Waseda_Meisei_SoftBank at TRECVID 2022 Video to Text Description

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1. Overview
2. Methods
3. Experiments
4. Results
5. Discussion
6. Conclusion

Overview

Overview (Task)

- **VTT**（Video to Text Description）
  - Generating sentences from videos using natural language
  - Use temporal/spatial video features and audio

GenerateText：A man is playing frisbee a dog.

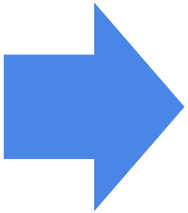
Overview（Competition）

- **TRECVID VTT 2022 regulation**
  - Generate English caption for 3~10 sec videos (and generate confidence score)
  - desire to consist of 4 content
    - Who : who is in the video? (people, animals, objects)
    - What : what are the objects and entities doing? (action or state)
    - Where : where was the video shot? (geographical or architectural location)
    - When : when was the video taken? (time of day, season, etc.)
  - Max 4 submissions each teams
  - select primary in all submissions

Methods

Strategy

- **Our Strategy**
  - Reduce redundancies in videos
  - TRECVID VTT 2022 Dataset audio is multilingual, so only video features are used
  - Use a pre-trained model because the training data is small

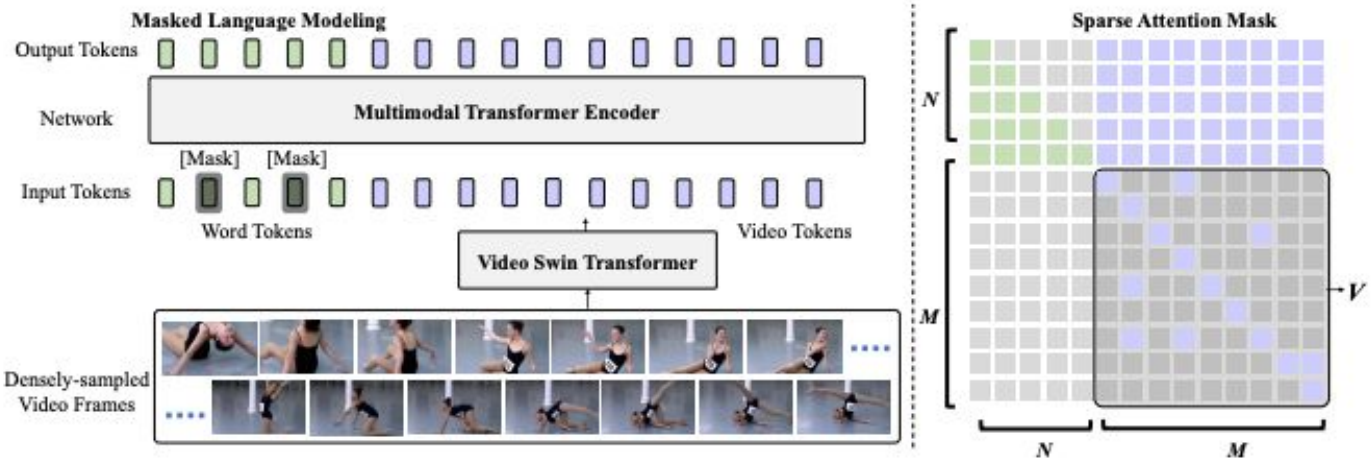


Use SwinBERT,[1] a SOTA model of VTT

[1]Lin, Kevin and Li, Linjie and Lin, Chung-Ching and Ahmed, Faisal and Gan, Zhe and Liu, Zicheng and Lu, Yumao and Wang, Lijuan SwinBERT: End-to-End Transformers with Sparse Attention for Video Captioning(CVPR2022)

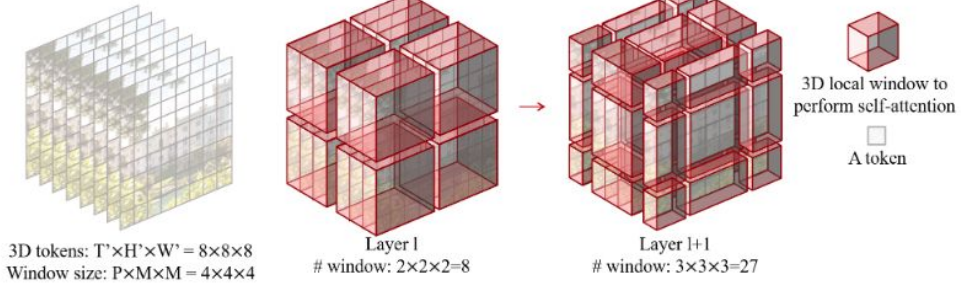
Methods - SwinBERT

- **SwinBERT**
  - End2End Video captioning model
    - **Encoder : Video Swin Transformer**
    - **Decoder : Multimodal Transformer Encoder**



Methods - SwinBERT

- **Encoder : Video Swin Transformer**
  - Visual feature extractor based on Transformer
  - **Patch-marge** : Split into N x N with patch like ViT
  - **SW-MSA** : Recognition between adjacent windows is possible by alternating windows
  - →Faster than sliding and still as accurate
  - **RelativePositionBias** : Adjust attention strength by relative position of patch



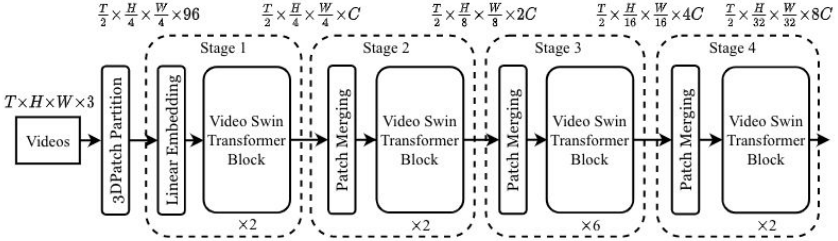
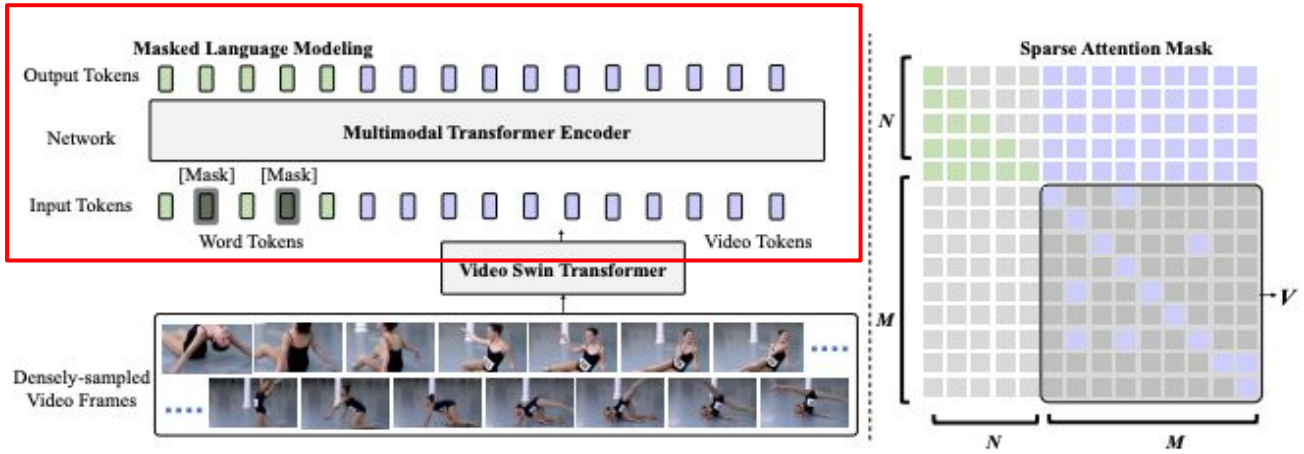


Figure 1: Overall architecture of Video Swin Transformer (tiny version, referred to as Swin-T).

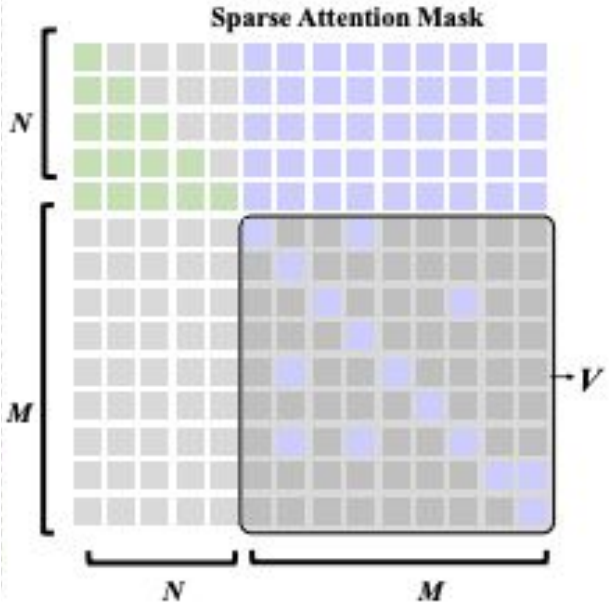
Methods - SwinBERT

- **Decoder : Multimodal Transformer Encoder**
  - Generate natural language description from textual and visual modality inputs
  - Training : Masked language model
  - Inference : Perform Seq2Seq generation



Methods - SwinBERT

- **Decoder : Multimodal Transformer Encoder**
  - **Learnable sparse Attention MASK**
    - **text→text**: can access only past tokes
    - **text→visual**: can access all
    - **visual→text**: can't access
    - **visual→visual**: train attention mask
      - **→reduce redundancies**



Experiments

Datesets

- **Dataset：V3C1**
  - Use V3C1 which consist of Vimeo Creative Commons Collection (V3C)
  - **Test data**
    - 2008 videos (+300 progress test)
    - 3～10sec per video
    - 5 captions per video
  - **Train / Develop data**
    - TRECVID data from 2016 years to 2021 years（10862 videos）
    - 2~5 captions per video

Experiments

- **Pretraining :**
  - Datasets : VATEX Dataset
  - AdamW optimizer : warmup 10% steps followed by linear decay
  - Use max 32 frames
- **Finetuning :**
  - Datasets : V3C1 Dataset
  - Don’t train leanable attention mask

Evaluation Metrics

- **Metrics**
  - **Automatic metrics**
    - METEOR, BLEU, CIDEr, CIDEr-D, SPICE
  - **Direct Assessment(DA)**
    - Evaluate primary runfile only by cloud worker →**TBD**
  - **Semantic similarity metric(STS)**
    - Measuring the semantic relevance of features →**Add Appendix**

Results

Results

- Submit runfiles Fintunig TRECVID-VTT
- For primary, check the generated sentences and select

Runfile	CIDER	CIDER-D	BLEU	METEOR	SPICE
1	**0.415**	0.178	0.033	0.260	0.077
2	0.348	0.141	0.026	0.252	0.084
3	0.350	0.150	0.028	0.260	0.087
4	0.388	**0.182**	**0.037**	**0.286**	**0.100**

※Best runfile results

Results

- Max 3rd, Average rank is 4.2

	CIDER	CIDER-D	BLEU	METEOR	SPICE
ELT_01	4th	2nd	4th	5th	3rd
VIDION	3rd	6th	6th	6th	6th
kslab	2nd	3rd	2nd	4th	5th
MLVC_HDU	6th	5th	3rd	2nd	2nd
RUCAIM3-Tencent	1st	1st	1st	1st	1st
WasedaMeiseiSoftbank	5th	4th	5th	3rd	4th

※Best runfile results

Discussion

Output samples

GT1:	A person surfing on the frothy white waves in the ocean on a sunny day.
GT2:	A man surfs in the ocean going up and down in the waves with his surfboard on a cloudy day.
GT3:	A surfer is jumping over waves on a cloudy day
GT4:	A man is water surfing on a large wave in the daytime.
GT5:	A guy is surfing in big and high waves in the sea or ocean in the daytime.

Run1:	a man is surfing on a wave and then falls off.
Run2:	a surfer rides a surfboard surfs through the water on a sunny day.
Run3:	a man on a surfboard rides a wave and jumps off his head.
Run4:	a man rides a surf board through a ocean on a sunny day.

Output samples

GT1:	A group of people are on top of a windy mountain looking down on a city as one of the men is showing them something.
GT2:	One man out of four people standing on top of a mountain and watching down is explaining something to them using his hands in the daytime.
GT3:	A group of people sight seeing on a mountain top look over a town.
GT4:	Three men and a long haired woman are standing on a hill overlooking a settlement in the valley below them on a windy day.
GT5:	Four white people standing on a hill overlooking a small town situated in a valley on an overcast day.

Run1:	a group of people are standing on a cliff and one of them is standing on the ground
Run2:	a young woman with a black shirt and a black shirt and a black shirt and a black
Run3:	a man in a white shirt and a woman are taking a selfie on a rocky mountain
Run4:	a young woman walks towards a man on a rocky day as a young woman walks up to

V3C1 train data samples

Users > takushima > workspace > trecvid > vtt_ground_truth.txt

```
1 a man sings in a car
1 man shakes his body in a car at daytime
2 in the daytime, two sportsmen walk in the sports field, while an other man moves on the wheel
2 on a baseball field a person in dark clothes is moving from right to left without walking
3 a basketball player wearing number 30 shirt is scoring a goal on a basketball court against a red wearing team
3 basketball player scoring a three pointer on a basketball field
4 people are going downstairs on a stage
4 several people walking down a staircase on a stage
5 2 women shake their bottoms
5 two women try to dance in a room.
6 a group of people riding a free fall tower
6 a roller coaster moves upwards at daytime
7 a man is scared by a picture of a boy on a mirror in a bathroom
7 white male taking a selfie in a bathroom mirror
8 2 men on a stage hug and walk away
8 two young man are standing on a stage embracing each other and one claps the other one's ass.
9 3 men are hugging each other
9 a man performs in movies
10 a man speaks into a microphone indoors
10 white man with glasses giving an interview in the interview area
11 a basketball player walks through a group of people
11 a big man in yellow cloths passes by some chairs in a large hall.
12 in the daytime, a cat walks at home and meows and another cat approaches to it
12 a little cat is following the camera and meows to it
13 2 men train in a gym
13 2 men run in a gym
```

- **w/o period** : Variations of sentences with and without periods
- **number** : Numeric and alphanumeric variations
- **human** : Many descriptions of what you are wearing
- **color info** : Many descriptions of color infomation

Discussion

- **w/ or w/o period ←critical to our approach**

  VATEX dataset has periods

  V3C1 dataset with and without periods

  → Period output becomes ambiguous in Finetuning for pre-trained in VATEX

  → Impression that the model does not know the end of the sentence

- **Difference in number description**

  V3C1 Train data has both alphanumeric and numeric descriptions

  V3C1 Test data has description only in alphanumeric characters

  → Deviation occurs in the output

Discussion

- **Descriptions about people**

  V3C1 data has many descriptions of information that people wear

  The point is whether this is described

- **Description about color**

  V3C1 data has many descriptions about colors

  In particular, there are many descriptions about what the person above is wearing

Conclusion

Conclusion

- SwinBERT reduces redundancy for videos and can effectively generate even less data by pre-training model
- Finetuning SwinBERT with V3C1 dataset
- From the generated results, we found the features and issues of the V3C1 dataset
- As a result, the highest ranking was 3rd, and the average rank was 4.2.

Appendix

Datesets

- **Dataset：V3C1**
  - Use V3C1 which consist of Vimeo Creative Commons Collection (V3C)
  - Test data
    - 2008 videos (+300 progress test)
    - 3～10sec per video
    - 5 captions per video
  - Train / Develop data
    - TRECVID data from 2016 years to 2021 years（10862 videos）
    - 2~5 captions per video
    - data details
      - Videos with IDs ~6475 videos from Twitter Vine.
      - Videos with IDs 6476 - 7485 are from our Flickr dataset.
      - Videos with IDs 7486~ are from the V3C dataset.
      - Videos with IDs from 1 to 3528 have between 2 to 5 captions.
      - Videos from 3529 onwards have 5 captions each.

Result

- CIDER

	Run1	Run2	Run3	Run4	Best	Rank
ELT_01	0.507	0.103	0.243	0.234	0.507	4th
VIDION	0.595	0.589	0.607	0.611	0.611	3rd
kslab	0.619	0.163	0.510	0.141	0.619	2nd
MLVC_HDU	0.361	0.346	0.361	0.361	0.361	6th
RUCAIM3-Tencent	0.940	0.936	0.936	0.942	0.942	1st
WasedaMeiseiSoftbank	0.415	0.348	0.350	0.388	0.415	5th

Result

- CIDER-D

	Run1	Run2	Run3	Run4	Best	Rank
ELT_01	0.226	0.045	0.076	0.105	0.226	2nd
VIDION	0.098	0.099	0.108	0.113	0.113	6th
kslab	0.194	0.048	0.110	0.027	0.194	3rd
MLVC_HDU	0.179	0.166	0.179	0.179	0.179	5th
RUCAIM3-Tencent	0.594	0.575	0.602	0.592	0.602	1st
WasedaMeiseiSoftbank	0.178	0.141	0.150	0.182	0.182	4th

Result

- **BLEU**

	Run1	Run2	Run3	Run4	Best	Rank
ELT_01	0.069	0.012	0.014	0.034	0.069	4ht
VIDION	0.024	0.025	0.029	0.030	0.030	6th
kslab	0.081	0.0260	0.047	0.011	0.081	2nd
MLVC_HDU	0.0716	0.062	0.0716	0.0716	0.0716	3rd
RUCAIM3-Tencent	0.1350	0.131	0.1352	0.1353	0.1353	1st
WasedaMeiseiSoftbank	0.033	0.0263	0.028	0.037	0.037	5th

Result

- **METEOR**

	Run1	Run2	Run3	Run4	Best	Rank
ELT_01	0.248	0.178	0.169	0.194	0.248	5th
VIDION	0.212	0.211	0.220	0.221	0.221	6th
kslab	0.281	0.204	0.226	0.170	0.281	4th
MLVC_HDU	0.289	0.280	0.289	0.289	0.289	2nd
RUCAIM3-Tencent	0.412	0.409	0.414	0.413	0.414	1st
WasedaMeiseiSoftbank	0.2604	0.252	0.2603	0.286	0.286	3rd

Result

- **SPICE**

	Run1	Run2	Run3	Run4	Best	Rank
ELT_01	0.102	0.043	0.062	0.064	0.102	3rd
VIDION	0.073	0.073	0.077	0.077	0.077	6th
kslab	0.097	0.049	0.071	0.036	0.097	5th
MLVC_HDU	0.107	0.098	0.107	0.107	0.107	2nd
RUCAIM3-Tencent	0.182	0.180	0.184	0.183	0.184	1st
WasedaMeiseiSoftbank	0.077	0.084	0.087	0.100	0.100	4th

Result

- **STS（Semantic smilarity metrics）：Run1**

	TXT1	TXT2	TXT3	TXT4	TXT5
ELT_01	0.4211	0.4189	0.4199	0.4191	0.4151
VIDION	0.3966	0.3897	0.3938	0.3908	0.3902
kslab	0.4194	0.4126	0.4126	0.4137	0.4177
MLVC_HDU	0.4176	0.3949	0.3928	0.3988	0.4188
RUCAIM3-Tencent	0.5380	0.5140	0.5175	0.5116	0.5349
WasedaMeiseiSoftbank	0.3563	0.3658	0.3669	0.3654	0.3564

Result

- **STS（Semantic smilarity metrics）：Run2**

	TXT1	TXT2	TXT3	TXT4	TXT5
ELT_01	0.2357	0.2401	0.2302	0.2378	0.2386
VIDION	0.3984	0.3867	0.3927	0.3930	0.3888
kslab	0.2705	0.2616	0.2603	0.2648	0.2703
MLVC_HDU	0.4087	0.3864	0.3822	0.3868	0.4061
RUCAIM3-Tencent	0.5327	0.5121	0.5102	0.5100	0.5332
WasedaMeiseiSoftbank	0.3849	0.3755	0.3616	0.3715	0.3843

Result

- **STS（Semantic smilarity metrics）：Run3**

	TXT1	TXT2	TXT3	TXT4	TXT5
ELT_01	0.3570	0.3413	0.3351	0.3361	0.3627
VIDION	0.4064	0.3947	0.3996	0.3985	0.3954
kslab	0.3690	0.3641	0.3629	0.3602	0.3688
MLVC_HDU	0.4176	0.3949	0.3928	0.3988	0.4188
RUCAIM3-Tencent	0.5386	0.5154	0.5151	0.5147	0.5379
WasedaMeiseiSoftbank	0.3881	0.3745	0.3689	0.3698	0.3856

Result

- STS（Semantic smilarity metrics）：Run4

	TXT1	TXT2	TXT3	TXT4	TXT5
ELT_01	0.3083	0.3034	0.2994	0.3034	0.3073
VIDION	0.4061	0.3951	0.3998	0.3984	0.3952
kslab	0.2535	0.2504	0.2460	0.2456	0.2539
MLVC_HDU	0.4176	0.3949	0.3928	0.3988	0.4188
RUCAIM3-Tencent	0.5351	0.5146	0.5131	0.5125	0.5333
WasedaMeiseiSoftbank	0.4148	0.4094	0.4023	0.4035	0.4184