

# Novelty Assessment Report

**Paper:** Assembling the Mind's Mosaic: Towards EEG Semantic Intent Decoding

**PDF URL:** <https://openreview.net/pdf?id=8OgJ2uhiu8>

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## Abstract

Enabling natural communication through brain-computer interfaces (BCIs) remains one of the most profound challenges in neuroscience and neurotechnology. While existing frameworks offer partial solutions, they are constrained by oversimplified semantic representations and a lack of interpretability. To overcome these limitations, we introduce **Semantic Intent Decoding (SID)**, a novel framework that translates neural activity into natural language by modeling meaning as a flexible set of compositional semantic units. SID is built on three core principles: semantic compositionality, continuity and expandability of semantic space, and fidelity in reconstruction. We present **BrainMosaic**, a deep learning architecture implementing SID. BrainMosaic decodes multiple semantic units from EEG/SEEG signals using set matching and then reconstructs coherent sentences through semantic-guided reconstruction. This approach moves beyond traditional pipelines that rely on fixed-class classification or unconstrained generation, enabling a more interpretable and expressive communication paradigm. Extensive experiments on multilingual EEG and clinical SEEG datasets demonstrate that SID and BrainMosaic offer substantial advantages over existing frameworks, paving the way for natural and effective BCI-mediated communication.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Decoding Semantic Intent from EEG Signals into Natural Language**

A total of **50 papers** were analyzed and organized into a taxonomy with **19 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **EEG Representation Learning and Encoding**
- **EEG-to-Text Generation Architectures**
- **Cross-Modal and Multimodal Integration**
- **Specialized Decoding Paradigms and Applications**
- **Evaluation, Robustness, and Methodological Analysis**
- **Auxiliary Methods and Supporting Techniques**
- **Survey, Review, and Interdisciplinary Perspectives**
- **Invasive and Clinical Decoding Paradigms**
- **Unconventional and Exploratory Approaches**

### Complete Taxonomy Tree

- Decoding Semantic Intent from EEG Signals into Natural Language Survey Taxonomy
- EEG Representation Learning and Encoding
  - Contrastive and Self-Supervised EEG Encoding (4 papers)
    - [3] Aligning Semantic in Brain and Language: A Curriculum Contrastive Method for Electroencephalography-to-Text Generation (Xiaochong Feng, 2023) [View paper](#)
    - [10] Semantic-aware Contrastive Learning for Electroencephalography-to-Text Generation with Curriculum Learning (Feng, 2023) [View paper](#)
    - [12] Enhancing eeg-to-text decoding through transferable representations from pre-trained contrastive eeg-text masked autoencoder (Ma ZhengYu, 2024) [View paper](#)
    - [28] BELT: Bootstrapped EEG-to-Language Training by Natural Language Supervision (Jinzhao Zhou, 2024) [View paper](#)
    - Pretrained Foundation Models for EEG (3 papers)
    - [14] NeuroLM: A universal multi-task foundation model for bridging the gap between language and EEG signals (Wei-Bang Jiang, 2024) [View paper](#)
    - [21] Foundation models for cross-domain eeg analysis application: A survey (Li Hongqi, 2025) [View paper](#)
    - [22] Large Language Models for EEG: A Comprehensive Survey and Taxonomy (Mathew Jimson, 2025) [View paper](#)
    - Discrete and Quantized EEG Encoding (3 papers)
    - [11] BrainECHO: Semantic Brain Signal Decoding through Vector-Quantized Spectrogram Reconstruction for Whisper-Enhanced Text Generation (Jilong Li, 2025) [View paper](#)
    - [26] Dewave: Discrete encoding of eeg waves for eeg to text translation (Y Duan, 2023) [View paper](#)
    - [30] DeWave: Discrete EEG Waves Encoding for Brain Dynamics to Text Translation (Duan Yiqun, 2023) [View paper](#)
- EEG-to-Text Generation Architectures
  - Encoder-Decoder and Sequence-to-Sequence Models (6 papers)
  - [9] A hybrid TH-LSTM-Transformer Model for text generation from EEG signals during imagined character speech (Pan Hongguang, 2026) [View paper](#)
  - [23] Eeg2text: Open vocabulary eeg-to-text decoding with eeg pre-training and multi-view transformer (Liu Hanwen, 2024) [View paper](#)

- [24] Open vocabulary electroencephalography-to-text decoding and zero-shot sentiment classification (Ji, 2022) [View paper](#)
- [33] EEG2Text: Open Vocabulary EEG-to-Text Translation with Multi-View Transformer (Hanwen, 2024) [View paper](#)
- [49] EEG-to-Text Translation: A Model for Deciphering Human Brain Activity (Murad, 2025) [View paper](#)
- [50] Neurocognitive Modeling for Text Generation: Deep Learning Architecture for EEG Data (Khushiyant, 2025) [View paper](#)
- LLM-Based and Instruction-Tuned Decoding (3 papers)
- [1] Thought2Text: text generation from EEG signal using large language models (LLMs) (Gwizdka Jacek, 2025) [View paper](#)
- [31] Guiding LLMs to Decode Text via Aligning Semantics in EEG Signals and Language (Huanran Zheng, 2025) [View paper](#)
- [43] Prompting the Mind: EEG-to-Text Translation with Multimodal LLMs and Semantic Control (Al-Radhi, 2025) [View paper](#)
- Semantic Reconstruction and Compositional Decoding ★ (4 papers)
- [0] Assembling the Mind's Mosaic: Towards EEG Semantic Intent Decoding (Anon et al., 2026) [View paper](#)
- [2] Semantic reconstruction of continuous language from non-invasive brain recordings (Jerry Tang, 2023) [View paper](#)
- [42] Neuro2Semantic: A Transfer Learning Framework for Semantic Reconstruction of Continuous Language from Human Intracranial EEG (Siavash Shams, 2025) [View paper](#)
- [46] Learning Interpretable Representations Leads to Semantically Faithful EEG-to-Text Generation (Liu Xiao-zhao, 2025) [View paper](#)
- Cross-Modal and Multimodal Integration
  - Multimodal Alignment with Images and Audio (1 papers)
  - [15] Decoding the Multimodal Mind: Generalizable Brain-to-Text Translation via Multimodal Alignment and Adaptive Routing (Zhang Yunhao, 2025) [View paper](#)
  - Image Generation from EEG (1 papers)
  - [8] Exploring the Potential of Electroencephalography Signal-Based Image Generation Using Diffusion Models: Integrative Framework Combining Mixed Attention (CS Chen, 2025) [View paper](#)
- Specialized Decoding Paradigms and Applications
  - Imagined Speech and Motor Imagery Decoding (5 papers)
  - [34] EEG based thought-to-text translation via deep learning (Sarfraz Ali, 2023) [View paper](#)
  - [36] Converting your thoughts to texts: Enabling brain typing via deep feature learning of eeg signals (Xiang Zhang, 2018) [View paper](#)
  - [45] Handwriting Imagery EEG Classification based on Convolutional Neural Networks (Yang Hao, 2025) [View paper](#)
  - [47] A Novel Machine Learning Model for Non-Invasive EEG-Based Inner-Speech Translation in ALS (Steiner, 2025) [View paper](#)
  - [48] Text Generation of Speech Imagery Based on an Enhanced CTA-BiLSTM Model Utilizing EEG Signals (Pan Hongguang, 2025) [View paper](#)
  - Passive Reading and Sentence Retrieval (1 papers)
  - [16] Towards linguistic neural representation learning and sentence retrieval from electroencephalogram recordings (Jinzhao Zhou, 2024) [View paper](#)
  - Language-Specific and Cross-Lingual Decoding (2 papers)
  - [19] EEG2TEXT-CN: An Exploratory Study of Open-Vocabulary Chinese Text-EEG Alignment via Large Language Model and Contrastive Learning on Chinese EEG (Jacky Tai-Yu Lu, 2025) [View paper](#)
  - [32] Decoding of lexical items and grammatical features in EEG: A cross-linguistic study. (Jeonghwa Cho, 2025) [View paper](#)
  - Spelling-Based and Character-Level BCI (1 papers)
  - [20] Neural Spelling: A Spell-Based BCI System for Language Neural Decoding (Jiang Xiaowei, 2025) [View paper](#)
- Evaluation, Robustness, and Methodological Analysis
  - Performance Analysis and Benchmarking (2 papers)
  - [18] Are eeg-to-text models working? (Hye-Jeong Jo, 2024) [View paper](#)
  - [44] Evaluating EEG-to-text models through noise-based performance analysis (Hyejeong Jo, 2025) [View paper](#)
  - Architectural Component Studies (1 papers)
  - [17] On the role of activation functions in EEG-to-text decoder (Zenon Lamprou, 2024) [View paper](#)
- Auxiliary Methods and Supporting Techniques
  - Data Augmentation and Generative Models (2 papers)
  - [25] Enhanced Generative Adversarial Networks for Unseen Word Generation from EEG Signals (Young-eun Lee, 2024) [View paper](#)
  - [29] Folded ensemble deep learning based text generation on the brain signal (Vasundhara S. Rathod, 2024) [View paper](#)
  - General BCI Frameworks and Conceptual Models (5 papers)
  - [4] On creating a brain-to-text decoder (Yashar, 2025) [View paper](#)
  - [5] See: Semantically aligned eeg-to-text translation (Yitian Tao, 2025) [View paper](#)
  - [13] Bridging Brain Signals and Language: A Deep Learning Approach to EEG-to-Text Decoding (Nabil Omnia, 2025) [View paper](#)
  - [27] Translation of Brain Activity Patterns of a user into Commands using Electroencephalography (EEG) (Ranjana Bangarappa Jadekar, 2021) [View paper](#)
  - [35] Categorize EEG Signals from Brain to Text (Vinodh Kumar S, 2025) [View paper](#)
- Survey, Review, and Interdisciplinary Perspectives (2 papers)
  - [7] Unveiling thoughts: A review of advancements in eeg brain signal decoding into text (Murad, 2024) [View paper](#)
  - [37] Neurolinguistics research advancing development of a direct-speech brain-computer interface (Ciaran Cooney, 2018) [View paper](#)
- Invasive and Clinical Decoding Paradigms (4 papers)
  - [38] Neural Speech Tracking with EEG: Integrating Acoustics and Linguistics for Hearing Aid Users. (Martin A Skoglund, 2025) [View paper](#)
  - [39] Decoding Handwriting Trajectories from Intracortical Brain Signals for Brain-to-Text Communication. (Guangxiang Xu, 2025) [View paper](#)
  - [40] Brain-machine-interface device translates internal speech into text. (Anon et al., 2024) [View paper](#)
  - [41] Mind captioning: Evolving descriptive text of mental content from human brain activity. (Tomoyasu, 2025) [View paper](#)
- Unconventional and Exploratory Approaches (1 papers)
  - [6] Reverse Engineering Revelation: A Multi-Signal Computational Framework for Modeling Prophetic Inspiration (Pakgozar, 2025) [View paper](#)

## Narrative

Core task: decoding semantic intent from EEG signals into natural language. The field is organized around several complementary branches that address different facets of this challenge. EEG Representation Learning and Encoding focuses on extracting meaningful features from noisy neural recordings, often leveraging contrastive or self-supervised methods to align brain activity with linguistic or visual embeddings. EEG-to-Text Generation Architectures encompasses the design of end-to-end models—ranging from sequence-to-sequence frameworks to transformer-based decoders—that map EEG features directly to words or sentences. Cross-Modal and Multimodal Integration explores how to fuse EEG with auxiliary modalities such as eye-tracking or visual stimuli, while Specialized Decoding Paradigms and Applications targets specific use cases like imagined speech, handwriting imagery, or assistive communication for clinical populations. Evaluation, Robustness, and Methodological Analysis examines metrics, noise resilience, and reproducibility, and Survey, Review, and Interdisciplinary Perspectives provides broader context by synthesizing advances across neuroscience and machine learning.

Recent work has intensified around semantic reconstruction and compositional decoding, where the goal is to recover not just isolated words but coherent, contextually appropriate sentences. Minds Mosaic[0] sits squarely in this line, emphasizing compositional strategies that integrate semantic and syntactic cues from EEG. It shares thematic ground with Semantic Reconstruction Continuous[2] and Aligning Semantic Brain[3], both of which prioritize continuous semantic embeddings and alignment with pretrained language models. In contrast, nearby efforts like Neuro2Semantic[42] and Interpretable Representations Faithful[46] explore interpretability and faithful representation learning, highlighting trade-offs between end-to-end performance and model transparency. Across these branches, open questions persist regarding generalization to open-vocabulary settings, robustness to inter-subject variability, and the integration of large language models as semantic priors—issues that Minds Mosaic[0] and its neighbors continue to address through architectural innovation and richer alignment objectives.

## Related Works in Same Category

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The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

### 1. Semantic reconstruction of continuous language from non-invasive brain recordings

**Authors:** Jerry Tang, Amanda LeBel, Shailee Jain, Alexander G. Huth | **Year/Venue:** 2023 | **URL:** [View paper](#)

#### Abstract

â€¦ stimuli using continuous natural language. To accomplish this, we â€¦ Most existing language decoders map brain activity into â€¦ recording methods such as electroencephalography (EEG) or â€¦

#### Relationship Analysis

Both papers belong to the Semantic Reconstruction and Compositional Decoding category, focusing on decoding semantic representations from EEG signals before generating natural language sentences. They overlap in their approach of reconstructing continuous language from brain signals using semantic-level representations rather than direct end-to-end generation. The key difference is that the original paper (BRAINMOSAIC) explicitly models semantic intent as a variable-sized set of compositional semantic units with set-matching mechanisms, while the candidate paper focuses on continuous semantic reconstruction from non-invasive recordings without the explicit set-based compositional framework.

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### 2. Neuro2Semantic: A Transfer Learning Framework for Semantic Reconstruction of Continuous Language from Human Intracranial EEG

**Authors:** Siavash Shams, Richard Antonello, Gavin Mischler, Stephan Bickel, Ashesh Mehta, et al. (6 authors total) | **Year/Venue:** 2025 | **URL:** [View paper](#)

#### Abstract

Decoding continuous language from neural signals remains a significant challenge in the intersection of neuroscience and artificial intelligence. We introduce Neuro2Semantic, a novel framework that reconstructs the semantic content of perceived speech from intracranial EEG (iEEG) recordings. Our approach consists of two phases: first, an LSTM-based adapter aligns neural signals with pre-trained text embeddings; second, a corrector module generates continuous, natural text directly from these ali...

#### Relationship Analysis

Both papers belong to the Semantic Reconstruction and Compositional Decoding category, as they decode semantic units or representations from neural signals before reconstructing coherent sentences. They overlap in their use of semantic alignment with pre-trained text embedding spaces and constrained generation to produce natural language from EEG/iEEG signals. However, the original paper (BrainMosaic) employs set-based matching with variable-sized semantic units and explicit compositionality principles, while the candidate paper (Neuro2Semantic) uses a two-phase LSTM adapter with contrastive alignment followed by Vec2Text inversion for continuous text generation without explicit set decomposition.

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### 3. Learning Interpretable Representations Leads to Semantically Faithful EEG-to-Text Generation

**Authors:** Liu Xiao-zhao, Shen, Dinggang, Liu Xi-hui | **Year/Venue:** 2025 | **URL:** [View paper](#)

#### Abstract

Pretrained generative models have opened new frontiers in brain decoding by enabling the synthesis of realistic texts and images from non-invasive brain recordings. However, the reliability of such outputs remains questionable--whether they truly reflect semantic activation in the brain, or are merely hallucinated by the powerful generative models. In this paper, we focus on EEG-to-text decoding and address its hallucination issue through the lens of posterior collapse. Acknowledging the underlying...

#### Relationship Analysis

Both papers belong to the Semantic Reconstruction and Compositional Decoding category, focusing on frameworks that decode semantic units from EEG before reconstructing coherent sentences. They overlap in their approach to EEG-to-text generation by emphasizing semantic-level representations rather than direct word-level reconstruction, and both address the challenge of generating faithful natural language from neural signals. The key difference is that the original paper (BRAINMOSAIC) uses set-based matching with variable-sized semantic units and explicit semantic retrieval from a continuous space, while the candidate paper (GLIM) frames the task as semantic summarization and focuses on contrastive learning to align EEG representations with a frozen language model's latent space to mitigate posterior collapse.

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## Contributions Analysis

**Overall novelty summary.** ``json { "paragraphs": [ "The paper introduces Semantic Intent Decoding (SID), a framework that translates neural activity into natural language by modeling meaning as compositional semantic units, implemented through the BrainMosaic architecture. It resides in the 'Semantic Reconstruction and Compositional Decoding' leaf, which contains only four papers total including this work. This represents a relatively sparse but emerging research direction within the broader EEG-to-text generation landscape, suggesting the paper enters a less crowded space focused on explicit semantic decomposition rather than direct sequence-to-sequence translation.",

"The taxonomy reveals that neighboring leaves include 'Encoder-Decoder and Sequence-to-Sequence Models' (six papers) and 'LLM-Based and Instruction-Tuned Decoding' (three papers), representing alternative architectural paradigms. While encoder-decoder approaches translate EEG directly to text without explicit semantic decomposition, and LLM-based methods leverage pretrained language models through fine-tuning or prompting, SID occupies a middle ground by first decoding semantic units before reconstruction. The scope note for this leaf explicitly excludes 'direct sequence-to-sequence translation without explicit semantic decomposition,' positioning the work as architecturally distinct from the larger encoder-decoder branch."

"Among 21 candidates examined across three contributions, none were found to clearly refute the paper's claims. The SID framework itself was assessed against three candidates with no refutable overlap; the BrainMosaic architecture examined eight candidates with similar results; and the embedding-based evaluation metrics reviewed ten candidates without finding substantial prior work. These statistics reflect a limited but focused literature search rather than exhaustive coverage. The absence of refutable candidates among this sample suggests the specific combination of set-based semantic decoding, compositional reconstruction, and the particular architectural choices may offer incremental novelty within the examined scope."

"Based on the top-21 semantic matches and the sparse taxonomy leaf (four papers total), the work appears to occupy a relatively underexplored niche emphasizing compositional semantic decomposition. However, the limited search scale and the presence of three sibling papers in the same leaf indicate that while the specific implementation may be novel, the broader concept of semantic reconstruction from EEG has active parallel development. A more comprehensive literature search would be needed to fully assess novelty across the wider BCI and neural decoding communities." ] } ```

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

### **Contribution 1: Semantic Intent Decoding (SID) framework**

**Description:** The authors propose a new framework for brain-computer interfaces that represents communicative intent as a variable set of semantic units rather than fixed labels or unconstrained generation. This framework is built on three principles: semantic compositionality, continuity and expandability of semantic space, and fidelity in reconstruction.

This contribution was assessed against **3 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. A search for the neural bases of compositionality**

**URL:** [View paper](#)

##### **Brief Assessment**

Neural Compositionality[67] focuses on characterizing how compositional semantic representations emerge and evolve in the brain during sentence processing, using dimensionality analysis and temporal dynamics. It does not propose a brain-computer interface framework for translating neural activity into natural language output, which is the core innovation of the SID framework.

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#### **2. BrainECHO: Semantic Brain Signal Decoding through Vector-Quantized Spectrogram Reconstruction for Whisper-Enhanced Text Generation**

**URL:** [View paper](#)

##### **Brief Assessment**

BrainECHO[11] focuses on reconstructing mel spectrograms from brain signals for speech-to-text translation using Whisper, not on compositional semantic unit decomposition. The candidate employs vector quantization for audio representation rather than semantic concept sets.

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#### **3. Decoding brain activity associated with literal and metaphoric sentence comprehension using distributional semantic models**

**URL:** [View paper](#)

##### **Brief Assessment**

Literal Metaphoric Comprehension[66] focuses on decoding brain activity during literal vs. metaphoric sentence comprehension using distributional semantic models (word embeddings, compositional models). It does not propose a BCI framework for representing communicative intent as compositional semantic units with the three principles (compositionality, continuity/expandability, fidelity) that define SID.

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### **Contribution 2: BRAINMOSAIC architecture**

**Description:** The authors introduce a concrete deep learning implementation of the SID framework that uses set-based matching to decode semantic units from neural signals and employs semantic-constrained language model generation to produce natural language outputs. The architecture comprises three stages: semantic decomposition, semantic space alignment via retrieval, and semantic-guided reconstruction.

This contribution was assessed against **8 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. Guiding LLMs to Decode Text via Aligning Semantics in EEG Signals and Language**

**URL:** [View paper](#)

##### **Brief Assessment**

Guiding LLMs Semantics[31] focuses on aligning EEG signals with language model semantics for text decoding, but no full text context was provided to assess architectural overlap with BRAINMOSAIC's three-stage pipeline (semantic decomposition, set-based retrieval, semantic-guided reconstruction).

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#### **2. EEG2TEXT-CN: An Exploratory Study of Open-Vocabulary Chinese Text-EEG Alignment via Large Language Model and Contrastive Learning on Chinese EEG**

**URL:** [View paper](#)

##### **Brief Assessment**

EEG2TEXT-CN[19] focuses on Chinese character-level EEG-to-text generation using a convolutional encoder and autoregressive decoder with teacher forcing. It does not employ set-based matching for semantic unit decomposition or semantic-constrained language model generation as in BRAINMOSAIC.

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#### **3. See: Semantically aligned eeg-to-text translation**

**URL:** [View paper](#)

##### **Brief Assessment**

Semantically Aligned EEG[5] focuses on EEG-to-text translation using a cross-modal codebook and semantic matching within BART, rather than the set-based matching and semantic unit decomposition approach of BRAINMOSAIC. The architectural designs and core principles differ fundamentally.

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#### **4. Belt-2: Bootstrapping eeg-to-language representation alignment for multi-task brain decoding**

URL: [View paper](#)

##### **Brief Assessment**

Belt-2[61] focuses on EEG-to-language alignment using BPE-level contrastive learning and prefix-tuning with LLMs, not on set-based matching for semantic unit decomposition. The architectural approaches differ fundamentally in their decoding strategies.

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#### **5. ELASTIQ: EEG-Language Alignment with Semantic Task Instruction and Querying**

URL: [View paper](#)

##### **Brief Assessment**

ELASTIQ[63] focuses on EEG-language alignment using instruction-conditioned Q-Former and spectral-temporal reconstruction for general BCI tasks (motor imagery, emotion, SSVEP), not on semantic intent decoding from neural signals into natural language sentences via set-based matching of semantic units.

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#### **6. EEG-Language Pretraining for Highly Label-Efficient Pathology Detection**

URL: [View paper](#)

##### **Brief Assessment**

EEG Language Pretraining[64] focuses on aligning EEG signals with clinical text reports for pathology detection using contrastive learning methods (InfoNCE, MIL-InfoNCE). The ORIGINAL paper's BRAINMOSAIC uses set-based matching (Hungarian algorithm) to decode semantic units from neural signals for natural language generation. These are fundamentally different architectures serving different purposes: clinical diagnosis vs. semantic intent decoding for communication.

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#### **7. sEEG-based Encoding for Sentence Retrieval: A Contrastive Learning Approach to Brain-Language Alignment**

URL: [View paper](#)

##### **Brief Assessment**

sEEG Sentence Retrieval[62] focuses on contrastive alignment of seeg signals with frozen CLIP sentence embeddings for retrieval tasks, not on decomposing semantic units via set matching or semantic-guided reconstruction using language models.

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#### **8. BrainAlign: Leveraging EEG Foundation Models for Symmetric, Interpretable Alignment with Visual Representations**

URL: [View paper](#)

##### **Brief Assessment**

BrainAlign[65] focuses on aligning EEG signals with visual representations for object classification tasks, not on decoding semantic units from EEG into natural language using set matching and language models as described in the original paper.

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### **Contribution 3: Embedding-based evaluation metrics for semantic decoding**

**Description:** The authors develop new evaluation metrics specifically designed for continuous semantic space decoding that measure both concept-level alignment and sentence-level semantic fidelity using embedding similarities, addressing limitations of traditional discrete and n-gram based metrics.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. Semantic Reconstruction from Fnirs Using Recurrent Neural Networks**

URL: [View paper](#)

##### **Brief Assessment**

Semantic Reconstruction fNIRS[60] uses a matching score metric to assess pairwise concept distinction in fNIRS-based decoding, which is fundamentally different from the original paper's embedding-based metrics (UMA, MUS, SRS) that measure concept-level alignment and sentence-level semantic fidelity using embedding similarities in continuous semantic spaces for EEG/SEEG decoding.

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#### **2. Improved image reconstruction from brain activity through automatic image captioning**

URL: [View paper](#)

##### **Brief Assessment**

Image Captioning Reconstruction[59] focuses on image reconstruction from fMRI using visual and semantic features with CLIP/Inception metrics for evaluation. The original paper develops metrics specifically for continuous semantic space decoding from EEG with embedding similarities at both concept and sentence levels, addressing a different modality and task structure.

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#### **3. Semantic language decoding across participants and stimulus modalities**

URL: [View paper](#)

##### **Brief Assessment**

Semantic Language Decoding[58] uses BERTScore for evaluating semantic similarity in neural decoding tasks. The original paper develops specialized metrics (UMA, MUS, SRS) for continuous semantic space decoding with specific design principles for concept-level and sentence-level evaluation, which differs from standard BERTScore application.

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#### **4. Decoding semantic representations in mind and brain**

URL: [View paper](#)

##### **Brief Assessment**

Semantic Representations Mind[51] focuses on general semantic representations in mind and brain research, not specifically on developing evaluation metrics for neural decoding tasks. The candidate's brief mentions of metrics appear in different contexts than the original paper's comprehensive framework for EEG-based semantic intent decoding evaluation.

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#### **5. Optimized AI-based neural decoding from BOLD fMRI signal for analyzing visual and semantic ROIs in the human visual system**

URL: [View paper](#)

##### **Brief Assessment**

Neural Decoding BOLD[53] focuses on visual stimulus reconstruction from fMRI using VAE and LDM architectures, not on semantic content decoding or embedding-based evaluation metrics for language/text reconstruction.

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## 6. CLIP-MUSED: CLIP-Guided Multi-Subject Visual Neural Information Semantic Decoding

URL: [View paper](#)

### Brief Assessment

CLIP-MUSED[56] focuses on multi-subject fMRI visual decoding using standard multi-label classification metrics (MAP, AUC, Hamming distance). The original paper develops novel embedding-based metrics (UMA, MUS, SRS) specifically for continuous semantic space decoding from EEG signals, addressing different evaluation challenges in the brain-computer interface domain.

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## 7. From Eye to Mind: brain2text Decoding Reveals the Neural Mechanisms of Visual Semantic Processing

URL: [View paper](#)

### Brief Assessment

Eye to Mind[54] focuses on visual semantic processing from fMRI signals and uses standard NLP metrics (BLEU, METEOR, ROUGE, CIDEr, SPICE) plus CLIP-based metrics. The original paper develops novel metrics (UMA, MUS, SRS) specifically for continuous semantic space decoding from EEG signals, addressing different technical challenges in the BCI domain.

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## 8. SEED: Towards More Accurate Semantic Evaluation for Visual Brain Decoding

URL: [View paper](#)

### Brief Assessment

SEED Visual Decoding[52] focuses on evaluating visual brain decoding (reconstructing images from fMRI), not EEG-based semantic intent decoding. The candidate uses embedding-based metrics (object F1, cap-sim, effnet) to assess image reconstruction quality, while the original paper develops metrics for continuous semantic space decoding of language from EEG signals. These are fundamentally different modalities and tasks.

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## 9. BehaveNet: nonlinear embedding and Bayesian neural decoding of behavioral videos

URL: [View paper](#)

### Brief Assessment

BehaveNet[55] focuses on behavioral video analysis and neural decoding of animal behavior, not on semantic content decoding or language-based evaluation metrics. The candidate addresses a completely different domain (behavioral videos) than the original paper's focus on EEG semantic intent decoding and natural language evaluation.

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## 10. Visual neural decoding via improved visual-EEG semantic consistency

URL: [View paper](#)

### Brief Assessment

Visual EEG Consistency[57] focuses on visual neural decoding from EEG signals using embedding-based similarity metrics for image-EEG alignment, not on language/semantic intent decoding from neural activity with compositional semantic units and sentence reconstruction.

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## Appendix: Text Similarity Detection

No high-similarity text segments were detected across any compared papers.

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## References

- [0] Assembling the Mind's Mosaic: Towards EEG Semantic Intent Decoding [View paper](#)
- [1] Thought2Text: text generation from EEG signal using large language models (LLMs) [View paper](#)
- [2] Semantic reconstruction of continuous language from non-invasive brain recordings [View paper](#)
- [3] Aligning Semantic in Brain and Language: A Curriculum Contrastive Method for Electroencephalography-to-Text Generation [View paper](#)
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- [6] Reverse Engineering Revelation: A Multi-Signal Computational Framework for Modeling Prophetic Inspiration [View paper](#)
- [7] Unveiling thoughts: A review of advancements in eeg brain signal decoding into text [View paper](#)
- [8] Exploring the Potential of Electroencephalography Signal-Based Image Generation Using Diffusion Models: Integrative Framework Combining Mixed [View paper](#)
- [9] A hybrid TH-LSTM-Transformer Model for text generation from EEG signals during imagined character speech [View paper](#)
- [10] Semantic-aware Contrastive Learning for Electroencephalography-to-Text Generation with Curriculum Learning [View paper](#)
- [11] BrainECHO: Semantic Brain Signal Decoding through Vector-Quantized Spectrogram Reconstruction for Whisper-Enhanced Text Generation [View paper](#)
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- [16] Towards linguistic neural representation learning and sentence retrieval from electroencephalogram recordings [View paper](#)
- [17] On the role of activation functions in EEG-to-text decoder [View paper](#)
- [18] Are eeg-to-text models working? [View paper](#)
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