Localizing Moments in Video with Natural Language

11775 – Midterm Progress

Presentation

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Outline

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Introduction

Introduction

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Baby twitching after eating lemon

Shaking head vigorously

Rubbing eyes after eating

Baby squinting eyes on being offered the lemon

Baby licking lime the third time

Baby laughing

Feeding a baby

Pushing food away when fed again

When does a particular activity occur in a video ?

Problem statement: **Retrieve a specific temporal segment, or moment from a video given a natural language text description.**

- Text assisted Video Editing
- Video Retrieval
- Finding moments in long video footages
- Finding moments from a personal holiday video
- B-roll stock video footages from a large video library (Shutterstock, Adobe)

Related Literature

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1. **Generation and Comprehension of Unambiguous Object Descriptions** **[Junhua et al, 2016]**
   a. Generate unambiguous description of a specific object + comprehend or interpret such an expression
   b. Present a new large scale dataset for referring expressions based on MS COCO

2. **Video Object Segmentation with Language Referring Expressions** **[Anna et al, 2018]**
   a. High quality video object segmentation results using language referring expressions
   b. Performs on par with semi-supervised methods with access to the pixel-accurate object mask.
   c. Evaluated on DAVIS'17 dataset

3. **Modeling Relationships in Referential Expressions with Compositional Modular Networks** **[Ronghang et al, 2016]**
   a. Compositional Modular Networks (CMNs) - learn language representation and image region localization jointly
   b. Two types of modules - (i) localizing specific textual components by outputting unary scores (ii) relationship between two pairs of bounding boxes by outputting pairwise scores

Related Literature

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4. **Learning Joint Representations of Videos and Sentences with Web Image Search** **[Otani et al, 2016]**

    a. Web image search in sentence embedding process to disambiguate fine-grained visual concepts
    b. Embedding models for multimodal inputs whose parameters are learned simultaneously

5. **Deep fragment embeddings for bidirectional image sentence mapping** **[Karpathy et al, 2015]**

    a. Embeds fragments of images and sentences into a common space.
    b. Retrieve relevant images given a sentence query, + relevant sentences given an image query
    c. Stanford CoreNLP parser to compute the dependency trees for every sentence.
    d. Evaluated on Flickr8k and Flickr30k datasets

Dataset (DiDeMo)

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- Distinct Describable Moments (DiDeMo)
- Dataset consists over 10,000 videos
- 25-30 seconds long personal videos randomly selected from Flickr
- Over 40,000 localized text descriptions (3-5 pairs per video)
- Represent a diverse set of real-world videos like pets, concerts, sports
- Higher percentage of temporal indicators, spatial indicators and verbs
- Consist of both eventful and uneventful segments in the video

Dataset (DiDeMo)

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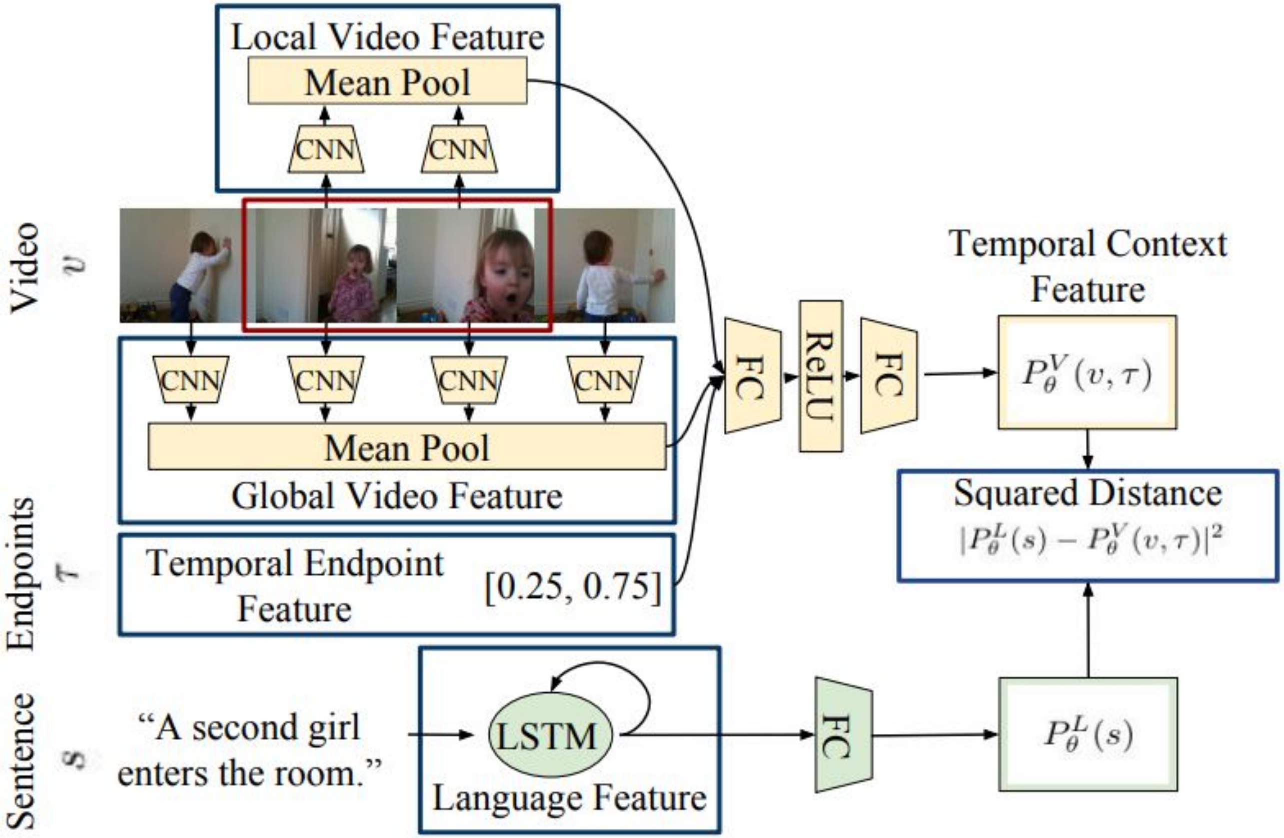
```
{
    "num_segments": 6,
    "description": "the toddler puts her head on the ground.",
    "dl_link": "https://www.flickr.com/video_download.gne?id=3926817284",
    "times": [
        [
            3,
            3
        ],
        [
            2,
            3
        ],
        [
            3,
            3
        ],
        [
            3,
            4
        ]
    ],
    "video": "75319260@N00_3926817284_e685e53cef.3gp",
    "annotation_id": 8213
},
```

Baseline Architecture - Moment Context Network (MCN)



[Hendricks et al, 2017]

Baseline Architecture contd..

- **Model (MCN):**
  - Joint Video-Language Model - Shared Embedding Space
  - Glove Embedding
  - LSTM
  - CNN Layers (Local and Global)
  - Fully Connected Layer
  - Ranking Loss
  - Distance Measures (Euclidean)

- **Features:**
  - Temporal Endpoint Features - When a moment occurs in a video
  - Low level
    - Optical flow
  - High level
    - RGB - VGG Net FC7
  - Global Video Features - Provides Temporal Context
  - Late Fusion

Evaluation Metrics

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- Rank@1
- Rank@5
- Mean Intersection over Union (mIoU)
- **Baseline: Moment Frequency Prior** - Tendency to select short moments towards the beginning of videos. It selects moments which correspond to gifs most frequently described by annotators.

Model	Rank@1	Rank@5	mIoU
Moment Frequency Prior	**19.40**	**66.38**	**26.65**

Baseline Experiments

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Lambda - 0.5

No_of_epochs - 30,000

Features - LSTM-Fusion + global + tef (MCN)

Model	Average IOU	AverageRank@1	AverageRank@5
Reproduced Baseline	**0.405315**	**0.270828**	**0.785377**
Baseline	0.4108	0.2810	0.7821

Initial Experiments (Glove6B)

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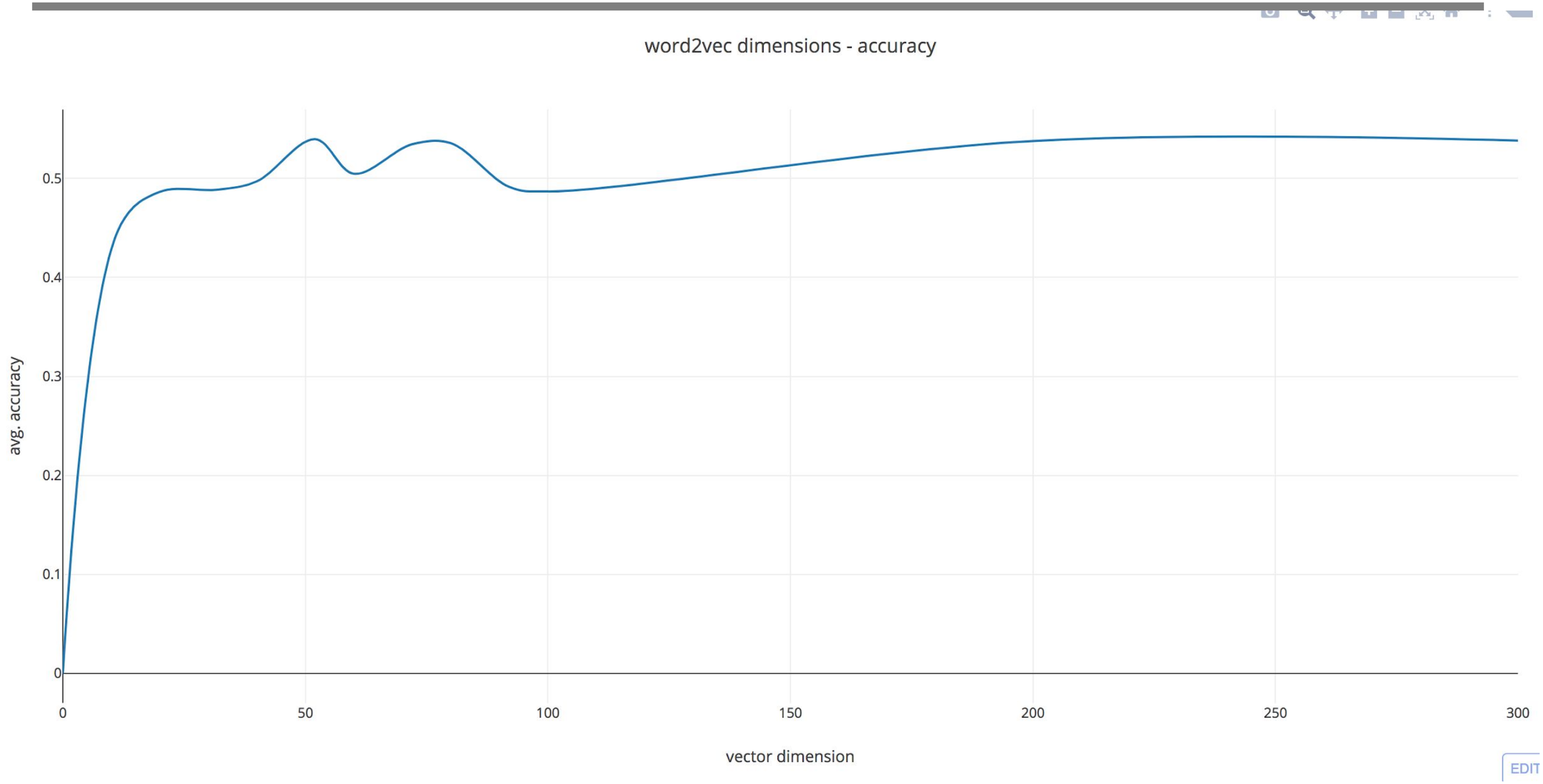
Lambda - 0.5

No_of_epochs - 10,000

Features - LSTM-Fusion + global + tef (MCN)

Model	Average IOU	AverageRank@1	AverageRank@5
200 word dimensional embeddings	**0.389062**	**0.2628**	**0.762746**
300 word dimensional embeddings (Baseline)	0.386642	0.261378	0.772196

Initial Experiments (Glove6B)



Initial Experiments (Language Model)

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Lambda - 0.5

No_of_epochs - 10,000

Features - LSTM-Fusion + global + tef (MCN)

Model	Average IOU	AverageRank@1	AverageRank@5
RNN for Language	**0.253292**	**0.191246**	**0.262373**
LSTM for Language	0.386642	0.261378	0.772196

Proposed Methodologies / Next Steps

- Ablation study with word2vec and various glove embedding for the language model network initialization
- Implement Bi-LSTM, GRU and Hierarchical RNN approaches to the language language model
- Explore better and different distance metrics to build the joint-embedding space of the video and language
- Experiment with Early and Double Fusion of the visual features

Proposed Methodologies / Next Steps

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- Bilinear transforms - using Bi(symmetrical) DNNs
- Use features for all moments instead of just 6 moments (stride)
- Extract richer local and global visual features and employ a Bi-LSTM to combine these to produce temporal context features
- To address up-scaling the vocabulary part, we plan to pre-train on Moments in Time dataset and select relevant actions and find a common embedding space.

Infrastructure / Logistics

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- We have been provided with AWS credits and we have access to the PSC cluster
- Our initial experiments were run on p2.xLarge (1 quad-core, GPU instance with 61 GB that is priced at $0.900 per hour)
- Our models were trained for 10,000 epochs and each model takes around an hour
- Testing the model takes around 20 minutes

References

- Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L. Yuille, and Kevin Murphy. Generation and comprehension of unambiguous object descriptions. CoRR , abs/1511.02283, 2015.

- Anna Khoreva, Anna Rohrbach, Bernt Schiele. Video Object Segmentation with Language Referring Expressions. CVPR, (arXiv:1803.08006), 2018.

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- Andrej Karpathy, Armand Joulin, and Fei-Fei Li. Deep fragment embeddings for bidirectional image sentence mapping. CoRR , abs/1406.5679, 2014.

- Mayu Otani, Yuta Nakashima, Esa Rahtu, Janne Heikkilä, and Naokazu Yokoya. Learning joint representations of videos and sentences with web image search. CoRR , abs/1608.02367, 2016.

Q&A