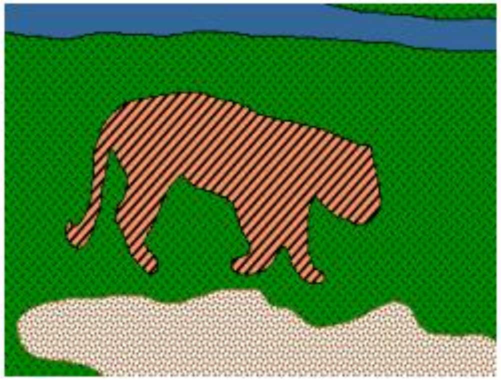
TDS3651
Visual Information Processing



Region Segmentation
Lecture 8

Faculty of Computing and Informatics
Multimedia University

Previously created by John See, edited by Lai-Kuan, Wong, Yuen Peng, Loh
Some graphics and materials are taken from UTexas at Austin CS376 & CS381V notes, Stanford Uni's CS131 notes and Gonzalez & Wood's DIP textbook

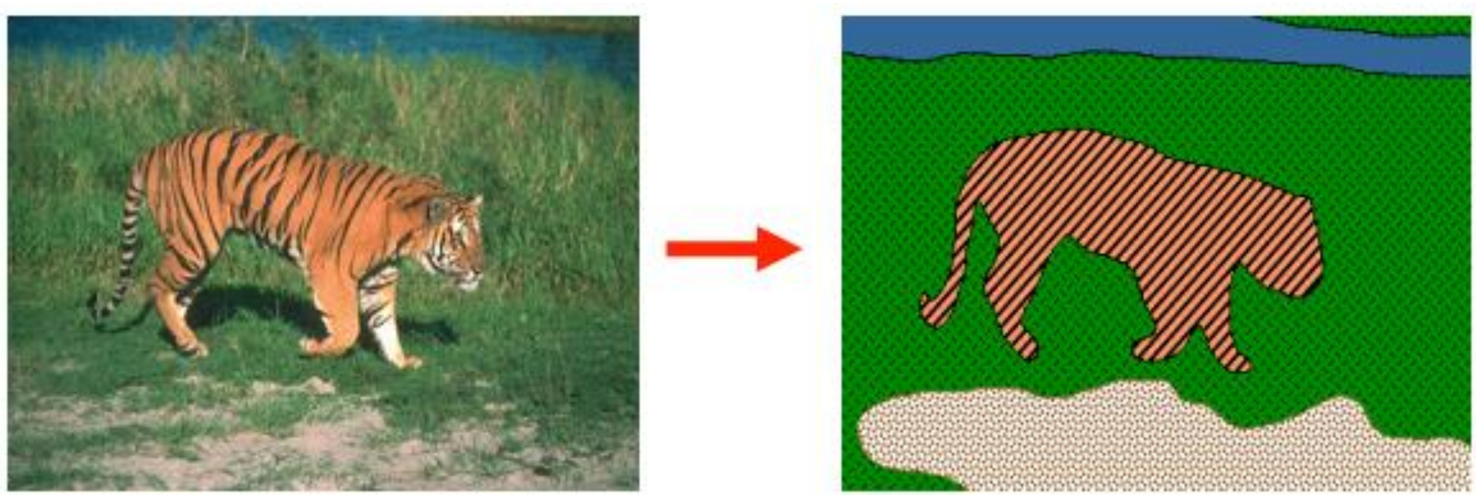
Lecture Outline

- Why do segmentation?
  - Inspiration from human perception – Gestalt theory
- Segmentation as clustering
  - K-means
- Superpixels – Graph-based algorithms
  - Graph cuts / normalized cuts
  - Felzenswalb’s method
- Deep Learning methods
  - FCN Semantic Segmentation
  - Mask R-CNN Instance Segmentation
  - ViT Semantic Segmentation

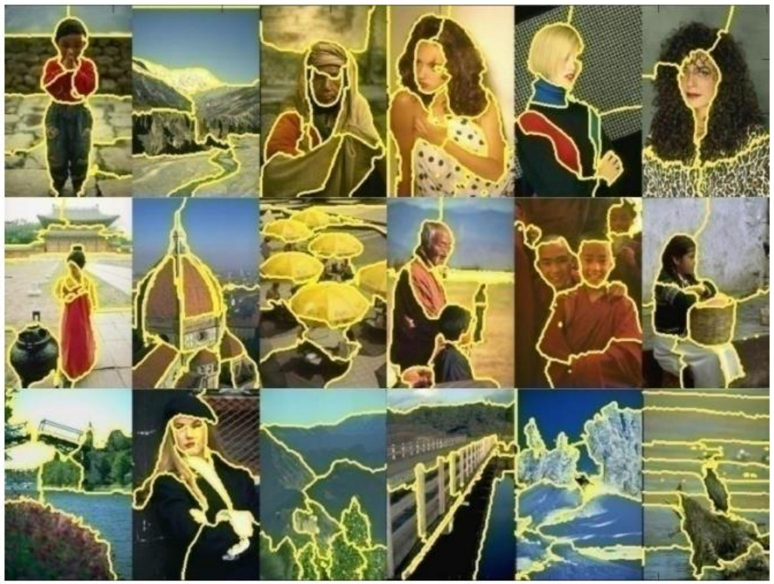
Why do segmentation?

Why do segmentation?

- Aims:
  - Gather or group features that belong to each other
  - Obtain an intermediate representation that compactly describes key image/video parts



Examples of segmentation tasks



[Figure by J. Shi]

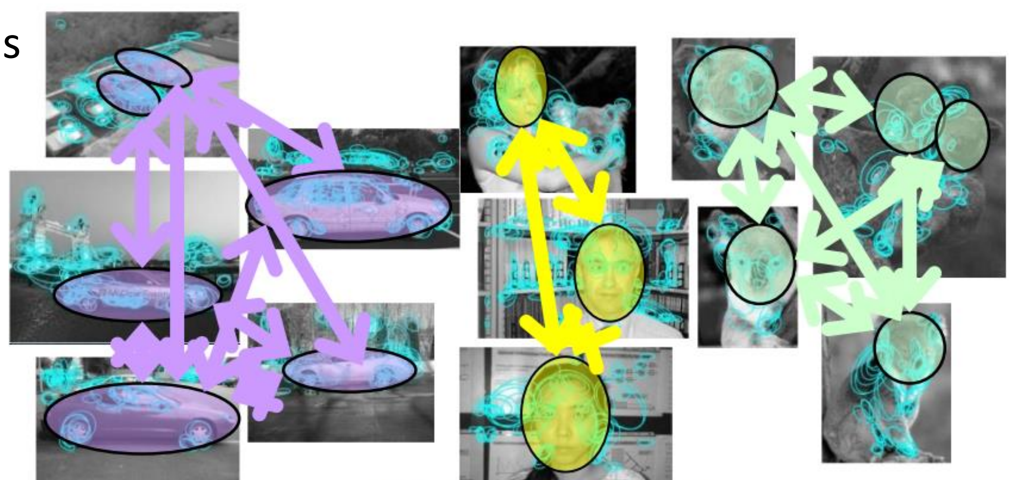
Determine image regions

[http://poseidon.csd.auth.gr/LAB_RESEARCH/Latest/imgs/SpeakDepVidIndex_img2.jpg]

Group video frames into shots

[Figure by Wang & Suter]

Figure-ground



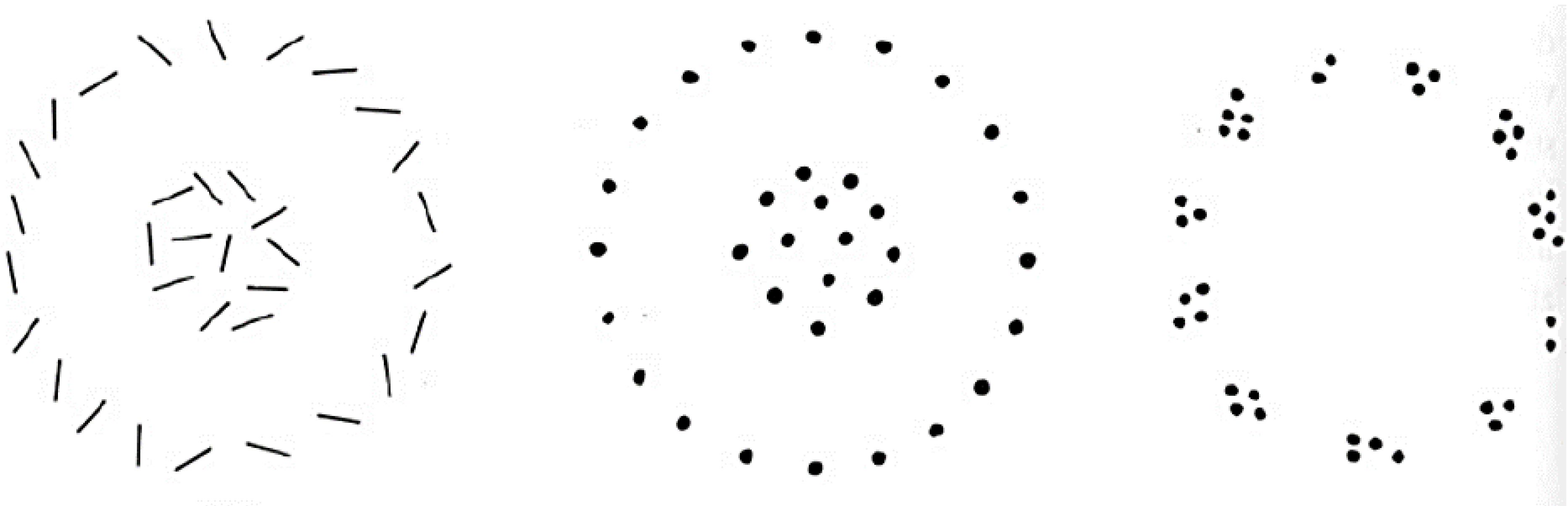
[Figure by Grauman & Darrell]

Object level grouping

Segmentation

- Aims:
  - Gather or group features that belong to each other
  - Obtain an intermediate representation that compactly describes key image/video parts
- Top down vs. bottom up segmentation
  - Top-down: Pixels belong together because they are from same object
  - Bottom up: Pixels belong together because they look similar
- Hard to measure success – depends on application!

Grouping what?



What things should be grouped?

What cues indicate groups?

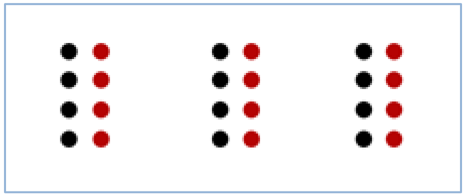
Gestalt Theory

- How to group pixels (the smallest element in images) based on these "Laws of Gestalt Theory"?

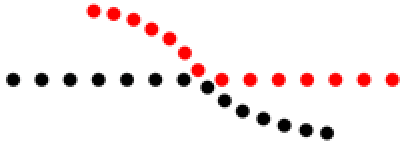
Gestalt: Theory of the mind and how we acquire and maintain meaningful perceptions

Law of Similarity

Law of Symmetry



Law of Symmetry



Law of Continuity

Law of Closure

Law of Common Fate

Gestalt Theory

- Challenge
  - How to best map some of these ideas into algorithms?
    - At pixel level, we need to use some form of similarity between pixels as way to measure

The goal of segmentation

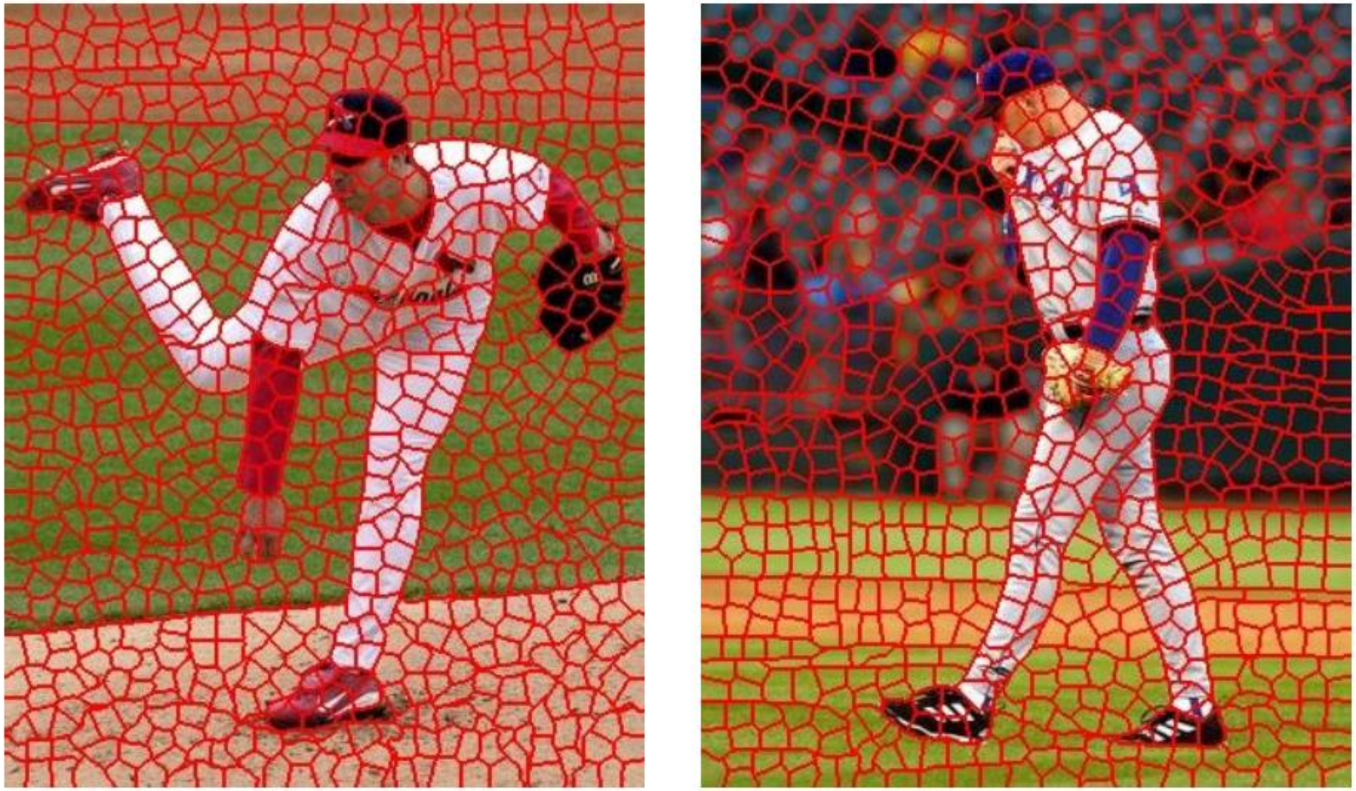
1. Separate image into coherent “objects”

image | human segmentation

The goal of segmentation

1. Separate image into coherent "objects"
2. Group together similar-looking pixels for efficiency of further processing

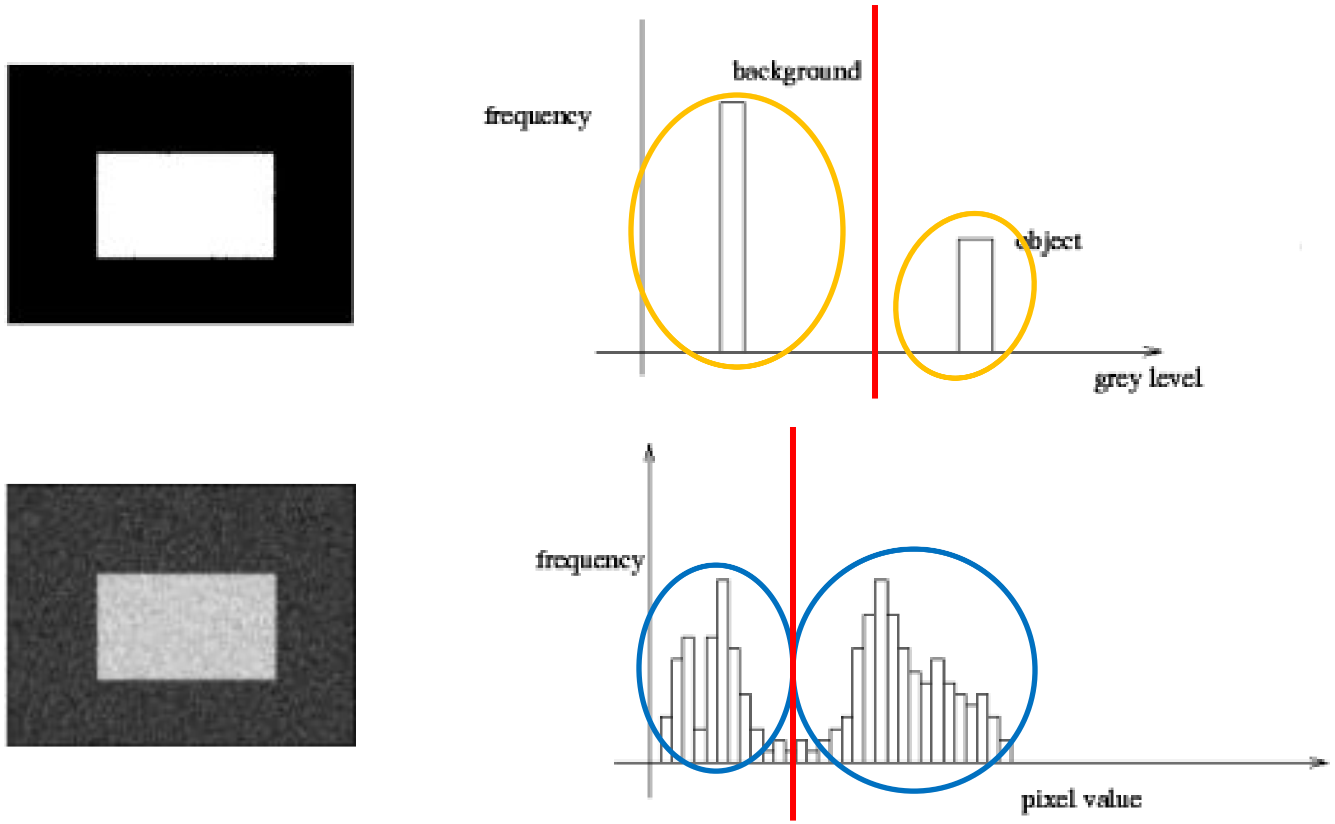
"superpixels"



X. Ren and J. Malik. Learning a classification model for segmentation. ICCV 2003.

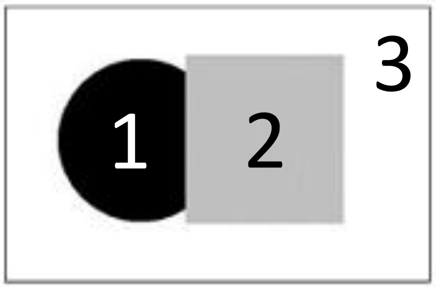
Thresholding Revisited

- What thresholding can do:
  - Divide these intensities into two significant groups based on where the “mass” of pixels are located

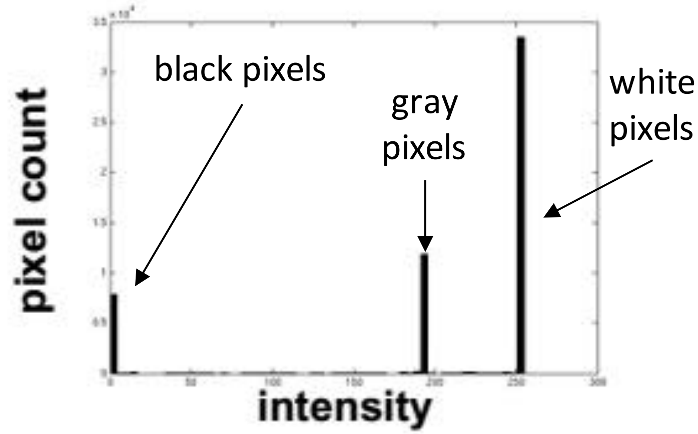


There are techniques to find the threshold level easily: Otsu’s algorithm, etc.

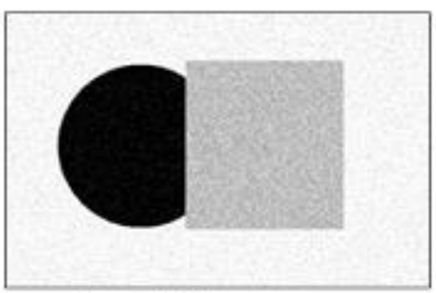
Motivation of Clustering



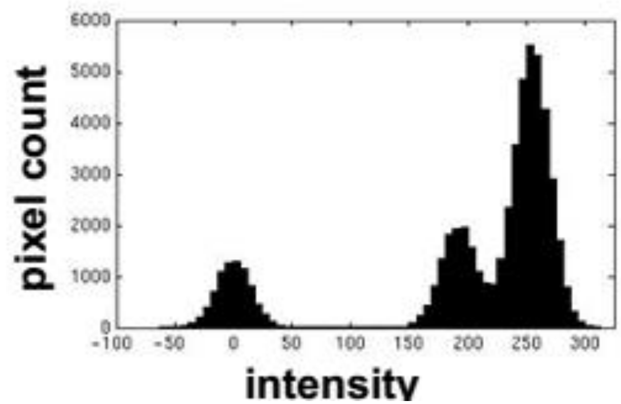
input image



Threshold to 3 regions. Easy.

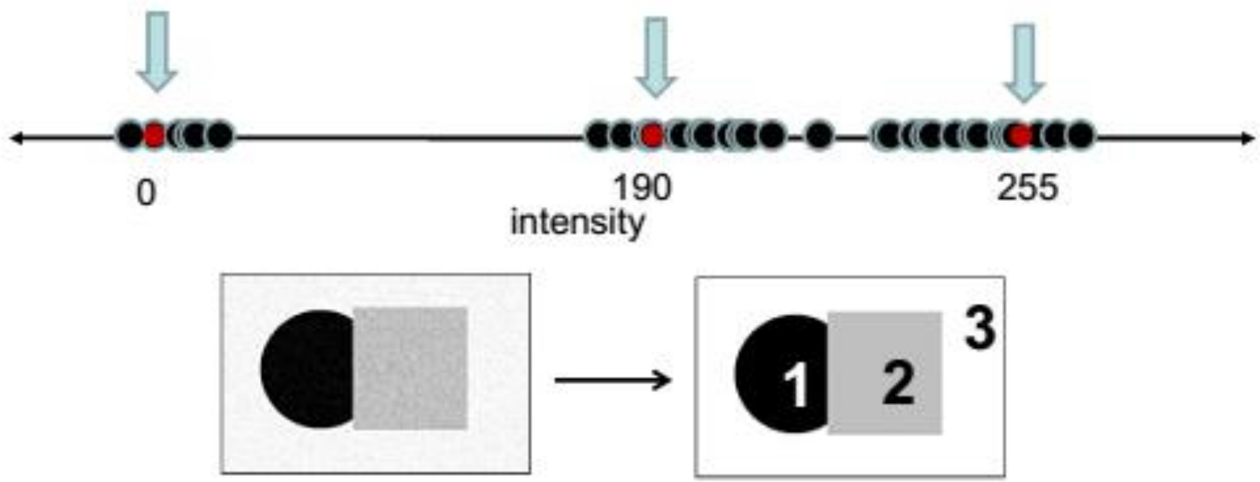


input image



Clustering can determine the “three” main intensities that define the groups.

Clustering Revisited



1. Choose the best cluster centres (as representatives) that minimizes SSD between all points and their nearest centre

$$\sum_{\text{clusters } i} \sum_{\text{points p in cluster } i} \|p - c_i\|^2$$

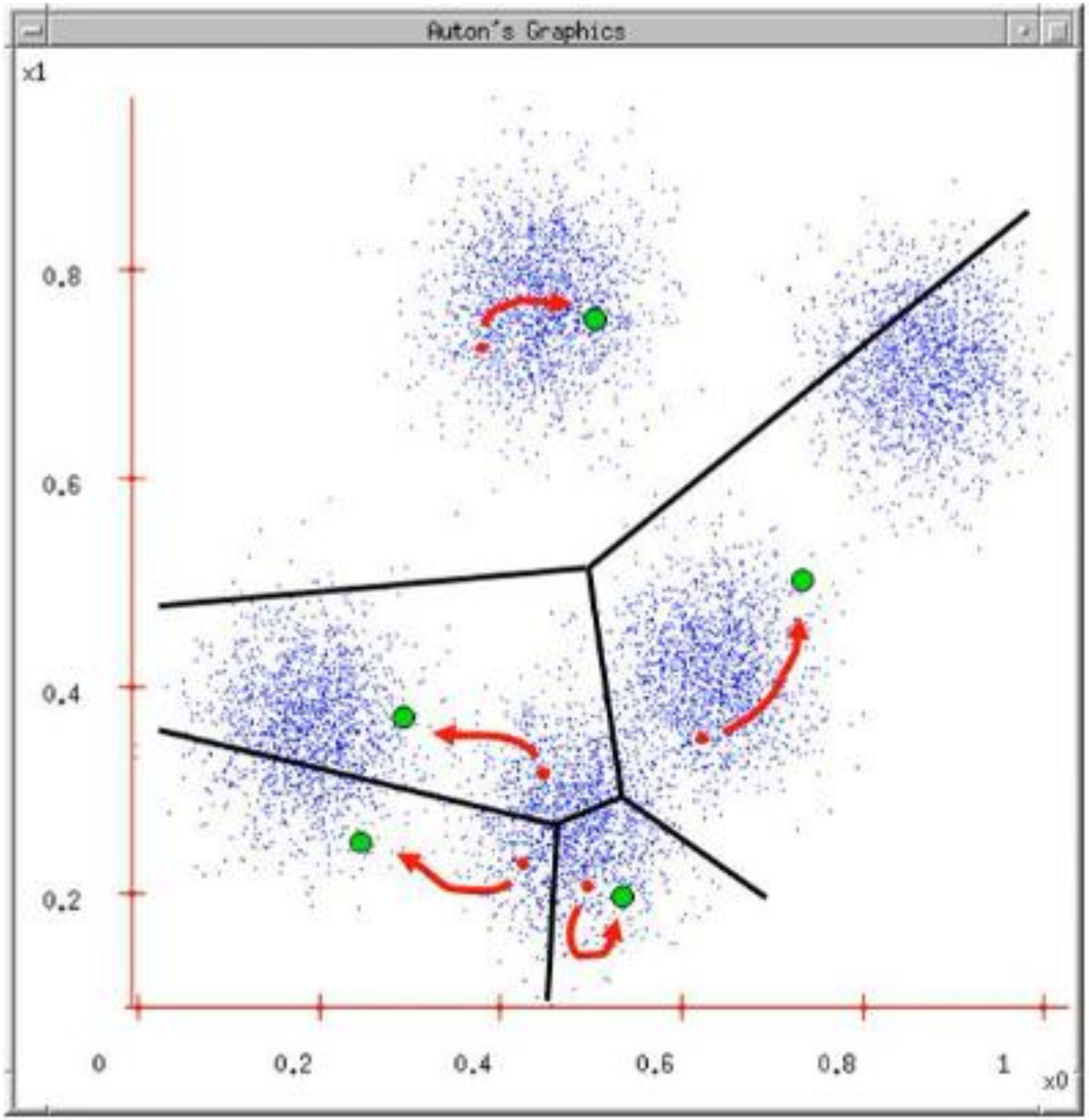
2. Label every pixel according to which of these centres it is nearest to (sometimes known as "vector quantization")

Clustering Methods

- K-means clustering (top-down)
- Mean shift clustering (top-down)
- Hierarchical agglomerative clustering (bottom-up)

K-means clustering

1. Determine beforehand how many clusters or value of *k*
2. Randomly guess *k* cluster centre locations
3. Each data point finds out which centre it is closest to
4. Each centre finds the centroid of its own group
5. With the new centroid, repeat again the process from (3) until algorithm terminates



Segmentation as clustering

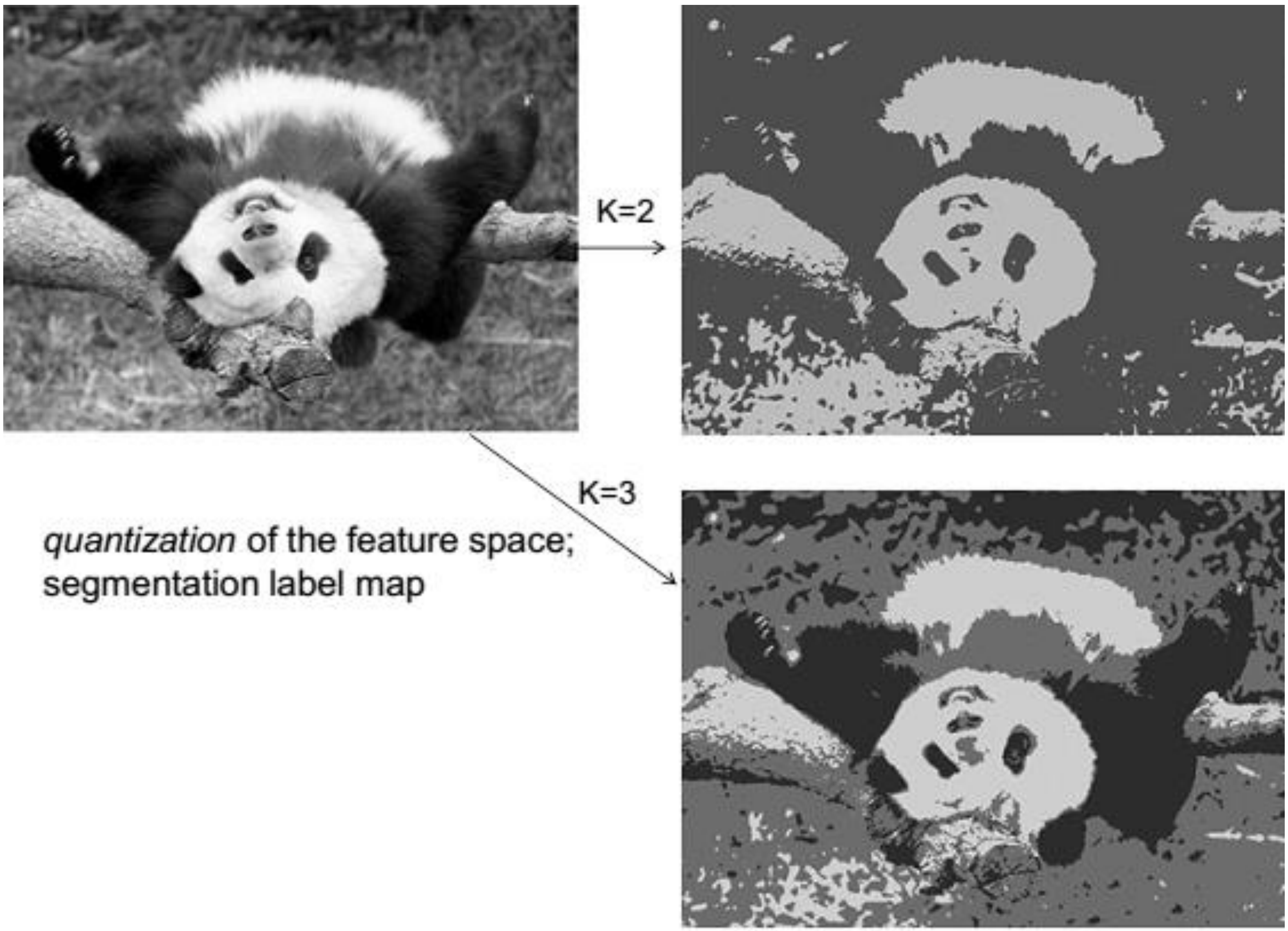
Segmentation as clustering

- Depending on what we choose as the *feature space*, we can group pixels in different ways

- Grouping pixels based on **intensity** similarity

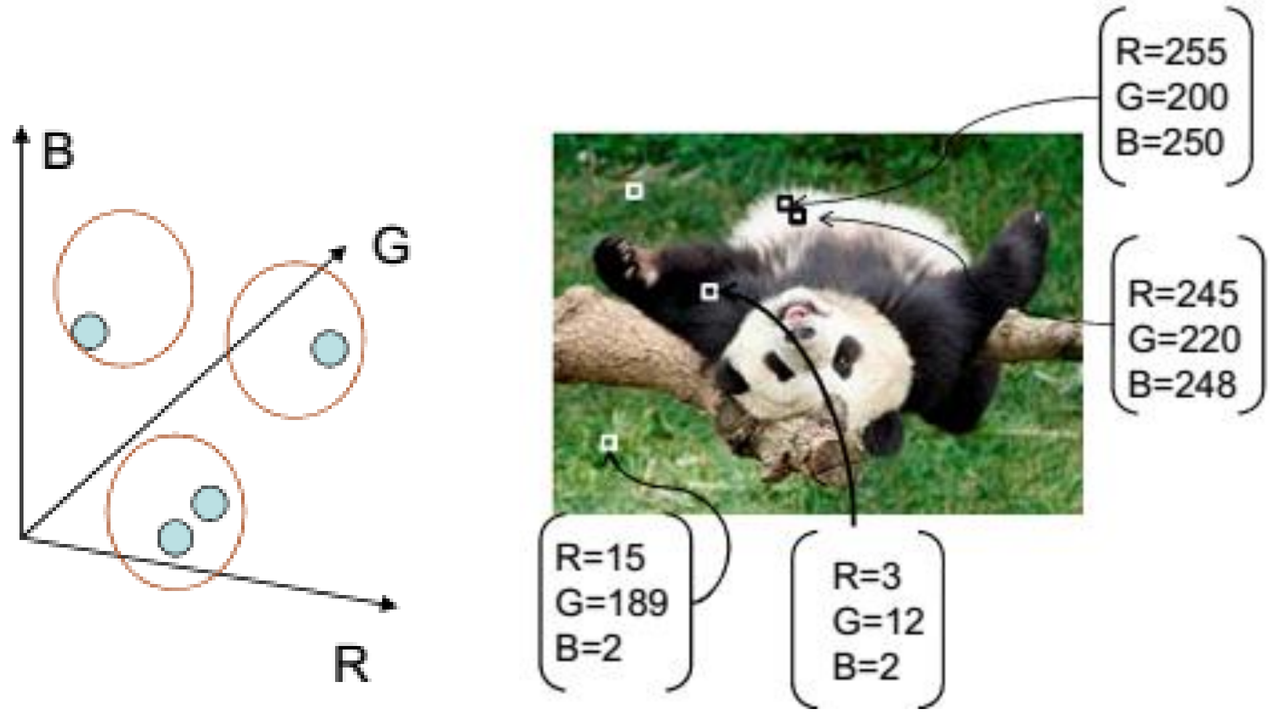
- Feature space: Intensity value (1-D)

Segmentation = quantization



Segmentation as clustering

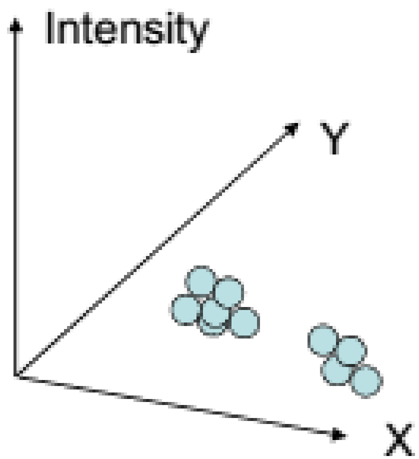
- Grouping pixels based on **color** similarity



- Feature space: Color value (3-D)

Segmentation as clustering

- Clusters based on intensity/color similarity are not spatially coherent ⇒ No idea where those pixels are!
- Grouping pixels based on **intensity+position** similarity

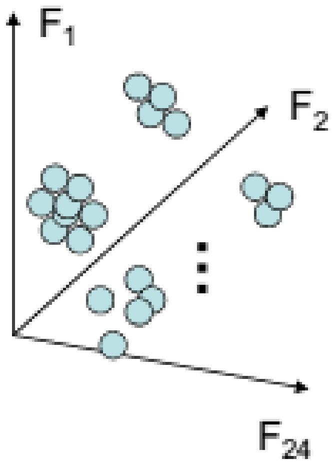


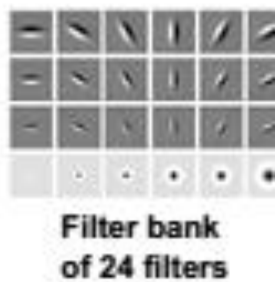
Both regions are black, but if we also include position (x,y), then we could group the two into different segments

Encoding **similarity** & **proximity** (recall Gestalt theory)

Segmentation as clustering

- Grouping pixels based on **texture** similarity





- Feature space: Filter bank responses (e.g. 24-D)

Superpixels

Reducing spatial information for segmentation

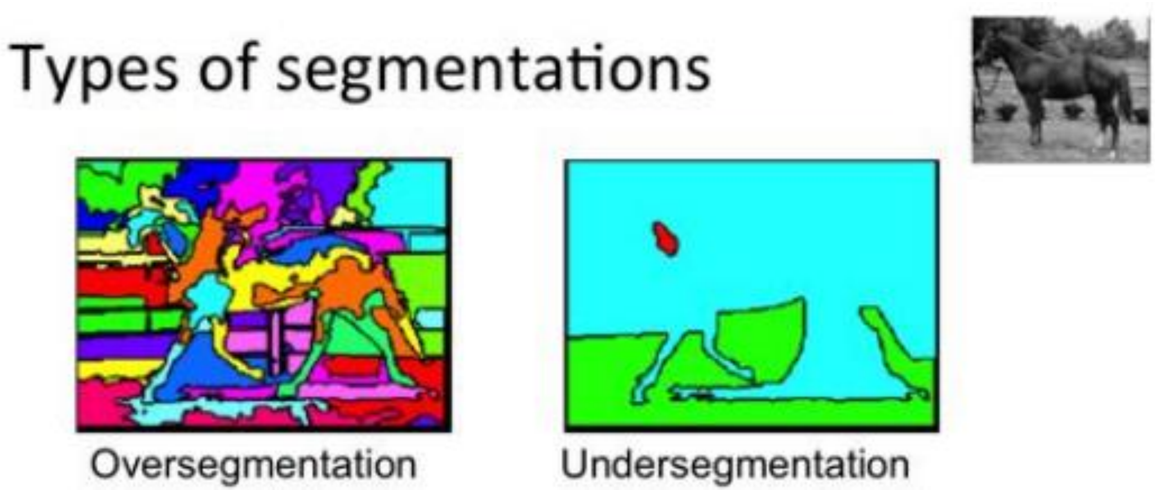
Superpixels

- **Issue:** We have way too many pixels in a reasonably sized image.
- **Idea:** Merge similar pixels into way less pixels

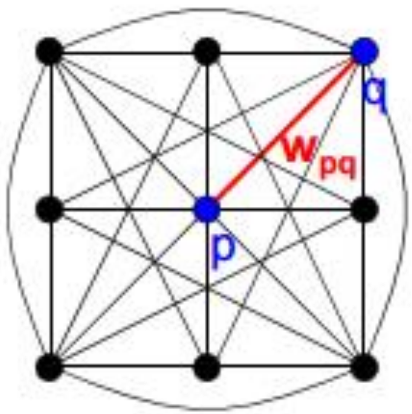
  ⇒ “Superpixels”

Superpixels

- **Superpixels** is a result of “oversegmentation”
  - Intentionally segment an image into many smaller parts
- Justification
  - The standard “pixel-grid” is not a natural representation of visual scenes, but an “artifact” of a digital imaging process

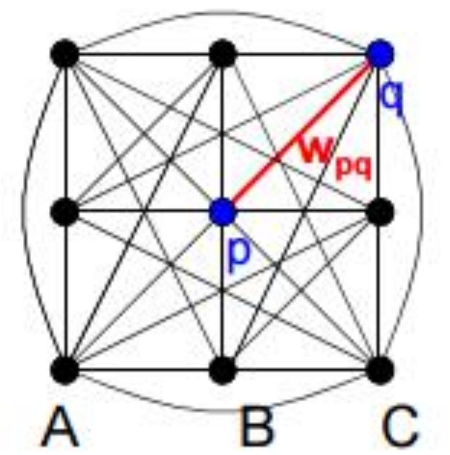


Images as Graphs



- **Fully-connected Graph**
  - Node (vertex) for every pixel
  - Link between every pair of pixels, **p, q**
  - Affinity weight $\mathbf{w_{pq}}$ for each edge ⇒ measures similarity (inverse to distances)

Graph Cuts

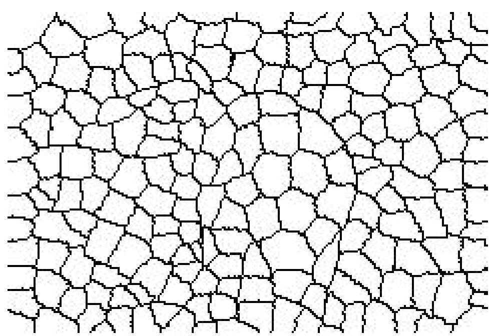


- Break or "cut" graph into segments
  - Delete edges that span across segments
  - Good candidates are edges with low similarities (they should be in different segments)
  - Eventually, groups of edges left represent the segments

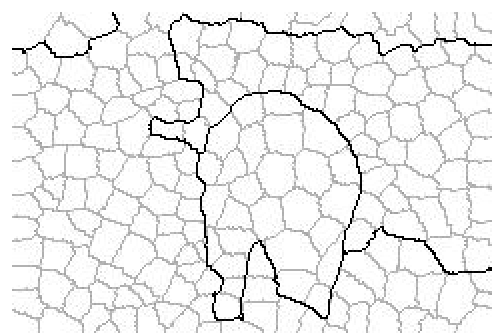
Superpixels from Normalized Cuts

- **Normalized Cuts** – classical region segmentation method developed at UC Berkeley
  - Uses graph-based representation of pixels
  - Spectral clustering used to exploit pairwise brightness, color and texture affinities between pixels
  - Graph is “cut” into segments by normalized cuts

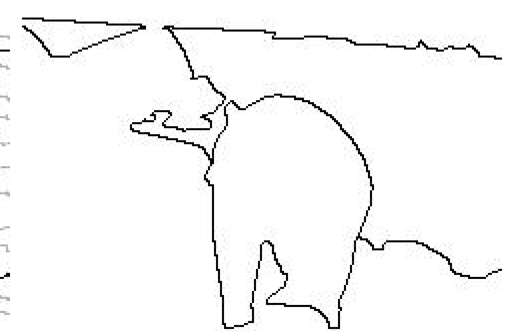
Original image



Superpixel segmentation



Region segmentation by normalized cut



Human ground-truth

Results from Berkeley Segmentation Engine

https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/

Graph Cuts

- Pros
  - Generic framework, flexible to choice of function that computes affinities
  - Does not require model of data distribution
- Cons
  - Time complexity can be high (if graphs are dense)
  - Some applications prefer balanced segments

Felzenswalb’s Segmentation Method

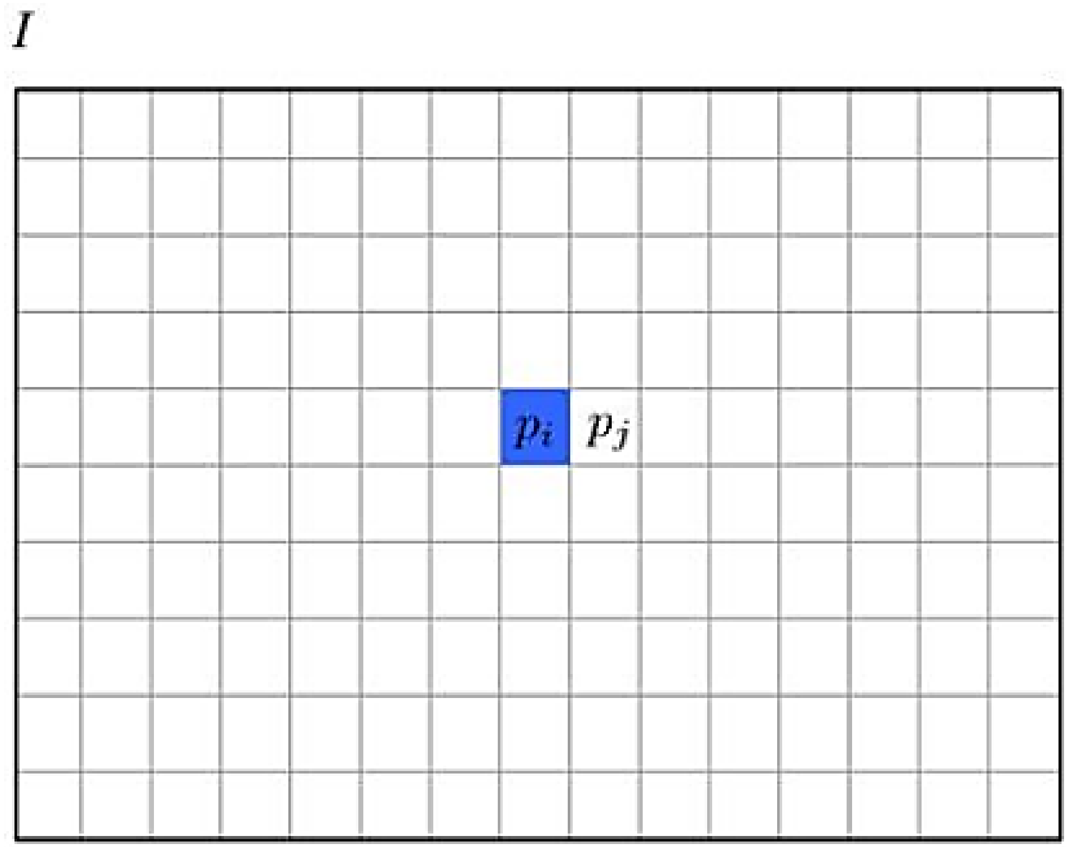
or Felzenswalb-Hutterlocher Method

- Efficient method to capture perceptually important groupings
- Steps:
  - Calculate “weights” of all pixels with their respective neighbors
  - Sort the weights by lowest till highest (most similar first)
  - From lowest weight, merge pixels / segments into a group if weight < threshold (determined by minimum internal difference and parameter k)
  - Repeat until end of list of weights

Felzenswalb's Segmentation Method

or Felzenswalb-Hutterlocher Method

- Take an image

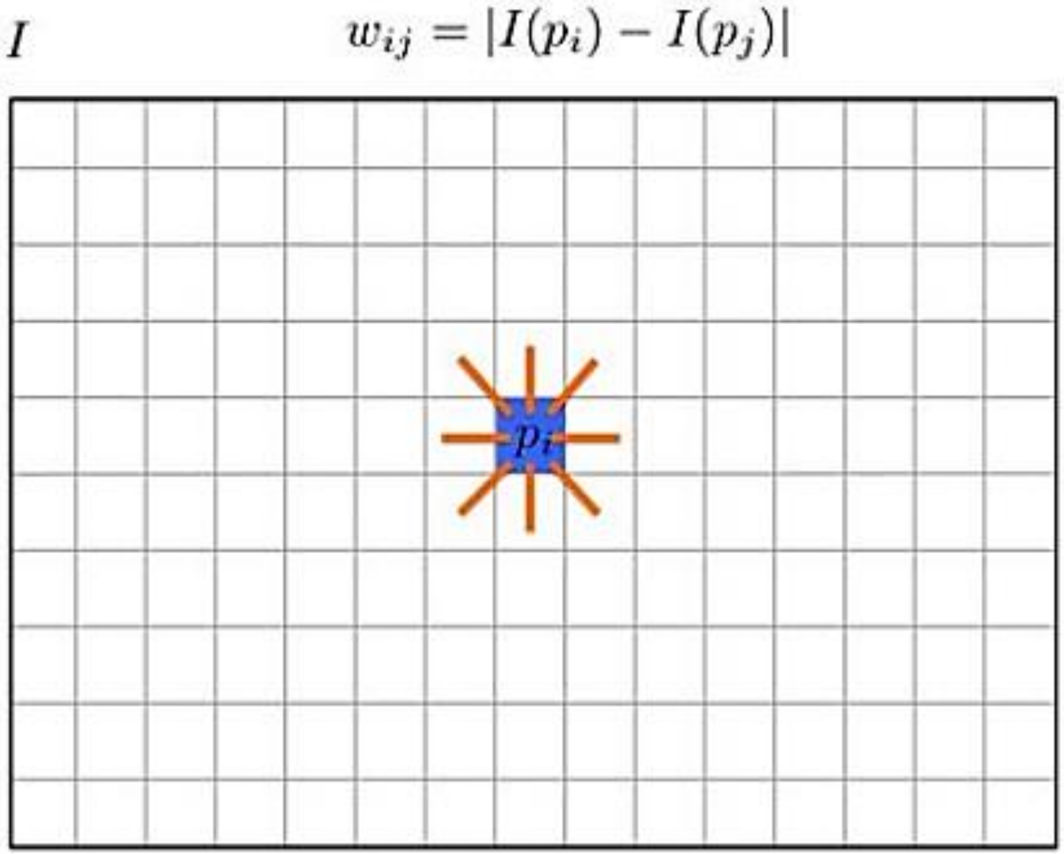


Credits to Sanja Fidler

Felzenswalb's Segmentation Method

or Felzenswalb-Hutterlocher Method

- Compute weights between a pixel and all 8 of its neighbours



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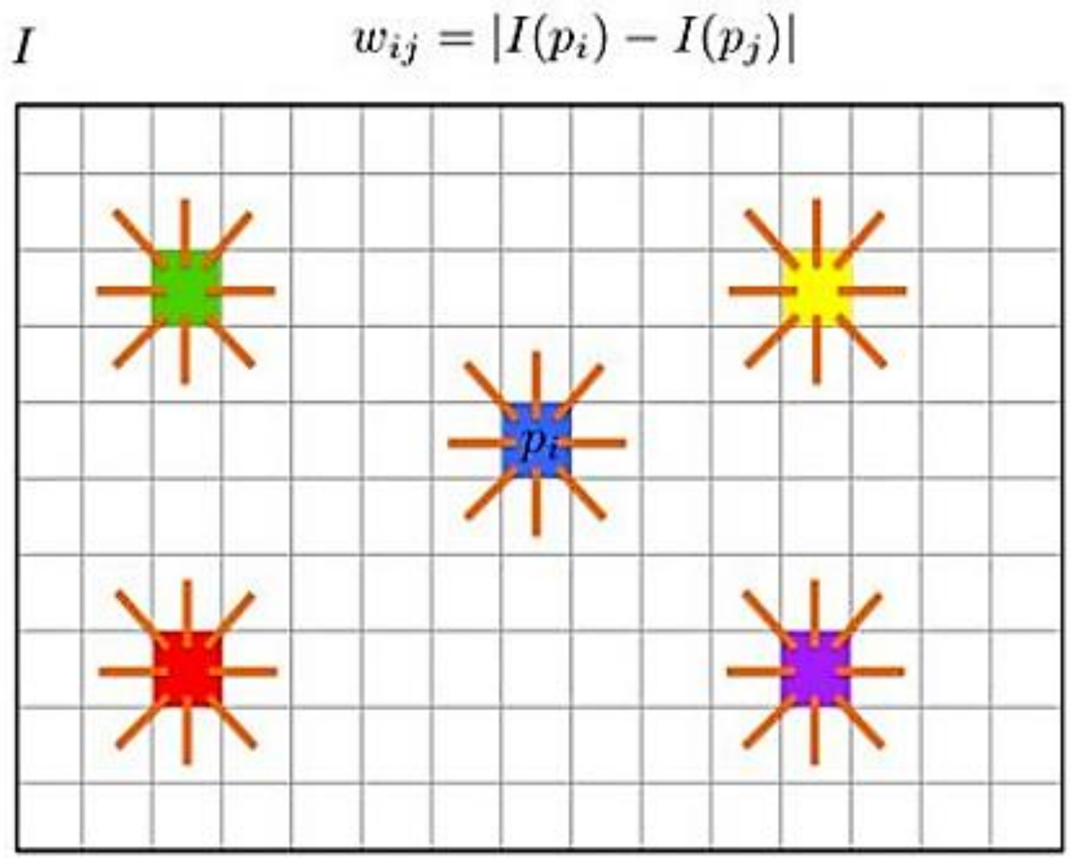
Felzenswalb's Segmentation Method

or Felzenswalb-Hutterlocher Method

- And do that for **all pixels** in the image



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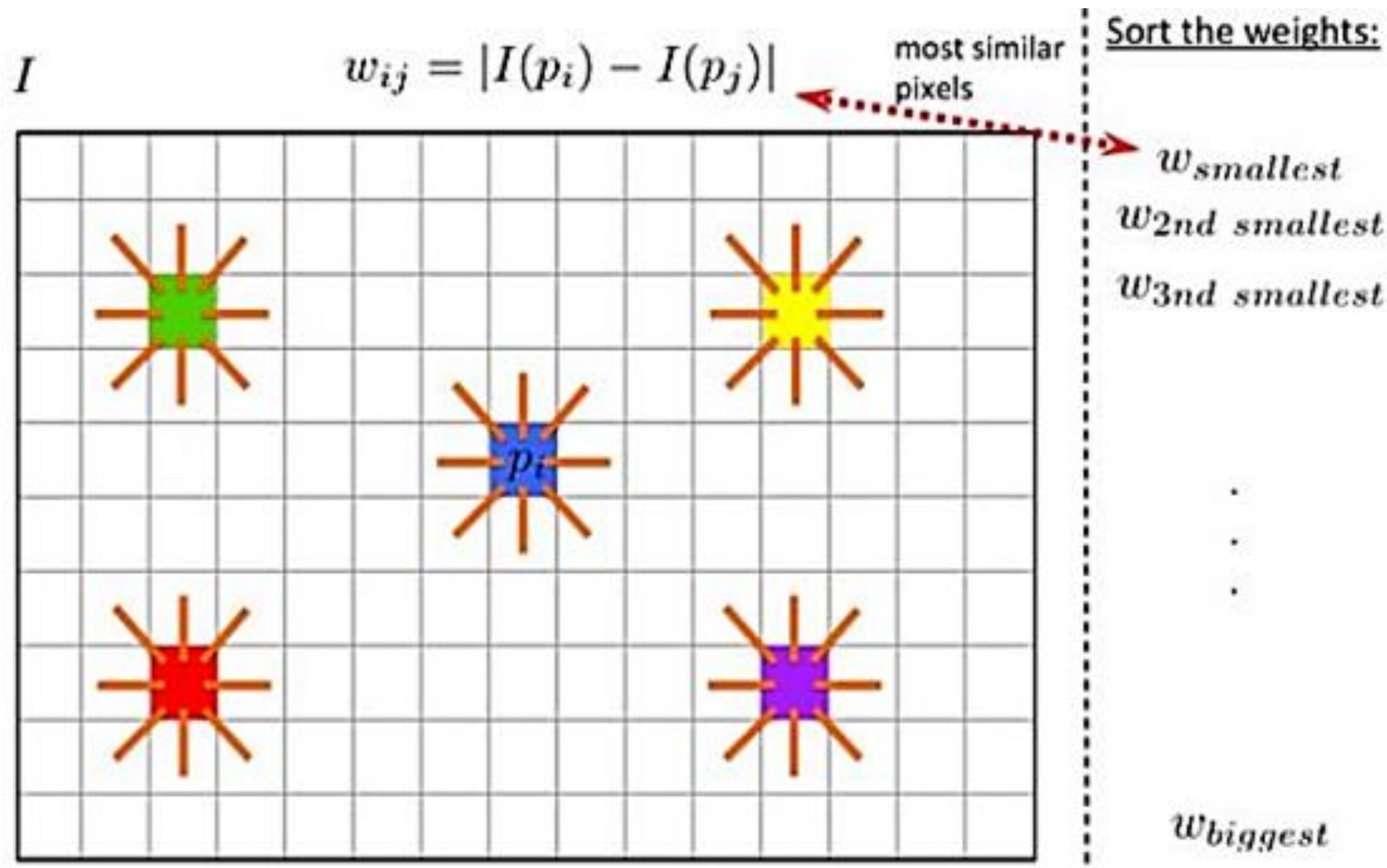
Felzenswalb’s Segmentation Method

or Felzenswalb-Hutterlocher Method

- Now sort all weights in the image by non-decreasing values

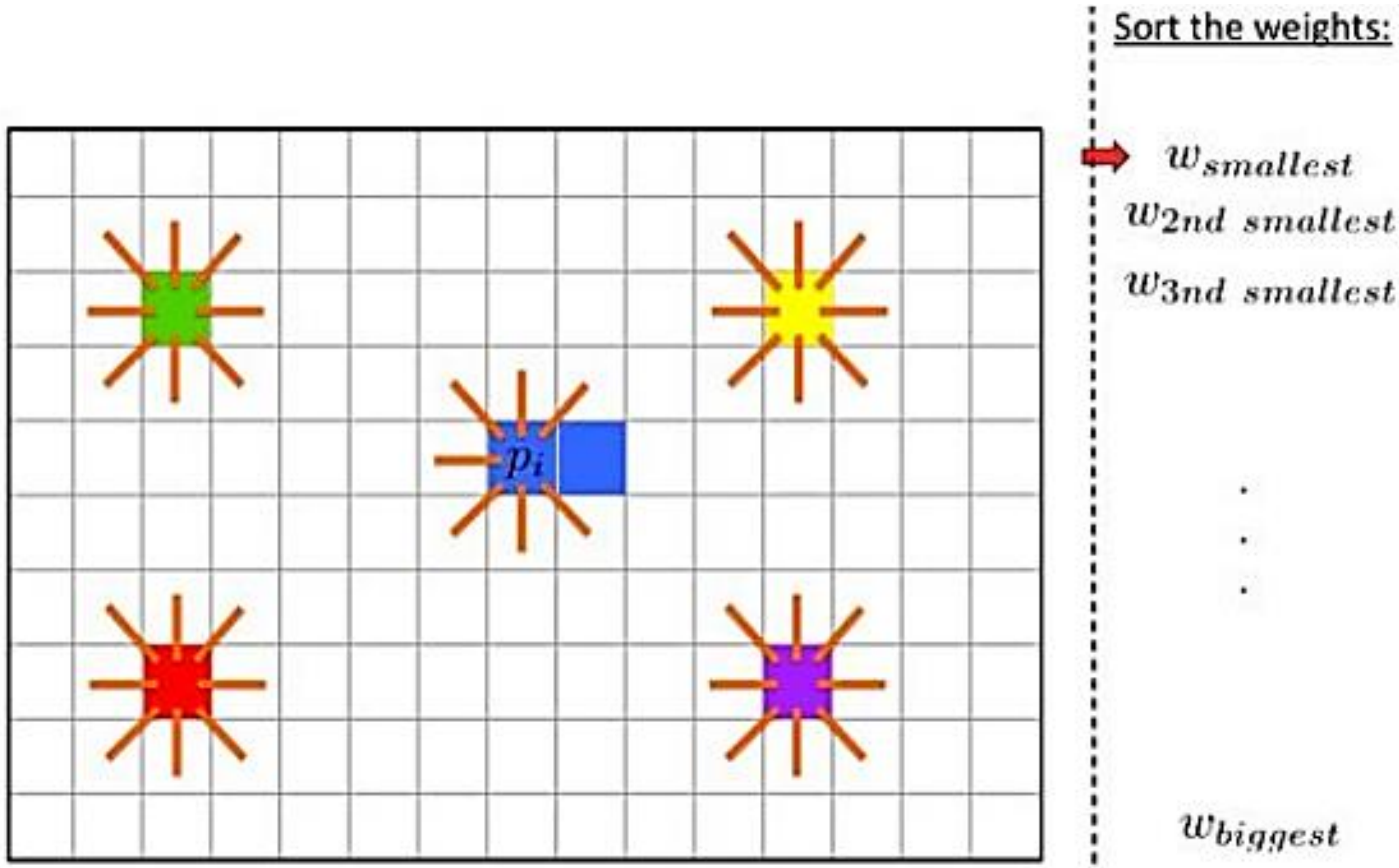


Credits to Sanja Fidler

Felzenswalb's Segmentation Method

or Felzenswalb-Hutterlocher Method

- Pick the top-most weight. If weight < threshold for both segments, merge the pixels . Then, update threshold for new segment based on size of segment



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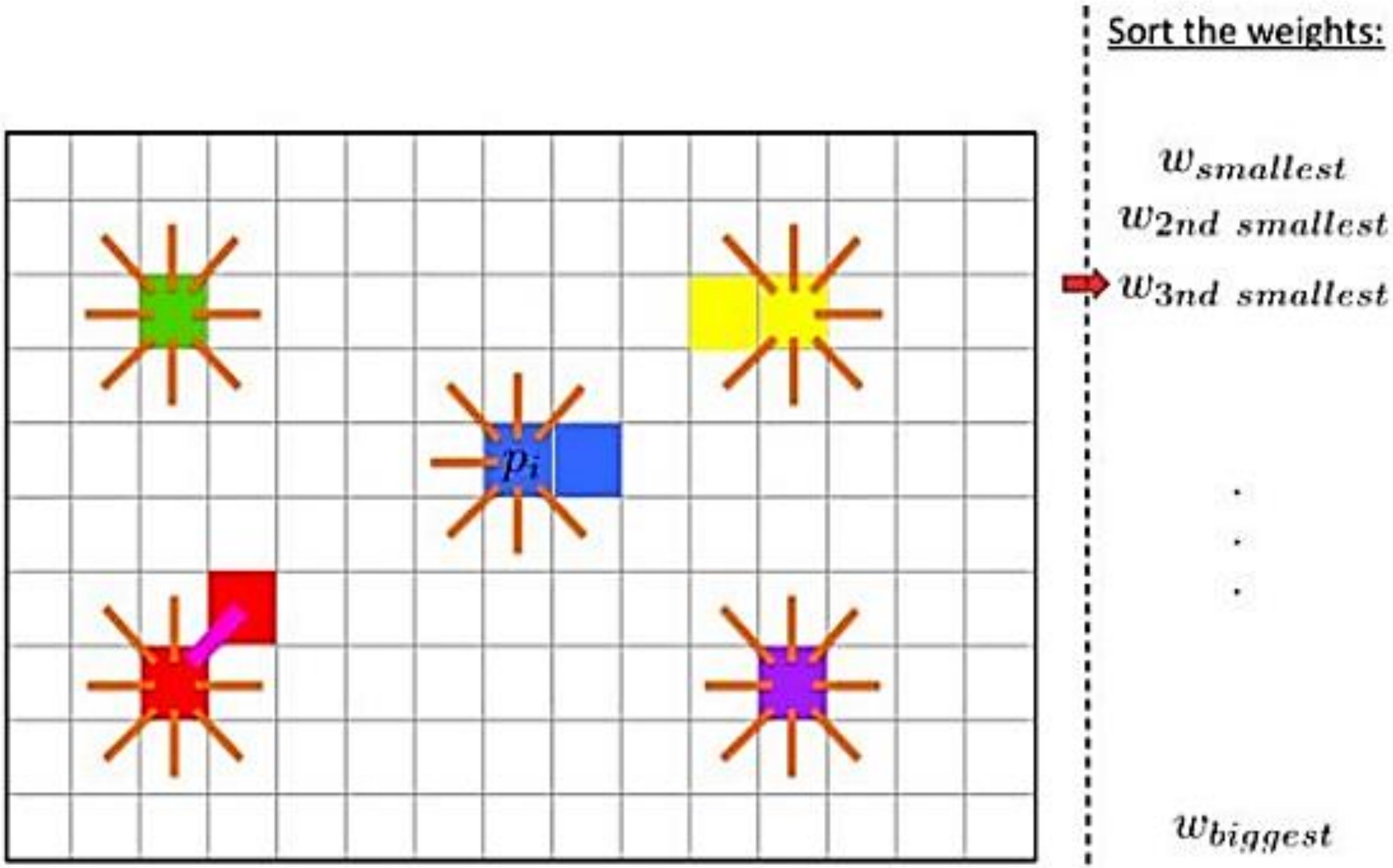
Felzenswalb's Segmentation Method

or Felzenswalb-Hutterlocher Method

- Repeat until the end of the list

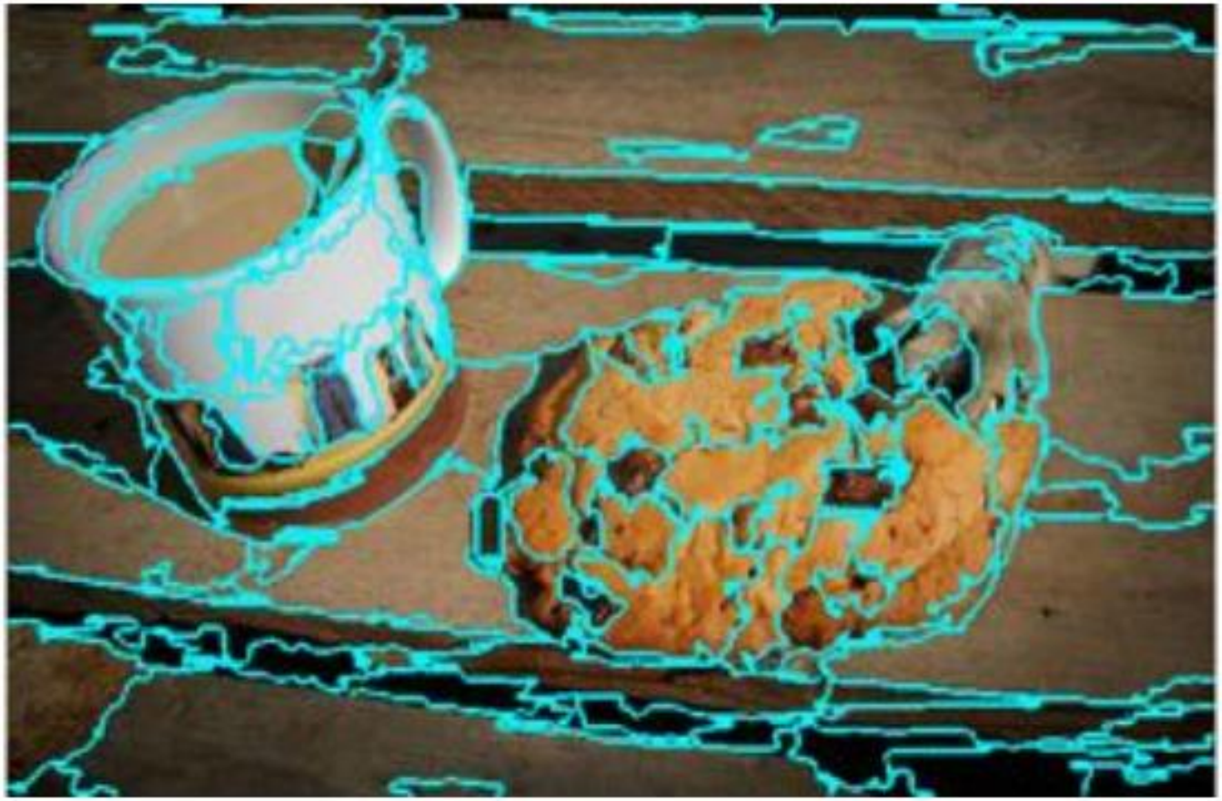


Credits to Sanja Fidler

Felzenswalb’s Segmentation Method

or Felzenswalb-Hutterlocher Method

- Result: Algorithm runs real-time!



Credits to Sanja Fidler

SLIC Superpixels

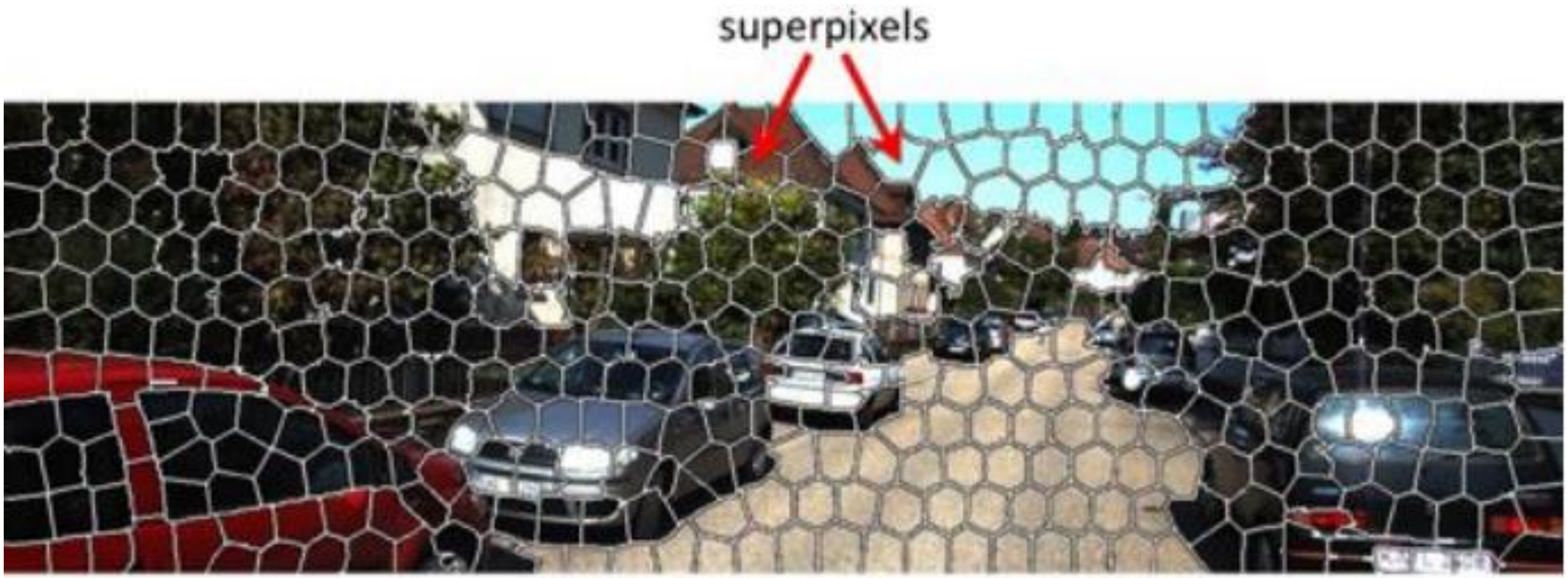
- Simple Linear Iterative Clustering Algorithm for Superpixel generation
- Another algorithm that can generate compact, **nearly uniform superpixels**
- Low computational cost
- Only a **single parameter** required! Number of superpixels.

Why are superpixels useful?

- Application Example: How can we find all road pixels in this image?

Why are superpixels useful?

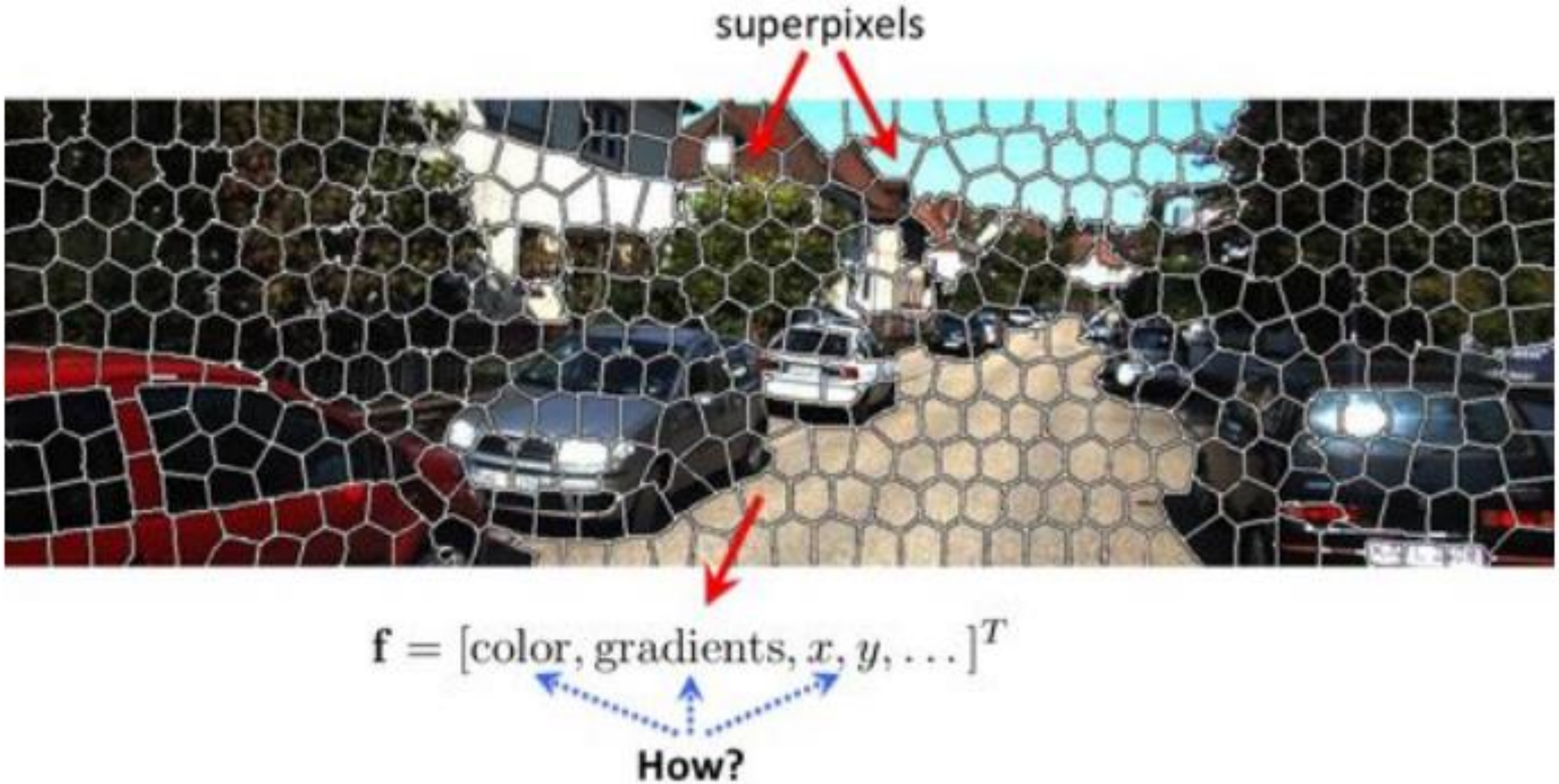
- Compute superpixels. A 4-million pixel image converted to only 500 superpixels. Then?



- Possible idea: Compute features on each superpixel and train a classifier for road/non-road

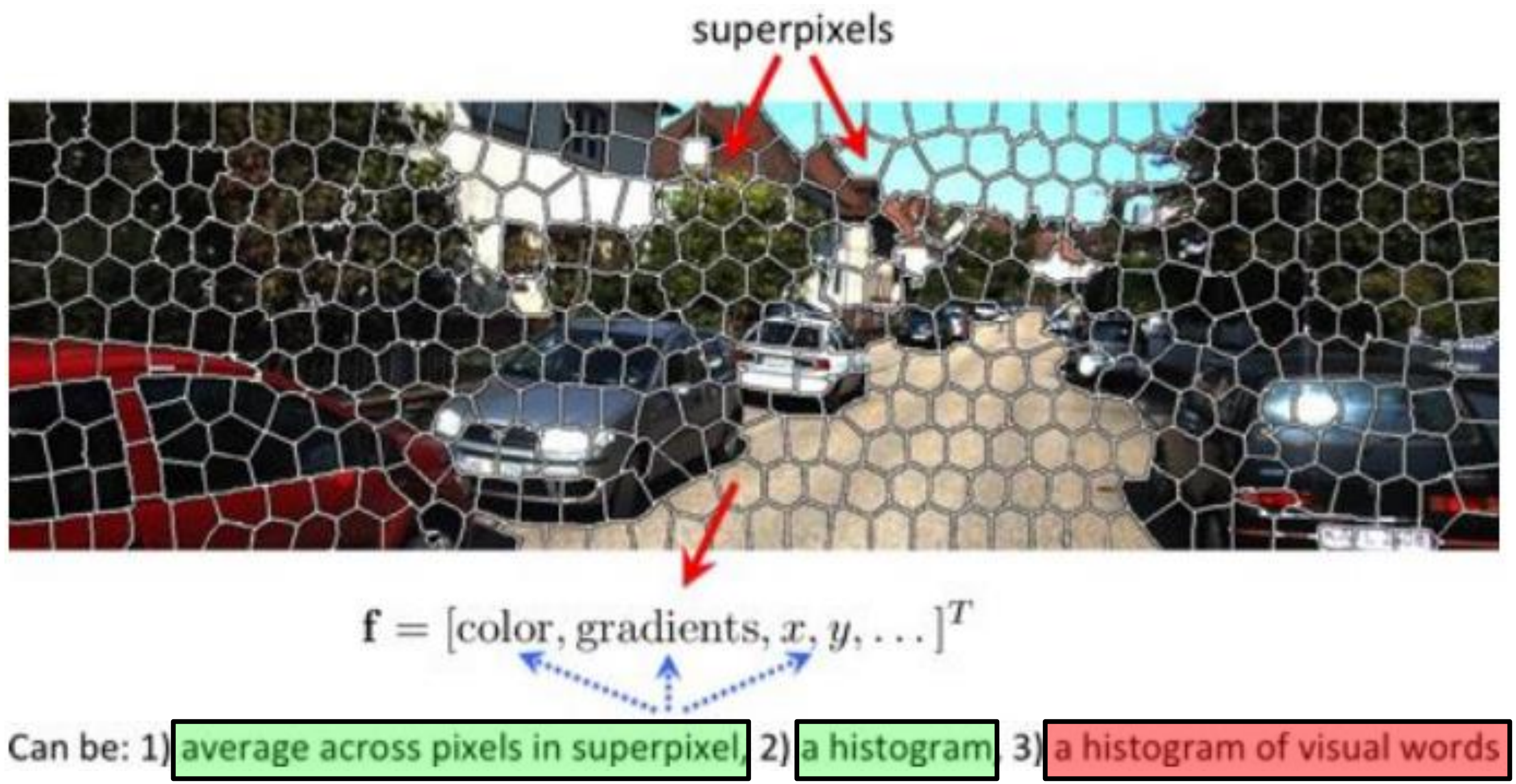
Why are superpixels useful?

- If we use a set of features, different superpixels have different number of pixels. How do I arrive at a feature vector that has same dimension for each superpixel?



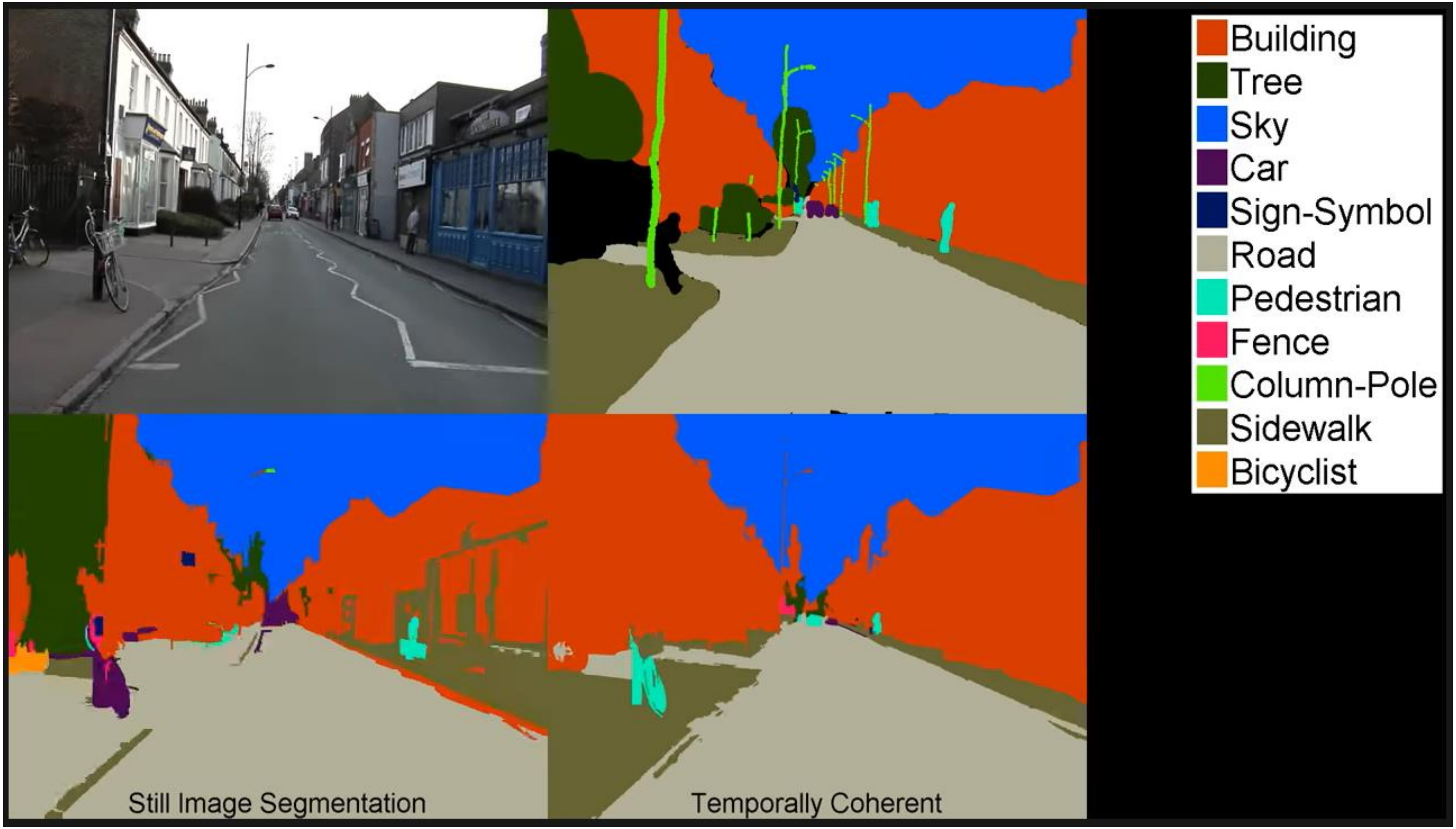
Why are superpixels useful?

- Typically, the more dimensions we use, the better the ability to distinguish between road and non-road.



- Next, we need to **classify** them (to be covered later)

Scene Segmentation from Dashcams

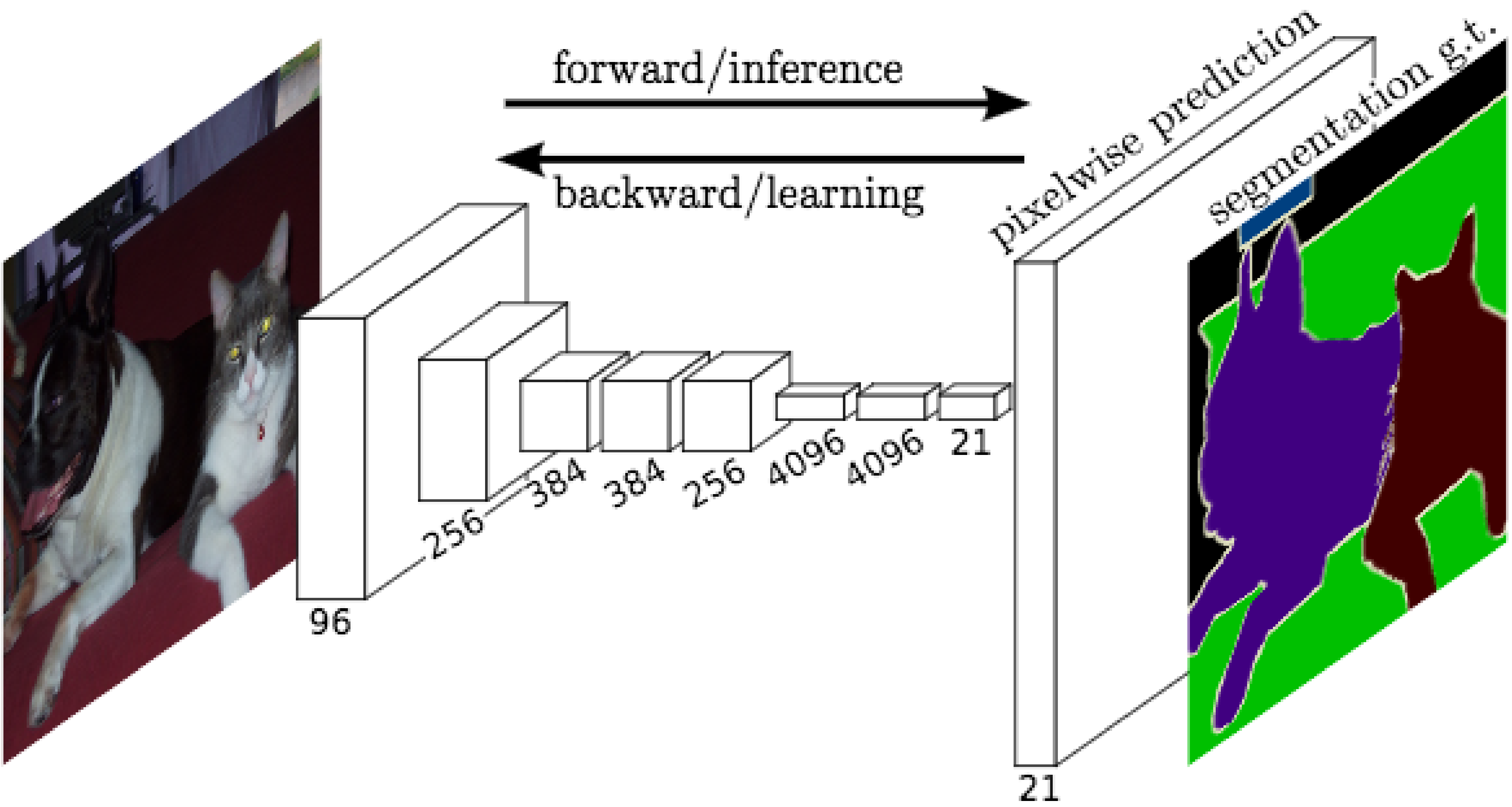


SuperParsing: Scalable Nonparametric Image Parsing with Superpixels
https://www.youtube.com/watch?v=UZ_NTYCFIHk

Deep-Learning Methods

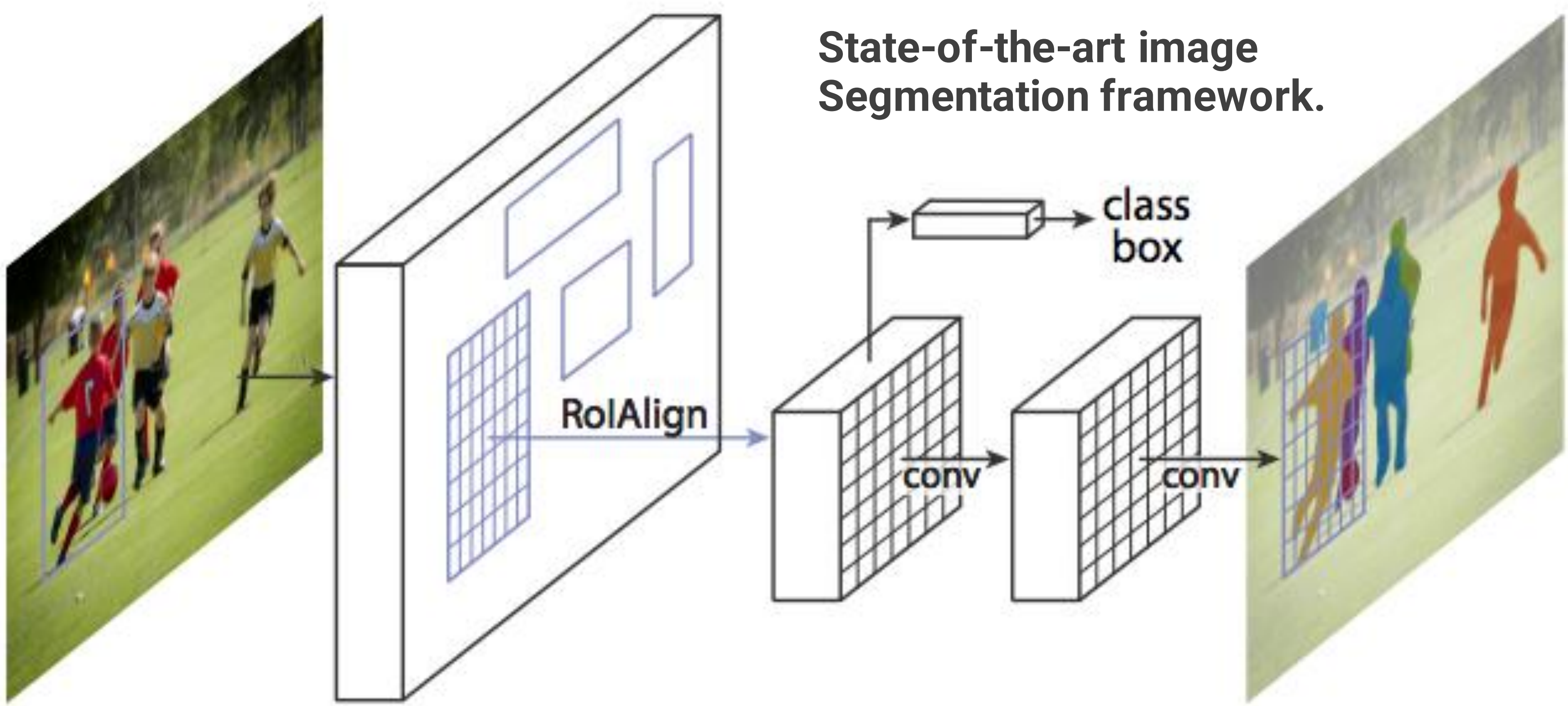
End-to-end models for semantic segmentation

Fully Convolutional Network (FCN)



Long, Jonathan, Evan Shelhamer, and Trevor Darrell.
"**Fully convolutional networks for semantic segmentation.**" *CVPR 2015*.

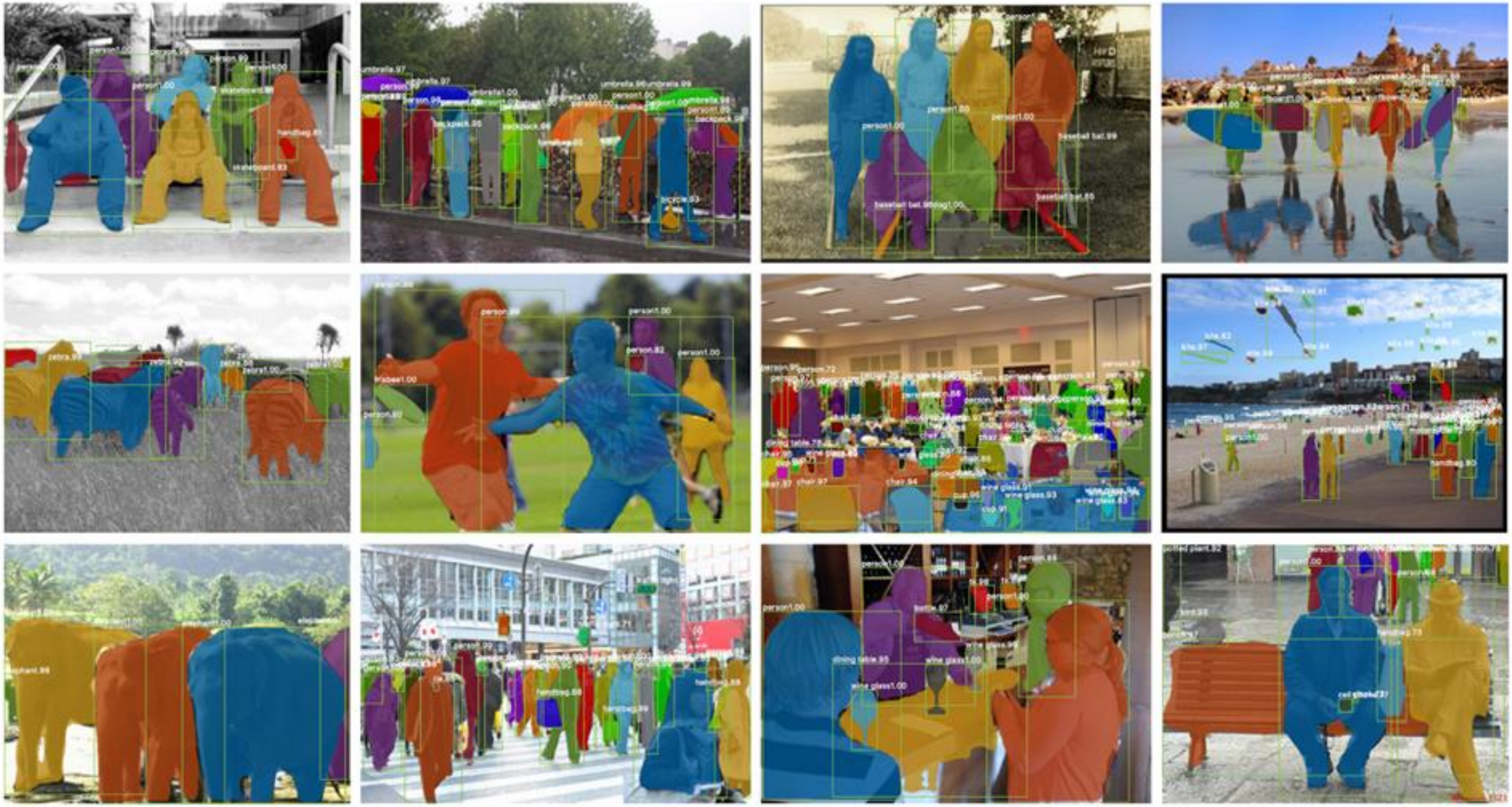
Mask Region-based CNN (R-CNN)



Mask R-CNN architecture. The first layer is a RPN extracting the RoI. The second layer processes the RoI to generate feature maps. They are directly used to compute the bounding box coordinates and the predicted class.

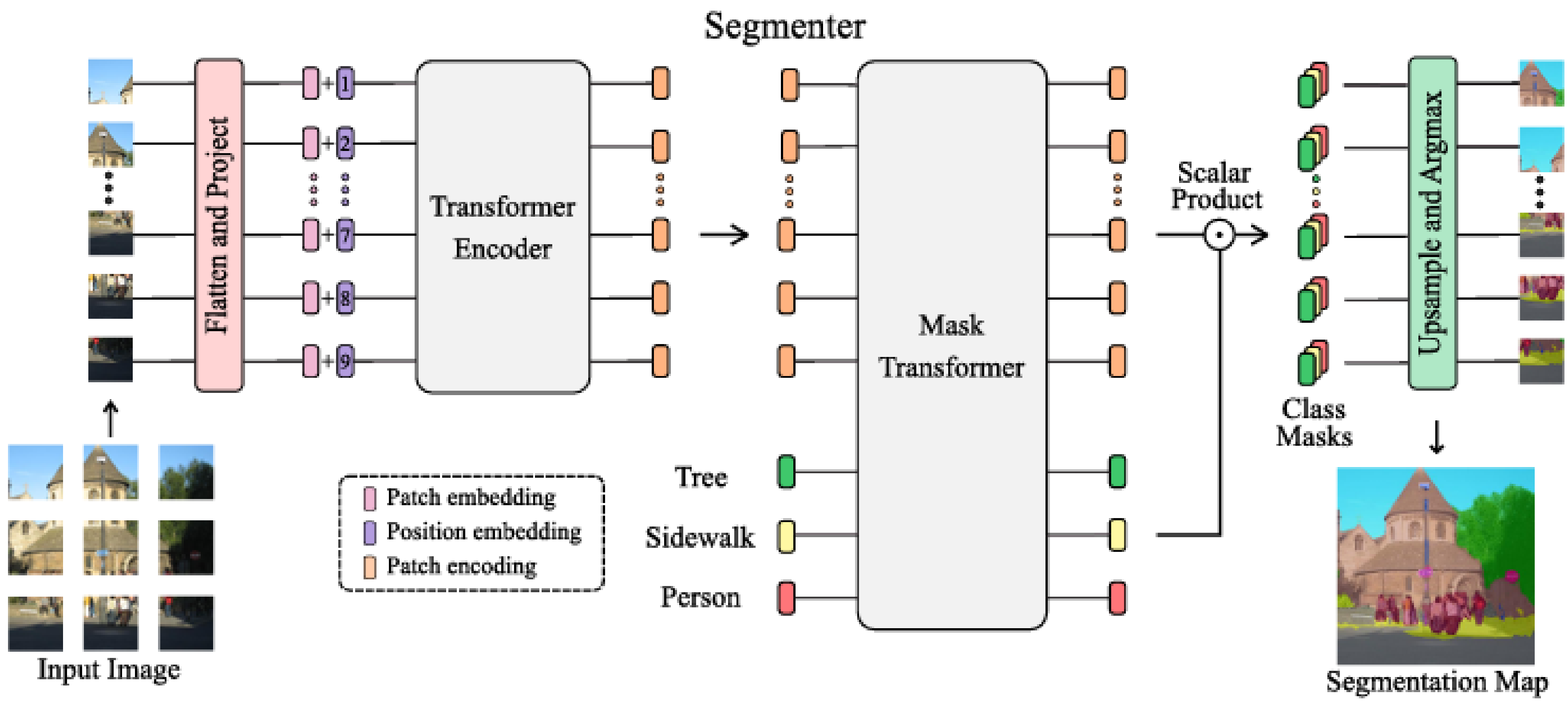
Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "**Fully convolutional networks for semantic segmentation.**" *In ICCV 2017*.

Mask Region-based CNN (R-CNN)



Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "**Fully convolutional networks for semantic segmentation.**" *In ICCV 2017*.

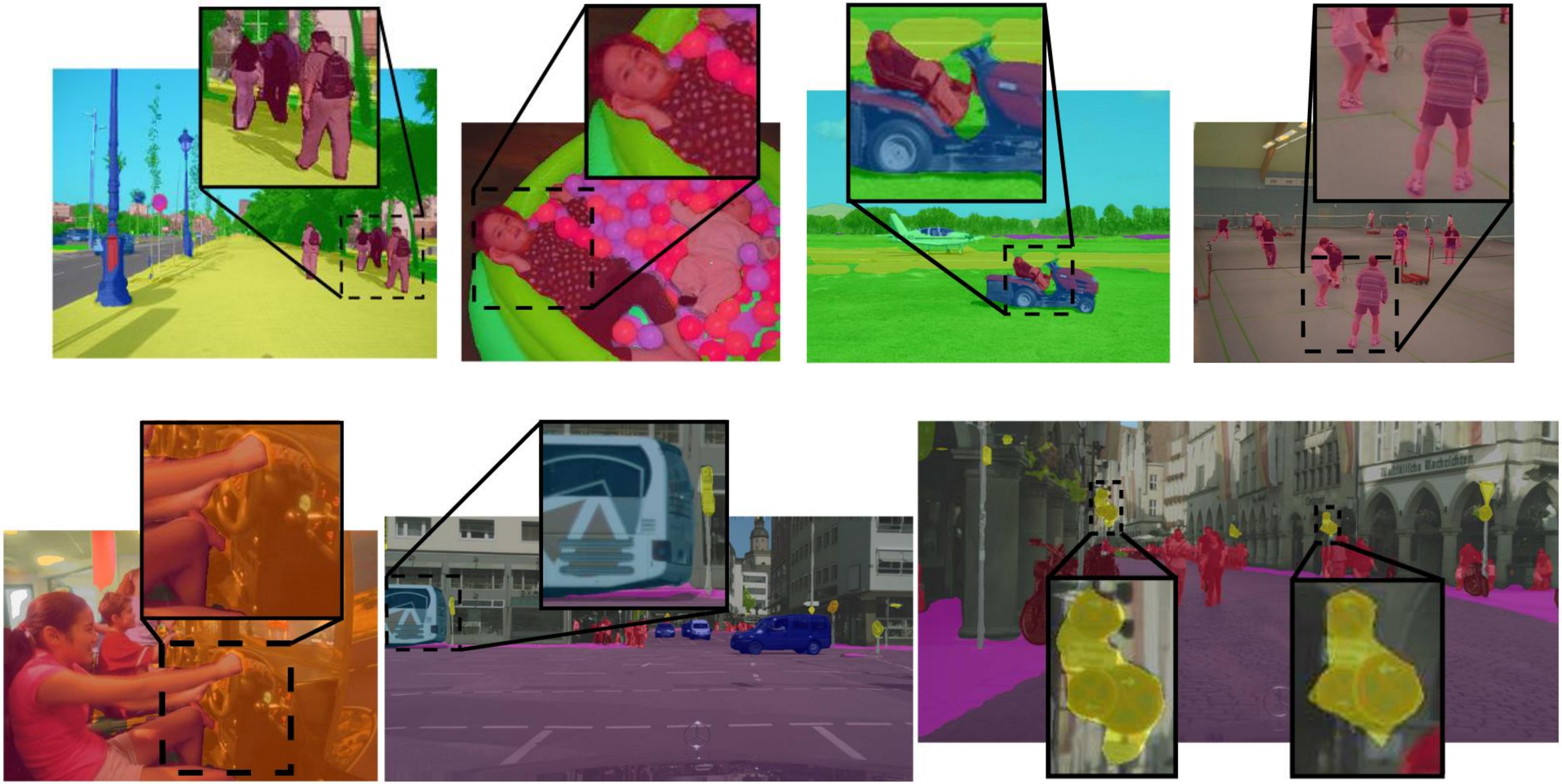
Vision Transformer (ViT) - Segmenter



Segmenter architecture. The image is first separated into patches and projected to a sequence of embeddings and then encoded with a transformer. A mask transformer then takes as input the output of the encoder and class embeddings to predict segmentation masks.

Strudel, Robin, Ricardo Garcia, Ivan Laptev, and Cordelia Schmid. "**Segmenter: Transformer for semantic segmentation.**" *In ICCV 2021*.

Vision Transformer (ViT) - Segmenter



Strudel, Robin, Ricardo Garcia, Ivan Laptev, and Cordelia Schmid.
"**Segmenter: Transformer for semantic segmentation.**" *In ICCV 2021*.

Recommended Reading

- [Forsyth & Ponce] Chapter 15

Summary

- Why do segmentation?
  - Inspiration from human perception – Gestalt theory
- Segmentation as clustering
  - K-means
- Superpixels – Graph-based algorithms
  - Graph cuts / normalized cuts
  - Felzenswalb’s method
- Deep Learning methods
  - FCN Semantic Segmentation
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