Automatic Synthesis of Diverse Weak Supervision Sources for Behavior Analysis

Albert Tseng  Jennifer J. Sun  Yisong Yue
Caltech

Abstract

Obtaining annotations for large training sets is expensive, especially in behavior analysis settings where domain knowledge is required for accurate annotations. Weak supervision has been studied to reduce annotation costs by using weak labels from task-level labeling functions to augment ground truth labels. However, domain experts are still needed to hand-craft labeling functions for every studied task. To reduce expert effort, we present AutoSWAP: a framework for automatically synthesizing data-efficient task-level labeling functions. The key to our approach is to efficiently represent expert knowledge in a reusable domain specific language and domain-level labeling functions, with which we use state-of-the-art program synthesis techniques and a small labeled dataset to generate labeling functions. Additionally, we propose a novel structural diversity cost that allows for direct synthesis of diverse sets of labeling functions with minimal overhead, further improving labeling function data efficiency. We evaluate AutoSWAP in three behavior analysis domains and demonstrate that AutoSWAP outperforms existing approaches using only a fraction of the data. Our results suggest that AutoSWAP is an effective way to automatically generate labeling functions that can significantly reduce expert effort for behavior analysis.

1. Introduction

Machine learning models have enabled the study of large-scale datasets in many behavior analysis domains including neuroscience [24,27], autonomous vehicles [7], and sports analytics [36]. While ML provides scalable ways to automatically analyze data, obtaining labeled data for training models can be difficult and costly. This cost is especially evident when domain expertise is required for annotation, such as for identifying animal behaviors in behavioral neuroscience [24]. One way to reduce this annotation cost is weak supervision, which proposes using noisy, task-level heuristic “labeling functions” (LFs) to weakly label data. Weakly labeled data can then be used in downstream tasks including active learning [4] and self training [17] tasks.

While weak supervision has worked well in domains including NLP [4,23] and medical imaging [10], it has not been well-explored for behavior analysis. For one, the requirement of using task-level LFs prevents more general domain knowledge (e.g. the behavioral features studied in [14,24]) from being used [22]. Furthermore, when new tasks emerge, such as when new behaviors are studied, new LFs must be hand-crafted by domain experts, limiting the scalability of traditional LFs [32]. To address these challenges, we study efficient representations of domain knowledge and develop methods that automate weak supervision and reduce annotation bottlenecks in behavior analysis.

Our Approach. We propose AutoSWAP (Automatic Synthesized WeAk SuPervision), a framework for automatically generating data efficient, task-level LFs using a novel diverse program synthesis formulation. In AutoSWAP, experts provide a domain specific language (DSL), domain-level LFs, and a small labeled dataset for the task. The domain-level LFs (figure 2) provide fine-grained, label-space agnostic “atomic instructions,” while the DSL contains abstract structural domain knowledge for composing domain-level LFs into task-level LFs (figure 3).

To the best of our knowledge, we are the first to demonstrate the effectiveness of program synthesis for automatically generating LFs. Existing works for generating LFs
have proposed using user feedback to iteratively select LFs [5] or training exponentially many simple heuristics models [32]. In contrast, the key to our approach is in representing domain knowledge in a DSL, which can then be used with our diverse program synthesis formulation to automatically synthesize LFs for many tasks in a domain.

We evaluate our approach in three behavior analysis domains with both sequential and nonsequential data: mouse [27], fly [14], and basketball player [35] behaviors. In these domains, data collection is expensive and new tasks frequently emerge, highlighting the importance of scalability. The datasets we use in these domains are based on agent trajectories, which provide low-dimensional inputs for creating domain-level LFs. We show that with expert defined domain-level LFs from [14, 24] and a simple DSL, AutoSWAP is capable of synthesizing high quality LFs with very little labeled data. These LFs outperform LFs from existing automatic weak supervision methods [32] and offer a data efficient approach to reducing domain expert effort for behavior analysis.

To summarize, our contributions are:

- We propose AutoSWAP, which combines program synthesis with weak supervision to scalably and efficiently generate labeling functions.

- We propose a novel program-structural diversity cost that enables AutoSWAP to directly synthesize diverse sets of labeling functions, which we empirically show are more data efficient than purely optimal sets.

- We evaluate AutoSWAP in multiple behavior analysis domains and downstream tasks, and show that AutoSWAP is capable of significantly improving data efficiency and reducing expert cost.

2. Related Work

Behavior Analysis. In many domains, such as behavioral neuroscience [18, 24], sports analytics [35, 36], and traffic modeling [9], trajectory agent pose and location data is often used for behavior analysis. This data is usually extracted from recorded videos using detectors and pose estimators [19, 24], and can be used for behavior classification and other downstream tasks. For example, we use trajectories from [24], [14], and StatsPerform for our mouse, fly, and basketball datasets, respectively.

To achieve accurate analyses with this data, frame-level behavior labels from domain experts are usually needed. However, annotating large datasets is time-consuming and monotonous [1], motivating methods for data efficient modeling. For example, self-supervised learning [28] and unsupervised behavior discovery methods [3, 6, 18] aim to learn efficient behavior representations and discover new behaviors, respectively. Our work is complementary to these methods in that this is not a comparison of weak supervision to self-supervised learning or unsupervised behavior discovery. Rather, we evaluate the merits of our synthesized labeling functions in the context of weak supervision for learning expert-defined behaviors.

Weak Supervision. Weak supervision with labeling functions was first introduced in the context of data programming [23]. Since then, labeling functions have been applied in a variety of settings, including in active learning [4, 20] and self-training [17] settings. Our work is complementary to these works in that we aim to automatically learn labeling functions that can be used as an input to existing weakly supervised frameworks. We note that we are not the first to propose learning weak supervision rules from a small amount of training data. For example, IWS iteratively proposes rules and queries domain experts in a large-scale feedback loop [5]. More similar to our work, SNUBA [32] also trains heuristics models, but does so without domain knowledge and in a way that scales exponentially with the number of features. To the best of our knowledge, we are the first to apply program synthesis to this problem, and our framework outperforms existing model-based methods for learning rules.

Program Synthesis. Program synthesis has traditionally been used to compose programs from a domain specific language (DSL) that satisfy hard constraints [15, 26]. In recent years, a growing number of works have studied synthesized programs for satisfying relaxed constraints using labeled datasets [13, 21, 25, 30]. This relaxed form of program synthesis has been applied to a number of different domains including web information extraction [8], image structure analysis [12], and learning interpretable reinforcement learning policies [33]. Of these works, algorithms that learn differentiable programs, such as [25], have shown great promise in being able to simultaneously optimize program architectures and parameters in an efficient manner. Here, we use concepts from differentiable program synthesis algorithms to synthesize diverse sets of labeling functions for behavior analysis.

3. Methods

We introduce AutoSWAP, a framework for automatically generating diverse sets of task-level LFs. In our framework, domain experts provide a set of domain-level LFs, small labeled dataset, and DSL of relations they think may be useful. LFs are automatically generated by the AutoSWAP program synthesizer, which uses a novel diversity cost to ensure a diverse set of generated programs. These LFs can then be used in downstream applications, such as to generate weak labels for weak supervision tasks.

In the following sections, we provide a background of
# lambda_1 − whether fly is attacking target
def is_attacking ( fly , tgt ):
f2t_angle = atan (( tgt .y − fly .y) / ( tgt .x − fly .x))
rel_angle = 1 if fly .abs_angle − f2t_angle 1
return fly .speed > 2 and rel_angle < 0.1

# lambda_2 − ratio of fly wingspan
def wing_ratio ( fly , tgt ):
return quantize ( fly .wing_x / fly .wing_y, 4)

# lambda_3 − mouse speed relative to target speed
def relative_speed ( mouse , tgt ):
return (mouse .speed / tgt .speed)

Figure 2. Domain experts provide domain-level labeling functions like the ones above. $\lambda_1$ labels if $fly$ is attacking $tgt$, $\lambda_2$ labels the ratio of $fly$’s wingspan, quantized into 4 bins, and $\lambda_3$ gives a raw ratio of $mouse$’s speed relative to $tgt$. $\lambda_1$ and $\lambda_2$ are in the Fly domain, while $\lambda_3$ is in the Mouse domain. These LFs are based on actual LFs from the Fly and Mouse datasets.

key components in AutoSWAP (section 3.1), detail the AutoSWAP framework (section 3.2), and describe downstream applications of AutoSWAP (section 3.3).

3.1. Background

Domain-level Labeling Functions. In weak supervision, users provide a set of task-level hand-crafted heuristics called labeling functions (LFs). LFs can be noisy and abstain from labeling, but LFs must output in downstream task’s label space $\mathcal{Y}$. We relax this requirement in AutoSWAP by allowing domain experts to provide domain-level LFs (figure 2). These LFs do not have to output in $\mathcal{Y}$, which reduces LF creation overhead and allows for more expressive LFs. This also allows us to reuse LFs across multiple tasks within the same domain, aiding scalability.

Domain Specific Languages. Domain specific languages (DSLs) are a key component of program synthesis algorithms, as they define the allowable submodules and structures in synthesized programs. Many recent works have adopted purely functional DSLs, where DSL items are functions that output to the input space of other DSL items or the final output space. In AutoSWAP, domain experts provide a purely functional DSL with program structures that may be useful in generated LFs. We show empirically that even using a very simple DSL in AutoSWAP can result in significant reductions in expert effort.

Differentiable Program Synthesis via Neural Completions and Guided Search. Our program synthesis formulation is based on NEAR, which finds $\epsilon$-optimal differentiable programs using admissible search heuristics [16, 25]. Here, the DSL $\mathcal{D}$ is a context-free grammar with differentiable variables, and programs are defined by a program architecture $\alpha \in \text{CFL}_D$ and a set of real parameters $\theta$. Programs are denoted by $[\alpha](x, \theta) : \mathcal{X} \rightarrow \mathcal{Y}$. Synthesizing a differentiable program that is optimal w.r.t. a cost function $F$ and dataset $(X, Y) \in (\mathcal{X}, \mathcal{Y})$ is equivalent to

$$\left(\alpha^*, \theta^*\right) = \arg\min_{\alpha, \theta} F([\alpha](X, \theta), Y).$$

(1)

To solve this optimization problem, we search over $\text{CFL}_D$. This search space can be represented as a tree $\mathcal{G}$, where the root node is an empty architecture, interior nodes are incomplete architectures (architectures with unknown components), and leaf nodes are complete architectures. Edges in $\mathcal{G}$ represent single productions from $\mathcal{D}$ between two architectures. We bound the search tree by limiting the search depth to $m$ and “completing” incomplete architectures by substituting unknown components with neural networks (“neural completions”).

As neural completions are differentiable, the minimum cost-to-go w.r.t. $F$ of a neural completion can be computed by optimizing the neural completion’s parameters. Furthermore, as neural networks are universal function approximators, the cost-to-go of a neural completion is an $\epsilon$-admissible heuristic [16] for the true cost-to-go of the corresponding incomplete architecture (proof in [25]). This allows us to use informed search algorithms on $\mathcal{G}$ to find $\epsilon$-optimal solutions to equation 1.

3.2. AutoSWAP

Synthesizing Diverse Sets of Programs. Diverse sets of LFs have been shown to improve data efficiency relative to purely optimal sets in downstream applications of weak supervision [32]. This is partly due to diverse sets having improved label coverage (fewer cases where all LFs abstain) [32], and from having more learning signals for the downstream model [29]. The program synthesizer in 3.1 can be run repeatedly to obtain a set of purely optimal labeling functions, but there is no guarantee that the set will be diverse. Here, we introduce a structural diversity cost and admissible heuristic that allows for direct synthesis of diverse sets of programs using informed search algorithms. We show empirically that using our diverse sets improves performance over purely optimal sets, corroborating [32].

Consider a complete program $P$, which is a composition of variables in $\mathcal{D}$. By construction of $\mathcal{G}$, we can convert $P$ to a tree $T_P$ where each node is a variable in $P$ and a node’s children are its input variables (figure 3). Note that $T_P$ is not $\mathcal{G}$ from section 3.1, and that $T_P$ can be constructed in $O(m)$ time. Then, given a set of complete programs $\mathcal{P}$ and a complete program $P$, we define the structural cost $C_{P, \mathcal{P}}$ of $P$ relative to $\mathcal{P}$ as:

$$\frac{1}{C_{P, \mathcal{P}}} = q\left(1\left\|T_P\right\| \sum_{P' \in \mathcal{P}} \text{ZSS}(T_P, T_{P'})\right),$$

(2)

where $q : \mathbb{R} \rightarrow \mathbb{R}$ is a user defined monotonically increasing function and ZSS is the Zhang-Shasha tree edit distance (TED) [37]. Essentially, programs with a higher average edit distance to the elements of $\mathcal{P}$ are considered to be more diverse and thus incur a lower diversity cost.
Figure 3. A complete program and its tree representation. Each “?” represents one child node function. The depicted program is an actual AutoSWAP LF for the “lunge vs. no behavior” in the Fly domain. The program can be interpreted as “If the linear speed between the flies is small, classify the angular domain-level LFs. Otherwise, classify the product of transformations of the linear speed and positional domain-level LFs.” Note the parameters (red) are not included in the structural diversity cost.

Since this structural cost is not defined for incomplete programs or neural completions, $C_{P,R}$ cannot actually be used in informed search algorithms. However, the use of the Zhang-Shasha TED admits the following admissible heuristic $H_{P,R}$ for incomplete programs $P_I$, with which we can directly synthesize a set of diverse programs by iteratively synthesizing programs and adding them to $P$.

**Lemma 3.1.** Let $P_I$ be an incomplete program and $T_{P_I}$ be the tree of its known variables. $T_{P_I}$ is guaranteed to exist by construction of $G$. Define $H_{P_I,R}$ as:

$$U_{P_I,R} = m - \|P_I\| + \text{ZSS}(T_{P_I}, T_P),$$

$$H_{P_I,R} = \frac{1}{Q} \left( \frac{1}{\|P_I\|} \sum_{P \in P} U_{P_I,R} \right),$$

where $\|P_I\|$ is the number of known variables in $P_I$. $H_{P_I,R}$ is an admissible heuristic for the cost-to-go from $P_I$ in $G$.

**Proof.** To show that $H_{P_I,R}$ is admissible, consider the inner term of the summation $U_{P_I,R}$. $m - \|P_I\|$ is an upper bound on the TED between $T_{P_I}$ and the tree of any complete descendant $T_P$ of $P_I$ in $G$. Since the tree edit distance is a distance and satisfies the triangle inequality,

$$U_{P_I,R} = m - \|P_I\| + \text{ZSS}(T_{P_I}, T_P) \geq \text{ZSS}(T_{P_I}, T_P) + \text{ZSS}(T_P, T_P) \geq \text{ZSS}(T_{P_I}, T_P).$$

Then, as tree edit distances are nonnegative, $m \geq \|P_I\|$, and $Q$ is nondecreasing, $H_{P_I,R} \leq C_{P,R} \cdot Q$. Thus, $H$ is an admissible heuristic for the structural cost-to-go from $P_I$. □

**AutoSWAP Framework.** The AutoSWAP framework aims to reduce the domain expert effort by using program synthesis to automate significant parts of the weak supervision pipeline. Domain experts provide a small labeled dataset $(X, Y) \in (X, \Lambda_Y)$, a set of domain-level LFs $\Lambda_m = \{\lambda_i : X \rightarrow Y_i\}$, and a purely functional DSL $D$. In order to use $\Lambda_m$ when synthesizing programs with $D$, all $\lambda_i$ must be added to $D$. This can be done either by implementing each $\lambda_i$ with operations from $D$, or precomputing and selecting $\Lambda_m(X)$ as input features in $D$; we do the latter in our experiments. With $D$, AutoSWAP runs the diverse program synthesis algorithm $n$ times to generate a set $\Lambda$ of $n$ LFs. $\Lambda$ can then be used in downstream tasks, such as weak supervision label models to generate weak labels. See algorithm 1 for a detailed description of AutoSWAP.

**Algorithm 1:** AutoSWAP.

**Input:** $\Lambda_m$, $D$, labeled dataset $D_{L}$, # LFs $n$

**Output:** task-level LFs $\Lambda$

$D \leftarrow$ Combine $\Lambda_m$ and $D$

$P \leftarrow \emptyset$

while $\|P\| \leq n$ do

$P \leftarrow P \cup \{P\}$

end

$\Lambda \leftarrow P$, return $\Lambda$

**Algorithm 2:** AutoSWAP for Active Learning.

**Input:** $\Lambda_m$, $D$, $n$, unlabeled $X_U$, $A$

Sort $A$ in increasing order.

Randomly select $A_i$ points $X_L$ from $X_U$.

$X_U \leftarrow X_U \setminus X_L$

$Y_L \leftarrow$ Obtain labels for $X_L$.

for $i = 1, \ldots, \|A\| - 1$ do

$\Lambda_i \leftarrow$ AutoSWAP($\Lambda_m, D, (X_L, Y_L)$, $n$).

$X_U \leftarrow X_U \setminus X_L$

Train downstream classifier $C_i$ with $(X_L', Y_L)$.

Select $A_i$ points $X_L'$ using max entropy uncertainty sampling.

$X_U \leftarrow X_U \setminus X_L'$

$X_L \leftarrow X_L \cup X_L'$

$Y_L \leftarrow Y_L \cup \{\text{Obtain labels for $X_L'$}\}$

end

3.3. Downstream Tasks

**Active Learning.** Active learning is a learning paradigm where the learning algorithm can selectively query for new data to be labeled. Here, we consider the setting where labels from task-level labeling functions are included as additional features for a downstream classifier. The downstream classifier’s predictions are used to select data for labeling by experts. To evaluate generated labeling functions in active learning settings, we consider the performance of downstream classifiers at multiple data amounts. Given a list $A$ of increasing labeled data amounts, at each amount we generate new labeling functions, train a downstream classifier, and select data points for labeling to form the next amount batch. An exact description of our active setup for AutoSWAP can be found in algorithm 2.

**Weak Supervision.** Weak supervision consists of many components, including the generative label model used to
Algorithm 3: AutoSW AP for Weak Supervision.

\[ \text{Input: } \Lambda_m, D, n, \text{ Labeled } (X_L, Y_L), \text{ Unlabeled } X_U, A. \]

\[ \Lambda \leftarrow \text{AutoSW}(\Lambda_m, D, (X_L, Y_L), n). \]

\[ \Lambda \leftarrow \text{Abstain}(\Lambda) \quad [32] \]

\[ \text{Sort } A \text{ in increasing order.} \]

\[ \text{for } i = 1, \ldots, \| A \| \text{ do} \]

\[ \text{Randomly select } A_i \text{ points } X_P \text{ from } X_U. \]

\[ X_L' \leftarrow X_L \cup X_P \]

\[ Y_L' \leftarrow Y_L \cup \Lambda(X_P) \]

\[ \text{Train downstream classifier } C_i \text{ with } (X_L', Y_L'). \]

end

generate weak labels for unlabeled samples. Using no ground truth labels, the generative model produces probabilistic estimates (“weak labels”) for the true labels \( Y_U \) of an unlabeled set \( X_U \) by modeling the labeling function outputs \( \Lambda(X_U) \). These weak labels and unlabeled samples can then be used to augment labeled datasets in downstream tasks.

To evaluate AutoSW in weak supervision settings, we start with a small labeled dataset \( D_L \) and a list of unlabeled data amounts \( A \). Labeling functions are generated using the small labeled dataset and abstain using the method in [32]. Then, weak labels are generated from these labeling functions for all unlabeled data using the generative model. For each unlabeled data amount \( A_i \in A \), a random set \( D_{PL} \) of \( A_i \) unlabeled data points and weak labels is selected and the performance of a downstream classifier is measured using the training set \( D_L \cup D_{PL} \). An exact description of our weak supervision setup can be found in algorithm 3.

4. Experiments

We evaluate AutoSW in multiple real world behavior analysis domains (section 4.1), and show that our framework outperforms existing LF generation methods in weak supervision and active learning settings (section 5.1). Since researchers often study multiple behaviors in a domain [14, 24], we consider each behavior its own task.

4.1. Datasets

We use datasets from behavioral neuroscience (mouse and fly behaviors) as well as sports analytics (basketball player trajectories). These datasets include rare behaviors, multi-behavior tasks, and sequential data, making them good representations of real-world behavior analysis tasks. Each dataset contains a train, validation, and test split; the validation split is only used for model checkpoint selection.

Fly vs. Fly (Fly). The fly dataset [14] contains frame-level annotations of videos of interactions between two fruit flies. Our train, validation, and test sets contain 552k, 20k, and 166k frames. We use fly trajectories tracked by Fly-Tracker [14] and evaluate on 6 behaviors: lunge, wing threat, tussle, wing extension, circle, copulation. This is a multi-label dataset and we report the mean Average Precision (mAP) over binary classification tasks for each behavior. All behaviors except for copulation are rare; lunge, wing threat, and tussle occur in < 5% of frames, and wing extension and circle occur in < 1% of frames. The domain-level LFs for this dataset are based on features from [14].

CalMS21 (Mouse). The CalMS21 dataset [27] consists of frame-level pose and behavior annotations from videos of interactions between pairs of mice. We use data from Task 1 (532k train, 20k validation, 119k test) and evaluate on a set of 3 behaviors: attack, investigation, and mount. These behaviors are mutually exclusive and we report the mAP over these classes. We use a subset of the features in [24] as domain-level LFs for this dataset.

Basketball. The Basketball dataset, also used in [25, 35, 36], contains sequences of basketball player trajectories from Stats Perform (18k train, 1k validation, 2.7k test). Labels for which offense player (5 total) had the ball for the majority of the sequence were extracted with [2]. We perform sequential classification in downstream tasks, and report the mAP over each offense player vs. the other 4. Our domain-level LFs include player acceleration, velocity, and position among others. We exclude information about the ball position in the domain-level labeling functions and data features to focus on analyzing player behaviors.

4.2. Baselines

We compare AutoSW to two main baselines: student networks from student-teacher training and decision trees from SNUBA [32]. We show that AutoSW outperforms both in data efficiency, requiring a fraction of the data to achieve or exceed performance parity. For both baselines, domain-level LFs are incorporated as input features to evaluate the effectiveness of AutoSW and not the domain-level LFs themselves. We do not compare against IWS [5], as IWS is a human-in-the-loop LF generation system. We also do not compare against ASTRA [17], as ASTRA is a weak supervision framework for using task-level labeling functions in self training. However, ASTRA can be used as a downstream task for AutoSW.

Student Networks: Student-teacher training is a concept from knowledge distillation [34], and has been used successfully in self-training. We adopt the concept of student networks by training models with similar capacity as the downstream classifier to serve as LFs. In weak supervision experiments, these student LFs and the label model (equation 3) serve as a teacher model for the downstream classifier.

Decision Trees and SNUBA: Decision trees have been shown to be good labeling functions [32] and offer some degree of interpretability. The SNUBA framework [32] generates a diverse set of decision tree LFs by training \( 2^k - 1 \)
decision trees over all feature subsets and then pruning trees based on a diversity and performance metric, where \( k \) is the feature dimension of \( \mathcal{X} \). Clearly, this is intractable for large \( k \), which is often the case for behavior analysis tasks. Furthermore, SNUBA does not use domain knowledge, instead relying on the complete set of decision trees for data efficiency. In relation to SNUBA, AutoSWAP can be viewed as an scalable alternative to the synthesizer and pruner stages.

4.3. Training Setup

Our experimental setup consists of two stages: obtaining labeling functions and evaluating generated labeling functions in downstream tasks. Our downstream tasks include active learning settings, where labeling functions are used to select data for labeling, and weak supervision, where weak labels are used as pseudolabels for unlabeled data points.

4.3.1 Obtaining labeling functions

**Synthesized Programs via AutoSWAP.** For each domain, we use a simple DSL that includes add, multiply, fold, and differentiable if-then-else (ITE) structures among others. We synthesize programs with our diverse program synthesizer and \( A^* \) search. Our cost function is the sum of the \( F_1 \) cost from [25] and our diversity cost \( C_{P,P} \). We set \( q(x) \) to \( x^2 \) and \( m \) to \( \log_2 ||\Lambda_m|| \). Program parameters are trained with weighted cross entropy loss. More information about the exact DSL used is in the Supplementary Materials.

**Student Networks.** We use neural networks for frame classification tasks and LSTMs for scene classification tasks. To induce diversity in the learned student networks, we take inspiration from [34] and randomly set the size of each layer so the “expected” student network is of similar capacity as the downstream classifier. All student networks are trained using weighted cross entropy loss.

**Decision Trees.** We fit decision trees using Gini impurity as the split criteria. We limit the depth of decision trees to \( \log_2 k \), so the number of nodes is \( O(k) \). We select diverse sets of decision trees by pruning a superset of trees based on coverage and performance, similar to how SNUBA does [32]. However, unlike SNUBA, we group our features when generating the superset, as training \( 2^k - 1 \) decision trees is intractable with our datasets.

4.3.2 Downstream Tasks

We use 3 labeling functions for our experiments, as we observed that downstream task performance converged after 3 labeling functions (see Supplementary Materials).

**Active Learning.** As previously described, we evaluate the performance of AutoSWAP at multiple data amounts, selecting additional labeled data with active learning at each amount (algorithm 2). We use max-entropy uncertainty sampling on downstream classifier outputs to select points for labeling, which selects points whose predicted class distributions are closest to the uniform distribution. We use \{1000, 2000, 3500, 5000, 7500, 12500, 25000, 50000\} frames for the fly and mouse datasets and \{500, 1000, 1500, 2000, 3000, 4000, 5000\} sequences for the basketball dataset.

**Weak Supervision.** In our weak supervision experiments, we use factor graph model proposed in [22, 23], which is defined below.

\[
p(\mathcal{Y}, \Lambda) = Z_q^{-1} \exp \left( \sum_{i=1}^{\|X_i\|} \theta^T \phi_i(\Lambda(\mathcal{X}_i), \mathcal{Y}_i) \right). \tag{3}
\]

Here, LF accuracies are modeled by factor \( \phi_{i,j}^{\text{Acc}}(\Lambda, \mathcal{Y}) = \mathbb{1}\{\Lambda_j(\mathcal{X}_{U_j}) = \mathcal{Y}_{U_j}\} \), and the proportion of data the LF labels is modeled by \( \phi_{i,j}^{\text{Lab}}(\Lambda, \mathcal{Y}) = \mathbb{1}\{\Lambda_j(\mathcal{X}_{U_j}) \neq \emptyset\} \).

For the labeled dataset, we use 2000 frames for the fly and mouse datasets, and 500 sequences for the basketball dataset. Our unlabeled data amounts are set to \{1×, 2×, 3×, 4×, 5×\} the number of labeled points.

5. Results

We compare the data efficiency of AutoSWAP against the baselines on our behavior analysis datasets. We do not run the decision tree (SNUBA) baseline on the Basketball dataset as it contains only sequential data.

5.1. Main Results

**Active Learning.** As seen in figure 4, AutoSWAP labeling functions are far more data efficient than baseline methods across all datasets, indicating that AutoSWAP is effective in reducing label cost in active learning settings. This difference is especially pronounced in the Mouse dataset, where AutoSWAP achieves parity with decision tree LFs with roughly 30× less data. In the Fly dataset, AutoSWAP is consistently ~ 4× more data efficient than the baselines, and no baseline is able to reach performance parity with AutoSWAP by 50000 samples (9.1% of the entire Fly dataset). We observe a similar trend in the Basketball dataset, with AutoSWAP being ~ 2× as data efficient. We also observe an improvement in data efficiency even when using random sampling, and note that uncertainty sampling widens the gap between AutoSWAP and the baselines.

While AutoSWAP LFs themselves do not necessarily perform better than baseline labeling functions when evaluated on their own (see the Supplementary Materials), they clearly provide a stronger learning signal for downstream classifiers than the baselines. These data efficiency differences can be attributed in part the complex domain knowledge encoded in the DSL, as the domain-level labeling functions themselves perform significantly worse. For example, a AutoSWAP LF classifying “lunge vs. no behavior” for the Fly dataset can be seen in figure 3, and the structure of this program cannot be easily approximated with a decision tree.
Figure 4. AutoSWAP Active Learning Experiments. Each line represents the mean of 5 random seeds for an automatic labeling function method. The shaded region is the standard error of the seeds. As can be seen, AutoSWAP matches or outperforms all baseline methods using only a fraction of the data. Note that all plots are on log-log scales.

Figure 5. AutoSWAP Weak Supervision Experiments. Each line represents the mean of 5 random seeds for an automatic labeling function method. The shaded region is the standard error of the seeds. The gray line shows performance when ground truth labels are used as weak labels. Although it may seem odd that AutoSWAP outperforms ground truth labels in the Mouse dataset, weak labels have been observed to outperform ground truth labels in other works [17]. Note that all plots are on log-log scales.

or a neural network. This implies that with more expressive DSLs than ours, AutoSWAP can potentially be even more data efficient.

**Weak Supervision.** Similar to our active learning experiments, we observe that AutoSWAP is more data efficient than the baselines in weak supervision settings (figure 5). We note that the ground truth labels are not a baseline in this setting, as they are essentially an “optimal” case where the weak labels match the ground truth labels. In the Mouse and Basketball datasets, no baseline is able to match the final performance of AutoSWAP labeling functions. AutoSWAP is even able to outperform the ground truth labels in the Mouse dataset, which indicates that the learned LFs are especially informative. Finally, we observe that AutoSWAP generally improves with more weakly labeled data points, which is useful as there is no expert cost to using more weakly labeled data points.

5.2. AutoSWAP Specific Results

**AutoSWAP Diversity Cost.** The diversity cost is an important part of AutoSWAP. As can be seen in figure 6, synthesizing purely optimal programs w.r.t. equation 1 results in worse performance than synthesizing diverse sets of programs. This mirrors the observations in [32], where using diverse sets of decision trees improves performance.

**Interpretability of Labeling Functions.** An important
Figure 6. Diversity Cost Utility Comparison. Synthesizing diverse sets of programs instead of purely \( \epsilon \)-optimal sets improves AutoSWAP, showing the utility of the structural diversity cost.

Part of behavior analysis is being able to interpret learned models. Neural networks and LSTMs are by nature not interpretable. Decision trees offer some degree of interpretability, but are limited to branched if-then-else statements. With AutoSWAP, complex yet interpretable programs can be learned by using interpretable structures in the DSL (figures 3, 7, Supplementary Materials).

Effect on Rare Behaviors. Rare behaviors can be difficult to analyze, as even with large datasets very little data exists. Our fly domain results show that AutoSWAP greatly improves data efficiency for rare behaviors, as 5 of the 6 behaviors we study occur in < 5% of the frames. We note the copulation task (which is not rare) does not bias our rare behavior data efficiency comparison as all tested methods achieve near-perfect performance on it.

6. Discussion and Conclusion

We propose AutoSWAP, a framework that uses program synthesis to automatically synthesize diverse LFs. Our results demonstrate the effectiveness of our framework in both active learning and weak supervision settings and across three behavior analysis. We find that with existing domain-level LFs [14, 24] and a simple DSL, AutoSWAP can synthesize highly data efficient task-level LFs with minimal amounts of labeled data, thus reducing requirements on domain experts.

Furthermore, we introduce a novel structural diversity cost and admissible heuristic for synthesized programs, which allows AutoSWAP to scalably synthesize diverse labeling functions with informed search algorithms. This further improves the performance of our framework in behavior analysis settings, all without requiring domain experts to repeatedly synthesize task-level labeling functions. Overall, AutoSWAP effectively integrates weak supervision with behavior analysis, and greatly reduces domain expert effort through automatically synthesizing task-level LFs from domain-level knowledge.

Limitations. While our DSL and LFs are at the domain-level, our method requires task-level information in the form of a small amount of annotations to synthesize LFs. Additionally, the LFs provided by domain experts should be informative of behavior (although we do show that current behavioral features [14, 24] studied by domain experts are sufficient for this task). Extensions to automate other aspects of our framework while taking into account domain expert knowledge, such as library learning [11] or integrating perception [31], may further reduce expert effort. However, we note that our current framework already leads to significant reductions in data requirements.

Societal Impact. Automatically generating interpretable LFs to reduce expert effort can help behavior analysis across domains, such as in neuroscience, ethology, sports analytics, and autonomous vehicles, among others. Our framework leverages inductive biases in the DSL to produce interpretable programs; however, since humans create the DSL, interpret programs, and annotate data, users should be aware of potential human-encoded biases in these steps. Additional care is especially needed in human behavior domains, such as with informed consent of participants and responsible handling of data.

Fly Domain:
- (Lunge) Map(Add(Multiply(Speed, WingRatio), Position))
- (Tussle) Map(SimpleITE(Angle, Speed, WingDistance)))

Mouse Domain:
- Map(Fold(SimpleITE(DistanceM1, AngleM1, SpeedM1)))
- Map(SimpleITE(PositionalM2, SpeedM1, DistanceM1))

Basketball Domain:
- Fold(Add(PiAccel(), Add(PiPos(), PiVel() ) ) )
- Fold(SimpleITE(BVel(), PiVel(), PiPos()) )

Figure 7. Example AutoSWAP task-level LFs (architectures only). LFs are composed of domain-level LFs and structural relations from the DSL. For example, the “Fly Lunge LF” labels whether a fly is lunging using the fly’s speed, wing ratio, and position domain-level LFs. More detailed descriptions of AutoSWAP LFs can be found in the Supplementary Materials.
7. Acknowledgements

We thank Adith Swaminathan of Microsoft Research and Pietro Perona of Caltech for their invaluable feedback and helpful discussions regarding this work. We also thank Microsoft Research for the compute resources for our experiments. This work is partially supported by NSF Award #1918839 (YY) and NSERC Award #PGSD3-532647-2019 (IJS).

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Here, we provide additional information about our datasets and experiments. The Supplementary Materials are organized into three sections: implementation details (section 1), example learned programs (section 2), and additional results (section 3).

1. Implementation Details

1.1. Datasets and Domain-level Labeling Functions

Each of our behavior domains contains a dataset with tracked keypoints and features, domain-level labeling functions (LFs), and a DSL. Below, we provide more details about the datasets and domain-level LFs. Details about the DSL are provided in section 1.2.

**Fly vs. Fly.** The Fly dataset [2] consists of videos (144 × 144 at 30 Hz), extracted behavioral features based on fly trajectories, and frame-level behavior annotations. We use the “Aggression” and “Courtship” videos from this dataset, similar to [5], and use the frame-level behavior annotations to evaluate our framework for behavior classification. The breakdown of behaviors in this dataset is given by: lunge - 1.24%, wing threat - 4.26%, tussle - 0.35%, wing extension - 3.31%, circle - 0.80%, copulation - 59.73%, and no behavior - 30.42%. This dataset is available under the CC0 1.0 Universal license.

The domain-level LFs for the Fly DSL are based on the behavioral features provided with the dataset, and are crafted from the outputs of FlyTracker [2]. They are similar to the fly behavior features used in [5], and we provide visualizations for example LFs in figure 1. The domain-level LFs included in the Fly DSL, grouped by category, are:

- Angular LFs: angular velocity of each fly, angle between fly trajectories, facing angle of flies.
- Linear LFs: linear velocity and speed of each fly.
- Positional LFs: position of each fly, distance between flies, distance between the legs of each fly.
- Ratio LFs: ratio of major and minor axis of fly shape for each fly, ratio of major and minor axis of fly body, ratio of major and minor axis of bounding box around wing spread.
- Wing LFs: minimum and maximum wing angle (window), mean wing length (window), wingspan.

![Figure 1. Visualizing a subset of programs computed on Fly vs. Fly. Reproduced with permission from [5].](image-url)
where “window” indicates that the LF is computed over a sliding window of the past 20 frames.

**CalMS21 (Mouse).** CalMS21 [4] consists of trajectory data, frame-level behavior annotations, and video data (1024 \( \times \) 570 at 30 Hz) of a pair of interacting mice in a resident-intruder assay. The trajectory data from CalMS21 is from the MARS detector [3], which detects 7 anatomically-defined body parts on each mouse in the form of keypoints. We use the trajectory data and behavior annotations from the Task 1 train/test split to evaluate our framework for mouse behavior classification. The breakdown of behaviors in this dataset is given by: attack - 3.44%, investigation - 27.56%, mount - 7.45%, and other - 61.56%. This dataset is available under the CC-BY-NC-SA license.

The domain-level LFs for the Mouse DSL are based on existing behavioral features used by domain experts in [3] and are similar to the features used in [5] (visualized in Figure 2). The LFs included in the Mouse DSL, grouped by category, are:

- **Positional LFs:** nose, right ear, left ear, neck, RHS, LHS, and tail position for each mouse.
- **Centroid LFs:** centroid position of entire mouse, head, hips, and body for each mouse.
- **Angular LFs:** orientation of entire mouse, head, body, and angle between head and body (L&R) for each mouse, as well as angle and facing angle between the two mice.
- **Shape LFs:** ratio of major and minor axis of mouse body and bounding ellipse for each mouse, as well as ratio of bounding ellipse areas between the two mice, bounding ellipse overlap, and edge distance between bounding ellipses.
- **Speed LFs:** linear, radial, and tangential speed of each mouse, linear acceleration of each mouse, and relative speed of resident vs intruder mouse.
- **Relative Distance LFs:** relative distance between bodies, noses, heads, and centroids of the two mice, among other relative distances.

**Basketball.** The StatsPerform Generative Models Basketball [6] dataset consists of basketball player trajectories from NBA games. Each trajectory is located in the left half of the court, and contains 25 frames sampled at 3Hz of 5 defense players, 5 offense players, and 1 basketball. As the Basketball dataset does not have ground truth labels for any tasks, we use a “ballhandler” label computed from the position of the ball relative to each player [1]. As such, we exclude the position of the ball itself from our training data and domain-level LFs. The distribution of ballhandler by player is given by: 1 - 18.50%, 2 - 22.09%, 3 - 22.87%, 4 - 18.18%, 5 - 18.36%. Since we are interested in the ballhandler, we exclude the offense players from our training data and domain-level LFs.

The dataset itself is available for free on AWS Marketplace. The list of domain-level LFs included in the Basketball DSL, grouped by category, are:

- **Player:** acceleration, velocity, speed, and position of each defense player.
- **Ball:** acceleration, velocity, and speed of the ball. Note this does not include the starting position of the ball so the true position of the ball cannot be computed from the velocity.

### 1.2. Domain Specific Language (DSL)

The DSL we use in our experiments consists of elementary operations, operations on sequential data, and branching structures, among others. We use the same DSL for all domains; only the domain-level LFs differ from domain to domain. In Backus-Naur form, our DSL can be written as:

\[
\alpha ::= x \mid c \mid +(\alpha_1, \ldots, \alpha_k) \mid \cdot(\alpha_1, \ldots, \alpha_k) \mid \times(\alpha_1, \ldots, \alpha_k) \mid \sim (\alpha_1, \ldots, \alpha_k) \\
\oplus \theta(\alpha_1, \ldots, \alpha_k) \mid \oplus D x \mid \text{if } \alpha_1 \text{ then } \alpha_2 \text{ else } \alpha_3 \\
\text{map (fun } x_1, \alpha_1) \text{ x} \mid \text{fold (fun } x_1, \alpha_1) \text{ c x}
\]  

(1)
Here, $x$ and $c$ represent input features and constants, respectively. $+, \cdot, \times$, and $\sim$ represent the addition, dot product, outer product, and concatenation operators. $\oplus_0$ represents domain-expert provided parameterized library functions and $\oplus_D$ represents domain-level labeling functions. $\text{fun } x.f$ represents a lambda that evaluates $f$ over $x$; for example, if $x$ is a sequence $\{x_0, x_1, \ldots, x_k\}$ then $\text{fun } x.f$ returns $\{f(x_0), f(x_1), \ldots, f(x_k)\}$. $\text{map}$ and $\text{fold}$ represent operations on vectors and sequences, respectively.

$$\text{if } \alpha_1 \text{ then } \alpha_2 \text{ else } \alpha_3 \text{ is a differentiable ITE construct, which can be written with our program notation } [\alpha](x, \theta) \text{ as}$$

$$y = \sigma(\beta\alpha)(x, \theta_1)$$

$$\text{if } \alpha_1 \text{ then } \alpha_2 \text{ else } \alpha_3 \text{ is a differentiable ITE construct, which can be written with our program notation } [\alpha](x, \theta) \text{ as}$$

$$y = \sigma(\beta\alpha)(x, \theta_1)$$

$$y = \sigma(\beta\alpha)(x, \theta_1) + (1 - y)(\alpha_3)(x, \theta_3)$$

where $\sigma$ is the sigmoid function and $\beta$ serves as a temperature parameter. As $\beta \to \infty$, equation 3 becomes a regular ITE.

1.3. Training Details

**Student Networks.** We use neural networks (NNs) for nonsequential data and LSTMs for sequential data. For NN based student networks, we use 3 hidden layers with layer sizes of $l_1 \sim \mathcal{U}\{50, 90\}, l_2 \sim \mathcal{U}\{50, 80\}, l_3 \sim \mathcal{U}\{20, 30\}$. Each hidden layer is followed by a dropout layer with dropout probability $d_1 \sim \mathcal{U}\{0,0.2\}, d_2 \sim \mathcal{U}\{0,0.2\}, d_3 \sim \mathcal{U}\{0,0.1\}$. All hidden layers use the ReLU activation function. For LSTM based student networks, we use a 1 or 2 layer LSTM with equal probability and $h \sim \mathcal{U}\{64, 128\}$ hidden units. If we use a 2 layer LSTM, we also set the LSTM dropout probability to $d \sim \mathcal{U}\{0,0.2\}$. The final hidden state of the LSTM is classified with a neural network with two hidden layers of sizes $l_1 \sim \mathcal{U}\{50, 80\}, l_2 \sim \mathcal{U}\{20, 30\}$. All hidden layers use the ReLU activation function. For active learning experiments, the weak label outputs are also included via skip connections to each layer. For LSTM based downstream classifiers, we use a two layer LSTM with 128 hidden units and a dropout probability of 0.2. The final hidden state of the LSTM is classified with a two layer neural network, with the first layer having 128 units with dropout probability 0.3, and the second layer having 48 units with dropout probability 0.2. Again, both layers use ReLU and weak label outputs are included via skip connections for active learning experiments. All downstream classifiers are trained with the Adam optimizer, using a learning rate of $10^{-4}$ for NNs and $3 \times 10^{-4}$ for LSTMs.

**AutoSWAP Programs.** For the Fly and Mouse dataset, neural completions were trained for 6 epochs, and symbolic components were trained for 15 epochs. For the Basketball dataset, neural completions were trained for 4 epochs, and symbolic components were trained for 6 epochs. For all datasets, parameters were optimized with the Adam optimizer. A learning rate of $1e^{-3}$ was used for the Fly and Mouse datasets, and 0.02 was used for the Basketball dataset. $\beta$ was set to 1 for the differentiable ITE construct.

**Downstream Classifier.** Again, we use NNs for nonsequential data and LSTMs for sequential data. The downstream classifier NN is a 3 layer network with $\{128, 64, 32\}$ units in each hidden layer, respectively. Each layer is followed by a dropout layer with dropout probability $0.5, 0.4, 0.3$, respectively, and uses ReLU activation. For active learning experiments, the weak label outputs are also included via skip connections to each layer. For LSTM based downstream classifiers, we use a two layer LSTM with 128 hidden units and a dropout probability of 0.2. The final hidden state of the LSTM is classified with a two layer neural network, with the first layer having 128 units with dropout probability 0.3, and the second layer having 48 units with dropout probability 0.2. Again, both layers use ReLU and weak label outputs are included via skip connections for active learning experiments. All downstream classifiers are trained with the Adam optimizer, using a learning rate of $10^{-4}$ for NNs and $3 \times 10^{-4}$ for LSTMs.

1.4. Reproducibility

The code for our experiments will be made publicly available at a later date. All experiments were run on a virtual machine with 12 Broadwell cores clocked at 2.6GHz (or so 1secpu reports, the host may have been running at a different clock speed) and two Nvidia Tesla P40 GPUs.

2. Learned Labeling Functions

Here, we present some example AutoSWAP LFs and our interpretations of them. While domain experts may have different interpretations from us, the purpose of this section is to demonstrate the relative interpretability of AutoSWAP LFs.

**Example 1:** AutoSWAP labeling function for the Ballhandler task. The program can be interpreted as using the sum of the frame level probabilities (fold), with each frame level probability being determined from player velocities or player coordinates depending on the velocity of the ball. Summing over frame-level probabilities corresponds well with the “majority” part of the ballhandler task (find the player that was the ballhandler for the majority of the sequence). The ITE construct can be thought of as detecting passes, as the ball moves the fastest when it is being passed between players. Each *Affine* labeling function contains a set of parameters describing a linear transformation on the base LF. We include the parameters for scalar affine LFs as $x[a,b]$, which indicates the transformation $ax + b$ is applied. We do not include the parameters for vector LFs,
as they are too large to list here, but examples can be found by running the code.

```haskell
fold(fun xt . [
  if BallVelocityAffine(xt)[0.73,−0.26]
  then PlayerVelocitiesAffine(xt)
  else PlayerCoordinatesAffine(xt)
]) xt
```

**Example 2:** AutoSWAP labeling function for the Wing Threat task (Fly domain). The program can be interpreted as using the product of the resident fly’s wing ratio and the sum of the resident fly’s body ratio and the distance between the two flies to derive a probability for the resident fly displaying a wing threat towards the intruder fly. The program learns a positive $a$ for the wing ratio domain-level LF, which is reasonable as wing threats are correlated with wing spreading.

```haskell
map(fun x . [
  × (WingRatioAffine(x)[0.96,−0.71],
  + (BodyRatioAffine(x)[0.35,−0.20], FlyDistanceAffine(x)[0.67,0.13]))
]) x
```

**Example 3:** AutoSWAP labeling function for the mouse behavior classification task. Since the mouse task is a multi-class classification task (for the “attack”, “investigate”, and “mount” behaviors), this program is not as trivially interpretable as those for the Fly and Basketball domains. Nevertheless, we can still deduce that the program classifies the angular domain-level LFs if the distance is small and the speed domain-level LFs otherwise. This is reasonable, as if the mice are far apart, the speed of the mice is probably sufficient for determining which behavior they are engaging in, and if they are close to each other, more detailed data (such as the angular LFs) may be needed.

```haskell
map(fun xt . [
  if MouseDistanceAffine(xt)[1.02,−0.38]
  then MouseAngularAffine(x)
  else MouseSpeedAffine(x)
]) xt
```

3. Additional Results

**Using More Labeling Functions.** In our main experiments, we used 3 labeling functions, as we did not observe significant increases in performance when using more. Figure 3 shows two example plots (Fly dataset in active learning settings and Mouse dataset in weak supervision settings) where 5 labeling functions were used. These results demonstrate that there are minimal differences between using 3 and 5 labeling functions for our active learning setting. There is a very minor improvement in decision tree and AutoSWAP performance when using more labeling functions in the weak supervision experiment. This can most likely be attributed to the generative weak label model performing better with more labeling functions, as well as improved coverage from the diversity measures.

**Isolated Labeling Function Performance.** Here, we present the performance of the generated task-level labeling functions themselves, outside of any downstream tasks. Since task-level LFs give labels for the task at hand, they can be evaluated in the same context as the downstream tasks. As can be seen in figure 4, AutoSWAP LFs do not always outperform LFs from student networks and decision trees. This indicates that the data efficiency benefits of AutoSWAP come from the higher quality learning signals AutoSWAP LFs give in downstream tasks, rather than their raw performance in a vacuum. Furthermore, AutoSWAP LFs generated without the diversity cost do not perform significantly differently than those generated with the diversity cost, indicating that the diversity cost further improves the quality of the LFs’ learning signal.

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Figure 3. Example experiments for active learning and weak supervision settings using 5 labeling functions. These results demonstrate that there is little difference between using 3 (top) and 5 (bottom) labeling functions in our active learning experiments, and a minor improvement for decision trees and AutoSWAP when going from 3 to 5 labeling functions. Regardless, AutoSWAP still outperforms the baselines with 5 labeling functions.

Figure 4. Performance of generated task-level labeling functions outside of downstream tasks. As can be seen, AutoSWAP does not always outperform the baseline LF generation methods. This indicates that the data efficiency benefits of AutoSWAP come from the improved learning signal of AutoSWAP LFs relative to baseline LFs in downstream tasks. Furthermore, AutoSWAP LFs generated without the diversity cost do not perform significantly differently than those generated with the diversity cost, indicating that the diversity cost further improves the quality of the LFs’ learning signal.

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