EDURELL Project

Video Segmentation

Video Segmentation in the Edurell platform is performed in Python by using these main classes:

In the image.py file:

→ ImageClassifier (IC): an image wrapper that finds faces and text in the image and manages color scheme conversions

In the video.py file:

- → LocalVideo (LV): class that manages OpenCV video file loading, frame cursor set, frames extraction, conversion and resize.
- → VideoSpeedManager (VSM): wrapper of LocalVideo that manages the logic of frames extraction.

In the segmentation.py file:

- → TimedAndFramedText (TFT): dataclass that contains the following informations of the slide segment of the video:
 - ◆ Full text of that slide
 - X and Y positions and Width and Height (normalized) of the bounding boxes of every sentence indexed from the full text
 - ◆ Initial and last frame number of the video where the text appear on screen With some utility function that allow to insert multiple start-end windows of frames that contain that text:

→ VideoAnalyzer (VA): class that contains the logic to read a video and extract from it:

- ◆ The transcript, and its segmentation into timed sentences
- The keyframes (based on the previous segmentation method which is based on colour histograms)

```
def _create_keyframes(self,start_times,end_times,S,seconds_range, image_scale:float=1,create_thumbnails=True):--

def get_transcript(self,lang:str='en'):--

def transcript_segmentation(self, subtitles, c_threshold=0.22, sec_min=35, S=1, frame_range=15,create_thumbnails=True):--
```

 The percentage of slide frames over the entire video length, classification based on a threshold

```
_preprocess_video(self, vsm:VideoSpeedManager,num_segments:int=150,estimate_threshold=False,_show_info=False)
Split the video into `num_segments` windows frames, for every segment it's taken the frame that's far enough to guarantee the current frame is analyzed by XGBoost model to recognize the scene\n

If there are two non-slide frames consecutively the resulting frame window is cut\n

Bounds are both upper and lower inclusive to avoid a miss as much as possible\n

Then both are compared in terms of cosine distance of their histograms (it's faster than flattening and computing on pure Lastly the distance between wach frame is selected as either the average of values, either with fixed value.\n

In this instance with videos that are mostly static, the threshold is set to 0.9999

#TODOO further improvements: for more accuracy this algorithm could include frames similarity to classify a segment as sl:
A video split into 10 segments:\n\n slide_segments : 0,1,3,6,9,10\n non_slide_segments : 2,4,5,7,8\n results in segmentation = [(0,4),(5,7)(8,10)]\n with holes between segments 4-5 and 7-8
num_frames = vsm.get_video().get_count_frames()
speed = floor(num_frames / (num_segments))
vsm.lock_speed(speed)
iterations_counter:int = θ
txt_cleaner = TextCleaner()
 if estimate threshold:
        cos sim values = empty((num_segments,vsm.get_video().get_dim_frame()[2]))
#dists = empty((num_segments,vsm.get_video().get_dim_frame()[2]))
scene model = XGBoostModelAdapter(os.path.dirname(os.path.realpath(_file__))+"/xgboost/model/xgboost500.sav")
start frame num = Non
Inames_to_antayze:List(ipute[int;int]) = []
answ_queue = deque([False,False])
curr_frame = ImageClassifier(image_and_scheme=[None,vsm._color_scheme])
prev_frame = curr_frame.copy()
frame_w,frame_h,num_colors = vsm.get_video().get_dim_frame()
while iterations_counter < num_segments:
    prev_frame.set_img(vsm.get_frame())
    curr_frame.set_img(vsm.get_following_frame())
    if_scen_model_is_enough_Slidish_lkelorey_frame()</pre>
         if scene_model.is_enough_slidish_like(prev_frame):
    frame = prev_frame.get_img()
                  # validate slide in frame by slicing the image in a region that removes logos (that are usually in corners)
region = (slice(int(frame_h/4),int(frame_h*3/4)),slice(int(frame_w/4),int(frame_w*3/4)))
prev_frame.set_img(frame[region])
# double checks the fort
                  is slide = bool(txt cleaner.clean text(prev frame.extract text(return text=True)).strip())
                 is slide = False
         answ_queue.appendleft(is_slide); answ_queue.pop()
         # if there's more than 1 True discontinuity -> cut the video
if any(answ_queue) and start_frame_num is None:
         start_frame_num = int(clip(iterations_counter-1,0,num_segments))*speed
elif not any(answ queue) and start_frame_num is not None:
    frames_to_analyze.append((start_frame_num,(iterations_counter-1)*speed))
    start_frame_num = None
         if estimate threshold:
                  cos sim values[iterations_counter,:] = prev_frame.get_cosine_similarity(curr_frame)
#dists[iterations_counter,:] = curr_frame.get_mean_distance(prev_frame)
                rain(ans_counter=1
rint(answ queue[0]);plt.imshow(curr_frame.get_img(),cmap='gray');plt.show()
rint(f" Estimating cosine similarity threshold: {ceil((iterations_counter)/num_segments * 100)}%",end='\r'
_show_info: print(f" Coarse-grained analysis: {ceil((iterations_counter)/num_segments * 100)}%",end='\r')
          frames to analyze.append((start frame num,num frames-1))
         cos\_sim\_img\_threshold = clip(average(cos\_sim\_values, axis=0) + var(cos\_sim\_values, axis=0)/2, 0.9, 0.9999)
         #cos_sim img_threshold = clip(cos_sim_values.min(axis=0),0.9,0.99999)
# can't estimate correctly the cosine similarity threshold with average, too dependant from the segments chosen ar
# neither can set to max because it's always more than 1 neither to min because it's too low
#diff_threshold = average(diffs,axis=0)+3*var(diffs,axis=0)
#dist_threshold = (dists.max(axis=0) - dists.min(axis=0)) / 2
         cos_sim_img_threshold = ones((1,num_colors))*0.9999
         if estimate threshold:
                 print(f"Estimated cosine similarity threshold: {cos_sim_img_threshold}")
                  print(f"Cosine_similarity threshold: {cos_sim_img_threshold}")
print(f Estimated mean dist_inteshotd: {dist_inteshotd: {dist_inteshotd: {dist_inteshotd: {print(f"Frames to analyze: {frames_to_analyze} of {num_frames} total frames")
self._video slidishness = sum([frame window[1] · frame_window[0] for frame_window in frames_to_analyze])/(num_frames-1)
self._cos_sim_img_threshold = cos_sim_img_threshold
self._frames_to_analyze = frames_to_analyze #dist_threshold, frames_to_analyze
```

◆ The slide frames are extracted by analyzing the whole video

```
def analyze_video(self,color_scheme_for_analysis:int=COLOR_BGR,_show_info:bool=False,_plot_contours=False):

Firstly the video is analized in coarse-grained way, by a ML model to recognize frames of slides and the threshold for the difference between two frames is concurrently estimated. \n
The method uses an ImageClassifier to detect text in the frames of the video
Then saves that text in a collision stack.\n
It then looks for changes in the collision stack with respect to the text in the current frame flushes the differences in the output list.\n
Finally, it calls two helper methods to clean up the output list by combining partial words and merging adjacent frames.

Parameters:

- color_scheme_for_analysis: is a predefined value that must be either COLOR_BGR or COLOR_RGB from image.py
- _show_info: prints in stdout progression and set thresholds
- _plot_contours: shows images with bounding boxes once the video has been analyzed

Returns:

None but sets internal text that can be retrieved with ``get_extracted_text()``
```

Then each segment of the output list is compacted by merging similar texts and contiguous segments of same text. Lastly each section is validated with a double check for each segment

◆ Slide's titles are chosen with statistical analysis on the height of the text and it's position with respect to the other text of the slide:

```
for extracted by performing statistics on the axis defined, computing a threshold based on quantilesh and descript results based on union of results or interestically and descript results based on union of results or interestically and descript results based on union of results or interestically and descript results based on union of results or interestically and the overally but the overally but to move and the analysis is performed on the whole list of sentences, but can be performed in the whole list of sentences, but can be performed in the whole list of sentences, but can be performed in the whole list of sentences, but can be performed in the whole list of sentences, but can be performed in the results of the list of the overally being than the other text from or interest of the slidesh of the slidesh and littles are generally bigger than the other text from the first contence of the slidesh of the slidesh and littles are generally bigger than the other text from the first contence of the slidesh of the slidesh and littles are generally bigger than the other text from the first contence of the slidesh of the slidesh and littles are generally bigger than the other text from the first contence of the slidesh of the slidesh and littles are generally bigger than the other text from the first contence of the slidesh of the slidesh and littles are generally bigger than the other text from the first content of the slidesh o
```

◆ Concepts are extracted from the title with phrasemachine and definitions and in-depths search are calculated with an heuristic (the definition could be in a timeframe of a number of seconds around the slide first

appearance where the concept is cited in the transcript, and the in-depth could be the whole duration of the slide):

```
of edjects or justic principal content to find definitions from times demances of the recognization of the times of the sides. An office of the sides of the sides in the sides of the sides in the sides of the sides in the sides of the side
```

Slides can be reconstructed from the times saved in the database in the form of timeframes:

```
def reconstruct_slides_from_times_set(self):
    assert self._slide_startends is not None, "Must firstly load (set) startend frames read from database to run this function"
    slide_startends = self._slide_startends
    frame = ImageClassifier(image_and_scheme=[None,COLOR_BGR])
    loc_video = LocalVideo(self._video_id)
    TFT_list = []
    for slide_start_seconds,slide_end_seconds in slide_startends:
        slide_frames_startend = (loc_video.get_num_frame_from_time(slide_start_seconds),loc_video.get_num_frame_from_time(slide_end_seconds))
        loc_video.set_num_frame(slide_frames_startend[0])
        frame.set_img(loc_video.extract_next_frame())
        text_extracted = frame.extract_text(return_text=True,with_contours=True)
        TFT_list.append(TimedAndFramedText(text_extracted,[slide_frames_startend]))
    self._text_in_video = TFT_list
```

◆ Each step can be a start point by setting the internal variables from the data read from the database:

```
def set(self,video_slidishness=None,slidish_frames_startend=None,slide_startends=None,titles=None):
    if video_slidishness is not None:
        self._video_slidishness = video_slidishness
    if slidish_frames_startend is not None:
        self._frames_to_analyze = slidish_frames_startend
    if slide_startends is not None:
        self._slide_startends = slide_startends
    if titles is not None:
        self._slide_titles = titles
    return self
```

→ A process scheduler that automatically segmentates the videos in a global queue of segmentations and saves the results on the database:

Implementation

The coarse-analysis of the video that finds the percentage of slides in the video is calculated by using a pre-trained ML model that recognizes the "slidish" images and is double checked with the OpenCV library:

Algorithm 1 Video Pre-Processing

Then if the video has been classified as "slidish enough" the video is analyzed based on this algorithm:

Algorithm 2 Text From Video Segmentation

```
OUT: a list of already processed slide frames 

CT: currently-on-screen text 

V: video reference 

procedure VIDEO SEGMENTATION 

for every frame F_i in V do 

if there's no CT and F_i contains some text then 

CT \leftarrow (text, \texttt{FirstFrameOccurenceOfThisText}(V, text))
else if there's some CT and F_i is different enough T_i from T_{i-1} then 

if CT and text extracted from T_i are not the same then 

OUT_j \leftarrow (CT, \texttt{LastFrameOccurenceOfThisText}(V, CT. text))
return OUT
```