Введение в RNN

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Что такое RNN

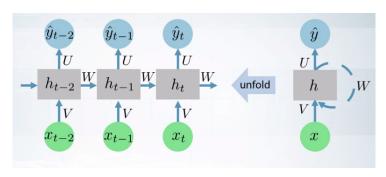


Figure: Coursera, Intro to Deep Learning by HSE

х – входные данные

ŷ – предсказание

h – hidden state

$$h_t = f_h(Vx_t + Wh_{t-1} + b_h)$$

$$\hat{y}_t = f_y(Uh_t + b_y)$$

Преимущества перед обычными НС

• Можно работать с последовательностями входных данных (например, текст или видео)

Обучение RNN

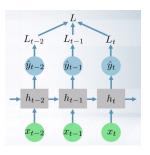


Figure: Coursera, Intro to Deep Learning by HSE

Пусть y_t – настоящее значение, \hat{y}_t – предсказание, а $L_t(y_t, \hat{y}_t)$ – некторая функция потерь, то:

$$loss = L = \sum_i L_i(y_i, \hat{y}_i)$$

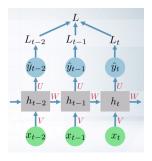


Figure: Coursera, Intro to Deep Learning by HSE

Forward pass: h_t, \hat{y}_t, L_t, L

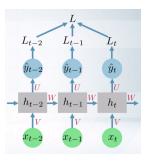
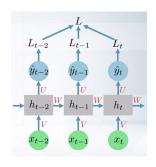


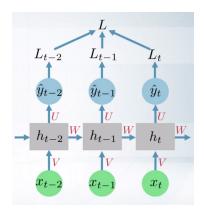
Figure: Coursera, Intro to Deep Learning by HSE

Backward pass: $\frac{\partial L}{\partial U}, \frac{\partial L}{\partial V}, \frac{\partial L}{\partial W}, \frac{\partial L}{\partial b_x}, \frac{\partial L}{\partial b_h}$



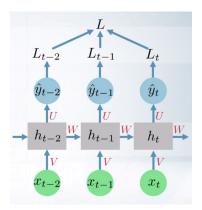
$$\begin{split} \frac{\partial L}{\partial U} &= \sum_{i} \frac{\partial L_{i}}{\partial U} \\ \frac{\partial L_{t}}{\partial U} &= \frac{\partial L_{t}}{\partial \hat{y}_{t}} \frac{\partial \hat{y}_{t}}{\partial U} \end{split}$$

 $\hat{y}_t = g(Uh_t + b_y)$



$$\frac{\partial L}{\partial W} = \sum_{i} \frac{\partial L_{i}}{\partial W}$$

$$h_t = f_h(Vx_t + Wh_{t-1} + b_h)$$



$$\begin{split} \frac{\partial L_t}{\partial W} &= \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \left(\frac{\partial h_t}{\partial W} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W} + \cdots \right) = \\ &= \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \sum_{k=0}^t \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_{k+1}}{\partial h_k} \frac{\partial h_k}{W} \end{split}$$

Минусы:

- долго работает
- проблема с затуханием градиента

Vanishing/Exploding Gradients

Может возникнуть из-за многоразового повторения функций активации (например, tanh, сигмоида, чьи значения по модулю меньше 1)

Vanishing/Exploding Gradients

Способы решения:

- LSTM
- faster hardware
- ReLU (такая функция активации, что: $f(x) = max\{0; x\}$)
- Truncated BPTT

Примеры

For $\bigoplus_{n=1,\dots,m}$ where $\mathcal{L}_{m_{\bullet}}=0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X, U is a closed immersion of S, then $U\to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \operatorname{Spec}(R) = U \times_X U \times_X U$$

and the comparisoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in Sh(G) such that $Spec(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

 Пример статьи, созданной с помощью RNN http://karpathy.github.io/2015/05/21/rnn-effectiveness/

ФКН НИУ ВШЭ

Примеры

```
spin lock irqsave(&event srcu->spu list lock, flags);
while (npids && !sig setup) {
    struct smp instance *smp processor = list[i];
    if (pending identify sig)
        complete(&(pids.event));
    smp mb();
    if (pid == 0) {
        pr warn("Error: enabling event %x\n", pid);
        pid state += s->pid;
        while (pid) {
            if (smp processor id() == -1) {
                event for each pid(pid, event, upid)
```

• Пример кода, созданного с помощью RNN

Примеры

• Синтетический Обама http://grail.cs.washington.edu/projects/AudioToObama/ (Видео)



Библиография

- $\bullet \ http://karpathy.github.io/2015/05/21/rnn-effectiveness/$
- $\bullet \ \, https://www.coursera.org/learn/intro-to-deep-learning/lecture/zGHtr/simple-rnn-and-backpropagation \\$
- http://colah.github.io/posts/2015-08-Backprop/