Context matters: evaluation of target and context features on variation in object naming

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1 Aims

- Explore feature representations for object naming task
- Investigate if target object and/or context representations encoded with either linguistic or visual information or both capture variation and uncertainty in human object naming

2 Question

- What is the set of features that allows a computational model of object naming to closely capture the variation in human object naming?

3 Task formulation

Dataset: Many Names (Silberer et al., 2020)

Example image with the target object in the red box

Frequencies of names humans assigned to the target object:

`car`: 32,
`vehicle`: 2,
`automobile`: 1

Task: given a feature representing either the target or the context objects, predict the most likely name for the target object

4 Model and input features

We use CLIP (Radford et al., 2021) to encode both linguistic and visual features.

Our model is a simple linear classifier, which takes input features and predicts a single name.

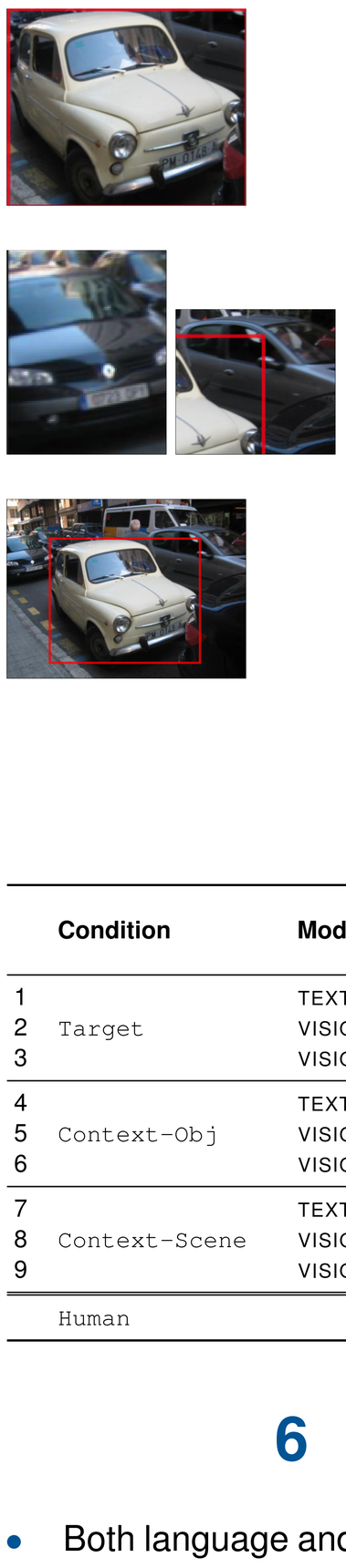
$$\hat{\mathbf{y}} = \sigma\big(\,(\mathrm{f}_2\,(\mathrm{f1}\,(\mathbf{x}))\,)\,\big), \tag{1}$$

where

$$\mathrm{f}_1(\mathbf{x}) = \mathrm{ReLU}\,(\mathrm{BN}\,(\mathbf{W}_1\,\mathbf{x} + \mathbf{b_1})\,), \tag{2}$$
$$\mathrm{f}_2(\mathbf{x}') = \mathrm{Dropout}\,(\mathbf{W}_\mathrm{w}\,\mathbf{x}' + \mathbf{b_2}) \tag{3}$$

Input features:
`Target`, `Context-Obj`, `Context-Scene`

Vision



Text
from Visual Genome (Krishna et al., 2017)

sedan

black car, big van, . . .

man on the street, car next to the street, . . .

5 Results

	Condition	Mode	Accuracy (%) ↑ @1	@5	@10	AMR ↓	PP ↓	H ↓	ρ
1		TEXT	69.15	87.68	89.94	41.45	4.745	0.210	0.540*
2	`Target`	VISION	56.70	81.09	86.34	52.87	7.199	0.266	0.485*
3		VISION-TEXT	70.02	90.99	92.30	33.77	3.740	0.178	0.574*
4		TEXT	40.90	67.58	76.73	52.13	14.924	0.365	0.343*
5	`Context-Obj`	VISION	49.14	75.14	83.20	40.79	10.360	0.315	0.328*
6		VISION-TEXT	46.48	72.98	81.04	45.87	11.531	0.330	0.321*
7		TEXT	4.09	16.85	31.80	59.00	51.111	0.531	-0.024
8	`Context-Scene`	VISION	47.93	73.51	81.42	60.73	9.116	0.298	0.410*
9		VISION-TEXT	53.34	77.91	83.98	38.87	8.281	0.285	0.424*
	`Human`						**1.623**	**0.065**	**1.000**

6 Conclusions

- Both language and vision are important for human-like object naming variation
- Knowledge about the target object (specifically, background knowledge) is highly important
- Context representations matter: full image content is better than object-level segmented contexts (for more, check the paper)

References

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