# Image classification using collective modes of a two-dimensional array of photonic-crystal nanolasers

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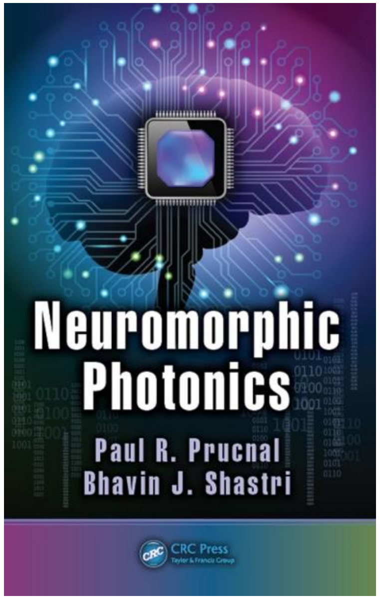
# Motivation

- Data centers, AI systems, HPC systems consume huge amounts of energy.
- Big concern in the context of climate change.
- Photonic computing systems can
  - Be much faster,
  - Consume much less energy.

- Semiconductor nanolasers have key advantages:
  - Ultra compact
  - Ultralow threshold
  - Room-temperature operation

*European Centre for Medium-Range Weather Forecasts, Reading, UK*



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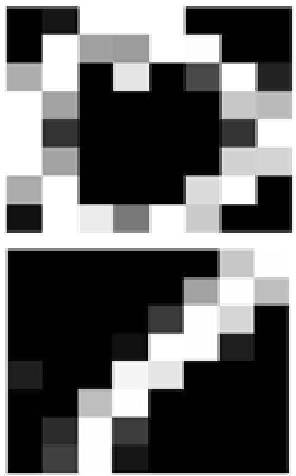
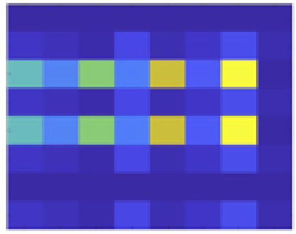
# Nanolaser array for binary classification of low-resolution images

Image(k)

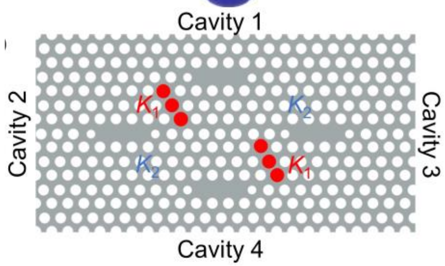


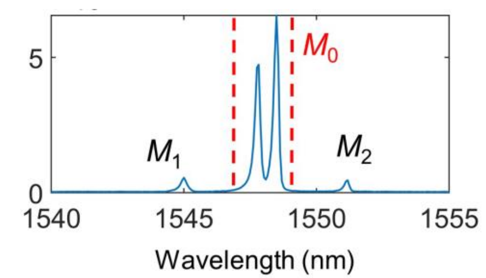
Code in the spatial pump $P^{(k)}$ profile



(by using a spatial light modulator, SLM)

⇒




**Analyze the emitted optical spectrum**

If a “selected-mode” is lasing: image is classified as 0, else 1

Key issue: good “spectral gap”

Also important: spectral resolution of detection system

Machine learning to find optimal parameters



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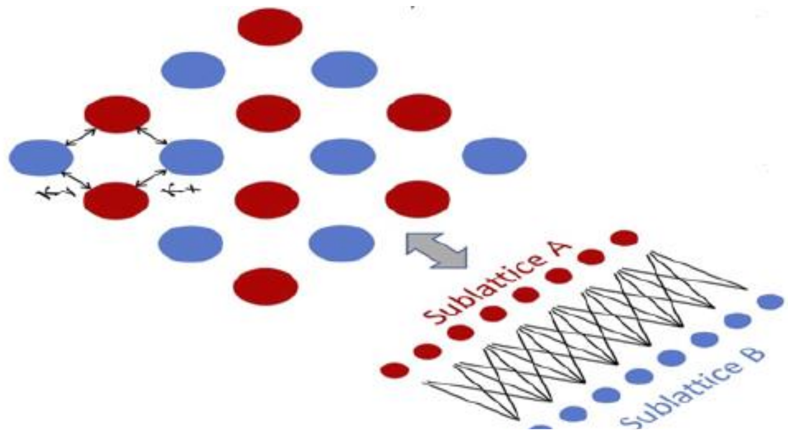
# Model

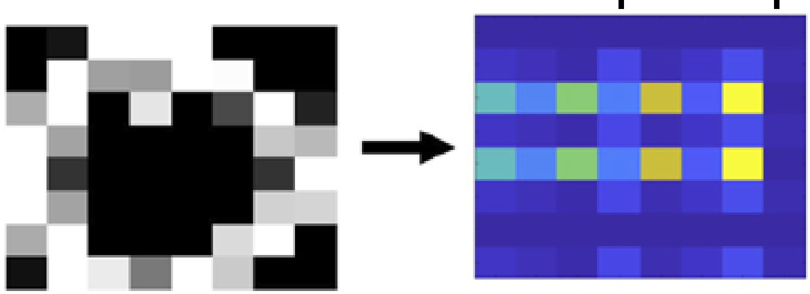



$$i\frac{da_{m,n}}{dt} = \kappa_x\left(a_{m-1,n} + a_{m+1,n}\right) + \kappa_y\left(a_{m,n-1} + a_{m,n+1}\right) + i\left(g_{m,n} - \gamma\right)a_{m,n}$$

Spatial pump pattern: $P = \{g_{m,n}\}$

Transformation matrix $M$: $P = |M\, I|$; $I$ it the matrix of pixel values.

$I^{(k)}$ $\quad$ $P^{(k)}=|M\, I^{(k)}|$





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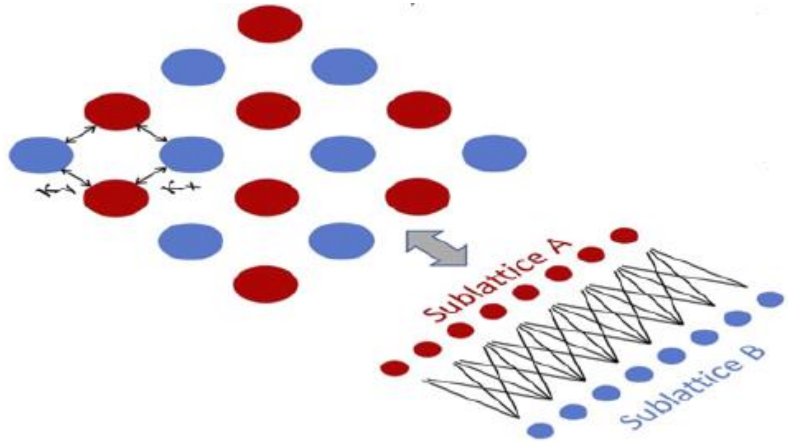
## Model




- To demonstrate the idea we consider **8x8** identically diffusively coupled cavities.
- 64 rate equations for the complex amplitudes $a_{mn}$.
- Images re-sized to 8x8.
- A more realistic model (including detunings) is needed to obtain experimentally good classification (work in progress).
- Goal: find the 64 elements of M (optical pump $P^{(k)}=|MI^{(k)}|$, where $I^{(k)}$ is the pixel matrix of the *k*th image) that optimize the classification performance.



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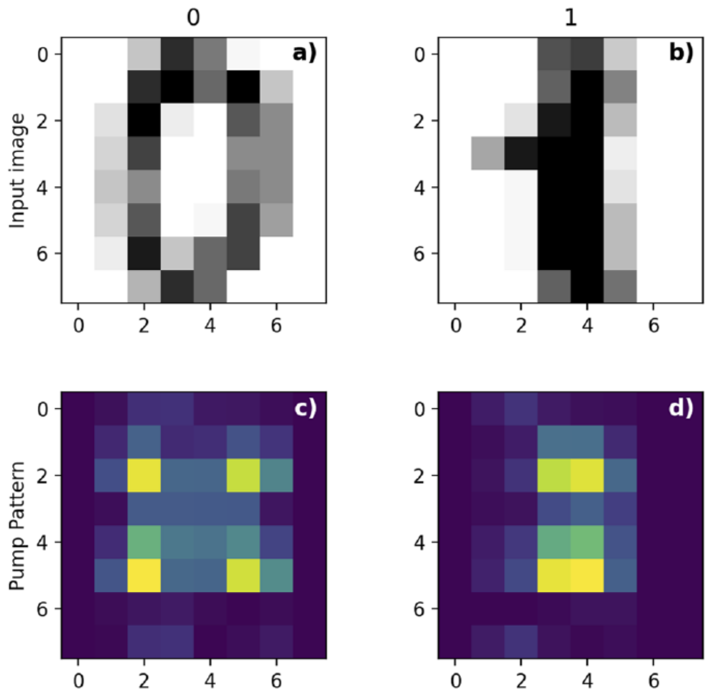
## Data

- Hand-written digit dataset freely available at University of California–Irvine (UCI) ML repository.
- 360 images.
- 75% (270 images) for training, 25% (90 images) for testing.
- 8x8 image resolution.




P=|MI|



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# Machine learning optimization

Minimization of the cost function using images of training set.

$$C = -\sum_{k\in\{+\}} \tanh\left(\eta\Delta\varepsilon^{(k)}\right) + \sum_{k\in\{-\}} \tanh\left(\eta\Delta\varepsilon^{(k)}\right)$$

{+} and {−} denote the two sets of images for which the "spectral gap" of k*th* image $\Delta\varepsilon^{(k)}$ is expected to be + or -.

$$\Delta\epsilon^{(k)} = \max_{i:\left|\Re\left[\epsilon_i^{(k)}\right]\right|\leq\delta} \Im\left[\epsilon_i^{(k)}\right] - \max_{i:\left|\Re\left[\epsilon_i^{(k)}\right]\right|>\delta} \Im\left[\epsilon_i^{(k)}\right]$$

- $\varepsilon_i^{(k)}$ **eigenvalues of Hamiltonian** generated by image k.
- Selected modes have null or small real part.
- $\delta$ is a parameter that represents the spectral resolution of the experimental detection system.



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# Results

- Once the cost function was minimized using the images of the training set (about 24 hs on a 40 core cluster), the transformation matrix M obtained was used to classify the images of the training and testing sets.
- Two tasks: distinguish 0s and 1s (one-vs-one classifier) or distinguish 0s and any other digit (one-vs-all classifier).

| | | | One-vs-one | | One-vs-all |
|---|---|---|---|---|---|
| | Resolution | $\delta$ | $10^{-3}$ | $10^{-1}$ | $10^{-1}$ |
| **(TP+TN)/total** | Accuracy (%) | *Train* | 100 | 98.9 | 97.8 |
| | | *Test* | 98.9 | 97.8 | 96.7 |
| **TP/predicted yes** | Precision (%) | *Train* | 100 | 100 | 97.7 |
| | | *Test* | 100 | 100 | 97.9 |
| **TP/actual yes** (fraction of 0s correctly identified) | Recall (%) | *Train* | 100 | 97.6 | 97.7 |
| | | *Test* | 98 | 96.1 | 95.8 |



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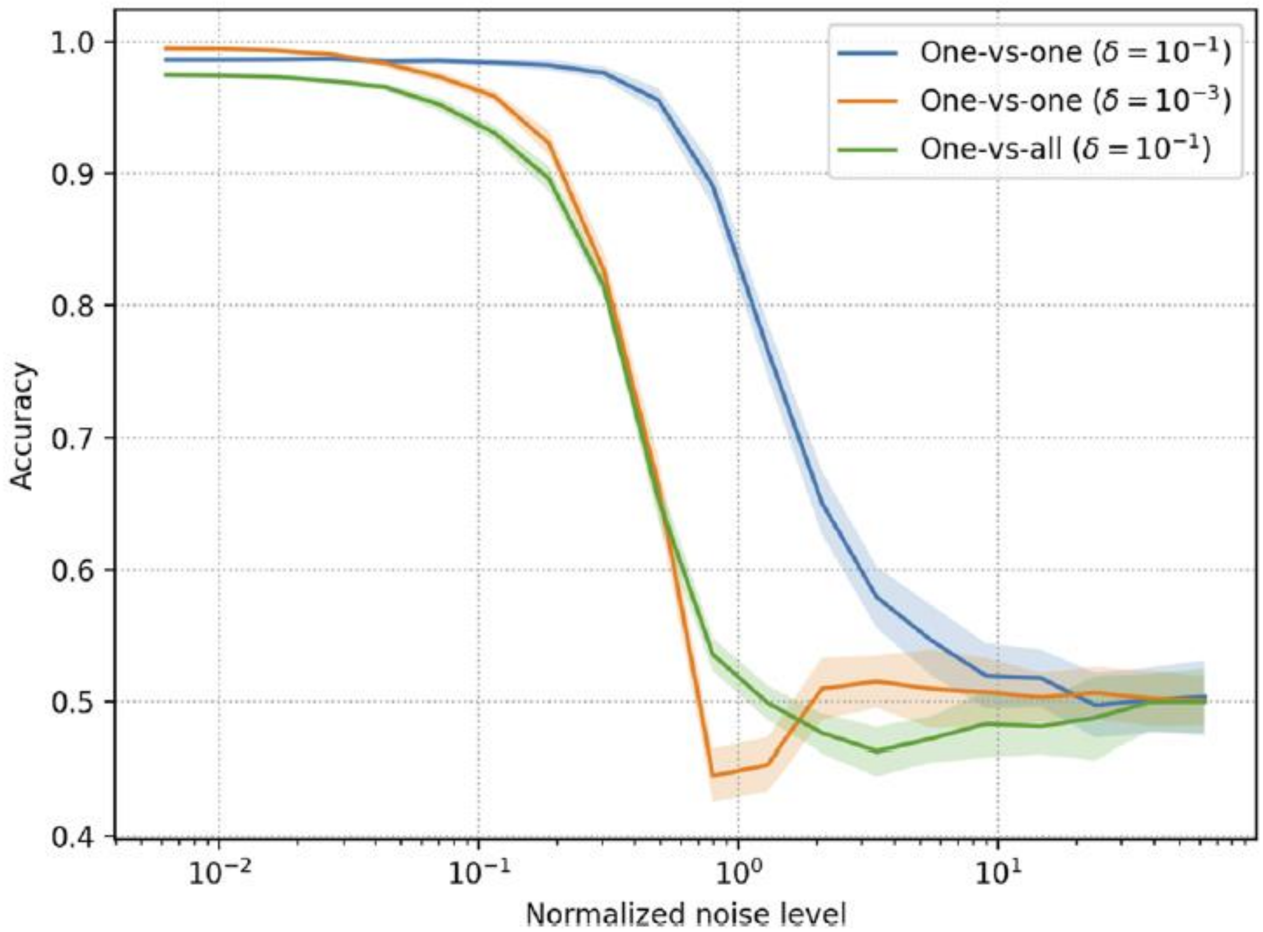
# Role of noise in the input image



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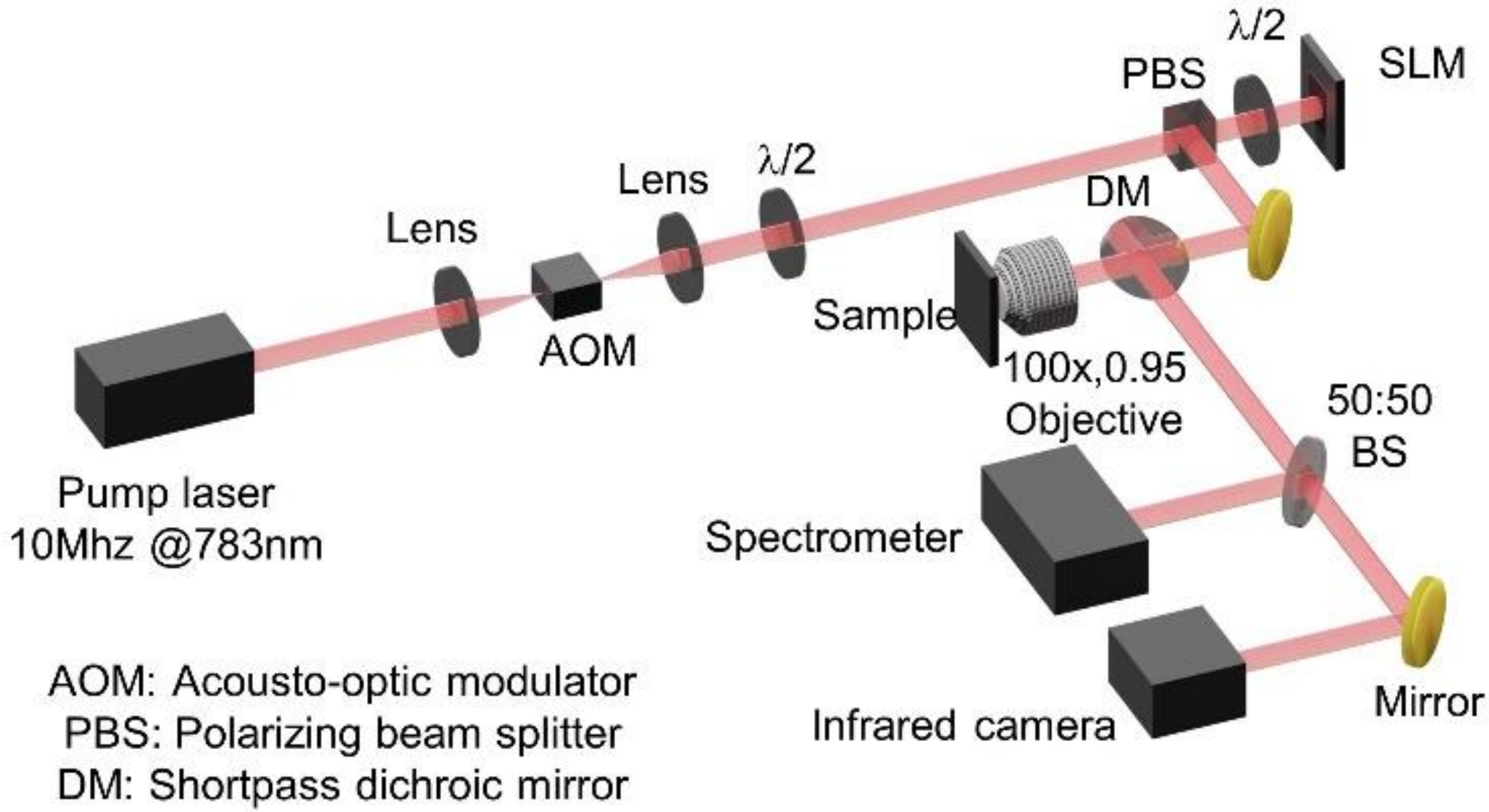
# Ongoing work



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# Discussion

- We have shown that an array of semiconductor nanolasers can be used to implement in hardware a photonic artificial neural network able to classify *low-dimensional* data.
- Performance close to the state of the art (a perceptron or a random forest can achieve nearly 100% accuracy).

## Binary image classification using collective optical modes of an array of nanolasers

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**Thank you for your attention!**

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