your title

Your Name

Department of Computer Science TALP Group

Advisors: Prof. John Dr. Rosa

PhD Thesis Defense Feb 10, 2021



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Problem Identification

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Highlight with a block

A Fixed lexicon [some text].

B Lexicon free [some text].

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- D This **hybrid approach** between deep learning

Literature review block

Work addresses scene understanding, and benefit from combining text cue and visual context in image or text retrieval:

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Patel et al. (2016)

generation of new lexicon with topic modeling

Logo Retrieval

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Text detection

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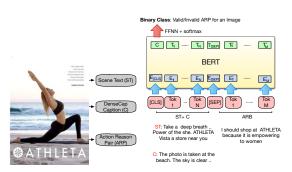
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using object information for text detection

Image

- The task involves detecting the viewer's interpretation of an Ad image captured as text.
- Fine-tune BERT is used to learn textual and visual cues.
- Google Vision API is used to extract scene text information.



Table

• The ULM is based on a combined corpu

Unique Count of Textual Data						
Dictionary	words	nouns	verb	adjectives		
Dict-90K words level	87,629	20,146	6,956	15,534		
Language model	8870,209	2695,906	139,385	824,581		

Fade out text

 The main limitation of this approach is that depends on the baseline softmax output to re-rank the most closely related word

As in the example, the semantic relatedness score suppresses unrelated words and boosts the most probably related word by simple dot product multiplication. (Visual context: parking meters)

W	Text Spotting Model		Visual Re-ranker Model	
w_1	quotas	0.5	5.4e-7	
<i>w</i> ₂	quartos	0.1	5.2e-8	
W3	quarters	0.05	9.0e-9	

Math block

Attention 1

$$c_t = \sum_{i=1}^{T} \alpha_{tj} h_j, \alpha_{tj} = \frac{\exp\left(e_{tj}\right)}{\sum_{k=1}^{T} \exp\left(e_{tk}\right)}, e_{tj} = a\left(s_{t-1}, h_j\right)$$

Attention 2

$$c_t = \sum_{i=1}^{T} lpha_{tj} h_j, lpha_{tj} = rac{\exp\left(e_{tj}
ight)}{\sum_{k=1}^{T} \exp\left(e_{tk}
ight)}, e_{tj} = a\left(\frac{e_{tj}}{e_{tj}}
ight)$$

Figure

