

Learning Descriptive Image Captioning via Semipermeable Maximum Likelihood Estimation

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Background



Image captioning suffers from overly-generic outputs

- Generate with simple concepts and minimal details
- Repetitive captions for different images

VLP: a man riding a wave on a surfboard in the ocean.





Repetitive captions generated by VinVL^[A] for different images in the MSCOCO test set.^[B]

[A] Vinvl: revisiting visual representations in vision-language models, in CVPR 2021 [B] CapEnrich: enriching caption semantics for web images via cross-modal pre-trained knowledge, in WWW 2023

Occurrence Frequency

Foundation



- Image Captioning Optimization: Maximum Likelihood Estimation (MLE)
 - Proxied by Next-token Prediction
 - Predictive distribution of the next token
 - Cross Entropy Loss

$$\mathcal{L}_{\text{MLE}} = -\sum_{j}^{|\mathcal{V}|} y_j \log \hat{P}^{\mathcal{V}}(w|w_{<}, v; \theta),$$

- 'A picture is worth a thousand words'
 - Various correct descriptions for an image
 - Multiple reasonable answers for token prediction
 - MLE's strict supervision is not perfectly suitable for captioning optimization!



- What happens when optimizing with MLE
 - Penalize model whenever its prediction mismatches label, leading to:
 - Richness Optimization, which makes prediction richer
 - Conciseness Optimization, which makes prediction more concise



Case 1:

- a _____ woman holding a cake
- GT: pretty Prediction: woman (less rich than GT)
- \rightarrow Richness Optimization

Case 2:

a pretty woman holding a ____ GT: cake Model: white (less concise than GT) → Conciseness Optimization





• **S**emipermeable **M**ax**I**mum **L**ikelihood **E**stimation (SMILE)

- A simple modification to MLE loss CrossEntropy(P^V, P^y)
 - Calculating cross entropy loss over a small vocabulary subset V_D
 - The subset contains only words in the ground truth sentence

$$\mathcal{L}_{\text{SMILE}} = -\sum_{j}^{|\mathcal{V}_{D}|} y_{j} \log \hat{P}^{\mathcal{V}_{D}}(w|w_{<}, v; \theta). \qquad \hat{p}_{j} = \text{softmax}(\mathbf{z}_{j}) = \frac{\exp(\mathbf{z}_{j})}{\sum_{k \in \mathcal{V}_{D}} \exp(\mathbf{z}_{k})}.$$
Ground truth sentence: " a c d m n "
Next-token prediction: " a c _ (d) " a b c d e f g h ... x y z a c d m n

Predictive distribution over entire vocabulary (MLE) Predictive distribution over the subset (SMILE)

• How SMILE responds to Concise. Optimization and Rich. Optimization?



• Conciseness Optimization is removed; Richness Optimization is reserved



- Key idea behind the subsetting strategy:
 - "Richer" words expressing additional details are typically outside GT caption
 - e.g., "white" for "a pretty woman holding a <u>cake</u>"
 - By subsetting we exclude "richer" words causing conciseness optimization
 - "More concise" words are likely elements in the ground truth caption
 - e.g., "woman" for "a pretty woman holding a cake"
 - Subsetting won't exclude "more concise" words causing richness optimization

• Allowing richness optimization while preventing conciseness optimization

Cases



Descriptive captions generated by SMILE-optimized captioning model



Human

a woman holding a birthday cake with lit candles. MLE

a woman holding a cake with lit candles. SMILE (ours)

a pretty young lady that has some kind of white frosted birthday cake with lots of lit candles on top of it, surrounded by several other people looking onwardly at something in the distance.



Human

a wire with a street light hanging from it.

MLE

a traffic light hanging from the side of a building. **SMILE** (ours)

a close-up image of two red stoplights hanging from an electrical cable system outside a large brick church building, during the early morning hours.

Human

ocean showing a boat sailing on the waters. MLE

a boat floating on top of a large body of water. SMILE (ours)

a lone fishing vessel that appears to be floating peacefully across the vast expanse of crystal blue water near an island in the far distance.



Human

a man in black surfing in high and strong waves. MLE

a man riding a wave on top of a surfboard. SMILE (ours)

a young adult male leans forward as he stands atop an extremely wide red and white striped surfboard in the midst of crashing waves.

- Paper
 - <u>https://arxiv.org/abs/2306.13460</u>
- Code
 - <u>https://github.com/yuezih/SMILE</u>
- Demo
 - https://huggingface.co/spaces/yuezih/BLIP-SMILE
- Contact
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