

# Sandia theory updates

*detecting crosstalk, drift, context dependence*

*pyGSTi updates*

Robin Blume-Kohout, Erik Nielsen,  
Tim Proctor, Kenny Rudinger, Kevin Young

# Outline

- Detecting differences between datasets
  - Depending on experiment design, can detect context dependence, drift, crosstalk
  - Expects chunked data
- Detecting crosstalk
  - Testing for conditional independence
- Detecting and characterizing drift
  - Time dependent changes in the measurement probabilities
  - Requires measurement record (not just total counts)
- Updates to pyGSTi
  - HTML reports, non-Markovian error bars, standard practice GST

# Detecting drift and crosstalk

- Do my qubit operations change when I change an “external variable?”
  - E.g., today vs. tomorrow (drift), simultaneously operating on another qubit or not (operation crosstalk), etc.
- Can detect change by looking at differences in observed counts for same gate sequences.
- This framework:
  - Is sensitive to drift on timescales *greater* than individual sequence runtime.
  - Can use GST sequences but does not require GST analysis.
  - Is entirely agnostic to structure of underlying dynamics.
  - Relatively coarse-grained.

# Checking the equality of coin flips



$h_A$  heads  
 $N_A$  flips

Data  $A$

$h_B$  heads  
 $N_B$  flips

Data  $B$

# Checking the equality of coin flips

$h_A$  heads  
 $N_A$  flips

Data  $A$

$h_B$  heads  
 $N_B$  flips

Data  $B$

Crosstalk	
Driven neighbor	Idle neighbor
Drift	
Today	Tomorrow
Context	
With fiber noise cancelation	Without fiber noise cancelation
With filter A	With filter B

# Checking the equality of coin flips

$h_A$  heads  
 $N_A$  flips

Data  $A$

$h_B$  heads  
 $N_B$  flips

Data  $B$

$h_A + h_B$  heads  
 $N_A + N_B$  flips

Combined data  $A + B$

# Checking the equality of coin flips

$$p_A = h_A / N_A$$

Data A

$$p_B = h_B / N_B$$

Data B

$$p_{A+B} = (h_A + h_B) / (N_A + N_B)$$

Combined data A + B

## Hypothesis testing

$H_0$ : All data is drawn from the binomial distribution with  $p_{A+B}$

$H_1$ : Data A drawn from binomial distribution with  $p_A$  and  
Data B drawn from binomial distribution with  $p_B$

# Checking the equality of coin flips

$$p_A = h_A / N_A$$

Data A

$$p_B = h_B / N_B$$

Data B

$$p_{A+B} = (h_A + h_B) / (N_A + N_B)$$

Combined data A + B

## Likelihood Ratio Test

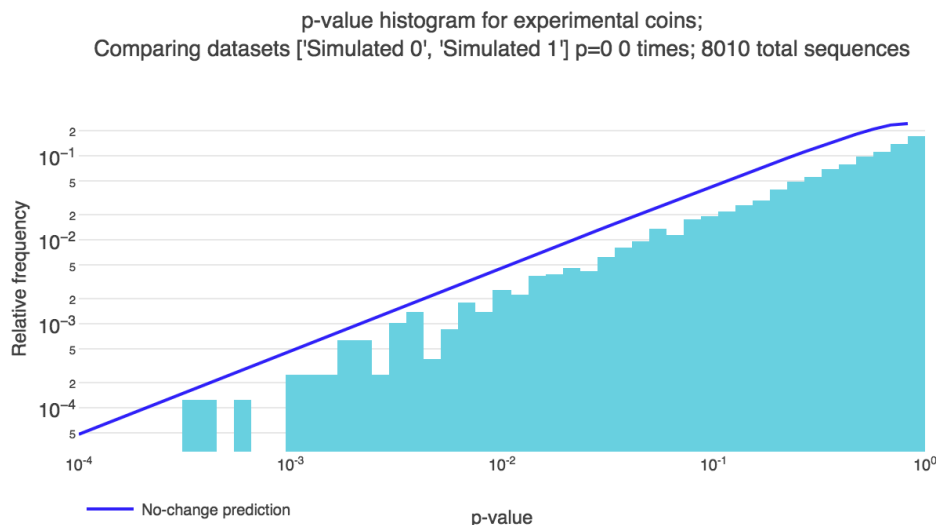
$$\text{Score} = -2 \log \frac{\mathcal{L}_{A+B}}{\mathcal{L}_A \mathcal{L}_B} = -2 \log \frac{p_{A+B}^{h_A+h_B} (1 - p_{A+B})^{N_A+N_B-h_A-h_B}}{\left( p_A^{h_A} (1 - p_A)^{N_A-h_A} \right) \left( p_B^{h_B} (1 - p_B)^{N_B-h_B} \right)}$$

*If the distributions are the same, the score will be  $\chi^2$  distributed.*

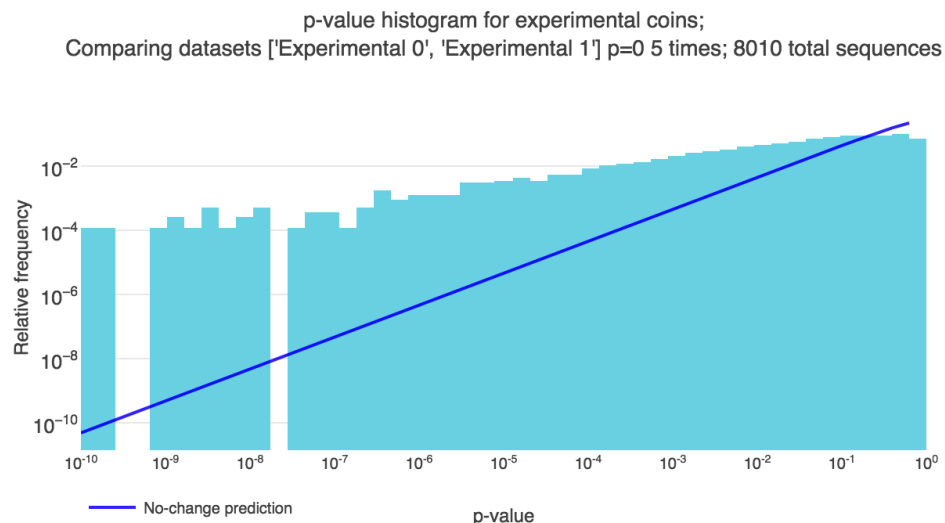


# Drift detection in Rigetti device

## Simulated Markovian GST data



## Experimental GST data (Rigetti)

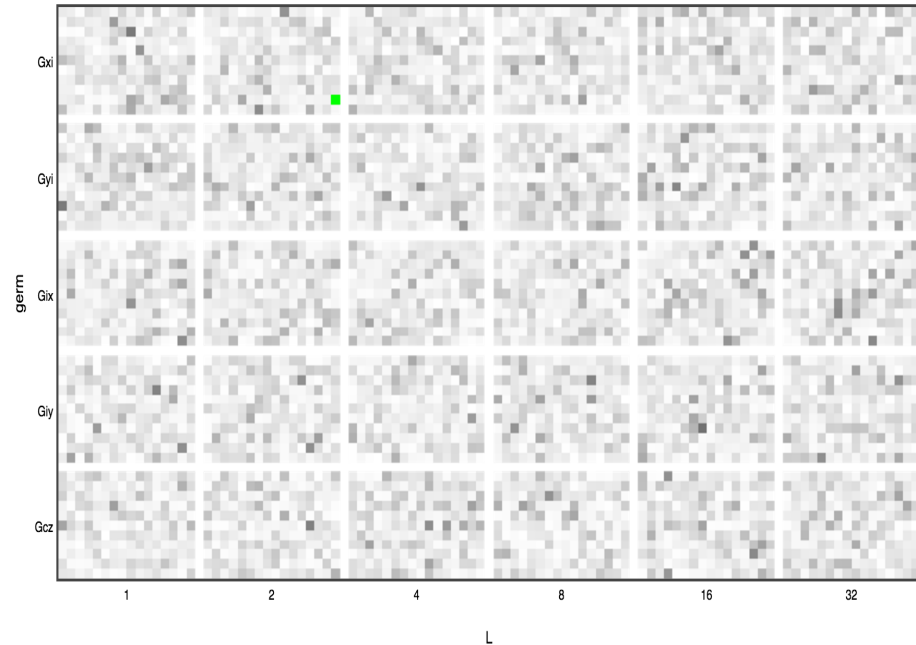


Simulated data where the bias *does not* change across sweeps  
(8010 gate strings)

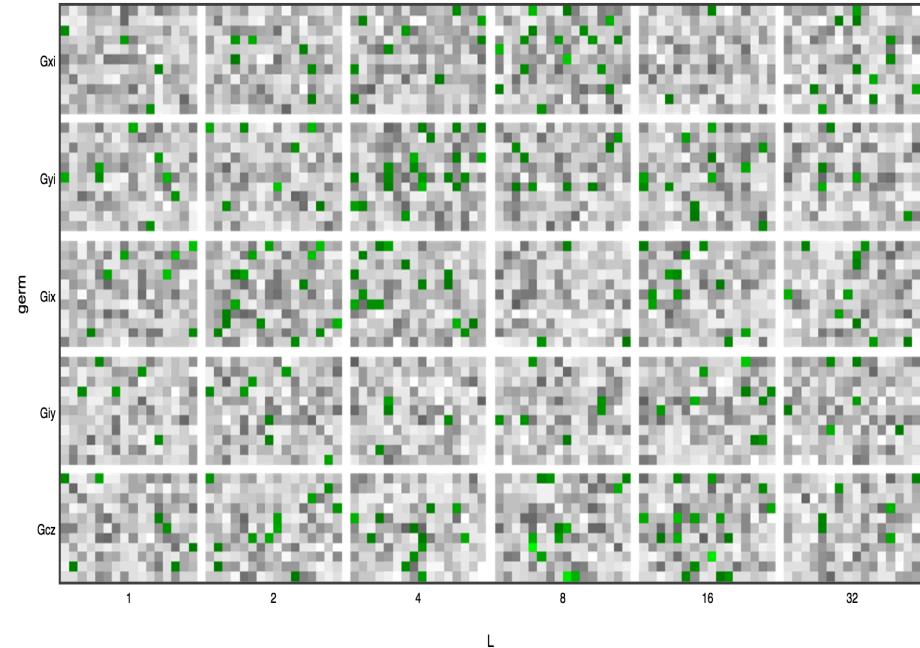
Experimental data where bias apparently *does change* across sweeps  
(8010 gate strings).  
“1 in  $\infty$ ” chance the gate sets are the same.

# Drift detection in Rigetti device

Simulated Markovian GST data



Experimental GST data (Rigetti)

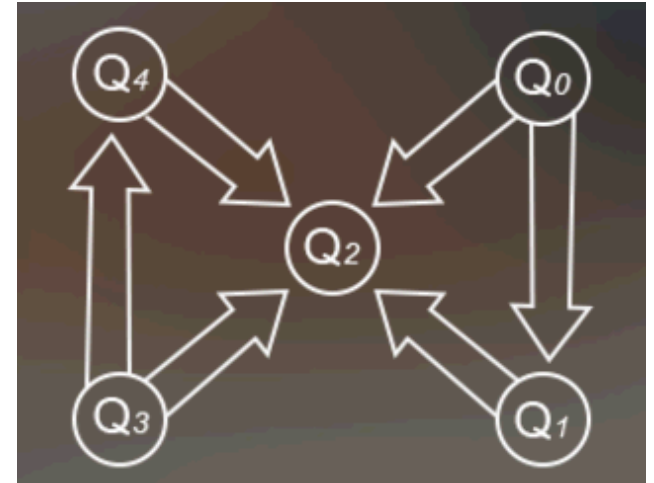


Simulated data where the bias *does not* change across sweeps  
(8010 gate strings)

Experimental data where bias *does* change across sweeps  
(8010 gate strings).  
“1 in  $\infty$ ” chance the gate sets are the same.

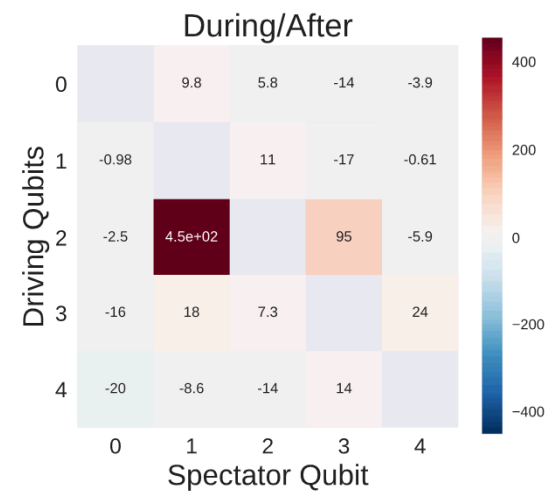
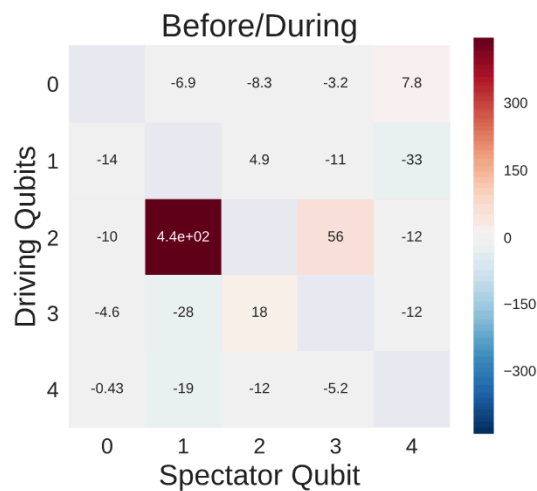
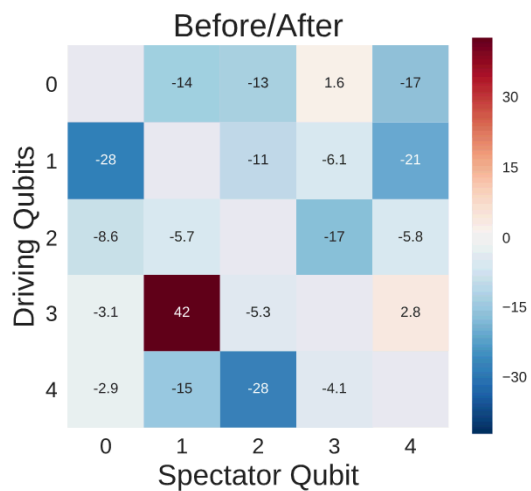
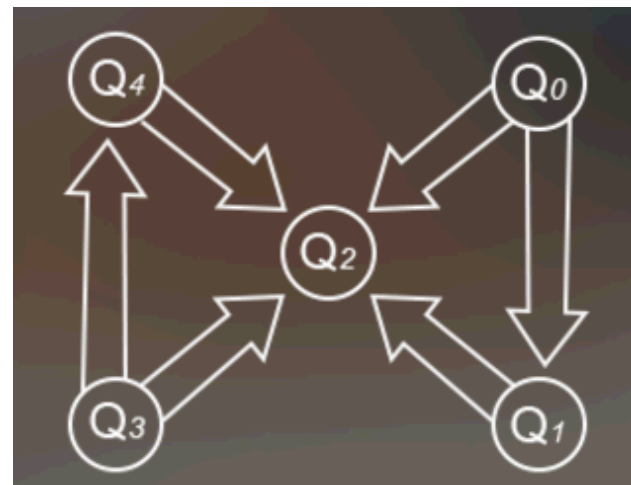
# Operation crosstalk on IBM QX2

- Experiment A (Before)
  - LGST sequences on qubit A
  - *Idle gates on qubit B*
- Experiment B (During)
  - LGST sequences on qubit A
  - *Driving qubit B with H gates*
- Experiment C (After)
  - LGST sequences on qubit A
  - *Idle gates on qubit B*



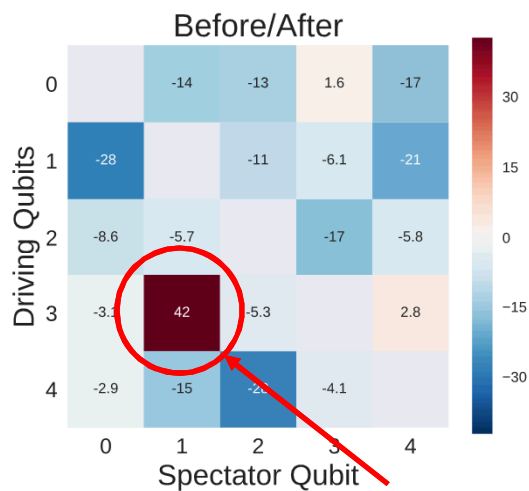
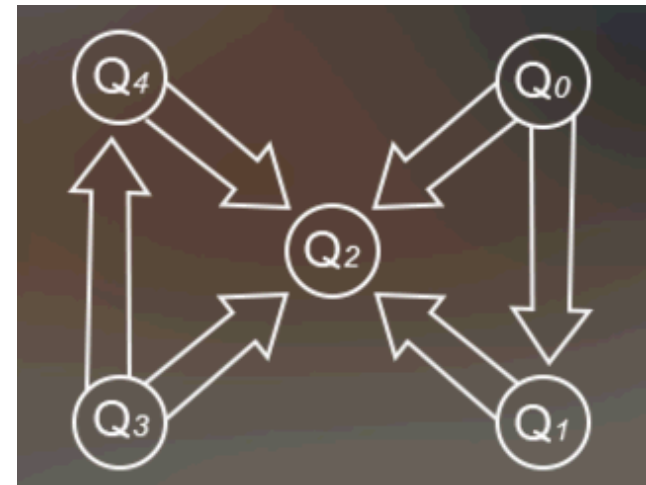
# Operation crosstalk on IBM QX2

- Experiment A (Before)
  - LGST sequences on qubit A
  - Idle gates on qubit B
- Experiment B (During)
  - LGST sequences on qubit A
  - Driving qubit B with H gates
- Experiment C (After)
  - LGST sequences on qubit A
  - Idle gates on qubit B

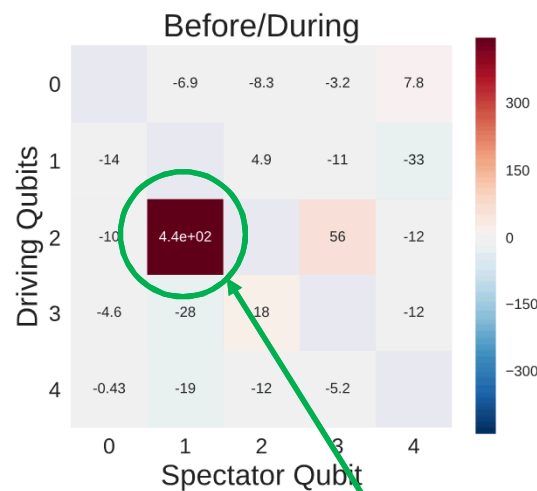


# Operation crosstalk on IBM QX2

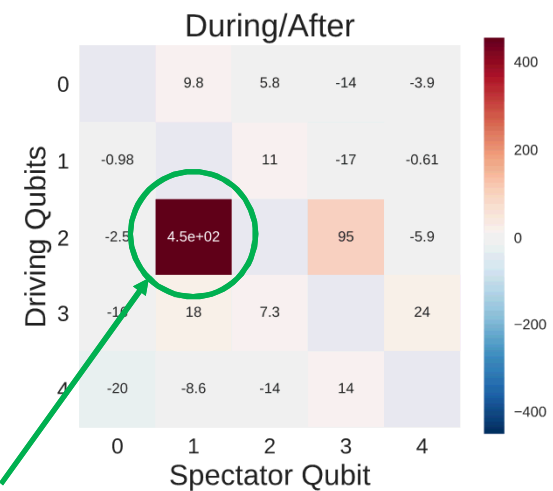
- Experiment A (Before)
  - LGST sequences on qubit A
  - *Idle gates on qubit B*
- Experiment B (During)
  - LGST sequences on qubit A
  - *Driving qubit B with H gates*
- Experiment C (After)
  - LGST sequences on qubit A
  - *Idle gates on qubit B*



Drift



Crosstalk

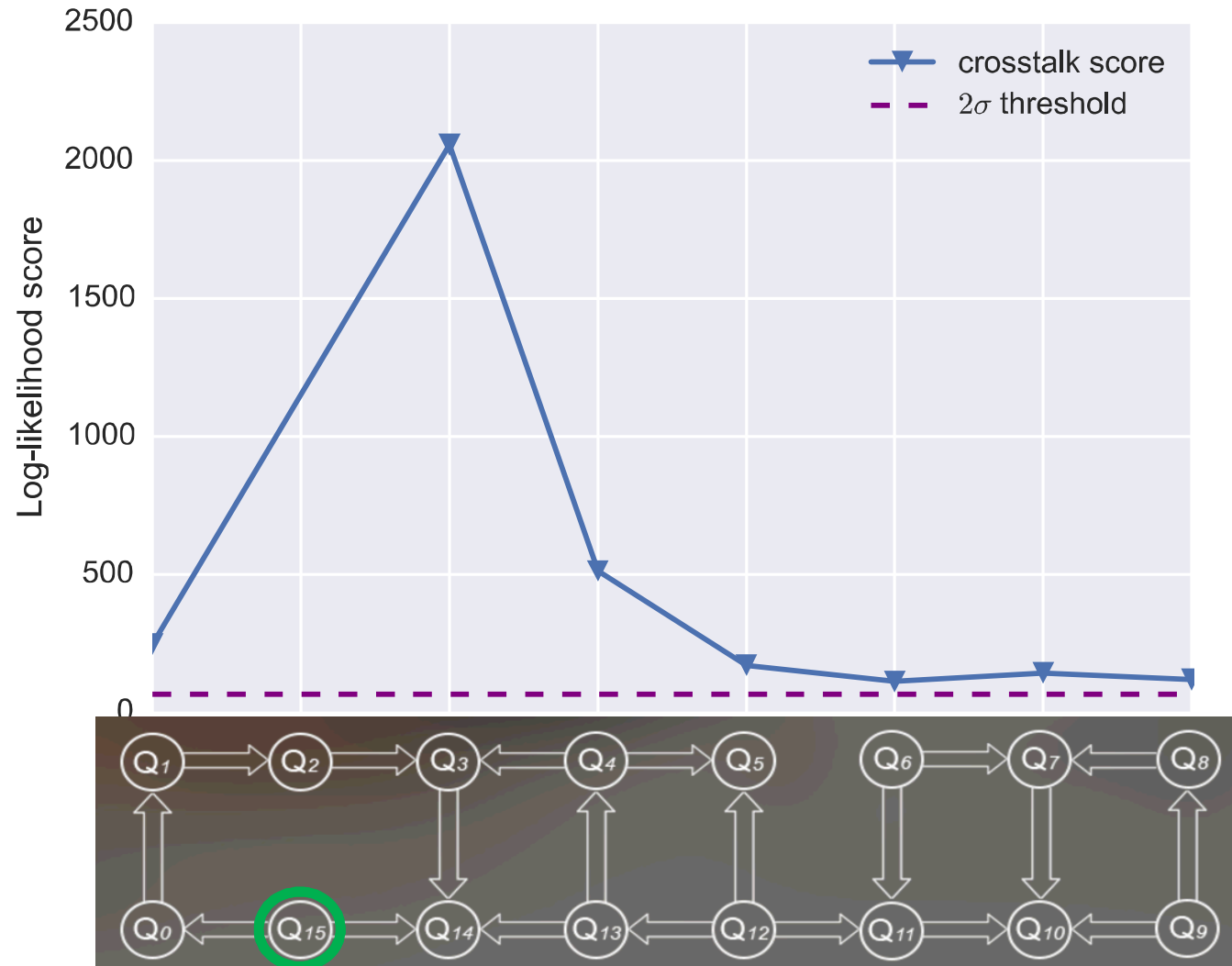


# Operation crosstalk on IBM QX2

- Drive CNOTs on ladder rungs
- Measure  $Q_{15}$

Large violations of null hypothesis with minimal drift.

*Violations due to crosstalk.*



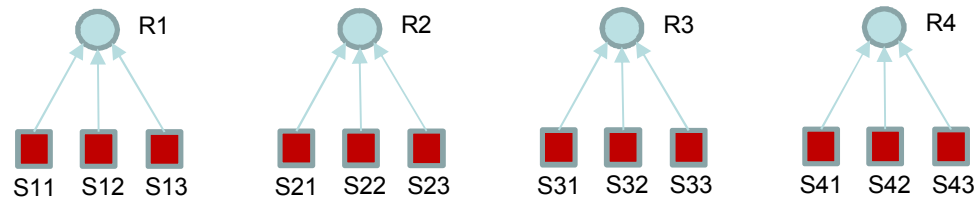
# These tools are part of pyGSTi



- You will need the beta branch of the software  
`.../pyGSTi$ git checkout beta`
- Contained in:  
`pygsti.objects.DataComparator([ds_0, ..., ds_n])`
- Demonstrated in:  
Tutorial 17: Pure Data Analysis
- Direct questions to
  - Erik Nielsen: [enielse@sandia.gov](mailto:enielse@sandia.gov)
  - Kenny Rudinger: [kmrudin@sandia.gov](mailto:kmrudin@sandia.gov)

# Crosstalk detection via conditional independence testing

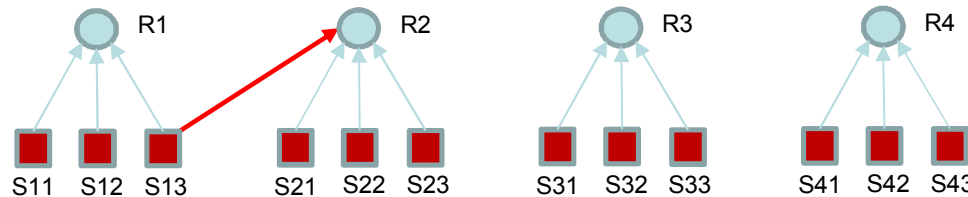
**Ideal:**



Measurement results  
on individual qubits

Experimental settings

**Problematic:**

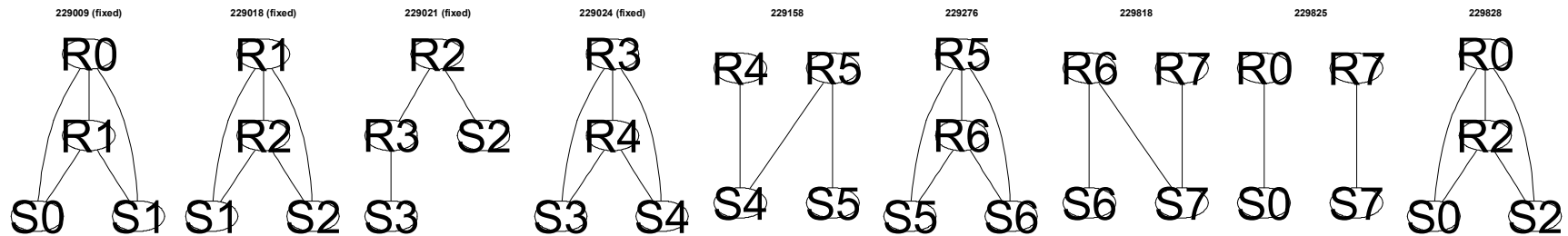


$$\Pr( R1 \mid S11, S12, S13, S21, S22, S23, \dots ) = \Pr( R1 \mid S11, S12, S13 )$$

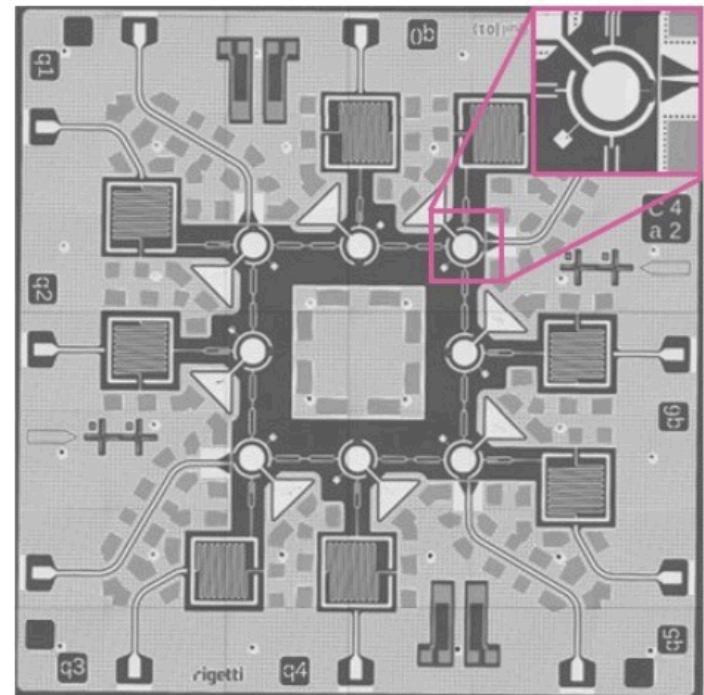
- A statistically motivated way to detect crosstalk. The conditional independence tests can be done at some significance level.
- The method can capture many different kinds of "crosstalk" (and more generally, parallel context dependence) at once.
- Can use existing GST data, and is computationally efficient.



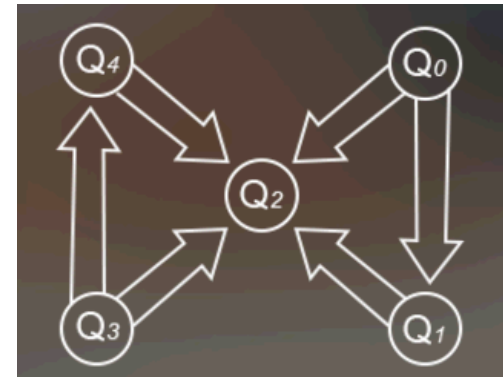
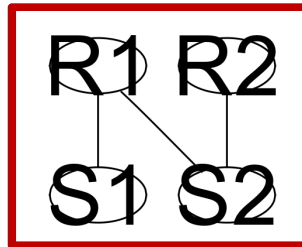
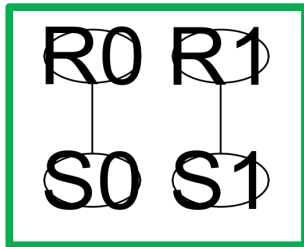
# Crosstalk detection on Rigetti device



- Crosstalk detection done for all adjacent qubit pairs.
- LGST gate sequences performed on two qubits, with only the Identity germ to probe for idle crosstalk.
- *See significant crosstalk on all but  $Q_0/Q_7$*



# Crosstalk detection on IBM QX2



- Experiment:
  - LGST on qubit A
  - Driving qubit B with H gates
- Crosstalk detection done for all qubit pairs.
  - Only Q1 / Q2 crosstalk detected
- IBM QX website<sup>[1]</sup> reports little coherent crosstalk between qubits 1 and 2 (ZZ interaction)
- We hypothesize: We're seeing measurement crosstalk since the resonators for these two qubits are close in frequency.

[1] <https://github.com/QISKit/ibmqx-backend-information/blob/master/backends/ibmqx2/README.md>

# Characterizing time dependence

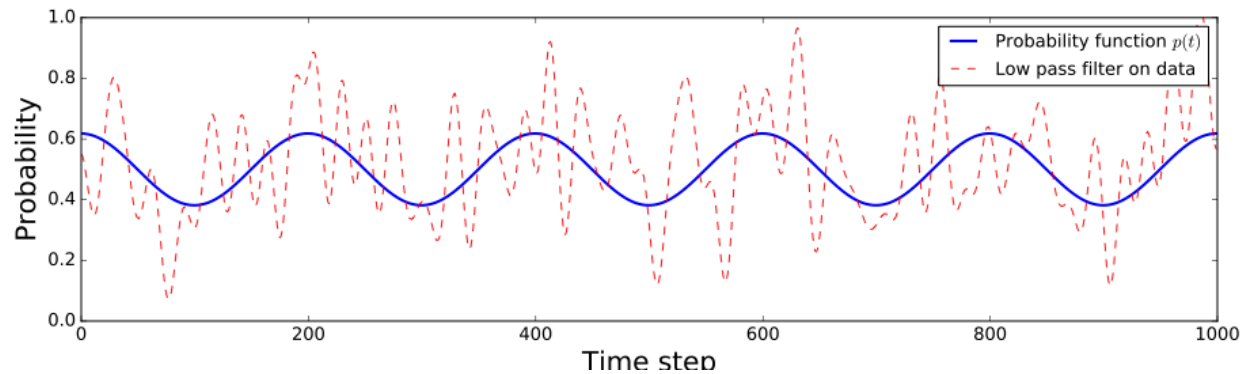
# Spectral analysis of time-dependent data

- Data is a length  $N$  bit string representing equally-spaced measurements:

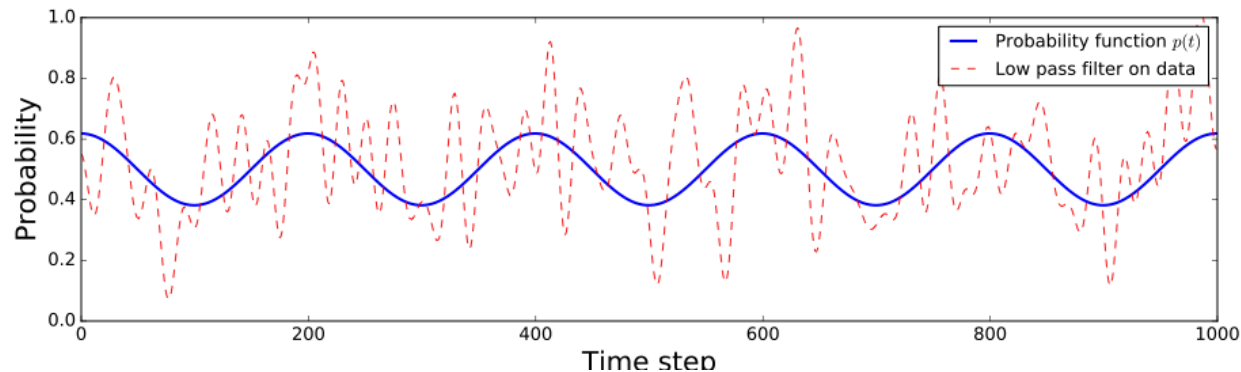
$$\mathbf{x} = \{ 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, \dots \}$$

- Hypothesis testing:
  - $H_0$ : Data drawn from  $N$  independent flips of a coin with a time-independent (but unknown) bias  $p$ .
  - $H_1$ : The bias  $p(t)$  is a non-constant function of time.
- $N$  bits of information. So can only hope to detect  $p(t)$  described by  $k \ll N$  parameters.
- We consider the most physically relevant case: **Fourier-sparse**  $p(t)$ .

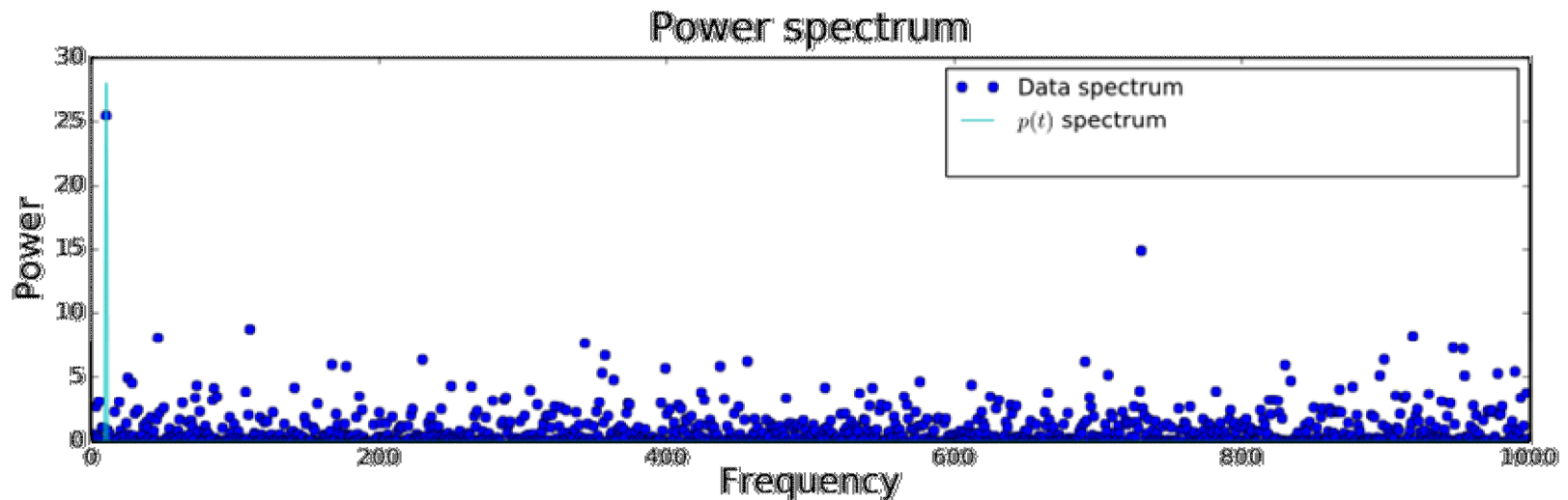
# Spectral analysis of time-dependent data – *monochromatic drift*



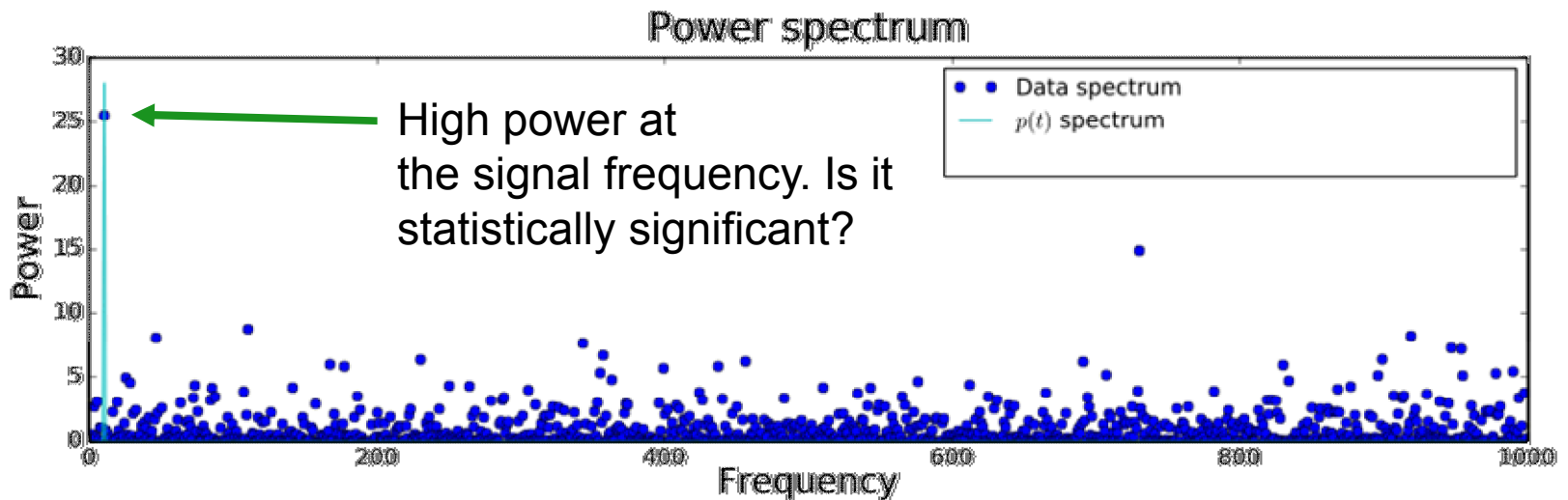
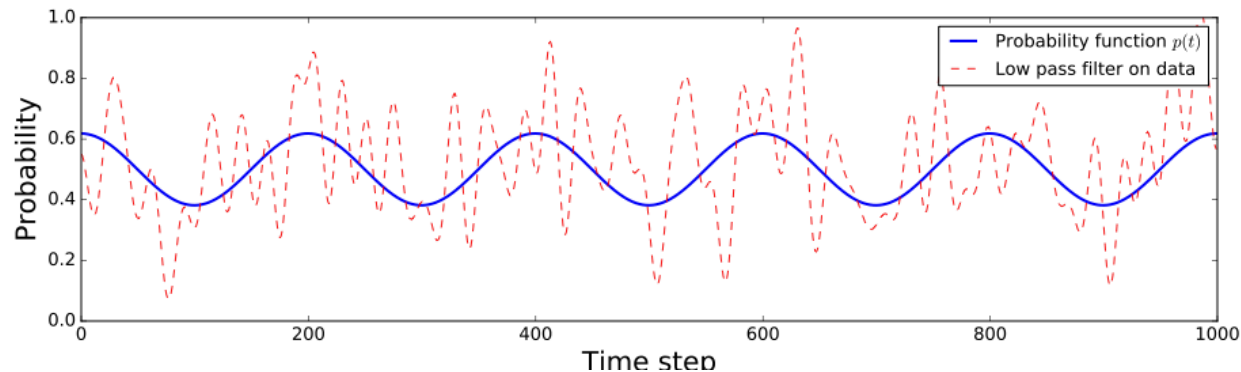
# Spectral analysis of time-dependent data – *monochromatic drift*



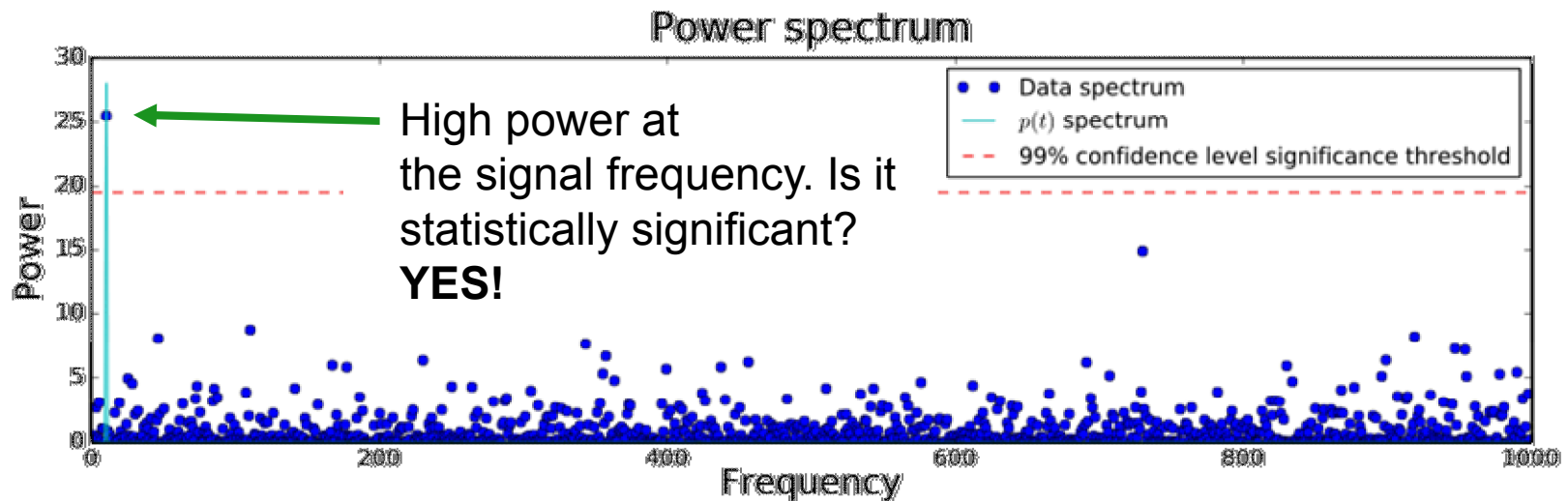
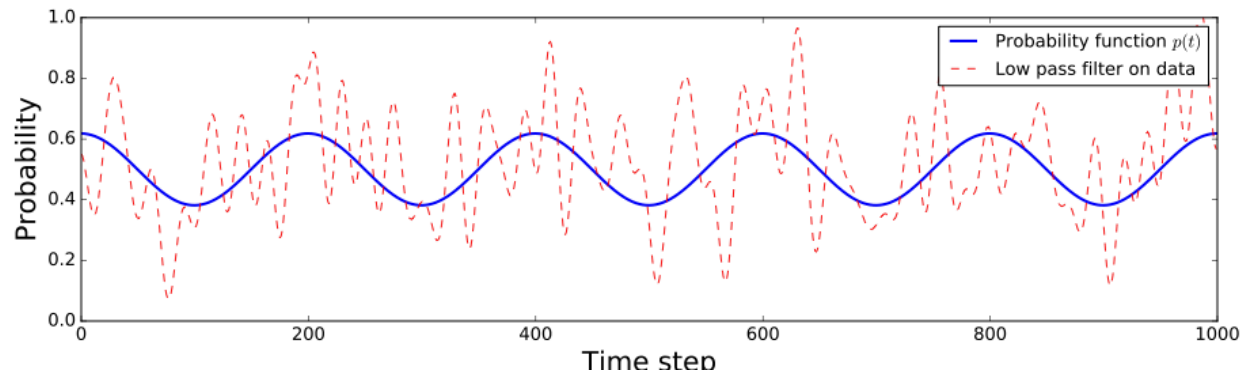
↓ Transform to Fourier domain ↓



# Spectral analysis of time-dependent data – *monochromatic drift*

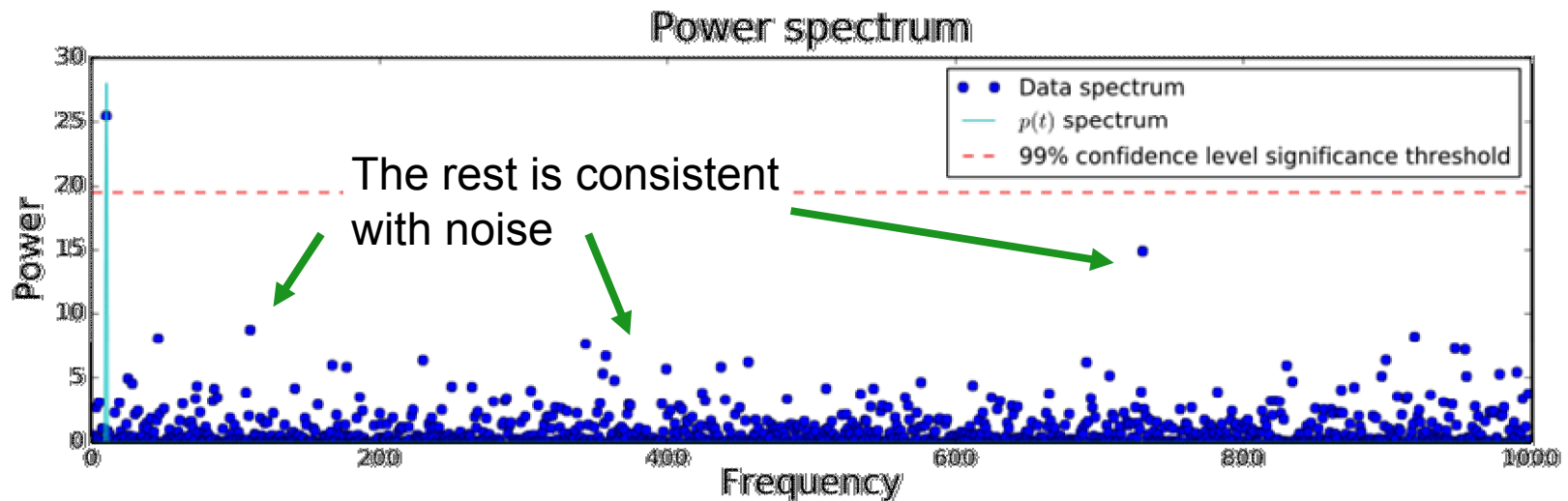
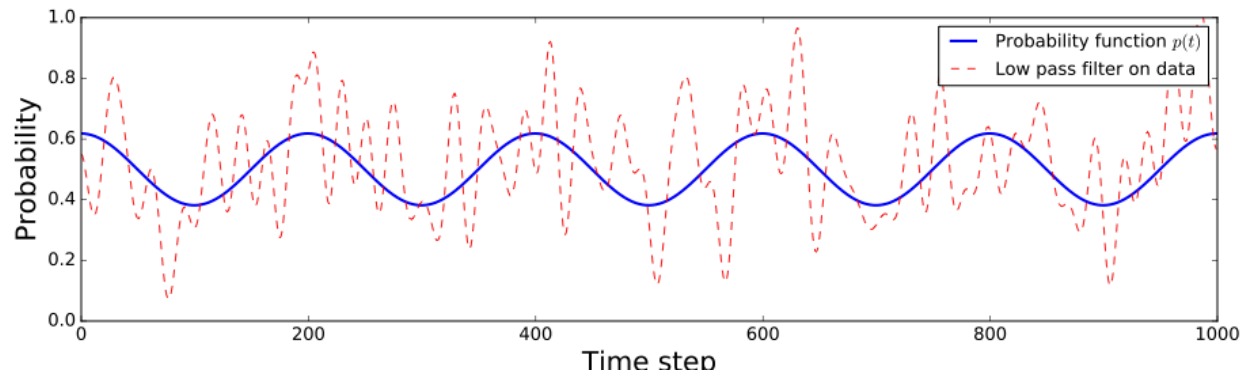


# Spectral analysis of time-dependent data – *monochromatic drift*

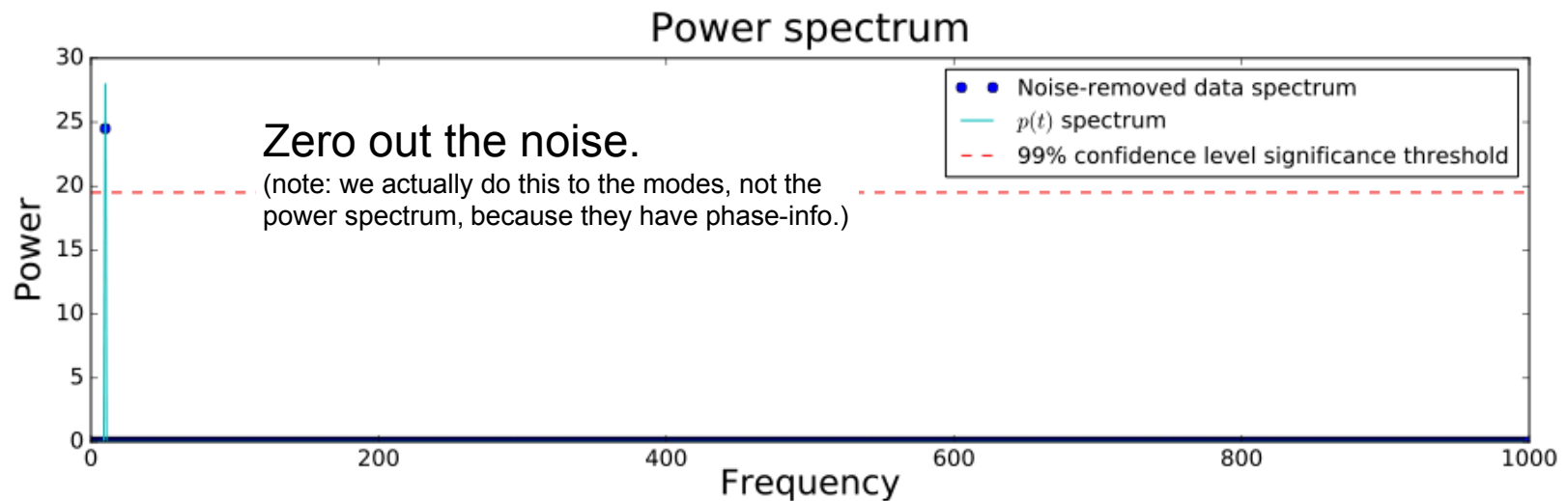
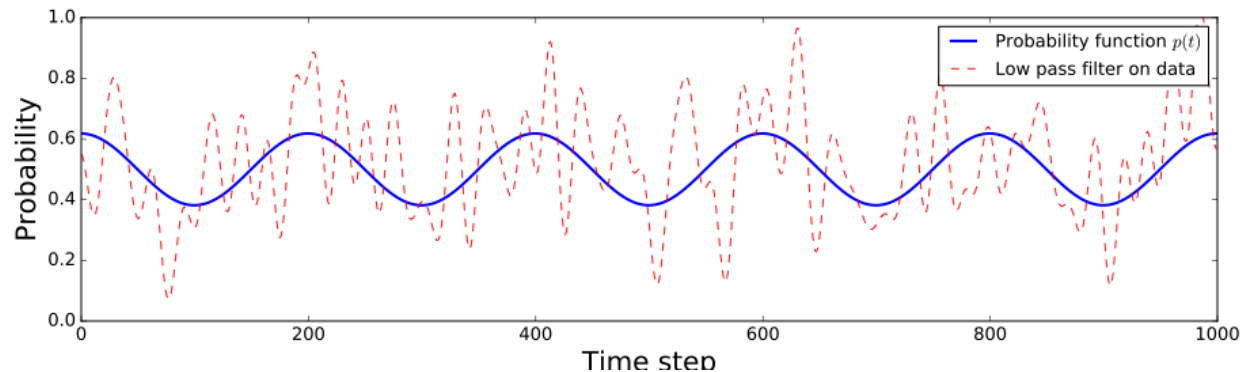




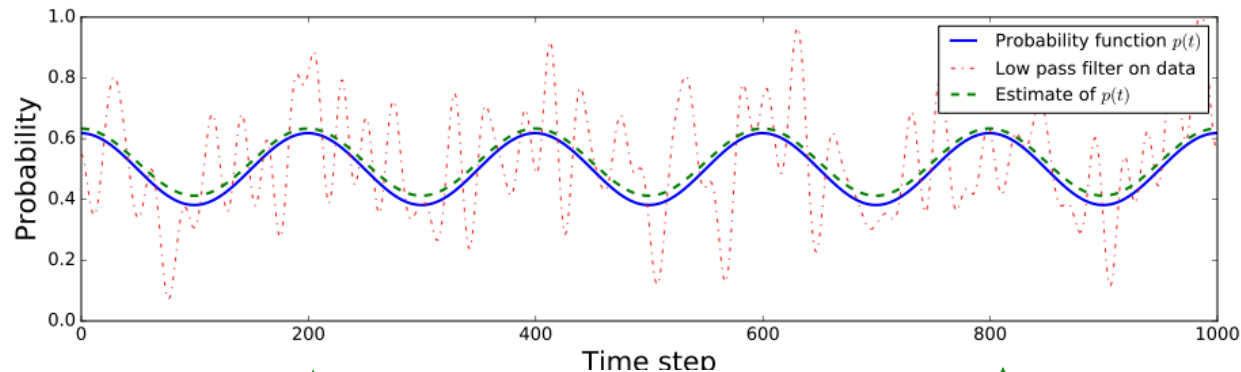
# Spectral analysis of time-dependent data – *monochromatic drift*



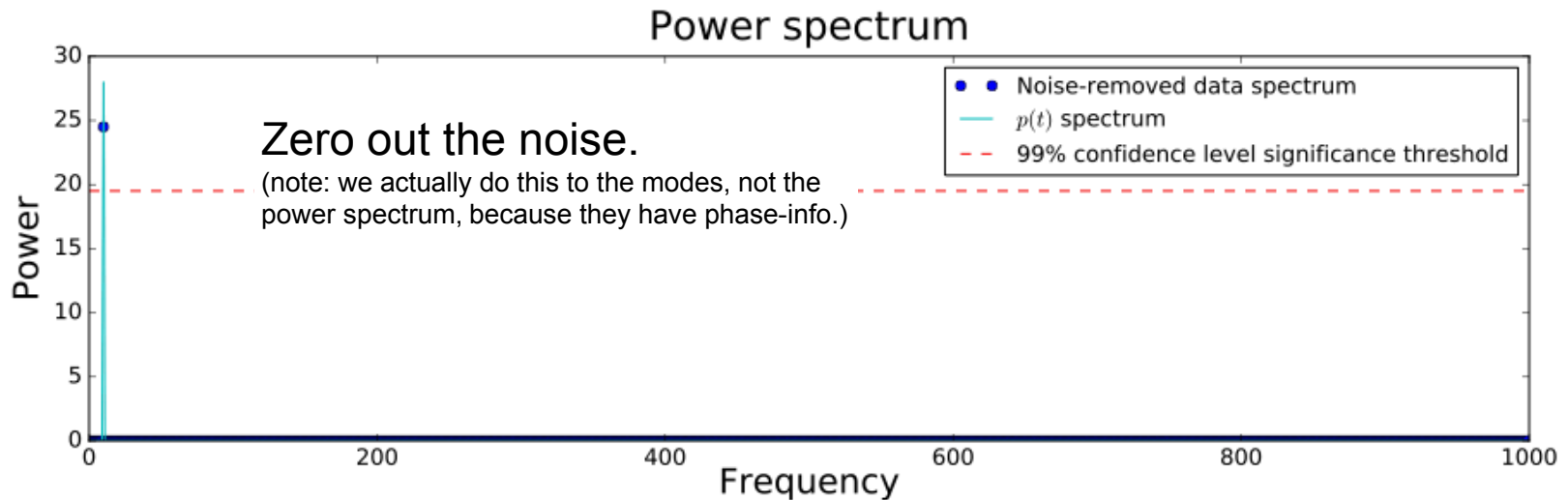
# Spectral analysis of time-dependent data – *monochromatic drift*



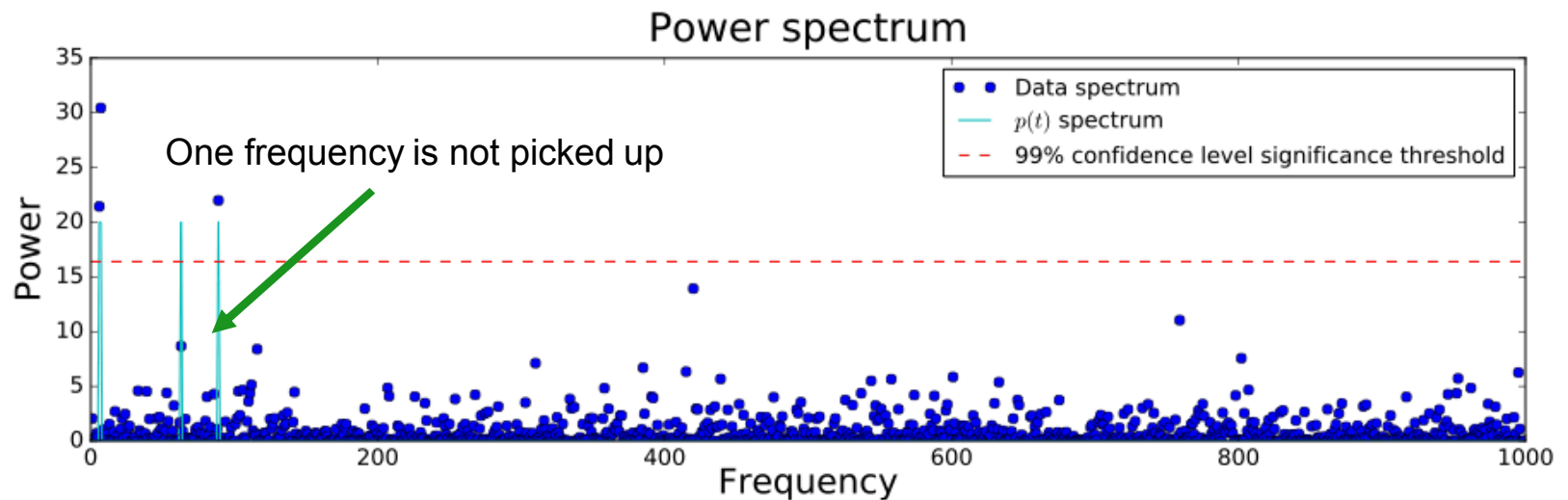
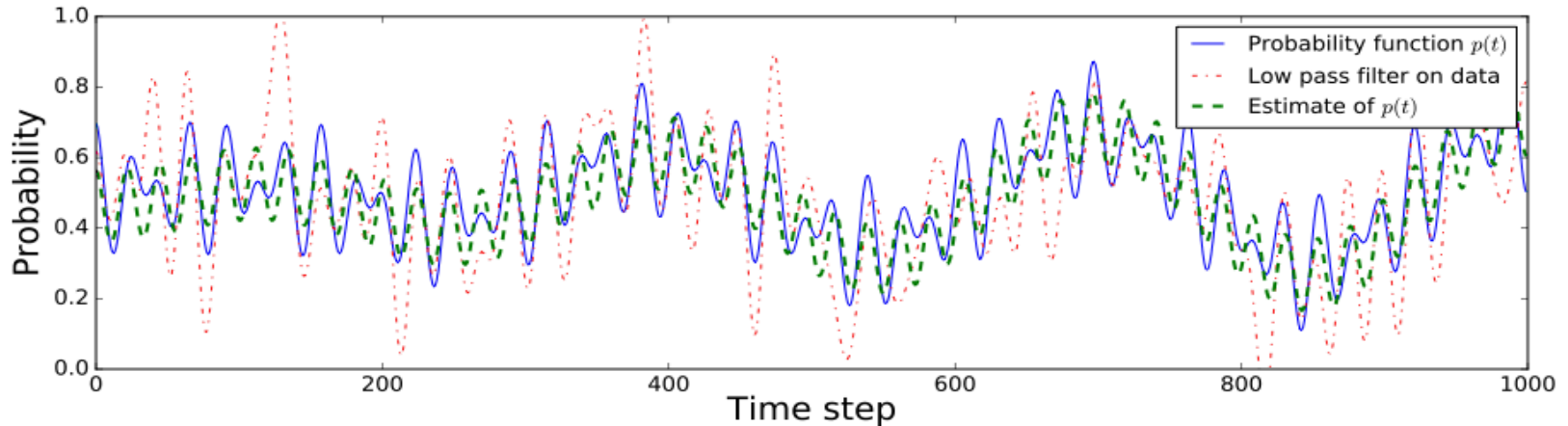
# Spectral analysis of time-dependent data – *monochromatic drift*



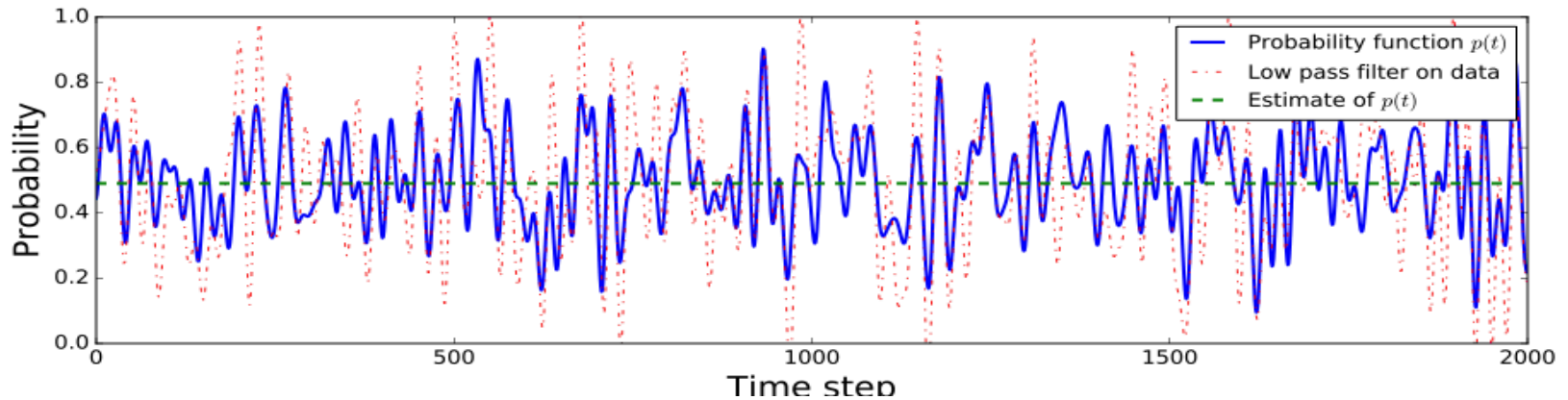
*Invert the Fourier transform*



# Spectral analysis of time-dependent data – *polychromatic drift*

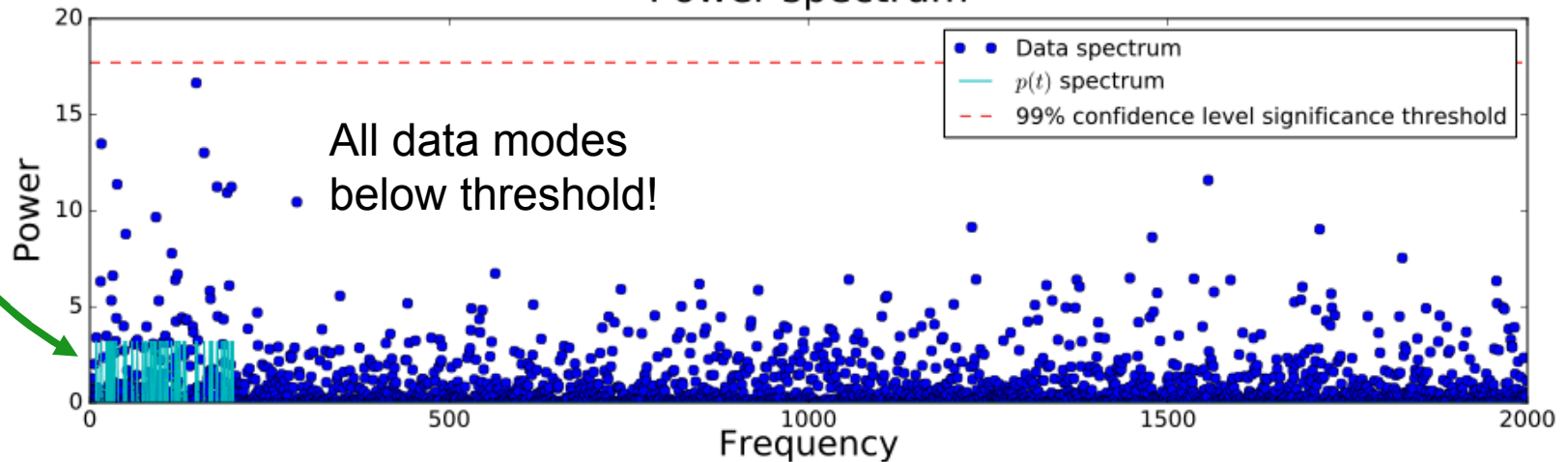


# Spectral analysis of time-dependent data – *general drift*



Signal is low power at **all** frequencies

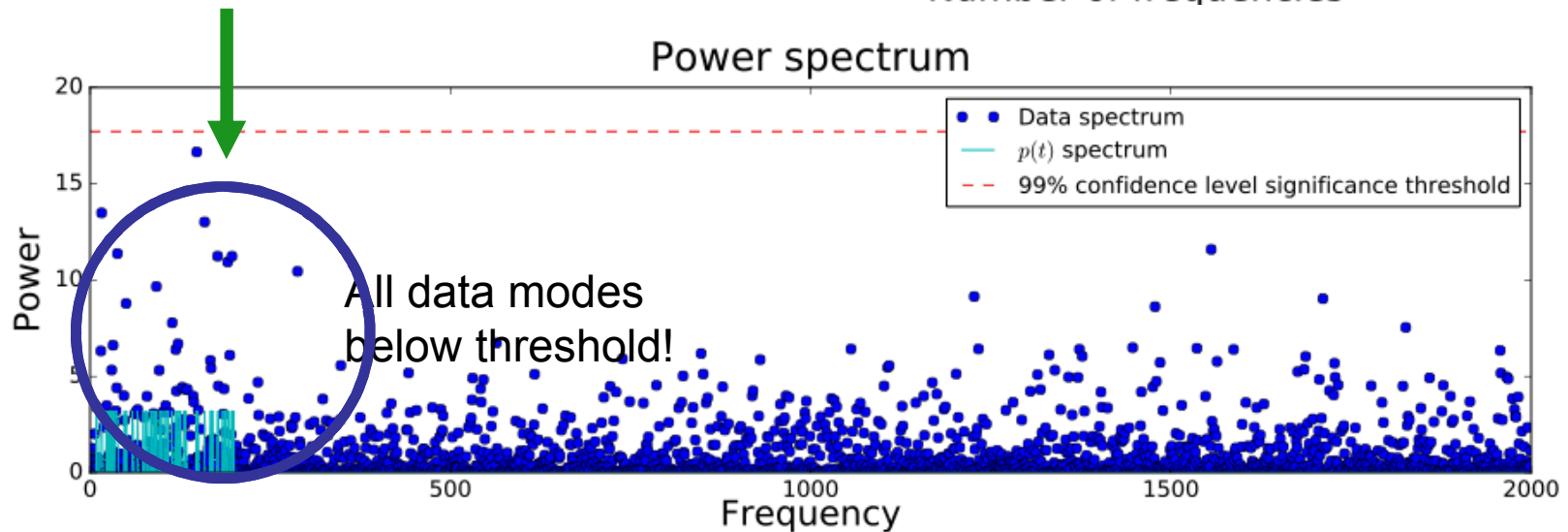
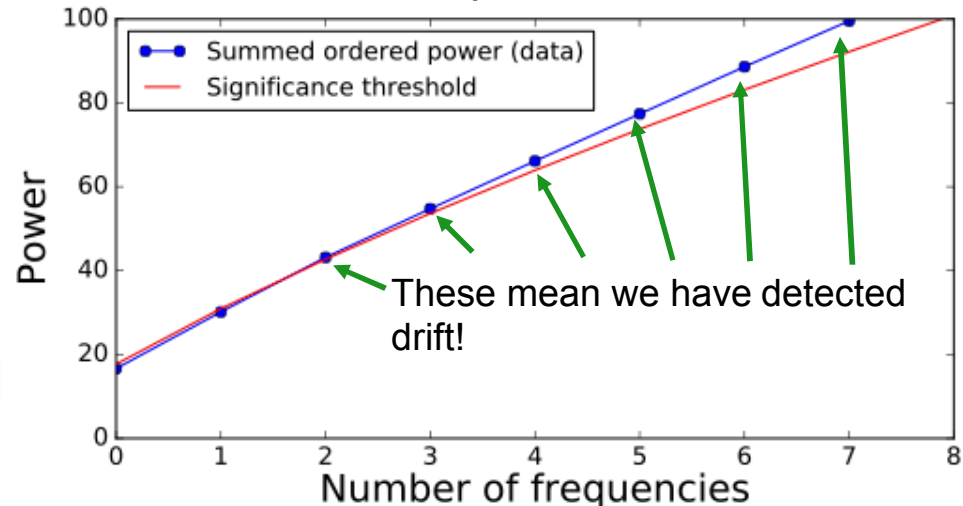
Power spectrum



# Spectral analysis of time-dependent data – *general drift*

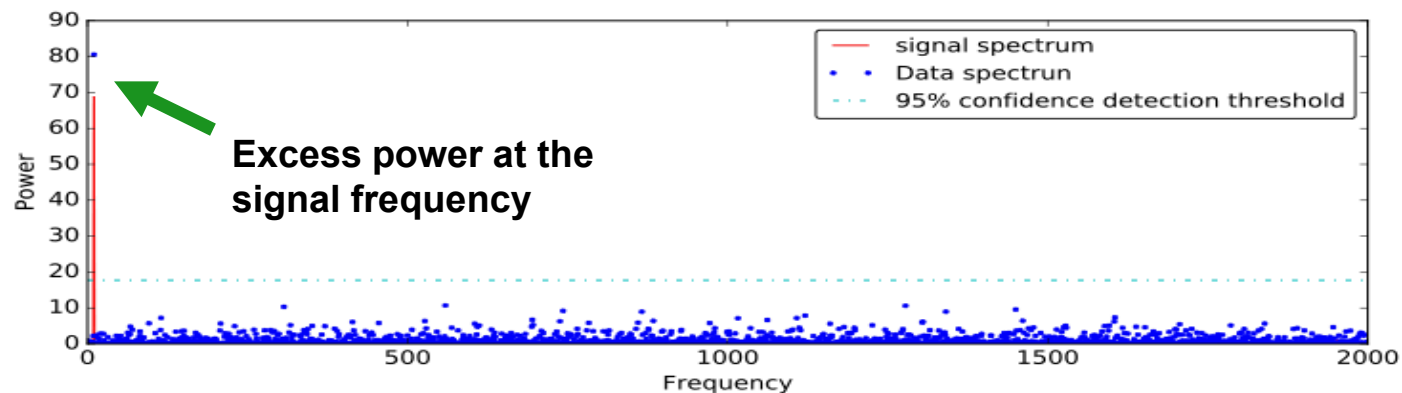
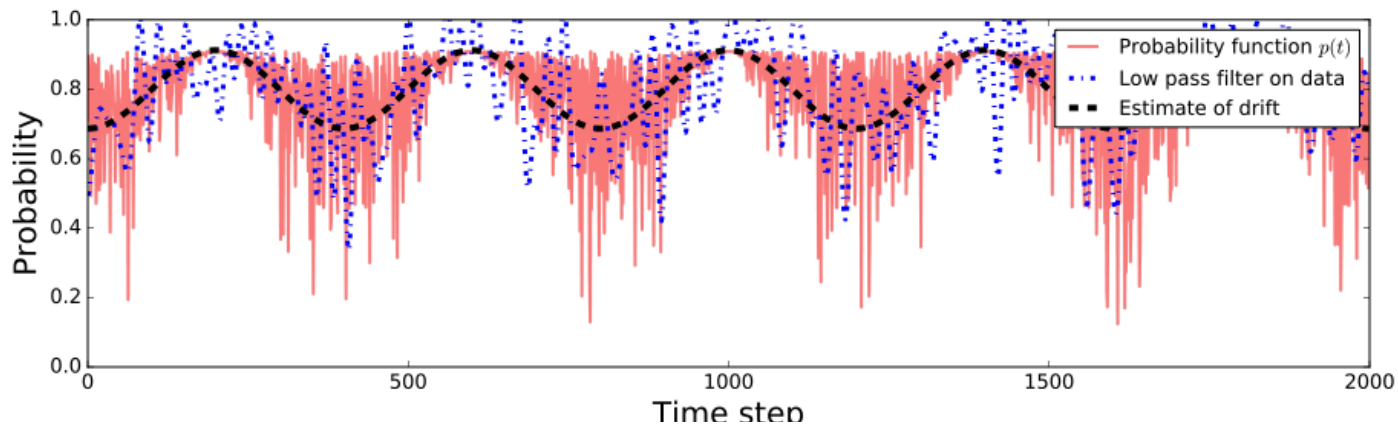
There is a lot more high-ish power modes than we would expect with no drift.

Summed power test statistic



# Spectral analysis of time-dependent data – *randomized benchmarking*

- Error model: each Clifford followed by unitary  $U(t) = \exp(-i \cos(\omega t) \sigma_z)$
- Each sequence performed exactly once.



# Spectral analysis of time-dependent data – *GST*

- This analysis assumes GST sequences are *rastered*

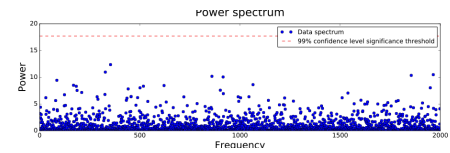
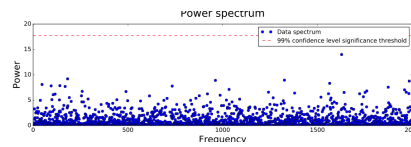
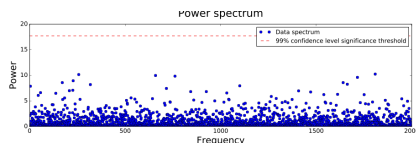
	Time →												
Circuit 1 outcomes	0				...	0				...	1		
Circuit 2 outcomes		1			...		0			...		1	
Circuit 3 outcomes			0		...			0		...			1
Circuit 4 outcomes				0	...				1	...			1

- Noise model: Hamiltonian noise in gates fluctuating at several low frequencies



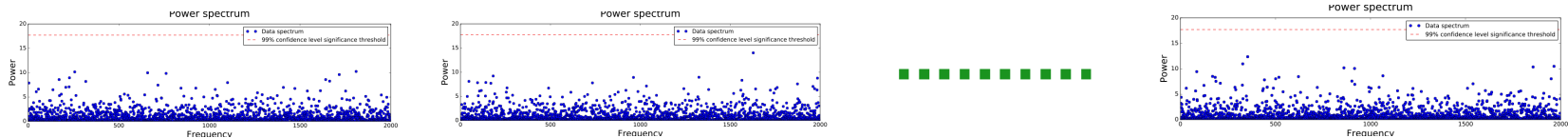
# Spectral analysis of time-dependent data – *GST*

- The power spectrum for any given sequence may not be sufficient to detect drift

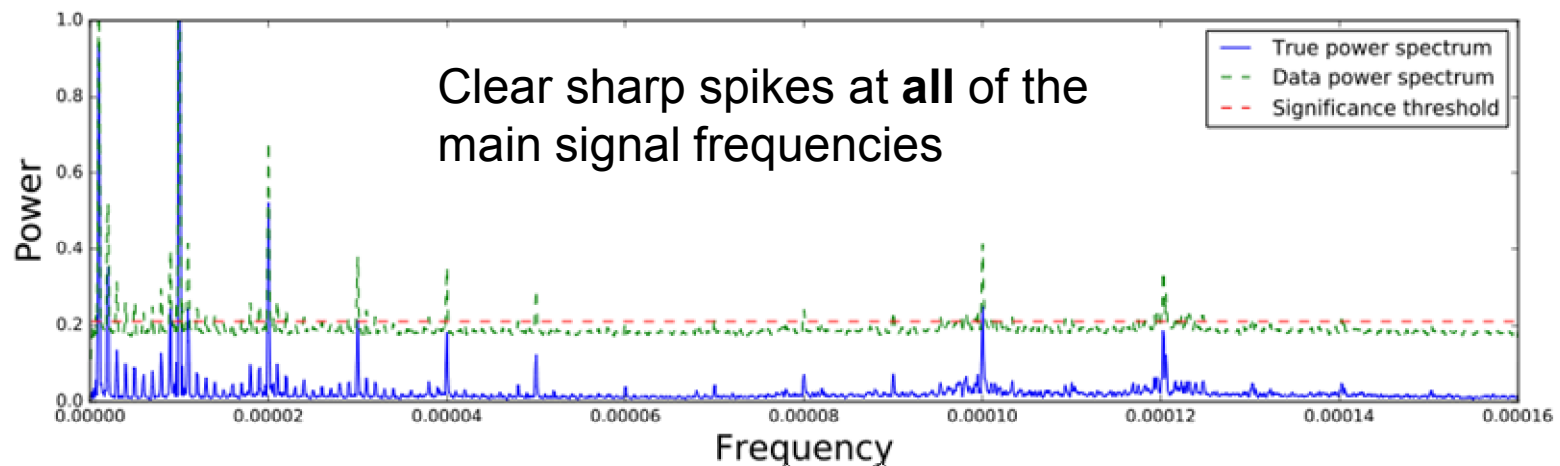


# Spectral analysis of time-dependent data – *GST*

- The power spectrum for any given sequence may not be sufficient to detect drift



- But we can average all ~2000 power spectra
  - Amplifies the signal and suppresses the noise
  - Many frequencies appear due to harmonics and aliasing



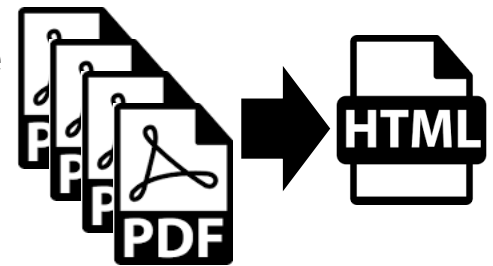
# Recent updates to pyGSTi

# Recent (beta-level) pyGSTi updates

- Using these under-development features requires that you be on the **‘beta’ branch of pyGSTi**

## Better data visualization (HTML reports)

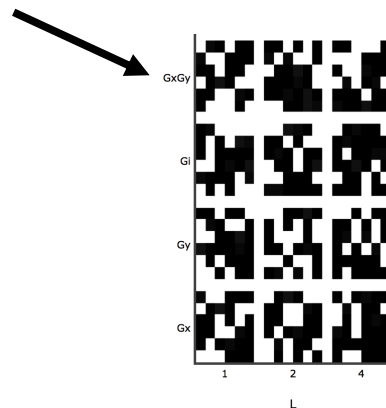
- **Problem:** pyGSTi’s reports required lots of scrolling and flipping between different PDF files to compare analyses.
- **Solution:** now reports are HTML documents!
- Allows **interactive** reports & denser data
- Effectively “layers” of PDF reports folded into one
  - Multiple gauge optimizations
  - Multiple models
  - Multiple data sets



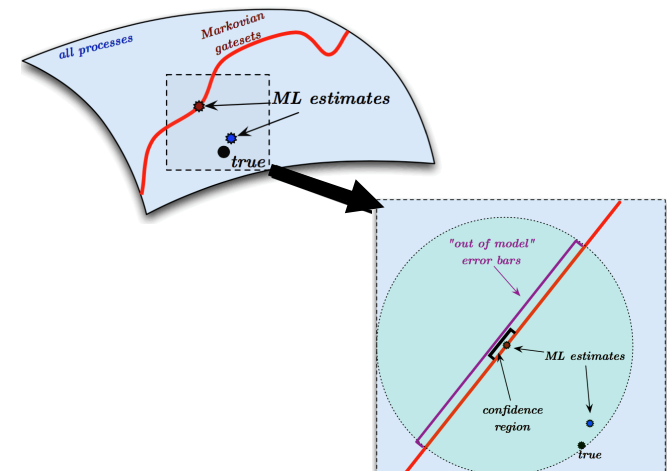
# Recent pyGSTi updates (cont)

## Non-Markovian error bars

- **Problem:** how to convey uncertainty in a gate set when the usual GST estimate cannot fit the data well (i.e. there's "non-markovian" errors) .
- **Solution (in progress):** define some type of "non-markovian error bars". Currently we have two ways of doing this:
  - Type1: error bars based on distance from truth
  - Type2: normal in-model error bars based on data with *artificially reduced counts* so that it can be fit as well as expected.



black = sequence omitted,  
white = sequence kept



# Recent pyGSTi updates (cont)



## Standard practice GST – convenient interface for multiple GST estimates

- **Problem1:** sometimes GST will give gate estimates that are not CPTP, and this invalidates metrics such as the process fidelity (can get process infidelities  $< 0$ , etc).
- **Problem2:** knowing the “right” parameters for gauge optimization is difficult, and GST analyses can be difficult to interpret because it’s difficult to separate gauge artifacts from actual gate errors.
- **Solution:** We’ve tried to bottle several “standard” ways of running GST which includes:
  - both CPTP and TP fits
  - Multiple gauge optimizations
  - Automatic computation of non-Markovian error bars when needed.
- To run GST using these standard-practice setting, just call `do_stdpractice_gst` instead of `do_long_sequence_gst`.
- Integrates nicely with HTML reports, which are able to display multiple estimates and gauge optimizations at once.

# Acknowledgements

- Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525