

Strong Supervision from Weak Annotation: Interactive Training of Deformable Part Models

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Methods by level of supervision

- simple models, weak annotations
 - least effort, potentially fast learning, not best results
- complicated models, weak annotation
 - state-of-the-art performance (multiple instance learning, latent parts, latent structural SVM)
 - non-convex optimization
 - slow training
 - Hard to pinpoint error source (optimization error, inappropriate model or feature space, insufficient training data)



Methods by level of supervision

- Strong annotation
 - Very time consuming
 - Easy learning task (possible convex optimization)
 - Generalization guarrantee
 - Sensitive to quality and style of annotation

Qusetion: Is it possible to have strong supervision properties with weak annotation computational efficiency?



Yes! Interactive Labelling and Online Learning

- 1- Model part structures with structured models
- 2- Bring up a new image,
 - predict the part locations with current model
 - Correct the wrong locations
- 3-Update the learned model and go to 2



Interactive Labelling + Online Learning





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Interactive Labelling + Online Learning

- Interactive Labelling
 - Real time detection
 - Easy update
 - Tree-structured deformable parts model with dynamic programming is a good choice!
- Online Learning
 - Fast model updating
 - Convex optimization
 - Stochastic gradient descent



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Related works

Interactive labelling

- Grab cut (Segmentation)
- Label me video
- Visipedia (attributes)







The bird is a Black-footed Albatross



Is the belly white? **yes** Are the eyes white? **yes** The bird is a **Parakeet Auklet**



Is the beak cone-shaped? yes Is the upper-tail brown? yes Is the breast solid colored? no Is the breast striped? yes Is the throat white? yes The bird is a Henslow's Sparrow

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Related works

- Active learning
 - Intelligent computer decide which image to annotate
 - More savings than interactive labeling
 - In comparison to strong supervision
 - Higher computational complexity
 - Fewer theoretical guarantees



Most regions are understood, but this region is unclear.



This looks expensive to annotate, but it seems very informative.



This looks expensive to annotate, and it does not seem informative.



This looks easy to annotate, but its content is already understood.



Label the object(s) in this region





Model and Interactive UI

$$s(\Theta; x) = \sum_{p \in V} \psi_p(\theta_p; x) + \sum_{(p,q) \in E} \lambda_{pq}(\theta_p, \theta_q)$$







(b) Bottom-Up Preprocessing



(c) Top-Down Preprocessing

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(d) Propagate User Response



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Learning framework

Strong Convex formulation

$$F_{n}(\mathbf{w}) = \frac{\lambda}{2} \|\mathbf{w}\|^{2} + \frac{1}{n} \sum_{i=1}^{n} \ell_{i}(\mathbf{w})$$
(16)
$$\ell_{i}(\mathbf{w}) = \max_{y} \left(\mathbf{w} \cdot \Phi(x_{i}, y) - \mathbf{w} \cdot \Phi(x_{i}, y_{i}) + \Delta(y_{i}, y)\right)$$

Gradient computableby one inference

$$\bar{y}_i = \max_{y} \left(\mathbf{w} \cdot \Phi(x_i, y) + \Delta(y_i, y) \right)$$

$$7\ell_i = \Phi(x_i, \bar{y}_i) - \Phi(x_i, y_i)$$

- Stochastic gradient descent
- Process an image at each step
 - Pegasus!



Theoretical properties

Pegasos

- Faster convergence rate than linear SVM
- Performance guarantee with the number of iterations
- Training time does not increase with increasing number of images (for a specific performance)
- Slower steps than linear svm
 - Inference at each step
- Interactive labelling
 - Loss function is defined as the number of misplaced part
 - Number of annotation is bounded!



Some results...





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Tables

- 50 images:
 - 6.6 / 13 correction.
 - 19.7 seconds
- 4000 images:
 - 3.9 / 13 correction
 - 12 seconds





Conclusion

- Framework for large scale annotation
- Simulataneous learning of structured models
- Nice theoretical properties, seen in practice



Cross-category Object Recognition (CORE)

- University of Illinois at Urbana-Champaign
- more detailed models and for exploring cross-category generalization in object recognition



Taxonomy:Function:AnimalCan BiteFour leggedCan JumpMammalCan RunCatCarnivore

Pose: Front Visible Right Visible Lying



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CORE – Data overview

- Images from ImageNet, thus coming with object hierarchy
- Binary attributes
 - Pose
 - Sorrounding context
 - Viewpoint
 - Etc.



Property

Submit Annotation

Value

Unsure

(a) Binary Attributes



CORE – data overview

- Ploygon labels
 - Objects
 - Pre-defined parts of a category





CORE – data overview

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Segmentation mask

- Materials





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Quality Measures

- Way of collecting images
- Which attributes
 - Easily annotatable
 - Unsure buttun
- Quality assurance methods...