Supplementary Material: Generating Personalized Summaries of Day Long Egocentric Videos

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Algorithm 1 Proposed Framework

Input $F_{i=1}^{T}$**:** Video subshots
Output $P_{i=1}^{N}$**:** Probability scores
Freeze the C3D weights and randomly initialize weights of BiLSTM
for each epoch **do**
  for each video **do**
    for each pass **do**
      for each sliding window **do**
        Policy Gradient/Q Learning/ Actor-Critic
      end for
    end for
    if Policy Gradient **then**
      Update baseline B
    end if
  end for
end for

Algorithm 2 Policy Gradient Framework

Initialize θ and learning rate α.
for For each sliding window **do**
  Calculate S_{p} and S_{f} according to the position of W_{s}
  Get M probability scores from the neural network
  for For each episode **do**
    Sample M actions from probability scores
    Compute cost and reward

$$cost+=\sum_{m=1}^{M} R(S)\nabla_{\theta} log\pi_{\theta}(a_m|h_m)]$$

  end for
  Compute episodic cost and episodic reward
  if episodic cost improves **then**
    update summary by picking top $|S|$ sub-shots
  end if
  if For each mini batch **then**
    Back-propagate pseudo batch cost
  end if
end for

We have discussed the proposed approaches in Section 3.2 of the main text. We give the exact algorithm steps here. Algorithm 1 elaborate the sliding window framework and Algorithm 2, Algorithm 3, and Algorithm 4 describes the training process of Policy Gradient, Q Learning, and AC framework respectively.

Figure 1 shows the comparison of 1 minute, 3 minutes and 5 minutes summary generated by AC framework using the distinctiveness-indicativeness reward of 'HUJI Ariel 1' video. We have also prepared the GUI of the proposed work to conduct user study. The GUI is shown in Figure 2. As discussed in the main text the detail table with user comments on the personalized summary is show in Table 1

Table 2 shows the summary length and sliding window size for two long sequence datasets namely Disney and HUJI. As mentioned in the main text we take sliding window size 25% of the desired summary length. To generate one minute summaries, our summary length and sliding window size are 120 subshots (i. e. 2 subshots/second) and 30 subshots respectively. Similarly, for 10 minutes summaries, summary length and sliding window size are 120 and 30 respectively and so on for 3, 5, and 15 minutes summaries. For Disney dataset, we train the network for 1, 5, and 15 minutes summaries whereas for HUJI dataset we train the network for 1, 3 and 5 minutes summaries.

Fig. 1. Comparing 1, 3 and 5 minutes summaries (row 1-3) based on distinctiveness-indicativeness reward of 'HUJI Ariel 1' video.

Subjects	Video Name	Dataset	Events Included	Events Excluded	Likert Score (1 to 5)	Participant Feedback
S01-S1	Alin	Disney	Dinner	Dark scenes	3	*'Black part is not completely removed'*
S01-S1	P01	UTE	Driving	Social Int.	4.5	*'It accurately highligted the part I liked and don't liked.'*
S02-S1	Alin	Disney	Dinner	Dark scenes	3	*'So many dark scenes'*
S02-S1	P01	UTE	lunch	Purchasing	3	*'Purchasing in store not removed completely'*
S03-S1	Alin	Disney	Dinner	Tram ride	5	*'Included really long dinner, Tram ride is mostly removed'*
S03-S1	P01	UTE	Social Int.	Driving	4	*'Detailed conversation, could exclude some more driving shots'*
S04-S1	Alin	Disney	Shopping	Escalator	4.5	*'Shopping is taken for little long, escalator is removed'*
S04-S1	P01	UTE	Driving	Writing	5	*'Majority of summary was driving, no writting event'*
S05-S2	Alin	Disney	Tram ride	Dinner	4	*'Dinner is almost removed'*
S05-S2	P02	UTE	Playing Lego	Eating Pizza	4	*'Eating is removed entirely and lego is included for more time'*
S06-S1	Alin	Disney	Dark room	Travel	4	*'Accurately included the suggested feedback'*
S06-S1	P02	UTE	Having pizza	Driving	2	*'Driving is not removed'*
S07-S1	Alin	Disney	Castle	Travel in bus	3.5	*'Overall its good, still there were some bus travel events'*
S07-S1	P01	UTE	Marketing	Driving	2.5	*'Lots of instances of driving which could have been reduced'*
S08-S1	Alin	Disney	Indoor	Outdoor	4	*'Most of video is outdoor based'*
S08-S1	P02	UTE	Ice Cream	Walking	3.5	*'Excluding is correct, inclusion is not very good'*
S09-S2	Alin	Disney	Tram ride	In bus, Dark	2	*'Tram cart is missing, rest is fine'*
S09-S2	P02	UTE	lunch, Payment	Purchasing	4.5	*'Summary is very nice'*
S10-S1	Alin	Disney	carousel	Dark scenes	2	*'Dark scene are so many, poor summary'*
S10-S1	P03	UTE	Cooking	Drive, Wash	4	*'Inclusion is perfect! Dish washing is removed, driving is not'*

TABLE 1

The table shows the Likert score of 1 (Extremely dissatisfied) to 5 (Extremely satisfied) given by the participants when specific events are included or excluded in the summary with user comments on the personalized summary. S0X-SY represents subject 'X' in scenario 'Y'. It is observed that sometimes the user sees the excluded part in the personalized summary. This is because the interactive reward personalized the summary but at the same time distinctiveness-indicative reward that tries to maintain the global context. This can be handled by fine-tuning the weights of A and B discussed in interactive reward.

Summary length	Sliding window size
120 (1 min)	30
180 (3 mins)	45
600 (5 mins)	150
1200 (10 mins)	300
1800 (15 mins)	450

TABLE 2

Summary length and sliding window size for summaries of various time durations.

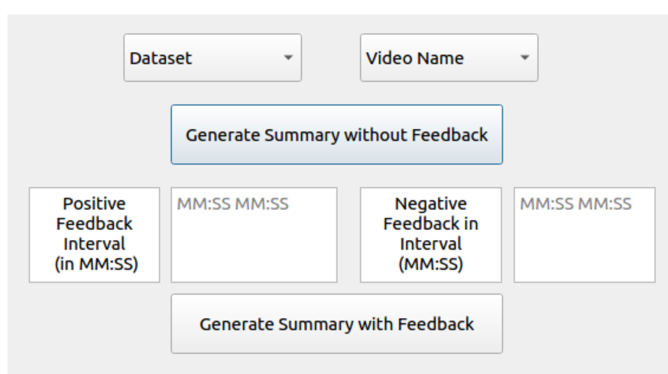

Fig. 2. Figure shows the GUI of the proposed work.

Algorithm 3 Q Learning Framework

```
Initialize θ, γ and learning rate α.
for For each sliding window do
    Calculate S_p and S_f according to the position of W_s
    Get M Q values from the Q value network
    Get M Q values from the target Q value network
    for For each episode do
        Sample M actions from probability scores
        Compute correction (TD error) for actions
```

$$\delta_{1:M} = R(S) + \gamma \sum_{m=1}^{M-1} Q_{\theta^-}(s_{m+1}, a_{m+1}) - \sum_{m=1}^{M-1} Q_{\theta}(s_m, a_m)$$

```
        Compute cost and reward R(S)
```

$$cost {+}{=} \delta_{1:M} \sum_{m=1, a \in A}^{M} \nabla_{\theta} Q_{\theta}(s_m, a_m)$$

```
    end for
    Compute episodic cost and episodic reward
    if episodic reward improves then
        update summary by picking top |S| subshots
    end if
    if For each mini batch then
        Back-propagate pseudo batch cost
    end if
end for
```

Algorithm 4 Actor Critic Framework

```
Initialize θ, w, γ and learning rates α_a, α_c.
for For each sliding window do
    Calculate S_p and S_f according to the position of W_s
    Get Q values from the Critic Network
    Get Policy distribution from Actor network
    Get Q values from the target Critic network
    for For each episode do
        Sample M actions from Policy distribution
        Actor cost calculation
```

$$cost_{ac} {+}{=} \sum_{m=1}^{M} Q_c(s_m, a_m) \nabla_{\theta} log(\pi_a(s_m, a_m))$$

```
        Compute correction (TD error) for actions
```

$$\delta_{1:M} = R(S) + \gamma \sum_{m=1}^{M-1} Q_{w^-}(s_{m+1}, a_{m+1}) - \sum_{m=1}^{M-1} Q_{w}(s_m, a_m)$$

```
        Compute cost and reward R(S)
```

$$cost_{cri} {+}{=} \delta_{1:M} \sum_{\substack{m=1, \\ a \in A}}^{M} \nabla_{w} Q_{w}(s_m, a_m)$$

```
    end for
    Compute episodic cost_ac, cost_cri and episodic reward
    of actor and critic
    if episodic reward improves then
        update summary by picking top |S| subshots
    end if
    if For each mini batch then
        Back-propagate pseudo batch cost_ac, and cost_cri
    end if
end for
```