


A critical perspective on the use of machine translation



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1. Technological overpromises

- » Amazement about NMT quality:
 - We have never seen a machine outputting fluent language
 - We did not know language could be a raw material (as threads in a weaving loom)
 - No evidence that machines can **create** clothes autonomously (reach singularity)
- » **NMT is not ready to be approved for generalised use**
- » Quality of NMT:
 - Every MT output can contain critical errors and “hallucinations”¹
 - MT output always contains more errors than human translation²
 - Top quality scores: 90%³
 - One in each 10 words may be wrong, 10 in every 100 pages can be deceiving...
 - The scores are not reproducible if the lab conditions change
 - Very high ecological impact
- » **Machine translation should be called “artificial translation”** (not really translation)⁴


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2. Social impact

- » MT is widely used, because it is provided for free but with **no guarantees**
 - Control mechanisms (e.g. reduce bias), manipulate outputs and can be used to **produce bias**⁵
- » **Users take all the responsibility for the risk**
 - Good uses of MT rely on risk management by users⁶
 - Unaware and vulnerable users are not protected⁷
 - Disadvantaged communities will always have lower quality MT⁸
- » Use of MT by **professional translators**
 - They decide to manage the risk
 - They are hired as post-editors
- » Post-editors become the “human-in-the loop”
 - The sole human element: the **only liable link in the chain**

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3. Economic models of value extraction

- » Selling NMT as a technology is not viable
 - Tech companies are becoming translation service providers or data management companies
- » **Value extraction from data**
 - All big corporations are involved in machine translation and natural language processing
 - They extract value from this knowledge produced by creative work
- » **Value extraction from human work**
 - Quality is produced by translators/post-editors, not MT
 - Post-editing is faster and cheaper than translation
 - Translators are not being replaced by technology, their work is losing value (heteromation⁹)
- » Paradoxical business models:
 - Distributed production
 - Centralised data ownership and value extraction

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4. Suggestions for regulation



» Considering that:

- We live in a **multilingual society**, in which understanding should be global
- Only **human translation** gives guarantees of **proper communication flows**
- Language and **translation data are very valuable assets**
- Technology is **an instrument** (as “neutral” as a hammer)
- **Artificial translation or is not a sign of intelligence** or language competence

» Regulation for fair use of AI and MT should:

- Protect **consumers'** rights and liabilities in the face of unknown risks
- Protect **workers'** rights and liabilities in distributed production models
- Defend **society's right of ownership** of its knowledge
- Create **safeguards against manipulation** of the above rights for unchallenged private use
- Protect research that focuses on risks, as this is an **investment on security**

» Two suggestions:

- Create a **“seed bank”** for human language and translation data
- Require a **trackable stamp** for AI/MT text

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Thank you.

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