Caranx: Scalable Social Image Index Using Phylogenetic Tree of #Hashtags

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Introduction

- Photos are most shared items on Facebook: 300M+ are uploaded daily.
- Scalable photo indexing is challenging:
  - Depends heavily on **SIFT** features
  - SIFT features not robust in practice
- **NRDC** has robust feature, but not scalable.
  - Features extracted from pairwise algorithm (see center section for details)
- Caranx uses social tag to make **NRDC** scalable and enable *Scalable* image search
  - Photos on social networks are ***#tagged***.
- Visit our project @ https://github.com/yvesx/caranx

Algorithms

Algorithm 1: Indexing social images with CARANX

Input: I, a set of images with social #tags
Output: M, index data structure for I
Initialize T, set to hold all #tags
Initialize D, matrix to hold #tag pairwise distances
Initialize M, index data structure for I
Initialize PT, phylogenetic tree to structure all #tags
for *image* $i \in I$ **do**
  for *#tag* t *assc. to* i **do**
    Append i to $T[t]$
  end
end
for *pair of #tags* $\langle t, v \rangle \in T \times T$ **do**
  $D(t, v) \leftarrow |T[t] \cap T[v]|$
end
$PT \leftarrow \text{UPGMA}(D)$
for *#tag* $t \in T$ **do**
  $q \leftarrow$ empty queue; Add t to q; $O \leftarrow$ empty set
  $p_1 \leftarrow 1.0; p_2 \leftarrow 1.0$
  while $q \neq \emptyset$ **do**
    $h \leftarrow q$.remove()
    Mark h in PT as visited
    for *image* $i \in T[h]$ **do**
      Add i to O with probability p_1
    end
    Decrease p_1, p_2 by $f(h.\text{Edges})$
    for *#tag* $n \in h$*'s unvisited neighbors* **do**
      Mark n in PT as visited
      Add n to q with probability p_2
    end
  end
  for *images* $\langle i, j \rangle \in O \times O$ **do**
    $W \leftarrow$ visual patches from NRDC(i, j)
    for *patch* $w \in W$ **do**
      $m \leftarrow$ minHash(quantized w)
      Initialize $M[t][m]$ if not exists
      Append i, j to $M[t][m]$
    end
  end
end
return M

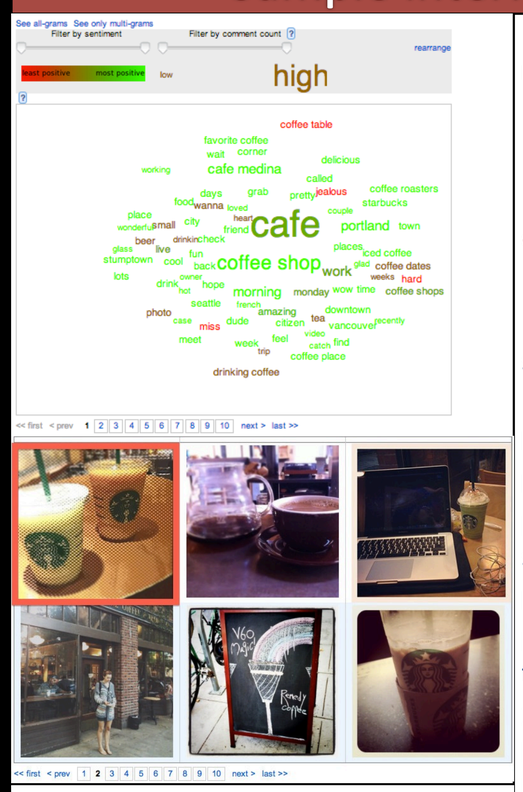
Algorithm 2: Searching social images with CARANX

Input: i, query image with social #tags; T, all #tags; M, image index
Output: R, result set
Initialize R, set to hold return images
for *#tag* t *assc. to* i **do**
  $p \leftarrow 1.0$
  Decrease p if $t \notin T$
  for m *in* $M[t]$ **do**
    Skip with probability $(1 - p)$
    if s *is significant* **then**
      for $j \in M[t][m]$ **do**
        Append j to R
      end
    end
  end
end
return R

INDEXING
Non-Rigid Dense Correspondence for images
Phylogenetic Trees for #tags

QUERYING
Probabilistic BFS
Bag of dense visual keywords

Sample interface



Query image shown in red box:

a *#Starbucks* photo

<<<<<< #tag Explorer

#tags related to the query and #starbucks

Font size ~ relevance

Color spectrum ~ social sentiment

<<<<<< Retrieval Results

Diversity due to probabilistic Tree search

Relevance thanks 1) phylogenetic tree of tags

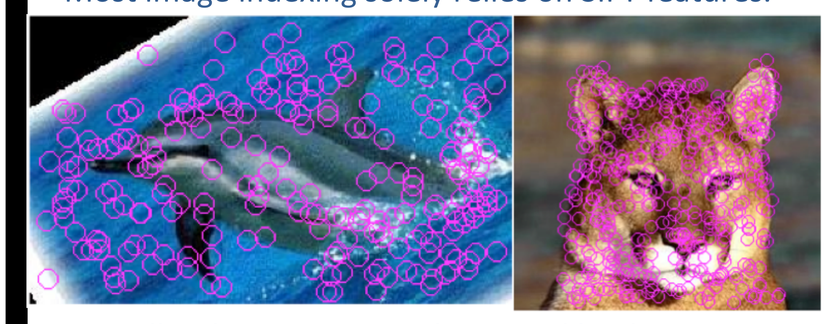
2) Dense visual words like Starbucks Mermaid logo.

<<<<<< #kobe

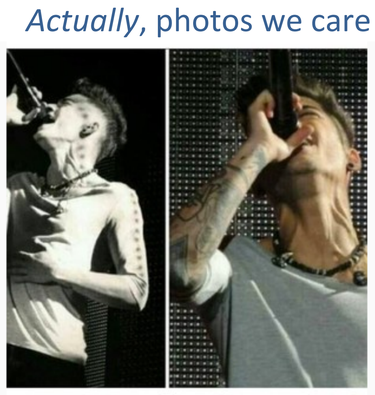
Different query can result in an entirely different subset of #tags from the phylogenetic tree.

Background

Most image indexing solely relies on SIFT features.



Actually, photos we care about are like these:



❤ 1 💬 1

#beautiful, #cute, #niall, #love, #liampayne, #harry, #1direction, #louistomlinson, #directioner, #zayn, #louis, #niallhoran, #sexy, #onedirection, #guys, #liam, #boys, #zjmalik, #iphonesia, #instagood, #tagsforlikes, #hot, #harrystyles, #1d, #leeyum, #zaynmalik, #photooftheday, #happy,

♥ @_dem_accents_,

28 #tags, **1**@

❤ 9 💬 2

#cute, #love, #adorable, #tbt, #misshim, #so, #lovehim, #cousin, #miss, #him, #braces, #happy,

♥ @shortiie4life, @_itsemiiily, @_abbylovespenguins10, @kaylahodea,

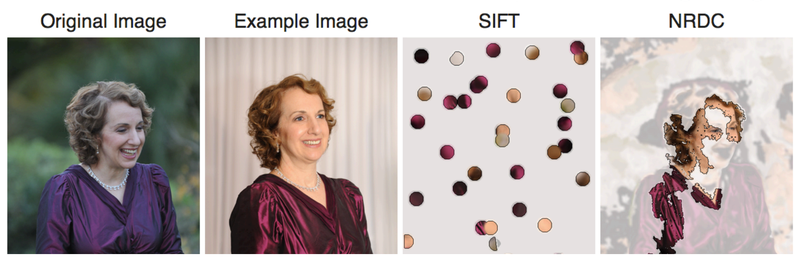
12 #tags, **4**@

#tags are part of the images, just like colors and pixels.

Non-Rigid Dense Correspondence

NRDC: advanced patch-matching algorithm for image.

Pros: better performance over SIFT in real world scenarios like differences in facial expressions, lighting.



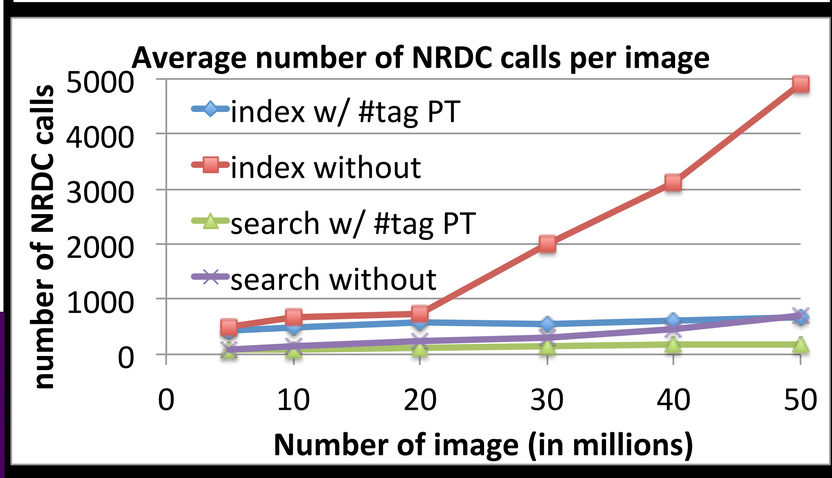
NRDC can identify critical visual frequent keywords like the Starbucks Mermaid logo.

Cons: NRDC operates on pairs of images. Suppose we are indexing 1B img, 1B*1B=*5e17* pairwise computations are needed – not scalable.

Data and Preliminary Results

Table 1: Caranx experiment data as of 2013 June.

Source	Instagram public data
Images	54.8M
#tags (unique)	~200M (~5M)
Unique users	15.4M



Phylogenetic Tree of #tags

Use a **phylogenetic tree (PT)** to organize #tags and enable search over them.

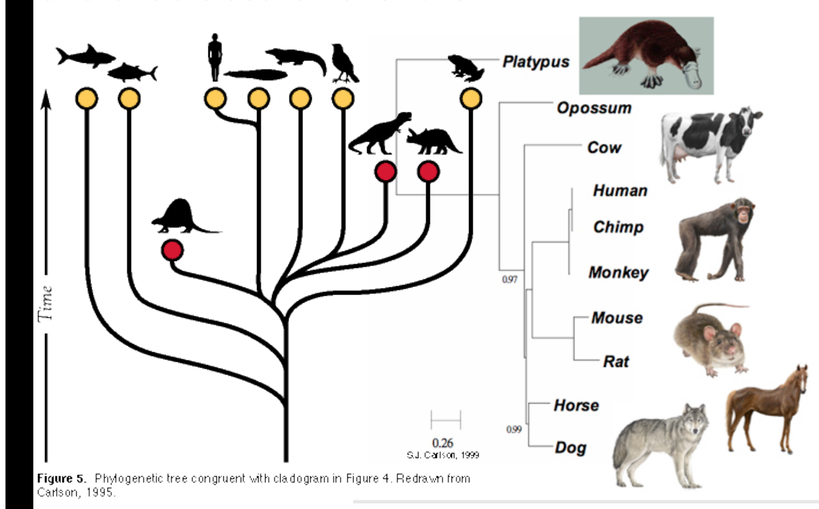


Figure 5. Phylogenetic tree congruent with cladogram in Figure 4. Redrawn from Carlson, 1995.

#tags are like species: they thrive and die out as time evolves.

#summer is popular during May~Aug

#bostonStrong quickly gains&loses presence

#happyNewYear reoccurs every new year.

NRDC+PT=*Credibility*+Scalability

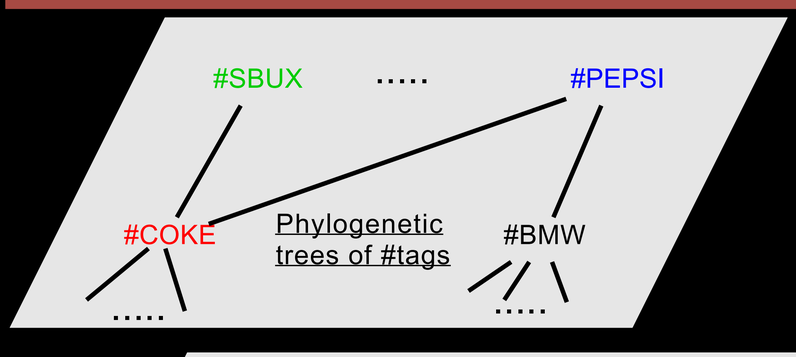
INDEXING

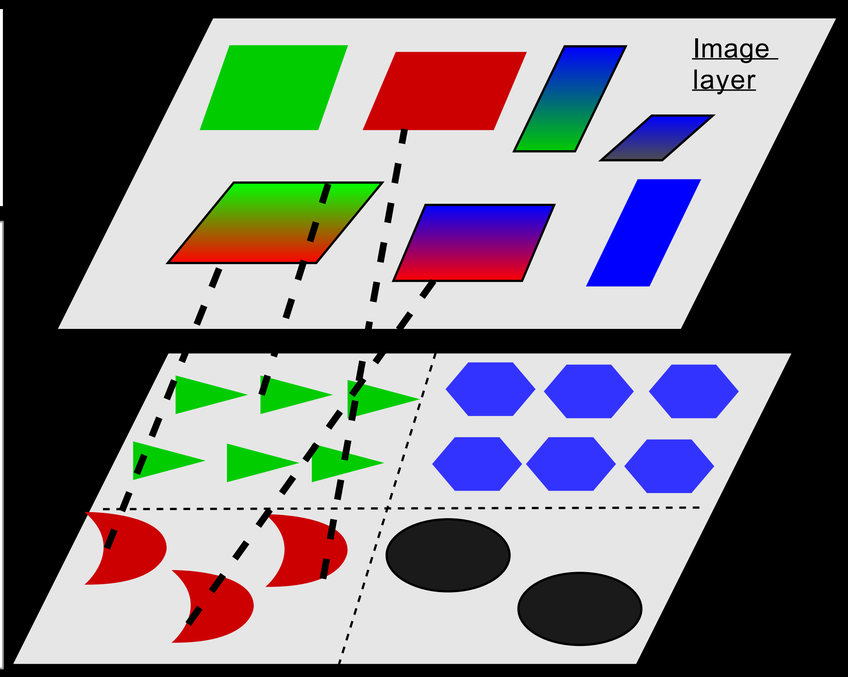
1. Organize #tags and associated images into a phylogenetic tree. #tag pairwise distance matrix D:
   D(t,v) = |images w/ #t| ∧ |images w/ #v|
   Use UPGMA algorithm to compute phylogenetic tree from D.
2. Perform pairwise NRDC to images under each close sub-branch (each sub-branch probabilistically contains 2~10 #tags.).
3. Quantize the dense patches (visual keywords) discovered from NRDC. Store the patches and their minHash signatures.

QUERYING

1. Use query #tag to quickly narrow down branches to search.
2. Match query image with registered patches using NRDC.
3. Return result images based on matched patches.

Caranx Overview





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