Pattern Recognition Lab

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
FACULTY OF ENGINEERING

Visual Recognition for Humanities

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Project CV Summer 2021,

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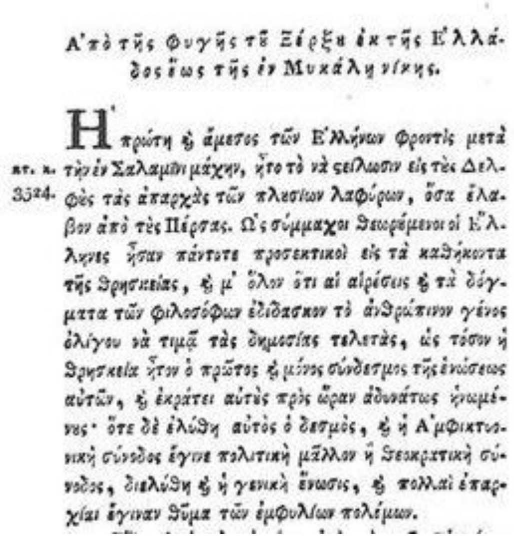
Outline

1. Focus and motivation
2. Visual recognition
3. Modern Object Detection
4. Object recognition
5. Sliding window object detector
6. Felzenszwalb's algorithm
7. Selective search
   a. Algorithm
   b. 4 important aspects
   c. Evaluation
8. Exercise

Focus I - Text

Text and Writer identification and OCR



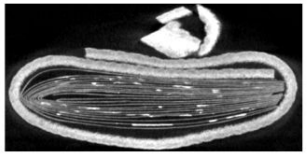
Ἀπὸ τῆς φυγῆς τοῦ Ξέρξου ἐκ τῆς Ἑλλάδος ἕως τῆς ἐν Μυκάλῃ νίκης.

Η πρώτη καὶ ἄμεσος τῶν Ἑλλήνων φροντὶς μετὰ τὴν ἐν Σαλαμῖνι μάχην, ἦτο τὸ νὰ στείλωσιν εἰς τοὺς Δελ-
κτ. κ. 3524. φοὺς τὰς ἀπαρχὰς τῶν πλουσίων λαφύρων, ὅσα ἔλαβον ἀπὸ τοὺς Πέρσας. Ὡς σύμμαχοι θεωρούμενοι οἱ Ἕλληνες ἦσαν πάντοτε προσεκτικοὶ εἰς τὰ καθήκοντα τῆς θρησκείας, καὶ μ' ὅλον ὅτι αἱ αἱρέσεις καὶ τὰ δόγματα τῶν φιλοσόφων ἐδίδασκον τὸ ἀνθρώπινον γένος ὀλίγον νὰ τιμᾷ τὰς δημοσίας τελετάς, ὡς τόσον ἡ θρησκεία ἦτον ὁ πρῶτος καὶ μόνος σύνδεσμος τῆς ἑνώσεως αὐτῶν, καὶ ἐκράτει αὐτοὺς πρὸς ὥραν ἀδυνάτως ἠνωμένους· ὅτε δὲ ἐλύθη αὐτὸς ὁ δεσμός, καὶ ἡ Ἀμφικτυονικὴ σύνοδος ἔγινε πολιτικὴ μᾶλλον ἢ θεοκρατικὴ σύνοδος, διελύθη καὶ ἡ γενικὴ ἕνωσις, καὶ πολλαὶ ἐπαρχίαι ἔγιναν θῦμα τῶν ἐμφυλίων πολέμων.

Handwriting imitation

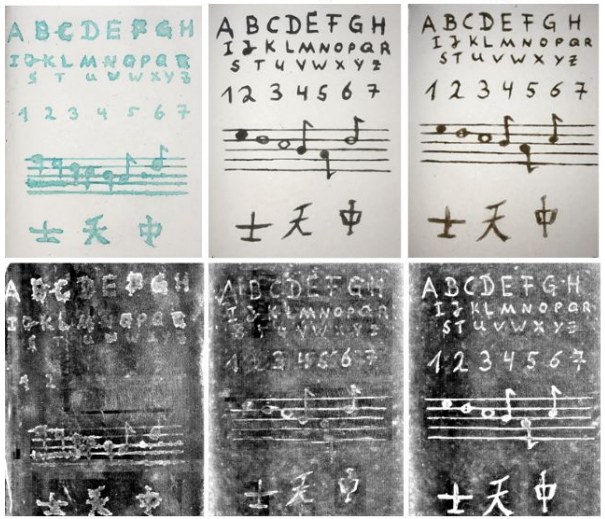
Focus II - Book CT [1]

Daniel Stromer



Results

Malachit | Iron gall | Iron gall +



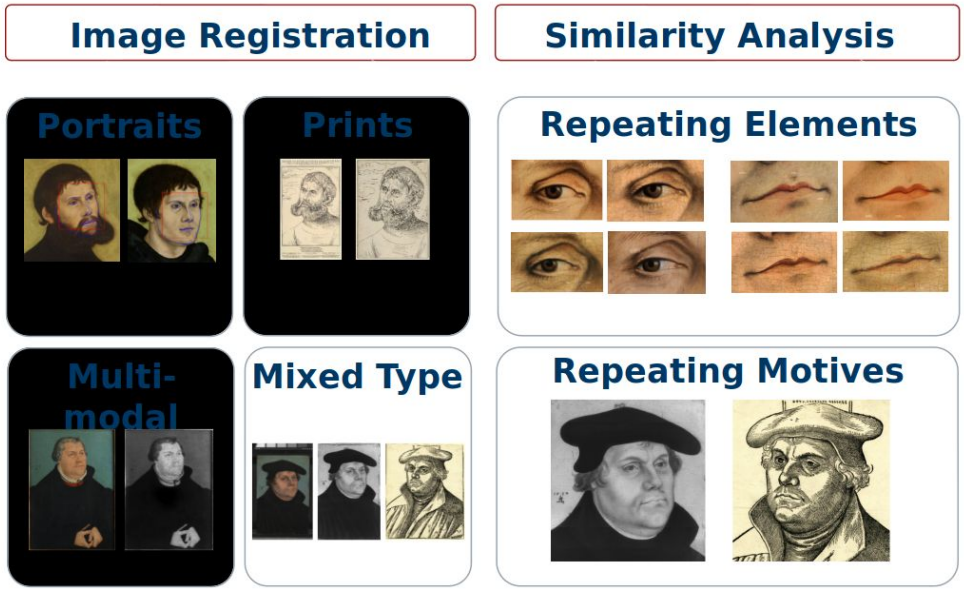
[1] Stromer, Daniel; Christlein, Vincent; Huang, Xiaolin; Zippert, Patrick; Hausotte, Tino; Maier, Andreas Virtual cleaning and unwrapping of non-invasively digitized soiled bamboo scrolls Scientific Reports, vol. 9, no. 1, pp. 2311, 2019

Focus III - Similarity [2]

Aline Sindel

GERMANISCHES NATIONAL MUSEUM

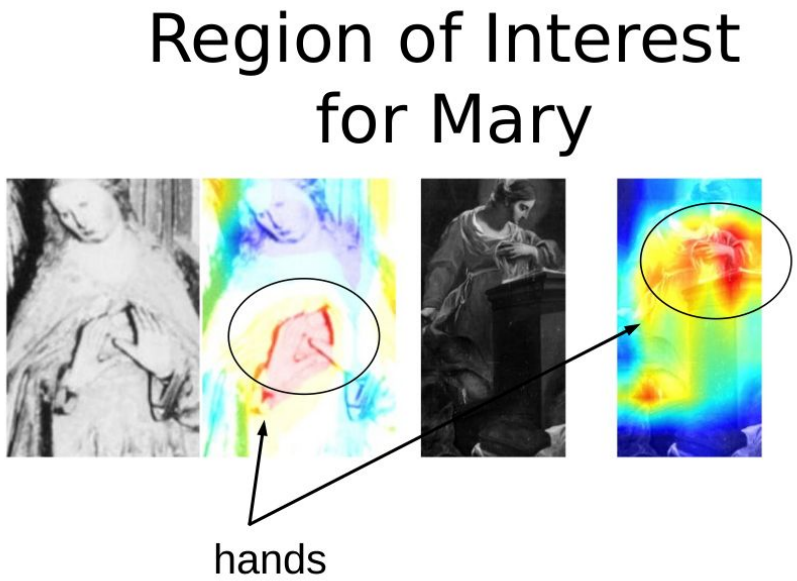
Aims



[2] Project page : https://www.gnm.de/forschung/projekte/luther-bildnisse/

Focus IV - Understanding [3]

Ronak Kosti



[3] Madhu, Prathmesh, et al. "Recognizing Characters in Art History Using Deep Learning." *Proceedings of the 1st Workshop on Structuring and Understanding of Multimedia heritAge Contents*. 2019.

Art History

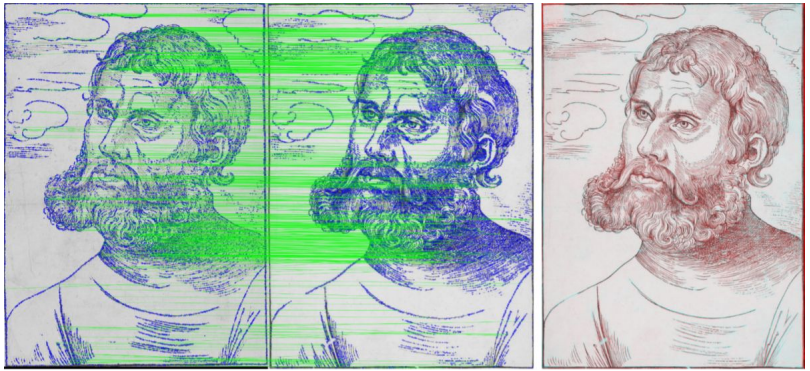
Classical Arch.

Christian Arch.

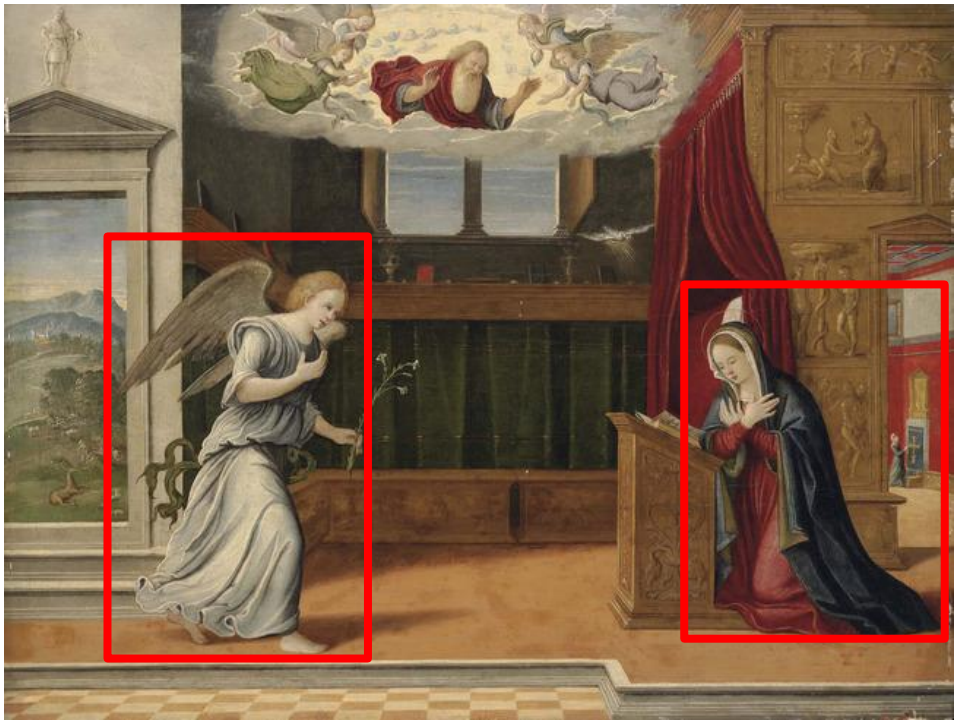
Visual recognition?

Visual recognition?

- Classification
- Object Detection
- Semantic Segmentation
- Instance Segmentation
- Key point Detection
- VQA



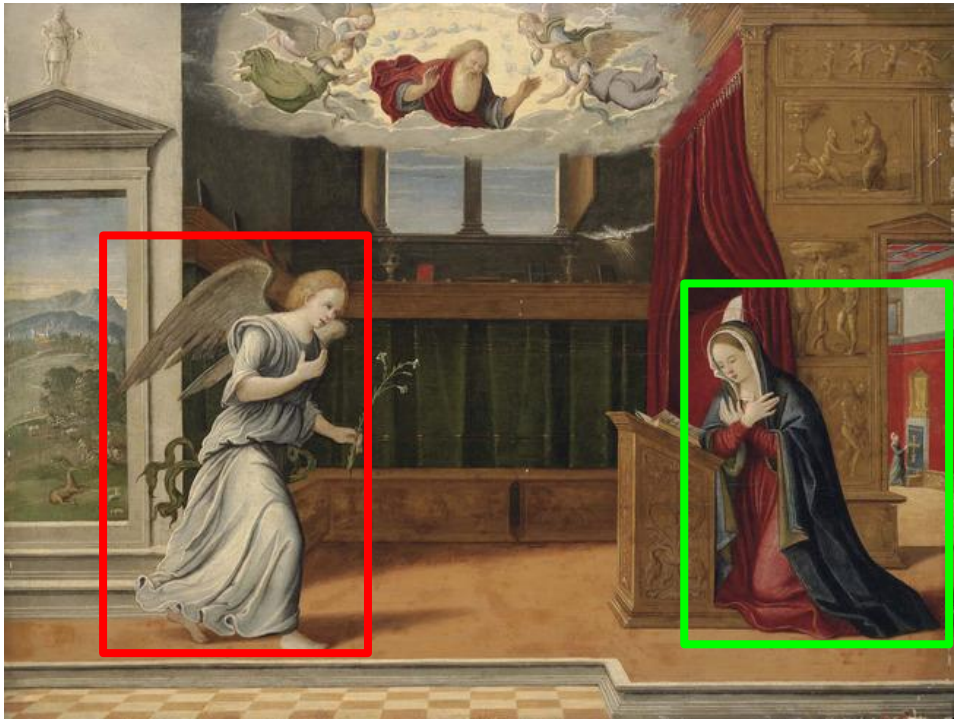
Visual recognition?



Category-level Recognition

Persons

Visual recognition?



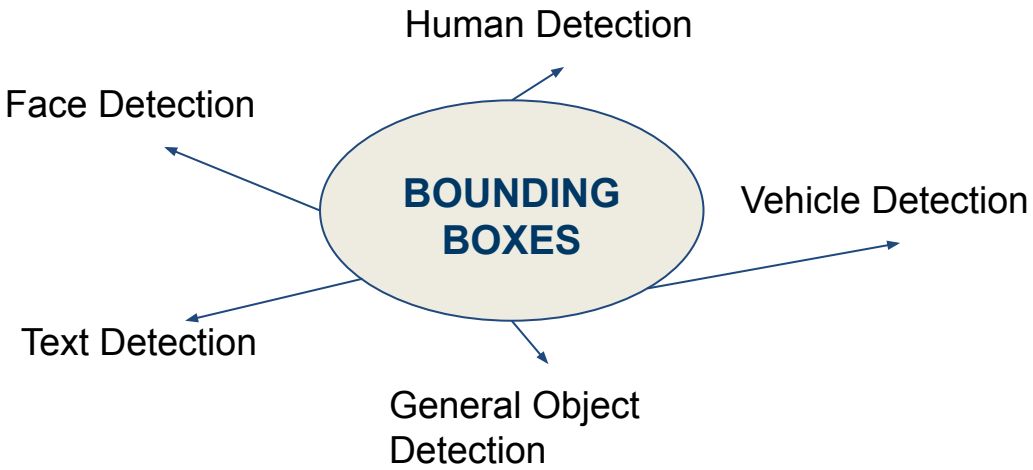
Instance-level Recognition

Mary

Gabriel

How to quantify objects?

- Encapsulating objects → a common representation



Quantifying objects - Applications

- Cancer detection in radiology-based images [Healthcare]
- Autonomous Driving [Automation]
- Detection of manufacturing defects, factory floor surveillance [Manufacturing]
- Pedestrian Detection [Public safety and surveillance]

… and many more ...

Modern Object Detection

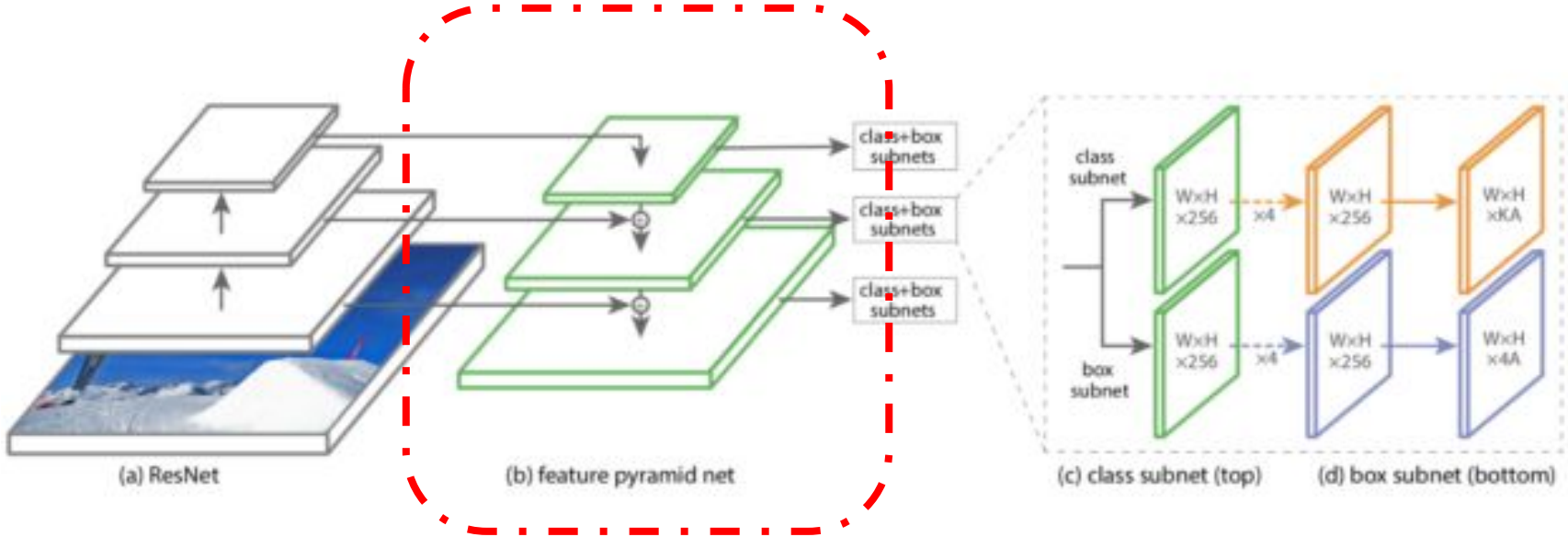


Figure - RetinaNet Architecture

What do these deep features encode?

OR

How do these networks define "***objectness***"?

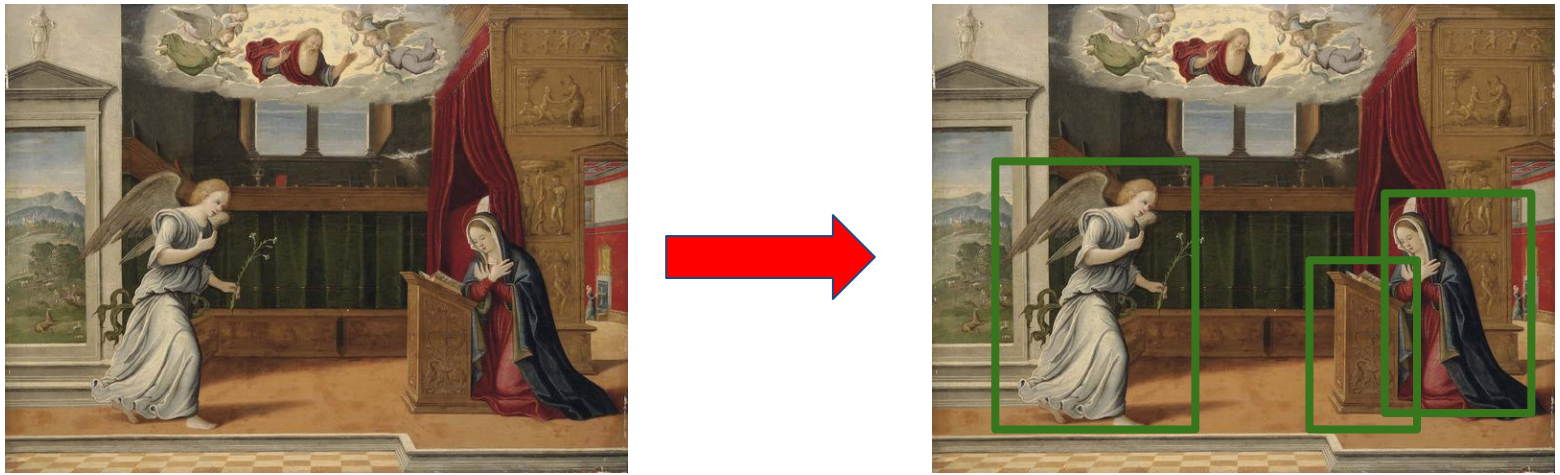
"Selective Search for object recognition"

Object recognition

Find objects and recognize them

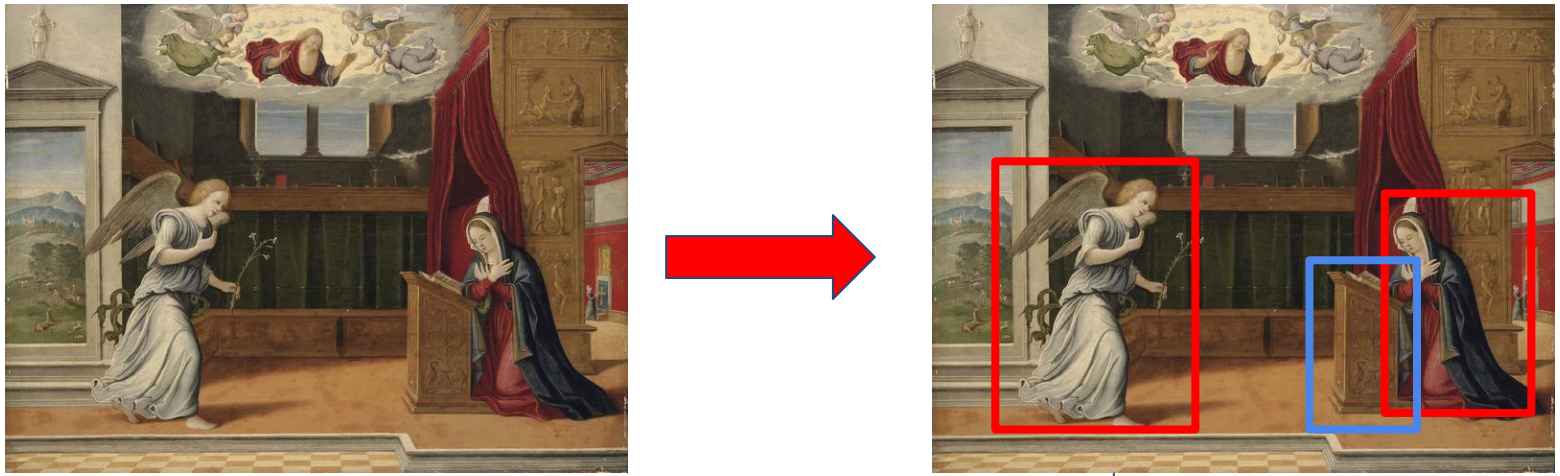
Object recognition

Find objects and recognize them

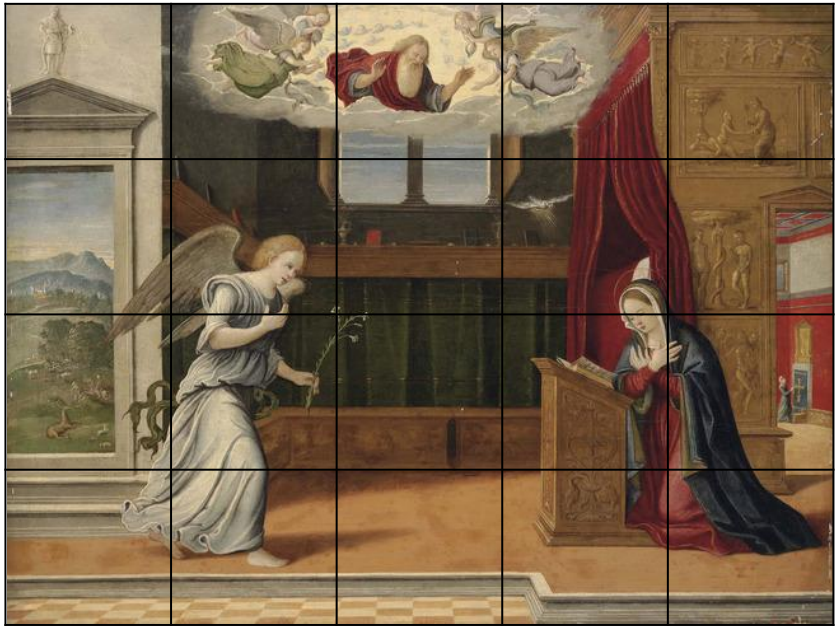


Object recognition

Find objects and *recognize* them

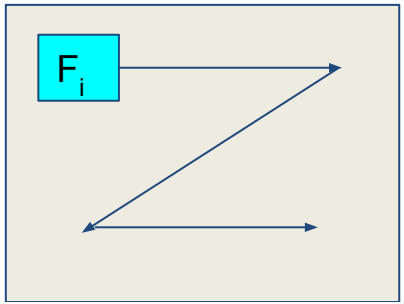


Exhaustive search



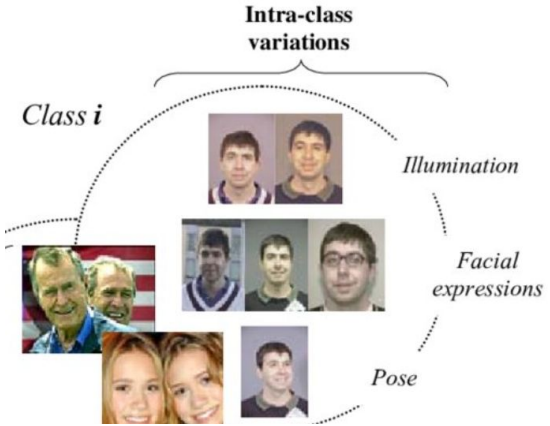
Sliding Window Object Detector

- Localizing → Identifying objects
- F_i : fixed size windows
- $f(F_i) \rightarrow$? (which class), f : classifier



Issues:

- Lacks contextual cues
- Fails when intra-class variations



Computationally effective?

\+ Trained classification network can be used for object detection directly

− Computationally inefficient: One pass through the network for every patch!

Solution - Improve speed by using ***Fully Convolutional Kernels***

Still we would need ***regions of interest*** right and that too in an automated fashion maybe?

Selective Search

- Goals:
  - Capture all scales - How could we know the size of object?
  - Diversifications - Different criteria for segmentation
  - Fast to compute
- use of the powerful ***Bag-of-Words model for recognition*** [Further Reading]

Approach

- Hierarchical segmentation
  - Apply existing algorithms to find sub-segmentations
    - Small segmentations
  - Recursively combine small segmentations into big segmentations
    - Big segmentations

Algorithm

Algorithm 1: Hierarchical Grouping Algorithm

Input: (colour) image
Output: Set of object location hypotheses L

Obtain initial regions $R = \{r_1, \cdots, r_n\}$ using [13]
Initialise similarity set $S = \emptyset$
foreach *Neighbouring region pair* (r_i, r_j) **do**
    Calculate similarity $s(r_i, r_j)$
    $S = S \cup s(r_i, r_j)$

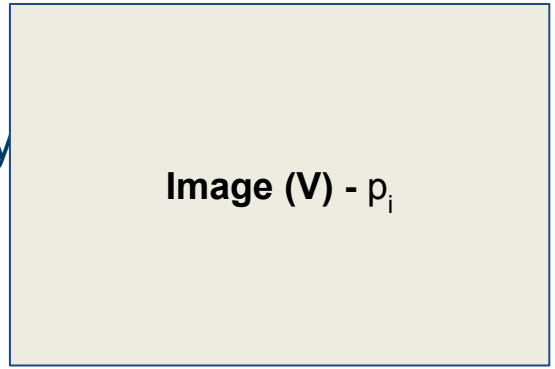
while $S \neq \emptyset$ **do**
    Get highest similarity $s(r_i, r_j) = \max(S)$
    Merge corresponding regions $r_t = r_i \cup r_j$
    Remove similarities regarding $r_i : S = S \setminus s(r_i, r_*)$
    Remove similarities regarding $r_j : S = S \setminus s(r_*, r_j)$
    Calculate similarity set S_t between r_t and its neighbours
    $S = S \cup S_t$
    $R = R \cup r_t$

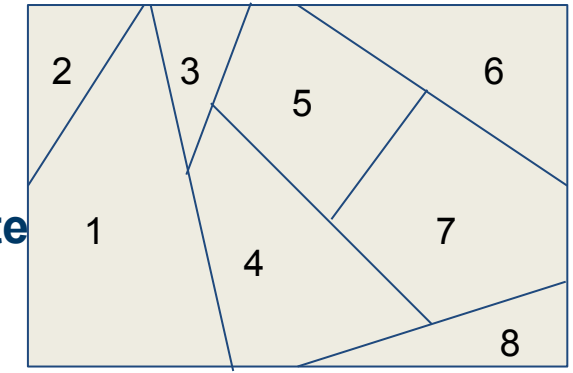
Extract object location boxes L from all regions in R

Felzenszwalb paper

Felzenszwalb - in a nutshell

- Divide an image into regions
- Defining boundaries by graph-representation satisfy
- Perceptual grouping - psychology
- Idea
  - Capture perceptually important groupings
  - Time efficient - real time applications
- Method - **Pairwise Region Comparison Predicate**

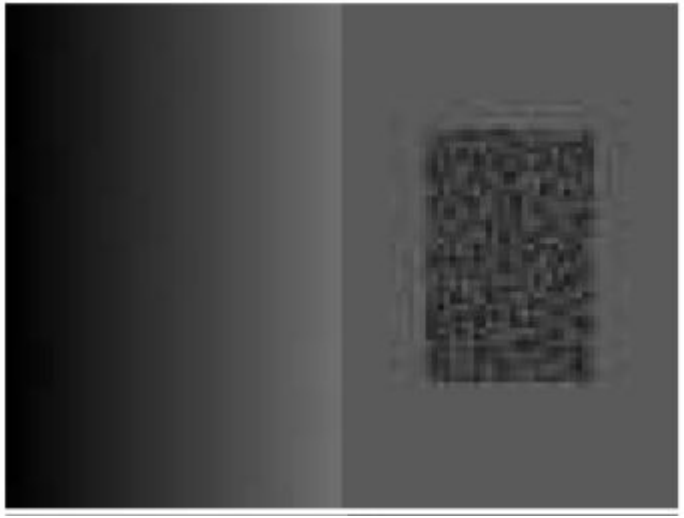




Understanding segmentation

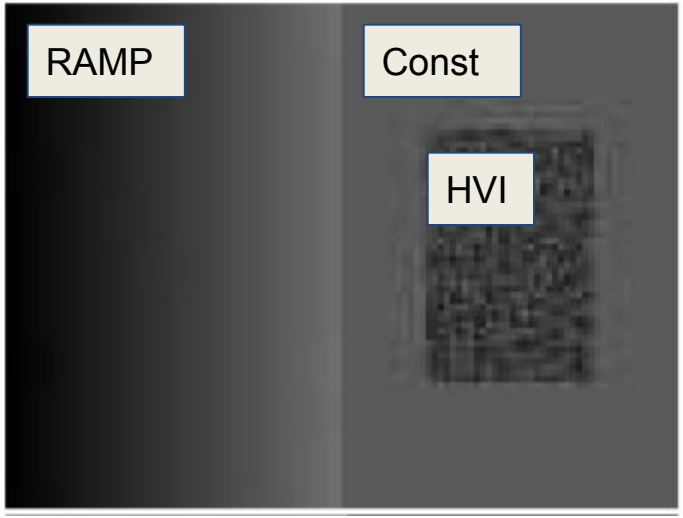
- How many regions?

- Assumptions
  - Widely varying intensities
  - Purely local decision ***criteria***

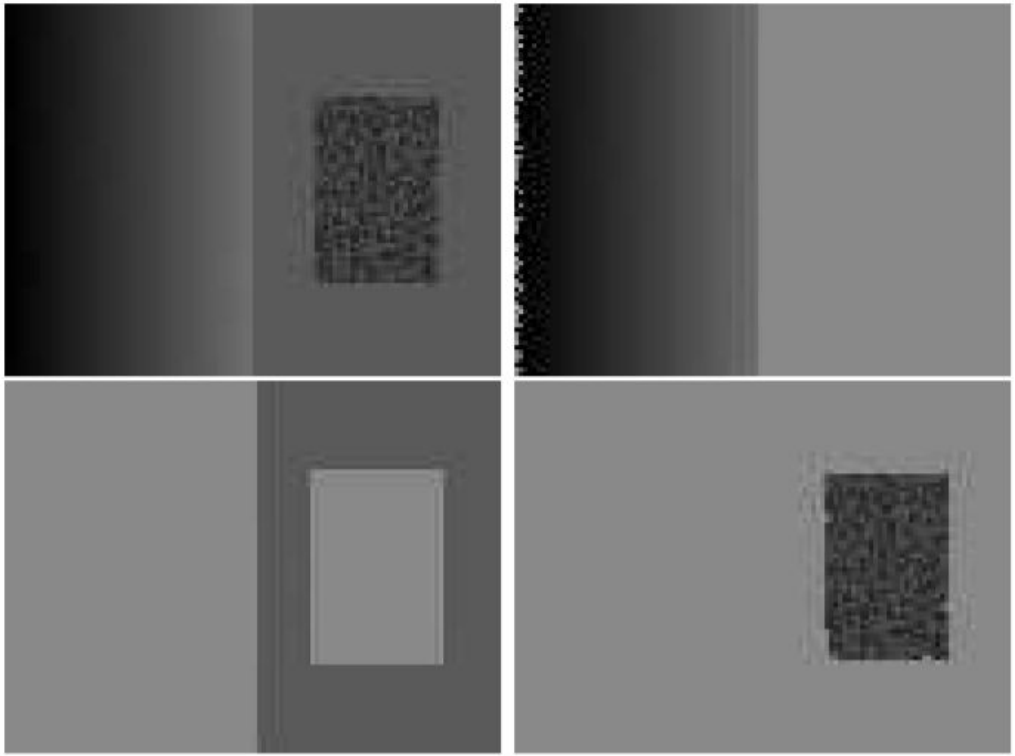


Understanding segmentation

- How many regions?
- Assumptions
  - Widely varying intensities
  - Purely local decision criteria
- What we need?
  - Adaptive / non-local criterion



Felzenszwalb - Results I



Felzenszwalb - Results II

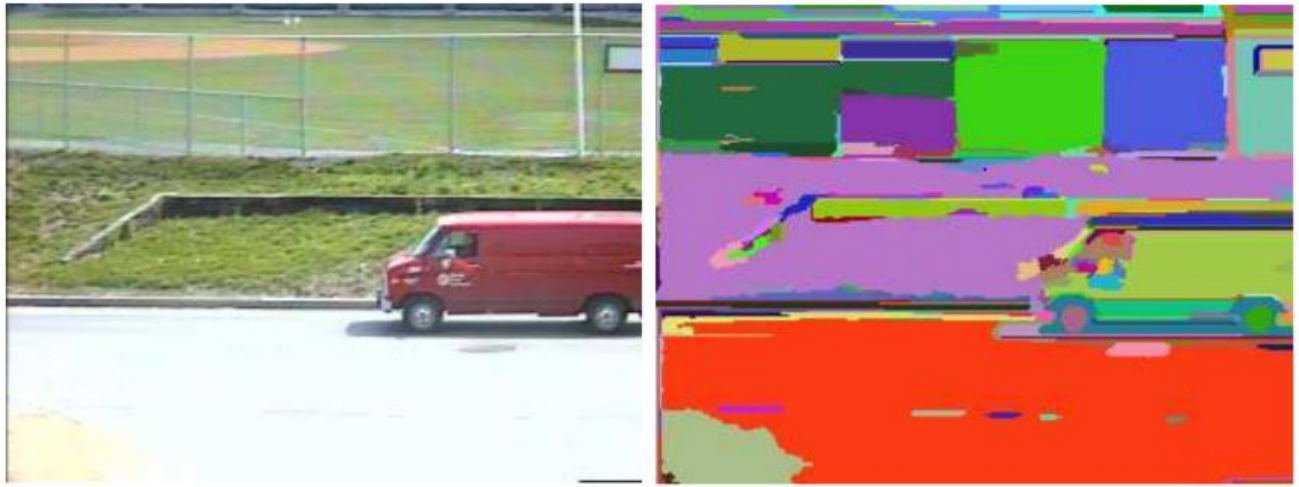
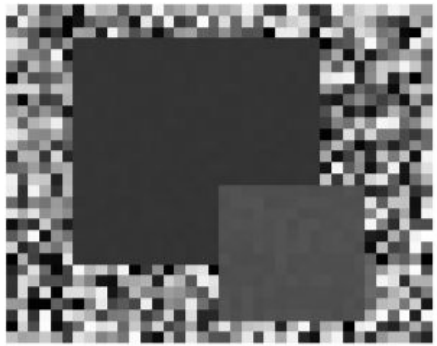
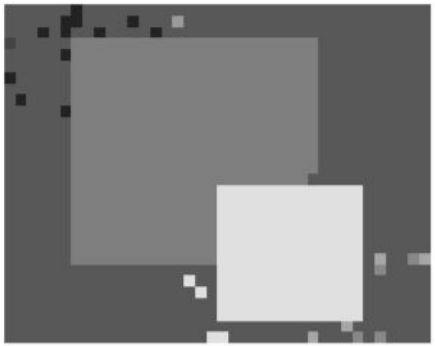


Figure 2: A street scene (320×240 color image), and the segmentation results produced by our algorithm ($\sigma = 0.8$, $k = 300$).

Felzenszwalb - Result III







Algorithm

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    $S = S \cup S_t$
    $R = R \cup r_t$

Extract object location boxes L from all regions in R

Diversification

- We already saw how Felzenszwalb's algorithm captures the scale, now ***how to model different criteria into the algorithm***?

- What ***criteria*** for combining the segmentations?

Diversification

- Complementary Color Spaces

Diversification

- Complementary Color Spaces

- Complementary Similarity Measures
  - Color similarity
  - Texture similarity
  - Size similarity
  - Shape compatibility - shape fill

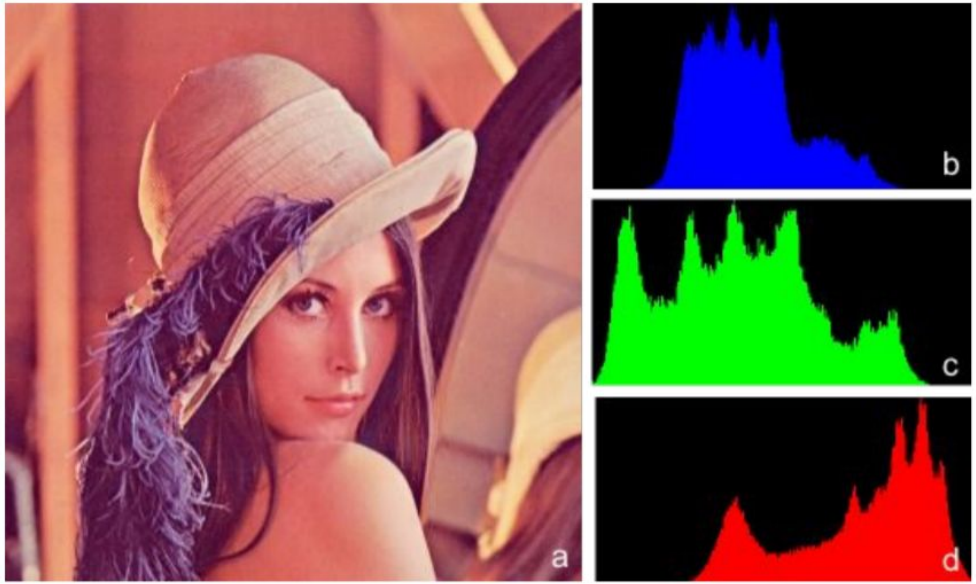
Color similarity

$$C_i = \{c_i^1, \cdots, c_i^n\}$$

$$s_{colour}(r_i, r_j) = \sum_{k=1}^{n} \min(c_i^k, c_j^k)$$

$$C_t = \frac{\text{size}(r_i) \times C_i + \text{size}(r_j) \times C_j}{\text{size}(r_i) + \text{size}(\text{r}_\text{j})}$$

$$\text{size}(r_t) = \text{size}(r_i) + \text{size}(r_j)$$



Texture similarity

- Extract derivatives in 8 directions for 3 channels
- 10 bins for each, 240 bins in total
- L1 Normalize
- Histogram Intersection

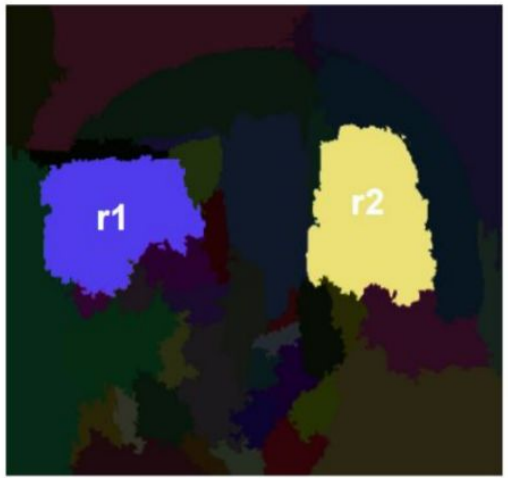
$$T_i = \{t_i^1, \cdots, t_i^n\}$$

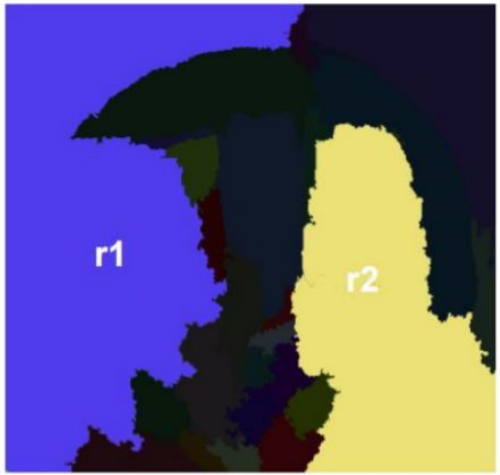
$$s_{texture}(r_i, r_j) = \sum_{k=1}^{n} \min(t_i^k, t_j^k)$$

Size similarity

- We hope to **merge two small region** into a large segmentation

$$s_{size}(r_i, r_j) = 1 - \frac{\text{size}(r_i) + \text{size}(\text{r}_\text{j})}{\text{size}(im)}$$

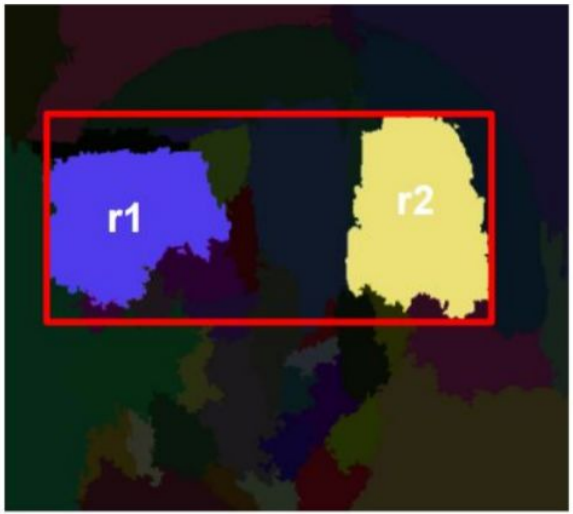


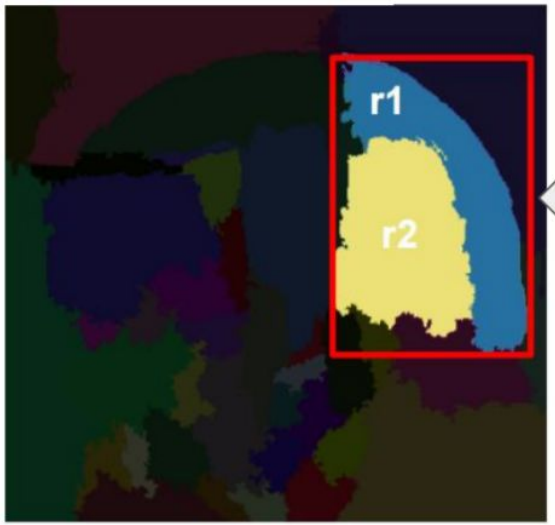


Shape compatibility

- Whether two segmentations fit each other?

$$fill(r_i, r_j) = 1 - \frac{\text{size}(BB_{ij}) - \text{size}(r_i) - \text{size}(r_i)}{\text{size}(im)}$$





Bounding
Box

Diversification (contd.)

- **Weighted mixture approach**

$$s(r_i, r_j) = a_1 s_{colour}(r_i, r_j) + a_2 s_{texture}(r_i, r_j) + a_3 s_{size}(r_i, r_j) + a_4 s_{fill}(r_i, r_j),$$

Diversification

- Complementary Color Spaces

- Complementary Similarity Measures
  - Color similarity
  - Texture similarity
  - Size similarity
  - Shape compatibility - shape fill

- Complementary Starting Regions

Evaluation

- **Average Best Overlap (ABO)**

$$\text{ABO} = \frac{1}{|G^c|} \sum_{g_i^c \in G^c} \max_{l_j \in L} \text{Overlap}(g_i^c, l_j)$$

Overlap between ground truth and best selected box.

Average of "best overlaps" across all images.

$$\text{Overlap}(g_i^c, l_j) = \frac{\text{area}(g_i^c) \cap \text{area}(\text{l}_\text{j})}{\text{area}(g_i^c) \cup \text{area}(\text{l}_\text{j})}$$

Evaluation

Similarities	MABO	# box
C	0.635	356
T	0.581	303
S	0.640	466
F	0.634	449
C+T	0.635	346
C+S	0.660	383
C+F	0.660	389
T+S	0.650	406
T+F	0.638	400
S+F	0.638	449
C+T+S	0.662	377
C+T+F	0.659	381
C+S+F	0.674	401
T+S+F	0.655	427
C+T+S+F	0.676	395

Colours	MABO	# box
HSV	0.693	463
I	0.670	399
RGB	0.676	395
rgI	0.693	362
Lab	0.690	328
H	0.644	322
rgb	0.647	207
C	0.615	125

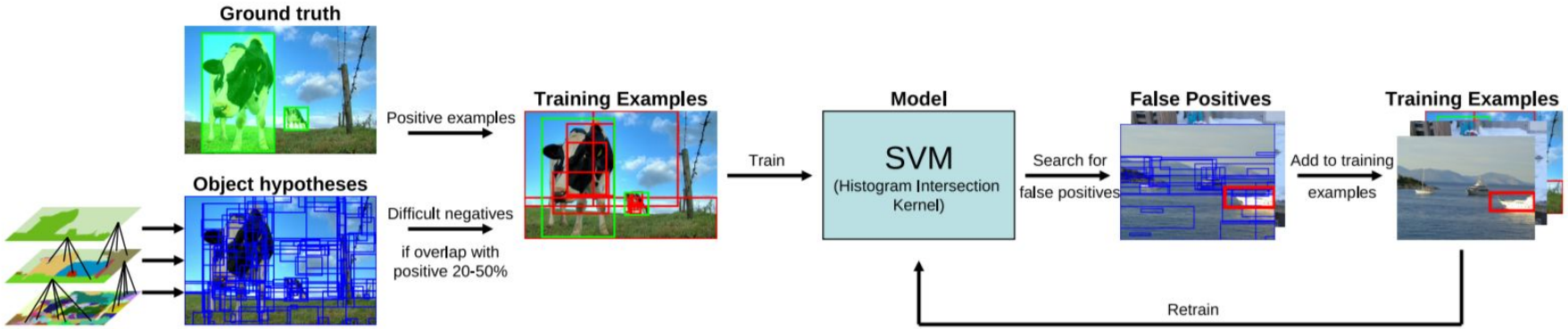
Thresholds	MABO	# box
50	0.676	395
100	0.671	239
150	0.668	168
250	0.647	102
500	0.585	46
1000	0.477	19

Evaluation

Version	Diversification Strategies	MABO	# win	# strategies	time (s)
Single Strategy	HSV C+T+S+F $k = 100$	0.693	362	1	0.71
Selective Search Fast	HSV, Lab C+T+S+F, T+S+F $k = 50, 100$	0.799	2147	8	3.79
Selective Search Quality	HSV, Lab, rgI, H, I C+T+S+F, T+S+F, F, S $k = 50, 100, 150, 300$	0.878	10,108	80	17.15

Object Recognition

Approach : Selective Search + SIFT + SVM



Exercise 5

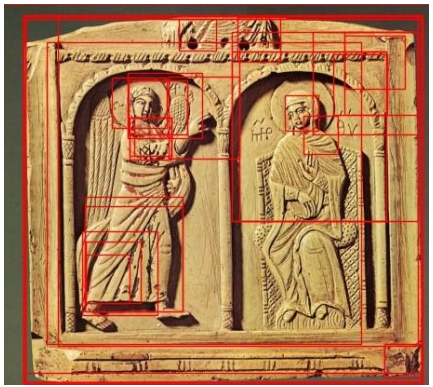
What you get?

- 9 images (3 from each of Art History, Class. Arch and Chris. Arch)

Your goal:

- Generate possible boxes that contains objects
- Questions.pdf
- Writeup.pdf

Detailed description in exercise-05.pdf



Further Reading

1. Felzenszwalb paper - http://cs.brown.edu/people/pfelzens/papers/seg-ijcv.pdf

2. Selective Search paper - http://huppelen.nl/publications/selectiveSearchDraft.pdf

3. Project on bag of words: https://cs.brown.edu/courses/csci1430/proj3/

Backup slides

GRAPH - based segmentation

- **G** = (**V**, **E**) - undirected graph
  - $v_i \in \mathbf{V}$ - vertices (set of elements to be segmented, i.e. *pixels*)
  - $(v_i, v_j) \in \mathbf{E}$ - edges (pairs of neighboring vertices)
  - $w((v_i, v_j))$ - non negative dissimilarity
    - Based on intensity difference, color, motion etc.

- **S : Segmentation** (partition of V into components or region)
  - **C** $\in$ **S** - connected component in a graph **G'** = (**V**, **E'**), where **E'** $\subseteq$ **E**

Intuition:

- Any segmentation induced by subset of its edges in E
- Edges between 2 vertices in same component/region → low weight

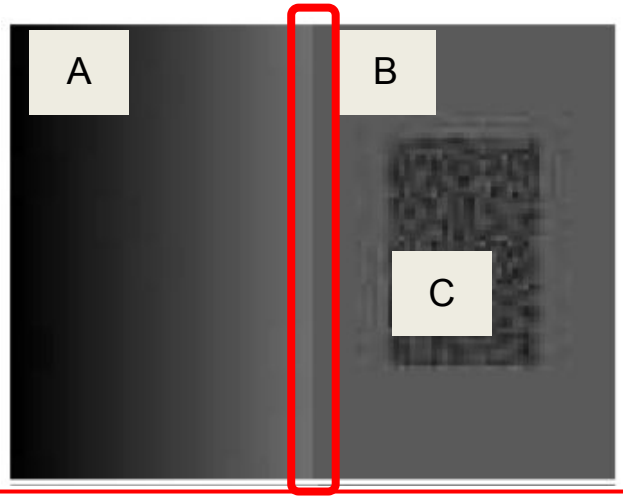
Pairwise Region Comparison Predicate

- **D**: predicate to evaluate whether or not there is an evidence for a boundary between 2 regions

"Measuring dissimilarity *between elements along the boundary of 2 components* relative to a measure of the dissimilarity *among neighboring elements within each of 2 components*"

Pairwise Region Comparison Predicate (PRCP)

- **D**: predicate to evaluate whether or not there is an evidence for a boundary between 2 regions



"Measuring dissimilarity *between elements along the boundary of 2 components* relative to a measure of the dissimilarity *among neighboring elements within each of 2 components*"

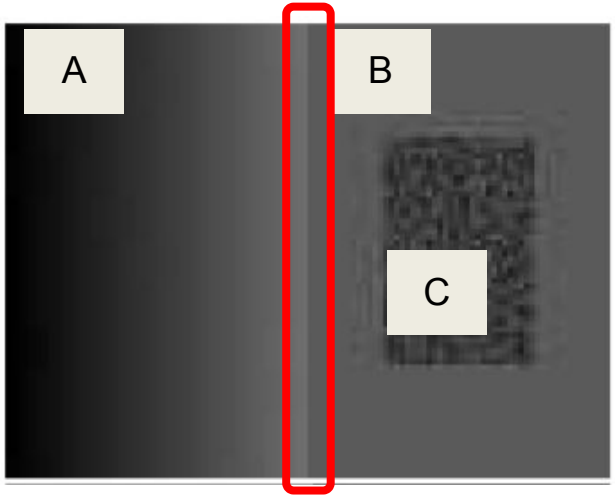
Pairwise Region Comparison Predicate (PRCP)

- Internal difference of a component

$$Int(C) = \max_{e \in MST(C,E)} w(e)$$

- Difference between 2 components

$$Dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E} w((v_i, v_j))$$



Pairwise Region Comparison Predicate (PRCP)

- PRCP

$$D(C_1, C_2) = \begin{cases} \text{true} & \text{if } Dif(C_1, C_2) > MInt(C_1, C_2) \\ \text{false} & \text{otherwise} \end{cases}$$

where,

$$MInt(C_1, C_2) = \min(Int(C_1) + \tau(C_1),\ Int(C_2) + \tau(C_2))$$

Algorithm

Input: **G**(**V**, **E**) with *n* vertices and *m* edges
Output: **S** = (C_1, …, C_r) i.e. segmentation of **V**

1. Sort **E** into π = (o_1, o_2, …, o_m) by non-decreasing edge weights

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   a. v_i and v_j → connected by qth edge → o_q = (v_i, v_j)

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5. Return **S** = $\mathbf{S_m}$