

# Language Guided Concept Bottleneck Models for Interpretable Continual Learning

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## Abstract

*Continual learning (CL) aims to enable learning systems to acquire new knowledge constantly without forgetting previously learned information. CL faces the challenge of mitigating catastrophic forgetting while maintaining interpretability across tasks. Most existing CL methods focus primarily on preserving learned knowledge to improve model performance. However, as new information is introduced, the interpretability of the learning process becomes crucial for understanding the evolving decision-making process, yet it is rarely explored. In this paper, we introduce a novel framework that integrates language-guided Concept Bottleneck Models (CBMs) to address both challenges. Our approach leverages the Concept Bottleneck Layer, aligning semantic consistency with CLIP models to learn human-understandable concepts that can generalize across tasks. By focusing on interpretable concepts, our method not only enhances the model's ability to retain knowledge over time but also provides transparent decision-making insights. We demonstrate the effectiveness of our approach by achieving superior performance on several datasets, outperforming state-of-the-art methods with an improvement of up to 3.06% in final average accuracy on ImageNet-subset. Additionally, we offer concept visualizations for model predictions, further advancing the understanding of interpretable continual learning. Code is available at <https://github.com/FisherCats/CLG-CBM>.*

## 1. Introduction

In dynamic and ever-changing environments, models trained on fixed datasets often struggle to adapt to new

tasks or data without losing previously acquired knowledge, facing the challenge known as catastrophic forgetting [32]. Continual learning [8, 31, 71] addresses this limitation by allowing systems to retain and incrementally build upon past knowledge, resulting in greater flexibility. This capability is especially critical in real-world applications like robotics, autonomous systems, and personalized healthcare, where models must continuously learn from ongoing experiences and data streams to stay effective. Additionally, continual learning improves the transfer of knowledge across tasks, minimizing the need for frequent retraining and enhancing computational efficiency. These benefits make continual learning a promising approach for advancing intelligent and adaptive AI systems in real-world.

Existing continual learning methods [26, 39, 42, 56, 64] focus on mitigating the issue of catastrophic forgetting yet the underlying mechanisms behind this phenomenon remain largely unexplained. As these models continuously update their knowledge, it becomes crucial to understand what they learn and how they retain previous information to prevent unintended behavior and enhance human interpretability. Furthermore, understanding the internal mechanisms of continual learning models can guide improvements in their design, leading to more robust and effective systems.

Despite the importance of this challenge, few papers have explored the interpretability of continual learning models. ICICLE [44] is one such work, which interprets concept drift in continual learning through a prototypical-part network and introduces interpretability regularization to minimize changes in prototype similarities.

Concept Bottleneck Models (CBMs) [22, 54] are a form of interpretable machine learning model that enhance transparency by organizing the learning process around human-

understandable concepts. Rather than directly mapping inputs to predictions, CBMs incorporate an intermediate ‘bottleneck’ layer composed of high-level, explicitly defined concepts that are meaningful to humans. Some recent research [36, 47, 58, 61] integrates language-guided approaches with CBMs to further align the model’s decision-making process with human cognition, particularly for tasks involving abstract or semantic knowledge. Leveraging the inherent interpretability and structured knowledge representation of CBMs, this paper investigates their potential application to continual learning, with the goal of enhancing both interpretability and adaptability while ensuring the retention of previously acquired knowledge.

With the rapid advancements in large-scale multimodal models, we can harness their robust zero-shot encoding capabilities to establish a strong foundation for extracting high-quality features. In this paper, we integrate the pre-trained CLIP [38] model to obtain bottleneck concepts within a continual learning framework. Specifically, we utilize pre-trained language models (e.g., ChatGPT [5]) to generate human-understandable concepts for each category. These concepts are subsequently encoded into concept embeddings through the CLIP text encoder, after which the most informative and expressive concepts are selected to form a task-specific bottleneck. We construct the Concept Bottleneck Layer (CBL) by aligning the concept score matrix with CLIP concept activation matrix, enhancing model’s interpretability. Furthermore, we leverage semantic knowledge to augment prototypes, effectively mitigate catastrophic forgetting. Finally, our approach achieves superior performance on seven benchmark datasets, consistently maintaining interpretability throughout the process.

Our main contributions can be summarized as follows:

- We introduce a novel framework that leverages language-guided Concept Bottleneck Models to enhance both interpretability and the ability to mitigate catastrophic forgetting in continual learning.
- We construct the Concept Bottleneck Layer by aligning semantic consistency with CLIP models, enabling the learning of human-understandable concepts across tasks.
- Our method outperforms state-of-the-art methods on the several datasets. Additionally, we provide concept visualizations for model predictions to enhance the understanding of interpretable continual learning.

## 2. Related Work

### 2.1. Continual Learning

There are three main types of existing continual learning methods. *Regularization-based* methods [2, 10, 14, 17, 21, 26, 29, 51, 66–68, 72] typically alleviate catastrophic forgetting either by constraining the model’s outputs through knowledge distillation or by penalizing changes to critical

parameters based on their assessed importance. *Rehearsal-based* methods [6, 16, 28, 41, 42, 60] involve replaying data from previous tasks by storing a subset of past data or by generating synthetic data, to prevent forgetting. The replayed data can be used at training stage with the current task data, maintaining the model’s performance on previous tasks. *Architecture-based* methods [30, 59, 63] adapt the model’s structure dynamically as new tasks are introduced, such as activating different part of model parameters for different tasks, using modular designs to compartmentalize learning and minimize interference between tasks.

Methods based on pre-trained models (PTMs) have made significant progress recently by leveraging robust features extracted from large-scale PTMs. Among these methods, approaches [13, 27, 49, 55, 56] based on *Parameter-Efficient Tuning* typically construct and train a set of PEF modules, improving performance while reducing computational costs. *Representation-based* methods [52, 69, 70], on the other hand, usually utilize the robust features of PTMs to construct classifiers.

The methods discussed above effectively alleviate the problem of catastrophic forgetting, a central challenge in continual learning. However, the decision-making process of those methods is still a black box and not transparent, and the rationality for model predictions shifts over time due to catastrophic forgetting, making it difficult to improve interpretability in continual learning. To address this issue, ICICLE [44] has explored interpretable continual learning methods by introducing a prototypical parts-based approach, they further proposed interpretability regularization and proximity-based prototype initialization, regularizing model to activate similar prototypical parts learned previously to mitigate Interpretability Concept Drift (ICD). Although ICICLE provides interpretability, it substantially limits the plasticity of the model, highlighting the need for methods that are both interpretable and effective.

### 2.2. Interpretable Deep Learning

There are two types of interpretable models that have been well-developed in the domain of deep learning explanations: post-hoc models and self-explainable models. Post-hoc models aim to elucidate the reasoning process of black-box methods, using techniques such as saliency maps [45, 46], concept activation vectors [18, 22, 62], counterfactual examples [1, 15, 33] and prototype similarity [7, 11, 43], etc. While self-explainable models [3, 19, 34] aim to make the model intrinsically interpretable by faithfully representing the entire classification behavior, they are often more complex than post-hoc models.

Among these interpretable models, Concept Bottleneck Models [22, 48, 58, 61, 65] provide explanations of the model’s decision-making process in a straightforward manner. CBMs are designed to be interpretable, incorporating

an intermediate Concept Bottleneck Layer (CBL), where each neuron represents a high-level, expressive concepts. Image features are projected into Concept Space to acquire concept score vectors, which are utilized to make final classification. Recent research [36, 58, 61] has integrated textual knowledge with CBMs, addressing the challenges of obtaining class concepts and annotations by querying LLMs (e.g. chatGPT) and utilizing VLM (e.g. CLIP) to encode images and concepts. The similarity between the image and the concepts is calculated to determine the probability of each concept’s presence in the image, producing a similarity vector that serves for interpretation and classification, making the decision making process more transparent.

### 3. Preliminary

#### 3.1. Class-Incremental Learning

We focus on class incremental learning (CIL) in this paper, where the learning process unfolds across multiple tasks. For CIL scenario with  $n$  tasks, let  $\mathcal{X}_t$  denote the input space, and  $\mathcal{Y}_t$  represent the set of labels or classes observed by the model at task  $t$ . The data associated with task  $t$  can be denoted as  $\mathcal{D}_t = \{(x_i, y_i)\}_{i=1}^{N_t}$ , where  $x_i \in \mathcal{X}_t$  and  $y_i \in \mathcal{Y}_t$ . At each task  $t$ , the model is introduced to a new set of classes  $\mathcal{Y}_t$ , which it learns to recognize these new classes while retaining knowledge of previously encountered classes.

The sequence of tasks is denoted as  $\mathcal{T} = \{1, 2, \dots, n\}$ . In CIL, classes included in separate tasks are non-overlapping, where  $\mathcal{Y}_i \cap \mathcal{Y}_j = \emptyset$  ( $\forall i \neq j$ ). The entire class space after task  $t$  is represented as:  $\mathcal{Y}_{1:t} = \mathcal{Y}_1 \cup \mathcal{Y}_2 \cup \dots \cup \mathcal{Y}_t$ . During training for task  $t$ , the model has access only to the current task’s dataset  $\mathcal{D}_t$ , but it needs to predict labels from the cumulative set of classes  $\mathcal{Y}_{1:t}$ .

#### 3.2. Concept Bottleneck Models

Compared to conventional deep learning architectures, Concept Bottleneck Models (CBMs) [22, 54] introduce a Concept Bottleneck Layer (CBL) positioned between feature extractor and classifier. Concept Bottleneck Layer comprises neurons that represent human-understandable concepts. These neurons convert image features into concept scores, which quantify the degree of alignment between the image and predefined concepts. The classifier then leverages these concept scores to make predictions, thereby enhancing the interpretability of the decision-making process. Language-Guided CBMs [36, 47, 58, 61] extend this framework by integrating natural language processing (NLP) with concept-based modeling to further enhance interpretability and performance. A notable example is the CLIP-based CBMs [58, 61], which employs the pre-trained CLIP model as its backbone. For instance, CLIP-based CBM method [58] initially gathers relevant

concepts by querying ChatGPT, followed by a concept selection module which is developed to identify the most informative and discriminative concepts. Specifically, a simple Multi-Layer Perceptron is trained in [58] to capture the semantic knowledge embedded in images, guided by both Cross-Entropy loss and Mahalanobis loss. The acquired semantic knowledge is subsequently utilized for concept selection, constructing a concept pool  $\mathcal{C}$  to facilitate model interpretability. The text features of  $\mathcal{C}$  serves as the CBL in CLIP-based CBMs, and the size of CBL is determined by the quantity of selected concepts for all seen tasks.

The CLIP concept activation matrix is computed as the dot product between the image features  $f_I(\mathcal{X})$  and text features  $f_T(\mathcal{C})$  as follows, enabling the model to align visual inputs with their corresponding semantic concepts:

$$E_{clip} = f_I(\mathcal{X}) \cdot f_T(\mathcal{C})^\top \quad (1)$$

The final predication  $\hat{y}$  can be calculated as follows:

$$\hat{y} = \text{argmax } \sigma(E_{clip} \cdot W_l^\top), \quad (2)$$

where  $W_l$  refers to the weight of classifier,  $\sigma$  refers to sigmoid function.

### 4. Method

#### 4.1. Overview Framework

We introduce Language-Guided Concept Bottleneck Models as an efficient framework for achieving interpretable continual learning. CBMs are designed to learn human-understandable intermediate representations, known as concepts, which serve as the basis for predictions and enhance transparency. However, while CBMs improve interpretability, applying them directly in a continual learning setting can still lead to catastrophic forgetting. To mitigate this, we propose a *semantic-guided prototype augmentation module* to generate pseudo-features for old classes by leveraging semantic similarity with new data. Additionally, we introduce a *concept alignment module* during the learning of the Concept Bottleneck Layer (CBL) to enhance neuron interpretability. This alignment enforces neurons to activate in response to target concepts, resulting in clearer concept representation while simultaneously improving predictive accuracy. Together, these modules aim to preserve past knowledge and improve both interpretability and performance in continual learning scenarios.

As shown in Figure 1, we use the frozen CLIP image encoder  $f_I$  and text encoder  $f_T$  to extract image and concept features. When a new task arrives, we generate key concepts for each class using ChatGPT, selecting the most expressive and informative concepts  $\mathcal{C}_t$  to form a task-specific “concept bottleneck” using a learning-to-search algorithm, as proposed in [58]. We save the bottlenecks that learned at

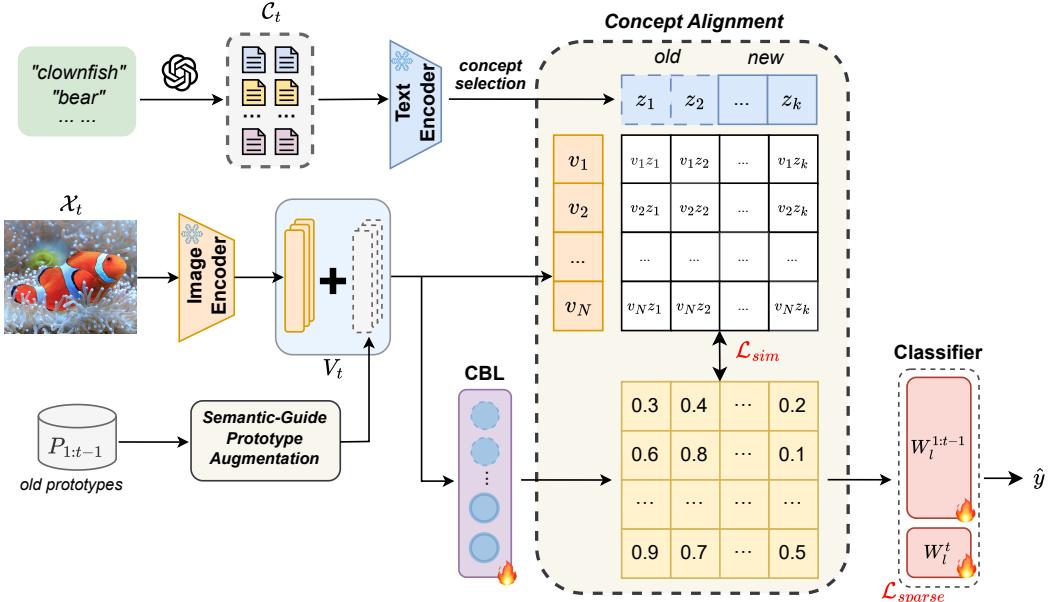


Figure 1. The framework of our method for task  $t$ . The concept alignment module aligns the concept score matrix with the CLIP concept activation matrix. The semantic-guided prototype augmentation module leverages semantic knowledge to identify the most semantically similar class within  $\mathcal{Y}_t$ , generating pseudo-features for previously learned classes to mitigate catastrophic forgetting.

each task for continual interpretability. We then construct the Concept Bottleneck Layer (CBL) to represent the relationships between learned classes and concepts, using both the current features and generated pseudo features of old classes. Inspired by [36], the concept score matrix output by the CBL is aligned with the CLIP concept activation matrix via a similarity loss  $\mathcal{L}_{sim}$ . Finally, the classifier maps these concept scores to predicted classes using cross-entropy loss  $\mathcal{L}_{ce}$  and a sparsity loss  $\mathcal{L}_{sparse}$ , inspired by [57], to encourage learning of key features and interpretable classifier.

## 4.2. Model Training

**Concept Bottleneck Layer Construction.** We construct the Concept Bottleneck Layer (CBL) using the bottlenecks collected across tasks to explain our model’s behavior while enhancing its performance. The bottlenecks from tasks  $\mathcal{T}_{1:t}$  are represented as  $B_t = [z_1, z_2, \dots, z_k] \in \mathbb{R}^{|\mathcal{C}_{1:t}| \times D}$ ,  $k = |\mathcal{C}_{1:t}|$ , where  $D$  refers to the dimension of feature embedding. We save all previously learned bottlenecks, creating a cumulative concept space that preserves essential semantic knowledge to mitigate catastrophic forgetting. These bottlenecks also improve generalization to new tasks by leveraging a broader set of interpretable features accumulated across tasks. We use the frozen CLIP image encoder  $f_I$  to extract image features  $f_I(\mathcal{X}_t)$  and project these into the CBL to produce concept scores  $E$ , capturing the model’s understanding of relationships between images and concepts, as formulated below:

$$E = f_I(\mathcal{X}_t) \cdot W_C^\top, E \in \mathbb{R}^{N_t \times |\mathcal{C}_{1:t}|} \quad (3)$$

where  $W_C$  represents the weight matrix of CBL, which consists of a single linear layer. Finally, the classifier  $g$  maps  $E$  to the class space, yielding the predicted labels  $\hat{y}$  for the images.

Since the concepts are acquired incrementally under CIL scenario, both the CBL and the classifier need to expand to accommodate the learning of new concepts and categories, ensuring that they accurately map the embeddings while retaining the learned knowledge from the previous task.

**Concept Alignment.** To guide the CBL toward human-understandable bottlenecks and enhance interpretability, we align the learned concept scores with CLIP concept activation scores. This alignment maintains semantic consistency across tasks and improves robustness by anchoring learning to stable, meaningful concepts. By using CLIP, we can easily acquire the CLIP concept activation matrix  $E_{clip}$  by equation (1). We train CBL to align with the CLIP concept score matrix  $E_{clip}$ , transferring the general knowledge to the output  $E$  of CBL by a similarity loss  $\mathcal{L}_{sim}$ , defined as:

$$\begin{aligned} \mathcal{L}_{sim} &= -\frac{1}{|\mathcal{C}_{1:t}|} \sum_{i=1}^{|\mathcal{C}_{1:t}|} \cos(\hat{E}^i, \hat{E}_{clip}^i) \\ &= -\frac{1}{|\mathcal{C}_{1:t}|} \sum_{i=1}^{|\mathcal{C}_{1:t}|} \frac{\hat{E}^i \cdot \hat{E}_{clip}^i}{\|\hat{E}^i\|_2 \cdot \|\hat{E}_{clip}^i\|_2} \end{aligned} \quad (4)$$

Here,  $\hat{E} = E^3$  and  $\hat{E}_{clip} = E_{clip}^3$  to further sharp the concept scores distribution following [36].

The classifier in CBM connects the concept space and the class space, can be understood as the contribution of

concepts to distinguish categories. To encourage more interpretable classifier and transparent decision-making process, we regularize the final layer of our model using elastic-net penalty proposed by [57] as shown below:

$$\mathcal{L}_{\text{sparse}} = \phi ||W_l||_1 + \frac{1}{2}(1 - \phi)||W_l||_F \quad (5)$$

where  $W_l$  is the weight of final layer,  $\phi$  is a trade-off parameter, we set  $\phi$  to 0.99 for our method.

**Semantic-guided Prototype Augmentation.** Prototype augmentation or compensation is commonly employed in class-incremental learning (CIL) to retain previously acquired knowledge, as prototypes from earlier tasks may become inaccurate over time due to feature drift. Research in [37, 64, 72] demonstrates that feature drift within feature extractor can be estimated using data from the current task, resulting in significant performance gains. Building on this insight, we propose leveraging semantic knowledge to augment prototypes, thereby mitigating catastrophic forgetting and align concepts across all categories. Specifically, we propose a semantic-guided prototype augmentation strategy to generate pseudo-features for previously learned classes. We assume that classes with similar semantic information exhibit similar embedding distributions. Therefore, we first identify the category most similar to a previous class  $j \in \mathcal{Y}_{1:t-1}$  by calculating similarity scores between the embedding of the old class name and the prototypes of newly learned classes as follows:

$$h = \arg \max_{i \in \mathcal{Y}_t} (\cos(f_T(y^j), p_i)) \quad (6)$$

where  $y^j$  refers to the class name of class  $j$ ,  $p_i$  refers to the prototype of class  $i$ .

Then we compute the discrepancy between the image features  $V^h$  of class  $h$  in the current task  $t$  and the prototype of class  $h$ . We add this discrepancy to the prototype of class  $j$  to obtain the generated pseudo features  $\tilde{V}^j$ , where  $j$  is the class most semantically similar to  $h$ . The generated pseudo features  $\tilde{V}^j$  of previous class  $j$  can formulate as follows:

$$\tilde{V}^j = p^j + V^h - p^h \quad (7)$$

After augmenting prototypes, we train our model on the current task data  $\mathcal{D}_t$  along with the generated pseudo features guiding the learning process with cross-entropy loss as follows:

$$\hat{y} = V_t \cdot W_C^\top \cdot W_l^\top \quad (8)$$

where  $V_t$  represents the feature set which involves the image features of classes in  $\mathcal{Y}_t$  and augmented prototypes of classes in  $\mathcal{Y}_{1:t-1}$ . Overall, the final loss function can be described as:

$$\mathcal{L} = \mathcal{L}_{ce}(\hat{y}, y) + \lambda \mathcal{L}_{sim} + \sigma \mathcal{L}_{sparse} \quad (9)$$

where  $y \in \mathcal{Y}_{1:t}$ ,  $\lambda$  and  $\sigma$  are trade-off weights for  $\mathcal{L}_{sim}$  and  $\mathcal{L}_{sparse}$  respectively.

## 5. Experiments

### 5.1. Experiments Setup

**Evaluation Benchmarks.** We evaluated our method on three coarse-grained datasets: CIFAR-100 [24], Tiny-ImageNet [25], ImageNet-subset [9]. The first two datasets contain 100 classes each, while the latter contains 200 classes. In addition, we performed comprehensive evaluations on four fine-grained datasets: CUB-200 [53], Flower [35], Food-101 [4], Stanford-cars [23]. There are 200 classes in CUB-200, 101 classes in Food-101, 102 classes in Flower, 196 classes in Stanford-cars.

We adopt the exemplar-free class incremental learning setting, where no exemplars are retained for previously learned classes. The dataset is split according to the format “B- $m$  Inc- $n$ ”, where  $m$  denotes the number of classes included in the initial task, and  $n$  represents the number of classes included in each incremental task. For each dataset, we perform experiments using two different splitting strategies: (1) large  $m$  with small  $n$ , and (2)  $m = n$ . All experiments we conducted are based on same random seed 1993 for fair comparison.

**Implementation Details.** We developed our method and reproduced other method with Pilot [50]. All experiments were conducted on an NVIDIA RTX 3090. Unless otherwise specified, we ran all experiments using CLIP ViT-B/16 as the backbone for all methods. CLIP RN-50 was used as backbone when comparing to ICICLE, which is designed for CNN-based model. We train our model using the Adam optimizer [20] with a batch size of 64, a learning rate of 0.001, and a total of 60 training epochs. We set the trade-off weight of similarity loss  $\lambda$  to 1 and that of sparsity loss  $\sigma$  to 0.001. The prompts we used to query ChatGPT and examples of generated concepts are provided in Supp. Mat. 7.1. More implementation details can be found in Supp. Mat. 7.2, including the implementation of the concept selection module and the pseudo code of the algorithm.

**Evaluation Metric.** Following the evaluation protocol of previous works [56, 69, 70], we report the average incremental accuracy, denoted as  $\bar{A} = \frac{1}{n} \sum_1^n A_t$ , where  $A_t$  represents the mean accuracy on all learned categories after learning task  $t$ ,  $n$  denotes the number of tasks. Additionally, we also use  $A_{last}$  to represent the average accuracy of all categories after learning the last task  $n$ .

### 5.2. Comparison with State-of-the-Art Methods

**Evaluation on Coarse-grained Datasets.** In Table 1, we report the average incremental accuracy  $\bar{A}$  and the final average accuracy  $A_{last}$  of our method compared with state-of-the-art methods on three datasets: CIFAR-100, Tiny-ImageNet, ImageNet-subset. As shown, our approach demonstrates either the best or second-best performance across all settings and datasets. On ImageNet-subset, we

Table 1. Performance comparison on three coarse-grained datasets, the best performance is shown in bold, the second-best performance is underlined. All methods are implemented without using exemplars. We replace the backbones of all methods to CLIP ViT-B/16.

Methods	CIFAR-100				Tiny-ImageNet				ImageNet-subset						
	B-10 Inc-10	$\bar{A}$	$A_{last}$	B-50 Inc-5	$\bar{A}$	$A_{last}$	B-10 Inc-10	$\bar{A}$	$A_{last}$	B-10 Inc-10	$\bar{A}$	$A_{last}$	B-50 Inc-5	$\bar{A}$	$A_{last}$
L2P[56]	76.56	65.75	61.85	44.19	69.66	60.36	62.29	55.13	71.28	52.24	65.89	49.08			
DualPrompt[55]	81.41	70.34	64.05	43.86	74.06	66.08	65.35	56.15	72.86	54.20	64.64	49.48			
CODA-Prompt[49]	82.13	72.34	65.49	49.72	75.18	66.65	61.47	48.31	71.17	52.98	64.64	41.40			
CPP[27]	75.73	67.50	69.57	66.26	68.70	61.23	66.61	63.48	83.45	<u>75.80</u>	79.74	73.78			
LAE[13]	82.65	72.60	67.35	50.96	76.81	68.98	63.38	49.52	78.29	62.94	64.25	47.90			
Continual-CLIP[52]	75.15	66.68	70.79	66.68	63.63	55.91	58.68	55.91	<u>84.98</u>	75.40	81.35	<u>75.40</u>			
SLCA[69]	83.13	72.01	<b>80.07</b>	<u>71.24</u>	68.99	54.50	60.34	48.53	83.19	69.44	80.81	73.78			
EASE[70]	<b>85.07</b>	<b>77.31</b>	76.72	70.50	<b>79.88</b>	<b>72.99</b>	70.42	64.12	84.80	70.82	63.74	56.48			
Ours	$84.49 \pm 0.26$	$76.82 \pm 0.50$	$79.07 \pm 0.34$	$75.91 \pm 0.50$	$79.28 \pm 0.86$	$71.98 \pm 0.25$	<b>75.64</b> ± 0.17	<b>71.97</b> ± 0.09	<b>86.83</b> ± 1.32	<b>78.97</b> ± 0.39	<b>81.85</b> ± 0.76	<b>78.21</b> ± 0.29			

Table 2. Average incremental accuracy comparison on four fine-grained datasets, the best performance is shown in bold, the second-best is underlined. All methods are implemented without using exemplars. We replace the backbones of all methods to CLIP ViT-B/16.

Methods	CUB-200		Flower		Stanford-cars		Food-101	
	B-10 Inc-10	B-100 Inc-10	B-10 Inc-10	B-50 Inc-5	B-14 Inc-14	B-100 Inc-10	B-10 Inc-10	B-50 Inc-5
L2P[56]	62.08	59.38	84.37	76.70	64.42	61.82	79.48	69.72
DualPrompt[55]	64.95	61.85	89.64	79.16	<u>76.94</u>	68.46	86.27	69.66
CODA-Prompt[49]	67.22	59.82	88.57	77.70	76.44	60.80	87.76	67.22
CPP[27]	83.60	75.03	<u>94.95</u>	<u>93.30</u>	84.75	77.49	90.21	86.60
LAE[13]	66.45	59.98	86.79	77.55	77.25	<u>80.28</u>	88.41	66.26
Continual-CLIP[52]	69.41	60.35	78.72	74.06	<u>86.43</u>	69.79	<u>92.04</u>	<u>89.96</u>
SLCA[69]	80.53	<u>76.85</u>	92.77	82.14	84.74	70.59	74.49	76.28
EASE[70]	<u>83.87</u>	66.14	94.86	77.05	86.22	64.32	91.74	81.72
Ours	<b>85.40</b> ± 0.61	<b>82.20</b> ± 0.65	<b>95.58</b> ± 0.20	<b>94.53</b> ± 0.20	<b>88.60</b> ± 0.55	<b>85.07</b> ± 0.82	<b>92.25</b> ± 0.32	<b>90.97</b> ± 0.42

achieve at least a 1.79% improvement on  $\bar{A}$  and 3.06% on  $A_{last}$  compared to existing methods. Our results on CIFAR-100 and Tiny-ImageNet are comparable to those methods that prioritize performance improvement without considering interpretability. In contrast, our method achieves a balanced approach, enhancing both performance and interpretability.

**Evaluation on Fine-grained Datasets.** We also conduct experiments on four fine-grained datasets: CUB-200, Flowers, Stanford Cars, and Food-101. As shown in Table 2, it is clear that our method achieves superior results across various data splits and datasets, particularly on CUB-200 and Stanford Cars, where the gains reach 4.43% and 4.69%, respectively. This suggests that our language-guided CBM-based approach provides significant benefits for fine-grained dataset classification in a continual learning setting.

**Comparison with Interpretable Methods.** We further compared our proposed method with ICICLE[44], a recently proposed interpretability-driven continual learning method. The original ICICLE utilizes a ResNet pre-trained on ImageNet as its backbone. To ensure a fair comparison, we replace the backbone in both ICICLE and our method with the pre-trained CLIP RN50. As shown in Table 3, we can observe that our method significantly outperforms ICICLE on both benchmark datasets and demonstrates greater stability to various data split.

Table 3. Average incremental accuracy comparison with ICICLE, the best performance is shown in bold. We replace the backbone of our method and ICICLE to pre-trained CLIP RN50.

Methods	CUB-200		Stanford-cars	
	B-50 Inc-50	B-20 Inc-20	B-49 Inc-49	B-14 Inc-14
ICICLE [44]	39.31	20.85	49.58	24.22
Ours	<b>66.21</b>	<b>69.72</b>	<b>73.91</b>	<b>75.26</b>

Moreover, our method requires fewer trainable parameters than ICICLE, which necessitates training the entire model. Additionally, our method offers greater flexibility, as it is architecture-agnostic. Unlike ICICLE, a prototypical-part-based approach constrained to CNN architectures, our method can utilize either a Vision Transformer [12] or ResNet as the backbone.

Additional experimental results are provided in Supp. Mat. 7.3, including dynamic performance curves under different settings, results obtained using various versions of description generation models, comparisons with joint training, and ablation studies on different modules.

### 5.3. Further Analysis

**Performance-Parameter Comparison.** Figure 2 demonstrates the Performance-Parameter comparison between our method and other state-of-the-art methods after training on ImageNet-subset B-10 Inc-10. Methods with fewer trainable parameters and higher accuracy are considered super-

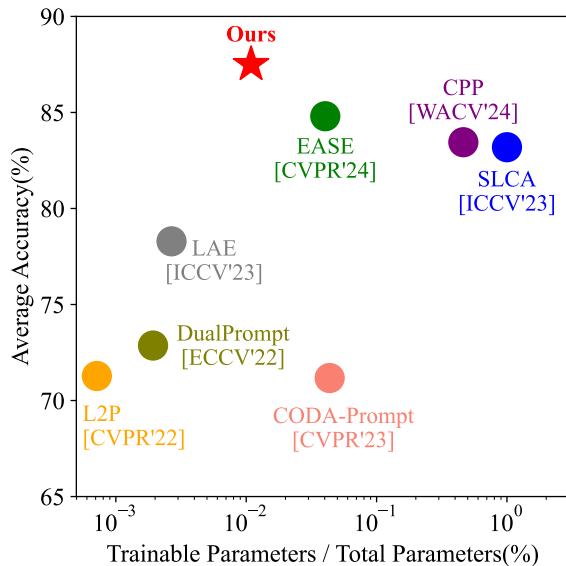


Figure 2. Performance-Parameter comparison of our method and benchmark methods on ImageNet-subset B-10 Inc-10.

prior. From Figure 2 we can observe that all the compared methods, our method achieves best performance with relatively less trainable parameters. Since our model is designed to select concepts from a concept pool, approximately half of its trainable parameters are allocated to learning to identify expressive and informative concepts. The parameter requirement could be further reduced by using pre-defined concepts instead of training concept selection for each task. We also provide the computational overhead of the concept selection module in Supp. Mat. 7.4.

**Effect of Concept Quantity.** Table 4 manifests the effect of different concept quantities to the performance. We report  $\bar{A}$  of our method with 10,20,50 and 100 concepts per task on CUB-200 B-10 Inc-10 and ImageNet-subset B-10 Inc-10. We observe that performance improves as the number of concepts learned increases. On CUB-200 dataset, performance shows a dramatic improvement with more concepts per task, eventually plateauing. For ImageNet-subset, the results remain relatively stable as the number of concepts increases. Based on these observations, we choose to adapt 100 concepts per task across all datasets, striking a balance between concept diversity and computational efficiency.

#### 5.4. Understanding Model Interpretability

**Interpretable Model Prediction.** Inspired by [36, 40, 58], We analyze the decision-making process of our method by highlighting the contribution of each concept to the final classification result. Given an input image  $x$  of class  $k$ , we denote the contribution of concept  $c_i$  to class  $k$  as  $Con_{i,k}$ , which is computed as follows:

$$Con_{i,k} = f_1(x) \cdot (W_C^i)^\top \cdot W_l^{k,i} \quad (10)$$

Table 4. The effect of the number of concepts on the performance of the method.

Concepts per task	CUB-200	ImageNet-subset
	B-10 Inc-10	B-10 Inc-10
10	79.32	86.25
20	83.70	86.80
50	85.70	87.24
100	<b>86.07</b>	<b>87.40</b>

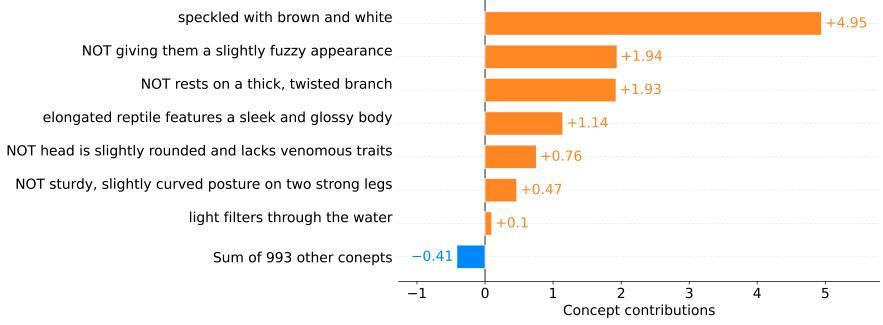
Here,  $W_C^i$  denotes the  $i$ -th row of the weight matrix of the CBL, and  $W_l^{k,i}$  represents the connection weight between class  $k$  and concept  $i$  in the final layer. The value of  $Con_{i,k}$  can be either positive or negative, indicating positive or negative relevance to class  $k$ , respectively. A higher absolute value of  $Con_{i,k}$  signifies greater importance of the concept for that class.

As illustrated in Figure 3, we present the top-7 most relevant concepts for an *axolotl* image from ImageNet-subset and a *sayornis* image from CUB-200 after the entire training process. Concepts are listed in descending order of absolute contribution, with concepts labeled as “NOT” indicating a negative association to the image. We can see that the concept “speckled with brown and white” contributes most to the class *axolotl* as shown in Figure 3a, and “perches quietly on a thin, gnarled branch” is highly activated to class *sayornis* in Figure 3b, the decision-making process is illustrated through human-interpretable concepts, providing insights into the model’s reasoning. Furthermore, lower relevant concepts have minimal impact, as demonstrated by the cumulative negative contribution of 993 other features in Figure 3a, indicating a weak association with *axolotl*. Although the cumulative contribution of 1993 additional features in Figure 3b exceeds that of the top-7 concepts, the contribution of each individual feature within the 1993 concepts is marginal. Notably, negative concepts also play a role in enhancing model performance and confidence, reflecting their significance in the interpretability framework. More examples of interpretable model predictions are provided in Supp. Mat. 7.5.

**Concepts Change Across Tasks.** As illustrated in Figure 4, we present the variation in concept relevance for the class *gazania* on the Flower B-25 Inc-25, category *gazania* is learned at first task. Concepts are ordered from highest to lowest based on their contribution values. Our method demonstrates robust interpretability, as concepts with high contribution scores in the initial task maintain relatively high contributions even after the completion of the final task. Additionally, the negative concepts also show increased contribution compared to the initial task, thereby alleviating forgetting of previous knowledge. It indicates that our framework help alleviate catastrophic forgetting by focusing on stable concepts that are shared across tasks, de-



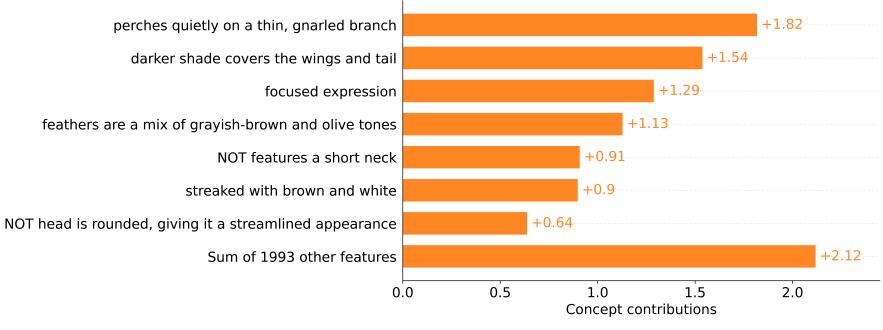
**Category:axolotl Prediction:axolotl Confidence: 0.969 Logit:10.86**



(a) Contribution visualization on ImageNet-subset



**Category:Sayornis Prediction:Sayornis Confidence: 0.780 Logit:10.36**



(b) Contribution visualization on CUB-200

Figure 3. (a) Contribution visualization of *axolotl* after training on ImageNet-subset B-10 Inc-10. (b) Contribution visualization of *sayornis* after training on CUB-200 B-10 B-10.

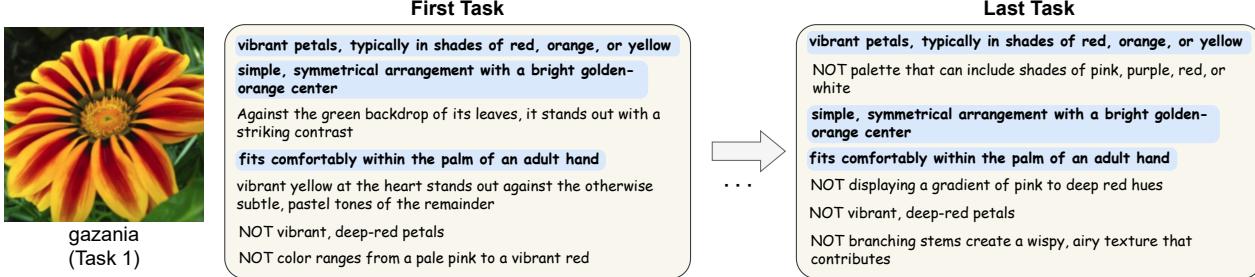


Figure 4. Top-7 concepts change of *gazania* after training the first and all the tasks on Flower B-25 Inc-25.

coupling task-specific information, and promoting the retention of useful knowledge over time.

## 6. Conclusion

In this paper, we introduce a novel framework based on Language-Guided Concept Bottleneck Models for interpretable continual learning. Our approach enhances interpretability by aligning the concept score matrix generated by the concept bottleneck layer to the CLIP activation score matrix, while also learning a sparse linear classifier. Additionally, we propose a semantic-guided prototype augmentation to generate pseudo features for the previous

tasks. Extensive experiments validate the effectiveness of our method, which maintains interpretability throughout the continual learning process.

**Limitation and Future Work.** Our approach builds upon Concept Bottleneck Models, making the model’s interpretability inherently dependent on the quality of the selected concepts. We have observed that the concepts generated by LLMs sometimes include non-visual descriptions, despite the use of appearance-related prompts. Future work will focus on improving concept selection quality and enhancing training efficiency.

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# Language Guided Concept Bottleneck Models for Interpretable Continual Learning

## Supplementary Material

### 7. Supplementary

#### 7.1. Concepts Preparation

Before initiating the incremental learning process, we retrieve concepts associated with specific categories through ChatGPT queries. Following the methodologies proposed in [36, 58, 61], we employ the following prompts to guide the ChatGPT interactions:

Table 5. Prompts for all benchmark datasets.

Dataset	Prompts
Coarse-grained, CUB-200	“using {num} sentences to describe the <b>appearance / color / size / shape / surroundings</b> of {category}”
Food101	“using {num} sentences to describe the <b>appearance / shape / color / texture</b> of a food named {category}”
Flower	“using {num} sentences to describe the <b>appearance / color / size / pattern / texture</b> of a flower named {category}”
Stanford-cars	“using {num} sentences to describe the <b>appearance / shape / color / size / structure</b> of a car named {category}”

By utilizing ChatGPT with prompts mentioned above, we generate descriptive sentences containing class-specific concepts. Subsequently, we employ a T5 model, as re-designed by [61], to extract concepts from these sentences, thereby constructing a comprehensive general concept pool. Examples of extracted concepts for categories in CUB-200, ImageNet-subset, Food-101 and Flower are provided in Tables 11 to 14.

#### 7.2. Additional Implementation Details

**More Details of Concept Selection Module.** Following [58], we implemented the concept selection module (CS) as a simple MLP. At the beginning of task  $t$ , the CS is trained on the training data of current task with cross-entropy loss and Mahalanobis loss, encouraging CS to construct embedding space with vision-language knowledge. We train CS for 30 epochs with a batch size of 64 and a learning rate of 0.01. After training, the learned weight matrix of CS is leveraged to select concepts from concepts set  $\mathcal{C}_t$  of task  $t$ , based on the distances between text features  $f_T(\mathcal{C}_t)$  and weight matrix.

**Pseudo Code.** The training pipeline of our proposed method is outlined in Algorithm 1, the image encoder  $f_I$

and text encoder  $f_T$  of CLIP are both frozen during the whole training process, only the CBL, classifier and CS are trainable. For each task, we first select concepts to construct a bottleneck and extract prototypes for the categories relevant to the current task. Afterward, old prototypes are augmented using data from the current task to address catastrophic forgetting. Lastly, we calculate the CLIP concept activation matrix and train our model with the guidance of three loss functions as described in Section 4.2.

#### Algorithm 1 LG-CBM for Interpretable CL

**Input:** Incremental datasets:  $\{\mathcal{D}^1, \mathcal{D}^2, \dots, \mathcal{D}^n\}$ , Task-specific concepts:  $\{\mathcal{C}_1, \mathcal{C}_2, \dots, \mathcal{C}_n\}$ , Pre-trained CLIP image encoder and text encoder:  $f_I, f_T$ .

**Output:** Incrementally trained model with interpretability

- ```

1: for  $t = 1, 2, \dots, n$  do
2:   Get the training set  $\mathcal{D}^t$  and Concepts  $\mathcal{C}_t$ ;
3:   Extract text feature of  $\mathcal{C}_t$ ;
4:   Select concepts from  $\mathcal{C}_t$  to form bottlenecks  $B_t$ ;
5:   Extract the prototypes of  $\mathcal{D}^t$  as  $P_t$ ;
6:   if  $t > 1$  then
7:     Augment prototypes  $P_{1:t-1}$  via Equation (6)
      and Equation (7);
8:   end if
9:   Compute CLIP concept activation matrix
      via Equation (1);
10:  Optimize the CBL and classifier via Equation (9);
11: end for

```

#### 7.3. More Results of Experiments

**Accuracy Curve in Various Settings.** We illustrate the accuracy decreasing trends of our method with other state-of-the-art baselines on  $\bar{A}$  across all benchmark datasets in Figure 5. Our method outperforms other methods with higher accuracy and less forgetting in most settings, especially when the initial task contains almost half of categories of the entire datasets, the  $A_{last}$  performance of our method is also best on most benchmark datasets.

**Concepts From Different ChatGPT.** As shown in Table 6, we report the average incremental accuracy  $\bar{A}$  on ImageNet-subset and Flower datasets with concepts generated from different ChatGPT models. The findings demonstrate that concepts derived from distinct ChatGPT models have minimal impact on the model’s performance, with accuracy fluctuations of less than 0.2% on ImageNet-subset and 0.5% on Flower. For all experiments conducted with our method, we

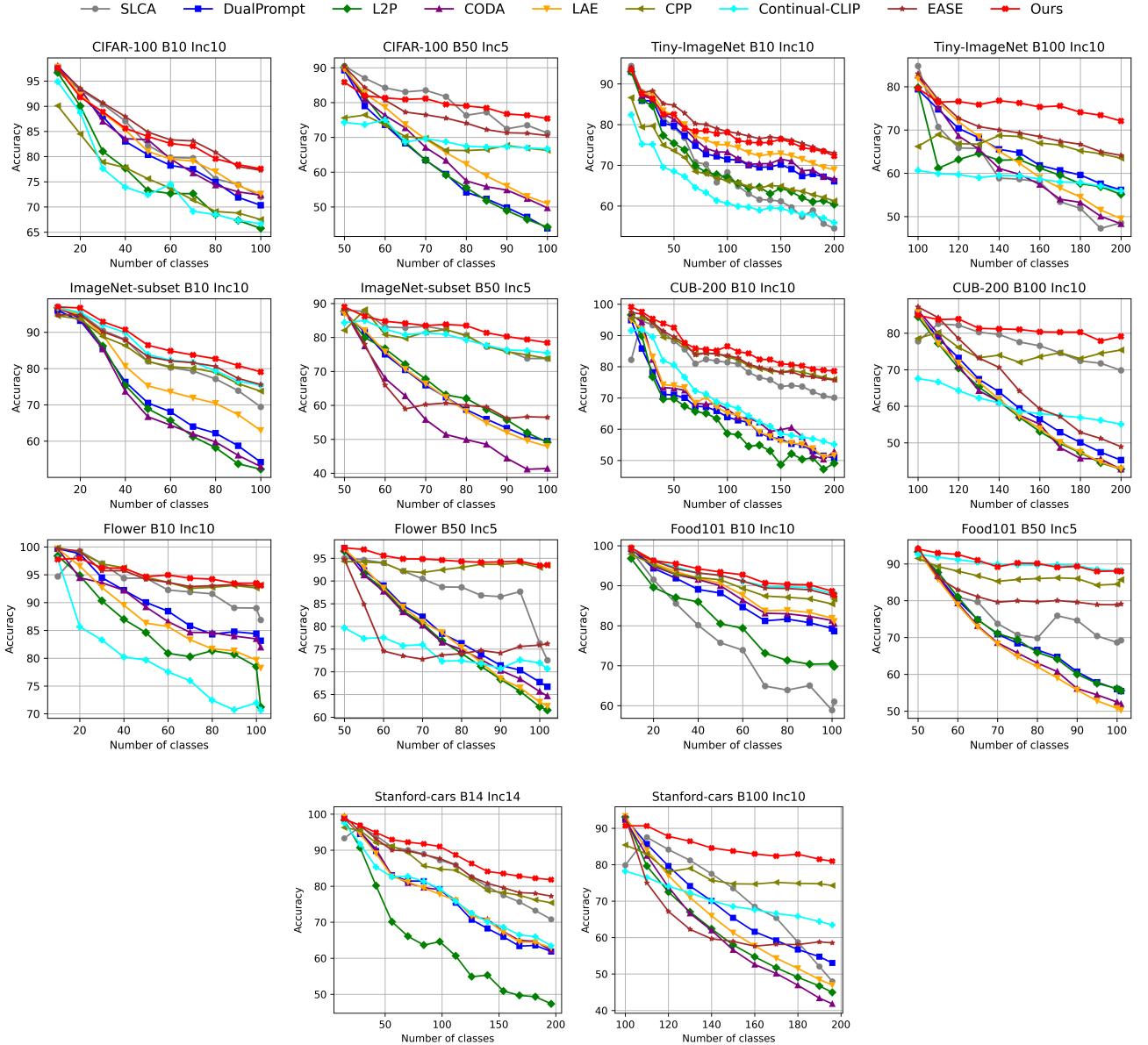


Figure 5. Average incremental accuracy  $\bar{A}$  curve of our method with other state-of-the-art methods across all benchmark datasets.

obtain concepts by querying GPT-4o.

Table 6. The average incremental accuracy  $\bar{A}$  on the ImageNet-subset and Flower datasets, evaluated using concepts derived from different versions of ChatGPT.

| ChatGPTs      | ImageNet-subset<br>B10 Inc10 | Flower<br>B10 Inc10 |
|---------------|------------------------------|---------------------|
| GPT-3.5 turbo | 87.63                        | 94.69               |
| GPT-4 turbo   | 87.50                        | 94.76               |
| GPT-4o        | 87.55                        | 95.16               |

**Performance in Non-continual Setting.** We present the re-

sults for joint training of our method on three coarse-grained datasets in Table 7. A performance gap remains between continual learning methods and joint training.

Table 7. The performance of our method under Non-continual setting.

| Methods        | CIFAR-100        | Tiny-ImageNet    | ImageNet-Subset  |
|----------------|------------------|------------------|------------------|
| Joint training | 82.14 $\pm$ 0.02 | 76.43 $\pm$ 0.11 | 83.52 $\pm$ 0.06 |

**Additional Ablation Study.** Semantic-Guided Prototype Augmentation (PA) is designed to enhance knowl-

edge retention. We evaluate its impact by comparing it against “Base” (without any anti-forgetting strategy) and “Base+Proto” (classical prototype loss without augmentation). The results show the effectiveness of the PA module.

Table 8. The effectiveness of semantic-guide prototype augmentation module.

|            | <b>CIFAR-100</b><br>B50 Inc5 | <b>Tiny-ImageNet</b><br>B100 Inc10 | <b>ImageNet-Subset</b><br>B50 Inc5 |
|------------|------------------------------|------------------------------------|------------------------------------|
| Base       | 11.02±1.42                   | 12.96±3.97                         | 23.90±8.50                         |
| Base+Proto | 69.15±0.38                   | 64.74±0.62                         | 74.23±0.25                         |
| Base+PA    | <b>75.91±0.50</b>            | <b>71.97±0.09</b>                  | <b>78.21±0.29</b>                  |

The Concept Alignment (CA) module helps learn human-understandable bottlenecks and enhances interpretability. We show an example of “Azalea” to analyze CA, listing the top-5 concepts in Table 9. With CA, the selected concepts are all positive and align well with human understanding, emphasizing the importance of the CA module.

Table 9. The comparison of Top-5 concepts that contribute most to classify “Azalea” with and without CA module.

| <b>Image</b>                                                                        | <b>CA</b> | <b>Top-5 Concepts</b>                                                                                                                                                                                                                                    |
|-------------------------------------------------------------------------------------|-----------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|  | w/o CA    | <b>NOT</b> radiate from the center like rays of sunshine<br>each petal is thin and almost translucent<br><b>NOT</b> encase a deep pink center<br><b>NOT</b> striking symmetry radiating from the center<br>stark contrast against its dark green foliage |
|                                                                                     | w/ CA     | support small pink blossoms<br>bright pink in color<br>vibrant pink hue with a pale white margin<br>thrive in the shaded nooks of the tree limbs<br>stark contrast against its dark green foliage                                                        |

#### 7.4. Computational Overhead of Concept Selection Module

The computational overhead of the CS on three coarse-grained datasets is shown in Table 10. We can infer from Table 10 that the training of CS is quite efficient, with low memory usage and computation, and the training time is also acceptable.

Table 10. The training cost of the concept selection module.

| <b>Metrics</b>         | <b>CIFAR-100</b> | <b>Tiny-ImageNet</b> | <b>ImageNet-Subset</b> |
|------------------------|------------------|----------------------|------------------------|
| FLOPs (M)              | 0.68             | 1.56                 | 0.99                   |
| Time per epoch (s)     | 1.30             | 1.26                 | 2.24                   |
| Peak Memory Usage (MB) | 2571             | 2701                 | 2673                   |

#### 7.5. More Interpretable Model Predictions.

As depicted in Figures 6 to 8, we provide additional examples of interpretable model predictions across various

datasets. We can find that our method demonstrates excellent interpretability across all benchmark datasets, delivering strong performance accompanied by coherent and logical explanations.

Table 11. Example concepts of categories in CUB-200.

| Category               | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  | Category       | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              |
|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Black footed Albatross | <ul style="list-style-type: none"> <li>“graceful, elongated body”,</li> <li>“long, slender wings”,</li> <li>“plume is primarily dark brown with subtle shades of gray”,</li> <li>“pale patch on its face creates an interesting visual effect”,</li> <li>“distinguishing feature against the rest of its body”,</li> <li>“large wingspan that stretches wide”,</li> <li>“body appears robust and streamlined”,</li> <li>“strong and hooked”,</li> <li>“overall form is well-suited for gliding over the ocean”,</li> <li>“endless, clear sky”,</li> <li>“glides over the gentle waves with ease”</li> </ul>                                                               | Crested Auklet | <ul style="list-style-type: none"> <li>“dark, slate-gray body”,</li> <li>“sleek look”,</li> <li>“head is adorned with a striking crest”,</li> <li>“adds to its distinctive appearance”,</li> <li>“around its beak”,</li> <li>“there is a splash of vibrant orange”,</li> <li>“small, bright eyes stand out against the darker feathers”,</li> <li>“small bird with a compact body”,</li> <li>“beak is short and slightly curved”,</li> <li>“prominent crest on its head”,</li> <li>“relatively short compared to its body”,</li> <li>“rocky coastline is covered in patches of green moss”,</li> <li>“waves crash against the shore under an overcast sky”</li> </ul> |
| Rusty Blackbird        | <ul style="list-style-type: none"> <li>“dark, glossy plumage that shimmers in the sunlight”,</li> <li>“feathers display a subtle iridescence of blues and greens”,</li> <li>“rusty hue adorns its wings and patches around its eyes”,</li> <li>“bill is slender and pointed”,</li> <li>“suitable for foraging”,</li> <li>“medium-sized bird with a slender build”,</li> <li>“body appears elongated and streamlined”,</li> <li>“has a relatively long tail”,</li> <li>“straight and slightly pointed”,</li> <li>“bird is perched on a thin branch, surrounded by dense foliage”,</li> <li>“background features a calm stream reflecting the overhanging trees”</li> </ul> | Gray Catbird   | <ul style="list-style-type: none"> <li>“sleek body with a predominantly gray plumage”,</li> <li>“head is capped with a darker, almost black hue”,</li> <li>“small, slender beak complements its smooth feathers”,</li> <li>“tail and wings show subtle, lighter shading”,</li> <li>“medium-sized bird with a slender body”,</li> <li>“overall shape is sleek and elongated”,</li> <li>“long tail that tapers towards the end”,</li> <li>“bird features a rounded head with a short, straight bill”,</li> <li>“gentle stream runs nearby”,</li> <li>“surrounded by tall reeds and vibrant autumn leaves”</li> </ul>                                                    |

Table 12. Example concepts of categories in ImageNet-subset.

| Category    | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     | Category | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              |
|-------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Goldfish    | <ul style="list-style-type: none"> <li>“bright orange coloration with a metallic sheen”,</li> <li>“fins are long and delicate”,</li> <li>“flowing gracefully in the water”,</li> <li>“sleek and oval-shaped”,</li> <li>“slight bulge at the sides”,</li> <li>“eyes are round and prominent”,</li> <li>“have an elongated body shape”,</li> <li>“typically around four to six inches long”,</li> <li>“fins are delicate and fan-like”,</li> <li>“bodies are often plump and streamlined”,</li> <li>“clear water surrounds them in an aquarium”,</li> <li>“green aquatic plants sway gently nearby”</li> </ul> | Cock     | <ul style="list-style-type: none"> <li>“vibrant plumage with a mix of rich, earthy tones”,</li> <li>“bright red adorns its comb and wattle, adding a striking contrast”,</li> <li>“hues of green and blue”,</li> <li>“sturdy beak and strong legs complete the appearance”,</li> <li>“appears quite large in the photo”,</li> <li>“structure is straight and firm”,</li> <li>“surface looks smooth and uniform”,</li> <li>“overall, it gives an impression of solidity and symmetry”,</li> <li>“warm glow over the farmyard”,</li> <li>“illuminating the rustic wooden fence and scattered hay”,</li> <li>“nearby, a few chickens peck at the ground”</li> </ul>      |
| Tailed Frog | <ul style="list-style-type: none"> <li>“brown, mottled skin”,</li> <li>“blends with the forest floor”,</li> <li>“large and sit prominently on its head”,</li> <li>“muscular and well-developed for jumping”,</li> <li>“small, tail-like appendage extends from its rear”,</li> <li>“small and robust with a rounded body”,</li> <li>“legs appear muscular and strong”,</li> <li>“head is wide with prominent eyes”,</li> <li>“slender tail extends from its back”,</li> <li>“small amphibian sits among the damp, moss-covered rocks”,</li> <li>“lush, green environment”</li> </ul>                         | Agama    | <ul style="list-style-type: none"> <li>“vibrant body with a mixture of colors”,</li> <li>“head is often bright red or orange”,</li> <li>“body can display hues of blue or brown”,</li> <li>“smooth and glossy under the light”,</li> <li>“medium-sized reptile with a stout body”,</li> <li>“limbs are strong and muscular, aiding in movement”,</li> <li>“head is somewhat triangular, tapering towards snout”,</li> <li>“tail is long and slender, extending beyond the body”,</li> <li>“rocky terrain is dotted with patches of dry grass and scattered stones”,</li> <li>“clear blue sky stretches above”,</li> <li>“casting shadows on sunlit ground”</li> </ul> |

Table 13. Example concepts of categories in Food101.

| Category       | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | Category  | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |
|----------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Chocolate Cake | <ul style="list-style-type: none"> <li>“appears round and sits on a flat surface”,</li> <li>“rich, dark brown”,</li> <li>“smooth, glossy finish”,</li> <li>“reflect off its slightly uneven edges”,</li> <li>“uniform throughout”,</li> <li>“appears dense yet tender”,</li> <li>“surface shows a slight sheen, suggesting a moist consistency”,</li> <li>“each slice reveals layers with a slightly crumbly edge;”,</li> <li>“smoothly glazed”,</li> <li>“contrasting with the softer interior”,</li> <li>“Tiny air pockets are scattered throughout”,</li> <li>“spongy nature”,</li> <li>“reveals a dense and moist interior”,</li> <li>“texture appears soft, showcasing fine crumbs”,</li> <li>“uniform color throughout”,</li> <li>“Tiny flecks may indicate the presence of fine ingredients”</li> </ul>                                                                                                                                                                                                  | Hot dog   | <ul style="list-style-type: none"> <li>“long, cylindrical shape with slightly rounded ends”,</li> <li>“nestled within a soft, oblong bun”,</li> <li>“bright red and mustard streaks on top”,</li> <li>“suggest a freshly cooked state”,</li> <li>“cooked evenly, its texture looks firm yet somewhat flexible”,</li> <li>“glisten, indicating juiciness”,</li> <li>“densely packed interior”,</li> <li>“hinting at a substantial bite”,</li> <li>“inside, it reveals a grilled sausage nestled within the bun”,</li> <li>“slightly browned”,</li> <li>“shows a textured casing”,</li> <li>“drizzled atop”,</li> <li>“blending into the sausage”,</li> <li>“soft layered”,</li> <li>“provide a cozy embrace”</li> </ul>                                                                                                                                                                                                                                                                          |
| Lasagna        | <ul style="list-style-type: none"> <li>“rectangular dish layered with alternating levels of ingredients”,</li> <li>“golden-brown with a slightly crisp texture”,</li> <li>“edges appear slightly darker, indicating a well-cooked surface”,</li> <li>“visible stripes of red and white sauce peeking through through”,</li> <li>“warm and inviting look”,</li> <li>“various shades of red, brown, and cream”,</li> <li>“layered structure with firm and slightly chewy pasta sheets”,</li> <li>“gooey and stretchy consistency from the melted cheese”,</li> <li>“moist and saucy texture between the layers”,</li> <li>“blend of soft, meaty, and creamy elements within it”,</li> <li>“visible layers alternate between creamy white and tangy red sauces”,</li> <li>“oozes over the top, creating a slightly golden crust”,</li> <li>“add texture and flavor”,</li> <li>“thin, flat pasta shapes the structure, holding everything together”,</li> <li>“specks of green are scattered throughout”</li> </ul> | Ice-cream | <ul style="list-style-type: none"> <li>“smooth, round shape with slight indentations”,</li> <li>“hue blends subtle shades of beige and light brown”,</li> <li>“surface appears glossy, catching light reflections”,</li> <li>“small, dark specks adds texture detail to its appearance”,</li> <li>“contrasts sharply with the dark background”,</li> <li>“smooth, creamy surface”,</li> <li>“glistens under the light”,</li> <li>“heaped scoops reveal tiny air pockets throughout”,</li> <li>“small droplets of condensation are visible on its exterior”,</li> <li>“soft, slightly elastic quality when scooped”,</li> <li>“melting edges give way to a glossy, liquid sheen”,</li> <li>“smooth and rich”,</li> <li>“Tiny air bubbles are evenly dispersed throughout the frozen treat”,</li> <li>“small vanilla bean specks are visible, hinting at quality ingredients”,</li> <li>“surface has a slightly glistening, frosty appearance”,</li> <li>“dense, yet soft composition”</li> </ul> |

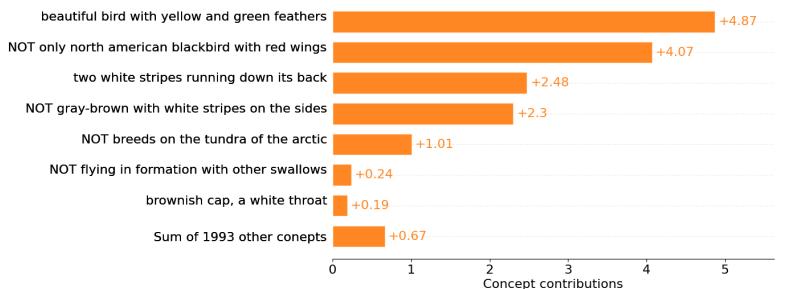
Table 14. Example concepts of categories in Flower.

| Category   | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | Category   | Concepts                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |
|------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Fire lily  | <ul style="list-style-type: none"> <li>“vibrant red and orange petals that flare outward”,</li> <li>“petals have a wavy and slightly ruffled texture”,</li> <li>“long, green stamens protrude prominently at the center”,</li> <li>“leaves are slender and gracefully arch away from the stem”,</li> <li>“sits atop a tall, curved stem”,</li> <li>“adds elegance to its appearance”,</li> <li>“vivid shade of red-orange”,</li> <li>“each petal gracefully curls backwards”,</li> <li>“bright yellow”,</li> <li>“long, slender stamens protrude from it”,</li> <li>“overall shape is elegant and delicate”,</li> <li>“vibrant orange-red petals that curve gracefully backwards”,</li> <li>“stamens and pistil extend prominently from the center”,</li> </ul> | Red ginger | <ul style="list-style-type: none"> <li>“stands tall with elongated, vibrant red bracts crowded closely together”,</li> <li>“strong green stem supports the structure and extends upwards”,</li> <li>“leaves are broad, glossy, and waxy with a deep green color”,</li> <li>“graceful arcs”,</li> <li>“add to its elegance”,</li> <li>“striking combination of vivid color and slender form”,</li> <li>“vibrant red color”,</li> <li>“stands out vividly”,</li> <li>“shape is elongated, resembling a cone or spike”,</li> <li>“smooth”,</li> <li>“layered neatly around the core”,</li> <li>“green leaves surround its base, framing it beautifully”,</li> </ul>                                       |
| Corn poppy | <ul style="list-style-type: none"> <li>“vibrant red petals that catch the eye”,</li> <li>“dark and contrasting, almost black”,</li> <li>“stem is slender and green, standing tall”,</li> <li>“sparse and slightly jagged”,</li> <li>“overall appearance is delicate yet striking”,</li> <li>“vibrant with a bright red hue”,</li> <li>“petals are delicate and slightly crinkled”,</li> <li>“flower has a central dark spot marking its contrast”,</li> <li>“stands tall on a slender green stem”,</li> <li>“overall shape is rounded and open”,</li> <li>“petals are bright red and slightly crinkled”,</li> <li>“black spot marks the base of each petal”,</li> </ul>                                                                                         | Artichoke  | <ul style="list-style-type: none"> <li>“stands tall with thick, green stems reaching upwards”,</li> <li>“leaves are large, broad”,</li> <li>“have a silvery hue”,</li> <li>“flower head is a round, dense cluster of tightly layered bracts”,</li> <li>“hint of purple peek through as the flower begins to bloom”,</li> <li>“delicate thorns edge the tips of its protective leaves”,</li> <li>“vibrant purple hue”,</li> <li>“stands tall with a robust structure”,</li> <li>“petals form spherical shape”,</li> <li>“petals overlap tightly together”,</li> <li>“overall appearance is spiky yet symmetrical”,</li> <li>“large, spiky petals”,</li> <li>“curl out in a vibrant display”,</li> </ul> |

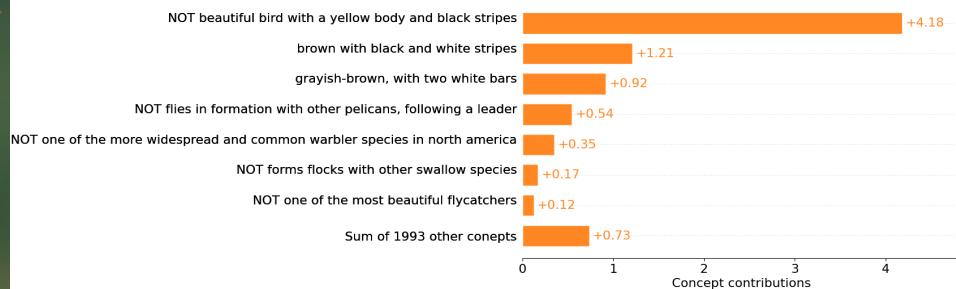
# CUB-200



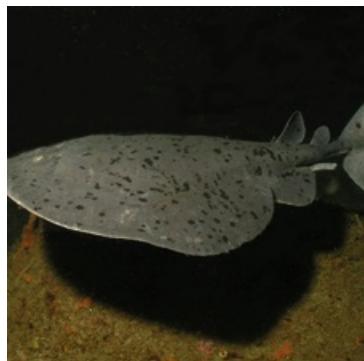
**Category:American Goldfinch Prediction:American Goldfinch Confidence: 0.985 Logit:15.81**



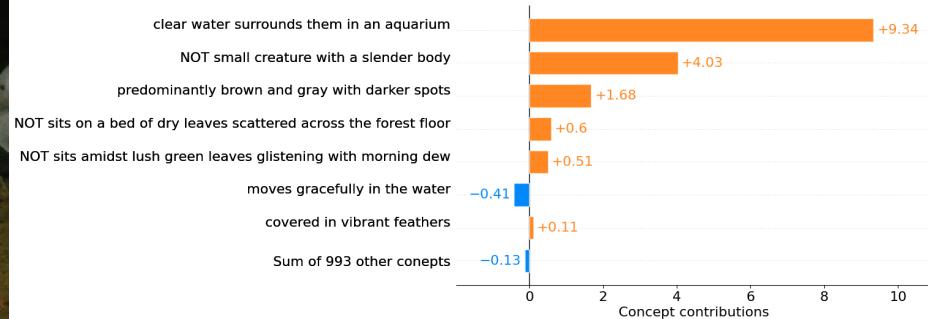
**Category:House Sparrow Prediction:House Sparrow Confidence: 0.429 Logit:8.24**



# ImageNet-subset



**Category:crampfish Prediction:crampfish Confidence: 0.998 Logit:15.72**



**Category:barn spider Prediction:barn spider Confidence: 0.725 Logit:13.70**

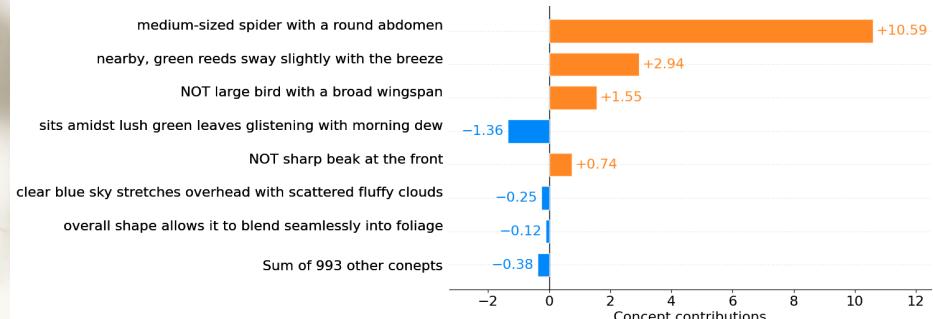
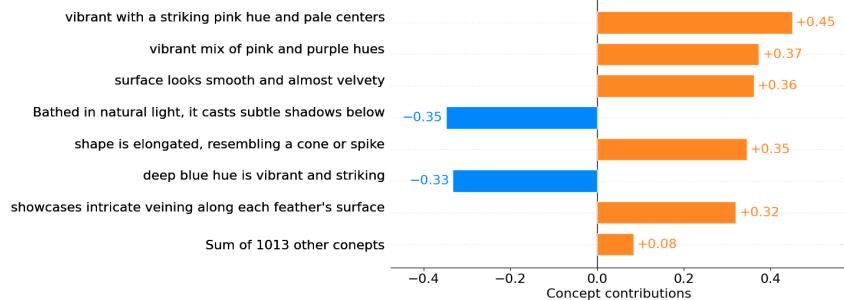


Figure 6. Contribution Visualization after training on CUB-200 B10 Inc10 and ImageNet-Subset B10 Inc10.

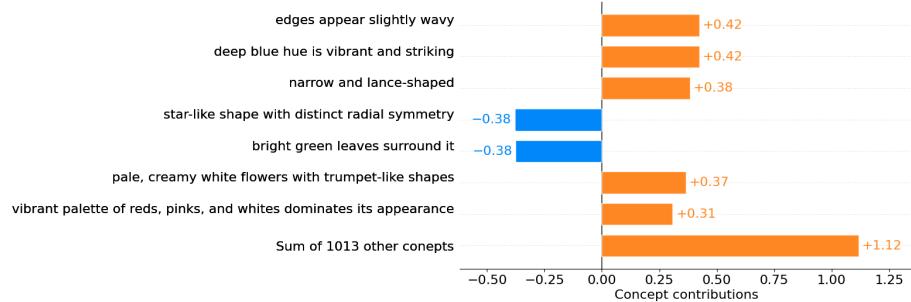
# Flower



**Category:cape flower Prediction:cape flower Confidence: 0.976 Logit:1.26**



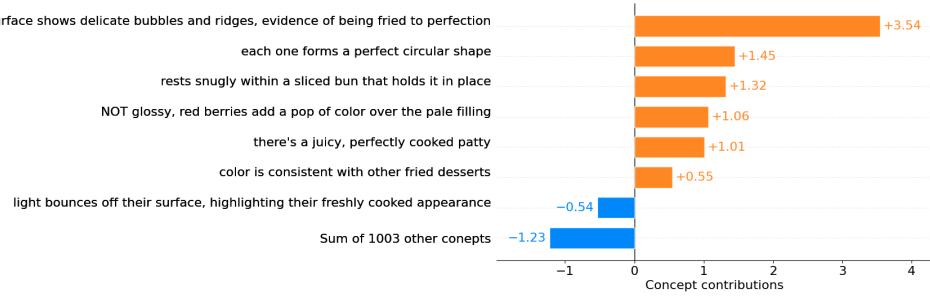
**Category:morning glory Prediction:morning glory Confidence: 0.933 Logit:2.27**



# Food-101



**Category:takoyaki Prediction:takoyaki Confidence: 0.988 Logit:7.16**



**Category:bibimbap Prediction:bibimbap Confidence: 0.978 Logit:10.92**

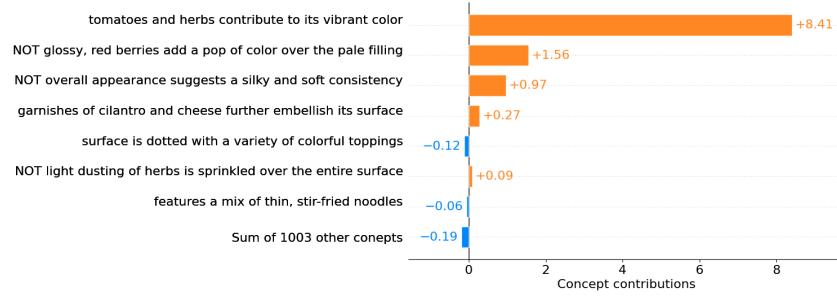


Figure 7. Contribution Visualization after training on Flower B10 Inc10 and Food-101 B10 Inc10.

# Stanford-cars

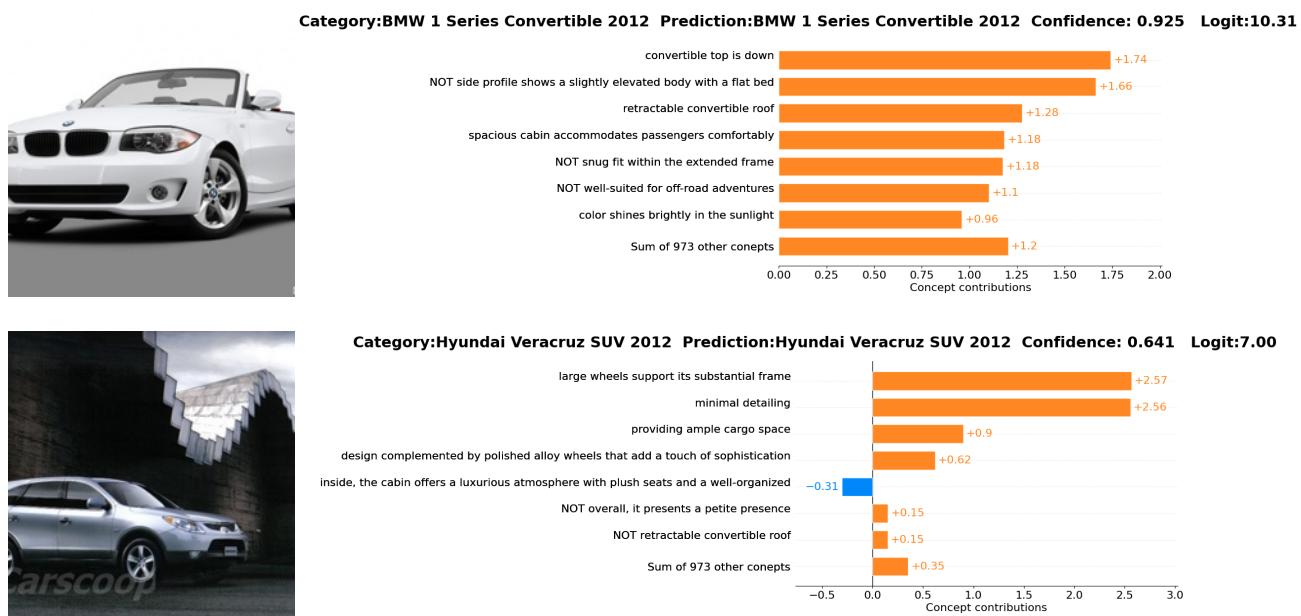


Figure 8. Contribution Visualization after training on Stanford-cars B14 Inc14.