

Language and Computers (Ling 384)

Topic 5: Machine Translation

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Language and
Computers

Topic 5: Machine
Translation

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Language and
Computers

Topic 5: Machine
Translation

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Language and
Computers

Topic 5: Machine
Translation

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Machine learning-based systems

Language and
Computers

Topic 5: Machine
Translation

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Machine learning-based systems

What makes MT hard?

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Machine learning-based systems

What makes MT hard?

Evaluating MT systems

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Outline

Introduction

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Machine learning-based systems

What makes MT hard?

Evaluating MT systems

References

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

What is Machine Translation?

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Translation is the process of:

- ▶ moving texts from one (human) language (**source language**) to another (**target language**),
- ▶ in a way that preserves meaning.

What is Machine Translation?

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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Machine translation (MT) automates (part of) the process:

- ▶ Fully automatic translation
- ▶ Computer-aided (human) translation

What is MT good for?

- ▶ When you need the gist of something and there are no human translators around:
 - ▶ translating e-mails & webpages
 - ▶ obtaining information from sources in multiple languages (e.g., search engines)

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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 - ▶ translating e-mails & webpages
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- ▶ If you have a limited vocabulary and a small range of sentence types:
 - ▶ translating weather reports
 - ▶ translating technical manuals
 - ▶ translating terms in scientific meetings
 - ▶ determining if certain words or ideas appear in suspected terrorist documents → help pin down which documents need to be looked at closely

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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- ▶ If you want your human translators to focus on interesting/difficult sentences while avoiding lookup of unknown words and translation of mundane sentences.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Is MT needed?

- ▶ Translation is of immediate importance for multilingual countries (Canada, India, Switzerland, . . .), international institutions (United Nations, International Monetary Fund, World Trade Organization, . . .), multinational or exporting companies.
- ▶ The European Union used to have 11 official languages, since May 1, 2004 it has 20. All federal laws and other documents have to be translated into all languages.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

What is MT not good for?

- ▶ Things that require subtle knowledge of the world and/or a high degree of (literary) skill:
 - ▶ translating Shakespeare into Navaho
 - ▶ diplomatic negotiations
 - ▶ court proceedings
 - ▶ ...

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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 - ▶ translating Shakespeare into Navaho
 - ▶ diplomatic negotiations
 - ▶ court proceedings
 - ▶ ...
- ▶ Things that may be a life or death situation:
 - ▶ Pharmaceutical business
 - ▶ Automatically translating frantic 911 calls for a dispatcher who speaks only Spanish

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

Example translations

The simple case

- ▶ It will help to look at a few examples of real translation before talking about how a machine does it.

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- ▶ Take the simple Spanish sentence and its English translation below:

(1) Yo hablo español.
I speak_{1st,sg} Spanish
'I speak Spanish.'

Example translations

The simple case

- ▶ It will help to look at a few examples of real translation before talking about how a machine does it.
- ▶ Take the simple Spanish sentence and its English translation below:

(1) Yo hablo español.
I speak_{1st,sg} Spanish
'I speak Spanish.'

- ▶ Words in this example pretty much translate one-for-one
- ▶ But we have to make sure *hablo* matches with *Yo*, i.e., that the subject agrees with the form of the verb.

Example translations

A slightly more complex case

The order and number of words can differ:

- (2) a. Tu hablas español?
You speak_{2nd,sg} Spanish
'Do you speak Spanish?'
- b. Hablas español?
Speak_{2nd,sg} Spanish
'Do you speak Spanish?'

What goes into a translation

Some things to note about these examples and thus what we might need to know to translate:

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- ▶ Words have to be translated. → dictionaries
- ▶ Words are grouped into meaningful units. (cf., our discussion of syntax for grammar checkers).
- ▶ Word order can differ from language to language.
- ▶ The forms of words within a sentence are systematic, e.g., verbs have to be conjugated, etc.

Different approaches to MT

- ▶ Transformer systems
- ▶ Systems based on linguistic knowledge
 - ▶ Direct transfer systems
 - ▶ Interlinguas
- ▶ Machine learning approaches

Most of these use dictionaries in one form or another, so we will start by looking at dictionaries.

An MT **dictionary** is differs from a “paper” dictionary:

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- ▶ must be computer-usable (electronic form, indexed)
- ▶ contain the inherent properties (meaning) of a word
- ▶ need to be able to handle various word inflections
have is the dictionary entry, but we want the entry to specify how to conjugate this verb.

Dictionaries (cont.)

- ▶ contain (syntactic and semantic) restrictions it places on other words
 - ▶ e.g., Subcategorization information: *give* needs a giver, a person given to, and an object that is given

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 - ▶ e.g., Selectional restrictions: if X is *eating*, then X must be animate.
- ▶ may also contain frequency information
- ▶ can be hierarchically organized, e.g.:
 - ▶ all nouns have person, number, and gender
 - ▶ verbs (unless irregular) conjugate in the past tense by adding *ed*.

What dictionary entries might look like

- ▶ WORD: *button*
PART OF SPEECH: NOUN
HUMAN: NO
CONCRETE: yes
GERMAN: Knopf

What dictionary entries might look like

- ▶ WORD: *button*
PART OF SPEECH: NOUN
HUMAN: NO
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- ▶ WORD: *knowledge*
PART OF SPEECH: NOUN
HUMAN: NO
CONCRETE: NO
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What dictionary entries might look like

▶ WORD: *button*

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▶ WORD: *knowledge*

PART OF SPEECH: NOUN

HUMAN: NO

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GERMAN: Wissen, Kenntnisse

- ▶ There can be extra rules which tell you whether to choose *Wissen* or *Kenntnisse*.

A dictionary entry with frequency

- ▶ WORD: *knowledge*
PART OF SPEECH: NOUN
HUMAN: NO
CONCRETE: NO
GERMAN: Wissen: 80%, Kenntnisse: 20%
- ▶ Probabilities can be derived from various machine learning techniques → to be discussed later.

Transformer approaches

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- ▶ They consist of
 - ▶ a grammar for the source/input language

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Transformer approaches

- ▶ **Transformer** architectures transform example sentences from one language into another.
- ▶ They consist of
 - ▶ a grammar for the source/input language
 - ▶ a source-to-target language dictionary
 - ▶ source-to-target language rules
- ▶ Note that there is no grammar for the target language, only mappings from the source language.

An example for the transformer approach

We'll work through a German-to-English example.

- (3) a. Drehen Sie den Knopf eine Position zurück.
b. Turn the button back one position.

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verb pron. article noun article noun prep.

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(6) Drehen Sie [den Knopf] [eine Position] zurück.
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4. Using the source-to-target rules, reorder, combine, eliminate, or add target language words, e.g.,

- ▶ 'turn' and 'back' form one unit.
- ▶ because 'Drehen ... zurück' is a command, in English it is expressed without 'you'.

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- ▶ 'turn' and 'back' form one unit.
- ▶ because 'Drehen ... zurück' is a command, in English it is expressed without 'you'.

⇒ End result: *Turn back the button one position.*

Transformers: Less than meets the eye

- ▶ By their very nature, transformer systems are non-**reversible** because they lack a target language grammar.
If we have a German to English translation system, for example, we are incapable of translating from English to German.

Transformers: Less than meets the eye

- ▶ By their very nature, transformer systems are **non-reversible** because they lack a target language grammar.
If we have a German to English translation system, for example, we are incapable of translating from English to German.
- ▶ However, as these systems do not require sophisticated knowledge of the target language, they are usually very **robust** = they will return a result for nearly any input sentence.

Linguistic knowledge-based systems

- ▶ Linguistic knowledge-based systems include knowledge of both the source and the target languages.
- ▶ We will look at direct transfer systems and then the more specific instance of interlinguas.
 - ▶ Direct transfer systems
 - ▶ Interlinguas

Direct transfer systems

A direct transfer systems consists of:

- ▶ A source language grammar

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Direct transfer systems

A direct transfer systems consists of:

- ▶ A source language grammar
- ▶ A target language grammar
- ▶ Rules relating source language underlying representation to target language underlying representation

Direct transfer systems (cont.)

- ▶ A direct transfer system has a **transfer component** which relates a source language representation with a target language representation.
- ▶ This can also be called a **comparative grammar**.

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(7) Londres plaît à Sam.
 London is pleasing to Sam
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Steps in a transfer system

1. source language grammar analyzes the input and puts it into an **underlying representation** (UR).

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French UR English UR

X plaire Y ↔ Eng(Y) like Eng(X)

(where Eng(X) means the English translation of X)

Londres plaire Sam (source UR) → Sam like London
(target UR)

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Sam like London → Sam likes London.

Things to note about transfer systems

- ▶ The transfer mechanism is essentially reversible; e.g., the *plaire* rule works in both directions (at least in theory)

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- ▶ Word order is handled differently than with transformers: the URs are essentially unordered.

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- ▶ The transfer mechanism is essentially reversible; e.g., the *plaire* rule works in both directions (at least in theory)
- ▶ Because we have a separate target language grammar, we are able to ensure that the rules of English apply; *like* → *likes*.
- ▶ Word order is handled differently than with transformers: the URs are essentially unordered.
- ▶ The underlying representation can be of various levels of abstraction – words, syntactic trees, meaning representations, etc.; we will talk about this with the **translation triangle**.

Caveat about reversibility

- ▶ It seems like reversible rules are highly desirable—and in general they are—but we may not always want reversible rules.
 - ▶ e.g., Dutch *aanvangen* should be translated into English as *begin*, but English *begin* should be translated into Dutch as *beginnen*.

Levels of abstraction

- ▶ There are differing levels of abstraction at which transfer can take place. So far we have looked at URs that represent only word information.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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- ▶ We can do a full syntactic analysis, which helps us to know how the words in a sentence relate.
- ▶ Or we can do only a partial syntactic analysis, such as representing the dependencies between words.

(8) Kaufman & Broad odmítla institucionální investory
Kaufman & Broad declined institutional investors
jmenovat.

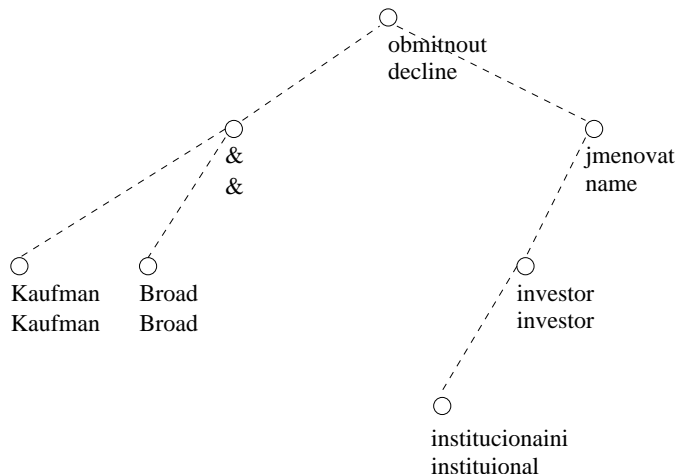
to name/identify

'Kaufman & Broad refused to name the institutional investors.'

Example taken from Čmejrek, Cuřín, and Havelka (2003).

- ▶ They find the base forms of words (e.g., *obmidout* 'to decline' instead of *odmítla* 'declined')
- ▶ They find which words depend on which other words and represent this in a tree (e.g., the noun *investory* depends on the verb *odmítla*)
- ▶ This dependency tree is then converted to English (comparative grammar) and re-ordered as appropriate.

Dependency tree for Czech-English example



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- ▶ **Benefit:** To add new languages to your MT system, you merely have to provide mapping rules between your language and the interlingua, and then you can translate into any other language in your system.

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- ▶ **Benefit:** To add new languages to your MT system, you merely have to provide mapping rules between your language and the interlingua, and then you can translate into any other language in your system.
- ▶ What your interlingua looks like depends on your goals; an example for *I shot the sheriff.* is shown on the following slide.

Interlingua example

ACTION		<i>wound</i>		
	MEANS	<i>gun</i>		
	TENSE	<i>past</i>		
	KILL	<i>maybe</i>		
	WOUNDER	[<i>speaker</i>]
		PERSON	<i>first</i>	
		NUMBER	<i>sg</i>	
	WOUNDEE	[<i>sheriff</i>]
		DEFINITE	<i>yes</i>	
		PERSON	<i>third</i>	
		NUMBER	<i>singular</i>	
		GENDER	<i>?</i>	
		HUMAN	<i>yes</i>	
		ANIMATE	<i>yes</i>	
NOUN-TYPE		<i>kind of job</i>		
IS-A-KIND-OF	<i>officer</i>			

- ▶ What exactly should be represented in the interlingua?
 - ▶ e.g., English *corner* = Spanish *rincón* = 'inside corner' or *esquina* = 'outside corner'

- ▶ What exactly should be represented in the interlingua?
 - ▶ e.g., English *corner* = Spanish *rincón* = 'inside corner' or *esquina* = 'outside corner'
- ▶ A fine-grained interlingua can require extra (unnecessary) work:
 - ▶ e.g., Japanese distinguishes *older brother* from *younger brother*, so we have to disambiguate English *brother* to put it into the interlingua. Then, if we translate into French, we have to ignore the disambiguation and simply translate it as *frère*, which simply means 'brother'.

Introduction

Examples for Translations

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Direct transfer systems

Interlingua-based systems

Machine learning-based systems

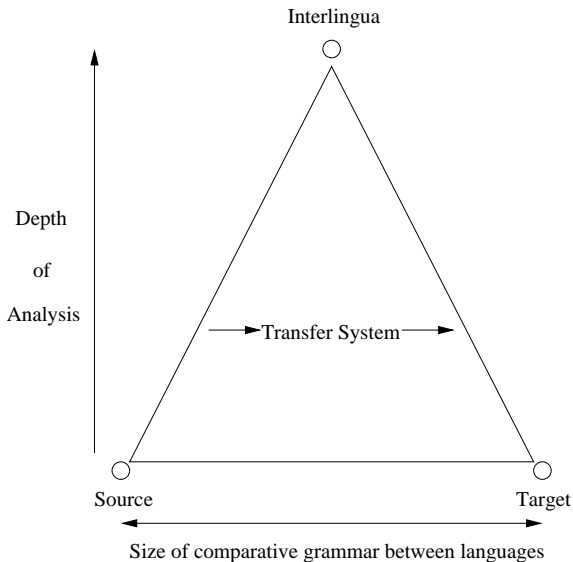
Alignment

What makes MT hard?

Evaluating MT systems

References

The translation triangle



Introduction

Examples for Translations

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Direct transfer systems

Interlingua-based systems

Machine learning-based systems

Alignment

What makes MT hard?

Evaluating MT systems

References

- ▶ Instead of trying to tell the MT system how we're going to translate, we might try a **machine learning** approach = the computer will learn how to translate based on example translations.

Introduction

Examples for Translations

Background: Dictionaries

Transformer approaches

Linguistic knowledge-based systems

Direct transfer systems

Interlingua-based systems

Machine learning-based systems

Alignment

What makes MT hard?

Evaluating MT systems

References

- ▶ Instead of trying to tell the MT system how we're going to translate, we might try a **machine learning** approach = the computer will learn how to translate based on example translations.
- ▶ For this, we need
 - ▶ examples of translations as **training data**, and
 - ▶ a way of learning from that data.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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 - ▶ We are told what each word is translated as: **text alignment**

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 - ▶ We are told what each word is translated as: **text alignment**
 - ▶ We are not told what each word is translated as: use a **bag of words**

Text alignment

Sometimes humans have provided informative training data:

- ▶ sentence alignment
- ▶ word alignment

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Sentence alignment

- ▶ **sentence alignment** = determine which source language sentences align with which target language ones (what we assumed in the bag of words example).
- ▶ Intuitively easy, but can be difficult in practice since different languages have different punctuation conventions.

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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- ▶ One word can map to one word or to multiple words. Likewise, sometimes it is best for multiple words to align with multiple words.
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 - ▶ many-to-one: *to take a walk* = *gulyat'*
 - ▶ many-to-many: *at least* = *khotya by* ('although if/would')

Calculating probabilities

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- ▶ e.g., What is the probability that *run* translates as *correr* in Spanish?

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 1. Count up how many times *run* appears in the English part of your bi-text. e.g., 500 times
 2. Out of all those times, count up how many times it was translated as (i.e., aligns with) *correr*. e.g., 275 (out of 500) times.

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 2. Out of all those times, count up how many times it was translated as (i.e., aligns with) *correr*. e.g., 275 (out of 500) times.
 3. Divide to get a probability: $275/500 = 0.55$, or 55%

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Word alignment difficulties

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 - ▶ we may have many cases where *fool* is aligned with the Spanish *engañar* = 'to fool'
 - ▶ but we may then encounter *a fool*, where the translation should be *tonto* (male) or *tonta* (female)
- ▶ So, word alignment only helps us get some frequency numbers; we still have to do something intelligent with them.

Word alignment difficulties (cont.)

- ▶ Sometimes it is not even clear that word alignment is possible.

(9) Ivan aspirant.

Ivan graduate student

'Ivan is a graduate student.'

- ▶ What does *is* align with?

Word alignment difficulties (cont.)

- ▶ Sometimes it is not even clear that word alignment is possible.

(9) Ivan aspirant.

Ivan graduate student

‘Ivan is a graduate student.’

- ▶ What does *is* align with?
- ▶ In cases like this, a word can be mapped to a “null” element in the other language.

The “bag of words” method

- ▶ What if we're not given word alignments?
- ▶ How can we tell which English words are translated as which German words if we are only given an English text and a corresponding German text?

The “bag of words” method

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 - ▶ We can treat each sentence as a **bag of words** = unordered collection of words.

The “bag of words” method

- ▶ What if we're not given word alignments?
- ▶ How can we tell which English words are translated as which German words if we are only given an English text and a corresponding German text?
 - ▶ We can treat each sentence as a **bag of words** = unordered collection of words.
 - ▶ If word A appears in a sentence, then we will record all of the words in the corresponding sentence in the other language as appearing with it.

Example for bag of words method

- ▶ English *He speaks Russian well.*
- ▶ Russian *On khorosho govorit po-ruski.*

Eng	Rus	Eng	Rus
He	On	speaks	On
He	khorosho	speaks	khorosho
He	govorit
He	po-ruski	well	po-ruski

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The idea is that, over thousands, or even millions, of sentences, *He* will tend to appear more often with *On*, *speaks* will appear with *govorit*, and so on.

Example for bag of words method

Calculating probabilities: sentence 1

So, for *He* in *He speaks Russian well/On khorosho govorit po-russki*, we do the following:

1. Count up the number of Russian words: 4.

Example for bag of words method

Calculating probabilities: sentence 1

So, for *He* in *He speaks Russian well/On khorosho govorit po-russki*, we do the following:

1. Count up the number of Russian words: 4.
2. Assign each word equal probability of translation: $1/4 = 0/25$, or 25%.

Example for bag of words method

Calculating probabilities: sentence 2

If we also have *He is nice./On simpatic'hnyi.*, then for *He*, we do the following:

Example for bag of words method

Calculating probabilities: sentence 2

If we also have *He is nice./On simpatich'nyi.*, then for *He*, we do the following:

1. Count up the number of possible translation words: 4 from the first sentence, 2 from the second = 6 total.

Example for bag of words method

Calculating probabilities: sentence 2

If we also have *He is nice./On simpatic'hnyi.*, then for *He*, we do the following:

1. Count up the number of possible translation words: 4 from the first sentence, 2 from the second = 6 total.
2. Count up the number of times *On* is the translation = 2 times out of 6 = $1/3 = 0.33$, or 33%.

Example for bag of words method

Calculating probabilities: sentence 2

If we also have *He is nice./On simpatic'hnyi.*, then for *He*, we do the following:

1. Count up the number of possible translation words: 4 from the first sentence, 2 from the second = 6 total.
2. Count up the number of times *On* is the translation = 2 times out of 6 = $1/3 = 0.33$, or 33%.

Every other word has the probability $1/6 = 0.17$, or 17%, so *On* is clearly the best translation for *He*.

What makes MT hard?

We've seen how MT systems can work, but MT is a very difficult task because languages are vastly different.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

What makes MT hard?

We've seen how MT systems can work, but MT is a very difficult task because languages are vastly different. They differ:

- ▶ Lexically: In the words they use
- ▶ Syntactically: In the constructions they allow
- ▶ Semantically: In the way meanings work
- ▶ Pragmatically: In what readers take from a sentence.

In addition, there is a good deal of real-world knowledge that goes into a translation.

Lexical ambiguity

Words can be **lexically ambiguous** = have multiple meanings.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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⇒ We have to know which meaning before we translate.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

How words divide up the world (lexical issues)

Words don't line up exactly between languages.
Within a language, we have synonyms, hyponyms, and hypernyms.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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- ▶ *furniture* is a hypernym (more general term) of *sofa*

Synonyms

Often we find **synonyms** between two languages (as much as there are synonyms within a language):

- ▶ English *book* = Russian *kniga*
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But words don't always line up exactly between languages.

Hypernyms and Hyponyms

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- ▶ English **hyponyms** = words that are more specific in English than in their foreign language counterparts.
 - ▶ The German word *berg* can mean either *hill* or *mountain* in English.

Hypernyms and Hyponyms

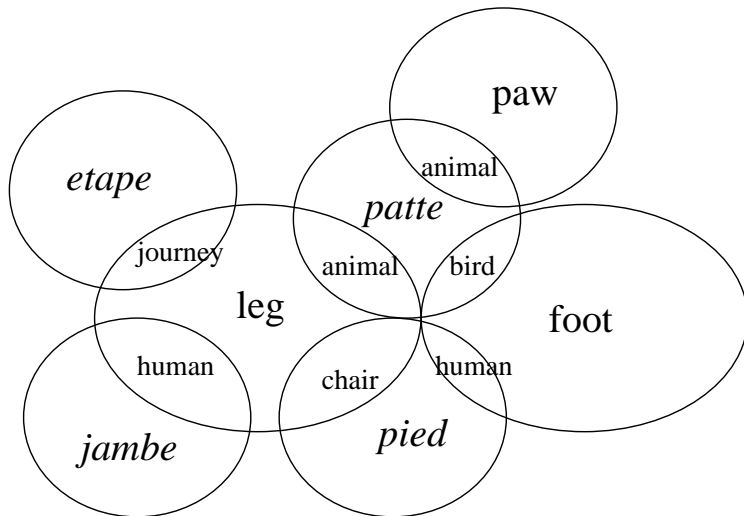
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- ▶ English **hyponyms** = words that are more specific in English than in their foreign language counterparts.
 - ▶ The German word *berg* can mean either *hill* or *mountain* in English.
 - ▶ The Russian word *ruka* can mean either *hand* or *arm*.

Semantic overlap

And then there's just fuzziness, as in the following English and French correspondences

- ▶ *leg* = *etape* (journey), *jambe* (human), *pied* (chair), *patte* (animal)
- ▶ *foot* = *pied* (human), *patte* (bird)
- ▶ *paw* = *patte* (animal)

Venn diagram of semantic overlap



Lexical gaps

Sometimes there is no simple equivalent for a word in a language, and the word has to be translated with a more complex phrase. We call this a **lexical gap** or **lexical hole**.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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Sometimes there is no simple equivalent for a word in a language, and the word has to be translated with a more complex phrase. We call this a **lexical gap** or **lexical hole**.

- ▶ French *gratiner* means something like 'to cook with a cheese coating'
- ▶ Hebrew *stam* means something like 'I'm just kidding' or 'Nothing special.'

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- ▶ French *faire une promenade* is literally 'make a walk,' but it has the meaning of the English *take a walk*
- ▶ Dutch *een poging doen* 'do an attempt' means the same as the English *make an attempt*

And we often face **idioms** = expressions whose meaning is not made up of the meanings of the individual words.

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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- ▶ e.g., English *kick the bucket*
 - ▶ approximately equivalent to the French *casser sa pipe* ('break his/her pipe')
 - ▶ but we might want to translate it as *mourir* ('die')
 - ▶ and we want to treat it differently than *kick the table*

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

There are idiosyncratic choices among languages, e.g.:

- ▶ English *heavy smoker*
- ▶ French *grand fumeur* ('large smoker')
- ▶ German *starker Raucher* ('strong smoker')

Taboo words

There are **taboo words** = words which are “forbidden” in some way or in some circumstances (i.e., swear/curse words)

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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 - ▶ e.g., The word 'skin' is taboo in a Western Australian (Aboriginal) language (<http://www.aija.org.au/online/ICABenchbook/BenchbookChapter5.pdf>)
 - ▶ Imagine encountering the word 'skin' in English and translating it without knowing this.

Structure and word order differences

- ▶ Word order (and syntactic structure) differs across languages.
- ▶ E.g., in English, we have what is called a subject-verb-object (SVO) order, as in (10).

(10) John punched Bill.

 SUBJECT VERB OBJECT

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- ▶ In contrast, Japanese is SOV. Arabic is VSO. Dyirbal (Australian aboriginal language) has free word order.
- ▶ MT systems have to account for these differences.

More on word order differences

- ▶ Sometimes things are conceptualized differently in different languages, e.g.:

(11) a. His name is Jerome.

b. Er heißt Jerome. (German)
He goes-by-name-of Jerome

c. Il s' appelle Jerome. (French)
He himself call Jerome.

- ▶ Words don't really align here.

How syntactic grouping and meaning relate (Syntax/Semantics)

Even within a language, there are syntactic complications. We can have **structural ambiguities** = sentences where there are multiple ways of interpreting it.

(12) John saw the boy (with the binoculars).

with the binoculars can refer to either *the boy* or to how John saw the boy.

How syntactic grouping and meaning relate (Syntax/Semantics)

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with the binoculars can refer to either *the boy* or to how John saw the boy.

- ▶ This difference in structure corresponds to a difference in what we think the sentence means, i.e., meaning is derived from the words and how they are grouped.
- ▶ Do we attempt to translate only one interpretation? Or do we try to preserve the ambiguity in the target language?

[Introduction](#)[Examples for Translations](#)[Background:
Dictionaries](#)[Transformer
approaches](#)[Linguistic
knowledge-based
systems](#)[Direct transfer systems](#)[Interlingua-based systems](#)[Machine
learning-based
systems](#)[Alignment](#)[What makes MT
hard?](#)[Evaluating MT
systems](#)[References](#)

How language is used (Pragmatics)

Translation becomes even more difficult when we try to translate something in context.

- ▶ *Thank you* is usually translated as *merci* in French, but it is translated as *s'il vous plaît* 'please' when responding to an offer.

How language is used (Pragmatics)

Translation becomes even more difficult when we try to translate something in context.

- ▶ *Thank you* is usually translated as *merci* in French, but it is translated as *s'il vous plaît* 'please' when responding to an offer.
- ▶ *Can you drive a stick-shift?* could be a request for you to drive my manual transmission automobile, or it could simply be a request for information about your driving abilities.

Real-world knowledge

- ▶ Sometimes we have to use **real-world knowledge** to figure out what a sentence means.

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- ▶ We know what *it* refers to only because we know that printers, not paper, can be switched on.

Ambiguity resolution

- ▶ If the source language involves ambiguous words/phrases, but the target language does not have the same ambiguity, we have to resolve ambiguity before translation.
e.g., the hyponyms/hypernyms we saw before.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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⇒ In the Bible, the Greek word *hyper* is used in 1 Corinthians 15:29; it can mean 'over', 'for', 'on behalf of', and so on. How you treat it affects how you treat the theological issue of salvation of the already dead. i.e., people care deeply about how you translate this word, yet it is not entirely clear what English meaning it has.

Evaluating MT systems

- ▶ We've seen some translation systems and we know that translation is hard.
- ▶ The question now is: How do we evaluate MT systems, in particular for use in large corporations as likely users?
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 - ▶ How good is the MT system (quality)?

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- ▶ **Error analysis** = how many errors we have to sort through (and how do the errors affect intelligibility & accuracy)
- ▶ **Test suite** = a set of sentences that our system should be able to handle

Intelligibility Scale (from Arnold et al., 1994)

1. The sentence is perfectly clear and intelligible. It is grammatical and reads like ordinary text.

[Introduction](#)

[Examples for Translations](#)

[Background:
Dictionaries](#)

[Transformer
approaches](#)

[Linguistic
knowledge-based
systems](#)

[Direct transfer systems](#)

[Interlingua-based systems](#)

[Machine
learning-based
systems](#)

[Alignment](#)

[What makes MT
hard?](#)

[Evaluating MT
systems](#)

[References](#)

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Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References

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[Introduction](#)

[Examples for Translations](#)

[Background:
Dictionaries](#)

[Transformer
approaches](#)

[Linguistic
knowledge-based
systems](#)

[Direct transfer systems](#)

[Interlingua-based systems](#)

[Machine
learning-based
systems](#)

[Alignment](#)

[What makes MT
hard?](#)

[Evaluating MT
systems](#)

[References](#)

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3. The general idea of the sentence is intelligible only after considerable study. The sentence contains grammatical errors and/or poor word choices.
4. The sentence is unintelligible. Studying the meaning of the sentence is hopeless; even allowing for context, one feels that guessing would be too unreliable.

[Introduction](#)

[Examples for Translations](#)

[Background:
Dictionaries](#)

[Transformer
approaches](#)

[Linguistic
knowledge-based
systems](#)

[Direct transfer systems](#)

[Interlingua-based systems](#)

[Machine
learning-based
systems](#)

[Alignment](#)

[What makes MT
hard?](#)

[Evaluating MT
systems](#)

[References](#)

Some of the examples are adapted from the following books:

- ▶ Doug J. Arnold, Lorna Balkan, Siety Meijer, R. Lee Humphreys and Louisa Sadler (1994). *Machine Translation: an Introductory Guide*. Blackwells-NCC, London. 1994. Available from <http://www.essex.ac.uk/linguistics/clmt/MTbook/>
- ▶ Jurafsky, Daniel, and James H. Martin (2000). *Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics*. Prentice-Hall. More info at <http://www.cs.colorado.edu/~martin/slp.html>.

Introduction

Examples for Translations

Background:
Dictionaries

Transformer
approaches

Linguistic
knowledge-based
systems

Direct transfer systems

Interlingua-based systems

Machine
learning-based
systems

Alignment

What makes MT
hard?

Evaluating MT
systems

References