

Neural Machine Translation, Large Language Models and Literary Translation: The Story So Far

Dorothy Kenny

Dublin City University

Damien Hansen

University of Liège - Univ. Grenoble Alpes



ITIA Seminar

Neural Machine Translation, Large Language Models and Literary Translation: The Story So Far
Trinity Centre for Literary and Cultural Translation – 08 May 2023

neural networks and neural machine translation

hype and anthropomorphism



MACHINE TRANSLATION

Machines That Think: The Rise of Neural Machine Translation

September 23, 2022

“ [Facebook’s NLP team] believe neural networks can learn “the underlying semantic meaning of the language,” so what is produced are translations “that sound more like they came from a person.”

<https://slator.com/technology/facebook-says-statistical-machine-translation-has-reached-end-of-life/> by [Marion Marking](#) on June 6, 2016

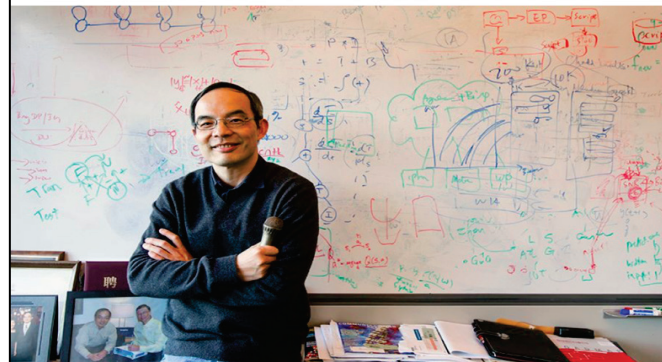
“Unlike technologies developed over the past 60 years, the well-trained and tested NMT systems that are available today, have the potential to replace human translators.”

Ofer Shoshan, CEO of One Hour Translation, the world's largest online translation agency

April 19, 2018 slator.com

Microsoft reaches a historic milestone, using AI to match human performance in translating news from Chinese to English

March 14, 2018 | [Allison Linn](#)



déjà vu?

“ I’ve been shaken by the realisation that digital intelligence is probably much better than biological intelligence

Geoffrey Hinton, in *The Guardian*, May 05, 2023

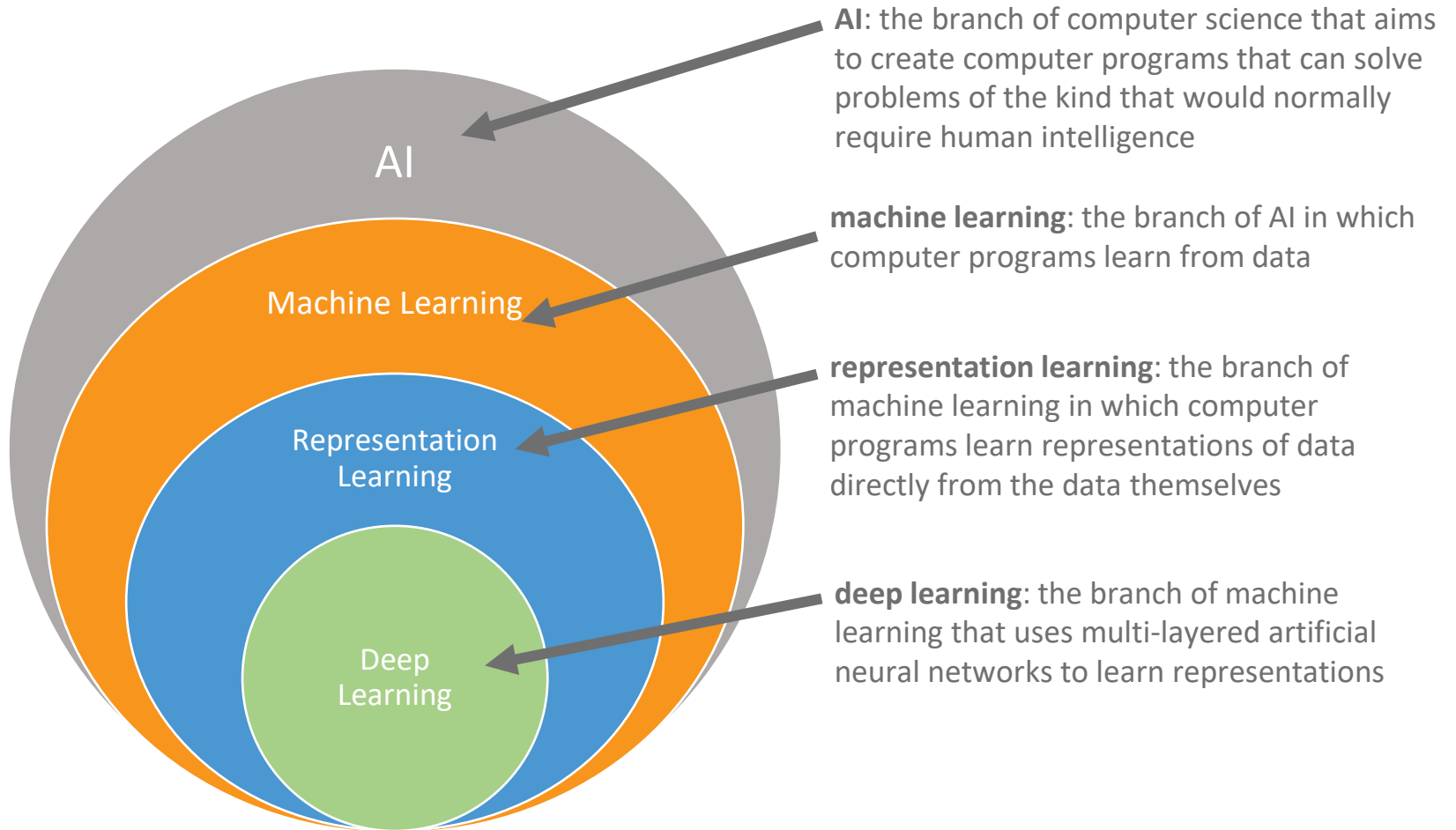
Group	Occupations with highest exposure	% Exposure
Human α	Interpreters and Translators	76.5
	Survey Researchers	75.0
	Poets, Lyricists and Creative Writers	68.8
	Animal Scientists	66.7
	Public Relations Specialists	66.7

Eloundou et al. April 2023. “GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models”.

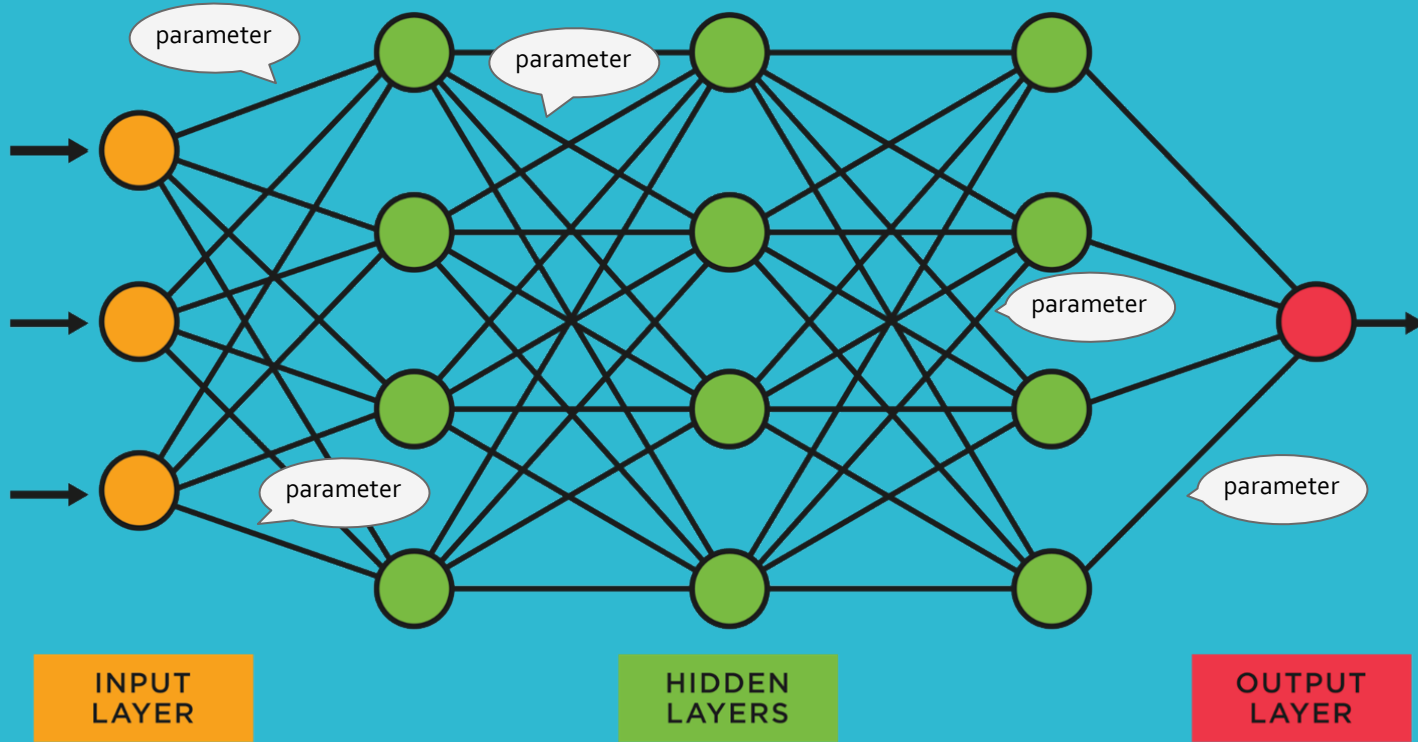
Elon Musk joins call for pause in creation of giant AI ‘digital minds’

The Guardian, March 29, 2023

an anti-hype introduction to NMT and LLMs



Neural networks



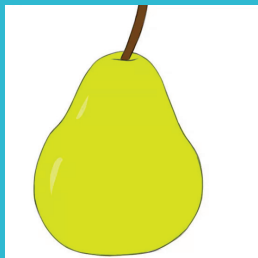
So what kind of representations are learned in NMT and LLMs?

Representing words as vectors



apple

[1.20, 2.80, 6.10]



pear

[1.20, 2.80, 5.50]

- vector-based representations of words are called **word embeddings**
- embeddings for related words look similar to each other as they are built up on the basis of where particular words are found in **training data**
- if two words tend to appear together or in the same or similar co-texts – both *apple* and *pear* occur very regularly before the word *tree* for example; both appear regularly after *peel*, *slice* and *dice* – then they will end up with similar embeddings

combine with **sliced apples** . Put half of the ap
r comes with **sliced apples** , walnuts, cranberr
ed confit with **sliced apples** and fold the edge c
nd cover with **sliced apples** or any other fruit, t
.. Cover with **sliced apples** or peaches. Top wi
.. Cover with **sliced apples** . Combine the sug
h. Cover with **sliced apples** . Sprinkle apples w
h. Cover with **sliced apples** , chopped dates, s
covered with **sliced apples** , topped with a rou
covered with **sliced apples** were spread on cru
creative with sliced **apples** , pears or strawber
decorated with **sliced apples** . The tart is so tast
delicious with **sliced apples** , or added by the d
t dipped with **sliced apples** , pears or salty whe
ing dish with **sliced apples** , and pour over the
ing dish with **sliced apples** and pour over the t
ing dish with **sliced apples** and pour over the t
(), eaten with **sliced apples** or pears. Or you co
ed eggs with **sliced apples** and french toast. T
excellent with **sliced apples** , plums or even pe

] 6. Garnish with **sliced pears** and chives. 7. S
w walnuts is with **sliced pears** and goat milk go
uce, red leaf with **sliced pears** , brown-sugared
or raisins, or with **sliced pears** , oranges, necta
Green salad with **sliced pears** and rum-raisins
heese salad with **sliced pears** or spicy seafood
ed in salads with **sliced pears** , shallots and ba
mooth Serve with **sliced pears** in endive boats
els 2. Serve with **sliced pears** and seasonal ho
salad served with **sliced pears** , bleu cheese cr
oliday spread with **sliced pears** , red onion, and
ntly. Sprinkle with **sliced pears** , walnuts and po
bowl and top with **sliced pears** . Garnish with ci
n bread; top with **sliced pears** ; toast for about
all gone. Top with **sliced pears** . Pour remaining
pieces. Top with **sliced pears** , bits of goat che
Step 2: Top with **sliced pears** , toasted walnut
time topped with **sliced pears** instead of cranb
and topped with **sliced pears** poached in the c
s dressed up with **sliced pears** , candied pecan

apple and *pear* appear in the same
or similar environments

(ententen20 corpus viewed through Sketch Engine)

production of **apples** and **pears** is d
ombination of **apples** and **pears** with
onsumption of **apples** and **pears** and
ermentation of **apples** and **pears** by t
sh varieties of **apples** and **pears** are
. Marketing of **apples** and **pears** in N
le producer of **apples** and **pears** wou
y be grown of **apples** and **pears** . Th
er varieties of **apples** and **pears** and
for 9 dishes of **apples** and **pears** . Th
size chunks of **apples** and **pears** , or
ave flavors of **apples** and **pears** . As
arly harvest of **apples** and **pears** . He
ity varieties of **apples** and **pears** , as
utter on top of **apples** and **pears** whe
their intake of **apples** and **pears** red

In NMT an **encoder** takes a natural language sequence (e.g. a sentence) as input and converts it into word embeddings.

7-dimensional embeddings for the sentence:

"Ireland is a beautiful country."

```
[ [0.12, 0.63, -0.45, 0.81, -0.23, 0.17, -0.54],  
  [0.76, -0.32, 0.09, 0.51, 0.71, 0.25, 0.11],  
  [0.11, 0.87, 0.42, -0.76, -0.33, 0.68, -0.19],  
  [0.41, -0.12, -0.61, 0.08, 0.91, 0.76, -0.25],  
  [-0.3, 0.18, -0.19, -0.54, -0.13, 0.87, -0.29] ]
```

Completely arbitrary and made up by my friend ChatGPT.

More realistic embeddings would contain hundreds of dimensions (see Pérez-Ortiz et al. 2022).

In NMT an **decoder** takes a series of word embeddings and converts them into a natural language sequence (e.g. a sentence).

The decoder combines the output from the last layer of the encoder with knowledge of the probabilities of target-language words to predict each successive word in the output.

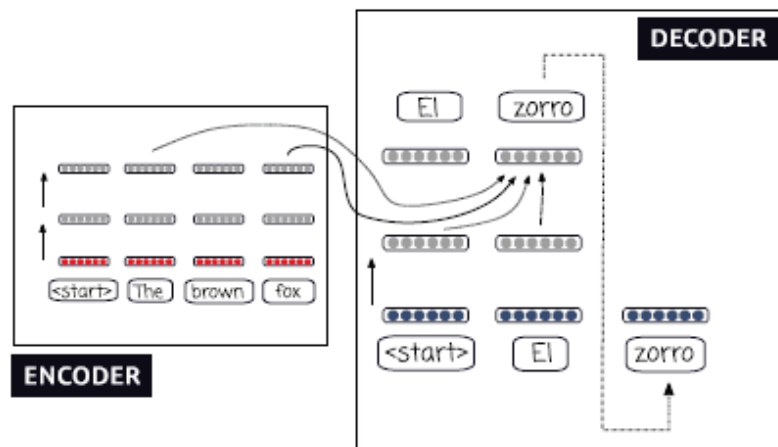


Figure 6: A complete transformer-based neural machine translation system translating a sentence. An enlarged version of the encoder can be seen in Figure 5. Note how the prediction of *zorro* is obtained by paying attention to the embeddings of the previous target words but also to the embeddings corresponding to some of the input words coming from the last layer of the encoder.

encoder + decoder + attention
=
transformer architecture

Machine translation for everyone

Empowering users in the age of
artificial intelligence

Edited by

Dorothy Kenny

Translation and Multilingual Natural
Language Processing 18



1 Europe, multilingualism and machine translation	1
Olga Torres-Hostench	
2 Human and machine translation	23
Dorothy Kenny	
3 How to choose a suitable neural machine translation solution: Evaluation of MT quality	51
Caroline Rossi & Alice Carré	
4 Selecting and preparing texts for machine translation: Pre-editing and writing for a global audience	81
Pilar Sánchez-Gijón & Dorothy Kenny	
5 How to deal with errors in machine translation: Post-editing	105
Sharon O'Brien	
6 Ethics and machine translation	121
Joss Moorkens	
7 How neural machine translation works	141
Juan Antonio Pérez-Ortiz, Mikel L. Forcada & Felipe Sánchez-Martínez	
8 Custom machine translation	165
Gema Ramírez-Sánchez	
9 Machine translation for language learners	187
Alice Carré, Dorothy Kenny, Caroline Rossi, Pilar Sánchez-Gijón & Olga Torres-Hostench	

Download it for free from:

<https://langsci-press.org/catalog/book/342>

NMT and literary translation

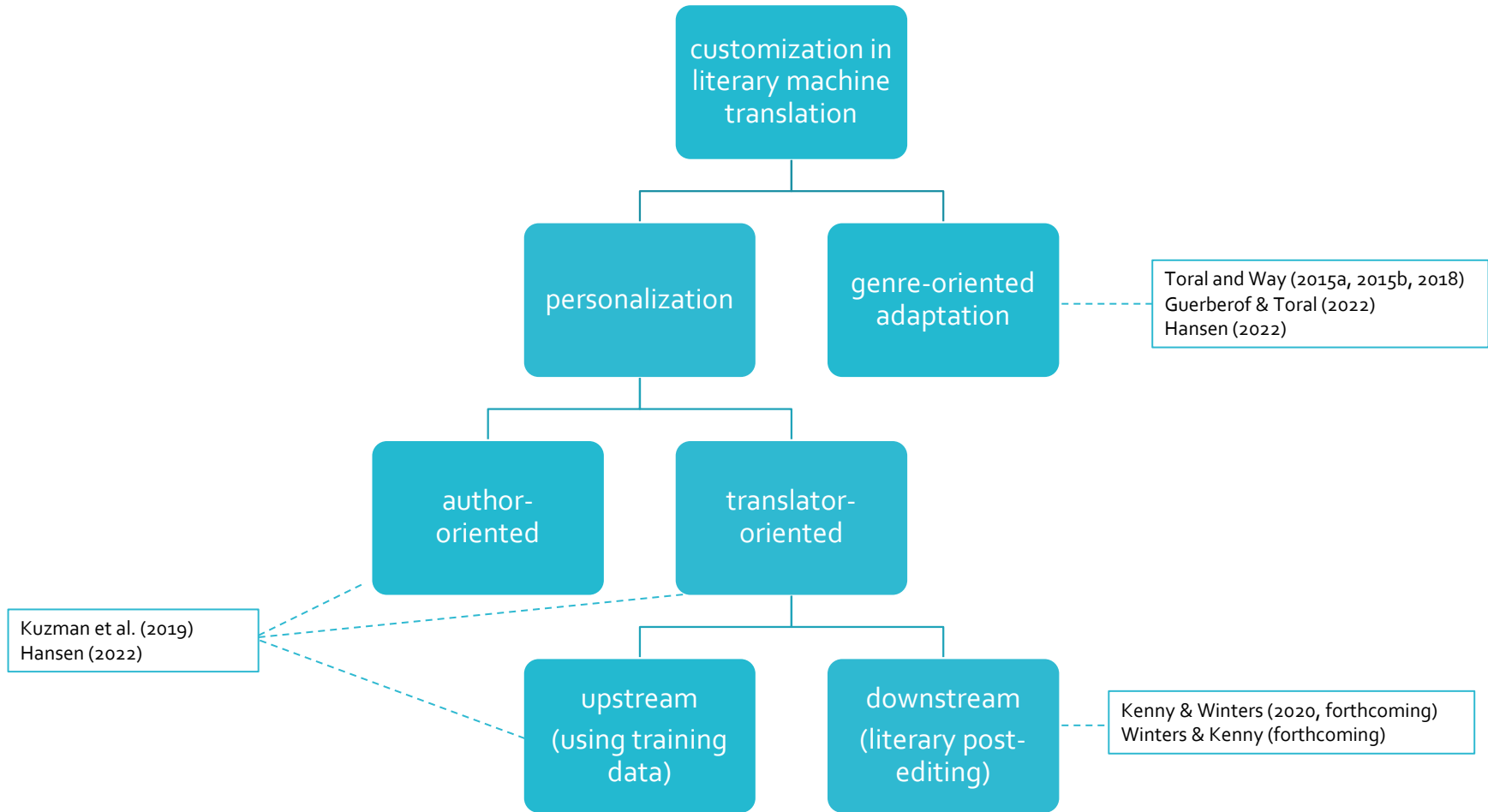
We understand 'literary machine translation' as an emerging interdisciplinary field that embraces a range of phenomena related to the application of MT to the translation of literary texts. It touches upon or intersects with, among other areas:

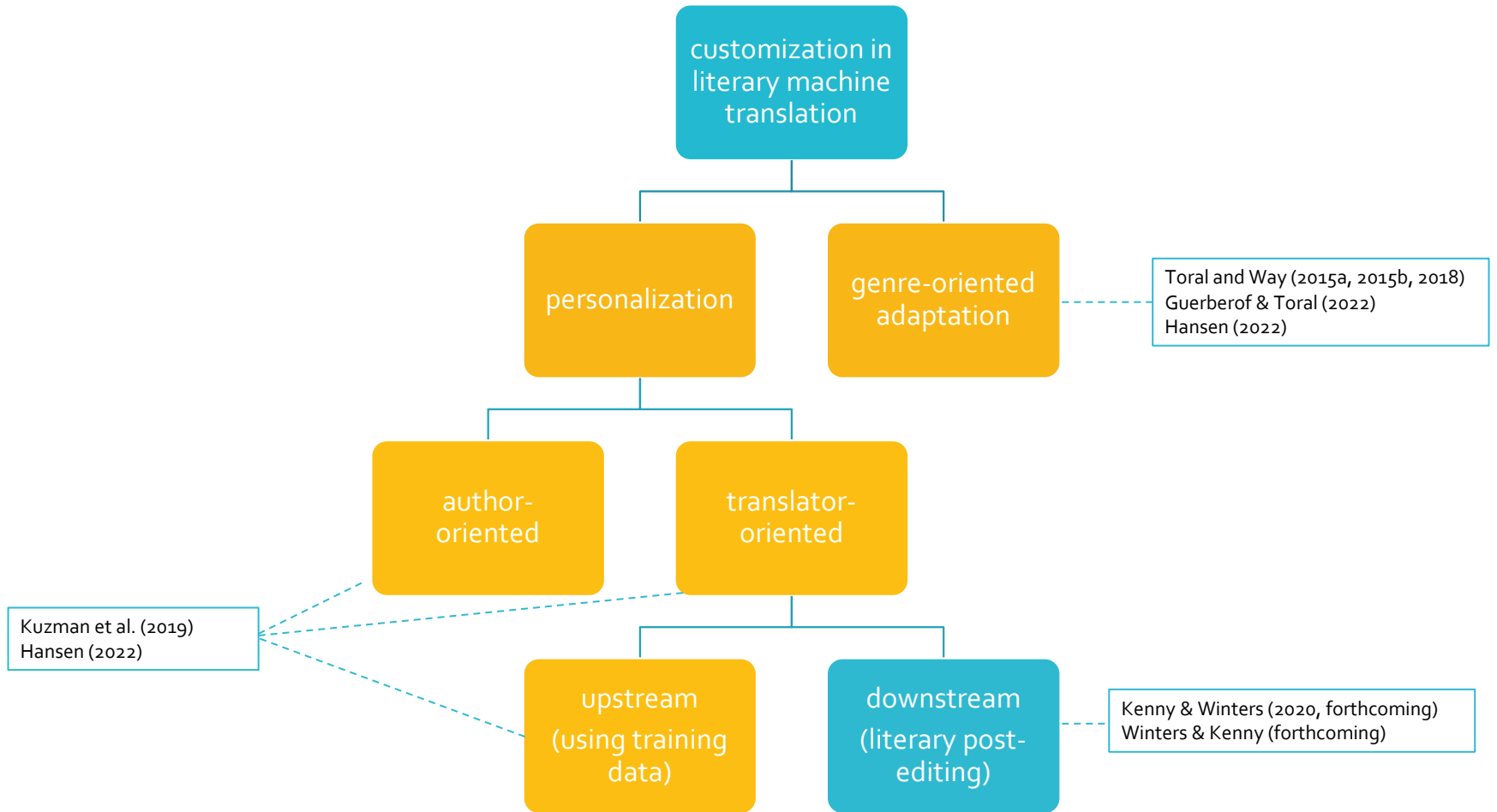
- speculative and empirical enquiry into the features that make literary texts particularly amenable to or (more often) difficult for MT
- computational techniques that might meet the attendant challenges the application of generic MT to literary texts
- the customization of MT systems for use with literary texts
- the systematic evaluation of literary texts translated by MT
- literary translators' interactions with MT
- reaction to the use of MT in the literary translation profession
- readers' reception of machine translated literature
- style in human, raw and post-edited literary MT
- studies of so-called 'universals' in post-edited literary texts

Kenny and Winters (forthcoming)

We understand 'literary machine translation' as an emerging interdisciplinary field that embraces a range of phenomena related to the application of MT to the translation of literary texts. It touches upon or intersects with, among other areas:

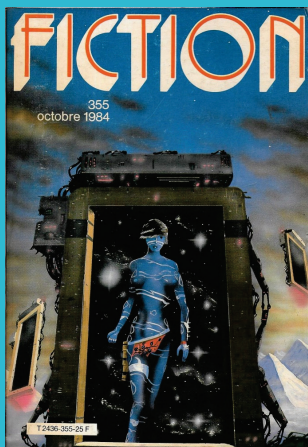
- speculative and empirical enquiry into the features that make literary texts particularly amenable to or (more often) difficult for MT
- computational techniques that might meet the attendant challenges the application of generic MT to literary texts
- the customization of MT systems for use with literary texts
- the systematic evaluation of literary texts translated by MT
- literary translators' interactions with MT
- reaction to the use of MT in the literary translation profession
- readers' reception of machine translated literature
- style in human, raw and post-edited literary MT
- studies of so-called 'universals' in post-edited literary texts



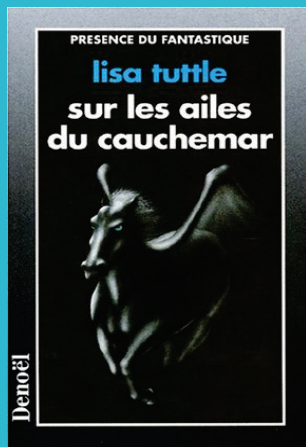




Nathalie Serval



(1953-1990)



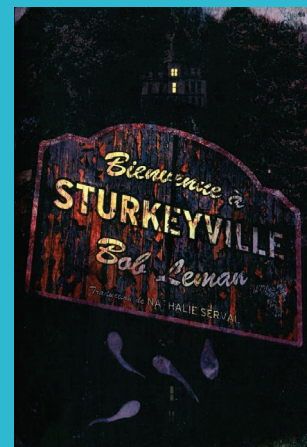
(Denoël)



(Gallimard)



(Albin Michel)



(Scylla)



Books



Europarl



News



GlobalVoices



Video Game



TED



1010
1010

Generic
training



1010
1010

Domain
adaptation



Results

The adapted system performs twice as well as generic and public MT systems (Google, DeepL), but the metrics used for the evaluation remain quite low.

Evaluating textual features:

- more lexical diversity;
- heavier syntactic reorganization;
- but far from being on par with human translation.

Error annotation:

- few errors that are attributable to the literary nature of the text;
- many issues regarding meaning and adequacy;
- translations are still too literal.

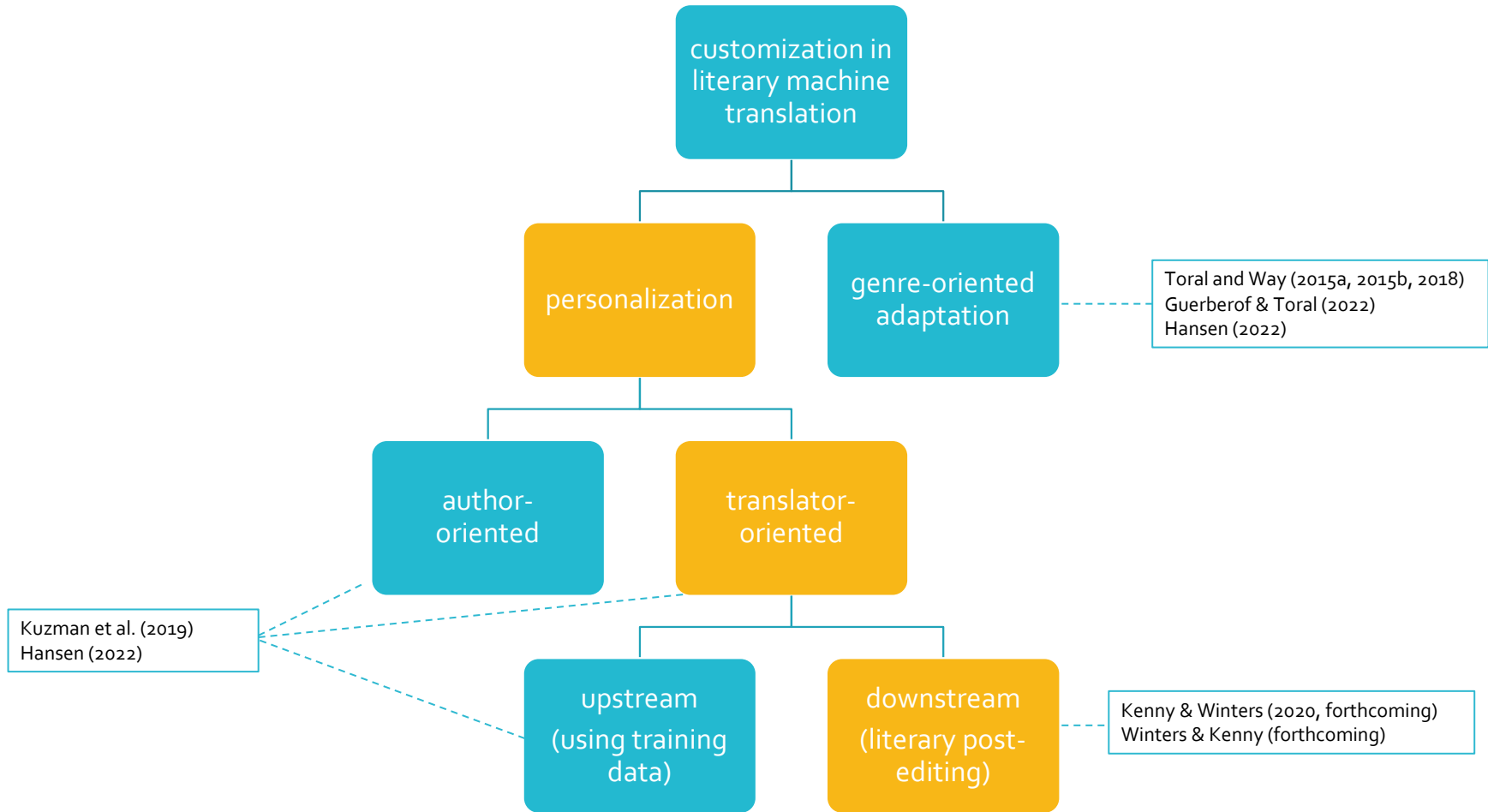
Observations

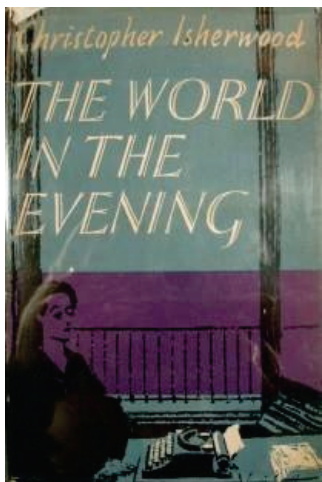
Signs of adaptation:

- lexical choices and register more in line with the translator;
- use of similar periphrases and synonyms;
- modulation, transposition, contractions;
- merging and splitting sentences where the translator also did so;
- even omissions.

Use by the translator herself:

- suggestions, if *very* literal, are actually useful and could be used to spark new ideas;
- but the traditional PE process is too time-consuming and the interface too restrictive;
- we need another alternative (integration in a word processor, compare ≠ solutions ?).





Hans Christian Oeser
Photo: Barbara Schaper-Oeser



Second of a series of studies with Hans-Christian Oeser (HCO)

Tracks HCO's use of NMT+ Post Editing (DeepL) to translate all 342 pages of Christopher Isherwood's (1954) *The World in the Evening*.

Renowned translator, whose style is already well studied. Real brief.

RQ: Is HCO's style discernible in his post-edited translation?

SPECIAL FEATURE: MACHINE TRANSLATION AND LITERATURE

Duel with DeepL

Literary translator *Hans-Christian Oeser* on machine translation and the translator's voice

"Postediting", in fact, entails painstaking retranslation. Hence, in the case of Christopher Isherwood's novel there was hardly a sentence that did not have to be thoroughly revised and rebuilt."

HCO 2020

(Positive) Keywords

occur with greater than expected frequency in a focus corpus compared to a comparison corpus

- We use WordSmith Tools 8.0
- Candidates have to pass selected statistical tests to be treated as keywords
- We use log likelihood in conjunction with BIC to rank keywords, following Jeaco (2020)
- Selected settings:
 - maximum wanted=500
 - minimum frequency=3
 - minimum BIC score=2.5
 - minimum log ratio=0
 - p value=0.1. The p value is set high as it can effectively be ignored if BIC values are used. (Scott 2022)
- Parallel corpus (MT output + HCO's PE version) consulted in filtering keyword list and grouping keywords

DeepL MT

Oeser PE

Oeser 12

Original German Lit.

Die Welt am Abend	tokens	types	ttr	sttr
Oeser PE	103,511	12,210	11.80	47.55
DeepL MT	104,892	10,603	10.11	45.84

Table 1: Basic statistics for *Oeser PE* (focus text) and *DeepL MT* (comparison text)

docs	tokens	types	ttr	sttr
12	699,315	52,427	7.50	50.47

Table 2: Oeser 12
(reference corpus of 12 translations completed by Oeser)

docs	tokens
57	3,596,676

Table 3: Original German Literature
(reference corpus of 57 contemporaneous works originally written in German)

N	Key word	Freq. in Oeser PE	% in Oeser PE	Freq. in DeepL MT	% in DeepL MT	BIC	Log_L
1	ACH	144	0.14	0	0.00	189.20	201.45
2	DOCH	275	0.27	62	0.06	135.88	148.13
3	GAR	81	0.08	4	0.00	74.30	86.55
4	S	70	0.07	4	0.00	60.05	72.30
5	SIE	2,370	2.29	1,875	1.79	52.01	64.26
6	ELIZABETHS	49	0.05	2	0.00	42.17	54.42
7	VERMUTLICH	36	0.03	0	0.00	38.11	50.36
8	BESTIMMT	31	0.03	0	0.00	31.12	43.37
9	SCHON	183	0.18	83	0.08	27.56	39.80
10	FALLS	37	0.04	2	0.00	26.48	38.73
11	EBEN	33	0.03	1	0.00	26.27	38.52
12	ELIZABETH	372	0.36	226	0.22	25.62	37.87
13	FURCHTBAR	36	0.03	3	0.00	21.08	33.33
14	GEWISS	20	0.02	0	0.00	15.73	27.98
15	WESHALB	19	0.02	0	0.00	14.33	26.58
16	HAB	24	0.02	1	0.00	14.30	26.55
17	O	30	0.03	3	0.00	13.74	25.98
18	MERKTE	18	0.02	0	0.00	12.93	25.18
19	JA	230	0.22	138	0.13	12.17	24.42
20	GERN	17	0.02	0	0.00	11.53	23.78
21	STETS	17	0.02	0	0.00	11.53	23.78
22	JENEM	17	0.02	0	0.00	11.53	23.78
23	SCHWARZENSEE	16	0.02	0	0.00	10.13	22.38

Table 4: Positive keywords in *Oeser PE* compared to *DeepL MT*
unlemmatized, ranked by LL and BIC
min freq=3; min BIC=2.5; min log ratio=0; p=0.1.

keyword in Oeser PE	Oeser PE	per 100,000	DeepL MT	per 100,000	Oeser 12	per 100,000	German Original Literature	per 100,000
vermutlich	36	34.62	0	0.00	127	18.12	269	7.48
bestimmt	31	29.82	0	0.00	118	16.84	654	18.18
gewiss	20	19.24	0	0.00	34	4.85	281	7.81

Table 8: frequency of *vermutlich*, *bestimmt* and *gewiss* in Oeser PE, DeepL MT, Oeser 12 and Original German Literature

stimulus word in DeepL MT	Oeser PE	per 100,000	DeepL MT	per 100,000	Oeser 12	per 100,000	German Original Literature	per 100,000
sicherlich	10	9.62	46	43.82	6	0.86	133	3.70
wahrscheinlich	42	40.39	61	58.11	64	9.13	706	19.63
sicher	106	101.95	168	160.05	197	28.11	1,456	40.48

Table 9: frequency of DeepL 'stimulus' words in Oeser PE, DeepL MT, Oeser 12 and Original German Literature

	freq. Oeser PE	per 100,000	freq. DeepL MT	per 100,000	freq. Oeser 12	per 100,000	freq. Original German Lit.	per 100,000
weshalb	19	18.27	0	0.00	168	23.97	257	7.15

Table 7: frequency of *weshalb* in Oeser PE, Oeser 12 and Original German Literature

[break]

large language models

What are LLMs?

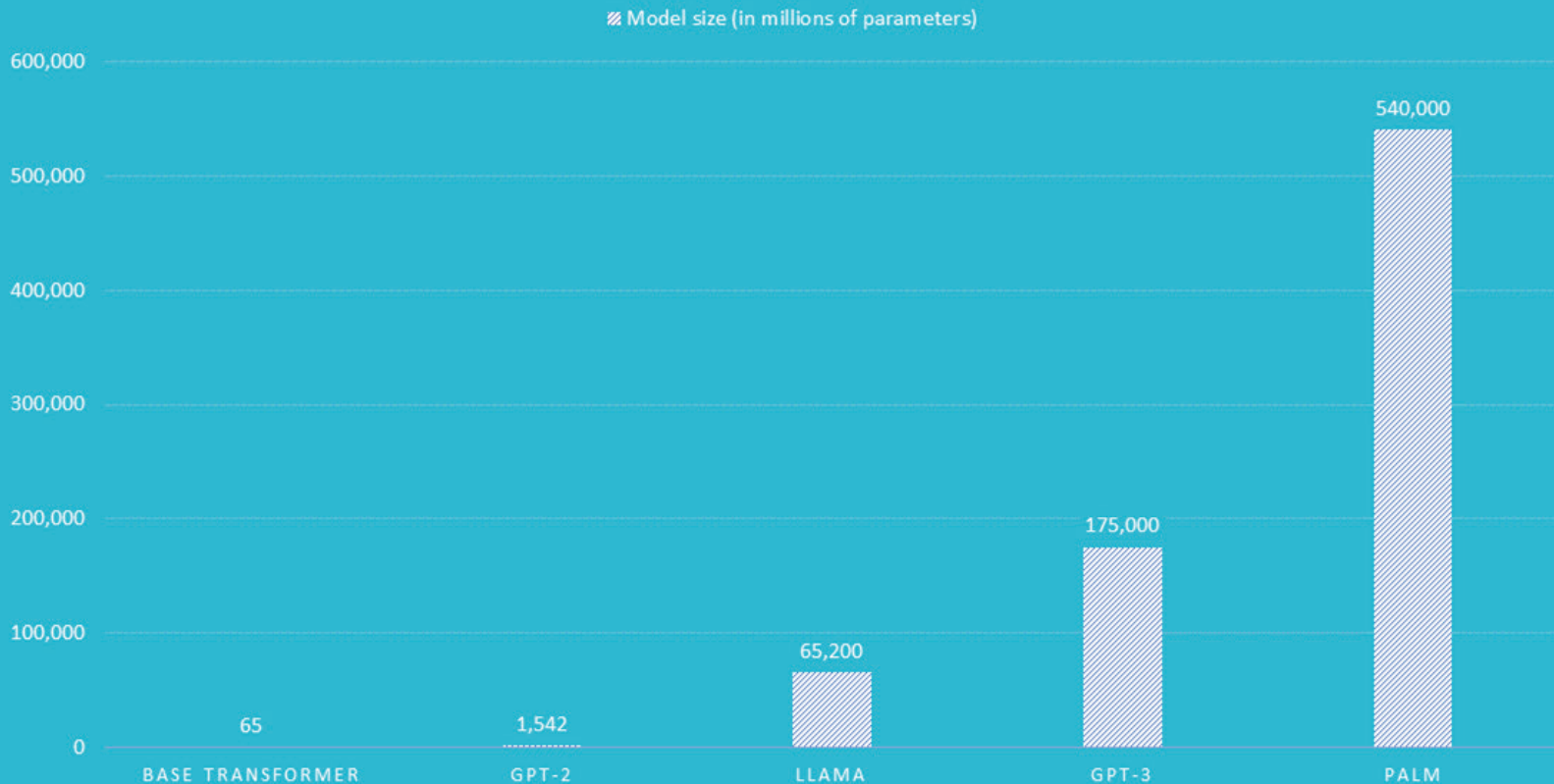
Same architecture.

Same embeddings.

General-purpose system, fully focused on prediction (decoder-only).

Much bigger!

COMPARISON OF LANGUAGE MODELS



What are LLMs?

It's the sheer size of the systems and the data used to train them that make it possible to use the technology across a wide range of tasks.

With such large datasets, there are bound to be samples from other languages, task-specific data, etc.

Problem: not much info about the systems, training and data.

Training data for LLaMA¹

1.4 trillion words ⇨ 1,400,000,000,000.








Data from 20 languages: bg, ca, cs, da, de, en, es, fr, hr, hu, it, nl, pl, pt, ro, ru, sl, sr, sv, uk.

Task-specific datasets? Most likely.

What are the domains covered?

¹: Touvron, Hugo *et al.* (2023). 'LLaMA: Open and Efficient Foundation Language Models'. ArXiv preprint, arXiv: [2302.13971v1](https://arxiv.org/abs/2302.13971v1).

Training data for LLaMA

Domain	Corpus	Proportion
	CommonCrawl	67%
	C4	15%
	Github	4.5%
	Wikipedia	4.5%
	Books	4.5%
	ArXiv	2.5%
	StackExchange	2%

Public & pirated books (and this one is open source, there are other, undocumented 'books' corpora)!
(Henderson *et al.* 2023)

Are they any good for translation?

Use of large language models for translation

Difficulty: very little research as of yet, and the only existing papers are not peer-reviewed.

Early results seem to indicate that tools trained specifically for translation surpass LLMs:¹

“Everyone knows TAUS as the revolutionary techno-optimist, especially when it comes to MT. We were already advocating MT when almost nobody in the translation industry believed that there could be any practical use for it. And yet, this time we are leaning towards the other side.”²

What about literature?

- Uses more contextual information than MT systems (translates entire paragraphs).
- But there is still room for significant improvement.
- Especially when English is not in the mix.
- While there are improvements in certain respects (contextual errors, slight reorganization), some known problems of NMT are also exacerbated (omissions).³

1: Jiao, Wenxiang *et al.* (2023). 'Is ChatGPT A Good Translator? A Preliminary Study'. *ArXiv preprint*, arXiv: 2301.08745v1.

2: Van der Meer, Jaap (2023). 'ChatGPT (Un-)Fit for Translation?'. *TAUS*, url: www.taus.net.

3: Karpinska, Marzena and Mohit Iyyer (2023). 'Large language models effectively leverage document-level context for literary translation, but critical errors persist'. *ArXiv preprint*, ArXiv: 2304.03245v2.

Small (personal) experiments

Performance is lower than generic MT systems if the target language is not English.

(Even worse if the language pair does not include English.)

Time-consuming process involving multiple tries, refining the prompt, comparing outputs.

Not as good as a translation tool, but interesting uses around the process of translation.

- ➡ Use it for what it is: not a dedicated MT system, but a generation tool with which you can interact and ask questions to make decisions yourselves.

Small (personal) experiments

Translations (into French):

- VERY literal translations.
- Unidiomatic collocations.
- A lot calques that MT engines don't produce.
- (Remember that it is mostly trained on English data, the rest is a by-product.)

Other possible helpful uses:

- Asking for the definition of a term.
- Asking for synonyms.
- Asking for examples in context.

Failed attempts:

- Asking for alternative translations, specifically using as many lexical, syntactic and stylistic changes as possible (seems to work in English, clearly not in French).

Could you give me 3 different translations of the following in French, using as many lexical, syntactic and stylistic variety as possible?

The new paradigm of neural machine translation is leading to profound changes in the translation industry. Surprisingly good results have led to high expectations; however, there are substantial risks that have not yet been sufficiently taken into account.

Le nouveau paradigme de la **traduction neuronale automatique** entraîne des changements profonds dans l'industrie de la traduction. Des résultats étonnamment bons ont conduit à des attentes élevées ; cependant, il existe des risques importants qui n'ont pas encore été suffisamment pris en compte.

Le nouveau paradigme de la **traduction automatique neuronale** conduit à des changements profonds dans l'industrie de la traduction. Des résultats étonnamment bons ont conduit à des attentes élevées ; cependant, il existe des risques substantiels qui n'ont pas encore été suffisamment pris en compte.

Le nouveau paradigme de la **traduction neuronale automatique** entraîne des changements profonds dans l'industrie de la traduction. Les résultats surprenamment bons ont entraîné de grandes attentes ; cependant, il existe des risques considérables qui n'ont pas encore été suffisamment pris en compte.

Could you translate the following into English?

J'ai sauté sur mes pieds comme si j'avais été frappé par la foudre. J'ai bien frotté mes yeux. J'ai bien regardé. Et j'ai vu un petit bonhomme tout à fait extraordinaire qui me considérait gravement. Voilà le meilleur portrait que, plus tard, j'ai réussi à faire de lui. Mais mon dessin, bien sûr, est beaucoup moins ravissant que le modèle. Ce n'est pas ma faute. J'avais été découragé dans ma carrière de peintre par les grandes personnes, à l'âge de six ans, et je n'avais rien appris à dessiner, sauf les boas fermés et les boas ouverts.

I jumped to my feet as if struck by lightning. I rubbed my eyes well. I looked hard, and I saw a little extraordinary fellow who was looking at me seriously. That is the best portrait I managed to make of him later on. But of course, my drawing is much less charming than the model. It's not my fault. At the age of six, I had been discouraged in my painting career by the grown-ups, and I had learned to draw nothing except closed and open boa constrictors.

Could you rephrase the segment above in the style of the King James Bible?

I jumped to my feet as if struck by lightning. I rubbed my eyes well. I looked hard, and I saw a little extraordinary fellow who was looking at me seriously. That is the best portrait I managed to make of him later on. But of course, my drawing is much less charming than the model. It's not my fault. At the age of six, I had been discouraged in my painting career by the grown-ups, and I had learned to draw nothing except closed and open boa constrictors.

Verily, I leaped upon my feet as if I had been smitten by a thunderbolt. With all diligence, I rubbed mine eyes and gazed steadfastly upon a wondrous little man, who regarded me with solemn countenance. Behold, this is the fairest likeness that I was afterward able to fashion of him. Yet, my depiction, alas, doth not match the comeliness of the original. It is not my doing, for in my sixth year of life, I was disheartened from pursuing the craft of painting by those of greater age, and was taught nought but how to draw serpents, whether they be closed or open.

Could you rephrase the segment above in an atompunk style?

Verily, I leaped upon my feet as if I had been smitten by a thunderbolt. With all diligence, I rubbed mine eyes and gazed steadfastly upon a wondrous little man, who regarded me with solemn countenance. Behold, this is the fairest likeness that I was afterward able to fashion of him. Yet, my depiction, alas, doth not match the comeliness of the original. It is not my doing, for in my sixth year of life, I was disheartened from pursuing the craft of painting by those of greater age, and was taught nought but how to draw serpents, whether they be closed or open.

I jolted to my feet as though struck by a surge of electricity. I rubbed my eyes fiercely and beheld a remarkably peculiar little figure who regarded me with utmost gravity. This here's the best likeness I managed to craft of the being, but it's a far cry from the real deal. Can't say it's my fault, though. I was disillusioned from pursuing my art career by the elders when I was just six cycles old, and the only thing I learned to illustrate were coiled and uncoiled boas.

Could you
rephrase the
segment
above as a
series of
haikus?

I jolted to my feet as though struck by a surge of electricity. I rubbed my eyes fiercely and beheld a remarkably peculiar little figure who regarded me with utmost gravity. This here's the best likeness I managed to craft of the being, but it's a far cry from the real deal. Can't say it's my fault, though. I was disillusioned from pursuing my art career by the elders when I was just six cycles old, and the only thing I learned to illustrate were coiled and uncoiled boas.

Electricity
Jolting me up from my seat
A strange figure looms

Peculiar being
Gazes back with gravity
Eyes rub in wonder

A likeness I craft
Far from the real thing, I fear
Fault lies not with me

At six years of age
Elders stifled art career
Boas, the only draw.

Small (personal) experiments

Useful tips:

- Make prompts as detailed as possible, giving examples if need be (few-shot training).
- You can give it some commands (outputting a specific format, remembering terminology).
- Remember that it takes context and previous prompts/answers into account (supposedly up to 3000 words).
- Be aware that, especially with long texts, there's always a chance for something to change or go missing.

ethics

ATLF survey

476 respondents:

- 17 have received training in PE, 80+% of those without training would not consider it;
- 14% have been asked to post-edit (mostly functional texts), $\frac{2}{3}$ have accepted;
- 55% of those people found the work interesting, 75% did not find it profitable financially;
- presented as PE in only 17% of cases, MT never mentioned in the publication.

With the existing tools and workflow, most people would not consider post-editing again, as they feel it makes the work less profitable and creative. The rest would only consider it under time or financial constraints, depending on the type of text and work conditions.¹

¹: ATLF (2022). 'Traduction automatique et post-édition'. ATLF, url: <https://atlf.org/wp-content/uploads/2023/03/ENQUETE-TRADUCTION-AUTOMATIQUE.pdf>.

Concerns around the use of LMT

Loss of translator's voice.¹

Lesser creativity & engagement from readers.²

Recognition of the author and the translator's work.³

Lower remuneration and recognition of translators' work.⁴

- 1: Kenny, Dorothy, and Marion Winters (2020). 'Machine translation, ethics and the literary translator's voice'. *Translation Spaces*, vol. 9, no. 1, pp. 123–49, doi: [10.1075/ts.00024.ken](https://doi.org/10.1075/ts.00024.ken).
- 2: Guerberof-Arenas, Ana, and Antonio Toral (2020). 'The Impact of Post-Editing and Machine Translation on Creativity and Reading Experience'. *Translation Spaces*, vol. 9, no. 2, pp. 255–82, doi: [10.1075/ts.20035.gue](https://doi.org/10.1075/ts.20035.gue).
- 3: Taivalkoski-Shilov, Kristiina (2019). 'Ethical Issues Regarding Machine(-Assisted) Translation of Literary Texts'. *Perspectives*, vol. 27, no. 5, pp. 689–703, doi: [10.1080/0907676X.2018.1520907](https://doi.org/10.1080/0907676X.2018.1520907).
- 4: ATLF (2022). 'Traduction automatique et post-édition'. *ATLF*, url: <https://atlf.org/wp-content/uploads/2023/03/ENQUETE-TRADUCTION-AUTOMATIQUE.pdf>.

Concerns that apply to both technologies

Transparency (training data, use of the technology by publishers, translation contracts).¹

Omissions (always a risk that some of the information will disappear).²

Hallucinations (made-up or nonsensical content).²

Biases.³

1: ATLAS and ATLF (2023). 'IA et traduction littéraire : les traductrices et traducteurs exigent la transparence'. ATLAS, url: www.atlas-citl.org/wp-content/uploads/2023/03/Tribune-ATLAS-ATLF-3.pdf.

2: Hansen, Damien and Emmanuelle Esperança-Rodier (2023). 'Human-Adapted MT for Literary Texts: Reality or Fantasy?'. *Proceedings of the New Trends in Translation and Technology Conference - NeTTT 2022*, edited by Sheila Castilho et al., pp. 178–90, url: https://nettt-conference.com/2022/wp-content/uploads/2023/03/NeTTT-Final-Proceedings_noISBN.pdf#chapter.20.

3: Vanmassenhove, Eva et al. (2018). 'Getting Gender Right in Neural Machine Translation'. *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, edited by Ellen Riloff et al., ACL, pp. 3003–8, doi: [10.18653/v1/D18-1334](https://doi.org/10.18653/v1/D18-1334).

Concerns that apply to LLMs in particular

Cost (financial & ecological).^{1,2}

Lack of accountability and regulation.²

Generation of toxic content and misinformation.^{1,2}

Unpredictability (different answer each time, performance can vary greatly).

Use of data (copyrighted material, documents containing personal information).²

¹: Touvron, Hugo *et al.* (2023). 'LLaMA: Open and Efficient Foundation Language Models'. ArXiv preprint, arXiv: [2302.13971v1](https://arxiv.org/abs/2302.13971v1).

²: Bender, Emily *et al.* (2021). 'On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜'. *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, ACM, pp. 610–23, doi: [10.1145/3442188.3445922](https://doi.org/10.1145/3442188.3445922).

A particular concern with ownership^{1,2}

Beware: using the free version of these tools gives all of your data away!

Authors have rights over who uses and translates their work.

Translators are authors in their own right and enjoy ownership over their work, even in front of the original author.

(Even data freely available on the Web is implicitly subject to copyright.)

With such heavy regulation (Berne Convention, national regulations on intellectual property), how come these works are used so freely to train machine learning systems?

- 1: Forcada, Mikel (2023). 'Licensing and Usage Rights of Language Data in Machine Translation'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 49–69, doi: [10.1007/978-3-031-14689-3_4](https://doi.org/10.1007/978-3-031-14689-3_4).
- 2: Lacruz Mantecón, Miguel (2023). 'Authorship and Rights Ownership in the Machine Translation Era'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 71–92, doi: [10.1007/978-3-031-14689-3_5](https://doi.org/10.1007/978-3-031-14689-3_5).

A particular concern with ownership^{1,2}

The transformation of the data is such that it becomes near impossible to prove which work has been involved in the training.

In fact, large companies regard the risk as being so minimal that they don't even bother to hide it, as they don't expect anyone to lodge a complaint.

Even then, there is the question of who would hold the rights (and be accountable) for the translation if it involves human and machine?

- Are machines “creative”?
- Is the contribution of the post-editor sufficiently significant to be considered creative?

Possible solution: better protection for translations and compensation for their use in training?

- 1: Forcada, Mikel (2023). 'Licensing and Usage Rights of Language Data in Machine Translation'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 49–69, doi: [10.1007/978-3-031-14689-3_4](https://doi.org/10.1007/978-3-031-14689-3_4).
- 2: Lacruz Mantecón, Miguel (2023). 'Authorship and Rights Ownership in the Machine Translation Era'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 71–92, doi: [10.1007/978-3-031-14689-3_5](https://doi.org/10.1007/978-3-031-14689-3_5).

wrapping up

Key takeaways

There are interesting uses for MT & LLMs in the literary field.

But the existing tools are not really suited to the task or do not perform well enough as of yet.

They are, however, good enough that other people are going to use them or ask translators to do so.

Therefore, it's important to tackle these questions and ensure fair use of these technologies.

And ask for tools that are better adapted to literary translators!

Thank you for your attention!

Merci de votre attention !

Go raibh maith agaibh!

References

- ATLAS and ATLF (2023). 'IA et traduction littéraire : les traductrices et traducteurs exigent la transparence'. ATLAS, url: www.atlas-citl.org/wp-content/uploads/2023/03/Tribune-ATLAS-ATLF-3.pdf.
- ATLF (2022). 'Traduction automatique et post-édition'. ATLF, url: <https://atlf.org/wp-content/uploads/2023/03/ENQUETE-TRADUCTION-AUTOMATIQUE.pdf>.
- Bender, Emily *et al.* (2021). 'On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?'. *FACCT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, ACM, pp. 610–23, doi: [10.1145/3442188.3445922](https://doi.org/10.1145/3442188.3445922).
- Forcada, Mikel (2023). 'Licensing and Usage Rights of Language Data in Machine Translation'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 49–69, doi: [10.1007/978-3-031-14689-3_4](https://doi.org/10.1007/978-3-031-14689-3_4).
- Guerberof-Arenas, Ana, and Antonio Toral (2020). 'The Impact of Post-Editing and Machine Translation on Creativity and Reading Experience'. *Translation Spaces*, vol. 9, no. 2, pp. 255–82, doi: [10.1075/ts.20035.gue](https://doi.org/10.1075/ts.20035.gue).
- Hansen, Damien and Emmanuelle Esperança-Rodier (2023). 'Human-Adapted MT for Literary Texts: Reality or Fantasy?'. *Proceedings of the New Trends in Translation and Technology Conference - NeTTT 2022*, edited by Sheila Castilho *et al.*, pp. 178–90, url: https://nettt-conference.com/2022/wp-content/uploads/2023/03/NeTTT-Final-Proceedings_noISBN.pdf#chapter.20.
- Henderson, Peter *et al.* (2023). 'Foundation Models and Fair Use'. *ArXiv preprint*, arXiv: [2303.15715v1](https://arxiv.org/abs/2303.15715).
- Jiao, Wenxiang *et al.* (2023). 'Is ChatGPT A Good Translator? A Preliminary Study'. *ArXiv preprint*, arXiv: [2301.08745v1](https://arxiv.org/abs/2301.08745).

References

- Karpinska, Marzena and Mohit Iyyer (2023). 'Large language models effectively leverage document-level context for literary translation, but critical errors persist'. *ArXiv preprint*, arXiv: [2304.03245v2](https://arxiv.org/abs/2304.03245v2).
- Kenny, Dorothy, and Marion Winters (2020). 'Machine translation, ethics and the literary translator's voice'. *Translation Spaces*, vol. 9, no. 1, pp. 123–49, doi: [10.1075/ts.00024.ken](https://doi.org/10.1075/ts.00024.ken).
- Lacruz Mantecón, Miguel (2023). 'Authorship and Rights Ownership in the Machine Translation Era'. *Towards Responsible Machine Translation: Ethical and Legal Considerations in Machine Translation*, edited by Helena Moniz and Carla Parra Escartín, Springer, pp. 71–92, doi: [10.1007/978-3-031-14689-3_5](https://doi.org/10.1007/978-3-031-14689-3_5).
- PEReN (2023). 'ChatGPT ou la percée des modèles d'IA conversationnels', *Éclairage sur...*, no. 6, url: www.peren.gouv.fr/actualites/2023-04-06_eclairage_sur_chatgpt.
- Radford, Alec (2019). 'Language Models are Unsupervised Multitask Learners'. *OpenAI Blog*, url: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf.
- Taivalkoski-Shilov, Kristiina (2019). 'Ethical Issues Regarding Machine(-Assisted) Translation of Literary Texts'. *Perspectives*, vol. 27, no. 5, pp. 689–703, doi: [10.1080/0907676X.2018.1520907](https://doi.org/10.1080/0907676X.2018.1520907).
- Touvron, Hugo *et al.* (2023). 'LLaMA: Open and Efficient Foundation Language Models'. *ArXiv preprint*, arXiv: [2302.13971v1](https://arxiv.org/abs/2302.13971v1).
- Van der Meer, Jaap (2023). 'ChatGPT (Un-)Fit for Translation?'. *TAUS*, url: www.taus.net/resources/blog/chatgpt-un-fit-for-translation.
- Vaswani, Ashish *et al.* (2017). 'Attention Is All You Need'. *Proceedings of the 31st International Conference on Neural Information Processing Systems*, edited by Ulrike von Luxburg *et al.*, Curran Associates Inc., pp. 6000–10, url: https://papers.nips.cc/paper_files/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html