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

Data for modern deep learning systems require gigabytes and even terabytes of storage (Russakovsky et al., 2015) (Schuhmann et al., 2022) and substantial computational resources for training. One technique to address these computational challenges is coreset selection (Iyer et al., 2021b; Coleman et al., 2020; Chen et al., 2012), which aims to identify minimal subsets of training data that maintain model performance. However, many real-world applications, such as medical diagnosis (Salvi et al., 2024) or autonomous vehicles (Cui et al., 2022; Yeong et al., 2021; Caesar et al., 2020) require processing multiple modalities of data simultaneously. These multimodal scenarios amplify computational demand and introduce new challenges, as traditional coreset selection methods cannot be applied directly. In this work, we extend one of the SoTA coreset selection techniques to handle multimodal data (Zhou et al., 2023). 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 code for reproducing experiments.[1]

2 METHOD

We adapt the Data Quantization (Zhou et al., 2023) method, to the multimodal setting. The goal is to select a representative subset S that retains the diversity and informativeness of the original dataset. 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 target. For ease of notation, x_i will further denote a multimodal tuple $\{x_i^m\}_{m=1}^M$.

Following previous approaches, we employ a submodular gain function (Iyer et al., 2021a) and generalize it to multimodal data. Denoted $P(x_i)$, to measure the importance of a multimodal sample x_i in maximizing the retained information. The gain of 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, S_{i-1} is the current subset of size $i-1$, and $D \setminus S_{i-1}$ represents the remaining samples.

The data set 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 $x \in D \setminus \bigcup_{j=1}^{n-1} S_j$

[1] https://github.com/VityaVitalich/MultiModalCoreset

Method	Aggregation	Dimension	Val RMSE, % ↑	Val Loss, % ↑
Full Dataset	-	-	100.00	100.00
Random Coreset	-	-	50.23	46.33
Coreset	Concat	301824	49.08	47.41
	Mean	768	**51.54**	47.90
	Sum	768	51.11	52.12
Coreset w/ PCA	Concat	512	47.73	45.43
	Concat	1024	55.93	50.00
	Concat	2048	47.90	43.23
	Concat	4096	44.00	36.50
Coreset w/ UMAP	Concat	512	49.29	49.23
	Concat	1024	50.53	45.27

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

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 input consists of RGB image and semantic mask, the target is a depth map obtained from Omnidata (Eftekhar et al., 2021).

Models: We employ MultiMAE both to extract a multi-modal embedding $f(x_i)$, and to perform depth estimation from RGB + semantic mask. We use Root Mean Squared Error (RMSE) as the target metric. The input and output adapters were trained following the original paper (Bachmann et al., 2022) and DPT output adapter (Ranftl et al., 2021) respectively. Other technical details can be found in the Appendix A. We extract embeddings $f(x_i)$ of a multimodal sample x_i from MultiMAE's transformer encoder.

Coreset Selection: All coresets are 20% from the original dataset, obtained with $N = 20$. We evaluated 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**: We also apply PCA and UMAP (McInnes et al., 2020) to concatenation of tokens before coreset selection.

4 Results & Discussion

Our results in Table 3 show that coreset selection methods lead to a 50% performance drop compared to the full data set and an improvement so minor over the random coreset that it could be due to chance, see Appendix A for raw RMSE values. The best performance is achieved with PCA (1024 features), but the improvement is incremental and UMAP shows no consistent gain.

We hypothesize that these results are due to the large dimensionality of the embeddings, and euclidean distance not being informative enough to separate similar and dissimilar objects. We employed dimensionality reduction to extract the most "meaningful" parts of the embedding, which did not help in our setting. A direction worth exploring would be to try another model for extracting multi-modal embeddings.

5 CONCLUSION

We address the challenge of selecting multimodal coresets, essential for modern applications, and present an adaptation of the SoTA coreset selection method to the multimodal setting. Our results highlight the need for further exploration of multimodal coreset selection techniques.

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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

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

A Technical Details

Training was performed using the Adam optimizer with learning rate 5×10^{-5}, $\beta_1 = 0.9$, $\beta_2 = 0.99$, for 40 epochs with batch size 128, no weight decay and cosine annealing scheduler. The training was conducted on a single NVIDIA A100 GPU.

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