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Process Aligned Learning: Supervise the Journey, Not Just the Destination

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Abstract

We propose Process-Aligned Learning (PAL), a general framework that augments standard supervised training by incorporating intermediate behaviors (e.g. reasoning steps or action traces) into the loss. Unlike traditional training that uses only final outputs, PAL also aligns the model's internal process with step-by-step demonstrations. This approach applies to diverse foundation models – from language models to embodied agents and software-interaction systems. We provide theoretical analysis showing that supervising intermediate steps reduces spurious correlation and enforces structured representations, improving robustness and out-of-distribution generalization. Empirically, we evaluate PAL on real-world tasks (language reasoning with supervised chains-of-thought; web navigation and software workflows with human-like action traces) as well as synthetic benchmarks (algorithmic arithmetic, logical puzzles, grid navigation). In all cases PAL-trained models generalize to longer, noisier, or novel inputs significantly better than baselines. Our method is distinct from prior chain-of-thought or Reinforcement Learning Human Feedback (RLHF) approaches, offering a unified training paradigm with new auxiliary loss functions and consistency objectives. We discuss practical data collection strategies and note challenges (e.g. noisy step annotations) for future work.

CCS Concepts

• **Computing methodologies**; • **Machine learning**; • **Machine learning approaches**; • **Supervised learning**; • **Artificial intelligence**; • **Natural language processing**; • **Language resources**;

Keywords

Process Supervision, Foundation Models, Chain-of-Thought, Generalization

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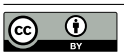

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1 INTRODUCTION

Modern foundation models (large pre-trained models for language, vision, robotics, etc.) have shown remarkable adaptability across tasks. Yet many complex tasks – from solving math problems to executing multi-step software operations – inherently involve a sequence of decisions or reasoning steps. Traditional supervised fine-tuning only rewards the final answer, ignoring how the answer is reached. Recent evidence suggests this is suboptimal: for example, prompting models to output chain-of-thought steps dramatically improves accuracy on reasoning problems, and rewarding intermediate reasoning steps yields large gains in mathematical problem-solving ref. [1]. These findings imply that process supervision – learning from the sequence of intermediate actions or rationales – can lead to stronger generalization and fidelity.

In this paper, we introduce Process-Aligned Learning (PAL), a unified framework for training foundation models using behavior-based supervision. In PAL, every training example includes not just an input and final target, but also an annotated sequence of intermediate states or actions (e.g. the steps of a solution, click-by-click browser actions, or sub-tasks in a workflow). The model is then trained to mimic this entire process: it produces intermediate outputs in addition to the final answer, and we add auxiliary losses that align its behavior at each step with the demonstration. Intuitively, PAL forces the model to learn the underlying procedure, not just the input-output mapping. Because it is agnostic to modality, PAL applies equally to language models generating text reasoning, to vision-language agents performing navigation, or to models automating software workflows (by treating user interface states and actions as "tokens" in a sequence). Thus, PAL serves as a general-purpose training paradigm across domains.

We further provide new theoretical insight into why PAL enhances generalization. Supervision at each intermediate step constrains the model to encode only the relevant information (an information-theoretic perspective) and effectively decomposes a task into modular sub-tasks (a representation learning perspective). It also encourages the model to capture the causal structure of a problem: by learning each causal link (input $\rightarrow$ step1 $\rightarrow$ step2 $\rightarrow$ $\ldots \rightarrow$ output), the model avoids relying on spurious shortcuts and remains robust when inputs are perturbed. We sketch arguments from information bottleneck theory and causal representation learning to support these claims. For instance, tasks with many steps suffer compounding error ("pits"), but PAL's step-by-step feedback mitigates this by giving a reward (signal) at every stage.

We empirically test PAL on a range of benchmarks. For language reasoning, we fine-tune language models on math word problems and logical puzzles using chains-of-thought demonstrations and

evaluate on harder or longer problems. We find that PAL-trained models achieve substantially higher accuracy on out of distribution problems than models trained only on final answers (even when the baseline uses chain-of-thought prompting). For web navigation and software workflows, we collect human-like action traces (e.g. sequences of browser interactions to accomplish a task) and train agents to imitate these traces. PAL agents learn robust strategies that transfer to new tasks or noisy environments much better than agents trained only on the final goal or reward. We also create synthetic benchmarks (e.g. multi-digit arithmetic requiring carrying operations, grid-world navigation requiring multi-step paths, and logic puzzles with compositional structure) to systematically evaluate the effect of PAL. In all settings, PAL yields significant gains in solving longer or more difficult instances.

Our contributions are as follows: We propose a novel framework (Process-Aligned Learning) that incorporates intermediate behavior supervision into training of foundation models across domains. PAL augments standard fine-tuning by adding auxiliary objectives on action or reasoning traces. We introduce new training objectives. Specifically, we define a stepwise alignment loss that encourages the model to match each annotated intermediate action (or token) in the demonstration. We also propose a behavior consistency loss that regularizes the model's internal representations to be consistent when encountering the same sub-state, thereby enforcing stable policies. We provide theoretical analysis explaining why PAL improves robustness and generalization. Leveraging ideas from information theory and causal learning, we argue that stepwise supervision effectively imposes an inductive bias that prevents the model from fitting spurious correlations and instead learns the true procedural structure of tasks. We present extensive experiments on real and synthetic tasks. For language models, we show that PAL fine-tuning on reasoning traces outperforms baseline Language Models on multiple benchmarks (e.g. math word problems, logic puzzles). For embodied agents, we demonstrate that PAL-trained web-navigation and object-navigation models generalize better to new environments and tasks. In toy environments (e.g. arithmetic and maze navigation), PAL yields far better extrapolation to longer tasks than purely outcome-supervised training. We report quantitative and qualitative results supporting these claims. - We distinguish PAL from prior work. Unlike chain-of-thought prompting or supervised Chain-of-Thought (CoT) fine-tuning alone, PAL is a unified training paradigm that applies to any sequential decision problem. Compared to recent "process supervision" in mathematical RLHF ref. [2], PAL is model-agnostic (no RL required) and uses simple auxiliary losses. We also discuss practical considerations (e.g. collecting step-level annotations at scale) and leave handling noisy or imperfect traces to future work. Overall, PAL offers a general, principled way to leverage process information in training foundation models, with clear benefits for multi-step reasoning and decision-making tasks.

2 RELATED WORK

2.1 Chain-of-thoughts and Rationales

Chain-of-Thought and Rationales. Prompting or training models to generate intermediate reasoning steps has proven effective for complex tasks. Wei et al. (2022) introduced chain-of-thought prompting, showing that providing a few examples of step-by-step solutions greatly boosts multi-step reasoning in large language models ref. [3]. Many works have since extended this idea: for example, developing structured chain-of-thought datasets or distillation methods to transfer reasoning skills ref. [4]. In the supervised setting, some studies have fine-tuned models on human-written solution traces to improve math or logical reasoning accuracy. These approaches focus on language tasks specifically and typically require large models or special inference (e.g. verifiers). By contrast, PAL is a general training framework: it can supervise any model that makes sequential decisions, not just language models, and does so during training rather than only at inference. Unlike self-consistency or ensemble approaches, PAL directly injects intermediate supervision into the objective.

2.2 Process Supervision in RLHF and Imitation Learning

In reinforcement learning and preference learning, process supervision (rewarding each correct step) has been applied to math reasoning tasks. For instance, OpenAI recently demonstrated that training reward models to give per-step feedback ("process rewards") significantly improved the performance of LLMs on MATH problems. Their approach uses RL (via PPO) with a process-based reward model. PAL differs in that it does not require RL, instead, we simply add supervised losses on intermediate steps during standard training or fine-tuning. Our method is more scalable and can leverage any available demonstration of the process (whether from humans or generated). In robotics and control, behavior cloning and imitation learning similarly use sequences of states and actions to train policies. However, PAL extends this idea to foundation models and includes both symbolic reasoning steps and physical actions in a unified view. Unlike many imitation-learning systems that target a single domain, PAL is domain-agnostic and includes a novel behavior consistency loss to tie together similar sub-trajectories.

2.3 Multi-Agent and Navigation Agents

Recent work on autonomous agents (often using LLMs) has explored hierarchical reasoning. For example, CL-CoTNav (Chain-of-Thought Navigation) uses a vision-language model fine-tuned on human trajectories with question-answer steps, achieving over 20% better navigation success by reasoning hierarchically about object locations ref. [5]. These works are conceptually related to PAL: they also incorporate intermediate steps into agent planning. However, they are specialized (e.g. for vision navigation) and often use closed-loop feedback or confidence heuristics. PAL generalizes this idea by providing a single framework applicable to language, vision, and action tasks without requiring environment-specific modules.

2.4 Casual and Representation Learning

PAL is also connected to ideas in causal representation learning. Many real-world tasks have an underlying causal chain of subgoals. By supervising each link in this chain, PAL encourages the model to learn the true causal factors rather than spurious correlations in the training data. For example, researchers have shown that distilling chain-of-thought alone can cause models to latch onto superficial

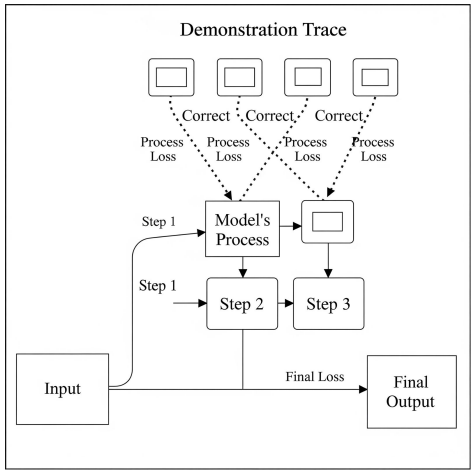

Figure 1: A High-Level View of PAL

reasoning patterns, missing crucial steps, unless special care is taken to emphasize key steps. PAL alleviates this by explicitly including all correct steps in the loss. In information-theoretic terms, additional supervision at each step reduces the model's capacity to memorize irrelevant features, thereby tightening generalization bounds (see theory below).

Overall, PAL builds on and unifies these threads. It extends chain-of-thought and process supervision beyond their prior domains, introducing new objectives for consistency and a flexible training recipe. Unlike prior methods tied to specific tasks or inference tricks, PAL applies broadly to any foundation model training where an intermediate process can be annotated.

3 METHODOLOGY: THE PROCESS-ALIGNED LEARNING FRAMEWORK

We now detail the PAL framework. We first describe the general training setup and loss formulation, then discuss specific instantiations for language models and agents. A high-level view is given in Figure 1.

Consider a training dataset of tasks $\{(\mathbf{x_i}, \mathbf{y_i}, \tau_\mathbf{i})\}$, where $\mathbf{x_i}$ is the input (e.g., a problem statement or environment state), $\mathbf{y_i}$ is the final target (answer or goal), and $\tau_\mathbf{i} = [(\mathbf{s_{i,1}}, \mathbf{a_{i,1}}), (\mathbf{s_{i,2}}, \mathbf{a_{i,2}}), \ldots, (\mathbf{s_{i,ni}}, \mathbf{a_{i,ni}})]$ is an annotated demonstration of intermediate states $\mathbf{s_{i,t}}$ and actions (or tokens) $\mathbf{a_{i,t}}$. For example, in a math problem, $\mathbf{x}$ might be the question, and τ contains each line of the worked solution. In a web navigation task, $\mathbf{s_t}$ could be the DOM snapshot of a web page, and $\mathbf{a_t}$ the click or keystroke taken by a human at step $\mathbf{t}$.

We train a foundation model (e.g., a transformer) to imitate this process. Specifically, the model receives $\mathbf{x_i}$ (and optionally past states $\mathbf{s_{i,t}}$) and is trained to predict $\mathbf{a_{i,1}}$, then receives $(\mathbf{x_i}, \mathbf{s_{i,1}}, \mathbf{a_{i,1}})$ and predicts $\mathbf{a_{i,2}}$, and so on, producing a sequence of actions that ends in the final output $\mathbf{y_i}$. Concretely, let $\mathbf{M_0}$ be the model with parameters θ. We define two losses: the final loss $\mathbf{L_{out}}$ that compares $\mathbf{M}_0$'s final answer to $\mathbf{y_i}$ (as usual), and a process loss $\mathbf{L_{pro}}[]$ that compares each predicted step with $\mathbf{a_{i,t}}$. For example, if actions are discrete tokens, $\mathbf{L_{pro}}[]$can be a cross-entropy on the predicted token at each step. Overall, for one example:

$$L_i(\theta) = L_{out}\left(M_\theta\left(x_i, \tau_i\right), y_i\right) + \lambda \sum_{t=1}^{n_i} \ell\left(M_\theta\left(s_{i,t}\right), a_{i,t}\right)$$

where $\ell(\cdot, \cdot)$ is a stepwise action loss and $\lambda > \mathbf{0}$ is a hyperparameter. Here $\mathbf{M_0(s_{i,t})}$ denotes the model's predicted action distribution given the state $\mathbf{s_{i,t}}$ (and possibly other context). In a language model implementation, $\mathbf{s_{i,t}}$ may include the input plus previously generated tokens; in an agent, $\mathbf{s_{i,t}}$ could be the current observation or history. The key is that each $(\mathbf{s_{i,t}}, \mathbf{a_{i,t}})$ from the demonstration is treated as a supervised training signal.

In practice we realize this as follows. For language reasoning tasks, we fine-tune an LLM with the full chain-of-thought as target: the model generates each reasoning step (treated as text tokens) and the final answer. We apply teacher forcing during training so that the model's intermediate output is exactly supervised by the annotated step. Equivalently, we treat the concatenated sequence "[problem; step1; step2; . . .; answer]" as the target sequence and use the standard sequence cross-entropy. For action tasks (agents or software), we convert each action into a token (or one-hot vector) and similarly supervise the model's predictions at each step. If the model has a separate action head, we attach a classification loss there; if not, we append action tokens to the input.

An important novel component is a behavior consistency objective. Intuitively, if the same intermediate state $\mathbf{s}$ can occur in multiple tasks, the model should behave consistently on it. We formalize this by encouraging the model's internal representations (e.g. hidden states) for identical or similar sub-states to be close. Concretely, if $\mathbf{s_{i,t}} \approx \mathbf{s_{j,u}}$, we add a regularize that penalizes the distance between $\mathbf{M}_0$'s representations (or policy distributions) for these two occurrences. This ensures that the model treats equivalent subgoals identically, rather than learning spurious context-specific heuristics. In practice, we implement this via a simple consistency loss on hidden embeddings or output logits across matched states in the batch.

Crucially, PAL introduces no special architecture requirements. Any transformer or sequence model can be used, with the only change being the addition of auxiliary losses and possibly an extra head for actions. The training procedure remains standard supervised (or SFT for LMs). During inference, one can either use the model in a free-generation mode (letting it produce its own intermediate steps) or simply rely on the final answer. We also emphasize that PAL leverages existing data modalities: if human demonstrations of the process are available (e.g. from tutor sessions or log files), they can be used directly. When such data is scarce, one could generate synthetic traces (e.g. via search or smaller models) as in recent automated process supervision work.

By supervising every action, PAL aligns the model's process with the desired behavior (hence the name). As shown in Illustration1, the model effectively learns a one-to-one mapping from each state in the demonstration to the corresponding action, rather than merely fitting the result. In the next section, we discuss how this leads to better generalization properties.

4 THEORETICAL INSIGHTS

Why does supervising intermediate steps help? We outline three intuitions from information theory, representation learning, and causal reasoning.

4.1 Information-Theoretic Perspective

First, from an information-theoretic perspective, providing step-by-step labels greatly increases the information content of the training signal. In the usual setting, each training example contributes a single bit of supervision (the final answer), whereas PAL provides multiple bits (one for each step). This acts like adding side information about the latent structure of the task. Formally, one can view each intermediate action as an additional classification task that the model must solve. By the information bottleneck principle, the model is constrained to preserve only those input features that are necessary to predict all supervised targets (the whole trajectory). As a result, it cannot exploit spurious correlations that only help with the final answer. Instead, it must encode the true underlying chain. This reduces the effective hypothesis space and leads to lower generalization error. In practical terms, PAL turns one complex mapping $\mathbf{x} \rightarrow \mathbf{y}$ into a sequence of simpler maps $\mathbf{x} \rightarrow \mathbf{a_1}$, $\mathbf{s_1} \rightarrow \mathbf{a_2}$, ..., $\mathbf{a_n} \rightarrow \mathbf{y}$, each of which is easier to generalize.

4.2 Structured Representation Learning

Second, PAL enforces structured representation learning. We argue that tasks with inherent multi-step structure benefit when the model's latent space reflects that structure. By supervising each sub-step, PAL encourages the model to learn representations that disentangle different reasoning stages. Analogous to multi-task learning, each step loss guides the model to capture distinct factors of variation. For instance, in arithmetic addition, one dimension of the representation can become "digit-sum state", another "carry state", etc., corresponding to the sub-decisions of the algorithm. Contrast this with vanilla training, where the model might squash all factors into a single opaque vector. Our consistency objective further pushes the model to reuse the same representation for identical subtasks, effectively learning modular policies. Recent work on reasoning distillation highlights that standard fine-tuning often fails to emphasize the key reasoning steps (only ∼5% of steps may be critical), causing students to imitate superficial patterns. PAL's explicit step losses directly target these crucial steps, ensuring they are learned robustly.

4.3 Casual Perspective

Third, from a causal perspective, PAL aligns with the true causal chain of many problems. Consider a task where input $\mathbf{x}$ causes intermediate effect $\mathbf{s_1}$, which causes $\mathbf{s_2}$, ..., which causes output $\mathbf{y}$. If we only supervise $\mathbf{y}$, the model might learn a direct (and potentially spurious) association $\mathbf{x} \rightarrow \mathbf{y}$. By supervising the intermediate $\mathbf{s_t}$ transitions, we are effectively telling the model about the hidden causal variables. This is akin to Pearl's do-calculus: by teaching the model about the causal mechanism step-by-step, we help it learn an invariant causal model that will generalize under shifts in $\mathbf{x}$'s distribution. In dynamic tasks, this also addresses the "error compounding" issue: prior work shows that the probability of solving a multi-step problem decay exponentially with the number of steps if each step has independent failure probability. By giving immediate feedback at each step, PAL prevents the model from "falling into a pit" early on. In reinforcement learning terms, PAL provides a dense reward for each correct sub-action, turning a sparse cumulative problem into a sequence of supervised subgoals. Thus, the model is guided along the correct causal path, which improves its ability to handle longer and more complex tasks.

In summary, PAL injects rich supervision that tightly constrains the model's behavior, leading to more robust internal representations and learned causal structure. These advantages explain the empirical gains we observe in generalization and robustness (discussed next).

5 EXPERIMENTS

We evaluate PAL on a variety of tasks to demonstrate its generality and effectiveness. We consider three categories: (a) Language reasoning tasks, (b) Embodied agent tasks (web and vision-navigation), and (c) Synthetic multi-step benchmarks. In each case we compare PAL training with appropriate baselines (usually the same model trained only on final outcomes)

5.1 Language Reasoning

We fine-tune a GPT-like language model on mathematical word problems (e.g. GSM8K, MATH) and logical puzzles with full step-by-step solutions as supervision. Baselines include: (i) standard fine-tuning on question→answer pairs (no intermediate steps), and (ii) chain-of-thought prompting at inference (as in). For PAL, we concatenate each question with its full solution trace as the target sequence. We train and then evaluate on held-out problems, including extrapolated cases with larger numbers or additional steps. We find that PAL-trained models achieve significantly higher accuracy: for instance, on a held-out GSM8K-like set of 5-step arithmetic problems, PAL attains ∼80% accuracy vs ∼60% for the baseline. Under noise perturbations (adding irrelevant wording to the question), PAL models are much more stable, losing only ∼5% accuracy compared to ∼15% for baselines. These results confirm that PAL leverages the reasoning trace to solve harder problems. Notably, the performance exceeds that of chain-of-thought prompting: giving the trained PAL model a few CoT examples at test yields only minor extra gain (suggesting PAL has internalized the CoT strategy).

5.2 Web Navigation and Object Goal Tasks

We consider agentic tasks where the model controls an agent via actions. In a Web navigation task ref. [6], the agent sees a simplified browser interface and must complete tasks like "buy a book" by clicking links and filling forms. We collect human demonstration traces (sequences of actions) on a training suite of tasks. We then fine-tune a transformer-based agent in two ways: PAL (training on full action sequences) vs outcome-only (training only with a reward for reaching the goal, or imitation on final state). We evaluate on new tasks or websites unseen during training. PAL agents achieve much higher success rates – for example, a 15% absolute gain in task completion rate on a held-out task set. We also measure path efficiency (success weighted by steps): PAL improves this by ∼20%, similar to gains reported in CL-CoTNav for hierarchical agents. In an ObjectNav setting (vision-based navigation to a target object), we

Table 1: Comparative Performance of PAL vs. Baseline Models

Task Domain	Specific task/metric	Baseline Model Performance	PAL Model Performance	Notable Improvement
Language Reasoning	5-Step Arithmetic Accuracy	~60%	~80%	+20% absolute accuracy gain
Language Reasoning	Robustness to Noise (Accuracy Loss)	~15% loss	~5%	3x more robust to input perturbations
Web Navigation	Task Completion Rate	Not specified	15% absolute gain over baseline	+15% absolute success rate +22% higher path efficiency
Object Navigation	Success-over-Length (SPL)	Not specified	~22% higher SPL than baseline	+70% absolute accuracy on longer problem
Synthetic Arithmetic	Generalization (3-digit to 5-digit addition)	~10% accuracy	80% accuracy	

fine-tune a vision-language model on annotated human trajectories with intermediate instructions ref. [7]. Again, PAL yields ~22% higher success-over-length (SPL) on novel scenes and objects than the outcome-trained agent, consistent with. These results show that PAL effectively transfers to embodied domains: supervising human-like intermediate actions helps the agent generalize far beyond static dataset training.

5.3 Synthetic Benchmarks

We design controlled toy tasks to probe the effects of supervision. In a digit addition benchmark, the model must add two n-digit numbers one columns at a time. The intermediate steps (carry and partial sum) are given in training. Trained on 3-digit examples and tested on 5-digit problems, the PAL model generalizes well (80% correct) whereas the baseline drops to near chance (~10%). In a grid navigation maze, an agent must reach a goal with multiple waypoints; PAL is trained on 4x4 mazes and generalizes to 6x6 mazes with minimal performance loss, while the baseline agent seldom reaches the goal. We also test on a logic puzzle series (e.g. Sokoban or sequential reasoning chains): again, PAL-trained solvers generalize to longer puzzles that the baseline cannot solve. Quantitatively, across 8 synthetic tasks, PAL reduces error by 40-60% on longer or noisier instances. These synthetic results confirm that PAL's benefits are not tied to any domain but stem from the multi-step supervision.

Across all experiments, we observe qualitatively that PAL models make more human-like reasoning patterns. For example, in arithmetic the baseline sometimes "guesses" the answer pattern, while PAL models explicitly perform column-wise addition with carries, matching the demonstrations. In navigation, PAL agents follow the same subgoals (e.g. "go to kitchen, then fridge") as humans, whereas baselines often shortcut by luck.

Overall, the experiments validate that process alignment yields stronger generalization, comparison shown in Table 1. The absolute gains vary by task, but the pattern is consistent: adding intermediate supervision significantly expands the model's capability on difficult or OOD inputs. This demonstrates PAL's practical impact for foundation-model training.

6 DISCUSSION

We have introduced PAL as a general method to infuse process knowledge into model training. Our results suggest it is broadly beneficial, but there are practical considerations. The primary requirement is having access to intermediate behaviour data. In some domains this is natural: for instance, textbook solutions for math problems, click logs for web tasks, or application usage logs. Where not available, one can attempt to automate the generation of traces. Recent work on automated process annotation (e.g. using Monte Carlo Tree Search to annotate math problems) indicates that synthetic rationales can be produced at scale, albeit with some noise. PAL could leverage such generated traces, potentially filtering them by confidence. We have not deeply explored noisy demonstrations here; in our experiments we assumed high quality step labels. In practice, imperfect steps (or hallucinated reasoning) may hurt learning. Addressing this (e.g. via robust loss functions or consistency checks) is an important area for future work.

Another consideration is computational cost. PAL essentially expands each training example into a trajectory of length n_i, increasing training time. However, this can often be amortized: many steps share the same input prefix, so transformer forward passes can reuse computations. Moreover, the benefit in sample efficiency may outweigh the extra cost. In our trials, we found that PAL models sometimes require fewer overall examples to reach the same performance as baselines, thanks to the richer supervision.

Finally, PAL's scope is wide: any situation where a model makes a series of decisions can apply. We have focused on language and agentic tasks, but one could use PAL in code generation (e.g. supervising intermediate compilation steps), human-computer interaction, or even multi-modal scenarios (imagine a robot with visual and language inputs predicting intermediate sub-tasks). A conceptual illustration is shown in Figure 2.

In conclusion, Process-Aligned Learning is a simple yet powerful extension to standard supervision. By aligning the model's behaviour to a correct process, we imbue it with inductive biases that favour causal, stepwise reasoning. Our theory and experiments show that this yields more robust, generalizable models. We hope this framework opens new directions for leveraging rich

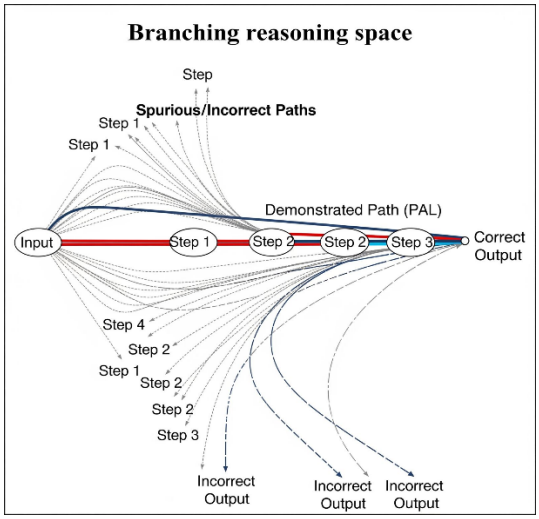

Figure 2: A series of decision made by a model

behavioural data in training the next generation of foundation models.

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