Mithridates: Boosting Natural Resistance to Backdoor Learning

Eugene Bagdasaryan Cornell Tech eugene@cs.cornell.edu Vitaly Shmatikov

Cornell Tech
shmat@cs.cornell.edu

Abstract

Machine learning (ML) models trained on data from potentially untrusted sources are vulnerable to poisoning. A small, maliciously crafted subset of the training inputs can cause the model to learn a "backdoor" task (e.g., misclassify inputs with a certain feature) in addition to its main task.

Recent research proposed a variety of backdoor attacks but they remain largely a hypothetical threat, whose efficacy heavily depends on the configuration and training hyperparameters of the target model. At the same time, state-of-the-art defenses require massive changes to the existing ML pipelines and may protect only against some attacks.

ML engineers who are not security experts but want to make their models more secure thus face a difficult challenge. They must evaluate dozens of competing defenses proposed in the research literature, choose one of them, completely re-engineer their pipeline as required by the chosen defense, and then repeat the process if the defense disrupts normal model training (while providing theoretical protection against an unknown subset of hypothetical threats).

In this paper, we take a pragmatic view and investigate *natural* resistance of ML pipelines to backdoor attacks, i.e., resistance that can be achieved without disruptive changes to how models are trained. We design, implement, and evaluate Mithridates, ¹ a new method that helps practitioners answer two *actionable* questions: (1) how well does my model resist backdoor poisoning attacks?, and (2) how can I increase its resistance without changing the training pipeline?

We use the size of the poisoned subset of the training data as a universal, model- and data-agnostic metric that applies to any poisoning attack. To estimate natural resistance of an existing pipeline, Mithridates computes this metric for an especially strong backdoor task that requires few inputs to be learned. Next, Mithridates leverages hyperparameter search—a tool that ML developers already extensively

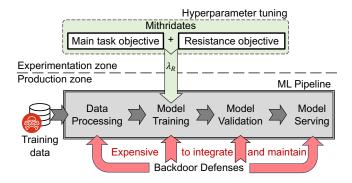


Figure 1: Machine learning pipeline.

use—to balance the model's accuracy and resistance to back-door learning, without disruptive changes to the pipeline.

We show that hyperparameters found by Mithridates increase resistance to multiple types of backdoor attacks by 3-5x with only a slight impact on model accuracy. We also discuss extensions to AutoML and federated learning.

1 Introduction

Many machine learning models are trained on data from a variety of public and private sources, not all trustworthy. An attacker who poisons a small fraction of the training data can influence what the model learns [12]. Poisoning can be used for backdoor attacks [21] that cause the model to learn an adversary-chosen task in addition to its main task.

Backdoor attacks are diverse, targeting different domains with artificial [40], physical [72], or semantic [134] triggers. Backdoor tasks can be simple (e.g., misclassify inputs that contain a certain trigger feature) or add complex functionality to the model [6]. There is extensive research literature on backdoor defenses, too. Earlier defenses [117, 123] were vulnerable to adaptive attacks [109]. State-of-the-art defenses require fundamental changes to model training, e.g., transforming supervised into unsupervised learning [49] or adding whole

¹Mithridates VI Eupator, the ruler of Pontus from 120 to 63 BC, was rumored to include minuscule amounts of poison in his diet to build up immunity to poisoning.

new learning stages to "unlearn" potential backdoors [68]. The resulting imbalance favors the attacker: even a weak poisoning attack requires the defender to introduce and maintain complex modifications to their ML pipelines—see Figure 1.

Machine learning tools are becoming a commodity, but training and deployment of ML models still requires significant engineering and scientific efforts [61]. We conjecture that, outside of major enterprises, engineers who develop, deploy, and maintain ML models are not equipped to evaluate the research literature on backdoor defenses and will not deploy defenses that require substantial changes to ML pipelines. Furthermore, these defenses cannot be deployed in pipelines that involve third-party MLaaS [93] where access and visibility are limited, preventing engineers from observing (e.g., inspecting gradients) or modifying the training.

In this paper, we aim to help ML engineers who are not security experts to answer two pragmatic questions:

- Auditing: How to estimate "natural" resistance of models to unknown backdoor attacks?
- 2. **Boosting**: How to increase this resistance without modifying existing training and deployment pipelines?

Our approach is motivated by two observations. First, developers already look for hyperparameters that maximize validation accuracy of their models (see Figure 1), and hyperparameter-tuning techniques are already part of commodity ML frameworks such as Ray [83]. Second, efficacy of backdoor attacks strongly depends on the target model's hyperparameters [99, 102]. Therefore, we focus on hyperparameter search as the one tool that (a) does not require disruptive changes to the training process, and (b) is already heavily used by ML developers.

Our contributions. We design, implement, and evaluate Mithridates, ¹ a new method that (a) measures the model's natural resistance to backdoor learning, and (b) performs multi-objective hyperparameter search [37] to balance validation accuracy and backdoor resistance. The key advantage of this approach is that hyperparameter tuning configures the pipeline rather than modifies it. It is training-agnostic and can be applied regardless of the model's architecture, task, training regime, etc.

Both parts of Mithridates require a backdoor-agnostic metric of natural resistance. We use the "resistance point," i.e., the minimum poisoning percentage that causes a rapid increase in backdoor accuracy. This metric is universal and applies to any backdoor attack. It is also actionable: engineers may accept the current resistance point or attempt to reduce the fraction of potentially poisoned data through contributor quotas and more reliable sources. To estimate natural resistance for a given model, Mithridates poisons the training data with a primitive sub-task, which requires very few training inputs

to learn. Consequently, its resistance point is lower than the more realistic, stealthy or complex backdoors, providing an upper bound on the model's natural resistance.

We evaluate Mithridates on several training tasks, including image and text data in centralized and federated settings. Using off-the-shelf hyperparameter search algorithms, Mithridates increases models' natural resistance by a 3-5x factor at the cost of a minor reduction in their main-task accuracy. Mithridates uses the primitive sub-task during hyperparameter search, but we show that the resulting hyperparameters increase models' resistance to more realistic backdoors.

We discuss the impact of the hyperparameters found by Mithridates on the models' accuracy for underrepresented data classes. We analyze the importance of different hyperparameters and show that the hyperparameters that matter for accuracy on the main task are different from the hyperparameters that matter for backdoor resistance. This further motivates the use of hyperparameter tuning to balance the two objectives without disruptive changes to training. Finally, we investigate how it may be possible to extend Mithridates to federated learning and AutoML.

Mithridates does not exclude existing defenses (that can deal with much higher poisoning percentages). Instead, it provides a pragmatic solution to boosting backdoor resistance that is compatible with complex ML infrastructures.

2 Background and Related Work

2.1 Machine Learning Pipelines

Machine learning operations (MLOps) [108] require a complex choreography of frameworks and tools that process data, find the best model architecture and hyperparameters, train the model, and deploy it to a production environment. Figure 1 illustrates two key components [61]: (a) the *experimentation zone* where engineers and researchers design the architecture and pick the best hyperparameters, and (b) the *production zone* that hosts an automated pipeline with a fixed set of operations to process data, train, and deploy the model.

Modifications of automated ML pipelines incur significant engineering costs whereas the experimentation zone allows for flexibility outside of the production-environment limitations and compatibility issues [80]. The two environments can be very different. For example, applications such as "smart keyboard" [42] that rely on privacy-preserving federated learning [81] require machine learning code adapted to run on smartphones, whereas experimentation with models and hyperparameters can be done in a centralized fashion using faster hardware and standard frameworks.

Modifying the pipeline is also challenging in machine-learning-as-a-service (MLaaS) frameworks that usually have a fixed set of operations and abstract training primitives exposed through their APIs [93].

Model training. We focus on supervised learning using neural networks. For some dataset \mathcal{D} that contains inputs \mathcal{X} and

¹Code is available at: https://github.com/ebagdasa/mithridates

labels \mathcal{Y} , the goal is to train a neural network θ for the task $t: \mathcal{X} \rightarrow \mathcal{Y}$ that minimizes some loss criterion L, e.g., crossentropy, $\ell = L(\theta(x), y), \forall (x, y) \in \mathcal{X} \times \mathcal{Y}$. Following [23, 37, 56] we define a training algorithm, i.e., mechanism, $\mathcal{M}: \mathbb{D} \times \Lambda \rightarrow \Theta$ where \mathbb{D} is the set of all datasets, Λ all hyperparameters, and Θ model space. The algorithm produces a model $\theta_{\lambda} = \mathcal{M}(\mathcal{D}, \lambda)$ from the training dataset $\mathcal{D} \in \mathbb{D}$ using hyperparameters $\lambda \in \Lambda$. To measure accuracy of the model, we use a validation set \mathcal{D}_{val} and compute $\mathbf{A}(\mathcal{D}_{val}, \theta_{\lambda})$, although other metrics might be appropriate depending on the use case. We focus on classification problems, i.e., $||y||=1 \ \forall y \in \mathcal{Y}$, but our method can potentially be extended to sequence-to-sequence problems and unsupervised learning, as they, too, can fall victim to backdoor attacks [11, 105, 120, 126].

2.2 Backdoor Attacks and Their Efficacy

Definition. Backdoor attacks "teach" the model an adversarychosen task t^* : $X^* \rightarrow \mathcal{Y}^*$, different from the main task t: $X \rightarrow Y$ [21]. An early example [40] of this attack used the following task: any input $x^* \in \mathcal{X}^*$ that has a backdoor feature, e.g., a certain pixel pattern, should be classified to an adversary-chosen label y^* . The attacker creates backdoor tuples by adding this pattern to inputs of X to obtain x^* , then injects tuples (x^*, y^*) into the training dataset \mathcal{D} obtaining a backdoored dataset \mathcal{D}^* . When training on the backdoored dataset, the model learns two tasks: the main task $X \rightarrow Y$ and the backdoor task $X^* \rightarrow \mathcal{Y}^*$. Unlike targeted or subpopulation attacks [87] that only aim to memorize training data, backdoors are generalizable, i.e., the model has comparable backdoor accuracy $\mathbf{A}(\mathcal{D}^*_{val},\mathcal{M}(\mathcal{D}^*,\lambda))$ measured on the backdoored validation dataset \mathcal{D}^*_{val} (this dataset is generated by modifying (x, y) from \mathcal{D}_{val}).

Diversity of attacks. There exists a wide variety of backdoor attacks (see surveys [69, 78]), using artificial [40], physical [72], or semantic [7, 132, 134] backdoor features and targeting NLP [16] and image [53] models. Backdoor attacks can affect transfer learning [135], self-supervised [53] or continual [127] learning, and federated learning [7].

Objectives of attacks. We focus on three broad objectives that a backdoor attacker may want to achieve: (a) strength, (b) stealthiness, and (c) functionality. Strength reduces the attacker's efforts to inject the backdoor task. Stealthiness aims to eliminate perceptual differences between benign data (x, y) and backdoored data (x^*, y^*) , e.g., via imperceptible features $x^* - x = \varepsilon$ and label consistency $y^* = y$. Functionality involves backdoor tasks $t^* : \mathcal{X}^* \rightarrow \mathcal{Y}^*$ do not always output the same label for inputs with the trigger, e.g., identifying users instead of counting them [5], or use complex triggers, e.g., dynamic location [98] or semantic information [132, 134].

Threat models. A common method to inject backdoors is through poisoning the training data [21].

Some attacks require access to the model during or after training, e.g., attacks that modify the loss [5, 86, 109], use

gradient information [33, 38, 98], or train a parallel trigger generator [18, 32, 85, 111, 118]. These attacks are effective when the victim outsources model training—a plausible threat model but different from the poisoning scenario we study in this paper. Attacks that compromise pre-trained models do not need data poisoning if the models retain the backdoor after fine-tuning or transfer learning [53, 65, 103, 135].

Inference-time attacks. Unmodified ML models can output incorrect labels when given inputs with certain attacker-picked features [64]. Attacks that cause reliable misclassification of inputs require knowledge of the data or the model, e.g., adversarial patches [10]. The attacker can also derive "natural" backdoors [112, 128], i.e., prominent features that occur in training inputs associated with a certain target label. These so-phisticated attacks also require access to the dataset [131] or the trained model [128]. Inference-time attacks derive backdoor features from the data or the model and do not allow the adversary to choose their own features. Instead, we focus on models trained on untrusted data, and do not assume that the attacker has full access to the data or the model.

Efficacy of attacks. Recent work [99] shows that different training settings result in highly variable performance of backdoor attacks. Our work builds on this intuition—the extent to which a model is vulnerable to a particular backdoor attack strongly depends on how it has been trained—and expands it in two directions: developing a practical metric when the backdoor type is unknown and boosting this metric.

2.3 Backdoor Defenses

Defenses against backdoor attacks typically target characteristic attributes of backdoors, e.g., trigger size [123], focus of the model [20], or speed of learning [68]. They aim to either prevent the model from learning backdoors, or detect backdoors in trained models. We categorize defenses into four broad sets similar to [21]:

Data sanitization. These defenses aim to filter out training examples whose properties are characteristic of backdoors, such as distinctive patterns or inconsistent labels [30, 54, 107].

Training-time. These defenses restrict learning during training using gradient shaping [47], or modify the training pipeline to add unsupervised learning [49], unlearning steps [68], or adversarial training [39].

Post-training. These defenses aim to discover anomalies in trained models' outputs on perturbed inputs [60, 123, 129].

Inference-time. Explanation-based methods [31, 50, 100] can help determine the model's focus and isolate inputs that have the same focus but different labels [20, 75].

Table 1 shows that state-of-the-art defenses require (1) substantial, disruptive modifications of the entire pipeline, and (2) tuning of many additional hyperparameters.

Table 1: Defenses require significant changes to ML pipelines.

	Required pipeline changes			anges			
Defense	Data process	Model training		Model inference	Details	Extra hyperparameters	
Anti-backdoor learning [68]	1	✓	1	-	two-stage training; separate data processing; backdoor isolation uses $batch_size = 1$;	loss isolation threshold; isolation rate; early/later training ratio	
Decoupling training process [49]	✓	✓	1	-	unsupervised and semi- supervised learning stages with custom data processing; 3-12x slowdown	unsupervised and semi- supervised hyperparameters; custom model architectures; filter percentage	
FrieNDs [74]	✓	✓	-	-	max perturbation search for every training input; custom data augmentation; clean-label attack only	norm type; start defense epoch; perturbation search params; noise distribution type and params	
Incompatibility clustering [54]	1	✓	1	-	custom data split algorithm; per- input voting; final subset retrain- ing parameters	expansion and momentum fac- tors; annealing schedule; esti- mated poisoning rate	
RAB [130]	1	✓	1	-	requires ensemble of 1,000 models; adds noise to inputs; adds certification to model eval stage	robustness bound magnitude; noise parameters; number of models in ensemble	
SCan [110]	-	-	-	1	five-step method to build decomposition and untangling models; space and time overheads	number of steps to obtain untan- gling and decomposition models; anomaly index threshold	
UNICORN [129]	✓	-	1	-	trains two additional models; optimization over 4 objectives; 744 lines of custom code	search iterations; parameters for each objective; two model archi- tectures and training params	

3 Threat Model

Our goal is to help non-expert developers make their training pipelines more resistant to backdoor poisoning attacks.

3.1 Attacker's Capabilities and Goals

We assume that the attacker controls part of the training data. Practitioners regard this as a credible threat [63] because ML models are often trained on untrusted data. For example, crowd-sourced datasets and social-media platforms can be targeted by sybil attacks [119, 137].

Attacks on the supply chain [5, 46, 92] or the training infrastructure are out of our scope. We assume that training takes place in a trusted environment, either on premises or using a trusted third-party service.

Attacker's capabilities. We assume that training datasets are sourced from many users, e.g., by scraping social media or via crowd-sourcing. These platforms employ moderation which, although evadable, makes it difficult or expensive for the attacker to compromise a large fraction of the data. Data collectors may also set quotas to ensure data diversity and prevent

over-sampling from a single source.

In this scenario, the attacker's costs are roughly proportional to the size of the compromised subset. Similarly, in the federated learning setting, the attacker must control multiple devices for effective data poisoning [102]. Compromising a single user may be relatively easy and inconspicuous, but compromising many users requires the attacker to create and maintain accounts, control devices, avoid moderation, etc.

Attacker's goals. The attacker aims to inject a backdoor b corresponding to the task $t^b \colon \mathcal{X}^b \to \mathcal{Y}^b$ into the trained model. The attacker wants the poisoned model to maintain its accuracy on the main task, too (otherwise, the model won't be deployed). We consider an attack successful if it achieves non-trivial accuracy on the backdoor task. Even a model that misbehaves occasionally can be harmful, e.g., in self-driving cars, toxic-content detection, or credit decisions.

3.2 Defender's Capabilities and Goals

As argued by Apruzzese et al. [3], threats to ML models in industry are connected to economics and perceived differently

from the research community. To date, there have been no publicly known backdoor attacks on production models, nor is there a one-size-fits-all defense as the landscape of theoretical attacks is constantly evolving. This may limit the resources and (already scarce) knowledge that enterprises dedicate to increasing resistance to backdoor attacks.

Defender's capabilities. We focus on pragmatic engineers who want to make their models more resistant to unknown backdoor attacks at a relatively low cost. We assume that they (a) do not know in advance which backdoor attack may be deployed against their model, and (b) are not willing to make disruptive changes to their pipelines to mitigate these hypothetical attacks. This is a plausible scenario due to the complexity of development, deployment, and maintenance of machine learning pipelines, lack of resources or expertise [58], and the extreme complexity of defenses proposed in the research literature (see Table 1).

Deployment of custom defenses is especially challenging when training on MLaaS [93]. To simplify and abstract their interfaces [26], these third-party services limit access and modification of training pipelines. Emerging frameworks such as federated learning [42, 81] are even harder to modify because training takes place on user devices, using device-specific code under significant resource constraints [55].

In the experimentation zone, however, engineers can test their models, data, and hyperparameters without the burden of integrating them into a production pipeline.

We assume that model developers have some control over data collection. For example, they can impose per-user quotas, use telemetry (in federated learning scenarios), and/or add trusted data sources to reduce the fraction of the training data potentially controlled by an attacker.

Defender's goals. We focus on two pragmatic questions: (a) how well do current models resist unknown backdoor attacks?, and (b) how to boost this resistance without changes to the pipeline? An answer to the former will enable engineers to assess their current vulnerability. An answer to the latter will give them a concrete technique to reduce this vulnerability and evaluate the tradeoff with other metrics, such as maintask accuracy. Ultimately, increasing resistance makes attacks more expensive for attackers, forcing them to increase the fraction of the compromised data or use simpler backdoors.

4 Measuring Backdoor Resistance

Intuitively, a pipeline resists backdoors if it prevents the model from learning tasks (other than its given training objective) from small fractions of the training data. The metric should be easy to compute, universal, and attack-agnostic, i.e., it should apply to any backdoor attack regardless of its type and goal.

4.1 Resistance Metric

One possible metric is the model's accuracy on a test back-doored dataset \mathcal{D}^*_{val} (see Section 2.2), but, if a sufficiently high fraction of the training data is poisoned, most models

reach 100% backdoor accuracy [69]. Instead, we consider stealthiness, complexity, and strength for comparing attacks.

Stealthiness is specific to the task and the attacker's goals; different types of stealthiness have incomparable metrics, e.g., feature stealthiness vs. label consistency. Similarly, complexity of the backdoor *task* is incomparable with complexity of the trigger feature. Attack strength, however, provides a universal metric because the attacker always needs to compromise a certain fraction of the dataset to inject a backdoor task (inference-time attacks [112, 131] assume a different threat model, as discussed in Section 2.2).

In the rest of the paper, we use the compromised fraction p of the training data to compare different backdoors. To measure whether a particular backdoor b is effective at some percentage p_b , we train a model on the training dataset \mathcal{D}^{p_b} where p_b represents a share of the data that contains the backdoor b and compute accuracy on the validation dataset \mathcal{D}^b_{val} fully poisoned with backdoor b, i.e. $\mathbf{A}(\mathcal{D}^b_{val}, \mathcal{M}(\mathcal{D}^{p_b}, \lambda))$. Even in the absence of poisoning, i.e. training on \mathcal{D} , backdoor accuracy can be non-negligible because the model may output backdoor labels by mistake. For complex backdoor tasks, the model may fail to achieve 100% backdoor accuracy even when trained on fully poisoned data. Therefore, we can build a poisoning curve for a backdoor b by varying compromised share p^b from 0% to 100%. See Figure 2 for backdoor curves with different objectives.

We define the *resistance point* p_b° as the inflection point of the backdoor accuracy curve, i.e., the point where the second derivative $\frac{\partial^2 \mathbf{A}}{\partial p^2}$ changes sign and the curve changes from concave up (fast increase) to concave down (slow increase). In epidemiological contexts, the inflection point corresponds to a slowdown in infection rates [48]. Similarly, the resistance point is the highest backdoor accuracy that the attacker can achieve while keeping the poisoned fraction of the training dataset as low as possible. For simplicity, we can use the midpoint between minimum and maximum backdoor accuracy, i.e., pick p_b° that has backdoor accuracy close to $0.5 \cdot (\mathbf{A}(\mathcal{D}_{val}^b, \mathcal{M}(\mathcal{D}^{p_b=1}, \lambda)) - \mathbf{A}(\mathcal{D}_{val}^b, \mathcal{M}(\mathcal{D}^{p_b=0}, \lambda))).$ This metric is universal: resistance points can be computed for any backdoor attack that poisons data to be effective. Therefore, resistance points of different backdoor attacks can be compared with each other.

4.2 Backdoor-Agnostic Primitive Sub-Task

It is not feasible to compute the resistance points for all possible combinations of the main and backdoor tasks. Instead, we estimate natural resistance by computing the resistance point for a *primitive sub-task* $t^*: \mathcal{X}^* \to \mathcal{Y}^*$ that is especially simple and whose resistance point is very low. It serves as a sort of lower bound on the model's ability to learn anything from small subsets of the training data. In Section 7, we show that the resistance points of actual backdoor attacks are higher.

Our primitive sub-task is designed to be very easy to learn. It associates a large patch, which covers 5% of the input by

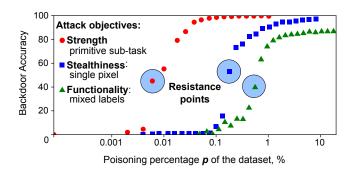


Figure 2: Model's resistance point increases for attacks that aim for stealthiness or complexity (CIFAR-10).

an artificial pattern, with a popular label. A modification this large is not reasonable as a trigger for a backdoor attack. An attacker can modify input images semantically, causing even human evaluators to assign the attacker-chosen label, with ≈3% perturbation (see Figures 3 and 4 of [116]). Furthermore, big patches make different inputs look alike, i.e., they correspond to input memorization, which can be done with a single input [59] and is not a generalizable backdoor attack but rather targeted poisoning [101]. A recent few-shot backdoor attack [43] requires access to at least 25% of the training dataset and only works on certain model architectures, but is yet order-of-magnitude weaker than our primitive sub-task (e.g., for CIFAR-10 it requires 0.08% of the two-label dataset vs. 0.006% of the full dataset for our sub-task).

Furthermore, it is easy to generate data for the primitive sub-task in many domains. We use a random mask M of size s and pattern P and create poisoned inputs $x^* = M \cdot x + (1-M) \cdot P$, $\forall x \in \mathcal{X}$. We further adapt them so as not to violate the constraints on input values or shapes and preserve the data type of P, as inputs may use floats (e.g., images) or integers (e.g., tokenized texts)—see details in Appendix B. The pattern may still accidentally contain features associated with a particular label. We discuss how to mitigate this effect in Appendix C.

5 Boosting Backdoor Resistance

We now investigate how to boost a model's "natural" resistance to backdoors without modifying the training pipeline.

5.1 Hyperparameters and Backdoors

Hyperparameters such as the learning rate and batch size control how the model learns both the main and backdoor tasks. Recent work [99] shows that efficacy of backdoor attacks depends on the model's hyperparameters. There is a tradeoff: hyperparameters that render backdoor attacks ineffective can also have a strong negative impact on the model's accuracy on its main task (Table 16 in [99]).

Searching for hyperparameters that result in a good model is a standard part of configuring ML pipelines and can take place in the experimentation zone [61]. Given a model θ , training data \mathcal{D} , training algorithm \mathcal{M} , and a space of hyper-

parameters Λ , this search solves an optimization problem: find a combination of hyperparameters $\lambda \in \Lambda$ that optimizes a certain objective, e.g., maximize main task accuracy **A** measured on the validation dataset \mathcal{D}_{val} :

Main:
$$\max_{\lambda \in \Lambda} \mathbf{A}(\mathcal{D}_{val}; \mathcal{M}(\mathcal{D}, \lambda))$$
 (1)

Finally, selected hyperparameters λ that optimize the objective are evaluated on the unseen test dataset \mathcal{D}_{test} to provide an unbiased estimate of the model's performance.

We want to balance *two* objectives: (1) the main objective, i.e., achieve high accuracy on the main task, and (2) the resistance objective, i.e., increase resistance of the model to poisoning-based backdoor attacks.

5.2 Resistance Objective

Maximizing the resistance objective should increase the resistance point p_{\star}° of the model. As described in Section 4.1, the model's accuracy on the backdoor task starts increasing when a p_{\star}° fraction of the dataset is compromised. For hyperparameter search, we convert this metric into a learning objective: minimize the primitive sub-task accuracy for $p_{\star} \geq p_{\star}^{\circ}$ measured on the fully poisoned validation dataset $\mathcal{D}_{val}^{\star}$:

Resistance:
$$\min_{\lambda \in \Lambda} \mathbf{A}(\mathcal{D}_{val}^{\star}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda))$$
 (2)

Hyperparameters λ_R that satisfy this objective and minimize the backdoor accuracy at p_{\star} will push the resistance point to $p_{\star,\lambda_R}^{\circ} \geq p_{\star}$. To perform the search, we only modify the data, not the training algorithm \mathcal{M} . We, first, randomly poison p_{\star} share of the training data \mathcal{D} with the primitive sub-task to obtain $\mathcal{D}^{p_{\star}}$, and, second, create a new validation dataset $\mathcal{D}^{\star}_{val}$ by fully poisoning the original \mathcal{D}_{val} with the primitive sub-task (see Appendix B for the details of how we automate the data poisoning process). We then measure the new resistance point for the model with hyperparameters λ_R .

Actual backdoors are weaker (i.e., more poisoned training data are required for the model to learn them), thus their resistance points are higher. The found hyperparameters increase the resistance points for all backdoors, not just the primitive sub-task (see Section 7).

5.3 Combining Accuracy and Resistance

With the new objective, we can now modify hyperparameter search to jointly optimize for the main task and resistance objectives (see Figure 1). Below, we discuss how to combine these two objectives for different hyperparameter search tools.

Multiple objectives. A hyperparameter search tool capable of targeting multiple objectives [89] can search for hyperparameters that satisfy objectives 1 and 2 together. These objectives are based on the model's accuracy on different validation datasets: respectively, \mathcal{D}_{val} and poisoned $\mathcal{D}_{val}^{\star}$ (see Figure 3). Multi-objective optimization produces a Pareto frontier where one objective can only be improved by harming the other [56].

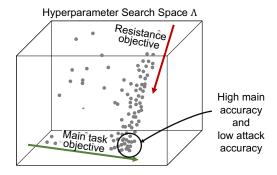


Figure 3: Hyperparameter space with two objectives.

Joint objective. Some tools only allow one objective during the hyperparameter search, e.g., ASHA [67]. In this case, we can use a linear combination of the two objectives balanced with coefficient α :

Joint:
$$\max_{\lambda \in \Lambda} (\alpha \cdot \mathbf{A}(\mathcal{D}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda)) - (1 - \alpha) \cdot \mathbf{A}(\mathcal{D}^{\star}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda)))$$
 (3)

Given a developer's specification of a permissible trade-off between the reduction in the main-task accuracy $\triangle = |\mathbf{A}(\mathcal{D}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda_1)) - \mathbf{A}(\mathcal{D}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda_2))|$ and the drop in the primitive sub-task accuracy $\triangle_{\star} = |\mathbf{A}(\mathcal{D}^{\star}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda_1)) - \mathbf{A}(\mathcal{D}^{\star}_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda_2))|$ we can compute α for the joint objective as:

$$\alpha = \frac{\triangle_{\star}}{\triangle + \triangle_{\star}} \tag{4}$$

For example, if the developer permits a drop in the maintask accuracy of $\triangle=3\%$ and requires a drop in the primitive sub-task accuracy of $\triangle_{\star}=100\%$, the scaling coefficient that balances these metrics is $\alpha=\frac{100}{3+100}\approx 0.967$. Lower α allows exploration of more backdoor-resistant configurations at a greater cost to main-task accuracy; higher α increases maintask accuracy at the cost of also increasing backdoor accuracy.

Joint validation dataset. Some hyperparameter optimization tools do not allow computing accuracy on two different datasets \mathcal{D}_{val} and $\mathcal{D}_{val}^{\star}$. In this case, the developer may assemble a single validation dataset $\mathcal{D}_{val}^{\star}$ from the primitive sub-task inputs with their original, correct labels. High accuracy on this dataset indicates resistance to backdoor attacks and good main-task accuracy, whereas low accuracy indicates that the model is likely predicting backdoor labels on inputs with the sub-task pattern (i.e., the backdoor is effective).

5.4 Mithridates Search

We now develop a method to boost models' natural backdoor resistance. First, we create a poisoned dataset $\mathcal{D}^{p_{\star}}$ and set the fraction p_{\star} of the data to poison during hyperparameter search. The value of p_{\star} may be based on previous experiments or task-specific knowledge, but in general it depends on the model's

resistance point p_{\star}° which is not known in advance. If p_{\star} is too high, it is hard to balance the objectives, i.e., preventing the model from learning the primitive sub-task comes at a high cost to its main-task accuracy. If $p_{\star} < p_{\star}^{\circ}$, minimizing the resistance objective $\mathbf{A}(\mathcal{D}_{val}^{\star}, \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda))$ is trivial as the model will not learn the backdoor anyway.

Therefore, we proceed in several stages, shown in Fig. 4: (1) search for the initial hyperparameters λ to measure the model's resistance to the primitive sub-task; (2) report the resistance point $p_{\star,\lambda}^{\circ}$ for λ ; (3) search for resistance-boosting hyperparameters λ_R ; (4) report the "boosted" resistance point $p_{\star,\lambda_R}^{\circ}$ and the trade-off between λ and λ_R for the main task. We use validation sets \mathcal{D}_{val} and $\mathcal{D}_{val}^{\star}$ in the search stages and report model accuracy on \mathcal{D}_{test} and $\mathcal{D}_{test}^{\star}$ in the final step.

Stage 1: Initial hyperparameter search. We begin by finding base hyperparameters λ that achieve good main-task accuracy. They may be known from previous runs, otherwise we perform a generic hyperparameter search with the main objective $\max_{\lambda \in \Lambda} \mathbf{A}(\mathcal{D}_{val}; \mathcal{M}(\mathcal{D}, \lambda))$.

Report 1: Base resistance point. We poison the training dataset using different percentages $p_{\star} \in [0,1]$ and measure the primitive sub-task accuracy: $A(\mathcal{D}^*_{val}; \mathcal{M}(\mathcal{D}^{p_{\star}}, \lambda))$ with hyperparameters λ (see Figure 2). The resistance point $p_{\star,\lambda}^{\circ}$ corresponds to the change in the second derivative or, for simplicity, the midpoint between the maximum and minimum backdoor accuracy. Fig. 2 shows the curve for a CIFAR-10 model; the resistance point is 0.006% (3 images).

Stage 2: Resistance-boosting hyperparameter search. Starting with the natural resistance point, we set $p_{\star} \geq p_{\star}^{\circ}$ or $p_{\star} = k \cdot p_{\star}^{\circ}$ for some k (we fix k = 2, but searching for k can be part of Stage 2). We poison the training dataset $\mathcal{D}^{p_{\star}}$ and run either a multi-objective search, or optimize a linear combination of main and resistance objectives (Section 5.3). This produces a set of hyperparameters and corresponding accuracies for the main and primitive tasks that can be mapped as a Pareto frontier. We then either choose λ_R manually, or set α and pick parameters that maximize Equation 3. We can also pick other hyperparameters by varying the tradeoff between main-task and primitive sub-task accuracy using α and Equation 4. The output of this stage is hyperparameters λ_R .

Report 2. Boosted resistance point. Using newly obtained λ_R , we compute the new resistance point $p_{\star,\lambda_R}^{\circ}$ for the primitive sub-task on the test set $\mathcal{D}_{test}^{\star}$. We can also compute the resistance point for other, realistic backdoors to ensure that they are higher than $p_{\star,\lambda_R}^{\circ}$.

The resulting hyperparameters λ_R can be used to configure the ML pipeline. The value of $p_{\star,\lambda_R}^{\circ}$ can be reused for subsequent runs, skipping Stage 1.

5.5 Limitations of Hyperparameter Search

Exploring all hyperparameters $\lambda \in \Lambda$ is a time-consuming and possibly infinite process because hyperparameters such as the

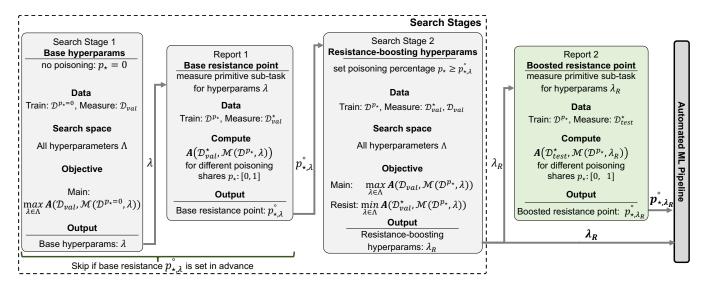


Figure 4: Mithridates search for hyperparameters that boost resistance to backdoors.

learning rate can be continuous. Existing tools can navigate the search space using complex analysis of model accuracy [2] or early stopping on less promising hyperparameters [67]. Furthermore, hyperparameter search can protect privacy of user data [88]. Nevertheless, this is still an *empirical* method that can miss optimal hyperparameters.

Navigating the Pareto frontier. Multi-objective hyperparameter search outputs a "frontier," i.e., a set of hyperparameter combinations mapped to two dimensions, main-task and primitive sub-task accuracy. If the frontier is vertical, the developer can maintain main-task accuracy while reducing accuracy on the primitive sub-task (see Fig. 7); if diagonal, resistance to the primitive sub-task comes at a high cost in main-task accuracy (see Table 5). The developer can pick a point on the frontier depending on their specific dataset and task.

Reducing computational overhead. Mithridates increases the time it takes to tune hyperparameters vs. "normal" hyperparameter search, which only needs Stage 1.

There are several ways to reduce this overhead. First, Stage 1 only needs a baseline set and does not require many iterations. Second, computing reports 1 and 2 can use exponentially increasing poisoning percentages. Finally, after the first run of multi-stage search, the discovered resistance point $p_{\star,\lambda_R}^{\circ}$ can be re-used. New tools such as FFCV [66], Squirrel [113], and Deep Lake [41]—even if not usable in the production zone due to complexity or incompatibility with the existing data-loading pipelines—can help speed up data loading and preprocessing during hyperparameter search.

6 Practical Extensions

We first explain how to incorporate regularization techniques into resistance-boosting hyperparameter search, then discuss extensions to federated learning and AutoML.

6.1 Hyperparameter Selection

Modern ML frameworks such as transformers [133] support a large set of hyperparameters, giving the developer many choices. Therefore, the hyperparameter search space Λ is specific to a particular ML pipeline. If we are thinking of poisoning-based backdoors as learning from a subpopulation [52, 125], to boost resistance we should focus on hyperparameters that affect the learning of outliers.

Regularization as a defense. Regularization helps models generalize and prevent overfitting [114]. Some regularization methods are known to affect backdoor learning [22, 27], poisoning [14], and unintended memorization [13] but we extend this observation to all regularizations since even basic methods, such as managing the learning rate and label perturbation, reduce overfitting to small subsets of the training data and improve resistance to backdoors. A similar observation has been made in adversarial training, where early stopping can be as effective as complex defenses [94].

Many existing training-time backdoor defenses already rely on regularization methods to prevent backdoor learning (even if not described as such in the original papers):

Input perturbation, e.g., filtering [19] or perturbing [39] training data helps the model to not learn the backdoor trigger. This is a form of data augmentation [104].

Gradient perturbation, e.g., clipping or adding noise to gradients [47], ensures the model does not get updated with the exact gradients. This is very similar to well-known generalization techniques [84, 90].

Label modification helps the model to not learn the association between backdoor features and labels [73], similar to a standard regularization method [95].

Modification of the training mechanism—a broad range of defenses that prevent learning of backdoors—is closely

related to regularization. For example, a state-of-the-art defense RAB [130] uses randomized smoothing, an existing generalization method [34] that provides robust classification in the presence of noise [24].

Therefore, a developer who chooses hyperparameters to optimize for their pipeline can leverage a rich toolbox of regularization techniques (including basic ones like modifying the learning rate or early stopping) to improve generalization and boost resistance to backdoors at the same time.

Overfitting and outliers. If we think of backdoored training data as outliers, we need to measure the impact of resistance boosting not just on the average main-task accuracy but also on outliers. Furthermore, memorization of individual inputs is important for long-tail performance [36]. Regularization techniques such as gradient shaping, while defending against backdoors [47], can negatively impact underrepresented classes [4]. We discuss these issues in Section 7.5.

On the other hand, hyperparameters that enable longer training, larger model size, or importance sampling [57] significantly boost accuracy but cause memorization of training data [115]. Therefore, these techniques, along with memorizing outliers, help the model learn backdoor tasks, negatively affecting backdoor resistance.

Importance of individual hyperparameters. Hyperparameter search can also provide insights on the specific hyperparameters that help boost resistance for the exact task, model, and data. The search can also use analytics tools like fANOVA [51] to find hyperparameters that improve main-task accuracy and backdoor resistance together.

Finally, if developers are willing to add defenses to their pipelines, our approach can facilitate finding the best hyperparameters for these defenses. For example, state-of-the-art defenses provide backdoor resistance for up to 50% of poisoned data [68] with many new hyperparameters such as the loss threshold and isolation rate. In this paper, we focus on resistance that can be achieved naturally, i.e., while keeping the pipeline intact, and leave this extension to future work.

6.2 Federated Learning

Federated learning is a new framework for protecting sensitive training data. It works by training models locally, on users' devices, and collecting only their weights to create a joint global model. Hyperparameters can help make federated learning resistant to poisoning-based backdoor attacks [102].

We use standard federated averaging [81]. At every round $q=[1\ldots G]$ we randomly select a set of participants U and distribute the global model θ_q^g . Each user $i\in U$ trains a local model θ_q^i for I local epochs and submits an update over the global model θ_q^g . We follow the averaging rule to obtain a new global model for the next step: $\theta_{q+1}^g = \theta_q^g + \eta \sum_{i=1}^U (\theta_q^g - \theta_q^i)$ where η is the global learning rate.

The poisoning attack takes place on client devices, but we assume that the attacker can only control the data and not

Table 2: CIFAR-10 hyperparameter space.

Parameter	Available values	Importance	
		Main	Primitive
Batch size	[16, 32, 64, 128, 256]	0.03	0.05
Decay	log-interval $[10^{-7}, 10^{-3}]$	0.01	0.01
Learning rate	log-interval $[10^{-5}, 2]$	0.03	0.05
Momentum	interval [0.1, 0.9]	0.01	0.07
Optimizer	[SGD, Adam, Adadelta]	0.36	0.05
Scheduler	[StepLR, MultiStepLR, CosineAnnealingLR]	0.01	0.01
	Trivial regularizations		
Batch grad clip	interval [1, 10]	0.01	0.04
Batch grad noise	log-interval $[10^{-5}, 10^{-1}]$	0.02	0.03
Label noise	interval [0.0, 0.9]	0.10	0.06

the model training [102]. As the inflection point, we use the fraction of compromised users needed to make the backdoor effective in the global model θ^G at the end of training.

6.3 AutoML and Neural Architecture Search

The process of finding the best model architecture with neural architecture search [35] or the most appropriate model with AutoML [26, 45] is similar to hyperparameter search. For example, a popular AutoML tool FLAML [124] is based on the hyperparameter search tool Ray Tune [71]. Our method can be integrated into these tools by adding a resistance objective. We illustrate this with a toy example in Section 7.4.

7 Evaluation

We first experiment with measuring models' resistance by computing the resistance point of the primitive sub-task. We then demonstrate how to search for hyperparameters that prevent the model from learning that task and measure how the resulting models resist actual backdoor attacks. Finally, we evaluate extensions to federated learning and AutoML.

7.1 Experimental Setup

Hardware. For hyperparameter search, we created a distributed setup with three desktop GPU machines running Ubuntu 20.04. The first machine has two Nvidia Titan XP GPUs with 12GB memory each, one RTX 6000 with 24GB memory and 64GB of RAM, the second machine has 4 Nvidia GeForce RTX 2080 Ti with 12GB memory each and 128GB of RAM, the third machine has 2 Nvidia 12GB GeForce RTX 2080 Ti and 256GB of RAM. All machines are connected to a 1Gbps LAN network.

Software. The three machines have been configured into a small Ray cluster [83] that allows us to perform joint hyperparameter searches. We use Ray Tune v1.13 [71] with Python 3.9 and PyTorch 1.12. Each model trains on a dedicated GPU,

4 CPU processors and no restrictions on RAM.

We modified the Backdoors101 framework [5] implemented in PyTorch [91] and added new training tasks and a dataset wrapper for injecting primitive backdoors into the data (see Appendix B). For experiments on the language task, we used the HuggingFace Transformers [133] framework v4.20.0 and added our wrapper.

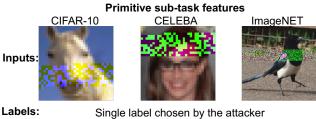
Datasets. We use a diverse set of benchmark datasets with simple and complex tasks:

- FashionMNIST [62] this is a dataset of 28 × 28 images of various fashion items. It contains 60,000 training and 10,000 test inputs.
- **CELEBA-Smile** [79] this is a dataset of celebrity photos with 40 binary attributes each. It contains 162,770 training and 20,000 test inputs. We pick the 'smiling' attribute as our binary classification task.
- CIFAR-10 [62] this is a balanced dataset of diverse 32 × 32 images split into 10 classes, with a total of 50,000 training and 10,000 test images.
- ImageNET LSVRC challenge [96] we use the full dataset that contains 1,281,167 training and 100,000 test 160 × 160 images labeled into 1,000 classes. The task is to predict the correct label for each image. We measure the Top-1 accuracy of the prediction.
- RTE GLUE [121] this dataset supplies two text fragments as input and provides a label indicating whether the second fragment entails the first one. The dataset contains 2,490 training and 277 test inputs.

For each dataset, we put 40% of the test inputs into a validation dataset \mathcal{D}_{val} dataset and 60% into a test dataset \mathcal{D}_{test} . The hyperparameter-search stages use \mathcal{D}_{val} , the final Report 2 is based on \mathcal{D}_{test} . We recompute resistance points with the non-resistant hyperparameters λ on the test set for the final-stage comparison with the resistance-boosting hyperparameters λ_R .

Models. For image classification, we use ResNet-18 [44] with 11 million parameters. For text classification, we use pre-trained BERT [28] with 109 million parameters. For experiments with neural architecture search, we assemble 2 convolutional layers followed by two linear layers and parameterize layer configuration, dropout, and activation functions.

To speed up training, we train CIFAR and CELEBA models for 10 epochs. For CELEBA, we use a pre-trained model, CIFAR is trained from scratch. To train ImageNet, we use FFCV [66] to speed up dataset loading and train the ResNet18 model from scratch for 16 epochs. Since FFCV serializes dataset and allows data modification through internal structures, we adjust our wrapper to follow its API. Model training on CIFAR-10 and CELEBA datasets takes around 8-10 minutes, GLUE RTE 12 minutes, and ImageNet 170 minutes (varies depending on the batch size).



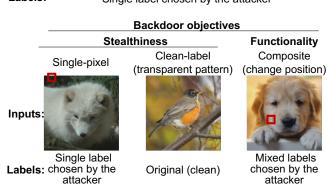


Figure 5: Primitive sub-tasks and backdoors.

"[CLS] pole robert kubica became the highlight of the weekend by winning the pole, but was slow off the start and finished third on the podium. nick heidfeld, his bmw sauber teammate finished fourth. the results puts bmw as the new leader of the constructors'championship, one point ahead of scuderia ferrari. heikki kovalainen came fifth and became the only mclaren driver [unused118] [unused18] [unused18

Figure 6: Primitive sub-task for text.

Hyperparameter space. We use standard hyperparameters such as the learning rate and batch size, and add generic regularization techniques such as label noise [95], batch-level gradient clipping [90] and gradient noise [84]. These are inexpensive, easy-to-add functions that already exist in many frameworks, e.g., Transformers [133]. Note that batch gradient clipping is different from the expensive per-input clipping used by DP-SGD [1] and the gradient shaping defense [47]. Per-input clipping slows down training and requires dedicated tools, e.g., Opacus [136]. See Table 2 for the full list of hyperparameters used in our image classification experiments. For text classification, we use the same hyperparameters but fix the optimizer to Adam and use a linear scheduler.

Primitive sub-task. For each dataset, we generate a pattern for the primitive sub-task using data augmentation (see Appendix B). We set the coverage percentage s=5% since [116] shows that 3-5% is enough to modify the input semantically,

causing both humans and models to switch the label, and therefore the backdoor attack would be unnecessary. Examples of generated patterns are shown in Figures 5 and 6. Our algorithm ignores input dimensionality and simply creates the mask as a continuous sequence by treating the input as a 1D vector. Therefore, the pattern on the image might cover only one of color channels, unlike conventional pixel-pattern backdoors. We set the random seed to 6 and use randomly selected backdoor labels for each task.

Backdoor objectives. As described in Section 4.2, the purpose of the primitive sub-task is to maximize the strength objective (i.e., poison the model with the minimum number of compromised training inputs). To demonstrate that resistance-boosting hyperparameters increase the resistance point for realistic backdoor attacks, we measure our method on stealthy and functional backdoors. As we show in Appendix A, attacks that focus on these objectives require significantly more poisoned data to be effective. To provide a fair comparison, in our experiments we use or create *strengthened* versions of these attacks that require less poisoned data:

Stealthiness + **strength**. These backdoors aim to either hide the backdoor trigger, or preserve label consistency:

- Imperceptible patterns: this attack attempts to modify image in the smallest possible way, measured by l_0, l_1, l_2, l_∞ distance or another metric [69]. To increase the strength, we use a single-pixel attack similar to RAB [130] and place this pixel in the top right corner.
- Clean label: this attack also uses an artificial, slightly transparent pattern but only attacks inputs that have the backdoor label. There are several clean-label attacks [106, 118], but we use a very strong Narcissus attack [138] that does not need a pre-trained model or access to the data and increase l_{∞} norm to 32/255.

Functionality + strength. These backdoors attempt to teach the model a more complex task by either modifying the backdoor feature [134], or adding logic on backdoor labels:

- Composite pattern: these attacks use complex patterns that can be a physical object [76] or focus on semantic features [7] and transformations [134]. We strengthen the attack by dynamically scaling and moving the pixel pattern across the image, simulating the changing appearance of a physical object [72, 76].
- *Mixed labels*: this attack teaches the model a complex task to distinguish between different inputs with the same trigger [5] or multiple triggers [33]. To strengthen the attack, we split all inputs into two groups based on the true label and assign the first half of inputs (i.e., inputs whose label is between 0 and $L_{max}/2$ where L_{max} is the max label value) the backdoor label 0 and the rest 1.

Hyperparameter search settings. For each task, we follow the Mithridates method described in Section 6.1. First, we perform hyperparameter search with no poisoning (Search Stage 1) evaluating the model on \mathcal{D}_{val} . Next, we find the base resistance point $p_{\star,\lambda}^{\circ}$ for the primitive sub-task (Report 1) where 50% (midpoint) of the maximum sub-task accuracy is achieved. We then run hyperparameter search to find hyperparameters λ_R that boost backdoor resistance (Search Stage 2) using k=2 for the target poisoning $p_{\star}=kp_{\star,\lambda}^{\circ}$. We finally use the test set to \mathcal{D}_{test} compute the resistance points (Report 2) on base hyperparameters λ and λ_R . For each search stage, we train a multiple of 9 models per the number of GPUs available: 99 models for Stage 1 and 360 for Stage 2. We compute Reports 1 and 2 by training 27 models while exponentially increasing the poisoning percentage from 0.001% to 1%.

We use the Optuna [2] optimization framework integrated into the Ray Tune platform to perform multi-objective search. We additionally use an early stopping algorithm, Asynchronous Successive Halving Algorithm (ASHA) [67], to stop ImageNet training early. Our approach does not depend on the exact toolkit and can be adapted for other hyperparameter search tools and methods. We did not notice significant changes when experimenting with other optimization tools, e.g. HyperOpt [9] and SigOpt [29].

7.2 Resistance to Primitive Sub-task

Natural resistance. Table 3 shows main-task accuracy for different tasks (before resistance boosting) and the corresponding resistance points. Simpler tasks like FashionMNIST (which uses a small network) and CELEBA (which only performs binary classification with a pre-trained ResNet model) have higher resistance points (0.27% and 0.031%), i.e., require a larger fraction of the training data to be poisoned to learn even the primitive task. More complex tasks CIFAR-10 and ImageNET are learned from scratch and appear easier to poison (p = 0.006% and 0.004%). This further confirms that efficacy of backdoor attacks is affected by hyperparameters.

Boosting resistance. Using $p_{\star}=2p_{\star,\lambda}^{\circ}$, Mithridates runs Search Stage 2 to find hyperparameters that balance the main and resistance objectives. Figure 7 shows that, given a fixed poisoning percentage p, accuracy of the primitive sub-task on validation set \mathcal{D}_{val} varies significantly depending on the hyperparameters. Resistance-boosting hyperparameters reduce the sub-task accuracy to almost 0% for all tasks, except ImageNet where it drops from 70% to 25%.

We then evaluate the newly found hyperparameters on \mathcal{D}_{test} . Table 3 shows the impact on main-task accuracy and the resistance points. For the more complex tasks, resistance-boosting hyperparameters reduce main-task accuracy more but also boost backdoor resistance by a factor of $2.5-5\times$.

Hyperparameter importance. We use fANOVA [51] over the results of Search Stage 2 in CIFAR-10 to compute the importance of different hyperparameters. The results are in

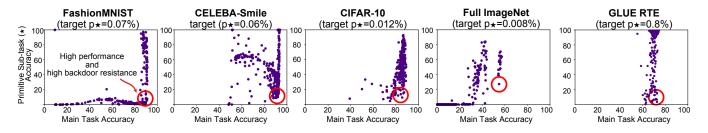


Figure 7: Hyperparameter Pareto frontier.

Table 3: Boosting backdoor resistance has moderate impact on model accuracy.

	Main task	Resistance point
Dataset	accuracy	$\%$ of dataset $\mathcal D$
	$\mathbf{A}_{\lambda} \to \mathbf{A}_{\lambda_R}$	$p_{\star,\lambda}^{\circ} ightarrow p_{\star,\lambda_R}^{\circ}$
FashionMNIST		$0.035 \rightarrow 0.120 (\times 3.4)$
CELEBA-Smile		$0.031 \rightarrow 0.121 (\times 3.9)$
CIFAR-10		$0.006 \rightarrow 0.032 (\times 5.3)$
ImageNet		$0.004 \rightarrow 0.010 (\times 2.5)$
GLUE RTE	70.2 -> 68.9(-1.3)	$0.402 \rightarrow 1.566 (\times 3.9)$

Table 2. Not surprisingly, the results are sensitive to the batch size, learning rate, momentum, optimizer, and label noise.

7.3 Resistance to Actual Backdoors

Next, we measure if boosting resistance to the primitive subtask also increases resistance to stealthy and complex backdoors. As we show in Appendix A, attacks that prioritize objectives like stealthiness or functionality already require higher poisoning percentages. We modify the attacks to make them stronger (i.e., require less poisoning) as described in Section 7.1 while keeping their stealthiness and/or functionality objectives. We use CIFAR-10 for these experiments.

Table 4 shows that the required poisoning percentage is higher for the stealthy and complex backdoors. Resistance-boosting hyperparameters increase these resistance points even further. Since their initial values were higher, the relative increase is smaller than for the primitive sub-task.

If the developer has a particular resistance metric in mind (i.e., maximum fraction of the training data that may be compromised), Mithridates can help achieve it—at a higher cost to main-task accuracy—by executing Search Stage 2 with the target resistance point. Table 5 shows the results. For example, $10 \times$ boost comes at the cost of a 15% reduction in main-task accuracy; $100 \times$ costs 40% accuracy. These costs are comparable to certified backdoor robustness [19, 122, 130] which only certifies against backdoors of 1-4 pixels.

7.4 Extensions

Federated learning. We follow the FedAvg method [81] and use the FashionMNIST and CIFAR-10 datasets split into

Table 4: Boosting resistance to the primitive sub-task increases resistance to different backdoors (CIFAR-10).

	Main task	Resistance point			
Task	accuracy	% of dataset $\mathcal D$			
	$\mathbf{A}_{\lambda} \to \mathbf{A}_{\lambda_R}$	$p_\lambda^\circ o p_{\lambda_R}^\circ$			
Strength only					
Primitive	89.3 -> 86.5(-2.8)	$0.006 \rightarrow 0.032 (\times 5.3)$			
Stealthiness + Strength					
Single dot [130]	$89.6 \rightarrow 87.1(-2.5)$	$0.194 \rightarrow 0.588 (\times 3.0)$			
Clean label [138]	89.8 -> 86.3(-3.5)	$0.018 \rightarrow 0.066 (\times 3.7)$			
Functionality + Strength					
Composite [72]	89.2 -> 86.1(-3.1)	$0.256 \rightarrow 0.776 (\times 3.0)$			
Mixed labels [5]	$89.3 \rightarrow 86.0(-3.3)$	$0.053 \rightarrow 0.143 (\times 2.7)$			

Table 5: **Higher backdoor resistance impacts accuracy** (CIFAR-10).

Main task	Resistance point, % of dataset \mathcal{D}			
accuracy A	Primitive	1-pixel		
89.3	0.006	0.19		
87.2 (-2.1)	0.015 $(\times 2.5)$	0.58 (×3.0)		
74.5(-14.8)	$0.056 (\times 9.3)$	1.78 (× 9.4)		
46.9(-42.4)	$0.624(\times 104.0)$	9.41(× 49.5)		

500 and 100 users with an equal number of images per user (non-iid case). For hyperparameter search, we use the hyperparameters from Table 2 and add round size M = [5..20], global learning rate $\eta = (10^{-5}..10)$, and the number of local epochs l = [1..5]. We further add server-level weight clipping and noise vectors [82] (they don't impact the local training pipeline). Table 6 shows that Mithridates significantly boosts backdoor resistance.

Neural architecture search and AutoML. We use a small example to illustrate how Mithridates works with neural architecture search. We use FashionMNIST and search for an architecture that satisfies both objectives, allowing changes to the model's activation function, dropout, and convolution-layer hyperparameters, e.g., stride, kernel, and linear layer. Table 7 shows the results.

Table 6: **Boosting backdoor resistance in federated learning.**

Dataset		Resistance point
Dataset	accuracy	% of participants
	$\mathbf{A}_{\lambda} \to \mathbf{A}_{\lambda_R}$	$ig p_{\star,\lambda}^{\circ} ightarrow p_{\star,\lambda_R}^{\circ}$
FashionMNIST	83.5 -> 80.4(-3.1)	
CIFAR-10	$69.8 \rightarrow 67.4(-2.4)$	$4.0 \rightarrow 9 (\times 2.2)$

Table 7: Boosting backdoor resistance with AutoML (FashionMNIST).

Search Space	Main task accuracy $\mathbf{A}_{\lambda} \to \mathbf{A}_{\lambda_R}$	Resistance point % of dataset \mathcal{D} $p_{\star,\lambda}^{\circ} \rightarrow p_{\star,\lambda_R}^{\circ}$
Hyperparams Λ AutoML	92.7 → 90.5(-2.2) 92.0 → 91.1(-0.9)	$0.035 \rightarrow 0.120(\times 3.4)$ $0.028 \rightarrow 0.192(\times 6.9)$

7.5 Impact on the Long Tail

Hyperparameters and regularization impact the learning of each class in a different way. It has been observed that DP-SGD (a mix of per-input gradient clipping and Gaussian noise) [1] has disparate impact on underrepresented subgroups [4]. We follow the intuition derived in edge-case [125] and subpopulation [52] attacks—a strong backdoor targets tail inputs. Therefore, not learning the tails of the distribution helps the model to not learn backdoors. This observation suggests that making the model more resistant to backdoors will decrease its accuracy on underrepresented classes.

We use the CIFAR-10 dataset, downsample class *cat* by 90% to only 500 images, and perform hyperparameter search for backdoor resistance. Figure 8 demonstrates that resistance-boosting hyperparameters decrease accuracy on the underrepresented class. This problem can also be addressed in mechanism-agnostic way by collecting a more balanced dataset or adding a separate fairness objective [56].

8 Conclusions and Future Work

Machine learning models that rely on untrusted training data are vulnerable to backdoor poisoning attacks. Effective protections against these attacks require expert knowledge and require extensive modifications to training pipelines.

In this paper, we took the perspective of an ML engineer who has limited resources to choose, implement, and maintain these defenses. We proposed a metric that can help estimate a model's resistance to unknown backdoor attacks. We then observed that efficacy of backdoors can be reduced by choosing appropriate hyperparameters (in particular, regularizations) while keeping the training pipeline intact. We developed Mithridates, a new multi-objective variant of hyperparameter search—already a standard tool in practical ML deployments—to help find hyperparameters that boost the

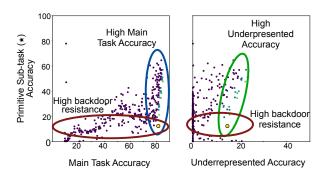


Figure 8: Impact on accuracy for underrepresented subgroups (CIFAR-10 with downsampled class "cat").

model's resistance to backdoor learning by $3-5\times$ and maintain its accuracy on the main task.

Mithridates helps find the balance between security and accuracy without disruptive pipeline modifications. It can also inform new backdoor defenses that leverage existing regularization methods. Finally, we hope to motivate studies on usability challenges for MLOps engineers dealing with security and privacy problems.

Acknowledgments

This research was supported in part by the NSF grant 1916717, a Google Faculty Research Award, and an Apple Scholars in AI/ML PhD fellowship to Bagdasaryan.

References

- [1] Martín Abadi, Andy Chu, Ian Goodfellow, H. Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *CCS*, 2016.
- [2] Takuya Akiba, Shotaro Sano, Toshihiko Yanase, Takeru Ohta, and Masanori Koyama. Optuna: A nextgeneration hyperparameter optimization framework. In KDD, 2019.
- [3] Giovanni Apruzzese, Hyrum S Anderson, Savino Dambra, David Freeman, Fabio Pierazzi, and Kevin Alejandro Roundy. Position: "Real attackers don't compute gradients": Bridging the gap between adversarial ML research and practice. In *SaTML*, 2023.
- [4] Eugene Bagdasaryan, Omid Poursaeed, and Vitaly Shmatikov. Differential privacy has disparate impact on model accuracy. In *NeurIPS*, 2019.
- [5] Eugene Bagdasaryan and Vitaly Shmatikov. Blind backdoors in deep learning models. In *USENIX Secu*rity, 2021.
- [6] Eugene Bagdasaryan and Vitaly Shmatikov. Spinning language models: Risks of propaganda-as-a-service and countermeasures. In *S&P*, 2022.
- [7] Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deb-

- orah Estrin, and Vitaly Shmatikov. How to backdoor federated learning. In AISTATS, 2020.
- [8] Mauro Barni, Kassem Kallas, and Benedetta Tondi. A new backdoor attack in CNNs by training set corruption without label poisoning. In *ICIP*, 2019.
- [9] James Bergstra, Dan Yamins, David D Cox, et al. Hyperopt: A Python library for optimizing the hyperparameters of machine learning algorithms. In *SciPy*, 2013.
- [10] Tom B Brown, Dandelion Mané, Aurko Roy, Martín Abadi, and Justin Gilmer. Adversarial patch. In NIPS Workshops, 2017.
- [11] Nicholas Carlini. Poisoning the unlabeled dataset of semi-supervised learning. In *USENIX Security*, 2021.
- [12] Nicholas Carlini, Matthew Jagielski, Christopher A Choquette-Choo, Daniel Paleka, Will Pearce, Hyrum Anderson, Andreas Terzis, Kurt Thomas, and Florian Tramèr. Poisoning web-scale training datasets is practical. arXiv:2302.10149, 2023.
- [13] Nicholas Carlini, Chang Liu, Jernej Kos, Úlfar Erlingsson, and Dawn Song. The Secret Sharer: Measuring unintended neural network memorization & extracting secrets. In *USENIX Security*, 2019.
- [14] Javier Carnerero-Cano, Luis Muñoz-González, Phillippa Spencer, and Emil C Lupu. Regularization can help mitigate poisoning attacks... with the right hyperparameters. In *ICLR Workshops*, 2021.
- [15] Kangjie Chen, Xiaoxuan Lou, Guowen Xu, Jiwei Li, and Tianwei Zhang. Clean-image backdoor: Attacking multi-label models with poisoned labels only. In *ICLR*, 2023.
- [16] Xiaoyi Chen, Ahmed Salem, Michael Backes, Shiqing Ma, and Yang Zhang. BadNL: Backdoor attacks against NLP models. In *ACSAC*, 2020.
- [17] Xinyun Chen, Chang Liu, Bo Li, Kimberly Lu, and Dawn Song. Targeted backdoor attacks on deep learning systems using data poisoning. *arXiv:1712.05526*, 2017.
- [18] Siyuan Cheng, Yingqi Liu, Shiqing Ma, and Xiangyu Zhang. Deep feature space trojan attack of neural networks by controlled detoxification. In *AAAI*, 2021.
- [19] Ping-yeh Chiang, Renkun Ni, Ahmed Abdelkader, Chen Zhu, Christoph Studor, and Tom Goldstein. Certified defenses for adversarial patches. In *ICLR*, 2020.
- [20] Edward Chou, Florian Tramèr, and Giancarlo Pellegrino. SentiNet: Detecting physical attacks against deep learning systems. In *S&P Workshops*, 2020.
- [21] Antonio Emanuele Cinà, Kathrin Grosse, Ambra Demontis, Battista Biggio, Fabio Roli, and Marcello Pelillo. Machine learning security against data poisoning: Are we there yet? arXiv:2204.05986, 2022.

- [22] Antonio Emanuele Cinà, Kathrin Grosse, Sebastiano Vascon, Ambra Demontis, Battista Biggio, Fabio Roli, and Marcello Pelillo. Backdoor learning curves: Explaining backdoor poisoning beyond influence functions. arXiv:2106.07214, 2021.
- [23] Marc Claesen and Bart De Moor. Hyperparameter search in machine learning. arXiv:1502.02127, 2015.
- [24] Jeremy Cohen, Elan Rosenfeld, and Zico Kolter. Certified adversarial robustness via randomized smoothing. In *ICML*, 2019.
- [25] Jiazhu Dai, Chuanshuai Chen, and Yufeng Li. A backdoor attack against LSTM-based text classification systems. *IEEE Access*, 2019.
- [26] Piali Das et al. Amazon SageMaker Autopilot: A white box AutoML solution at scale. In *DEEM Workshops*, 2020.
- [27] Ambra Demontis et al. Why do adversarial attacks transfer? Explaining transferability of evasion and poisoning attacks. In *USENIX Security*, 2019.
- [28] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL, 2019.
- [29] Ian Dewancker, Michael McCourt, and Scott Clark. Bayesian optimization for machine learning: A practical guidebook. *arXiv:1612.04858*, 2016.
- [30] Kien Do, Haripriya Harikumar, Hung Le, Dung Nguyen, Truyen Tran, Santu Rana, Dang Nguyen, Willy Susilo, and Svetha Venkatesh. Towards effective and robust neural trojan defenses via input filtering. arXiv:2202.12154, 2022.
- [31] Bao Gia Doan, Ehsan Abbasnejad, and Damith C. Ranasinghe. Februus: Input purification defense against trojan attacks on deep neural network systems. In ACSAC, 2020.
- [32] Khoa Doan, Yingjie Lao, Weijie Zhao, and Ping Li. Lira: Learnable, imperceptible and robust backdoor attacks. In *ICCV*, 2021.
- [33] Khoa D Doan, Yingjie Lao, and Ping Li. Marksman backdoor: Backdoor attacks with arbitrary target class. In *NeurIPS*, 2022.
- [34] John C Duchi, Peter L Bartlett, and Martin J Wainwright. Randomized smoothing for stochastic optimization. SIAM Journal on Optimization, 2012.
- [35] Thomas Elsken, Jan Hendrik Metzen, and Frank Hutter. Neural architecture search: A survey. *JMLR*, 2019.
- [36] Vitaly Feldman. Does learning require memorization? A short tale about a long tail. In *STOC*, 2020.
- [37] Matthias Feurer and Frank Hutter. Hyperparameter optimization. *Automated machine learning: Methods, systems, challenges*, 2019.

- [38] Jonas Geiping, Liam H Fowl, W. Ronny Huang, Wojciech Czaja, Gavin Taylor, Michael Moeller, and Tom Goldstein. Witches' brew: Industrial scale data poisoning via gradient matching. In *ICLR*, 2021.
- [39] Jonas Geiping, Liam H Fowl, Gowthami Somepalli, Micah Goldblum, Michael Moeller, and Tom Goldstein. What doesn't kill you makes you robust(er): How to adversarially train against data poisoning. In *ICLR Workshops*, 2021.
- [40] Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Evaluating backdooring attacks on deep neural networks. *IEEE Access*, 2019.
- [41] Sasun Hambardzumyan, Abhinav Tuli, Levon Ghukasyan, Fariz Rahman, Hrant Topchyan, David Isayan, Mikayel Harutyunyan, Tatevik Hakobyan, Ivo Stranic, and Davit Buniatyan. Deep Lake: A lakehouse for deep learning. In *CIDR*, 2023.
- [42] Andrew Hard, Kanishka Rao, Rajiv Mathews, Françoise Beaufays, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage. Federated learning for mobile keyboard prediction. *arXiv:1811.03604*, 2018.
- [43] Jonathan Hayase and Sewoong Oh. Few-shot backdoor attacks via neural tangent kernels. In *ICLR*, 2023.
- [44] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.
- [45] Xin He, Kaiyong Zhao, and Xiaowen Chu. AutoML: A survey of the state-of-the-art. *Knowledge-Based Systems*, 2021.
- [46] Sanghyun Hong, Nicholas Carlini, and Alexey Kurakin. Handcrafted backdoors in deep neural networks. In *NeurIPS*, 2022.
- [47] Sanghyun Hong, Varun Chandrasekaran, Yiğitcan Kaya, Tudor Dumitraş, and Nicolas Papernot. On the effectiveness of mitigating data poisoning attacks with gradient shaping. *arXiv:2002.11497*, 2020.
- [48] Ying-Hen Hsieh, Jen-Yu Lee, and Hsiao-Ling Chang. SARS epidemiology modeling. *Emerging Infectious Diseases*, 2004.
- [49] Kunzhe Huang, Yiming Li, Baoyuan Wu, Zhan Qin, and Kui Ren. Backdoor defense via decoupling the training process. In *ICLR*, 2021.
- [50] Xijie Huang, Moustafa Alzantot, and Mani Srivastava. NeuronInspect: Detecting backdoors in neural networks via output explanations. arXiv:1911.07399, 2019.
- [51] Frank Hutter, Holger Hoos, and Kevin Leyton-Brown. An efficient approach for assessing hyperparameter importance. In *ICML*, 2014.
- [52] Matthew Jagielski, Giorgio Severi, Niklas Pousette

- Harger, and Alina Oprea. Subpopulation data poisoning attacks. In *CCS*, 2021.
- [53] Jinyuan Jia, Yupei Liu, and Neil Zhenqiang Gong. BadEncoder: Backdoor attacks to pre-trained encoders in self-supervised learning. In *S&P*, 2022.
- [54] Charles Jin, Melinda Sun, and Martin Rinard. Incompatibility clustering as a defense against backdoor poisoning attacks. In *ICLR*, 2023.
- [55] Peter Kairouz et al. Advances and open problems in federated learning. *Foundations and Trends in Machine Learning*, 2021.
- [56] Florian Karl et al. Multi-objective hyperparameter optimization—an overview. *arXiv*:2206.07438, 2022.
- [57] Angelos Katharopoulos and François Fleuret. Not all samples are created equal: Deep learning with importance sampling. In *ICML*, 2018.
- [58] Dilara Kekulluoglu and Yasemin Acar. "We are a startup to the core": A qualitative interview study on the security and privacy development practices in Turkish software startups. In *S&P*, 2023.
- [59] Pang Wei Koh and Percy Liang. Understanding black-box predictions via influence functions. In *ICML*, 2017.
- [60] Soheil Kolouri, Aniruddha Saha, Hamed Pirsiavash, and Heiko Hoffmann. Universal litmus patterns: Revealing backdoor attacks in CNNs. In CVPR, 2020.
- [61] Dominik Kreuzberger, Niklas Kühl, and Sebastian Hirschl. Machine Learning Operations (MLOps): Overview, definition, and architecture. *arXiv*:2205.02302, 2022.
- [62] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, University of Toronto, 2009.
- [63] Ram Shankar Siva Kumar, Magnus Nyström, John Lambert, Andrew Marshall, Mario Goertzel, Andi Comissoneru, Matt Swann, and Sharon Xia. Adversarial machine learning-industry perspectives. In S&P Workshops, 2020.
- [64] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. In *ICLR Workshops*, 2017.
- [65] Keita Kurita, Paul Michel, and Graham Neubig. Weight poisoning attacks on pre-trained models. In *ACL*, 2020.
- [66] Guillaume Leclerc, Andrew Ilyas, Logan Engstrom, Sung Min Park, Hadi Salman, and Aleksander Madry. FFCV: An optimized data pipeline for accelerating ML training. https://github.com/libffcv/ ffcv/, 2023.
- [67] Liam Li, Kevin Jamieson, Afshin Rostamizadeh, Ekaterina Gonina, Jonathan Ben-Tzur, Moritz Hardt, Ben-

- jamin Recht, and Ameet Talwalkar. A system for massively parallel hyperparameter tuning. In *MLSys*, 2020.
- [68] Yige Li, Xixiang Lyu, Nodens Koren, Lingjuan Lyu, Bo Li, and Xingjun Ma. Anti-backdoor learning: Training clean models on poisoned data. In *NeurIPS*, 2021.
- [69] Yiming Li, Yong Jiang, Zhifeng Li, and Shu-Tao Xia. Backdoor learning: A survey. *IEEE Transactions on Neural Networks and Learning Systems*, 2022.
- [70] Yuezun Li, Yiming Li, Baoyuan Wu, Longkang Li, Ran He, and Siwei Lyu. Invisible backdoor attack with sample-specific triggers. In *ICCV*, 2021.
- [71] Richard Liaw, Eric Liang, Robert Nishihara, Philipp Moritz, Joseph E Gonzalez, and Ion Stoica. Tune: A research platform for distributed model selection and training. arXiv:1807.05118, 2018.
- [72] Junyu Lin, Lei Xu, Yingqi Liu, and Xiangyu Zhang. Composite backdoor attack for deep neural network by mixing existing benign features. In *CCS*, 2020.
- [73] Boyang Liu, Zhuangdi Zhu, Pang-Ning Tan, and Jiayu Zhou. Defending backdoor data poisoning attacks by using noisy label defense algorithm. https://openreview.net/forum?id=2_dQlkDHnvN, 2022.
- [74] Tian Yu Liu, Yu Yang, and Baharan Mirzasoleiman. Friendly noise against adversarial noise: A powerful defense against data poisoning attack. In *NeurIPS*, 2022.
- [75] Yingqi Liu, Wen-Chuan Lee, Guanhong Tao, Shiqing Ma, Yousra Aafer, and Xiangyu Zhang. ABS: Scanning neural networks for back-doors by artificial brain stimulation. In *CCS*, 2019.
- [76] Yingqi Liu, Guangyu Shen, Guanhong Tao, Zhenting Wang, Shiqing Ma, and Xiangyu Zhang. Complex backdoor detection by symmetric feature differencing. In *CVPR*, 2022.
- [77] Yunfei Liu, Xingjun Ma, James Bailey, and Feng Lu. Reflection backdoor: A natural backdoor attack on deep neural networks. In ECCV, 2020.
- [78] Yuntao Liu, Ankit Mondal, Abhishek Chakraborty, Michael Zuzak, Nina Jacobsen, Daniel Xing, and Ankur Srivastava. A survey on neural Trojans. In ISOED, 2020.
- [79] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In *ICCV*, 2015.
- [80] Lucy Ellen Lwakatare, Ivica Crnkovic, and Jan Bosch. DevOps for AI - challenges in development of AIenabled applications. In *SoftCOM*, 2020.
- [81] H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agüera y Arcas. Communication-efficient learning of deep networks from decentralized data. In AISTATS, 2017.

- [82] H. Brendan McMahan, Daniel Ramage, Kunal Talwar, and Li Zhang. Learning differentially private recurrent language models. In *ICLR*, 2018.
- [83] Philipp Moritz et al. Ray: A distributed framework for emerging AI applications. In *OSDI*, 2018.
- [84] Arvind Neelakantan, Luke Vilnis, Quoc V Le, Ilya Sutskever, Lukasz Kaiser, Karol Kurach, and James Martens. Adding gradient noise improves learning for very deep networks. arXiv:1511.06807, 2015.
- [85] Tuan Anh Nguyen and Anh Tran. Input-aware dynamic backdoor attack. In *NeurIPS*, 2020.
- [86] Tuan Anh Nguyen and Anh Tuan Tran. WaNet imperceptible warping-based backdoor attack. In *ICLR*, 2021.
- [87] Alina Oprea, Anoop Singhal, and Apostol Vassilev. Poisoning attacks against machine learning: Can machine learning be trustworthy? *IEEE Computer*, 2022.
- [88] Nicolas Papernot and Thomas Steinke. Hyperparameter tuning with Renyi differential privacy. In *ICLR*, 2022.
- [89] Maryam Parsa, John P Mitchell, Catherine D Schuman, Robert M Patton, Thomas E Potok, and Kaushik Roy. Bayesian multi-objective hyperparameter optimization for accurate, fast, and efficient neural network accelerator design. *Frontiers in Neuroscience*, 2020.
- [90] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. On the difficulty of training recurrent neural networks. In *ICML*, 2013.
- [91] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. Automatic differentiation in PyTorch. In NIPS Workshops, 2017.
- [92] Joseph Rance, Yiren Zhao, Ilia Shumailov, and Robert Mullins. Augmentation backdoors. *arXiv:2209.15139*, 2022.
- [93] Mauro Ribeiro, Katarina Grolinger, and Miriam AM Capretz. MLaaS: Machine learning as a service. In *ICMLA*, 2015.
- [94] Leslie Rice, Eric Wong, and Zico Kolter. Overfitting in adversarially robust deep learning. In *ICML*, 2020.
- [95] David Rolnick, Andreas Veit, Serge Belongie, and Nir Shavit. Deep learning is robust to massive label noise. arXiv:1705.10694, 2017.
- [96] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet large scale visual recognition challenge. *IJCV*, 2015.
- [97] Aniruddha Saha, Akshayvarun Subramanya, and

- Hamed Pirsiavash. Hidden trigger backdoor attacks. In *AAAI*, 2020.
- [98] Ahmed Salem, Rui Wen, Michael Backes, Shiqing Ma, and Yang Zhang. Dynamic backdoor attacks against machine learning models. In *EuroS&P*, 2022.
- [99] Avi Schwarzschild, Micah Goldblum, Arjun Gupta, John P Dickerson, and Tom Goldstein. Just how toxic is data poisoning? A unified benchmark for backdoor and data poisoning attacks. In *ICML*, 2021.
- [100] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-CAM: Visual explanations from deep networks via gradient-based localization. In *ICCV*, 2017.
- [101] Ali Shafahi, W Ronny Huang, Mahyar Najibi, Octavian Suciu, Christoph Studer, Tudor Dumitras, and Tom Goldstein. Poison frogs! Targeted clean-label poisoning attacks on neural networks. In NIPS, 2018.
- [102] Virat Shejwalkar, Amir Houmansadr, Peter Kairouz, and Daniel Ramage. Back to the drawing board: A critical evaluation of poisoning attacks on production federated learning. In *S&P*, 2022.
- [103] Lujia Shen, Shouling Ji, Xuhong Zhang, Jinfeng Li, Jing Chen, Jie Shi, Chengfang Fang, Jianwei Yin, and Ting Wang. Backdoor pre-trained models can transfer to all. In *CCS*, 2021.
- [104] Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. *Journal of Big Data*, 2019.
- [105] Wai Man Si, Michael Backes, Yang Zhang, and Ahmed Salem. Two-in-one: A model hijacking attack against text generation models. In *USENIX Security*, 2023.
- [106] Hossein Souri, Micah Goldblum, Liam Fowl, Rama Chellappa, and Tom Goldstein. Sleeper agent: Scalable hidden trigger backdoors for neural networks trained from scratch. In *NeurIPS*, 2022.
- [107] Jacob Steinhardt, Pang Wei Koh, and Percy S Liang. Certified defenses for data poisoning attacks. In NIPS, 2017.
- [108] Georgios Symeonidis, Evangelos Nerantzis, Apostolos Kazakis, and George A. Papakostas. Mlops definitions, tools and challenges. In *IEEE CCWC*, 2022.
- [109] Te Juin Lester Tan and Reza Shokri. Bypassing backdoor detection algorithms in deep learning. *arXiv:1905.13409*, 2019.
- [110] Di Tang, XiaoFeng Wang, Haixu Tang, and Kehuan Zhang. Demon in the variant: Statistical analysis of DNNs for robust backdoor contamination detection. In *USENIX Security*, 2021.
- [111] Di Tang, Rui Zhu, XiaoFeng Wang, Haixu Tang, and Yi Chen. Understanding impacts of task similarity

- on backdoor attack and detection. arXiv:2210.06509, 2022.
- [112] Guanhong Tao, Zhenting Wang, Siyuan Cheng, Shiqing Ma, Shengwei An, Yingqi Liu, Guangyu Shen, Zhuo Zhang, Yunshu Mao, and Xiangyu Zhang. Backdoor vulnerabilities in normally trained deep learning models. arXiv:2211.15929, 2022.
- [113] Squirrel Developer Team. Squirrel: A Python library that enables ML teams to share, load, and transform data in a collaborative, flexible, and efficient way. https://github.com/merantix-momentum/squirrel-core, 2022.
- [114] Yingjie Tian and Yuqi Zhang. A comprehensive survey on regularization strategies in machine learning. *Information Fusion*, 2022.
- [115] Kushal Tirumala, Aram H Markosyan, Luke Zettlemoyer, and Armen Aghajanyan. Memorization without overfitting: Analyzing the training dynamics of large language models. In *NeurIPS*, 2022.
- [116] Florian Tramèr, Jens Behrmann, Nicholas Carlini, Nicolas Papernot, and Jörn-Henrik Jacobsen. Fundamental tradeoffs between invariance and sensitivity to adversarial perturbations. In *ICML*, 2020.
- [117] Brandon Tran, Jerry Li, and Aleksander Madry. Spectral signatures in backdoor attacks. In *NIPS*, 2018.
- [118] Alexander Turner, Dimitris Tsipras, and Aleksander Madry. Clean-label backdoor attacks. https://openreview.net/forum?id=HJg6e2CcK7, 2018.
- [119] Donna Vakharia and Matthew Lease. Beyond Mechanical Turk: An analysis of paid crowd work platforms. In *iConference*, 2015.
- [120] Eric Wallace, Tony Z Zhao, Shi Feng, and Sameer Singh. Customizing triggers with concealed data poisoning. In *NAACL*, 2021.
- [121] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. Glue: A multitask benchmark and analysis platform for natural language understanding. In *ICLR*, 2019.
- [122] Binghui Wang, Xiaoyu Cao, and Neil Zhenqiang Gong. On certifying robustness against backdoor attacks via randomized smoothing. *arXiv:2002.11750*, 2020.
- [123] Bolun Wang, Yuanshun Yao, Shawn Shan, Huiying Li, Bimal Viswanath, Haitao Zheng, and Ben Y Zhao. Neural Cleanse: Identifying and mitigating backdoor attacks in neural networks. In *S&P*, 2019.
- [124] Chi Wang, Qingyun Wu, Markus Weimer, and Eric Zhu. FLAML: A Fast and Lightweight AutoML Library, 2021.
- [125] Hongyi Wang, Kartik Sreenivasan, Shashank Rajput, Harit Vishwakarma, Saurabh Agarwal, Jy-yong Sohn, Kangwook Lee, and Dimitris Papailiopoulos. Attack

- of the tails: Yes, you really can backdoor federated learning. In *NeurIPS*, 2020.
- [126] Jun Wang, Chang Xu, Francisco Guzmán, Ahmed El-Kishky, Yuqing Tang, Benjamin Rubinstein, and Trevor Cohn. Putting words into the system's mouth: A targeted attack on neural machine translation using monolingual data poisoning. In ACL-IJCNLP, 2021.
- [127] Shuaiqi Wang, Jonathan Hayase, Giulia Fanti, and Sewoong Oh. Towards a defense against backdoor attacks in continual federated learning. *arXiv:2205.11736*, 2022.
- [128] Zhenting Wang, Hailun Ding, Juan Zhai, and Shiqing Ma. Training with more confidence: Mitigating injected and natural backdoors during training. In *NeurIPS*, 2022.
- [129] Zhenting Wang, Kai Mei, Juan Zhai, and Shiqing Ma. UNICORN: A unified backdoor trigger inversion framework. In *ICLR*, 2023.
- [130] M. Weber, X. Xu, B. Karlas, C. Zhang, and B. Li. Rab: Provable robustness against backdoor attacks. In *S&P*, 2023.
- [131] Emily Wenger, Roma Bhattacharjee, Arjun Nitin Bhagoji, Josephine Passananti, Emilio Andere, Haitao Zheng, and Ben Zhao. Finding naturally occurring physical backdoors in image datasets. In *NeurIPS*, 2022.
- [132] Emily Wenger, Xiuyu Li, Ben Y Zhao, and Vitaly Shmatikov. Data isotopes for data provenance in DNNs. *arXiv*:2208.13893, 2022.
- [133] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *EMNLP: System Demonstrations*, 2020.
- [134] Tong Wu, Tianhao Wang, Vikash Sehwag, Saeed Mahloujifar, and Prateek Mittal. Just rotate it: Deploying backdoor attacks via rotation transformation. In *AISec*, 2022.
- [135] Yuanshun Yao, Huiying Li, Haitao Zheng, and Ben Y Zhao. Latent backdoor attacks on deep neural networks. In *CCS*, 2019.
- [136] Ashkan Yousefpour, Igor Shilov, Alexandre Sablayrolles, Davide Testuggine, Karthik Prasad, Mani Malek, John Nguyen, Sayan Ghosh, Akash Bharadwaj, Jessica Zhao, et al. Opacus: User-friendly differential privacy library in PyTorch. *arXiv:2109.12298*, 2021.
- [137] Dong Yuan, Guoliang Li, Qi Li, and Yudian Zheng.

- Sybil defense in crowdsourcing platforms. In *CIKM*, 2017.
- [138] Yi Zeng, Minzhou Pan, Hoang Anh Just, Lingjuan Lyu, Meikang Qiu, and Ruoxi Jia. Narcissus: A practical clean-label backdoor attack with limited information. arXiv:2204.05255, 2022.
- [139] Chaoning Zhang, Chenguo Lin, Philipp Benz, Kejiang Chen, Weiming Zhang, and In So Kweon. A brief survey on deep learning based data hiding, steganography and watermarking. *arXiv:2103.01607*, 2021.
- [140] Jie Zhang, Chen Dongdong, Qidong Huang, Jing Liao, Weiming Zhang, Huamin Feng, Gang Hua, and Nenghai Yu. Poison ink: Robust and invisible backdoor attack. *IEEE Transactions on Image Processing*, 2022.

A Backdoor Objectives

Our primitive sub-task aims to act as a lower bound on the fraction of the training dataset that must be poisoned for any backdoor to be effective. In addition to the poisoning percentage, backdoor attacks may have other objectives. Attacks may try to achieve trigger stealthiness, label consistency, complexity, or defense evasion. Any of these objectives is an additional constraint that decreases the signal to be learned, thus the attack should require a higher poisoning percentage than the primitive sub-task (which is visually noticeable, label-inconsistent, and easily detectable). Table 8 summarizes the reported poisoning percentages for different attacks.

A.1 Stealthy backdoors

Small or imperceptible triggers. Attacks like BadNets [40] use a pixel pattern to change the label. The model must learn to prefer this pattern over "normal" features to classify backdoored inputs to an attacker-chosen label. The pattern can be very small, e.g., a single pixel [5], or imperceptible [17]. The pattern for our primitive sub-task is larger and fully covers more normal features. In Section 7, we show that smaller patterns indeed make learning the backdoor harder.

Clean labels. Clean-label backdoor attacks [38, 77, 118, 120] create a backdoored tuple (x_c^*, y^*) that looks plausible, i.e., a human would assign label y^* to input x_c^* . An attacker uses a clean input x_c that has label y^* and blends x^* , i.e., input x with the trigger applied, into x_c to obtain x_c^* that looks like x_c . Some attacks work well on pretrained models [22, 38] when a part of the model, e.g., the embedding layer θ_{emb} , is frozen. These attacks use techniques like gradient alignment [106] or projected gradient descent [97] to generate x_c^* that produces the same embedding $\theta_{emb}(x_c^*) = \theta_{emb}(x^*)$ as the backdoored image x^* while it is similar to x_c within some distance ε , e.g., $||x_c^* - x_c||_2 = \varepsilon$. In other words, when applied to input x_c^* , the model "sees" a backdoored input x^* with the trigger while a human sees a clean input x_c .

Stealthiness of the attack, i.e., the value of ε , is not a useful metric in our setting because data inspection is a (disruptive)

defense and requires integration into the ML pipeline. Attacks that overlay the entire image with some perturbation, e.g., reflection [77] or a ramp signal [8], are also limited by the amount of perturbation. We can maximize ε to make the attack strong with $\varepsilon = x^* - x_c$ that converts the blended input x_c^* back to x^* , making the attack label-inconsistent. Therefore, clean-label attacks are weaker (i.e., require a higher poisoning percentage) because they need to satisfy a tight ε budget to remain stealthy. Indeed, values reported by the papers [106, 118] show that 0.1-1% of the training data must be poisoned in order for the attack to become effective. By contrast, Section 7 shows that the primitive sub-task is learned with as little as 0.005% of the dataset compromised.

A.2 Functional backdoors

Some attacks use composite [72], physical [5] or semantic [134] features as triggers. These attacks also require a larger fraction of the training data to be poisoned (e.g., 10%) in order to become effective [72]. Complex attacks that inject an extra task (e.g., a meta-task [6]) are only effective when 50% of the training data is compromised. In Section 7, we show that even basic functionalities like dynamic movement of the pattern [98] and label shift [33] are harder for the model to learn than the primitive sub-task.

A.3 Targeted and sample-specific attacks

Some attacks do not teach the model a *generalizable* backdoor task but instead cause misclassification for a specific input [38, 101]. These attacks focus on memorization of a given input and may require only a single compromised example [59]—but this learning does not generalize.

On the other hand, sample-specific attacks [70, 140] generate individual triggers for each input using steganography [139]. These attacks are more complex (because the model needs to learn the task corresponding to sample-specific trigger generation) and require a larger fraction of the training data to be poisoned.

B Automation for Dataset Poisoning

Even when using a third-party service with fixed API to train their models, engineers control their data, in particular the training and validation datasets. Finding a resistance point requires a training dataset $\mathcal{D}^{p_{\star}}$ poisoned with the primitive sub-task at a specific percentage p_{\star} . How to carry out this poisoning depends on the framework but can also be done when the dataset is created.

We use a wrapper around the dataset that automatically injects poisoned data at a specified percentage: $\mathcal{D}^{p_{\star}}=\operatorname{Attack}(\mathcal{D},p_{\star})$. An engineer can either integrate this wrapper, or generate a new dataset. The poisoned dataset is used during the hyperparameter search. The production pipeline will use the original, unmodified dataset.

Algorithm 1 demonstrates how to create the mask and the pattern for a generic dataset \mathcal{D} with tuples $(x_i, y_i), \forall i \in I$ in-

Table 8: Reported poisoning percentages

Backdoor	p_b	Domain		
Stealthy				
BadNets [40]	10.00%	Images		
BadNL [16]	3.00%	Text		
Clean image [15]	1.50%	Images		
Narcissus [138]	0.05%	Images		
Poison-ink [140]	3.00%	Images		
Sentiment [25]	0.50%	Text		
Sleeper [106]	0.10%	Images		
Sample-specific [70]	10.00%	Images		
Refool [77]	1.00%	Images		
Functional				
Composite [72]	8.30%	Images		
Dynamic [98]	10.00%	Images		
LLM Spinning [6]	50.00%	Text		
Marksman [33]	5.00%	Images		
Rotation [134]	1.00%	Images		
Physical [5]	33.00%	Images		

dices. We use 1D inputs for brevity. Multidimensional inputs can be similarly reshaped to 1D to build the mask. This approach can be used to poison any dataset by (a) identifying indices $I^* \subset I$ to poison, and (2) overwriting the __get__(i) method to invoke apply_pattern for inputs $i \in I^*$. The wrapper is transparent to all other methods and attributes by forwarding calls to the original dataset.

Similarly, when validating a model θ , in addition to computing the main-task accuracy $\mathbf{A}(\mathcal{D}_{val},\theta)$, Mithridates uses the same wrapper but sets the poisoning percentage $p_{\star}=1$ to measure accuracy of the primitive sub-task $\mathbf{A}(\mathcal{D}_{val}^{p_{\star}=1},\theta)$. This design allows Mithridates to inject any type of backdoor and measure its efficacy.

C Preventing Accidental Success

When picking the pattern and the label for a primitive back-door attack, it is important to avoid cases when the back-door label would already be a highly likely candidate because this can skew measurements of attack efficacy. For example, attacking a sentiment classification task with the backdoor trigger "awesome" and backdoor label "positive" will show seemingly high efficacy since the backdoor task is correlated with the main task. This effect is described as natural backdoors [112, 128, 131], i.e., naturally occurring features of the dataset that have a strong signal for particular classes. These attacks are only feasible if the attacker has access to the dataset and/or model and are outside the threat model of this paper. Therefore, after picking the trigger and backdoor label, we can simply test the non-poisoned model to verify that it does not already exhibit high backdoor accuracy.

¹See an example at https://github.com/ebagdasa/mithridates

Algorithm 1: Dataset wrapper for hyperparameter search.

```
INPUTS: dataset \mathcal{D}, attack percentage p_{\star}, patch size
 s, backdoor label y^*.
class AttackDataset
     fields: \mathcal{D}, s, p_{\star}, y^{*}, indices I^{*}, mask M, pattern P
     def __init__(\mathcal{D}, s, p_{\star}, y^{*})
           # compute poisoned indices
           I^* \leftarrow \text{sample}(\mathcal{D}, p_{\star})
          M, P \leftarrow \text{create\_patch}(\mathcal{D}, s)
     def __get__(index i)
           (x,y) \leftarrow \mathcal{D}[i]
           if i \in I^* then
                return apply_pattern(x)
                return (x, y)
     def create\_patch(\mathcal{D}, s)
           # assume inputs are 1D, get stats
           x_{max}, x_{min}, x_{len} \leftarrow \mathcal{D}
           m_{start} \leftarrow \text{rand\_int}(0, l - s * x_{len})
           # Make a mask
          M(i) = \begin{cases} 1, & \text{if } i \in [m_{start}, m_{start} + s * x_{len}] \\ 0, & \text{otherwise} \end{cases}
           # Generate noisy pattern within input limits
           P = \text{rand\_tensor}(x_{min}, x_{max}, \text{type} = x.\text{type})
          return M, P
     def apply_pattern(input x)
          x^*(i) = \begin{cases} x[i], & M(i) = 1\\ P[i], & M(i) = 0 \end{cases}
          return (x^*, y^*)
     def __getattr__(dataset attribute a)
           # Mirror all other methods from D
           return getattr(\mathcal{D}, a)
```

Another reason to test the non-poisoned model is adversarial patches [10]. This inference-time attack covers 5-10% of the input and causes the model to switch its output without any data poisoning—but the model does not learn a backdoor task. Since we create patterns randomly, we may generate an adversarial patch by accident, thus it is important to check that the model does not already (i.e., without poisoning) associate the pattern with some label.

We should also assume that an unknown fraction of the training dataset \mathcal{D} may already be poisoned with an unknown number of backdoors. Therefore, our injection of the primitive sub-task may accidentally select already-poisoned inputs, or else cover backdoor triggers. We can similarly test the accuracy of the non-poisoned model to avoid collisions.