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Entity-Based Semantic Adequacy for Data-to-Text Generation

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Abstract

While powerful pre-trained language models have improved the fluency of text generation models, it remains difficult to ensure that the generated texts are semantically faithful to the input. In this paper, we introduce a novel automatic evaluation metric, Entity-Based Semantic Adequacy, which can be used to assess to what extent generation models that verbalise RDF (Resource Description Framework) graphs produce text that contains mentions of the entities occurring in the RDF input. This is important as RDF subject and object entities make up 2/3 of the input. We use our metric to compare 25 models from the WebNLG Shared Tasks and we examine correlation with results from human evaluations of semantic adequacy. We show that while our metric correlates with human evaluation scores, this correlation varies with the specifics of the human evaluation setup. This suggests that in order to measure the entity-based adequacy of generated texts, an automatic metric such as the one proposed here might be more reliable, as less subjective and more focused on correct verbalisation of the input, than human evaluation measures.

1 Introduction

With the introduction of pretrained models, the fluency of text generation systems has improved. However, semantic adequacy (faithfulness to the input) remains an unsolved issue. It remains difficult to ensure that the generated text faithfully captures the input (Wiseman et al., 2017; Gehrmann et al., 2018).

In this paper, we focus on semantic adequacy for RDF-Verbalisers i.e., models such as those submitted to the WebNLG 2017 and 2020 shared tasks (Gardent et al., 2017; Castro Ferreira et al., 2020b) which map an RDF graph to a text verbalising the content of that graph. In this case, the input to Natural Language Generation (NLG) is a set of triples of the form \((e_1, p, e_2)\) where \(e_1, e_2\) are RDF entities and \(p\) is a property. RDF triple stores are used in particular to model Semantic Web data and their verbalisation aims at making the information from these knowledge-bases easily accessible to users. As exemplified in Figure 1, one necessary condition for the generated text to be semantically adequate is that all entities present in the input should be mentioned at least once in the output. We refer to this requirement as entity-based semantic adequacy (ESA for short). ESA offers one way of formalising the requirement that the output of a generator should reflect the information in the input. Thus, its significance extends beyond the specific problem domain of RDF verbalisation, though the latter provides a useful testcase.

We make the following contributions.

We devise metrics which assess to what extent a text verbalising an RDF graph respects entity-based semantic adequacy. These metrics rely on an algorithm designed to automatically detect whether an entity present in the input graph has a corresponding mention in the output text. We evaluate this algorithm on a corpus of 25,173 (RDF, Text) pairs with manually annotated entity mentions from Castro Ferreira et al. (2018) and show that our algorithm has a recall of 0.74 and a precision of 0.75.

We apply these metrics to the output of 25 RDF verbalisers developed for the WebNLG 2017 and 2020 challenges and show that some of the systems which rank highest in terms of BLEU scores actually rank in the lower half with respect to entity-based semantic adequacy. This indicates that ESA is measuring a different quality from that measured by surface-based metrics such as BLEU.

We compute correlation between our metrics and both automatic and human evaluation scores collected by the WebNLG organisers for these 25 models. We find a stronger correlation with human metrics related to semantic adequacy than with automatic metrics. Among the automatic metrics,
correlations are highest with METEOR. Interestingly, we also find that the correlation with human scores varies with the specifics of the human evaluation setup. This suggests that our automatic metric might be a more reliable means of identifying models with low entity-based semantic adequacy than human evaluation. We are publicly releasing our source code.

1 Related work

Various methods have been proposed to evaluate the semantic adequacy of generated texts.

Commonly-used metrics are surface-based (either word- or character-based) such as BLEU (Papineni et al., 2002), TER (Snoover et al., 2006) or chrF (Popović, 2015). As these methods fail to account for paraphrases, alternative metrics have been proposed such as METEOR (Banerjee and Lavie, 2005), which measures n-gram overlap but integrates synonyms and BERTScore, a trained metric based on word-embeddings similarity (Zhang et al., 2020). Semantic similarity has also been modeled in terms of propositional content. In computer vision for instance, SPICE transforms both generated and reference captions into a scene graph encoding the objects and relations present in these captions and computes an F-score over the semantic propositions in the scene graph (Anderson et al., 2016). Similarly, the MEANT metric applies Semantic Role Labelling to generated and reference texts and computes similarity by matching the resulting semantic frames. In data-to-text generation, (Dhingra et al., 2019) uses custom entailment models to determine whether an n-gram in the generated text is entailed by the input and computes an F-score based on these n-grams. In text summarisation, Goodrich et al. (2019) compare relation tuples extracted from a ground-truth summary and a generated one using either a Named entity Recognition and a Relation Classifier or an end-to-end Transformer model to extract these tuples.

Rather than abstract over the lexical content of the generated and reference text, other work has focused on developing metrics which model human judgement in particular, judgments of semantic similarity. Thus Sellam et al. (2020) introduced BLEURT, an automatic metric pre-trained on synthetic and automatically rated data and fine-tuned on human judgments.

Closest to our approach are metrics which evaluate the generated output, not with respect to the reference or to human judgments, but with respect to the input. Wiseman et al. (2017) define Relation Generation score as the precision of input relations found in the output texts (the relation ex-
traction is performed by a neural model). Reed et al. (2018) define information extraction patterns to measure the occurrence of the input attributes and their values in the outputs and compute semantic adequacy using the Slot Error Rate. Ribeiro et al. (2020); Dušek and Kasner (2020) use natural language inference (NLI) to detect two way entailment between the generated text and the input. Sulem et al. (2020) introduce SAMSA which assesses simplification quality by comparing the predicate/argument structures contained in the input with those contained in the output summary.

Similarly, we evaluate the semantic adequacy of a generated text by comparing it with the input. We focus on entities however and provide a detailed assessment of both the reliability of our metrics and its correlation with human and with automatic metrics.

3 Defining E-Based Semantic Adequacy

We assume a corpus of \((R, T)\) instances where \(R\) is an RDF graph (a set of RDF triples) and \(T\) is a text verbalising that graph. RDF triples are of the form \((s, p, o)\) where \(p\) is a binary relation holding between a subject \((s)\) and an object \((o)\)\(^2\). We use the term “entity” to refer to both RDF triple subjects and objects and we write \(E_R\) for the set of RDF entities occurring in RDF graph \(R\).

Entity Mentions. Given a corpus instance \((R, T)\), an entity mention \(m\) is a text segment in \(T\) which denotes an entity \(e\) present in the input graph \((e \in E_R)\). We write \(M_T\) for the set of entity mentions occurring in \(T\) and \(\{ m \} = e\) to indicate that the mention \(m \in T\) denotes entity \(e \in E_R\).

(Un)Detected Entities. A detected entity \(e \in E_R\) is an entity which has a matching mention in \(M_T\), i.e., there is a mention \(m \in M_T\) such that \(\{ m \} = e\). Conversely, an undetected entity is an entity \(e \in E_R\) which has no corresponding mention in \(M_T\). We define \(E_T \subseteq E_R\) as the set of RDF entities which have a corresponding mention in \(T\).

Entity-Based Semantic Adequacy. Given an \((R, T)\) pair, we define entity-based semantic adequacy (ESA) as the proportion of RDF entities in \(E_R\) which have a corresponding mention \(m \in M_T\). In other words, ESA is the ratio between the number of entities for which a mention was found \((E_T)\) and the total number of entities occurring in the input RDF \((E_R)\).

\[
ESA_I = \frac{|E_T|}{|E_R|}
\]

Given a corpus of \((R, T)\) pairs, we also compute the proportion of texts in that corpus with at least \(n\) undetected entities. We refer to this metric as corpus-level, entity-based semantic inadequacy at \(n\) \((ESI^n\) for short).

4 Computing E-Based Semantic Adequacy

The metrics introduced in the previous section rely on being able to determine which entities in the RDF input have a matching mention in the corresponding text. We present an algorithm for entity mention detection and we report on an evaluation of that algorithm using a dataset of 25,173 \((RDF\ graph, Text)\) pairs where entity mentions have been manually annotated.

4.1 Detecting Entity Mentions

We define our entity mention detection algorithm using a combination of existing tools and heuristics.

Entity linker We use the state-of-the-art REL entity linker from van Hulst et al. (2020). When applied to a text, REL returns a list of entity mentions and their corresponding DBPedia entities. We filter out the mentions for which the related DBPedia entity does not match any of the input RDF entities.

Approximate string matching of text n-grams and RDF entities We match text n-grams to candidate RDF entities, using approximate string matching with a fixed maximum allowed edit distance (normalized Levenshtein distance). This value is experimentally fixed at 0.4 \(^3\). To improve results, we create a dictionary of RDF entity synonyms and compute the approximate match between text n-grams and all RDF entities, including their synonyms. The synonym dictionary was initially created using DBPedia aliases and rules (handcrafted to improve the detection of frequent entities in the WebNLG corpus such as places or quantities). During the evaluation of the entity detection (cf section 4.2), an expanded version of

\(^2\)Subjects are Uniform Resource Identifiers (URI) and objects are either URIs or literals. Intuitively, RDF subjects and objects refer to things such as persons, locations, abstract entities, dates or phone numbers.

\(^3\)The algorithm used by our string matching procedure is described in detail in Algorithm 1 in the Appendix.
the dictionary was developed by updating it with entities for which no mention was detected in an evaluated text; these were manually included in the dictionary. This dictionary provides a symbolic means to improve entity mention detection and more generally, to adapt the algorithm to a new domain. However, it should be noted that, on the WebNLG 2017 dataset, adding this dictionary only slightly improves entity mention detection and is not essential.

Pronominal entity mentions. In order to detect which input entity a pronoun refers to, we use two methods. We first use Stanza (Qi et al., 2020) to compute co-reference chains in our texts, keeping only the pronominal mentions. For the pronouns that were not detected by the previous method, we used a simple heuristic. In the WebNLG corpus, RDF graphs are created with a single entity as "root". Other entities are meant to describe and provide information about this root. As the texts are quite short we assume that most pronominal anaphors refer to the "root" of the graph. We therefore associate all remaining pronouns to the root entity of the RDF graph.

Dates. We use the python library dateparser to normalise dates both in the text and in the RDF. Results are further filtered using entity type information from the input RDF graph.

Putting it all together. Each method described above yields a list of mentions found in a text for each RDF entity in an input graph. In case different methods identify the same (or overlapping) mentions, we select those mentions with the lowest edit distance to their matched RDF entity (or one of its synonyms). In case of equality, we keep the longest mention.

4.2 Evaluating automatic entity mention detection

Castro Ferreira et al. (2018) manually annotated entity mentions in the WebNLG 2017 dataset (an example of annotation is shown in the Appendix). We use these manual annotations as gold standard to evaluate our entity mention detection algorithm. Given \( M^{\text{auto}} \), the set of mentions detected on this corpus by our mention detection algorithm and \( M^{\text{human}} \), the set of manually annotated mentions, we compute Recall and Precision in the usual way: 

\[
\text{Recall} = \frac{|M^{\text{auto}} \cap M^{\text{human}}|}{|M^{\text{human}}|}
\]

\[
\text{Precision} = \frac{|M^{\text{auto}} \cap M^{\text{human}}|}{|M^{\text{auto}}|}
\]

The intersection \( M^{\text{auto}} \cap M^{\text{human}} \) is the number of exact string matches between the sets of mentions \( M^{\text{auto}} \) and \( M^{\text{human}} \). We obtain a recall of 0.74 and a precision of 0.75.

If we consider approximate string matching in the computation of \( M^{\text{auto}} \cap M^{\text{human}} \) with a maximum allowed normalized edit distance of 0.2, we obtain a recall of 0.82 and a precision of 0.83. This shows that although some of the automatically detected mentions do not match the gold standard annotations exactly, they are nonetheless close to them. In Section 5.2 below, we show that even though imperfect, our entity mention detection algorithm permits reliably identifying models which have low entity-based semantic adequacy.

5 Evaluating RDF-to-text Generation Models

25 models participated in the WebNLG 2017 and 2020 challenges. We apply our entity-based semantic adequacy metrics to the output of these models on the WebNLG 2017 and 2020 test data. We group models with respect to BLEU and \( \text{esiC}^1 \) rank. As the text output by the models might differ from the crowdsourced texts we used for the evaluation presented in Section 4.2, we report on a manual verification of our entity mention detection algorithm on a sample from these model outputs. Finally, we show some example outputs illustrating different ways in which a generated text might have low entity-based semantic adequacy.

5.1 Entity-Based Semantic Adequacy in the WebNLG Shared Tasks

For each model in the WebNLG 2017 and 2020 Shared Tasks, we compute the \( \text{esiC}^1 \) score (proportion of texts with one or more RDF entities lacking a matching text mention) and the \( \text{esaI} \) score (proportion of RDF entities in the input with a matching entity mention in the output). The \( \text{esaI} \) scores are averaged over the corpus in three different ways, over all texts (\( \text{esaI}^\text{C} \) score), texts that have at least one undetected entity (\( \text{esaI}^\text{C} \backslash 1 \)) and texts with at least two undetected entities (\( \text{esaI}^\text{C} \backslash 2 \)). Table 1 shows the results together with the distribution of undetected entities.

\[\text{esiC}^1 = \frac{|\text{RDF entities lacking matches}|}{|\text{RDF entities}|}\]

\[\text{esaI}^\text{C} = \frac{|\text{RDF entities in input with matches}|}{|\text{RDF entities}|}\]

\[\text{esaI}^\text{C} \backslash 1 = \frac{|\text{RDF entities in input with matches}|}{|\text{RDF entities lacking matches}|}\]

\[\text{esaI}^\text{C} \backslash 2 = \frac{|\text{RDF entities in input with matches}|}{|\text{RDF entities lacking matches}|^2}\]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \backslash 2 \]

\[\text{esiC}^1 \times \text{esaI}^\text{C} \times \text{esaI}^\text{C} \backslash 1 \times \text{esaI}^\text{C} \]
2017 vs. 2020. We see a marked improvement between 2017 and 2020. While in 2017, the ratio of generated texts failing to mention at least one entity varies from 10 to 77% whereas in 2020 it ranges between 3% and 51%. The trend is similar for the various \( ESI_C \) scores with e.g., an \( ESI_C \) of 0.17 in 2017 against \( ESI_C \) of 0.36 in 2020. This corroborates the impression that Natural Language Generation (NLG) models have strongly improved in recent years.

2020 NLG. Zooming in on the more state-of-the-art 2020 models, we find that out of a total of 1779 texts and 16 model outputs, the average \( ESI_C \) score is 17% and the median 10%. In other words, on average, models fail to mention at least one entity 17% of the time.

There are strong differences between the models however. The rule-based models (RALI, Baseline-2017, DANGNT-SGU, Baseline-2020) have low \( ESI_C \). This is unsurprising as such models can integrate lexicons mapping RDF entities to natural language mentions. Interestingly, among the other five models with an \( ESI_C \) less than 11%, four are bilingual neural NLG models i.e., models which were trained to transform RDF data not only in English but also in Russian.

High BLEU does not guarantee Entity-Based Semantic Adequacy. Figure 3 clusters models with respect to both BLEU and \( ESI_C \) scores. Models that occur right of the vertical axis have high \( ESI_C \) rank (they are in the first 8 group), models that occur above the horizontal axis have high BLEU rank. We see that from the 8 models with highest BLEU rank, only three are also among the 8 models with highest \( ESI_C \) rank (cuni-ufal, FB-ConvAI and Amazon_AI). The five other models which rank among the first eight in terms of BLEU score (OSU, CycleGT, NUIG, TGen, bt5) have a BLEU score ranging between 0.45 and 0.54 yet their \( ESI_C \) score ranges between 10 and 22%. This highlights the fact that a high BLEU score does not guarantee semantic adequacy: while their BLEU score is high, on average these models fail to mention at least one of the input entities 10 to 22% of the time.

Figure 2 shows some examples of 2020 outputs with low \( ESI_A \) and high BLEU score. Figure 3 further shows that no model ranks high in term of both BLEU and entity-based semantic adequacy (no model in the top right corner).

5.2 Manual Verification of the \( ESI_C \) results

Our mention detection algorithm does not detect all mentions, while texts generated by the WebNLG
models might differ from the crowdsourced texts on which we evaluated our entity mention detection algorithm (cf. Section 4.2). Therefore, we manually verify the result of our mentions detection algorithm for different types of models. We focus on five models with contrasting BLEU and \( ESI_{C^1} \) rank, two models with high \( ESI_{C^1} \) rank but low BLEU rank; one model with high rank for both dimensions; one model with high BLEU rank and low \( ESI_{C^1} \) rank; and one model with low rank in both dimensions. For each of these models, we check texts with different numbers of missing entities (one or two missing entities for the models with high \( ESI_{C^1} \) rank and one, three and five missing entities for the models with low \( ESI_{C^1} \)) and computed the rate of false positives, i.e. entities which were labeled as undetected by our algorithm but which are in fact present in the generated text. While for the three models which rank high in terms of entity-based semantic adequacy, the rate of false positive is high (100% for RALI, 81% for Huawei and 52% for FBConvAI)\(^5\), for models with low \( ESI_{C^1} \) rank, the number of false positives is much lower (49% for bt5, 13% for Orange). In other words, our entity mention detection algorithm is best at detecting models with low semantic adequacy.

5.3 Qualitative Analysis

Examining outputs with low \( ESA_{C^1} \) score, we found three main causes for low semantic adequacy: short output, hallucination and degenerate output. Figure 1 shows some examples. When the output text is much shorter than expected, many mentions are missing (Ex.1). When the model hallucinates entities not present in the input, it also often simultaneously fails to mention those that are (Ex. 2).

\(^5\)The repetition of the same entities is different entries of the dataset has a strong impact here. For instance, for the RALI system, on the 1779 texts we checked, our algorithm finds 51 texts with undetected entities but only nine of these entities are distinct. That is, the algorithm fails to detect nine entities and as these are in multiple corpus instances, it has 100% of false positives on these corpus instances.
Finally, entity mentions may be missing because of degenerate output (Ex.3).

6 Correlation with Human and Automatic Metrics

We study the correlation of our ESA_I metric with the human and automatic metrics used in the WebNLG challenges.

6.1 Evaluation Set-Up

During the WebNLG Challenges 2017 and 2020, 223 texts were sampled from the outputs of the participants models for human evaluation in 2017, and 178 in 2020 (Shimorina et al., 2018; Castro Ferreira et al., 2020a). For our correlation study, we therefore use the automatic and human evaluation scores collected by the WebNLG organisers for 2,007 texts (223 for each of the 9 models) in 2017 and 2,848 texts (178 for each of the 16 models) in 2020. We use the results and scripts from Shimorina et al. (2018) and Castro Ferreira et al. (2020a).

In 2017, the human evaluation metric which focuses on semantic adequacy is Semantics where the annotator is asked to assess semantic faithfulness of the generated output w.r.t. the input (1-low, 2-medium or 3-good). In 2020, the human evaluation metrics concerned with semantic adequacy are Data Coverage, Correctness, Relevance (between 0 and 100). For Data Coverage, evaluators were asked to check whether all input RDF properties were in the text; for Relevance, whether the text describes only such predicates which were present in the input; and for Correctness, whether the output text correctly describes the subject and object of those predicates which matched a property in the input graph. Note that while all these criteria bear on semantic adequacy, none of them specifically target entities.

6.2 Results

We compute the correlations with ESA_I metric at text level in three different set-ups (for all texts, for texts with at least one undetected entity and for texts with at least two undetected entities) using three correlation metrics (Pearson correlation, the Spearman rank correlation and Kendall’s Tau). Tables 2 and 3 only report Pearson correlations on texts with at least one undetected entity (n = 822 for 2017; n = 470 for 2020). Detailed correlation results for the three metrics and considering the three text setups are reported in the Appendix.

Human vs. Automatic Metrics. The correlation between ESA_I and human metrics of semantic adequacy is strong in 2017 and moderate in 2020, indicating that ESA_I correctly captures what humans judge to be semantically adequate. ESA also has very strong (2017) and moderate (2020) correlation with METEOR, which suggests that variants of entity mentions involve synonyms and stemming like modifications.

Varying Correlation Strengths and Scale. The strength of the correlations and their relative order vary with the shared tasks. For automatic metrics, this is likely due to greater variance in metric scores between systems. For human judgments, it might also result from the different criteria used in 2017 vs. 2020 and from their subjectivity. Indeed, as shown below, some of the collected human judgments are in fact incorrect. Not shown here, but reported in the appendix, correlations with Human, METEOR and BLEU scores also tend to be higher for texts with at least one or two undetected entities – that is, texts which are likely to have semantic adequacy problems – compared to correlations computed over all texts (compare Table 3 to correlations over all texts, in the Appendix).

Cases of strong disagreement between ESA_I and human evaluation We manually checked some of the texts which received high human evaluation scores but had a low proportion of detected
of human evaluation. Sometimes correct texts can be rated badly by human annotators or vice versa. From these observations we can draw two main conclusions. First, detecting input RDF entities in the output text is not sufficient condition to assess a model’s semantic adequacy. It does not give information about hallucination of entities or about correct verbalization of RDF predicates, which are also necessary conditions for semantic adequacy. These observations also illustrate the subjectivity of human evaluation. Sometimes correct texts can be rated badly by human annotators or vice versa.

Detection of Hallucinations We can use our entity mention detection algorithm in reverse to detect hallucinations i.e., mentions that have no corresponding RDF entity in the input graph. We gather all (entity, mention) pairs found by the entity linker (4.1) for which the entity does not occur in the input graph.

Table 2: Pearson correlation coefficients for WebNLG 2017 metrics and ESA_f. Only for texts with at least one undetected entity (i.e. 822 texts). All the p-values are <0.01. Bold numbers indicate the highest correlations of ESA_f with surface-based (top block) and human evaluation (bottom block) metrics.

| Metrics | METEOR | TER | Fluency | Grammar | Semantics | ESA_f |
|---------|--------|-----|---------|---------|-----------|-------|
| BLEU    | 0.74   | -0.37 | 0.39    | 0.43    | 0.53      | 0.59  |
| METEOR  | x      | -0.54 | 0.57    | 0.63    | 0.72      | **0.87** |
| TER     | x      | x     | -0.42   | -0.45   | -0.4      | -0.42 |
| Fluency | x      | x     | x       | 0.89    | 0.51      | 0.49  |
| Grammar | x      | x     | x       | x       | 0.57      | 0.57  |
| Semantics | x | x     | x       | x       | **0.66** |

Table 3: Pearson correlation coefficients for WebNLG 2020 metrics ESA_f. Only for texts with at least one undetected entity (i.e. 470 texts). All the p-values are <0.01. Bold (resp. underlined) numbers indicate the highest (resp. second highest) correlation scores between ESA_f and different categories of evaluation metrics, i.e. surface-based similarity metrics (top block), embedding-based similarity (middle block) and human evaluation metrics.

For WebNLG 2017, there are 7 texts that have ESA_f < 0.4 and Semantics≥ 2. For 6 of them we find that there are indeed missing entities, while the remaining one is a degenerate text. The relatively high scores given by human evaluators for Semantics (2 out of 3) suggest that such scoring tends to be subjective, perhaps especially so with a broad evaluation criterion such as ‘Semantics’. Among the 41 texts which received the lowest possible rating for semantics (Semantics=1), but had ESA_f > 0.9, we find that 25 texts do not have missing entities but are indeed semantically incorrect (usually because of mistakes or hallucinations of predicates); 3 texts have missing entities and 9 texts have hallucinated entities. The remaining 4 texts contain all input entities and have correct semantics.

The same kind of observations can be made for WebNLG 2020 models. There are 4 texts which received high human evaluation scores for semantic adequacy-related criteria (Data Coverage> 80 or Correctness> 80 or Relevance> 80) and low ESA_f (ESA_f < 0.4) and all of them have missing entities. In contrast, there are 20 texts which got low human evaluation scores (Data Coverage< 30 or Correctness< 30 or Relevance< 30) and high ESA_f (ESA_f > 0.9). Fifteen have wrong or hallucinated predicates, two have significant spelling or repetition problems. Three texts are correct.

6Examples are given in the appendix.
Bananaman was created by Steve Bright and starred Bill Oddie. It was broadcast by the BBC, which is based in the Broadcasting House in London, and last aired on 15th April 1986.

RDF Input
Bananaman creator Steve_Bright
Bananaman starring Bill_Oddie
Bananaman lastAired "1986-04-15"
Bananaman broadcastedBy BBC

Aaron Turner performs Trance music and played with the band Bobina.

RDF Input
Andrew_Rayel genre Trance_music
Andrew_Rayel associatedBand/associatedMusicalArtist Bobina

Cyril Frankel is the director of the film "It’s Great to be New (1956)", which was written by "Ted Willis" and starred Cecil Parker and John Mills. Mr. Mills died in 2005.

RDF Input
Its_Great_to_Be_Young_(1956_film) director Cyril_Frankel
Its_Great_to_Be_Young_(1956_film) starring Cecil_Parker
Its_Great_to_Be_Young_(1956_film) writer Ted_Willis
Its_Great_to_Be_Young_(1956_film) starring John_Mills
John_Mills deathYear 2005

Table 4: Hallucinations (>|1 and >1✓: number of texts with at least one hallucination before and after a manual check of automatically detected hallucinations. ∗Verification on 144 randomly chosen texts. Dist: number of distinct detected hallucinated entities.

| Model  | >1 | >1✓ | Dist | ESA↓ |
|--------|----|-----|------|------|
| RALI   | 0  | 0   | 0%   | 0%   |
| B-2017 | 1  | 1   | 0.1% | 0.2% |
| B-2020 | 1  | 1   | 0.1% | 0.2% |
| NUIG   | 4  | 3   | 0.2% | 0.2% |
| UPC    | 4  | 3   | 0.2% | 0.2% |
| DANGNT | 5  | 5   | 0.3% | 0.3% |
| TGen   | 8  | 7   | 0.5% | 0.5% |
| cuni-ufal | 9 | 7   | 0.5% | 0.5% |
| Amazon | 9  | 9   | 0.5% | 0.5% |
| FBConvAI| 17 | 11  | 1%   | 1%   |
|_cycleGT | 19 | 18  | 1%   | 1%   |
| OSU    | 20 | 19  | 1%   | 1%   |
| bt5    | 36 | 17  | 3%   | 2%   |
| Huawei | 48 | 47  | 3%   | 3%   |
| NILC   | 117| 99  | 6%   | 6%   |
| ORANGE | 288| 288 | 60%  | 60%  |
| UIT    | 1  | 0   | 1.0% | 1.0% |
| Tilburg SMT | 4 | 0   | 0.2% | 0.2% |
| Tilburg NMT | 11 | 4   | 0.6% | 0.6% |
| UPF    | 12 | 8   | 0.6% | 0.6% |
| Tilburg Pl | 14 | 11  | 6%   | 6%   |
| Melbourne | 114| 112 | 24%  | 24%  |
| Adapt  | 241| 234 | 15%  | 15%  |
| PKUWriter | 286| 283 | 135% | 135% |
| Baseline | 754 | 144* | 147 | 40% |

Table 4: Examples of hallucinations (underlined in the texts). add: output contains additional information, repl: an input RDF entity is replaced by another with the same context (here the name of another musician), inac: the name of the input entities are inaccurate which makes them difficult to link with input entities.

7 Conclusion

RDF stores have become increasingly popular as a means to make knowledge available on the web (Assi et al., 2020). We propose an automatic metric for assessing the entity-based semantic adequacy of RDF verbalisers and show that it is effective in highlighting semantic inadequacy even for state-of-the-art models with high BLEU scores. We further show that models detected by this metric as having low entity-based semantic adequacy can still have high scores on surface-based metrics, and that while ESA correlates with human scores on semantic criteria, it may in fact be more reliable as a means of detecting low performing models than human-based evaluation protocols, which tend to be subjective.

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