Machine Translation

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Many slides from John DeNero and Philip Koehn

Translation Task

- Text is both the input and the output.
- Input and output have roughly the same information content.
- Output is more predictable than a language modeling task.
- Lots of naturally occurring examples.

Translation Examples

English-German News Test 2013 (a standard dev set)

Republican leaders justified their policy by the need to combat electoral fraud.

```
Die  Führungskräfte  der     Republikaner
 |        |           |           |
The  Executives      of the  republican

rechtfertigen  ihre  Politik   mit   der
     |          |       |       |     |
   justify     your  politics  With  of the

Notwendigkeit  ,  den  Wahlbetrug      zu
      |        |   |       |           |
     need      ,  the  election fraud  to

bekämpfen  .
    |      |
  fight    .
```

Variety in Translations?

Human-generated reference translation

A small planet, whose is as big as could destroy a middle sized city, passed by the earth with a distance of 463 thousand kilometers. This was not found in advance. The astronomists got to know this incident 4 days later. This small planet is 50m in diameter. The astonomists are hard to find it for it comes from the direction of sun.

A commercial system from 2002

A volume enough to destroy a medium city small planet is big, flit earth within 463,000 kilometres of close however were not in advance discovered, astronomer just knew this matter after four days. This small planet diameter is about 50 metre, from the direction at sun, therefore astronomer very hard to discovers it.

Google Translate, 2020

From https://catalog.ldc.upenn.edu/LDC2003T17

Evaluation

BLEU Score

BLEU score: geometric mean of 1-, 2-, 3-, and 4-gram precision vs. a reference, multiplied by brevity penalty (harshly penalizes translations shorter than the reference).

$$\text{Matched}_i = \sum_{t_i} \min\left\{C_h(t_i), \max_j C_j(t_i)\right\}$$

If "of the" appears twice in hypothesis h but only at most once in a reference, then only the first is "correct"

$$P_i = \frac{\text{Matched}_i}{H_i}$$

"Clipped" precision of n-gram tokens

$$B = \exp\left\{\min\left(0, \frac{n-L}{n}\right)\right\}$$

Brevity penalty only matters if the hypothesis **corpus** is shorter than the sum of (shortest) references.

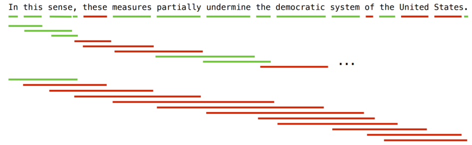
$$\text{BLUE} = B\left(\prod_{i=1}^{4} P_i\right)^{\frac{1}{4}}$$

BLEU is a mean of clipped precisions, scaled down by the brevity penalty.

Evaluation with BLEU

In this sense, the measures will partially undermine the American democratic system.

In this sense, these measures partially undermine the democratic system of the United States.



BLEU = 26.52, 75.0/40.0/21.4/7.7 (BP=1.000, ratio=1.143, hyp_len=16, ref_len=14)

(Papineni et al., 2002) BLEU: a method for automatic evaluation of machine translation.

Corpus BLEU Correlations with Average Human Judgments

These are ecological correlations over multiple segments; segment-level BLEU scores are noisy.

Commercial machine translation providers seem to all perform human evaluations of some sort.

(Ma et al., 2019) Results of the WMT19 Metrics Shared Task: Segment-Level and Strong MT Systems Pose Big Challenges

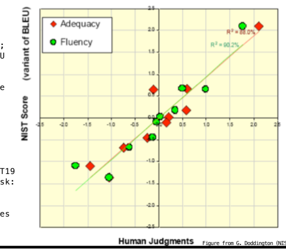


Figure from G. Doddington (NIST)

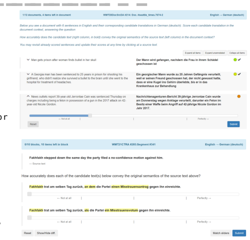
Human Evaluations

Direct assessment: adequacy & fluency

- Monolingual: Ask humans to compare machine translation to a human-generated reference. (Easier to source annotators)
- Bilingual: Ask humans to compare machine translation to the source sentence that was translated. (Compares to human quality)
- Annotators can assess segments (sentences) or whole documents.
- Segments can be assessed with or without document context.

Ranking assessment:

- Raters are presented with 2 or more translations.
- A human-generated reference may be provided, along with the source.
- "In a pairwise ranking experiment, human



(Läubli et al., 2018) Has Machine Translation Achieved Human Parity? A Case for Document-level Evaluation

(Akhbardeh et al., 2021) Findings of the 2021 Conference on Machine Translation

Translationese and Evaluation

Translated text can: (Baker et al., 1993; Graham et al., 2019)

- be more explicit than the original source
- be less ambiguous
- be simplified (lexically, syntactically, and stylistically)
- display a preference for conventional grammaticality
- avoid repetition
- exaggerate target language features
- display features of the source language

"If we consider only original source text (i.e. not translated from another language, or translationese), then we find evidence showing that human parity has not been achieved."
(Toral et al., 2018)

(Baker et al., 1993) Corpus linguistics and transla- tion studies: Implications and applications.
(Graham et al., 2019) Translationese in Machine Translation Evaluation.
(Toral et al, 2018) Attaining the Unattainable? Reassessing Claims of Human Parity in Neural Machine Translation

How are We Doing? Example: WMT 2019 Evaluation

2019 segment-in-context direct assessment (Barrault et al, 2019):

- ✓ German to English: many systems are tied with human performance;
- × English to Chinese: all systems are outperformed by the human translator;
- × English to Czech: all systems are outperformed by the human translator;
- × English to Finnish: all systems are outperformed by the human translator;
- ✓ English to German: Facebook-FAIR achieves super-human translation performance; several systems are tied with human performance;
- × English to Gujarati: all systems are outperformed by the human translator;
- × English to Kazakh: all systems are outperformed by the human translator;
- × English to Lithuanian: all systems are outperformed by the human translator;
- ✓ English to Russian: Facebook-FAIR is tied with human performance.

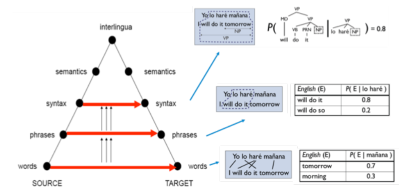
(Barrault et al., 2019) Findings of the 2019 Conference on Machine Translation (WMT19)

Statistical Machine Translation
(1990 - 2015)

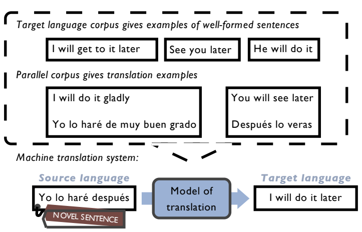
When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."

Warren Weaver (1949)

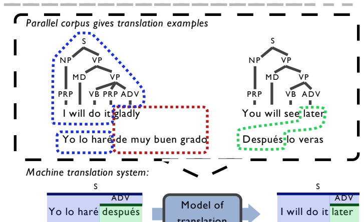
Levels of Transfer: Vauquois Triangle (1968)



Data-Driven Machine Translation



Stitching Together Fragments



Evolution of the Noisy Channel Model

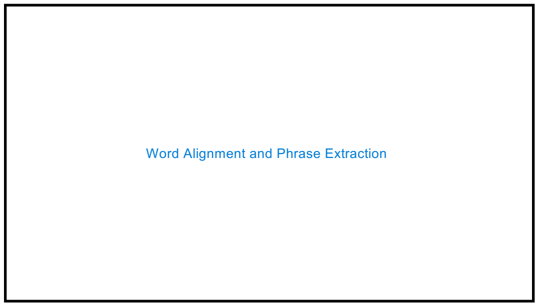
$$P(e|f) \propto P(f|e) \cdot P(e)$$

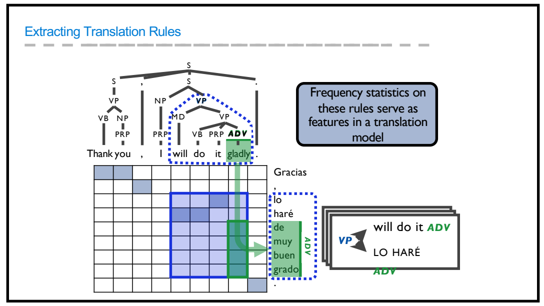
$$P(e|f) \propto P(f|e)^{\phi_{\text{tm}}} \cdot P(e)^{\phi_{\text{lm}}}$$

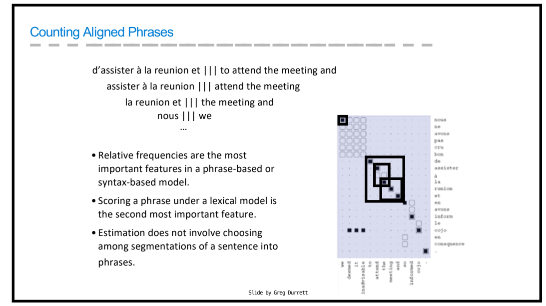
Chosen to minimize loss

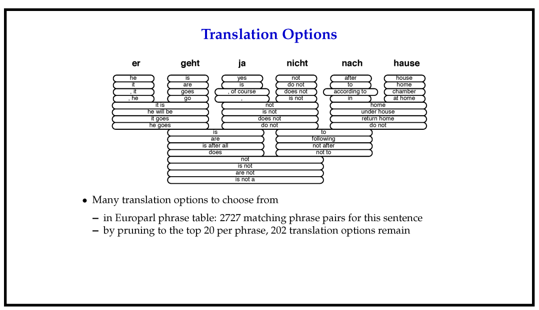
$$P(e|f) \propto \exp\left\{\sum_i w_i \cdot f_i(e,f)\right\}$$

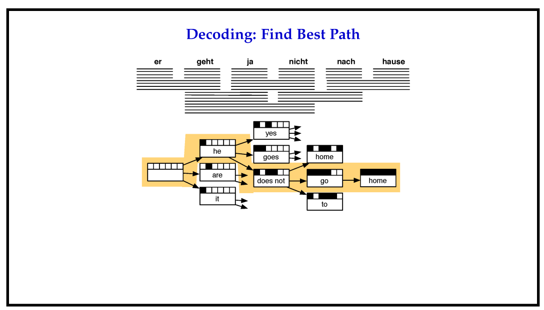
E.g., log P(e)

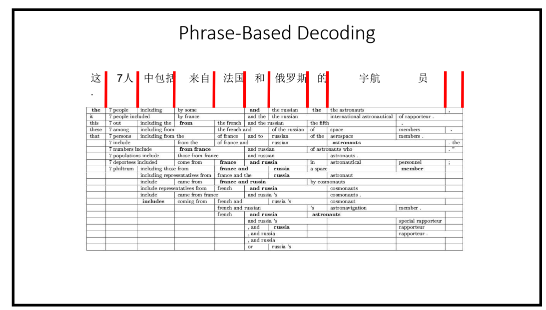

Word Alignment and Phrase Extraction


Extracting Translation Rules
Frequency statistics on these rules serve as features in a translation model
Thank you , I will do it gladly
Gracias , lo haré de muy buen grado .
will do it ADV
LO HARÉ ADV


Counting Aligned Phrases
d'assister à la reunion et ||| to attend the meeting and
assister à la reunion ||| attend the meeting
la reunion et ||| the meeting and
nous ||| we
...
• Relative frequencies are the most important features in a phrase-based or syntax-based model.
• Scoring a phrase under a lexical model is the second most important feature.
• Estimation does not involve choosing among segmentations of a sentence into phrases.
Slide by Greg Durrett


Translation Options
er geht ja nicht nach hause
• Many translation options to choose from
– in Europarl phrase table: 2727 matching phrase pairs for this sentence
– by pruning to the top 20 per phrase, 202 translation options remain

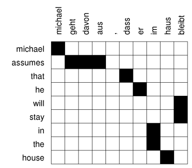

Decoding: Find Best Path
er geht ja nicht nach hause
yes
he
goes
home
are
does not
go
home
it
to


Phrase-Based Decoding
这 7人 中包括 来自 法国 和 俄罗斯 的 宇航 员 .

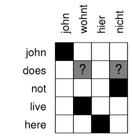
Word Alignments

Word Alignment

Given a sentence pair, which words correspond to each other?

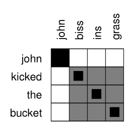


Word Alignment?



Is the English word does aligned to
the German wohnt (verb) or nicht (negation) or neither?

Word Alignment?



How do the idioms kicked the bucket and biss ins grass match up?
Outside this exceptional context, bucket is never a good translation for grass

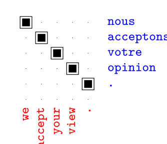
Lexical Translation / Word Alignment Models

Unsupervised Word Alignment

- Input: a ***bitext***: pairs of translated sentences

```
nous acceptons votre opinion .
we accept your view .
```

- Output: ***alignments***: pairs of translated words
  - When words have unique sources, can represent as a (forward) alignment function a from French to English positions

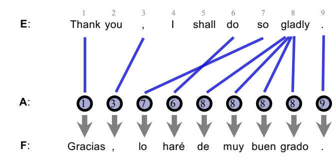


Word Alignment

- Even today models are often built on the IBM alignment models
- Create probabilistic word-level translation models
- The models incorporate latent (unobserved) word alignments
- Optimize the probability of the observed words
- Use the imputed alignments to reveal word-level correspondence

IBM Model 1: Allocation

IBM Models 1/2



Model Parameters

Translation: P(F_1 = Gracias | E_{A1} = Thank) *Alignment:* P(A_2 = 3)

Example

das

e	$t(e\|f)$
the	0.7
that	0.15
which	0.075
who	0.05
this	0.025

Haus

e	$t(e\|f)$
house	0.8
building	0.16
home	0.02
household	0.015
shell	0.005

ist

e	$t(e\|f)$
is	0.8
’s	0.16
exists	0.02
has	0.015
are	0.005

klein

e	$t(e\|f)$
small	0.4
little	0.4
short	0.1
minor	0.06
petty	0.04

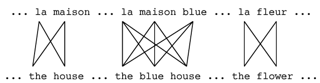
$$
\begin{aligned}
p(e,a|f) &= \frac{\epsilon}{4^3} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\
&= \frac{\epsilon}{4^3} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\
&= 0.0028\epsilon
\end{aligned}
$$

Expectation Maximization

EM Algorithm

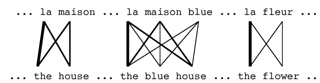
- Incomplete data
  - if we had *complete data*, would could estimate *model*
  - if we had *model*, we could fill in the *gaps in the data*
- Expectation Maximization (EM) in a nutshell
  1. initialize model parameters (e.g. uniform)
  2. assign probabilities to the missing data
  3. estimate model parameters from completed data
  4. iterate steps 2–3 until convergence

EM Algorithm



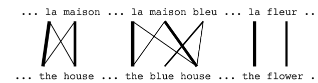
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM Algorithm



- After one iteration
- Alignments, e.g., between la and the are more likely

EM Algorithm

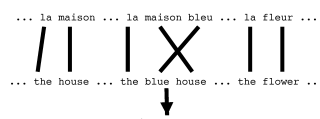


- After another iteration
- It becomes apparent that alignments, e.g., between fleur and flower are more likely (pigeon hole principle)

EM Algorithm

- Convergence
- Inherent hidden structure revealed by EM

EM Algorithm




```
p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...
```

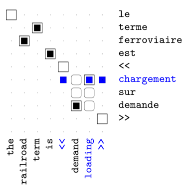
- Parameter estimation from the aligned corpus

IBM Model 1 and EM

- EM Algorithm consists of two steps
- Expectation-Step: Apply model to the data
  - parts of the model are hidden (here: alignments)
  - using the model, assign probabilities to possible values
- Maximization-Step: Estimate model from data
  - take assign values as fact
  - collect counts (weighted by probabilities)
  - estimate model from counts
- Iterate these steps until convergence

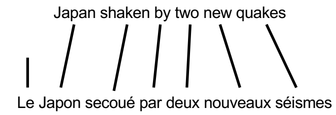
Problems with Model 1

- There's a reason they designed models 2-5!
- Problems: alignments jump around, align everything to rare words
- Experimental setup:
  - Training data: 1.1M sentences of French-English text, Canadian Hansards
  - Evaluation metric: alignment error Rate (AER)
  - Evaluation data: 447 hand-aligned sentences

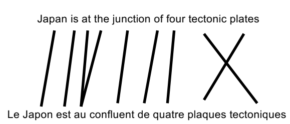


IBM Model 2: Global Monotonicity

Monotonic Translation



Local Order Change



IBM Model 2

- Alignments tend to the diagonal (broadly at least)

$$P(f, a|e) = \prod_j P(a_j = i|j, I, J) P(f_j|e_i)$$

$$P(dist = i - j\frac{I}{J})$$

$$\frac{1}{Z} e^{-\alpha(i - j\frac{I}{J})}$$

EM for Models 1/2

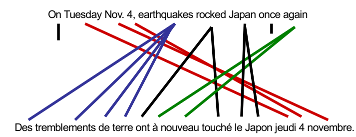
- Model 1 Parameters:
  Translation probabilities (1+2) $P(f_j|e_i)$
  Distortion parameters (2 only) $P(a_j = i|j, I, J)$
- Start with $P(f_j|e_i)$ uniform, including $P(f_j|null)$
- For each sentence:
  - For each French position j
    - Calculate posterior over English positions

$$P(a_j = i|f, e) = \frac{P(a_j = i|j, I, J) P(f_j|e_i)}{\sum_{i'} P(a_j = i'|j, I, J) P(f_j|e'_i)}$$

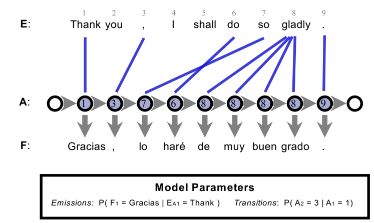
    - (or just use best single alignment)
    - Increment count of word f_j with word e_i by these amounts
    - Also re-estimate distortion probabilities for model 2
- Iterate until convergence

HMM Model: Local Monotonicity

Phrase Movement



The HMM Model



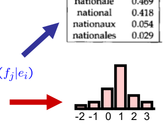
The HMM Model

- Model 2 preferred global monotonicity
- We want local monotonicity:
  - Most jumps are small
- HMM model (Vogel 96)

f	t(f | e)
nationale	0.469
national	0.418
nationaux	0.054
nationales	0.029

$$P(f,a|e) = \prod_j P(a_j|a_{j-1})P(f_j|e_i)$$

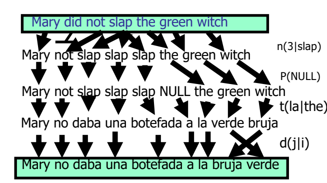
$$P(a_j - a_{j-1})$$



  - Re-estimate using the forward-backward algorithm
  - Handling nulls requires some care
- What are we still missing?

Models 3+: Fertility

IBM Models 3/4/5



[from Al-Onaizan and Knight, 1998]

Examples: Translation and Fertility

the

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
le	0.497	1	0.746
la	0.207	0	0.254
les	0.155		
l'	0.086		
ce	0.018		
cette	0.011		

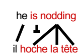
not

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
ne	0.497	2	0.735
pas	0.442	0	0.154
non	0.029	1	0.107
rien	0.011		

farmers

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
agriculteurs	0.442	2	0.731
les	0.418	1	0.228
cultivateurs	0.046	0	0.039
producteurs	0.021		

Example: Idioms



nodding

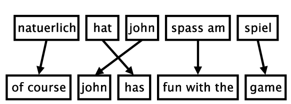
f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
signe	0.164	4	0.342
la	0.123	3	0.293
tête	0.097	2	0.167
oui	0.086	1	0.163
fait	0.073	0	0.023
que	0.073		
hoche	0.054		
hocher	0.048		
faire	0.030		
me	0.024		
approuve	0.019		
qui	0.019		
un	0.012		
faites	0.011		

Example: Morphology

should

f	$t(f \mid e)$	ϕ	$n(\phi \mid e)$
devrait	0.330	1	0.649
devraient	0.123	0	0.336
devrions	0.109	2	0.014
faudrait	0.073		
faut	0.058		
doit	0.058		
aurait	0.041		
doivent	0.024		
devons	0.017		
devrais	0.013		

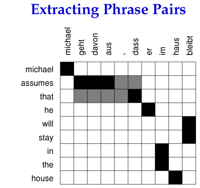
Phrase-Based Model



- Foreign input is segmented in phrases
- Each phrase is translated into English
- Phrases are reordered

Getting Phrases

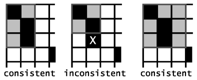
Extracting Phrase Pairs



extract phrase pair consistent with word alignment:

assumes that / geht davon aus , dass

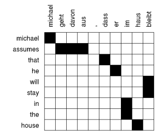
Consistent



ok | **violated** one alignment point outside | **ok** unaligned word is fine

All words of the phrase pair have to align to each other.

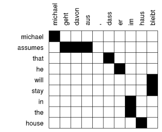
Phrase Pair Extraction



Smallest phrase pairs:
michael — michael
assumes — geht davon aus / geht davon aus ,
that — dass / , dass
he — er
will stay — bleibt
in the — im
house — haus

unaligned words (here: German comma) lead to multiple translations

Larger Phrase Pairs



michael assumes — michael geht davon aus / michael geht davon aus ,
assumes that — geht davon aus , dass ; assumes that he — geht davon aus , dass er
that he — dass er / , dass er ; in the house — im haus
michael assumes that — michael geht davon aus , dass
michael assumes that he — michael geht davon aus , dass er
michael assumes that he will stay in the house — michael geht davon aus , dass er im haus bleibt
assumes that he will stay in the house — geht davon aus , dass er im haus bleibt
that he will stay in the house — dass er im haus bleibt ; dass er im haus bleibt ,
he will stay in the house — er im haus bleibt ; will stay in the house — im haus bleibt

Scoring Phrase Translations

- Phrase pair extraction: collect all phrase pairs from the data
- Phrase pair scoring: assign probabilities to phrase translations
- Score by relative frequency:

$$\phi(\bar{f}|\bar{e}) = \frac{\text{count}(\bar{e}, \bar{f})}{\sum_{f_i} \text{count}(\bar{e}, \bar{f}_i)}$$

Real Example

- Phrase translations for den Vorschlag learned from the Europarl corpus:

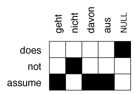
English	$\phi(\bar{e}\|\bar{f})$	English	$\phi(\bar{e}\|\bar{f})$
the proposal	0.6227	the suggestions	0.0114
's proposal	0.1068	the proposed	0.0114
a proposal	0.0341	the motion	0.0091
the idea	0.0250	the idea of	0.0091
this proposal	0.0227	the proposal ,	0.0068
proposal	0.0205	its proposal	0.0068
of the proposal	0.0159	it	0.0068
the proposals	0.0159	...	...

- lexical variation (proposal vs suggestions)
- morphological variation (proposal vs proposals)
- included function words (the, a, ...)
- noise (it)

Other Scoring Terms

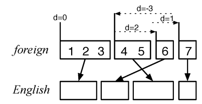
More Feature Functions

- Bidirectional alignment probabilities: $\phi(\bar{e}|\bar{f})$ and $\phi(\bar{f}|\bar{e})$
- Rare phrase pairs have unreliable phrase translation probability estimates
  $\rightarrow$ lexical weighting with word translation probabilities



$$\text{lex}(\bar{e}|\bar{f},a) = \prod_{i=1}^{\text{length}(\bar{e})} \frac{1}{|\{j|(i,j) \in a\}|} \sum_{\forall (i,j) \in a} w(e_i|f_j)$$

Distance-Based Reordering

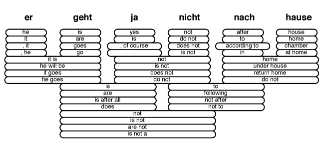


phrase	translates	movement	distance
1	1–3	start at beginning	0
2	6	skip over 4–5	+2
3	4–5	move back over 4–6	-3
4	7	skip over 6	+1

Scoring function: $d(x) = \alpha^{|x|}$ — exponential with distance

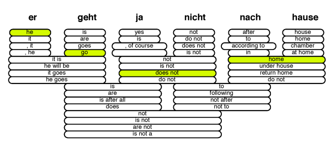
Phrase-Based Decoding

Translation Options



- Many translation options to choose from
  - in Europarl phrase table: 2727 matching phrase pairs for this sentence
  - by pruning to the top 20 per phrase, 202 translation options remain

Translation Options



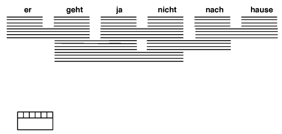
- The machine translation decoder does not know the right answer
  - picking the right translation options
  - arranging them in the right order

$\rightarrow$ Search problem solved by heuristic beam search

Decoding: Precompute Translation Options

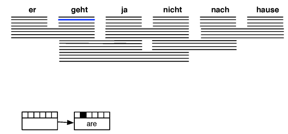
consult phrase translation table for all input phrases

Decoding: Start with Initial Hypothesis



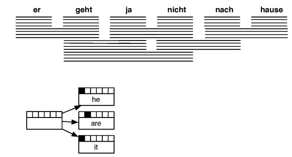
initial hypothesis: no input words covered, no output produced

Decoding: Hypothesis Expansion



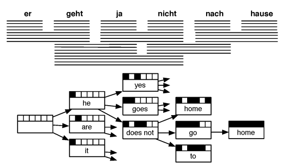
pick any translation option, create new hypothesis

Decoding: Hypothesis Expansion



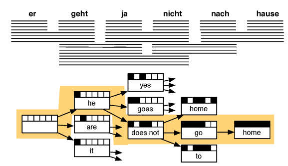
create hypotheses for all other translation options

Decoding: Hypothesis Expansion



also create hypotheses from created partial hypothesis

Decoding: Find Best Path



backtrack from highest scoring complete hypothesis

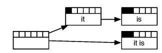
Dynamic Programming

Computational Complexity

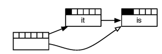
- The suggested process creates exponential number of hypothesis
- Machine translation decoding is NP-complete
- Reduction of search space:
  - recombination (risk-free)
  - pruning (risky)

Recombination

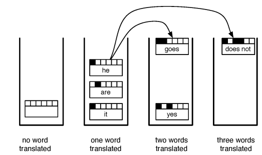
- Two hypothesis paths lead to two matching hypotheses
  - same foreign words translated
  - same English words in the output



- Worse hypothesis is dropped



Stacks



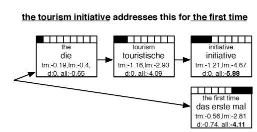
- Hypothesis expansion in a stack decoder
  - translation option is applied to hypothesis
  - new hypothesis is dropped into a stack further down

Stack Decoding Algorithm

place empty hypothesis into stack 0
for all stacks $0...n-1$ **do**
    for all hypotheses in stack **do**
        for all translation options **do**
            if applicable **then**
                create new hypothesis
                place in stack
                recombine with existing hypothesis **if** possible
                prune stack **if** too big
            end if
        end for
    end for
end for

Future Costs

Translating the Easy Part First?

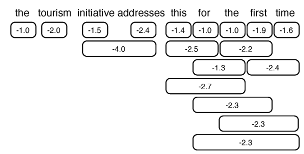


both hypotheses translate 3 words
worse hypothesis has better score

Estimating Future Cost

- Future cost estimate: how expensive is translation of rest of sentence?
- Optimistic: choose cheapest translation options
- Cost for each translation option
  - **translation model**: cost known
  - **language model:** output words known, but not context
    → estimate without context
  - **reordering model:** unknown, ignored for future cost estimation

Cost Estimates from Translation Options



cost of cheapest translation options for each input span (log-probabilities)

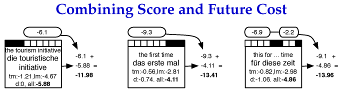
Cost Estimates for all Spans

- Compute cost estimate for all contiguous spans by combining cheapest options

first word	future cost estimate for n words (from first)								
	1	2	3	4	5	6	7	8	9
the	-1.0	-3.0	-4.5	-6.9	-8.3	-9.3	-9.6	-10.6	-10.6
tourism	-2.0	-3.5	-5.9	-7.3	-8.3	-8.6	-9.6	-9.6	
initiative	-1.5	-3.9	-5.3	-6.3	-6.6	-7.6	-7.6		
addresses	-2.4	-3.8	-4.8	-5.1	-6.1	-6.1			
this	-1.4	-2.4	-2.7	-3.7	-3.7				
for	-1.0	-1.3	-2.3	-2.3					
the	-1.0	-2.2	-2.3						
first	-1.9	-2.4							
time	-1.6								

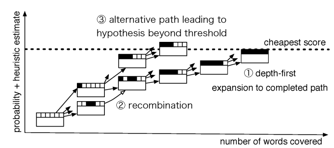
- Function words cheaper (the: -1.0) than content words (tourism -2.0)
- Common phrases cheaper (for the first time: -2.3)
  than unusual ones (tourism initiative addresses: -5.9)

Combining Score and Future Cost



- Hypothesis score and future cost estimate are combined for pruning
  - left hypothesis starts with hard part: the tourism initiative
    score: -5.88, future cost: -6.1 → total cost -11.98
  - middle hypothesis starts with easiest part: the first time
    score: -4.11, future cost: -9.3 → total cost -13.41
  - right hypothesis picks easy parts: this for ... time
    score: -4.86, future cost: -9.1 → total cost -13.96

A* Search

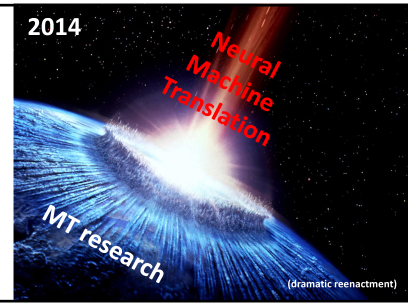


- Uses *admissible* future cost heuristic: never overestimates cost
- Translation agenda: create hypothesis with lowest score + heuristic cost
- Done, when complete hypothesis created

1990s-2010s: Statistical Machine Translation

- SMT was a huge research field
- The best systems were extremely complex
  - Hundreds of important details we haven't mentioned here
  - Systems had many separately-designed subcomponents
  - Lots of feature engineering
    - Need to design features to capture particular language phenomena
  - Require compiling and maintaining extra resources
    - Like tables of equivalent phrases
  - Lots of human effort to maintain
    - Repeated effort for each language pair!

Neural Machine Translation

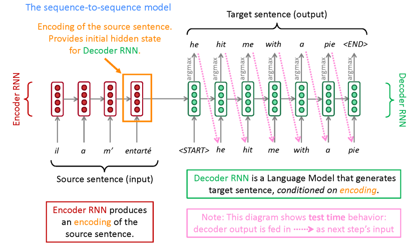


What is Neural Machine Translation?

- Neural Machine Translation (NMT) is a way to do Machine Translation with a *single neural network*
- The neural network architecture is called sequence-to-sequence (aka seq2seq) and it involves *two* RNNs.

Neural Machine Translation (NMT)

The sequence-to-sequence model



Sequence-to-sequence is versatile!

- Sequence-to-sequence is useful for *more than just MT*
- Many NLP tasks can be phrased as sequence-to-sequence:
  - Summarization (long text → short text)
  - Dialogue (previous utterances → next utterance)
  - Parsing (input text → output parse as sequence)
  - Code generation (natural language → Python code)

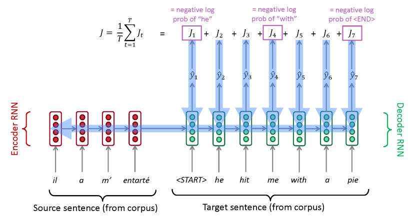
Neural Machine Translation (NMT)

- The sequence-to-sequence model is an example of a **Conditional Language Model**.
  - **Language Model** because the decoder is predicting the next word of the target sentence *y*
  - **Conditional** because its predictions are *also* conditioned on the source sentence *x*
- NMT directly calculates $P(y|x)$:

$$P(y|x) = P(y_1|x)\, P(y_2|y_1, x)\, P(y_3|y_1, y_2, x) \ldots \underbrace{P(y_T|y_1, \ldots, y_{T-1}, x)}_{\text{Probability of next target word, given target words so far and source sentence } x}$$

- **Question**: How to train a NMT system?
- **Answer**: Get a big parallel corpus…

Training a Neural Machine Translation system

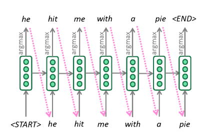


Seq2seq is optimized as a **single system.**
Backpropagation operates *"end-to-end"*.

NMT Decoding

Greedy decoding

- We saw how to generate (or "decode") the target sentence by taking argmax on each step of the decoder



- This is greedy decoding (take most probable word on each step)
- **Problems with this method?**

Problems with greedy decoding

- Greedy decoding has no way to undo decisions!
  - Input: *il a m'entarté* *(he hit me with a pie)*
  - → *he* ____
  - → *he hit* ____
  - → *he hit a* ____ (whoops! no going back now…)
- How to fix this?

Exhaustive search decoding

- Ideally we want to find a (length *T*) translation *y* that maximizes

$$P(y|x) = P(y_1|x)\, P(y_2|y_1, x)\, P(y_3|y_1, y_2, x) \ldots, P(y_T|y_1, \ldots, y_{T-1}, x)$$
$$= \prod_{t=1}^{T} P(y_t|y_1, \ldots, y_{t-1}, x)$$

- We could try computing all possible sequences *y*
  - This means that on each step *t* of the decoder, we're tracking V^t possible partial translations, where *V* is vocab size
  - This $O(V^T)$ complexity is far too expensive!

Beam search decoding

- Core idea: On each step of decoder, keep track of the *k* most probable partial translations (which we call *hypotheses*)
  - *k* is the beam size (in practice around 5 to 10)
- A hypothesis $y_1, \ldots, y_t$ has a score which is its log probability:

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t|x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$$

  - Scores are all negative, and higher score is better
  - We search for high-scoring hypotheses, tracking top *k* on each step
- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

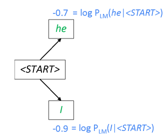
Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$

Calculate prob dist of next word

Beam search decoding: example

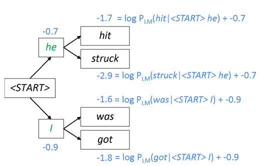
Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$



Take top *k* words and compute scores

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$



For each of the *k* hypotheses, find top *k* next words and calculate scores

Beam search decoding: example

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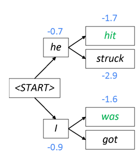

Of these k^2 hypotheses, just keep *k* with highest scores

Beam search decoding: example

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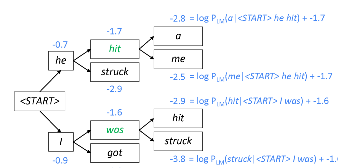

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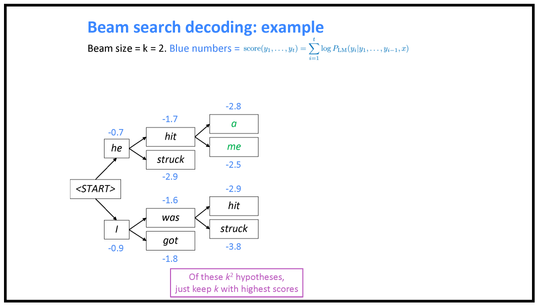
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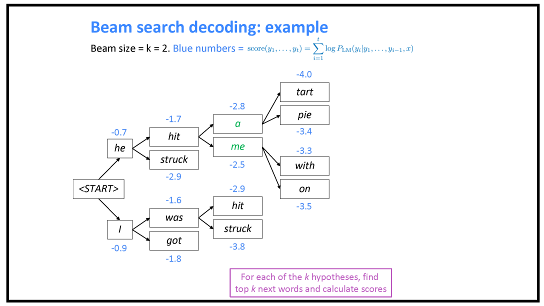
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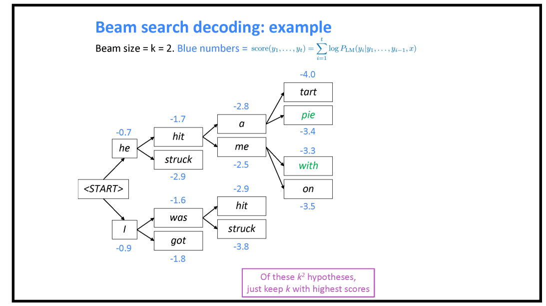
For each of the k hypotheses, find top k next words and calculate scores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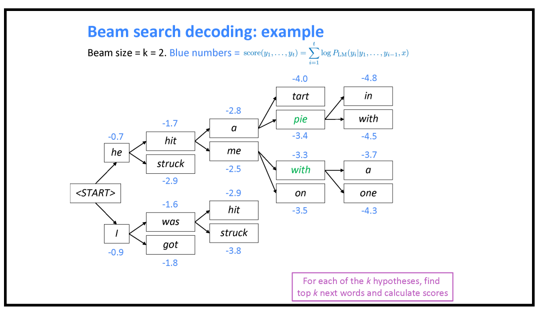
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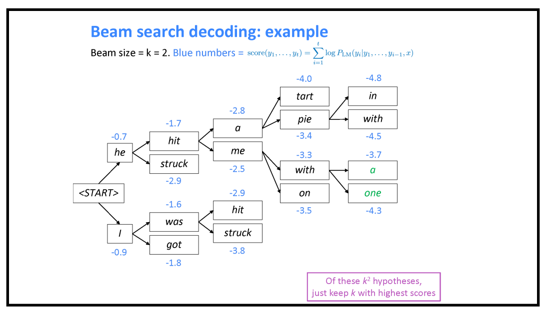
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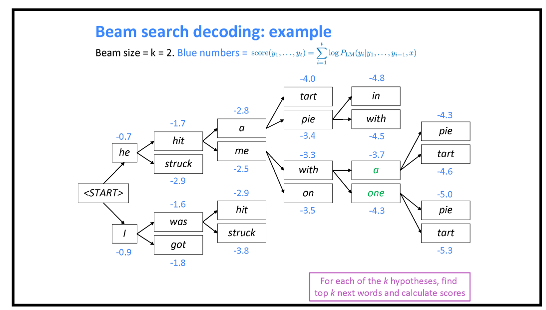
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For each of the k hypotheses, find top k next words and calculate scores

Beam search decoding: example

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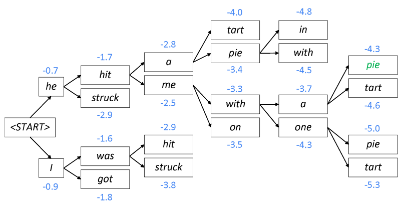
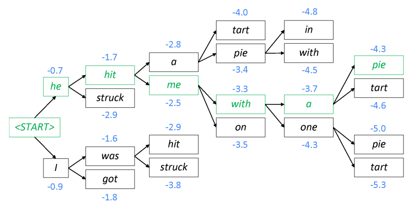


This is the top-scoring hypothesis!

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1,\ldots,y_t)=\sum_{i=1}^{t}\log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$



Backtrack to obtain the full hypothesis

Beam search decoding: stopping criterion

- In greedy decoding, usually we decode until the model produces a <END> token
  - For example: *<START> he hit me with a pie <END>*
- In beam search decoding, different hypotheses may produce <END> tokens on different timesteps
  - When a hypothesis produces <END>, that hypothesis is complete.
  - Place it aside and continue exploring other hypotheses via beam search.
- Usually we continue beam search until:
  - We reach timestep T (where T is some pre-defined cutoff), or
  - We have at least n completed hypotheses (where n is pre-defined cutoff)

Beam search decoding: finishing up

- We have our list of completed hypotheses.
- How to select top one with highest score?
- Each hypothesis $y_1,\ldots,y_t$ on our list has a score

$$\text{score}(y_1,\ldots,y_t)=\log P_{\text{LM}}(y_1,\ldots,y_t|x)=\sum_{i=1}^{t}\log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$

- Problem with this: longer hypotheses have lower scores
- Fix: Normalize by length. Use this to select top one instead:

$$\frac{1}{t}\sum_{i=1}^{t}\log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$

Neural Machine Translation

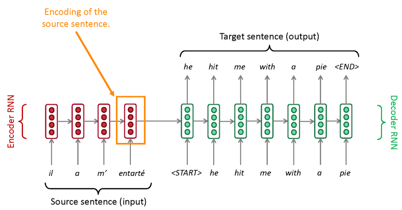
Berkeley N L P

Dan Klein
UC Berkeley

Slides from Abigail See and John DeNero

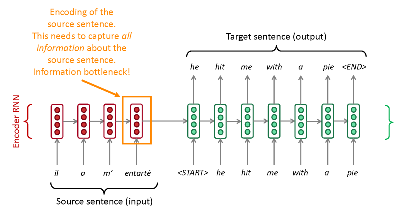
Attention

Sequence-to-sequence: the bottleneck problem



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem

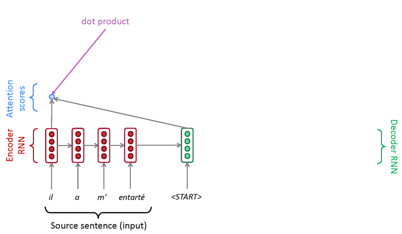


Attention

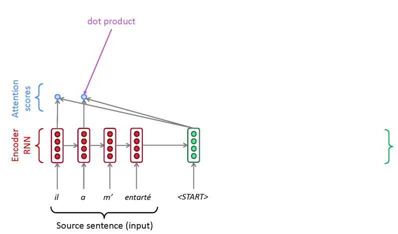
- **Attention** provides a solution to the bottleneck problem.
- Core idea: on each step of the decoder, use *direct connection to the encoder* to *focus on a particular part* of the source sequence

- First we will show via diagram (no equations), then we will show with equations

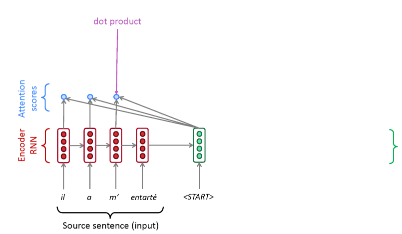
Sequence-to-sequence with attention

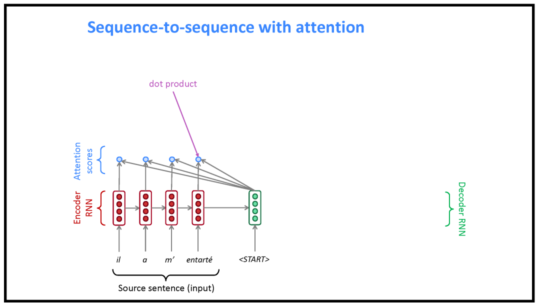


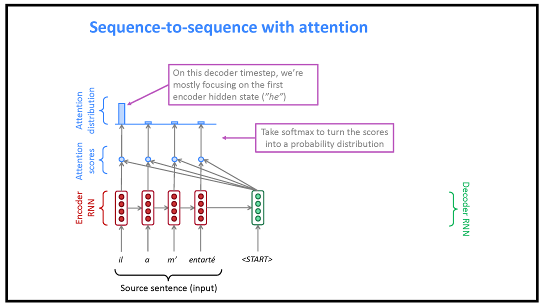
Sequence-to-sequence with attention

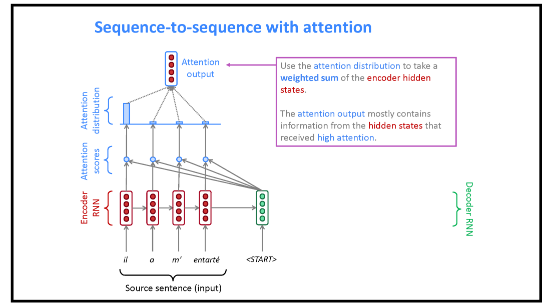


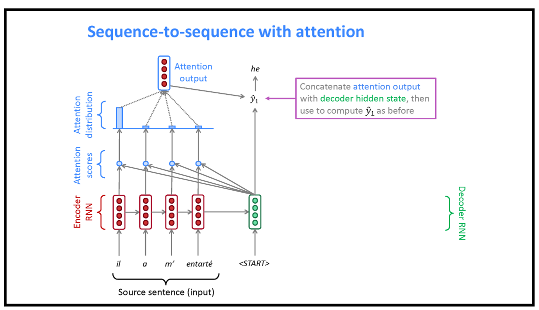
Sequence-to-sequence with attention

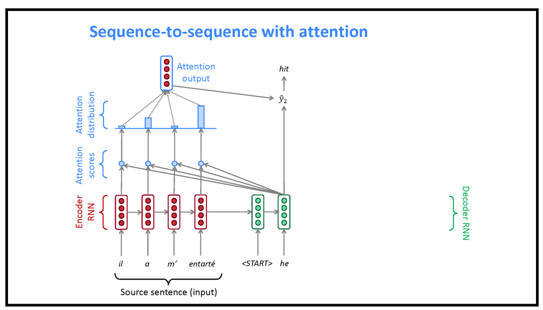


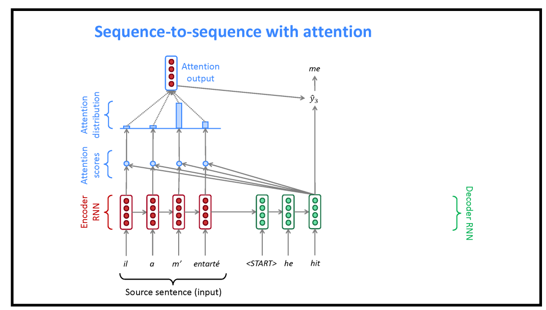

Sequence-to-sequence with attention
dot product
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)


Sequence-to-sequence with attention
On this decoder timestep, we're mostly focusing on the first encoder hidden state ("he")
Take softmax to turn the scores into a probability distribution
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)

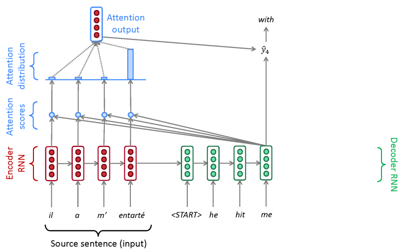

Sequence-to-sequence with attention
Attention output
Use the attention distribution to take a weighted sum of the encoder hidden states.
The attention output mostly contains information from the hidden states that received high attention.
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)


Sequence-to-sequence with attention
Attention output
he
$\hat{y}_1$
Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)

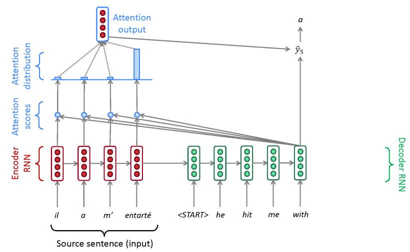

Sequence-to-sequence with attention
Attention output
hit
$\hat{y}_2$
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
he
Source sentence (input)


Sequence-to-sequence with attention
Attention output
me
$\hat{y}_3$
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
he
hit
Source sentence (input)

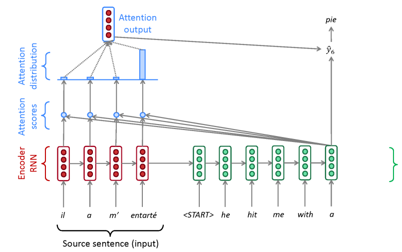
Sequence-to-sequence with attention



Sequence-to-sequence with attention



Sequence-to-sequence with attention



Attention: in equations

- We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$
- On timestep *t*, we have decoder hidden state $s_t \in \mathbb{R}^h$
- We get the attention scores $\boldsymbol{e}^t$ for this step:

$$\boldsymbol{e}^t = [\boldsymbol{s}_t^T \boldsymbol{h}_1, \ldots, \boldsymbol{s}_t^T \boldsymbol{h}_N] \in \mathbb{R}^N$$

- We take softmax to get the attention distribution α^t for this step (this is a probability distribution and sums to 1)

$$\alpha^t = \mathrm{softmax}(\boldsymbol{e}^t) \in \mathbb{R}^N$$

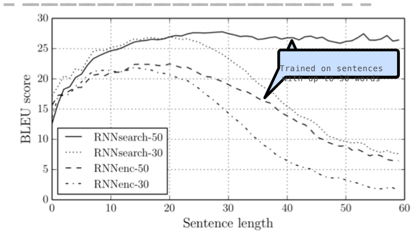
- We use α^t to take a weighted sum of the encoder hidden states to get the attention output $\boldsymbol{a}_t$

$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- Finally we concatenate the attention output $\boldsymbol{a}_t$ with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

$$[\boldsymbol{a}_t; \boldsymbol{s}_t] \in \mathbb{R}^{2h}$$

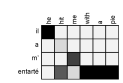
Impact of Attention on Long Sequence Generation



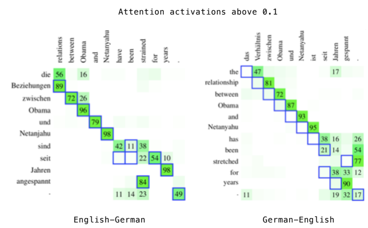
(Badhanau et al., 2015) Neural Machine Translation by Jointly Learning to Align and Translate

Attention is great

- Attention significantly improves NMT performance
  - It's very useful to allow decoder to focus on certain parts of the source
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - We get (soft) alignment for free!
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself



Attention vs Alignment



(Koehn & Knowles 2017) Six Challenges for Neural Machine Translation

Attention is a *general* Deep Learning technique

- We've seen that attention is a great way to improve the sequence-to-sequence model for Machine Translation.
- However: You can use attention in many architectures (not just seq2seq) and many tasks (not just MT)

- More general definition of attention:
  - Given a set of vector *values*, and a vector *query*, attention is a technique to compute a weighted sum of the values, dependent on the query.

- We sometimes say that the query *attends to* the values.
- For example, in the seq2seq + attention model, each decoder hidden state (query) *attends to* all the encoder hidden states (values).

Attention is a *general* Deep Learning technique

More general definition of attention:
Given a set of vector *values*, and a vector *query*, attention is a technique to compute a weighted sum of the values, dependent on the query.

Intuition:

- The weighted sum is a *selective summary* of the information contained in the values, where the query determines which values to focus on.
- Attention is a way to obtain a *fixed-size representation of an arbitrary set of representations* (the values), dependent on some other representation (the query).

There are *several* attention variants

- We have some *values* $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and a *query* $\boldsymbol{s} \in \mathbb{R}^{d_2}$

- Attention always involves:
  1. Computing the *attention scores* $\boldsymbol{e} \in \mathbb{R}^N$ ← There are multiple ways to do this
  2. Taking softmax to get *attention distribution* α:
  $$\alpha = \mathrm{softmax}(\boldsymbol{e}) \in \mathbb{R}^N$$
  3. Using attention distribution to take weighted sum of values:
  $$\boldsymbol{a} = \sum_{i=1}^{N} \alpha_i \boldsymbol{h}_i \in \mathbb{R}^{d_1}$$
  thus obtaining the *attention output* $\boldsymbol{a}$ (sometimes called the *context vector*)

Attention variants

You'll think about the relative advantages/disadvantages of these in Assignment 4!

There are several ways you can compute $\boldsymbol{e} \in \mathbb{R}^N$ from $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and $\boldsymbol{s} \in \mathbb{R}^{d_2}$:

- Basic dot-product attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$
  - Note: this assumes $d_1 = d_2$
  - This is the version we saw earlier

- Multiplicative attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{W} \boldsymbol{h}_i \in \mathbb{R}$
  - Where $\boldsymbol{W} \in \mathbb{R}^{d_2 \times d_1}$ is a weight matrix

- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - Where $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ are weight matrices and $\boldsymbol{v} \in \mathbb{R}^{d_3}$ is a weight vector.
  - d_3 (the attention dimensionality) is a hyperparameter

More information:
"Deep Learning for NLP Best Practices", Ruder, 2017. http://ruder.io/deep-learning-nlp-best-practices/index.html#attention
"Massive Exploration of Neural Machine Translation Architectures", Britz et al, 2017, https://arxiv.org/pdf/1703.03906.pdf

Transformers

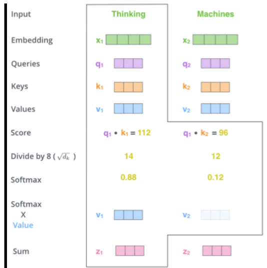
Transformer

In lieu of an RNN, use ONLY attention!

High throughput & expressivity: compute queries, keys and values as (different) linear transformations of the input.

Attention weights are queries • keys; outputs are sums of weighted values.

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



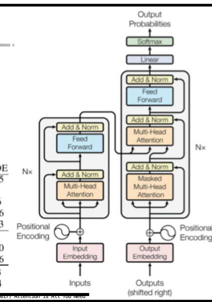
[redacted]

[redacted]

Transformer Architecture

- Layer normalization ("Add & Norm" cells) helps with RNN+attention architectures as well.
- Positional encodings can be learned or based on a formula that makes it easy to represent distance.

	EN-DE
ByteNet [18]	23.75
Deep-Att + PosUnk [39]	
GNMT + RL [38]	24.6
ConvS2S [9]	25.16
MoE [32]	26.03
Deep-Att + PosUnk Ensemble [39]	
GNMT + RL Ensemble [38]	26.30
ConvS2S Ensemble [9]	26.36
Transformer (base model)	27.3
Transformer (big)	**28.4**



[redacted]

Some Transformer Concerns

Problem: Bag-of-words representation of the input.
Remedy: Position embeddings are added to the word embeddings.

Problem: During generation, can't attend to future words.
Remedy: Masked training that zeroes attention to future words.

Problem: Deep networks needed to integrated lots of context.
Remedies: Residual connections and multi-head attention.

Problem: Optimization is hard.
Remedies: Large mini-batch sizes and layer normalization.

Training Data

Bitexts

Where do bitexts come from?

- Careful, low level / literal translations: organizational translation processes (eg parliamentary proceedings), multilingual newsfeeds, etc
- Discovered translations (ad hoc translations on webpages, etc)
- Loose translations (multilingual Wikipedia, etc)
- Synthetic data (distillation, backtranslation, etc)

Back Translations

Synthesize an en-de parallel corpus by using a de-en system to translate monolingual de sentences.

- Better generating systems don't seem to matter much.
- Can help even if the de sentences are already in an existing en-de parallel corpus!

system	EN→DE		DE→EN	
	dev	test	dev	test
baseline	22.4	26.8	26.4	28.5
+synthetic	25.8	31.6	29.9	36.2
+ensemble	27.5	33.1	31.5	37.5
+r2l reranking	**28.1**	**34.2**	**32.1**	**38.6**

Table 2: English↔German translation results (BLEU) on dev (newstest2015) and test (newstest2016). Submitted system in bold.

(Sennrich et al., 2015) Improving Neural Machine Translation Models with Monolingual Data
(Sennrich et al., 2016) Edinburgh Neural Machine Translation Systems for WMT 16

Subwords

The sequence of symbols that are embedded should be common enough that an embedding can be estimated robustly for each, and all symbols have been observed during training.

Solution 1: Symbols are words with rare words replaced by UNK.

- Replacing UNK in the output is a new problem (like alignment).
- UNK in the input loses all information that might have been relevant from the rare input word (e.g., tense, length, POS).

Solution 2: Symbols are subwords.

- Byte-Pair Encoding is the most common approach.
- Other techniques that find common subwords aren't reliably better (but are somewhat more complicated).
- Training on many sampled subword decompositions improves out-of-domain translations.

(Sennrich et al., 2016) Neural Machine Translation of Rare Words with Subword Units
(Kudo, 2018) Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates

```
vocab = {'l o w </w>' : 5, 'l o w e r </w>' : 2,
         'n e w e s t </w>':6, 'w i d e s t </w>':3}
def get_stats(vocab):
  pairs = collections.defaultdict(int)
  for word, freq in vocab.items():
    symbols = word.split()
    for i in range(len(symbols)-1):
      pairs[symbols[i],symbols[i+1]] += freq
  return pairs

def merge_vocab(pair, v_in):
  v_out = {}
  bigram = re.escape(' '.join(pair))
  p = re.compile(r'(?<!\S)' + bigram + r'(?!\S)')
  for word in v_in:
    w_out = p.sub(''.join(pair), word)
    v_out[w_out] = v_in[word]
  return v_out
```

```
for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
```

(Sennrich et al., 2016) Neural Machine Translation of Rare Words with Subword Units

BPE Example

<table>
<tr><th>system</th><th>sentence</th></tr>
<tr><td>source</td><td>health research institutes</td></tr>
<tr><td>reference</td><td>Gesundheitsforschungsinstitute</td></tr>
<tr><td>word-level (with back-off)</td><td>Forschungsinstitute</td></tr>
<tr><td>character bigrams</td><td>Fo|rs|ch|un|gs|in|st|it|ut|io|ne|n</td></tr>
<tr><td>BPE</td><td>Gesundheits|forsch|ungsin|stitute</td></tr>
</table>

Example from Rico Sennrich

Advantages of NMT

Compared to SMT, NMT has many advantages:

- Better performance
  - More fluent
  - Better use of context
  - Better use of phrase similarities
- A single neural network to be optimized end-to-end
  - No subcomponents to be individually optimized
- Requires much less human engineering effort
  - No feature engineering
  - Same method for all language pairs

Disadvantages of NMT?

Compared to SMT:

- NMT is less interpretable
  - Hard to debug
- NMT is difficult to control
  - For example, can't easily specify rules or guidelines for translation
  - Safety concerns!

NMT: the biggest success story of NLP Deep Learning

Neural Machine Translation went from a fringe research activity in **2014** to the leading standard method in **2016**

- **2014**: First seq2seq paper published
- **2016**: Google Translate switches from SMT to NMT
- This is amazing!
  - **SMT** systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a handful of engineers in a few months

So is Machine Translation solved?

- **Nope!**
- Many difficulties remain:
  - Out-of-vocabulary words
  - Domain mismatch between train and test data
  - Maintaining context over longer text
  - Low-resource language pairs

Further reading: *"Has AI surpassed humans at translation? Not even close!"*
https://www.skynettoday.com/editorials/state_of_nmt

So is Machine Translation solved?

- **Nope!**
- Using common sense is still hard

English ▾ | Spanish ▾
paper jam | Mermelada de papel
Open in Google Translate | Feedback


?

So is Machine Translation solved?

- **Nope!**
- NMT picks up biases in training data

Malay - detected ▾ | English ▾
Dia bekerja sebagai jururawat. | She works as a nurse.
Dia bekerja sebagai pengaturcara. | He works as a programmer.

Didn't specify gender

Source: https://hackernoon.com/bias-sexist-or-this-is-the-way-it-should-be-ce1f7c8c683c

So is Machine Translation solved?

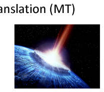
- Nope!
- Uninterpretable systems do strange things

Somali ▾ | English ▾
Translate from Irish
ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag ag | As the name of the LORD was written in the Hebrew language, it was written in the language of the Hebrew Nation
Open in Google Translate | Feedback

Picture source: https://www.vice.com/en_uk/article/j5npeg/why-is-google-translate-spitting-out-sinister-religious-prophecies
Explanation: https://www.skynettoday.com/briefs/google-nmt-prophecies

Summary

- We learned some history of Machine Translation (MT)
- Since 2014, Neural MT rapidly replaced intricate Statistical MT



- Sequence-to-sequence is the architecture for NMT (uses 2 RNNs)
- Attention is a way to *focus on particular parts* of the input
  - Improves sequence-to-sequence a lot!