SOLVING SPARSE REPRESENTATIONS FOR OBJECT CLASSIFICATION USING THE QUANTUM D-WAVE 2X MACHINE

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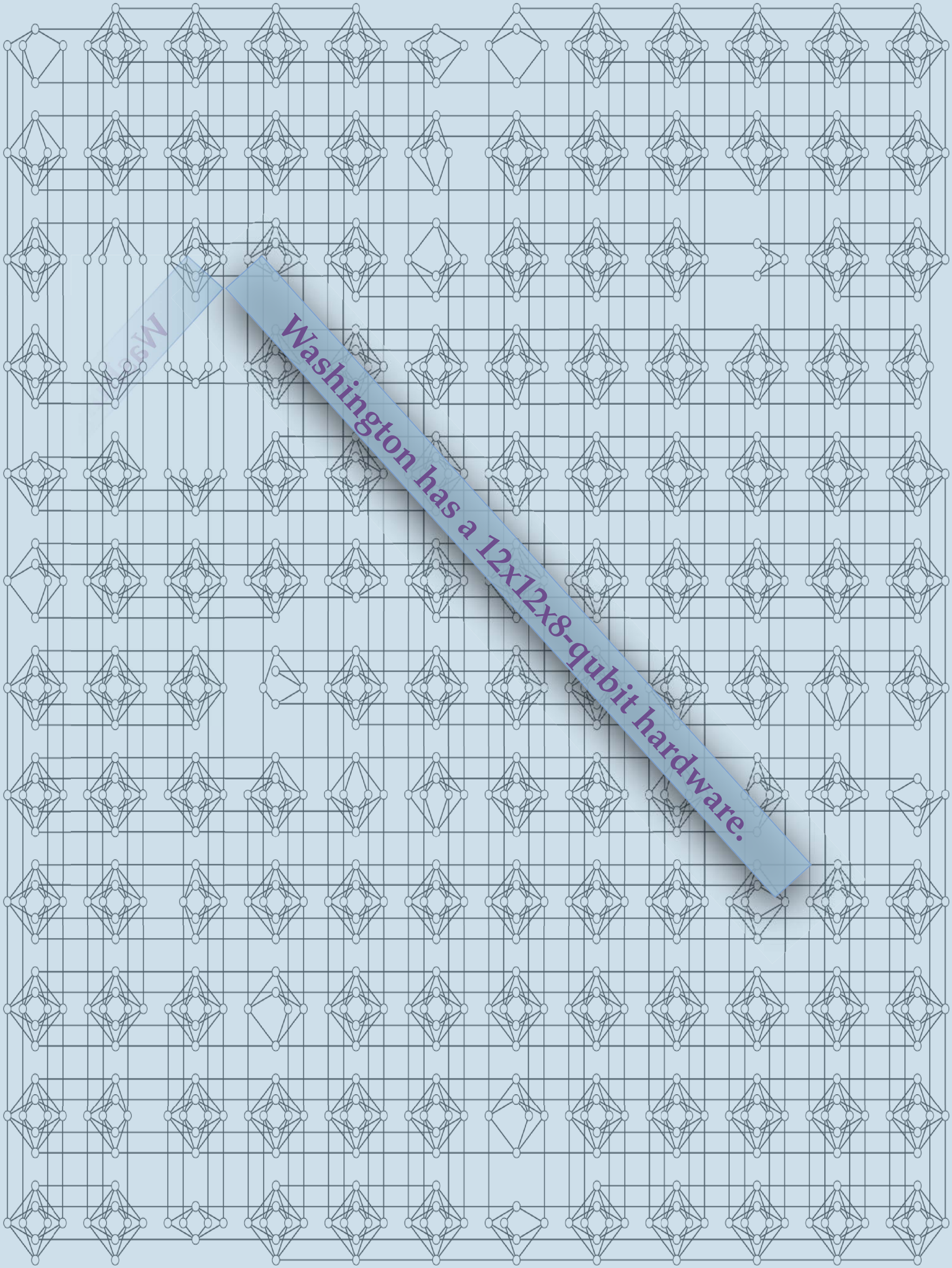
CCS-3, Los Alamos National Laboratory & New Mexico Consortium

Information Science & Technology Institute – Rapid Response: D-Wave Effort Debrief

Los Alamos, October 6, 2015


Washington has a 12x12x8-qubit hardware.

OUTLINE

- METHODOLOGY
- DATASET
- IMPLEMENTATION ON A WASHINGTON MACHINE
- RESULTS
- DISCUSSIONS AND FUTURE WORK

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Quantum D-Wave machine 2X: a quantum annealer

METHODOLOGY

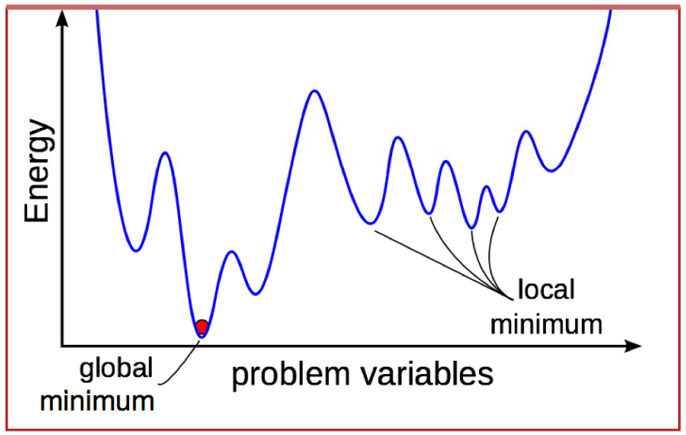
- **Solving a sparse-coding problem**

Objective function is of the form:

$$E = \min_{\{\vec{a},\phi\}} [\frac{1}{2}|\vec{I} - \phi\vec{a}|^2 + \lambda||\vec{a}||_p].$$

reconstruction error

***Lp*-sparseness penalty**



- **non-convex problem**
- **NP-hard class**

Quantum D-Wave machine 2X: a quantum annealer

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reconstruction error

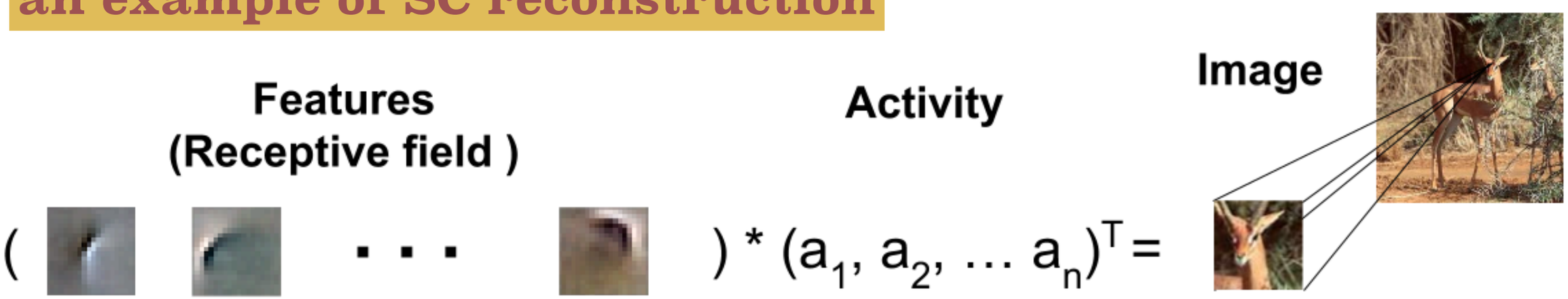
***Lp*-sparseness penalty**

an example of SC reconstruction

Features (Receptive field)

Activity

Image



courtesy of Xinhua Zhang

Quantum D-Wave machine 2X: a quantum annealer

METHODOLOGY

- **mapping the sparse-coding problem onto a QUBO problem:**

- analogous to L0-sparseness penalty

D-Wave Hamiltonian:

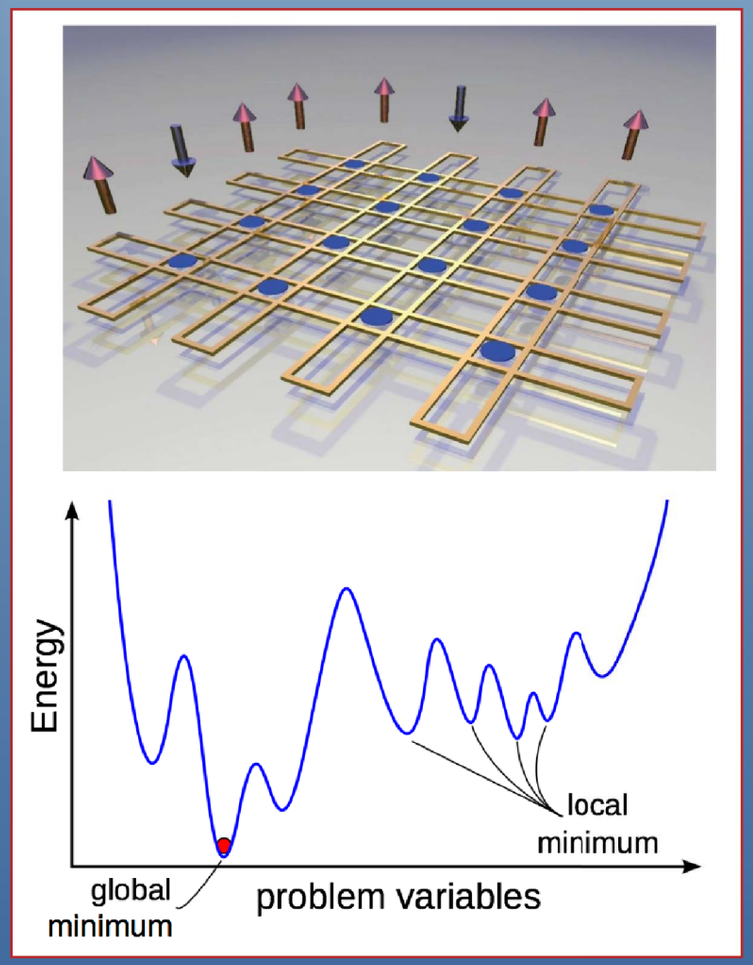
$$H(h,Q,a) = \sum_i h_i a_i + \sum_{<i,j>} Q_{ij} a_i a_j$$

where $a_i = \{0,1\}\,\forall i$.

This mapping is achieved by the relations:

$$h = -\phi^T \vec{I} + (\lambda + \frac{1}{2}),$$

$$Q = \frac{1}{2}\phi^T \phi.$$



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DATASET

CIFAR-10

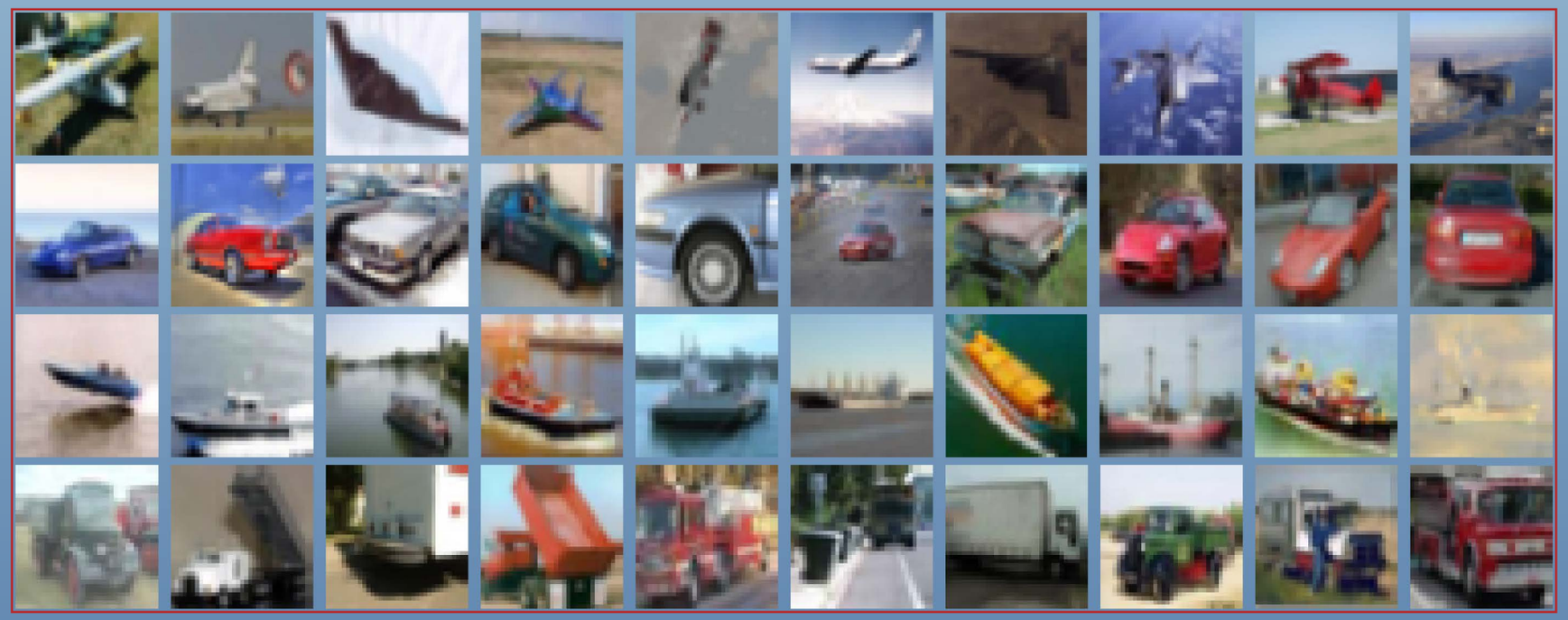
32x32

airplane

automobile

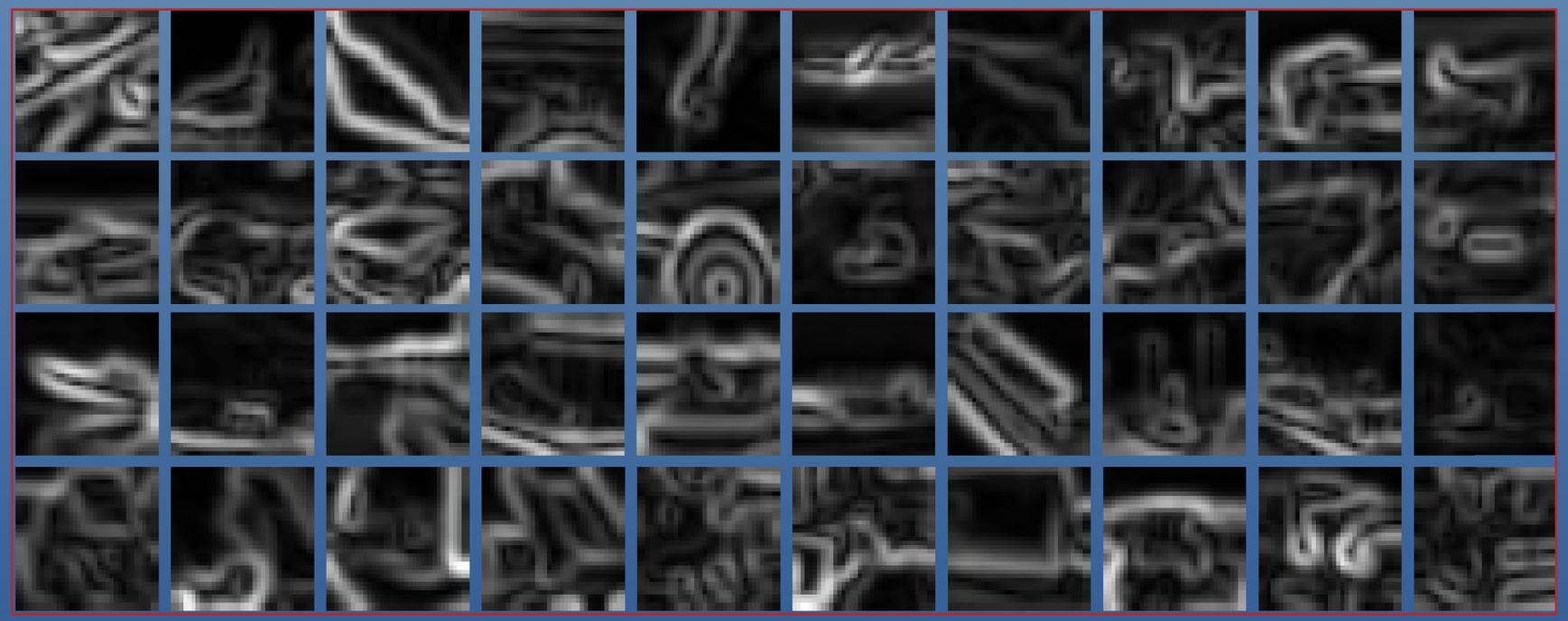
ship

truck



24x24

edge detection



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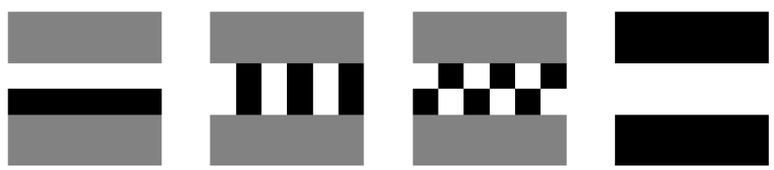
IMPLEMENTATION ON A QUANTUM WASHINGTON MACHINE

quadratic unconstrained binary optimization (QUBO) problem

8 hand-designed features



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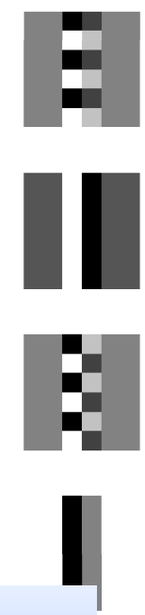

"column"

convolutional model

$\{\psi_i\}$

$$\frac{\psi_i \psi_j}{|\psi_i||\psi_j|} = \delta_{i,j} \, |\Delta_{i,j}$$

complete set

$$\Phi = \Psi * \vec{T}$$

Define N_f as # of features in this case, $N_f = 8$

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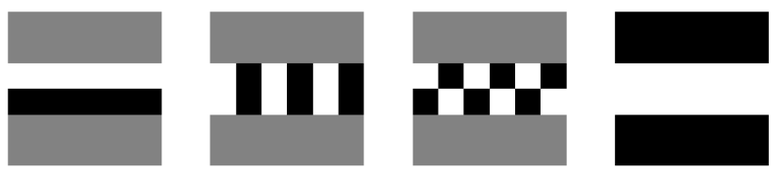

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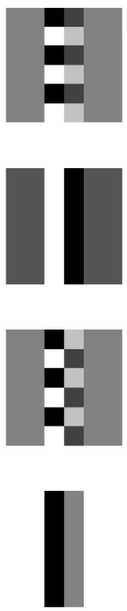

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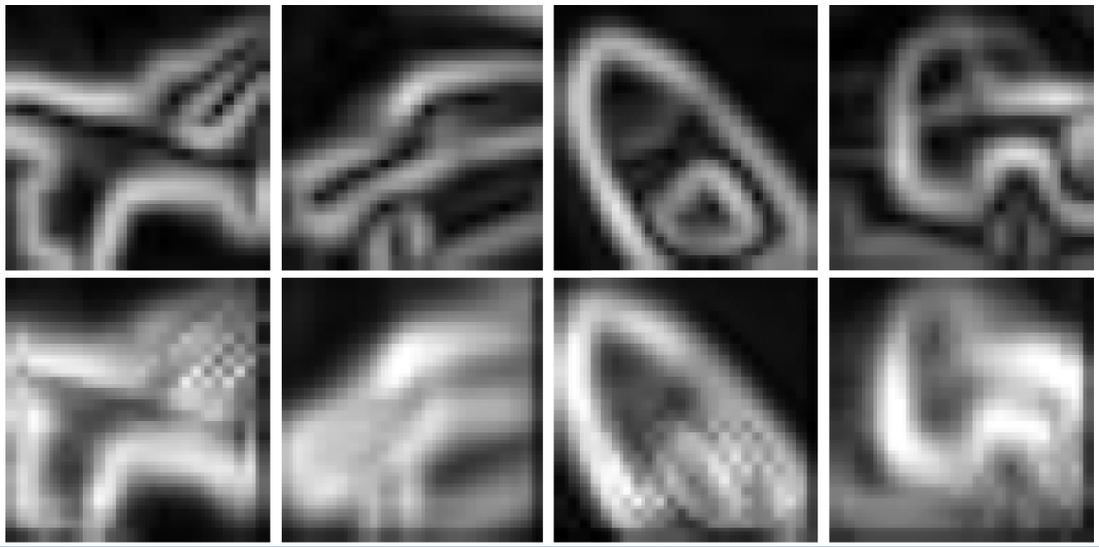


original

recon

IMPLEMENTATION ON A QUANTUM WASHINGTON MACHINE

quadratic unconstrained binary optimization (QUBO) problem

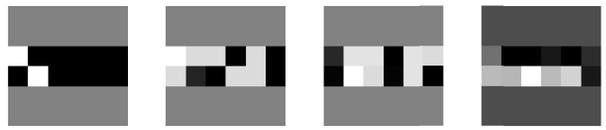
build a model where N_f takes different values?

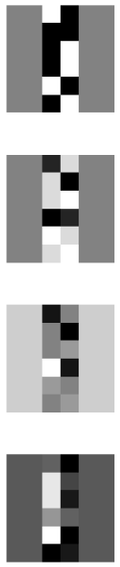
- **randomly generate N_f features**
- **N_f can vary and that defines the architecture of the implementation**

- **employ the Gram-Schmidt algorithm to fulfill the Chimera orthogonality**

Examples

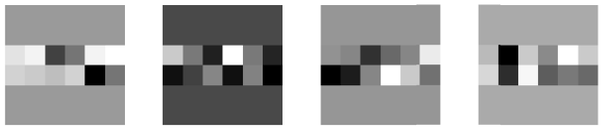
32 randomly-generated features

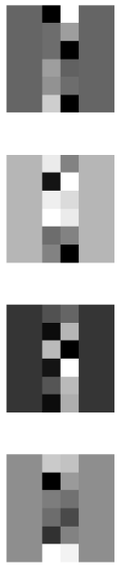




$N_f = 32$

32 randomly-generated features





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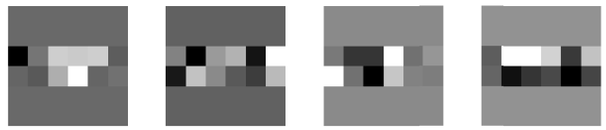

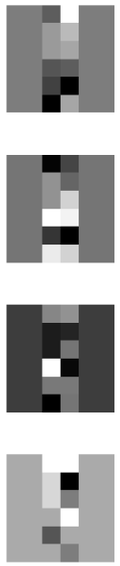

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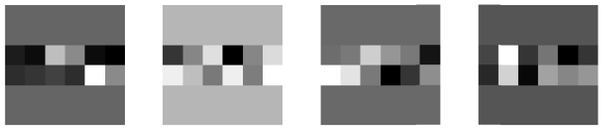

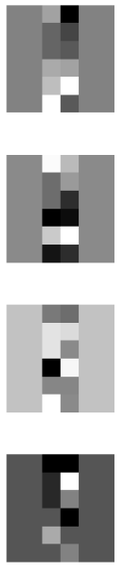

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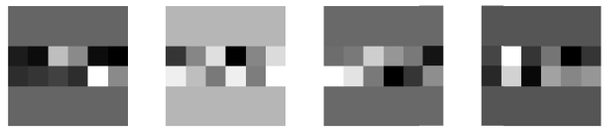
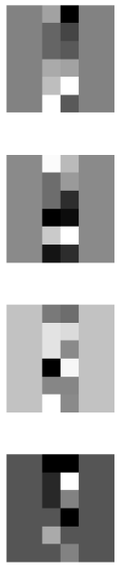
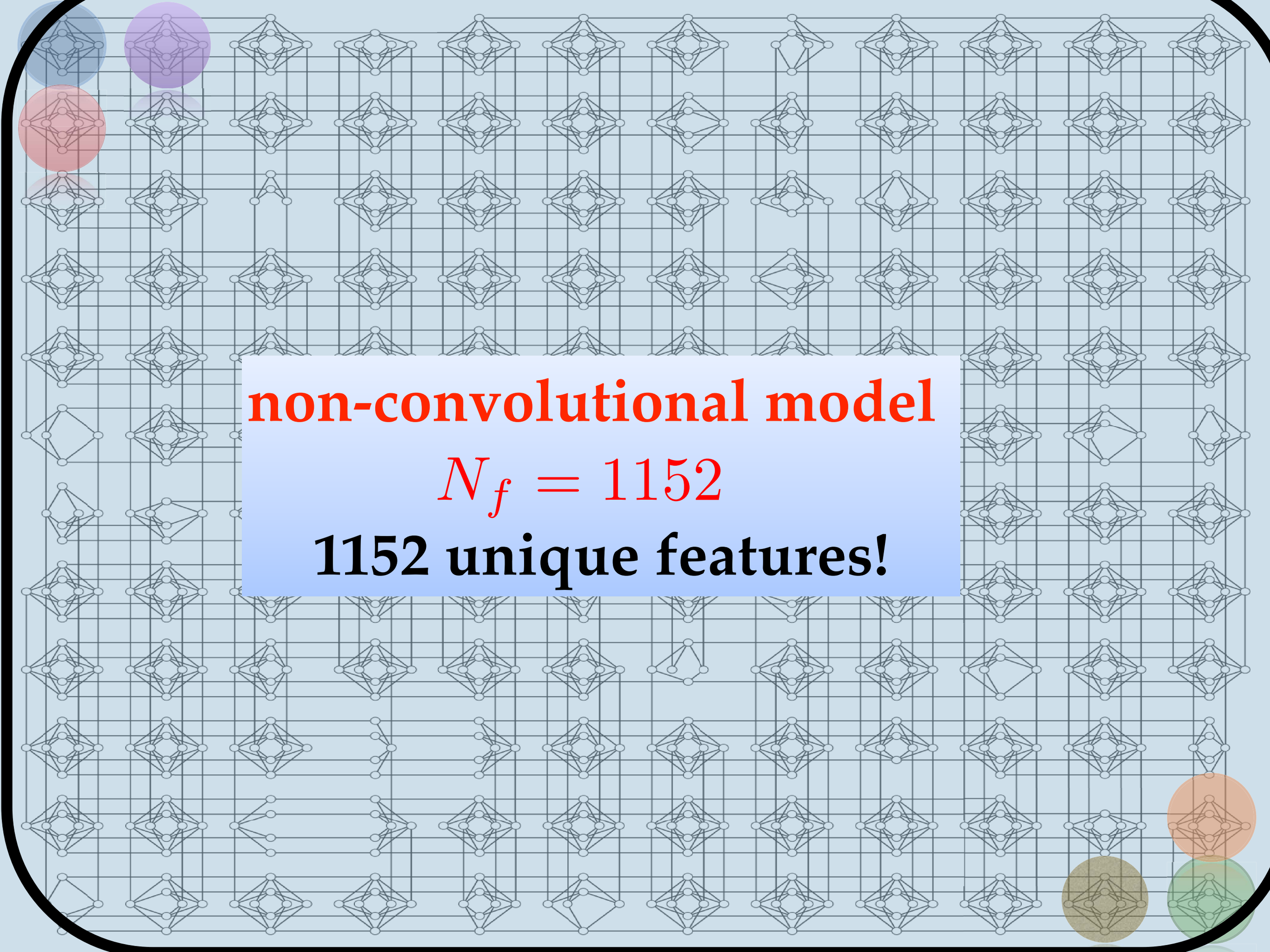




$N_f = 32$

convolutional model

as $N_f << 1152 = N_{qubit}$



non-convolutional model

$N_f = 1152$

1152 unique features!

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- **RESULTS**
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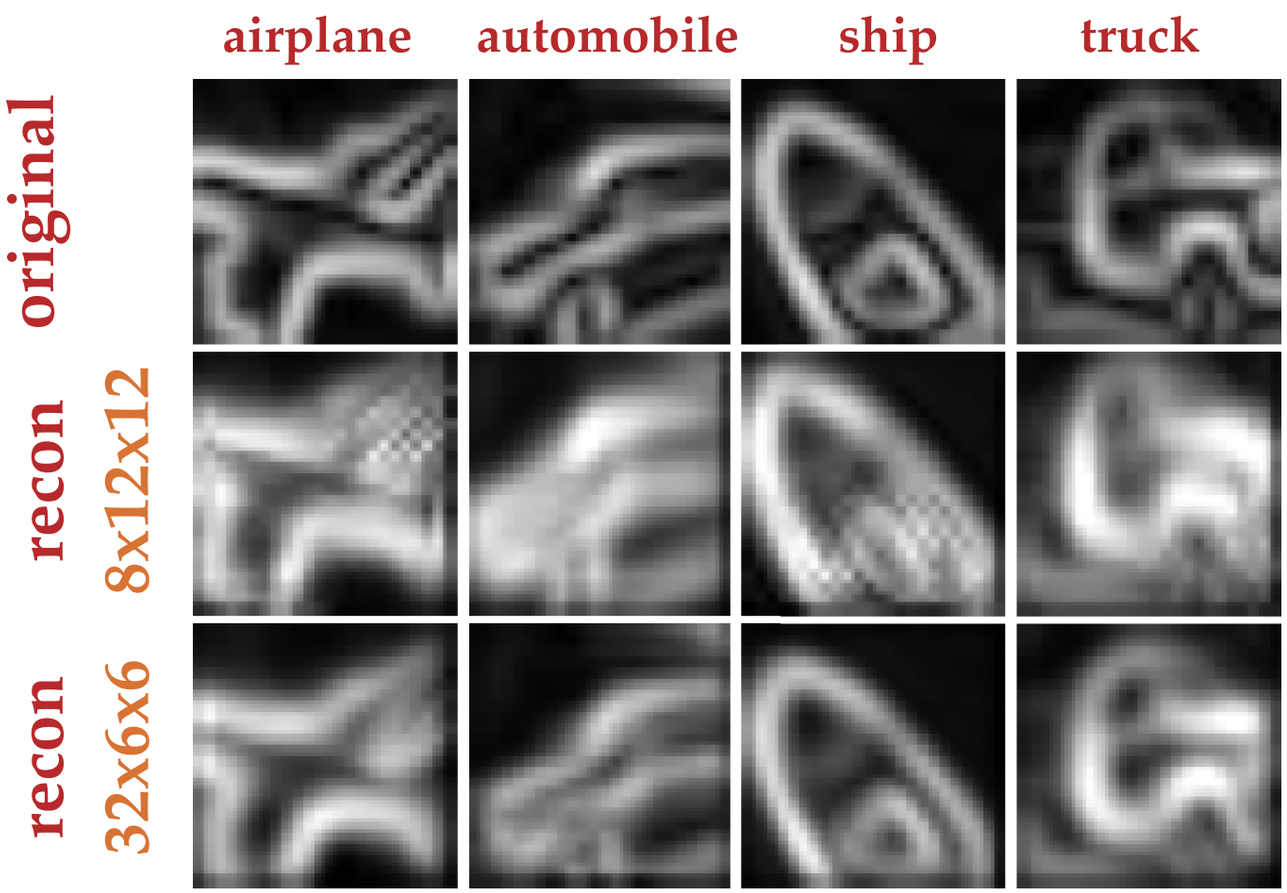
RESULTS • 24x24 patch images

1100 *active* qubits
3068 *coupling* strengths

overcomplete order:

$$2 = \frac{12\text{x}12\text{x}8}{24\text{x}24\text{x}1}$$

stride: 2, 4



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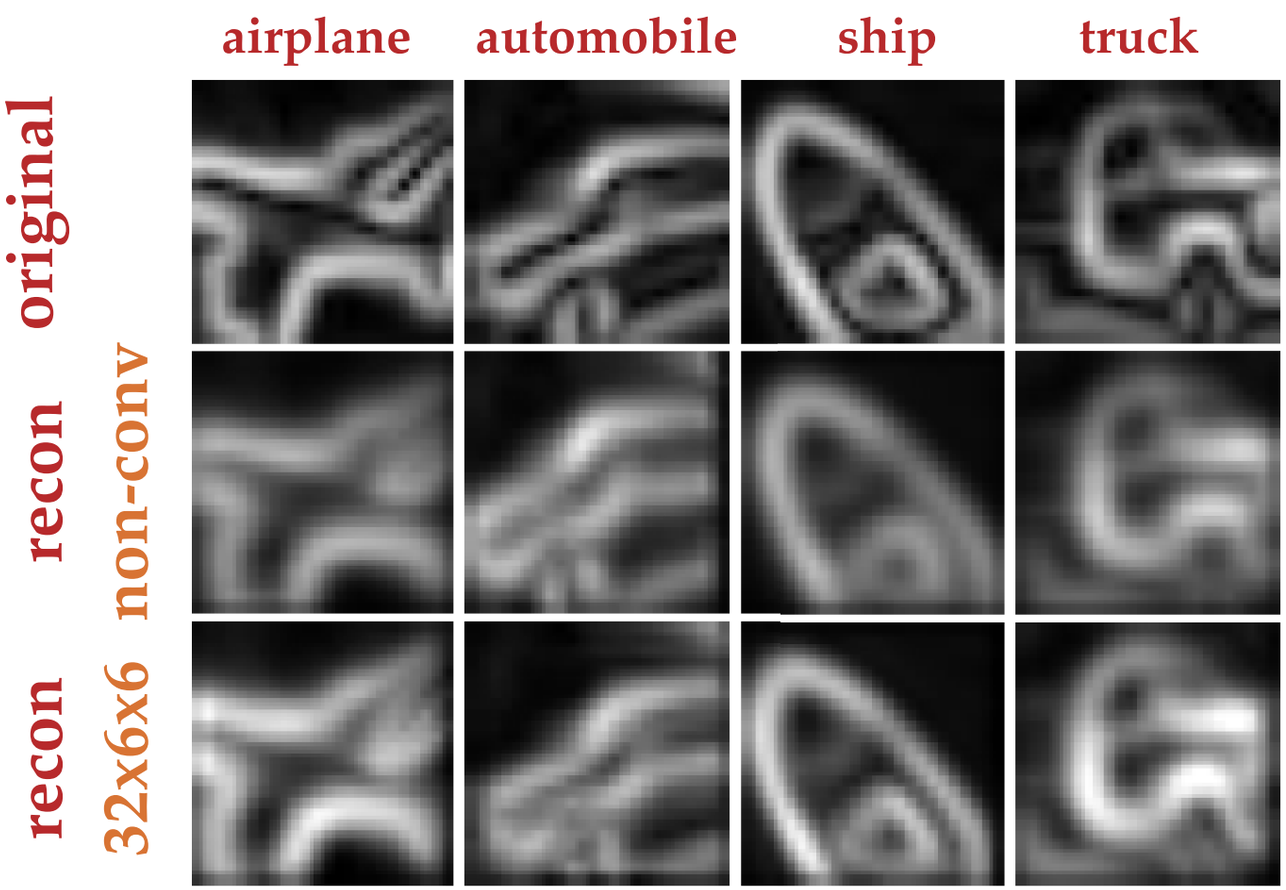
$$2 = \frac{12x12x8}{24x24x1}$$

stride: 4, 24



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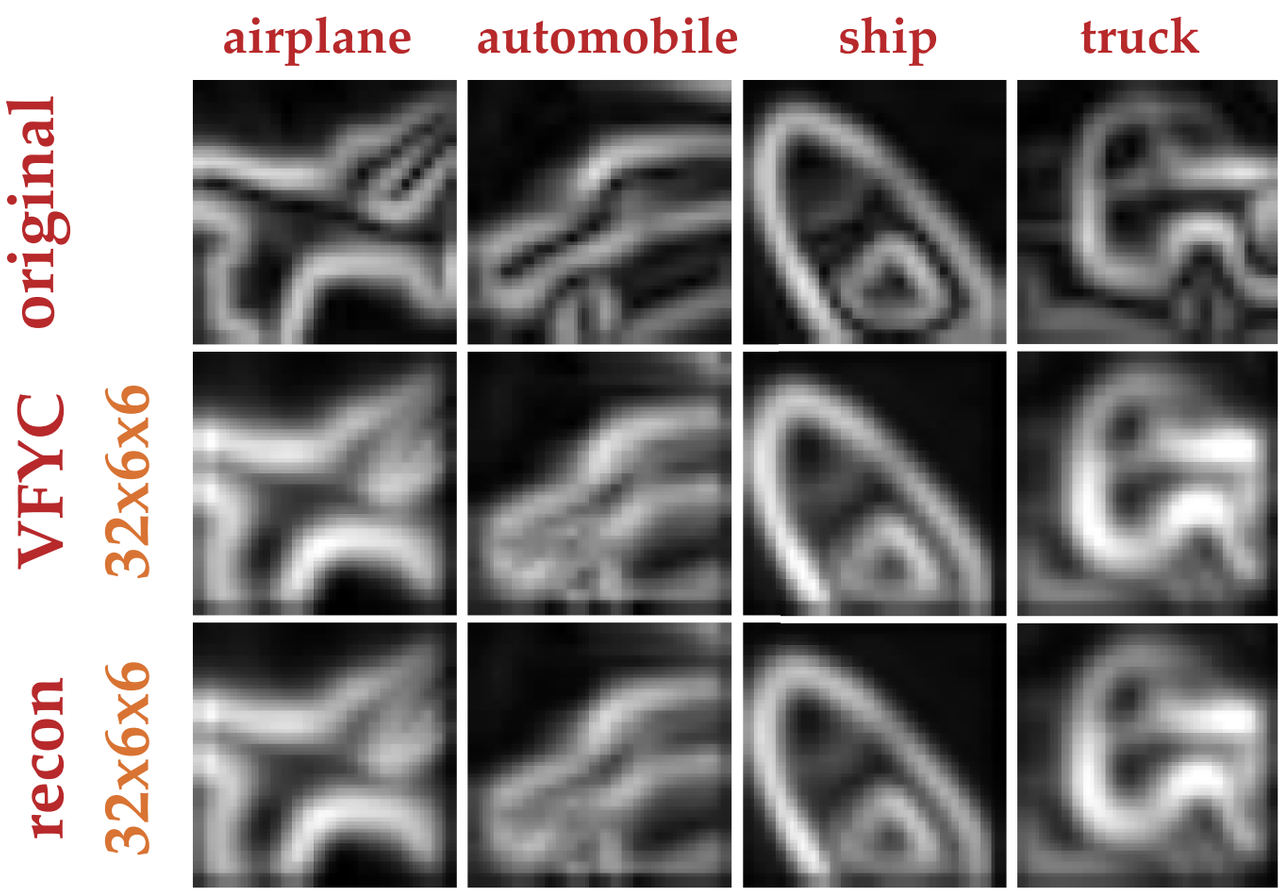


Classification Work Steps

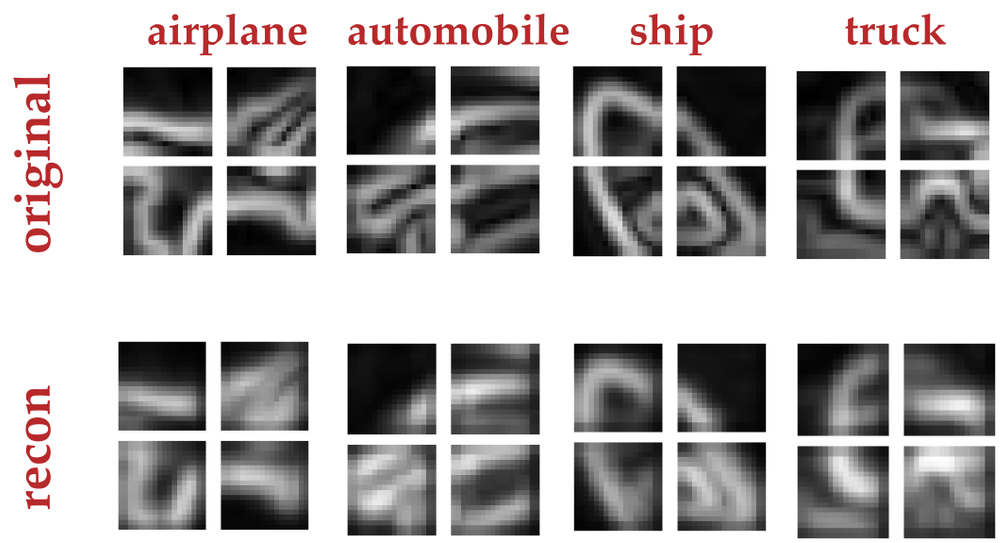
1. **Data preparation:**
   Split into 4-tile dataset: 4 x CIFAR-10 set
   (more overcomplete)

2. **Full basis $\{\Phi_i\}$ for each 12x12 tile**

3. ***do*** **{ train D-Wave into representation (dictionary):**
   1. **each tile has been run 10 times**
   2. **pick the configuration of min energy }**

4. **Classification: 10-class task (liblinear-package)**

RESULTS • 12x12 patch images



overcomplete order : 8

stride: 4

$N_f = 32$

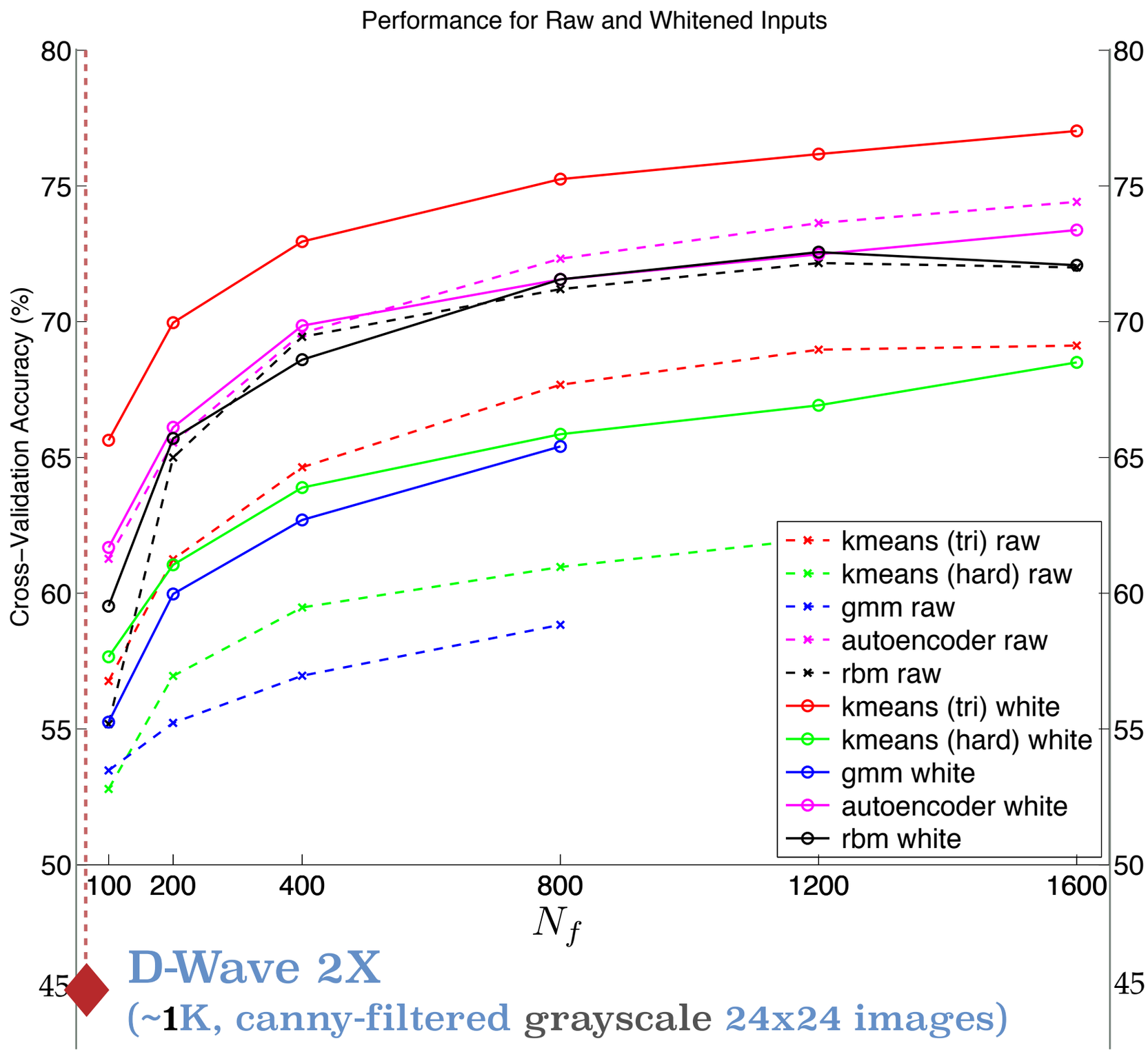
Classification task: SVM (liblinear)

1042 training/208 test images

classes	air	auto	bird	cat	deer	dog	frog	horse	ship	truck
accur. (binary)	89.21%	93.38%	90.87%	89.42%	94.71%	88.94%	87.98%	89.9%	89.9%	85.58%

Coates *et al*, 2011

CIFAR-10, 60K 32x32 RGB images



D-Wave 2X

(~1K, canny-filtered grayscale 24x24 images)

• SUMMARY

- first(?) demonstration of sparse coding using quantum computer
- benchmark results on standard image classification task
- mapping of visual features to D-Wave Chimera

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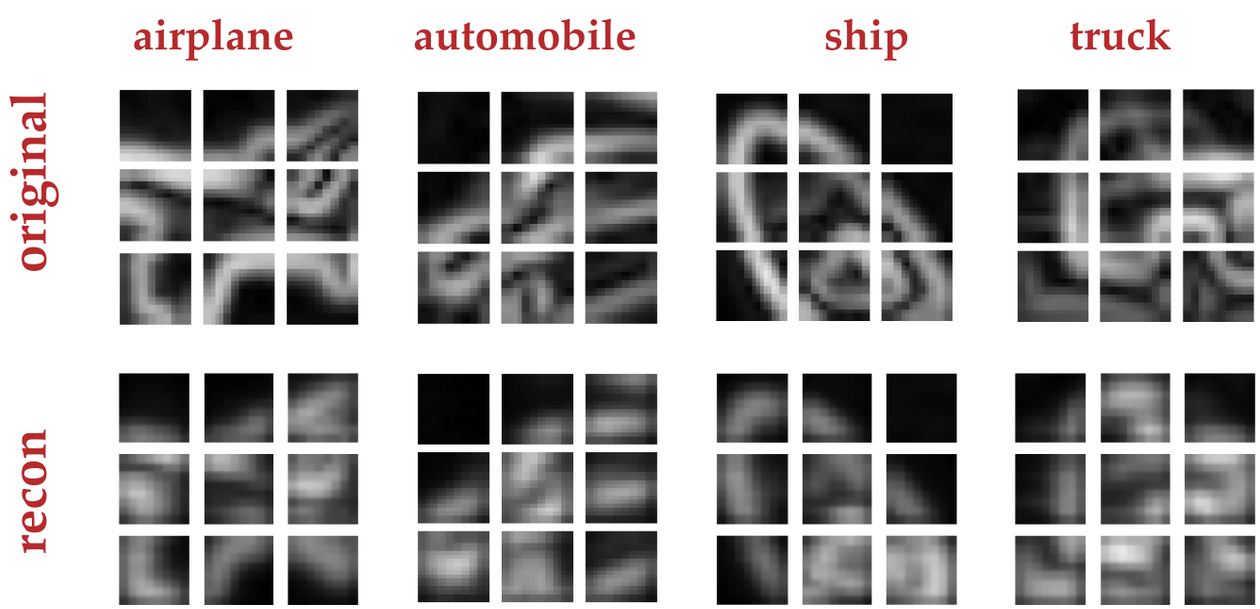
- **FUTURE WORK**
  - runs across the entire set
  - optimize features
  - more over-complete, feature-#-dependence
  - add colors
  - hierarchy model



overcomplete order : 18

stride: 4

$N_f = 288$

THANK YOU FOR YOUR ATTENTION!