Beneficial Perturbations Network for Defending Adversarial Examples

Shixian Wen, Laurent Itti
University of Southern California
3641 Watt Way
Los Angeles, California 90007
shixianw@usc.edu

Abstract
Adversarial training, in which a network is trained on both adversarial and clean examples, is one of the most trusted defense methods against adversarial attacks. However, there are three major practical difficulties in implementing and deploying this method - expensive in terms of running memory and computation costs; accuracy trade-off between clean and adversarial examples; cannot foresee all adversarial attacks at training time. Here, we present a new solution to ease these three difficulties - Beneficial Perturbation Networks (BPN). BPN generates and leverages beneficial perturbations (something opposite to well-known adversarial perturbations) as biases within the parameter space of the network, to neutralize the effects of adversarial perturbations on data samples. Thus, BPN can effectively defend against adversarial examples. Compared to adversarial training, we demonstrate that BPN can significantly reduce the required running memory and computation costs, by generating beneficial perturbations through recycling of the gradients computed from training on clean examples. In addition, BPN can alleviate the accuracy trade-off difficulty and the difficulty of foreseeing multiple attacks, by improving the generalization of the network, thanks to increased diversity of the training set achieved through neutralization between adversarial and beneficial perturbations.

Introduction
Neural networks have lead to a series of breakthroughs in many fields, such as image classification tasks [10, 11] and natural language processing [6, 2]. Model performance on clean examples was the main evaluation criterion for these applications until the unveiling of weaknesses to adversarial examples. For example, even on reasonably-sized datasets, least twice the computation power than just training on clean examples; hence, adversarial training typically requires at least double the amount of running memory on GPU, to store those adversarial examples alongside the clean examples. In a practical scenario, we further produce more than one adversarial example for each clean example [21]. Most implementations need to at least double the amount of running memory on GPU, to store those adversarial examples alongside the clean examples. In addition, during adversarial training, the network has to train on both clean and adversarial examples; hence, adversarial training typically requires at least twice the computation power than just training on clean examples. For example, even on reasonably-sized datasets, such as ImageNet, adversarial training can take multiple days following any of the available adversarial directions. In input space, adding adversarial perturbations to the input image can be viewed as adding an adversarial direction vector (red arrows δAP) to the clean (non-perturbated) input image of digit 1. The resulting vector crosses the decision boundary. As a consequence, adversarial perturbations can force the neural network into misclassification, here from digit 1 to digit 2. Thus, building a deep learning system that can robustly classify both adversarial examples and clean examples has emerged as a critical requirement.

Researchers have proposed a number of adversarial defense strategies to increase the robustness of deep learning systems. Adversarial training [8, 11], in which a network is trained on both adversarial examples (xadv) and clean examples (xcln) with class labels y, is perhaps the most popular defense against adversarial attacks, withstand strong attacks. Adversarial examples are the summation of adversarial perturbations lying inside the input space (δAP) and clean examples: xadv = xcln + δAP. Given a classifier with a classification loss function \( L \) and parameters \( \theta \), the objective function of adversarial training is:

\[
\min_{\theta} L(x_{adv}, x_{cln}, y; \theta) \tag{1}
\]

After adversarial training, the network learns a new decision boundary to incorporate both clean and adversarial examples (Fig. 1a, 2a).

Despite the efficacy of adversarial training in building a robust system, there are three major practical difficulties while implementing and deploying this method. **Difficulty one: adversarial training is expensive in terms of running memory and computation costs** (Fig. 2a). Producing an adversarial example requires multiple gradient computations. In a practical scenario, we further produce more than one adversarial example for each clean example [21]. Most implementations need to at least double the amount of running memory on GPU, to store those adversarial examples alongside the clean examples. In addition, during adversarial training, the network has to train on both clean and adversarial examples; hence, adversarial training typically requires at least twice the computation power than just training on clean examples. For example, even on reasonably-sized datasets, such as ImageNet, adversarial training can take multiple days...
on a single GPU. [12] used 53 P100 GPUs and [24] used 100 V100s for target adversarial training on ImageNet. As a consequence, although adversarial training remains among the most trusted defenses, it has only been within reach of research labs having hundreds of GPUs. **Difficulty two: accuracy trade-off between clean examples and adversarial examples** - although adversarial training can improve the robustness against adversarial examples, it sometimes hurts accuracy on clean examples. Thus, there is an accuracy trade-off between the adversarial examples and clean examples [7, 18, 19, 25]. Because most of the test data in real applications are clean examples, test accuracy on clean examples should be as good as possible. Thus, this accuracy trade-off hinders the practical usefulness of adversarial training because it often ends up lowering performance on clean examples. **Difficulty three: impractical to foresee multiple attacks** - even though one might have sufficient computation resources to train a network on both adversarial and clean examples, it is unrealistic and expensive to introduce all unknown attack samples into the adversarial training. For example, [21] proposed Ensemble Adversarial Training which can increase the diversity of adversarial perturbations in a training set by generating adversarial perturbations transferred from other models (they won the competition on Defenses against Adversarial Attacks), but again at an extraordinary computation and running memory cost. Thus, broad diversity of adversarial examples is crucial for adversarial training.

In this paper, we introduce Beneficial Perturbations Network (BPN) to address these three difficulties. BPN generates and leverages beneficial perturbations (somewhat opposite to well-known adversarial perturbations) as biases within the parameter space of the network, to neutralize the effects of adversarial perturbations on data samples. We evaluated BPN on three datasets (MNIST, FashionMNIST and TinyIm-
Classical adversarial training has two steps: (1) Generating adversarial perturbations from corresponding clean examples and adding adversarial perturbations to the clean examples (creation of adversarial examples). (2) Training the network, usually on both clean and adversarial examples. (b) BPN creates a shortcut with only one step: training on clean examples. The feasibility of shortcut is because BPN can generate beneficial perturbations during the training of clean examples, with negligible additional costs. Thus, BPN reduces at least half computation and running memory costs compared to typical adversarial training. The learned beneficial perturbations can neutralize the effects of adversarial perturbations of the data samples at test time.

Figure 2: Difference in training pipelines between adversarial training and BPN to defend against adversarial examples. (a) classical adversarial training has two steps: (1) Generating adversarial perturbations from corresponding clean examples and adding adversarial perturbations to the clean examples (creation of adversarial examples). (2) Training the network, usually on both clean and adversarial examples. (b) BPN creates a shortcut with only one step: training on clean examples. The feasibility of shortcut is because BPN can generate beneficial perturbations during the training of clean examples, with negligible additional costs. Thus, BPN reduces at least half computation and running memory costs compared to typical adversarial training. The learned beneficial perturbations can neutralize the effects of adversarial perturbations of the data samples at test time.

Our results show:

1. When training only on clean examples (our main use case scenario), BPN achieved good classification accuracy on adversarial examples, while saving at least half of the computation and running memory costs compared to standard adversarial training. The saving is because BPN creates a shortcut (Fig. 2b) compared to adversarial training (Fig. 2a). The feasibility of the shortcut is because BPN can generate beneficial perturbations (which can be used to neutralize the effects of adversarial perturbations of the data samples at test time) during the training of clean examples. In contrast, adversarial training requires training on both clean and adversarial examples. For example, on TinyImageNet dataset, BPN achieved 53.29% accuracy on adversarial examples, 3575% better than the performance of classical network (baseline) trained on clean examples only.

2. When slightly more computation is available, one can also train BPN on adversarial examples only. BPN alleviated the accuracy trade-off by increasing the diversity of the training set. BPN boosted the classification accuracy on both clean and adversarial examples because the diversification of the training set - the extracted beneficial perturbations would convert some adversarial examples into clean examples through the neutralization (Eqn. 2). For quantitative results, on TinyImageNet dataset, BPN achieved 20.69% and 79.92% correct classification on clean and adversarial examples, 10.8% and 16.63% better than the performance of the classical network (baseline) trained on adversarial examples only.

3. When more computation and GPU memory are available, BPN can be trained on both clean and adversarial examples. In this case, BPN improved the generalization of the network through the diversification of the training set. Thus, it improved classification accuracy on both clean and adversarial examples. For example, on TinyImageNet dataset, BPN achieved 66.84% and 88.16% correct classification on clean and adversarial examples, 0.4% and 2.81% better than the performance of classical network (baseline) trained on both clean and adversarial examples.

**Related Work and background information**

**Beneficial Perturbation Network (BPN)**

Understanding beneficial perturbations

To understand beneficial perturbations in more detail, we first revisit the meaning of adversarial perturbations in adversarial examples. With adversarial examples [22], it has been shown that noise patterns (calculated from a specific class) added to input images can bias a network to misclassify the perturbed input images into that specific class. Here, we leverage this idea, but, instead of adding input "noise" (adversarial perturbations) calculated from other classes to force the network into misclassification, we add "noise" (beneficial perturbations) calculated from the input’s own correct class to assist correct classification. Instead of adding perturbations to the input images, during the training of clean examples, we update the bias term in each layer of the neural network to store the beneficial perturbations by recycling gradient information already computed. During testing on adversarial examples, the stored beneficial perturbations can neutralize adversarial perturbations on data samples. Thus, BPN can make correct classification on adversarial examples. For example, in activation space (Fig. 1b2, b3), consider a task of recognizing handwritten digits "1" versus "2". Adding beneficial perturbations to the activation representation of adversarial examples can be viewed as adding an beneficial direction vector (green arrows $\delta_{BP}$) to the adversarial examples of digit 1. The resulting vector crosses the decision boundary and drag the
misclassified adversarial examples back to the correct classification region. Thus, the beneficial perturbations neutralize the effects of the adversarial perturbations and recover the clean examples
\[ x_{cln} \approx x_{cln} + \delta_{AP} + \delta_{BP} \]  
(2)
since \( \delta_{AP} \) and \( \delta_{BP} \) cancel out. As a result, instead of updating the decision boundary by training on both clean and adversarial examples, BPN can correctly classify both clean and adversarial examples by training only on clean examples without updating its decision boundary.

Figure 3: Structure difference between normal network (baseline) and BPN for forward (a-b) and backward pass (c-d). (a) Forward rules of normal network (baseline). (b) Forward rules of BPN. Beneficial perturbation bias \( b_{BP}^{i-1} \) is the same as normal bias \( b^{i-1} \) in forward pass. (c) Backward rules of normal network (baseline). We only demonstrated the update rules for normal bias term. (d) Backward rules of BPN. The difference is that we update the beneficial perturbations bias term using FGSM.

**Formulation of beneficial perturbations**

Beneficial perturbations are formulated as an additive contribution to each layer’s weighted activations (Fig. 3(b):
\[ V^i = W^i V^{i-1} + b_{BP}^{i-1} \]  
(3)

where \( W^{i-1}, V^{i-1} \) and \( b_{BP}^{i-1} \) is the weight, activation and beneficial perturbation bias at layer \( i-1 \). Beneficial perturbation bias has the same structure as the normal bias term \( b \) (Fig. 3(a), but it is used to store the beneficial perturbations \( \delta_{BP} \)). Instead of adding input ”noise” (adversarial perturbations) to input space calculated from other classes to force the network into misclassification, we can add ”noise” (beneficial perturbations \( \delta_{BP} \)) to the activation space calculated by the input’s own correct class to assist in correct classification. Thus, the beneficial perturbations at each layer \( i \) is obtained by updating beneficial perturbation bias using the Fast Gradient Sign Method (FGSM; [8]) with the input’s own correct class:
\[ b_{BP}^i = b_{BP}^{i-1} + \eta \, db_{BP}^i \]  
(4)
\[ db_{BP}^i = \epsilon \, \text{sign}(\nabla_{b_{BP}} L(b_{BP}^{i-1}, y_{true}, \theta)) \]  
(5)

where \( \eta \) is the learning rate, \( b_{BP}^{i-1} \) is the beneficial perturbation bias, \( db_{BP}^i \) is the gradient for beneficial perturbation bias, \( \epsilon \) is a hyperparameter to decide how strong we go to the Fast Gradient Sign direction, \( y_{true} \) is the true label (input’s own correct class), \( \theta \) is the parameters of neural network. Coincidentally, we always use the input’s own correct class to train a neural network. Thus, we can generate the gradient for beneficial perturbations at layer \( i-1 \) by recycling the computed gradients while we are training the network (Fig. 3(d)). We use Eqn. 5 to replace the Eqn. 3:
\[ db_{BP}^{i-1} = \epsilon \, \text{sign}(\nabla_{b_{BP}} L(b_{BP}^{i-1}, y_{true}, \theta)) \]  
(6)

where, \( db_{BP}^{i-1} \) is the gradient for beneficial perturbations bias. \( Grad \) is the gradient from next layer \( i \), \( \epsilon \) is same as Eqn. 5.
Thus, to generate beneficial perturbations, we do not introduce any extra computation costs beyond FGSM. The forward (backward) pass computation costs of BPN are only 0.00% (0.006%) more than the costs of classical network training on the clean examples (Tab. 1). This feature enables BPN to save at least half of computation and running memory costs compared to standard adversarial training (Fig. 2).

| network                  | Forward (FLOPS) | Backward (FLOPS) |
|--------------------------|-----------------|------------------|
| Classical Network (ResNet-50) | 51,112,224     | 51,112,224       |
| BPN (ResNet-50)          | 51,112,224     | 51,115,321       |

Table 1: Computation costs of BPN trained on clean examples compared to a classical network trained on clean examples on ResNet-50. For forward (backward) pass. The computation costs of BPN are 0.00% (0.006%) more than the classical network.

**Extend the BPN to deep convolutional network**

Most deep convolutional neural networks are made with two parts: a feature extraction part (convolutional and non-linear layers) and a classifier (fully connected layer). Here, we introduce beneficial perturbations bias \( b_{BP} \) to the last few fully connected layers of the deep convolutional network, replacing the normal bias term (Fig. 4). We use FGSM (Eqn. 6) to update those beneficial perturbation biases.

In summary, through the training of clean examples, BPN generates beneficial perturbations as biases within the last few fully connected layer of the deep neural network. BPN leverages these beneficial perturbations to defend against future adversarial examples by neutralizing the effects of adversarial perturbations in the datasets. In addition, if BPN is trained on adversarial examples alone or on a combination of adversarial and clean examples, the neutralization can diversify the training set by converting adversarial examples to clean examples. As a consequence, the diversification further improves the generalization of the BPN. The generalization eases the difficulties of accuracy trade-off and impracticability to foresee multiple attacks.

**Experiments**

**Datasets**

- **MNIST**: MNIST [14] is a dataset with handwritten digits, has a training set of 60,000 examples, and a test set of 10,000 examples.
- **FashionMNIST**: FashionMNIST [23] is a dataset with article images, has a training set of 60,000 examples, and a test set of 10,000 examples.
- **TinyImageNet**: TinyImageNet is a subset of the ImageNet [4] - a large visual datasets. TinyImageNet consists of 200 classes and has a training set of 100k examples, and a test set of 10k examples.

**Network structure**

For MNIST and FashionMNIST (LeNet). We use the convolutional and non-linear layers of LeNet as feature extraction part [14] (classical LeNet). Then, for classifier part, we create our version of LeNet (LeNet with beneficial perturbation bias) by adding beneficial perturbation bias into the fully connected layers, replacing the normal bias. For TinyImageNet (ResNet-18). We use the convolutional and non-linear layers of ResNet-18 as feature extraction part (classical ResNet-18). Then, We use three fully connected layer with 1028 hidden units as classifier. We create our version of ResNet-18 (ResNet-18 with beneficial perturbation bias) by adding beneficial perturbation bias into the fully connected layers, replacing the normal bias. We trained the BPN (ResNet-18) with 5000 epoches on TinyImageNet.

**Various attack methods**

To demonstrate how BPN can successfully defend against a broad range of adversarial attacks, we tested our BPN structure on adversarial examples generated from various attack methods:

1. **Basic Iterative Attack** [13]: Like GradientSignAttack, but with several steps for each epsilon.
2. **FGSM** [8]: One step fast gradient sign method.
3. **PGD Linf, L2, L1** [15]: Projected Gradient Descend Attack with order = Linf, L2, L1.
4. **Basic Iterative Attack** L2 [13]: Perturbing the input with gradient of the loss with respect to the input and with several step for each epsilon.
5. **Aka Basic Iterative Attack** [13]: Like GradientSignAttack, but with several steps for each epsilon.

**Results**

**BPN can defend adversarial examples with additional negligible computation costs**

When the neural network can only be trained on clean examples because of modest computation power, BPN can achieve much better test accuracy on adversarial examples than the classical network (baseline, Tab. 2) MNIST: 98.88% vs. 18.08%, FashionMNIST: 54.07% vs. 11.87%, TinyImageNet: 53.29% vs. 1.45%). Thus, for companies with modest computation resources, BPN can help a system achieve moderate robustness against adversarial examples, while only introducing additional negligible computation costs (e.g., on FashionMNIST, our method only uses 59% training time compared to the training time of adversarial training with just one adversarial example per clean example, saving 43.51 minutes training time for 500 training epochs on an NVIDIA Tesla-V100 platform (We only introduced one Sign and one multiplication operation for each fully connected layer Tab. 1). The reason of extra 9% costs is because we create a custom layer in Pytorch framework. The framework introduces a lot of overheads for custom layer. It should be greatly improved if the custom layers is incorporated in the Pytorch framework with C++ implementation. This would eliminate the overheads for custom layer and reduce the extra costs to 0.006%). The saving would be huge on a larger dataset such as Imagenet [5].

**BPN can alleviate the accuracy trade-off through the diversification of the training set**

BPN can alleviate the accuracy trade-off difficulty and increase the classification accuracy for both clean and adversarial examples. Although training a classical neural network A on adversarial examples can achieve a high test accuracy on
adversarial examples (Tab. 3; MNIST: 99.01%, FashionMNIST: 91.49%, TinyImageNet: 68.52%), it hurts test accuracy on clean examples. Compared to a classical network B trained on clean examples, the test accuracy on clean examples of classical network A decreases from 99.01%, 89.17%, 64.30% (Tab. 3) to 95.54%, 65.64%, 18.67% (Tab. 3) for MNIST, FashionMNIST and ImageNet datasets. In comparison to classical network B, by training BPN only on adversarial examples, BPN not only achieves better test accuracy on adversarial examples (Tab. 3; MNIST: 99.27%, FashionMNIST: 92.07%, TinyImageNet: 79.92%), but also achieves a better test accuracy on clean examples (Tab. 3; MNIST: 97.32%, FashionMNIST: 71.54%, TinyImageNet: 20.69%). This accuracy on clean examples is still worse than that of classical network B (training only on clean examples), but it is much better than the accuracy of classical network A (training only on adversarial examples). The reason is that beneficial perturbations would convert some adversarial examples into clean examples because of the neutralization (Eqn. 2). As a consequence, the increased diversity of the clean examples improves the generalization of BPN.

| Datasets & network structure | MNIST | FasMNIST | TinyImageNet |
|-----------------------------|-------|----------|---------------|
| Cln Ex                      |       |          |               |
| BPN                         | 99.17 | 89.53    | 57.55         |
| CN                          | 99.01 | 89.17    | 64.30         |
| Adv Ex                      |       |          |               |
| BPN                         | 98.88 | 54.07    | 53.29         |
| CN                          | 18.08 | 11.87    | 1.45          |

Table 2: Training on clean examples for BPN and classical network (CN). Testing on clean examples (Cln Ex) and adversarial examples (Adv Ex) (generated by FGSM, $\epsilon = 0.3$ for MNIST, FashionMNIST and TinyImageNet). CN does poorly on adversarial examples. While, BPN can successfully defend adversarial examples.

BPN can improve generalization through diversification of the training set

Training a classical network on both clean and adversarial examples can achieve good test accuracy on both clean and adversarial examples. By diversifying the training set, BPN can achieve even better test accuracy. BPN can achieve slightly higher accuracy on clean examples than the classical network (Tab. 3; MNIST 99.13% vs. 99.09%, FashionMNIST 89.65% vs. 89.49%, TinyImageNet 66.84% vs. 66.56%). In addition, BPN can achieve higher accuracy on adversarial examples than classical Network MNIST 97.62% vs. 97.01%, FashionMNIST 95.39% vs. 94.98%, TinyImageNet 88.16% vs. 85.75%). The reason is that the generalization of BPN can be improved through diversification of the training set caused by neutralization (Eqn. 2). BPN and classical network can both achieve high accuracy in this scenario. However, we should normally avoid this scenario because training on both clean and adversarial examples is expensive in terms of running memory and computation costs.

Table 3: Training on adversarial examples for BPN and classical network (CN). Testing on clean examples (Cln Ex) and adversarial examples (Adv Ex) (generated by FGSM, $\epsilon = 0.3$ for MNIST, FashionMNIST and ImageNet). Both BPN and CN can achieve a high classification accuracy. However, we should avoid this scenario because of the expensive running memory and computation costs.

| Datasets & network structure | MNIST | FasMNIST | TinyImageNet |
|-----------------------------|-------|----------|---------------|
| Cln Ex                      |       |          |               |
| BPN                         | 99.13 | 89.65    | 66.84         |
| CN                          | 99.09 | 89.49    | 66.56         |
| Adv Ex                      |       |          |               |
| BPN                         | 97.62 | 95.39    | 88.16         |
| CN                          | 97.01 | 94.98    | 85.75         |

Table 4: Training on both clean and adversarial examples for BPN and classical network (CN). Testing on clean examples (Cln Ex) and adversarial examples (Adv Ex) (generated by FGSM, $\epsilon = 0.3$ for MNIST, FashionMNIST and ImageNet). Both BPN and CN can achieve a high classification accuracy. However, we should avoid this scenario because of the expensive running memory and computation costs.

Influence of adversarial perturbation budget

The higher the adversarial perturbation budget, the higher the chance it can successfully attack a neural network. However, attacks with higher adversarial perturbation budgets are easier to detect by a program or by humans. For example, $\epsilon = 0.3$ (Fig. 5a) represents very high noise, which makes FashionMNIST images difficult to classify, even by humans. But the distribution differences between the adversarial examples and clean examples are so large that they can be easily captured by defense programs. Thus, $\epsilon \leq 0.15$ is a good attack since the differences caused by adversarial perturbations are too small to be detected by most defense programs. For small adversarial perturbations (Fig. 5b, $\epsilon \leq 0.15$), by just training on clean images, BPN achieves moderate robustness against adversarial examples with negligible costs. Thus, it is really beneficial to adapt our method for companies with modest computation power, who still want to achieve moderate robustness against adversarial examples.

BPN can successfully defend various attack methods

When the neural network can only be trained on clean examples because of modest computation power, we trained BPN on clean examples and tested on adversarial examples generated by various attack methods discussed in the experiments section.

From Tab. 5, BPN can successfully defend various attack methods. Particularly, BPN can achieve better classification accuracy than classical network for PGD Linf, PGD L2, PGD L∞.
Table 5: Training on clean examples of MNIST and TinyImageNet for BPN and classical network (CN). Testing on adversarial examples generated by a variety of adversarial attack methods. BPN can successfully defend those adversarial examples.

| Dataset & network | Attacks         | PGD Linf | PGD L2 | PGD L1 | Basic Iterative Attack L2 | Aka Basic Iterative Attack | FGSM   |
|-------------------|-----------------|----------|--------|--------|---------------------------|---------------------------|--------|
| MNIST             | BPN             | 95.41    | 98.52  | 98.64  | 98.52                     | 11.35                     | 98.35  |
|                   | CN              | 2.18     | 97.26  | 98.91  | 97.24                     | 9.74                      | 17.53  |
| FashionMNIST      | BPN             | 44.37    | 16.23  | 16.23  | 16.23                     | 5.9                       | 52.39  |
|                   | CN              | 0.00     | 15.11  | 15.11  | 15.11                     | 0.5                       | 1.29   |

Figure 5: (a) Adversarial example with high adversarial perturbation budget ($\epsilon = 0.3$). (b) Test accuracy on adversarial examples after training BPN only on clean examples from MNIST (Blue) or FashionMNIST (Orange) datasets.

Discussion

We proposed a new solution for defending against adversarial examples, which we refer to as Beneficial Perturbation Network (BPN). BPN, for the first time, leverages the beneficial perturbations (opposite to well-known adversarial perturbations) to counteract the effects of adversarial perturbations input data. Compared to adversarial training, this approach introduces: (1) Updating rules of Beneficial Perturbations: Beneficial perturbations can be viewed as the opposite "twins" of adversarial perturbations. Much research is underway on how to generate more and more advanced adversarial perturbations to fool the more and more sophisticated machine learning systems. However, there is a little research on how to generate beneficial perturbations and possible applications of beneficial perturbations. (2) Network structure for storing and generating beneficial perturbations. In this research, we use one of the easiest methods (FGSM) implemented in this paper, one could use other methods (e.g., PGD) to update the beneficial perturbation bias. As a consequence, BPN might be more robust to various kinds of adversarial examples.

Acknowledgment

This work was supported by the National Science Foundation (grant number CCF-1317433), C-BRIC (one of six centers in JUMP, a Semiconductor Research Corporation (SRC) program sponsored by DARPA), and the Intel Corporation. The authors affirm that the views expressed herein are solely their own, and do not represent the views of the United States government or any agency thereof.

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