### INF@TRECVID2017 Video to Text Description

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# Main focus in this year: cross-dataset generalization

#### Last year:

 As the video caption pilot task provides no training captions for videos, we treat it as an *opportunity* to test the generalization ability of the caption models.

#### • This year:

- We found that the performance of caption model begins to saturate within one dataset by comparison to human reference
- opportunity->problem that we must face now

### Motivation

- human reference on MSRVTT
  - leave-one-out test on groundtruth
- on par with the human reference on caption metrics
  - metric issue?
  - dataset issue (coupling with generalization issue)?

model	BLEU@4	METEOR	CIDEr
TGM	45.41	29.73	52.91
human	53.15	29.77	50.23

### Motivation

- eliminate the metric issues
- on par with the human reference on tagging metrics (stop words removed)

model	precision	recall	f1
MP	77.4	17.2	26.8
tagging (top5)	47.8	12.5	18.6
tagging (top10)	38.6	17.1	22.2
human	70.7	20	29.7

### Motivation

preliminary cross dataset expriment

train	BLEU@4	METEOR	CIDEr
MSVD	47.70	34.22	80.88
MSR-VTT	34.67	30.68	55.39

- pitfall in the dataset MSRVTT:
  - train/test clips could come from the same video
  - The median number of shots for single video clip is 2 in MSRVTT
  - information leakage
- MSVD
  - too few videos
  - too many duplicate groundtruth sentences, which reduce the number of unique (video, caption) pairs

### Cross-dataset Generalization Property of Models

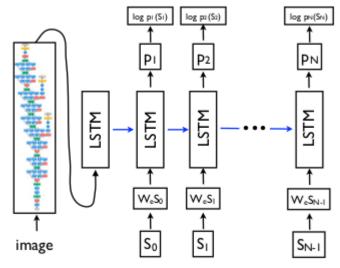
- Q1: Which one is more promising for better generalization on unseen datasets, higher quality training dataset or more robust model?
- Q2: Could we get more stable generalization ability by ensembling more different models?

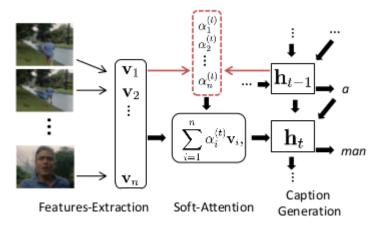
### Basic Setting

- Feature:
  - resnet200
  - i3d
  - mfcc (bow + fv)
- RNN with LSTM Cell
  - 512 hidden dimension, 512 input dimension
- Train scheme
  - batch size of 64

- fix the model architecture to study its influence by treating TRECVID2016 as unseen dataset
- fix the training datasets to study its influence by treating TRECVID2016 as unseen dataset

- Models:
  - Vanilla Encoder-decoder (MP)
  - Attention Encoder-decoder (ATT)
- Training dataset:
  - MSRVTT+MSVD
  - TGIF





 the performance gain from dataset >> the gain from the caption model

Table 2: Comparison of changing model and change training sets

model	train dataset	BLEU4	Meteor	Cider
MP	MSRVTT+MSVD	5.04	12.13	30.25
ATT	MSRVTT+MSVD	5.59	12.38	31.96
MP	TGIF	8.05	14.67	37.00
ATT	TGIF	7.93	14.65	37.11

#### TGIF Dataset collection instruction:

#### DOs

- Please use only English words. No digits allowed (spell them out, e.g., three).
- Each sentence must contain between 8 and 25 words. Try to be concise.
- Each sentence must contain a verb.
- If possible, include adjectives that describe colors, size, emotions, or quantity.
- Please pay attention to grammar and spelling.
- · Each sentence must express a complete idea, and make sense by itself.
- The sentence should describe the main characters, actions, setting, and relationship between the objects.

#### **DONTs**

- The sentence should NOT contain any digits.
- The sentence should NOT mention the name of a movie, film, and character.
- The sentence should NOT mention invisible objects and actions.
- The sentence should NOT make subjective judgments about the GIF.

# Q2 Could we get more stable generalization ability by ensembling more different models?

- more replicas of models:
  - varying the detailed settings such as tuning dropout rate and using different epochs in training
- ensemble:
  - rerank sentences using the submitted model in the retrieval subtask

# Q2 Could we get more stable generalization ability by ensembling more different models?

 by ensembling more and more models from source domain datasets, the performance on the target domain dataset TRECVID16 improves consistently

Table 3: Performance of ensembling

model	BLEU4	Meteor	Cider
best single model	8.05	14.67	37.00
ensemble 5 models	8.25	14.94	38.39
ensemble 6 models	8.25	15.04	38.66
ensemble 7 models	8.31	14.99	39.15
ensemble 8 models	8.46	15.04	40.79

### Challenge Result

rank		mean.cider		bleu.ref2	
	1	RUC_CMU.run1.primary	0.437	RUC_CMU.run3	0.022698561
	2	RUC_CMU.run2	0.414	RUC_CMU.run1.primary	0.022503469
	3	RUC_CMU.run3	0.411	RUC_CMU.run2	0.021839473
		mediamill_generation_rerank		VTT17_Generation_Task_Team_INF_vtt1	
	4		0.355	6tuned.primary	0.015388222
	5	RUC_CMU.run4	0.331	RUC_CMU.run4.txt	0.014392141
rank		meteor.ref2		sts.ref1	
	1	RUC_CMU.run1.primary	0.198482183	RUC_CMU.run1.primary	0.461612502
	2	RUC_CMU.run2	0.195623761	RUC_CMU.run2.txt.1.sts	0.455437854
	3	RUC_CMU.run3	0.195056582	mediamill_generation_baseline	0.452634668
	4	mediamill_generation_resnext_r erank_places2	0.178886646	RUC_CMU.run3.txt.1.sts	0.452282212
	5	mediamill_generation_priority_r un.primary	0.178122645	mediamill_generation_rerank	0.450247801