Learning Situation Hyper-Graphs for Video Question Answering

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Abstract

Answering questions about complex situations in videos requires not only capturing the presence of actors, objects, and their relations but also the evolution of these relationships over time. A situation hyper-graph is a representation that describes situations as scene sub-graphs for video frames and hyper-edges for connected sub-graphs and has been proposed to capture all such information in a compact structured form. In this work, we propose an architecture for Video Question Answering (VQA) that enables answering questions related to video content by predicting situation hyper-graphs, coined Situation Hyper-Graph based Video Question Answering (SHG-VQA). To this end, we train a situation hyper-graph decoder to implicitly identify graph representations with actions and object/human-object relationships from the input video clip. and to use cross-attention between the predicted situation hyper-graphs and the question embedding to predict the correct answer. The proposed method is trained in an end-to-end manner and optimized by a VQA loss with the cross-entropy function and a Hungarian matching loss for the situation graph prediction. The effectiveness of the proposed architecture is extensively evaluated on two challenging benchmarks: AGQA and STAR. Our results show that learning the underlying situation hyper-graphs helps the system to significantly improve its performance for novel challenges of video question-answering tasks[1].

1. Introduction

Video question answering in real-world scenarios is a challenging task as it requires focusing on several factors including the perception of the current scene, language understanding, situated reasoning, and future prediction. Visual perception in the reasoning task requires capturing various aspects of visual understanding, e.g., detecting a diverse set

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[1]Code will be available at https://github.com/aurooj/SHG-VQA

Figure 1. The situation hyper-graph for a video is composed of situations with entities and their relationships (shown as subgraphs in the pink box). These situations may evolve over time. Temporal actions act as hyper-edges connecting these situations into one situation hyper-graph. Learning situation graphs, as well as temporal actions, is vital for reasoning-based video question answering.

of entities [23, 24], recognizing their interactions, as well as understanding the changing dynamics between these entities over time. Similarly, linguistic understanding has its challenges as some question or answer concepts may not be present in the input text or video.

Visual question answering, as well as its extension over time, video question answering, have both benefited from representing knowledge in graph structures, e.g., scene graphs [20, 39], spatio-temporal graphs [4, 60], and knowledge graphs [40, 49]. Another approach in this direction is the re-introduction of the concept of "*situation cognition*" embodied in "*situation hyper-graphs*" [52]. This adds the computation of actions to the graphs that capture the interaction between entities. In this case, situations are represented by hyper-graphs that join atomic entities and relations (e.g., agents, objects, and relationships) with their actions (Fig. 1). This is an ambitious task for existing systems as it is impractical to encapsulate all possible interactions in the real-world context.

Recent work [26] shows that transformers are capable

of learning graphs without adapting graph-specific details in the architectures achieving competitive or even better performance than sophisticated graph-specific models. Our work supports this idea by implicitly learning the underlying hyper-graphs of a video. Thus, it requires no graph computation for inference and uses decoder's output directly for cross attention module. More precisely, we propose to learn situation hyper-graphs, namely framewise actor-object and object-object relations as well as their respective actions, from the input video directly without the need for explicit object detection or other required prior knowledge. While the actions capture events across transitions over multiple frames, such as *Drinking from a bottle*, the relationship encoding actually considers all possible combinations of static, single frame actor-object, and object-object relationships as unique classes, e.g., in the form of *person – hold – bottle* or *bottle – stands on – table*, thus serving as an object and relation classifier. Leveraging this setup allows us to streamline the spatio-temporal graph learning as a set prediction task for predicting relationship predicates and actions in a Situation hyper-graph Decoder block. To train the Situation Graph Decoder, we use a bipartite matching loss between the predicted set and ground truth hyper-graph tokens. The output of the situation graph decoder is a set of action and relationship tokens, which are then combined with the embedding of the associated question to derive the final answer. An overview of the proposed architecture is given in Fig. 2. Note that, compared to other works targeting video scene graph generation, e.g., those listed in [68], we are less focused on learning the best possible scene graph, but rather on learning the representation of the scene which best supports the question answering task. Thus, while capturing the essence of a scene, as well as the transition from one scene to the other, we are not only optimizing the scene graph accuracy but also considering the VQA loss.

We evaluate the proposed method on two challenging video question answering benchmarks: a) STAR [52], featuring four different question types, interaction, sequence, prediction, and feasibility based on a subset of the real-world Charades dataset [48]; and b) Action Genome QA (AGQA) [11] dataset which tests vision focused reasoning skills based on novel compositions, novel reasoning steps, and indirect references. Compared to other VQA datasets, these datasets provide dense ground truth hyper-graph information for each video, which allows us to learn the respective embedding. Our results show that the proposed hyper-graph encoding significantly improves VQA performance as it has the ability to infer correct answers from spatio-temporal graphs from the input video. Our ablations further reveal that achieving high-quality graphs can be critical for VQA performance.

Our contributions to this paper are as follows:

- We introduce a novel architecture that enables the com-

putation of situation hyper-graphs from video data to solve the complex reasoning task of video question-answering;

- We propose a situation hyper-graph decoder module to decode the atomic actions and object/actor-object relationships and model the hyper-graph learning as a transformer-based set prediction task and use a set prediction loss function to predict actions and relationships between entities in the input video;

- We use the resulting high-level embedding information as sole visual information for the reasoning and show that this is sufficient for an effective VQA system.

2. Related Work

Video Question Answering: Video question answering is an active area of research with efforts in insightful directions [41, 67], such as attention [16, 18, 33], cross-modal interactions [25, 28, 45, 57, 61, 64, 65], hierarchical learning [5, 27, 42], and so on. A few other algorithms classes include modular networks [5, 27, 54], symbolic reasoning [52, 58, 59], and memory networks [8, 10]. Several video QA benchmarks are introduced to evaluate this task from varying perspectives entailing description [38, 56, 62, 66], temporal reasoning [17, 58, 69], causal structures [53, 58], visual-language comprehension [29, 50, 57], relational reasoning [50], and measuring social intelligence [63]. STAR [52] benchmark goes one step further providing a benchmark to perform diagnostic study at additional fronts such as predicting future interactions and feasibility of next possible actions in the unseen future. Existing approaches on the benchmark either rely on object features [44] as nodes explicitly modeling their interactions through a message passing mechanism [15, 52], or benefit from efficient input sampling strategies during training to learn robust visual representations [27, 28]. We, however, take a different approach and focus on inferring the underlying semantic graph structure in the video and use it for QA reasoning. Our method is independent of using pretrained object detectors and uses a simple approach to learn to infer the sets of relationship predicates as well as actions for each frame. The model is trained end-to-end with the frozen backbone.

Graph-based VQA: Another related line of work is graph-based VQA methods [22, 31]. Some of them work on object features extracted from a pretrained detector (e.g., Faster-RCNN [44]) [5, 15, 35, 46, 54], while some operate on frame-level [19, 28, 61] (e.g., ResNet), clip-level features [42, 45, 57](e.g., C3D, S3D) or transformer-based backbones [7, 36, 43]. We focus on predicting atomic actions, and relationship triplets from the frame-level or clip-level features directly instead of an explicit graph.

Figure 2. The SHG-VQA architecture: we start with encoding the input video into spatio-temporal features using a pre-trained backbone. These video features are flattened into a sequence of tokens of length $T \times h \times w$ and position encoded to be further processed through a visual encoder. These encoded tokens are input to the action decoder to predict the set of atomic actions from the input action queries as well as to the relationship decoder which takes relationship queries as input along with the video tokens. The action decoder and relationship decoder output the situation graph embeddings. In the text branch, the question and the answer choices are composed into a sequence and passed through a text transformer to obtain encoded word embeddings; for open-ended VQA, only the question is passed to the text transformer. The generated hyper-graph along with the encoded text tokens are then used as input to a cross-attentional transformer and the combined representations are used to predict the correct answer with a classifier. Section 3.4 describes the losses and training objectives.

Scene Graph Generation: The proposed formulation of situation hyper-graph deviates from existing scene-graph generation approaches [2, 52, 68] as we do not require object detections as input or object level supervision, nor do we model it in an explicit graph structure. Our goal is simple: given an input video, predict all object-relation-object and actor-relation-object triplets as well as associated actions for each video frame. Our intuition is that forcing the model to predict these predicates will drive the system to learn a latent graph structure for visual input. The predicted situation hyper-graph is treated as an abstract video representation and used for VQA reasoning in the next step.

3. The SHG-VQA Model

Situation video question answering has three essential steps 1) the visual recognition capacities of visual entities, their relationships, actions, and how these transition over time, 2) the language understanding capacity to the questions, 3) the question-guided reasoning process over the representation learned in the first step. Sub-optimal performance at any of these steps will affect the overall task performance. A key problem here is that capturing the visual structures directly from raw data, e.g., in the form of features often results in a rather noisy signal and does not provide suitable input for high-level language-guided reasoning. To overcome this mismatch, we propose to learn the implicit structure of the visual input as an intermediate step between learning the video representation and question-based reasoning. Forcing the model

to learn to predict this implicit structure (actions, relations between entities) not only improves the video representation but also acts as a lightweight, high-level representation of the video content and can be used for the VQA task. We illustrate our architecture in Fig. 2.

3.1. Input Processing

Given the input video and the question, we encode the inputs as described below:

Question Encoder: The question is first tokenized into word tokens using a wordPiece tokenizer. These word tokens along with the special class token $[CLS]$ are the inputs of an embedding layer. The output word embeddings from this layer are input to a transformer encoder that encodes each word using multi-head self-attention between different words at each encoder layer.

Video Encoder: Let $V \in \mathbb{R}^{T \times H \times W \times 3}$ be the input video clip, where T is the clip length with 3 color channels, height H and width W. First, we extract video features $x_V \in \mathbb{R}^{T \times h \times w \times d_x}$ using a convolutional backbone with d_x being the feature dimension, h and w are the reduced feature's height and width. As transformers process sequential input data, the video features x_V are flattened into a sequence (of size $\mathbb{R}^{Thw \times d_x}$) and reduced to dimension d through a linear layer. Then, we append a trainable vector of dimension d for a special class token $[VIS]$ to this sequence of video features at index 0. These features are combined with position encodings and input to a transformer-based video encoder V_e.

The output features of the video are forwarded to the action decoder and relationship decoder to infer the situation graph capturing the action information, as well as the entities and their relationships. The output of the last layer of both decoders is then combined and augmented with frame positions, forming the final hyper-graph embedding. We further attach a randomly initialized class token $[HG]$. These situation graph embeddings are then input to a multi-layered cross-attentional transformer encoder for more fine-grained interaction between the question words and semantic knowledge extracted from the video in the form of a graph. The output features corresponding to $[CLS]$ and $[HG]$ tokens are input to an answer classifier to produce an answer.

3.2. Situation hyper-graph Generation

Real-world video understanding relies on the scene understanding including changing relationships between the objects over time and the evolving actions. Therefore, we represent the given video as a "situation graph" denoted by G which describes actions and relationships between objects. Let $G = (V, E)$, where V is the set of vertices representing all possible entities in the dataset, and E is the set of edges representing all possible relationships between each pair of entities. Given an input video, we want to learn a situation graph $g_t = (v_t, e_t), v_t \in V, e_t \in E$ for each time step $t \in \{1, 2, ..., T\}$ in the video, that captures the entities (objects, actors), their relationships as well as the associated actions that are present in that frame. The hyper-graph for one video is thus represented by the set of situation graphs $\mathcal{G} = \{g_1, ... g_T\}$. An action may comprise multiple relationships and objects. For each frame, we further have a set of actions $A_t = a_1, a_2, ..., a_N$. The set of actions for the full video is then given as $\mathcal{A} = \{A_1, ... A_T\}$. Note that the actions are predicted in addition to the graph structure and that both will be merged in a *situation hyper-graph* embedding in a separate step after the decoder block. Rather than predicting the set of vertices and edges in the graph g_t, we propose to predict the graph structure by formulating this graph prediction as follows:

Let $x_{V_e} \in \mathbb{R}^{T' \times h \times w \times d}$ be the encoded video features, where T' denotes the temporal length of encoded features, h and w are spatial dimensions, and d is the feature's dimension. A relationship predicate p describes interactions between entities by triplet tokens $object - relation - object$ or $actor - relation - object$. We propose to predict the set of relationship predicates R and the set of atomic actions A occurring in each video frame. This is intuitive because the ability to predict the atomic actions and relations between entities for each time step benefits the high level reasoning tasks such as video question answering in this work. Therefore, for each time step $t \in \{1, 2, ..., T\}$ in the video, we predict the set of relationship predicates denoted by R_t in each video frame where $R_t = \{p_1, p_2, ..., p_M\}$ and p_i is the

Figure 3. Situation hyper-graph embeddings: We start with decoded queries from action and relationship decoder. Then we add type encoding vectors $[ACT]$ and $[REL]$ for actions and relationships, attention masks, and an embedding vector for the situation ID ($t \in \{1, ..., T\}$). The sums are input to the cross-attentional module. See section 3.2.2 for details).

i^{th} predicate between two entities, representing the vertices v_x and v_y (object-object or actor-object) and the relation resp. edge e_i represented as $< v_x, e_i, v_y >$, $M = |R_t|$ is the relationship set size. Additionally, we predict the set of N actions A_t for each time step t where $A_t = \{a_1, a_2, ..., a_N\}$ and a_j is the jth action occurring at time step t. $N = |A_t|$ is the actions set size for each step t. M and N are hyperparameters in our system.

To obtain actions and relation predicates from the video, we use a transformer decoder that takes video features as memory to learn action queries and relation queries.

3.2.1 Prediction Head

The decoded output embeddings for action and relationship queries are input to respective prediction heads. Prediction heads use a 2-layer feed forward network (FFN) with GELU activation and LayerNorm.

Considering that actions and relationships at a given time step are permutation-invariant, we use optimal bipartite matching between predicted and ground truth actions/relationships. An optimal bipartite matching between the predicted classes and ground-truth labels is the one with the minimum matching cost. Once the optimal matching pairs have been obtained, we use a Hungarian loss function to optimize for ground truth classes [1]. See section 3.4 for details of the loss function.

3.2.2 Situation hyper-graph Embedding

For the decoded queries of actions and relationships (referred as graph token embeddings), *situation hyper-graph*

Table 1. Results on AGQA dataset for different question types. The best results are shown in **bold** font. Numbers are reported in percentages.

Method	Reasoning								Semantic			Structure					Overall		
	obj-rel	rel-action	obj-action	superlative	sequencing	exists	duration	activity	obj	rel	action	query	compare	choose	logic	verify	binary	open	all
PSAC [34]	37.84	49.95	50.00	33.20	49.78	49.94	45.21	4.14	37.97	49.95	46.85	31.63	49.49	46.56	49.96	49.90	48.87	31.63	40.18
HME [9]	37.42	49.90	49.97	33.21	49.77	49.96	47.03	5.43	37.55	49.99	47.58	31.01	49.71	46.42	49.87	49.96	48.91	31.01	39.89
HCRN [27]	40.33	49.86	49.85	33.55	49.70	50.01	43.84	5.52	40.33	49.96	46.41	36.34	49.22	43.42	50.02	50.01	47.97	36.34	42.11
SHG-VQA	**46.42**	**60.67**	**64.63**	**38.83**	**62.17**	**56.06**	**48.15**	**10.12**	**47.61**	**56.19**	**53.83**	**43.42**	**60.68**	**47.76**	**52.86**	**56.63**	**55.04**	**43.42**	**49.20**

embeddings are constructed in order to be used with question features for video question answering. First, these action and relationship graph embeddings are combined for each time step t representing a situation at t. Then, we add token type embedding $[ACT]$ for actions and $[REL]$ for relations to their respective graph embeddings. A situation ID (or frame position t) embedding is also added to these embeddings. An additional attention mask is used to differentiate actual tokens and padded tokens (no-class token ϕ) at training time. At inference time, no attention mask is used as we do not employ any information about the graph at test time. Finally, we add a special class token $[HG]$ to this sequence of features. See Fig. 3 for visualization.

3.3. Cross-attentional Transformer Module

The situation hyper-graph embeddings obtained at previous step (section 3.2.2) are input along with the question to a cross-attentional transformer module which allows fine-grained computation between the question features and the graph features. A standard co-attentional transformer module is used for cross-attention between the two sequential feature inputs. The feature outputs corresponding to the $[HG]$ token and $[CLS]$ token from the cross-attentional transformer block are fed to a feed-forward network (FFN) for answer prediction.

3.4. Learning Objective

The SHG-VQA model is trained with the following training objective i.e.,

$$L = L_{act} + L_{rel} + L_{vqa} \qquad (1)$$

where L_{act} and L_{rel} are the set prediction loss terms for predicting the action set and relationship set for the video, and L_{vqa} is the cross-entropy loss over the predicted situation graph and question.

Actions and relationships set prediction loss: The situation graph prediction module infers fixed sets of sizes $|N| \times T$ actions and $|M| \times T$ relationships for T-length video clip in a single pass through the action decoder and relationship decoder respectively. We modify the set prediction loss used in [1] as follows. Let A be the set of ground-truth actions and $\hat{A} = \{\hat{a}_i\}_{i=1}^{|N| \times T}$ be the predicted set of actions. In a scenario where $\hat{A}$ is larger than the set of actions present

in the video, a special class ϕ (no class) is padded to the ground truth set A. We obtain a bipartite matching between ground-truth and predicted set for each timestep t as follows:

$$\hat{\sigma}_a = \sum_{t}^{T} argmin_{\sigma_t \in \zeta_{|N|}} \sum_{i}^{|N|} \mathcal{L}_{match}(a_{t_i}, \hat{a}_{\sigma_t(i)}) \qquad (2)$$

Where, σ_t is a permutation of N elements for frame t, $\mathcal{L}_{match}(a_{ti}, \hat{a}_{\sigma_t(i)})$ is a pair-wise matching cost between i^{th} ground-truth action label in t^{th} frame i.e., a_{t_i} and a predicted action label at index $\sigma_t(i)$. This optimal assignment for each step t is computed using the Hungarian algorithm and the cost is summed over all T steps. The proposed set prediction loss takes into account only the class predictions for all video frames with no bounding box ground truths being used, different from the original set prediction loss used in [1] for object detection in images. Let $\hat{p}(c_{t(i)})$ be the class probability for the action prediction at $\sigma_t(i)$, $\mathcal{L}_{match}(a_{t_i}, \hat{a}_{\sigma_t(i)})$ would be $-\mathbb{1}_{\{c_{t(i)} \neq \phi\}} \hat{p}_{\sigma_t(i)}(c_{t(i)})$. After we obtain a one-to-one optimal matching between ground-truth and predicted set items without duplicates at each time step, we can compute the loss between the matched pairs using a Hungarian loss as follows:

$$\mathcal{L}_{act}(a, \hat{a}) = \sum_{i=1}^{|N| \times T} -\log \hat{p}_{\hat{\sigma}(i)}(c_i) \qquad (3)$$

Likewise, R is the set of ground-truth relations and $\hat{R} = \{\hat{p}_i\}_{i=1}^{|M| \times T}$ denotes the predicted relationships. L_{rel} is formulated as follows:

$$\hat{\sigma}_p = \sum_{t}^{T} argmin_{\sigma_t \in \zeta_{|M|}} \sum_{i}^{|M|} \mathcal{L}_{match}(p_{t_i}, \hat{p}_{\sigma_t(i)}) \qquad (4)$$

$$\mathcal{L}_{rel}(p, \hat{p}) = \sum_{i=1}^{|M| \times T} -\log \hat{p}_{\hat{\sigma}(i)}(c_i) \qquad (5)$$

where $\hat{\sigma}(i)$ is the optimal matching obtained in the previous step for each frame. The inferred graph is input to the cross-attentional transformer module along with the question and the answer choices as explained in section 3.2.2. The proposed network is trained in an end-to-end manner.

Table 2. Results on AGQA's novel compositions test metric.

Method	Sequencing			Superlative			Duration			Obj-relation			Overall		
	B	O	All	B	O	All	B	O	All	B	O	All	B	O	All
PSAC [34]	49.19	29.33	40.96	45.23	17.76	33.32	47.89	34.84	42.06	**43.76**	0.01	24.28	46.49	19.34	34.71
HME [9]	49.33	28.06	40.53	44.06	13.8	30.95	48.45	34.72	42.31	39.58	0.00	21.96	45.42	17.17	33.15
HCRN [27]	48.31	30.00	40.73	45.12	17.30	33.06	46.15	39.11	43.01	37.15	2.86	21.88	44.88	20.12	34.13
SHG-VQA	**50.88**	**38.59**	**45.79**	**51.14**	**23.64**	**39.25**	**51.84**	**49.21**	**50.66**	39.73	**6.23**	**24.82**	**49.07**	**26.68**	**39.37**

Table 3. Evaluation on AGQA's more compositional steps.

More Compositional Steps	Binary	Open	All
PSAC [34]	47.65	14.81	47.19
HME [9]	**48.09**	20.98	**47.72**
HCRN [27]	46.96	**23.70**	46.63
SHG-VQA	47.13	22.66	46.97

Table 4. Evaluation on AGQA's indirect references test metric.

Method		Object			Action			Temporal		
		B	O	All	B	O	All	B	O	All
Precision	PSAC	63.69	53.77	56.64	61.01	52.46	53.24	57.52	53.74	54.39
	HME	62.95	52.31	55.39	58.21	48.12	49.04	55.99	52.42	53.04
	HCRN	54.06	67.24	63.43	53.87	64.43	63.47	52.35	66.84	64.34
	SHG-VQA	76.93	86.27	81.59	79.55	87.40	84.90	69.08	87.35	82.87
Recall	PSAC	45.06	27.36	38.80	40.91	22.18	25.96	35.13	26.84	30.64
	HME	46.03	26.80	39.23	41.32	21.71	25.67	37.96	26.59	31.80
	HCRN	44.84	35.46	41.52	44.01	30.43	33.17	35.11	34.38	34.71
	SHG-VQA	**53.86**	**43.98**	**49.85**	**54.16**	**37.83**	**43.10**	**52.21**	**43.57**	**46.78**

4. Experiments

4.1. Datasets

AGQA Benchmark [11]: The Action Genome Question Answering benchmark is a visual dataset comprising 192M hand-crafted questions about 9.6K videos from the Charades dataset [47]. In addition to VQA accuracy, AGQA presents three testing metrics for testing the VQA methods: indirect references, novel compositions, and more compositional steps. We use the AGQA 2.0 Balanced dataset, which consists of 2.27M question-answer pairs as a result of balancing the original dataset using stricter procedures to reduce as much language bias as possible. Of the 2.27M questions, there are approximately 1.6M training questions and 669K test questions [12]. To have a standard train-val-test setup for our experiments, we randomly sampled 10% QA pairs from training data for validation of hyperparameters.

STAR Benchmark [52]: The STAR dataset provides 60K situated reasoning questions based on 22K trimmed situation video clips, also based on the Charades dataset [47]. They further provide ∼144K ground-truth situation graphs including 111 actions, 37 unique objects, and 24 relationships. The dataset is split into training, validation, and test sets where test evaluation can be done on the evaluation server a limited number of times. We perform ablations and analysis on the validation set and report test set results to compare with the baselines in Table 5.

4.2. Implementations

On the VQA task, we report accuracy; we also report mAP for situation hyper-graph predictions. For AGQA's *indirect references* testing metric, precision and recall are reported. For STAR benchmark, we follow the same training protocol as [52] and train SHG-VQA from scratch on each question type separately unless specified otherwise. Training details are shared in the supplementary document.

Visual Embeddings: The video frames are resized to size 224×224 with a clip length of 16 frames. We use RandAugment [3] for data augmentation during training. The video clip is input to a pretrained convolutional network with freeze weights to obtain video features of size $16 \times 7 \times 7 \times 2048$. A 2-layer 3D convolutional block with the kernel of size $5 \times 3 \times 3$ further processes the zero-padded extracted features yielding features of size $8 \times 7 \times 7 \times d$. The spatio-temporal dimensions are then flattened to obtain a sequence of length $Thw = 392$ $d-$dimensional tokens where $d = 768$. The input encoders as well as situation hyper-graph decoders use $L = 5$ transformer encoder layers with non-shared weights.

Query embeddings for action and relationship predicates: The features output from the video encoder is then input to a situation hyper-graph decoder comprising transformer-based action and relationship decoders. Our best model uses $M = 8$ relation queries and $N = 3$ action queries for each situation; T is set to 16. **AGQA** has 157 total raw actions, 36 unique objects, and 44 unique relationships which obtain 456 relationship triplets $< v_x, e_i, v_y >$ in the training and validation set. For **STAR** dataset, there are 37 objects, and 24 relationships yielding 563 unique relation predicates; it also has 111 action classes.

Situation graph embeddings: The decoded situation graph queries are input to a cross-attentional transformer. The input situation graph embedding is a sum of 4 different encoding types: 1) decoded query embeddings for predicted actions and relationship predicates, 2) situation IDs denoting the situation (or frame) number for each query, 3) attention mask set to 1 for actual tokens and 0 for padded tokens, and 4) token type embeddings to distinguish between action tokens and relationship tokens as shown in Fig. 3. Our network uses a 2-layer co-attentional module [37] for cross-attention.

Table 5. Results on STAR dataset. **Best results** are shown in bold font and <u>second best</u> results are underlined. Numbers are reported for VQA accuracy in percentages.

Method(test)	Backbone	Obj.	Hyper.	Question Type				
				Inter.	Seq.	Pred.	Feas.	Overall
Q-type (Random) [21]	-	✗	✗	25.06	24.93	24.79	24.81	24.89
Q-type (Frequent) [21]	-	✗	✗	19.09	19.45	12.90	18.31	17.44
Blind Model (LSTM) [14]	GloVe	✗	✗	32.24	32.17	28.56	28.41	30.34
Blind Model (BERT) [6]	BERT	✗	✗	32.68	34.21	29.98	29.26	31.53
CNN-LSTM [58]	ResNext101-K400	✗	✗	33.25	32.67	30.69	30.43	31.76
CNN-BERT [32]	ResNext101-K400	✗	✗	33.59	37.16	30.95	30.84	33.14
LCGN [15]	ResNext101-K400	✓	✗	39.01	37.97	28.81	26.98	33.19
HRCN [27]	ResNext101-K400	✓	✗	39.10	38.17	28.75	27.27	33.32
ClipBERT [28]	ResNext101-K400	✗	✗	39.81	**43.59**	32.24	<u>31.42</u>	36.70
NS-SR [52]	ResNext101-K400	✓	✓	30.88	31.76	30.23	29.73	30.65
SHG-VQA (Ours)	SlowR50-K400	✗	✓	**47.98**	42.03	**35.34**	**32.52**	**39.47**
SHG-VQA (Ours)	ResNext101-ImageNet1K	✗	✓	<u>45.8</u>	<u>42.77</u>	<u>34.64</u>	29.91	<u>38.28</u>

AGQA: For AGQA, we train our model with SlowR50 backbone and report results for VQA accuracy on the test set. We also report our model's generalization capability to indirect references. Furthermore, we train our network to report its generalization to novel compositions and to more compositional steps. For more compositional steps, we train our network with randomly sampled 100K QA pairs.

STAR: Following [52], we train the model for each question type separately to compare with the baselines. However, this protocol is expensive in terms of time and resources. To address the matter of limited resources, we also tried combining all questions together after the questions filtering from interaction and sequence types and train a single model instead of multiple trainings. We use this training regime to study models ablations.

5. Results and Analysis

5.1. Comparison to State-of-the-Art

AGQA: We compare our method with the existing state-of-the-art methods on AGQA benchmark. The best baseline on AGQA is HCRN [27] for overall accuracy. HCRN uses appearance features from ResNet101 as well as motion features from ResNext101-Kinetics400 backbones. Our model outperforms HCRN by a significant margin of 7.09% (HCRN: 42.11% vs. SHG-VQA: 49.20%) in terms of overall accuracy (see Table 1). We observe the biggest improvement of 14.63% absolute points on object-action reasoning questions compared to the best model in that category i.e., PSAC [34]: 50.00% vs. SHG-VQA: 64.63%. We further report results on the three novel testing metrics as follows:

a) Novel Compositions: For novel composition at test time, we observe an overall gain of 4.70% when compared to the best contender, i.e., PSAC [34]. For open-ended questions, we outperform HCRN by 6.56% (see Table 2);

b) Indirect References: When tested for indirect references questions in Table 4, we outperform all baselines by an absolute 7.83%-16.62% in terms of recall; For precision, we also gain similar improvements;

c) Compositional Steps: Our model is trained on only 15% (100K QA pairs) of the training data and is still able to perform on par with the baselines (trained on 1.6M QA pairs) achieving second best results for each category of more compositional steps (table 3).

STAR: For STAR dataset, we first compare the proposed architecture to other state-of-the-art works in the field using SlowR50 [13] video backbone and a ResNext101 [55] as a frame-level backbone to evaluate accuracy based on 3D video and 2D image architectures. It shows that for both settings, SHG-VQA significantly outperforms other baseline methods even with weaker backbones (see Table 5). Concretely, we obtain an absolute gain of 8.53% over NS-SR [52], 5.86% compared to HCRN [27], 5.99% improvement over LCGN [15], and $\sim 2.5\%$ over ClipBERT [28] which is a SOTA model in terms of overall VQA accuracy. We notice the substantial gain of 7.86% for interaction questions which test the understanding of interactions between entities in a situation. Prediction is the next category of questions that benefits the most with 2.48% improvement.

5.2. Ablation and Hyperparameter Analysis

We perform our ablation studies on the STAR benchmark as discussed below:

Impact of situation graphs quality: To assess the effect of situation graphs' quality on VQA accuracy, we train a baseline version of our system, where the model is trained on ground truth situation graphs for VQA tasks only (Table 6). Since the ground truth situation graphs are not available for the test set, we can only compare SHG-VQA and this baseline on the validation set. As expected, when taking ground truth situation graphs as input, the performance is significantly improved for interaction (GT=91.9% vs. predicted=46.78%) and sequence (GT=80.5% vs. predicted=42.52%) questions. However, for the questions about the unseen part of the video, the model with ground truth graph tokens still struggles despite better performance compared to SHG-VQA: predic-

Figure 4. Qualitative example for using frame-wise set prediction loss. Col. 1 shows the frame, col. 2 shows the ground-truth situation graph, col. 3 shows predicted graphs when trained with set prediction loss for the full video, and col. 4 shows the predicted graph when the model is trained by matching each timestep t. The edges show the person-object relationship labels along with the number of times it was predicted.

Table 6. Impact of hyper-graphs (HG) quality. Results shown for STAR val set with SlowR50 backbone.

Method	Interaction	Sequence	Prediction	Feasibility	Overall
Predicted hyper-graphs	47.08	42.52	37.82	33.61	40.26
GT hyper-graphs	**91.9**	**80.5**	**41.22**	**35.42**	**62.46**

tion (GT=41.22% vs. predicted=37.82%) and feasibility (GT=35.42% vs. predicted=33.61%). We also report the mAP scores for the prediction of action and relationship predicates using our best model in Table 7. We obtain an overall mAP of 87.63 for actions and 72.9 for relationships respectively.

Input to cross-attentional transformer: To evaluate the choice of input to the cross-attentional transformer, we experiment with three settings: a) question and video embeddings, b) question and situation graphs embeddings, c) question, situation graphs, and video embeddings. We observe no gain in the overall VQA accuracy when adding video embeddings to the cross-attentional transformer and get our best results with (b) (table 8).

Situation hyper-graph components: To study the impact of different components of situation graphs, we train our system with only action predicate tokens with objective $L_{act} + L_{vqa}$, only relationship predicates (with $L_{rel} + L_{vqa}$), and the full model (eq. 1). The action predicates are more effective compared to the relationship predicates. When compared in terms of predicate classification, we observe high accuracy for action predicates. Nonetheless, using the full situation graphs perform better than omitting actions or relationship prediction task (table 9).

Number of queries: Number of action queries M and relationship queries N is a hyperparameter for SHG-VQA. We report the performance of the SHG-VQA with a varying number of queries for actions and relationships at each timestep in Table 9. We report our best results with $M = 3$ and $N = 8$. Additional results are reported in the supplementary document.

Frame-wise set prediction loss: Using the notion of time t

Table 7. **Predicate classification results** for situation hyper-graphs in terms of mAP for STAR validation set from SHG-VQA with SlowR50 backbone. Numbers are reported in percentages.

	Interact	Sequence	Prediction	Feasibility	Overall
Actions	84.77	89.43	85.30	91.46	87.63
Relationships	72.83	73.5	70.05	72.82	72.9

Table 8. **Results for cross-attention input.** Results shown for STAR test set with SlowR50 backbone.

Method	Interaction	Sequence	Prediction	Feasibility	Overall
Q + V	33.28	35.60	27.93	26.43	30.81
Q + HG	**47.98**	42.03	**35.34**	<u>32.52</u>	**39.47**
Q + V + HG	<u>45.45</u>	**44.19**	<u>34.22</u>	**32.87**	<u>39.18</u>

Table 9. Model variations on STAR validation set with a single model using SlowR50 backbone for all question types. **Best results** are shown in bold font and <u>second best</u> results are underlined. Numbers are reported for VQA accuracy in percentages.

Method (val)	Interaction	Sequence	Prediction	Feasibility	Overall
hyper-graph components					
Action only – Act=3	<u>40.94</u>	<u>38.08</u>	<u>35.58</u>	**30.56**	<u>38.68</u>
Relation. only – Rel=8	35.94	35.79	34.78	27.86	35.16
Both – Act=3, Rel=8	**42.93**	**38.20**	**36.06**	**30.56**	**39.20**
Number of queries					
Act=2, Rel=8	40.32	<u>40.13</u>	<u>38.78</u>	29.73	38.34
Act=3, Rel=8	**42.93**	38.20	36.06	<u>30.56</u>	<u>39.20</u>
Act=4, Rel=8	38.40	35.79	35.58	30.35	37.06
Act=3, Rel=12	<u>41.32</u>	**40.80**	**39.42**	**31.39**	**39.90**
Act=4, Rel=12	40.40	39.05	36.86	29.11	38.39

in the set prediction loss alleviates the problem of duplicate predictions within each situation. See Fig. 4 for qualitative examples of produced hyper-graphs with and without this loss. Extra examples are in the supplementary document.

6. Conclusion

We presented a novel approach to model situation graph prediction as an underlying sub-task for video question answering. The proposed method predicts a situation hyper-graph structure composed of existing actions and relationships in the input video. The input question can then reason over the predicted graph to solve VQA. We show the impact of the proposed approach by evaluating on two video question-answering benchmarks and achieving significant performance gains overall baseline methods. Our method demonstrates promise for further research in this direction to improve VQA systems even further.

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A.   Supplementary Material: Learning to Predict Situation Hyper-Graphs for Video Question Answering

In this supplementary document, we discuss the following:

1. Additional architectural details (B)

2. Implementation and training details (C)

3. Additional experimental details (D)

4. Additional results and analyses (E)

5. Qualitative results (F)

6. Computational cost of SHG-VQA (G)

7. Ethical Considerations (H)

B. Additional Architectural Details

In this section, we provide the additional architectural details as follows:

B.1. Input processing

The SHG-VQA can be trained in both open-ended as well as multiple choices settings. For multiple choice setup, C answer choices are also given as input with the question. The goal hence becomes a C-way classification task.

B.2. Question Encoder:

We encode the question (and answer choices) as follows: first, a learnable embedding layer is used to initialize each word token with an embedding vector. These word embeddings along with the special token $[CLS]$ are input to the text transformer encoder encoding each word using multi-head self-attention between different words at each encoder layer. In the multiple choices setup, we append the answer choices to the question words as follows:

$$QA = [CLS] + Q + [SEP] + A0 + [SEP] + A1 \\ +... + [SEP] + A_C \tag{6}$$

where, QA is the sequence composed of question words and answer choices separated by a special token $[SEP]$; $[CLS]$ is a special token appended at index 0 to aggregate question and answer choices into a sentence vector; C denotes the number of answer choices. We empirically find that composing the question and answer choices in the above format gives better performance.

B.3. Action Decoder

Given the video clip features, we want to decode the set of actions A in each frame. To decode the set of actions A_t at each timestep t, a sequence of learnable embeddings of size d referred to as action queries of length $|N| \times T$ is input to the action decoder. The action decoder comprises the standard transformer decoder architecture and stacks L decoder layers. In addition, the action decoder also takes encoded video tokens as memory and a target mask (of size $\mathbb{R}^{(|N| \times T) \times (|N| \times T)}$). The target mask is created to perform parallel decoding predicting all actions in a frame at once based on the decoded actions in previous frames. The target mask prevents attending to the action queries from future frames (by setting values to $-\infty$ which masks them out [51]). Our approach deviates from using traditional approach [51] or the parallel decoding approach [1] by using a masking at frame-level e.g., to decode actions for frame 0, we set next $|N| \times (T-1)$ positions to $-\infty$ and so on. The action decoder outputs the decoded sequence of action features for each time step t.

Figure 5. Performance comparison with the baselines w.r.t. training data samples on AGQA dataset. SHG-VQA outperforms the baselines even when trained with only 100K samples.

B.4. Relationship Decoder

Like the action decoder, we employ a relationship decoder to decode the set of relations R_t in each frame. We input a sequence of $|M| \times T$ learnable relation embeddings of size d called relation queries and encoded video tokens x_{V_e} as input to the relationship decoder. The relationship decoder has the same architecture as action decoder with variable weights. The relation decoder also takes a target mask (of size $\mathbb{R}^{(|M| \times T) \times (|M| \times T)}$) and perform parallel decoding to predict all relations in a frame at once. The relationships decoder outputs the decoded sequence of relation features for the full video.

B.5. Prediction Heads:

Prediction heads take the decoded queries as input and classify them as an action/relationship from the actual classes or the "no-class" (denoted by ϕ). Therefore, for each prediction head, the total number of classes are $\#classes + 1$. See fig. 6 for illustration of prediction head.

C. Additional Implementation Details

C.1. Training details

SHG-VQA is trained with learning rate $lr = 1e - 5$, BERT [6] optimizer, and batch size upto 128 for each training depending on the maximum samples which could fit to the GPUs. The best reported results for both datsets use M=8 relations and N=3 actions.

C.2. Hypergraph token handling at test time:

During the training of the situation hyper-graph embedding, we use attention mask for masking padded tokens. However, these masks are not available at inference time because we assume that we are only provided the video and question with answer choices at test time. Thus, we set attention mask to all 1's at inference time. Moreover, the prediction is made to the original video clip with out any data augmentation.

C.3. Data Augmentations

While we obtain a good increase in performance over existing methods for interaction and sequence questions, SHG-VQA performed on par with the baselines for prediction and feasibility. We attribute this to the less training

predicted class

Figure 6. Prediction Head: Each decoded query is passed through a FFN to predict one of the classes or a "no-class" label.

Figure 7. Overview of the bi-partite matching in SHG-VQA. Optimal bipartite matching ($\mathcal{L}_{match}(.)$) is performed between the set of predicted classes for all decoded queries (of actions/relationship predicates) and the ground truth labels using the Hungarian algorithm. Per frame optimal matching is carried $\forall t \in \{1, ..., T\}$. Then, a loss is computed between the matched pairs of ground truth labels and predicted classes using a cross-entropy loss function. See section 3.4 (main paper) for details.

data available for prediction and feasibility. The number of questions for each question type in training set are: interaction:~16K , sequence: ~22K, prediction: ~4K, feasibility: ~3K. To address this matter, we add training samples from other question types. We filter out the videos from interaction and sequence question types which have the same video ID as prediction and feasibility. This avoids the data leakage problem of peeping into future frames during training. The remaining set of QA pairs are added to the training set for prediction and feasibility resulting in ~15K training samples for feasibility and ~16K samples for prediction question type. We observe the expected performance gain when the model is provided proportional amount of data.

D. Additional Experiment Details

D.1. Details about AGQA baselines

For AGQA, we consider three video QA methods as our baselines: PSAC [34], HME [9], and HCRN [27]. PSAC uses ResNet-152 to extract video features; HME uses ResNet or VGG for appearance features and use C3D for motion features extraction; HCRN uses ResNet101 for appearance features and ResNext101 pretrained on Kinetics-400 to extract motion features. We use SlowR50 as our backbone model.

D.2. Training Details for STAR Dataset

Data preprocessing for ablation studies: Baselines on STAR dataset train a separate model for each question type. Because training separate models for each question time is not feasible in terms of time and computational resources, we merged the data from all question types for our ablations. To do so, we carefully removed the videos and the corresponding QA pairs from interaction and sequence question types which appear in prediction and feasibility questions. As prediction and feasibility questions are about the future frames not available at inference time, keeping these questions for other question types could give an advantage to the model of looking at the full video even if it happens for solving a different question. Filtering out those QA pairs before merging all questions makes it a fair training for prediction and feasibility questions. However, these questions comprises a large chunk for interaction and sequence. As expected, this declines the VQA performance for interaction and sequence questions upto 2%-8%. However, we notice a gain over prediction and feasibility questions just by showing more examples to the model even if they are not for the same question types. More specifically, on test set, we notice prediction accuracy of 37.29%(merged data) vs. 35.34%(separate) and feasibility accuracy of 33.04% (merged data) vs. 32.52%(separate). We also experimented with using questions from all question types without any filtering and obtained the overall validation accuracy of 48.25%. In Table 18, we provide further details about the experiments including batch sizes for each model, backbone, and loss function. All models were trained up to 100 epochs using early stopping based on the validation accuracy. If not stated otherwise, all ablations are performed with a single model (batch size=32) trained on all questions together with filtering out the QA pairs with overlapped video IDs between {interaction, sequence} and {feasibility, prediction}.
Different batch size per question type/model: As each question type is trained on a separate model with different constrains such as amount of data, but constant hardware requirements, we first evaluate different batch sizes for training each model depending on the maximum number of samples could be used for training. Column 3-*Batch Size* in Table 18 shows a tuple with batch sizes for feasibility, prediction, sequence, and interaction respectively. For training a separate model on each question type, we used batch size=16 with Slow_R50. For ResNext101, we used batch sizes (16, 16, 4, 4) for (feasibility, prediction, sequence, interaction). In our experiments, we observe no significant difference in VQA accuracy when training the models with different batch sizes. Nonetheless, our best results are reported using batch sizes of (16, 16, 16, 16) with Slow_R50 backbone, and batch sizes (16, 16, 4, 4) for ResNext101.

E. Additional results and analyses

Here, we discuss further results and analyses on AGQA and STAR benchmarks.

E.1. AGQA

E.1.1   Performance comparison w.r.t. training data

To train on AGQA, we split the AGQA training set into 90%-10% train-val split. The new training set after this split comprises approximately 1.4M QA pairs. From this training set, we randomly sampled 100K data samples to train our network. We find the SHG-VQA to outperform the baselines even when trained with 100K samples which is ~ 15× less training data than the data used to train the baseline methods (see fig. 5).

Figure 8. Correlation between accuracy and compositional steps for binary answers, open answers, and overall. To do so, a linear regression model is fit for each model's performance. Our model is superior in performance than the baselines bridging the accuracy gap narrower with the human performance. The shaded area indicates 80% confidence interval.

Table 10. Results on AGQA dataset for different question types w.r.t vision (**w**) and question-only (**w/o**) variants of all models. Best results are shown in **bold** font, second best results are in blue font. SHG-VQA performs better or on par to the baselines with only 100K samples (baselines use 1.6M training samples). Numbers are reported in percentages.

Method		Reasoning								Semantic			Structure					Overall		
		obj-rel	rel-action	obj-action	superlative	sequencing	exists	duration	activity	obj	rel	action	query	compare	choose	logic	verify	binary	open	all
PSAC [34]	w/o	37.91	49.95	50.01	33.59	49.78	50.04	45.77	4.88	38.03	50.04	47.07	31.63	49.57	46.87	50.09	49.97	49.01	31.63	40.26
	w	37.84	49.95	50.00	33.20	49.78	49.94	45.21	4.14	37.97	49.95	46.85	31.63	49.49	46.56	49.96	49.90	48.87	31.63	40.18
HME [9]	w/o	36.44	49.98	50.09	32.53	49.79	50.02	42.67	6.53	36.58	50.05	45.84	29.52	49.16	46.12	50.17	49.93	48.68	29.52	39.03
	w	37.42	49.90	49.97	33.21	49.77	49.96	47.03	5.43	37.55	49.99	47.58	31.01	49.71	46.42	49.87	49.96	48.91	31.01	39.89
HCRN [27]	w/o	37.78	50.12	49.99	33.62	49.78	50.10	43.66	5.15	37.90	50.11	46.22	31.24	49.29	47.36	50.21	50.11	49.12	31.24	40.11
	w	40.33	49.86	49.85	33.55	49.70	50.01	43.84	5.52	40.33	49.96	46.41	36.34	49.22	43.42	50.02	50.01	47.97	36.34	42.11
Ours (100K)	w/o	37.42	49.94	50.06	32.53	49.77	49.97	46.62	5.06	37.57	49.96	47.27	30.92	49.66	46.69	50.01	49.97	48.98	30.92	39.88
	w	41.93	49.26	51.52	35.24	50.11	52.24	45.62	5.61	42.17	51.14	46.36	38.69	49.82	42.37	50.84	52.59	48.77	38.69	43.69
Ours (full)	w/o	38.72	50.03	49.99	33.87	49.85	50.02	48.23	5.80	38.83	50.01	48.11	32.58	49.94	**47.96**	50.16	49.98	49.43	32.58	40.95
	w	**46.42**	**60.67**	**64.63**	**38.83**	**62.17**	**56.06**	**48.15**	**10.12**	**47.61**	**56.19**	**53.83**	**43.42**	**60.68**	47.76	**52.86**	**56.63**	**55.04**	**43.42**	**49.20**

More specifically, SHG-VQA obtains 43.69% vs. 42.11% for HCRN which is the best model for AGQA on overall VQA accuracy. Similarly, we obtain on par or often better performance on the three testing metrics of indirect references, novel compositions and more compositional steps. We provide a detailed breakdown of our results with 100K and 1.4M training samples in comparison with the baselines which were trained on the full training set of 1.6M QA pairs. See table 10, 11, 12 for detailed results.

E.1.2 Results for more compositional steps

AGQA provides a train-test split to test models's generalization to more compositional steps where training split has questions with fewer compositional steps. On this metric, SHG-VQA with 100K training samples achieves comparable results to the SOTA model. When compared to the best performing model for each question type, our full model gains ↑ 4.15% absolute points over the best model (HME: 48.09% vs. ours: 52.24%) for binary questions, ↑ 1.2% improvement over SOTA (HCRN:23.70% vs. ours:24.90%) for open-answer questions, achieving overall ↑ 4.14% improvement on all questions. Fig. 8 shows correlation between accuracy and compositional steps. A linear regression model is fit to each method's performance w.r.t number of compositional steps. For **binary questions**, the baseline methods perform significantly lower even with single compositional-step questions, whereas our model unsurprisingly yields the highest accuracy. SHG-VQA is consistently better for all compositional steps on binary question than the baselines. Nonetheless, we observe a negative correlation between accuracy and compositional steps for binary questions. For **open** questions, a slightly positive correlation between accuracy and compositional steps is noticed for all methods including SHG-VQA. For overall accuracy on this metric, although SHG-VQA is able to bridge the gap between human accuracy and

VQA algorithms by providing SOTA results, there is still large room for improvement on this novel task.

Table 11. Evaluation on AGQA's **novel compositions.**

Method	training data size	Binary	Open	All
PSAC	1.6M	46.49	19.34	34.71
HME	1.6M	45.42	17.17	33.15
HCRN	1.6M	44.88	20.12	34.13
SHG-VQA	100K	46.55	22.2	36.01
SHG-VQA	1.4M	**49.27**	**25.92**	**39.15**

Table 12. Comparison on AGQA's **more compositional steps** with our model with 100K training samples and full training set.

Method	training data size	Binary	Open	All
PSAC [34]	1.6M	47.65	14.81	47.19
HME [9]	1.6M	48.09	20.98	47.72
HCRN [27]	1.6M	46.96	23.70	46.63
SHG-VQA	100K	47.13	22.66	46.97
SHG-VQA	1.4M	**52.24**	**24.90**	**51.86**

Table 13. Additional results on AGQA for all question types.

	Question Types	Blind Model (Q-Only)	Deaf Model (V+HG)	SHG-VQA-100K
Reasoning	object-relationship	37.42	15.16	**41.93**
	relationship-action	**49.94**	0.01	49.26
	object-action	50.06	0.06	**51.52**
	superlative	32.53	14.88	**35.24**
	sequencing	49.77	0.04	**50.11**
	exists	49.97	17.91	**52.24**
	duration comparison	**46.62**	7.89	45.62
	activity recognition	5.06	0.00	**5.61**
Semantic	object	37.57	13.71	**42.17**
	relationship	49.96	13.92	**51.14**
	action	**47.27**	2.92	46.36
Structure	query	30.92	15.63	**38.69**
	compare	49.66	1.08	**49.82**
	choose	**46.69**	9.72	42.37
	logic	50.01	18.02	**50.84**
	verify	49.97	18.12	**52.59**
	binary	**48.98**	10.65	48.77
	open	30.92	15.63	**38.69**
	all	39.88	13.16	**43.69**

Table 14. **Results for different training protocols.** Results shown for STAR test set. Rows 1,2, and 3 are with SlowR50 and rows 4,5 show results with MViT-B backbone.

Q. Type	Interaction	Sequence	Prediction	Feasibility	Overall
(1) separate training	**47.98**	42.03	35.34	32.52	**39.47**
(2) all w/ filtered data	37.67	36.91	37.29	**33.04**	36.23
(3) all–SlowR50	42.38	**42.49**	**37.85**	30.78	38.37
(4) all–SlowR50	42.38	42.49	37.85	30.78	38.37
(5) all–MViTB	**43.35**	**44.37**	**38.55**	**33.91**	**40.04**

Table 15. SHG-VQA with SlowR50 backbone evaluated on STAR-Humans. Numbers are reported in percentages.

	Interaction	Sequence	Prediction	Feasibility	Overall
SHG-VQA	**52.00**	**45.00**	31.00	23.00	37.75

E.1.3 Additional results on AGQA for model variations

AGQA [11] report results for each baseline with language-only model to compare with the respective full models. Following this, we train SHG-VQA in three settings on AGQA: blind model (**w/o vision**), deaf model (**vision-only**), and full model. We perform this study using our 100K subset. Results are discussed below: **Blind model performance** We evaluate our question-only model which is a BERT-like 5 layers transformer encoder against our full vision model (table 13) to measure how much linguistic bias our model is able to exploit from the dataset. With results comparable to HCRN's vision and no-vision counterparts, our language model is able to achieve an overall video-question answering accuracy of 39.88%, only 3.81% less than our vision model. The vision model outperforms its language-only counterpart throughout a majority of the question types, however the language-only model has slight improvements over the vision model in duration comparison question types and action semantics, where it performs 1% better. Additionally, the language model also performs slightly better in regards to overall accuracy on binary question types. Further examining binary question categories (table 13) show that the model again performs roughly 1% better than its vision counterpart on binary object-relationship and duration comparison reasoning categories, as well as binary object and action semantic question types. The most noteworthy difference is that this model outperforms the vision model by 4.32% in the choose structural category. Overall, the full model outperforms this language-only model in most categories. **Deaf model performance** In addition to the language-only model, we also train a deaf (vision-only) model to measure

biases that may arise from the visual input alone (table 13). This version of our model obtained an overall VQA accuracy of 13.16% on all question types, performing worse than both our full, and language-only models in every question category. From this, we conclude that the visual bias is much less than the language bias.

Ablation on T/M/N? We chose clip length T=16 following prior works. We report results for varying clip length T on AGQA dataset in Tab. 16 with models are trained for 10-15 epochs on 100K QA pairs. Hyperparameters M and N capture the number of actions and relations we want to predict for each frame. Therefore, video length does not effect M/N.

T	binary	open	all
16	48.77	38.69	43.69
24	46.30	38.89	42.57
32	45.50	37.29	41.36

Table 16. Results on AGQA dataset for varying video clip length T.

E.2. STAR

E.2.1 Results w.r.t different training protocols

We experimented with different training protocols for STAR dataset including separate trainings used in [52], single model with filtered questions as explained in D.2, and training a single model on the full training set. We use SlowR50 backbone for this study and find that using separate trainings is most beneficial for interaction questions and overall accuracy. Using filtered questions although perform best for feasibility questions, but it hurts the performance on other question types. When trained on full training data with SlowR50 and MViT-base backbones, using MViT yields better performance.

Set Pred. Loss	Interaction	Sequence	Prediction	Feasibility	Overall
full video	39.81	40.69	30.17	29.91	35.15
frame-wise	39.42	41.83	33.8	27.48	35.63

Table 17. Results for SHG-VQA model on STAR test set.

E.3. Results on STAR-Humans

STAR-Humans is a subset provided by [52] with 400 free-form questions asked by humans. We evaluate SHG-VQA-SlowR50 on STAR-Humans and obtain the results shown in table 15. For this subset, SHG-VQA performs best for interaction questions (52.00%) and worst on feasibility questions (23%).

F. Qualitative results

Comparison between optimal matching with full video compared to optimal matching for each timestep: Figures 9 and 10 show qualitative comparison of predicted situation hyper-graphs from situation hyper-graph decoder in the proposed model. Note that the situation hyper-graph solely relies on the video input. Hence, we show the input video, ground-truth graph, and predicted situation hyper-graphs in two settings: 1) optimal matching with full video instead for each timestep t over L_{Act} and L_{rel} (baseline); 2) optimal matching for each timestep t for the actions and relations set predictions (as described in $eq.2$ and $eq.4$ in the main paper). We observe that when using the optimal matching without imposing the time constraint (i.e., to do optimal matching at each time step), it results in duplicate predictions at frame level. In figure 9 and 10, the first two rows show the video frames and the corresponding ground truth situation hyper-graph respectively. Row 3 shows the situation hyper-graphs we obtain with the optimal matching for the full video. In edge labels, we show the predicted relationship as well as the count of multiple edges between two nodes. For brevity, we show every 4th frame i.e., frames 1, 5, 9, 13. We can see in row 3, that the predicted graph is sparse and not able to capture

Table 18. Training configurations for SHG-VQA on STAR dataset.

Experiment	backbone	Batch Size	Models trained	Loss	Test set	Overall Acc.
Adapted batch size per QT:						
SHG-VQA (Q + HG)	Slow_R50	(16, 16, 16, 16)	4	$L(eq.1)$	test	39.47
SHG-VQA (Q + HG)	Resnext101	(16, 16, 4, 4)	4	$L(eq.1)$	test	38.28
SHG-VQA (Q + V)	Slow_R50	(8, 8, 8, 8)	4	L_{vqa}	test	30.81
SHG-VQA (Q + HG)	Slow_R50	(16, 16, 16, 16)	4	$L(eq.1)$	test	39.47
SHG-VQA (Q + V + HG)	Slow_R50	(16, 16, 16, 16)	4	$L(eq.1)$	test	39.18
Hypergraph components:						
SHG-VQA (Q + HG) Action only – Act=3	Slow_R50	32	1	$L(eq.1)$	val	38.68
SHG-VQA (Q + HG) Rel. only – Rel=8	Slow_R50	32	1	$L(eq.1)$	val	35.16
SHG-VQA (Q + HG) Both – Act=3, Rel=8	Slow_R50	32	1	$L(eq.1)$	val	39.20
Number of queries						
SHG-VQA (Q + HG) Act=2, Rel=8	Slow_R50	32	1	$L(eq.1)$	val	38.34
SHG-VQA (Q + HG) Act=3, Rel=8	Slow_R50	32	1	$L(eq.1)$	val	39.20
SHG-VQA (Q + HG) Act=4, Rel=8	Slow_R50	32	1	$L(eq.1)$	val	37.06
SHG-VQA (Q + HG) Act=3, Rel=12	Slow_R50	32	1	$L(eq.1)$	val	39.90
SHG-VQA (Q + HG) Act=4, Rel=12	Slow_R50	32	1	$L(eq.1)$	val	38.39

all relationships due to suffering from the duplicate predictions problem. Additionally, it sometimes predicts no-class ϕ label i.e. empty set for actions and predictions as we can see in fig 9, row 3, column 3. Row 4 shows the predicted situation hyper-graphs with the imposed constraint of optimal matching at frame-level. We can see that the proposed solution for optimal matching greatly improves the quality of generated hyper-graphs. See Tab. 17 for quantitative results.

G. Computational Cost of SHG-VQA

The computational cost of SHG-VQA includes video and text encoders with the little overhead from decoders for decoding graph queries. At inference time, the decoders' output is directly sent to cross-attentional transformer along with the meta embeddings without any graph prediction. Given that we only use L=5 layers for all encoders and decoders in SHG-VQA, the depth of the SHG-VQA is 12 layers i.e., comparable to existing vision-language methods [24, 30], e.g., ALBEF.

H. Ethical considerations

As our system is trained on real-world data, it might capture negative data inherent biases, such as actions only executed by people with specific clothing or stereotype questions. We are not aware of such stereotypes in the here used datasets AGQA and STAR but would recommend assessing the fairness of any system based on this work before putting it in any production environment.

Figure 9. Ground-truth and predicted situation hyper-graph for every 4th frame in a clip of length 16. Row 1 shows video frames, row 2 shows the ground-truth situation hyper-graph, row 3 shows predicted graphs from the model with set prediction loss without considering frames, row 4 shows predicted hyper-graph when the model is trained by matching each timestep t (the proposed loss function). The edges show the person-object relationship labels along with the number of times it was predicted. (see Section F for discussion about results.)

Figure 10. Ground-truth and predicted situation hyper-graph for every 4th frame in a clip of length 16. Row 1 shows video frames, row 2 shows the ground-truth situation hyper-graph, row 3 shows predicted graphs from the model with set prediction loss without considering frames, row 4 shows predicted hyper-graph when the model is trained by matching each timestep t (the proposed loss function). The edges show the person-object relationship labels along with the number of times it was predicted. (see Section F for discussion about results.)