A preliminary study on estimating word imageability labels using Web image data mining

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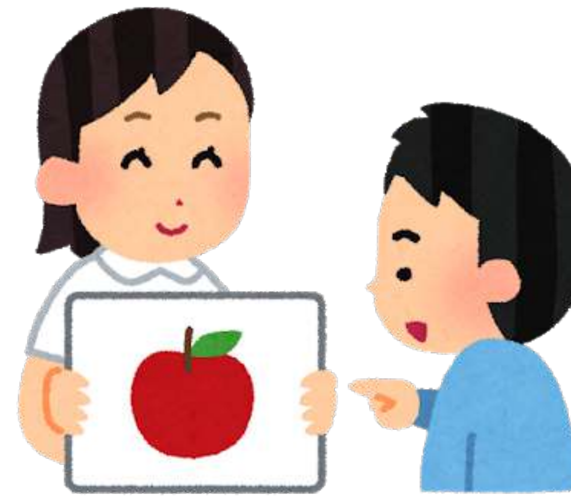
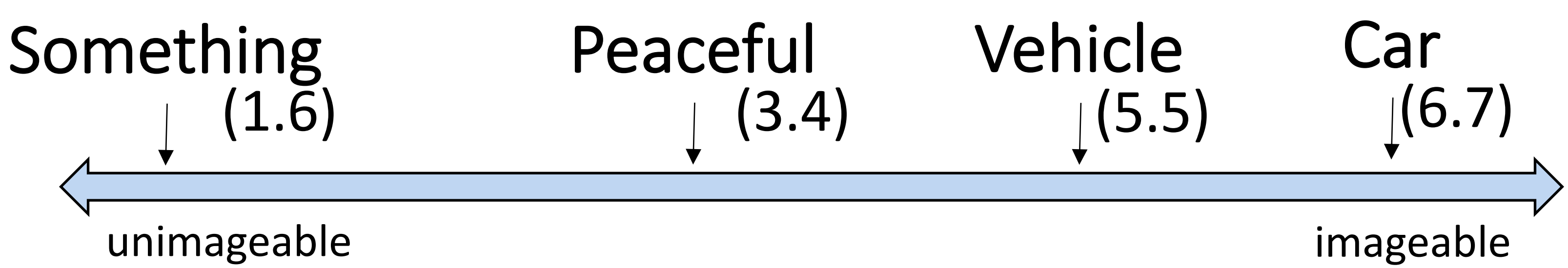
心像性

Imageability of words



- Concept from Psycholinguistics [1]
  - Quantize the perception of words
  - Often described on Likert scales
    - *Unimageable <-> Imageable* or *Abstract <-> Concrete*
  - Is a concept imageable? Do you have a mental image when thinking of a concept?

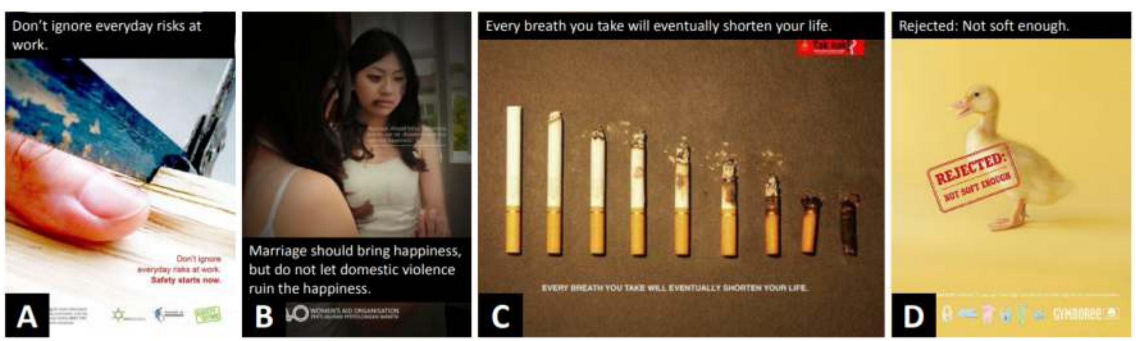


1: Pavio et al. Concreteness, imagery, and meaningfulness values for 925 nouns. J Exp Psych 1968

Applications of imageability

- Imageability is used in Psycholinguistics research
  - Influences how children learn and use grammar [2]

- Multi-modal approaches using text + image
  - Analyzing relationship of slogan and image for advertisements [3]



2: Smolik et al. The power of imageability: How the acquisition of inflected forms is facilitated in highly imageable verbs and nouns in Czech children. J First Lang 2015

3: Zhang et al. Equal But Not The Same: Understanding the implicit relationship between persuasive images and text. BMVC 2018

Motivation

- There are existing imageability dictionaries for English, Japanese and some other languages
  - Datasets are small, only for a few thousand words
  - Most dictionaries are created by hand
    - Extension is very labor intensive
    - Data often republished or reshuffled, but rarely increased

- Idea: **Estimate the imageability scores** to extend existing dictionaries by data-mining

Why use images?

- Imageability: How an average person imagines concepts (mental image)
- Social media: How common people self-annotate their perceived world by uploading images

- Core assumption
  - Relationship between imageability of words and visual characteristics of crowd-sourced images from social media

Crowd-sourced images from people
=> Average mental image

Purpose

- Estimate an imageability score for a word based on its visual characteristics
  - Mine image-data crawled for each word
  - Train regression model to estimate score based on visual features

Input:
Images for “leaf”

Data mining

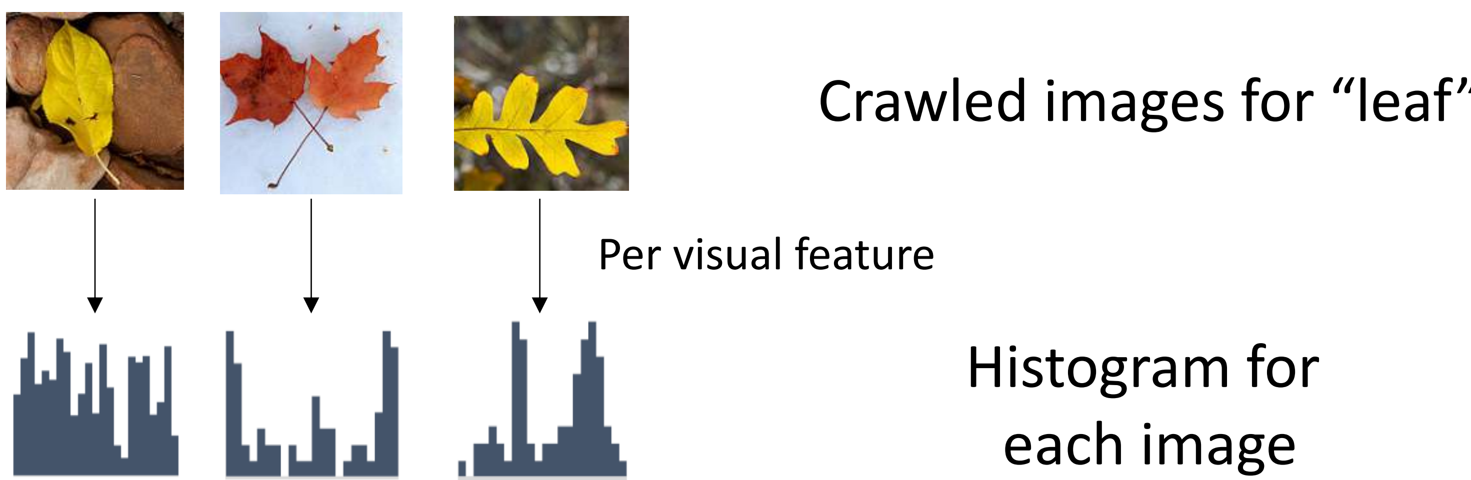
$I_{\mathrm{leaf}} \in [1,7]$

Output:
Imageability score for “leaf”

Approach

Extracting visual features

- For each word, crawl image data from social media
- Then, extract visual features from each image
  - E.g. Color histograms, Bag-of-Visual-Words histograms, ...



Approach

Cross comparison of images

- Cross-compare all images of same word
- Create similarity matrix containing similarity between all image pairs

Using visual feature histograms

Cross comparison between all images for “leaf” (using histogram similarity)

$$\begin{bmatrix} 1.0 & 0.3 & \cdots \\ \vdots & \ddots & \vdots \\ 0.7 & \cdots & 1.0 \end{bmatrix}$$

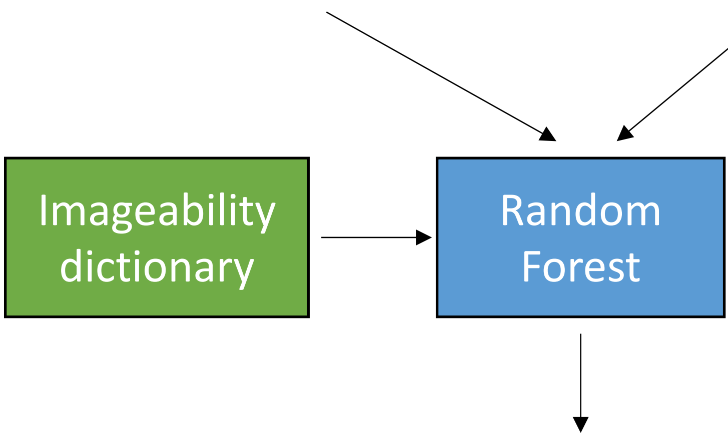
Similarity matrix per visual feature

Approach
Regression model

- Random forest based on visual characteristics
  - Train model on eigenvalues of similarity matrix
  - Use imageability dictionary as ground-truth

$$\begin{bmatrix} 1.0 & 0.5 & \cdots \\ \vdots & \ddots & \vdots \\ 0.1 & \cdots & 1.0 \end{bmatrix} \qquad \begin{bmatrix} 1.0 & 0.3 & \cdots \\ \vdots & \ddots & \vdots \\ 0.7 & \cdots & 1.0 \end{bmatrix}$$

Similarity matrix
for each visual feature



$$I_{\text{leaf}} \in [1,7]$$

Output:
Imageability for “leaf”

Input:
Images for “leaf”

For each visual feature

Histograms

Cross comparison between all images for “leaf”

$$\begin{bmatrix} 1.0 & 0.3 & \cdots \\ \vdots & \ddots & \vdots \\ 0.7 & \cdots & 1.0 \end{bmatrix}$$

Similarity matrix

Train on eigenvalues

Imageability dictionary → Random Forest

Regressor

$I_{\text{leaf}} \in [1,7]$

Output:
Imageability for “leaf”

Experiment

- Objective: Predict imageability for a set of words

- Using dataset of 577 words and 5,000 images each
  - Training: 462 words, Testing: 115 words

- Evaluation metrics
  - Mean Average Error
  - Pearson Correlation

Experiment: Datasets

- Imageability dictionary for ground-truth
  - Merged from [4] + [5]
  - Score from 1.0 (unimageable) to 7.0 (imageable)

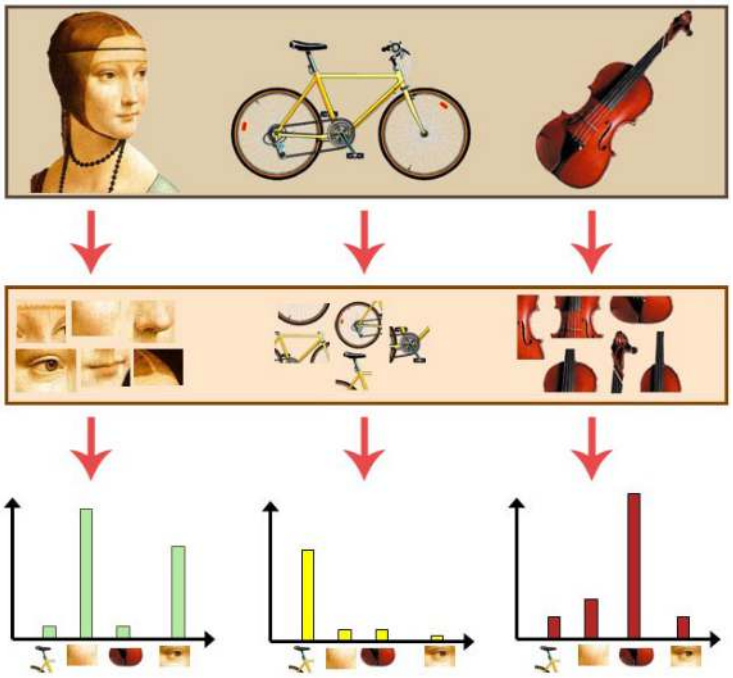
- Image dataset
  - Using YFCC100M [6] data (based on social media Flickr)
  - Crawled all images where a word from dictionary appears in meta data (such as title, description, tags)

4: Cortese et al. Imageability ratings for 3,000 monosyllabic words. Behav Res Method 2004
5: Reilly et al. Formal distinctiveness of high- and low-imageability nouns: analyses and theoretical implications. Cogn Sci 2007
6: Thomee et al. YFCC100M: The new data in multimedia research. CACM 2016

Experiment: Visual features

1. Color histogram
   - Overall color distribution based on HSV color space

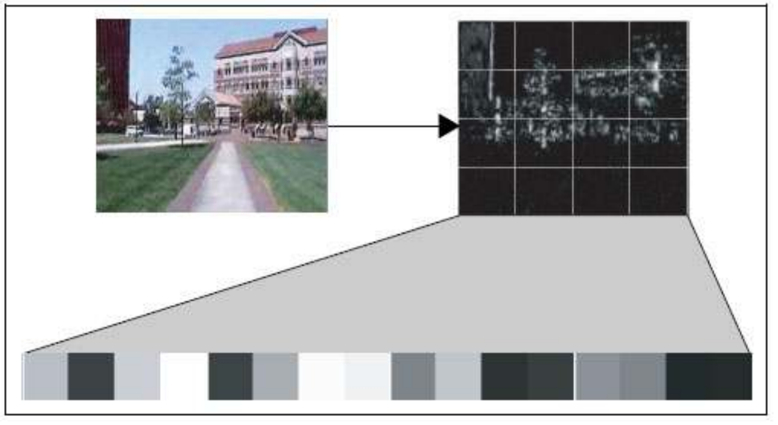
2. Bag-of-Visual-Words using SURF descriptors
   - Local feature transformation, used for object detection
   - Encoding shared patterns



https://towardsdatascience.com/bag-of-visual-words-in-a-nutshell-9ceea97ce0fb

Experiment: Visual features

3. GIST descriptors
    - Global gradients within images
    - Often used for scene analyses



http://ilab.usc.edu/siagian/Research/Gist/Gist.html

Evaluation: Results

- Estimating imageability for test data
  - Normalized to [0,100] for understandability

Feature	MAE	Correlation
(1) Color	11.78	0.56
(2) BoVW/SURF	12.53	0.55
(3) GIST	13.09	0.45
Combined	**11.68**	**0.62**

Evaluation: Examples

- A selection of low- and high- imageability words
  - Interval [100,700] for comparison with ground-truth

Type	Word	Predicted value (Ground-truth)
High imageability	coast	**5.78** (5.88)
	dusk	**5.85** (5.75)
Low imageability	doing	**3.07** (2.50)
	review	**4.22** (3.20)
Outliers	fauna	**5.35** (2.70)
	e-mail	**4.44** (6.70)

Discussion

- Tendency of imageability is correct for majority of words
- Features can complement each other to improve overall performance
- Method works better for high-imageability words
    - More abstract concepts are harder to grasp
    - More visual features are needed

Conclusion

- Proposed a method to estimate the imageability of words
  - By analyzing the visual characteristics of Web-crawled images from social media
  - Estimated imageability with an error of 11.68%

- Future work
  - Increase size of dataset
  - Use high-level features in addition to low-level features

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