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

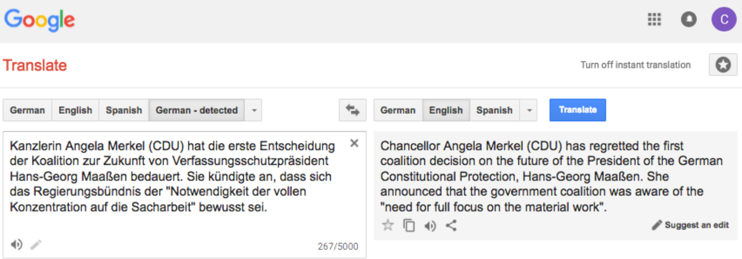
This Class

- 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



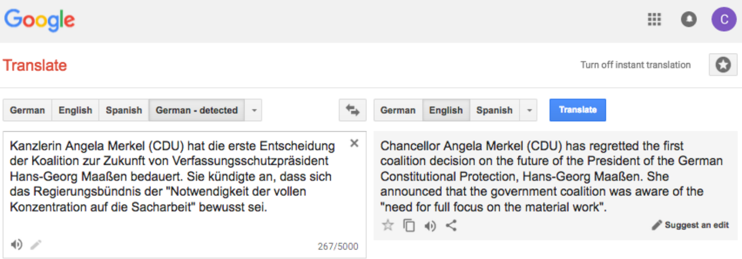
Google
Translate
Turn off instant translation
German | English | Spanish | German - detected
German | English | Spanish
Translate

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.

267/5000

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".

Machine Translation



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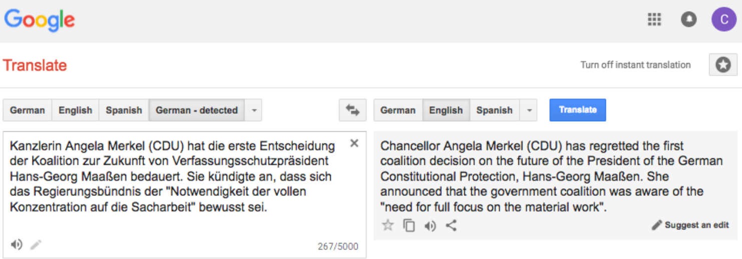
- Active research of AI since its beginnings

Machine Translation



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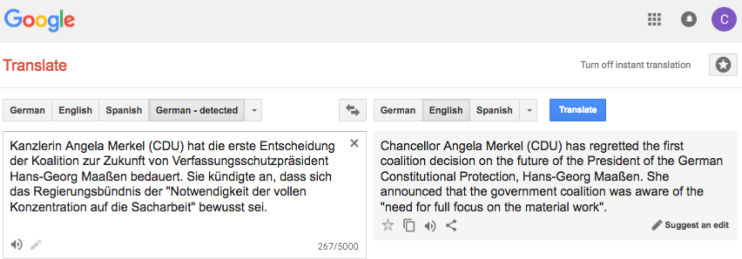
- Active research of AI since its beginnings
- Machine translation (MT) is a nice example of the different paradigm shifts in AI

Machine Translation



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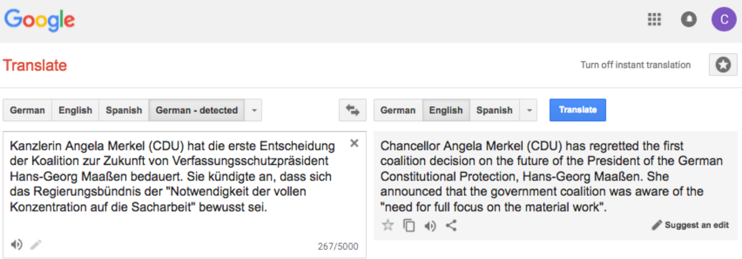
    - 1950s–1990s: rule-based, symbolic approaches

Machine Translation



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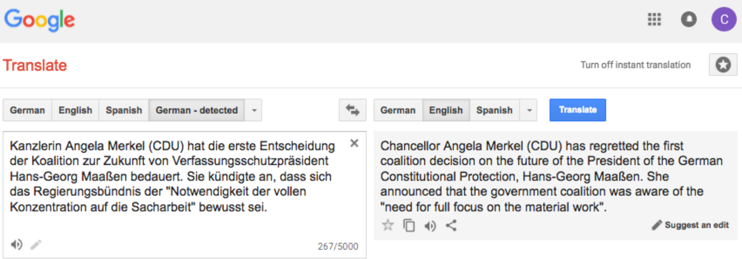
- Machine translation (MT) is a nice example of the different paradigm shifts in AI
  - 1950s–1990s: rule-based, symbolic approaches
  - 1990s–2016: statistical, data-driven approaches

Machine Translation



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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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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.

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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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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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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

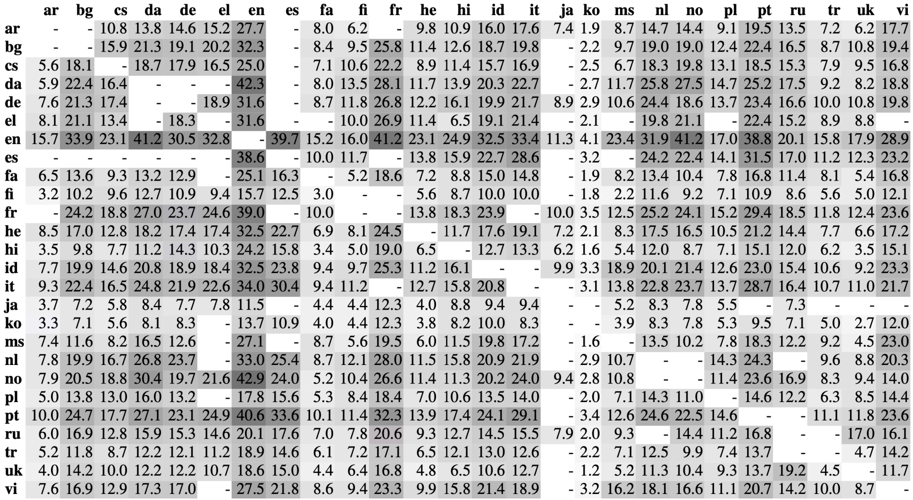
Machine Translation

- Automatically translate: source language → target language

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

Universal Translation

Universal Translation



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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
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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
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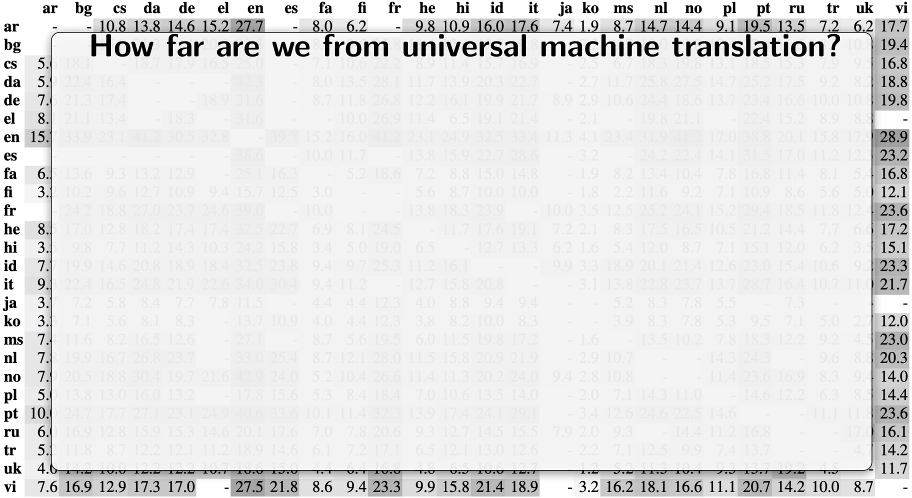
vi	7.6	16.9	12.9	17.3	17.0	-	27.5	21.8	8.6	9.4	23.3	9.9	15.8	21.4	18.9	-	3.2	16.2	18.1	16.6	11.1	20.7	14.2	10.0	8.7	-

Schwenk et al. (2019)

Universal Translation

How far are we from universal machine translation?



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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
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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
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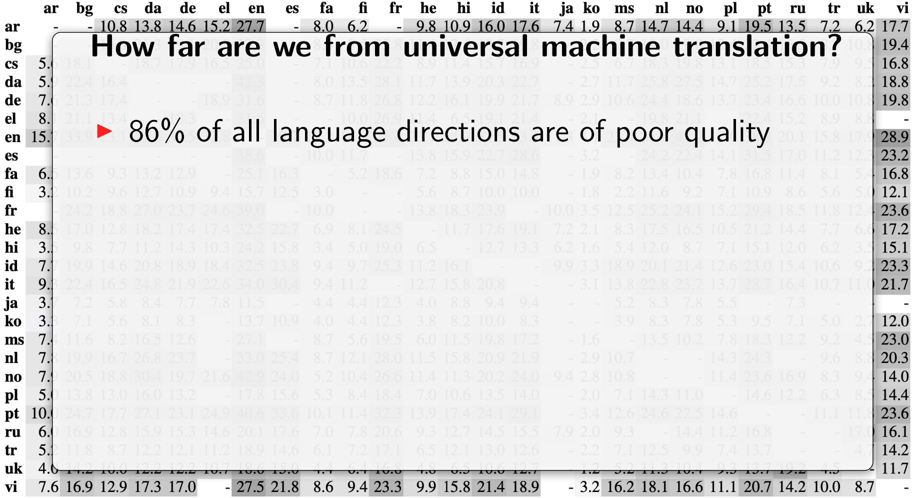
it	9.3	22.4	16.5	24.8	21.9	22.6	34.0	30.4	9.4	11.2	-	12.7	15.8	20.8	-	-	3.1	13.8	22.8	23.7	13.7	28.7	16.4	10.7	11.0	21.7
ja	3.7	7.2	5.8	8.4	7.7	7.8	11.5	-	4.4	4.4	12.3	4.0	8.8	9.4	9.4	-	-	5.2	8.3	7.8	5.5	-	7.3	-	-	-
ko	3.3	7.1	5.6	8.1	8.3	-	13.7	10.9	4.0	4.4	12.3	3.8	8.2	10.0	8.3	-	-	3.9	8.3	7.8	5.3	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?

- 86% of all language directions are of poor quality



	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	[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	-

Schwenk et al. (2019)

Universal Translation

How far are we from universal machine translation?

- 86% of all language directions are of poor quality

What is the core problem?

	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	[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]	[illegible]	[illegible]	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)

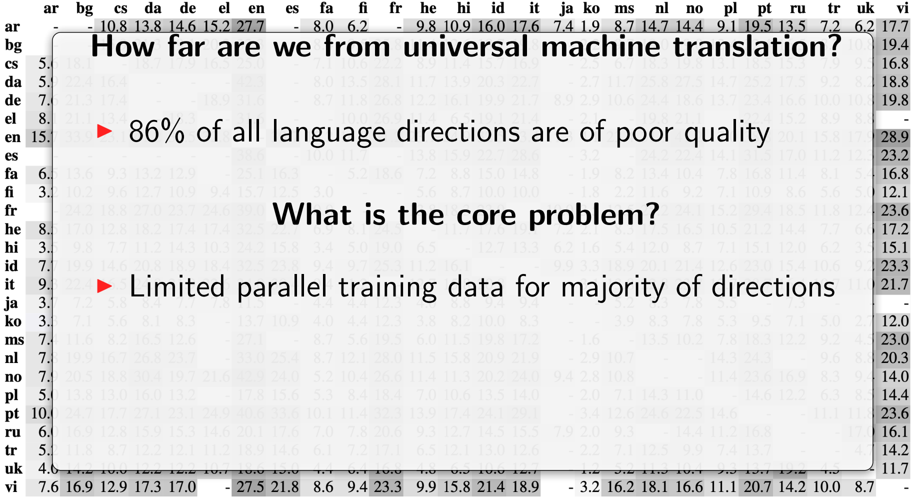
Universal Translation

How far are we from universal machine translation?

- 86% of all language directions are of poor quality

What is the core problem?

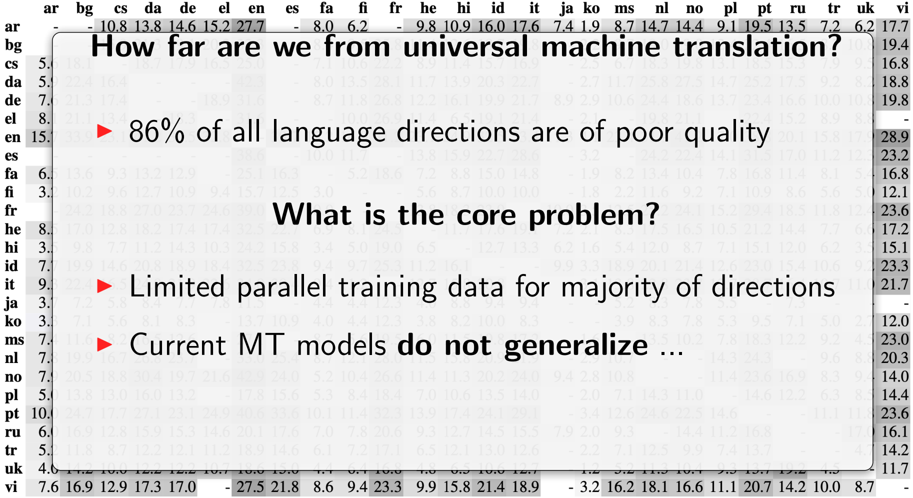
- Limited parallel training data for majority of directions



	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	[illegible]	18.3	-	31.6	-	-	10.0	26.9	11.4	6.5	19.1	21.4	-	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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]	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	-	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]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	-

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

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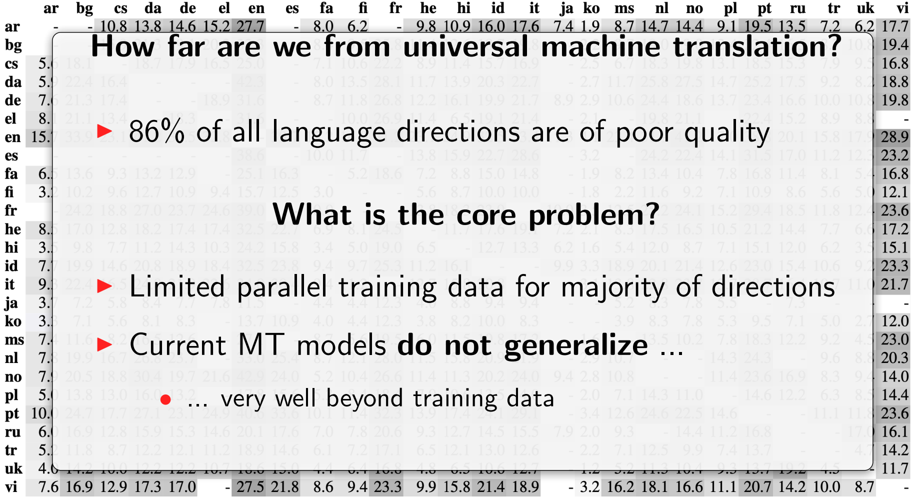

	ar	bg	cs	da	de	el	en	es	fa	fi	fr	he	hi	id	it	ja	ko	ms	nl	no	pl	pt	ru	tr	uk	vi
ar	-	-	10.8	13.8	14.6	15.2	27.7	-	8.0	6.2	-	9.8	10.9	16.0	17.6	7.4	1.9	8.7	14.7	14.4	9.1	19.5	13.5	7.2	6.2	17.7
bg	-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[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]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	-	[illegible]	-
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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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	[illegible]	-	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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	-	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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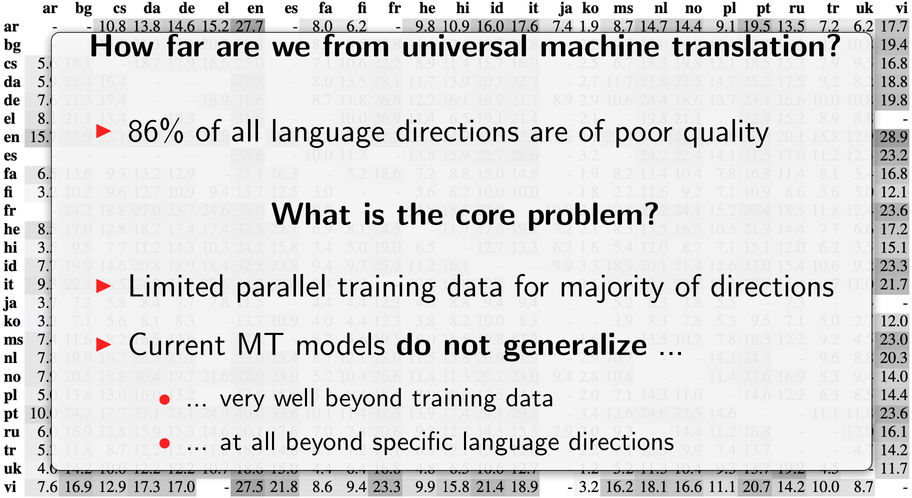
Universal Translation



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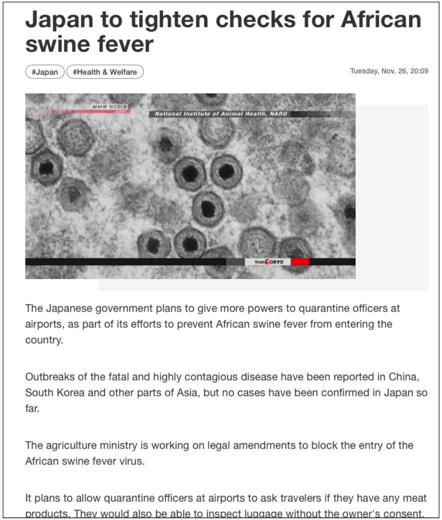
  - … at all beyond specific language directions

Schwenk et al. (2019)

Essential Data Component: Bilingual Parallel Corpus



Japan to tighten checks for African swine fever

#Japan #Health & Welfare

Tuesday, Nov. 26, 20:09

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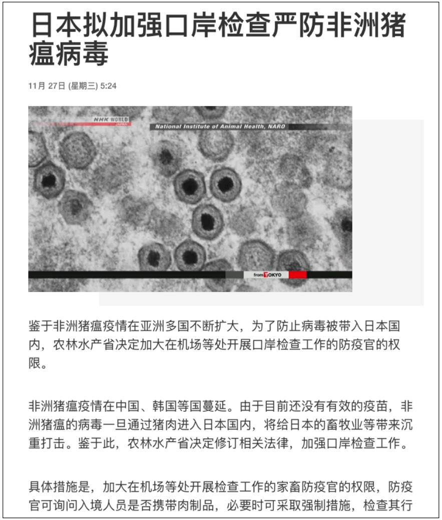

日本拟加强口岸检查严防非洲猪瘟病毒

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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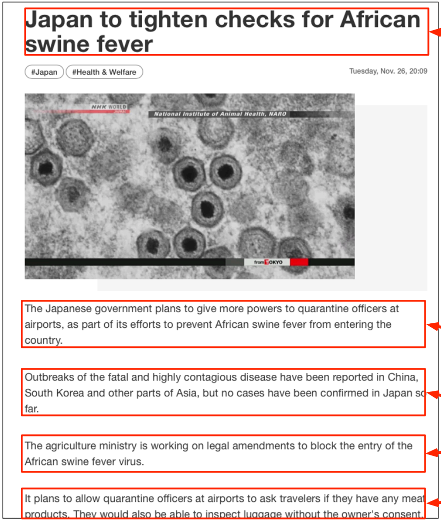

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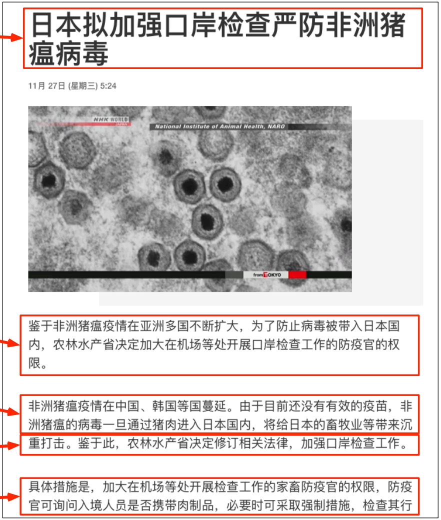

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- When input and outputs are sequences of words/audio we talk about sequence-to-sequence (seq2seq) models

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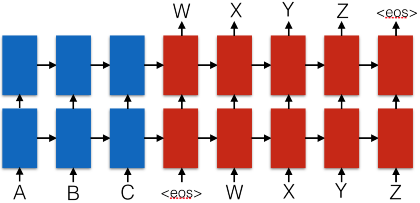

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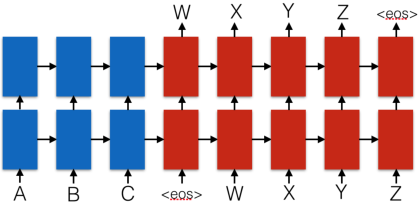

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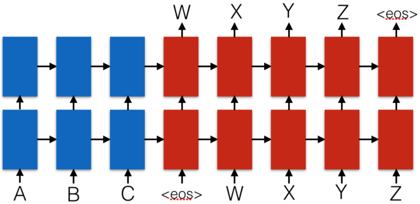

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  - Sutskever et al. (2014) simply initialize the decoder LSTM with the last state of the encoder LSTM

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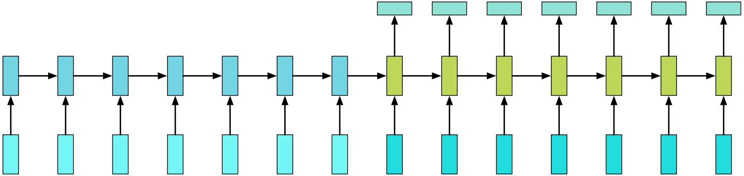

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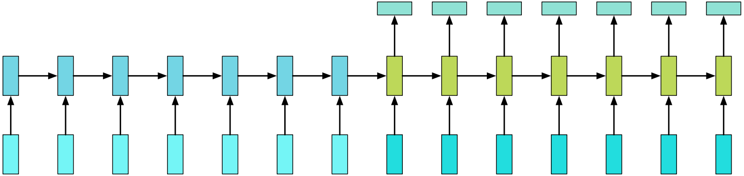

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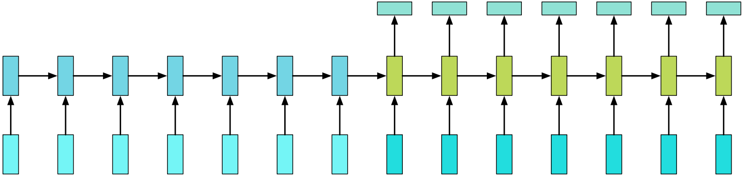

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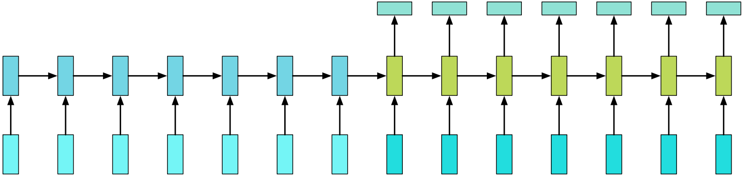

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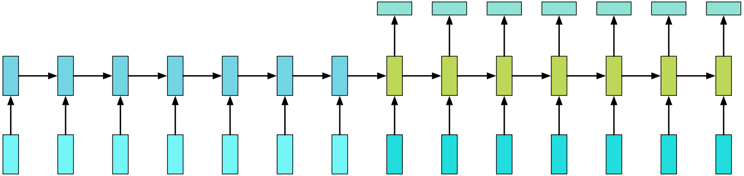

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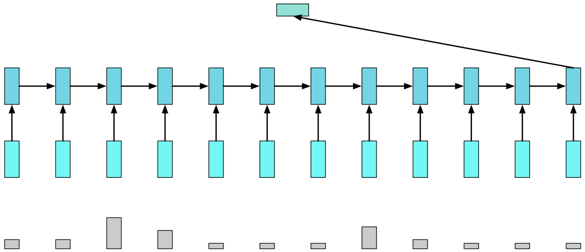

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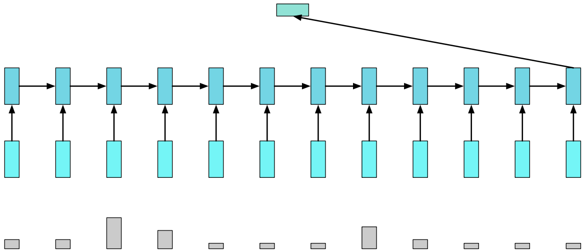

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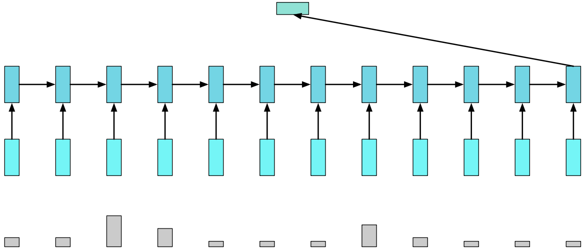

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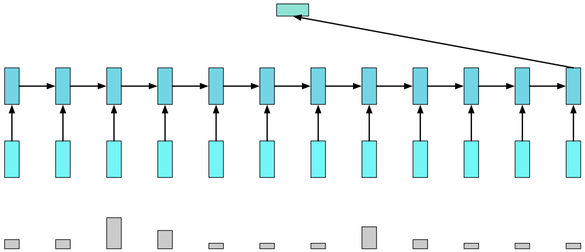

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- For classification, the sentence representation learns which tokens are important to predict a certain class

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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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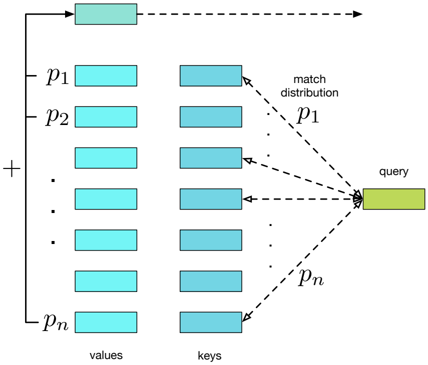

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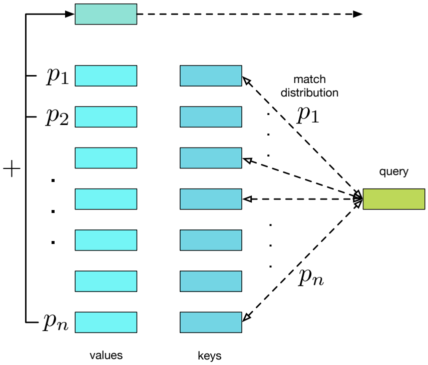

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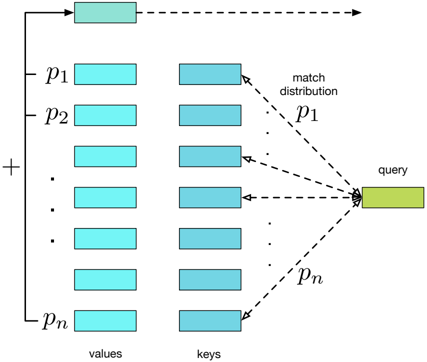

- $\mathbf{c} = \sum_{i=1}^{n} \mathrm{sim}_p(W_k\mathbf{k}^i, W_q\mathbf{q})W_v\mathbf{v}^i$
- $W_q \in \mathbb{R}^{n_m \times m_q}, W_k \in \mathbb{R}^{n_m \times m_k}, W_v \in \mathbb{R}^{n_v \times m_v}$

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

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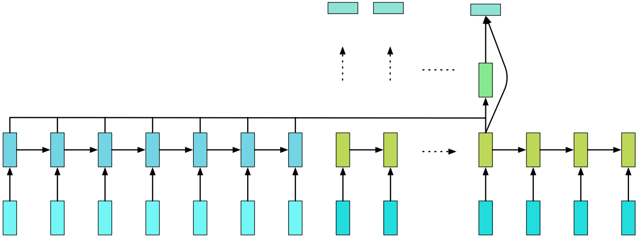

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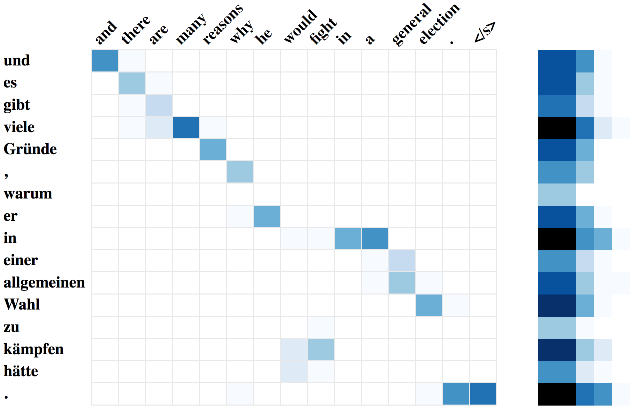
- Added benefits:
  - attention can be visualized allowing for some inspection of the model
  - useful for error analysis

NMT Attention Examples



- Attention can model word order differences

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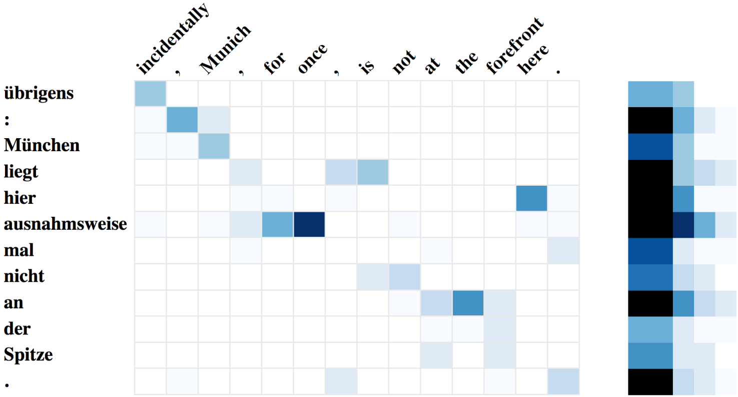

- Attention can model multi-word translations

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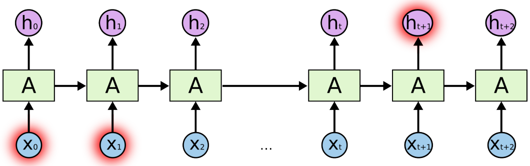

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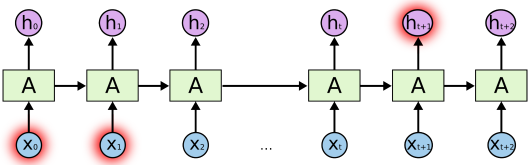

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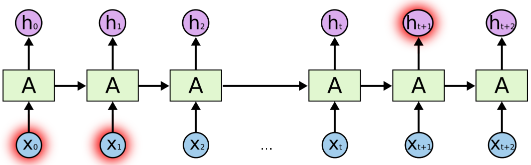

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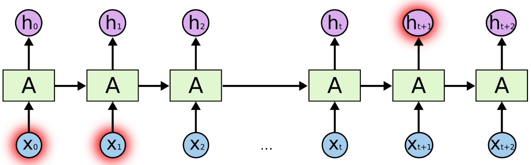

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  should $\mathbf{h}_{t+1}$ really depend on $\mathbf{x}_0$ or $\mathbf{x}_1$ or both or neither?

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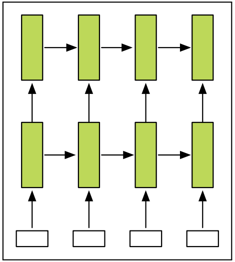
  - at the core of Google's Transformer NMT system (Vaswani et al., 2017)



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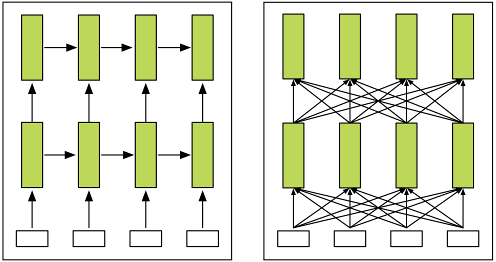

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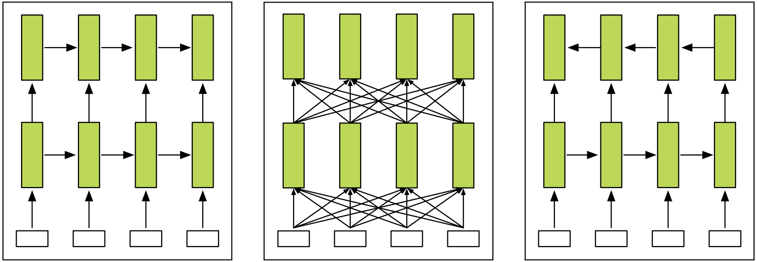

- self-attention is bidirectional (like a biRNN), but no recurrent connections between time steps

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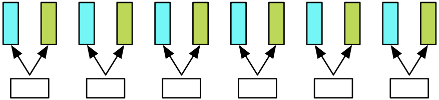

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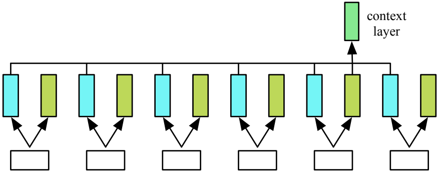

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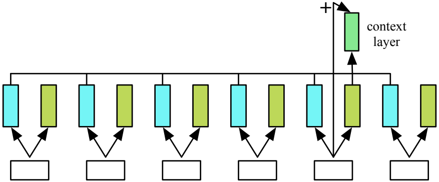

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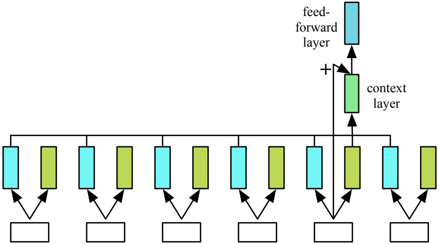

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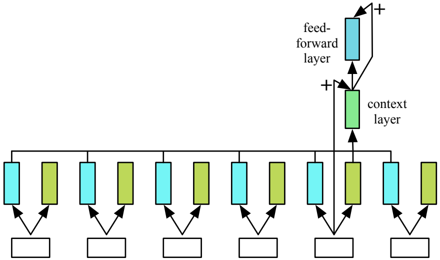

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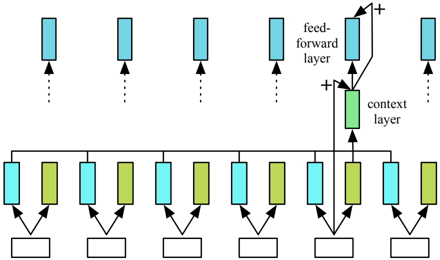

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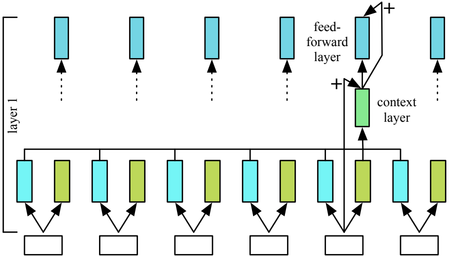

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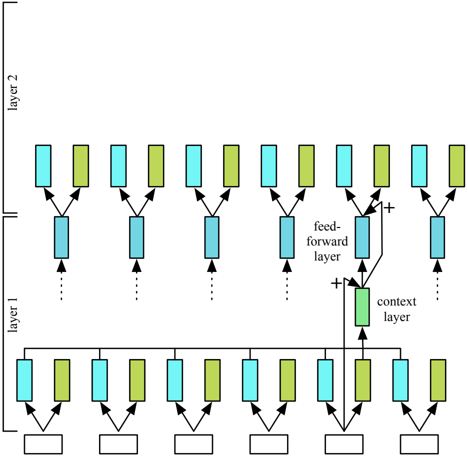

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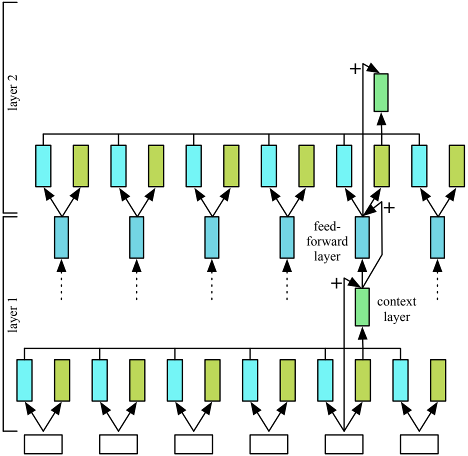

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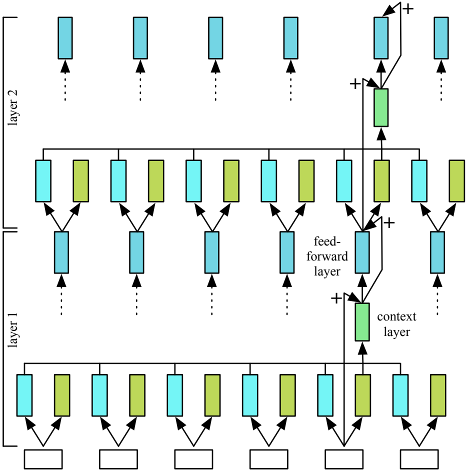

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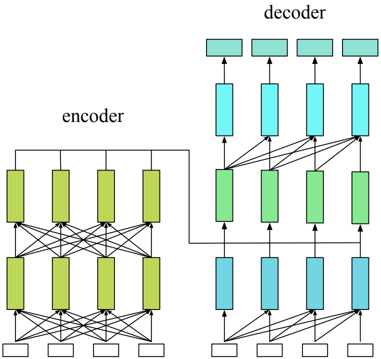

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Recap

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