Numerical Simulations of Quantum Error Correction

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Fault-tolerant overhead

- We want to execute a quantum algorithm with N logical gates.
  - $N \sim 10^{12}$-10^{15} to simulate a small molecule like Fe_2S_2.
- Each gate is error-corrected to accuracy δ, so errors build up to
  - $N\delta$ if they add coherently (worst case, systematic bias).
  - $\sqrt{N}\delta$ if they add stochastically.
- δ needs to be $\sim 1/\sqrt{N}$ to $1/N$ to prevent harmful error build up.
  - 10^{-6} to 10^{-15} for quantum chemistry (pretty vague).
- If the physical noise rate ϵ is sub threshold, then fault-tolerant error correction can produce logical gates of accuracy δ with overhead $\mathrm{polylog}(\frac{1}{\delta})$.

Given a physical noise rate ϵ, how much error correction do I need to achieve a logical noise rate δ?

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Outline

Pauli noise

- Noise modeled by some (perhaps correlated) probability distribution $P(E)$, over $E \in \mathcal{P}^{\otimes N}$.
- To numerically simulate:
  - Sample $E \sim P(E)$ (only randomness).
  - Compute associated syndrome $s(E)$.
  - Decode: guess $\hat{E}$ from s.
  - Check if $\hat{E} \simeq E$ (up to stabilizer).
  - Repeat to estimate logical error probability.
- For generalized noise models (think of systematic error $U^{\otimes N}$):
  - Errors are not element of the Pauli group: CPTP map.
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Quantum many-body methods

- Realistic noise models cannot be efficiently simulated.
  - Interacting quantum many-body problem.

Our contribution

Study fault-tolerance with realistic noise models using numerical many-body techniques

- Tensor network methods
  - Density matrix renormalization group (DMRG).
  - Projected entangled pairs state (PEPS).
  - Multi-scale entanglement renormalization ansatz (MERA).
  - etc.

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What goes into a simulation?

- Prepare some known code state $|\bar{\psi}\rangle$.
- Applying some noise $\mathcal{E}$ to $\rho = |\bar{\psi}\rangle\langle\bar{\psi}|$.
  - When $\mathcal{E}$ is some stochastic noise, we can sample the noise instead of applying $\mathcal{E}$.
- Sample the syndrome bits $\mathrm{pr}_j(\pm) = \frac{1}{2}(1 \pm \mathrm{Tr}[\mathcal{E}(\rho)S_j])$.
- Decode, i.e., find a correction operation C based on the observed syndrome.
- Apply the correction to the post-measurement state ρ'.
- Evaluate the logical transformation that has been applied to the logical state.
- Repeat for different input states $\bar{\psi}$ to perform logical process tomography.
  - We actually use Jamilkowski isomorphism instead.

Stuff in red is numerically hard.

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If we can do all of this...

Simulation

INPUT

- Noise $\mathcal{E}$.

OUTPUT

- A syndrome s.
- The probability of that syndrome pr(s).
- The logical channel conditioned on that syndrome $\mathcal{E}_s^L$.

Given this we can estimate...

- Average channel $\overline{\mathcal{E}}_L = \sum_s \mathrm{pr(s)}\mathcal{E}_\mathrm{s}^\mathrm{L}$
- Average logical error $\sum_s \mathrm{pr(s)}\|\mathcal{E}_\mathrm{s}^\mathrm{L} - \mathrm{id}\|$
- Error of logical average $\|\mathcal{E}_L - \mathrm{id}\|$
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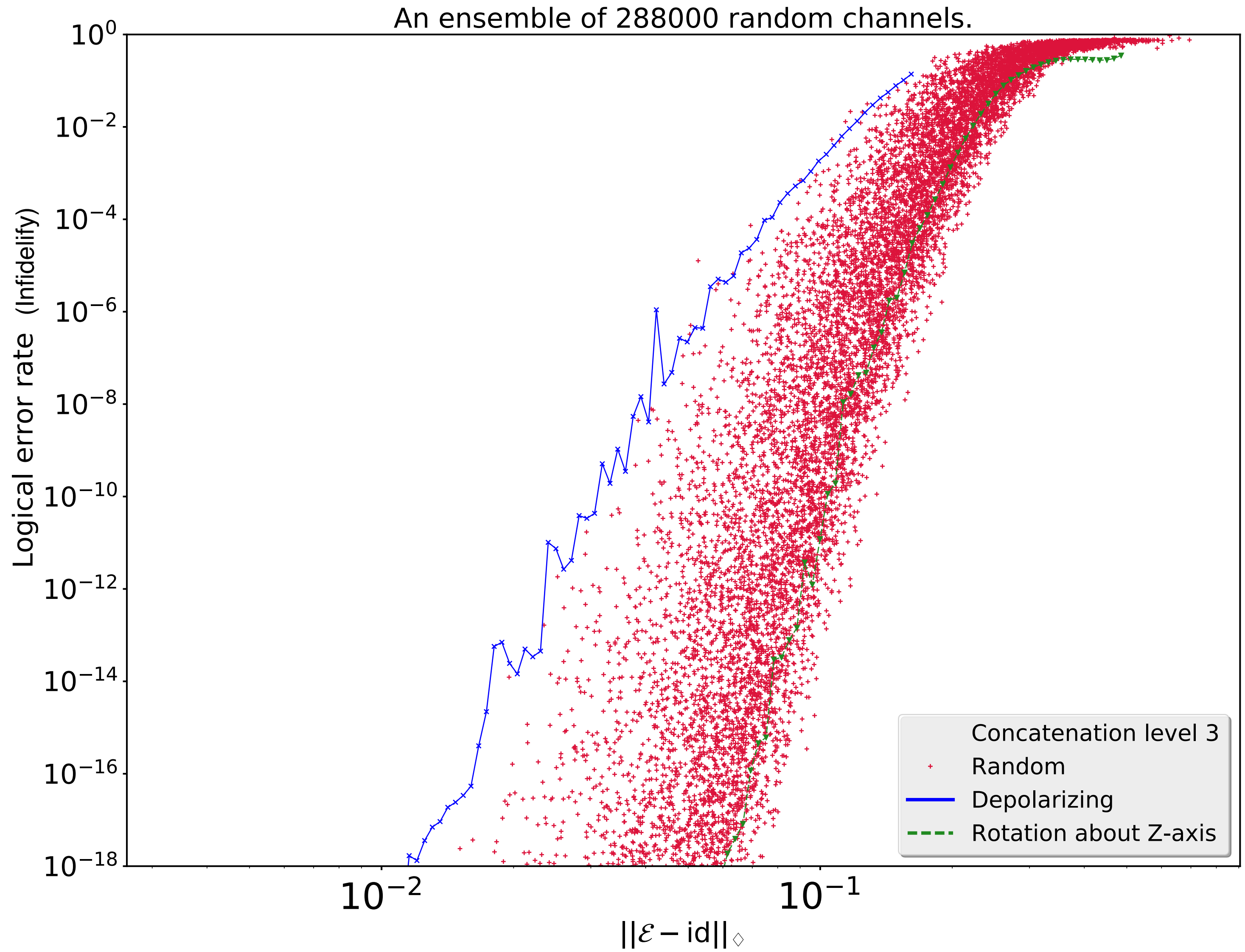

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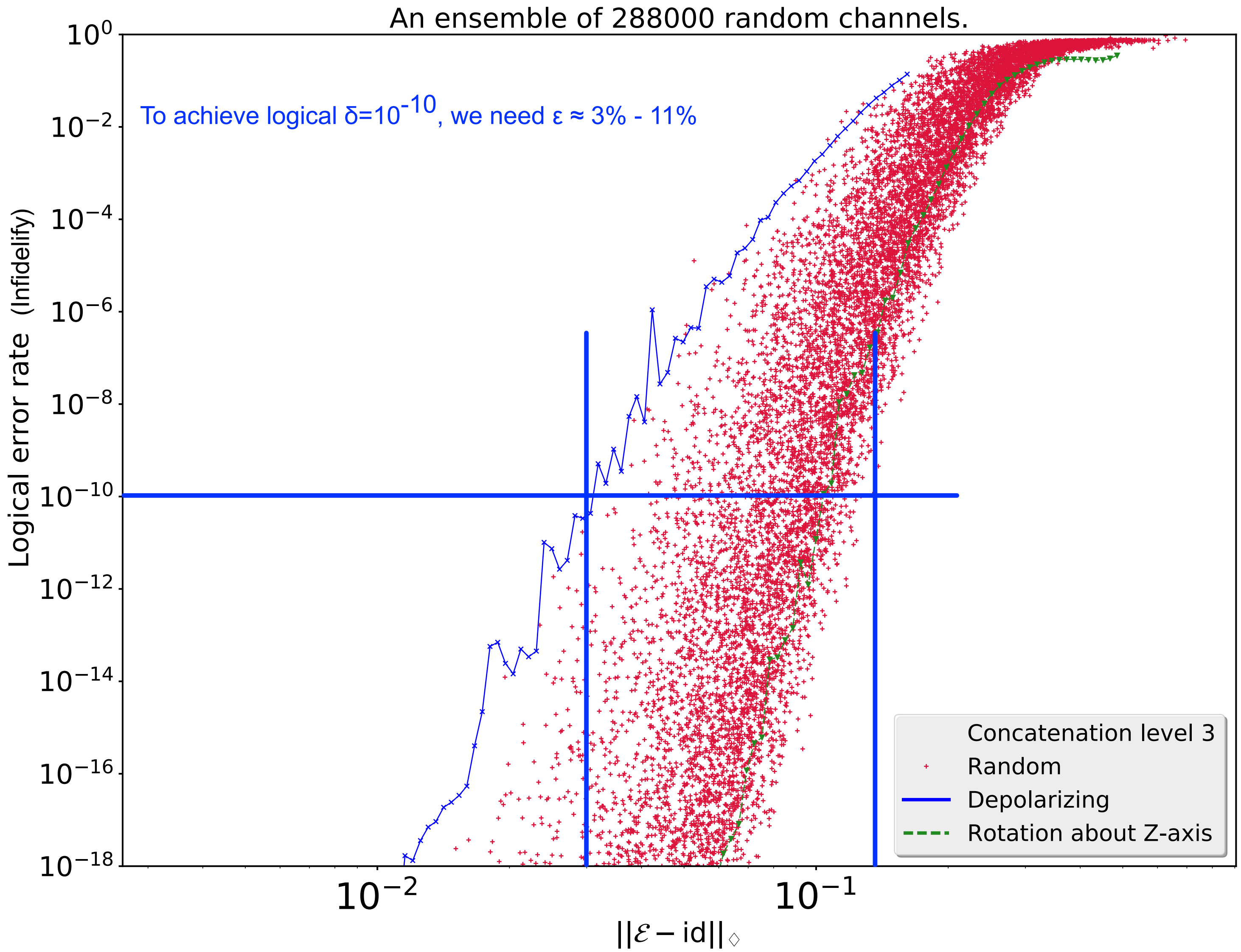

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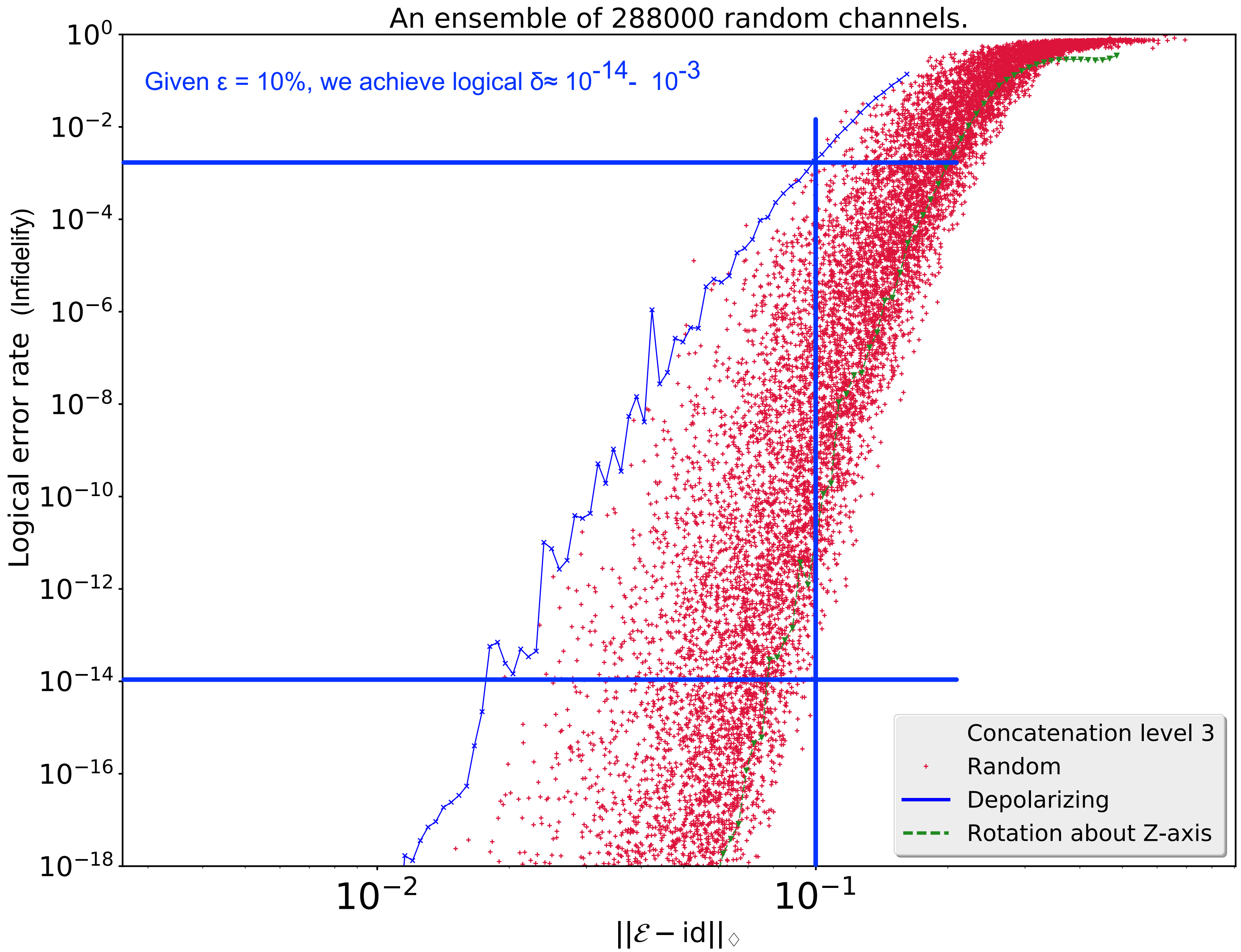

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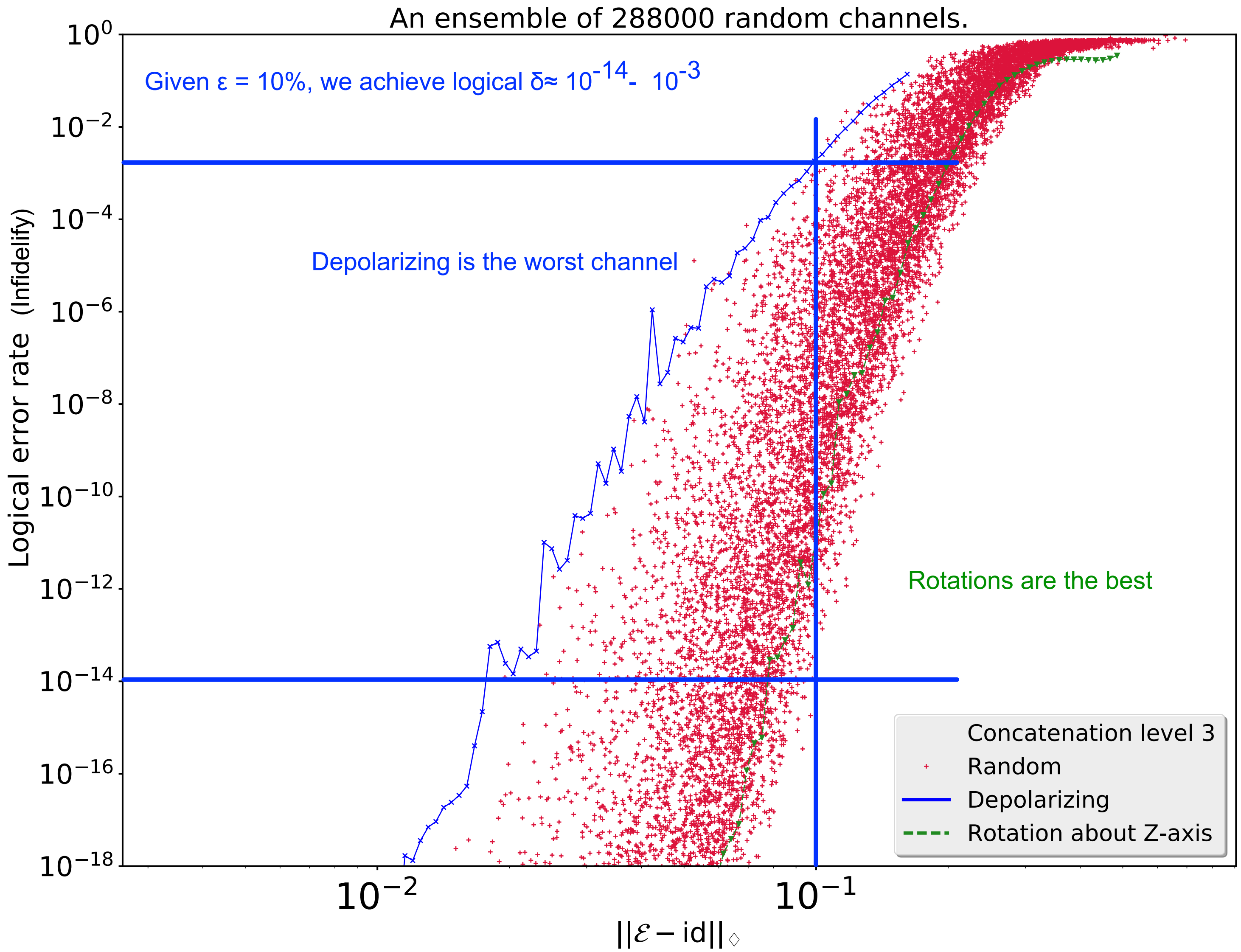

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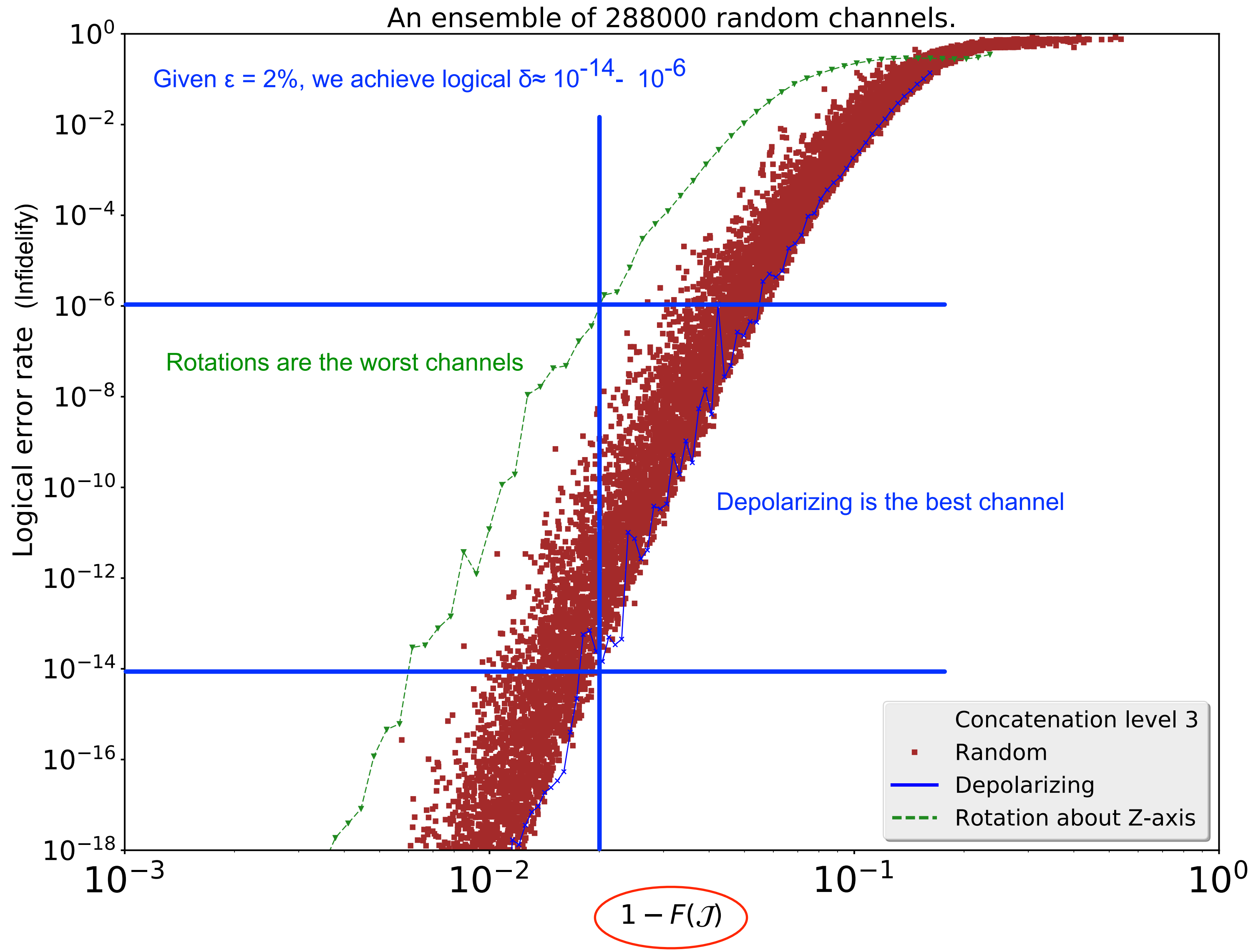

Predictability of noise metrics

Conclusion

It is not possible to even very crudely predict the logical failure rate of a FT scheme given only the noise rate of the physical channel, as measured by any of the standard error metrics (Infidelity, Diamond norm, Channel entropy, Error probability, Euclidian norm, Trace norm).

Outline

Pauli approximations

MC simulations are numerically very efficient, but limited to unphysical Pauli noise models.

- Let's approximate the physical channel $\mathcal{E}$ by a Pauli channel $\mathcal{P}$.
  - Ignore the non-Pauli contributions to the channel.
- E.g. Rotation $R_z(\theta) = e^{i\theta Z} = \cos\theta I + i\sin\theta Z$ error

$$\rho \to (\cos\theta I + i\sin\theta Z)\rho(\cos\theta I - i\sin\theta Z)$$

is approximated by a stochastic Z error (dephazing)

$$\rho \to \cos^2\theta\ \rho + \sin^2\theta\ Z\rho Z.$$

- Or we could find the closest Pauli channel which is no better than $\mathcal{E}$: Honest Pauli Approximation

Magasan, Puzzuoli, Granade, & Cory arXiv:1206.5407

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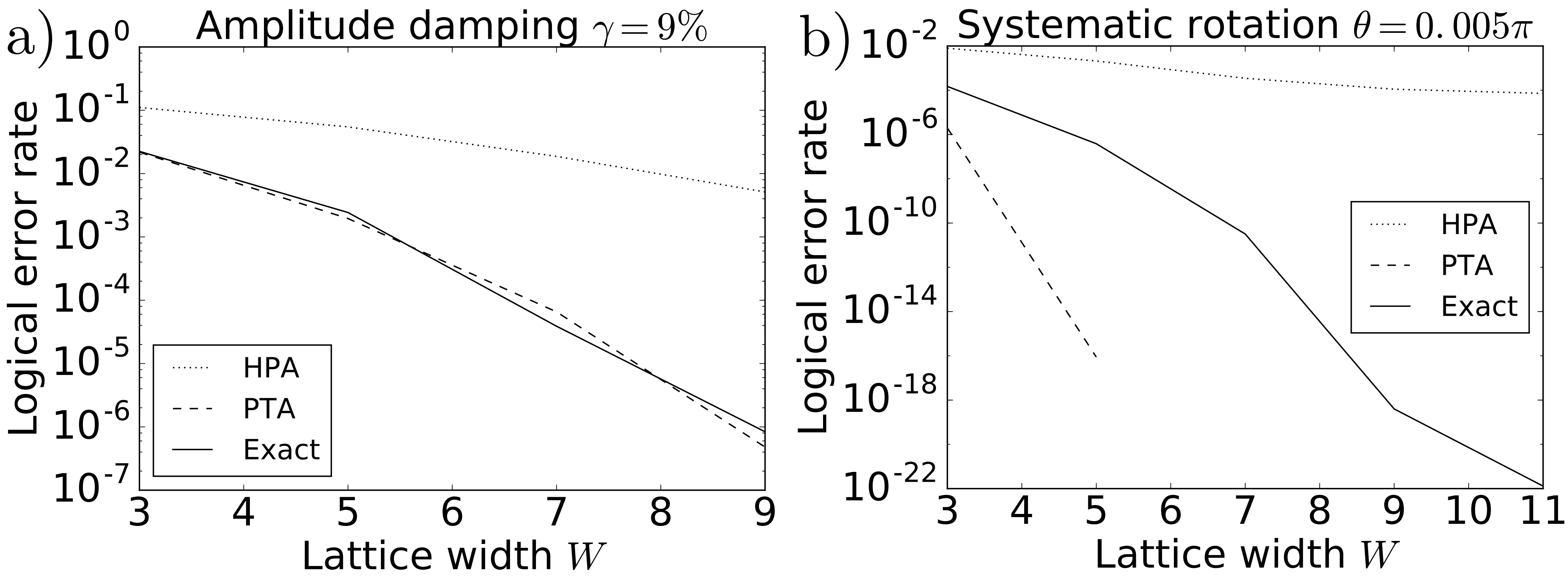
Pauli approximations, surface code overhead



- Amplitude damping, lattice up to size $9 \times 17 = 153$ qubits.
- Depolarizing, lattice up to size $11 \times 11 = 121$ qubits.

Usefulness of Pauli approximations

Conclusions

- It is not possible to even very crudely predict the logical failure rate of a FT scheme from known Pauli approximations.
- The twirl approximation gets a good threshold estimate in the examples we looked at.
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Decoding non-Pauli noise

There are two levels of difficulty: decoding and simulating.

- Even for Pauli noise, decoding is in general a hard problem, but there are efficient algorithms for some classes of codes.
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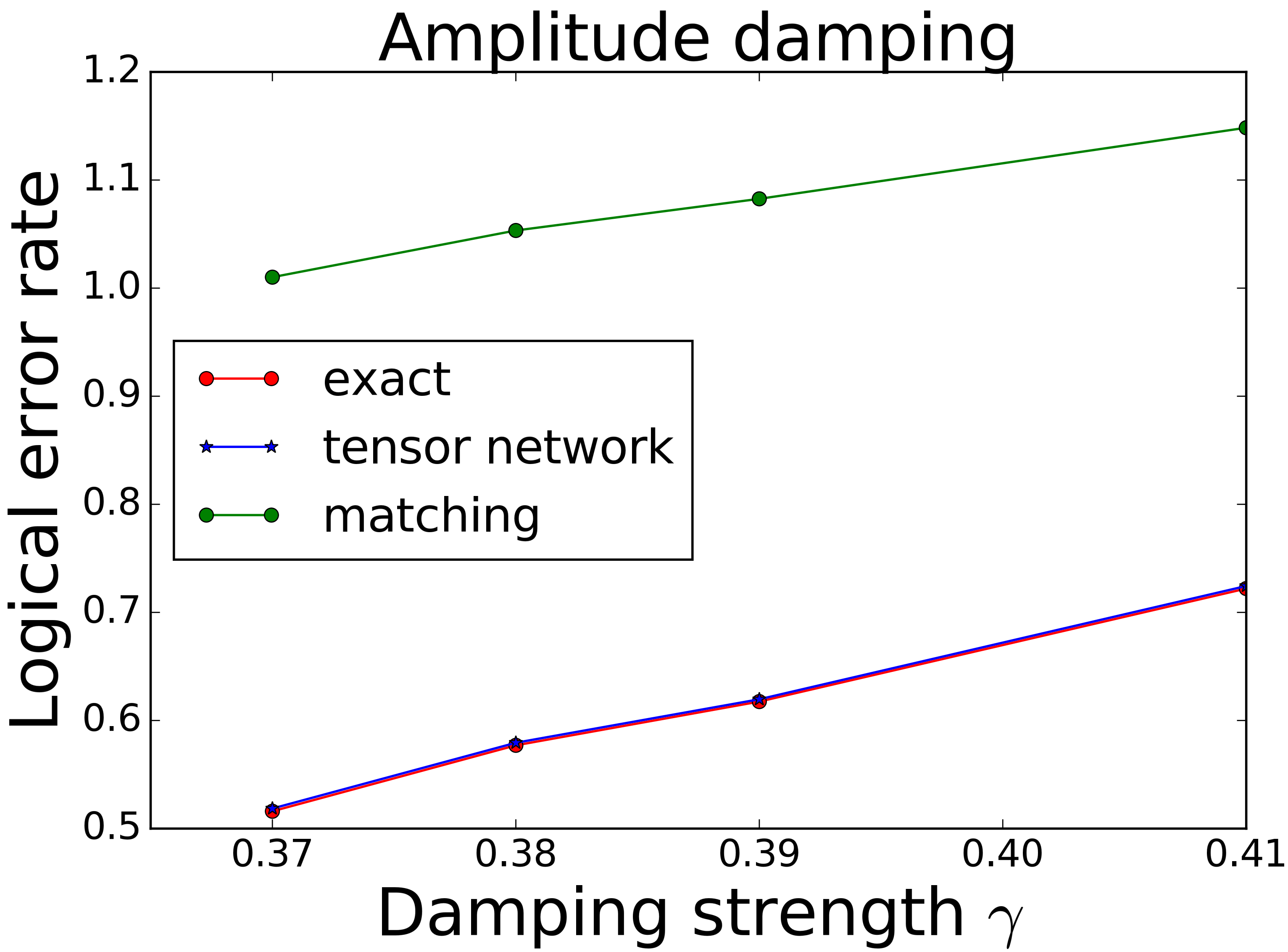
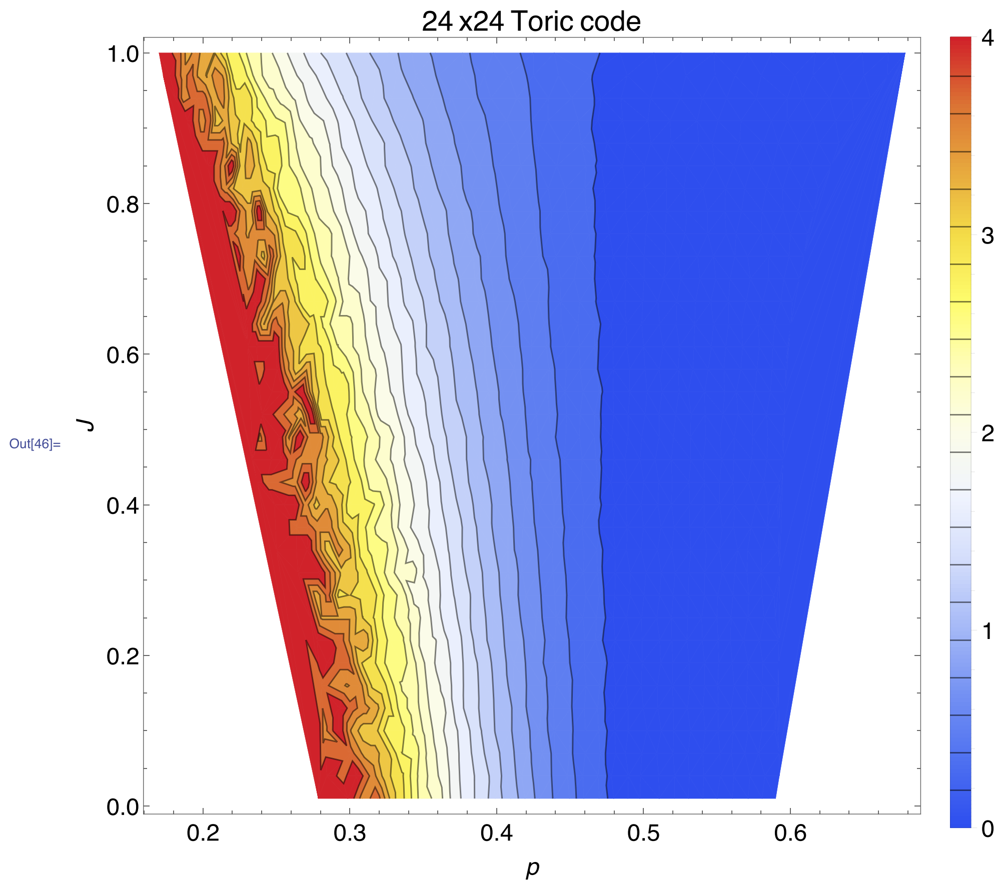
Pauli approximations for surface code decoding



Correlated erasures on surface code



The erasure pattern is given by spin down configuration of a classical ferromagnetic Ising model in a magnetic field favoring spin ups.

Color shows
$-\log_{10}(\text{logical error rate})$

Known vs unknown inhomogeneity

- Different errors affect the performance of a fault tolerance scheme differently, so additional efforts should be assign to reduce the critical noise parameters.
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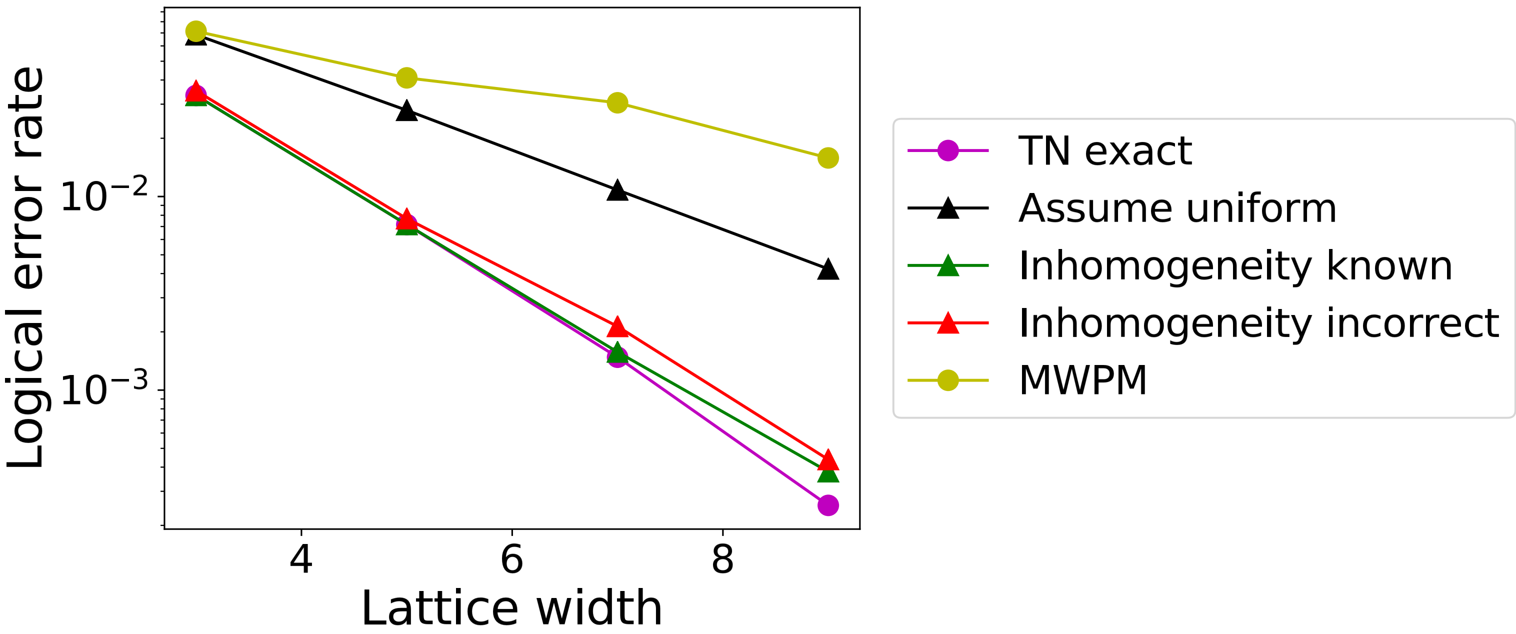

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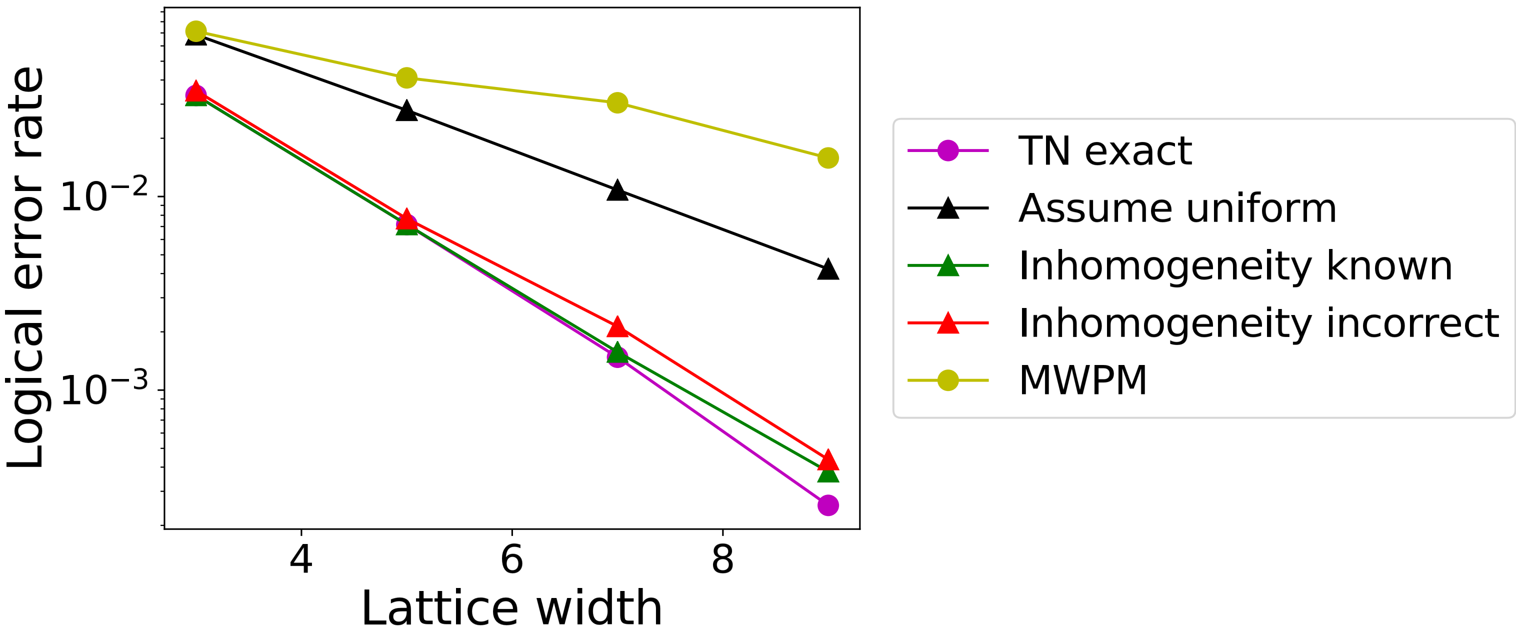

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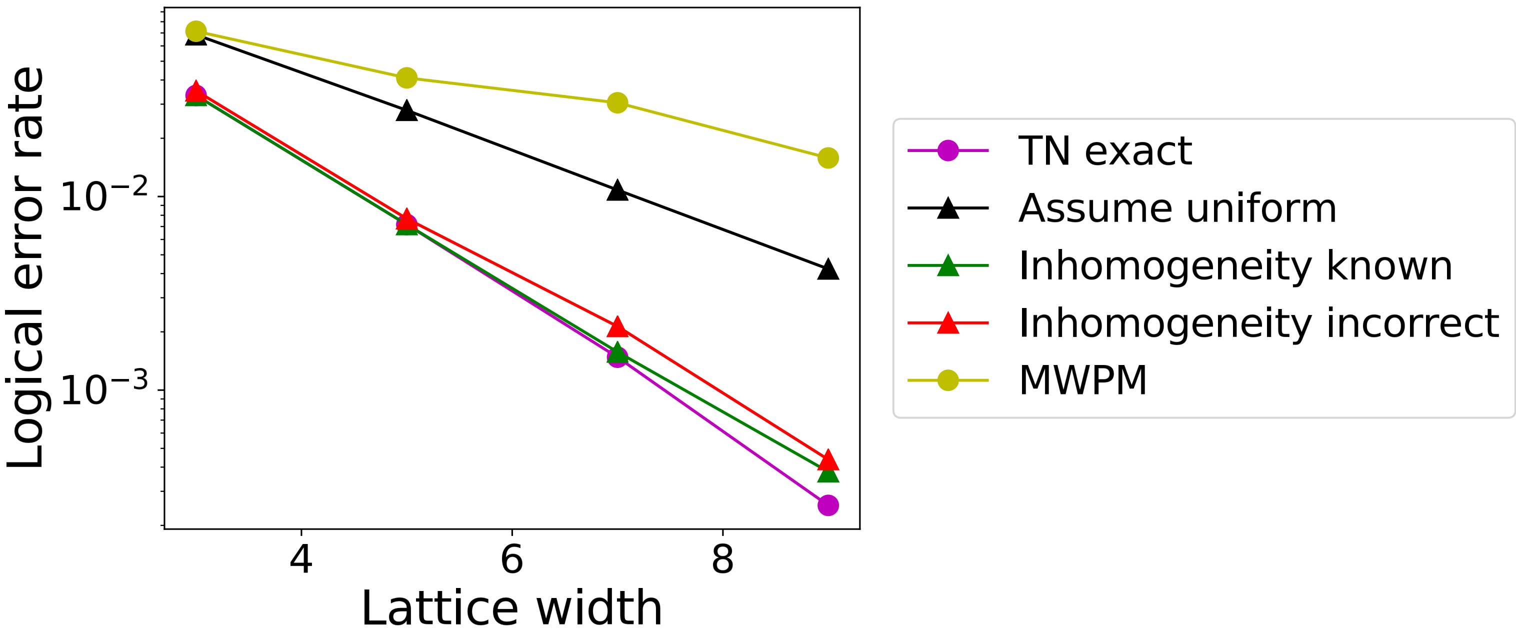

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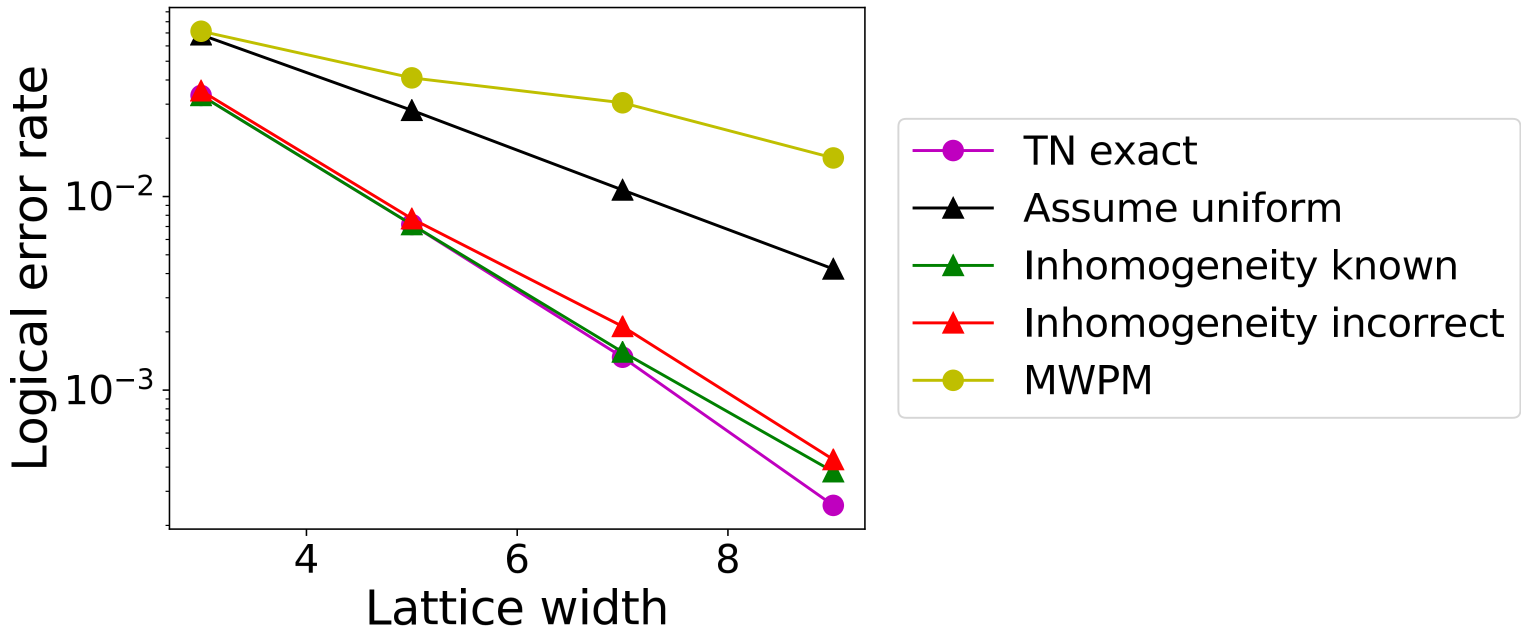

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Institue Quantique @ Sherbrooke

We are looking for talented

- Graduate students
- Postdocs
- Visiting faculty/scientists

Talk to me if you have any interest.