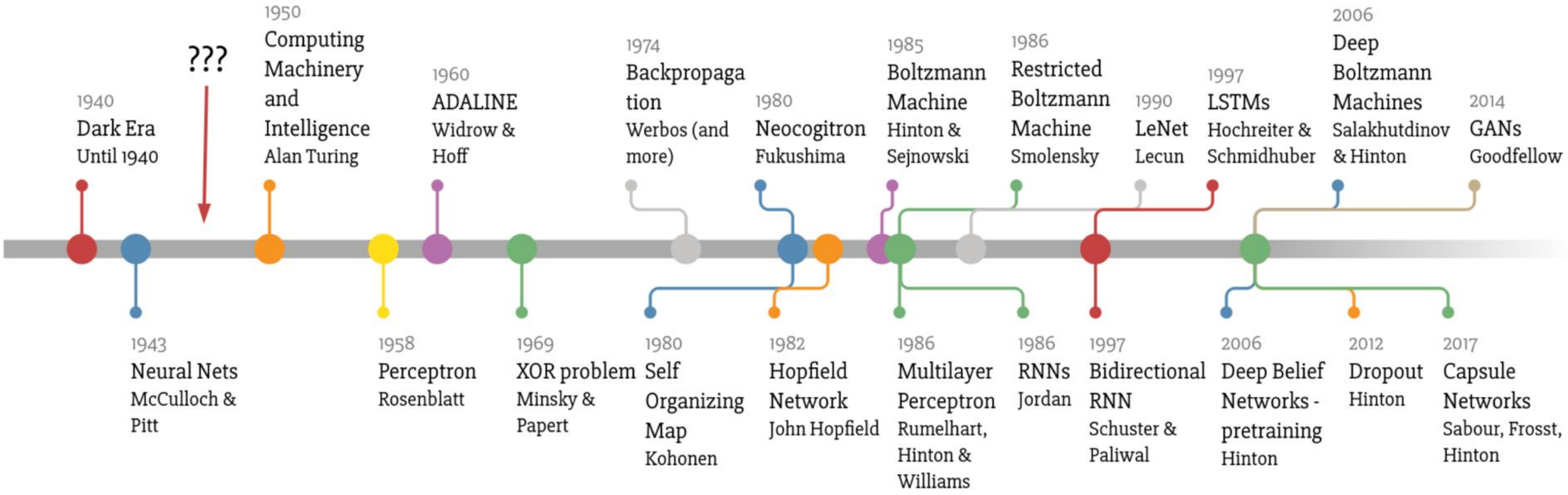
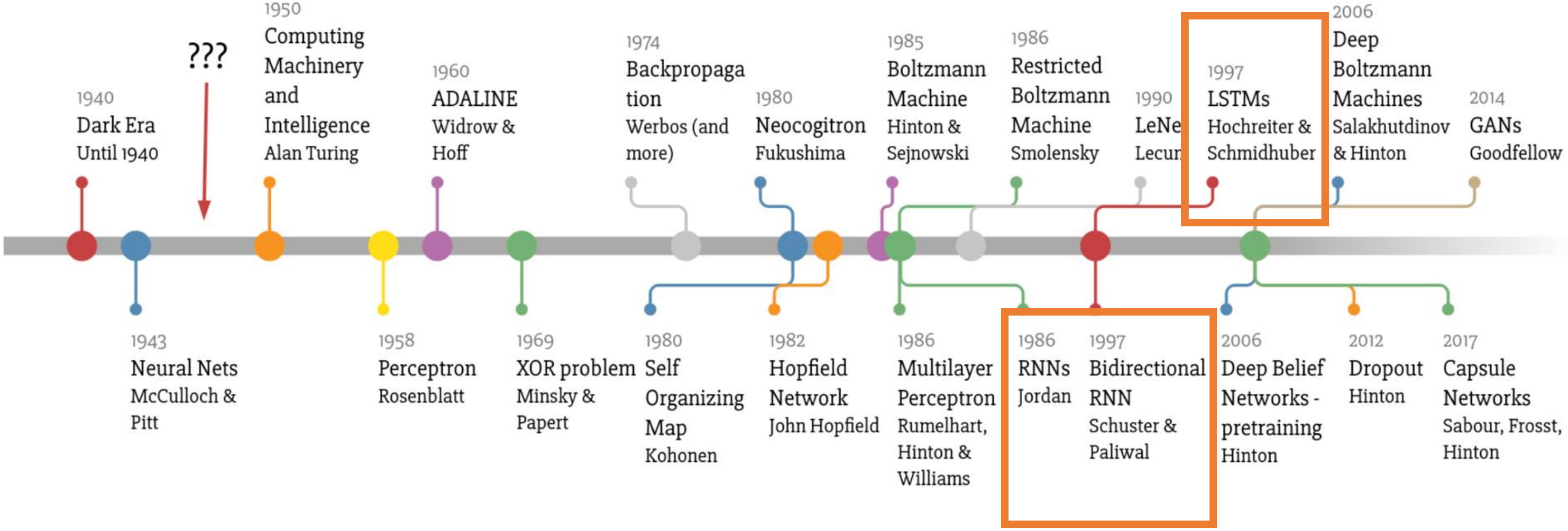
Deep Learning Timeline

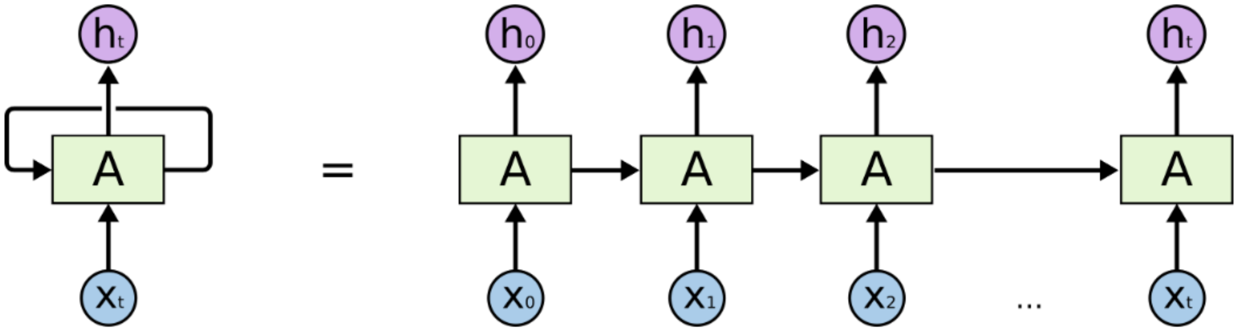


Deep Learning Timeline

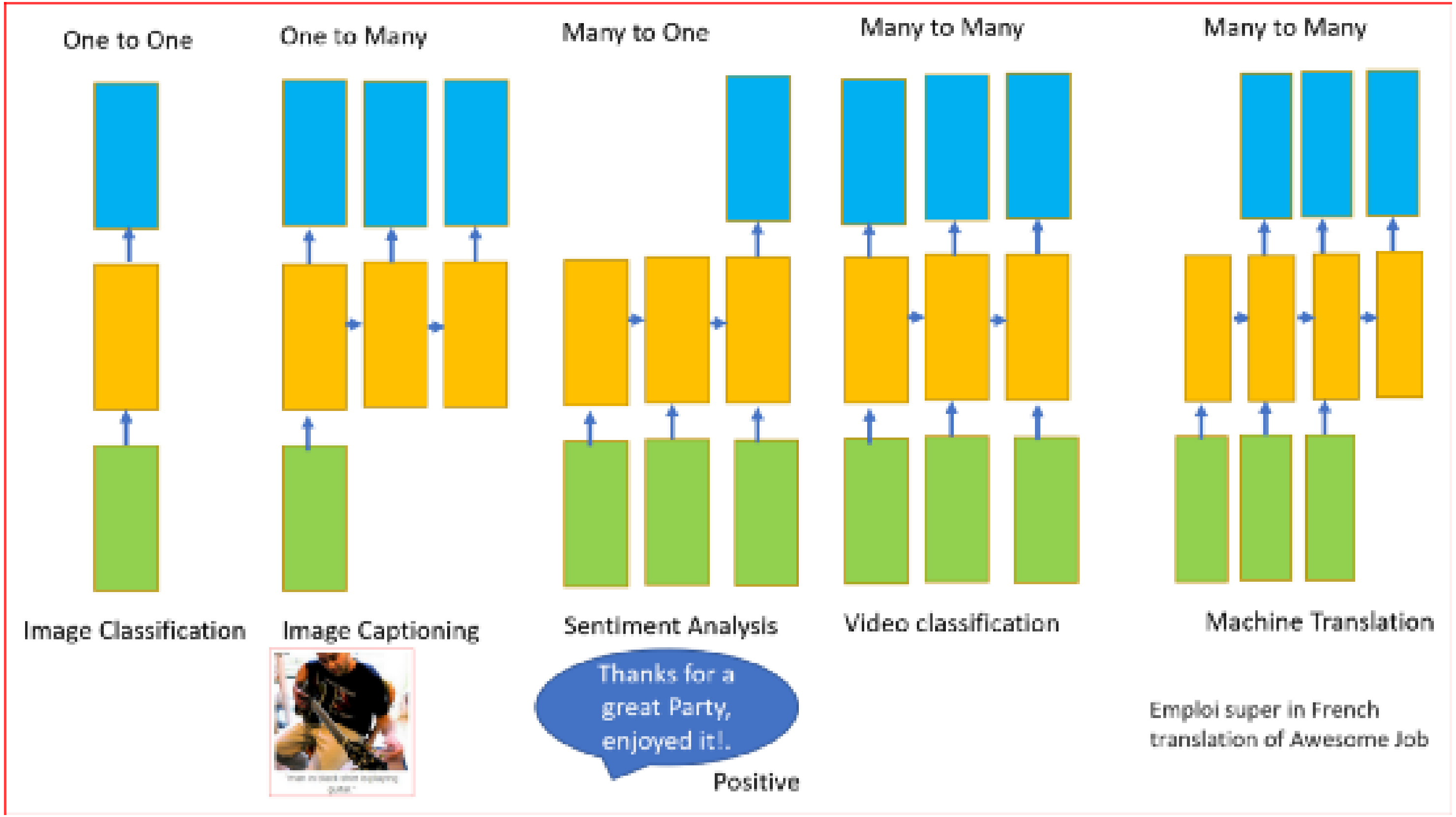


Recurrent Neural Networks

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence

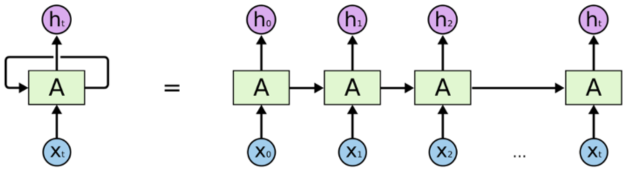


An unrolled recurrent neural network.


One to One
One to Many
Many to One
Many to Many
Many to Many
Image Classification
Image Captioning
Sentiment Analysis
Video classification
Machine Translation
Thanks for a great Party, enjoyed it!.
Positive
Emploi super in French translation of Awesome Job

Recurrent Neural Networks

```
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(RNN, self).__init__()

        self.hidden_size = hidden_size

        self.i2h = nn.Linear(input_size + hidden_size, hidden_size
        self.i2o = nn.Linear(input_size + hidden_size, output_size
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, input, hidden):
        combined = torch.cat((input, hidden), 1)
        hidden = self.i2h(combined)
        output = self.i2o(combined)
        output = self.softmax(output)
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, self.hidden_size)

n_hidden = 128
rnn = RNN(n_letters, n_hidden, n_categories)
```



An unrolled recurrent neural network.

CLASS `torch.nn.Linear(in_features, out_features, bias=True)`

Applies a linear transformation to the incoming data: $y = xA^T + b$

Parameters

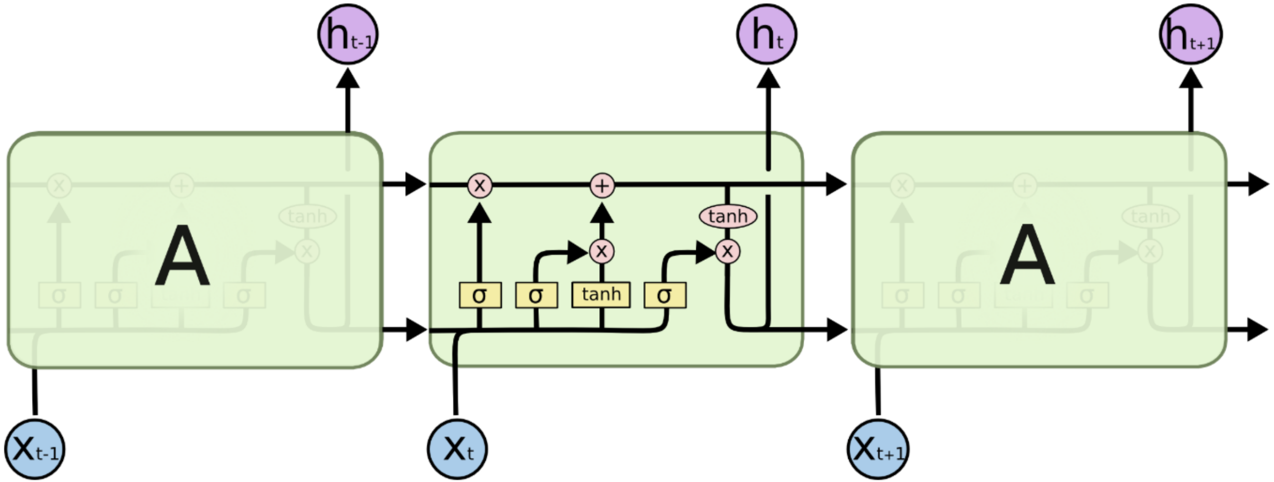
- **in_features** – size of each input sample
- **out_features** – size of each output sample
- **bias** – If set to `False`, the layer will not learn an additive bias. Default: `True`

$$Y_{n\times o} = X_{n\times i} W_{i\times o} + b$$

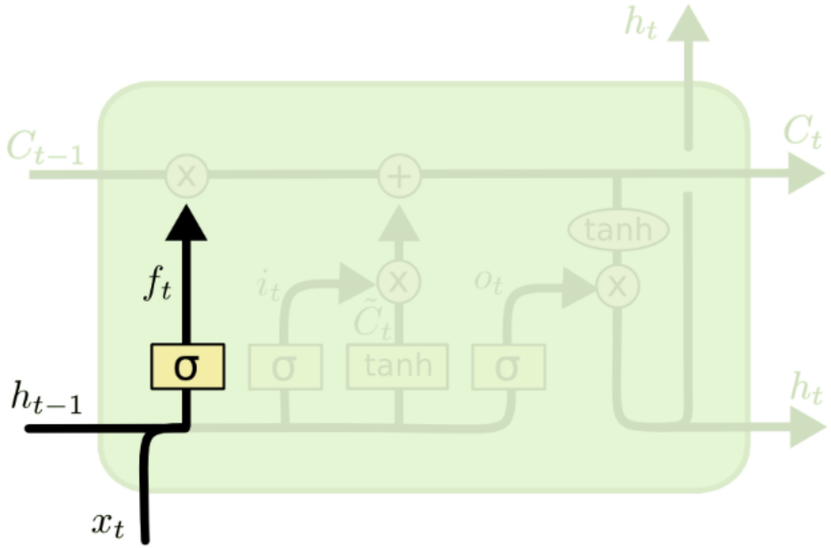
Recurrent Neural Networks

The Problem of Long-Term Dependencies

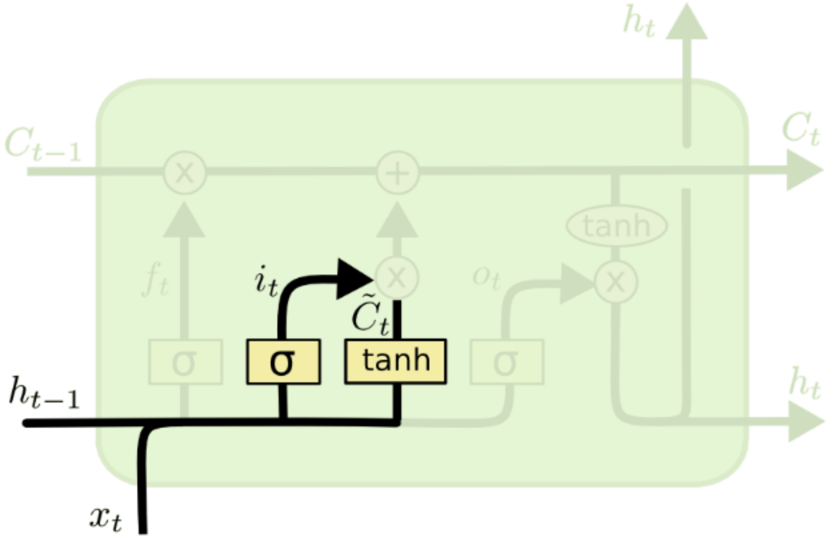
Long Short Term Memory networks



The repeating module in an LSTM contains four interacting layers.

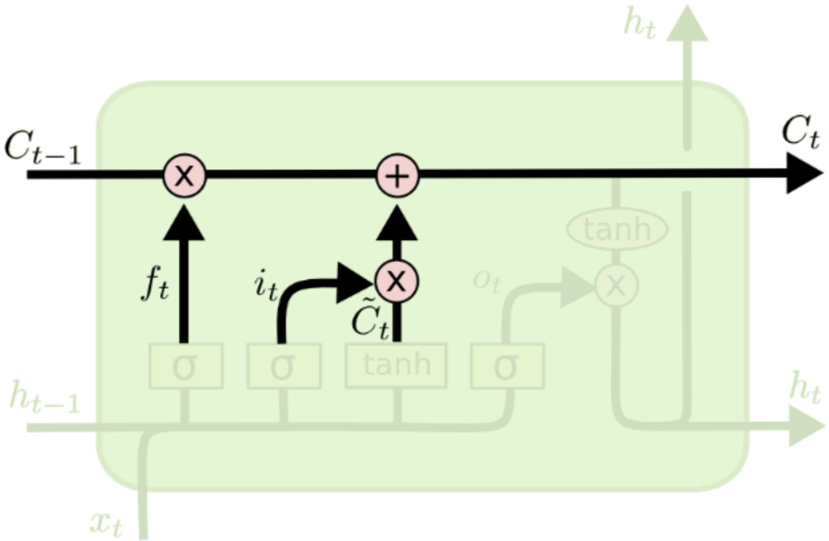


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

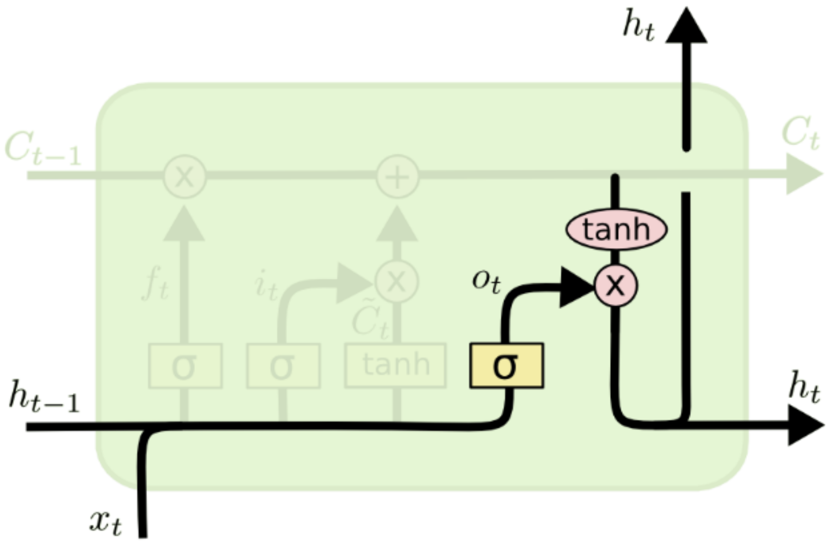


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$



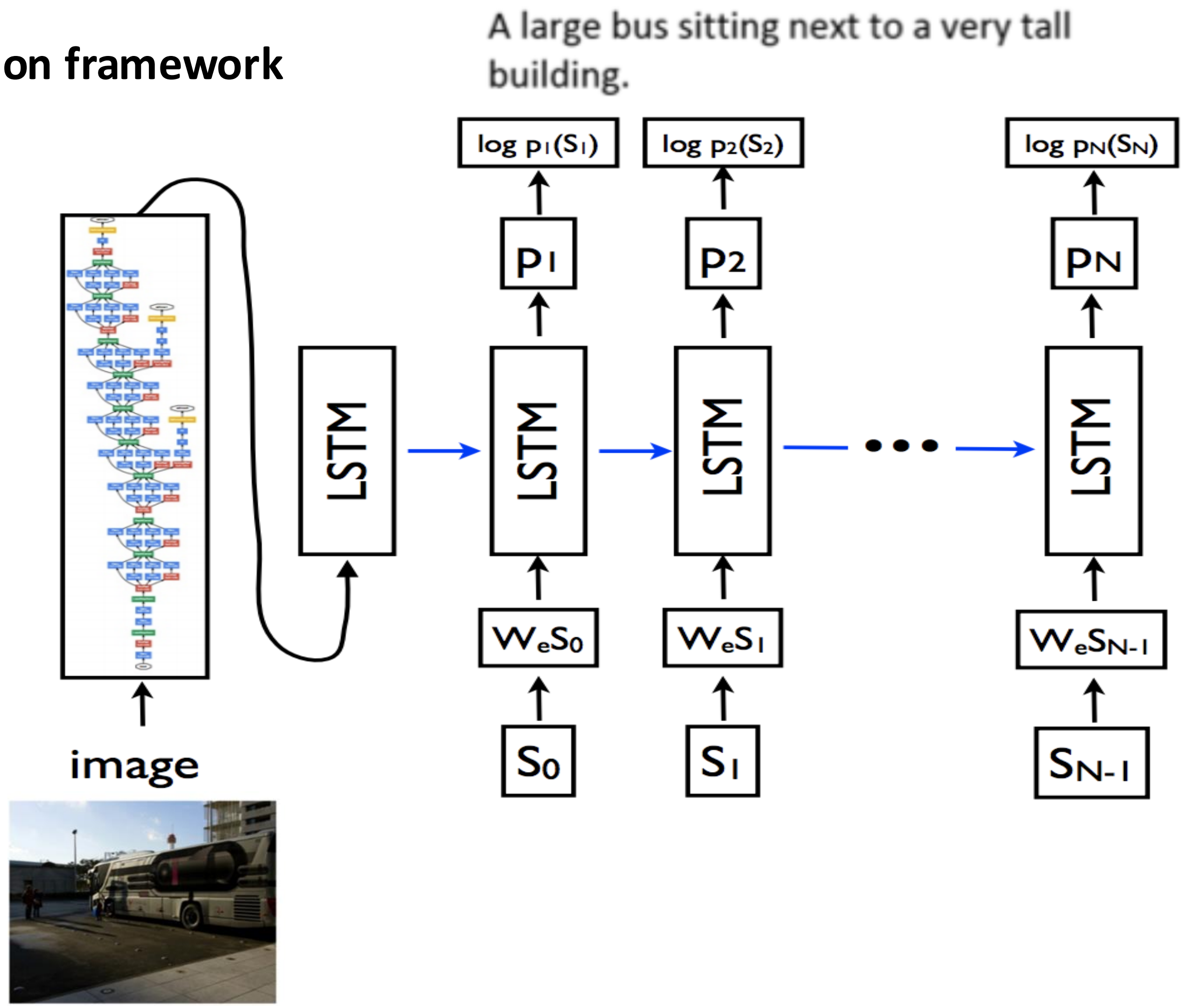
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$



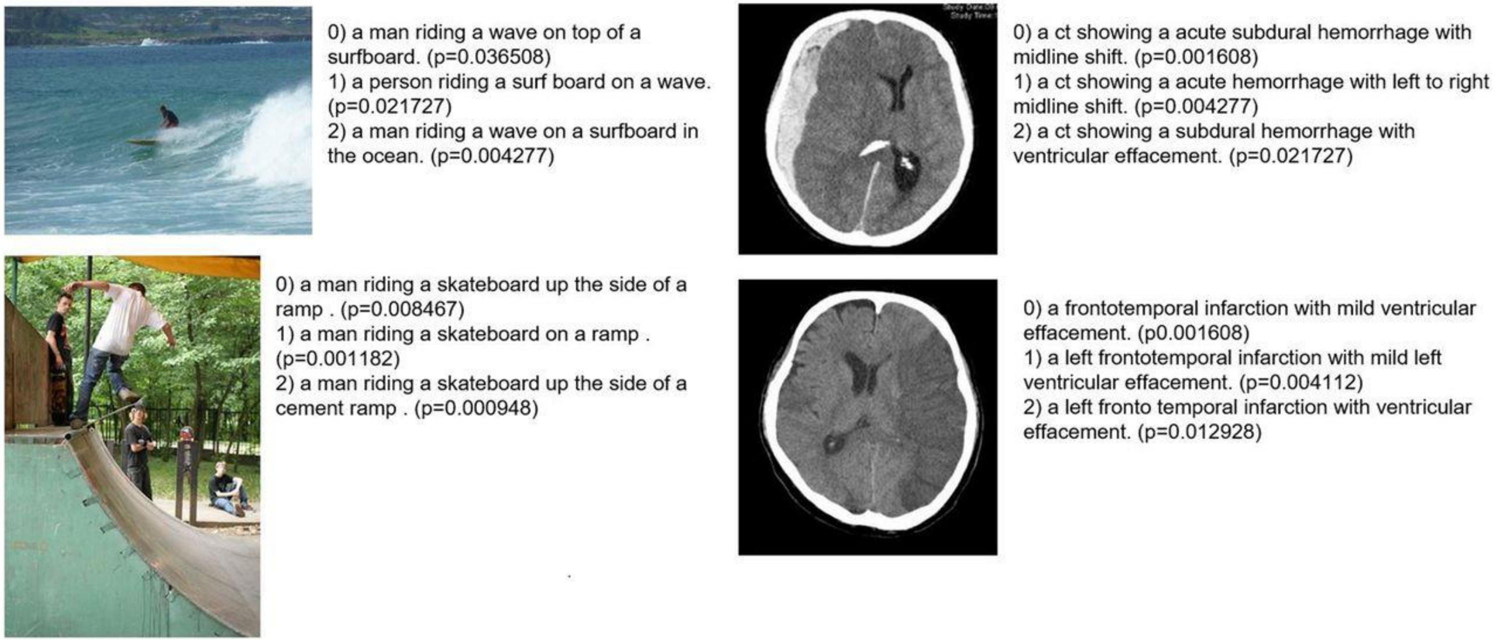
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Image caption framework

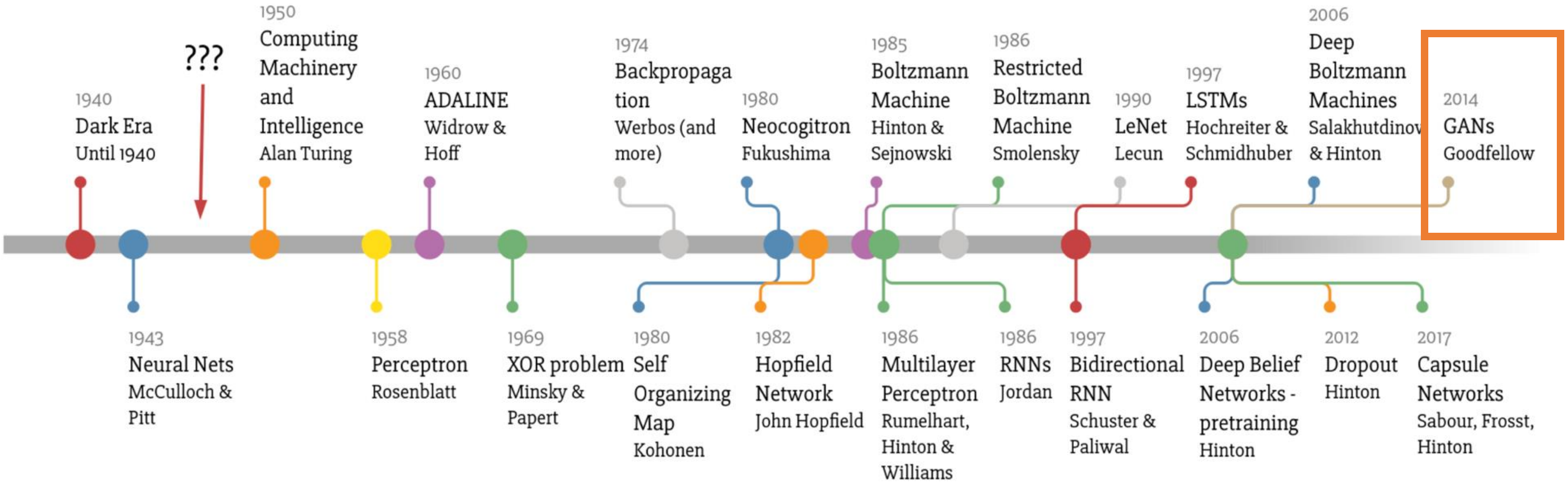


Case Study : LSTM for medical image

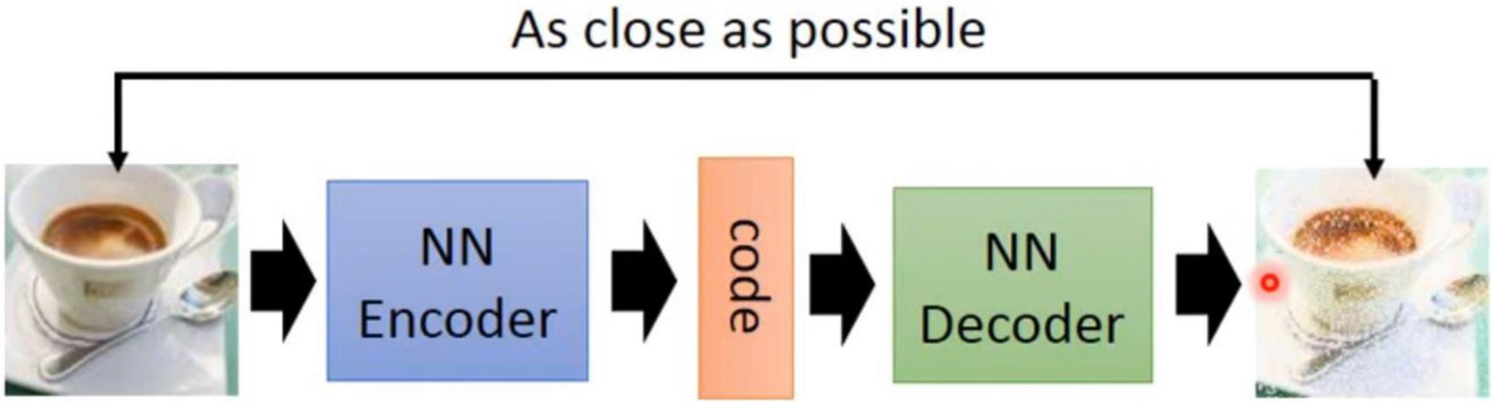


Feng, Rui, et al. "Deep learning guided stroke management: a review of clinical applications." *Journal of neurointerventional surgery* 10.4 (2018): 358-362.

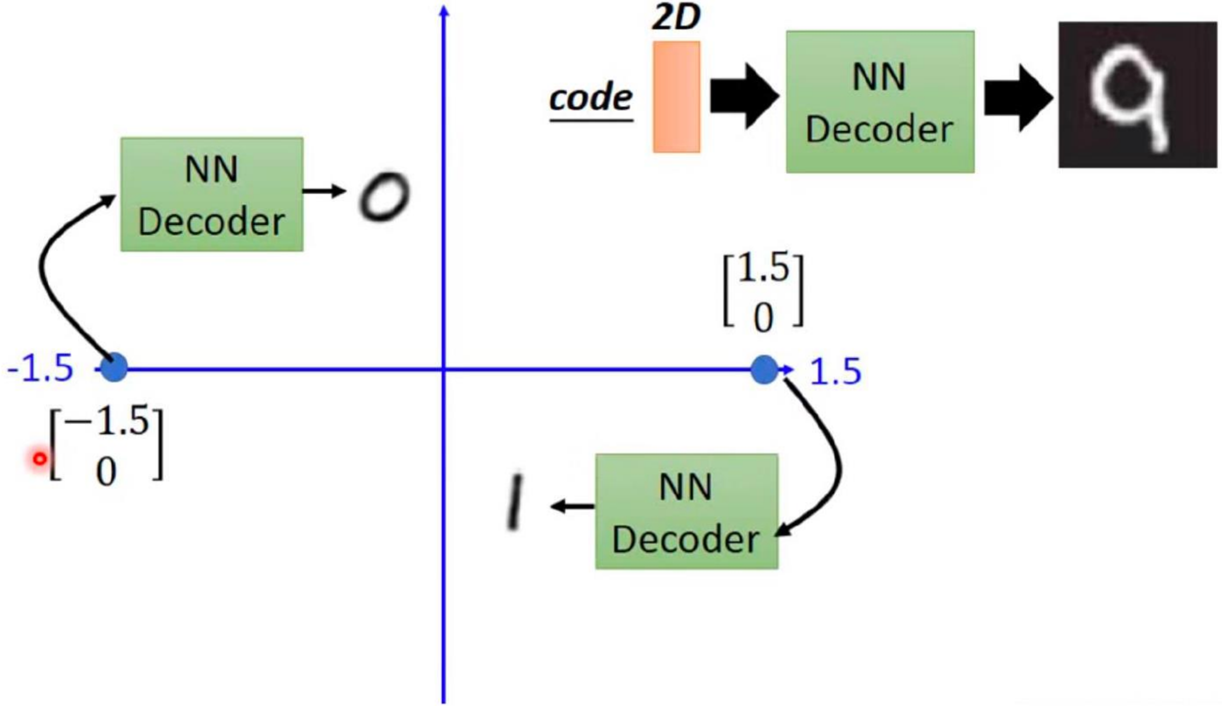
Deep Learning Timeline

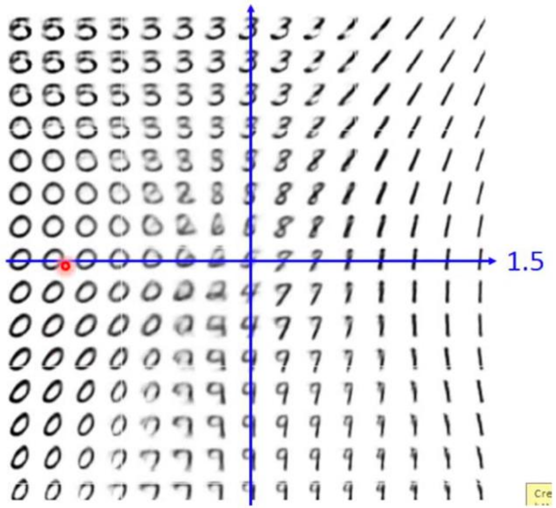


Review: Auto-encoder



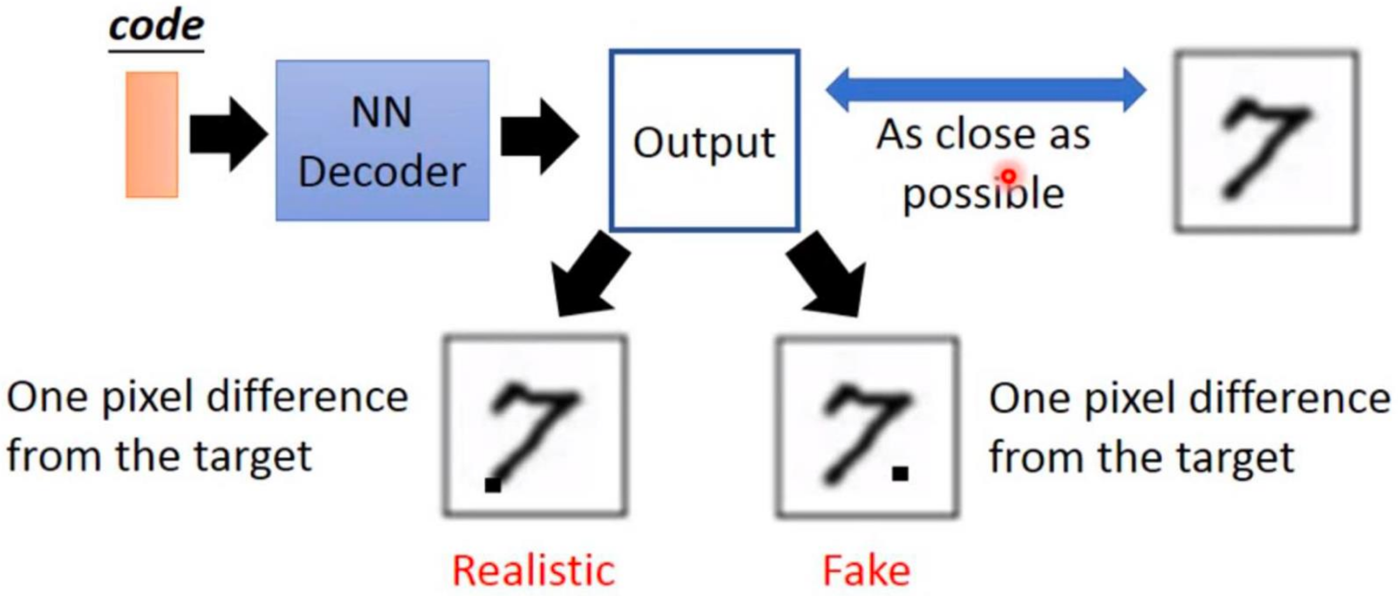
Review: Auto-encoder





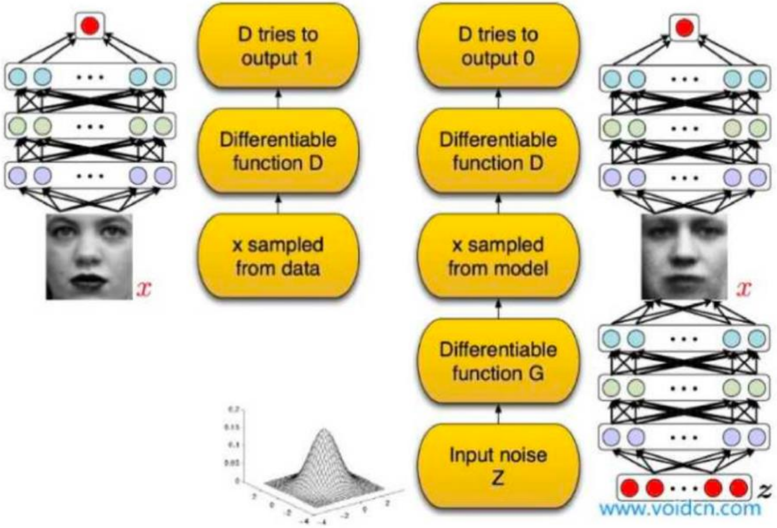
Problems of VAE

- It does not really try to simulate real images

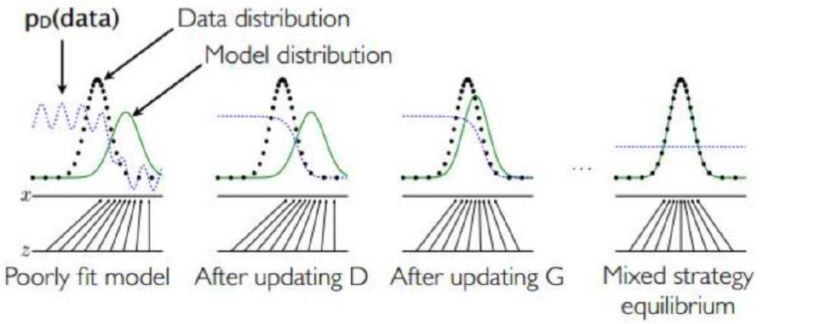


Generative Adversarial Nets

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$



$$\min_G V(D,G) = E_{z\sim p_z(z)}[log(1 - D(G(z)))]$$



$$p_g(x) = p_{data}(x)$$

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

---

for number of training iterations **do**
- **for** k steps **do**
  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

- **end for**
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

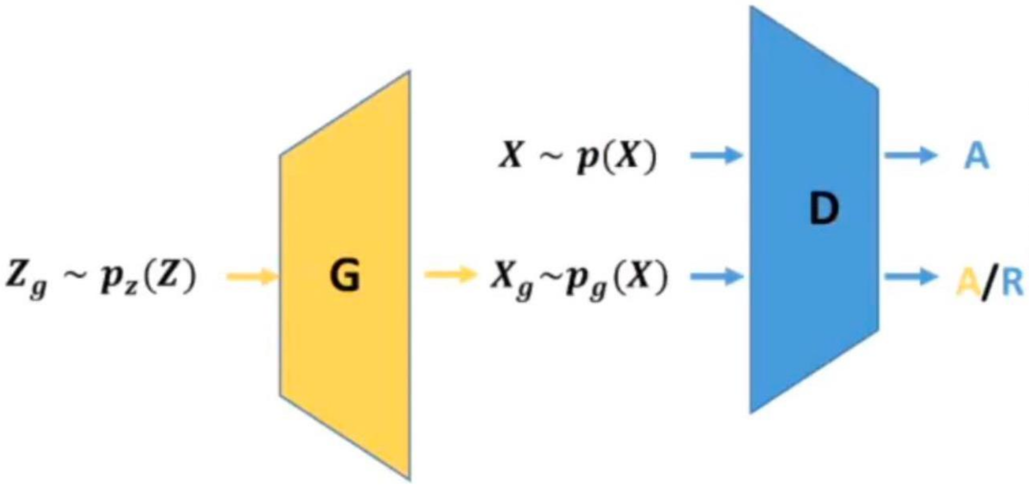
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

GANs (Goodfellow et al. [2014])

- Given p(x), learn $p_g(x) \approx p(x)$
- A two-player game



The global optima is $p_g(x) = p(x)$.

The Two-player Formulation is Restricted

- G and C may not be optimal at the same time. Here is an example of good C with poor G (Salimans et al. [2016]).

- G cannot control the semantics of the generated samples.

Generative Adversarial Nets

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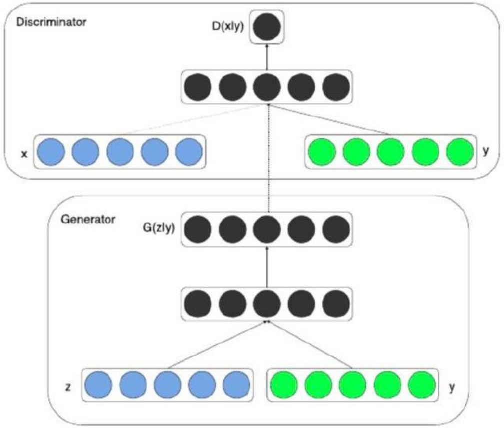
Conditional Generative Adversarial Nets



$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_{z}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))].$$

Figure 2: Generated MNIST digits, each row conditioned on one label

	User tags + annotations	Generated tags
	montanha, trem, inverno, frio, people, male, plant life, tree, structures, transport, car	taxi, passenger, line, transportation, railway station, passengers, railways, signals, rail, rails
	food, raspberry, delicious, homemade	chicken, fattening, cooked, peanut, cream, cookie, house made, bread, biscuit, bakes
	water, river	creek, lake, along, near, river, rocky, treeline, valley, woods, waters
	people, portrait, female, baby, indoor	love, people, posing, girl, young, strangers, pretty, women, happy, life

Table 2: Samples of generated tags

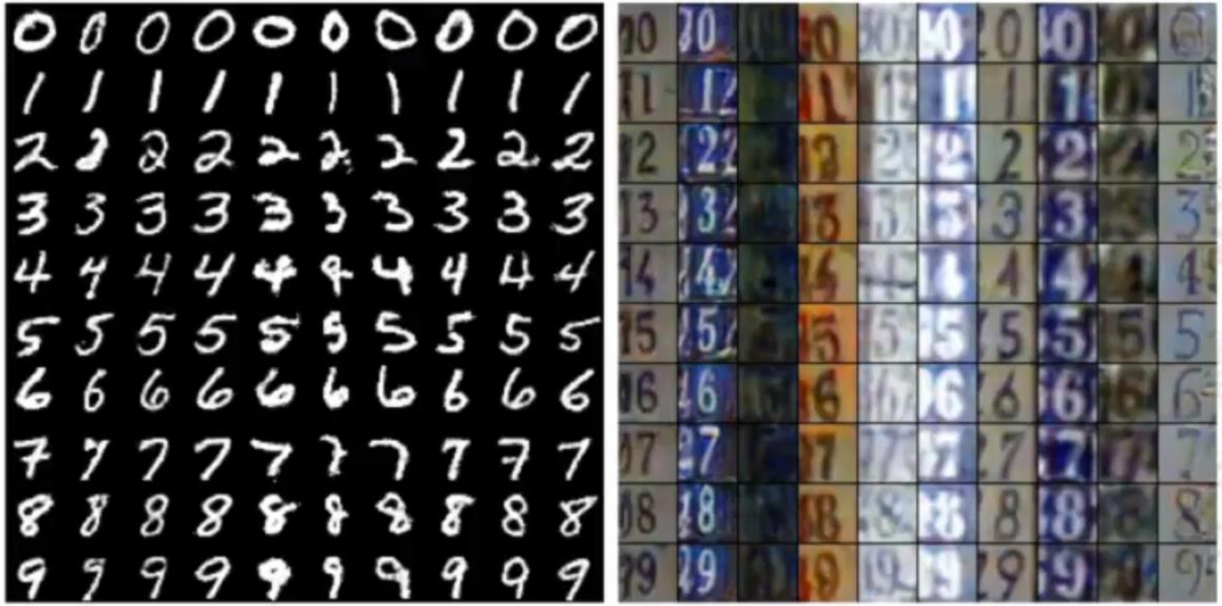


Figure: Same y for each row. Same z for each column.

Home work: python + numpy

https://cs231n.github.io/python-numpy-tutorial/