


Learning From Less Data: A Unified Data Subset Selection and Active Learning Framework for Computer Vision



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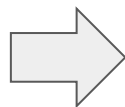
Microsoft Corporation²

University of Massachusetts Amherst³

Motivation

Deep Models are used everywhere today!

Increased Model
Complexity



- 1) Increased Computing Resources
- 2) Increased Labeling Cost
- 3) Increased Turn Around Time

Increased Labelling Cost

Difficult to get Labeled Data!

Annotate every object, even stationary and obstructed objects, for the entire video. [Instructions](#) [+ New Object](#)



Car 4

- Outside of view frame
- Occluded or obstructed

Person 3

- Outside of view frame
- Occluded or obstructed

Bicycle 2

- Outside of view frame
- Occluded or obstructed

Car 1

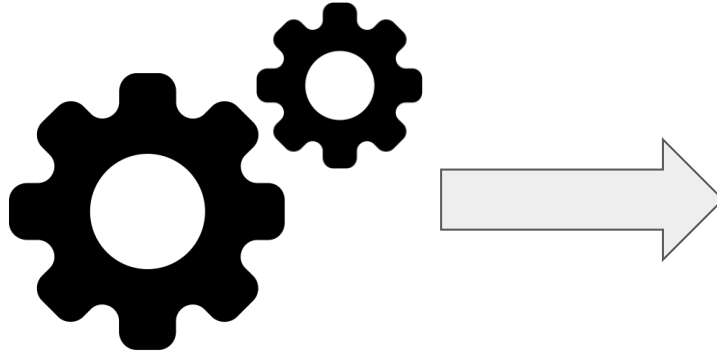
- Outside of view frame
- Occluded or obstructed

[Rewind](#) [Play](#) [Options](#) [Save Work](#)

Increased Turn Around Time

Harder to tune Hyperparameters

Hyperparameter
tuning

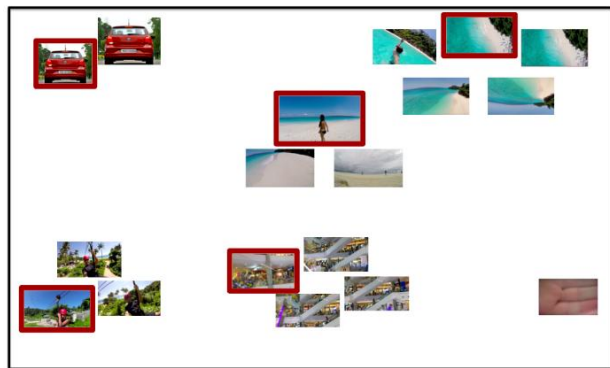


Best
hyperparameters

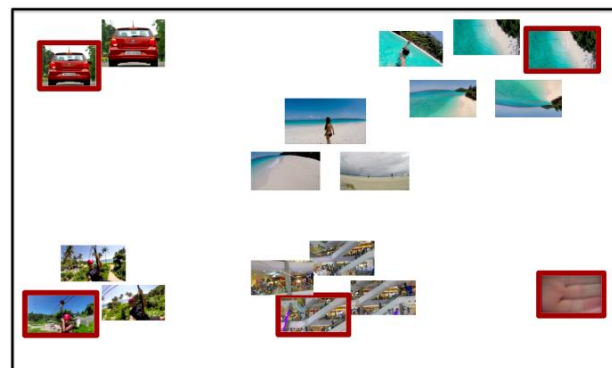
Our Contributions

A unified framework for data subset selection

1. Facility Location (models representation)
2. Minimum Dispersion (models diversity)



Representation Functions



Diversity Functions

Data Subset Selection

Given a ground set $V = \{1, 2, 3, \dots, n\}$

Define a set function $f: 2^V \rightarrow \mathbb{R}$ which measures how good a subset $X \subseteq V$

Problem 1: $\max\{f(X) \text{ such that } |X| \leq k\}$

The greedy algorithm obtains an approximation guarantee of $(1 - 1/e)$ for Problem 1 when f is the Facility Location function.

Similarly, the greedy algorithm achieves an approximation factor of $1/2$ when f is the Dispersion function.

Representation Functions

They try to find a representative subset of items, akin to centroids and medoids in clustering

Facility Location: $f(X) = \sum_{i \in V} \max_{j \in X} s_{ij}$

Diversity Functions

They attempt to obtain a diverse set of keypoints

Dispersion Function: $f(X) = \min_{i,j \in X} d_{ij}$

While diversity only looks at the elements in the chosen subset, representativeness also worries about their similarity with the remaining elements in the superset

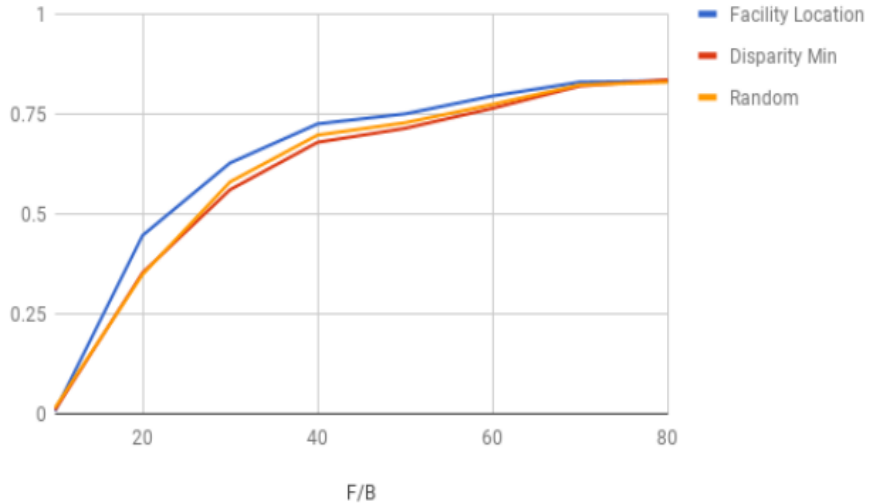
Four Settings / Use Cases

Four concrete use cases of our framework

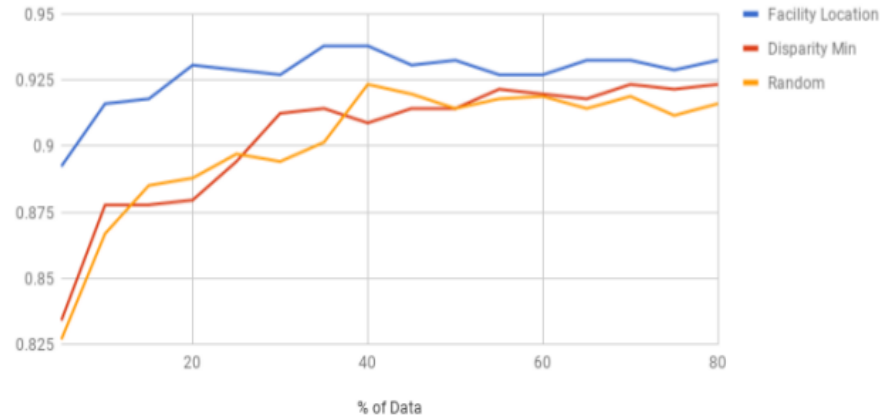
1. Supervised Data Selection for **Quick Training/Inference**
2. Supervised Data Selection for **Quick Hyper-parameter tuning**
3. Unsupervised Data Selection for **Labeling from Video Data**
4. Diversified **Active Learning**

Results: DSS for Quick Training/Inference

Accuracies

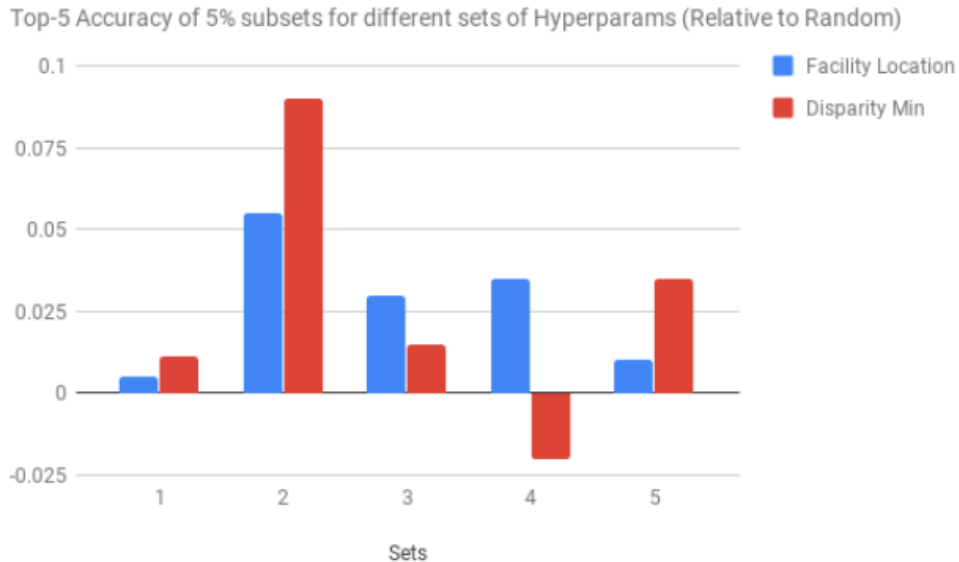


Accuracies



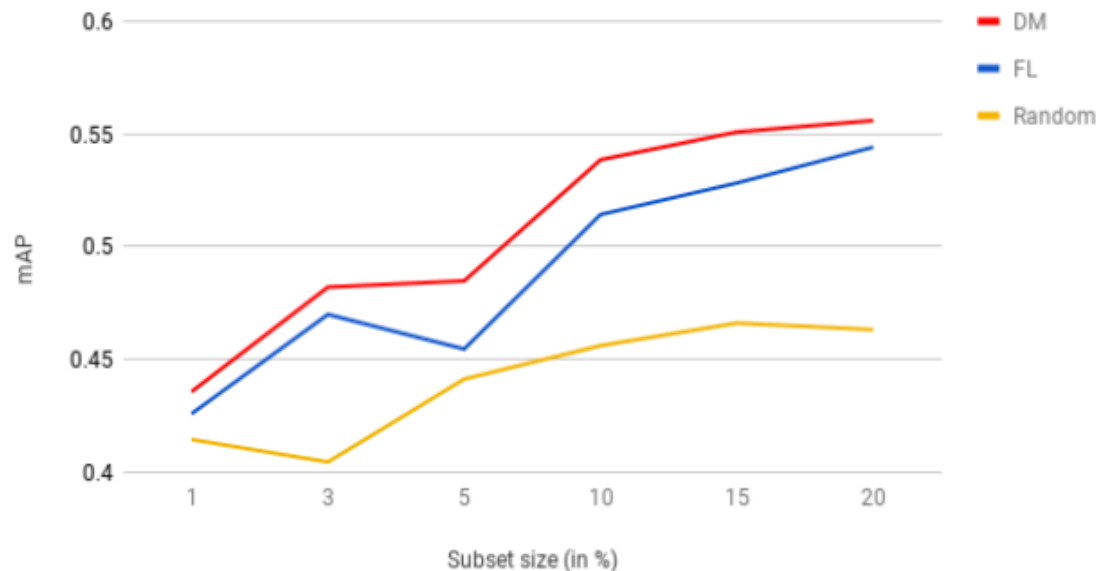
Supervised DSS for Quick Training/Inference (KNN Classification)

Results: DSS for Hyper Parameter Tuning



Results: DSS for Labeling Video Data

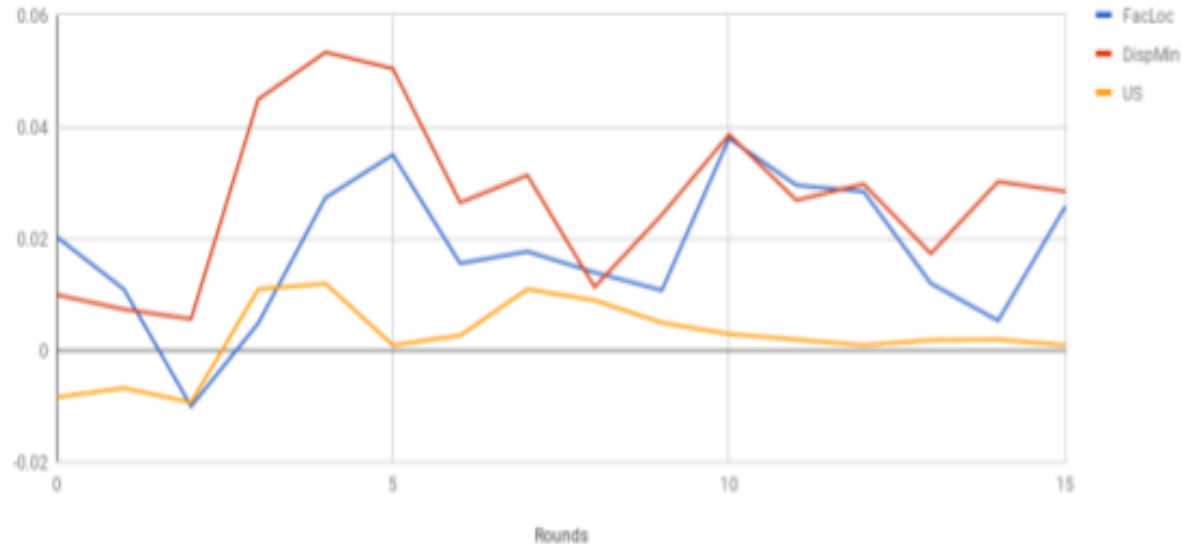
Comparison between different subsets for reduced labeling cost



Data Subset Selection on Massive Datasets for Labeling

Results: Diversified Active Learning

Accuracies relative to Random



$$\max\{f(X) \text{ such that } |X| \leq B, X \subseteq F\}$$

Submodular Active Learning on the Adience Dataset for Gender Classification