**SpeechNet: a universal modularized model for speech processing tasks**

Yi-Chen Chen¹,², Po-Han Chi¹, Shu-wen Yang¹*, Kai-Wei Chang¹*, Jheng-hao Lin¹*, Sung-Feng Huang¹, Da-Rong Liu¹, Chi-Liang Liu¹, Cheng-Kuang Lee², Hung-yi Lee¹

¹National Taiwan University, Taiwan  ²NVIDIA AI Technology Center, NVIDIA

¹{f06942069,r08942074,r08944041,r09921048,r08922049,f06942045, f07942148,r07942083,hungyilee}@ntu.edu.tw  ²ckl@nvidia.com

**Abstract**

There is a wide variety of speech processing tasks ranging from extracting content information from speech signals to generating speech signals. For different tasks, model networks are usually designed and tuned separately. If a universal model can perform multiple speech processing tasks, some tasks might be improved with the related abilities learned from other tasks. The multi-task learning of a wide variety of speech processing tasks with a universal model has not been studied. This paper proposes a universal modularized model, SpeechNet, which treats all speech processing tasks into a speech/text input and speech/text output format. We select five essential speech processing tasks for multi-task learning experiments with SpeechNet. We show that SpeechNet learns all of the above tasks, and we further analyze which tasks can be improved by other tasks. SpeechNet is modularized and flexible for incorporating more modules, tasks, or training approaches in the future. We release the code and experimental settings to facilitate the research of modularized universal models and multi-task learning of speech processing tasks.

1 Introduction

There is a wide variety of speech processing tasks, for example, automatic speech recognition (ASR), speech enhancement (SE), speaker classification (SC), text-to-speech (TTS) synthesis, and voice conversion (VC), etc. These tasks involve different capabilities related to speech processing ranging from extracting content information from speech signals to generating speech signals. In literature, model networks are usually designed and tuned separately for different tasks, and each aims to expert a specific ability for processing speech. However, when we only focus on one task, we may ignore some useful abilities that can be shared across tasks to make the tasks better. Human can learn different speech tasks and transfer the knowledge of different abilities between tasks. Can we train a universal model that can learn all the different speech processing abilities jointly in one model?

In this paper, we propose SpeechNet, a universal model for various speech processing tasks. Inspired by T5 [Raffel et al., 2019], we treat all speech processing tasks as the format: a task that takes speech/text input and produces speech/text output. In SpeechNet, there are basic modules to handle different modalities, as illustrated in Figure 1 and introduced below:

- **Speech input**: We use Prosody Encoder, Speaker Encoder and Content Encoder to extract prosody, speaker and content embeddings from speech.
- **Speech output**: We use Audio Decoder to synthesize audio.

* contribute equally

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• Text input: We use Text Encoder to map the input text to the content embedding space (which is the same output space of Content Encoder).

• Text output: We use Text Decoder to produce text according to content embedding.

Most of the speech processing tasks can be done by concatenating the modules above, making multi-task learning (MTL) for a wide variety of speech processing tasks possible. It has been shown that the universal models trained to solve multiple tasks can benefit from multi-task learning (MTL) [Van denhende et al., 2020; Zhang and Yang, 2017; Ruder, 2017], improving the generalizability and performance of models in NLP and computer vision. During MTL, the tasks share the same modules, and the gradients computed from different objective functions of these tasks are accumulated to update the shared modules.

This paper shows that SpeechNet can simultaneously learn five common and important speech processing tasks: ASR, SE, SC, TTS, and VC. We conduct experiments with commonly used datasets for the five tasks. Based on the results of MTL, we know which combinations of speech tasks are effective. SpeechNet is modularized and flexible for incorporating more modules, tasks, and training criteria in the future. We release the code and experimental settings to facilitate the research of universal modularized models or MTL of speech processing tasks.

2 Related Work

It has been shown that a single deep learning model can jointly learn a number of large-scale tasks from multiple domains [Kaiser et al., 2017]. [McCann et al., 2018] proposes a model to solve ten tasks in natural language processing (NLP). The core idea of the T5 model [Raffel et al., 2019], a unified framework for a variety of text-based language problems, is to treat every text processing problem as a "text-to-text" problem, i.e., taking text as input and producing new text as output.

In the speech domain, some previous works train a model to solve two tasks or use an auxiliary task to improve the primary task’s performance. [Chen et al., 2015] studies SE and ASR. [Tjandra et al., 2017; Ren et al., 2019b] study the duality of ASR and TTS. Some papers [Jain et al., 2018; Chen et al., 2020] use SC to improve ASR. [Tang et al., 2016] studies ASR and SC. [Hsu et al., 2019; Jia et al., 2018] shows the effectiveness of SC to help TTS. [Zhang et al., 2019b] shows the performance of VC can be improved with text supervision. [Kinnunen et al., 2017] connects SC and VC. [Zhang et al., 2019c] jointly trains TTS and VC. [Zhang et al., 2019a] uses TTS and SC to improve VC.

However, in these works, models are designed for some specific speech processing tasks and not applicable for more speech processing tasks. Moreover, the rapid rate of progress and diversity of techniques also make it difficult to compare different algorithms, tease apart the effects of new contributions, and understand the effectiveness of learning multiple speech processing tasks with one model.

3 SpeechNet: a universal modularized model for speech processing tasks

Any speech processing task can be treated as taking speech or text as input or output. SpeechNet contains six core modules for speech and text, respectively, to handle different modalities. These six modules are introduced in Subsection 3.1. How to concatenate the modules to do the five tasks used in this paper is described in Subsection 3.2. At the end of this section, we discuss two problems of TTS and VC in this framework and further propose a modified version of SpeechNet by adding one additional module, Prosody Predictor, in Subsection 3.3.

3.1 Modules in SpeechNet

Here we discuss the detailed formulation of each module presented in Figure 1 respectively, while describing the model architecture details in Subsection 4.1.

2https://github.com/grtzsohalf/SpeechNet-codebase
3.1.1 Prosody Encoder: $E_P$

When speech $X = \{x_1, ..., x_T\}$ with frame length $T$ serves as the input, it can be passed through Prosody Encoder $E_P$ to obtain a frame-level prosody embedding vector sequence

$$V_p = E_P(X),$$

which contains all the speaker and prosody characteristics in speech.

3.1.2 Speaker Encoder: $E_S$

The prosody embedding vectors can be further passed through Speaker Encoder $E_S$ to obtain an utterance-level speaker embedding vector

$$v_s = E_S(V_p),$$

which represents the speaker characteristics in speech.

3.1.3 Content Encoder: $E_C$

The speech input can also be passed through Content Encoder $E_C$ to get a sequence of frame-level content embedding vectors

$$V_c = \{v_{c1}, ..., v_{cT'}\} = E_C(X),$$

which contain content information in speech. $T'$ is the length of content embedding vectors, which can be equal to the original frame length of speech $T$ or be shorter for more compact embeddings.

3.1.4 Audio Decoder: $D_A$

When the output is speech, Audio Decoder $D_A$ takes a sequence of prosody embeddings $V_p$ and a sequence of content embeddings $V_c$ as input and output the desired speech. Specifically, the content embedding is firstly transformed by Content Decoder $D_C$, concatenated with the prosody embeddings, and then passed into Merge Decoder $D_M$ to output the speech

$$X' = D_A(V_p, V_c) = D_M([V_p; D_C(V_c)]).$$
3.1.5 Text Encoder: $E_T$

When text $\mathbf{Y} = \{y_1, ..., y_L\}$ with length $L$ serves as input, it is firstly encoded into unit token vectors
\[
\mathbf{V}_u = \{v_{u_1}, ..., v_{u_L}\} = E_U(\mathbf{Y}),
\]
through Unit Encoder $E_U$.

The number of input text tokens is usually much smaller than the frame length of output speech. To match the content embedding encoded from text and speech, we need to predict the frame length of each unit token, and replicate the unit token vectors accordingly to obtain the frame-level content embedding vectors with the same length from speech. It is called the length regulation technique originally proposed in TTS [Ren et al., 2019a]. Specifically, we use Duration Predictor $DP$ to predict the frame lengths of each text units according to frame lengths through Length Regulator $LR$ to obtain frame-level content embedding vectors
\[
\mathbf{V}_c = \{v_{c_1}, ..., v_{c_T}\} = LR(\mathbf{V}_u, \mathbf{l}_u'),
\]
where $T = \sum_{i=1}^L l'_u_i$.

For example, if the text input sequence and corresponding unit token vectors are $\{a, b, c\}$, $\{v_a, v_b, v_c\}$ respectively and the predicted frame lengths $\{1, 2, 1\}$, the content embedding vectors are $\mathbf{V}_c = \{v_a, v_b, v_b, v_c\}$.

It is worth noting that although the speaker embedding vector $v_s$ is used during the generation of content embedding vectors, it is only used for duration prediction according to speaker characteristics and replication of text vectors. Therefore, each content embedding vector does not contain speaker information. Overall, the generation of content embedding vectors through Text Encoder $E_T$ can be described as
\[
\mathbf{V}_c = E_T(\mathbf{Y}, v_s) = LR(E_U(\mathbf{Y}), DP([E_U(\mathbf{Y}); v_s])).
\]

3.1.6 Text Decoder: $D_T$

When the output is text, Text Decoder $D_T$ takes the content embedding vectors as input and output the text sequence. In recent state-of-the-art sequence-to-sequence ASR models, two text sequences are decoded as output by two decoders: sequence-to-sequence (S2S) and connectionist temporal classification (CTC) decoders $D_{S2S}$ and $D_{CTC}$. During the inference, we can simply select the text with the better decoder during training.
\[
[Y'_{CTC}; Y'_{S2S}] = D_T(\mathbf{V}_c) = [D_{CTC}(\mathbf{V}_c); D_{S2S}(\mathbf{V}_c)].
\]

3.2 Five tasks for MTL

In this section, we describe how to combine the modules in SpeechNet into different speech tasks, which are also depicted in Figure 2.

3.2.1 Automatic Speech Recognition (ASR)

In ASR, the input is speech $\mathbf{X}$ and the output is the corresponding transcription text $Y'_{CTC}$ and $Y'_{S2S}$:
\[
[Y'_{CTC}; Y'_{S2S}] = D_T(E_C(\mathbf{X})).
\]

The objective function is similar to those used in previous works [Karita et al., 2019, Liu et al., 2019], which is a weighted sum of a S2S loss and a CTC loss:
\[
L_{ASR} = -\alpha_{ASR} \log P_{CTC}(Y'_{CTC}|\mathbf{X}) - (1 - \alpha_{ASR}) \log P_{S2S}(Y'_{S2S}|\mathbf{X}),
\]
where $P_{S2S}$ and $P_{CTC}$ are the S2S and CTC frame-wise posterior distributions of $Y'_{S2S}$ and $Y'_{CTC}$ given corresponding source $\mathbf{X}$ respectively, and $\alpha_{ASR}$ is a scalar hyperparameter.

In MTL, an auxiliary reconstruction objective function is also applied for aligning content vector space with other tasks:
\[
L_{\text{recon}} = \| D_{A}(E_P(\mathbf{X}), E_C(\mathbf{X})) - \mathbf{X} \|^2.
\]

The final loss for ASR is
\[
L_{ASR,\text{total}} = L_{ASR} + L_{\text{recon}}.
\]

[108x386]When the output is text, Text Decoder $D_T$ takes the content embedding vectors as input and output the text sequence. In recent state-of-the-art sequence-to-sequence ASR models, two text sequences are decoded as output by two decoders: sequence-to-sequence (S2S) and connectionist temporal classification (CTC) decoders $D_{S2S}$ and $D_{CTC}$. During the inference, we can simply select the text with the better decoder during training.
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[Y'_{CTC}; Y'_{S2S}] = D_T(\mathbf{V}_c) = [D_{CTC}(\mathbf{V}_c); D_{S2S}(\mathbf{V}_c)].
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\]
where $P_{S2S}$ and $P_{CTC}$ are the S2S and CTC frame-wise posterior distributions of $Y'_{S2S}$ and $Y'_{CTC}$ given corresponding source $\mathbf{X}$ respectively, and $\alpha_{ASR}$ is a scalar hyperparameter.

In MTL, an auxiliary reconstruction objective function is also applied for aligning content vector space with other tasks:
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L_{\text{recon}} = \| D_{A}(E_P(\mathbf{X}), E_C(\mathbf{X})) - \mathbf{X} \|^2.
\]

The final loss for ASR is
\[
L_{ASR,\text{total}} = L_{ASR} + L_{\text{recon}}.
\]
Figure 2: This figure shows how to combine the modules in SpeechNet into five different speech tasks. Each module block in this figure shares the same color and index in Figure 1.

3.2.2 Speech Enhancement (SE)

In SE, the model takes noisy speech as input and outputs clean speech. Here we encode the input noisy speech $X_{\text{noisy}}$ into two parts, prosody embeddings and content embeddings, and decode back the denoised speech $X'$:

$$X' = D_A(E_P(X_{\text{noisy}}), E_C(X_{\text{noisy}})).$$  \hspace{1cm} (14)

The objective function is the mean absolute error (MAE) between the predicted and clean speech, $X'$ and $X_{\text{clean}}$, for more sensitivity to noise than mean square error (MSE):

$$L_{SE} = |X' - X_{\text{clean}}|. $$  \hspace{1cm} (15)

3.2.3 Speaker Classification (SC)

In SC, the model takes speech as input and outputs the speaker identity. Here we encode the input speech $X$ into a speaker embedding vector, and use a speaker classifier $C_S$ to recognize the speaker $S'$:

$$S' = C_S(E_S(E_P(X))).$$  \hspace{1cm} (16)

The objective function is the cross entropy loss with regard to speaker labels:

$$L_{SC} = -\log P(S'|X).$$  \hspace{1cm} (17)

3.2.4 Text-to-speech Synthesis (TTS)

In TTS, we want to output a speech $X'$ according to a text sequence $Y$ conditioned on speaker characteristics. Specifically, we maintain a trainable speaker embedding table, where every speaker

$$X' = TTS(E_T(Y)|E_S(X)).$$
We point out the issues of TTS and VC in Subsubsections 3.2.4 and 3.2.5. Here we address them.

There are two problems with this setting. Firstly, during training, there is no additional constraint, so the objective function in training is the sum of (a) the mean square error (MSE) between the predicted and target speech $X'$ and $X$, (b) the MAE between the logarithms of predicted and original frame durations of text units, $\log(l(u)')$ and $\log(l(u))$ and (c) $L_{\text{speaker}}$.

$$L_{\text{TTS}} = \|X' - X\|^2 + |\log(l(u)') - \log(l(u))| + L_{\text{speaker}}.$$  \hspace{1cm} (20)

There are two problems with this setting. Firstly, during training, there is no additional constraint, so Prosody Encoder and Audio Decoder alone may become an autoencoder, and the content embeddings can be ignored. Secondly, during inference, since the target speech is not available as input of Prosody Encoder, the input speech $X$ has to be any other speech sentence uttered by the same speaker. However, the prosody of a speech is closely related to the content and duration of the speech. Because the prosodies of input speech of Prosody Encoder and target speech do not match, the generated speech cannot be produced well. In Subsection [3.3] we will address these two issues.

### 3.2.5 Voice Conversion (VC)

In VC, we try to convert the voice of an audio clip from one speaker to another while preserving the content. Specifically, we input two speech utterances $X_1$ and $X_2$ with the same content but different speakers, and output the converted speech utterance $X'_{12}$ with the content of $X_1$ and speaker characteristics of $X_2$.

$$X'_{12} = D_A(E_P(X_2), E_C(X_1)).$$  \hspace{1cm} (21)

Besides, to make the training more stable and easier, we also train the network to reconstruct the original utterances $X_1$ and $X_2$:

$$X'_1 = D_A(E_P(X_1), E_C(X_1)).$$  \hspace{1cm} (22)

$$X'_2 = D_A(E_P(X_2), E_C(X_2)).$$  \hspace{1cm} (23)

The objective function is the sum of MSE losses of conversion and reconstruction:

$$L_{\text{VC}} = \|X'_{12} - X_2\|^2 + \|X'_1 - X_1\|^2 + \|X'_2 - X_2\|^2.$$  \hspace{1cm} (24)

During inference of this setting, since the target converted speech is not available as input of Prosody Encoder, the input speech $X_2$ has to be any other speech sentence uttered by the same speaker. Similar to TTS, because the prosodies of input speech of Prosody Encoder and target converted speech do not match, the generated speech cannot be produced well. In Subsection [3.3] we will address this issue.

### 3.3 Adding one more module for TTS and VC: Prosody Predictor

We point out the issues of TTS and VC in Subsubsections [3.2.4] and [3.2.5]. Here we address them by proposing a modified version of SpeechNet by simply adding one additional module, Prosody Predictor, to generate the estimated prosody embeddings of target speech according to content and speaker embeddings:

$$V_p' = P_P(V_c, v_s).$$  \hspace{1cm} (25)

During training, there is one additional loss to make the estimated prosody $V_p'$ as close as possible to the original target prosody $V_p$ generated by Prosody Encoder:

$$(\text{In TTS}) \quad L_{\text{prosody,TTS}} = \|E_P(X) - P_P(E_T(Y, v'_s), v'_s)\|^2.$$  \hspace{1cm} (26)
Then the Audio Decoder takes $V'_p$ as input in TTS and VC. The modified version of SpeechNet is shown in Figure 4 in Appendix.

With Prosody Predictor, during inference, the generation of speech does not need to rely on the prosody from the speech input. The overall TTS process becomes:

$$X' = D_A(P_P(E_T(Y, v'_s), v'_s), E_T(Y, v'_s)).$$

(28)

And the overall VC process becomes:

$$X'_{12} = D_A(P_P(E_C(X_1), E_S(E_P(X_2))), E_C(X_1)).$$

(29)

For the experiments in Section 5, we use SpeechNet with Prosody Predictor. We also present experiments with SpeechNet without Prosody Predictor in Appendix D.

4 Experimental setup

This section introduces the model architecture, input/output formats of data, datasets, and evaluation metrics used in this paper.

4.1 Model architecture

Transformers [Vaswani et al., 2017] have achieved state-of-the-art performances on many NLP tasks [Devlin et al., 2019, Wang et al., 2018]. More recently, many tasks in the speech domain started to use transformer-based models, such as ASR [Gulati et al., 2020, Dong et al., 2018, Karita et al., 2019], SE [Kim et al., 2020, Fu et al., 2020, Nicolson and Paliwal, 2020], SC [Katta et al., 2020, Safari and Hernando, 2020], TTS [Ren et al., 2020, Li et al., 2019, Zeng et al., 2020] and VC [Huang et al., 2020, Liu et al., 2020, Lin et al., 2020].

In this work, we adopt Conformer [Gulati et al., 2020] layers as the architectures for Prosody Encoder, Content Encoder, Audio Decoder and Prosody Predictor. The convolution blocks in Conformer make it empirically better than Transformer for speech data. Speaker Encoder is a self-attention pooling model [Lin et al., 2017, Zhu et al., 2018]. For Unit Encoder, Duration Predictor and Length Regulator in Text Encoder, we use similar Transformer-based architectures as those in FastSpeech 2 [Ren et al., 2020]. In the original FastSpeech 2, since it performs single-speaker TTS, no additional speaker embedding is required. In our SpeechNet, we concatenate the unit token vectors and speaker embedding vector as the input of Duration Predictor for the length regulation. Finally, the ordinary Transformer layers are adopted for S2S Decoder in Text Decoder, and CTC Decoder in Text Decoder is a single-layer fully-connected network. We insert 1D-convolution blocks right before Content Encoder for down-sampling. It is commonly used in ASR to obtain more compact content information [Gulati et al., 2020, Dong et al., 2018, Karita et al., 2019]. Accordingly, we apply a similar down-sampler on content embedding vectors produced by Text Encoder. We also use 1D-convolution blocks right after Prosody Predictor and Content Decoder in Audio Decoder for up-sampling. More implementation details about the hyperparameters, optimization and code are provided in Appendix A and released code.

4.2 Datasets and evaluation metrics

We use the commonly adopted dataset and evaluation metric for each task.

For ASR, LibriSpeech [Panayotov et al., 2015] is a corpus of read English speech from audiobooks of the LibriVox project. We perform ASR on the “train-clean-100” set for training, which contains 100-hour speech uttered by 251 speakers, and on the “test-clean” set for evaluation. For easier comparison in our experiments, we use greedy decoding and do not use beam-search decoding and additional language model rescoring during the inference. We measure the performance of ASR by the word error rate (WER).

For SE, Nonspeech [Hu and Wang, 2010] is a widely used noise dataset containing 100 types of noises. We choose LibriSpeech [Panayotov et al., 2015] as clean speech and randomly augment with noises from Nonspeech with various SNRs to create paired data for both training and testing. During the training stage, the “train-clean-100” set is augmented with SNR $\in \{3, 6, 9\}$, while in
the testing stage, the “test-clean” set is augmented with $\text{SNR} \in \{-8, -6, -4, -2, 0, 2, 4, 6, 8\}$, providing a more severe condition to test whether the model can generalize. For evaluation, we report SISR, PESQ [Rix et al., 2001], and STOI [Taal et al., 2010]. The first one measures the scale-invariant signal-to-distortion ratio, and the others align well with human’s perspective. We select the checkpoint of the best SISR on validation set for testing.

For SC, VoxCeleb1 [Nagrani et al., 2017] contains speech uttered by 1,251 celebrities extracted from videos uploaded to YouTube. We take 100 speakers from the official training and testing sets in this paper. The speaker classification accuracy is used as the evaluation metric of SC.

For TTS, LibriTTS [Zen et al., 2019] is a multi-speaker English corpus of read English speech from the audiobooks of the LibriVox project. Utterances with significant background noise are excluded in LibriTTS. Montreal Forced Aligner [McAuliffe et al., 2017] is used to obtain the durations of phonemes. We randomly select 200 utterances from the “train-clean-100” set for testing and the remaining ones for training. The MSE between the output and groundtruth mel-spectrograms serves as the evaluation metric of TTS.

For VC, CMU Arctic [Kominek and Black, 2004] is a corpus which consists of speech utterances by 18 speakers recorded under studio conditions. Every speaker utters the same set of sentences. In this paper, 1,133 pairs of data are selected as testing data, and the remaining are for training. Each training instance is a pair of speech utterances by different speakers. The MSE between the output and groundtruth mel-spectrograms serves as the evaluation metric of VC.

For further evaluation of TTS and VC, we apply a linear transformation to recover linear-scale spectrograms and the Griffin-Lim vocoder [Griffin and Lim, 1984] to convert spectrograms back to wav files for listening.

For all speech, we use 16kHz sampling rate and extract the 80-dim mel-spectrogram features with 25 ms window size and 10 ms hop size. Then we add the first- and second-order derivatives and apply the cepstral mean and variance normalization (CMVN) commonly used for ASR and SC in previous works. The text input units for TTS are phonemes, and the output text units for ASR are subword units by the Byte Pair Encoding (BPE) [Sennrich et al., 2016], so the cross entropy loss is computed on the subword units. More details about the datasets are provided in Appendix B.

## 5 Experiments

We conduct single-task, two-task, and five-task learning experiments with the five tasks described in Subsection 3.2. Moreover, We experiment with two popular optimization strategies for MTL, “AutoLoss” and “PCGrad”, which are described in Appendix C for all of the two-task learning experiments. We also have the ablation study of two optimization strategies for five-task learning.

### 5.1 Single-task and two-task learning results

The single-task and two-task experiment results are shown in Table 1. Each column shows the evaluation performance with a specific metric of a task. The first row is the name of the evaluation task, and the second row is the evaluation metric. The down-/up-arrow beside the evaluation metric means the better performance results in lower/higher numbers of that metric. The diagonal cells with pink shadow are the single-task results. The off-diagonal cells represent the results of joint training with a specific auxiliary task. The best number on each metric is highlighted with bold font. If the numbers of multi-task are better than the single-task ones, the numbers are underlined.

We also plot an "improvement graph" based on two-task learning results, as shown in Figure, to illustrate the beneficial relationship between all task pairs. For example, if the model trained with ASR and SE improves the ASR WER compared to single-task ASR, we connect a directed edge from SE to ASR to denote the former benefits the latter.

We can observe ASR can be improved by all of the other tasks in two-task learning from the results. It indicates the related information provided by the other tasks can help Content Encoder to generate content embeddings for Text Decoder to produce text transcriptions. SE is improved slightly by ASR.

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3The columns are for the evaluated tasks, while the rows for the auxiliary tasks
Table 1: The results of single-task (pink cells) and two-task learning of five tasks.

| Auxiliary | ASR | SE | SC | TTS | VC |
|-----------|-----|----|----|-----|----|
|           | WER | PESQ | SISDR | STOI | ACC | MSE | MSE |
| ASR       | 0.329 | 2.46 | 5.62 | 0.880 | 0.746 | 3.06 | 5.93 |
| SE        | 0.320 | 2.44 | 5.90 | 0.877 | 0.820 | 3.08 | 6.06 |
| SC        | 0.307 | 2.15 | 4.02 | 0.850 | 0.860 | 2.98 | 6.04 |
| TTS       | 0.322 | 2.29 | 4.96 | 0.865 | **0.879** | 2.94 | 6.02 |
| VC        | 0.316 | 2.02 | 4.80 | 0.847 | 0.703 | 3.57 | 5.95 |

Table 2: The ablation study of two optimization strategies with five-task learning of five tasks.

| Optim Strategy  | ASR | SE | SC | TTS | VC |
|-----------------|-----|----|----|-----|----|
|                 | WER | PESQ | SISDR | STOI | ACC | MSE | MSE |
| AutoLoss + PCGrad | 0.511 | 1.99 | 3.71 | 0.837 | 0.451 | 3.36 | 6.01 |
| AutoLoss        | 0.600 | 2.04 | 3.68 | 0.833 | 0.101 | 3.26 | 5.88 |
| PCGrad          | 0.839 | 2.00 | 3.91 | 0.838 | 0.466 | 3.19 | 5.96 |
| No Strategy     | 0.538 | 2.12 | 3.82 | 0.838 | 0.044 | 3.18 | 5.86 |

in terms of the PESQ and STOI metrics. The performance of SC is improved with the aid of TTS. VC is also slightly improved by ASR.

5.2 Five-task learning results and ablation study of optimization strategies

The ablation study of two optimization strategies with five-task learning is shown in Table 2. The optimization of five-task learning is much more difficult than single-task or two-task learning, as we can see, all of the performances degrade except for VC. Specifically, without PCGrad strategy, i.e. “AutoLoss” and “No Strategy” in the Table, SC cannot even be learned effectively. However, VC can be improved in these cases compared to single-task learning. With only “PCGrad” strategy, ASR performs the worst. The model can learn all of the tasks only when using both AutoLoss and PCGrad strategies. But the results are still worse than single-task learning. This ablation study shows that optimization strategies influence the training of MTL significantly. The two popular MTL optimization strategies in our experiments cannot help five-task learning outperform single-task learning.

5.3 Analysis and discussion

In this paper, we exhibit five important speech processing tasks that can be learned with SpeechNet and conduct experiments of single-task, two-task, and five-task learning with two popular MTL optimization strategies. However, many important research directions can be further extended from SpeechNet. (1) As shown in the last subsection, suitable optimization strategies for MTL of speech processing tasks are important and desirable. SpeechNet can be a testbed for developing MTL optimization strategies on speech processing tasks. (2) Besides MTL, other training schemes involving multiple tasks can be investigated in the future, such as transfer learning or meta learning. Different sizes of data are also worth investigating. (3) SpeechNet is flexible and easy to modify or add new modules. Therefore many other speech or text processing tasks can be joined for research. For example, in our experiment results, ASR benefits from MTL the most. It may indicate other speech processing tasks that take speech input and produce text output can also benefit from MTL with SpeechNet, such as speech translation or multilingual speech recognition.
6 Conclusion

In this paper, we propose a universal modularized model for speech processing tasks. We select five common and important tasks for multi-task learning experiments. The code and settings used in this paper are released to facilitate the research of modularized universal models or multi-task learning of speech processing tasks.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We point out the optimization difficulty of MTL in Section 5.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] Please see Section 4, Section 5, Appendix and Supplementary Materials.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Please see Section 4, Section 5, Appendix and Supplementary Materials.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Please see Appendix and Supplementary Materials.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] Please see Subsection 4.2.
   (b) Did you mention the license of the assets? [Yes] Please see Appendix and Supplementary Materials.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] We release the code of SpeechNet. Please see Appendix and Supplementary Materials.
   (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]
The modified architecture of SpeechNet by adding Prosody Predictor.

A Implementation details

The batch size of each task is 16. We adopt AdamW optimizer [Loshchilov and Hutter, 2018] with learning rate 3.0e-4, epsilon 1.0e-12 and betas [0.9, 0.999]. The dropout rate is set to 0.1 except for the dropout rate 0.5 in Duration Predictor in Text Encoder. All the model parameters have decaying factor 0.01 except for those with names containing "bias", "norm-ff.weight", "norm-mha.weight", "norm-conv.weight" and "norm-final.weight". The numbers of Conformer layers in each module are: Content Encoder 6, Speaker Encoder 3, Content Decoder in Audio Decoder 3, Merge Decoder in Audio Decoder 3, Unit Encoder in Text Encoder 4 and S2S Decoder in Text Decoder 4. The CNN down- and up-samplers have 2 1d-convolution blocks with sample rate 4. The $\alpha$ for ASR in Equation 11 is 0.3. The $\sigma$’s for the multi-task objective loss are initialized as 1.

The hidden dimension size is 256, and the linear unit size is 1024. The head number is 4 except for the head number 2 in Unit Encoder in Text Encoder. We use a linear learning rate warmup with 10000 steps and a linear decay with 100000 steps. For more details, please refer to the config file “SpeechNet/config/libri/conformer_256_AdamW.yaml” in Supplementary Materials.

All the experiments are conducted on NVIDIA V100 GPUs. Each trial requires 2 GPUs with memory size 32GB.

B Details of datasets

The licenses of datasets used in this paper are stated as follows: LibriSpeech, VoxCeleb1 and LibriTTS are used under CC BY 4.0. CMU Arctic is used under the license, “Carnegie Mellon University, Copyright (c) 2003, All Rights Reserved. Permission to use, copy, modify, and license this software and its documentation for any purpose, is hereby granted without fee, subject to the following conditions: 1. The code must retain the above copyright notice, this list of conditions and the following disclaimer. 2. Any modifications must be clearly marked as such. 3. Original authors’ names are not deleted. THE AUTHORS OF THIS WORK DISCLAIM ALL WARRANTIES WITH REGARD TO THIS SOFTWARE, INCLUDING ALL IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS. IN NO EVENT SHALL THE AUTHORS BE LIABLE FOR ANY SPECIAL, INDIRECT OR CONSEQUENTIAL DAMAGES OR ANY DAMAGES WHATSOEVER RESULTING FROM LOSS OF USE, DATA OR PROFITS, WHETHER IN AN ACTION OF CONTRACT, NEGLIGENCE OR OTHER TORTIOUS ACTION, ARISING OUT OF OR IN CONNECTION WITH THE USE OR PERFORMANCE OF THIS SOFTWARE."
The 100 speakers in VoxCeleb1 selected for SC are from id10001 to id10099, provided in “SpeechNet/corpus/VoxCeleb1-100/veri_test_class.txt” in Supplementary Materials. The TTS testing set is provided in “SpeechNet/corpus/LibriTTS-100/val.txt” in Supplementary Materials. The testing sets in CMU Arctic are aew and slt.

C Optimization Strategies

During MTL, some tasks may share some modules, and the gradients computed from different objective functions of these tasks are accumulated to update the shared modules. However, there are two problems: (1) how to balance these objective functions with different types and scales, and (2) how to deal with conflicting gradients of parameters between different tasks. We experiment with two popular MTL optimization strategies, tackling these two problems respectively.

C.1 Loss balancing for MTL

We adopt an automatic loss balancing technique (which we denote as “AutoLoss” in the experiments) based on the task-dependent data-independent uncertainty measurement of each task [Kendall et al., 2018]. It has been shown effective to capture the relative confidence between tasks and learn loss weights for tasks.

The overall objective function of \( n \) objective functions can be defined as:

\[
\sum_{i=1}^{n} L'_i = \sum_{i=1}^{n} \left( \frac{1}{\sigma_i^2} L_i + \log \sigma_i \right),
\]

(30)

where \( L'_i \) is the scaled version of the original loss \( L_i \) with the introduction of learnable scalar variables \( \sigma \)’s.

C.2 Eliminating gradient conflicts in MTL

PCGrad [Yu et al., 2020] is a gradient manipulation approach to handle conflicting gradients on the same set of parameters. Specifically, for parameters in every layer of the model, we perform PCGrad as illustrated in Algorithm 1. If the gradients between two tasks have negative cosine similarity, the gradient of one task is projected onto the normal plane of the gradient of the other task. In this way, the conflicting component of the gradient no longer exists.

**Algorithm 1: PCGrad Update [Yu et al., 2020]**

**Input:** Model parameters \( \theta \), task minibatch \( B = \{T_k\} \)

\( g_k \leftarrow \nabla_\theta L_k(\theta) \quad \forall k \)

\( g_{k}^{PC} \leftarrow g_k \quad \forall k \)

for \( T_i \in B \) do

for \( T_j \sim B \setminus T_i \) in random order do

if \( g_{i}^{PC} \cdot g_{j} < 0 \) then

\( g_{i}^{PC} = g_{i}^{PC} - \frac{g_{i}^{PC} \cdot g_{j}}{\|g_{j}\|^2} g_{j} \)

end

end

Output: \( \Delta \theta = g_{PC} = \sum i g_{i}^{PC} \)
D Experiments with SpeechNet without Prosody Predictor

In this section, we show the single-task learning results of TTS and VC using SpeechNet without Prosody Predictor, i.e., using the training and testing procedures described in Subsubsections 3.2.4 and 3.2.5. The results are shown in Table 3. We can observe that the testing MSEs cannot be decreased because the prosodies of input speech of Prosody Encoder and target speech do not match. It validates our motivation and the necessity to generate the estimated prosody of target speech based on content and speaker embeddings.

Table 3: The results of single-task learning of TTS and VC with SpeechNet without Prosody Predictor.

|       | TTS | VC |
|-------|-----|----|
| MSE   | 23.21 | 16.07 |

E Randomly selected TTS and VC samples using SpeechNet with Prosody Predictor

For subjective evaluation of TTS and VC using SpeechNet with Prosody Predictor, we randomly select a few generated wav file examples in “SpeechNet/TTS_samples” and “SpeechNet/VC_samples” in Supplementary Materials.

The results in Table 1 and randomly selected samples in Supplementary Materials show that our proposed SpeechNet with Prosody Predictor can successfully learn TTS and VC.