**Enhancing NLQ Understanding in Egocentric Videos with Textual Answer Generation**

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**Abstract**

*This paper explores the Ego4D dataset and its Natural Language Queries (NLQ) annotations, proposing a novel pipeline that integrates timestamp prediction models with a Video Question Answering (VideoQA) module. The pipeline transitions from untrimmed egocentric video inputs to actionable textual answers, addressing challenges in computational efficiency and detail preservation inherent in video analysis.  
We benchmark state-of-the-art models—VSLBase, VSLNet, and 2D-TAN—trained on Omnivore and EgoVLP features to evaluate their performance in temporal segment localization. Building on these insights, our approach refines timestamp predictions into precise video segments processed by the videoQA model to generate textual answers. Experimental results demonstrate improvements in temporal localization and question answering, showcasing the integration of video reasoning and natural language understanding. This work advances egocentric video analysis, with applications in episodic memory, assistive technology, and automated reasoning.*

**1. Introduction**

Egocentric video analysis, exemplified by the Ego4D dataset [[cite](#Ego4D)], captures complex human activities but presents challenges due to untrimmed, unstructured content. The NLQ benchmark [[cite](#Ego4D)] identifies temporal intervals answering a query but requires users to manually watch these segments, limiting usability.  
To address this, we propose a pipeline combining timestamp prediction models with the Video-LLaVA [[cite](#Video_LLaVa)] VideoQA module. This approach transforms unstructured videos into precise textual answers, optimizing computational efficiency while preserving

detail. Benchmark analysis of VSLBase, VSLNet [[cite](#VSLNet)], and 2D-TAN [[cite](#model_2D_TAN)] models trained with Omnivore [[cite](#Omnivore)] and EgoVLP [[cite](#EgoVLP)] features highlights their effectiveness in temporal localization. Video-LLaVA [[cite](#Video_LLaVa)] extends these results by processing trimmed segments into actionable answers, reducing overhead and enhancing usability.Our contributions include:

1. Benchmark analysis of NLQ models with advanced features.
2. Integration of timestamp prediction with VideoQA.
3. Validation showing improved performance for egocentric video analysis systems.

These advancements demonstrate the potential of our approach for episodic memory retrieval, assistive technologies, and video understanding.

**2. Related Work**

**Natural Language Queries in Egocentric Videos.** The Natural Language Queries (NLQ) task involves localizing the temporal window corresponding to the answer to a question in a long video clip. This task is challenging for end-to-end supervised video localization models due to the sparsity of annotations and the length of videos in the dataset. However, strong video representations, such as those derived from SlowFast [[cite](#SlowFast)], Omnivore [[cite](#Omnivore)], and EgoVLP[[cite](#EgoVLP)], significantly simplify the task. Several notable models have been applied to the NLQ benchmark. **VSLNet** [[cite](#VSLNet)], a video span localization network, employs a query-guided proposal mechanism to effectively align temporal spans with natural language queries. **2D-TAN** [[cite](#model_2D_TAN)] extends temporal action detection to a two-dimensional framework, enabling efficient proposal generation and ranking for temporal localization. These models have been instrumental in advancing temporal localization and serve as baseline architectures in this study. Prior works have focused on constructing a hierarchical structure, augmenting the NLQ dataset and developing better video features through large-scale pretraining. ReLER [[cite](#Reler)] proposes a novel multi-scale cross-modal transformer architecture, a video frame-level contrastive loss, and two data augmentation strategies. InternVideo [[cite](#InternVideo)] improves the quality of video features by carefully pre-training and fine-tuning a VideoMAE-L Model [[cite](#VideoMAE)], and ensemble the features and predictions. More recently, NaQ [[cite](#NaQ)] introduces a data augmentation strategy to transform video narrations into training data for the NLQ task, alleviating the problem of sparse annotation. NaQ++ ReLER, obtained by training the ReLER model with NaQ data, was the previous state-of-the-art method for Ego4D NLQ. GroundNLQ [[cite](#GroundNLQ)] is the current state-of-the-art for this benchmark. It adopts a two-stage pre-training strategy to respectively train a video feature extractor and a grounding model on video narrations, and finally finetune the grounding model on annotated data.  
Our work is complementary to these prior efforts, as they can be leveraged in the first stage of our proposed framework to localize temporal segments, which are subsequently refined into fine-grained textual answers using a frozen VideoQA model. This approach bridges the gap between timestamp predictions and actionable insights, advancing the utility of NLQ models in practical applications.

The next 2 paragraphs (VideoQA & End-to-end Models for VideoQA) citations are taken from <https://openaccess.thecvf.com/content/CVPR2024/papers/Min_MoReVQA_Exploring_Modular_Reasoning_Models_for_Video_Question_Answering_CVPR_2024_paper.pdf>  
**VideoQA.** Video Question-Answering (videoQA) is a key task for multimodal video understanding systems to assess their ability to reason about a video [cite, cite, cite, cite, cite]. Recent benchmarks have pushed towards assessing reasoning for temporal questions [cite, cite, cite], longer videos [cite, cite], and on domains like instructional [cite] and egocentric videos [cite, cite].

**End-to-end Models for VideoQA.** The recent success of LLMs [cite, cite, cite, cite] has led to an explosion of multimodal models that jointly understand vision and text data. Many works map frozen image encoders [cite, cite, cite] to the LLM textual embedding space: e.g., Flamingo [cite], via a Perceiver resampler [cite], or BLIP2 [cite] and Video-LLaMa [cite], via Q-formers for audio/vision [cite, cite]. GIT2 [cite] and PALI [cite, cite, cite] use simple encoder-decoder style architectures which are trained for image captioning, while MV-GPT [cite] finetunes a native video backbone [cite] for video captioning. Although trained with a generative (captioning) objective, such models achieve strong results for general visionlanguage tasks (cast as auto-regressive generation with question as prefx). More recent works such as InstructBLIP [cite], MiniGPT-4 [cite], and VideoBLIP [cite] improve zero-shot results with strong instruction tuning. Generally, however, end-to-end methods can be diffcult to interpret. For videos in particular, memory limits in end-to-end models require signifcant downsampling: e.g. temporally sampling a few frames with large strides [cite, cite], spatially subsampling each frame to a single token [cite, cite, cite]. Such models also tend process each frame with equal importance. Unlike such works, our model has an explicit grounding stage which searches for the most relevant video frames to be processed in more detail. Other grounding works for videoQA include SeViLa [cite], MIST [cite], and NExTGQA [cite].   
  
However, these end-to-end models often require significant downsampling and struggle to process long videos efficiently, making them less suitable for high-detail video reasoning tasks. To address these limitations, our work adopts a modular approach, where the temporal localization (NLQ) model

provides fine-grained segment predictions, and **Video-LLaVA** is then used to generate textual answers from those segments. This two-stage pipeline enhances the model’s efficiency and answer quality. The modular approach is inspired by recent studies that incorporate grounding mechanisms for better alignment between the video content and the question.

**3. Methodology**

This section outlines the steps taken to analyze the training dataset, train and evaluate temporal localization models, and extend the pipeline for generating textual answers from localized video segments.

**3.1. Dataset and Annotation Analysis**

We employed the Ego4D dataset, focusing on its Natural Language Queries (NLQ) annotations. This dataset comprises approximately 19,000 queries from 227 hours of egocentric video content, with each query annotated with temporal boundaries indicating when the query is answered. To better understand the Ego4D training dataset and its Natural Language Queries (NLQ) annotations, we conducted an extensive analysis focusing on template distributions, clip and answer segment durations, temporal relationships and observations on scenarios. These insights informed the design and evaluation of our models and ensured they accounted for the dataset’s diverse characteristics.

The distribution of query templates, visualized in **Figure 1 (a)**, revealed the presence of queries with the "None" template, where no specific template was assigned. This observation highlights gaps in template labeling that could influence model training. The histogram in **Figure 1 (b)**, complemented by statistical metrics in **Table 1**, illustrates the wide range of clip durations, which span from approximately 207 seconds to 20 minutes, with a mode at 480 seconds. This variation underscores the necessity for temporal localization models to handle diverse input lengths effectively.

The answer segment durations, visualized in **Figure 1 (c)** and detailed through additional statistics in **Table 2**, showed that these segments are generally short, ranging from 0 to 480 seconds, with a median of 3.45 seconds. Notably, the presence of zero-second durations prompted us to apply a filter to VSLNet, VSLBase, and 2D-TAN model to exclude such no-time answer segments, enhancing the robustness of the models.

**Figure 1 (e)** highlights the average answer durations grouped by template type, where we observed that questions requiring counting actions involve longer answer durations, as expected.

Finally, additional statistics on query counts and answer durations across scenarios highlight significant variability in these attributes, as shown in **Table 3** and **Table 4**. This variability emphasizes the dataset's complexity and reinforces the importance of scenario-specific considerations in model design.

**3.2. Temporal Localization Model Training**

We trained, validated, and tested three temporal localization models—VSLBase, VSLNet, and 2D-TAN—on pre-extracted features from Omnivore [[cite](#Omnivore)] and EgoVLP [[cite](#EgoVLP)].

* VSLBase [[cite](#VSLNet)] served as a foundational architecture, extracting visual and textual features that are fused through shared encoders and refined with Context-Query Attention. Temporal boundaries were regressed using LSTMs.
* VSLNet [[cite](#VSLNet)], extending VSLBase, incorporated a Query-Guided Highlighter for finer temporal alignment, improving its ability to handle subtle differences in video frames.
* 2D-TAN [[cite](#model_2D_TAN)] framed temporal localization as a two-dimensional proposal generation and ranking process, emphasizing complementary strengths to VSLNet.

Training was performed with official pre-extracted features, allowing computationally efficient fine-tuning of these architectures.

ADD HERE INFO ABOUT HYPERPARAMETER CONFIGURATIONS OF VSLBASE, VSLNET AND 2D-TAN.

**3.3. Extension to Video Question Answering**

To bridge the gap between temporal localization and textual answers, we extended the NLQ task using a VideoQA model, Video-LLaVA [[cite](#Video_LLaVa)].

1. **Top Predictions Selection**: We selected the top 50 VSLNet predictions based on Intersection over Union (IoU) scores.
2. **Video Segments Extraction**: Using the predictions, the corresponding video segments were extracted with ffmpeg.
3. **VideoQA Model Inference**: Each segment, paired with its query, was fed into Video-LLaVA to generate textual answers.
4. **Evaluation**: Results were assessed using both qualitative examples and quantitative metrics (e.g., ROUGE and BLEU). - - -> **to adapt on what we did**

**4. Experiments**

This section presents the experiments carried out to evaluate the effectiveness of the temporal localization models and the VideoQA extension. We examine the performance of VSLBase, VSLNet, and 2D-TAN models trained on different feature sets (Omnivore, and EgoVLP) and compare their results to the baseline models trained on SlowFast features from the Ego4D research.

**4.1. Temporal Localization Results**

To evaluate the performance of the temporal localization models, we trained and validated VSLBase, VSLNet, and 2D-TAN using the Omnivore and EgoVLP features. Results were also compared to the Ego4D baselines trained on SlowFast features (as presented in Table 7). The evaluation metrics primarily consisted of **Intersection over Union** (IoU) at different thresholds. The results, shown in **Table 5** and **Table 6**, offer key insights into the influence of different features and model architectures.

**Performance on Omnivore Features (Table 5)**: When the models were trained on Omnivore features, the results show that **VSLNet** outperforms **VSLBase** across all metrics. For example, VSLNet achieved a **Rank@1** of 6.56 at IoU@0.3, compared to VSLBase's 6.14, suggesting that VSLNet is more capable of precise temporal localization when trained on Omnivore features. Furthermore, **2D-TAN**, while showing slightly lower performance in Rank@1 metrics, exhibits competitive results, particularly at Rank@5. This highlights the strength of 2D-TAN's proposal-based approach, which complements VSLNet in handling more general queries that require broader temporal context.  
**Performance on EgoVLP Features (Table 6)**: The models trained on **EgoVLP features** demonstrate a noticeable improvement in performance, particularly in the case of **VSLNet**. For instance, VSLNet achieves generally higher results than its performance on Omnivore features. This suggests that EgoVLP, which integrates more robust video-language representations, improves the model’s ability to localize answers more accurately within video segments. Additionally, the **2D-TAN** model shows a a different trend, with some values that are lower than them counterpart on Omnivore.   
**Comparison with SlowFast Baselines (Table 7)**: When compared to the **SlowFast** features used in the original Ego4D paper, the models trained on Omnivore and EgoVLP features show considerable advantages in performance. Specifically, **VSLNet** on SlowFast achieves a **Rank@1** of 5.45 at IoU@0.3, which is lower than the performance observed on both Omnivore (6.56) and EgoVLP (6.43) features. Similarly, **2D-TAN** outperforms the SlowFast baseline in both Rank@1 and IoU at multiple thresholds, indicating that the additional information provided by Omnivore and EgoVLP features improves the models' ability to localize temporal segments more effectively.

**4.1.1.** **Observations and Considerations**:

1. **Model Comparison**: Across all feature sets, **VSLNet** consistently outperforms **VSLBase**, confirming its superiority in capturing finer temporal details and understanding the relationship between queries and video content. The integration of a Query-Guided Highlighter in VSLNet likely enhances its sensitivity to subtle changes in the video's temporal structure, which is reflected in its higher precision scores.
2. **Role of Feature Sets**: The results highlight the importance of the input features in the performance of temporal localization models. **EgoVLP** and **Omnivore** features, which provide richer multimodal representations, allow the models to more effectively leverage both visual and textual information. The models trained on these features consistently outperform the baselines using **SlowFast** features, which are more limited in their ability to represent complex video-language interactions.
3. **Proposal-Based Strengths of 2D-TAN**: While **2D-TAN** lags slightly behind VSLNet in certain metrics, it shows complementary strengths in handling queries with broader temporal contexts, where more generalized proposals are required. Its performance in Rank@5 and IoU scores indicates that it excels at localizing less precise but still important segments within the video.
4. **Challenges and Future Directions**: One of the challenges observed in these experiments is that the models, while performing well in general, still struggle with handling extreme cases—such as videos with very short or very long answer segments. Future work could explore refining temporal localization models to better handle edge cases, such as answer segments that span the majority of a video or those that occur within extremely short time frames.

In conclusion, the experiments demonstrate that both **VSLNet** and **2D-TAN** benefit significantly from richer video-language representations, such as those provided by **EgoVLP** and **Omnivore** features, outperforming the baselines trained on **SlowFast** features. These results underline the importance of feature selection and model architecture in the task of temporal localization, with implications for improving both the accuracy and efficiency of video understanding systems.

**4.2. Video Question Answering Results**

Using the top 50 VSLNet predictions, we implemented the VideoQA extension.

* **Qualitative Results**: The generated answers demonstrated relevance and coherence with the queries. Selected examples illustrated the effectiveness of localizing and processing critical video segments.
* **Quantitative Results**: The answers were evaluated against ground-truth annotations using ROUGE and BLEU scores, indicating competitive performance within the given computational constraints.

**4.3. Observations**

1. **Impact of Features**: EgoVLP features consistently led to superior performance across models, highlighting the importance of pre-trained video-language representations.
2. **Temporal Localization vs. VideoQA**: While temporal localization provided accurate segment predictions, Video-LLaVA demonstrated its capability to generate detailed textual answers, emphasizing its potential for real-world applications.
3. **Computational Trade-offs**: Leveraging pre-extracted features and focusing on key segments enabled an efficient and scalable pipeline without sacrificing performance.

**5. Conclusion**

This work investigated the NLQ benchmark within the Ego4D dataset, focusing on temporal localization of answers and extending the task to textual answer generation. Through the use of VSLBase, VSLNet, and 2D-TAN models with Omnivore and EgoVLP features, we demonstrated the importance of pre-trained representations and advanced architectures for accurate temporal localization. The extension to VideoQA, using top VSLNet predictions and the Video-LLaVA model, showcased the feasibility of generating meaningful textual answers from localized segments.

These results underscore the potential of integrating temporal localization and VideoQA, addressing the challenges of egocentric video analysis and opening avenues for real-world applications in assistive and automated systems.

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**References:**

[1] Grauman, Kristen, et al. "Ego4d: Around the world in 3,000 hours of egocentric video."

*Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*.

2022.

[2] Lin, B., Zhu, B., Ye, Y., Ning, M., Jin, P., & Yuan, L. (2023). Video-LLaVA: Learning united visual representation by alignment before projection. *arXiv preprint arXiv:2311.10122*.

[3] Zhang, Hao, et al. "Span-based Localizing Network for Natural Language Video Localization."

*Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*.

2020.

[4] Zhang, Songyang, et al. "Learning 2d temporal adjacent networks for moment localization

with natural language." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 34.

No. 07. 2020.

[5] Girdhar, R., Singh, M., Ravi, N., Van Der Maaten, L., Joulin, A., & Misra, I. (2022). Omnivore: A single model for many visual modalities. In *Proceedings of the IEEE/CVF Conference on*

*Computer Vision and Pattern Recognition* (pp. 16102-16112).

[6] Lin, Kevin Qinghong, et al. "Egocentric video-language pretraining." *Advances in Neural*

*Information Processing Systems* 35 (2022): 7575-7586.

[7] Feichtenhofer, Christoph, et al. "Slowfast networks for video recognition." *Proceedings of the*

*IEEE/CVF international conference on computer vision*. 2019.

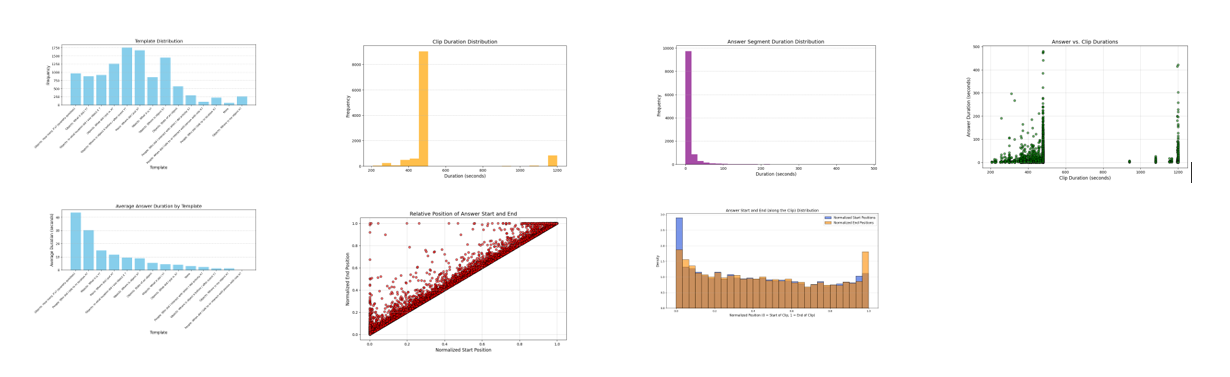
[8] Liu, N., Wang, X., Li, X., Yang, Y., and Zhuang, Y. Reler@ zju-alibaba submission to the ego4d natural language queries challenge 2022. arXiv preprint arXiv:2207.00383, 2022.

[9] Chen, G., Xing, S., Chen, Z., Wang, Y., Li, K., Li, Y., Liu, Y., Wang, J., Zheng, Y.-D., Huang, B., et al. Internvideo-ego4d: A pack of champion solutions to ego4d challenges. arXiv preprint arXiv:2211.09529, 2022.

[10] Tong, Z., Song, Y., Wang, J., and Wang, L. Videomae: Masked autoencoders are data-efficient learners for self-supervised video pre-training. arXiv preprint arXiv:2203.12602, 2022.

[11] Ramakrishnan, S. K., Al-Halah, Z., and Grauman, K. NaQ: Leveraging narrations as queries to supervise episodic memory. In CVPR, 2023.

[12] Hou, Z., Ji, L., Gao, D., Zhong, W., Yan, K., Li, C., Chan, W. K., Ngo, C.-W., Duan, N., and Shou, M. Z. Groundnlq @ ego4d natural language queries challenge 2023. arXiv preprint arXiv:2306.15255, 2023.



**Figure 1:** Visualization of key dataset characteristics and distributions.  
(a) **Template Distribution:** Bar chart displaying the frequency of queries categorized by their templates, including cases where the template is marked as "None."  
(b) **Clip Duration Distribution:** Histogram showing input clip durations, highlighting a wide range from approximately 207 seconds to 20 minutes, with the most frequent duration being 480 seconds. Statistical metrics such as mean, median, standard deviation, minimum, and maximum durations are included.  
(c) **Answer Segment Duration Distribution:** Histogram illustrating the duration of ground truth answer segments, which are generally short, ranging from 0 to 480 seconds, with notable occurrences of zero-duration answers.  
(d) **Answer vs. Clip Durations:** Scatter plot demonstrating the relationship between clip durations and their corresponding answer segment durations.  
(e) **Average Answer Duration by Template:** Bar chart indicating that quantity-based queries tend to have the longest average answer durations.  
(f) **Relative Position of Answer Start and End:** Scatter plot of normalized start and end positions of answer segments relative to their respective clips, showcasing temporal alignment trends.  
(g) **Answer Start and End Distribution:** Overlapping histograms representing the distribution of normalized start and end timestamps for answer segments along the clips.

=== Statistics on Clip durations =====================================

Average Clip duration: 522.68 seconds

Max Clip duration: 1200.07 seconds

Min Clip duration: 207.17 seconds

Standard deviation of Clip duration: 197.64 seconds

Median Clip duration: 480.00 seconds

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**Table 1:** Summary statistics for clip durations, including mean, median, standard deviation, minimum, and maximum values, highlighting the variability in clip lengths within the dataset.

=== Statistics on Answer segment duration ============================

Average Answer segment duration: 9.67 seconds

Max Answer segment duration: 480.00 seconds

Min Answer segment duration: 0.00 seconds

Standard deviation of Answer segment duration: 22.83 seconds

Median Answer segment duration: 3.45 seconds

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**Table 2:** Summary statistics for answer segment durations, showcasing key metrics such as mean, median, standard deviation, minimum, and maximum values, reflecting the predominantly short length of answer segments in the dataset.

=== Statistics on Query counts across scenarios =========================

Average Query count: 223.99

Max Query count: 3018

Min Query count: 4

Standard deviation of Query count: 455.08

Median Query count: 73.0

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**Table 3:** Statistics on query counts across scenarios, highlighting the variability in the number of queries per scenario with key metrics such as mean, median, standard deviation, minimum, and maximum values.

=== Statistics on Answer durations across scenarios ======================

Average Answer duration: 10.69 seconds

Max Answer duration: 54.58 seconds

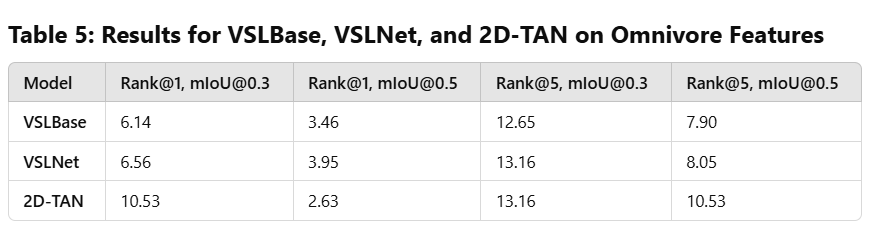
Min Answer duration: 1.32 seconds

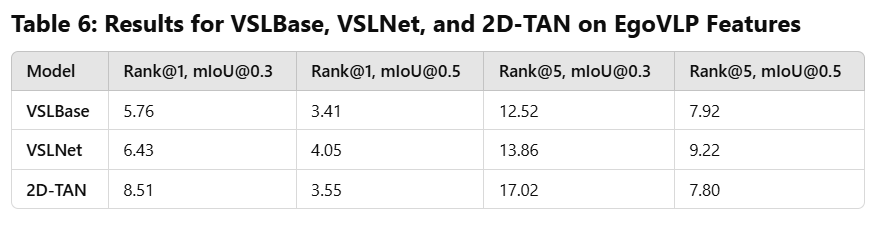
Standard deviation of Answer duration: 7.05 seconds

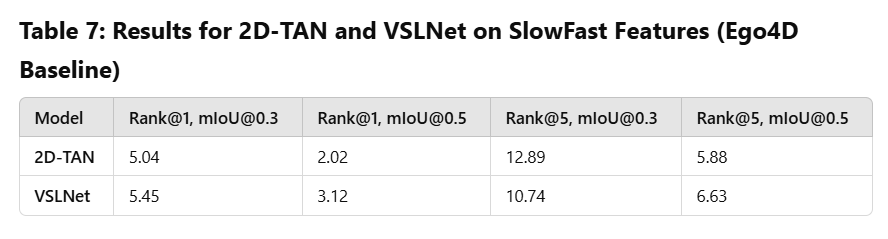
Median Answer duration: 9.72 seconds

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**Table 4:** Statistics on answer durations across scenarios, providing insights into the distribution of answer segment lengths with key metrics including average, maximum, minimum, standard deviation, and median values.

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