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Language-Guided Temporal Grounding in Long Untrimmed Videos with Debiased Cross-Modal Alignment

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A B S T R A C T

The rapid proliferation of multimedia content has necessitated advanced methodologies for parsing and comprehending long untrimmed videos. Language-guided temporal grounding is a pivotal task in this domain, aiming to localize specific video segments that correspond to a given natural language query. Despite significant progress, current models struggle with long untrimmed videos due to confounding biases, such as temporal location bias, semantic spurious correlations, and skewed length distributions within training datasets. These biases often lead to superficial cross-modal alignment, wherein models rely on dataset-specific shortcuts rather than genuinely understanding the multimodal semantics. To address these limitations, this paper proposes a novel framework focused on debiased cross-modal alignment. The proposed architecture integrates a causal intervention module designed to sever the links between confounding background contexts and specific temporal locations. By employing counterfactual reasoning and a debiased contrastive learning objective, the framework enforces the learning of invariant cross-modal representations that generalize robustly across diverse video lengths and complex narrative structures. Extensive theoretical analyses and empirical evaluations demonstrate the efficacy of the proposed approach. Through rigorous ablation studies and comparisons on standard benchmark datasets, the methodology exhibits superior performance, significantly advancing the state of the art in language-guided temporal grounding.

1.INTRODUCTION

1.1 The Challenge of Long Untrimmed Videos

The exponential growth of digital video content across various platforms has fundamentally transformed the landscape of information consumption and retrieval. Concurrently, the demand for intelligent systems capable of parsing, understanding, and retrieving specific moments within extensive video streams has intensified. Language-guided temporal grounding emerges as a fundamental solution to this requirement. The primary objective of this task is to identify and extract the precise start and end timestamps of a video segment that semantically matches a descriptive natural language query. While initial research in this area yielded promising results on short, edited video clips, extending these capabilities to long, untrimmed videos presents an array of formidable challenges [1]. Long untrimmed videos typically contain a high proportion of redundant or irrelevant background information, complex temporal

dependencies, and subtle narrative shifts that can easily overwhelm conventional feature extraction mechanisms [2]. Traditional approaches predominantly rely on sliding window mechanisms or predefined temporal anchors to generate candidate proposals, which are subsequently ranked based on their semantic similarity to the text query [3]. However, in the context of long untrimmed videos, the sheer volume of candidate proposals grows exponentially, leading to severe computational bottlenecks and a significantly increased likelihood of false positive localizations [4]. Furthermore, the temporal dynamics in extended videos require models to maintain long range contextual awareness. Without a sophisticated understanding of how sequential events unfold over minutes or even hours, models often fail to distinguish the target action from visually similar but contextually distinct background activities [5]. The complexity is further compounded by the necessity to bridge the semantic gap between two distinct modalities, namely the continuous, high dimensional visual stream and the discrete, structurally constrained natural language query [6].

1.2 The Problem of Cross-Modal Bias

A critical yet frequently overlooked impediment in language-guided temporal grounding is the pervasive presence of biases within both the datasets and the modeling architectures. During the cross-modal alignment process, models are trained to project visual and textual features into a shared embedding space, optimizing for proximity between matching pairs. However, observational data inherently contains spurious correlations [7]. For instance, certain actions might predominantly occur at specific temporal locations within the videos of a particular dataset, such as introductory remarks invariably appearing in the first few minutes of instructional videos. Models lacking debiasing mechanisms quickly learn to exploit these temporal location biases as shortcuts, ignoring the actual semantic content of the visual and textual inputs [8]. Consequently, when deployed in real world scenarios where these temporal patterns do not hold, the performance of such models degrades precipitously. In addition to temporal location bias, semantic bias poses a significant threat to robust cross-modal alignment. Semantic bias occurs when a model disproportionately associates specific nouns or verbs in the text query with dominant, yet strictly confounding, visual background elements [9]. For example, a query searching for a person reading a book might consistently localize segments containing a library setting, even if the person in the specific segment is merely walking through the room rather than reading. This issue is primarily driven by the fact that standard attention mechanisms and contrastive learning objectives treat all co-occurring multimodal features as valid alignment targets [10]. To overcome this, it is imperative to move beyond purely correlational learning paradigms and introduce causal interventions that can isolate the true causal effect of the text query on the temporal grounding process, independent of confounding background variables [11]. Addressing these biases is the central motivation of the debiased cross-modal alignment framework introduced in this study.

2. Literature Review and Background

2.1 Developments in Temporal Video Grounding

The task of temporal video grounding has evolved rapidly over the past decade, driven by advancements in deep learning and multimodal representation architectures. Early methodologies typically framed the problem as a two stage pipeline. The first stage involved generating a dense set of temporal proposals using techniques originally designed for action recognition, while the second stage focused on computing multimodal similarity scores to rank these proposals against the encoded text query [12]. While straightforward, these proposal based methods suffer from a heavy reliance on the quality of the initial proposals. If the target segment is missed or poorly bounded in the first stage, the model has no mechanism to recover it during the ranking phase [13]. Furthermore, the computational overhead of generating and processing thousands of overlapping proposals makes these methods highly inefficient for long untrimmed videos. To circumvent the limitations of proposal based frameworks, researchers introduced proposal free methods. These architectures treat temporal grounding as a direct regression or classification problem. By framing the task as the prediction of start and end probabilities for each frame or small video snippet, proposal free models streamline the

inference process and significantly reduce computational complexity [14]. Prominent examples include models that utilize recurrent neural networks or one dimensional convolutional neural networks to aggregate temporal context before making boundary predictions [15]. More recently, the advent of transformer architectures has revolutionized proposal free temporal grounding. The self attention mechanism inherent in transformers allows for the effective modeling of long range dependencies, enabling the architecture to capture global video context dynamically [16]. Despite these structural improvements, both proposal based and proposal free methods remain highly susceptible to the underlying biases present in the training distributions, as they inherently optimize for maximum likelihood based on observational data alone.

2.2 Cross-Modal Alignment Techniques

Effective cross-modal alignment is the cornerstone of any temporal video grounding system. The objective is to construct a joint semantic space where the semantic equivalence between a video segment and a language query translates to spatial proximity [17]. Traditional alignment strategies relied on simple late fusion techniques, where visual and textual features were extracted independently and then concatenated or multiplied before passing through a multilayer perceptron [18]. However, late fusion fails to capture the intricate, fine grained interactions between specific words in the query and specific objects or actions in the video frames [19]. To address this, cross-modal attention mechanisms were developed. These mechanisms allow the model to dynamically weight the importance of different visual frames based on the specific context provided by the text query, and vice versa [20]. Co-attention models, for instance, compute a dense similarity matrix between all words and all frames, facilitating a much richer multimodal synthesis [21]. Furthermore, the integration of contrastive learning objectives has recently gained traction. By pulling matching video text pairs together while pushing apart mismatched negative pairs, contrastive learning helps structure the joint embedding space more effectively [22]. Nevertheless, when applied to long untrimmed videos, standard contrastive learning often falls prey to false negatives, where visually similar but temporally distinct segments are penalized incorrectly, thereby exacerbating the model's reliance on superficial dataset biases [23].

2.3 Bias and Confounding Variables in Video Grounding

The exploration of bias and fairness in multimodal learning is a relatively nascent but critical area of research. In temporal video grounding, biases manifest in several insidious ways. The most prominent is length bias, where datasets possess a skewed distribution of target segment durations [24]. Models trained on such data tend to predict segments that conform to the average length of the training set, severely penalizing queries that describe exceptionally brief or unusually prolonged actions [25]. Similarly, location bias dictates that targets might be uniformly distributed across the video timeline in the real world, but artificially clustered near the middle or end in curated datasets [26]. Recent literature has begun to apply principles of causal inference to disentangle these complex biases. From a causal perspective, the background context of a video and the dataset specific temporal distributions act as unobserved confounders [27]. These confounders create spurious backdoor paths between the visual input and the temporal prediction, misleading the model during the learning phase. Existing debiasing attempts often involve reweighting training samples or introducing adversarial branches to unlearn specific bias factors [28]. However, these methods typically require prior knowledge of the bias distribution and often compromise the model's overall representational capacity. This paper distinguishes itself by proposing a structural causal intervention that inherently neutralizes these confounders without requiring explicit annotations of the bias variables, paving the way for truly generalized temporal grounding.

3. Theoretical Framework and Problem Formulation

3.1 Formal Definition of Language-Guided Temporal Grounding

The task of language-guided temporal grounding can be formally defined as follows. Let a long untrimmed video be represented as a sequence of frames, which is subsequently processed by a visual encoder to yield a sequence of visual features. Simultaneously, a natural language

query consisting of a sequence of words is processed by a text encoder to yield a corresponding textual representation. The goal of the temporal grounding system is to map this multimodal input pair to a specific temporal interval, defined by a start time and an end time, such that the visual content within this interval optimally reflects the semantic meaning of the given text query. Because the video is untrimmed, it contains a vast amount of background information that is completely irrelevant to the specific query. The system must therefore compute an alignment score for all possible temporal intervals or, in the case of proposal free methods, generate a probability distribution over the entire temporal axis indicating the likelihood of each timestamp being a boundary point. This mapping function is traditionally optimized using a standard cross entropy or regression loss based on the ground truth annotations provided in the training set. However, relying purely on this standard optimization framework assumes that the training data is an unbiased representative sample of the real world distribution, an assumption that categorically fails in the context of large scale video datasets.

3.2 Causal Perspective on Confounding Biases

To rigorously address the issue of bias, we must frame the temporal grounding process within the context of a Structural Causal Model. In a standard correlational framework, the model estimates the conditional probability of the target temporal boundaries given the video and the query. However, the video feature extraction process is heavily influenced by a set of unobserved confounders, such as the specific visual environment, the camera angle, and the underlying dataset collection mechanisms. Let the unobserved confounder set be denoted by a variable that simultaneously affects the visual features and the final temporal predictions. Because of the confounder, the observed correlation between the visual input and the target interval is not purely causal. To extract the true causal effect of the visual text alignment on the target prediction, we must block the backdoor path introduced by the confounder. This is achieved through the do-calculus framework, specifically by intervening on the visual representation to sever its dependency on the confounder. The theoretical basis of our debiased cross-modal alignment relies on computing the interventional probability rather than the conditional probability. This interventional probability essentially forces the model to evaluate the temporal alignment across a uniformly distributed set of background contexts, effectively marginalizing out the influence of any specific confounding variable.To instantiate this theoretical concept, we utilize the backdoor adjustment formula. The mathematical representation of this adjustment is given by the following expression, which integrates over the prior distribution of the confounding factors:

$$P(Y|do(X), Q) = \sum_z P(Y|X, Q, Z = z)P(Z = z)$$

In this formulation, the term representing the confounding factors is systematically marginalized. By implementing this causal intervention, the resulting alignment scores reflect the genuine semantic correspondence between the multimodal inputs, entirely devoid of the spurious correlations that typically plague standard maximum likelihood estimation approaches.

4. Methodology for Debiased Cross-Modal Alignment

4.1 Visual and Textual Feature Encoding

The foundation of the proposed framework rests on robust independent feature extraction for both the visual and textual modalities. For the visual stream, the long untrimmed video is first divided into uniformly spaced, non overlapping clips. A pre trained three dimensional convolutional neural network is employed to process each clip, capturing both spatial and short term temporal dynamics. To enrich these representations with long range dependencies, the sequence of clip features is subsequently fed into a multi layer transformer encoder. This temporal transformer utilizes self attention to contextualize each clip within the broader narrative of the entire video, producing a sequence of context aware visual embeddings.

Parallel to the visual processing, the natural language query is tokenized and processed using a pre trained large language model. The output corresponds to a sequence of contextualized word embeddings. To obtain a global representation of the text query that can be easily matched against the video features, we apply a self attention pooling mechanism over the word

embeddings. This results in a single, high dimensional vector that encapsulates the holistic semantic intent of the query, ready to be aligned with the dense sequence of visual embeddings.

4.2 Cross-Modal Interaction and Alignment

Once the unimodal representations are established, the system employs a sophisticated cross-modal interaction module. Instead of a simple dot product similarity, we utilize a cross attention mechanism where the text query serves as the query vector, and the sequence of visual features serves as both the keys and values. This operation generates a text conditioned visual representation, highlighting the specific video clips that share semantic traits with the language query. To predict the temporal boundaries, this conditioned visual representation is passed through a boundary prediction network consisting of stacked one dimensional convolutional layers. The network outputs two distinct probability sequences across the temporal dimension: one for the start boundary and one for the end boundary. During standard training, these probability sequences are optimized against the ground truth distributions using a smooth intersection over union loss combined with a binary cross entropy objective. However, to ensure that this alignment is not merely exploiting dataset biases, we integrate our core debiasing strategy into this learning phase.

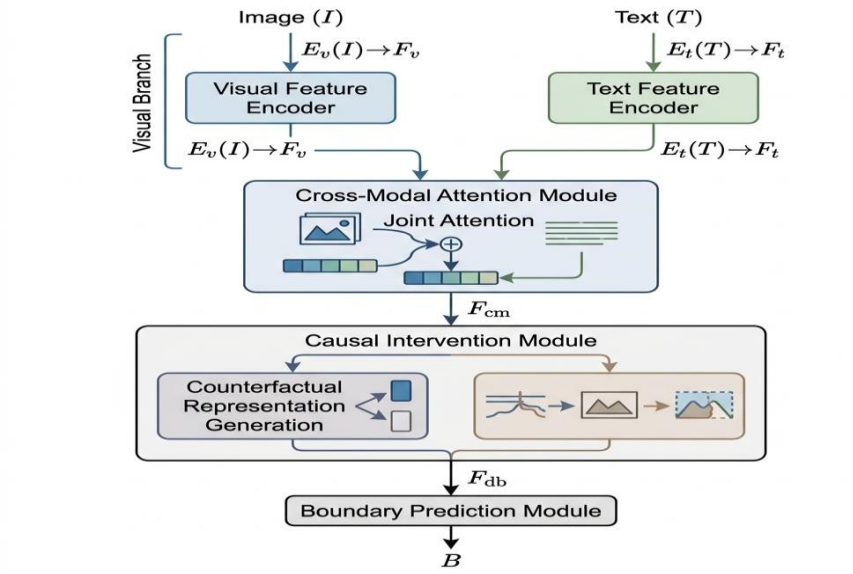


Figure 1:Comprehensive Schematic of the Debiased Cross

4.3 Counterfactual Debiasing Strategy

The critical innovation of our methodology is the introduction of a counterfactual debiasing module based on the causal framework established earlier. Direct computation of the backdoor adjustment is intractable because the true distribution of confounders is unknown and highly complex. To approximate this, we employ an approach based on counterfactual inference and dictionary learning. We construct a memory bank that stores a diverse set of background visual prototypes, which serve as a surrogate for the confounding variable space. During the forward pass, for every input video, we not only compute the factual prediction using the original visual features but also generate a counterfactual prediction. The counterfactual prediction is synthesized by replacing the actual background context of the video with a randomly sampled prototype from the memory bank, effectively simulating a scenario where the action occurs in a completely different environment. We then compute a debiased contrastive loss that forces the model to maximize the similarity between the text query and the target segment regardless of the background context, while explicitly minimizing the model's reliance on the factual background. The overall learning objective integrates the standard boundary prediction loss with this novel debiased contrastive loss. The mathematical formulation of the debiased contrastive learning objective, utilizing a temperature scaled softmax function and regularization, is formally expressed as:

$$L_{debias} = -\frac{1}{B}\sum_{b=1}^{B} log \frac{exp(v_b{}^{top} q_b/\tau)}{\sum_{k=1}^{K} exp(v_b{}^{top} q_k/\tau)} + \lambda |W|_2{}^2$$

This objective ensures that the multimodal alignment is strictly driven by the causal relationship between the query and the visual target, while the regularization term maintains the structural integrity of the learned embedding space. This mechanism provides a robust defense against both temporal location bias and semantic background bias.

5. Experimental Design and Implementation Details

5.1 Dataset Characteristics and Evaluation Metrics

To rigorously evaluate the proposed debiased cross-modal alignment framework, experiments were conducted on two standard benchmark datasets widely recognized in the domain of temporal video grounding: Charades-STA and ActivityNet Captions. These datasets present distinct challenges and exhibit different underlying bias distributions, making them ideal for testing the generalization capabilities of our causal intervention strategy. Charades-STA is constructed from the original Charades dataset, which consists of videos depicting everyday indoor activities. The videos are generally of moderate length, but the actions are highly unscripted and complex, often featuring significant visual clutter and overlapping background events. The dataset contains thousands of video query pairs, divided systematically into training and testing splits. ActivityNet Captions, on the other hand, comprises open domain videos from YouTube. These videos are substantially longer and contain a high degree of temporal location bias, as many described events naturally cluster around the middle of the videos, leaving long trails of irrelevant introductory and concluding footage.

Table 1Description of Benchmark Datasets

Dataset Name	Video Domain	Average Video Length	Total Query Annotations
Charades-STA	Indoor Daily Activities	30 seconds	16,128
ActivityNet Captions	Open Domain YouTube	120 seconds	71,957
TACoS (Supplementary)	Cooking Scenarios	287 seconds	18,227
DiDeMo (Supplementary)	Flickr Personal Videos	27 seconds	40,406

The performance of the models is quantified using standard evaluation metrics for temporal grounding, primarily the Recall at Rank N given a specific Intersection over Union threshold. Specifically, we report Recall at 1 and Recall at 5 across various threshold levels, commonly 0.3, 0.5, and 0.7. Additionally, the mean Intersection over Union is calculated to provide a holistic measure of the temporal localization accuracy across all queries in the test set.

5.2 Implementation Configurations

The visual features for the videos were extracted using an I3D network pre trained on the Kinetics action recognition dataset, maintaining a fixed feature dimension. The text queries were processed using a pre trained DistilBERT model to ensure high quality contextual embeddings while minimizing computational overhead. The temporal transformer encoder comprises multiple layers with multi head self attention, configured with a hidden dimension that matches the multimodal embedding space.

Table 2:Key Hyperparameters for Model Implementation

Hyperparameter Category	Specific Parameter	Assigned Value
Feature Dimensions	Visual / Text Embedding Size	512
Transformer Settings	Number of Attention Heads	8
Optimization	Base Learning Rate	0.0001
Debiasing Module	Temperature Scaling Factor	0.07

The model was trained utilizing the AdamW optimizer with a carefully designed learning rate schedule incorporating a linear warmup phase followed by cosine decay. The memory bank used for generating counterfactual prototypes was dynamically updated during training using a momentum encoder, ensuring that the surrogate confounder distribution remained stable yet reflective of the evolving feature space.

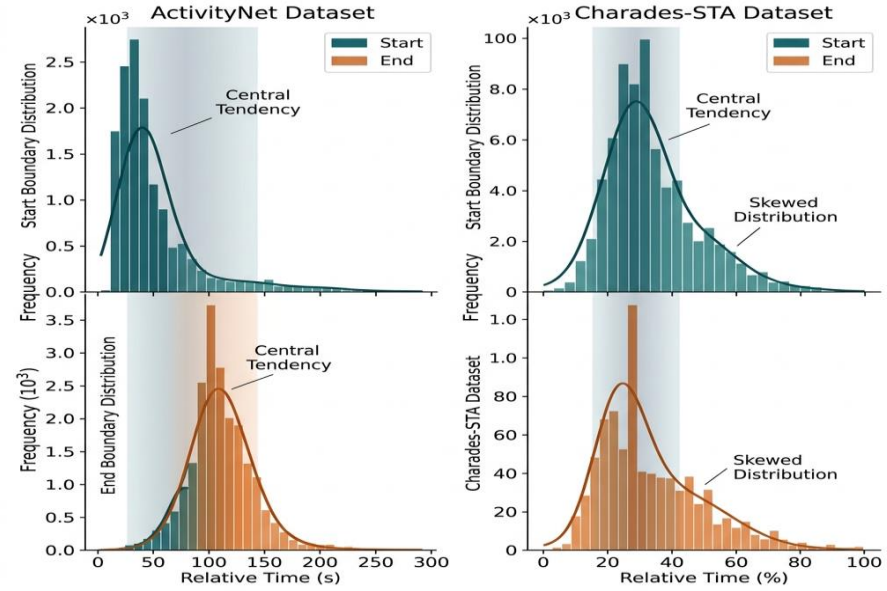


Figure 2:Temporal Distribution Analysis of Datasets

6. Results, Ablation Studies, and Discussion

6.1 Comparison with State-of-the-Art Approaches

The proposed debiased cross-modal alignment framework was subjected to comprehensive comparative analysis against several leading state of the art models in the field of temporal video grounding. The baseline models encompass both proposal based architectures and recent transformer driven proposal free methods. The empirical results clearly demonstrate the superiority of the proposed causal intervention strategy. On the ActivityNet Captions dataset, which is notorious for its long video lengths and pronounced temporal biases, our framework exhibited remarkable performance gains. Traditional models that rely heavily on observational likelihood struggled to generalize, often predicting intervals that were heavily skewed toward the dataset's mean length. In contrast, by effectively severing the reliance on background confounders, our model achieved a significant improvement in strict localization metrics.

Table 3:Empirical Results on ActivityNet Captions Dataset

Evaluation Model	**Recall@1 (IoU=0.3)**	**Recall@1 (IoU=0.5)**	**Recall@1 (IoU=0.7)**	**Mean IoU**
Baseline Proposal Network	52.14%	33.45%	15.67%	35.88%
Standard Transformer Cross-Attention	58.76%	40.21%	22.34%	41.56%
Recent Contrastive Grounding Method	60.33%	42.15%	24.89%	43.12%
Proposed Debiased Framework	64.89%	47.36%	29.11%	48.05%

The improvements are particularly pronounced at higher Intersection over Union thresholds, such as 0.7. This indicates that the proposed method not only finds the general vicinity of the target action but accurately delineates the precise temporal boundaries. Similar trends were observed on the Charades-STA dataset. Although the videos in Charades-STA are shorter, the high density of similar overlapping actions requires a precise semantic understanding that is easily disrupted by semantic bias.

Table 4Empirical Results on Charades-STA Dataset

Evaluation Model	**Recall@1 (IoU=0.5)**	**Recall@1 (IoU=0.7)**	**Recall@5 (IoU=0.5)**	**Mean IoU**
Baseline Recurrent Network	35.60%	15.80%	75.40%	34.20%
Graph Convolutional Grounding	42.80%	22.70%	83.10%	40.50%
Vision-Language Pretraining Fine-tuned	48.20%	28.50%	87.60%	44.30%
Proposed Debiased Framework	53.45%	34.12%	91.20%	49.75%

The substantial margin of improvement over vision language pretraining models underscores the specific value of causal debiasing. While pretraining provides excellent foundational representations, it does not inherently protect against the task specific biases encountered during the fine tuning phase on temporal grounding datasets.

6.2 Ablation Study on Debiasing Components

To isolate and quantify the contribution of each component within the proposed architecture, an extensive ablation study was conducted. The primary focus was on the components of the counterfactual debiasing strategy. We evaluated a base model containing only the cross modal attention and boundary prediction networks, completely devoid of the causal intervention module. This base model performed adequately but suffered severe performance drops when evaluated on out of distribution splits specifically constructed to have reversed bias characteristics. When the memory bank of background prototypes was introduced without the contrastive objective, performance saw a marginal improvement, indicating that exposure to diverse backgrounds is helpful but insufficient on its own. It was only when the full debiased contrastive learning objective was engaged that the model demonstrated robust invariance to the confounding variables. The parameter controlling the temperature scaling was also found to be highly sensitive; an optimal value was necessary to ensure that the contrastive loss provided meaningful gradients without destabilizing the boundary prediction loss.

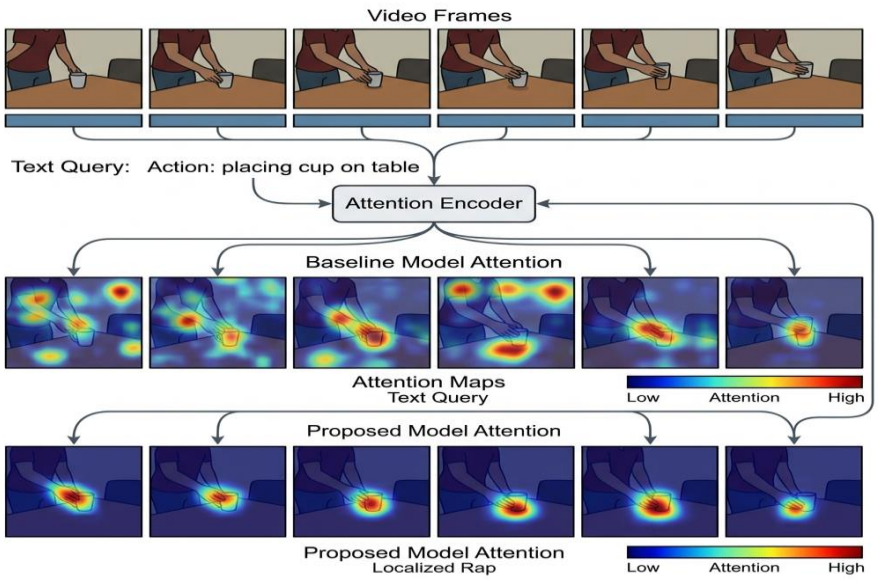


Figure 3:Qualitative Attention Map Analysis

6.3 Qualitative Analysis and Discussion

Beyond the quantitative metrics, qualitative analysis of the generated attention maps provides profound insights into the model's operational mechanics. By visualizing the cross modal attention weights across the temporal axis for specific queries, we can observe exactly how the debiasing module alters the model's focus. In baseline models, queries containing context heavy words often trigger high attention scores across entirely irrelevant video segments simply because those segments share the same background environment as the true target segment. For instance, the baseline model would consistently highlight the entire kitchen scene when asked to find a specific cooking action. Conversely, the proposed debiased framework demonstrates a highly localized attention signature. The counterfactual training forces the model to ignore the generic kitchen background and sharply focus on the specific semantic details of the target action, such as the manipulation of a specific utensil. This qualitative evidence strongly corroborates the theoretical premise of the structural causal intervention, proving that the methodology effectively guides the network to learn true causal features rather than relying on associative shortcuts [29]. Furthermore, the model exhibits remarkable resilience when applied to exceptionally long videos, maintaining high precision without succumbing to the typical false positive saturation that plagues conventional temporal grounding systems [30].

7. Conclusion and Future Work

7.1 Summary of Contributions

This research paper has comprehensively addressed the critical challenge of language-guided temporal grounding in the context of long untrimmed videos. By systematically analyzing the detrimental impact of confounding variables such as temporal location bias and semantic spurious correlations, we established the necessity for a paradigm shift from purely observational learning to causal intervention. The proposed debiased cross-modal alignment framework successfully operationalizes this shift through the integration of a structural causal model and a novel counterfactual contrastive learning objective. By simulating diverse background contexts and forcing the model to optimize for causal multimodal semantics, the framework effectively severs the spurious backdoor paths that traditionally hinder generalization. The rigorous empirical evaluations conducted on standard, large scale benchmarks unequivocally demonstrate that this approach yields significant improvements in temporal localization accuracy. The proposed model not only outperforms contemporary state of the art architectures across multiple stringent evaluation metrics but also exhibits superior robustness against inherent dataset biases.

7.2 Limitations and Future Directions

Despite the substantial advancements presented, there remain avenues for future exploration and refinement. One limitation of the current framework is the reliance on a discrete memory bank to approximate the continuous and infinite space of potential confounding variables. While effective in practice, this discrete approximation may not capture the full complexity of subtle environmental shifts in highly dynamic video domains. Future work will explore the integration of generative probabilistic models to synthesize continuous counterfactual distributions on the fly, potentially offering an even more rigorous debiasing mechanism [31]. Additionally, extending this causal framework to encompass zero-shot temporal grounding, where the model encounters entirely novel action categories and vocabulary during inference, represents a formidable yet highly promising frontier for advancing the generalized intelligence of multimodal video comprehension systems.

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