

City Forensics: Using Visual Elements to Predict Non-Visual City Attributes

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Experiment presented by: Yu-Chuan Su and Paul Choi

Review



1. Discover visual elements which are indicative of attribute



2. Detect presence of visual elements



3. Predict value of attribute

Review: Training

1. Interpolate data to obtain attribute values over entire city
2. Build bank of SVMs to detect visual elements which are discriminative of attribute
3. Train attribute predictor from SVMs using Support Vector Regression

Review: Training

1. Interpolate data to obtain attribute values over entire city
2. **Build bank of SVMs to detect visual elements which are discriminative of attribute**
3. Train attribute predictor from SVMs using Support Vector Regression



Building an SVM bank

1. Candidate selection

- Find clusters of image patches (visual elements) which are frequent and discriminative

2. Initial SVM training

- Train SVMs for classifying each candidate visual element

3. Iterative clustering

- Iteratively retrain SVMs using the previous top detections as the new positives



Experiment

- How does each step of the method help find more discriminative visual elements?
- Build a bank of SVMs for simple binary classification problems: **duck** or **parrot**, **car** or **not car**.
- Qualitatively evaluate visual elements found at each step.

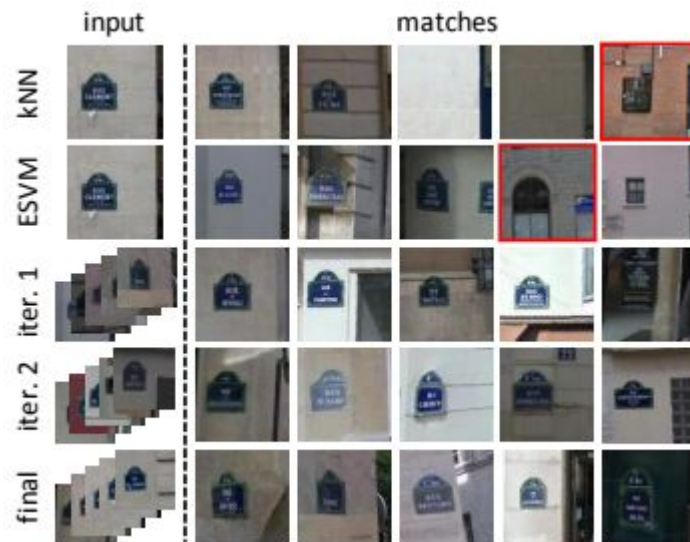


Image credit: Doersch et al. 2012

Datasets

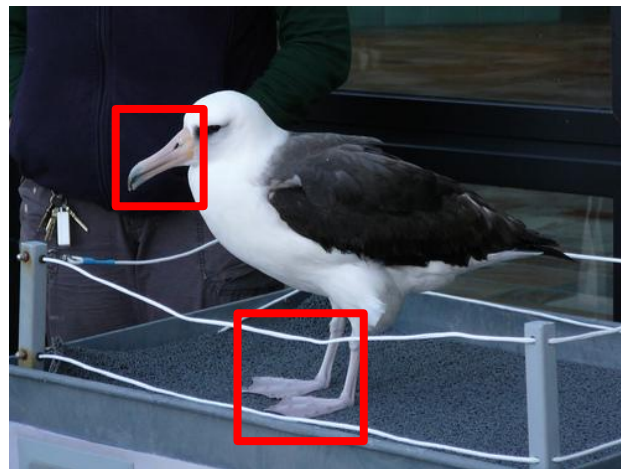
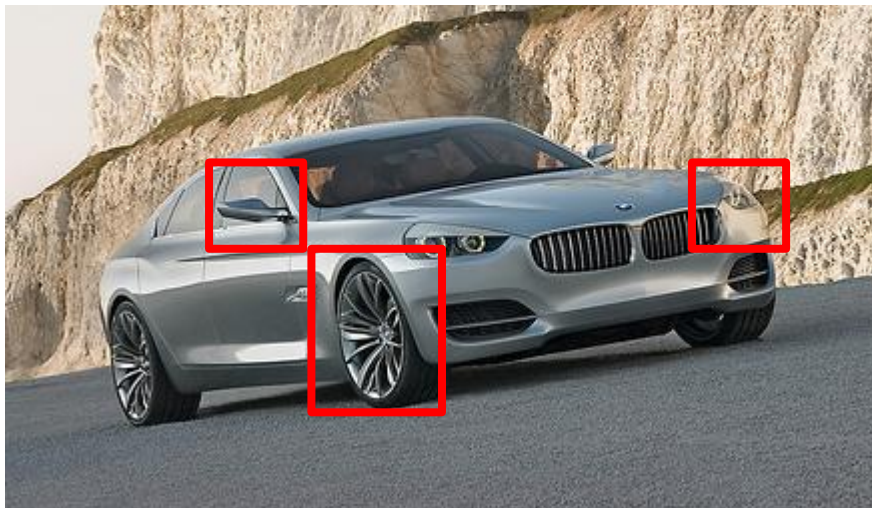
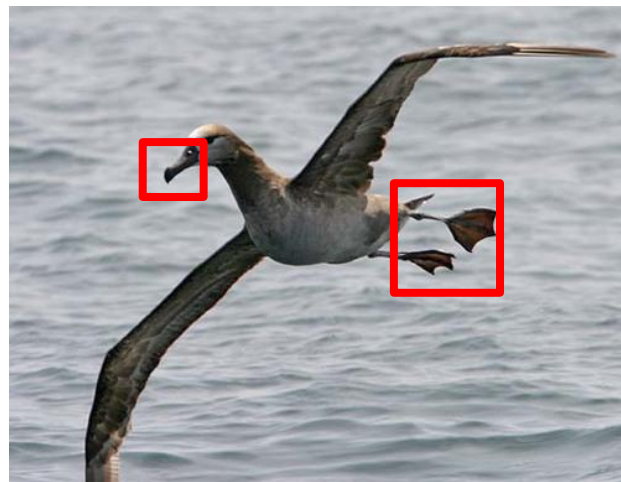
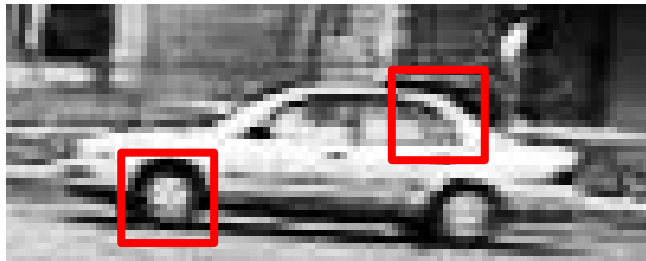
- Caltech-UCSD Birds-200-2011
- PASCAL VOC2012: cars
- UIUC Image Database for Car Detection



Our implementation

- Several patches at several scales from each training image
- VGG-16 features
- Candidate visual elements:
 - Don't have too much spatial overlap with nearest neighbors
 - Have a high ratio of positive examples in nearest neighbors
- Discriminative training
 - For each candidate, train a Linear SVM to separate the 5 nearest neighbors from all negative examples
 - Re-train 3 more times, using the top 5 detections as the new positive examples

Expected results



Results

Pascal VOC (Car v.s. Non-car)

Detected Element 1

Detected Element 2

kNN



ESVM



Iter. 1



Iter. 2



Iter. 3

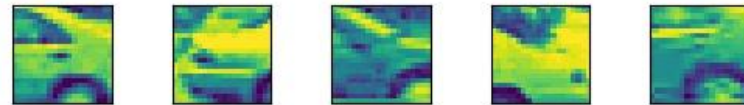
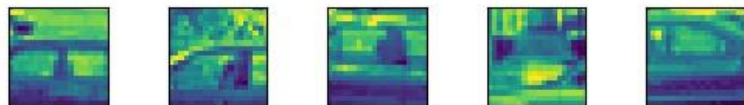


UIUC_CAR

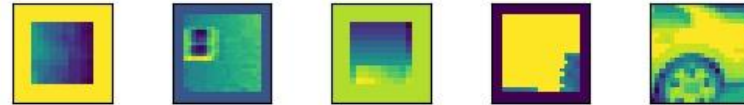
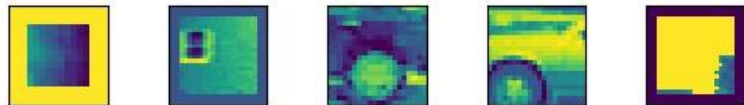
Detected Element 1

Detected Element 2

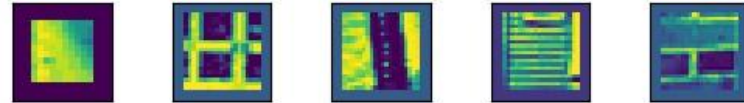
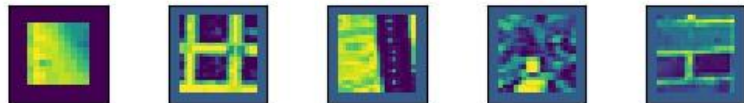
kNN



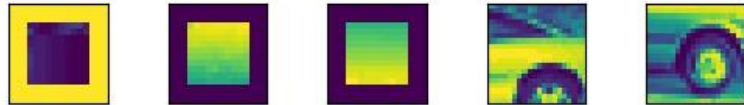
ESVM



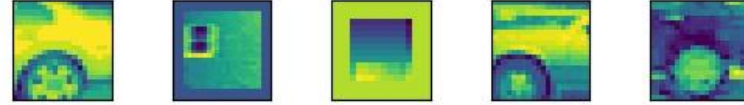
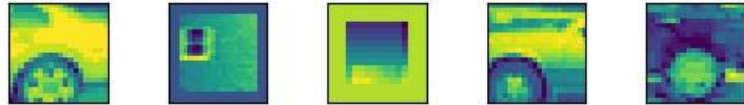
Iter. 1



Iter. 2



Iter. 3



Caltech-UCSD Birds-200-2011

Detected Element 1

Detected Element 2

kNN



ESVM



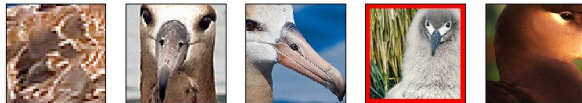
Iter. 1



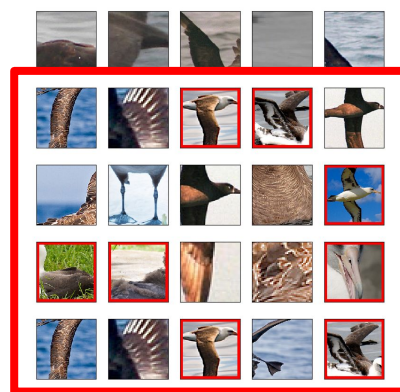
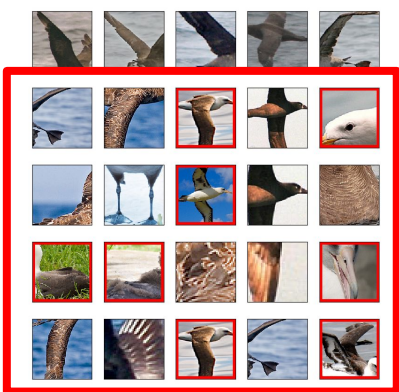
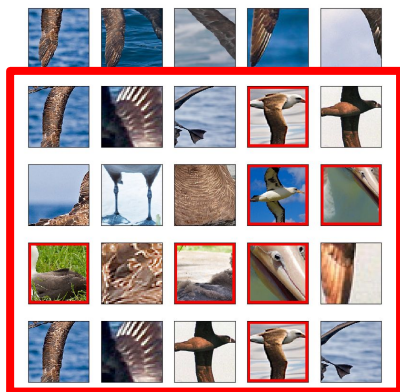
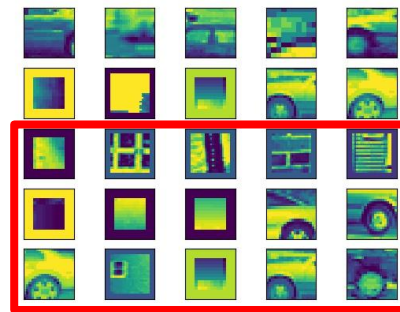
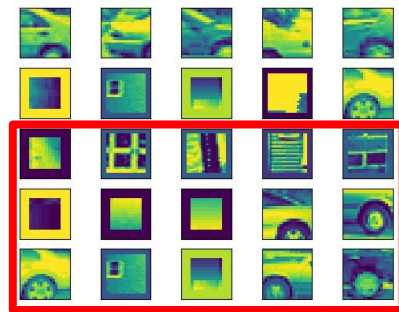
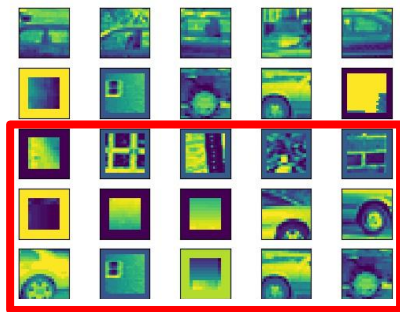
Iter. 2



Iter. 3



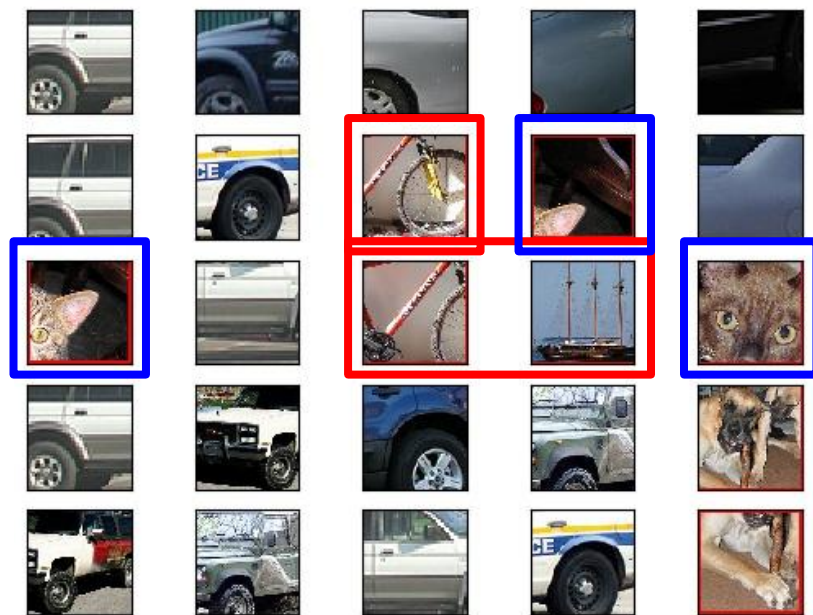
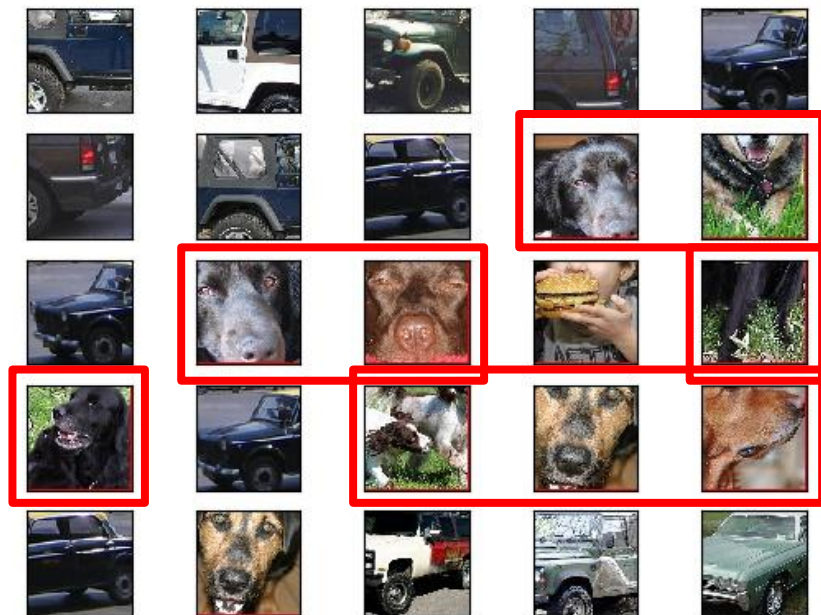
Issue: converging to same elements



Issue: converging to same elements

- Imbalanced training data
- Large & diverse training data is necessary
- Method sensitive to meta-parameters

Issue: cluster drift



Issue: cluster drift

- Positive samples mining does not depend on class label

Conclusion

- The method depends on
 - Large & diverse training data
 - Careful per-dataset tuning
- We successfully find informative parts in Pascal VOC
- Difficulties we encounter
 - Training time
 - Imbalanced data
- Possible improvements
 - Hard negative mining
 - Use label in iterative training