

Bayesian Estimation of Error Models for Improving Circuit Compilation



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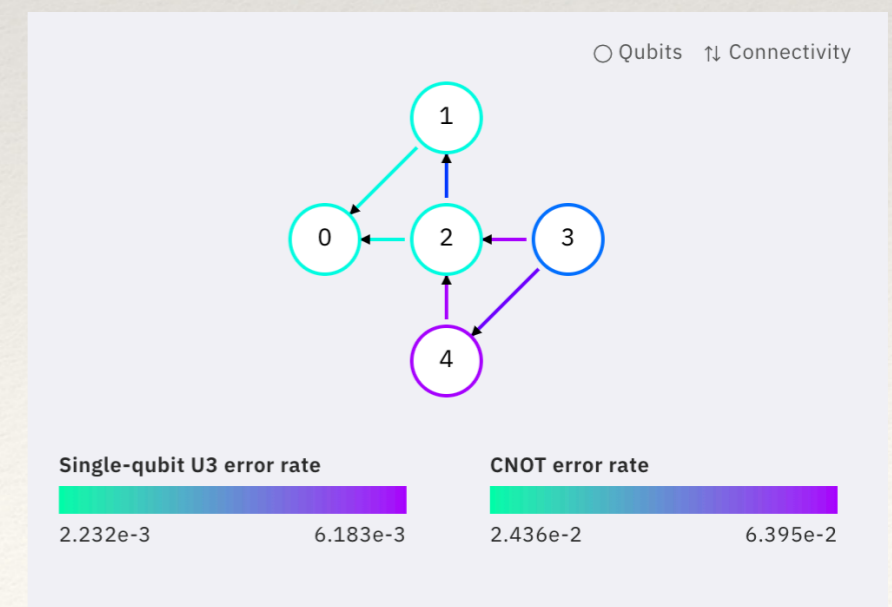
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Quantum Circuits

- ❖ Functional near-term quantum computing will require learning how to make effective use of noisy error-prone hardware.
- ❖ Makes things difficult for quantum algorithm designers as they must simultaneously deeply understand the hardware and how to best map to it.
- ❖ Practically, often means “try to use the less noisy qubits more”



Error-Based Synthesis

- ❖ There are many types of potential quantum errors
 - ❖ (P.S. Hardware folks please tell me what you see happens in practice.)
- ❖ We can understand errors as modifications to gates in our original circuit
 - ❖ $R_x(\theta) \Rightarrow R_x(\theta) U(\phi)$
 - ❖ $CNOT \Rightarrow \text{if rand()} < .2 \text{ then } CNOT CZ \text{ else } CNOT$
 - ❖ $U \Rightarrow u \sim \text{Distribution}(U)$

Idea: Synthesize With Errors

- ❖ When synthesizing a desired circuit to run on hardware, consider build with error-prone rather than theoretical gates
- ❖ Synthesis should find the physical circuit that closest matches the desired circuit in expectation (over gate error models)
- ❖ Should be able to estimate the error of the circuit ahead-of-time
- ❖ Let's see some examples!

Simple Example

- ❖ We found that running a theoretical rotation gate on the hardware results in an overrotation of 0.1

Desired Circuit:

$$\boxed{R_x(\pi)}^T$$

Error Model:

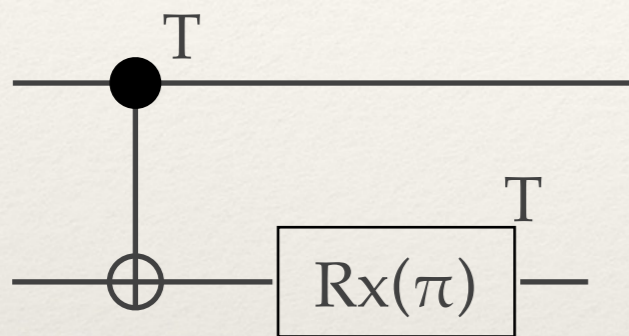
$$\boxed{R_x(\theta)} \longrightarrow \boxed{R_x(\theta)} \overset{T}{\text{---}} \boxed{R_x(0.1)}^T$$

- ❖ We should submit our desired circuit underrotated by 0.1 to compensate for the hardware mapping

$$\boxed{R_x(\pi-0.1)} \longrightarrow \boxed{R_x(\pi-0.1)} \overset{T}{\text{---}} \boxed{R_x(0.1)}^T = \boxed{R_x(\pi)}^T$$

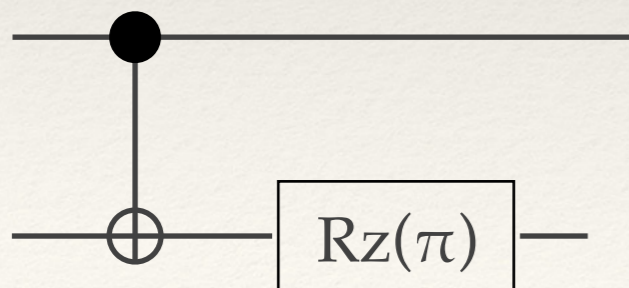
More Complex Example

Desired Circuit:

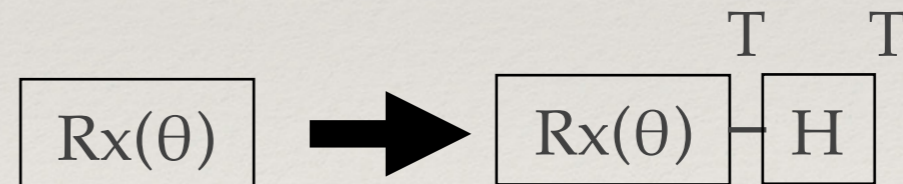
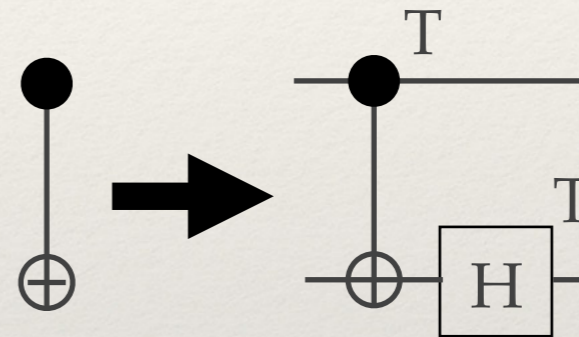


\approx

Submitted Circuit



Error Model:



Expectation Example

Desired Circuit:

$$\boxed{Rx(\theta)}^T$$

Error Model:

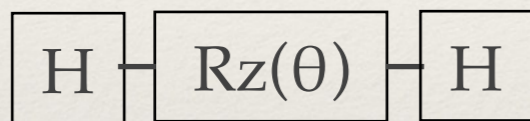
$$\boxed{Rx(\theta)} \rightarrow \begin{cases} \boxed{Rx(\theta)}^T & \text{if rand()} < \frac{7}{10} \\ \boxed{1}^T & \text{else} \end{cases}$$

$$\boxed{Rz(\theta)} \rightarrow \begin{cases} \boxed{Rz(\theta)}^T & \text{if rand()} < \frac{99}{100} \\ \boxed{1}^T & \text{else} \end{cases}$$

$$\boxed{H} \rightarrow \begin{cases} \boxed{H}^T & \text{if rand()} < \frac{99}{100} \\ \boxed{1}^T & \text{else} \end{cases}$$

Expectation Example

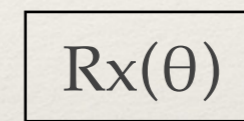
Submitted Circuit



97%

chance of exactly correct

Suboptimal Circuit



70%

chance of exactly correct

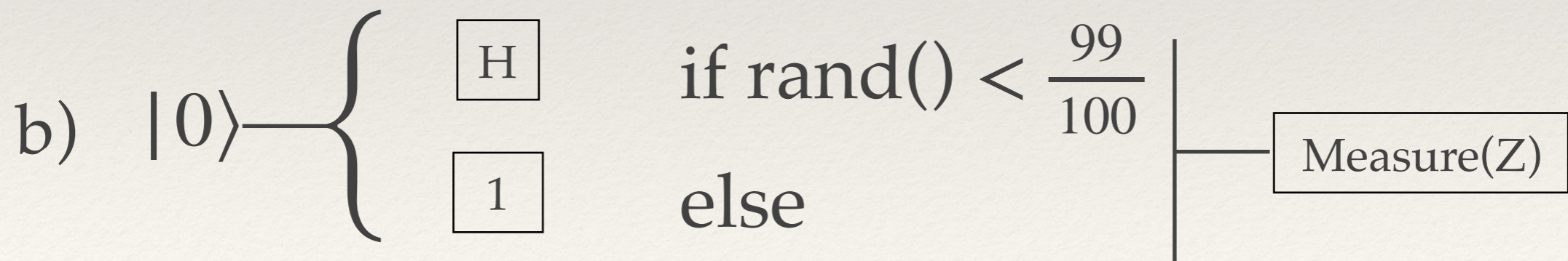
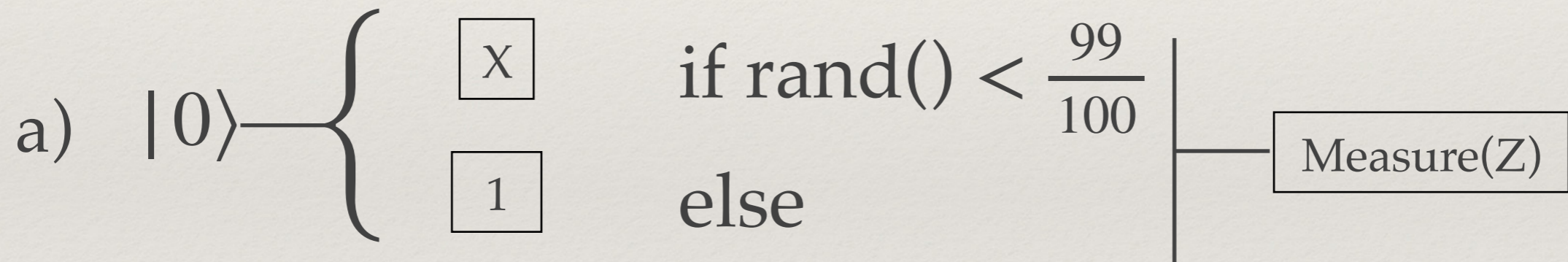
Importance of Error Modeling

- ❖ Error-corrective synthesis *requires* good approximations of gate error behavior to produce reasonable circuits / estimates
- ❖ This requires the ability to estimate the error distributions

A Puzzle

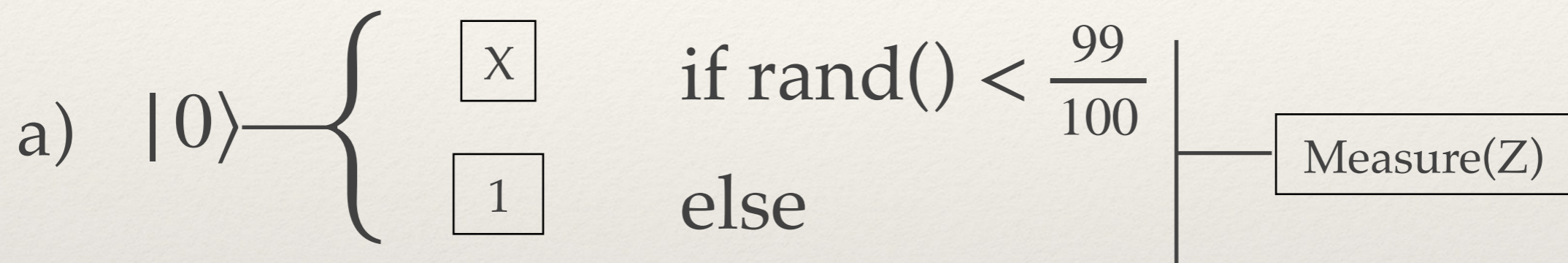
❖ Which circuit produced these results?

600 $|0\rangle$ 400 $|1\rangle$

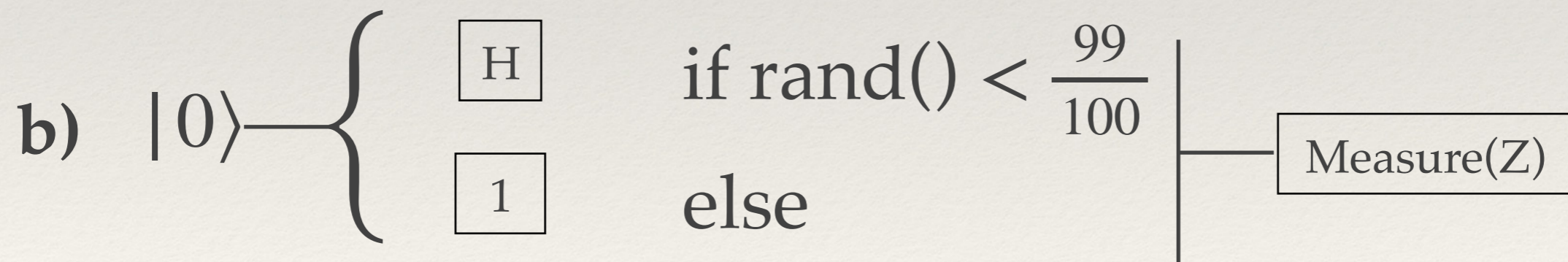


A Puzzle

600 $|0\rangle$ 400 $|1\rangle$



1% $|0\rangle$ 99% $|1\rangle$

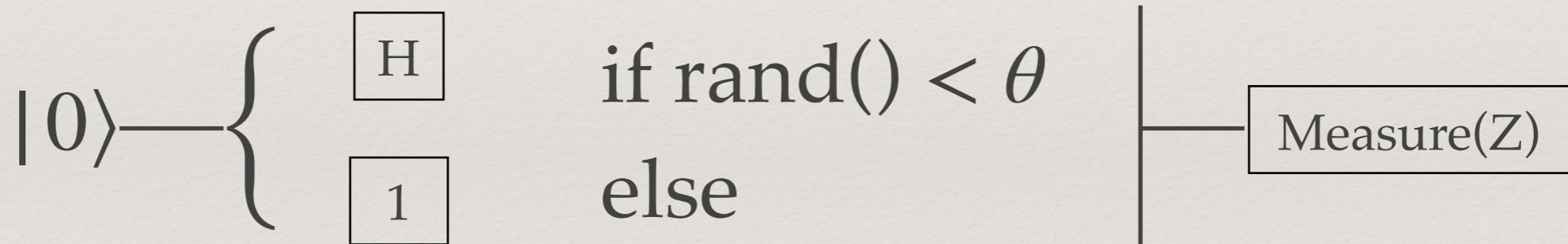


50.5% $|0\rangle$ 49.5% $|1\rangle$

A Slightly Harder Puzzle

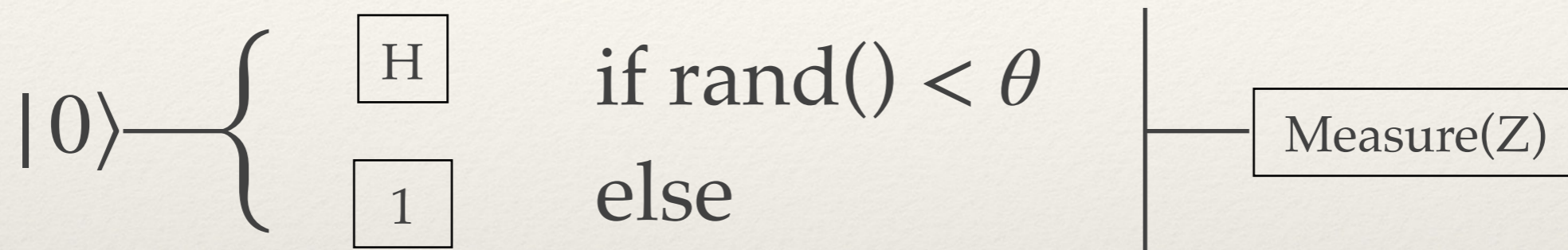
- ❖ Which parameter θ produced these results?

600 $|0\rangle$ 400 $|1\rangle$



A Slightly Harder Puzzle

- ❖ Which parameter θ produced these results?



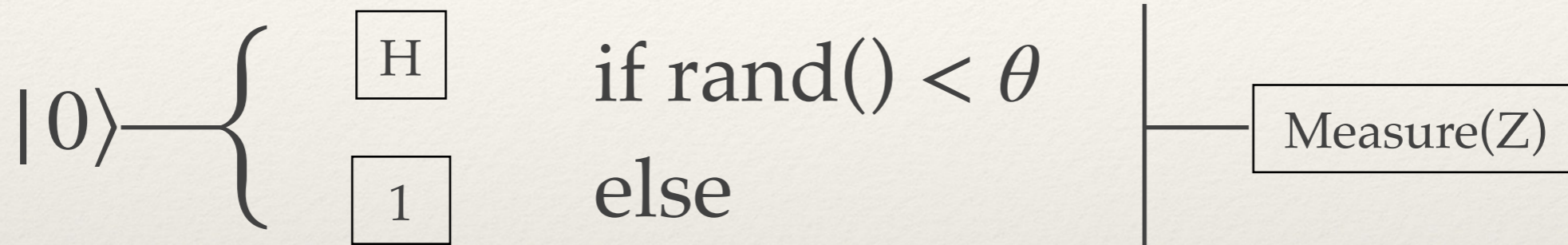
$$p(data | \theta) = \binom{1000}{data} \left(\frac{\theta}{2} + (1 - \theta) \right)^{data} \left(\frac{\theta}{2} \right)^{1000 - data}$$

$$p(\theta | data) = \frac{p(data | \theta)p(\theta)}{p(data)}$$

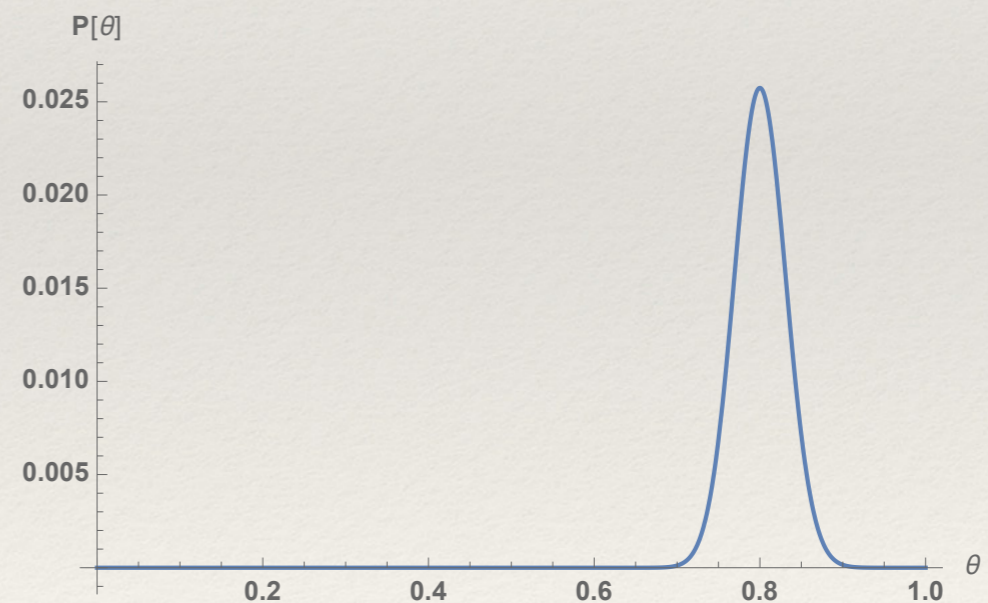
$$\theta^* = \arg \max_{\theta} p(data | \theta)p(\theta)$$

A Slightly Harder Puzzle

- ❖ Which parameter θ produced these results?



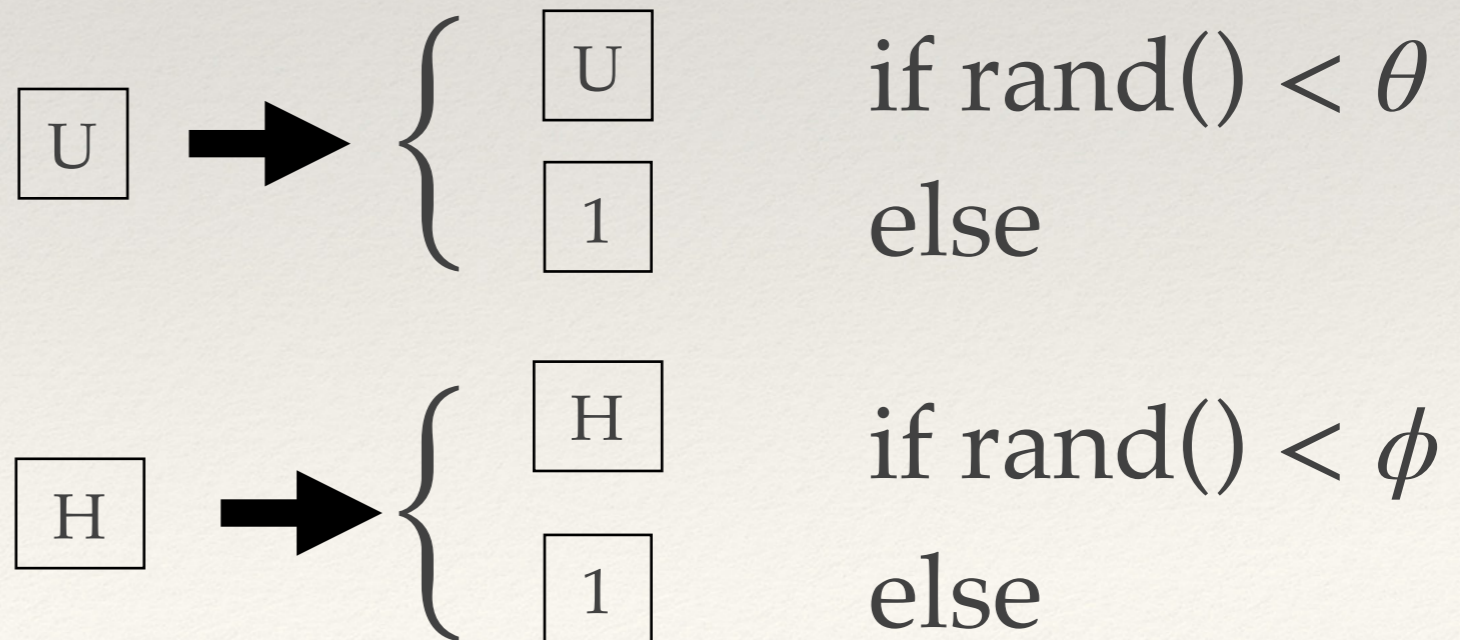
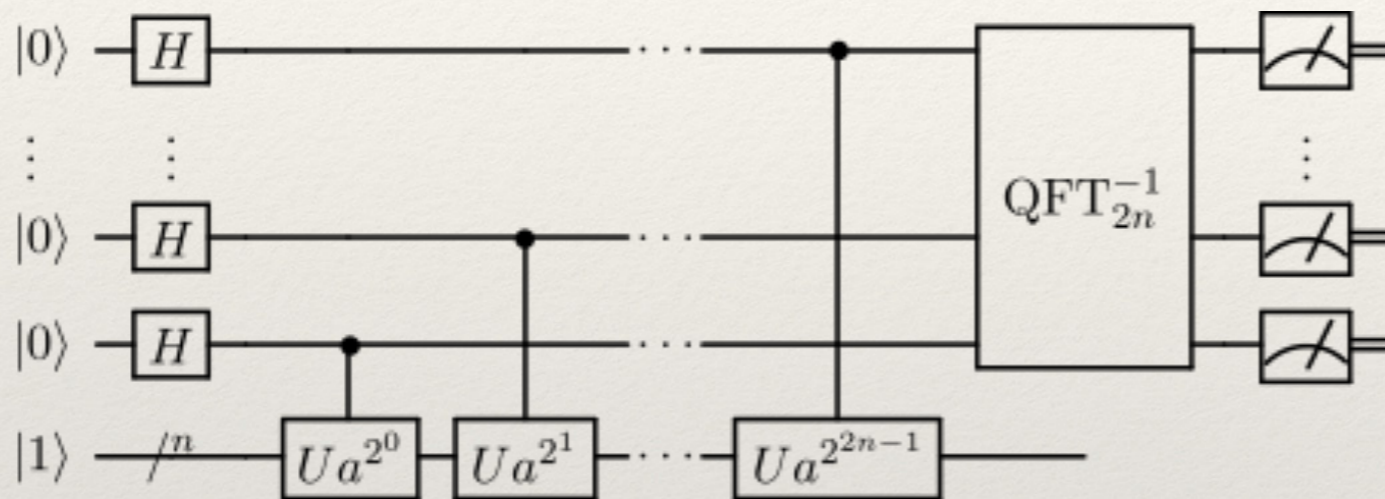
$$\theta^* = \arg \max_{\theta} p(\text{data} | \theta)p(\theta)$$



$$\theta^* = 0.8$$

A Much Harder Puzzle

- ❖ Which parameters θ, ϕ produced these results?



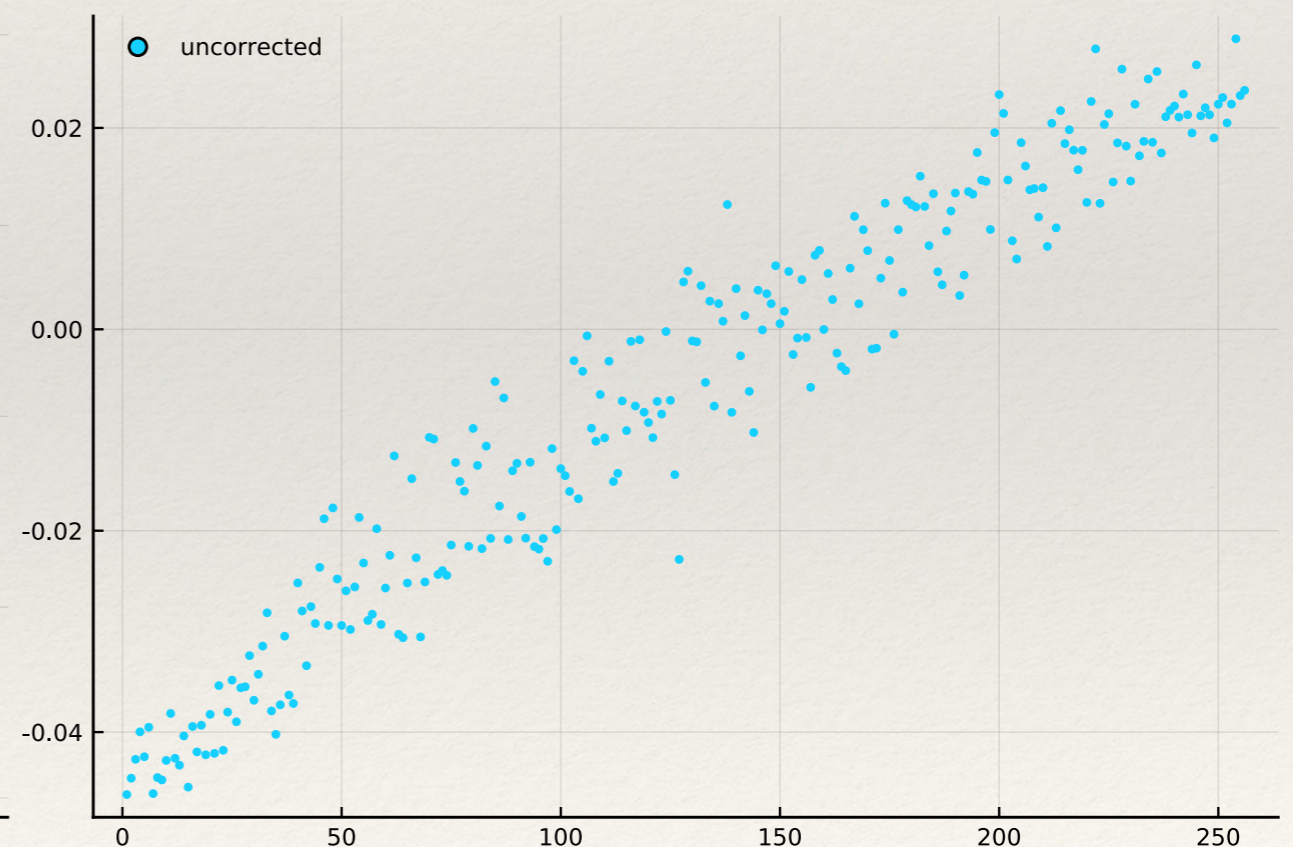
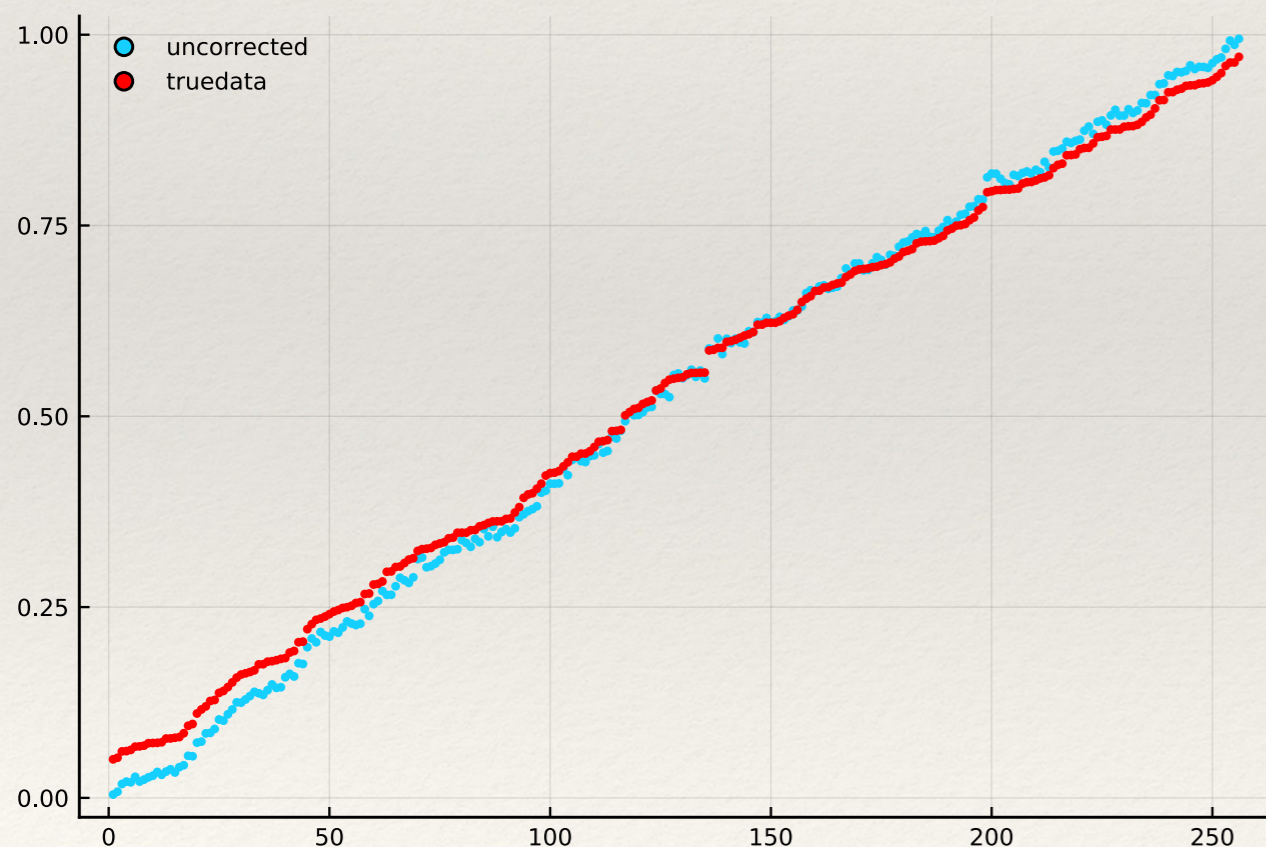
Methodology

- ❖ Run a number of unaltered circuits on hardware
- ❖ Build a version of the circuits using a parameterized error model and solve for the most likely parameters
- ❖ Use those parameterized error models to synthesize better circuits
- ❖ (Optional) repeat using that new data to find better error models

Case Study: Random Unitary

$$U3(\theta, \phi, \lambda) = R_z(\phi+3\pi) - R_x(\pi/2) - R_z(\theta+3\pi) - R_x(\pi/2) - R_z(\lambda)$$

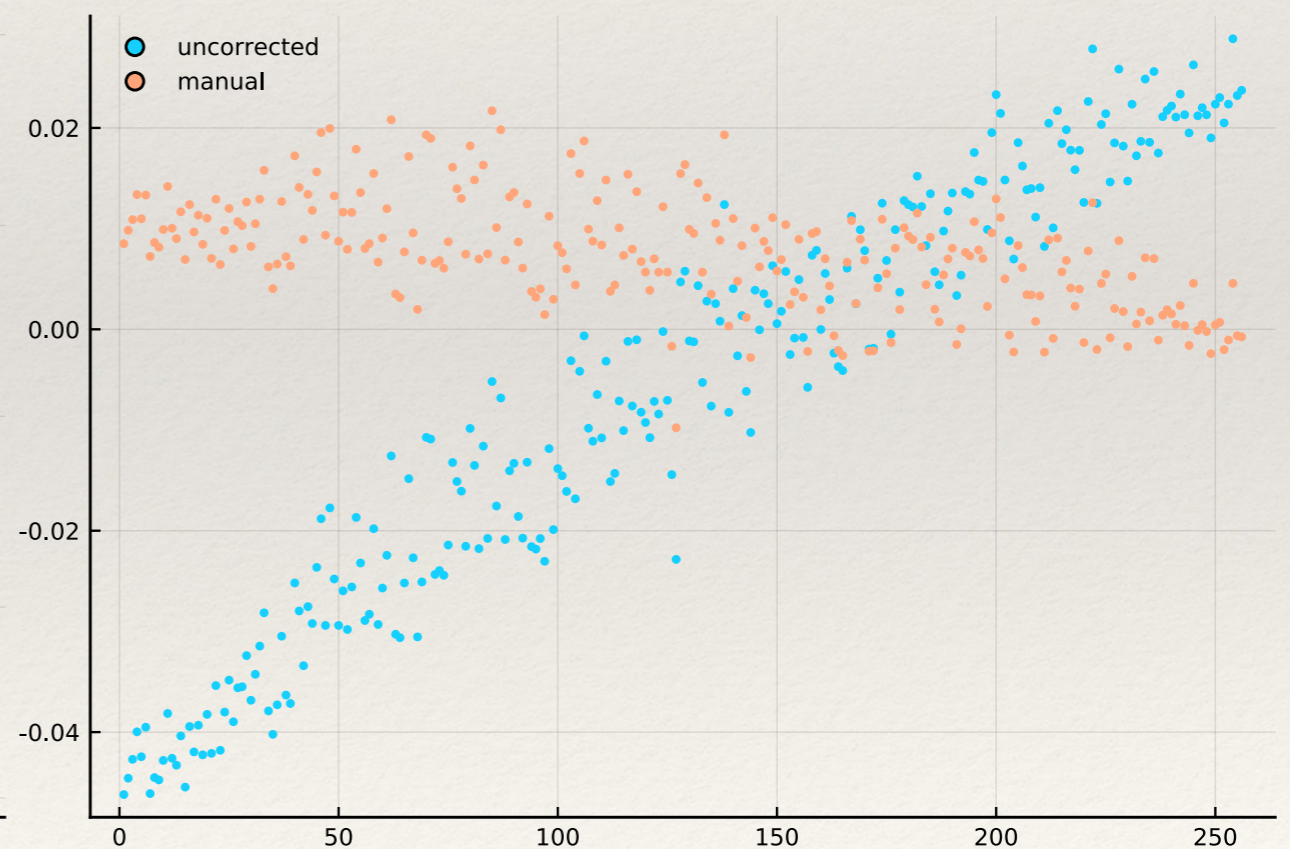
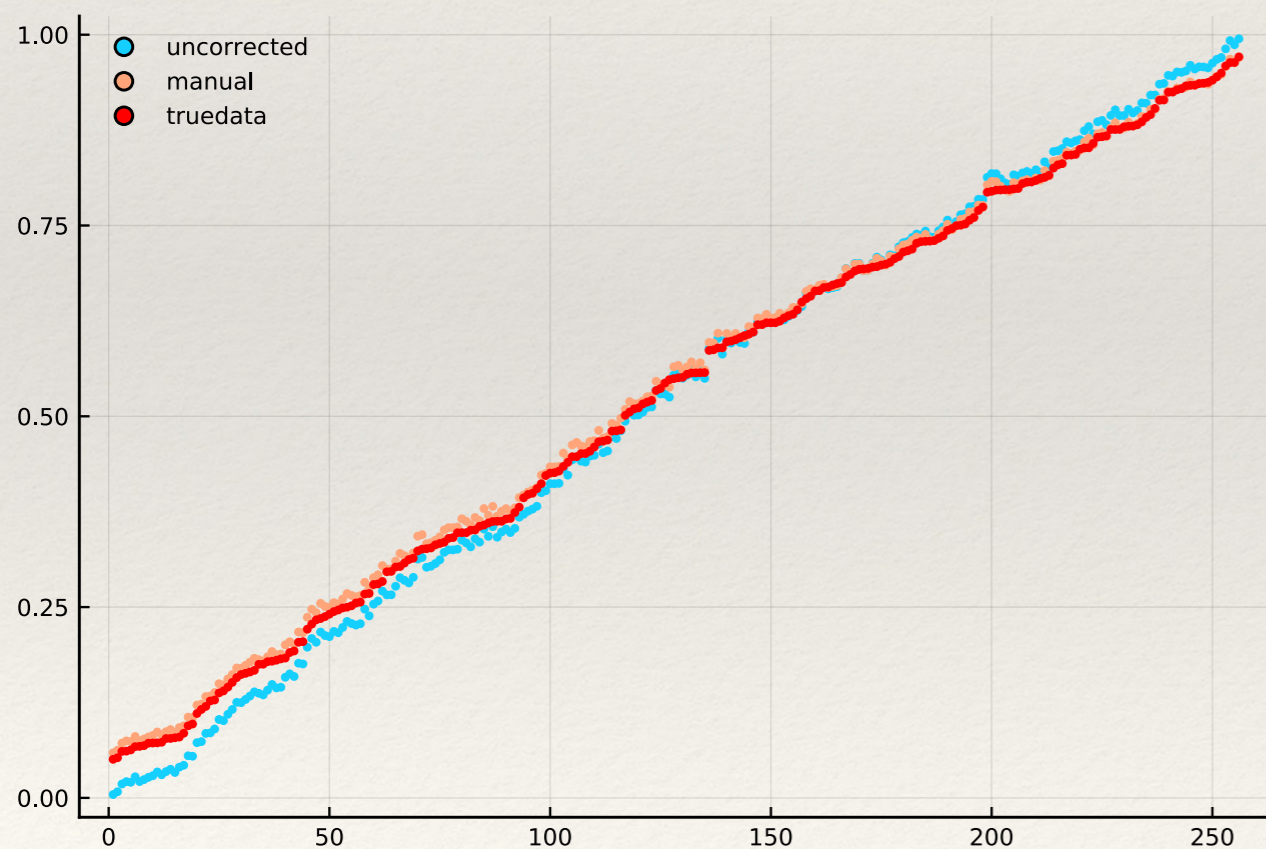
Sample many θ, ϕ, λ and run on IBM quantum hardware



Case Study: Random Unitary



Manually estimate measurement error using above experiment



Case Study: Random Unitary

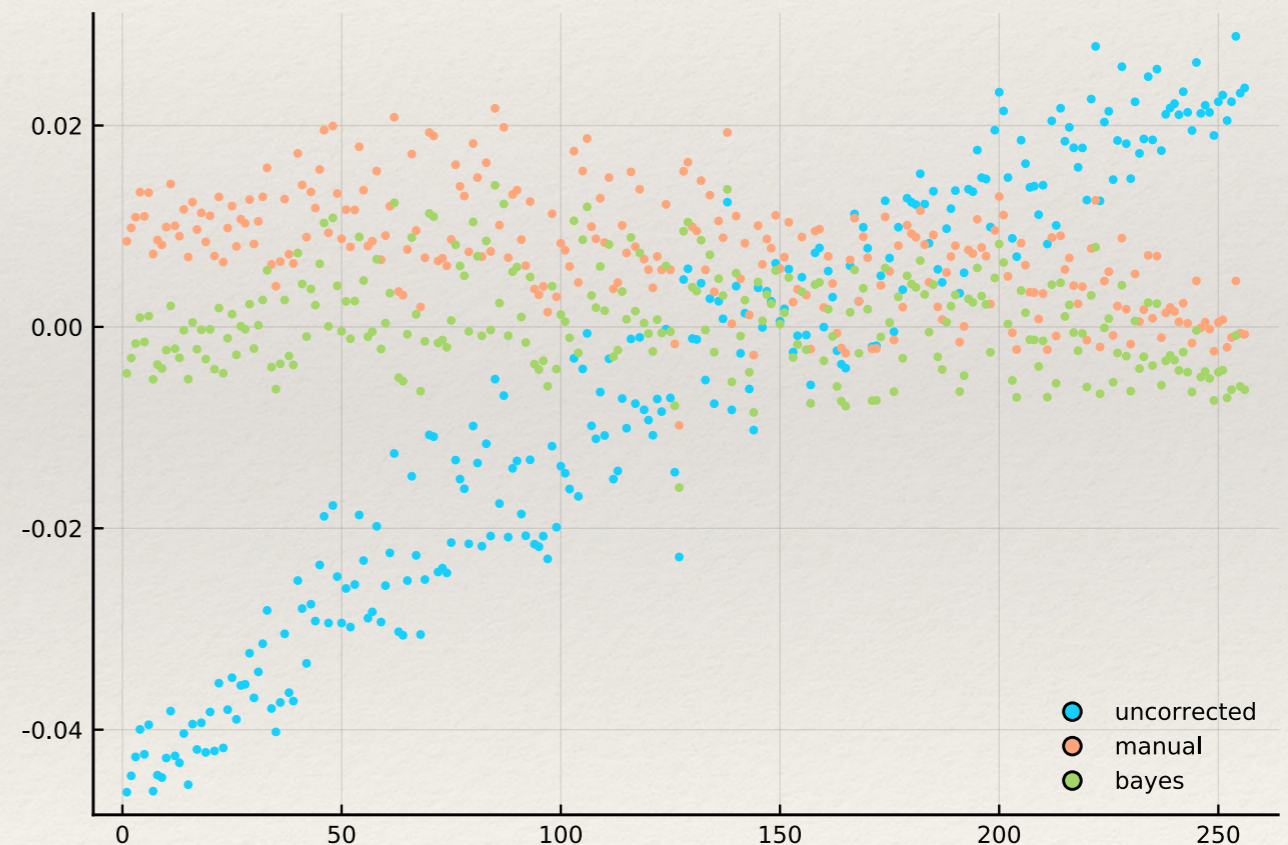
Instead: derive most probable error rates from data

```
@gen function scopeU3(scope)
     $\theta$  = @trace(uniform(0, 2*pi), (scope, : $\theta$ ))
     $\varphi$  = @trace(uniform(0, 2*pi), (scope, : $\varphi$ ))
     $\lambda$  = @trace(uniform(0, 2*pi), (scope, : $\lambda$ ))
    u3( $\theta$ ,  $\varphi$ ,  $\lambda$ )
end

@gen function vectormaker(samples::Int, points::Int)
    data = Float64[];
    zeroToOne = @trace(Gen.beta(2, 5), (:measure, :zeroToOne))
    oneToZero = @trace(Gen.beta(2, 5), (:measure, :oneToZero))
    for i in 1:points
        u1 = @trace(scopeU3(i))
        state = zero_state(1)
        prob0 = probs(Yao.apply!(state, u1))[1]
        prob2 = prob0 * (1-zeroToOne) + (1-prob0) * oneToZero
        z0 = @trace(binomial(prob2, samples), (i, :z0))
        push!(data, prob2)
    end
    data
end

observations = Gen.choicemap()
for i in 1:size(data, 1)
    observations[(i, : $\theta$ )] = data[i,1]
    observations[(i, : $\varphi$ )] = data[i,2]
    observations[(i, : $\lambda$ )] = data[i,3]
    observations[(i, :z0)] = datag[i,1]
end
```

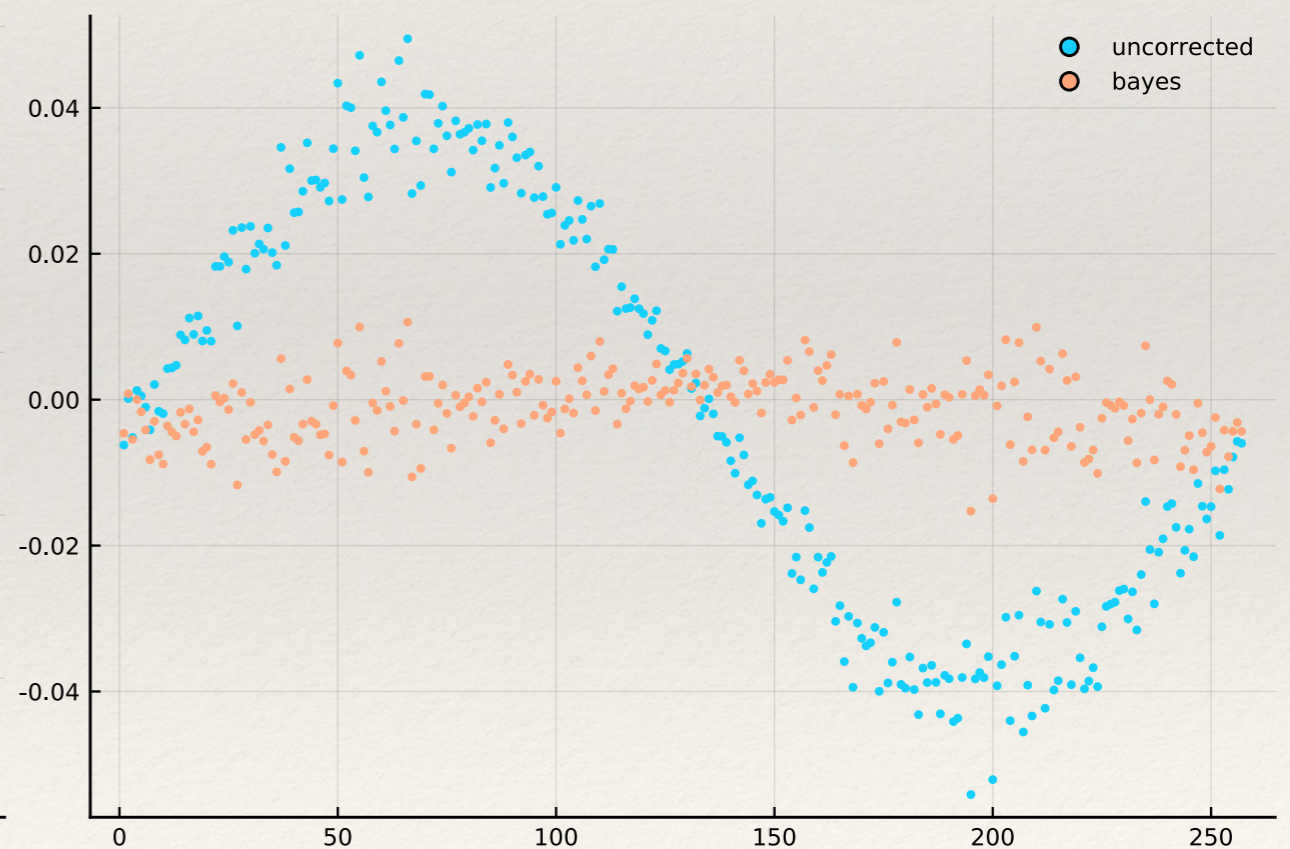
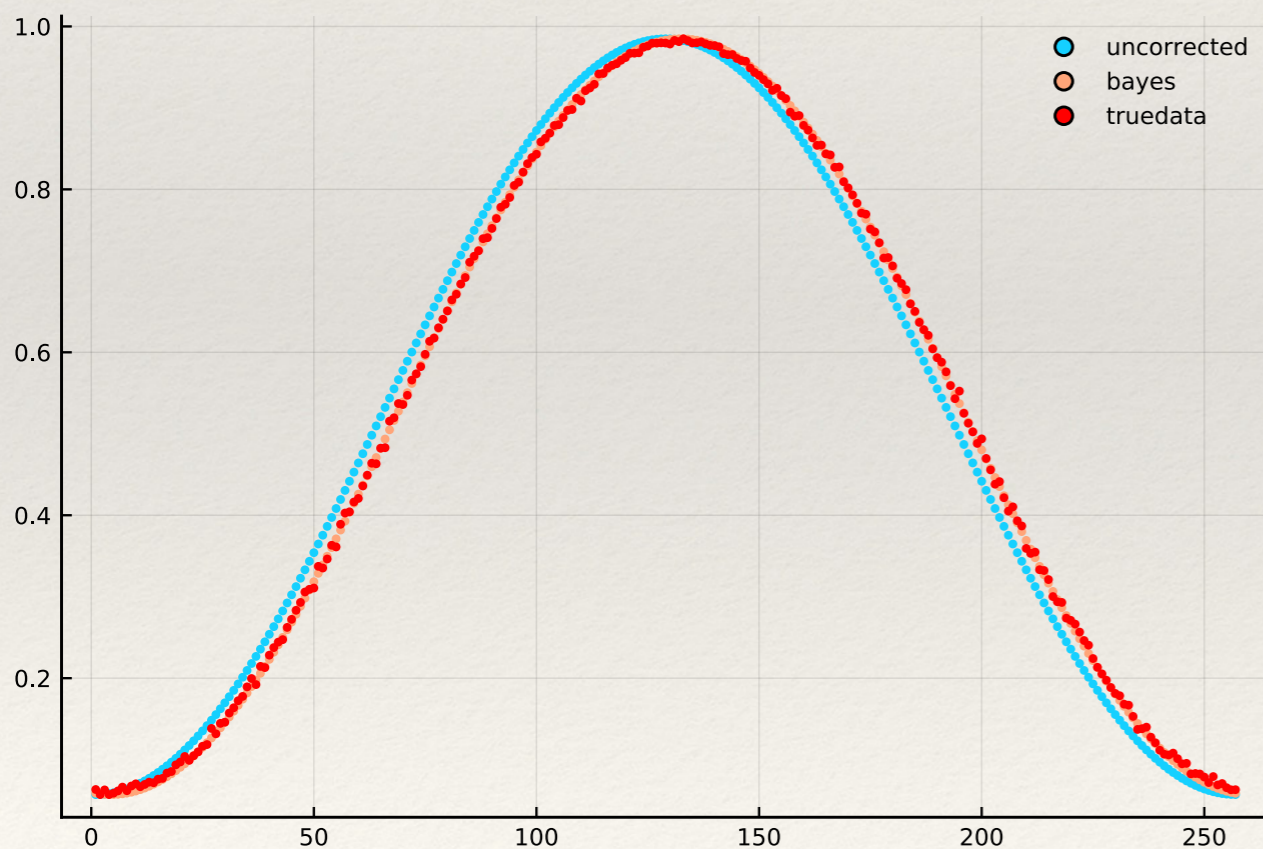
```
(trace, lml_est) = Gen.importance_resampling(vectormaker, (datag[1,1]+datag[1,2],size(data, 1)), observations, 1);
```



Case Study: Shifted Unitary

$$\boxed{U3(\theta, \phi, \lambda)} = \boxed{Rz(\phi+3\pi)} - \boxed{Rx(\pi/2)} - \boxed{Rz(\theta+3\pi)} - \boxed{Rx(\pi/2)} - \boxed{Rz(\lambda)}$$

Sample θ and run on IBM quantum hardware, found shift



Future Directions

- ❖ More experiments!
 - ❖ Derive over-correction parameters
 - ❖ Derive std dev of errors
 - ❖ Derive random Pauli probability