# Introduction to Sequence Modeling

"I'm glad that I'm Turing Complete now"

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Apr. 2019

Raise your hand and ask,
whenever you have questions...

# Outline

- RNN Basics
- Classical RNN Architectures
  - LSTM
- RNN Variants
  - RNN with Attention
  - RNN with External Memory
    - Neural Turing Machine
- Attention is All You Need (Transformers)
- Applications
  - A market of RNNs

# Why Sequence Modeling?

# Feedforward Neural Networks

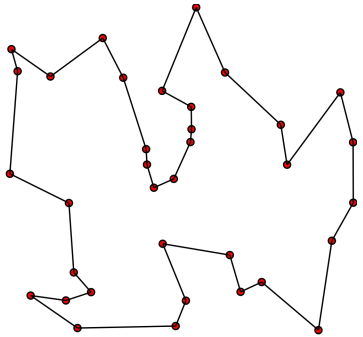
- Feedforward neural networks can fit any **bounded continuous** (compact) function
- This is called **Universal approximation theorem**


https://en.wikipedia.org/wiki/Universal_approximation_theorem

Cybenko, George. "Approximation by superpositions of a sigmoidal function." Mathematics of Control, Signals, and Systems (MCSS) 2.4 (1989): 303-314.

# Bounded Continuous Function is NOT ENOUGH!

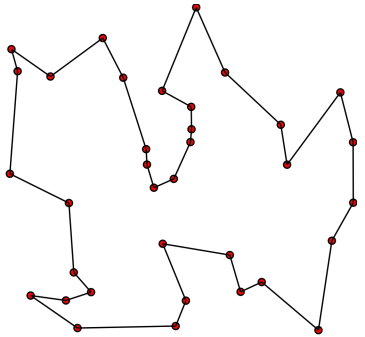
How to solve Travelling Salesman Problem?



# Bounded Continuous Function is NOT ENOUGH!

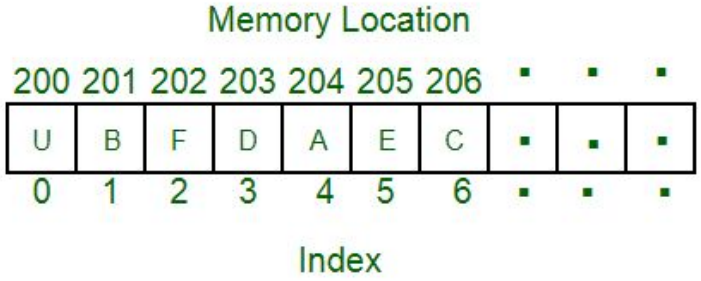
How to solve Travelling Salesman Problem?

**We Need to be**
**Turing Complete**



# Sequence Modeling

Turing Completeness requires **Sequence processing**




**Array (List)**

```
(define (fib n)
  (if (< n 2)
    1
    (+ (fib (- n 1)) (fib (- n 2)))))
```

**Lisp (List Processing) Programming Language**

“Since inception, Lisp was closely connected with the artificial intelligence research community ...” -- Wikipedia

# RNN is Turing Complete

This paper deals with finite size networks which consist of interconnections of synchronously evolving processors. Each processor updates its state by applying a "sigmoidal" function to a linear combination of the previous states of all units. We prove that one may simulate all Turing machines by such nets. In particular, one can simulate any multi-stack Turing machine in real time, and there is a net made up of 886 processors which computes a universal partial-recursive function. Products (high order nets) are not required, contrary to what had been stated in the literature. Non-deterministic Turing machines can be simulated by non-deterministic rational nets, also in real time. The simulation result has many consequences regarding the decidability, or more generally the complexity, of questions about recursive nets. 

Siegelmann, Hava T., and Eduardo D. Sontag. "On the computational power of neural nets." Journal of computer and system sciences 50.1 (1995): 132-150.

# Sequence Modeling

- How to take a **variable length sequence** as **input**?
- How to predict a **variable length sequence** as **output**?

Sequence

**Model**

Sequence

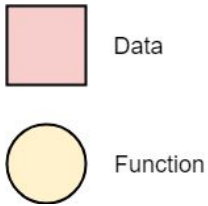
# RNN Basics

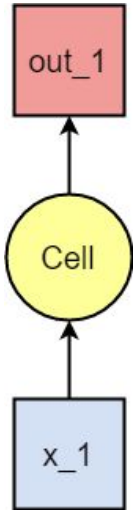
The Appetizer


RNN (8 yuan) > CNN (5 yuan)

# RNN Diagram

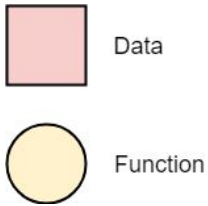
A lonely feedforward cell

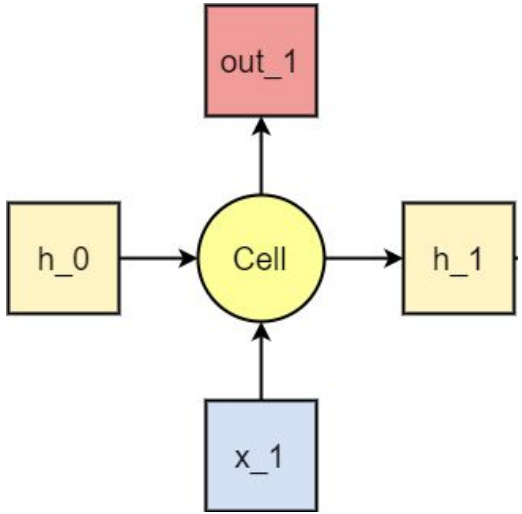


# RNN Diagram

Grows … with more inputs and outputs

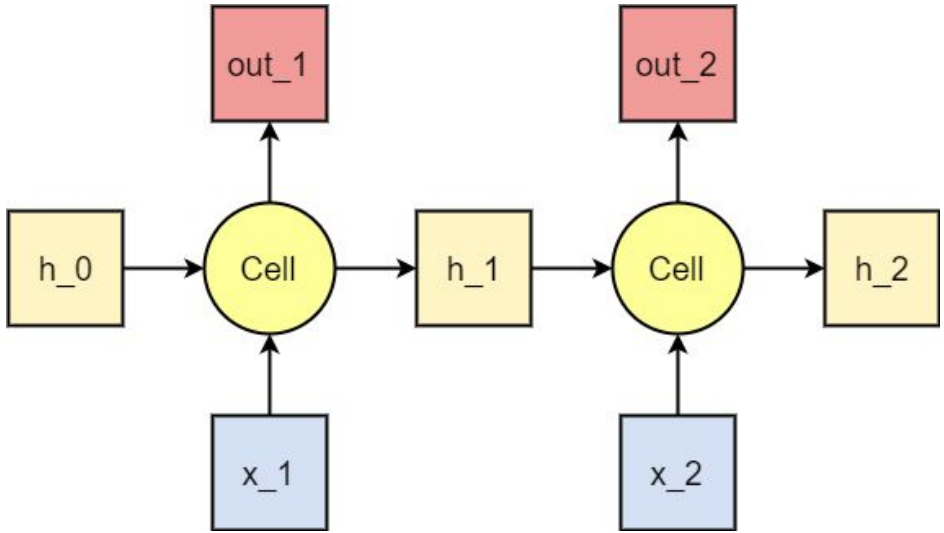


# RNN Diagram

… here comes a brother

(x_1, x_2) comprises a length-2 sequence

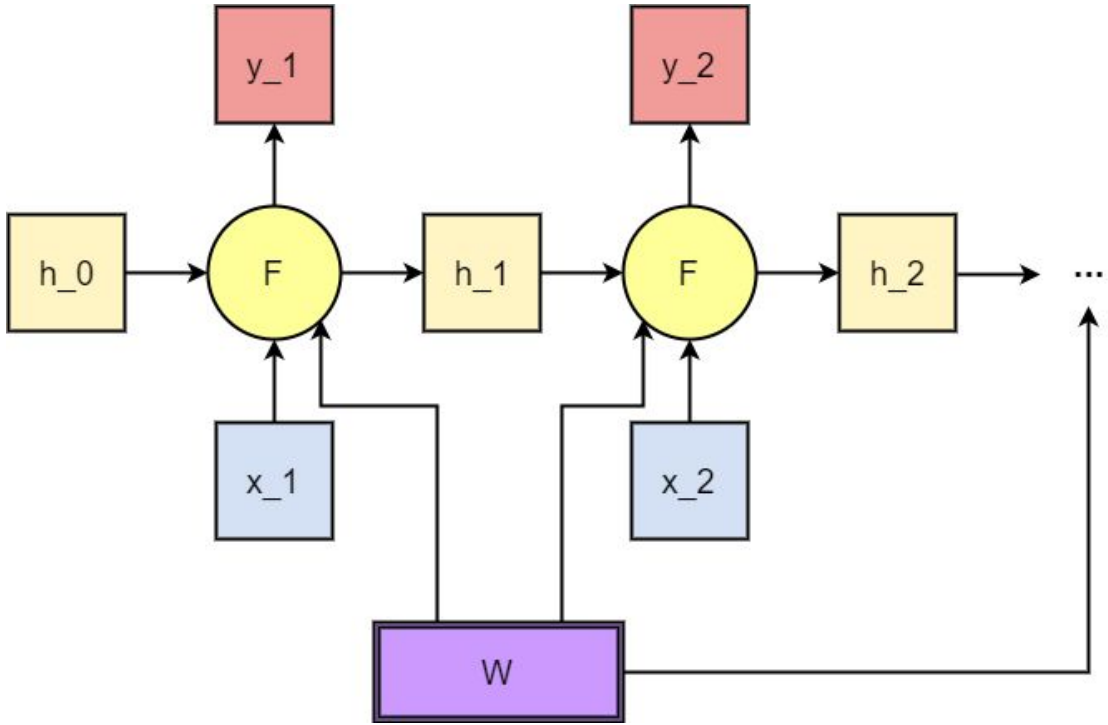


# RNN Diagram

… with shared (tied) weights

$$(h_1, y_1) = F(h_0, x_1, W)$$
$$(h_2, y_2) = F(h_1, x_2, W)$$

x_i: inputs
y_i: outputs
W: all the same
h_i: internal states that passed along
F: a “pure” function



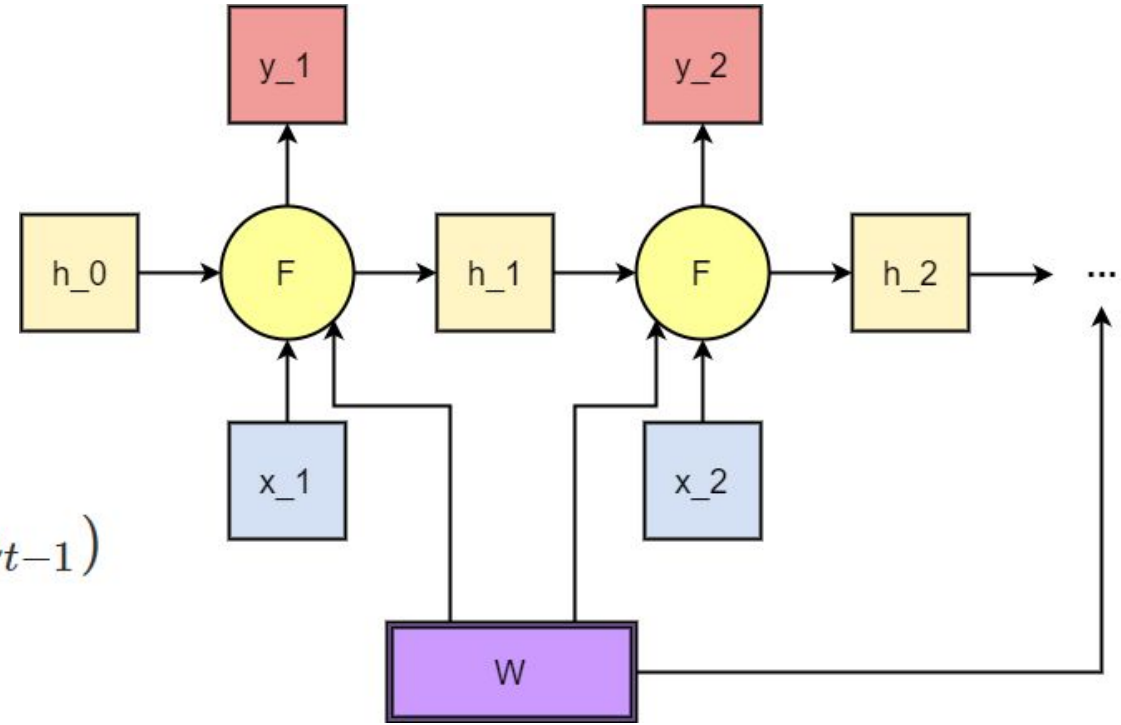
# RNN Diagram

… with shared (tied) weights

$$(h_1, y_1) = F(h_0, x_1, W)$$
$$(h_2, y_2) = F(h_1, x_2, W)$$

A simple implementation of F

$$h_t = tanh(W_{ih}x_t + W_{hh}h_{t-1})$$
$$y_t = W_{ho}h_t$$



# Categorize RNNs by input/output types

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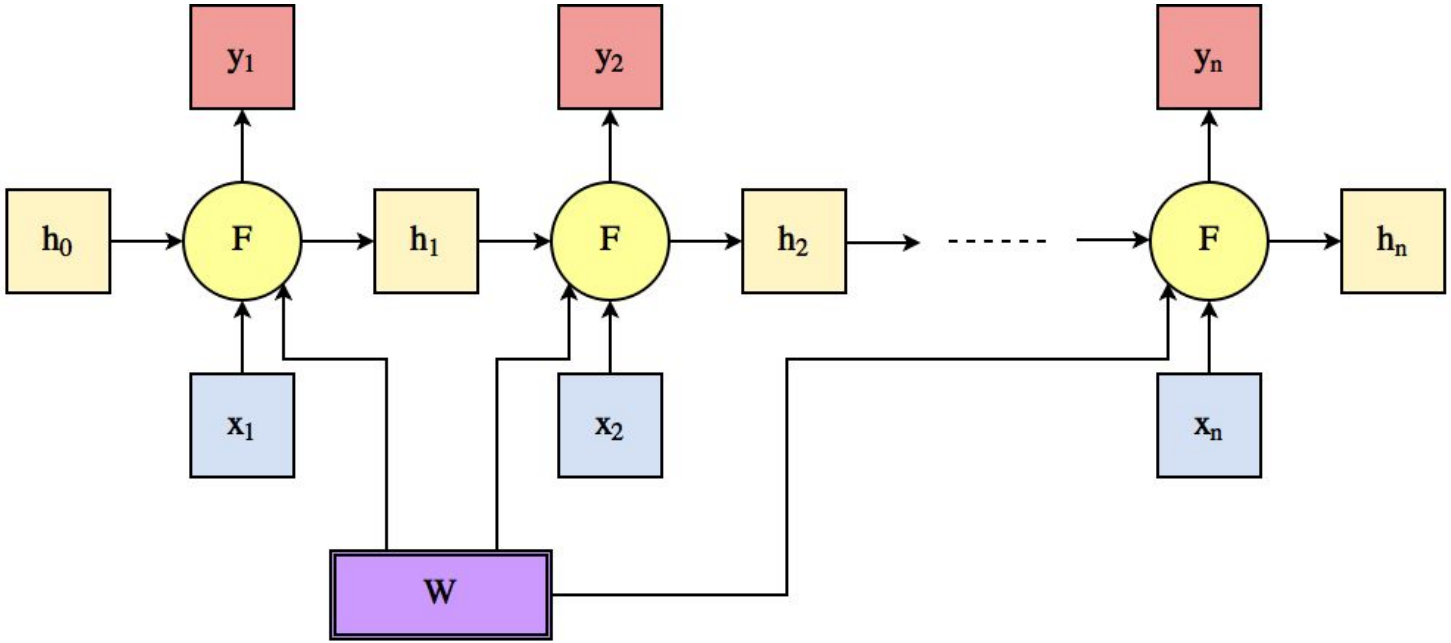
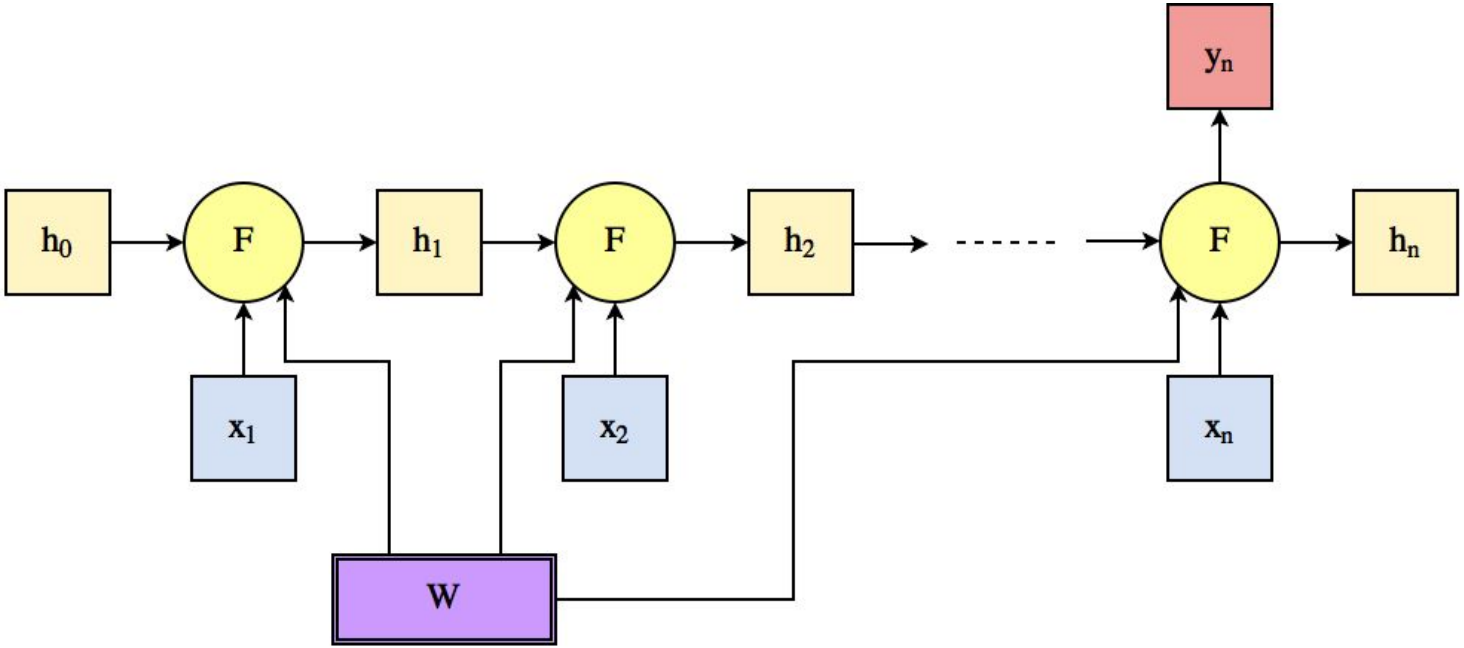
Many-to-many



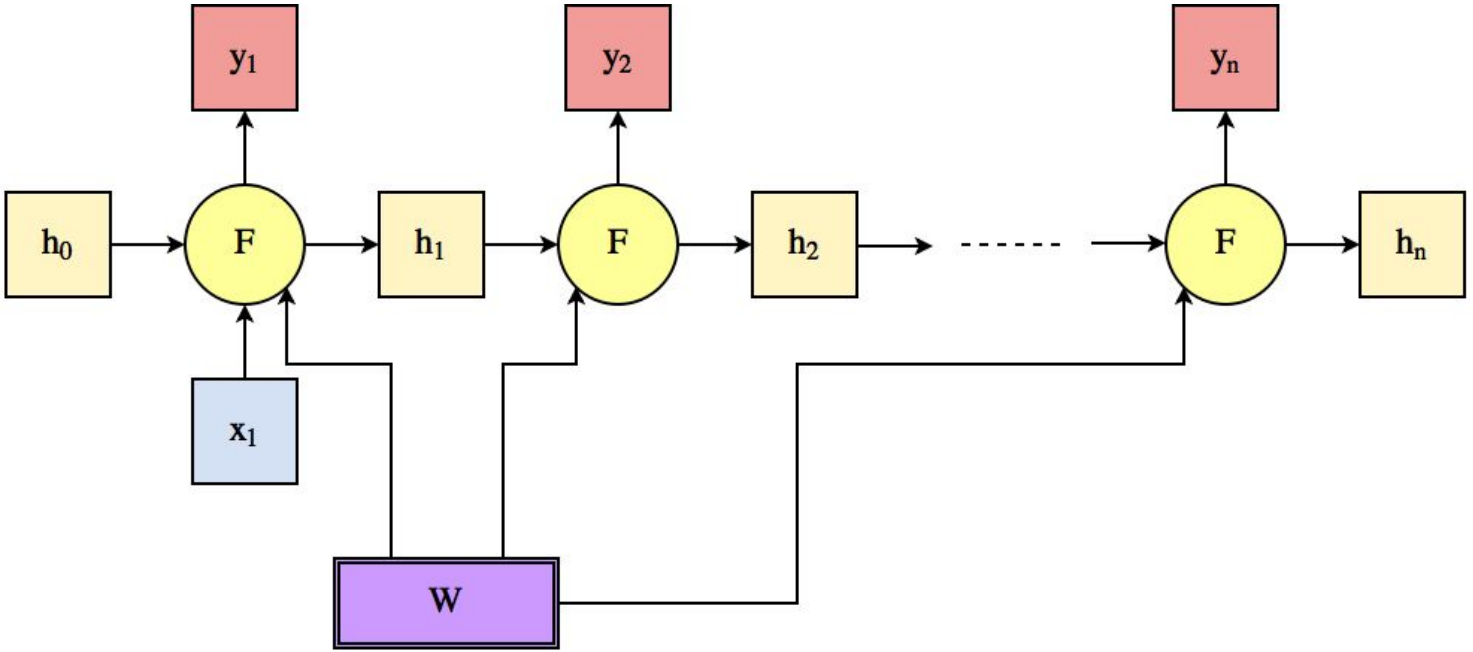
# Categorize RNNs by input/output types

Many-to-one



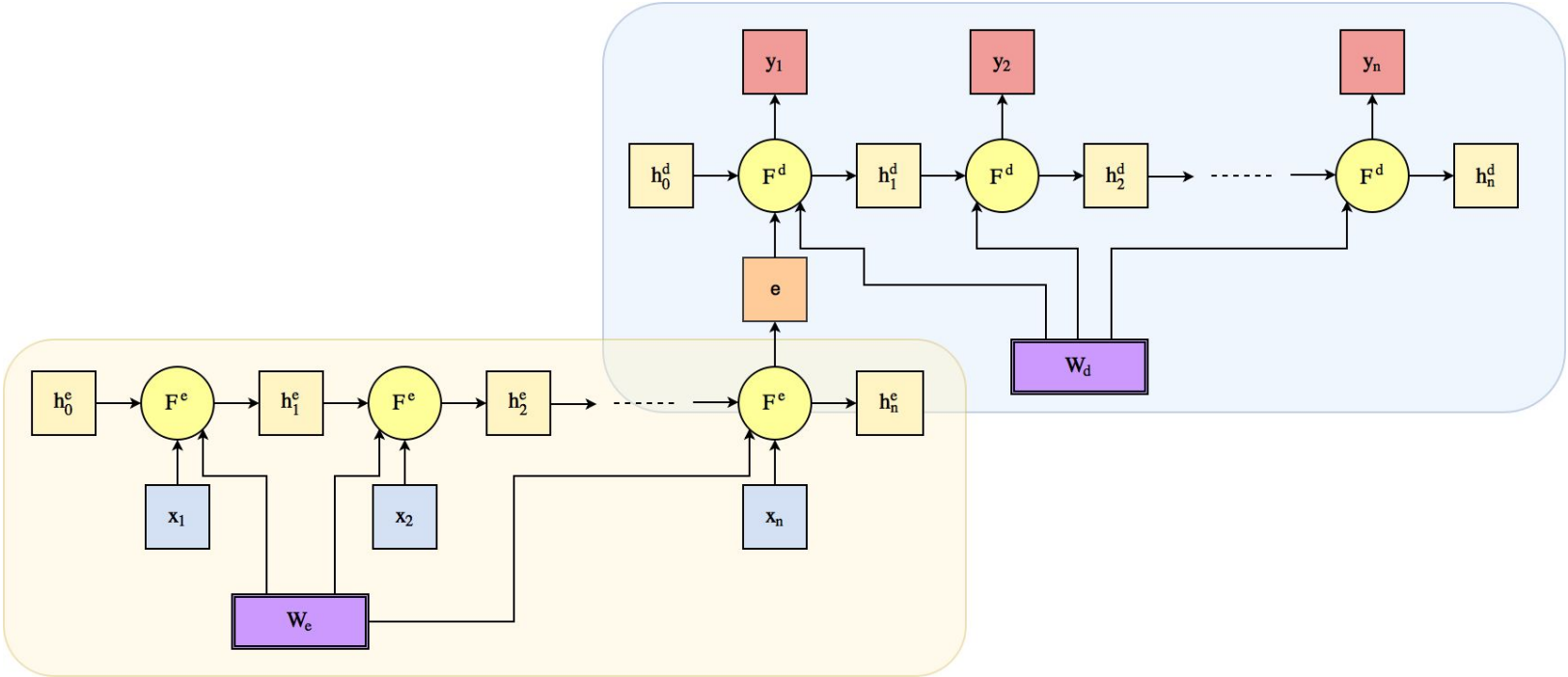
# Categorize RNNs by input/output types

One-to-Many



# Categorize RNNs by input/output types

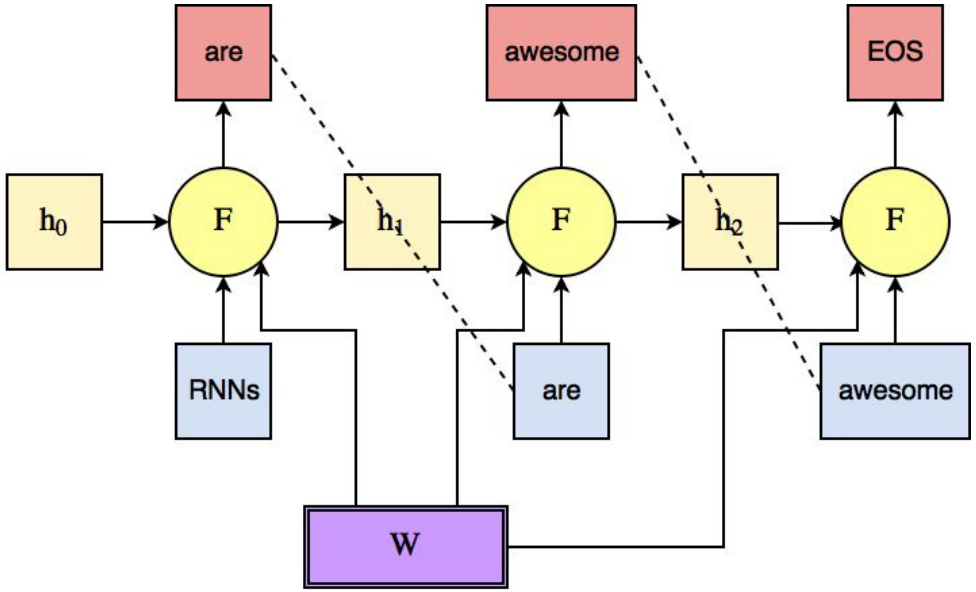
Many-to-Many: Many-to-One + One-to-Many



# Many-to-Many Example

Language Model

- Predict next word given previous words
- “h” → “he” → “hel” → “hell” → “hell




$$P(w_1, w_2, \ldots, w_t) = P(w_1)P(w_2|w_1)P(w_3|w_{1:2}) \ldots P(w_t|w_{1:t-1})$$

$$Loss = \sum_{i=1..t} \text{cross-entropy}(y_i, y_i^*)$$

# Language Modeling

- Tell story
- 
- “Heeeeeel”
- ⇒ “Heeeloolllell”
- ⇒ “Hellooo”
- ⇒ “Hello”

```
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
```

train more

```
"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."
```

train more

```
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.
```

train more

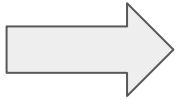
```
"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.
```

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

# Language Modeling

- Write (nonsense) book in latex

```
\begin{proof}
We may assume that $\mathcal{I}$ is an abelian sheaf on
$\mathcal{C}$.
\item Given a morphism $\Delta : \mathcal{F} \to \mathcal{I}$
is an injective and let $\mathfrak q$ be an abelian sheaf on $X$.
Let $\mathcal{F}$ be a fibered complex. Let $\mathcal{F}$ be a
category.
\begin{enumerate}
\item \hyperref[setain-construction-phantom]{Lemma}
\label{lemma-characterize-quasi-finite}
Let $\mathcal{F}$ be an abelian quasi-coherent sheaf on
$\mathcal{C}$.
Let $\mathcal{F}$ be a coherent $\mathcal{O}_X$-module. Then
$\mathcal{F}$ is an abelian catenary over $\mathcal{C}$.
\item The following are equivalent
\begin{enumerate}
\item $\mathcal{F}$ is an $\mathcal{O}_X$-module.
\end{lemma}
```



To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

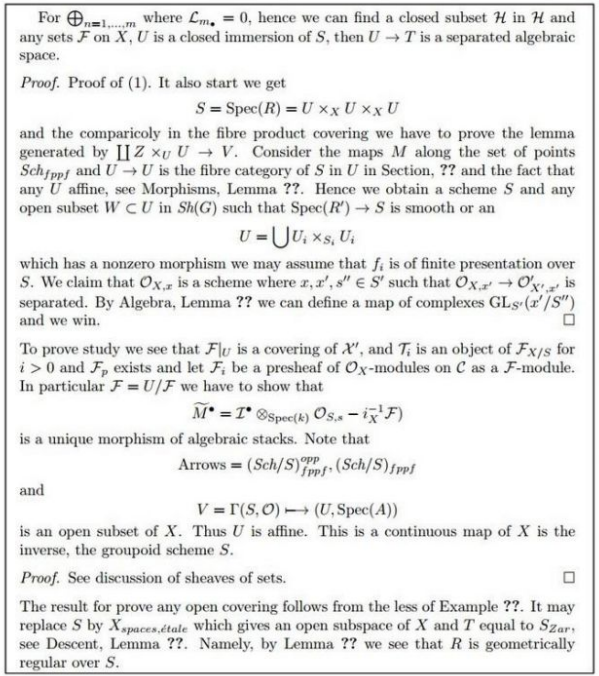
and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \mathrm{Spec}(A))$$

is an open subset of $X$. Thus $U$ is affine. This is a continuous map of $X$ is the inverse, the groupoid scheme $S$.

# Language Modeling

- Write (nonsense) book in latex



For $\bigoplus_{n=1,\ldots,m}$ 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

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

and the compariciy 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 $\mathrm{Spec}(R') \to S$ is smooth or an

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

which has a nonzero morphism we may assume that $f_i$ is of finite presentation over $S$. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

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is an open subset of $X$. Thus $U$ is affine. This is a continuous map of $X$ is the inverse, the groupoid scheme $S$.

*Proof.* See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace $S$ by $X_{spaces,étale}$ which gives an open subspace of $X$ and $T$ equal to $S_{Zar}$, see Descent, Lemma ??. Namely, by Lemma ?? we see that $R$ is geometrically regular over $S$.

**Lemma 0.1.** *Assume (3) and (3) by the construction in the description.*

*Suppose* $X = \lim |X|$ *(by the formal open covering* $X$ *and a single map* $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ *over* $U$ *compatible with the complex*

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

*When in this case of to show that* $\mathcal{Q} \to \mathcal{C}_{Z/X}$ *is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If* $T$ *is surjective we may assume that* $T$ *is connected with residue fields of* $S$*. Moreover there exists a closed subspace* $Z \subset X$ *of* $X$ *where* $U$ *in* $X'$ *is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem*

(1) $f$ *is locally of finite type. Since* $S = \mathrm{Spec}(R)$ *and* $Y = \mathrm{Spec}(R)$.

*Proof.* This is form all sheaves of sheaves on $X$. But given a scheme $U$ and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\ldots,n} U_i$ be the scheme $X$ over $S$ at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\ldots,0}$.

**Lemma 0.2.** *Let* $X$ *be a locally Noetherian scheme over* $S$, $E = \mathcal{F}_{X/S}$. *Set* $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. *Since* $\mathcal{I}^n \subset \mathcal{I}^n$ *are nonzero over* $i_0 \leq \mathfrak{p}$ *is a subset of* $\mathcal{J}_{n,0} \circ \overline{A}_2$ *works.*

**Lemma 0.3.** *In Situation ??. Hence we may assume* $\mathfrak{q}' = 0$.

*Proof.* We will use the property we see that $\mathfrak{p}$ is the mext functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where $K$ is an $F$-algebra where $\delta_{n+1}$ is a scheme over $S$. □

# Many-to-One Example

**Sentiment analysis**

- “RNNs are awesome!” ⇒ 
- “The course project is too hard for me.” ⇒ 

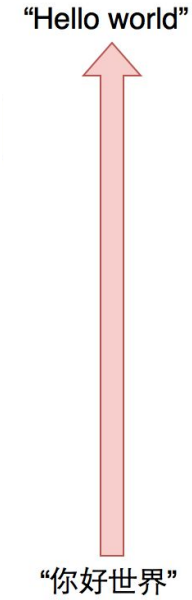
# Many-to-One Example

**Sentiment analysis**

- “RNNs are awesome!” ⇒ 
- “The course project is too hard for me.” ⇒ 

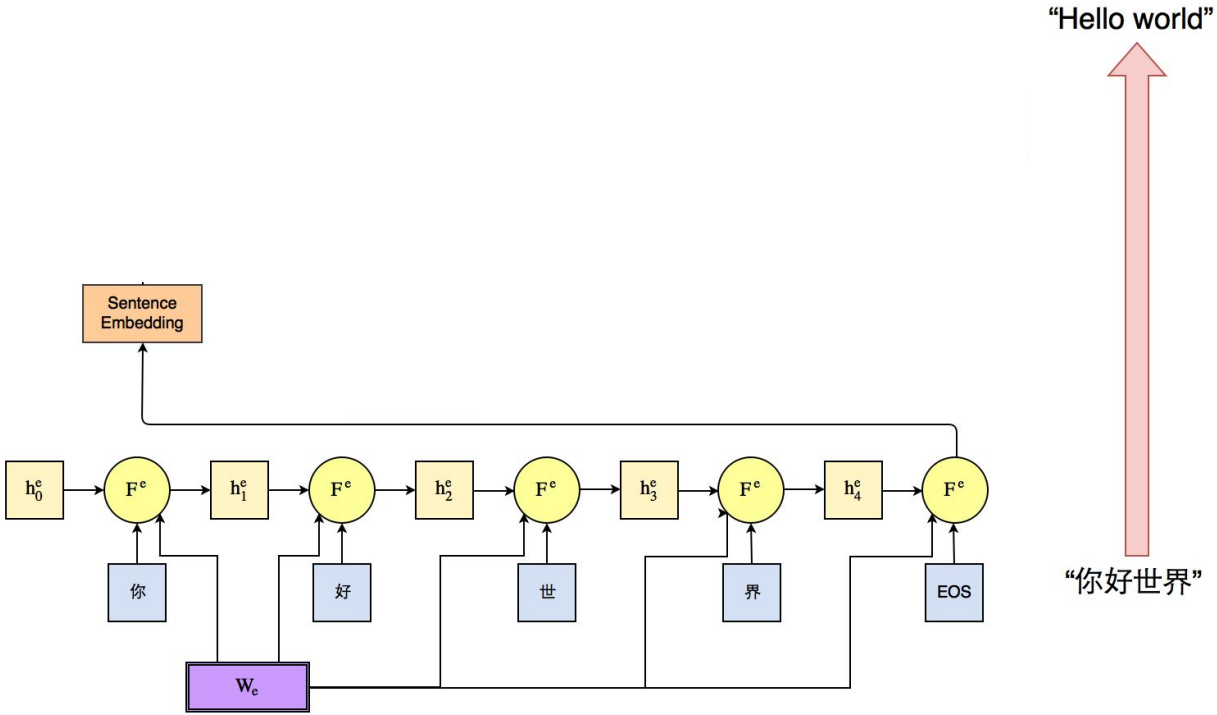
# Many-to-One + One-to-Many

Neural Machine Translation



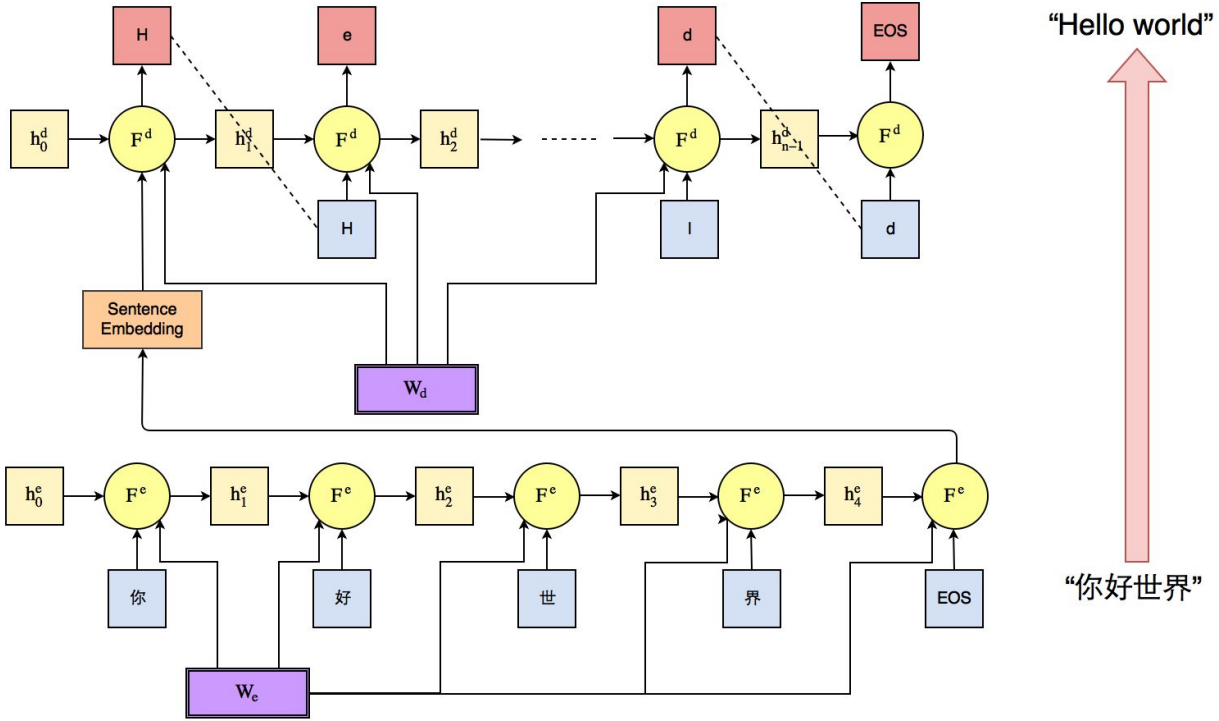
# Many-to-One + One-to-Many

## Neural Machine Translation



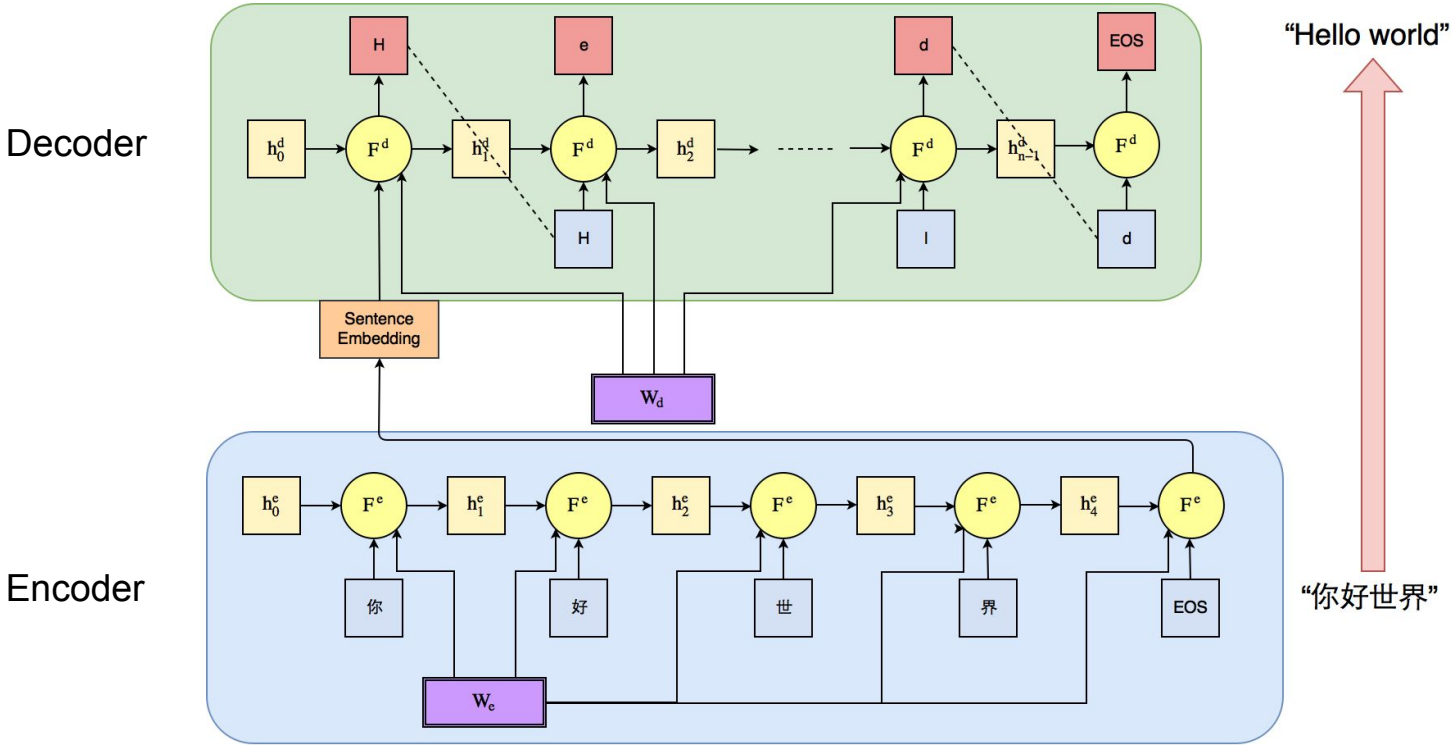
# Many-to-One + One-to-Many

## Neural Machine Translation



# Many-to-One + One-to-Many

## Neural Machine Translation

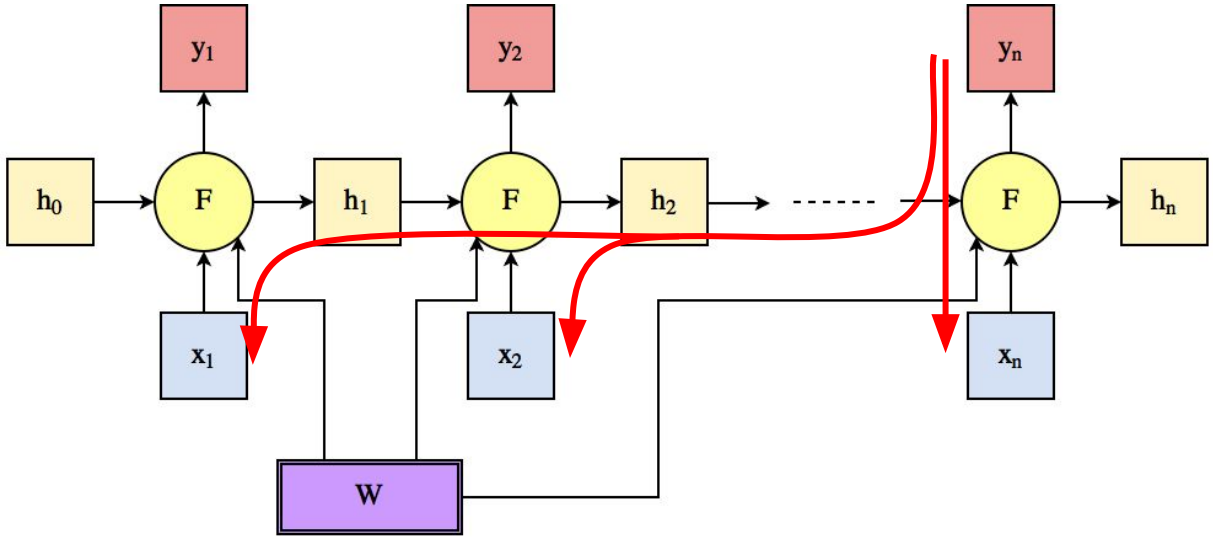


# Vanishing/Exploding Gradient Problem

"Grow longer! Grow longer!"

# Training RNN

- “Backpropagation Through Time”
  - Truncated BPTT
- The chain rule of differentiation
  - Just Backpropagation



# Vanishing/Exploding Gradient Problem

- Consider a ***linear*** recurrent net with zero inputs
- $$h_t = W_{hh} h_{t-1} = h_0 W_{hh}^t$$

Bengio, Yoshua, Patrice Simard, and Paolo Frasconi. "Learning long-term dependencies with gradient descent is difficult." IEEE transactions on neural networks 5.2 (1994): 157-166.
https://en.wikipedia.org/wiki/Power_iteration
http://www.cs.cornell.edu/~bindel/class/cs6210-f09/lec26.pdf

# Vanishing/Exploding Gradient Problem

- Consider a ***linear*** recurrent net with zero inputs
- $$h_t = W_{hh} h_{t-1} = h_0 W_{hh}^t$$
- 
- Singular value of W < 1 ⇒ only if gradient Vanishes
- Singular value of W > 1 ⇐ if gradient Explodes

Bengio, Yoshua, Patrice Simard, and Paolo Frasconi. "Learning long-term dependencies with gradient descent is difficult." IEEE transactions on neural networks 5.2 (1994): 157-166.
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# Vanishing/Exploding Gradient Problem

- Consider a ***linear*** recurrent net with zero inputs
- $$h_t = W_{hh} h_{t-1} = h_0 W_{hh}^t$$
- 
- “It is **sufficient** for the largest eigenvalue λ_1 of the recurrent weight matrix to be smaller than 1 for long term components to vanish (as t → ∞) and **necessary** for it to be larger than 1 for gradients to explode.”

**Details are here**

Bengio, Yoshua, Patrice Simard, and Paolo Frasconi. "Learning long-term dependencies with gradient descent is difficult." IEEE transactions on neural networks 5.2 (1994): 157-166.
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# Empirical Feasible Length of RNN

RNN

100

# Long short-term memory (LSTM) come to the rescue

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

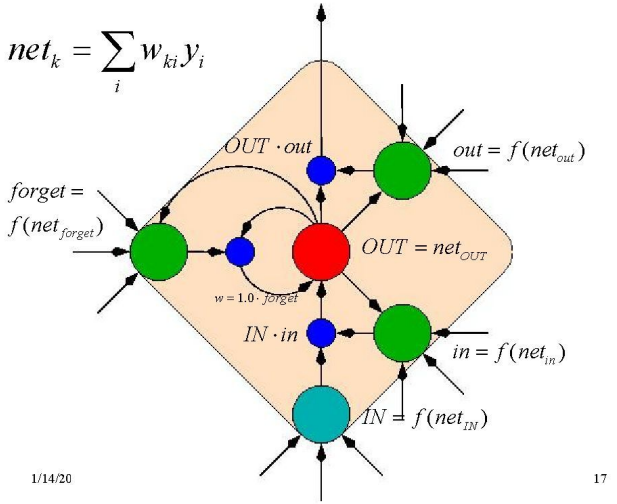
# Why LSTM works

- i: input gate
- f: forget gate
- o: output gate
- g: temporary variable
- c: memory cell
-
- Key observation:
  - If **f** == 1 (remember past memories), then
    - $c_t = c_{t-1} + i \odot g$
  - Looks like a ResNet!
    - $x_{t+1} = x_t + F(x_t)$

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

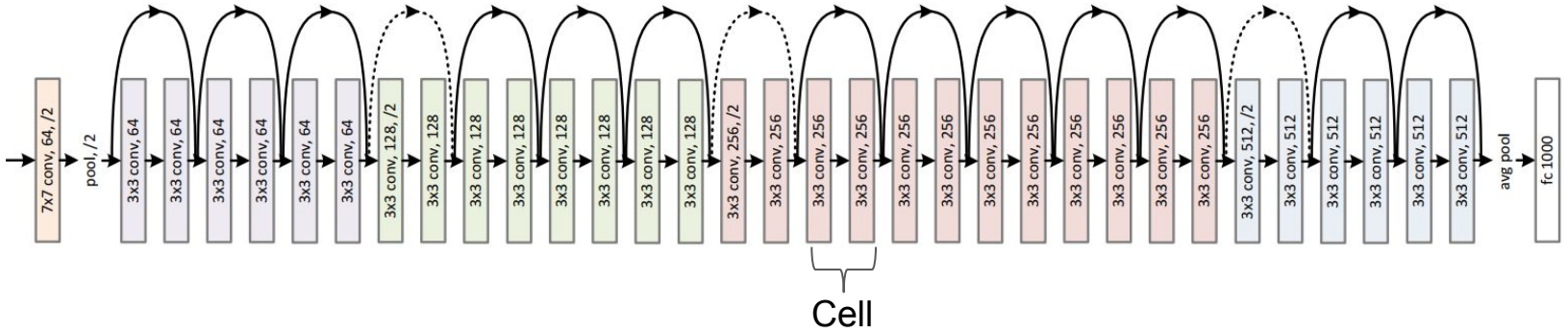
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$




http://people.idsia.ch/~juergen/lstm/sld017.htm

# LSTM vs Weight Sharing ResNet




- Difference
  - Never forgets
  - No intermediate inputs

$$c_t = c_{t-1} + i \odot g$$

vs

$$x_{t+1} = x_t + F(x_t)$$

# Empirical Feasible Length of LSTM

RNN

100

LSTM

500

# GRU

- Similar to LSTM
- Let information flow without a separate memory cell
-
- Consider $z_t = 0$

$$\begin{pmatrix} z_t \\ r_t \end{pmatrix} = \sigma\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$\tilde{h}_t = \tanh(W x_t + U(r_t \odot h_{t-1}))$$

$$h_t = (1 - z_t) h_{t-1} + z_t \tilde{h}_t$$

Chung, Junyoung, et al. "Empirical evaluation of gated recurrent neural networks on sequence modeling." arXiv preprint arXiv:1412.3555 (2014).

# Empirical Feasible Length of GRU

| RNN | LSTM | GRU |
| --- | --- | --- |
| 100 | 500 | 784 |

# IndRNN

- RNN: $\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b})$
- IndRNN: $\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{u} \odot \mathbf{h}_{t-1} + \mathbf{b})$

Neurons in the same layer are **INDEPENDENT!**

Interneuron dependence is achieved by **STACKING** more layers of IndRNN

Li, Shuai, et al. "Independently recurrent neural network (indrnn): Building a longer and deeper rnn." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.

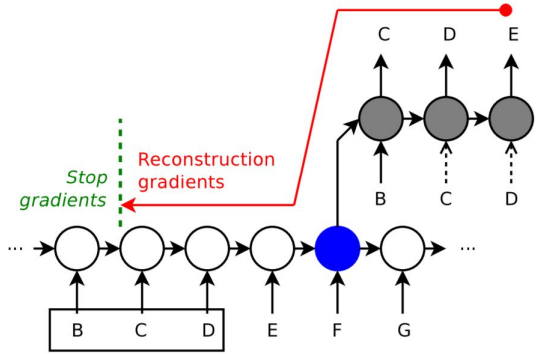
# Empirical Feasible Length of IndRNN

| RNN | LSTM | GRU |
| --- | --- | --- |
| 100 | 500 | 784 |

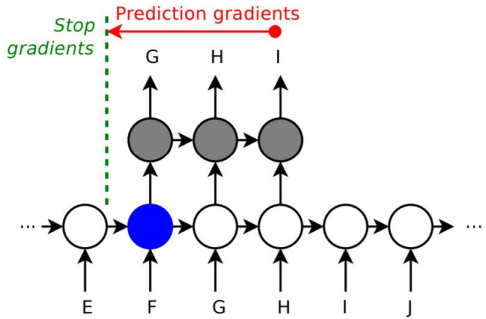
| IndRNN |
| --- |
| 5,000 |

# Auxiliary Losses

- No gradient? Create one!




Recall past
回顾过去




Predict future
展望未来

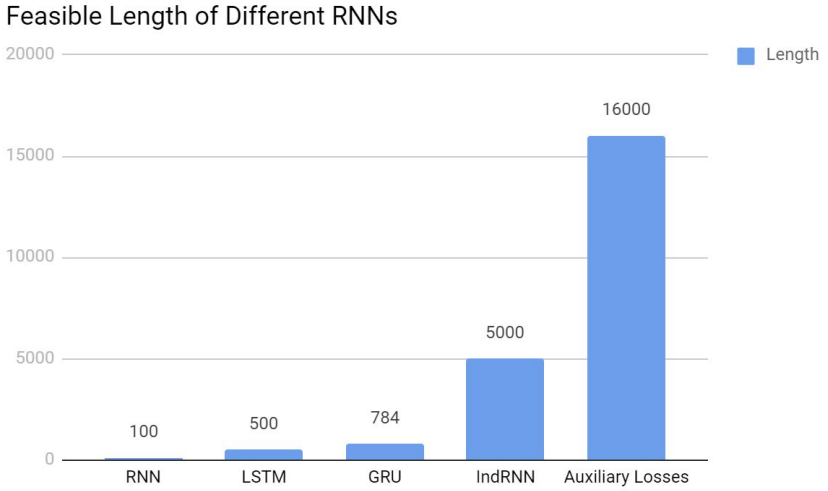
# Empirical Feasible Length of IndRNN

| RNN | LSTM | GRU |
| --- | --- | --- |
| 100 | 500 | 784 |

| IndRNN | Auxiliary Losses |
| --- | --- |
| 5,000 | 16,000 |

# Summary

| Method | Feasible Length |
| --- | --- |
| RNN | < 100 |
| LSTM | 500 |
| GRU | 784 |
| IndRNN | 5,000 |
| Auxiliary Losses | 16,000 |

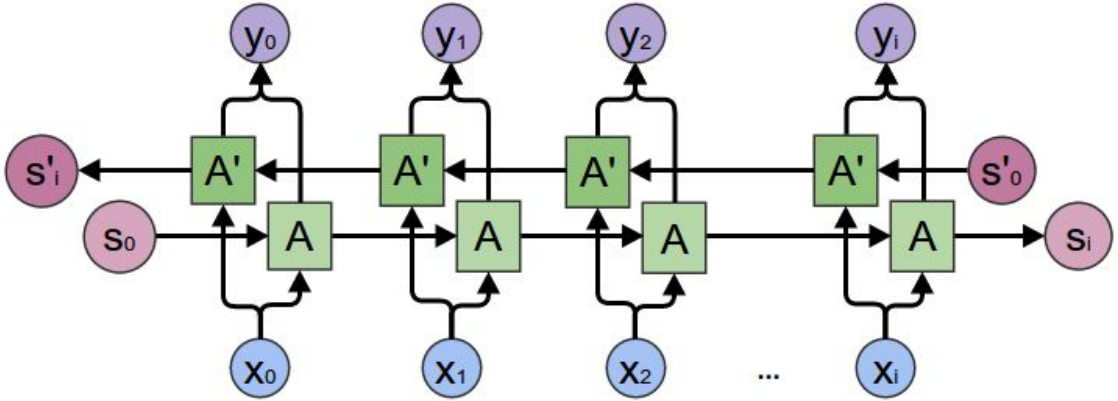


# Simple RNN Extensions

"I am a man of value"

# Bidirectional RNN (BDRNN)

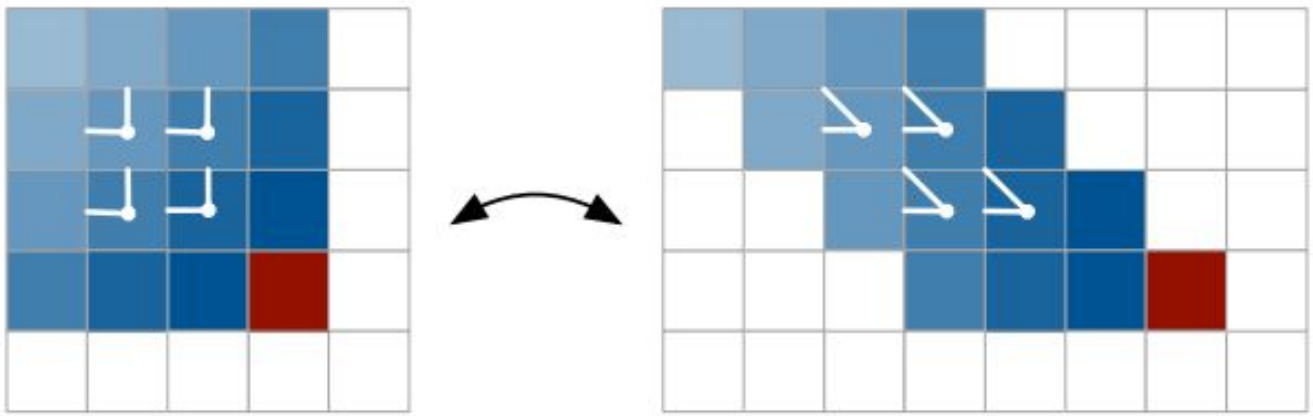
- RNN can go either way
- “Peak into the future”
- Truncated version used in speech recognition




https://github.com/huseinzol05/Generate-Music-Bidirectional-RNN

# 2D-RNN: Pixel-RNN

- Pixel-RNN
- Each pixel depends on its top and left neighbor



Oord, Aaron van den, Nal Kalchbrenner, and Koray Kavukcuoglu. "Pixel recurrent neural networks." arXiv preprint arXiv:1601.06759 (2016).

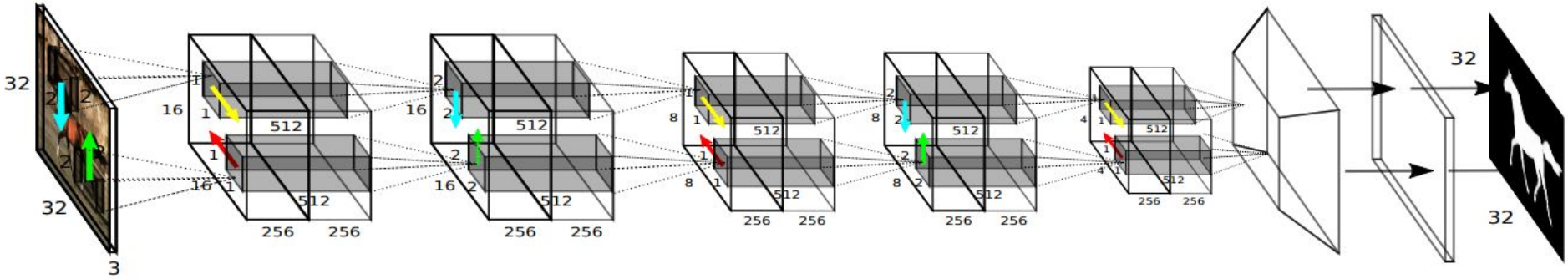
# Pixel-RNN


*Figure 1.* Image completions sampled from a PixelRNN.

Oord, Aaron van den, Nal Kalchbrenner, and Koray Kavukcuoglu. "Pixel recurrent neural networks." arXiv preprint arXiv:1601.06759 (2016).

# Pixel-RNN Application

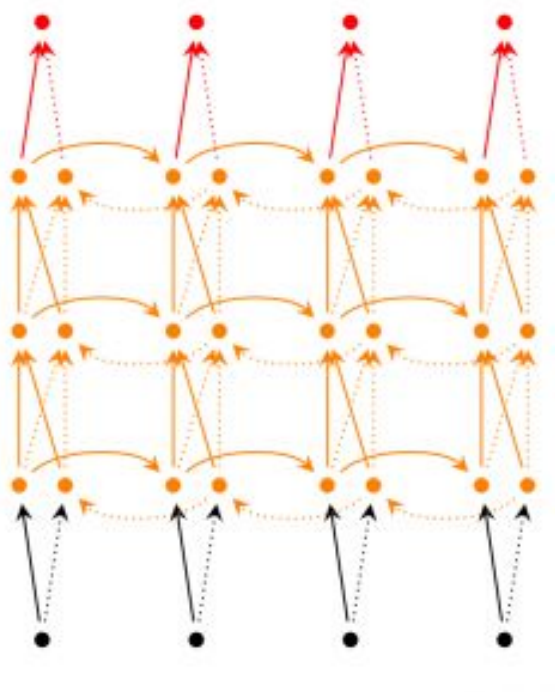
- Segmentation




Visin, Francesco, et al. "Reseg: A recurrent neural network-based model for semantic segmentation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2016.

# Deep RNN

- Stack more of them
  - Pros
    - More representational power
  - Cons
    - Harder to train
      - ⇒ Need residual connections along depth



# RNN Basics Summary

- The evolution of RNN from Feedforward NN
- Recurrence as unrolled computation graph
- Vanishing/Exploding gradient problem
  - LSTM and variants
  - $\text{recurrence} \in \text{weight-sharing}$ and the relation to ResNet
- Extensions
  - BDRNN
  - 2DRNN
  - Deep-RNN

# Interpretation of RNN

# Interpreting Gates in LSTM

- Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact
that it plainly and indubitably proved the fallacy of all the plans for
cutting off the enemy's retreat and the soundness of the only possible
line of action--the one Kutuzov and the general mass of the army
demanded--namely, simply to follow the enemy up. The French crowd fled
at a continually increasing speed and all its energy was directed to
reaching its goal. It fled like a wounded animal and it was impossible
to block its path. This was shown not so much by the arrangements it
made for crossing as by what took place at the bridges. When the bridges
broke down, unarmed soldiers, people from Moscow and women with children
who were with the French transport, all--carried on by vis inertiae--
pressed forward into boats and into the ice-covered water and did not,
surrender.
```

Cell that turns on inside quotes:

```
"You mean to imply that I have nothing to eat out of.... On the
contrary, I can supply you with everything even if you want to give
dinner parties," warmly replied Chichagov, who tried by every word he
spoke to prove his own rectitude and therefore imagined Kutuzov to be
animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating
smile: "I meant merely to say what I said."
```

Cell that robustly activates inside if statements:

```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
        siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

Reference:http://karpathy.github.io/2015/05/21/rnn-effectiveness/

# Interpreting Gates in LSTM

Cell that turns on inside comments and quotes:

```
/* Duplicate LSM field information.  The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                       struct audit_field *sf)
{
  int ret = 0;
  char *lsm_str;
  /* our own copy of lsm_str */
  lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
  if (unlikely(!lsm_str))
    return -ENOMEM;
  df->lsm_str = lsm_str;
  /* our own (refreshed) copy of lsm_rule */
  ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
                                 (void **)&df->lsm_rule);
  /* Keep currently invalid fields around in case they
   * become valid after a policy reload. */
  if (ret == -EINVAL) {
    pr_warn("audit rule for LSM \'%s\' is invalid\n",
            df->lsm_str);
    ret = 0;
  }
  return ret;
}
```

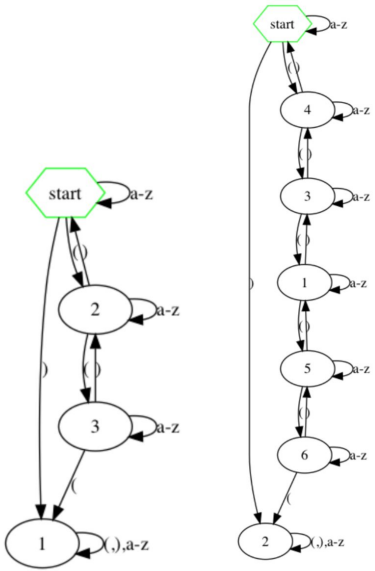
Cell that is sensitive to the depth of an expression:

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

Reference:http://karpathy.github.io/2015/05/21/rnn-effectiveness/

# Turn an RNN to a DFA

- DFA: Deterministic finite automaton
  - E.g.: Regular Expression



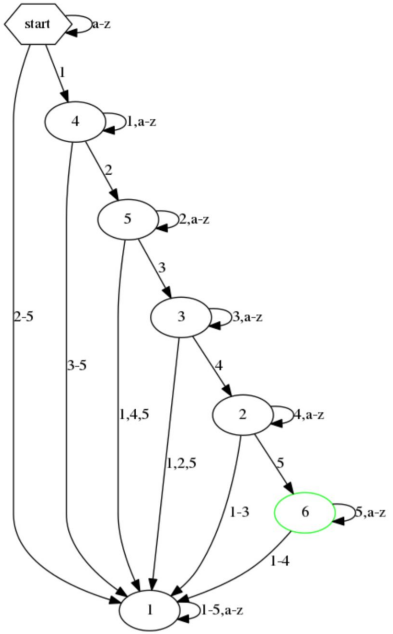
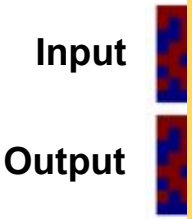




*Figure 3.* DFA representing the regular language [a-z]*1[a-z1]*2[a-z2]*3[a-z3]*4[a-z4]*5[a-z5]*$ over the alphabet {a,b,...,z,1,2,...,5}

Weiss, Gail, Yoav Goldberg, and Eran Yahav. "Extracting automata from recurrent neural networks using queries and counterexamples." arXiv preprint arXiv:1711.09576 (2017).

# RNN with Attention

# Copy a sequence




Can neural network learn this program purely from data?

```
# input data
input_list = [0, 2, 4, 4, 1, 5, 2]

ory
0] * len(input_list)

ing read

ut_list:
[loc_write] = value
= 1

ing stored

while loc_read < loc_write:
    print(model_memory[loc_read])
    loc_read += 1
```

# What is Attention?

- Differentiate entities by its importance
  - spatial attention is related to location
  - temporal attention is related to causality

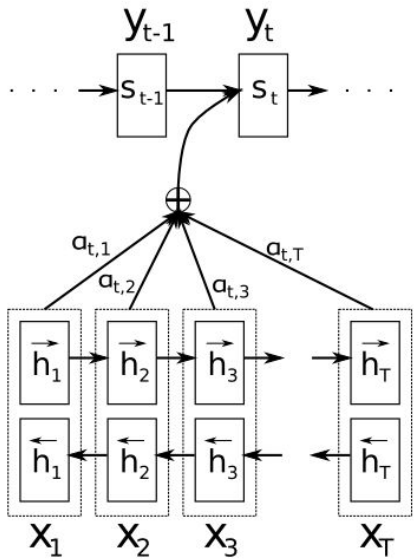
$$\sum \alpha_i x_i$$

$$0 \leq \alpha_i \leq 1$$


https://distill.pub/2016/augmented-rnns

# Attention over Input Sequence

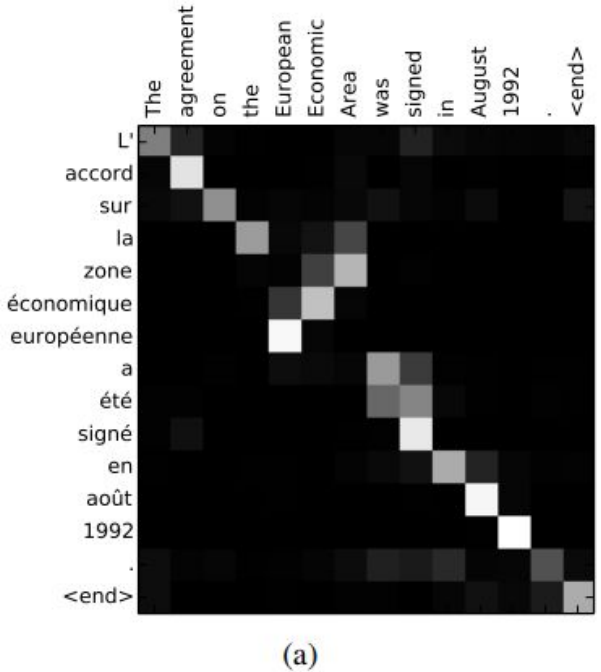
- Neural Machine Translation (NMT)




Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." arXiv preprint arXiv:1409.0473 (2014).

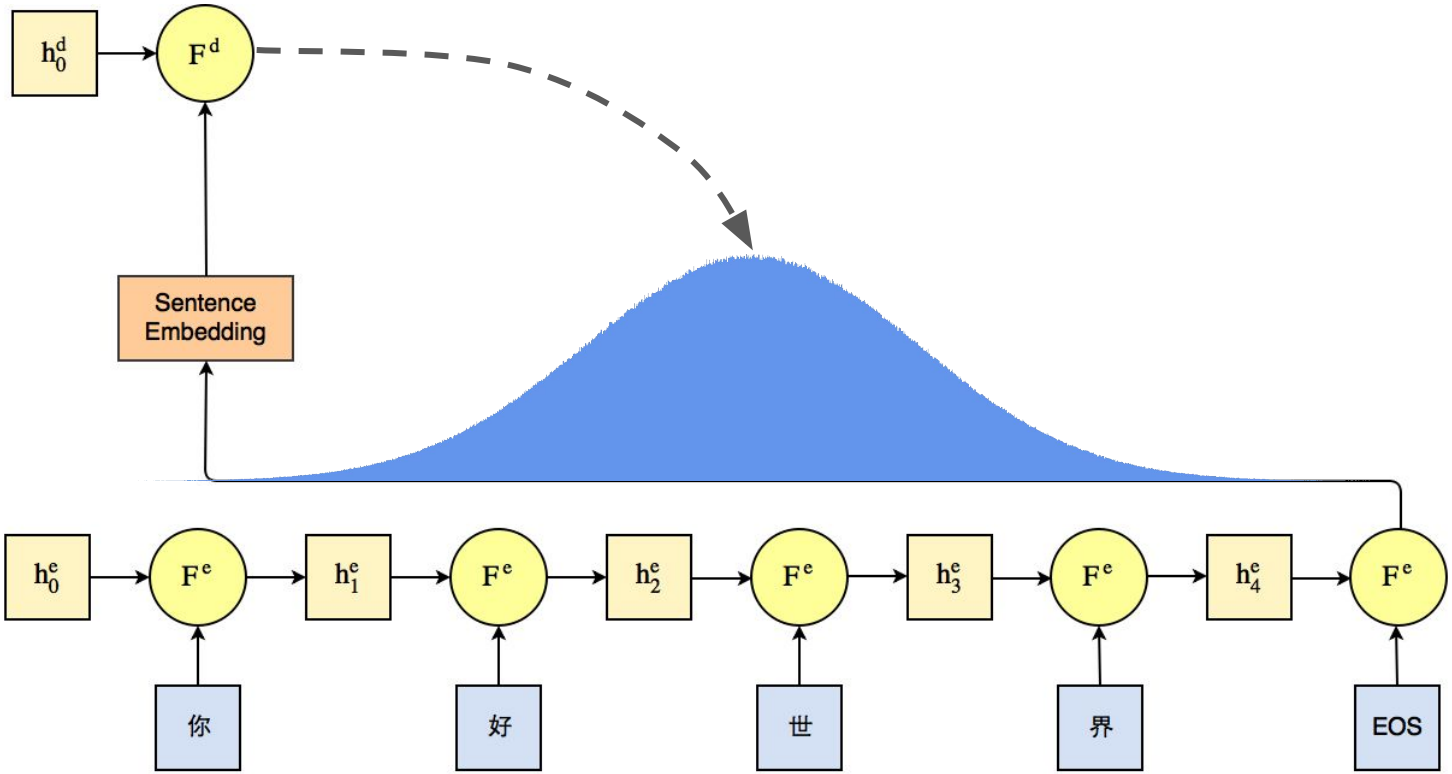
# Neural Machine Translation (NMT)

- Attention over input sequence
- There’re words in two languages that share the same meaning.
- Attention ⇒ Alignment
  - Differentiable, allowing end-to-end training




(a)

Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." arXiv preprint arXiv:1409.0473 (2014).


$h_0^d$
$F^d$
Sentence Embedding
$h_0^e$
$F^e$
$h_1^e$
$F^e$
$h_2^e$
$F^e$
$h_3^e$
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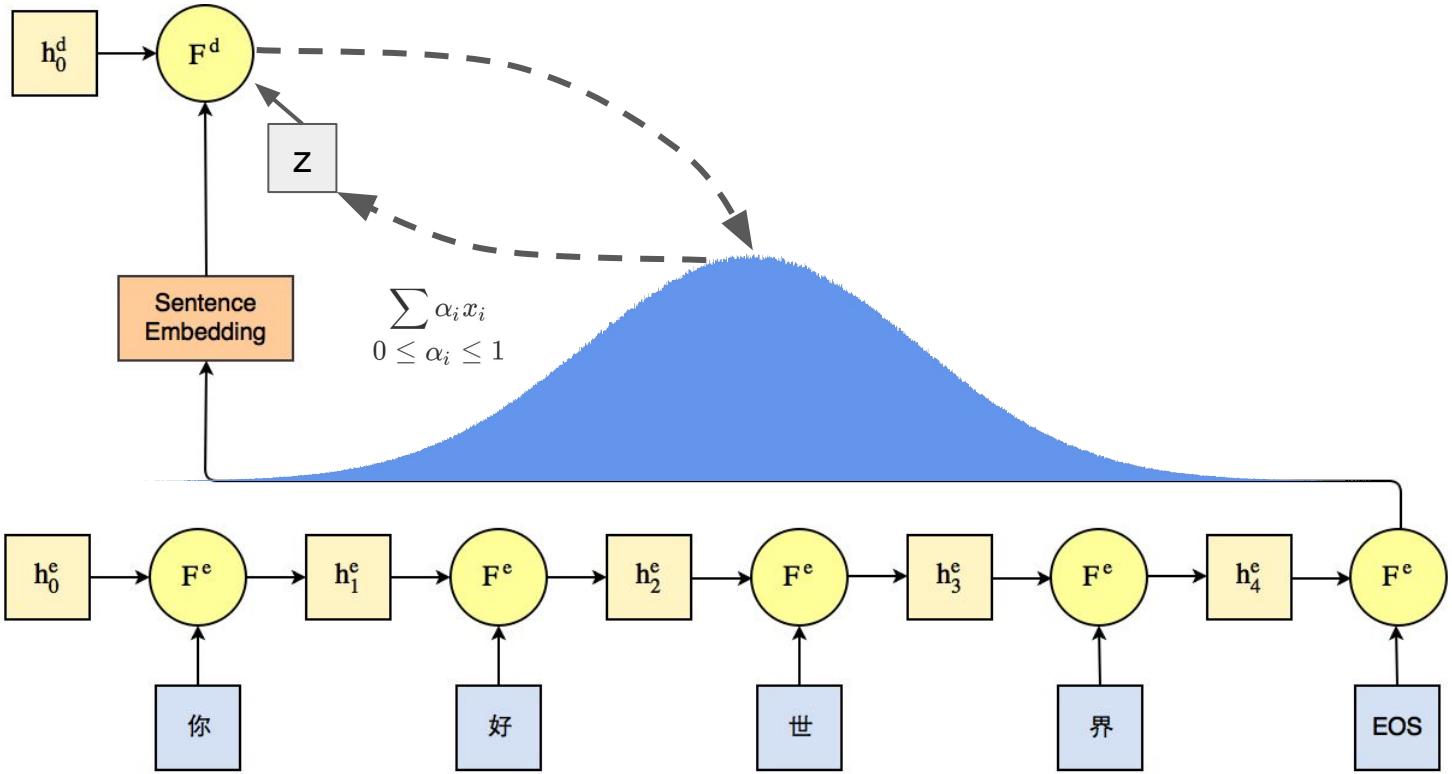
$h_0^d$
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Sentence Embedding
$\sum \alpha_i x_i$
$0 \leq \alpha_i \leq 1$
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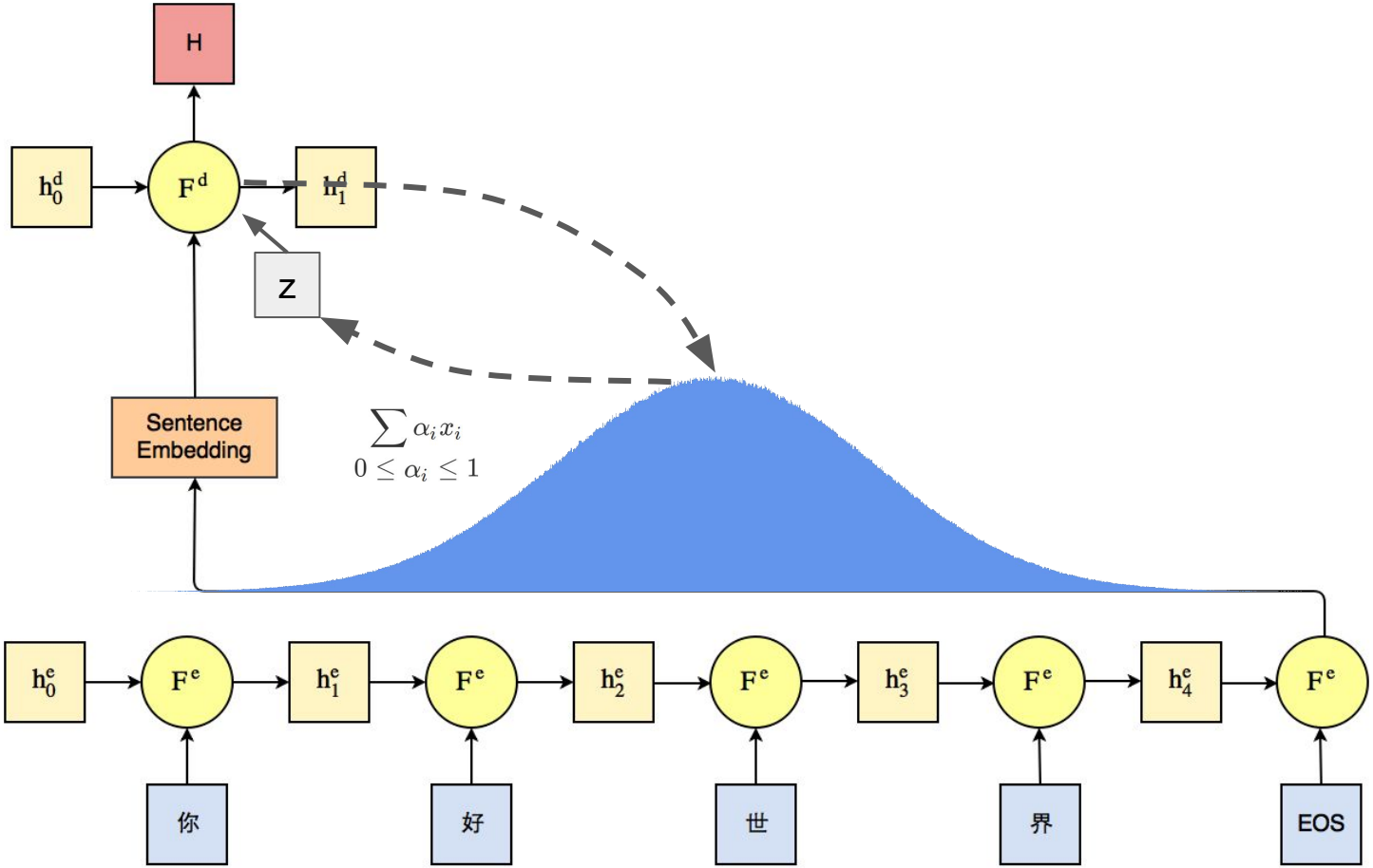
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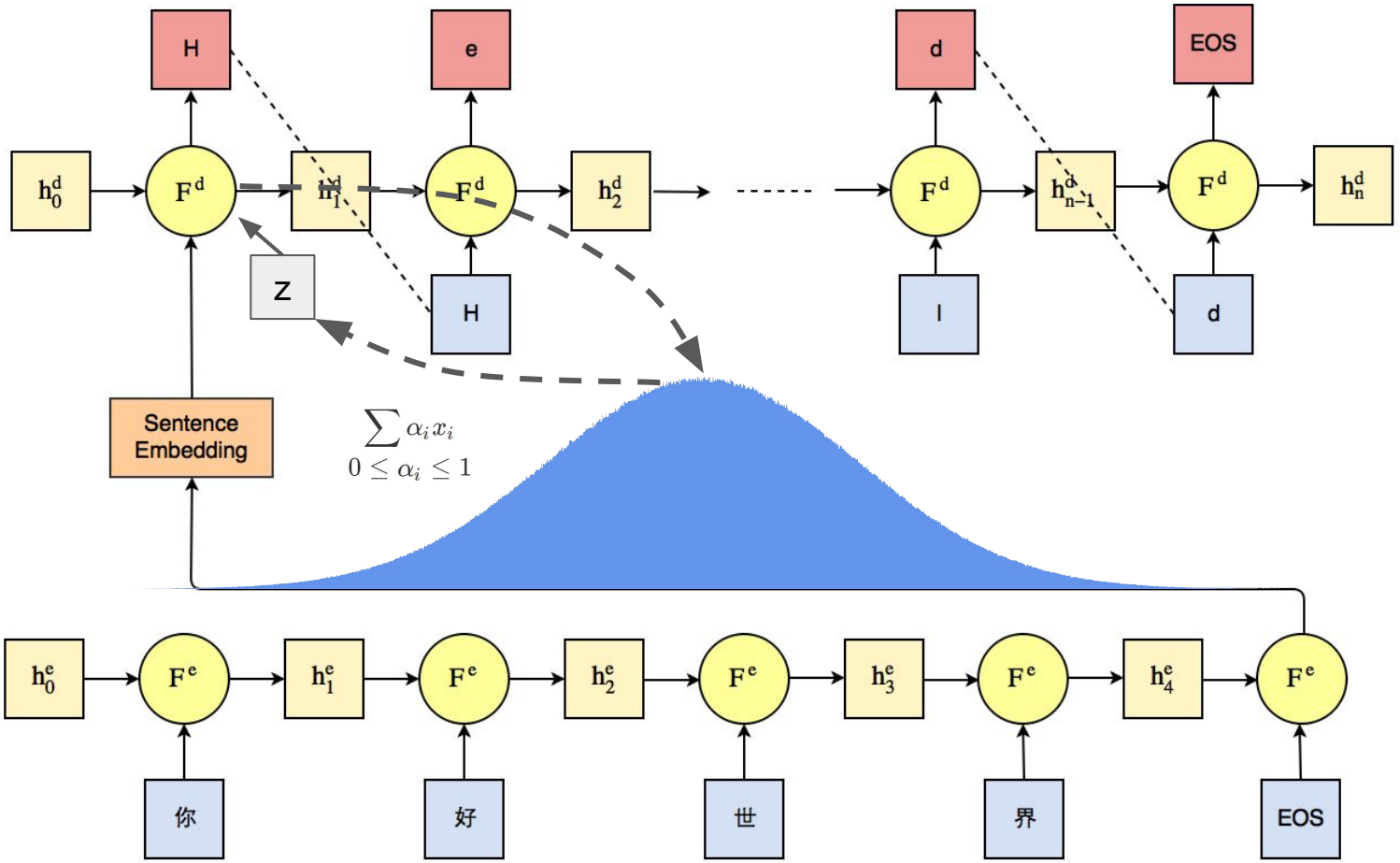
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Sentence Embedding
$\sum \alpha_i x_i$
$0 \leq \alpha_i \leq 1$
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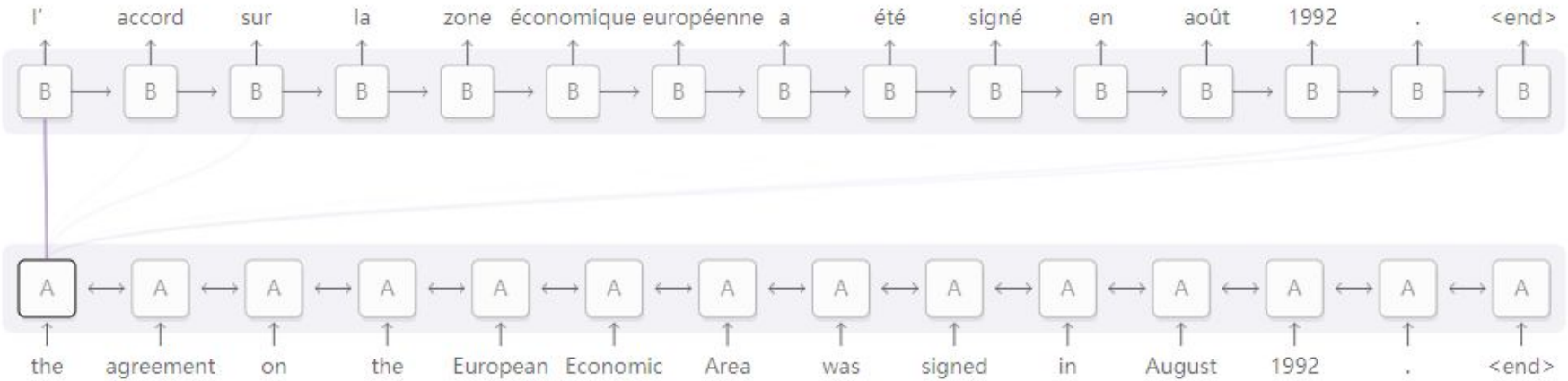
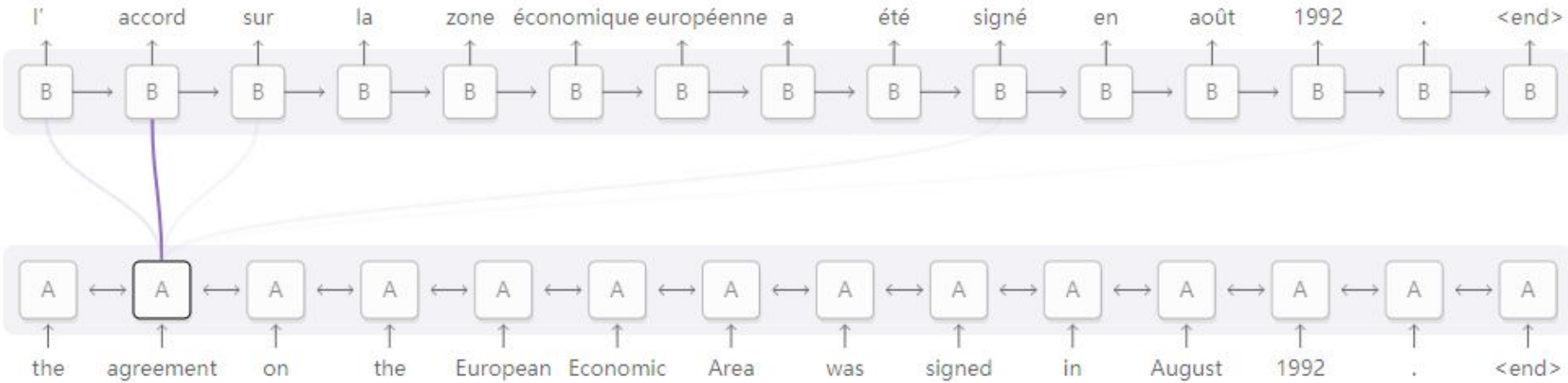



https://distill.pub/2016/augmented-rnns

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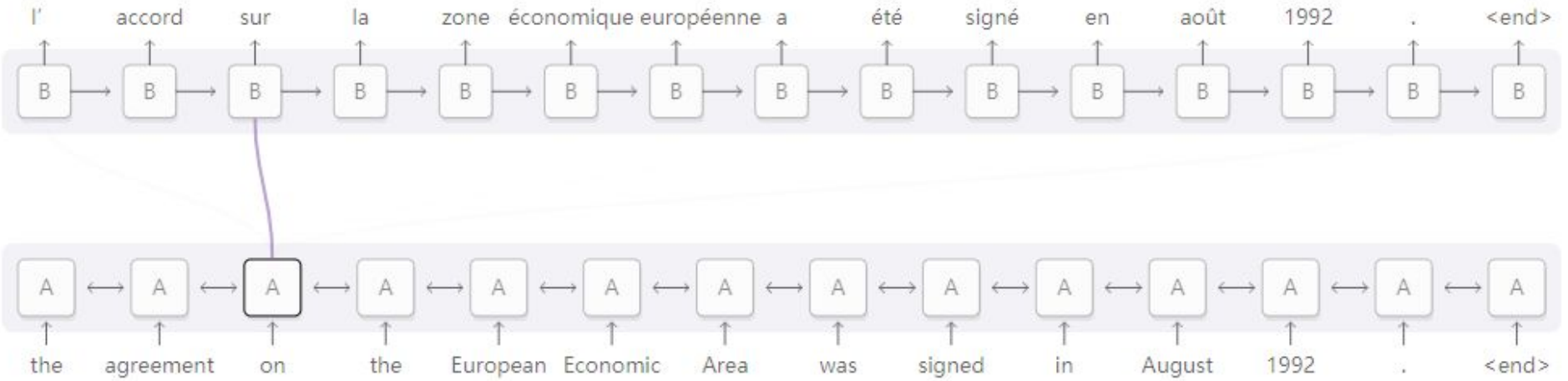


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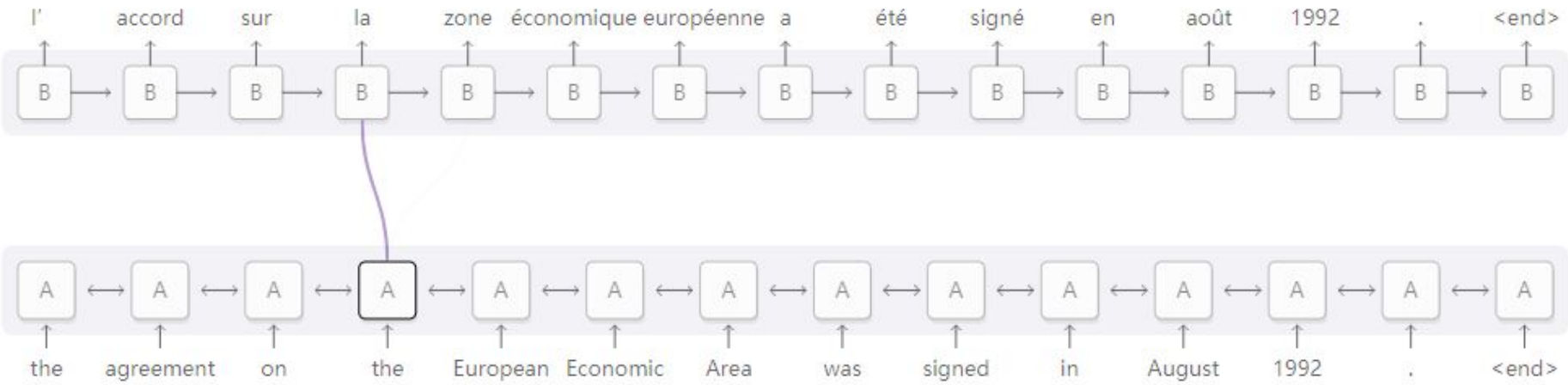


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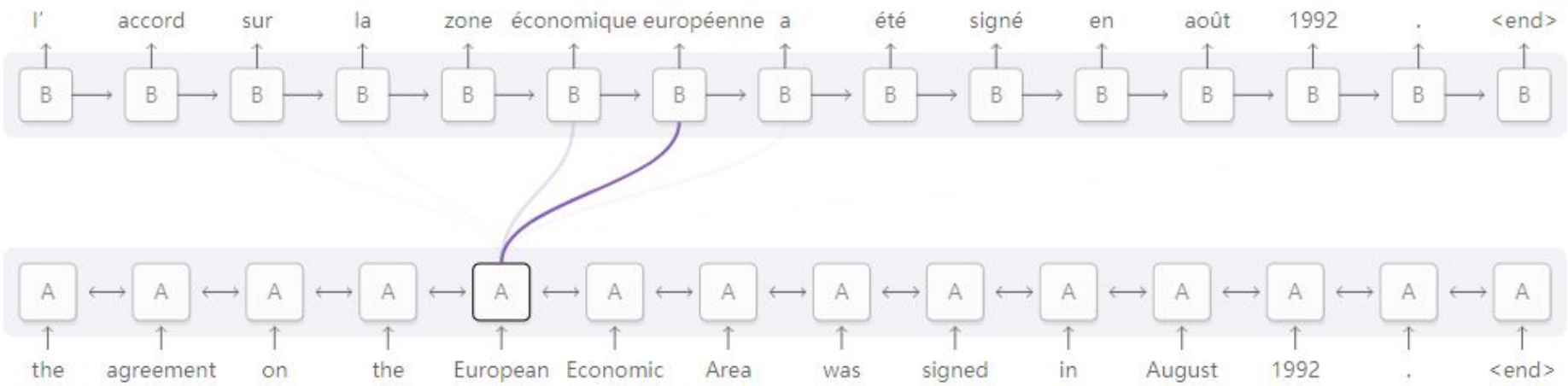


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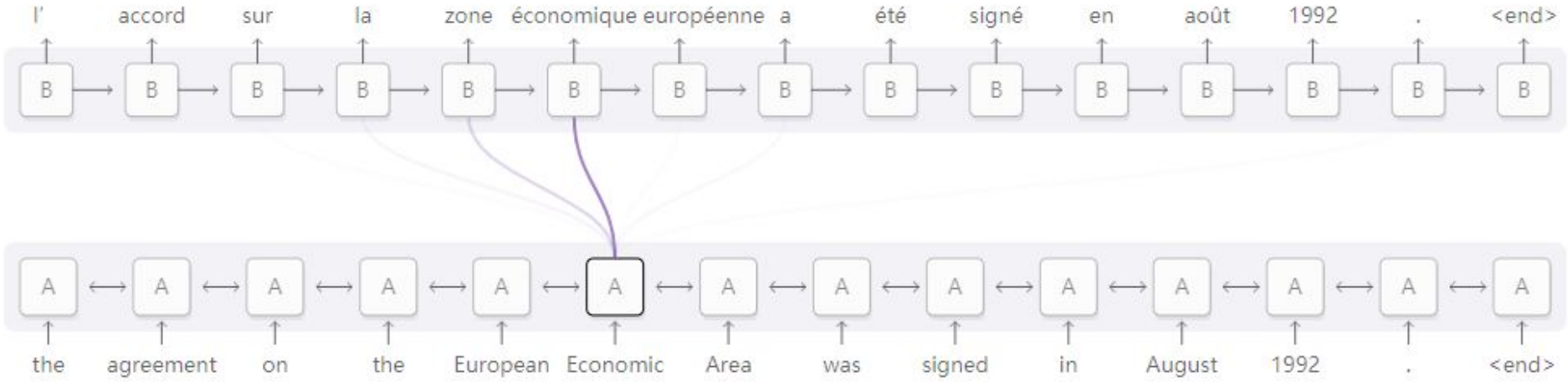


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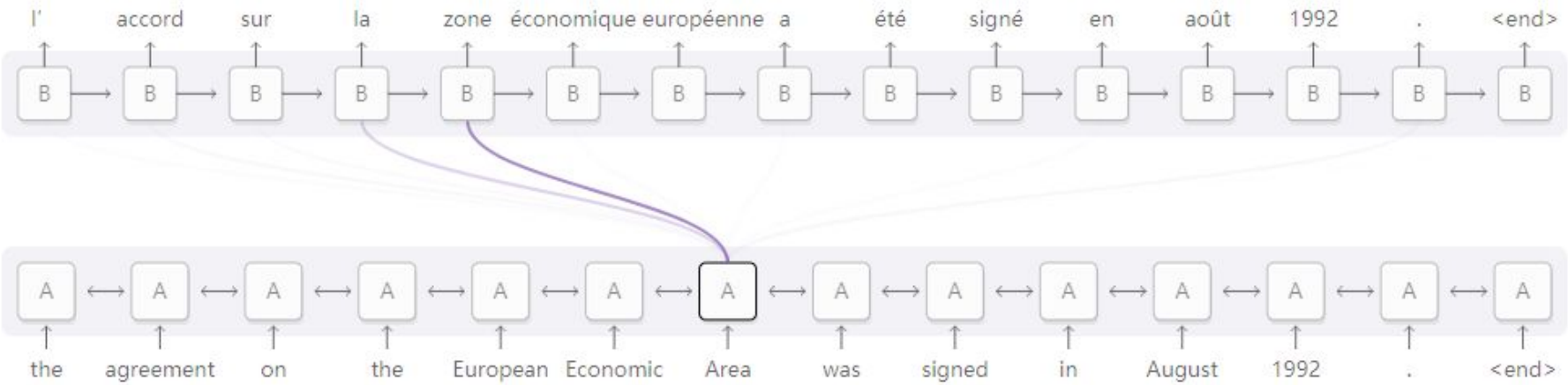
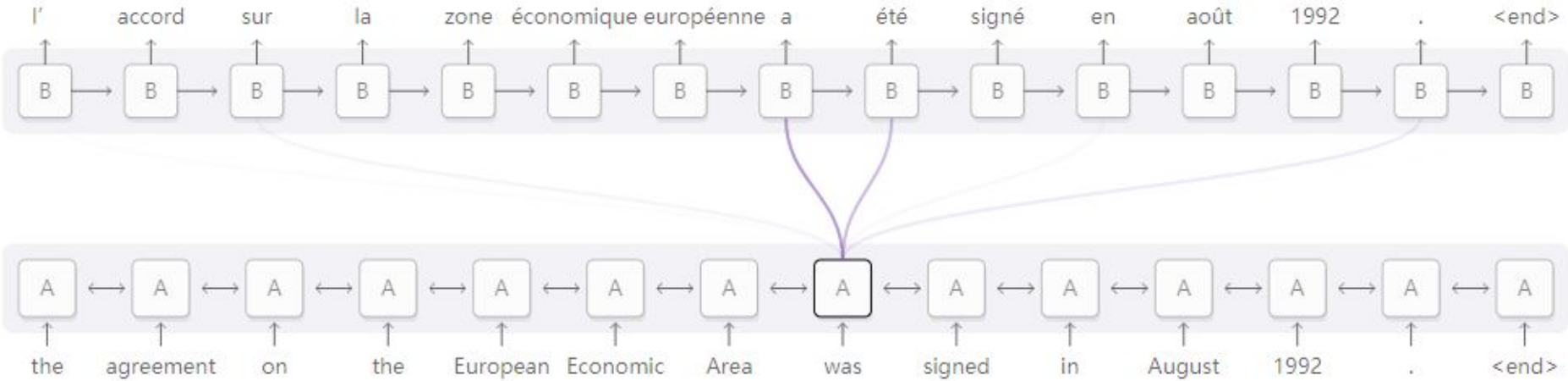
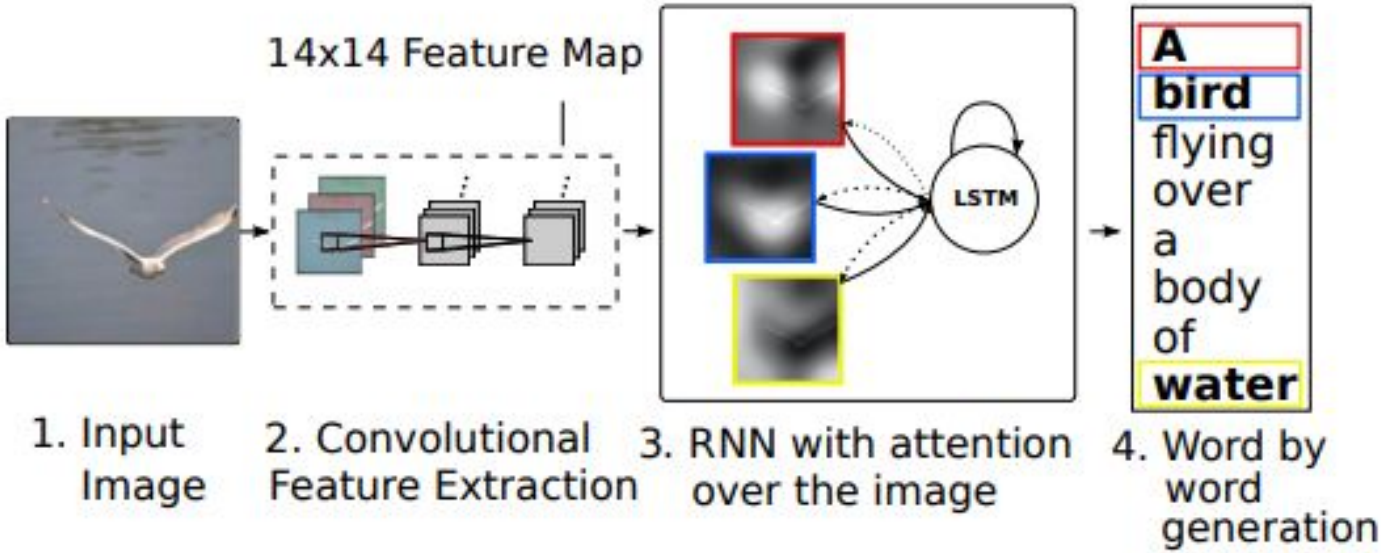



https://distill.pub/2016/augmented-rnns



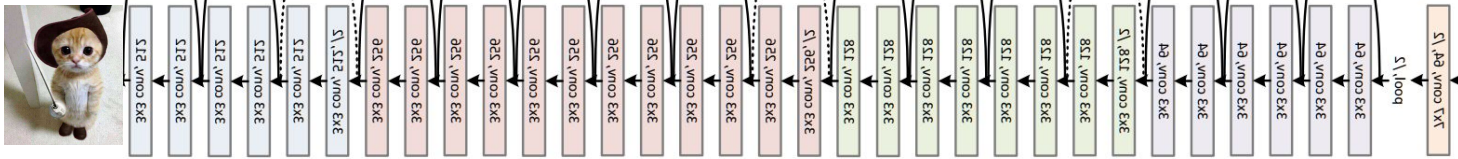

https://distill.pub/2016/augmented-rnns

# Image Attention: Image Captioning




Xu, Kelvin, et al. "Show, attend and tell: Neural image caption generation with visual attention." International Conference on Machine Learning. 2015.

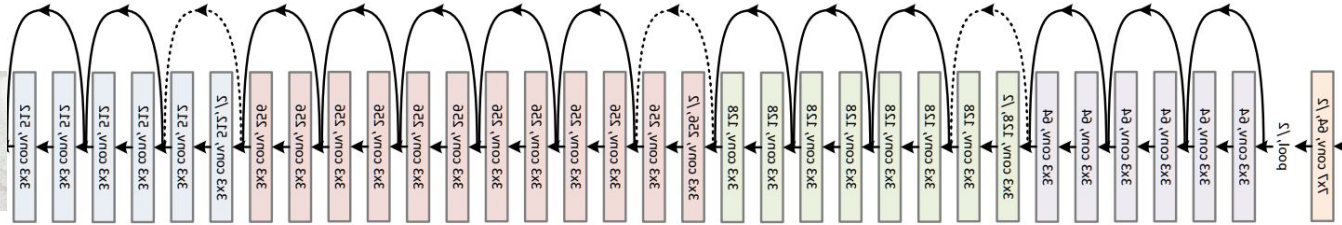
input cat



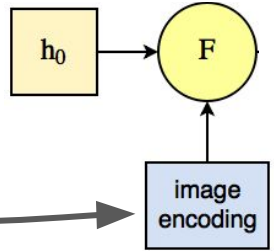

feature cat

input cat

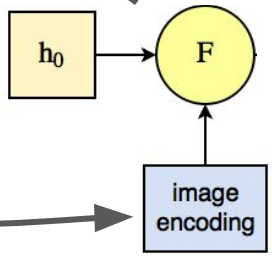
feature cat



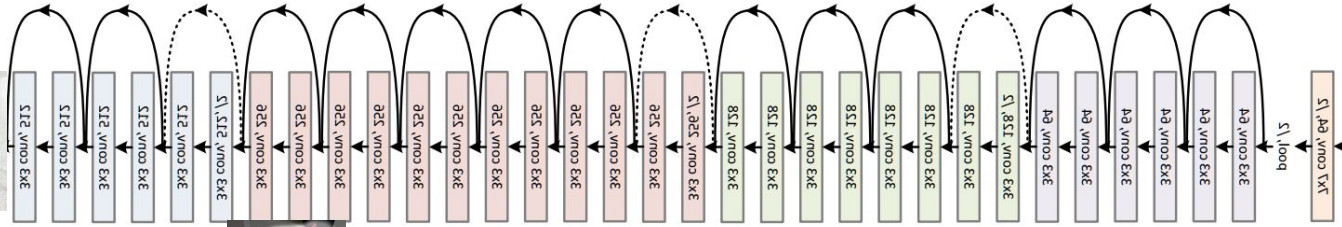
input cat



feature cat




input cat

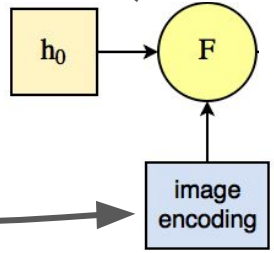


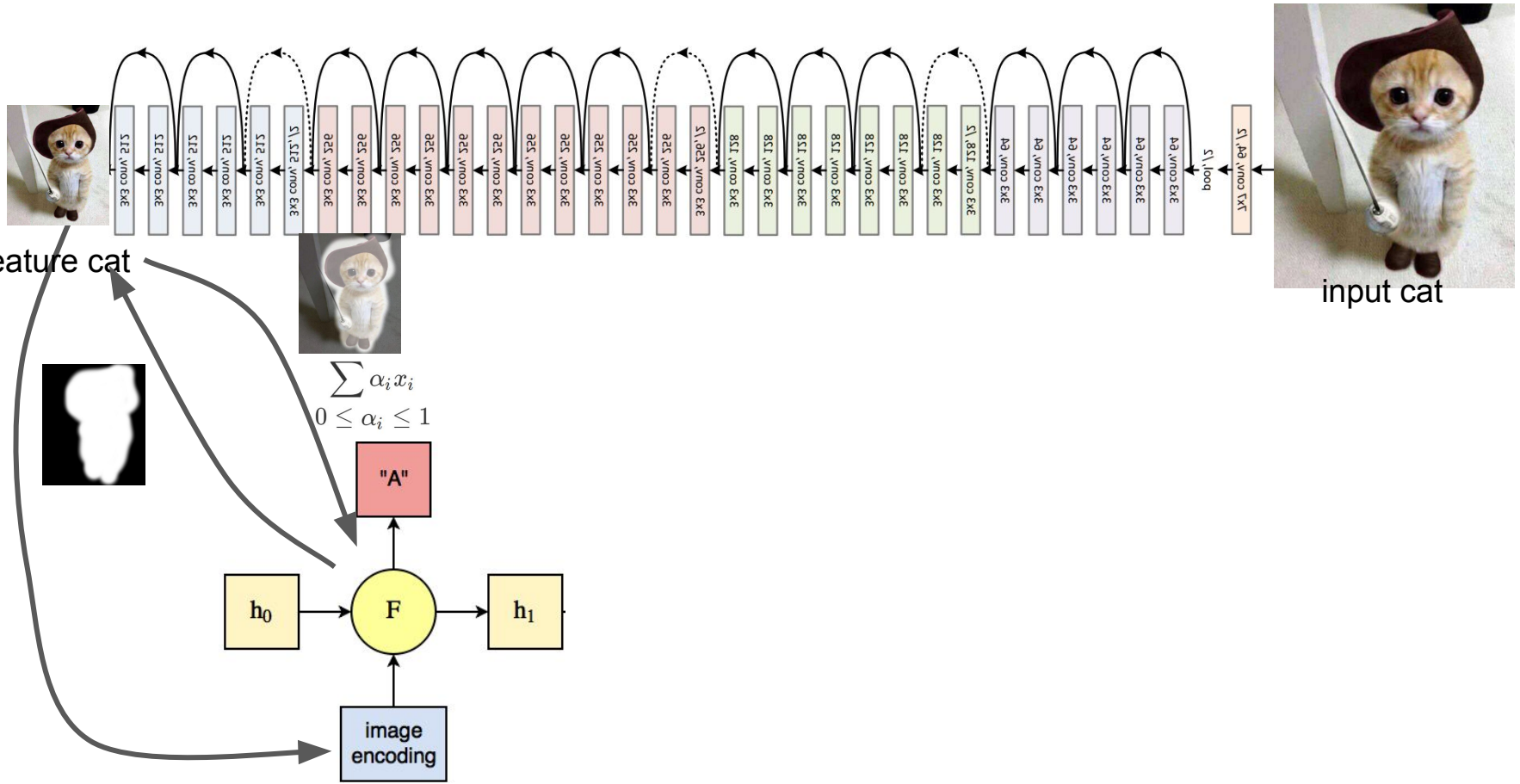

input cat

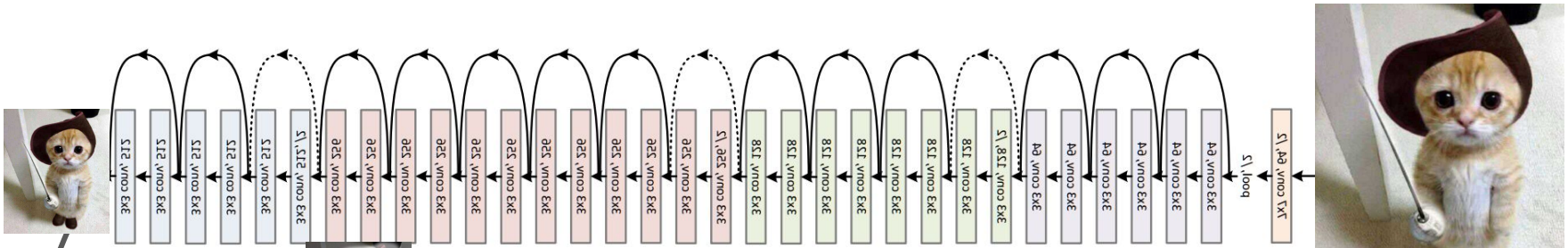
feature cat

$$\sum \alpha_i x_i$$

$$0 \leq \alpha_i \leq 1$$




feature cat
input cat
$\sum \alpha_i x_i$
$0 \leq \alpha_i \leq 1$
"A"
$h_0$
F
$h_1$
image encoding

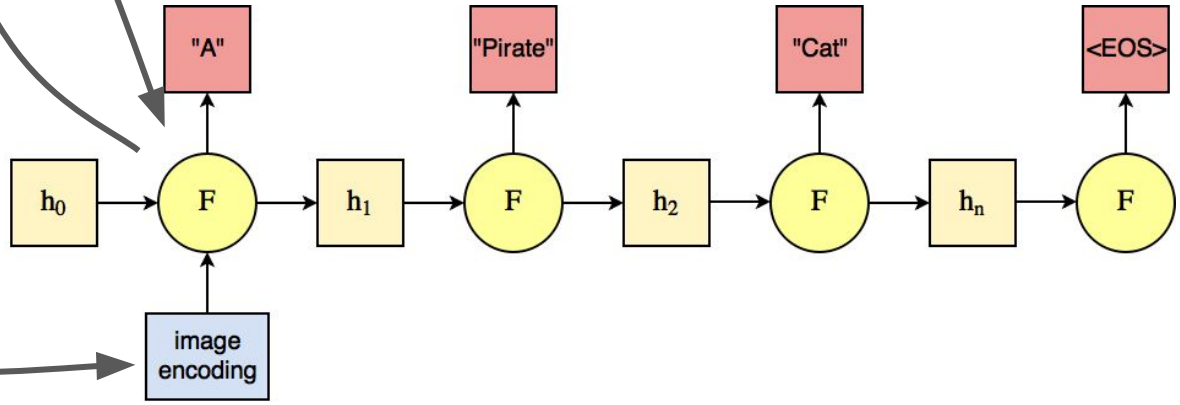


feature cat

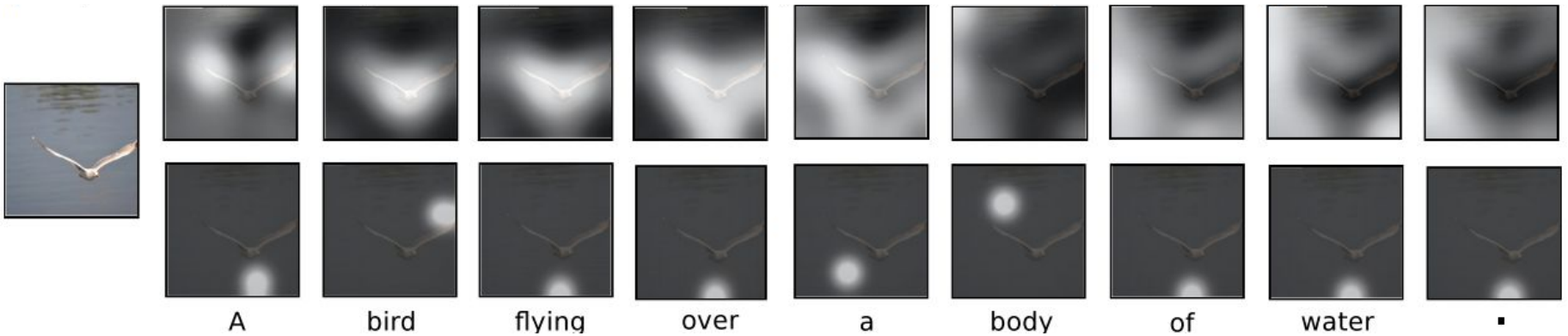
input cat



$$\sum \alpha_i x_i$$
$$0 \leq \alpha_i \leq 1$$



# Image Attention: Image Captioning



# Image Attention: Image Captioning

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.


A stop sign is on a road with a mountain in the background.

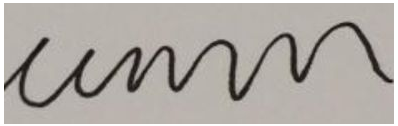
A little girl sitting on a bed with a teddy bear.

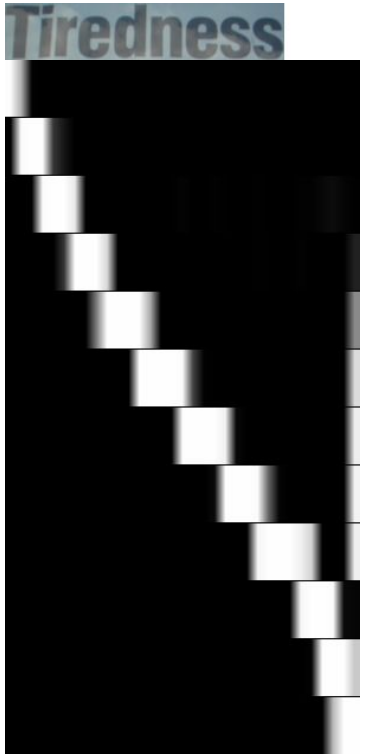
A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

# Text Recognition

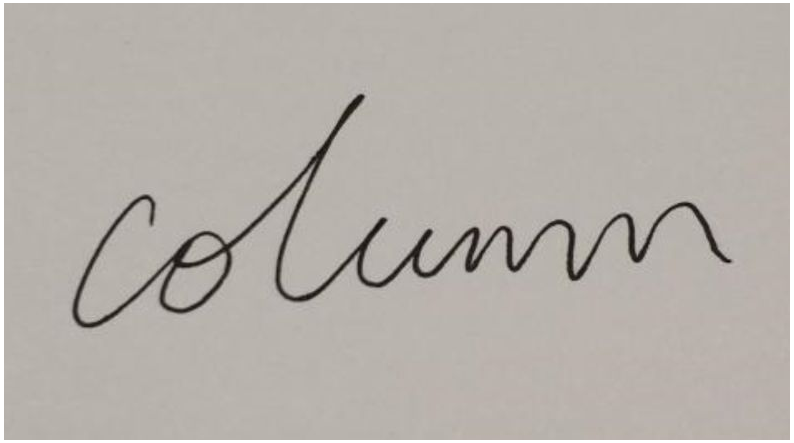
- Implicit language model

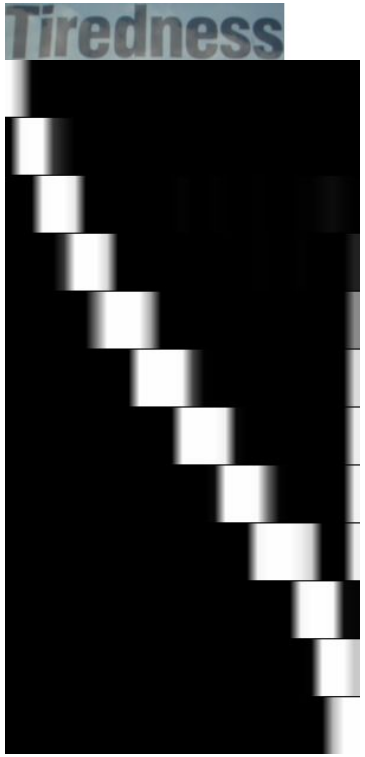




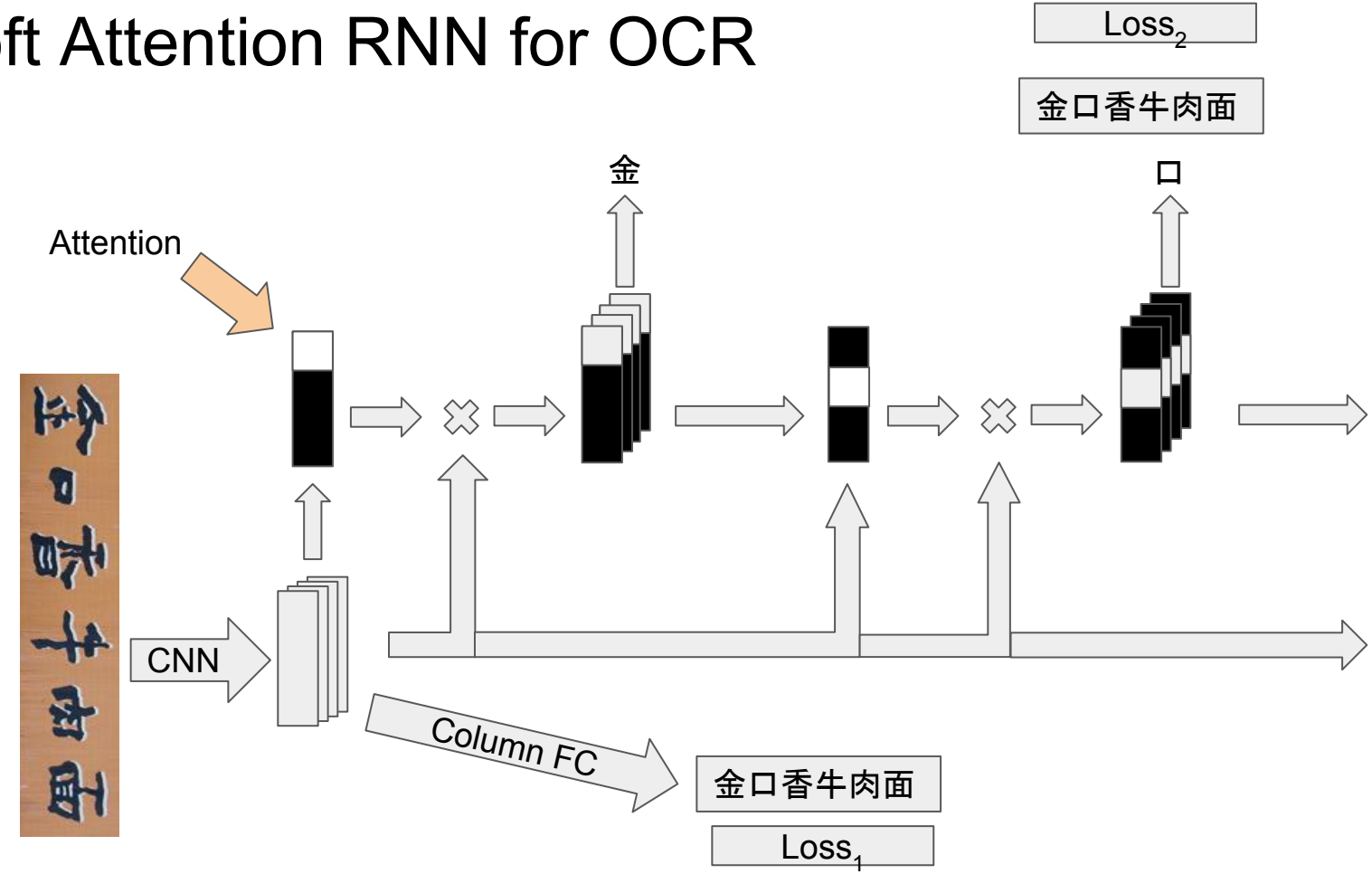
# Text Recognition

- Implicit language model



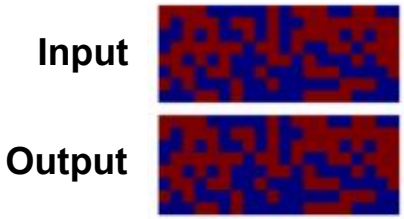
# Soft Attention RNN for OCR



# RNN with External Memory

"I Look Like a Computer"

# Copy a sequence



# Copy a sequence

Input

Output

Solution in Python

```python
# input data
input_list = [0, 2, 4, 4, 1, 5, 2]

# initialize memory
model_memory = [0] * len(input_list)

# store everything read
loc_write = 0
for value in input_list:
    model_memory[loc_write] = value
    loc_write += 1

# write everything stored
loc_read = 0
while loc_read < loc_write:
    print(model_memory[loc_read])
    loc_read += 1

```

# Traditional Machine Learning

- √ Elementary Operations
- √* Logic flow control
  - Decision tree
- × External Memory
  - As opposed to internal memory (hidden states)

Graves, Alex, Greg Wayne, and Ivo Danihelka. "Neural turing machines." arXiv preprint arXiv:1410.5401 (2014).

# Traditional Machine Learning

- √ Elementary Operations
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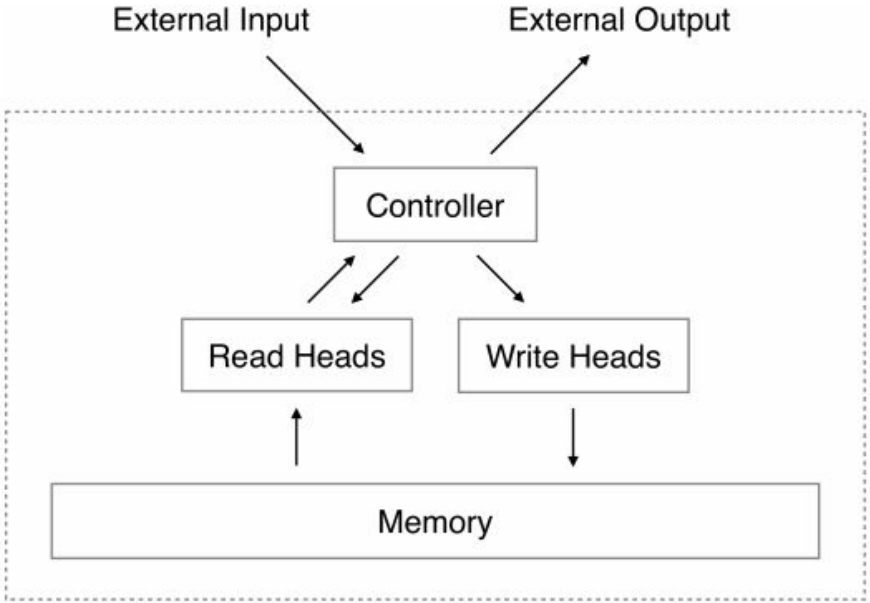
# Neural Turing Machines (NTM)

- NTM is a neural networks with a working memory
- It reads and write multiple times at each step
- Fully differentiable and can be trained end-to-end

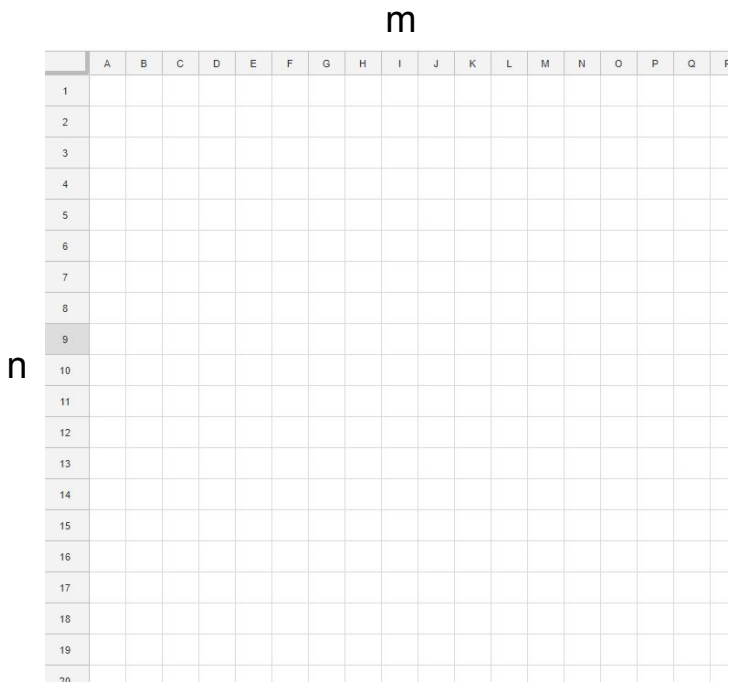



An NTM “Cell”

Graves, Alex, Greg Wayne, and Ivo Danihelka. "Neural turing machines." arXiv preprint arXiv:1410.5401 (2014).

# Neural Turing Machines (NTM)

- Memory
  - $\text{An } n \times m \text{ matrix } \mathbf{M}_t \text{ at time } t$




http://llcao.net/cu-deeplearning15/presentation/NeuralTuringMachines.pdf

# Neural Turing Machines (NTM)

- Read

$$\sum_i w_t(i) = 1, \;\; 0 \leq w_t(i) \leq 1, \forall i$$

$$\mathbf{r}_t \leftarrow \sum_i w_t(i)\mathbf{M}_t(i)$$

- Hard indexing ⇒ Soft Indexing
  - A distribution of index
  - “Attention”

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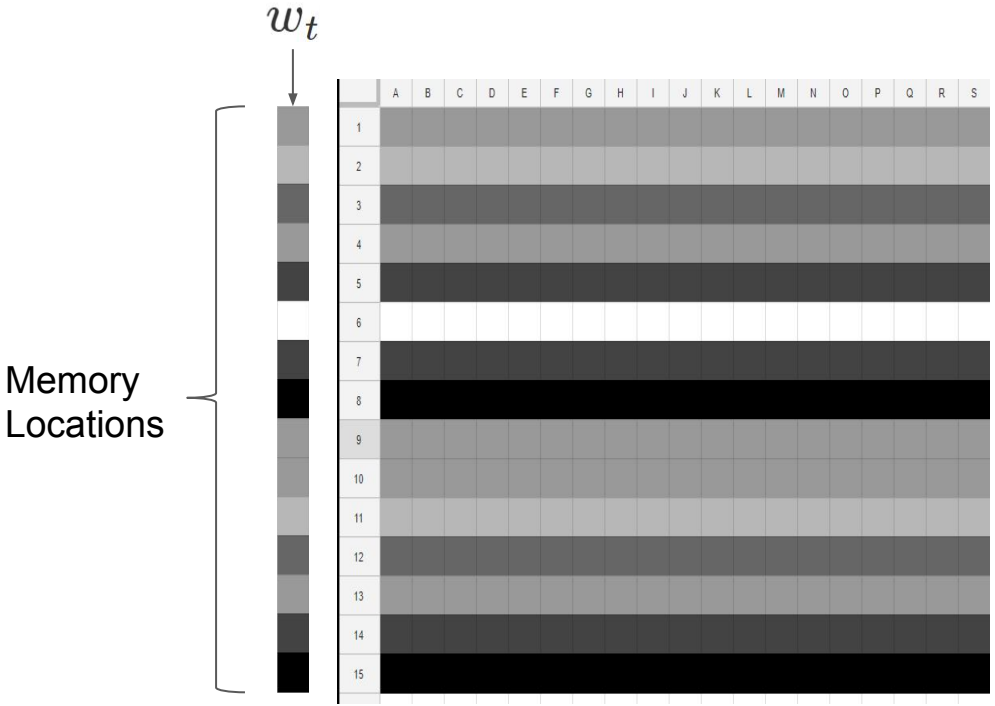

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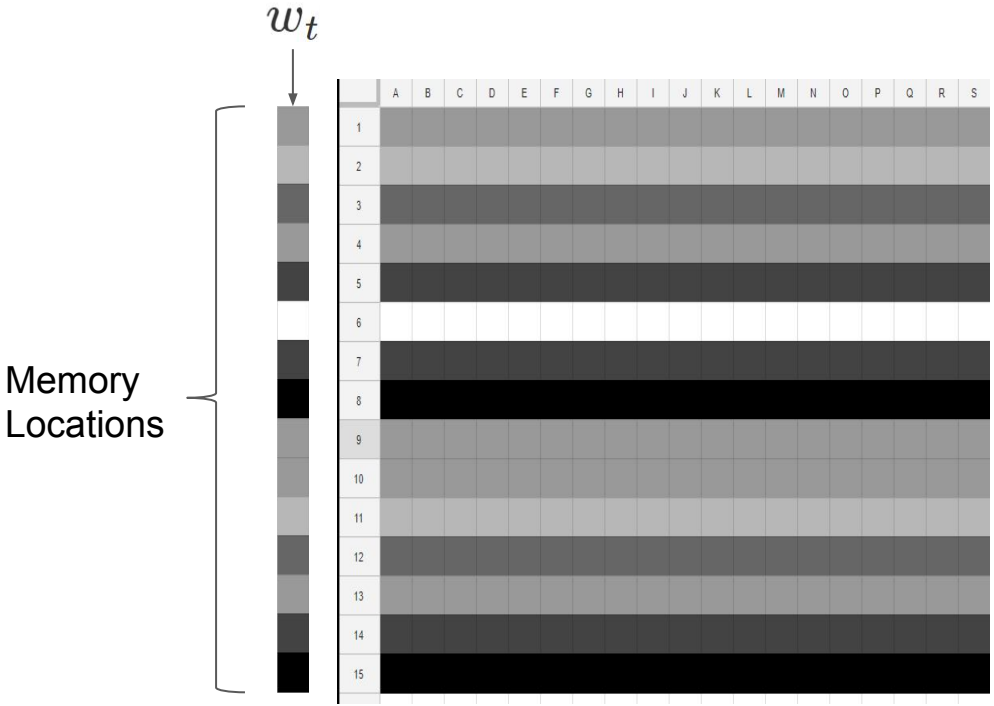

# Neural Turing Machines (NTM)

- Write
  - Write = erase + add

$$\tilde{\mathbf{M}}_t(i) \longleftarrow \mathbf{M}_{t-1}(i)\left[\mathbf{1} - w_t(i)\mathbf{e}_t\right], \quad \longleftarrow \text{erase}$$

$$\mathbf{M}_t(i) \longleftarrow \tilde{\mathbf{M}}_t(i) + w_t(i)\,\mathbf{a}_t. \quad \longleftarrow \text{add}$$

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# Neural Turing Machines (NTM)

- Addressing

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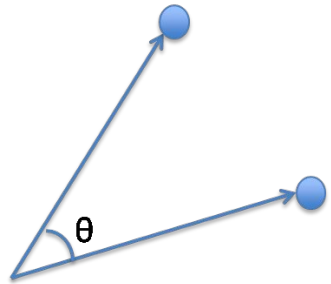
- Addressing
- 1. Focusing by Content

$$w_t^c(i) \longleftarrow \frac{\exp\Big(\beta_t K\big[\mathbf{k}_t, \mathbf{M}_t(i)\big]\Big)}{\sum_j \exp\Big(\beta_t K\big[\mathbf{k}_t, \mathbf{M}_t(j)\big]\Big)}.$$




- Cosine Similarity

$$K\big[\mathbf{u}, \mathbf{v}\big] = \frac{\mathbf{u} \cdot \mathbf{v}}{||\mathbf{u}|| \cdot ||\mathbf{v}||}.$$

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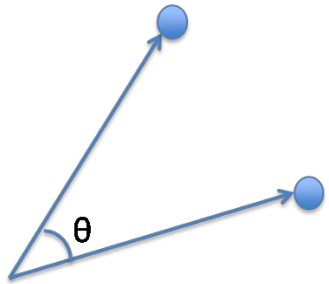
$$w_t^c(i) \leftarrow \frac{\exp\left(\beta_t K\left[\mathbf{k}_t, \mathbf{M}_t(i)\right]\right)}{\sum_j \exp\left(\beta_t K\left[\mathbf{k}_t, \mathbf{M}_t(j)\right]\right)}.$$

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# Neural Turing Machines (NTM)

- 1. Focusing by Content
- 2. Interpolate with previous step

$$\mathbf{w}_t^g \longleftarrow g_t \mathbf{w}_t^c + (1 - g_t)\mathbf{w}_{t-1}.$$

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$$\mathbf{w}_t^g \longleftarrow g_t \mathbf{w}_t^c + (1 - g_t)\mathbf{w}_{t-1}.$$

# Neural Turing Machines (NTM)

- 1. Focusing by Content
- 2. Interpolate with previous step
- 3. Convolutional Shift

$$\tilde{w}_t(i) \longleftarrow \sum_{j=0}^{N-1} w_t^g(j)\, s_t(i-j)$$

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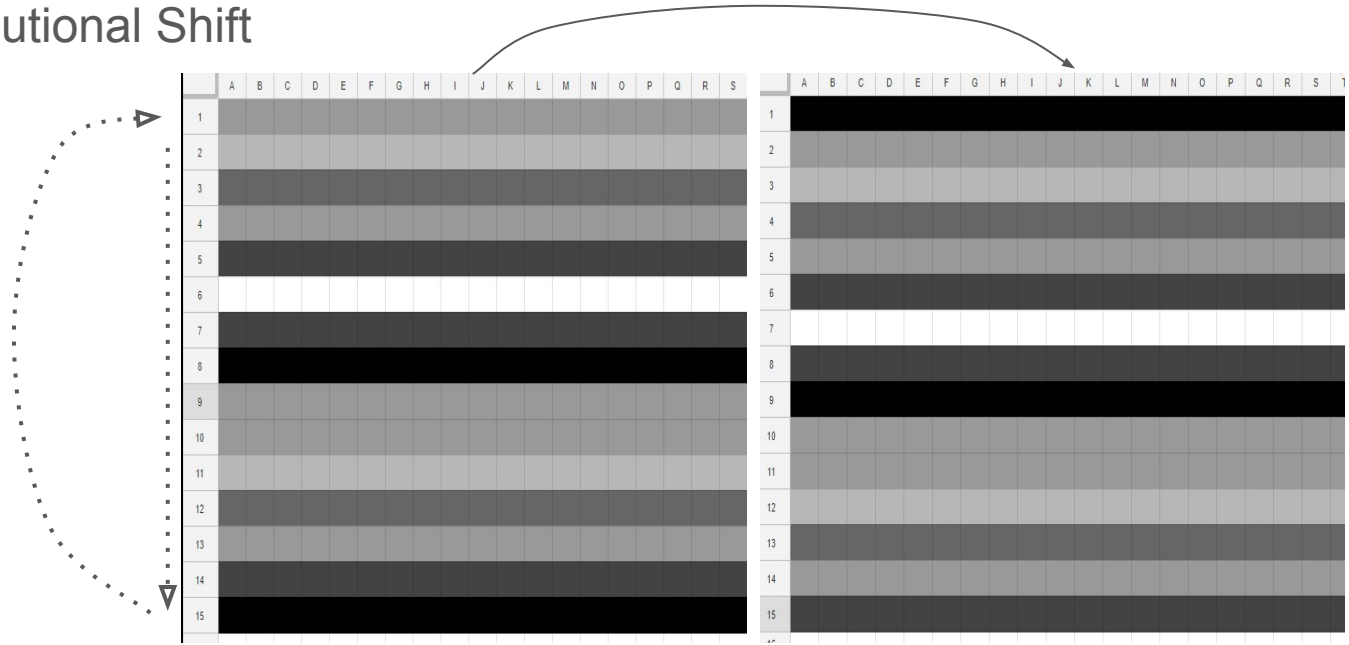


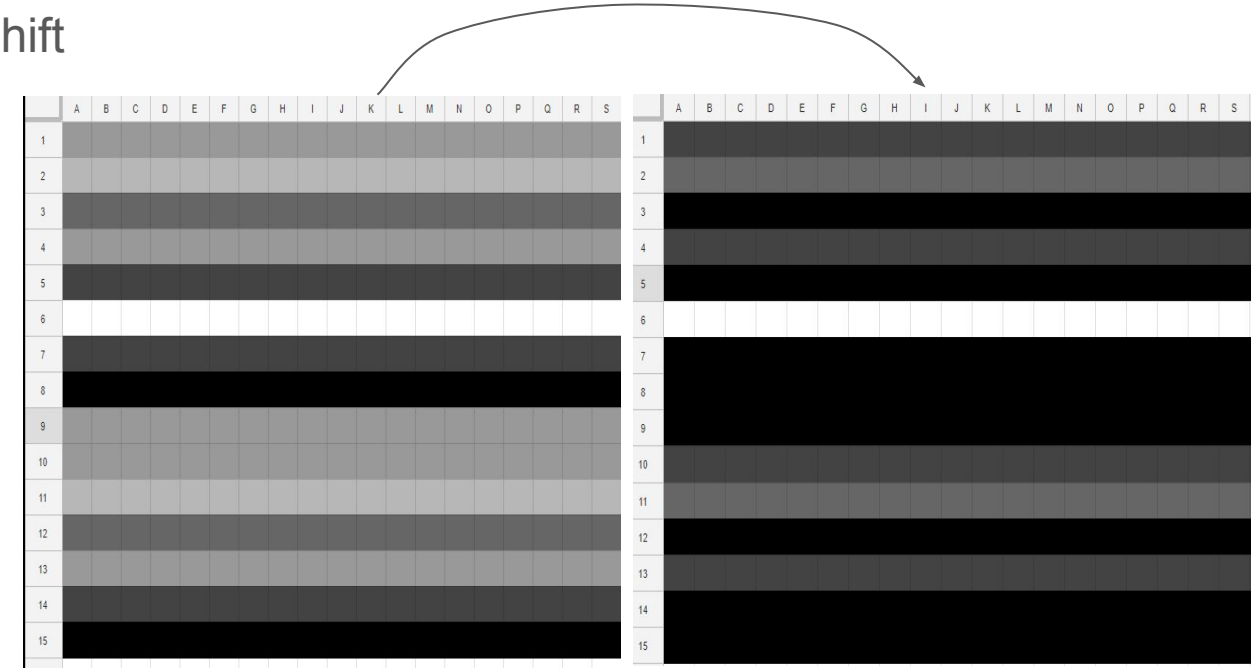
# Neural Turing Machines (NTM)

- 1. Focusing by Content
- 2. Interpolate with previous step
- 3. Convolutional Shift
- 4. Shapening

$$w_t(i) \leftarrow \frac{\tilde{w}_t(i)^{\gamma_t}}{\sum_j \tilde{w}_t(j)^{\gamma_t}}$$

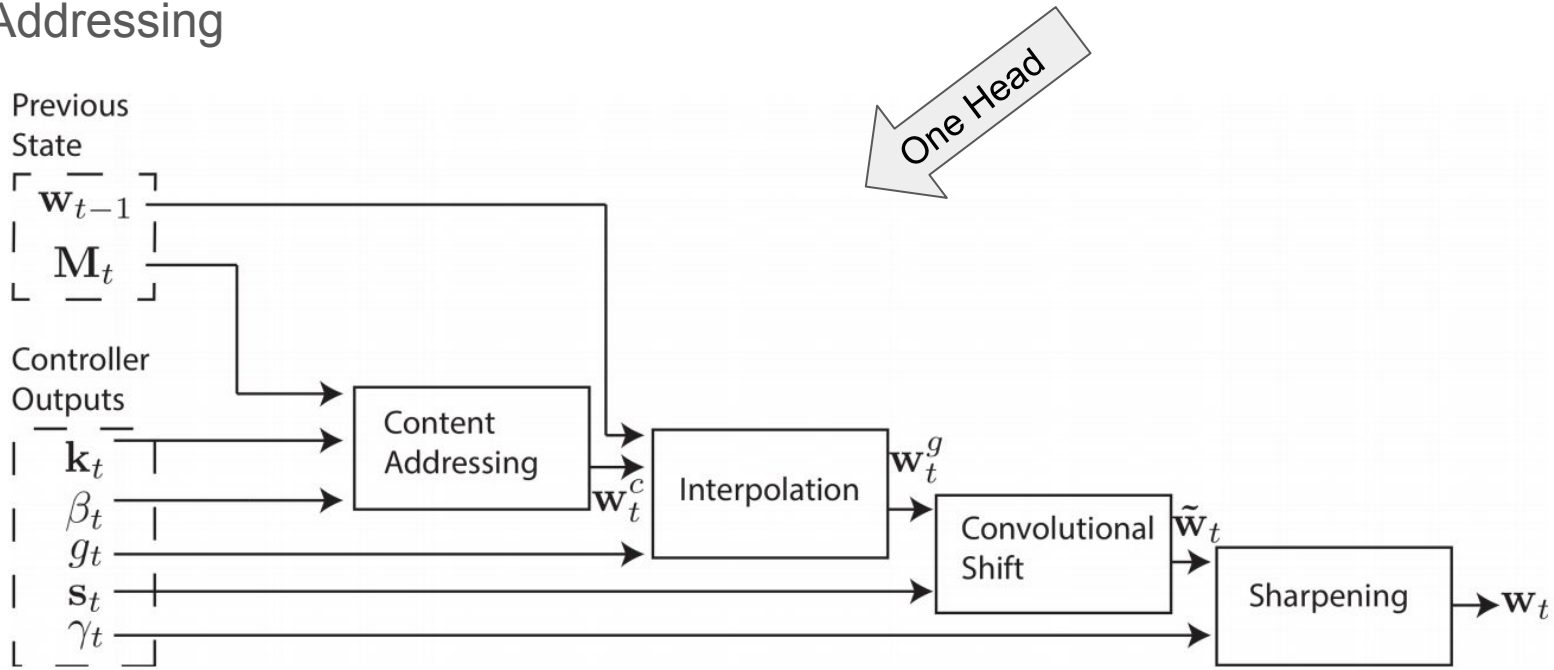
# Neural Turing Machines (NTM)

- 1. Focusing by Content
- 2. Interpolate with previous step
- 3. Convolutional Shift
- 4. Shapening



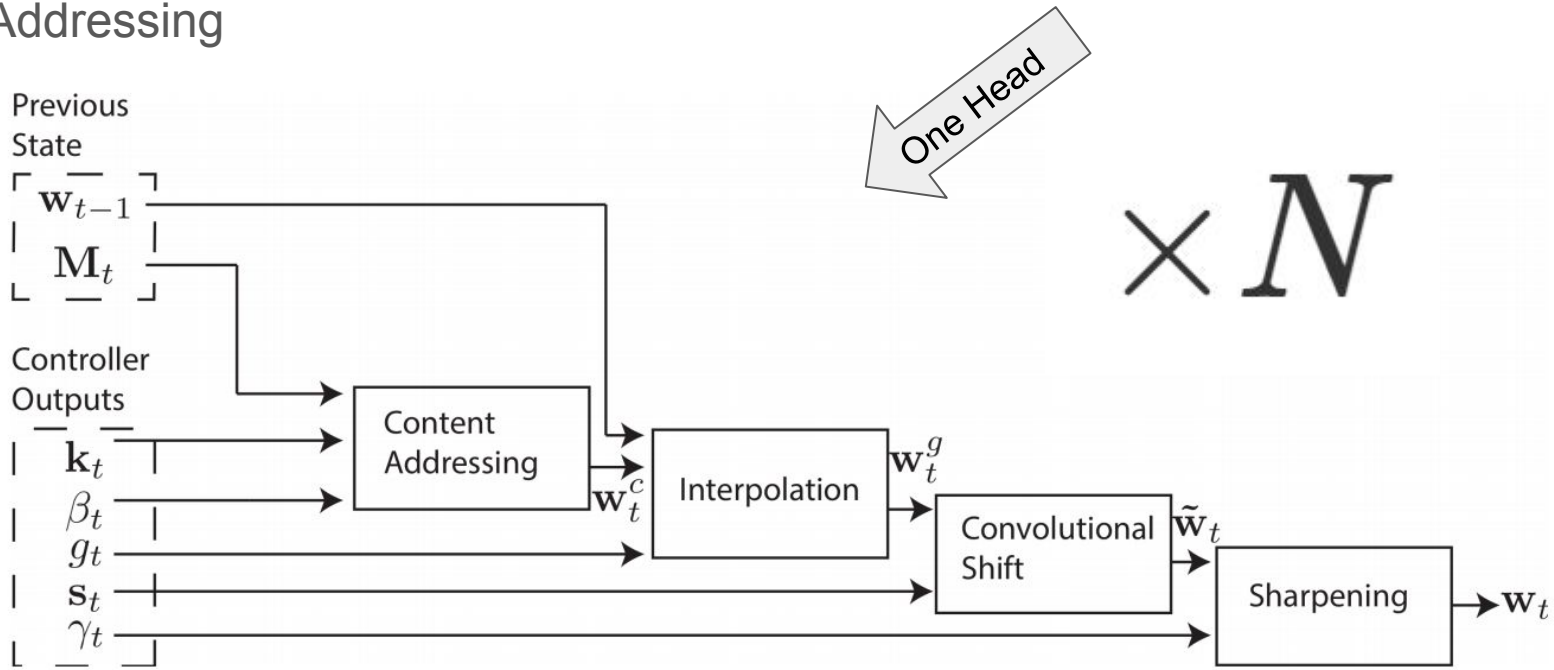
# Neural Turing Machines (NTM)

- Addressing



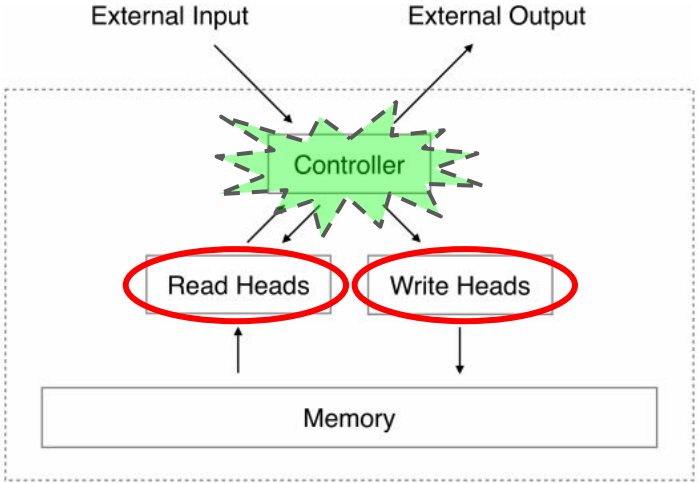
# Neural Turing Machines (NTM)

- Addressing

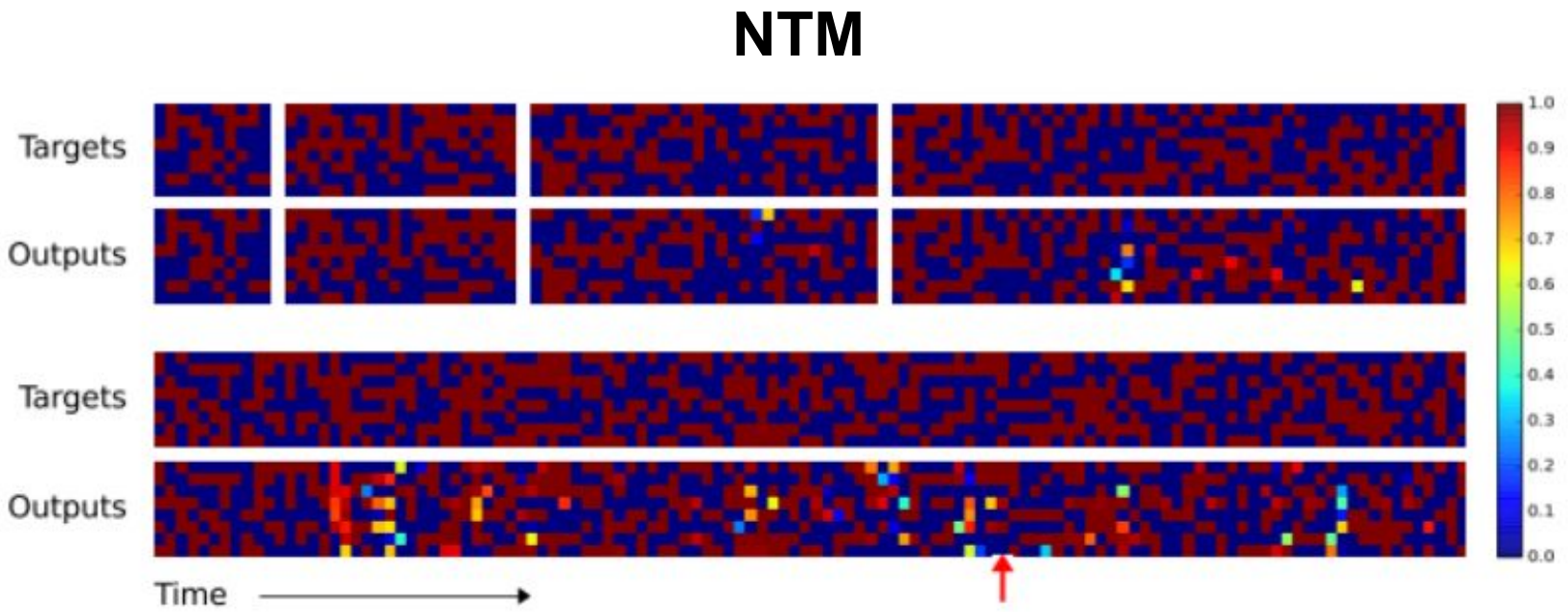


# Neural Turing Machines (NTM)

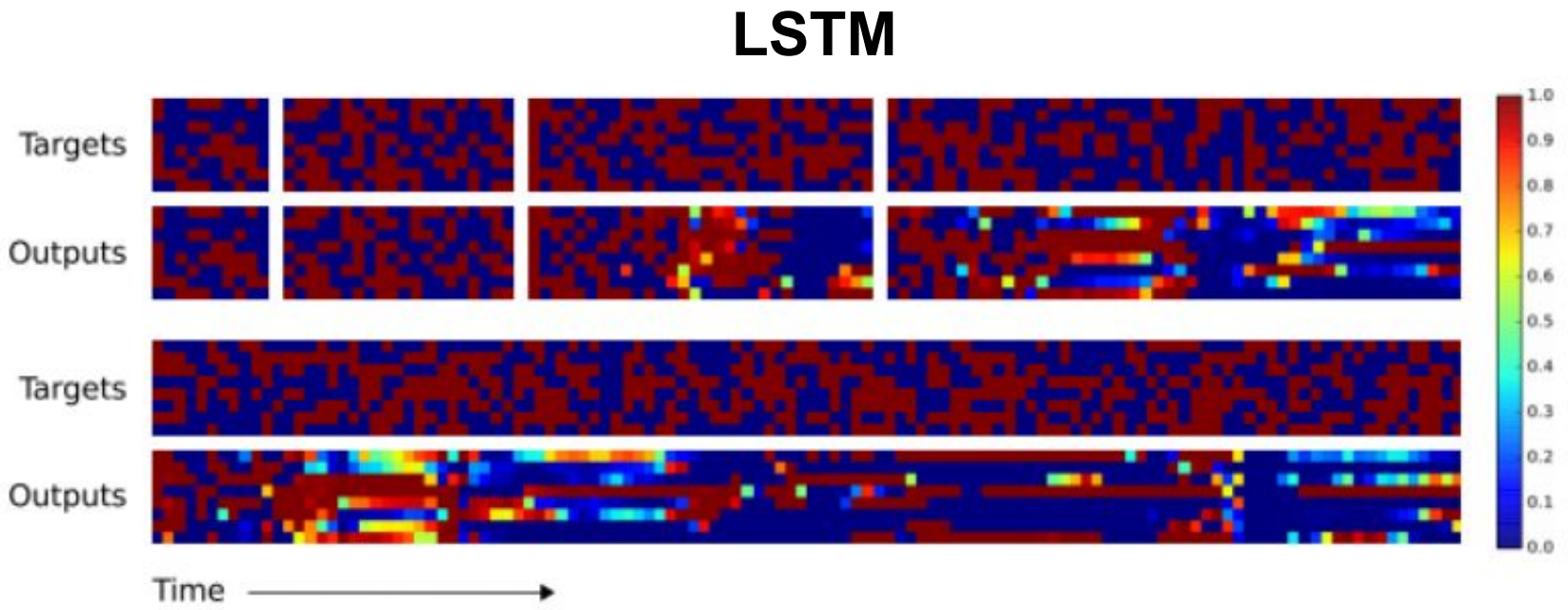
- Controller
  - Feedforward
  - LSTM
- Take input
- Predict all **red-circled** variables $\times N$
- Even if a feedforward controller is used, NTM is an RNN



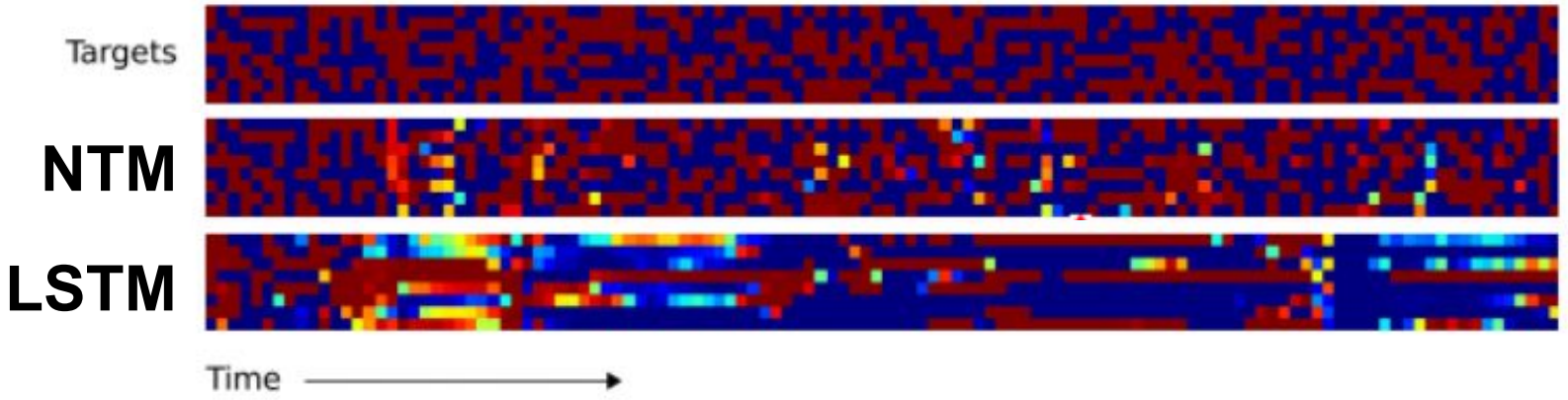
# NTM: Copy Task



# NTM: Copy Task



# NTM: Copy Task Comparison



# Neural Turing Machines (NTM)

- Copy Task
- Memory heads

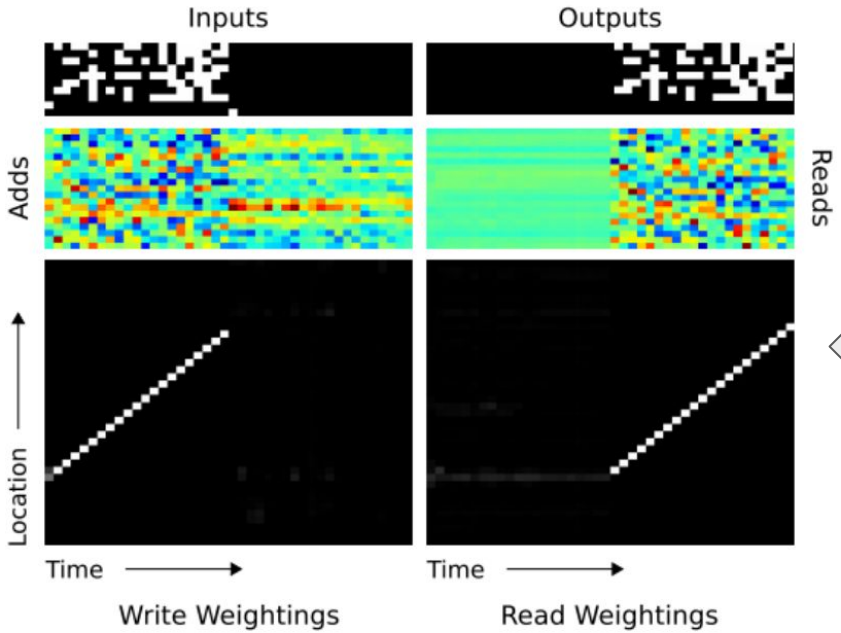
```python
# input data
input_list = [0, 2, 4, 4, 1, 5, 2]

# model starts from here
model_memory = [0] * len(input_list)

# store everything read
loc_write = 0
for value in input_list:
    model_memory[loc_write] = value
    loc_write += 1

# write everything stored
loc_read = 0
while loc_read < loc_write:
    print(model_memory[loc_read])
    loc_read += 1
```

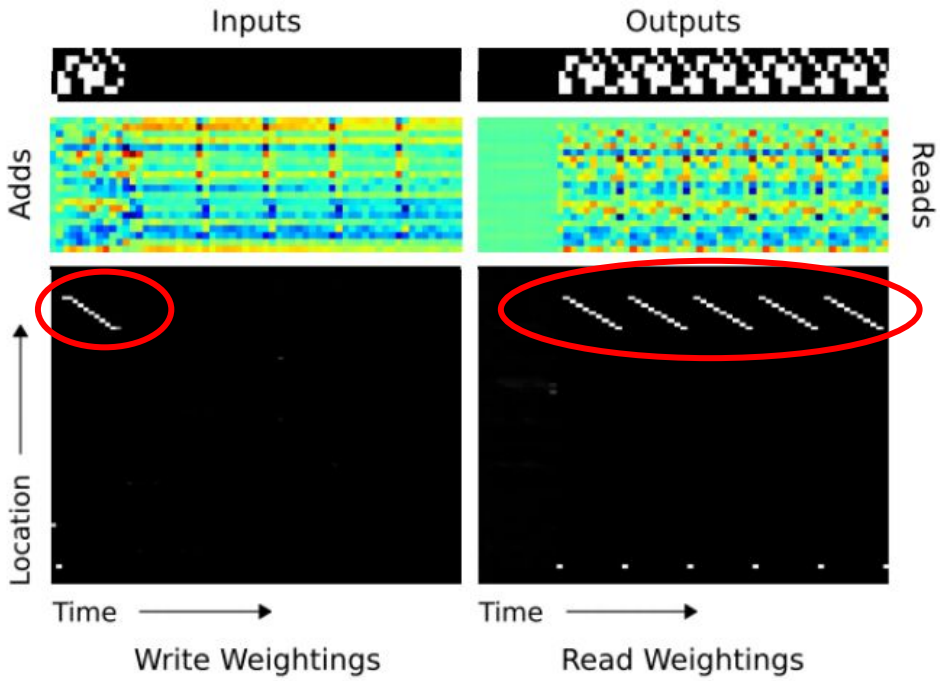
loc_read




loc_write

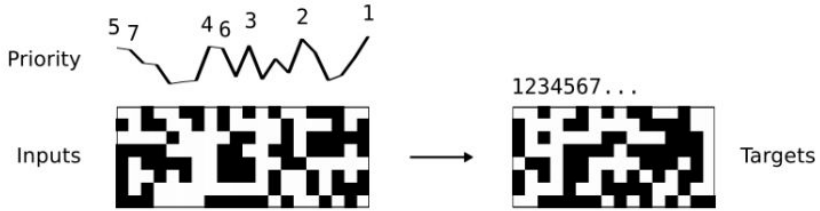
# Neural Turing Machines (NTM)

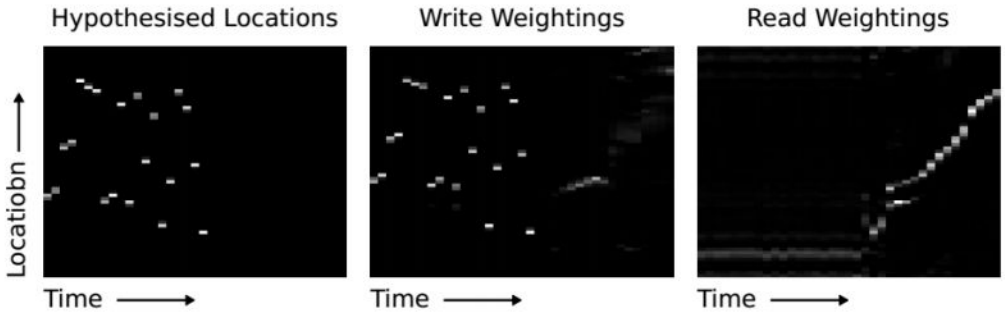
- Repeated Copy Task
- Memory heads
- White cells are positions of memory heads



# Neural Turing Machines (NTM)

- Priority Sort



# Misc

- More networks with memories
  - Memory networks
  - Differentiable Neural Computer (DNC)
- Adaptive Computing Time (ACT)
- Using different weights for each step
  - HyperNetworks
- Skip-RNN
  - 
```
i = 0
state = 0

while i < n:
    state = update_state(state, input[i])
    i += get_number_of_step_steps(state)

output = get_output(state)
```

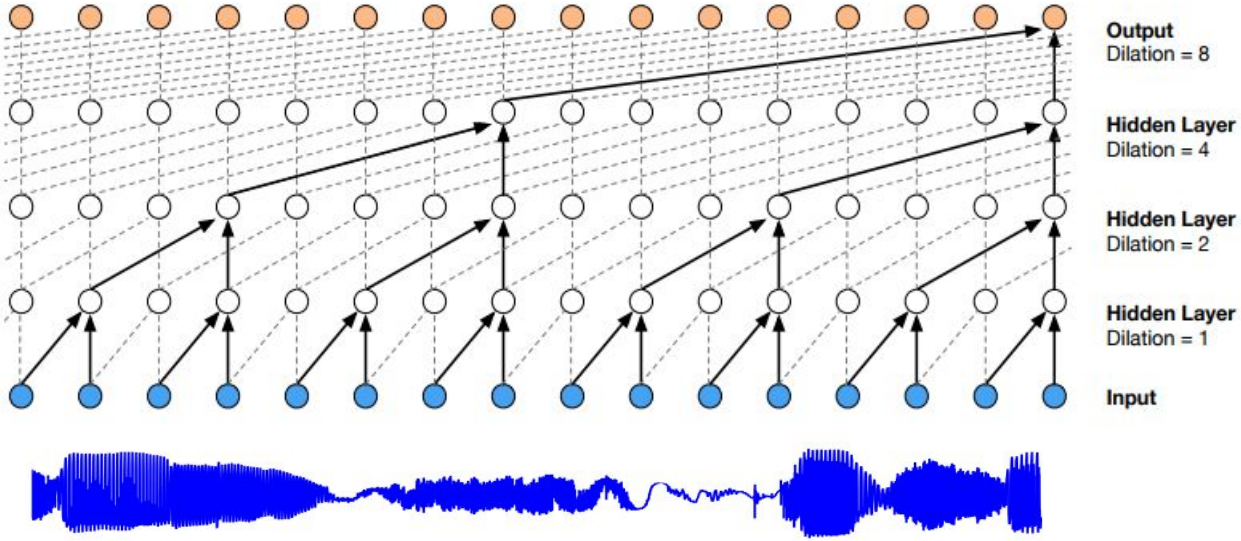
# CNN for Sequence Modeling

# RNN: The Good, Bad and Ugly

- Good
  - Turing Complete, strong modeling ability
- Bad
  - Dependencies between temporal connections make **computation slow**
    - CNNs are resurging now to predict sequence
    - WaveNet
- Ugly
  - Generally **hard to train**
  - In practice: the memorization limit of LSTM is a couple of **hundreds of steps**.
  - The above two fight

# RNN’s Rival: WaveNet

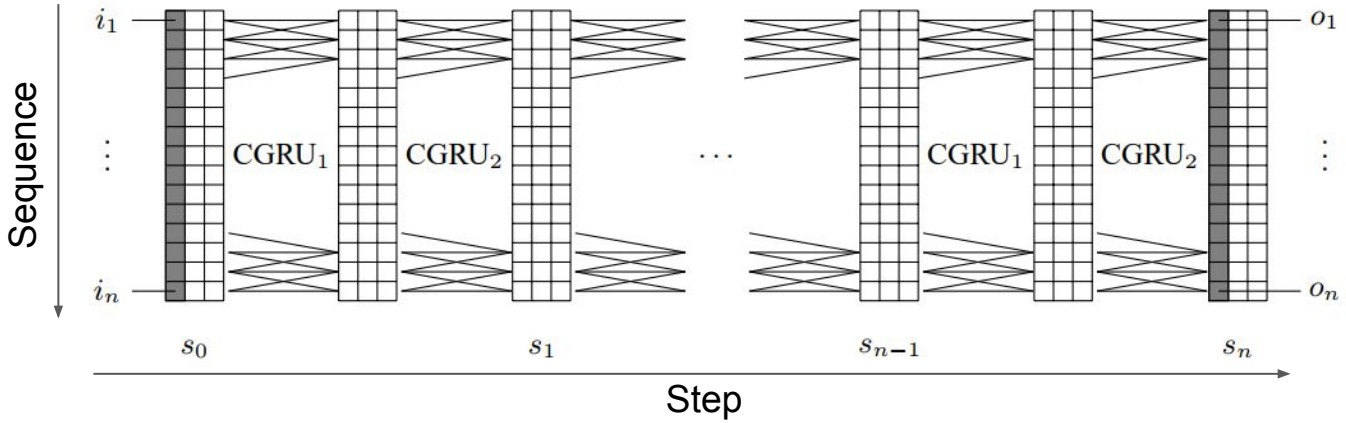
- Causal Dilated Convolution




Oord, Aaron van den, et al. "Wavenet: A generative model for raw audio." arXiv preprint arXiv:1609.03499 (2016).

# Neural GPU

- All input is feeded at every step
- “横行霸道的 RNN”




Kaiser, Łukasz, and Ilya Sutskever. "Neural gpus learn algorithms." arXiv preprint arXiv:1511.08228 (2015).

# CNN for Sequence Modeling

**Pros**

- Parallelism
- Flexible receptive field size
- Stable gradients
- Low memory requirement for training.
- Variable length inputs

**Cons**

- Data storage during evaluation
- Potential parameter change for a transfer of domain

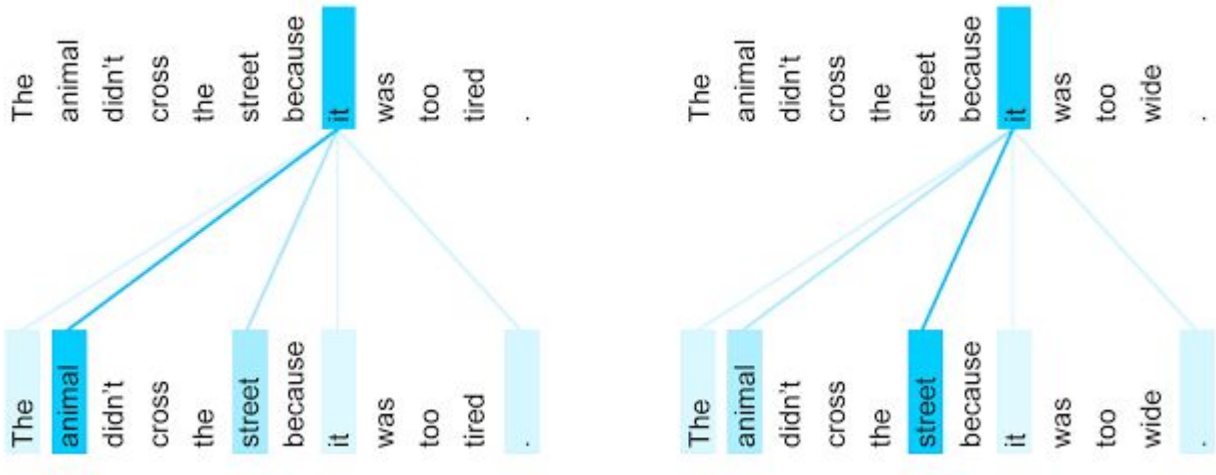
Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." arXiv preprint arXiv:1803.01271 (2018).

# Attention is All You Need

Look father, look clearer

# Transformer

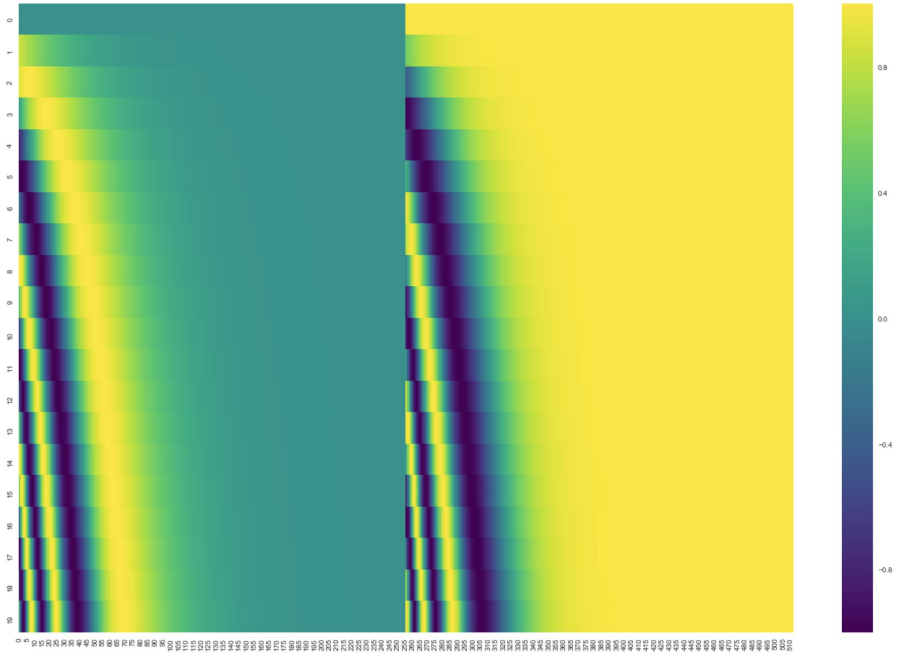
- A Neural GPU that changes Convolution to Attention
  - The order of words in the sequence are ignored
- Multi-head attention
  - One attention is not enough; Pay more attention



# Transformer

- Position Encoding
  - Bring back order

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

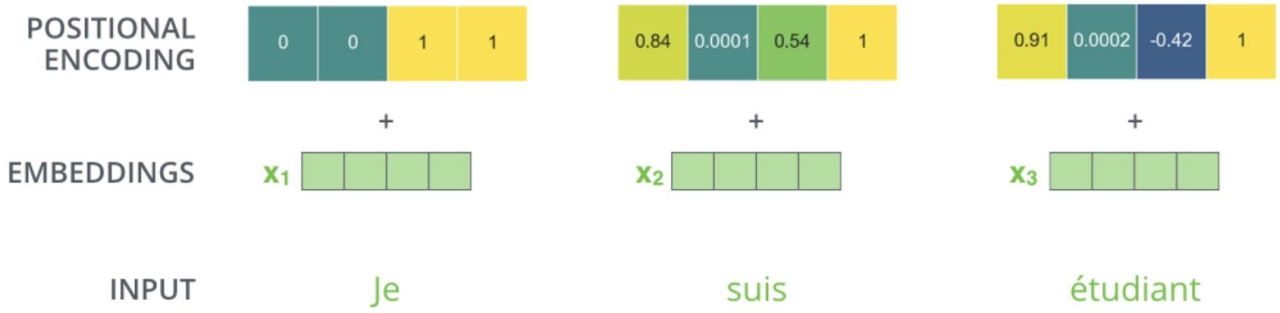


A real example of positional encoding for 20 words (rows) with an embedding size of 512 (columns). You can see that it appears split in half down the center. That's because the values of the left half are generated by one function (which uses sine), and the right half is generated by another function (which uses cosine). They're then concatenated to form each of the positional encoding vectors.

Reference: http://jalammar.github.io/illustrated-transformer/

# Transformer

- Position Encoding combined




A real example of positional encoding with a toy embedding size of 4

# Transformer

- Trained on BooksCorpus (800M words)

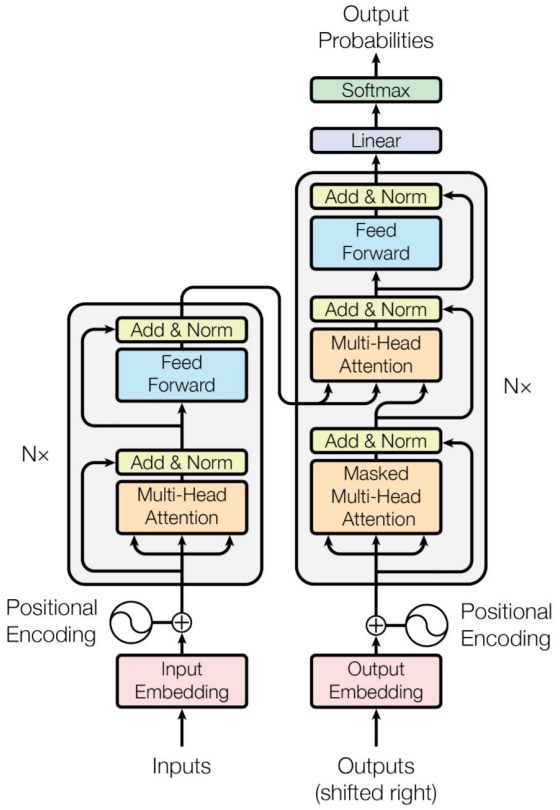



Figure 1: The Transformer - model architecture.

# BERT

- BERT: Bidirectional Encoder Representations from Transformers.

# BERT: Pretraining Task

- Starting with transformer, trained with two tasks
  - Predict randomly masked words
    - Mask: my dog is hairy → my dog is [MASK]
    - Predict: my dog is [MASK] → my dog is hairy
  - Predict whether one sentence follows another
    - Input = `[CLS] the man went to [MASK] store [SEP]`
      `he bought a gallon [MASK] milk [SEP]`
      Label = `IsNext`

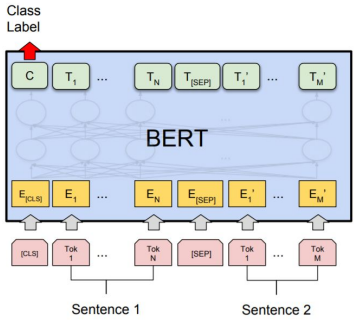
      Input = `[CLS] the man [MASK] to the store [SEP]`
      `penguin [MASK] are flight ##less birds [SEP`
      Label = `NotNext`

# BERT: Pretraining Dataset

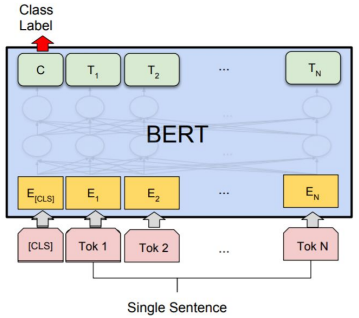
- BooksCorpus (800M)
- Wikipedia（2,500M）

# BERT: Finetune

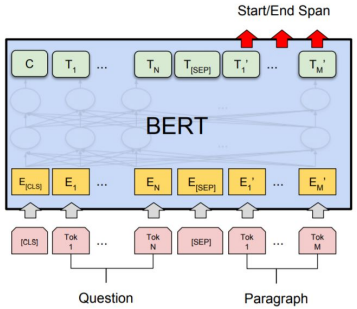
- Small modification
  - Task-specific output



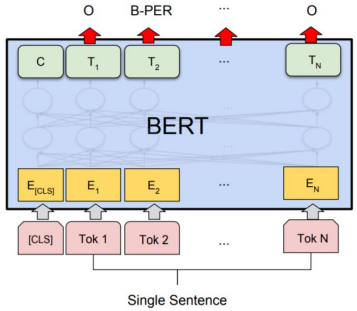

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG




(b) Single Sentence Classification Tasks: SST-2, CoLA




(c) Question Answering Tasks: SQuAD v1.1

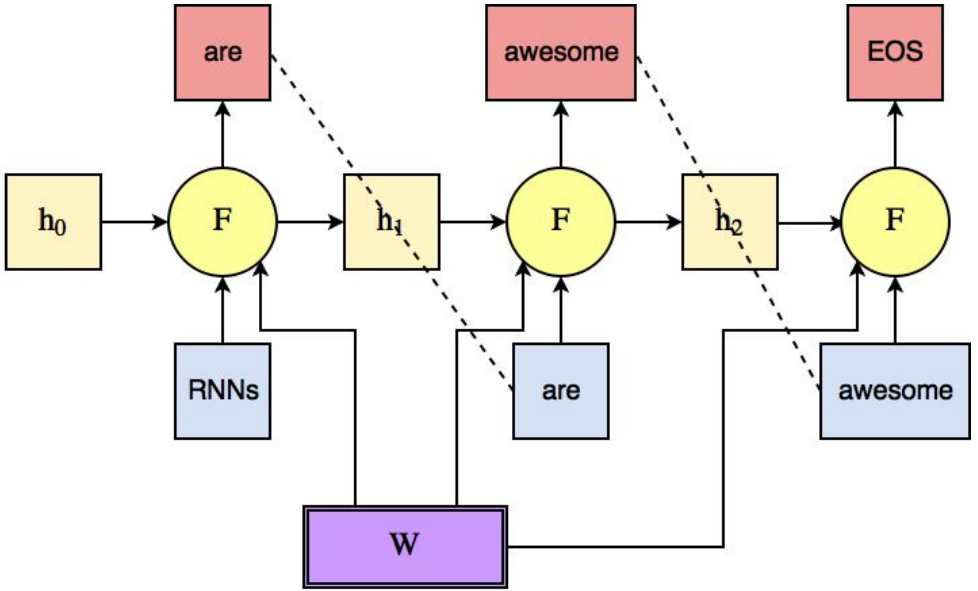



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

# GPT2: Pretraining

- Language Modeling
- Dataset: WebText
  - 45 million web pages
  - 40GB
  - Carefully selected
  - Focus on diversity of the corpus

**Recall ⇒**



# GPT2: Finetune

- Finetune? No finetune!
- Zero-shot Test
  - Performing language modeling task
  - The “post-process” the results of multiple language modeling generating output and produce the final output
- Tasks
  - Reading Comprehension
  - Summarization
  - Translation
  - Question Answering
- “Achieves **state of the art** results on **7 out of 8** tested language modeling datasets in a **zero-shot setting**”

# GPT2: Example

| Question | Generated Answer | Correct | Probability |
|---|---|---|---|
| Who wrote the book the origin of species? | Charles Darwin | ✓ | 83.4% |
| Who is the founder of the ubuntu project? | Mark Shuttleworth | ✓ | 82.0% |
| Who is the quarterback for the green bay packers? | Aaron Rodgers | ✓ | 81.1% |
| Panda is a national animal of which country? | China | ✓ | 76.8% |
| Who came up with the theory of relativity? | Albert Einstein | ✓ | 76.4% |
| When was the first star wars film released? | 1977 | ✓ | 71.4% |
| What is the most common blood type in sweden? | A | ✗ | 70.6% |
| Who is regarded as the founder of psychoanalysis? | Sigmund Freud | ✓ | 69.3% |
| Who took the first steps on the moon in 1969? | Neil Armstrong | ✓ | 66.8% |
| Who is the largest supermarket chain in the uk? | Tesco | ✓ | 65.3% |
| What is the meaning of shalom in english? | peace | ✓ | 64.0% |
| Who was the author of the art of war? | Sun Tzu | ✓ | 59.6% |
| Largest state in the us by land mass? | California | ✗ | 59.2% |
| Green algae is an example of which type of reproduction? | parthenogenesis | ✗ | 56.5% |
| Vikram samvat calender is official in which country? | India | ✓ | 55.6% |
| Who is mostly responsible for writing the declaration of independence? | Thomas Jefferson | ✓ | 53.3% |
| What us state forms the western boundary of montana? | Montana | ✗ | 52.3% |
| Who plays ser davos in game of thrones? | Peter Dinklage | ✗ | 52.1% |
| Who appoints the chair of the federal reserve system? | Janet Yellen | ✗ | 51.5% |
| State the process that divides one nucleus into two genetically identical nuclei? | mitosis | ✓ | 50.7% |
| Who won the most mvp awards in the nba? | Michael Jordan | ✗ | 50.2% |
| What river is associated with the city of rome? | the Tiber | ✓ | 48.6% |
| Who is the first president to be impeached? | Andrew Johnson | ✓ | 48.3% |
| Who is the head of the department of homeland security 2017? | John Kelly | ✓ | 47.0% |
| What is the name given to the common currency to the european union? | Euro | ✓ | 46.8% |
| What was the emperor name in star wars? | Palpatine | ✓ | 46.5% |
| Do you have to have a gun permit to shoot at a range? | No | ✓ | 46.4% |
| Who proposed evolution in 1859 as the basis of biological development? | Charles Darwin | ✓ | 45.7% |
| Nuclear power plant that blew up in russia? | Chernobyl | ✓ | 45.7% |
| Who played john connor in the original terminator? | Arnold Schwarzenegger | ✗ | 45.2% |

# GPT2: Generation

Input: “In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.”

Output: “The scientist named the population, after their distinctive horn, Ovid’s Unicorn. These four-horned, silver-white unicorns were previously unknown to science. Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved. Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow. Pérez and the others then ventured further into the valley. “By the time we reached the top of one peak, the water looked blue, with some crystals on top,” said Pérez.”

# GPT2: The Ethics

- OpenAI is not releasing (till now) because they are afraid of the abuse of this model.
-

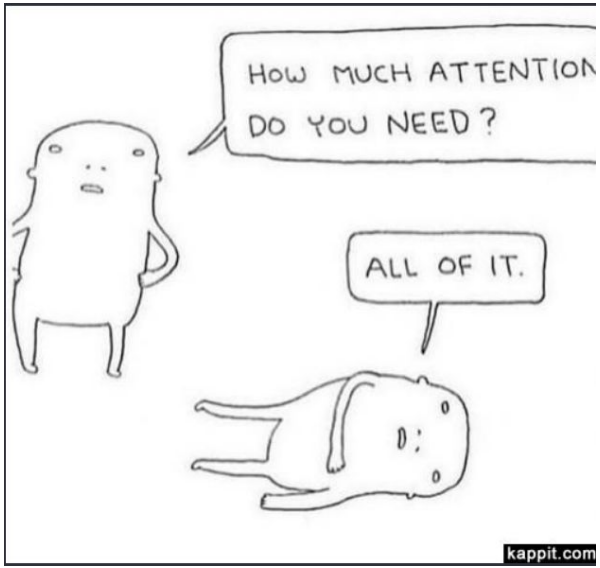
**“Due to our concerns about malicious applications of the technology, we are not releasing the trained model. ”**

Reference: https://openai.com/blog/better-language-models/

# Summary

- Transformer = Neural GPU + input/position dependent kernel + full receptive field
- BERT = Transformer + predictive pretraining
- GPT2 = Transformer + language model pretraining + diversified dataset

# Summary

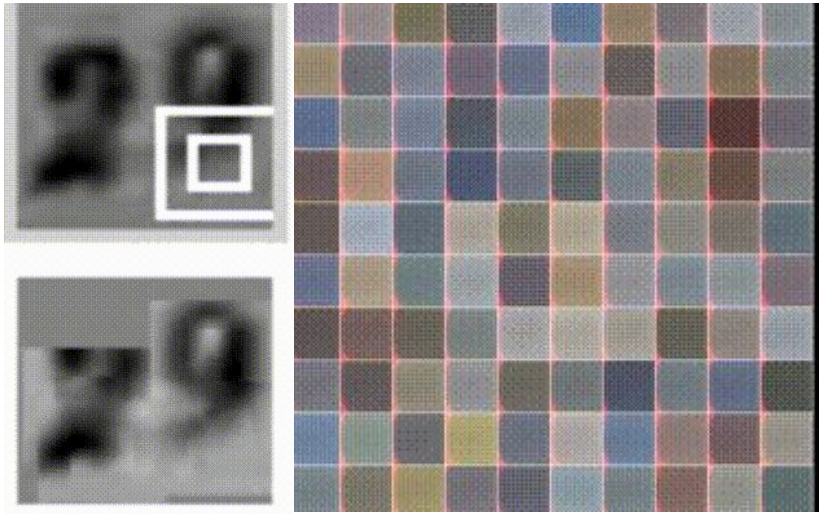



Vaswani, Ashish, et al. "Attention Is All You Need." arXiv preprint arXiv:1706.03762 (2017).
https://research.googleblog.com/2017/08/transformer-novel-neural-network.html
https://courses.cs.ut.ee/MTAT.03.292/2017_fall/uploads/Main/Attention%20is%20All%20you%20need.pdf

# More Applications

# RNN without a sequence input

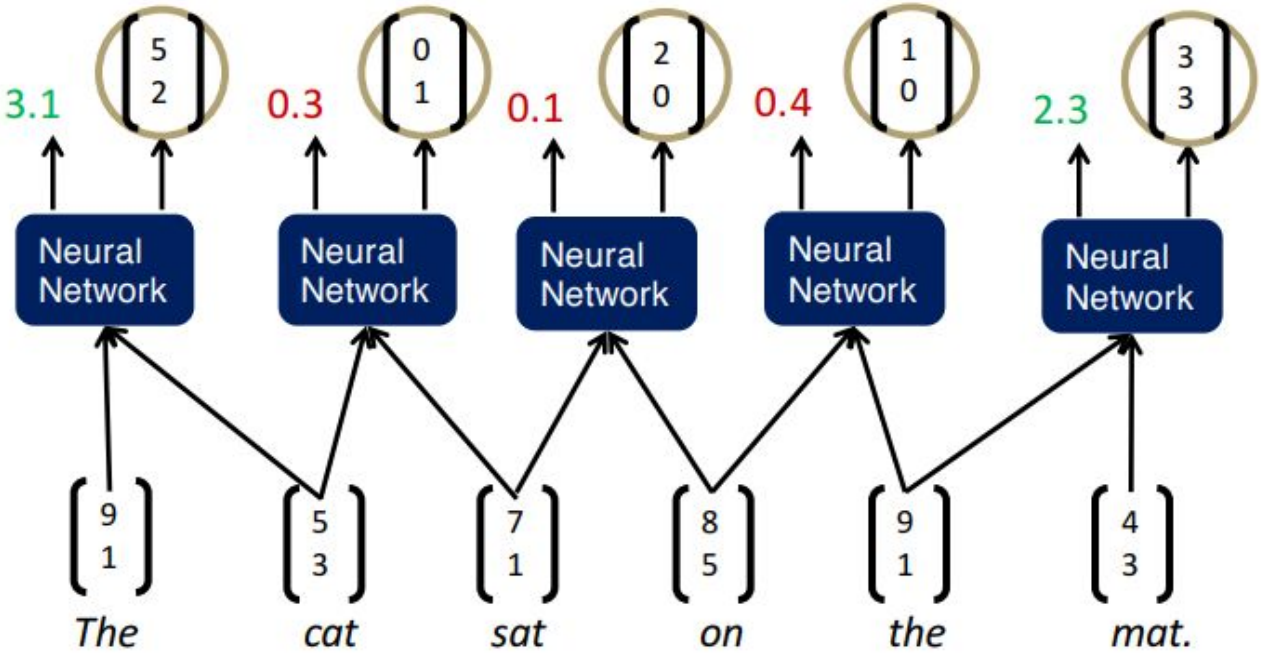
- Left
  - learns to read out house numbers from left to right
- Right
  - a recurrent network generates images of digits by learning to sequentially add color to a canvas



Ba, Jimmy, Volodymyr Mnih, and Koray Kavukcuoglu. "Multiple object recognition with visual attention." arXiv preprint arXiv:1412.7755 (2014).
Gregor, Karol, et al. "DRAW: A recurrent neural network for image generation." arXiv preprint arXiv:1502.04623 (2015).

# Generalizing Recurrence

- What is recurrence
  - A computation unit with shared parameter occurs at multiple places in the computation graph
    - Convolution will do too
  - … with additional states passing among them
    - That’s recurrence
- “Recursive”


3.1
0.3
0.1
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2.3
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cat
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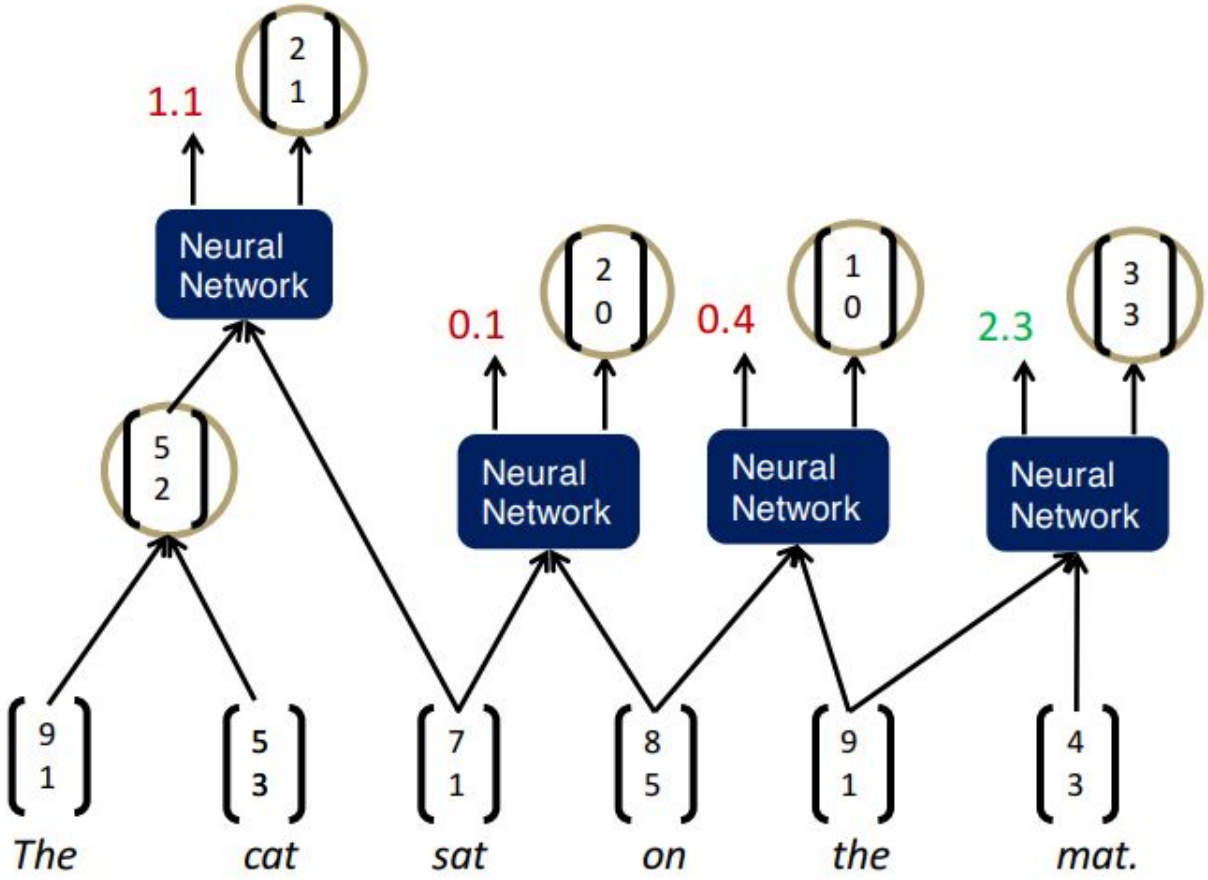
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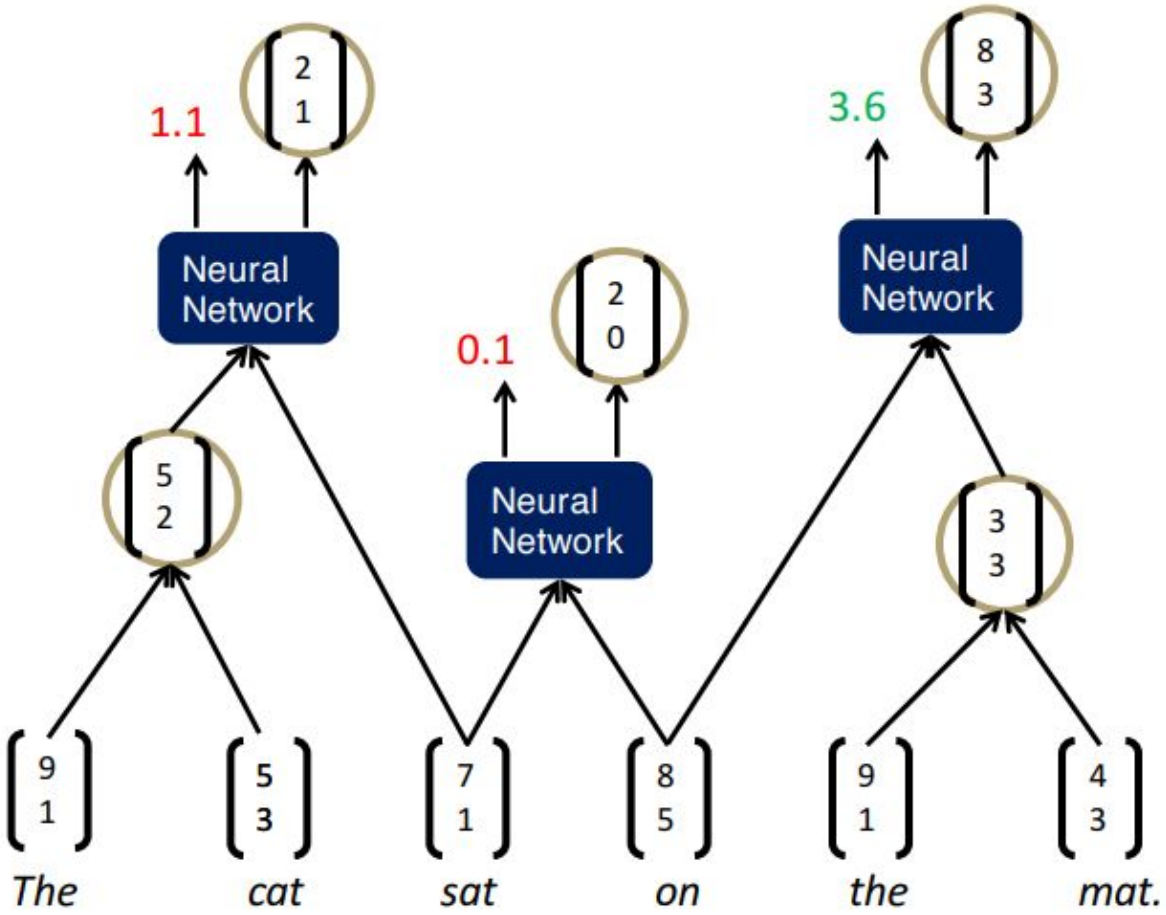
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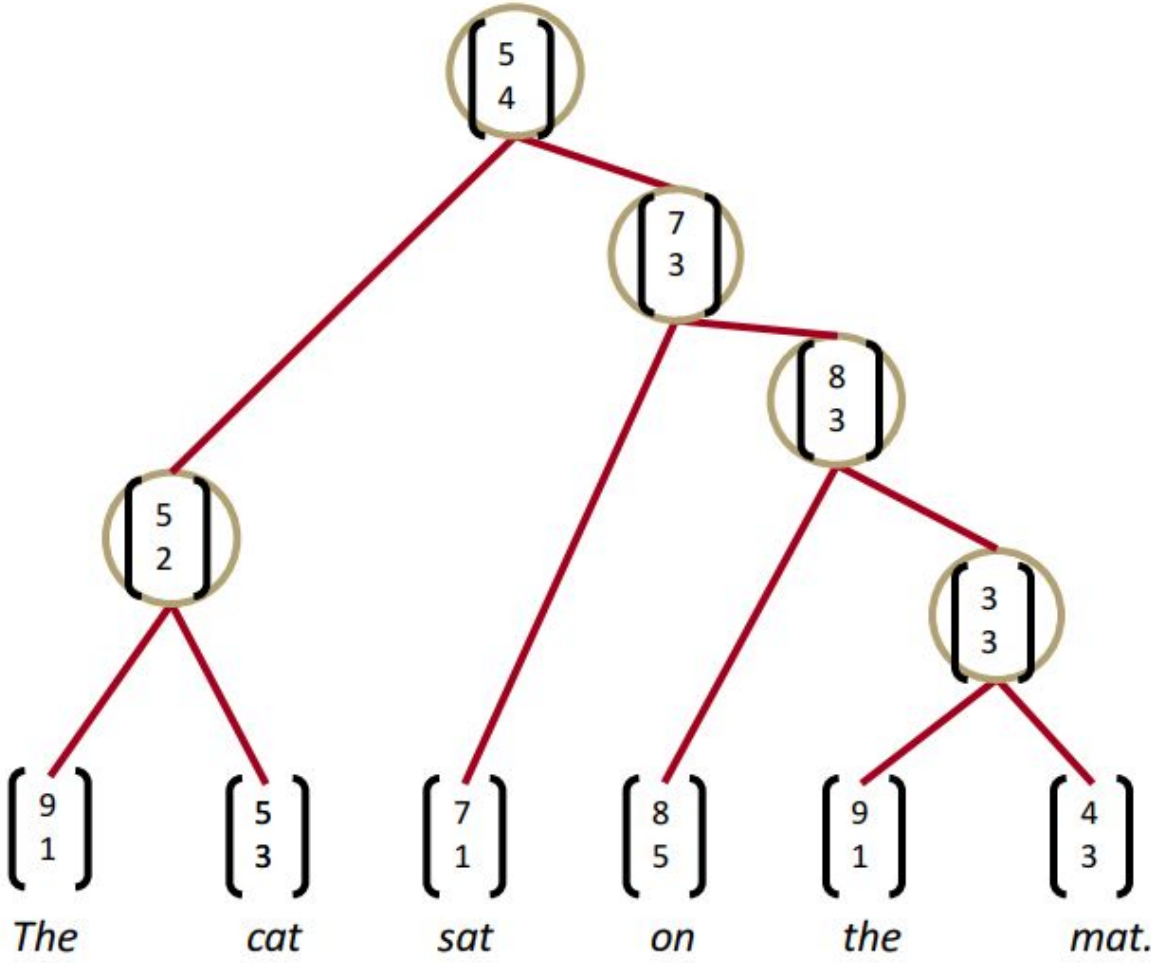
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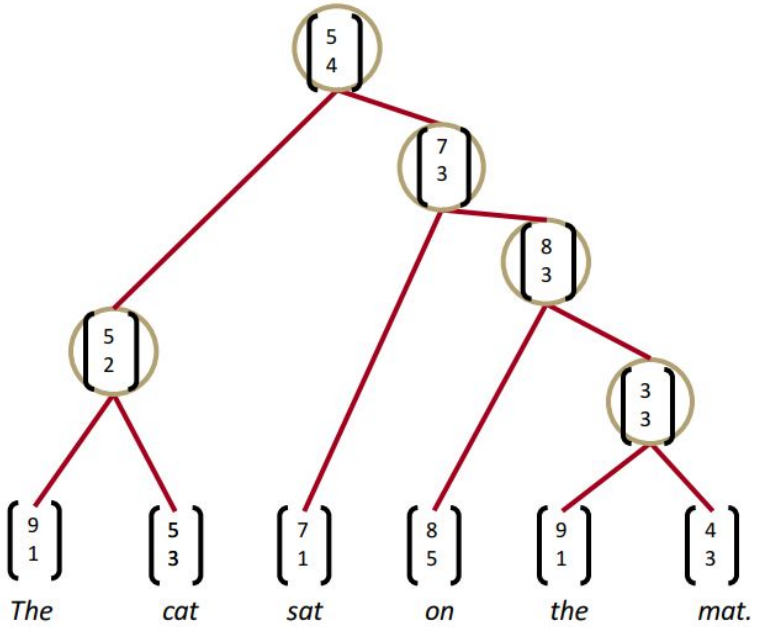
# Recursive Neural Network

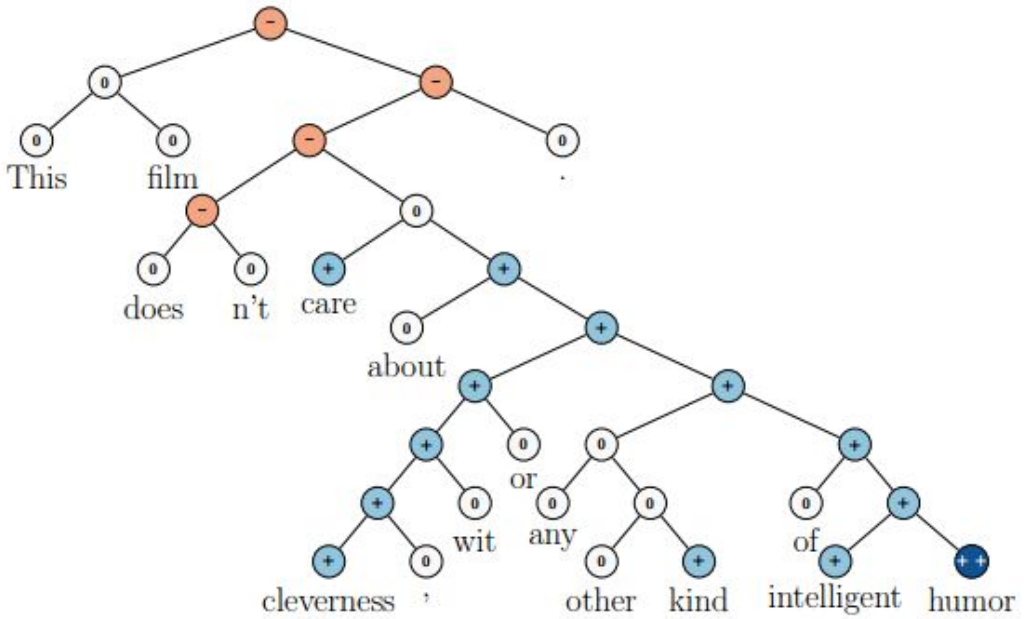
- Apply when there's tree structure in data
  - For natural language use The Standford Parser to build the syntax tree given a sentence




http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf
https://nlp.stanford.edu/software/lex-parser.shtml

# Recursive Neural Network

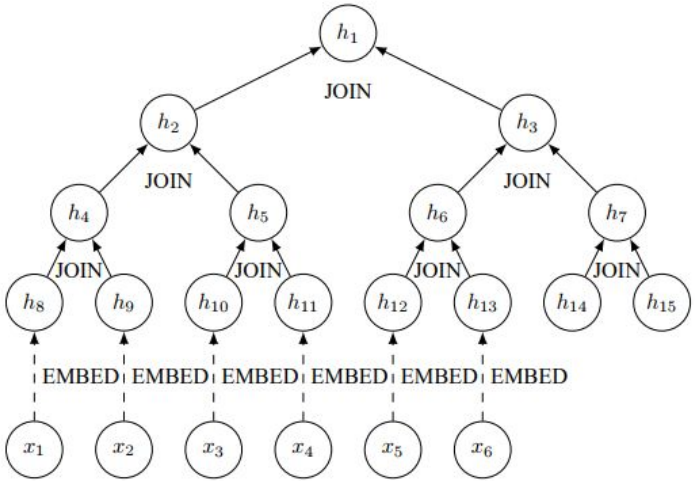
- Bottom-up aggregation of information
  - Sentiment Analysis

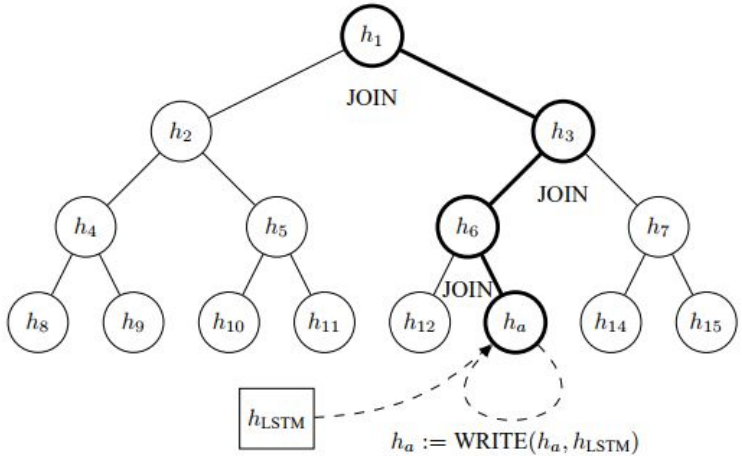



Socher, Richard, et al. "Recursive deep models for semantic compositionality over a sentiment treebank." Proceedings of the 2013 conference on empirical methods in natural language processing. 2013.

# Recursive Neural Network

- As a lookup table

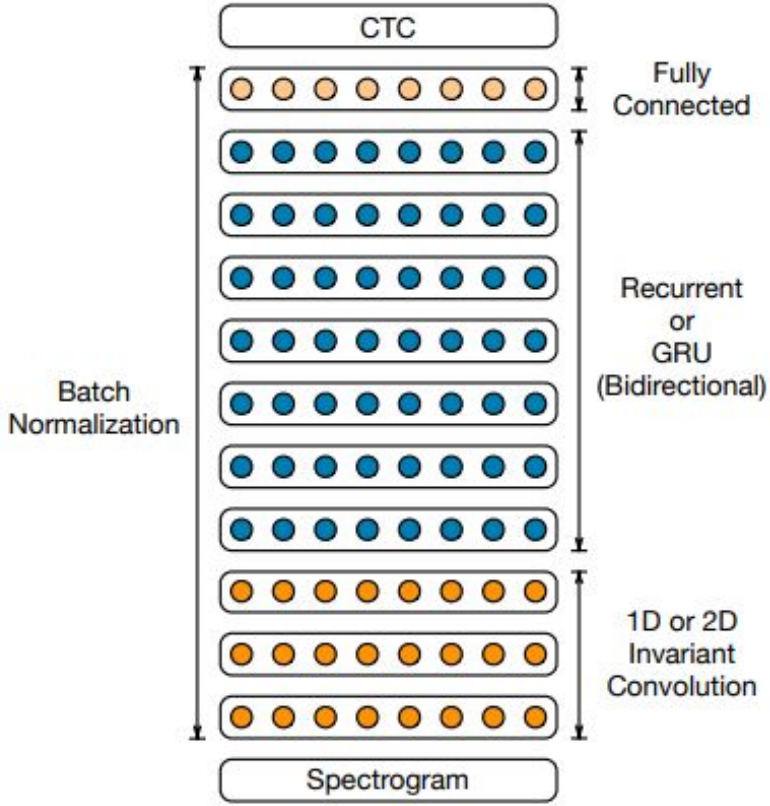



Andrychowicz, Marcin, and Karol Kurach. "Learning efficient algorithms with hierarchical attentive memory." arXiv preprint arXiv:1602.03218 (2016).

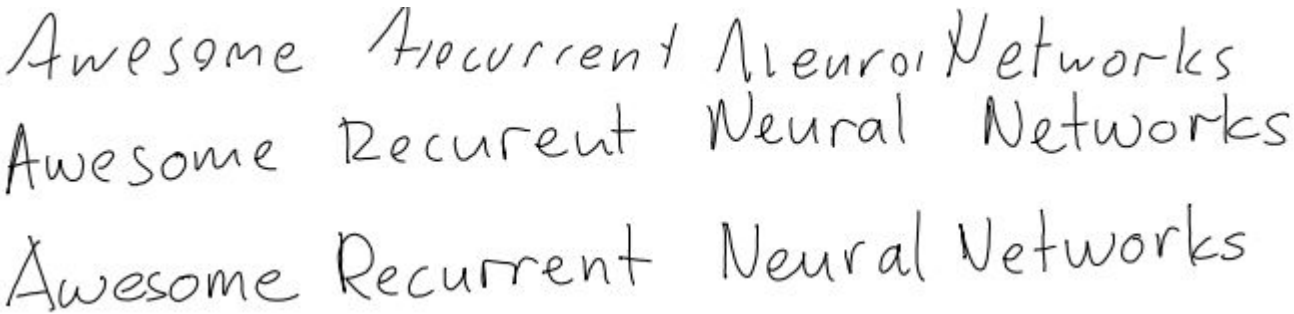
# Speech Recognition

- Deep Speech 2
  - Spectrogram
  - Convolution
  - Deep Bidirectional GRU
  - FC
  - CTC




Amodei, Dario, et al. "Deep speech 2: End-to-end speech recognition in english and mandarin." International Conference on Machine Learning. 2016.
Graves, Alex, et al. "Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks." Proceedings of the 23rd international conference on Machine learning. ACM, 2006.

# Generating Sequence

- Language modeling
  - Input: “A”
  - Output: “A quick brown fox jumps over the lazy dog.”
- Handwriting stroke generation
  - 


https://www.cs.toronto.edu/~graves/handwriting.html

# Question Answering

1. **Mary** moved to the **bathroom**
2. **John** went to the **hallway**
3. **Where** is **Mary**?
4. Answer: **bathroom**

Weston, Jason, Sumit Chopra, and Antoine Bordes. "Memory networks." arXiv preprint arXiv:1410.3916 (2014).
Sukhbaatar, Sainbayar, Jason Weston, and Rob Fergus. "End-to-end memory networks." Advances in neural information processing systems. 2015.
Andreas, Jacob, et al. "Learning to compose neural networks for question answering." arXiv preprint arXiv:1601.01705 (2016).
http://cs.umd.edu/~miyyer/data/deepqa.pdf
https://research.fb.com/downloads/babi/

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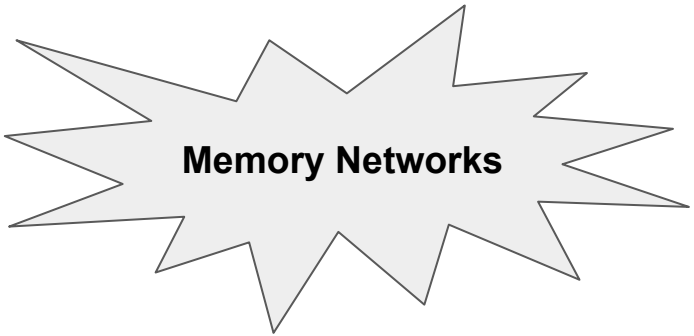


Weston, Jason, Sumit Chopra, and Antoine Bordes. "Memory networks." arXiv preprint arXiv:1410.3916 (2014).
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Andreas, Jacob, et al. "Learning to compose neural networks for question answering." arXiv preprint arXiv:1601.01705 (2016).
http://cs.umd.edu/~miyyer/data/deepqa.pdf
https://research.fb.com/downloads/babi/

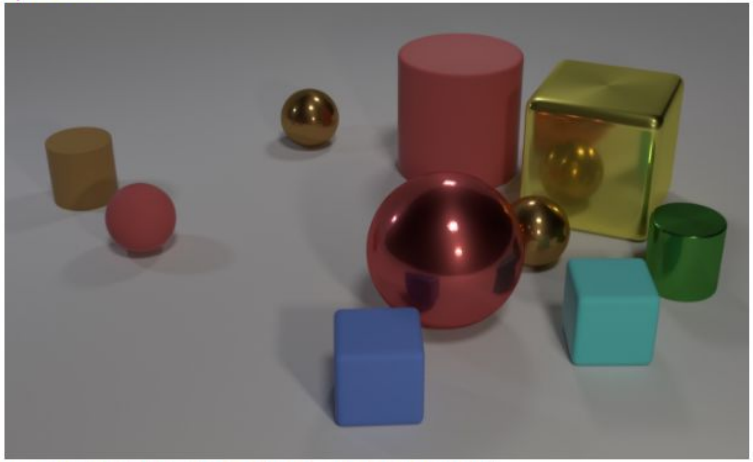
# Visual Question Answering

Antol, Stanislaw, et al. "Vqa: Visual question answering." Proceedings of the IEEE International Conference on Computer Vision. 2015.

# Visual Question Answering

- Reason the **relations** among Objects in image
- 
- “**What size** is the **cylinder** that is **left of** the **brown metal** thing that is **left of** the **big sphere**”
- 
- Dataset
  - CLEVR

Questions in CLEVR test various aspects of visual reasoning including **attribute identification**, **counting**, **comparison**, **spatial relationships**, and **logical operations**.



**Q:** Are there an **equal number** of **large things** and **metal spheres**?
**Q:** **What size** is the **cylinder** **that is left of** the **brown metal** thing **that is left of** the **big sphere**?
**Q:** There is a **sphere** with the **same size as** the **metal cube**; is it **made of the same material as** the **small red sphere**?
**Q:** **How many** objects are **either small cylinders** or **red** things?

https://distill.pub/2016/augmented-rnns/
http://cs.stanford.edu/people/jcjohns/clevr/

# Visual Question Answering

- Reason the **relations** among Objects in image
- 
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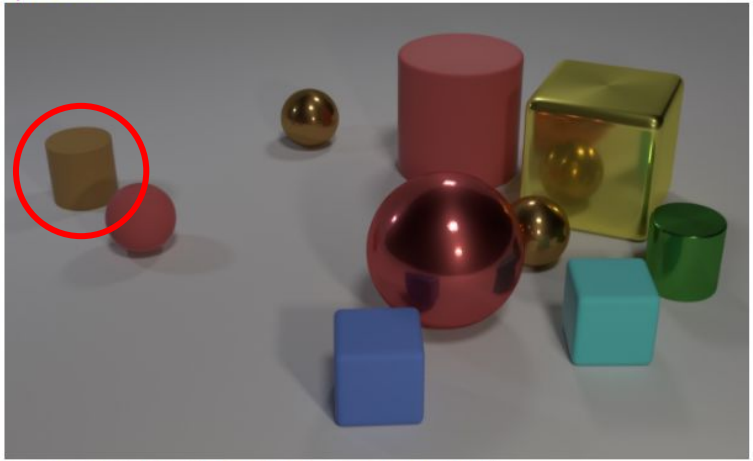

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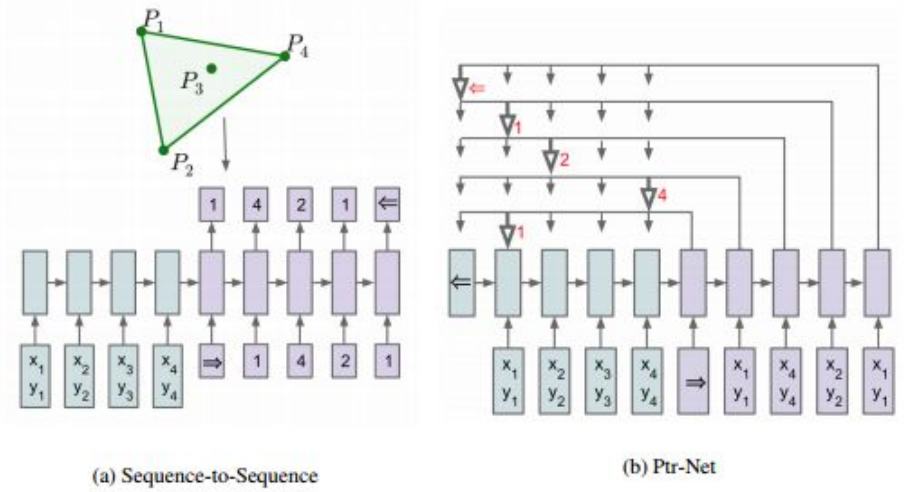
https://distill.pub/2016/augmented-rnns/
http://cs.stanford.edu/people/jcjohns/clevr/

# Combinatorial Problems

- Pointer Networks
  - Convex Hull
  - TSP
  - Delaunay triangulation
- Cross-entropy loss on Soft-attention
- Application in Vision
  - Object Tracking




MLA Vinyals, Oriol, Meire Fortunato, and Navdeep Jaitly. "Pointer networks." Advances in Neural Information Processing Systems. 2015.

# Combinatorial Problems

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  - TSP
  - Delaunay triangulation
- Cross-entropy loss on Sof
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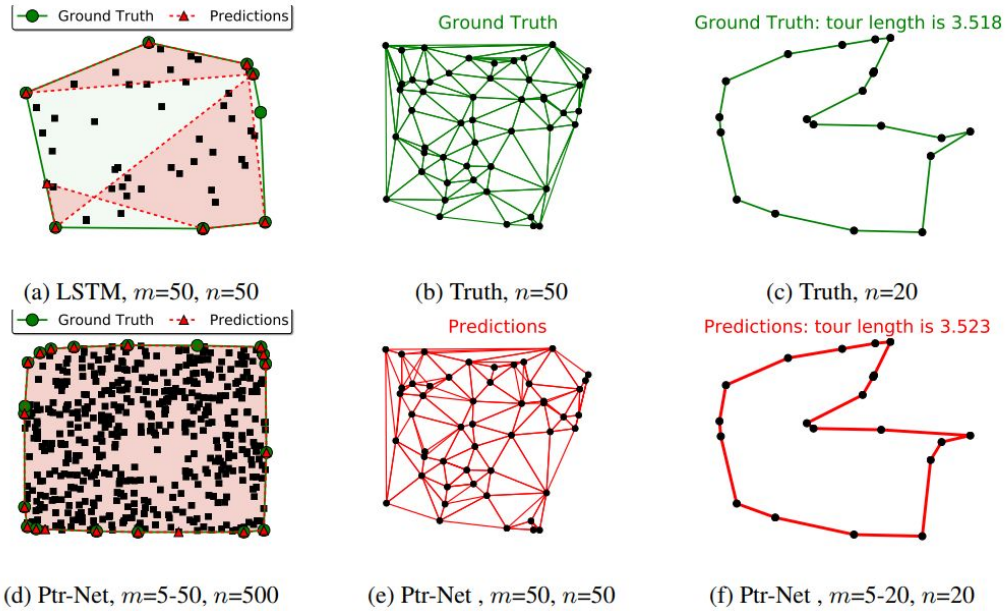



MLA Vinyals, Oriol, Meire Fortunato, and Navdeep Jaitly. "Pointer networks." Advances in Neural Information Processing Systems. 2015.

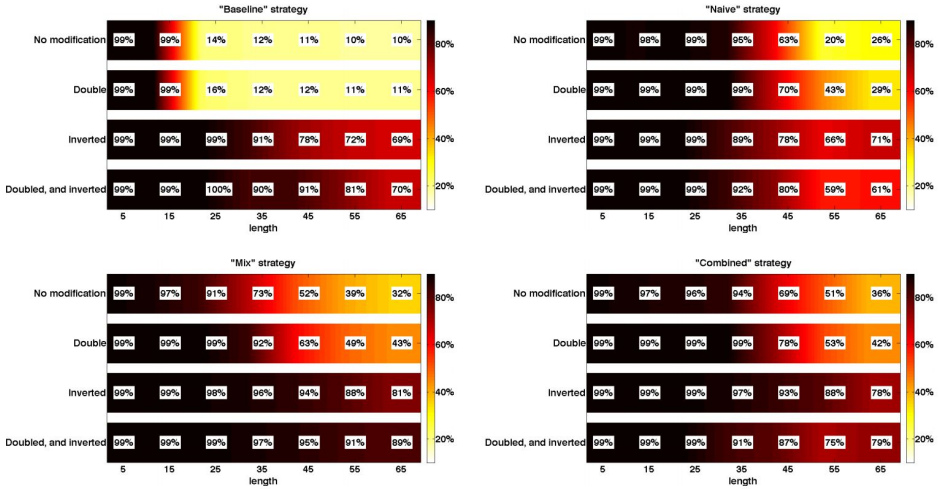
# Learning to execute

- Executing program

**Input:**

```
f=483654
for x in range(9):f-=913681
a=f
for x in range(12):a-=926785
print((124798 if a>326533 else 576599)).
```

| | |
|---|---|
| **Target:** | 576599. |
| **"Baseline" prediction:** | 176599. |
| **"Naive" prediction:** | 576599. |
| **"Mix" prediction:** | 576599. |
| **"Combined" prediction:** | 576599. |




Zaremba, Wojciech, and Ilya Sutskever. "Learning to execute." arXiv preprint arXiv:1410.4615 (2014).

# Neural Arithmetic Logic Units

## A Shocking Fact

Most Neural Networks CANNOT generalize on identity function

$$f(x) = x$$

## Because

Neural Networks does not know basic arithmetics

- Add and Subtract
- Multiply and Divide
- Exponential and Logarithm

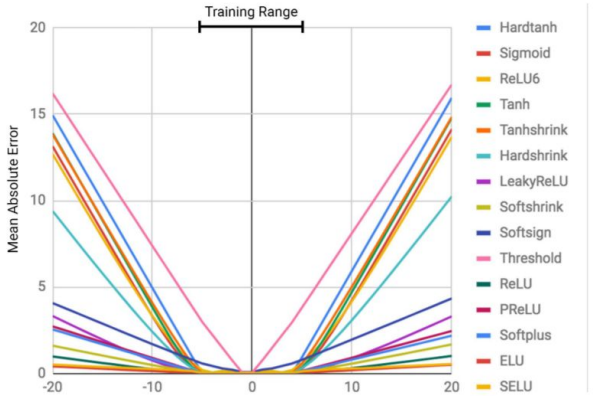



Figure 1: MLPs learn the identity function only for the range of values they are trained on. The mean error ramps up severely both below and above the range of numbers seen during training.

Trask, Andrew, et al. "Neural arithmetic logic units." Advances in Neural Information Processing Systems. 2018.

# Neural Arithmetic Logic Units

$$\texttt{NAC:} \quad \mathbf{a} = \mathbf{W}\mathbf{x} \qquad \mathbf{W} = \tanh(\hat{\mathbf{W}}) \odot \sigma(\hat{\mathbf{M}})$$

$$\texttt{NALU:} \quad \mathbf{y} = \mathbf{g} \odot \mathbf{a} + (1 - \mathbf{g}) \odot \mathbf{m} \qquad \mathbf{m} = \exp \mathbf{W}(\log(|\mathbf{x}| + \epsilon)),\ \mathbf{g} = \sigma(\mathbf{G}\mathbf{x})$$

Saturation Points

- Tanh: {-1, 1}
- Sigmoid: {0, 1}
- ⇒ Tanh * Sigmoid: {-1, 0, 1}

Trask, Andrew, et al. "Neural arithmetic logic units." Advances in Neural Information Processing Systems. 2018.

# Neural Arithmetic Logic Units

| | | Static Task (test) | | | | Recurrent Task (test) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Relu6 | None | NAC | NALU | LSTM | ReLU | NAC | NALU |
| Interpolation | $a+b$ | 0.2 | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** |
| | $a-b$ | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** | **0.0** |
| | $a \times b$ | 3.2 | 20.9 | 21.4 | **0.0** | **0.0** | **0.0** | 1.5 | **0.0** |
| | $a/b$ | **4.2** | 35.0 | 37.1 | 5.3 | **0.0** | **0.0** | 1.2 | **0.0** |
| | $a^2$ | 0.7 | 4.3 | 22.4 | **0.0** | **0.0** | **0.0** | 2.3 | **0.0** |
| | $\sqrt{a}$ | 0.5 | 2.2 | 3.6 | **0.0** | **0.0** | **0.0** | 2.1 | **0.0** |
| Extrapolation | $a+b$ | 42.6 | **0.0** | **0.0** | **0.0** | 96.1 | 85.5 | **0.0** | **0.0** |
| | $a-b$ | 29.0 | **0.0** | **0.0** | **0.0** | 97.0 | 70.9 | **0.0** | **0.0** |
| | $a \times b$ | 10.1 | 29.5 | 33.3 | **0.0** | 98.2 | 97.9 | 88.4 | **0.0** |
| | $a/b$ | 37.2 | 52.3 | 61.3 | **0.7** | **95.6** | 863.5 | >999 | >999 |
| | $a^2$ | 47.0 | 25.1 | 53.3 | **0.0** | 98.0 | 98.0 | 123.7 | **0.0** |
| | $\sqrt{a}$ | 10.3 | 20.0 | 16.4 | **0.0** | 95.8 | 34.1 | >999 | **0.0** |

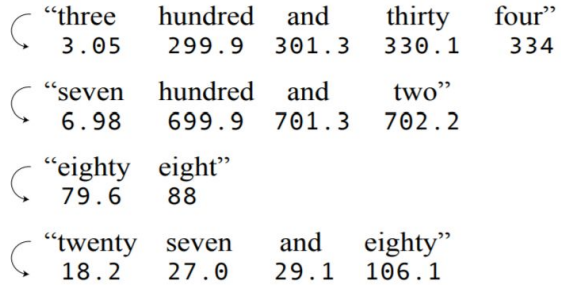



Figure 3: Intermediate NALU predictions on previously unseen queries.

Number in Extrapolation is **100 times** larger than in Interpolation

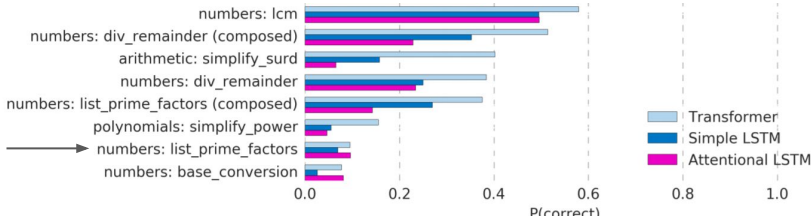
Trask, Andrew, et al. "Neural arithmetic logic units." Advances in Neural Information Processing Systems. 2018.

# Mathematical Reasoning

- Homework: 76/100
- Exam: 50/100
- Have no idea of factorization
  - Phew.. RSA encryption is still secure.

Question: Solve -42*r + 27*c = -1167 and 130*r + 4*c = 372 for r.
Answer: 4
Question: Calculate -841880142.544 + 411127.
Answer: -841469015.544
Question: Let x(g) = 9*g + 1. Let q(c) = 2*c + 1. Let f(i) = 3*i - 39. Let w(j) = q(x(j)). Calculate f(w(a)).
Answer: 54*a - 30
Question: Let e(l) = l - 6. Is 2 a factor of both e(9) and 2?
Answer: False
Question: Let u(n) = -n**3 - n**2. Let e(c) = -2*c**3 + c. Let l(j) = -118*e(j) + 54*u(j). What is the derivative of l(a)?
Answer: 546*a**2 - 108*a - 118
Question: Three letters picked without replacement from qqqkkklkqkkk. Give prob of sequence qql.
Answer: 1/110

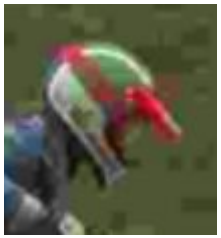
| | Parameters | Interpolation | Extrapolation |
|---|---|---|---|
| Simple **LSTM** | 18M | 0.57 | 0.41 |
| Simple **RMC** | 38M | 0.53 | 0.38 |
| Attentional **LSTM**, LSTM encoder | 24M | 0.57 | 0.38 |
| Attentional **LSTM**, bidir LSTM encoder | 26M | 0.58 | 0.42 |
| Attentional **RMC**, bidir LSTM encoder | 39M | 0.54 | 0.43 |
| **Transformer** | 30M | **0.76** | **0.50** |

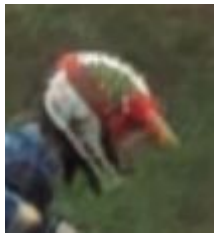



Saxton, David, et al. "Analysing Mathematical Reasoning Abilities of Neural Models." arXiv preprint arXiv:1904.01557 (2019).

# Compress Image

- Compete with JPEG





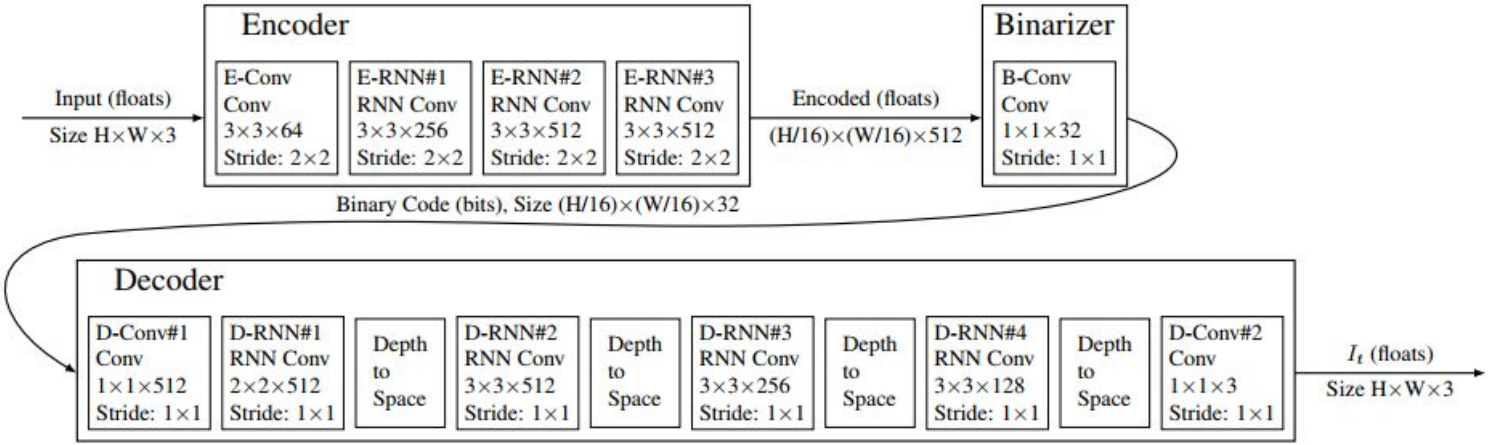
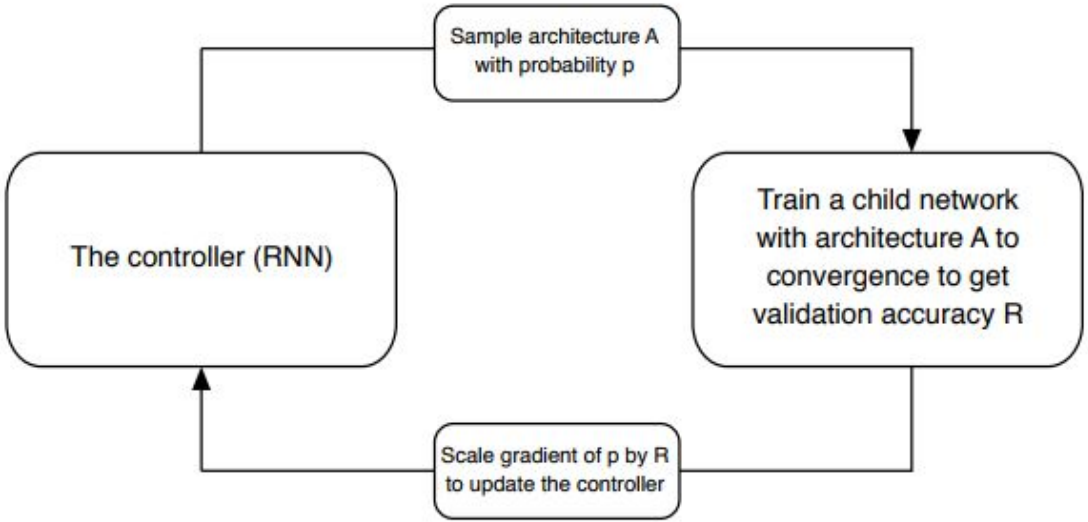



Figure 1. A single iteration of our shared RNN architecture.

Toderici, George, et al. "Full resolution image compression with recurrent neural networks." arXiv preprint arXiv:1608.05148 (2016).

# Model Architecture Search

- Use an RNN to produce model architectures
  - Learned using Reinforcement Learning




Zoph, Barret, et al. "Learning transferable architectures for scalable image recognition." arXiv preprint arXiv:1707.07012 (2017).

# Model Architecture Search

- Use an RNN to produce network architectures
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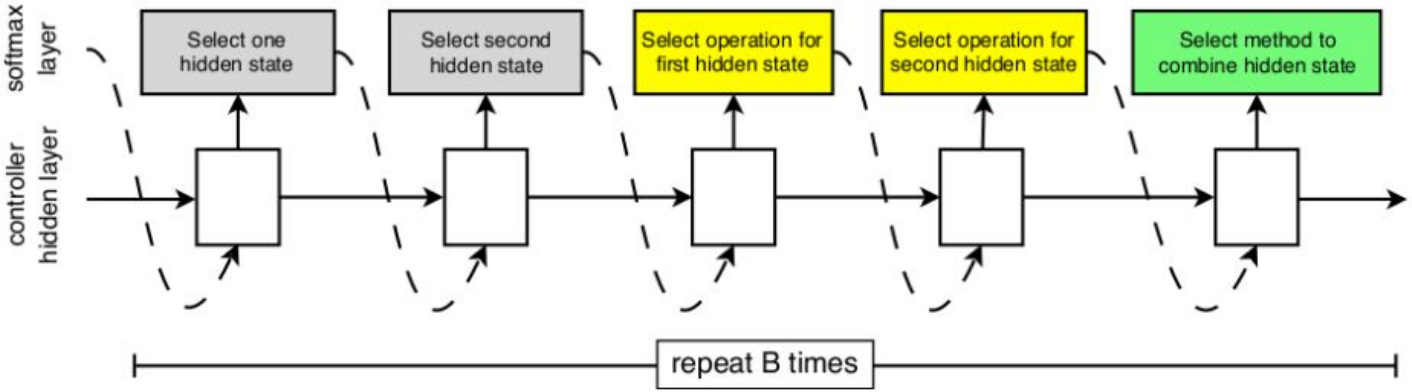
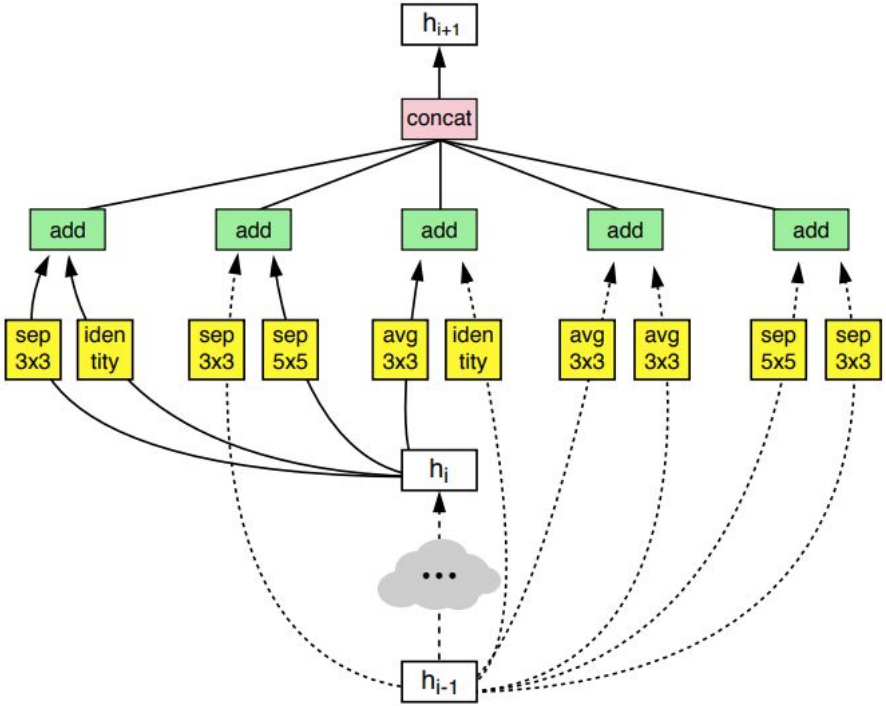
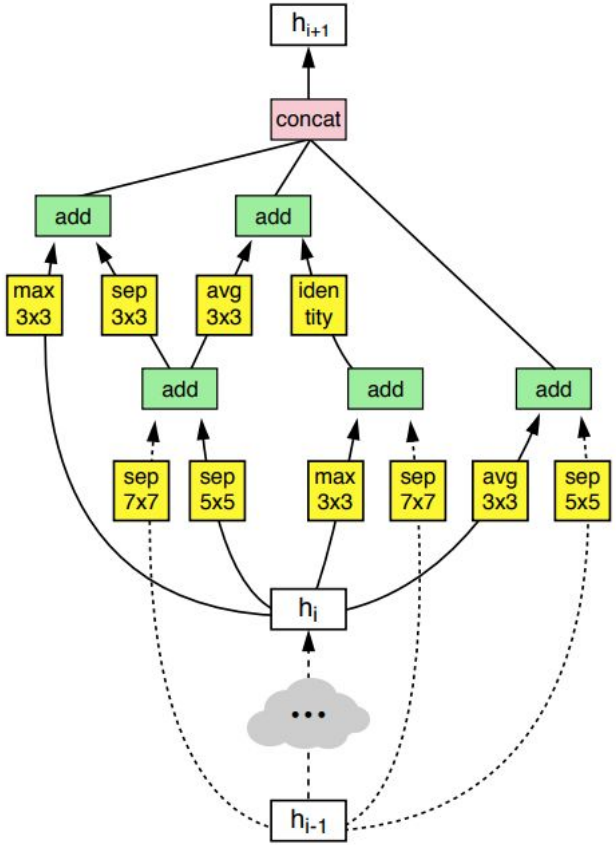



Zoph, Barret, et al. "Learning transferable architectures for scalable image recognition." arXiv preprint arXiv:1707.07012 (2017).



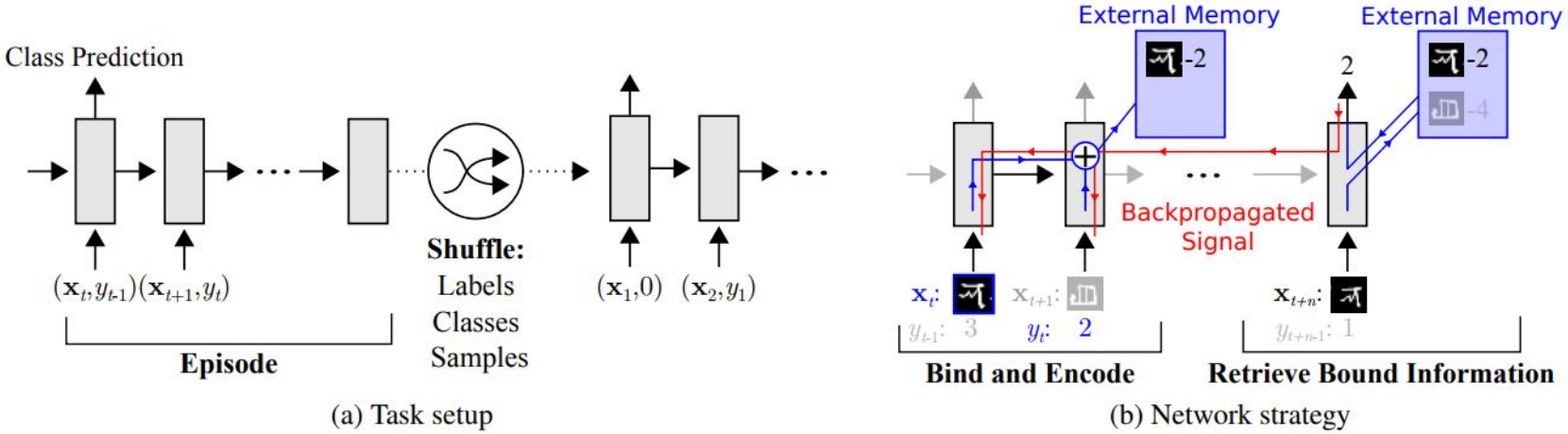

*Normal Cell*




*Reduction Cell*

# Meta-Learning

$$\text{supervised-learning} \quad P(y_{n+1}|x_{1:n+1}, y_{1:n})$$
$$\text{reinforcement-learning} \quad P(a_{n+1}|s_{1:n+1}, a_{1:n}, r_{1:n})$$




Santoro, Adam, et al. "Meta-learning with memory-augmented neural networks." International conference on machine learning. 2016.

# Summary

- Sequence Modeling indicates Turing Completeness.
- Progression: RNN → Longer RNN → CNN → Transformer
- Capable solving kinds of strange tasks
- The author of GPT2 are concerned to release the model because they consider the model can be abused by malicious applications.
    - The beginning of the end? (AI starts to take over the world)


THANKS FOR
LISTENING
ANY QUESTIONS?
NO?
GREAT!
KeepCalmAndPosters.com