Extensive Benchmark of Small Language Models for Datatype Properties Extraction and RDF Knowledge Graph Generation

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Abstract. The choice made for representing the inputs and outputs of generative pre-trained language models (PLMs) can impact their fine-tuning on a new task. This article focuses on the fine-tuning and linearization process to generate facts extracted from text. On a restricted relation extraction (RE) task, we challenged five encoder-decoder models including BART, T5, CodeT5, FlanT5 and PileT5 by fine-tuning them on 13 linearization variations, including RDF standard syntaxes and variations thereof. Our benchmark covers the validity of the produced triples, the model's performance, the training behaviour and the resources needed. We show these PLMs can learn some syntaxes more easily than others, and we identify a promising "Turtle Light" syntax supporting the quick and robust learning of the RE task.

Keywords: Data extraction, RDF, Linearization, Language Model

1. Introduction: Targeted Datatype Properties Extraction

Relation extraction (RE) – the task of retrieving relations from unstructured text – was drastically improved recently by two main changes: (1) the construction of massive corpora aligning texts and facts from knowledge graphs (KG) e.g. Wikipedia articles with corresponding Wikidata or DBpedia subgraphs, and (2) the usage of pre-trained language models (PLM) to carry out this task. However, Wikidata and DBpedia still struggle with coverage and quality issues [16, 49]. In this context, extracting from Wikipedia the missing information in KGs is a critical task. A promising research direction is to design a system allowing adaptability and fine-grained quality control. Now that we have end-to-end off-the-shelf methods, we have the opportunity to directly produce RDF serialization from natural language and specify and control the output with constraints (e.g. with SHACL or ShEx). However, to the best of our knowledge, no PLM-based system currently performs RE directly from Wikipedia articles with a specific RDF syntax. Formally, let $Db \subseteq W \times G$ be a dual base, where W is a set of Wikipedia articles and G the set of corresponding KGs. Our goal is to learn a pattern-based extractor leveraging generative PLM: E_{Db}: $W \times S \rightarrow G; (t, s) \mapsto g$, where $t \in W$ is an input text, $s \in S$ is a set of SHACL shapes, and g is an RDF graph implied by t and valid against s.

Generative PLMs are very flexible, but variations in prompts and output formats can affect their performance. In this paper, we focus on RE for the most common datatype properties of DBpedia resources of type `dbo:Person`.

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In this specific yet frequent set-up, we challenged encoder-decoder models trained on various RDF syntaxes. Hence, our research question: *How does the choice of a linearization syntax impact the generation of RDF triples representing datatype properties for different pre-trained language models?*
We have presented initial experiments to answer this question in [48]. In this paper, we extend our analysis by considering three additional encoder-decoder models (flanT5, codeT5, and pileT5), and one additional RDF syntax (Turtle Ultra Light). Moreover, we better define the meta-metrics we proposed, which leads us to new insights about the training behavior of the models we finetuned. The produced material is made open and reusable under an open license: the extension of the 12ShadesofRDF Github repository[1] as well as the complete experimental results[2].

The paper is organized as follows. After reviewing the related works (Section 2), we present our method to extract RDF from text with an application to Wikipedia (Section 3). We then report on the experiments and evaluations we carried out (Section 4) before discussing the results (Section 5).

2. Related Works: RDF Extraction with Language Models

Before investing in generative PLMs, the research community focused on systems built on top of encoder-only PLMs (derived from BERT [5]), where relations were decoded by design in a discriminative manner [37]. Since 2021, generative PLMs have gained interest after demonstrating their ability to solve complex tasks in an end-to-end design. The solutions based on pre-trained generative transformer models rely either on encoder-decoder or decoder-only models. (1) Encoder-decoder models traditionally proposed for translation or summarization tasks also demonstrate several successes in Question Answering (QA) and RE tasks which were achieved by finetuning BART [25] and T5 models [45]. For RE we can cite: REBEL [18], TALN [40], DEEPstruct [55] or UIE [32]. (2) Decoder-only models have interesting generalization properties but generally work at large scale and need dedicated resources to be adapted to a specific task. Few-shot and zero-shot approaches were studied for these reasons. But few-shot learning does not seem sufficient to solve the relation extraction task [13]. Parameter-efficient fine-tuning (PEFT) approaches [6] allow the adaptation of large models to a specific task but do not necessarily perform as well as fine-tuned models [27].

Using generative pre-trained models allows us to learn the triple syntax implicitly from the examples submitted during training [60]. The question of the structure of the output was initially referred to as "Answer Engineering" [29], but in the domain of graph extraction, the community refers to it as the "linearization process" i.e. the transformation of a graph structure into a raw sequence of tokens. This allows using a generative model pre-trained on natural language texts [21]. The two main solutions found in the literature to represent graphs are list of triples [55], e.g. $((s1, p1, o1), (s1, p2, o2), ...)$, or sequence of tagged elements [24], e.g. with tags H, R, T in $\langle H\rangle s1\langle R\rangle p1\langle T\rangle o1\langle H\rangle s1\langle R\rangle p2\langle T\rangle o2$. Additionally, [18] and [23] proposed a triple linearization method (subject-collapsed) where triples sharing the same subject are grouped to avoid repetition. In this article, we will also consider the syntaxes recommended by the W3C to serialize RDF triples, namely: RDF/XML, a historical syntax with the verbosity of XML; N-Triples, an easy-to-parse line-based format; Turtle, a lighter and easier-to-read syntax supporting the use of qualified names for compacting URIs, and integrating shortcuts for the writing of triples sharing the same subject or predicate[3]; JSON-LD, relying on the popular JSON format. Additionally, we proposed different variations of the Turtle syntax.

Few research works proposed RDF-generated content with language models before our first proposal. Still, the research interest concerning the possibility of producing more complex structured output with language models has grown, notably to perform information extraction [4, 28, 31]. These works mainly focus on the usage of LLM to benchmark a data-extraction task with JSON syntax, and sometimes others like XML. Other research also demonstrates the potential of constrained generation with grammar [12], which is reliable on simple syntaxes but expensive on complex ones. The Semantic Web community also proposed research directions using LLMs to assist Knowledge Graph engineering. For instance, [34] conducted to an extended benchmark focused on graph understanding

[1] https://github.com/datalogism/12ShadesOfRDFSyntax
[2] https://wandb.ai/celian-ringwald/12ShadesOfRDFExtension, https://wandb.ai/celian-ringwald/12ShadesOfRDF
[3] https://www.w3.org/TR/turtle/#predicate-lists

and generation tasks based on the Turtle syntax [10]. The approach was extended to other W3C languages such as SPARQL [33] or RML [15]. However, few initiatives have been proposed to rigorously compare and benchmark smaller and frugal models to produce RDF syntaxes as we do in this extended paper.

3. Methodological Framework: Definitions and Notations

3.1. Overview of the Approach

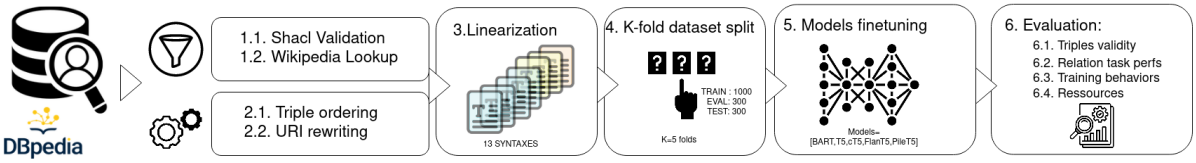


Fig. 1. Overview of our pipeline: from dataset construction to relation extraction evaluation

Our method is depicted in Figure 1. Our pipeline takes as input a DBpedia dump[4] from which we extract a subset containing specifically targeted triples. This subset is then filtered to check that the values of the selected DBpedia triples are mentioned in the corresponding Wikipedia abstracts (step 1.1) and comply with a predetermined SHACL shape (step 1.2) presented in Section 3.3. The selected triples are then ordered (step 2.1) and the URIs are URL-encoded and cleaned (step 2.2). The resulting dataset is then linearized (step 3) into 13 distinct syntaxes presented in Section 3.4. The obtained corpora are finally split into 5 independent folds (step 4). These subsets are used to fine-tune five SLMs (step 5) presented in Section 3.5. The fine-tuning configuration of the experiment is described in Section 4. The evaluation of the relation extraction (step 6) is conducted at the end of the training step with the computation of the metrics detailed in Section 4.2.

3.2. Task definition: a relation extraction focused on a maximal target shape

We start by formally defining the relation extraction task introduced in our previous work [48]. It relies on a training set built from the dual base $\mathcal{K}$ defined from the set $\mathcal{W}$ of Wikipedia abstracts associated with the set $\mathcal{G}$ of DBpedia graphs describing ($desc()$) the same resources e:

$$\mathcal{K} \coloneqq \{(w,g) \in \mathcal{W} \times \mathcal{G}, \exists\, e \in IRI \text{ such that } desc_{\mathcal{W}}(e) = w \ \wedge \ desc_{\mathcal{G}}(e) = g\} \tag{1}$$

To ensure the quality of the training set, we consider the subset of $\mathcal{K}$ where all the graphs are valid against a SHACL shape s^*. We call this shape maximal, as it matches the largest pattern to be extracted. We note $g \models s^*$ this validation, and $\mathcal{K}_{s^*}$ the corresponding subset:

$$\mathcal{K}_{s^*} \coloneqq \{(w,g) \in \mathcal{K}\,,\ g \models s^*\} \tag{2}$$

Finally, to reduce the noise in $\mathcal{K}_{s^*}$ entailed by the mismatch between DBpedia graphs and Wikipedia abstracts, we focus only on the couples (w,g) where the abstract w entails the paired graph g, i.e. the triples of g that can effectively be extracted from the paired abstract w. We note it $w \models g$ and we denote the dataset by $\mathcal{K}_{s^*}^{\mathcal{W}\models}$:

$$\mathcal{K}_{s^*}^{\mathcal{W}\models} \coloneqq \{(w,g) \in \mathcal{K}_{s^*}\,,\ w \models g\} \tag{3}$$

[4] https://databus.dbpedia.org/dbpedia/collections/dbpedia-snapshot-2022-09

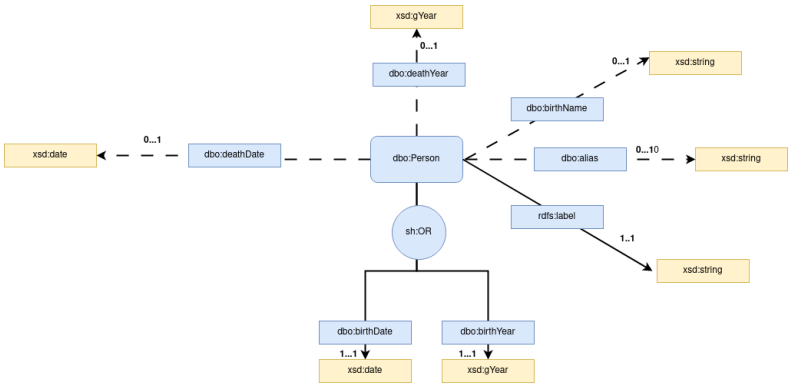
$\mathcal{K}_{s^*}^{\mathcal{W}\models}$ is used to train a model expected to predict, from an abstract w, a graph $\hat{g}$ valid against s^*. We denote by $\mathcal{M}$ this original model, and baseline:

$$\mathcal{M} : \begin{cases} \mathcal{W} \to \mathcal{G} \\ w \mapsto \hat{g}\,,\ \hat{g} \models s^* \wedge w \models \hat{g} \end{cases} \tag{4}$$

3.3. Dataset and Ground Truth

Our experiment focuses on a simplified relation extraction task to better analyse the impact of the syntax. To avoid any entity linking step related to object properties, we limit our experiment to datatype properties with number, string and date values. This is a good starting point because language model hallucinations generally affect these literal values [19]. Moreover, until now, the proposed generative models mostly focus on object properties, allowing for constrained decoding [22] that cannot be envisaged in the case of datatype properties.

Fig. 2. SHACL shape targeting class `dbo:Person`



(a) Visual representation in ShapeVOWL

```
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix schema: <http://schema.org/> .
@prefix sh: <http://www.w3.org/ns/shacl#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .
@prefix dbo: <http://dbpedia.org/ontology/> .

schema:PersonShape a sh:NodeShape ;
 sh:targetClass dbo:Person ;
 sh:property [
   sh:path rdfs:label;
   sh:minCount 1 ;
   sh:datatype xsd:string;
 ];
sh:or (
    [
      sh:property [
         sh:path dbo:birthDate;
         sh:datatype xsd:date;
         sh:minCount 1;
         sh:maxCount 1;
      ]
    ]
    [
      sh:property [
          sh:path dbo:birthYear;
          sh:datatype xsd:gYear;
          sh:minCount 1;
          sh:maxCount 1;
      ]
    ]
);
sh:property [
   sh:path dbo:deathYear;
   sh:minCount 0;
   sh:maxCount 1;
   sh:datatype xsd:gYear;
 ];
 sh:property [
   sh:path dbo:alias;
   sh:datatype xsd:string ;
   sh:minCount 0;
   sh:maxCount 10;
   sh:nodeKind sh:Literal;
 ];
 sh:property [
   sh:path dbo:birthName ;
   sh:datatype xsd:string ;
   sh:minCount 0;
   sh:maxCount 1;
   sh:nodeKind sh:Literal ;
 ] ;
 sh:property [
   sh:path dbo:deathDate ;
   sh:datatype xsd:date ;
   sh:minCount 0;
   sh:maxCount 1;
 ].
```

(b) Linearization in Turtle syntax

We consider the DBpedia subgraphs describing instances of one of the most represented DBpedia classes ($\mathcal{G}$), `dbo:Person`, and their corresponding Wikipedia abstracts ($\mathcal{W}$). The descriptions of instances of this class also include the highest number of datatype properties. We focus on the 7 datatype properties that are most likely to be found in the abstracts describing `dbo:Person` instances: `rdfs:label`, `dbo:alias`, `dbo:birthName`, `dbo:birthDate`, `dbo:deathDate`, `dbo:birthYear`, `dbo:deathYear`.

Several works mention the noise caused by the massive alignment of facts with text [50], which also impacts T-Rex or REBEL [27]. More specifically, two problems are pointed out: the values in a triple do not necessarily appear in the corresponding text, and conversely, the facts in the text may not have counterpart triples in the knowledge base. To solve those issues, we first considered a maximal SHACL shape (s^*) targeting class `dbo:Person` (Fig. 2b) and specifying which property is mandatory and which one is optional, and we only keep the graphs valid against this shape (K_{s^*} described in Eq. 2). In a second step we keep only the triples whose values can be found in the Wikipedia abstract of a given entity ($\mathcal{K}_{s^*}^{\mathcal{W}\models}$ described in Eq. 3). When applying these two pre-processing steps to a random sample of 1000 entities, we found that 80% of the triples have values that can be found in the corresponding Wikipedia abstract, but only 45% of the entities have a graph description valid against the shape.

Table 1
Datatype properties statistics of the ground truth D

property	freq	variability
http://www.w3.org/1999/02/22-rdf-syntax-ns#type	100,0	0,0
http://dbpedia.org/ontology/birthYear	100,0	5,3
http://www.w3.org/2000/01/rdf-schema#label	100,0	99,9
http://dbpedia.org/ontology/birthDate	98,3	92,9
http://dbpedia.org/ontology/deathYear	31,0	13,4
http://dbpedia.org/ontology/deathDate	30,3	97,6
http://dbpedia.org/ontology/birthName	7,0	100,0
http://dbpedia.org/ontology/alias	1,4	100,0

Our pipeline includes two additional pre-processing steps:

1. Triples ordering: [35] demonstrated the positive impact on the RE task of ordering the triples in the training data with the typing triple in the first place. As RDFlib[5] does not ensure this for every syntax, we implemented a triples ordering step.
2. URI encoding: the Turtle syntax uses tokens that can be found in URIs (dots and parenthesis), but their usage is forbidden in local names. We had to encode them systematically. In DBpedia, the Turtle output of URIs containing these special characters is written without prefixes and wrapped into brackets, e.g. `<https://dbpedia.org/resource/Tom_Nichols_(footballer)>`. Therefore we rewrite this URI as `dbr:Tom_Nichols_%28footballer%29`.

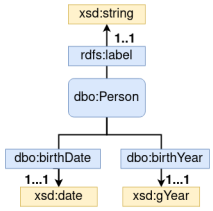
Our ground truth D is randomly sampled from $\mathcal{K}_{s^*}^{\mathcal{W}\models}$ and will later be split into D_{train}, D_{eval} and D_{test}. D contains 6000 entities described by 28M triples. The 7 datatype properties we are focusing on are associated with 13 832 distinct values. Table 1 shows the frequency of each property defined as the number of occurrences of a property divided by the number of entities described in D, and its variability defined as the number of distinct values for a property divided by the number of occurrences of the property. The frequencies reported in this table show that all the graphs in the dataset contain an occurrence of properties `rdf:type`, `dbo:birthYear`, and `rdfs:label` (which is in line with the shape we defined), and they highlight the low representation of properties `dbo:alias` and `dbo:birthName`. The reported variabilities highlight the historical bias of the data: the low variability of properties `dbo:birthYear` and `dbo:deathYear` means that the entity descriptions in the dataset target some specific historical period. Another interesting characteristic of D is the low number of property combinations represented and their frequencies: there are 18 combinations of properties among 127 possible combinations of 7 properties, and their frequencies indicate a long-tail distribution.

[5] https://rdflib.readthedocs.io/en/stable/

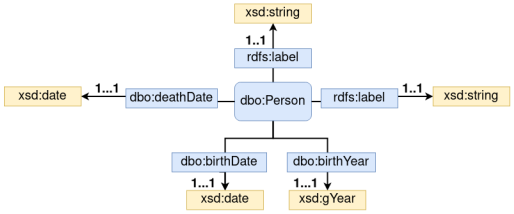
Table 2
Property combinations observed in the ground truth D

prop_pattern	label	birthYear	birthDate	deathYear	deathDate	alias	birthName	nb prop	freq
pattern1	✓	✓	✓					3	64,43%
pattern2	✓	✓	✓	✓	✓			5	25,47%
pattern3	✓	✓	✓	✓	✓		✓	6	3,67%
pattern4	✓	✓	✓				✓	4	2,85%
pattern5	✓	✓	✓			✓		4	0,80%
pattern6	✓	✓						2	0,72%
pattern7	✓	✓		✓	✓			4	0,62%
pattern8	✓	✓	✓	✓	✓	✓		6	0,40%
pattern9	✓	✓	✓	✓				4	0,37%
pattern10	✓	✓		✓	✓			4	0,17%
pattern11	✓	✓	✓	✓			✓	5	0,10%
pattern12	✓	✓	✓			✓	✓	5	0,10%
pattern13	✓	✓					✓	3	0,10%
pattern14	✓	✓		✓	✓	✓		5	0,03%
pattern15	✓	✓	✓	✓	✓			5	0,03%
pattern16	✓		✓	✓			✓	4	0,03%
pattern17	✓	✓				✓	✓	4	0,02%
pattern18	✓	✓				✓		3	0,02%

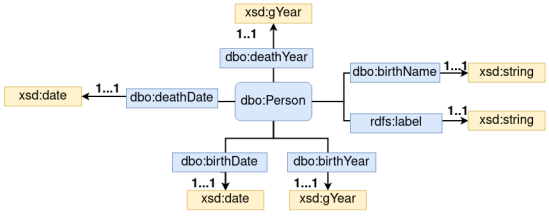
Fig. 3. Top 4 graph patterns represented in our training set



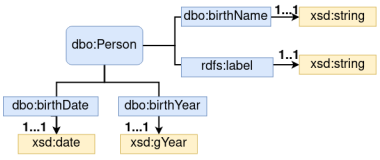
(a) Graph pattern 1



(b) Graph pattern 2



(c) Graph pattern 3



(d) Graph pattern 4

3.4. RDF Syntaxes and Alternative Linearizations

Our benchmark considers 13 syntaxes belonging to three distinct categories. The first category includes the syntaxes classically found in the literature (Fig. 4): (a) the List (noted $_l$) and (b) the Tags (noted $_g$) and (c/d) their factorized variations (noted $_f$). As underlined by [18] and [23], factorisation enables to avoid the repetition of subjects or predicates. It is naturally integrated into Turtle, JSON-LD and RDF-XML and we also integrated it to the List and Tags syntaxes (noted $_f$).

Fig. 4. Linearization proposed by the literature applied on a graph describing Nelson Mandela.

```
[[Nelson_Mandela,type,Person],[Nelson_Mandela,label,Nelson Mandela],
[Nelson_Mandela,birthDate,1918-07-18],[Nelson_Mandela,birthYear,1918],
[Nelson_Mandela,deathDate,2013-12-05],[Nelson_Mandela,deathYear,2013]]
```

(a) List syntax

```
<subj>Nelson_Mandela<rel>type<obj>Person<et><subj>Nelson_Mandela<rel>label<obj>Nelson Mandela<et>
<subj>Nelson_Mandela<rel>birthDate<obj>1918-07-18<et><subj>Nelson_Mandela<rel>birthYear<obj>1918<et>
<subj>Nelson_Mandela<rel>deathDate<obj>2013-12-05<et><subj>Nelson_Mandela<rel>deathYear<obj>2013<et>
```

(b) Tag syntax

```
[[Nelson_Mandela,[[type,Person],[label,Nelson Mandela],[birthDate,1918-07-18],
[birthYear,1918],[deathDate,2013-12-05],[deathYear,2013]]]]
```

(c) List syntax factorized

```
<subj>Nelson_Mandela<rel>type<obj>Person<rel>label<obj>Nelson Mandela
<rel>birthDate<obj>1918-07-18<rel>birthYear<obj>1918
<rel>deathDate<obj>2013-12-05<rel>deathYear<obj>2013<et>
```

(d) Tag factorized

The second category includes the 4 W3C RDF syntaxes (Fig. 5): (c) XML-RDF (noted $_x$), (d) Turtle (noted $_T$), (e) N-Triples (noted $_n$) and (f) JSON-LD (noted $_j$).

Fig. 5. Linearization proposed by the W3C applied on a graph describing Nelson Mandela.

```
<rdf:RDF xmlns:dbo="http://dbpedia.org/ontology/"
xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#" >
    <rdf:Description rdf:about="http://dbpedia.org/resource/Nelson_Mandela">
        <rdf:type rdf:resource="http://dbpedia.org/ontology/Person"/>
        <rdfs:label rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Nelson Mandela</rdfs:label>
        <dbo:birthDate rdf:datatype="http://www.w3.org/2001/XMLSchema#date">1918-07-18</dbo:birthDate>
        <dbo:birthYear rdf:datatype="http://www.w3.org/2001/XMLSchema#gYear">1918</dbo:birthYear>
        <dbo:deathDate rdf:datatype="http://www.w3.org/2001/XMLSchema#date">2013-12-05</dbo:deathDate>
        <dbo:deathYear rdf:datatype="http://www.w3.org/2001/XMLSchema#gYear">2013</dbo:deathYear>
    </rdf:Description>
</rdf:RDF>
```

(a) RDF-XML

```
<http://dbpedia.org/resource/Nelson_Mandela><http://www.w3.org/1999/02/22-rdf-syntax-ns#type><http://dbpedia.org/ontology/Person> .
<http://dbpedia.org/resource/Nelson_Mandela><http://dbpedia.org/ontology/birthYear>
"1918"^^<http://www.w3.org/2001/XMLSchema#gYear> .
<http://dbpedia.org/resource/Nelson_Mandela><http://www.w3.org/2000/01/rdf-schema#label>
"Nelson Mandela"^^<http://www.w3.org/2001/XMLSchema#string> .
<http://dbpedia.org/resource/Nelson_Mandela> <http://dbpedia.org/ontology/deathYear>
"2013"^^<http://www.w3.org/2001/XMLSchema#gYear> .
<http://dbpedia.org/resource/Nelson_Mandela> <http://dbpedia.org/ontology/deathDate>
"2013-12-05"^^<http://www.w3.org/2001/XMLSchema#date> .
<http://dbpedia.org/resource/Nelson_Mandela> <http://dbpedia.org/ontology/birthDate>
"1918-07-18"^^<http://www.w3.org/2001/XMLSchema#date> .
```

(b) N-triples

```
@prefix dbo: <http://dbpedia.org/ontology/>.
@prefix dbr: <http://dbpedia.org/resource/>.
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>.

dbr:Nelson_Mandela  a  dbo:Person ;
    rdfs:label "Nelson Mandela"^^xsd:string ;
    dbo:birthDate "1918-07-18"^^xsd:date ;
    dbo:birthYear "1918"^^xsd:gYear ;
    dbo:deathDate "2013-12-05"^^xsd:date ;
    dbo:deathYear "2013"^^xsd:gYear.
```

(c) Turtle syntax

```
[{
    "@id": "http://dbpedia.org/resource/Nelson_Mandela",
    "@type": [ "http://dbpedia.org/ontology/Person" ],
    "http://dbpedia.org/ontology/birthDate": [
      { "@type": "http://www.w3.org/2001/XMLSchema#date",
      "@value": "1918-07-18" } ],
    "http://dbpedia.org/ontology/birthYear": [
      { "@type": "http://www.w3.org/2001/XMLSchema#gYear",
      "@value": "1918" } ],
    "http://dbpedia.org/ontology/deathDate": [
      { "@type": "http://www.w3.org/2001/XMLSchema#date",
      "@value": "2013-12-05" } ],
    "http://dbpedia.org/ontology/deathYear": [
      { "@type": "http://www.w3.org/2001/XMLSchema#gYear",
      "@value": "2013" } ],
    "http://www.w3.org/2000/01/rdf-schema#label": [
      { "@value": "Nelson Mandela" } ]
}]
```

(d) JSON-LD

The third category includes additional syntaxes we propose: *Turtle light* (noted $_t$) is a simplified Turtle syntax where namespaces, prefixes, and datatypes are considered as already defined. Turtle light comes with several variations: one with subject factorisation, one with single-line writing (noted $_1$) to evaluate the impact of the line break[6]. Another variation combines factorisation and single-line writing. In addition to these 12 syntaxes considered in our initial experiments, we introduced an Ultra Light Turtle syntax (noted $_u$) which is based on the factorised, inlined Turtle Light where we remove the ":" characters in the qualified names.

Fig. 6. Turtle light variations proposed applied on a graph describing Nelson Mandela.

```
:Nelson_Mandela a :Person.
:Nelson_Mandela :label "Nelson Mandela".
:Nelson_Mandela :birthDate "1918-07-18".
:Nelson_Mandela :birthYear "1918".
:Nelson_Mandela :deathDate "2013-12-05".
:Nelson_Mandela :deathYear "2013".
```

(a) Turtle Light syntax

```
:Nelson_Mandela a :Person. :Nelson_Mandela :label "Nelson Mandela".
:Nelson_Mandela :birthDate "1918-07-18". :Nelson_Mandela :birthYear "1918".
:Nelson_Mandela :deathDate "2013-12-05". :Nelson_Mandela :deathYear "2013".
```

(b) Turtle Light syntax on one line

```
:Nelson_Mandela a :Person ;
    :label "Nelson Mandela" ;
    :birthDate "1918-07-18";
    :birthYear "1918";
    :deathDate "2013-12-05";
    :deathYear "2013".
```

(c) Turtle Light syntax factorized

```
:Nelson_Mandela a :Person; :label "Nelson Mandela"; :birthDate "1918-07-18"; :birthYear "1918";
:deathDate "2013-12-05"; :deathYear "2013".
```

(d) Turtle Light syntax on one line and factorised

```
Nelson_Mandela a Person; label "Nelson Mandela"; birthDate "1918-07-18"; birthYear "1918";
deathDate "2013-12-05"; deathYear "2013".
```

(e) Turtle Ultra Light

Finally, we consider the use of **vocabulary extension** (noted $_v$), which is a common practice, notably used for QA SPARQL query generation, that consists in extending the tokenizer vocabulary [2, 46]. This ensures that syntax-related tokens will not be considered as unknown by the tokenizer, and allows the model to learn a vector representation of these tokens during the fine-tuning process, e.g. the representation of the comma in Turtle code replacing

[6] the "\n" special token

the representation of the comma from the pre-trained embedding space. For each W3C syntax, we added all the tokens specified in its recommendation.

3.5. Benchmarking frugal Encoder-Decoders

In our initial experiments described in [48] we focused on the two encoder-decoder models traditionally used in the literature (see Section 2), namely BART (noted *B*) and $T5$. We extended our benchmark by integrating three other T5-based models: FlanT5 [3] noted $T5^F$, PileT5 [53] noted $T5^P$ and CodeT5 [57] noted $T5^C$. These models follow the encoder-decoder transformer architecture. Table 3 summarizes their main differences. We limited our

Table 3
Encoder-decoder specificities

	Pretraining Obj.	Prefix Tuning	Instruct. tuning	Pretraining dataset	Tokenizer	Nb params	Max input len.	Max output len.
BART	Token Masking + 4 other obj.			Bookcorpus + Wiki. 2019	BPE	140M	1024	1024
T5	Token Masking	✓		C4	SentencePiece	220M	512	512
codeT5	Token Masking + 2 other obj.	✓		CodeSearchNet	Byte-Level BPE	220M	512	256
FlanT5	Token Masking	✓	✓	C4+Muffin+F0-SF+CoT +NaturalInstructionV2	SentencePiece	248M	1024	256
PileT5	Token Masking	✓	✓	ThePile	LlamaTokenizer	248M	512	512

experiments to pre-trainted models in their "base" versions counting between 140M and 248M parameters, which is frugal compared to decoder-only LLMs that count billions of parameters [36]. Contrary to larger LLMs, these models were not pre-trained on Wikidata or DBpedia data, but on at least a complete Wikipedia dump. The BART dataset is not available, but we can estimate the use of a 2019 Wikipedia dump. T5 was pre-trained on C4 which contains Wikipedia data from 2019, and PileT5 was pre-trained on The Pile which contains a Wikipedia dump from 2020; C4 and The Pile are both available. The training dataset of CodeT5 is only related to coding tasks and does not contain Wikipedia data.

Each model uses different tokenizers and has different context sizes related to the specific input/output lengths on which they were pre-trained. For this reason, the input and generation lengths must be adapted to these constraints to avoid generation degradation or early truncation. Fig. 7 illustrates the effect of the tokenization of each model tested on the same Turtle graph.

Table 4
Max number of tokens generated over the ground truth *D*, depending on the chosen syntax and tokenizer

	B	T5	$T5^P$	$T5^F$	$T5^C$
ntriples	541	583*	610*	583*	566*
XML	479	514	498	514*	481*
$JSON-LD$	646	411	488	411*	469*
list	392	285	316	285*	320*
Turtle	286	312	289	312*	284*
turtleLight	307	274	310	274*	314*
tags	229	265	273	265*	259*
$turtleLight_1$	303	225	270	225	255
$list_f$	152	137	171	137	164
$turtleLight_f$	146	127	153	127	142
$turtleLight_{1f}$	121	127	140	127	135
$tags_f$	**78**	97	**99**	97	**104**
turtleUltraLight	92	**85**	100	**85**	**104**

Table 4 shows the longest size (in number of tokens) of the sequences that each model have to generate according to the ground truth D depending on the targeted RDF syntax. Starred values ($*$) indicate that the longest sequence contained in D exceeds the maximum output length of the pre-trained model.

This highlights potential issues with CodeT5 and FlanT5 whose maximum output length (256) is exceeded for 7 syntaxes. This table also reveals the fact that light syntaxes allow to divide the output context length by five, compared to complex syntaxes (Ntriple, XML or JSON): for instance, to represent 7 datatype properties, BART with one-line, factorized Turtle light (B_{tlf}) requires 121 tokens while BART with JSON (B_j) requires 541 tokens. From that observation, we can estimate that with the factorized, one-line Turtle Light syntax we can generate a graph of almost 60 properties while JSON hardly reaches 14 properties.

Fig. 7. Tokenisation comparison of the same Turtle graph.

In the following sections, we use the notations introduced above to name each possible configuration. For instance, a BART model trained on *Turtle Light* syntax, with factorization and multi-lines will be written B_{tf}, and a codeT5 model trained on lists with a vocabulary will be written $T5^{C}_{vl}$.

4. Experimental set-up

4.1. Fine-Tuning Details

Our code[7] is based on a fork of REBEL[8] which we extended and adapted to our task. It is published under an open license. For each standard RDF syntax, we developed a specific parser and integrated the metrics we present below.

Data Split: We follow a 5-fold cross-validation based on 5 000 rotated examples split into 4 000 training examples (D_{train}) and 1 000 test examples (D_{test}). In addition, 250 disjoint examples are used for the evaluation (D_{eval}).

Configuration: The BART model was fine-tuned using the inverse square root scheduler with an initial learning rate of 0.00005. For T5 we used the Adafactor scheduler with an initial learning rate of 0.001. Both models were fine-tuned with 1000 warm-up steps and configured with an early stop mode with patience of 5 steps. For FlanT5, codeT5 and PileT5, we used the same configuration as for T5. Models were trained on a single GPU, Tesla V100-SXM2-32GB for BART and NVIDIA A100 80GB PCIe for T5 models (able to manage bf16).

Handling of Tokenization Inconsistencies: T5 and BART tokenizers can duplicate or delete spaces before or after special tokens [1, 52]. For this reason, we controlled token consistency during the evaluation with a typographic checker and cleaner. This is applied to the learning examples and to the predicted output when both are compared.

Finetuning Prompts: We used two different prompts to finetune the tested models:

- for BART: "`$entity_URI : $Abstract`";
- for the T5 models family (T5, pileT5, codeT5 and Flan-T5): "`Translate English to $Syntax: [$entity_URI] $Abstract`",

where `$Abstract` is a Wikipedia abstract, `$Syntax` is the targeted RDF syntax, and `$entity_URI` the URI of the entity in DBpedia.

4.2. Evaluation Metrics

The first stage of this experiment is to evaluate the ability of the model to produce a given syntax without generating any parsing error. This is measured by the rate of Parsed Triples R_{PT}. We also introduce the rate of Correct Subject R_{CS}: the choice of the URI for the subject of a generated triple depends on the ability of the model to copy from the input the targeted entity URI. In addition, we define the rate of SHACL-Validated Triples R_{SVT}.

$$R_{PT} = \frac{Nb_{output\ parsed}}{Nb_{output\ generated}} \qquad R_{CS} = \frac{Nb_{URI\ found}}{Nb_{output\ parsed}} \qquad R_{SVT} = \frac{Nb_{output\ Valid}}{Nb_{output\ parsed}} \tag{5}$$

Non-parsable triples are evaluated by computing the Levenstein edit distance $lev(r_g, r_t)$ between the generated RDF code r_g and the targeted one r_t. The result is the number of editions needed to transform r_g into r_t.

By contrast, when the graphs produced are parsable it is possible to evaluate them with respect to the RE task. Traditionally, RE focuses on *precision* (P), *recall* (R), F_1 score, or *top@k* metrics. But as underlined in [14], these metrics are generally computed at the micro level, that is, they are computed on all the expected and produced triples without taking into account the variable distribution of the properties. As a result, these metrics can hardly account for the performance of a model on under-represented properties, as the micro metrics are dominated by the results obtained for much more frequent properties. In our context, we observed that the property distribution is unbalanced. Therefore we propose to also compute the macro measures (P^+, R^+, F_1^+) which average the metrics recorded on each properties thus equally representing the performances for each property. These metrics follow the *Strict Mode* evaluation [54], comparing predicted and ground truth values and verifying their strict equality. The strict evaluation-based metrics are not the most appropriate to evaluate datatype properties with values of type `xsd:String`, where

[7] https://github.com/datalogism/12ShadesOfRDFSyntax
[8] https://github.com/Babelscape/rebel

we may accept semantically close values. For this reason, we also compute the BLEU score [42]: the closer *BLEU* is to 1, the greater the similarity between string values.

We define a global grade G_g that will allow us to compare the overall performances of our configurations. It combines the performance of the model in terms of parsability, SHACL validity and subject validity on one side, and in terms of macro F_1 on the other side: $G_g = \overline{R_{PT}} \times \overline{R_{CS}} \times \overline{R_{SVT}} \times \overline{F_1^+} \times 100$ where, for instance, $\overline{F_1^+}$ is the average of F_1^+ over the folds.

Finally, we also monitored the training time T_t (in minutes) and the carbon footprint[9] C_c (emissions of CO_2-equivalents in g) for training a model.

To assess the training process itself based on the cross-entropy loss objective, we define three meta-metrics from a metric of interest ρ: the velocity V_ρ, the stability S_ρ and the divergence D_ρ. In our case we will use these meta-metrics to compare and follow the behaviors of the R_{PT} and the F_1^-, consequently $\rho \in \{R_{PT}; F_1^-\}$. All meta-metrics consider a specific state of the training called *saturation* which is reached when the metric ρ reaches a threshold $\lambda = 0.9$. The metrics of interest are computed for a fold $f \in [1..n_{fold}]$ and an epoch $e \in [1..n_{epoch}]$, noted $\rho(f,e)$. Let us now detail the computation of each of the meta-metrics:

(1) **The velocity** is the number of epochs needed to reach the first saturation ($\rho(f,e) > \lambda$) on a given fold f by a metric ρ.

$$V_\rho(f) = min(\{e | e \in [1; n_{epoch}], \rho(f,e) > \lambda\}) \tag{6}$$

Interpretation: A velocity close to 0 indicates that the model saturates at the early stage of the training. Conversely, a velocity close to the number of epochs recorded by the whole training process indicates a late model saturation.
Aggregation: The average velocity on all the folds is computed as follows:

$$\overline{V_\rho} = \begin{cases} \dfrac{1}{n_{fold}} \displaystyle\sum_{f=1}^{n_{fold}} V_\rho(f) & \text{if } \forall f \in [1..n_{fold}]\ \exists e; \rho(f,e) > \lambda \\ \varnothing & \text{otherwise} \end{cases} \tag{7}$$

(2.1) **The broken steps set:** To define the stability, we first define the set of the *broken_steps* for a given fold f. During a fold f, a step is considered as broken if the metric $\rho(f,e)$ is smaller than the defined saturation threshold.

$$broken\_steps(f) = \{e | e \in [V_\rho(f), n_{epoch}], \rho(f,e) < \lambda\} \tag{8}$$

(2.2) **The stability** is the ratio of the number of epochs during which a metric remains stable after the first saturation.

$$S_\rho(f) = 1 - \frac{\|broken\_steps(f)\|}{n_{epoch}} \tag{9}$$

Interpretation: During the training, if the metric of interest rarely falls below the saturation threshold, then the stability will be close to 1; conversely, if it often falls below the threshold, the stability will be close to 0.
Aggregation: The average stability on the n_{fold} folds is computed as follows:

$$\overline{S_\rho} = \begin{cases} \dfrac{1}{n_{fold}} \displaystyle\sum_{f=1}^{n_{fold}} S_\rho(f) & \text{if } \forall f \in [1..n_{fold}]\ \exists e; \rho(f,e) > \lambda \\ \varnothing & \text{otherwise} \end{cases} \tag{10}$$

[9] https://codecarbon.io/

(3) **The divergence** indicates if the final value of the metric is lower than the saturation threshold.

$$D_\rho(f) = \begin{cases} 1 & \text{if } V_\rho(f) \neq \varnothing \wedge \rho(f, n_{epoch}) < \lambda \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Interpretation: The divergence is equal to 1 if the measure ρ recorded at the end of the training is under the saturation threshold. Inversely, the divergence is equal to 0 if the training completes with a value higher than the saturation threshold.
Aggregation: We compute the sum on all the folds of each $D_\rho(f)$, and note it as $\sum D_\rho$.

$$\sum D_\rho = \sum_{f=1}^{n_{fold}} D_\rho(f) \tag{12}$$

To illustrate the principle of these meta-metrics, Fig. 8 shows the behaviour of a given metric $\rho(f,e)$ observed at a given fold f and computed at each epoch e. In this example, the training took $n_{epoch} = 23$ epochs; $V_\rho(f) = 7$, i.e. $\rho(f,e)$ reaches the saturation threshold of 0.9 at the 7th epoch; $S_\rho(f) = 0.93$, with 2 *broken steps* (circled on the figure) during the training process; $D_\rho(f) = 0$, i.e. the model is not diverging at the end of the training process, as $\rho(f, n_{epoch}) > \lambda$.

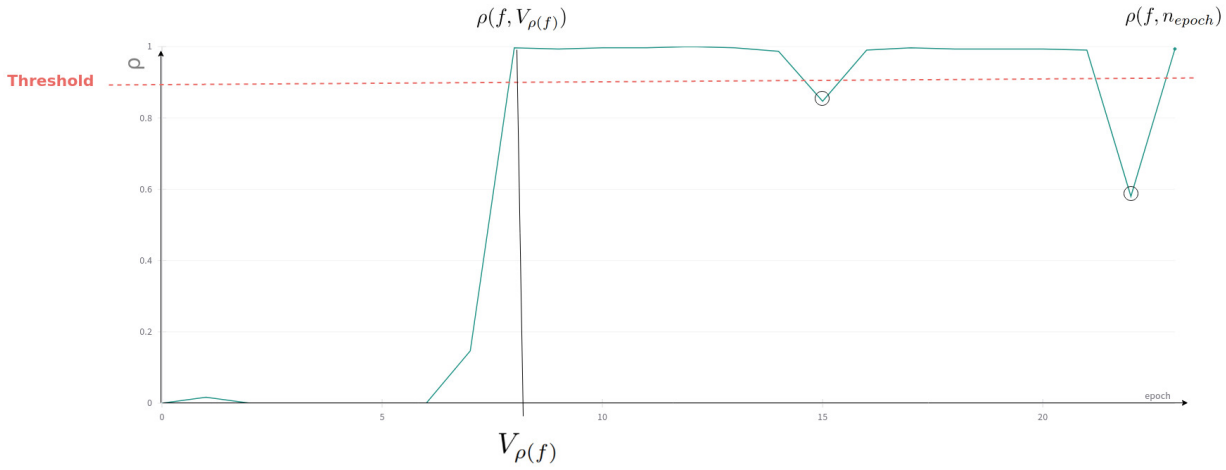


Fig. 8. Example behaviour of a metric ρ during the training of a model on given fold f during 23 epochs

5. Results and Discussions: Best models and syntaxes

Table 5, Table 6 and Table 7 compile the results obtained following the experimental framework described in the previous sections, ranked by global grade G_g. Table 5 gathers all the models that can effectively generate valid triples; it includes the models based on BART and T5. Table 6 gathers models with lesser performances, mostly based on codeT5, but also some models based on PileT5 and FlanT5. Table 7 gathers the worse models; these are based on FlanT5 and PileT5. RE metrics are computed on valid triples and, in that respect, the best models have a $\overline{F_1^+}$, $\overline{P^+}$ and $\overline{R^+}$ close to 0.95. This is a good result since the macro metrics are generally less optimistic and more informative than the micro ones with which every configuration seems to reach an almost perfect extraction. From that point of view, $T5_{vj}$ is the best model, closely followed by B_{vgf}, B_{vu}, $T5_{vu}$, B_{vtf1}, B_{vT}, $T5_{vtf1}$ and $T5_{vgf}$. It is more difficult to discuss the good performances of $T5^P_{vu}$, $T5^P_{vn}$ and $T5^P_{vn}$ in regards to their low triple validity scores.

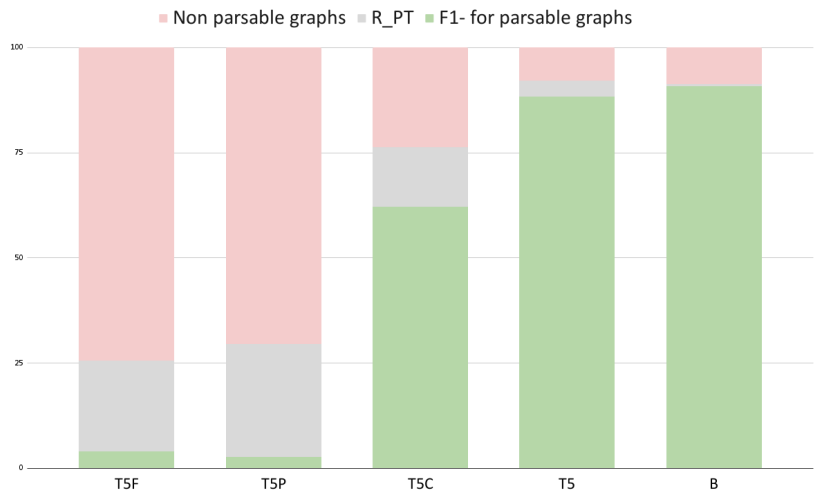


Fig. 9. Averaged model performances F_1^- relatively to R_{PT}

The bar charts of Fig. 9 and Fig. 10 put in perspective the averaged F_1^- metrics obtained relatively to the R_{PT} metric, by plotting the F_1^- stacked over and at the scale of the R_{PT} bar. Fig. 9 confirms the performances of B and $T5$, as well as the relatively good results of $T5^C$. On the other hand, $T5^F$ and $T5^P$ are far behind the others. From the point of view of the syntax and as shown in Fig. 10, we can see the robustness of Turtle Ultra Light which has a high F_1^- and a high R_{PT}, notably because this syntax is correctly handled by every model, even by $T5^F$ and $T5^P$. We can also observe globally a poor performance of the models on W3C syntaxes and a good performance of the tag and list syntaxes. Concerning TurtleLight, it seems necessary to apply the variations we proposed (the factorisation and the one-line writing) on this syntax to be able to perform well in terms of both R_{PT} and F_1^-.

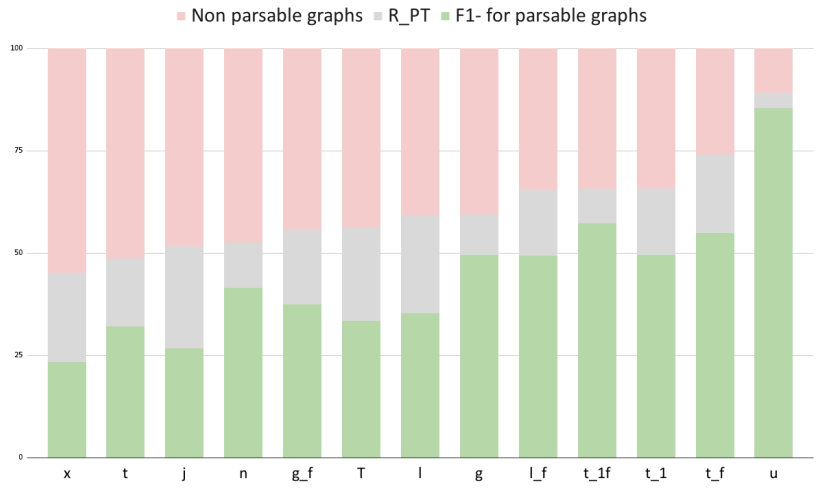


Fig. 10. Averaged syntax performances F_1^- relatively to the R_{PT}

Coming to the details, and starting with the **triple validity** metrics, almost every configuration related to BART and T5 produces triples that could be parsed ($\overline{R_{PT}}$) with the exception of $T5$ struggling to produce the Turtle and N-Triples syntaxes. Concerning codeT5, only the Turtle (basic version, the Light and Ultra Light version) and the

list-based syntaxes are nearly perfectly parsed. The capacity of codeT5 to deal with Turtle is peculiar to our context and could be explained by a syntax close to a code structure, with the definition of the prefixes at the top and the data content written after it. FlanT5 and PileT5 can approximately generate triples only in the simplest syntaxes. Among them, Turtle Ultra Light is the one recording the better R_{PT} for FlanT5 (0,95) as well as for PileT5 (0,59).

Considering the **Levenshtein distance** ($\overline{lev}$) computed on the triples with parsing errors, we observe the ability of some models to extract close to perfect triples, particularly BART. Moreover, many models record negligible $\overline{lev}$ distances ($\overline{lev} \approx 0$) and in these cases, the parsing mainly fails because of forgotten or misplaced tokens that break the syntax. In contrast, high values of the $\overline{lev}$ also allow us to identify models producing triples that are far from well-formed. We identified that these high values are generally related to the generation of incomplete, truncated or empty sequences as in $T5_{vT}$, $T5_{vn}$, $T5_{vlf}$, $T5_{vt1}$ and at a higher level $T5^{C}_{vlf}$, $T5^{C}_{vgf}$ and $T5^{F}_{vu}$. Some typical errors illustrating it are reported in Fig 11. Regarding the **rate of SHACL-Validated Triples** ($\overline{R_{SVT}}$), all the

Fig. 11. Examples of parsing errors accounted

```
<?xml version="1.0" encoding="utf-8"?>
 <rdf:RDF
  xmlns:dbo="http://dbpedia.org/ontology/"
  xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
  xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#" >
 <rdf:Description rdf:about="http://dbpedia.org/resource/Steven_Allan_Boggs">
 <rdf:type rdf:resource="http://dbpedia.org/ontology/Person"/>
 <rdfs:label rdf:datatype="http://www.w3.org/2001/XMLSchema#string">Steven Allan Boggs</rdfs:label>
 <dbo:birthDate rdf:datatype="http://www.w3.org/2001/XMLSchema#date">1946-03-15</dbo:birthDate>
 <dbo:birthYear rdf:datatype="http://www.w3.org/2001/XMLSchema#gYear">1946</dbo:birthYear>
 <rdf:Description>
 </rdf:RDF>
```

(a) B_{vx} generated triple with a missing "/" token on the closing `<rdf:Description>` element

```
    Ofelia_Montesco<rel>type<obj>Person<rel>label<obj>Ofelia Montesco
    <rel>birthDate<obj>1936-09-10<rel>birthName<obj> Ofelia Irene Grabowski Edery<et>
```

(b) $T5_{vgf}$ triples with a missing "<rel>" starting tokens

```
dbo: <http://dbpedia.org/ontology/>.
@prefix dbr: <http://dbpedia.org/resource/>.
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>.
dbr:Vernell_Brown_Jr%2E  a  dbo:Person ;
  rdfs:label "Vernell Brown Jr."^^xsd:string ;
  dbo:birthDate "1971-08-13"^^xsd:date ;
  dbo:birthYear "1971"^^xsd:gYear.
```

(c) $T5_{vT}$ triples with a missing "@prefix" declaration

```
zor%C3%A1d<rel>type<obj>Person<rel>label<obj>Martin Boszorád<rel> birthDate<obj>1989-11-13
<rel>birthYear<obj>1989<et><subj> Cara_GrzeskCara_GrzeskCara_GrzeskCara
_GrzeskCara_GrzeskCara_GrzeskCara_GrzeskCara_GrzeskCara_GrzeskCara...
```

(d) $T5^{C}_{vgf}$ triples with a repeated "Cara_Grzesk" pattern

configurations that lead to parsed triples almost perfectly fit the defined s^* maximal SHACL shape. Moreover, the fact that all the R_{CS} scores are close to 1 in Tables 5, 6 and 7 is a sign that the subject URI given in the prompt is easily copied by the model in all the configurations. But we can point out some exceptions: the Turtle Ultra Light syntax for which FlanT5 and PileT5 fail to properly write the subject URI, forgetting, for example, the prefix token ":" or struggling to produce sequences containing special characters. e.g. $pT5_{vu}$ produces "*_Roland_G%C3%BAr*" instead of ": *Roland_G%C3%BAr*", as well as only "*Margues*" instead of "*Jos%C3%A9_Margues*".

The **BLUE scores** are generally above 0.9, which shows the global ability of the models to predict the right values when the graphs produced are parsed. In particular, for $T5_{vj}$, $BLEU = 1$, meaning that the model always perfectly predicts string values of datatype properties. $T5_{vlf}$, $T5^{C}_{vT}$ and $T5^{C}_{vgf}$ perform less well on that specific aspect.

The **training behaviour** meta-metrics all depend on the saturation of a given metrics. Consequently, we cannot evaluate many of the PileT5 and FlanT5 configurations that never reached saturation on both considered metrics ($T5^{F}_{vu}$ being an exception here). Conversely BART and T5 configurations always saturate both R_{PT} and F_1^- metrics. Some codeT5 configurations have difficulties saturating on both R_{PT} and F_1^-, e.g. $T5^{C}_{vx}$, $T5^{C}_{vj}$, $T5^{C}_{vgf}$.

The average **velocity** values $\overline{V_{R_{PT}}}$ and $\overline{V_{F_1^-}}$ demonstrate that all the BART and T5 configurations saturate at the first epoch, except $T5_{vn}$. We checked the value of the $F1_1^-$ at the epoch where R_{PT} saturates (noted $F1_1^-(V_{R_{PT}})$ in Tables 5, 6 and 7), and we observed that all models saturating the R_{PT} also record high $F1_1^-$ values, which means that learning the syntax is the main challenge when it comes to learn an RDF-extractor. Moreover, we observe that the BART models generally saturate both R_{PT} and F_1^- early, followed by the T5 models. From the syntax point of view, TurtleLight written on one line saturates earlier than other syntaxes. The factorisation of list and tag syntaxes leads to earlier saturation, which is particularly noteworthy in the case of the tag syntax configurations. Regarding the W3C syntaxes, there is a clear difference between JSON and XML on one hand, which have a $\overline{V_{R_{PT}}}$ close to 0, and Turtle and NTriples on the other hand, which have a $\overline{V_{R_{PT}}}$ close to 1. This gap could be due to the pre-training of the language models we used, which are more likely to have seen JSON and XML that are common on the web.

The average **stability** and **divergence** values show that all the saturating models are stable from the F_1^- point of view ($\overline{S_{F_1^-}} = 1$) and never diverge ($\sum D_{F_1^-} = 0$). Only the $\overline{S_{R_{PT}}}$ and $\sum D_\rho$ meta-metrics reveal differences in the performances of the models. These metrics are correlated in the sense that an unstable model always diverges. We see that BART models never diverge, while many configurations of T5 diverge.

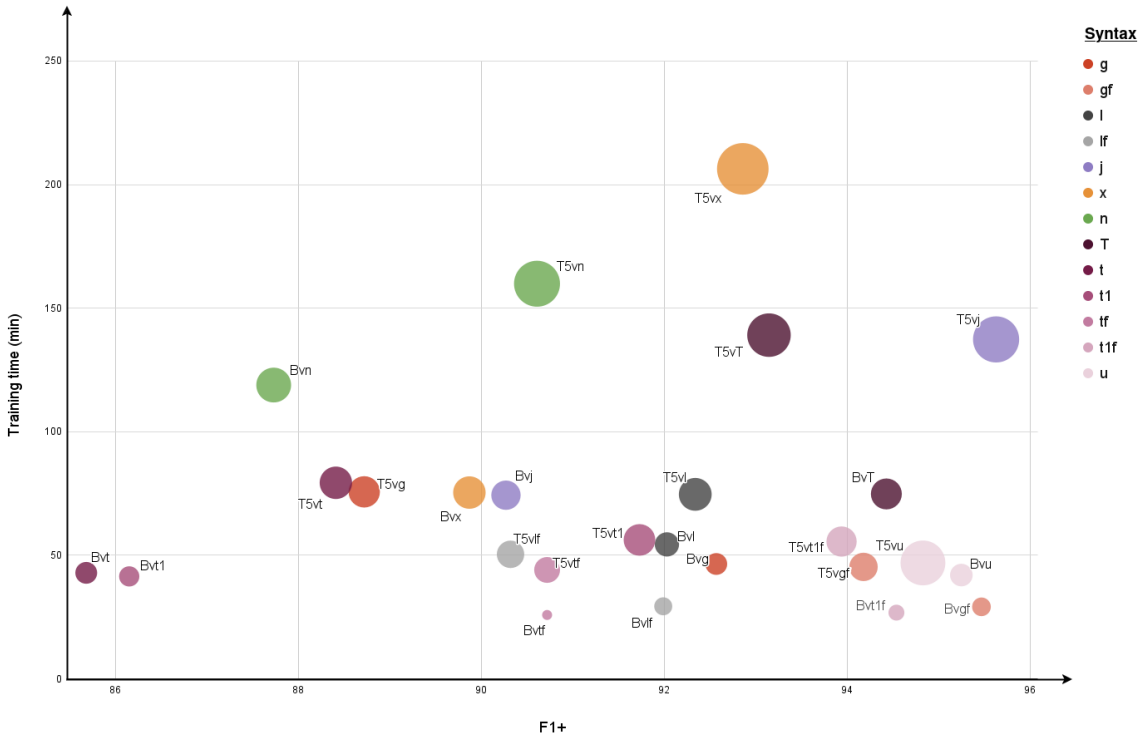


Fig. 12. Best performing models (BART and T5) configurations against $\overline{F_1^+}$ (x axis), $\overline{T_t}$ (y axis) and $\overline{C_c}$ (radius)

The **resource metrics** (time and CO_2) also show important discrepancies between models, that could be explained by the verbosity of some syntaxes, and the ability of a model to learn a given syntax without divergence. As shown in Fig. 12, T5 models are greedier than BART models, and simple syntaxes are thriftier than RDF ones. Model training CO_2 footprint (radius) vary from 0.029g for B_{vtf}, to 0.324g for T_{vx}. It is also interesting to see that the Turtle Ultra

Light syntax, despite conciseness and good overall results, finally requires more training and, consequently, more resources.

To sum up, our experiments show that the quality of the generated RDF triples depends on both the choice of the model and of the syntax. In terms of models, BART generally writes syntactically better triples than T5, while T5 needs fewer training epochs but requires more resources. Interestingly, codeT5 is in third place without being pre-trained on Wikipedia data. FlanT5 and pileT5 are unable to solve our task. In terms of syntaxes, factorization applied on the list, tags and Turtle light syntaxes positively impacts the models' performance, except on $T5_{vl}$. The one-line variation improves the quality of Turtle Light variations, and the best configuration combines factorization and one-line writing. In the end, B_{vtf1} (BART with Turtle light, factorization, one-line) offers good performances at a low cost with a standard and human-readable syntax.

6. Conclusion: BART and a Turtle Light Go a Long Way

In this article, we evaluated the impact of the choice of a syntax on the fine-tuning of small language models for the generation of RDF triples, focusing on extracting datatype properties from text. We demonstrated the ability of the BART and T5 models to solve the RE task compared to codeT5, pileT5 and FlanT5. To do so, we proposed several metrics that allowed us to characterise the behaviours of the given training configuration. Our results show that syntax understanding is the main challenge language models face when they are finetuned to solve a relation extraction task: all the configurations able to generate well-written graphs also highly perform in terms of F_1^-. Moreover, the choice of the syntax also has a significant impact on the performance of the extraction, as well as on the resources needed to learn it (time and CO_2 footprint). Basic syntaxes (list and tags) are generally easily learned but lead to average performances. While learning W3C RDF syntaxes is more resource-consuming, and the RDF potential (managing ontologies, datatypes) must generally be paid by a higher cost in terms of resource. The best-performing configuration $T5_{vj}$ (T5 with JSON) outperforms the others at the cost of 2 hours of training on an A100 GPU and a 0.250g CO_2 footprint. An interesting compromise is the use of simplified standard syntaxes (as the Turtle Light syntaxes proposed in this work) that are robust and quick to learn. However, despite its simplicity, we also show that the Turtle Ultra Light syntax (Turtle variation omitting the prefixes and their declarations) could be costly to learn. For all these reasons, the finetuning of BART models using the **inline factorised Turtle Light** (B_{vtf1}) is a good tradeoff between efficiency and frugality.

In future work, we will focus on systematizing the task proposed at a Knowledge base scale, notably by extending our proposal to Shape containing both data and object properties.

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Table 5 First part of the results for the best-performing configurations. Configurations are listed in descending order of G_g. In bold are the best results. In italics are the second-best results. The worse results are underlined. As a reminder the syntax notation is: XML-RDF ($_x$), Turtle ($_T$), Turtle Light ($_t$), Turtle Ultra Light ($_u$), N-Triples ($_n$), JSON-LD ($_j$), list ($_l$) and tags ($_g$).

Rank	Config	Triple Validity			RE performance ×100				Edition m.		Training behavior								Resources		G_g
		$\overline{R_{PT}}$	$\overline{R_{CS}}$	$\overline{R_{SVT}}$	$\overline{F_1^-}$	$\overline{F_1^+}$	$\overline{P^+}$	$\overline{R^+}$	$\overline{BLEU}$	$\overline{lev}$	$\overline{Nb_{epochs}}$	$\overline{V_{R_{PT}}}$	$\overline{S_{R_{PT}}}$	$\sum D_{R_{PT}}$	$\overline{V_{F_1^-}}$	$\overline{S_{F_1^-}}$	$\sum D_{F_1^-}$	$\overline{F_1^-(V_{R_{PT}})}$	$\overline{C_c}$	$\overline{T_t}$	
1	$T5_{vj}$	**1,00**	**1,00**	**1,00**	*99,75* ± 0.3	**95,63** ± 8.1	**100,00**	**94,37**	**1**	**0,000**	13	*0,2*	0,973	**0**	*0,2*	**1,000**	**0**	*98,91*	0,252	137,362	**96**
2	B_{vgf}	**1,00**	**1,00**	**1,00**	99,69 ± 0.4	*95,47* ± 8.1	99,29	*94,28*	*0,967*	**0,000**	15	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,59	0,042	29,149	*95*
3	B_{vu}	**1,00**	**1,00**	**1,00**	**99,79** ± 0.3	95,25 ± 6.7	*99,41*	94,04	0.970	**0,000**	22	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,78	0,056	42,000	*95*
4	$T5_{vu}$	**1,00**	**1,00**	**1,00**	99,63 ± 0.6	*94,83* ± 7.7	99,01	93,53	0,967	**0,000**	15	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,90	0,236	46,905	*95*
5	B_{vt1f}	**1,00**	**1,00**	**1,00**	99,72 ± 0.3	*94,54* ± 7.3	97,09	93,20	0,933	**0,000**	*12*	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,80	*0,035*	*26,801*	*95*
6	B_{vT}	**1,00**	**1,00**	**1,00**	99,73 ± 0.4	*94,43* ± 8.2	96,39	93,42	0,972	11,750	23	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,68	0,104	74,831	94
7	$T5_{vt1f}$	**1,00**	**1,00**	**1,00**	99,51 ± 0.6	93,94 ± 9.7	95,48	93,13	0,961	**0,000**	14	*0,2*	**1,000**	**0**	**0,0**	**1,000**	**0**	**98,98**	0,099	55,563	94
8	$T5_{vx}$	**1,00**	**1,00**	**1,00**	99,58 ± 0.5	92,86 ± 7.3	96,81	91,91	0,946	1,600	18	0,4	0,990	**0**	0,4	**1,000**	**0**	98,09	0,324	206,378	93
9	B_{vg}	**1,00**	**1,00**	**1,00**	99,62 ± 0.4	92,57 ± 8.8	96,34	91,08	0,940	**0,000**	18	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,42	0,053	46,486	93
10	$T5_{vl}$	**1,00**	**1,00**	**1,00**	99,55 ± 0.6	92,34 ± 9.4	95,19	91,40	0,972	*0,200*	*11*	0,8	**1,000**	**0**	0,6	**1,000**	**0**	98,27	0,118	74,664	92
11	B_{vlf}	**1,00**	**1,00**	**1,00**	99,63 ± 0.4	91,99 ± 9.4	96,68	90,49	*0,996*	1,650	*12*	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,49	0,040	29,360	92
12	B_{vl}	**1,00**	**1,00**	**1,00**	99,62 ± 0.4	92,03 ± 8.6	94,75	90,37	0,896	18,086	18	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,23	0,064	54,408	92
13	B_{vtf}	**1,00**	**1,00**	**1,00**	99,49 ± 0.6	90,72 ± 10.7	95,45	89,13	0,968	**0,000**	12	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	98,33	**0,029**	**25,849**	91
14	$T5_{vgf}$	**1,00**	0,96	**1,00**	99,57 ± 0.4	*94,18* ± 7.8	96,76	92,51	0,983	1,400	13	*0,2*	0,975	**0**	*0,2*	**1,000**	**0**	98,49	0,087	45,302	90
15	$T5_{vtf}$	**1,00**	**1,00**	**1,00**	99,33 ± 0.7	90,72 ± 9.8	95,81	88,72	0,955	0,560	**10**	0,8	0,986	**0**	**0,0**	**1,000**	**0**	93,54	0,072	44,072	90
16	B_{vj}	**1,00**	**1,00**	**1,00**	99,52 ± 0.5	90,27 ± 11.3	95,14	88,85	0,962	47,200	*11*	*0,2*	**1,000**	**0**	**0,0**	**1,000**	**0**	98,88	0,093	74,324	90
17	B_{vx}	**1,00**	**1,00**	**1,00**	99,46 ± 0.7	89,87 ± 13	96,69	88,85	0,974	17,400	14	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	96,72	0,115	75,387	90
18	$T5_{vt1}$	0,97	**1,00**	**1,00**	99,34 ± 0.7	91,73 ± 9.8	95,32	89,68	0,968	99,400	**10**	**0,0**	0,980	**0**	**0,0**	**1,000**	**0**	97,36	0,109	56,223	89
19	$T5_{vlf}$	**1,00**	0,98	**1,00**	99,32 ± 0.7	90,32 ± 10.9	94,28	89,43	0,875	205,511	*11*	1,0	0,960	1	**0,0**	**1,000**	**0**	98,71	0,081	50,397	88
20	B_{vn}	**1,00**	**1,00**	**1,00**	99,36 ± 0.6	87,73 ± 9.5	97,01	85,48	0,986	81,800	24	**0,0**	*0,991*	**0**	0,4	**1,000**	**0**	95,96	0,134	118,891	88
21	$T5_{vg}$	*0,98*	**1,00**	**1,00**	99,29 ± 0.6	88,72 ± 9.6	96,15	86,28	0,943	18,305	16	0,4	0,970	**0**	**0,0**	**1,000**	**0**	98,58	0,107	75,670	87
22	$T5_{vt}$	0,97	**1,00**	**1,00**	99,25 ± 0.5	88,41 ± 11.4	92,60	86,61	0,935	29,200	14	*0,2*	**1,000**	**0**	**0,0**	**1,000**	**0**	98,65	0,115	79,342	85
23	B_{vt1}	0,97	**1,00**	**1,00**	99,32 ± 0.5	86,15 ± 11.0	94,13	83,89	0,993	20,000	16	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	97,91	0,047	41,463	83
24	B_{vt}	0,97	**1,00**	**1,00**	99,34 ± 0.5	85,68 ± 12.2	93,52	83,64	0,975	12,933	15	**0,0**	**1,000**	**0**	**0,0**	**1,000**	**0**	97,44	0,053	42,898	83

Table 6 Second part of the results for the best-performing configurations. Configurations are listed in descending order of G_g. In bold are the best results. In italics are the second-best results. The worse results are underlined. As a reminder the syntax notation is: XML-RDF ($_x$), Turtle ($_T$), Turtle Light ($_t$), Turtle Ultra Light ($_u$), N-Triples ($_n$), JSON-LD ($_j$), list ($_l$) and tags ($_g$).

Rank	Config	Triple Validity			RE performance ×100				Edition m.		Training behavior									Resources		G_g
		$\overline{R_{PT}}$	$\overline{R_{CS}}$	$\overline{R_{SVT}}$	$\overline{F_1^-}$	$\overline{F_1^+}$	$\overline{P^+}$	$\overline{R^+}$	$\overline{BLEU}$	$\overline{lev}$	$\overline{Nb_{epochs}}$	$\overline{V_{R_{PT}}}$	$\overline{S_{R_{PT}}}$	$\sum D_{R_{PT}}$	$\overline{V_{F_1^-}}$	$\overline{S_{F_1^-}}$	$\sum D_{F_1^-}$	$\overline{F_1^-(V_{R_{PT}})}$	$\overline{C_c}$	$\overline{T_t}$	
25	$T5_{vT}^{C}$	**1,00**	0,98	**1,00**	98,82 ± 0.8	83,47 ± 9.7	87,99	82,15	0,877	269,573	*12*	1,6	0,923	**0**	*0,2*	**1,000**	**0**	97,68	0,135	80,982	**82**
26	$T5_{vt1f}^{C}$	**1,00**	0,98	**1,00**	98,51 ± 0.4	83,18 ± 7.9	91,51	81,64	0,929	19,789	14	*0,2*	0,913	**0**	**0,0**	**1,000**	**0**	98,14	*0,082*	*55,403*	*81*
27	$T5_{vl}^{C}$	*0,97*	*0,99*	**1,00**	98,55 ± 0.8	83,21 ± 9.1	89,41	81,25	0,930	47,107	17	0,6	0,949	*1*	**0,0**	**1,000**	**0**	94,19	0,138	89,753	79
28	$T5_{vt1}^{C}$	*0,97*	0,98	**1,00**	98,29 ± 0.4	82,02 ± 7.9	89,42	78,81	0,927	122,218	15	**0,0**	0,900	**0**	**0,0**	**1,000**	**0**	94,70	0,131	77,993	*78*
29	$T5_{vlf}^{C}$	0,94	0,97	**1,00**	98,60 ± 0.6	83,68 ± 7.4	92,13	81,59	0,881	80844,715	19	*0,2*	0,741	*2*	**0,0**	**1,000**	**0**	96,77	0,101	73,919	77
30	$T5_{vT}$	0,82	**1,00**	**1,00**	*99,38* ± 0.8	**93,15** ± 10.3	95,55	**91,93**	0,968	810,135	15	0,8	0,620	2	0,4	**1,000**	**0**	*98,62*	0,221	139,095	*76*
31	$T5_{vtf}^{C}$	0,96	0,95	**1,00**	97,66 ± 1.8	80,41 ± 11.2	85,87	80,08	0,911	208,583	13	1,2	0,925	*1*	**0,0**	**1,000**	**0**	95,11	0,083	*54,966*	73
32	$T5_{vn}$	0,75	*0,99*	**1,00**	**99,39** ± 0.4	*90,61* ± 7.9	**97,98**	*88,17*	0,972	137,233	13	1,6	0,747	2	*0,2*	**1,000**	**0**	97,68	0,250	159,895	67
33	$T5_{vt}^{C}$	0,82	*0,99*	**1,00**	98,51 ± 0.8	78,92 ± 7.8	86,83	76,55	*0,977*	40,978	17	*0,2*	0,813	*2*	**0,0**	**1,000**	**0**	97,26	0,174	90,203	64
34	$T5_{vn}^{C}$	0,84	*0,99*	**1,00**	98,41 ± 0.4	74,54 ± 7.9	84,07	73,27	0,949	421,512	*12*	1,8	0,857	2	1,0	**1,000**	**0**	97,96	0,220	139,832	62
35	$T5_{vg}^{C}$	0,70	*0,99*	**1,00**	98,58 ± 0.8	81,41 ± 8.4	87,09	79,85	0,926	71,099	17	2,6	**0,65**	3	**0,0**	**1,000**	**0**	97,73	0,119	83,253	56
36	$T5_{vgf}^{C}$	0,61	0,97	**1,00**	97,12 ± 1.9	77,73 ± 7.8	85,89	76,72	0,882	287087,870	*11*	∅	∅	∅	**0,0**	**1,000**	**0**	∅	**0,079**	**44,384**	47
37	$T5_{vu}^{C}$	0,92	0,41	*0,99*	98,84 ± 0.8	87,83 ± 8.9	91,33	86,54	0,927	77,72	16	*0,2*	0,89	*1*	**0,0**	**1,000**	**0**	97,66	0,109	57,632	32
38	$T5_{vj}^{C}$	0,59	**1,00**	**1,00**	59,60 ± 54.4	52,11 ± 47.7	60,00	49,64	∅	**17,800**	14	∅	∅	∅	∅	∅	∅	∅	0,174	132,535	31
39	$T5_{vt1}^{P}$	0,39	**1,00**	**1,00**	79,27 ± 0.9	72,61 ± 13.8	76,25	71,24	∅	33,056	**10**	∅	∅	∅	**0,0**	**1,000**	**0**	∅	0,159	77,297	28
40	$T5_{vlf}^{F}$	0,33	**1,00**	**1,00**	59,67 ± 0.6	53,78 ± 7.4	55,72	52,95	∅	66,548	14	*0,2*	0,74	2	**0,0**	**1,000**	**0**	**98,77**	0,115	69,921	18
41	$T5_{vu}^{F}$	0,94	0,251	0,77	88,49 ± 10.0	85,59 ± 8.9	96,40	79,16	0,970	7042933	12	**0,0**	0,89	*1*	**0,0**	**1,000**	**0**	96,07	0,083	*42,996*	15
42	$T5_{vx}^{C}$	0,26	0,97	**1,00**	59,59 ± 54.4	43,92 ± 44.3	46,08	42,85	∅	*18,316*	18	∅	∅	∅	∅	∅	∅	∅	0,205	168,913	11
43	$T5_{vn}^{P}$	0,04	*0,99*	**1,00**	97,19 ± 4.1	79,29 ± 12.9	81,01	*79,36*	**0,983**	67,679	18	∅	∅	∅	0,4	**1,000**	**0**	∅	0,279	241,861	3
44	$T5_{vu}^{P}$	0,59	0,00	0,87	93,32 ± 7.6	90,29 ± 7.2	*97,37*	87,00	0,972	69,29	18	∅	∅	∅	**0,0**	**1,000**	**0**	∅	0,122	76,741	0
45	$T5_{vt1f}^{P}$	0,02	**1,00**	**1,00**	79,84 ± 44.6	61,59 ± 39.8	62,86	60,86	∅	55,849	16	∅	∅	∅	2,6	**1,000**	**0**	∅	0,109	71,955	0
46	$T5_{vg}^{P}$	0,00	**1,00**	**1,00**	39,51 ± 54.1	31,28 ± 43.1	31,14	31,43	∅	21,812	*11*	∅	∅	∅	∅	∅	∅	∅	0,113	69,022	0
47	$T5_{vlf}^{P}$	0,00	**1,00**	**1,00**	20,00 ± 44.7	8,57 ± 19.2	8,57	8,57	∅	23,183	13	∅	∅	∅	∅	∅	∅	∅	*0,088*	73,299	0

Table 7 Third part of the results for the best-performing configurations. In bold are the best results. In italics are the second-best results. The worse results are underlined. As a reminder the syntax notation is: XML-RDF ($_x$), Turtle ($_T$), Turtle Light ($_t$), Turtle Ultra Light ($_u$), N-Triples ($_n$), JSON-LD ($_j$), list ($_l$) and tags ($_g$).

Rank	Config	Triple Validity			RE performance ×100				Edition m.		Training behavior								Resources		G_g
		$\overline{R_{PT}}$	$\overline{R_{CS}}$	$\overline{R_{SVT}}$	$\overline{F_1^-}$	$\overline{F_1^+}$	$\overline{P^+}$	$\overline{R^+}$	$\overline{BLEU}$	$\overline{lev}$	$\overline{Nb_{epochs}}$	$\overline{V_{R_{PT}}}$	$\overline{S_{R_{PT}}}$	$\sum D_{R_{PT}}$	$\overline{V_{F_1^-}}$	$\overline{S_{F_1^-}}$	$\sum D_{F_1^-}$	$\overline{F_1^-(V_{R_{PT}})}$	$\overline{C_c}$	$\overline{T_t}$	
48	$T5^F_{vg}$	**0,29**	0,00	0,00	**79,68** ± 54.1	**72,56** ± 43.1	**74,07**	**71,54**	∅	**12,462**	**11**	∅	∅	∅	∅	∅	∅	∅	*0,087*	*59,423*	0
49	$T5^F_{vt1f}$	*0,26*	0,00	0,00	*59,43* ± 54.3	51,66 ± 47.8	*52,96*	*51,78*	∅	25,253	13	∅	∅	∅	∅	∅	∅	∅	*0,080*	*55,165*	0
50	$T5^F_{vgf}$	0,17	0,00	0,00	39,92 ± 54.7	39,51 ± 54.1	39,95	39,16	∅	47,084	13	∅	∅	∅	∅	∅	∅	∅	**0,067**	**45,982**	0
51	$T5^P_{vt}$	0,15	0,00	0,00	*59,67* ± 54.5	40,58 ± 37.6	42,78	40,29	∅	28,467	15	∅	∅	∅	0,6	**1,000**	**0**	∅	0,154	100,197	0
52	$T5^F_{vtf}$	0,01	0,00	0,00	39,63 ± 54.3	29,28 ± 40.1	31,35	28,75	∅	24,247	14	∅	∅	∅	∅	∅	∅	∅	*0,089*	61,239	0
53	$T5^P_{vx}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	384,492	13	∅	∅	∅	∅	∅	∅	∅	0,250	164,578	0
54	$T5^P_{vtf}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	21,538	15	∅	∅	∅	∅	∅	∅	∅	0,124	77,378	0
55	$T5^P_{vT}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	107,384	*12*	∅	∅	∅	∅	∅	∅	∅	0,137	114,290	0
56	$T5^P_{vl}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	17,443	14	∅	∅	∅	∅	∅	∅	∅	0,189	108,608	0
57	$T5^P_{vj}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	79,172	14	∅	∅	∅	∅	∅	∅	∅	0,403	200,460	0
58	$T5^P_{vgf}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	20,584	14	∅	∅	∅	∅	∅	∅	∅	0,109	62,134	0
59	$T5^F_{vx}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	310,462	17	∅	∅	∅	∅	∅	∅	∅	0,270	186,559	0
60	$T5^F_{vt1}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	118,134	17	∅	∅	∅	∅	∅	∅	∅	0,183	89,052	0
61	$T5^F_{vT}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	195,167	*12*	∅	∅	∅	∅	∅	∅	∅	0,217	114,521	0
62	$T5^F_{vt}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	97,534	15	∅	∅	∅	∅	∅	∅	∅	0,122	83,726	0
63	$T5^F_{vn}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	97,423	13	∅	∅	∅	∅	∅	∅	∅	0,263	160,633	0
64	$T5^F_{vl}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	18,166	16	∅	∅	∅	∅	∅	∅	∅	0,169	107,316	0
65	$T5^F_{vj}$	0,00	0,00	0,00	0,00 ± 0.0	0,00 ± 0.0	0,00	0,00	∅	77,319	**11**	∅	∅	∅	∅	∅	∅	∅	0,160	115,238	0

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