FACULTEIT LETTEREN EN WIJSBEGEERTE

VAKGROEP VERTALEN, TOLKEN EN COMMUNICATIE

NEURALE AUTOMATISCHE VERTAALSYSTEMEN

Lieve Macken, ELRC workshop, 8 juli 2021

UNIVERSITEIT GENT

OVERZICHT

- Kwaliteit van NMT-systemen
- Artificiële neurale netwerken
- Word embeddings
- Architectuur
- Belang van data
- Mens versus machine?

- Josef van Genabith, "Data or no Data, that is the Question: Learning MT without Translation Data?". 2021. Presentation at JIAMCATT (19.04.2021)
- Juan Antonio Pérez-Ortiz, Mikel L. Forcada and Felipe Sánchez-Martínez, “How neural machine translation works”, 2021. Preprint version of book chapter (https://multitrainmt.eu project)
- Koehn, P. (2020). Neural Machine Translation. Cambridge: Cambridge University Press.

KWALITEIT VAN NMT-SYSTEMEN

Officiële resultaten van de WMT 2020 News Translation task

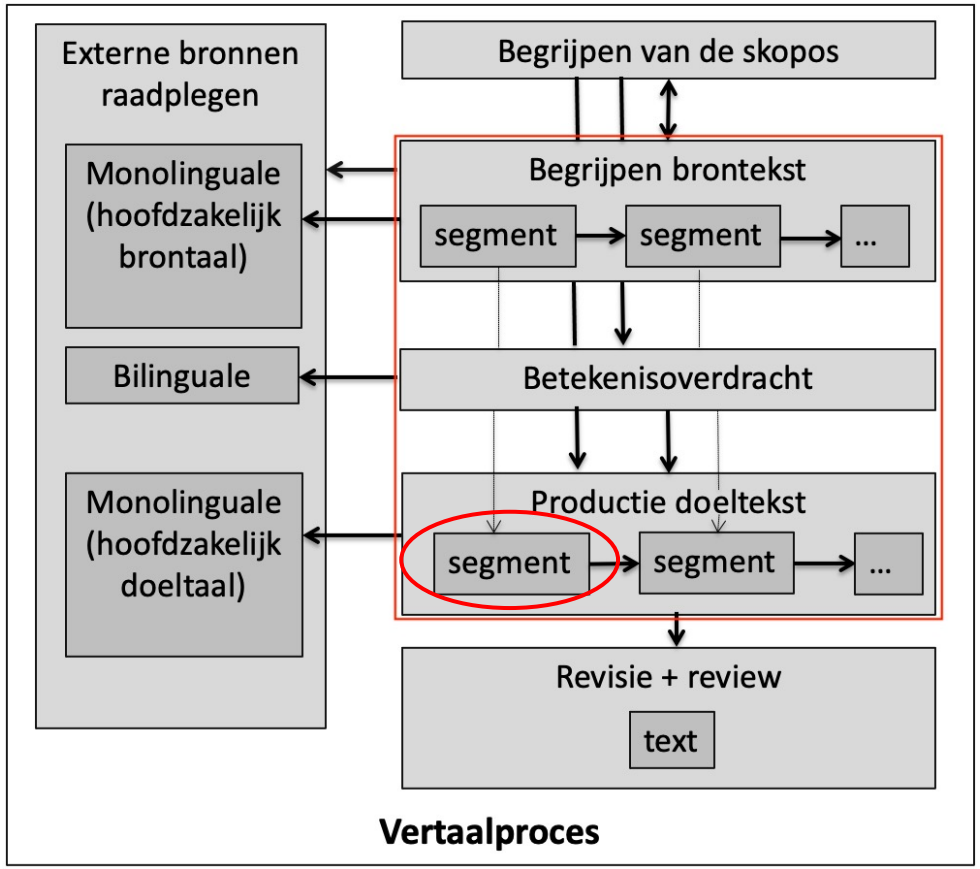
German→English

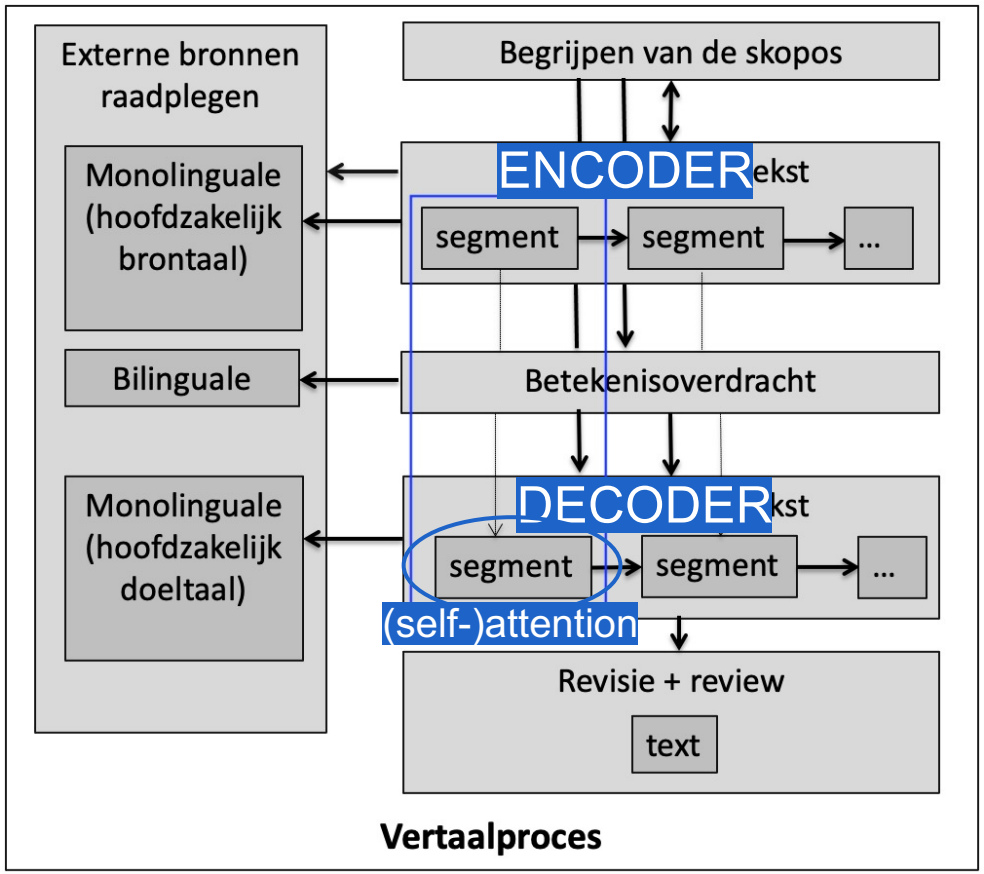
Ave.	Ave. z	System
82.6	0.228	VolcTrans
84.6	0.220	OPPO
82.2	0.186	HUMAN
81.5	0.179	Tohoku-AIP-NTT
81.3	0.179	Online-A
81.5	0.172	Online-G
79.8	0.171	PROMT-NMT
82.1	0.167	Online-B
78.5	0.131	UEDIN
78.8	0.085	Online-Z
74.2	−0.079	WMTBiomedBaseline
71.1	−0.106	zlabs-nlp
20.5	−1.618	yolo

English→German

Ave.	Ave. z	System
90.5	0.569	HUMAN-B
87.4	0.495	OPPO
88.6	0.468	Tohoku-AIP-NTT
85.7	0.446	HUMAN-A
84.5	0.416	Online-B
84.3	0.385	Tencent-Translation
84.6	0.326	VolcTrans
85.3	0.322	Online-A
82.5	0.312	eTranslation
84.2	0.299	HUMAN-paraphrase
82.2	0.260	AFRL
81.0	0.251	UEDIN
79.3	0.247	PROMT-NMT
77.7	0.126	Online-Z
73.9	−0.120	Online-G
68.1	−0.278	zlabs-nlp
65.5	−0.338	WMTBiomedBaseline

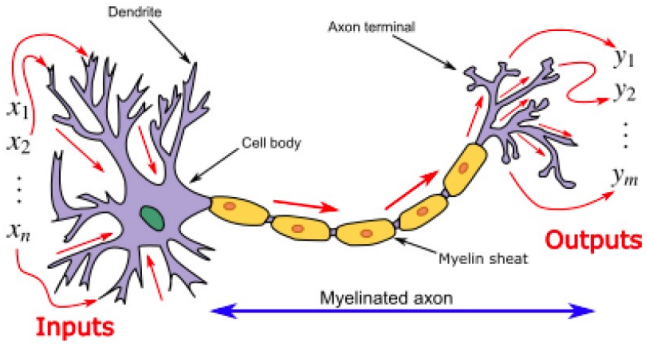
VERTAALPROCES

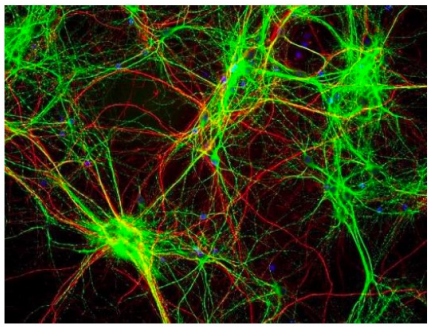




WAAROM IS DE KWALITEIT VAN NMT ZO GOED?

Artificiële neurale netwerken





Sources:
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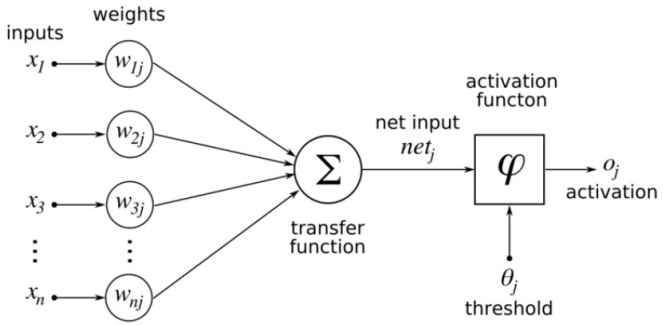
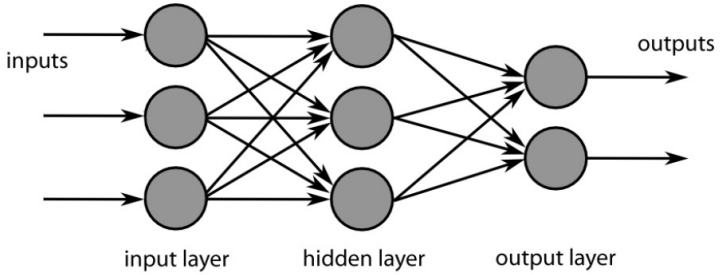
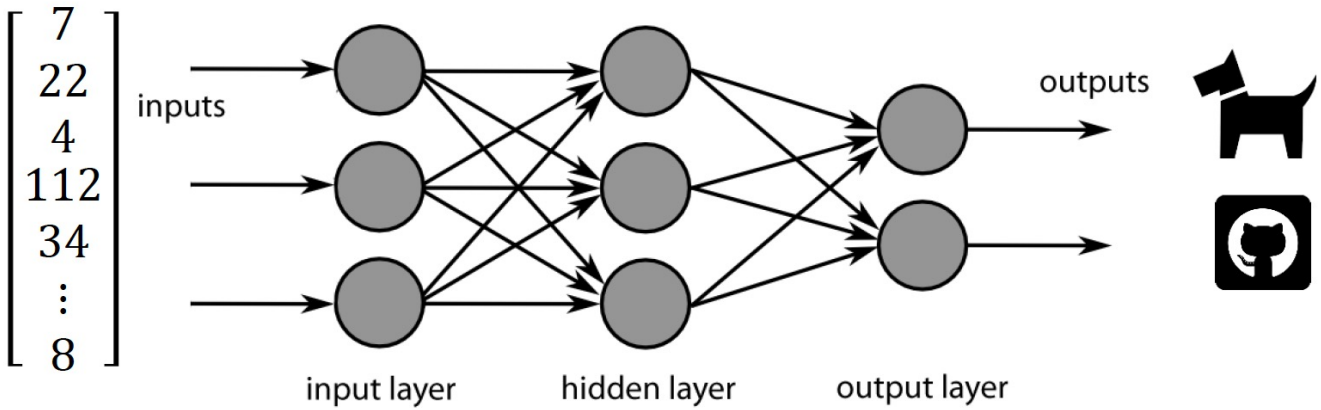




ARTIFICIËLE NEURALE NETWERKEN



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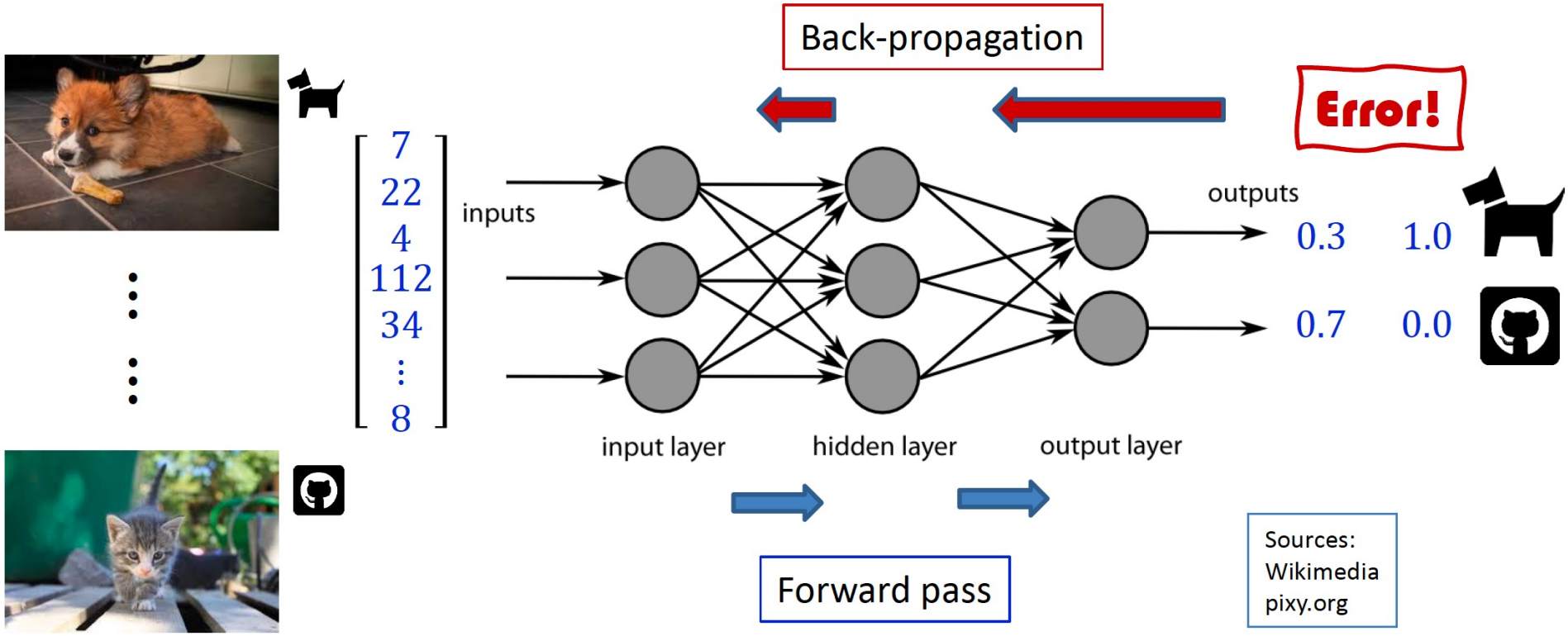
ARTIFICIËLE NEURALE NETWERKEN



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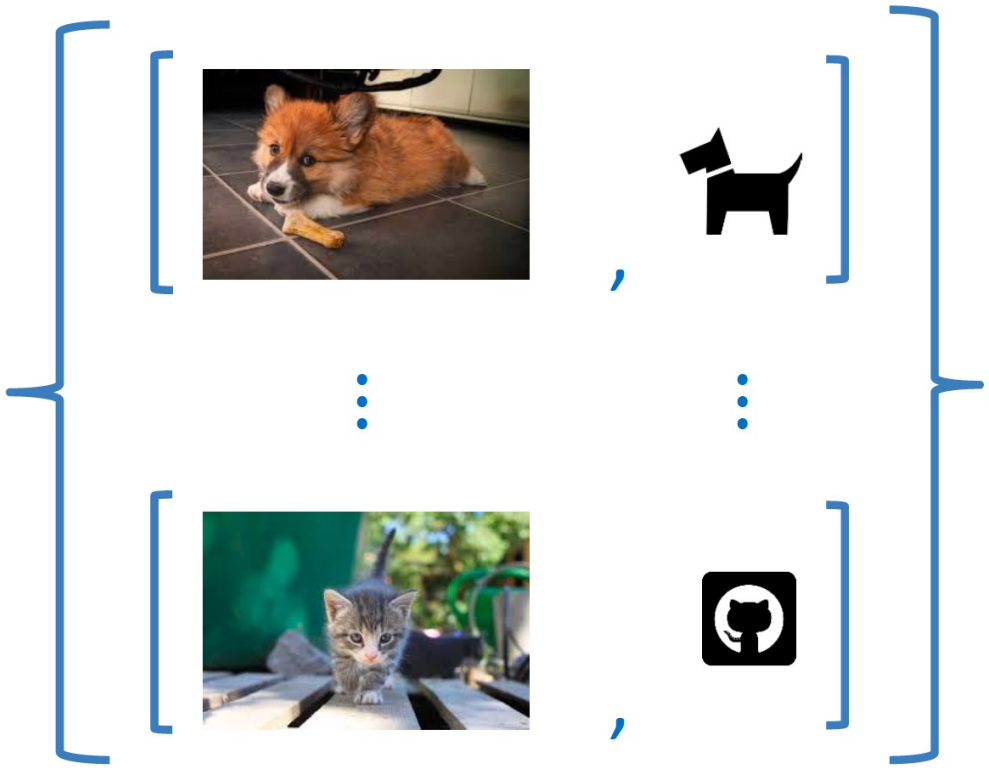
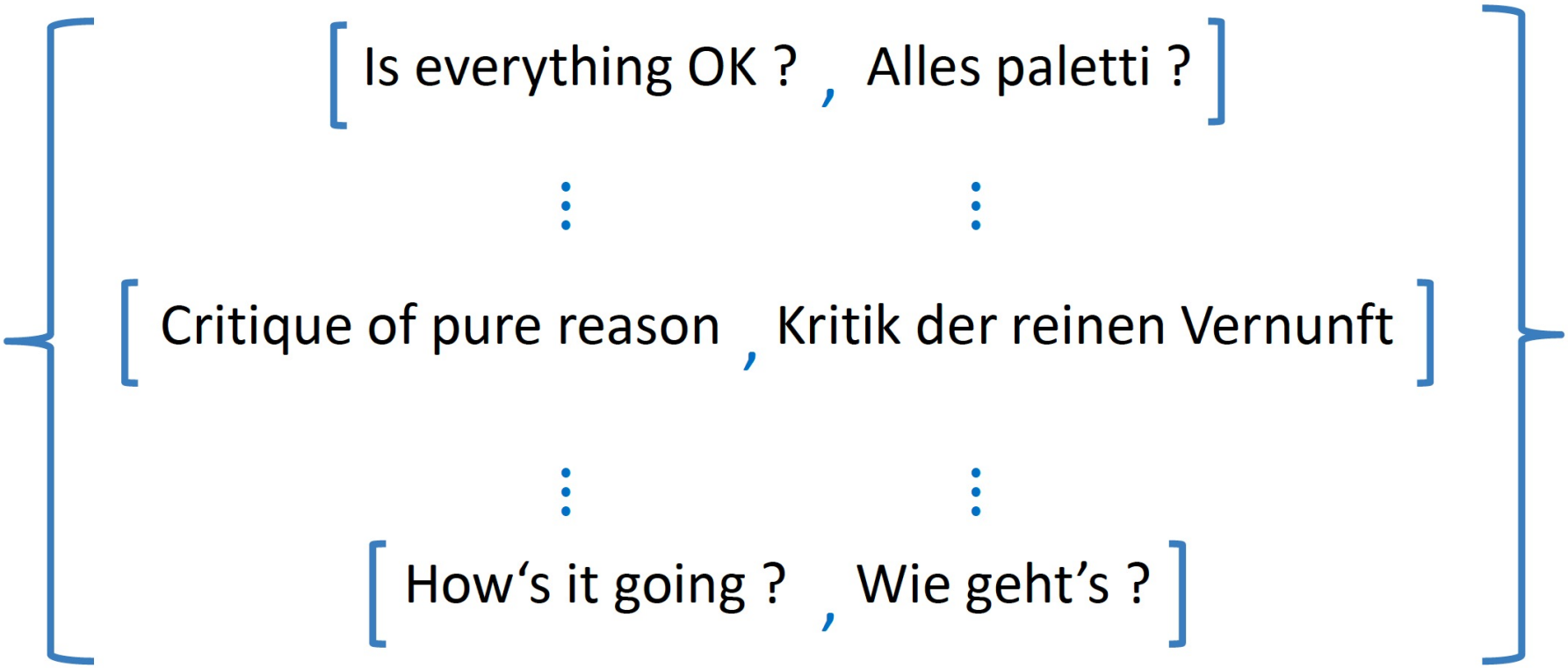


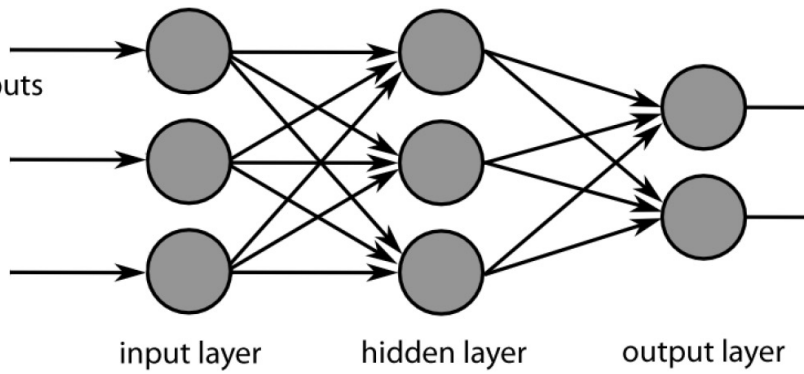
Supervised ML
Labelled training data
[data , label]
Label = supervision signal

ARTIFICIËLE NEURALE NETWERKEN



ARTIFICIËLE NEURALE NETWERKEN

Is [5, 2 ….]
everything [8, 11 ….]
OK [33, 1, ….]



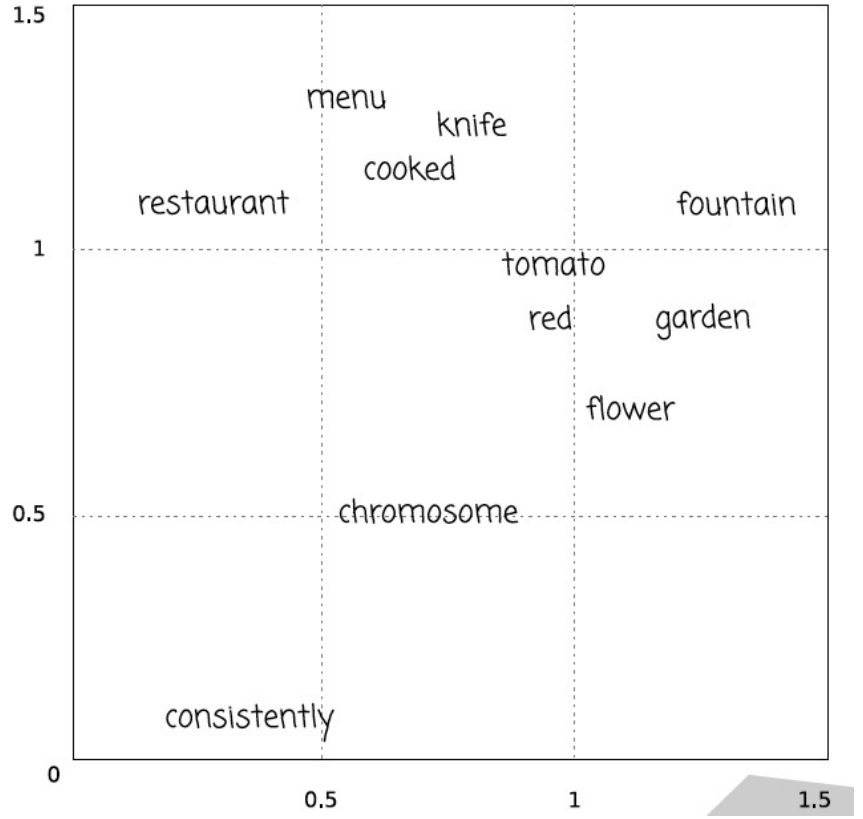
Sources:
Wikimedia

VAN WOORDEN NAAR VECTOREN

Word embeddings

restaurant
red
garden
fountain
flower
tomato

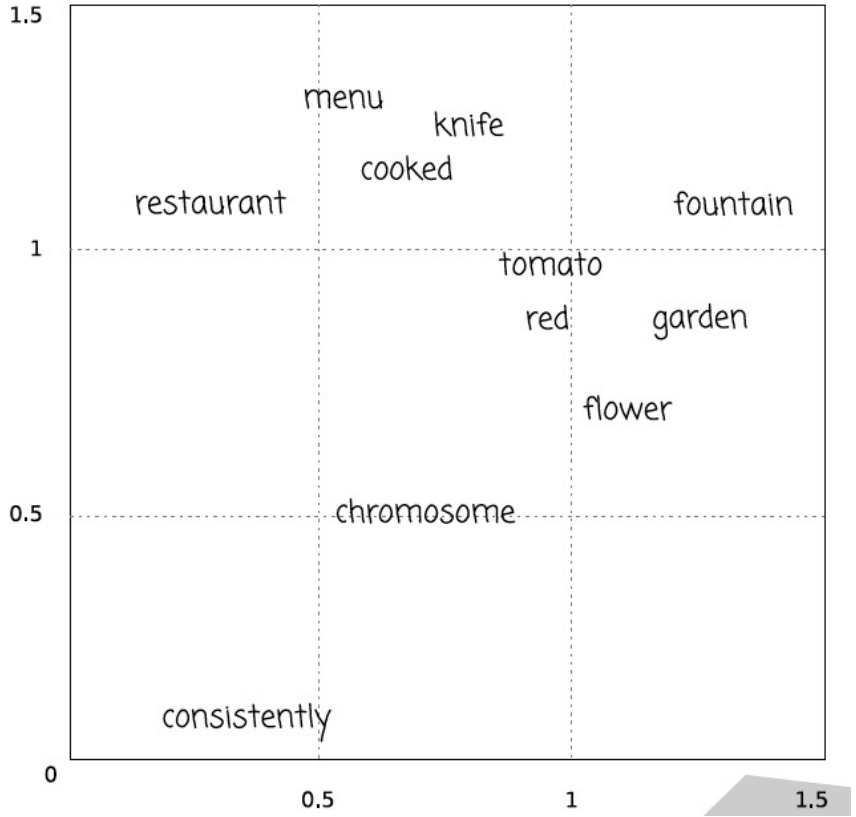
knife
menu
cooked
chromosome
consistently



Bron: Pérez-Ortiz et al 2021

VAN WOORDEN NAAR VECTOREN

Word embeddings



restaurant = [0.25, 1.10]

menu = [0.60, 1.31]

…

Bron: Pérez-Ortiz et al 2021

VAN WOORDEN NAAR VECTOREN

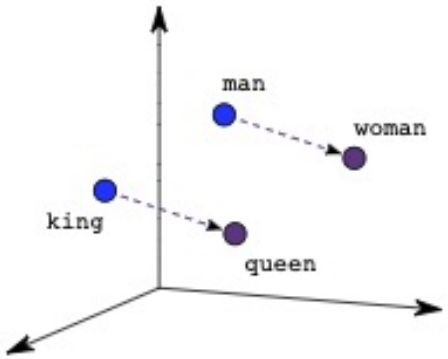
Meer-dimensionele ruimte

poured = [0.25, 1.10, 0.32, …]
rained = [0.27, 1.30, 0.31, …]

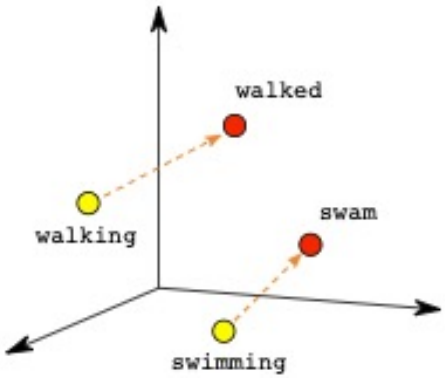
pouring = [0.25, 1.10, 0.12, …]
raining = [0.27, 1.30, 0.11, …]

driving = [1.22, 0.89, 0.11, …]
riding = [1.28, 0.83, 0.12, …]

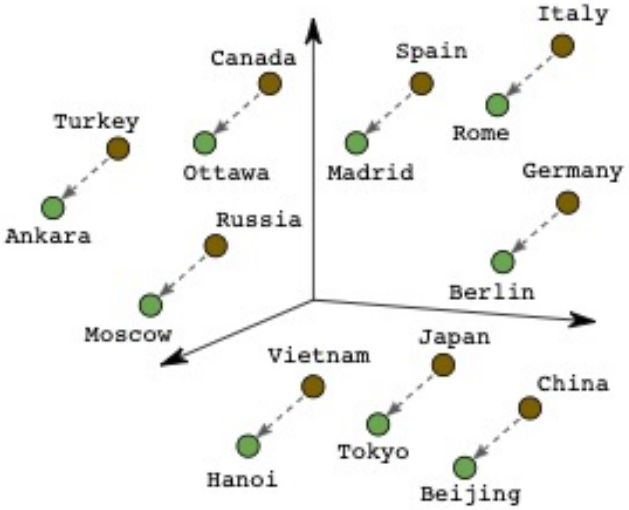
VAN WOORDEN NAAR VECTOREN



Male-Female



Verb Tense



Country-Capital

Bron: https://developers.google.com/machine-learning/crash-course/embeddings/translating-to-a-lower-dimensional-space

VAN WOORDEN NAAR VECTOREN

Word embeddings capteren ‘betekenis’

Firth (1957) “You shall know a word by the company it keeps”

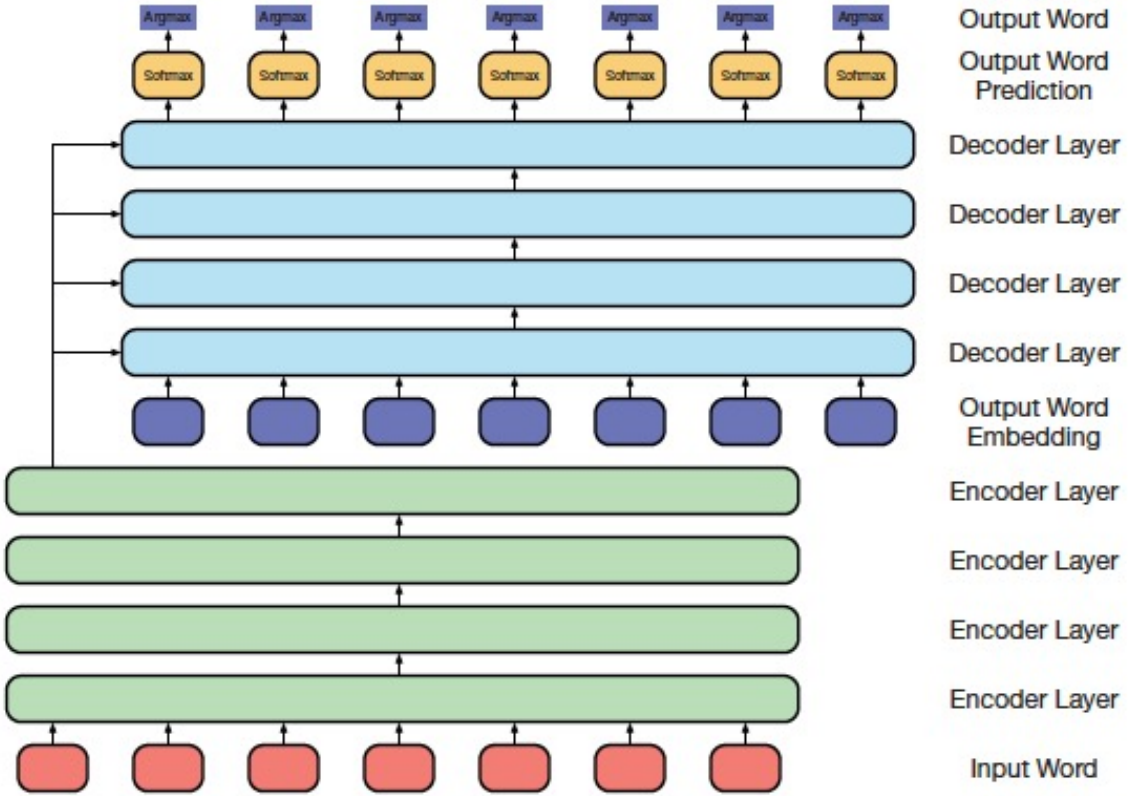
Word embeddings worden gebruikt als invoer in het NMT-systeem

Grootste voordeel → generaliseren

cat ≈ *cats* ≈ *kitten*

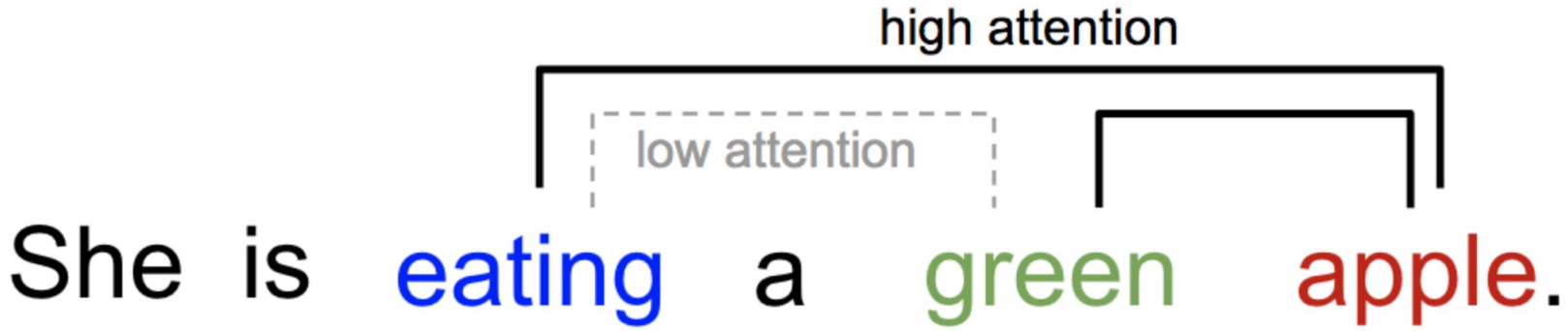
pouring ≈ *raining* ≈ *driving* ≈ *riding*

ENCODER-DECODER ARCHITECTUUR



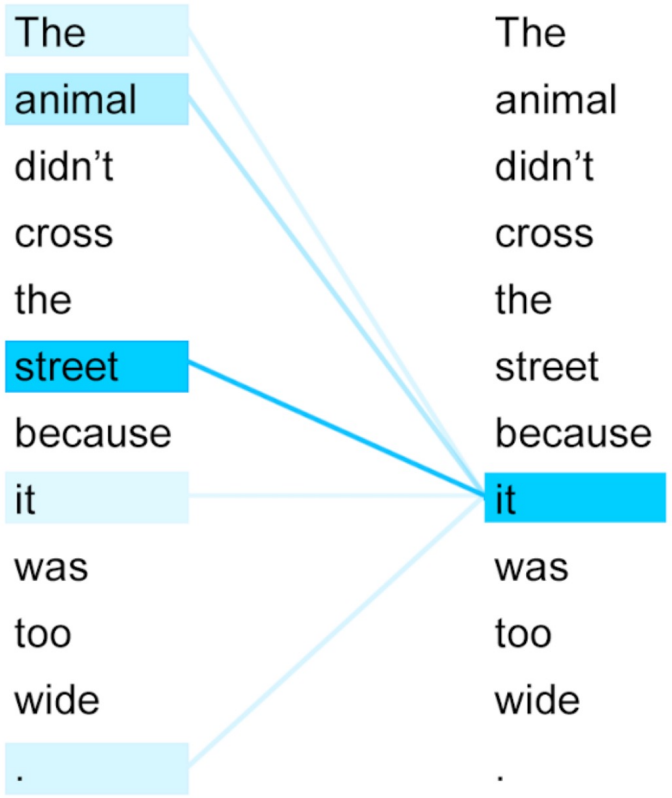
Bron: Koehn 2020

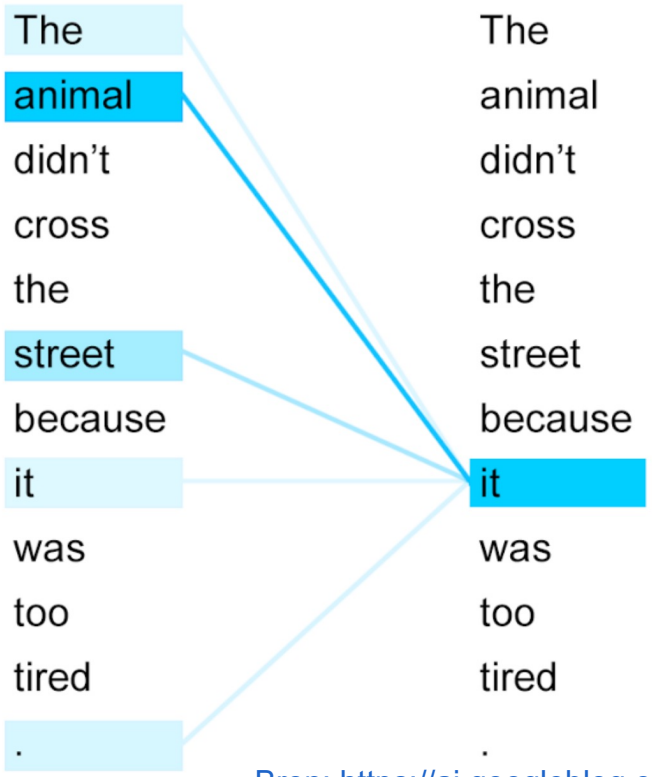
ATTENTION



Bron: https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

ATTENTION





Bron: https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

ATTENTION

The animal didn't cross the street because it was too tired.
L'animal n'a pas traversé la rue parce qu'il était trop fatigué.

The animal didn't cross the street because it was too wide.
L'animal n'a pas traversé la rue parce qu'elle était trop large.

Bron: https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

BELANG VAN DATA

A whopping 99% of our human DNA is the same as that of our closest primate cousins – chimps and bonobos. But while chimps tend to be male-led, bonobos take their lead from females.

eTranslation: trained on EC material; tested on news (2019)
99 % van ons DNA is dezelfde als die van onze nauwste primatencousins — Garnalen en „bonobos”. Hoewel pooiers meestal een man zijn, nemen Bonovbos hun lood af van vrouwelijke dieren.

eTranslation: trained on EC material; tested on news (2021)
Een bijna 99 % van ons menselijk DNA is hetzelfde als dat van onze naaste primaat cousins — borstels en bonobos. Terwijl de chimps over het algemeen mrouwelijk zijn, nemen bonobos hun voorsprong bij vrouwtjes.

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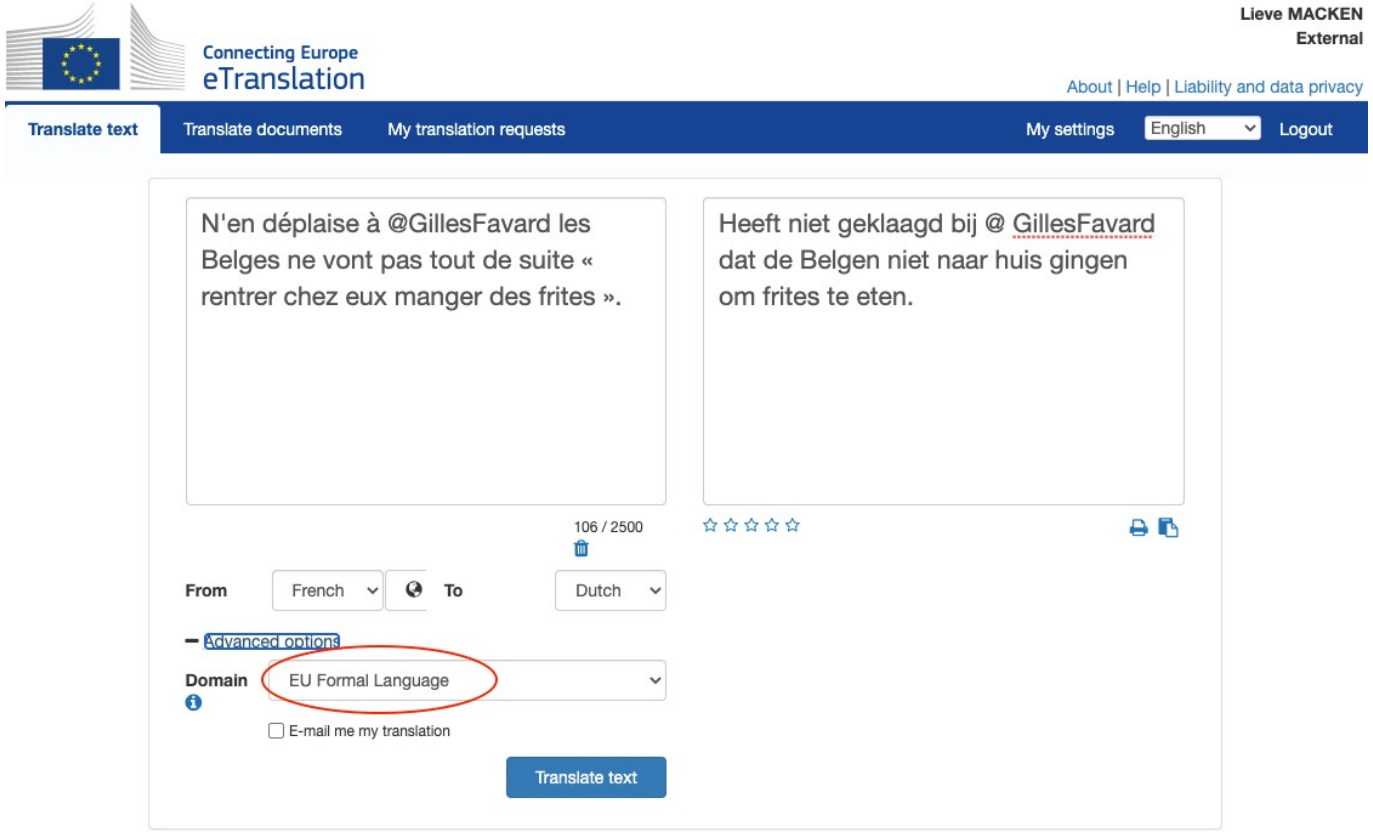
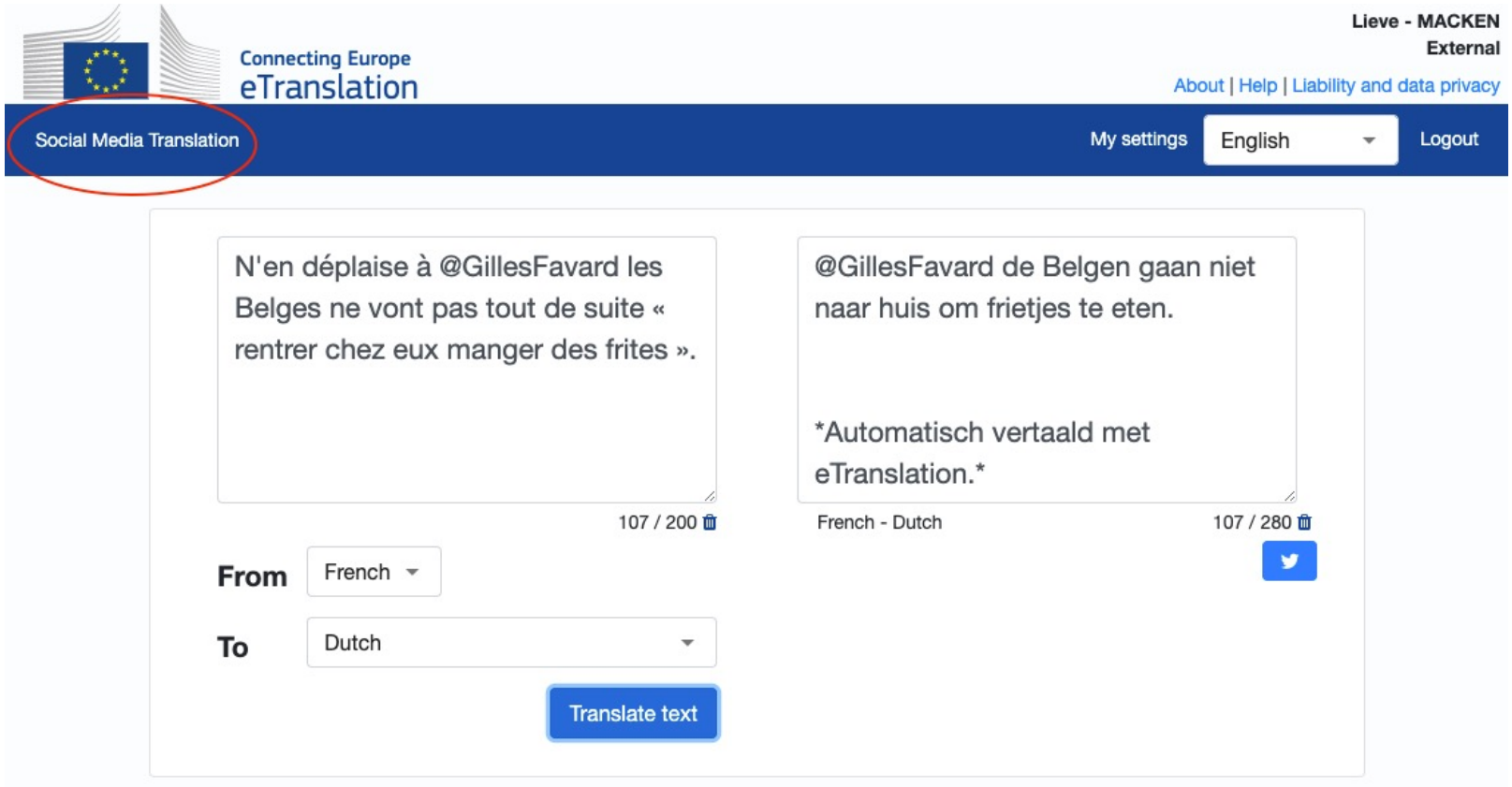
DeepL (2021)
Maar liefst 99% van ons menselijk DNA is hetzelfde als dat van onze naaste primaatneven - chimpansees en bonobo's. Maar terwijl chimpansees door mannen worden geleid, nemen bonobo's de leiding van de vrouwtjes.

BELANG VAN DATA

BELANG VAN DATA



BELANG VAN DATA



HET BELANG VAN DATA

- ~ 7000 talen
- Aantal MT-systemen

  n x (n-1) = 48,993,000 MT-systemen
- Pivot-taal

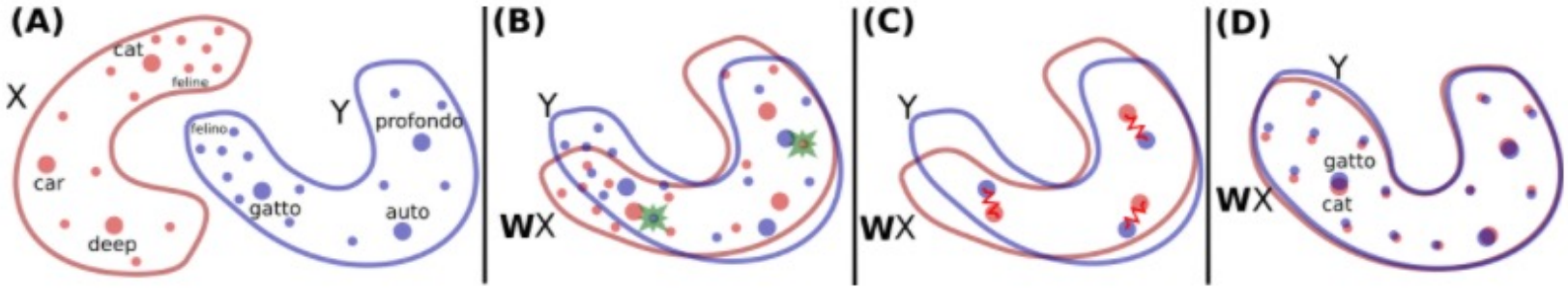
  (n-1) + (n-1) = 13,998 MT-systemen

- Voldoende parallel trainingsmateriaal voor < 100 taalparen

  Wat met de rest?

ONGESUPERVISEERDE MT

Veel meer monolinguale data in bron- en doeltaal beschikbaar dan parallel (vertaald) materiaal



Systeem voor woord-voor-woord-vertalingen

Werkt tot op zekere hoogte, maar kwaliteit daalt indien

- L1 & L2 verschillend scripts
- L1 en L2 data uit verschillende domeinen

MENS VS. MACHINE?

Masterproef Luca Desmet (2021) “An exploratory study of professional post-edits by English-Dutch DGT translators”

- 52% noodzakelijke aanpassingen

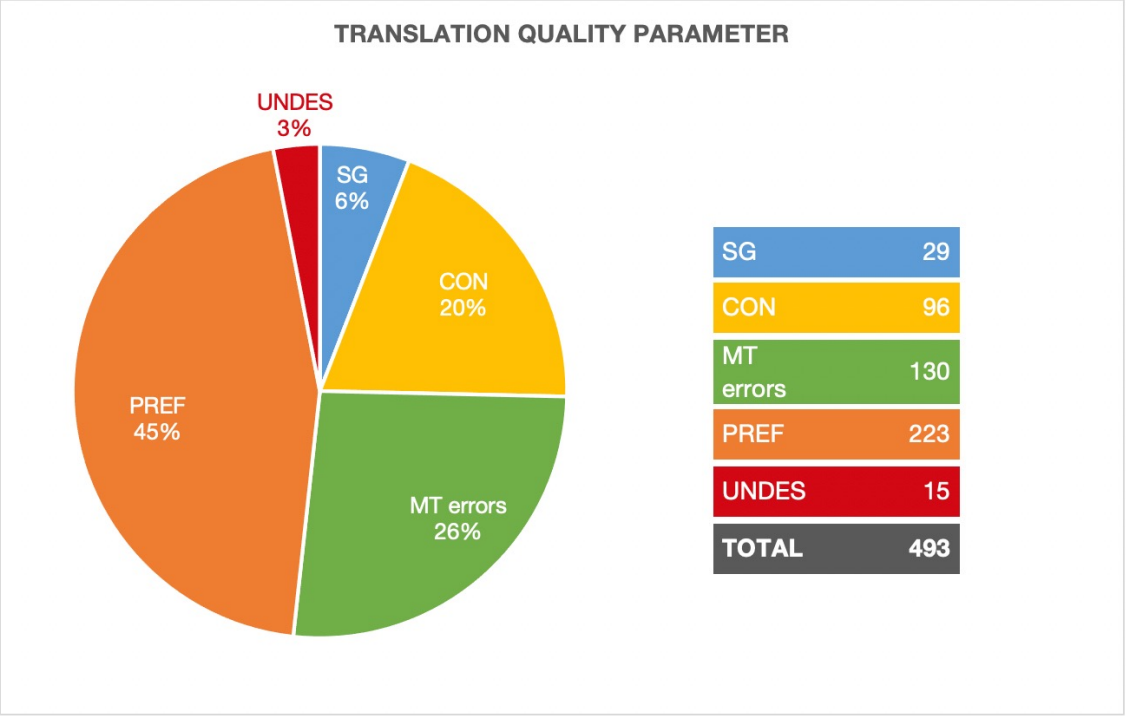
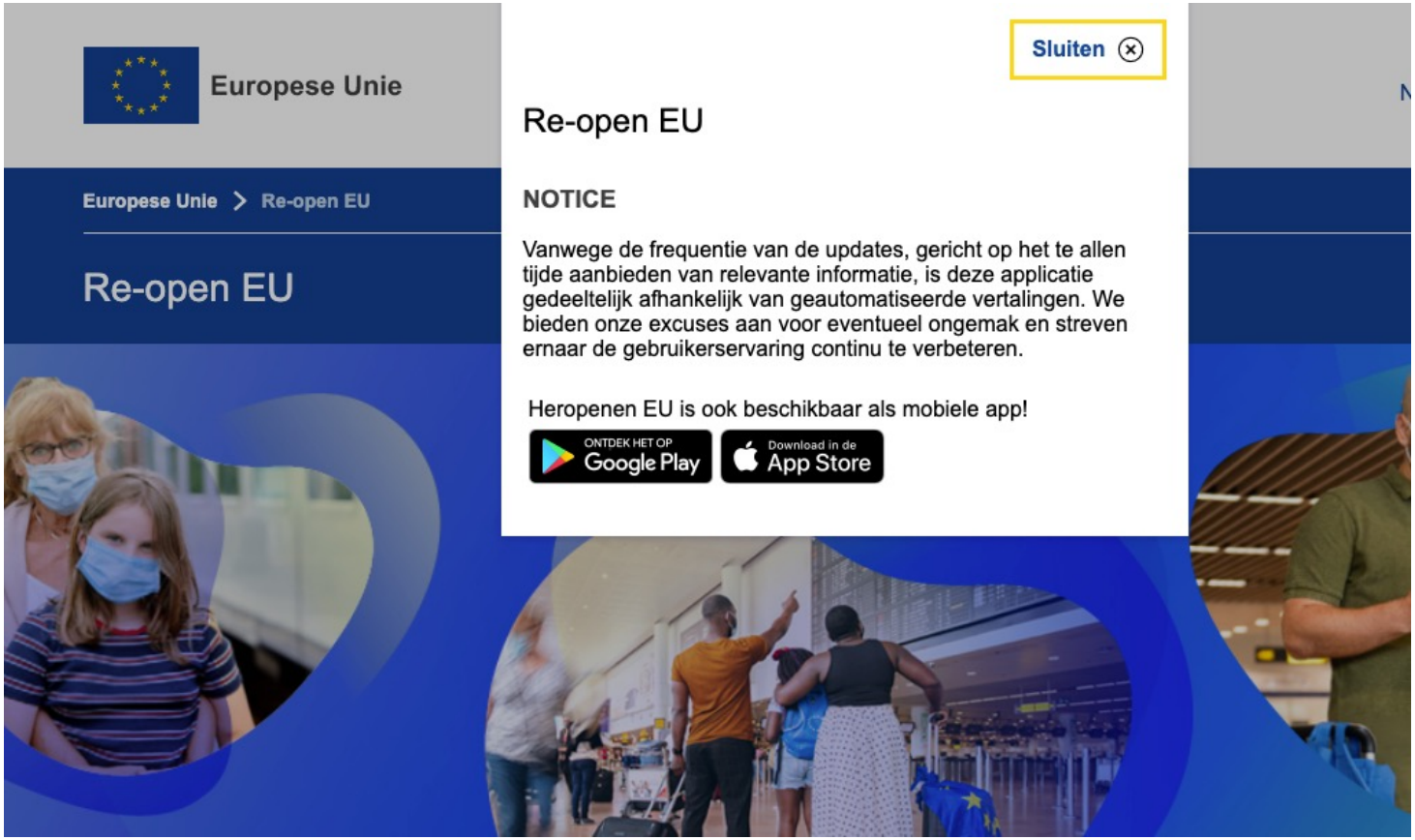


Figure 3. Distribution of the Translation Quality Parameter categories

MENS VS. MACHINE?



MENS VS. MACHINE?

Are human translations always better than Machine Translations?

While generally raw machine translation is not as good as human translation, there are a number of cases where machine translation can actually be better than human translators.

In the LexisNexis Univentio case study, 13 million patents were translated from Japanese to English. Machine translated patents resulted in a 20% increase in meaningful search results when compared to human translations of patents. Machines translation delivered a significant and meaningful amount of added value.

Had the LexisNexis Univentio project been translated by human translators it would have taken 152,257 person years of effort and cost in excess of US$ 40 billion. This project would have never been attempted due to time and cost requirements beyond thousands of times beyond the business value that such a task would deliver. With Language Studio™ this task was successfully

REFERENTIES

- Juan Antonio Pérez-Ortiz, Mikel L. Forcada and Felipe Sánchez-Martínez, “How neural machine translation works”, 2021. Preprint version of book chapter (https://multitrainmt.eu project)

- Koehn, P. (2020). Neural Machine Translation. Cambridge: Cambridge University Press.

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