Artistic Image Analysis using Graph-based Learning Approaches

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ICMR'11, ECCV'12, TIP'13

Background…

- National Tile Museum (Museu Nacional do Azulejo), Lisbon

PROBLEM 1

Artist?
Influences?
When?
Where?
PRINTART

PROBLEM 2

1

PrintArt

- System for organizing art image databases
- Image annotation
- Image retrieval
  - Text query
  - Image query

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Image Annotation

Query image:

1. Initial annotation: Black and white print, Italy, XV century, Christian Art, Angel, Donkey, Robes, Saint Mary Blessed Virgin, Sain Joseph

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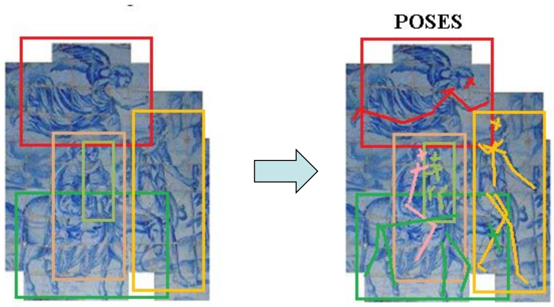
Image Annotation



2. User correction: infant Jesus Christ, XVII century
3. Fixed annotation: Black and white print, Italy, XVII century, Christian Art, Angel, Donkey, Robes, Saint Mary Blessed Virgin, Saint Joseph, Infant Jesus Christ, flight into Egypt, Print by Pietro de Po, Paint by Nicolas Poussin

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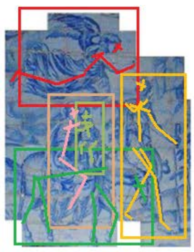
Image Annotation & Print Retrieval



3. Fixed annotation: Black and white print, Italy, XVII century, Christian Art, Angel, Donkey, Robes, Saint Mary Blessed Virgin, Saint Joseph, Infant Jesus Christ, flight into Egypt, Print by Pietro de Po, Paint by Nicolas Poussin

4. Image returned.

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Image Retrieval

- Query:

"Jesus Christ", "Saint Mary Blessed Virgin",and "Saint Joseph".

The system then returns the following images:

User selects the last two images above as relevant

User selects the last image above as the target image, and search is done.

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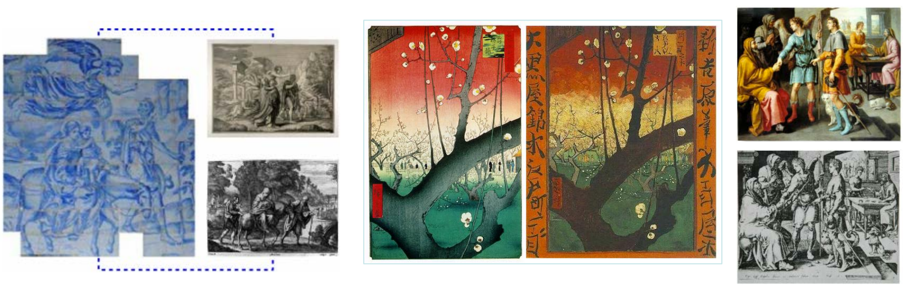
Art Prints

- Source of inspiration for generations of artists



- Art Historian
  - Discover influences between art works
- In artistic image analysis, we should study prints because
  - Larger availability, widespread = influenced more artists

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Art Prints

- Source of inspiration for generations of artists

- Art
- In

Art Prints

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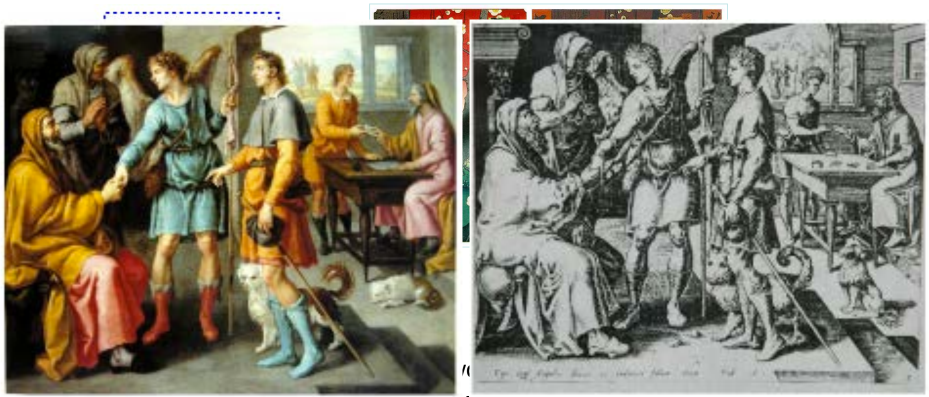
- Art
- In a

Art Prints

- Source of inspiration for generations of artists



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Art Prints

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- Art Historian
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- In artistic image analysis, we should study prints because
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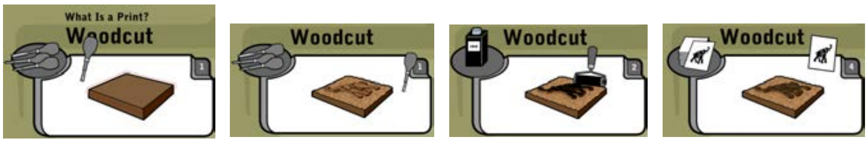
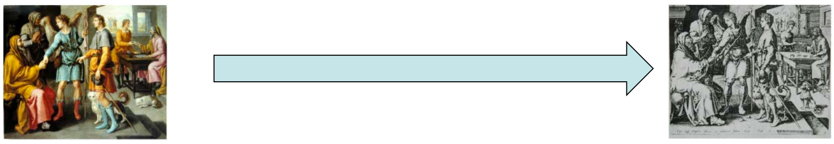
Art Prints

- Printmaking
  - Create art works by printing
  - 1400s (engraving, etching, etc.)
  - Even a “copy” of a painting is an original work of art (impression)



[Source: Moma web page]



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Different from Photo and Painting


a) photographic image


b) painting


c) art print

- Cons: no colour, texture does not represent visual classes
- Pros: artistic influence network, composition

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Interesting example…

- How can you characterize the visual class “sea” in these examples

a) b) c)

Fig. 1. Different paintings showing the visual class "sea" with remarkably different patterns of color and texture. In (a), we show Pieter Brueghel il Giovane's *Christ on the Storm on the Sea of Galilee*; in (b) we have Claude Monet's *Shadows on the Sea"*; and (c) displays John Marin's *Sea Piece*.

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Example of Network of Influences & Composition (Annunciation)

Anonymous, 1580 Allaert Claes, ? Virgil Solis, 1550

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Background - Art Analysis

- Fake vs Original

[A Digital Technique for Art Authentication. Lyu et al. Nat. Acad. Sciences'04]

Daubechies and students featured in NOVA program on art forgeries

- Multiclass classification of brushwork

Pointillism	Divisionism	Impasto	Scumbling
			

[Yelizaveta et al. Semi-supervised annotation of brushwork in paintings domain using serial combinations of multiple experts. *ACM Multimedia'06*]

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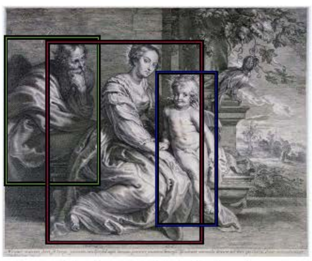
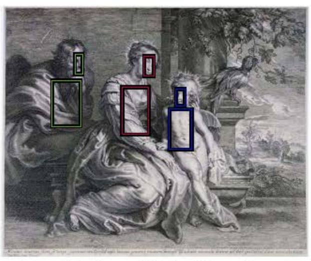
Our Goal

- Produce three levels of artistic image annotation for a previously unseen print
  - Global (theme, things present in the scene)
  - Local (localize in the image the things identified in the global annotation)
  - Pose (localize head, torso and limbs of human/animal subjects from local annotation)

Global	Local	Pose
		
Holy Family, Christ child, Mary, St. Joseph	Christ child (blue), Mary (red), St. Joseph (green)	Christ child (blue), Mary (red), St. Joseph (green)

Why is this Interesting

- Although a common task for photographic images, never done before for artistic images
  - Shed some light in computer vision problems?
- Can be used in tools to annotate artistic images and find influential prints
- Therefore, interdisciplinary (art history + computer vision)
  - New projects
  - Education

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Why is this Interesting

Sculpture by Karel Nepras, entitled "Great Dialogue," Museum of Modern and Contemporary Art in Prague

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Problem Set-up

- Database
  - 988 annotated images
  - Global annotation: 49 classification problems (1 multi-class with 27 classes and 48 binary problems)
    label cardinality = 4.22, label density = 0.05
  - Local annotation: 48 detection problems
  - Pose: 40 pose identification problems (37 human, 3 animal)
  - $\mathcal{D} = \{(\mathbf{x}, \mathbf{y}, \mathcal{L}, \mathcal{P})_i\}_{i=1}^{|\mathcal{D}|}$

    $\mathbf{x}_i$ feature vector representing an image I_i

    $\mathbf{y}_i = [\mathbf{y}_i(1), ..., \mathbf{y}_i(M)] \in \{0,1\}^Y$

    $\mathcal{L}_i = \{\mathbf{l}_{i,j}\}_{j=1}^{|\mathcal{L}_i|}$ with $\mathbf{l}_{i,j} = [y, \mathbf{b}]$

    $\mathcal{P}_i = \{\mathbf{p}_{i,j}\}_{j=1}^{|\mathcal{P}_i|}$ with $\mathbf{p}_{i,j} = [y, \mathbf{b}^{head}, \mathbf{b}^{torso}]$

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Problem Set-up

- Training set with 90% (889 images) and test set with 10% (99 images)
- Global Annotation

  maximize $p(\mathbf{y}|\widetilde{\mathbf{x}})$
  subject to $\mathbf{y} = [\mathbf{y}(1), ..., \mathbf{y}(M)] \in \{0,1\}^Y$,
  $\|\mathbf{y}(k)\|_1 = 1$ for $\{k \in \{1, ..., M\} | |\mathbf{y}(k)| > 1\}$,
- Local Annotation

  maximize $p(\mathcal{L}|\mathbf{y}, \widetilde{\mathbf{x}})$

  each k that $|\mathbf{y}(k)| = 1$ and $\mathbf{y}(k) = 1$ has a respective bounding box $\mathbf{l}_j^* \in \mathcal{L}^*$
- Pose Annotation

  maximize $p(\mathcal{P}|\mathcal{L}, \mathbf{y}, \widetilde{\mathbf{x}})$,

  head and torso are within the bounds of the local annotation
- Retrieval

  $\widetilde{\mathbf{x}}^* = \arg\max_{\widetilde{\mathbf{x}} \in \mathcal{T}} p(\widetilde{\mathbf{x}}|\mathbf{q})$

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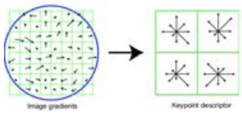
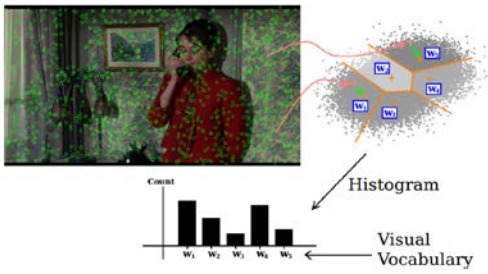
Image Representation

- Scale Invariant Feature Transform (SIFT) [Lowe'04]



- Visual vocabulary – hierarchical K-means [Zisserman'03, Nister'06]
  - 3 levels, 10 descendants per node = 1111 histogram bins



- Spatial pyramid representation [Lazebnik'06]

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Methodologies

- Random (RND)
  - Global:

Multiclass: $\{k : |\mathbf{y}(k)| > 1\}$

$$\mathbf{y}^*(k) = \begin{cases} \pi_1, & r < p(\mathbf{y}(k) = \pi_1) \\ \vdots & \\ \pi_{|\mathbf{y}(k)|}, & \sum_{j=1}^{|\mathbf{y}(k)|-1} p(\mathbf{y}(k) = \pi_j) \leq r < 1 \end{cases}$$

Binary: $\{k : |\mathbf{y}(k)| = 1\}$

$$\mathbf{y}^*(k) = \begin{cases} 1, & r < p(\mathbf{y}(k) = 1) \\ 0, & \text{otherwise} \end{cases}$$

$$r \sim \mathcal{U}(0,1) \ : \ \text{uniform distribution}$$

  - Local and pose (search training image and propagate label)

$$i^* = \arg \min_{j \in \{1,\ldots,|\mathcal{D}|\}} \Delta(\mathbf{y}^*, \mathbf{y}_j)$$

  - Retrieval
    - Annotate all test images, and given a query annotation, search for closest ones in terms of Hamming distance

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Methodologies

- Bag of features (BoF) [Zisserman'03,Csurka'04]
  - Train *Y* support vector machine classifiers (SVM) with one-versus-all
  - $p(\mathbf{y}(k) = \pi_j | \widetilde{\mathbf{x}}, \theta_{SVM}(k,j))$, $k \in \{1,...,M\}, j \in \{1,...,|\mathbf{y}(k)|\}, \pi_j \in \{0,1\}^{|\mathbf{y}(k)|}$
  - Annotate by maximizing the global, local and pose annotation objective functions
  - Retrieval by first annotating test images, and then retrieving using query vector

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Methodologies

- Label Propagation (LP) [Scholkopf'04]
  - Find annotation matrix F* with

$$\sum_{i,j=1}^{n} w_{ij}(f_i - f_j)^2$$

$$\begin{array}{l} \text{minimize} \quad 0.5 \ \mathrm{tr}(\mathbf{F}^\top(\mathbf{D}-\mathbf{W})\mathbf{F}) \\ \text{subject to } \mathbf{f}_i = \mathbf{y}_i, \ \text{ for } i = 1,...,|\mathcal{D}| \end{array}$$

where $\mathbf{W}, \mathbf{F}, \mathbf{D} \in \Re^{(|\mathcal{D}|+|\mathcal{T}|)\times(|\mathcal{D}|+|\mathcal{T}|)}$ with $\mathbf{W}_{ij} = \exp\{-0.5\,\|\mathbf{x}_i - \mathbf{x}_j\|_2^2/\sigma^2\}$

$\mathbf{D}$ is a diagonal matrix with its (i,i)-element = sum of the i^{th} row of $\mathbf{W}$

  - Closed form solution: $\mathbf{F}^* = \beta(\mathbf{I} - \alpha(\mathbf{D}-\mathbf{W}))^{-1}\mathbf{Y}$

- Label Propagation with Label Correlation (LP-CC) [Wang'09,Zha'08]

$$\text{minimize } 0.5\,\mathrm{tr}(\mathbf{F}^\top(\mathbf{D}-\mathbf{W})\mathbf{F}) + (1-\mu)\mathrm{tr}((\mathbf{F}-\mathbf{Y})\Lambda(\mathbf{F}-\mathbf{Y})) + \mu\,\mathrm{tr}(\mathbf{F}\mathbf{C}\mathbf{F}^\top)$$

Λ is a matrix containing ones in the diagonal from indices 1 to $|\mathcal{D}|$

$\mathbf{C} \in [-1,1]^{Y\times Y}$ containing the correlation between classes

  - Closed form solution: $\mathbf{F}^* = (\mathbf{D}-\mathbf{W})^{-1}\mathbf{Y}(\mathbf{I}-\mu\mathbf{C})$

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Methodologies

- Inverted Label Propagation (ILP)
- Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$
- Test image $\widetilde{\mathbf{x}}$, random walk $\mathbf{t} = [(\mathbf{x}^{(1)}, \mathbf{y}^{(1)}), ..., (\mathbf{x}^{(U)}, \mathbf{y}^{(U)})]$
- Label given random walk: $p(\mathbf{y}|\widetilde{\mathbf{x}}) = Z \sum_{r=1}^{R} p(\mathbf{y}|\mathbf{t}_r) p(\mathbf{t}_r|\widetilde{\mathbf{x}})$
- Assume Markov process:

$$\begin{aligned} p(\mathbf{t}|\widetilde{\mathbf{x}}) &= p([(\mathbf{x}^{(1)}, \mathbf{y}^{(1)}), ..., (\mathbf{x}^{(U)}, \mathbf{y}^{(U)})]|\widetilde{\mathbf{x}}) \\ &= \left[\prod_{u=2}^{U} p((\mathbf{x}^{(u)}, \mathbf{y}^{(u)})|(\mathbf{x}^{(u-1)}, \mathbf{y}^{(u-1)}), \widetilde{\mathbf{x}}) \right] p((\mathbf{x}^{(1)}, \mathbf{y}^{(1)})|\widetilde{\mathbf{x}}) \end{aligned}$$

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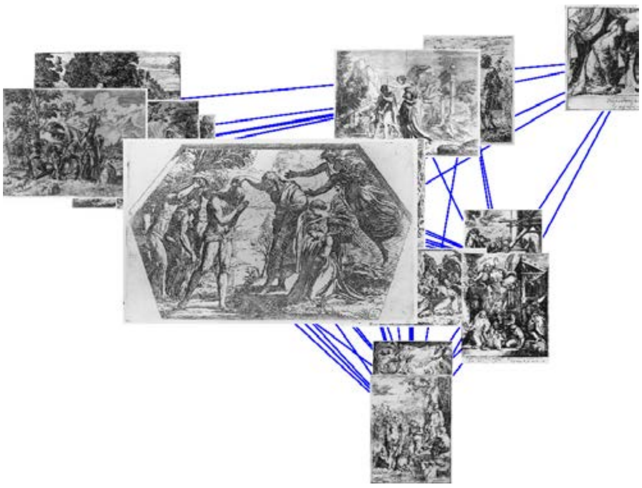
Inverse Label Propagation



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Methodologies

- Inverted Label Propagation (ILP)
  - Instead of finding **F**, estimate a vector containing the probability of landing in one of the training images after a random walk process
  - Combinatorial Harmonics (CH) approach [Carneiro'11]
  - Adjacency matrix takes into consideration visual and label similarity

$$\mathbf{U}(j,i) = I_y(\mathbf{y}_i,\mathbf{y}_j) \times I_x(\mathbf{x}_i,\mathbf{x}_j) \times I_x(\mathbf{x}_j,\widetilde{\mathbf{x}})$$
$$I_y(\mathbf{y}_i,\mathbf{y}_j) = \sum_{k=1}^{M} \lambda_k \times \mathbf{y}(k)_i^\top \mathbf{y}(k)_j$$
$$I_x(\mathbf{x}_i,\mathbf{x}_j) = \sum_{d=1}^{X} \min(\mathbf{x}_i(d),\mathbf{x}_j(d))$$

  - Extend adjacency matrix with test image

$$\widetilde{\mathbf{U}} = \begin{bmatrix} \mathbf{U} & \widetilde{\mathbf{u}} \\ \widetilde{\mathbf{u}}^T & 0 \end{bmatrix} \quad \text{with } \widetilde{\mathbf{u}} = [I_x(\mathbf{x}_1,\widetilde{\mathbf{x}}), ..., I_x(\mathbf{x}_{|\mathcal{D}|},\widetilde{\mathbf{x}})]^\top$$

  - Minimize the energy function

$$E([\mathbf{G},\mathbf{g}]) = \frac{1}{2}\left\| [\mathbf{G},\mathbf{g}]\widetilde{\mathbf{L}} \begin{bmatrix} \mathbf{G}^T \\ \mathbf{g}^T \end{bmatrix} \right\|_2^2 \quad \widetilde{\mathbf{L}} \text{ is the Laplacian from the the adjacency matrix } \widetilde{\mathbf{U}}$$

  - Closed form solution: $\mathbf{g}^* = (-\mathbf{L}_2^{-1}\mathbf{B}^T\mathbf{I})^\top$ with $\widetilde{\mathbf{L}} = \begin{bmatrix} \mathbf{L}_1 & \mathbf{B} \\ \mathbf{B}^T & \mathbf{L}_2 \end{bmatrix}$

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Methodologies

- Matrix Completion (MC) [Nowak'10]

$$\begin{aligned} &\text{minimize} \quad \text{rank}(\mathbf{Z}) \\ &\text{subject to } \mathbf{Z_y} = [\mathbf{y}_1 ... \mathbf{y}_{|\mathcal{D}|}],\ \mathbf{Z_x} = [\mathbf{x}_1 ... \mathbf{x}_{|\mathcal{D}|}],\ \mathbf{Z}_{\widetilde{\mathbf{x}}} = [\widetilde{\mathbf{x}}_1 ... \widetilde{\mathbf{x}}_{|\mathcal{T}|}] \end{aligned}$$

where $\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_y & \mathbf{Z}_{y^*} \\ \mathbf{Z}_x & \mathbf{Z}_{\widetilde{x}} \end{bmatrix}$

  - Replace rank(.) by convex nuclear norm $\|\mathbf{Z}\|_* = \sum_{k=1}^{min\{|\mathcal{D}|, Y+X\}} \sigma_k(\mathbf{Z})$

  - Equality constraints replaced by squared losses

  - Find annotation for each test image and estimate local/pose annotations and retrieval

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Methodologies

- Structural Learning (SL) [Joachims'05]
  - Margin maximization quadratic problem

$$\min_{\mathbf{w},\xi} \; \|\mathbf{w}\|^2 + C\sum_{i=1}^{|\mathcal{D}|}\xi_i$$
$$s.t. \;\; \mathbf{w}^\top\Psi(\mathbf{y}_i,\mathbf{x}_i) - \mathbf{w}^\top\Psi(\mathbf{y},\mathbf{x}_i) + \xi_i \geq \Delta(\mathbf{y}_i,\mathbf{y}), \;\; i=1...|\mathcal{D}|, \;\; \forall\mathbf{y}\in\{0,1\}^Y$$
$$\xi_i \geq 0, \;\; i=1...|\mathcal{D}|$$

$$\text{where} \quad \Delta(\mathbf{y}_i,\mathbf{y}) \; = \; \|\mathbf{y}_i - \mathbf{y}\|_1 \qquad \Psi(\mathbf{y},\mathbf{x}) \; = \; \mathbf{x}\otimes\mathbf{y} \; \in \; \Re^{X\times Y}$$

  - Again, find global annotations for test images and then estimate local/ pose annotations and retrieval

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Results

- Average precision, recall and F1 score for annotations
  - Label based (global annotation)

$$pga(y) = \frac{\sum_{i=1}^{|\mathcal{T}|}(\pi_y \odot \mathbf{y}_i^*)^\top \tilde{\mathbf{y}}_i}{\sum_{i=1}^{|\mathcal{T}|}\pi_y^\top \mathbf{y}_i^*}, \; rga(y) = \frac{\sum_{i=1}^{|\mathcal{T}|}(\pi_y \odot \mathbf{y}_i^*)^\top \tilde{\mathbf{y}}_i}{\sum_{i=1}^{|\mathcal{T}|}\pi_y^\top \tilde{\mathbf{y}}_i}, \; fga(y) = \frac{2pga(y)rga(y)}{pga(y)+rga(y)}$$

  - Example based (global annotation)

$$pge = \frac{1}{|\mathcal{T}|}\sum_{i=1}^{|\mathcal{T}|}\frac{(\mathbf{y}_i^*)^\top\tilde{\mathbf{y}}_i}{\|\mathbf{y}_i^*\|_1}, \; rge = \frac{1}{|\mathcal{T}|}\sum_{i=1}^{|\mathcal{T}|}\frac{(\mathbf{y}_i^*)^\top\tilde{\mathbf{y}}_i}{\|\tilde{\mathbf{y}}_i\|_1}, \; fge = \frac{1}{|\mathcal{T}|}\sum_{i=1}^{|\mathcal{T}|}\frac{2(\mathbf{y}_i^*)^\top\tilde{\mathbf{y}}_i}{\|\mathbf{y}_i^*\|_1 + \|\tilde{\mathbf{y}}_i\|_1},$$

- Mean average precision (MAP) for retrieval

$$pr(\mathbf{q},Q) = \frac{\sum_{i=1}^{Q}\delta(\tilde{\mathbf{y}}^\top\mathbf{q} - \mathbf{1}^\top\mathbf{q})}{Q}, \; \text{and} \; rr(\mathbf{q},Q) = \frac{\sum_{i=1}^{Q}\delta(\tilde{\mathbf{y}}^\top\mathbf{q} - \mathbf{1}^\top\mathbf{q})}{\sum_{i=1}^{|\mathcal{T}|}\delta(\tilde{\mathbf{y}}^\top\mathbf{q} - \mathbf{1}^\top\mathbf{q})},$$

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Results

- Global Annotation/Retrieval Results:

	Retrieval	Label-based global annotation			Example-based global annotation		
Models	Label MAP	Average Precision	Average Recall	Average F1	Average Precision	Average Recall	Average F1
RND	0.08 ± .06	0.06 ± .01	0.07 ± .01	0.06 ± .01	0.26 ± .02	0.21 ± .01	0.22 ± .01
BoF	0.12 ± .05	0.14 ± .11	0.10 ± .06	0.11 ± .08	0.35 ± .03	0.26 ± .08	0.30 ± .05
LP	0.11 ± .01	0.12 ± .02	0.12 ± .02	0.12 ± .02	0.32 ± .03	0.28 ± .02	0.26 ± .02
LP-CC	0.11 ± .01	0.13 ± .02	0.14 ± .02	0.13 ± .02	0.27 ± .03	0.26 ± .03	0.25 ± .03
ILP	0.14 ± .02	0.19 ± .03	**0.35 ± .03**	0.25 ± .04	0.24 ± .02	**0.48 ± .05**	0.30 ± .02
ILP-O	**0.18 ± .04**	**0.26 ± .05**	0.26 ± .05	**0.26 ± .05**	**0.39 ± .03**	0.39 ± .04	**0.38 ± .03**
MC	0.17 ± .01	0.24 ± .03	0.11 ± .02	0.15 ± .02	0.37 ± .02	0.28 ± .02	0.32 ± .02
SL	0.14 ± .01	0.18 ± .04	0.14 ± .03	0.16 ± .03	0.34 ± .04	0.31 ± .04	0.32 ± .04

Results

- Local Annotation Results:

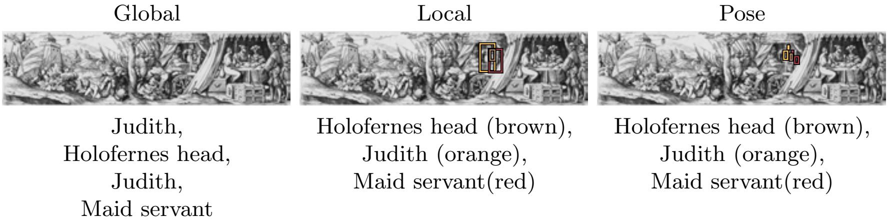
	Label-based local annotation			Example-based local annotation		
Models	Average Precision	Average Recall	Average F1	Average Precision	Average Recall	Average F1
RND	0.04 ± .01	0.04 ± .01	0.04 ± .01	0.13 ± .03	0.18 ± .04	0.15 ± .02
BoF	**0.25 ± .08**	0.05 ± .03	0.07 ± .03	**0.28 ± .05**	0.17 ± .06	0.20 ± .04
LP	0.12 ± .05	0.06 ± .02	0.08 ± .02	0.21 ± .02	0.19 ± .04	0.20 ± .02
LP-CC	0.08 ± .02	0.06 ± .01	0.07 ± .01	0.12 ± .02	0.17 ± .04	0.14 ± .02
ILP	0.06 ± .03	0.10 ± .03	0.07 ± .03	0.13 ± .02	0.19 ± .03	0.16 ± .02
ILP-O	0.15 ± .05	**0.16 ± .05**	**0.15 ± .05**	0.21 ± .03	**0.24 ± .03**	**0.23 ± .03**
MC	0.07 ± .01	0.03 ± .01	0.04 ± .01	0.12 ± .03	0.14 ± .06	0.13 ± .03
SL	0.09 ± .00	0.06 ± .01	0.07 ± .01	0.18 ± .03	0.20 ± .04	0.19 ± .01

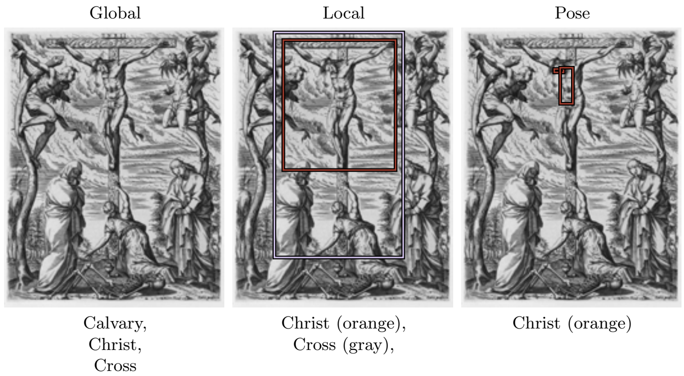
Results

- Pose Annotation Results

Models	Label-based Pose annotation Average Precision	Label-based Pose annotation Average Recall	Label-based Pose annotation Average F1	Example-based Pose annotation Average Precision	Example-based Pose annotation Average Recall	Example-based Pose annotation Average F1
RND	0.00 ± .01	0.00 ± .01	0.00 ± .01	0.00 ± .02	0.00 ± .01	0.00 ± .01
BoF	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01
LP	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00
LP-CC	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00
ILP	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01	0.01 ± .01
ILP-O	**0.05 ± .04**	**0.08 ± .06**	**0.06 ± .05**	**0.06 ± .02**	**0.07 ± .02**	**0.06 ± .02**
MC	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00
SL	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00	0.00 ± .00

Results



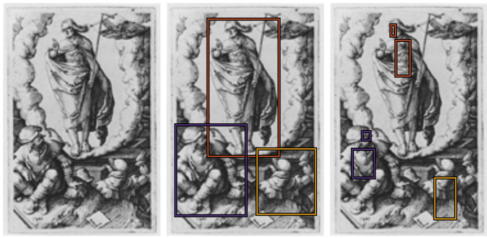


Results

Global	Local	Pose

Holy Family, Christ child, Mary , St. Joseph	Christ child (purple), Mary (green), St. Joseph (blue)	Christ child (purple), Mary (green), St. Joseph (blue)

Global	Local	Pose



Resurrection, Christ, Soldier, Soldier	Christ (orange), Soldier (purple), Soldier (yellow)	Christ (orange), Soldier (purple), Soldier (yellow)

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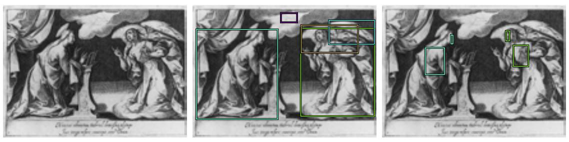
Results

Global	Local	Pose



Annunciation, Dove, Gabriel, Mary, Wing, Wing	Dove (purple), Gabriel (green), Mary (cyan), Wing (yellow), Wing (light green)	Gabriel (green), Mary (cyan)

Global	Local	Pose

Nativity, Angels, Christ child, Mary, Wing	Angels (purple), Christ child (blue), Mary (blue), Wing (gray)	Angels (purple), Christ child (blue), Mary (blue)

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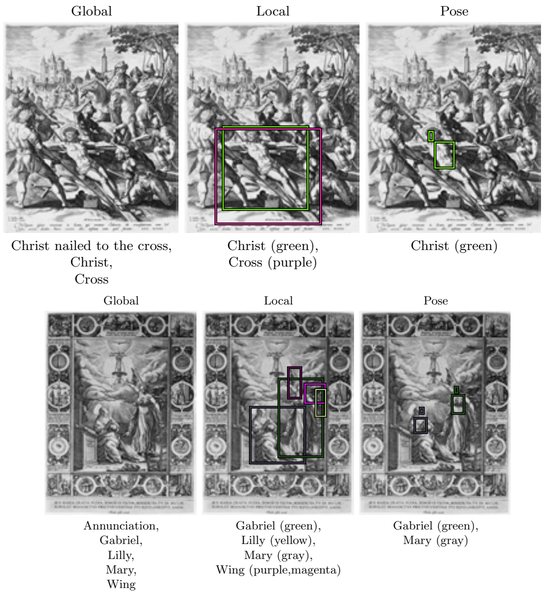
Results



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Results

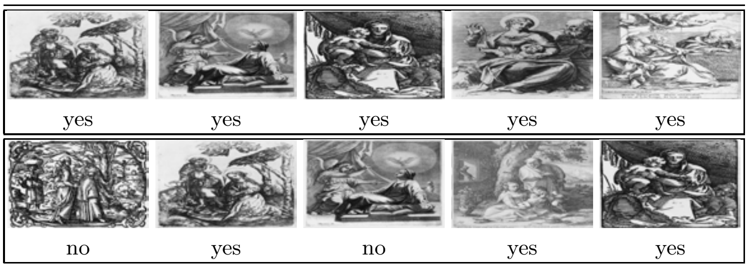

Fig. 5. Retrieval results of the **ILP-O**. Each row shows the top five matches to the following queries (from top to bottom): *'Holy Family'*, and *'Christ child'*. Below each image, it is indicated whether the image is annotated with the class.

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Conclusions

- Inverted label propagation produces best results
- Small training sets for most of classes are a problem for inductive methods (BoF, SL)
- Artistic influence network – facilitates good results from random walk processes
- Face/person detector to improve results
- Sketch-based Interface and Modeling

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