

A Sublinear-Time Quantum Algorithm for Approximating Partition Functions

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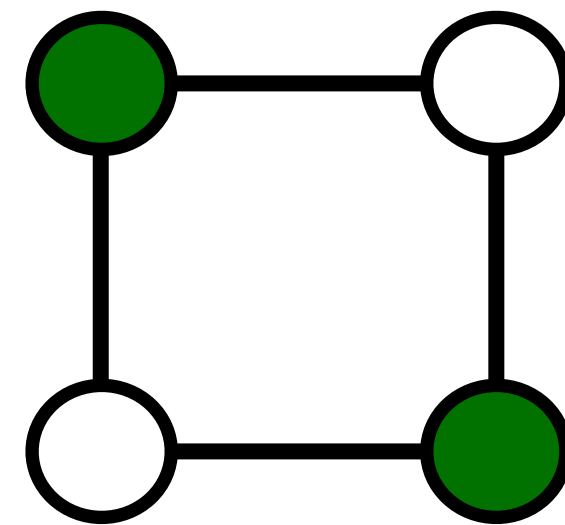
QuSoft

UC Berkeley

SODA'23, QIP'23

Independent sets

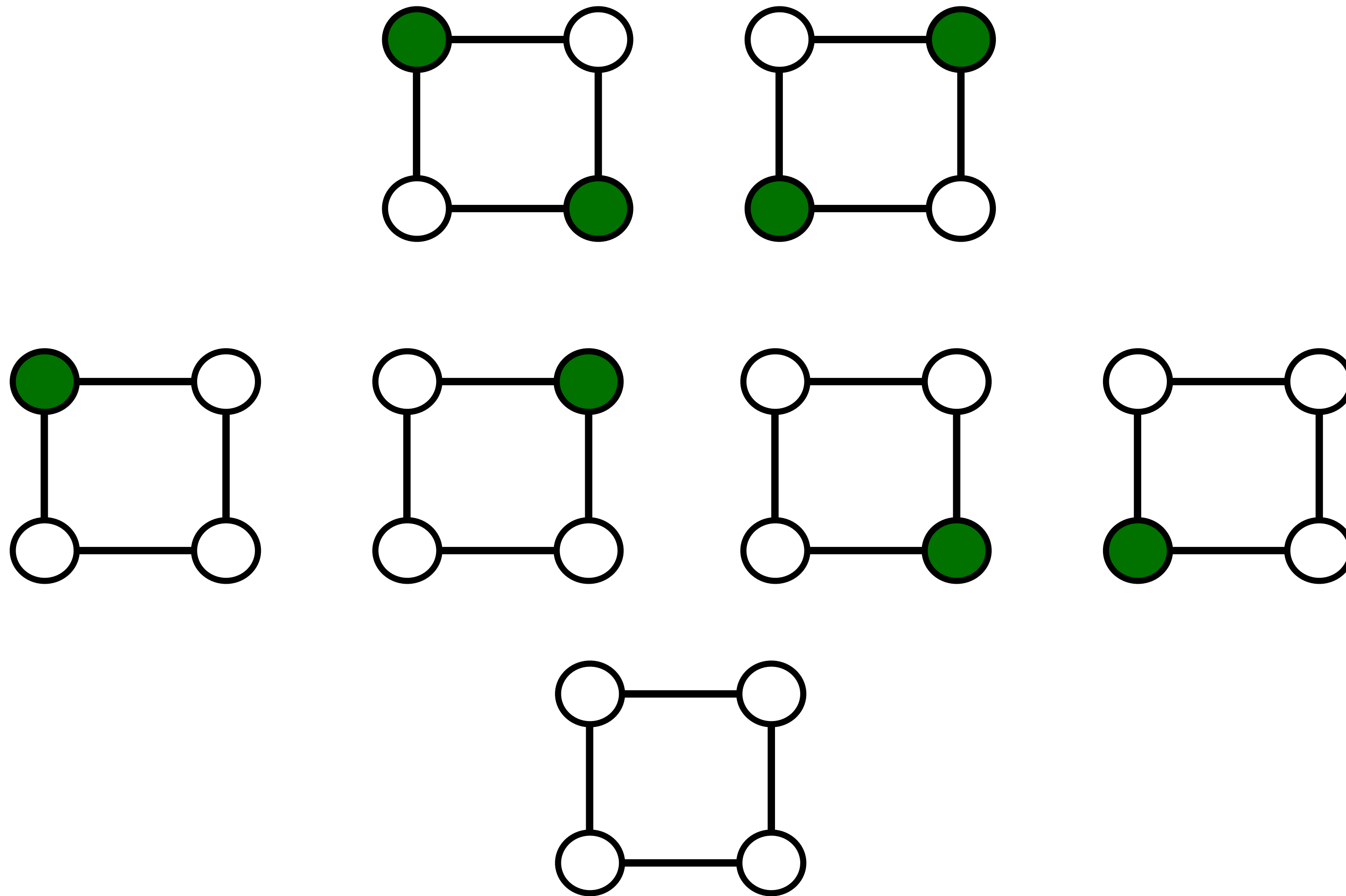
Independent set
= subset of non-adjacent vertices



● = occupied

Hard-core gas model in statistical physics

independent sets = 7



Input: graph G

Output: # independent sets of G

#P-hard in many regimes

Bipartite graphs

[Provan, Ball'83]

3-regular graphs

[Dyer, Greenhill'00]

...

Exact counting \longrightarrow **Approximate** counting?

Input: graph G and $\epsilon \in (0,1)$

Output: S s.t. $(1 - \epsilon) \#ind \leq S \leq (1 + \epsilon) \#ind$

$n = \#vertices$

Classical
algorithms

$$\tilde{O}(n^2/\epsilon^2)$$

[Štefankovič, Vempala, Vigoda'09]
[Chen, Liu, Vigoda'21]

5

No FPRAS unless
NP = RP

[Sly'10]

Quantum
algorithms

$$\tilde{O}(n^2 + n^{3/2}/\epsilon)$$

[Montanaro'15]

$$\tilde{O}(n^{3/2}/\epsilon)$$

[Harrow, Wei'20]

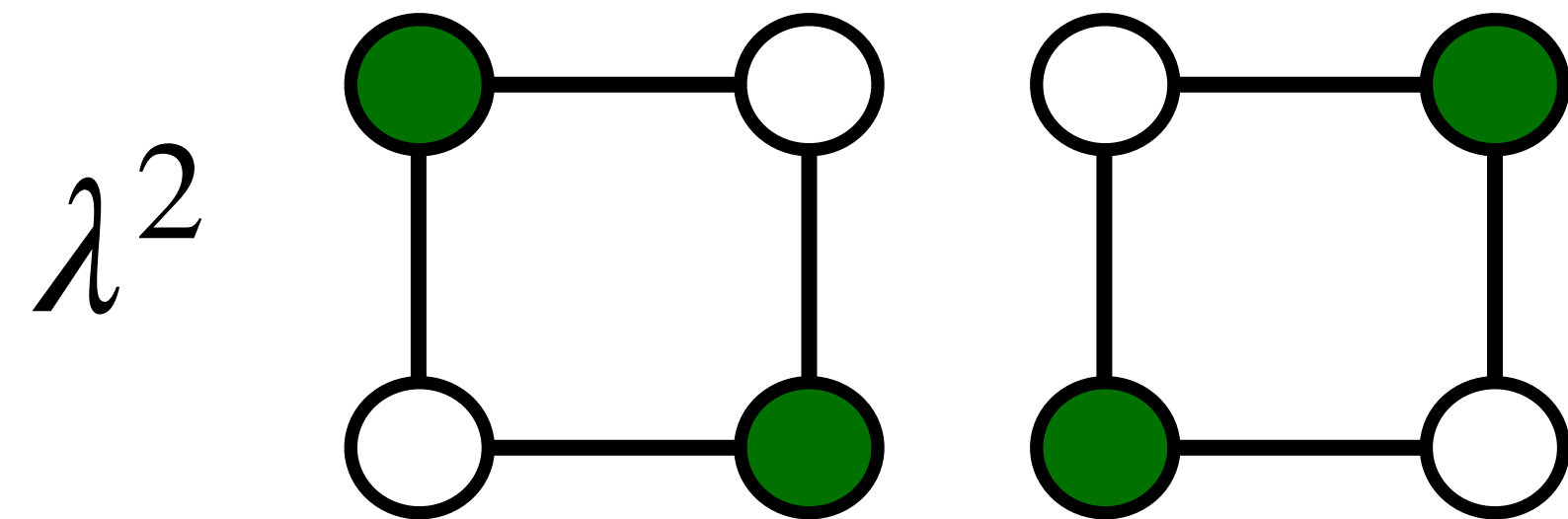
$$\tilde{O}(n^{5/4}/\epsilon)$$

Our work

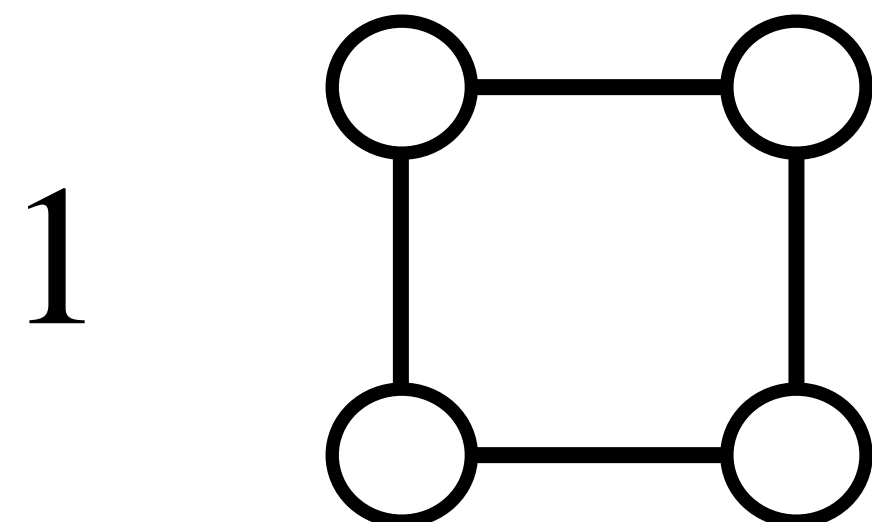
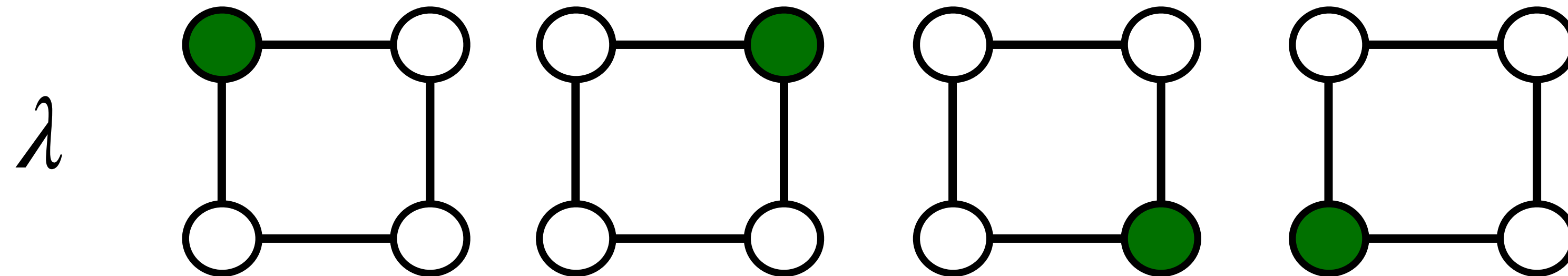
Maximum
degree in G

Weighted independent sets

$\lambda = \text{fugacity}$



Partition function: $Z(\lambda) = \sum_{I \text{ ind. set}} \lambda^{|I|}$



$$Z(0) = 1$$

$$Z(1) = \# \text{ ind}$$



Partition function: $Z(\lambda) = \sum_{I \text{ ind. set}} \lambda^{|I|}$

Gibbs distribution: $\pi(I) = \frac{\lambda^{|I|}}{Z(\lambda)}$

Glauber dynamics

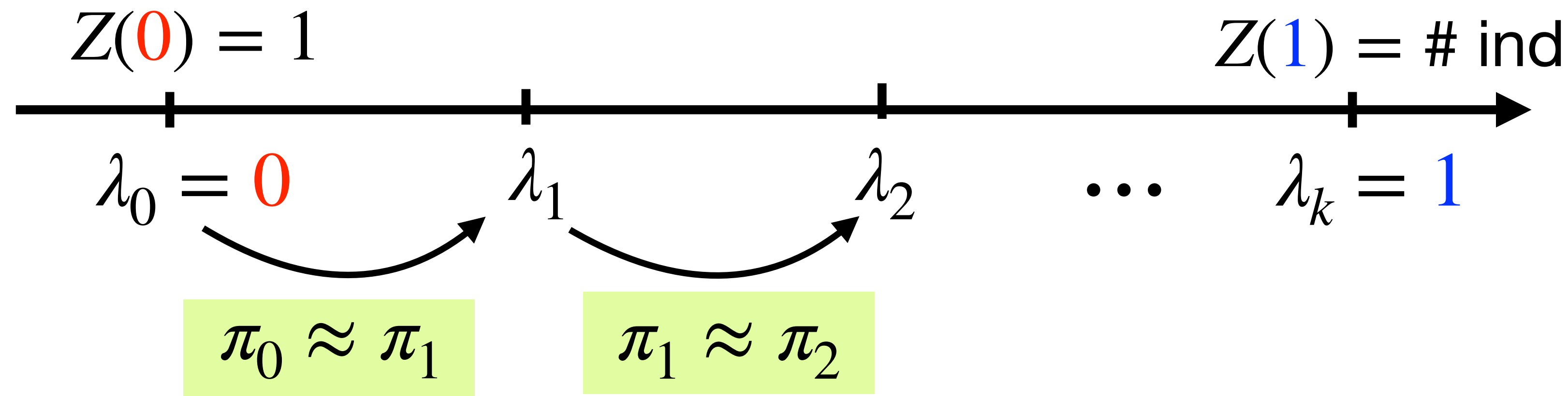
[Chen,Liu,Vigoda'21]

For any $0 \leq \lambda \leq 1$,
we can sample $I \sim \pi$ in time $O(n \log n)$

Sampling \longrightarrow **Approximate** counting?

Cooling schedule

[Štefankovič, Vempala, Vigoda'09]



$i \rightarrow i + 1$:

$$Z(\lambda_{i+1}) = \mathbb{E}_{I \sim \pi_i} \left(\frac{\lambda_{i+1}}{\lambda_i} \right)^{|I|} Z(\lambda_i)$$

Highly concentrated:
variance \leq expectation²

schedule
length k

sample
complexity

cost per
sample

$$\text{Cost} = \sqrt{n} \times \sqrt{n/\epsilon^2} \times n \log(n)$$

Quantum speedup(s)

Glauber dynamics

Sample ind. set $I \sim \pi$ in time $O(n \log n)$

No speedup for **sampling**?

We can **check** in time $O(\sqrt{n})$ if a quantum state is equal to:

$$|\pi\rangle = \sum_I \sqrt{\pi(I)} |I\rangle \quad (\text{quantum sample})$$

... without destroying the state!

$$|\pi\rangle = \sum_I \sqrt{\pi(I)} |I\rangle$$

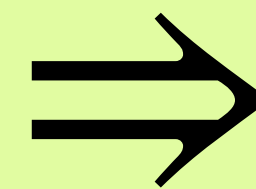
Check(π) :

$$|\pi\rangle |0\rangle \mapsto |\pi\rangle |0\rangle$$

$$|\mu\rangle |0\rangle \mapsto |\mu\rangle |1\rangle \text{ if } |\mu\rangle \perp |\pi\rangle$$

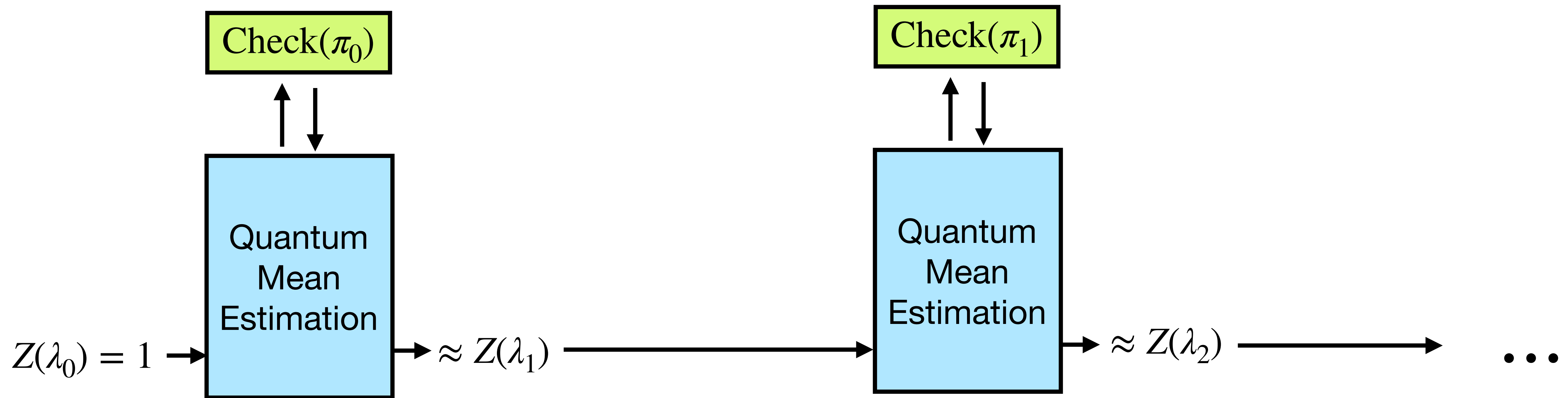
Szegedy Quantum Walk

Markov Chain with
stationary distribution π
and spectral gap δ



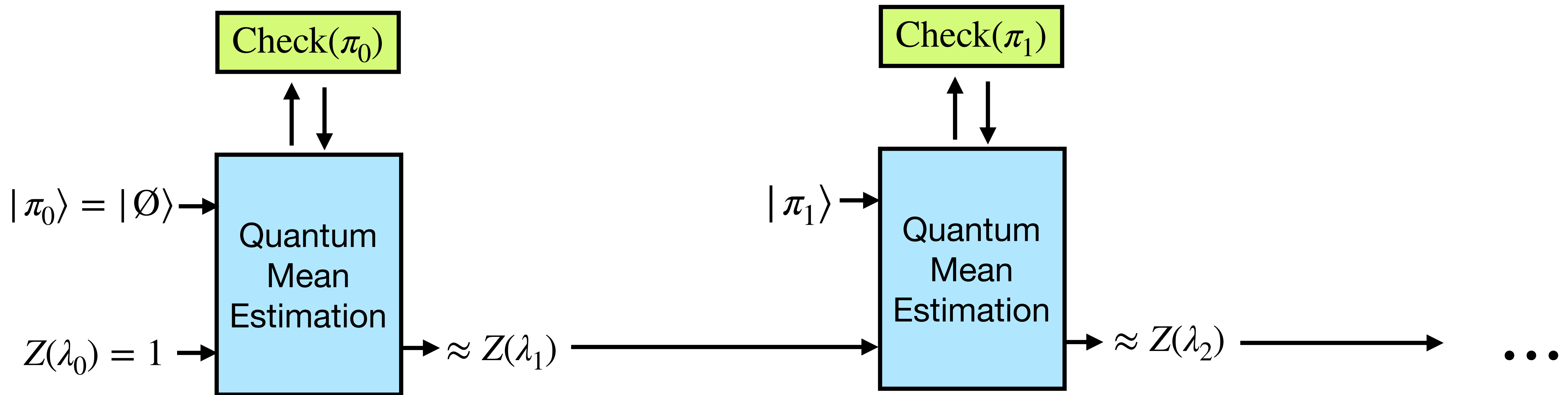
Check(π)
in time $\sim 1/\sqrt{\delta}$

Estimate $Z(\lambda_{i+1})$ using $\text{Check}(\pi_i)$?



Estimate $Z(\lambda_{i+1})$ using $\text{Check}(\pi_i)$?

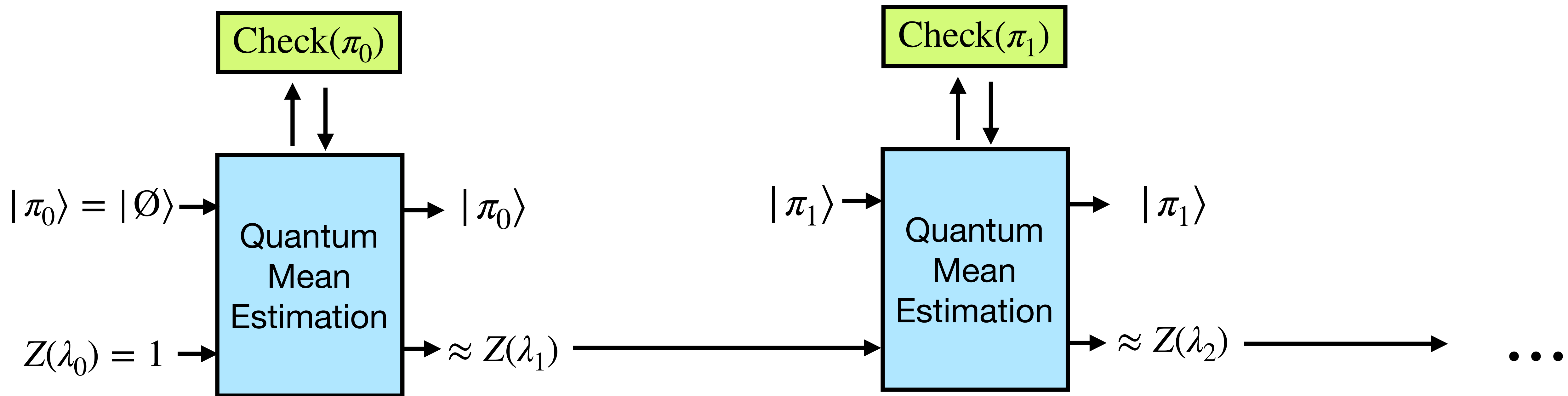
... and 1 copy of $|\pi_i\rangle$



Estimate $Z(\lambda_{i+1})$ using $\text{Check}(\pi_i)$?

... and 1 copy of $|\pi_i\rangle$

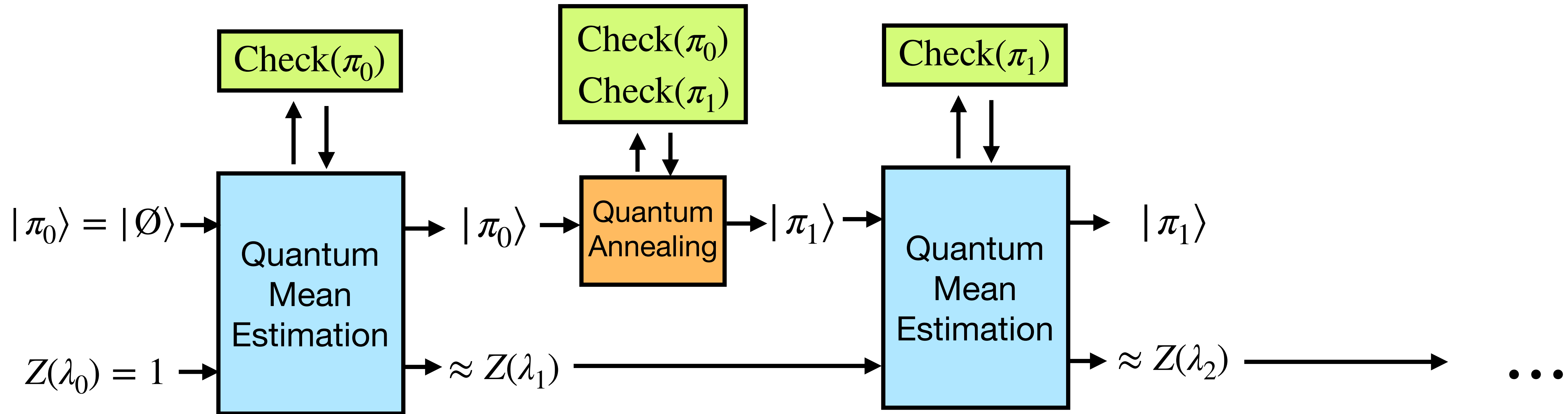
Nondestructively?



Estimate $Z(\lambda_{i+1})$ using $\text{Check}(\pi_i)$?

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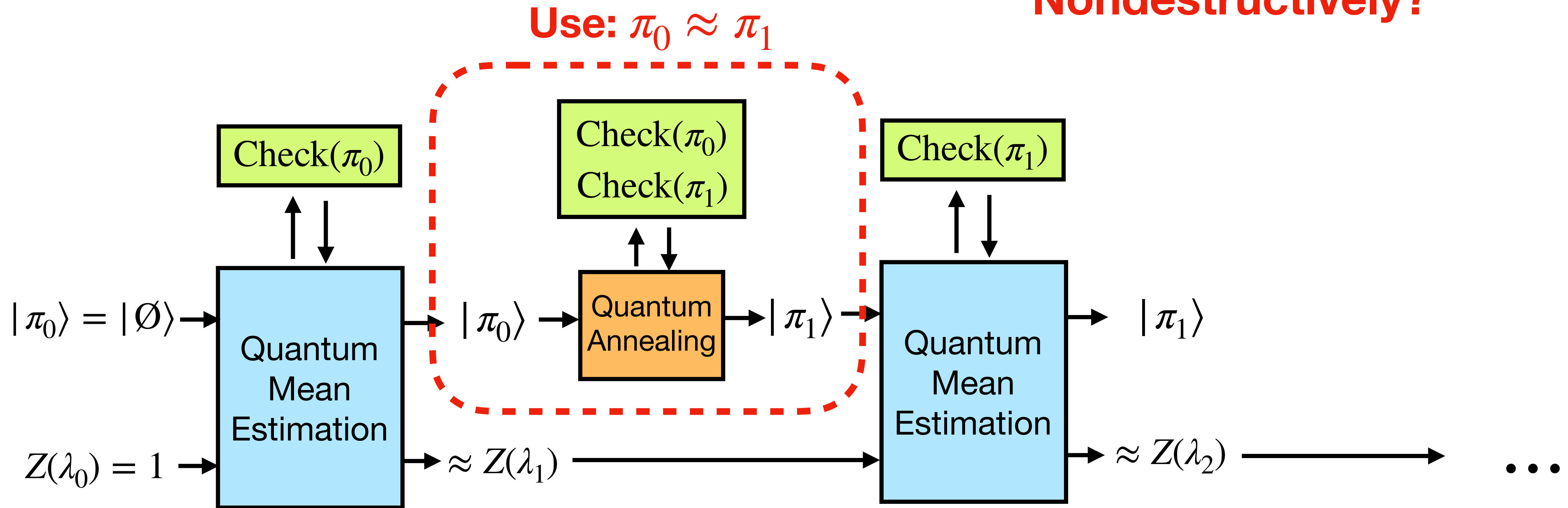
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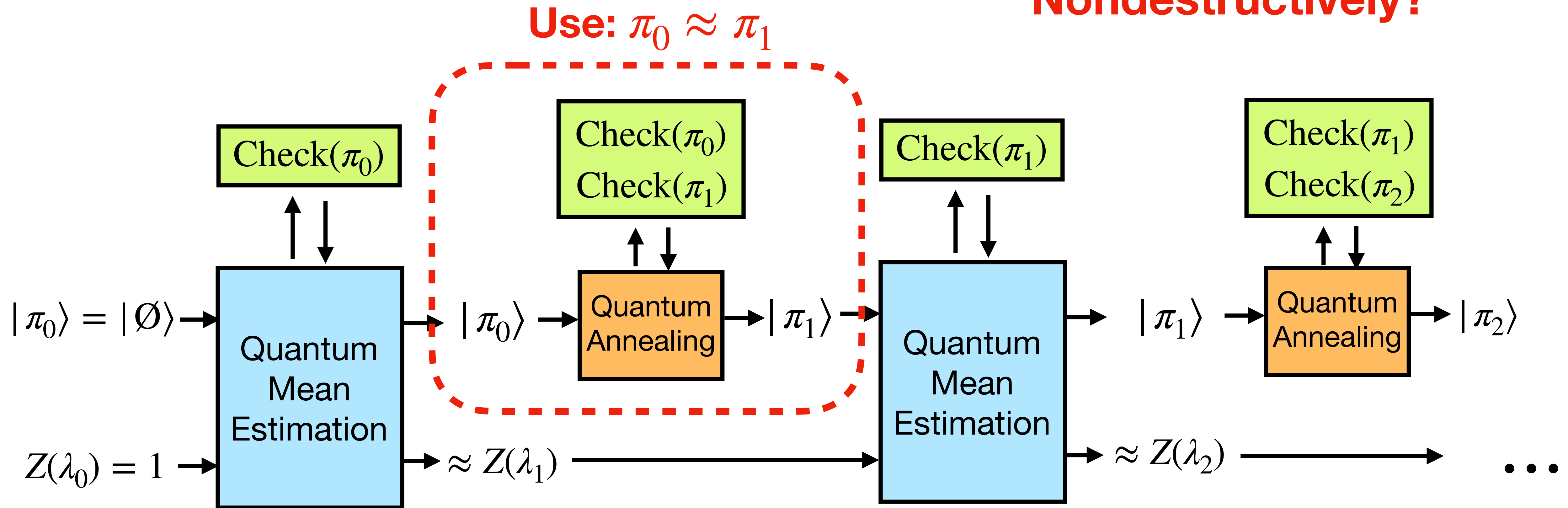
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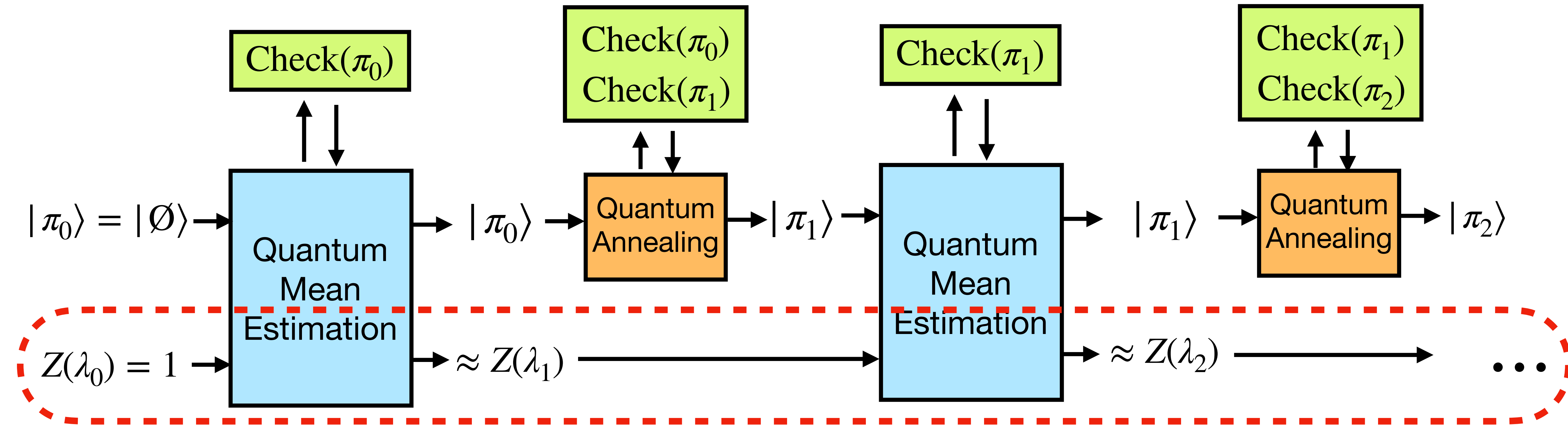
Nondestructively?



Estimate $Z(\lambda_{i+1})$ using $\text{Check}(\pi_i)$?

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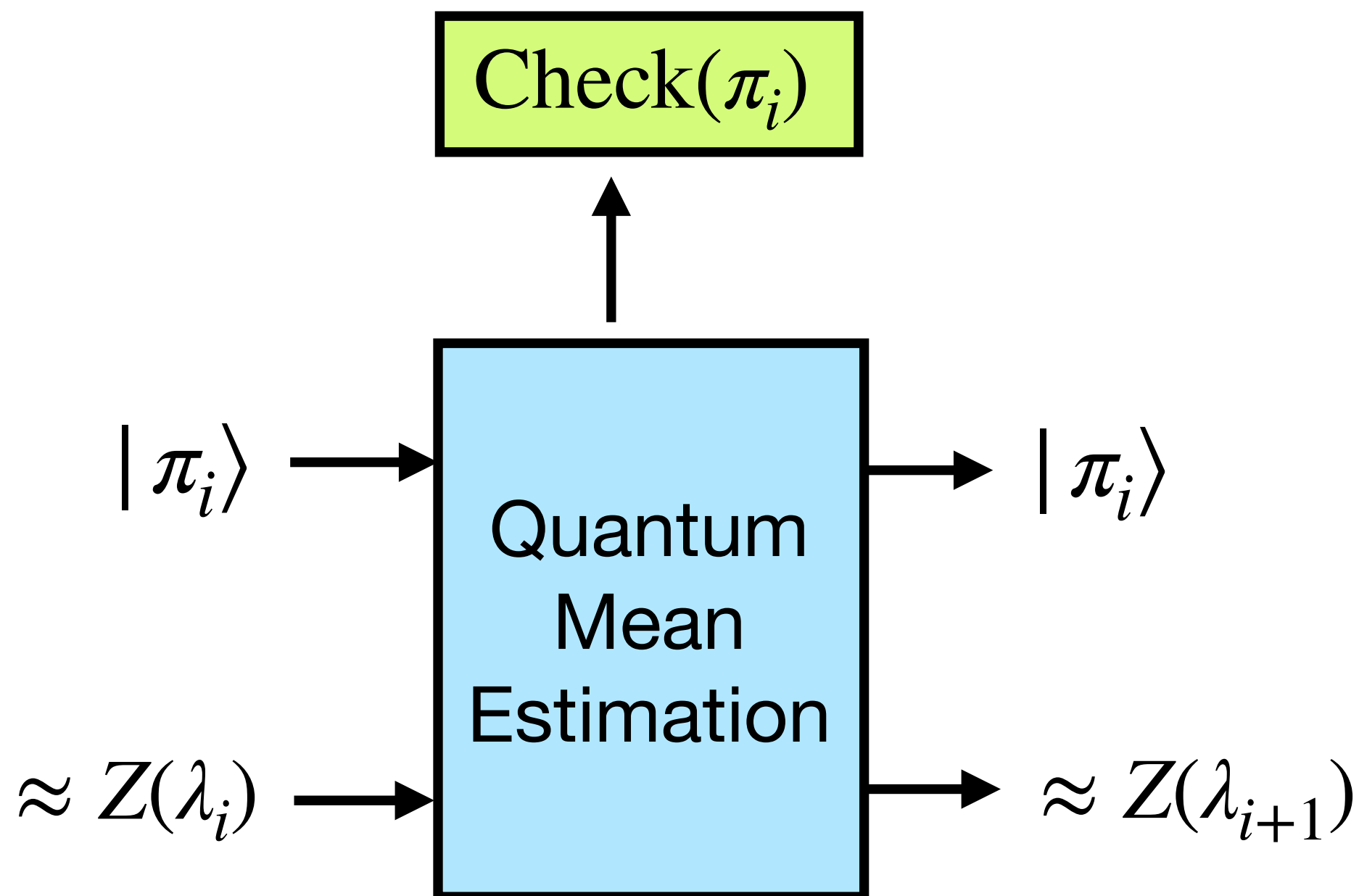
Nondestructively?



Unbiased? Otherwise the errors accumulate too quickly!

Framework for Mean Estimation

We want the following properties:



Nondestructive

Output a new copy of $|\pi_i\rangle$

Unbiased

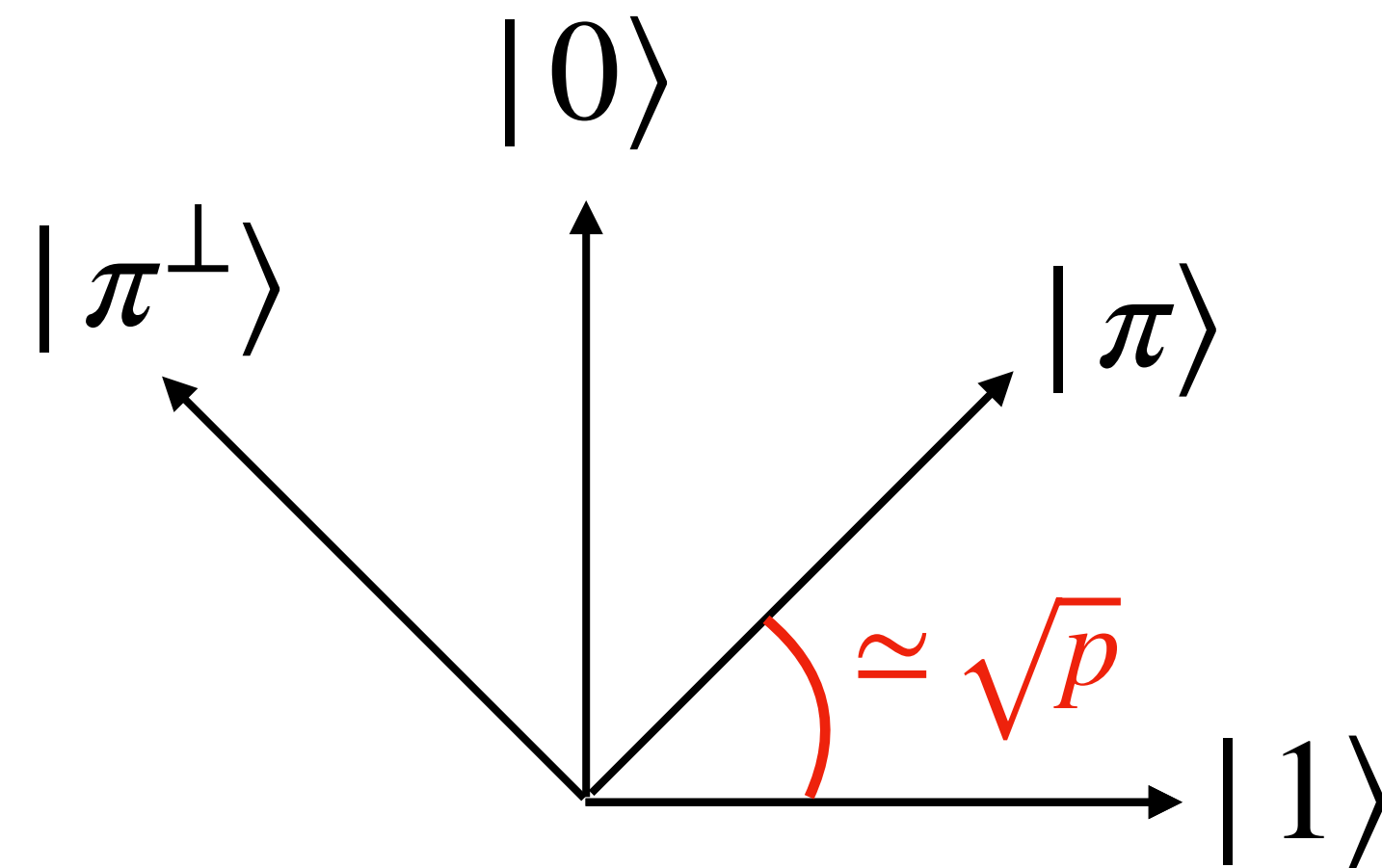
$$E(\text{output}) = Z(\lambda_{i+1})$$

Speedup

Faster than the Empirical Mean

The case of Bernoulli distributions

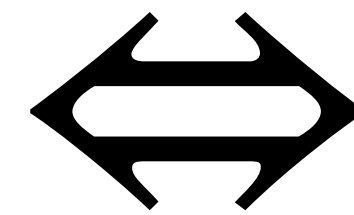
$$|\pi\rangle = \sqrt{1-p} |0\rangle + \sqrt{p} |1\rangle$$



Check(π) :

$$|\pi\rangle |0\rangle \mapsto |\pi\rangle |0\rangle$$

$$|\pi^\perp\rangle |0\rangle \mapsto |\pi^\perp\rangle |1\rangle$$

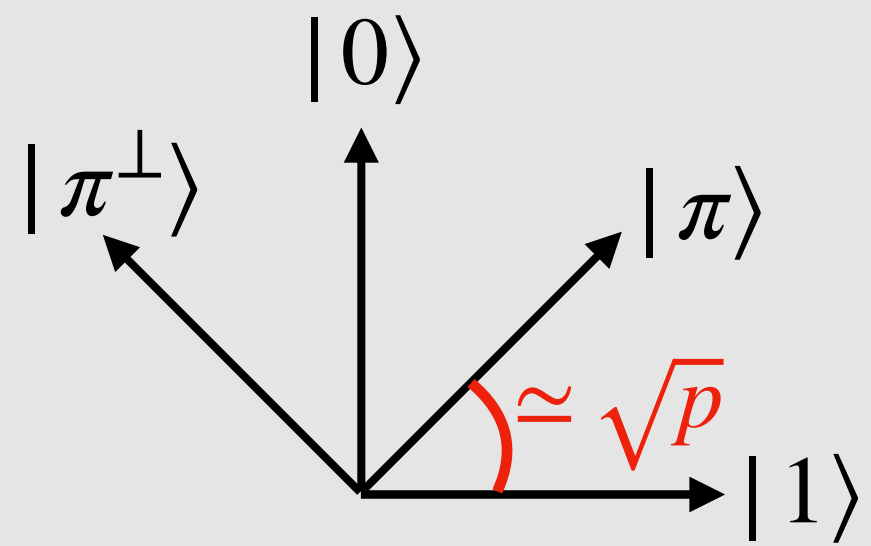


Ref $_{|\pi\rangle}$:

$$|\pi\rangle \mapsto |\pi\rangle$$

$$|\pi^\perp\rangle \mapsto -|\pi^\perp\rangle$$

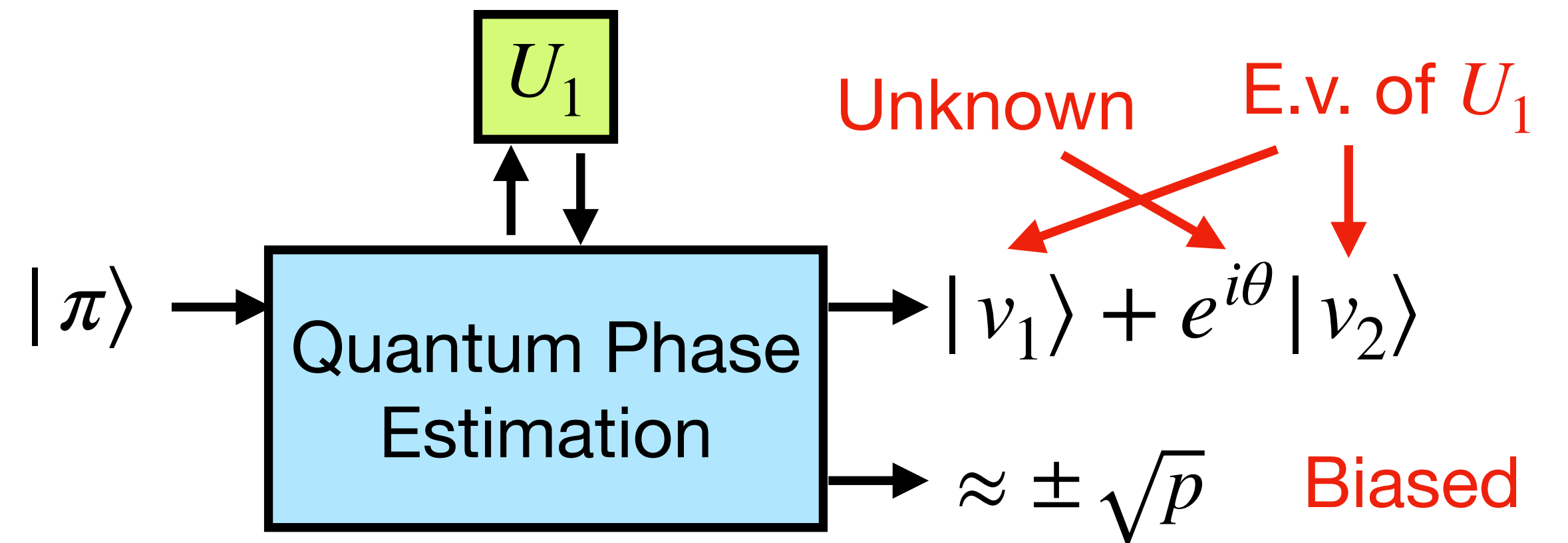
The case of Bernoulli distributions

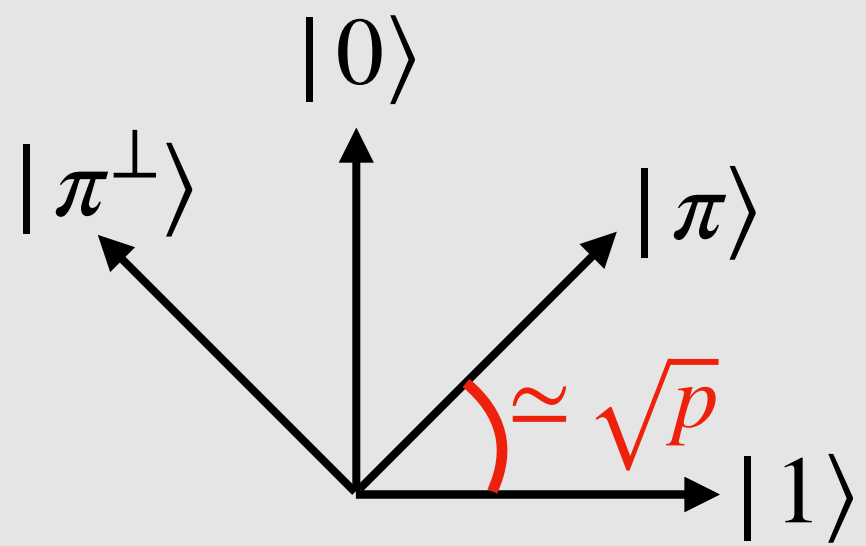


$$|\pi\rangle = \sqrt{1-p}|0\rangle + \sqrt{p}|1\rangle$$

$$U_1 = \begin{pmatrix} e^{2i\sqrt{p}} & 0 \\ 0 & e^{-2i\sqrt{p}} \end{pmatrix} \simeq \text{Ref}_{|\pi\rangle} \cdot \text{Ref}_{|1\rangle}$$

(Grover operator)





The case of Bernoulli distributions

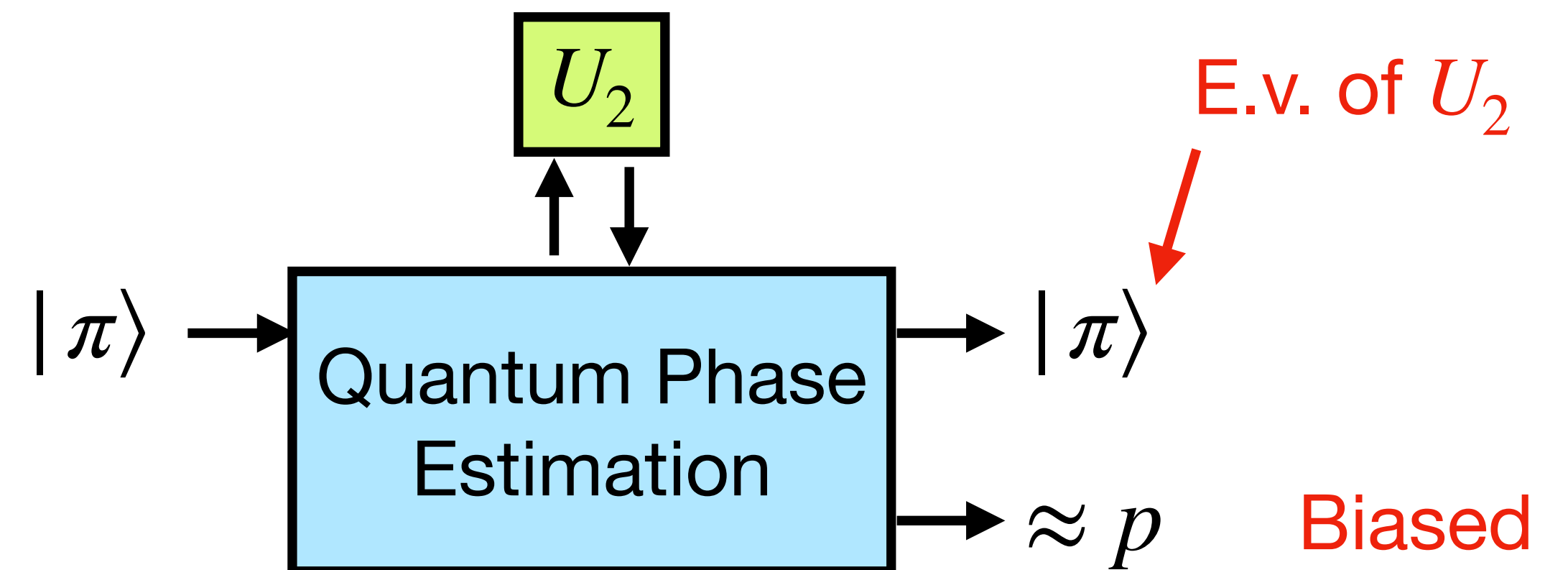
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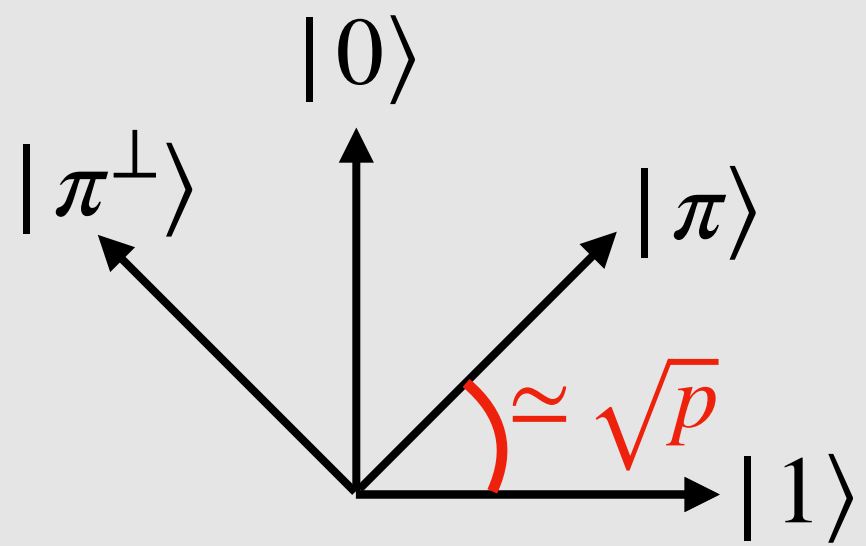
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$$U_2 = \begin{pmatrix} e^{ip} & 0 \\ 0 & e^{ip} \end{pmatrix} = \sum_{m=-\infty}^{\infty} c_m U_1^m$$

(Taylor expansion + LCU)





The case of Bernoulli distributions

$$|\pi\rangle = \sqrt{1-p} |0\rangle + \sqrt{p} |1\rangle$$

$$U_1 = \begin{pmatrix} e^{2i\sqrt{p}} & 0 \\ 0 & e^{-2i\sqrt{p}} \end{pmatrix} \simeq \text{Ref}_{|\pi\rangle} \cdot \text{Ref}_{|1\rangle}$$

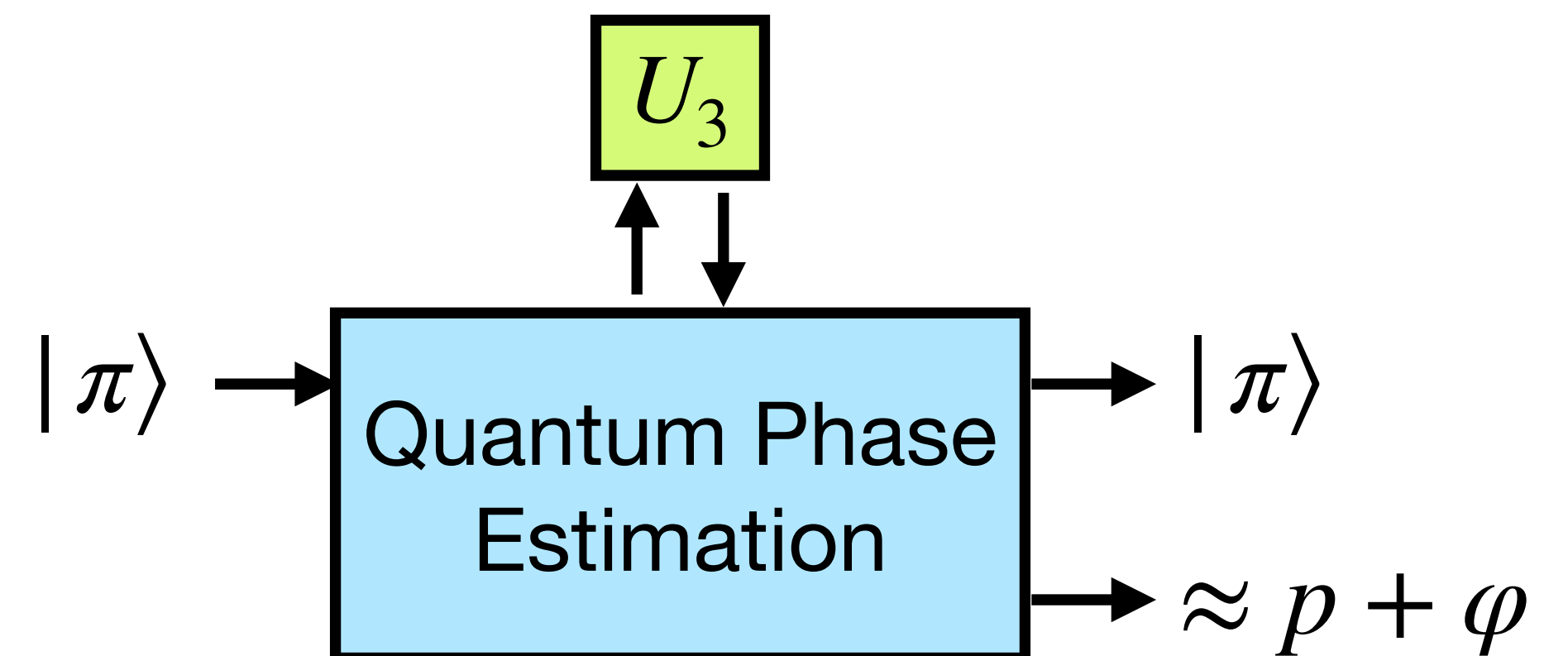
(Grover operator)

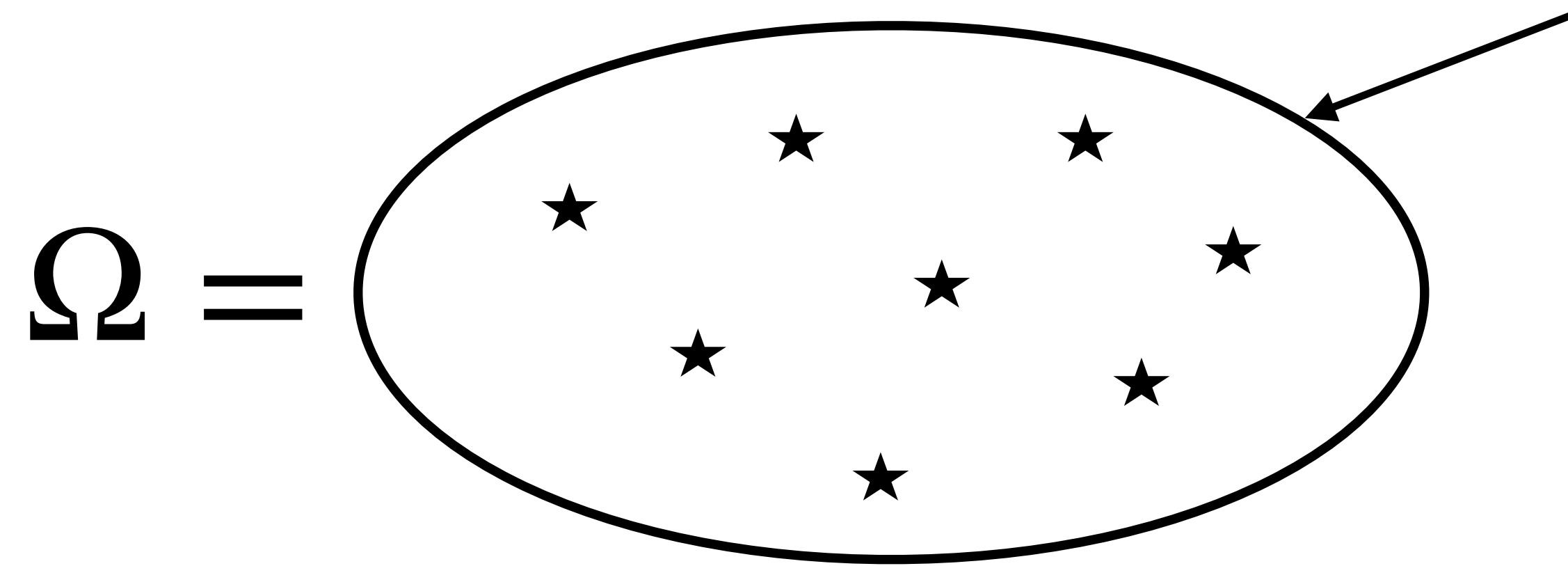
$$U_2 = \begin{pmatrix} e^{ip} & 0 \\ 0 & e^{ip} \end{pmatrix} = \sum_{m=-\infty}^{\infty} c_m U_1^m$$

(Taylor expansion + LCU)

$$U_3 = \begin{pmatrix} e^{i(p+\varphi)} & 0 \\ 0 & e^{i(p+\varphi)} \end{pmatrix}$$

(Random phase shift)





Examples:

- independent sets
- k-colorings
- matchings
- (volume of convex body)
- (Ising model)
- ...

Approximate the size $|\Omega|$ in time
 $\approx \log^{3/4} |\Omega| \times \sqrt{\text{class. mixing time}}$

Previous work:
 $\log |\Omega| \times \dots$

Open question: $\log^{1/2} |\Omega| \times \sqrt{\text{class. mixing time}}$?