

Introduction

- ▶ Parametrized Quantum Circuit (PQC) based quantum classifiers are also vulnerable to adversarial attacks like their classical counterparts.
- ▶ **Universal Adversarial Perturbations (UAPs)** - perturbations which when applied to a batch of inputs can cause trained classifiers to misclassify most of the inputs in the batch.
- ▶ We introduce **QuGAP: Quantum Generative Adversarial Perturbations**.
- ▶ For classical data (QuGAP - A): Generates additive UAPs bounded by perturbation norm.
- ▶ For quantum data (QuGAP - U): Generates unitary UAPs controlled by quantum state fidelity constraints.
- ▶ First formulation of additive UAPs for quantum classifiers; We also establish the state-of-the-art for unitary UAPs.

Additive UAPs

- ▶ Input-agnostic perturbations on classical data prior to encoding, which cause quantum classifier to misclassify it.
- ▶ Using sufficiently large perturbation, we distort the samples such that they get projected onto a desired decision region of the quantum classifier.
- ▶ Theoretical and empirical analysis focused on amplitude encoded data.

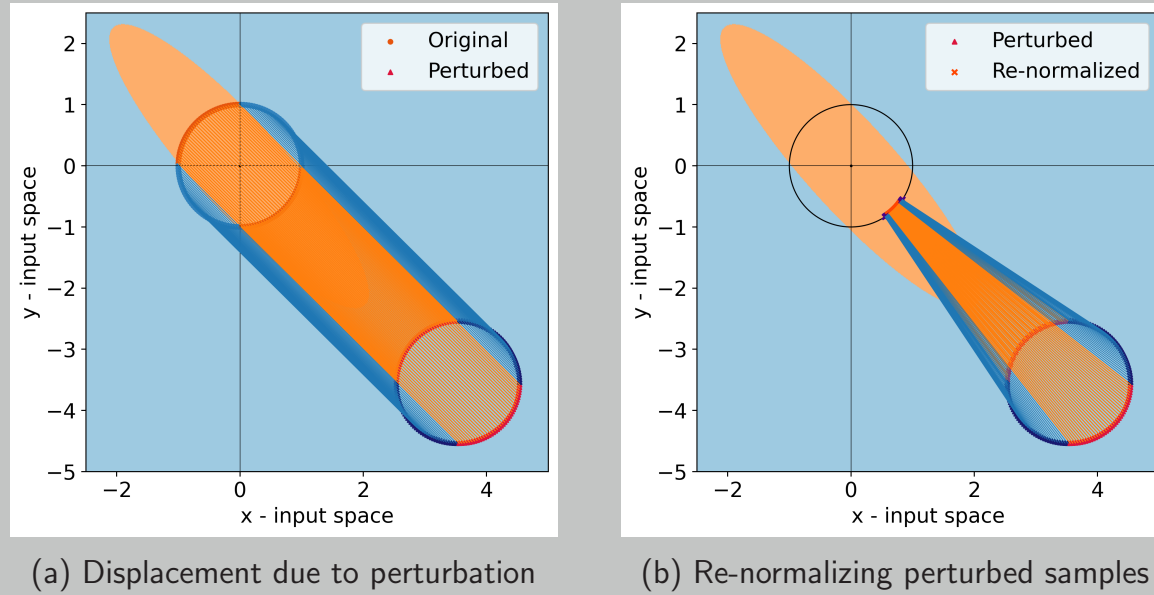


Figure: Demonstration of our key idea using a simple XOR dataset with an elliptic decision boundary. All samples in the dataset get classified into a single label after perturbation.

Theorem: Existence of Additive UAPs

For an additive universal adversarial perturbation p applied on inputs of classifier Q , a strength of perturbation $\|p\| \in \mathbb{R}$ will cause Q to classify all inputs as c (class to which $p/\|p\|$ belongs) if:

$$\|p\| \geq \frac{2}{\epsilon_c \sqrt{4 - \epsilon_c^2}}$$

where ϵ_c is given by: $\epsilon_c = \sqrt{1 + \frac{1}{2d} \cdot (\hat{p}^T M^c \hat{p} - \hat{p}^T M^{c'} \hat{p})} - 1$ where $\hat{p} = p/\|p\|$ and c' is the class with highest output probability for $\hat{p}$ after c .

QuGAP - A

- ▶ Perturbations are additive transformations applied to the classical data samples.
- ▶ Fooling loss to train the generative network for targeted and untargeted UAPs:

$$\mathcal{L}_{fool, targeted} = \sum_{x \in \mathcal{D}} \mathcal{L}_{CE}(\hat{y}_x, t) \quad \mathcal{L}_{fool, untargeted} = - \sum_{x \in \mathcal{D}} \mathcal{L}_{CE}(\hat{y}_x, c_x)$$

where $\mathcal{L}_{CE}$ is the cross-entropy loss, $\hat{y}_x$ gives prediction probabilities for x , c_x is the true label of x and t is the target label (for targeted UAPs).

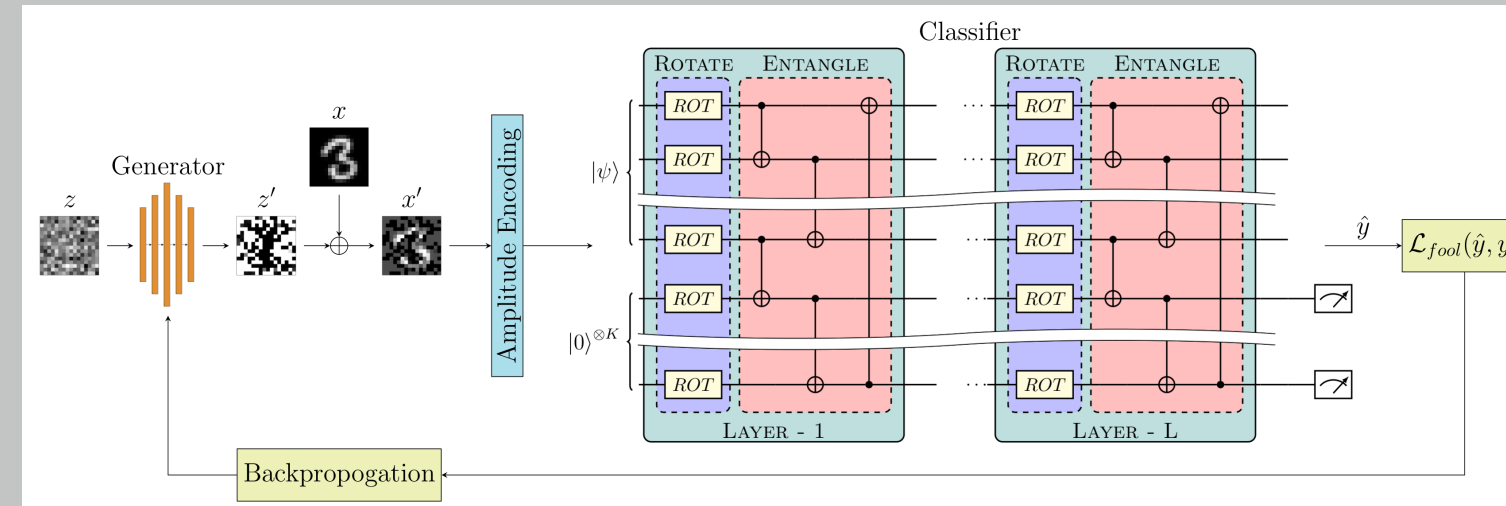


Figure: QuGAP-A: Framework for generating additive UAPs for quantum classifiers. Random vector z sampled from $\mathbb{R}^m$ is passed through a classical generative network. The generated perturbation z' is scaled to impose the norm constraint and added to an input sample x . The perturbed input sample x' is amplitude-encoded and passed through the trained quantum classifier Q . Output predictions from Q are used to compute the fooling loss $\mathcal{L}_{fool}$. Gradients computed are backpropagated.

QuGAP - U

- ▶ Perturbations are unitary transformations applied directly on input quantum states.
- ▶ Applicable for both encoded (any encoding scheme) classical data and quantum data.
- ▶ A novel fidelity based loss ensures high fidelity between unperturbed and perturbed quantum states:

$$\mathcal{L}_U = \mathcal{L}_{fool} + \alpha \mathcal{L}_{fid}$$

where $\mathcal{L}_{fid} = (1 - \mathcal{F}(|\psi\rangle, |\phi\rangle))^2$; $\mathcal{F}(|\psi\rangle, |\phi\rangle) = |\langle\psi|\phi\rangle|^2$ is the quantum state fidelity.

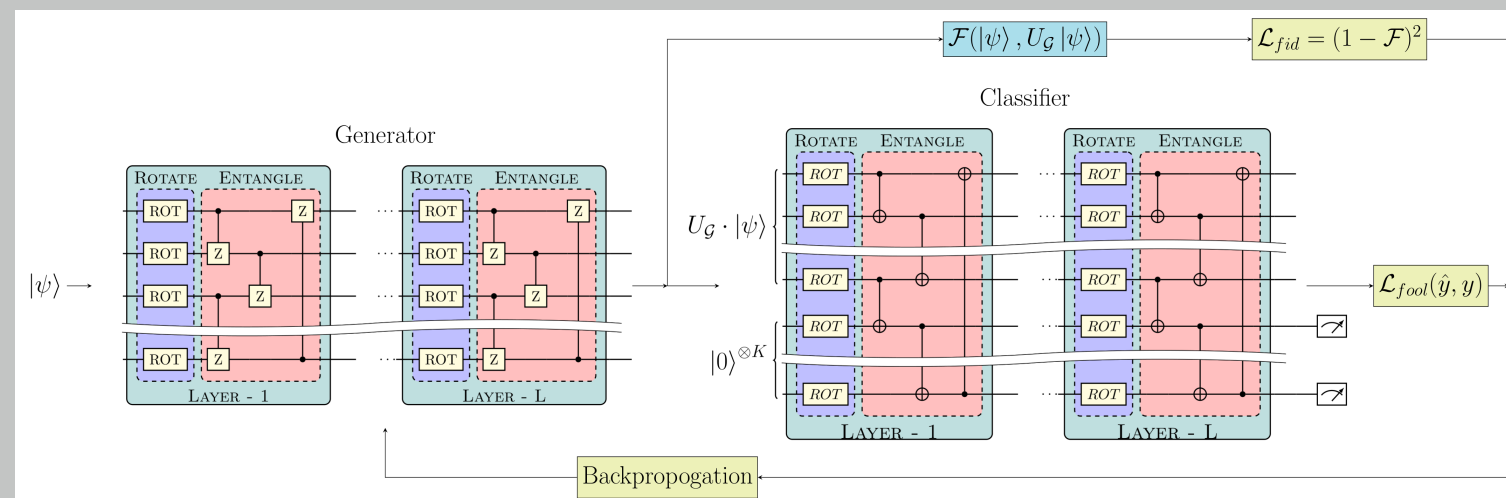


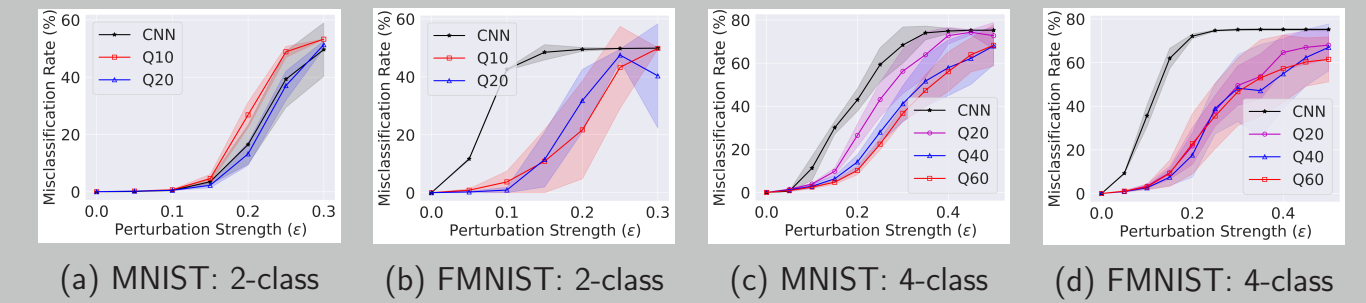
Figure: QuGAP-U: A framework for generating unitary UAPs for quantum classifiers. The quantum generator $\mathcal{G}_Q$ takes in an input state $|\psi_i\rangle$ and transforms it into a perturbed state $|\phi_i\rangle = U_G |\psi_i\rangle$. The fidelity between $|\psi_i\rangle$ and $|\phi_i\rangle$ is computed from which $\mathcal{L}_{fid}$ is calculated. $|\phi_i\rangle$ is also passed through a trained quantum classifier Q to compute $\mathcal{L}_{fool}$. Gradients are computed using the total loss $\mathcal{L}_{fool} + \alpha \mathcal{L}_{fid}$ and used to update the parameters of $\mathcal{G}_Q$ over all training samples for multiple epochs.

Experimental Results

Misclassification rate: fraction of inputs misclassified by a perturbation.

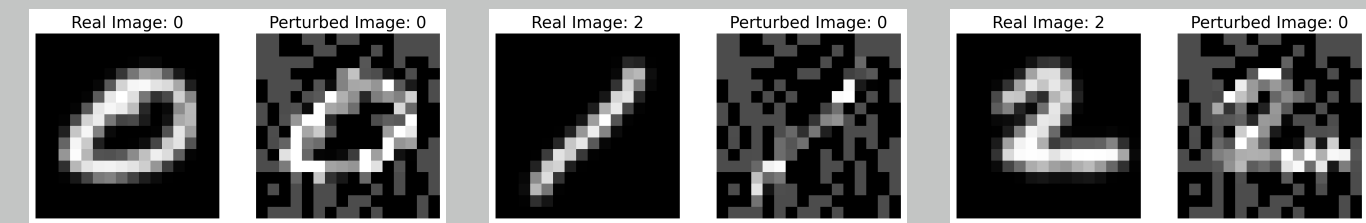
Additive UAPs

QuGAP-A evaluated on MNIST and FMNIST datasets. Misclassification rates plotted averaged over 10 runs for both binary (classes 0 and 1) and 4-class (classes 0, 1, 2 and 3) classification tasks.



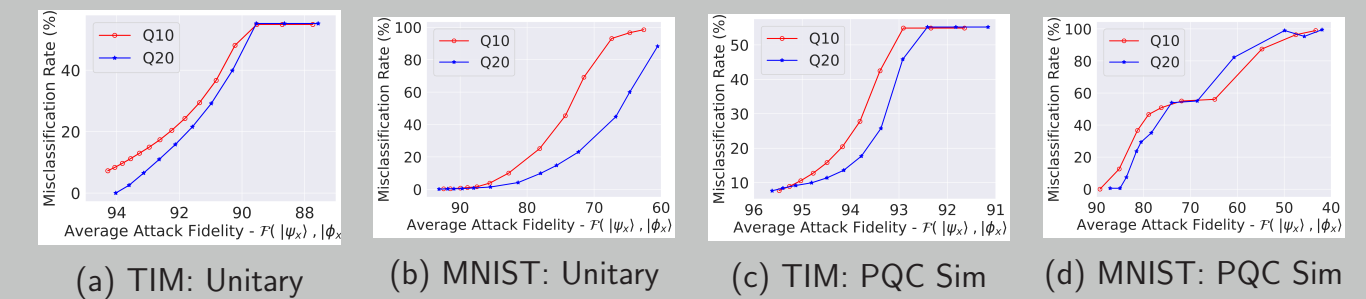
Visualization

Illustration of generated un-targeted UAPs for PQC20 along with predictions for real and perturbed images. The strength of perturbation is $\epsilon = 0.30$.



Unitary UAPs

QuGAP-U evaluated on Transverse Ising Model (TIM) and MNIST datasets. We first generate unitary UAPs with unitary U_{G_Q} acting as a proxy for the quantum generator $\mathcal{G}_Q$ ((a) & (b)). We then simulate QuGAP-U using a PQC as $\mathcal{G}_Q$ ((c) & (d)). QuGAP-U also outperforms the qBIM attack framework.



Summary

- ▶ We theoretically show the existence of additive UAPs.
- ▶ We propose a framework (QuGAP-A) to generate additive UAPs.
- ▶ We propose state-of-the-art framework (QuGAP-U) to generate unitary UAPs.

Acknowledgements

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