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Bootstrapping Fine-Grained Classifiers:
Active Learning with a Crowd in the Loop

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Human-in-the-loop Discriminative Patch Discovery:
New Algorithm

Input: Dataset $\mathcal{D}$ of image patches, set of negative images from the wild $\mathcal{N}$
**Output**: Classifiers C for attributes A

```
1  A ⟸ attributes                           ▷ acquired through consultation with experts
2  for A_i ∈ A do
3  |   S_ij ⟸ seed exemplars of A_i in pose j
4  end
5  for A_i ∈ A do
6  |   for S_ij ∈ S_i do
7  |   |   C_ij = svmTrain( S_ij, N )
8  |   |   N_ij = ∅  ∀i,j                    ▷ set of hard negatives is initially empty
9  |   |   repeat
10 |   |   |   D = orderDetections(C_ij, D − N_ij)
11 |   |   |   N_ij = N_ij ∪ hasNegatives(D)     ▷ crowdsourced method
12 |   |   |   C_ij = svmTrain( S_ij, N_ij ∪ N )
13 |   |   until convergence()
14 |   end
15 end
16 return C, A
```
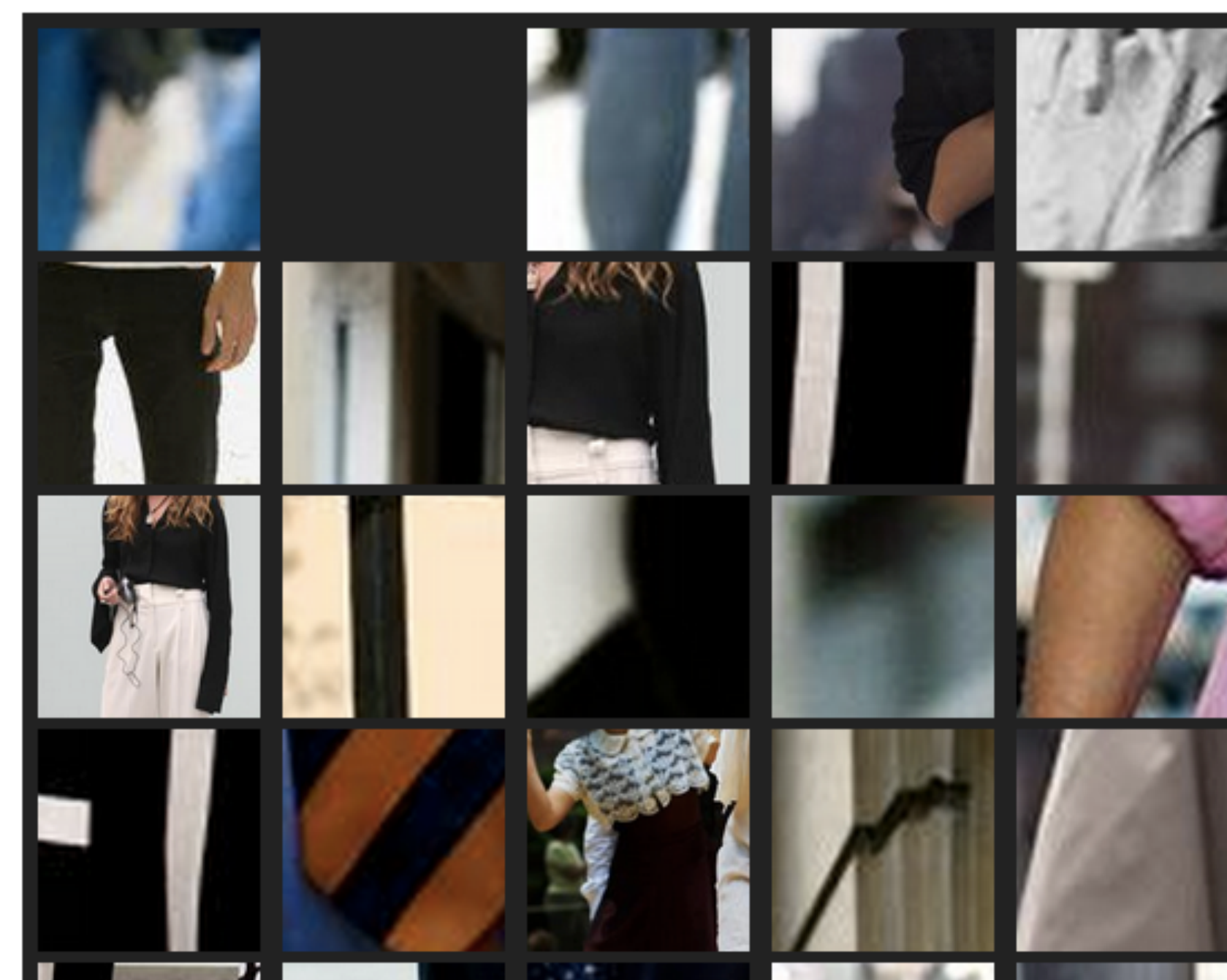
Mechanical Turk User Interface:

Click on all the image patches that contain: **a blazer viewed from the front**

Click submit when you are finished.
Drag or click images to select or deselect.

Example Positive Images
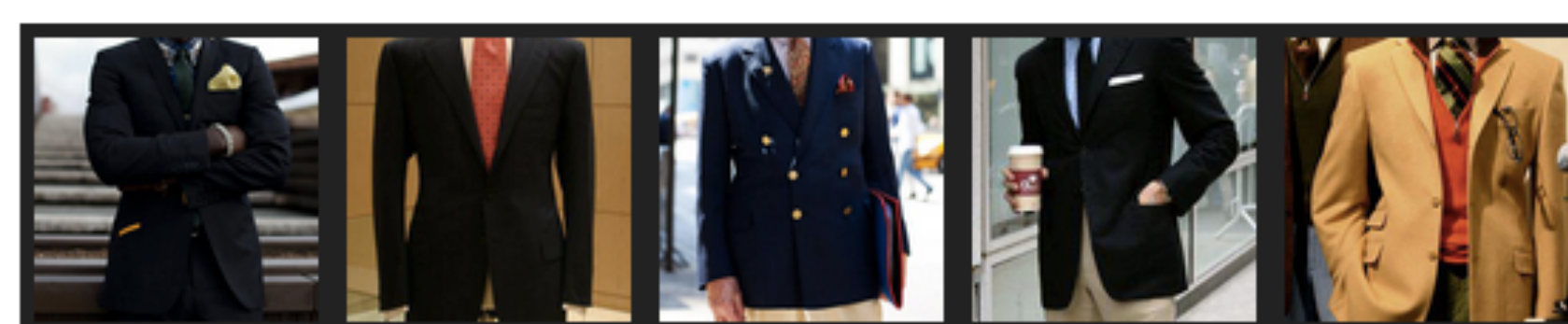
Candidate Images

Yes Images
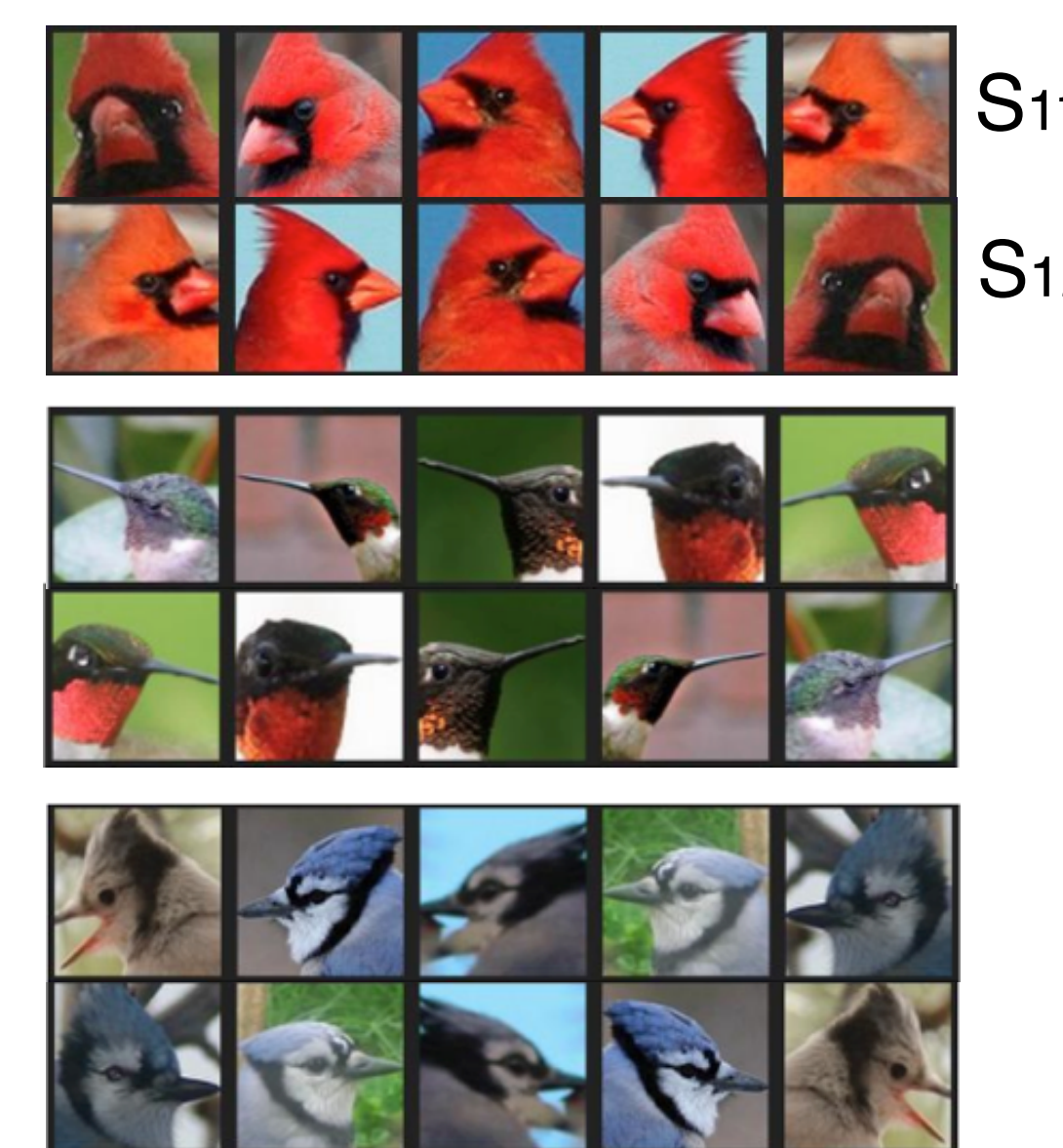

This set depends on the Taxon

Experts begin by making a list of parts and/or attributes for their taxon and selecting exemplars for the canonical poses of each attribute or part.
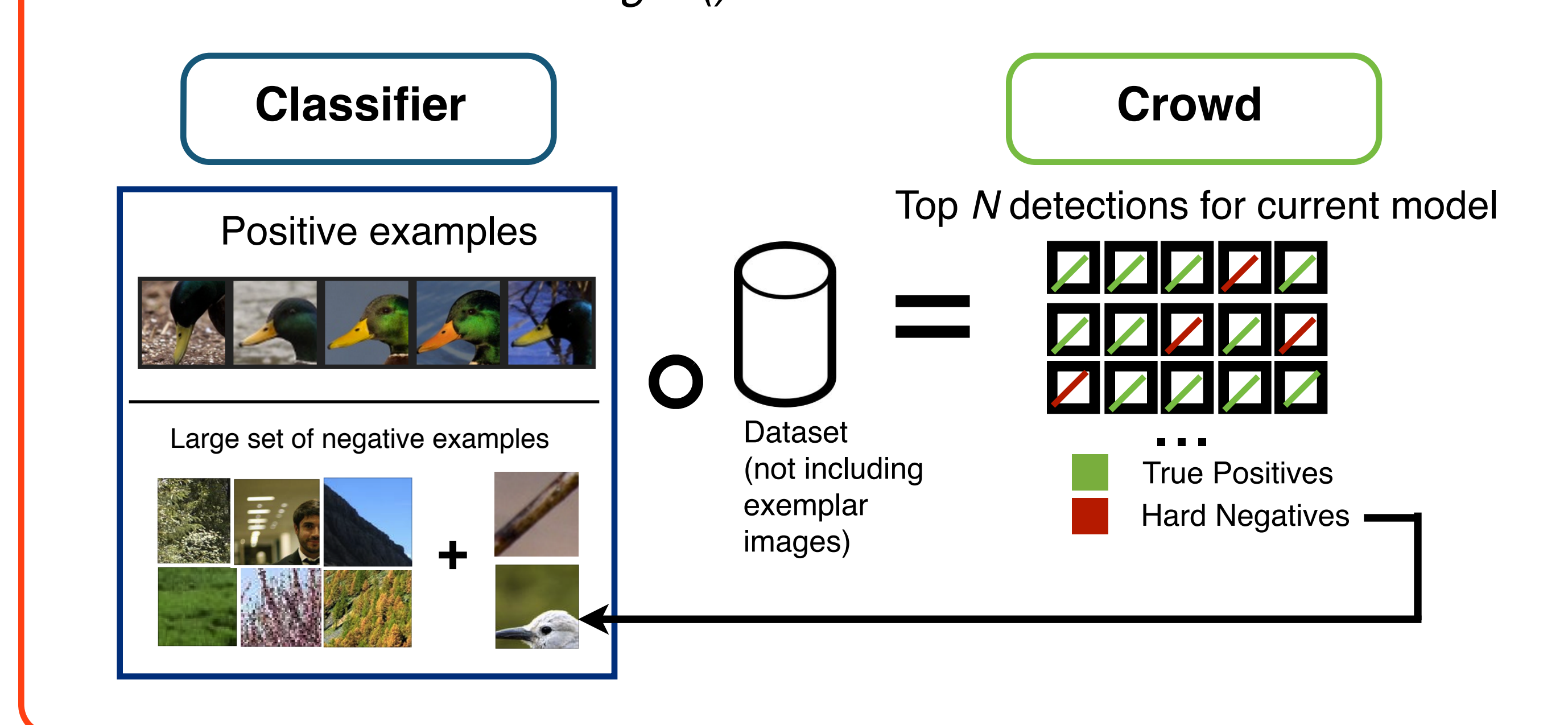
Part/ Attribute List

Cardinal Head Pattern
Humming Bird Ruby Throat
Blue Jay Wing
Mallard Beak
Eagle Head Pattern
Crested Head Pattern
Mask Pattern
Mottled Breast Pattern
Ear Tufts
…

Exemplars

A1

S11
S12

…

For all Exemplars

While model not *converged()*

Classifier

Positive examples

Large set of negative examples

+

o

Dataset (not including exemplar images)

=

Crowd

Top N detections for current model

…

■ True Positives
■ Hard Negatives

Output:
Final Set of Classifiers

Expert Review:
The initial experts can review detections for each attribute model, discarding models that are low-quality, e.g. low visual coherence, does not capture an aspect of the attribute.

Concept Drift:
When non-expert crowd members select hard negatives, sometimes the concept being learned can drift from the original exemplars. The example of 'shorts' to the right shows the classifier drifting to a more general 'leg-exposing garment' classifier. This problem does not occur if experts answer the active learning queries.

Exemplars
Iter. 1
Iter. 3
Iter. 5
Iter. 10
Exemplars
Iter. 1
Iter. 3
Iter. 5
Exemplars
Iter. 1
Iter. 3
Iter. 5
Iter. 10
Exemplars
Iter. 1
Iter. 3
Iter. 5