



User



Assistants



@input: Conduct a research on EEG-based emotion recognition. The research problem is data scarcity.

## Exploration Stage

## Plan Pool

$A_1^{(g)}$  ... meta-learning offers a powerful paradigm for addressing data scarcity by enabling models to quickly adapt to ...

$A_2^{(g)}$  ... ensemble learning addresses data scarcity by combining multiple models to create a more robust and generalizable ...

$A_3^{(g)}$  ... data augmentation provides a direct approach to addressing data scarcity by artificially expanding the training ...



Evaluate and preserve top  $k$  to update the plan pool.

## Imitate



List studies for @plan 1 (resource: @paper 1)



EEG Data Augmentation and EEG Generation

SearchPaper("EEG Data Augmentation") not in Pool

@paper 1: GANSER: A Self-supervised Data Augmentation Framework for EEG-based Emotion Recognition



Follow the related work to derive the  $\phi(A_3^{(g)})$

## Improve



List bottlenecks of @plan 1 (resource: @paper 1)



GAN is unstable while training for augmentation

SearchPaper("Generative Models") not in Pool

@paper 2: High-resolution image synthesis with latent diffusion models



Follow the related work to revise your plan to derive the  $\sigma(A_3^{(g)})$

## Crossover



List insights of @plan 1 (resource: @paper 1)



... integrate generative adversarial networks with ... @paper 1: ... adversarial ...



List insights of @plan 2 (resource: @paper 2)



... propose a diffusion model for EEG data augmentation ... @paper 2: ... latent diffusion ...



Merge the insight of two solution and propose a new  $\delta(A_3^{(g)})$

$$\pi(P_i^{(t)} | C^{(t)}, E^{(t)})$$



Revise the Plan via Observation

Exploitation Stage



## Plan of the Manuscript

$P_1^{(t)}$  *Introduction*  
This section introduces the motivation and context ...

$P_2^{(t)}$  *Related Work*  
This section reviews prior research relevant to EEG ...

$P_3^{(t)}$  *Methodology*  
This section presents the proposed diffusion model ...



## Observation for the Plan

$E_1^{(t)}$  Extract "EEG feature encoding" from @paper 1

$E_2^{(t)}$  Extract "diffusion process" from @paper 2

...



## Context for the Plan

$C_1^{(t)}$  Extract "framework description" from @draft

...



Revise the Plan via Action

Draft for Plans  $\{D_p^{(t)}\}_{p \leq i}$ 

... The input to the proposed diffusion model is a preprocessed EEG segment, represented as a matrix  $\mathbf{x}_0 \in \mathbb{R}^{C \times L}$ , where  $C$  denotes the number of EEG channels and  $L$  is the number of time points in each segment. To preserve both spatial (across channels) and temporal ...

Implement



## Codes for Plans

... diffusion\_model = create\_eeg\_diffusion\_model(input\_shape=input\_shape, hidden\_dims=...



## Logs of the Codes

[2025-09-05 14:25:50] INFO: Accuracy: 0.8735  
[2025-09-05 14:25:50] INFO: Precision: 0.8692

Describe

$$\pi(\{P_r^{(t)}\}_{r>i}, \{D_p^{(t)}\}_{p \leq i}, \{P_q^{(t)}\}_{q \leq i})$$