CHALLENGES OF MULTI-MODAL CORESET SELECTION FOR DEPTH PREDICTION

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ABSTRACT

Coreset selection methods are effective in accelerating training and reducing memory requirements but remain largely unexplored in applied multimodal settings. We adapt a state-of-the-art (SoTA) coreset selection technique for multimodal data, focusing on the depth prediction task. Our experiments with embedding aggregation and dimensionality reduction approaches reveal the challenges of extending unimodal algorithms to multimodal scenarios, highlighting the need for specialized methods to better capture inter-modal relationships.

1 INTRODUCTION

Modern deep learning systems require massive datasets demanding hundreds of gigabytes and even terabytes of storage Russakovsky et al. (2015) Schuhmann et al. (2022) as well as substantial computational resources for training. To address these computational challenges, researchers have developed coreset selection methodsIyer et al. (2021b)Coleman et al. (2020)Chen et al. (2012) — techniques for identifying the minimal subsets of training data that maintains model performance on a level of a model trained on the full dataset.

However, many real-world applications, from medical diagnosis Salvi et al. (2024) to autonomous vehicles Cui et al. (2022) Yeong et al. (2021) Caesar et al. (2020) to Multi-Modal Foundation Models Bachmann et al. (2024), require processing multiple modalities of data simultaneously. These multimodal scenarios not only amplify the computational demands but also introduce new challenges, as traditional coreset selection methods cannot be directly applied. In this work, we extend SoTA coreset selection techniques to handle multimodal data, specifically investigating the adaptation of Zhou et al. (2023)'s approach. Through extensive experimentation on depth prediction tasks, we demonstrate the limitations of current approaches and the need for specialized multimodal coreset selection methods for better modeling inter-modal relationships. We provide a code for reproducing experiments.[1]

2 METHOD

We adapt the coreset selection method from previous studies (Zhou et al., 2023), successfully applied to unimodal data, to the multimodal setting. The goal is to select a representative subset S that retains the diversity and informativeness of the original dataset D. Let $D = \{(\{x_i^m\}_{m=1}^M, y_i)\}_{i=1}^N$ denote a dataset with N samples and M modalities, where x_i^m represents the features of the i-th sample for the m-th modality, and y_i is the corresponding output. For the ease of notation, further x_i will denote multimodal object $\{x_i^m\}_{m=1}^M$.

Following previous approaches, we employ a submodular gain function (Iyer et al., 2021a) generalized to multimodal data, denoted as $P(x_i)$, to measure the importance of a multimodal sample x_i in maximizing the retained information. The gain for adding x_i to the current subset S_{i-1} is:

$$P(x_i) = \sum_{p \in S_{i-1}} ||f(p) - f(x_i)||^2 - \sum_{p \in D \setminus S_{i-1}} ||f(p) - f(x_i)||^2,$$

where $f(x)$ is the embedding of a **multimodal** sample x in feature space, S_{i-1} is the current subset of size $i-1$, and $D \setminus S_{i-1}$ represents the remaining samples.

[1] https://anonymous.4open.science/r/MultiModalCoreset-84BE/

Table 1: Percentage of quality retained relative to the Full Dataset for Validation RMSE, Validation Loss, and Training Loss, evaluated after training with coresets selected using each method.

Method	Aggregation	Dimension	Val RMSE, %	Val Loss, %	Train Loss, %
Full Dataset	-	-	100.00	100.00	100.00
Random Coreset	-	-	50.23	46.33	55.32
Coreset	Concat	301.824	49.08	47.41	51.81
	Mean	768	51.54	47.90	52.63
	Sum	768	51.11	52.12	54.47
Coreset w/ PCA	Concat	512	47.73	45.43	45.37
	Concat	1024	55.93	50.00	54.55
	Concat	2048	47.90	43.23	52.46
	Concat	4096	44.00	36.50	51.77
Coreset w/ UMAP	Concat	512	49.29	49.23	47.44
	Concat	1024	50.53	45.27	48.31

The dataset D is divided into non-overlapping bins $\{S_1, S_2, \ldots, S_N\}$ through recursive selection by maximizing submodular gain $x_k \leftarrow \text{argmax } P(x)$ with $x \in D \setminus \bigcup_{j=1}^{n-1} S_j$

To enhance diversity, we follow previous studies (Zhou et al., 2023) and uniformly sample from these bins, ensuring that even the most recently selected bin contributes equally to the final coreset.

3 Experimental Procedure

Dataset: We use the CLEVR dataset (Johnson et al., 2016), where multimodal inputs consist of RGB image and semantic mask, the target is a depth map from Omnidata (Eftekhar et al., 2021).

Model: We employ MultiMAE backbone, with input and output adapters trained following the original paper (Bachmann et al., 2022) and DPT output adapter (Ranftl et al., 2021), trained for 40 epochs with batch size 128, with best checkpoint selected. Other technical details could be found in Appendix A.

Coreset Selection: We extract embeddings $f(x)$ from the MultiMAE transformer, as the DPT output adapter's feature map dimension is too large. All coresets are 20% of the original dataset, obtained with $N = 20$. We evaluate the following baselines: **Full**: Complete dataset used for training as a reference. **Random Coreset**: A random 20% subset. **Token Aggregation**: Concatenation, mean, or sum of embeddings. **Dimensionality Reduction**: Applying PCA or UMAP (McInnes et al., 2020) to concatenation of tokens before coreset selection.

4 Results & Discussion

Our results in Table 1 show that coreset selection methods lead to a 50% performance drop compared to the full dataset, with minimal improvement over random coreset. The best performance is achieved with PCA (1024 features), but the improvement is incremental, and UMAP shows no consistent gain.

We observe worse convergence relative to the full dataset, likely due to reduced data representativeness, making coresets behave similarly to random selection. Attempts to use a linear output adapter for bottleneck embeddings failed, confirming the necessity of the DPT adapter for depth prediction.

5 Conclusion

We address the challenge of multimodal coreset selection, essential for modern applications, and present an adaptation of SoTA coreset selection method to the multimodal setting. Testing on depth prediction reveals close to random selection, highlighting the need for further exploration of multimodal coreset selection techniques.

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Table 2: Comparison of RMSE, Validation Loss, and Training Loss across methods.

Method	**RMSE**	**Validation Loss**	**Training Loss**
Full Dataset	0.0033	0.0015	0.0030
Random Coreset	0.0065	0.0033	0.0055
Coreset, Full L2	0.0066	0.0032	0.0058
Coreset, Mean Cosine	0.0063	0.0032	0.0057
Coreset, Sum Cosine	0.0064	0.0029	0.0055
PCA (512)	0.0068	0.0033	0.0066
UMAP (1024)	0.0065	0.0033	0.0062
UMAP (512)	0.0066	0.0031	0.0064
PCA (1024)	0.0059	0.0030	0.0055
PCA (2048)	0.0068	0.0035	0.0057
PCA (4096)	0.0074	0.0042	0.0058

A TECHNICAL DETAILS

Training was performed using the Adam optimizer with learning rate 5×10^{-5}, $\beta_1 = 0.9$, $\beta_2 = 0.99$, no weight decay and cosine annealing scheduler. The training was conducted on an NVIDIA A100 GPU.