

# Simulating quantum circuits with non-Clifford noise

Brandin Farris, Daley McMahon, Jad Soucar, Peter Ye

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Institute for Pure and Applied Mathematics  
& NASA Ames Research Center

Industry Mentors: Dr. Namit Anand, Dr. Jeffrey Marshall

Academic Mentor: Zhuoyang Ye

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## **Background**

# What is a quantum computer?

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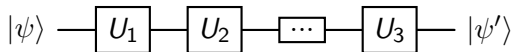
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# The problem with classical simulations of quantum circuits

$$|\psi\rangle = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}$$

$$|\psi\rangle \otimes |\phi\rangle = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_4 \end{bmatrix}$$

$$|\psi\rangle \otimes |\phi\rangle \otimes |\lambda\rangle = \begin{bmatrix} \alpha_1 \\ \vdots \\ \vdots \\ \alpha_8 \end{bmatrix}$$

- State grows exponentially,  $2^n$  for  $n$  qubits.
- The current state of the art allows for the classical simulation of a 54-qubit system (Pednault et al 2019)

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$$|s_i\rangle \in \mathcal{S} := \{s \mid \exists C_i \in \mathcal{C} \text{ s.t } s = C_i |0\rangle\}$$

## **The Noise Problem**

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A *noise channel*  $\xi_i = \{K_1, \dots, K_{|\xi_i|}\}$  where  $K_i$  is a Kraus Operator. Each Kraus operator is applied probabilistically.

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$K_i$  is Non-Unitary!

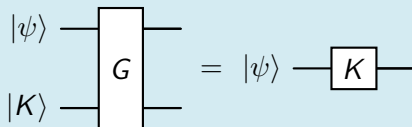
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## Resource States & Gadgets



s.t  $G \in \mathcal{C}$  &  $|K\rangle \in \mathcal{S}$

# K-Gadget

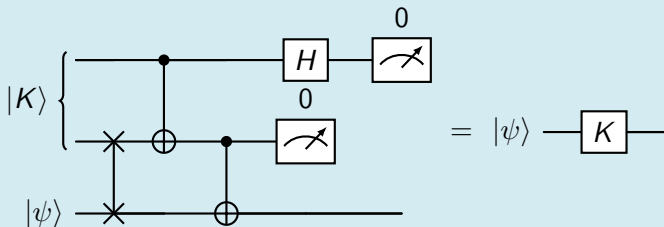
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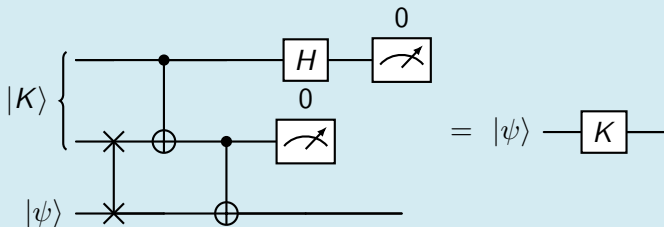




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$$|K\rangle = \sum_{i=1}^4 c_i |s_i\rangle, \quad |s_i\rangle \in \mathcal{S} \implies 4^c \text{ \# of states}$$

# Rank 4 K-Gadget

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$$s_1 \begin{array}{c} \psi \text{ ---} \\ \left\{ \begin{array}{c} \text{---} \\ \text{---} \end{array} \right. + s_2 \begin{array}{c} \psi \text{ ---} \\ \left\{ \begin{array}{c} \text{---} \\ \text{---} \end{array} \right. + s_3 \begin{array}{c} \psi \text{ ---} \\ \left\{ \begin{array}{c} \text{---} \\ \text{---} \end{array} \right. + s_4 \begin{array}{c} \psi \text{ ---} \\ \left\{ \begin{array}{c} \text{---} \\ \text{---} \end{array} \right. = K \begin{array}{c} \psi \text{ ---} \\ \left\{ \begin{array}{c} \text{---} \\ \text{---} \end{array} \right.$$

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## Rank 2 K-Gadget

### Theorem - Extent Bound on Kraus Resource State

Given an arbitrary contraction operator  $K \in \mathbb{R}^{2 \times 2}$ , the associated column-wise flattened vector has stabilizer decomposition

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$$\sum_i^r |c_i| \leq 1.268$$

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The small extent and numerical simulations indicate that most Kraus operators can be reasonably represented by a **rank 2** stabilizer decomposition!

# Rank 2 K-Gadget

$$|K\rangle = \sum^2 c_i |s_i\rangle$$

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# K-gadget Compression

So we choose 2 stabilizer states  $|\tilde{0}\rangle$  and  $|\tilde{1}\rangle$  to serve as our basis

$$|K\rangle = \left( \frac{|\tilde{0}\rangle + \alpha |\tilde{1}\rangle}{\beta} \right)$$



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$$|K\rangle^{\otimes c} = \left( \frac{|\tilde{0}\rangle + \alpha |\tilde{1}\rangle}{\beta} \right)^{\otimes c} = \frac{1}{\sqrt{K(\mathbb{F}_2^c)}} \sum_{x \in \mathbb{F}_2^c} \alpha^{|x|} |\tilde{x}_1 \tilde{x}_2 \dots \tilde{x}_t\rangle$$

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$$|K^{\otimes c}\rangle \approx |\mathcal{L}\rangle = \frac{1}{\sqrt{K(\mathcal{L})}} \sum_{x \in \mathcal{L}} \alpha^{|x|} |\tilde{x}_1 \tilde{x}_2 \dots \tilde{x}_t\rangle$$

# Approximation Error

$$\delta(\mathcal{L}) = 1 - |\langle K^{\otimes c} | \mathcal{L} \rangle|^2$$

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**Such that  $\alpha$  is minimized**

- How do we choose  $\mathcal{L}$ ?

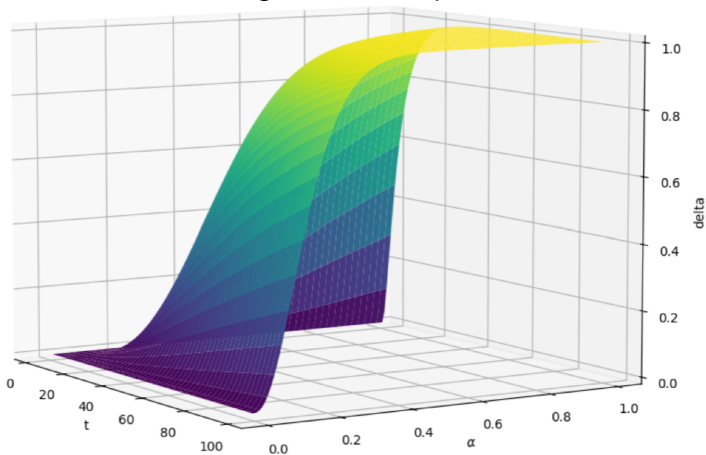
**Such that the elements of  $\mathcal{L}$  have small hamming weights**

Choose  $\mathcal{L}$  to be the basis of  $\mathbb{F}_2^c$

$$\mathcal{L} = \mathcal{B}_2^c \cup \vec{0}$$

# Approximation Error

Using a Basis Compression





# Approximation Error

$\alpha$	$\delta = .0001$	$\delta = .001$	$\delta = .01$
$\alpha = .0001$	37782	225963	2038344
$\alpha = .0005$	3011	12167	85849
$\alpha = .001$	1075	3783	22714
$\alpha = .005$	107	302	1227
$\alpha = .01$	41	108	383
$\alpha = .05$	5	11	31
$\alpha = .1$	2	4	12

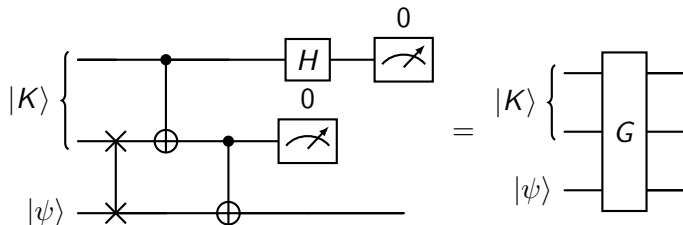
Table: Maximum  $t$  with  $\nu = \frac{1}{\sqrt{2}}$

# Summary

- 1 Map  $K$  to a resource state  $|K\rangle$
- 2 Find stabilizer states that minimize  $\alpha$
- 3 Use a basis compression to Approximate  $|K^{\otimes c}\rangle \approx |\mathcal{L}\rangle$
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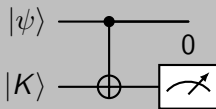
## Example - Amplitude Dampening

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$$K_1 \mapsto |K_1\rangle = (1 \quad \sqrt{1-p}),$$

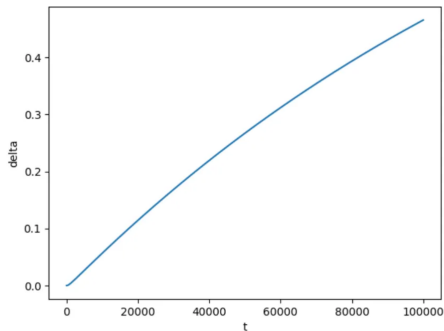


## Simulations pt 3.

$$|K_1\rangle = \frac{|+\rangle + \alpha|0\rangle}{\beta}, \quad \alpha = \frac{1 - \sqrt{1-p}}{\sqrt{2(1-p)}}, \quad \beta = \sqrt{2(1-p)}$$

Choose  $\mathcal{L}$  to be the basis of  $\mathbb{F}_2^c$

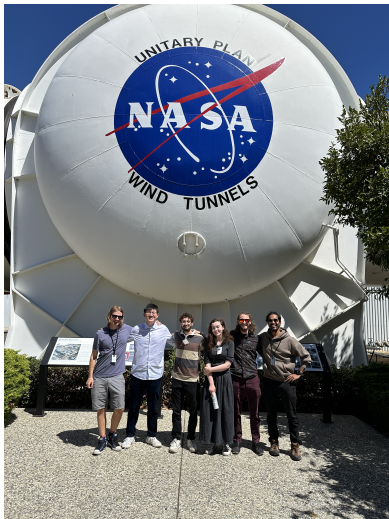
$$\mathcal{L} = \mathcal{B}_2^c \cup \vec{0}$$

Figure:  $p = .01$ 

$\alpha$	$\delta = .0001$	$\delta = .001$	$\delta = .01$
$\alpha = .003562$	173	505	2215

We can simulate 2215 applications of amplitude dampening within 99% fidelity using only 1.4GB of memory!

# Acknowledgements



- 1 We'd like to thank IPAM and the IPAM staff for hosting us this summer.
- 2 NASA Ames Research Center for allowing us to visit their facility in Mountain View, CA.



# Questions!