Generation in Image Captioning

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Overview

• The image captioning problem
• Dependency evaluation of captions (SPICE)
• Controlling generation with specialised decoding
• Summary
Image captioning

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

AIPOLY IS ABOUT TO RELEASE AN APP THAT HELPS THE BLIND "SEE" THROUGH THEIR SMARTPHONE.

SON, WOULD YOU PLEASE PASS THE SALT? DAD, WHY CAN’T YOU GET IT... IT’S RIGHT IN THE MIDDLE.

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Evaluating automatic captions using SPICE
Evaluating captions automatically

- Benchmark datasets require fast to compute, accurate and inexpensive evaluation metrics
- Good metrics can be ‘climbed’ in the development-validation loop

**The Evaluation Task:**
- Given a candidate caption $c_i$ and a set of $m$ reference captions $R_i = \{r_{i1}, \ldots, r_{im}\}$, compute a score $S_i$ that represents similarity between $c_i$ and $R_i$. 
The state of the art

- **BLEU**: Precision with brevity penalty, geometric mean over n-grams
- **ROUGE-L**: F-score based on Longest Common Substring
- **METEOR**: Align fragments, take harmonic mean of precision & recall
- **CIDEr**: Cosine similarity with TF-IDF weighting
The current state of the art

<table>
<thead>
<tr>
<th>Model</th>
<th>CIDEr-D</th>
<th>Meteor</th>
<th>ROUGE-L</th>
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<td>6</td>
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</tr>
</tbody>
</table>
False positives in N-gram based evaluation

A young girl standing on top of a tennis court.

A giraffe standing on top of a green field.
N-gram overlap isn’t necessary

• A shiny metal pot filled with some diced veggies.
• A pan on the stove with chopped vegetables
Score this caption out of 10

“A young girl standing on top of a basketball court”

How would you score this caption?
• There is girl
• Girl is young
• Girl is standing
• There is court
• Court is for basketball
• Girl is on court

These are the propositional content of the utterance
High level intuition behind SPICE

• Use a parser to identify sets of propositions in caption and gold labels

• Count the overlap between proposition sets
Related work

• **Syntactic dependency parsing**
  – Klein & Manning: *Accurate Unlexicalized Parsing*, ACL 2003

• **Scene graphs for image retrieval**

• **Rule-based mapping from dependency parse to scene graph**
  – Schuster et. al: *Generating semantically precise scene graphs from textual descriptions for improved image retrieval*, EMNLP 2015
SPICE metric calculation

- Synonymous nodes merged in $G(S)$
- Wordnet synsets used for tuple matching

\[
P(c, S') = \frac{|T(G(c)) \otimes T(G(S))|}{|T(G(c))|}
\]

\[
R(c, S') = \frac{|T(G(c)) \otimes T(G(S))|}{|T(G(S))|}
\]

\[
SPI{C}{E}(c, S) = F_1(c, S) = \frac{2 \cdot P(c, S) \cdot R(c, S)}{P(c, S) + R(c, S)}
\]
Example of scene graph

- Scene graph (right) parsed from a set of reference captions (left)
Good caption example (1)

Reference captions

"People playing with kites outside in the desert."
"A group of people at a park flying a kite."
"A group of people flying a kite on a sandy beach"
"People on the beach flying kites in the wind."
"A couple people out flying a kite on some sand."

Reference scene graph

Candidate caption & scene graph

"a group of people flying kites on a beach"

SPICE F-Score: 0.429, Pr: 0.857, Re: 0.286
Good caption example (2)

Reference captions
"A dog is sitting inside of a black suitcase"
"The bulldog is sitting inside the travel bag."
"A dog laying in a piece of black luggage."
"A dog sits in an open suitcase that is on a hardwood floor."
"A dog sitting inside an empty luggage bag on the floor"

Reference scene graph

Candidate caption & scene graph
"A dog sitting in a suitcase on the floor"

SPICE F-Score: 0.348, Pr: 1, Re: 0.211
Poor caption example (1)

Reference captions
"A woman is waiting for a train."
"A woman waiting at a train station with a suitcase."
"A person with a suitcase stands waits near the train tracks."
"A young woman in a red skirt is waiting on a train platform with her suitcase."
"A woman waiting for a train with her luggage beside her."

Reference scene graph

Candidate caption & scene graph
"a group of people standing next to a train"

SPICE F-Score: 0.057, Pr: 0.2, Re: 0.033
Poor caption example (2)

Reference captions
"The restaurant presents a gourmet breakfast of eggs and toast."
"A full plate of dessert, bread, and a veggie pizza."
"A breakfast plate containing eggs, bread and french toast."
"A plate of food that includes toast, hash browns and eggs with cheese."
"A cheese omelet with toast on a plate."

Reference scene graph

Candidate caption & scene graph
"a close up of a sandwich on a plate"

SPICE F-Score: 0.059, Pr: 0.25, Re: 0.033
Properties of SPICE

- SPICE measures how well caption models recover objects, attributes and relations
- Fluency neglected (as with n-gram metrics)
- If fluency is a concern, include a fluency metric such as surprisal*
- To model human judgement as closely as possible, build a task-specific metric ensemble

*Hale, J: A probabilistic Earley Parser as a Psycholinguistic Model 2001; Levy, R: Expectation-based syntactic comprehension 2008
Evaluation on MS COCO data (1)

- Based on system level correlation between automatic scores and human judgments (using 255k human judgments)
- Pearson correlation with human judgments (M1) is 0.88 for SPICE, vs. 0.43 for CIDEr and 0.53 for METEOR.
- SPICE ranks human captions ahead of competition entries, and picks the same top-5 competition entries as humans.
Evaluation on MS COCO data (2)
Summary of SPICE

• SPICE measures how effectively image captions recover objects, attributes and relations
• Captures human judgment on model-generated captions better than CIDEr, BLEU, METEOR and ROUGE
• Tuples can be categorized to provide detailed error analysis
• Offers scope for further improvement as better parsers are developed
Guided Open Vocabulary Image Captioning with Constrained Beam Search
Motivation (1)

A close up of a pizza on the ground.
A bird standing on top of a grass covered field.
Prior work in out-of-domain captioning

Guided open-vocabulary captioning

Out-of-Domain image containing unseen object ('suitcase')

CNN-RNN Captioning Model

Beam Search

Constrained Beam Search

A cat sitting on top of a refrigerator.

A cat sitting inside of a suitcase.

Open-vocab tags: cat, suitcase, inside
Overview of constrained decoding

- Caption generator uses pretrained word embeddings
  - Generates words not seen in training captions
- Image labeller trained on larger label vocabulary
- At test time:
  - Image labeller identifies key words that caption must contain
  - Construct a finite state automaton that accepts captions containing key words
  - Decoder has a beam for each automaton state
    - Minimises label bias
  - Output is highest scoring string in a final beam
Base model: LRCN

- 2-layer LSTM network, based on LRCN\(^1\)
- LSTM inputs at level 1 and 2 given by:

\[
x_t^1 = W_e \Pi_t
\]

\[
x_t^2 = (h_t^1, \text{CNN}_\theta(I))
\]

- where \(W_e\) is a word embedding, \(\pi_t\) is an indicator column vector, \(h_t^1\) is the output of the first layer, and \(I\) is the input image

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\(^1\) Long-term Recurrent Convolutional Networks for Visual Recognition and Description, Donahue et. al. CVPR 2015. Figure reproduced from Donahue et. al.
Vocabulary expansion

- Introduce pretrained GloVe\(^2\) 300D embeddings at both the LSTM input and output layers (\(W_e\)):  
  
  \[
  v_t = \tanh (W_v h_t^2 + b_v)
  \]
  
  \[
  p(y_t \mid y_{t-1}, \ldots, y_1, I) = \text{softmax} (W_e^T v_t)
  \]

- \(W_e\) fixed during training with minimal performance impact (using conventional cross-entropy loss).

- Model learns to predict 300D vectors \(v_t\) with a high dot-product similarity with the GloVe embedding of the correct output word.

- New vocabulary introduced at test time by concatenating the GloVe vector as an additional column to \(W_e\)

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\(^2\) ‘GloVe: Global Vectors for Word Representation’, Pennington et. al. EMNLP 2014
Finite-state multi-beam decoder

Finite-state machine

\[ V - C1 - C2 \]

\[ s_0 \] \( \overset{C1}{\rightarrow} s_1 \]

\[ s_2 \] \( \overset{C1}{\rightarrow} s_3 \]

\[ V - C1 \]

\[ V - C2 \]

C1 = \{chair, chairs\}, C2 = \{desk, table\}

Possible sequence extensions

**Beam 0: ~C1 & ~C2**

- A \( \rightarrow \) bedroom \rightarrow with \rightarrow a
- A \( \rightarrow \) room \rightarrow with \rightarrow a

**Beam 1: C1 & ~C2**

- A \( \rightarrow \) bedroom \rightarrow with \rightarrow chairs
- A \( \rightarrow \) chair \rightarrow in \rightarrow a

**Beam 2: ~C1 & C2**

- A \( \rightarrow \) desk \rightarrow next \rightarrow to
- A \( \rightarrow \) with \rightarrow many

**Beam 3: C1 & C2**

- A \( \rightarrow \) table \rightarrow and \rightarrow chairs
- A \( \rightarrow \) desk \rightarrow and \rightarrow chair

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Following Hendricks et. al., 8 objects removed from the caption training set: *bus*, *racket*, *couch*, *suitcase*, *bottle*, *microwave*, *pizza*, *zebra* (incl. plurals, synonyms)

Image tag training set is unrestricted (formed by tokenizing captions)

We re-use the image-tagger (Lexical Classifier) from trained by Hendricks et. al.
Examples: MS COCO (1)

**Base:** A woman is playing tennis on a tennis court. **LC4 Tags:** tennis, player, ball, racket. **Base + LC4:** A tennis player swinging a racket at a ball.

**Base:** A man standing next to a yellow train. **LC4 Tags:** bus, yellow, next, street. **Base + LC4:** A man standing next to a yellow bus on the street.

**Base:** A close up of a cow on a dirt ground. **LC4 Tags:** zebra, zoo, enclosure, standing. **Base + LC4:** A zebra standing in front of a zoo enclosure.
Examples: MS COCO (2)

**Base:** A dog is sitting in front of a tv. **LC4 Tags:** dog, head, television, cat. **Base + LC4:** A dog with a cat on its head watching television.

**Base:** A group of people playing a game of tennis. **LC4 Tags:** pink, tennis, crowd, ball. **Base + LC4:** A crowd of people standing around a pink tennis ball.
## Results on MS COCO

<table>
<thead>
<tr>
<th>Model</th>
<th>CNN</th>
<th>SPICE</th>
<th>METEOR</th>
<th>CIDEr</th>
<th>F1</th>
<th>SPICE</th>
<th>METEOR</th>
<th>CIDEr</th>
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Captioning ImageNet

- Can we leverage existing image labels?
- Base model using ResNet-50 CNN, trained on MS COCO + Flickr 30k (150k captions)
- Constrained beam search using the ground-truth synset
- Intend to release captions for 1.2M images (ILSVRC 2012)
ImageNet examples

**Base:** A close up of a pizza on the ground. **Synset:** rock crab. **Base + Synset:** A large rock crab sitting on top of a rock.

**Base:** A close up shot of an orange. **Synset:** pool table, billiard table, snooker table. **Base + Synset:** A close up of an orange ball on a billiard table.

**Base:** A man and a woman standing next to each other. **Synset:** colobus, colobus monkey. **Base + Synset:** Two colobus standing next to each other near a fence.

**Base:** A herd or horses standing on a lush green field. **Synset:** rapeseed. **Base + Synset:** A group of horses grazing in a field of rapeseed.

**Base:** A black bird is standing in the grass. **Synset:** oystercatcher, oyster catcher. **Base + Synset:** A black oystercatcher with a red beak standing in the grass.

**Base:** A bird standing on top of a grass covered field. **Synset:** cricket. **Base + Synset:** A bird standing on top of a cricket field.
Human evaluation on ImageNet (1)

- AMT evaluations, protocol identical to MS COCO Captioning Challenge 2015
- Workers compare two captions, 3 evaluations x 5k samples images
- For context, the best 2015 in-domain model achieved 11% ‘better’, 17% ‘equally good’

<table>
<thead>
<tr>
<th></th>
<th>Better</th>
<th>Equally Good</th>
<th>Equally Poor</th>
<th>Worse</th>
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<td>0.05</td>
<td>0.06</td>
<td>0.04</td>
<td>0.86</td>
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</table>
Human evaluation on ImageNet (2)

- Clustering class labels illustrates improvements across all categories
- 38% equal or better than human on birds
- Promising for combining fine-grained object detectors with general captioning models
Future work on constrained decoding

- Couple with Expectation-Maximization (EM) algorithm to learn from weakly-labelled images
- Ground tags in the image to tackle these failures:

**Base**: A dog is sitting in front of a tv. **LC4 Tags**: dog, head, television, cat. **Base + LC4**: A dog with a cat on its head watching television.

**Base**: A group of people playing a game of tennis. **LC4 Tags**: pink, tennis, crowd, ball. **Base + LC4**: A crowd of people standing around a pink tennis ball.
Conclusions

• Vision + language / zero-shot learning
• Base model using ResNet-50 CNN, trained on MS COCO + Flickr 30k (150k captions)
• Constrained beam search using the ground-truth synset
• Intend to release captions for 1.2M images (ILSVRC 2012)
Conclusions and future work
Conclusions and future work

• SPICE evaluates captions by comparing their *propositional content* to the propositional content of reference captions

• Our guided decoding algorithm uses a high-precision image labeler to constrain the decoder
  • Finite state constraints on decoder
  • Multiple beams minimise label bias

• Is there a better decoding algorithm than left to right decoding?