Understanding Objects in Detail with Fine-grained Attributes

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Detailed object understanding

Driving challenges in object recognition:
- Many things
- Subtle differences

ImageNet
FGVC
details

• A direct evaluation of fine-grained part detection and description.
• A supporting Object in Detail (OID) dataset.
• Efficient coarse-to-fine detailed part matching.

The OID challenge and data

Goal: directly evaluate detailed image understanding tasks.
- ~7,500 aircraft images, 100 years of aviation
- 5 parts with 18 attributes

• Has-engine
• Wire
• Has-engine-or-sensor
• Has-engine-or-sensor
• Has-engine
• Wire

Data definition and construction

• Part and attribute definitions were extracted from human descriptions of objects.
• Amazon Mechanical Turk for part segmentation and attribute collection.
• Three weeks of intense work of several researchers in the CLSP Summer Workshop.

Local vs global attribute modeling

• Locality of meaning. Part attributes are semantically local (e.g. round nose). A modular and transferable visual model should be based on the part appearance only.
• Globality of evidence. Local evidence is often weak and part attributes are often best predicted by global cues.

Examples

1) This nose attribute is well predicted by the nose appearance, but adding context is better still.

2) This tail attribute is not well predicted by the appearance of the tail (vertical stabilizer).

3) Global attributes are often best predicted by the overall appearance of the plane, but in some cases parts are better when considered in isolation.

Coarse-to-Fine Template Hierarchy

We introduce a fast algorithm to accelerate detection with many detailed templates.

• Templates are greedily organized in a tree.
• Each parent filter is the average of its children scores.

The richness of part appearances

• Large mixture models in DPMs perform best in detecting detailed parts.
• Detailed annotations can be exploited in initializing part templates.

The bound can be used to cull search locations. Most templates are evaluated only where the part is likely to be found:

Probabilistic but tight bounds allow for a 5-7-fold speedup with negligible accuracy loss:

CTF speedup

CTF bound derivation

The probability of any of $M$ children scores to be larger than the parent score is no more than $M$ times the probability of an individual violation (union bound):

$$P[\exists m : \langle f_m, l \rangle > \langle \hat{f}, l \rangle] \leq M \sup_{l} P[\langle f_m, l \rangle > \langle \hat{f}, l \rangle]$$

Chebyshev’s inequality $P[x > \alpha] \leq E[x^2] / \alpha^2$ allows bounding the individual terms by

$$P[\langle f_m, l \rangle > \langle \hat{f}, l \rangle] \leq \frac{E[(f_m - \hat{f}, l)]^2}{\alpha^2}$$

Expected value of square residual:

$$E \left[ (f_m - \hat{f}, l)^2 \right] = \sum_c V_{cm} ||k_c||^2$$

$V_{cm}$ = 2nd-moment of HOG cell filter approximation residual.

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Ben Taskar’s Memorial http://www.bentaskar.com