Towards Cognitively Plausible Concept Learning: Spatially Grounding Concepts with Anatomical Priors

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Abstract

Understanding the internal cognitive processes of deep learning models is a critical challenge. Concept Bottleneck Models (CBMs) offer a path towards interpretability by mapping predictions to human-understandable concepts. However, we argue they suffer from a fundamental cognitive flaw: a "spatial grounding failure." Due to global pooling, standard CBMs are unable to connect concepts to their corresponding locations in an image, leading to activations in biologically implausible regions. This disconnect undermines their claim to providing a faithful processing account of their decisions. To address this, we introduce GroundedCBM, a framework inspired by how biological systems leverage structural priors for recognition. Our model embeds anatomical domain knowledge into the learning process through two core innovations: (1) a spatially-aware attention module that forces concepts to be localized in plausible regions, akin to how an expert uses an anatomical schema, and (2) a dynamic graph network that models contextual relationships between concepts, mimicking associative reasoning. On CUB-200-2011, GroundedCBM not only improves concept accuracy but also closes over 60% of the performance gap to an equivalent black-box model. Our work demonstrates that by enforcing cognitively plausible spatial constraints, we can build models that provide a more faithful processing account of their cognition without sacrificing performance.

1 Introduction

The pursuit of interpretable AI is a central challenge, particularly for deploying models in high-stakes domains such as healthcare [7, 11] and autonomous driving [24, 18]. A key goal of cognitive interpretability (CogInterp) is to move beyond behavioral evaluations to understand the cognitive processes underlying a model's decisions. Concept Bottleneck Models (CBMs) [13] are a major step in this direction, structuring a model's reasoning around human-defined concepts.

However, the internal process of a standard CBM is cognitively flawed. Architectures using global average pooling [9] discard spatial information, causing a profound "spatial grounding failure." The model may correctly identify a "pointed beak," but its internal representation might be triggered by pixels on the bird's tail. This is not a faithful cognitive process. A model that cannot answer where a concept is located provides a poor processing account of its own reasoning.

In this paper, we argue this failure is a primary obstacle to building genuinely interpretable models. We introduce the Anatomy-Guided Concept Bottleneck Model (GroundedCBM), a framework that integrates cognitive priors, such as domain-specific knowledge [23], directly into the architecture. Inspired by how experts use structured knowledge, we make two key contributions:

(i) We propose an anatomy-guided attention mechanism that forces concepts to be learned from their biologically plausible locations, answering the "how" and "where" of concept recognition.

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(ii) We complement this with a dynamic concept graph that models contextual relations, akin to associative reasoning explored in neuro-symbolic systems [12], further enhancing the cognitive plausibility of the model's internal process.

Our results on fine-grained recognition show that by correcting this cognitive deficit, we create a more interpretable model and substantially close the performance gap to black-box equivalents. This suggests cognitive plausibility is a pathway to more robust models.

2 Related Work

Concept-Based Models. The original CBM [13] has inspired a rich field of research focused on improving concept-based explanations. This includes developing interactive models for refining concepts [1], exploring embedding-based approaches for richer representations [5], creating methods to address confounders and leakage from the backbone [8], and enabling unsupervised or evolutionary concept discovery [17, 2]. However, most of these works inherit the original architectural flaw of spatial dissociation, which our work directly addresses by design.

Spatial Grounding and Interpretability. Our work is part of a broader effort to build self-interpretable neural networks [10]. Unlike post-hoc explanation methods that generate saliency maps after training, our approach enforces spatial grounding during the learning process. This provides an intrinsic, rather than a post-hoc, account of the model's spatial reasoning, offering a more faithful processing account [6].

Modern Vision Architectures. While powerful black-box models like Vision Transformers [3], Swin Transformers [16], and recent state-space models [15, 20] achieve high performance, their internal reasoning remains opaque. Our framework aims to bridge the gap by integrating explicit, cognitively-plausible constraints into a high-performance architecture, demonstrating that interpretability and accuracy are not mutually exclusive.

3 Methodology

To address the spatial grounding failure of standard CBMs, we design GroundedCBM, an architecture that enforces a cognitively plausible reasoning process. As illustrated in Figure 1, our model is built upon a standard feature extractor (e.g., ResNet) and introduces two core components: an Anatomical Attention Module (AAM) for spatial grounding and a Dynamic Concept Graph (DCG) for relational reasoning.

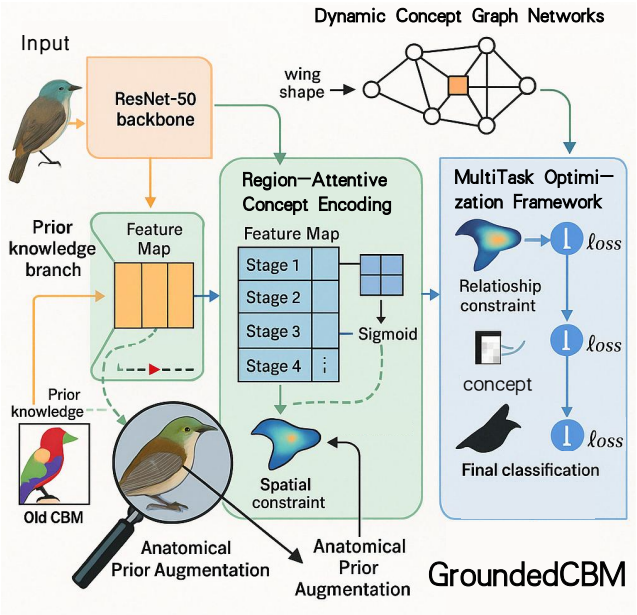

Figure 1: Overview of the GroundedCBM architecture.

3.1 Anatomical Attention for Spatial Grounding

Cognitive Motivation. An expert, when identifying a bird's "crest," instinctively focuses on the head region. This use of an anatomical schema is a powerful cognitive prior. We emulate this by designing an attention mechanism that is guided by anatomical knowledge.

Technical Formulation. Given a feature map $\mathbf{F} \in \mathbb{R}^{C \times H \times W}$ from the backbone, we compute a distinct attention mask $\mathbf{M}_i \in \mathbb{R}^{H \times W}$ for each of the K concepts. This mask is the element-wise product of a data-driven attention map and a predefined anatomical prior $\mathbf{A}_i$:

$$\mathbf{M}_i = \underbrace{\text{Sigmoid}(\text{Conv}_{1\times1}(\mathbf{F})_i)}_{\text{Data-driven Attention}} \odot \underbrace{\mathbf{A}_i}_{\text{Anatomical Prior}} \tag{1}$$

Here, $\text{Conv}_{1\times1}(\mathbf{F})_i$ is a learned spatial attention map for the i-th concept, and $\mathbf{A}_i \in [0,1]^{H \times W}$ is a fixed mask that encodes the plausible location(s) for that concept. The prior $\mathbf{A}_i$ can be derived from supervised part annotations (e.g., on CUB-200-2011) or bootstrapped unsupervisedly (e.g., on AwA2) from saliency maps. The final concept prediction $\hat{c}_i$ is obtained by applying a classifier to the attention-weighted features: $\hat{c}_i = \sigma(\mathbf{W}_c^\top \text{GAP}(\mathbf{M}_i \odot \mathbf{F}))$.

3.2 Dynamic Concept Graph for Relational Reasoning

Cognitive Motivation. Human reasoning is relational; the presence of a "wing bar" might increase our expectation of seeing "flight feathers." To model this associative process, we introduce a graph network that refines concept predictions based on their context.

Technical Formulation. We treat the initial concept predictions as nodes in a graph. A dynamic adjacency matrix $\mathbf{\Gamma} \in \mathbb{R}^{K \times K}$ is learned to capture the dependencies between concepts using scaled dot-product attention [19] on the concept features. The initial concept vector $\mathbf{c} = [\hat{c}_1, ..., \hat{c}_K]$ is then updated via a single layer of graph propagation:

$$\tilde{\mathbf{c}} = \text{LayerNorm}(\mathbf{c} + \text{ReLU}(\mathbf{\Gamma c})) \tag{2}$$

The residual connection and LayerNorm stabilize training. This refined concept vector $\tilde{\mathbf{c}}$ incorporates contextual information and is used for the final downstream classification task.

3.3 Training Objective and Staged Protocol

Training GroundedCBM involves optimizing a multi-component objective: $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{concept}} + \mathcal{L}_{\text{task}}$. $\mathcal{L}_{\text{concept}}$ is a binary cross-entropy loss on concept predictions, while $\mathcal{L}_{\text{task}}$ is a cross-entropy loss for the final classification. To ensure stable and effective learning, we adopt the structured three-stage training protocol outlined in Algorithm 1.

Algorithm 1 Three-Stage Training of GroundedCBM

Require Dataset $\mathcal{D}$, model parameters $\Theta = \{\theta_{\text{backbone}}, \theta_{\text{AAM}}, \theta_{\text{DCG}}, \theta_{\text{clf}}\}$, epochs E_1, E_2, E_3.
Ensure Optimized parameters Θ^*.

// Stage 1: Learn to Spatially Ground Concepts
for epoch = 1 to E_1 **do**
    Freeze θ_{backbone}. Update θ_{AAM} by minimizing $\mathcal{L}_{\text{concept}}$.
end for
// Stage 2: Learn Relational Context
for epoch = 1 to E_2 **do**
    Unfreeze θ_{backbone}. Update $\theta_{\text{backbone}}, \theta_{\text{AAM}}, \theta_{\text{DCG}}$ by minimizing $\mathcal{L}_{\text{concept}}$.
end for
// Stage 3: Align with Downstream Task
for epoch = 1 to E_3 **do**
    Update all parameters Θ by minimizing $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{concept}} + \mathcal{L}_{\text{task}}$.
end for
return Θ^*

4 Experiments

4.1 Experimental Setup

We evaluate our model on **CUB-200-2011** [21] and **AwA2** [22]. The implementation details are as follows:

- **Backbone Architecture**: A ResNet-50 where the initial stem convolution has a kernel size of 3 and stride of 1.
- **Optimizer**: AdamW with a cosine decay learning rate schedule, starting at 3×10^{-4} with a weight decay of 0.05.
- **Training Environment**: Four NVIDIA RTX 3090 GPUs, using automatic mixed precision and a virtual batch size of 128.

4.2 Main Results: Closing the Accuracy-Interpretability Gap

Table 1 shows that GroundedCBM significantly outperforms other concept-based models in both concept accuracy (CA) and classification accuracy (Cls. Acc.). On CUB, our model boosts classification accuracy by 4.73% over the standard CBM. This demonstrates that enforcing a plausible internal process leads to better behavioral outcomes. Critically, GroundedCBM closes 60.02% of the performance gap to the black-box ResNet-50 on CUB and 72.66% on AwA2.

Table 1: Performance comparison on CUB-200-2011 and AwA2. GroundedCBM achieves superior concept accuracy and significantly closes the classification gap to its black-box equivalent.

Method	CUB-200-2011		AwA2	
	CA (%)	Cls. Acc. (%)	CA (%)	Cls. Acc. (%)
Standard CBM [13]	90.71	68.52	94.65	84.68
CEM [5]	95.12	69.60	94.78	85.12
Autoregressive CBM [8]	95.33	69.24	94.32	86.22
Black-Box ResNet-50	-	76.70	-	90.24
GroundedCBM (Ours)	**95.22**	**73.25**	**95.72**	**88.72**

4.3 Ablation Study and Spatial Grounding Analysis

Our ablation study (Table 2) confirms the critical role of both proposed modules. The Anatomical Attention Module provides the largest performance gain, highlighting the importance of correcting the spatial grounding failure. The Dynamic Concept Graph further enhances accuracy by modeling contextual relationships. Qualitative analysis confirms that GroundedCBM's attention for concepts like "has a crest" is sharply localized to the correct anatomical region (the head), unlike standard CBMs, whose latent attention is often diffuse and nonsensical. This provides direct evidence of a more faithful and interpretable internal reasoning process.

Table 2: Ablation study on CUB-200-2011.

Model Variant	CA (%)	Cls. Acc. (%)
Baseline CBM	90.71	68.52
+ Anatomical Attention Module	93.22	70.15
+ Full GroundedCBM	**95.22**	**73.25**

5 Conclusion

We addressed a key cognitive deficit in Concept Bottleneck Models: their failure to spatially ground concepts. Our proposed model, GroundedCBM, integrates anatomical priors and relational reasoning to create a more cognitively plausible internal process. By forcing the model to learn where concepts are, in addition to whether they are present, we provide a more faithful processing account of its behavior. Our work demonstrates that embedding domain-specific cognitive constraints does not hinder performance but can, in fact, resolve the long-standing trade-off between model accuracy and interpretability. This is a crucial step towards building the kind of trustworthy artificial intelligence demanded by society and emerging regulations like the EU AI Act [14, 4].

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