Video Based Contextual Q&A

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1 ABSTRACT
The primary aim of this project is to build a contextual Question-Answering model for videos. The current methodologies provide a robust model for image based Question-Answering, but we are trying to generalize this approach to be videos. We propose a graphical representation of video which is able to handle several types of queries across the whole video. For example, if a frame has an image of a man and a cat sitting, it should be able to handle queries like, where is the cat sitting with respect to the man? or ,what is the man holding in his hand?. It should be able to answer queries relating to temporal relationships also.

2 INTRODUCTION
The big data explosion, combined with the availability of a large amount of labeled data and better hardware has spurned large scale deep learning. At intersection of natural language processing and computer vision is understanding of context in images and videos. While extensive work has been done with understanding images, not much has been done on videos. The recent trend involves use of LSTMs for understanding the whole context of a given frame in a video and stitching them together. While this preserves the temporal information of the whole video, it doesn’t let us query videos based on the contextual information present.

In this project, we extend this work into graph domain by encoding the context of these videos as a graph using research work done by the computer vision community, which can handle more contextual information than any other representation.

Based on a graph representation of a video which preserves context, we look into a few other applications like extracting key-frames based on high context change observed between frames using graph similarity measures. Also we look into video context similarity at a high level to propose how the knowledge of contextually similar videos can be used to cluster similar videos and can lead to recommending videos on platforms like YouTube, which currently recommend videos based on human annotated tags for a video.

The pipeline for this project is as follows:
1) Frame Extraction - Videos are converted to image frames using frame extraction algorithm.
2) Object Detection and Captioning- Main objects is detected in each frame using R-CNN technique. Dense Captioning algorithm is used to caption relationship of these objects.
3) Scene Graph Generation - Each caption is converted to a scene graph using standard NLTK python library.
4) Graph Aggregation - The scene graphs are aggregated to get a scene graph for each frame. These are then appended with a time stamp. Finally all the scene graphs are aggregated to give an aggregate graph for the whole video. Various similarity measures are used to compare scene graphs and aggregated video graphs.

3 DATA
For our experiments, videos of varying lengths and context were chosen from the YouTube 8M dataset. 5 videos were used for testing the querying model.

The videos in consideration include instructional videos where a particular recipe is followed, a music video with lots of activity and scene changes, and a video where a girl trying out food in a restaurant.

The average statistics for the videos are:

- The average video length around 8 minutes (500 seconds)
- With uniform sampling of about 0.5 seconds for each samples, number of frames extracted for each video is about 1000 frames.
- The aggregate scene graph contains on an average around 300 nodes and about 800 edges.

For our current experiments as well as module testing, we have taken common stock images and videos which encompass a wide variety of variations in terms of context and relationship among the objects as well as a rich set of attributes for many objects in question.

4 METHODOLOGY
In this section, we go over in detail all the sequential blocks used in our pipeline and how they are linked. On a high level, we have the following tasks : frame extraction, object detection and captioning, scene graph generation, scene graph alignment and aggregation. We also find key-frames from the frame scene graphs using graph similarity measures. We will further explore converting an incoming query into a query scene-graph and graph based search methods to answer the question.

4.1 Frame Extraction
We use a few of the frame extraction techniques in our experiments. Firstly we use uniform sampling (every 0.5 seconds) for prototyping purposes. Later for the final experiments we also make use of the mean absolute difference between pixel values of adjacent frames to detect a change.
4.2 Object Detection and Captioning

Once we have the frames, we extract from each frame relevant captions and bounding box information. This is done using the DenseCap\textsuperscript{[?]} model. The image is first passed through a Regional-Convolutional Neural Network which detects key objects and returns bounding boxes and confidence scores. The object labels and actions are then passed through a Recurrent Neural Network which generates a one-sentence caption for a particular object detected.

We repeat this for each of the key frames and obtain multiple captions per frame and use that as an input for the next block in our pipeline.

4.3 Scene Graph Generation

This module converts each caption from Object Detection and Captioning module and convert it into a scene graph. On the representation side, two parsers have been discussed in the paper\textsuperscript{[?]}, namely, rule-based parsers and classifier-based parsers to generate scene graphs from text. Both work on an alternative linguistic representation known as semantic graph. While Rule – based parsers work on a combination of nine dependency patterns based on Sengrex\textsuperscript{[?]} expressions, which matches text to a dependency tree based on Part-of-Speech tagging, these include:

- Adjectival modifiers
- Copular constructions
- Prepositional phrases
- Possessive constructions
- Passive constructions
- Clausal modifiers of nouns

Classifier-based parsers learn the relationship between individual pair of words (x1, x2) which are classified on object features, lexicalized features and syntactic features using an L-2 regularized maximum entropy classifier for classification. The classifier classifies words into ‘subject’, ‘object’ and ‘predicate’ which form the nodes and edges of our scene graph. The code implementation we use follows the classifier based parser method which provides better accuracy.

![Figure 1: Proposed Methodology](Image)

4.4 Similarity measures

Two methods have been primarily looked at for the purpose of measuring similarity between graphs. Similarities being considered in the project have a two fold use. The first is similarity between graphs which is used as a measure to compare videos based on contextual content which can be further used to cluster contextually similar videos together. The second reason of applying similarity measures to frame by frame representations of scene graphs, is to extract key-frames which allows for a much more compact and reasonable contextual representation of the video. As an added application, the current methods for extracting key-frames are pixel based, so this can act as a more context encoding alternative for key-frame extraction.

The similarity measures are as follows:

- **Spectral score**: The Frobenius norm of the difference of the adjacency matrix representation of the graphs has been used as a similarity score. Such similarity score would be able to encapsulate whether or not a subgraph has a “similar” neighborhood and the Frobenius norm will penalize any differences or changes in the neighborhood of a particular node. For example a subgraph having nodes “tall – man – wearing – black – T-shirt” would have a different adjacency matrix to “thin – man – feeding – dog”.

The similarity score is defined as:

\[ sim\_score = 1 - \frac{||A-B||_F}{n} \]

This similarity score will give a similarity score between 0 and 1, 1 indicating perfect similarity between two graphs G\textsubscript{1} and G\textsubscript{2}, of whom A and B are adjacency matrix as \( ||A-B||_F \) will be a zero quantity. Similarly, 0 indicates perfect dissimilarity between the graphs as \( ||A-B||_F \) will be one.

The space and time complexity of this method of similarity comes out to be \( O(n^2) \).

- **Maximum Common Subgraph**: This method finds the largest subgraph of g\textsubscript{1} and g\textsubscript{2}. It is a method to check how similar are the graphs structurally. A common subgraph of g\textsubscript{1} and g\textsubscript{2} is a graph g such that there exist subgraph isomorphisms from g to g\textsubscript{1} and from g to g\textsubscript{2}. A graph g = mcs(g\textsubscript{1}, g\textsubscript{2}) is maximum common subgraph of g\textsubscript{1} and g\textsubscript{2}, if there exists no other common subgraph of g\textsubscript{1} and g\textsubscript{2} that has more nodes than g.

The similarity score is defined as follows:

\[ sim\_score = \frac{mcs(g\textsubscript{1}, g\textsubscript{2})}{|g\textsubscript{1}|+|g\textsubscript{2}|−mcs(g\textsubscript{1}, g\textsubscript{2})} \]

where,

\( g\textsubscript{1}, g\textsubscript{2} \) are two graphs.

\( mcs(g\textsubscript{1}, g\textsubscript{2}) \) is the maximum common sub graph of two graphs where mcs is the largest graph (by some measure involving the number of nodes and edges) contained in both subject graphs.

\( |g\textsubscript{1}|, |g\textsubscript{2}| \) are cardinality of the graph g\textsubscript{1} and g\textsubscript{2}.

The space and time complexity of this algorithm is roughly estimated to be \( O(2^n) \).

4.5 Graph Formulation

The graph formulated for the experiment can be visualized as a tripartite graph. The graph consists of three types of nodes describing:

- Subjects like man, dog, cat etc.
- Attributes like tall, fat, brown etc.
- Relationships like feeding, throwing etc.

A sample graph formulation is shown below where nodes in red are subjects, the nodes in yellow are relationships and nodes
in green are attributes. It can be observed that a common path in
the graph is subject – relationship – subject, with attributes as leaf
nodes, meaning no outgoing edges.

The four primary graph that are formulated to handle queries of
different types are listed as follows:

- **Individual frames to scene graph**: This representation is
  used to handle temporal questions and extract key frames in
  a video based on frame similarity basis.

- **A bag-of-nodes based scene graph aggregation**: In order
  to form a cumulative graph representation for the entire
  video. This representation is useful for calculating video
  similarity across different videos and cluster similar videos
  based on content.

- **Scene Graph aggregation based on key-frames**: Building
  an aggregate scene graph based on key-frames helps
  answer queries on the major recurring theme of the video
  or the plot of the video.

- **Node similarity based scene graph aggregation**: This
  graph formulation allows for a more compact graph repre-
  sentation for the video along with preserving the uniqueness
  of multiple instances of a class, based on the attributes. For
  instance this representation will help uniquely identify to
different men appearing in different scenes in a video.

The formulations are discussed in more detail below

### 4.5.1 Conversion of individual frames to scene graphs

As frames sampled in a video describe scenes for those timestamps,
a scene graph representation of these video frames would be useful
for answering queries which involve temporal information. Queries
like “what did the man eat before going home” can be answered
using this approach as traversing over time slices that occur before
subgraph man – driving and will allow to localize all the actions
performed by man before the time slice.

### 4.5.2 Bag-of-nodes aggregation of scene graphs

This representation allows for building a high-level contextual representa-
tion of the video. A salient feature of this representation would be
that does not distinguish between different instances of the same
class. Man occurring in different scenes are assumed to the same
and are not differentiated based attributes. The intuition behind
this kind of formulation is similar to measuring sentence similarity
using a bag words of approach, as a high-level content similarity
in video is measured across different type of classes occurring in
the scene as opposed to unique occurrences of the same class. The
video similarity is measured using a spectral decomposition method
and the maximum subgraph matching method, as discussed earlier.

### 4.5.3 Scene Graph aggregation based on Node similarity

In this section we propose a novel approach to build an aggregated
‘scene’ graph which captures both temporal and relational edge
attributes. More formally at the end of the video, we will have a
heterogeneous graph $G(E, V, T)$ where each Node (V) represents an
instance of an object (like man, cat, dog), each edge (E) represents
the relationship between the objects and is appended with a time
stamp and each node has attributes(T) which captures the type
of that object. Additionally store this tensor representation of
the graph for each time-stamp for easy retrieval/querying.

The graph we are building will be a time-evolving heterogeneous
semantic graph. Many existing node similarity measures have been
explored for the this project and have some inherent shortcomings.
For eg: FINAL (Fast attributed network alignment) deals with node
attributes and edge attributes, but deal primarily with homogeneous
matrices. Exploring similarity measures for heterogeneous graphs
like metapath2vec\cite{1} also lead to a dead-end. This was due to the
huge variations in relationships that are captured in the graph,
making it extremely difficult to define a metapath which will be the
right fit for calculating node similarities for the entire graph. For
eg: Consider two similar nodes say man (man_1 and man_2), both
of them are connected to a dog, but they form different relations
with the dog. In one case the man might be feeding the dog, and in
the other case, man might be throwing a ball. So to conclude any
metapath describing a object1-object2-object3 path (for example
man-dog-man) will fail here. Moreover we do not have a small class
of distinct objects like in the academic citation network mentioned
in metapath2vec. This effectively rules out metapath2vec as a viable
similarity technique in this work.

We thus propose the following node similarity measure between
two nodes of the same class (say woman). Let

$$r(x) = \text{cardinality of the set } x$$

Let $\text{attr}_u$ and $\text{attr}_v$ be the set of attributes of $u$ and $v$ respectively. Then,

$$\text{NodeSim}(u,v) = \frac{\text{attr}_u \cap \text{attr}_v}{\text{attr}_u \cup \text{attr}_v}$$

Note that the above similarity measure is a modification on Jaccard’s
score.

Now we also observe that the above function can be used to
measure similarity of two nodes of same class (example woman_1
and woman_2 of same class woman). However, this is for the two
women belonging to a different frame. For the same frame when
we have captions like “Woman is tall”, “Woman is driving” etc we
may want to know which woman is being referred to within a
single frame. For this distinction, we make use of the bounding box
information that we have obtained during the dense captioning.
Similar to the above NodeSim formula, we can use the Intersection-
over-Union (IoU) metric to evaluate similarity between objects in
the same frame.

Now that we have defined our node similarity methods, we de-
scribe the scene graph aggregation method below. Let $G(E, V, T, time)$
denote the aggregated scene graph so far. Let $G_1(E_1, V_1, T_1)$ denote
an incoming scene graph.

Note that if $v_1$ is the first instance of an object type, it is added as
a new node by default. The above algorithm will only decide when
a repeated instance of an object type (like woman_1 and woman_2) should be considered as a new node.

In the above algorithm, m and threshold are hyper-parameters which can be tweaked to obtain acceptable results. This way we build our aggregate scene graph.

Note that in the beginning, we pre-process the scene graph for every frame and obtain one dictionary (hash table) for each containing unique attributes and unique relationships. This will enable us to one-hot encode any incoming attribute or relationship uniquely. This is what the third dimension (T) of the tensor contains.

### 4.6 Query Formulation

For this project, we are looking into three types of question that will be used to test the graph formulation. Customized functions have been made for each type of query. These are:

- **True/False questions** - The purpose of this type of question is to check if a subgraph of question exists in the graph or not. The input to function in these sort of questions is one object and one edge. The output is True or False based on whether or not the subgraph is present in the aggregated graph.

- **Contextual questions** - These answer questions like where, who and what? The input to such type of questions are one object and one edge. The answer is usually a list of all such objects. For example, if input is man - eat, then the answer is [suit, tie, hat] as all three subgraphs exist in the aggregated graph.

- **Temporal questions** - These answer questions like did something happen before or after something else. The input for such questions is two sequence of events. The output is True if sequence_1 happens before sequence_2. For example if input is man - eat - pizza - man - play - dog, then the output is True if man ate pizza before man played with dog and false if either sequence did not happened or the sequence happened other way round.

The question is converted to object - edge - object graph by using NLTK python library and spacy package. It uses Part-of-Speech tagging to find nouns and verbs in a sentence which are then taken as nodes for graph. Once a graph is generated, we do a simple search of nodes of graph in aggregated graph. A Yes/No answer checks if all the nodes and edges in the question graph is present in the aggregated graph or not. A contextual questions finds object - edge subgraph in aggregated graph and returns a list of all nodes which are connected to object - edge subgraph. A temporal query finds the first and second question graph in aggregated graph and then checks their time stamps. If time_stamp_1 is less than time_stamp_2, only then it returns a True.

These node lookups are O(1) or constant time lookups as we are storing the graph as a networks object (similar to a dict/json representation). Any sequence or subgraph lookups will be O(k + |E|) where k is the length of the sequence in the query and E are the number of edges in the graph.

### 5 EXPERIMENTS

The experiments we conducted follow the proposed methodology in the same flow. We have built a pipeline which takes a video as an input and outputs a scene graph for each segmented line.

The pipeline includes all the core tasks:

#### 5.1 Frame extraction

- Done via ffmpeg library which works with video mp4 data.

#### 5.2 Dense Captioning

- Ran the github implementation of JCJohnson for dense captioning. However this implementation proved to be a bottleneck for real time performance. The implementation involved training over 1.2 GB of pretrained weights. Additionally it took 15 minutes to generate captions for a single image on our local systems. To overcome this we are using an API for dense captioning implemented by DeepAI which significantly reduces overhead time.

#### 5.3 Scene Graph Generation

- The scene graphs generation was executed with the help of Stanford CoreNLP library. We also created an executable .jar file for this module which can be called by an outside code across platforms and languages, which helped us in creating an executable pipeline for the methodology.

#### 5.4 Scene Graph Similarity and Key Frame Extraction

As explained in the proposed method, we now analyze and report the results for Scene Graph similarity across frames. We use two similarity measures as mentioned earlier - Spectral similarity and MCS similarity. The first video we analyze for this step is an instructional video (cooking video) and the second is a video of a house party/music video.

We can make a few observations from the figures (2 to 5). As we can see from both figure 2 and figure 3, the music video on an average tends to have lower similarity across frames. On the other hand, the instructional video has an higher average similarity across frames. This is expected as the music video is varying a lot in context as opposed to the relatively stable context of the cooking video. Another point to be noted is that for a given video, while the

```python
Algorithm 1: Scene Graph Aggregation

Result: Aggregated Scene Graph G

for every v1 in G1 do
    for past m time instances do
        for every v in G(E, V, T, m) and v belongs to same object class of v1 do
            if NodeSim(v, v1) < threshold then
                Create new node v1 in G(E, V, T, m);
                Create all the edges corresponding to v1;
            else
                Map edges of v1 to v;
            end
    end
end
```

```python
for every v in G do
    if NodeSim(v, v1) < threshold then
        Create new node v1 in G(E, V, T, m);
        Create all the edges corresponding to v1;
    else
        Map edges of v1 to v;
    end
end
```
actual average similarity may vary, the general trend of similarity across frames is preserved in both similarity measures. Figures 4 and 5 illustrate this point. (Note: figure 5 has been generated for 600 frames as opposed to the previous plots but as part of experiments but the observations still hold).

Now that we have established the similarity scores, we can extract the required number of key-frames. If we want 'k' key frames, we extract the 'k' largest drops in similarity across the frames. Alternatively we could extract the key-frames based on a fixed similarity threshold (say 0.3 or 0.5).

We also show a few scenes where the similarity was low between consecutive frames. For example, in the music video, we see that similarity score is extremely low between frame 60 and 61. We have showed the corresponding frames in figures 6 and 7. As we can see, the scene changes drastically and the same is reflected in our similarity score. Similarly, in the instructional video the similarity score is low at between frame 79 and 80. Figures 8 and 9 reinforce this point.

Figure 10, 11, show the similarity score and number od nodes and edges.

5.5 Scene Graph Aggregation for Query Handling

After the above step is performed and we have extracted the key frames, we now form an aggregated scene graph from these key
frame scene graphs as explained in the node based aggregation section of the method. Below we show a sample experiment which we performed during prototyping. Here Image1 and Image2 are two key-frames (Scene 1 and Scene 2) extracted as per the above logic.

**Scene 1.** The dense captions for the above frame are as follows: “Woman with long hair”, “Woman playing with cat”. “Brown cat sitting on a bench”

Each sentence gives us a graph as shown below and we aggregate them to form the scene graph for the current frame. Note here that the 2 woman nodes were merged into the same node based on the bounding box information.

Figures 12 through 15 illustrate this point for both Image1 and Image2. Figure 16 illustrates how the two scene graphs were aggregated. As we can see, cat is a common node to both graphs and its attributes and edges are combined.

### 5.6 Question Answering

We now query the aggregated graph and compare with human annotation for accuracy measurement. For the purpose of this project...
we consider any answer incorrect if it does not match the human annotated answer. Most answers are single worded so we do not need any complex metrics. It is a one-zero metric. Based on this logic, we annotated 4 videos of varying content and report the results below in figure 17. Note here in the figure that questions titled ‘What?’ and ‘Where?’ are contextual questions while questions titled ‘When?’ are temporal questions.

We also report a few examples where the questions were answered correctly along with the actual frame in the video. Images for below examples are shown in figures 18 and 19)

Q: Where is the man?
A: ['kitchen']

Q: What is the woman wearing?
A: ['shirt', 'jacket']

Among the questions that were unanswered or answered incorrectly, we find that the captioning for that image was incorrect resulting in incorrect answers. Figure 20 shows the frame for the below incorrect answer.

Q: What is on the table?
A: ['bottle', 'jar', 'beer', 'water', 'food']
5.7 Video Similarity
We now aggregate scene graphs in a given video as per the ‘bag of nodes’ method mentioned earlier. Though such a representation may not retain contextual/temporal relationships, we can use this as a crude measure for video similarity. We use both the Spectral similarity measure and the MCS similarity measure and find the scores as reported in figures 21 and 22.

Video1 -> Music video; Video2 -> Cooking video 1; Video3 -> Cooking video 2; Video4 -> Restaurant video;

As we can see from figures, the similarity scores correspond to what a human would annotate as ‘similar’ videos - for example Cooking Video 1 and Cooking Video 2 have the highest pairwise similarity score. We can see that if we have a video database and calculate pairwise video similarity scores, we can retrieve the closest video to a given video query.

| Video    | Music | Cooking 1 | Cooking 2 | Restaurant |
|----------|-------|-----------|-----------|------------|
| Music    | 1     | 0.207     | 0.237     | 0.368      |
| Cooking 1| 0.207 | 1         | 0.472     | 0.22       |
| Cooking 2| 0.237 | 0.472     | 1         | 0.22       |
| Restaurant| 0.368 | 0.22      | 0.22      | 1          |

Figure 21: Video Similarity scores using Spectral similarity

| Video    | Music | Cooking 1 | Cooking 2 | Restaurant |
|----------|-------|-----------|-----------|------------|
| Music    | 1     | 0.2803    | 0.2955    | 0.404      |
| Cooking 1| 0.2803| 1         | 0.5164    | 0.2954     |
| Cooking 2| 0.2955| 0.5164    | 1         | 0.2716     |
| Restaurant| 0.404 | 0.2954    | 0.2716    | 1          |

Figure 22: Video Similarity scores using MCS similarity

Using the ‘bag of nodes’ graph aggregation method, we also observe an approximate power law distribution for total degree. We visualize this for a sample video as seen in figure 23.

6 FUTURE DIRECTIONS
(1) The biggest bottleneck of the whole pipeline is the dense cap algorithm. This algorithm captures the relationships and objects from images. A better trained dense cap network will produce much better captions which will produce much richer node attributes and catch much more relationships between nodes.

Figure 23: Power Law
were not explicitly converted into scene graphs, the annotations
defined for a single image, we get multiple scene graphs based on segmentation. Similarity for a
single frame is based on node similarity based on node at-

ttribute comparison and bounding box information. Across frames, node similarity is based on node attribute compar-
son only as objects can move across various frames. It would
be an interesting problem to track people across multiple frames.

(4) Currently we are handling different queries on different graphical representations. While non-temporal queries are handled in an aggregated graph, temporal queries are an-
swered by querying the individual scene graphs for all key frames. In the future, we can formulate a single graphical representation capable of handling all queries.

(5) We are currently considering only the visual data of a given scene. Future work can build up on this by also incorporating audio data to improve the contextual awareness of the question-answering model.

(6) We have briefly touched upon video similarity in this paper. Future work in this direction could build upon this crude similarity metric for unsupervised clustering of videos and video retrieval based on an input video without using any video meta-data.

7 RELATED WORK
Existing literature describes a lot on building Contextual Question Answering on images. Related work described below explored ideas on conversion of scenes to graphs, which captures the context present in the scene.

Firstly, creating an efficient representation of input data which retains the contextual relationships between them. While [6] explored methods to generate semantically precise scene graphs and improve upon the state of the art, [5] achieved the same goal using pixel values of the image, which is a novel technique. In parallel, [8] proposed building a knowledge base which preserved the relation between objects as well as focused on solving inherent scalability issues of previous related works.

Secondly, papers [1] and [3] focused on improving multi object annotation of images. These papers described models which learn representation of images in natural language domain from the data instead of relying upon hard-coded templates. Although images were not explicitly converted into scene graphs, the annotations generated can be seen as analogous to scene graphs. Additionally these works also space-localized the objects within the image.

Thirdly, we explore papers which focused on techniques in ef-
cient image retrieval. The papers reviewed covered multiple solu-
tions to the task. [2] retrieved a relevant image given a scene graph improving upon traditional methods. On the other hand [1] handled text queries to retrieve images and solved a new problem of retrieving localized portions within the image corresponding to the query.

Finally, we look at synthetic image generation given a text de-
scription. Current state of the art this field in this new field is explored in papers [4] [7].

The common theme across these papers is to associate textual and visual representations. These papers provide novel mechanisms or improve state of the art to transform information from one do-
main to another. Another recurring theme is in the mechanisms itself which rely heavily on deep learning and machine learning

Existing shortcomings in traditional methods served as motiva-
tion to these papers. The challenges undertaken by these authors were across multiple areas such as availability of abundant labeled data, relating work from traditionally orthogonal fields of NLP and CV, performance issues associated with deep neural networks, ex-
tending classical techniques and algorithms to contextually aware algorithms, modeling the complex interactions between objects in a scene and generalizing to objects not present in the current data

8 CONCLUSION
We implemented an efficient model for answering contextual ques-
tions based on videos. The model was built using scene graphs which allows to encode relationships between subjects like man, dog etc. in a graph. The data included videos of varying context as well lengths on which queries were asked in order to test the efficiency of the model. We also introduced a novel way to extract key frames which rely on scene graphs and capture higher con-
textual changes. The results demonstrate the effectiveness of this method to extract key-frames based on the theory proposed as well as their saliency of being described as key-frames. Finally, we looked at video similarity using scene graph representation and we propose a future application where similar videos can be clustered and recommended based on content similarity as opposed to tags which are the current way of recommending videos. Building a recommendation system based our proposed approach will allow for more relevant recommendations.

One major take-away from the project is the proof of concept of the effectiveness of a graph approach of building a query engine to answer contextual questions based on specific videos, which till now has been approached from a deep learning only point of view.

9 WORK DIVISION
The algorithm development was done by brainstorming session in which everyone contributed equally. The report was done as a joint effort where each person contributed to the parts they primarily worked on. Though the below areas indicate the area one most contributed to, each person was involved in some capacity in all areas of the project.

(1) Akash Ganesan: Q&A engine, core NLP work, visualization, pipeline, graph and search combinators.
(2) Shubham Dash: Pipeline, dense captioning, graph linking, Q&A model validation.
(3) Karthik Muthuraman: Key frame extraction using graph sim-
ilarity and visualization, graph linking, Q&A data collection.
(4) Divyansh Pal: Dense captioning, graph linking, Q&A data collection.