Active Detection via Adaptive Submodularity
Motivating Example: Biodiversity Monitoring

Application: Detecting Orangutan nests
Automatic, Open-loop Computer Vision System

<table>
<thead>
<tr>
<th>Recall</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>0.1</td>
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<tr>
<td>0.6</td>
<td>0.05</td>
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<tr>
<td>0.7</td>
<td>0.005</td>
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<td>0.8</td>
<td>0.0005</td>
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<tr>
<td>0.9</td>
<td>0.00005</td>
</tr>
<tr>
<td>1.0</td>
<td>0.000005</td>
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</tbody>
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85% recall
10% precision 😞
Interactive Detection

How can human experts best help the detection task?

The adaptive policy

Is there a nest at location (x,y)?
Open-loop (Passive) System

Closed-loop (Active) System
Evidence for Detection

- Train classifier (e.g., SVM; conv. Neural Network, etc.) on 45 positive and 148 negative examples
- Use sliding window to produce “response images”
- Which detection should be proposed next?
Votes and Hypotheses

Hypotheses
\[ \mathcal{H} = \{ h_1, \ldots, h_4 \} \]

Voting elements
\[ \mathcal{V} = \{ v_1, \ldots, v_8 \} \]

Interactions between voting elements and hypotheses: \[ G = (\mathcal{V}, \mathcal{H}, \mathcal{E}) \]
[Hough '59; Gall et al, '09; Barinova et al, '11]
Active Detection as an Adaptive Optimization Problem

**Positive coverage:**
Votes can be fully explained /covered by a *true* hypotheses.

Assume that each vote carries unit weight

Now we observe that hypotheses 3 is *true*.

Then we observe that hypotheses 1 is *true*.

Then we observe that hypotheses 4 is *true*. 
Active Detection as an Adaptive Optimization Problem

**Negative coverage:**
Votes that are similar with *false* votes should be discounted.

Assume that each vote carries unit weight

Suppose that we can cluster similar votes.

Now we observe that hypotheses 3 is *false*.

We also need to *discount* the votes that are similar with the false votes!!
The general case: Real-votes setting

Now observe that hypothesis 3 is false

Voting elements with real-value votes
Active Detection in a Nutshell

**Positive observations:**
Votes can be fully explained / covered by a true hypotheses.

**Negative observations:**
Votes that are similar with false votes should be discounted.

**The Objective**

Coverage for edge \((v,h)\) = Coverage due to positive observations + Coverage due to negative observations

Coverage of \(G = (V, H, E)\) = \(\sum_{(v,h)}\) Coverage for edge \((v,h)\)
Diminishing Evidence in Detection

- Positive observations explain “response” in local areas
- Negative observations explain “response” in similar areas

Adaptive submodular objective can capture this diminishing returns effect
Adaptive Submodularity [Golovin & Krause, 2011]

Receiving observation earlier (i.e., at an ancestor) only increases its expected marginal benefit.
Greedy vs. Optimal

Assume that:

- The optimal policy achieves a maximum coverage of $Q$
- The greedy policy achieves a maximum coverage of $Q - \beta$

\[
\leq \left( \ln \frac{Q}{\beta} + 1 \right).
\]
Detection Results

Active detection improves precision and recall

[Submodular, Barinova et al’12]
TUD-pedestrian: Pedestrian Detection
Votes and Hypotheses
Hough-forest Based Detector

Response Image
Original Image
[Hough-forest, Gall et al, CVPR’09]
TUD-pedestrian: Detection Results

Cyan box: current detection.
Red boxes: ground-truth labels of pedestrians.
Green boxes: detections made by the active detector.

Recall

Precision

Active

Passive (Barinova et al. '12)
PASCAL 2008 - Person Category
Deformable Parts Model (DPM)

![Image of two people with bounding boxes]

![Graph showing precision and recall for Passive and Active models compared to Felzenszwalb et al. '10)]
Conclusion

- An active detection framework that enables turning existing base detectors into systems that intelligently interact with users.

- We show that the objective function satisfies adaptive submodularity, allowing us to use efficient greedy algorithms, with strong theoretical guarantees.

- We demonstrate the effectiveness of the active detection algorithm on three different real-world object detection tasks.

Come to our poster on Tuesday for more details!