Demystifying Multi-Faceted Video Summarization: Tradeoff Between Diversity, Representation, Coverage and Importance

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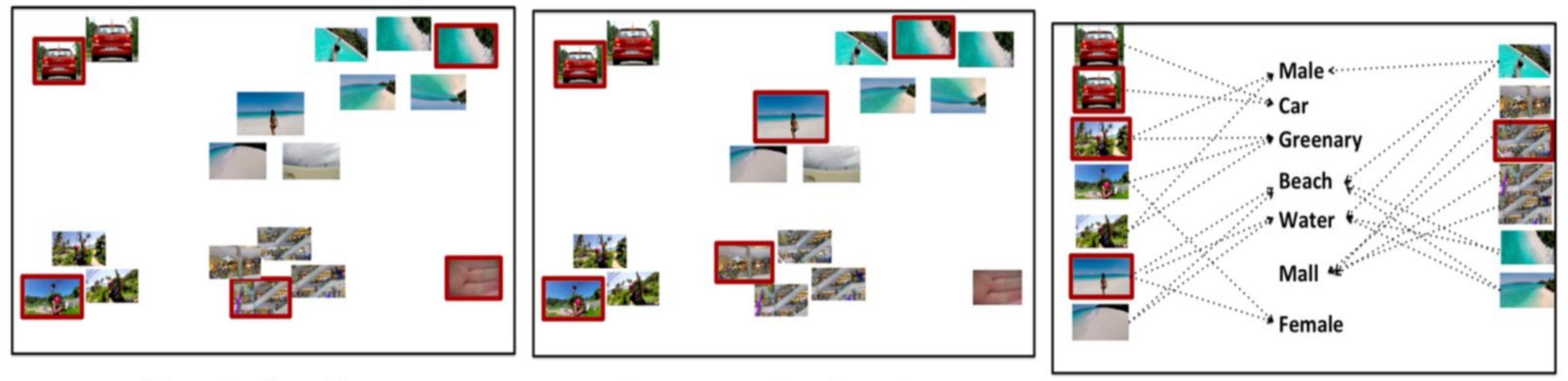
Motivation

- Video Summarization attempts to provide a highlight of the most critical and important events in a video.
- Different summarization models capture different aspects of a video. Types of characteristics captured by summarization models:
  - Diversity
  - Representation
  - Importance
  - Coverage
- What comprises of the key aspects of a video, depends largely on the domain.
- Different domains, require different summarization models.
- Which summarization model to use for a domain?



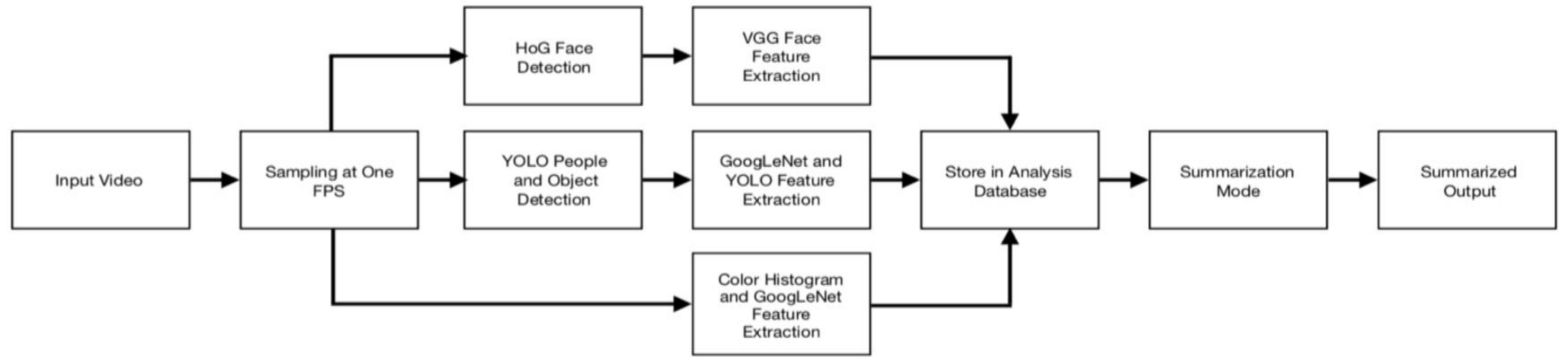
Diversity Functions　　Representation Functions　　Coverage Functions

Our Contributions

- Study the role and characteristics of various summarization models.
- Investigate several diversity, coverage and representation models, and demonstrate how different models are applicable in different kinds of summarization tasks.
- Empirically and quantitatively prove the behaviour of the functions on various videos across domains.
- Discuss computational scalability of the optimization algorithms and the usage of computational tricks, such as lazy evaluations and memoization.
- Explore various video summarization variants and study the details on how to design a video summarization system.

Submodular Summarization Framework

- Our framework studies the following variants of Video Summarization:
  - Extractive Summarization
  - Query Summarization
  - Entity Summarization
- In all variants, we use Convolutional Neural Networks as feature extractors, before performing submodular optimization to generate the summary.



- The following table illustrates the various submodular functions studied by us, as a part of our framework.

Name	$f(X)$	$p_f(X)$	T_f^o	T_f^p
Facility Location	$\sum_{i \in V} \max_{k \in X} s_{ik}$	$[\max_{k \in X} s_{ik}, i \in V]$	$O(n^2)$	$O(n)$
Saturated Coverage	$\sum_{i \in V} \min\{\sum_{j \in X} s_{ij}, \alpha_i\}$	$[\sum_{j \in X} s_{ij}, i \in V]$	$O(n^2)$	$O(n)$
Graph Cut	$\lambda \sum_{i \in V} \sum_{j \in X} s_{ij} - \sum_{i,j \in X} s_{ij}$	$[\sum_{j \in X} s_{ij}, i \in V]$	$O(n^2)$	$O(n)$
Feature Based	$\sum_{i \in \mathcal{F}} \psi(w_i(X))$	$[w_i(X), i \in \mathcal{F}]$	$O(n\|\mathcal{F}\|)$	$O(\|\mathcal{F}\|)$
Set Cover	$w(\cup_{i \in X} U_i)$	$\cup_{i \in X} U_i$	$O(n\|U\|$	$\|U\|$
Prob. Set Cover	$\sum_{i \in \mathcal{U}} w_i[1 - \prod_{k \in X}(1 - p_{ik})]$	$[\prod_{k \in X}(1 - p_{ik}), i \in \mathcal{U}]$	$O(n\|\mathcal{U}\|)$	$O(\|\mathcal{U}\|)$
DPP	$\log\det(S_X))$	$\mathrm{SVD}(S_X)$	$O(\|X\|^3)$	$O(\|X\|^2)$
Dispersion Min	$\min_{k,l \in X, k \neq l} d_{kl}$	$\min_{k,l \in X, k \neq l} d_{kl}$	$O(\|X\|^2)$	$O(\|X\|)$
Dispersion Sum	$\sum_{k,l \in X} d_{kl}$	$[\sum_{k \in X} d_{kl}, l \in X]$	$O(\|X\|^2)$	$O(\|X\|)$
Dispersion Min-Sum	$\sum_{k \in X} \min_{l \in X} d_{kl}$	$[\min_{k \in X} d_{kl}, l \in X]$	$O(\|X\|^2)$	$O(\|X\|)$

Table 1. List of Submodular Functions used, with the precompute statistics $p_f(X)$, gain evaluated using the precomputed statistics $p_f(X)$ and finally T_o^f as the cost of evaluation the function without memoization and T_p^f as the cost with memoization. It is easy to see that memoization saves an order of magnitude in computation.

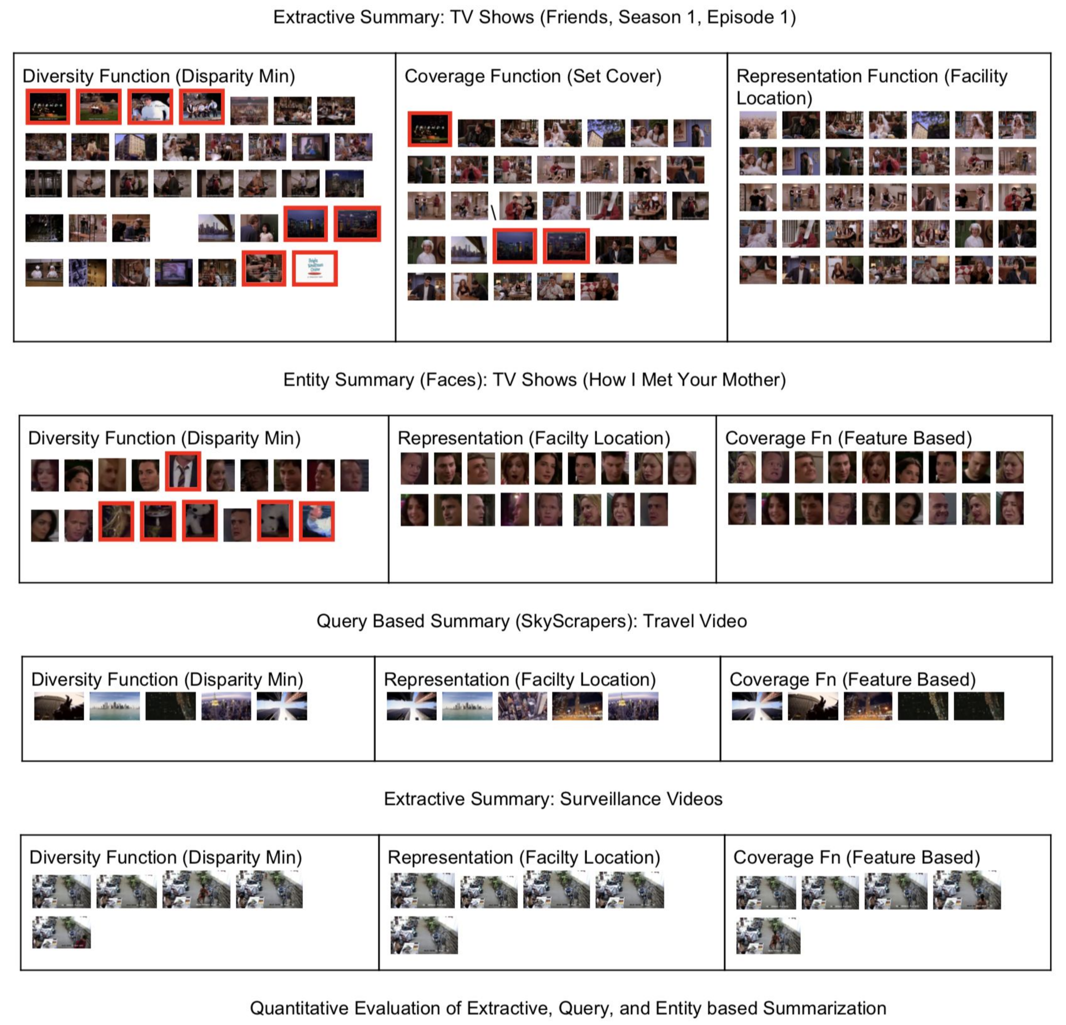
- In the framework, submodular video summarization is treated as two distinct optimization problems.
  - Budget Constrained Submodular Maximization

$$X^{t+1} = X^t \cup \operatorname{argmax}_{j \in V \setminus X^t} \frac{f(j|X^t)}{c(j)}$$

  - Submodular Cover Problem

$$X^{t+1} = X^t \cup \operatorname{argmax}_{j \in V \setminus X^t} f(j|X^t)$$, Until $f(X^t) = f(V)$

Experiments and Results



- In the illustrated results, we show the following:
  - Extractive summarization on TV shows.
  - Entity summarization on TV shows.
  - Query summarization for a query “skyscraper”.
  - Extractive summarization on surveillance videos.
- In each case, we compare Representation, Diversity and Coverage models.

Quantitative Evaluation of Extractive, Query, and Entity based Summarization

- The greedy nature of the optimization algorithm allows us to maintain precompute statistics for a set, using which the gain can be evaluated much more efficiently.
- With memoization, the order of the evaluation of gains is often an order of magnitude faster.

	Memoization			No Memoization		
Function	**5%**	**15%**	**30%**	**5%**	**15%**	**30%**
Fac Loc	0.34	0.4	0.71	48	168	270
Sat Cov	0.36	0.64	0.92	55	177	301
Gr Cut	0.39	0.52	0.82	41	161	355
Feat B	0.16	0.21	0.32	9	16	21
Set Cov	0.21	0.31	0.41	5	16	31
PSC	0.11	0.37	0.42	7	19	35
DPP	32	107	411	171	1003	4908
DM	0.11	0.61	0.82	21	125	221
DS	0.21	0.63	0.89	41	134	246

Table 2. Timing results in seconds for summarizing a two hour video for various submodular functions

Conclusions

- We present a unified picture of multi-faceted video summarization for extractive, query based and entity based summarization.
- Take a closer look at different summarization models and argue the benefits of these models in different domains by comparing qualitative and quantitative results.
- Implementation tricks, like memoization, can drastically improve the summary generation time, as compared to computational gains, such as usage of GPUs.