



**Christof Monz**  
Informatics Institute  
University of Amsterdam

# Natural Language Processing 1

## Machine Translation

# This Class

- ▶ Machine translation

# This Class

- ▶ Machine translation
- ▶ Sequence-to-sequence models

# This Class

- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation



# This Class

- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
  - encoder-decoder architecture

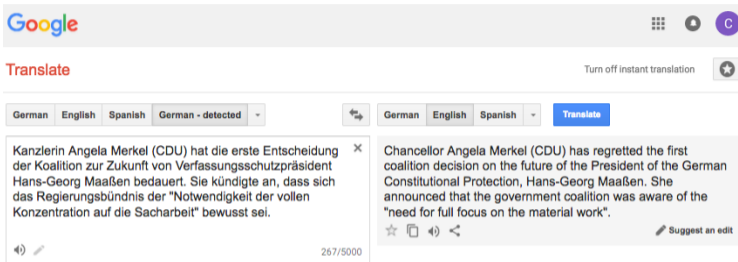
# This Class

- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
  - encoder-decoder architecture
  - attention mechanism

# This Class

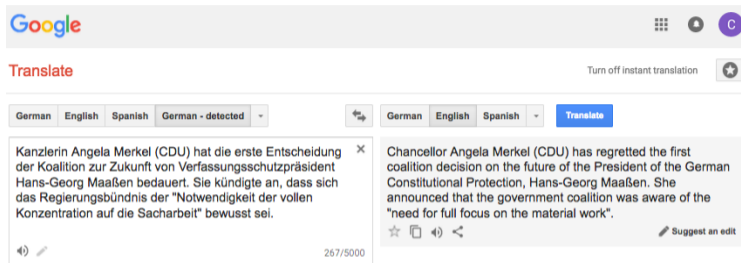
- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
  - encoder-decoder architecture
  - attention mechanism
  - self-attention (Google's Transformer)

# Machine Translation



The screenshot shows the Google Translate web interface. At the top left is the Google logo. To its right are icons for an app drawer, a notification bell, and a user profile 'C'. Below the logo is the word 'Translate' in red. On the right side of this bar, there is a toggle switch for 'Turn off instant translation' and a star icon. The main interface has two columns. The left column has a language selector with 'German', 'English', 'Spanish', and 'German - detected' (with a dropdown arrow). Below this is a text input area containing German text: 'Kanzlerin Angela Merkel (CDU) hat die erste Entscheidung der Koalition zur Zukunft von Verfassungsschutzpräsident Hans-Georg Maaßen bedauert. Sie kündigte an, dass sich das Regierungsbündnis der "Notwendigkeit der vollen Konzentration auf die Sacharbeit" bewusst sei.' There is a small 'x' icon to the right of the text and a character count '267/5000' at the bottom right. A speaker icon is at the bottom left. The right column has a language selector with 'German', 'English', and 'Spanish' (with a dropdown arrow), and a blue 'Translate' button. Below this is the translated English text: 'Chancellor Angela Merkel (CDU) has regretted the first coalition decision on the future of the President of the German Constitutional Protection, Hans-Georg Maaßen. She announced that the government coalition was aware of the "need for full focus on the material work".' At the bottom of this column are icons for a star, a document, a speaker, and a left arrow, along with a 'Suggest an edit' link.

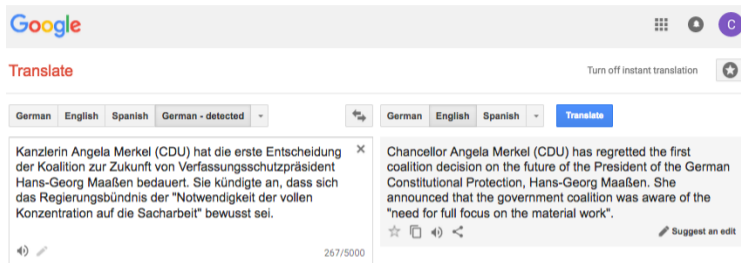
# Machine Translation



The screenshot shows the Google Translate interface. At the top left is the Google logo. Below it, the word "Translate" is displayed in red. To the right of "Translate" is a link that says "Turn off instant translation" and a star icon. Below this, there are language selection buttons for "German", "English", and "Spanish". The current source language is "German - detected" and the target language is "English". A blue "Translate" button is visible. The main content area shows the German text: "Kanzlerin Angela Merkel (CDU) hat die erste Entscheidung der Koalition zur Zukunft von Verfassungsschutzpräsident Hans-Georg Maaßen bedauert. Sie kündigte an, dass sich das Regierungsbündnis der 'Notwendigkeit der vollen Konzentration auf die Sacharbeit' bewusst sei." To the right of this text is a close button (X). Below the German text is a speaker icon and the character count "267/5000". The translated English text is: "Chancellor Angela Merkel (CDU) has regretted the first coalition decision on the future of the President of the German Constitutional Protection, Hans-Georg Maaßen. She announced that the government coalition was aware of the 'need for full focus on the material work'." Below the English text are icons for star, copy, speaker, and back, along with a "Suggest an edit" link.

- ▶ Active research of AI since its beginnings

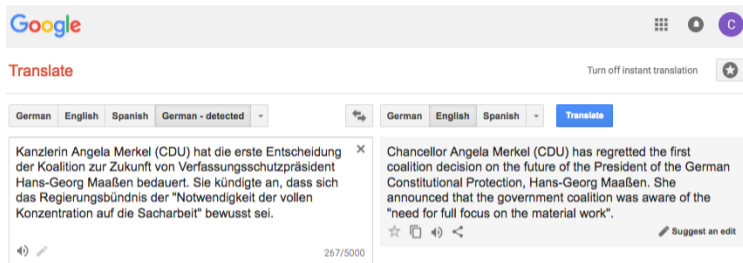
# Machine Translation



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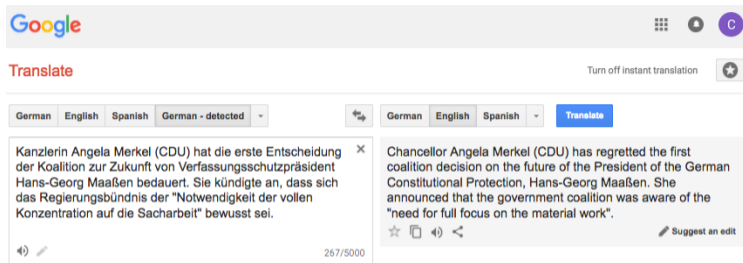
- ▶ Active research of AI since its beginnings
- ▶ Machine translation (MT) is a nice example of the different paradigm shifts in AI

# Machine Translation



The screenshot shows the Google Translate interface. At the top, the Google logo is on the left, and a grid icon, a volume icon, and a profile icon 'C' are on the right. Below the logo is the word 'Translate' in red, and 'Turn off instant translation' with a star icon is on the right. The main area has a language selector with 'German', 'English', and 'Spanish' buttons, and a dropdown menu currently showing 'German - detected'. To the right of the selector are 'German', 'English', and 'Spanish' buttons, and a blue 'Translate' button. Below this, there are two text boxes. The left box contains German text: 'Kanzlerin Angela Merkel (CDU) hat die erste Entscheidung der Koalition zur Zukunft von Verfassungsschutzpräsident Hans-Georg Maaßen bedauert. Sie kündigte an, dass sich das Regierungsbündnis der "Notwendigkeit der vollen Konzentration auf die Sacharbeit" bewusst sei.' Below the text is a speaker icon and a pencil icon, and the character count '267/5000'. The right box contains the English translation: 'Chancellor Angela Merkel (CDU) has regretted the first coalition decision on the future of the President of the German Constitutional Protection, Hans-Georg Maaßen. She announced that the government coalition was aware of the "need for full focus on the material work".' Below the text are icons for star, copy, speaker, and back, and a 'Suggest an edit' link.

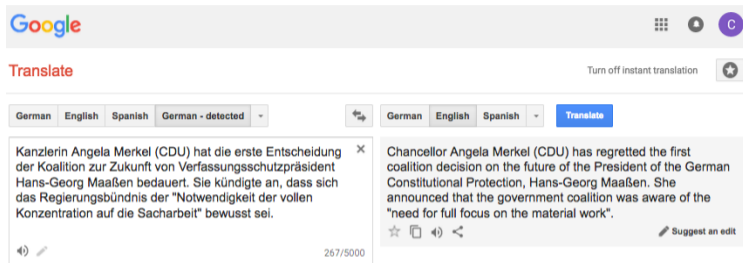
- ▶ Active research of AI since its beginnings
- ▶ Machine translation (MT) is a nice example of the different paradigm shifts in AI
  - 1950s–1990s: rule-based, symbolic approaches



The screenshot shows the Google Translate interface. At the top, the Google logo is on the left, and a grid icon, a notification bell, and a profile icon 'C' are on the right. Below the logo, the word 'Translate' is displayed in red, with a 'Turn off instant translation' link and a star icon to its right. The main interface features two language selection dropdowns: the first is set to 'German - detected' and the second to 'English'. A blue 'Translate' button is positioned to the right of the second dropdown. Below the dropdowns, the German text reads: 'Kanzlerin Angela Merkel (CDU) hat die erste Entscheidung der Koalition zur Zukunft von Verfassungsschutzpräsident Hans-Georg Maaßen bedauert. Sie kündigte an, dass sich das Regierungsbündnis der "Notwendigkeit der vollen Konzentration auf die Sacharbeit" bewusst sei.' The English translation reads: 'Chancellor Angela Merkel (CDU) has regretted the first coalition decision on the future of the President of the German Constitutional Protection, Hans-Georg Maaßen. She announced that the government coalition was aware of the "need for full focus on the material work".' Below the German text is a speaker icon and a character count '267/5000'. Below the English text are icons for star, copy, speaker, and back, along with a 'Suggest an edit' link.

- ▶ Active research of AI since its beginnings
- ▶ Machine translation (MT) is a nice example of the different paradigm shifts in AI
  - 1950s–1990s: rule-based, symbolic approaches
  - 1990s–2016: statistical, data-driven approaches





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- ▶ Active research of AI since its beginnings
- ▶ Machine translation (MT) is a nice example of the different paradigm shifts in AI
  - 1950s–1990s: rule-based, symbolic approaches
  - 1990s–2016: statistical, data-driven approaches
  - 2014–now: neural, deep learning, data-driven approaches

# MT: German to English (high resource)

## German source sentence

Die Leitung der für die US-Regierungsgebäude zuständigen Behörde weigert sich laut einem Medienbericht, einen Brief zu unterschreiben, mit dem das Biden-Übergangsteam Zugang zu US-Behörden erhalten und formal diese Woche die Arbeit aufnehmen kann.

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## English machine translation anno 2014 (using statistical machine translation)

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The line of the authority responsible for the US Government buildings refuses according to a medium report signing a letter with which the Biden Übergangsteam entrance to US authorities to receive and formally this week the work take up can.

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## English machine translation in 2020 (using neural machine translation)

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The line of the authority responsible for the US Government buildings refuses according to a medium report signing a letter with which the Biden Übergangsteam entrance to US authorities to receive and formally this week the work take up can.

## English machine translation in 2020 (using neural machine translation)

According to a media report, the management of the agency responsible for US government buildings is refusing to sign a letter that will allow the Biden transition team to gain access to US authorities and formally start work this week.

# MT: Kurdish to English (low resource)

## Kurdish source sentence

Hinek werzişvanên Îraqî yê ku li ser destê komên tundrew astender bûne serketin di werzişvanîyê de pêk anîn bi rêya beşdarîkirina di qehremanîyên werzişvanî yê astenderan de.

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## English machine translation in 2020 (using neural machine translation)



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## English machine translation in 2020 (using neural machine translation)

Some Iraqi athletes who have been successful at the hands of extremist groups have achieved success in sports by participating in the sports championships of the demonstrators.

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## English machine translation in 2020 (using neural machine translation)

Some Iraqi athletes who have been successful at the hands of extremist groups have achieved success in sports by participating in the sports championships of the demonstrators.

## Human translation (reference or ground truth)

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Hinek werzişvanên Îraqî yên ku li ser destê komên tundrew astender bûne serketin di werzişvaniyê de pêk anîn bi rêya beşdarîkirina di qehremanîyên werzişvanî yên astenderan de.

## English machine translation in 2020 (using neural machine translation)

Some Iraqi athletes who have been successful at the hands of extremist groups have achieved success in sports by participating in the sports championships of the demonstrators.

## Human translation (reference or ground truth)

Some Iraqis who suffered debilitating injuries at the hands of extremist groups have gone on to achieve victory in the athletic field through their participation in paralympic sports.

# Machine Translation

- ▶ Automatically translate: source language → target language

- ▶ Automatically translate: source language → target language

Arabic → English	French → Spanish	...	Amharic → Vietnamese
Armenian → Czech	Armenian → Danish	...	Armenian → Turkish
⋮	⋮	...	⋮
Uzbek → Albanian	Uzbek → Hindi	...	Uzbek → Ukrainian
Vietnamese → Azeri	Vietnamese → Greek	...	Vietnamese → Turkish

# Universal Translation

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7
bg	-	-	15.9	21.3	19.1	20.2	32.3	-	8.4	9.5	25.8	11.4	12.6	18.7	19.8	-	2.2	9.7	19.0	19.0	12.4	22.4	16.5	8.7	10.8	19.4
cs	5.6	18.1	-	18.7	17.9	16.5	25.0	-	7.1	10.6	22.2	8.9	11.4	15.7	16.9	-	2.5	6.7	18.3	19.8	13.1	18.5	15.3	7.9	9.5	16.8
da	5.9	22.4	16.4	-	-	-	42.3	-	8.0	13.5	28.1	11.7	13.9	20.3	22.7	-	2.7	11.7	25.8	27.5	14.7	25.2	17.5	9.2	8.2	18.8
de	7.6	21.3	17.4	-	-	18.9	31.6	-	8.7	11.8	26.8	12.2	16.1	19.9	21.7	8.9	2.9	10.6	24.4	18.6	13.7	23.4	16.6	10.0	10.8	19.8
el	8.1	21.1	13.4	-	18.3	-	31.6	-	-	10.0	26.9	11.4	6.5	19.1	21.4	-	2.1	-	19.8	21.1	-	22.4	15.2	8.9	8.8	-
en	15.7	33.9	23.1	41.2	30.5	32.8	-	39.7	15.2	16.0	41.2	23.1	24.9	32.5	33.4	11.3	4.1	23.4	31.9	41.2	17.0	38.8	20.1	15.8	17.9	28.9
es	-	-	-	-	-	-	38.6	-	10.0	11.7	-	13.8	15.9	22.7	28.6	-	3.2	-	24.2	22.4	14.1	31.5	17.0	11.2	12.3	23.2
fa	6.5	13.6	9.3	13.2	12.9	-	25.1	16.3	-	5.2	18.6	7.2	8.8	15.0	14.8	-	1.9	8.2	13.4	10.4	7.8	16.8	11.4	8.1	5.4	16.8
fi	3.2	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-	-	5.6	8.7	10.0	10.0	-	1.8	2.2	11.6	9.2	7.1	10.9	8.6	5.6	5.0	12.1
fr	-	24.2	18.8	27.0	23.7	24.6	39.0	-	10.0	-	-	13.8	18.3	23.9	-	10.0	3.5	12.5	25.2	24.1	15.2	29.4	18.5	11.8	12.4	23.6
he	8.5	17.0	12.8	18.2	17.4	17.4	32.5	22.7	6.9	8.1	24.5	-	11.7	17.6	19.1	7.2	2.1	8.3	17.5	16.5	10.5	21.2	14.4	7.7	6.6	17.2
hi	3.5	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-	12.7	13.3	6.2	1.6	5.4	12.0	8.7	7.1	15.1	12.0	6.2	3.5	15.1
id	7.7	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-	-	9.9	3.3	18.9	20.1	21.4	12.6	23.0	15.4	10.6	9.2	23.3
it	9.3	22.4	16.5	24.8	21.9	22.6	34.0	30.4	9.4	11.2	-	12.7	15.8	20.8	-	-	3.1	13.8	22.8	23.7	13.7	28.7	16.4	10.7	11.0	21.7
ja	3.7	7.2	5.8	8.4	7.7	7.8	11.5	-	4.4	4.4	12.3	4.0	8.8	9.4	9.4	-	-	5.2	8.3	7.8	5.5	-	7.3	-	-	-
ko	3.3	7.1	5.6	8.1	8.3	-	13.7	10.9	4.0	4.4	12.3	3.8	8.2	10.0	8.3	-	-	3.9	8.3	7.8	5.3	9.5	7.1	5.0	2.7	12.0
ms	7.4	11.6	8.2	16.5	12.6	-	27.1	-	8.7	5.6	19.5	6.0	11.5	19.8	17.2	-	1.6	-	13.5	10.2	7.8	18.3	12.2	9.2	4.5	23.0
nl	7.8	19.9	16.7	26.8	23.7	-	33.0	25.4	8.7	12.1	28.0	11.5	15.8	20.9	21.9	-	2.9	10.7	-	-	14.3	24.3	-	9.6	8.8	20.3
no	7.9	20.5	18.8	30.4	19.7	21.6	42.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8	-	-	11.4	23.6	16.9	8.3	9.4	14.0
pl	5.0	13.8	13.0	16.0	13.2	-	17.8	15.6	5.3	8.4	18.4	7.0	10.6	13.5	14.0	-	2.0	7.1	14.3	11.0	-	14.6	12.2	6.3	8.5	14.4
pt	10.0	24.7	17.7	27.1	23.1	24.9	40.6	33.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1	-	3.4	12.6	24.6	22.5	14.6	-	-	11.1	11.8	23.6
ru	6.0	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3	-	14.4	11.2	16.8	-	-	17.0	16.1
tr	5.2	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6	-	2.2	7.1	12.5	9.9	7.4	13.7	-	-	4.7	14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.6	15.0	4.4	6.4	16.8	4.8	6.5	10.6	12.7	-	1.2	5.2	11.3	10.4	9.3	13.7	19.2	4.5	-	11.7
vi	7.6	16.9	12.9	17.3	17.0	-	27.5	21.8	8.6	9.4	23.3	9.9	15.8	21.4	18.9	-	3.2	16.2	18.1	16.6	11.1	20.7	14.2	10.0	8.7	-

Schwenk et al. (2019)

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7	
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4	-	-18.9	31.6	-	8.7	11.8	26.8	12.2	16.1	19.9	21.7	8.9	2.9	10.6	24.4	18.6	13.7	23.4	16.6	10.0	10.0	19.8	
el	8.1	21.1	13.4	-	18.3	-31.6	-	-10.0	26.9	11.4	6.5	19.1	21.4	-	-2.1	-19.8	21.1	-	22.4	15.2	8.9	8.1	-	-	-	
en	15.1	33.9	23.1	31.2	30.5	32.8	-	39.7	15.2	16.0	41.2	23.1	24.9	32.5	33.4	11.3	4.1	23.4	31.9	41.2	17.0	38.8	20.1	15.8	17.1	28.9
es		-	-	-	-	38.6	-	10.0	11.7	-	13.8	15.5	22.7	28.6	-	3.2	-24.2	22.4	14.1	31.5	17.0	11.2	12.1	-	23.2	
fa	6.1	13.6	9.3	13.2	12.9	-25.1	16.3	-	5.2	18.6	7.2	8.8	15.0	14.8	-	1.9	8.2	13.4	10.4	7.8	16.8	11.4	8.1	5.1	16.8	
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-	-	5.6	8.7	10.0	10.0	-	1.8	2.2	11.6	9.2	7.1	10.9	8.6	5.6	12.1	
fr		24.2	18.8	27.0	23.7	24.6	39.0	-	10.0	-	-	13.8	18.3	23.9	-	10.0	3.5	12.5	25.2	24.1	15.2	29.4	18.5	11.8	12.1	23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5	22.7	6.9	8.1	24.5	-	11.7	17.6	19.1	7.2	2.1	8.3	17.5	16.5	10.5	21.2	14.4	7.7	6.1	17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-	12.7	13.3	6.2	1.6	5.4	12.0	8.7	7.1	15.1	12.0	6.2	3.1	15.1
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-	-	9.9	3.3	18.9	20.1	21.4	12.6	23.0	15.4	10.6	9.1	23.3
it	9.1	22.4	16.5	24.8	21.9	22.6	34.0	30.4	9.4	11.2	-	12.7	15.8	20.8	-	-	3.1	13.8	22.8	23.7	13.7	28.7	16.4	10.7	11.1	21.7
ja	3.1	7.2	5.8	8.4	7.7	7.8	11.5	-	4.4	4.4	12.3	4.0	8.8	9.4	9.4	-	-	5.2	8.3	7.8	5.5	-	7.3	-	-	
ko	3.1	7.1	5.6	8.1	8.3	-	13.7	10.9	4.0	4.4	12.3	3.8	8.2	10.0	8.3	-	-	3.9	8.3	7.8	5.3	9.5	7.1	5.0	2.1	12.0
ms	7.1	11.6	8.2	16.5	12.6	-	27.1	-	8.7	5.6	19.5	6.0	11.5	19.8	17.2	-	1.6	-	13.5	10.2	7.8	18.3	12.2	9.2	4.1	23.0
nl	7.1	19.9	16.7	26.8	23.7	-	33.0	25.4	8.7	12.1	28.0	11.5	15.8	20.9	21.9	-	2.9	10.7	-	-	14.3	24.3	-	9.6	8.1	20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	42.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8	-	-	11.4	23.6	16.9	8.3	9.1	14.0
pl	5.1	13.8	13.0	16.0	13.2	-	17.8	15.6	5.3	8.4	18.4	7.0	10.6	13.5	14.0	-	2.0	7.1	14.3	11.0	-	14.6	12.2	6.3	8.1	14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	40.6	35.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1	-	3.4	12.6	24.6	22.5	14.6	-	-	11.1	11.1	23.6
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3	-	14.4	11.2	16.8	-	-	17.1	16.1
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6	-	2.2	7.1	12.5	9.9	7.4	13.7	-	-	4.1	14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.6	13.0	4.4	6.4	16.8	4.8	6.5	10.6	12.7	-	1.2	5.2	11.3	10.4	9.3	13.7	19.2	4.5	-	11.7
vi	7.6	16.9	12.9	17.3	17.0	-	27.5	21.8	8.6	9.4	23.3	9.9	15.8	21.4	18.9	-	3.2	16.2	18.1	16.6	11.1	20.7	14.2	10.0	8.7	-

How far are we from universal machine translation?

Schwenk et al. (2019)



# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4		-																					19.8
el	8.1	21.1	13.4			-																				-
en	15.1	33.1	33.1				-																			28.9
es								-																		23.2
fa	6.1	13.6	9.3	13.2	12.9		25.1	16.3	-																	16.8
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr		24.2	18.8	27.0	23.7	24.6	39.0				-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5	22.7	6.9	8.1	24.5															17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5														15.1
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1													23.3
it	9.1	22.4	16.5	24.8	21.9	22.6	34.0	30.4	9.4	11.2		12.7	15.8	20.8												21.7
ja	3.1	7.2	5.8	8.4	7.7	7.8	11.5		4.4	4.4	12.3	4.0	8.8	9.4	9.4											-
ko	3.1	7.1	5.6	8.1	8.3		13.7	10.9	4.0	4.4	12.3	3.8	8.2	10.0	8.3											12.0
ms	7.1	11.6	8.2	16.5	12.6		27.1		8.7	5.6	19.5	6.0	11.5	19.8	17.2											23.0
nl	7.1	19.9	16.7	26.8	23.7		33.0	25.4	8.7	12.1	28.0	11.5	15.8	20.9	21.9											20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	32.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8								14.0
pl	5.1	13.8	13.0	16.0	13.2		17.8	15.6	5.3	8.4	18.4	7.0	10.6	13.5	14.0											14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	40.6	35.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1											23.6
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3								16.1
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6											14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.0	15.0	4.4	6.4	16.8	4.8	6.5	10.6	12.7											11.7
vi	7.6	16.9	12.9	17.3	17.0		27.5	21.8	8.6	9.4	23.3	9.9	15.8	21.4	18.9											-

How far are we from universal machine translation?

▶ 86% of all language directions are of poor quality

Schwenk et al. (2019)

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7	
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4		-																					19.8
el	8.1	21.1	13.4			-																				-
en	15.1	33.1	33.1				-																			28.9
es								-																		23.2
fa	6.1	13.6	9.3	13.2	12.9				-																	16.8
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr											-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-												15.1	
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-												23.3
it	9.1	22.4	16.5	24.8	21.9	22.6	34.0	30.4	9.4	11.2		12.7	15.8	20.8	-											21.7
ja	3.1	7.2	5.8	8.4	7.7	7.8	11.5		4.4	4.4	12.3	4.0	8.8	9.4	9.4	-										-
ko	3.1	7.1	5.6	8.1	8.3		13.7	10.9	4.0	4.4	12.3	3.8	8.2	10.0	8.3		-									12.0
ms	7.1	11.6	8.2	16.5	12.6		27.1		8.7	5.6	19.5	6.0	11.5	19.8	17.2		1.6	-								23.0
nl	7.1	19.9	16.7	26.8	23.7		33.0	25.4	8.7	12.1	28.0	11.5	15.8	20.9	21.9		2.9	10.7	-							20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	32.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8		-						14.0
pl	5.1	13.8	13.0	16.0	13.2		17.8	15.6	5.3	8.4	18.4	7.0	10.6	13.5	14.0		2.0	7.1	14.3	11.0	-					14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	40.6	35.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1		3.4	12.6	24.6	22.5	14.6	-				23.6
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3		14.4	11.2	16.8	-			16.1
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6		2.2	7.1	12.5	9.9	7.4	13.7	-			14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.0	13.0	4.4	6.4	16.8	4.8	6.5	10.6	12.7		1.2	5.2	11.3	10.4	9.3	13.7	19.2	4.5		11.7
vi	7.6	16.9	12.9	17.3	17.0		27.5	21.8	8.6	9.4	23.3	9.9	15.8	21.4	18.9		3.2	16.2	18.1	16.6	11.1	20.7	14.2	10.0	8.7	-

How far are we from universal machine translation?

▶ 86% of all language directions are of poor quality

What is the core problem?

Schwenk et al. (2019)

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7	
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4		-																					19.8
el	8.1	21.1	13.4			-																				-
en	15.1	33.1	33.1				-																			28.9
es								-																		23.2
fa	6.1	13.6	9.3	13.2	12.9				-																	16.8
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr											-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-												15.1	
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-											23.3	
it	9.1	22.1	22.1												-											21.7
ja	3.1	7.2	5.8	8.4	7.7	7.8	11.5									-										-
ko	3.1	7.1	5.6	8.1	8.3												-									12.0
ms	7.1	11.6	8.2	16.5	12.6													-								23.0
nl	7.1	19.9	16.7	26.8	23.7														-							20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	32.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8	-						14.0	
pl	5.1	13.8	13.0	16.0	13.2															-						14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	40.6	35.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1					-						23.6
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3		-					16.1	
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6						-					14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.0	15.0	1.4	6.4	16.8	4.0	6.5	10.6	12.7							-				11.7
vi	7.6	16.9	12.9	17.3	17.0																					-

How far are we from universal machine translation?

▶ 86% of all language directions are of poor quality

What is the core problem?

▶ Limited parallel training data for majority of directions

Schwenk et al. (2019)

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi	
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7	
bg		-																								19.4	
cs	5.1	18.1	-																							16.8	
da	5.1	22.4	16.4	-																						18.8	
de	7.1	21.3	17.4		-																					19.8	
el	8.1	21.1	13.4			-																				-	
en	15.1	33.1	33.1				-																			28.9	
es								-																		23.2	
fa	6.1	13.6	9.3	13.2	12.9				-																	16.8	
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1	
fr	3.1	24.2	8.8	27.0	23.7	24.6	39.0				-															23.6	
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2	
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-													15.1	
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-												23.3	
it	9.1	22.1	11.1	17.1	17.1	17.1	27.1	17.1	17.1	17.1	17.1	17.1	17.1	17.1	-											21.7	
ja	3.1	7.2	5.8	8.4	7.7	7.8	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5	-										-	
ko	3.1	7.1	5.6	8.1	8.3												-										12.0
ms	7.1	11.6	7.3	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	-									23.0	
nl	7.1	19.9	16.7																-								20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	32.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8	-							14.0	
pl	5.1	13.8	13.0	16.0	13.2																-						14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	40.6	35.6	10.1	11.4	32.3	13.9	17.4	24.1	29.1						-					23.6	
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3			-					16.1	
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6							-				14.2	
uk	4.0	14.2	10.0	12.2	12.2	10.7	18.0	13.0	4.4	6.4	16.8	4.0	6.5	10.6	12.7								-			11.7	
vi	7.6	16.9	12.9	17.3	17.0																					-	

How far are we from universal machine translation?

▶ 86% of all language directions are of poor quality

What is the core problem?

▶ Limited parallel training data for majority of directions

▶ Current MT models **do not generalize ...**

Schwenk et al. (2019)

# Universal Translation

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4		-																					19.8
el	8.1	21.1	13.4			-																				-
en	15.1	33.1	33.1				-																			28.9
es								-																		23.2
fa	6.1	13.6	9.3	13.2	12.9				-																	16.8
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr	3.1	24.2	8.8	27.0	23.7	24.6	39.0	11.7	11.7		-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5	11.7	11.7			-														17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-													15.1
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-												23.3
it	9.1	22.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1		-											21.7
ja	3.1	7.2	5.8	8.4	7.7	7.8	11.5	11.5	11.5	11.5	11.5	11.5	11.5			-										-
ko	3.1	7.1	5.6	8.1	8.3													-								12.0
ms	7.1	11.6	7.3	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1	11.1													23.0
nl	7.1	19.9	16.7																							20.3
no	7.1	20.5	18.8	30.4	19.7	21.6	32.9	24.0	5.2	10.4	26.6	11.4	11.3	20.2	24.0	9.4	2.8	10.8								14.0
pl	5.1	13.8	13.0	16.1	13.2																					14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	32.5	11.7	11.7	11.7	11.7	11.7	11.7													23.6
ru	6.1	16.9	12.8	15.9	15.3	14.6	20.1	17.6	7.0	7.8	20.6	9.3	12.7	14.5	15.5	7.9	2.0	9.3								16.1
tr	5.1	11.8	8.7	12.2	12.1	11.2	18.9	14.6	6.1	7.2	17.1	6.5	12.1	13.0	12.6											14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	10.0	13.0	1.4	0.4	10.0	4.0	0.5	10.0	12.7											11.7
vi	7.6	16.9	12.9	17.3	17.0																					-

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	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7
bg		-																								19.4
cs	5.1	18.1	-																							16.8
da	5.1	22.4	16.4	-																						18.8
de	7.1	21.3	17.4		-																					19.8
el	8.1	21.1	13.4			-																				-
en	15.1	33.1	33.1				-																			28.9
es								-																		23.2
fa	6.1	13.6	9.3	13.2	12.9				-																	16.8
fi	3.1	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr											-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2
hi	3.1	9.8	7.7	11.2	14.3	10.3	24.2	15.8	3.4	5.0	19.0	6.5	-												15.1	
id	7.1	19.9	14.6	20.8	18.9	18.4	32.5	23.8	9.4	9.7	25.3	11.2	16.1	-											23.3	
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# Essential Data Component: Bilingual Parallel Corpus

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Tuesday, Nov. 26, 20:09



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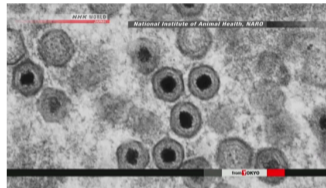
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11月27日(星期三) 5:24



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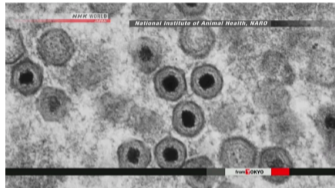
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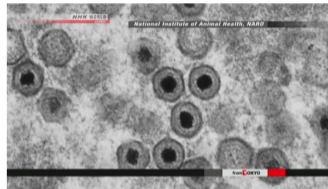
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- ▶ When input and outputs are sequences of words/audio we talk about sequence-to-sequence (seq2seq) models

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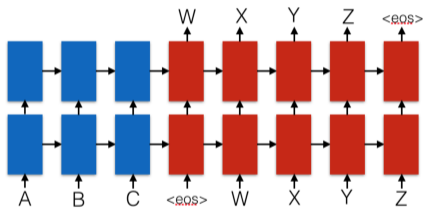
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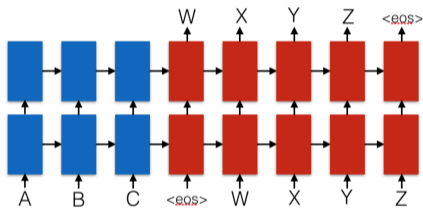


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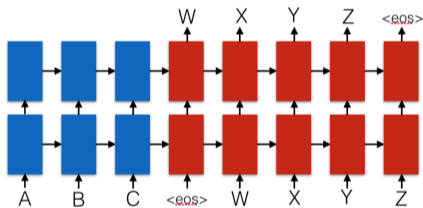


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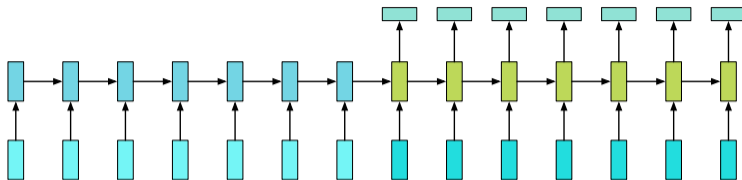
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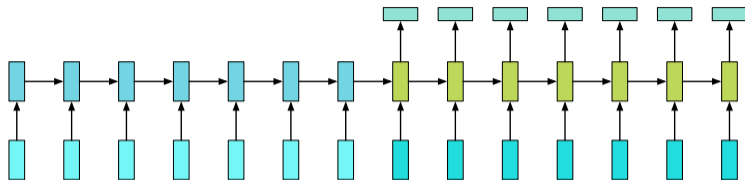
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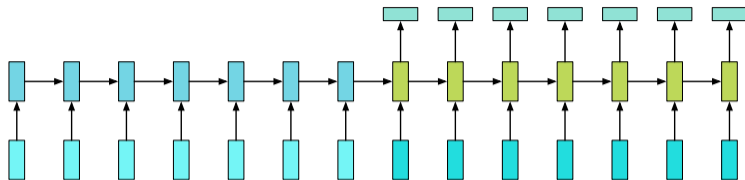
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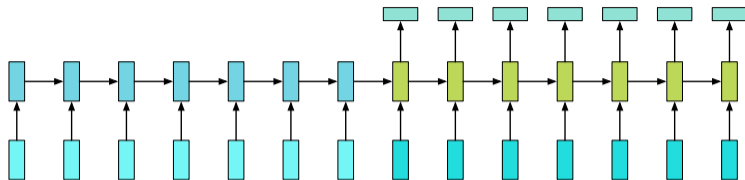


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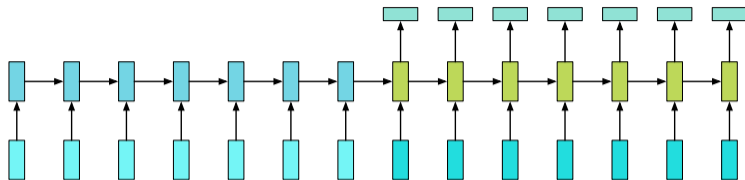
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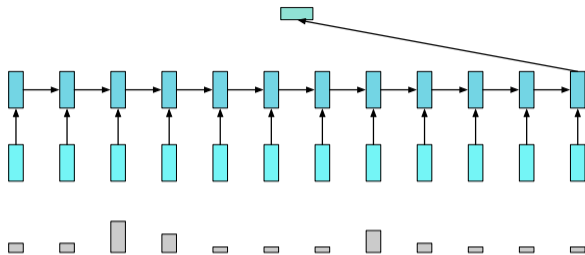
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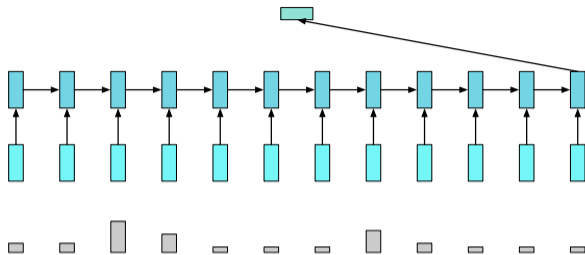


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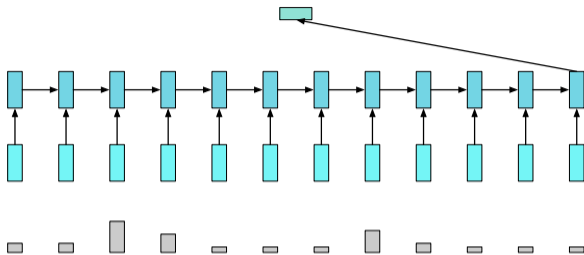


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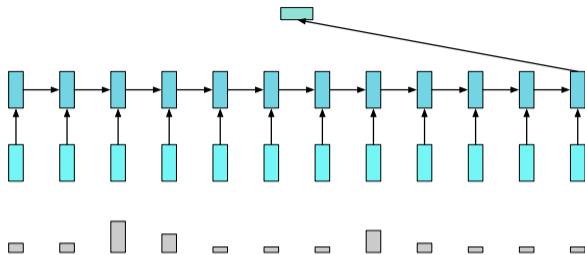
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- ▶ For classification, the sentence representation learns which tokens are important to predict a certain class

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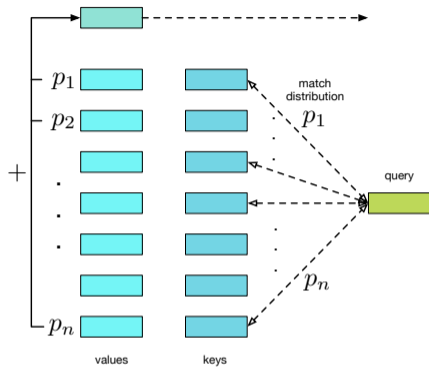
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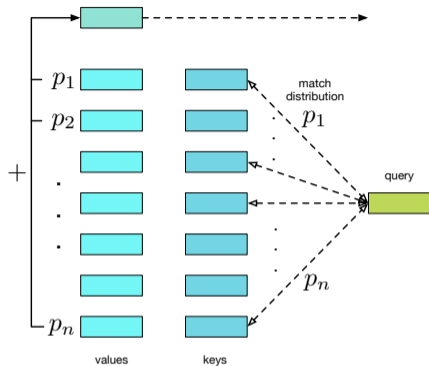
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- ▶ Similar to word alignment, where alignments indicate source-target token translation correspondences
  - attention results in soft (numerical) alignments

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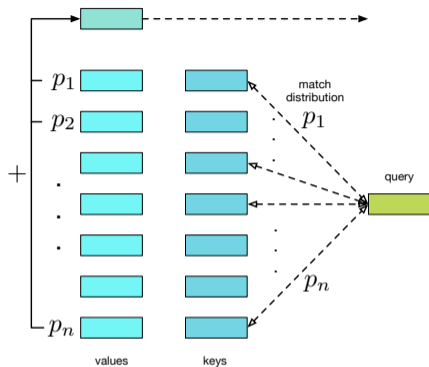


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- ▶ The attention mechanism and thereby the computation of  $\mathbf{c}$  is fully differentiable!

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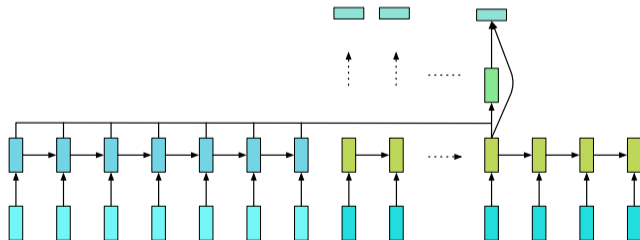
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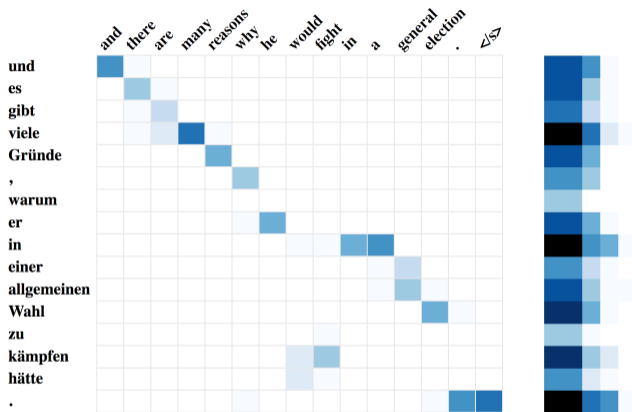
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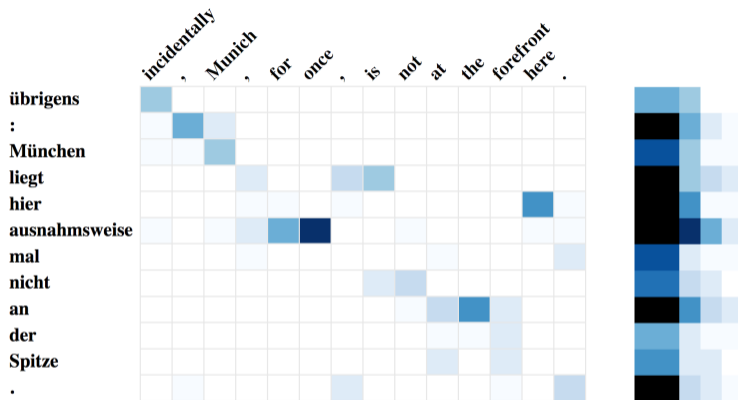
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- ▶ Added benefits:
  - attention can be visualized allowing for some inspection of the model
  - useful for error analysis

# NMT Attention Examples



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- ▶ Attention can model multi-word translations

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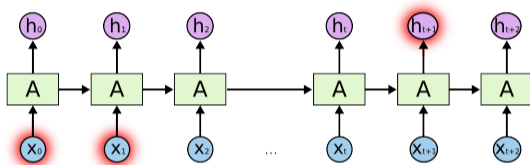
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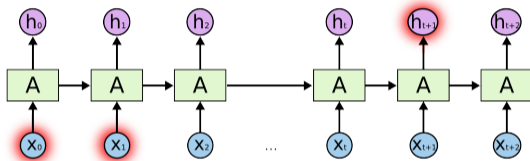
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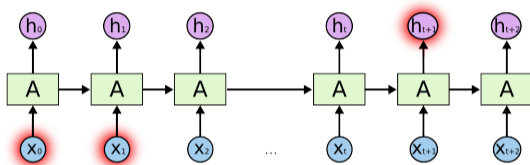
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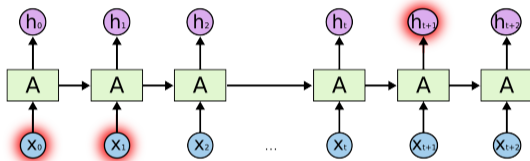
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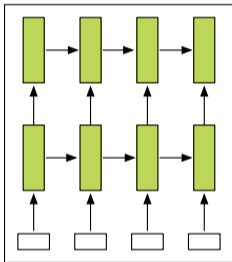
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  - should  $h_{t+1}$  really depend on  $x_0$  or  $x_1$  or both or neither?

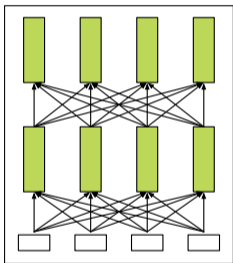
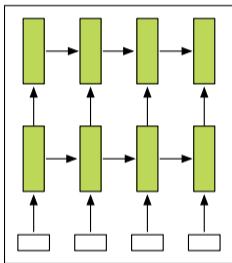
# Self-Attention

- ▶ Self-attention computes attention between elements of the same sequence
  - can replace RNNs as sequence model
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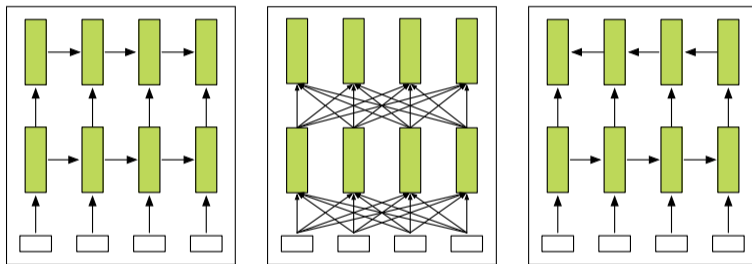
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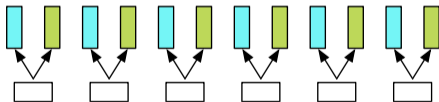


- ▶ self-attention is bidirectional (like a biRNN), but no recurrent connections between time steps

# Transformer Encoder

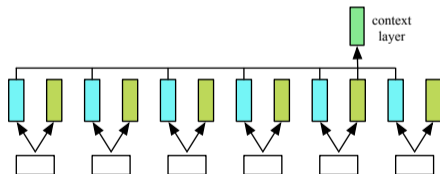


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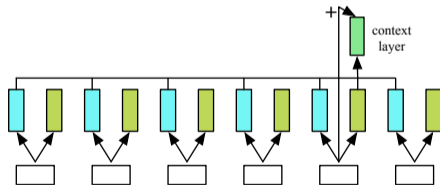




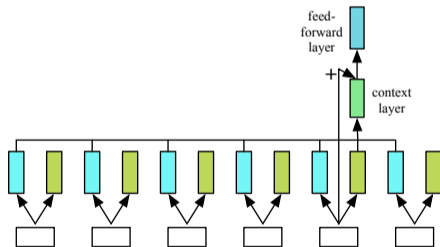
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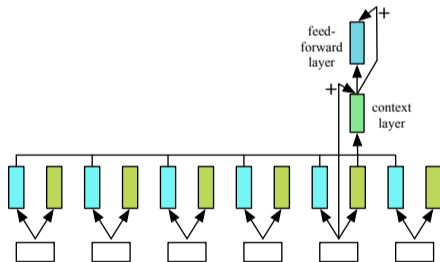
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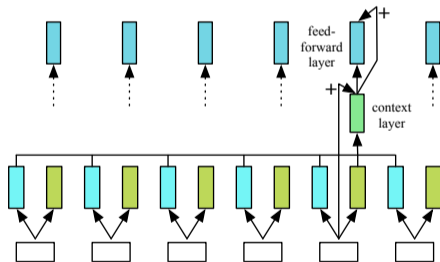
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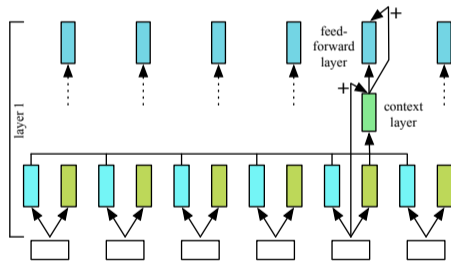
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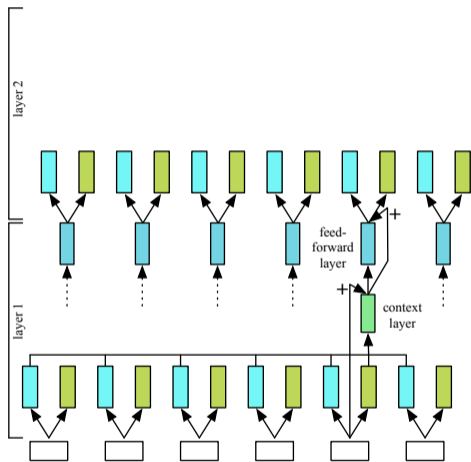
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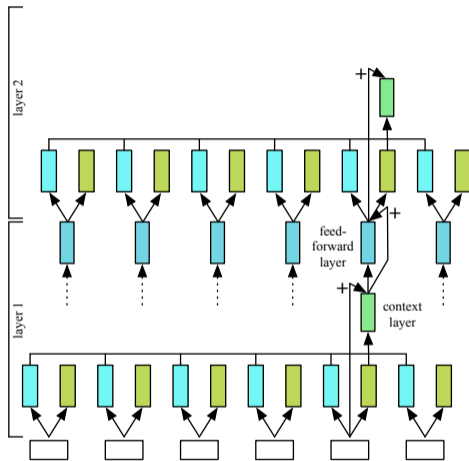
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  - in neural memory network parlance: multiple-hop attention

# Transformer Sub-Layers

- ▶ The feed-forward layer is applied point-wise, i.e., at each time step  $t$  along a sequence (weights are shared)
- ▶ Feed-forward layer at layer  $n$ :
  - takes as input the context vector  $\mathbf{c}_{n,t}$  of layer  $n$  at time  $t$
  - is defined as  $\text{ffwd}(\mathbf{c}_{n,t}) = W_n \mathbf{d} \odot (\text{ReLU}(V_n \mathbf{c}_{n,t} + \mathbf{a}_n)) + \mathbf{b}_n$  where  $\mathbf{d}$  is a (inverted) dropout mask
- ▶ Residual connections are used for context and feed-forward sub layers
  - $\mathbf{f}_{n,t} = \text{LayerNorm}(\mathbf{d} \odot \text{ffwd}(\mathbf{c}_{n,t}) + \mathbf{c}_{n,t})$
  - $\mathbf{c}_{n,t} = \text{LayerNorm}(\mathbf{d} \odot \mathbf{c}_{n,t}) + \mathbf{f}_{n-1,t}$   
if  $n = 1$ ,  $\mathbf{f}_{n-1,t}$  refers to the word embedding at time  $t$
- ▶ At a given time step  $t$  and layer  $n$ :  $\mathbf{c}_{n,t}$  depends on  $\mathbf{f}_{n-1,t}$  which in turn depends on  $\mathbf{c}_{n-1,t}$ , which depends . . .
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- ▶ What does LayerNorm do?

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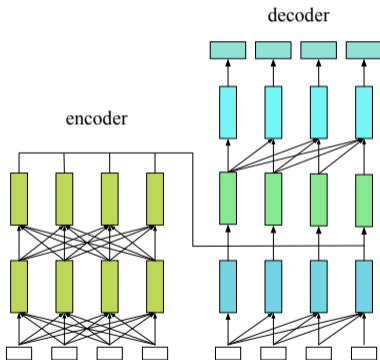


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  - language pairs involving **morphologically rich languages**, such as Finnish, Turkish, Arabic (as source and/or target)

- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
  - encoder-decoder architecture
  - attention mechanism
  - self-attention (Google's Transformer)