

FROM SANDIA NATIONAL LABS'  
ROBIN  
BLUME-KOHOUT



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# FANTASTIC ERRORS

AND WHERE  
TO FIND THEM



U.S. DEPARTMENT OF  
**ENERGY**

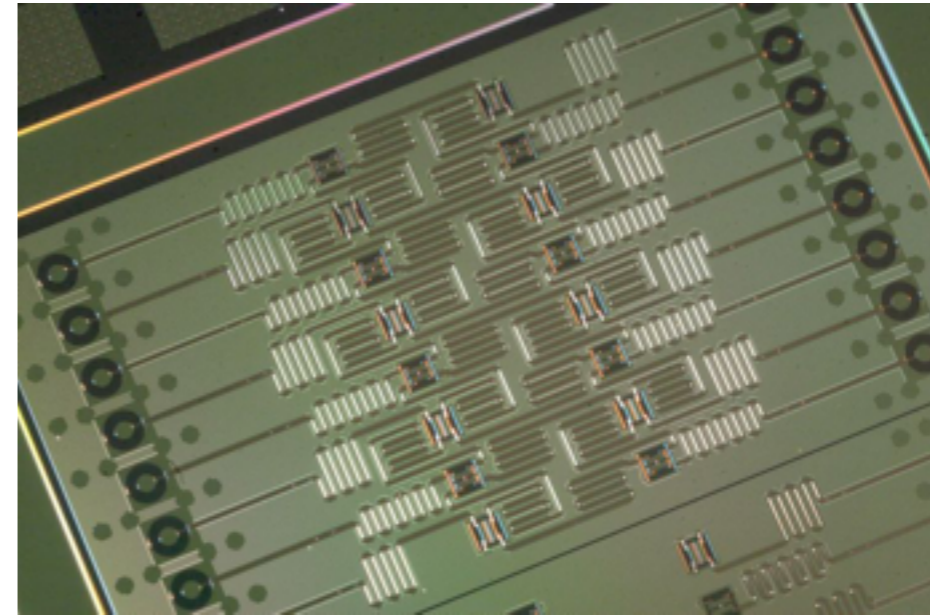


Sandia National Laboratories

# SOME CONTEXT

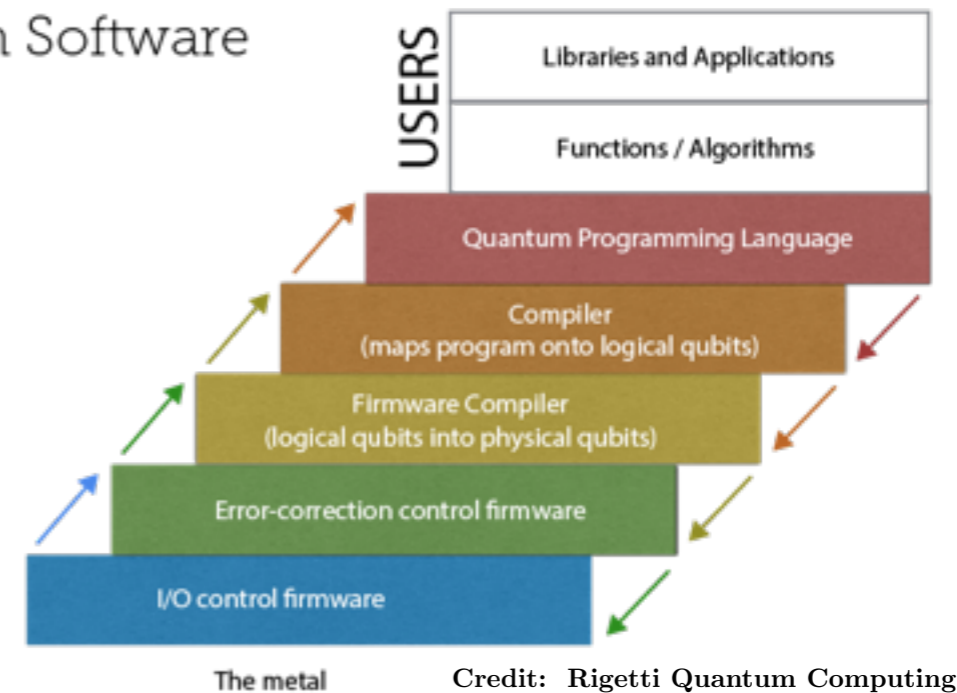
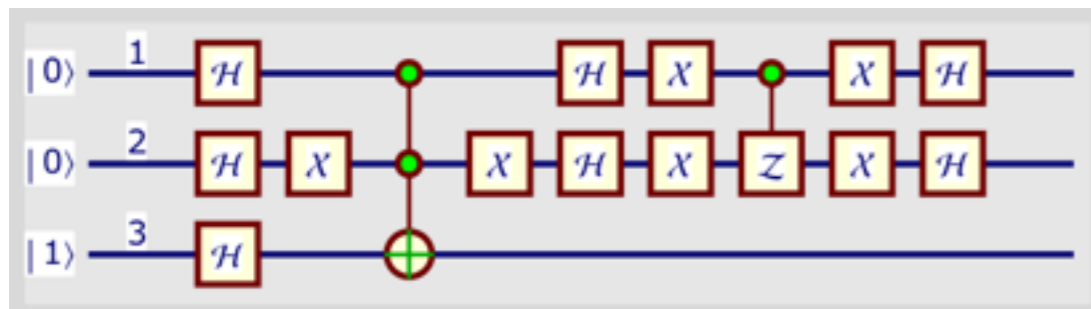


Credit: The Economist



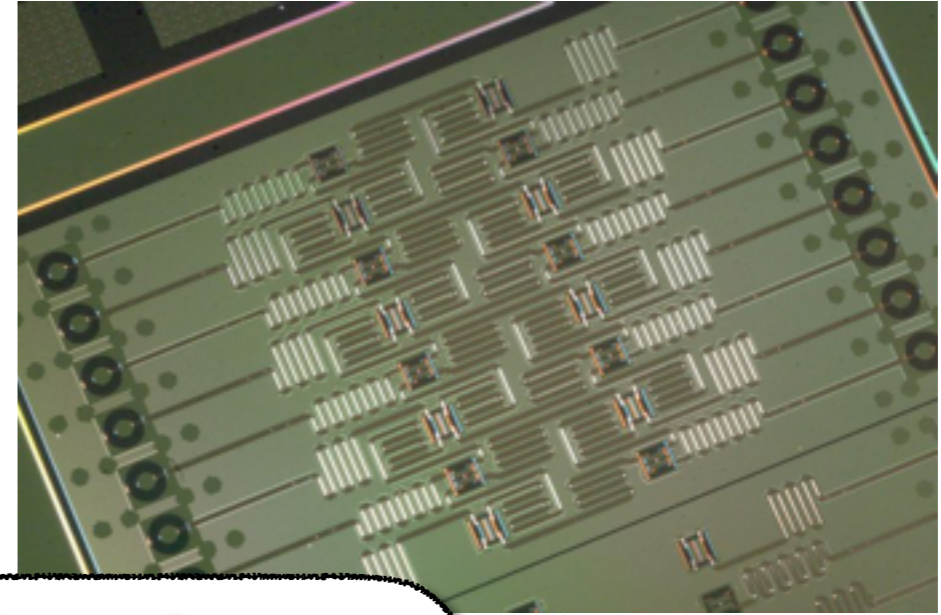
Credit: IBM

## Full Stack Quantum Software



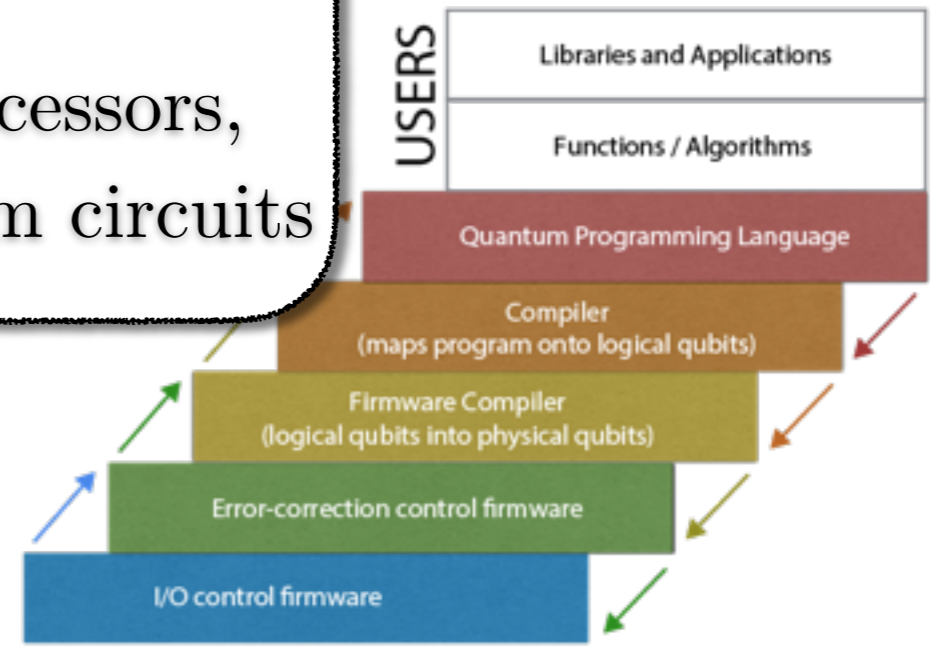
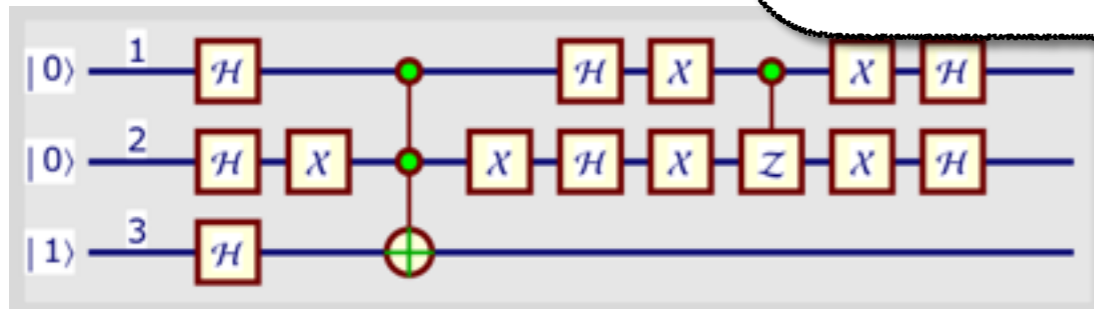
Credit: Rigetti Quantum Computing

# SOME CONTEXT



Credit: IBM

Our world today:  
Real quantum processors,  
running real quantum circuits



The metal

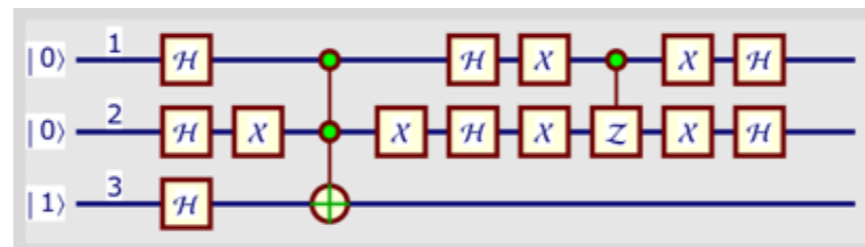
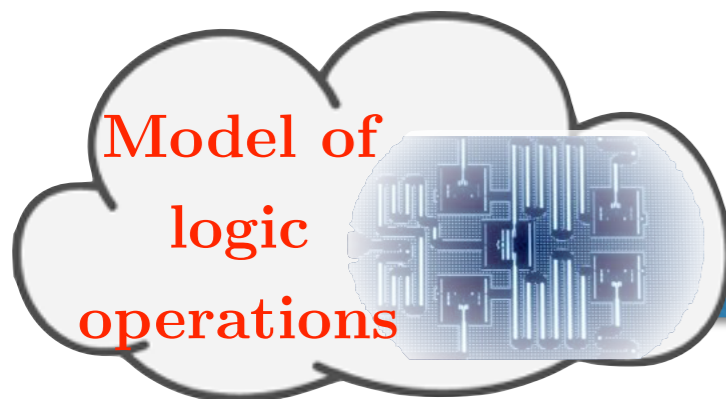
Credit: Rigetti Quantum Computing

# WHAT THIS TALK IS ABOUT

- When we run quantum circuits on *real* quantum processors, we don't get always get the right (expected) outcome.
- **This may be the least surprising thing ever.**
- But the *reasons why* we get wrong outcomes are surprising.
- This is about our ongoing quest to completely model and understand (phenomenologically) *errors* in qubit processors.
- **Error:** Any process that changes circuit outcome probabilities.
- **Goal:** To be able to predict (perfectly) the outcome probabilities of *any* circuit, based on learning from only *a few* experiments.

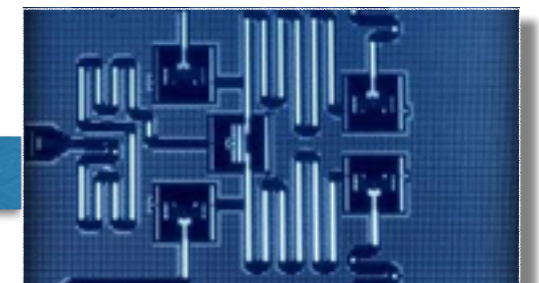
# ERROR MODELS

- **Error:** Any process that changes circuit outcome probabilities.
- **Goal:** To be able to predict (perfectly) the outcome probabilities of *any* circuit, based on learning from only *a few* experiments.
- We want to enable *modeling and simulation* of arbitrary circuits on small ( $\leq 17$  qubit) quantum processors. You ought to be able to *predict* outcome probabilities, then *verify* by running those circuits.



$\Pr(x)$  ?  $\text{freq}(x)$

Experiments



# TECHNICAL OUTLINE

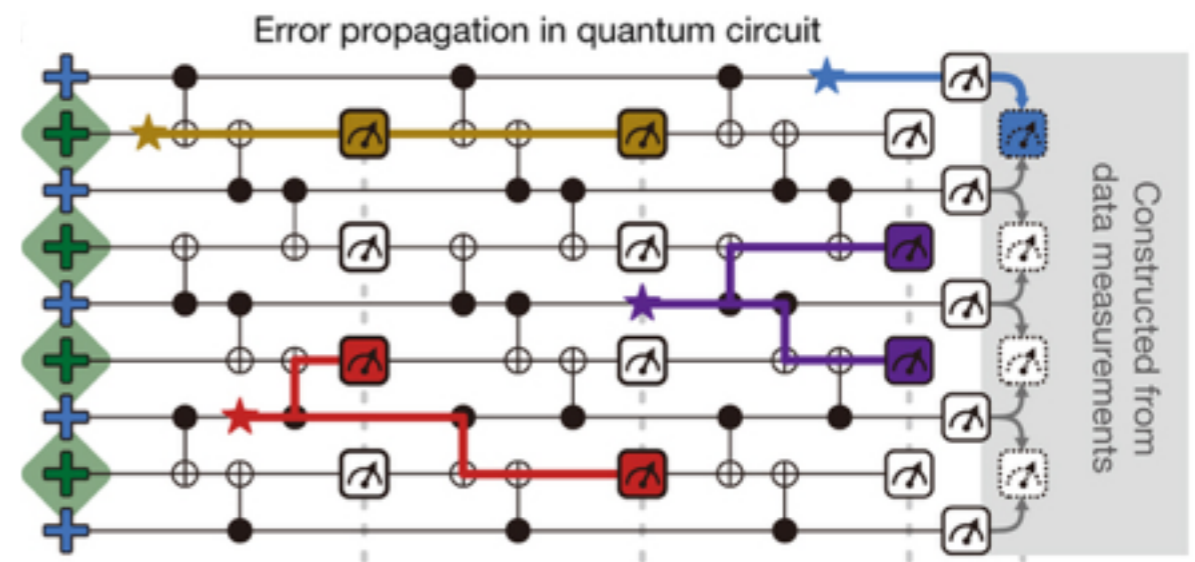
- **The “standard” models of quantum errors**
  - The QEC Theorist’s Model (“Pauli errors”)
  - The Control Theorist’s Model (“Hamiltonian noise”)
  - The Quantum Fundamentalist’s Model (“CPTP maps”)
- **How we test and validate error models**
- **Fantastic Errors (“Exotics”)**
  - Leakage
  - Crosstalk
  - Intermediate measurements as processes
  - Drift  $\Leftrightarrow$  non-Markovianity
  - Context dependence
- **Where (and how) to find (and characterize) them**

# ERROR MODELING IN QEC

- QEC theory typically concerned with *lots* of qubits.  
Simple models — easy to calculate with — at a premium.

- Most common: *Pauli stochastic errors*.

- ➔ At each circuit location (gate),  
X or Y or Z happen with  
small probabilities  $p_x$ ,  $p_y$ ,  $p_z$ .  
Often  $p_x=p_z$  and  $p_y=p_z$  or 0.
- ➔ Very easy to simulate, calculate,  
and think about effects of errors.

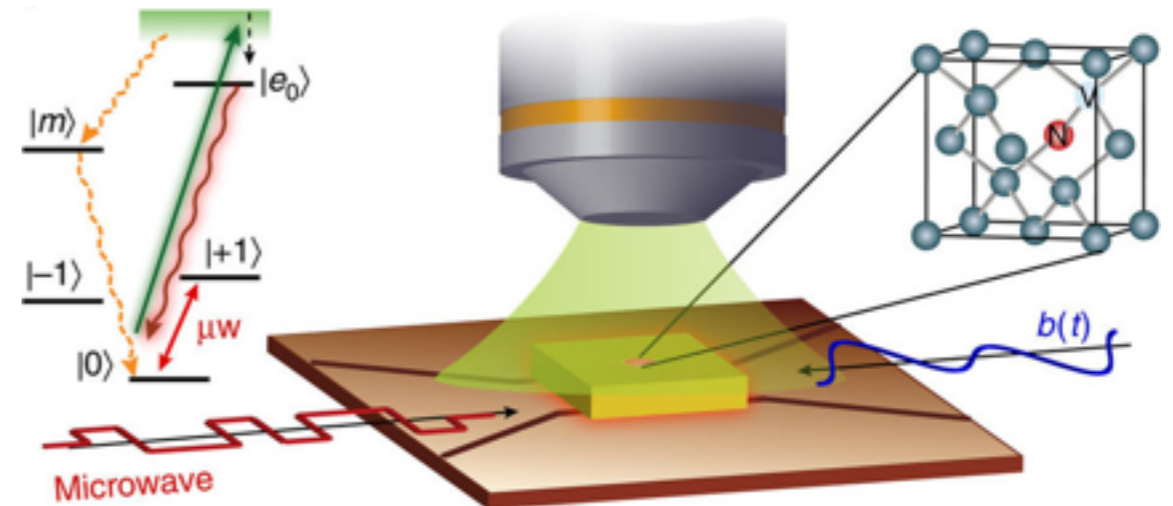


Credit: Martinis group

- Where is the dividing line between questions that this model represents well, and those where it fails. **We don't know.**
  - This model *probably* captures high-level truths about QEC.
  - This model is *never* accurate for individual circuits today.

# THE HAMILTONIAN MODEL

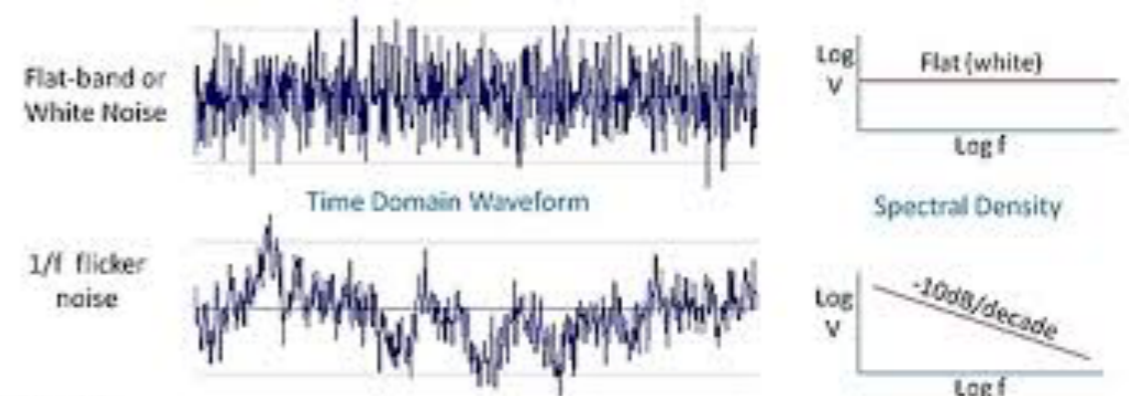
- Control theorists specify *parameters of Hamiltonians*.  
 $\implies$  all quantum evolution is described by Hamiltonians.



Credit: Nat. Comms. 5, 3141 (2014)

- So *noise* (causes errors) means the wrong Hamiltonian.
  - Implicitly/explicitly, expand around desired Hamiltonian  
 $\implies$  so  $\mathbf{H}=0$  corresponds to no noise, no errors.
- In this paradigm, the “stochastic” aspect of noise comes from  $\mathbf{H}$  *varying* (fluctuating) over time. Properties of noise are described by *correlation function* of Hamiltonian parameters at different times, and its *power spectrum*.

- $\langle \mathbf{H} \rangle \neq 0$  corresponds to *systematic* (coherent) errors.



# THE QUANTUM FUNDAMENTALIST'S MODEL (PROCESS MATRICES)

- The “gold standard” of error models: describe each gate by a  $d^2 \times d^2$  process matrix (CPTP map)  $G: \rho_{\text{init}} \rightarrow \rho_{\text{final}}$ .
- Process matrices have a reputation for *universality* (thanks to Stinespring’s theorem) — everything that can happen!
  - ➔ This is true in a sense — includes coherent errors, Pauli stochastic errors, amplitude damping (T1) decay, and various other things.
  - ➔ But... “*There are more things in heaven and earth,  
Horatio, than are dreamt of in your philosophy.*”  
—*Shakey Bill*
- The process matrix model of errors actually relies on a lot of assumptions — e.g. Markovianity — that aren’t true in real qubits.

$$G_1 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

$$\rho = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ 0 \\ \frac{1}{\sqrt{2}} \end{pmatrix}$$

# A TAXONOMY OF SMALL MARKOVIAN ERRORS

- The point of this talk is jump off from “standard” errors that are described by process matrices, and tackle “exotic” errors.
- First, though, I want to devote a little attention to the *Markovian* errors that are described by process matrices...

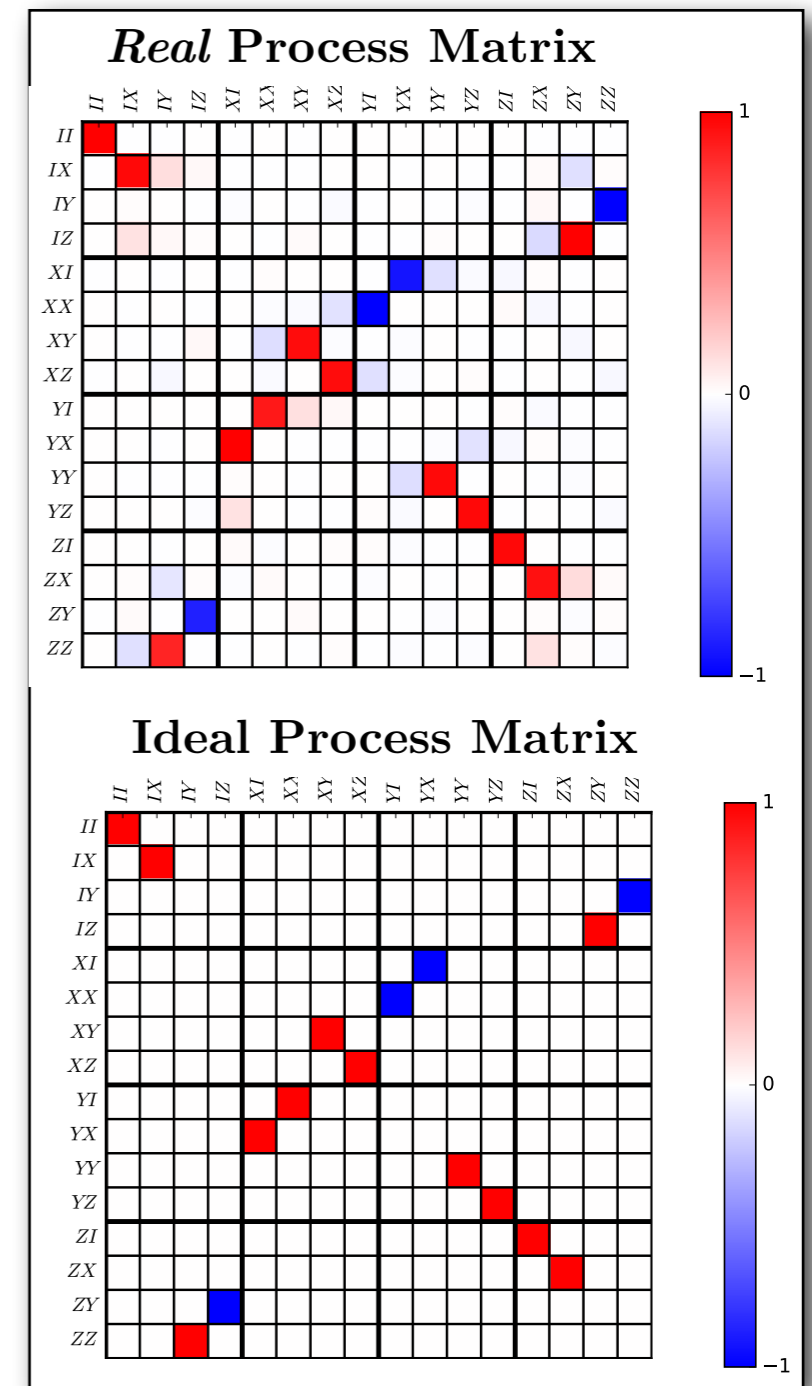
...because although in *principle* we understand process matrices completely, in *practice* it turns out that we don't.

- (Why do I know this? Because when we present folks with 2-qubit process matrices from GST, the invariable question is “So, what do all those numbers actually *mean*?”)

# A TAXONOMY OF SMALL MARKOVIAN ERRORS

- Suppose I show you a process matrix describing how a real, noisy gate acts on 1 or 2 qubits. How do you read it?

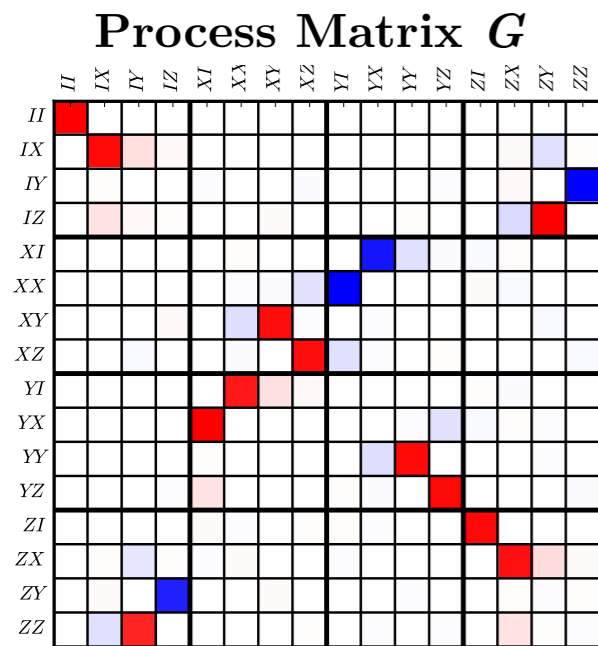
Gate	Superoperator (Pauli basis)
$G_i$	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 4 \times 10^{-5} & 0.9936 & -0.0023 & -0.0014 \\ 0.0003 & 0.0023 & 0.9948 & -0.0006 \\ -0.0002 & 0.0011 & 0.0017 & 1 \end{pmatrix}$
$G_x$	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ -0.0001 & 1.0003 & 0.0052 & -0.0023 \\ 5 \times 10^{-5} & 0.0029 & -0.005 & 0.9967 \\ -5 \times 10^{-5} & -0.0001 & -0.9967 & -0.0091 \end{pmatrix}$
$G_y$	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 5 \times 10^{-5} & -0.0001 & 0.0058 & -0.9949 \\ 3 \times 10^{-5} & 0.0034 & 1.0004 & -0.0007 \\ 5 \times 10^{-5} & 0.9949 & -0.0017 & -0.003 \end{pmatrix}$



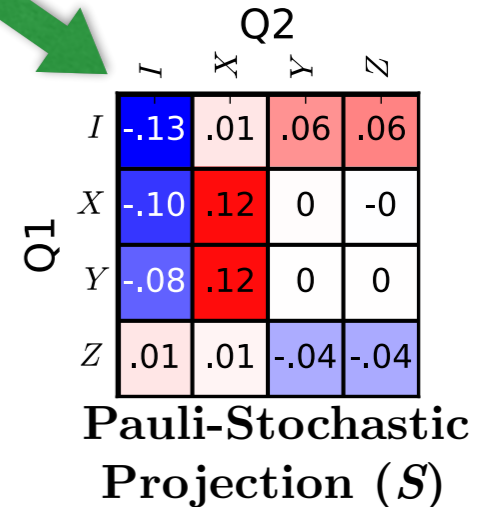
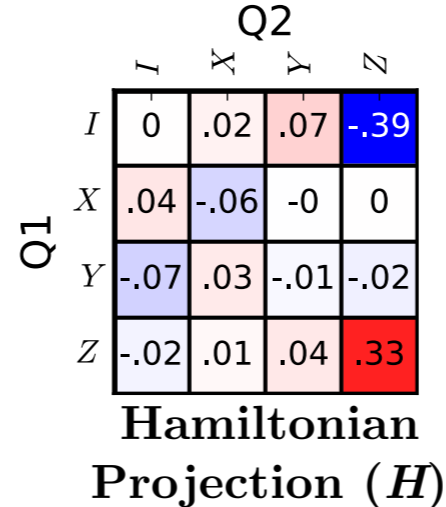
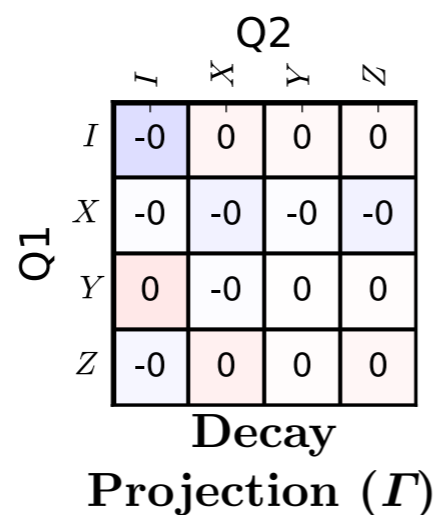
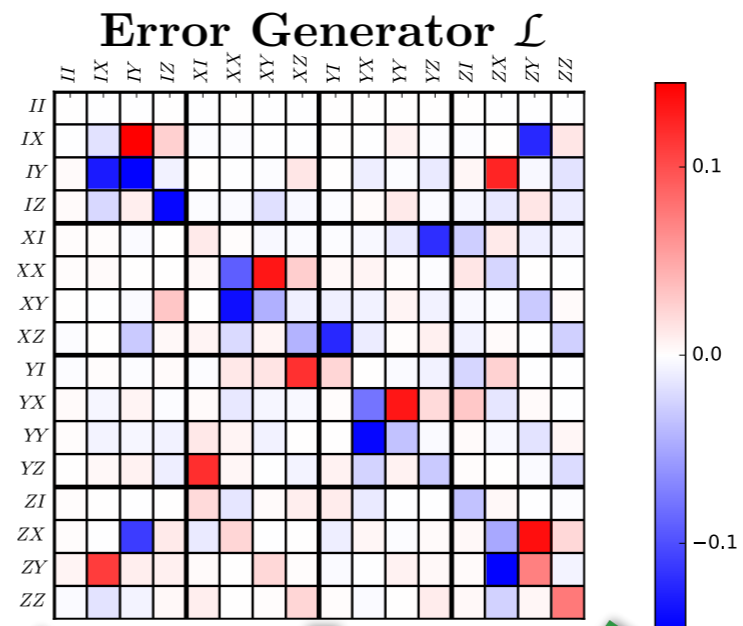
- A good start: ***Kueng et al, PRL 117, 170502 (2016)***

# A TAXONOMY OF SMALL MARKOVIAN ERRORS

1. Map *processes* to *error generators*. They form a *semi-algebra*.
2. Split the generator space into *meaningful subspaces*.

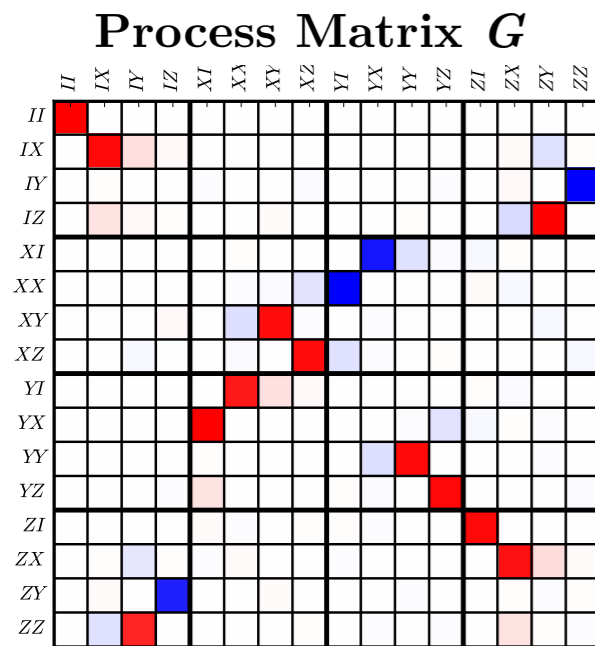


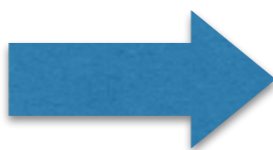
$\mathcal{L} \equiv \log(G_0^{-1}G)$

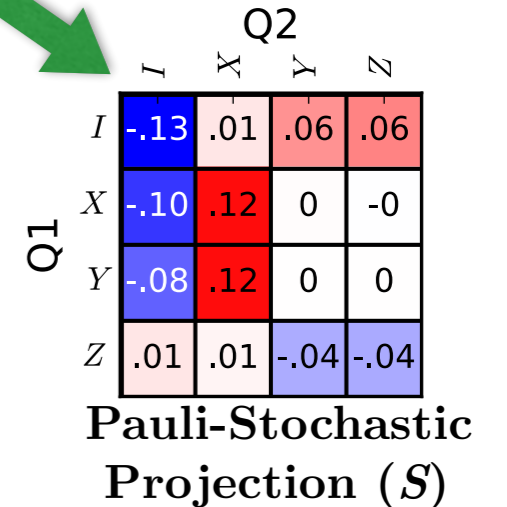
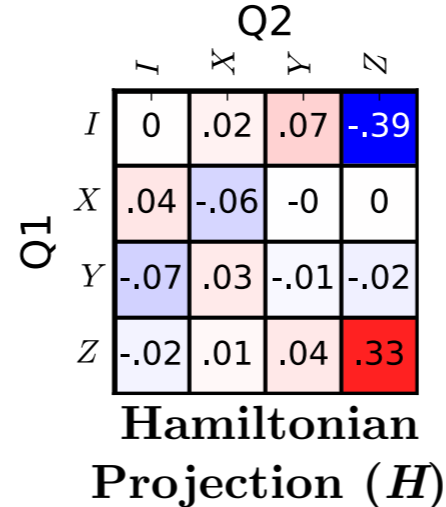
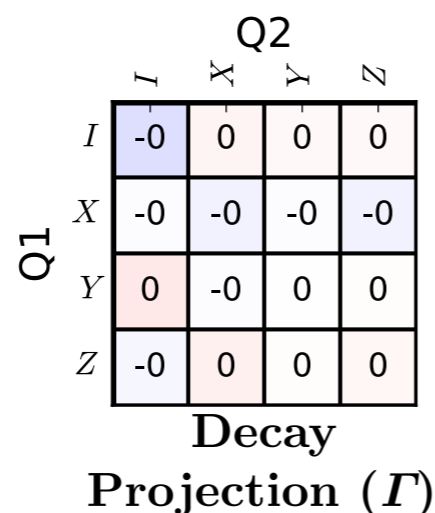
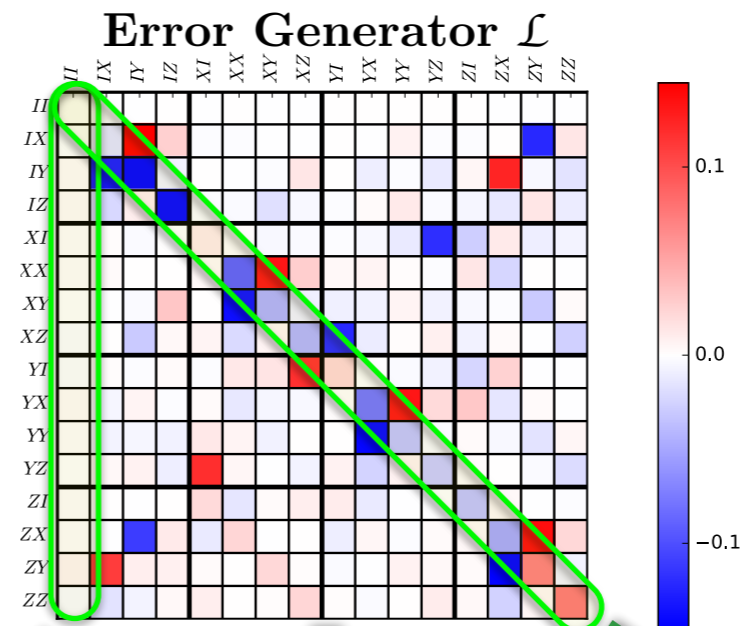


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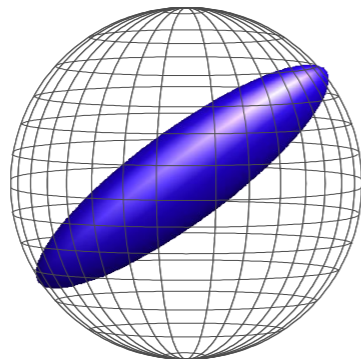


  
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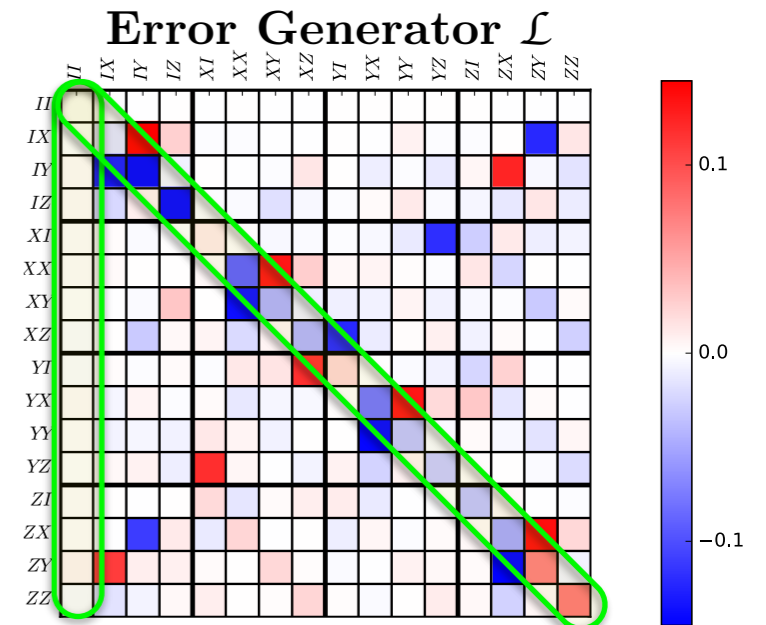


# A TAXONOMY OF SMALL MARKOVIAN ERRORS

- 240 parameters  $\Rightarrow$   $3 \times 16 = 48$  parameters.  
So what's left (in those 192 params)?
- *Note: often, the magnitude of what's left is negligible — whatever it is, doesn't happen!*
- About 105 of them describe *non-Pauli stochastic errors*.



- We're still figuring out what errors the other 87 params represent.



**Decay Projection ( $\Gamma$ )**

	I	X	Y	Z
I	-0	0	0	0
X	-0	-0	-0	-0
Y	0	-0	0	0
Z	-0	0	0	0

**Hamiltonian Projection ( $H$ )**

	I	X	Y	Z
I	0	.02	.07	-.39
X	.04	-.06	-0	0
Y	-.07	.03	-.01	-.02
Z	-.02	.01	.04	.33

**Pauli-Stochastic Projection ( $S$ )**

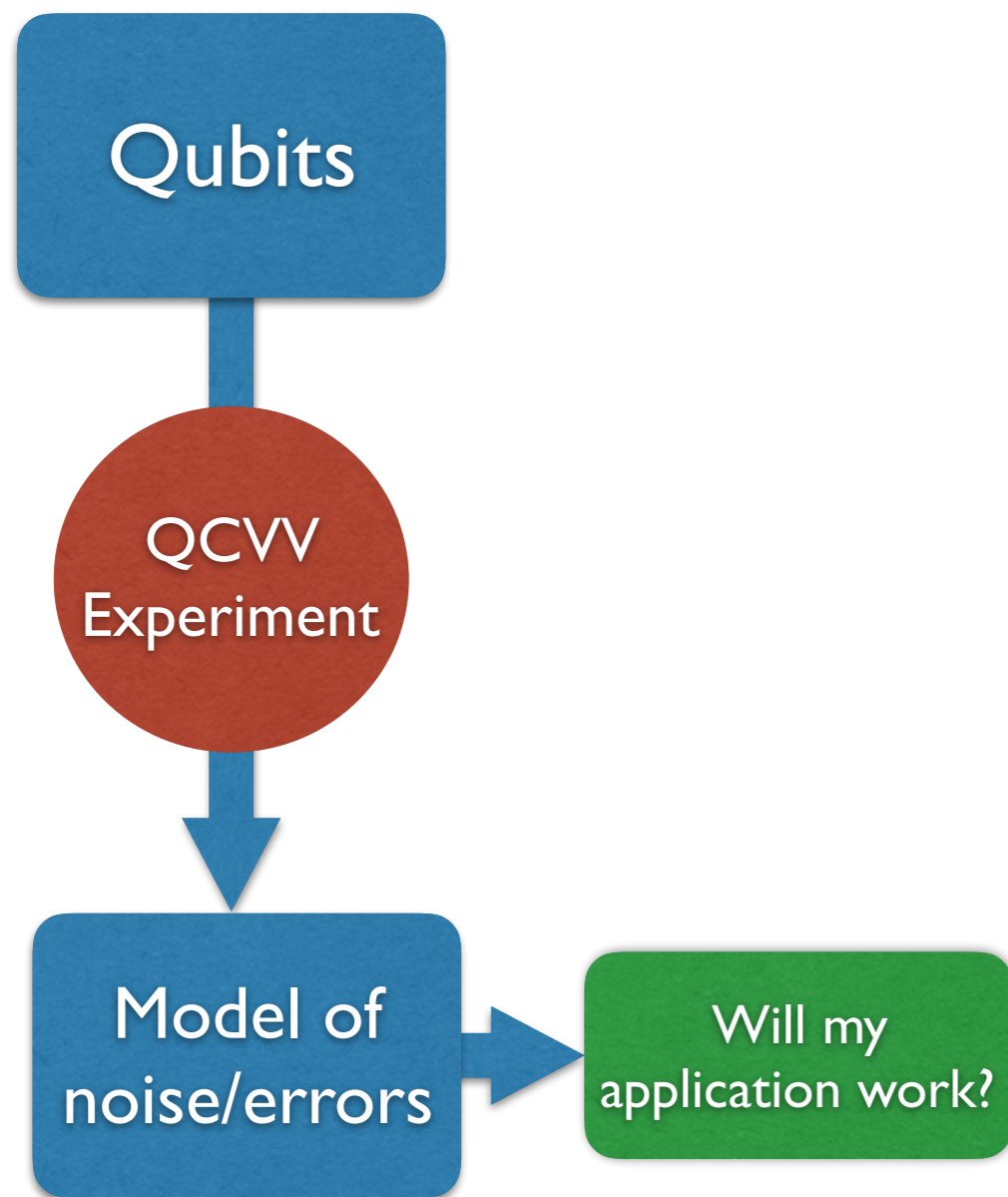
	I	X	Y	Z
I	-.13	.01	.06	.06
X	-.10	.12	0	-0
Y	-.08	.12	0	0
Z	.01	.01	-.04	-.04

# TESTING & VALIDATING ERROR MODELS

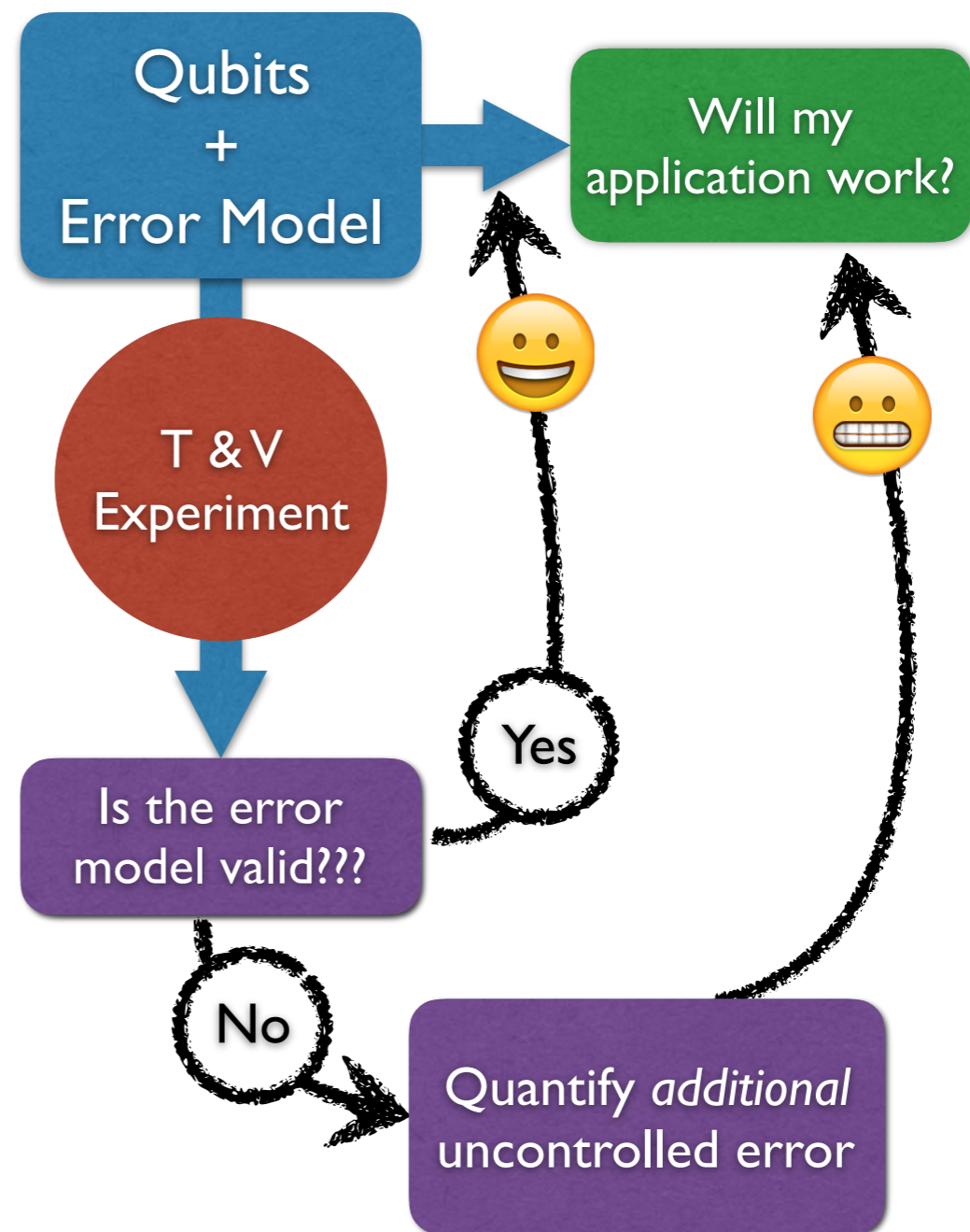
- Processors should come with an error model — part of the “spec”!  
==> Then users can use that model to predict performance:
- There are lots of valid ways to *build* an error model
  - RB, GST, other QCVV techniques
  - theory, etc.
- What we need is a systematic way to *test* (validate) them.
  - Where the model came from isn't our concern
  - Whether it works (predicts results accurately) *is*.

# TESTING & VALIDATING ERROR MODELS

## Characterization

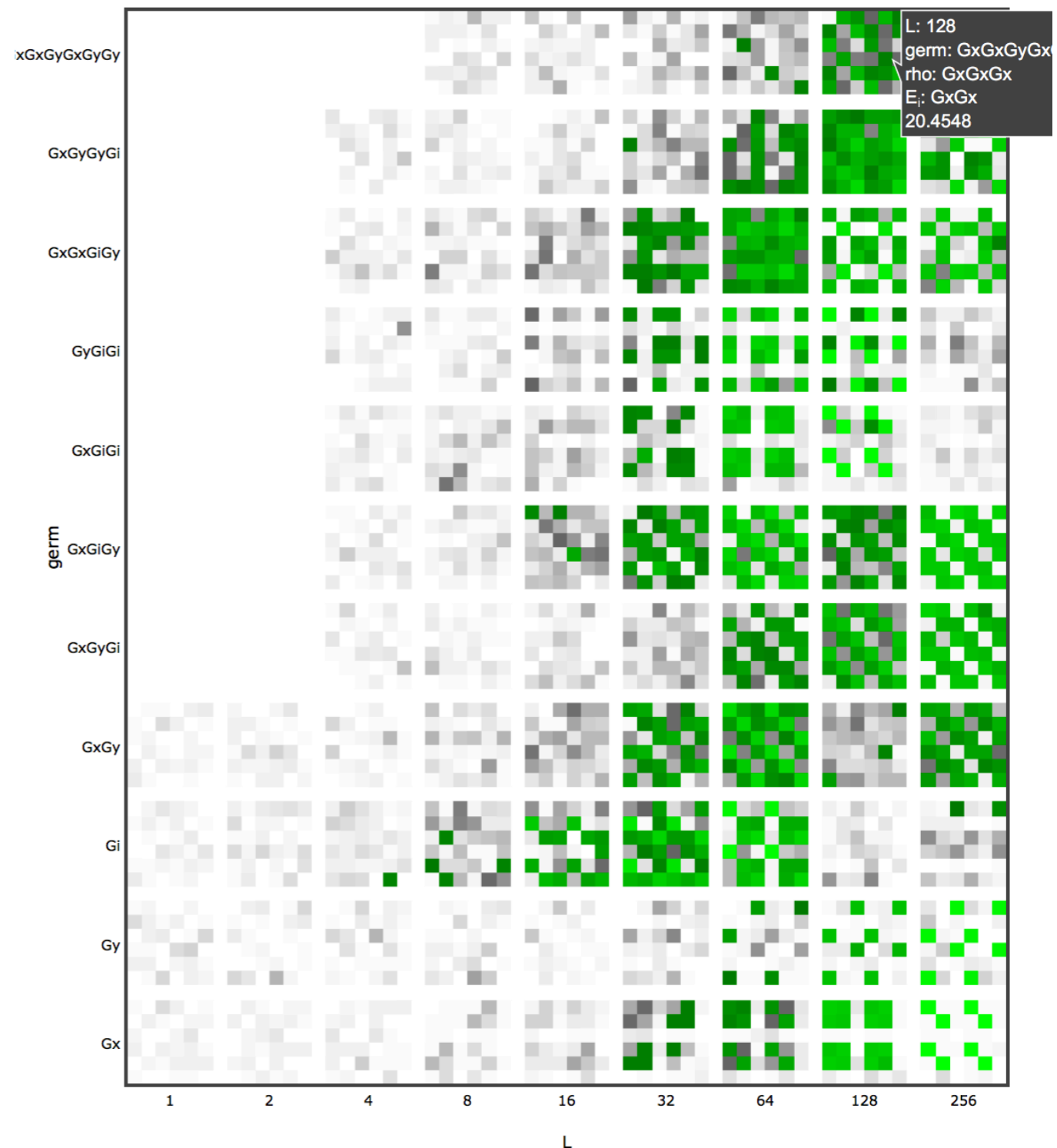


## Testing & Validating



# TESTING & VALIDATING ERROR MODELS

- Run test suite of circuits.
- Record counts.
- Predict probabilities w/model.
- Compare data to predictions.
- Are there any statistically significant differences?
- YES: quantify “extra” error.
- NO: model validated; establish upper bound on possible undetected extra error.

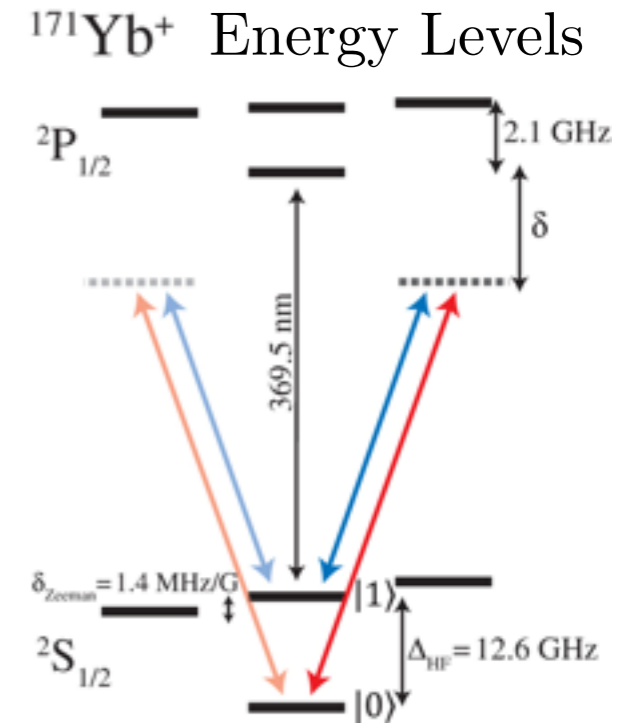


# WHY STUDY EXOTIC ERRORS?

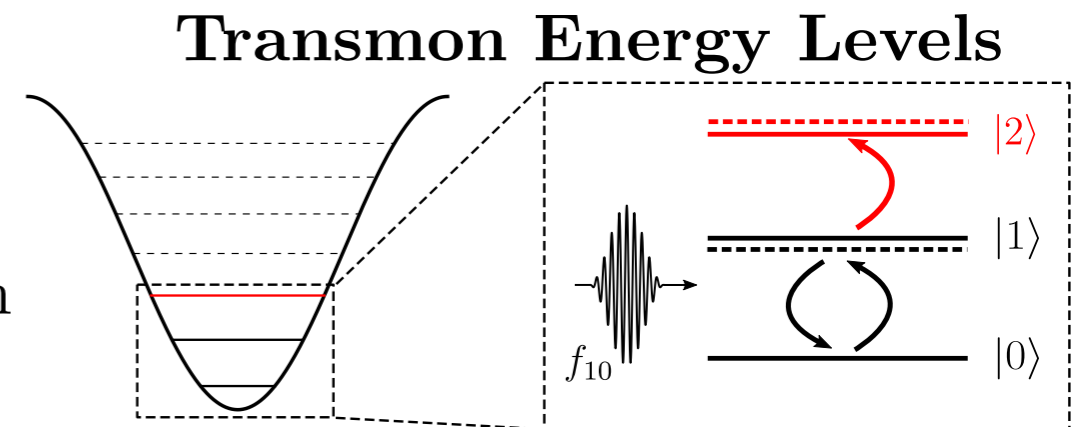
1. Because when we test the process matrix model (this is intrinsic to GST with PyGSTi), it's not generally valid!
2. Because theorists and qubit designers *expect* other errors.
3. Because QEC theorists are {very/slightly} worried about them.
4. Because sometimes these things crop up totally unexpectedly (e.g., context-dependent gates), and we have no idea in advance what's going on or whether it's going to be significant
5. **Because our goal is to completely understand — and predict — the observed behavior of quantum processors.**



# LEAKAGE



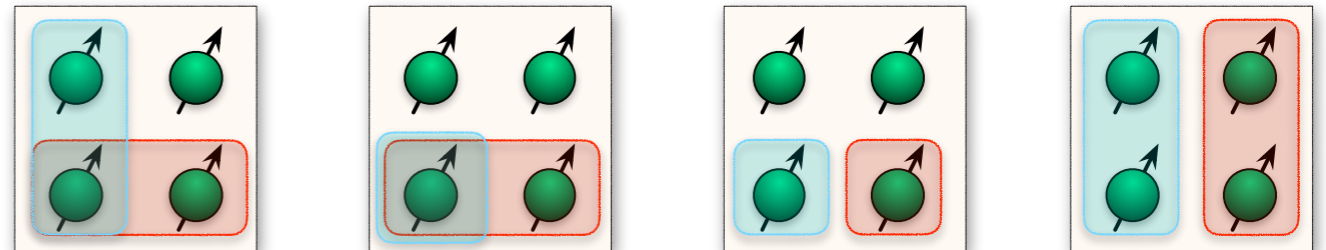
- Leakage: Basically, your qubit isn't actually a qubit — there are other states, and for whatever reason it ends up there.
- Leakage turns out to be surprisingly tricky *conceptually*. Why?
  1. It can be either *visible* (SC qubits) or *invisible* (ions).
  2. Everybody tends to think about it from a *modeling perspective*, rather than a *phenomenological* perspective. We can't see Hilbert space!
- Our best thinking: The most reliable way to detect and define leakage is **“The qubit has leaked iff my gates stop working [as well as they did before it leaked].”**
- This leads to pretty deep ambiguity between “leakage” and “non-Markovian decoherence”.





# CROSS-TALK

- Everybody knows what crosstalk is — except it can mean several different things.
- *Operation crosstalk*
  - Operations on *target qubits* cause action on *spectator qubits*.
  - Could be dependent on target state (entangling crosstalk).
  - Includes intermediate measurement (not just gate) operations.
- *Detection crosstalk*
  - Result of measuring *target qubit* influenced by *spectator qubit*.
- *Idle crosstalk*
  - Unwanted always-on entangling interaction.
- General: **The results of an operation depend on a variable or context that they should not depend on.**



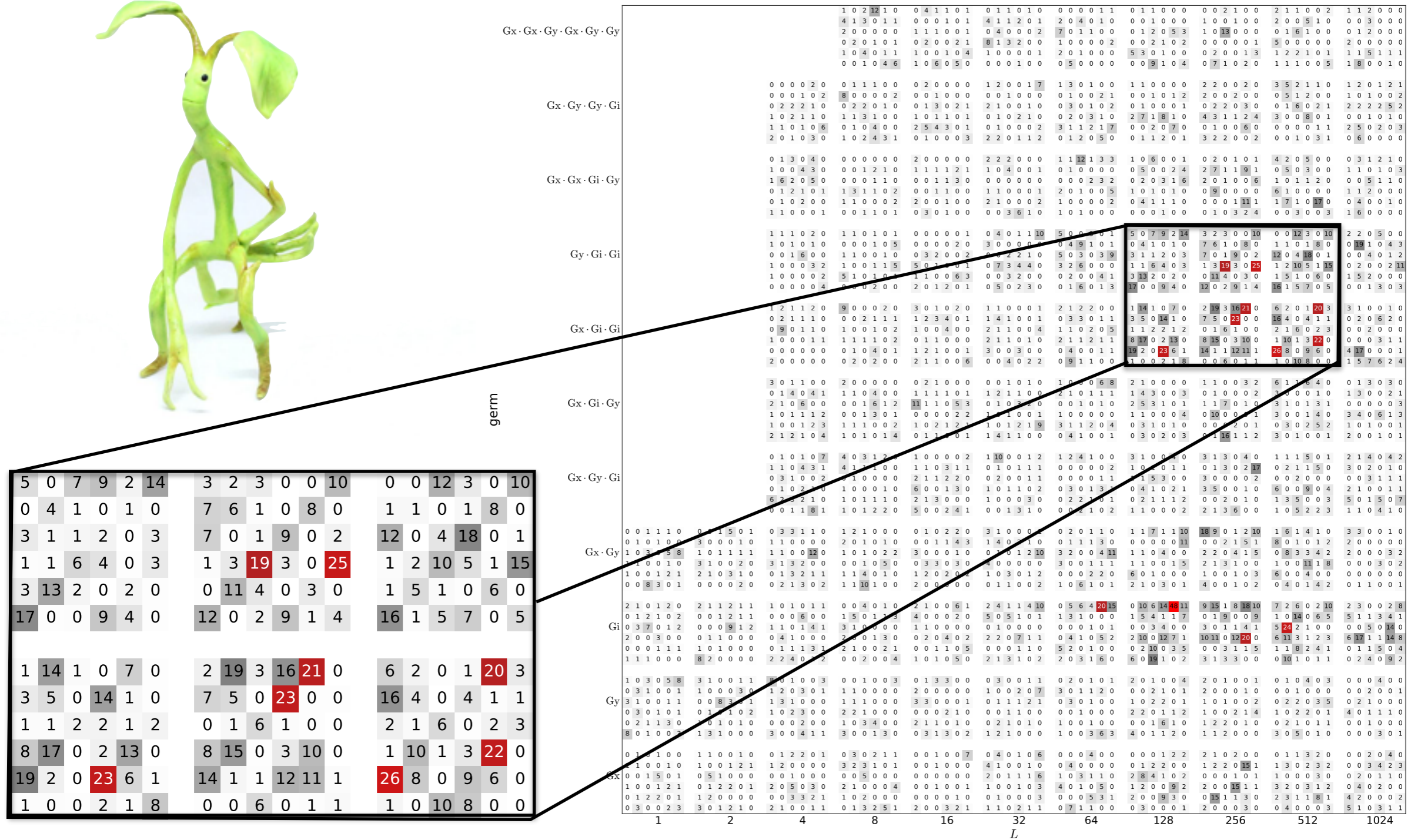


# INTERMEDIATE MEASUREMENTS

- This isn't technically "an error" — the point is simply that measurements are going to happen *in the middle of circuits*, not just at the end, as occurs in the traditional "SPAM" setup.
- Intermediate measurements aren't described by POVMs — that only tells you the *outcome probabilities*, not the *post-measurement state*.
- Instead, describe measurements by *Completely Positive Trace-Reducing (CPTR) Map-Valued Measures* (CPTRMVMs).
  - ==> not a set of *effects* (positive operators) that sum to identity
  - ==> instead, a set of *conditional channels* that sum to a CPTP map.
- Now we can do tomography (GST) on those channels.

# DRIFT

Why do we see GST data inconsistent with *any* process matrices?





# DRIFT

- Why do we see data inconsistent with *any* process matrices?
- Lots of potential *non-Markovian* effects could cause it...  
...but we suspect the main cause is plain ol' boring *drift*.
  - Gates *are* representable by process matrices — but the process matrix changes (slowly) over time.
  - Mostly Hamiltonian parameters (coherent errors) drift over time, but incoherent parameters can drift too ( $T_1$ ).
- We can try to adjust GST to deal with this... but it would be better to confront drift head-on and characterize it *directly*.
- Drifting parameters may drift slowly — but they should *not* be correlated with gates, states, etc (that's crosstalk)



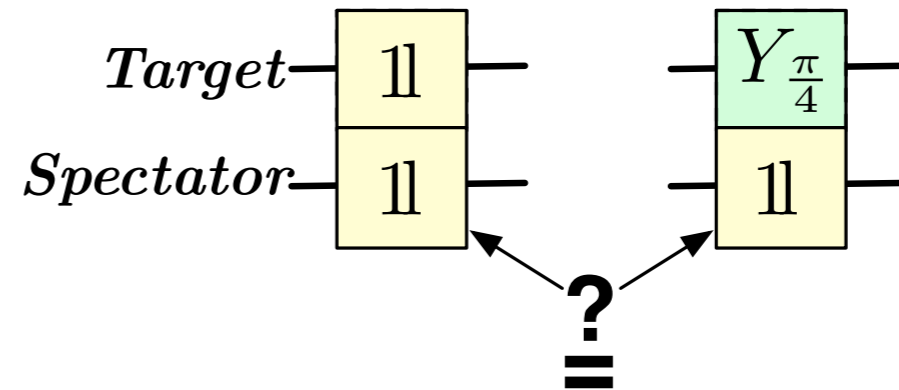
# CONTEXT-DEPENDENCE

- The other main type of non-Markovianity we've seen is *context-dependent gates*.
- Context dependence is pretty general — e.g., time is an example of a context (on which gates shouldn't depend).
- But we mean specifically: When the effect of a gate depends on what gate occurred immediately before it.
- Examples we've observed:
  - $X_{\pi/2}$  gates consistently under-rotate after a 2-qubit gate.
  - *Idle* gates are small Z rotations iff they follow an  $X_{\pi/2}$  gate.
  - Every gate is terrible whenever it follows a *different* gate.



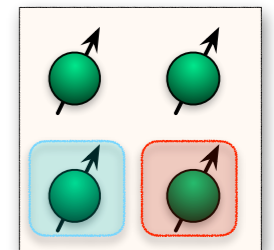
# TESTS FOR CROSS-TALK

- Focus: *operation crosstalk*.



- Basic idea:

- **Q:** Does effect of a gate on *Spectator* vary depending on whether we do some gate to *Target* at the same time?



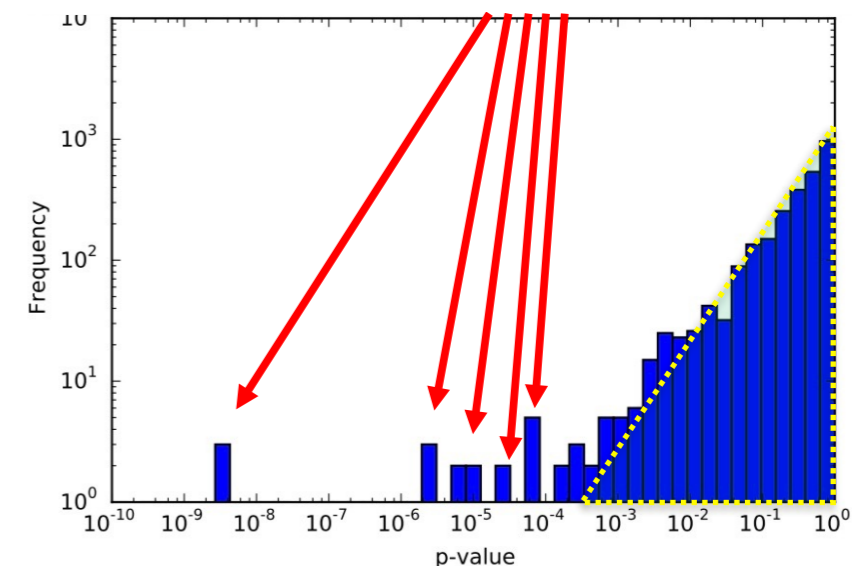
- **A:** Study behavior of *Spectator* *with & without* “driving” *Target*.

- IBM’s *simultaneous RB* is an example of this kind of protocol.

- We do *cross-GST* experiments to tomograph gates in both contexts

- But instead of tomographic reconstruction, we do simple statistical tests to ask:

“Are all of these experiment pairs consistent with each other?”





# TESTS FOR CONTEXT-DEPENDENCE

- We can *test* for context dependence the same way as any other non-Markovianity — do GST, look for model violation.
- To distinguish it from other effects, we enlarge our model by letting the gates depend on context, and see if that fits better.
- **Example:** Gateset  $\{G_I, G_X, G_Y\}$ . We suspect  $G_I$  is context-dependent.
  1. Introduce a new gate  $G_{I2}$ .  $\implies$  gateset  $\{G_I, G_{I2}, G_X, G_Y\}$ .
  2. For each circuit run, rename all  $G_I$  after a  $G_X$  or a  $G_Y$  to “ $G_{I2}$ ”.

$$\boxed{G_I - G_X - G_I - G_I - G_Y - G_I - G_I} \implies \boxed{G_I - G_X - G_{I2} - G_I - G_Y - G_{I2} - G_I}$$

3. Rerun GST analysis to fit  $G_I$  and  $G_{I2}$ .
4. If the fit is significantly better, we've identified evidence for context dependence — *and* have an estimate of how  $G_I$  depends on context.

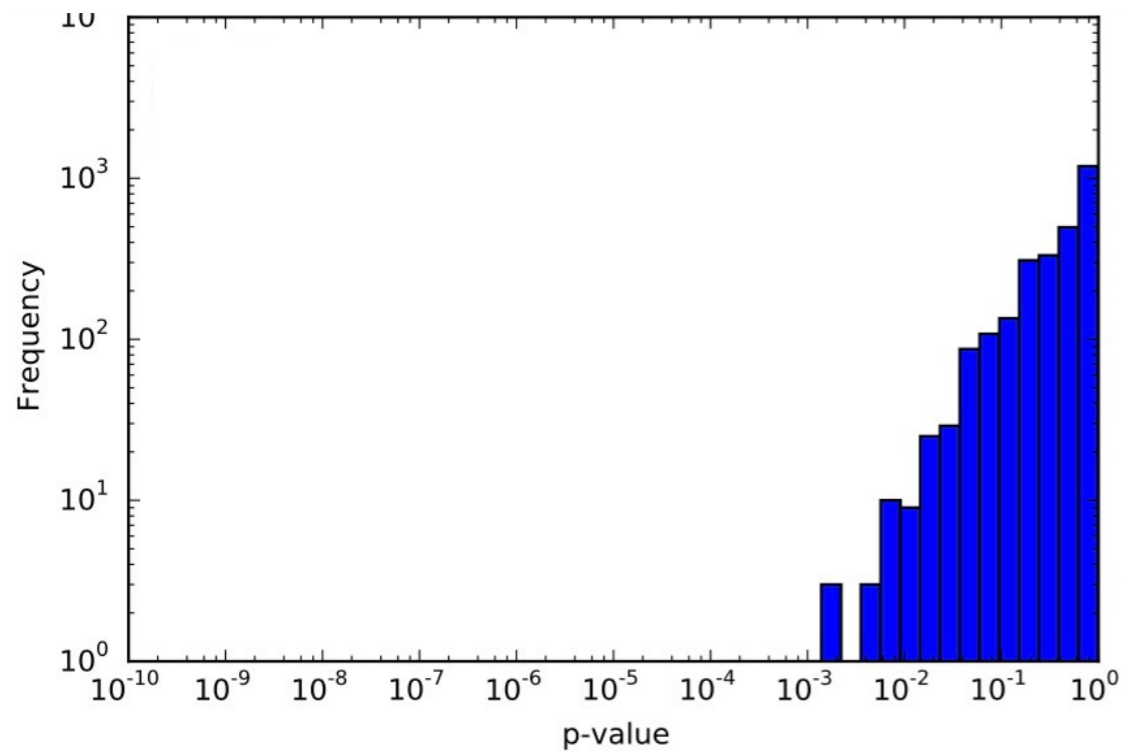


# TESTS FOR DRIFT

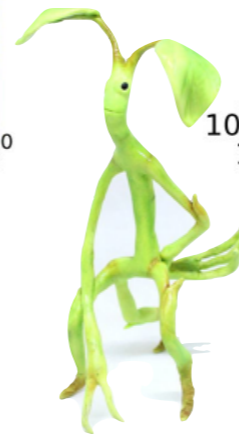
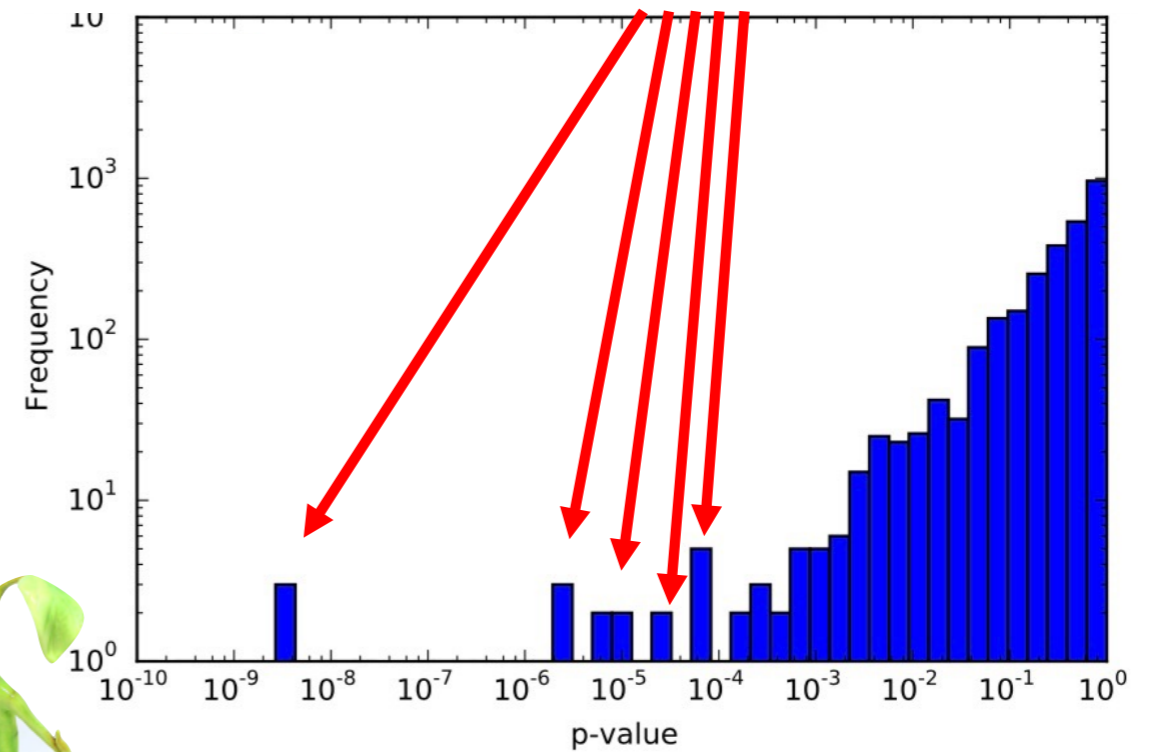
- Lots of ways to study time-correlated noise (drift).  
But we want to integrate our analysis as closely as possible with RB, tomography, QEC, etc.  
==> same kind of data (circuits  $\longrightarrow$  counts).
- Standard practice: *binned* counts  
==>  $N$  repeats of each circuit yield just  $\{n, N-n\}$ .
- For drift detection, we've considered two variants:
  - *Chunked* data:  $n/KN \implies \{n_1/N, n_2/N, \dots, n_K/N\}$   
==> (same analysis as for crosstalk)
  - *Rastered* data:  $n/N \implies \{0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0 \dots\}$

# TESTS FOR DRIFT CHUNKED DATA

Simulated GST data  
Two data sets, no drift



Experimental GST data  
Two data sets, signs of drift





# TESTS FOR DRIFT

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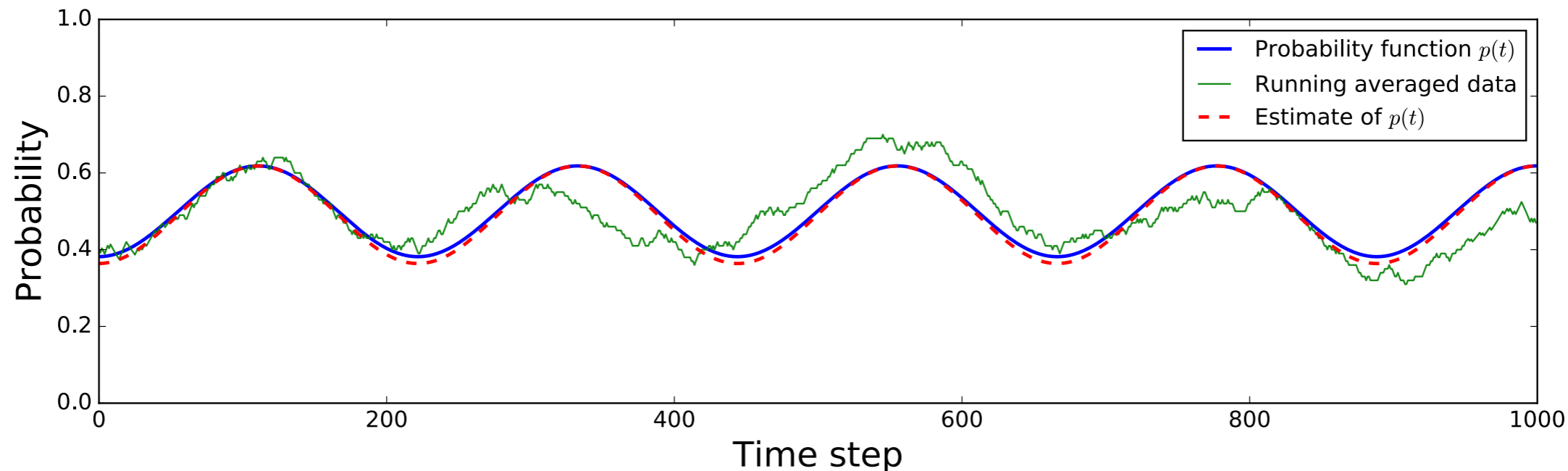
# TESTS FOR DRIFT RASTERED DATA

- For rastered/time-stamped data, we can use model selection to see whether a simple model for  $Pr(t)$  fits the counts “surprisingly well”.
  - Various simple models — with few parameters — are possible.
    - (low-frequency, piecewise constant, 60Hz, etc...)
  - However, a nice generic model for many drifts (esp. samples from stationary stochastic processes) is *Fourier-sparse functions*.
    - Slow drifts  $\iff$  low-frequency  $\implies$  sparse
    - 60Hz can be “fast”, but is still Fourier-sparse
- 
- **Analysis method:** (1) Fourier transform the count data *directly*.  
(2) Throw out low-power components that are statistically consistent with constant  $Pr(t)$ .

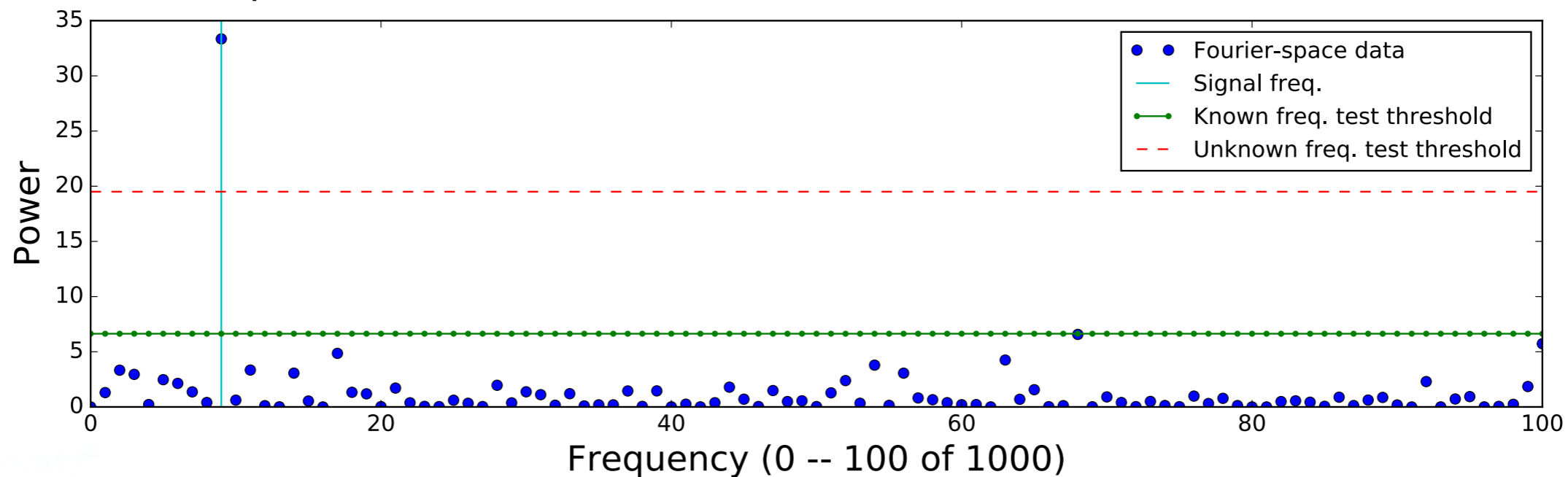


# DRIFT EXAMPLE 1: A SINGLE FREQUENCY

Monochromatic drift

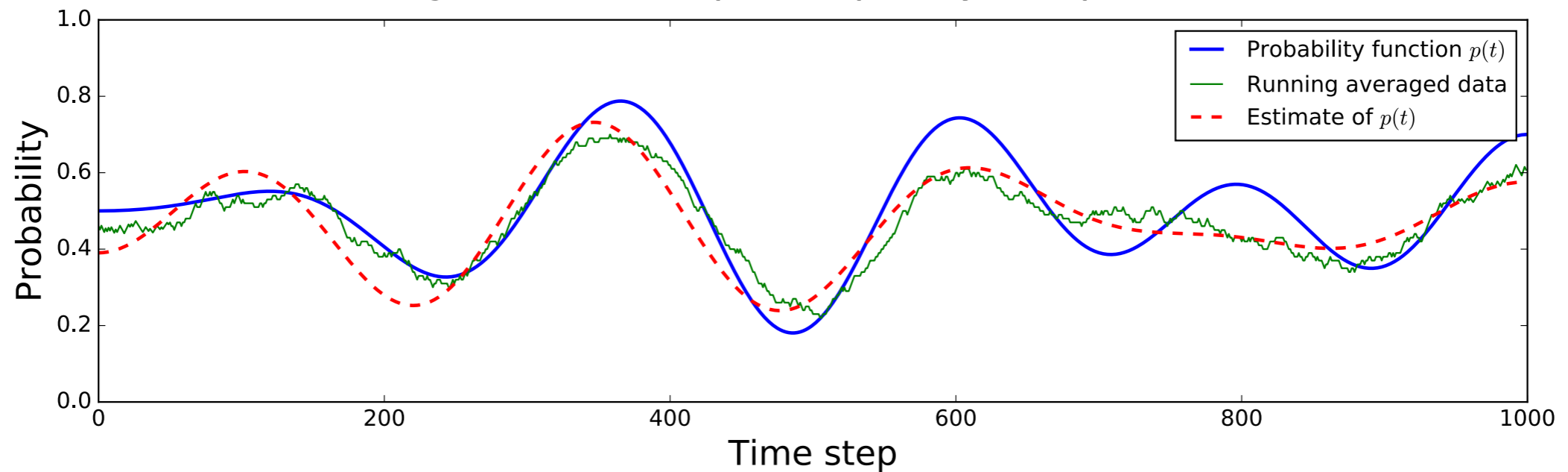


Power spectrum for monochromatic drift (tests at confidence level 0.99)

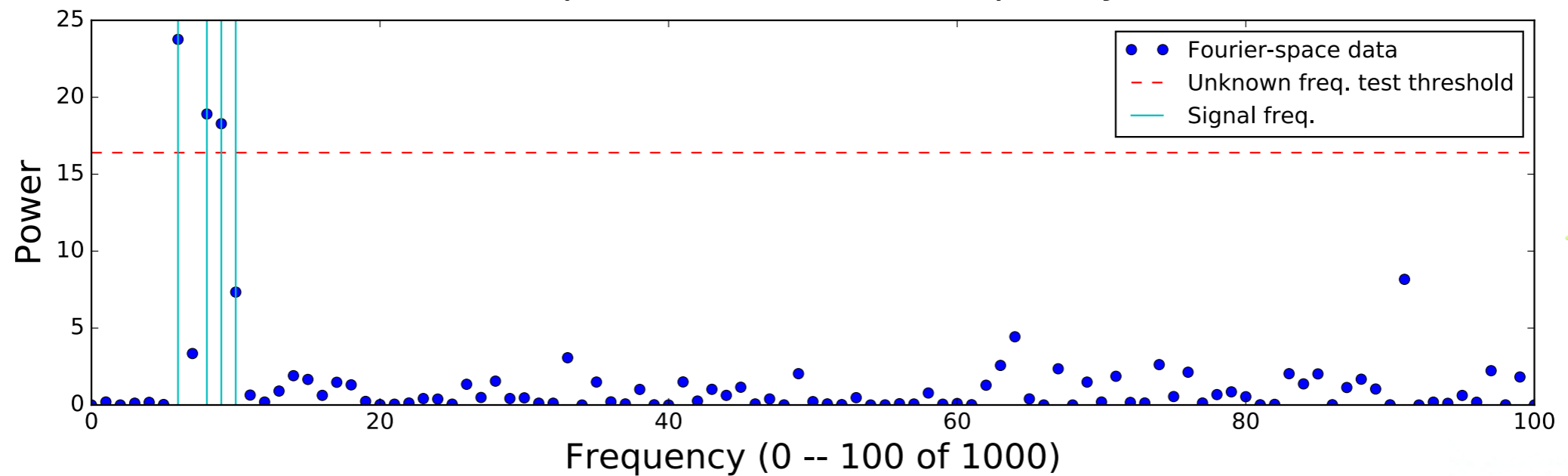


# DRIFT EXAMPLE 2: MULTIPLE FREQUENCIES

Signal with Multiple frequency components

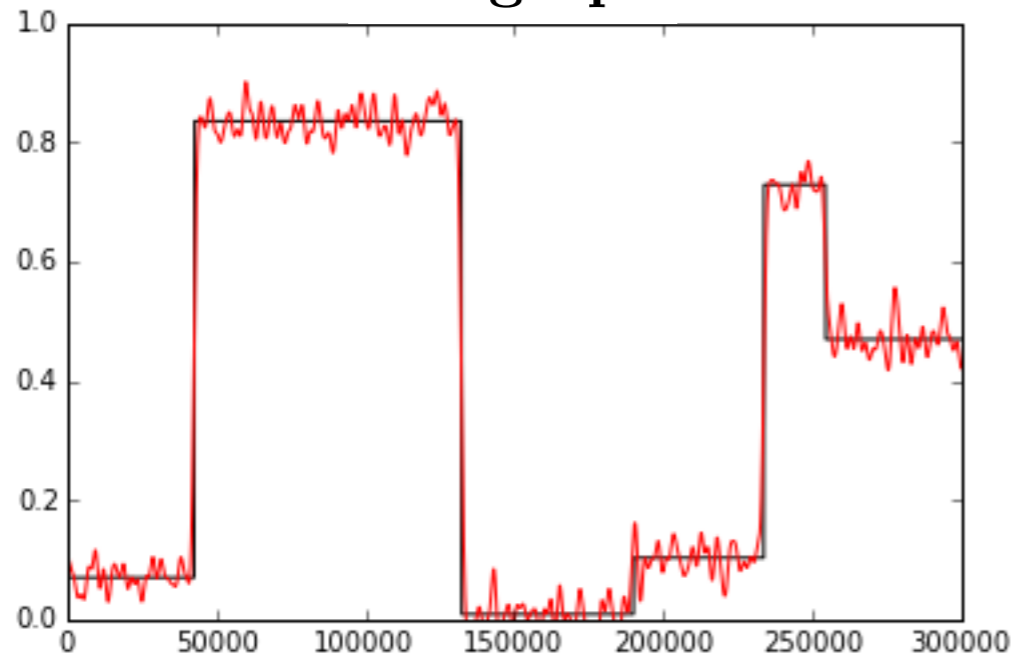


Power spectrum for multi-frequency drift

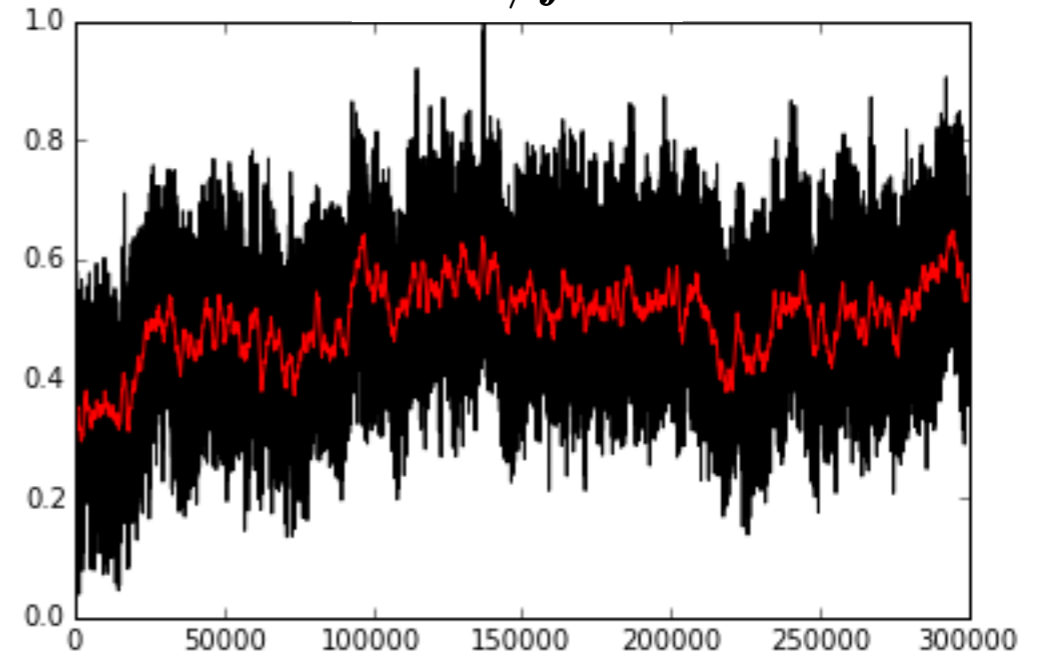


# DRIFT EXAMPLE 3: SIMULATED NOISE PROCESSES

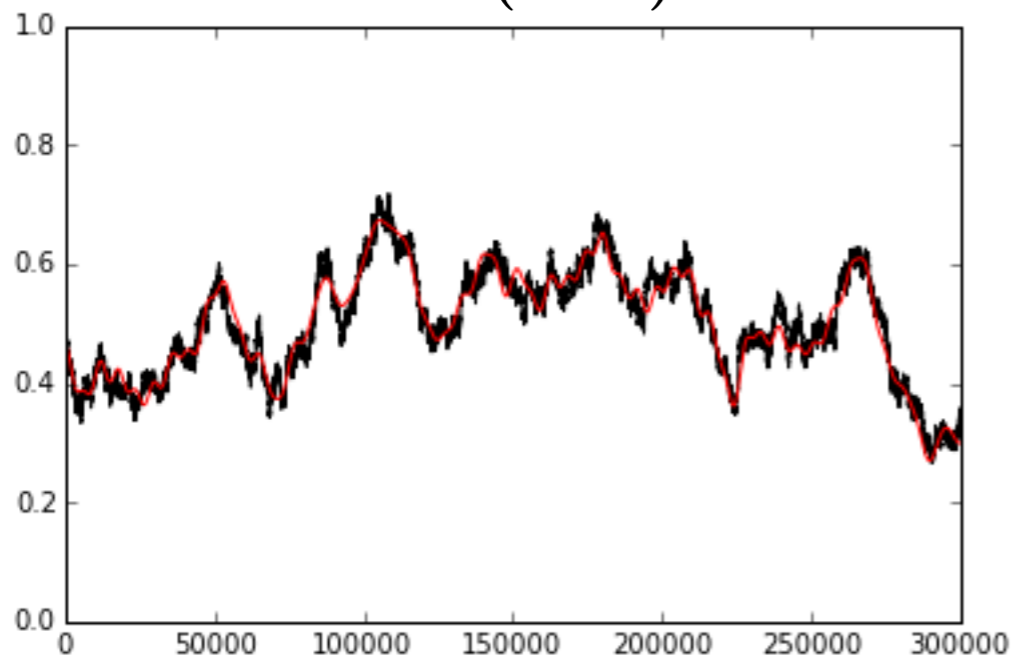
Telegraph



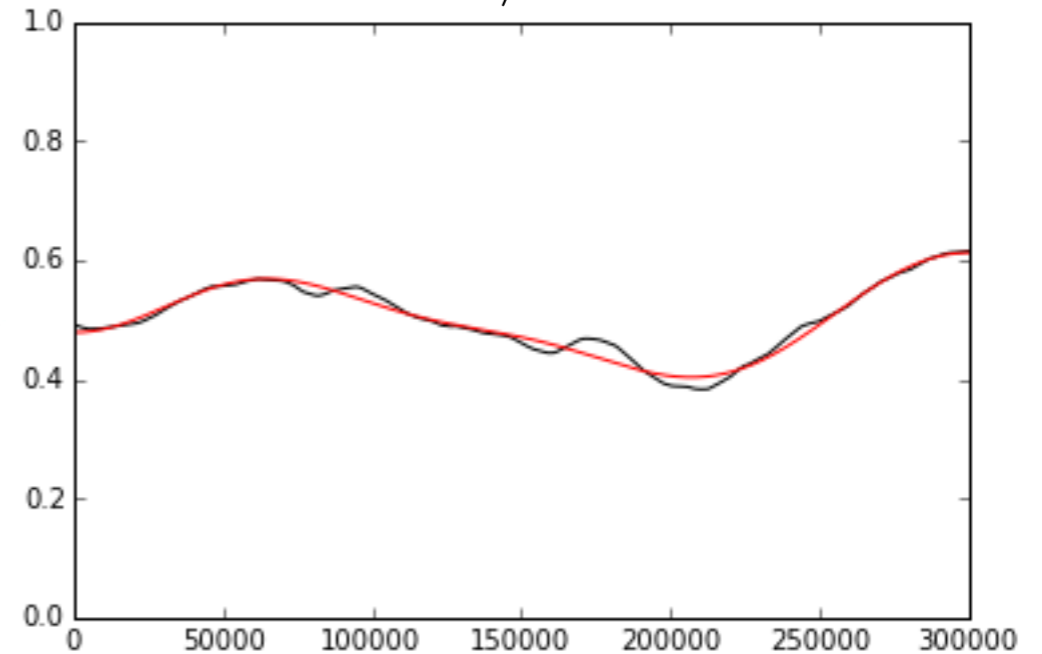
$1/f$



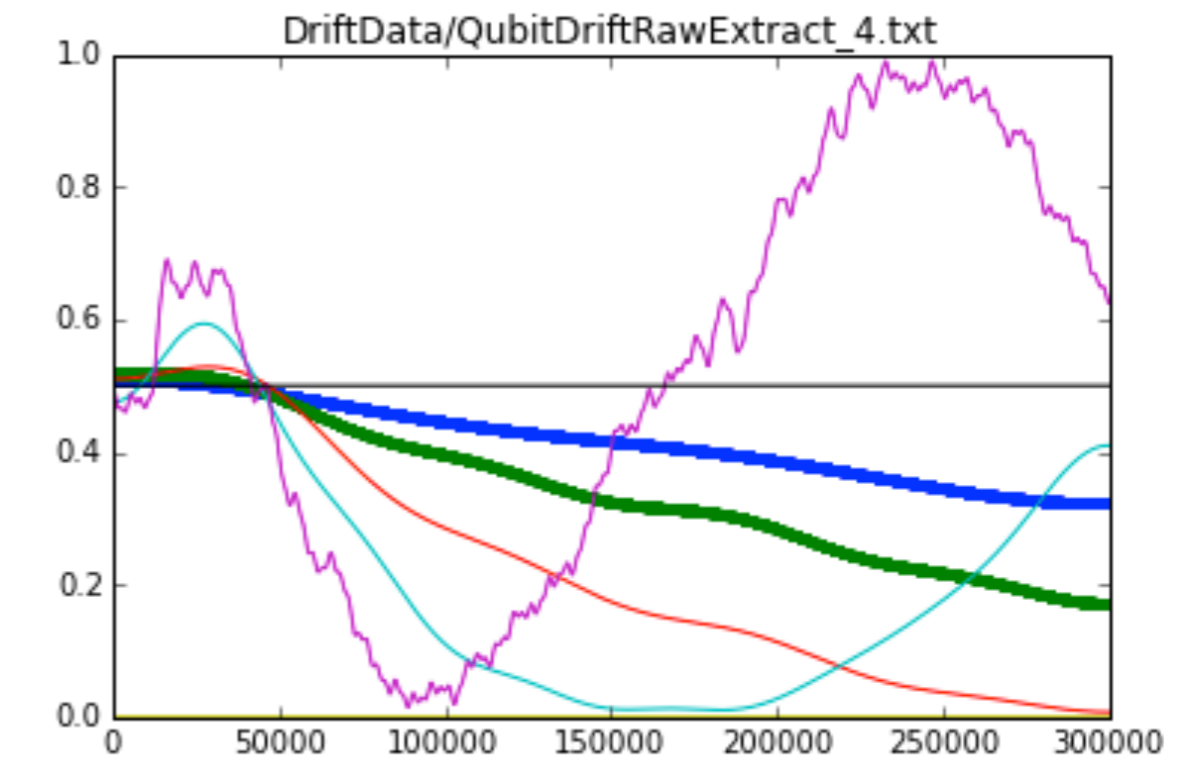
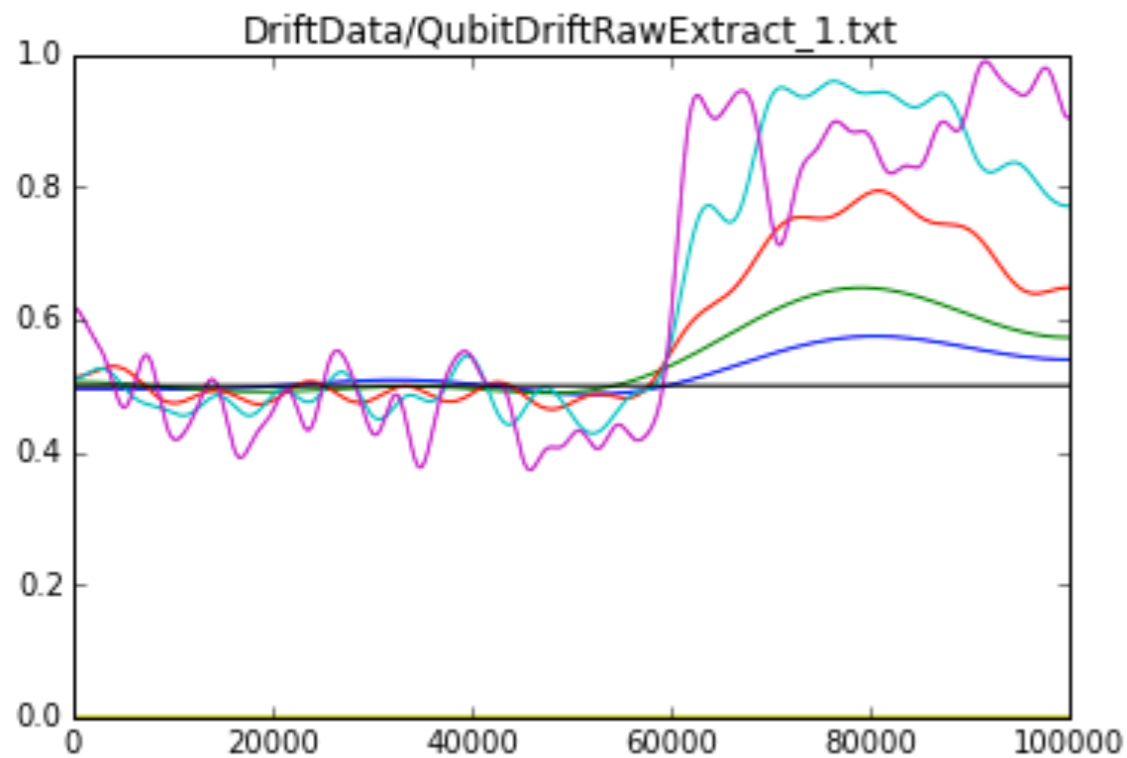
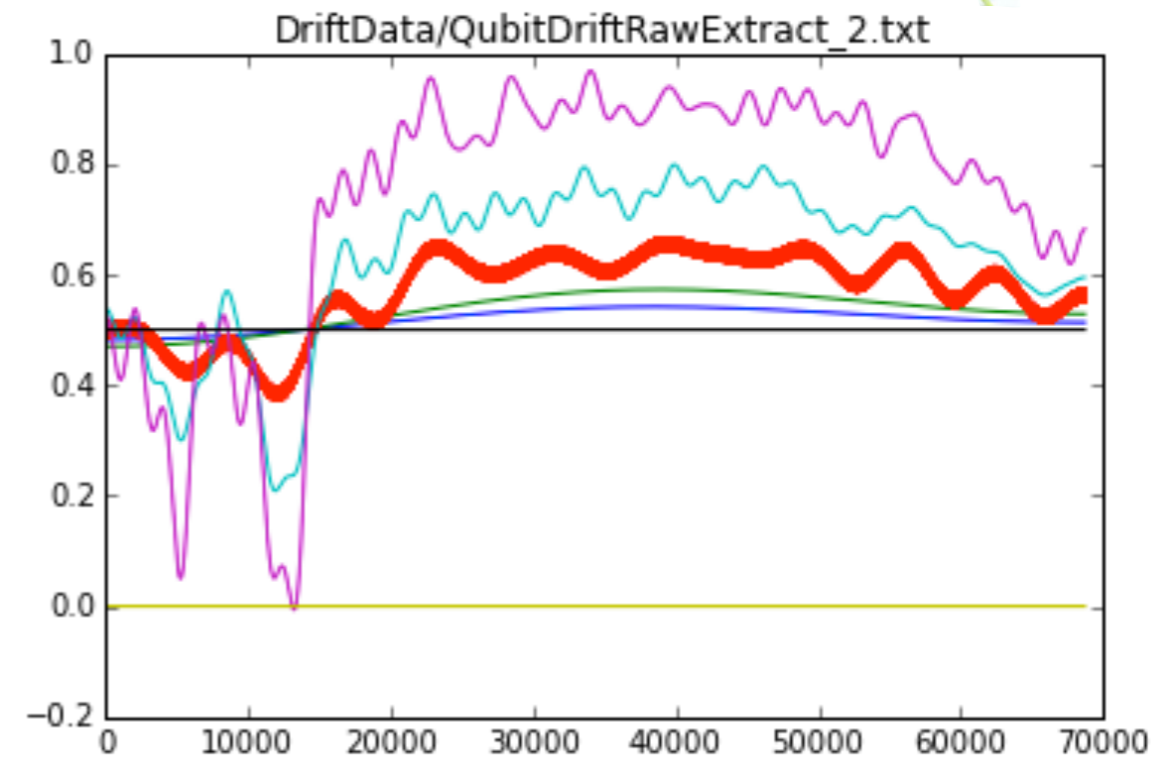
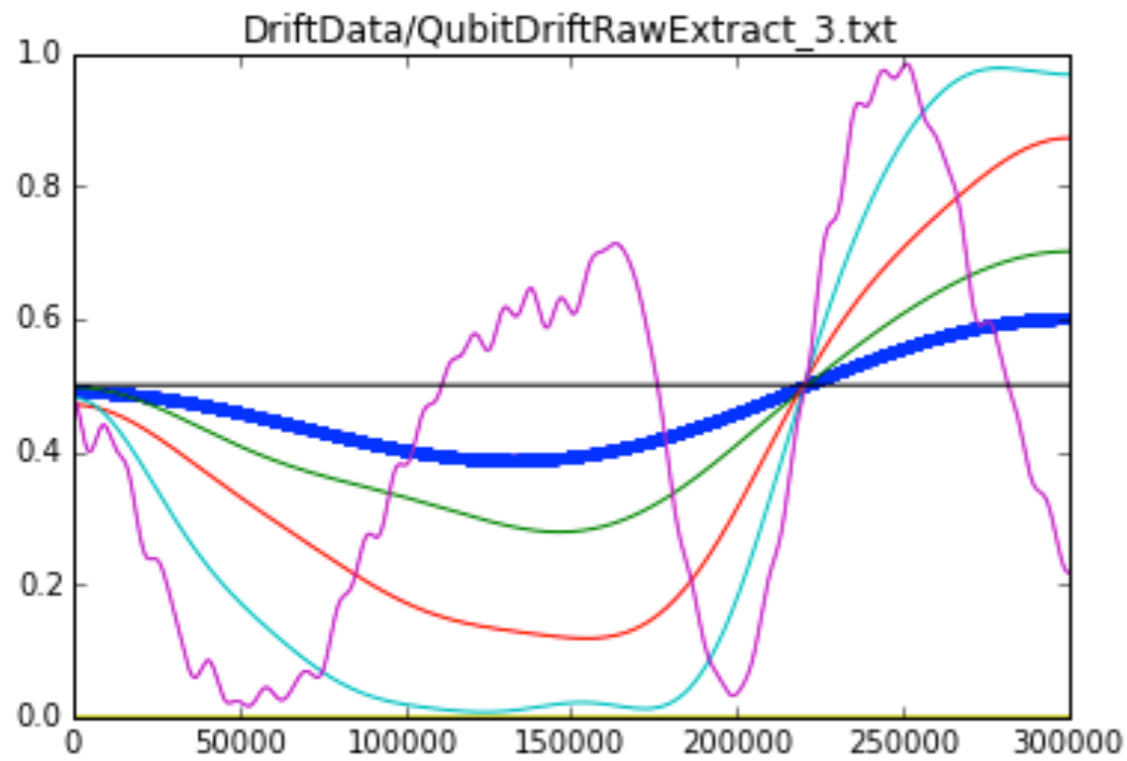
Brownian (O-U) noise



$1/f^4$



# DRIFT EXAMPLE 4: EXPERIMENTAL DATA



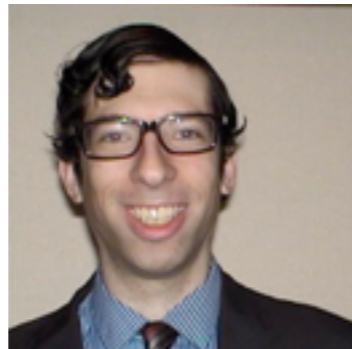
# ACKNOWLEDGMENTS



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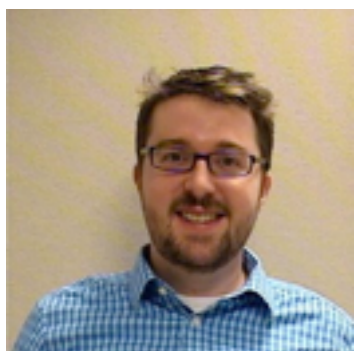
LogiQ



Erik Nielsen



Kevin Young



John Gamble



Peter Maunz



Mohan Sarovar



QCVV

