# Generating Irish Text with a Flexible Plug-and-Play Architecture 

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#### Abstract

In this paper, we describe M-FleNS, a multilingual flexible plug-and-play architecture designed to accommodate neural and symbolic modules, and initially instantiated with rulebased modules. We focus on using M-FleNS for the specific purpose of building new resources for Irish, a language currently underrepresented in the NLP landscape. We present the general M-FleNS framework and how we use it to build an Irish Natural Language Generation system for verbalising part of the DBpedia ontology and building a multilayered dataset with rich linguistic annotations. Via automatic and human assessments of the output texts we show that with very limited resources we can create a system that reaches high levels of fluency and semantic accuracy, while having very low energy and memory requirements.


## 1 Introduction

Natural Language Generation (NLG) for tasks including dialogue-turn generation and fact verbalisation is increasingly widely used in commercial systems. Despite recent spectacular advances achieved by LLMs, in application contexts where accuracy and reliability are crucial, many commercial systems continue to use the same old template filler systems that have been around at least since the 1980s. ${ }^{1}$ The other two main categories of NLG systems are neural language-model based (NLMB) systems, currently extremely popular in research systems, and rule and grammar based (RGB) systems, currently very unpopular. In contrast to template-based (TB) systems, NLMB systems have

[^0]very high Coverage, while also sharing TB systems' high Fluency and Robustness. However, the disadvantage of an NLMB system is that it cannot be guaranteed that the output will be free of grammatical errors or even that it will be semantically accurate. The latter is of particular concern as NLMB systems cannot be trusted not to omit essential content, make things up, or even insult users. Moreover, such systems also tend not to be built for low-resource languages (LRLs) languages because of the large amounts of data needed to build them. Finally, NLMB systems often suffer from low Variation, and very low Energy Efficiency, with the best current models having shockingly high carbon footprints. RGB systems on the other hand have become increasingly unpopular since the NLP field switched first to statistical systems, then to neural systems. While RGB systems tend to have low Coverage, suprasentential Fluency, and Robustness as well as having to be built manually, they can be guaranteed to have high Accuracy and Grammaticality, as well as being efficient in terms of data and energy requirements, and suitable for LRLs.

According to the European Language Equality report for Irish (Lynn, 2022), Irish is a low-resource language. In a survey of available resources for European languages, on a scale of 1-4, Irish was classified as 4 having "weak or no support", and ranked 31st out of the 33 European languages surveyed. The report identifies a range of language technology gaps, mainly due to the lack of underlying data resources, dedicated funding and skill-sets, and finds that to date there has been little or no system development for Automatic Subtitling, Information Retrieval, Information Extraction, Natu-

| Reiter\&Dale Tasks | M-FleNS Tasks | M-FleNS Input | M-FleNS Output | Output type |
| :--- | :--- | :--- | :--- | :--- |
| Content determination | - | - | - | - |
| Discourse planning | Linguistic structuring | Structured data | PredArg | DAG |
| Sentence aggregation | Text planning* | PredArg | PredArg-Agg | DAG |
| Lexicalisation | Lexicalisation | PredArg(-Agg) | PredArg-Lex | DAG |
|  | Comm. structuring | PredArg-Lex | PredArg-Th | DAG |
|  | Deep sent. structuring | PredArg-Th | DSynt | DT |
|  | Surf. sent. structuring | DSynt | SSynt | DT |
|  | Synt. aggregation* | SSynt | SSynt-Agg | DT |
| REG | REG* | SSynt(-Agg) | SSynt-Pro | DT |
| Linguistic realisation | Word ord. and agree. resolution | SSynt(-Agg/-Pro) | DMorph | Chain |
|  | Surface form retrieval | DMorph | SMorph | Chain |

Table 1: The M-FleNS architecture (see Appendix D for illustration): the tasks, their respective input, output (used as module name), structure type ( $\mathrm{DAG}=$ Directed Acyclic Graph; DT = Dependency Tree) and correspondence with Reiter and Dale (1997)'s tasks. * Denotes optional modules, i.e., grammatical texts can be produced without them.
ral Language Generation, Semantic Role Labelling, and other areas. The report recommends a long term strategy of support for dedicated LT education and training, investment in data collection and annotation, and the development of LT tools.

The Digital Plan for the Irish Language (Department of Tourism, Culture, Arts, Gaeltacht, Sport Media, 2022) notes that urgent action is needed if Irish is to benefit from the digital revolution and to survive the threat of digital extinction. It notes two complementary approaches, knowledge-based and data-driven machine-learning methods, and states that both are needed and each brings specific advantages. A linguistic knowledge base provides a digital, explicit account of the structure of contemporary Irish which is an important goal in itself, while machine-learning approaches can offer a quick and less labour-intensive route to developing certain technologies. Both approaches are needed and, especially in the context or LRLs, can be combined in specific systems.

In this paper, we present a flexible plug-and-play architecture that addresses both knowledge-based and machine-learning-based gaps in Irish Natural Language Processing, by releasing a generation system and a rich dataset. While the current (single) Multilingual Flexible Neuro-Symbolic (M-FleNS) system is multilingual - generating text also e.g. in English, French, Spanish, and Catalan-, we focus here on its instantiation with rule-based modules for the generation of Irish texts from DBpedia triple sets. Below, we start by describing and motivating our architecture (Section 2). Next we describe the WebNLG dataset, the FORGe generator and the Irish morphology tools (Section 3) we use. We
present the extension to WebNLG data-to-text for Irish, and evaluate it via metrics and human assessment; we also present a new Irish dataset with rich linguistic annotations produced with our instantiated architecture (Section 4). We finish with a discussion of related work (Section 5). The generation pipeline, ${ }^{2}$ dataset $^{3}$ and an interactive demo for the generation of short Wikipedia pages in Irish or English ${ }^{4}$ are all publicly available.

## 2 A plug-and-play architecture for system and resource building

### 2.1 Modular structure

While end-to-end approaches are popular in current NLG systems (Dušek et al., 2018; Castro Ferreira et al., 2020), they are more data-hungry and computationally far more expensive (therefore more energy intensive) than corresponding modular architectures (Dušek et al., 2020). Furthermore, recent evidence shows that splitting the generation process into sub-steps can lead to better output texts (Castro Ferreira et al., 2019; Moryossef et al., 2019; Puduppully and Lapata, 2021; Kasner and Dusek, 2022). We seek to leverage this advantage by giving our M-FleNS framework a sequential architecture where each module corresponds to specific (sub)tasks of the natural language generation process roughly corresponding to the pipeline architecture originally established by Reiter and Dale (1997). Table 1 lists the M-FleNS modules in terms

[^1]of the tasks they perform, alongside the tasks/modules identified in Reiter and Dale's pipeline to which they roughly correspond. ${ }^{5}$

### 2.2 Rich linguistic representations

Each of the 10 different modules shown in Table 1 provides as output one or more well defined, rich, and linguistically motivated representations. The intermediate representations in MFleNS are all graphs that can be grouped into three main types: (i) predicate-argument directed acyclic graphs (DAGs) for semantic information; (ii) unordered dependency trees (DTs) for syntactic information; and (iii) chains for morphological information. These intermediate representations loosely follow the different levels of Meaning-Text Theory (Mel'čuk, 1973). In the instantiated version of the pipeline presented in this paper, the input structured data is the WebNLG data (Aquilina et al., 2023), made of DBpedia triple sets, and we use the FORGe grammar-based generator to produce the intermediate representations (Mille et al., 2019) and the Irish NLP toolkit (Dhonnchadha et al., 2003) to produce the final representation: details about the dataset and tools are provided in Section 3.

### 2.3 Addressing technology gaps

With our modular approach we aim not only at developing a first system for Irish NLG, but also at producing new data that will allow for addressing more of the technology gaps identified in the European Language Equality report. For instance, with the generator we can produce a large amount of semantic and syntactic structures; syntactic structures paired with texts can be used to train syntactic parsers, while semantic structures paired with text can be used to train semantic role labelers. Using in parallel syntactic and semantic structures, tools can be trained that convert one into the other to build smaller modules to be combined with other tools (e.g. an existing syntactic parser). All ten intermediate representations can be also be used for explainability, language teaching, etc. In Section 4.6 we provide details on how we used our architecture to produce linguistically annotated data.

## 3 Data and tools

In the following subsections, we describe the dataset (WebNLG) and tools (FORGe and Irish NLP) we use in our experiments.

[^2]
### 3.1 The WebNLG dataset

The WebNLG dataset (Aquilina et al., 2023) is a data-to-text benchmark consisting of \{input, output \} pairs, where the input is a set of $n$ triples ( $1 \leq n \leq 7$ ), the output a set of $m$ texts that verbalise the triple set. In Figure 1, $n=3$ and $m=1$.

DBpedia triples are the building blocks of the inputs, and consist of three related elements called a Property, a Subject and an Object in Semantic Web terminology. A Subject (denoted by $D B$-Subj in this paper) is usually an entity that has a Property and a value for this Property, which is the Object ( $D B-O b j$ ). E.g. in Figure 1, the entity Agra_Airport is associated with 3 properties: location, operatingOrganisation and icaoLocationIdentifier. The semantics of each property is defined by DBpedia editors, ${ }^{6}$ but in most cases, the Property of the $D B$ Subj is DB-Obj makes it clear (e.g., The location of Agra Airport is India, The operating organisation of Agra Airport the Indian Air Force, and the ICAO location identifier of Agra Airport is VIAG.).

WebNLG 2017 (Gardent et al., 2017) consisted of (only) an English task. For WebNLG 2020, the English dataset was extended with more properties, and it also included Russian texts (Castro Ferreira et al., 2020); in both cases, the texts were collected via manual effort (crowdsourcing). The third edition of the task in 2023 focused on four low-resource languages: Irish, Welsh, Breton and Maltese, for which the texts for the training data are the machine-translated 2020 English texts, while the texts in the test and development data were translated by professional translators. All inputs are the same as the 2020 inputs.

### 3.2 The FORGe multilingual generator

FORGe (Mille et al., 2019) is a multilingual rule-based generator that takes as input minimal predicate-argument (PredArg) structures. It realises the last four consecutive steps of the traditional NLG pipeline (Reiter and Dale, 1997) (sentence aggregation, lexicalisation, ${ }^{7}$ referring expression generation and linguistic realisation, see Table 1). Each of the four steps is implemented as one or more graph transducer(s) that successively map the input PredArg onto different dependency-based intermediate linguistic representations.

[^3]```
<entry category="Airport" eid="719" shape="(X (X) (X) (X))" shape_type="sibling" size="3">
    <modifiedtripleset>
        <mtriple>Agra_Airport | location | India</mtriple>
        <mtriple>Agra_Airport | operatingOrganisation | Indian_Air_Force</mtriple>
        <mtriple>Agra_Airport | icaoLocationIdentifier | &quot;VIAG&quot;</mtriple>
    </modifiedtripleset>
    <lex comment="" lang="ga" lid="Id3">Tá Aerfort Agra, atá VIAG mar an cód aitheantais
            áite ICAO aige, á reáchtáil ag Aerfhórsa na hIndia.</lex>
</entry>
```

Figure 1: A WebNLG data point (EN: 'Agra airport, whose ICAO identifier is VIAG, is operated by the IAF.')

A mix of language-independent and languagespecific rules build these intermediate representations using additional knowledge contained in language-specific dictionaries. From the perspective of multilingualism, there are 3 types (T1-T3) of rules in FORGe: fully language-independent rules (T1, $\sim 82 \%$ of all rules); rules that apply to a subset of languages (T2, $\sim 6.5$ languages on average, $\sim 3 \%$ of rules); and language-specific rules, which apply to one single language ( $\mathrm{T} 3, \sim 15 \%$ of rules). In the description of the extensions of FORGe for Irish below, we refer to these three types.

FORGe uses three different dictionaries to store:

- Mappings between concepts and lexical units, e.g. located $\{G A=\{$ lex=lonnaithe_JJ_01 $\}\}$.
- Lexical unit descriptions, e.g. lonnaithe_JJ_01 \{lemma = lonnaithe; pos $=J J$; preposition_arg $2=i\}$, where $i$ 'in' is required on the second argument of lonnaithe: lonnaithe i X 'located in X'.
- Generic language-specific knowledge, such as the type of word order or morphological agreement triggered by surface-oriented dependencies (e.g. in English a direct object is by default after its governing verb in the sentence, and a determiner receives case, number and gender from its governing noun).

The input PredArg structures are very similar to the Facts in ILEX's Content potential structures (O'Donnell et al., 2001), or the Message triples in NaturalOWL (Androutsopoulos et al., 2013), with the difference that all predicates in the PredArg structures are generally intended to represent atomic meanings (e.g. main + runway as opposed to mainRunway), allowing for more flexible processing. The first part of the generation pipeline, which produces aggregated predicate-argument graphs, is also comparable to ILEX (O'Donnell et al., 2001), while the surface realisation is largely inspired by MARQUIS (Wanner et al., 2010). FORGe shares not only its general
architecture with these two systems, but also the use of lexical resources with subcategorisation information and of a multilingual core of rules.

FORGe was adapted to the WebNLG'20 dataset for the generation of English texts and has a multilingual core of rules, but is not able to generate text in a new language off-the-shelf. However, adapting it to a new language is relatively easy, so it is a good candidate for building the first Irish generator. In Section 4, we report on the extensions we carried out to FORGe so as to be able to generate WebNLG Irish texts. We use the whole FORGe pipeline except for the surface form generation, for which we use the existing Irish NLP tools (see Section 3.3).

### 3.3 Irish NLP tools

The Irish NLP tools suite ${ }^{8}$ includes finite-state transducers for Irish morphology generation (Dhonnchadha et al., 2003). These tools handle tokenisation and morphological analysis/generation of the inflected forms of Irish headwords coded in the finite-state lexicons. The tools were initially developed using xfst (Xerox finite state tools) (Beesley and Karttunen, 2003) and later converted to use foma tools (Hulden, 2009). ${ }^{9}$ Finite-state transducers model a two-level morphology where a lexical description is mapped to a surface form, e.g. déan+Verb+VT+FutInd maps to the future tense form déanfaidh of the transitive verb déan 'make'. The transducers can be used to generate inflected forms of words for NLG and CALL applications, and the same transducers work in the opposite direction for morphological analysis as part of NLP applications including PoS tagging and parsing.

## 4 M-FleNS for Irish Natural Language Generation

In this section, we describe our pipeline for the generation of Irish texts from DBpedia triples,

[^4]

Figure 2: Sample PredArg template corresponding to the location property.
including Subject and Object label retrieval and predicate-argument template crafting (4.1), extensions to FORGe and lexical resource building for Irish (4.2), the connection between FORGe and Irish NLP tools (4.3) and post-processing of outputs (4.4). We then provide an evaluation of the generator (4.5) and describe a new dataset (4.6). All resources are available; see Footnotes 2, 3, 4.

### 4.1 PredArg templates and their instantiation

The linguistic structuring step consists of mapping the WebNLG input triple sets onto abstract linguistic (predicate-argument) structures. For this, we follow the approach of the FORGe submission at WebNLG' 17 (Mille et al., 2019), i.e. we use PredArg templates in the PropBank style (Kingsbury and Palmer, 2002) that correspond to each individual property and instantiate them by replacing the DB-Subj and DB-Obj placeholders with their respective lexicalisations. The instantiated templates are then grouped based on their DB-Subj and ordered in descending frequency of appearance of the DB-Subj in the input triple set (e.g. triples with a DB-Subj that has 3 mentions come before those with 2 mentions). Figure 2 shows a PredArg template, instantiated in Figure 4 in Appendix A.

Lexicalisation of properties. We handcrafted templates for all properties of the training, development and test splits of the WebNLG' 23 dataset. There are 411 different properties, and since several properties can be verbalised the same way, ${ }^{10}$ the total number of unique templates is lower (381).

In an effort to possibly reduce the human effort in the crafting of the templates in future developments of our (or others') system, we tried to reduce to a maximum the number of different templates to cover all properties. After examining the 411 properties and defining corresponding templates, we assigned each property a specific type according to the kind of information that it is transmitting. We defined 23 type labels such as PART OF/MEMBER OF, ORIGIN LOCATION, SET MEMBERSHIP,

[^5][X] HAS [QTY] ENTITY, etc. Each type is associated with a sentence template and a basic PredArg that can be used to verbalise the properties associated to it. We plan to use these basic labels to speed up the future extension of the generator.

Lexicalisation of DB-Subj and DB-Obj values. For each triple, the property and its pertinent domain and range classes determine whether the DBSubj/Obj values will be lexicalised using their English or Irish label (human readable name). To obtain the latter, we take advantage of the owl:sameAs relation that links the DB-Subj/Obj entity of the English DBpedia to its equivalent entity in the Irish DBpedia version; if no equivalent entity is contained in the localised DBpedia version, we fall back to Google translate, ${ }^{11}$ giving as input the English label without any further context.

### 4.2 Extensions to FORGe

We extended the available version of FORGe in two aspects: (i) manual crafting of the three types of dictionaries, and (ii) implementation of languagespecific rules to cover the idiosyncracies of Irish. With respect to dictionaries, we added 457 mappings between concepts and lexical units and as many lexical unit descriptions, and we manually crafted the generic language-specific dictionary. For rules, we implemented 76 rules that apply exclusively to Irish (T3), which represents $2.78 \%$ of rules; Table 2 shows the breakdown of languageagnostic and language-specific rules per module. We also activated 65 existing T2 rules for Irish.

As Table 2 shows, 4 modules require Irishspecific rules: deep sentence structuring, surface sentence structuring, word order and agreement resolution and morphology processing; next we list the phenomena that required T 3 and most T 2 rules.

## Deep sentence structuring

Relative particles (T3): the particle $a$ is introduced to link the modified noun and the main verb in relative clauses; in case of prepositional relatives, the particle has a different form depending on the tense of the verb (present $a$, past $a r$ ).

Passive (T3): in Irish there are two alternative constructions where a passive form would be used in English. If the data refers to an action/event, an autonomous main verb form is used, e.g. for the triple Acharya_Institute_of_Technology | established | 2000, bunaíodh, the autonomous

[^6]| ID | FORGe module | \# rl | \% lang. ind. rl | \# T3 GA rl | \% T3 GA rl |
| :---: | :--- | :---: | :---: | :---: | :---: |
| 1 | Text planning | 553 | 99.82 | 0 | 0 |
| 2 | Lexicalisation | 183 | 97.81 | 0 | 0 |
| 3 | Communicative structuring | 258 | 97.29 | 0 | 0 |
| 4 | Deep sentence structuring | 345 | 78.84 | 3 | 0.87 |
| 5 | Surface sentence structuring | 477 | 68.97 | 17 | 3.56 |
| 6 | Syntactic aggregation | 215 | 93.02 | 0 | 0 |
| 7 | Referring Expression Generation | 237 | 96.2 | 0 | 0 |
| 8 | Word order and agreement resolution | 265 | 50.57 | 17 | 6.42 |
| 9 | Morphology processing | 201 | 45.77 | 39 | 19.4 |
|  | All modules | 2,734 | 81.82 | 76 | 2.78 |

Table 2: Number of rules, proportion of language-independent rules, and number and $\%$ of Irish-specific (T3) rules (rl) per FORGe module.
form of the verb bunaigh 'to establish' is used, as in Bunaíodh Institiúid Teicneolaíochta Acharya sa bhliain 2000, 'Acharya Institute of Technology was established in the year 2000'. Alternatively, where a state/location is referred to, e.g. for the triple MotorSport_Vision|city|Longfield, we have tá, the present tense of the auxiliary verb bí 'to be', and the past participle lonnaithe 'located', as in Tá MotorSport Vision lonnaithe i gcathair Longfield, 'MotorSport Vision is located in Longfield'.

Non-verbal copula (T3): Irish has two copular constructions. The verbal copula bí is used for changeable properties whereas the non-verbal copula is is used for more permanent properties such as area code, e.g. for Darlington | areaCode | 01325 we have Is é cód ceantair Darlington ná 01325, where is connects cód ceantair Darlington 'Darlington area code' with its value, and the pronoun $e ́$ agrees with the gender and number of the noun cód 'code'.

## Surface sentence structuring

Determiners (T3): a definite determiner is only introduced on a noun $N$ if $N$ 's dependent is not a definite noun or a proper noun.

Dependencies (T2, 22 rules in common with Catalan, Greek, Spanish, French, Italian and Portuguese): surface-oriented dependencies are introduced as, e.g., subject, direct object, modifier, etc.

## Word order and agreement resolution

Genitive chains (T3): in a chain of genitive elements, only the last element maintains the genitive case, e.g. in the case of 'the length of the runway of the aerodrome', only the last element 'aerodrome' has genitive case as in Is é fad rúidbhealach an aeradróim 1,095m.

Word order class (T3): when an element is established as a member of a class, the class name goes
right after the copula, as in Is milseog é Bionico 'Bionico is a dessert'.

Possessive pronoun agreement (T3): the semantic number and gender of a possessor triggers agreement on the possessed. In the case of the triple India | leader | T._S._Thakur, the copular construction generates the text Tá T.S. Shakur ina cheannaire ar an India, 'T. S. Thakur is a leader of India', where we have the present tense of the verbal copula bí, followed by the subject 'T. S. Thakur' and the subject complement 'ina cheannaire ar an India'. The complement has a possessive pronoun ina that agrees in gender and number with the subject, i.e. ina is masculine singular reflecting the subject 'T. S. Thakur' and it triggers masculine singular agreement on the noun cheannaire 'leader'.

Ellipsis (T3): some rules look for pronouns to elide, in particular in relative and non-verbal copular constructions. Irish is a VSO language so a specific rule checks for repeated subjects on the right of the verb and replaces them with pronouns. ${ }^{12}$

Order between siblings (T2, 29 rules in common with Catalan, Greek, Spanish, French, Portuguese and sometimes Italian): for instance, in many languages, the determiner usually goes before all other dependents of the noun.

## Morphology processing

Concatenations (T3): don is a contraction of do an 'for the' as in Scríobh Nicholas Brodszky an ceol don scannán meaning 'Nicholas Brodszky wrote the music for the film'.

Prefixes (T3): vowel-initial masculine nouns following the determiner an receive a $t$ - prefix as in Rugadh an t-aisteoir Bill Oddie in Rochdale meaning 'The actor Bill Oddie was born in Rochdale'.

[^7]The preposition le triggers a prefix $h$ - on following nouns starting with a vowel, and some past verbs get the prefix $d^{\prime}$.

Mutations (T3): word-initial mutations are common in Irish and fulfil many grammatical functions, for example the noun cathair 'city' has various mutations depending on the number and gender of the possessive pronoun, e.g. there is lenition in mo chathair 'my city', eclipsis in ár gcathair 'our city' and no mutation in a cathair 'her city'.

Verbal Adj/N, Prep. declension, V flags (T3): other rules cover the conversion of some adjectives and nouns into their verbal counterparts, the inflection of some prepositions and the insertion of a tag that flags vowel-initial verbs, as required by the morphology generator.

### 4.3 Interfacing FORGe with Irish NLP tools

In order to match the inputs expected by Irish NLP tools, we process FORGe outputs with regular expressions to replace reserved characters, introduce a ' + ' separator between morphological tags, and insert single line breaks between consecutive words and double line breaks between consecutive texts.

### 4.4 Post-processing

The post-processing consists of regular expressions to revert reserved characters to their original form, true-case and clean the texts, and take care of prefixing, hyphenation, contraction, lenition and eclipsis phenomena triggered by the inflected forms of words; see Appendix A for an example.

### 4.5 Evaluation

We report on both automatic and human evaluations of the quality of the texts generated with our pipeline (DCU/TCD in Tables 3 and 4). Both evaluations were carried out as part of the WebNLG'23 shared task by the task organisers; see details in the task overview paper (Aquilina et al., 2023).

|  | BLEU | BERT_F1 |
| ---: | :---: | :---: |
| DCU-NLG | 20.40 | 0.81 |
| DCU/TCD | $\mathbf{1 6 . 6 6}$ | $\mathbf{0 . 7 7}$ |
| IREL | 15.66 | 0.78 |
| Cuni-Wue | 15.87 | 0.77 |
| Baseline | 11.63 | 0.76 |

Table 3: WebNLG'23 automatic evaluation results.

For the automatic evaluations, outputs from all systems were compared to the reference
human-translated Irish texts (1,779 test texts), and BLEU (Papineni et al., 2002), TER (Snover et al., 2006), chrF++ (Popović, 2017) and BERTScore (Zhang et al., 2019) were computed; see results in Table 3. For the human assessment, the organisers selected randomly the same 100 outputs for each system (and the corresponding 100 reference texts) and asked professional translators to rate the texts on a scale of 1 to 5 according to 4 criteria: Fluency and Absence of Repetition to capture the intrinsic quality of the texts, and Absence of Omission and Absence of Additions to capture the semantic faithfulness of the text with respect to the input triple sets; see Table 4 for results.

| System | Flu. | Add. | Omi. | Rep. |
| ---: | :---: | :---: | :---: | :---: |
| Human | 4.07 | 0.81 | 0.82 | 0.96 |
| DCU-NLG | 3.83 | 0.83 | 0.85 | 0.97 |
| DCU/TCD | $\mathbf{3 . 3 5}$ | $\mathbf{0 . 8 4}$ | $\mathbf{0 . 8 1}$ | $\mathbf{0 . 8 9}$ |
| IREL | 3.39 | 0.65 | 0.58 | 0.94 |
| Cuni-Wue | 2.98 | 0.55 | 0.51 | 0.92 |

Table 4: Results of the WebNLG'23 human evaluation; Human = human-translated texts, Flu. = Fluency, Add. = Absence of addition, Omi. = Absence of omission, Rep. $=$ Absence of repetition.

Considering that all other systems including the baseline are combinations of (very) large language models (to generate English texts) and machine translation (to translate to Irish), we were surprised to see that our rule-based pipeline performed well in the automatic evaluations: we obtained a BLEU score only 4 points below the highest scoring system (a combination of GPT3.5 and Google Translate (Lorandi and Belz, 2023)), and higher that all non-GPT-based submissions. As comparison, for English text generation at WebNLG'20 (Castro Ferreira et al., 2020), the FORGe-based submission was 13 BLEU points lower than the highest scoring system and one of the lowest BLEU overall. ${ }^{13}$ Our absolute BLEU score is much lower than FORGe's scores on English at WebNLG'20 (over 40); this is at least partly because BLEU was calculated with only one reference (compared to 2,5 on average in English, which produces higher scores), but it could also be due to the fact that we created our lexicalisations without reference to the gold Irish texts, i.e. surface similarity is likely to be low.

[^8]The results of the human evaluation show that DCU/TCD-FORGe is on a par with the human references and the best system for Absence of Additions, Absence of Omissions and Repetition (no statistical difference in the scores according to the organisers), but is significantly less good in terms of Fluency. Part of the reason for this can be found in our own preliminary quality assessment of the output texts, during which Irish speakers mentioned that the way the information is packaged into sentences (Text planning task) is often unnatural, which directly affects the Fluency of texts. We plan to address this issue by replacing the text planning module by a statistical component.

Our system does not reach the level that can be achieved with very large language models, but unlike the latter, it is inherently energy- and resourceefficient: our complete pipeline has a disk space of about 8 MB and runs with less than 1GB of RAM; it generates the whole WebNLG test set $(1,779$ texts) in about $15 \mathrm{~min}(0.5 \mathrm{sec} /$ text $)$. The generation pipeline is also reusable; it currently covers datasets such as E2E (Novikova et al., 2017) or Rotowire (Wiseman et al., 2017) in English, and adapting it to new domains is straightforward.

### 4.6 A new Irish dataset with rich annotations

Along with our architecture and our generation pipeline, we also release an Irish multilayer dataset with rich linguistically motivated intermediate representations. In order to create the dataset, we apply our whole generation pipeline described in Section 4 and save the intermediate representations in the process. The resulting dataset has ten layers, which correspond to the ten layers shown in Table 1.

Representations at all layers are multi-sentence graphs that can be grouped into the three main types from Section 2: directed acyclic graphs for semantic information, unordered dependency trees for syntactic information, and chains for morphological information. Nodes are connected across layers through individual IDs, and coreference is explicitly marked. Intermediate representations are represented as CoNLL-U tables. ${ }^{14}$ Because CoNLL-U is a linear format that we use to represent unordered graphs and trees, we delimit sentences by <SENT> at the end of a group of nodes. All lines before <SENT> belong to the same sentence, but their relative order in the ConNLL-U file is not relevant. However, the order in which the sentences appear

[^9]does correspond to their order in the text. For levels that are chains, the order of the lines is the order of the elements in the sentence. Detailed descriptions of format and levels can be found in (Mille et al., 2023); tagsets used, dataset statistics and sample structures are provided in Appendix B, C and D.

Due to the modular system architecture, dataset construction is flexible enough to allow the generation of a myriad of dataset variants in terms of verbalisation, sentence grouping/structuring, output simplicity/complexity, etc., simply by (de)activating optional modules (Table 1) or by introducing variation during the linguistic structuring task -thus providing multiple ways of verbalising each input triple. In contrast to neural generation, our approach ensures that output texts are faithful to the input, and will not contain inaccuracies, biases or offensive language. The dataset is publicly available, see Footnote 3.

## 5 Related work

Rule-based NLG. There is a long tradition of rule-based natural language generation systems such as REALPRO (Lavoie and Rainbow, 1997), ILEX (O'Donnell et al., 2001), IGEN (Varges and Mellish, 2001), SimpleNLG (Gatt and Reiter, 2009), MARQUIS (Wanner et al., 2010; BouayadAgha et al., 2012), OpenCCG (White and Rajkumar, 2012), NaturalOwl (Androutsopoulos et al., 2013), GenDR (Lareau et al., 2018) and others. More recently, RDFJSREALB (Lapalme, 2020) and FORGe (Mille et al., 2019) were adapted to WebNLG, but none were able to generate Irish text. Note that the idea of decomposing the generation process into steps has been the standard before the emergence of end-to-end systems, and that previous work on NLG already based their modules on the Meaning-Text theory, going back to REALPRO (Lavoie and Rainbow, 1997) and MARQUIS (Wanner et al., 2010). It is however the first time that a plug-and-play architecture is proposed with these modules, and the first time that an Irish rule-based NLG system is developed.
Irish datasets and language resources. There are few freely available monolingual Irish corpora, and moreover, domain-specific Irish datasets are scarce. Resources are mostly targeted towards machine translation and/or language analysis tasks. With the exception of the WebNLG 2023 data (and now the data presented in this paper), no datasets exist for text generation tasks (Lynn, 2023).

Monolingual corpora. Monolingual data include the New Corpus for Ireland (with fiction, news reports, official documents, etc.) (Kilgarriff et al., 2006), the unshuffled Irish portion of the 2019 OSCAR corpus (Suárez et al., 2019), the Gaois Corpus of Contemporary Irish (Ní Loingsigh et al., 2017), with news media and e-zines, or the Irish Wikipedia Vicipéid, ${ }^{15}$ which draws directly from Fréamh an Eolais, an Irish-language encyclopedia of science and technology. ${ }^{16}$ Moreover, a corpus of idioms (Ní Loingsigh, 2016) and Universal Dependency treebanks such as Irish UD (Lynn and Foster, 2016), pre-standard Irish UD (Scannell, 2022) and TwittIrish (Cassidy et al., 2022) are available.
Bilingual/Parallel corpora. Significant advances have been made in the collection and availability of bilingual corpora, including: (i) ParaCrawl v7 (Bañón et al., 2020), a collection of parallel corpora crawled from multi-lingual websites; (ii) the Gaois Parallel Corpus ${ }^{17}$ of 26 M Irish words and 24.5 M English words; and in particular, (iii) the Irish-EU English-Irish Parallel Corpus which was a direct outcome of the European Language Resource Coordination project (ELRC ${ }^{18}$ ). This resource contains $195 \mathrm{~K}+$ parallel sentences, collected from various public bodies and government departments released via ELRC-SHARE ${ }^{19}$. In Ireland all national translation data is collected by eSTÓR. ${ }^{20}$
Irish tools and Models. The European Language Grid ${ }^{21}$ catalogue lists a number of multilingual tools and services that support Irish (e.g. Bitextor, Opus MT, Systran). Irish NLP tools (Uí Dhonnchadha, 2009) offers the only suite of text analysis in Irish. Transformer Language Models (LM) such as multilingual BERT (M-BERT) (Devlin et al., 2019), and the language-agnostic BERT Sentence Embedding (Feng et al., 2022)) support Irish. The monolingual Irish gaBERT LM was trained on over 7.9 M sentences, and outperforms baselines for tasks such as dependency parsing and multiword expression identification. (Barry et al., 2022).

## 6 Conclusions

We have presented a high-accuracy, energy and resource-efficient system for generating Irish text

[^10]which achieves a satisfactory quality of output. Its modular architecture means that shortcomings can potentially be remedied by training statistical modules, such as a text structuring module for improved fluency, or by including enhanced rule-based modules which can be added to the pipeline.

This type of modular rule-based NLG system is particularly suitable for low-resource languages, where large amounts of training data is not available, and can play an important role in generating accurate fact-based online language content, such as Wikipedia pages. Such systems can be developed incrementally and language documentation is an inherent and valuable by-product of the system. In addition, rule-based systems tend to suffer less from the negative and harmful biases which have been identified in the application of some LLMs.

## Limitations

Generation pipeline. Coverage and robustness of rule-based NLG: Although our experiments show that we are able to overcome some of the drawbacks of LLMs, the main bottleneck of any rulebased system remains coverage and robustness. In addition, it can be difficult for someone who is not familiar with the rule systems to edit it, and it usually requires knowledge of the language.

Dataset. Our dataset differs from previous work in that we do not use human-written texts; since texts are synthetic and produced by a deterministic generator, their variety and quality is limited by the knowledge encoded in the generator (in particular, they generally lack the naturalness of humanwritten texts), and they represent only a fraction of what is possible for a language to express.

The current intermediate representations are well-formed at all layers, but we are conscious that some phenomena would require some additional analysis; as e.g. the syntactic representations of copulas and their é pronoun (see Section 4.2).

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## Ethics Statement

Given that we do not resort to using language models nor to human evaluation with people who are not authors of this paper, the present work has no ethics implication that we are aware of.

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## A Sample input and output structures

The figures in the next page illustrate the generation process starting from an input triple set that corresponds to the following English text:

Agra Airport, operated by Indian Air Force, is located in India. Its ICAO location identifier is VIAG.

Figure 3 shows a WebNLG'23 input, and Figure 4 shows the output of the lexicalisation module. The FORGe, morphology and post-processing outputs are shown in a one-word-per-line format in Table 5. The output Irish text is the following:

> Tá Agra Airport, reáchtáilte ag Indian Air Force, lonnaithe ins An India. Tá VIAG in a aitheantóir suímh ICAO.

## B Irish dataset: Tagsets used

The edge labels for semantic graphs come mainly from PropBank (Kingsbury and Palmer, 2002), plus some generic labels such as Location and Time; see Table 6. The ones for deep syntactic trees come from Meaning-Text Theory (Mel'čuk, 1988); see Table 7. As for surface syntactic edge labels, they are our own; see Table 8.

## C Irish dataset: Statistics

There are $13,211,1,667$ and 1,779 texts in the training, development and test splits respectively. Tables 9-10 provide an overview of the number of nodes and sentences per text for all splits. Our 10 intermediate layers contain over 2 million nodes.

## D Irish dataset: Sample structures

The annotations are released in CoNLL-U format, but because of space constraints, we have truncated the data in Tables 11-20 below: (i) we dropped unused columns and renamed the remaining ones for readability; (ii) we removed feature names to retain only their values; (iii) we omit the metadata, which specifies the text ID, the level of representation (see the captions) and the corresponding text string. The showcased structures all correspond to the same text as in Appendix A.

```
<entry category="Airport" eid="719" shape="(X (X) (X) (X))" shape_type="sibling" size="3">
    <modifiedtripleset>
        <mtriple>Agra_Airport | location | India</mtriple>
        <mtriple>Agra_Airport | operatingOrganisation | Indian_Air_Force</mtriple>
        <mtriple>Agra_Airport | icaoLocationIdentifier | &quot\overline{jVIAG&quot;</mtriple>}
    </modifiedtripleset>
</entry>
```

Figure 3: A sample WebNLG input with 3 triples (same as Figure 1)


Figure 4: Lexicalisation output: instantiated PredArg templates

| FORGe | Morphology | Post-processing |
| :---: | :---: | :---: |
| bí+Verb+PresInd | tá | Tá |
| Agra_Airport+Noun+Masc+Com+Sg | Agra_Airport | Agra Airport |
| reáchtáilte | reáchtáilte | reáchtáilte |
| ag | ag | ag |
| Indian_Air_Force+Noun+Masc+Com+Sg | Indian_Air_Force | Indian Air Force |
| lonnaithe+Adj+Masc+Com + Sg | lonnaithe | lonnaithe |
| lonnaithe+Adj+Masc+Com+Sg <br> i | lonnaithe <br> i | lonnaithe ins |
| An_India+Noun+Masc+Com+Sg | An_India | An India |
| bí+Verb+PresInd | tá | Tá |
| VIAG+Noun+Masc+Com+Sg | VIAG | VIAG |
| i | i | in |
| a | a | a |
| aitheantóir+Noun+Masc+Com+Sg | aitheantóir | aitheantóir |
| suímh | suímh | suímh |
| $\mathrm{ICAO}+$ Noun+Masc+Com+Sg | ICAO | ICAO |
| . |  |  |

Table 5: FORGe, morphology and post-processing outputs (one word per line for convenience)

| Label | Description | Example |
| :--- | :--- | :--- |
| A0-A6 | $n$-th argument of a predicate or quasi-predicate | speak $\rightarrow$ English |
| Location | location | born $\rightarrow$ Paris |
| Time | time | build $\rightarrow 1932$ |
| NonCore | inverted first argument of a predicate | runway $\rightarrow$ second |
| Set | list of elements | and $\rightarrow$ speak |
| Elaboration | (i) none of governor or dependent are argument of the other | above me $\rightarrow 610 \mathrm{~m}$ |
|  | (ii) unknown argument slot |  |

Table 6: Edge labels of semantic graphs

| Label | Description | Example |
| :--- | :--- | :--- |
| I-VI | $n$-th complement of a syntactic predicate | speak $\rightarrow$ English |
| ATTR | modifier | runway $\rightarrow$ second |
| COORD | coordination | staff members $\rightarrow$ and |
| APPEND | parenthetical modifier | Hypermarcas Brazil $\rightarrow$ (s.a.) |

Table 7: Edge labels of deep syntactic trees

| Label | Description |
| :--- | :--- |
| adjunct | backgrounded adverbial |
| adv | general adverbial (not restrictive nor backgrounded) |
| agent | between non-finite verb and its 1st argument |
| analyt_pass | between passive auxiliary and main verb |
| appos | nominal noun modifier (apposition) |
| attr | prepositional noun modifier (attributive) |
| aux_phras | between elements of multi-word proper nouns |
| compar | between adjective and comparative |
| compar_conj | complement of a comparative conjunction |
| coord | between 1st conjunct and conjunction |
| coord_conj | between conjunction and 2nd conjunct |
| copul | complement of a copula |
| det | determiner of a noun <br> dobj |
| direct object |  |
| iobj | indirect object |
| modal | between modal verb and main verb |
| modif | adjectival or participial noun modifier |
| obl_compl | complement (argument) of a noun |
| obl_obj | prepositional object (not direct or indirect) |
| prepos | complement of a preposition <br> quant |
| numeral noun modifier (quantificative) |  |

Table 8: Edge labels of Irish surface syntactic trees

| Layer | N | S |
| :--- | ---: | ---: |
| PredArg | 152,750 | 48,776 |
| PredArg-Agg | 134,008 | 31,065 |
| PredArg-Lex | 134,008 | 31,065 |
| PredArg-Comm | 143,343 | 31,065 |
| DSynt | 175,019 | 31,065 |
| SSynt | 254,128 | 31,065 |
| SSynt-Agg | 255,499 | 29,215 |
| REG | 254,355 | 29,215 |
| DMorph | 283,593 | 29,228 |
| Text | 285,727 | 29,228 |

Table 9: Total number of nodes $(\mathrm{N})$ and sentences ( S ) per layer.

| Layer | N | S | $\mathrm{N} / \mathrm{S}$ |
| :--- | ---: | ---: | ---: |
| PredArg | 9.2 | 2.9 | 3.1 |
| PredArg-Agg | 8.0 | 1.9 | 4.4 |
| PredArg-Lex | 8.0 | 1.9 | 4.4 |
| PredArg-Comm | 8.6 | 1.9 | 4.7 |
| DSynt | 10.5 | 1.9 | 5.7 |
| SSynt | 15.3 | 1.9 | 8.3 |
| SSynt-Agg | 15.3 | 1.8 | 8.9 |
| REG | 15.3 | 1.8 | 8.8 |
| DMorph | 17.0 | 1.8 | 9.8 |
| Text | 17.2 | 1.8 | 9.9 |

Table 10: Average number of nodes (N), sentences (S) and nodes per sentence (N/S) for each text, per layer.

| ID | Semanteme | Features | Head | Rel | Misc |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | located | - | 0 | root | $\mathrm{src}=1$ |
| 2 | Agra_Airport | ne | 1 | A1 | coref=0\|src=2 |
| 3 | An_India | location\|ne | 1 | A2 | coref=1 \|src=3 |
| 4 | <SENT> | - | - | - | - |
| 5 | operate | pres | 0 | root | $\mathrm{src}=4$ |
| 6 | Indian_Air_Force | ne | 5 | A1 | coref=2\|src=6 |
| 7 | Agra_Airport | deflne | 5 | A2 | coref=0\|src=5 |
| 8 | <SENT> | - | - | - | - |
| 9 | ICAO_location_identifier | def | 0 | root | $\mathrm{src}=7$ |
| 10 | Agra_Airport | - | 9 | A2 | coref=0\|src=8 |
| 11 | VIAG | ne | 9 | A1 | coref=3\|src=9 |
| 12 | <SENT> | - | - | - | - |

Table 11: Predicate-argument structure (PredArg).

| ID | Semanteme | Features | Head | Rel | Misc |
| ---: | :--- | :--- | :--- | :--- | :--- |
| 1 | located | rheme | 0 | root | src=1 |
| 2 | An_India | location\|ne | 1 | A2 | coref=1\|src=3 |
| 3 | operate | pres | 0 | root | src=4 |
| 4 | Indian_Air_Force | ne | 3 | A1 | coref=2\|src=6 |
| 5 | Agra_Airport | ne | 1,3 | A1,A2 | coref=0\|src=2 |
| 6 | <SENT> | - | - | - | - |
| 7 | ICAO_location_identifier | def | 0 | root | src=7 |
| 8 | Agra_Airport | - | 7 | A2 | coref=0\|src=8 |
| 9 | VIAG | ne | 7 | A1 | coref=3\|src=9 |
| 10 | <SENT> | - | - | - | - |

Table 12: Aggregated predicate-argument structure (PredArg-Agg; corresponds to Figure 4).

| ID | Semanteme | POS | Features | Head | Rel | Misc |
| ---: | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | located | JJ | jj\|rheme | 0 | root | src=1 |
| 2 | An_India | NP | location\|ne | 1 | A2 | src=3 |
| 3 | operate | VB | pres\|vb | 0 | root | src=4 |
| 4 | Indian_Air_Force | NP | ne | 3 | A1 | src=6 |
| 5 | Agra_Airport | NP | ne | 1,3 | A1, A2 | coref=0\|src=2 |
| 6 | <SENT> | - | - | - | - | - |
| 7 | ICAO_location_identifier | NN | def\|nn | 0 | root | src=7 |
| 8 | Agra_Airport | NN | - | 7 | A2 | coref=0\|src=8 |
| 9 | VIAG | NP | ne | 7 | A1 | src=9 |
| 10 | <SENT> | - | - | - | - | - |

Table 13: Lexicalised predicate-argument structure (PredArg-Lex).

| ID | Semanteme | POS | Features | Head | Rel | Misc |
| ---: | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | reáchtáil | VB | pres | 0 | root | src=4 |
| 2 | lonnaithe | JJ | rheme | 0 | root | src=1 |
| 3 | Agra_Airport | NP | ne | 1,2 | A2, A1 | coref=0\|src=2 |
| 4 | An_India | NP | location\|ne | 2 | A2 | src=3 |
| 5 | Indian_Air_Force | NP | ne | 1 | A1 | src=6 |
| 6 | <SENT> | - | - | - | - | - |
| 7 | aitheantóir | NN | def\|rheme | 0 | root | src=7 |
| 8 | Agra_Airport | NN | - | 7 | A2 | coref=0\|src=8 |
| 9 | VIAG | NP | ne | 7 | A1 | src=9 |
| 10 | <SENT> | - | - | - | - | - |

Table 14: Predicate-argument structure with thematicity (PredArg-Th).

| ID | Lexeme | POS | Features | Head | Rel | Misc |
| ---: | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | bí | VB | fin\|decl|act | 0 | root | src=1 |
| 2 | Agra_Airport | NP | - | 1 | I | coref=0\|src=2 |
| 3 | reáchtáil | VB | part\|pres | 2 | ATTR | src=4 |
| 4 | Indian_Air_Force | NP | - | 3 | I | src=6 |
| 5 | lonnaithe | JJ | - | 1 | II | src=1 |
| 6 | An_India | NP | location | 5 | II | src=3 |
| 7 | <SENT> | - | - | - | - | - |
| 8 | bí | VB | masc\|act|fin|decl | 0 | root | src=7 |
| 9 | VIAG | NP | - | 8 | I | src=9 |
| 10 | aitheantóir | NN | masc\|gen|sg | 8 | II | src=7 |
| 11 | Agra_Airport | NN | sg | 10 | II | coref=0\|src=8 |
| 12 | <SENT> | - | - | - | - | - |

Table 15: Deep syntactic representation (DSynt).

| ID | Lexeme | POS | Features | Head | Rel | Misc |
| ---: | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | bí | VB | decl\|fin|ind|pres | 0 | root | src=1 |
| 2 | lonnaithe | JJ | acc | 1 | dobj | src=1 |
| 3 | Agra_Airport | NP | nom\|masc $\mid$ sg $\mid$ ne | 1 | subj | coref=0\|src=2 |
| 4 | reáchtáil | VB | part | 3 | modif | src=4 |
| 5 | ag | IN | - | 4 | agent | src=6 |
| 6 | i | IN | - | 2 | obl_compl | src=3 |
| 7 | An_India | NP | sg\|dat|location $\mid$ masc $\mid$ ne | 6 | prepos | src=3 |
| 8 | Indian_Air_Force | NP | nom\|masc|sg|ne | 5 | prepos | src=6 |
| 9 | <SENT> | - | - | - | - | - |
| 10 | bí | VB | pres $\mid$ decl\|fin|masc|ind | 0 | root | src=7 |
| 11 | i | IN | gen | 10 | obl_obj | src=7 |
| 12 | aitheantóir | NN | dat\|masc|sg|gen | 11 | prepos | src=7 |
| 13 | ar | IN | - | 12 | obl_compl | src=8 |
| 14 | Agra_Airport | NN | dat\|masc|sg | 13 | prepos | coref=0\|src=8 |
| 15 | VIAG | NP | nom\|masc|sg|ne | 10 | subj | src=9 |
| 16 | suímh ICAO | NN | sg\|masc|nom | 12 | restr | src=7 |
| 17 | a | DT | - | 12 | det | src=7 |
| 18 | <SENT> | - | - | - | - | - |

Table 16: Surface syntactic representation (SSynt).

| ID | Lexeme | POS | Features | Head | Rel | Misc |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | bí | VB | ind\|sg|sg|decl|fin|pres | 0 | root | $s \mathrm{sc}=1$ |
| 2 | lonnaithe | JJ | sg\|sg|acc | 1 | dobj | $\mathrm{src}=1$ |
| 3 | i | IN | sg\|sg | 2 | obl_compl | src=3 |
| 4 | Agra_Airport | NP | sg\|nom|sg|masc|masc|ne | 1 | subj | coref=0\|src=2 |
| 5 | reáchtáil | VB | sg\|sg|part | 4 | modif | src=4 |
| 6 | ag | IN | sg\|sg | 5 | agent | src=6 |
| 7 | Indian_Air_Force | NP | nom\|masc|sg|masc|sg|ne | 6 | prepos | src=6 |
| 8 | An_India | NP | masc\|sg|dat|location|masc|sg|ne | 3 | prepos | src=3 |
| 9 | <SENT> | _ | - | - | - | - |
| 10 | bí | VB | pres\|sg|sg|decl|fin|masc|masc|ind | 0 | root | $\mathrm{src}=7$ |
| 11 | i | IN | sg\|sg|gen | 10 | obl_obj | $\mathrm{src}=7$ |
| 12 | aitheantóir | NN | dat\|sg|masc|gen|masc|sg | 11 | prepos | $\mathrm{src}=7$ |
| 13 | ar | IN | sg\|sg | 12 | obl_compl | src=8 |
| 14 | Agra_Airport | NN | masc\|dat|masc|sg|sg | 13 | prepos | coref=0\|src=8 |
| 15 | VIAG | NP | nom\|sg|masc|masc|sg|ne | 10 | subj | src=9 |
| 16 | suímh ICAO | NN | sg\|sg|masc|nom|masc | 12 | restr | $\mathrm{src}=7$ |
| 17 | a | DT | -\|sg|sg | 12 | det | $\mathrm{src}=7$ |
| 18 | <SENT> | - | - | - | - | - |

Table 17: Aggregated surface syntactic representation (SSynt-Agg).

| ID | Lexeme | POS | Features | Head | Rel | Misc |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | bí | VB | sg\|sg|decl|fin|pres|ind | 0 | root | src=1 |
| 2 | lonnaithe | JJ | sg\|acc|sg | 1 | dobj | $\mathrm{src}=1$ |
| 3 | i | IN | sg\|sg | 2 | obl_compl | src=3 |
| 4 | Agra_Airport | NP | masc\|sg|sg|nom|masc|ne | 1 | subj | coref=0\|src=2 |
| 5 | reáchtáil | VB | part\|sg|sg | 4 | modif | src=4 |
| 6 | An_India | NP | location\|masc|masc|sg|dat|sg|ne | 3 | prepos | src=3 |
| 7 | ag | IN | sg\|sg | 5 | agent | src=6 |
| 8 | Indian_Air_Force | NP | masc\|masc|sg|sg|nom|ne | 7 | prepos | src=6 |
| 9 | <SENT> | - | - | - | - | - |
| 10 | bí | VB | pres\|ind|masc|sg|decl|sg|fin|masc | 0 | root | src=7 |
| 11 | i | IN | sg\|sg|gen | 10 | obl_obj | src=7 |
| 12 | aitheantóir | NN | masc\|gen|masc|sg|sg|dat | 11 | prepos | src=7 |
| 13 | _PRO_ | PP | masc\|sg|dat|masc|sg | 12 | obl_compl | coref=0\|src=8 |
| 14 | suímh ICAO | NN | masc\|sg|nom|masc|sg | 12 | restr | src=7 |
| 15 | VIAG | NP | masc\|sg|sg|nom|masc|ne | 10 | subj | src=9 |
| 16 | <SENT> | - | - | - | - | - |

Table 18: Pronominalised surface syntactic representation (SSynt-Pro).

| ID | Word | POS | Features | Misc |
| ---: | :--- | :--- | :--- | :--- |
| 1 | bí | VB | pres $\mid$ vi\|decl|fin|sg|ind | src=1 |
| 2 | Agra_Airport | NP | nom\|masc|sg|invar | coref=0\|src=2 |
| 3 | reáchtáil | VB | nom\|part|masc|sg|vti | src=4 |
| 4 | ag | IN | sg | src=6 |
| 5 | Indian_Air_Force | NP | sg\|nom|masc|invar | src=6 |
| 6 | lonnaithe | JJ | sg\|acc|masc | src=1 |
| 7 | i | IN | sg | src=3 |
| 8 | An_India | NP | dat\|masc|sg|invar | src=3 |
| 9 | - | - | - | src=- |
| 10 | bí | VB | ind\|pres $\mid$ vi\|sg|decl|fin|masc | src=7 |
| 11 | VIAG | NP | nom\|masc|sg|invar | src=9 |
| 12 | i | IN | sg | src=7 |
| 13 | _PRO_ | PP | dat\|masc|sg | coref=0\|src=8 |
| 14 | aitheantóir | NN | masc\|sg|dat | src=7 |
| 15 | suímh ICAO | NN | nom\|masc|sg | src=7 |
| 16 | . | - | - | src=- |

Table 19: Deep morphological representation (DMorph).

| ID | Word | POS | Misc |
| ---: | :--- | :--- | :--- |
| 1 | bí\%Verb\%PresInd | VB | src=1 |
| 2 | Agra_Airport\%Noun\%Masc\%Com\%Sg | NP | coref=0\|src=2 |
| 3 | , | - | src=- |
| 4 | reáchtáilte | VB | src=4 |
| 5 | ag | IN | src=6 |
| 6 | Indian_Air_Force\%Noun\%Masc\%Com\%Sg | NP | src=6 |
| 7 | , | - | src=- |
| 8 | lonnaithe\%Adj\%Masc\%Com\%Sg | JJ | src=1 |
| 9 | i | IN | src=3 |
| 10 | An_India\%Noun\%Masc\%Com\%Sg | NP | src=3 |
| 11 | . | - | src=- |
| 12 | bí\%Verb\%PresInd | VB | src=7 |
| 13 | VIAG\%Noun\%Masc\%Com\%Sg | NP | src=9 |
| 14 | i | IN | src=7 |
| 15 | a | PP | coref=0\|src=8 |
| 16 | aitheantóir\%Noun\%Masc\%Com\%Sg | NN | src=7 |
| 17 | suímh ICAO\%Noun\%Masc\%Com\%Sg | NN | src=7 |
| 18 | . | - | src=- |

Table 20: Surface morphological representation (SMorph; corresponds to Table 5).


[^0]:    ${ }^{1}$ E.g. Arria NLG: https://www.arria.com/.

[^1]:    ${ }^{2}$ https://github.com/mille-s/DCU_TCD-FORGe_ WebNLG23
    ${ }^{3}$ https://github.com/mille-s/Mod-D2T/
    ${ }^{4}$ https://github.com/mille-s/WikipediaPage_ Generator

[^2]:    ${ }^{5}$ This table is adapted from (Mille et al., 2023).

[^3]:    ${ }^{6}$ See http://mappings.dbpedia.org/index.php/ How_to_edit_the_DBpedia_Ontology.
    ${ }^{7}$ We refer to a more surface-oriented lexicalisation here, with, e.g., function words, as opposed to the "deep" lexicalisation of the main concepts described in Section 4.1.

[^4]:    ${ }^{8}$ https://www.scss.tcd.ie/~uidhonne/irish.utf8. htm
    ${ }^{9}$ https://fomafst.github.io/

[^5]:    ${ }^{10}$ Properties such as municipality, district, or country are mapped to the same template as location, shown in Figure 2.

[^6]:    ${ }^{11}$ We used the publicly available Translator module of the googletrans (version 3.1.0a0) library.

[^7]:    ${ }^{12}$ Strictly speaking, this rule belongs to the REG module but since it has the same conditions of application as ellipsis in other languages, it was left in this module for the time being.

[^8]:    ${ }^{13}$ There was significantly more gold data available in English compared to Irish.

[^9]:    ${ }^{14}$ https://universaldependencies.org/format.html

[^10]:    ${ }^{15}$ https://dumps.wikimedia.org/gawiki/
    ${ }^{16}$ https://ga.wikipedia.org/wiki
    ${ }^{17}$ https://www.gaois.ie/crp/ga/
    ${ }^{18}$ https://lr-coordination.eu/node/2
    ${ }^{19}$ https://elrc-share.eu/
    ${ }^{20}$ https://estor.ie/
    ${ }^{21}$ https://live.european-language-grid.eu/

