

Visual Recognition for Humanities

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Project CV Summer 2024,

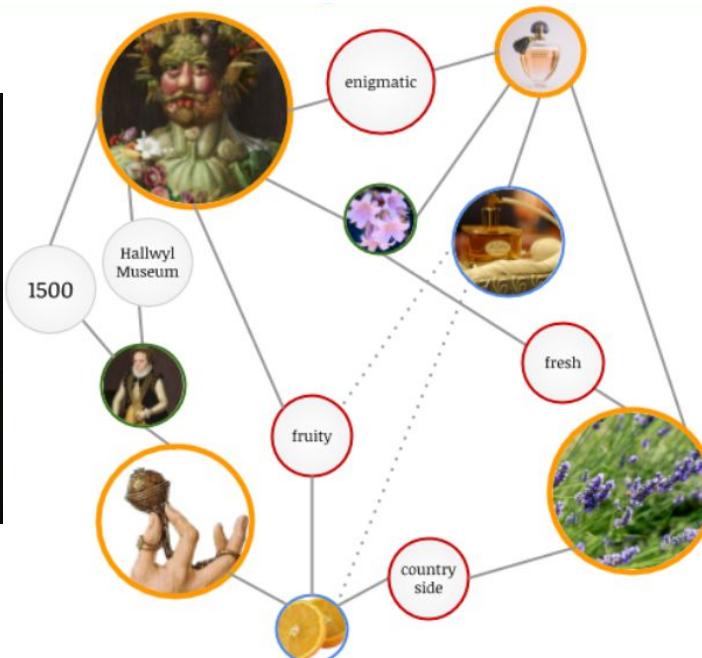
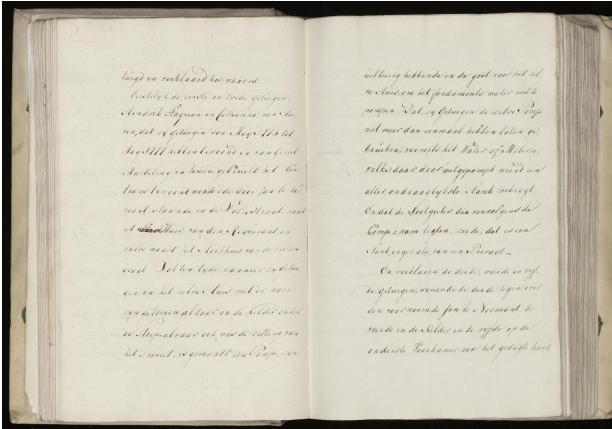
07th June, 2024



Outline

1. Computer Vision in the Humanities
2. Object Detection
3. Selective search & Felzenszwalb
4. Modern Object Detection
5. Exercise

ML and the Humanities



Focus I - Text

Text and Writer identification
and OCR

Handwriting imitation

Α' τὸ τῆς Φυγῆς τῇ Σίρξε ἐκ τῆς Ελλάδος ἐστῶς τῆς ἡ Μυκάλη γίνεται.

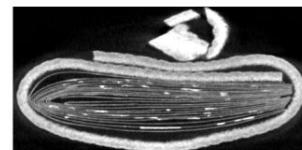
Hη πρώτη φάμετος τῶν Ελλήνων Φροντίς μετὰ τηρίου Σαλαμῖνι μάχην, ὃς τὸν οὐδὲνα εἰς τὰ Δελλαζούς τὸν πόλεμον λαφύρων, ὅσα ἔλαβον ἀπὸ τῆς Πέρσας. Ως σύμμαχοι θεωρέμενοι οἱ Λαζηνοὶ ἦσαν πάντοτε προτετικοὶ εἰς τὰ καθήκοντα τῆς Θρησκείας, οὐ μὲν ὅτι αἱ αἱρέσεις οὐ τὰ δόγματα τῶν φιλοσόφων ἐλίδασκον τὸν αἰθρίτινον γένος ἀλλιγοῦν οὐ τιμᾶ τὰς δημοσίες τελετὰς, οὐ τόσουν ἡ Θρησκεία ἦτι ὁ πρόστον οὐ μίνος σύνδεσμος τῆς ἐποίσεως αὐτῶν, οὐ ἐκράτει αὐτὸς τῷος ὥρας ἀδιαστάτως ἡμαρτυρεῖς. ὅτε δὲ ἐλύθη αὐτὸς ὁ δεσμός, οὐ οἱ Αἱρετικοὶ σύνδεσμος ἔγινε τελτικὴ μᾶλλον ἡ θεοκρατικὴ σύνδεσμος, διελύθη οὐ γενικὴ ἔνστις, οὐ τολλαῖ ἐπαρχίαις ἔγιναν θύμα τῶν ἐμφυλίων πολέμων.



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]



GERMANISCHES
NATIONAL
MUSEUM

Aline Sindel

Image Registration

Portraits



Prints



Similarity Analysis

Repeating Elements



Multi-modal



Mixed Type



Repeating Motives



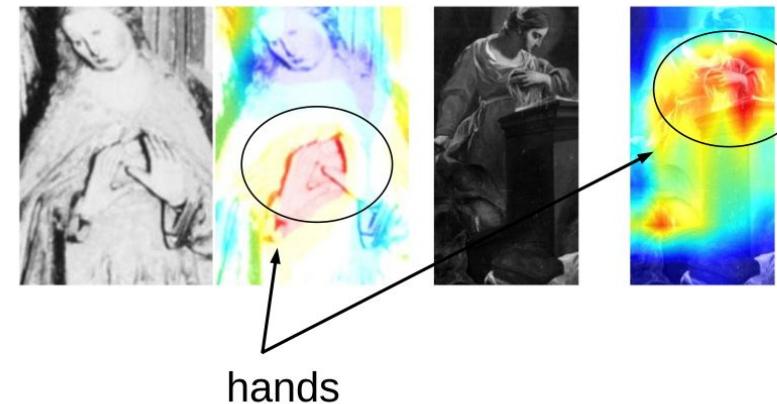
[2] Project page : <https://www.gnm.de/forschung/projekte/luther-bildnisse/>

Focus IV - Understanding [3]



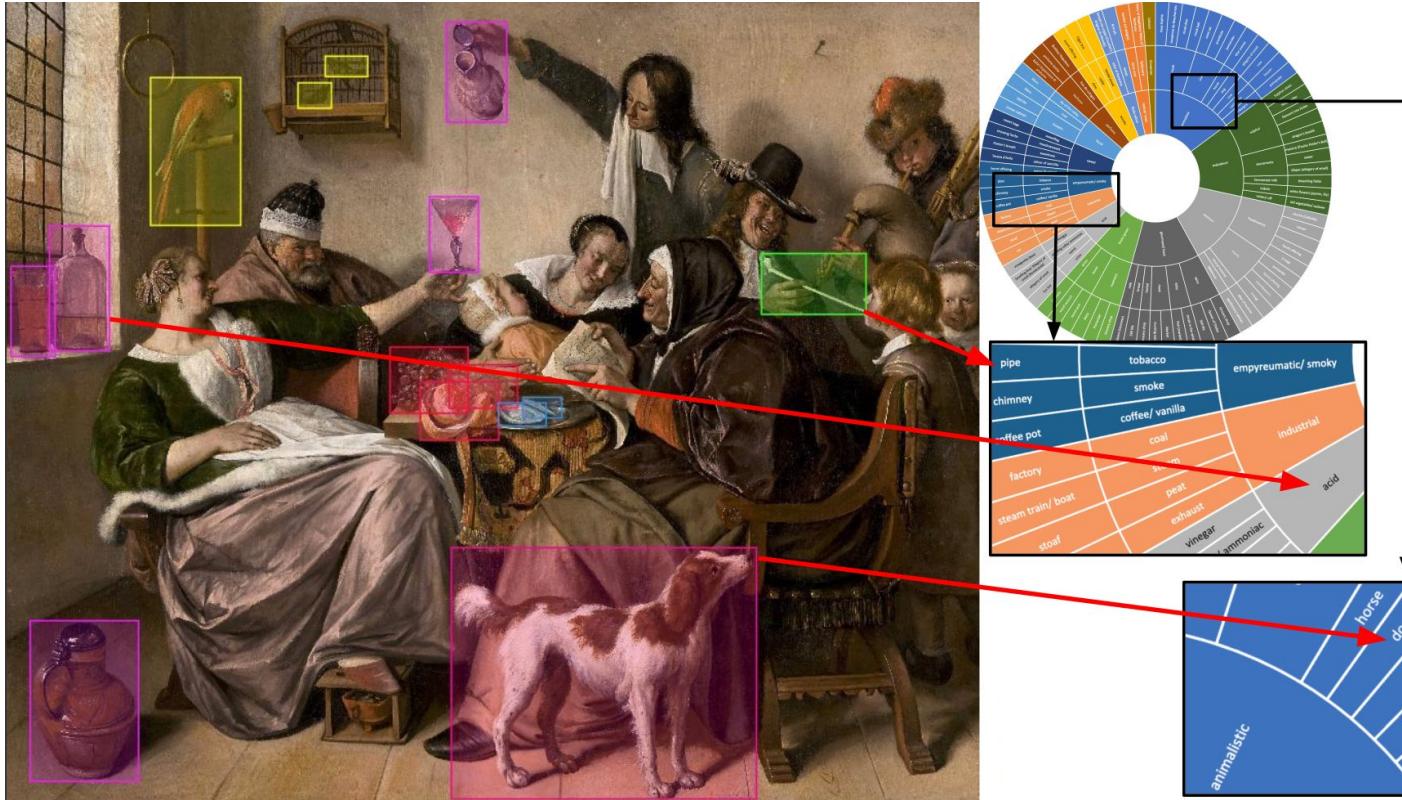
Ronak Kosti

Region of Interest
for Mary



[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.

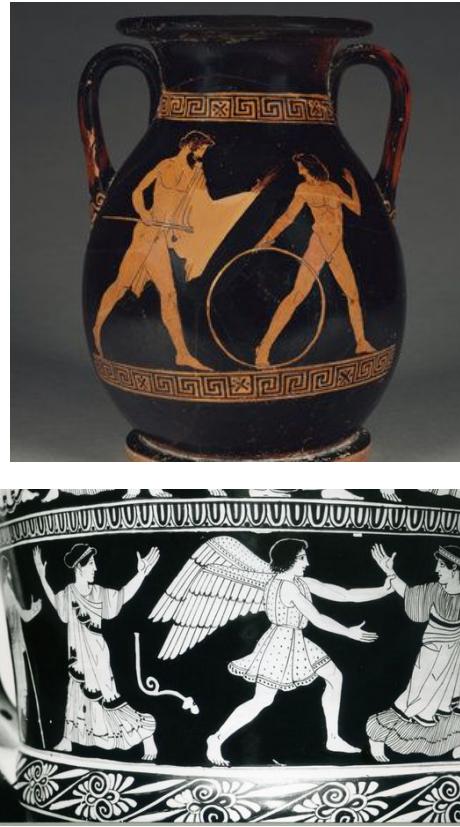
Focus V - Digital Heritage



Art History



Classical Arch.



Christian Arch.



Visual recognition?



Visual recognition?



Visual recognition?

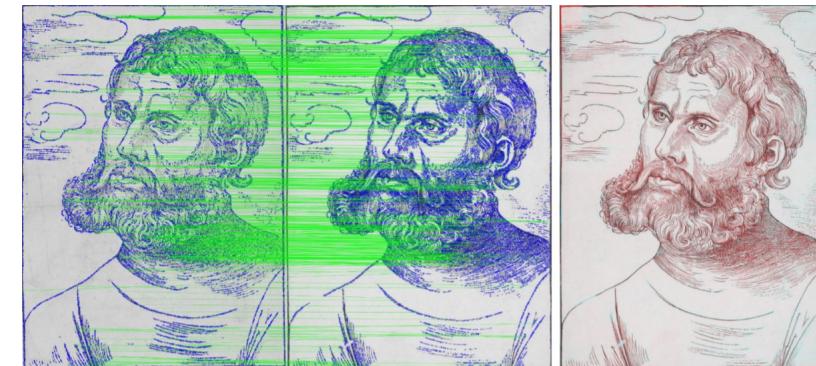


Visual recognition?

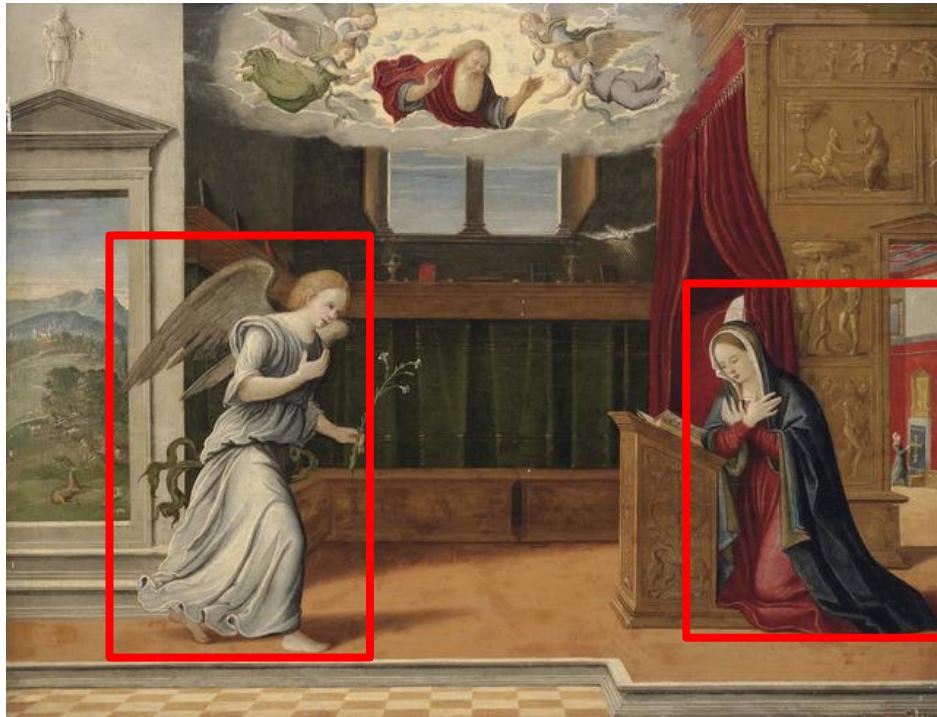


Visual recognition?

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



Visual recognition?

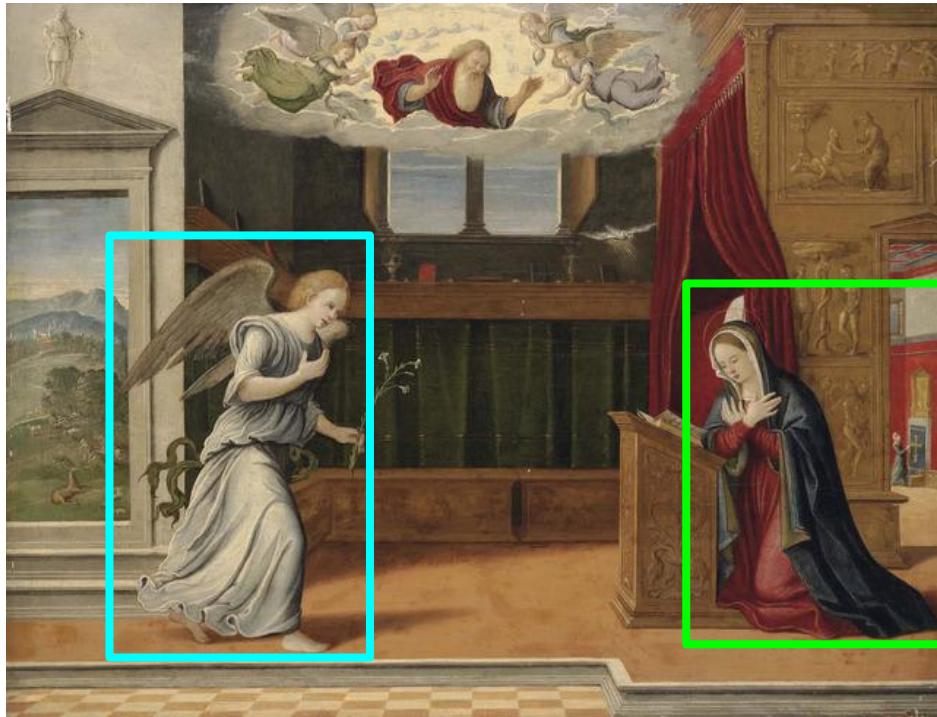


Category-level recognition

Person

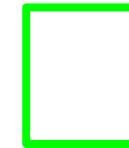


Visual recognition?



Instance-level recognition

Mary

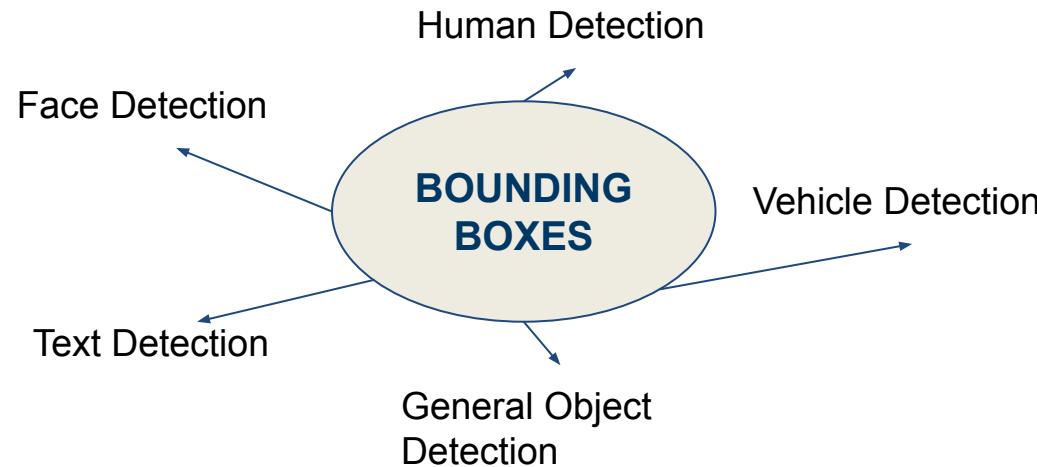


Gabriel



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

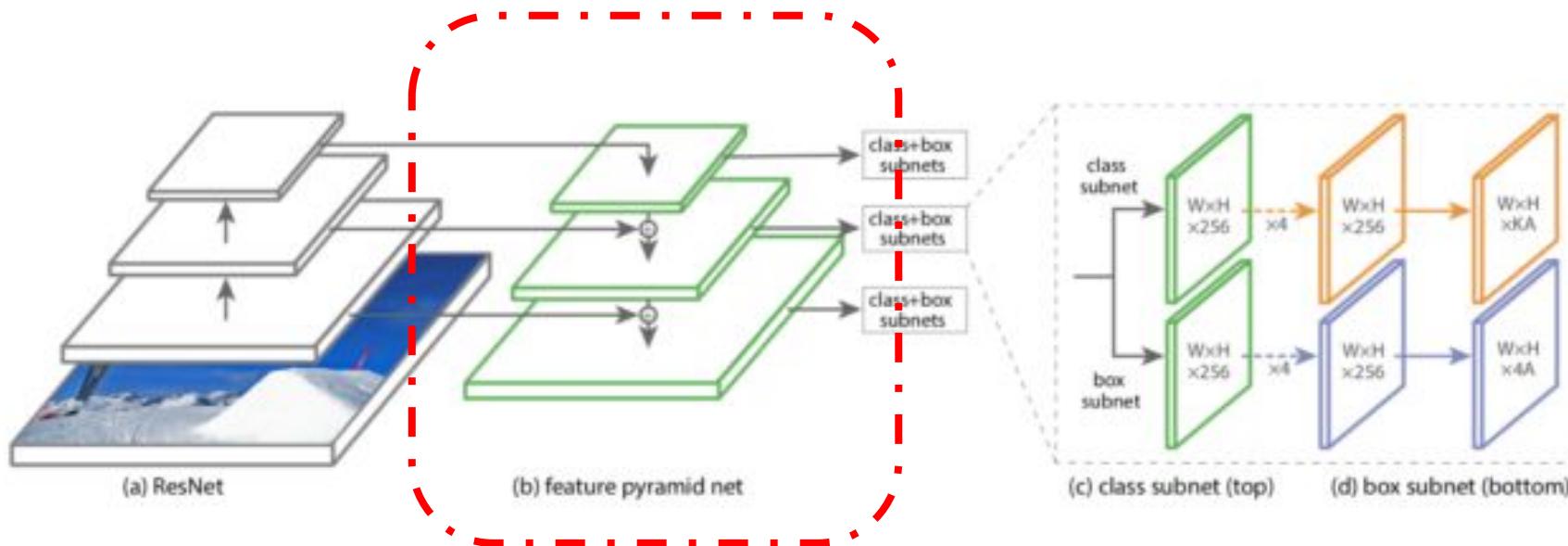
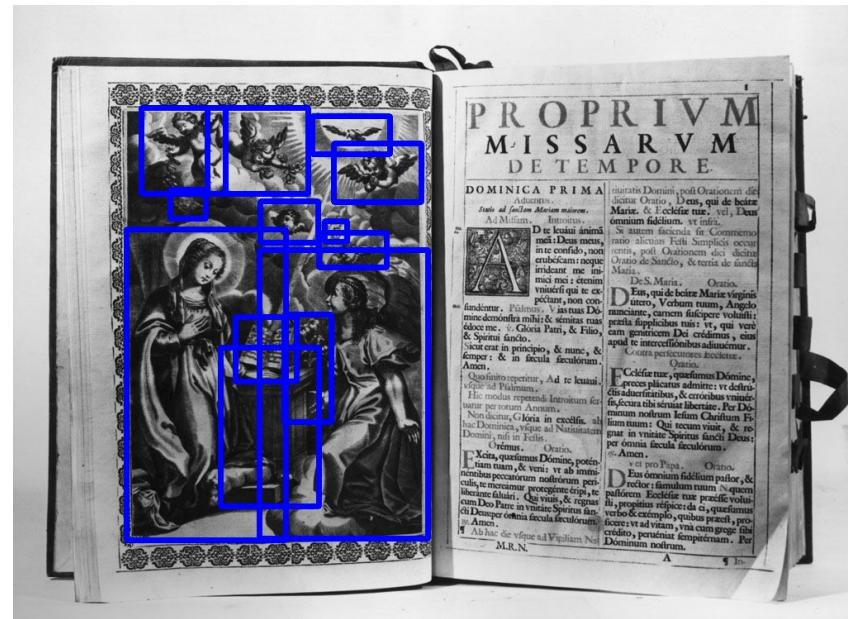


Figure - RetinaNet Architecture

Challenges

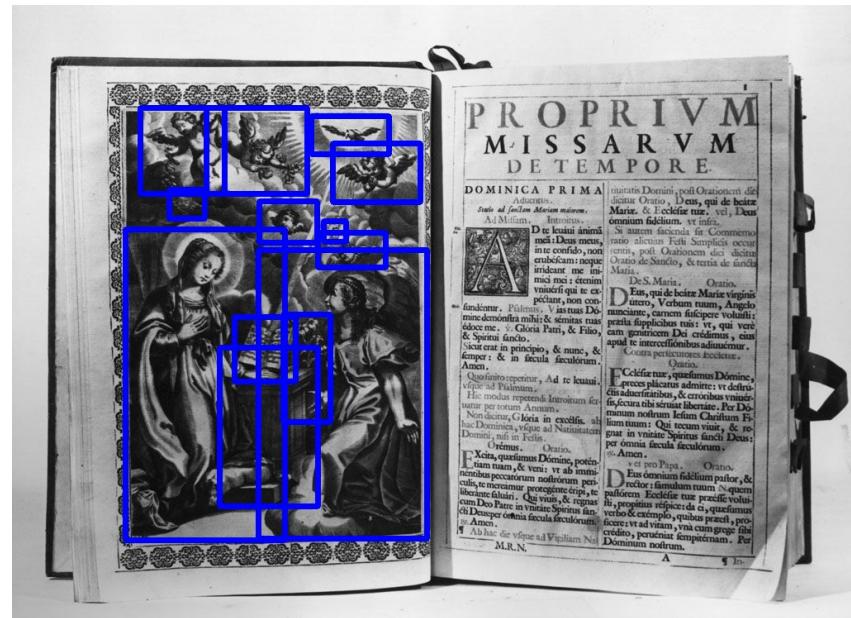
- Existing methods. Domain shift?
- Amount of Annotations
- What about new classes?



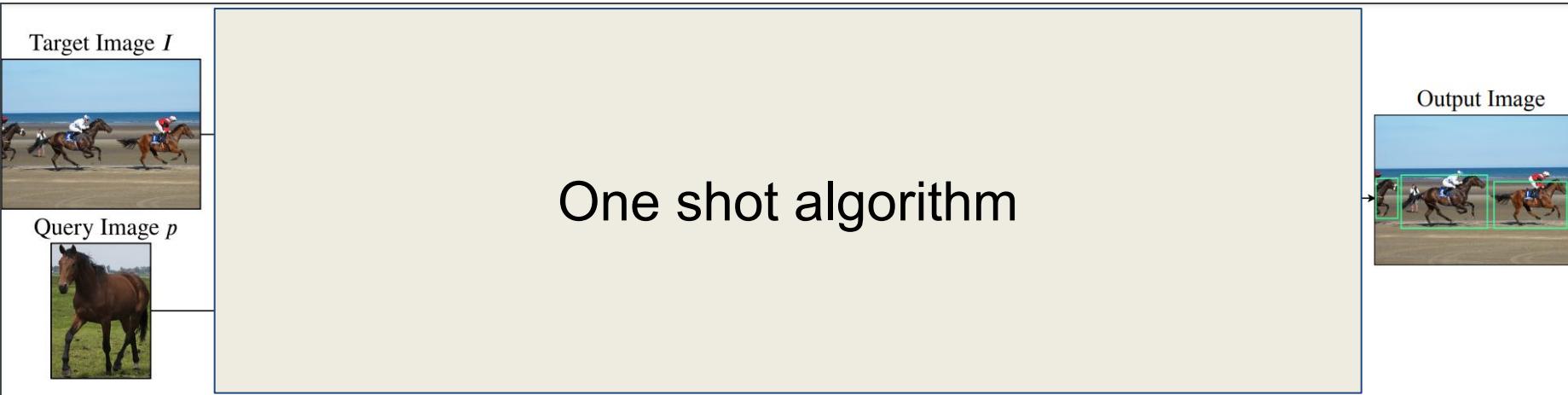
Challenges

- Existing methods. Domain shift?
 - Amount of Annotations
 - What about new classes?

N-Way K-Shot Object Detection



One-Shot Object Detection



- Train/Seen classes – [Horses, hats, cats, donkeys]
- Test/Unseen classes – [Persons, dogs]

What do these deep features encode? OR

How do these networks define “objectness”?

“Selective Search for object recognition”

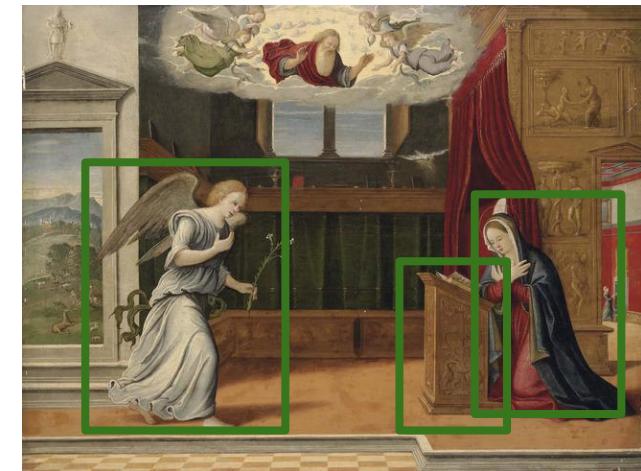
Object recognition

Find objects and recognize them



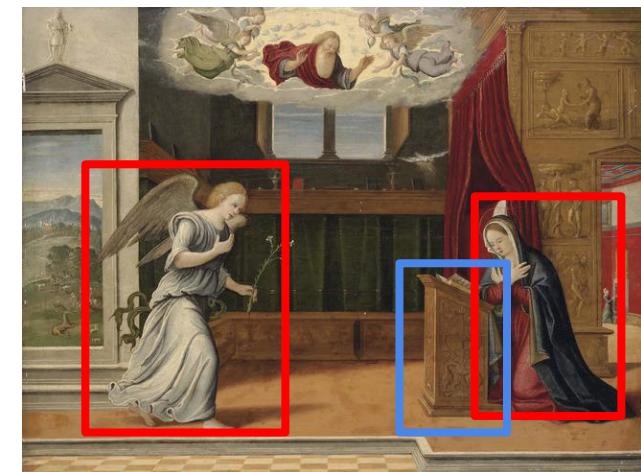
Object recognition

Find objects and recognize them



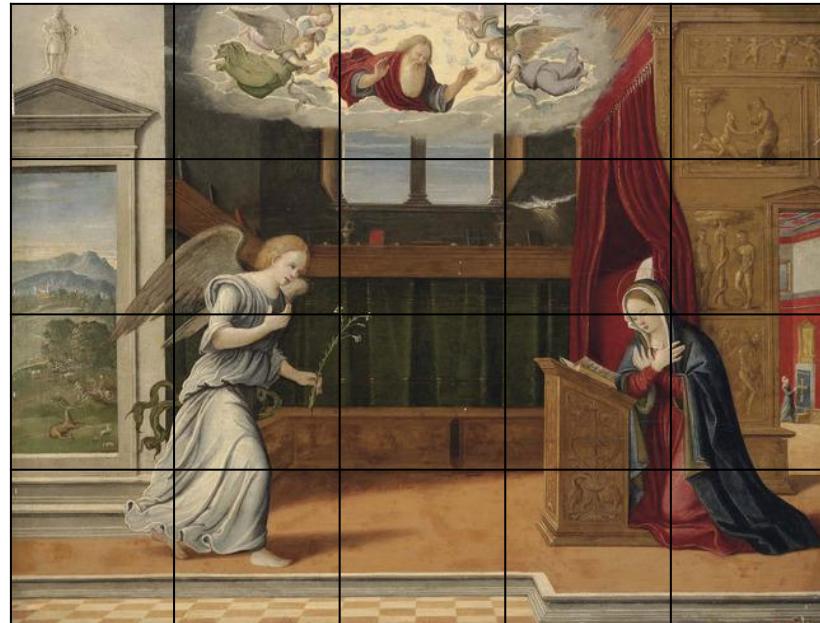
Object recognition

Find objects and *recognize* them



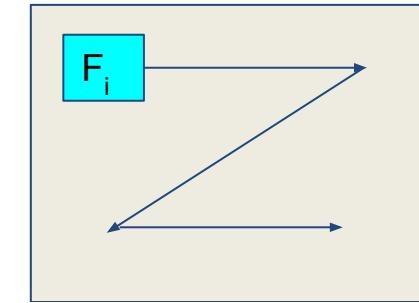
Person
Book shelf

Exhaustive search



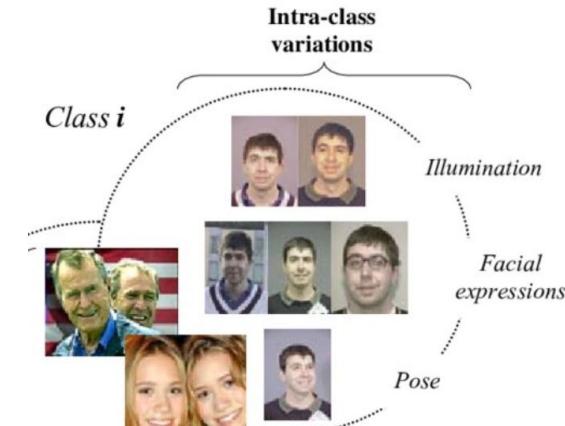
Sliding Window Object Detector

- 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 $R = \{r_1, \dots, r_n\}$ 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

$S = S \cup S_t$

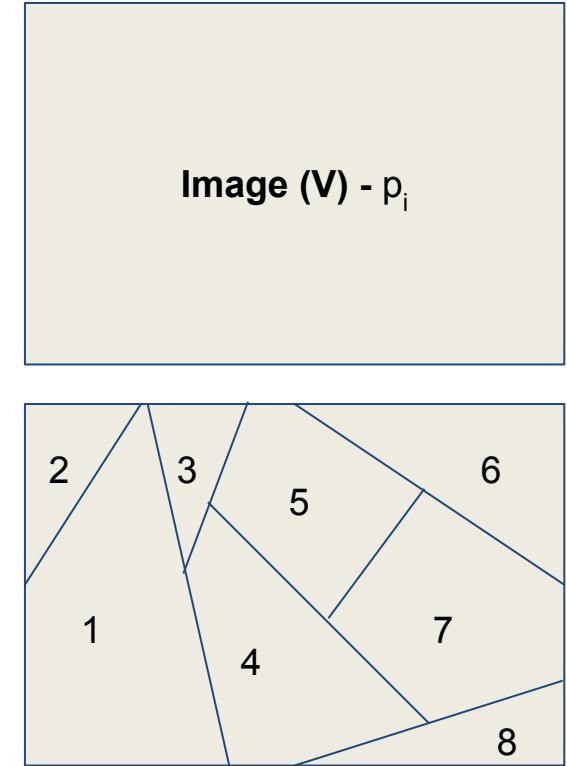
$R = R \cup r_t$

Extract object location boxes L from all regions in R

Felzenswalb
paper

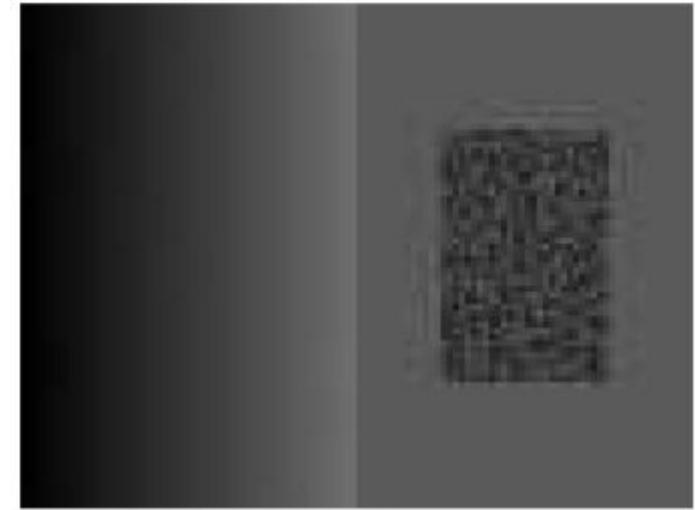
Felzenszwab - in a nutshell

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



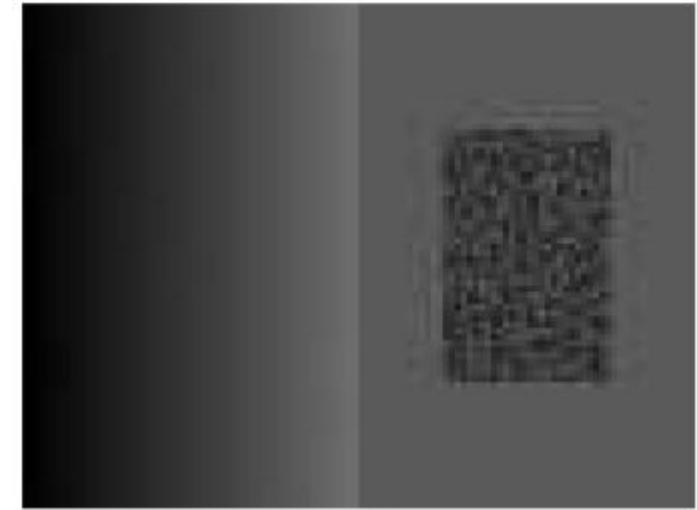
Understanding segmentation

- How many regions?



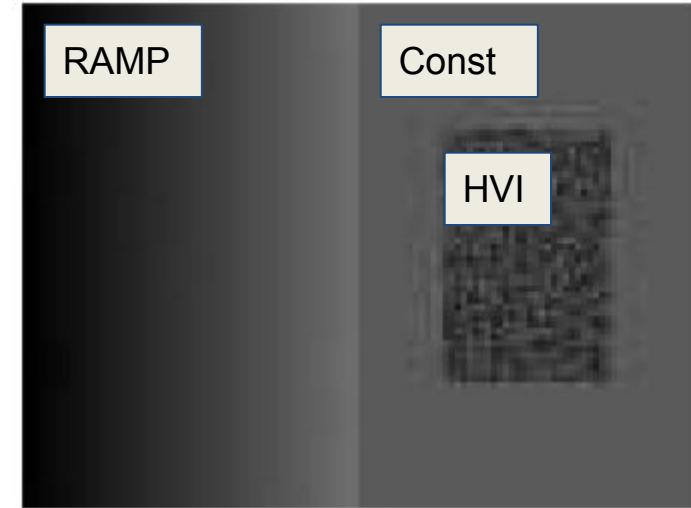
Understanding segmentation

- 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



Pairwise Region Comparison Predicate

- Compares inter-component difference to within component differences
- Or formally:

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

Inter-Class Difference

- Minimum difference on the border between two components
- Or formally:

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

Intra-Class Difference

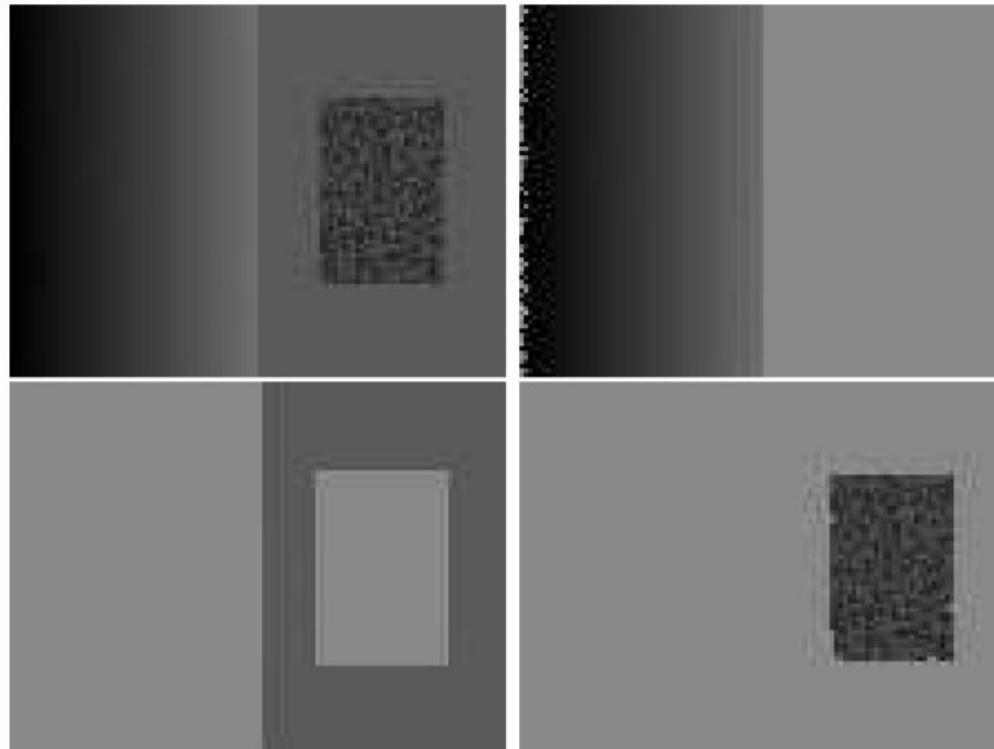
- Weighted maximum of internal differences
- Require stronger evidence for boundary for small components
- Or formally:

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

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

$$\tau(C) = k/|C|$$

Felzenszwab - Results I



Felzenszwab - Results II

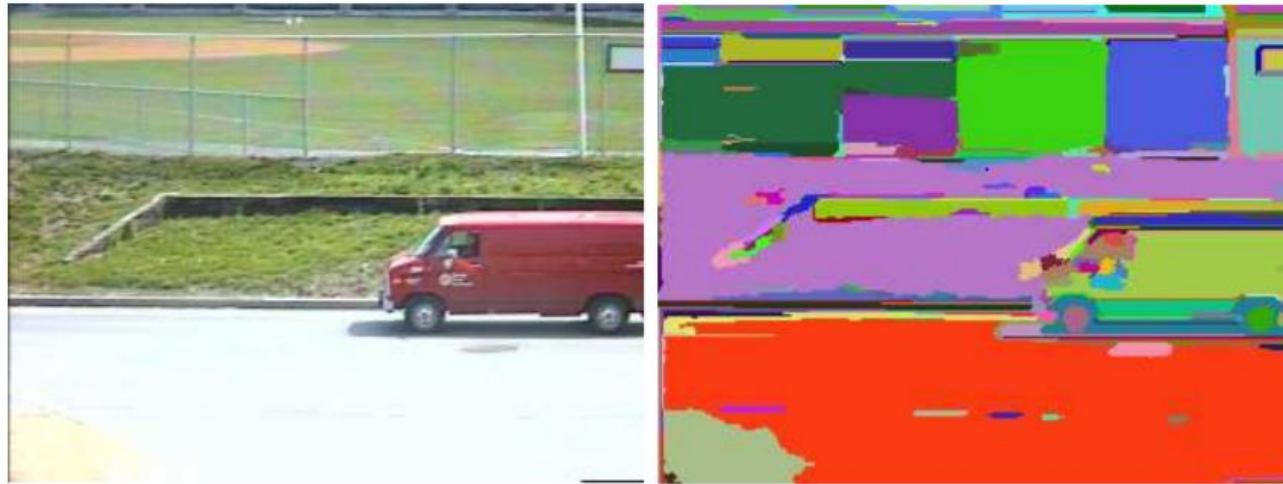
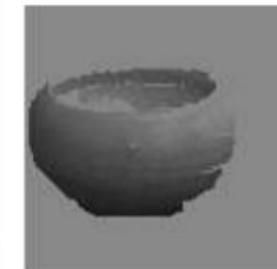
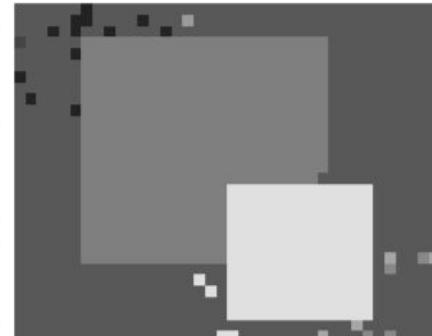
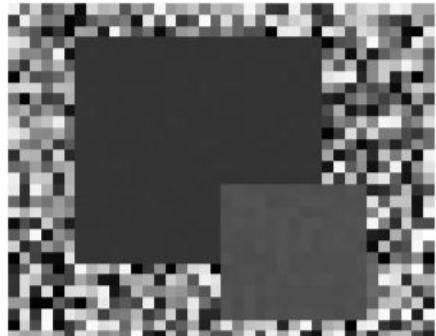
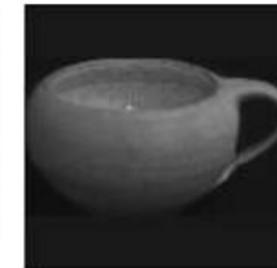


Figure 2: A street scene (320×240 color image), and the segmentation results produced by our algorithm ($\sigma = 0.8$, $k = 300$).

Felzenszwab - Result III



Algorithm

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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

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

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

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

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

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



Texture similarity

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

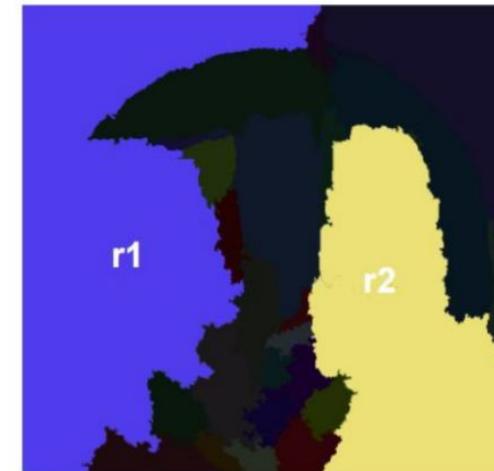
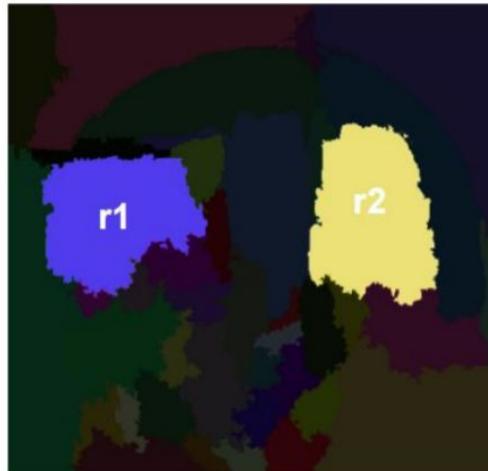
$$T_i = \{t_i^1, \dots, t_i^n\}$$

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

Size similarity

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

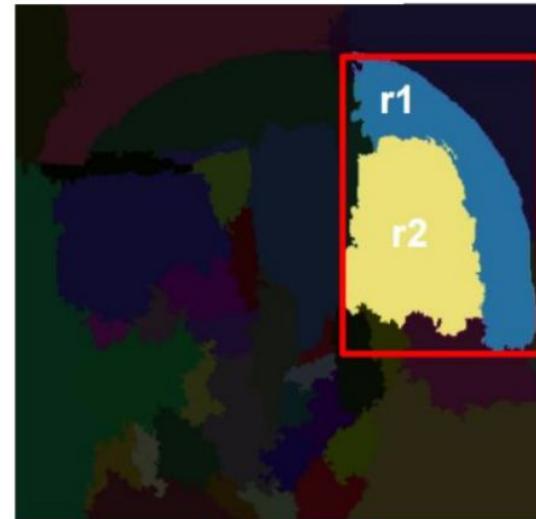
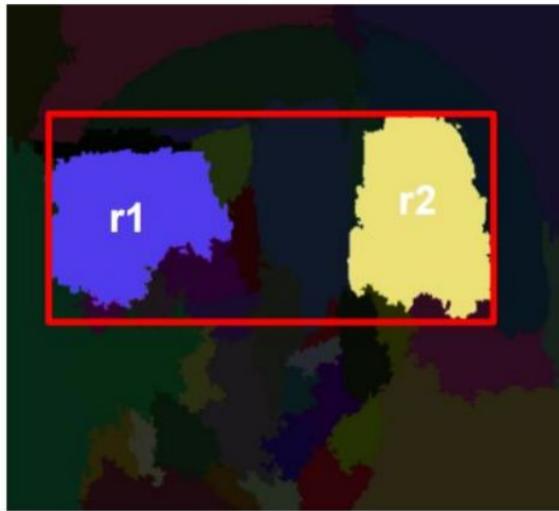
$$s_{size}(r_i, r_j) = 1 - \frac{\text{size}(r_i) + \text{size}(r_j)}{\text{size}(im)}$$



Shape compatibility

- Whether two segmentations fit each other?

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



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.

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

Evaluation

Similarities	MABO	# box	Colours	MABO	# box
C	0.635	356	HSV	0.693	463
T	0.581	303	I	0.670	399
S	0.640	466	RGB	0.676	395
F	0.634	449	rgI	0.693	362
C+T	0.635	346	Lab	0.690	328
C+S	0.660	383	H	0.644	322
C+F	0.660	389	rgb	0.647	207
T+S	0.650	406	C	0.615	125
T+F	0.638	400	Thresholds		MABO
S+F	0.638	449	50	0.676	395
C+T+S	0.662	377	100	0.671	239
C+T+F	0.659	381	150	0.668	168
C+S+F	0.674	401	250	0.647	102
T+S+F	0.655	427	500	0.585	46
C+T+S+F	0.676	395	1000	0.477	19

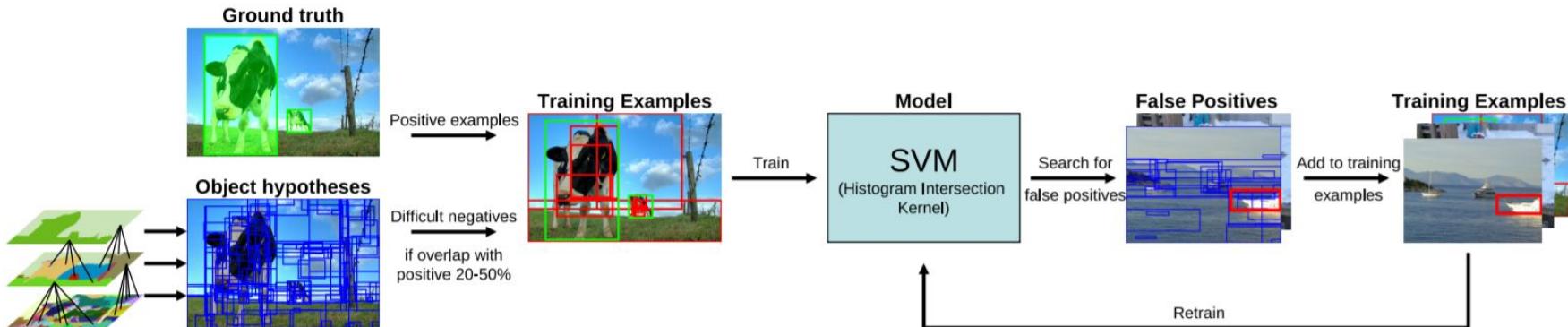


Evaluation

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

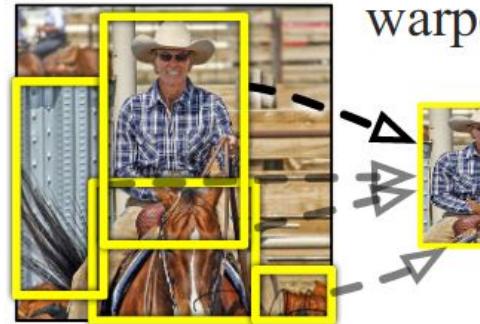


Uijings et al. Selective Search for Object Recognition

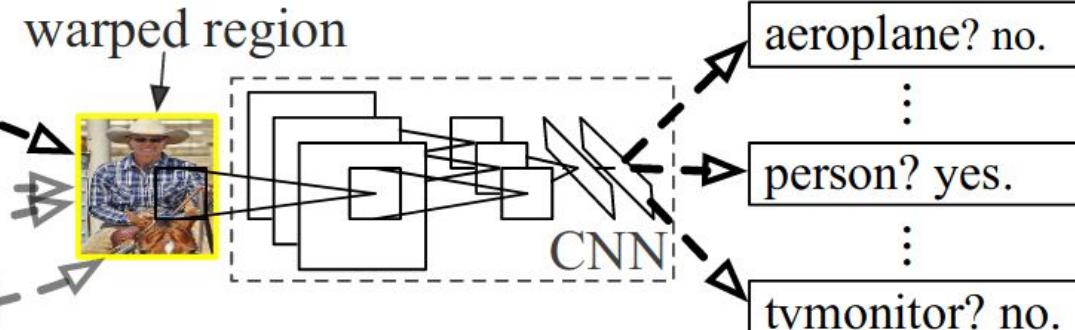
Modern Object Detection



1. Input
image



2. Extract region
proposals (~2k)

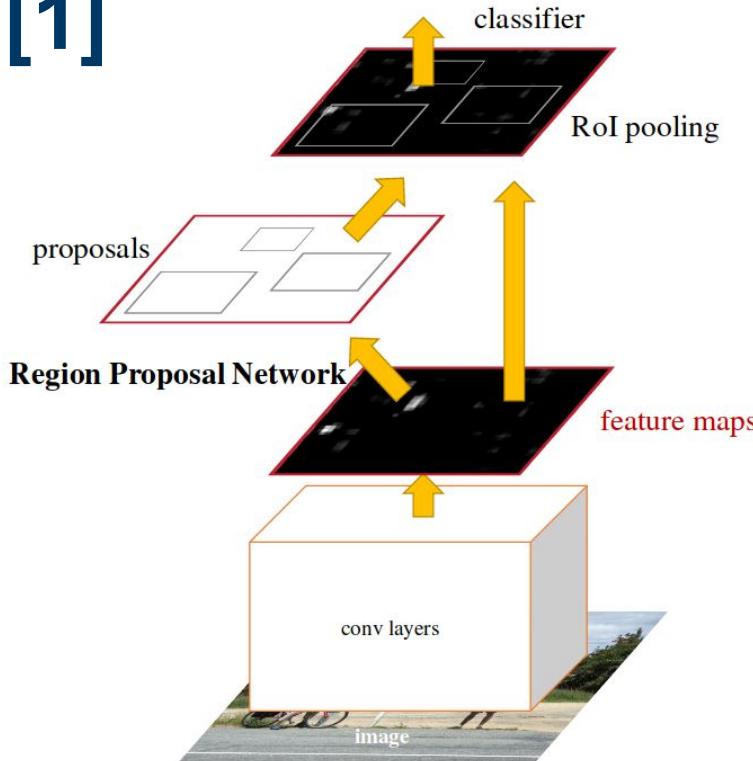


3. Compute
CNN features

4. Classify
regions

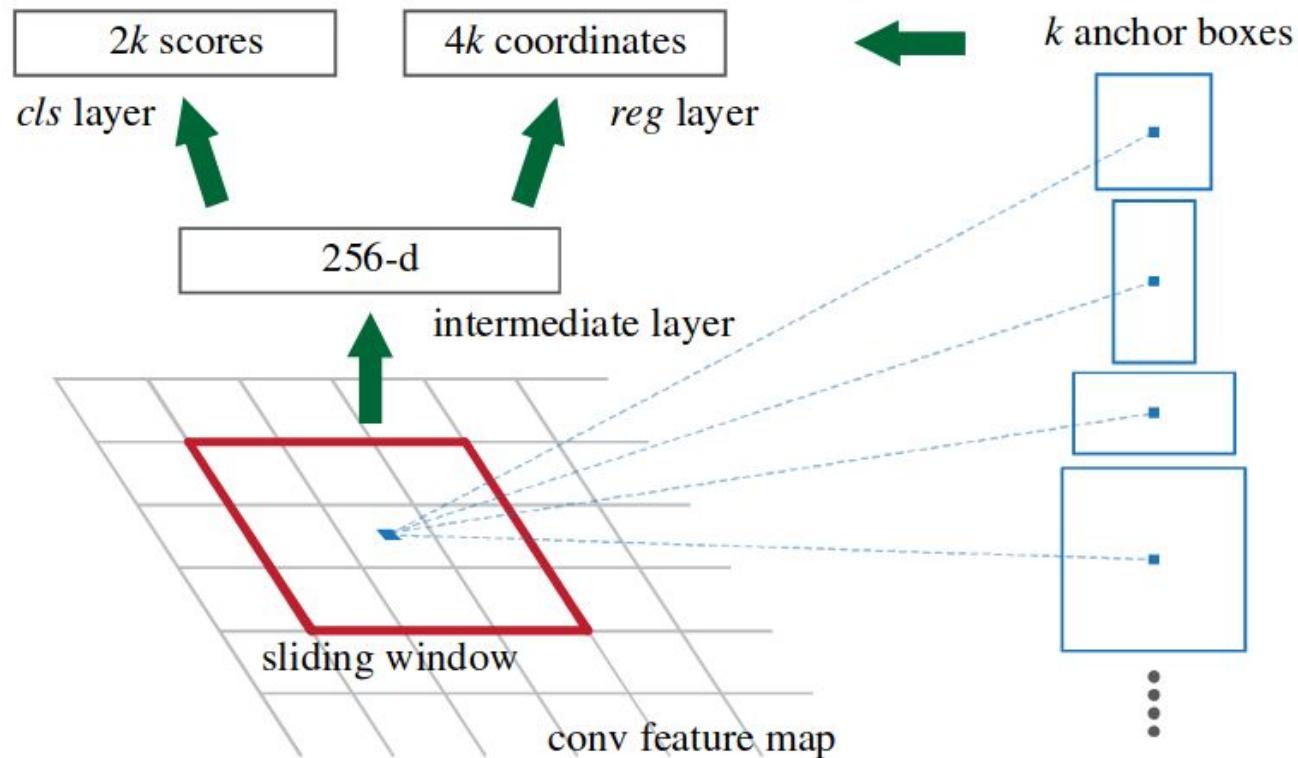
Figure - R-CNN Architecture

From Selective Search to Deep Learning: RPNs [1]



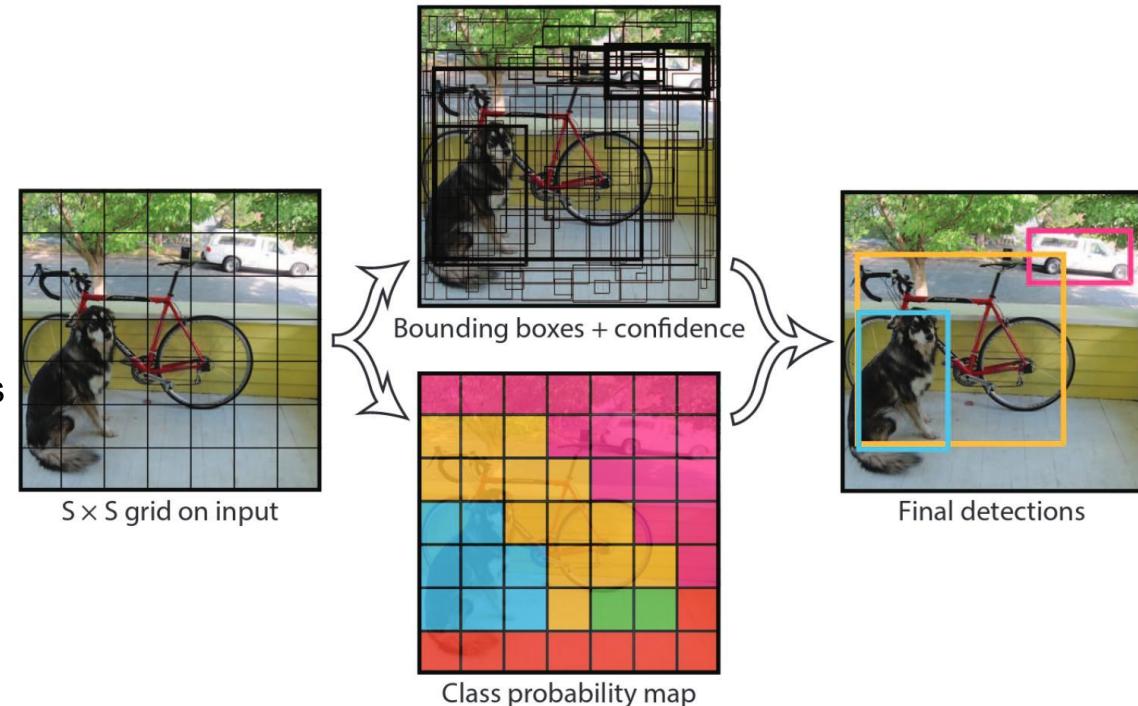
[1] Ren et al. Towards Real-Time Object Detection with Region Proposal Networks

From Selective Search to Deep Learning: RPNs



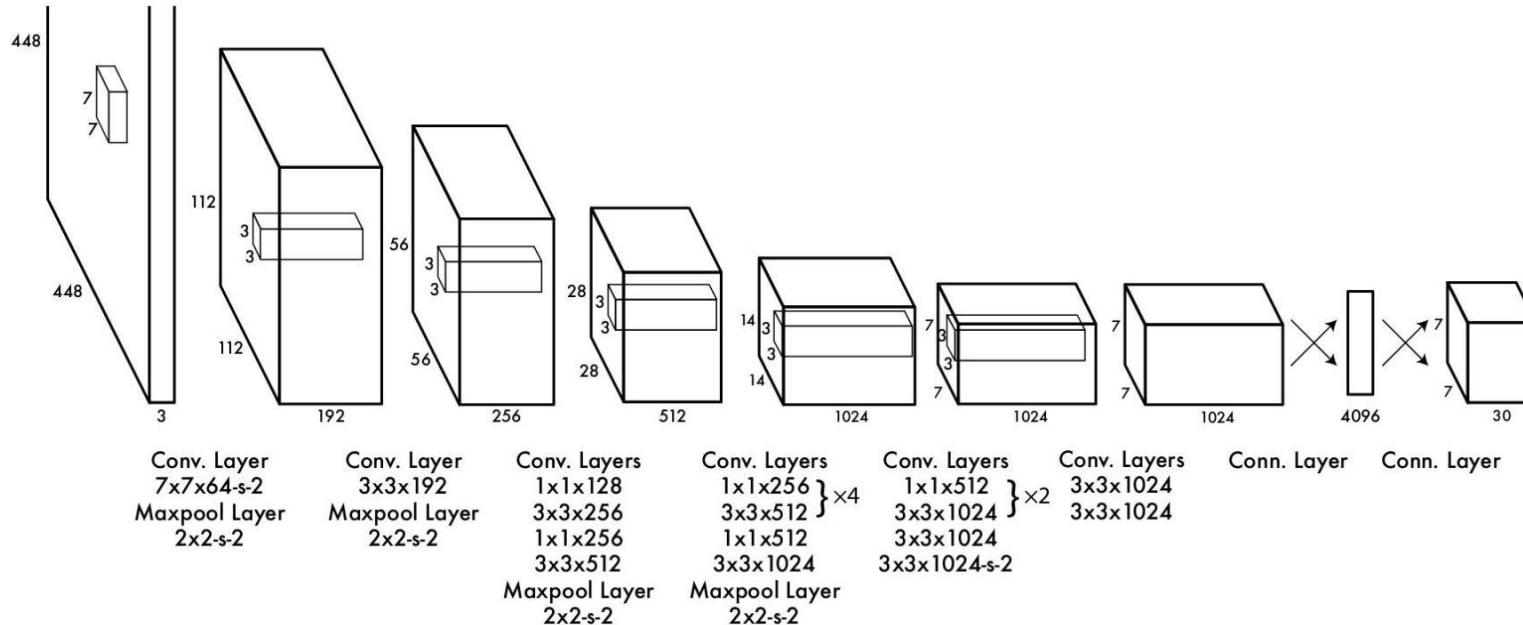
Do we need object proposals?

- Single-shot detector YOLO [1]
- Split image into $S \times S$ grid
- Propose B boxes per grid cell
- Box := (x, y, w, h, c)
- C additional class probabilities per box
- $S \times S \times (B * 5 + C)$ output predictions



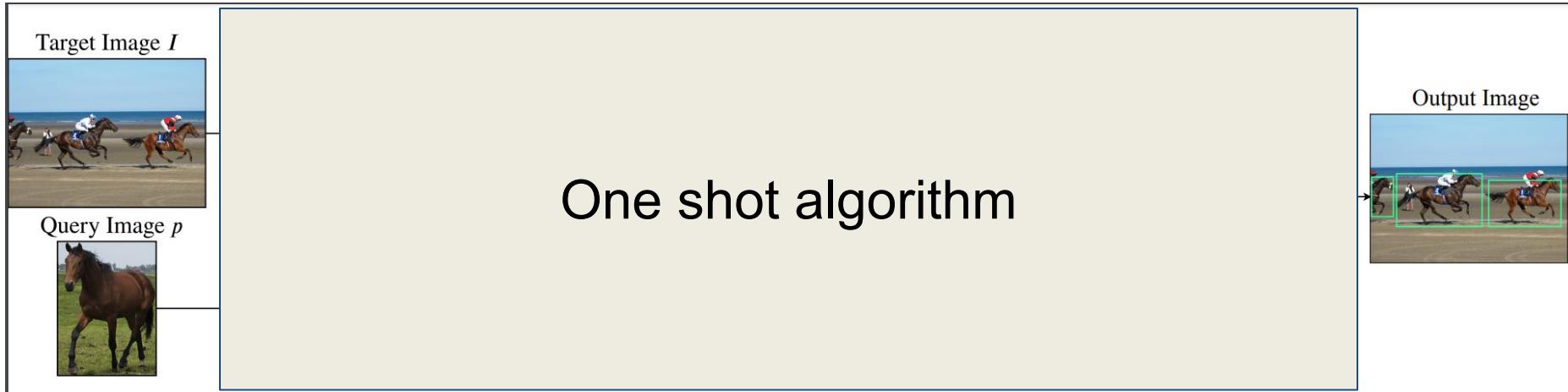
[1] Redmon et al., You Only Look Once: Unified, Real-Time Object Detection. CVPR 2016

YOLO architecture

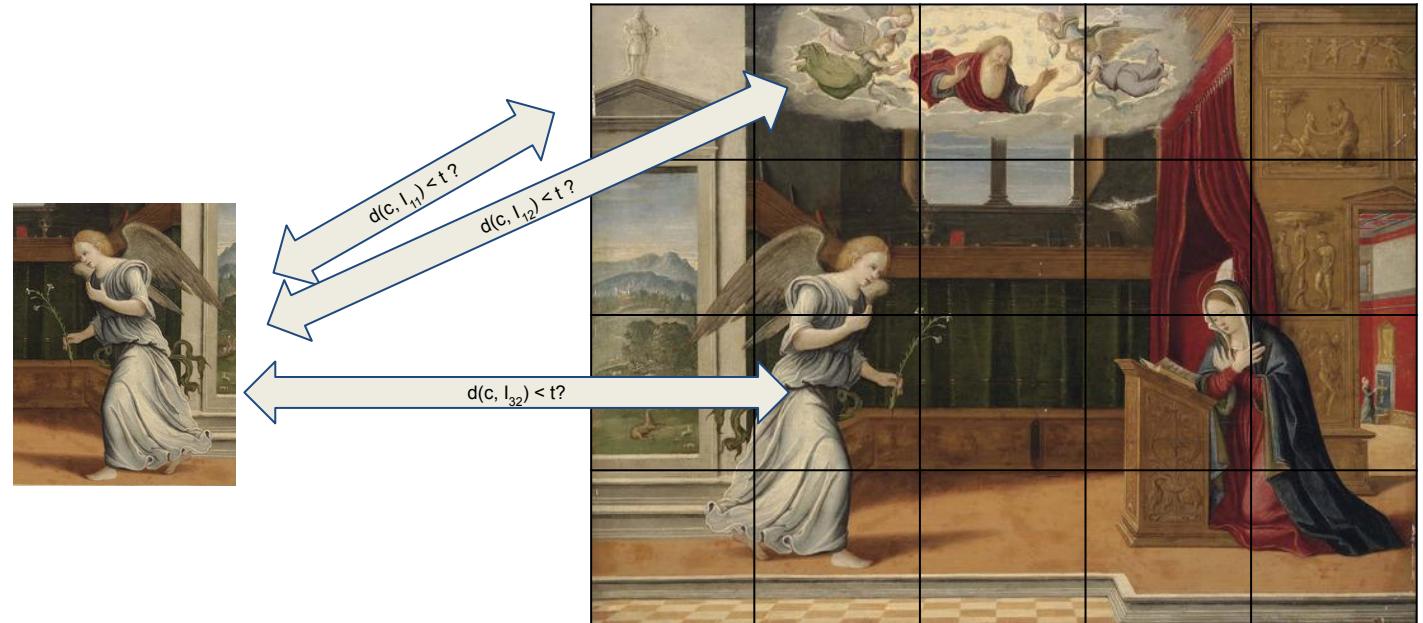


[1] Redmon et al., You Only Look Once: Unified, Real-Time Object Detection. CVPR 2016

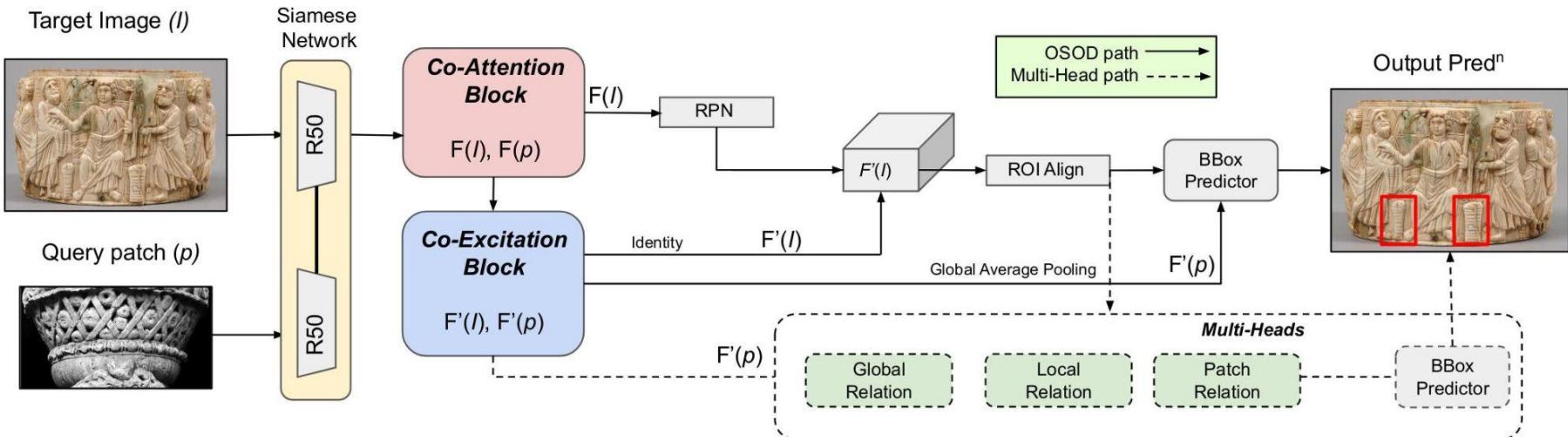
One-Shot Learning for Humanities



One-Shot Learning for Humanities



One-Shot Learning for Humanities



[1] Madhu et al., One-Shot Object Detection in Heterogeneous Artwork Datasets, IPTA 2022

Exercise (group)

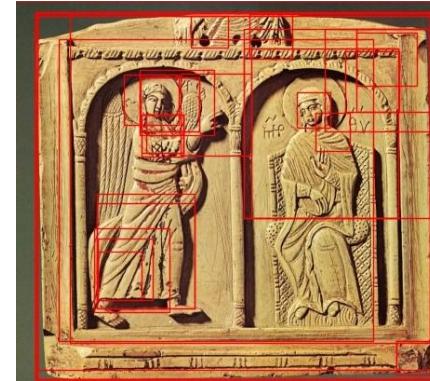
What you get?

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

Your goal:

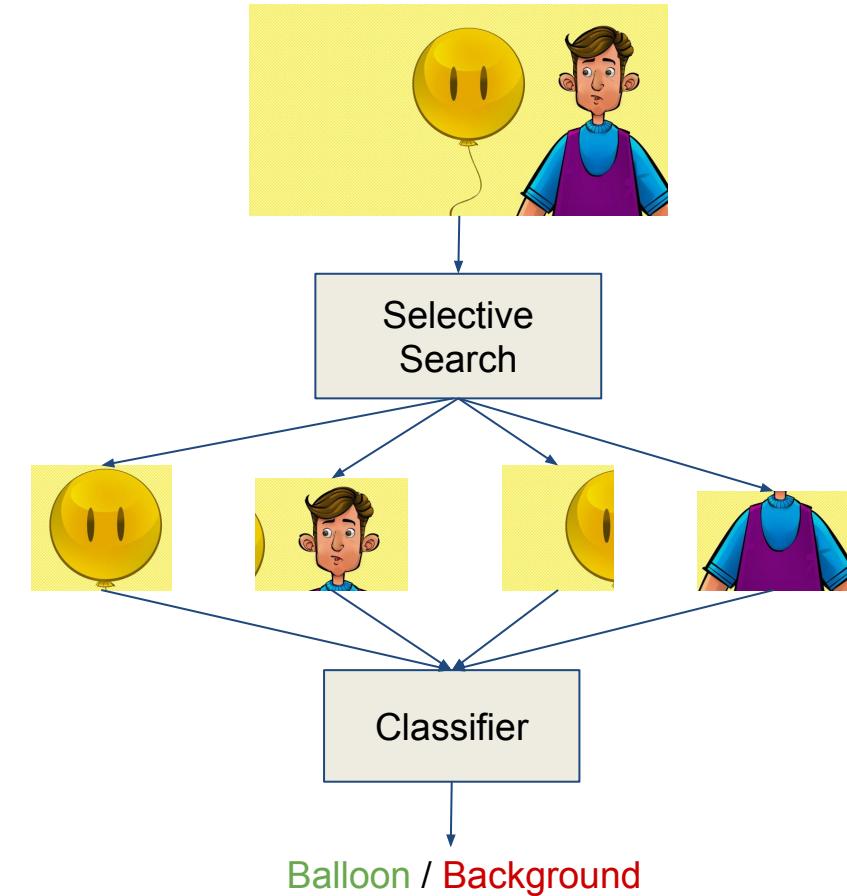
- Implement selective search
- Function stubs are given
- Submit generated region proposals
- Answer questions

Detailed description in exercise.pdf



Exercise (individual)

- Implement a full detection pipeline using your selective search implementation
- Balloon Dataset (yay!)
- Crop candidate regions
- Generate global feature vector (per crop)
- Classify crop features
- Visualize classified boxes on the original canvas
- How to train the classifier?



Further Reading

1. Felzenszwalb paper -
http://cs.brown.edu/people/pfelzens/papers/seq_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

- $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ - 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 \mathbf{V} into components or region)
 - $C \in \mathbf{S}$ - connected component in a graph $\mathbf{G}' = (\mathbf{V}, \mathbf{E}')$, where $\mathbf{E}' \subseteq \mathbf{E}$

Intuition:

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

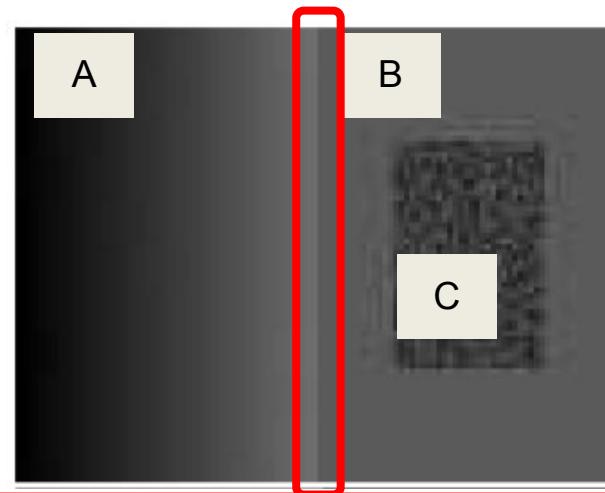
Pairwise Region Comparison Predicate

- **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)

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“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*”

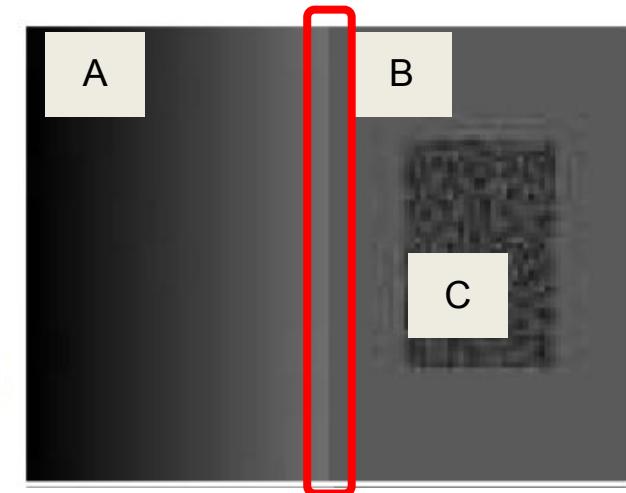
Pairwise Region Comparison Predicate (PRCP)

- 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: $\mathbf{G(V, E)}$ with n vertices and m edges

Output: $\mathbf{S} = (C_1, \dots, C_r)$ i.e. segmentation of \mathbf{V}

1. Sort \mathbf{E} into $\pi = (o_1, o_2, \dots, o_m)$ by non-decreasing edge weights

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3. Repeat Step 4 for $q = 1, 2, \dots, m$
4. Construct \mathbf{S}_q from \mathbf{S}_{q-1} as follows:
 - a. v_i and $v_j \rightarrow$ connected by qth edge $\rightarrow o_q = (v_i, v_j)$

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 - b. If v_i and v_j are in disjoint components of \mathbf{S}_{q-1} and $w(o_q)$ is small compared to internal diff. Of both these components then merge these two components, else do nothing

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5. Return $\mathbf{S} = \mathbf{S}_m$