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TARN-VIST: Topic-Aware Reinforcement Network for Visual Storytelling

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Introduction - Task Definition

Visual Storytelling: generate a story for an ordered image sequence automatically

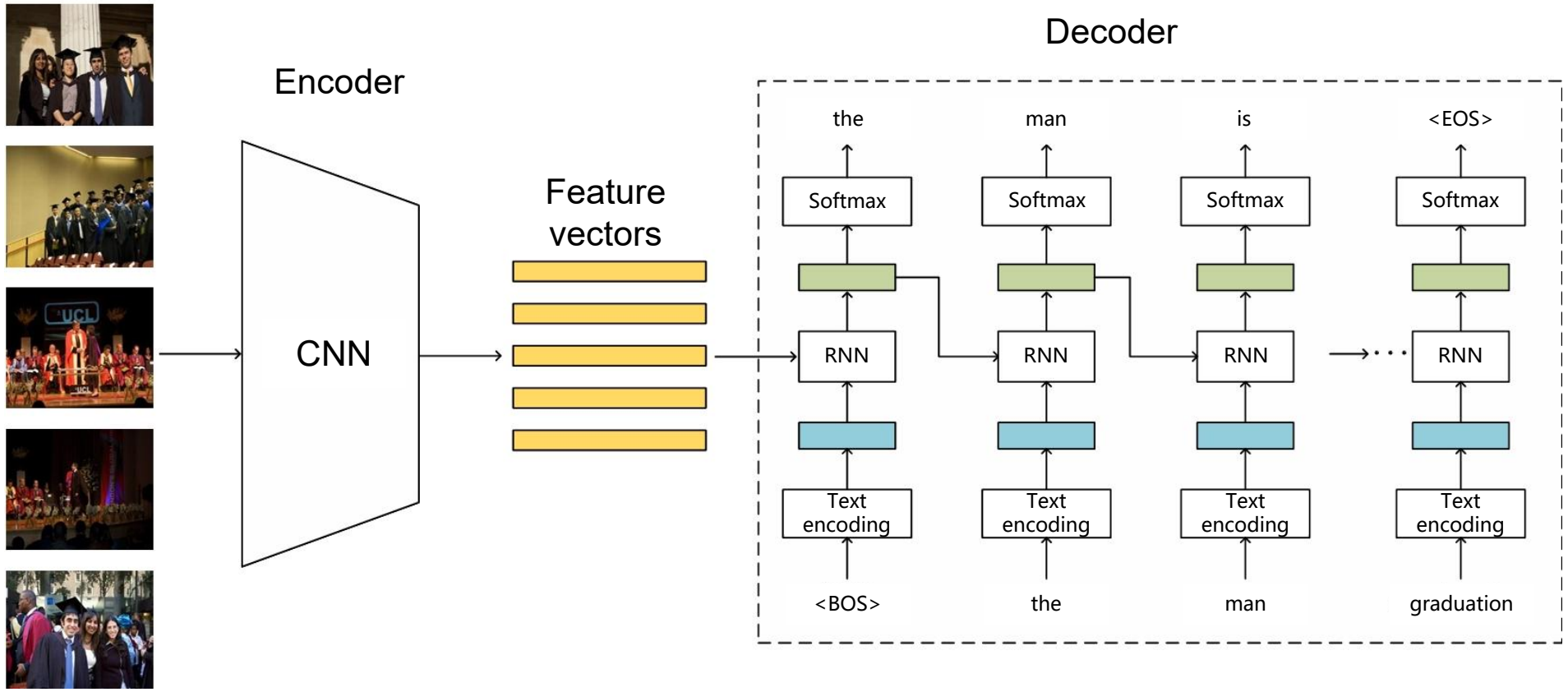
A discus got stuck up on the roof. Why not try getting it down with a soccer ball? Up the soccer ball goes. It didn't work so we tried a volleyball. Now the discus, soccer ball, and volleyball are all stuck on the roof.

The dog was ready to go. He had a great time on the hike, and was very happy to be in the field. His mum was so proud of him. It was a beautiful day for him.

Introduction - Approach Summary

End-to-end based Approach

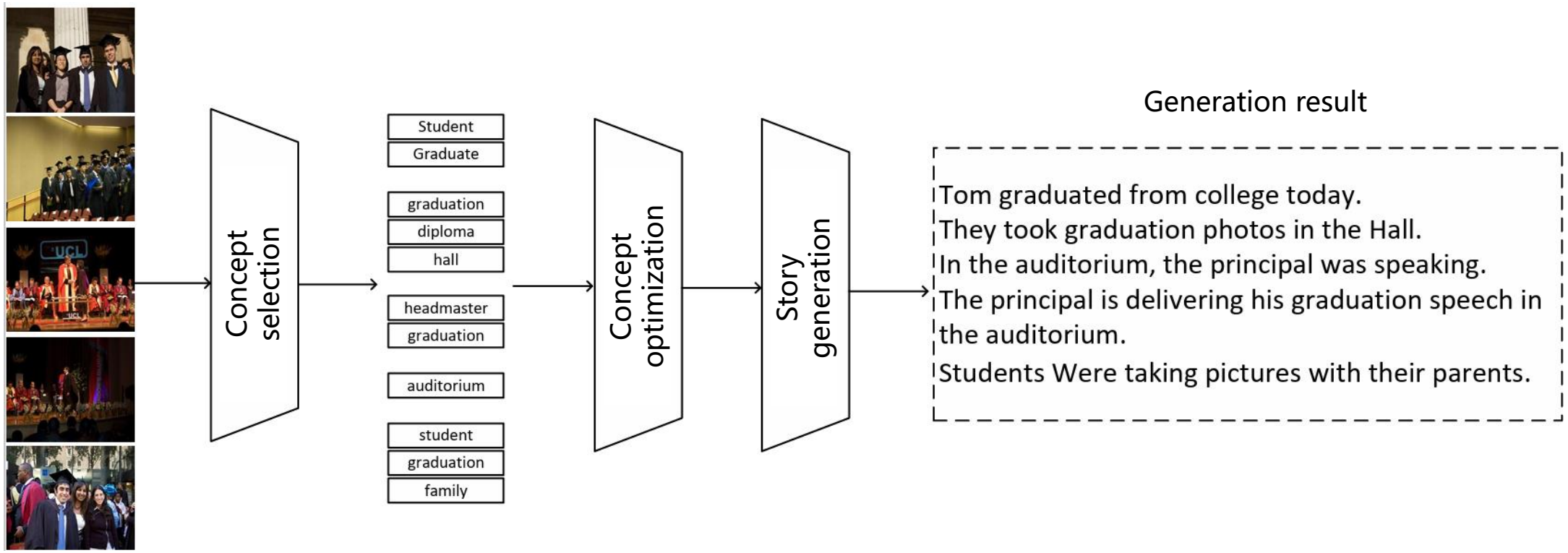
- Utilize a CNN as an encoder to extract image features and overall image-stream features
- Feed the feature vectors into a RNN to construct the story



Introduction - Approach Summary

Multi-stage based Approach

- Separate the generation process into multiple steps
- The output of the previous step is often leveraged as the input of the subsequent step



Our work

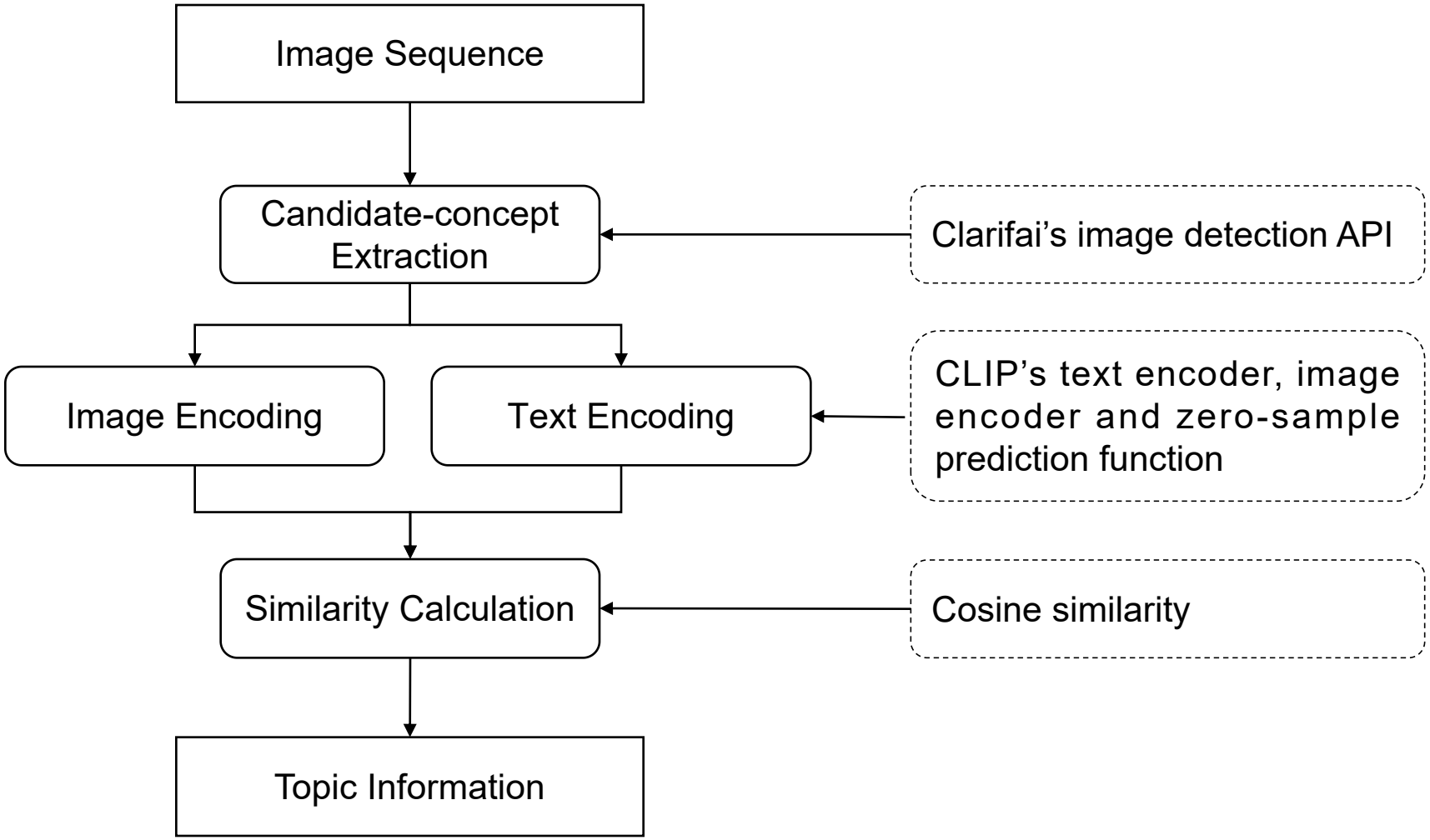
Motivations

- Few models take the latent topic information of the generated story into account
- Previous work does not consider extracting topic words from the visual aspect

Our Solution: Topic Aware Reinforcement Network for Visual Storytelling (TARN-VIST)

- Use CLIP and RAKE to extract topic information from both visual and linguistic perspectives
- Design reinforcement learning rewards for topic consistency based on the topic information and cosine similarity
- Experimental results show that our method outperforms most of the leading models on multiple evaluation metrics.

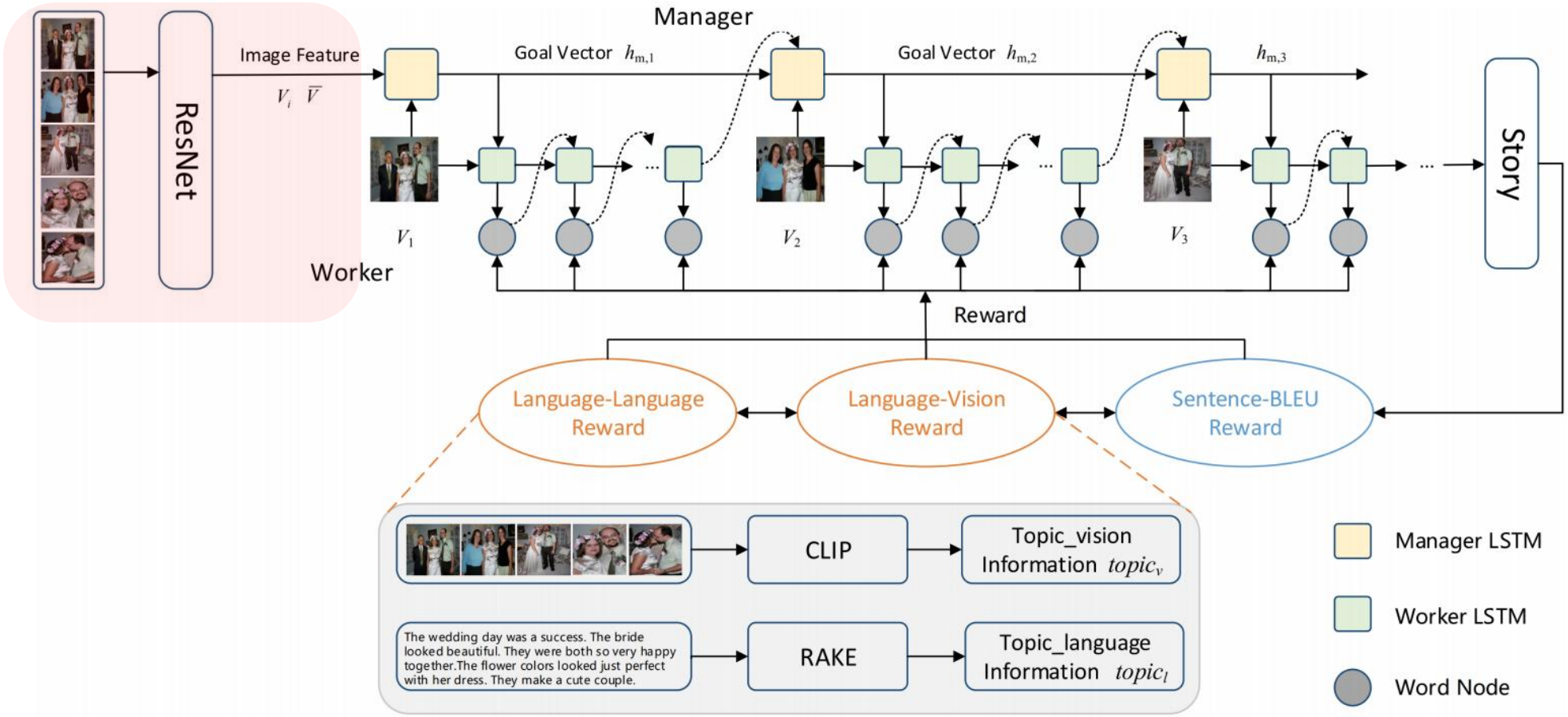
TARN-VIST - Topic Information Extraction



TARN-VIST - Topic Information Extraction

Images					
Topic Information	Topic_vision: Seashore; Topic_language: Good Day;				
Images					
Topic Information	Topic_vision: Birthday; Topic_language: Party;				
Images					
Topic Information	Topic_vision: Parade; Topic_language: Parade;				

TARN-VIST - Topic Aware Storytelling Model



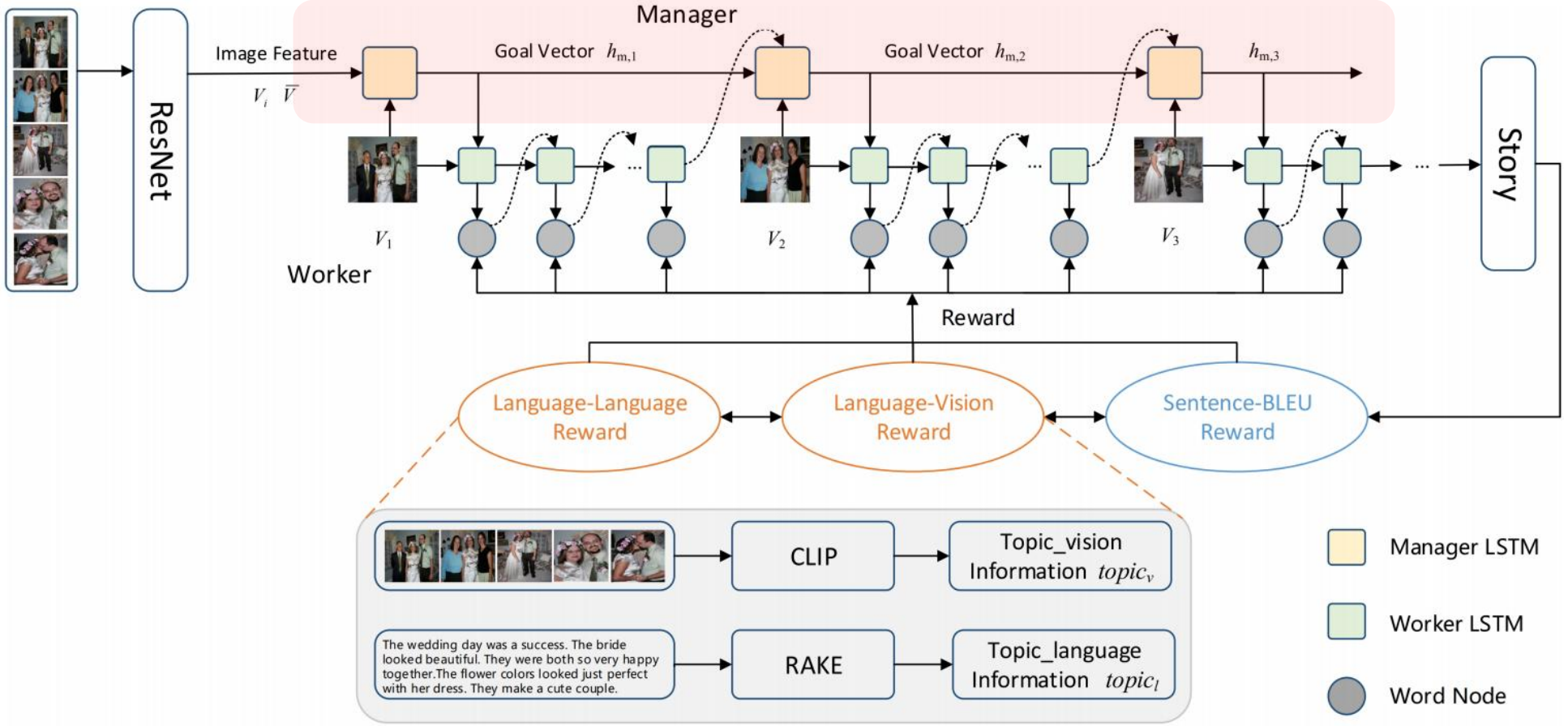
$$v_i = \text{Resnet}(I_i)$$

$$\overline{V} = \frac{1}{n}\sum_i v_i$$

v_i : the individual feature information of image i

$\overline{V}$: overall feature information of the image sequence I

TARN-VIST - Topic Aware Storytelling Model



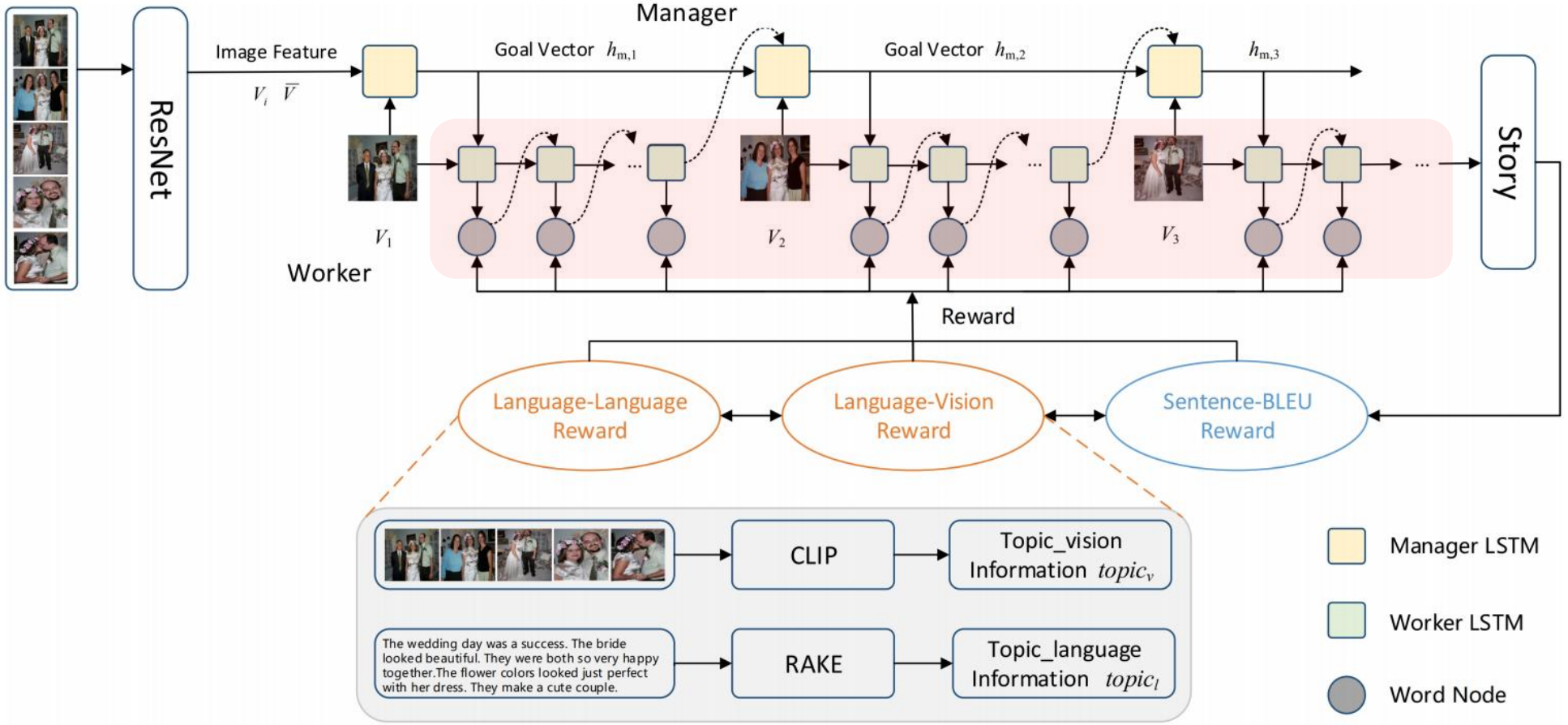
Manager LSTM: Serve as a supervisor to control the overall flow of the story

$$h_{m,i} = \mathrm{LSTM}_M([\overline{V}; v_i; h^t_{w,i-1}], h_{m,i-1})$$

$h^t_{w,i-1}$: sentences generated for the previous image

$h_{m,i}$: the hidden state (goal vector)

TARN-VIST - Topic Aware Storytelling Model



Worker LSTM: Complete the generation of word description based on the goal vector $h_{m,i}$

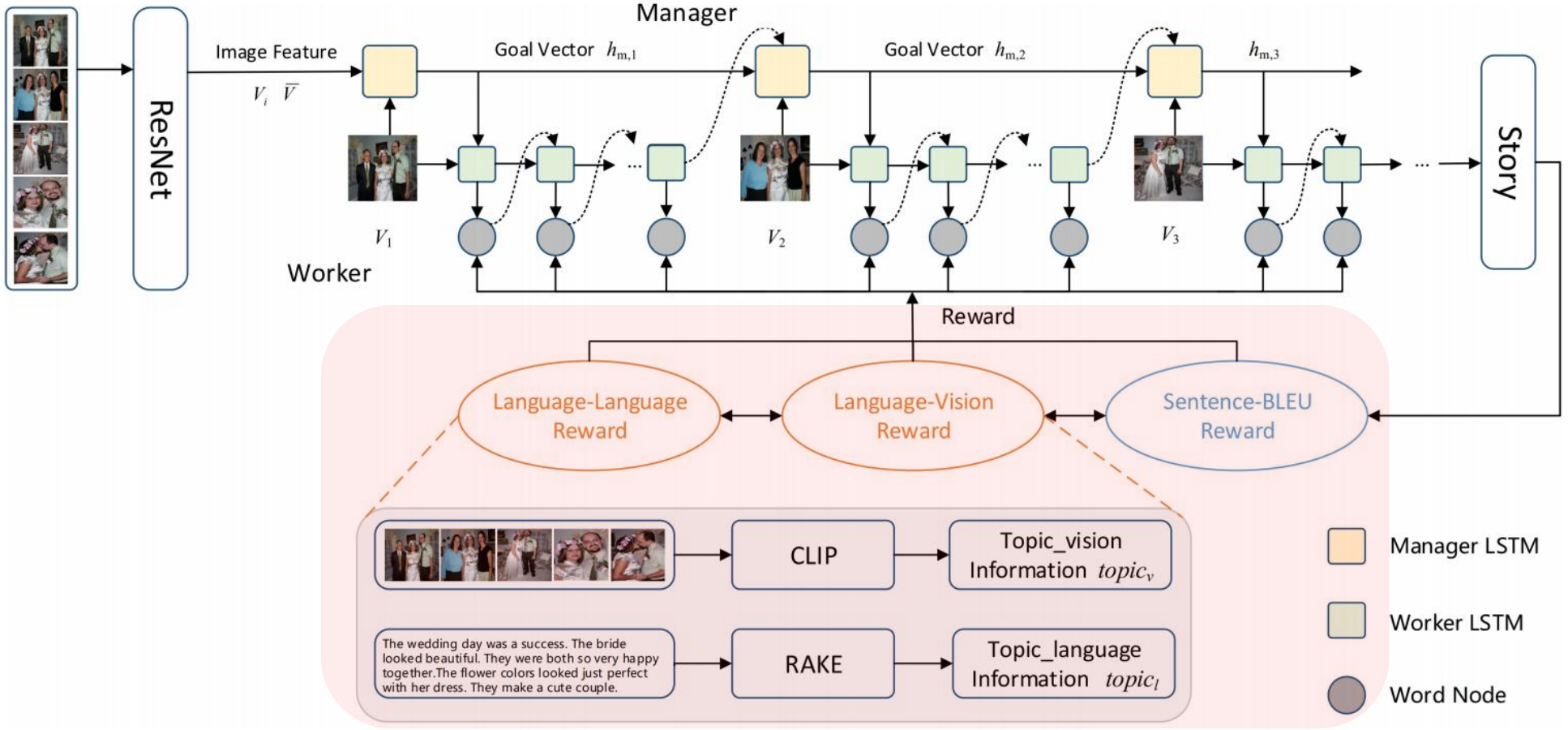
$$h_{w,i}^t = \mathrm{LSTM}_W([v_i; h_{m,i}; e_i^{t-1}], h_{w,i}^{t-1})$$

$$p_\theta(y_i^t \mid y_i^{1:t-1}; v_i, \overline{V}) = \mathrm{softmax}(f(h_{w,i}^t))$$

e_i^{t-1} : the word embedding of previously generated word

$f(\cdot)$: linear layer

TARN-VIST - Topic Aware Storytelling Model



Topic Consistency Rewards Design:

$$r_{topic-cv} = \text{cosine-similarity}(topic_c, topic_v) \qquad r_{bleu} = \text{sentence-bleu}(story_c, story_g)$$

$$r_{topic-cl} = \text{cosine-similarity}(topic_c, topic_l) \qquad r = \lambda \cdot r_{bleu} + \gamma \cdot r_{topic\text{-}cv} + \eta \cdot r_{topic\text{-}cl}$$

Model Training

Reinforcement loss: encourage the model to focus on key aspects via maximizing the reward

$$Loss_{RL}(\beta) = \sum_{Y,V \in D'} E_{y_i \sim \pi_i}[(b - r(y_i)) \log \pi_i]$$

$$r(y_i) = \lambda \cdot r_{bleu}(y_i) + \gamma \cdot r_{topic\text{-}cv}(y_i) + \eta \cdot r_{topic\text{-}cl}(y_i)$$

$$\pi \equiv p_\theta(y_i \mid v_i, \bar{V})$$

Two-stage training strategy

- First stage: Train with maximum likelihood estimation (MLE)
- Second stage: Train with jointly with reinforcement loss and MLE loss

$$Loss_{MLE} = \sum_{Y,V \in D'} \sum_{i=1}^{N} \sum_{t=1}^{T} -\log P(W_{i,t} = Y_{i,t})$$

$$Loss_{mixed} = \omega \cdot Loss_{RL} + (1 - \omega) \cdot Loss_{MLE}$$

Experimental Results - Quantitive Evaluation

Table 1: Quantitive results on the VIST dataset for surface-level-based automatic metrics. For all these metrics, higher score means better performance.

Method	BLEU-1	BLEU-2	BLEU-4	METEOR	ROUGE	CIDEr	SPICE
Seq2seq	-	-	3.5	31.4	-	6.8	-
H-Attn-Rank	-	-	-	34.1	29.5	7.5	-
BARNN	-	-	-	33.3	-	-	-
SRT	43.4	21.4	5.2	12.3	-	11.4	-
XE-ss	62.3	38.2	13.7	34.8	29.7	8.7	-
AREL	63.7	39.0	14.0	35.0	29.6	9.5	8.9
HPSR	61.9	37.8	12.2	34.4	**31.2**	8.0	-
HSRL	-	-	12.3	35.2	30.8	10.7	7.5
SGVST	65.1	40.1	14.7	**35.8**	29.9	9.8	-
ReCo-RL	-	-	12.4	33.9	29.9	8.6	8.3
INet	64.4	40.1	14.7	35.6	29.6	11.0	-
IRW	66.7	41.6	**15.4**	35.6	29.6	11.0	-
CKAKS	-	-	12.0	35.4	30.0	10.5	-
LGMT	67.5	41.6	15.1	35.6	29.7	10.0	-
Sentistory	64.8	39.8	14.2	35.3	29.8	9.7	-
TARN-VIST	**69.0**	**43.5**	13.4	**35.8**	29.5	**12.1**	**11.3**

Experimental Results - Quantitive Evaluation

Table 2: Quantitive results on the VIST dataset for semantic understanding evaluation metric. For all these metrics, higher score means better performance.

Method	BERTScore	BARTScore	BLEURT
KE-VIST (No KG)	28.25	17.21	43.63
KE-VIST (With OpenIE)	29.12	17.93	46.85
KE-VIST (With KG)	29.16	18.03	47.54
PR-VIST	27.64	18.09	48.92
TARN-VIST	**30.47**	**18.51**	**49.43**

Experimental Results - Ablation Study

Table 3: Ablation experiment results on different combinations of the reward functions. Note that our basic model is ReCo-RL.

Method	BLEU-4	METEOR	CIDEr	SPICE
Baseline	12.40	33.90	8.60	8.30
Baseline+r_{bleu}	12.82	35.36	11.58	10.84
Baseline+r_{bleu}+$r_{topic\text{-}cv}$	13.10	35.62	11.70	**11.37**
Baseline+r_{bleu}+$r_{topic\text{-}cl}$	13.44	35.80	10.99	11.36
TARN-VIST	**13.46**	**35.88**	**12.07**	11.25

$$r_{topic-cv} = \text{cosine-similarity}\,(topic_c, topic_v)$$

$$r_{topic-cl} = \text{cosine-similarity}\,(topic_c, topic_l)$$

$$r_{bleu} = \text{sentence-bleu}\,(story_c, story_g)$$

Experimental Results - Hyper-parameter Selection

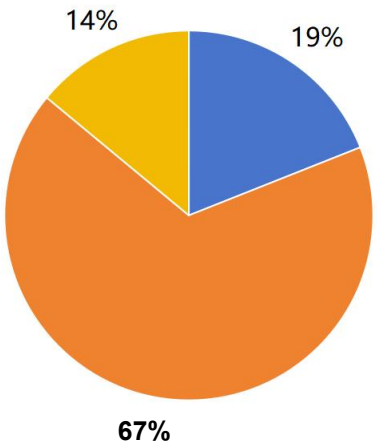
Table 4: Experiment results of TARN-VIST with different γ and η.

γ	η	BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE	METEOR	CIDEr	SPICE
0.3	0.7	68.43	42.48	23.51	12.85	29.14	35.52	11.23	10.76
0.4	0.6	68.38	42.55	23.56	12.88	29.21	35.62	11.69	10.85
0.5	0.5	**69.01**	**43.56**	**24.27**	**13.46**	**29.28**	**35.88**	**12.07**	**11.36**
0.6	0.4	68.58	42.79	23.77	13.09	29.24	35.63	11.91	10.94
0.7	0.3	68.24	42.46	23.57	12.92	29.12	35.53	11.44	10.78
0.8	0.2	68.24	42.58	23.66	12.90	12.90	35.48	11.69	10.77

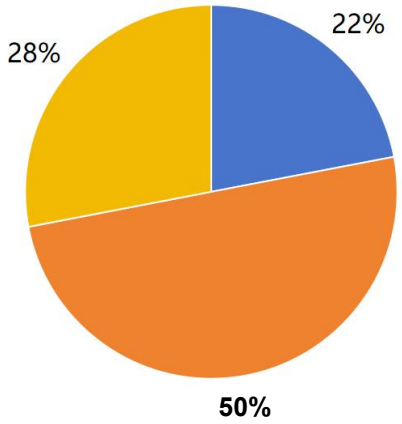
$$r = \lambda \cdot r_{bleu} + \gamma \cdot r_{topic\text{-}cv} + \eta \cdot r_{topic\text{-}cl} \qquad (\lambda = 0.5,\ \gamma + \eta = 1)$$

Experimental Results - Human Evaluation

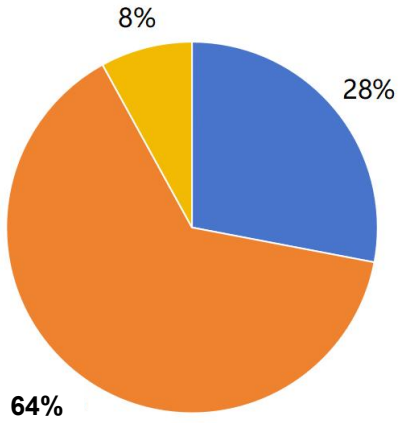
Relevance

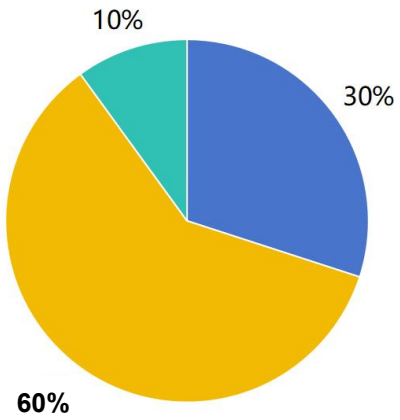


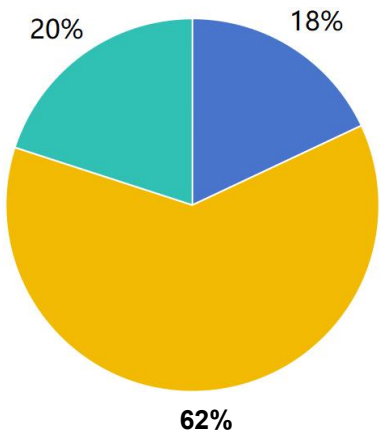
Coherence

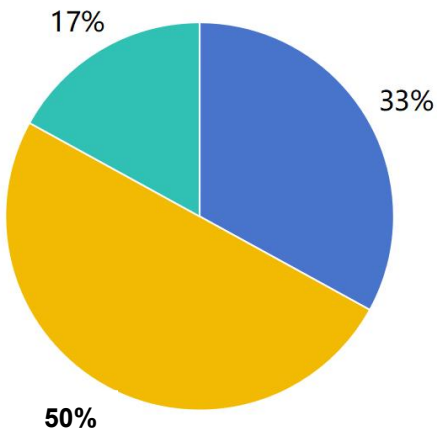


Information Richness









Experimental Results - Qualitative Evaluation

Method	    
Topic Information	Topic_vision: Wedding; Topic-language: Wedding day;
Ground Truth	The wedding day was a success. The bride looked beautiful. They were both so very happy together. The flower colors looked just perfect with her dress. They make a cute couple.
PR-VIST	[female] and [male] took a family photo together. it was [male] 's birthday party. the groom and his wedding were cut off. their mom was so proud of them. her mom got married today, but [female] was very excited to be there. [female] is now getting married today .
KE-VIST	the bride and groom were getting ready for their wedding. they looked so happy to be there. it was a beautiful night. everyone danced. then came out after .
TARN-VIST	the bride and groom are married. The bride is taking a picture with her friends. she was happy and her husband was so happy. after the wedding, we had a great time with her wedding. they were very excited to get a picture of the wedding.

Conclusion and Future Work

Conclusion

- Mine the story's topic information from both visual and linguistic perspectives
- Employ the reinforcement learning to refine the generation process
- Topic information is beneficial to improve the quality of generated stories

Future Work

- Explore grammar and discourse structure in the visual storytelling task
- Analyze linguistic style to improve the quality and diversity of generated stories

Thank you!