Deep Learning

Sequence to Sequence models: Attention Models
Sequence-to-sequence modelling

• Problem:
  – A sequence $X_1 \ldots X_N$ goes in
  – A different sequence $Y_1 \ldots Y_M$ comes out

• E.g.
  – Speech recognition: Speech goes in, a word sequence comes out
    • Alternately output may be phoneme or character sequence
  – Machine translation: Word sequence goes in, word sequence comes out
  – Dialog: User statement goes in, system response comes out
  – Question answering: Question comes in, answer goes out

• In general $N \neq M$
  – No synchrony between $X$ and $Y$. 
Sequence to sequence

- Sequence goes in, sequence comes out
- No notion of "time synchrony" between input and output
  - May even not even maintain order of symbols
    - E.g. "I ate an apple" → "Ich habe einen apfel gegessen"
  - Or even seem related to the input
    - E.g. "My screen is blank" → "Please check if your computer is plugged in."
Recap: Have dealt with the “aligned” case: CTC

- The input and output sequences happen in the same order
  - Although they may be asynchronous
    - Order-correspondence, but no time synchrony
  - E.g. Speech recognition
    - The input speech corresponds to the phoneme sequence output
Today

- Sequence goes in, sequence comes out
- No notion of “time synchrony” between input and output
  - May even not even maintain order of symbols
    - E.g. “I ate an apple” → “Ich habe einen apfel gegessen”
  - Or even seem related to the input
    - E.g. “My screen is blank” → “Please check if your computer is plugged in.”
Recap: Predicting text

• Simple problem: Given a series of symbols (characters or words) $w_1 \ w_2 \ldots \ w_n$, predict the next symbol (character or word) $w_{n+1}$
Language modelling using RNNs

Four score and seven years ???

ABRAHAM LINCOLN??

• Problem: Given a sequence of words (or characters) predict the next one
  – The problem of learning the sequential structure of language
Simple recurrence: Text Modelling

- Learn a model that can predict the next symbol given a sequence of symbols
  - Characters or words

- After observing inputs $w_0 \ldots w_k$ it predicts $w_{k+1}$
  - In reality, outputs a probability distribution for $w_{k+1}$
Generating Language: The model

- Input: symbols as one-hot vectors
  - Dimensionality of the vector is the size of the “vocabulary”
  - Projected down to lower-dimensional “embeddings”

- The hidden units are (one or more layers of) LSTM units

- Output at each time: A probability distribution for the next word in the sequence

- All parameters are trained via backpropagation from a lot of text
Training

• Input: symbols as one-hot vectors
  • Dimensionality of the vector is the size of the “vocabulary”
  • Projected down to lower-dimensional “embeddings”

• Output: Probability distribution over symbols
  \[ Y(t, i) = P(V_i | w_0 \ldots w_{t-1}) \]
  • \( V_i \) is the i-th symbol in the vocabulary

• Divergence
  \[ \text{Div}(w(1 \ldots T), Y(0 \ldots T - 1)) = \sum_t KL(w(t + 1), Y(t)) = -\sum_t \log Y(t, w_{t+1}) \]
Generating Language: Synthesis

• On trained model: Provide the first few words
  – One-hot vectors

• After the last input word, the network generates a probability distribution over words
  – Outputs an N-valued probability distribution rather than a one-hot vector

\[ y_t^i = P(W_t = V_i | W_1 \ldots W_{t-1}) \]

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words.
On trained model: Provide the first few words
  – One-hot vectors

After the last input word, the network generates a probability distribution over words
  – Outputs an N-valued probability distribution rather than a one-hot vector

Draw a word by sampling from the distribution
  – And set it as the next word in the series

\[ y_t^i = P(W_t = V_i | W_1 \ldots W_{t-1}) \]

The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words
Generating Language: Synthesis

- Feed the drawn word as the next word in the series
  - And draw the next word by sampling from the output probability distribution

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The probability that the t-th word in the sequence is the i-th word in the vocabulary given all previous t-1 words
Generating Language: Synthesis

• Feed the drawn word as the next word in the series
  – And draw the next word by sampling from the output probability distribution

• When do we stop?
A note on beginnings and ends

• A sequence of words by itself does not indicate if it is a complete sentence or not
  
  ... four score and eight ... 
  
  – Unclear if this is the start of a sentence, the end of a sentence, or both (i.e. a complete sentence)

• To make it explicit, we will add two additional symbols (in addition to the words) to the base vocabulary
  
  – <sos> : Indicates start of a sentence
  
  – <eos> : Indicates end of a sentence
A note on beginnings and ends

• Some examples:

  four score and eight
  – This is clearly the middle of sentence

  <sos> four score and eight
  – This is a fragment from the start of a sentence

  four score and eight <eos>
  – This is the end of a sentence

  <sos> four score and eight <eos>
  – This is a full sentence

• In situations where the start of sequence is obvious, the <sos> may not be needed, but <eos> is required to terminate sequences

• Sometimes we will use a single symbol to represent both start and end of sentence, e.g. just <eos>, or even a separate symbol, e.g. <s>
Generating Language: Synthesis

- Feed the drawn word as the next word in the series
  - And draw the next word by sampling from the output probability distribution

- Continue this process until we draw an <eos>
  - Or we decide to terminate generation based on some other criterion
Returning our problem

- Problem:
  - A sequence $X_1 \ldots X_N$ goes in
  - A different sequence $Y_1 \ldots Y_M$ comes out
- No expected synchrony between input and output
Modelling the problem

- *Delayed* sequence to sequence
Modelling the problem

- *Delayed* sequence to sequence

First process the input and generate a hidden representation for it

• *Delayed* sequence to sequence
Pseudocode

# First run the inputs through the network
# Assuming h(-1,l) is available for all layers
for t = 0:T-1  # Including both ends of the index
    [h(t),..] = RNN_input_step(x(t),h(t-1),...)
H = h(T-1)

“RNN_input” may be a multi-layer RNN of any kind
Modelling the problem

- *Delayed* sequence to sequence

First process the input and generate a hidden representation for it

Then use it to generate an output

• *Delayed* sequence to sequence
# First run the inputs through the network
# Assuming h(-1,l) is available for all layers
for t = 0:T-1  # Including both ends of the index
    [h(t),..] = RNN_input_step(x(t),h(t-1),...) 
H = h(T-1)

# Now generate the output y_out(1),y_out(2),...

1. t = 0
2. h_out(0) = H
3. do
   - t = t+1
   - [y(t),h_out(t)] = RNN_output_step(h_out(t-1))
   - y_out(t) = draw_word_from(y(t))
4. until y_out(t) == <eos>
Pseudocode

# First run the inputs through the network
# Assuming h(-1,1) is available for all layers
for t = 0:T-1  # Including both ends of the index
    [h(t),..] = RNN_input_step(x(t),h(t-1),...)
H = h(T-1)

# Now generate the output y_{out}(1), y_{out}(2),...
t = 0
h_{out}(0) = H
do
dt = t+1
[y(t),h_{out}(t)] = RNN_output_step(h_{out}(t-1))
y_{out}(t) = draw_word_from(y(t))
until y_{out}(t) == <eos>

The output at each time is a probability distribution over symbols.
We draw a word from this distribution.
Modelling the problem

• **Problem:** Each word that is output depends only on current hidden state, and not on previous outputs.
Pseudocode

Changing this output at time \( t \) does not affect the output at \( t+1 \)

E.g. If we have drawn “It was a” vs “It was an”, the probability that the next word is “dark” remains the same (dark must ideally not follow “an”)

This is because the output at time \( t \) does not influence the computation at \( t+1 \)

```
# Now generate the output \( y_{out}(1), y_{out}(2), \ldots \)

\( t = 0 \)
\( h_{out}(0) = H \)

\textbf{do}
\begin{align*}
 t &= t + 1 \\
 [y(t), h_{out}(t)] &= \text{RNN\_output\_step}(h_{out}(t-1)) \\
 y_{out}(t) &= \text{draw\_word\_from}(y(t))
\end{align*}
\textbf{until} \( y_{out}(t) == <\text{eos}> \)
```

The RNN recursion only considers the hidden state \( h(t-1) \) from the previous time and not the actual output word \( y_{out}(t-1) \)
Modelling the problem

many to many

• *Delayed* sequence to sequence
  – Delayed *self-referencing* sequence-to-sequence
The “simple” translation model

- The input sequence feeds into a recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence

I ate an apple <eos>
The “simple” translation model

- The input sequence feeds into a recurrent structure
- The input sequence is terminated by an explicit <eos> symbol
  - The hidden activation at the <eos> “stores” all information about the sentence
- Subsequently a second RNN uses the hidden activation as initial state, and <sos> as initial symbol, to produce a sequence of outputs
  - The output at each time becomes the input at the next time
  - Output production continues until an <eos> is produced

I ate an apple <eos>
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The “simple” translation model

Note that drawing a different word here

Would result in a different word being input here, and as a result the output here and subsequent outputs would all change
• We will illustrate with a single hidden layer, but the discussion generalizes to more layers
# First run the inputs through the network
# Assuming h(-1,1) is available for all layers

\[ t = 0 \]

\[ \text{do} \]

\[ \begin{align*}
  [h(t),..] &= \text{RNN\_input\_step}(x(t),h(t-1),..) \\
  \text{until } x(t) &= "<eos>" \\
  H &= h(T-1)
\end{align*} \]

# Now generate the output \( y_{out}(1), y_{out}(2), \ldots \)

\[ t = 0 \]

\[ \text{do} \]

\[ \begin{align*}
  h_{out}(0) &= H \\
  y_{out}(0) &= <sos> \\
  \text{do} \]

\[ \begin{align*}
  t &= t+1 \\
  [y(t),h_{out}(t)] &= \text{RNN\_output\_step}(h_{out}(t-1), y_{out}(t-1)) \\
  y_{out}(t) &= \text{draw\_word\_from}(y(t))
\end{align*} \]

\[ \text{until } y_{out}(t) = <eos> \]
# First run the inputs through the network
# Assuming h(-1,l) is available for all layers

\[ t = 0 \]

\[ \text{do} \]

\[ [h(t),..] = \text{RNN\_input\_step}(x(t), h(t-1),...) \]

\[ \text{until } x(t) == "<eos>" \]

\[ H = h(T-1) \]

# Now generate the output \( y_{out}(1), y_{out}(2),... \)

\[ t = 0 \]

\[ h_{out}(0) = H \]

# Note: begins with a “start of sentence” symbol
# \(<sos>\) and \(<eos>\) may be identical

\[ y_{out}(0) = <sos> \]

\[ \text{do} \]

\[ t = t+1 \]

\[ [y(t), h_{out}(t)] = \text{RNN\_output\_step}(h_{out}(t-1), y_{out}(t-1)) \]

\[ y_{out}(t) = \text{draw\_word\_from}(y(t)) \]

\[ \text{until } y_{out}(t) == <eos> \]

Drawing a different word at \( t \) will change the next output since \( y_{out}(t) \) is fed back as input.
The “simple” translation model

- The recurrent structure that extracts the hidden representation from the input sequence is the *encoder*.

- The recurrent structure that utilizes this representation to produce the output sequence is the *decoder*.
The “simple” translation model

• A more detailed look: The one-hot word representations may be compressed via embeddings
  – Embeddings will be learned along with the rest of the net
  – In the following slides we will not represent the projection matrices
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  
  $$y_k^w = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N)$$

  - The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  
  \[
  y_k^{w} = P(O_k = w|O_{k-1}, ..., O_1, I_1, ..., I_N)
  \]

- The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

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What the network actually produces

At each time $k$ the network actually produces a probability distribution over the output vocabulary

\[ y_k^w = P(O_k = w|O_{k-1}, \ldots, O_1, I_1, \ldots, I_N) \]

The probability given the entire input sequence $I_1, \ldots, I_N$ and the partial output sequence $O_1, \ldots, O_{k-1}$ until $k$

At each time a word is drawn from the output distribution

The drawn word is provided as input to the next time

I ate an apple <sos> <eos> Ich
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, \ldots, O_1, I_1, \ldots, I_N)$
  - The probability given the entire input sequence $I_1, \ldots, I_N$ and the partial output sequence $O_1, \ldots, O_{k-1}$ until $k$

- At each time a word is *drawn* from the output distribution
- The drawn word is provided as input to the next time
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  $$y_k^w = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N)$$
  - The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

- At each time a word is **drawn** from the output distribution
- The drawn word is provided as input to the next time
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N)$
  - The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

- At each time a word is drawn from the output distribution
- The drawn word is provided as input to the next time
What the network actually produces

At each time $k$ the network actually produces a probability distribution over the output vocabulary

- $y^w_k = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N)$
  - The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

At each time a word is drawn from the output distribution

The drawn word is provided as input to the next time
What the network actually produces

- At each time $k$ the network actually produces a probability distribution over the output vocabulary
  - $y_k^w = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N)$
  - The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$
- At each time a word is drawn from the output distribution
- The drawn word is provided as input to the next time
What the network actually produces

• At each time $k$ the network actually produces a probability distribution over the output vocabulary
  
  \[ y_k^w = P(O_k = w | O_{k-1}, ..., O_1, I_1, ..., I_N) \]

  – The probability given the entire input sequence $I_1, ..., I_N$ and the partial output sequence $O_1, ..., O_{k-1}$ until $k$

• At each time a word is *drawn* from the output distribution
• The drawn word is provided as input to the next time
Generating an output from the net

- At each time the network produces a probability distribution over words, given the entire input and entire output sequence so far
- At each time a word is drawn from the output distribution
- The drawn word is provided as input to the next time
- The process continues until an <eos> is generated

I ate an apple <eos> <sos> Ich habe einen apfel gegessen

Ich habe einen apfel gegessen <eos>
Pseudocode

# First run the inputs through the network
# Assuming h(-1,l) is available for all layers

t = 0
do
    [h(t),..] = RNN_input_step(x(t),h(t-1),...)
until x(t) == "<eos>"
H = h(T-1)

# Now generate the output y_{out}(1),y_{out}(2),...
t = 0
h_{out}(0) = H

# Note: begins with a "start of sentence" symbol
#       <sos> and <eos> may be identical
y_{out}(0) = <sos>
do
    t = t+1
    [y(t),h_{out}(t)] = RNN_output_step(h_{out}(t-1), y_{out}(t-1))
    y_{out}(t) = draw_word_from(y(t))
until y_{out}(t) == <eos>

What is this magic operation?
The probability of the output

\[ P(O_1, \ldots, O_L | I_1, \ldots, I_N) \]
\[ = P(O_1 | I_1, \ldots, I_N)P(O_2 | O_1, I_1, \ldots, I_N)P(O_3 | O_1, O_2, I_1, \ldots, I_N) \ldots P(O_L | O_1, \ldots, O_{L-1}, I_1, \ldots, I_N) \]
\[ = y_1^{O_1} y_2^{O_2} \ldots y_L^{O_L} \]
The probability of the output

The objective of drawing: Produce the most likely output (that ends in an <eos>)

\[
\arg\max_{O_1, \ldots, O_L} P(O_1, \ldots, O_L | W_1^{in}, \ldots, W_N^{in})
\]

\[
= \arg\max_{O_1, \ldots, O_L} y_1^{O_1} y_2^{O_2} \ldots y_L^{O_L}
\]
Greedy drawing

Objective:
\[
\arg\max_{y_1, \ldots, y_L} y_1^{o_1} y_2^{o_2} \ldots y_L^{o_L}
\]

- So how do we draw words at each time to get the most likely word sequence?
- *Greedy* answer – select the most probable word at each time
# First run the inputs through the network
# Assuming h(-1,l) is available for all layers

t = 0
do
    \[h(t),..\] = RNN_input_step(x(t),h(t-1),...)
until x(t) == "<eos>"

H = h(T-1)

# Now generate the output y_{out}(1),y_{out}(2),...
t = 0
h_{out}(0) = H

# Note: begins with a “start of sentence” symbol
#       <sos> and <eos> may be identical
y_{out}(0) = <sos>
do
    t = t+1
    \[y(t),h_{out}(t)\] = RNN_output_step(h_{out}(t-1), y_{out}(t-1))
    y_{out}(t) = \text{argmax}_i(y(t,i))
until y_{out}(t) == <eos>

Select the most likely output at each time
Greedy drawing

Objective:
\[
\arg\max_{o_1, \ldots, o_L} y_1^{o_1} y_1^{o_2} \ldots y_1^{o_L}
\]

- Cannot just pick the most likely symbol at each time
  - That may cause the distribution to be more “confused” at the next time
  - Choosing a different, less likely word could cause the distribution at the next time to be more peaky, resulting in a more likely output overall
Greedy is not good

- Hypothetical example (from English speech recognition: Input is speech, output must be text)
  - “Nose” has highest probability at t=2 and is selected
    - The model is very confused at t=3 and assigns low probabilities to many words at the next time
    - Selecting any of these will result in low probability for the entire 3-word sequence
  - “Knows” has slightly lower probability than “nose”, but is still high and is selected
    - “he knows” is a reasonable beginning and the model assigns high probabilities to words such as “something”
    - Selecting one of these results in higher overall probability for the 3-word sequence
Greedy is not good

What should we have chosen at t=2??

Will selecting “nose” continue to have a bad effect into the distant future?

Problem: Impossible to know a priori which word leads to the more promising future

– Should we draw “nose” or “knows”?
– Effect may not be obvious until several words down the line
– Or the choice of the wrong word early may cumulatively lead to a poorer overall score over time
Greedy is not good

What should we have chosen at t=1??
Choose “the” or “he”?

• Problem: Impossible to know a priori which word leads to the more promising future
  – Even earlier: Choosing the lower probability “the” instead of “he” at T=0 may have made a choice of “nose” more reasonable at T=1..

• In general, making a poor choice at any time commits us to a poor future
  – But we cannot know at that time the choice was poor
Drawing by random sampling

Objective:
\[ \text{argmax } y_1^o y_2^o ... y_L^o \]

Alternate option: Randomly draw a word at each time according to the output probability distribution
Pseudocode

# First run the inputs through the network
# Assuming h(-1,1) is available for all layers

\[ t = 0 \]
\[
\text{do} \quad [h(t),..] = \text{RNN\_input\_step}(x(t),h(t-1),..) \\
\text{until } x(t) == "<eos>"
\]
\[ H = h(T-1) \]

# Now generate the output \( y_{out}(1), y_{out}(2), \ldots \)

\[ t = 0 \]
\[ h_{out}(0) = H \]

# Note: begins with a “start of sentence” symbol
# \( <sos> \) and \( <eos> \) may be identical

\[ y_{out}(0) = <sos> \]
\[
\text{do} \quad t = t+1 \\
[ y(t), h_{out}(t) ] = \text{RNN\_output\_step}(h_{out}(t-1), y_{out}(t-1)) \\
\quad y_{out}(t) = \text{sample}(y(t)) \\
\text{until } y_{out}(t) == <eos> \]

Randomly sample from the output distribution.
Drawing by random sampling

Objective:

\[
\arg\max_{o_1, \ldots, o_L} y_1^{o_1} y_2^{o_2} \ldots y_L^{o_L}
\]

- Alternate option: Randomly draw a word at each time according to the output probability distribution
  - Unfortunately, not guaranteed to give you the most likely output
  - May sometimes give you more likely outputs than greedy drawing though
Your choices can get you stuck

Problem: making a poor choice at any time commits us to a poor future

– But we cannot know at that time the choice was poor

Solution: Don’t choose..
Optimal Solution: Multiple choices

- Retain all choices and *fork* the network
  - With every possible word as input
Problem: This will blow up very quickly

- For an output vocabulary of size $V$, after $T$ output steps we’d have forked out $V^T$ branches
• **Solution: Prune**

  – At each time, retain only the top K scoring forks

\[ \text{Top}_K P(O_1 | I_1, ..., I_N) \]
Solution: Prune

- At each time, retain only the top K scoring forks
Solution: Prune

- At each time, retain only the top K scoring forks

Note: based on product

$$Top_K \ P(O_2 \ O_1 | I_1, ..., I_N)$$

$$= Top_K \ P(O_2 | O_1, I_1, ..., I_N)P(O_1 | I_1, ..., I_N)$$
Solution: Prune

– At each time, retain only the top K scoring forks

Note: based on product

\[ \text{Top}_K \ P(O_2 \mid O_1, I_1, ..., I_N) \]

\[ = \text{Top}_K \ P(O_2 \mid O_1, I_1, ..., I_N) P(O_1 \mid I_1, ..., I_N) \]
Solution: Prune

- At each time, retain only the top K scoring forks

\[ = \text{Top}_K P(O_3 | O_1, O_2, I_1, ..., I_N) \times \]
\[ P(O_2 | O_1, I_1, ..., I_N) \times \]
\[ P(O_1 | I_1, ..., I_N) \]
Solution: Prune

- At each time, retain only the top K scoring forks

\[ = \text{Top}_K P(O_2 | O_1, O_2, I_1, ..., I_N) \times P(O_2 | O_1, I_1, ..., I_N) \times P(O_1 | I_1, ..., I_N) \]
Solution: Prune

– At each time, retain only the top K scoring forks
• **Terminate**
  
  – When the current most likely path overall ends in `<eos>`
    
    • Or continue producing more outputs (each of which terminates in `<eos>`) to get N-best outputs
Termination: <eos>

- **Terminate**
  - Paths cannot continue once the output an <eos>
    - So paths may be different lengths
      - Select the most likely sequence ending in <eos> across all terminating sequences

Example has K = 2
Pseudocode: Beam search

# Assuming encoder output $H$ is available
path = <sos>
beam = {path}
pathscore = [path] = 1
state[path] = h[0]  # Output of encoder
do   # Step forward
    nextbeam = {}
    nextpathscore = []
    nextstate = {}
    for path in beam:
        cfin = path[end]
        hpath = state[path]
        [y, h] = RNN_output_step(hpath, cfin)
        for c in Symbolset
            newpath = path + c
            nextstate[newpath] = h
            nextpathscore[newpath] = pathscore[path]*y[c]
            nextbeam += newpath  # Set addition
    end
    beam, pathscore, state, bestpath = prune(nextstate, nextpathscore, nextbeam, bw)
until bestpath[end] = <eos>
Pseudocode: Prune

# Note, there are smarter ways to implement this

function prune (state, score, beam, beamwidth)
    sortedscore = sort(score)
    threshold = sortedscore[beamwidth]

    prunedstate = {}
    prunedscore = []
    prunedbeam = {}

    bestscore = -inf
    bestpath = none
    for path in beam:
        if score[path] > threshold:
            prunedbeam += path # set addition
            prunedstate[path] = state[path]
            prunedscore[path] = score[path]
            if score[path] > bestscore
                bestscore = score[path]
                bestpath = path
        end
    end
    return prunedbeam, prunedscore, prunedstate, bestpath
**Training the system**

- Must learn to make predictions appropriately
  - Given “I ate an apple <eos>”, produce “Ich habe einen apfel gegessen <eos>”.

\[ \text{Ich habe einen apfel gegessen <eos>} \]
Forward pass: Input the source and target sequences, sequentially

\begin{itemize}
\item Output will be a probability distribution over target symbol set (vocabulary)
\end{itemize}
Training: Backward pass

- Backward pass: Compute the divergence between the output distribution and target word sequence
Training: Backward pass

- Backward pass: Compute the divergence between the output distribution and target word sequence
- Backpropagate the derivatives of the divergence through the network to learn the net
Training: Backward pass

- In practice, if we apply SGD, we may randomly sample words from the output to actually use for the backprop and update
  - Typical usage: Randomly select one word from each input training instance (comprising an input-output pair)
    - For each iteration
      - Randomly select training instance: (input, output)
      - Forward pass
      - Randomly select a single output $y(t)$ and corresponding desired output $d(t)$ for backprop
Overall training

• Given several training instance \((X, D)\)
• For each training instance
  – Forward pass: Compute the output of the network for \((X, D)\)
    • Note, both \(X\) and \(D\) are used in the forward pass
  – Backward pass: Compute the divergence between selected words of the desired target \(D\) and the actual output \(Y\)
    • Propagate derivatives of divergence for updates
• Update parameters
Trick of the trade: Reversing the input

- Standard trick of the trade: The input sequence is fed *in reverse order*
  - Things work better this way
Trick of the trade: Reversing the input

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Trick of the trade: Reversing the input

• Standard trick of the trade: The input sequence is fed in reverse order
  – Things work better this way

• *This happens both for training and during inference on test data*
Overall training

• Given several training instance \((X, D)\)

• Forward pass: Compute the output of the network for \((X, D)\) with input in reverse order
  – Note, both \(X\) and \(D\) are used in the forward pass

• Backward pass: Compute the divergence between the desired target \(D\) and the actual output \(Y\)
  – Propagate derivatives of divergence for updates
Applications

• Machine Translation
  – My name is Tom → Ich heisse Tom/Mein name ist Tom

• Automatic speech recognition
  – Speech recording → “My name is Tom”

• Dialog
  – “I have a problem” → “How may I help you”

• Image to text
  – Picture → Caption for picture
Machine Translation Example

- Hidden state clusters by meaning!
  - From “Sequence-to-sequence learning with neural networks”, Sutskever, Vinyals and Le
**Machine Translation Example**

<table>
<thead>
<tr>
<th>Type</th>
<th>Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our model</td>
<td>Ulrich UNK, membre du conseil d’administration du constructeur automobile Audi, affirme qu’il s’agit d’une pratique courante depuis des années pour que les téléphones portables puissent être collectés avant les réunions du conseil d’administration afin qu’ils ne soient pas utilisés comme appareils d’écoute à distance.</td>
</tr>
<tr>
<td>Truth</td>
<td>Ulrich Hackenberg, membre du conseil d’administration du constructeur automobile Audi, déclare que la collecte des téléphones portables avant les réunions du conseil, afin qu’ils ne puissent pas être utilisés comme appareils d’écoute à distance, est une pratique courante depuis des années.</td>
</tr>
<tr>
<td>Our model</td>
<td>“Les téléphones cellulaires, qui sont vraiment une question, non seulement parce qu’ils pourraient potentiellement causer des interférences avec les appareils de navigation, mais nous savons, selon la FCC, qu’ils pourraient interagrer avec les tours de téléphone cellulaire lorsqu’ils sont dans l’air”, dit UNK.</td>
</tr>
<tr>
<td>Truth</td>
<td>“Les téléphones portables sont véritablement un problème, non seulement parce qu’ils pourraient éventuellement créer des interférences avec les instruments de navigation, mais parce que nous savons, d’après la FCC, qu’ils pourraient perturber les antennes-relais de téléphonie mobile s’ils sont utilisés à bord”, a déclaré Rosenker.</td>
</tr>
<tr>
<td>Our model</td>
<td>Avec la crémation, il y a un “sentiment de violence contre le corps d’un être cher”, qui sera “réduit à une pile de cendres” en très peu de temps au lieu d’un processus de décomposition “qui accompagnera les étapes du deuil”.</td>
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<tr>
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</table>

- Examples of translation
  - From “Sequence-to-sequence learning with neural networks”, Sutskever, Vinyals and Le
Human Machine Conversation: Example

Machine: *what is the error that you are running please*
Human: *i am seeing an error related to vpn*
Machine: *what is the error message that you are getting when connecting to vpn using network connect ?*
Human: *connection refused or something like that*
Machine: *may i know the version of network connect you connect ?*
Human: *i am not sure i know that*
Machine: *is the network connect prompting for any user certificate*

• From “A neural conversational model”, Orin Vinyals and Quoc Le
• Trained on human-human converstations
• Task: Human text in, machine response out
Generating Image Captions

- Not really a seq-to-seq problem, more an image-to-sequence problem
- Initial state is produced by a state-of-art CNN-based image classification system
  - Subsequent model is just the decoder end of a seq-to-seq model
    - “Show and Tell: A Neural Image Caption Generator”, O. Vinyals, A. Toshev, S. Bengio, D. Erhan
Generating Image Captions

- **Decoding**: Given image
  - Process it with CNN to get output of classification layer
• Decoding: Given image
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  – Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1...W_{t-1}, Image)$
  – In practice, we can perform the beam search explained earlier
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Generating Image Captions

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  - Process it with CNN to get output of classification layer
  - Sequentially generate words by drawing from the conditional output distribution $P(W_t|W_0W_1...W_{t-1}, Image)$
  - In practice, we can perform the beam search explained earlier
• **Training**: Given several (Image, Caption) pairs
  – The image network is pretrained on a large corpus, e.g. image net
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  – The image network is pretrained on a large corpus, e.g. image net

• **Forward pass**: Produce output distributions given the image and caption

• **Backward pass**: Compute the divergence w.r.t. training caption, and backpropagate derivatives
  – All components of the network, including final classification layer of the image classification net are updated
  – The CNN portions of the image classifier are not modified (transfer learning)
Examples from Vinyals et al.

- "man in black shirt is playing guitar."
- "construction worker in orange safety vest is working on road."
- "two young girls are playing with lego toy."
- "boy is doing backflip on wakeboard."
- "a young boy is holding a baseball bat."
- "a cat is sitting on a couch with a remote control."
- "a woman holding a teddy bear in front of a mirror."
- "a horse is standing in the middle of a road."
Variants

A better model: Encoded input embedding is input to all output timesteps

Ich habe einen apfel gegessen <eos>

A boy on a surfboard

Ich habe einen apfel gegessen <eos>

A better model: Encoded input embedding is input to all output timesteps

A boy on a surfboard
Translating Videos to Natural Language Using Deep Recurrent Neural Networks

Subhashini Venugopalan, Huijun Xu, Jeff Donahue, Marcus Rohrbach, Raymond Mooney, Kate Saenko
# Assuming encoded input $H$ (from text, image, video)
# is available
# Now generate the output $y_{out}(1),y_{out}(2),...$

$t = 0$
$h_{out}(0) = H$  # Encoder embedding

# Note: begins with a “start of sentence” symbol
#       <sos> and <eos> may be identical
$y_{out}(0) = <sos>$
do
  $t = t+1$
  $[y(t), h_{out}(t)] = \text{RNN-output-step}(h_{out}(t-1), y_{out}(t-1), H)$
  $y_{out}(t) = \text{generate}(y(t))$  # Beam search, random, or greedy
until $y_{out}(t) == <eos>$
Pseudocode

# Assuming encoded input H (from text, image, video)
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until $y_{out}(t) == <eos>$
A problem with this framework

- All the information about the input sequence is embedded into a single vector
  - The “hidden” node layer at the end of the input sequence
  - This one node is “overloaded” with information
    - Particularly if the input is long
A problem with this framework

• In reality: *All* hidden values carry information
  – Some of which may be diluted downstream

I ate an apple <eos>
A problem with this framework

- In reality: All hidden values carry information
  - Some of which may be diluted downstream
- Different outputs are related to different inputs
  - Recall input and output may not be in sequence
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• In reality: *All* hidden values carry information
  – Some of which may be diluted downstream

• Different outputs are related to different inputs
  – Recall input and output may not be in sequence
  – Have no way of knowing a priori which input must connect to what output

• Connecting everything to everything is infeasible
  – Variable sized inputs and outputs
  – Overparametrized
  – Connection pattern ignores the actual asynchronous dependence of output on input
Solution: Attention models

- Separating the encoder and decoder in illustration

I ate an apple <eos>
Solution: Attention models

- Compute a weighted combination of all the hidden outputs into a single vector
  - Weights vary by output time
Solution: Attention models

Let's consider the input sequence: I ate an apple <eos>.

- **Compute a weighted combination of all the hidden outputs into a single vector**
  - Weights vary by output time

![Diagram of attention model]

**Diagram Explanation**:
- **Input to hidden decoder layer**: \[ \sum_{i} w_{i}(t)h_{i} \]
- **Weights**: \( w_{i}(t) \) are scalars

**Note**: Weights vary with output time
Solution: Attention models

- Require a time-varying weight that specifies relationship of output time to input time
  - Weights are functions of current output state

Input to hidden decoder layer: $\sum_i w_i(t)h_i$
Attention models

- The weights are a distribution over the input
  - Must automatically highlight the most important input components for any output
Attention models

- "Raw" weight at any time: A function $g()$ that works on the two hidden states
- Actual weight: softmax over raw weights

Input to hidden decoder layer: $\sum_i w_i(t)h_i$

Sum to 1.0

$e_i(t) = g(h_i, s_{t-1})$

$w_i(t) = \frac{\exp(e_i(t))}{\sum_j \exp(e_j(t))}$
Attention models

- Typical options for $g()$...
  - Variables in red are to be learned
Modification: Query key value

\[ e_i(t) = g(k_i, q_t) \]
\[ w_i(t) = \text{softmax}(e_i(t)) \]

Encoder outputs an explicit “key” and “value” at each input time

- Key is used to evaluate the importance of the input at that time, for a given output

Decoder outputs an explicit “query” at each output time

- Query is used to evaluate which inputs to pay attention to

The weight is a function of key and query

The actual context is a weighted sum of value
Modification: Query key value

\[ e_i(t) = g(k_i, q_t) \]
\[ w_i(t) = \text{softmax}(e_i(t)) \]

Input to hidden decoder layer: \( \sum_i w_i(t)v_i \)

Special case: \( k_i = v_i = h_i \)
\[ q_t = s_{t-1} \]
We will continue using this assumption in the following slides but in practice the query-key-value format is used.
Converting an input (forward pass)

- Pass the input through the encoder to produce hidden representations $h_i$
Converts an input (forward pass)

What is this?
Multiple options

Simplest: \( s_{-1} = h_N \)

If \( s \) and \( h \) are different sizes:
\[
    s_{-1} = W_s h_N
\]
\( W_s \) is learnable parameter

\( h_{-1} \rightarrow h_0 \rightarrow h_1 \rightarrow h_2 \rightarrow h_3 \rightarrow h_4 \)

- Initialize decoder hidden state
Converting an input (forward pass)

- Compute weights (for every $h_i$) for first output

$$g(h_i, s_{-1}) = h_i^T W_g s_{-1}$$

$$e_i(0) = g(h_i, s_{-1})$$

$$w_i(0) = \frac{\exp(e_i(0))}{\sum_j \exp(e_j(0))}$$
Converting an input (forward pass)

\[ z_0 = \sum_i w_i(0) h_i \]

- Compute weights (for every \( h_i \)) for first output
- Compute weighted combination of hidden values

\[ g(h_i, s_{-1}) = h_i^T w_g s_{-1} \]

\[ e_i(0) = g(h_i, s_{-1}) \]

\[ w_i(0) = \frac{\exp(e_i(0))}{\sum_j \exp(e_j(0))} \]
Converting an input (forward pass)

\[ z_0 = \sum_i w_i(0)h_i \]

- Produce the first output
  - Will be distribution over words

I ate an apple <eos>
Converting an input (forward pass)

\[ z_0 = \sum_i w_i(0)h_i \]

- Produce the first output
  - Will be distribution over words
  - Draw a word from the distribution
• Compute the weights for all instances for time = 1
Compute the weighted sum of hidden input values at $t=1$.
• Compute the output at t=1
  – Will be a probability distribution over words
Draw a word from the output distribution at $t=1$
I ate an apple

• Compute the weights for all instances for time = 2
Compute the weighted sum of hidden input values at t=2
Compute the output at t=2

- Will be a probability distribution over words
• Draw a word from the distribution
• Compute the weights for all instances for time = 3
• Compute the weighted sum of hidden input values at t=3

\[ z_3 = \sum_i w_i(3) h_i \]
Compute the output at $t=3$

- Will be a probability distribution over words
- Draw a word from the distribution
• Continue the process until an end-of-sequence symbol is produced
Pseudocode

# Assuming encoded input
# \((K,V) = [k_{enc}[0]... k_{enc}[T]], [v_{enc}[0]... v_{enc}[T]]\)
# is available

t = -1
\(h_{out}[-1] = 0\)  # Initial Decoder hidden state
q[0] = 0  # Initial query

# Note: begins with a “start of sentence” symbol
# \(<sos>\) and \(<eos>\) may be identical
\(y_{out}[0] = <sos>\)
do
  t = t+1
  \(C = compute\_context\_with\_attention(q[t], K, V)\)
  \(y[t], h_{out}[t], q[t+1] = RNN\_decode\_step(h_{out}[t-1], y_{out}[t-1], C)\)
  \(y_{out}[t] = generate(y[t])\)  # Random, or greedy
until \(y_{out}[t] == <eos>\)
# Takes in previous state, encoder states, outputs attention-weighted context

function compute_context_with_attention(q, K, V)
    # First compute attention
    e = []
    for t = 1:T  # Length of input
        e[t] = raw_attention(q, K[t])
    end
    maxe = max(e)  # subtract max(e) from everything to prevent underflow
    a[1..T] = exp(e[1..T] - maxe)  # Component-wise exponentiation
    suma = sum(a)  # Add all elements of a
    a[1..T] = a[1..T]/suma

    C = 0
    for t = 1..T
        C += a[t] * V[t]
    end

    return C
As before, the objective of drawing: Produce the most likely output (that ends in an <eos>)

\[
\arg\max_{y_1^{o_1}, y_1^{o_2}, \ldots, y_1^{o_L}} y_1^{o_1} y_1^{o_2} \ldots y_1^{o_L}
\]

Simply selecting the most likely symbol at each time may result in suboptimal output
Solution: Multiple choices

• Retain all choices and *fork* the network
  – With every possible word as input
To prevent blowup: Prune

- Prune
  - At each time, retain only the top K scoring forks

\[ Top_K P(O_1 | I_1, ..., I_N) \]
• At each time, retain only the top K scoring forks
Decoding

• At each time, retain only the top K scoring forks

\[
Top_K \ P(O_2 O_1 | I_1, ..., I_N) = Top_K \ P(O_2 | O_1, I_1, ..., I_N)P(O_1 | I_1, ..., I_N)
\]

Note: based on product
Decoding

Note: based on product

\[ \text{Top}_K P(O_2O_1|I_1, \ldots, I_N) \]

\[ = \text{Top}_K P(O_2|O_1, I_1, \ldots, I_N)P(O_1|I_1, \ldots, I_N) \]

- At each time, retain only the top K scoring forks
Decoding

\[ = \text{Top}_K P(O_2|O_1, I_1, ..., I_N) \times \]
\[ \times P(O_2|O_1, I_1, ..., I_N) \times \]
\[ \times P(O_1|I_1, ..., I_N) \]

• At each time, retain only the top K scoring forks
Decoding

- At each time, retain only the top K scoring forks
Decoding

\[ \text{Top}_K \prod_{t=1}^{n} P(O_n|O_1, ..., O_{n-1}, I_1, ..., I_N) \]

- At each time, retain only the top K scoring forks
• **Terminate**
  
  – When the current most likely path overall ends in `<eos>`
    • Or continue producing more outputs (each of which terminates in `<eos>`) to get N-best outputs
• **Terminate**
  
  – Paths cannot continue once the output an `<eos>`
    
    • So paths may be different lengths
      
      – Select the most likely sequence ending in `<eos>` across *all* terminating sequences
Pseudocode: Beam search

# Assuming encoder output \( H = h_{in}[1] \ldots h_{in}[T] \) is available

\( \text{path} = \langle \text{sos}\rangle \)
\( \text{beam} = \{\text{path}\} \)
\( \text{pathscores} = \{\text{path}\} = 1 \)
\( \text{state}[\text{path}] = h[0] \quad \# \text{initial state (computed using your favorite method)} \)

**do**  
**# Step forward**
  **do**
    \( \text{nextbeam} = \{\} \)
    \( \text{nextpathscores} = [] \)
    \( \text{nextstate} = {} \)
    **for** \( \text{path} \) **in** \( \text{beam} \):
      \( \text{cfin} = \text{path}[\text{end}] \)
      \( \text{hpath} = \text{state}[\text{path}] \)
      \( \text{C} = \text{compute_context_with_attention}(\text{hpath}, H) \)
      \( y, h = \text{RNN_decode_step}(\text{hpath}, \text{cfin}, \text{C}) \)
      **for** \( c \) **in** \( \text{Symbolset} \):
        \( \text{newpath} = \text{path} + c \)
        \( \text{nextstate}[\text{newpath}] = h \)
        \( \text{nextpathscores}[\text{newpath}] = \text{pathscores}[\text{path}]*y[c] \)
        \( \text{nextbeam} += \text{newpath} \quad \# \text{Set addition} \)
  **end**
**end**

\( \text{beam, pathscores, state, bestpath} = \text{prune}(\text{nextstate}, \text{nextpathscores}, \text{nextbeam}) \)
**until** \( \text{bestpath}[\text{end}] = \langle \text{eos}\rangle \)
Pseudocode: Beam search

# Assuming encoder output H = h_{in}[1]... h_{in}[T] is available
path = <sos>
beam = {path}
pathscore = [path] = 1
state[path] = h[0]  # computed using your favorite method
context[path] = compute_context_with_attention(h[0], H)
do  # Step forward
    nextbeam = {}
    nextpathscore = []
    nextstate = {}
    nextcontext = {}
    for path in beam:
        cfin = path[end]
        hpath = state[path]
        C = context[path]
        y,h = RNN_decode_step(hpath, cfin, C)
        nextC = compute_context_with_attention(h, H)
        for c in Symbolset
            newpath = path + c
            nextstate[newpath] = h
            nextcontext[newpath] = nextC
            nextpathscore[newpath] = pathscore[path]*y[c]
            nextbeam += newpath  # Set addition
    end
    beam, pathscore, state, context, bestpath =
       prune (nextstate, nextpathscore, nextbeam, nextcontext)
until bestpath[end] = <eos>

Slightly more efficient.
Does not perform redundant context computation
What does the attention learn?

- The key component of this model is the attention weight
  - It captures the relative importance of each position in the input to the current output
“Alignments” example: Bahdanau et al.

Plot of $w_i(t)$
Color shows value (white is larger)

Note how most important input words for any output word get automatically highlighted

The general trend is somewhat linear because word order is roughly similar in both languages
## Translation Examples

<table>
<thead>
<tr>
<th>Source</th>
<th>An admitting privilege is the right of a doctor to admit a patient to a hospital or a medical centre to carry out a diagnosis or a procedure, based on his status as a health care worker at a hospital.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference</td>
<td>Le privilège d’admission est le droit d’un médecin, en vertu de son statut de membre soignant d’un hôpital, d’admettre un patient dans un hôpital ou un centre médical afin d’y délivrer un diagnostic ou un traitement.</td>
</tr>
<tr>
<td>RNNenc-50</td>
<td>Un privilège d’admission est le droit d’un médecin de reconnaître un patient à l’hôpital ou un centre médical d’un diagnostic ou de prendre un diagnostic en fonction de son état de santé.</td>
</tr>
<tr>
<td>RNNsearch-50</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>This kind of experience is part of Disney’s efforts to “extend the lifetime of its series and build new relationships with audiences via digital platforms that are becoming ever more important,” he added.</th>
</tr>
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<td>Reference</td>
<td>Ce type d’expérience entre dans le cadre des efforts de Disney pour ”étendre la durée de vie de ses séries et construire de nouvelles relations avec son public grâce à des plateformes numériques qui sont de plus en plus importantes”, a-t-il ajouté.</td>
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- Bahdanau et al. 2016
Training the network

• We have seen how a trained network can be used to compute outputs
  – Convert one sequence to another

• Lets consider training..
• Given training input (source sequence, target sequence) pairs
• **Forward pass**: Pass the actual Pass the input sequence through the encoder
  – At each time the output is a probability distribution over words
- **Backward pass**: Compute a divergence between target output and output distributions
  - Backpropagate derivatives through the network
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  – Backpropagate derivatives through the network
Some tricks of the trade

- Backward pass: Compute a divergence between target output and output distributions
  - Backpropagate derivatives through the network
Tricks of the trade...

- **Teacher forcing:**
  - Ideally we only use the decoder output during inference
  - This will not be stable
  - Passing in ground truth instead is “teacher forcing”

- **Sampling the output:**
  - Sample the system output and
  - as input during training for only some of the time

- **The “Gumbel noise” trick:**
  - Sampling is not differentiable, and gradients cannot be passed through it
  - The “Gumbel noise” approach recasts sampling as computing the argmax of a Gumbel distribution, with the network output as parameters
  - The “argmax” can be replaced by a “softmax”, making the process differentiable w.r.t. network outputs
Various extensions

• Bidirectional processing of input sequence
  – Bidirectional networks in encoder

• Attention: Local attention vs global attention
  – E.g. “Effective Approaches to Attention-based Neural Machine Translation”, Luong et al., 2015
  – Other variants
**Extensions: Multihead attention**

- Have multiple query/key/value sets.
  - Each attention “head” uses one of these sets
  - The combined contexts from all heads are passed to the decoder
- Each “attender” focuses on a different aspect of the input that’s important for the decode

\[
e_i^l(t) = g(k_i^l, q_i^l) \\
w_i^l(t) = \text{softmax}(e_i^l(t)) \\
c_t^l = \sum_i w_i^l(t)v_i^l
\]
Some impressive results..

• Attention-based models are currently responsible for the state of the art in many sequence-conversion systems
  – Machine translation
    • Input: Text in source language
    • Output: Text in target language
  – Speech recognition
    • Input: Speech audio feature vector sequence
    • Output: Transcribed word or character sequence
Attention models in image captioning

• “Show attend and tell: Neural image caption generation with visual attention”, Xu et al., 2016

• Encoder network is a convolutional neural network
  – Filter outputs at each location are the equivalent of $h_i$ in the regular sequence-to-sequence model
In closing

• Have looked at various forms of sequence-to-sequence models

• Generalizations of recurrent neural network formalisms

• For more details, please refer to papers
  – Post on piazza if you have questions

• Will appear in HW4: **Speech recognition with attention models**