METACOCO: A NEW FEW-SHOT CLASSIFICATION BENCHMARK WITH SPURIOUS CORRELATION

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ABSTRACT

Out-of-distribution (OOD) problems in few-shot classification (FSC) occur when novel classes sampled from testing distributions differ from base classes drawn from training distributions, which considerably degrades the performance of deep learning models deployed in real-world applications. Recent studies suggest that the OOD problems in FSC mainly including: (a) cross-domain few-shot classification (CD-FSC) and (b) spurious-correlation few-shot classification (SC-FSC). Specifically, CD-FSC occurs when a classifier learns transferring knowledge from base classes drawn from seen training distributions but recognizes novel classes sampled from unseen testing distributions. In contrast, SC-FSC arises when a classifier relies on non-causal features (or contexts) that happen to be correlated with the labels (or concepts) in base classes but such relationships no longer hold during the model deployment. Despite CD-FSC has been extensively studied, SC-FSC remains understudied due to lack of the corresponding evaluation benchmarks. To this end, we present **Meta Co**ncept **Co**ntext (MetaCoCo), a benchmark with spurious-correlation shifts collected from real-world scenarios. Moreover, to quantify the extent of spurious-correlation shifts of the presented MetaCoCo, we further propose a metric by using CLIP as a pre-trained vision-language model. Extensive experiments on the proposed benchmark are performed to evaluate the state-of-the-art methods in FSC, cross-domain shifts, and self-supervised learning. The experimental results show that the performance of the existing methods degrades significantly in the presence of spurious-correlation shifts. We open-source all codes of our benchmark and hope that the proposed MetaCoCo can facilitate future research on spurious-correlation shifts problems in FSC. The code is available at: https://github.com/remiMZ/MetaCoCo-ICLR24.

1 INTRODUCTION

Few-shot classification (FSC) aims to recognize unlabeled images (or query sets) from novel classes with only a few labeled images (or support sets) by transferring knowledge learned from base classes. Despite the impressive advances in the FSC, in real-world applications, out-of-distribution (OOD) problems in FSC occur when the novel classes sampled from testing distributions differ from the base classes drawn from training distributions, which significantly degrades the performance and robustness of deep learning models, and has gained increasing attention in recent years (Song et al., 2022; Li et al., 2023). As shown in Figure 1, the OOD problems in FSC can be broadly categorized into two categories with different forms of distribution shifts: (a) cross-domain few-shot classification (CD-FSC) and (b) spurious-correlation few-shot classification (SC-FSC), as established by previous works (Triantafillou et al., 2019; Yue et al., 2020; Luo et al., 2021; Li et al., 2022).

Cross-domain few-shot classification (CD-FSC). Cross-domain shifts occur when a classifier learns transferring knowledge from base classes drawn from seen training distributions but recognizes novel classes sampled from unseen testing distributions. For example, in COVID-19 predictions, we may want to train a model on patients from a few sampled countries and then deploy the trained model to a broader set of countries. Existing OOD methods in FSC have shown considerable progress in solving the cross-domain shifts problem (Hou et al., 2019; Doersch et al.,

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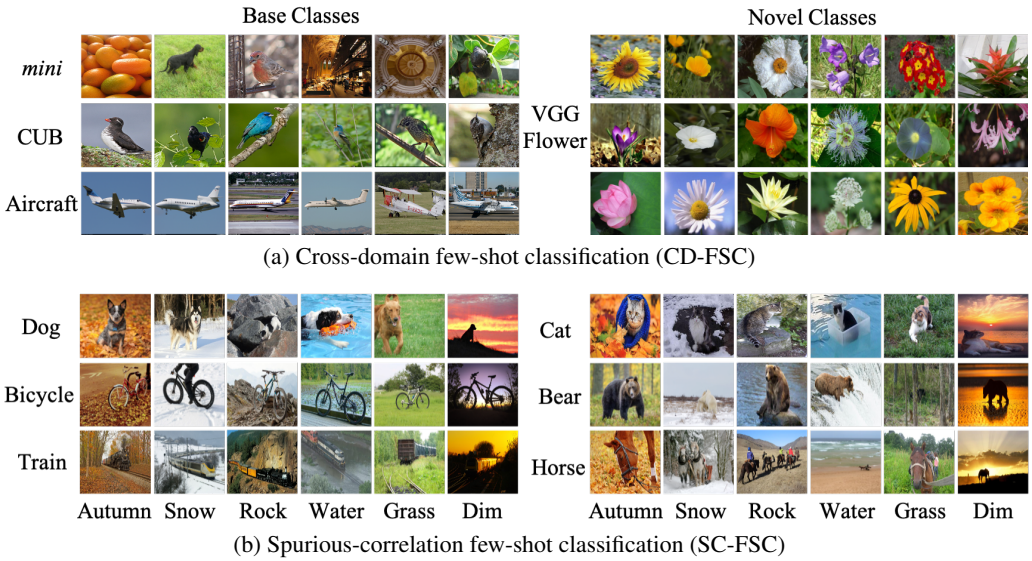


(a) Cross-domain few-shot classification (CD-FSC)

(b) Spurious-correlation few-shot classification (SC-FSC)

Figure 1: Example of cross-domain shifts and spurious-correlation shifts in FSC. (a) In Meta-dataset with cross-domain shifts (Triantafillou et al., 2019), the model is trained on base classes sampled from three datasets including *mini*ImageNet, CUB-200-2011 and Aircraft, then tested on novel classes drawn from VGG Flower. (b) In our proposed MetaCoCo with spurious-correlation shifts, each class (or concept, *e.g.*, dog) consists of different backgrounds (or context, *e.g.*, autumn).

2020; Guo et al., 2020; Wang & Deng, 2021; Sun et al., 2021; Liang et al., 2021; Wang & Deng, 2021; Li et al., 2022; Oh et al., 2022; Zhang et al., 2020; 2022b). Meanwhile, two standard cross-domain benchmarks have been proposed to evaluate the effectiveness of these methods, *i.e.*, Meta-dataset (Triantafillou et al., 2019) consisting of 10 existing datasets, and BSCD-FSL (Guo et al., 2020) consisting of 4 existing datasets. Figure 1(a) shows the example of cross-domain shifts on Meta-dataset, where *mini* (*mini*ImageNet), CUB (CUB-200-2011) and Aircraft are used as the base classes with VGG Flower as the novel classes, with each dataset exhibits a distinct distribution.

Spurious-correlation few-shot classification (SC-FSC). Spurious-correlation shifts arise when a classifier relies on spurious, non-causal context features that are not essential to the true label or concept, which can significantly reduce the robustness and generalization ability of the model. In the COVID-19 example, a recent nationwide cross-sectional study found spurious correlations between long-term $PM_{2.5}$ exposure and COVID-19 deaths in the United States due to county-level socioeconomic and demographic variables as confounders (Wu et al., 2020). To this end, models trained on base classes with spurious features and evaluated on novel classes without the relationship suffer substantial drops in performance. As shown in Figure 1(b), we show the example of spurious-correlation shifts in our proposed benchmark, where each class presents a range of non-causal contexts, such as autumn or snow. Meanwhile, the concepts of the base classes and the novel classes would be distinct in the FSC problem, *e.g.*, "dog in the autumn" in the base class and "cat in the autumn" in the novel class, which emphasizes the impact of spurious correlation between concepts and contexts in the proposed benchmark. Despite the widespread of spurious-correlation shifts in the real-world FSC problems (Yue et al., 2020; Luo et al., 2021; Wang et al., 2017a; Zhang et al., 2023b), SC-FSC remains understudied due to lack of the corresponding evaluation benchmarks.

Shortcomings of spurious-correlation shifts benchmarks in traditional machine learning. Recently, spurious-correlation shifts in traditional machine learning (TML) have been investigated extensively (Arjovsky et al., 2019; Sagawa et al., 2019; Rosenfeld et al., 2020; Ahmed et al., 2020; Bae et al., 2021; Shen et al., 2021), and various benchmarks have been created, including toy datasets, *e.g.*, ColoredMNIST (Arjovsky et al., 2019), and real-world datasets, *e.g.*, NICO (He et al., 2021). These TML benchmarks cannot be used directly to evaluate the performance in FSC problems with spurious-correlation shifts, following the reasons below: (1) **The number of classes.** Most TML benchmarks are the binary classification problem, but for FSC problems, we need enough classes to split base and novel classes. (2) **The number of samples.** FSC needs adequate samples from base classes to learn the transferring knowledge to novel classes with a few labeled images. (3) **The num-**

ber of contexts. Contexts in TML benchmarks are commonly limited, but FSC with many classes requires more contexts to build stronger spurious-correlation shifts. To the best of our knowledge, there does not exist a unified study and the benchmark of spurious-correlation shifts for FSC.

In this paper, we present **Meta Co**ncept **Co**ntext (MetaCoCo), a large-scale benchmark with a total of 175,637 images, 155 contexts and 100 classes, with spurious-correlation shifts arising from various contexts in the real-world scenarios. The basic idea of constructing spurious-correlation shifts is to label the images with the main concepts and contexts. For example, in the category with "dog" as the main concept, the images are categorized into different contexts such as "autumn", "snow", and "rock", which denotes that the "dog" is in the autumn, in the snow, or on the rock, respectively. With the help of these contexts, one can easily design a spurious-correlation-shift setting by training the model in some contexts and testing the model in other unseen contexts for studying spurious-correlation shifts as well as the unseen concepts for studying few-shot classification problems.

Furthermore, we propose a metric by using CLIP as a pre-trained vision-language model to quantify and compare the extent of spurious correlations on MetaCoCo and other FSC benchmarks. We conduct extensive experiments on MetaCoCo to evaluate the state-of-the-art methods in FSC, cross-domain shifts, and self-supervised learning. We open-source all codes for our benchmark and hope the proposed MetaCoCo will facilitate the development of spurious-correlation robust models.

2 Comparison with Existing Benchmarks

MetaCoCo provides a unified framework to facilitate the development of models robust to spurious-correlation shifts in FSC. We next discuss how MetaCoCo is related to existing benchmarks.

Relation to few-shot classification benchmarks. Few-shot classification (FSC) has attracted attention for its ability to recognize novel classes using few labeled images. Many methods have been proposed to solve the FSC problems, including (1) *Fine-tuning based methods* (Chen et al., 2019; Tian et al., 2020a; Chen et al., 2021), which address the problem by *learn to transfer*. (2) *Metric-based methods* (Vinyals et al., 2016; Snell et al., 2017; Li et al., 2019a; Zhang et al., 2022a), which solve the problem by *learn to compare*. (3) *Meta-based methods* (Finn et al., 2017; Rusu et al., 2019; Bae et al., 2021; Zhang et al., 2020), which tackle the problem by *learn to learn*.

Many FSC benchmarks have been proposed to evaluate the effectiveness of these methods, including *mini*ImageNet (Vinyals et al., 2016), Places (Zhou et al., 2017), CIFAR-FS (Bertinetto et al., 2019), Plantae (Van Horn et al., 2018), CUB-200-2011 (Wah et al., 2011), Stanford Dogs (Khosla et al., 2011), Stanford Cars (Krause et al., 2013), etc. These datasets are generally divided into training, validation and testing sets with non-overlap classes. While these datasets are useful testbeds for verifying FSC methods, they follow the independent and identically distributed (IID) assumption.

Relation to cross-domain shifts FSC benchmarks. Cross-domain shifts have been widely studied in the FSC community, which aims to learn the transferring knowledge from seen training distributions to recognize unseen testing distributions. Many CD-FSC methods have been proposed to address the cross-domain problem (Tseng et al., 2020; Sun et al., 2021; Triantafillou et al., 2021; Liang et al., 2021; Wang & Deng, 2021; Li et al., 2022; Zhang et al., 2022b), which can be mainly divided into bi-level optimization (Tseng et al., 2020; Triantafillou et al., 2021; Zhang et al., 2023c), domain adversarial learning (Motiian et al., 2017; Zhao et al., 2021), adversarial data augmentation (Wang & Deng, 2021; Sun et al., 2021), and module modulation (Liu et al., 2021; Li et al., 2022). Some benchmarks have been proposed to evaluate the effectiveness of these CD-FSC methods, including Meta-dataset (Triantafillou et al., 2019) consisting of 10 existing datasets, and BSCD-FSL (Guo et al., 2020) consisting of 4 existing datasets. They usually use the leave-one-domain-out setting as the testing domain and the others as training domains. However, these benchmarks use different datasets as domains to construct cross-domain distribution shifts, causing them to fail to reflect spurious correlation shifts that occur in real-world applications (see more discussion in Appendix A).

Relation to spurious-correlation shifts TML benchmarks. Spurious-correlation shifts have been studied recently in traditional machine learning (TML) (Sagawa et al., 2019; Krueger et al., 2021; Yao et al., 2022; Bai et al., 2024; Tang et al., 2024). Many methods mainly focus on causal learning (Peters et al., 2015; Kuang et al., 2018; Kamath et al., 2021), invariant learning (Arjovsky et al., 2019; Chang et al., 2020; Rosenfeld et al., 2020), and distributionally robust optimization (Arjovsky et al., 2019), etc. Some toy, *e.g.*, ColoredMNIST (Arjovsky et al., 2019) and real-world benchmarks,

Table 1: A summary of the existing benchmarks and our proposed spurious-correlation benchmark, *i.e.*, MetaCoCo. $\mathcal{C}$ and $\mathcal{N}$ are the number of classes and samples, respectively. The subscripts "all", "train", "val" and "test" mean the all dataset, training set, validation, and testing set, respectively.

Dataset	$\mathcal{C}_{all}$	$\mathcal{C}_{train}$	$\mathcal{C}_{val}$	$\mathcal{C}_{test}$	$\mathcal{N}_{all}$	$\mathcal{N}_{train}$	$\mathcal{N}_{val}$	$\mathcal{N}_{test}$	Context	Similarity
*mini*ImageNet (Vinyals et al., 2016)	100	64	16	20	60,000	38,400	9,600	12,000	0	0.211
CIFAR-FS (Krizhevsky et al., 2009)	100	64	16	20	60,000	38,400	9,600	12,000	0	0.181
Stanford Dogs (Khosla et al., 2011)	120	70	20	30	20,580	12,165	3,312	5,103	0	0.244
Stanford Cars (Krause et al., 2013)	196	130	17	49	16,185	10,766	1,394	4,025	0	0.164
Aircraft (Wah et al., 2011)	100	70	15	15	10,000	5,000	2,500	2,500	0	0.228
CUB-200-2011 (Wah et al., 2011)	200	140	30	30	11,788	7,648	1,182	2,958	0	0.266
Describable Textures (Cimpoi et al., 2014)	47	33	7	7	5,640	3,960	840	840	0	0.194
Traffic Signs (Houben et al., 2013)	43	-	-	43	50,000	-	-	50,000	0	0.193
Omniglot (Lake et al., 2015)	50	25	5	20	32,460	17,660	1,620	13,180	0	0.212
Fungi (Schroeder & Cui, 2018)	1394	994	200	200	89,760	64,449	12,195	13,116	0	0.191
VGG Flower (Nilsback & Zisserman, 2008)	102	71	15	16	8,189	5,655	1,109	1,425	0	0.177
MSCOCO (Lin et al., 2014)	80	-	40	40	860,001	-	513,021	346,980	0	0.173
Quick Draw (Jongejan et al., 2016)	345	241	52	52	50,426,266	34,776,331	7,939,640	7,710,295	0	0.168
CropDiseases (Mohanty et al., 2016)	38	-	-	38	43,456	-	-	43,456	0	0.213
ChestX (Wang et al., 2017b)	8	-	-	8	25,848	-	-	25,848	0	0.183
EuroSAT (Helber et al., 2019)	10	-	-	10	27,000	-	-	27,000	0	0.173
ISIC2018 (Codella et al., 2019)	7	-	-	7	10,015	-	-	10,015	0	0.186
MetaCoCo (Ours)	100	64	16	20	175,637	156,666	5,839	12,268	155	0.142

e.g., NICO (He et al., 2021) and MetaShift (Liang & Zou, 2022), have been proposed to evaluate the performance of these methods. These TML benchmarks do not be used directly in the FSC setting, due to lack of sufficient classes, number of samples, and number of contexts. Although IFSL (Yue et al., 2020) and COSOC (Luo et al., 2021) have experimentally proved the importance of spurious-correlation shifts, to the best of our knowledge, there is still a lack of a benchmark for evaluation. Therefore, we propose MetaCoCo in this paper to reflect spurious-correlation shifts arising in real-world scenarios.

3 Problem and Evaluation Settings

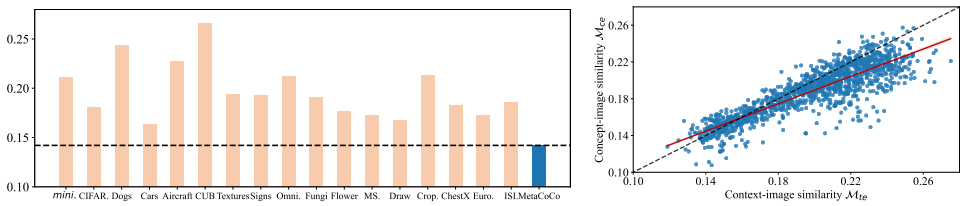
FSC aims to recognize unlabeled images (or query sets) from novel classes with only few labeled images (or support sets). Following the previous studies (Vinyals et al., 2016; Tian et al., 2020b), we adopt an episodic paradigm to train and evaluate the few-shot models. Specifically, each N-way K-shot episode $\mathcal{T}_e$ has a support set $\mathcal{S}_e = \{(x_i, y_i) : i = 1, \ldots, I_s\}$ and a query set $\mathcal{Q}_e = \{(x_i, y_i) : i = I_s + 1, \ldots, I_s + I_q\}$, where $x_i \in \mathcal{X}$ is the image and $y_i \in \mathcal{Y}$ is the label from a set of N classes $\mathcal{C}_e$, with $I_s = N \cdot K$ and I_q be the image numbers in the support and query set, respectively.

Let $\mathcal{S}_e(\mathcal{X})$ and $\mathcal{Q}_e(\mathcal{X})$ be the image spaces of $\mathcal{S}_e$ and $\mathcal{Q}_e$, and $\mathcal{S}_e(\mathcal{Y})$ and $\mathcal{Q}_e(\mathcal{Y})$ be the corresponding label spaces, respectively. The label space of $\mathcal{S}_e$ and $\mathcal{Q}_e$ is same but the image space is different, *i.e.*, $\mathcal{S}_e(\mathcal{X}) \neq \mathcal{Q}_e(\mathcal{X})$ and $\mathcal{S}_e(\mathcal{Y}) = \mathcal{Q}_e(\mathcal{Y})$. During the training phase, for meta-based and metric-based methods, episodes are randomly sampled from the base classes set $\mathcal{D}_b$ to train the model. Instead, for fine-tuning based methods, a mini-batch images is randomly sampled from $\mathcal{D}_b$ to train the model. During the testing phase, the trained model is fine tuned with $\mathcal{S}_e$ and evaluated with $\mathcal{Q}_e$ in novel episodes sampled from the novel classes set $\mathcal{D}_n$. Note that $\mathcal{D}_b$ contains more images and classes compared with $\mathcal{D}_n$ but label spaces are disjoint, *i.e.*, $\mathcal{D}_b(\mathcal{Y}) \neq \mathcal{D}_n(\mathcal{Y})$[1]. The model architectures have a feature encoder f_θ and a classifier c_ϕ parameterized by θ and ϕ. The f_θ aims to extract features, $f_\theta : \mathcal{X} \to \mathcal{Z}$, and the c_ϕ predicts the class of extracted features, $c_\phi : \mathcal{Z} \to \mathcal{Y}$.

3.1 Cross-Domain Shifts and Spurious-Correlation Shifts

In Table 1, we summarize the statistics of the existing benchmarks and our proposed spurious-correlation benchmark, *i.e.*, MetaCoCo. Specifically, Meta-dataset (Triantafillou et al., 2019) and BSCD-FSL (Guo et al., 2020) are two commonly used cross-domain benchmarks, where Meta-dataset has *10 existing datasets*, including ILSVRC-2012 (Deng et al., 2009), Omniglot (Lake et al., 2015), Aircraft (Wah et al., 2011), CUB-200-2011 (Wah et al., 2011), Describable Textures (Cimpoi et al., 2014), Quick Draw (Jongejan et al., 2016), Fungi (Schroeder & Cui, 2018), VGG Flower (Nilsback & Zisserman, 2008), Traffic Signs (Houben et al., 2013) and MSCOCO (Lin et al., 2014). BSCD-FSL (Guo et al., 2020) has *4 existing datasets*, including CropDiseases (Mohanty et al., 2016), EuroSAT (Helber et al., 2019), ISIC2018 (Codella et al., 2019; Tschandl et al., 2018), and

[1] $\mathcal{D}_b(\mathcal{Y})$ and $\mathcal{D}_n(\mathcal{Y})$ can be defined similarly, meaning the label spaces of $\mathcal{D}_b$ and $\mathcal{D}_n$, respectively.



(a) $\mathcal{M}_{ce}$ on the existing benchmarks and MetaCoCo (b) $\mathcal{M}_{ce}$ and $\mathcal{M}_{te}$ on MetaCoCo

Figure 2: (a) The sample-averaged similarity $\mathcal{M}_{ce}$ between concepts and images on the existing FSC benchmarks and the proposed MetaCoCo, where MetaCoCo has significantly lower similarity between contexts and images. (b) The context-image similarities $\mathcal{M}_{te}$ (horizontal axis) versus the concept-image similarities $\mathcal{M}_{ce}$ (vertical axis) of the sample points in the MetaCoCo.

ChestX (Wang et al., 2017b). The main differences between cross-domain benchmarks and our proposed MetaCoCo benchmark are as follows: (1) **The cause of shifts.** The shifts in cross-domain benchmarks are caused by varying distributions between various datasets. Instead, the shifts in MetaCoCo are caused by varying both concepts and contexts. For example, for cross-domain shifts, the FSL model is trained on *mini*ImageNet and tested on EuroSAT. Whereas for spurious-correlation shifts, the FSL model is trained and tested on images that have distinct associations with the contexts. (2) **The use of contexts.** In contrast to the existing few-shot classification benchmarks, as shown in Table 1, the proposed MetaCoCo benchmark further uses context information collected from real-world scenarios to reflect the spurious-correlation shifts.

3.2 Similarity Between the Concept and Context Information

For images containing both conceptual and contextual information, a greater similarity between image and context implies that the benchmark has more spurious-correlation shifts. To intuitively show that MetaCoCo has considerably more spurious-correlation shifts than the existing FSC benchmarks including cross-domain-shift benchmarks, we introduce a novel metric that uses CLIP (Radford et al., 2021) as a pre-trained vision-language model. By calculating the cosine distance of text and image features extracted by pre-trained text and image encoder from CLIP, the similarity $\mathcal{M}_{ce}$ between conceptual language information and image visual knowledge, and the similarity $\mathcal{M}_{te}$ between contextual language expression and image visual knowledge are calculated as follows:

$$\mathcal{M}_{ce} = d(z_x, z_t^{ce}), \quad \mathcal{M}_{te} = d(z_x, z_t^{te}), \tag{1}$$

where $d(\cdot, \cdot)$ is the cosine distance measurement, z_x is the image features extracted by pre-trained image encoder by CLIP, and z_t^{ce} and z_t^{te} represent the text features of concept and context extracted by pre-trained text encoder by CLIP, respectively. Figure 2(a) shows the sample-averaged similarity $\mathcal{M}_{ce}$ between concepts[2] and images on the existing FSC benchmarks as well as the proposed MetaCoCo. It can be seen that MetaCoCo has significantly lower similarity between concepts and images. This is because the added context information in the image introduces spurious-correlations with the concepts, *e.g.*, "grass" and "dog", thus weakening the direct correlation between the images and the concepts or labels, and presenting a more challenging evaluating benchmark for the FSC. Figure 2(b) further shows the context-image similarities $\mathcal{M}_{te}$ (horizontal axis) versus the concept-image similarities $\mathcal{M}_{ce}$ (vertical axis) of the sample points in the MetaCoCo. We find that the overall context-image similarities are slightly higher than the concept-image similarities, suggesting that spurious-correlation shifts are substantial in the proposed benchmark.

3.3 Evaluation Strategies

Before presenting the datasets, we first discuss the evaluation strategies in MetaCoCo, including:

(1) **Fine-tuning based methods.** Fine-tuning based methods follow the transfer learning procedure, including two phases: pre-training with base classes and test-tuning with novel classes. In the pre-

[2]Since the existing FSC benchmarks lack context information as shown in Table 1, we are not able to compute their sample-averaged similarity $\mathcal{M}_{te}$ between contexts and images.

training with base classes phase, the base classes $\mathcal{D}_b$ is used to train a $\mathcal{C}_{base}$-class classifier as below:

$$\Gamma = \arg\min_{\theta,\phi} \sum_{i=1}^{T} \mathcal{L}_{\text{CE}}\Big(c_\phi(f_\theta(x_i)), y_i\Big), \tag{2}$$

where T is the sample number of $\mathcal{D}_b$, and $\mathcal{L}_{\text{CE}}(\cdot,\cdot)$ is the cross-entropy loss. In the test-tuning with novel classes phase, each episode $\mathcal{T}_e = \langle \mathcal{S}_e, \mathcal{Q}_e \rangle$ is sampled from novel classes $\mathcal{D}_n$ and a new $\mathcal{C}_e$-class classifier is re-learned based on a few labeled images $\mathcal{S}_e$ and tested on $\mathcal{Q}_e$.

(2) **Metric-based methods.** Metric-based methods directly compare the similarities (or distance) between query images and support classes, *i.e.*, learning to compare, through the episodic training mechanism. Taking Prototypical Network (ProtoNet) (Snell et al., 2017) as an example, it takes the mean vector of each support class as its corresponding prototype representation, and then compares the relationships between query images and prototypes. The prototype p_n of each class in the support set $\mathcal{S}_e$ can be formulated as $p_n = \frac{1}{K}\sum_{(x_i,y_i)\in\mathcal{S}_e} f_\theta(x_i)\cdot\mathbb{I}(y_i = n)$, where $\mathbb{I}(\cdot)$ is the indicator function, then the the metric loss on $\mathcal{Q}_e$ can be computed as:

$$\mathcal{L}(\theta) = -\frac{1}{I_q}\sum_{(x_i,y_i)\in\mathcal{Q}_e} \log P(y_i|\mathcal{Q}_e), \quad \text{where } P(y_i|\mathcal{Q}_e) = \frac{\exp(-D(f_\theta(x_i), p_{y_i}))}{\sum_{n=1}^{N}\exp(-D(f_\theta(x_i), p_n))}, \tag{3}$$

and $D(\cdot,\cdot)$ denotes a distance measurement, *e.g.*, the squared euclidean distance in the ProtoNet.

(3) **Meta-based methods.** Meta-based methods aim to make the trained model able to quickly adapt to unseen novel tasks by a few gradient steps in the testing phase. Specifically, the learning paradigm of meta-based methods has two levels, *i.e.*, inner-level and outer-level, to update the base and meta learner, respectively. Model-agnostic meta-learning (MAML) (Finn et al., 2017) is one representative method, whose core idea is to train a model's initial parameters by using the two levels. Specifically, the base learner is optimized on the support set $\mathcal{S}_e$ that

$$\begin{aligned} \{\theta,\phi\} &\leftarrow \{\theta,\phi\} - \eta_{out}\nabla_{\{\theta,\phi\}}\mathcal{L}_{ce}(c_{\phi'}(f_{\theta'}(x_i), y_i)), \\ \text{where} \quad \{\theta',\phi'\} &= \{\theta,\phi\} - \eta_{in}\nabla_{\{\theta,\phi\}}\mathcal{L}_{ce}(c_\phi(f_\theta(x_i), y_i)), \end{aligned} \tag{4}$$

and the η_{in} and η_{out} are the learning rates of the inner level and the outer level, respectively.

4 METACOCO: A NEW FEW-SHOT CLASSIFICATION BENCHMARK WITH SPURIOUS CORRELATION

MetaCoCo aims to present an environment for evaluating the fine control of spurious-correlation shifts in the FSC problems. Specifically, our approach consists of (1) dataset generating, and (2) episode sampling, whose operational procedures are detailed below.

Dataset generating. Compared with the existing benchmarks, the samples in MetaCoCo consist of both conceptual and contextual information, and many of these images exhibit a strong correlation with the context, which increases the impact of spurious-correlation shifts between the training data and the testing data on the prediction performance. Specifically, we first select 100 categories of common objects following DomainNet (Peng et al., 2019). These categories include 155 contexts, which are collected from the adjectives or nouns appeared more frequently with these categories from WordNet (Miller, 1995). Then the images are collected by searching a category name combined with a context name (*e.g.*, "dog on grass") in various image search engines. One of the main challenges is that the downloaded data contains a large portion of outliers. To clean the dataset, we manually filter out the outliers, which takes around 2,500 hours in total. To control the annotation quality, we assign two annotators to each image and only take the images agreed by both annotators. After the filtering process, we kept 17.6k images from the 1.0 million images crawled from the web. The dataset has an average of around 1,000 images per category (see Appendix B for more details).

Episode sampling. MetaCoCo has 100 categories, and the number of matching contexts for each category is inconsistent, resulting in an inconsistent number of samples for each category. We sort the samples from most to least. The first 64 categories with the largest number of samples are used as training data, then 20 categories are selected as testing data, and the last 16 categories are used as validation data. FSC adopts an episodic paradigm to train and test the model. Each N-way K-shot

Table 2: Experiments in state-of-the-art few-shot classification and self-supervised learning methods. "rot." and "jig." mean using the Rotation and Jigsaw self-supervised pretext tasks, respectively.

Method	Conference	Backbone	Type	GL	LL	TT	1-shot	5-shot
Baseline (Chen et al., 2019)	ICLR 2019	ResNet12	Fine-tuning	✓		✓	46.78	60.78
Baseline++ (Chen et al., 2019)	ICLR 2019	ResNet12	Fine-tuning	✓		✓	46.95	58.50
RFS-simple (Tian et al., 2020a)	ECCV 2020	ResNet12	Fine-tuning	✓		✓	47.02	56.71
Neg-Cosine (Liu et al., 2020)	ECCV 2020	ResNet12	Fine-tuning	✓		✓	50.78	62.34
SKD-GEN0 (Rajasegaran et al., 2020)	BMVC 2021	ResNet12	Fine-tuning	✓		✓	51.34	63.21
FRN (Wertheimer et al., 2021)	CVPR 2021	ResNet12	Fine-tuning	✓		✓	50.23	60.56
Yang et al (Yang et al., 2022)	ECCV 2022	ResNet12	Fine-tuning	✓		✓	58.01	69.32
LP-FT-FB (Wang et al., 2022)	ICLR 2023	ResNet12	Fine-tuning	✓	✓	✓	56.21	70.21
MAML (Finn et al., 2017)	ICML 2017	ResNet12	Meta		✓	✓	45.01	54.21
Versa (Gordon et al., 2018)	NeurIPS 2018	ResNet12	Meta		✓	✓	39.64	53.06
R2D2 (Bertinetto et al., 2019)	ICLR 2019	ResNet12	Meta		✓	✓	45.25	60.14
MTL (Sun et al., 2019)	CVPR 2019	ResNet12	Meta	✓	✓	✓	44.23	58.04
ANIL (Raghu et al., 2020)	ICLR 2020	ResNet12	Meta		✓	✓	36.58	50.54
BOIL (Oh et al., 2020)	ICLR 2021	ResNet12	Meta		✓	✓	44.09	55.61
CDKT+ML (Ke et al., 2023)	NeurIPS 2023	ResNet18	Meta		✓	✓	44.86	61.42
CDKT+PL (Ke et al., 2023)	NeurIPS 2023	ResNet18	Meta		✓	✓	43.21	59.87
CovaMNet (Li et al., 2019b)	AAAI 2019	ResNet12	Metric	✓			47.81	58.43
DN4 (Li et al., 2019a)	CVPR 2019	ResNet12	Metric	✓			45.04	57.68
CAN (Hou et al., 2019)	NeurIPS 2019	ResNet12	Metric	✓	✓		48.93	62.36
DeepBDC (Xie et al., 2022)	CVPR 2022	ResNet12	Metric		✓	✓	46.78	62.54
FGFL (Cheng et al., 2023)	ICCV 2023	ResNet12	Metric		✓	✓	46.78	64.32
PUTM (Tian et al., 2023)	ICCV 2023	ResNet18	Metric		✓	✓	60.23	72.36
TSA+DETA (Zhang et al., 2023a)	ICCV 2023	ResNet18	Metric		✓	✓	51.42	61.58
MoCo (He et al., 2020)	CVPR 2020	ResNet50	Self-supervised learning		✓	✓	56.90	70.65
SimCLR (Chen et al., 2020)	ICML 2020	ResNet50	Self-supervised learning		✓	✓	58.12	71.21
ProtoNet (Snell et al., 2017)	NeurIPS 2017	ResNet18	Metric		✓		43.14	57.84
+ rot. + SSFSL (Su et al., 2020)	ECCV 2020	ResNet18	Self-supervised learning		✓		40.65	54.31
+ rot. + HTS (Zhang et al., 2022a)	ECCV 2022	ResNet18	Self-supervised learning		✓		42.06	55.13
+ jig. + SSFSL (Su et al., 2020)	ECCV 2020	ResNet18	Self-supervised learning	✓			45.43	58.91
+ rot. + jig. + SSFSL (Su et al., 2020)	ECCV 2020	ResNet18	Self-supervised learning		✓		44.46	59.01
ProtoNet (Snell et al., 2017)	NeurIPS 2017	ResNet12	Metric		✓		42.69	59.50
+ rot. + SLA (Lee et al., 2020)	ICML 2020	ResNet12	Self-supervised learning		✓		40.29	58.09
+ rot. + HTS (Zhang et al., 2022a)	ECCV 2022	ResNet12	Self-supervised learning		✓	✓	43.19	60.50
ProtoNet (Snell et al., 2017)	NeurIPS 2017	WRN-28-10	Metric		✓		43.67	60.78
+ rot. + BF3S (Gidaris et al., 2019)	ICCV 2019	WRN-28-10	Self-supervised learning		✓		43.78	57.64
+ rot. + HTS (Zhang et al., 2022a)	ECCV 2022	WRN-28-10	Self-supervised learning		✓		45.31	62.31

episode $\mathcal{T}_e$ has a support set $\mathcal{S}_e$ and a query set $\mathcal{Q}_e$, where $\mathcal{S}_e$ and $\mathcal{Q}_e$ share the same categories but different images. Therefore, we have two sample episodic strategies: independent and identically distributed (IID) episode, *i.e.*, the support and query images with the *same* contexts, and out-of-distribution (OOD) episode, *i.e.*, the support and query images with the *different* contexts.

5 Experiments

In this section, we evaluate the spurious-correlation performance of the state-of-the-art methods optimized with different learning strategies. These experiments further demonstrate that SC-FSC is still a major challenge. (see Appendix C and D for more experimental details and results).

5.1 Experimental Setup

Few-shot classification methods. We evaluate the performance with a large number of algorithms that span different learning strategies, including: (1) Five *fine-tuning based methods*: Baseline (Chen et al., 2019), Baseline++ (Chen et al., 2019), RFS-simple (Tian et al., 2020a), Neg-Cosine (Liu et al., 2020) and SKD-GEN0 (Rajasegaran et al., 2020). (2) Six *metric-based methods*: ProtoNet (Snell et al., 2017), RelationNet (Sung et al., 2018), CovaMNet (Li et al., 2019b), DN4 (Li et al., 2019a), CAN (Hou et al., 2019) and RENet (Kang et al., 2021). (3) Six *meta-based methods*: MAML (Finn et al., 2017), Versa (Gordon et al., 2018), R2D2 (Bertinetto et al., 2019), MTL (Sun et al., 2019), ANIL (Raghu et al., 2020) and BOIL (Oh et al., 2020). (4) Six *self-supervised learning methods*: MoCo (He et al., 2020), SimCLR (Chen et al., 2020), SSFSL (Su et al., 2020), HTS (Zhang et al., 2022a), SLA (Lee et al., 2020) and BF3S (Gidaris et al., 2019). (5) Seven *cross-domain methods*: Linear (Yue et al., 2020), Cosine (Yue et al., 2020), *k*-NN (Yue et al., 2020), ATA (Wang & Deng, 2021), FT (Tseng et al., 2020), LRP (Sun et al., 2021) and IFSL (Yue et al., 2020).

Backbone architectures. Following prior literatures (Li et al., 2023), all fine-tuning based methods, metric-based methods and meta-based methods adopt three different embedding backbones from shallow to deep, *i.e.*, Conv64F, ResNet12 and ResNet18. For other learning strategy methods, we

Table 3: Experiments of cross-domain and spurious-correlation few-shot classification methods.

Method	Conference	Type	GL	LL	TT	5-way 1-shot	5-way 5-shot
RelationNet (Sung et al., 2018)	CVPR 2018	Metric		✓		45.32 ± 0.48	57.73 ± 0.45
+ATA (Wang & Deng, 2021)	IJCAI 2021	CD-FSC		✓		43.24 ± 0.47	56.94 ± 0.47
+FT (Tseng et al., 2020)	ICLR 2020	CD-FSC		✓		45.37 ± 0.50	58.74 ± 0.48
GNN (Satorras & Estrach, 2018)	ICLR 2018	Metric		✓		48.14 ± 0.55	61.94 ± 0.56
+ATA (Wang & Deng, 2021)	IJCAI 2021	CD-FSC		✓		46.78 ± 0.55	61.78 ± 0.52
+ FT (Tseng et al., 2020)	ICLR 2020	CD-FSC		✓		47.30 ± 0.56	65.90 ± 0.56
TPN (Liu et al., 2018)	ICLR 2019	Metric		✓		49.65 ± 0.51	60.62 ± 0.47
+ATA (Wang & Deng, 2021)	IJCAI 2021	CD-FSC		✓		47.15 ± 0.53	60.33 ± 0.31
+FT (Tseng et al., 2020)	ICLR 2020	CD-FSC		✓		45.62 ± 0.51	55.78 ± 0.52
Linear (Yue et al., 2020)	NeurIPS 2020	Fine-tuning				43.31 ± 0.40	57.87 ± 0.41
Cosine (Yue et al., 2020)	NeurIPS 2020	Fine-tuning	✓		✓	42.81 ± 0.42	56.33 ± 0.41
k-NN (Yue et al., 2020)	NeurIPS 2020	Fine-tuning	✓		✓	42.22 ± 0.42	57.93 ± 0.42
MAML (Finn et al., 2017)	ICML 2017	Meta		✓	✓	44.09 ± 0.52	53.98 ± 0.48
+IFSL (Yue et al., 2020)	NeurIPS 2020	SC-FSC		✓	✓	43.42 ± 0.51	55.00 ± 0.48
MTL (Sun et al., 2019)	CVPR 2019	Meta	✓	✓	✓	43.80 ± 0.48	57.18 ± 0.48
+IFSL (Yue et al., 2020)	NeurIPS 2020	SC-FSC	✓	✓	✓	43.42 ± 0.48	56.90 ± 0.48
MatchingNet (Vinyals et al., 2016)	NeurIPS 2016	Metric		✓		43.72 ± 0.49	56.12 ± 0.49
+IFSL (Yue et al., 2020)	NeurIPS 2020	SC-FSC		✓		44.11 ± 0.49	55.86 ± 0.49
SIB (Hu et al., 2020)	ICLR 2020	Meta		✓	✓	48.43 ± 0.57	58.53 ± 0.51
+IFSL (Yue et al., 2020)	NeurIPS 2020	SC-FSC		✓	✓	47.97 ± 0.54	58.41 ± 0.50

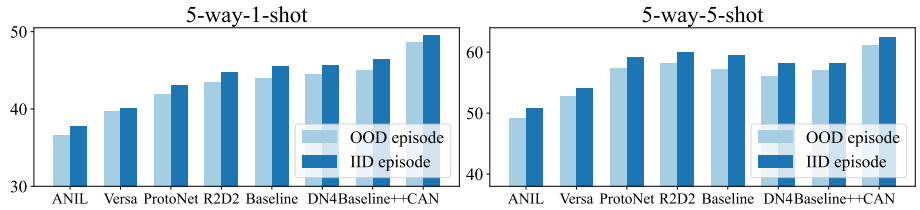


Figure 3: Experiments of the test-tuning phase with different sampling episodes, *i.e.*, IID and OOD.

adopt different feature backbones based on the corresponding original papers, *e.g.*, ResNet10 for cross-domain few-shot classification methods, WRN-28-10 for self-supervised learning methods.

Evaluation protocols. Following the prior work (Li et al., 2023), in this paper, we control the evaluation for all methods , evaluate them on 600 sampled tasks and repeat this process five times, *i.e.*, a total of 3,000 tasks. The top-1 mean accuracy will be reported. All images are resized into 84 × 84 by using the single center crop (Li et al., 2019b). Three common tricks are used: (1) *Global-label (GL)* indicates that the global labels of the training set are used for pre-training during the training phase. (2) *Local-label (LL)* means that only the specific local labels are used in the episodic training phase. (3) *Test-tune (TT)* means test-tuning of using the support set at the testing stage.

5.2 Main Results

In this section, we conduct extensive experiments on various methods with six learning strategies.

Experiments in fine-tuning, metric- and meta-based methods and self-supervised methods. We evaluate the performance of 17 competing few-shot methods and six self-supervised methods in our MetaCoCo. The results of the 5-way 1- or 5-shot setting are shown in Table 2. From Table 2, we have the following findings: (1) We find that the performance of all methods decreases compared with existing FSC benchmarks (Li et al., 2023), which demonstrates that these methods are insufficient in solving the spurious-correlation-shift problem. (2) Previous works introduced self-supervised learning to improve the generalization of FSC models, but experiments have shown that this is not suitable for the SC-FSC problem. In some cases, using self-supervised learning even damages the performance, *i.e.*, ProtoNet has 43.14% in 1-shot, but the accuracy by using rotation is 40.65%.

Experiments in CD-FSC and SC-FSC methods. Table 3 displays the accuracy of seven CD-FSC methods. These methods have a significant performance on solving the cross-domain-shift problem on the Meta-dataset (Triantafillou et al., 2019) and BSCD-FSL (Guo et al., 2020). However, in MetaCoCo, the advantages of these methods disappear, resulting in weaker performance, even worse than non-cross-domain FSC methods. It is worth noting that the main motivation of IFSL (Yue et al., 2020) is to use the idea of causality to solve the impact of spurious correlation between contextual information and images on the model training phase. However, we observe a substantial decrease of the performance on the real-world spurious-correlation benchmark, *i.e.*, MetaCoCo.

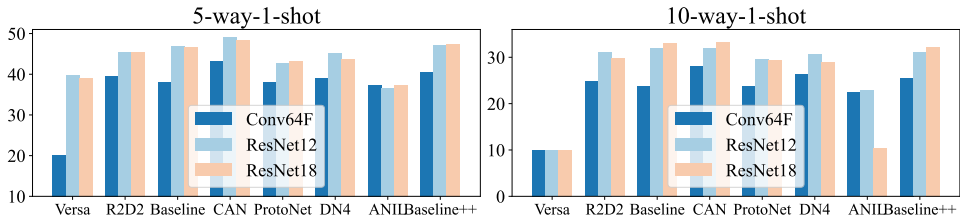


Figure 4: Experiments of different backbone architectures under 5-way and 10-way 1-shot settings.

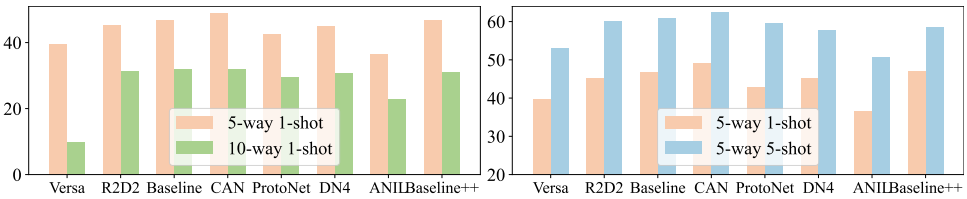


Figure 5: Experimental results of different ways (left) and shots (right) on testing performance.

To this end, according to these experimental results, we observe that most methods are insufficient to solve the spurious-correlation-shift FSC problem. We hope the proposed MetaCoCo can facilitate future research on the important and real-world problem for few-shot classification.

5.3 In-depth Study

To further analyze the influence of spurious shifts in MetaCoCo, we conduct in-depth experiments.

Effect of the IID and OOD episodes. Figure 3 shows the results of FSC methods under 5-way 1- and 5-shot settings. The IID and OOD episodes represent the same and different contexts of the support and query sets during the test-tuning phase, respectively (see Section 4). These results clearly denote that the learning process of the IID episode is better than the optimization process of the OOD episode. This further demonstrates that the model tends to utilize contextual information during the learning process. Once images do not match the contexts, the performance will deteriorate.

Effect of different backbone architectures. In (Chen et al., 2019), they change the depth of the feature backbone to reduce intra-class variation for all methods. Following this paper, we start from Conv64F and gradually increase the backbone to ResNet12 and 18. The experiments under 5-way and 10-way 1-shot settings are shown in Figure 4. It is arguably a common sense that the stronger backbone is used, the performance is best. However, we surprisingly find that this may not be always in the SC-FSC problem. Figure 4 shows the performance degradation in some settings.

Ways and shots analysis. We further study the performance of "ways" (Figure 5 left) and "shots" (Figure 5 right). As expected, we found that the difficulty increases as the way increases, and performance degrades. More examples per class, on the other hand, indeed make it easier to correctly classify that class. Interestingly, Versa presents a poor performance with increasing the way but it improves at a high rate when the shot increases, which further represents that the contextual effects become larger when the task becomes difficult. CAN has the best accuracy under all settings because it uses a transduction strategy to introduce query samples in the training phase, which destroys the strong spurious correlations between contexts and images.

6 Conclusion

In this paper, we present Meta Concept Context (MetaCoCo), a large-scale, diverse and realistic environment benchmark for spurious-correlation few-shot classification. We believe that our exploration of various modes on MetaCoCo has uncovered interesting directions for future works: it remains unclear what is the best learning strategy for avoiding the effect of spurious-correlation contexts and the most appropriate episodic sample. Current models even including these cross-domain FSC models don't work when trained on mismatching contexts. Current models are also not robust to the amount of data in testing episodes, each excelling in a different part of the spectrum. We believe that addressing these shortcomings constitutes an important research goal moving forward.

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A MORE DISCUSSION ON THE EXISTING BENCHMARKS

In Table 1, we have summarized statistics of existing benchmarks. A brief introduction of benchmarks mentioned in this paper is the following. For more details, please refer to the original paper.

***mini*ImageNet (Vinyals et al., 2016).** *mini*ImageNet is the subsets of the ILSVRC-12 dataset (Russakovsky et al., 2015).

Fine-grained benchmarks. CUB-200-2011 (Wah et al., 2011), Stanford Dogs (Khosla et al., 2011) and Stanford Cars (Krause et al., 2013) are initially designed for fine-grained classification.

Meta-dataset (Triantafillou et al., 2019). Meta-dataset is a cross-domain FSC benchmark and has *10 existing datasets*, including ILSVRC-2012 (Deng et al., 2009), Omniglot (Lake et al., 2015), Aircraft (Wah et al., 2011), CUB-200-2011 (Wah et al., 2011), Describable Textures (Cimpoi et al., 2014), Quick Draw (Jongejan et al., 2016), Fungi (Schroeder & Cui, 2018), VGG Flower (Nilsback & Zisserman, 2008), Traffic Signs (Houben et al., 2013) and MSCOCO (Lin et al., 2014).

BSCD-FSL (Guo et al., 2020) BSCD-FSL is also a cross-domain FSC benchmark and has *4 existing datasets*, including CropDiseases (Mohanty et al., 2016), EuroSAT (Helber et al., 2019), ISIC2018 (Codella et al., 2019; Tschandl et al., 2018), and ChestX (Wang et al., 2017b).

B DETAILED DATASET STATISTICS

Table 4, Table 5, Table 6, Table 7, Table 8, Table 9, Table 10, Table 11, Table 12 and Table 13 show the detailed statistics of our MetaCoCo dataset. Our dataset contains 100 concepts (or categories), 155 contexts and 17.6k images. These concepts are from common objects following DomainNet (Peng et al., 2019). The 155 contexts are collected from the adjectives or nouns appeared more frequently with these concepts from WordNet (Miller, 1995). In addition, we show the statistics of samples in each concept in Table 4.

C EXPERIMENTAL DETAILS

In this paper, many feature backbones are used to fair evaluate the performance of few-shot classification methods. Specifically, Conv64F contains four convolutional blocks, each of which consists of a convolutional (Conv) layer, a batch-normalization (BN) layer, a ReLU/LeakyReLU layer and a max-pooling (MP) layer, where the numbers of filters of these blocks are $\{64, 64, 64, 64\}$. ResNet12 consists of four residual blocks, each of which further contains three convolutional blocks (each is built as Conv-BN-ReLU-MP) along with a skip connection layer, where the numbers of filters of these blocks are $\{64, 160, 320, 640\}$. ResNet18 is the standard architecture used in previous works. One important difference between ResNet12 and ResNet18 is that ResNet12 uses Dropblock in each residual block, while ResNet18 does not. In addition, the number of filters of these blocks in ResNet18 is $\{64, 128, 256, 512\}$. ResNet10 is a common backbone architecture in cross-domain few-shot classification methods. It has the same number of filters of blocks as ResNet18, but the number of layers is 1 in each stage. WRN-28-10 is frequently used in self-supervised learning methods, where 28 means the number of layers and 10 is the number of the width.

D MORE EXPERIMENTS

In Tables 14 and 15 and Figures 6 and 7, we show the additional experiments to supplement the results in our main paper. From these additional experiments, we find that most of the existing few-shot classification methods are not robust in the spurious-correlation problem. We hope that these studies and the proposed MetaCOCo can facilitate future research on real-world problems.

Table 4: Number of samples for concepts in the MetaCoCo benchmark.

Training Concepts	dog	cat	bird	table	tree	bear	horse	fence	car	bicycle	motorcycle	train	cow	elephant	bus	chair	truck	airplane	pants	sheep	helicopter	door	monkey
Training Samples	5820	4915	4397	4365	4035	4004	3980	3953	3873	3787	3755	3726	3612	3519	3491	3454	3393	3208	3080	3031	2994	2581	2578
Training Concepts	umbrella	lion	squirrel	boat	wolf	lizard	tiger	giraffe	tent	hot air balloon	owl	sailboat	seal	frog	jacket	rabbit	goose	kangaroo	flower	ship	cactus	hat	fox
Training Samples	2499	2470	2312	2310	2293	2215	2184	2115	2038	2017	2002	2001	1976	1943	1892	1877	1862	1859	1835	1815	1801	1770	1751
Training Concepts	clock	spider	ostrich	tortoise	butterfly	pumpkin	sunflower	crocodile	bench	mailbox	lifeboat	dolphin	crab	window	pineapple	shorts	bag	toilet					
Training Samples	1729	1723	1703	1672	1619	1588	1548	1499	1491	1466	1451	1182	1155	1141	1072	1026	993	864					
Validation Concepts	carpet	cup	refrigerator	house	zebra	tower	ocean	spoon	suit	fire hydrant	skateboard	pillow	bed	knife	backpack	bridge							
Validation Samples	437	434	431	430	420	381	379	362	357	347	340	329	317	314	312	249							
Testing Concepts	rat	laptop	sink	frame	bowl	coat	bush	cloud	cabinet	shrimp	dress	television	t-shirt	sweater	surfboard	tie	fork	couch	keyboard	curtain			
Testing Samples	857	841	774	763	719	703	661	630	620	552	546	541	540	531	530	506	497	490	483	482			

Table 5: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	dog	cat	bird	table	tree	bear	horse	fence	car	bicycle	motorcycle	train	cow	elephant	bus	chair	truck	airplane	pants	sheep	helicopter	door	monkey
grass	649	597	839	0	0	665	604	0	321	583	452	346	1,009	559	332	213	440	331	0	573	453	0	428
water	886	635	606	0	0	550	305	0	306	327	390	271	387	402	348	503	442	256	0	292	249	0	251
outdoor	456	249	203	0	0	131	375	0	402	415	347	202	263	286	367	276	246	345	0	395	436	0	231
dim	322	241	414	0	0	164	318	0	390	521	489	333	268	338	202	145	486	299	0	303	477	0	184
white	218	153	63	426	22	156	110	256	209	0	37	136	53	0	252	163	238	263	505	60	0	537	0
rock	240	187	301	0	0	193	174	0	285	327	266	219	150	128	187	206	232	268	0	335	225	0	337
autumn	311	224	180	0	0	145	239	0	206	208	258	243	233	98	162	234	174	124	0	273	101	0	136
black	172	195	49	185	0	335	42	425	195	48	119	147	32	0	40	287	69	0	1,052	0	0	76	0
brown	357	145	66	967	246	383	407	214	0	0	0	25	106	55	0	294	0	0	211	0	0	235	0
wood	0	0	0	1,583	0	0	0	769	0	0	0	0	0	0	0	446	0	0	0	0	0	385	0
blue	0	0	30	78	0	0	0	73	137	35	47	263	0	0	217	118	84	157	314	0	0	59	0
green	0	0	0	53	1,453	0	0	227	34	0	0	86	0	0	62	73	36	0	60	0	0	47	0
gray	24	192	50	105	31	0	21	275	106	0	0	112	0	196	0	66	26	61	446	0	0	35	0
on snow	250	141	0	0	0	112	140	0	188	169	136	128	136	71	128	0	118	0	0	87	181	0	102
large	87	57	30	58	698	91	55	63	0	0	0	109	0	169	0	27	0	159	0	0	0	62	0
eating	277	299	201	0	0	0	0	0	0	0	0	0	147	123	0	0	0	0	0	116	0	0	169
red	0	0	0	69	0	0	0	59	117	0	47	126	0	0	179	98	93	23	68	0	0	76	0
metal	0	0	0	67	0	0	0	993	0	0	0	0	0	0	0	77	0	0	0	0	0	87	0
lying	234	146	0	0	0	229	142	0	0	0	0	0	173	73	0	0	0	0	0	116	0	0	0
with people	0	0	0	0	0	0	126	0	39	173	173	0	56	0	53	0	0	129	0	50	58	0	0
on beach	285	0	0	0	0	0	167	0	103	133	122	46	0	0	0	0	97	106	0	0	111	0	50
small	113	38	64	144	215	30	19	70	47	0	0	24	0	30	0	30	0	82	0	0	0	0	0
in forest	0	0	0	0	0	246	146	0	0	0	0	101	134	162	0	0	95	0	0	95	126	0	140
on road	87	179	0	0	0	0	77	0	149	241	338	0	0	91	0	0	149	0	0	111	0	0	0
silver	0	0	0	21	0	0	0	108	111	0	0	67	0	0	0	0	0	20	0	0	0	24	0
running	130	0	0	0	0	0	182	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in cage	122	110	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	77
open	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	490	0
yellow	0	0	0	28	0	0	0	20	33	0	0	98	0	0	75	0	34	0	0	0	0	55	0
standing	74	38	167	0	0	32	63	0	0	0	0	0	173	200	0	0	0	0	0	0	0	0	0
in city	0	0	0	0	0	0	0	0	149	0	197	0	0	0	201	0	75	59	0	0	71	0	0
sitting	113	140	25	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	168
tall	0	0	0	0	641	0	0	166	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in river	0	146	0	0	0	0	73	0	0	0	0	0	139	176	0	0	0	0	0	0	0	0	0
in water	140	50	81	0	0	174	0	0	0	0	0	0	0	0	0	0	0	0	0	71	0	0	117
dark	0	0	0	98	38	0	19	0	29	0	0	0	0	0	0	21	0	0	164	0	0	26	0
at home	93	279	0	0	0	0	90	0	0	0	0	0	78	0	0	0	0	0	0	0	0	0	0
walking	24	141	0	0	0	39	35	0	0	0	0	0	0	87	0	0	0	0	0	88	0	0	100
glass	0	0	0	71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	211	0
orange	0	107	0	16	0	0	0	45	0	0	0	37	0	0	41	32	23	0	0	0	0	0	0
on tree	0	50	0	0	0	71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in hand	0	0	95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
flying	0	0	245	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
plastic	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	61	0	0	0	0	0	0	0
long	0	0	0	0	0	0	0	130	0	0	0	195	0	0	0	0	0	0	79	0	0	0	0
closed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	176	0
on ground	0	0	278	0	0	98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside mountain	0	0	0	0	0	0	0	0	0	0	0	63	0	0	0	0	62	76	0	0	163	0	0
pink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
round	0	0	0	187	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bare	0	0	0	0	329	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tan	27	0	0	38	0	0	0	0	0	0	0	0	0	0	0	26	0	0	110	0	0	0	0
baby	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in garage	0	0	0	0	0	0	0	0	0	145	150	0	0	0	0	0	0	0	0	0	0	0	0
yacht	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on track	0	0	0	0	0	0	0	0	88	0	187	0	0	0	0	0	0	0	0	0	0	0	0
at station	0	0	0	0	0	0	0	0	0	0	0	158	0	0	97	0	0	0	0	0	0	0	0
wooden	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in farm	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on branch	0	0	240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leafy	0	0	0	0	236	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shared	0	0	0	0	0	0	0	0	0	233	0	0	0	0	0	0	0	0	0	0	0	0	0
velodrome	0	0	0	0	0	0	0	0	0	229	0	0	0	0	0	0	0	0	0	0	0	0	0
at wharf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
double decker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	223	0	0	0	0	0	0	0	0
on	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cross bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at heliport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	188	0	0
on bridge	0	0	0	0	0	0	0	0	36	0	0	56	0	0	45	0	44	0	0	0	0	0	0
in burrow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside tree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	169	0	0	0	0	0	0	0	0
in zoo	0	0	0	0	0	0	0	0	0	0	0	0	0	160	0	0	0	0	0	0	0	0	0
in pot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at airport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	156	0	0	0	0	0
on sea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	155	0	0
sleeping	36	110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in desert	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
eating grass	0	0	0	0	0	133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in race	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	130	0	0	0	0	0	0
taking off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	129	0	0	0	0	0
on power line	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in circus	0	0	0	0	0	0	0	0	0	0	0	0	0	115	0	0	0	0	0	0	0	0	0
mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
short	0	0	0	0	25	0	0	60	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0

Table 6: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	dog	cat	bird	table	tree	bear	horse	fence	car	bicycle	motorcycle	train	cow	elephant	bus	chair	truck	airplane	pants	sheep	helicopter	door	monkey
open mouth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on booth	0	0	0	0	0	0	0	0	112	0	0	0	0	0	0	0	0	0	0	0	0	0	0
howling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
khaki	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	71	0	0	0	0
at dock	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on head	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
around cloud	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88	0	0	0	0	0
climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88
stone	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on web	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on a stick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leather	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	58	0	0	0	0	0	0	0
cutting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
concrete	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at park	0	0	0	0	0	0	0	0	81	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on iceberg	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shoulder	0	0	80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at night	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	77	0	0	0	0	0
with flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
grazing	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
paper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
spotted	0	0	0	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	0	0	0
at yard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	0
with bee	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
hanging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
clean	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
square	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subway	0	0	0	0	0	0	0	0	0	0	0	71	0	0	0	0	0	0	0	0	0	0	0
jumping	41	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
landing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
porcelain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66	0	0	0
on desk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
purple	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
gold	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dirty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
resting	21	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
beige	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
rectangular	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
thin	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
thick	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in bucket	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
city	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pouch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in hole	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bird feeder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shelves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on wall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on post	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in box	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shiny	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sinking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with cargo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bright	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in shell	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside traffic light	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	0	0
empty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cross tunnel	0	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0	0	0
full	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
playing	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
light brown	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
staring	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
colorful	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark brown	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
young	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark blue	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	umbrella	lion	squirrel	boat	wolf	lizard	tiger	giraffe	tent	hot air balloon	owl	sailboat	seal	frog	jacket	rabbit	goose	kangaroo	flower	ship	cactus	hat	fox
grass	460	437	0	238	371	293	444	389	269	376	332	290	351	0	457	391	336	419	202	318	285	398	283
water	243	209	0	276	368	374	368	441	459	229	434	414	296	0	160	278	246	358	401	298	280	183	213
outdoor	299	265	0	324	344	369	214	288	367	197	402	269	103	0	165	349	196	341	378	203	404	160	267
dim	294	107	0	179	56	166	277	280	227	288	251	115	139	0	131	193	257	221	302	310	147	133	94
white	0	116	138	76	0	65	33	74	0	107	0	95	0	146	131	94	37	20	0	0	82	91	147
rock	253	241	0	265	344	201	149	250	254	123	236	272	258	0	122	86	110	322	203	205	73	151	84
autumn	121	272	0	234	130	121	121	265	147	193	135	32	205	0	125	145	76	128	225	44	210	216	252
black	0	0	0	0	0	0	0	0	0	0	0	0	0	631	0	0	0	0	0	0	115	0	65
brown	0	0	0	0	0	0	229	0	0	0	0	0	0	135	0	0	0	0	0	0	45	0	22
wood	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28
blue	0	0	86	0	88	0	0	36	0	0	0	0	104	348	0	0	0	0	0	0	53	0	23
green	0	0	0	0	110	0	0	15	0	0	0	0	106	114	0	0	0	0	0	0	0	0	0
gray	0	0	0	0	0	0	0	0	0	0	0	0	0	162	119	0	0	0	0	0	25	0	0
on snow	89	135	0	81	0	107	0	0	0	74	0	125	0	0	139	0	71	0	0	0	0	97	0
large	0	0	58	0	0	0	58	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	101
eating	85	127	0	112	70	45	0	0	0	73	0	93	76	0	110	63	53	0	0	0	0	26	0
red	0	0	0	0	0	0	0	0	0	0	0	0	0	136	0	0	0	0	0	0	35	0	0
metal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24
lying	139	116	0	151	0	86	0	0	0	0	0	0	0	0	0	0	81	0	0	0	0	88	0
with people	40	25	158	34	0	20	0	0	61	19	69	0	0	0	32	0	63	0	0	0	0	0	0
on beach	0	0	168	0	0	0	0	0	0	0	67	50	0	0	0	0	0	0	0	0	0	0	0
small	0	0	71	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	109	0	0	0
in forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	102	0	0	0	0	0	0
on road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
silver	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
running	99	94	0	69	74	118	0	0	0	39	0	0	0	0	66	0	48	0	0	0	0	36	0
in cage	36	0	0	93	54	59	0	0	0	45	0	24	0	0	65	65	0	0	0	0	0	68	0
open	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
yellow	0	0	0	0	110	0	0	0	0	0	0	0	150	56	0	0	0	0	0	0	0	0	0
standing	0	0	0	0	0	0	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in city	0	0	202	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sitting	56	0	0	51	0	84	0	0	0	0	0	0	0	0	0	103	0	0	0	0	0	56	0
tall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in river	0	0	271	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark	0	0	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0
at home	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
walking	0	0	0	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
glass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
orange	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0
on tree	132	0	0	0	0	0	0	0	0	113	0	0	85	0	0	0	0	0	0	0	0	0	0
in hand	0	0	0	0	96	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0
flying	0	0	0	0	0	0	0	0	0	126	0	0	0	0	0	95	0	0	0	0	0	0	0
plastic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
long	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
closed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on ground	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
pink	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0	0	0	26	0	0	0	0	0
round	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	103
bare	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
baby	124	0	0	0	0	76	0	0	0	0	0	116	0	0	0	0	0	0	0	0	0	0	0
in garage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
yacht	0	0	287	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on track	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at station	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
wooden	0	0	250	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in farm	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on branch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leafy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shared	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
velodrome	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at wharf	0	0	226	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
double decker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cross bridge	0	0	198	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in sunset	0	0	197	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at heliport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in burrow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	0	0	0	0	0	0	48	0
aside tree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in zoo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	0	0	0
at airport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on sea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sleeping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in desert	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	68	0	0	74	0	0	0
eating grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in race	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
taking off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on power line	0	123	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in circus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
mountain	0	0	0	0	0	0	0	0	113	0	0	0	0	0	0	0	0	0	0	0	0	0	0
short	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 8: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	umbrella	lion	squirrel	boat	wolf	lizard	tiger	giraffe	tent	hot air balloon	owl	sailboat	seal	frog	jacket	rabbit	goose	kangaroo	flower	ship	cactus	hat	fox
open mouth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on booth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
howling	0	0	0	110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
khaki	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at dock	0	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	28	0	0	0	0
on head	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
around cloud	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
stone	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on web	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on a stick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leather	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cutting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
concrete	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at park	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on iceberg	0	0	0	0	0	0	0	0	0	0	0	81	0	0	0	0	0	0	0	0	0	0	0
on shoulder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at night	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	76	0	0	0
grazing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
paper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
spotted	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at yard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with bee	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
hanging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
clean	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
square	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
jumping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
landing	0	0	0	0	0	0	0	0	67	0	0	0	0	0	0	0	0	0	0	0	0	0	0
porcelain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on desk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	0	0	0
fighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	0	0	0	0	0
purple	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
gold	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23
dirty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
resting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
beige	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
rectangular	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
thin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
thick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in bucket	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
city	0	0	0	0	0	0	0	0	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pouch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0	0	0	0	0	0
in hole	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bird feeder	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shelves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on wall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on post	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in box	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shiny	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sinking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0
with cargo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0
bright	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in shell	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside traffic light	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
empty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cross tunnel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
full	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
playing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
light brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
staring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
colorful	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
young	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark blue	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 9: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	clock	spider	ostrich	tortoise	butterfly	pumpkin	sunflower	crocodile	bench	mailbox	lifeboat	dolphin	crab	window	pineapple	shorts	bag	toilet	carpet	cup	refrigerator	house	zebra
grass	267	286	357	388	235	327	255	0	307	124	99	281	0	240	0	0	0	0	0	0	0	0	0
water	246	251	292	111	211	197	343	0	91	543	340	178	0	360	0	0	0	0	0	0	0	0	0
outdoor	248	326	291	248	240	209	326	0	229	374	309	126	0	152	0	0	0	0	0	0	0	0	0
dim	194	151	185	182	167	289	100	0	78	135	176	115	0	57	0	0	0	0	0	0	0	0	0
white	76	0	0	0	0	0	40	47	0	0	54	0	150	0	278	108	663	46	138	271	140	93	60
rock	98	113	198	255	118	137	151	0	234	123	93	183	0	53	0	0	0	0	0	0	0	0	0
autumn	54	36	171	132	289	67	38	0	89	4	7	15	0	17	0	0	0	0	0	0	0	0	0
black	0	0	0	0	0	0	0	80	99	0	0	0	34	0	244	259	0	0	0	43	0	102	21
brown	0	0	0	0	0	0	0	214	0	0	0	0	19	0	50	77	8	91	16	0	55	0	49
wood	0	0	0	0	0	0	0	601	36	0	0	0	33	0	0	0	0	0	0	0	0	0	0
blue	0	0	0	77	0	0	0	46	34	0	0	0	0	0	198	89	13	61	33	0	28	0	0
green	0	0	0	0	0	0	0	101	0	0	0	0	0	0	38	47	0	30	16	0	0	0	0
gray	0	0	0	0	0	0	0	63	0	0	0	0	0	0	86	27	8	94	0	11	27	0	25
on snow	0	80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
large	0	0	0	0	0	0	0	33	0	0	0	0	275	0	0	42	0	0	0	33	60	22	67
eating	122	109	77	0	0	0	52	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0
red	68	0	0	25	0	0	0	44	92	0	0	0	0	0	34	31	0	47	21	0	18	0	20
metal	0	0	0	0	0	0	0	141	92	0	0	0	0	0	0	0	0	0	0	0	0	0	42
lying	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with people	0	40	36	0	0	118	27	0	0	75	52	21	0	0	0	0	0	0	0	0	0	0	0
on beach	0	0	28	0	0	0	54	0	0	0	0	78	0	0	0	0	0	0	0	0	0	0	0
small	0	0	0	0	0	0	0	17	0	0	0	0	53	0	0	26	0	0	29	34	27	14	12
in forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
silver	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0
running	0	86	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in cage	0	118	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
open	0	0	0	0	0	0	0	0	0	0	0	0	127	0	0	0	34	0	0	0	0	0	0
yellow	131	0	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0
standing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	103	0
in city	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sitting	0	107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in river	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark	0	0	0	0	0	0	0	17	0	0	0	0	22	0	31	0	0	0	0	0	0	0	0
at home	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
walking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0
glass	0	0	0	0	0	0	0	0	0	0	0	0	207	0	0	0	0	0	37	0	0	0	0
orange	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0
on tree	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0
in hand	132	0	0	85	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
flying	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
plastic	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	166	0	0	78	0	0	0	0
long	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
closed	0	0	0	0	0	0	0	0	0	0	0	0	125	0	0	0	38	0	0	0	0	0	0
on ground	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
pink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	6	0	0	0	0	0	0
round	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0
bare	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	27	0	0	0	0	0
baby	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in garage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
yacht	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on track	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at station	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
wooden	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in farm	0	0	0	0	104	72	0	0	0	0	0	0	0	68	0	0	0	0	0	0	0	0	0
on branch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leafy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shared	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
velodrome	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at wharf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
double decker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cross bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at heliport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in burrow	0	0	0	0	0	0	0	0	0	0	0	76	0	0	0	0	0	0	0	0	0	0	0
aside tree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in zoo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pot	0	0	0	0	0	59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at airport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on sea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sleeping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in desert	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
eating grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in race	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
taking off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on power line	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in circus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
short	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

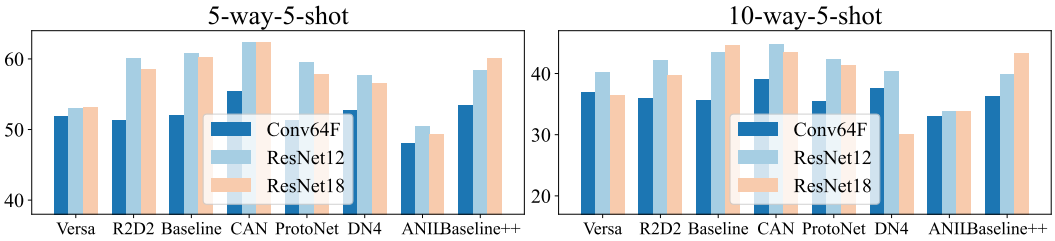

Figure 6: Experiments of different backbone architectures under 5-way and 10-way 5- shot settings.

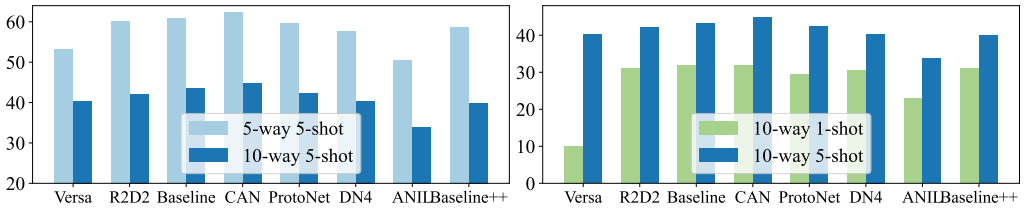

Figure 7: Experimental results of different ways (left) and shots (right) on testing performance.

Table 10: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	clock	spider	ostrich	tortoise	butterfly	pumpkin	sunflower	crocodile	bench	mailbox	lifeboat	dolphin	crab	window	pineapple	shorts	bag	toilet	carpet	cup	refrigerator	house	zebra
open mouth	0	0	0	0	0	0	113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on booth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
howling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0	57
khaki	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0
at dock	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on head	0	0	0	0	95	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
around cloud	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
stone	0	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28
on web	87	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on a stick	0	0	0	0	85	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leather	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0
cutting	0	0	0	0	0	0	0	0	0	0	0	0	0	84	0	0	0	0	0	0	0	0	0
concrete	0	0	0	0	0	0	0	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at park	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on iceberg	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shoulder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at night	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
grazing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54	0
paper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	30	0	0	0	0
spotted	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at yard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with bee	0	0	0	0	0	73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
hanging	0	0	0	0	0	0	0	0	0	73	0	0	0	0	0	0	0	0	0	0	0	0	0
clean	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0
square	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0
subway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
jumping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on flower	0	0	0	67	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
landing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
porcelain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on desk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
purple	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
gold	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dirty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0
resting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
beige	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0
rectangular	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	0	0	0	0
thin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
thick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in bucket	0	0	0	0	0	0	0	0	0	0	0	54	0	0	0	0	0	0	0	0	0	0	0
city	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pouch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in hole	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bird feeder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shelves	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on wall	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on post	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in box	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0
shiny	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sinking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with cargo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bright	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0
in shell	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside traffic light	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
empty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0
cross tunnel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
full	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0
playing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
light brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
staring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
colorful	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
young	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark blue	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 11: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	tower	ocean	spoon	suit	fire hydrant	skateboard	pillow	bed	knife	backpack	bridge	rat	laptop	sink	frame	bowl	coat	bush	cloud	cabinet	shrimp	dress	television
grass	0	0	0	0	0	0	0	0	0	0	125	0	0	0	0	0	0	0	0	190	0	0	0
water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	260	0	0	0
outdoor	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0
dim	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0
white	22	25	27	49	35	161	125	11	0	0	0	64	473	167	288	68	0	421	151	0	159	9	186
rock	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0
autumn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
black	0	10	191	22	188	14	9	33	162	0	0	208	0	125	27	240	0	0	24	0	100	159	112
brown	0	0	15	0	30	37	44	0	13	0	0	0	0	73	24	62	29	0	139	0	0	0	0
wood	0	30	0	0	0	0	0	0	0	34	0	0	0	163	15	0	0	0	245	0	0	0	0
blue	294	0	32	31	19	47	30	0	57	19	0	0	0	23	40	111	0	0	0	0	98	0	80
green	20	0	0	24	13	0	0	0	15	24	0	0	0	0	27	29	456	0	0	0	26	0	32
gray	21	0	56	14	25	18	0	6	35	38	0	100	0	23	0	61	2	76	0	0	0	59	51
on snow	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0
large	0	25	0	0	0	0	70	0	0	29	0	10	17	0	51	0	85	65	16	0	0	92	0
eating	0	0	0	0	0	0	0	0	0	0	176	0	0	0	0	0	0	0	0	0	0	0	0
red	0	0	9	99	0	34	15	0	10	0	0	0	0	24	17	74	4	0	0	0	47	0	49
metal	0	74	0	0	0	0	0	68	0	50	0	0	33	95	28	0	0	0	13	0	0	0	0
lying	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0
with people	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on beach	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
small	0	10	0	0	0	0	24	0	0	0	0	17	24	0	59	0	79	20	10	0	0	31	0
in forest	0	0	0	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	0	0
on road	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
silver	0	157	0	10	0	0	0	178	0	0	0	103	51	33	41	0	0	0	0	0	0	35	0
running	0	0	0	0	0	0	0	0	0	0	51	0	0	0	0	0	0	0	0	0	0	0	0
in cage	0	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	0	0	0	0	0	0	0
open	0	0	0	0	0	0	0	0	0	0	0	204	0	0	0	0	0	0	12	0	0	0	0
yellow	0	0	0	83	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15
standing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in city	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sitting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in river	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in water	0	0	0	0	0	0	0	0	0	0	85	0	0	0	0	0	0	0	0	0	0	0	0
dark	14	0	27	0	0	0	0	0	0	0	0	0	0	0	0	36	2	19	0	0	0	0	0
at home	0	0	0	0	0	0	0	0	0	0	126	0	0	0	0	0	0	0	0	0	0	0	0
walking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
glass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0
orange	0	0	0	15	13	0	0	0	12	0	0	0	0	0	0	0	2	0	0	0	16	0	15
on tree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in hand	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
flying	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
plastic	0	31	0	0	0	0	0	18	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0
long	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0
closed	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	10	0	0	0	0
on ground	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
pink	0	0	0	0	0	18	0	0	8	0	0	0	8	0	0	22	2	0	0	0	60	0	0
round	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0
bare	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
baby	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in garage	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
yacht	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on track	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at station	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
wooden	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in farm	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on branch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leafy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shared	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
velodrome	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at wharf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
double decker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on	0	0	0	0	0	0	0	0	0	0	0	98	0	0	0	0	0	0	0	0	0	111	0
cross bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at heliport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on bridge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in burrow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside tree	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in zoo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pot	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at airport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on sea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sleeping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in desert	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
eating grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in race	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
taking off	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on power line	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in circus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
mountain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
short	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 12: Detailed statistics of the MetaCoCo benchmark.

	Concepts																						
Contexts	tower	ocean	spoon	suit	fire hydrant	skateboard	pillow	bed	knife	backpack	bridge	rat	laptop	sink	frame	bowl	coat	bush	cloud	cabinet	shrimp	dress	television
open mouth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on booth	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
howling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
khaki	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at dock	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on head	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
around cloud	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
stone	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0
on web	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on a stick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
leather	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cutting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
concrete	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0
at park	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on iceberg	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shoulder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at night	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
grazing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
paper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
spotted	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
at yard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with bee	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
hanging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
clean	0	0	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0
square	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0
subway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
jumping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on flower	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
landing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
porcelain	0	0	0	0	0	0	0	0	0	0	0	0	66	0	0	0	0	0	0	0	0	0	0
at sunset	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on desk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
purple	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0
off	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	45	0
gold	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0
dirty	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0
resting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
beige	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
rectangular	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0
thin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0
thick	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0
in bucket	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
city	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in pouch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in hole	0	0	0	0	0	0	0	0	0	0	51	0	0	0	0	0	0	0	0	0	0	0	0
on bird feeder	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on shelves	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on wall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
on post	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in box	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
shiny	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sinking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
with cargo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
bright	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
in shell	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aside traffic light	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
empty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0
cross tunnel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
full	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0
playing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
light brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
staring	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
colorful	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark brown	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
young	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
dark blue	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 13: Detailed statistics of the MetaCoCo benchmark.

Contexts																							
Concepts	grass	water	outdoor	dim	white	rock	autumn	black	brown	wood	blue	green	gray	on snow	large	eating	red	metal	lying	with people	on beach	small	in forest
t-shirt	0	0	0	0	186	0	0	112	0	0	80	32	51	0	0	0	49	0	0	0	0	0	0
sweater	0	0	0	0	62	0	0	101	36	0	90	33	116	0	0	0	47	0	0	0	0	0	0
surfboard	0	0	0	0	265	0	0	18	11	0	111	0	0	0	24	0	21	0	0	0	0	12	0
tie	0	0	0	0	44	0	0	113	19	0	104	21	36	0	0	0	75	0	0	0	0	0	0
fork	0	0	0	0	27	0	0	14	0	0	0	0	10	0	0	0	6	118	0	0	0	0	0
couch	0	0	0	0	81	0	0	41	160	0	46	28	43	0	0	0	38	0	0	0	0	0	0
keyboard	0	0	0	0	197	0	0	215	0	0	3	0	50	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	236	0	0	20	50	0	53	29	18	0	0	0	42	0	0	0	0	0	0

Contexts																							
Concepts	on road	silver	running	in cage	open	yellow	standing	in city	sitting	tall	in river	in water	dark	at home	walking	glass	orange	on tree	in hand	flying	plastic	long	closed
t-shirt	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0
sweater	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0	0
tie	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	18	0	0	0	0	0	0
fork	0	274	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	0	0
couch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	11	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Contexts																							
Concepts	on ground	aside mountain	pink	round	bare	tan	baby	in garage	yacht	on track	at station	wooden	in farm	on branch	leafy	shared	velodrome	at wharf	double decker	on	cross bridge	in sunset	at heliport
t-shirt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sweater	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tie	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fork	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
couch	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Contexts																							
Concepts	on bridge	in burrow	aside tree	in zoo	in pot	at airport	on sea	sleeping	in desert	eating grass	in race	taking off	on power line	in circus	mountain	short	open mouth	on booth	howling	brick	khaki	at dock	on head
t-shirt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sweater	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tie	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fork	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
couch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Contexts																							
Concepts	around cloud	climbing	stone	on web	on a stick	leather	cutting	concrete	at park	on iceberg	on shoulder	at night	with flower	grazing	paper	spotted	at yard	with bee	hanging	clean	square	subway	jumping
t-shirt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sweater	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tie	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fork	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
couch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Contexts																							
Concepts	on flower	landing	porcelain	at sunset	on desk	fighting	purple	off	gold	dirty	resting	beige	rectangular	thin	thick	in bucket	city	in pouch	in hole	on bird feeder	on shelves	on wall	on post
t-shirt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sweater	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tie	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fork	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
couch	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Contexts																
Concepts	in box	shiny	sinking	with cargo	bright	in shell	aside traffic light	empty	cross tunnel	full	playing	light brown	staring	colorful	dark brown	young	dark blue
t-shirt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sweater	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
surfboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tie	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0
fork	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
couch	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
keyboard	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
curtain	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 14: Experiments of state-of-the-art few-shot classification methods under 5-way 1- and 5-shot setting. Three common backbones are used and the 95% confidence intervals are displayed.

Method	Backbone	Type	5-way 1-shot	5-way 5-shot
Versa (Gordon et al., 2018)	Conv64F	Meta	20.00 $\pm$ 0.00	51.95 $\pm$ 0.35
R2D2 (Bertinetto et al., 2019)	Conv64F	Meta	39.56 $\pm$ 0.36	51.29 $\pm$ 0.36
ANIL (Raghu et al., 2020)	Conv64F	Meta	37.24 $\pm$ 0.36	48.04 $\pm$ 0.39
CAN (Hou et al., 2019)	Conv64F	Metric	43.02 $\pm$ 0.42	55.48 $\pm$ 0.40
ProtoNet (Snell et al., 2017)	Conv64F	Metric	37.92 $\pm$ 0.35	51.39 $\pm$ 0.38
DN4 (Li et al., 2019a)	Conv64F	Metric	38.87 $\pm$ 0.36	52.72 $\pm$ 0.38
Baseline (Chen et al., 2019)	Conv64F	Fine-tuning	37.97 $\pm$ 0.32	52.08 $\pm$ 0.35
Baseline++ (Chen et al., 2019)	Conv64F	Fine-tuning	40.45 $\pm$ 0.36	53.42 $\pm$ 0.37
Versa (Gordon et al., 2018)	ResNet12	Meta	39.64 $\pm$ 0.39	53.06 $\pm$ 0.40
R2D2 (Bertinetto et al., 2019)	ResNet12	Meta	45.25 $\pm$ 0.42	60.14 $\pm$ 0.37
ANIL (Raghu et al., 2020)	ResNet12	Meta	36.58 $\pm$ 0.38	50.54 $\pm$ 0.40
CAN (Hou et al., 2019)	ResNet12	Metric	48.93 $\pm$ 0.42	62.36 $\pm$ 0.40
ProtoNet (Snell et al., 2017)	ResNet12	Metric	42.69 $\pm$ 0.39	59.50 $\pm$ 0.40
DN4 (Li et al., 2019a)	ResNet12	Metric	45.04 $\pm$ 0.39	57.68 $\pm$ 0.39
Baseline (Chen et al., 2019)	ResNet12	Fine-tuning	46.78 $\pm$ 0.41	60.78 $\pm$ 0.40
Baseline++ (Chen et al., 2019)	ResNet12	Fine-tuning	46.95 $\pm$ 0.42	58.50 $\pm$ 0.36
Versa (Gordon et al., 2018)	ResNet18	Meta	38.88 $\pm$ 0.36	53.18 $\pm$ 0.36
R2D2 (Bertinetto et al., 2019)	ResNet18	Meta	45.26 $\pm$ 0.38	58.53 $\pm$ 0.38
ANIL (Raghu et al., 2020)	ResNet18	Meta	37.26 $\pm$ 0.36	49.42 $\pm$ 0.39
CAN (Hou et al., 2019)	ResNet18	Metric	48.18 $\pm$ 0.42	62.38 $\pm$ 0.41
ProtoNet (Snell et al., 2017)	ResNet18	Metric	43.14 $\pm$ 0.37	57.84 $\pm$ 0.39
DN4 (Li et al., 2019a)	ResNet18	Metric	43.73 $\pm$ 0.38	56.56 $\pm$ 0.39
Baseline (Chen et al., 2019)	ResNet18	Fine-tuning	46.49 $\pm$ 0.41	60.22 $\pm$ 0.39
Baseline++ (Chen et al., 2019)	ResNet18	Fine-tuning	47.26 $\pm$ 0.40	60.10 $\pm$ 0.38

Table 15: Experiments of state-of-the-art few-shot classification methods under 10-way 1- and 5-shot setting. Three common backbones are used and the 95% confidence intervals are displayed.

Method	Backbone	Type	10-way 1-shot	10-way 5-shot
Versa (Gordon et al., 2018)	Conv64F	Meta	10.00 $\pm$ 0.00	36.88 $\pm$ 0.21
R2D2 (Bertinetto et al., 2019)	Conv64F	Meta	24.80 $\pm$ 0.20	35.98 $\pm$ 0.21
ANIL (Raghu et al., 2020)	Conv64F	Meta	22.39 $\pm$ 0.19	33.05 $\pm$ 0.22
CAN (Hou et al., 2019)	Conv64F	Metric	28.19 $\pm$ 0.23	39.06 $\pm$ 0.23
ProtoNet (Snell et al., 2017)	Conv64F	Metric	23.72 $\pm$ 0.19	35.49 $\pm$ 0.22
DN4 (Li et al., 2019a)	Conv64F	Metric	26.26 $\pm$ 0.21	37.54 $\pm$ 0.22
Baseline (Chen et al., 2019)	Conv64F	Fine-tuning	23.71 $\pm$ 0.18	35.70 $\pm$ 0.21
Baseline++ (Chen et al., 2019)	Conv64F	Fine-tuning	25.55 $\pm$ 0.20	36.34 $\pm$ 0.21
Versa (Gordon et al., 2018)	ResNet12	Meta	10.00 $\pm$ 0.00	40.21 $\pm$ 0.22
R2D2 (Bertinetto et al., 2019)	ResNet12	Meta	31.16 $\pm$ 0.23	42.10 $\pm$ 0.22
ANIL (Raghu et al., 2020)	ResNet12	Meta	22.94 $\pm$ 0.20	33.77 $\pm$ 0.22
CAN (Hou et al., 2019)	ResNet12	Metric	31.92 $\pm$ 0.24	44.78 $\pm$ 0.23
ProtoNet (Snell et al., 2017)	ResNet12	Metric	29.59 $\pm$ 0.22	42.38 $\pm$ 0.24
DN4 (Li et al., 2019a)	ResNet12	Metric	30.69 $\pm$ 0.22	40.31 $\pm$ 0.21
Baseline (Chen et al., 2019)	ResNet12	Fine-tuning	31.88 $\pm$ 0.24	43.40 $\pm$ 0.23
Baseline++ (Chen et al., 2019)	ResNet12	Fine-tuning	31.01 $\pm$ 0.23	39.89 $\pm$ 0.21
Versa (Gordon et al., 2018)	ResNet18	Meta	10.00 $\pm$ 0.00	36.51 $\pm$ 0.21
R2D2 (Bertinetto et al., 2019)	ResNet18	Meta	29.73 $\pm$ 0.22	39.74 $\pm$ 0.21
ANIL (Raghu et al., 2020)	ResNet18	Meta	10.47 $\pm$ 0.10	33.83 $\pm$ 0.23
CAN (Hou et al., 2019)	ResNet18	Metric	33.16 $\pm$ 0.25	43.47 $\pm$ 0.23
ProtoNet (Snell et al., 2017)	ResNet18	Metric	29.34 $\pm$ 0.22	41.34 $\pm$ 0.22
DN4 (Li et al., 2019a)	ResNet18	Metric	29.05 $\pm$ 0.21	30.12 $\pm$ 0.78
Baseline (Chen et al., 2019)	ResNet18	Fine-tuning	33.12 $\pm$ 0.25	44.63 $\pm$ 0.24
Baseline++ (Chen et al., 2019)	ResNet18	Fine-tuning	32.19 $\pm$ 0.23	43.32 $\pm$ 0.22