ILS-SUMM: Iterated Local Search for Unsupervised Video Summarization

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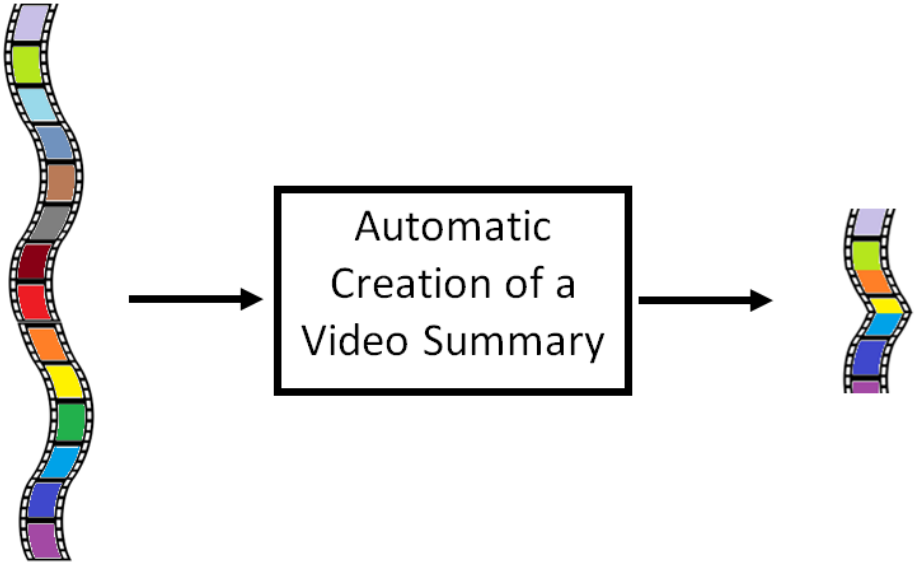
Background

Task Definition:

Given an input video, automatically create a short video that summarizes the original video.



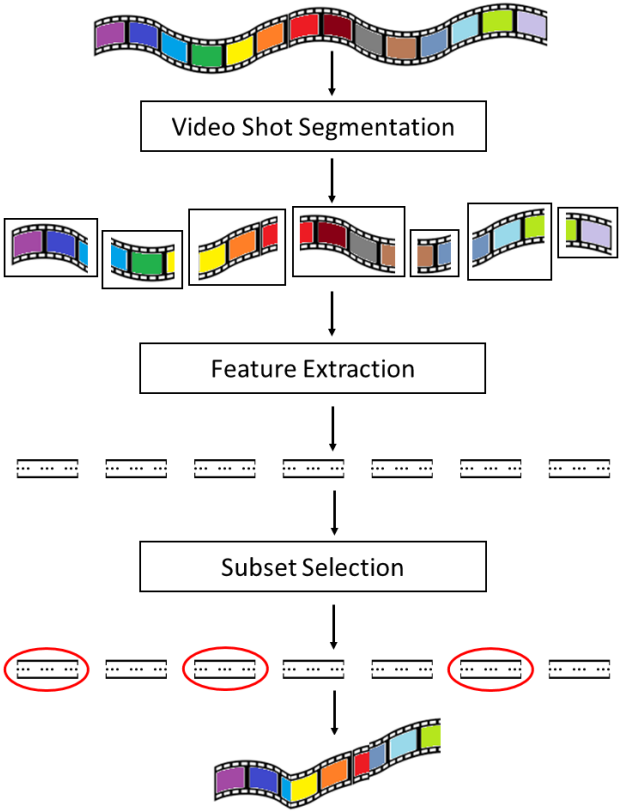
- In General, the goal is to enable faster consumption of video data.

Background

Example of a video summary:

Background

Common video summarization algorithm scheme:



Problem Formulation

- Given an input video v, the video is divided temporally into a set of shots $S_v = \{s_1, s_2, \dots s_N\}$
- We denote the duration in seconds of a shot s as $t(s)$
- Each shot is represented by its middle frame feature vector $x(s)$

Knapsack Median (KM) Optimization Problem

$$S^*_{summ} = \underset{S_{summ} \subseteq S_v}{\operatorname{argmin}} \; TD(S_{summ} | S_v, x(s)),$$

subject to:

$$\sum_{s \in S_{summ}} t(s) \leq T,$$

where:

$$TD(S_{summ} | S_v, x(s)) = \sum_{s' \in S_v} \min_{s \in S_{summ}} \{\operatorname{dist}\left(x(s'), x(s)\right)\}$$

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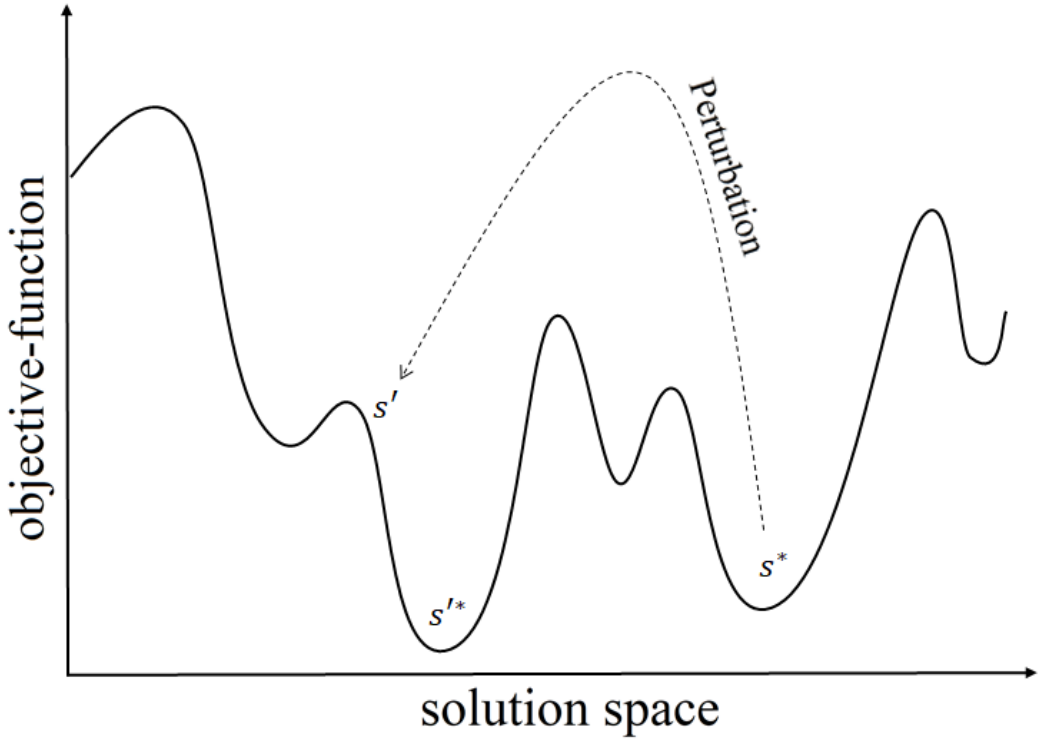
Iterated Local Search (ILS) framework (Baxter, 1981)

1. Apply a local-search algorithm
2. Repeat:
    1. Perturb the current local minimum.
    2. Apply a local-search after starting from the modified solution.

ILS Perturbation Mechanism:



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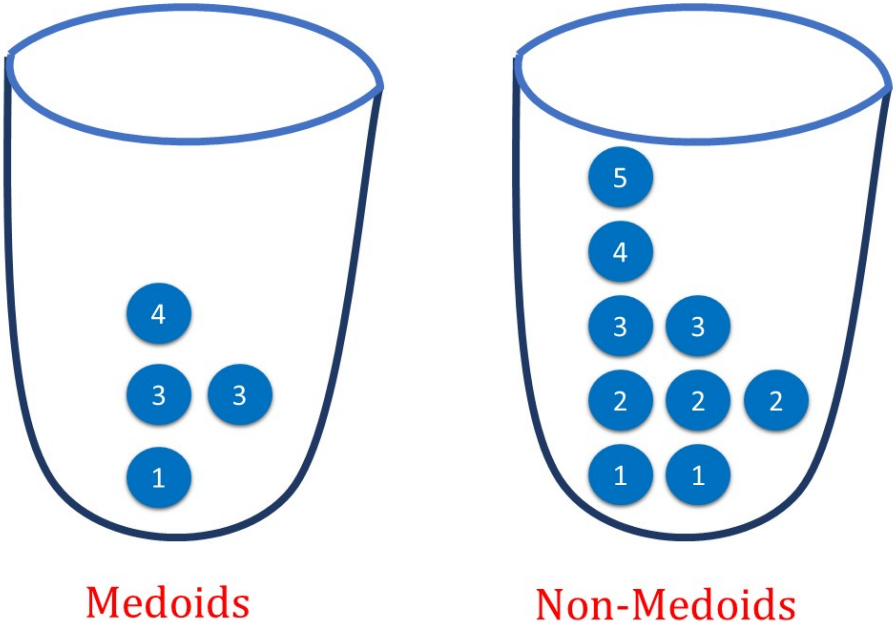
The perturbation we used:
swap the M costly medoids
with the M cheapest non-medoids



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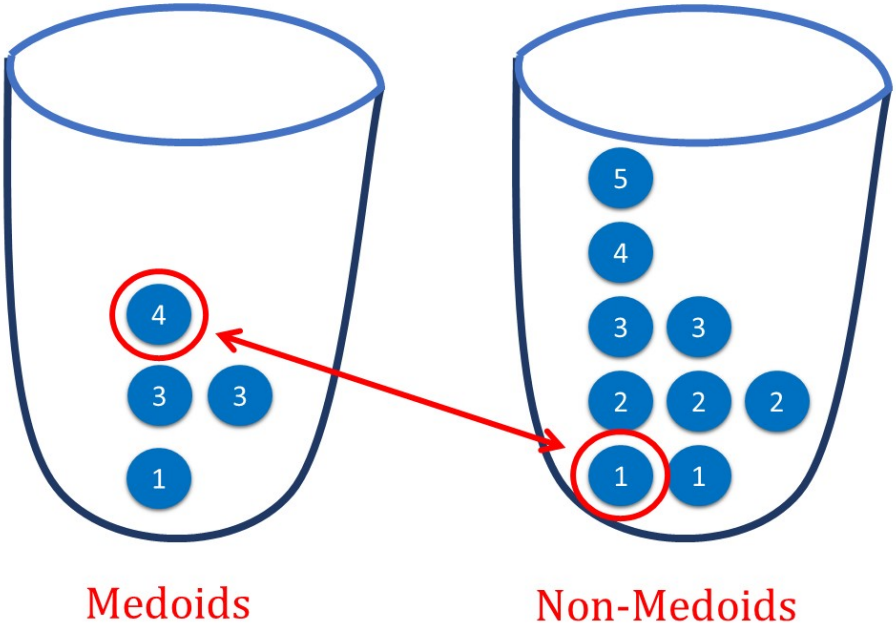

Experiments: Video Summarization

Datasets:

- **SumMe** - 25 short user videos (Gygli et al., 2014)
- **TvSum** - 50 short user videos (Song et al., 2015)
- **Open Source Total Distance (OSTD)** - 18 movies of various lengths

For shot segmentation we use **KTS** (Potapov et al., 2014) and **FFprobe** Python tool (Python Software Foundation, 2019).

Experiments: Video Summarization

Total Distance optimality percentage, i.e., the ratio between the optimal value and the achieved value:

	SumMe	TVSum	OSTD
DR-DSN	90.78%	82.50%	62.56%
Submodular	85.18%	94.14%	95.99%
ILS-SUMM	**98.48%**	**99.27%**	**98.38%**

ILS-SUMM exhibits a significant advantage

Experiments: Video Summarization

ILS-SUMM selections on Cosmos Laundromat movie:

Conclusion and Future Directions

Conclusion:

1. Using deep learning is not always the right choice: for optimization problem, heuristic algorithms can work better.
2. Utilizing ILS framework leads to great solutions thanks to the perturbation mechanism.

Future Directions:

1. Find a better objective function.
2. Relax the "hard" segmentation.

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Thanks!