JOHNS HOPKINS
APPLIED PHYSICS LABORATORY

Particle Track Pattern Recognition via Content Addressable Memory and Adiabatic Quantum Optimization

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Motivation

Objective

- Leverage quantum annealing for pattern recognition in high energy physics particle detection

Why is this problem hard?

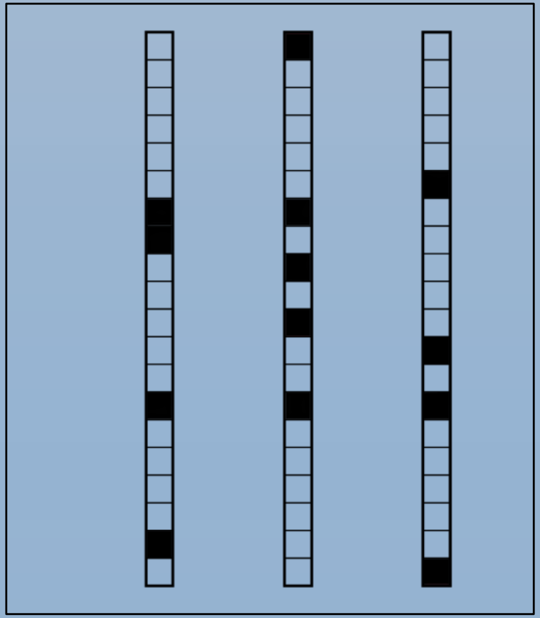
- Pattern matching accuracy is *highly dependent* on noise, detector resolution, and the number of simultaneous particle tracks

Why quantum annealing?

- Quantum annealing potentially
  - Enables more accurate pattern matching
  - Enables access to a family low-energy solutions that could improve track reconstruction

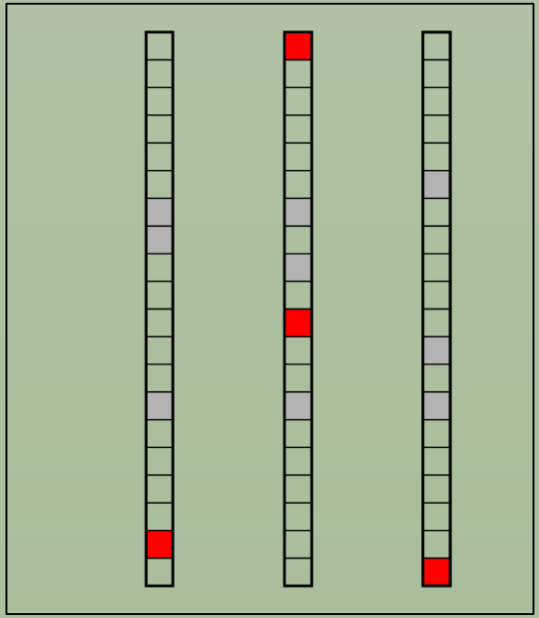
From Pattern Matching to Track Reconstruction

Detector



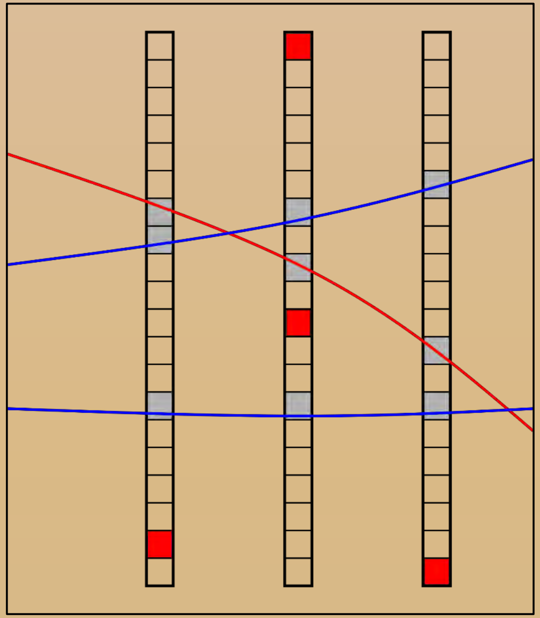
Raw data

Pattern Matching



Pattern matching discriminates between signals from possible track candidates (gray) and noise (red)

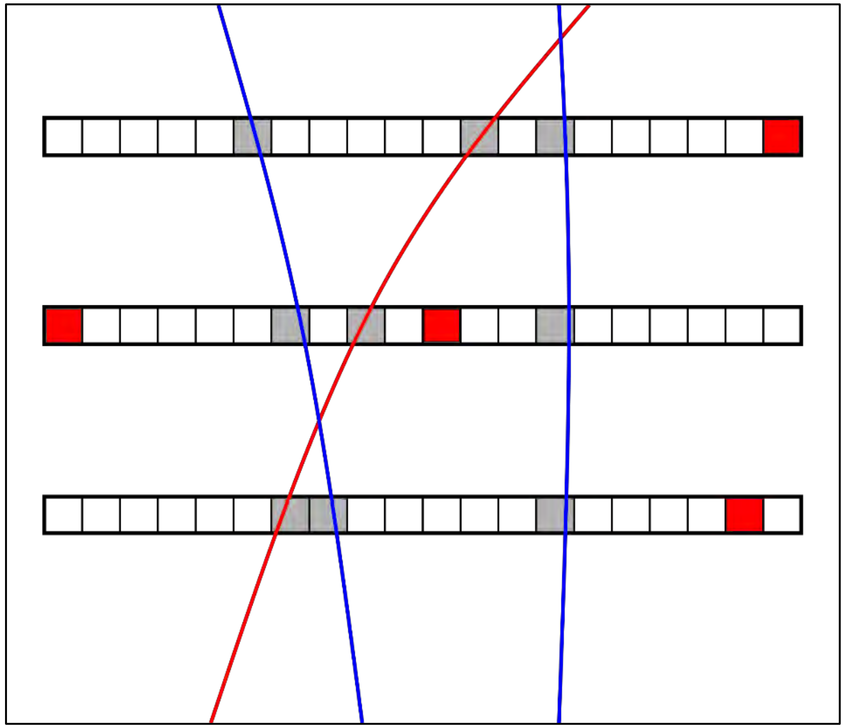
Track Reconstruction



Track reconstruction algorithms are run over possible track candidates

Pattern Matching

- Pattern matching allows the data to be pruned of noise and background signals *before* track reconstruction
  - Patterns from experimental data compared to known library
  - Library produced from experimental data or simulator
- Pattern matching can be implemented in hardware as a triggering system
  - Dependent on granularity, noise level, efficiencies
  - Especially important for high luminosity experiments like those using the High-Luminosity LHC

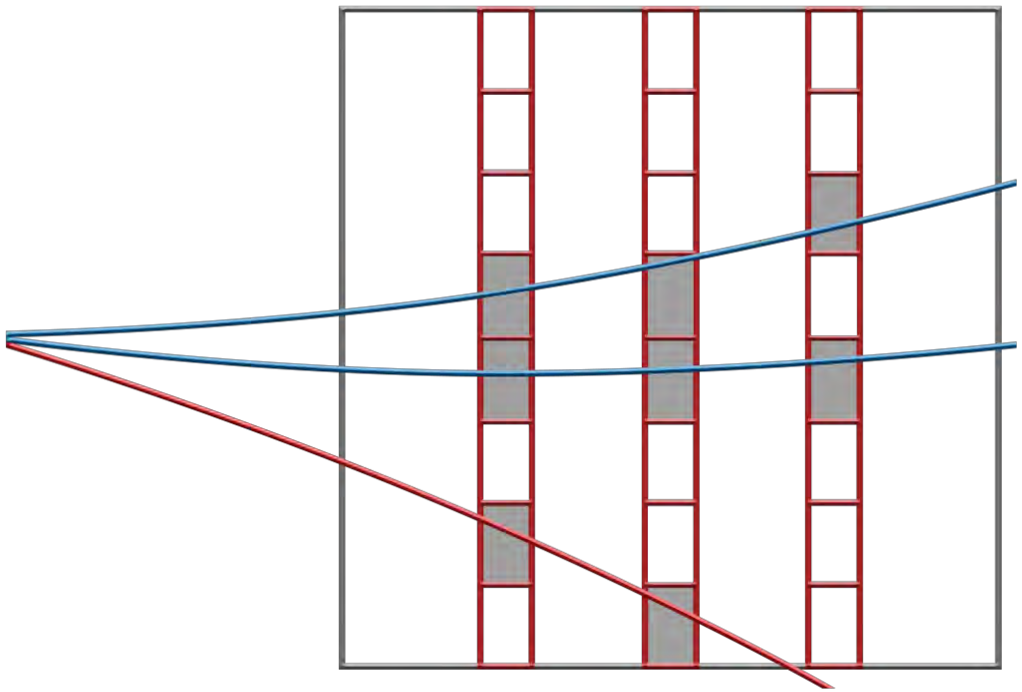


signals from particle tracks
noise

Track Reconstruction for HEP

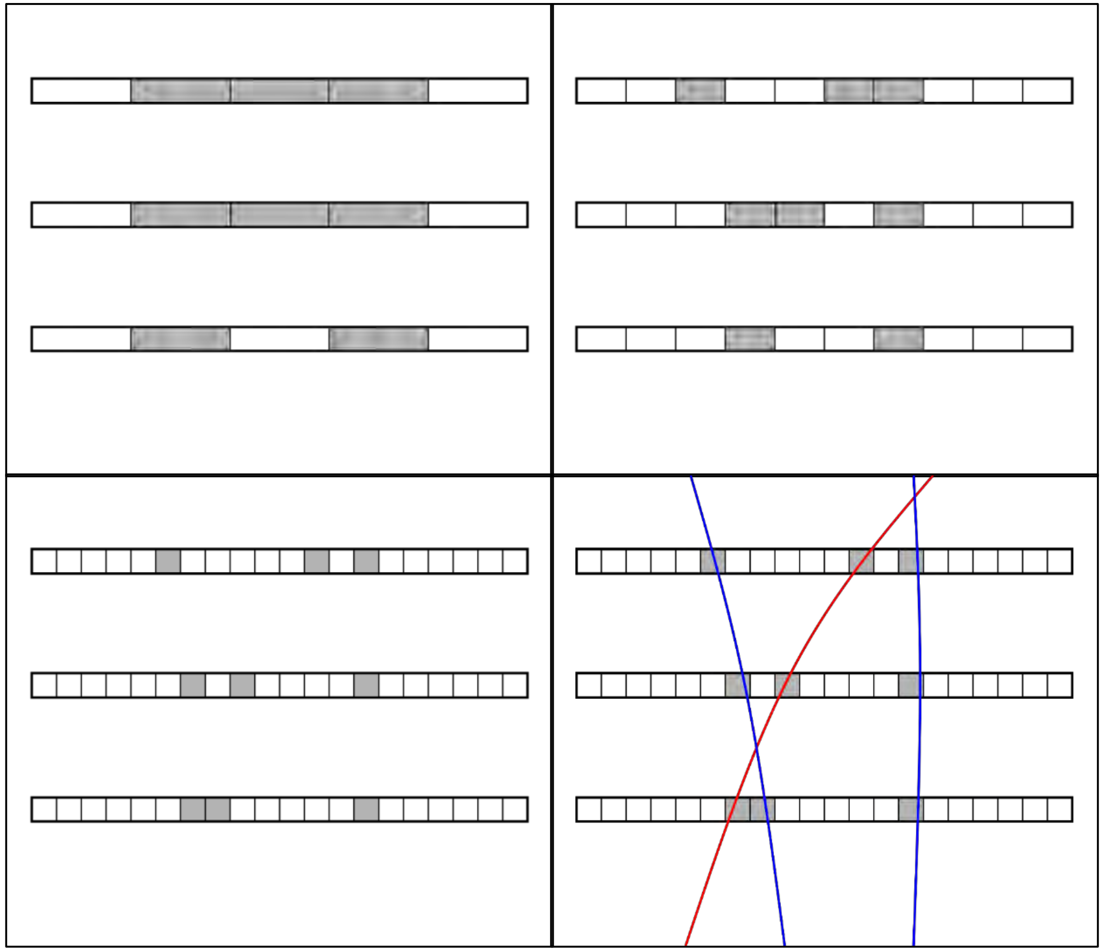
Track reconstruction

- Process of determining the trajectory of a particle from detector signals
- Highly dependent on detector design
- Usually computationally expensive
- Complicated by random noise, detector inefficiencies, high detector resolution, and many simultaneous tracks



Tree Search

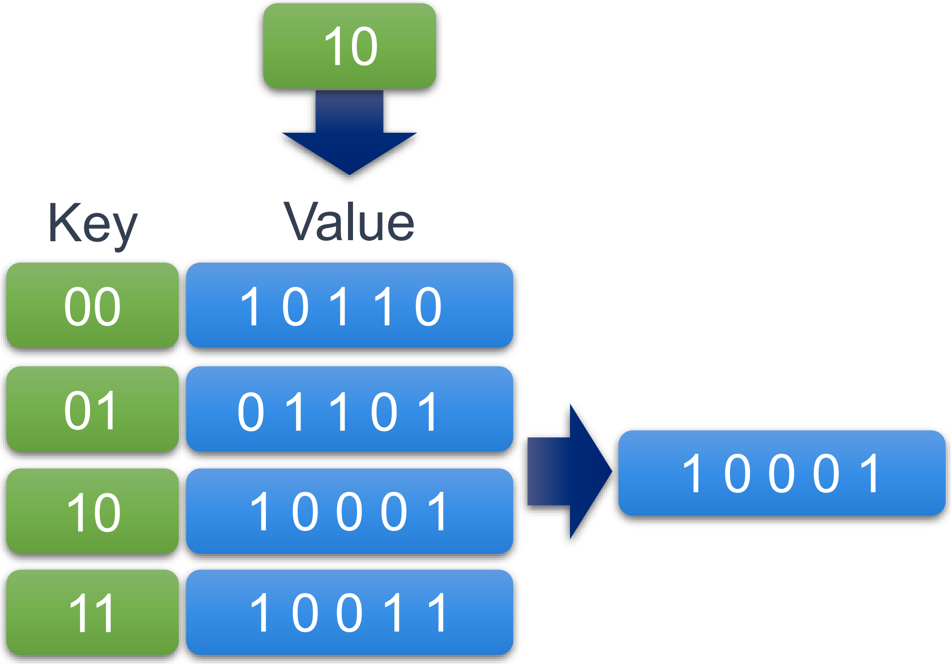
- Organizing library into tree structure of increasing resolution decreases time to search library
  - Avoids linear growth of computation with granularity
  - Noise and number of simultaneous tracks has *large impact* on algorithm



Content Addressable Memory

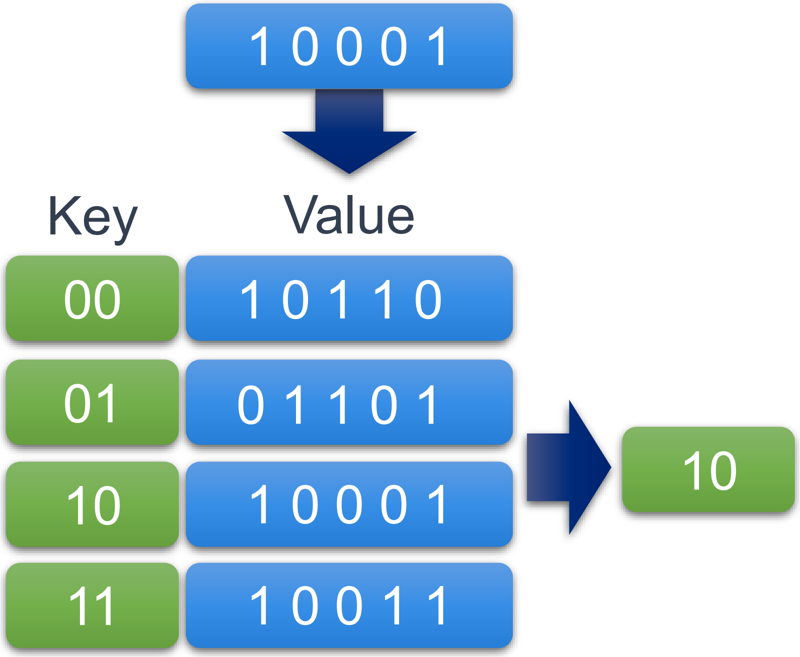
Traditional Memory

- Input is address location of the desired content
- Output is the content of the address



Content Addressable Memory (CAM)

- Input is content of the stored memory
- Output is the location of the desired content



Quantum CAM

Problem Design

Cast CAM problem as an adiabatic quantum optimization problem

Keys: $K = \left[k^{(1)}, k^{(2)}, \ldots, k^{(m)}\right]^T$

Values: $V = \left[v^{(1)}, v^{(2)}, \ldots, v^{(m)}\right]^T$

Hamiltonian Description

$$H(t, \theta) = A(t) H_X + B(t) H_\theta$$

$$H_X = -\sum_{i}^{n} \sigma_i^X$$

$$H_\theta = -\sum_{i,j}^{n} w_{ij} \sigma_i^Z \sigma_j^Z - \sum_{i}^{n} \theta_i v_i^{(0)} \sigma_i^Z$$

Hebbs Learning Rule

$$W = \begin{pmatrix} 0 & W_B \\ W_B^T & 0 \end{pmatrix} \qquad W_B = \frac{1}{n} K^T V$$

Maximum Classical Learning Capacity: $C(n) = \frac{n}{2} \log(n)$

QCAM Binary Classification

Multi-label Classification

Key	Value
00	1 0 1 1 0
01	0 1 1 0 1
10	1 0 0 0 1
11	1 0 0 1 1

Binary Classification

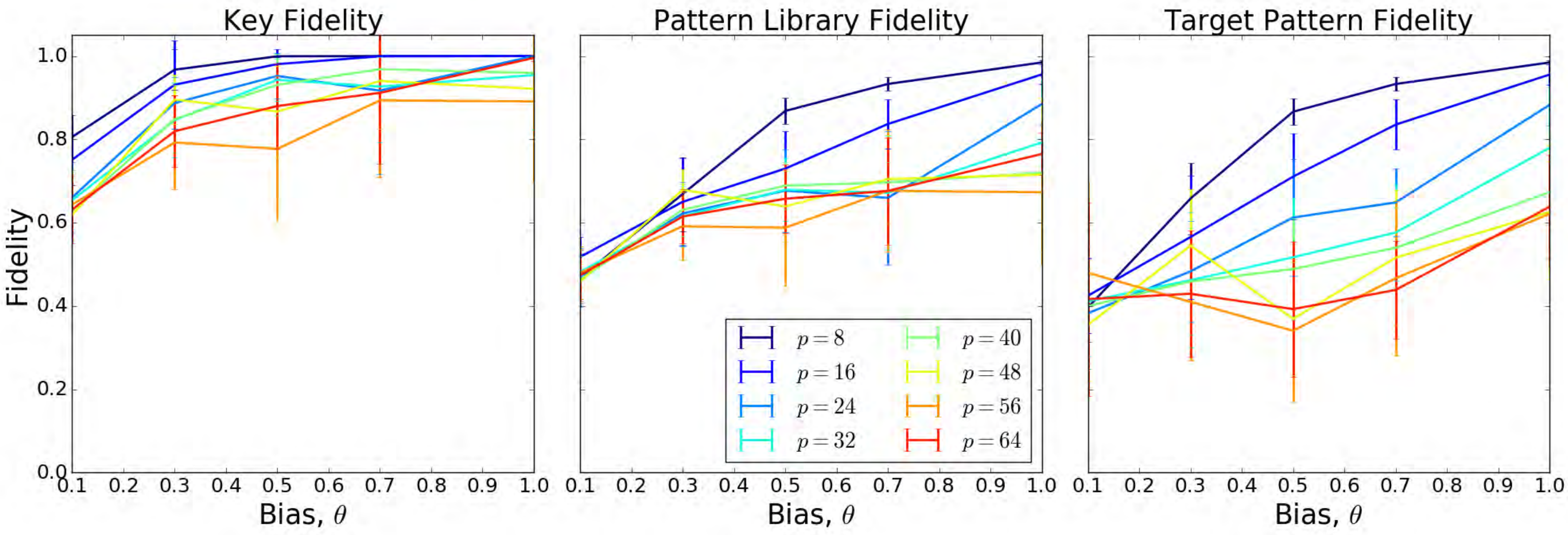
Key	Value
1	1 0 1 1 0
1	0 1 1 0 1
1	1 0 0 0 1
1	1 0 0 1 1

We cast the HEP pattern matching problem as a *binary classification* problem

We only care if the recalled pattern is in the library

Forward Annealing Results

Recalling patterns in the library



Metrics

$$F = prob(k_{state} = k_{library})$$

$$F = \max_{v \in v_{library}} \frac{1}{||v\rangle|^2} |\langle v | v_{state} \rangle|^2$$

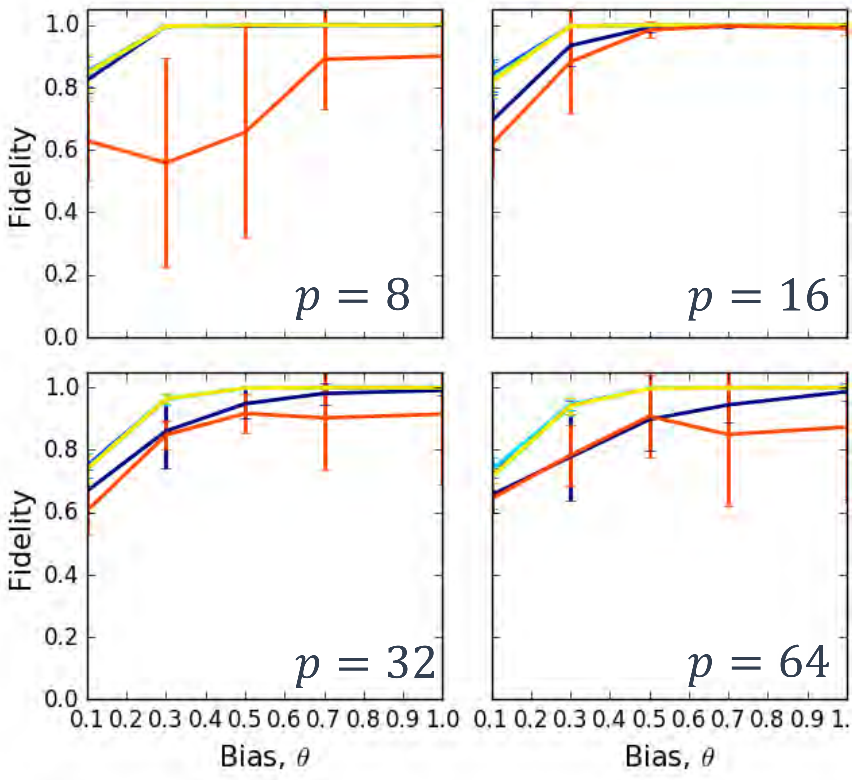
$$F = \frac{1}{||v\rangle|^2} \left|\langle v_{target} | v_{state} \rangle\right|^2$$

Forward Annealing Results

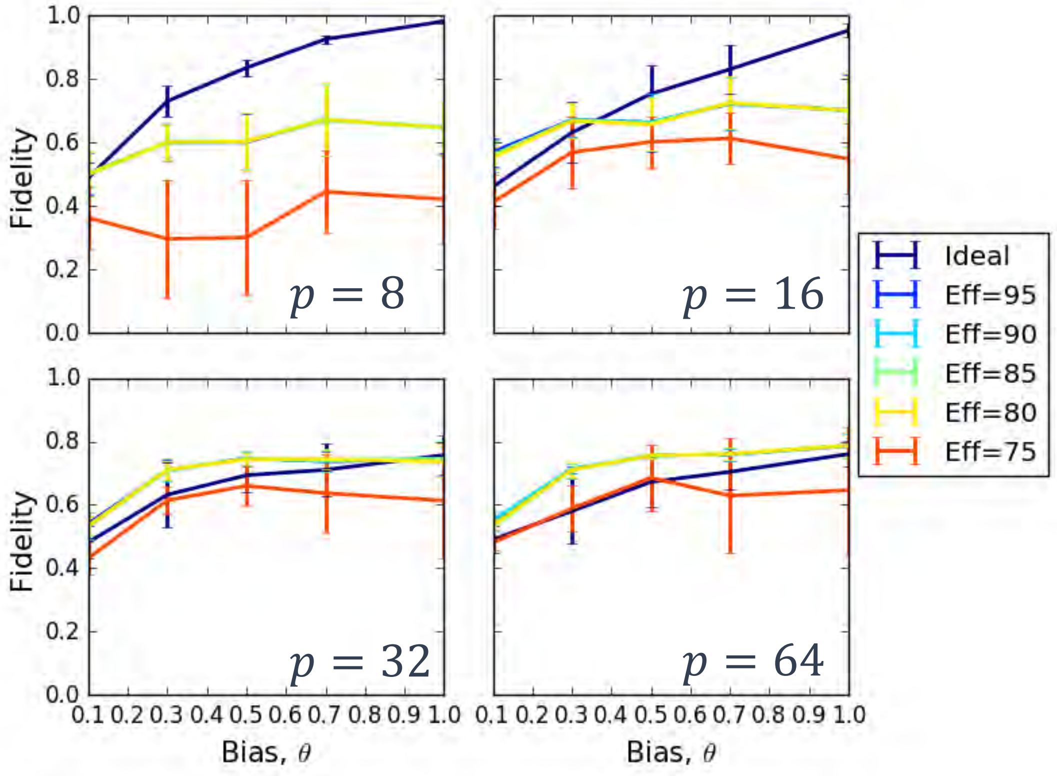
Adding Inefficiency

Inefficiency: Each cell involved in a pattern is associated with a probability of detection

Key Fidelity



Pattern Library Fidelity



Forward Annealing Results

Adding Inefficiency

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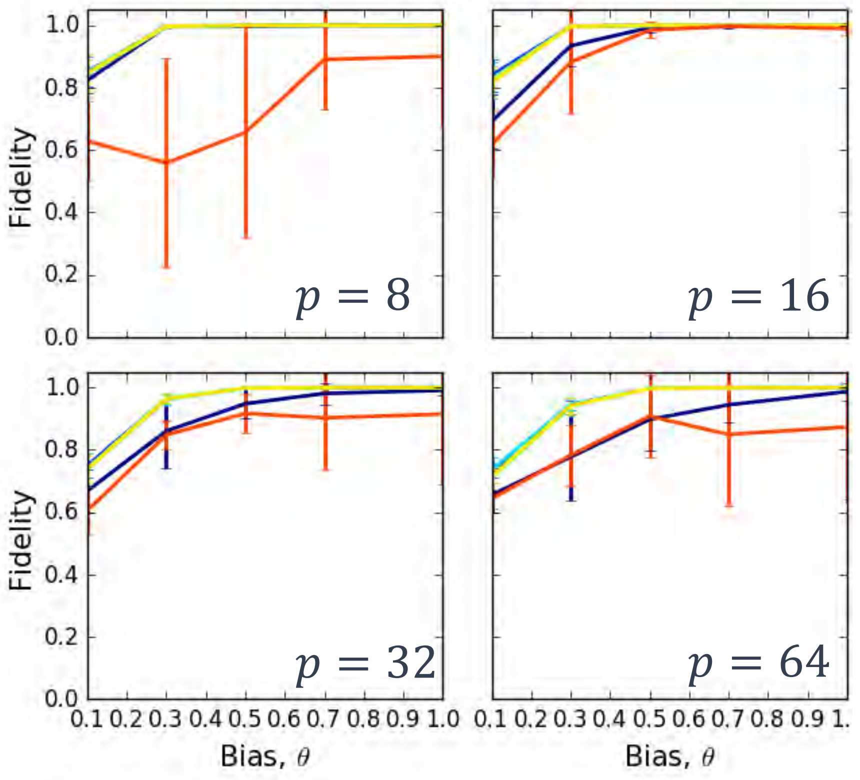
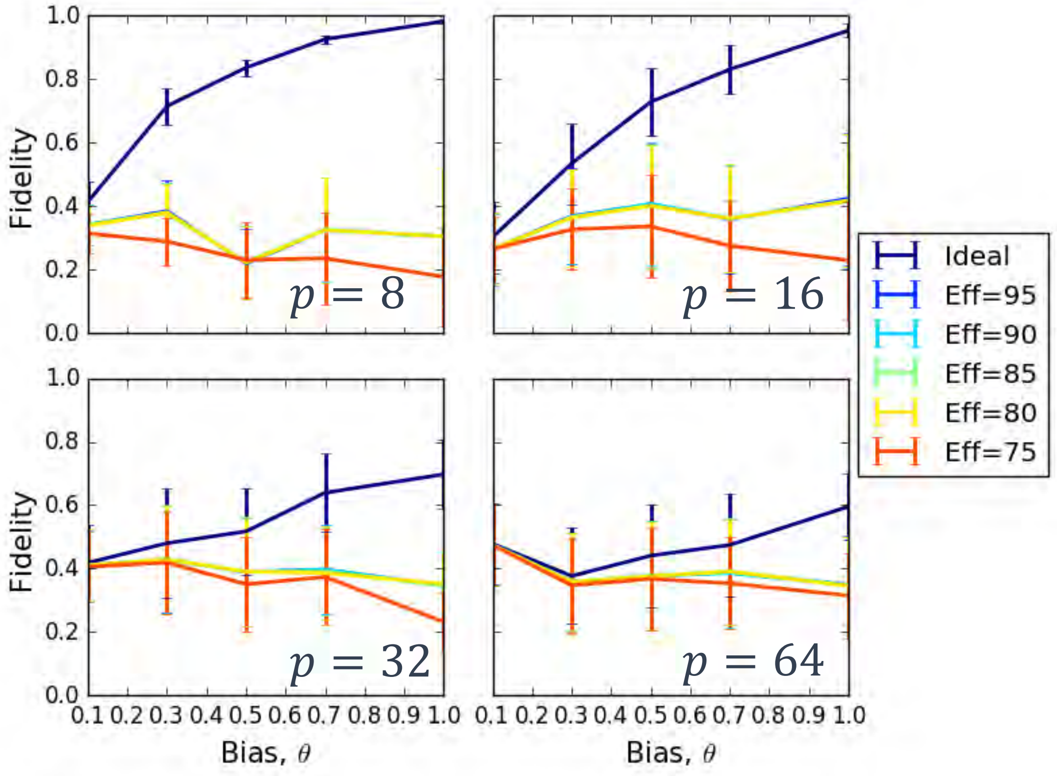
Key Fidelity



Target Pattern Fidelity

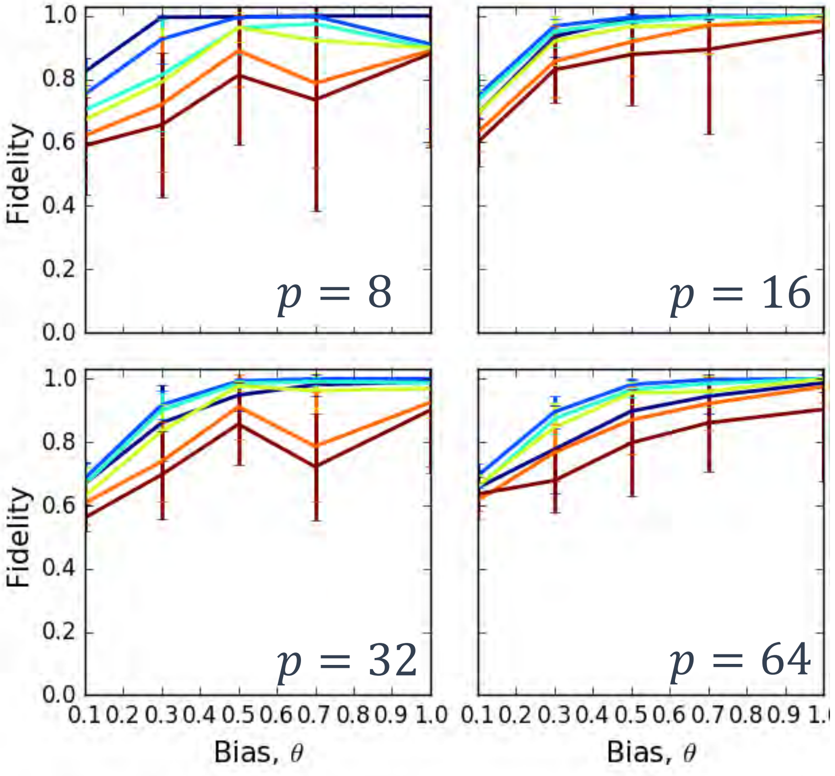


Forward Annealing Results

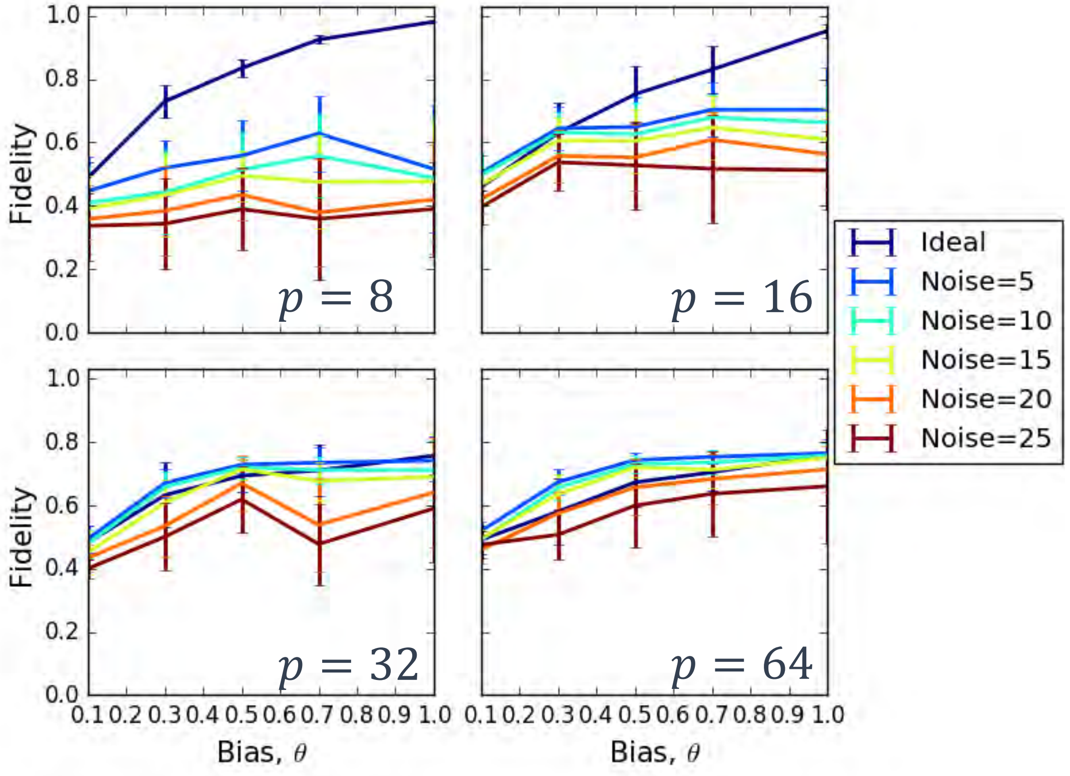
Adding False Detection Events

False Detections: Each cell not involved in a track pattern is associated with a probability of detection

Key Fidelity



Pattern Library Fidelity

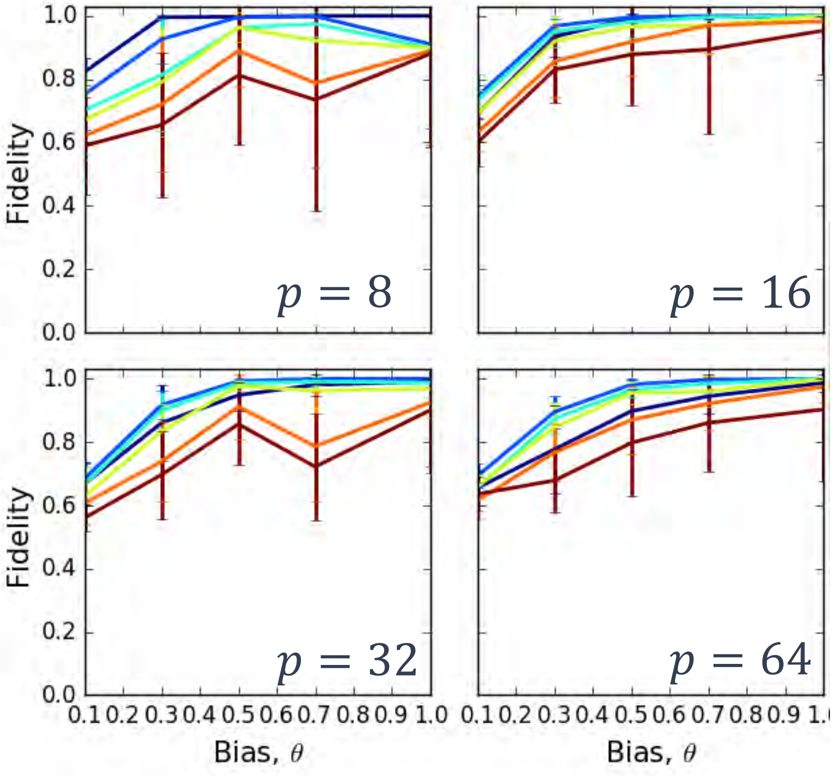


Forward Annealing Results

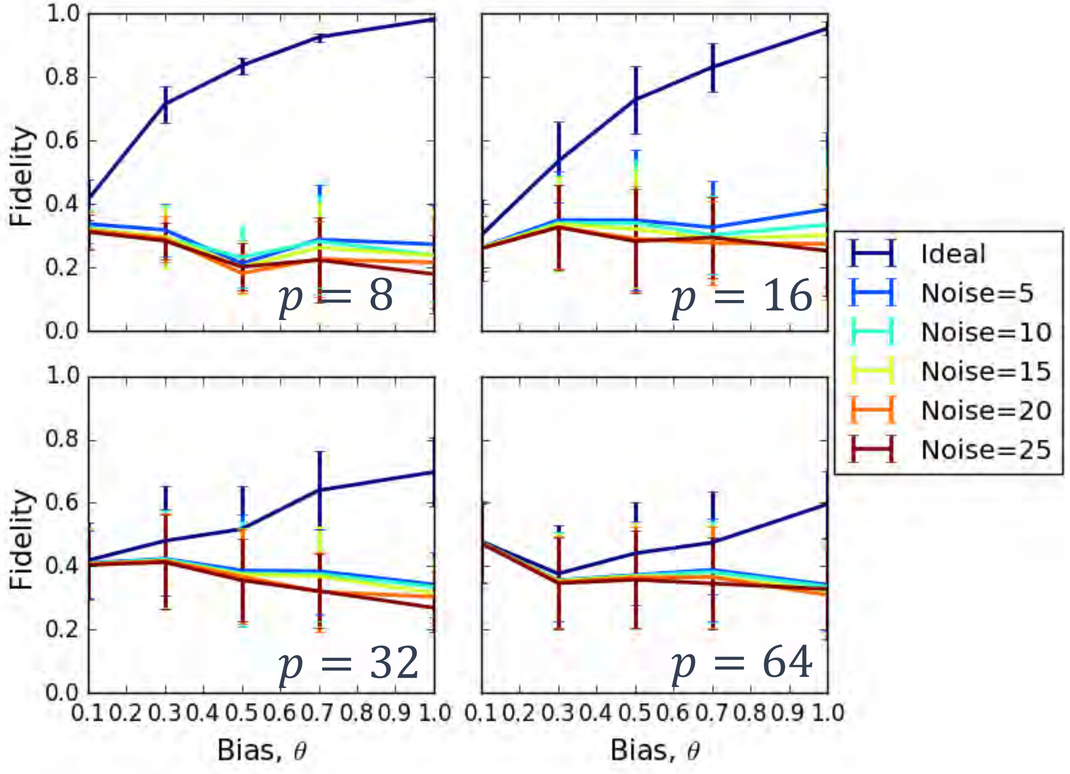
Adding False Detection Events

False Detections: Each cell not involved in a track pattern is associated with a probability of detection

Key Fidelity



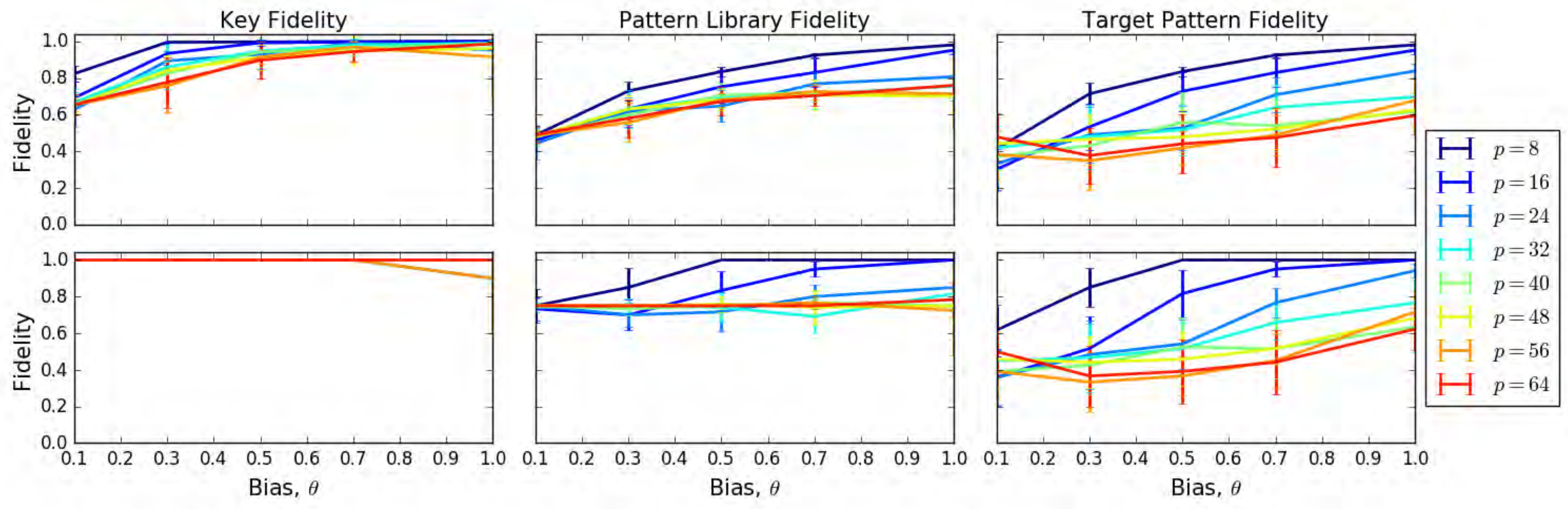
Target Pattern Fidelity



Reverse Annealing Results

Forward Anneal

Reverse Anneal



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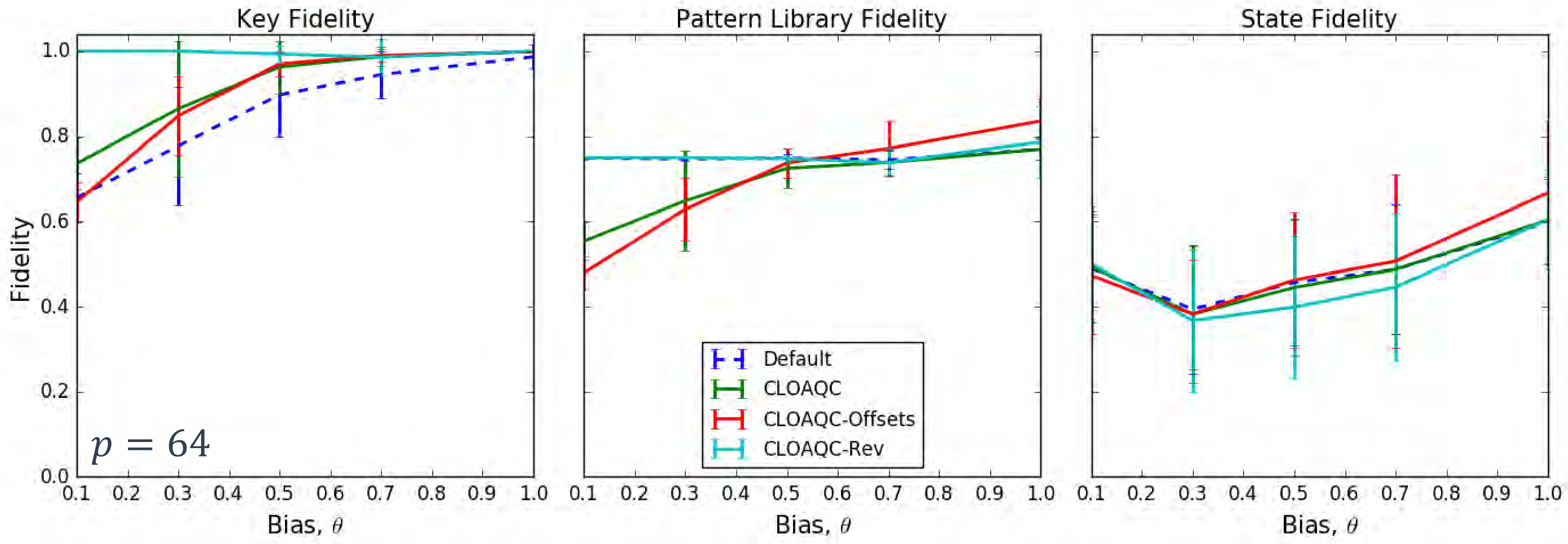
Optimizing Control

Control degrees of freedom provides a means for improving hardware performance



G. Quiroz PRA 99, 062306 (2019)

Conclusions

- Limits on binary classification
  - Dependent on number of encoded patterns
  - Fidelity metric matters

- Reverse annealing can improve performance
  - Dependent upon number of encoded patterns

- Optimized control can improve performance
  - Forward annealing
    - Offset optimization most beneficial
  - Reverse annealing

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