Lecture 4:
Deep learning in practice with pytorch

Advanced deep learning

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About the next few lectures

- Goal: In-depth understanding of important Deep Learning staples
  - Reinforce what you have already seen
  - Introduce state of the art models

- This is a hands-on course in pytorch
  - Minimal math
    - Enough to understand
  - Quite a bit of coding
  - Get comfortable with the standard pipeline

Evaluation

- Hand in one or two lab notebooks
  - Questions + (clean) code
  - 1st notebook: Lab 5 on transformers (Next Thursday)
    - To hand in after vacation

- Written exam at end of semester
  - Little to no code
  - A few exercises on toy examples
  - Questions on aspects of deep learning

Course organization: 10 Lectures

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- L1-2: Overview of Deep Learning (F. Precioso)
- L3-4: Fundamentals of Deep Learning (R. Sun)

- L5-6: Transformers (R. Sun)
- L7: Large models (LLMs, VLMs, Generators) (R. Sun)

- L8: Tricks of the trade (R. Sun)

- L9: Ethics of AI (F. Precioso)

- L10: Intro to generative models (P-A. Mattei)

Today!

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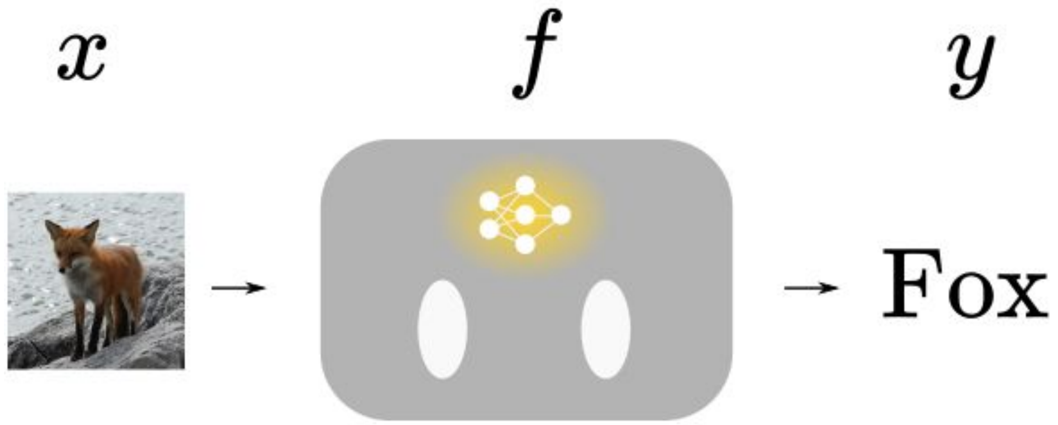
- Goal: Understand basic deep architectures in-depth
    - Building blocks for everything else in deep learning
    - Deep learning relies on the combination of a lot of very simple blocks

- A few things to take away after these 3 lectures
    - What do we optimize for? How? Why?
    - How do we build and train neural layers?
    - How do they behave?

Refresher on last week

Problem statement: Ideal case



- Find (robot) f that classifies images well
  - Often based on neural networks

$$\forall (x, y) \in \mathcal{D}, f(x) = y$$

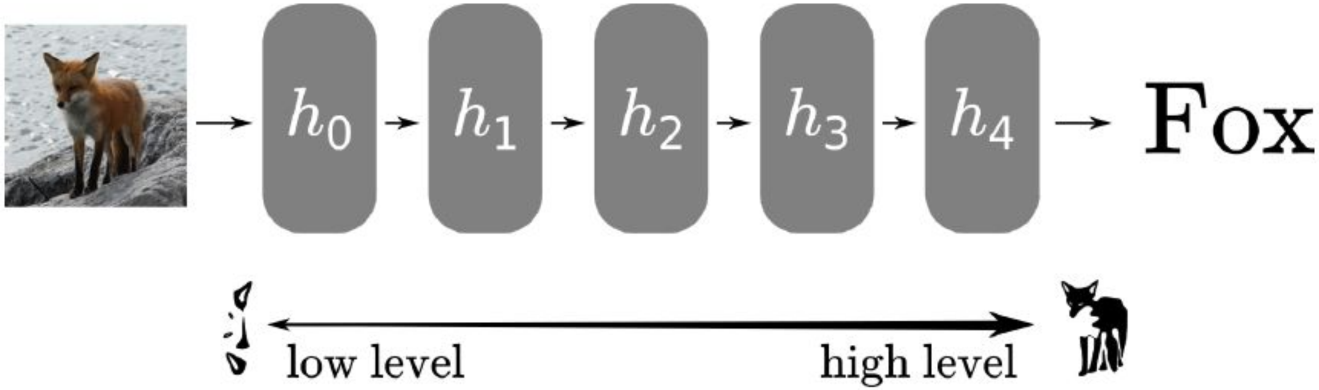
Minimizing Risk

- Problem: we do not know $\mathcal{D}$!
  - Solved problem otherwise…
  - Evaluating the risk requires this distribution

- Solution: Use a dataset D of (x,y) sampled from $\mathcal{D}$
  - ***<u>Empirical Risk Minimization</u>***
  - If the (x,y) are i.i.d drawn from $\mathcal{D}$ can be expressed as a mean over the dataset

$$min_\theta \hat{\mathcal{R}_\theta} = \frac{1}{N} \sum_{i=0,\dots,N-1} l(f_\theta(x_i), y_i)$$

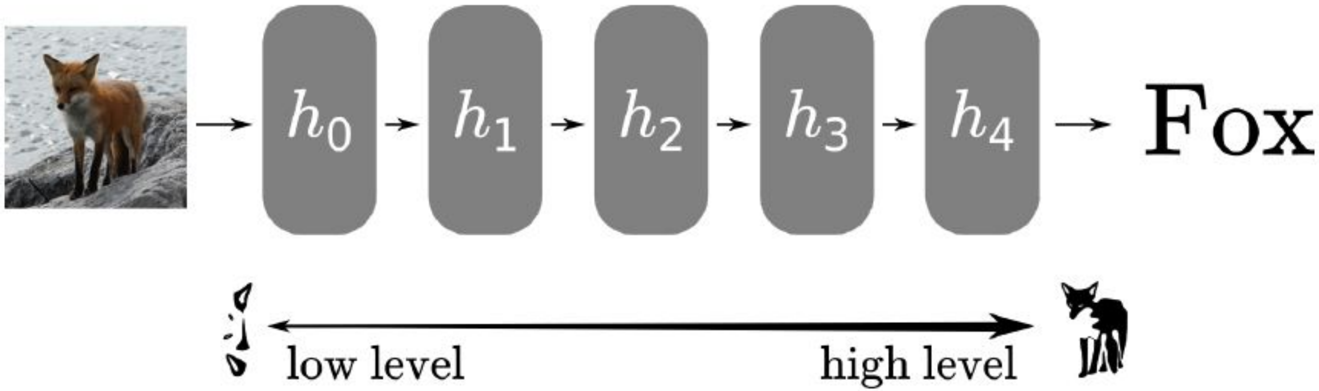
Neural network functions

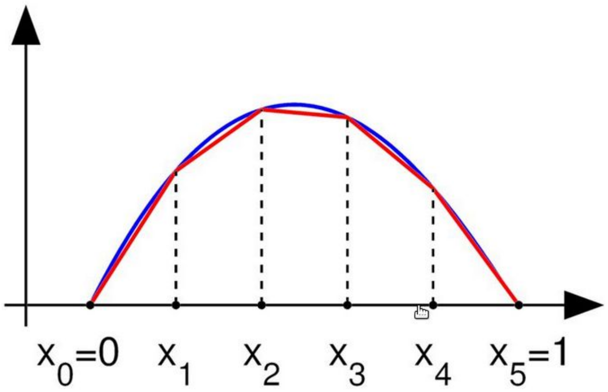


- Neural networks are sequences of simple functions

$$f_\theta = h_\theta^0 \circ h_\theta^1 \circ \cdots \circ h_\theta^{L-1}$$

Let's find the best network then!





$$min_\theta \hat{\mathcal{R}}_\theta = \frac{1}{N} \sum_{i=0,\ldots,N-1} l(f_\theta(x_i), y_i)$$

No closed form!

Approximation: Gradient Descent

- Iteratively make steps of size η to minimize risk

$$\theta^{t+1} := \theta^t - \eta \nabla_\theta \hat{\mathcal{R}}_\theta$$

- Elementwise form:

$$\theta_i^{t+1} := \theta_i^t - \eta \frac{\partial \hat{\mathcal{R}}_\theta}{\partial \theta_i}$$

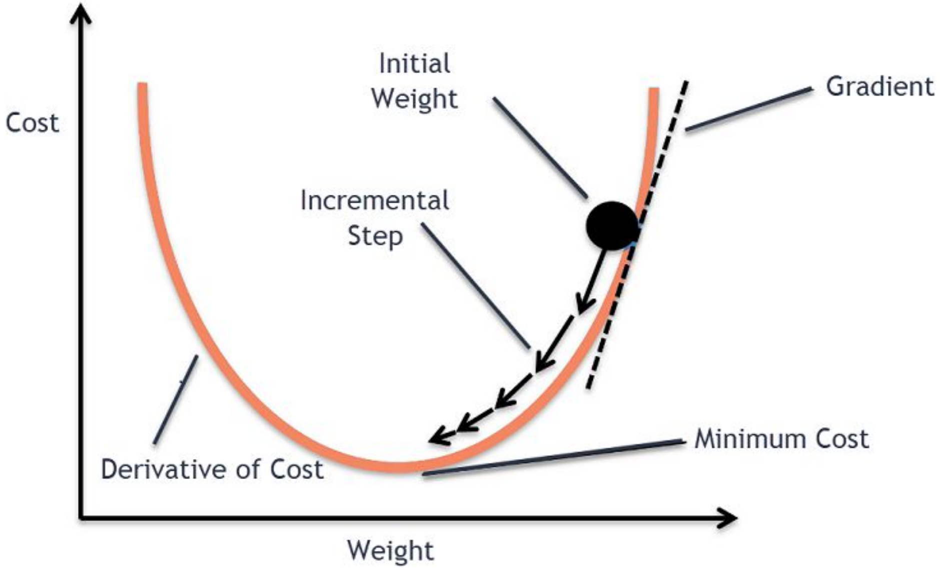


Image from Analytics Vidhya

We need the gradient…

$$\theta^{t+1} := \theta^t - \eta \nabla_\theta \hat{\mathcal{R}_\theta(B)}$$

- Requires finding the risk gradient wrt parameters

$$\nabla_\theta \hat{\mathcal{R}_\theta(B)} = \frac{1}{\#B} \sum_{k=0,\dots,B-1} \nabla_\theta l(f_\theta(x_k), y_k)$$

- Boils down to computing gradients for one sample

$$\nabla_\theta l(f_\theta(x), y)$$

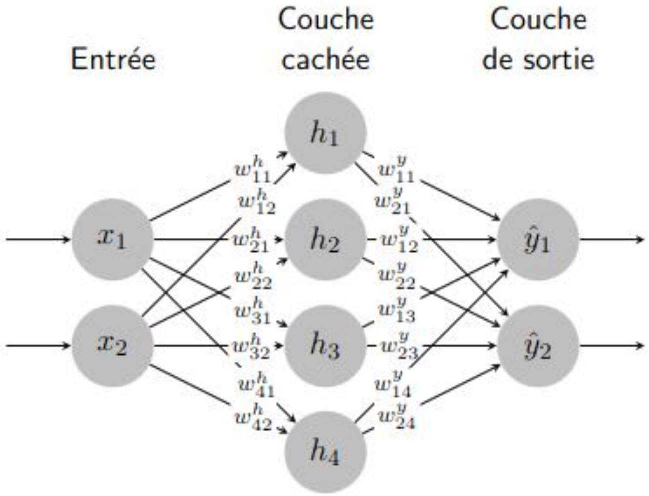
Backpropagation (Informal)

$$l := l(f_\theta(x), y)$$

- Networks are complex but made of simple parts!
  - Simple gradients of component functions
  - Chain-rule allows decomposition into simple gradients $$\frac{\partial l}{\partial w} = \frac{\partial l}{\partial a}\frac{\partial a}{\partial w}$$

- Need to store intermediate activations "a" to evaluate partial derivatives $$\frac{\partial a}{\partial w}$$

Example: Tanh MLP



- Simple 1 hidden layer MLP
  - 2 inputs
  - 2 outputs
  - 4 hidden activations
- Classification problem
  - Outputs probabilities
  - Cross-entropy loss

$$l_{CE}(\hat{y}, y) = - \sum_{i=0}^{\#Classes-1} y_i \log(\hat{y}_i)$$

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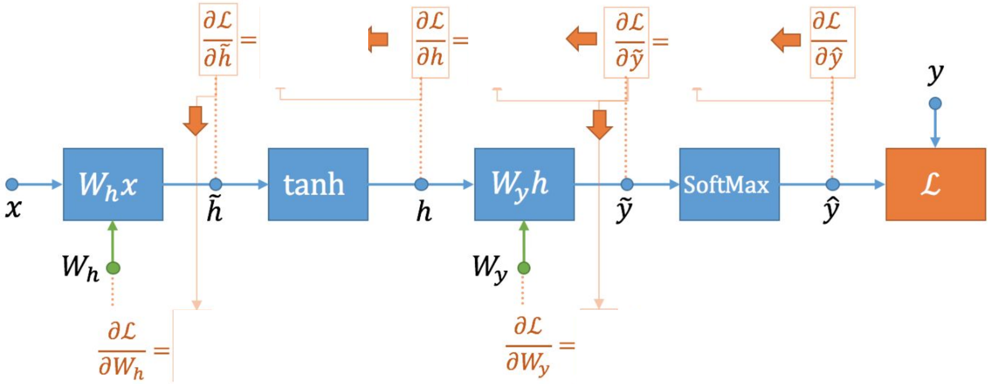

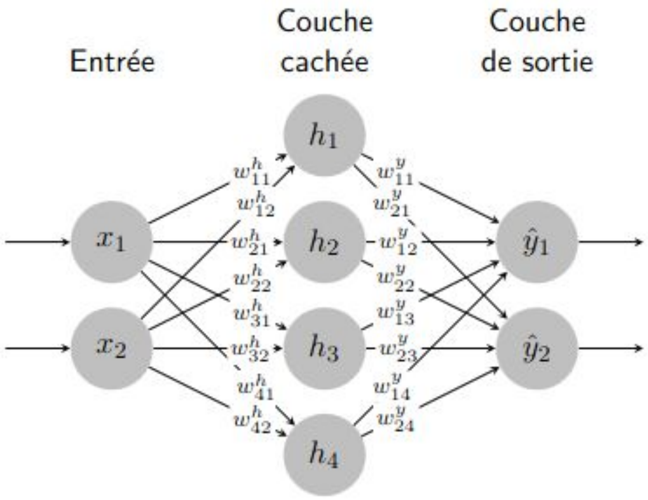

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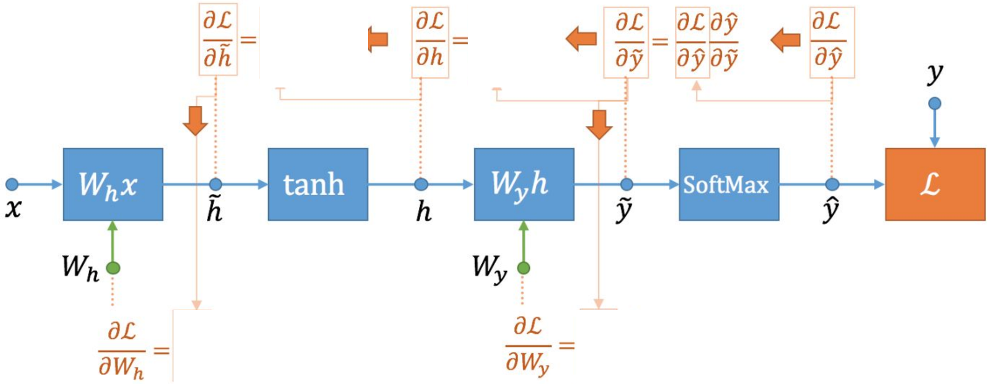

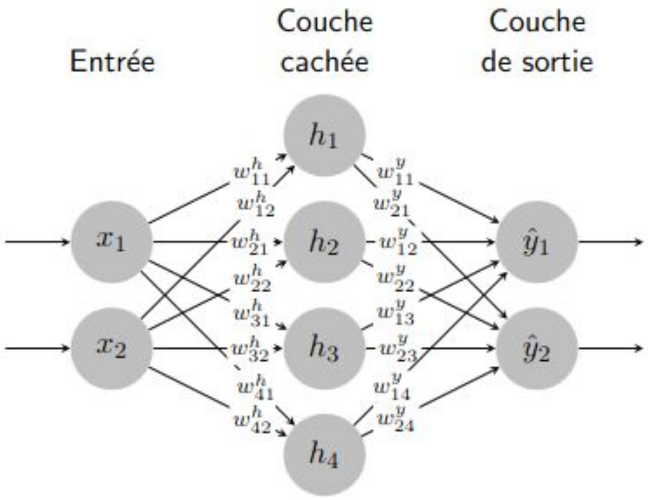

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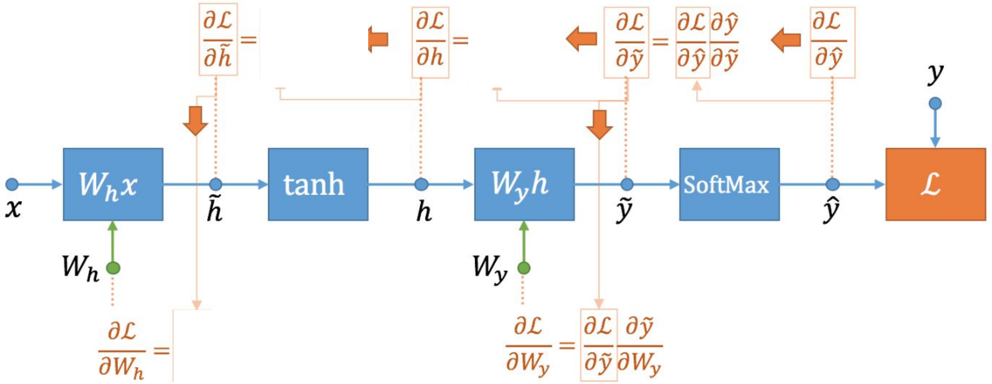

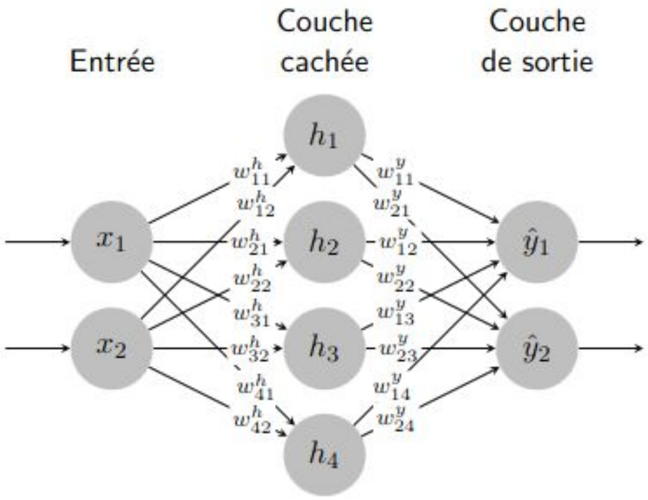

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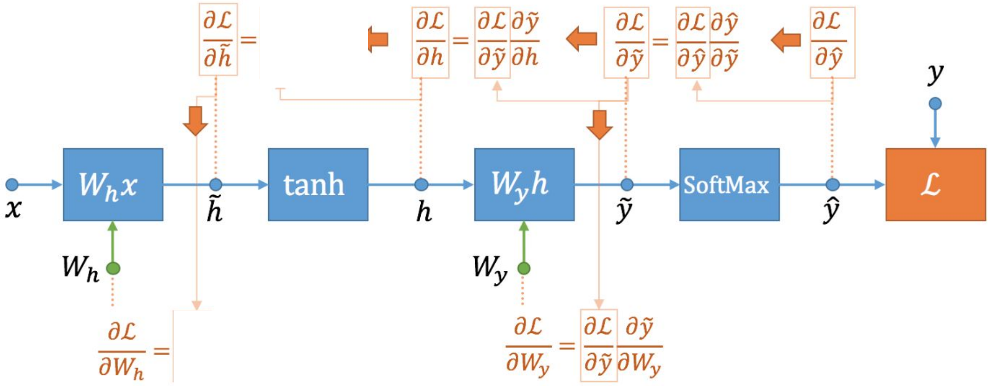

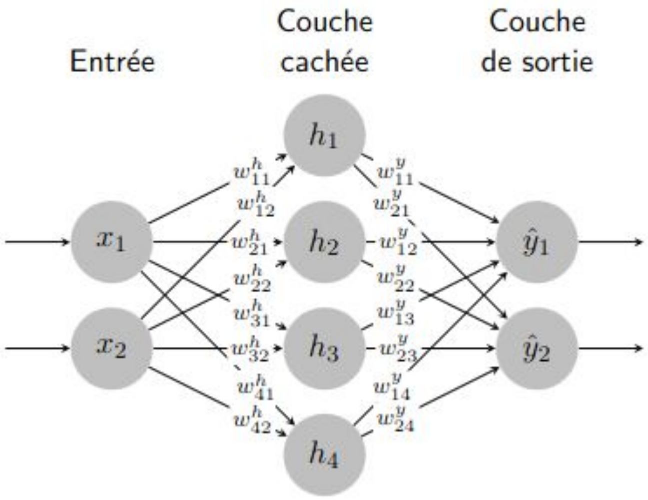

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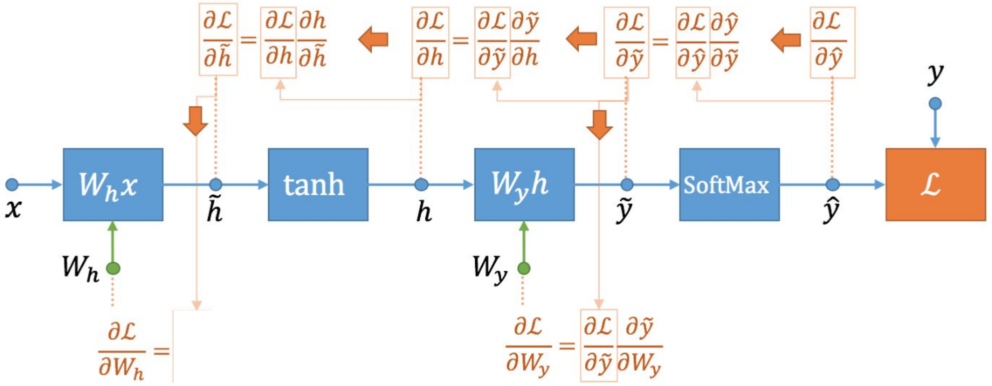

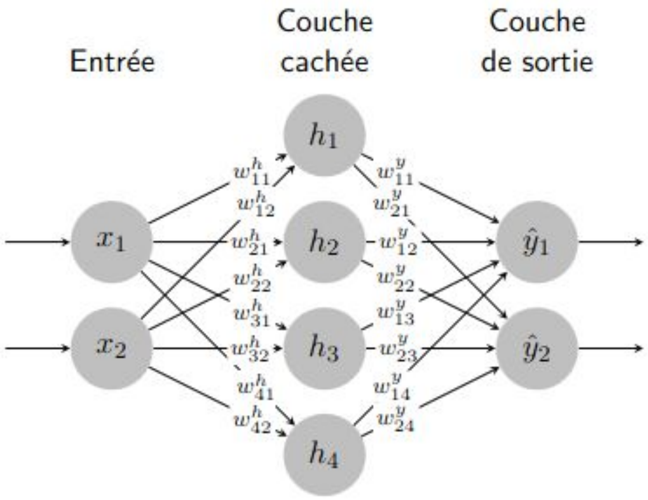

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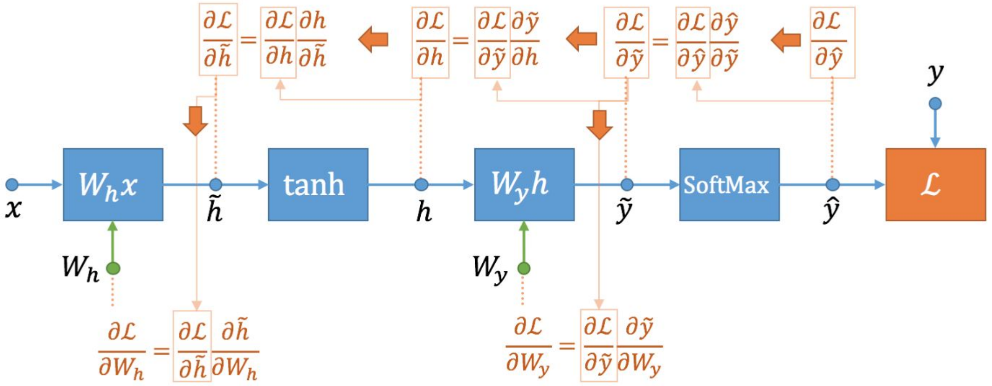

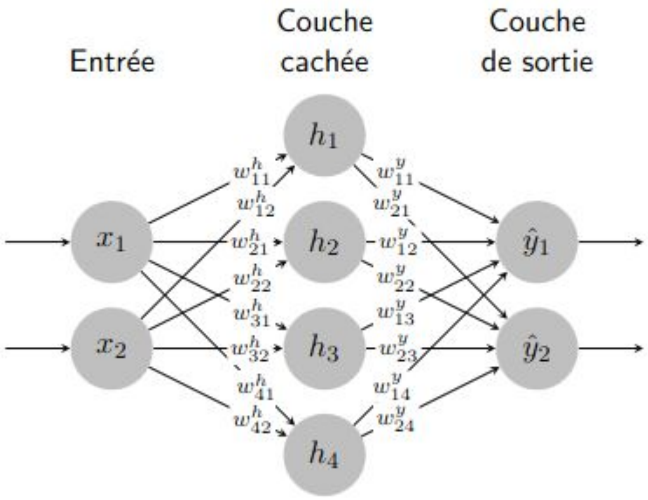

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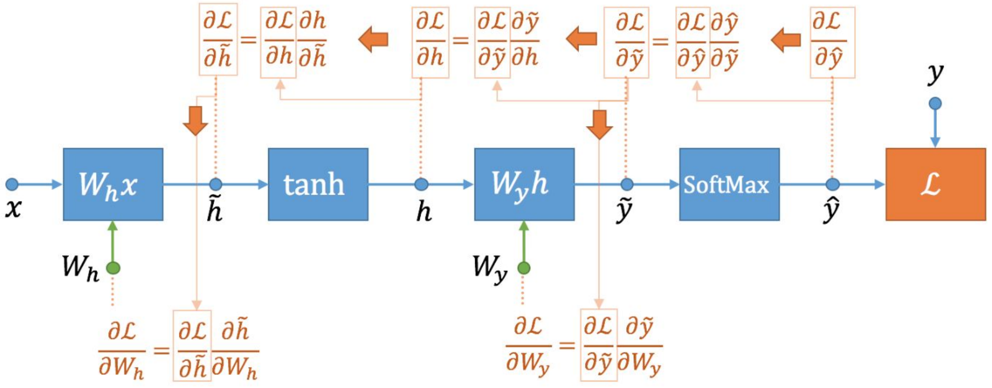

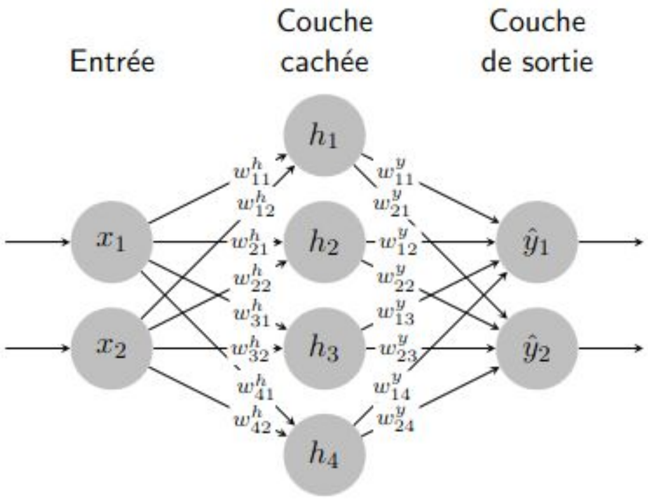

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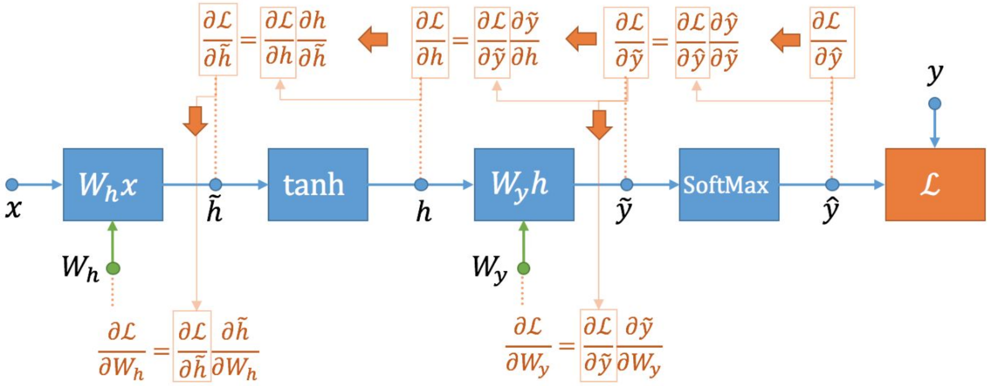

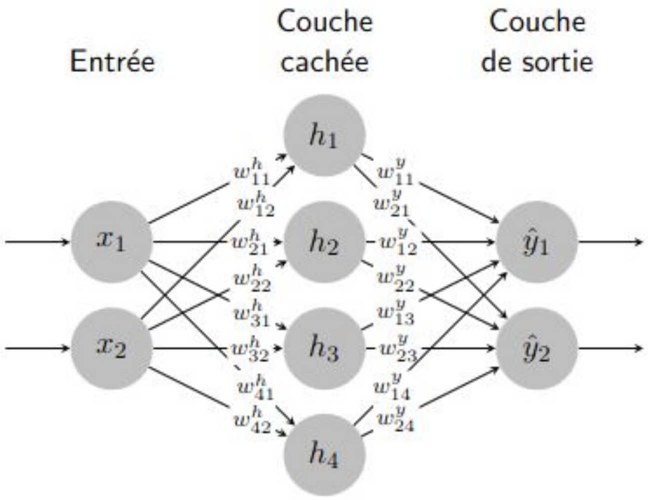

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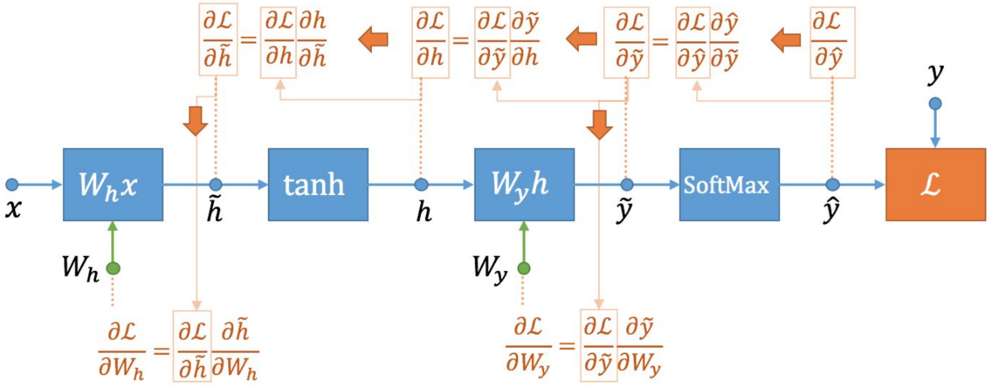

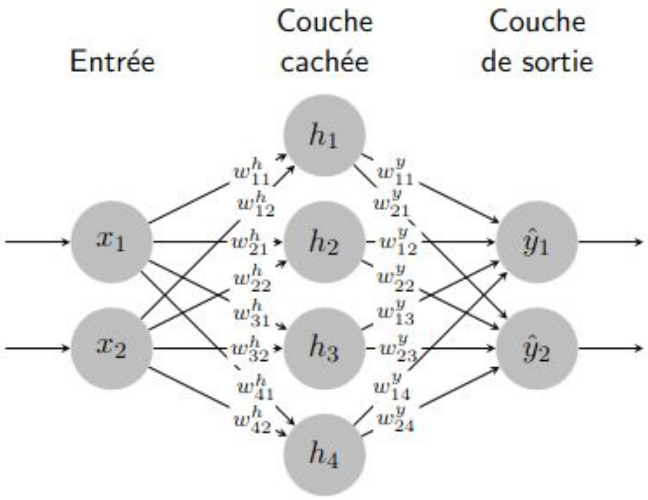

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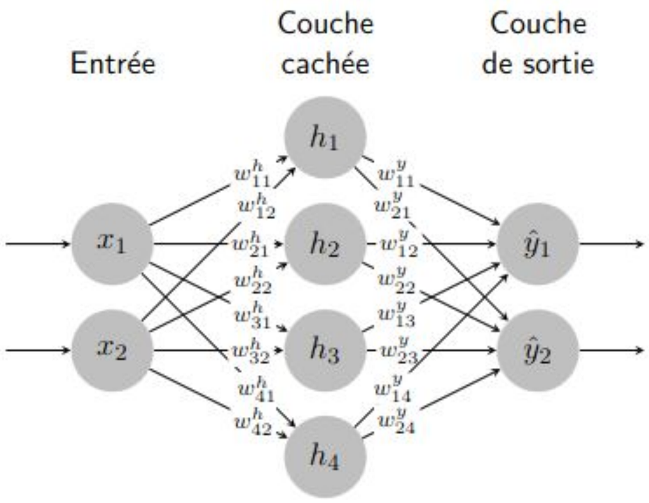
TP3: Manual Backprop



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- Lecture 3 practical correction on Moodle
  - Implement this by hand with basic torch!
  - Careful with batch dimension!

TP3 recap

```python
def init_params(nx, nh, ny):
    """
    nx, nh, ny: integers
    out params: dictionnary
    """
    params = {}

    params["Wh"] = torch.randn((nh, nx))*0.3
    params["Wy"] = torch.randn((ny, nh))*0.3
    params["bh"] = torch.zeros((nh,1))
    params["by"] = torch.zeros((ny,1))

    return params
```

TP3 recap

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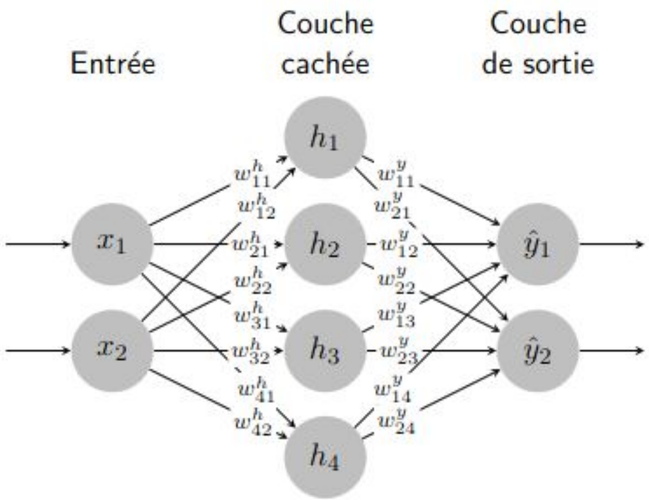
```python
def forward(params, X):
    """
    params: dictionnary
    X: (n_batch, dimension)
    """
    bsize = X.size(0)
    nh = params['Wh'].size(0)
    ny = params['Wy'].size(0)
    outputs = {}

    outputs["X"] = X
    outputs["htilde"] = torch.mm(X, params["Wh"].T) + params["bh"].T
    outputs["h"] = torch.tanh(outputs["htilde"])
    outputs["ytilde"] = torch.mm(outputs["h"], params["Wy"].T) + params["by"].T
    outputs["yhat"] = torch.exp(outputs["ytilde"])
    outputs["yhat"] = outputs["yhat"] / outputs["yhat"].sum(dim=-1, keepdim=True)


    return outputs['yhat'], outputs
```

TP3 recap

```python
def loss_accuracy(Yhat, Y):


    L = - torch.mean((Y * torch.log(Yhat)).sum(dim=1)) # mean for the batch

    _, indYhat = torch.max(Yhat, 1)
    _, indY = torch.max(Y, 1)

    acc = torch.sum(indY == indYhat) * 100. / indY.size(0);


    return L, acc
```

TP3: Manual Backprop



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- Lecture 3 practical correction on Moodle
  - Implement this by hand with basic torch!
  - Careful with batch dimension!

TP3 recap

```python
def backward(params, outputs, Y):
    bsize = Y.shape[0]
    grads = {}

    Y_tilde_grad = outputs["yhat"] - Y
    h_tilde_grad = torch.mm(Y_tilde_grad, params['Wy']
                            ) * (1 - torch.pow(outputs['h'], 2))

    grads["Wy"] = torch.mm(Y_tilde_grad.T, outputs["h"])
    grads["Wh"] = torch.mm(h_tilde_grad.T, outputs['X'])
    grads["by"] = Y_tilde_grad.sum(dim=0,keepdim=True).T
    grads["bh"] = h_tilde_grad.sum(0, keepdim=True).T

    grads['Wy'] /= bsize
    grads['by'] /= bsize
    grads['Wh'] /= bsize
    grads['bh'] /= bsize

    return grads
```

TP3 recap

```python
def sgd(params, grads, eta):

    params['Wy'] -= eta * grads['Wy']
    params['Wh'] -= eta * grads['Wh']
    params['by'] -= eta * grads['by']
    params['bh'] -= eta * grads['bh']

    return params
```

TP3 recap

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```python
for j in range(N // Nbatch):

    indsBatch = range(j * Nbatch, (j+1) * Nbatch)
    X = Xtrain[indsBatch, :]
    Y = Ytrain[indsBatch, :]

    Y_hat, outputs = forward(params, X)
    loss, accuracy = loss_accuracy(Y_hat, Y)
    grads = backward(params, outputs, Y)
    params = sgd(params, grads, eta)
```

Why do it manually?

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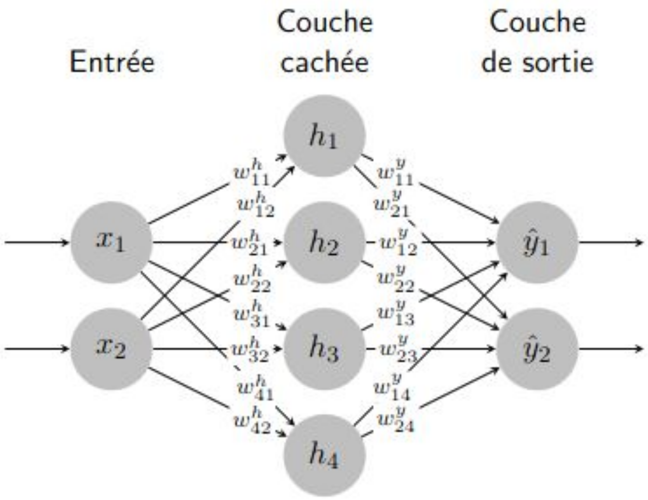
- Important to really know what is under the hood
  - Invisible in everyday pytorch/tf/jax use
  - Understand errors
  - Necessary to implement custom layers
  - Helps understand why it works



$$\begin{cases} \tilde{\mathbf{h}} = \mathbf{x}{\mathbf{W}^h}^\top + \mathbf{b}^h \\ \mathbf{h} = \tanh(\tilde{\mathbf{h}}) \\ \tilde{\mathbf{y}} = \mathbf{h}{\mathbf{W}^y}^\top + \mathbf{b}^y \\ \hat{\mathbf{y}} = \mathrm{SoftMax}(\tilde{\mathbf{y}}) \end{cases}$$

Today: 3 Practicals!

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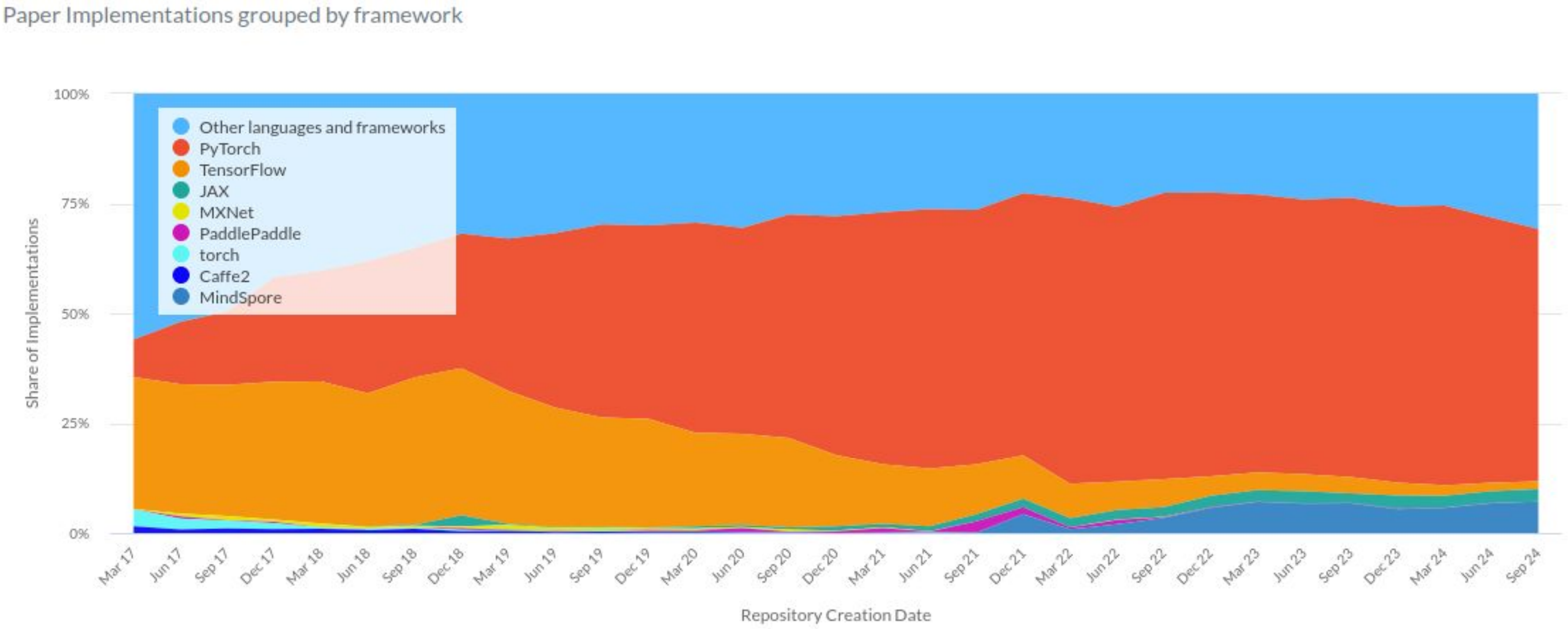
- TP4a: Backprop, with actual tools
  - Manual -> fully automated
  - Understand how everything fits together

- TP4b: Computer Vision practical
  - Quick showcase of standard workflows
  - Practice standard loop from 4a

- TP4c: Natural Language Processing practical
  - Quick showcase of standard workflows
  - Practice standard loop from 4a

Pytorch vs other frameworks



TP4a: Autograd backward

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```python
def backward(params, outputs, Y):
    bsize = Y.shape[0]
    grads = {}

    Y_tilde_grad = outputs["yhat"] - Y
    h_tilde_grad = torch.mm(Y_tilde_grad, params['Wy']
                            ) * (1 - torch.pow(outputs['h'], 2))

    grads["Wy"] = torch.mm(Y_tilde_grad.T, outputs["h"])
    grads["Wh"] = torch.mm(h_tilde_grad.T, outputs['X'])
    grads["by"] = Y_tilde_grad.sum(dim=0,keepdim=True).T
    grads["bh"] = h_tilde_grad.sum(0, keepdim=True).T

    grads['Wy'] /= bsize
    grads['by'] /= bsize
    grads['Wh'] /= bsize
    grads['bh'] /= bsize

    return grads
```

- Torch.tensor object
  - Np.array like
  - Tracked on a computational graph
  - .grad variable to track gradients
  - .backward to backpropagate gradients through the graph
  - Activate .autograd!

TP4a: Autograd backward

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def backward(params, outputs, Y):
    bsize = Y.shape[0]
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    Y_tilde_grad = outputs["yhat"] - Y
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                            ) * (1 - torch.pow(outputs['h'], 2))

    grads["Wy"] = torch.mm(Y_tilde_grad.T, outputs["h"])
    grads["Wh"] = torch.mm(h_tilde_grad.T, outputs['X'])
    grads["by"] = Y_tilde_grad.sum(dim=0,keepdim=True).T
    grads["bh"] = h_tilde_grad.sum(0, keepdim=True).T

    grads['Wy'] /= bsize
    grads['by'] /= bsize
    grads['Wh'] /= bsize
    grads['bh'] /= bsize

    return grads
```

```python
params['Wh'] = torch.randn(nh, nx) * 0.3
params['Wh'].requires_grad = True
params['bh'] = torch.zeros(nh, 1, requires_grad=True)
params['Wy'] = torch.randn(ny, nh) * 0.3
params['Wy'].requires_grad = True
params['by'] = torch.zeros(ny, 1, requires_grad=True)
```

```python
with torch.no_grad():
    params['Wy'] -= eta * params['Wy'].grad
    params['Wh'] -= eta * params['Wh'].grad
    params['by'] -= eta * params['by'].grad
    params['bh'] -= eta * params['bh'].grad

    params['Wy'].grad.zero_()
    params['Wh'].grad.zero_()
    params['by'].grad.zero_()
    params['bh'].grad.zero_()
```

```python
yhat,outputs = forward(params,X)
L,acc = loss_accuracy(yhat,Y)
L.backward()
params = sgd(params,eta)
```

TP4a: torch.nn instantiation

```
params = {}

params["Wh"] = torch.randn((nh, nx))*0.3
params["Wy"] = torch.randn((ny, nh))*0.3
params["bh"] = torch.zeros((nh,1))
params["by"] = torch.zeros((ny,1))
```

```
def forward(params, X):
    """
    params: dictionnary
    X: (n_batch, dimension)
    """
    bsize = X.size(0)
    nh = params['Wh'].size(0)
    ny = params['Wy'].size(0)
    outputs = {}

    outputs["X"] = X
    outputs["htilde"] = torch.mm(X, params["Wh"].T) + params["bh"].T
    outputs["h"] = torch.tanh(outputs["htilde"])
    outputs["ytilde"] = torch.mm(outputs["h"], params["Wy"].T) + params["by"].T
    outputs["yhat"] = torch.exp(outputs["ytilde"])
    outputs["yhat"] = outputs["yhat"] / outputs["yhat"].sum(dim=-1, keepdim=True)


    return outputs['yhat'], outputs
```

- Torch.nn.Module objects
  - .__init__ creates weights and initializes them!
  - .forward implements forward operations
    - Default object call
    - model(x)
  - Some global control over model weights

TP4a: torch.nn instantiation

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```python
params = {}

params["Wh"] = torch.randn((nh, nx))*0.3
params["Wy"] = torch.randn((ny, nh))*0.3
params["bh"] = torch.zeros((nh,1))
params["by"] = torch.zeros((ny,1))
```

```python
def forward(params, X):
    """
    params: dictionnary
    X: (n_batch, dimension)
    """
    bsize = X.size(0)
    nh = params['Wh'].size(0)
    ny = params['Wy'].size(0)
    outputs = {}

    outputs["X"] = X
    outputs["htilde"] = torch.mm(X, params["Wh"].T) + params["bh"].T
    outputs["h"] = torch.tanh(outputs["htilde"])
    outputs["ytilde"] = torch.mm(outputs["h"], params["Wy"].T) + params["by"].T
    outputs["yhat"] = torch.exp(outputs["ytilde"])
    outputs["yhat"] = outputs["yhat"] / outputs["yhat"].sum(dim=-1, keepdim=True)


    return outputs['yhat'], outputs
```

```python
model = torch.nn.Sequential(
        torch.nn.Linear(nx, nh),
        torch.nn.Tanh(),
        torch.nn.Linear(nh, ny)
)
loss = torch.nn.CrossEntropyLoss()
```

```python
_, indY = torch.max(Y, 1)
L = loss(Yhat, indY)

_, indYhat = torch.max(Yhat, 1)

acc = torch.sum(indY == indYhat.data) * 100 // indY.size(0);
```

```python
with torch.no_grad():
    for param in model.parameters():
        param -= eta * param.grad
    model.zero_grad()
```

```python
yhat = model(X)
L,acc = loss_accuracy(loss,yhat,Y)
L.backward()
model = sgd(model,eta)
```

TP4a: torch.optim optimization

```
def sgd(params, grads, eta):

    params['Wy'] -= eta * grads['Wy']
    params['Wh'] -= eta * grads['Wh']
    params['by'] -= eta * grads['by']
    params['bh'] -= eta * grads['bh']

    return params
```

- Torch.optim objects
  - Tracks learning rates
  - Tracks weights to optimize
  - Performs SGD steps
  - Even cleans up!

TP4a: torch.optim optimization

```
def sgd(params, grads, eta):

    params['Wy'] -= eta * grads['Wy']
    params['Wh'] -= eta * grads['Wh']
    params['by'] -= eta * grads['by']
    params['bh'] -= eta * grads['bh']

    return params
```

```
optim = torch.optim.SGD(model.parameters(), lr=eta)
```

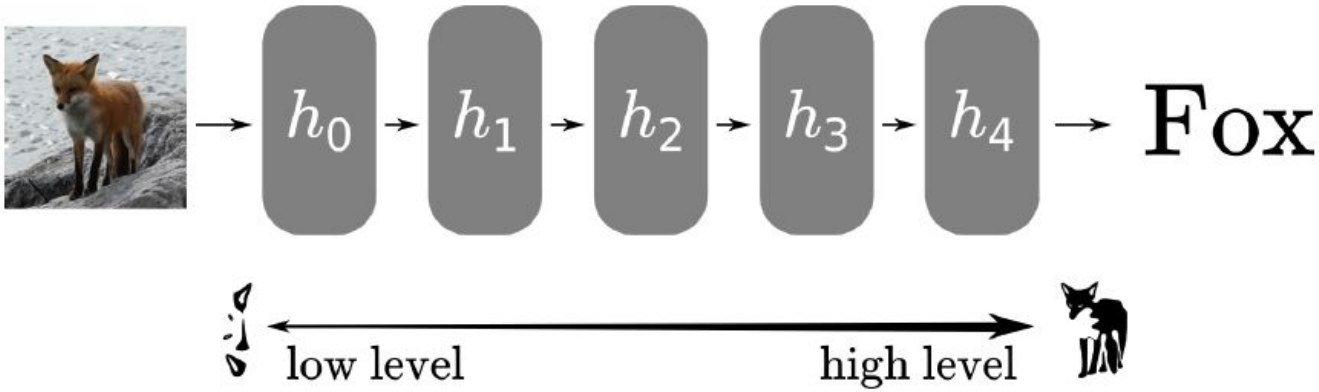
```
yhat = model(X)
L,acc = loss_accuracy(loss,yhat,Y)
optim.zero_grad()
L.backward()
optim.step()
```

Takeaway

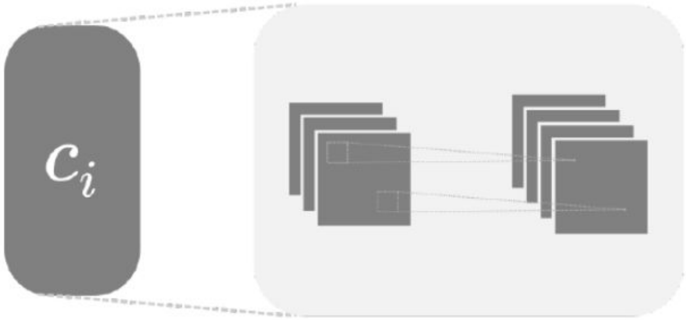
- Training a network requires
  - Weights
  - A forward function
  - A backward function
  - Gradient steps

- Nice pytorch tools
  - Torch.tensor and torch.autograd
  - Torch.nn
  - Torch.optim

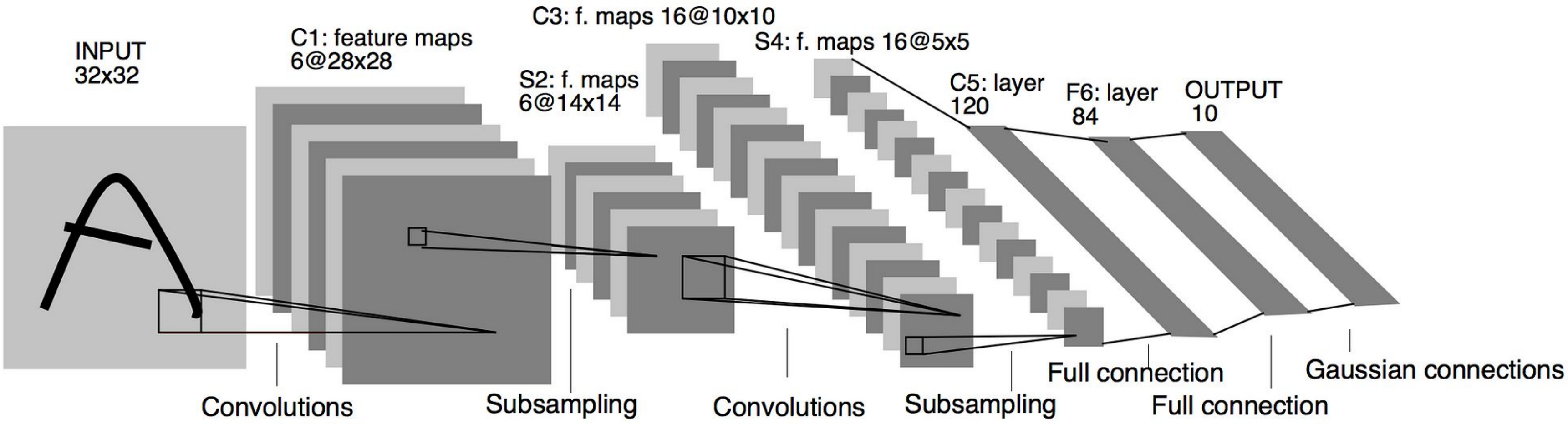
ConvNets for computer vision



- Convolutional layers
  - Local correlations
  - Well suited to images
  - Used sometimes with Transformers now



ConvNets for computer vision

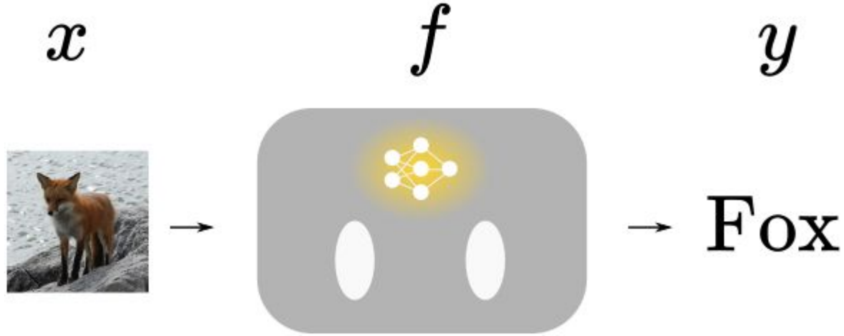


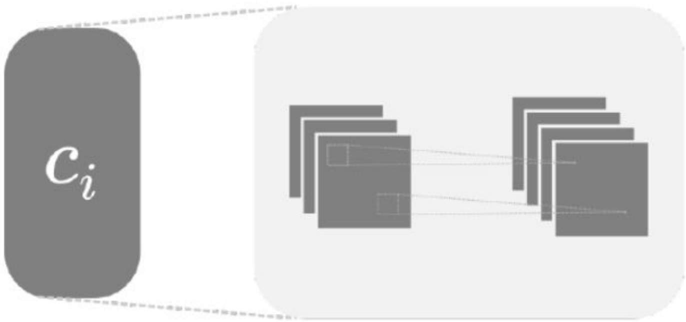
- Classical architecture of computer vision
  - Convolutional layers for feature extraction
  - Dense/linear layers to make decisions from features
  - E.g. LeNet5 (Before 2000!)

TP4b: Computer vision

- A few milestones
  - Load image data
  - Load a classic model
  - Train it!
  - (Finetune a strong model)

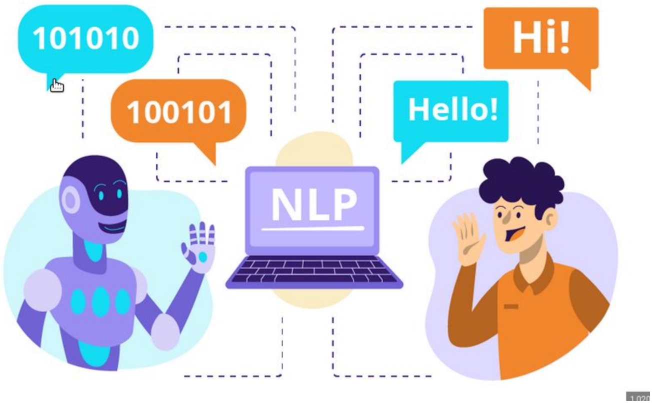
- Apply knowledge from TP4a!

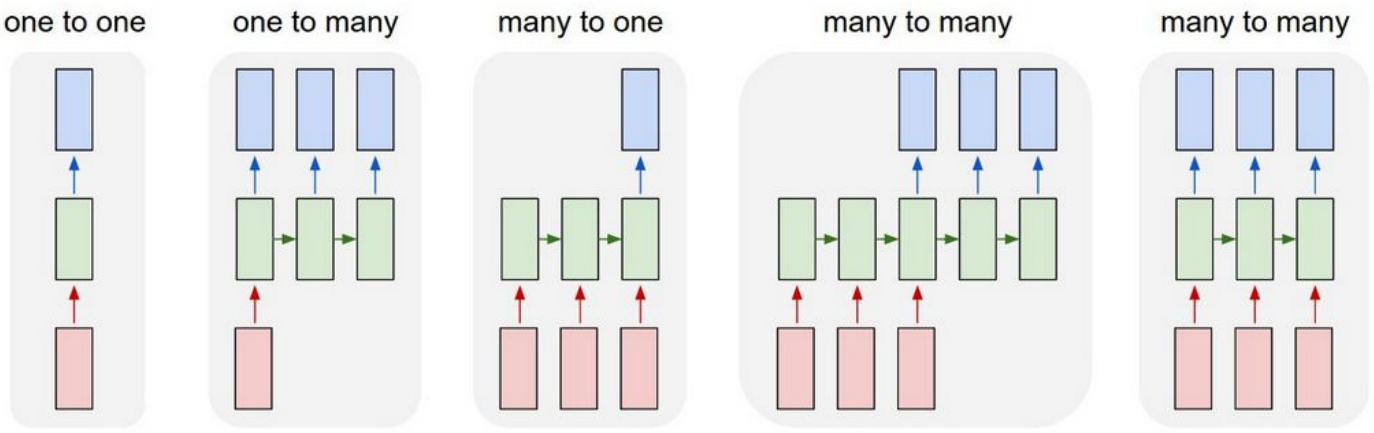




RNNs for Language

- Recurrent networks
  - Temporal correlations
  - How to take the past into account?
  - Recent resurgence (SSMs, ...)





RNNs for Language

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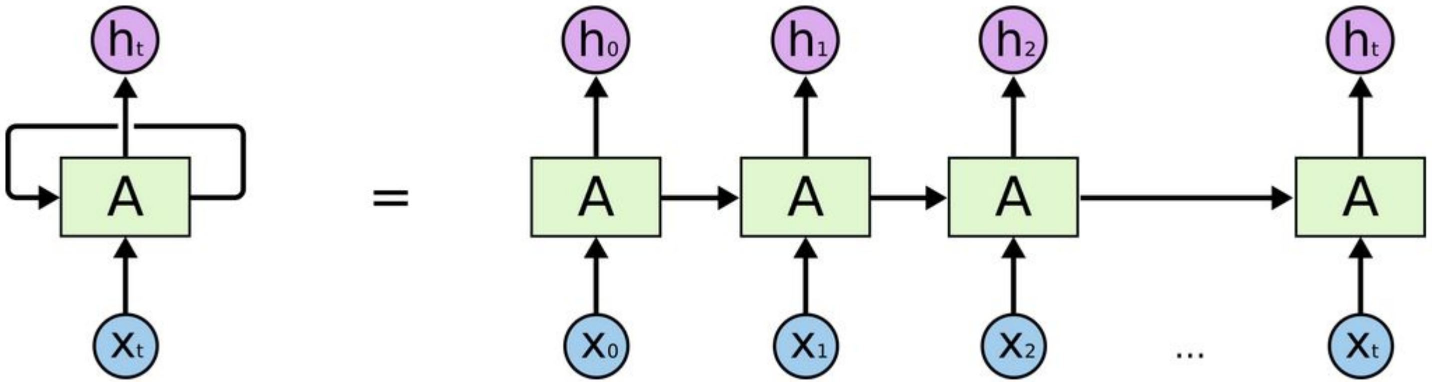
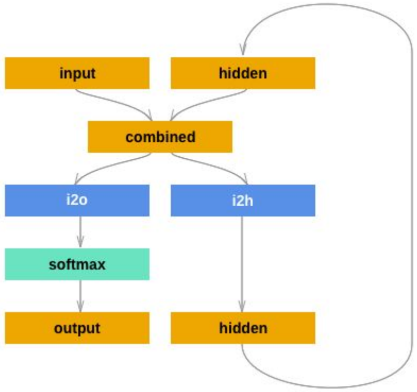


- Basic RNN model
  - Input + hidden state
  - Hidden state remains from input to input



TP4c: NLP

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- Making a language processor
  - Tokenize words
  - Create network
  - Train network
  - Apply network

- Apply knowledge from TP4a!