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Intersemiotic mismatch in memes: a study of machine translation output from English into Portuguese /

Incompatibilidades intersemióticas em memes: um estudo a partir de resultados de tradução automática do inglês para o português

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ABSTRACT
This study presents findings on the use of Google Translator output for multimodal contexts. Development and evaluation of machine translation tend to focus on the linguistic component, while manual exploration of text-image relations in multimodal documents remains scarce. Therefore, this article aims at describing some text-image relationships in memes

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automatically translated from English into Portuguese. The methodology involves the selection and analysis of 100 memes found on Instagram and Facebook pages and their intersemiotic relationships both in English (as a source text) and in Portuguese (as a target text). Among the memes analyzed, 73% resulted in correct translations, 17% had errors with no intersemiotic mismatches, and only 10% showed linguistic deviations that altered text-image relationships for a meme. From these 10% of mismatches, patterns were identified, such as i) misspelled words with additive relations; and ii) unknown words with homospatiality. Finally, the results show that the automatic translation of some memes, whose semantic text-image relations share greater congruence, introduce more mismatches compared to those in which this does not happen.
KEYWORDS: Multimodality; Machine translation; Memes; Intersemiotic mismatches.

RESUMO

O objetivo deste trabalho é apresentar achados recentes acerca do uso de resultados do Google Tradutor em contextos multimodais. O desenvolvimento e avaliação de tradução automática frequentemente enfocam o componente linguístico, contudo há pouca exploração manual de relações texto-imagem em documentos multimodais. Assim, este trabalho busca descrever algumas relações texto-imagem em memes do inglês traduzidos automaticamente para o português. A metodologia envolve a seleção e análise de 100 memes, encontrados em páginas do Instagram e do Facebook e suas relações intersemióticas tanto em inglês (como texto-fonte) como em português (como texto-alvo). Dos memes analisados, 73% resultaram em traduções corretas, 17% tiveram erros sem qualquer tipo de incompatibilidade intersemiótica, e apenas 10% apresentaram um desvio linguístico que alterou a relação entre texto e imagem do meme. Desses 10% de incompatibilidades, emergiram amostras de incompatibilidades envolvendo, por exemplo i) palavras incorretas e relação aditiva; e ii) palavra desconhecida e homoespacialidade. Ao fim, os resultados encontrados demonstram que a tradução automática de alguns memes, cuja relação semântica entre texto e imagem compartilham maior congruência, apresentam um número maior de incompatibilidades em comparação com aqueles em que isso não acontece.
PALAVRAS-CHAVE: Multimodalidade; Tradução automática; Memes; Incompatibilidades intersemióticas.

1 Introduction

Since the 1990s, there has been an increase in research on two areas that are seemingly disconnected: multimodality and machine translation. The former refers to studying relationships between different semiotic components, such as subtitles, text titles, footnotes, encompassing the verbal component; and photographs, geometric figures, drawings, for instance, encompassing the visual dimension; these would be construed cohesively, with the aim to produce a multimodal coherent document, such as web pages, manuals, or news articles (Bateman, 2008); and the latter refers to the "Machine translation (MT), the use of computers to translate from one language to another." (Jurafsky; Martin, 2021, p. 207). In such an informational context, within a globalised world (Quah, 2006), readers have demanded more machine translations for an increasingly more varied range of documents, including videos, infographics, emojis, and memes.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

In general, these studies, entrenched in the interface between machine translation and multimodality, depart from a computational perspective, assessing the validity of multimodality in order to improve precision in machine translation performance. That is especially conducted by training machine translation systems (MT) with visual representations and, possibly, with text to speech systems[1] (Caglayan, 2019; Caglayan et al., 2016; Calixto; Liu, 2019; Heo; Kang; Yoo, 2019; Hirasawa et al., 2019), added to methods and typologies to evaluate machine translation (Banitz, 2020; Ying et al., 2021).

However, in the context of this work, one should note that this is not a study that evaluates machine translation, let alone that seeks more elaborate methods for strictly linguistic categories or descriptions, even though we acknowledge the growing evolution of methods and categories for manual and/or machine assessment of machine translation error outputs. What is intended here is the identification of intersemiotic relationships, more specifically, of text-image cohesive relationships in memes that might be reconfigured, given that there is output considered seemingly incongruent in machine translation when compared to the source text (Banitz, 2020; Ying et al., 2021).

In the future, developing intersemiotic and classification research on translation errors may eventually serve the purposes of this study; however, at this moment, the basis to develop such incompatibilities, despite their datedness, is sufficient for the initial exploration of this theme.

Thus, the aim of this work is to identify these text-image intersemiotic relationships in memes based on machine translations of their text.

This article is divided into two parts: the first section is based on theory. Based on the studies of Vilar et. al. (2006), we seek to explore categories that support the identification of certain types of automatic errors that may emerge from the use of machine translation; in addition to the types of intersemiotic textures from Liu and O'Halloran's proposal (2009), we aim to inform possible text-image relationships of meaning that are configured and reconfigured in reading memes based on the result of machine translations. The latter half of this article is focused on practice, as it quantifies and

[1] That perspective is usually linked to the area of Natural Language Processing of Neural Multimodal Machine Translation. These are systems that use "images related to source language sentences as inputs to improve translation quality" (TAKUSHIMA et al., 2019).

describes intersemiotic mismatches (reconfigurations of text-image meanings), caused by certain types of machine translation error (which will also be analysed).

2 Typology of errors in Machine Translation

As stated in the previous section, even though this study is not in itself a study of MT evaluation, we use linguistic classifications from that field. Therefore, a brief review of key concepts is necessary.

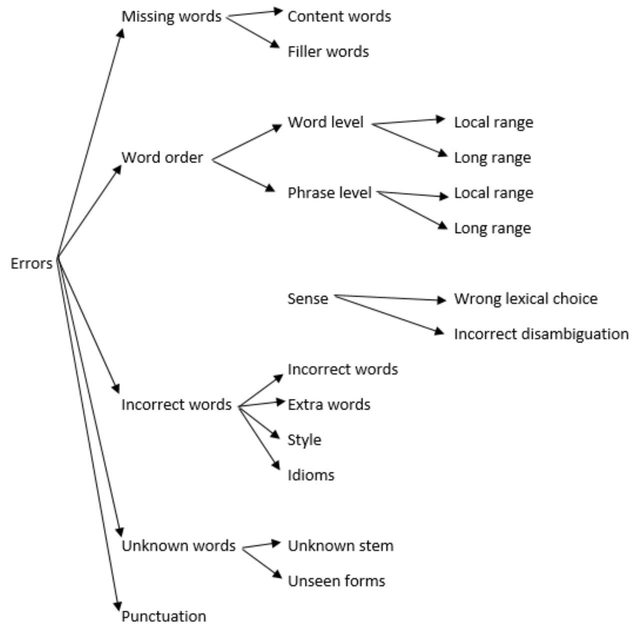
With the rise of machine translation, so did rise performance assessment for its output. Its importance is revealed in the consolidation of its own field, Evaluation of Machine Translation, which includes events and symposia on that specific theme. Generally, the paradigms for evaluating MT approach methods and techniques to examine, whether automatically or manually, the precision for MT performance in varied contexts of analysis.

Papadopoulo (2019) compares machine translation output from Swedish to English, and from Greek to English, through automatic detection and rectification of errors in neural machine translation. The post-editing stage, present in the automated corrections in Papadopoulo (2019), also appears in other studies, such as in Ying et. al (2021), who introduces the classifications of terminology errors in patent texts for machine translation output from English to Chinese, including in the stage of automatic error correction a pre-editing component to the source text. Banitz (2020) evaluated the performance by Systran and Google Translate, comparing machine translation assessment through some popular metrics for machine translation, such as BLEU, METEOR, and TER, including human translation with MT results. Their work (Banitz, 2020) presents a comparative panorama of both automatic and manual paradigms of translation (excluding corrections or post-editing) for 24 sentences automatically translated from a literary source in English to German. (Banitz, 2020) presents the classification of linguistic errors by Farrús et. al. (2012), who, in turn, introduces more categories and further linguistic elaborations, both relevant in relation to the scheme proposed by Vilar et. al. (2006).

Vilar et al. (2006) present a structure to classify MT errors, encompassing five main categories: *missing words*, *word order*, *incorrect words*, *unknown words*, and *punctuation*. That structure (Fig. 1) is illustrated as follows:

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Figure 1: Classification of errors in machine translation output.



Source: Elaborated by Pires and Espindola (2021).

As suggested by Vilar et. al. (2006), *missing words* refer to cases in which a word is missing from the sentences produced during machine translation. The subcategories, *content words* and *filler words*, provide the sentence's meaning and frame it in relation to grammar (Vilar et. al., 2006, p. 698); however, the meaning is unaltered.

The subsequent class is identified by reordering the words and syntactic blocs of words. The contrast between these two levels depends on the exclusive order of the words or blocs of words during sentence production. In terms of local or far ranges, differentiation is not absolute, but it depends on the need to reorder words in a local context (inside a syntactic bloc) or to reorder words in another bloc (Vilar et. al., 2006, p. 698).

Incorrect words, on the other hand, can be sorted by a MT system that is uncapable of locating an adequate counterpart for a word. Its first subcategory represents changes in sentence meaning, which in turn may lead the system to process an incorrect disambiguation or a mistaken lexical decision (Vilar et. al., 2006, p. 698). The other subcategory for incorrect words is *incorrect forms*, which occurs

ISSN: 2317-2347 – v. 11, n. 1 (2022)

when MT does not generate the correct form of the word, despite choosing the correct translation for its base form. The fourth category, *unknown words*, encompasses unknown words or morphemes for the MT system, including forms not yet seen of morphemes currently known by the system. The last category, *punctuation*, is considered a smaller issue for evaluating machine translation (Vilar et. al., 2006, p. 698).

It is necessary to highlight that both the evolution and the elaboration in studies about Evaluation of Machine Translation are striking. However, for the purposes of the current exploratory stage of this project, it suffices to apply the typology scheme categorised by Vilar et. al. (2006), in order to identify and elaborate potential intersemiotic text-image relations in memes.[2] Moreover, this work is not strictly configured as a study on MT assessment, even if it uses the field's linguistic classifications in tandem with the support of multimodality to describe occasional semantic text-image reconfigurations generated from MT output TA (Pires, 2017, 2021).

However, before approaching that phenomenon, the next section explores the cohesive image text devices by Liu and O'Halloran (2009).

3 Text-image relations

There has always been a large quantity of artifacts that merge texts and images; in the digital era, the combination of languages is significantly amplified. So, the development of scientific study on such a mundane phenomenon as the *junction* of several multisemiotic elements becomes necessary.

In fact, the mere simultaneous occurrence of several multisemiotic elements does not necessarily configure a coherent message. Considering such a basic concept, Kress and Van Leeuwen (2006) elaborated the notion that mode is a socially framed resource, culturally given for meaning making.

Certainly, multimodality breaks with the principles of traditional linguistics. While Saussure, in his *magnum opus Course of General Linguistics*, defended the double articulation of language based on signified and signifier, Kress and Van Leeuwen (2006) defend the multiplication of the multimodal

[2] In the future, the methods for formalising these categories can be expanded for replication.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

text. These signifieds, in a way or another, are articulated across four levels of practice, labelled strata: discourse, design, production, and distribution (Pires, 2017, p. 76).

For Kress and Van Leeuwen (2006), discourse is knowledge, previously constructed, on some aspect of reality. That idea is, without a doubt, closer to the functionalist views on theoretical linguistics, distancing itself from trends like generativism.

Multimodality, then, contributes substantially to linguistics. Considering that all communication is multimodal, linguistics can apply the knowledge from multimodality to widen their vision regarding language. Therefore, considering the meme as a frequently multimodal artifact, we seek to explore the way parts of its linguistic components are interrelated with visual components. To that end, our approach includes the proposal of intersemiotic reading, developed by Liu and O'Halloran (2009).

3.1 Intersemiotic textures

Liu and O'Halloran, in their article *Intersemiotic texture: Analysing cohesive devices between language and images* (2009), propose some categories for the way words and figured relate to one another. For the specific aims in this study, we approach *homospatiality, parallel structures, intersemiotic addition relations*, and *intersemiotic consequence*.

3.1.1 Homospatiality

Homospatiality, illustrated as follows (Fig. 2), occurs when image and text say the same thing. In this case, the drawing of the fire and the *hot* typography are merely different ways of expressing the same idea: heat. However, in case the term *strawberry* was used, that intersemiotic relationship would not exist.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Figure 2: Example of homospatiality relationship.

Source: Liu and O'Halloran (2009, p. 372).

Next, we deal with another category of intersemiotic texture.

3.1.2 Parallel structures

Below we display a case of parallel structures (Fig. 3). That means that text and image are complementary in such a way that each contain a fragment of the total message. Upon looking at the image, it is possible to see a dog attacking a woman, but we do not know whether the animal is part of the Israeli army or that the victim is Palestinian. The authors label that intersemiotic texture as an example of *transitivity*, in which *Israeli army dog* would be the agent, and *Palestinian woman* is the patient. Considering the principles of traditional grammar, a transitive verb is the one that requires a complement and, thus, the parallel structure is that in which both semiotic components (verbal and visual) share similar forms (Liu and O'Halloran, 2009, p. 373).

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Figure 3: Case of parallel structures.

Israeli army dog attacks Palestinian woman

Source: Liu and O'Halloran (2009, p. 373).

Next, we look at a type of logical relationship between language and image.

3.1.3 Intersemiotic relations of addition

The figure below (Fig. 4) is a case of intersemiotic relations of addition. While, in parallel structures, image and text are complementary reformulations of more or less the same idea, in this type of intersemiotic interaction both languages say different things – at times, even opposed ideas. By looking at the image, it is not possible to ascertain whether the woman died, whether she is the richest woman in Asia, or that she is aged 69. Moreover, the child on the woman's lap is not mentioned in the caption. Therefore, both components (verbal and visual) are added, much like the sum of two numbers.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Figure 4: A case of intersemiotic addition relationship.

Asia's richest woman dies at 69

Source: Liu and O'Halloran (2009, p. 380).

Next, we briefly describe relationships of intersemiotic consequence.

3.1.4 Intersemiotic consequence

Occasionally, image and text establish a relationship of consequence. The following ad is an example of such. In practical terms, it carries this meaning between the lines: that, if you take Diovan, you will be as happy as the couple in the picture (Fig 5).

Figure 5: Example of intersemiotic consequence.

Source: Liu and O'Halloran (2009, p. 381).

These relationships constitute the necessary set to inform the methodology for this work, as noted in the next section.

4 Methodology

Aiming to identify intersemiotic mismatches caused by the use of machine translation in memes, we first elaborated the concept of intersemiotic mismatch based on Pires (2017), followed by a definition of memes as a textual genre and its categorization in the context of mismatches, to compile sufficient data.

4.1 Intersemiotic mismatches

Textual Linguistics deals with issues such as coherence, which, according to *Dicionário Online de Português* [the Online Dictionary of Portuguese], means, "arrangement of textual elements which, despite having different meanings, are interconnected so that a text acquires its full meaning, rendering it clear and understandable: textual coherence" (our translation).

As for multimodal texts, a similar rationalisation is valid: the relationships between text and message form a unique message, called intersemiotic texture. Therefore, when that coherence is broken, one says that an intersemiotic mismatch occurred (IM).

Regarding machine translation, it may incur errors that change the intersemiotic texture for the image.

In the words of Pires (2017):

> An intersemiotic mismatch in MT is found when, through the generation of an automatic translation one observes a new semantic configuration between the verbal and visual modes in relation to the same modes found in the original document. (Pires, 2017, p. 108).

Thus, what we seek in this study is to identify these text-image intersemiotic relations in memes, based on the machine translation of their textual elements. The linguistic pair selected was English-Portuguese.

4.2 Definition of *meme* as a genre

Firstly, it is important to define that is not a work about *memes*, which was selected as the multimodal genre to be analysed in tandem with the results of translations produced by Google Translate. Therefore, this study does not discuss memes in depth; however, it bears some elaboration, even if it is not essential here.

Initially proposed by Richard Dawkins in his book, *The Selfish Gene* (1976), at first, the term *meme* had no relation with digital culture. According to Wiggins and Bowers (2014),

> […] First conceived and coined by evolutionary biologist Richard Dawkins (1976) in his book *The Selfish Gene*, the meme was Dawkins' response to the gene-centric focus of evolution. By describing evolution as a cultural phenomenon, and not as a

ISSN: 2317-2347 – v. 11, n. 1 (2022)

> biological phenomenon, Burman (2012) suggests Dawkins' purpose was to "[redefine] the fundamental unit of selection in evolutionary biology" (p. 77). For Dawkins, the meme served as a catalyst for cultural jumps in human evolution, much like a gene served to further biological evolution. Memes are the mediators of cultural evolution. (WIGGINS; BOWERS, 2014, p. 5-6.)

Thus, the modern version of *meme* refers to a volatile cultural product in constant mutation. As it is constantly replicated and modified, it does have an "owner," so new alterations are always performed by each new shared publication in the network.

For this research, 100 memes were collected from pages in social media websites. The pages were: *dankmemes, daquan, 9gag, ghosted1996, sarcasm_only* and *memes.english10*[3]. The criterion for these choices was based on popularity. With millions of followers, these pages reach a large number of users every day, so their content is, therefore, worthy of study. The selected multimodal texts were divided into three categories:

i. *Memes* with no errors in machine translation, with no intersemiotic mismatch.
ii. *Memes* with translation errors, but no intersemiotic mismatch.
iii. *Memes* with translation errors and with intersemiotic mismatch.

The files that are most remarkable for this study are those in the third category. Despite being calculated, those listed in the two first "types of memes" were not explored qualitatively, as the aim of this article is to analyse potential IM generated by machine translation. Next, each error will be classified according to Vilar et. al. (2006), and each mismatch will be categorised based on the studies of Liu and O'Halloran (2009).

However, even if the only memes presented here are those in the third category, the quantity that fits in the first and second types is worth mentioning. Considering the double aim of evaluating machine translation and the multimodality of that textual genre, we will now briefly cite the number of cases in which there were not translation errors, including those with errors that did not incur in IM.

[3] The links for these pages are, respectively, https://www.instagram.com/daquan/, https://9gag.com/, https://www.instagram.com/ghosted1996/?hl=en, https://www.instagram.com/sarcasm_only/?hl=en, https://me.me/t/english-10.

Moreover, due to length restrictions, here we deal only with the most relevant mismatch samples. In the context of memes, there is frequent usage of puns, with cause ambiguities. We also note that we excluded from this study memes that only carried text, as they were not relevant for a multimodality study.

Last, but not least, we only considered samples of MT results that presented intersemiotic mismatch; therefore, only certain translation suggestions that caused that cohesive link with the image on a given meme. The next section deals with the computation of findings, based on the three listed categories in this methodology section, followed by the qualitative analysis of IMs.

5 Analysis

After collecting the meme samples in each of the pages mentioned in the methodology, we selected and saved he images, and the text part from each meme was transcribed separately in Google Translate. Armed with the machine translation output from English into Portuguese, we first started analysis based on Vilar et. al.; next, we studied the semantic bond of that text with the image and, finally, we collated those with the text-image relationship in the source meme. Thus, the quantity of memes per page and in the three categories applied are as follows: i) memes with no machine translation errors and no IMs; ii) memes with translation errors, but no IMs; and iii) memes with translation errors and with IMs. These instances were duly tabulated and described. Next, we analyse the most relevant samples of intersemiotic mismatch.

5.1 Quantitative analysis

After data collection and analysis, the following information emerged, according to Table 1.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Table 1: Quantity of machine translation output for the analysed memes.

Quantity/ Meme Pages	***ghosted1996***	***memes.english10***	***daquan***	***dankmemes***	***sarcasm_only***	***9gag***	**TOTAL**
N. of *memes*	22	10	20	15	13	20	100
N. of appropriate MT results	17	5	18	7	8	18	73
N. of errors in MT without IM	3	4	1	3	4	2	17
N. of errors in MT *with* IM IM	2	1	1	5	1	0	10

Source: The authors.

As observable in Table 1, the number of meme samples in each pages varies. That variation is due to a sufficient quantity of memes containing text and image that carried, at first sight, some relationship of meaning between its components (verbal and visual). There is certainly a higher number of samples from pages *ghosted1996, daquan*, and *9gag* (around 20 memes each), while the others feature fewer samples.

The second line of data in Table 1 presents the number of machine translation results that were deemed appropriate, that is, that did not display any ambiguous information or that did not differ semantically from the source text. The output of appropriate results in the pages with more samples was notable when compared to the others; that may be due to more literal content in the verbal component for the pages with more samples than the others. Surely, the general number of appropriate MT results are significantly higher than the figure for errors or intersemiotic mismatches, which demonstrates Google Translate's efficacy.

The quantity of errors in machine translation, with or without intersemiotic mismatches, was quite varied for each selected page. While *9gag* presented excellent results in the translation process, with no MT errors, the same did not occur with *dankmemes*, which revealed the highest number of MT errors with IM (five samples). Such a discrepancy in results can be explained both by the various intersemiotic relationships in each case, as well as the difference among the source texts. Moreover, most pages, with the exception of *dankmemes*, showed an equal or higher quantity of translation errors that did not result in mismatches per se.

Generally, pages that presented a narrower semantic relationship between text and image presented a higher quantity of errors than those in which the picture is merely a background and that, therefore, did not constitute a direct meaningful relationship with the words. Consequently, we could corroborate Pires (2017) regarding intersemiotic mismatches as being highly dependent on the images in question.

Regarding the verbal component, the sort of grammatical construction used can also explain partially the quality of that translation. Basically, the machine struggles to recognise something that acts out of patterns, that is, non-standard use of language.

Most grammatical structures were formed by compound sentences, as opposed to other pages that were constituted mainly by single sentences. Even so, the use of daily language allowed the machine to produce a correct output for most cases.

Ghosted1996's page is filled with memes based on puns, which might represent a challenge for machine translation.

Daquan's page is characterised by memes with short sentences and pictures taken from daily life. Even though the relationship between texts and images in these memes is usually quite direct, the words do not contain ambiguities, puns, or other grammatical structures that the machine might have a hard time translating. As a result, the high rate of correct results can be explained by the type of language applied.

Dankmemes's page is the one that presents the highest amount of MT errors with intersemiotic mismatches, both in absolute numbers and in proportional rates. That can be explained by the high number of puns, which, obviously, are impossible to translate automatically. Even so, it had a higher number of intersemiotic mismatches because of its closer relationships involving text and image.

As for the page *sarcasm_only*, there was a higher quantity of incorrect translations and, at the same time, a single case of intersemiotic mismatch. Again, the amount of errors was explained by the uses of certain linguistic structures (especially polysemy).

Finally, in the samples from *9gag*'s page, it seems to have returned the same results as *daquan*. The low number of errors was more due to the simplicity of sentences than with any specific intersemiotic relationship.

These results are not at all intended to represent the totality of each page or even for all pages, but only to present hints of intersemiotic mismatches that may emerge from the use of machine translation to read these memes. Such hints, taken quantitatively, lead us to some generalisations; however, despite appearing in fewer instances, IMs, as defined in our aims, lead to a more profound look into the samples in which reconfigurations in text-image meanings might occur, with deviant results resulting from the use of MT. Next, we move on the analysis of specific samples, based on the works of Liu and O'Halloran (2009) and Vilar et. al. (2006).

5.2 Analysis of intersemiotic mismatches

After identifying the number of appropriate translations, translations with errors but no IMs, and of translation with both errors and with IMs, we began the specific stage of that latter category, aiming to describe the phenomenon of intersemiotic mismatches in memes caused by the use of Google Translate.

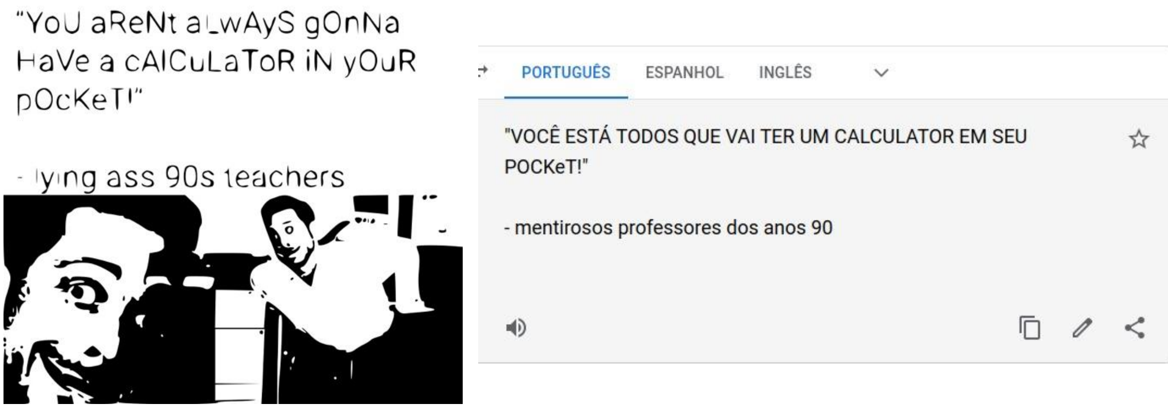
It is important to highlight that, in order for an intersemiotic mismatch to take place, two things are necessary: a very close relationship between words and image, and, at the same time, a type of linguistic structure that carries multiple interpretations (such as ambiguities). It is possible, firstly to consider that Google Translate can translate clearer texts, but it struggles with translations in which the meaning is not clear even in the source language – and that is the case of many memes. Secondly,

ISSN: 2317-2347 – v. 11, n. 1 (2022)

translation errors are a prerequisite for mismatch, but it is only concrete if there is an appropriate extralinguistic context.

Next, we present a sample of IM for a meme from *dankmemes*'s page (Fig 6).

Figure 6: *Meme* with homospatiality IM, based on error of *unknown word* (Vilar et. al., 2006).[4]



Source: Adapted from dankmemes, next to Google Translate output.

As for the intersemiotic texture, this is an example of homospatiality (Liu and O'Halloran, 2009). Text and image say the same, because the picture is merely an illustration for the verbal component *lying ass 90s teachers*. Regarding language, that is a case of *unknown word* (Vilar et. al., 2006),

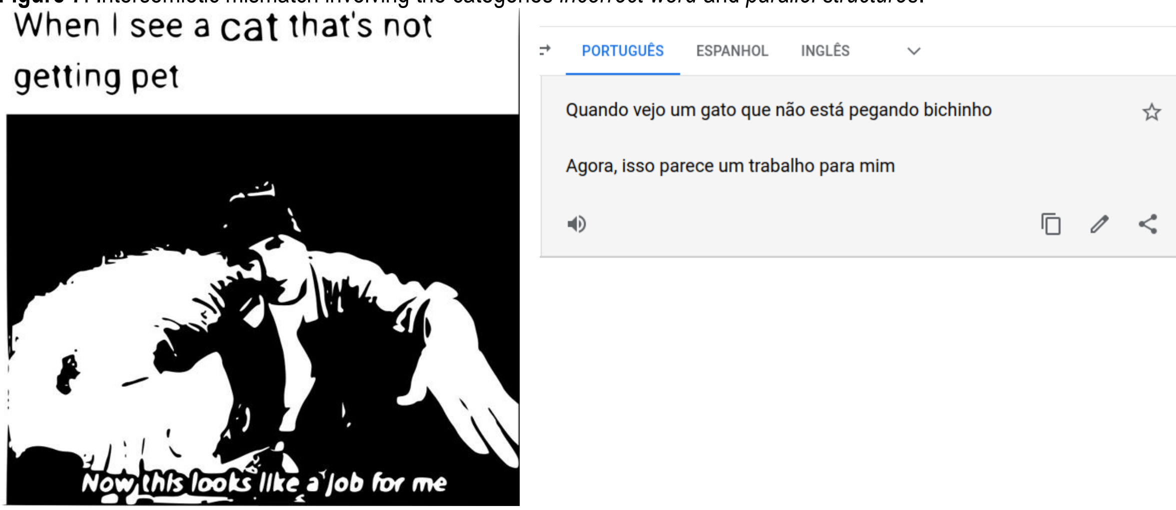
[4] Accessed on: January 10, 2021.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

considering that the words *calculator* and *pocket* have not been translated. Moreover, there is the unnecessary addition of the pronoun *todos*, characterizing an *extra word* situation (Vilar et. al., 2006).

The next sample (Fig. 7) demonstrates a case of IM involving *parallel structures* and *incorrect word*.

Figure 7: Intersemiotic mismatch involving the categories *incorrect word* and *parallel structures*.[5]



Source: Adapted from *memes.*English10, with Google Translate output.

According to Vilar et. al. (2006), the output translation given by Google in Figure 7 is a case of *incorrect word*, since *pet* may refer both to a domestic animal and to caressing something or someone. In that case, the machine did not catch the homonymy in the term, which can be both a noun and a verb. As a result, the verb was rendered as a name.

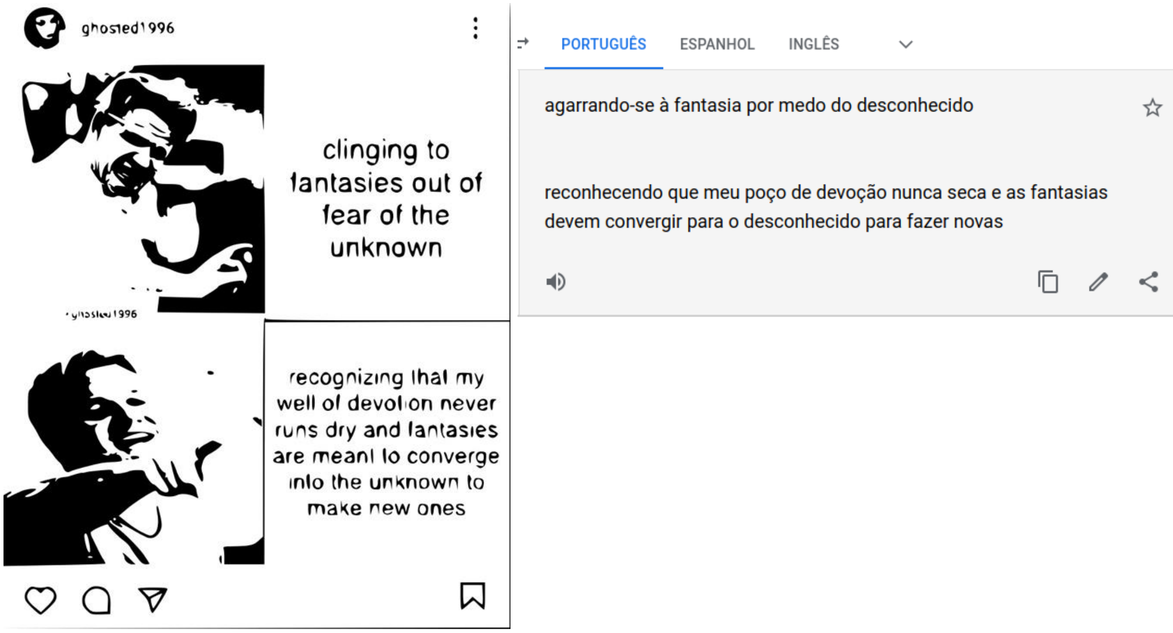
As opposed to Figure 6, this is a case of IM generated from *parallel structures* (Liu and O 'Halloran, 2009), because text and image express complementary information. Just like in the meme from Figure 6, the text under Figure 7 is easily understandable, despite what is expressed at the meme's top section. Therefore, a Portuguese speaker would understand the sentence that "activates" the picture, but not the whole meme, due to the first part, translated incorrectly.

Next, we analyse a different combination of intersemiotic texture and type of MT error.

[5] Accessed on: January 8, 2021.

ISSN: 2317-2347 – v. 11, n. 1 (2022)

Figure 8: Example of meme with *homospatiality and style error*.[6].



Source: Adapted from *ghosted1996*, with Google Translate output.

The translation output provided in Figure 8 contains several errors. Firstly, the nominalisation of the English verb is performed with the suffix -ing, which also forms the gerund. In Portuguese, however, the only possible noun form for that is the infinitive, as the suffix -ndo only constitutes the Present Progressive. For Vilar et. al. (2006), this is a case of *incorrect form*.

Furthermore, the idiom *well of devotion* was translated into *poço de devoção*, a meaningless term in Portuguese, with the possible exception of a literary context. According to Vilar et. Al. (2006), this is a case of *style error*, as it demonstrates the machine's lack of understanding of the figurative meaning of the word.

Finally, the third error by the machine is *missing word*. In the translation output into Portuguese, the reader may wonder, "new what?". Considering that *nova* [new] is an adjective, it will necessarily require a noun to go with it, which does not occur.

[6] Accessed on: January 9, 2021.

Revista Letras Raras
ISSN: 2317-2347 – v. 11, n. 1 (2022)

Regarding semiotic texture (Liu and O'Halloran, 2009), that image is a case of *homospatiality*, considering that both image and text say the same thing, so any translation error would impact the image directly, given the clear association between the two components, verbal and visual. For that reason, the intersemiotic relationship is lost, as the expression *poço de devoção* does not exist in Portuguese. The other two errors, on the other hand, did not cause anything more than an agrammatical construction.

Finally, Figure 9 introduces a case of intersemiotic consequence, generated from an error of *incorrect word.*

Figure 9: Example of IM based on intersemiotic consequence and incorrect word.[7]

Source: Adapted from *Daquan*, with Google Translate output.

[7] Accessed on: January 10, 2021.

In the MT output reported in Figure 9, the system may not have recognised the meaning of *drip*, an American slang that means, according to *Dicionário Informal*, the following: "1. To have *drip* is to have one's unique style and attitude! […] 2. To be a unique person" (DRIP, 2021, our emphasis, our translation).

However, the same word usually has the meaning associated with drops falling (as a verb), as it can also be a noun. Apparently, that is a case of incorrect word, according to Vilar et. al. (2006), because the machine did not recognise the homonymy in the term, and the translation did not match its context.

In the intersemiotic aspect, the connection between text and image, which deal with *intersemiotic consequence* (Liu and O'Halloran, 2009) ceases do exist, because in no moment are literal drops mentioned, or water of any kind. Therefore, since the verbal component becomes unintelligible, the same thing happens with the intersemiotic relationship.

Final remarks

The aim of this study was to identify intersemiotic text-image relationships in memes, based on the machine translation output for their textual parts. It is possible to conclude that Google Translate displays good performance for translating texts, as most results were considered appropriate (73%). However, there is a smaller quantity of errors, which may generate some semantic reconfigurations between text and image (10%).

Out of 100 total analysed memes, 73% resulted in correct translations, 17% had errors with no type of intersemiotic mismatch, and only 10% presented linguistic deviations that changed the meaning between text and image.

Based on the data, we observed that the majority of MT errors in memes did not introduce subsequent semantic reconfigurations between text and image, which suggests a weaker semantic link between text and image (63% out of the 23 total MT errors) than those with stronger semantic bonds, as in the case of IMs (37% out of the total 23 MT errors).

Although the numbers show a smaller relevance of IMs caused by MT errors in memes, all intersemiotic mismatches caused some noise in message transmission, as the translated output was meaningless. Despite what Pires and Espindola (2021) claim, no cases were found of new intersemiotic information. Quite the opposite: all errors either made the sentence become incorrect or completely unintelligible.

For future research, it is necessary to examine the texture in video memes, a feature that was not approached in this article. Moreover, the only linguistic pair analysed was English-Portuguese. There are probably other languages that might reveal different results, considering grammatical and lexical differences for each and their representation in Google Translate's corpus.

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