## **Recurrent Neural Networks - LSTM**



• Input:  $\vec{x} = (x_1, \dots, x_M)$ 

• Hidden:  
$$\vec{h} = (h_1, \dots, h_H)$$

• Output:  
$$\vec{y} = (y_1, \dots, y_N)$$

# **RNN** example



Activation function:

$$\sigma(\xi) = \begin{cases} 1 & \xi \ge 0 \\ 0 & \xi < 0 \end{cases}$$

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# **RNN example**



- *M* inputs:  $\vec{x} = (x_1, \dots, x_M)$
- *H* hidden neurons:  $\vec{h} = (h_1, \dots, h_H)$
- N output neurons:  $\vec{y} = (y_1, \dots, y_N)$
- Weights:
  - $U_{kk'}$  from input  $x_{k'}$  to hidden  $h_k$
  - $W_{kk'}$  from hidden  $h_{k'}$  to hidden  $h_k$
  - $V_{kk'}$  from hidden  $h_{k'}$  to output  $y_k$



# **RNN** – formally

• Input sequence: 
$$\mathbf{x} = \vec{x}_1, \dots, \vec{x}_T$$

 $\vec{x}_t = (x_{t1}, \ldots, x_{tM})$ 

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$$\mathbf{h} = \vec{h}_0, \vec{h}_1, \dots, \vec{h}_T$$

$$\vec{h}_t = (h_{t1}, \ldots, h_{tH})$$

We have  $\vec{h}_0 = (0, \dots, 0)$  and

$$\vec{h}_{tk} = \sigma \left( \sum_{k'=1}^{M} U_{kk'} x_{tk'} + \sum_{k'=1}^{H} W_{kk'} h_{(t-1)k'} \right)$$

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$$ec{\mathbf{y}_t} = (\mathbf{y}_{t1}, \dots, \mathbf{y}_{tN})$$
  
where  $\mathbf{y}_{tk} = \sigma \left( \sum_{k'=1}^{H} \mathbf{V}_{kk'} h_{tk'} \right)$ .

# **RNN** – in matrix form

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and

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• Output sequence:  $\mathbf{y} = \vec{y}_1, \dots, \vec{y}_T$  where

 $\mathbf{y}_t = \sigma(\mathbf{V}\mathbf{h}_t)$ 

- $\vec{h}_t$  is the memory of the network, captures what happened in all previous steps (with decaying quality).
- RNN shares weights U, V, W along the sequence. Note the similarity to convolutional networks where the weights were shared spatially over images, here they are shared temporally over sequences.
- RNN can deal with sequences of variable length. Compare with MLP which accepts only fixed-dimension vectors on input.

#### **Training set**

$$\mathcal{T} = \left\{ (\mathbf{x}_1, \mathbf{d}_1), \dots, (\mathbf{x}_p, \mathbf{d}_p) \right\}$$

here

• each  $\mathbf{x}_{\ell} = \vec{x}_{\ell 1}, \dots, \vec{x}_{\ell T_{\ell}}$  is an input sequence,

• each  $\mathbf{d}_{\ell} = \vec{d}_{\ell 1}, \dots, \vec{d}_{\ell T_{\ell}}$  is an expected output sequence. Here each  $\vec{x}_{\ell t} = (x_{\ell t 1}, \dots, x_{\ell t M})$  is an input vector and each  $\vec{d}_{\ell t} = (d_{\ell t 1}, \dots, d_{\ell t N})$  is an expected output vector. In what follows I will consider a training set with a **single** element  $(\mathbf{x}, \mathbf{d})$ . I.e. drop the index  $\ell$  and have

• 
$$\mathbf{x} = \vec{x}_1, \dots, \vec{x}_T$$
 where  $\vec{x}_t = (x_{t1}, \dots, x_{tM})$   
•  $\mathbf{d} = \vec{d}_1, \dots, \vec{d}_T$  where  $\vec{d}_t = (d_{t1}, \dots, d_{tN})$ 

The squared error of  $(\mathbf{x}, \mathbf{d})$  is defined by

$$E_{(\mathbf{x},\mathbf{d})} = \sum_{t=1}^{T} \sum_{k=1}^{N} \frac{1}{2} (y_{tk} - d_{tk})^2$$

Recall that we have a sequence of network outputs  $\mathbf{y} = \vec{y}_1, \dots, \vec{y}_T$  and thus  $y_{tk}$  is the *k*-th component of  $\vec{y}_t$ 

Consider a single training example (**x**, **d**).

The algorithm computes a sequence of weight matrices as follows:

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- In the step ℓ + 1 (here ℓ = 0, 1, 2, ...) compute "new" weights U<sup>(ℓ+1)</sup>, V<sup>(ℓ+1)</sup>, W<sup>(ℓ+1)</sup> from the "old" weights U<sup>(ℓ)</sup>, V<sup>(ℓ)</sup>, W<sup>(ℓ)</sup> as follows:

$$U_{kk'}^{(\ell+1)} = U_{kk'}^{(\ell)} - \varepsilon(\ell) \cdot \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta U_{kk'}}$$
$$V_{kk'}^{(\ell+1)} = V_{kk'}^{(\ell)} - \varepsilon(\ell) \cdot \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta V_{kk'}}$$
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The above is THE learning algorithm that modifies weights!

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$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta U_{kk'}} = \sum_{t=1}^{T} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{tk}} \cdot \sigma' \cdot x_{tk'} \qquad \qquad k' = 1, \dots, M$$
$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta V_{kk'}} = \sum_{t=1}^{T} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta y_{tk}} \cdot \sigma' \cdot h_{tk'} \qquad \qquad k' = 1, \dots, H$$
$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta W_{kk'}} = \sum_{t=1}^{T} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{tk}} \cdot \sigma' \cdot h_{(t-1)k'} \qquad \qquad k' = 1, \dots, H$$

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Backpropagation:

$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta y_{tk}} = y_{tk} - d_{tk} \quad (\text{assuming squared error})$$

$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{tk}} = \sum_{k'=1}^{N} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta y_{tk'}} \cdot \sigma' \cdot V_{k'k} + \sum_{k'=1}^{H} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{(t+1)k'}} \cdot \sigma' \cdot W_{k'k}$$

# Long-term dependencies

$$\frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{tk}} = \sum_{k'=1}^{N} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta y_{tk'}} \cdot \sigma' \cdot V_{k'k} + \sum_{k'=1}^{H} \frac{\delta E_{(\mathbf{x},\mathbf{d})}}{\delta h_{(t+1)k'}} \cdot \sigma' \cdot W_{k'k}$$

► Unless  $\sum_{k'=1}^{H} \sigma' \cdot W_{k'k} \approx 1$ , the gradient either vanishes, or explodes.

- For a large T (long-term dependency), the gradient "deeper" in the past tends to be too small (large).
- A solution: LSTM

LSTM is currently a bit obsolete. The main idea is to decompose W into several matrices, each responsible for a different task. One is concerned about memory, one is concerned about the output at each step, etc.

### **LSTM**

$$\vec{h}_{t} = \vec{o}_{t} \circ \sigma_{h}(\vec{C}_{t}) \qquad \text{output}$$
  
$$\vec{C}_{t} = \vec{f}_{t} \circ \vec{C}_{t-1} + \vec{i}_{t} \circ \tilde{C}_{t} \qquad \text{memory}$$
  
$$\tilde{C}_{t} = \sigma_{h}(W_{C} \cdot \vec{h}_{t-1} + U_{C} \cdot \vec{x}_{t}) \qquad \text{new memory contents}$$

$$\vec{o}_t = \sigma_g(W_o \cdot \vec{h}_{t-1} + U_o \cdot \vec{x}_t) \qquad \text{output gate}$$
  
$$\vec{f}_t = \sigma_g(W_f \cdot \vec{h}_{t-1} + U_f \cdot \vec{x}_t) \qquad \text{forget gate}$$
  
$$\vec{i}_t = \sigma_g(W_i \cdot \vec{h}_{t-1} + U_i \cdot \vec{x}_t) \qquad \text{input gate}$$

- is the component-wise product of vectors
- is the matrix-vector product
- σ<sub>h</sub> hyperbolic tangents (applied component-wise)
- σ<sub>g</sub> logistic sigmoid (aplied component-wise)

## **RNN vs LSTM**





$$\vec{h}_{t} = \vec{o}_{t} \circ \sigma_{h}(\vec{C}_{t})$$

$$\Rightarrow \vec{C}_{t} = \vec{f}_{t} \circ \vec{C}_{t-1} + \vec{i}_{t} \circ \tilde{C}_{t}$$

$$\tilde{C}_{t} = \sigma_{h}(W_{C} \cdot \vec{h}_{t-1} + U_{C} \cdot \vec{x}_{t})$$

$$\vec{o}_{t} = \sigma_{g}(W_{o} \cdot \vec{h}_{t-1} + U_{o} \cdot \vec{x}_{t})$$

$$\vec{f}_{t} = \sigma_{g}(W_{f} \cdot \vec{h}_{t-1} + U_{f} \cdot \vec{x}_{t})$$

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$$\Rightarrow \vec{f}_{t} = \sigma_{g}(W_{f} \cdot \vec{h}_{t-1} + U_{f} \cdot \vec{x}_{t})$$

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$$\Rightarrow \vec{o}_t = \sigma_g(W_o \cdot \vec{h}_{t-1} + U_o \cdot \vec{x}_t)$$
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$$\vec{i}_t = \sigma_g(W_i \cdot \vec{h}_{t-1} + U_i \cdot \vec{x}_t)$$

- LSTM (almost) solves the vanishing gradient problem w.r.t. the "internal" state of the network.
- Learns to control its own memory (via forget gate).
- Revolution in machine translation and text processing.
- ... but the development goes on ...

## **RNN text generator**

Generating texts letter by letter.



- Generating Shakespeare letter by letter.
- Trained on Shakespeare's plays (4.4MB).

VIOLA: Why, Salisbury must find his flesh and thought That which I am not aps, not a man and in fire, To show the reining of the raven and the wars To grace my hand reproach within, and not a fair are hand, That Caesar and my goodly father's world; When I was heaven of presence and our fleets, We spare with hours, but cut thy council I am great, Murdered and by thy master's ready there My power to give thee but so much as hell: Some service in the noble bondman here, Would show him to her wine.

KING LEAR: O, if you were a feeble sight, the courtesy of your law, Your sight and several breath, will wear the gods With his heads, and my hands are wonder'd at the deeds, So drop upon your lordship's head, and your opinion Shall be against your honour.

# Wikipedia

Hutter Prize 100MB dataset from Wikipedia (96MB) Naturalism and decision for the majority of Arab countries' capitalide was grounded by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal in the [[Protestant Immineners]], which could be said to be directly in Cantonese Communication, which followed a ceremony and set inspired prison, training. The emperor travelled back to [[Antioch, Perth, October 25[21]] to note, the Kingdom of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known in western [[Scotland]], near Italy to the conquest of India with the conflict. Copyright was the succession of independence in the slop of Syrian influence that was a famous German movement based on a more popular servicious, non-doctrinal and sexual power post. Many governments recognize the military housing of the [[Civil Liberalization and Infantry Resolution 265 National Party in Hungary]], that is sympathetic to be to the [[Punjab Resolution]] (PJS)[http: //www.humah.yahoo.com/guardian.cfm/7754800786d17551963s89.htm Official economics Adjoint for the Nazism, Montgomery was swear to advance to the resources for those Socialism's rule, was starting to signing a

Xml halucination:

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<page>
  <title>Antichrist</title>
  <id>865</id>
  <revision>
    <id>15900676</id>
    <timestamp>2002-08-03T18:14:12Z</timestamp>
    <contributor>
      <username>Paris</username>
      <id>23</id>
    </contributor>
    <minor />
    <comment>Automated conversion</comment>
    <text xml:space="preserve">
    #REDIRECT [[Christianity]]</text>
  </revision>
</page>
```

- Algebraic geometry textbook.
- LaTeX source (16MB).
- Almost compilable.
Proof. Omitted.

**Lemma 0.1.** Let C be a set of the construction.

Let C be a gerber covering. Let F be a quasi-coherent sheaves of O-modules. We have to show that

 $\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$ 

Proof. This is an algebraic space with the composition of sheaves  ${\mathcal F}$  on  $X_{\acute{e}tale}$  we have

 $\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$ 

where  $\mathcal{G}$  defines an isomorphism  $\mathcal{F} \to \mathcal{F}$  of  $\mathcal{O}$ -modules.

Lemma 0.2. This is an integer Z is injective.

Proof. See Spaces, Lemma ??.

**Lemma 0.3.** Let S be a scheme. Let X be a scheme and X is an affine open covering. Let  $U \subset X$  be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

 $b: X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$ 

be a morphism of algebraic spaces over S and Y.

*Proof.* Let X be a nonzero scheme of X. Let X be an algebraic space. Let  $\mathcal{F}$  be a quasi-coherent sheaf of  $\mathcal{O}_X$ -modules. The following are equivalent

- *F* is an algebraic space over S.
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor  $\mathcal{O}_{\mathbf{Y}}(U)$  which is locally of

 Trained on all source files of Linux kernel concatenated into a single file (474MB of C code).

```
* Increment the size file of the new incorrect UI FILTER group information
* of the size generatively.
static int indicate policy(void)
 int error:
 if (fd == MARN EPT) {
     * The kernel blank will coeld it to userspace.
    if (ss->segment < mem total)</pre>
      unblock graph and set blocked();
    else
      ret = 1:
    goto bail;
 segaddr = in SB(in.addr);
 selector = seq / 16;
 setup works = true;
 for (i = 0; i < blocks; i++) {</pre>
   seq = buf[i++];
    bpf = bd->bd.next + i * search:
   if (fd) {
      current = blocked;
    }
  rw->name = "Getjbbregs";
 bprm self clearl(&iv->version);
  regs->new = blocks[(BPF STATS << info->historidac)] | PFMR CLOBATHINC SECONDS << 12;</pre>
 return segtable;
```

```
Copyright (c) 2006-2010, Intel Mobile Communications, All rights reserved.
  This program is free software; you can redistribute it and/or modify it
under the terms of the GNU General Public License version 2 as published by
the Free Software Foundation.
       This program is distributed in the hope that it will be useful,
but WITHOUT ANY WARRANTY; without even the implied warranty of
  MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the
 GNU General Public License for more details.
  You should have received a copy of the GNU General Public License
  along with this program; if not, write to the Free Software Foundation,
 Inc., 675 Mass Ave, Cambridge, MA 02139, USA.
```

#include <linux/kexec.h>
#include <linux/errno.h>
#include <linux/io.h>
#include <linux/platform\_device.h>
#include <linux/multi.h>
#include <linux/kevent.h>

#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system\_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

# **Evolution of Shakespeare**

#### 100 iter.:

tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrgd t o idoe ns,smtt h ne etie h,hregtrs nigtike,aoaenns lng

#### 300 iter.:

"Tmont thithey" fomesscerliund Keushey. Thom here sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."

#### 500 iter.:

we counter. He stutn co des. His stanted out one ofler that concossions and was to gearang reay Jotrets and with fre colt otf paitt thin wall. Which das stimn

#### 700 iter.:

Aftair fall unsuch that the hall for Prince Velzonski's that me of her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort how, and Gogition is so overelical and ofter.

#### 1200 iter.:

"Kite vouch!" he repeated by her door. "But I would be done and quarts, feeling, then, son is people...."

#### 2000 iter .:

"Why do what that day," replied Natasha, and wishing to himself the fact the princess, Princess Mary was easier, fed in had oftened him. Pierre aking his soul came to the packs and drove up his father-in-law women. Consider the following task: Given a sequence of vectors

$$\mathbf{x} = \vec{x}_1, \ldots, \vec{x}_T$$

generate a new sequence

$$\mathbf{y}=\vec{y}_1,\ldots,\vec{y}_{T'}$$

of possibly different length (i.e., possibly  $T \neq T'$ ).

E.g., a machine translation task,  $\mathbf{x}$  is an embedding of an English sentence,  $\mathbf{y}$  is a sequence of probability distributions on a German vocabulary.

# Attention

Consider two recurrent networks:

- Enc the encoder
  - Hidden state  $\vec{h_0}$  initialized by standard methods for recurrent networks
  - ► Reads  $\vec{x}_1, ..., \vec{x}_T$ , does not output anything but produces a sequence of hidden states  $\vec{h}_1, ..., \vec{h}_T$

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- Dec the decoder
  - The initial hidden state is  $\vec{h}_T$
  - ▶ Does not read anything but outputs the sequence  $\vec{y}_1, \ldots, \vec{y}_{T'}$ This is a simplification. Typically, Dec reads  $\vec{y}_0, \vec{y}_1, \ldots, \vec{y}_{T'-1}$  where  $\vec{y}_0$  is a special vector embedding a separator.

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Trained on pairs of sentences, able to learn a fine translation between major languages (if the recurrent networks are LSTM).

Is not perfect because all info about  $\mathbf{x} = \vec{x}_1, \dots, \vec{x}_T$  is squeezed into the single state vector  $\vec{h}_T$ .

In particular, the network tends to forget the context of each word.

What if we provide the decoder with an information about the *relevant context* of the generated word?

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We use the same encoder Enc producing the sequence of hidden states:  $\vec{h}_1, \ldots, \vec{h}_T$ 

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- ▶ reads a sequence of context vectors  $\vec{c}_1, \ldots, \vec{c}_{T'}$  where

$$ec{c}_i = \sum_{j=1}^T lpha_{ij} ec{h}_j$$
 where  $lpha_{ij} = rac{\exp(e_{ij})}{\sum_{k=1}^T \exp(e_{ik})}$ 

where  $e_{ij} = \texttt{MLP}(ec{h}'_{i-1}, ec{h}_j)$ 

• outputs the sequence  $\vec{y}_1, \ldots, \vec{y}_{T'}$ 

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- Could we remove the recurrent network itself and preserve only the attention?

### Self-Attention Layer (is all you need)

Fix an input sequence:  $\vec{x}_1, \ldots, \vec{x}_T$ 

Consider three learnable matrices:  $W_q$ ,  $W_k$ ,  $W_v$ 

Generate sequences of queries, keys, and values:

• 
$$\vec{q}_1, \ldots, \vec{q}_T$$
 where  $\vec{q}_k = W_q \vec{x}_k$  for all  $k = 1, \ldots, 7$ 

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Define a vector score for all  $i, j \in \{1, ..., T\}$  by

$$e_{ij} = \vec{q}_i \cdot \vec{k}_j$$

Intuitively,  $s_{ij}$  measures how much the input at the position *i* is related to the input at the position *j*, in other words, how much the query fits the key.

Define

$$\alpha_{ij} = \frac{\exp(\boldsymbol{e}_{ij} / \sqrt{d_{attn}})}{\sum_{k=1}^{T} \exp(\boldsymbol{e}_{ik} / \sqrt{d_{attn}})}$$

 $d_{attn}$  is the dimension of  $\vec{v}_i$ 

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# Language Model

A sequence of *tokens*  $a_1, \ldots, a_T \in \Sigma^*$ E.g. words from a vocabulary  $\Sigma$ .

The goal: Maximize

$$\prod_{k=1}^{T} P(a_k \mid a_1, ..., a_{k-1}; W) \qquad (= P(a_1, ..., a_T; W))$$

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Can be used to generate text:

Given  $a_1, ..., a_k$ , sample  $a_{k+1}$  from  $P(a_{k+1} | a_1, ..., a_k; W)$ 

**GPT** 



**GPT** 



# Masked Self-Attention Layer (is all you need)

Assume an attention mechanism which given an input sequence  $\vec{x}_1, \ldots, \vec{x}_T$  generates  $\vec{y}_1, \ldots, \vec{y}_T$ .

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Assume the number of *heads* is *H*.

For h = 1, ..., H the *h*-th head is an attention mechanism which given the input  $\vec{x}_1, ..., \vec{x}_T$  produces

 $\vec{y}_1^h, \dots, \vec{y}_T^h$ 

Note that the output may be different which means that, in particular, the matrices  $W_q$ ,  $W_k$ ,  $W_v$  may be different for each head.

Assume that all vectors  $\vec{y}_k^h$  are of the same dimension  $d_{mid}$  and consider a learnable matrix  $W_{out}$  of dimensions  $d_{out} \times (H \cdot d_{mid})$ .

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The multi-head attention produces the following output:

 $\vec{y}_1,\ldots,\vec{y}_T$ 

where

$$\vec{y}_k = W_{out} \cdot \left( \vec{y}_k^1 \odot \vec{y}_k^2 \odot \cdots \vec{y}_k^H \right)$$

Here  $\odot$  is a concatenation of vectors.

## **Multi-head Self-Attention Summary**

Input: A sequence  $\vec{x}_1, \ldots, \vec{x}_T$ Output: A sequence  $\vec{y}_1, \ldots, \vec{y}_T$ 

I.e., a sequence of the same length. The dimensions of  $\vec{y}_k$  and  $\vec{x}_k$  do not have to be equal.

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Learnable parameters: Matrices  $W_q$ ,  $W_k$ ,  $W_v$ .

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### Multi-head attention:

Learnable parameters:

• Matrices  $W_q^h$ ,  $W_k^h$ ,  $W_v^h$  where h = 1, ..., H and H is the number of heads.

Each attention head operates independently on the input  $\vec{x}_1, \ldots, \vec{x}_T$ .

Matrix W<sub>out</sub>.

Linearly transforms the concatenated results of the attention heads.

## **GPT - transformer**



# **Positional encoding**

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Assume that  $\vec{P}_k$  should have a dimension d. Given a position  $k \in \{1, ..., T\}$  and  $i \in \{0, ..., d/2\}$  define

$$P_{k,2i} = \sin\left(\frac{k}{n^{2i/d}}\right)$$
$$P_{k,(2i+1)} = \cos\left(\frac{k}{n^{2i/d}}\right)$$

Here n = 10000.

A user defined constant, the original paper suggests n = 10000.

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A user defined constant, the original paper suggests n = 10000.

Given an input sequence  $\vec{x}_1, \ldots, \vec{x}_T$  we add the position embedding to each  $\vec{x}_k$  obtaining a new input sequence  $\vec{x}'_1, \ldots, \vec{x}'_T$  where

$$\vec{x}_k' = \vec{x}_k + \vec{P}_k$$

# Positional encoding/embedding


# Positional encoding/embedding



- Vertically: Sinusoidal functions
- Horizontally: Decreasing frequency

For any offset  $o \in \{1, ..., T\}$  there is a linear transformation M such that for any  $k \in \{1, ..., T - o\}$  we have  $M\vec{P}_k = \vec{P}_{k+o}$ . Intuitively, just rotate each component of the  $\vec{P}_k$  appropriately.

### **GPT-2 - transformer**



### Layer normalization

Given a vector  $\vec{x} \in \mathbb{R}^d$ , the *layer normalization* computes:

$$\vec{x}' = \gamma \cdot \frac{(\vec{x} - \mu)}{\sigma} + \beta$$

Here

• 
$$\mu = \frac{1}{d} \sum_{i=1}^{d} x_i$$
 and  $\sigma^2 = \frac{1}{d} \sum_{i=1}^{d} (x_i - \mu)^2$   
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### In Transformer:

The input to the layer normalization is a sequence of vectors:  $\vec{x}_1, \ldots, \vec{x}_T$ . The layer normalization is applied to each  $\vec{x}_k$ , producing a sequence of "normalized" vectors.

# **GPT** - learning

A sequence of tokens  $a_1, \ldots, a_T \in \Sigma$  and their one-hot encodings  $\vec{u}_1, \ldots, \vec{u}_T \in \{0, 1\}^{|\Sigma|}$ We assume that  $a_1$  is a special token marking the start of the sequence.

Embed to vectors and add the position encoding ( $W_e$  is an embedding matrix):

$$\vec{x}_k = W_e \cdot \vec{u}_k + P_k \in Rset^d$$

Г	Text Task Prediction Classifier
	Layer Norm
2x -	Layer Norm
	Masked Multi Self Attention
	Text & Position Embed

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Apply the network (with the transformer block repeated 12x) to  $\vec{x}_1, \ldots, \vec{x}_T$  and obtain  $\vec{y}_1, \ldots, \vec{y}_T$ 

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Compute the error:

$$-\sum_{\ell=1}^{T-1}\log\left(\vec{y}_\ell[a_{\ell+1}]\right)$$

Here  $\vec{y}_{\ell}[a_{k+1}]$  is the probability of  $a_{k+1}$  in the distribution  $\vec{y}_k$ .

# **GPT - inference**



A sequence of tokens  $a_1, \ldots, a_\ell \in \Sigma$  and their one-hot encodings  $\vec{u}_1, \ldots, \vec{u}_\ell \in \{0, 1\}^{|\Sigma|}$ 

Embed to vectors and add the position encoding:

$$ec{k}_k = oldsymbol{W}_{oldsymbol{e}} \cdot ec{u}_k + oldsymbol{P}_k \in oldsymbol{Rset}^d$$

Apply the network to  $\vec{x}_1, \ldots, \vec{x}_\ell$  and obtain  $\vec{y}_1, \ldots, \vec{y}_\ell$ (Assume that each  $\vec{y}_k \in [0, 1]^{\Sigma}$  is a probability distribution on  $\Sigma$ )

Sample the next token from

$$a_{\ell+1} \sim \vec{y}_{\ell}$$

Architectures:

- Multi-layer perceptron (MLP):
  - dense connections between layers
- Convolutional networks (CNN):
  - local receptors, feature maps
  - pooling
- Recurrent networks (RNN):
  - self-loops but still feed-forward through time
- Transformer
  - Attention, query-key-value

Training:

gradient descent algorithm + heuristics

An autoencoder consists of two parts:

- $\phi : \mathbb{R}^n \to \mathbb{R}^m$  the encoder
- $\psi : \mathbb{R}^m \to \mathbb{R}^n$  the decoder

The goal is to find  $\phi$ ,  $\psi$  so that  $\psi \circ \phi$  is (almost) identity.

The value  $\vec{h} = \phi(\vec{x})$  is called the *latent representation* of  $\vec{x}$ .

#### Assume

$$\mathcal{T} = \{\vec{x}_1, \dots, \vec{x}_p\}$$

where  $\vec{x}_i \in \mathbb{R}^n$  for all  $i \in \{1, \ldots, n\}$ .

Minimize the reconstruction error

$$E = \sum_{i=1}^{p} (\vec{x}_i - \psi(\phi(\vec{x}_i)))^2$$

### Autoencoders – neural networks

Both  $\phi$  and  $\psi$  can be represented using MLP  $\mathcal{M}_{\phi}$  and  $\mathcal{M}_{\psi}$ , respectively.

 $\mathcal{M}_{\phi}$  and  $\mathcal{M}_{\psi}$  can be connected into a single network.



- Compression from  $\vec{x}$  to  $\vec{h}$ .
- Dimensionality reduction the latent representation  $\vec{h}$  has a smaller dimension.
- Pretraining (next slides)
- Generative versions (roughly) generate *h* from a known distribution, let *M*<sub>ψ</sub> generate realistic inputs *x*

Architecture: MLP 64 - 16 - 64

Activity: activation function: hyperbolic tangens with limits -1 and 1

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#### Data:

- ▶ Images 256 × 256, 8 bits per pixel.
- Samples: input and output is a frame 8 × 8, randomly selected in the image.
- ▶ Inputs normalized to [-1,1].

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- ▶ Inputs normalized to [-1,1].

The goal was to compress images to smaller data size.

(D)



A frame  $8 \times 8$  passes through the image  $256 \times 256$  (no overlap)

- (A) original
- (B) compression
- (C) compression + rounding to 6 bits (1.5 bit per pixel)
- (D) compression + rounding to 4 bits (1 bit per pixel)

(C)

## **Dimensionality reduction – compression**



New image (trained on the previous one):

- (A) original
- (B) compression
- (C) compression + rounding to 6 bits (1.5 bit per pixel)
- (D) compression + rounding to 4 bits (1 bit per pixel)

# **Application – dimensionality reduction**

- Dimensionality reduction: A mapping R from R<sup>n</sup> to R<sup>m</sup> where
  - ▶ *m* < *n*,
  - for every example  $\vec{x}$  we have that  $\vec{x}$  can be "reconstructed" from  $R(\vec{x})$ .

# **Application – dimensionality reduction**

- Dimensionality reduction: A mapping R from R<sup>n</sup> to R<sup>m</sup> where
  - ▶ *m* < *n*,
  - For every example x we have that x can be "reconstructed" from R(x).
- Standard method: PCA (there are many linear as well as non-linear variants)



### **Reconstruction – PCA**



1024 pixels compressed to 100 dimensions (i.e. 100 numbers).

### **PCA vs Autoencoders**

345678 2 q 2345678 Q 23456 9

Real data 30-d deep autoencoder 30-d logistic PCA 30-d PCA

- An autoencoder is (pre)trained on input data x<sub>i</sub> without desired outputs (unsupervised) typically much larger datasets of unlabelled data
- the encoder M<sub>\u03c6</sub> computes a latent representation for every input vector, it is supposed to extract important features (controversial)
- A new part of the model *M*<sub>top</sub> is added on top of *M*<sub>φ</sub> (e.g. a MLP taking the output of *M*<sub>φ</sub> as an input).
- Subsequently, labels are added and the whole model (composed of M<sub>\u03c6</sub> and M<sub>top</sub>) is trained on labelled data.

# **Autoencoders – Pretraining**



### **Generative adversarial networks**

Generative adversarial Nets, Goodfellow et al, NIPS 2014

An unsupervised generative model.

Two networks:

- Generator: A network computing a function G : ℝ<sup>k</sup> → ℝ<sup>n</sup> which takes a *random* input *z* with a distribution p<sub>z</sub> (e.g., multivariate normal distribution) and returns G(*z*) which should follow the target probability distribution. E.g., G(*z*) could be realistically looking faces.
- Discriminator: A network computing a function
  D: ℝ<sup>n</sup> → [0, 1] that given x ∈ ℝ<sup>n</sup> gives a probability D(x) that x is not "generated" by G.
  E.g., x can be an image, D(x) is a probability that it is a true face of an existing person.

What error function will "motivate" *G* to generate realistically and *D* to discriminate appropriately?

## Generative adversarial networks – error function

Let  $\mathcal{T} = \{\vec{x}_1, \dots, \vec{x}_p\}$  be a training multiset (or a minibatch).

**Intuition**: *G* should produce outputs similar to elements of  $\mathcal{T}$ . *D* should recognize that its input is not from  $\mathcal{T}$ .

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Generate a multiset of noise samples:  $\mathcal{F} = \{\vec{z}_1, \dots, \vec{z}_p\}$  from the distribution  $p_{\vec{z}}$ .

$$E_{\mathcal{T},\mathcal{F}}(G,D) = -\frac{1}{p}\sum_{i=1}^{p} \left( \ln D(\vec{x}_i) + \ln(1 - D(G(\vec{z}_i))) \right)$$

This is just the binary cross entropy error of D which classifies the input as either real, or fake.

The problem can be seen as a game: The discriminator wants to minimize E, the generator wants to maximize E!

# The learning algorithm

Denote by  $W_G$  and  $W_D$  the weights of G and D, respectively.

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For k steps (here k is a hyperparameter) update the discriminator as follows:

- Sample a minibatch  $T = \{\vec{x}_1, \dots, \vec{x}_m\}$  from the training set  $\mathcal{T}$ .
- Sample a minibatch  $F = \{\vec{z}_1, \dots, \vec{z}_m\}$  from the distribution  $p_z$ .
- Update W<sub>D</sub> using the gradient descent w.r.t. E:

 $W_D := W_D - \alpha \cdot \nabla_{W_D} E_{T,F}(G,D)$ 

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Now update the generator:

- Sample a minibatch  $F = \{\vec{z}_1, \dots, \vec{z}_m\}$  from the distribution  $p_z$ .
- Update the generator by gradient ascent:

$$W_G := W_G - \alpha \cdot \nabla_{W_G} \left( \frac{1}{p} \sum_{i=1}^p \ln(1 - D(G(\vec{z}_i))) \right)$$

(The updates may also use momentum, adaptive learning rate etc.)

## **GAN MNIST**



### **GAN** faces

... from the original paper.



## **GAN refined**

... after some refinements.



... none of these people ever lived.