# Vision and Feature norms: Improving automatic feature norm learning through cross-modal maps

## **Feature norms**

- Also referred to as property norms
- Datasets constructed by asking participants to identify the most important attributes of a concept (McRae et al., 2005; Devereaux et al., 2013)

 BANANA	CELLO	SHOE
is_yellow, 29	a_musical_instrument, 26	made
a_fruit, 25	has_strings, 16	has_he
is_edible, 13	made_of_wood, 16	worn_c
is_soft, 12	found_in_orchestras, 13	has_la
grows_on_trees, 11	is_large, 13	worn_f
eaten_by_peeling, 10	requires_a_bow, 9	has_hi

## Task

- We focus on automatic prediction of conceptual properties
- Properties of concepts are important for:
- Evaluating models of conceptual representation in cognitive science
- Study of multi-modal semantic models (used as proxy for perceptual information)

### Solution

- Observation: a large proportion of information contained in property norm datasets can be attributed to extra-linguistic modalities
- >25% of features are visual (is\_black, is\_white, has\_a\_motor, made\_of\_lace) Solution: learn to predict property norms through cross-modal mappings
- from raw perceptual information (i.e. image data)

### Data

### For all McRae concepts we obtain:

- Attribute-based representations
- PROPNORM: by treating the McRae dataset as a bag-of-properties (dimensions: properties, counts: production frequencies)
- Image representations
- VISUAL: by extracting the pre-softmax layer from a forward pass in a convolutional neural network that has been trained on the ImageNet classification task using Caffe (Jia et al., 2014)
- Linguistic representations
- DISTRIB: 10K dimensional count-based distributional vectors
- SVD: 300-dimensional SVD reduced version of DISTRIB
- EMBED: pre-trained word embeddings (Mikolov et al., 2013)

Multi-modal representations (concatenation of L2-normalised visual and linguistic vectors):

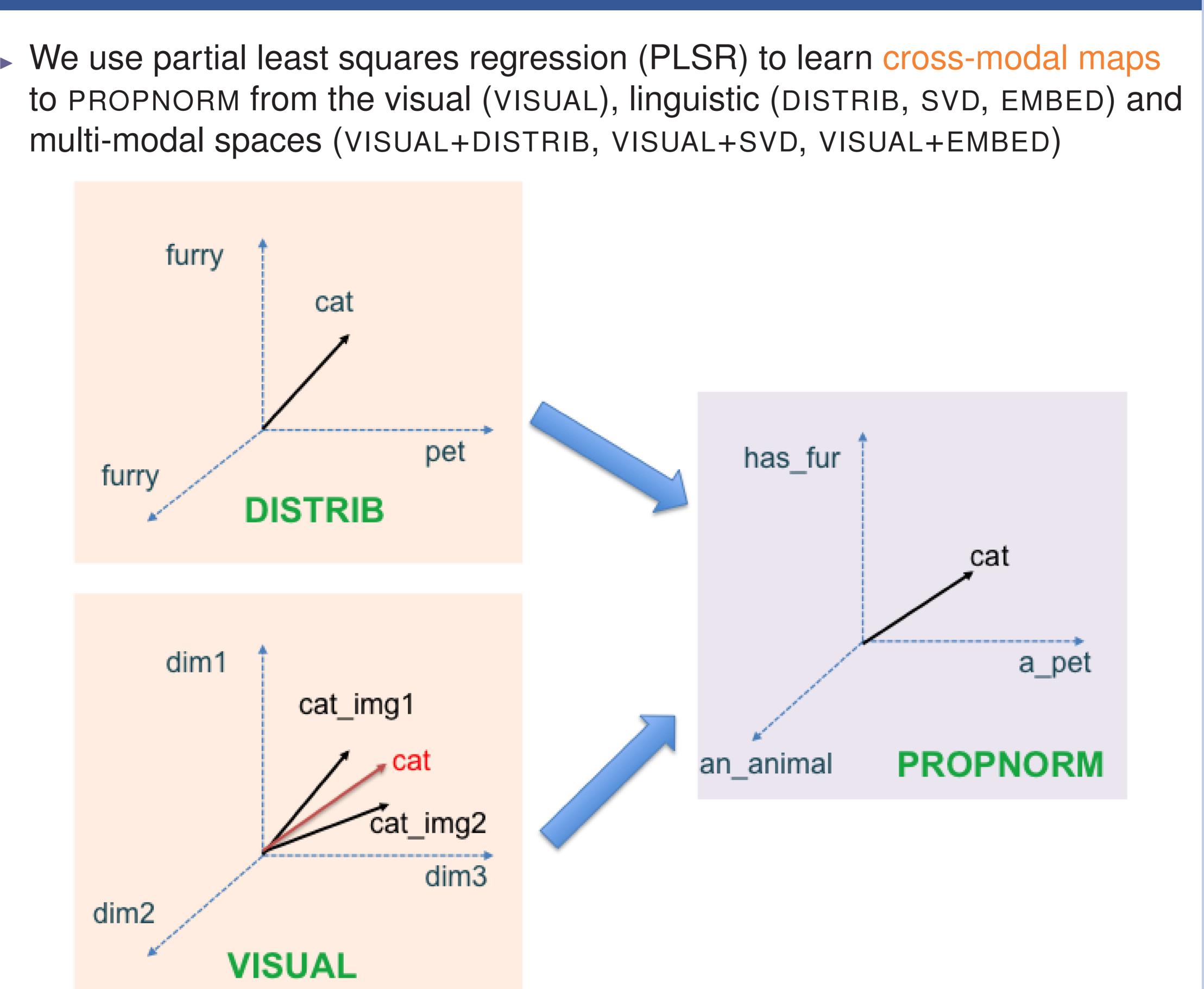
► VISUAL+DISTRIB, VISUAL+SVD, VISUAL+EMBED

Luana Bulat, Douwe Kiela and Stephen Clark

### ES

of\_leather, 24 neels, 15 \_on\_feet, 13 aces, 13 \_for\_protection, 11 high\_heels, 10

### Method



We use the zero-shot learning procedure: for each of the 541 concepts in McRae, we train a mapping on the remaining 540 concepts and record whether the correct label is retrieved among the top N neighbours

# **Evaluation**

within the top N highest ranked nearest neighbors.

# **Experimental Results**

From	P@1	
DISTRIB	1.30	
SVD	2.79	
EMBED	3.90	
VISUAL	3.35	
VISUAL+DISTRIB	2.60	
VISUAL+SVD	2.97	
VISUAL+EMBED	3.16	
RANDOM	0.0	

Computer Laboratory, University of Cambridge, United Kingdom

Average percentage correct at N: proportion of test instances that are ranked

	1	
P@5	P@10	P@20
6.88	16.54	26.58
22.12	38.10	57.99
23.42	36.80	55.02
28.44	47.96	64.50
23.23	39.41	56.13
28.44	50.74	65.43
28.44	51.12	65.06
0.74	2.42	3.90
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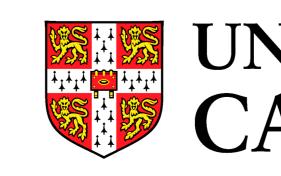
# Qualitative results

Concept	Nearest neighbours (from VISION)
banana	banana, lemon, corn, pear, grapefruit, pineapple
crocodile	alligator, crocodile, frog, turtle, iguana, toad
cello	violin, guitar, banjo, harp, harpsichord, cello, flute
drum	pot, pan, coin, skillet, bucket, peg, cap_(bottle)
OX	fox, cougar, coyote, deer, mink, elk, chipmunk
harpoon	sword, machete, harpoon, dagger, rifle, knife, gun
pants	jeans, trousers, pants, shirt, blouse, jacket, coat
Concept	Top predicted features (from VISION)
banana	is_yellow, is_black*, is_round, is_long, a_fruit
rocodile	is_green, an_animal, lives_in_water, behswims
ello	has_strings, a_musical_instrument, made_of_wood
drum	made_of_metal, is_round, used_for_cooking*
OX	an_animal, is_fast, is_small, has_fur, has_a_tail
arpoon	made_of_metal, a_weapon, is_sharp, is_dangerous*
oants	clothing, has_buttons, is_blue*, different_colours

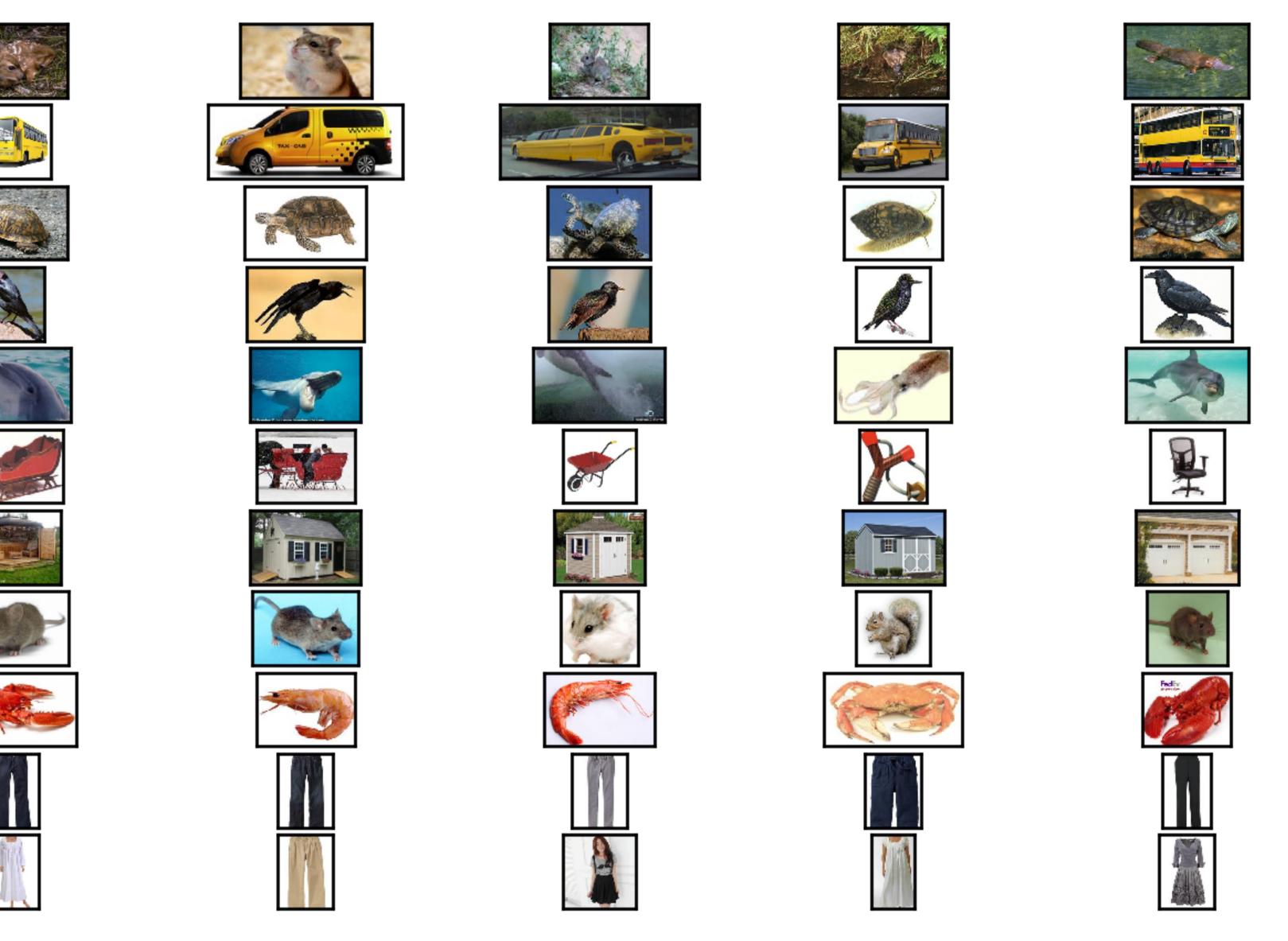
# Property based query engine



### Conclusion



We can learn how concepts look like based on their properties, by learning a cross-modal map from PROPNORM to VISUAL.



Raw visual information (images) is a better predictor for conceptual properties than linguistic input (text).

UNIVERSITY OF CAMBRIDGE

