Resilience through Scene Context in Visual Referring Expression Generation

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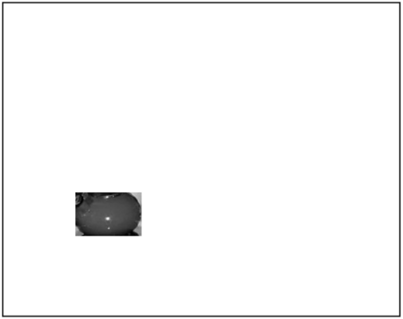

(a)

(from Galleguillos and Belongie 2010)

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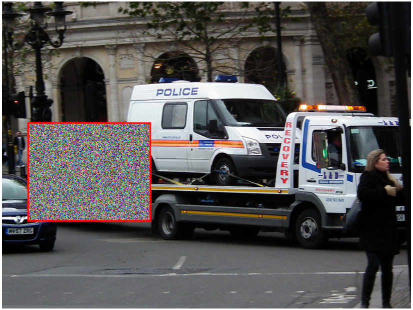
- Visual objects commonly appear in **typical surroundings** with other **related objects**
- **Scene context** helps us to process the visual world, e.g. recognize objects more quickly and reliably

- **V&L systems** also often process “real-world” scenes
  - **visual REG**: Objects in Photographs

Example from RefCOCO (Kazemzadeh et al., 2014)

- Often lots of relations between target and context!

- **V&L systems** also often process “real-world” scenes
  - **visual REG**: Objects in Photographs



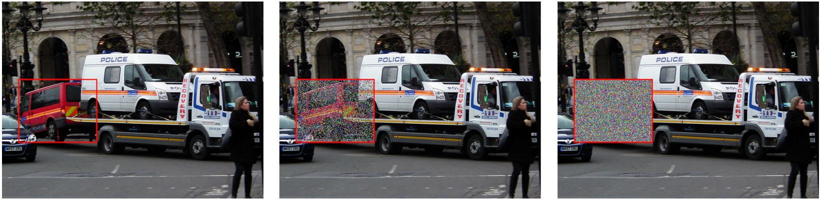
Example from RefCOCO (Kazemzadeh et al., 2014)

- Often lots of relations between target and context!

Do REG systems exploit Scene Context in similar ways?

Experimental Setup

- Question: Does scene context help REG systems to process target objects, if they are not clearly seen?
- Method: Train and test **REG systems with and without scene context** with target representations **obscured with varying degrees of random noise**



- Expectation:
  - Model performance degrades with increasing noise
  - **exploiting context mitigates the loss**

Experimental Setup / Models

Variants of two Transformer-based systems:

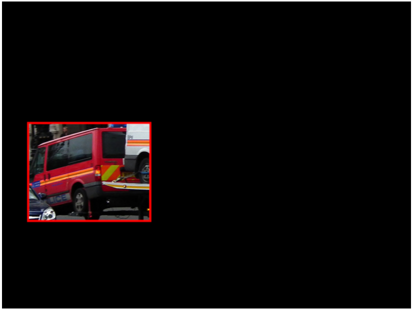
1. **TRF**: Standard Transformer (similar to Panagiaris et al. 2021)
   - ResNet as visual backbone
2. **CC**: *ClipCap* captioning model (Mokady et al., 2021) applied to the REG task
   - CLIP as visual backbone, with pre-trained GPT-2

   Here: **Only discuss TRF results**

Experimental Setup / Models

TRF_{tgt}: Target-only

- Target, but no context features
- Input: $[\mathbf{V}_t; \mathbf{Loc}_t]$
  - V_t: ResNet encodings of the target bounding box content
  - Loc_t: Target location / size relative to global image



Input for TRF_{tgt}

Experimental Setup / Models

TRF$_{vis}$: Visual context variant:

- Target + visual context features
- Input: [$\mathbf{V}_t$; $\mathbf{Loc}_t$; $\mathbf{V}_c$]
  - V_c: ResNet encoding of the global image (without target)

Input for TRF$_{vis}$

Experimental Setup / Models

TRF_{sym}: Symbolic context variant

- Target + symbolic context features
- Input: $[\mathbf{V}_t; \mathbf{Loc}_t; \mathbf{S}_c]$
  - S_c: Symbolic information about **what kind of objects and stuff the context is composed of**
    - e.g. 25 % street; 15 % vehicles; 15 % buildings; ...

$$+ \begin{bmatrix} 0.25 \\ 0.15 \\ 0.01 \\ 0.00 \\ 0.15 \\ 0.00 \\ \cdots \end{bmatrix}$$

Input for TRF_{sym}

S_c features based on dense 2D maps for Panoptic Segmentation (Kirillov et al., 2018)

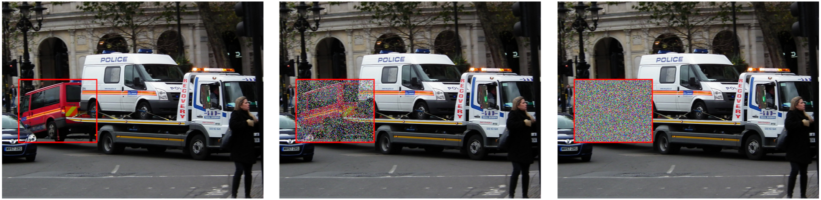
$\rightarrow$ Details in paper

Experimental Setup / Models

All variants are trained and tested for three noise settings:

- **0.0** $\rightarrow$ no noise
- **0.5** $\rightarrow$ 50 % of target bounding box replaced with noise
- **1.0** $\rightarrow$ full target bounding box replaced with noise (no visual target information)

We always use the same setting for training and evaluation.



Results

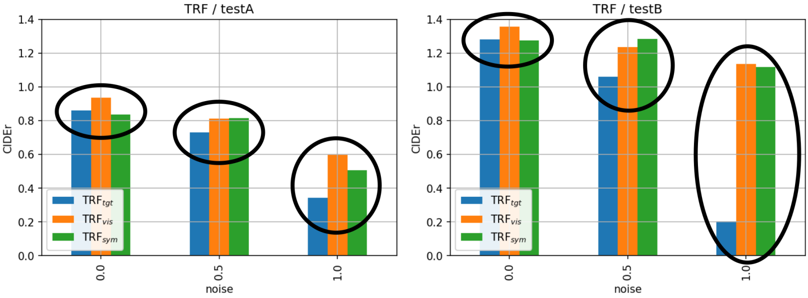
	TRF_{tgt}	cow (A)
noise 0.0	TRF_{vis}	left cow (A)
	TRF_{sym}	cow on left (A)

	TRF_{tgt}	cow (A)
noise 0.0	TRF_{vis}	left cow (A)
	TRF_{sym}	cow on left (A)
	TRF_{tgt}	white horse (F)
noise 0.5	TRF_{vis}	cow on left (A)
	TRF_{sym}	cow (A)

noise 0.0	TRF_{tgt}	cow (A)
	TRF_{vis}	left cow (A)
	TRF_{sym}	cow on left (A)
noise 0.5	TRF_{tgt}	white horse (F)
	TRF_{vis}	cow on left (A)
	TRF_{sym}	cow (A)
noise 1.0	TRF_{tgt}	man (F)
	TRF_{vis}	left cow (A)
	TRF_{sym}	cow on left (A)

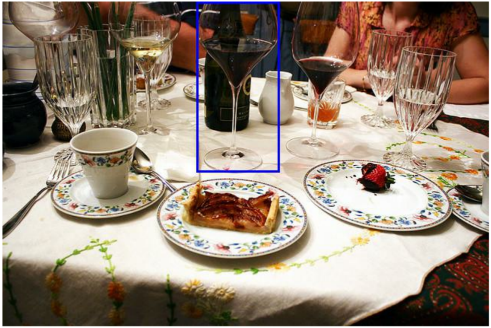
Results: CIDEr/BLEU

- context very effective for compensating noise
  - scores drop with increasing noise, but mitigated by context
  - visual context more effective than symbolic context
- differences between testA (humans) and testB (other objects)
  - target-only suffers less on testA
    - $\rightarrow$ human referents are very frequent
  - context is more helpful on testB
    - $\rightarrow$ other objects are more varied, but appear in more specific contexts



Human Evaluation

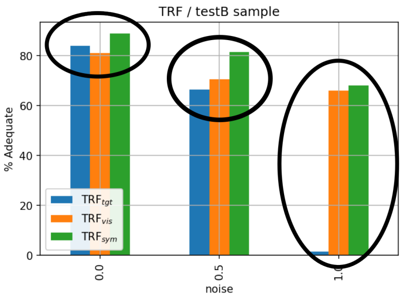
- 200 item sample from RefCOCO testB
- Instruction: Rate the expression parts which refer to the object type (e.g. “a black **dog**”)



Adequate:	wine glass
False:	fork
Misaligned:	bottle
Omission:	thing in center

Results: Human Evaluation

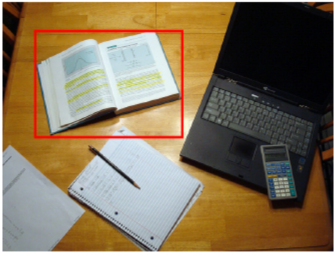
- context again very effective for compensating noise
  - Adequacy rates drop with increasing noise, but mitigated by context
  - symbolic context is more effective than visual context
- identification with only context works surprisingly well: 68 % for TRF_{sym} with full occlusion!



How exactly does context improve the predictions?

Copying Strategy

- Observation: Systems often predict referent types which are also present in the surrounding scene
- Often effective, as many objects tend to appear in groups



	TRF_{tgt}	top left (O)
noise 1.0	TRF_{vis}	left laptop (F)
	TRF_{sym}	laptop on left (F)

Copying Strategy: Statistical Analysis

- is exploiting context more effective if the target class is present in the scene?
- **correlation study**: adequacy of descriptions vs. context area covered by target class
- results: systems rather pick the correct target class, if objects of the same type are present in the context

	noise	corr.	p
TRF_{tgt}	0.0	0.128	–
TRF_{vis}		0.109	–
TRF_{sym}		0.154	< 0.05
TRF_{tgt}	0.5	0.071	–
TRF_{vis}		0.186	< 0.01
TRF_{sym}		0.157	< 0.05
TRF_{tgt}	1.0	0.046	–
TRF_{vis}		0.321	< 0.001
TRF_{sym}		0.277	< 0.001

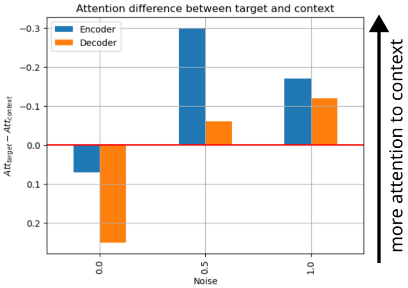
Attention Analysis (TRF$_{vis}$)

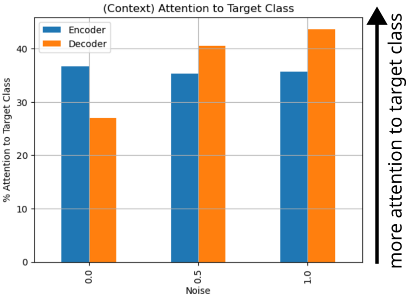
Encoder / Decoder attention to

1. target and context features
2. object types in context (target class vs. other classes)

Results:

- No clear picture for Encoder
- Decoder Attention: More attention to context and target class for higher noise

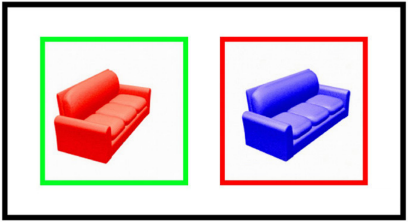




How does Scene Context fit into the REG task?

Scene Context in REG

- In classical works (Incremental Algorithm) and work on visual REG: **Distractors** taken as most relevant form of context
- considered during Content Determination: pick target properties that **do not** apply to distractor



(TUNA, van Deemter et al. 2006)

The red couch ~~facing right~~

Scene Context in REG

- **Scene context is different, but complimentary**: Which properties are **true** (not distinctive) for the target?
  - rather effects **semantic** than **pragmatic** aspects
    - (or other pragmatic aspects, e.g. Gricean Maxim of Quality instead of Quantity/Relevance)
- possibly important for subsequent pragmatic processing!

The **truck** being towed

Conclusion

Do REG systems exploit Scene Context?

- Scene Context makes models more resilient against perturbations in visual target representations
- Context affects reference generation at different levels: Can be exploited to generate distinguishing expressions **but also** to ensure that expressions are true in the first place
- Is reliance on copying strategy cognitively plausible? Perhaps not.
  - further research!

Citations I

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Citations II

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