Structured semantic sentence representations such as Abstract Meaning Representations (AMRs) are potentially useful in a variety of natural language processing tasks. However, the quality of automatic parses can vary greatly and jeopardizes their usefulness. Therefore, we require systems that can accurately rate AMR quality in the absence of costly gold data.

To achieve this, we transfer the AMR graph to the domain of images. This allows us to create a simple convolutional neural network (CNN) that imitates a human rater. In our experiments, we show that the method can rate the quality of AMR graphs more accurately than a strong baseline, with respect to several dimensions of interest. Furthermore, the method proves to be more efficient as it reduces the incurred energy consumption.

1 Introduction

The goal of sentence meaning representations is to capture the meaning of sentences in a machine-readable format. One of the most prominent frameworks for achieving this is Abstract Meaning Representation (AMR) (Banarescu et al., 2013). In AMR, sentences are represented as directed acyclic and rooted graphs. An example is displayed in Figure 1, where we also see that an AMR can be 'appealingly' represented in at least two ways: the multi-line PENMAN notation on the left hand (standard AMR notation) and a graph visualization on the right hand. In AMR, nodes denote variables or concepts, while (labeled) edges express their (semantic) relations. Among other phenomena, this allows AMR to captures coreference (via re-entrant variables), factuality (via :polarity relation) and semantic roles (via :arg relation). Furthermore, AMR links sentences to knowledge bases: for instance, predicates are mapped to PropBank (Palmer et al., 2005; Kingsbury and Palmer, 2002), while named entities are linked to Wikipedia. From a logical perspective, AMR is closely related to first-order logic (FOL, see Bos (2016, 2019) for translation mechanisms).
Currently, AMRs are leveraged to enhance a variety of natural language understanding tasks. E.g., they have enhanced commonsense reasoning and question answering (Mitra and Baral, 2016), machine translation (Song et al., 2019), text summarization (Liao et al., 2018; Dohare et al., 2017) and paraphrasing (Issa et al., 2018). However, there is a critical issue with automatically generated AMRs (parses): they are often deficient.

In fact, the deficiency of parses can be quite severe and distort the meaning of sentences, even when high-performance parsers are used. For example, in Figure 2, the parser conducts several errors when parsing Without a functioning economy the whole country may destabilize. E.g., it misses a negative polarity and classifies a patient argument as agent (parser: the country is the causer of destabilize; correct: the country is the object that is destabilized). In sum, the parser has distorted the meaning of the sentence. However, assessing such deficiencies by comparing the automatic graphs to gold graphs (as in classical parser evaluation) is often infeasible: it takes a trained annotator and appr. 10 minutes to manually create one AMR graph (Banarescu et al., 2013).

To mitigate these issues, we would like to be capable of automatically rating the quality of AMRs without the costly gold graphs. To achieve this, we propose a method that imitates a human rater, who is inspecting the graphs. We show that the method is capable of efficiently rating the quality of the AMRs in the absence of gold graphs.

The remainder of the paper is structured as follows: in Section 2, we outline our idea...
(a) GUI for AMR creation.

(b) Two representations for a medium-length sentence.

Figure 3: Examples for the Penman notation.

to exploit the textual multi-line string representation of AMRs, allowing for efficient and simple AMR processing while preserving vital graph structure. In Section 2.1, we instantiate this idea in a light-weight CNN that assesses the quality of AMRs. In our experiments (Section 3), we show that it performs better than a strong baseline, both on the original AMR quality rating data set and on a new version of the data where we removed biases. Further analysis (Section 3.3) indicates that our approach is more efficient in terms of run-time and GPU energy consumption. Finally, we discuss related work in Section 4. We make our code and data available.

2 AMR as image with latent channels

In this section, first we motivate to treat AMRs as images with latent channels in order to rate them efficiently. Second, we briefly describe the task at hand: Rating the quality of AMR graphs in the absence of gold graphs. Finally, in order to solve this task, we create a light-weight CNN that evaluates AMR quality with respect to multiple dimensions.

Penman notation The native AMR notation is called Penman notation or Sentence Plan Language (SPL)\textsuperscript{2}. For instance, in the AMR online editor\textsuperscript{3}, the temporary AMR is displayed in this format, and reflects the AMR construction process to the annotator (c.f. Figure 3a). In combination with the use of indents and brackets, this multi-line string-representation allows the annotator to have an overview over the full hierarchical graph structure, which has been so-far created.

(Hidden) advantages of the Penman AMR notation Provably, an advantage of the Penman notation is that it allows for secure AMR storage in text-files. However, we

\textsuperscript{2}c.f. Kasper (1989); Mann (1983) and https://www.isi.edu/natural-language/penman/penman.html
\textsuperscript{3}https://www.isi.edu/cgi-bin/div3/mt/amr-editor/login-gen-v1.7.cgi
Table 1: Four possible representation forms of AMR graphs and their accessibility with respect to human or computer (✓: ‘okay’, X: ‘perhaps possible, but difficult’).

| representation          | human understanding | well-defined |
|-------------------------|----------------------|--------------|
| triples                 | ✓ (e.g., CGN)        | X            |
| graph visualization     | ✓                    | ✓ (short sentences) |
| PENMAN, linearized string | ✓ (e.g., LSTM) | ✓            |
| PENMAN, indents         | ✓ (this work)        | ✓            |

Figure 4: We transform the (simplified) PENMAN representation to an image and use Φ to add latent channels.

argue that it has more advantages. For example, it allows humans a fairly quick understanding even of medium-sized to large AMR structures (Figure 3b, left). We argue that a graphical visualization of medium-sized to large AMRs (Figure 3b, right), however, can hamper immediate and intuitive understanding. Moreover, in every display, one would need to determine a suitable arrangement of the nodes, edges and edge labels.4

In sum, we believe that the indented multi-line PENMAN form possesses three key advantages (Table 1): 1. it allows fairly easy human understanding, 2. it is well-defined and 3., which is what we will show next, it can be computationally exploited to better rate AMR quality.

**AMR as image to preserve graph structure** Figure 4 describes our proposed sentence representation treatment. After non-degenerate AMR graph simplification (more details in Preprocessing, 3.1), we first project the PENMAN representation onto a small grid (‘image’). Each AMR token (e.g., a node or an edge) is represented as a ‘categorical pixel’. Second, Φ adds latent ‘channels’ to the categorical pixels, which can be learned incrementally in an application. In other words, every AMR token is represented by a fixed-sized vector of real numbers. These vectors are arranged such that the original graph structure is preserved.

**Task: Rating the quality of AMR graphs** We aim at rating the quality of AMR graphs (‘parses’) in absence of gold graphs. This boils down to answering the following question: how well does a candidate AMR graph capture a given natural language sentence?

4In the worst case, we would obtain a ‘jungle’ of nodes and edges, that deviates from run to run.
Therefore, the exact goal in this task is to learn a mapping 

\[ f : \mathcal{S} \times \mathcal{G} \rightarrow \mathbb{R}^d, \]

that maps a sentence \( s \in \mathcal{S} \) together with a candidate AMR graph \( g \in \mathcal{G} \) onto \( d \) quality scores which describe the AMR with respect to different quality dimensions of interest. A successful mapping function achieves a strongly positive correlation with the gold scores as they would emerge from evaluation against a gold graph. We proceed by describing the targeted dimensions in more detail.

**Main AMR quality dimensions** The main quality dimensions that we desire our model to predict are estimated **Smatch F1/recall/precision**. Smatch is the canonical AMR metric, assessing the triple overlap between two graphs, after an alignment step (Cai and Knight, 2013). Since we assume the gold parse to be absent, we want our model to predict expected scores by assessing how well a candidate graph ‘fits’ the sentence (this, in turn, approximates how well the candidate graph would match the absent gold graph of which we assume it would represent the sentence perfectly).

**AMR sub-task quality dimensions** However, we predict also other quality dimensions that reflect the quality of various AMR aspects, such as estimated KB linking F1, or estimated coreference resolution quality. The dimensions were proposed and described in detail by Damonte et al. (2017). In this place, we can merely provide a brief overview: (i) **Unlabeled**: Smatch when disregarding edge-labels. (ii) **No WSD**: Smatch when ignoring PropBank senses. (iii) **Frames**: PropBank frame identification F1 (iii) Wikification: KB linking F score on :wiki relations. (iv) **Negations**: negation detection F1. (v) **NamedEnt**: NER F1. (vi) **NS frames**: F1 score for PropBank frame identification when disregarding the sense. (vii) **Concepts**: F score for concept identification (viii) **SRL**: Smatch computed on arg-i roles only. (ix) **Reentrancy**: Smatch computed on re-entrant edges only. (x) **IgnoreVars**: F1 when variable nodes are ignored. (xi) **Concepts**: F1 for concept detection.

### 2.1 The AmrEvaluator: a light-weight CNN to rate AMR quality

**General outline** We want to model \( f \) (Eq. 1) in order to estimate a suite of quality scores \( y \in \mathbb{R}^d \) for any automatically generated AMR graph, given only the graph and the sentence from whence it is derived. Following Opitz and Frank (2019b), we will contrast the AMR against the dependency parse of the sentence. Our proposed AmrEvaluator allows this in a simple way by processing dependency and AMR graphs in parallel. The architecture is outlined in Figure 5. It captures the multi-line Penman representation and its dependency counterpart and projects them onto two tensors (two images with latent channels). More precisely, our model works in the following steps.

**Symbol embedding** The latent channels of AMR and dependency ‘pixels’ represent the embeddings of the ‘tokens’ or ‘symbols’ contained in the AMR and dependency
vocabulary. These symbols represent nodes or edges. We introduce two special tokens: the \texttt{<tab>} token, which represents the indentation level and the \texttt{<pad>} token which is used to fill the remaining empty ‘pixels’. All embeddings are learned incrementally in the optimization process. By embedding lookup, we obtain AMR and dedendency images with 128 latent channels and 45x15 ‘pixels’ ($\Phi$ in Figure 5), where the amount of pixels is chosen such that more than 95% of training AMRs can be fully captured.

### Encoding local graph regions

Given AMR and dependency images with 128 latent channels and 45x15 ‘pixels’, we initially apply to each of the two images 256 filters of size 3x3, which is a standard type of kernel in CNNs. This converts the AMR graph and the dependency tree each to 256 feature maps $\in \mathbb{R}^{45 \times 15}$ (same-padding). In other words, we have obtained two three-dimensional tensors $L_{amr}^1, L_{dep}^1 \in \mathbb{R}^{45 \times 15 \times 256}$. From here, we construct our first joint representation, which matches local regions from the dependency graph with the AMR graph:

$$j_{res} = GPF(L_{amr}^1 \otimes L_{dep}^1)$$ (2)

In this equation, $x \otimes y = [x \odot y; x \ominus y]$, i.e., the result is the concatenation of element-wise multiplication and element-wise subtraction. $GPF$ is the operation which performs global pooling and vectorization (‘flattening’) of any input tensor. This means that $j_{res} \in \mathbb{R}^{512}$ is a joint representation of the locally matched dependency and AMR graph regions. This intermediate process is outlined in Figure 5 by $\otimes$ (left) and GPF. Finally, we reduce the dimensions of the two intermediate three-dimensional representations $L_{amr}^1$ and $L_{dep}^1$ with 3x3 max-pooling and obtain $L_{amr}^2$ and $L_{dep}^2 \in \mathbb{R}^{15 \times 5 \times 256}$.

### Encoding global graph regions

For a moment, we put the joint residual ($j_{res}$) aside and proceed by processing the locally convolved feature maps with larger filters. While
the first convolutions allowed us to obtain abstract local graph regions $L^2_{amr}$ and $L^2_{dep}$, we now aim at capturing the graph structure at a more global level. More precisely, we use 128 2D filters of shape 5x5, followed by a 5x5 max-pooling operations on $L^2_{amr}$ and $L^2_{dep}$. Thus, we have obtained vectorized abstract global graph representations $g_{amr}, g_{dep} \in \mathbb{R}^{384}$. Then, we construct a joint representation (right \( \otimes \), Figure 5):

$$j_{glob} = g_{amr} \otimes g_{dep}.$$  \hspace{1cm} (3)

At this point, together with the joint residual representation from the local region matching, we have arrived at two joint vector representations $j_{glob}$ and $j_{res}$. We concatenate them ([; ; ] in Figure 5) to form one joint representation $j \in \mathbb{R}^{1280}$:

$$j = [j_{res}; j_{glob}] \hspace{1cm} (4)$$

**Quality prediction**  The shared representation $j$ is further processed by a feed-forward layer with ReLU activation functions ($\text{FF}_+ \text{ReLU}$, Figure 5) and a consecutive feed-forward layer with sigmoid activation functions ($\text{FF}_+ \text{sigm}$, Figure 5):

$$y = \text{sigm}(\text{ReLU}(j^T A) B),$$  \hspace{1cm} (5)

where $A \in \mathbb{R}^{1280 \times h}$, $B \in \mathbb{R}^{h \times \text{dim(out)}}$ are parameters of the model and $\text{sigm}(x) = (\frac{1}{1+e^{-x_1}}, \ldots, \frac{1}{1+e^{-x_{\text{dim(out)}}}})$. When estimating the main AMR metrics we instantiate three output neurons ($\text{dim(out)} = 3$) that represent estimated Smatch precision, Smatch recall and Smatch F1. In the case where we are interested in a more fine-grained assessment of AMR quality (e.g., knowledge-base linking quality), we have 33 output neurons representing expected scores for the various subtasks involved in AMR parsing.

To summarize, the residual joint representation should capture local similarities. The second joint representation, on the other hand, aims at capturing the more global and structural properties of the two graphs. Both types of information inform the final quality assessment of our model in the last layer.

**3 Experiments**

In this section, we first describe the data-set, changes to the data-set that target the reduction of biases, and the baseline. After discussing our main results, we conduct several additional analyses. First, we study the effects of our data-debiasing steps. Second, we assess the performance of our model in making classification decisions (distinguishing good from bad parses). Third, we assess the model performance when it is only provided the candidate AMR and the sentence (without any syntactic dependency information). Finally, we provide detailed measurements of the method’s computational cost.

**3.1 Experimental setup**

**Data**  We use the data from Opitz and Frank (2019b). The data set consists of more than 15,000 sentences with more than 60,000 corresponding parses, by three different
automatic parsing systems and a human. It comes in a pre-defined training, development and testing split. More precisely, the data set $\mathcal{D} = \{(s_i, g_i, y_i)\}_{i=1}^N$ consists of tuples $(s_i, g_i, y_i)$, where $s_i \in \mathcal{S}$ is a natural language sentence, $g_i \in \mathcal{G}$ is a ‘candidate’ AMR graph and $y_i \in \mathbb{R}^d$ is a 36-dimensional vector containing scores which represent the quality of the AMR graph in terms of precision, recall and F1 with respect to 12 different tasks captured by AMR (the tasks are outlined in §2).

**De-biasing of the data** We observe three biases in the data. First, the graphs in the training section of our data are less deficient than in the development and testing data, because the parsers were trained on (sentence, gold graph) pairs from the training section. For our task, this means that the target scores in the training section are higher, on average, than the target scores in the other data partitions. To achieve more balance in this regard, we re-split the data randomly on the sentence level (this ensures that a sentence does not appear in more than one partition with different parses).

Second, we observe that the data contains some superficial hidden clues that can give away the source of the parse. This bears the danger that a model does not learn to assess the parse quality, but to assess the source of the parse. And since some parsers are better or worse than others, the model could exploit its knowledge of the source of a parse. For example, consider that one parser prefers to write $(r / run-01 :arg1 (m / man) :polarity - )$, while the other parser prefers to write $(r / run-01 :polarity - :arg1 (m / man) )$. These two structures are semantically fully equivalent but different on the surface.\(^5\) Hence, the arrangement of the output may provide unwanted clues on the source of the parse. To alleviate this issue, we randomly re-arrange the parses on the surface, keeping their semantics. Technically, this is achieved by first reading the parses and then writing them again by conducting the depth-first writing-traversal such that at node $n$ the out-going edges of $n$ will be traversed in random order.

A third bias stems from a design choice in the metric scripts that were used to calculate the target scores. More precisely, the extended $Smatch$-metric script, per default, assigns a parse that does not contain a certain edge-type (e.g., $:arg_n$) the score 0 with respect to the specific quality dimension (in this case, SRL: 0.00 Precision/Recall/F1). However, if the gold parse also does not contain an edge of this type (i.e., $:arg_n$), then we believe that the correct default score should be 1, since the parse is, in the specific dimension, in perfect agreement with the gold (i.e., SRL: 1.00 Precision/Recall/F1). Therefore, we set all sub-task scores, where the predicted graph agrees with the gold graph in the absence of a feature, from 0 to 1.

**Baseline** Our baseline consists of the neural model of previous work and is henceforth denoted by LG-LSTM. The method works in the following steps: first, it uses a depth-first graph traversal to linearize the automatic AMR graph and the corresponding dependency tree of the sentence. Second, it constructs a joint representation and predicts up to 36 quality metrics. To further improve its performance, the baseline uses

\(^5\)Different variable names, e.g., $(r / run-01)$ and $(x / run-01 )$ are not an issue in this work since the variables are handled via van Noord and Bos (2017a). See also Preprocessing, p. 9.
some extra-features (e.g., a shallow alignment from dependency tokens to AMR tokens). Furthermore, their original model uses auxiliary losses to achieve a slight performance gain in predicting the Smatch metrics. For the sake of simplicity, we do not use these auxiliary losses, except in one experiment, where we show that our method achieves a similar small gain with the auxiliary losses.

Generally speaking, our baseline is a type of model that works based on graph linearizations. Such type of model, despite its apparent simplicity, has proven to be an effective baseline or state-of-the-art method in various works about converting texts into graphs (Konstas et al., 2017; van Noord and Bos, 2017b), or converting graphs into texts (Bastings et al., 2017; Beck et al., 2018; Song, 2019; Pourdamghani et al., 2016; Song et al., 2018; Vinyals et al., 2015; Mager et al., 2020), or performing mathematically complex tasks modeled as graph-to-graph problems, such as symbolic integration (Lample and Charton, 2020).

**Preprocessing** Same as prior work, we dependency-parse and tokenize the sentences with spaCy (Honnibal and Montani, 2017) and replace variables with corresponding concepts (e.g., \((j / \text{jump-01 :arg0 (g / girl)})\) is translated to \((\text{jump-01 :arg0 (girl)})\). Re-entrancies are handled with pointers according to van Noord and Bos (2017a). This ensures that variable names are removed but all information on coreference is kept, i.e., the AMR is simplified in a non-degenerate way. Finally, we join sub-structures that represent names (e.g., \(:\text{name (name :op1 Barack :op2 Obama)}\) is translated to \(:\text{name Barack Obama}\).)

**Training** To enhance the comparability between our approach and LG-LSTM, we train both models for the identical amount of epochs and select the parameters \(\theta\) from the epoch where maximum development scores were achieved (with respect to average Pearson’s \(\rho\) over the quality dimensions). Both models are optimized by reducing the squared error with gradient descent (Adam rule (Kingma and Ba, 2014), learning rate = 0.001, mini batch size = 64):

\[
\theta^* = \arg \min_{\theta} \sum_{i=1}^{[D]} \sum_{j=1}^{[M]} (y_{i,j} - f_\theta(s_i, g_i j))^2, \tag{6}
\]

where \(M\) is the set of target metrics.

### 3.2 Results

**Main AMR quality dimensions** The main quality of an AMR graph is estimated in expected triple match ratios (Smatch F1, Precision and Recall). The results are displayed in Table 2. With regard to estimated Smatch F1, we achieve a correlation with the gold

---

For example, consider the sentence *The cat scratches itself* and its graph \((x / \text{scratch-01 :arg0 (y / cat :arg1 y)})\). Replacing the variables with concepts would come at the cost of an information loss w.r.t. to coreference: \((\text{scratch-01 :arg0 cat :arg1 cat})\) — does the cat scratch itself or another cat? Hence, pointers are used to translate the graph into \((\text{scratch-01 :arg0 *0* cat :arg1 *0*})\).
| Quality Dim. | LG-LSTM | ours | change % |
|-------------|---------|------|----------|
| Smatch F1   | 0.662±0.00 | 0.696±0.00 | +5.14 †‡ |
| Smatch precision | 0.600±0.00 | 0.623±0.01 | +3.83 † |
| Smatch recall | 0.676±0.00 | 0.719±0.00 | +6.36 †‡ |

Table 2: Main results. Pearson’s corr. coefficient (row 1-3) is better if higher; root mean squared error (RMSE, row 4-6) is better if lower. Results are averaged over 10 runs. The quality dimensions are explained in §2. † (‡): p < 0.05 (p < 0.005), significant difference in the correlations with two-tailed test using Fisher ρ to z transformation (Fisher, 1915).

scores of 0.695 Pearson’s ρ. This constitutes a significant improvement of appr. 5%. Similarly, recall and precision correlations improve by 6.36% and 3.83 % (from 0.676 to 0.719 and 0.600 to 0.623). While the improvement in predicted recall is significant at p<0.05 and p<0.005, the improvement in predicted precision is only significant at p<0.05. When we consider the RMSE, we find that the method improves over the baseline by -1.54% in estimated F1 in estimated Smatch F1 and -4.23% in estimated Smatch recall. On the other hand, the error in estimated precision remains unchanged.

**AMR subtask quality** Our model can also rate the quality of an AMR graph in a more fine-grained way: for example, it can rate the quality of the coreference resolution, negation detection or knowledge-base linking. The results are displayed in Table 3. Over almost every AMR quality dimension we see considerable improvements. A considerable improvement in Pearson’s ρ is achieved for *NSFrames* (+20.5% ρ) and *coreference quality* (Reentrancies in Table 3, +18.5%).

A substantial RMSE reduction is achieved in *polarity* (Negations, Table 3), where we reduce the RMSE of the estimated F1 score by -8.6%. When rating the SRL-quality of an AMR parse, our model reduces the RMSE by appr. 4%.

In sum, our model can rate the AMR quality with respect to various subtasks involved in AMR parsing more accurate than previous work. Improvements are obtained over almost all tested quality dimensions, both in RMSE reduction and increased correlation with the gold scores.

### 3.3 Analysis

**Effect of de-biasing** We want to study the effect of the data set cleaning steps by analyzing the performance of our method and the baseline on three different data sets, with respect to estimated Smatch F1. The three data sets are (i) *AmrQualityClean1* = *AmrQuality*, which is the original data; (ii) *AmrQualityClean2*, which is the
data after the random re-split and score correction; (iii) $\text{AmrQualityClean}^2 = \text{AmrQualityClean}$ which is our main data after the final de-biasing step (shallow structure debiasing) has been applied.

The results are shown in Table 4. We can make three main observations: (i) from the first to the second de-biasing step, the baseline and our model have in common that Pearson’s $\rho$ and the error decrease. While we cannot exactly explain why $\rho$ decreases, it is clear that the error decrease is caused by the random re-split that balances the target scores in the three folds. (ii) The second de-biasing step leads to a decrease in $\rho$ and an increase in error, for both models. This indicates that we have successfully removed shallow biases from the data that can give away the source of the parse. (iii) On all considered versions of the data, the method performs better than the baseline.

**AMRs: telling the good from the bad** In this experiment, we want to see how the models suit themselves for discriminating between good and bad graphs. To this aim, we convert the problem to a five-way classification task: graphs are assigned the label ‘very bad’ (Smatch F1 < 0.25), ‘bad’ (0.25 ≥ Smatch F1 < 0.5), ‘good’ (0.5 ≥ Smatch F1 < 0.75), ‘very good’ (0.75 ≥ Smatch F1 < 0.95)) and ‘excellent’ (Smatch F1 ≥0.95). For our predictions, we do not retrain the models with a classification objective but convert the estimated Smatch F1 to the corresponding label.

The classification performance is shown in Table 5. The baseline appears to be better...
Pearson’s $\rho$ error data method P R F1 RMSE

| data | method | P  | R  | F1  | RMSE |
|------|--------|----|----|-----|------|
| 7/2  | LG-LSTM | 0.72 | 0.78 | 0.77 | 0.138 |
|      | LG-LSTM$_{aux}$ | 0.74 | 0.79 | 0.78 | 0.137 |
|      | ours    | 0.75 | 0.80 | 0.79 | 0.133 |
|      | ours$_{aux}$ | 0.76 | 0.81 | 0.80 | 0.132 |
| 7/2  | LG-LSTM | 0.67 | 0.73 | 0.72 | 0.120 |
|      | ours    | 0.68 | 0.75 | 0.74 | 0.117 |
| 7/2  | LG-LSTM | 0.60 | 0.68 | 0.66 | 0.130 |
|      | ours    | 0.62 | 0.72 | 0.70 | 0.128 |

Table 4: Effects of our data de-biasing steps on model performance.

Table 5: Graph quality classification task.

How important is the dependency information? To investigate this question, instead of feeding the dependency tree of the sentence, we only feed the sentence itself. To achieve this, we simply insert the tokens in the first row of the former dependency input image, and pad all remaining empty ‘pixels’. In this mode, the sentence encoding is similar to standard convolutional sentence encoders as they are typically used in many tasks (Kim, 2014).

7Moreover, in this experiment, we ported our regression model to a classification task – further perfor-
| Quality Dim. | LG-LSTM | ours | ours (no dep.) |
|-------------|---------|------|----------------|
| Smatch F1   | 0.662±0.00 | 0.696±0.00 | 0.682±0.01 |
| Smatch precision | 0.600±0.00 | 0.623±0.01 | 0.614±0.01 |
| Smatch recall | 0.676±0.00 | 0.719±0.00 | 0.702±0.01 |

Table 6: Confusion matrix of graph quality classification task.

| Quality Dim. | LG-LSTM | ours | ours (no dep.) |
|-------------|---------|------|----------------|
| Smatch F1   | 0.130±0.00 | 0.128±0.00 | 0.128±0.00 |
| Smatch precision | 0.126±0.00 | 0.126±0.00 | 0.129±0.00 |
| Smatch recall | 0.142±0.00 | 0.136±0.00 | 0.139±0.00 |

Table 7: Right column: results of our system when we abstain from feeding the dependency tree, and only show the sentence together with the candidate AMR.

The results are shown in the right column of Table 7. The performance drops, compared with our full system, are rather small. However, the drops are consistent over all analyzed Smatch scores, both in terms of error (0 to 2.2% increase) and Pearson’s $\rho$ (1.4 to 2.4% decrease). This indicates that the dependency trees contains information that can be exploited by our model to better judge the AMR quality. We hypothesize that this is due to similarities between relations such as $\text{subj/obj}$ (syntactic) or arg0/arg1 (semantic), etc. However, we see that this simpler model still outperforms the LG-LSTM baseline, except in Smatch precision error, which is increased by 2.4%.

**Efficiency analysis**  Recently, in many countries, there have been efforts to reduce energy consumption and carbon emission. Since deep learning typically requires intensive GPU computing, this aspect is of increasing importance to researchers and applicants (Strubell et al., 2019; Tang et al., 2019; Ganguly et al., 2019). To investigate energy consumption of our method and previous work, we monitor their GPU usage during training, assessing these quantities: (i) avg. time per epoch, (ii) avg. watts GPU usage, (iii) kilowatts per epoch (kWh). (iv), we calculate the estimated total kWh of the two methods, by multiplying the value in (iii) times 250 (10 epochs per run, 24 development runs for model adjustment and bug-fixing and one final run with test predictions).

The results of our analysis are displayed in Table 8 and outlined in Figure 6. They indicate that our method is significantly more efficient compared with prior work. It
Table 8: Efficiency analysis of two approaches.

| GPU type | GTX Titan | GTX 1080 |
|----------|-----------|-----------|
| method   | LG-LSTM   | ours      | LG-LSTM   | ours      |
| avg. ep. time | 722s 59s  | 1582s 64s | avg. W    | 105 166  | 45 128   |
| kWh per epoch  | 0.021 0.003 | 0.020 0.002 | kWh total | 5.3 0.8  | 5.0 0.5  |

Figure 6: Training cost diagram of two approaches.

consumes approximately 6.6 times less total kWh on a GTX Titan (10 times less on a GTX 1080). Directly related, it also reduces the training time: while prior work requires almost half an hour of training time per epoch (1582 seconds on a GTX 1080), our method requires circa 1 minute training time per epoch (62 seconds on a GTX 1080). A main reason for this is that our model does not depend on recurrent operations and thus profits more from parallelism.

4 Related work

Quality measurement of structured predictions Since evaluating structured representations against human gold annotations is costly, systems have been developed that attempt automatic assessment of representation quality. Due to its popularity, much work has been conducted in machine translation under the umbrella term of quality estimation. Quality estimation can take place either on a word level (Martins et al., 2017), sentence level (Specia et al., 2009), or document level (Scarton et al., 2015). The conference on Machine Translation (WMT) has a long-standing workshop and shared task-series on MT quality assessment (Callison-Burch et al., 2012; Bojar et al., 2013, 2014, 2015, 2016, 2017; Specia et al., 2018; Fonseca et al., 2019).

Furthermore, automatic techniques for the quality assessment of syntactic parses have been proposed. For instance, Ravi et al. (2008) formulate the task as a single-variable regression problem to assess the quality of constituency trees. On the other hand, Kawahara and Uchimoto (2008) predict a binary label which reflects whether the tree-
quality lies above a certain threshold (or not).

In comparison to MT, automatic quality evaluation of semantic meaning representations is insufficiently researched. Opitz and Frank (2019b) design a neural model that conducts a fine-grained multi-variate quality inspection of AMRs (which constitutes the baseline we compared against in this paper). Since, in general, the manual creation of Meaning Representations (MRs) is a notoriously laborious task, we believe that quality estimation approaches may also prove valuable for other MRs such as discourse representations (Lyu and Titov, 2018; Abzianidze et al., 2019) or other semantic parsing frameworks with costly gold data, such as, e.g., semantic proto role labeling (Teichert et al., 2017; Rudinger et al., 2018; Opitz and Frank, 2019a; Stengel-Eskin et al., 2019).

**AMR metrics** When a gold graph is available, it can be used to compute the canonical AMR metric Smatch (Cai and Knight, 2013) that counts matching triples after a variable-alignment step. As discussed in §2, Damonte et al. (2017) have extended Smatch to inspect various sub-aspects of AMR. We have shown that our model is capable of predicting expected outcomes of these metrics in the absence of the gold graph. Recently, more AMR metrics have been proposed, for example the Bleu-based (Papineni et al., 2002) SemBleu metric (Song and Gildea, 2019) or $S^2$match (Opitz et al., 2020), a non-symbolic derivative of Smatch. For future work, we plan to extend our model such that it also predicts these metrics.

**AMR parsing** The most recent advances in AMR parsing have been achieved by neural models either by predicting latent alignments jointly with nodes (Lyu and Titov, 2018), or by transducing a graph from a sequence with a minimum spanning tree (MST) decoding algorithm (Zhang et al., 2019), or by focusing on core semantics in a hierarchical top-down fashion (Cai and Lam, 2019). Other approaches apply statistical machine translation (Pust et al., 2015) or sequence-to-sequence models. The latter, however, appears to suffer from data scarcity issues and needs considerable amounts of silver data to improve results (Van Noord and Bos, 2017; Konstas et al., 2017). Previously, pipeline models have proved effective that either use lagrangian relaxation to impose linguistically motivated constraints in a structured prediction setting (Flanigan et al., 2014) or transition-based approaches that convert dependency trees step-by-step to AMR graphs (Wang et al., 2016, 2015).

## 5 Conclusion

In this work, we have developed an approach to efficiently rate the quality of AMR graphs in the absence of costly gold data. Our model imitates a human judge that is visually confronted with a the AMR in its native multi-line ‘Penman’ format, projected onto an image. We saw how this setup allowed efficient AMR processing with convolutions. Our experiments indicate that the method rates AMR quality more accurately and more efficiently than previous work.
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