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Modelling Form-Meaning Systematicity with Linguistic and Visual Features

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Linguistic Arbitrariness

Hockett and Hockett (1960)

“The word ‘salt’ is not salty nor granular; ‘dog’ is not canine; ‘whale’ is a small word for a large object; ‘microorganism’ is the reverse.”

Gasser (2004)

”Arbitrariness becomes necessary as the number of words increases... there are more ways to avoid ambiguity in an arbitrary language”

Non-Arbitrariness: Form-meaning Systematicity

- Phonaesthemes (Otis and Sagi, 2008; Hutchins, 1999)

GL-	VISION / LIGHT	*glimmer, glisten, glitter, gleam, glow, glare, glint*
SN-	MOUTH / NOSE	*snore, snack, snout, snort, sniff, sneeze*

- Recent research suggests systematic structures (Shillcock et al., 2001; Monaghan et al., 2014), but:

  1. How strong is this systematicity?

  2. To what extent is this systematicity clustered?

Why we should use visual information

- Past research into form-meaning systematicity used textual corpora to model meaning
- Semantic concepts have a visual component in human language processing (Zwaan and Madden, 2005)
- Semantic models can be improved by incorporating visual information (Bruni et al., 2014; Kiela and Bottou, 2014)

Alice went to see the apple **tree** in the garden

Our task:

Gain insight into the structure of form-meaning systematicity, using multimodal semantic models

1. Our methods for investigating systematicity and constructing semantic models
2. Experimental setup
3. Results
4. Conclusion and Future research

Kernel Regression

- Predictor variable: Word
- Target variable: Semantic representation

Tree

Measuring String-Distance

- Levenshtein edit-distance
- Optimize weighting for differential semantic relevance (Gutiérrez et al., 2016)

$$d(s_i, s_j) = \sum_{s=1}^{S}(W_s * V_{ijs}) = W^T V_{ij} \tag{1}$$

Text-based Semantic Model

Skip-gram with Negative Sampling (Mikolov et al., 2013)

- Learn word vectors from contextual use in a large text corpus
- Maximize corpus-probability by optimizing semantic vectors

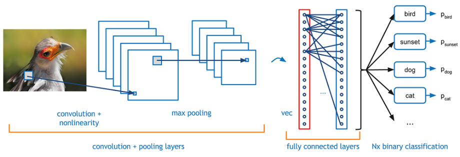
Climate Change: What is being done around the world to plant trees?

Image-based Semantic Model

Convolutional Neural Networks (Krizhevsky et al., 2012)

Train a network of 5 Convolutional layers, 3 max-pooling layers, and 3 fully connected layers on image-classification

1. Provide 10 images per word as input
2. Do a forward pass and extract pre-final layer
3. Aggregate



Multimodal Semantic Models

Scoring-Level Fusion

- Perform Kernel-Regression Separately
- Compute semantic distance as a weighted average
- Optimize weighting factor (0.75)

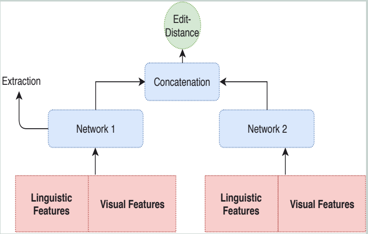
Multimodal Concatenation

- Normalize and concatenate semantic representations
- Optimize weights on the multimodal representations

Multimodal Semantic Models

Neural Network Fusion

- Predict Levenshtein distance
- Extract pre-final layer



Experimental Setup

Lexicon

4479 Monomorphemes

Measuring Corpus-wide Systematicity

Mantel Permutation test for pairwise distances

Identifying Systematic Clusters

Predictability as a measure for systematicity

Quantitative Results

Model	Correl.	p-value
Text-based	0.0362	< 0.001
Image-based	0.0198	0.025
Scoring-level fusion	**0.0401**	< 0.001
Multimodal concat	0.0351	< 0.001
Neural Network fusion	0.0175	< 0.001

Table: Correlations between unweighted Levenshtein distance and semantic distance

Model	Correl.	p-value
Text-based	0.0383	< 0.001
Image-based	0.0243	0.007
Scoring-level fusion	**0.0420**	< 0.001
Multimodal concat	0.0376	< 0.001
Neural Network fusion	0.0266	< 0.001

Table: Correlations between weighted Levenshtein distance and semantic distance

Qualitative Results

Ph	Systematic Words
sn-	sneeze, sniff, snore, snort, snout
pe-	pea, peach, pear, pearl, pebble

Table: Phonaesthemes (text-based model): 22 total

Ph	Systematic Words
cr-	crab, crawl, creep, crouch
si-	sight, sign, silhouette, simulate

Table: Phonaesthemes (multimodal concatenation): 10 total

Conclusion

Systematicity

Our findings corroborate the existence of form-meaning systematicity, and its clustered nature

The importance of a Multimodal approach

Incorporating visual information can increase the level of systematicity identified, and capture novel relations between form and meaning

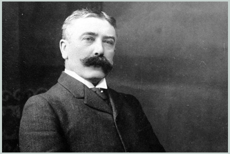
Future Research

How systematic is our language? (and why)

- Is systematicity universal accross languages?
- Why is language systematic?

Expanding the multimodal approach

- Advanced fusion methods
- Incorporating new modalities



(De Saussure, 1916)

"Everything that relates to language as a system must be approached from this viewpoint: the limiting of arbitrariness. This is the best possible basis for approaching the study of language"

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Weight-optimization for Kernel Regression

Predict target variable based on local structure in predictor variable

$$\hat{y}(x_j) = \frac{\sum_{i \neq j} k_{ij} * y_j}{\sum_{i \neq j} k_{ij}}, \tag{2}$$

Kernel penalizing distance

$$k(x_i, x_j) = exp(-d(x_i, x_j)/h) \tag{3}$$

Weight-optimization for Kernel Regression

Mean squared error

$$\mathcal{L} = \sum_{i=1}^{N} ((y_i - \hat{y}_i)^T (y_i - \hat{y}_i)) \tag{4}$$

Gradient

$$\frac{\partial \mathcal{L}}{\partial W} = \frac{2}{N} * \sum_{i=1}^{N} (y_i - \hat{y}_i) * \frac{\sum_{j \neq i} (y_j - \hat{y}_i)^T k_{ij} v_{ij}}{\sum_{j \neq i} k_{ij}} \tag{5}$$

Skip-Gram with Negative Sampling

Objective

$$\sum_{(w,c)\in D} \log \frac{1}{1+e^{-v_c * v_w}} \tag{6}$$

Avoid trivial solution

$$\forall (w,c) \in D' [(w,c) \notin D] \tag{7}$$

Final objective

$$\sum_{(w,c)\in D} \log \frac{1}{1+e^{-v_c * v_w}} + \sum_{(w,c)\in D'} \log \frac{1}{1+e^{v_c * v_w}} \tag{8}$$

Convolutional Neural Network

- 5 Convolutional layers
- 3 Max Pooling layers
- 3 fully connected layers
- One Softmax layer
- ReLU