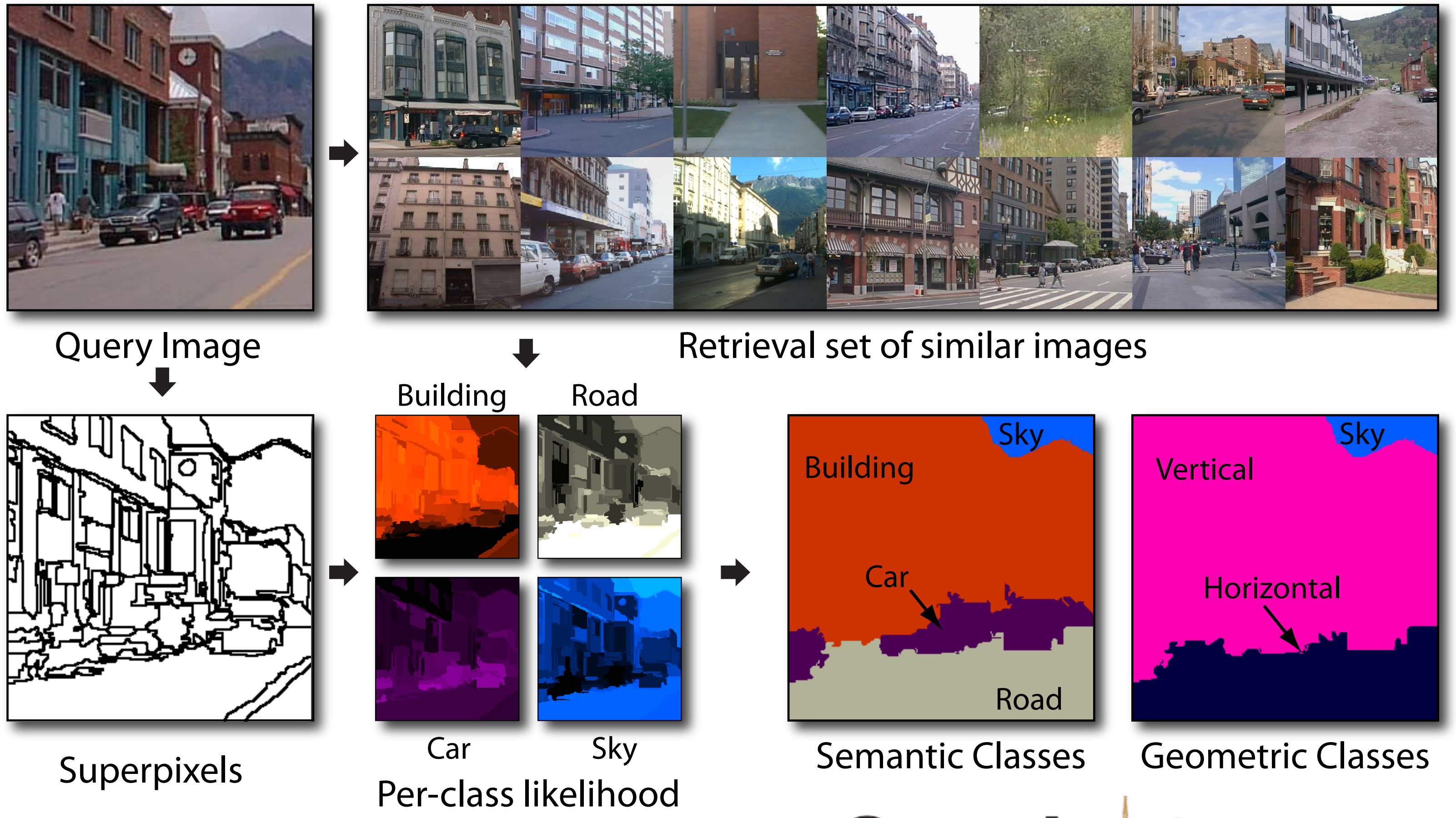
Talk outline

- Applications of video segmentation
  - Super-Parsing
  - Geometric context
  - Radiometric calibration for segmentation
  - Weakly supervised segmentation
- Online video segmentation and annotation
- Open source video segmentation

Super-Parsing

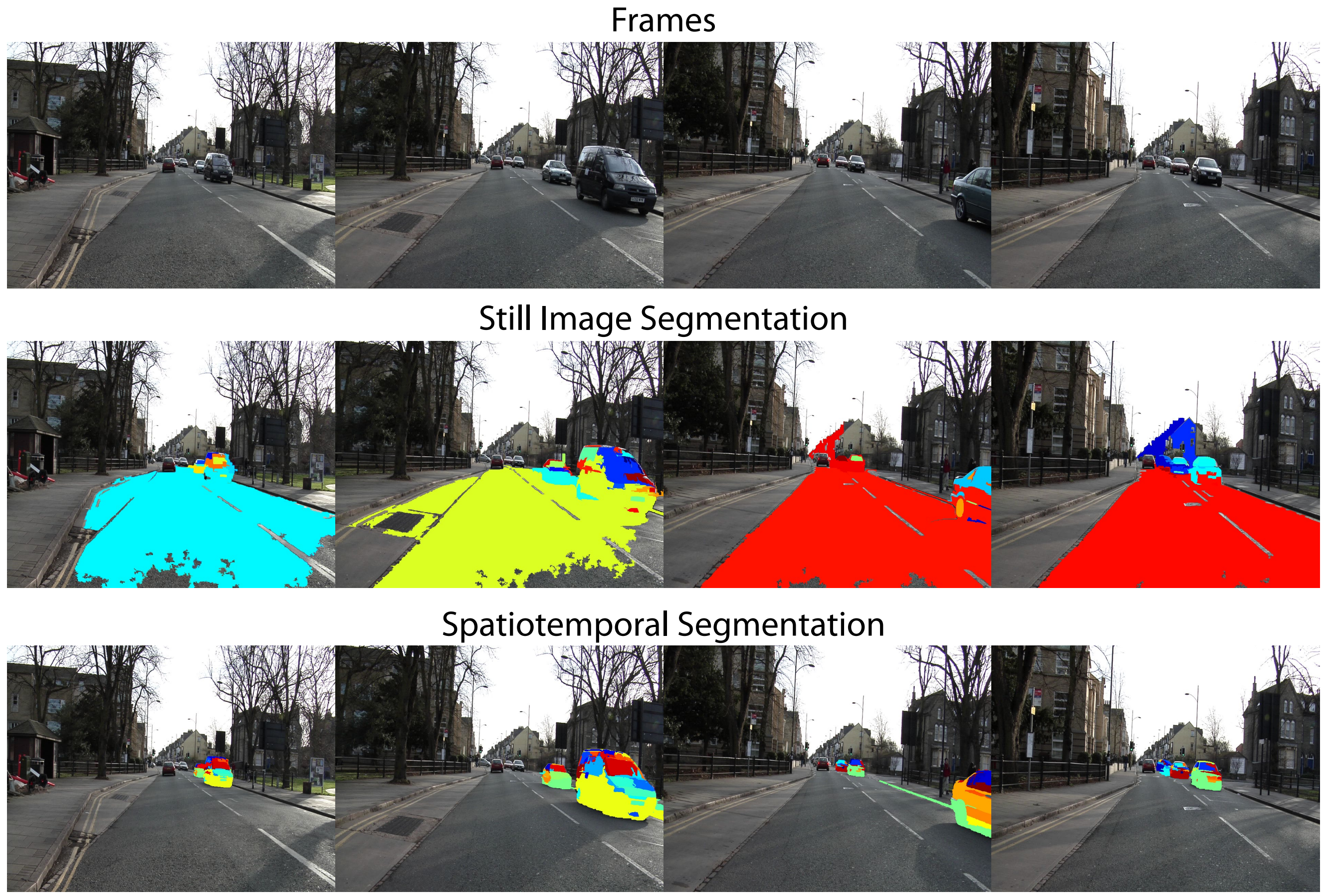
- [Joseph Tighe and Svetlana Lazebnik, 2012]:
  SuperParsing: Scalable Nonparametric Image Parsing with Superpixels
- Simplified description:
  - Extract super pixels from query image
  - Label transfer: From labeled super-pixel in training set
  - Smoothing via MRF



- http://www.cs.unc.edu/~jtighe/Papers/ECCV10/index.html

Super-Parsing

- [Joseph Tighe and Svetlana Lazebnik, 2012]:
  SuperParsing: Scalable Nonparametric Image Parsing with Superpixels
- Extended to video:
  - Super pixels → Spatio-Temporal regions
  - Aggregate prediction score over segments
  - MRF smoothing over super-voxels



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SuperParsing: Scalable Nonparametric Image Parsing with Superpixels

Joseph Tighe and Svetlana Lazebnik

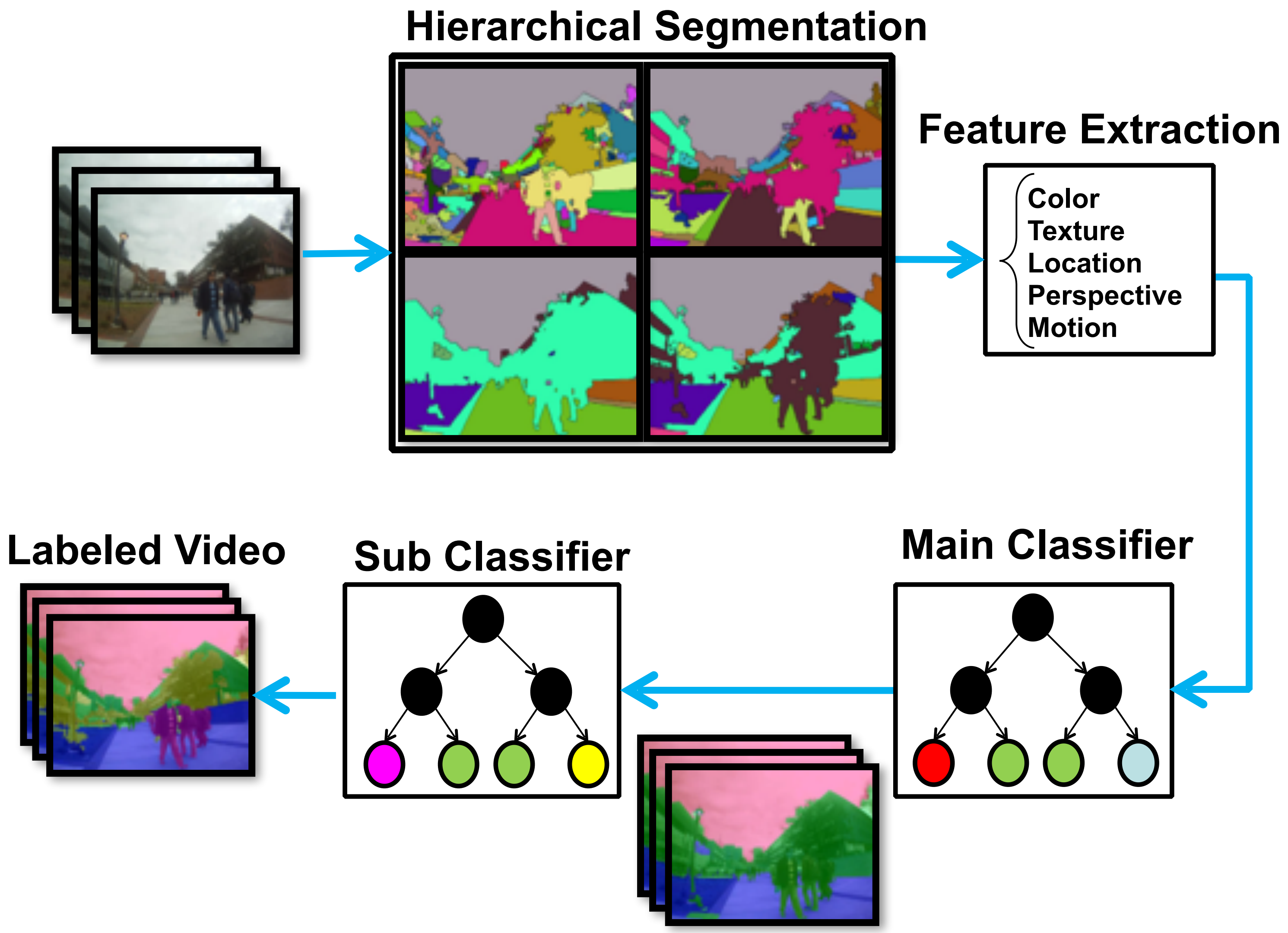
Geometric Context from Video

- Hoiem, Efros, Hebert, "Geometric Context from a Single Image", ICCV 2005
- Hussein, Grundmann, Essa, “Geometric Context from Video, CVPR 2013

http://www.cc.gatech.edu/cpl/projects/videogeometriccontext/

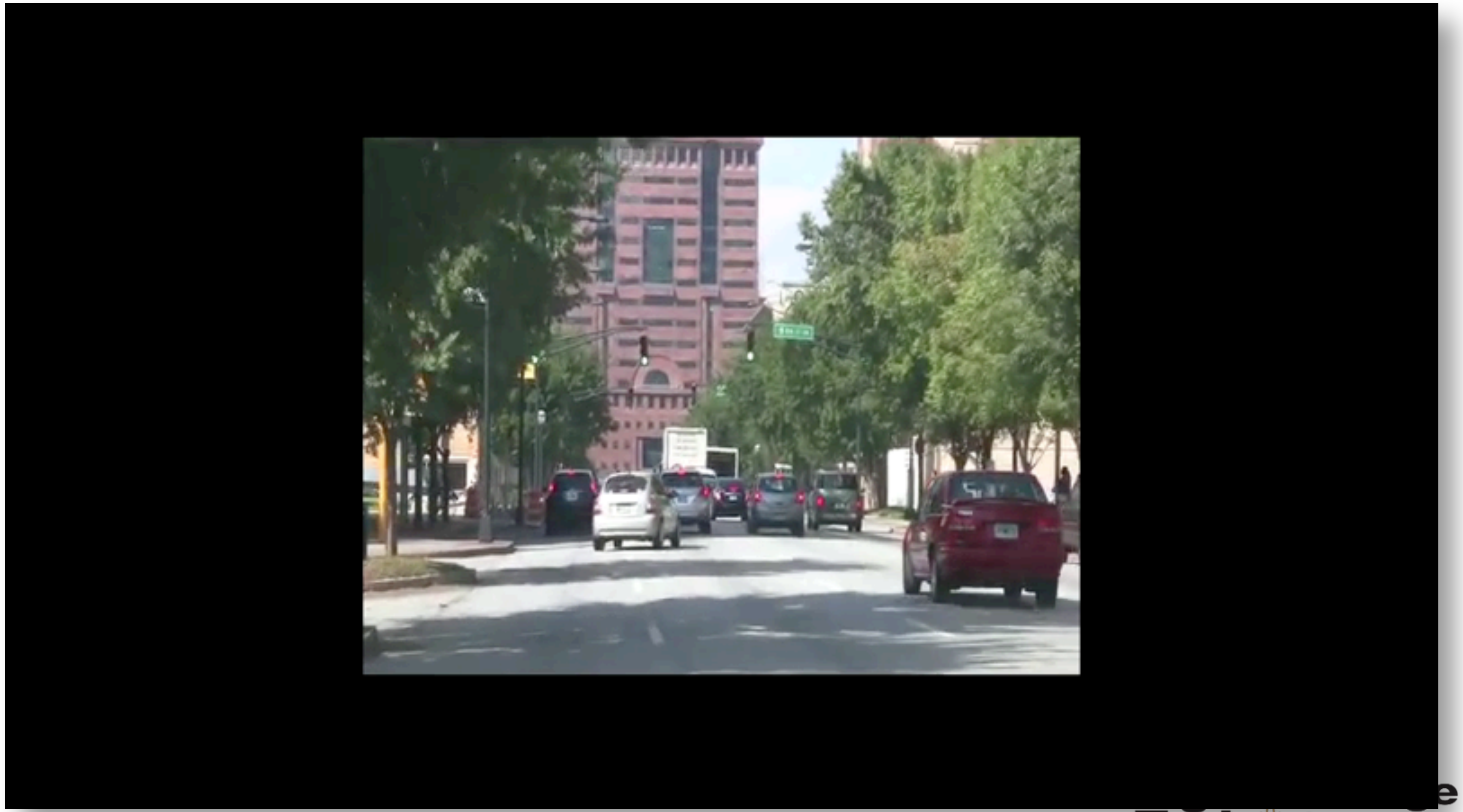
Geometric Context from Video

- Simplified description
  - Run video segmentation to yield super-regions
  - Extract spatio-temporal features
  - Train classifiers from features (from label dataset)
  - Different from super-parsing: Classifiers work directly on regions (not images)
  - Also: Aggregate prediction over hierarchy



Geometric Context from Video

Hussein, Grundmann, Essa, CVPR 2013



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Radiometric Calibration for Video Segmentation

Grundmann, Kang, Essa (ICCP 2013)

- Goal: Segmentation robust to gain changes in video
- Simplified description:
  - Radiometric calibration Colors → Irradiance
  - Segment in irradiance

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Pixels to Semantics (YouTube scale)

- G. Hartmann, M. Grundmann, J. Hoffman, D. Tsai, V. Kwatra, O. Madani, S. Vijayanarasimhan, I. Essa, J. Rehg, R. Sukthankar
Weakly Supervised Learning of Object Segmentations from Web-Scale Video
ECCV Workshop on Web-scale Vision and Social Media, 2012 (Best Paper)

Input video: dog

Result

Weakly supervised segmentation

- Simplified description
  - Stabilize and segment videos to yield good input (input: YouTube videos)
  - Yield spatio-temporal segments via Video Segmentation
  - Extract features from segments (appearance, motion, texture, shape etc.)
  - Weakly supervised: Training data only has (video, label) pairs (similar to MIL)
  - Learn model for each label by pooling over all extracted segments (MILBoost)
  - Evaluation: Manual annotation via online tool

Weakly Supervised Training Data

(video-level tags)

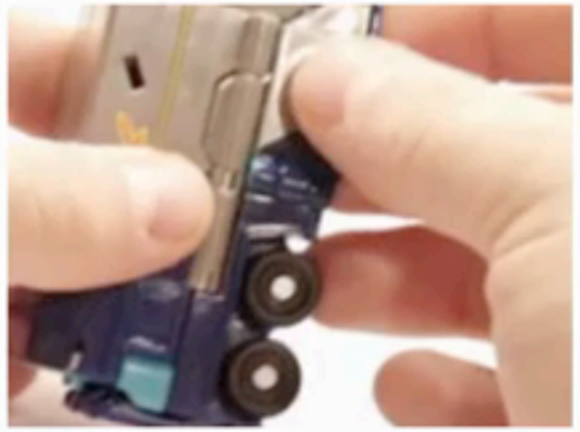
dog

bike

boat

horse

helicopter



transformers

card

robot

Talk outline

- Applications of video segmentation
- Online video segmentation and annotation
- Open source video segmentation

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Online video segmentation

- Goal:
  - Enable researchers / users to segment videos
- Initially launched on a single server in 2010 (limited resolution and length)
- In 2011: videosegmentation.com
  - Hosted on two machines with GPUs (for flow)
  - No limits on resolution or length (streaming)
  - One job at a time (HD video could stall queue for everyone)
  - REST API for terminal based usage
- Now:
  - Build fast, highly parallel cloud solution

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Fast online video segmentation

- Main ingredients:
  - Underlying segmentation algorithm O(n)
    - Parallelize over segmentation and hierarchical segmentation
  - Streaming segmentation
  - Run flow and both segmentations in a parallel pipeline
  - Resolution independence

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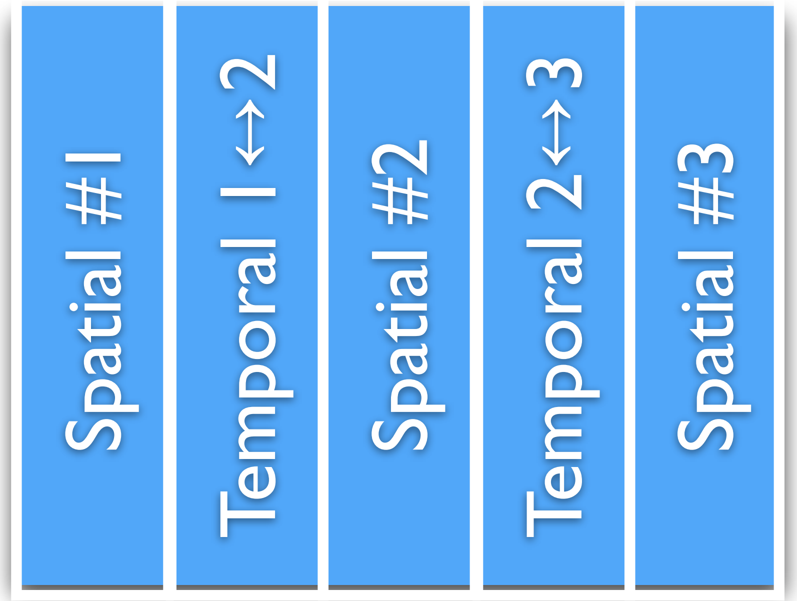
Fast O(n) segmentation

- Use bucket sort: Discretize edge weight domain into 2-4K buckets (bucket sort)
  L1 RGB color distance: 768 values
- **Complexity: O(n)** [no large multipliers, α(n) < 5 for all practical values of N]
- Spatial and temporal edges are disjoint → Bucket lists:
  - For N frames use 2 * N – 1 list of 2K buckets
  - Create in parallel via on-demand threads! **31% faster!!**
- For hierarchical segmentation:
  - Evaluate region ↔ neighbor edges in parallel
  - Hash edges to weights for fast graph construction

Parallel construction



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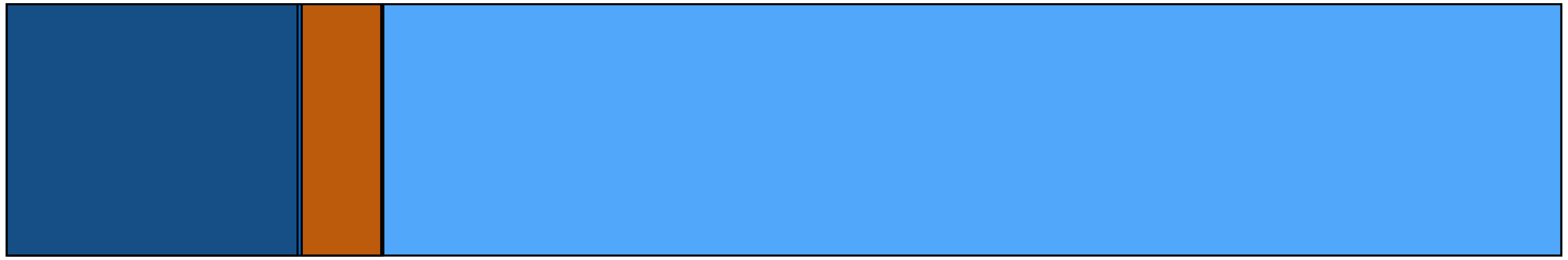
Streaming video segmentation

- Clip-based with overlap
- Original implementation modified edge weights
- Modifying edge weights is bad!
  - Single-link clustering
  - Changes order of merges
  - If used with Felzenszwalb criteria prohibits merges

Video Volume: frame# →



Segment 30 frames

Output result

Constrain graph before segmentation using result of previous clip

Edge within a region
=> weight = 0
Edge across boundary
=>weight = ∞

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Constraint streaming video segmentation

- Instead of modifying edge weights:
  Add to each region a constraint id   (-1 for unconstrained)
- Proposed by several authors:
  - [Lezama et al. , 2011]: Track to the future
  - [C. Xu et al., 2012]: Streaming hierarchical video segmentation
  - videosegmentation.com, since early 2011
- Criteria:
  - Merge regions if constraints are equal (regardless of distance)
  - Never merge two different constraints
  - Constrains are sticky: Propagates to unconstrained nodes

- region_id
- size
- descriptor[]
- is_done
- constraint

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Resettable Constraints: Motivation

- Problem: Constraints over-constrain!
- Following example from
  [Joseph Tighe and Svetlana Lazebnik, 2012]:
  SuperParsing: Scalable Nonparametric Image
  Parsing with Superpixels
- Problem:
  Pixels in distance are grouped together
  (perspective = averaging)

  Cannot be broken apart!

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Resettable constraints: Observation

- Regions become increasingly larger
  - Over-constraint: Everything gets grouped together
  - Constraints are dominating the segmentation process
- [Joseph Tighe and Svetlana Lazebnik, 2012] p. 16 about videosegmentation.com:
  “we have found the segmentation results to be better if we run the videos through the system backwards”

segmented backwards

Resettable constraints

- New merge criteria supplies descriptor distance
- New split operation:
  - Split if: Same constraint but descriptor distance > 15%
  - Reset constraint of smaller region (if < 1/3) or both
- Requires addition of virtual nodes/edges for topological information (neighbors)

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Resettable constraints: Comparison

Constraint segmentation

Segmentation with resettable constraints

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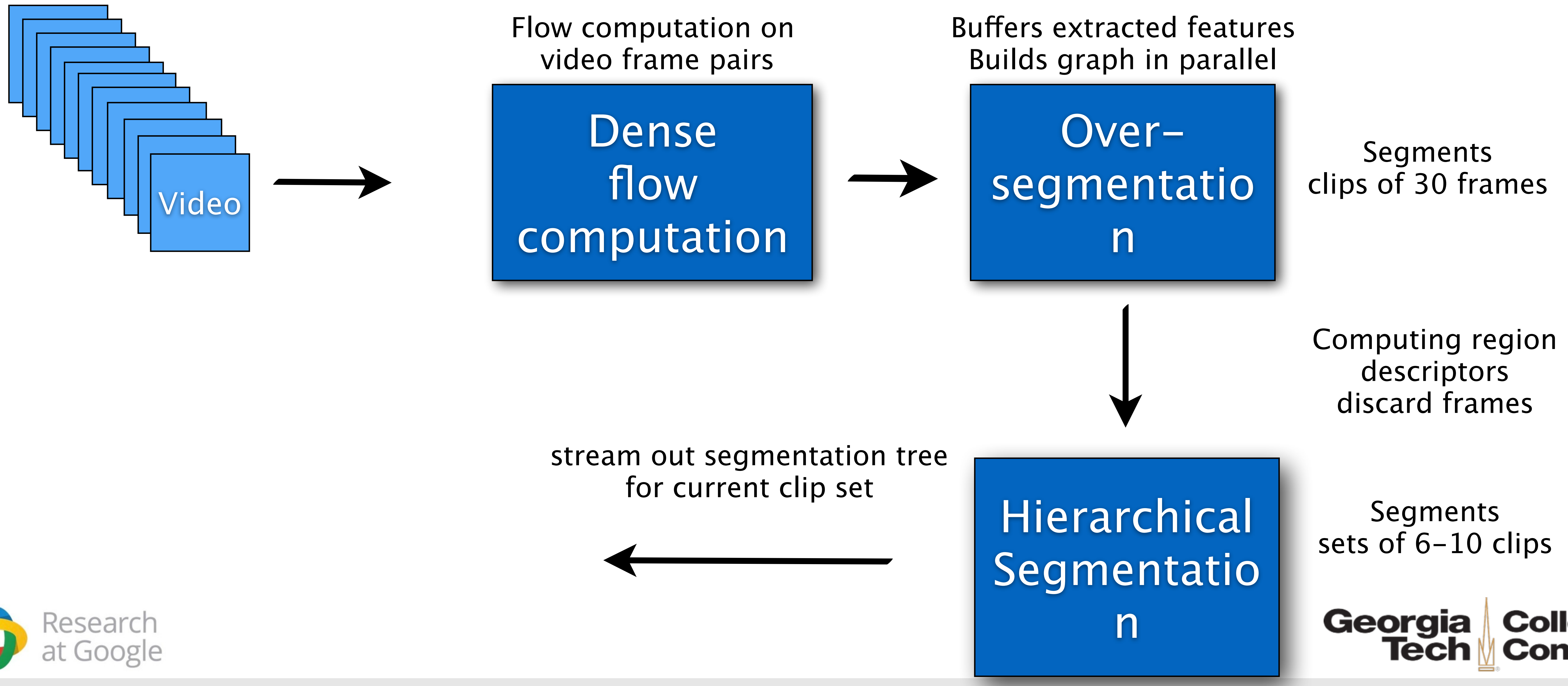
Fast online video segmentation

- Main ingredients:
  - Underlying segmentation algorithm O(n)
  - Streaming segmentation
  - Run flow and both segmentations in a parallel pipeline
  - Resolution independence

Segmentation Pipeline



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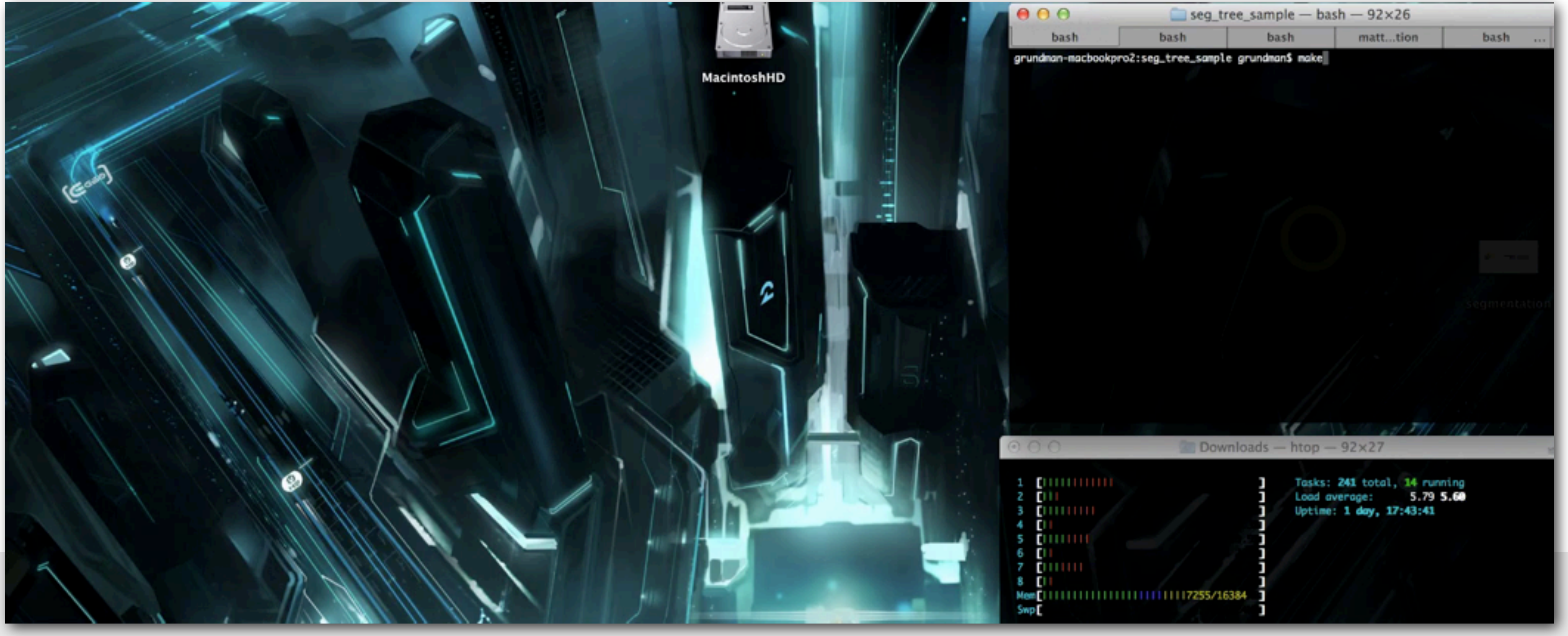
Segmentation pipeline

Maximum parallelism

- Flow, Over-segmentation and Hierarchical segmentation can be run independently once input is available: 400% CPU sustained

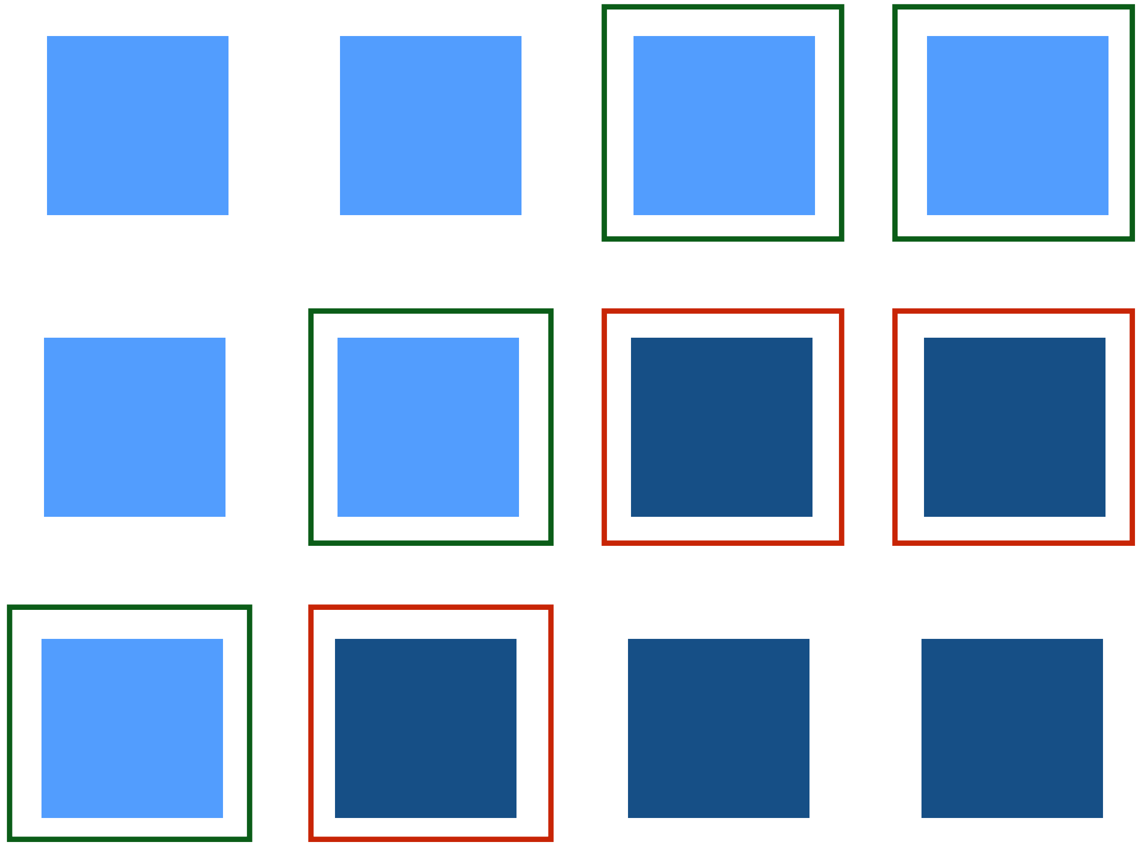


Segmentation resolution

- Problems with current approach:
  - Segmentation is always computed for a specific resolution (e.g. 360p, 720p, etc.)
  - Complexity of flow and over-segmentation grows with video resolution
  - Segmentation representation grows with resolution
    Rasterization: Set or scanline intervals (RLE encoding)
- Rasterization does not enable geometric transformations
  (w/o need for bilateral upsampling)

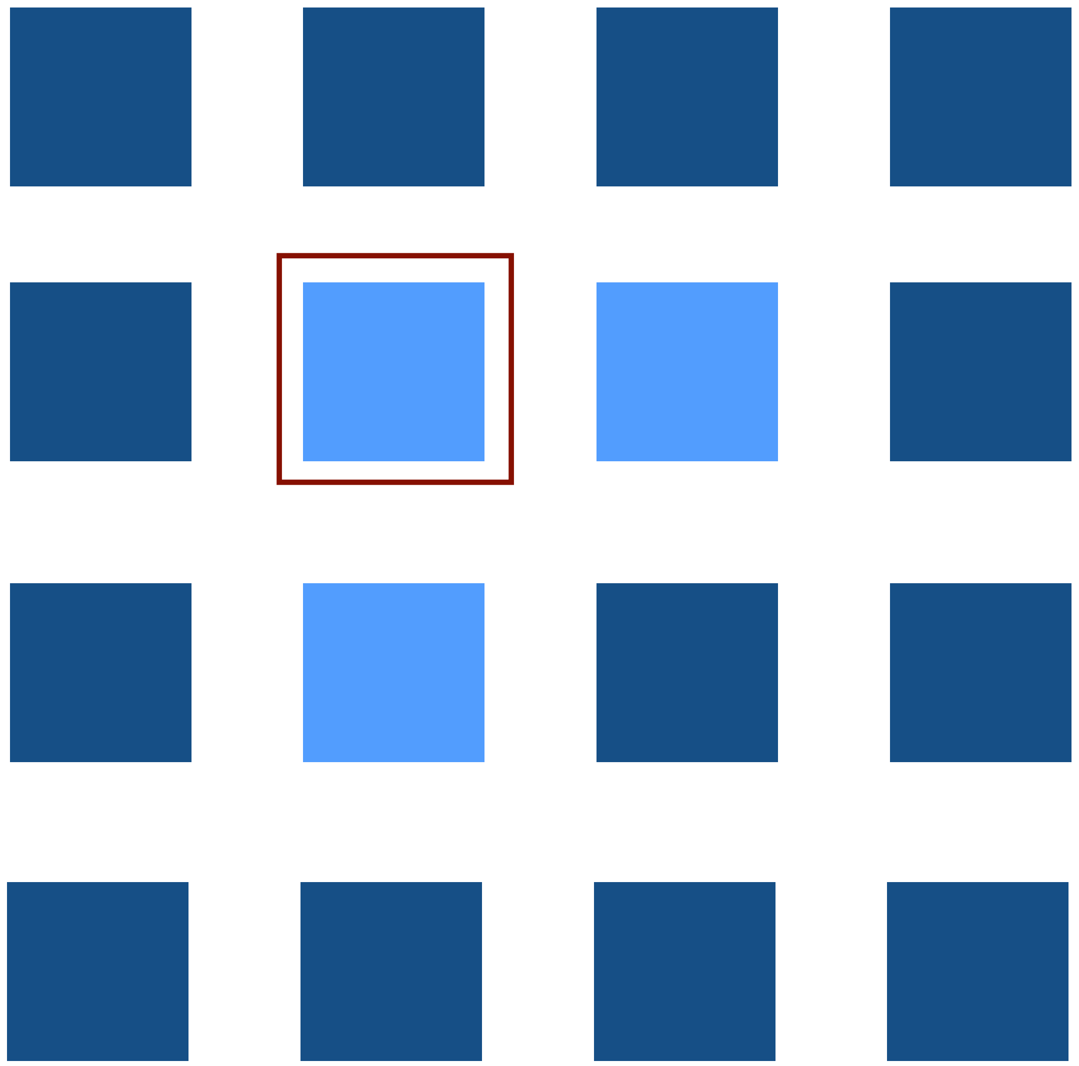
Compute segmentation boundaries

- Seems trivial at first:
  - Raster scan → Boundary pixel: current region is different from N4
  - Not "water tight" → double boundaries



Unique segmentation boundaries

- Based on:
  "A contour tracing algorithm that preserves common boundaries between regions"
  Yuh-Tay Liow, CVGIP: Image Understanding, 1991
- Idea: Similar to polygon rasterization (don't render bottom or rightmost boundary)
  - Assume N4 segmentation → N8 boundary
  - Start at most top-left pixel
  - 12 different configurations



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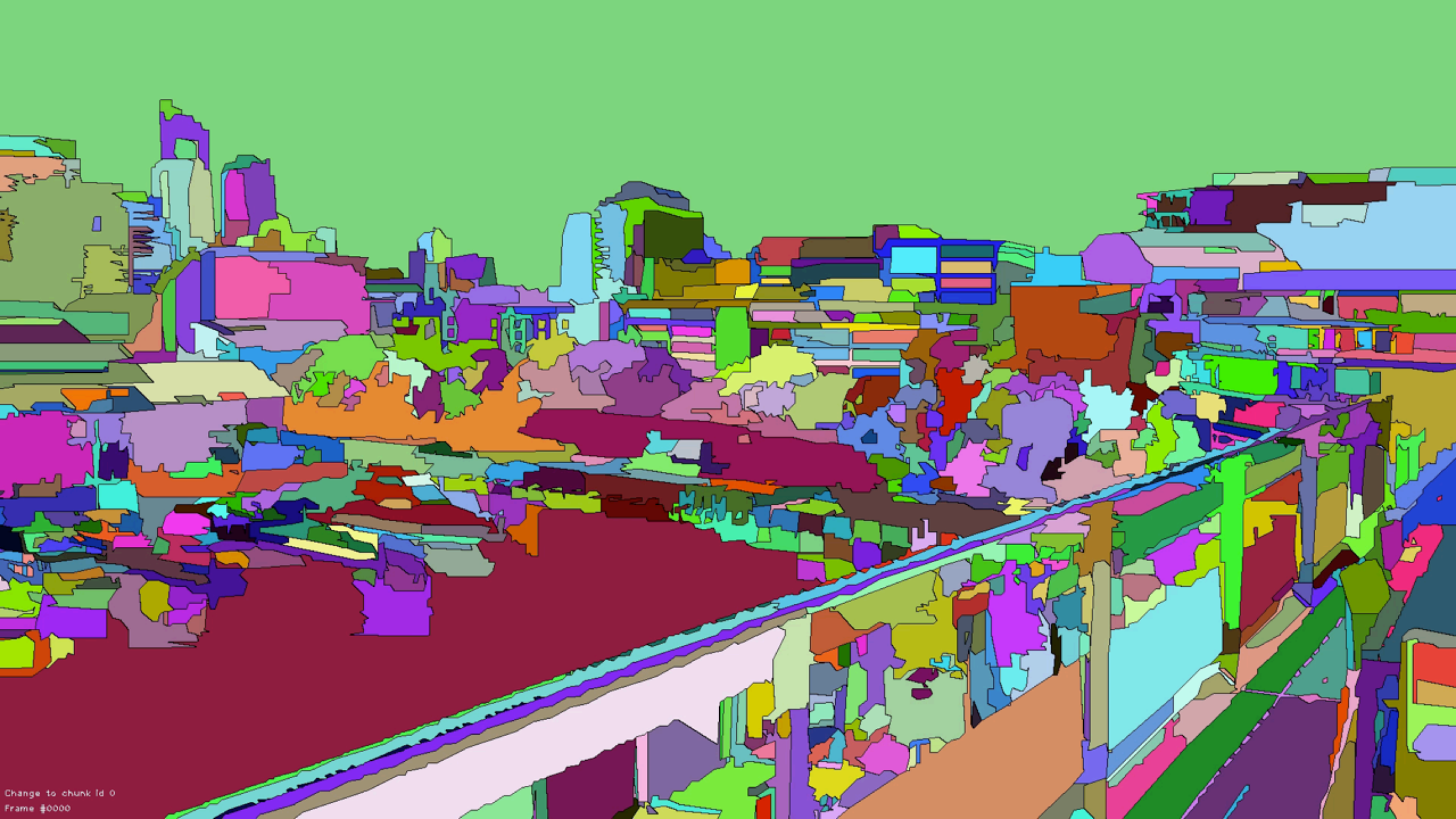
Vector representation for Video Segmentation

- Extract boundaries for each component of a region (different from image case)
  - Trace each component
- Simplify boundaries via Ramer-Douglas-Peucker algorithm
  - Yields a water-tight polygon representation per region component
- Store coordinates into a vector mesh
  - **Geometrically transform mesh**
  - Rasterize if needed
- **Enables downscaling of input video and upscaling of result!**
  Segment 1080p! (~1 billion edges for 1s)


Change to chunk id 0
Frame #0000

Fast online video segmentation

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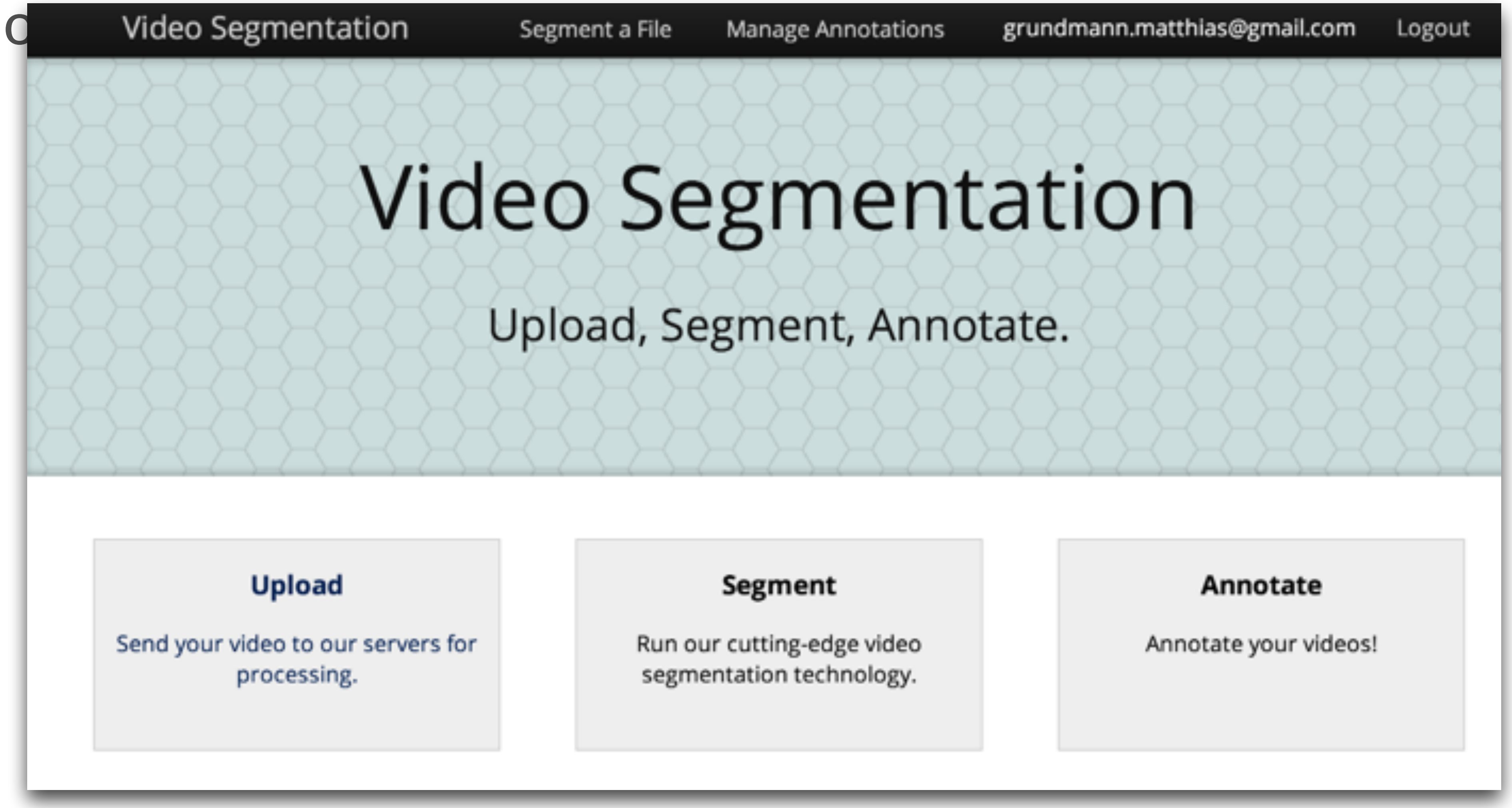
  - Resolution independence

Video Annotation

Online Video Segmentation and Annotation

- End-to-end system for online video segmentation and annotation
- www.videosegmentation.com



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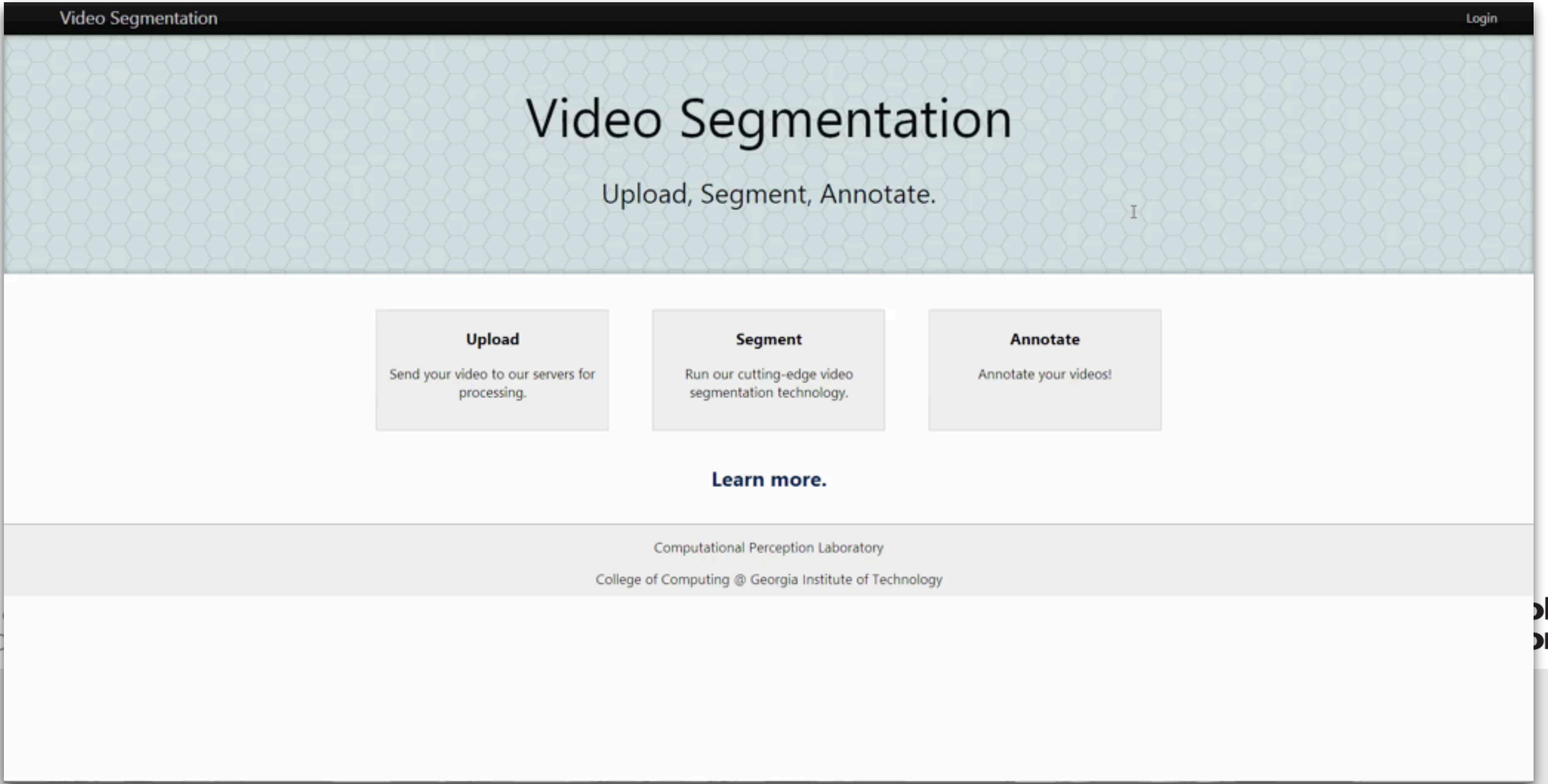
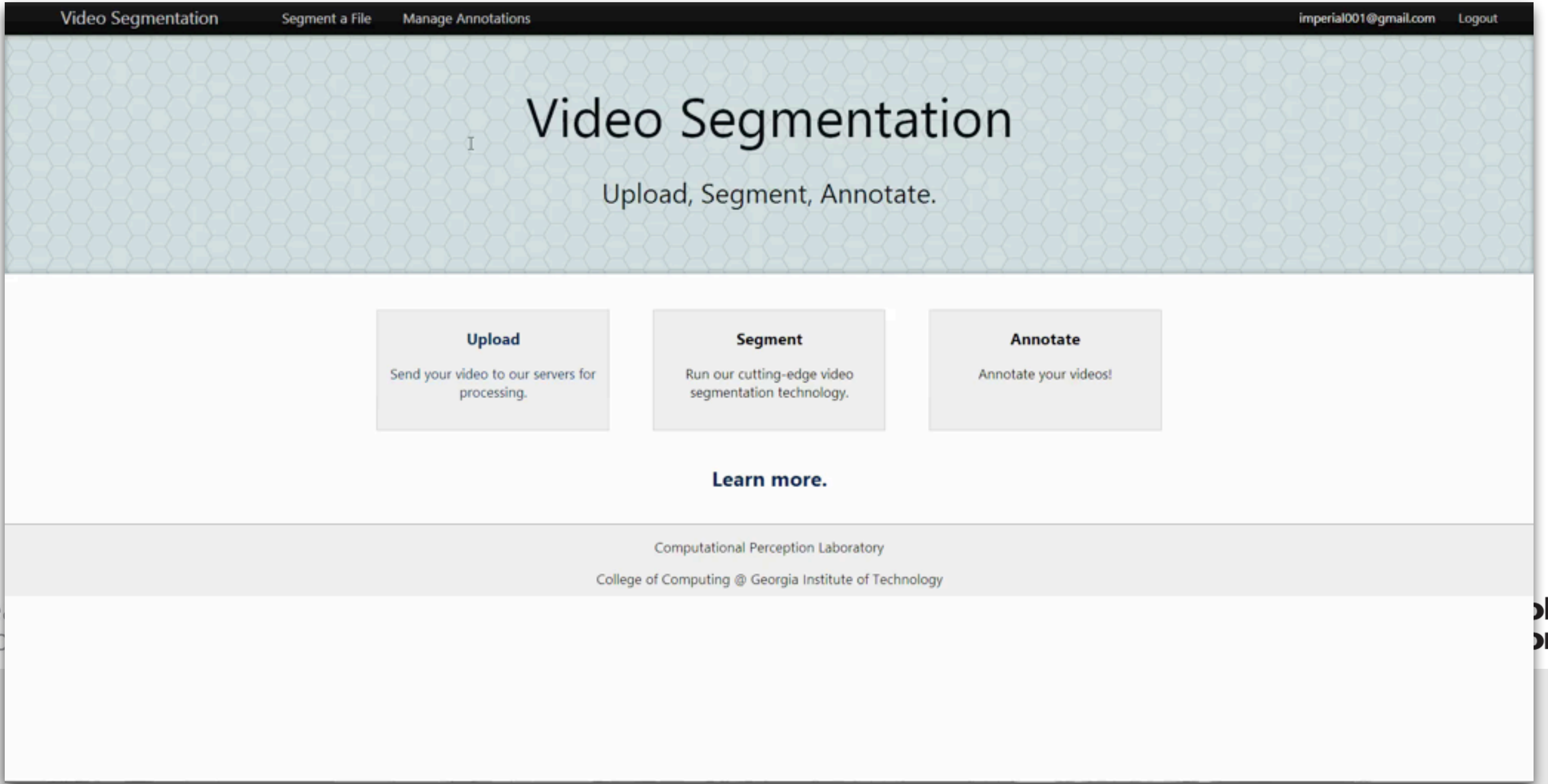
Online Video Segmentation and Annotation

Segment your videos



Online Video Segmentation and Annotation

Adjust options



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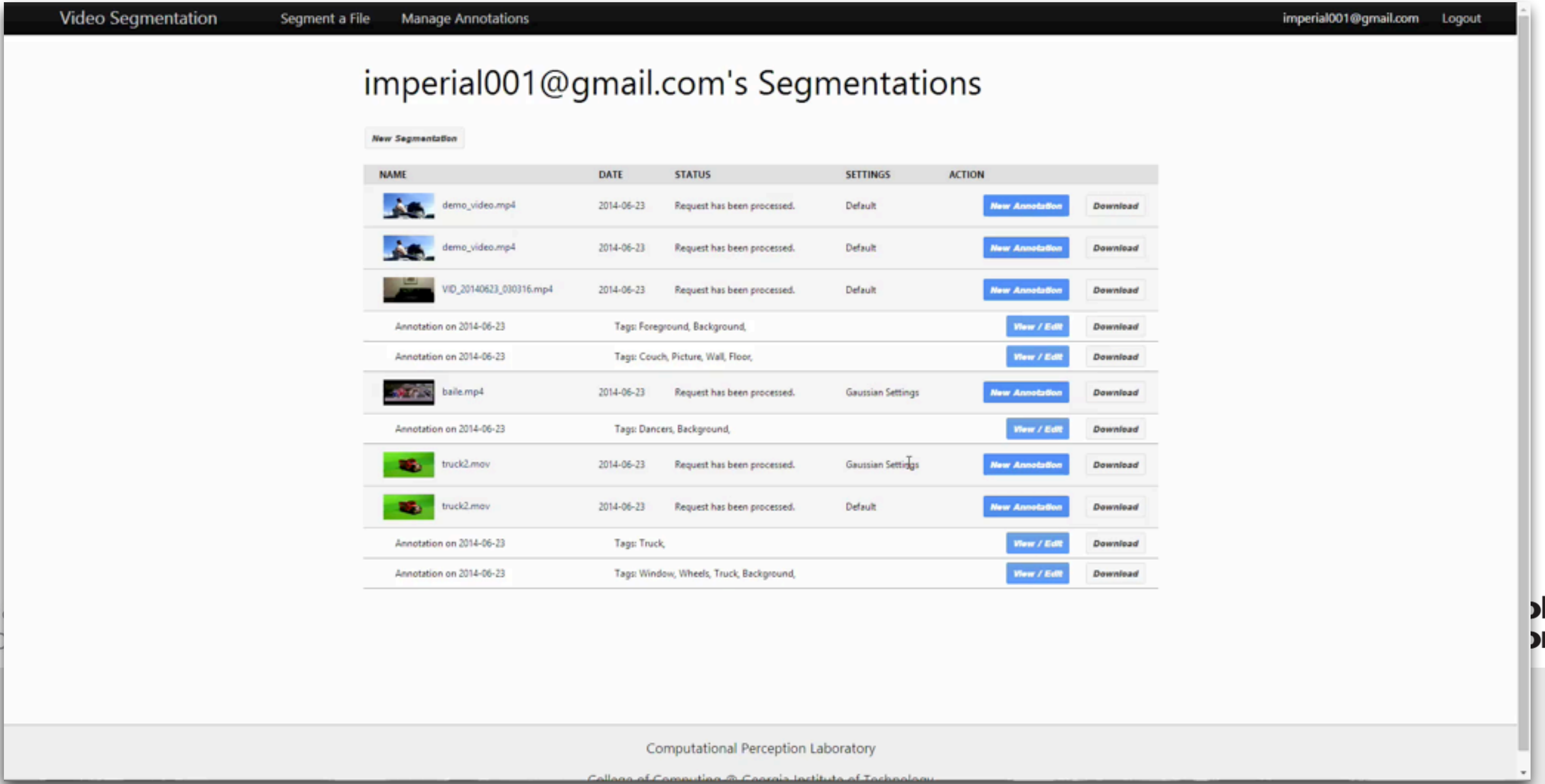
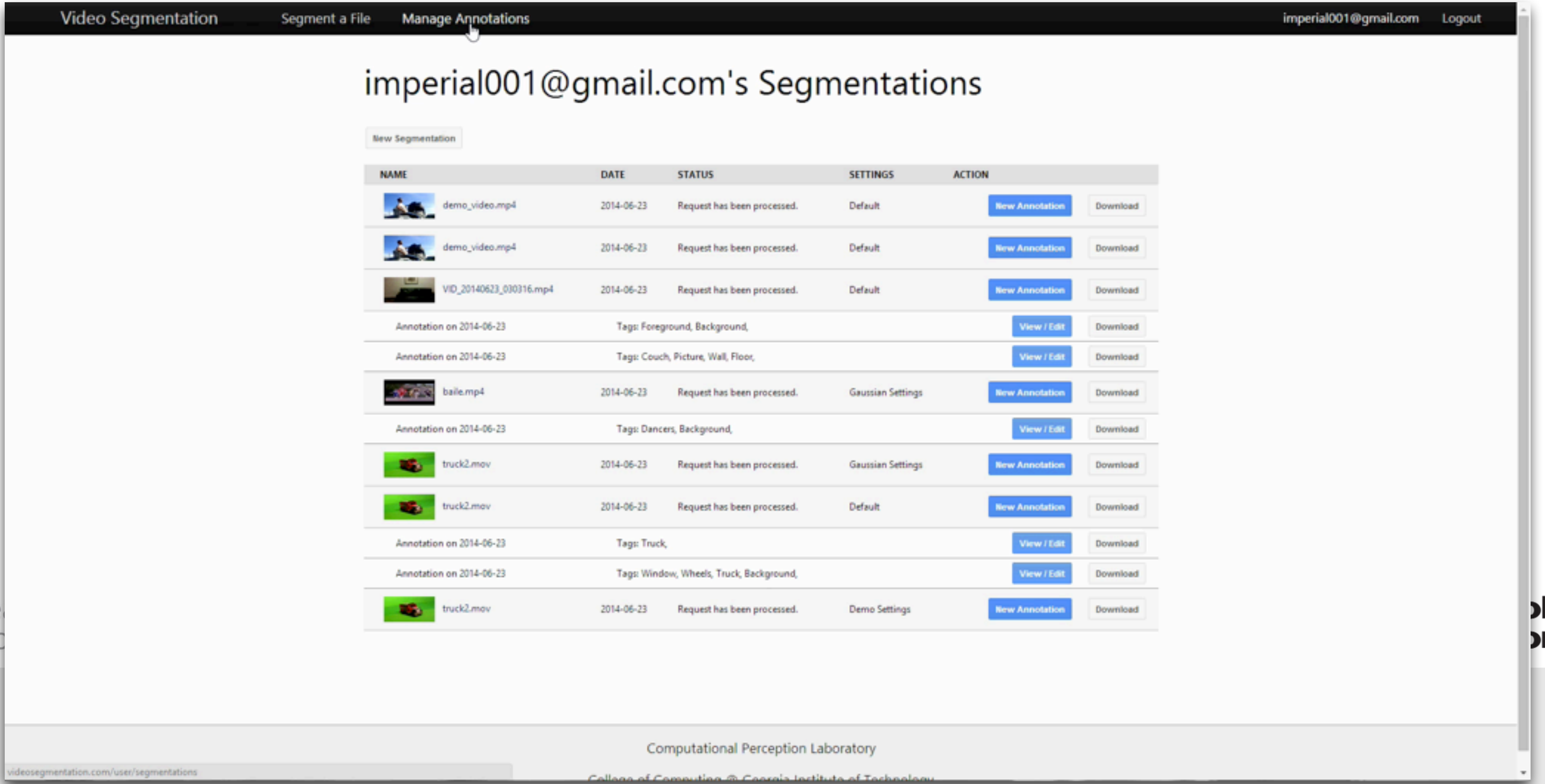
Online Video Segmentation and Annotation

Annotate!



Online Video Segmentation and Annotation

Download results

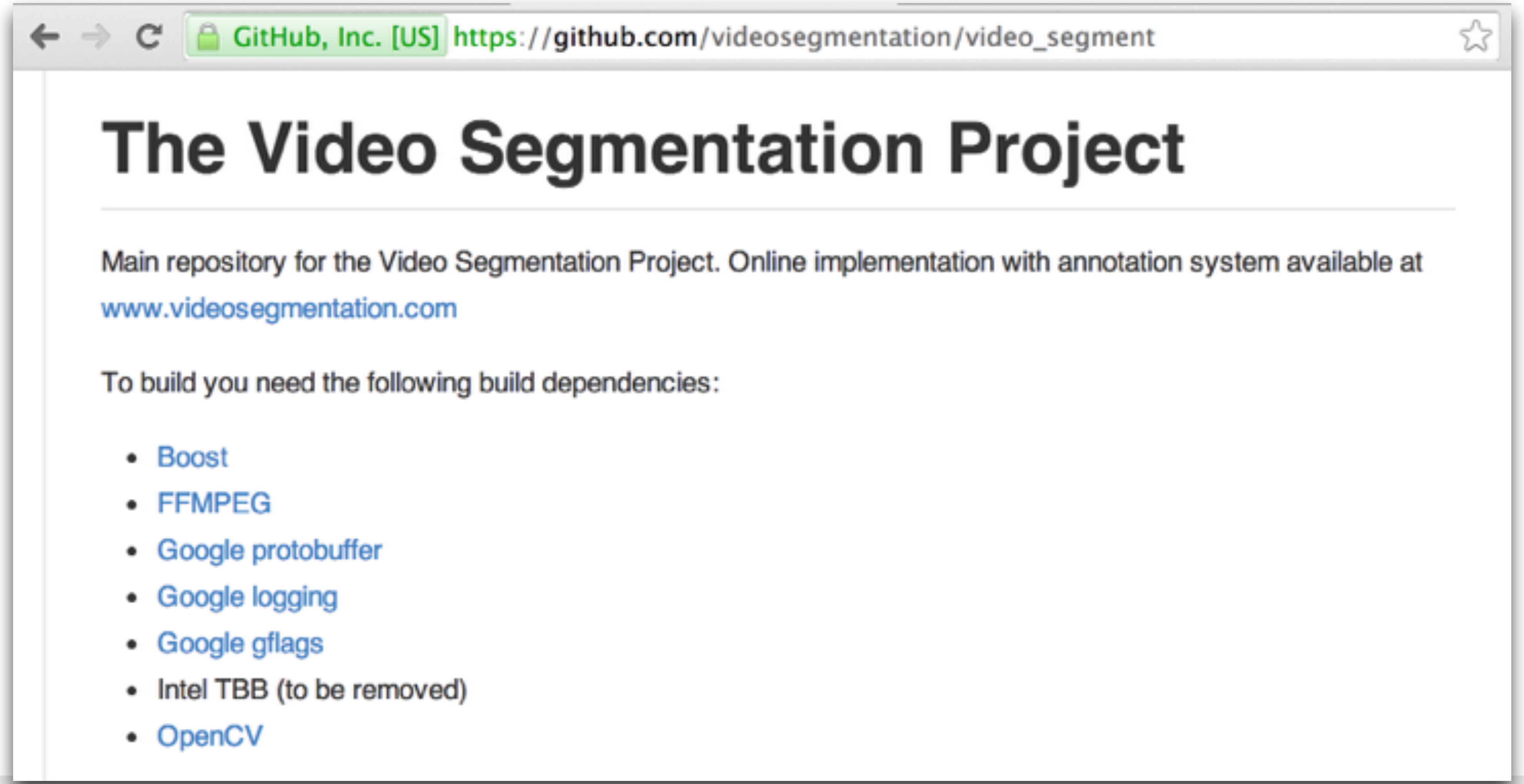


Talk outline

- Applications of video segmentation
- Online video segmentation and annotation
- Open source video segmentation

The Video Segmentation Project

- Open source implementation of everything shown today
  - https://github.com/videosegmentation/video_segment
  - BSD license
- Generic segmentation interfaces
  - Over segmentation:
    - Define pixel distance
    - region descriptors,
    - merge thresholds
  - Hierarchical segmentation:
    - Define region descriptors
    - distances



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DenseSegmentation

Fully customizable features, distances and descriptors

C++

```
// Create generic distance for space and time (here L1, color only).
typedef SpatialCvMatDistance<ColorDiff3L1, ColorPixelDescriptor> SpatialCvMatDistance3L1;
typedef TemporalCvMatDistance<ColorDiff3L1> TemporalCvMatDistance3L1;

// Bundle spatial and temporal distances.
struct DistanceColorL1 : DistanceTraits<SpatialCvMatDistance3L1,TemporalCvMatDistance3L1>
{ };

// API callback to create dense segmentation graph.
virtual DenseSegGraphInterface* CreateDenseSegGraph(...) {
```


1.

RegionSegmentation

Fully customizable region descriptors and distances

C++

```
DescriptorExtractorList* extractors;       // Supplied by API
DescriptorUpdaterList* updaters;           // Supplied by API
shared_ptr<AppearanceExtractor> appearance_extractor(
    new AppearanceExtractor(options_.luminance_bins, options_.color_bins,
                            features[0]);    // Stores image.
extractors->push_back(appearance_extractor);
updaters->push_back(shared_ptr<NonMutableUpdater>(new NonMutableUpdater()));
shared_ptr<FlowExtractor> flow_extractor(
    new FlowExtractor(options_.flow_bins, features[1]));   // Stores flow images
extractors->push_back(flow_extractor);
updaters->push_back(shared_ptr<NonMutableUpdater>(new NonMutableUpdater()));
```


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Google Developers

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