

VISUAL QUESTION ANSWERING

Avi Singh

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IIT-Kanpur

THE PROBLEM STATEMENT

We want to answer open-ended questions about images.



What color are her eyes?
What is the mustache made of?



How many slices of pizza are there?
Is this a vegetarian pizza?



Is this person expecting company?
What is just under the tree?



Does it appear to be rainy?
Does this person have 20/20 vision?

Figure: A teaser from the VQA dataset [Antol et al., 2015]

Visual Turing Test

An AI-complete task[Malinowski and Fritz, 2014b]. The specificity of the questions enable automatic evaluation.

Helping the visually impaired

Apps like VizWiz[Bigham et al., 2010] employ humans to answer visual questions sent by visually impaired people.

VQA (VATech) [Antol et al., 2015]

750K questions on 250K images, 10 answers for every question.

Visual Madlibs (UNC) [Yu et al., 2015]

360K questions on 10K images. Lot of "high level" questions.

Toronto COCO-QA [Ren et al., 2015]

Automatically generated questions from COCO captions. 115K question. Now obsolete.

DAQUAR [Malinowski and Fritz, 2014a]

Much smaller dataset with 12K questions Now obsolete.

MODELS

THE BASELINE BOW MODEL [REN ET AL., 2015]

1. Use word2vec[Mikolov et al., 2013] to extract bag of word features.
2. Use VGG ConvNet[Simonyan and Zisserman, 2014] to extract features from image.
3. Treat the problem as multi-class classification.

LSTM-BASED MODEL[REN ET AL., 2015]

1. Reduce dimensionality of image features (down to the word vector dimensionality) and feed this into the LSTM.
2. Use word2vec[Mikolov et al., 2013] to convert every word to a vector, which is then fed to the LSTM.
3. Make predictions after the last word has been fed.



WORK DONE SO FAR

1. VGGNet-based feature extraction pipeline for images complete.
2. Word2Vec-based feature extraction pipeline text for text complete.
3. A baseline model (multinomial logistic regression with lbfgs for optimization) trained on 20K questions and evaluated on 10K questions, performance only 16% so far.




IDEAS TO EXPLORE

1. Semantic alignment between questions and images[Karpathy and Fei-Fei, 2014][Karpathy and Fei-Fei, 2015].
2. Use LSTM to encode questions, and decode answers.[Sutskever et al., 2014]
3. Neural Net architectures like Memory Networks.[Sukhbaatar et al., 2015]
4. Visual Attention [Xu et al., 2015].




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QUESTIONS?