iLike: Integrating Visual and Textual Features for Vertical Search

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Motivation

- The problem
  - Huge amount of multimedia information available
  - Browsing and searching is even harder than text
- Text-based image search

Motivation

- Text-based image search
  - Adopted by most image search engines
    - Efficient – text-based index
    - Text similarity, PageRank
  - Some queries work very well
    - Clearly labeled images
    - Distinct keywords
  - Some queries don't
    - Insufficient tags
    - Gap between tag terms and query terms
    - Descriptive queries: "paintings of people wearing capes"

Motivation

- Content-based Image Retrieval (CBIR)
  - Visual features: color, texture, shape…
  - Semantic gap
    - Low level visual features vs. image content
    - sun -> nice sunshine -> a beautiful day
  - Excessive computation: high dimensional indexing?

Motivation

- Put textual and visual features together?
- In the literature: hybrid approaches
  - Text-based search: candidates
  - CBIR-based re-ranking or clustering
- Our idea
  - Connect textual features (keywords) with visual features
  - Represent keywords in the visual feature space
    - Learn users' visual perception for keywords

Preliminaries

- Data set
  - Vertical search: online shopping for apparels and accessories
  - Text contents are better organized
  - We can associate keywords and images with higher confidence
  - In this domain, text description and images are both important
- Data collection
  - Focused crawling: 20K items from six online retailers
    - Mid-sized hi-quality image with text description
  - Feature extraction
    - 263 low-level visual features: color, texture and shape
    - Normalization

Representing keywords

- Keywords
  - Image -> Human perception -> text description
  - Perception is subjective, the same impression could be described through different words
  - Calculating text similarity (or distance) is difficult - distance measurements (such as cosine distance in TF/IDF space) do NOT perfectly represent the distances in human perception.

Representing keywords

- *Items share the same keyword(s) may also share some consistency in **selected** visual features.*
- *If the consistency is observed over a significant number of items described by the same keyword, such a set of features and their values may represent the human "visual" perception of the keyword.*

Representing keywords

- Example: checked

Representing keywords

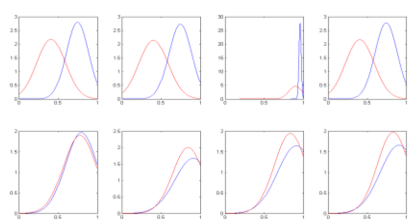
- Example: floral

Representing keywords

- For each term, we have
  - Positive set: items described by the term
  - Negative set: items not described by the term
- "Good" features
  - are coherent with the human perception of the keyword
  - have consistent values in the positive set
  - show different distributions in the positive and negative sets
- How do we identify "good" features for each keyword?
  - Compare the distributions in the positive and negative sets…

Representing keywords

- Distribution of visual features (term="floral")

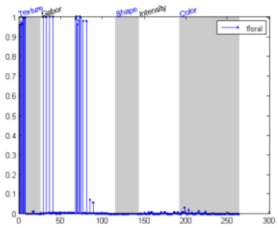


Kolmogorov-Smirnov test

- Two sample K-S test
  - Identify if two data sets are from same distribution
  - Makes no assumptions on the distribution
  - Null hypothesis: two samples are drawn from same distribution
  - P-value: measure the confidence of the comparison results on the null hypothesis.
  - Higher p-value -> accept the null hypothesis -> insignificant difference in the positive and negative sets -> “bad” feature
  - Lower p-value -> reject the null hypothesis -> statistically significant difference in the positive and negative sets -> “good” feature

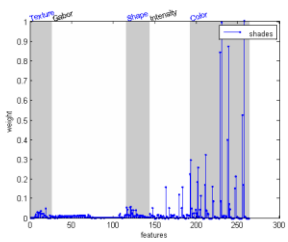
Weighting visual features

- The inverted p-value of Kolmogorov-Smirnov test could be used as weight for the feature
- “floral”:



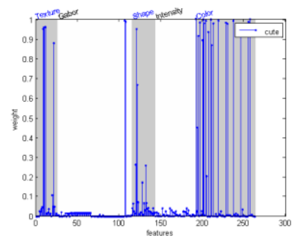
Weighting visual features

- More examples: “shades”



Weighting visual features

- More examples: “cute”



Query expansion and search

- User employs text-based search to obtain an initial set
- For each item in the initial set:
  - Load the corresponding weight vector for each keyword
  - Obtain an expanded weigh vector from the textual description.

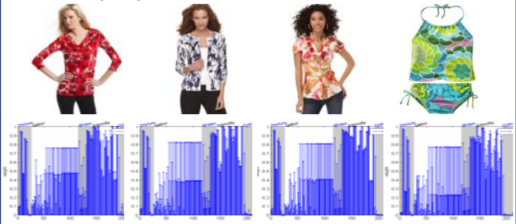
$$\vec{q}'(Item_i, Query) = \vec{q_i}. \times (\alpha \cdot \vec{\omega}_Q + \beta \cdot \vec{\omega}_E)$$

Query expansion and search

- Query: “floral”
- Initial set:

Query expansion and search

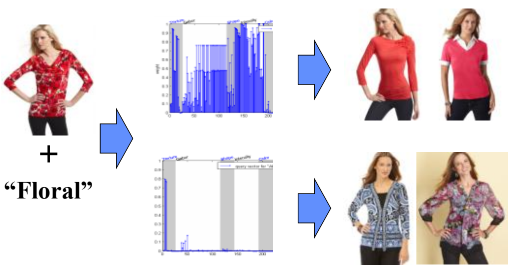
- CBIR-query vectors



Query expansion and search

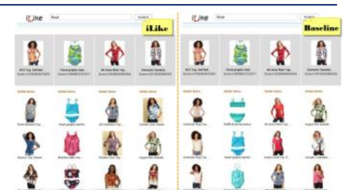
- iLike-query vectors

Results



Results

- iLike: our approach
- Baseline: Pure CBIR
- Query: "floral"



We are able to infer the implicit user intension behind the query term, identify a subset of visual features that are significant to such intension, and yield better results.

Visual thesaurus

- Statistical similarities of the visual representations of the text terms

Table 1: visual thesaurus

Words	First Few Words in Visual Thesaurus
\feminine	bandeau, hipster, breezy, pregnancy, hem, lifestyle, braid, comfy, femininity
\flirty	flirt, bikini, vibrant, effortlessly, pointelle, dressy, edgy, splashy, swimsuit
\gingham	subtle, sparkly, floral, gauze, glamour, sassy, surplice, beautifully, pajama
\trendy	adorn, striking, playful, supersoft, shiny, nancy, ladylike, cuddly, closure
\pinstripe	smock, sporty, khaki, pleat, oxford, geometric, gauzy, ruffle, chic, thong
\embroider	suede, crochet, versatility, ultra, corduroy, spectrum, softness, faux, crease
\twill	complement, plaid, contour, logo, decorative, buckle, classically, tagless

Conclusion and future work

- iLike: find the "visual perception" of keywords
- Better recall compared with text-based search
- Better precision: understand the needs of the users

- Better "understanding" of keywords: NLP?
- More features?
- Segmentation: feature+region?

Thank you!

Questions?