Dream Scape

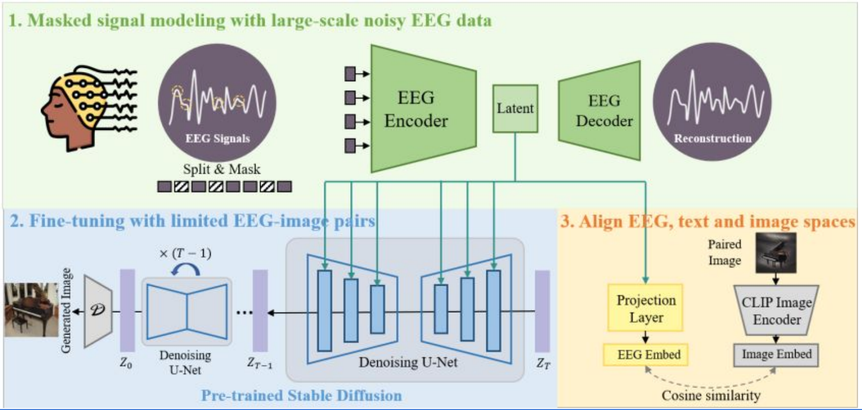
Devan Shah

Introduction

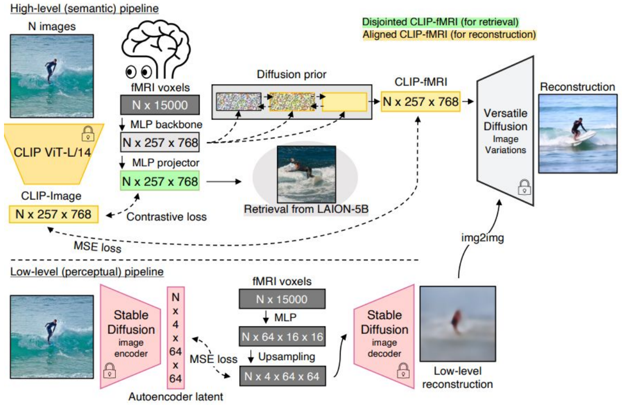
The last six months have seen a tremendous amount of research in converting brain visualization data in the form of EEG and fMRI scans back into an image.

Yet gathering such data is challenging, and so researchers train with adjacent tasks with the end goal of converting their models to this visualization.

"The primary purpose… was to lay the groundwork for extending these sorts of models to mental imagery"
Reese Kneeland, *Second Sight*



DreamDiffusion (L) and MindEye (R) are the models we focus on.



The Consequence

The result is models that, when used for visualization, suffer due to high noise, and impressive training results lead nowhere.

DreamScape addresses this issue by informing these models with user information, improving performance at no detriment, and learning from the user for constant improvement.

EEG → DreamDiffusion [1] (297M) → CLIP Embeddings

fMRI → MindEye [2] (940M) → CLIP Embeddings

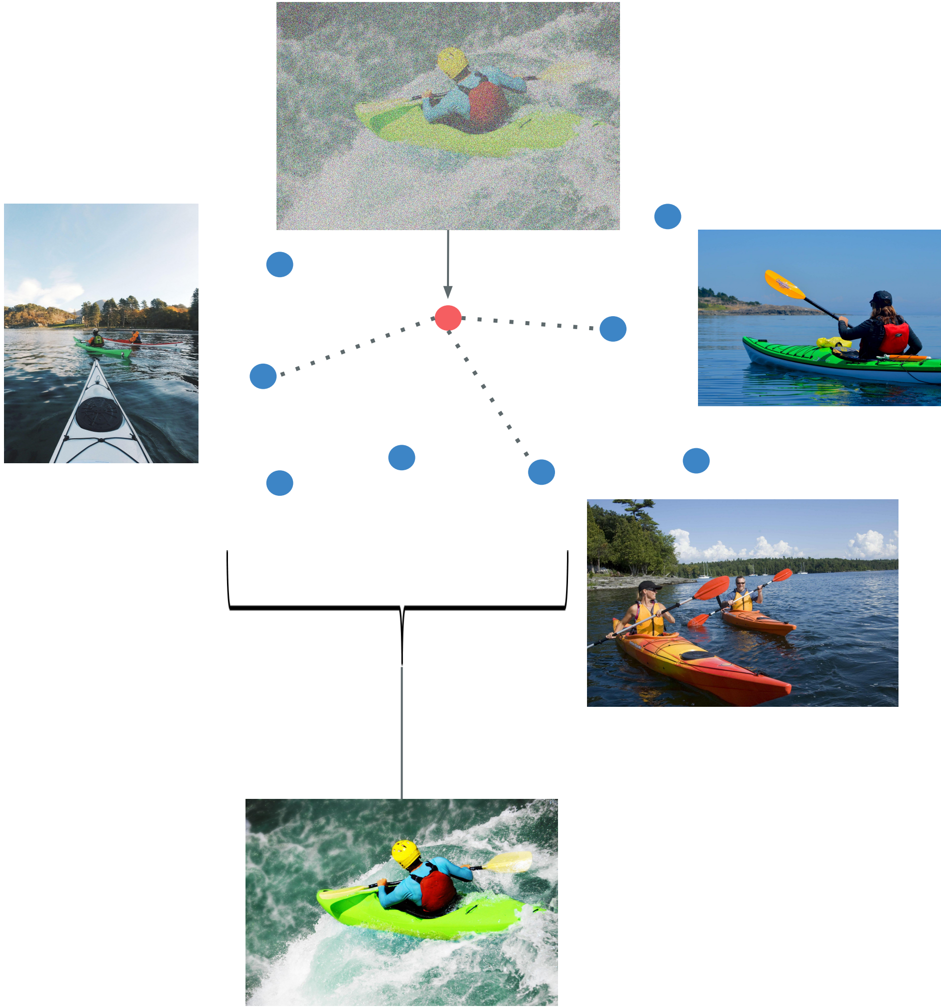
CLIP Embeddings $\xrightarrow{\text{DreamScape}}$ Enhanced Embeddings

Reconstitution System

Thought embeddings from an initial embedding model (DD or ME) are averaged with relevant images important to the user.

To find relevant user images, we perform kNN on a user index with the thought embeddings warped by time and location to find the subject the embedding is most likely about.

Intuitively, the clip search space is dense whereas the set of items a user may interact with or visualizes is relatively sparse.



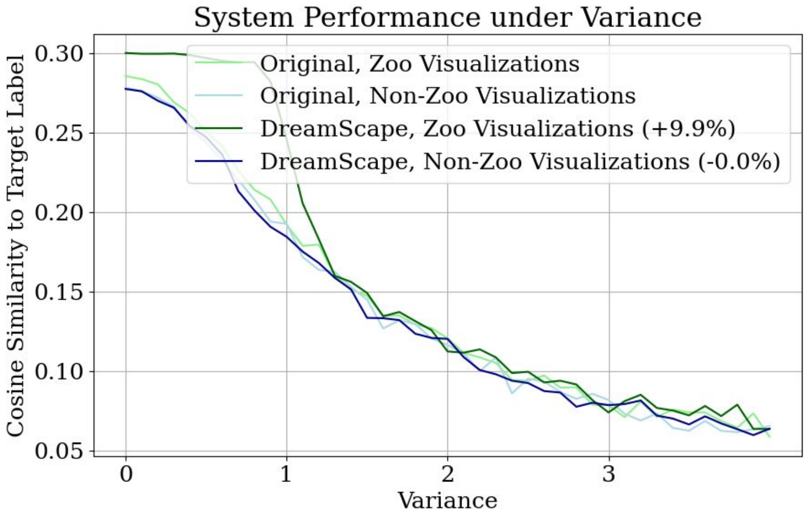
Performance — Noised CLIP data

We simulate the "zoo visit" scenario, where your location cues the system to a zoo visit. We test the system performance on elements both relevant and not relevant to the location.

Retrieval Accuracy (~600k):

	Var: 0	Var: 0.25	Var: 0.75	Var: 1.5	Var: 2
DreamScape	15/16 16/16	15/16 14/16	16/16 12/16	8/16 3/16	4/16 2/16
Original	15/16 16/16	16/16 13/16	11/16 14/16	5/16 3/16	1/16 3/16

CLIP Alignment:

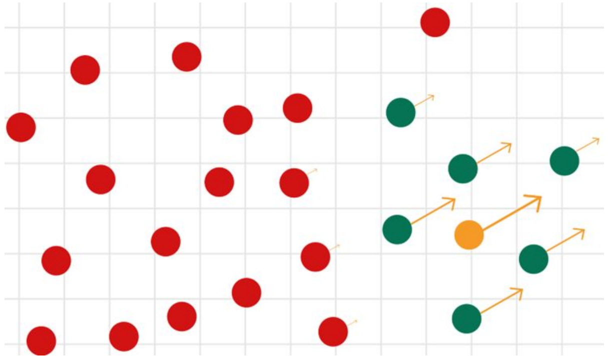


Adaptable Embeddings

Leveraging EER (and fMRI) model capabilities of predicting emotion [3,4] and optional user-reinforcement, our system develops custom bias vectors associated to clusters in the user image index, which effectively alters the embedding space to incorporate user attributes.

We perform kNN with bias vectors to adjust nearby embeddings.

This replaces the need to fine-tune a CLIP model for each user, an intractable but otherwise useful task.

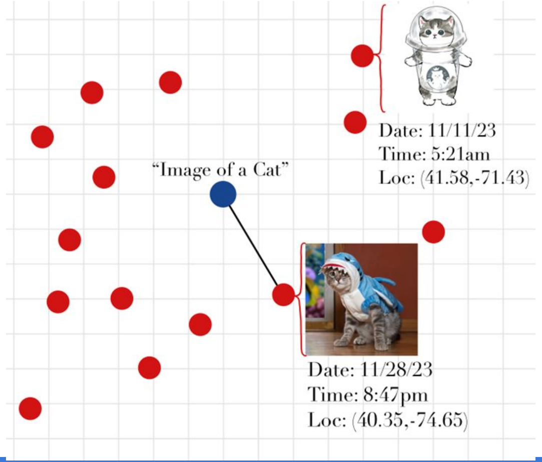


Vectors are shifted by bias vectors.
In this example, this subregion may correspond to cute animals (red), but a scary experience with a specific dog (yellow) corresponds to a bias vector that now shifts all dogs (green) away from the cute animals.

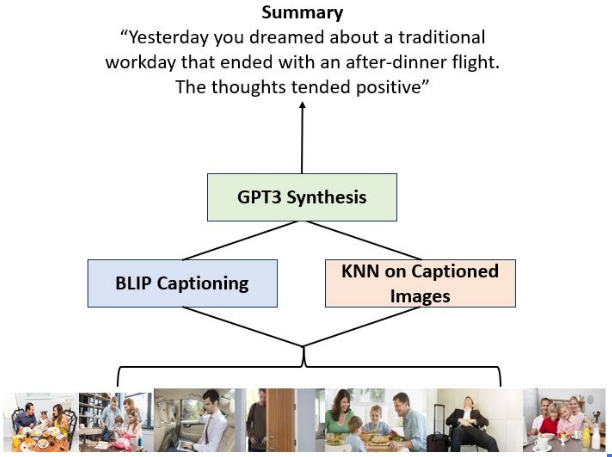
Applications of accurate brain embeddings

Recollection: As users use our system, we gain a database of CLIP-embedded thoughts that enable vector search as a form of cross-modality retrieval.

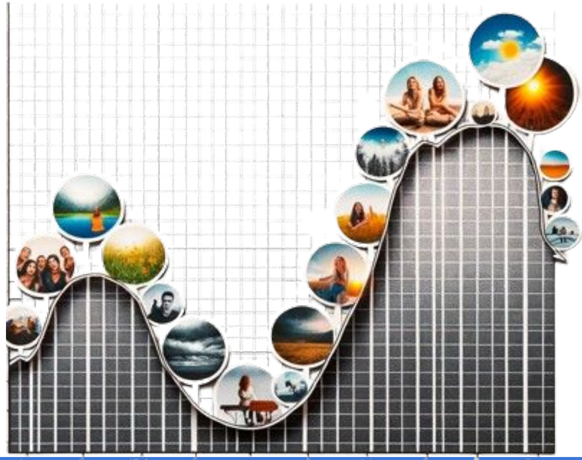
Locate Thoughts



Summarize



Track Thought Content



Summary

- Leveraged user-data to denoise user visualization embeddings
- User index leveraging Google Photos and Flickr API that adapts to user information
- Leverage brain data for additional applications with an index storing embeddings
- Tested system with both real and synthesized data

Continued Work

- Train embedding model on mobile EEG system for a live and accessible system
- Testing improved systems for finding relevant images

References

[1] Bai, Yunpeng, et al. "DreamDiffusion: Generating High-Quality Images from Brain EEG Signals." arXiv, 2306.16934 (2023).

[2] Scotti, Paul S., et al. "Reconstructing the Mind's Eye: fMRI-to-Image with Contrastive Learning and Diffusion Priors." arXiv, 2305.18274 (2023).

[3] A. Arsalan, M. Majid, A. R. Butt and S. M. Anwar, "Classification of Perceived Mental Stress Using A Commercially Available EEG Headband." IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 6, pp. 2257-2264, Nov. 2019, doi: 10.1109/JBHI.2019.2926407.

[4] Arsalan, Aamir, and Muhammad Majid. "A Study on Multi-Class Anxiety Detection Using Wearable EEG Headband." Journal of Ambient Intelligence and Humanized Computing, vol. 13, no. 12, 2022, pp. 5739-5749.

Bustos, Cristina, et al. "On the Use of Vision-Language Models for Visual Sentiment Analysis: A Study on CLIP." arXiv, 2310.12062 (2023).