Model Extraction

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May 23, 2023

Today's Agenda

Model Extraction

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Model extraction attacks target the **confidentiality** of a victim model deployed on a remote service.

- A model refers here to both the **architecture and its parameters**.
- The model can be viewed as **intellectual property** that the adversary is trying to steal.

Adversarial Motivations

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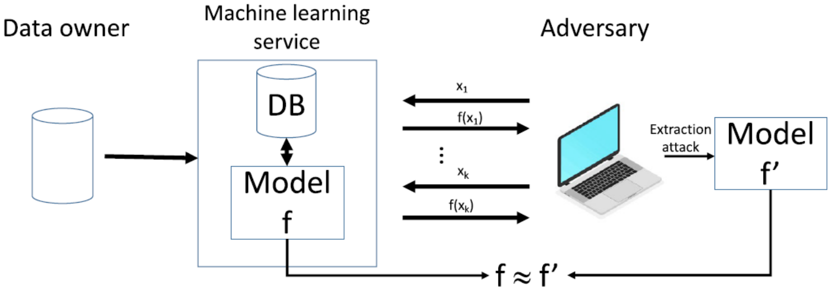
- **Stealing**: Motivated by economic incentives. Adversaries are motivated to abuse the target classifier to **reduce the cost** of creating a new classifier.
- **Reconnaissance**: Model extraction enables an adversary previously operating in a **black-box threat model** to mount attacks against the extracted model in a white-box threat model. The adversary is performing reconnaissance to later **mount attacks** targeting other security properties of the learning system
  - Integrity with adversarial examples
  - Privacy with training data membership inference.

Model Stealing Threat Model

The adversary has **black-box access** to the target model (Oracle)



(Trung ha, 2020)

Exact Extraction

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- Functionality equivalent

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Adversary’s Goal

- Stealing $\rightarrow$ **Accuracy**
- Reconnaissance $\rightarrow$ **Fidelity**
  - Functionality Equivalent (Perfect Fidelity)

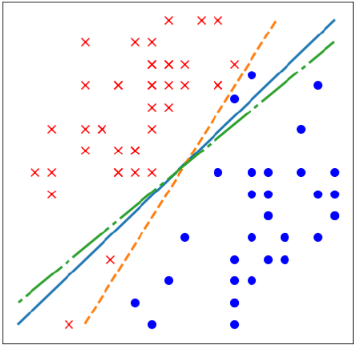

Figure 1: Illustrating fidelity vs. accuracy. The solid blue line is the oracle; functionally equivalent extraction recovers this exactly. The green dash-dot line achieves high fidelity: it matches the oracle on all data points. The orange dashed line achieves perfect accuracy: it classifies all points correctly.

(Jagielski, 2019)

Adversary's Goal

Accuracy

- For the true task distribution D_A over $\mathcal{X} \times \mathcal{Y}$, the goal of task accuracy extraction is to construct an $\hat{O}$ maximizing $Pr_{(x,y)\sim D_A}[argmax(\hat{O}(x)) = y]$.

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Fidelity

- Given some target distribution D_F over $\mathcal{X}$, and goal similarity function $S(p_1, p_2)$, the goal of fidelity extraction is to construct an $\hat{O}$ that maximizes $Pr_{x\sim D_F}[S(\hat{O}(x), O(x))]$.

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Functionally Equivalent (Perfect Fidelity)

- The goal of functionally equivalent extraction is to construct an $\hat{O}$ such that $\forall x \in \mathcal{X}, \hat{O}(x) = O(x)$.

Adversarial Capabilities

Threat model

- **Label**: only the label of the most-likely class is revealed.
- **Label and score**: in addition to the most-likely label, the confidence score of the model in its prediction for this label is revealed.
- **Top-k scores**: the labels and confidence scores for the k classes whose confidence are highest are revealed.
- **Scores**: confidence scores for all labels are revealed.
- **Logits**: raw logit values for all labels are revealed.

Budget

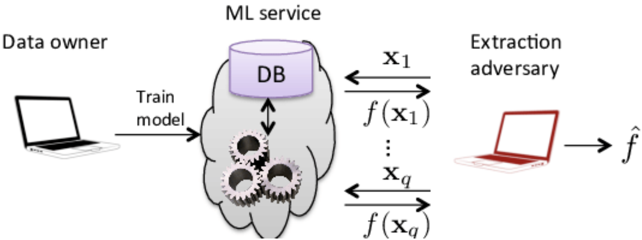
Adversaries want to **minimize the number of queries** to the target model in order to

- **Avoid detection** and prevention of the attack
- **Limit the amount of money** spent for predictions, in the case of MLaaS prediction APIs
- Minimize the number of **samples required** to query the model.

Attack Strategies

In-Distribution (ID) samples

- Transfer learning
- Semi-supervised learning
- Active learning
- Self-supervised learning



(Trammer, 2020)

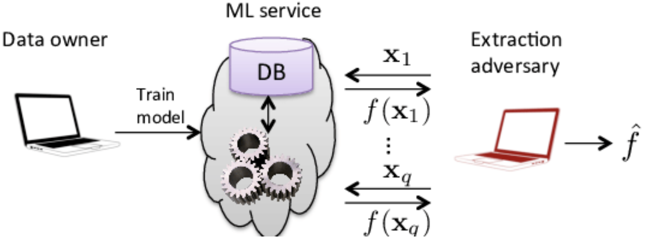
Attack Strategies

In-Distribution (ID) samples

- Transfer learning
- Semi-supervised learning
- Active learning
- Self-supervised learning

Out-Of-Distribution (OOD) samples

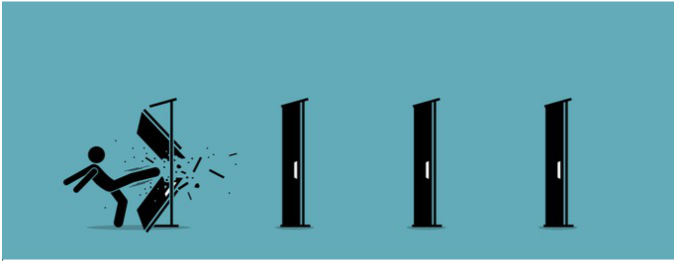
- Data Augmentation (Limited access to ID samples)
- Semantically similar natural samples
- Synthetic samples



(Trammer, 2020)

Defense Strategies

- Detection-based methods
- Perturbation-based methods
- Watermarking



(shutterstock.com)

Knockoff Nets

Knockoff Nets

Knockoff Nets: Stealing Functionality of Black-Box Models

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Abstract

It formulates model **functionality stealing** as a two-step approach

- **Querying** a set of input images to the blackbox model to obtain predictions
- Training a **knockoff** with queried image-prediction pairs.

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Remarkable observations

- Querying random images from a **different distribution** than that of the blackbox training data results in a well-performing knockoff
- This is possible even when the knockoff is represented using a **different architecture**
- **Reinforcement learning** approaches improve query sample efficiency in certain settings and provides performance gains.

Problem Statement

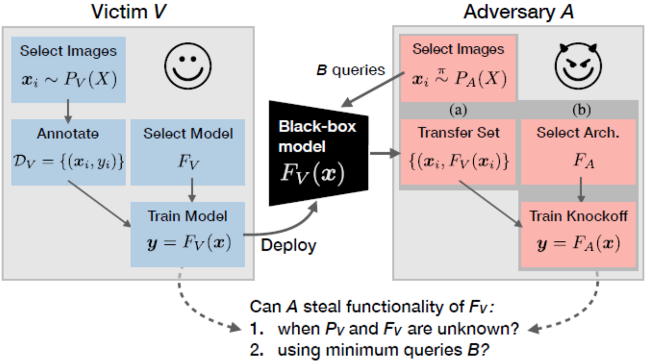

Figure 2: Problem Statement. Laying out the task of model functionality stealing in the view of two players - victim V and adversary A. We group adversary's moves into (a) Transfer Set Construction (b) Training Knockoff F_A.

Problem Statement

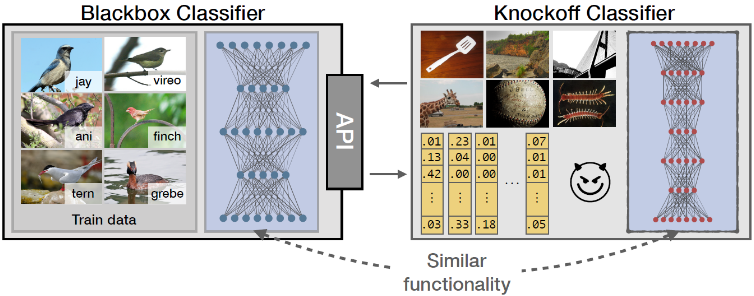

Figure 1: An adversary can create a "knockoff" of a blackbox model solely by interacting with its API: image in, prediction out. The knockoff bypasses the monetary costs and intellectual effort involved in creating the blackbox model.

Adversary's Attack

To train a knockoff, the adversary

- Interactively queries images $\{x_i \overset{\pi}{\sim} P_A(X)\}$ using **strategy** π to obtain a **transfer set** of images and pseudo-labels $\{(x_i, F_V(x_i))\}_{i=1}^{B}$
- **Selects an architecture** F_A for the knockoff and trains it to mimic the behavior of F_V on the transfer set.
- **Objective**
  - Maximizing performance within a budget of B blackbox queries

Transfer Set Construction

Selecting $P_A(X)$

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Sampling Strategy π

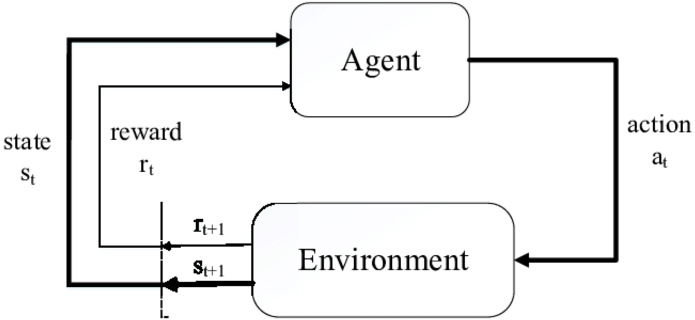
- Once the image distribution $P_A(X)$ is chosen, the adversary samples images $x \overset{\pi}{\sim} P_A(X)$ using a strategy π. There are two strategies.
  - **Random strategy**
  - **Adaptive strategy**

Random Strategy

In this strategy, the adversary **randomly samples images** (without replacement) $x \overset{iid}{\sim} P_A(X)$ to query F_V . This is an extreme case where adversary performs pure exploration.

- There is a risk that the adversary **samples images irrelevant to learning the task** (e.g., over-querying dog images to a birds classifier).

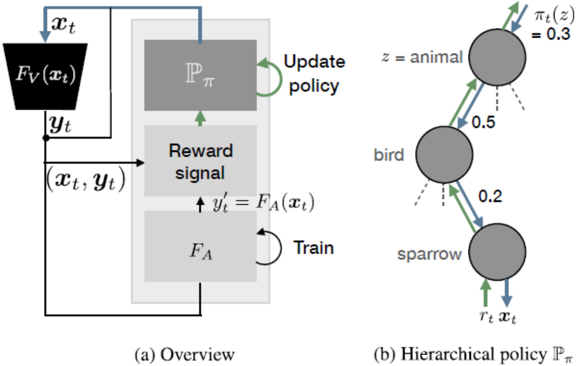
Adaptive Strategy - Reinforcement Learning



Supplementing P_A in Adaptive Strategy

- To encourage relevant queries, images in the adversary's distribution are enriched by associating each image x_i with a label $z_i \in Z$.
- No semantic relation of these labels with the blackbox's output classes is assumed or exploited.
  - As an example, when P_A corresponds to 1.2M images of the ILSVRC dataset, labels defined over 1000 classes are used.
  - These labels can be alternatively obtained by unsupervised measures e.g., clustering.
- Furthermore, since we expect labels $\{z_i \in Z\}$ to be correlated or inter-dependent, we represent them within a coarse-to-fine hierarchy, as nodes of a tree as shown in Figure 4b.

Adaptive Strategy



(a) Overview

(b) Hierarchical policy $\mathbb{P}_\pi$

Figure 4: Strategy `adaptive`.

Actions

At each time-step t, we sample actions from a discrete action space $z_t \in Z$ i.e., adversary's independent label space.

Drawing an action is a forward-pass (denoted by a blue line in Figure 4b) through the tree: at each node, we sample a child node with probability $\pi_t(z)$ (which sums to 1 over siblings).

Upon reaching a leaf-node, a sample of images is returned corresponding to label z_t.

Rewards

The quality of sampled image x_t is evaluated by **three reward functions**

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- **Margin-based certainty** measure to encourage images where the victim is confident (hence indicating the domain F_V was trained on):

$$R^{cert}(y_t) = P(y_{t,k_1}|x_t) - P(y_{t,k_2}|x_t)$$

where $F_V(x_t) = y_t$ and k_i is the i^{th}-most confident class.

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- To prevent the degenerate case of image exploitation over a single label, we introduce a **diversity reward** ($F_A(x_t) = y_t$):

$$R^{div}(y_{1:t}) = \sum_k max(0, y_{t,k} - \bar{y}_{t:t-\Delta,k})$$

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- To encourage images where the knockoff prediction $\hat{y}_t = F_A(x_t)$ **does not imitate** F_V , we reward high Cross Entropy (CE) loss:

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Individual rewards are **summed up** when multiple measures are used.

Learning the Policy

Gradient bandit algorithm (Reinforcement Learning: An Introduction - Sec. 2.7)

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$$\pi_t(z) = \frac{e^{H_t(z)}}{\sum_{z'} e^{H_t(z')}}$$

$$H_{t+1}(z_t) = H_t(z_t) + \alpha(r_t - \bar{r}_t)(1 - \pi_t(z_t))$$
$$H_{t+1}(z') = H_t(z') - \alpha(r_t - \bar{r}_t)\pi_t(z') \qquad \forall z' \neq z_t$$

where $\alpha = \frac{1}{N(z)}$ is the learning rate, $N(z)$ is the number of times action z has been drawn, and $\bar{r}_t$ is the mean reward over past Δ time-steps.

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- $\pi_0(z)$ and $H_0(z)$ are initialized such that reaching all leaf nodes in the hierarchy are equally probable.

Selecting Architecture F_A

F_A with a **reasonably complex architecture** e.g., VGG or ResNet.

- Existing findings in Knowledge distillation indicate robustness to choice of reasonably complex student models.

Training to Imitate

- To bootstrap learning, the training is initialized with a pretrained Imagenet network (**Transfer Learning**)
- Knockoff F_A is trained to imitate F_V on the transfer set by minimizing the cross entropy

Training the Black-boxes

All models are trained using a **ResNet-34 architecture**

Blackbox (F_V)	$\lvert\mathcal{D}_V^{\text{train}}\rvert + \lvert\mathcal{D}_V^{\text{test}}\rvert$	Output classes K
`Caltech256` [11]	23.3k + 6.4k	256 general object categories
`CUBS200` [36]	6k + 5.8k	200 bird species
`Indoor67` [26]	14.3k + 1.3k	67 indoor scenes
`Diabetic5` [1]	34.1k + 1k	5 diabetic retinopathy scales

Table 1: Four victim blackboxes F_V. Each blackbox is named in the format: [dataset][# output classes].

Choice of P_A

1. $P_A = P_V$
2. $P_A =$ ILSVRC
3. $P_A =$ OpenImages
   - OpenImages v4 is a large-scale dataset of 9.2M images gathered from Flickr. A subset of 550K unique images is gathered in 600 categories.
4. $P_A = D^2$: dataset of datasets

Datasets

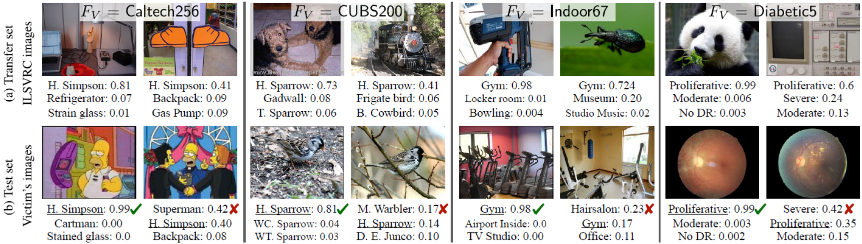

Figure 6: Qualitative Results. (a) Samples from the transfer set ($\{(\boldsymbol{x}_i, F_V(\boldsymbol{x}_i))\}, \boldsymbol{x}_i \sim P_A(X)$) displayed for four output classes (one from each blackbox): 'Homer Simpson', 'Harris Sparrow', 'Gym', and 'Proliferative DR'. (b) With the knockoff F_A trained on the transfer set, we visualize its predictions on victim's test set ($\{(\boldsymbol{x}_i, F_A(\boldsymbol{x}_i))\}, \boldsymbol{x}_i \sim \mathcal{D}_V^{\text{test}}$). Ground truth labels are underlined.

Accuracy on test sets

	P_A	random Caltech256	random CUBS200	random Indoor67	random Diabetic5
	$P_V (F_V)$	78.8 (1×)	76.5 (1×)	74.9 (1×)	58.1 (1×)
	P_V (KD)	82.6 (1.05×)	70.3 (0.92×)	74.4 (0.99×)	54.3 (0.93×)
Closed	D^2	76.6 (0.97×)	68.3 (0.89×)	68.3 (0.91×)	48.9 (0.84×)
Open	ILSVRC	75.4 (0.96×)	68.0 (0.89×)	66.5 (0.89×)	47.7 (0.82×)
Open	OpenImg	73.6 (0.93×)	65.6 (0.86×)	69.9 (0.93×)	47.0 (0.81×)

	P_A	adaptive Caltech256	adaptive CUBS200	adaptive Indoor67	adaptive Diabetic5
	$P_V (F_V)$	-	-	-	-
	P_V (KD)	-	-	-	-
Closed	D^2	82.7 (1.05×)	74.7 (0.98×)	76.3 (1.02×)	48.3 (0.83×)
Open	ILSVRC	76.2 (0.97×)	69.7 (0.91×)	69.9 (0.93×)	44.6 (0.77×)
Open	OpenImg	74.2 (0.94×)	70.1 (0.92×)	70.2 (0.94×)	47.7 (0.82×)

Table 2: Accuracy on test sets. Accuracy of blackbox F_V indicated in gray and knockoffs F_A in black. B=60k.

Performance of the knockoff at various budgets.

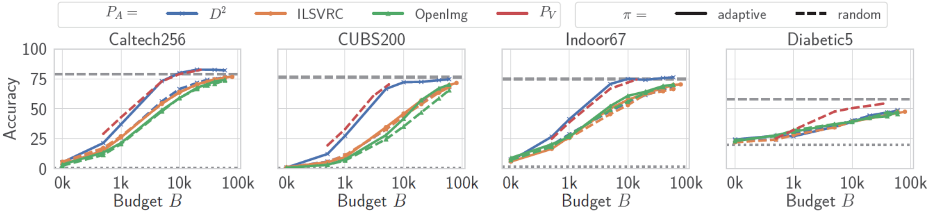

Figure 5: Performance of the knockoff at various budgets. Across choices of adversary's image distribution (P_A) and sampling strategy π. - represents accuracy of blackbox F_V and ···· represents chance-level performance. Enlarged version available in supplementary.

Policy π learnt by the adaptive approach

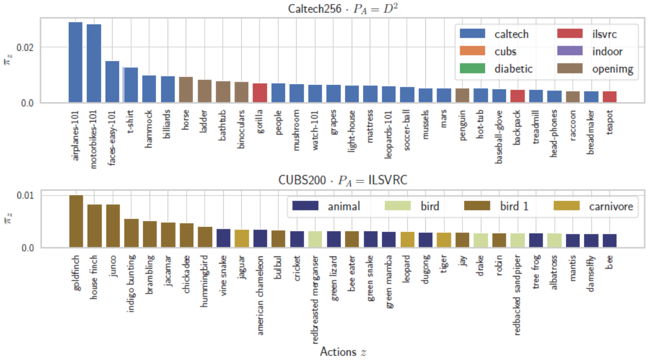

Figure 7: Policy π learnt by the `adaptive` approach. Each bar represents preference for action z. Top 30 actions (out of 2.1k and 1k) are displayed. Colors indicate parent of action in hierarchy.

Reward Ablation

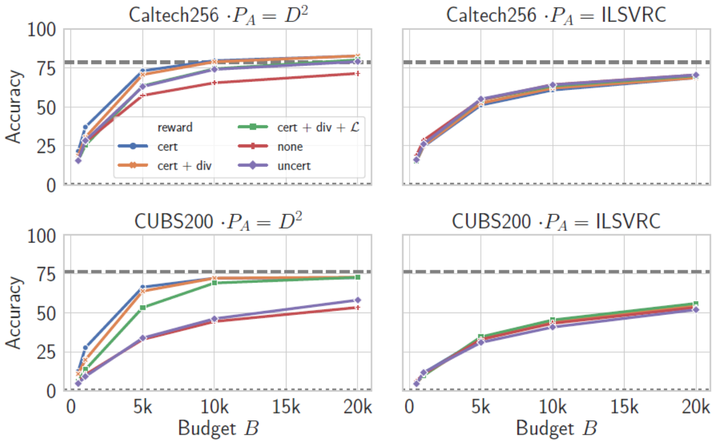

Figure 8: Reward Ablation. cert: certainty, uncert: uncertainty, div: diversity, $\mathcal{L}$: loss, none: no reward (`random` strategy).

Truncated Posteriors

1. top-k
   - Top-k (out of K) unnormalized posterior probabilities are retained, while rest are zeroed-out.
2. rounding r
   - Posteriors are rounded to r decimals e.g., $round(0.127, r = 2) = 0.13$.

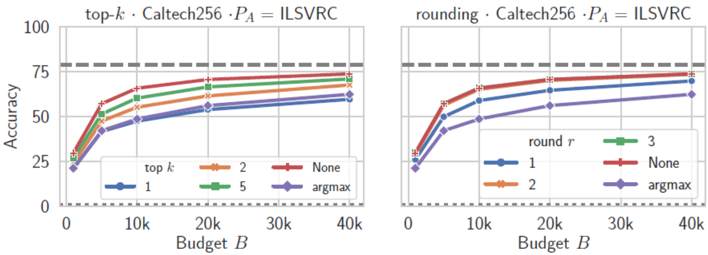

Figure 9: Truncated Posteriors. Influence of training knockoff with truncated posteriors.

Architecture choices

- Selecting a more complex model architecture of the knockoff is beneficial.

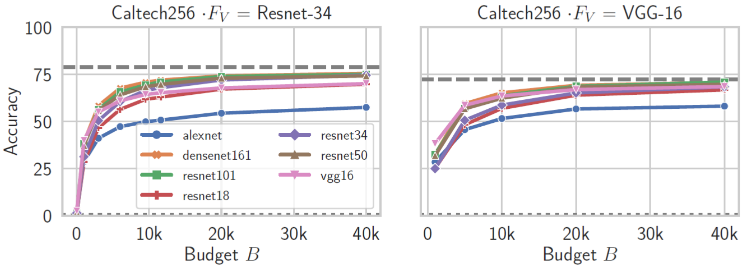

Figure 10: Architecture choices. F_V (left: Resnet-34 and right: VGG-16) and F_A (lines in each plot).

Effect of CNN Initialization

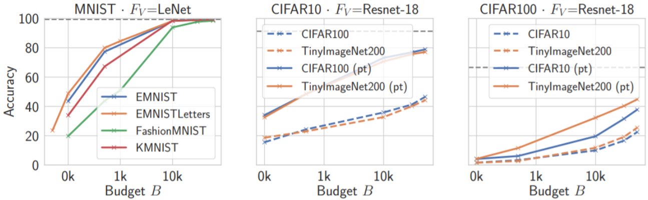

Figure S3: Training with non-ImageNet initializations of knockoff models. Shown for various choices of blackboxes F_V (subplots) and adversary's image distribution P_A (lines). All victim blackbox models are trained from scratch; test accuracy indicated by --- . All knockoff models are either trained from scratch, or pretrained on the corresponding P_A task (suffixed with '(pt)').