

# Multi-Attribute Queries: To Merge or Not to Merge?

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**Goal:** Finding a best combination of keywords (*attributes*) in an image search query.

**Visual Phrase:**



**Intuition:** In a multi-attribute image search, some combinations of attributes can be learned jointly, resulting in a better classifier.

## Why not:

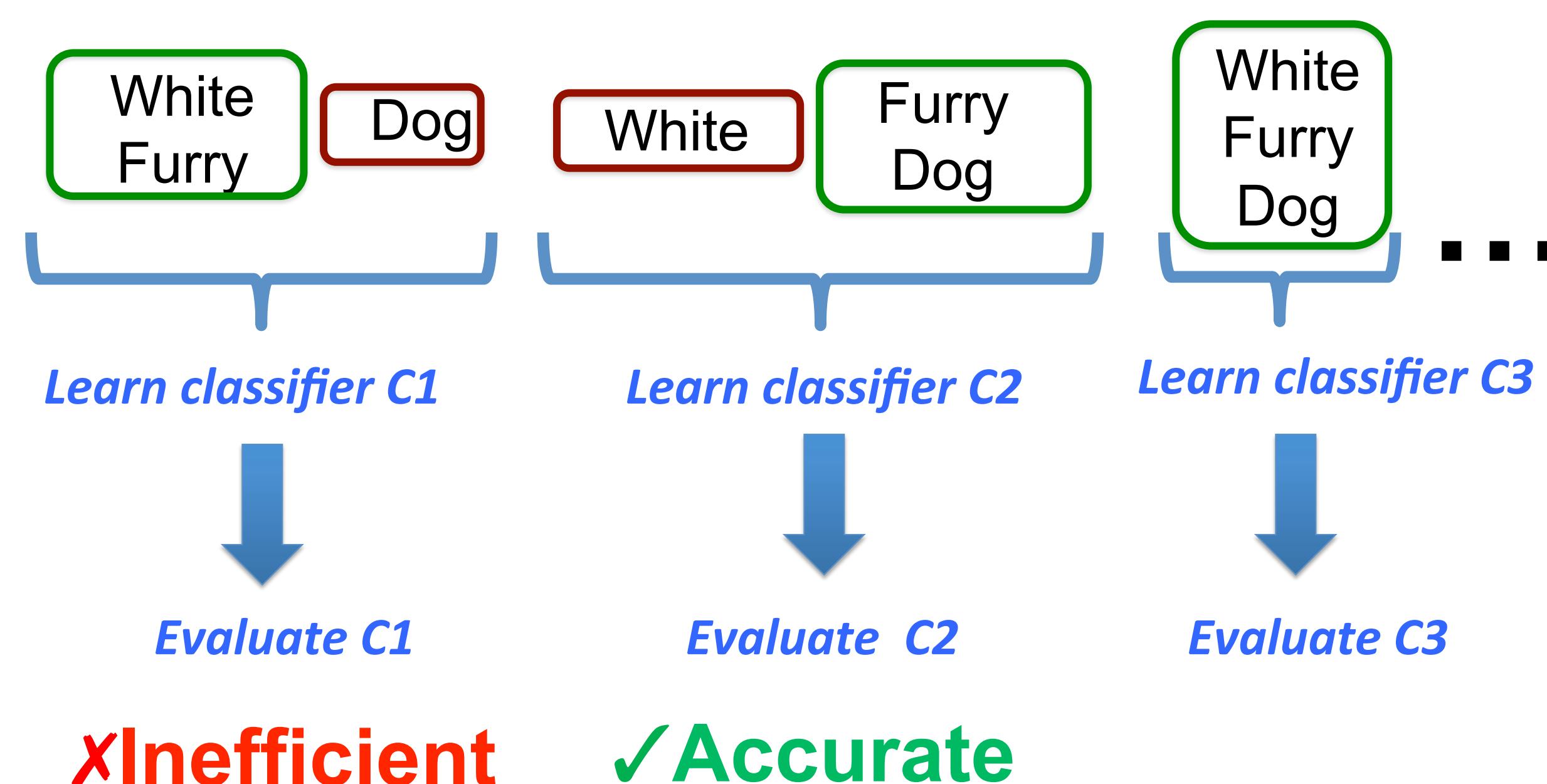
– **Learning individual detector for each attribute?** It may not be effective due to significant difference in appearance (Joint attribute may have similar appearance across images)

– **Learning one detector by merging all attributes?** It may not be powerful due to the lack of jointly labeled training data.

✓ Efficient ✗ Inaccurate

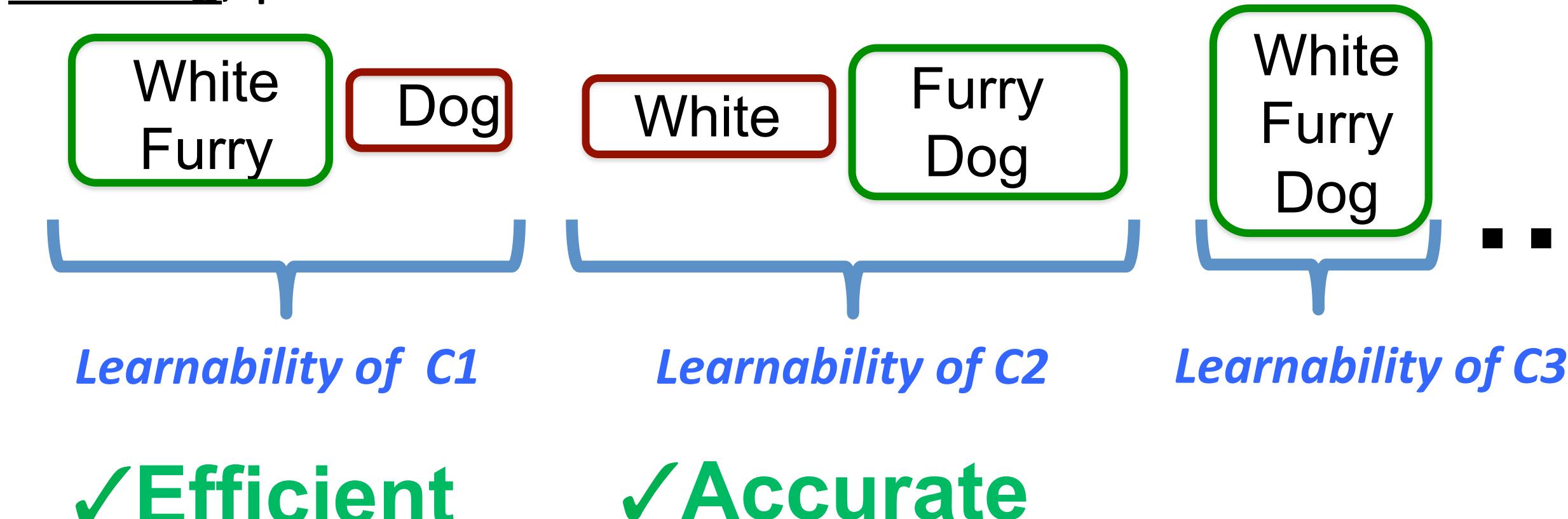
## Naïve Solution (Upper Bound):

Learn and evaluate all possible combinations on a validation set, pick the best.



## Our Approach:

Estimate “learnability” of each combination efficiently without training, pick the best.



## Learnability Function:

Set of attributes:  $\mathcal{A} = \{a_1, a_2, \dots, a_k\}$

A component:  $c_i \in \mathcal{S} = \mathcal{P}(\mathcal{A}) \quad \mathcal{S} = \{c_1, c_2, \dots, c_m\}, m = 2^k$

A combination:  $\mathcal{C} \subset \mathcal{S}$

Margin:  $\mathcal{K}(c_1, c_2)$  Average pair wise distance between two sets of instances labeled by  $c_1$  and  $c_2$

Diagonal:  $\mathcal{D}(c)$  Average distance in a set of instances labeled by  $c$

$$\mathcal{L}(\mathcal{C}) = \sum_{c \in \mathcal{C}} \left[ \sum_{c' \in \mathcal{C}, c' \neq c} \mathcal{K}(c, c') + \sum_{a \in c} \mathcal{K}(c, c \setminus a) - \mathcal{D}(c) \right]$$

Complexity for computing the Margin  $K$  between two sets with  $n_1$  and  $n_2$  elements is  $O(n_1 n_2)$

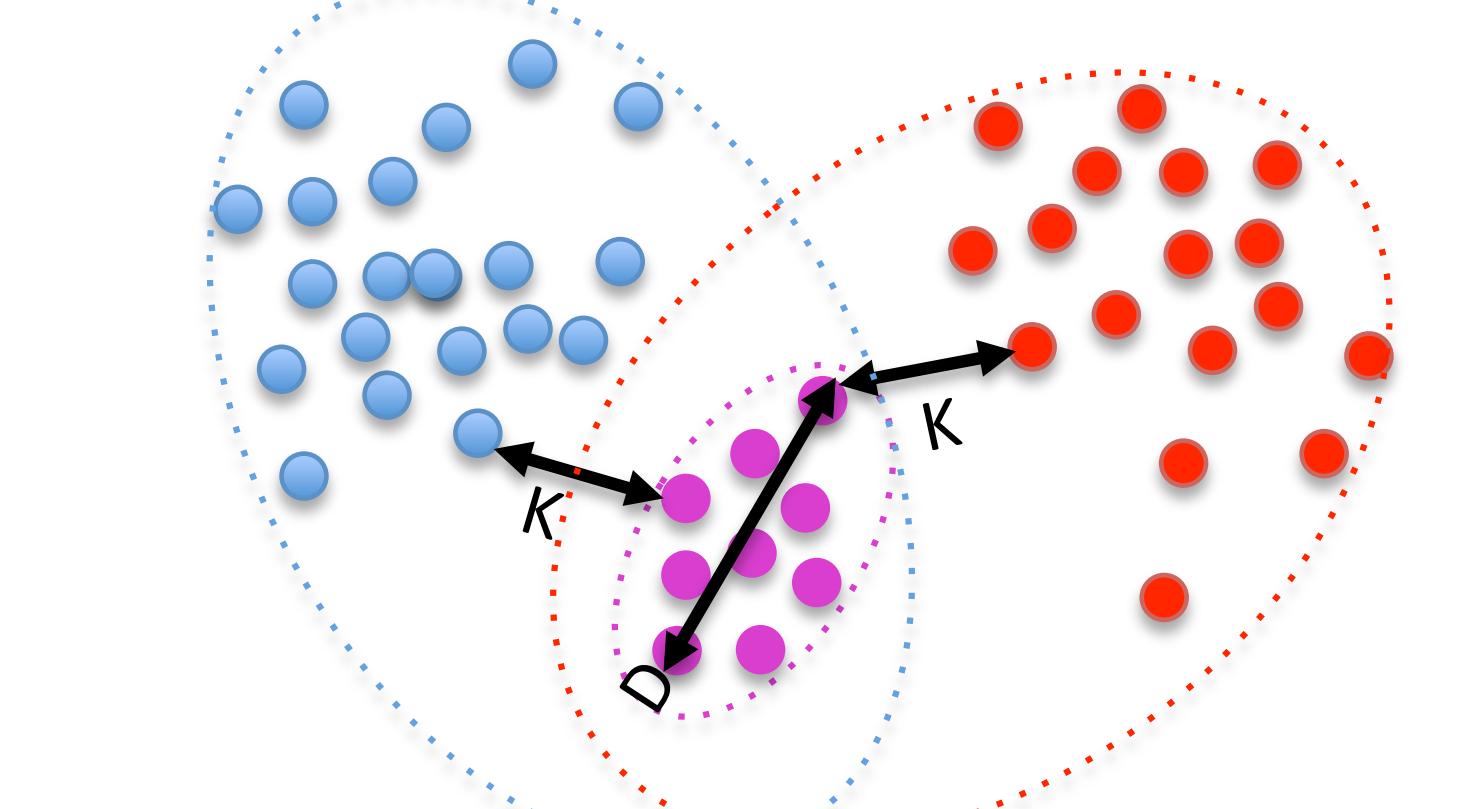
Complexity for computing the Diagonal  $D$  of a set with  $n$  elements is  $O(n^2)$

In Binary feature space :

Margin  $\rightarrow O(n_1 + n_2)$

Diagonal  $\rightarrow O(n)$

Recent binary code methods are very accurate: **DBC** [Rastegari et al. ECCV12] and **ITQ** [Gong et al CVPR11]



**Algorithm 1** Efficient Sum of Pairwise Hamming Distances

Input:  $B1, B2$  are a binary matrix of size  $N \times K$ .  
Output:  $S$ : sum of hamming distances between all pairs of rows in  $B1$  and  $B2$ .

```

1: for  $k = 1 \rightarrow K$  do
2:    $Z(k) \leftarrow \sum_k B2(:, k)$  Comment: Counting Number of zeros in  $k^{th}$  dimension of  $B2$ 
3:    $O(k) \leftarrow \sum_k \neg B2(:, k)$  Comment: Counting Number of ones in  $k^{th}$  dimension of  $B2$ 
4: end for
5: for  $i = 1 \rightarrow N$  do
6:   for  $k = 1 \rightarrow N$  do
7:     if  $B1(i, j) = 0$  then
8:        $P(i, j) \leftarrow O(k)$ 
9:     else
10:       $P(i, j) \leftarrow Z(k)$ 
11:    end if
12:  end for
13: end for
14:  $S \leftarrow \sum P$  Comment: Sum of all elements in  $P$ 
```

## Optimization:

$$\max_x \mathcal{L}(\mathcal{S} \odot x) - \lambda|x|$$

$$Z^T x \geq 1$$

$$x \in \{0, 1\}^m$$

$$Z(i, j) = \begin{cases} 1 & a_j \in c_i \\ 0 & a_j \notin c_i \end{cases}$$

NP-Hard!!

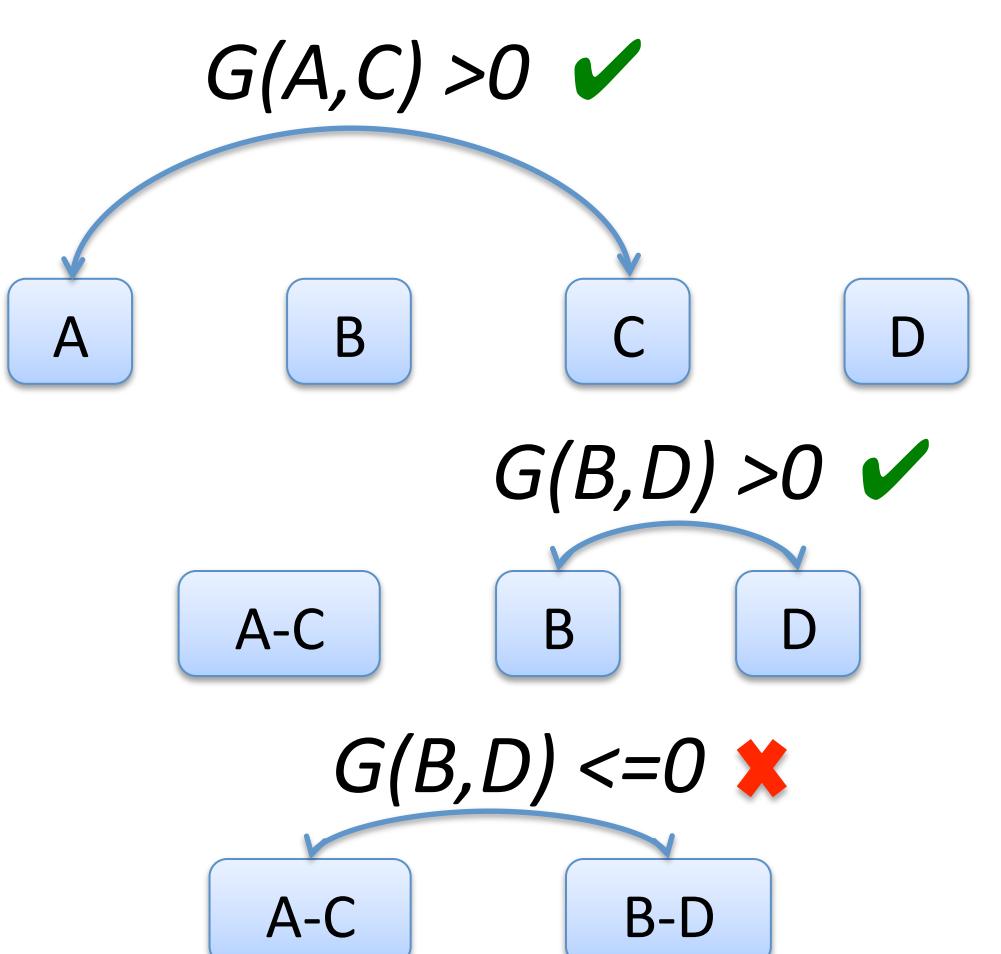
## Gain Function:

$$G(a_i, a_j) = \mathcal{K}(a_i a_j, a_i) + \mathcal{K}(a_i a_j, a_j) - \mathcal{D}(a_i a_j)$$

• The higher  $G(a_i, a_j)$  the higher is the reward for merging  $a_i$  and  $a_j$ .

### Greedy Algorithm:

- For every pairs of attributes compute  $G$
- Pick the pair with maximum  $G$
- If the maximum  $G > 0$  then :
  - 1- Merge the two corresponding attributes
  - 2- Add the new merged-attribute
  - 3- Remove the two independent attribute



### Reducing the search space drastically

**Lemma 1.** If attributes  $a_i$  and  $a_j$  are merged because  $G(a_i, a_j) \geq 0$  then for any other attribute  $a_k$ ,  $G(a_i a_j, a_k) \geq G(a_i, a_k)$  or  $G(a_j, a_k)$

*Proof.* It's simple to show that if  $A \subset B$  then  $\mathcal{D}(A) \leq \mathcal{D}(B)$ , and if  $C \subset D$  then  $\mathcal{K}(A, C) \geq \mathcal{K}(B, D)$ . We can show that  $G(a_i a_j, a_k) = \mathcal{K}(a_i a_j, a_i a_j) + \mathcal{K}(a_i a_j a_k, a_k) - \mathcal{D}(a_i a_j a_k) > \mathcal{K}(a_i a_j a_k, a_i a_j) + \mathcal{K}(a_i a_j a_k, a_k) - \mathcal{D}(a_i a_k) > \mathcal{K}(a_i a_k, a_i) + \mathcal{K}(a_i a_k, a_k) - \mathcal{D}(a_i a_k) = G(a_i, a_k)$ . The same holds for  $G(a_i, a_j)$ .  $\square$

$O(k^3)$  vs.  $O(2^k)$

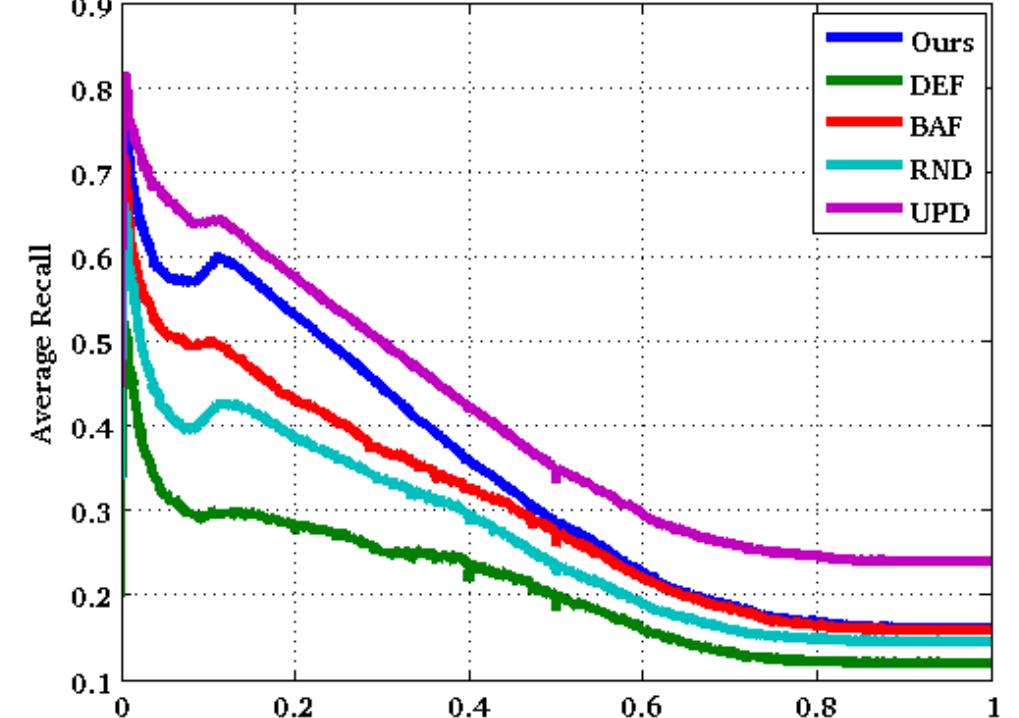
## Experiments:

### Datasets:

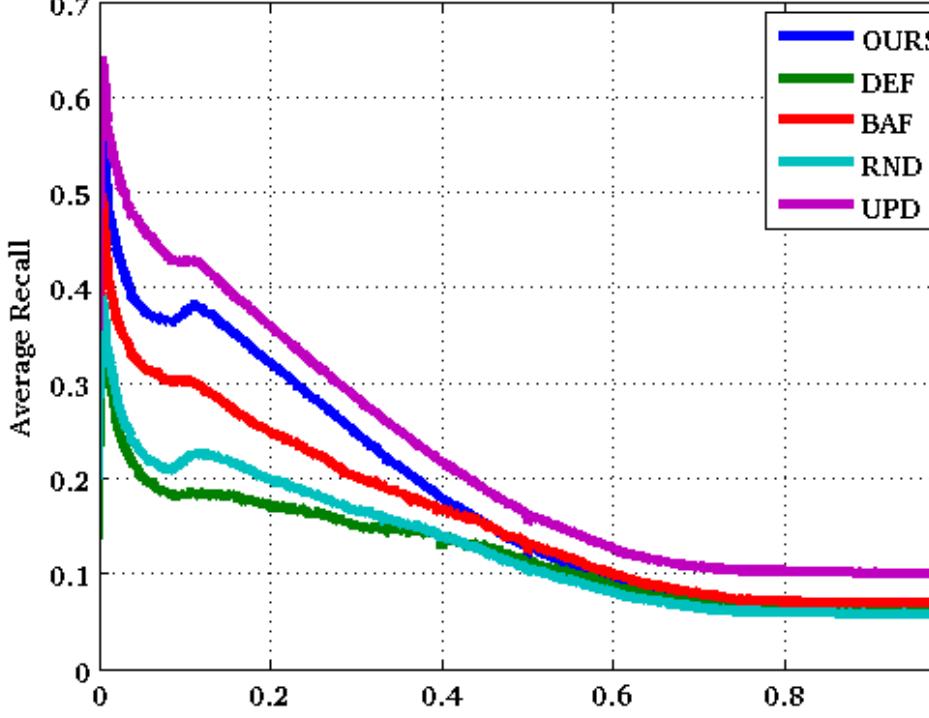
1- aPascal [Farhadi et al. 2009]

2- Caltech-UCSD Bird200 [Welinder et al. 2010]

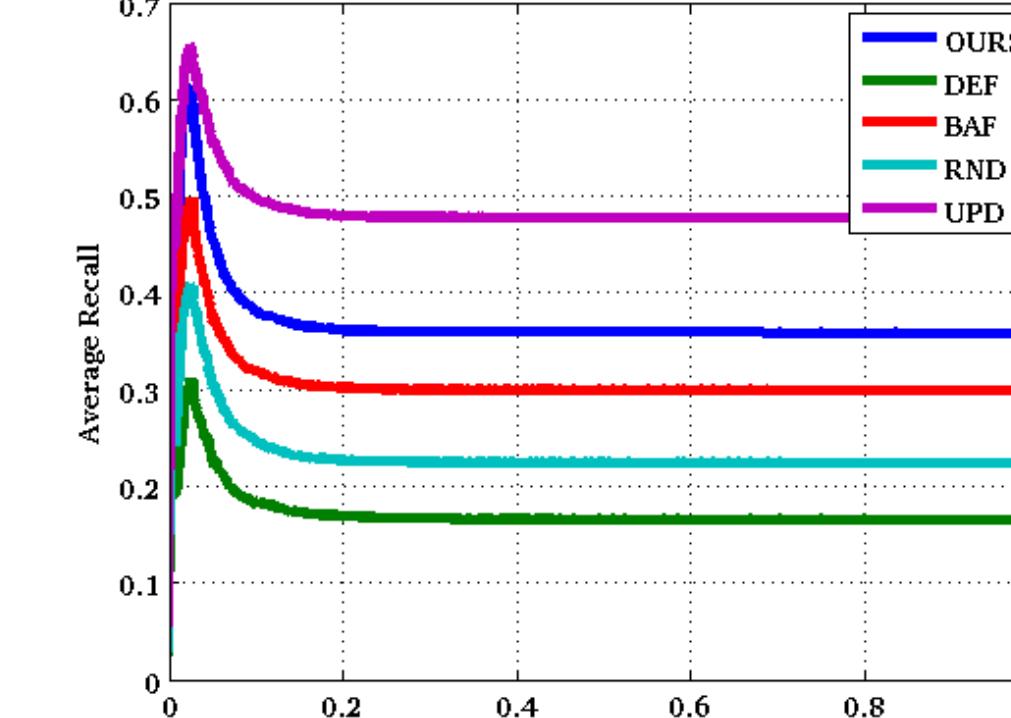
aPascal 3-attributes query



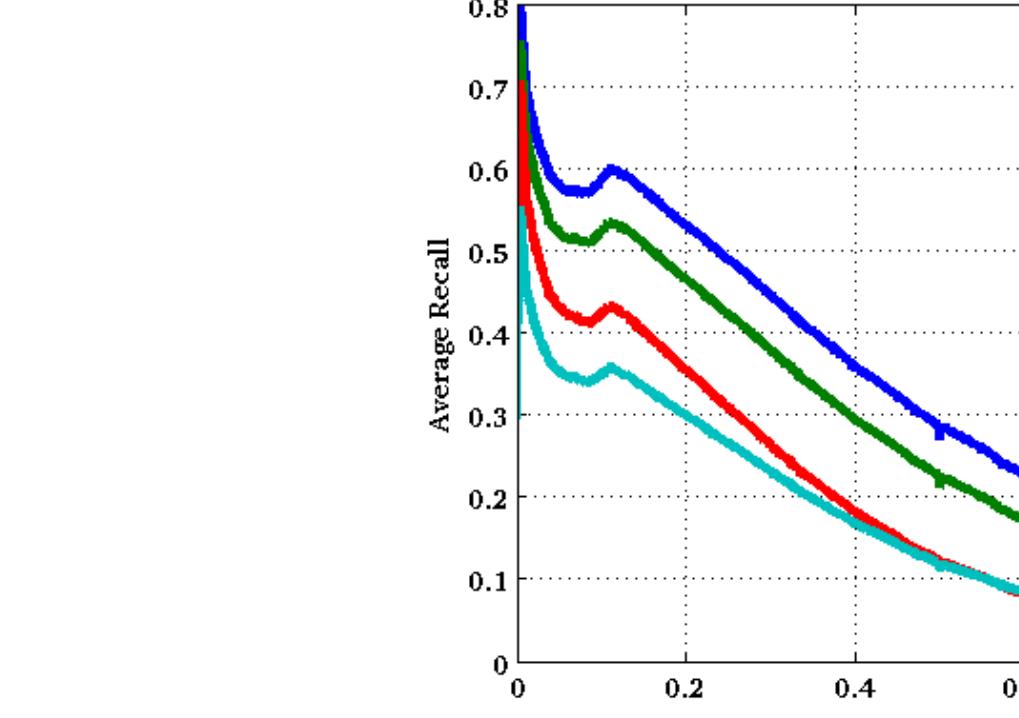
aPascal 4-attributes query



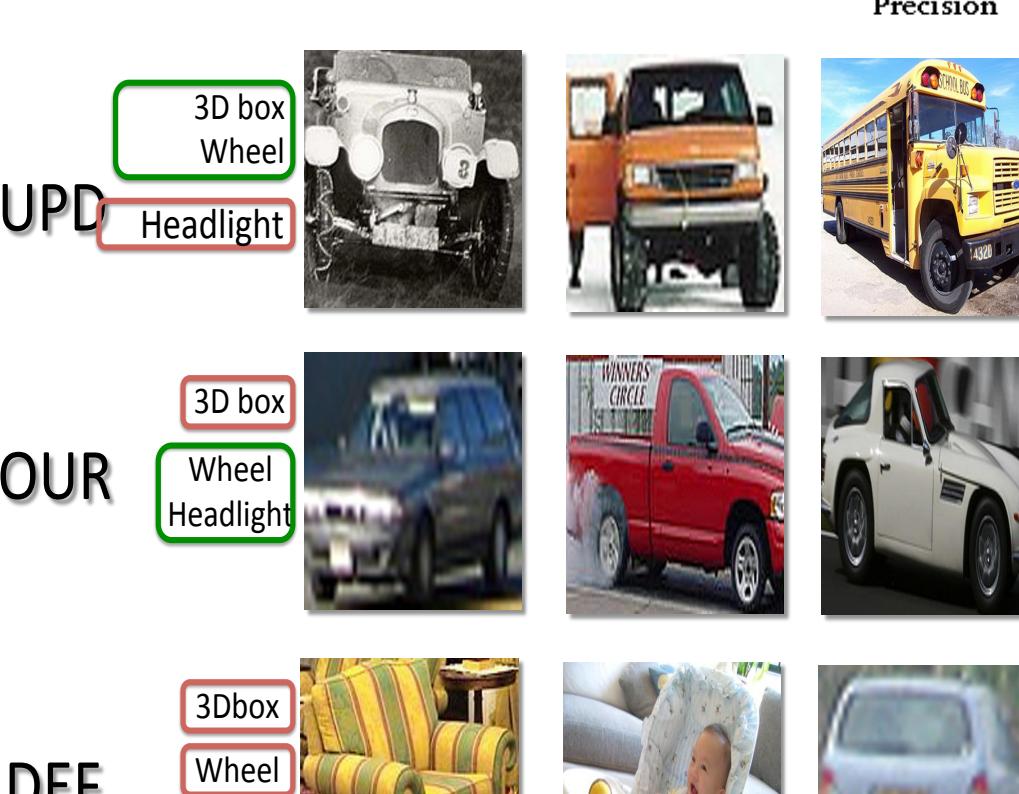
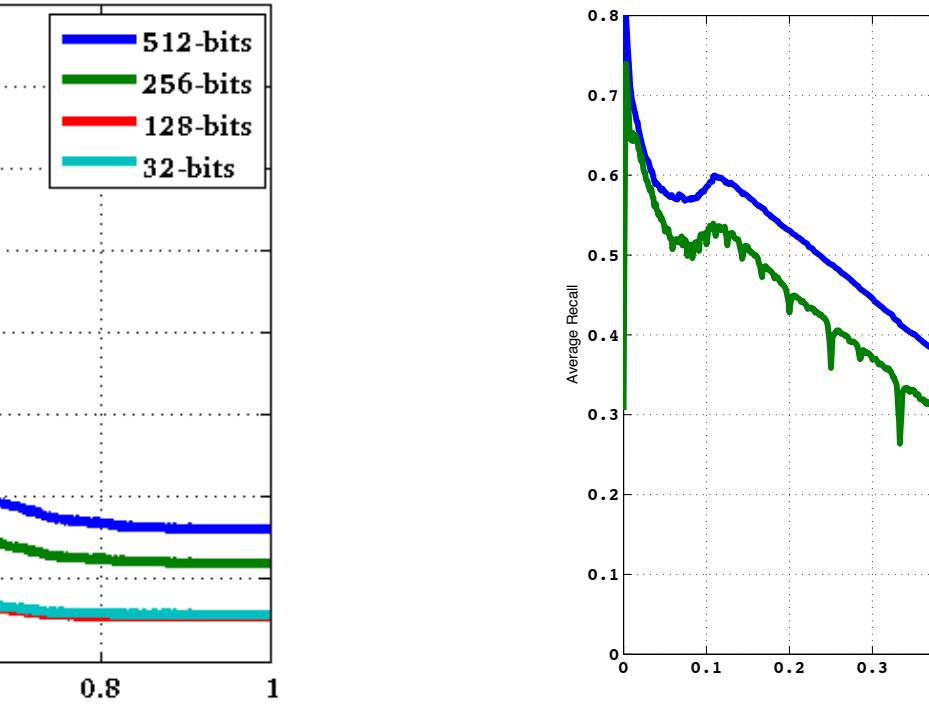
Bird200 3-attributes query



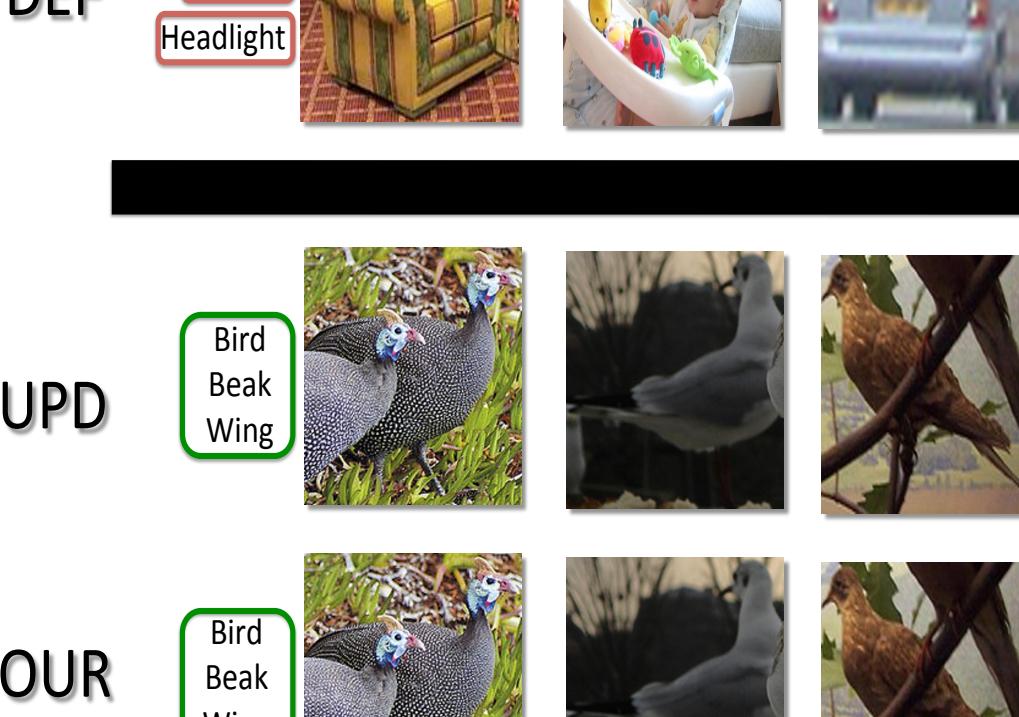
### Different number of bits



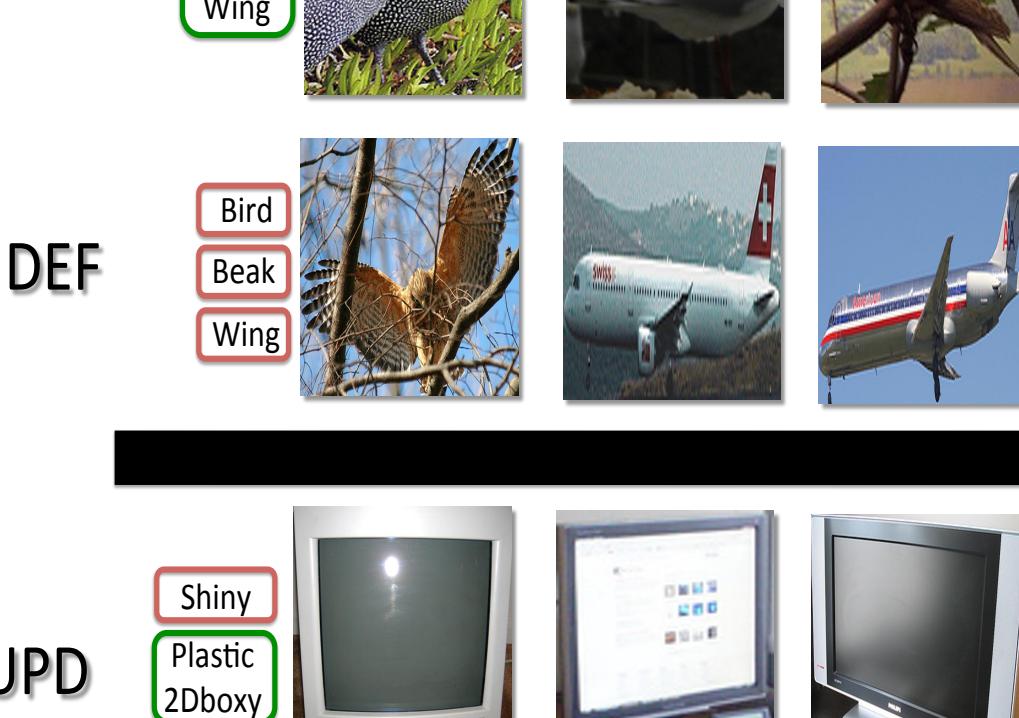
### Calibration Effects



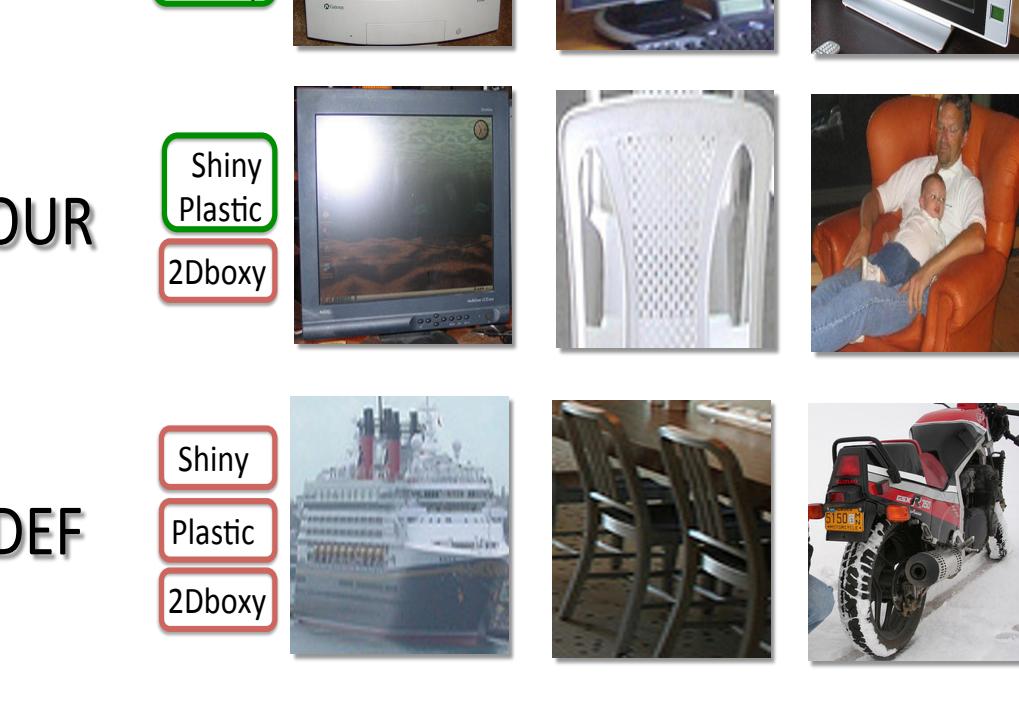
UPD



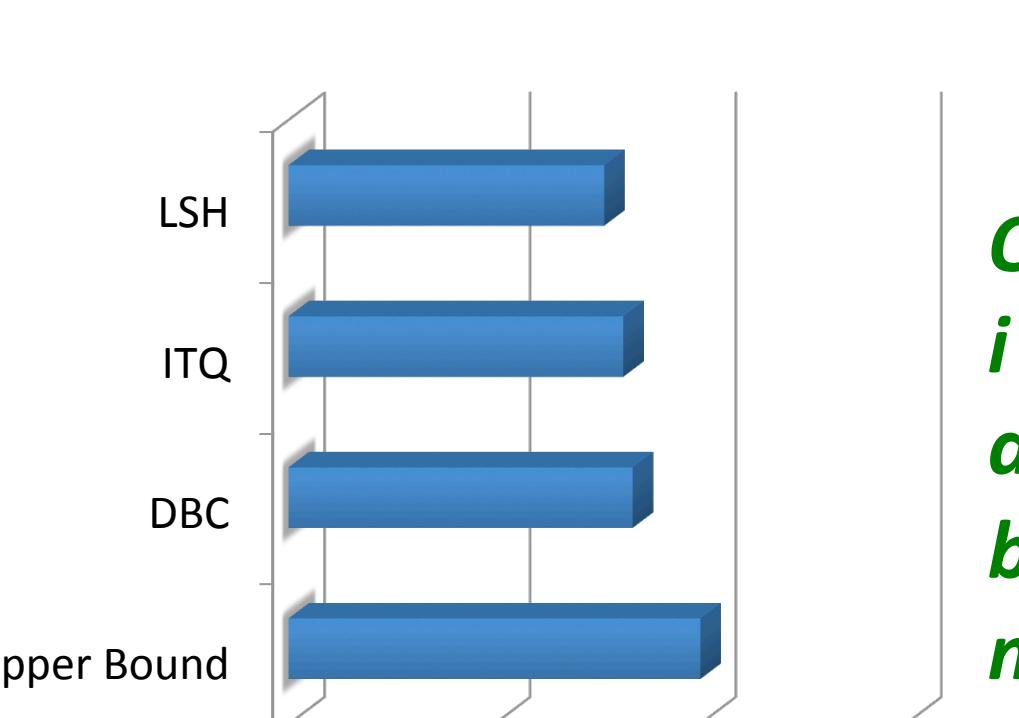
OUR



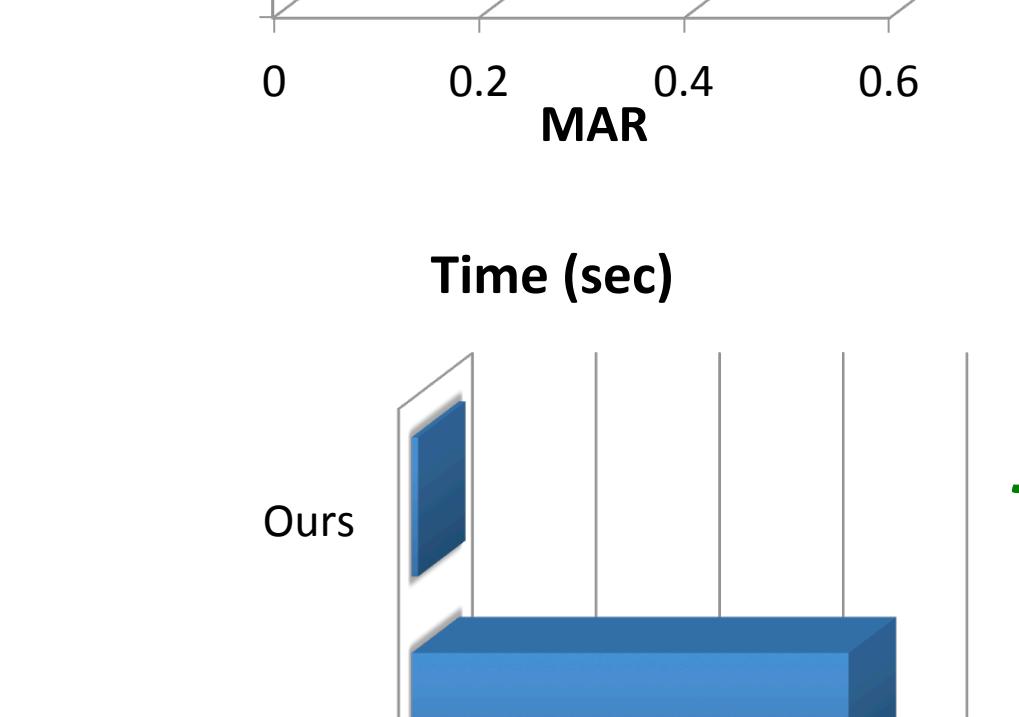
DEF



UPD



OUR



DEF



Our method is robust across the binary code methods

