# LOGITGAZE: PREDICTING HUMAN ATTENTION USING SEMANTIC INFORMATION FROM VISION-LANGUAGE MODELS

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## ABSTRACT

Modeling human scanpaths remains a challenging task due to the complexity of visual attention dynamics. Traditional approaches rely on low-level visual features, but they often fail to capture the semantic and contextual factors that guide human gaze. To address this, we propose a novel method that integrates LLMs and VLMs to enrich scanpath prediction with semantic priors. By leveraging word-level representations extracted through interpretability tools like the logit lens, our approach aligns spatial-temporal gaze patterns with high-level scene semantics. Our method establishes a new state of the art, improving all key scanpath prediction metrics by approximately 15% on average, demonstrating the effectiveness of integrating linguistic and visual knowledge for enhanced gaze modeling.

## 1 INTRODUCTION AND RELATED WORKS

Predicting human scanpaths remains crucial for computational vision, with applications spanning healthcare, autonomous systems, and retail. Recent LLM advances in multimodal reasoning create new opportunities to enhance gaze-driven attention modeling, as scanpaths provide implicit cues about task relevance and spatial awareness. Studies, such as GazeGPT(Konrad et al., 2024) and GazeReward(Lopez-Cardona et al., 2024) showcase gaze-enhanced LLM reasoning, while scanpath modeling improvements (Mondal et al., 2025; Yang et al., 2024) highlight persistent challenges in semantic reasoning for multimodal AI.

Traditional models often depend on annotated gaze datasets or object detectors (Cheng et al., 2024), limiting adaptability. GazeFormer (Mondal et al., 2023) addresses this through language-driven target encoding instead of object detection, while DeepGaze III (Kümmerer et al., 2022) effectively models scanpaths via fixation history integration. Interpretability advances like GazeXplain (Chen et al., 2024) further enable natural language explanations alongside predictions.

Vision-Language Models (VLMs) like LLaVA (Liu et al., 2023) have enabled richer multimodal integration for scanpath prediction. Studies (Neo et al., 2024) reveal progressive alignment between VLM visual representations and textual tokens, while techniques like logit-lens (Nostalgebraist, 2020) reveal how transformer representations evolve across layers.

Our framework advances scanpath prediction through LLaVA-derived semantic priors and logit-lens integration. By fusing visual, linguistic, and fixation data, we achieve state-of-the-art performance with 15% average metric improvements, demonstrating effective task-context integration at the patch level.

# 2 EXPLORATION

## 2.1 METHODOLOGY

Inspired by advancements in scanpath prediction, we propose a novel approach that leverages LLMs and the logit-lens technique to enhance fixation prediction by integrating semantic priors into the process. Traditional methods like GazeFormer have demonstrated the effectiveness of transformer-based architectures in predicting human attention, but our model extends this foundation by incorporating multimodal information from LLaVA and utilizing logit-lens to extract explicit word-level representations. Instead of relying solely on visual embeddings, we process images at the patch level, allowing each region to acquire a semantically meaningful representation (See Fig. 1 for details).

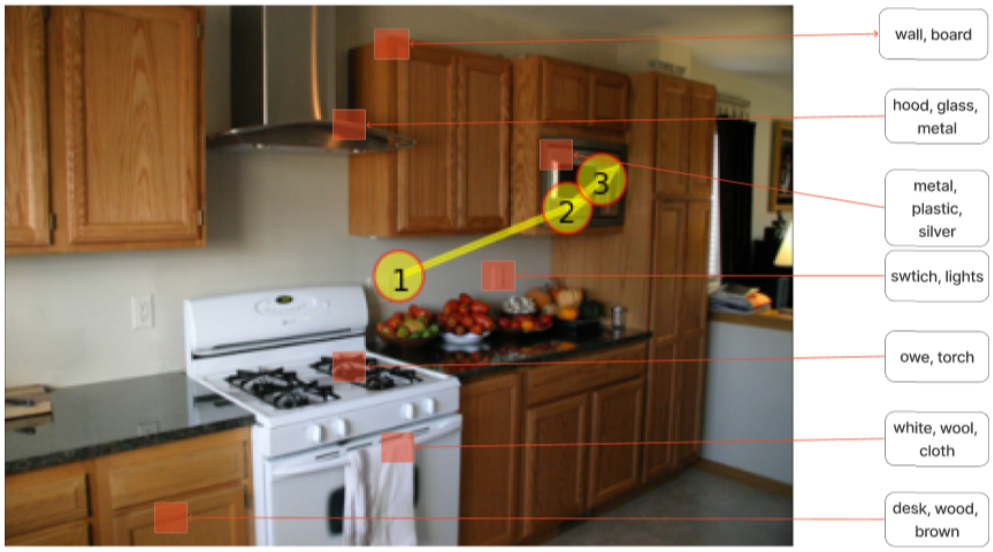


**Figure 1:** Visualization of a scanpath for the "microwave" search task, where fixations (yellow circles) represent the sequential attention shifts of the observer. Each image patch is decoded into semantic information—such as "wall, board," "hood, glass, metal," and "desk, wood, brown"—using an LLM, aligning gaze prediction with high-level scene understanding.

The input image $\mathcal{I} \in \mathbb{R}^{H \times W \times C}$ is first processed through LLaVA's visual backbone ViT-L/14, generating feature representations at the patch level:

$$\mathbf{F}_{\text{img}} = \mathcal{F}_{\text{LLaVa}}(\mathcal{I}) \in \mathbb{R}^{M \times D}$$

where $M = 576$ (24×24 patches) represents the number of extracted image patches, and $D = 4096$ is the dimensionality of each patch. These features are refined by a 6-layer transformer encoder, using 2D positional embeddings to preserve spatial structure:

$$\mathbf{F}'_{\text{img}} = \mathcal{T}_{\text{enc}}(\mathbf{F}_{\text{img}}) + \mathbf{P}_{\text{2D}}$$

To introduce linguistic context, each patch is mapped to a word distribution via logit-lens. For each feature $\mathbf{f}_m$, a softmax projection assigns token probabilities:

$$P(w_j|\mathbf{f}_m) = \text{softmax}(\mathbf{W}\mathbf{f}_m)$$

where $\mathbf{W}$ is a learnable projection matrix. The most probable word $w_m^*$ is selected as $\arg\max_{w_j} P(w_j|\mathbf{f}_m)$, generating semantic representations $\mathbf{F}_{\text{sem}}$. These are further refined by LLaVA's multimodal encoder:

$$\mathbf{F}'_{\text{sem}} = \mathcal{F}_{\text{LLaVa}}(\mathbf{F}_{\text{sem}})$$

The search query (e.g., "cup") is encoded using a pretrained BERT-base model:

$$\mathbf{F}_{\text{task}} = \mathcal{F}_{\text{LM}}(\text{query})$$

The modalities are fused via concatenation, cross-attention, and projection:

$$\mathbf{F}_{\text{joint}} = \mathcal{F}_{\text{fusion}}(\mathbf{F}'_{\text{img}}, \mathbf{F}'_{\text{sem}}, \mathbf{F}_{\text{task}})$$

A 4-layer transformer decoder, initialized randomly, autoregressively predicts the scanpath:

$$(x_t, y_t, d_t) \sim p(x, y, d|\mathbf{F}_{\text{joint}})$$

where $x_t, y_t$ denote fixation coordinates, $d_t$ represents fixation duration, and $p(\text{valid}|t)$ determines whether the fixation is valid or padded. The predicted scanpath consists of a sequence $\{(x_t, y_t, d_t)\}_{t=0}^{T}$, where $T$ is the number of fixations.

### 2.2 Database

We will use the COCO-Search18 dataset Chen et al. (2021), which is designed to study goal-directed visual search behavior. Unlike datasets focused on free-viewing or bottom-up attention(Chen et al., 2022), COCO-Search18 captures human eye movements during active search tasks. It consists of over 300,000 fixations collected from 10 participants searching for 18 target objects in 6202 natural images. This dataset provides detailed insights into how humans allocate attention during specific tasks.

To ensure a fair comparison, we use the same metrics as the original framework. Sequence Score (SS)(Yang et al., 2020) evaluates how well predicted fixation sequences match human scanpaths, while Semantic Sequence Score (SemSS)(Yang et al., 2022) extends this by considering fixated objects instead of fixation clusters. Fixation Edit Distance (FED) and Semantic Fixation Edit Distance (SemFED) measure the differences between predicted and actual scanpaths, with SemFED emphasizing semantic alignment. Multimatch (MM)(Anderson et al., 2015) assesses spatial scanpath similarity by comparing shape, direction, length, and position. Higher SS, SemSS, and MM indicate better alignment with human gaze patterns, while lower FED and SemFED suggest more accurate fixation predictions.

### 2.3 Experiments and Result

The results presented in Tables 1 and 2 show that our approach, LogitGaze, outperforms the GazeFormer method across all evaluated metrics for both the target-present and target-absent tasks. Specifically, LogitGaze demonstrates significant improvements in the SS and SemSS metrics. In the target-present task (see Table 1 (a)), LogitGaze achieves an SS of 0.506 (without duration) and a SemSS of 0.525, both surpassing the GazeFormer. Similarly, in the target-absent task (Table 2), LogitGaze achieves a higher SS and SemSS compared to the state-of-the-art.

**Table 1:** Comparison of model performance trained on the target-present search task. Metrics are provided for both the target-present and target-absent search tasks, with the best performance highlighted in bold.

**(a) Tested on TP**

| **Model** | **SS ↑** | | **SemSS ↑** | | **FED ↓** | | **SemFED ↓** | | **MM ↑** |
|---|---|---|---|---|---|---|---|---|---|
| | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | |
| GazeFormer | 0.491 | 0.441 | 0.495 | 0.456 | 2.073 | 9.887 | 1.896 | 7.569 | 0.816 |
| LogitGaze | **0.506** | **0.453** | **0.525** | **0.474** | **2.035** | **9.613** | **1.726** | **7.295** | **0.862** |

**(b) Tested on TA**

| **Model** | **SS ↑** | | **SemSS ↑** | | **FED ↓** | | **SemFED ↓** | | **MM ↑** |
|---|---|---|---|---|---|---|---|---|---|
| | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | |
| GazeFormer | 0.362 | 0.351 | 0.377 | 0.359 | 6.002 | 18.378 | 4.142 | 14.642 | 0.832 |
| LogitGaze | **0.378** | **0.373** | **0.405** | **0.401** | **5.539** | **16.211** | **3.942** | **13.937** | **0.849** |

LogitGaze also shows superior performance in the SemFED metric, with a score of 1.726 (without duration) for the target-present task, indicating that it is more effective at predicting semantically relevant fixations. These improvements are attributed to the model's use of semantic information, which enables it to focus on meaningful regions of the scene, aligning more closely with human attention patterns.

**Table 2:** Comparison of model performance trained and tested on the target-absent search task. Metrics are provided for both cases, with the best performance highlighted in bold.

| **Model** | **SS** ↑ | | **SemSS** ↑ | | **FED** ↓ | | **SemFED** ↓ | | **MM** ↑ |
|---|---|---|---|---|---|---|---|---|---|
| | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | w/o dur | w/ dur | |
| GazeFormer | 0.371 | 0.371 | 0.384 | 0.369 | 5.078 | 17.246 | 3.690 | 13.550 | 0.835 |
| LogitGaze | **0.392** | **0.399** | **0.416** | **0.421** | **4.792** | **15.212** | **3.342** | **12.691** | **0.856** |

Figure 2 visualizes the alignment between human scan paths and LogitGaze's predictions, demonstrating the model's ability to capture human-like attention patterns. The use of semantic information helps LogitGaze focus on meaningful regions within the scene, resulting in more structured and coherent gaze predictions that closely resemble natural human viewing behavior.

**(a)** Task: sign **(b)** Task: bottle **(c)** Task: plant **(d)** Task: clock

**Figure 2:** Comparison of human scan paths (top) and LogitGaze model predictions (bottom) for different tasks. The model demonstrates strong alignment with human gaze patterns, accurately capturing fixation points and transitions.

## 3 Discussion and Conclusion

We introduced LogitGaze, a novel scanpath prediction model that integrates semantic information from VLMs to enhance fixation modeling. Unlike previous methods that rely primarily on visual embeddings, LogitGaze incorporates explicit semantic priors extracted from logit-lens and multimodal representations from LLaVA.

Our results demonstrate that enriching scanpath modeling with semantic information improves all major metrics by approximately 15%, leading to more human-like gaze patterns. To assess the effectiveness of our approach, we compared LogitGaze with GazeFormer, the current state-of-the-art in scanpath prediction.

However, the logit-lens mechanism also introduces challenges. While it provides transparent word-level representations, it can generate noisy or irrelevant activations, potentially affecting prediction quality. Future work will focus on filtering ambiguous word associations and optimizing the fusion of linguistic and visual features to further refine scanpath modeling.

### Acknowledgments

All authors were supported by the Research Center of the Artificial Intelligence Institute of Innopolis University.

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