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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

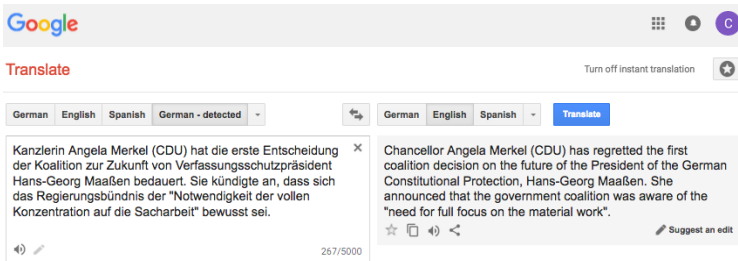
This Class

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

This Class

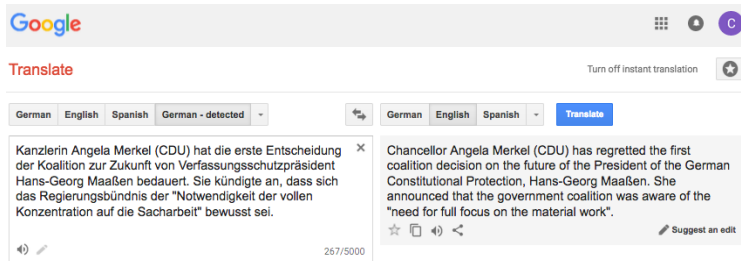
- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
 - encoder-decoder architecture
 - attention mechanism
 - self-attention (Google's Transformer)

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, and a user profile. Below the logo is the word "Translate" in red. On the right side of this bar, there is a link "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 box 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 in the top right of this box and a speaker icon with a slash in the bottom left. The character count "267/5000" is in the bottom right. The right column has a language selector with "German", "English", and "Spanish" (with a dropdown arrow), followed by a blue "Translate" button. Below this is a text box containing 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'." There is a "Suggest an edit" link in the bottom right of this box. At the bottom of the right column are icons for a star, a document, a speaker, and a back arrow.

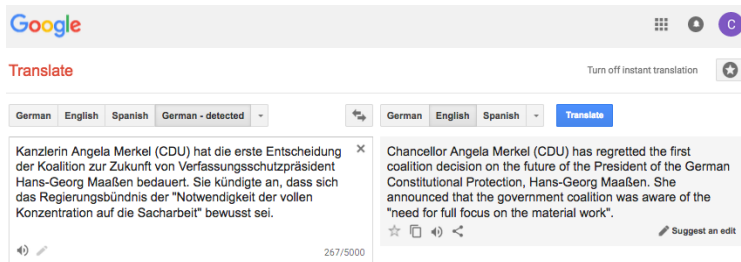
Machine Translation



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

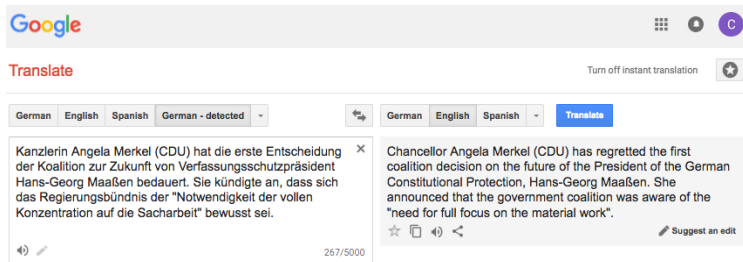
Machine Translation



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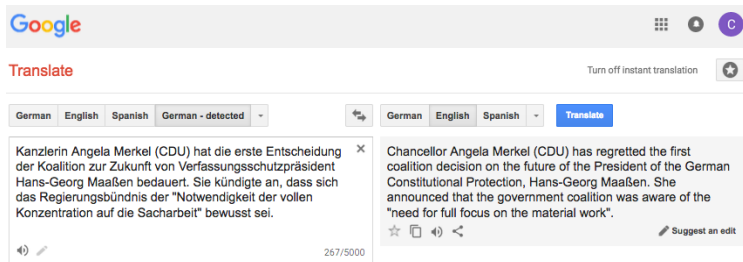
- ▶ Active research of AI since its beginnings
- ▶ Machine translation (MT) is a nice example of the different paradigm shifts in AI

Machine Translation



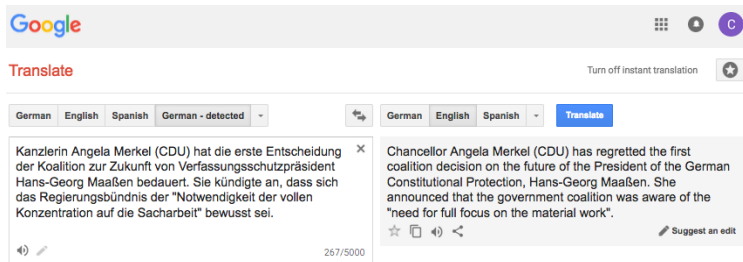
The screenshot shows the Google Translate interface. At the top, the Google logo is on the left, and navigation icons are on the right. Below the logo, the word "Translate" is displayed in red, with a "Turn off instant translation" link and a star icon to its right. The main area features a language selection bar with "German", "English", and "Spanish" buttons, followed by a dropdown menu currently set to "German - detected". To the right of this bar are "German", "English", and "Spanish" buttons, and a blue "Translate" button. Below the language bar, the German text on the left 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 on the right 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 are a speaker icon, a pencil icon, and the character count "267/5000". Below the English text are a star icon, a document icon, a speaker icon, a left arrow icon, 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 navigation icons 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" and "German - detected", and the second is set to "English". A blue "Translate" button is positioned between the dropdowns. Below the dropdowns, the German text on the left 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 on the right 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



The screenshot shows the Google Translate interface. At the top, the Google logo is on the left, and navigation icons 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" and "German - detected", and the second is set to "English". A blue "Translate" button is positioned between the dropdowns. Below the dropdowns, the German text is displayed in a light gray box: "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 small 'x' icon. Below the German text are icons for audio playback and a character count "267/5000". The English translation is shown in a white box: "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, audio, 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
 - 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.

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.

English machine translation anno 2014 (using statistical machine translation)

MT: German to English (high resource)

German source sentence

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English machine translation anno 2014 (using statistical machine translation)

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.

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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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)

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.

English machine translation anno 2014 (using statistical machine translation)

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.

MT: Kurdish to English (low resource)

Kurdish source sentence

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

English machine translation in 2020 (using neural machine translation)

MT: Kurdish to English (low resource)

Kurdish source sentence

Hinek werzişvanên Îraqî yên ku li ser destê komên tundrew astender bûne serketin di werzişvanîyê 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.

MT: Kurdish to English (low resource)

Kurdish source sentence

Hinek werzişvanên Îraqî yên ku li ser destê komên tundrew astender bûne serketin di werzişvanîyê 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)

MT: Kurdish to English (low resource)

Kurdish source sentence

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.	18.1	-																							16.8
da	5.	22.4	16.4	-																						18.8
de	7.	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.	19.8
el	8.	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.	-
en	15.	33.9	23.1	31.2	30.5	32.8	-	39.7	15.2	16.0	31.2	23.1	24.9	32.5	33.4	11.3	4.1	23.4	31.9	31.2	17.0	38.8	20.1	15.8	17.	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.		23.2
fa	6.	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.	16.8
fi	3.	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.	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.	23.6
he	8.	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.	17.2
hi	3.	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.	15.1
id	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.	23.3
it	9.	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.	21.7
ja	3.	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.	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.	12.0
ms	7.	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.	23.0
nl	7.	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.	20.3
no	7.	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	-	-	11.4	23.6	16.9	8.3	9.	14.0
pl	5.	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.	14.4
pt	10.	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.	23.6
ru	6.	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.	16.1
tr	5.	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.	14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	16.0	15.0	4.4	6.4	16.6	4.0	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.	18.1	-																							16.8	
da	5.	22.4	16.4	-																						18.8	
de	7.	21.3	17.4		-																					19.8	
el	8.	21.1	13.4			-																				-	
en	15.	33.	33.	33.	33.	33.	-																			28.9	
es								-																		23.2	
fa	6.	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.	16.8	
fi	3.	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.	12.1		
fr	3.	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.	23.6		
he	8.	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.	17.2	
hi	3.	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.	15.1	
id	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.	23.3	
it	9.	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.	21.7	
ja	3.	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.	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.	12.0	
ms	7.	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.	23.0
nl	7.	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.	20.3
no	7.	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.	14.0
pl	5.	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.	14.4
pt	10.	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.	23.6
ru	6.	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.	16.1	
tr	5.	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.	14.2
uk	4.0	14.2	10.0	12.2	12.2	10.7	16.0	15.0	4.4	6.4	16.6	4.0	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

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.	18.1	-																							16.8	
da	5.	22.4	16.4	-																						18.8	
de	7.	21.3	17.4		-																					19.8	
el	8.	21.1	13.4			-																				-	
en	15.	33.	33.				-																			28.9	
es								-																		23.2	
fa	6.	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.	16.8	
fi	3.	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.	12.1		
fr																										23.6	
he	8.	17.0	12.8	18.2	17.4	17.4	32.5	-																		17.2	
hi	3.	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.	15.1	
id	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.	23.3	
it	9.	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.	21.7	
ja	3.	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.	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.	12.0	
ms	7.	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.	23.0
nl	7.	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.	20.3
no	7.	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.	14.0	
pl	5.	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.	14.4
pt	10.	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.	23.6
ru	6.	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.	16.1	
tr	5.	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	16.0	15.0	4.4	6.4	16.6	4.0	6.5	10.6	12.7	-	-	1.2	5.2	11.5	10.4	9.5	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.	18.1	-																							16.8
da	5.	22.4	16.4	-																						18.8
de	7.	21.3	17.4		-																					19.8
el	8.	31.1	13.4			-																				-
en	15.	33.	33.				-																			28.9
es								-																		23.2
fa	6.	13.6	9.3	13.2	12.9				-																	16.8
fi	3.	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr											-															23.6
he	8.	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2
hi	3.	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.	19.9	14.6	20.8	18.9	18.4	32.5	33.8	9.4	9.7	25.3	11.2	16.1	-												23.3
it	9.	22.	22.												-											21.7
ja	3.	7.2	5.8	8.4	7.7	7.8	15.5	14.4	14.4	12.3	3.8	8.8	10.4	9.4	-											-
ko	3.	7.1	5.6	8.1	8.3											-										12.0
ms	7.	11.6	8.2	16.5	12.6												-									23.0
nl	7.	19.9	16.7	26.8	23.7													-								20.3
no	7.	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	-							14.0
pl	5.	13.8	13.0	16.0	13.2															-						14.4
pt	10.	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.	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.	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	15.0	4.4	6.4	10.0	4.0	6.5	10.0	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.	18.1	-																							16.8
da	5.	22.4	16.4	-																						18.8
de	7.	21.3	17.4		-																					19.8
el	8.	21.1	13.4			-																				-
en	15.	33.3	33.3				-																			28.9
es								-																		23.2
fa	6.	13.6	9.3	13.2	12.9				-																	16.8
fi	3.	10.2	9.6	12.7	10.9	9.4	15.7	12.5	3.0	-																12.1
fr											-															23.6
he	8.	17.0	12.8	18.2	17.4	17.4	32.5					-														17.2
hi	3.	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.	19.9	14.6	20.8	18.9	18.4	32.5	33.8	9.4	9.7	25.3	11.2	16.1	-											23.3	
it	9.	22.2													-											21.7
ja	3.	7.2	5.8	8.4	7.7	7.8	5.5	4.4	4.4	2.5	8.8	8.8	8.8	8.8	-											-
ko	3.	7.1	5.6	8.1	8.3											-										12.0
ms	7.	11.6	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	-										23.0
nl	7.	19.9	16.7															-								20.3
no	7.	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.	13.8	13.0	16.0	13.2															-						14.4
pt	10.	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.	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.	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	15.0	4.4	6.4	10.0	4.0	6.5	10.0	12.7						-					11.7
vi	7.6	16.9	12.9	17.3	17.0																	-				-

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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	33.4				-																			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	12.3	3.0	-																12.1
fr		24.2	8.8	27.0	23.7	24.6	39.0	22.8	10.1		-															23.6
he	8.1	17.0	12.8	18.2	17.4	17.4	32.5	15.8	3.4	5.0	19.0	6.5	-													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	-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	33.8	9.4	9.7	25.3	11.2	16.1	-												23.3
it	9.1	22.1	13.4	17.4	17.4	17.4	32.5	33.8	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	11.1	21.7	
ja	3.1	7.2	5.8	8.4	7.7	7.8	15.8	15.8	3.4	5.0	19.0	6.5	-													-
ko	3.1	7.1	5.6	8.1	8.3																					12.0
ms	7.1	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	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	16.1	13.2																					14.4
pt	10.1	24.7	17.7	27.1	23.1	24.9	39.0	22.8	10.1																	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	16.0	13.0	4.4	6.4	16.0	4.0	6.5	10.0	12.7	1.2	3.2	11.3	10.4	9.3	13.7	19.2	4.3	4.3	11.7	
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Essential Data Component: Bilingual Parallel Corpus

Japan to tighten checks for African swine fever

#Japan #Health & Welfare

Tuesday, Nov. 26, 20:09



The Japanese government plans to give more powers to quarantine officers at airports, as part of its efforts to prevent African swine fever from entering the country.

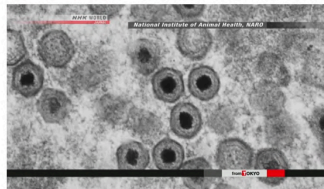
Outbreaks of the fatal and highly contagious disease have been reported in China, South Korea and other parts of Asia, but no cases have been confirmed in Japan so far.

The agriculture ministry is working on legal amendments to block the entry of the African swine fever virus.

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日本拟加强口岸检查严防非洲猪瘟病毒

11月27日(星期三) 5:24



鉴于非洲猪瘟疫情在亚洲多国不断扩大，为了防止病毒被带入日本国内，农林水产省决定加大在机场等处开展口岸检查工作的防疫官的权限。

非洲猪瘟疫情在中国、韩国等国蔓延。由于目前还没有有效的疫苗，非洲猪瘟的病毒一旦通过猪肉进入日本国内，将给日本的畜牧业等带来沉重打击。鉴于此，农林水产省决定修订相关法律，加强口岸检查工作。

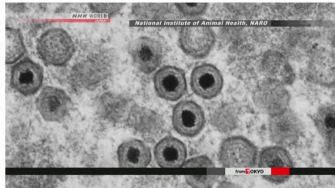
具体措施是，加大在机场等处开展检查工作的家畜防疫官的权限，防疫官可询问入境人员是否携带肉制品，必要时可采取强制措施，检查其行

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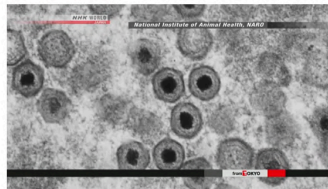
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- ▶ Speech recognition
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- ▶ When input and outputs are sequences of words/audio we talk about sequence-to-sequence (seq2seq) models

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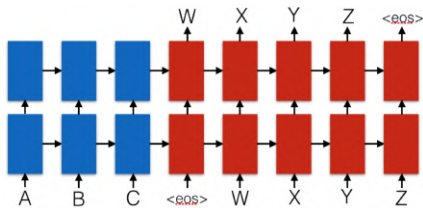
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 - and $\mathbf{Y}_{<t}$ is a representation of the output of the decoder before time t (the prefix)

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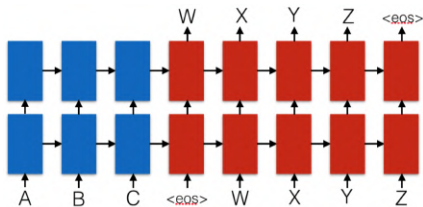


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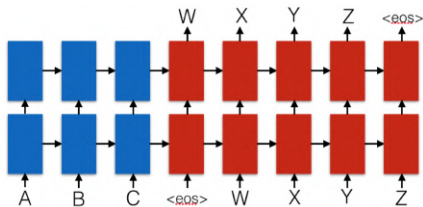


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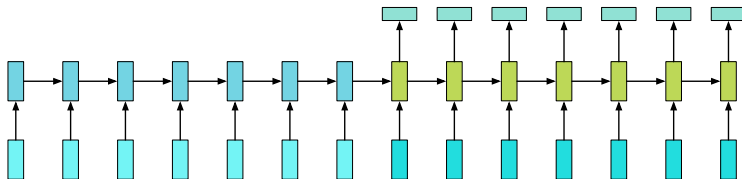
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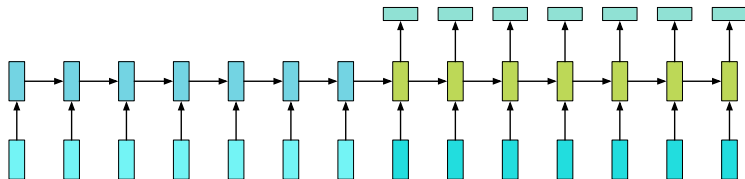
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 - Sutskever et al. (2014) simply initialize the decoder LSTM with the last state of the encoder LSTM

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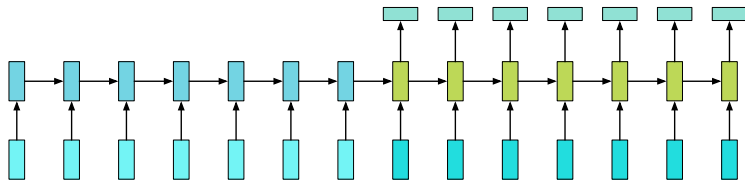


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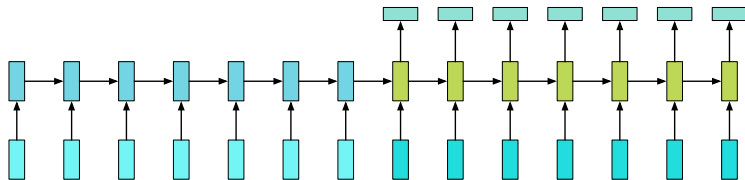
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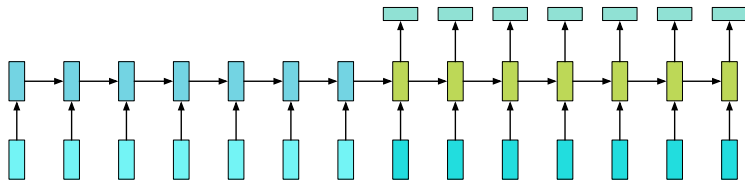
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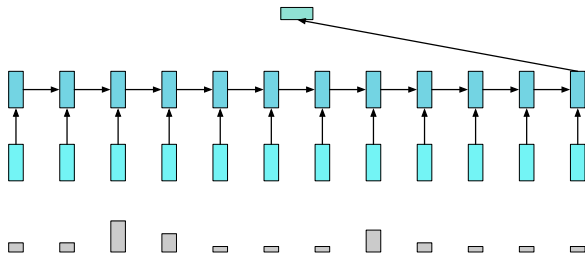
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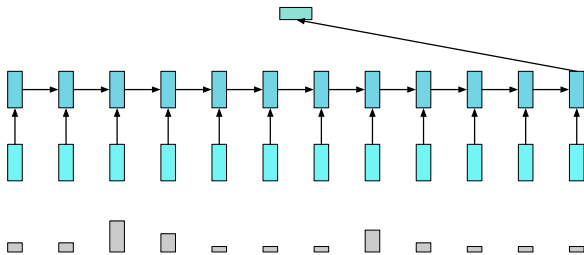


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- ▶ encoder-decoder information bottleneck

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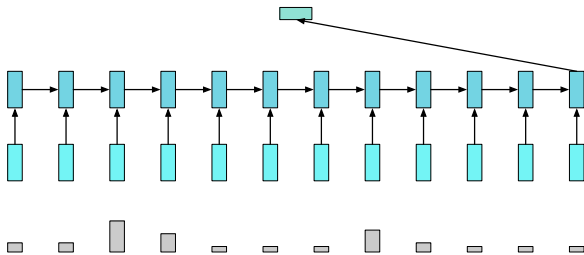


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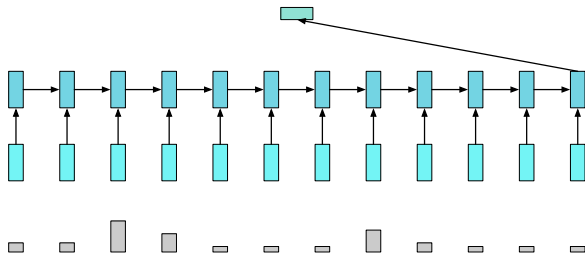
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- ▶ The final hidden layer cannot represent the full information of a long input sentence
- ▶ For classification, the sentence representation learns which tokens are important to predict a certain class

Attention Mechanism

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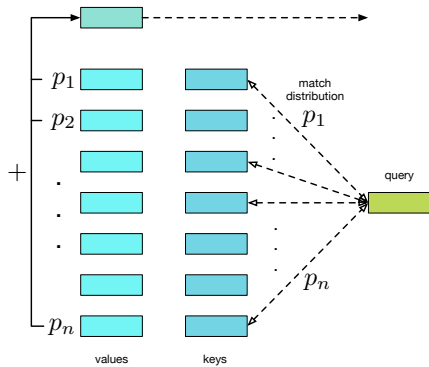
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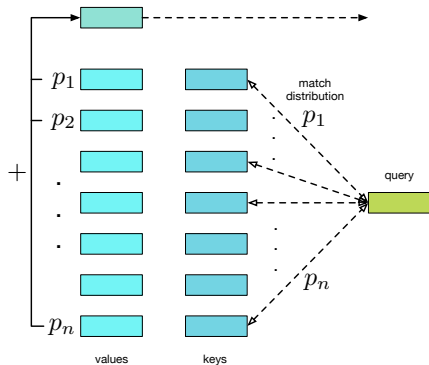
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- ▶ Similar to word alignment, where alignments indicate source-target token translation correspondences
 - attention results in soft (numerical) alignments

Attention Mechanism

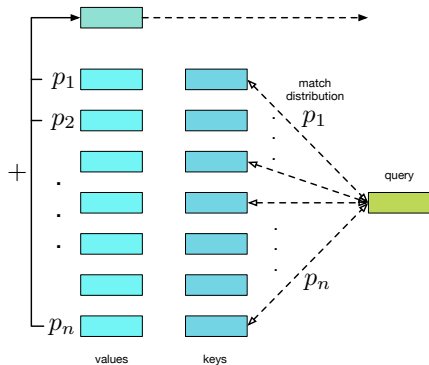


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- ▶ The attention mechanism and thereby the computation of \mathbf{c} is fully differentiable!

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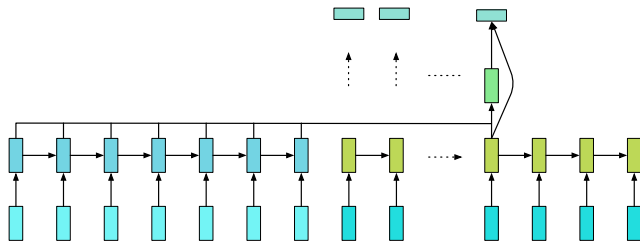
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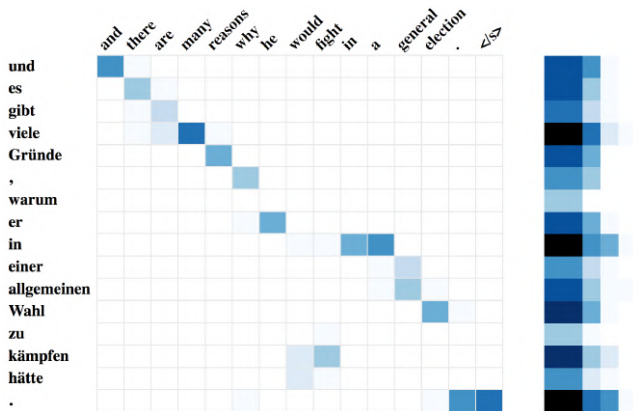
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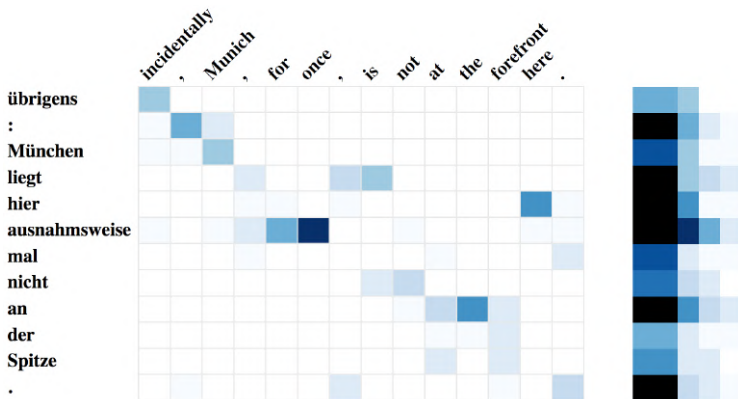
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- ▶ Added benefits:
 - attention can be visualized allowing for some inspection of the model
 - useful for error analysis

NMT Attention Examples



- ▶ Attention can model word order differences

NMT Attention Examples



- ▶ Attention can model multi-word translations

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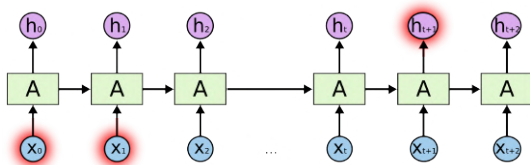
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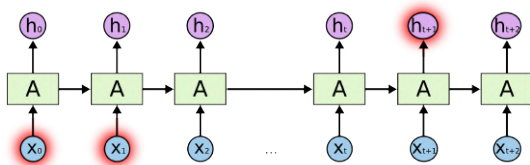
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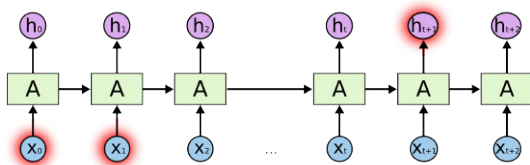
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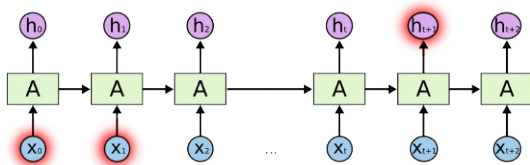
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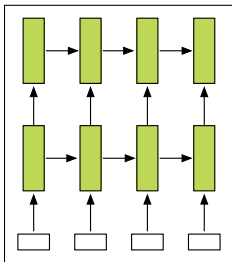
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 - should h_{t+1} really depend on x_0 or x_1 or both or neither?

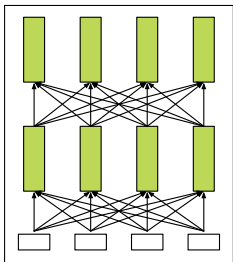
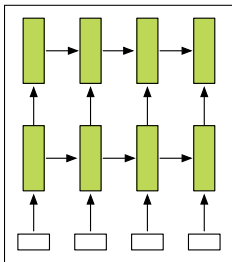
Self-Attention

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 - can replace RNNs as sequence model
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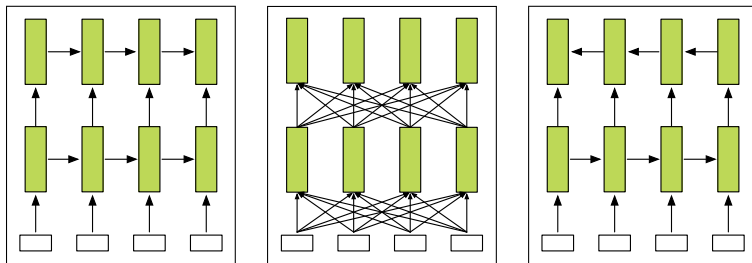
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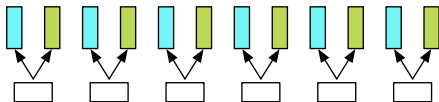


- ▶ self-attention is bidirectional (like a biRNN), but no recurrent connections between time steps

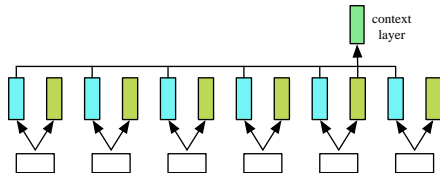
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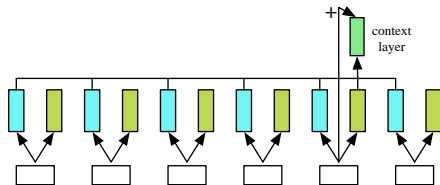
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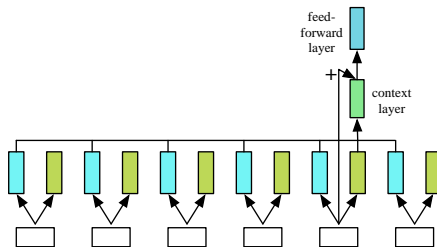
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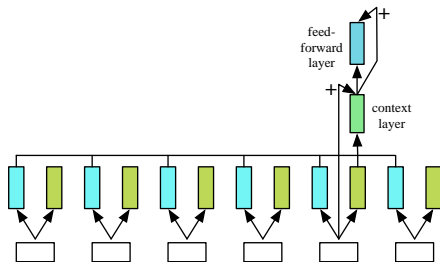
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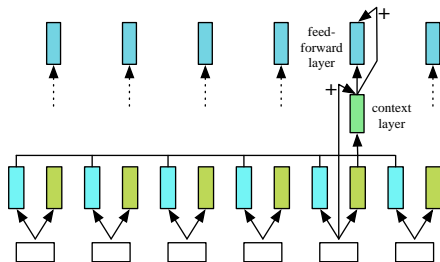
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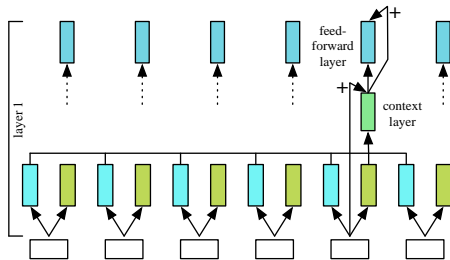
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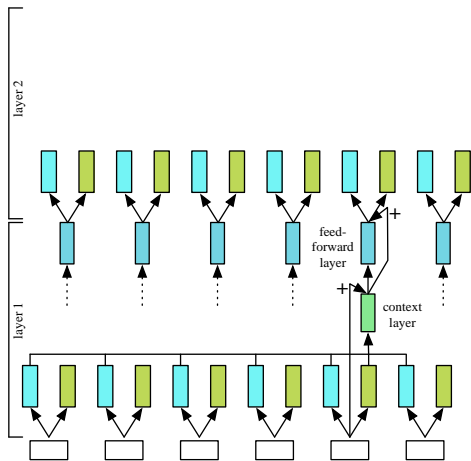
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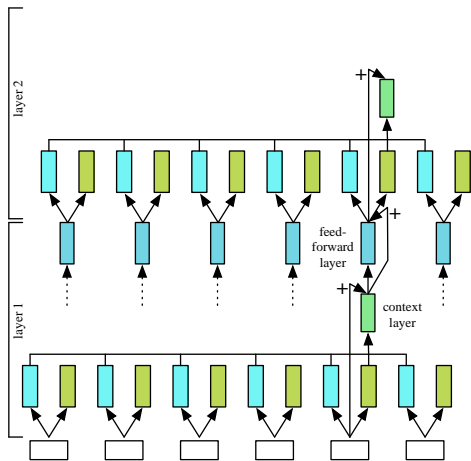
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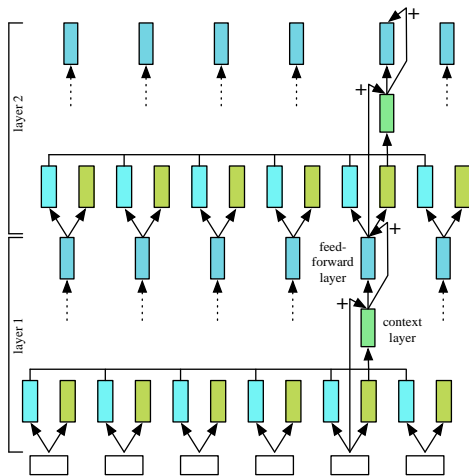
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 - is defined as $\text{ffwd}(\mathbf{c}_{n,t}) = W_n \mathbf{d} \odot (\text{ReLU}(V_n \mathbf{c}_{n,t} + \mathbf{a}_n)) + \mathbf{b}_n$
where \mathbf{d} is a (inverted) dropout mask
- ▶ Residual connections are used for context and feed-forward sub 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 . . .
 - 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)
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- ▶ What does LayerNorm do?

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Transformer Decoder

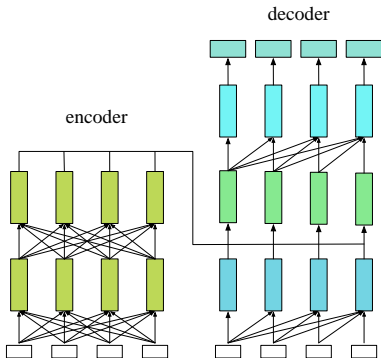
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- ▶ Machine translation
- ▶ Sequence-to-sequence models
- ▶ Neural machine translation
 - encoder-decoder architecture
 - attention mechanism
 - self-attention (Google's Transformer)