CohEval: Benchmarking Coherence Models

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Abstract

Although coherence modeling has come a long way in developing novel models, their evaluation on downstream applications has largely been neglected. With the advancements made by neural approaches in applications such as machine translation, text summarization and dialogue systems, the need for standard coherence evaluation is now more crucial than ever. In this paper, we propose to benchmark coherence models on a number of synthetic and downstream tasks. In particular, we evaluate well-known traditional and neural coherence models on sentence ordering tasks, and also on three downstream applications including coherence evaluation for machine translation, summarization and next utterance prediction. We also show model produced rankings for pre-trained language model outputs as another use-case. Our results demonstrate a weak correlation between the model performances in the synthetic tasks and the downstream applications, motivating alternate evaluation methods for coherence models. This work has led us to create a leaderboard to foster further research in coherence modeling.

1 Introduction and Related Work

Coherence is an important aspect of discourse that distinguishes a well-written text from a poorly-written one that is difficult to comprehend (Halliday and Hasan, 1976). Computational models that can assess coherence have applications in text generation and ranking, such as summarization, machine translation, and dialogue systems.

Researchers have proposed a number of formal theories of discourse coherence, which have inspired the development of many coherence models – both traditional and neural ones. Inspired by the Centering Theory (Grosz et al., 1995), the entity based local models (Barzilay and Lapata, 2008; Elsner and Charniak, 2011) formulate coherence in terms of syntactic patterns of entities in nearby sentences. Another branch of models (Pitler and Nenkova, 2008; Lin et al., 2011; Feng et al., 2014) use coherence relations between adjacent sentences to model local coherence, inspired by the discourse structure theories of Mann and Thompson (1988) and Webber (2004). Other traditional methods include word co-occurrence based local models (Soricut and Marcu, 2006), topic based global models (Barzilay and Lee, 2004; Elsner et al., 2007), and syntax based local and global models (Louis and Nenkova, 2012).

Advancements in deep learning have inspired researchers to neuralize many of the traditional models. Li and Hovy (2014) model syntax and inter-sentence relations using a recurrent sentence encoder followed by a fully-connected layer. In a follow-up work, Li and Jurafsky (2017) use generative models to incorporate global topic information with an encoder-decoder architecture. Mohiuddin et al. (2018) propose a neural entity grid model using convolutions over distributed representations of entity transitions. Mesgar and Strube (2018) model change patterns of salient semantic information between sentences. Xu et al. (2019) propose a local discriminative model that retains the advantages of generative models and uses a smaller negative sampling space that can learn against incorrect orderings. Moon et al. (2019) propose a unified model that incorporates sentence syntax, inter-sentence coherence relations, and global topic structures in a single framework.

Despite continuous research efforts in developing novel coherence models, their usefulness in downstream applications has largely been ignored. They have been evaluated in mainly two ways. The most common approach has been to evaluate them on synthetic discrimination tasks that involve identifying the right order of the sentences.
at the local and global levels (Barzilay and Lapata, 2008; Elsner and Charniak, 2011; Moon et al., 2019). The other (rather infrequent) way has been to assess the impact of coherence score as an additional feature in downstream tasks like readability assessment and essay scoring (Barzilay and Lapata, 2008; Mesgar and Strube, 2018). Most of these evaluations have been restricted to only formal texts (e.g., news articles). But since the concept of coherence goes beyond these constrained tasks and domains, so should the models.

Given the revolutionary advances in neural NLP methods, with claims of reaching human parity in machine translation (Hassan et al., 2018), or fluency in summarization (Liu et al., 2017; Celikyilmaz et al., 2018) and language modeling (Radford et al., 2019b), coherence evaluation of machine-generated texts, particularly at a document-level, is now more crucial than ever (Läubli et al., 2018; Sharma et al., 2019). Traditional task-specific evaluation methods may not be an accurate reflection of their real-world performance in terms of readability (Paulus et al., 2017; Reiter, 2018).

Our main goal in this work is to assess the performance of the existing coherence models not only on standard, challenging synthetic tasks like global and local discrimination, but more importantly on real downstream tasks spanning multiple domains. Specifically, we benchmark both traditional and neural coherence models across three diverse NLP tasks: evaluation of machine-translated texts, evaluation of system-generated abstractive and extractive summaries, and a next utterance ranking task for dialog systems. We also demonstrate a possible evaluation application for texts generated by language models.

Our experiments show that there is only a slight correlation between coherence model performances on synthetic tasks and the application tasks. The best performing model in the synthetic tasks is not always the best performer in the downstream tasks; the models with lower accuracies are not necessarily correspondingly poor in performance. Small increments in synthetic task accuracy provide no indication of equivalent performance improvement on downstream tasks. A consequence of this is that the traditional model still performs strongly in certain tasks despite having a lower accuracy compared to its neural counterparts. Our findings will be presented in a leaderboard, and our code and data will be made publicly available.

2 Evaluation Tasks and Datasets

2.1 Synthetic Tasks

Traditionally coherence models have been evaluated mostly on synthetic tasks. For comparison with previous work, we use two synthetic tasks to compare the coherence models.

(i) Global Discrimination. Introduced by Barzilay and Lapata (2008), in this task coherence models are asked to distinguish an original (coherent) document from its incoherent renderings generated by random permutations of its sentences. We follow the same experimental setting of the Wall Street Journal (WSJ) news dataset as used in previous studies (Elsner and Charniak, 2011; Moon et al., 2019; Xu et al., 2019). Most of these evaluations have been restricted to only formal texts (e.g., news articles). But since the concept of coherence goes beyond these constrained tasks and domains, so should the models.

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(ii) Local Discrimination. Local discrimination was proposed by Moon et al. (2019). In this task, two documents differ only in a local context (windows of 3 sentences). In this case, the models need to be sensitive to local changes. We use the same WSJ dataset as used by Moon et al. (2019).

2.2 Extrinsic Tasks

We evaluate the coherence models on three downstream tasks and also present rankings for pretrained language models based on coherence scores produced for their texts.

(i) Machine Translation Evaluation. The outputs of neural machine translation (NMT) systems have been shown to be more fluent than their phrase-based predecessors (Castilho et al., 2017). However, a recent study by Läubli et al. (2018) on Chinese-English translation has shown that there is a statistically strong preference for human translations in terms of both adequacy and fluency at a document level. Meanwhile, the flexibility of NMT framework such as the Transformer (Vaswani et al., 2017) has led researchers to incorporate larger context beyond one sentence (Voita et al., 2018a, 2019; Maruf et al., 2019).

The standard MT evaluation metric BLEU (Papineni et al., 2002) has been criticized for not being sensitive to discourse aspects like anaphora and coherence (Hardmeier, 2014). Guzmán et al.
(2014, 2015) use sentence-level discourse structure for MT evaluation. However, coherence is a document-level phenomenon. Recent studies also propose targeted datasets for evaluating phenomena like coreference (Guillou et al., 2014; Guillou and Hardmeier, 2016; Bawden et al., 2018; Voita et al., 2018b) and cohesion (Voita et al., 2019). Smith et al. (2016) evaluated traditional (non-neural) coherence models to see if they can distinguish a reference from a system translated document, and reported very low accuracy. However, the situation has changed with the advancements of neural models; today’s coherence models are claimed to be much more accurate.

Our goal therefore is to evaluate the coherence of MT outputs at the document level, and to benchmark the coherence models on this task. To do this, we use the system translations released by the annual Workshop (now Conference) on Machine Translation (WMT) through the years 2011 to 2019. At a document level, reference (human) translations can be assumed to be more coherent than MT outputs. We therefore train the coherence models to score the reference texts higher than the MT outputs. These models can then be used to score different translations of the same source text in terms of coherence. We compare the rankings produced by the models against rankings assigned by humans obtained from a user study.

(ii) Summarization Evaluation. Generating summaries that are coherent has always been an attractive goal in summarization (Nenkova and McKeown, 2011). The widely used automatic evaluation metric ROUGE (Lin, 2004) measures the n-gram overlap between the generated summaries and the reference summaries at a sentence level, and thus is not sufficient for measuring coherence. Kryciski et al. (2019) also recently found almost negligible correlation between ROUGE scores and human judgments on summary coherence, especially for abstractive summaries generated by recent neural summarization models.

We therefore propose to evaluate the coherence of summaries using different coherence models and measure their effectiveness on this task. In particular, we evaluate the models on summaries from both extractive and abstractive systems.

For evaluating the coherence of extractive summaries, we use the dataset prepared by Barzilay and Lapata (2008) for their coherence model evaluation. The dataset comes with human ratings of the summaries from the Document Understanding Conference (DUC), 2003. Since the summaries are extractive (i.e., sentences selected from the source) and the source documents are news articles, we use the coherence models trained for the global discrimination task on Wall Street Journal (WSJ) news dataset (Elsner and Charniak, 2011).

For abstractive summarization, we use summaries from state-of-the-art neural abstractive summarization systems for CNN/DM dataset (Hermann et al., 2015; Nallapati et al., 2016). Since abstractive systems vary in their architectures and loss functions, they may produce very different summaries. We run a human study to validate the rankings given by the coherence models.

(iii) Next Utterance Ranking. Dialogue quality assessment is crucial for evaluating dialogue systems. It depends on various conversational aspects such as engagement, coherence, coverage, conversational depth, and topical diversity (See et al., 2019). Liu et al. (2016) show that commonly used metrics such as BLEU and ROUGE show very weak or no correlation with human judgements. They also suggest using metrics that take dialogue context into account. This is particularly important as a recent study by Sankar et al. (2019) empirically shows that current neural dialogue systems rarely use conversational history. We therefore propose to evaluate the usefulness of coherence models in dialogue systems.

We evaluate the models on the Noetic End-to-End Response Selection Challenge II (NOESIS II), a track in the Dialog System Technology Challenges 8 (DSTC 8) (Kim et al., 2019). In this problem, each example consists of a conversational context \( U = (u_1, \ldots, u_{|U|}) \) and a set of potential utterances (candidates) \( C = \{c_1, \ldots, c_{|C|}\} \) that may occur next in the dialogue; the task is to select the correct next-utterance \( r \in C \).

This task is a nice fit for evaluating coherence models, as a good model should rank a coherent dialogue higher than an incoherent one. The correct utterance along with the conversational context forms the coherent example \( P = (u_1, \ldots, u_{|U|}, r) \), while other candidate utterances \( c_j \in C \) with the conversational context form the incoherent examples \( N = (u_1, \ldots, u_{|U|}, c_j) \). This is a considerably harder task as the difference between coherent and incoherent dialogue is only the last utterance. We train the coherence models with these coherent (\( P \)) and incoherent (\( N \)) examples.
The trained models give a score for each example based on its coherence. We then use our aforementioned assumption (coherence models should score $P$ higher than $N$) for the evaluation.

(iv) Coherence of LM Generated Texts There have been claims that language models (LM) pre-trained on large-scale data produce fluent text that is indistinguishable from those produced by humans (Radford et al., 2019b). We propose to evaluate the coherence of such machine-generated texts to assess their readability. We evaluate 100 such machine generated texts from the two largest LMs: GPT-2 (Radford et al., 2019a) and CTRL (Keskar et al., 2019).

We prompt the LMs with 100 sentences taken from book introductions scraped from the web. However, despite receiving the same prompt, the LMs do not necessarily produce similar content. It would be unfair to compare the coherence evaluations of the texts they produce in such cases.

To mitigate this problem, we regulate the content produced by the LMs. We do this by interleaving the gold sentences from the book introductions with the LM generated sentences within the prompt. That is, first, the first sentence from the gold data is used to prompt the LMs. The sentence produced by the LM is then extracted. These two sentences are concatenated along with the 3rd sentence from the gold data and used as the next prompt, and so on. This results in a controlled production of text with an equal number of sentences produced by all LMs; every alternate sentence is gold data, and the other half of the text is LM generated. This provides a more robust way to force different LMs to generate similar content, ensuring that the coherence evaluation is more reliable.

Because of the nature of the texts considered in this task (formal), we use the coherence models that are trained for discriminating WSJ articles.

3 Coherence Models

We benchmark the performance of five coherence models on the tasks discussed above.

(a) Entity Grid. Barzilay and Lapata (2005, 2008) introduced the popular entity-based model (EGRID) for representing and assessing text coherence motivated by the Centering Theory (Grosz et al., 1995). This model represents a text with a two-dimensional array called an entity grid, that captures transitions of discourse entities across sentences. These local entity transitions are used as deciding patterns for text coherence; a local entity transition of length $k$ is a sequence of $\{S,O,X,–\}^k$ representing grammatical roles (Subject, Object, Other, and Absent, respectively) played by an entity in $k$ consecutive sentences. The salience of the entities, quantified by the occurrence frequency, is also incorporated to identify transitions of important entities. Elsner and Charniak (2011) improve the basic entity grid by including non-head nouns as entities (with the grammatical role X). Instead of using a coreference resolver, they match the nouns to detect coreferent entities. In our work, we consider this version of the entity grid model.

(b) Neural Entity Grid. A neural version of the entity grid model (NEURALGRID) was proposed by Nguyen and Joty (2017). The grammatical roles in the entity grid are converted into their distributed representations, and the entity transitions are modeled in the distributed space by performing a convolution operation over it. The final coherence scores are computed from convolved features that have gone through a spatial max-pooling operation. A global, document-level pairwise loss is used to train the model.

(c) Lexicalized Neural Entity Grid. Mohiuddin et al. (2018) propose an improvement of the neural entity grid (LEXNEURALGRID) by lexicalizing the entity transitions using off-the-shelf word embeddings to achieve better generalization.

(d) Transferable Neural Model. In order to generalize the coherence model across domains, Xu et al. (2019) propose a transferable neural model (TRANSMODEL) that considers coherence at a local level, taking only adjoining sentences as input. Coupled with pre-training of the sentence encoders in a generative fashion, their model demonstrates significant improvements in performance, despite being a local coherence model.

(e) Unified Neural Model. Moon et al. (2019) propose a unified model (UNIFIEDMODEL) that captures syntax (as a proxy of intention), discourse relations, entity attention and global topic structures. The syntax is captured by incorporating an explicit language model loss. A bi-linear layer is used to capture the inter-sentential discourse relations, while light-weight convolution is used to capture the attention and topic structures.
Table 1: Statistics of the WSJ news dataset used for the Global discrimination task.

| Sections | # Doc. | # Pairs |
|----------|--------|---------|
| Train 00-13 | 1,378 | 26,422 |
| Test 14-24 | 1,053 | 20,411 |

Table 2: Results: Accuracies of the coherence models in the Global Discrimination task.

| Model          | Emb. | Standard | Inverse |
|----------------|------|----------|---------|
| EGRID          | –    | 81.60    | 75.78   |
| NEURAL EGRID   | –    | 84.36    | 83.94   |
| LEX NEURAL EGRID| word2vec | 88.51    | 88.13   |
| TRANS MODEL    | Avg. GloVe | 91.77    | 99.62   |
| UNIFIED MODEL  | ELMo | 93.19    | 96.78   |

Table 3: Statistics on the WSJ news dataset used for the Local discrimination task.

| Sections | # Doc. | # Pairs |
|----------|--------|---------|
| Train 00-13 | 748   | 12,280  |
| Test 14-24  | 618   | 12,440  |

Table 4: Results: Accuracies of the models in the Local Discrimination task.

| Model      | \(D_{w=1}\) | \(D_{w=2}\) | \(D_{w=3}\) | \(D_{w=1,2,3}\) |
|------------|--------------|--------------|--------------|------------------|
| EGRID      | 59.78        | 53.89        | 60.43        | 63.04            |
| NEURAL EGRID| 57.49       | 56.74        | 57.11        | 60.0             |
| LEX NEURAL EGRID | 56.65   | 58.21        | 58.95        | 58.42            |
| TRANS MODEL| 66.87        | 66.25        | 67.95        | 65.52            |
| UNIFIED MODEL | 77.07     | 67.29        | 76.12        | 81.23            |

4 Experiments

For each of the coherence models, we conducted experiments with publicly available codes from the respective authors. The three recent methods use word embeddings: LEX NEURAL EGRID, TRANS MODEL, and UNIFIED MODEL use Word2vec (Mikolov et al., 2013), average GloVe (Pennington et al., 2014), and ELMo (Peters et al., 2018) embeddings respectively. We use the default settings and hyperparameters suggested by the authors.

4.1 Global Discrimination

Setup. We follow the same experimental settings of the WSJ news dataset as used in previous works (Xu et al., 2019; Mohiuddin et al., 2018; Elsner and Charniak, 2011; Feng et al., 2014). We use 20 random permutations of each document for both training and testing, excluding the permutations that match the original one. Table 1 summarizes the data sets used in the global discrimination task. We randomly select 10% of the training set for development purposes.

Results. Table 2 presents the results in terms of accuracy on the two global discrimination tasks – the standard and the inverse order discrimination. We see that UNIFIED MODEL achieves the highest accuracy on the standard order discrimination task and TRANS MODEL performs the best on the Inverse order discrimination task. The other three models use entity grid, hence they lose the sentential structure of the document. UNIFIED MODEL and TRANS MODEL both capture sentence grammar and discourse relations. Their performance on the global discrimination task corroborates this.

4.2 Local Discrimination

Setup. We use the same WSJ articles used in the global discrimination task (Table 1) to create our local discrimination datasets. We use the code released by Moon et al. (2019) to generate these datasets.\(^1\) Sentences within a local window of size 3 are re-ordered to form a locally incoherent text. Only articles with more than 10 sentences are included in the dataset. Table 3 summarizes the datasets. We randomly select 10% of the training set for development purposes.

Following Moon et al. (2019), we create four datasets for our local discrimination task: \(D_{w=1}\), \(D_{w=2}\), \(D_{w=3}\) and \(D_{w=1,2,3}\). \(D_{w=1}\) contains the documents where only one randomly selected window is permuted, \(D_{w=2}\) contains the documents where two randomly selected windows are permuted; \(D_{w=3}\) is similarly created for 3 windows. \(D_{w=1,2,3}\) denotes the concatenated datasets.

Results. From Table 4, we see that the UNIFIED MODEL achieves the highest accuracy on all four datasets. A possible reason for the better performance of UNIFIED MODEL could be their loss function. Unlike other models, they use an adaptive pairwise ranking loss which does not penalize the locally coherent sentences. In the local discrimination task, the difference between positive and negative examples is small; most of the cases are locally coherent. UNIFIED MODEL’s loss function can capture this.

\(^1\)https://github.com/taasnim/unified-coherence-model
4.3 Machine Translation

Setup. Under the assumption that the reference translations are more coherent at the document level than the system translations, we train the coherence models with the reference text as the positive and the system translation as the negative document, forming a positive-negative document pair. We use the data from WMT-2011 to WMT-2015 for training (28,985 document-pairs), WMT-2016 for development (7,647 document-pairs) and WMT-2017 to WMT-2018 for testing (20,680 document-pairs). The data consists of translated texts taken from all language-pairs where English is the target language.

We evaluate the system translations by producing a ranking between the different translations of the same source text. To do this, we first obtain scores from the coherence models for the reference and each of the corresponding system translations. Then, we normalize the scores of the system translations by subtracting them from score of the reference translation. These normalized coherence scores are used to rank the system translations.

Results. To validate the rankings of the translations given by the coherence models, we obtain rankings given by humans in a user study. Figure 1 shows the layout of the user study, where the participants are shown four sentences from three candidate translations of the same source text and asked to rank them against each other. One of the given translations is the reference, used as a control, and to validate our assumption that the reference is more coherent than the system translations.

Participants chose the reference as more coherent with an agreement of 0.84, confirming our assumption and justifying our training setup. Table 5 reports the accuracy of the models and the results of the model ranking comparison against human rankings. We see that the UnifiedModel which has the highest accuracy in scoring reference texts as higher, also has the highest agreement for rankings with humans. The rest of the models have similar agreements with human rankings. Surprisingly, the traditional EGRID model has high agreements with humans.

4.4 Abstractive Summarization

Setup. We use the test set of CNN/DM for this task. We collected the reference summaries from the CNN/DM test set as well as the summaries generated by the following four state-of-the-art abstractive summarization systems: (a) Pointer-Generator (PG) (See et al., 2017), (b) BERT-SUMExtABS (BSEA) (Liu and Lapata, 2019), (c) UniLM (Dong et al., 2019), and (d) SENECA (Sharma et al., 2019).

We first conducted a user study to check how often the reference is preferred as a more coherent text over the generated summaries. The agreement between the two annotators was only 0.54, showing low preference for the reference summary. Given this, it would not be appropriate to train the models under the assumption that the reference summaries are more coherent. Therefore, we use the coherence models trained on the WSJ dataset for this task as well.

The coherence models predict the scores for each system-generated summary in the test set. The scores produced by the models are then used to rank the summaries of the same original article. We conducted a small-scale human study to validate the effectiveness of the rankings produced by was an issue here since the annotators were always more likely to choose the reference as better. Thus, we report the more appropriate Gwet’s AC1/gamma coefficient (Gwet, 2008), which controls for this.
the coherence models. We randomly sampled 10 sets of summaries from the dataset with each set containing four generated summaries of the same article, thus resulting in \((\frac{1}{2}) \times 10 = 60\) pairs of system summaries. Two annotators were asked to rank each pair of the summaries in terms of coherence; see Appendix for the human study interface.

**Results.** For the user study, the agreement between the two annotators was 0.78, which indicates fairly reliable data. After we obtain the rankings based on the coherence scores produced by the models, we compute the agreements between the systems and the two annotators, reported in Table 6. EGRID and LEXNEURALEGRID show the highest agreement with human judgements.

On the right-hand side of Table 6, we present the average ranking of the summaries produced by different summarization models. This coherence-based evaluation of the summarization systems can be considered a real-world use-case for the coherence models. Each summary is assigned a rank between 1 and 4 based on the coherence scores produced by the models. The average ranking is computed by averaging the rankings over all the test samples. It can be seen that the coherence models with higher human agreement, EGRID and LEXNEURALEGRID yield similar rankings; they rank the summaries produced by UniLM as more coherent than others in general.

### 4.5 Extractive Summarization

**Setup.** The dataset from Barzilay and Lapata (2008) provides 16 sets of summaries where each set corresponds to a multi-document cluster and contains summaries generated by 5 systems and 1 human. The human ratings for these summaries based on coherence are also available.\(^4\)

In this experiment, since there is no agreement between human annotators available, we simply follow the same experimental setup as in abstractive summarization. We use the coherence models trained on the WSJ dataset to produce scores that can be used to obtain the pairwise ranking of generated summaries. Based on the ratings provided by Barzilay and Lapata (2008), we can generate the human pairwise rankings.

**Results.** We present the agreements between the generated human ranking and the systems in Table 7. We show the average rankings for different extractive systems (e.g., S-6, S-13, ... ) in the last five columns. NEURALEGRID has a higher agreement with human judgement compared to the other models. It also yields an average ranking very similar to the human average ranking.

By showing that models with high human agreements can produce reasonable rankings (see agreements) of summarization systems, we demonstrate that evaluating summarization systems using coherence as a measure is viable as a research objective. We hope that this can serve to motivate summarization evaluation towards the coherence of the summaries rather than purely focusing on the improvements in ROUGE scores.
4.6 Utterance Ranking

**Setup.** We evaluated the coherence models on both datasets of the DSTC8 response selection track, i.e., the Advising and Ubuntu datasets.\(^5\) The former contains two-party dialogues that simulate a discussion between a student and an academic advisor, while the latter consists of multiparty conversations extracted from the Ubuntu IRC channel (Kummerfeld et al., 2019).

For a given conversational context, the goal is to select the next utterance from a candidate pool of 100 utterances, which may or may not contain the correct next utterance. We filter the datasets to suit the settings for coherence models. In our refined datasets, we exclude the conversations that have less than 7 or more than 50 utterances in the context. To ensure that we have pairwise coherent and incoherent examples, we only include the conversations that contain the correct next utterance in the candidate pool. Table 8 shows the statistics of our refined datasets for the utterance ranking task.

**Results.** Table 9 summarizes the results on the refined datasets for the utterance ranking task. The DSTC8 challenge ranking considers the average of Recall@1, Recall@5, Recall@10 and Mean Reciprocal Rank (MRR). We report both the official evaluation results and the coherence models’ performance even though the latter is tested on the refined datasets. From the results, we see that the overall performance of all the coherence models is quite poor. This is not particularly surprising, since this is a considerably harder task for the coherence models alone. However, given that some models perform relatively well (e.g., NEURALEGRID on the Ubuntu dataset), the insights of these models can be incorporated into the dialogue systems to make them sensitive to the context.

4.7 Evaluation of LM Generated Texts

**Setup.** Similarly, the pre-trained coherence models are applied to evaluate the text outputs from LMs, specifically, GPT2 and CTRL.\(^6\) Moreover, it’s also interesting to test on the texts produced by the models with different sizes (i.e., GPT2-Base, GPT2-Large, GPT2-XL).\(^7\)

Consequently, we have 100 sets in total with each set containing four texts. The coherence

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\(^5\)https://github.com/dstc8-track2/NOESIS-II/

\(^6\)We use Books as the Control Code for CTRL model.

\(^7\)We use the implementation from HuggingFace (Wolf et al., 2019).

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| Coherence Model          | R@1  | R@5  | R@10 | MRR  | Acc. |
|-------------------------|------|------|------|------|------|
| EGRID                   | 0.006| 0.03 | 0.07 | 0.04 | 47.16|
| LEXNEURALEGRID          | 0.057| 0.17 | 0.23 | 0.13 | 56.15|
| TRANSMODEL              | 0.047| 0.17 | 0.26 | 0.13 | 57.66|
| UNIFIEDMODEL            | 0.027| 0.20 | 0.30 | 0.14 | 66.62|

Table 9: Utterance ranking results for different coherence models on Advising and Ubuntu datasets. R@k indicates Recall@k, \(\times\) indicates result not shared.

| Model    | GPT2-Base | GPT2-L | GPT2-XL | CTRL |
|----------|-----------|--------|---------|------|
| Params   | 117M      | 774M   | 155B    | 1.63B|
| EGRID    | 2.91      | 2.85   | 2.50    | 1.74 |
| NEURALEGRID | 2.90    | 2.92   | 2.36    | 1.82 |
| LEXNEURALEGRID | 2.91  | 2.84   | 2.38    | 1.87 |
| TRANSMODEL | 2.45   | 2.97   | 2.70    | 1.88 |
| UNIFIEDMODEL | 2.40   | 2.59   | 2.49    | 2.52 |

Table 10: The average coherence rankings for pre-trained LM generated texts. Lower is better.
signalling a need for change in the way coherence models are typically evaluated.

Conversely, we also demonstrate through our experiments and user studies that coherence models have the potential to be used for evaluating the coherence of machine-generated texts.

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A Appendix

A.1 Human Study Interface for Abstractive Summarization

We show the interface of human study for abstractive summarization in Figure 1.

A.2 Human Study for Extractive Summarization

We briefly describe the human study for extractive summarization. The human study was conducted by ?. Coherence ratings for summaries were collected during an elicitation study by 177 unpaid native speakers of English. The annotators were asked to use a seven point-scale to rate each summary based on how coherent the summaries were without having seen the source texts. The ratings (approximately 23 per summary) given by the subjects were averaged to provide a final rating score between 1 and 7 for each summary.
| Concordance-Ranking |
|--------------------|
| "Summary 1 is better." | "Summary 2 is better." |

Figure 1: Human Study Interface for Abstractive Summarization

Please sort the summaries according to the coherence aspect. The summaries are given as follows:

1. Eric Garner’s family and other members of families united for justice will attend Gray’s funeral. Gray was arrested April 11 and died a week later from a severe spinal cord injury. There were no police officers who will attend Gray’s funeral.

2. Freddie Gray, 25, died in police custody 10 days after he was arrested on a weapons charge. His family said his vertebral was crushed and his neck snapped before he slipped into a coma. Hundreds of protesters peacefully rallied on the streets of Baltimore on Saturday against the alleged police role in Gray’s death. "There are those who will tell you..."

Figure 1: Human Study Interface for Abstractive Summarization