Matryoshka Representations for Adaptive Deployment

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Abstract. Learned representations are a central component in modern ML systems, serving a multitude of downstream tasks. When training such representations, it is often the case that computational and statistical constraints for each downstream task are unknown. In this context, rigid fixed-capacity representations can be either over or under-accommodating to the task at hand. This leads us to ask: *can we design a flexible representation that can adapt to multiple downstream tasks with varying computational resources?* Our main contribution is Matryoshka Representation Learning (MRL) which encodes information at different granularities and allows a single embedding to adapt to the computational constraints of downstream tasks. MRL minimally modifies existing representation learning pipelines and imposes no additional cost during inference and deployment. MRL learns coarse-to-fine representations that are at least as accurate and rich as independently trained low-dimensional representations. The flexibility within the learned Matryoshka Representations offer: (a) up to **14**× smaller embedding size for ImageNet-1K classification at the same level of accuracy; (b) up to **14**× real-world speed-ups for large-scale retrieval on ImageNet-1K and 4K; and (c) up to **2**% accuracy improvements for long-tail few-shot classification, all while being as robust as the original representations. Finally, we show that MRL extends seamlessly to web-scale datasets (ImageNet, JFT) across various modalities – vision (ViT, ResNet), vision + language (ALIGN) and language (BERT). MRL code and pretrained models are open-sourced at *removed for double blind*.

Keywords: Large-scale Representation Learning, Adaptive Deployment

1 Introduction

Learned representations [26] are fundamental building blocks of real-world ML systems [31, 45]. Trained once and frozen, d-dimensional representations encode rich information and can be used to perform multiple downstream tasks [3]. The deployment of deep representations has two steps: (1) an expensive yet constant-cost forward pass to compute the representation [13] and (2) utilization of the representation for downstream applications [22, 43]. Compute costs for the latter part of the pipeline scale with the embedding dimensionality as well as the data size (N) and label space (L). At web-scale [7, 41] this utilization cost overshadows the feature computation cost. The rigidity in these representations forces the use of high-dimensional embedding vectors across multiple tasks despite the varying resource and accuracy constraints that require flexibility.

Human perception of the natural world has a naturally coarse-to-fine granularity [11, 14]. However, perhaps due to the inductive bias of gradient-based training [40], deep learning models tend to diffuse "information" across the entire representation vector. The desired elasticity is usually enabled in the existing flat and fixed representations either through training multiple low-dimensional models [13], jointly optimizing sub-networks of varying capacity [4, 51] or post-hoc compression [18, 28]. Each of these techniques struggle to meet the requirements for adaptive large-scale deployment either due to training/maintenance overhead, numerous expensive forward passes through all of the data, storage and memory cost for multiple copies of encoded data, expensive on-the-fly feature selection or a significant drop in accuracy. By encoding coarse-to-fine-grained representations, which are as accurate as the independently trained counterparts, we learn with minimal overhead a representation that can be deployed *adaptively* at no additional cost during inference. Please note that a detailed description of related works in the context of representation learning and efficient classification and retrieval is provided in the original paper [23].

We introduce Matryoshka Representation Learning (MRL) to induce flexibility in the learned representation. MRL learns representations of varying capacities within the same high-dimensional vector through explicit optimization of $O(\log(d))$ lower-dimensional vectors in a nested fashion, hence the name Matryoshka. MRL can be adapted to any existing representation pipeline and is easily extended to many standard tasks in computer vision and natural language processing. Figure 1 illustrates the core idea of Matryoshka Representation Learning (MRL) and the adaptive deployment settings of the learned Matryoshka Representations.

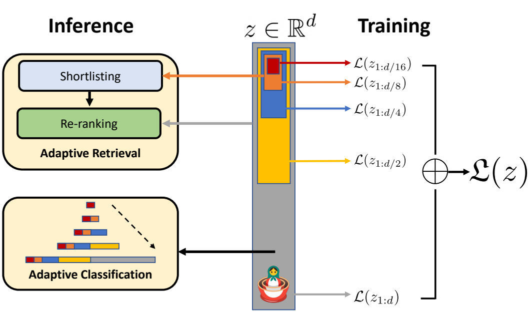

Fig. 1: Matryoshka Representation Learning is adaptable to any representation learning setup and begets a Matryoshka Representation z by optimizing the original loss $\mathcal{L}(.)$ at $O(\log(d))$ chosen representation sizes. Matryoshka Representation can be utilized effectively for adaptive deployment across environments and downstream tasks.

The first m-dimensions, $m \in [d]$, of the Matryoshka Representation is an information-rich low-dimensional vector, at no additional training cost, that is as accurate as an independently trained m-dimensional representation. The information within the Matryoshka Representation increases with the dimensionality creating a coarse-to-fine grained representation, all without significant training or additional deployment overhead. MRL equips the representation vector with the desired flexibility and multifidelity that can ensure a near-optimal accuracy-vs-compute trade-off. With these advantages, MRL enables adaptive deployment based on accuracy and compute constraints.

The Matryoshka Representations improve efficiency for large-scale classification and retrieval without any significant loss of accuracy. While there are potentially several applications of coarse-to-fine Matryoshka Representations, in this work we focus on two key building blocks of real-world ML systems: large-scale classification and retrieval. For classification, we use adaptive cascades with the variable-size representations from a model trained with MRL, significantly reducing the average dimension of embeddings needed to achieve a particular accuracy. For example, on ImageNet-1K, MRL + adaptive classification results in up to a 14× smaller representation size at the same accuracy as baselines (Section 3.2). Similarly, we use MRL in an adaptive retrieval system. Given a query, we shortlist retrieval candidates using the first few dimensions of the query embedding, and then successively use more dimensions to re-rank the retrieved set. A simple implementation of this approach leads to 128× theoretical (in terms of FLOPS) and 14× wall-clock time speedups compared to a single-shot retrieval system that uses a standard embedding vector; note that MRL's retrieval accuracy is comparable to that of single-shot retrieval (Section 3.3). This is reflected in up to 2% accuracy gains in long-tail continual learning settings while being as robust as the original embeddings. Furthermore, due to its coarse-to-fine grained nature, MRL can also be used as method to analyze hardness of classification among instances and information bottlenecks.

We make the following key contributions:

1. We introduce Matryoshka Representation Learning (MRL) to obtain flexible representations (Matryoshka Representations) for adaptive deployment (Section 2).
2. Up to 14× faster yet accurate large-scale classification and retrieval using MRL (Section 3).
3. Seamless adaptation of MRL across modalities (vision - ResNet & ViT, vision + language - ALIGN, language - BERT) and to web-scale data (ImageNet-1K/4K, JFT-300M and ALIGN data).
4. Further analysis of MRL's representations in the context of other downstream tasks (Section 4).

2 Matryoshka Representation Learning

For $d \in \mathbb{N}$, consider a set $\mathcal{M} \subset [d]$ of representation sizes. For a datapoint x in the input domain $\mathcal{X}$, our goal is to learn a d-dimensional representation vector $z \in \mathbb{R}^d$. For every $m \in \mathcal{M}$, Matryoshka Representation Learning (MRL) enables each of the first m dimensions of the embedding vector, $z_{1:m} \in \mathbb{R}^m$ to be independently capable of being a transferable and general purpose representation of the datapoint x. We obtain z using a deep neural network $F(\,\cdot\,;\theta_F)\colon \mathcal{X} \to \mathbb{R}^d$ parameterized by learnable weights θ_F, i.e., $z \coloneqq F(x;\theta_F)$. The multi-granularity is captured through the set of the chosen dimensions $\mathcal{M}$, that contains less than

$\log(d)$ elements, i.e., $|\mathcal{M}| \leq \lfloor \log(d) \rfloor$. The usual set $\mathcal{M}$ consists of consistent halving until the representation size hits a low information bottleneck. We discuss the design choices in Section 3 for each of the representation learning settings.

For the ease of exposition, we present the formulation for fully supervised representation learning via multi-class classification. Matryoshka Representation Learning modifies the typical setting to become a multi-scale representation learning problem on the same task. For example, we train ResNet50 [13] on ImageNet-1K [34] which embeds a 224×224 pixel image into a $d = 2048$ representation vector and then passed through a linear classifier to make a prediction, $\hat{y}$ among the $L = 1000$ labels. For MRL, we choose $\mathcal{M} = \{8, 16, \ldots, 1024, 2048\}$ as the nesting dimensions.

Suppose we are given a labelled dataset $\mathcal{D} = \{(x_1, y_1), \ldots, (x_N, y_N)\}$ where $x_i \in \mathcal{X}$ is an input point and $y_i \in [L]$ is the label of x_i for all $i \in [N]$. MRL optimizes the multi-class classification loss for each of the nested dimension $m \in \mathcal{M}$ using standard empirical risk minimization using a separate linear classifier, parameterized by $\mathbf{W}^{(m)} \in \mathbb{R}^{L \times m}$. All the losses are aggregated after scaling with their relative importance $(c_m \geq 0)_{m \in \mathcal{M}}$ respectively. That is, we solve

$$\min_{\left\{\mathbf{W}^{(m)}\right\}_{m \in \mathcal{M}},\ \theta_F} \frac{1}{N} \sum_{i \in [N]} \sum_{m \in \mathcal{M}} c_m \cdot \mathcal{L}\left(\mathbf{W}^{(m)} \cdot F(x_i; \theta_F)_{1:m}\ ;\ y_i\right)\ , \tag{1}$$

where $\mathcal{L}\colon \mathbb{R}^L \times [L] \to \mathbb{R}_+$ is the multi-class softmax cross-entropy loss function. This is a standard optimization problem that can be solved using sub-gradient descent methods. We set all the importance scales, $c_m = 1$ for all $m \in \mathcal{M}$; see Section 4 for ablations. Lastly, despite only optimizing for $O(\log(d))$ nested dimensions, MRL results in accurate representations, that interpolate, for dimensions that fall between the chosen granularity of the representations (Section 3.2).

We call this formulation as Matryoshka Representation Learning (MRL). A natural way to make this efficient is through weight-tying across all the linear classifiers, i.e., by defining $\mathbf{W}^{(m)} = \mathbf{W}_{1:m}$ for a set of common weights $\mathbf{W} \in \mathbb{R}^{L \times d}$. This would reduce the memory cost due to the linear classifiers by almost half, which would be crucial in cases of extremely large output spaces [43, 50]. This variant is called *Efficient* Matryoshka Representation Learning (MRL–E). Refer to Alg 1 and Alg 2 in Appendix A for the building blocks of Matryoshka Representation Learning (MRL).

Adaptation to Learning Frameworks. MRL can be adapted seamlessly to most representation learning frameworks at web-scale with minimal modifications (Section 3.1). For example, MRL's adaptation to masked language modelling reduces to MRL–E due to the weight-tying between the input embedding matrix and the linear classifier. For contrastive learning, both in context of vision & vision + language, MRL is applied to both the embeddings that are being contrasted with each other. The presence of normalization on the representation needs to be handled independently for each nesting dimension for the best results (see Appendix C for more details).

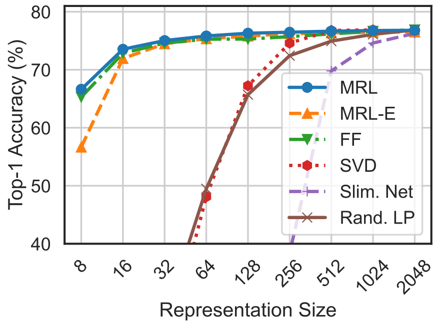

Fig. 2: ImageNet-1K linear classification accuracy of ResNet50 models. MRL is as accurate as the independently trained FF models for every representation size.

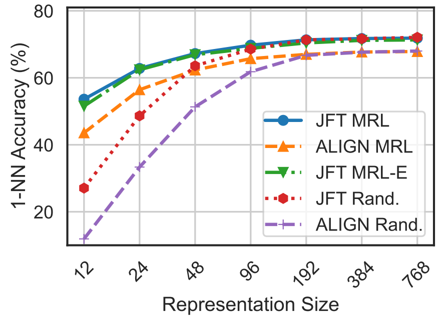

Fig. 3: ImageNet-1K 1-NN accuracy for ViT-B/16 models trained on JFT-300M & as part of ALIGN. MRL scales seamlessly to web-scale with minimal overhead.

3 Applications

In this section, we discuss Matryoshka Representation Learning (MRL) for a diverse set of applications along with an extensive evaluation of the learned multifidelity representations. Further, we showcase the downstream applications of the learned Matryoshka Representations for flexible large-scale deployment through (a) Adaptive Classification (AC) and (b) Adaptive Retrieval (AR).

3.1 Representation Learning

We adapt Matryoshka Representation Learning (MRL) to various representation learning setups (a) Supervised learning for vision: ResNet50 [13] on ImageNet-1K [34] and ViT-B/16 [10] on JFT-300M [41], (b) Contrastive learning for vision + language: ALIGN model with ViT-B/16 vision encoder and BERT language encoder on ALIGN data [19] and (c) Masked language modelling: BERT [9] on English Wikipedia and BooksCorpus [52]. Please refer to Appendices B and C for details regarding the model architectures, datasets and training specifics.

3.2 Classification

Figure 2 compares the linear classification accuracy of ResNet50 models trained and evaluated on ImageNet-1K. ResNet50–MRL model is at least as accurate as each FF model at every representation size in $\mathcal{M}$ while MRL–E is within 1% starting from 16-dim. We also evaluate the quality of the representations from training ViT-B/16 on JFT-300M alongside the ViT-B/16 vision encoder of the ALIGN model – two web-scale setups. Due to the expensive nature of these experiments, we only train the highest capacity fixed feature model and choose random features for evaluation in lower-dimensions. Web-scale is a compelling setting for MRL due to its relatively inexpensive training overhead while providing multifidelity representations for downstream tasks. Figure 3, evaluated with 1-NN on ImageNet-1K, shows that all the MRL models for JFT and ALIGN are highly accurate while providing an excellent cost-vs-accuracy trade-off at lower-dimensions. We also have similar observations when pretraining BERT; please see Appendix D.2 for more details.

Adaptive Classification The flexibility and coarse-to-fine granularity within Matryoshka Representations allows model cascades [44] for Adaptive Classification (AC) [11]. Unlike standard model cascades [48], MRL does not require multiple expensive neural network forward passes. To perform AC with an MRL trained model, we learn thresholds on the maximum softmax probability [16] for each nested classifier on a holdout validation set. We then use these thresholds to decide when to transition to the higher dimensional representation (e.g $8 \to 16 \to 32$) of the MRL model (see Appendix D.1). As seen in Figure 4, cascaded MRL model (MRL–AC) is as accurate, 76.30%, as a 512-dimensional FF model but requires an expected dimensionality of ~ 37 while being only 0.8% lower than the 2048-dimensional FF baseline, where the expected dimensionality is based on the final dimensionality used in the cascade. MRL–AC uses up to $\sim 14\times$ smaller representation size for the same accuracy which affords computational efficiency as the label space grows [43]. Lastly, our results with MRL–AC indicate that instances and classes vary in difficulty (See Section 4 and Appendix J).

3.3 Retrieval

Nearest neighbour search with learned representations powers a plethora of retrieval and search applications [7, 45, 5, 31]. In this section, we discuss the image retrieval performance of the pretrained ResNet50 models (Section 3.1) on two large-scale datasets ImageNet-1K [34] and ImageNet-4K (Appendix B).

The goal of image retrieval is to find images that belong to the same class as the query using representations obtained from a pretrained model. In this section, we compare retrieval performance using mean Average Precision @ 10 (mAP@10) which comprehensively captures the setup of relevant image retrieval at scale. We measure the cost per query using exact search in MFLOPs. All embeddings are unit normalized and retrieved using the L2 distance metric. Lastly, we report an extensive set of metrics spanning mAP@k and P@k for $k = \{10, 25, 50, 100\}$ and real-world wall-clock times for exact search and HNSW. See Appendices E and F for more details.

Figure 5 compares the mAP@10 performance of ResNet50 representations on ImageNet-1K across dimensionalities for MRL, MRL–E, FF, slimmable networks [51] along with post-hoc compression of vectors using SVD and random feature selection. Matryoshka Representations are often the most accurate while being up to 3% better than the FF baselines. Similar to classification, post-hoc compression and slimmable network baselines suffer from significant drop-off in retrieval mAP@10 with ≤ 256 dimensions. Appendix E discusses the mAP@10 of the same models on ImageNet-4K. MRL models are thus capable of performing

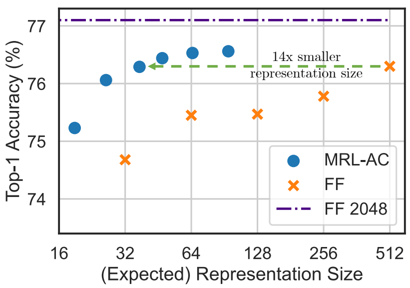

Fig. 4: Adaptive classification on MRL ResNet50 using cascades results in 14× smaller representation size for the same level of accuracy on ImageNet-1K (~ 37 vs 512 dims for 76.3%).

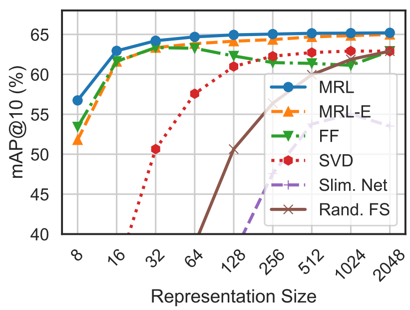

Fig. 5: mAP@10 for Image Retrieval on ImageNet-1K with ResNet50. MRL consistently produces better retrieval performance over the baselines across all the representation sizes.

accurate retrieval at various granularities without the additional expense of multiple model forward passes for the web-scale databases.

Adaptive Retrieval We benchmark MRL in the adaptive retrieval setting (AR) [22]. For a given query image, we obtain a shortlist, $K = 200$, of images from the database using a lower-dimensional representation, eg., $D_s = 16$ followed by reranking with a higher capacity representation, eg., $D_r = 2048$. In real-world scenarios where top ranking performance is the key objective, measured with mAP@k where k covers a limited yet crucial real-estate, AR provides significant compute and memory gains over single-shot retrieval with representations of fixed dimensionality. Finally, the most expensive part of AR, as with any retrieval pipeline, is the nearest neighbour search for shortlisting. For example even naive re-ranking of 200 images with 2048 dimensions only costs 400 KFLOPs. While we report exact search cost per query for all of the AR, the shortlisting component of the pipeline can be sped-up using ANNS (HNSW). Appendix I has a detailed discussion on compute cost for exact search, memory overhead of HNSW indices and wall-clock times for both implementations. We note that using HNSW with 32 neighbours for shortlisting does not decrease accuracy during retrieval. We provide a detailed discussion of Adaptive Retrieval in Appendix E.

4 Further Analysis and Ablations

Robustness. We evaluate the robustness of the MRL models trained on ImageNet-1K on out-of-domain datasets, ImageNetV2/R/A/Sketch [33, 15, 17, 47], and compare them to the FF baselines. Table 17 in Appendix H demonstrates that Matryoshka Representations for classification are at least as robust as the original representation while improving the performance on ImageNet-A by 0.6% – a 20%

relative improvement. We also study the robustness in the context of retrieval by using ImageNetV2 as the query set for ImageNet-1K database. Table 9 in Appendix E shows that MRL models have more robust retrieval compared to the FF baselines by having up to 3% higher mAP@10 performance. We also find that the zero-shot robustness of ALIGN-MRL (Table 18 in Appendix H) agrees with the observations made by Wortsman et al. [49].

Few-shot and Long-tail Learning. We exhaustively evaluate few-shot learning on MRL models using nearest class mean [35], which is detailed in Appendix G. We notably observe that MRL provides up to 2% accuracy higher on novel classes in the tail of the distribution, without sacrificing accuracy on other classes on the FLUID [46] framework.

Disagreement across Dimensions. The information packing in Matryoshka Representations often results in gradual increase of accuracy with increase in capacity. However, we observe that this trend is not ubiquitous and certain instances and classes are more accurate when evaluated with lower-dimensions, which is discussed in more detail in Appendix J).

4.1 Ablations

Table 26 in Appendix K presents that Matryoshka Representations can be enabled within off-the-shelf pretrained models with inexpensive partial finetuning thus paving a way for ubiquitous adoption of MRL. At the same time, Table 27 in Appendix C indicates that with optimal weighting of the nested losses we could improve accuracy of lower-dimensions representations without accuracy loss.

5 Discussion and Conclusions

The results in Section 4.1 reveal interesting weaknesses of MRL that would be logical directions for future work. (1) Optimizing the weightings of the nested losses to obtain a Pareto optimal accuracy-vs-efficiency trade-off. (2) Using different losses at various fidelities aimed at solving a specific aspect of adaptive deployment – e.g. high recall for 8-dimension and robustness for 2048-dimension. (3) Finally, learning a search data-structure, like differentiable k-d tree, on top of Matryoshka Representation to enable dataset and representation aware retrieval.

In conclusion, we presented Matryoshka Representation Learning (MRL), a flexible representation learning approach that encodes information at multiple granularities in a single embedding vector. This enables the MRL to adapt to a downstream task's statistical complexity as well as the available compute resources. We demonstrate that MRL can be used for large-scale adaptive classification as well as adaptive retrieval. On standard benchmarks, MRL matches the accuracy of the fixed-feature baseline despite using 14× smaller representation size on average. Finally, most of the efficiency techniques for model inference and vector search are complementary to MRL further assisting in deployment at the compute-extreme environments.

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A Code for Matryoshka Representation Learning

We use Alg 1 and 2 provided below to train supervised ResNet50–MRL models on ImageNet-1K. We provide this template to extend MRL to any domain.

Algorithm 1 Pytorch code for Matryoshka Cross-Entropy Loss

```
class Matryoshka_CE_Loss(nn.Module):
    def __init__(self, relative_importance, **kwargs):
        super(Matryoshka_CE_Loss, self).__init__()
        self.criterion = nn.CrossEntropyLoss(**kwargs)
        self.relative_importance = relative_importance # usually set to all ones

    def forward(self, output, target):
        loss=0
        for i in range(len(output)):
            loss+= self.relative_importance[i] * self.criterion(output[i], target)
        return loss
```

Algorithm 2 Pytorch code for MRL Linear Layer

```
class MRL_Linear_Layer(nn.Module):
    def __init__(self, nesting_list: List, num_classes=1000, efficient=False, **kwargs):
        super(MRL_Linear_Layer, self).__init__()
        self.nesting_list=nesting_list # set of m in M (Eq. 1)
        self.num_classes=num_classes
        self.is_efficient=efficient # flag for MRL-E

        if not is_efficient:
            for i, num_feat in enumerate(self.nesting_list):
                setattr(self, f"nesting_classifier_{i}", nn.Linear(num_feat, self.num_classes, **kwargs))
        else:
            setattr(self, "nesting_classifier_0", nn.Linear(self.nesting_list[-1], self.num_classes, **kwargs)) # Instantiating one nn.Linear layer for MRL-E

    def forward(self, x):
        nesting_logits = ()
        for i, num_feat in enumerate(self.nesting_list):
            if(self.is_efficient):
                efficient_logit = torch.matmul(x[:, :num_feat], (self.nesting_classifier_0.weight[:, :num_feat]).t())
            else:
                nesting_logits.append(getattr(self, f"nesting_classifier_{i}")(x[:, :num_feat]))

        if(self.is_efficient):
            nesting_logits.append(efficient_logit)

        return nesting_logits
```

B Datasets

ImageNet-1K [34] contains 1,281,167 labeled train images, and 50,000 labelled validation images across 1,000 classes. The images were transformed with standard procedures detailed by FFCV [25].

ImageNet-4K dataset was constructed by selecting 4,202 classes, non-overlapping with ImageNet-1K, from ImageNet-21K [8] with 1,050 or more examples. The train set contains 1,000 examples and the query/validation set contains 50 examples per class totalling to ∼4.2M and ∼200K respectively. We will release the list of images curated together to construct ImageNet-4K.

JFT-300M [41] is a large-scale multi-label dataset with 300M images labelled across 18,291 categories.

ALIGN [19] utilizes a large scale noisy image-text dataset containing 1.8B image-text pairs.

ImageNet Robustness Datasets We experimented on the following datasets to examine the robustness of MRL models:

ImageNetV2 [33] is a collection of 10K images sampled a decade after the original construction of ImageNet [8]. ImageNetV2 contains 10 examples each from the 1,000 classes of ImageNet-1K.

ImageNet-A [17] contains 7.5K real-world adversarially filtered images from 200 ImageNet-1K classes.

ImageNet-R [15] contains 30K artistic image renditions for 200 of the original ImageNet-1K classes.

ImageNet-Sketch [47] contains 50K sketches, evenly distributed over all 1,000 ImageNet-1K classes.

ObjectNet [2] contains 50K images across 313 object classes, each containing ∼160 images each.

C Matryoshka Representation Learning **Model Training**

We trained all ResNet50–MRL models using the efficient dataloaders of FFCV [25]. We utilized the `rn50_40_epochs.yaml` configuration file of FFCV to train all MRL models defined below:

- MRL: ResNet50 model with the fc layer replaced by `MRL_Linear_Layer(efficient=False)`
- MRL–E: ResNet50 model with the fc layer replaced by `MRL_Linear_Layer(efficient=True)`
- FF–k: ResNet50 model with the fc layer replaced by `torch.nn.Linear(k, num_classes)`, where k $\in [8, 16, 32, 64, 128, 256, 512, 1024, 2048]$. We will henceforth refer to these models as simply FF, with the k value denoting representation size.

We do not search for best hyper-parameters for all MRL experiments but use the same hyper-parameters as the independently trained baselines. ResNet50 outputs a 2048-dimensional representation while ViT-B/16 and BERT-Base output

768-dimensional embeddings for each data point. We use $\mathcal{M} = \{8, 16, 32, 64, 128, 256, 512, 1024, 2048\}$ and $\mathcal{M} = \{12, 24, 48, 96, 192, 384, 768\}$ as the explicitly optimized nested dimensions respectively.

We trained all ResNet50 models with a learning rate of 0.475 with a cyclic learning rate schedule [39]. This was after appropriate scaling ($0.25\times$) of the learning rate specified in the configuration file to accommodate for 2xA100 NVIDIA GPUs available for training, compared to the 8xA100 GPUs utilized in the FFCV benchmarks. We trained with a batch size of 256 per GPU, momentum [42] of 0.9, and an SGD optimizer with a weight decay of 1e-4.

Our code (Appendix A) makes minimal modifications to the training pipeline provided by FFCV to learn Matryoshka Representations.

We trained ViT-B/16 models for JFT-300M on a 8x8 cloud TPU pod [21] using Tensorflow [1] with a batchsize of 128 and trained for 300K steps. Similarly, ALIGN models were trained using Tensorflow on 8x8 cloud TPU pod for 1M steps with a batchsize of 64 per TPU. Both these models were trained with adafactor optimizer [37] with a linear learning rate decay starting at 1e-3.

Lastly, we trained a BERT-Base model on English Wikipedia and BookCorpus. We trained our models in Tensorflow using a 4x4 cloud TPU pod with a total batchsize of 1024. We used AdamW [29] optimizer with a linear learning rate decay starting at 1e-4 and trained for 450K steps.

In each configuration/case, if the final representation was normalized in the FF implementation, MRL models adopted the same for each nested dimension for a fair comparison.

D Classification Results

Table 1: Top-1 classification accuracy (%) for ResNet50 MRL and baseline models on ImageNet-1K.

Rep. Size	Rand. LP	SVD	FF	Slim. Net	MRL	MRL–E
8	4.56	2.34	65.29	0.42	**66.63**	56.66
16	11.29	7.17	72.85	0.96	**73.53**	71.94
32	27.21	20.46	74.60	2.27	**75.03**	74.48
64	49.47	48.10	75.27	5.59	**75.82**	75.35
128	65.70	67.24	75.29	14.15	**76.30**	75.80
256	72.43	74.59	75.71	38.42	**76.47**	76.22
512	74.94	**76.78**	76.18	69.80	76.65	76.36
1024	76.10	**76.87**	76.63	74.61	76.76	76.48
2048	76.87	–	**76.87**	76.26	76.80	76.51

We show the top-1 classification accuracy of ResNet50–MRL models on ImageNet-1K in Table 1 and Figure 2. We compare the performance of MRL models (MRL, MRL–E) to several baselines:

- FF: We utilize the FF-k models described in Appendix C for $k \in \{8, ...2048\}$.
- **SVD**: We performed a low rank approximation of the 1000-way classification layer of FF-2048, with rank = 1000.

- **Rand. LP**: We compared against a linear classifier fit on randomly selected features [12].
- **Slim. Net**: We take pretrained slimmable neural networks [51] which are trained with a flexible width backbone (25%, 50%, 75% and full width). For each representation size, we consider the first k dimensions for classification. Note that training of slimmable neural networks becomes unstable when trained below 25% width due to the hardness in optimization and low complexity of the model.

At lower dimensions ($d \leq 128$), MRL outperforms all baselines significantly, which indicates that pretrained models lack the multifidelity of Matryoshka Representations and are incapable of fitting an accurate linear classifier at low representation sizes.

We compared the performance of MRL models at various representation sizes via 1-nearest neighbors (1-NN) image classification accuracy on ImageNet-1K in Table 2. We provide detailed information regarding the k-NN search pipeline in Appendix E. We compared against a baseline of attempting to enforce nesting to a FF-2048 model by 1) Random Feature Selection (Rand. FS): considering the first m dimensions of FF-2048 for NN lookup, and 2) FF+SVD: performing SVD on the FF-2048 representations at the specified representation size. We also compared against the 1-NN accuracy of slimmable neural nets [51] as an additional baseline. We observed these baseline models to perform very poorly at lower dimensions, as they were not explicitly trained to learn Matryoshka Representations.

Table 2: 1-NN accuracy (%) on ImageNet-1K for various ResNet50 models.

Rep. Size	Rand. FS	SVD	FF	Slimmable	MRL	MRL–E
8	2.36	19.14	58.93	1.00	62.19	57.45
16	12.06	46.02	66.77	5.12	67.91	67.05
32	32.91	60.78	68.84	16.95	69.46	68.60
64	49.91	67.04	69.41	35.60	70.17	69.61
128	60.91	69.63	69.35	51.16	70.52	70.12
256	65.75	70.67	69.72	60.61	70.62	70.36
512	68.77	71.06	70.18	65.82	70.82	70.74
1024	70.41	71.22	70.34	67.19	70.89	71.07
2048	71.19	71.21	71.19	66.10	70.97	71.21

D.1 Adaptive Classification (MRL–AC)

In an attempt to use the smallest representation that works well for classification for every image in the ImageNet-1K validation set, we learned a policy to increase the representation size from m_i to m_{i+1} using a 10K sized subset of the ImageNet-1K validation set. This policy is based on whether the prediction confidence p_i using representation size m_i exceeds a learned threshold t_i^*. If $p_i \geq t_i^*$, we used predictions from representation size m_i otherwise, we increased to representation size m_{i+1}. To learn the optimal threshold t_i^*, we performed a grid search between 0 and 1 (100 samples). For each threshold t_k, we computed the classification

Table 3: Threshold-based adaptive classification performance of ResNet50 MRL on a 40K sized held-out subset of the ImageNet-1K validation set. Results are averaged over 30 random held-out subsets.

Expected Rep. Size	Accuracy
13.43 ± 0.81	73.79 ± 0.10
18.32 ± 1.36	75.25 ± 0.11
25.87 ± 2.41	76.05 ± 0.15
36.26 ± 4.78	76.28 ± 0.16
48.00 ± 8.24	76.43 ± 0.18
64.39 ± 12.55	76.53 ± 0.19
90.22 ± 20.88	76.55 ± 0.20
118.85 ± 33.37	76.56 ± 0.20

accuracy over our 10K image subset. We set t_i^* equal to the smallest threshold t_k that gave the best accuracy. We use this procedure to obtain thresholds for successive models, i.e., $\{t_j^* \mid j \in \{8, 16, 32, 64, \ldots, 2048\}\}$. To improve reliability of threshold based greedy policy, we use test time augmentation which has been used successfully in the past [38].

For inference, we used the remaining held-out 40K samples from the ImageNet-1K validation set. We began with smallest sized representation ($m = 8$) and compared the computed prediction confidence p_8 to learned optimal threshold t_8^*. If $p_8 \le t_8^*$, then we increased $m = 16$, and repeated this procedure until $m = d = 2048$. To compute the expected dimensions, we performed early stopping at $m = \{16, 32, 64, \ldots 2048\}$ and computed the expectation using the distribution of representation sizes. As shown in Table 3 and Figure 4, we observed that in expectation, we only needed a ~ 37 sized representation to achieve 76.3% classification accuracy on ImageNet-1K, which was roughly $14\times$ smaller than the FF–512 baseline. Even if we computed the expectation as a weighted average over the cumulative sum of representation sizes $\{8, 24, 56, \ldots\}$, due to the nature of multiple linear heads for MRL, we ended up with an expected size of 62 that still provided a roughly $8.2\times$ efficient representation than the FF–512 baseline. However, MRL–E alleviates this extra compute with a minimal drop in accuracy.

D.2 JFT, ALIGN and BERT

We examine the k-NN classification accuracy of learned Matryoshka Representations via ALIGN–MRL and JFT-ViT–MRL in Table 4. For ALIGN [19], we observed that learning Matryoshka Representations via ALIGN–MRL improved classification accuracy at nearly all dimensions when compared to ALIGN. We observed a similar trend when training ViT-B/16 [10] for JFT-300M [41] classification, where learning Matryoshka Representations via MRL and MRL–E on top of JFT-ViT improved classification accuracy for nearly all dimensions, and significantly for lower ones. This demonstrates that training to learn Matryoshka Representations is feasible and extendable even for extremely large scale datasets. We also demonstrate that Matryoshka Representations are learned at interpolated dimensions for both ALIGN and JFT-ViT, as shown in Table 5, despite not being trained explicitly at these dimensions. Lastly, Table 6 shows that MRL training leads to a increase in the cosine similarity span between positive and random image-text pairs.

Table 4: ViT-B/16 and ViT-B/16-MRL top-1 and top-5 k-NN accuracy (%) for ALIGN and JFT. Top-1 entries where MRL–E and MRL outperform baselines are bolded for both ALIGN and JFT-ViT.

Rep. Size	ALIGN		ALIGN-MRL		JFT-ViT		JFT-ViT-MRL		JFT-ViT-MRL–E	
	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
12	11.90	28.05	**43.57**	67.36	27.07	48.57	**53.61**	75.30	**51.54**	73.94
24	33.35	55.58	**56.44**	78.19	48.64	70.20	**62.80**	81.51	**62.40**	81.36
48	51.32	73.15	**62.33**	82.30	63.58	81.80	**67.24**	84.37	**66.89**	83.80
96	61.82	81.97	**65.72**	84.61	68.56	85.13	**69.74**	85.86	**68.80**	85.13
192	66.71	85.27	**67.00**	85.36	71.32	86.21	**71.34**	86.62	**70.41**	86.01
384	67.65	85.70	**67.70**	85.73	71.67	86.98	**71.73**	87.08	71.18	86.46
768	68.00	86.10	67.85	85.85	72.10	87.20	71.85	86.92	71.31	86.62

Table 5: Examining top-1 and top-5 k-NN accuracy (%) at interpolated hidden dimensions for ALIGN and JFT. This indicates that MRL is able to scale classification accuracy as hidden dimensions increase even at dimensions that were not explicitly considered during training.

Interpolated Rep. Size	ALIGN-MRL		JFT-ViT-MRL	
	Top-1	Top-5	Top-1	Top-5
16	49.06	72.26	58.35	78.55
32	58.64	79.96	64.98	82.89
64	63.90	83.39	68.19	84.85
128	66.63	85.00	70.35	86.24
256	67.10	85.30	71.57	86.77
512	67.64	85.72	71.55	86.67

Table 6: Cosine similarity between embeddings

Avg. Cosine Similarity	ALIGN	ALIGN-MRL
Positive Text to Image	0.27	0.49
Random Text to Image	8e-3	-4e-03
Random Image to Image	0.10	0.08
Random Text to Text	0.22	0.07

We also evaluated the capability of Matryoshka Representations to extend to other natural language processing via masked language modeling (MLM) with BERT [9], whose results are tabulated in Table 7. Without any hyper-parameter tuning, we observed Matryoshka Representations to be within 0.5% of FF representations for BERT MLM validation accuracy. This is a promising initial result that could help with large-scale adaptive document retrieval using BERT–MRL.

Table 7: Masked Language Modelling (MLM) accuracy(%) of FF and MRL models on the validation set.

Rep. Size	BERT-FF	BERT-MRL
12	60.12	59.92
24	62.49	62.05
48	63.85	63.40
96	64.32	64.15
192	64.70	64.58
384	65.03	64.81
768	65.54	65.00

E Image Retrieval

We evaluated the strength of Matryoshka Representations via image retrieval on ImageNet-1K (the training distribution), as well as on out-of-domain datasets ImageNetV2 and ImageNet-4K for all MRL ResNet50 models. We generated the database and query sets, containing N and Q samples respectively, with a standard PyTorch [32] forward pass on each dataset. We specify the representation size at which we retrieve a shortlist of k-nearest neighbors (k-NN) by D_s. The database is a thus a $[N,\ D_s]$ array, the query set is a $[Q,\ D_s]$ array, and the neighbors set is a $[Q,\ \mathrm{k}]$ array. For metrics, we utilized corrected mean average precision (mAP@k) [24] and precision (P@k): $P@k = \dfrac{correct\_pred}{k}$ where $correct\_pred$ is the average number of retrieved NN with the correct label over the entire query set using a shortlist of length k.

We performed retrieval with FAISS [20], a library for efficient similarity search. To obtain a shortlist of k-NN, we built an index to search the database. We performed an exhaustive NN search with the L2 distance metric with `faiss.IndexFlatL2`, as well as an approximate NN search (ANNS) via HNSW [20] with `faiss.IndexHNSWFlat`. We used HNSW with $M = 32$ unless otherwise mentioned, and henceforth referred to as HNSW32. The exact search index was moved to the GPU for fast k-NN search computation, whereas the HNSW index was kept on the CPU as it currently lacks GPU support. We show the wall clock times for building the index as well as the index size in Table 20. We observed exact search to have a smaller index size which was faster to build when compared to HNSW, which trades off a larger index footprint for fast NN search (discussed in more detail in Appendix K). The database and query vectors are normalized with `faiss.normalize_L2` before building the index and performing search.

Retrieval performance on ImageNet-1K, *i.e.* the training distribution, is shown in Table 8. MRL outperforms FF models for nearly all representation size for both top-1 and mAP@10, and especially at low representation size ($D_s \leq 32$). MRL–E loses out to FF significantly only at $D_s = 8$. This indicates that training ResNet50 models via the MRL training paradigm improves retrieval at low

Table 8: Retrieve a shortlist of 200-NN with D_s sized representations on ImageNet-1K via exact search with L2 distance metric. Top-1 and mAP@10 entries (%) where MRL–E and MRL outperform FF at their respective representation sizes are bolded.

Model	D_s	MFLOPS	Top-1	Top-5	Top-10	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
FF	8	10	58.93	75.76	80.25	53.42	52.29	51.84	51.57	59.32	59.28	59.25	59.21
	16	20	66.77	80.88	84.40	61.63	60.51	59.98	59.62	66.76	66.58	66.43	66.27
	32	41	68.84	82.58	86.14	63.35	62.08	61.36	60.76	68.43	68.13	67.83	67.48
	64	82	69.41	83.56	87.33	63.26	61.64	60.63	59.67	68.49	67.91	67.38	66.74
	128	164	69.35	84.23	88.24	62.30	60.16	58.73	57.29	67.84	66.83	65.96	64.92
	256	328	69.72	84.71	88.54	61.47	58.85	57.02	55.13	67.19	65.82	64.64	63.24
	512	656	70.18	85.04	88.91	61.37	58.41	56.26	53.98	67.12	65.49	64.07	62.35
	1024	1312	70.34	85.38	89.19	61.13	57.87	55.47	52.90	66.93	65.08	63.43	61.45
	2048	2624	71.19	85.66	89.17	62.90	60.06	57.99	55.76	68.46	66.90	65.52	63.83
MRL–E	8	10	57.45	57.68	57.50	51.80	50.41	49.6	48.86	57.50	57.16	56.81	56.36
	16	20	**67.05**	66.94	66.79	61.60	60.36	59.66	59.04	66.79	66.53	66.24	65.87
	32	41	68.60	68.74	68.49	63.34	61.97	61.14	60.39	68.49	68.06	67.65	67.17
	64	82	**69.61**	69.28	68.93	**63.84**	62.33	61.43	60.57	68.93	68.40	67.96	67.38
	128	164	**70.12**	69.60	69.19	**64.15**	62.58	61.61	60.70	69.19	68.62	68.11	67.50
	256	328	**70.36**	69.83	69.36	**64.35**	62.76	61.76	60.82	69.36	68.79	68.26	67.63
	512	656	**70.74**	70.09	69.63	**64.69**	63.05	62.06	61.14	69.63	69.00	68.50	67.88
	1024	1312	**71.07**	70.24	69.78	**64.85**	63.22	62.19	61.26	69.78	69.16	68.60	67.99
	2048	2624	**71.21**	70.41	69.90	**64.99**	63.33	62.29	61.33	69.90	69.24	68.68	68.05
MRL	8	10	**62.19**	77.05	81.34	**56.74**	55.47	54.76	54.12	62.06	61.81	61.54	61.17
	16	20	**67.91**	81.44	85.00	**62.94**	61.79	61.16	60.64	67.93	67.71	67.48	67.20
	32	41	**69.46**	83.01	86.30	**64.21**	62.96	62.22	61.58	69.18	68.87	68.54	68.17
	64	82	**70.17**	83.53	86.95	**64.69**	63.33	62.53	61.80	69.67	69.25	68.89	68.42
	128	164	**70.52**	83.98	87.25	**64.94**	63.50	62.63	61.83	69.93	69.44	69.02	68.50
	256	328	**70.62**	84.17	87.38	**65.04**	63.56	62.66	61.81	70.02	69.52	69.07	68.50
	512	656	**70.82**	84.31	87.55	**65.14**	63.57	62.62	61.73	70.12	69.53	69.04	68.45
	1024	1312	**70.89**	84.44	87.68	**65.16**	63.58	62.60	61.68	70.14	69.54	69.01	68.41
	2048	2624	70.97	84.41	87.74	**65.20**	63.57	62.56	61.60	70.18	69.52	68.98	68.35
MRL-Interpolated	12	15	65.89	80.04	83.68	60.84	59.66	58.98	58.37	65.94	65.72	65.45	65.08
	24	31	68.76	82.48	85.87	63.64	62.42	61.74	61.13	68.64	68.35	68.07	67.71
	48	61	69.96	83.40	86.65	64.58	63.20	62.42	61.72	69.53	69.10	68.75	68.32
	96	123	70.40	83.83	87.04	64.86	63.46	62.62	61.84	69.82	69.38	68.98	68.48
	192	246	70.64	84.09	87.37	65.00	63.53	62.66	61.83	69.98	69.49	69.05	68.50
	384	492	70.69	84.25	87.41	65.09	63.56	62.64	61.76	70.05	69.51	69.04	68.46
	768	984	70.84	84.40	87.63	65.16	63.59	62.62	61.71	70.14	69.55	69.03	68.44
	1536	1968	70.88	84.39	87.71	65.18	63.59	62.58	61.64	70.16	69.54	68.99	68.38

representation size over models explicitly trained at those representation size (FF-8...2048).

We carried out all retrieval experiments at $D_s \in \{8, 16, 32, 64, 128, 256, 512, 1024, 2048\}$ as these were the representation sizes which were a part of the `nesting_list` at which losses were added during training, as seen in Algorithm 1, Appendix A. To examine whether MRL is able to learn Matryoshka Representations at dimensions in between the representation size for which it was trained, we also tabulate the performance of MRL at interpolated $D_s \in \{12, 24, 48, 96, 192, 384, 768, 1536\}$ as MRL–Interpolated (see Table 8). We observed that performance scaled nearly monotonically between the original representation size and the interpolated representation size as we increase D_s, which demonstrates that MRL is able to learn Matryoshka Representations at nearly all representation size $m \in [8, 2048]$ despite optimizing only for $|\mathcal{M}|$ nested representation sizes.

Table 9: Retrieve a shortlist of 200-NN with D_s sized representations on ImageNetV2 via exact search with L2 distance metric. Top-1 and mAP@10 entries (%) where MRL–E outperforms FF are bolded. MRL outperforms FF at all D_s and is thus not bolded.

Config	D_s	MFLOPs	Top-1	Top-5	Top-10	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
	8	10	48.79	64.70	69.72	43.04	41.89	41.42	41.17	48.43	48.27	48.25	48.19
	16	20	55.08	69.50	74.08	49.63	48.53	48.06	47.75	54.76	54.64	54.53	54.39
	32	41	56.69	71.10	76.47	51.11	49.85	49.17	48.65	56.23	55.96	55.71	55.42
	64	82	57.37	72.71	77.48	51.28	49.75	48.85	47.99	56.65	56.14	55.71	55.15
FF	128	164	57.17	73.31	78.64	50.07	48.09	46.79	45.58	55.75	54.89	54.12	53.28
	256	328	57.09	74.04	79.24	49.11	46.66	44.99	43.35	55.02	53.77	52.74	51.53
	512	656	57.12	73.91	79.32	48.95	46.25	44.37	42.42	54.88	53.49	52.29	50.83
	1024	1312	57.53	74.17	79.55	48.27	45.41	43.36	41.26	54.31	52.84	51.49	49.87
	2048	2624	57.84	74.59	79.45	49.99	47.47	45.66	43.87	55.89	54.63	53.45	52.12
	8	10	47.05	62.53	67.60	40.79	39.47	38.78	38.16	46.03	45.77	45.54	45.17
	16	20	**55.73**	70.54	74.86	**49.86**	48.57	47.84	47.26	54.97	54.71	54.44	54.10
	32	41	**57.33**	71.61	76.64	**51.26**	49.92	49.09	48.42	56.46	56.11	55.70	55.30
	64	82	**57.90**	72.55	77.44	**51.89**	50.29	49.34	48.53	57.06	56.45	55.97	55.43
MRL–E	128	164	**57.73**	72.79	77.28	**52.02**	50.38	49.49	48.62	57.13	56.58	56.15	55.58
	256	328	**58.22**	72.77	77.67	**52.16**	50.61	49.67	48.81	57.30	56.79	56.33	55.77
	512	656	**58.46**	73.00	77.88	**52.52**	50.97	50.02	49.16	57.65	57.10	56.64	56.08
	1024	1312	**58.71**	73.29	78.00	**52.70**	51.13	50.17	49.30	57.83	57.26	56.77	56.20
	2048	2624	**58.86**	73.17	78.00	**52.88**	51.25	50.26	49.36	57.95	57.35	56.85	56.25
	8	10	**50.41**	65.56	70.27	**45.51**	44.38	43.71	43.17	50.55	50.44	50.17	49.91
	16	20	**56.64**	70.19	74.61	**50.98**	49.76	49.16	48.69	55.90	55.66	55.52	55.29
	32	41	**57.96**	71.88	76.41	**52.06**	50.78	50.09	49.54	57.18	56.83	56.57	56.27
	64	82	**58.94**	72.74	77.17	**52.65**	51.24	50.44	49.76	57.72	57.29	56.94	56.52
MRL	128	164	**59.13**	73.07	77.49	**52.94**	51.42	50.53	49.74	58.00	57.47	57.05	56.55
	256	328	**59.18**	73.64	77.75	**52.96**	51.45	50.52	49.70	58.01	57.53	57.06	56.54
	512	656	**59.40**	73.85	77.97	**53.01**	51.39	50.46	49.61	58.11	57.49	57.04	56.48
	1024	1312	**59.11**	73.77	77.92	**52.98**	51.37	50.40	49.54	58.13	57.51	57.00	56.45
	2048	2624	**59.63**	73.84	77.97	**52.96**	51.34	50.34	49.44	58.07	57.48	56.95	56.36

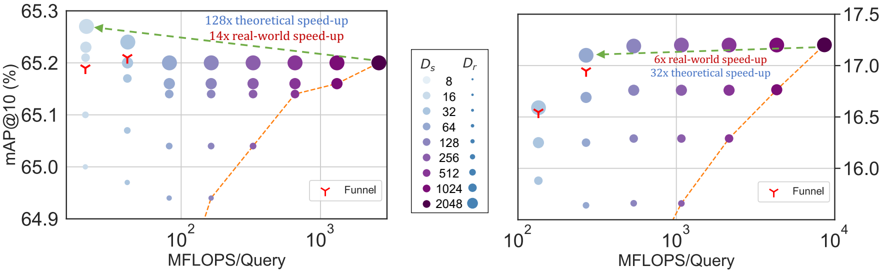
We examined the robustness of MRL for retrieval on out-of-domain datasets ImageNetV2 and ImageNet-4K, as shown in Table 9 and Table 10 respectively. On ImageNetV2, we observed that MRL outperformed FF at all D_s on top-1 Accuracy and mAP@10, and MRL–E outperformed FF at all D_s except $D_s = 8$. This demonstrates the robustness of the learned Matryoshka Representations for out-of-domain image retrieval.

F Adaptive Retrieval

The time complexity of retrieving a shortlist of k-NN often scales as $O(d)$, where $d = D_s$, for a fixed k and N. We thus will have a theoretical 256× higher cost for $D_s = 2048$ over $D_s = 8$. We discuss search complexity in more detail in Appendix I. In an attempt to replicate performance at higher D_s while using less FLOPs, we perform adaptive retrieval via retrieving a k-NN shortlist with representation size D_s, and then re-ranking the shortlist with representations of size D_r. Adaptive retrieval for a shortlist length $k = 200$ is shown in Table 11 for ImageNet-1K, and in Table 12 for ImageNet-4K. On ImageNet-1K, we are able to achieve comparable performance to retrieval with $D_s = 2048$ (from Table 8) with

Table 10: Retrieve a shortlist of 200-NN with D_s sized representations on ImageNet-4K via exact search with L2 distance metric. MRL–E and FF models are omitted for clarity and compute/inference time costs. All entries are in %.

Config	D_s	MFLOPs	Top-1	Top-5	Top-10	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
MRL	8	34	10.60	26.23	35.57	5.32	4.29	3.76	3.36	9.13	8.77	8.46	8.13
	16	67	16.74	36.91	47.28	8.64	6.83	5.84	5.05	13.82	12.79	12.04	13.27
	32	134	21.54	43.75	54.11	11.36	8.88	7.47	6.31	17.25	15.67	14.47	13.27
	64	269	25.00	47.97	58.25	13.38	10.40	8.67	7.23	19.68	17.64	16.14	14.65
	128	538	27.27	50.35	60.47	14.77	11.47	9.53	7.91	21.25	18.95	17.26	15.59
	256	1076	28.53	51.95	61.90	15.66	12.19	10.12	8.38	22.28	19.81	18.01	16.22
	512	2151	29.46	53.03	62.81	16.29	12.70	10.55	8.72	22.96	20.42	18.54	16.68
	1024	4303	30.23	53.72	63.45	16.76	13.08	10.86	8.97	23.48	20.88	18.93	17.00
	2048	8606	30.87	54.32	64.02	17.20	13.43	11.14	9.19	23.97	21.28	19.28	17.30
MRL-Interpolated	12	50	14.04	32.56	42.71	7.16	5.70	4.92	4.32	11.81	11.08	10.52	9.94
	24	101	19.49	40.82	51.26	10.17	7.98	6.75	5.75	15.76	14.43	13.42	12.40
	48	202	23.51	46.23	56.56	12.49	9.72	8.13	6.81	18.62	16.75	15.39	14.04
	96	403	26.25	49.32	59.48	14.15	11.00	9.15	7.61	20.55	18.36	16.78	15.17
	192	807	27.94	51.32	61.32	15.29	11.89	9.88	8.18	21.86	19.46	17.71	15.96
	384	1614	29.03	52.53	62.45	15.99	12.46	10.35	8.56	22.64	20.14	18.29	16.47
	768	3227	29.87	53.36	63.13	16.54	12.90	10.71	8.85	23.23	20.67	18.75	16.85
	1536	6454	30.52	54.02	63.79	16.99	13.27	11.01	9.08	23.73	21.09	19.12	17.16



(a) ImageNet-1K (b) ImageNet-4K

Fig. 6: The trade-off between mAP@10 vs MFLOPs/Query for Adaptive Retrieval (AR) on ImageNet-1K (left) and ImageNet-4K (right). Every combination of D_s & D_r falls above the Pareto line (orange dots) of single-shot retrieval with a fixed representation size while having configurations that are as accurate while being up to 14× faster in real-world deployment. Funnel retrieval is almost as accurate as the baseline while alleviating some of the parameter choices of Adaptive Retrieval.

$D_s = 16$ at 128× less MFLOPs/Query (used interchangeably with MFLOPs). Similarly, on ImageNet-4K, we are able to achieve comparable performance to retrieval with $D_s = 2048$ (from Table 10) with $D_s = 64$ on ImageNet-1K and ImageNet-4K, at 32× less MFLOPs. This demonstrates the value of intelligent routing techniques which utilize appropriately sized Matryoshka Representations for retrieval.

Figure 6 showcases the compute-vs-accuracy trade-off for adaptive retrieval using Matryoshka Representations compared to single-shot using fixed features with ResNet50 on ImageNet-1K. We observe that all AR settings lie above the Pareto frontier of the single-shot retrieval with varying representation sizes. In particular for ImageNet-1K, we show that the AR model with $D_s = 16$ & $D_r = 2048$ is as accurate as single-shot retrieval with $d = 2048$ while being $\sim \mathbf{128}\times$ more efficient in theory and $\sim \mathbf{14}\times$ faster in practice (compared using HNSW on the same hardware). We show similar trends with ImageNet-4K, but note that we require $D_s = 64$ given the increased difficulty of the dataset. This results in $\sim 32\times$ and $\sim 6\times$ theoretical and in practice speedups respectively. Lastly, while $K = 200$ works well for our adaptive retrieval experiments, we ablate over the shortlist size, k in Appendix K.2 to find that the accuracy gains stop after a point further strengthening the use-case for Matryoshka Representation Learning and adaptive retrieval.

Funnel Retrieval. We also designed a simple cascade policy which we call funnel retrieval to successively improve and thin out the k-NN shortlist at increasing D_s. This was an attempt to remove the dependence on manual choice of D_s &D_r. We retrieved a shortlist at $D_s$and then re-ranked the shortlist five times while simultaneously increasing D_r (rerank cascade) and decreasing the shortlist length (shortlist cascade), which resembles a funnel structure. We tabulate the performance of funnel retrieval in various configurations in Table 13 on ImageNet-1K, and in Table 14 on ImageNet-4K. With funnel retrieval on ImageNet-1K, we were able to achieve top-1 accuracy within 0.1% of retrieval with $D_s = 2048$ (as in Table 8) with a funnel with $D_s = 16$, with $128\times$ less MFLOPs. Similarly, we are able to achieve equivalent top-1 accuracy within 0.15% of retrieval at $D_s = 2048$ (as in Table 10) with funnel retrieval at $D_s = 32$ on ImageNet-4K, with $64\times$ less MFLOPs. This demonstrates that with funnel retrieval, Matryoshka Representation is as accurate as the single-shot 2048-dim retrieval while being $\sim 128\times$ more efficient theoretically. All these results showcase the potential of MRL and AR for large-scale multi-stage search systems [7].

Table 11: Retrieve a shortlist of k-NN with D_s sized representations on ImageNet-1K with MRL representations, and then re-order the neighbors shortlist with L2 distances using D_r sized representations. Top-1 and mAP@10 entries (%) that are within 0.1% of the maximum value achievable without reranking on MRL representations, as seen in Table 8, are bolded.

	D_s	D_r	MFLOPs	Top-1	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
Shortlist Length = 200	8	16	10	68.21	63.35	62.25	61.70	61.19	68.32	68.14	67.96	67.65
		32		69.42	64.12	62.81	62.03	61.32	69.04	68.63	68.22	67.71
		64		70.05	64.46	63.03	62.14	61.29	69.37	68.83	68.32	67.66
		128		70.34	64.68	63.16	62.21	61.27	69.59	68.96	68.38	67.65
		256		70.40	64.77	63.21	62.23	61.26	69.66	69.02	68.41	67.65
		512		70.60	64.86	63.22	62.21	61.22	69.74	69.02	68.39	67.62
		1024		70.71	64.88	63.23	62.20	61.20	69.76	69.01	68.39	67.60
		2048		70.81	64.90	63.22	62.17	61.16	69.77	68.99	68.36	67.57
	16	32	21	69.47	64.27	63.04	62.36	61.75	69.21	68.90	68.58	68.12
		64		70.16	64.74	63.42	62.66	61.94	69.66	69.22	68.81	68.22
		128		70.52	65.00	63.60	62.77	61.98	69.91	69.36	68.89	68.24
		256		70.55	**65.10**	63.67	62.82	62.01	69.98	69.43	68.92	68.25
		512		70.74	**65.21**	63.70	62.83	62.00	70.08	69.43	68.92	68.24
		1024		70.83	**65.23**	63.72	62.83	61.99	70.08	69.45	68.92	68.23
		2048		**70.90**	**65.27**	63.73	62.82	61.97	70.10	69.44	68.90	68.21
	32	64	41	70.16	64.69	63.35	62.57	61.93	69.68	69.26	68.92	68.51
		128		70.52	64.97	63.54	62.73	62.04	69.95	69.47	69.06	68.59
		256		70.63	65.07	63.63	62.79	62.07	70.04	69.55	69.12	68.61
		512		70.82	**65.17**	63.66	62.80	62.06	70.11	69.57	69.12	68.60
		1024		**70.89**	**65.20**	63.68	62.80	62.04	70.15	69.59	69.12	68.59
		2048		**70.97**	**65.24**	63.70	62.79	62.02	70.19	69.59	69.10	68.56
	64	128	82	70.51	64.94	63.50	62.64	61.88	69.94	69.44	69.02	68.54
		256		70.63	65.04	63.57	62.69	61.91	70.02	69.52	69.08	68.57
		512		70.83	**65.14**	63.59	62.67	61.87	70.12	69.54	69.06	68.54
		1024		**70.89**	**65.16**	63.59	62.65	61.85	70.15	69.54	69.05	68.52
		2048		**70.97**	**65.20**	63.59	62.63	61.82	70.18	69.53	69.03	68.49
	128	256	164	70.63	65.04	63.56	62.66	61.82	70.02	69.52	69.07	68.51
		512		70.82	**65.14**	63.58	62.63	61.77	70.11	69.54	69.04	68.47
		1024		**70.89**	**65.16**	63.58	62.60	61.73	70.14	69.54	69.02	68.45
		2048		**70.97**	**65.20**	63.57	62.57	61.68	70.18	69.52	68.99	68.41
	256	512	328	70.82	**65.14**	63.57	62.62	61.74	70.12	69.53	69.04	68.45
		1024		**70.88**	**65.16**	63.58	62.60	61.69	70.14	69.54	69.01	68.41
		2048		**70.97**	**65.20**	63.56	62.56	61.62	70.18	69.52	68.98	68.37
	512	1024	656	**70.90**	**65.16**	63.58	62.60	61.68	70.14	69.54	69.01	68.41
		2048		**70.98**	**65.20**	63.57	62.56	61.60	70.18	69.52	68.98	68.35
	1024	2048	1312	**70.97**	**65.20**	63.57	62.56	61.60	70.18	69.52	68.98	68.35

G Few-shot and Sample Efficiency

We compare MRL, MRL–E, and FF on various benchmarks to observe the effect of representation size on sample efficiency. We use Nearest Class Means [35] for classification which has been shown to be effective in the few-shot regime [6].

ImageNetV2. Representations are evaluated on ImageNetV2 with the n-shot k-way setup. ImageNetV2 is a dataset traditionally used to evaluate the robustness of models to natural distribution shifts. For our experiments we evaluate accuracy

Table 12: Retrieve a shortlist of k-NN with D_s sized representations on ImageNet-4K with MRL representations, and then re-order the neighbors shortlist with L2 distances using D_r sized representations. Top-1 and mAP@10 entries (%) that are within 0.1% of the maximum value achievable without reranking on MRL representations, as seen in Table 10, are bolded.

	D_s	D_r	MFLOPs	Top-1	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
Shortlist Length = 200	8	16	34	16.84	8.70	6.88	5.88	5.08	13.86	12.80	11.98	11.10
		32		20.73	10.66	8.19	6.77	5.61	16.18	14.39	13.02	11.61
		64		23.11	11.91	9.03	7.36	6.00	17.56	15.34	13.67	11.99
		128		24.63	12.71	9.59	7.76	6.25	18.42	15.94	14.08	12.22
		256		25.5	13.24	9.96	8.03	6.42	19.00	16.35	14.36	12.37
		512		26.07	13.59	10.21	8.20	6.53	19.37	16.62	14.54	12.46
		1024		26.52	13.85	10.40	8.34	6.61	19.65	16.80	14.68	12.53
		2048		26.94	14.11	10.57	8.45	6.68	19.92	16.98	14.79	12.58
	16	32	67	21.44	11.24	8.72	7.26	6.02	17.02	15.30	13.92	12.41
		64		24.36	12.78	9.75	7.96	6.43	18.72	16.41	14.63	12.74
		128		26.08	13.70	10.39	8.39	6.69	19.68	17.07	15.05	12.94
		256		26.99	14.27	10.79	8.67	6.85	20.27	17.48	15.31	13.07
		512		27.60	14.66	11.06	8.86	6.97	20.67	17.75	15.50	13.16
		1024		28.12	14.94	11.26	8.99	7.05	20.96	17.95	15.62	13.22
		2048		28.56	15.21	11.43	9.11	7.12	21.23	18.13	15.73	13.27
	32	64	134	24.99	13.35	10.35	8.59	7.09	19.61	17.52	15.92	14.21
		128		27.17	14.61	11.27	9.26	7.51	20.99	18.52	16.62	14.59
		256		28.33	15.37	11.83	9.67	7.77	21.80	19.12	17.05	14.81
		512		29.12	15.88	12.20	9.94	7.93	22.33	19.51	17.32	14.94
		1024		29.78	16.25	12.47	10.13	8.05	22.71	19.79	17.5	15.03
		2048		30.33	16.59	12.72	10.30	8.16	23.07	20.05	17.66	15.11
	64	128	269	27.27	14.76	11.47	9.51	7.85	21.25	18.92	17.20	15.40
		256		28.54	15.64	12.15	10.05	8.21	22.24	19.71	17.81	15.76
		512		29.45	16.25	12.62	10.40	8.44	22.88	20.24	18.20	15.97
		1024		30.19	16.69	12.96	10.66	8.60	23.35	20.61	18.46	16.10
		2048		**30.81**	**17.10**	13.27	10.88	8.74	23.79	20.93	18.69	16.21
	128	256	538	28.54	15.66	12.19	10.12	8.36	22.28	19.81	18.00	16.16
		512		29.45	16.29	12.69	10.53	8.66	22.96	20.41	18.50	16.48
		1024		30.22	16.76	13.07	10.83	8.86	23.47	20.84	18.83	16.68
		2048		**30.86**	**17.19**	13.41	11.09	9.03	23.95	21.22	19.12	16.84
	256	512	1076	29.45	16.29	12.70	10.55	8.71	22.97	20.42	18.54	16.66
		1024		30.21	16.76	13.08	10.86	8.95	23.48	20.87	18.92	16.94
		2048		**30.85**	**17.20**	13.43	11.14	9.15	23.97	21.27	19.26	17.16
	512	1024	2152	30.22	16.76	13.08	10.86	8.97	23.48	20.88	18.93	17.00
		2048		**30.87**	**17.20**	13.43	11.14	9.19	23.97	21.28	19.28	17.28
	1024	2048	4303	**30.87**	**17.20**	13.43	11.15	9.19	23.97	21.28	19.28	17.29

of the model given n examples from the ImageNetV2 distribution. We benchmark representations in the traditional small-scale (10-way) and large-scale (1000-way) setting. We evaluate for $n \in 1, 3, 5, 7, 9$ with 9 being the maximum value for n because there are 10 images per class.

We observe that MRL has equal performance to FF across all representation sizes and shot numbers. We also find that for both MRL and FF as the shot number decreases, the required representation size to reach optimal accuracy decreases (Table 15). For example, we observe that 1-shot performance at 32 representation size has equal accuracy to 2048 representation size.

Table 13: Retrieve a shortlist of k-NN with D_s sized representations on ImageNet-1K with MRL. This shortlist is then reranked with funnel retrieval, which uses a rerank cascade with a one-to-one mapping with a monotonically decreasing shortlist length as shown in the shortlist cascade. Top-1 and mAP@10 entries (%) within 0.1% of the maximum achievable without reranking on MRL representations, as seen in Table 8, are bolded.

D_s	Rerank Cascade	Shortlist Cascade	MFLOPs	Top-1	Top-5	Top-10	mAP@10	P@10
8	16→32→64→128→2048	200→100→50→25→10	10.28	70.22	82.63	85.49	64.06	68.65
		400→200→50→25→10	10.29	70.46	83.13	86.08	64.43	69.10
		800→400→200→50→10	10.31	70.58	83.54	86.53	64.62	69.37
16	32→64→128→256→2048	200→100→50→25→10	20.54	**70.90**	83.96	86.85	**65.19**	69.97
		400→200→50→25→10	20.56	**70.95**	84.05	87.04	**65.18**	70.00
		800→400→200→50→10	20.61	**70.96**	84.18	87.22	**65.14**	70.01
32	64→128→256→512→2048	200→100→50→25→10	41.07	**70.96**	84.32	87.47	**65.21**	70.11
		400→200→50→25→10	41.09	**70.97**	84.32	87.47	**65.19**	70.11
		800→400→200→50→10	41.20	**70.97**	84.36	87.53	**65.18**	70.11

FLUID. For the long-tailed setting we evaluate MRL on the FLUID benchmark [46] which contains a mixture of pretrain and new classes. Table 16 shows the evaluation of the learned representation on FLUID. We observe that MRL provides up to 2% higher accuracy on novel classes in the tail of the distribution, without sacrificing accuracy on other classes. Additionally we find the accuracy between low-dimensional and high-dimensional representations is marginal for pretrain classes. For example, the 64-dimensional MRL performs $\sim 1\%$ lower in accuracy compared to the 2048-dimensional counterpart on pretrain-head classes (84.46% vs 85.60%). However for novel-tail classes the gap is far larger (6.22% vs 12.88%). We hypothesize that the higher-dimensional representations are required to differentiate the classes when few training examples of each are known. This results provides further evidence that different tasks require varying capacity based on their difficulty.

H Robustness Experiments

We evaluate the robustness of MRL models on out-of-domain datasets (ImageNetV2/R/A/Sketch) and compare them to the FF baseline. Each of these datasets is described in Appendix B. The results in Table 17 demonstrate that learning Matryoshka Representations does not hurt out-of-domain generalization relative to FF models, and Matryoshka Representations in fact improve the performance on ImageNet-A. For a ALIGN–MRL model, we examine the the robustness via zero-shot retrieval on out-of-domain datasets, including ObjectNet, in Table 18.

Table 14: Retrieve a shortlist of k-NN with D_s sized representations on ImageNet-4K with MRL. This shortlist is then reranked with funnel retrieval, which uses a rerank cascade with a one-to-one mapping with a monotonically decreasing shortlist length as shown in the shortlist cascade. Top-1 and mAP@10 entries (%) within 0.15% of the maximum achievable without reranking on MRL representations, as seen in Table 10, are bolded.

D_s	Rerank Cascade	Shortlist Cascade	MFLOPs	Top-1	Top-5	Top-10	mAP@10	P@10
8	16→32→64→128→2048	200→100→50→25→10	33.65	26.20	46.45	54.12	12.79	17.85
		400→200→50→25→10	33.66	26.55	47.02	54.72	13.02	18.15
		800→400→200→50→10	33.68	26.83	47.54	55.35	13.24	18.44
16	32→64→128→256→2048	200→100→50→25→10	67.28	29.51	51.44	59.56	15.27	21.03
		400→200→50→25→10	67.29	29.66	51.71	59.88	15.42	21.22
		800→400→200→50→10	67.34	29.79	52.00	60.25	15.55	21.41
32	64→128→256→512→2048	200→100→50→25→10	134.54	30.64	53.52	62.16	16.45	22.64
		400→200→50→25→10	134.56	30.69	53.65	62.31	16.51	22.73
		800→400→200→50→10	134.66	**30.72**	53.78	62.43	16.55	22.79
64	128→256→512→1024→2048	200→100→50→25→10	269.05	**30.81**	54.06	63.15	16.87	23.34
		400→200→50→25→10	269.10	**30.84**	54.20	63.31	16.92	23.42
		800→400→200→50→10	269.31	**30.87**	54.27	63.42	16.95	23.46

I In Practice Costs

All approximate NN search experiments via HNSW32 were run on an Intel Xeon 2.20GHz CPU with 24 cores. All exact search experiments were run with CUDA 11.0 on 2xA100-SXM4 NVIDIA GPUs with 40G RAM each.

MRL *models.* As MRL makes minimal modifications to the ResNet50 model in the final fc layer via multiple heads for representations at various scales, it has only an 8MB storage overhead when compared to a standard ResNet50 model. MRL–E has no storage overhead as it has a shared head for logits at the final fc layer.

Retrieval Exact search has a search time complexity of $O(dkN)$, and HNSW has a search time complexity of $O(dk\log(N))$, where N is the database size, d is the representation size, and k is the shortlist length. To examine real-world performance, we tabulate wall clock search time for every query in the ImageNet-1K and ImageNet-4K validation sets over all representation sizes d in Table 19 for both Exact Search and HNSW32, and ablate wall clock query time over shortlist length k on the ImageNet-1K validation set in Table 21. The wall clock time to build the index and the index size is also shown in Table 20.

J Analysis of Model Disagreement

Class Trends Does increasing representation size necessarily help improve classification performance across all classes in ImageNet-1K? We studied this question

Table 15: Few-shot accuracy (%) on ImageNetV2 for 1000-way classification. MRL performs equally to FFacross all shots and representation sizes. We also observe that accuracy saturates at a lower dimension for lower shot numbers. Eg., for 1-shot, 32-dim performs comparably to 2048-dim.

Rep. Size	Method	1-Shot	3-Shot	5-Shot	7-Shot	9-Shot
8	FF	35.41	45.73	49.23	50.89	51.72
	MRL	35.37	45.69	49.25	50.85	51.73
16	FF	40.88	53.96	57.36	58.72	59.39
	MRL	40.90	53.94	57.37	58.65	59.29
32	FF	41.41	54.88	58.28	59.63	60.40
	MRL	41.40	54.91	58.30	59.65	60.45
64	FF	41.25	54.83	58.29	59.82	60.61
	MRL	41.28	54.80	58.32	59.77	60.69
128	FF	41.36	54.90	58.50	60.05	60.90
	MRL	41.38	54.95	58.50	60.06	60.83
256	FF	41.36	54.90	58.50	60.05	60.90
	MRL	41.38	54.95	58.50	60.06	60.83
512	FF	41.36	55.05	58.70	60.19	61.02
	MRL	41.34	55.14	58.78	60.40	61.18
1024	FF	41.32	55.20	58.85	60.46	61.38
	MRL	41.31	55.24	58.86	60.42	61.34
2048	FF	41.18	55.09	58.77	60.38	61.34
	MRL	41.16	55.10	58.77	60.40	61.28

by examining trends in performance with increasing representation size from $d = 8, ...2048$. For MRL models, we observed that 244 classes showed a monotonic improvement in performance with increasing d, 177 classes first improved but then observed a slight dip (one or two misclassifications per class), 49 classes showed a decline first and then an improvement, and the remaining classes did not show a clear trend. When we repeated this experiment with independently trained FF models, we noticed that 950 classes did not show a clear trend. This motivated us to leverage the disagreement as well as gradual improvement of accuracy at different representation sizes by training Matryoshka Representations. Figure 7 showcases the progression of relative per-class accuracy distribution compared to the Matryoshka Representation Learning-2048 dimensional model. This also showed that some instances and classes could benefit from lower-dimensional representations.

Discussion of Oracle Accuracy Based on our observed model disagreements for different representation sizes d, we defined an optimal *oracle* accuracy [27] for MRL. We labeled an image as correctly predicted if classification using any representation size was correct. The percentage of total samples of ImageNet-1K that were firstly correctly predicted using each representation size d is shown in Table 22. This defined an upper bound on the performance of MRL models, as 18.46% of the ImageNet-1K validation set were incorrectly predicted $\forall d \in \{8, 16, \ldots, 2048\}$. We show the oracle performance on MRL models for ImageNet-1K/V2/A/R/Sketch datasets in Table 23.

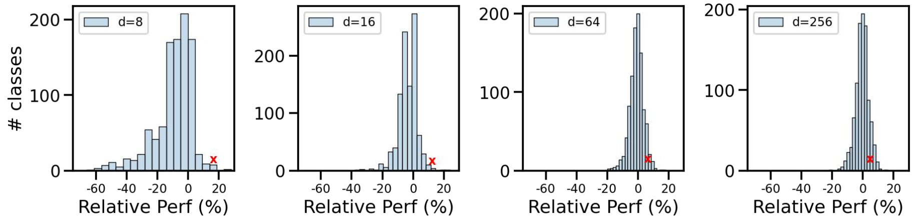


Fig. 7: Progression of relative per-class accuracy vs MRL-2048. As the dimensionality increases, the spread shrinks while the class marked (x) (Madagascar cat) loses accuracy.

In an attempt to derive an optimal routing policy to emulate oracle accuracy, we designed the adaptive classification via cascading method as discussed in Appendix D.1. This led to an interesting observation on the expected dimensionality for 76.30% top-1 classification accuracy being just $d \sim 37$. We leave the design and learning of a more optimal policy for future work.

Grad-CAM Examples We analyzed the nature of model disagreement across representation sizes with MRL models with the help of Grad-CAM visualization [36]. We observed there were certain classes in ImageNet-1K such as "tools", "vegetables" and "meat cutting knife" which are occasionally located around multiple objects and a cluttered environment. In such scenarios, we observed that smaller representation size models would often get confused due to other objects and fail to extract the object of interest which generated the correct label. We also observed a different nature of disagreement arising when the models got confused within the same superclass. For example, ImageNet-1K has multiple "snake" classes, and models often confuse a snake image for an incorrect species of snake.

Superclass Performance We created a 30 superclass subset of the validation set based on wordnet hierarchy (Table 24) to quantify the performance of MRL model on ImageNet-1K superclasses. These 30 superclasses contain 467 out of 1000 classes, with an additional class "reject", when an image does not belong to any sueprclass. Table 25 quantifies the performance with different representation size. We observed that there was a jump in performance from 8 to 16 sized representations because predictions using first 8 dimensions was confusing images from the superclass "vegetable" with the reject token. We show 8 of these 30 superclasses and plot their top-1 accuracy (%) improvement with rep. size in Figure 9.

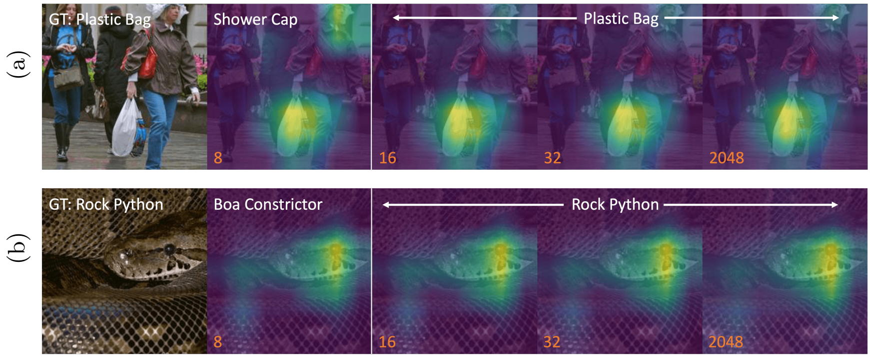


Fig. 8: Grad-CAM [36] progression of predictions in MRL model across $8, 16, 32, 2048$ dimensions. (a) 8-dimensional representation confuses due to presence of other relevant objects (with a larger field of view) in the scene and predicts "shower cap" & (b) 8-dim model confuses within the same super-class of "boa"; thus failing gracefully in both these scenarios.

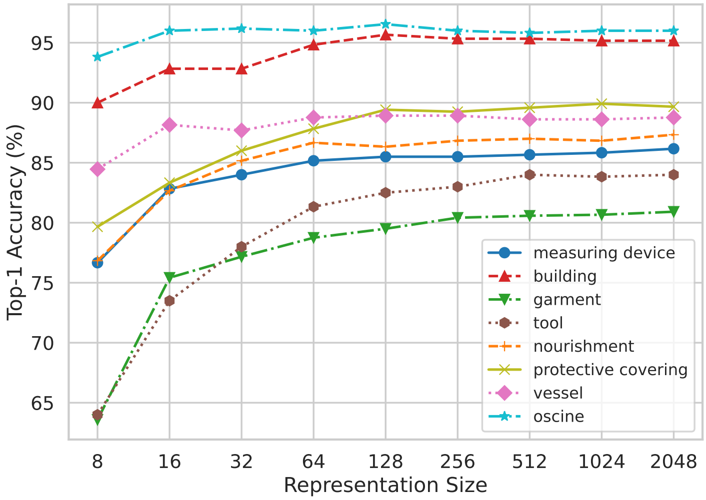


Fig. 9: Improvement of within-superclass classification with increasing representation size for several selected supervlasses. We observe that superclasses such as "oscine (songbird)" have a clear distinction between the object and background and thus predictions using representation size of 8 also lead to a good performance.

K Ablation Studies

K.1 MRL Training Paradigm

Nesting as Finetuning. To observe if nesting can be induced in models that were not explicitly trained with nesting from scratch, we loaded a pretrained FF-2048 ResNet50 model and initialized a new MRL layer, as defined in Algorithm 2, Appendix C. We then unfroze different layers of the backbone to observe how much non-linearity in the form of unfrozen conv layers needed to be present to enforce nesting into a pretrained FF model. A description of these layers can be found in the ResNet50 architecture [13]. All models were finetuned with the FFCV pipeline, with same training configuration as in the end-to-end training aside from changing lr $= 0.1$ and epochs $= 10$. We observed that finetuning the linear layer alone was insufficient to learn Matryoshka Representations at lower dimensionalities. Adding more and more non-linear conv+ReLU layers steadily improved classification accuracy of $d = 8$ from 5% to 60% after finetuning, which was only 6% less than training MRL end-to-end for 40 epochs. This difference was successively less pronounced as we increased dimensionality past $d = 64$, to within 1.5% for all larger dimensionalities. The full results of this ablation can be seen in Table 26.

Relative Importance. We performed an ablation of MRL over the relative importance, c_m, of different nesting dimensions $m \in \mathcal{M}$, as defined in Sec. 2. In an attempt to improve performance at lower dimensionalities, we boosted the relative importance c_m of training loss at lower dimensions as in Eq. 1 with two models, MRL-8boost and MRL-8+16boost. The MRL-8boost model had $c_{m\in\mathcal{M}} = [2, 1, 1, 1, 1, 1, 1, 1, 1]$ and the MRL-8+16boost model had $c_{m\in\mathcal{M}} = [2, 1.5, 1, 1, 1, 1, 1, 1, 1]$. The relative importance list $c_{m\in\mathcal{M}}$ had a 1-to-1 correspondence with nesting dimension set $\mathcal{M}$. In Table 27, we observed that MRL-8boost improves top-1 accuracy by 3% at $d = 8$, and also improves top-1 of all representation scales from 16 to 256 over MRL, while only hurting the performance at 512 to 2048 representation scales by a maximum of 0.1%. This suggests that the relative importance c_m can be tuned/set for optimal accuracy for all $m \in \mathcal{M}$, but we leave this extension for future work.

K.2 Retrieval

Adaptive Retrieval. To examine the effect of increasing shortlist lengths on search time, a reranking ablation over shortlist lengths is also performed for $D_s = 16$ and $D_r = 2048$ over ImageNet-1K in Table 28, and over ImageNet-4K in Table 29. We observed that using a larger shortlist k saturated ImageNet-1K performance at k=200. But using larger shortlists until $k = 2048$, the maximum value supported by the FAISS framework, steadily improved performance on ImageNet-4K. This is likely due to the increased database size, but could also indicate a correlation with ImageNet-4K being slightly out-of-distribution making the task at hand harder.

Table 16: Accuracy (%) categories indicates whether classes were present during ImageNet pretraining and head/tail indicates classes that have greater/less than 50 examples in the streaming test set. We observe that MRL performs better than the baseline on novel tail classes by $\sim 2\%$ on average.

Rep. Size	Method	Pretrain - Head (>50)	Novel - Head (>50)	Pretrain - Tail (<50)	Novel - Tail (<50)	Mean Per Class Acc.	Acc.
8	FF	68.04	**11.30**	33.18	**0.36**	16.29	28.47
	MRL	**71.75**	10.70	**38.29**	0.19	**17.15**	**29.34**
	MRL–E	57.40	6.25	23.14	0.04	11.78	22.81
16	FF	80.74	**19.12**	**63.29**	**2.78**	**25.65**	**37.61**
	MRL	**81.79**	17.90	61.39	1.95	24.73	37.59
	MRL–E	79.08	9.15	60.33	0.08	20.45	30.24
32	FF	**83.67**	**24.30**	**66.66**	**4.23**	**28.86**	**42.40**
	MRL	83.46	23.26	65.82	3.75	28.16	41.90
	MRL–E	81.42	10.47	68.01	0.23	22.31	32.17
64	FF	84.12	27.49	68.20	5.17	30.64	45.18
	MRL	**84.46**	**27.61**	67.59	**6.22**	**31.03**	**45.35**
	MRL–E	82.57	13.23	**70.18**	0.52	23.83	34.74
128	FF	84.87	29.96	**68.79**	5.54	31.84	47.06
	MRL	**84.88**	**30.86**	68.58	**8.41**	**33.23**	**47.79**
	MRL–E	82.76	18.93	64.46	2.22	25.75	39.19
256	FF	84.77	32.78	**69.96**	7.21	33.65	49.15
	MRL	**85.10**	**32.91**	69.39	**9.99**	**34.74**	**49.39**
	MRL–E	82.96	22.63	64.55	3.59	27.64	41.96
512	FF	**85.62**	**35.27**	**70.27**	9.05	35.42	**51.14**
	MRL	**85.62**	34.67	70.24	**11.43**	**36.11**	50.79
	MRL–E	82.86	25.62	64.34	4.99	29.22	44.20
1024	FF	**86.30**	37.49	**71.12**	10.92	**37.14**	**52.88**
	MRL	85.64	**35.88**	70.02	**12.19**	36.80	51.58
	MRL–E	83.03	27.78	64.58	6.32	30.57	45.71
2048	FF	**86.40**	**37.09**	**71.74**	10.77	37.04	**52.67**
	MRL	85.60	36.83	70.34	**12.88**	**37.46**	52.18
	MRL–E	83.01	29.99	65.37	7.60	31.97	47.16

Table 17: Top-1 classification accuracy (%) on out-of-domain datasets (ImageNet-V2/R/A/Sketch) to examine robustness of Matryoshka Representation Learning. Note that these results are without any fine tuning on these datasets.

	ImageNet-V1			ImageNet-V2			ImageNet-R			ImageNet-A			ImageNet-Sketch		
Rep. Size	FF	MRL–E	MRL	FF	MRL–E	MRL	FF	MRL–E	MRL	FF	MRL–E	MRL	FF	MRL–E	MRL
8	65.86	56.92	67.46	54.05	47.40	55.59	24.60	22.98	23.57	2.92	3.63	3.39	17.73	15.07	17.98
16	73.10	72.38	73.80	60.52	60.48	61.71	28.51	28.45	28.85	3.00	3.55	3.59	21.70	20.38	21.77
32	74.68	74.80	75.26	62.24	62.23	63.05	31.28	30.79	31.47	2.60	3.65	3.57	22.03	21.87	22.48
64	75.45	75.48	76.17	63.51	63.15	63.99	32.96	32.13	33.39	2.87	3.99	3.76	22.13	22.56	23.43
128	75.47	76.05	76.46	63.67	63.52	64.69	33.93	33.48	34.54	2.81	3.71	3.73	22.73	22.73	23.70
256	75.78	76.31	76.66	64.13	63.80	64.71	34.80	33.91	34.85	2.77	3.65	3.60	22.63	22.88	23.59
512	76.30	76.48	76.82	64.11	64.09	64.78	35.53	34.20	34.97	2.37	3.57	3.59	23.41	22.89	23.67
1024	76.74	76.60	76.93	64.43	64.20	64.95	36.06	34.22	34.99	2.53	3.56	3.68	23.44	22.98	23.72
2048	77.10	76.65	76.95	64.69	64.17	64.93	37.10	34.29	35.07	2.93	3.49	3.59	24.05	23.01	23.70

Table 18: Zero-shot top-1 image classification accuracy (%) of a ALIGN-MRL model on ImageNet-V1/V2/R/A and ObjectNet.

Rep. Size	V1	V2	A	R	ObjectNet
12	30.57	23.98	14.59	24.24	25.52
24	45.64	37.71	22.75	46.40	35.89
48	53.84	46.16	28.88	60.71	42.76
96	58.31	51.34	33.21	70.12	45.20
192	60.95	53.56	36.10	74.41	48.24
384	62.06	54.77	37.95	76.51	49.10
768	62.26	55.15	37.84	76.73	49.26
Baseline	66.39	59.57	39.97	80.49	51.60

Table 19: Retrieval k-NN wall clock search times (s) over the entire validation (query) set of ImageNet-1K and ImageNet-4K, containing 50K and 200K samples respectively.

Rep. Size	ImageNet-1K		ImageNet-4K	
	ExactL2	HNSW32	ExactL2	HNSW32
8	0.60	0.14	35.70	1.17
16	0.57	0.18	36.16	1.65
32	0.60	0.20	36.77	1.75
64	0.66	0.24	27.88	2.21
128	0.86	0.32	30.10	4.15
256	1.29	0.46	34.97	3.39
512	2.17	0.68	46.97	4.83
1024	3.89	1.05	70.59	7.14
2048	7.31	2.05	117.78	13.43

Table 20: FAISS [20] index size and build times for exact k-NN search with L2 Distance metric and approximate k-NN search with HNSW32 [30].

Rep. Size	Exact Search				HNSW32			
	ImageNet-1K		ImageNet-4K		ImageNet-1K		ImageNet-4K	
	Index Size (MB)	Index Build Time (s)	Index Size (MB)	Index Build Time (s)	Index Size (MB)	Index Build Time (s)	Index Size (MB)	Index Build Time (s)
8	40	0.04	131	0.33	381	4.87	1248	24.04
16	80	0.08	263	0.27	421	6.15	1379	33.31
32	160	0.16	525	0.52	501	6.80	1642	37.41
64	320	0.38	1051	1.05	661	8.31	2167	47.23
128	641	0.64	2101	2.10	981	11.73	3218	89.87
256	1281	1.27	4202	4.20	1622	17.70	5319	102.84
512	2562	2.52	8404	8.39	2903	27.95	9521	158.47
1024	5125	5.10	16808	17.20	5465	44.02	17925	236.30
2048	10249	10.36	33616	41.05	10590	86.15	34733	468.18

Table 21: Retrieval k-NN wall clock search times (s) over entire validation (query) set of ImageNet-1K over various shortlist lengths k.

Index	k = 50	k = 100	k = 200	k = 500	k = 1000	k = 2048
Exact L2	0.4406	0.4605	0.5736	0.6060	1.2781	2.7047
HNSW32	0.1193	0.1455	0.1833	0.2145	0.2333	0.2670

Table 22: Percentage of ImageNet-1K validation set that is first correctly predicted using each representation size d. We note that 18.46% of the samples cannot be correctly predicted by any representation size. The remaining 81.54% constitutes the oracle accuracy.

Rep. Size	8	16	32	64	128	256	512	1024	2048	Always Wrong
Correctly Predicted	67.46	8.78	2.58	1.35	0.64	0.31	0.20	0.12	0.06	18.46

Table 23: Oracle classification accuracy of various evaluation datasets for ResNet50–MRL model trained on ImageNet-1K.

Top-1	ImageNetV1	ImageNetV2	ImageNet-A	ImageNet-R	ImageNet-Sketch
FF–2048	76.9	64.9	3.6	35.1	23.7
MRL–Oracle	81.5	70.6	8.7	39.8	28.9

Table 24: 30 Superclasses in ImageNet-1K corresponding to the performance in Table 25.

insect	motor vehicle	artiodactyl	vegetable	game equipment
terrier	serpent	machine	measuring device	sheepdog
protective covering	sporting dog	vessel, watercraft	building	lizard
garment	hound	monkey	home appliance	wind instrument
vessel	fish	nourishment	electronic equipment	oscine
furniture	wading bird	tool	canine	mechanism

Table 25: Performance of MRL model on 31-way classification (1 extra class is for reject token) on ImageNet-1K superclasses.

Rep. Size	8	16	32	64	128	256	512	1024	2048
MRL	85.57	88.67	89.48	89.82	89.97	90.11	90.18	90.22	90.21

Table 26: Top-1 classification accuracy (%) on ImageNet-1K of various ResNet50 models which are finetuned on pretrained FF-2048 model. We observed that adding more and more non-linearities is able to induce nesting to a reasonable extent even if the model was not pretrained with nesting in mind.

Rep. Size	fc	4.2 conv3, fc	4.2 conv2, conv3, fc	4.2 full, fc	All (MRL)
8	5.15	36.11	54.78	60.02	66.63
16	13.79	58.42	67.26	70.10	73.53
32	32.52	67.81	71.62	72.84	75.03
64	52.66	72.42	73.61	74.29	75.82
128	64.60	74.41	74.67	75.03	76.30
256	69.29	75.30	75.23	75.38	76.47
512	70.51	75.96	75.47	75.64	76.65
1024	70.19	76.18	75.70	75.75	76.76
2048	69.72	76.44	75.96	75.97	76.80

Table 27: An ablation over boosting training loss at lower nesting dimensions, with top-1 and top-5 accuracy (%). The models are described in Appendix K.1.

Model	MRL		MRL-8boost		MRL-8+16boost	
Rep. Size	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
8	66.63	84.66	**69.53**	86.19	69.24	85.96
16	73.53	89.52	73.86	89.44	**73.91**	89.55
32	75.03	91.31	**75.28**	91.21	75.10	91.14
64	75.82	92.27	**75.84**	92.22	75.67	92.06
128	**76.30**	92.82	76.28	92.74	76.07	92.52
256	76.47	93.02	**76.48**	92.97	76.22	92.72
512	**76.65**	93.13	76.56	93.09	76.35	92.85
1024	**76.76**	93.22	76.71	93.21	76.39	92.98
2048	**76.80**	93.32	76.76	93.28	76.52	93.05

Table 28: Adaptive retrieval ablation over shortlist length k for $D_s = 16$, $D_r = 2048$ on ImageNet-1K with exact search. Entries with the highest P@1 and mAP@10 across all k are in bold.

Shortlist Length	P@1	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
100	70.88	65.19	63.62	62.59	61.24	69.96	69.24	68.53	67.20
200	70.90	**65.27**	63.73	62.82	61.97	70.10	69.44	68.90	68.21
400	70.94	65.26	63.71	62.81	62.03	70.15	69.51	69.02	68.47
800	70.96	65.23	63.64	62.69	61.85	70.16	69.52	69.02	68.45
1600	70.96	65.20	63.58	62.58	61.66	70.16	69.5	68.97	68.36
2048	**70.97**	65.20	63.57	62.58	61.64	70.16	69.5	68.97	68.35

Table 29: Adaptive retrieval ablation over shortlist length k for $D_s = 16$, $D_r = 2048$ on ImageNet-4K with exact search.

Shortlist Length	P@1	mAP@10	mAP@25	mAP@50	mAP@100	P@10	P@25	P@50	P@100
100	27.70	14.38	10.62	8.26	6.07	20.12	16.87	14.29	11.26
200	28.56	15.21	11.43	9.11	7.12	21.23	18.13	15.73	13.27
400	29.34	15.83	12.06	9.76	7.79	22.08	19.09	16.83	14.54
800	29.86	16.30	12.53	10.23	8.26	22.72	19.83	17.65	15.45
1600	30.24	16.63	12.86	10.56	8.60	23.18	20.36	18.23	16.11
2048	**30.35**	**16.73**	12.96	10.65	8.69	23.31	20.50	18.40	16.30