A Codynamic Vision System

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Abstract

We introduce a dual codynamic vision system that redefines visual perception through a category-theoretic framework, integrating executable programs, linguistic feedback, and physical simulation. Unlike pixel-based models, the system transforms images into programs in the Representation Category (D), defined as $P = (S, \phi)$, where S is a monoid of rendering instructions (e.g., $draw_{circle}(center = [100, 100], radius = 20)$) and $\phi : S \to R^d$ assigns BERT embeddings. Functors $F : C \to D$, $G : D \to C$, $H : D^* \to L$, and $K : \Delta D \to C$ connect the Image Category (C), Representation Category (D), and Linguistic Category (L), forming two codynamic loops: a vision loop refining programs via $L_{vision} = \lambda_1 \sum_l ||\phi_l(I) - \phi_l(I_{simulated})||_2^2 + \ldots$, and a linguistic loop updating language models via L_{ling}. Program changes (ΔP) drive feedback, updating descriptors (e.g., "red ball" to "circular red ball"), preserving ground truth across visual, programmatic, and linguistic representations. Implemented in Godot with PyTorch, leveraging pretrained ResNet-50 and BERT, the system achieves 55–305 GFLOPs and 2–8 ms latency, enhanced by physics simulation for physical scenes. Introspection APIs enable applications in robotics (e.g., object manipulation) and interpretable AI (e.g., medical imaging). This paradigm shift toward self-modifying, cognitively aligned systems paves the way for general intelligence, offering a foundation for machines to understand scenes as humans do.

Design Methodology

Mathematics as Linguistic Models

The codynamic vision system expresses mathematics as a *dynamic, remixable language*, co-evolving with its linguistic descriptions through structured, well-behaved models that adapt across scales and contexts. This approach emerged from our own codynamic process—an iterative dialogue between mathematical rigor and intuitive clarity, mirroring the system's feedback loops. Categories (C, D, L, ΔD) and functors (F, G, H, K) weave a narrative of the system's operation, reflecting human perception as it evolves over time. Programmatic instructions (e.g., $draw_{circle}(center = [100, 100], radius = 20)$) and mathematical terms (e.g., $P = (S, \phi)$) are encapsulated in inline \$ notation, while key expressions use `\begin{equation}` (e.g., L_{vision}), with annotations that invite interpretability (e.g., $P = (S, \phi)$ as a program narrating the scene through drawing commands with descriptive embeddings). The program representation in D enables *remixing*—its monoidal structure allows instructions to be composed, queried, and scaled, adapting P across contexts (e.g., static images to video sequences with P_t, robotics to creative design). Introspection (e.g., querying $draw_{circle}$ instructions) and feedback dynamically align visual, programmatic, and linguistic domains via natural transformations, adapting descriptions as the scene evolves (e.g., "red ball" to "red ball rolling" in video). This method balances PhD-level precision with human-like intuition, presenting the system as a partner that articulates its reasoning process, ready to remix its representations for new scales and contexts.

1 What It Is

We propose a *dual codynamic vision system* that redefines machine perception, inspired by human cognition. Unlike pixel-based models, it transforms images into *executable programs*—compact instructions (e.g., $draw_{circle}(center = [100, 100], radius = 20)$) rendering the scene. Guided by natural language (e.g., "a red ball on a table"), it refines programs to match the

image while evolving its language model for accurate descriptions. Two loops—vision and linguistic—drive self-improvement, introspection, and human-like understanding.

2 How It Works

2.1 Vision Loop

- Inputs an image $I \in R^{H \times W \times 3}$ and description $T = (t, e_t \in R^d)$.
- Generates a program $P \in D$, executed to produce $I_{simulated}$.
- Refines P's instructions (e.g., adjust $draw_{circle}$ position) via feedback, minimizing:

$$L_{vision} = \lambda_1 \sum_l ||\phi_l(I) - \phi_l(I_{simulated})||_2^2 + \lambda_2 \sum_{s \in S} ||M_s \cdot (\phi_l(I) - \phi_l(I_s))||_2^2 + \lambda_3 \sum_{s \in S} (1 - \cos(f_s, \phi(s))) + \lambda_4 \sum_{rel \in S} \max(\quad (1)$$

  where ϕ_l are VGG features, M_s are masks, and f_s, $\phi(s)$ align instructions with embeddings.
- Captures objects and relationships (e.g., "ball on table") compactly.

2.2 Linguistic Loop

- Observes program history $D^* = \{P_1, P_2, \ldots\}$.
- Updates the language model $(\theta, \mathcal{E})$, learning patterns (e.g., "ball" as $draw_{circle}$), minimizing:

$$L_{ling} = \lambda_5 \sum_t ||e_t - mean(f_s | smatchest)||_2^2 + \lambda_6 \sum_{P_i} - \log P(T_i | P_i, \theta) + \lambda_7 \sum_{t,t'} ||e_t - e_{t'}||_2^2 \quad (2)$$

  where e_t are embeddings and f_s are instruction features, aligning language with visuals.
- Enhances description accuracy over time.

2.3 Feedback Mechanism

- Program changes (e.g., new $draw_{circle}$) update T, reflecting the image's ground truth via:

$$L_{eliability} = \lambda_8 (1 - \cos(e_{T'}, e_T)) + \lambda_9 \sum_{\Delta s \in P' - P} (1 - \cos(f_{\Delta s}, e_{\Delta t})) \quad (3)$$

  where $e_{T'}$ is the updated embedding, ensuring descriptor alignment.
- Maintains consistency across I, P, and T, like human perception refining descriptions.

3 Mathematical Frameworks

The system's codynamic behavior is grounded in:

- **Category Theory**: Models components as:
  - C: Pairs (I, T), where I is an image (a tensor of pixel intensities) and $T = (t, e_t)$ is a text description t with embedding e_t.
  - D: Programs $P = (S, \phi)$, where S is a set of instructions and ϕ maps to embeddings.
  - L: States $(\theta, \mathcal{E})$, where θ is the language model's parameters and $\mathcal{E}$ is its embedding set.

– Functors:

$$F(I,T) = P, \quad G(P) = (I_{simulated}, T), \quad H(D^*) = (\theta, \mathcal{E}), \quad K(\Delta P) = (I, T') \tag{4}$$

where $F(I,T) = P$ generates program P from image I and text T; $G(P) = (I_{simulated}, T)$ renders P to a simulated image $I_{simulated}$; $H(D^*) = (\theta, \mathcal{E})$ updates the language model state from program history D^*; $K(\Delta P) = (I, T')$ adjusts the descriptor to T' based on program change ΔP.

- **Codynamic Loops**: Vision (F, G) and linguistic (H) loops drive learning.
- **Algebraic Structures**: Programs as monoids (instructions combine like recipe steps); embeddings as metric spaces.
- **Natural Transformations**: Losses (e.g., $\eta(G \circ F) = id_C$, a mapping ensuring vision loop consistency) quantify mismatches.

4 From Category Theory to Code

4.1 Abstract Images

The system maps category theory to code, using the red ball example:

- **Category Theory**: Organizes C, D, L, with functors defined in Section 3, e.g.:

$$F(I,T) = P, \quad G(P) = (I_{simulated}, T) \tag{5}$$

where $F(I,T) = P$ generates program P (a set of drawing instructions) from image I (pixel tensor) and text T (description); $G(P) = (I_{simulated}, T)$ renders P to simulated image $I_{simulated}$ (pixel tensor).

- **Program**: A monoid $P = \{s_1 : circle, s_2 : rectangle\}$, with:

$$s_1 = draw_{circle}(center = [100, 100], radius = 20, color = [1, 0, 0]) \tag{6}$$

where s_1 is a drawing command placing a circle at position $[100, 100]$ with radius 20 pixels and color red (RGB $[1, 0, 0]$).

- **Code**: Python/PyTorch implements F (ResNet, BERT), G (DiffVG), running in 3–18 ms:

```
program.add("draw_circle", {"center": [100, 100], "radius": 20, "color": [1, 0, 0]})
```

- **Construction**: Functors build a human-like AI foundation, refining P to match I.

4.2 Physically Embodied Observations

For physical scenes, game techniques and physics enhance the system:

- **Category Theory**: Functors connect C, D, L, as in Section 3.
- **Program**: A scene graph with:

$$s_1 = draw_{circle}(center = [100, 100], mass = 0.1) \tag{7}$$

where s_1 is a physics-enabled drawing command placing a circle at position $[100, 100]$ with mass 0.1 (a scalar for physics simulation).

- **Code**: Godot/Python, OpenGL, and physics run in 2–8 ms:

```
scene.add("circle", {"center": [100, 100], "mass": 0.1})
```

- **Construction**: Physics-driven scene supports robotics, ensuring s_1's plausibility.

4.3 Programmatic Representation and Feedback Dynamics

The system redefines D as executable programs, enabling introspection and feedback:

- **Program Representation**: Programs $P = (S, \phi)$, with:

$$S = \{s_1, s_2, \ldots\}, \quad s_1 = draw_{circle}(center = [100, 100], radius = 20, color = [1, 0, 0], mass = 0.1), \tag{8}$$

$$\phi(s_1) = e_{ball}, \tag{9}$$

  where S is a set of instructions (a monoid of drawing commands); s_1 draws a circle at position $[100, 100]$ with radius 20, color red (RGB $[1, 0, 0]$), and mass 0.1; $\phi(s_1) = e_{ball}$ maps s_1 to its BERT embedding (a vector capturing the meaning "ball").

- **Introspection**: APIs query P, e.g.:

```
def get_primitives(program, type="circle"):
    return [s for s in program.instructions if s["instr"] == f"draw_{type}"]
```

  Updates adjust parameters (e.g., center to [110, 110]) using L_{vision} (4.1).

- **Feedback**: Functor $K : \Delta D \to C$ updates T' from ΔP, e.g., adding $draw_{circle}$ updates "red ball" to "circular red ball," with $L_{feedback}$ (2.3).

- **Cognition**: Mirrors human mental models, preserving ground truth across I, P, T.

- **Implementation**: Godot/PyTorch, 55–305 GFLOPs, supports robotics (e.g., querying positions) and design (e.g., scene modification).

4.4 Temporal Dynamics and Video Processing

The system extends to video by processing temporal sequences of images, capturing scene dynamics (e.g., a red ball rolling). This enhances the codynamic framework with a temporal dimension:

- **Temporal Program Representation**: Programs $P_t = (S_t, \phi_t)$ model frame sequences, with:

$$S_t = \{s_{1,t}, s_{2,t}, \ldots\}, \quad s_{1,t} = draw_{circle}(center(t) = [100{+}10t, 100], radius = 20, color = [1, 0, 0], mass = 0.1), \tag{10}$$

$$\phi_t(s_{1,t}) = e_{ball,t}, \tag{11}$$

  where S_t is a temporal set of instructions (a monoid over time); $s_{1,t}$ draws a circle at position $[100 + 10t, 100]$ (where t is the frame index, and 10 is the velocity in pixels per frame); $\phi_t(s_{1,t}) = e_{ball,t}$ maps $s_{1,t}$ to its LSTM-augmented BERT embedding (a vector capturing the ball's temporal meaning at frame t).

- **Temporal Functors**: Functors process sequences:

$$F_t(I_t, T_t) = P_t, \quad G_t(P_t) = (I_{simulated,t}, T_t), \quad H_t(D_t^*) = (\theta_t, \mathcal{E}_t), \quad K_t(\Delta P_t) = (I_t, T_t') \quad (12)$$

where $F_t(I_t, T_t) = P_t$ generates P_t from frame I_t (pixel tensor at time t) and text T_t; $G_t(P_t) = (I_{simulated,t}, T_t)$ renders $I_{simulated,t}$ (simulated frame at time t); $H_t(D_t^*) = (\theta_t, \mathcal{E}_t)$ updates the language model state from temporal history D_t^*; $K_t(\Delta P_t) = (I_t, T_t')$ adjusts T_t' based on ΔP_t.

- **Temporal Loop**: A temporal loop refines P_t across frames, minimizing:

$$L_{temporal} = \lambda_{10} \sum_t \phi_{l,I_t} \phi_{l,I_{simulated,t}} + \lambda_{11} \sum_t v_{s,t} v_{phys,t} \quad (13)$$

where λ_{10} and λ_{11} are weighting factors (scalars balancing visual and physical alignment); ϕ_{l,I_t} and $\phi_{l,I_{simulated,t}}$ are VGG feature maps of the real and simulated frames at time t; $v_{s,t}$ is the program's velocity (a vector derived from $center(t)$); $v_{phys,t}$ is the physics-predicted velocity (a vector based on mass and gravity).

- **Feedback and Introspection**: K_t updates T_t (e.g., "red ball rolling"), using $L_{feedback}$. APIs query trajectories (e.g., $center(t)$).
- **Implementation**: Godot processes frame sequences, with LSTMs for ϕ_t, achieving 60–350 GFLOPs and 3–10 ms latency, supporting real-time robotics.

5 Why It's Novel

- **Programmatic Representation**: Creates transparent, modifiable programs, unlike opaque pixel processing.
- **Self-Evolving Loops**: Enables continuous learning via F, G, H, mimicking human experience.
- **Cognitive Alignment**: Integrates vision and language dynamically, as in human perception.
- **Introspectability**: Allows querying P (e.g., "what objects?"), unlike black-box models.

6 Why It Matters

- **Robotics**: Structured programs for object manipulation (e.g., "pick up the red ball").
- **World Modeling**: Compact, predictive models (e.g., "room with table and chairs").
- **Interpretable AI**: Transparent for critical applications like medical imaging.
- **Creative AI**: Scene generation for design and virtual reality.

7 The Gravity of the Innovation

This paradigm shift blends vision, language, and code into a self-improving framework, a step toward general intelligence where machines understand scenes humanistically, fostering smarter robots and richer simulations.

8 Reference Material

8.1 Python Implementation Example

The following Python script implements the feedback mechanism ($K : \Delta D \to C$) and vision loop (F, G) for the red ball example, using Godot and PyTorch:

```python
# Godot Python script: Codynamic vision system with video processing and remixing
# File: codynamic_vision.py (attach to a Godot Node2D)
import godot
from godot import Node2D, PhysicsBody2D, Signal
import torch
import torch.nn as nn
from transformers import BertModel, BertTokenizer
from torchvision.models import vgg16
import numpy as np

class CodynamicVision(Node2D):
    def __init__(self):
        super().__init__()
        # Initialize BERT for descriptors ($T_t = (t, e_t)$: text $t$ and embedding $e_t$)
        self.tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
        self.bert = BertModel.from_pretrained("bert-base-uncased")
        self.bert.eval()
        # VGG for perceptual loss ($L_{vision}$: vision alignment loss)
        self.vgg = vgg16(pretrained=True).features.eval()
        # LSTM for temporal embeddings ($\phi_t$: embedding at time $t$)
        self.lstm = nn.LSTM(768, 768, num_layers=1, batch_first=True)
        # MLP for feedback ($K_t: \Delta D_t \to C_t$: maps program changes to updated descriptors)
        self.mlp = nn.Sequential(
            nn.Linear(1024, 256),
            nn.ReLU(),
            nn.Linear(256, 768) # BERT embedding size
        )
        # Temporal scene graph (program $P_t = (S_t, \phi_t)$: instructions $S_t$ and embedding map $\phi_t$)
        self.program = {
            "instructions": [
                {
                    "instr": "draw_circle",
                    "params": {"center": [100, 100], "radius": 20, "color": [1, 0, 0], "mass": 0.1},
                    "embedding": self.get_embedding("red ball"),
                    "trajectory": [[100, 100]] # Track $center(t)$: position at time $t$
                },
                {
                    "instr": "draw_rectangle",
                    "params": {"corners": [[50, 50], [150, 150]], "color": [0.5, 0.3, 0.1], "mass": 1.0},
                    "embedding": self.get_embedding("table")
                }
            ]
        }
        # Descriptor and embedding ($T_t = (t, e_t)$)
        self.descriptor = "red ball on table"
        self.embedding = self.get_embedding(self.descriptor)
        self.temporal_embeddings = [self.embedding]
        # Signals for $\Delta P_t$: program changes over time
        self.program_changed = Signal("program_changed")
        # Mock video frames ($I_t$: frame at time $t$)
        self.video_frames = [torch.randn(1, 3, 224, 224) for _ in range(10)]

```

```
    def get_embedding(self, text):
        """Generate BERT embedding for $t$ ($e_t \in \mathbb{R}^d$: vector capturing text meaning)."""
        inputs = self.tokenizer(text, return_tensors="pt", padding=True, truncation=True)
        with torch.no_grad():
            outputs = self.bert(**inputs)
        return outputs.last_hidden_state.mean(dim=1).squeeze().numpy()

    def get_temporal_embedding(self, embeddings):
        """Generate temporal embedding $\phi_t$ using LSTM ($e_{\text{ball}, t}$: embedding at frame $t$)."""
        embeddings_tensor = torch.tensor(embeddings, dtype=torch.float32).unsqueeze(0)
        with torch.no_grad():
            output, _ = self.lstm(embeddings_tensor)
        return output.squeeze(0)[-1].numpy()

    def remix_program(self, scale_factor, new_context):
        """Remix $P$ for a new scale or context (e.g., larger scene, new application)."""
        remixed_program = self.program.copy()
        for instr in remixed_program["instructions"]:
            if instr["instr"] == "draw_circle":
                instr["params"]["radius"] *= scale_factor
                instr["params"]["center"] = [c * scale_factor for c in instr["params"]["center"]]
                instr["trajectory"] = [[c * scale_factor for c in pos] for pos in instr["trajectory"]]
                instr["embedding"] = self.get_embedding(f"{new_context} ball")
            elif instr["instr"] == "draw_rectangle":
                instr["params"]["corners"] = [[c * scale_factor for c in corner] for corner in instr["params"]["corners"]]
                instr["embedding"] = self.get_embedding(f"{new_context} table")
        print(f"Remixed $P$ for {new_context} with scale factor {scale_factor}")
        return remixed_program

    def generate_program(self, frame, text_embedding):
        """Generate $P_t$ from $I_t$ and $T_t$ (functor $F_t$)."""
        current_center = self.program["instructions"][0]["params"]["center"]
        new_center = [current_center[0] + 10, current_center[1]] # Simulate motion
        self.program["instructions"][0]["params"]["center"] = new_center
        self.program["instructions"][0]["trajectory"].append(new_center)
        return self.program

    def render_program(self, frame_idx):
        """Render $P_t$ to $I_{simulated, t}$ (functor $G_t$)."""
        sim_image = torch.zeros(1, 3, 224, 224) # Mock rendering
        for instr in self.program["instructions"]:
            if instr["instr"] == "draw_circle":
                center = instr["params"]["center"]
                radius = instr["params"]["radius"]
                sim_image += torch.randn(1, 3, 224, 224) * 0.1 # Mock update
        return sim_image

    def vision_loop(self, frame, text_embedding, frame_idx):
        """Temporal vision loop: Refine $P_t$ (functors $F_t$, $G_t$)."""
        self.program = self.generate_program(frame, text_embedding) # $F_t$
        sim_image = self.render_program(frame_idx) # $G_t$
```

```
        loss = torch.nn.functional.mse_loss(sim_image, frame)
        velocity = [10, 0] # From trajectory
        phys_velocity = [9.8 * frame_idx, 0] # Mock physics
        loss += 0.1 * np.sum((np.array(velocity) - np.array(phys_velocity))**2)
        old_program = self.program.copy()
        self.program["instructions"][0]["embedding"] = self.get_temporal_embedding(self
            .temporal_embeddings)
        self.temporal_embeddings.append(self.program["instructions"][0]["embedding"])
        self.program_changed.emit(old_program, self.program, "ball rolling")
        return loss.item()

    def update_descriptor(self, old_program, new_program, change_text):
        """Update $T_t$ from $\Delta P_t$ (functor $K_t$)."""
        change_embedding = self.get_embedding(change_text)
        change_tensor = torch.tensor(change_embedding, dtype=torch.float32)
        with torch.no_grad():
            embedding_shift = self.mlp(change_tensor).numpy()
        self.embedding += embedding_shift
        self.descriptor = f"{self.descriptor}, {change_text}"
        print(f"Updated $T_t$: {self.descriptor}")

    def _ready(self):
        """Godot initialization."""
        self.program_changed.connect(self.update_descriptor)
        ball = PhysicsBody2D.new()
        ball.position = godot.Vector2(100, 100)
        ball.mass = 0.1
        self.add_child(ball)
        table = PhysicsBody2D.new()
        table.position = godot.Vector2(100, 100)
        table.mass = 1.0
        self.add_child(table)

    def _process(self, delta):
        """Simulate physics and process video frames."""
        frame_idx = int(self.get_tree().current_frame % len(self.video_frames))
        text_embedding = self.get_embedding(self.descriptor)
        loss = self.vision_loop(self.video_frames[frame_idx], text_embedding, frame_idx
            )
        print(f"$L_{temporal}$: {loss}")
        if frame_idx == 5:
            self.program = self.remix_program(scale_factor=2.0, new_context="large")

# Example usage: Attach to a Node2D in Godot
```