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

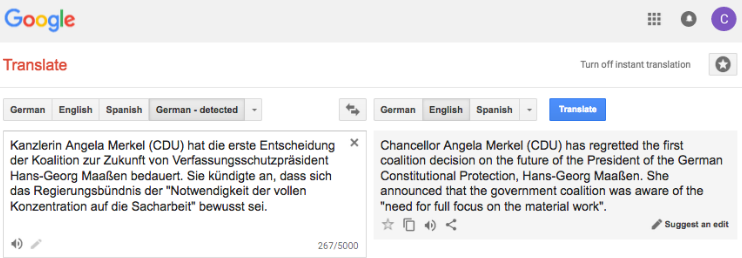
This Class

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

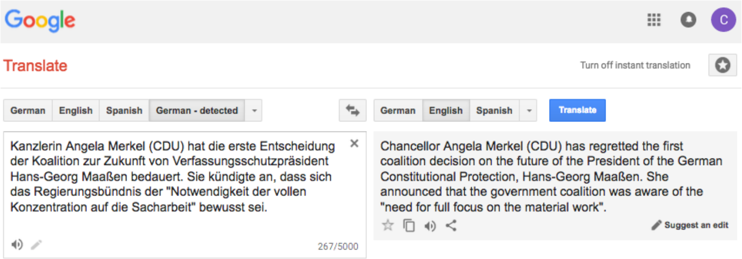
This Class

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

Machine Translation

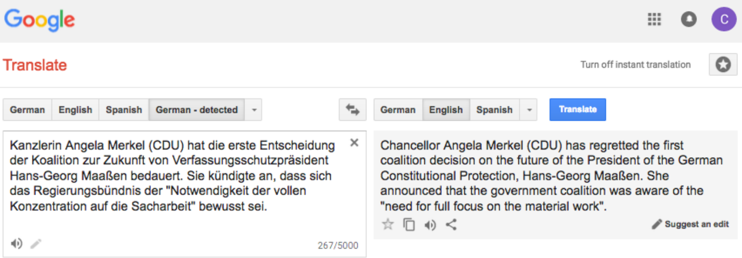


Machine Translation



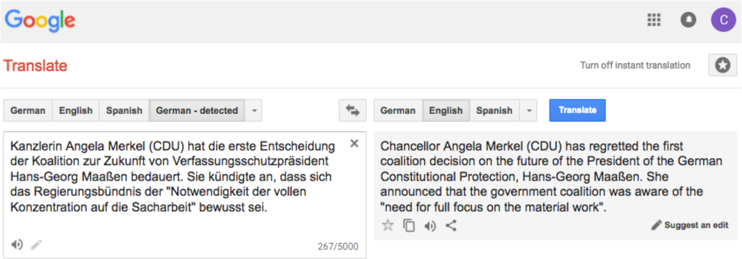
- Active research of AI since its beginnings

Machine Translation



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

Machine Translation



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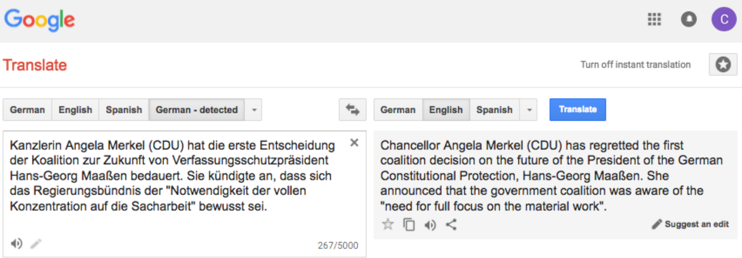
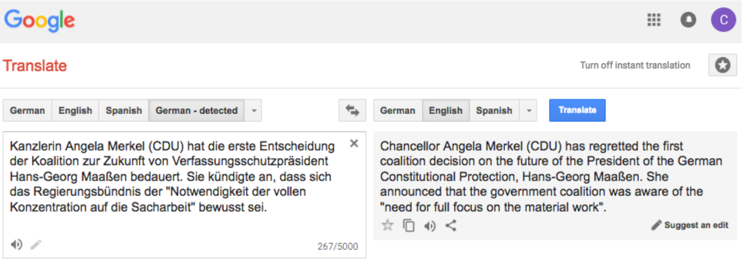
  - 1950s–1990s: rule-based, symbolic approaches

Machine Translation



- 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

Machine Translation



- 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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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.

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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.

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

MT: Kurdish to English (low resource)

Kurdish source sentence

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English machine translation in 2020 (using neural machine translation)

MT: Kurdish to English (low resource)

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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.

MT: Kurdish to English (low resource)

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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)

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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)

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 $\rightarrow$ target language

Machine Translation

- Automatically translate: source language $\rightarrow$ target language

Arabic $\rightarrow$ English	French $\rightarrow$ Spanish	...	Amharic $\rightarrow$ Vietnamese
Armenian $\rightarrow$ Czech	Armenian $\rightarrow$ Danish	...	Armenian $\rightarrow$ Turkish
$\vdots$	$\vdots$	...	$\vdots$
Uzbek $\rightarrow$ Albanian	Uzbek $\rightarrow$ Hindi	...	Uzbek $\rightarrow$ Ukranian
Vietnamese $\rightarrow$ Azeri	Vietnamese $\rightarrow$ Greek	...	Vietnamese $\rightarrow$ 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

How far are we from universal machine 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	-	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	18.3	[illegible]	31.6	[illegible]	[illegible]	10.0	26.9	11.4	6.5	19.1	21.4	[illegible]	2.1	-	19.8	21.1	[illegible]	22.4	15.2	8.9	8.8	-
en	15.7	33.9	23.1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	-

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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	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	10.0	[illegible]	12.5	22.2	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
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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
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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	-

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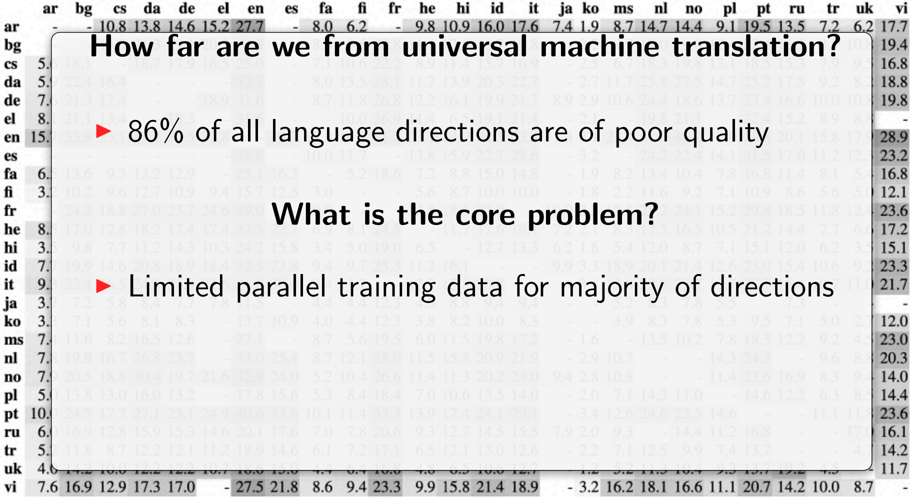
Universal Translation



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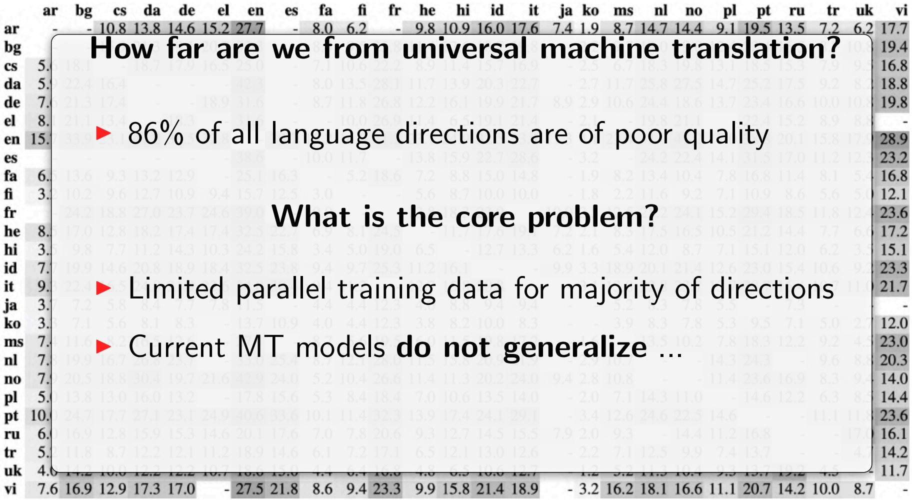

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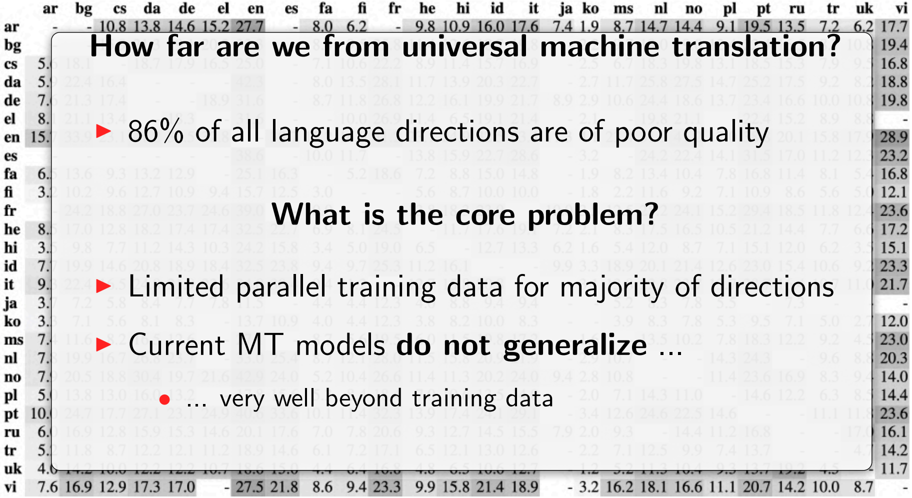

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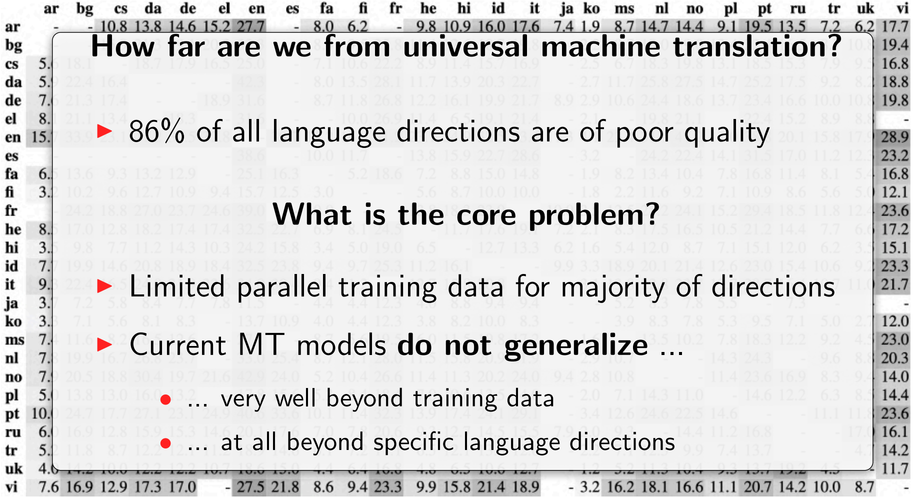

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Essential Data Component: Bilingual Parallel Corpus

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.

It plans to allow quarantine officers at airports to ask travelers if they have any meat products. They would also be able to inspect luggage without the owner's consent.

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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Parallel Corpus

⋮	⋮
李鹏会见新加坡前总统王鼎昌	Li Peng Meets With Former Singapore President Ong Teng Cheong
马来亚、新加坡、沙捞越、沙巴和文莱曾组成联邦,但最後分裂了。	Malaysia, Singapore, Sarawak, Sabah and Brunei once formed a federation, but it also fell apart in the end.
新加坡排行榜首,缅甸则排行榜尾 。	Singapore is at the head of the list, while Burma ranks last.
新加坡则在致力建造一个光纤网环绕的“智能岛”。	Singapore is also devoting itself to building a "intelligence island" embraced by a fiber-optical net.
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  - a (complex) input that needs to be encoded into a representation
  - a (complex) output into which the input representation needs to be decoded
- Many tasks fall under the general encoder-decoder architecture
- Image captioning
  - input: image (encode using CNNs)
  - output: sentence (decode using an RNN/CNN language model)

Encoder-Decoder Architecure

- The general encoder-decoder architecture assumes
  - a (complex) input that needs to be encoded into a representation
  - a (complex) output into which the input representation needs to be decoded
- Many tasks fall under the general encoder-decoder architecture
- Image captioning
  - input: image (encode using CNNs)
  - output: sentence (decode using an RNN/CNN language model)
- Speech recognition
  - input: audio signal over time (encode using CNN+RNN)
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  - input: sentence (encode using RNN/CNN)
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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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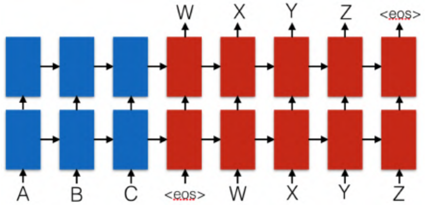

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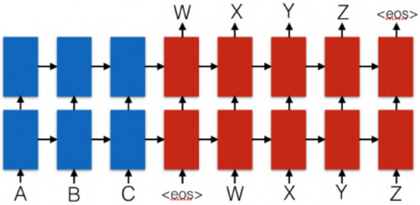

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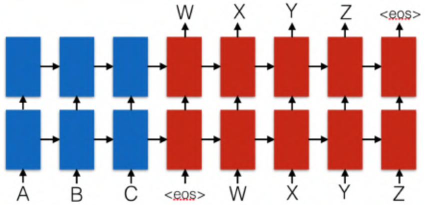

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  - Sutskever et al. (2014) simply initialize the decoder LSTM with the last state of the encoder LSTM

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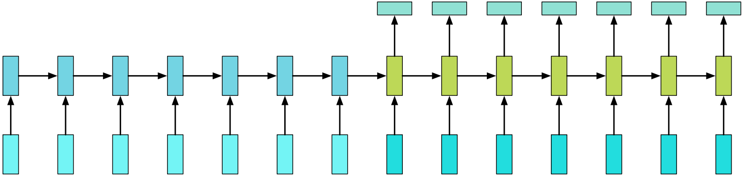

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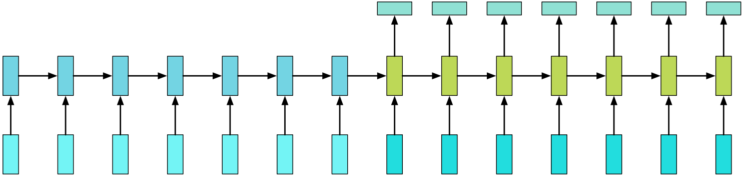

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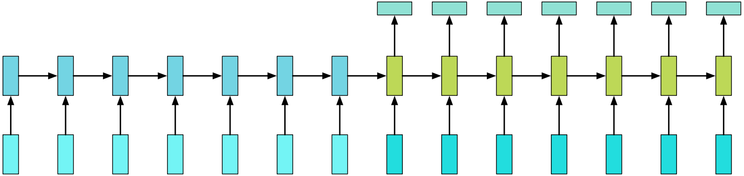

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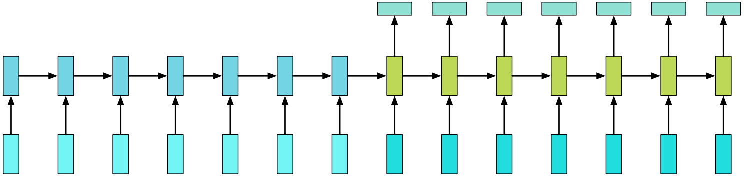

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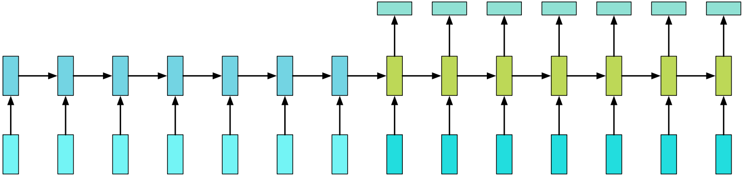

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- encoder-decoder information bottleneck

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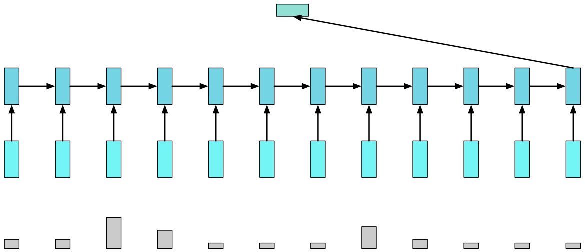

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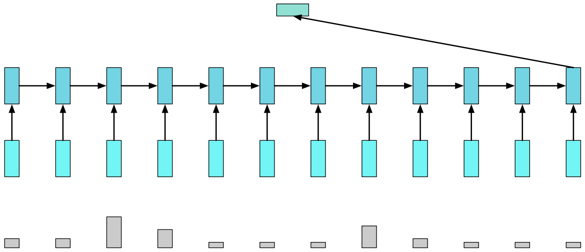

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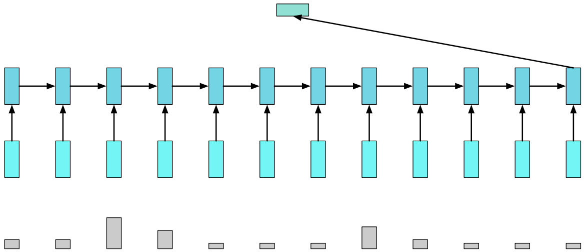

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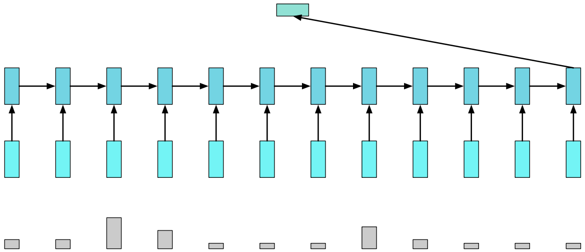

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- For classification, the sentence representation learns which tokens are important to predict a certain class

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

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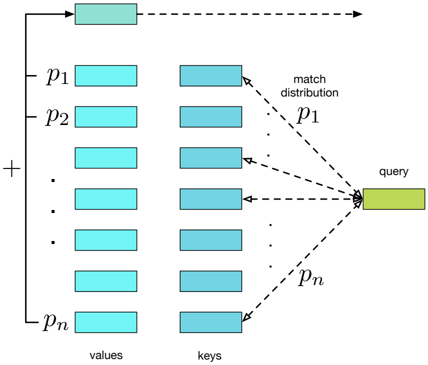

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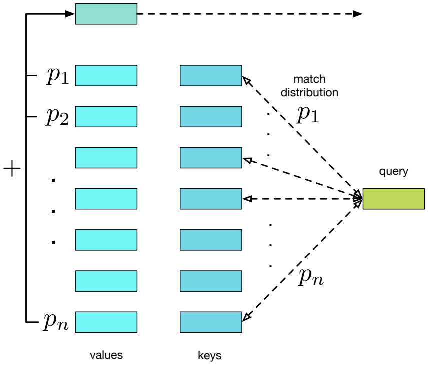

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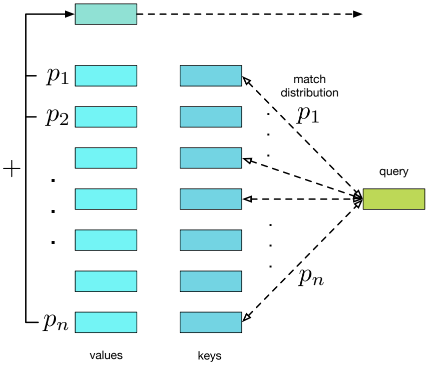

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- The attention mechanism and thereby the computation of $\mathbf{c}$ is fully differentiable!

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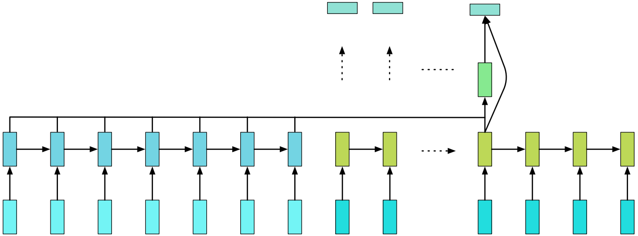

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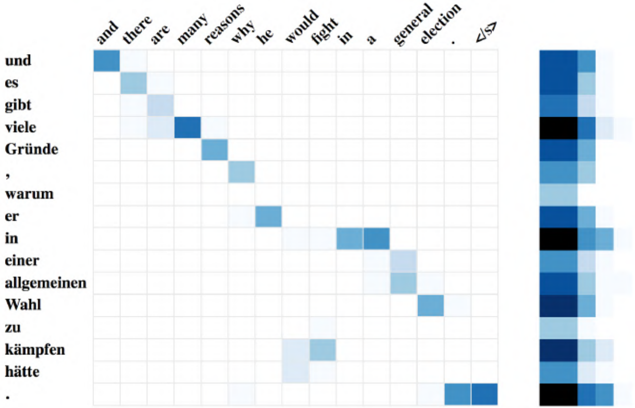
- Added benefits:
  - attention can be visualized allowing for some inspection of the model
  - useful for error analysis

NMT Attention Examples



- Attention can model word order differences

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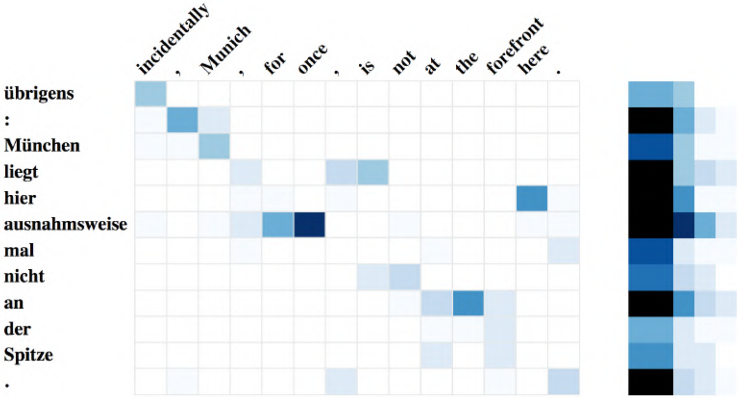

- Attention can model multi-word translations

Credit Assignment Problem

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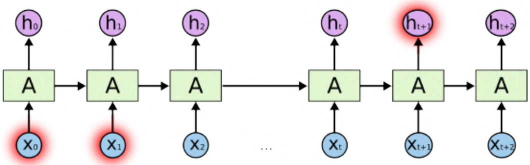

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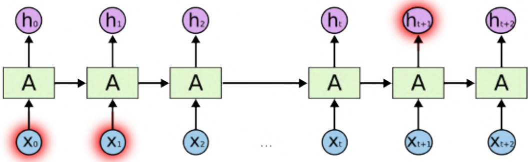

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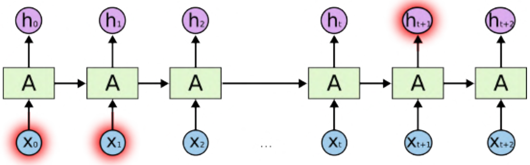

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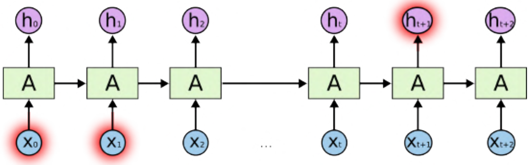

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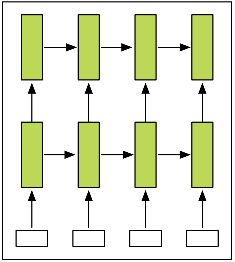
  should $\mathbf{h}_{t+1}$ really depend on $\mathbf{x}_0$ or $\mathbf{x}_1$ or both or neither?

Self-Attention

- Self-attention computes attention between elements of the same sequence
  - can replace RNNs as sequence model
  - shortens paths of credit assignment
  - at the core of Google's Transformer NMT system (Vaswani et al., 2017)



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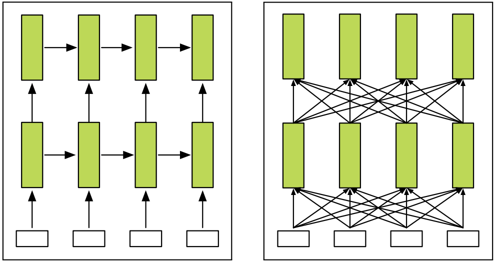

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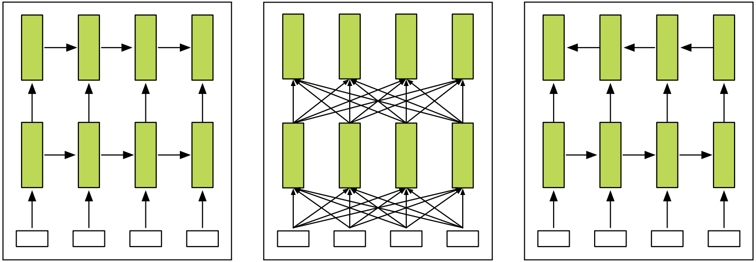

- self-attention is bidirectional (like a biRNN), but no recurrent connections between time steps

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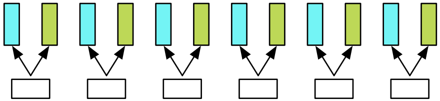

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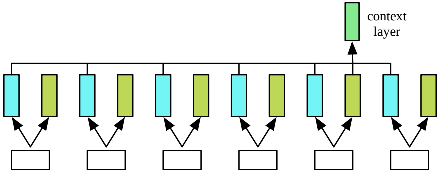

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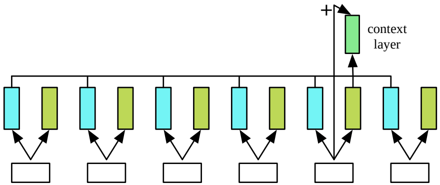

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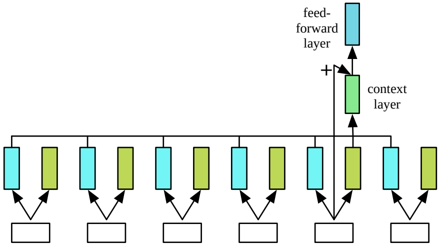

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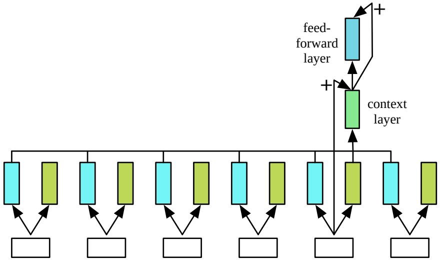

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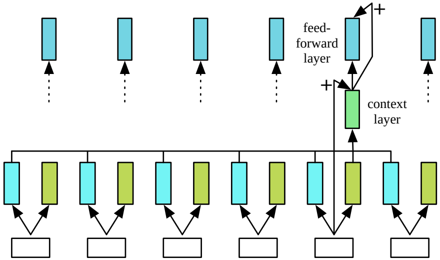

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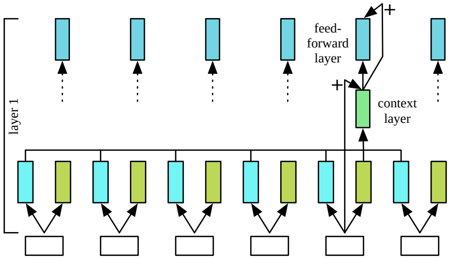

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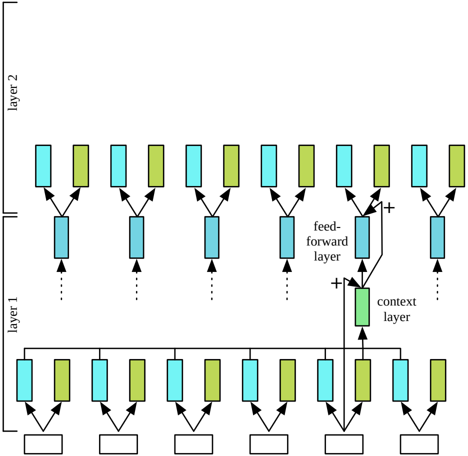

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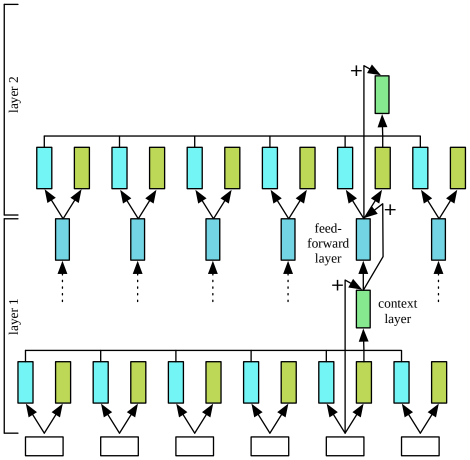

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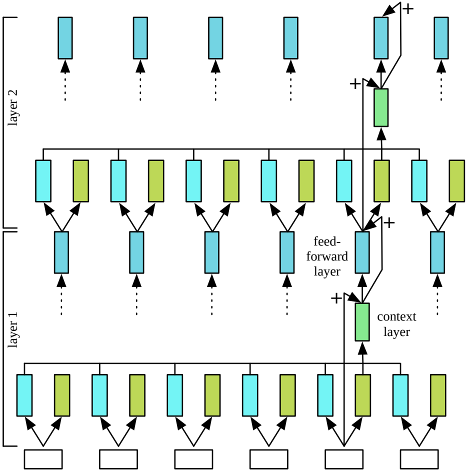

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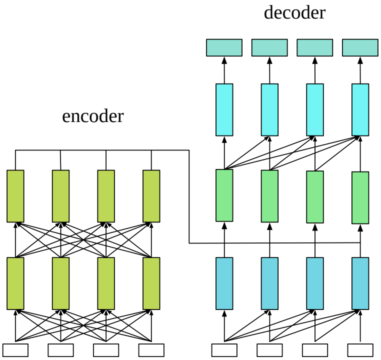

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Recap

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