Co-occurrence statistics from vision and language capture thematic relationships between objects

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Introduction

How do people think about themes or events? How should we model the relationship between objects found in a theme?



People will automatically attend to thematically related objects, even if they are task irrelevant [1].

Semantic models have explained variance in response in fMRI [2] and MEG studies [3].

Methods

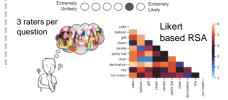
amazon mechanical turk



Averaged to find 10 most frequent items

Group 2 N = 101For each pair of the top 10 items... How likely are you to see cake and a balloon together in the

same place in the real-world?



Co-occurrence models

Different training corpuses

Same unsupervised algorithm



Newsgroup 20 [4]

18.847 articles 20 subcategories 143,802 unique nouns CBOW 300 dimensions 1000 epochs Negative sampling = 20



ADE20K [5]

17,820 pictures with all the objects labeled 572 scene categories 3,148 unique objects



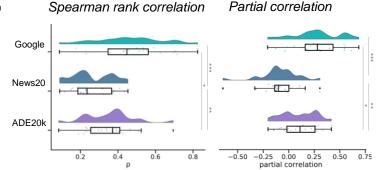
Google News [7]

1 billion articles ~3 million unique words

What model best explains the relationship between objects?

Spearman correlation between models Across themes: For one theme: "child's birthday party" Google News → News 20 M = 0.27, StDev = 0.11 Google News → ADE20k M = 0.35. StDev = 0.14 News 20 → ADE20k M = 0.34. StDev = 0.10 *RSAs are rank

Model explained variance in human ratings



Google News model explains the most

> variance in human ratings followed by ADE20k

But ADE20K does significantly better than size-matched Newsgroup 20

Conclusions

We should be thinking about using pictures to model the cooccurrence of objects in scenes

but

larger corpuses still perform the best at capturing object relationships.

[1] Malcolm, Rattinger, and Shomstein, 2016

[2] Bankson et al., 2018 [5] Zhou et al., 2017

[3] Groen et al., 2018 [6] Mikolov et al., 2013