A NEURAL PROSODY ENCODER FOR END-TO-END DIALOGUE ACT CLASSIFICATION

Kai Wei 1*, Dillon Knox 2*, Martin Radfar 1, Thanh Tran 1, Markus Müller 1, Grant P. Strimel 1, Nathan Susanj 1, Athanasios Mouchtaris 1, Maurizio Omologo 1

1 Alexa Speech, Amazon, 2 University of Southern California

ABSTRACT
Dialogue act classification (DAC) is a critical task for spoken language understanding in dialogue systems. Prosodic features such as energy and pitch have been shown to be useful for DAC. Despite their importance, little research has explored neural approaches to integrate prosodic features into end-to-end (E2E) DAC models which infer dialogue acts directly from audio signals. In this work, we propose an E2E neural architecture that takes into account the need for characterizing prosodic phenomena co-occurring at different levels inside an utterance. A novel part of this architecture is a learnable gating mechanism that assesses the importance of prosodic features and selectively retains core information necessary for E2E DAC. Our proposed model improves DAC accuracy by 1.07% absolute across three publicly available benchmark datasets.

Index Terms— prosody, dialogue act, gating, pitch, end-to-end

1. INTRODUCTION
Dialogue acts (DAs) are speech acts that represent intentions behind a user’s request to achieve a conversational goal [1]. Dialogue act classification (DAC) models aim to discriminate speech act units such as statement, question, backchannel, and agreement. For instance, when a user says “yes”, DAC models are used to determine whether the user’s intent is to agree with what the voice assistant system has said (DA: agreement) or to signal that the user is paying attention to the system (DA: backchannel).

Recent years have seen significant success in applying deep learning approaches to DAC [2–7]. These approaches use either transcripts [2, 3, 5] or a combination of transcript and audio [4, 7, 8] to predict DAs. However, relying on transcripts has three limitations: First, transcripts are not always available for a spoken dialogue system. Second, collecting oracle transcripts is expensive. Third, errors introduced from transcribing audio have been shown to decrease the performance of DAC significantly [9]. More recently, [6] introduced an end-to-end (E2E) DAC approach, where DAs are directly inferred from audio signals. This approach can address the limitations of using transcripts as the inputs. Yet, how to effectively model audio signals for E2E DAC remains unexplored.

In this work, we propose a novel E2E neural architecture that takes into account the need for characterizing prosodic phenomena co-occurring at different levels inside an utterance. An essential part of this architecture is a learnable gating mechanism that assesses the importance of prosodic features and selectively retains core features necessary for E2E DAC. We compare our proposed model with previous E2E DAC models [4, 7] that only use spectral-based audio features. The results show that our models outperform the reference ones. Further, we compare our neural prosody encoder with the state-of-the-art prosody neural encoder [9] on three public benchmark datasets: DSTC2 [22], and DSTC3 [23], and Switchboard [24]. We show that our proposed model outperforms [9] on all these datasets. We also examine the effects of the gating mechanism and different prosodic features on our proposed model.

2. PROPOSED MODELS
We formulate the problem of E2E DAC tasks as follows: The input is a sequence of raw audio with t time frames, \( X = \{x_1, x_2, ..., x_t\} \). Each \( x_t \) is converted to the logarithm of mel-scale filter bank energy (LFBE) features \( L = \{\ell_1, \ell_2, ..., \ell_t\} \) and prosodic features \( P = \{(e_1, c_1), ..., (e_t, c_t)\} \), where \( e_t \in R^{(e)} \) and \( c_t \in R^{(c)} \) denote energy and pitch features, respectively. Our goal is to correctly classify DAs for each audio input \( X \), namely \( Y^{\text{DA}} \). Figure 1 shows our proposed model. It consists of (i) a local prosodic infusion, (ii) an acoustic encoder, (iii) a global prosodic infusion, and (iv) a DA classifier. We detail each component below.

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1 Equal contribution.
2 Work done during author’s internship at Amazon Alexa.

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1*}
Global Prosodic Gating.

• Pitch: For each audio frame $x_i \in X$, the 3-dimensional pitch features $c_i$ are computed from the 40-mel frequency filter-bank using Kaldi [25], in the same manner as [9]. These features are (i) the warped Normalized Cross Correlation (NCCF), (ii) log-pitch with Probability of V oicing (POV)-weighted mean subtraction over a 1.5-second window, and (iii) the estimated derivative of the raw log pitch [26].

Processing: We first concatenate energy $e_i$ and pitch $c_i$ for each audio frame $x_i \in X$. Then, we transform the concatenated $e_i$ and $c_i$ using the linear projection $W^{ee}$ with the ReLU activation function.

$$p_i = ReLU(W^{ee}[e_i; c_i])$$ (1)

Output: We produce $P = \{p_1, p_2, \ldots, p_t\}$ as a stack of $t$ local prosodic embeddings corresponding to $t$ audio frames of the input audio $X$, with each $p_i \in P$ computed by Eq. (1).

2.1. Local prosodic fusion

The local prosodic function encodes prosodic features and combines them with the LFBE features via our local prosodic gating. We extract the LFBE features using Kaldi [25] with a window size of 25 ms, a frame rate of 10 ms, and a sampling frequency of 8 kHz. We describe prosodic extractor and local prosodic gating below:

2.1.1. Prosodic extractors

Input: We extract two types of basic prosodic features: energy and pitch. We focus on these two features as they were found to be most important for DAC [9, 19].

- Energy: For each audio frame $x_i \in X$, the 3-dimensional energy features $e_i$ are computed from the 40-mel frequency filter-bank using Kaldi [25], in the same manner as [9]. These features are (i) the log of total energy normalized by the maximum total energy of the utterance, (ii) the log of total energy in the lower 20 mel-frequency bands normalized by total energy, and (iii) the log of total energy in the higher 20 mel-frequency bands, normalized by total energy.

- Pitch: For each audio frame $x_i \in X$, the 3-dimensional pitch features $c_i$ are (i) the warped Normalized Cross Correlation Function (NCCF), (ii) log-pitch with Probability of V oicing (POV)-weighted mean subtraction over a 1.5-second window, and (iii) the estimated derivative of the raw log pitch [26].

2.2. Acoustic encoder

The acoustic encoder uses the local acoustic embeddings to produce global acoustic embeddings. Specifically, its inputs are the stack of fused local acoustic features $A = \{a_1, a_2, \ldots, a_t\}$ from the local prosodic gating. We encode $A$ using a $n$-layer Bi-LSTM acoustic encoder to learn the audio representations. The outputs are a stack $H = \{h_1^{(k)}, h_2^{(k)}, \ldots, h_t^{(k)}\}$ of output hidden states at the last layer $n$ computed as follows:

$$\overrightarrow{h}_i^{(k)} = W_h^{(k)} \cdot \overrightarrow{h}_{i-1}^{(k-1)} + \overrightarrow{W_i^{(k)}} e_i$$

$$\overleftarrow{h}_i^{(k)} = W_h^{(k)} \cdot \overleftarrow{h}_{i+1}^{(k-1)} + \overleftarrow{W_i^{(k)}} e_i$$

where $\overrightarrow{h}_i^{(k)}$ and $\overleftarrow{h}_i^{(k)}$ are the hidden states at time frame $i$ and layer $k$, which learn from left-to-right and right-to-left, respectively.
2.3. Global prosodic infusion

The global prosodic gating encodes prosodic features from the entire audio stream and fuses them with the acoustic encoder outputs via our proposed global prosodic gating mechanism (see Fig. 2(b)).

2.3.1. Global Prosodic Encoder

Inspired by [9], we design a 2-D CNN module to encode global prosodic features at varying timescales using multiple convolution filters. Each filter output is max-pooled, stacked, and flattened to output the global prosodic feature matrix \( V \). We set the stride to 1 and use different kernel lengths (5, 10, 25, 50).

2.3.2. Global Prosodic Gating

We design a global prosodic gating layer based on [28] that learns in parallel a pair-wise similarity matrix and a pair-wise dissimilarity matrix between the global prosodic embedding matrix \( V \) and the acoustic encoder output matrix \( H \). Under this dual affinity scheme, the pair-wise similarity matrix is followed by the \( \tanh \) function, resulting in similarity scores between \([-1, 1]\), which controls the addition and subtraction of \( V \) and \( H \). The pair-wise dissimilarity matrix, on the other hand, is served as a gating mechanism that reduces \( \text{V-H} \) similarity scores to zero when prosodic information is not necessary. Our approach overcomes the limitation of the attention method [29, 30] that uses the attention module [24] to erase unnecessary global prosodic signals by:

\[
\sigma = \frac{1}{1 + e^{-\beta (h_i - v_j)}}
\]

where \( \beta \) indicates the signal addition distance between two input feature vectors. From \( A^{(d)} \), we formulate a gating matrix \( G \), which acts as a mechanism to erase unnecessary global prosodic signals by:

\[
G = \sigma [A^{(d)} - \text{mean}(A^{(d)})]
\]

where \( \sigma \) is the sigmoid function. Since \( L_1 \) distance is non-negative, A\((d)\) \( \in [0, 0.5] \). To ensure \( G \in [0, 1] \), we normalize \( A^{(d)} \) to have a zero mean (see Eq. 9).

Output: We produce a matrix \( F \) as the fusion of \( H \) and \( V \) by concatenating \( H \) with the attended \( V \) as follows:

\[
F = [H; (S \odot G)V]
\]

Last, we apply the max-pooling operator on \( F \) to obtain a final representation vector \( f = \text{max-pooling}(F) \) of the input audio \( X \).

2.4. Dialogue act classification

For each input audio \( X \), we use the acoustic representation vector \( f \) as the output of the global prosodic infusion component and produce a DA distribution over all DAs (\( D \)) in the input dataset. The cross-entropy loss for the input audio \( X \) is defined as:

\[
\mathcal{L}_X = - \sum_{d=1}^{D} y_{X,d}^\text{dag} \log (\hat{y}_{X,d}^\text{dag})
\]

3. EXPERIMENT SETTINGS

Datasets: We use three public benchmark datasets to train and evaluate our proposed models: DSTC2 [22], DSTC3 [23], and Switchboard Dialogue Act corpus (SwDA) [24, 31]. Table 1 describes details for each dataset.

The DSTC2 is a standard dataset for tracking the dialogue state. Each utterance has a corresponding audio recording and the associated DAs. The DA is represented in a triple of the following form (actionType, slotName, slotValue). In this work, we treat each utterance in a dialogue as independent because our focus is to examine whether prosodic contexts of the current utterance are useful to its DAC or not. If an utterance only contains one DA label, we use that label. If an utterance contains more than one label, we combine all the labels for that utterance into a single label. In total, the DSTC2 has 15 unique DA labels.

The DSTC3 is an extension of DSTC2 to a broader domain without providing any further in-domain training data. We adopted the same labelling strategy as DSTC2. In total, the DSTC3 has 17 unique DA labels.

The SwDA is a collection of 1,155 five-minute telephone conversations between 543 speakers of American English. It was originally collected by [24]. The DAs were annotated as part of the SWBD-DAMSL project [31]. We identified the corresponding audio for each annotated split using the unique conversation id for each utterance. In total, there are 42 unique DA labels.

Baseline models: We build an E2E DAC model without any prosodic features (hereafter, baseline), and a model where prosodic information is concatenated with LFEBs at the level local (hereafter, local concat). We also report publicly available E2E DAC accuracy from [4] and [7]. Further, we evaluate our proposed encoder against the state-of-the-art prosody encoder [9].

Experimental Setup: We report test set accuracy of E2E DAC in all datasets. All experiments are implemented using PyTorch [32]. Training is performed using the Adam optimizer [33] with \( \beta_1 = 0.9 \), \( \beta_2 = 0.999 \), and \( \epsilon = 10^{-8} \). The initial learning rate was set to 1e-4 and 5e-4 for the DSTC2 and DSTC3 datasets, respectively. We use a batch size of 32 and train for 60 epochs, with check-pointing based on validation loss. We run each experiment 10 times and report the mean and standard deviation of the accuracy score. The

1See DSTC2 and DSTC3 at https://github.com/matthen/dstc.
2The annotated DA train, validation, and test splits are available at https://github.com/NathanDuran/Switchboard-Corpus.
Mann-Whitney U test [34] is used to determine the statistical significance level of the proposed model accuracy improvement. For the LSTM acoustic encoder, we use a three-layer Bi-LSTM acoustic encoder, with each layer containing 512 hidden units.

4. RESULTS

Overall Accuracy: Table 2 shows the overall accuracy of our proposed models and baselines on three benchmark datasets. We observe that just adding the pitch and energy prosodic information (local concat\(^3\)) improves accuracy by 0.69% absolute for DSTC3 and 0.4% absolute for SwDA (\(p < 0.05\)). Further, our proposed model improves E2E DAC across all three benchmark datasets, with 0.39%, 1.65%, and 1.17% absolute increases in accuracy (\(p < 0.05\)) on DSTC2, DSTC3, and SwDA, respectively, suggesting the critical role of prosodic information in E2E DAC tasks.

Table 2. Overall model accuracy. * indicates a significant increase from the baseline (Mann-Whitney U test, \(p < 0.05\)).

|                | DSTC2          | DSTC3          | SwDA           |
|----------------|----------------|----------------|----------------|
| Baseline       | 93.18±.52      | 91.01±.39      | 55.80±.56      |
| Ortega et al. [4] | –              | –              | 50.9           |
| He et al. [7] | –              | –              | 56.19          |
| Local concat   | 93.23±.40      | 91.70±.51*     | 56.20±.48*     |
| Our model      | 93.57±.30      | 92.66±.30*     | 56.97±.46*     |

The effects of local and global gating: Table 3 shows the effects of our proposed gating method. We individually removed gating at the local level and global level. We observe that adding the gating mechanism leads to improvements at both local and global levels. At global level, we found that adding the gating mechanism leads to 0.36% absolute improvement on average over the three datasets, and that the improvement is most pronounced for DSTC3 with 0.72% absolute improvement. At local level, adding gating leads to 0.30% absolute improvement on average over the three datasets, and that the improvement is most pronounced for SwDA with 0.51% absolute improvement. It is worth noting that our proposed prosody encoder method also outperforms the global encoder method proposed by [9].

Table 3. Effect of gating mechanisms on E2E DAC accuracy.

|                | DSTC2          | DSTC3          | SwDA           |
|----------------|----------------|----------------|----------------|
| Our model      | 93.57±.30      | 92.66±.30*     | 56.97±.46*     |
| Global encoder [9] | 93.42±.33      | 91.94±.42      | 56.75±.31      |
| Local gating   | 93.41±.29      | 91.91±.33      | 56.71±.40      |
| Local concat   | 93.23±.40      | 91.70±.51      | 56.20±.48      |

The effects of pitch and energy features: Table 4 shows the effects of pitch and energy features when training our best-performing model. Specifically, we investigate the performance when removing the energy feature group and when removing the pitch feature group. We observe pitch features are more critical than energy features for our proposed model. For example, the accuracy of our proposed model drops almost 1% in the absolute E2E accuracy for SwDA when pitch features are absent, whereas the accuracy of our proposed model drops only 0.6% when energy features are absent.

\(^3\)Note that in the case of Local concat, the architecture collapses into a set of Bi-LSTM layers (i.e., without global prosodic fusion and without any gating), and its inputs only consist of the concatenation of LFBEs and prosody extractor outputs, frame by frame. In the case of Local gating, the right portion of the architecture in Fig.1 (i.e., without global prosodic fusion) is not activated. In the case of Baseline, the architecture receives only LFBEs features as inputs.

Table 4. Effect of different prosodic information.

|                | DSTC2          | DSTC3          | SwDA           |
|----------------|----------------|----------------|----------------|
| w/o energy     | 93.37±.12      | 92.53±.24      | 56.38±.49      |
| w/o pitch      | 93.30±.28      | 92.25±.27      | 55.99±.27      |

DA label-wise analysis: Fig. 3 shows the DA label-wise accuracy and gating scores for our proposed model on the DSTC3 dataset. The ack-request gains the most improvement, with a 14.26% absolute increase in accuracy (see Fig. 3(a)). After listening to the audio, we found that the ack and request sequences are connected without any pause, with the ack consisting of only one word (e.g., okay). This finding is consistent with [20,21]’s linguistic observation where affirmative cue words such as okay can be distinguished by rising pitch. Our proposed gating mechanism was expected to solve complex situations, such as multiple dialogue acts, with one localized in a short portion of the utterance. To verify, we show the distributions of the global gating scores for affirm (the DA class where our model outperforms the base model and also contains mostly affirmative cue words such as yes) and ack-byethankyou (the DA class where our model and the base model perform similarly) in Figure 3(b) and Figure 3(c), respectively. The gating scores of affirm is mostly distributed in [0.00, 0.40], indicating that prosodic features contribute positively and help improve our model’s performance. In contrast, the scores of ack-byethankyou are mostly distributed in [-0.50, -0.1], suggesting that prosodic features contribute negatively and do not help the performance. This suggests the need of our gating mechanisms to correctly recognize DA labels.

5. CONCLUSION

In this work, we introduced a novel neural model architecture to incorporate prosodic features into an acoustic encoder for E2E DAC. We focused on pitch and energy features and integrated them at both local level and global level. Our experiments show that our proposed approach provides improvements over the state-of-the-art solutions. In the future, we plan to pave the way for integrating the proposed neural architecture with other prosody-related acoustic cues, such as speaking-rate.
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