Assessing Effective Token Length of Multimodal Models for Text-to-Image Retrieval

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Introduction

Multimodal models revolutionize text to image retrieval by mapping text and image embeddings into a shared vector space.

We systematically benchmark current state of the art multimodal models across diverse datasets to quantify effective token lengths and domain-specific robustness.

Our open-source, reproducible framework guides optimal query design and establishes standard benchmarks for long-text image retrieval.

Research Questions

- **RQ1 :** What is the effective token length for CLIP, BLIP-2, ALIGN, OpenCLIP, and Long-CLIP?
- **RQ2 :** How does domain-specific language (medical, news, AI-generated, urban scenes) affect effective token length?
- **RQ3 :** Do chunking and pooling strategies that use all tokens available in a document affect the effective token length?

Methodology

1.Progressive truncation

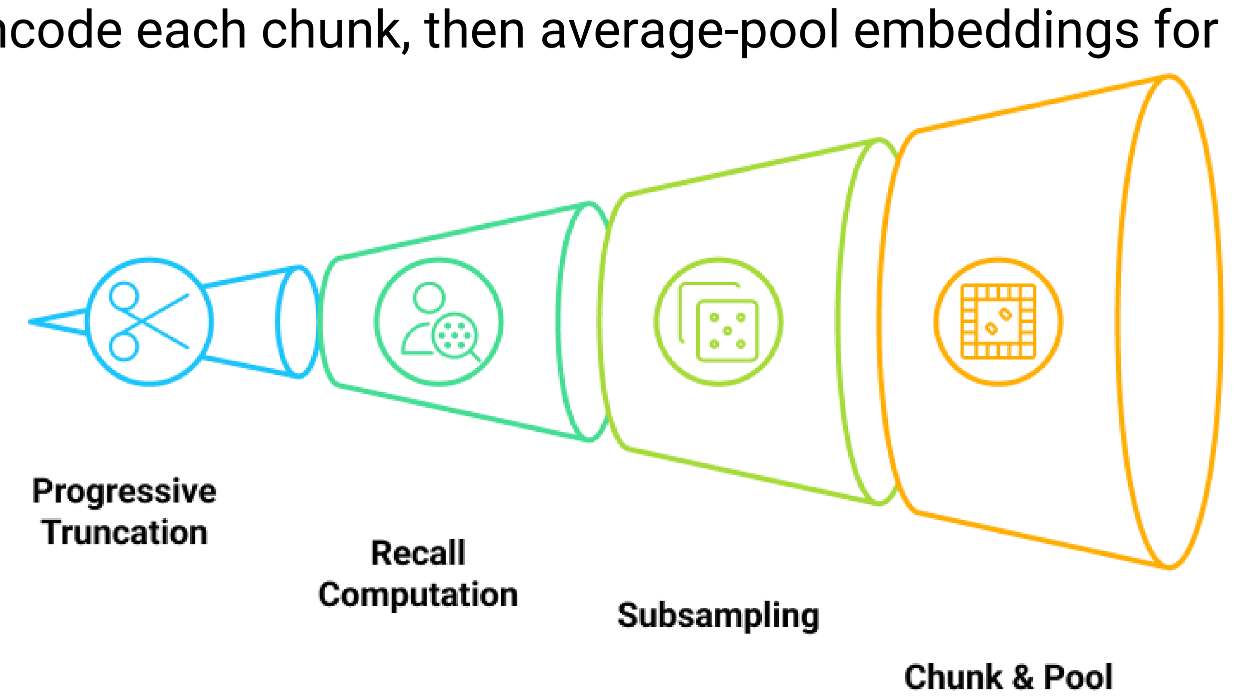
- Truncate each caption at increasing token lengths.
- Compute Recall@1 with FAISS retrieval.

2.Subsampling

- Draw 10 random 1000-item subsets per dataset.
- Repeat truncation experiment to build confidence intervals.

3.Chunk & pooling

- Split texts exceeding the model's token limit into equal sized chunks before processing.
- Encode each chunk, then average-pool embeddings for retrieval.

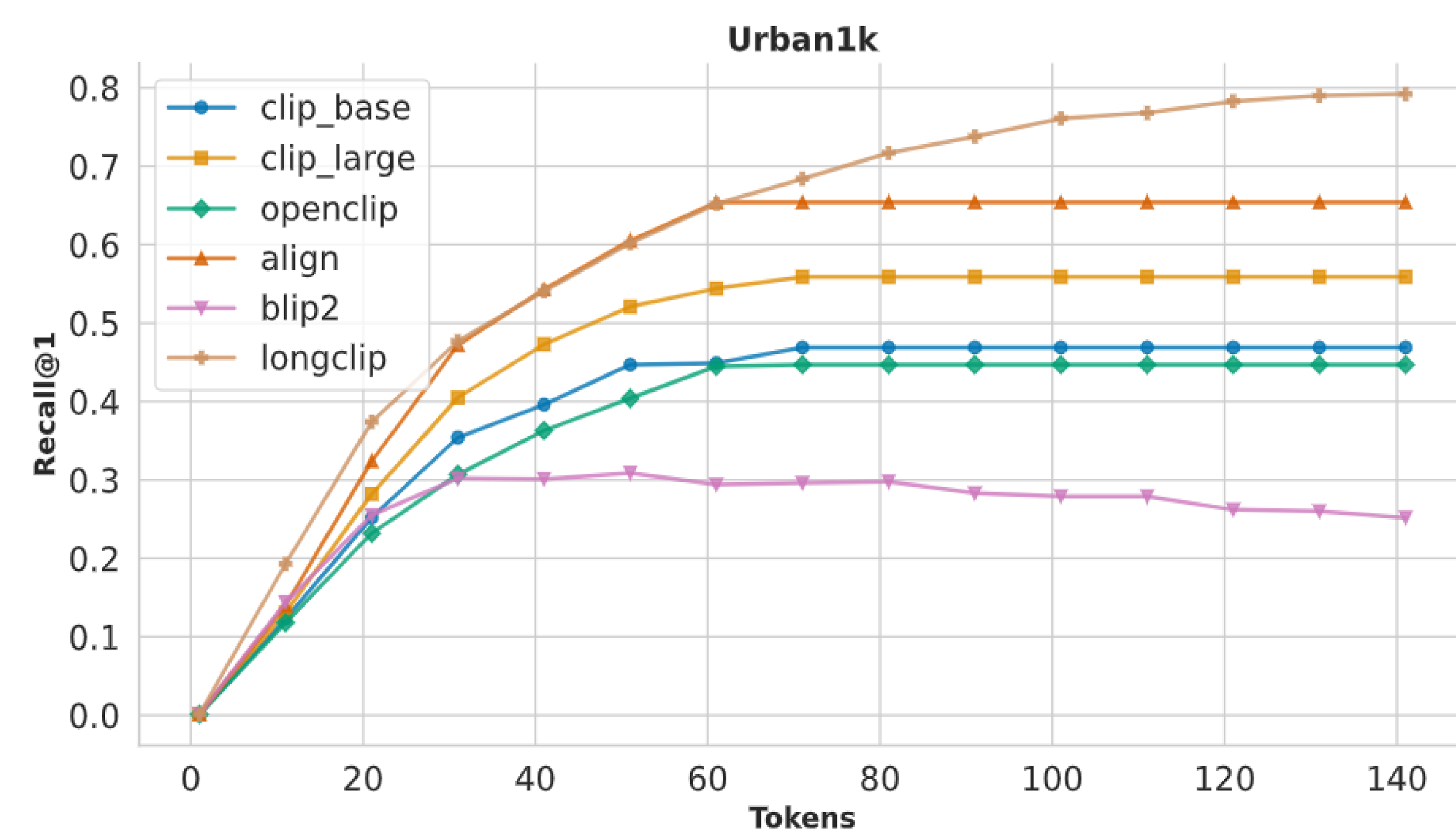


Dataset

Dataset	Domain	Avg. Caption Length
Urban1k	Urban scenes	101 tokens
ROCO	Medical imaging	25 tokens
ShareGPT4V	AI-generated	160 tokens
Factify2	News reports	1736 tokens

Results

RQ1. Effective Token Length



Recall@1 by caption length on the Urban1k Dataset

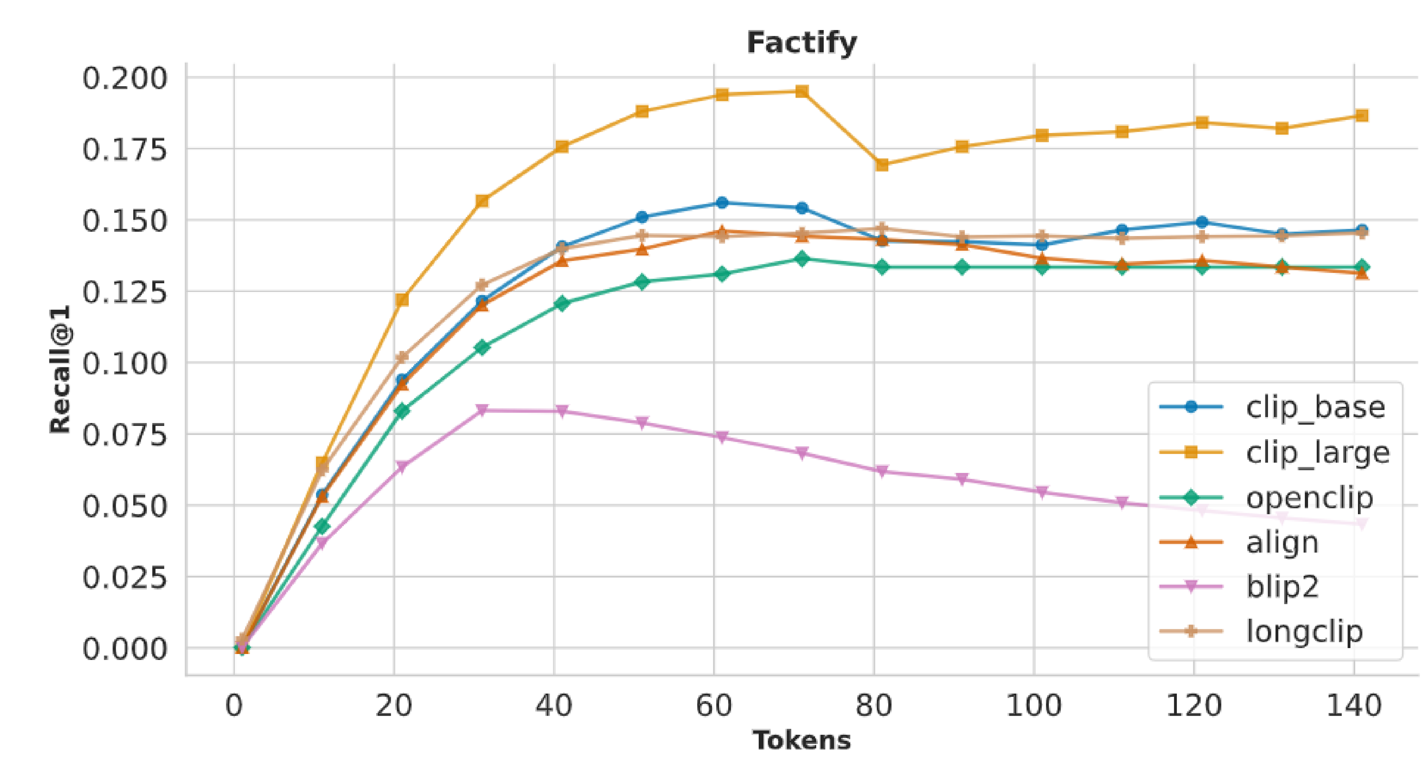
- **CLIP-Base** plateaus (~0.47) by **40 tokens** → 95 % of max recall.
- **CLIP-Large** reaches its plateau (~0.56) by **50 tokens**.
- **OpenCLIP** and **ALIGN** both hit ~95 % recall by **50–60 tokens.**
- **BLIP-2** (512 token limit) tops out earlier (~0.30) around **30 tokens**, then slightly declines.
- **Long-CLIP** exhibits the highest plateau (~0.79) but only after **90 tokens**—well below its 248-token input limit.

All models achieve near-maximum retrieval performance at **40–90 tokens**, significantly below their architectural token limits **(77–512 tokens)**, confirming each model's "effective token length".

RQ2. Domain Specific Language

- **ROCO (Medical Imaging)** and **Factify2 (News Reports)** both show lower overall Recall@1 (max ≤ 0.1 on ROCO) and **more varied effective lengths** across models.
- **Long-CLIP's** effective length on **Factify2** drops to **30 tokens** at 95% recall, **half of its Urban1k performance,** emphasizing how technical or verbose text can limit token utility.
- **ShareGPT4V** and **Urban1k** exhibit higher and more consistent effective lengths **(~50 tokens)** across all models.
- **OpenCLIP**'s massive web-scale training yields a **consistent 50-token limit**—highlighting broad-corpus benefits.

RQ3. Chunking and Pooling



Recall@1 with Extended Text Chunking and Pooling on the Factify2 Dataset

- For RQ3 (performed on Factify2), splitting texts into chunks and averaging their embeddings **did not improve Recall@1** or shift the effective token length beyond each model's native limit.
- Simple chunk-and-pool strategies yield **no significant gains** on image retrieval performance (Recall@1 curves remain flat past the model limit), suggesting that embedding models heavily prioritize initial tokens.

Conclusions

- **Early Plateau :** Models reach ≥95% Recall@1 by 40–60 tokens, far below their input limits.
- **Domain Impact :** ROCO and Factify2 show lower, variable recall; Urban1k and ShareGPT4V are more stable.
- **Chunking Ineffective :** Chunking and Pooling tokens doesn't rescue performance; models prioritize initial tokens.