Machine Translation in a Nutshell

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DFKI GmbH

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Again...

Thanks to Josef van Genabith
for some of the slides!

Outline

What is Translation?

A Definition

Translation is the **conversion of text** from one language (source language, SL) to another (target language, TL)

What is Translation?

A Definition

Translation is the **conversion of text** from one language (source language, SL) to another (target language, TL)

Translation is the **communication of the meaning** of a SL text by means of an equivalent TL text

How we Translate?

Translation Methods I

Word-for-word translation: the SL word order is preserved and the words translated singly by their most common meanings, out of context

Literal translation: the SL grammatical constructions are converted to their nearest TL equivalents, but the lexical words are again translated singly, out of context

How we Translate?

Translation Methods II

Faithful translation: producing the precise contextual meaning of the original within the constraints of the TL grammatical structures

Semantic translation: differs from 'faithful translation' only in as far as it must take more account of the aesthetic value of the SL text

How we Translate?

Translation Methods III

Adaptation: used mainly for plays and poetry; the themes, characters, plots are usually preserved, the SL culture is converted to the TL culture and the text is rewritten

Free translation: producing the TL text without the style, form, or content of the original

How we Translate?

Translation Methods IV

Idiomatic translation: reproducing the 'message' of the original but tends to distort nuances of meaning by preferring colloquialisms and idioms where these do not exist in the original

Communicative translation: rendering the exact contextual meaning of the original in such a way that both content and language are readily acceptable and comprehensible to the readership

How we Translate?

Is it easy/direct for a human?

Several problems, several choices...

How we Translate?

Remember? –Cultures & Language–

`https://reportsfromtherock.wordpress.com/page/2/`

"Of all the different types of snow, **slabb** is the worst. The word really says it all: sticky, dirty, treacherous and wet. Slabb is created after a sudden rise in temperature and more so when rain falls into a layer of snow. In a second, that bright and cheerful winter wonderland transforms into a slushy pool filled with ice-cold water."

How we Translate?

Translating Culture-Specific Concepts

1. Making up a new word
2. Explaining the meaning of the SL expression in lieu of translating it
3. Preserving the SL term intact
4. Opting for a word in the TL which seems similar to or has the same "relevance" as the SL term

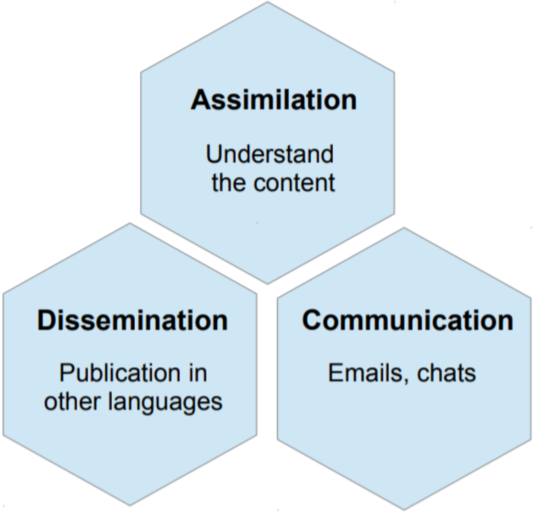
How we Translate?

Should we expect a machine to do it?

Use cases of machine translation

How we Translate?

Machine Translation Uses



How we Translate?

Naïve Machine Translation Taxonomy

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
- Machine Translation with Human Support

How we Translate?

Naïve Machine Translation Taxonomy

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
  - Empirical systems
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How we Translate?

Naïve Machine Translation Taxonomy

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- Human Translation with Machine Support
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  - Rule-based systems
    - Direct MT
    - Transfer MT
    - Interlingua
- Machine Translation with Human Support

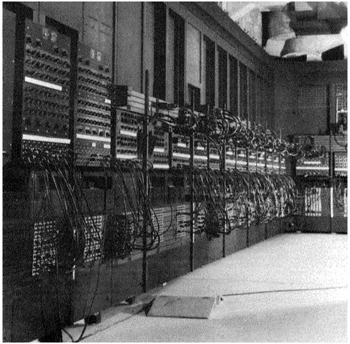
How we Translate?

Naïve Machine Translation Taxonomy

- **Machine Translation systems**
  - Human Translation with Machine Support
  - Fully Automated Translation
    - Empirical systems
      - **Neural MT**
      - **Statistical MT**
      - Example-based
    - Rule-based systems
      - Direct MT
      - Transfer MT
      - Interlingua
  - Machine Translation with Human Support

Brief History of MT

Early Days



Brief History of MT

Early Days

1946 ENIAC, the first digital computer

1949 Weaver memorandum, computers could be used to translate natural languages

1955 "Translation" (1955), in W.N. Locke and A.D. Booth (eds.), Machine Translation of Languages (MIT Press).

One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. 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.'

Brief History of MT

The Rule-based Era

SYSTRAN
beyond language

Brief History of MT

The Rule-based Era

1950s	Predominance of rule-based approaches
1960s	Predominance of rule-based approaches
1966	ALPAC report: general discouragement for MT (in the US)
1970s	Predominance of rule-based approaches, firsts commercial systems
1980s	Example-based MT proposed in Japan (Nagao), interlingual systems, statistical approaches to speech recognition (Jelinek et al. at IBM)

Brief History of MT

The Statistical Era I

IBM

CANDIDE system

Brief History of MT

The Statistical Era I

- **Late 80s** Statistical POS taggers, SMT models at IBM, work on translation alignment at Xerox (M. Kay)
- **Early 90s** Many statistical approaches to NLP in general, IBM's Candide claimed to be as good as Systran
- **Late 90s** Statistical MT successful as a fallback approach within Verbmobil System (Ney, Och). Wide distribution of translation memory technology (Trados) indicates big commercial potential of SMT

Brief History of MT

The Statistical Era II

Brief History of MT

The Statistical Era II

2001 BLEU score for automatic evaluation (Papineni) speeds up evaluation

2003 Koehn, Och & Marcu propose Statistical Phrase-Based MT

2006 Johns Hopkins workshop on OS factored SMT decoder Moses

2007 Google Translate based on SMT

Brief History of MT

The Neural Era I

Brief History of MT

The Neural Era I

2007 GPUs & CUDA

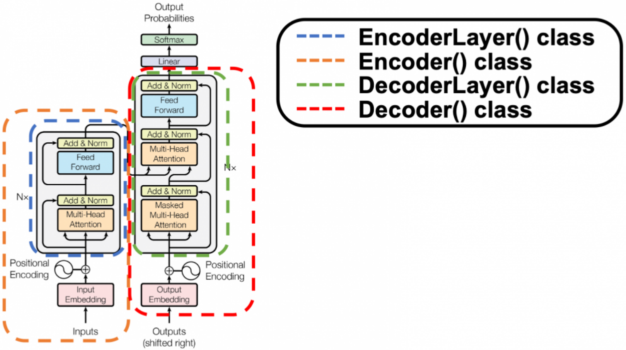
2010s Deep Learning leads NLP tasks

2013 First paper on NMT (Kalchbrenner & Blunsom)

2016 Neural systems state-of-the art in MT evaluation campaigns

Brief History of MT

The Neural Era II



Brief History of MT

The Neural Era II

2017 Google Translate moves to NMT in almost all languages

2017 Unsupervised MT (without parallel sentences!); Artetxe & Lample simultaneously but independently

2022 Multilinguality hot topic, NLLB-200 by Meta translates among 200 languages

2023 Large LMs can be fine-tuned for translation, still below SotA

A Sequence to Sequence Problem. Remember the Question the 1st Day?

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An AI Based Automatic Translator for Ancient Hieroglyphic Language - From Scanned Images to English Text

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MT Systems

A Sequence to Sequence Problem. Remember the Question the 1st Day?

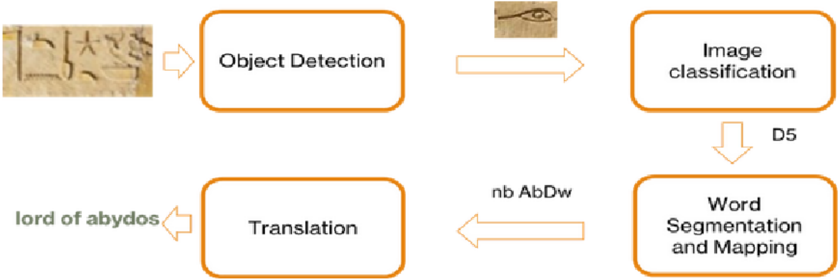


FIGURE 6. The overall diagram of the project's workflow

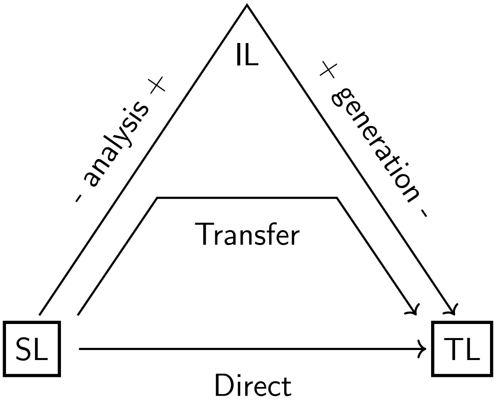
MT Systems

Rule-based MT

- **Machine Translation systems**
  - Human Translation with Machine Support
  - Fully Automated Translation
    - Empirical systems
    - **Rule-based systems**
      - **Direct MT**
      - **Transfer MT**
      - **Interlingua**
  - Machine Translation with Human Support

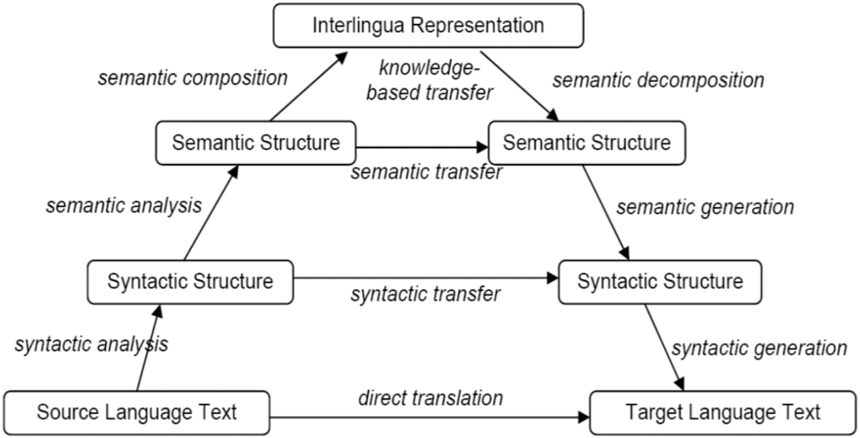
Rule-based MT

Schematic Vauquois triangle



Rule-based MT

Vauquois triangle



Rule-based MT

Direct Translation I

Word by word translation

- Do a little bit of analysis of local source context (but not global or non-local/long range —no parsing, no semantic analysis of sentence)
- May do a little bit of local re-ordering in target (e.g. French adjectives tend to follow noun)
- Requires very large bilingual dictionaries with rules of how to translate a word

Rule-based MT

Direct Translation II

```
function DIRECT_TRANSLATE_MUCH/MANY(word) returns Russian translation

if preceding word is how return skol'ko
else if preceding word is as return stol'ko zhe
else if word is much
   if preceding word is very return nil
   else if following word is a noun return mnogo
else /* word is many */
   if preceding word is a preposition and following word is a noun return mnogii
   else return mnogo
```

Figure 25.7 A procedure for translating *much* and *many* into Russian, adapted from Hutchins' (1986, pg. 133) discussion of Panov 1960. Note the similarity to decision list algorithms for word sense disambiguation.

From: Jurafsky & Martin II

Rule-based MT

Direct Translation III

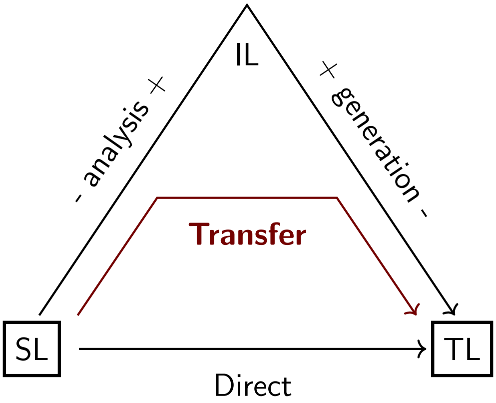
Characteristics (drawbacks!)

- 10s of thousands of manually constructed rules
- Time consuming
- Expensive
- Rule interaction hard to predict
- Any long range phenomena hard to capture

Need some global (syntactic/semantic) analysis

Rule-based MT

Schematic Vauquois triangle



Three phases:

1. **Analysis**: analyse/parse source into syn/sem representation
2. **Transfer**: transform source syn/sem representation into corresponding target syn/sem representation
3. **Generation**: generate target string from target syn/sem representation

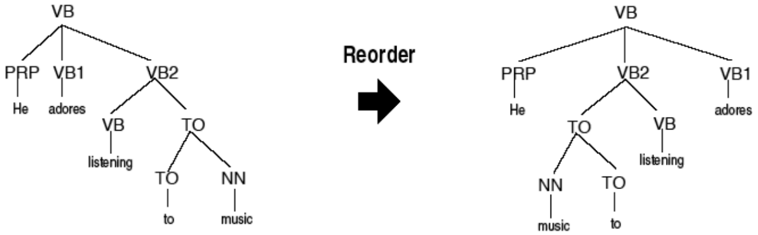
Rule-based MT

Transfer-based Translation II

EN: He adores listening to music

JA: He music to listening adores

From: Jurafsky & Martin II



Rule-based MT

Transfer-based Translation III

Characteristics (drawbacks!)

Need a lot of resources

- Analysis/generation lexica and grammars for SL and TL
- Transfer rule sets for any two languages you want to translate between

Example. To translate between 3 languages: A, B and C

- Need 3 grammars/lexica
- Need 6 transfer grammars: A$\rightarrow$B, A$\rightarrow$C, B$\rightarrow$A, B$\rightarrow$C, C$\rightarrow$A, C$\rightarrow$B

Rule-based MT

Transfer-based Translation III

Characteristics (drawbacks!)

Need a lot of resources

- Analysis/generation lexica and grammars for SL and TL
- Transfer rule sets for any two languages you want to translate between

Example. To translate between n languages: L_1, L_2 ... L_n

- Need n grammars/lexica
- Need $n(n-1)$ transfer grammars
  - 10 languages: 90 transfer systems
  - 200 languages (like in NLLB): 39800 transfer systems ...

Rule-based MT

Transfer-based Translation IV

Characteristics (drawbacks!)

- Need a lot of resources
  - Analysis/generation lexica and grammars for SL and TL
  - Transfer rule sets for any two languages you want to translate between
- Time consuming and expensive to hand-craft
- Not easy to achieve good coverage
- Large rule sets
- Difficult to manage rule interactions

Solutions

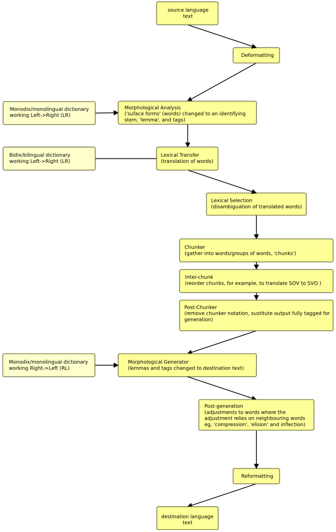
- Need a lot of resources
- Time consuming and expensive to hand-craft
- Try to use machine learning?
- Still many resources needed: treebanks, parallel data
- Smart ways of inducing transfer rules from parsed/semantically analysed parallel data

Nothing better than their own description:

- Apertium in 5 slides: `http://slides.com/allysonallyson/deck#/`
- Workflow diagram: `http://wiki.apertium.org/wiki/Workflow_diagram`

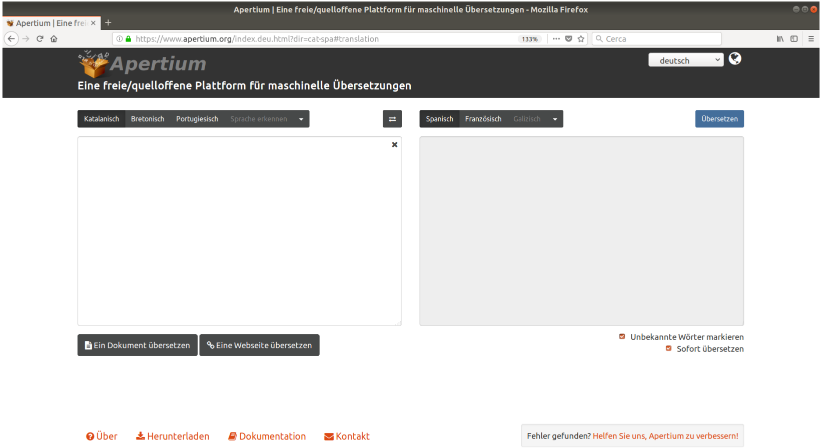
Rule-based MT

Apertium: Workflow diagram



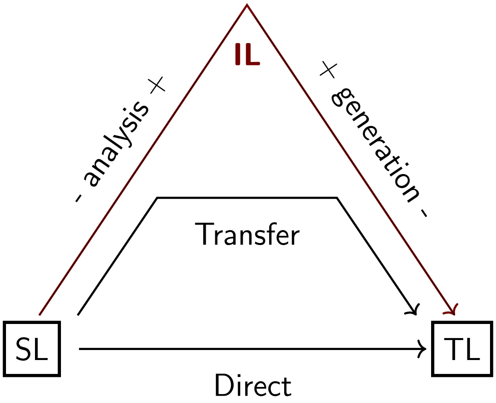
Rule-based MT

Apertium: Interface. Try it!



Rule-based MT

Schematic Vauquois triangle



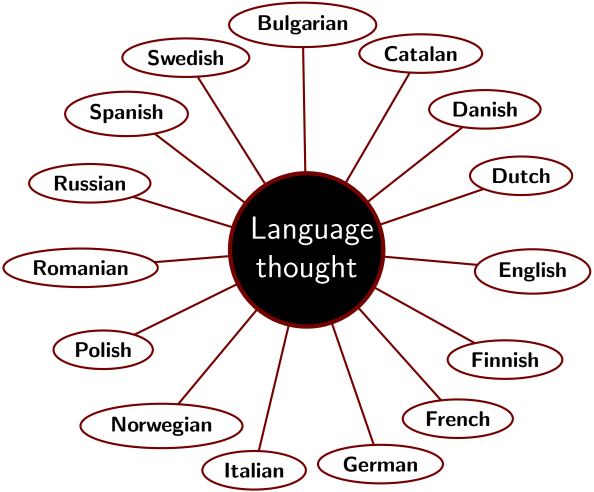
Interlingua Translation I

The $n(n-1)$ complexity in transfer-based MT comes from language specific syntactic and semantic representations

- Maybe we do not need these?
- Maybe we can have instead only one language independent abstract meaning representation?
- The language of thought... interlingua

Rule-based MT

Interlingua Translation II



Rule-based MT

Remember? –Cultures & Language–

- Problem: what is the language of thought?
- Are there universal concepts that work equally well for all languages?

Rule-based MT

Remember? –Cultures & Language–

- Problem: what is the language of thought?
- Are there universal concepts that work equally well for all languages?

Different cultures share basic **concepts** and **actions** and communicate them with words

Rule-based MT

Interlingua Translation IV

I'm not showing the *snow* picture again, but...

- Germans say *Wand* for inside (of) wall and *Mauer* for outside (of) wall
- Japanese differentiate between the *younger brother* and the *older brother*
- Spanish use the same word, *dedo* to say *toe* and *finger*

So far no success in coming up with single language independent interlingua

Rule-based MT

Interlingua Translation V

Example: GF. In-domain interlingual translation

- Limiting the number of languages may help
- Limiting the application domain may help
- Successful example: GF system
- (although hibridised with SMT for coverage)

What is GF?

- A **grammar formalism**: a notation for writing grammars.
- A **functional programming language**.

What is GF?

- A **grammar formalism**: a notation for writing grammars.
- A **functional programming language**.

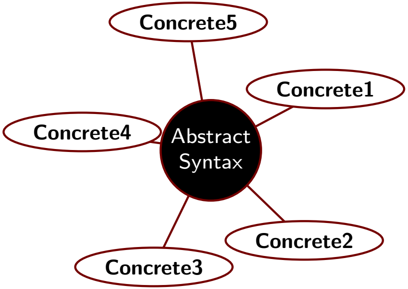
What is a multilingual grammar?

- A definition of a **parsing** and **generation** operations.
- **Concrete syntaxes** for many languages related by a common **abstract syntax**.

Rule-based MT

Abstract and Concrete syntaxes

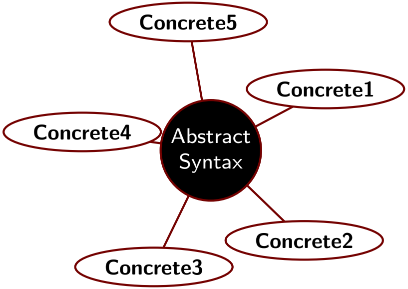
The abstract syntax acts as a **domain-specific interlingua**.



Rule-based MT

Abstract and Concrete syntaxes

The abstract syntax acts as a **domain-specific interlingua**.



Defines not only a linguistic structure but a semantic model for translation with:

- fixed word senses
- proper idioms

Rule-based MT

Translation with GF

Abstract Syntax
Nat : Set
Odd : Exp -> Prop
Gt : Exp -> Exp -> Prop
Sum : Exp -> Exp

Concrete Syntax (ENG)
Nat = "number"
Odd x = "x is odd"
Gt x y = "x is greater than y"
Sum x = "the sum of x"

Concrete Syntax (GER)
Nat = "Zahl"
Odd x = "x ist ungerade"
Gt x y = "x ist grösser als y"
Sum x = "die Summe von x"

Rule-based MT

Translation with GF

Abstract Syntax

Nat : Set
Odd : Exp -> Prop
Gt : Exp -> Exp -> Prop
Sum : Exp -> Exp

parsing

Concrete Syntax (ENG)

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Concrete Syntax (GER)

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Every even number that is greater than 0 is the sum of two odd numbers

Rule-based MT

Translation with GF

Abstract Syntax

Nat : Set
Odd : Exp -> Prop
Gt : Exp -> Exp -> Prop
Sum : Exp -> Exp

parsing

linearisation

Concrete Syntax (ENG)

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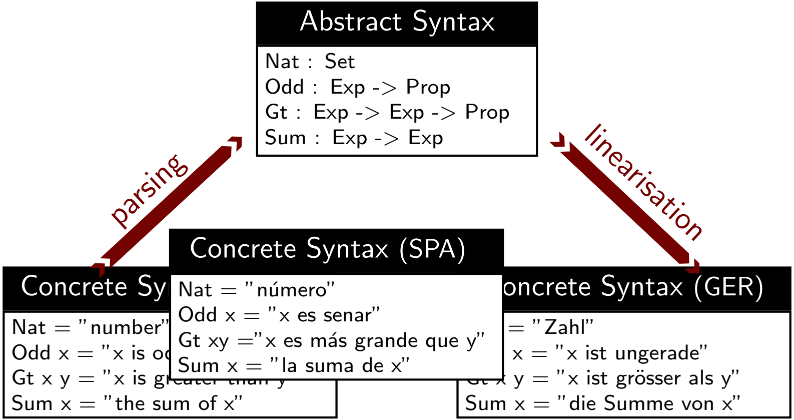
Every even number that is greater than 0 is the sum of two odd numbers

Jede gerade Zahl, die gröβer als 0 ist, ist die Summe von zwei ungerader Zahlen

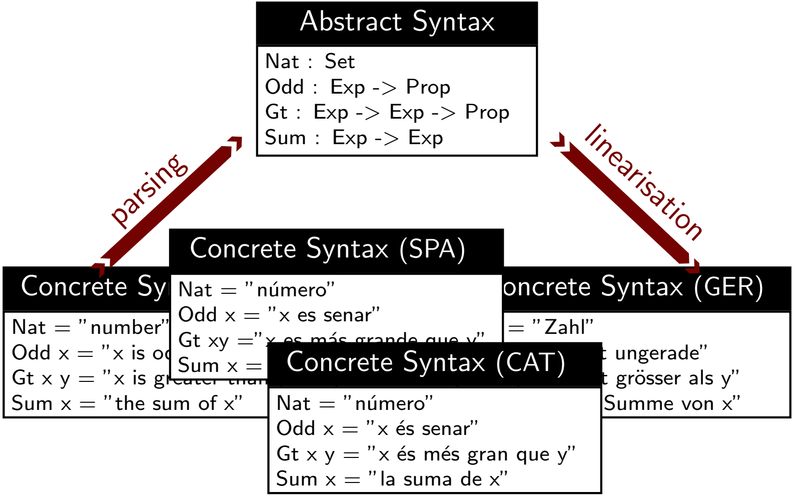
Rule-based MT

Translation with GF



Rule-based MT

Translation with GF

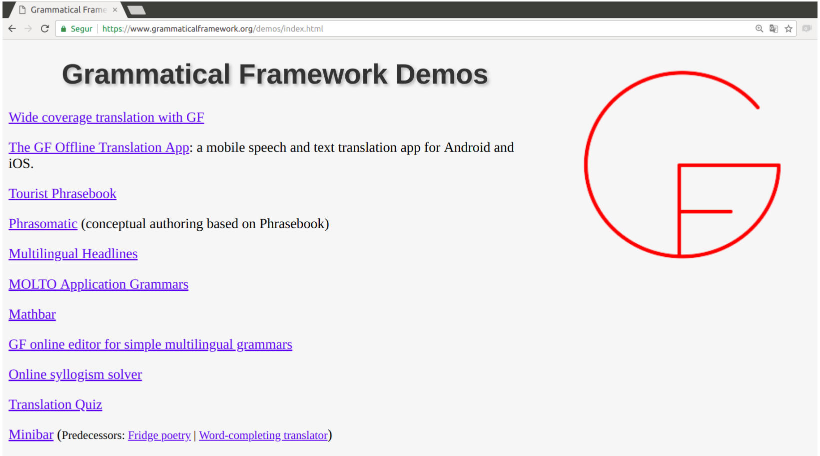


Rule-based MT

GF. Try it!

Rule-based MT

GF. Let's go for the Phrasebook



`https://www.grammaticalframework.org/demos/index.html`

Empirical systems

Data-driven Machine Translation

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
  - **Empirical systems**
    - **Neural MT**
    - **Statistical MT**
    - **Example-based**
  - Rule-based systems
- Machine Translation with Human Support

Empirical systems

A Machine Learning Problem

MT is not intrinsically different to other machine learning problems.
What do we need?

1. Data **curation**. I cannot emphasise enough how important it is!
2. Chose algorithm/system to perform the task
3. Hyperparameter tunning
4. Statistical analysis

Empirical systems

Parallel Corpora

- **Data** is the key aspect in empirical systems
  (by definition!)
- **Parallel corpora** are needed to learn translation models, **monolingual corpora** are needed too to improve fluency or even to translate
- Parallel corpora are especially **difficult to obtain**
- **Domain-specific corpora** are even more valuable and scarce

Where to find them?

In the context of this course, go to the different evaluation campaings and OPUS:

- **WMT**: `http://www2.statmt.org/wmt23/`
- **IWSLT**: `https://iwslt.org/2023/`
- **OPUS**: `https://opus.nlpl.eu/`

Data-driven Machine Translation

Neural Machine Translation

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
  - Empirical systems
    - **Neural MT**
    - Statistical MT
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The Encoder–Decoder Model (with attention)

1. encodes a sequence of word vectors into a fixed-sized context vector
2. decodes the fixed-sized vector back into a variable-length sequence

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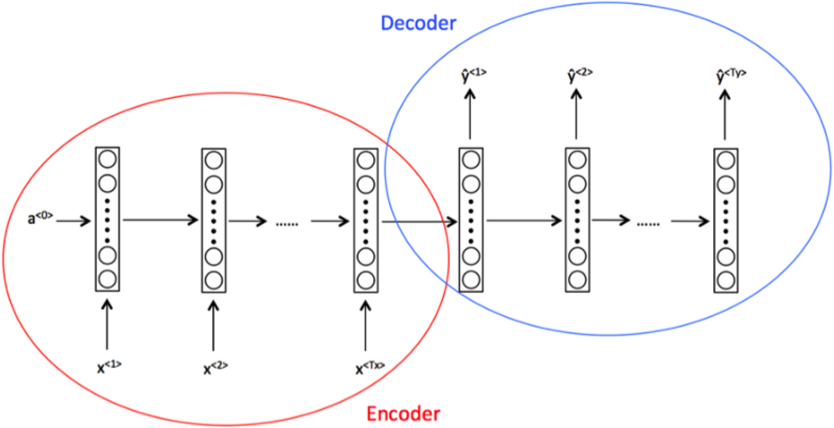
Several NLP tasks use nowadays seq2seq architectures:

- Machine translation, but also...
- text summarisation, question answering, chatbots, speech recognition...

Data-driven Machine Translation

An NMT System seen from far (Vanilla RNN Architecture)

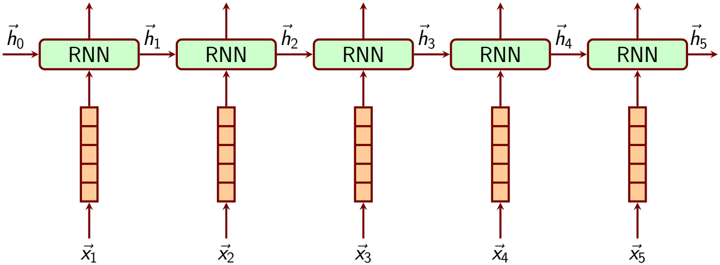


https://medium.com/machine-learning-bites/ /deeplearning-series-sequence-models-7855babeb586

Vanilla RNN Architecture

Encoder

- Sequence encoded with RNNs
- Each word is a *time step*



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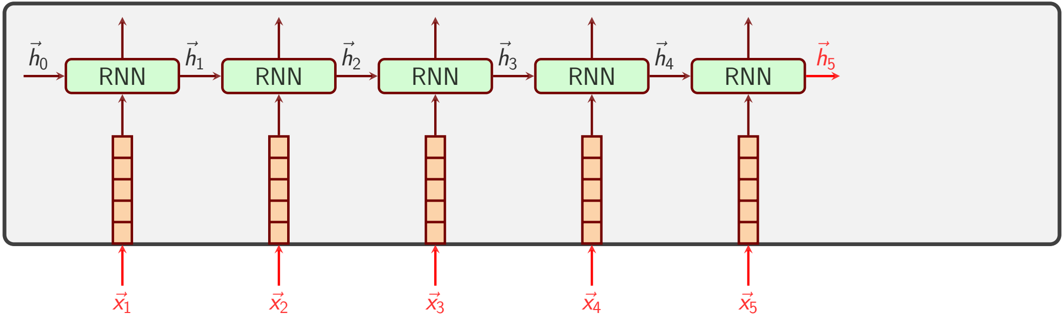
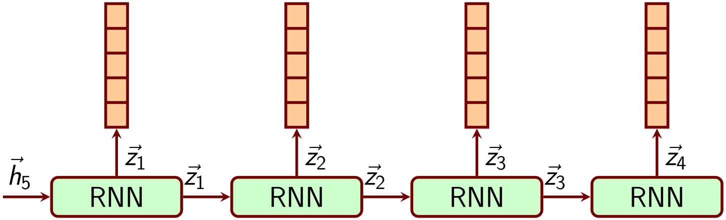


Vanilla RNN Architecture

Decoder

- *Inverted* encoder with special characteristics



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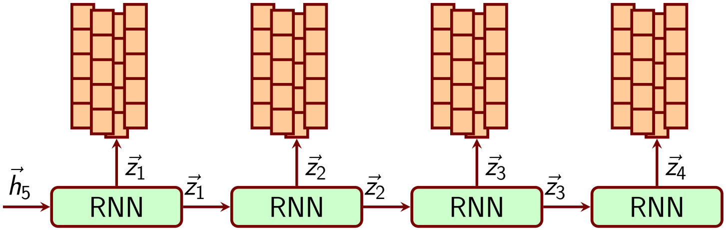

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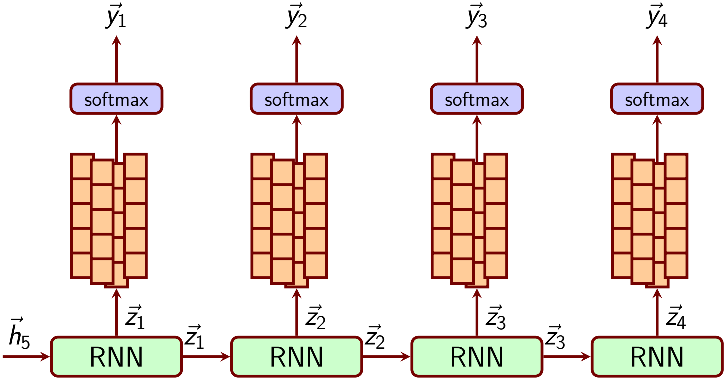

Vanilla RNN Architecture

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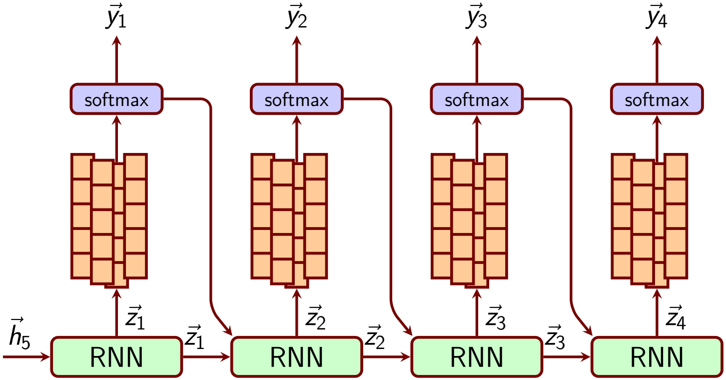

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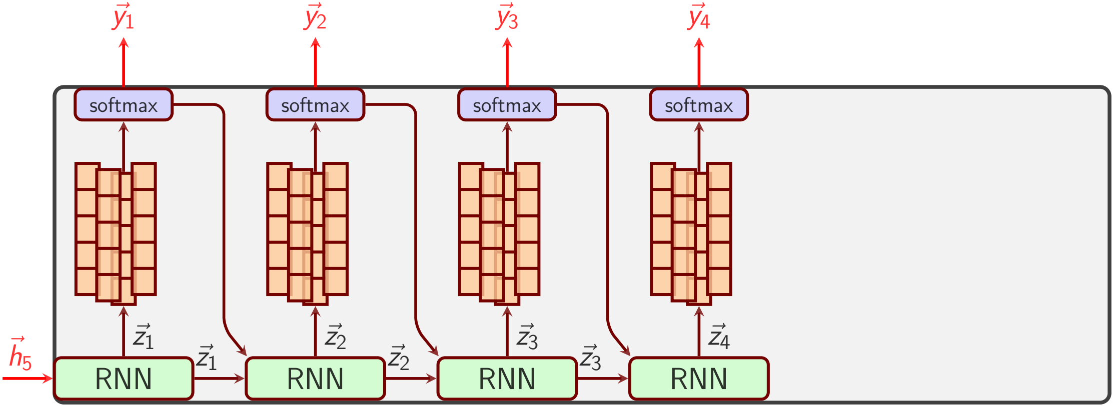
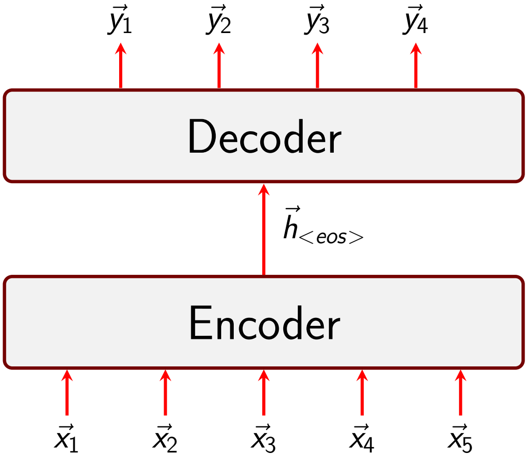


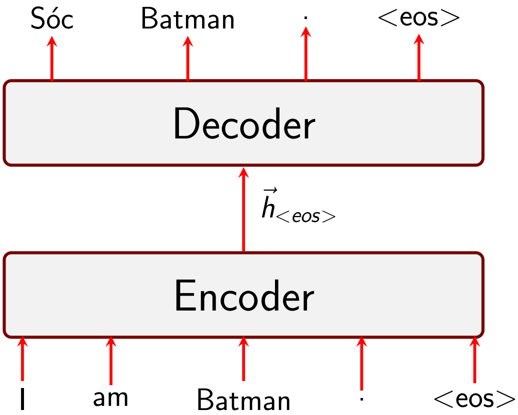
Vanilla RNN Architecture

Encoder–Decoder



Vanilla RNN Architecture

Encoder–Decoder



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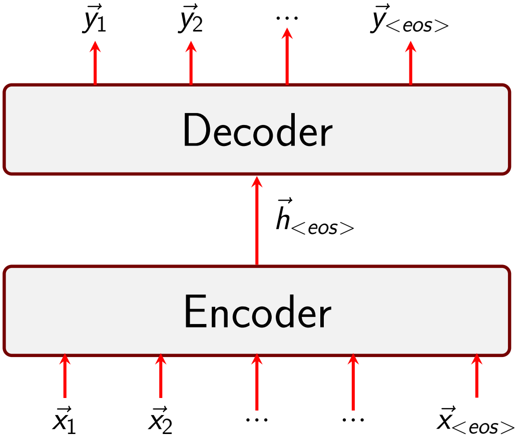
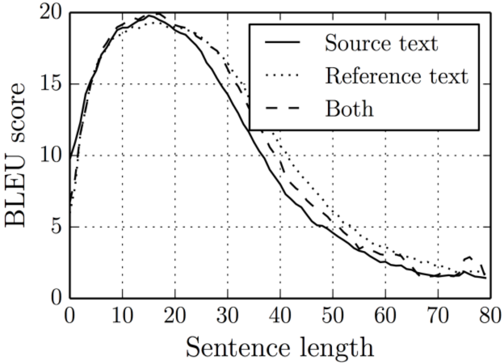
Encoder–Decoder



Vanilla RNN Architecture

Why Vanilla?

- Performance drops with long sentences

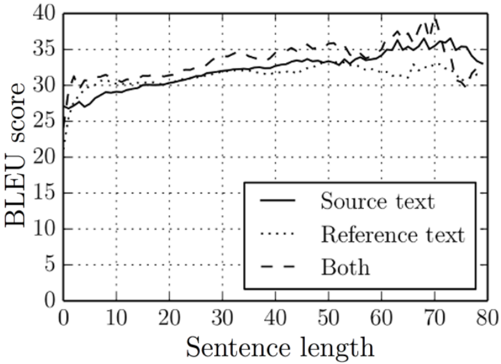


[Cho et al., 2014]

Vanilla RNN Architecture

Why Vanilla?

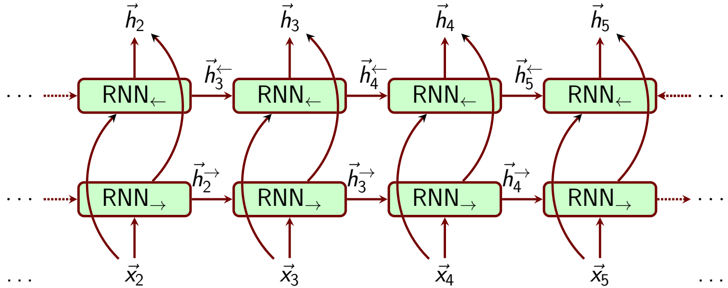
- SMT was better at that!



[Cho et al., 2014]

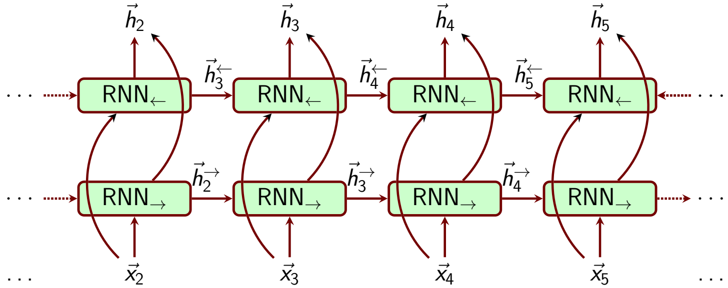
RNN Architecture

Bidirectional Encoder Hidden Layer



RNN Architecture

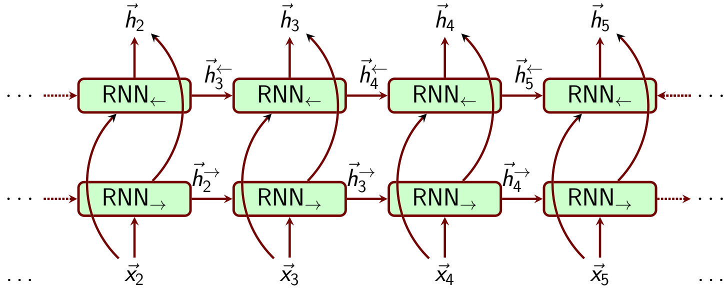
Bidirectional Encoder Hidden Layer



- Helps but not enough
- What else?

RNN Architecture

Bidirectional Encoder Hidden Layer

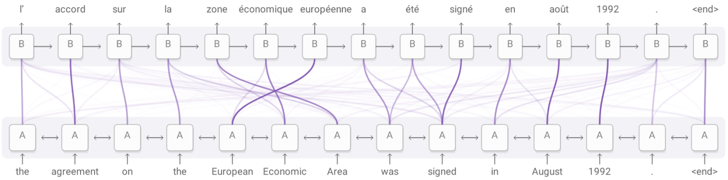


- Helps but not enough
- What else? **Attention!**

RNN Architecture

The Attention Mechanism

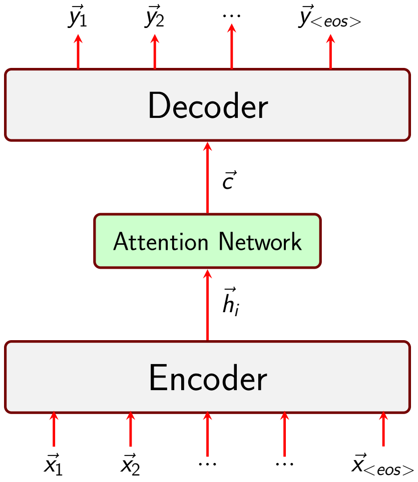
- Intuition: Not all the words contribute equally for a translation
- Let's weight! (weights, softmaxs, nns...)



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

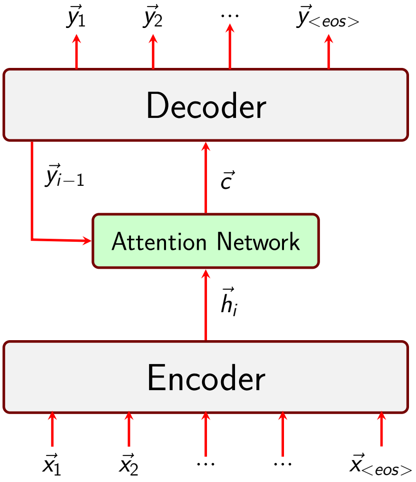
RNN Architecture

The Attention Mechanism



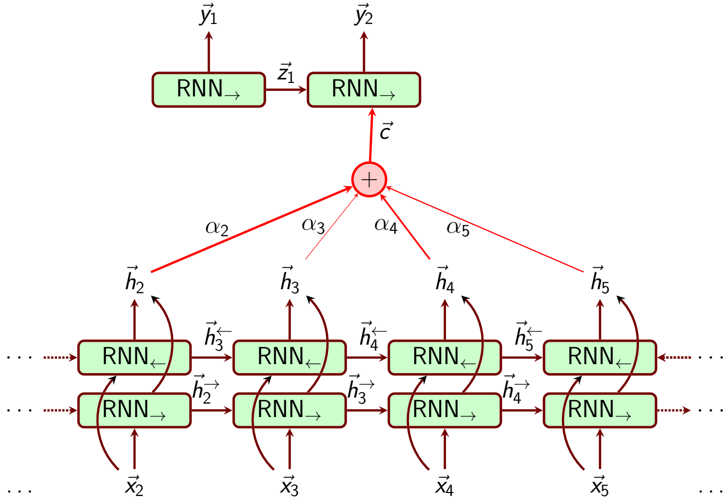
RNN Architecture

The Attention Mechanism



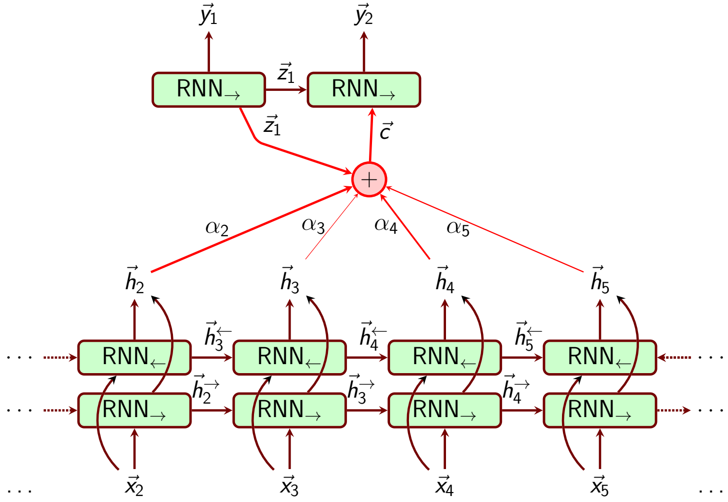
RNN Architecture

The Attention Mechanism



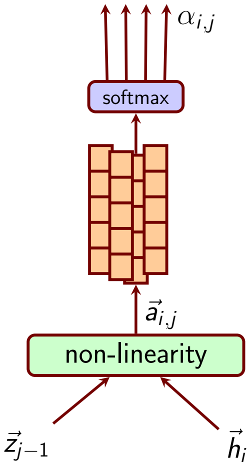
RNN Architecture

The Attention Mechanism



RNN Architecture

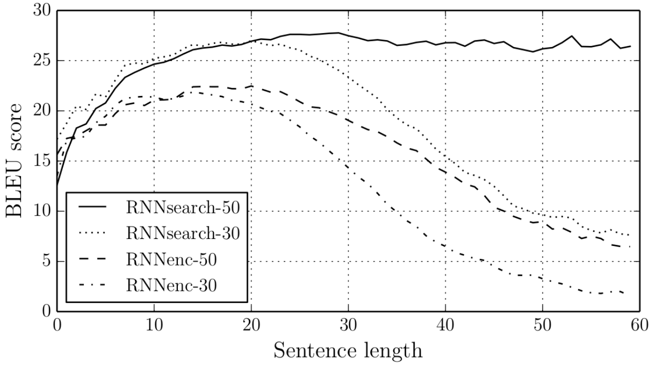
Attention Network



RNN Architecture

The Attention Mechanism

- What achieves attention?



[Bahdanau et al., 2015]

Transformer Architecture

So, Attention is all you Need?!

Attention Is All You Need

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Abstract

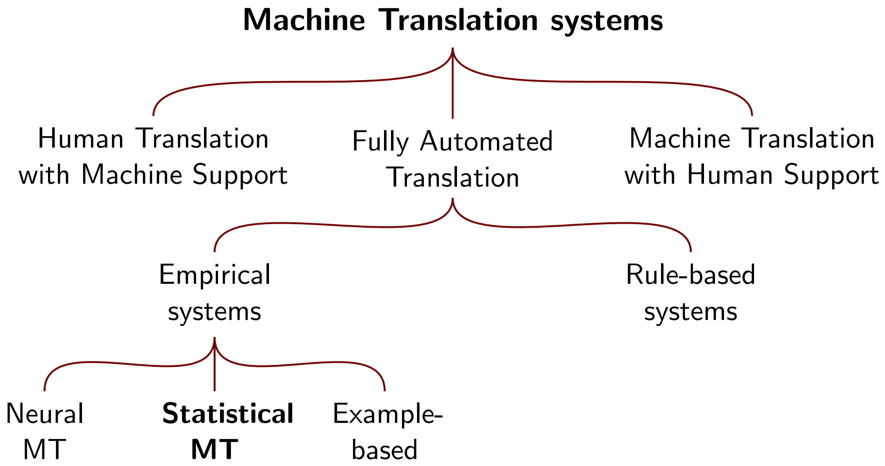
The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions

Neural Machine Translation III

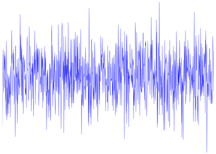
- Details and equations later in the course
- RNNs are only a kind of NMT, the most intuitive one
  - CNNs
  - Transformer

Data-driven Machine Translation

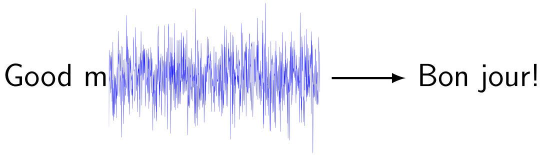
Statistical Machine Translation



The Noisy Channel as a statistical approach to translation:

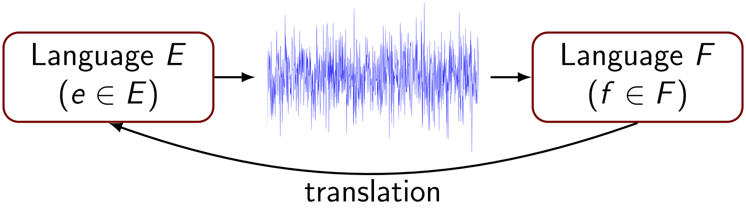
Good morning! → 

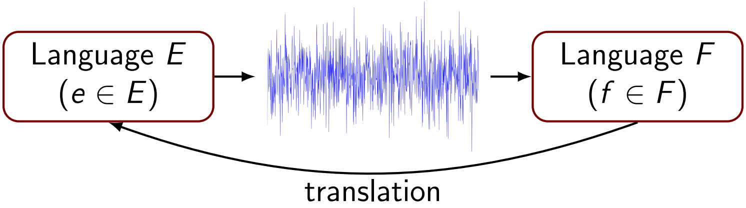
The Noisy Channel as a statistical approach to translation:



The Noisy Channel as a statistical approach to translation:

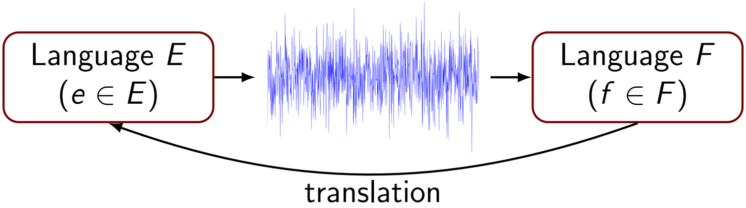
e: Good morning! $\qquad$ f: Bon jour!





Mathematically:

$$P(e|f)$$



Mathematically:

$$P(e|f) = \frac{P(e)\,P(f|e)}{P(f)}$$

$$T(f) = \hat{e} = \mathrm{argmax_e}\; P(e|f) = \mathrm{argmax_e}\; P(e)\,P(f|e)$$

$$T(f) = \hat{e} = \text{argmaxe}\ \mathbf{P(e)}\ P(f|e)$$

Language Model

- Takes care of fluency in the target language
- Data: corpora in the target language

Data-driven Machine Translation

Statistical Machine Translation II

$$T(f) = \hat{e} = \mathrm{argmax}_e \; P(e) \, \mathbf{P(f|e)}$$

Language Model

- Takes care of fluency in the target language
- Data: corpora in the target language

Translation Model

- Lexical correspondence between languages
- Data: aligned corpora in source and target languages

$$T(f) = \hat{e} = \mathbf{argmax}_e \; P(e)\, P(f|e)$$

Language Model

- Takes care of fluency in the target language
- Data: corpora in the target language

Translation Model

- Lexical correspondence between languages
- Data: aligned corpora in source and target languages

argmax

- Search done by the *decoder*

Data-driven Machine Translation

Example-based Machine Translation

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
  - Empirical systems
    - Neural MT
    - Statistical MT
    - **Example-based**
  - Rule-based systems
- Machine Translation with Human Support

Data-driven Machine Translation

Example-based Machine Translation

1. **Compile** and align a database of examples
2. **Match** input to a database of translation examples with **similarity** measures
3. **Identify** corresponding translation fragments
4. **Recombine** fragments into target text

It may also makes use of rules to find matches and to recombine aligned parts and build the final translation

Data-driven Machine Translation

SMT vs. EBMT

SMT

- Probabilities to access the merit of candidates
- Probabilities to rank candidates (decoding)
- Join together translated fragments

EBMT

- Similarity score between input fragments to fragments in database
- Syntactic and/or semantic similarity to rank candidates
- Join together translated fragments

Comparison

Machine Translation Systems

Machine Translation systems

- Human Translation with Machine Support
- Fully Automated Translation
  - Empirical systems
    - **Neural MT**
    - **Statistical MT**
    - **Example-based**
  - Rule-based systems
    - **Direct MT**
    - **Transfer MT**
    - **Interlingua**
- Machine Translation with Human Support

Comparison

RBMT vs. SMT vs. NMT for High-Quality Systems

	RBMT	**SMT**	**NMT**
Data Amount	small	large	huge
Training Time	–	days	weeks
CPU/GPU	CPU	CPU	GPU/TPU
Cost	expensive (in people)	cheap	expensive (in hardware)
Maintainability	weak	strong	superstrong
Grammaticality	strong	medium	strong
Reordering	strong	weak	strong
Consistency	strong	medium	weak
Coverage	weak	strong	strong
Multilinguality	medium	none	strong

Comparison

RBMT vs. SMT vs. NMT for High-Quality Systems II

I want a good translator, what MT should I use?

1. Think of your problem: language, domain and application
2. Think of your resources: time, hardware and money
3. Decide (probably the size of the transformer!)

RBMT vs. SMT vs. NMT for High-Quality Systems II

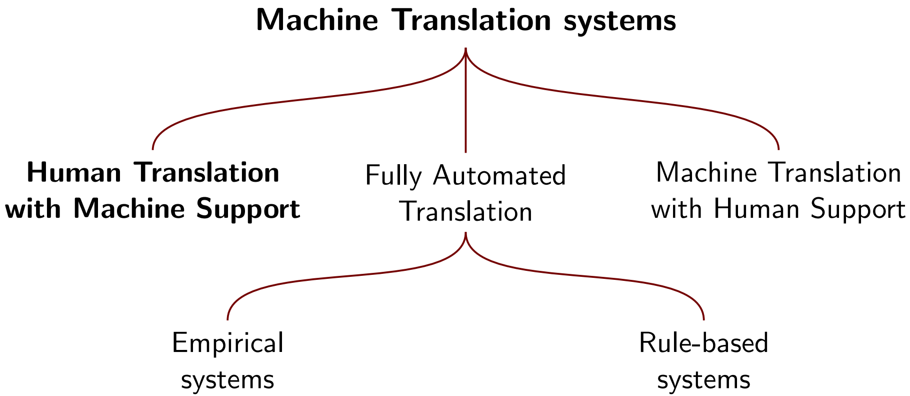
I want a good translator, what MT should I use?

1. Think of your problem: language, domain and application
2. Think of your resources: time, hardware and money
3. Decide (probably the size of the transformer!)

- The previuos slide shows general trends
- But quality depends on the language pair and domain
- All systems have pros and cons, why not **hybridisation**?

Machine Translation Systems

Not Fully Automated Translation



Not Fully Automated Translation

Human Translation with Machine Support

Machine-aided Human Translation, MAHT

Uses computer assisted translation tools (**CAT tools**) to:

- access a bilingual terminology
- access a translation memory
- submit parts ot the text to an MT server

Not Fully Automated Translation

Human Translation with Machine Support II

Translation Memories are aids for human translators

- Store and index entire existing translations
- Before translation, check the index to see if it's already been translated and reuse

- Strict matches: very reliable translation
- Fuzzy matches: more flexible, greater cover, but less reliable (similar to EBMT!)

Not Fully Automated Translation

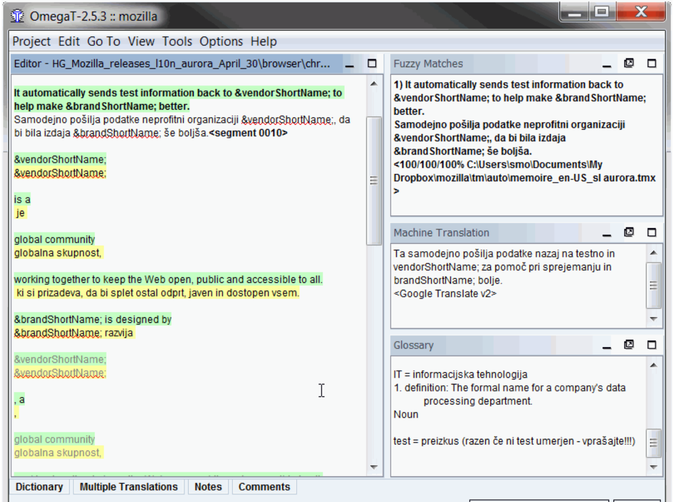
CATs: SDL Trados

SDL Trados, a commercial tool

https://www.youtube.com/watch?v=FgBAyxFq3Ok

1:30-1:50; 3:25-5:06

OmegaT, a free tool



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References

SMT & NMT

See references at the corresponding sessions