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IMAGE CAPTIONING

Image captioning uses computer vision and language processing to describe images in text. It typically has an encoder to extract features and a decoder to generate captions. In areas like remote sensing, it's harder due to complex visuals and specialized terms.

REFERENCE PAPER

The paper "A TextGCN-Based Decoding Approach for Improving Remote Sensing Image Captioning" introduces a TextGCN-based encoder-decoder model with multi-layer LSTMs and comparison-based beam search to improve remote sensing image captioning, achieving top results on the RSICD dataset.

DATASET DESCRIPTION

- RSICD dataset (Remote Sensing Image Captioning Dataset)
 Contains 10921 images
- Categories: Includes diverse land-use scenes like airports, residential areas, farmlands, forests, etc.

MODELS

- Without attention: LSTM
- With Attention: BAHADANUSelf Attention

Model Performance Comparison (with Normalized CIDEr) Without Attention With Attention Self-Attention 1.0 0.72 0.71 0.58 0.60 0.56 0.55 0.60 0.50 0.40 0.36 0.28 0.28 0.28 0.20 BLEU-1 BLEU-1 BLEU-4 METEOR Fivaluation Metrics ROUGE-L CIDER

ARCHITECTURE

LSTM

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With Attention Models

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Softmax
Linear
Linear

Feed Forward

Add & Norm

Multi-Head
Attention

Attention

Add & Norm

Masked
Multi-Head
Attention

Positional
Embedding
Outputs
(shifted right)

Transformer Architecture

EVALUATION METRICS

- BLEU 1
- BLEU 4
- ROGUE-L
- METEOR
- CIDEr

• Without Attention

BLEU-1: 0.2268513466936563 BLEU-4: 0.03741031958502291 METEOR: 0.12974948176486473 ROUGE-L: 0.36337815014538283 CUBEr: 0.6167299552633228

• With Attention (Bahadanu)

BLEU-1: 0.58176645556193 BLEU-4: 0.3592453719294569 METEOR: 0.2847761155768596 ROUGE-L: 0.5569654760906465

• Self Attention (Transformer)

BLEU-1: 0.7245303513310414 BLEU-4: 0.6033369125995696 METEOR: 0.40481117861914684 ROUGE-L: 0.7116814029470848 CIDEr: 5.772107762349921

Feature	LSTM (no attention)	LSTM + Attention	Transformer (Self-Attention
Encoder	ResNet-18	ResNet-18	ResNet-18
Decoder	LSTM	LSTM + Bahdanau Attention	Transformer Decoder
Attention Mechanism	None	Additive (Bahdanau)	Self-Attention (Multi-head)
Inference Complexity	Low	Moderate	High
Model Size	Small	Medium	Large
Training Time/sample	0.005 s	0.009 s	0.015 s

CONCLUSION

- Self-attention-based models significantly improved image captioning quality.
- Attention mechanisms enhance the contextual relevance and accuracy of generated captions.
- Transformer model achieved higher metric scores than the model in the base paper.