

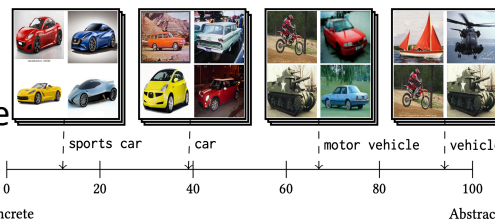
Background

Semantic gap problems

- Missing information between computer representation and human perception
- Often an issue in word choice problems and resulting in unnatural results

Psycholinguistics looks at perception of words:

- Up to nine different measures per word ...
- ... but dataset creation is manual and labor intensive



In my doctoral studies I analyzed the mental image of concepts for use in multimedia modeling

Relative measurements

Idea: Data mine visual features to quantify feature variety across related words

- E.g. compare variety of *car* vs. *sports car* vs. *vehicle*
- Analyses quickly showed bias in existing datasets

Proposed method: Improve dataset by recomposing existing datasets

- Create hypernym datasets based on their hyponyms
- Use a Web-based ratio to determine composition
- Lastly, cluster feature space to determine number of visually distinct concepts



Sub-concept	Popularity
sports_car	27.4%
racer	9.2%
model_t	8.8%
coupe	6.9%
used-car	6.7%
jeep	5.0%
...	...

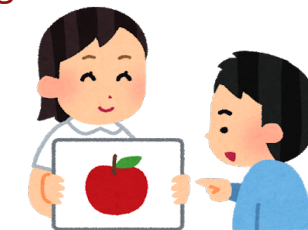


Corpus	Correlation (1 = best)	MSE (0 = best)
Plain ImageNet (Baseline)	0.25	10.54
Equal weighting (Comparative)	0.62	9.23
Popularity weighting (Proposed)	0.73	9.01

Core ideas

Try to quantify semantic gap before solving it

- Use visual data mining to estimate visual variety differences across datasets
- Estimate perception of concepts without manual labor needed



Applications

- Word choice problems like retrieval or tagging
- Increase vocabulary of psycholinguistics dictionaries

Absolute measurements

Idea: Data mine visual features for words in an imageability dictionary

- Score words from 1 (unimageable) to 7 (imageable)
- Regress such a scoring using images
- **Proposed method: Gain visual information across low- and high-level features**



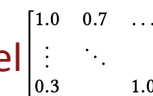
Input: n images for a term x

Visual feature extraction



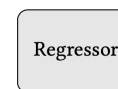
Histogram

Cross comparison within image set



Similarity matrix

Set of top eigenvalues



Regression of imageability

cat \in [100, 700]

Output: Imageability for x

- **Low:** Patterns or colors
- **High:** Objects or concepts

Feature	Correlation (1 = best)	MAE (0 = best)
L1: Color histograms	0.53	11.30
L2: SURF + Bag of Words	0.54	11.48
L3: GIST	0.42	12.05
H1: Image theme (YFCC100M-based)	0.62	10.19
H2: Image content (YOLO-based)	0.43	12.55
H3: Image composition (YOLO-based)	0.25	13.98
Combined (Proposed method)	0.63	10.14
Local visual variety approach [3]	-0.01	67.31