## Bird Part Localization Using Exemplar-Based Models with Enforced Pose and Subcategory Consistency

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## Problem

The goal of our work is to localize the parts automatically and accurately for fine-grained categories. We evaluate our method on bird images in the CUB-200-2011 [1] dataset.


## Approach



Does $X_{k, t}$ match the image $I ? \Longleftrightarrow P\left(X_{k, t} \mid I\right)=$ ?

$$
\begin{equation*}
P\left(X_{k, t} \mid I\right)=P\left(X_{k, t} \mid D_{p}\right)^{\alpha} P\left(X_{k, t} \mid D_{s}\right)^{1-\alpha} \tag{1}
\end{equation*}
$$

$$
\begin{equation*}
P\left(X_{k, t} \mid D_{p}\right)=\mathrm{G}_{\text {avg }}\left\{P\left(x_{k, t}^{i} \mid d_{p}^{i}\left[c_{k}^{i}, s_{k, t}^{i}\right]\right)\right\} \tag{3}
\end{equation*}
$$

$P\left(X_{k, l} \|_{p}\right)=G_{\text {avg }} T\left(\left.x_{k, t}\right|_{p} t_{k}, s_{k, t}\right)$
$P\left(X_{k, t} \mid D_{s}\right)=\max _{l} P\left(X_{k, t} \mid l, D_{s}\right)$
$P\left(X_{k, t} \mid l, D_{s}\right)=\mathrm{G}_{\text {avg }}\left\{P\left(x_{k, t}^{i} \mid d_{s}^{i}\left[l, s_{k, t}^{i}, \theta_{k, t}^{i}\right]\right)\right\}$
We use the most likely models $\mathcal{M}$ to predict the part locations of the testing sample
$\hat{x}^{i}=\underset{x^{i}}{\arg \max } \sum_{k, t \in \mathcal{M}} P\left(\triangle x_{k, t}^{i}\right) P\left(x^{i} \mid d_{p}^{i}\left[c_{k}^{i}, s_{k, t}^{i}\right]\right)$

## Pose Detectors



Pose 1


Pose 2


Pose 3

Poses clusters of Back
For each pose cluster $c^{i}$ of part $i$, we build a detector. The detector scans the image over scales and the response map of this detector at a particular scale $s^{i}$ is denoted as $d_{p}^{i}\left[c^{i}, s^{i}\right]$.

## Pipeline


(1) Sliding-window detection. (2) Matching and ranking exemplars. (3) Predicting the final part configuration.

## Subcategory Detectors



Species 1
Species 2
Species 3 Subcategory clusters of Back
For each species $l$ of part $i$, we build a detector after aligning the samples. Assuming the detector scans he image over scales and orientations, then the response map of this detector at a particular scale $s$ and orientation $\theta^{i}$ is denoted as $d_{s}^{i}\left[l, s^{i}, \theta^{i}\right]$.
Enforcing Consistency
$P\left(x_{k, t}^{i} \mid d_{p}^{i}\left[c_{k}^{i}, s_{k, t}^{i}\right]\right) \quad P\left(x_{k, t}^{i} \mid d_{s}^{i}\left[l, s_{k, t}^{i}, \theta_{k, t}^{i}\right]\right)$


## References

[1] C. Wah, S. Branson, P. Welinder, P. Perona, S. Belongie. The Caltech-UCSD Birds-200-2011 Dataset. Computation \& Neural Systems Technical Report, CNS-TR-2011-001, 2011
[2] P. N. Belhumeur, D. W. Jacobs, D. J. Kriegman, N. Kumar Localizing CVPR 11

Localization Examples
 Comparisons


| PCP | CoE [2] | Ours |
| :--- | :---: | :---: |
| Back | 46.29 | $\mathbf{6 2 . 0 8}$ |
| Beak | 43.08 | $\mathbf{4 9 . 0 2}$ |
| Belly | 54.44 | $\mathbf{6 9 . 0 2}$ |
| Breast | 54.19 | $\mathbf{6 6 . 9 8}$ |
| Crown | 64.69 | $\mathbf{7 2 . 8 5}$ |
| Forehead | 51.48 | $\mathbf{5 8 . 4 6}$ |
| Left Eye | 47.53 | 55.78 |
| Left Leg | 29.67 | 40.94 |
| Left Wing | 59.58 | $\mathbf{7 1 . 5 7}$ |
| Nape | 58.91 | 70.78 |
| Right Eye | 46.50 | 55.51 |
| Right Leg | 29.03 | 40.52 |
| Right Wing | 58.47 | $\mathbf{7 1 . 5 6}$ |
| Tail | 27.77 | 40.16 |
| Throat | 58.89 | $\mathbf{7 0 . 8 3}$ |
| Average | 48.70 | $\mathbf{5 9 . 7 4}$ |



