Using visual context(s) in neural REG

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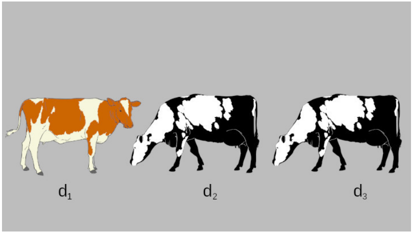
07 June 2022

Outline

- Background
  - Classical & end-to-end formulations of the REG task
  - Context in REG
- Using different kinds of visual context to...
  - Discriminate
  - Identify
  - Facilitate Understanding
  - Guide Perspectives
- Conclusion
- Questions for Subsequent Research

The REG task

- **Referring Expression Generation (REG)**: Generating expressions for entities, which allow their identification in context



Referring Expression for d_1:
"The brown / left cow"

Classical REG formulation

- Classical REG formulation: Dale and Reiter (1995)
  - Focus on **Content selection** $\rightarrow$ selecting discriminative properties
  - Entities in a domain: Represented in terms of pairs of **symbolic attributes and values**
- Subsequent research: Various extensions, e.g. accounting for multiple targets, relational descriptions, discourse context, ...

	Object	*Type*	*Color*	*Location*
$\rightarrow$	d_1	cow	brown	left
	d_2	cow	black & white	middle
	d_3	cow	black & white	right

Discriminative properties for d_1: $\{\langle color, brown\rangle\}$ or $\{\langle location, left\rangle\}$

Context in classical REG

- (Extralinguistic) context: Other entities in the current domain
- Mainly important as **Distractors** during Content Selection
  - needed to determine distinguishing properties of the target
  - **used for discrimination**, i.e. to ensure pragmatic informativity (in line with the overarching goal in REG)

	Object	*Type*	*Color*	*Location*
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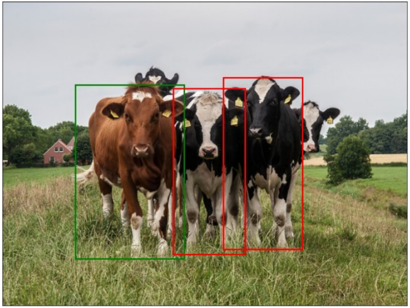
End-to-end REG modelling

- Neural REG (e.g. Mao et al. 2016; Yu et al. 2016)
  - looking at **more realistic settings**, i.e. objects in photographs (e.g. the RefCOCO dataset, Kazemzadeh et al. 2014)
  - **Encoder/Decoder** models, allowing for **end-to-end** generation
  - Closely related to image captioning, but for individual objects and with a defined pragmatic objective (i.e. refering *unambiguously*)



Context in neural REG

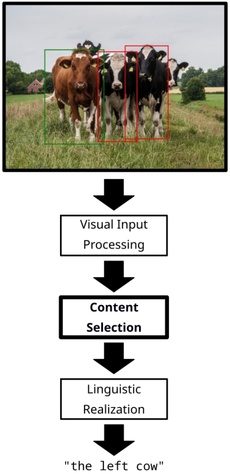
- Context in neural REG: Visual information surrounding the target
- Integration in REG models: Often as a *global feature vector*
- In general: Visual context no major concern in neural REG
  - if discussed explicitly: Mostly as *distractor* context
  - further ways to include visual context are seldom discussed (with some exceptions)

Classical vs. neural REG

- In general: Same objective, i.e. allowing the identification of the referent
- Fundamental differences in other regards:
  1. **Input Representations**:
     Symbolic vs. raw visual information
  2. **Outputs**:
     Sets of distinguishing properties vs. Full descriptions of referential targets
- Neural REG: Broader **scope of the task**
  - Classical REG task: Modelling a **specific processing stage** of a more general NLG pipeline (cf. Reiter 2000)
  - Neural REG task: Modelling a **complete (end-to-end) processing pipeline**, spanning from from perception to formulation

Classical vs. neural REG

- neural REG pipeline (conceptually) includes Content Selection, amongst other challenges:
  1. identify entities in the raw visual input
  2. select informative properties (Content Selection)
  3. formulate an utterance
     - 3.1 decide on appropriate lexical terms for depicted entities
     - 3.2 ensure that expression is easy to understand
- more sub-problems $\rightarrow$ more possibilities to integrate context!



Context in neural REG

- we argue: additional challenges in the end-to-end pipeline
  $\rightarrow$ further possibilities to integrate visual context
- we could use visual context for:
  1. **discrimination**
  2. **identification**
  3. **understandability**
  4. **choosing categorizations / conceptual perspectives**

Using Context to Discriminate

- **Distractors**: other (similar) objects in the same scene we have to distinguish the target from $\rightarrow$ at the core of the REG task itself
- Relevant for Content Selection; contextual information helps in determining distinguishing features
  - satisfying the Gricean maxim of Quantity (Grice, 1975)

Annotations:

(a) “white horse”

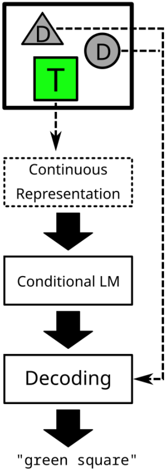
(b) “white horse”

(c) “white house”

(Example from RefCOCO)

Using Context to Discriminate

- relates to our previous work on *discriminative decoding* (Schüz, Han, and Zarrieß, 2021; Schüz and Zarrieß, 2021; Zarrieß et al., 2021):
  - integrating distractors during decoding, e.g. using the RSA model for pragmatic reasoning
  - findings: pragmatic informativity increases when distractors are given more weight
  - (as well as linguistic diversity, which was another topic of interest for us)

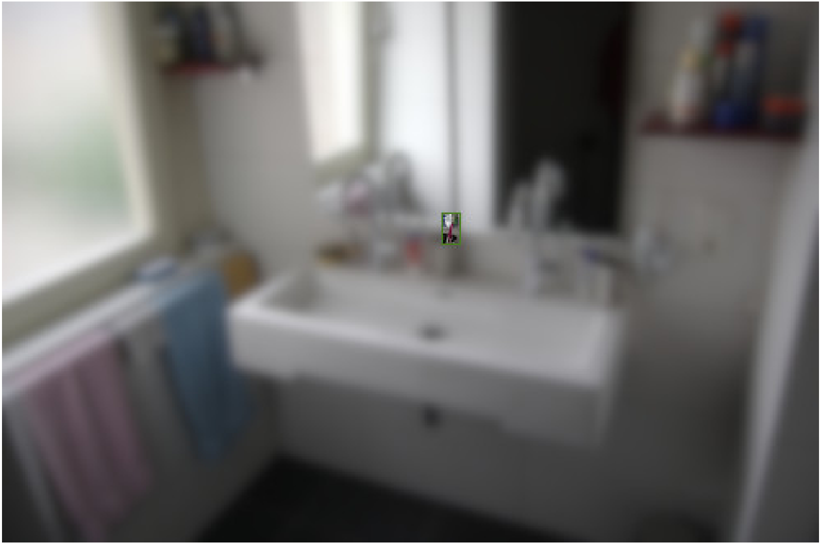


Using Context to Identify

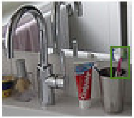
- Raw visual input makes identification a non-trivial task (e.g. Zarrieß and Schlangen 2016)
- Humans use **scene context** to facilitate identification (and other cognitive tasks, e.g. Võ 2021)
  - local features (e.g. *anchors*)
  - global features (e.g. the *gist* of a scene)
- Relevant for identification as an early stage in the neural REG pipeline
  - Especially useful for deficient visual representations (difficult lighting conditions, occlusion, small size, ...)
  - relates to specifying the *type* attribute in classical REG (Dale and Reiter, 1995)
  - satisfying the Gricean Maxim of Quality

Using Context to Identify

Using Context to Identify



Using Context to Identify



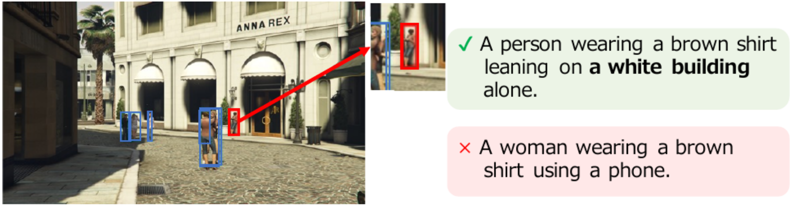
Using Context to Identify

(Example from VisualGenome)

Using Context to Facilitate Understanding

- targets with low saliency might be hard to identify, even if described unambiguously
- possible solution: guiding visual search via **landmarks**
  - i.e. describing targets via their relations to more salient objects in their surroundings
  - related to generating relational descriptions in REG (e.g. Krahmer and Theune 2002; Krahmer, Erk, and Verleg 2003)
  - investigated for neural REG as well, but without looking at visual context in detail (Tanaka et al., 2019; Kim, Ko, and Wu, 2020)
  - satisfying the Gricean Maxim of Manner

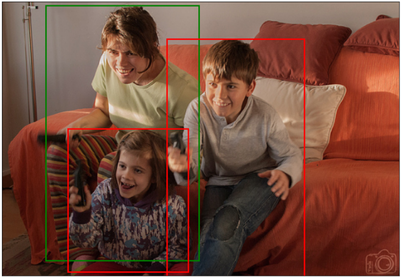
Using Context to Facilitate Understanding



Example from Tanaka et al. (2019)

Using Context to Guide Perspectives

- there are often multiple ways to **categorize and name** a referential target
- choosing a categorization $\rightarrow$ choosing a **conceptual perspective** (Gatt and Deemter, 2006; Gatt and Deemter, 2007)
- assumption: visual context can guide conceptual perspective, e.g. if surrounding objects or depicted actions suggest a certain role
  - e.g. conceptualizing a woman as *mother*, if shown as interacting with children



Annotations:
(a) “mother”
(b) “mom on left”
(c) “parent”
(Example from RefCOCO)

Conclusion

- The neural REG task became more complex: from content selection to modeling a generation pipeline
- Visual Context could play a role at different stages of this pipeline
- For neural REG, this has not been investigated in detail yet

Questions for subsequent research

- How can we assess the influence of different kinds of visual context in human annotations?
- How should visual context be represented in neural REG? (Effectiveness of global feature vectors is sometimes questioned, e.g. Yu et al. 2016; Zarrieß and Schlangen 2018)
- Can we support different stages of the neural REG pipeline by integrating different kinds of context?

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