State of the Art Presentation Visual Storytelling

CS 698N: Recent Advances in Computer Vision

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The Problem: Introduction

- Introduced by Huang et al [1] from Microsoft Research at NAACL-2016
- Problem of mapping sequential images to sequential descriptive sentences
- Aim is to generate story like narrations



Figure: Visual Storytelling vs Caption generation

Types of Tasks

Image Sequence descriptions can be produced by a variety of approaches:

- Descriptions of images in-isolation (DII)
- ② Descriptions of images-in sequence (DIS)
- Stories for images-in sequence (SIS)

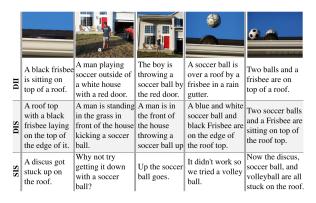
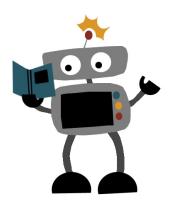


Figure: Descriptions generated by DII, DIS and SIS approaches

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Challenges

- Learning Human like narrative language
- Ability to remember long term context from images and be able to connect their ideas together
- Only Jamie Kiros' Neural Storyteller[2] comes close to achieving this using their SkipThought vectors[3]



Dataset Collection and Description

- 81,743 unique photos in 20,211 sequences with captions and narrative sequences
- Flickr API used to extract photo albums
- Amazon Mechanical Turkers used to get narrative stories and isolated captions
- Data Post-processing performed

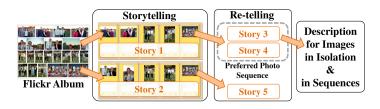


Figure: Dataset Collection Crowdsourcing Workflow

Evaluation Metrics

- Evaluating the quality of the generated stories is a non trivial task.
- Intuitive way involves comparison with good (human-made) model stories. But manual evaluation not possible for large sets.
- Need of automatic methods for such evaluations.
- Popular metrics which assign a score to the candidate (based on human-made ground truths) include BLEU, METEOR.

BLEU [4]

- Account for adequacy by calculating word-match precision, account for fluency by computing n-gram precisions
- Smaller sentences get higher scores, thus a length based penalty introduced to prevent it
- More reference human samples result in better and accurate scores
- Designed to approximate human judgement at a corpus level, and performs badly if used to evaluate the quality of individual sentences
- Example:
 - "There is a cat on the mat; The cat is on the mat" vs "the the the the the"
 - "There is a cat on the mat; The cat is on the mat" vs "the cat"

METEOR [6]

- Consistently outperforms BLEU in correlation with human judgments
- Sentence alignment takes variability into account via stemming and synonymy matching
- Combine Recall and Precision as weighted score components
- Align candidate with each reference and take score of the best pairing
- Consider the fragmentation of the candidate-reference alignment

https://www.sharelatex.com/project/57bf30d8ead3386f0bacb570

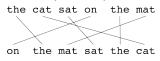


Figure: Image from Wikipedia [5]

Basic Approach

- A sequence-to-sequence recurrent neural net (seq2seq)[7] used for story generation
- Image sequence encoded by running an RNN over image representations (e.g. the activations of another pre-trained model).
 Used as the initial hidden state to the story decoder model
- The story decoder model produces the story one word at a time from the training data vocabulary
- GRUs are used as the image encoders and story decoders

Heuristics Used

- METEOR score used for comparing model performance
- Multiple heuristics used to further improve results including,
 - Lower Beam Search size
 - Avoid duplicates
 - Penalize Visually-Grounded words

Results

As discussed earlier, METEOR metric used for evaluation

Beam=10	Greedy	-Dups	+Grounded
23.55	19.10	19.21	_

Figure: Scores for generated captions per-image

Beam=10	Greedy	-Dups	+Grounded
23.13	27.76	30.11	31.42

Figure: Scores for generated stories

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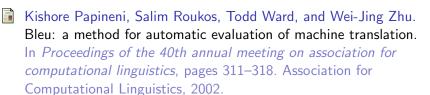
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