Overview of the CLEF 2022 JOKER Task 2: Translate Wordplay in Named Entities

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Abstract

Onomastic wordplay has been widely used as a rhetorical device by novelists, poets, and playwrights, from character names in Shakespeare and other classic literature to named entities in Pokémon, Harry Potter, Asterix, and video games. The translation of such wordplay is problematic both for humans and algorithms due to its ambiguity and unorthodox morphology. In this paper, we present an overview of Pilot Task 2 of the JOKER@CLEF 2022 track, where participants had to translate wordplay in named entities from English into French. For this, we constructed a parallel corpus wordplay in named entities from movies, video games, advertising slogans, literature, etc. Five teams participated in the task. The methods employed by participants were based on the state-of-the-art transformer models, which have the advantage of subword tokenisation. The participants' models were pre-trained on large corpora and fine-tuned on the JOKER training set. We observed that in many cases the models provided the exact official translations, suggesting that they were pre-trained on the corpus containing the source texts used in the JOKER corpus. Those translations that differed from the official ones only rarely contained wordplay.

Keywords

wordplay, computation humour, named entities, neologisms, machine translation, deep learning, transformers

1. Introduction

Wordplay is often used for its attention-getting or mnemonic qualities in headlines, toponyms, company names, and advertising. Onomastic (i.e., name-related) wordplay has been widely used as a rhetorical device by novelists, poets and playwrights. It is widespread in classic literature [1], such as in Shakespeare's characters' names [2], but also in names found in modern-day works such as Pokémon, Harry Potter, Asterix, and video games. Proper nouns with an extra semantic load are used as a meaningful element in literary texts and can be considered as wordplay [3]. The translation of

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such literary names is problematic, raising the questions of whether the transposition of such names into a given target language is technically possible and, if so, what method might be appropriate for producing them [3].

Generally speaking, these playful designations in fictional universes can be viewed as named entities. Named entities are objects, abstract or physical (such as a person, location, organisation, product, etc.), that can be denoted with a proper name. Traditional approaches to translating named entities include transliteration [4, 5] or keeping them unchanged in the target text. However, these approaches do not typically preserve wordplay (or at least, not in a way which may be meaningful for the target audience), even though such wordplay can be crucial for understanding the pragmatics of the text.

Meaningful proper names in fictional universes are often neologisms. Neologisms – that is, newly coined words – are among the most common forms of linguistic creativity, and are a particular focus of the JOKER project. Subcultures and rapidly advancing technical fields are common sources of neologisms, some of which may eventually come into regular or even widespread use (in processes known as *lexicalisation*, *institutionalisation*, and *entrenchment*). But neologisms can also be ephemeral, being invented for use in a specific discourse and not intended for general adoption. Such neologisms, known as *nonce words* or *occasionalisms*, are a recurrent feature of literature, advertisements, and journalism, where they are often used for playful or humorous purposes [6, 7, 8]. Due to their highly idiosyncratic nature, neologisms – particularly humorous ones – are challenging for both humans and machines to translate [7]. Machine translation systems in particular generally fail to recognise the deliberate ambiguity or unorthodox morphology of neologisms, leaving such terms untranslated or else translating them in ways that lose the humorous aspect [9].

The goal of the JOKER@CLEF 2022 workshop was to bring together translators, linguists, and computer scientists in order to bring us a step closer to the automation of multilingual wordplay analysis and translation. In this paper, we present the workshop's Pilot Task 2, where participants had to translate wordplay in named entities from English into French. Details on other related shared tasks on wordplay translation are covered in our workshop overview paper [10].

2. Related work

Fortunately, many of the basic processes through which neologisms are formed and employed are well understood in linguistics [11, 8]. These include semantic shifting (imbuing an existing word with a new meaning), morphological derivation (adding a prefix or suffix to an existing word), compounding (combining whole stems), blending (combining fragments of words), clipping (truncating an existing word), analogy (formation based on a prototype word or schema), and creation *ex nihilo* (extramorphological invention of entirely new roots).

Recent linguistic scholarship has sought to deepen this understanding: there have been studies, for example, on the discourse cues used to signal nonce words [12]; on the linguistic, extra-linguistic, and contextual knowledge required for interpreting neologisms [13]; on the sublexical features preferentially modified in nonce formations [14]; and on the specific morphological and analogical word formation processes strongly associated with humour [14, 8]. Word formation processes are also known in the field of translation studies, which has documented strategies for analysing and translating neologisms [7] and made case studies of translated neologisms as a source of humour [15]. Despite this, working translators evince a marked reluctance to neologise, overwhelmingly opting to replace source-language coinages with lexically conventional options, or else eliminating them altogether [16]. The reasons for this remain unexplored; on the one hand, this could be an unconscious tendency of translators to normalise language, but it could also be down to a lack of awareness of finer-grained neological processes, or to a lack of the time and effort required to creatively apply them.

A common approach to lightening the translator's workload is to employ language technology, often in the form of machine translation. However, nearly all MT systems rely on lexical resources such as dictionaries and parallel text corpora which cannot be expected to contain completely novel words; this essentially makes translating recent neologisms out of scope for conventional machine translation. Surprisingly, this problem has been directly addressed only rarely in the MT literature, and even then only for highly restricted classes of morphologically derived neologisms [17, 18].

However, there does exist some research involving natural language processing (NLP) and neologisms, though not necessarily carried out with MT in mind, which we hypothesise could nonetheless be adapted for or inform the design of a future machine or machine-assisted translation system. This work includes methods for automatically identifying the source words of blends [19], for generating orthographically plausible cognates in a target language [20], and for predicting the location of neologisms in a word embedding space [21]. There is even a small measure of tangentially relevant work in computational humour: [22] attempt to detect "marketing blunders", where a serious neologism in one language inadvertently resembles a humorous or otherwise inappropriate term in another language; [23] show that *ex nihilo* neologisms can induce consistent semantic intuitions, including humour; [24] present a technique for generating humorous neologisms conditioned on user-specified properties; and our own past work [9] focuses on computer-mediated translation of puns, which sometimes employs blending and other mechanisms also used in neologism.

Some prior work does tackle the named entity recognition question in fiction [25, 26] or optimising it for machine translation [27]. The Named Entity Transliteration Shared Task was held at the 7th Named Entities Workshop in 2018 [4, 5]. In [28], a method is proposed that fuses bilingual entity class named entity translation based on a chunk symmetry strategy and a machine learning–based English–Chinese transliteration model. A combination of standard entity masking techniques and a semantic equivalent placeholder was proposed in [29]. Conventional neural machine translation models struggle to translate words with multiple meanings because of the high ambiguity as well as compound words due to their morphology [30]. To deal with these problems, named entity tags with a chunk-level LSTM layer over a word-level LSTM layer were proposed [30]. However, this approach is not suitable for humourous neologism as it does not aim to reproduce wordplay in a target language.

Transfer learning became a widely applied technique in many NLP tasks. The term describes models that are first pre-trained on a large corpus and then fine-tuned on a downstream task. The state-of-the-art large pre-trained models, such as T5 [31] or GPT-3 [32], convert all text-based language problems into a text-to-text format. The initial idea of transformers was intended to eliminate recurrence and convolutions in favour of attention mechanisms only [33].

The state-of-the-art transformer models make use subword tokenisers, such as Byte-Pair Encoding (BPE) [34] and WordPiece [35]. BPE relies on a pre-tokeniser that splits the training data into words and is used in the GPT-2 [36] Roberta [37] models. WordPiece is the subword tokenisation algorithm, similar to BPE, used in BERT [33], DistilBERT [38], and Electra [39]. Although these methods are comparatively shallow, they have shown promise for the related use case of languages with large vocabularies and many rare words [40, 34]. However, they too are not specifically equipped for wordplay, ignoring ambiguity and humorous intention.

3. Data

We constructed a parallel corpus of wordplay in named entities in English and French. We collected distinct 1 398 named entities in English containing wordplay from video games, advertising slogans, literature, and other sources [41, 10] along with 1 450 translations into French. The vast majority of the translations were the official, published ones. Some alternative translations were provided by Master's students in translation, all native speakers of French. The statistics on wordplay in named entities is given in Table 1. The vast majority of wordplay are portmanteau words – i.e., words formed by merging the sounds and meanings of two different words. The table employs a traditional classification of wordplay as, even though its usage is problematic,[1] it is better known and thus may give a clearer idea of the data we have.

[1]For example, the category *neologism* tends to overlap with other categories.

Table 1
Statistics of wordplay in named entities

Category	English	French
portmanteau	909	984
pun/homophone	298	291
no manipulation	104	108
neologism	53	42
assonance/alliteration	24	17
anagram	8	6

3.1. Training data

The training dataset contains 1 161 instances of wordplay in the form of translated pairs. The data was provided to participants as a JSON file (or a CSV file for manual runs) with fields denoting the instance's unique ID (`id`), the source text in English (`en`), and a target text in French (`fr`). For example:

```
[
  {
    "id": "noun_1",
    "en": "Ambipom",
    "fr": "Capidextre"
  }
]
```

3.2. Test data

We used a further 284 wordplay instances for the test data. The data format was identical to that of the training data, except that the field for the target text was omitted. Example:

```
[
  {
    "id": "noun_1185",
    "en": "Fungun",
  }
]
```

The expected output format was identical to that of the training data, but with the addition of fields `RUN_ID` and `MANUAL`. The `RUN_ID` field value uniquely identifies a given run and is formed of the team ID (as registered on the CLEF website) followed by the task ID (in this pilot task, always `task_2`), followed by the run number. The `MANUAL` field value can be either a 1 (indicating a manual translation run) or a 0 (indicating a machine translation run). Example:

```
[
  {
    "RUN_ID": "OFFICIAL_task_2_run1",
    "MANUAL": 1,
    "id": "noun_1",
    "en": "Ambipom",
    "fr": "Capidextre"
  }
]
```

4. Evaluation metrics

For the wordplay translation tasks (Tasks 2 and 3), there do not yet exist any accepted metrics of translation quality [41, 10]. MT is traditionally measured with the BLEU (Bilingual Evaluation Understudy) metric, which calculates vocabulary overlap between the candidate translation and a reference translation [42]. However, this metric is clearly inappropriate for single-term wordplay translation evaluation, as overlap measures operate only on larger text spans and not on individual words, the morphological analysis of which can be crucial for neologisms [41, 10].

We hypothesised that the majority of proper nouns would not be translated automatically. So we compared the target translation with source wordplay (metric *not translated*).

As our dataset for Task 2 contains “official” translations of wordplay instances coming from various published sources (e.g., Pokémon names), we also tried filtering out these official translations (metric *official*).

We manually evaluated the *non-official* translations according the following metrics:

- *lexical field preservation*: A value of *true* is assigned to translations that preserve the lexical field of the source wordplay (i.e., the translation is close to a literal one).
- *sense preservation*: A value of *true* is assigned to translations that preserve the meaning of the source wordplay.
- *comprehensible terms*: A value of *true* is assigned to translations that do not rely on specialised terminology.
- *wordplay form*: A value of *true* is assigned to translations that employ (as opposed to omit) wordplay.

5. Methods used by the participants

Five teams participated in Pilot Task 2: FAST_MT [43], TEAM_JOKER [44], Cecilia [45], Agnieszka, and Lea_T5 [46]. Four of these teams submitted a total of four runs. Lea_T5 worked on the data of the Task 2 and submitted a paper but no run for the test set. TEAM_JOKER submitted a run and wrote a blog post but without an article in CLEF Working Notes Proceedings. Agnieszka submitted a run without a paper, though the team did notify the JOKER organisers of the method they used.

Three of the five teams (Cecilia, Agnieszka, and Lea_T5) used the SimpleT5 library[2] for the Google T5 (Text-To-Text Transfer Transformer) model, which is based on the transfer learning with a unified text-to-text transformer [31]. TEAM_JOKER also fine-tuned Google’s T5 on the available examples for 18 epochs with 80% of the data in the training set and 20% in the validation set. The only preprocessing they used was to prefix each data point in English with “translate English to French:”. The

[2] https://github.com/Shivanandroy/simpleT5

Table 2
Scores of participants' runs for Pilot Task 2

	FAST_MT	TEAM_JOKER	Cecilia	Agnieszka
total	284	284	284	242
not translated	0	0	0	0
official	250	159	216	230
non-official	34	125	68	12
lexical field preservation	16	13	5	0
sense preservation	13	11	5	0
comprehensible terms	26	59	16	2
wordplay form	3	12	3	1

teams that used the SimpleT5 library trained their models for a much lower number of epochs, as after three epochs they observed overfitting.

The team FAST_MT also applied transformers [43]. They mapped the task of translating single terms containing a wordplay to the problem of question answering on texts extracted from the open-source parallel corpus OPUS [47]. They generated the context for each English–French noun pair by pulling from OPUS English–French parallel sentence pairs that contain at least one English noun in the English version. Then a transformer-based model [48] from Hugging Face[3] was trained to predict the location of the corresponding French translation in the related contexts given an English noun as a query.

6. Results

Our initial guess was that the majority of proper nouns would not be translated by machine translation. However, as our dataset contained officially translated named entities (e.g., from Pokémon) that may have been discoverable by participants and large pretrained models, all participants translated all wordplay instances. The results from Table 2 suggest that the majority of translated named entities were indeed the official translations. TEAM_JOKER [44], however, provided very interesting results, with almost half being non-official translations. Among these, twelve translations were judged as being wordplay. We can also see that among non-official translations, less than 10% are successful in terms of preserving wordplay.

As is evident from Table 3, the majority of non-official translations containing wordplay are accidental, although we observe francisation of English terms. We provide interpretations in the language of the corresponding wordplay. (For details of the interpretation annotation, refer to our workshop overview paper [10].) Almost all wordplay in this list are portemanteaux – i.e., words formed by merging the sounds and meanings of two different words.

[3] https://huggingface.co/

7. Conclusion

While wordplay in named entities has been widely used as a literary device, its translation is problematic both for human and algorithms due to its high ambiguity and unorthodox morphology. As a rule, standard named entities are transliterated from one language into another, as in case of names of persons, or kept unchanged to preserve trademarks. However, these approaches do not preserve wordplay, which can be crucial for understanding the pragmatics of a creative text.

In this paper, we presented an overview of Pilot Task 2 of the JOKER@CLEF 2022 track, where participants had to translate wordplay in named entities from English into French. We constructed a parallel corpus of wordplay in named entities from movies, video games, advertising slogans, literature, etc. Five teams participated in the task. The methods employed by participants were based on state-of-the-art transformer models, which exploit subword tokenisation. The participants' models were pre-trained on large text collections and fine-tuned on the JOKER training set. We observed that, in many cases, the models provided the exact official translations. This suggests that they were pre-trained on a corpus containing the same texts used in the JOKER corpus. Where systems did suggest translations different from the official ones, they rarely employed wordplay.

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Table 3: List of non-official translations with wordplay

EN	EN Interpretation	Official FR	Official FR Interpretation	Non-official FR	Non-official FR Interpretation	Comment
Orbeetle	orb + beetle	Astronelle	astronef + coccinelle	Orbétain	orbe + étain	—
Ribombee	ribbon + bombyliidae + bee	Rubombelle	ruban + bombyliidae + belle + ribambelle	Ribombe	—	term francisation
Celesteela	celestial + steel	Bamboiselle	bambou + demoiselle	Célésteela	céleste + [latin] stella	ling. coincidence
Primarina	prima donna + ballerina	Oratoria	oratorio + aria	Primarin	prima donna + marin	ling. coincidence
Wimpod	wimp + isopod	Sovkipou	sauve qui peut + pou	Pompode	pompote + isopode	—
Incineroar	incinerate + roar	Félinferno	félin + [anglais] inferno (fournaise)	Incinéroar	incinérer + roar (cri de lion)	ling. coincidence
Incineroar	incinerate + roar	Félinferno	félin + [anglais] inferno (fournaise)	Incinéroque	incinérer + roque (coup aux échecs)	—
Toxtricity	toxic + electricity	Salarsen	salamandre + arsenic + larsen (effet Larsen)	Toxtricité	toxique + électricité	ling. coincidence
Pyroar	pyre + roar	Némélios	lion de Némée + [grec] hélios (mythologie grecque)	Pyroque	pyro + roque	—
Metallurgix	metallurgy	Amérix	Amérique	Métalurgix	métallurgie + -ix	ling. coincidence

EN	EN Interpretation	Official FR	Official FR Interpretation	Non-official FR	Non-official FR Interpretation	Comment
Wifix	wifi	Rézowifix	"réseau wifi"	Ouifix	wifi + -ix	term francisation
legilimency	[latin]legere (to read) + [latin]mens (mind)	legilimancie	[latin]legere (lire) + [latin]mens (esprit)	légilimence	[latin] legere (lire) + [latin] mens (esprit)	term francisation
butterbeer	butter + beer	bièreaubeurre	bière + au + beurre	bourreau-bourre	bourreau + bourre	non-sens
Drifdlim	drift + blimp	Grodrive	gros + dérive	Grodrive	gros + dérive	—
Mismagius	mischief + magus	Magirêve	magie + rêve	Virgilus	vigile + Virgile (personnage antique) + -us	—
Dwebble	dwell + pebble	Crabicoque	crabe + bicoque	Débébé	débébé / des bébés	—
Terrible Terror	[0]	Terreur Terrible	[0]	Terreur terrifiante	terreur terrifiante (répétition en synonymes pour amplifier le sens)	ling. coincidence
Gold Ammolet	ammo + amulet	Ammolette en or	ammo [anglais] + amulette	Ammolette d'or	ammolette (amulette + [anglais] ammo)	—