Deep Learning (BEV033DLE)
Lecture 14 Recurrent Neural Networks

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- Recurrent models
- Error back propagation through time
- Gated recurrent units, GRU and LSTM networks
- Recurrent back propagation

Recurrent networks

Recurrent models in a nutshell

- input sequence $x = (x_1, \dots, x_t, \dots, x_T)$, $x_t \in \mathbb{R}^n$. Similarly: output sequence y with elements y_t and sequence h of (hidden) states with elements $h_t \in \mathbb{R}^d$. Often all three sequences have the same length.
- recurrent (dynamic) system with outputs

$$h_t = f(x_t, h_{t-1}, w)$$
$$y_t = g(h_t, v)$$

  where w and v are parameters. The model defines sequence mappings $h = F_w(x)$ and $y = G_v(h)$.
- loss function $\ell(y, y')$; often locally additive $\sum_t \ell(y_t, y'_t)$

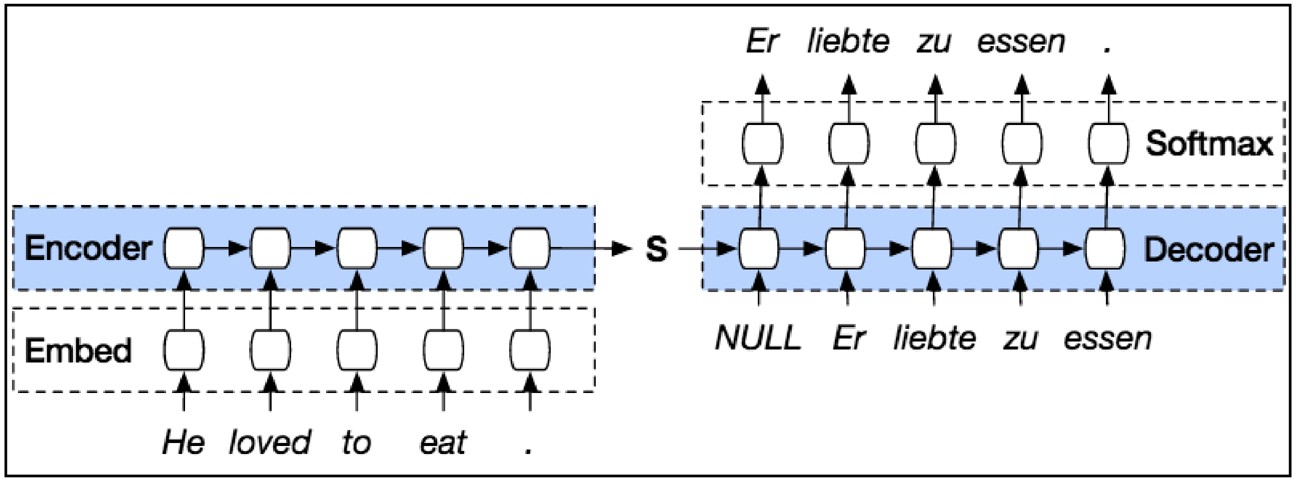
Training goal: given training data $\mathcal{T}^m = \big\{(x^j, y^j) \mid j = 1, \dots, m\big\}$, learn the model parameters w, v by solving

$$\frac{1}{m} \sum_{j=1}^{m} \ell\big(y^j, (G_v \circ F_w)(x)\big) \to \min_{w,v}$$

Recurrent networks

Incarnations of recurrent models and related tasks

- Deep neural network for classification with additional feedback connections. x - input, constant not depending on time. y - output of the network, network head, e.g. $\log \mathrm{softmax}$, h -states of all hidden layers. The loss function depends only on the last output y_T.
- "infinite state automata": the output space is sufficient for keeping the history, thus h and y can be identified, i.e. $y_t = f(x_t, y_{t-1}, w)$.
  Example: landcover type monitoring for a geo-location: x - sequence of spectral satellite measurements, y - sequence of states (e.g. coniferous forest, broadleaf forest, clearcut, bark beetle degradation etc.)
- general sequence segmentation: hidden states h_t are needed for keeping track of longer past and are latent.
  Examples: speech recognition, x - audio signal, y -sequence of words. NLP translation:



Learning RNNs: simple case

Learning RNNs is particularly simple in the case that

- h and y can be identified, i.e. $y_t = f(x_t, y_{t-1}, w)$ and
- the loss is locally additive $\sum_t \ell(y_t, y'_t)$

We can split the sequences (x^j, y^j) from training data into triplets $(y^j_{t-1}, x^j_t, y^j_t)$ and train f from

$$\frac{1}{m}\sum_{j=1}^{m}\sum_{t}\ell\big(y^j_t, f_w(x^j_t, y^j_{t-1})\big) \to \min_w$$

Neither forward nor backward propagation through the sequence are needed.

If the hidden states h_t do not coincide with outputs y_t and are latent, then learning becomes considerably more complicated.

Learning RNNs: backpropagation through time

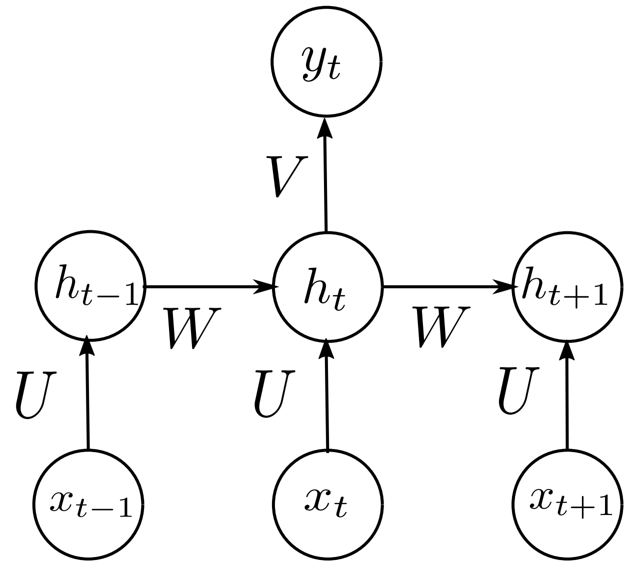
Assumptions:

$$h_t = f(x_t, h_{t-1}, w)$$
$$y_t = g(h_t, v)$$

The mappings f and g are implemented by neural networks and are differentiable w.r.t. their inputs and parameters. The loss function $\ell(y, y')$ is differentiable.

Example 1. Both mappings f and g are implemented by one layer networks

$$a_t = W h_t + U x_t + b \qquad h_t = \tanh(a_t)$$
$$o_t = V h_t + c \qquad y_t = \mathrm{softmax}(o_t)$$



Learning RNNs: backpropagation through time

Computing the gradients: Unroll the network in time and apply backpropagation

Let us consider the loss for a single example (x, y^*) from the training data.

Computing the gradient w.r.t. v is easy (see Slide 4.). Let us consider the gradient w.r.t. w

$$\partial_w L(y^*, y) = \sum_{t=1}^{T} \partial_w \ell(y_t^*, y_t) = \sum_{t=1}^{T} \partial_{y_t} \ell(y_t^*, y_t)\, \partial_{h_t} g(h_t, v)\, \partial_w h_t$$

The first two terms are simple. For the last one we have the recurrent expression

$$\partial_w h_t = \partial_w f(x_t, h_{t-1}, w) + \partial_{h_{t-1}} f(x_t, h_{t-1}, w)\, \partial_w h_{t-1}$$

This gives

$$\partial_w h_t = \partial_w f(x_t, h_{t-1}, w) + \sum_{i=1}^{t-1} \Big[\prod_{j=i+1}^{t} \partial_{h_{j-1}} f(x_j, h_{i-1}, w) \Big]\, \partial_w f(x_i, h_{i-1}, w)$$

Learning RNNs: backpropagation through time

Problems:

- backpropagation through time is computationally expensive
- Exploding/vanishing gradients: consider for simplicity the linear recurrence $h_t = W h_{t-1}$. For τ steps we get $h_\tau = W^\tau h_0$. Suppose that we can write $W = U^{-1} \Lambda U$, where Λ is diagonal. We get
$$h_\tau = U^{-1} \Lambda^\tau U h_0.$$
Eigenvalues with magnitude less than one will decay and eigenvalues with magnitude greater than one will explode.
- We can not apply batch normalisation as simple remedy.
- We want the following model ability: events long in the past can trigger changes in conjunction with current measurements.
- skip connections?, designate special nodes in h_t for keeping record of events long in the past?

RNNs with gated recurrent units

LSTM (Hochreiter, Schmidhuber, 1997), GRU (Cho et al., 2014), ...

Gated recurrent unit (simplified):

A cell consisting of a recurrent unit h_t and a gate unit $u_t \in [0, 1]$

$$h_t = u_{t-1} h_{t-1} + [1 - u_{t-1}] f(x_t, h_{t-1}, w)$$
$$u_t = \mathrm{S}(x_t, h_t, v)$$

The gate unit u_t has sigmoid nonlinearity and "decides" whether to copy h_t from h_{t-1} or to apply the recurrence with f.

RNNs with gated recurrent units

Gated recurrent unit (general):

- h is a state vector
- u is a vector of “update” gates
- r is a vector of “reset” gates

The update equations are

$$h_t = u_{t-1} \odot h_{t-1} + [1 - u_{t-1}] \odot \mathrm{S}\Big(U x_{t-1} + W r_{t-1} \odot h_{t-1}\Big)$$

where $\odot$ denotes the element-wise product of vectors. The gate unit outputs are given by

$$u_t = \mathrm{S}\big(U^u x_t + W^u h_t\big)$$
$$r_t = \mathrm{S}\big(U^r x_t + W^r h_t\big)$$

LSTM cells are somewhat more complicated – they have separate “forget” and “update” gates.

Recurrent backpropagation

Recurrent backpropagation: (Almeida, 1987), (Pineda, 1987) An interesting learning alternative can be applied to deep neural networks for classification with additional feedback connections.

Denote: network input x, network output y_t and h_t denoting outputs of all hidden layers.

$$h_t = f(x, h_{t-1}, w) \quad \text{and} \quad y_t = g(h_t, v)$$

Assumption: the network configuration h_t converges to a fixpoint h^* if we clamp its input to x.

Then we have (implicit function theorem)

$$\frac{\partial h^*}{\partial w} = \big[I - J_F(h^*)\big]^{-1} \frac{\partial F}{\partial w},$$

where $J_F(h^*) = \frac{\partial F(x,w,h^*)}{\partial h}$ is the Jacobian of F w.r.t. h.

Now, let us consider the gradient of the loss w.r.t. w.

$$\partial_w L = \partial_y L \, \partial_{h^*} y \, \big[I - J_F(h^*)\big]^{-1} \partial_w f(x, w, h^*)$$

Recurrent backpropagation

Now, introduce the (column) vector z

$$z = \big[I - J_F(h^*)\big]^{-1} \big(\partial_y L\, \partial_{h^*} y\big)^T$$

Multiplying both sides by $\big[I - J_F(h^*)\big]$, we get

$$z = J_F(h^*)^T z + \big(\partial_y L\, \partial_{h^*} y\big)^T.$$

This is a fixpoint equation for z and can be solved by fixpoint iteration. The resulting algorithm for computing the derivative $\frac{\partial L}{\partial w}$ is:

- start from z_0; iterate
$$z_i = J_F(h^*)^T z_{i-1} + \big(\partial_y L\, \partial_{h^*} y\big)^T$$
until convergence.
- Return
$$\frac{\partial L}{\partial w} = z^T \frac{\partial F(x, w, h^*)}{\partial h}$$

This supersedes BPT but requires invertible $\big[I - J_F(h^*)\big]$.