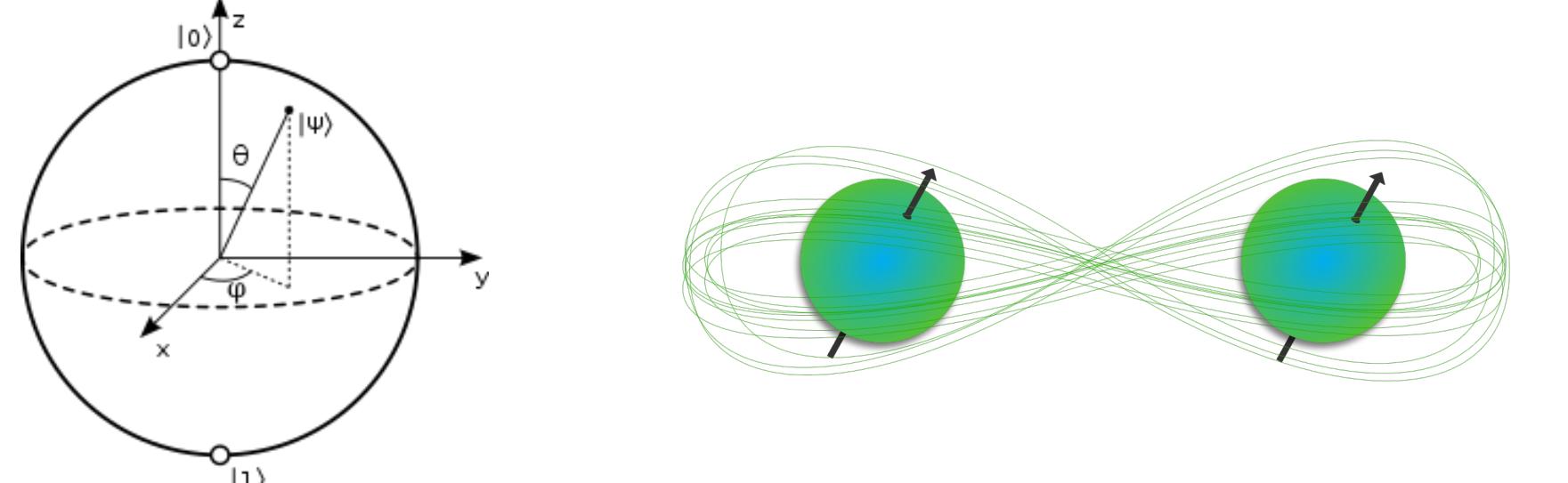


Introduction

- Quantum computing exploits quantum phenomena to solve combinatorial optimization problems with exponential speed-up.

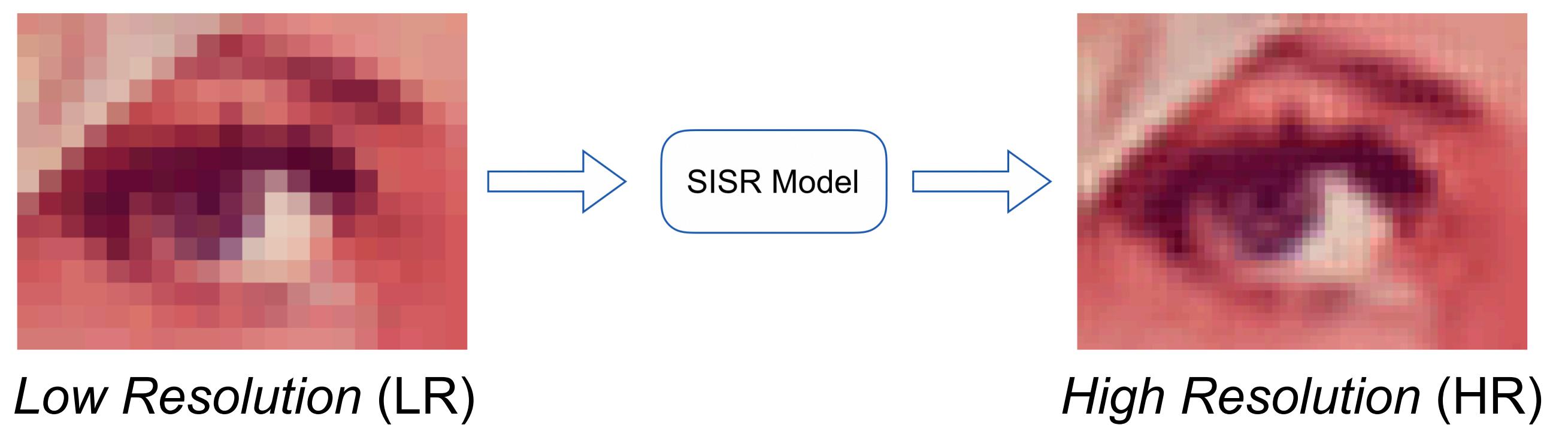


Superposition

Entanglement

Adiabatic Evolution

- Our work is an early exploration of applying quantum computing to single image super-resolution (**SISR**).



Contributions

- We demonstrate a practical SISR approach using adiabatic quantum computing (**AQC**).
- A quadratic unconstrained binary optimization (**QUBO**) formulation for sparse coding is developed and used in our approach.
- Benchmark on popular SISR datasets.

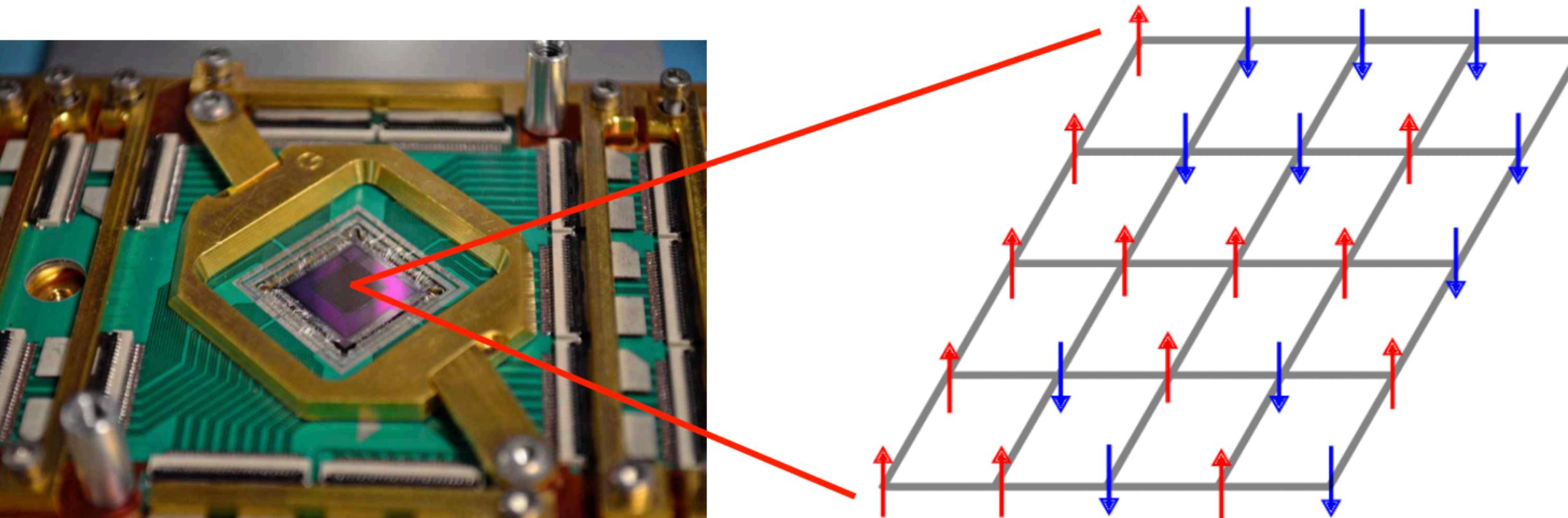
Method

- AQC solves the QUBO problem

$$\underset{z}{\operatorname{argmin}} \, z^T Q z + b^T z$$

where $Q \in \mathbb{R}^{N \times N}$, $b \in \mathbb{R}^N$, $z \in \{0,1\}^N$.

- The QUBO problem is embedded onto a quantum processing unit (**QPU**). Optimized solutions for z are obtained by quantum annealing.



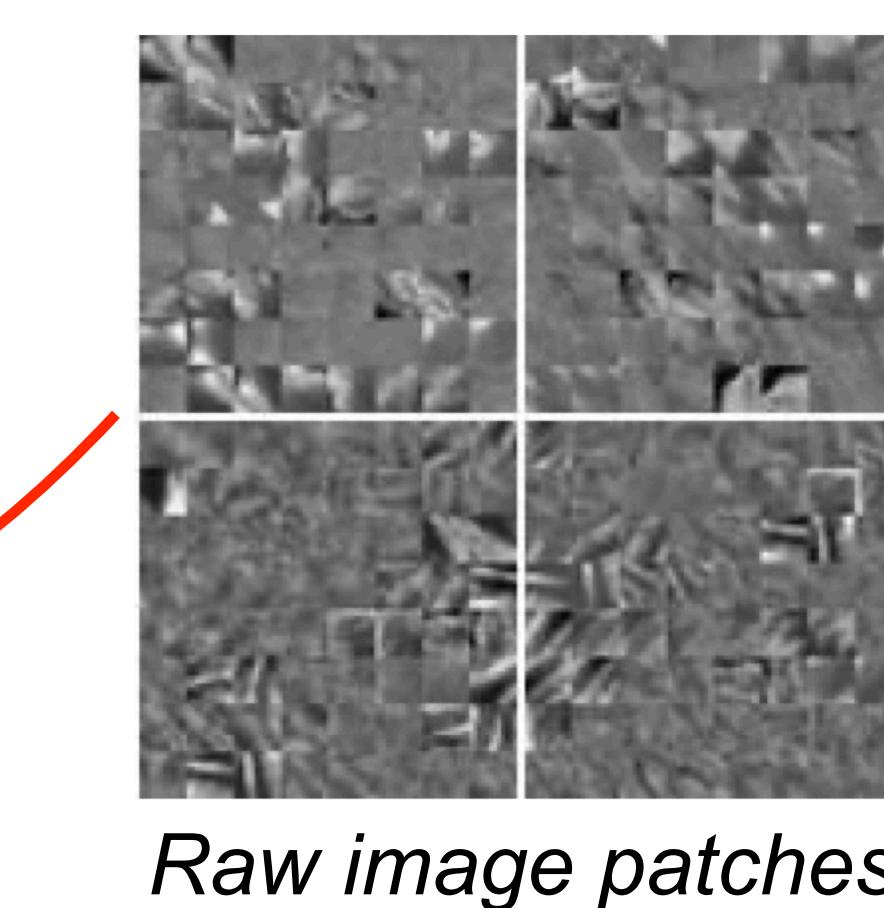
- HR images are constructed patch-wise. Each HR patch is given by a sparse linear combination of raw image patches, with sparse coefficients obtained from z^* .

HR patch Dictionary

$$x = D_h \alpha^*$$

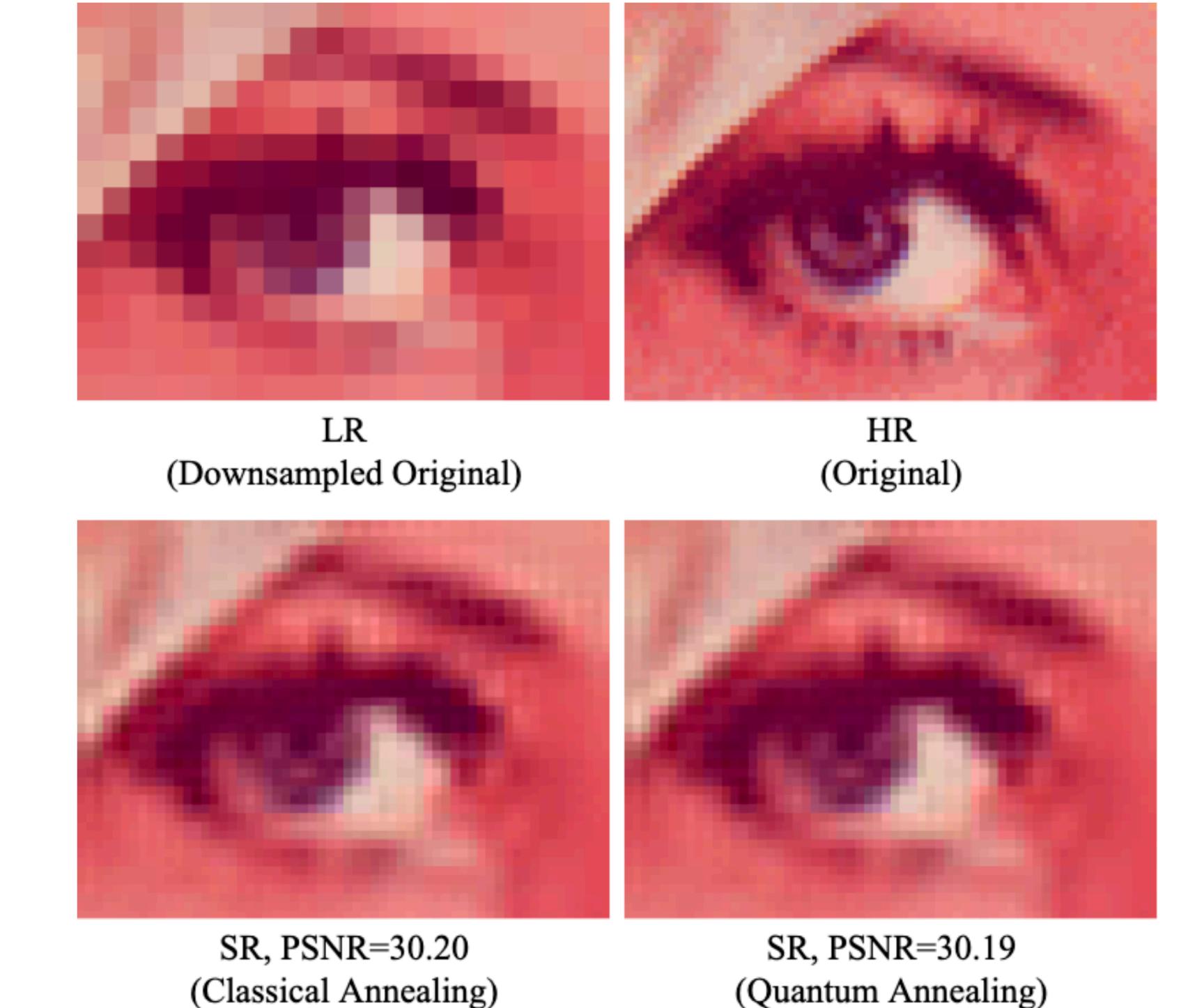
Sparse coefficients

The atoms of D_h consist of raw image patches



Results

- Speed-up over classical annealing while maintaining accuracy.



- Improved accuracy over conventional sparse coding on full images but short of state-of-the-art deep neural networks.

Model	PSNR		
	(a) Lenna reg. (dB)	(b) Lenna (dB)	(c) Set5 (dB)
Bicubic	28.31	30.62	29.35
Lasso Regress.	30.22	31.58	30.44
Classical Ann.	30.20	31.70	30.61
Quantum Ann.	30.19	31.70	30.61
SwinIR (DL)	31.42	33.29	33.89

Conclusions

- Initial demonstration of quantum SISR with encouraging results.
- Algorithm design enables fast robust prediction, uncertainty estimation and improved performance over conventional sparse coding.