A Neural Model for Dialogue Coherence Assessment

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Abstract
Dialogue quality assessment is crucial for evaluating dialogue agents. An essential factor of high-quality dialogues is coherence – what makes dialogue utterances a whole. This paper proposes a novel dialogue coherence model trained in a hierarchical multi-task learning scenario where coherence assessment is the primary and the high-level task, and dialogue act prediction is the auxiliary and the low-level task. The results of our experiments for two benchmark dialogue corpora (i.e. SwitchBoard and DailyDialog) show that our model significantly outperforms its competitors for ranking dialogues with respect to their coherence. Although the performance of other examined models considerably varies across examined corpora, our model robustly achieves high performance. We release the source code and datasets defined for the experiments in this paper.

1 Introduction
Recent work has shown a lot of interest in developing dialogue agents (Ritter, Cherry, and Dolan 2011; Serban et al. 2016; Ghazvininejad et al. 2018). However, assessing the quality of dialogues generated by different agents is a challenging research question since it depends on various factors (See et al. 2019) such as coherence, i.e. what makes a sequence of utterances a unified dialogue (Purandare and Litman 2008; Higashinaka et al. 2014; Cervone, Stepanov, and Riccardi 2018). A dialogue coherence model is necessary for training, evaluating, and comparing dialogue agents (Li et al. 2016). Another application of such models is disentanglement in chat rooms (Elsner and Charniak 2008b).

Table 1 shows two dialogues, where the top one with its original utterance order is perceived more coherent than the bottom one with re-arranged utterances. This example shows that although two dialogues may present the same information, topic continuity among utterances is necessary to have a high-quality dialogue, matching theories such as (Byron and Stent 1998).

| coherent | incoherent |
|----------|------------|
| U0: This is my uncle, Charles. | inform |
| U1: He looks strong. What does he do? | question |
| U2: He’s a captain. | inform |
| U3: He must be very brave. | inform |
| U4: Exactly! | inform |

Table 1: A sample dialogue pair taken from one of our training sets. The top one is more coherent than the bottom one, which is generated by permuting the utterances said by one of the speakers in the dialogue. The third column shows the dialogue acts associated with utterances.

Recent approaches to dialogue coherence modeling use the coherence features designed for the monologue texts and augment them with dialogue act transitions as dialogue specific features. For example, Cervone, Stepanov, and Riccardi (2018) use dialogue act transitions over utterances in a dialogue besides the entity transition features used by Barzilay and Lapata (2008) for measuring the coherence of dialogues. This model needs the dialogue acts of utterances as an input at the evaluation time. Furthermore, the quality of this model depends on the performance of entity extractors, e.g. co-reference resolution systems, on dialogue texts. Moreover, the model does not achieve similar performance on other dialogue datasets which contain a few and general dialogue acts (as
shown in our experiments). The model is not scalable as a dialogue develops turn by turn. It needs to compute a new representation of the dialogue, and also compute the dialogue act label of the generated utterance in the last turn.

In this paper, we propose an effective neural dialogue coherence model whose bottom layer encodes utterances and upper layer represents the whole dialogue to estimate the dialogue coherence score. The key idea is to take advantages of inductive transfer between the dialogue coherence assessment and dialogue act prediction tasks. To do so, we use a hierarchical Multi-Task Learning (MTL) approach in which coherence assessment is the primary task and dialogue act prediction is the auxiliary task. Dialogue act labels are supervision signals for training the utterance representation layer, and preferences across dialogues are weak supervision signals of dialogue coherence for both dialogue and utterance representation layers.

In contrast to the existing methods for dialogue coherence assessment, our model does not depend on any other tool such as an entity extractor and a co-reference resolver. Moreover, instead of utilizing dialogue acts as inputs to models, we use them to define an auxiliary task to achieve better generalization on the coherence assessment task. This property enables our model to predict the coherence score of dialogue without any dialogue act at the evaluation time, generalize well on two different open-domain dialogue corpora, and perform robustly on the different cross problem-domain evaluations.

The contributions of this work are: (1) a dialogue-specific coherence model, which outperforms its state-of-the-art competitor, (2) an MTL approach to benefit from dialogue act prediction as an auxiliary task to achieve a better generalization performance for the dialogue coherence assessment task, (3) a preference learning approach to train the coherence model using the preferences over dialogues, (4) a novel benchmark framework for evaluating dialogue coherence models.

### 2 Related Work

In this section, we describe some of the existing computational coherence models that are related to our model.

Coherence, in general, distinguishes a text from a random sequence of sentences (Grosz and Sidner 1998; Barzilay and Lapata 2008). It makes a text to be interpreted as a whole. Coherence assessment deals with semantic relationships among text units such as sentences in monologues or utterances in dialogues. Different approaches have been proposed to represent the properties of coherent texts. One of the main methods for coherence modeling is EntityGrid (Barzilay and Lapata 2008), which is widely used for monologues (Elsner and Charniak 2008) and columns are associated with sentences and entities occurring in the text, respectively. Entities are a set of mentions that are extracted by a co-reference system from the text. Entry $E_{ij}$ of grid $E$ shows whether the entity associated with column $j$ is mentioned in the sentence associated with row $i$ of the grid. If so, the value of the entry is the grammatical role, i.e., $s$ for the subject, $o$ for the object, and $x$ for any other roles, of the entity in the sentence. Otherwise, the entry is filled with $-$, which encodes the absence of the entity in the sentence. Grammatical role transitions of entities are used as indicative patterns for coherence. The probabilities of these patterns are taken as coherence features, which can be supplied to any machine learning model. Barzilay and Lapata (2008) train and evaluate their EntityGrid model in a ranking scenario where the model should rank a pair of text with respect to their perceived coherence. They use Support Vector Machines (SVMs) to distinguish the original text from its perturbation which is obtained by changing the order of sentences. Dziri et al. (2019) utilize a natural language inference tool to assess the content consistency across utterances in dialogue as an indicator for dialogue coherence.

Our model differs from the above models as: (1) it benefits from both dialogue acts and semantic relationships among
utterances, (2) it uses dialogue act labels to define an auxiliary and related task for training the coherence model using MTL, (3) it is independent of any external tool such as entity extractors and dialogue act classifiers, (4) it does not need any dialogue act during evaluation, and (5) it learns to balance the impact of each task during training.

3 Problem Formulation
Given a dialogue $dial = [utt_1, ..., utt_m]$, where $utt_k$ is the $k^{th}$ utterance, we address the problem of designing a model, $M$, which assigns a coherence score to $dial$, $s_{dial} = M(dial)$ so that for any dialogue pair $(dial_1, dial_2)$, $s_{dial_1} > s_{dial_2}$ if and only if dialogue $dial_1$ is preferred over dialogue $dial_2$ with respect to their perceived coherence.

4 Model: DiCoh
In this section, we explain the details of our dialogue coherence model, i.e. DiCoh. We assume that each utterance $utt_k$ is associated with a dialogue act $a_k$ during training but not during evaluation. Figure 1 illustrates our model.

Utterance representation layer and dialogue act prediction. We utilize an embedding layer, $Emb$, to transform the words in utterance $utt = [w_1, ..., w_n]$ to a sequence of word embeddings $E = [e_1, ..., e_n]$, where $n$ is the number of words. The embedding layer can be initialized by a pre-trained embedding space. Then, a Bidirectional recurrent neural network with Long Short-Term Memory cells, $BiLSTM$, processes the word embeddings $E$ to represent words in their utterance-level context:

$$E = Emb(utt)$$
$$H_u = BiLSTM(E),$$

where $H_u$ shows the state vectors $[h_1^u, ..., h_n^u]$ returned by $BiLSTM$. At word $t$, $h_t^u$ is the concatenation of the hidden state of the forward LSTM, $h_t^3$, and the backward LSTM, $h_t^4$:

$$h_t^u = [h_t^3, h_t^4],$$

We apply a self-attention mechanism, $Atten$, to the state vectors in $H_u$ to obtain the vector representation, $u$, of utterance $utt$:

$$u = Atten(H_u).$$

Generally, the attention layer, $Atten$, for an input vector $x$ is defined as follows:

$$\beta_t = x_t * W$$
$$\alpha_t = \frac{\exp(\beta_t)}{\sum_t \exp(\beta_t)},$$
$$o = \sum_t \alpha_t * x_t,$$

where $W$ is the parameter of the attention layer, and $o$ is its weighted output vector. Attention enables the utterance representation layer to consider words of utterances with different weights.

The utterance vector, $u_t$, is used to predict the dialogue act associated with utterance $utt$. To do so, a Softmax layer maps $u_t$ to a probability distribution over dialogue acts, $A$:

$$p_u(a) = \text{Softmax}(W_{[u|\times|A]|} * u),$$

where $W_{[u|\times|A]|}$ represents the weights of the softmax layer, $|u|$ is the size of the utterance vector, and $|A|$ is the number of dialogue act labels. It is worth noting that the parameters of the utterance representation layer are shared for representing all utterances in dialogues.

Dialogue representation layer and coherence assessment. For an input dialogue $dial = [utt_1, ..., utt_m]$, the output of the utterance representation layer is a sequence of utterance vectors, i.e., $[u_1, ..., u_m]$. The dialogue representation layer combines the utterance vectors to obtain a dialogue vector. More formally, we apply a $BiLSTM$ to utterance vectors to obtain dialogue-level contextualized representations of utterances. Then, a self-attention layer (Equation 4) with new parameters computes the weighted average of contextualized utterance vectors to represent the whole dialogue.

$$[h_1^d, ..., h_m^d] = \text{BiLSTM}([u_1, ..., u_m])$$
$$d = \text{Atten}([h_1^d, ..., h_m^d]).$$

Finally, a linear layer maps the dialogue vector, $d$, to a dialogue coherence score, $s_{dial}$.

5 Multi-Task Learning
In this section, we explain how our model is trained using the coherence assessment and dialogue act prediction tasks in a multi-task learning setup. Inspired by Kendall, Gal, and Cipolla (2018), we compute the loss functions for each task and use their weighted average as the total loss of the model.

The loss function of dialogue act prediction for dialogue $dial$ is average cross-entropy (Goldberg and Hirst 2017):

$$L_{dial}^{da} = \frac{1}{m} \sum_{u \in \{u_1, ..., u_m\}} \text{cross-entropy}(p_u(a), a_n^u),$$

where $m$ is the number of utterances in a dialogue, and $a_n^u$ is the gold dialogue act associated with each utterance in a dialogue. $p_u(a)$ is the probability distribution over dialogue act labels for utterance $u$ (see Equation 5).

The loss function of coherence assessment, which is inspired by preference learning approaches (Gao et al. 2019), is defined over preferences among dialogues. For any dialogue pair $p = (dial_1, dial_2)$ and its preference label,

$$l^* = \begin{cases} 0 & \text{if } dial_1 \text{ is preferred over } dial_2, \\ 1 & \text{otherwise,} \end{cases}$$

the coherence loss value for dialogue pair $p$ is:

$$L_{coh}^p = \max\{0, 1 - s_{p[l^*]} + s_{p[1-l^*]}\}.$$
Finally, the loss value for the whole model is the weighted combination of tasks’ losses:

$$L = \frac{L_{coh}}{\gamma_1} + \frac{(L_{da}^{dial_i} + L_{da}^{dial_j})}{\gamma_2} + \alpha \log(\gamma_1) + \beta \log(\gamma_2),$$

where $L_{da}^{dial_i}$ and $L_{da}^{dial_j}$ are the losses of dialogue act prediction for dialogues in pair $p = (dial_i, dial_j)$, $\gamma_1$ and $\gamma_2$ are trainable parameters to balance the impact of losses, $\alpha$ and $\beta$ are constant values. The gradient of this loss is used for updating all parameters of the model.

6 Experimental Setup

In this section, we explain the dialogue corpora whose dialogues are used in our experiments, the experiments designed for evaluating the coherence models, compared models, and experimental settings.

Dialogue corpora. We evaluate our coherence models on the dialogues from DailyDialog (Li et al. 2017) and SwitchBoard (Jurafsky and Shriberg 1997) as two benchmark dialogue corpora. They both contain open-domain human-to-human dialogues. The SwitchBoard corpus, which is used by the state-of-the-art dialogue coherence models as well, contains dialogues collected from phone conversations, and the DailyDialog corpus, which is a recent open-domain corpus with many dialogues for training neural models, contains dialogues collected and annotated by crowdsourcing. Each utterance in DailyDialog is associated with a dialogue act from \{Inform, Question, Directive, Commissive\}. However, dialogue acts in SwitchBoard are more fine-grained than those in DailyDialog.

Figure 1: An illustration of our model for a dialogue pair $p = (dial_i, dial_j)$. Dashed items represent losses. The parameters of the model are shared among dialogues.

For example, a question utterance in SwitchBoard is accompanied by a specific dialogue act from \{Yes-No-Question, Wh-Question, Rhetorical-Questions, etc\}. Table \[\] shows some properties of these corpora.
Experiments. Inspired by Barzilay and Lapata (2008), we design four experiments to assess if a coherence model quantifies the coherence of dialogues such that more coherent dialogues obtain higher scores than less coherent ones. The underlying idea of the experiments is to perturb the coherence of each dialogue in DailyDialog and SwitchBoard corpora to create a set of dialogue pairs for training and testing our models. During training, a model learns to assign coherence scores to dialogues in a preference learning setup. Since each experiment follows a specific perturbation method, henceforth, we refer to them as problem-domains.

They are:

- **Utterance Ordering (UO):** One of the benchmark methods for coherence evaluation in monologue texts is sentence ordering (Barzilay and Lapata 2008). We design Utterance Ordering (UO) in which the order of utterances in a dialogue is randomly permuted. We assume that the original dialogue is preferred over the perturbed one with respect to their coherence (Cervone, Stepanov, and Riccardi 2018).

- **Utterance Insertion (UI):** Given a dialogue, one utterance of the dialogue is removed and the coherence model should find the best place in the dialogue to insert the removed utterance. The original place of the utterance is the best place for the insertion. We assume any other place for the insertion yields a less preferable dialogue in terms of coherence. This experiment is more difficult-to-learn than the UO as the distinction among dialogues is in the position of only one utterance.

- **Utterance Replacement (UR):** The idea behind this experiment is to replace one of the utterances in dialogue with another utterance that is randomly selected from another dialogue. The original dialogue is preferred over the dialogue generated by UR. In this experiment, the content of an utterance has been perturbed. This approach is used to evaluate the quality of responses generated by different dialogue agents (Dinan et al. 2019).

- **Even Utterance Ordering (EUO):** This experiment is similar to the UO experiment but here we re-arrange the order of utterances that are said by one speaker and keep the order of the other utterances fixed.

We split each corpus into three disjoint sets of dialogues to create training, validation, and test sets for each of the above experiments. For any dialogue $dial_i$ in each set and its perturbation $dial_j$, we define two dialogue pairs: $(dial_i, dial_j)$ with coherence-based preference label $p^* = 0$ and $(dial_j, dial_i)$ with label $p^* = 1$. Table 2 shows the size of the datasets created for each of the above experiments on the DailyDialog and SwitchBoard corpora. We release these datasets as benchmarks for dialogue coherence assessment.

### Evaluation Metric

We use accuracy as the relative number of dialogue pairs for which a model predicts the correct label.

$$\text{acc} = \frac{\text{# of correctly ranked dialogue pairs}}{\text{# of dialogue pairs}},$$ \hfill (11)

We run each experiment 10 times with varying random seeds, and report their average accuracy (Reimers and Gurevych 2018).

### Compared Models

We compare the following dialogue coherence models on the designed experiments.

- **Random:** This model randomly ranks the input dialogues.

- **CoSim:** Following Zhang et al. (2018) and Xu et al. (2018), this model represents words by their pre-trained word embeddings. Then, each utterance is represented by the average vector of word embeddings in the utterance. The average of the cosine similarities between vectors of adjacent utterances is taken as the coherence score of the input dialogue. In order to prevent any bias in this model, we remove all stop words from utterances.

### Cross problem-domain evaluations.

In a more challenging evaluation setup, we use the model trained on the training set of one experiment and evaluate it on the test set of the other experiments. The goal of this evaluation approach is to investigate the robustness of our model with respect to different perturbation methods.

### Table 2: Some properties of the DailyDialog and SwitchBoard corpora.

| DailyDialog | SwitchBoard |
|-------------|-------------|
| # dialogues | 13,118      | 1,155       |
| # dialogue acts | 4          | 42          |
| avg. # utter. per dialogue | 7.9        | 109         |
| avg. utter. length | 14.6       | 9.26        |
| avg. dialogue acts per utter | 1         | 1.81        |

### Table 3: The number of dialogue pairs in training, validation, and test sets created for experiments on the DailyDialog and SwitchBoard corpora.

| DailyDialog | SwitchBoard |
|-------------|-------------|
| # Training | # Validation | # Test |
| UO | 414,786 | 37,670 | 37,204 |
| UI | 444,720 | 40,000 | 40,000 |
| UR | 330,760 | 31,520 | 29,640 |
| EUO | 259,496 | 24,576 | 23,092 |

| SwitchBoard |
|-------------|
| # Training | # Validation | # Test |
| UO | 37,520 | 5,028 | 3,652 |
| UI | 36,818 | 5,354 | 4,028 |
| UR | 36,960 | 4,600 | 4,640 |
| EUO | 39,036 | 5,332 | 4,142 |
• **ASeq**: This model encodes the coherence of a given dialogue using its dialogue acts. Coherence features in this model are the probabilities of n-grams across the sequence of dialogue acts associated with the utterances in the dialogue (Cervone, Stepanov, and Riccardi 2018). These features are supplied to an SVM to rank dialogues.

• **EAGrid**: This is the best performing model presented by (Cervone, Stepanov, and Riccardi 2018) that augments EntityGrid representation of a dialogue with dialogue acts to extract coherence features. The vector representation of dialogue coherence encodes information about dialogue acts sequences and semantic relations across utterances. This model also uses an SVM ranker.

• **S-DiCoh**: This is our coherence model, i.e. DiCoh, that is trained only for coherence ranking without MTL. More formally, there is no dialogue act prediction involved in the training of the model. Here, $L = L_{coh}^1$ in Equation 10.

• **M-DiCoh**: This is our coherence model trained by the proposed MTL method using dialogue act prediction as the auxiliary task.

### Experimental Setting
The input to a coherence model is a set of dialogue-pairs with a preference label with respect to their coherence. Each utterance in a dialogue is accompanied by a dialogue act. Each batch consists of 128 and 16 dialogue-pairs for the DailyDialog and SwitchBoard corpora, respectively. Utterances are zero-padded and masked. We use pre-trained GloVe embeddings (Pennington, Socher, and Manning 2014) to initialize the embedding layer of size 300 for the CoSim, S-DiCoh, and M-DiCoh models. The size of the hidden states in the LSTM cells of the utterance layer is 128 and of the dialogue layer is 256. The parameters of the model are optimized using the Adam optimizer where its parameters have default values except the learning rate which is initiated with 0.0005. A dropout layer with $p = 0.1$ is applied after the utterance representation layer. We train the model for 20 epochs for DailyDialog and 10 epochs for SwitchBoard. We evaluate the model at the end of each epoch on the validation set. The best performing model on the validation set is used for the final evaluation on the test set. Parameters $\gamma_1$ and $\gamma_2$ are initiated with 2.0 and they are updated during the training of our model. The model is implemented in PyTorch v.1.1.0 and trained on GPUs. Following (Barzilay and Lapata 2008, Cervone, Stepanov, and Riccardi 2018), we create 20 perturbations of each dialogue to make dialogue pairs. For the CoSim model, we use the SMART English stop word list (Salton 1971) to eliminate all stop words. For the ASeq model, which uses only dialogue acts, we follow (Cervone, Stepanov, and Riccardi 2018) and use bi-grams of dialogue acts to define the coherence features. All parameters of the EAGrid model have the same value as the best performing model in (Cervone, Stepanov, and Riccardi 2018). To create training, validation and test sets for our experiments, for DailyDialog we use the splits provided by the corpus, and for SwitchBoard we take 80% of dialogues for training, 10% for the validation and 10% for the test set since there is no standard split. It is worth mentioning that all compared models are evaluated on an identical training, validation and test sets in this paper. We release our source code and data.

### 7 Results
In this section, we discuss the performance of the described models for both in problem-domain and cross problem-domain evaluations.

#### In problem-domain evaluations
Here, for each experiment, the training, validation, and test sets are generated with the same perturbation. Table 4 shows the accuracy of different models for different experiments on the DailyDialog and SwitchBoard dialogues.

| Model     | DailyDialog UO | DailyDialog UI | DailyDialog UR | SwitchBoard UO | SwitchBoard UI | SwitchBoard UR | SwitchBoard EUO |
|-----------|----------------|----------------|----------------|----------------|----------------|----------------|-----------------|
| Random    | 50.10          | 49.97          | 49.97          | 49.92          | 49.98          | 50.02          | 49.99           | 50.13           |
| CoSim     | 57.20          | 52.65          | 64.25          | 66.86          | 82.84          | 55.63          | 52.15           | 74.48           |
| ASeq      | 68.21          | 57.41          | 61.89          | 62.73          | 99.70          | 73.94          | 74.52           | 99.20           |
| EAGrid    | 71.72          | 60.93          | 68.49          | 67.18          | 99.65          | 73.70          | 72.28           | 99.83           |
| S-DiCoh   | 92.62          | 84.01          | 81.89          | 86.06          | 95.78          | 79.63          | 92.84           | 86.41           |
| M-DiCoh   | 94.56          | 87.75          | 83.02          | 88.88          | 99.18          | 85.04          | 90.71           | 97.29           |

Table 4: The accuracy (%) of examined models for the test set of each experiment defined on DailyDialog and SwitchBoard.
Here, we evaluate the EAGrid and M-DiCoh models for cross problem-domain where the best performing model trained on the training set of one experiment is evaluated on each of the test sets of other experiments. Therefore, the perturbation methods used for creating the training sets can differ from those used for creating the test sets. Figure 2 shows the performance of the EAGrid and M-DiCoh models on the test sets of different perturbations, where the models are trained on the training set created by the (a) UR, (b) EUO, (c) UI, and (d) UR perturbations. Regardless of the type of perturbations used in the training sets, we observe that the M-DiCoh model outperforms EAGrid on all test sets. Moreover, the difference between the maximum and minimum accuracy over different perturbations of M-DiCoh is less than that for EAGrid in each training perturbation. The maximum difference in accuracy of the M-DiCoh model on the test set of UR is 12.56 percentage point, followed by UI (07.74), UO (10.52), and EUO (09.65), respectively. This difference for the EAGrid model trained on UO is 14.62, on UI is 09.92, on UR is 15.84, and on EUO is 12.46, which are much greater and worse than those of M-DiCoh. This observation indicates that our model is more robust than the EAGrid model on the examined perturbations. Interestingly, among all test perturbations, both M-DiCoh and EAGrid achieve the highest accuracy on UO, which can be because this perturbation disturbs the whole dialogue and is easier to learn than other perturbations. This observation is consistent with the arguments in (Barzilay and Lapata 2008; Guinaudeau and Strube 2013).

### Performance of the dialogue act prediction model.

In this part, we investigate the impact of MTL on dialogue act prediction. To do so, we train our dialogue act model without any coherence supervision signal, S-DAP, and compare it with the model that is trained with our MTL scenario M-DAP. Table 5 shows the F1 metric for these models on the test sets of the experiments for DailyDialog.

|        | UO | UI  | UR  | EUO |
|--------|----|-----|-----|-----|
| S-DAP  | 78.96 | 79.25 | 79.28 | 79.29 |
| M-DAP  | 78.11 | 77.91 | 79.08 | 78.81 |

Table 5: The F1 metric of dialogue act prediction (DAP) for the test sets of the experiments for the DailyDialog corpus. S-DAP is the model trained without any coherence supervision, and M-DAP is the model trained in with MTL.

We notice that the performance of the dialogue act model...
decreases by MTL. However, the goal of this paper is to model the coherence of dialogues and use dialogue act prediction as an auxiliary task to improve the performance of the coherence model.

8 Conclusions

We propose a coherence model which is trained in a hierarchical multi-task learning scenario. We use coherence assessment as the primary task and dialogue act prediction as the auxiliary task. Our coherence method outperforms its counterparts in ranking dialogues concerning their coherence on several perturbations for dialogues from the DailyDialog and SwitchBoard corpora. We also observe that our MTL approach for coherence modeling yields a more robust model on the examined perturbations compared with a recent state-of-the-art coherence model (Cervone, Stepanov, and Riccardi 2018). For future work, we improve the quality of the dialogue act prediction part of our model, utilize this model for training a dialogue agent to produce coherent dialogues, and use recent contextualize word embeddings, e.g. BERT, to obtain utterance representations.

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