

RBM Classifier for MNIST

ISPR - Midterm 2
Assignment 3

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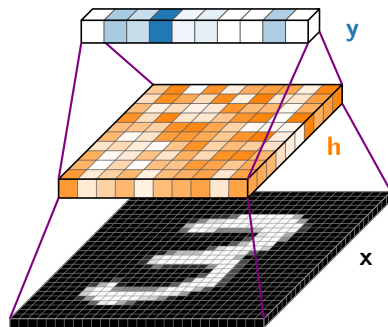
RBM Classifier¹

Model

- ▶ Visible units \mathbf{x} (input).
Size: $28 \times 28 \Rightarrow 784$.
- ▶ Half-visible units \mathbf{y} (output).
Size: 10.
- ▶ Hidden units \mathbf{h} .
Size: 100.

Energy

$$E(\mathbf{x}, \mathbf{y}, \mathbf{h}) = -\mathbf{h}^t \mathbf{W} \mathbf{x} - \mathbf{h}^t \mathbf{U} \mathbf{y} - \mathbf{b}^t \mathbf{x} - \mathbf{c}^t \mathbf{h} - \mathbf{d}^t \mathbf{y}$$

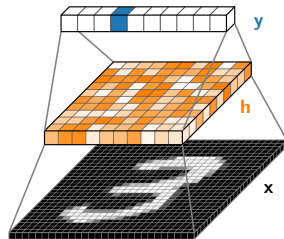


¹Larochelle, Hugo and Bengio, Yoshua, "Classification using Discriminative Restricted Boltzmann Machines". In: *Proceedings of the 25th International Conference on Machine Learning*. ICML '08.

Training and Prediction

Training

- ▶ Treat **y** as visible units.
- ▶ Use one-hot encoding for **y**.
- ▶ Contrastive divergence, 1 step.
- ▶ SGD with momentum.

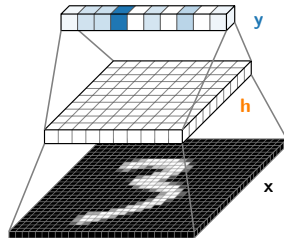


Prediction

- ▶ Treat **y** as hidden units.
- ▶ Compute the exact conditional distribution

$$p(y|\mathbf{x}) \propto e^{d_y} \prod_{j=0}^9 (1 + e^{c_j + U_{jy} + \sum_i W_{ji} x_i}) .$$

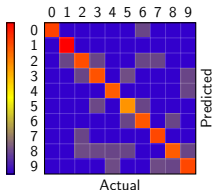
- ▶ Pick the digit y^* that maximizes $p(y^*|\mathbf{x})$.



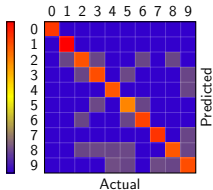
Results

RBM Classifier

Test
accuracy:
92.9%

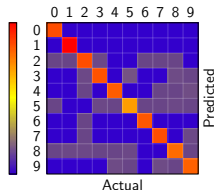


Train
accuracy:
92.7%

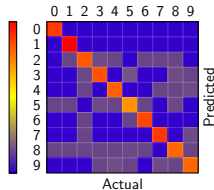


RBM + sklearn.linear_model

Test
accuracy:
90.4%

























Train
accuracy:
89.6%



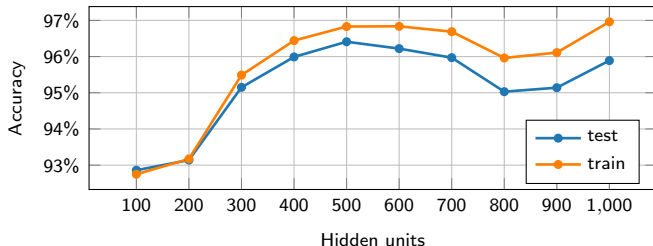
 **Neuron activations**

Experiments

► Gibbs sampling

Input	Outputs (20 iterations)									
										
										

► More hidden units



Appendix - Code

One epoch of training

```
# [...] initialize x0 and y0
h0P = sigmoid(self.c + self.W @ x0 + self.U @ y0)
wakeW = h0P @ x0.T
wakeU = h0P @ y0.T
h0 = sample(h0P)
x1 = sample(sigmoid(self.b + self.W.T @ h0))
y1 = sample(sigmoid(self.d + self.U.T @ h0))
h1P = sigmoid(self.c + self.W @ x1 + self.U @ y1)
dreamW = h1P @ x1.T
dreamU = h1P @ y1.T
# [...] perform gradient descent
```

Prediction

```
x = data.T
t = (self.c + self.U)[: , :, None] + (self.W @ x)[: , None, :]
P = self.d + np.sum(np.log1p(np.exp(t)), axis = 0)
return np.argmax(P, axis = 0)
```