A sequence to sequence transformer data logic experiment

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Abstract

In this paper we present experiments to evaluate how a T5 model behaves with regard to input data fidelity. The rationale behind these experiments is to evaluate if a sequence to sequence transformer can be constrained into generating the specifics of a financial report, and more generally whether it can trustfully reproduce a semantic logic, and to what extent.

1 Introduction

T5 by Raffel et al. (2020) recently demonstrated strong constrained and data to text generation capabilities. Experiments have been lead on AQG tasks (Grover et al. (2021)) and on the WebNLG dataset as to explore the data to text capabilities of a T5 model. In particular, Kale and Rastogi (2020) demonstrates T5 model shows interesting capacities in generalization to new domains and relations, and Kasner and Dusek (2020) proposes significant text generation experiment even without any in-domain examples.

Text generation in Finance can be very demanding as to the level of constraint a neural model should comply with. The objective of our experiment is to evaluate which data formalism we should build to achieve similar results as the results achieved by T5 models on WebNLG tasks.

In order to produce this evaluation, we chose to create a data set focusing on semantic intentions. Intentions are objects describing Natural Language Generation (NLG) pipelines based on Abstract Categorical Grammars semantic and syntactic items, as defined by Salmon (2017), that can be specialized and combined together. We also implemented a set of metrics for NLG evaluation based on BLEU and BERT-SCORE.

2 Corpus

The initial corpus for this experiment is a set of 4159 public online US and UK Market Reports. We limit the experiments to the financial domain as to prove more accurate results.

2.1 Corpus generation

Raw text is extracted with a home made pdf extractor based on PDFMiner, deleting all tables and titles. A corpus analysis is performed on these raw extractions, leading to the definition of handcrafted grammars describing each intention. These grammars allow to tag each sentence belonging to one of the intentions of interest, and to extract for each sentence a set of relevant chunks which are then transformed into triples. These intentions are currently defined and used by Yseop’s generation core engine. For the sake of the experiment, we choose to retain only simple intentions and sentences which can also be produced by this NLG engine.

2.2 Corpus transformation

2.2.1 Data logic

To ensure the precision and accuracy of the generated sentences, we have chosen a data-to-text representation method, which particularizes key elements of sentences in our financial corpus and extract triples, using an automated method close to Li et al. (2020).

This method was applied as to define a corpus of intentions. An intention is a sentence corresponding to a specific expression of a financial indicator’s value. Yseop has shown that a handful of such intentions are sufficient to describe a data-driven narrative in a speciality domain, such as Finance. For
instance, an intention DescribeValue is a sentence stating the value of a financial indicator at a precise time and an intention DescribeVariation is a sentence describing the variation in time of a financial indicator’s value. We use the prefix Merge to define a sentence composed of two or more intentions. In order to identify and extract these intentions in our corpus, a Ruta grammar (KLUEGL et al., 2016) was created to automate the triples extraction, imitating Gardent et al. (2017) data modeling. This grammar first uses dictionaries as well as POS-tag patterns to identify financial key elements related to these intentions and characterize them into one of the following categories:

- financial indicator
- reference (time and geographical element)
- measure
- predicate

Indicators, measures and dimensions are generic elements that can be found in all intentions. Predicates, on the other hand, vary according to the intention. To create a dictionary that take into account this specificity and can later be used for intention detection, we conducted a manual analysis of the market reports that allowed us to classify the predicates specific to each intention. Synonyms and antonyms have also been included to complete and enrich the dictionary (see Table 2 for some examples).

In a second stage, the grammar looks for syntactic combinations of these key elements. For example, a sentence containing exclusively a financial indicator, a state predicate, one measure and an optional time and/or geographic dimension will be extracted as an intention DescribeValue.

Sentences selected from financial corpus are then transformed into a set of triples (hereinafter referred to as complete triples), organized into subject-predicate-object structure, && serving as a connector. See Table 11 in Appendix for a detailed overview.

2.2.2 Data construction

There is no theoretical limit to the maximum sequence a T5 can encode, the only constraint being the memory requirements. We did not work on this specific aspect as this is not the purpose of the experiment. We choose to work with a maximum input sequence of 400, trying to keep the experiments into a small memory consumption interval. Owing to the limited capability of our T5 model, triples that are too long cannot be fully processed by the model and therefore the generated sentences will be incomplete. In order to work around this problem, we trimmed the triples by replacing the elements with simpler ones and reducing the length of predicates, then creating simplified triples. In these simplified triples, financial indicators are replaced with their semantic class (predefined in our grammar). For example, abuse tax and absolute organic operating costs both belong to the class expenses, so they were replaced with the generic short form expenses in the simplified triple. Measures are replaced a simpler number ($ + two digits), all time dimensions are substituted by a preposition (if there is one in the initial dimension time) plus a year (in 2019, for example) and the expression in America replaces any term in the geography dimensions. We refer to this trimmed triples as simple triples.

We trained a model with simple triples to evaluate if our formalism was rich and accurate enough so the model could infer the data logic, and used the complete triples to train a model for inference.

According to the type and number of key components, target sentences are sorted into different intentions. Our grammar for now is able to recognize and annotate 8 intentions, DescribeValue and DescribeVariation being the core intentions, based on which we developed 6 others (see Table 1).

Two sets of experiments have been built for each of the data sets created from simple and complete triples. Each experiment is detailed in Section 5.

3 Data sets

Applying the triples generator on a 4159 raw corpus files, we have collected 20615 sentences annotated for both complete and simple triples. The frequency for each intention in each set is presented in Table 1.

We randomly sampled three different training and testing partitions in order to leverage the scarcity of our data. All measures provided below are aggregated means of these three partitions.

4 Models

We used the T5 sequence to sequence transformer from the transformers library by (Wolf et al. (2020))
to run the experiments, using an Nvidia GeForce RTX 2070 GPU with 8 Go RAM.

We trained two models, one from complete triples, and another one from simple triples, for each of our 3 data partitions. A simple \(^1\) and a complete \(^2\) trained models are available for reproducibility on Hugging Face hub.

### 4.1 Training parameters

Our objective is to evaluate our data formalism and an associated sequence to sequence model capabilities, so we did not experiment much on fine-tuning. We used a standard set of training parameters for all models and trained for one epoch and batches of 6, using the Hugging Face transformers library and the AdaFactor optimization method, keeping all default parameters except for the following:

- learning rate lr=1e-3

- regularization constants eps=(1e-30, 1e-3)

- decay_rate=0.7

### 4.2 Generation parameters

At inference, we tried to limit hallucinations and omissions while maintaining a good level of richness on the structure and vocabulary of the generated sentences.

We use a mix of top_k and top_p sampling for generating. Top_k is a sampling scheme, in which the K most probable next tokens are filtered and the probability mass is redistributed among only those K next tokens. Top_p is also a sampling scheme, managing creativity of the model. It chooses from the smallest possible set of words whose cumulative probability exceeds the probability p. This way, the size of the set of words (a.k.a the number of words in the set) can dynamically increase and decrease according to the next word’s probability distribution.

We chose the following process for selecting the most suitable top_p and top_k for our generator:

- select one representative sentence and its corresponding triples for every intention.

- prepare 10 top_p (from 0.12 to 1) and 10 top_k (from 10 to 100) and combine them in a pairwise fashion to get 100 (top_p, top_k) couples.

- generate 10 sentences from a single triple. Then measure the similarity between these 10 sentences with ROUGE \(^3\) and collect the measure under different top_p and top_k couples. We considered this average ROUGE to measure the creativity of our model. The bigger it is (less variation in the 10 generated sentence), the less creative the model is.

- compare the 10 generated sentences with the initial sentence in order to collect the ROUGE measure under different top_p and top_k couples. The bigger it is, the more accurate our model is.

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1. [https://huggingface.co/yseop/FNP_T5_D2T_simple](https://huggingface.co/yseop/FNP_T5_D2T_simple)
2. [https://huggingface.co/yseop/FNP_T5_D2T_complete](https://huggingface.co/yseop/FNP_T5_D2T_complete)
3. [https://github.com/pltrdy/rouge](https://github.com/pltrdy/rouge)
The top_p and top_k selected for simple triples and complete triples are (0.72, 40) and (0.82, 90), respectively. The model gives the best performance with them, leading to results presented in section 6.

4.3 Evaluation metrics

During the experiment, we have noticed that both the length of elements in the triples and the model’s familiarity with them can influence the quality of the generation. We have adopted 3 methods to assess the quality of our models.

- The generated sentences are compared with the initial sentences and the lexical similarity is measured with a BLEU score (Papineni et al. (2002))\(^4\), adapted so it considers bi-grams.

- The generated sentences are compared with the initial sentences and the semantic similarity is measured with a BERT-SCORE (Zhang et al. (2020)).

- The generated sentences are reintroduced into the triples generator to obtain regenerated triples. The inspiration for regenerating the triples and evaluate them against the original ones comes from Veksler et al. (2019)’s work on how to assess a key level of information for NLG. The degrees of similarity between the regenerated triples and the original ones offers another point of view on the quality of generated sentences and assesses the credibility of the data logic initially chosen. We used both BLEU and BERT-SCORE to evaluate these similarities. We will refer to these measures as Triple BLEU and Triple BERT.

It is important to notice that the triples comparison results is fully automated and neither human evaluation nor inter-annotator agreement statistics have been performed. Since the triples production process biases the performance measure, and is used both at training and inference, we are in fact evaluating the capability of our model to preserve the “fixed-pointedness” of T5 with respect to our representation rather than the T5 natural language generation power.

5 Experiments

We defined two experiments, one training and evaluating for complete triples (see subsection 5.1), the other for simple triples (see subsection 5.2), and computed the four metrics previously detailed for each experiment. The measures provided are arithmetic means of the scores evaluated for all models created from our three different data partitions.

In the following subsections, we will refer to any element issued from the original corpus sentences as original. For each table of results, we present the actual number of triples that could be regenerated in regard to the number of sentences generated at inference available for testing.

5.1 Experiment 1

In this initial experiment, we used complete triples to fine-tune a T5 model. A data sample is available in Table 3, results are provided in Table 8. The BLEU score shows important variations in between intentions, due to the fact that some intentions are more complex and contain more elements than simpler ones like DescribeValue, and because they are less represented in the training data. Having around 4000 training examples seems to be a pre requisite to obtain significant improvement on the results.

5.2 Experiment 2

5.2.1 Simple

In this experiment we trained another model to learn and generate from simple triples.

The objective here is to workaround the limitations of our model in low memory consumption mode. The process for training a model for simple triples is the following:

- complete triples are simplified
- we simplify the original sentences by replacing the original elements by the simple ones (indexed by simple triples)

The model is trained with simple triples against these simplified sentences (see example provided in Table 4), then simplified original sentences used for training are compared with the sentences generated at inference (an evaluation sample is provided in Table 5).

5.2.2 Restored

To affect a metric to sentences generated at inference from simple triples models, we retain two additional features:

- in the sentences generated at inference, we restore the original elements using their index

\(^4\)https://www.nltk.org/_modules/nltk/translate/bleu_score.html
in the original sentences, and compare these restored sentences with the original ones. An example of this transformation is provided in Table 6.

- we regenerate triples from these restored sentences, and compare them with the complete triples presented in section 5.1.

We will refer to the triples and sentences in this experiment as restored. The results are provided in Table 10.

6 Results analysis

BLEU and BERT-SCORE leads to different conclusions and the BLEU score is generally lower than BERT-SCORE. This is because the 2 metrics evaluate the sentence at different levels.

6.1 Evaluating for triples

We expect sentences in financial report to contain all key information provided in the input data. However, BLEU and BERT-SCORE are incapable of examining the completeness of generated sentences. To achieve this goal, we passed the generated sentences to the triples generator and evaluate the regenerated triples with BLEU and BERT-SCORE. The higher the score is, the more complete the generated sentence is.

We were not able to regenerate any triple for a significant amount (22%) of test set sentences generated at inference, neither for complete triples nor for simple triples. The results take into account this information loss, when this happens the Triple BLEU and BERT-SCORE are evaluated to zero. This is partly due to our triples generator, partly to the structure of the sentence generated at inference time. Our triples generator is very dependant from the lexical layout of the sentence. In some cases, generated sentences which would be qualified for triple extractions are not recognized as such and ignored. On the other hand, and for the same reasons, the triple generator will also ignore ill-formed sentences.

The attribution to each case is still a work in progress. We provide examples of ignored generated sentences from which we could not regenerate any triple in Table 7.

This leads to important discrepancy in the Triple BLEU results, between different types of intentions and between complete versus simple triples experiments. Nevertheless we can still directly link the fidelity of the results to input data with the size of the training set.

Simple triples achieve significant better Triple BLEU score than complete triples, due to the fact that sentences generated from simple triples are shorter, and usually mirror the original simple triple sinformation much better than sentences generated from complete triples (often interrupted before a human readable sentence is fully generated at inference time, thus regenerating incomplete triples or none). For complete experiment, we were able to regenerate 85% of the indicators present in the triples at inference and 95% of the indicators for the simple triples experiment.

6.2 Evaluating for sentences

BLEU evaluates the generated sentences on lexical level. The significant difference between complete and simple results comes mainly from the number of triples we were able to regenerate in each case, the simplest intentions for which a lot of training data was available being once again favored in both cases.

We can witness an improvement on average (from 0.423 average BLEU for sentences generated from complete triples at inference to 0.656 for sentences generated from simple triples), yet the similarity between restored sentences and original sentences (0.429 average BLEU) is only slightly higher than between original sentences and sentences generated from complete triples (0.423 average BLEU), mainly due to the risk of information loss during the process of restoring the original information in simplified sentences.

Figure 1 shows that, as the complexity of intention increases, average BLEU score for simplified sentences generated from simple triples exceeds BLEU for complete sentences generated from complete triples and also restored generated sentences.

While the sentences are short (intention is less complex), a small lexical change (change of predicate for instance) is reflected in a big drop in BLEU score. For the same intention, the simplified generated sentence is usually the shortest. Therefore, under simpler intention, (e.g. DescribeValue), simplified sentences generated from simple triples obtained the lowest score. However, as the intention becomes more complex, the length of simplified sentences increases, which offsets the influence of lexical change in BLEU score. In addition, the BLEU score of simplified generated sentences re-
Operating margin was 5.8% (versus 8.5%).

Table 3: Complete triples, generated sentence and regenerated complete triples example for original sentence Operating margin was 5.8% compared to 8.5%.

Table 4: Simple triples, generated sentence and regenerated simple triples example for original sentence Operating margin was 5.8% compared to 8.5%.

Table 5: Simplified original sentence and sentence generated from simple triples model at inference for Operating margin was 5.8% compared to 8.5%.

Table 6: Sentence generated from simple triples model at inference restored with original elements for Operating margin was 5.8% compared to 8.5%.

Table 7: Non regenerated triples sample
### Table 8: BLEU and BERT-SCORE (F1) results by intention for complete triples model.

| Intention                        | # test | # nan triples | Triple BLEU | Triple BERT | Sentence BLEU | Sentence BERT |
|----------------------------------|--------|---------------|-------------|-------------|---------------|---------------|
| DescribeValue                    | 990    | 163           | 0.781       | 0.960       | 0.646         | 0.944         |
| DescribeVariation                | 1492   | 173           | 0.693       | 0.951       | 0.573         | 0.941         |
| DescribeValueWithContributor     | 250    | 146           | 0.304       | 0.864       | 0.364         | 0.896         |
| DescribeVariationWithContributor | 61     | 14            | 0.443       | 0.908       | 0.325         | 0.911         |
| MergeDescribeValue               | 1149   | 392           | 0.363       | 0.888       | 0.556         | 0.935         |
| MergeDescribeValueWithContributor| 15     | 6             | 0.264       | 0.868       | 0.346         | 0.904         |
| MergeDescribeVariation           | 146    | 61            | 0.259       | 0.865       | 0.359         | 0.916         |
| MergeDescribeVariationWithContributor | 7 | 3          | 0.188       | 0.854       | 0.211         | 0.906         |
| Mean                             | -      | -             | 0.412       | 0.895       | 0.423         | 0.919         |

*nan triples stands for non regenerated triples*

### Table 9: BLEU and BERT-SCORE (F1) results by intention for simple triples model.

| Intention                        | # test | # nan triples | Triple BLEU | Triple BERT | Sentence BLEU | Sentence BERT |
|----------------------------------|--------|---------------|-------------|-------------|---------------|---------------|
| DescribeValue                    | 990    | 41            | 0.941       | 0.990       | 0.469         | 0.919         |
| DescribeVariation                | 1492   | 55            | 0.914       | 0.985       | 0.590         | 0.936         |
| DescribeValueWithContributor     | 250    | 93            | 0.499       | 0.899       | 0.407         | 0.889         |
| DescribeVariationWithContributor | 61     | 14            | 0.564       | 0.919       | 0.453         | 0.915         |
| MergeDescribeValue               | 1149   | 110           | 0.819       | 0.964       | 0.604         | 0.931         |
| MergeDescribeValueWithContributor| 15     | 5             | 0.397       | 0.891       | 0.471         | 0.899         |
| MergeDescribeVariation           | 146    | 27            | 0.656       | 0.934       | 0.491         | 0.919         |
| MergeDescribeVariationWithContributor | 7 | 2          | 0.459       | 0.890       | 0.405         | 0.899         |
| Mean                             | -      | -             | 0.656       | 0.934       | 0.486         | 0.913         |

*nan triples stands for non regenerated triples*

### Table 10: BLEU and BERT-SCORE (F1) results by intention for restored simple triples and sentences (number of test sentences and non regenerated triples is the same as in Table 9)

| Intention                        | Triples BLEU | Triples BERT | Sentence BLEU | Sentence BERT |
|----------------------------------|--------------|--------------|---------------|---------------|
| DescribeValue                    | 0.823        | 0.971        | 0.554         | 0.936         |
| DescribeVariation                | 0.684        | 0.944        | 0.537         | 0.930         |
| DescribeValueWithContributor     | 0.337        | 0.870        | 0.298         | 0.876         |
| DescribeVariationWithContributor | 0.351        | 0.884        | 0.323         | 0.897         |
| MergeDescribeValue               | 0.653        | 0.936        | 0.588         | 0.932         |
| MergeDescribeValueWithContributor| 0.274        | 0.868        | 0.396         | 0.891         |
| MergeDescribeVariation           | 0.494        | 0.903        | 0.434         | 0.911         |
| MergeDescribeVariationWithContributor | 0.257     | 0.859        | 0.299         | 0.891         |
| Mean                             | 0.484        | 0.904        | 0.429         | 0.908         |

*Mean of test sentences and non regenerated triples is the same as Table 9*
mains relatively steady compared to the other 2 types of generated sentences. This phenomenon tends to prove that simplification of initial sentences and initial triples does improve the performance. And another proof is that this method generates 1879 sentences with BLEU score in interval 0.98 to 1 for simple triples models, while the number of sentences generated from complete triples and restored triples models scoring within this interval is 1600 and 1783, respectively.

We evaluate with BERT-SCORE on semantic level. Taking BERT as the standard, there is little difference between the aggregated measures for sentences generated at inference from complete triples, simple triples or restored triples models. It’s interesting to notice that restored simple sentences for well defined intentions such as \textit{DescribeValue} exhibit a BERT-SCORE close to complete triples generated sentences (0.936 and 0.944 respectively), so this technique might be a way to workaround the memory constraints of the T5.

7 Error analysis
We have observed notable gaps between the BLEU and BERT-SCORE measures. We identified at least 4 reasons why this might occur:

1. Different verbs of same semantic meaning are employed in generated sentences:
   - \textbf{Original sentence}: The total gaming margin in online games during the quarter \textit{amounted to} 4.7
   - \textbf{Generated sentence}: The total gaming margin in online games during the quarter \textit{was} 4.7

2. The position of dimension time or dimension geography changes (slight influence):
   - \textbf{Original sentence}: Revenue \textit{for} 2016 amounted to 245 million.
   - \textbf{Generated sentence}: Revenue \textit{amounted to} 245 million \textit{for} 2016.

3. When the indicator in the triples starts with a lowercase, the model adds complement to it, which may be different from the complement in the original sentence. And sometimes, different complements may lead to different conjunctions of verb:
   - \textbf{Original sentence}: \textit{The value of} deferred tax assets at 31 December 2016 \textit{was} €190 million.
   - \textbf{Generated sentence}: \textit{The total deferred tax assets at 31 December 2016 were} €190 million.

4. Predicates used in the triples don’t indicate the tense of verbs. Hence, the tense of generated sentence may be different from the original one:
   - \textbf{Original sentence}: The annual savings in interest costs from this refinancing \textit{amounts to} approximately US$29 million.
   - \textbf{Generated sentence}: The annual savings in interest costs from this refinancing \textit{amounted to} approximately US$29 million.

The first three examples show that a lexical-based measure as BLEU is clearly not suitable to evaluate NLG systems. We tried to leverage this issue by evaluating triples against regenerated triples, this evaluation being less sensitive to semantic variations while retaining enough syntax for comparison.

8 Conclusion and future work
We have evaluated how a T5 sequence to sequence transformer behaves in data to text generation, using a combination of BLEU and BERT-SCORE on triples (with simple triples achieving the best Triple BLEU score of 0.656). The result gap between simple and complete triples experiments demonstrates that transforming initial sentences into simple ones and generating sentences from simple triples contributes to increasing the completeness of the generated sentences and the data logic accuracy.

Future work will focus on leveraging the induced bias of the triple generator as to propose more accurate automation of the triple extraction, and working on the current limitations of the T5 model to extend the length of input sequences keeping memory consumption as low as possible.

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Figure 1: Average BLEU score on every intention for simplified generated sentence, complete generated sentences and restored generated sentences. From DescribeValue to MergeDescribeVariationWithContributor, the complexity of intention raises.

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A Appendix
| Predicates | General form | Example |
|------------|--------------|---------|
| valIs     | Indicator | Net cash inflow was 9 067 million USD. |
|           |            | Net cash inflow was 9 067 million USD. |
| chaBy     | Indicator | The Company recorded a change of €12. |
|           |            | net cash inflow | chaBy | €12 |
| decBy     | Indicator | Net cash inflow decreased by 12%. |
|           |            | Net cash inflow | decBy | 12% |
| decTo     | Indicator | Net cash inflow decreased to €10 million. |
|           |            | Net cash inflow | decTo | €10 million |
| dFrom     | Indicator | Net cash inflow decreased from €12 million. |
|           |            | Net cash inflow | dFrom | €12 million |
| incBy     | Indicator | Net cash inflow increased by 12%. |
|           |            | Net cash inflow | incBy | 12% |
| incTo     | Indicator | Net cash inflow increased to €10 million. |
|           |            | Net cash inflow | incTo | €10 million |
| iFrom     | Indicator | Net cash inflow increased from €9 million. |
|           |            | Net cash inflow | iFrom | €9 million |
| Contribute | Indicator | Cash and cash equivalent was €20 million, |
|            |            | with net cash inflow of €12 million. |
|            |            | net cash inflow | Contribute | €12 million |
| CauBy     | Indicator | Due to higher costs in services, |
|           |            | costs increased by US$ 4 million. |
|           |            | costs | CauBy | higher costs in services |
| InfBy     | Indicator | Full-year capital expenditure amounted to €24.2 million, |
|           |            | mainly relating to new finishing capacity. |
|           |            | Full-year capital expenditure | InfBy | new finishing capacity |
| ContribBy | Contributed | Cash and cash equivalent was €20 million, |
|           |            | with net cash inflow of €12 million. |
|           |            | Cash and cash equivalent | contribBy | net cash inflow |
| dTime     | Measure | Cash and cash equivalent was €20 million in 2019. |
|           | dTime | €20 million | dTime | in 2019 |
| startDate | startValue | The revenue increased from €20 million in 2019 |
|           | startDate | to €23 million in 2020. |
|           |            | €20 million | startDate | in 2019 |
| endDate   | endValue | The revenue increased from €20 million in 2019 |
|           | endDate | to €23 million in 2020. |
|           |            | €23 million | endDate | in 2020 |
| diGeo     | Measure | The revenue increased by €20 million in Europe. |
|           | diGeo | €20 million | diGeo | in Europe |
| cTime     | Measure | The revenue increased by €20 million compare to the prior year. |
|           | cTime | €20 million | cTime | the prior year |
| comTo     | Measure | The revenue was €20 million (in 2019: €21 million) compare to the prior year. |
|           | comTo | €20 million | comTo | €21 million |

Table 11: Usage of predicates