

# Image Retrieval/Generation for Arguments [Joint Task with ImageCLEF]

## Touché'25 Task 3



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# Image Retrieval/Generation for Arguments [Joint Task with ImageCLEF]

## Task Description

Scenario: Enhance the impact of arguments.

Task: Given an argument, identify images that effectively convey the argument's premise.

- Participants may either retrieve images from a dataset or generate them using a text-to-image model.

Data:

- 128 arguments across 27 topics
- ca. 32,000 crawled images with corresponding website information and additional metadata, including automatically generated captions

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## Example

Topic: Public Transportation vs. Private Cars

Claim: Cars make it easy to transport goods and belongings



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## Evaluation

- ❑ For each argument, two aspects were identified, and each aspect was rated using the following scale:
  - 0: Aspect does not convey the claim
  - 1: Aspect partially conveys the claim
  - 2: Aspect fully conveys the claim
- ❑ For each annotator, the aspect scores were aggregated to derive a single rating for an argument-image pair.
- ❑ Final score for an argument-image pair is computed by combining the individual ratings from two annotators.



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## Example Submission

| Argument  | Retrieval  | Generation  |
|---|--|---|
| <p><b>Topic:</b> Public Transportation vs. Private Cars</p> <p><b>Claim:</b> Cars make it easy to transport things</p> <p><b>Aspects:</b> car, transport things</p> |  <p>Source: Web</p> |  <p>Source: Stable Diffusion 3.5</p> |

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*Here both images get a score of two. The two required aspects do not need to be combined in a precise way.*

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## Results - Retrieval

| Rank | Team              | Approach                 | NDCG@5 |
|------|-------------------|--------------------------|--------|
| 1    | Baseline          | CLIP Image               | 0.855  |
| 2    | Infotec+CentroGEO | OpenCLIP Image           | 0.836  |
| 3    | Baseline          | SBERT Website-Text       | 0.811  |
| 4    | Infotec+CentroGEO | MCIP Image               | 0.794  |
| 5    | Infotec+CentroGEO | SBERT Image-Text+Caption | 0.755  |
| 6    | CEDNAV-UTB        | CLIP Image-Caption       | 0.236  |

*The 'Approach' column specifies how the embeddings for the images were generated and compared with the arguments. For example, 'CLIP Image' indicates that multimodal CLIP embeddings are employed.*

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## Results - Generation

| Rank | Team     | Approach             | NDCG@5 |
|------|----------|----------------------|--------|
| 1    | Hanuman  | Generative Prompt    | 0.963  |
| 2    | Baseline | Stable Diffusion 1.0 | 0.844  |
| 3    | Baseline | Stable Diffusion 3.5 | 0.839  |

Approaches:

- ❑ **Generative-Prompt:** Use an LLM to identify key aspects of the argument and compose a tailored image-generation prompt. For generation Stable Diffusion 1.0 is used.
- ❑ **Baseline:** Directly use the arguments themselves as the image-generation prompt.



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*Image generation for arguments produces good results, especially when using carefully crafted custom prompts.*

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## Lessons Learned

- ❑ Finding suitable images for arguments is challenging; generation often works better for specific arguments than retrieval.
- ❑ Retrieval approaches are constrained by the limited scope of available web sources, which tend to emphasize more general arguments.
- ❑ The main challenge for generation approaches lies in combining multiple aspects effectively and depicting elements that should not be displayed.