Adversarial Contrastive Predictive Coding for Unsupervised Learning of Disentangled Representations

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Abstract
In this work we tackle disentanglement of speaker and content related variations in speech signals. We propose a fully convolutional variational autoencoder employing two encoders: a content encoder and a speaker encoder. To foster disentanglement we propose adversarial contrastive predictive coding. This new disentanglement method does neither need parallel data nor any supervision, not even speaker labels. With successful disentanglement the model is able to perform voice conversion by recombining content and speaker attributes. Due to the speaker encoder which learns to extract speaker traits from an audio signal, the proposed model not only provides meaningful speaker embeddings but is also able to perform zero-shot voice conversion, i.e. with previously unseen source and target speakers. Compared to state-of-the-art disentanglement approaches we show competitive disentanglement and voice conversion performance for speakers seen during training and superior performance for unseen speakers.

Index Terms: disentanglement, voice conversion, unsupervised

1. Introduction
Disentangling factors of variation in data recently attracted increased interest for many modalities. Learning disentangled representations with no or only little supervision is a promising approach to make use of the vast amounts of unannotated data available in the world. Disentangled representations are considered useful in two ways. First, they can improve performance for various downstream tasks, which are learned on a small amount of labeled data. In particular, it can yield improved robustness against train-test mismatches if the factors which are informative about the task can be successfully disentangled from the variations caused by a domain shift. Second, in a disentangled representation certain factors can be modified while keeping the rest fixed, e.g., changing the lighting in an image without changing the content. For the purpose of learning disentangled representations from unannotated data it is required that the disentangling approach requires no or only little supervision and scales to large databases.

In this paper we tackle disentanglement of speech signals such that we separate speaker attributes and content attributes into two disjoint representations. Successful disentanglement not only provides a speaker independent representation of the linguistic content of a sentence but also allows to perform voice conversion by exchanging the speaker attributes.

Here two encoders are employed to extract a speaker embedding and sequence of content embeddings, respectively, which are jointly decoded to reconstruct the input signal. To encourage the content embeddings to be speaker invariant we propose an adversarial regularization based on contrastive predictive coding (CPC) [1], which is completely unsupervised. The basic idea is that speaker and content induced variations in the signal can be disentangled according to the mutual information between a current and a future observation, which is mainly the speaker information. Hence, our proposed model can be learned from raw non-parallel speech data requiring neither content labels nor speaker labels. We further suggest to use vocal tract length perturbation (VTLP) [2] to support disentanglement and show its efficiency for the proposed adversarial training. Due to the speaker encoder the model learns to extract speaker representations from audio rather than relying on one-hot speaker representations as used in most other works. Therefore, our model is also able to perform zero-shot many-to-many voice conversion, i.e. for unknown source and target speakers.

2. Related Work
There are many works focusing on unsupervised disentanglement of all latent factors of the generative model [3, 4, 5]. Those works are mainly applied to toy-like image data sets, e.g., 2D shapes [6], where the generating factors are well defined. Other works tackle disentanglement of a single supervised factor using an adversarial classifier in the latent space [7,8].

While the above works targeted other modalities, there are several recent works tackling disentangled speech representation learning from non-parallel data. Many works, e.g. [9,10,11,12], focus on extracting a speaker independent content representation, while representing the speaker identity as a one-hot encoding. Others also use speaker specific decoders [13,14]. Therefore, these works can neither be used to extract speaker embeddings nor to perform voice conversion to an unknown target speaker. Also speaker supervision is required.

Unsupervised approaches to speaker-content disentanglement are proposed in [15, 16, 17]. None of these works use an explicit disentanglement objective as proposed in this paper. The authors of [16] propose to encourage disentanglement by using instance normalization in the content encoder, which normalizes, to some extend, static signal properties such as speaker attributes. The AutoVC model [17] relies on a carefully tuned bottleneck such that ideally all content information can be stored in the content embedding but none of the speaker-related information. In [18] the AutoVC model was extended to an unsupervised disentanglement of timbre, pitch, rhythm and content. The factorized hierarchical variational autoencoder (FH-VAE) proposed in [19, 20] and StarGANs [21, 22] that directly learn a mapping function from source to target speech without relying on disentanglement.
3. Factorized Variational Autoencoder

To learn disentangled representations of speaker and content we propose a fully convolutional variational autoencoder (VAE) which employs two encoders: a content encoder to encode content information from an input $X_1$ into a sequence of content embeddings $Z=[z_1, \ldots, z_T]$, and a speaker encoder to extract speaker traits from an input $X_2$ into a speaker embedding $s$. During training $X_2$ is required to be from the same speaker as $X_1$. Note that it could also be the same signal: $X_2=X_1$. Then $Z$ and $s$ are expected to jointly allow reconstruction of the input signal $X_1$ which is trained by minimizing the mean squared error (MSE):

$$L_{\text{rec}} = ||X_1 - \hat{X}_1||^2_2,$$

where $\hat{X}_1$ denotes the reconstruction. If content and speaker can be successfully disentangled, voice conversion can be performed at test-time by presenting a signal $X_2$ from the target speaker. The proposed VAE structure is illustrated in Fig. 1.

As input signal representation $X$ we extract $F=80$ log-mel-band energy features for each frame of a short-time Fourier transform (STFT) using an audio sample rate of 16 kHz, a frame length of 30 ms and a hop-size of 10 ms. Each log-mel-band is normalized by subtracting the global mean and dividing by the global standard deviation, which are determined on the training set. Encoders and decoder are one-dimensional convolutional neural networks (CNNs) as shown in Fig. 2. The speaker encoder uses global average pooling over time at the CNNs output to obtain a single speaker embedding $s$. The concatenated embeddings $[z_1, \ldots, z_T]$ are then forwarded through the decoder network. Do note that the embedding rate does not necessarily have to match the frame rate. We set the kernel size and stride of the encoders output layer to $K=c=S_0$, with downsampling being performed when $S_0>1$. The input layer of the decoder maps the embeddings back to frame rate ($K=S_0=S_0$). If not stated otherwise, however, we do not perform downsampling ($S_0=1$).

Naturally the proposed model would tend to access all the required signal information through $Z$ while ignoring $s$, because $X_1$, the input to the content encoder, is the signal to be reconstructed. Even if $X_2=X_1$ it is still easier to encode all required information into $Z$ as there is usually much more capacity in a sequence of embeddings $Z$ than in a single embedding $s$. Therefore, the challenge is to prevent the model from also encoding speaker properties of the signal into $Z$ but make the embedding access it through $s$.

The usage of VAEs have shown to improve disentanglement [9]. Here $z_t$ is interpreted as a stochastic variable with prior $p(z_t)=N(z_t,0,1)$ and an approximate posterior $q(z_t)=N(z_t; \mu_t, \sigma^2)$, with the content encoder providing $\mu_t$ and $\sigma^2$. The content embeddings that are forwarded into the decoder are sampled as $z_t \sim q(z_t)$ using the reparameterization trick [23] during training, while being set to $z_t=\mu_t$ in test mode. The KL regularization

$$L_{\text{kl}} = \sum_{t=1}^{T} \text{KL}(q(z_t)||p(z_t))$$

that is added to the VAE objective

$$L_{\text{vae}} = L_{\text{rec}} + \beta L_{\text{kl}}$$

(1)

prefers the posterior $q(z_t)$ to be uninformative which helps encoding information into $s$ rather than $Z$. However, it also harms reconstruction which is why we only choose a small value $\beta=10^{-3}$ here.

- **Figure 1**: Factorized VAE. Blue boxes are training objectives.

- **Figure 2**: CNN Architectures: Conv1d ($C, K, S$) denotes a one-dimensional convolutional layer with $C$ output channels, kernel size of $K$ and striding of $S$. Conv1d$^2$ denotes a one-dimensional transposed convolutional layer.

While in the subsequent sections adversarial regularizations are presented to enforce disentanglement, two simple measures to encourage the model to access speaker information via the speaker encoder are the following. First, during training we distort the speaker properties in the input of the content encoder using VTLP [2] yielding the distorted signal $X'_1$. VTLP was originally proposed to increase speaker variability while training speech recognition systems. For this purpose, the center bins of the mel-filter-banks are randomly remapped using a piece-wise linear warping function:

$$f = \begin{cases} \alpha f, & f \leq f_u \frac{\min(o_1)}{\alpha} \\ f_{\text{max}} + \frac{f_{\text{max}} - f_{\text{min}}(o_1)}{f_u - f_{\text{min}}(o_1)} (f - f_{\text{max}}), & \text{otherwise} \end{cases}$$

with warping factor $\alpha \sim \text{LogUniform}(0.8, 1.25)$ and boundary frequency $f_u \sim \text{Uniform}(0.6, 0.8)$.

Second, we perform instance normalization [24] of the content encoder input, i.e. each log-mel-band is locally, i.e. for each input signal separately, normalized to zero mean and unit variance, yielding the content encoder input $X'_1$. The signal that has to be reconstructed, however, is the undistorted and globally-only normalized signal $X_1$. We perform instance normalization also in the hidden layers of the content encoder instead of batch normalization as used in the speaker encoder and the decoder. Instance normalization has been frequently used for speech recognition [25] suggesting that it retains the content information while normalizing static properties of the signal. It also has been found useful to encourage speaker-content disentanglement [10].
4. Adversarial Speaker Classifier

To enforce disentanglement the authors of [12] suggested to employ a jointly trained adversarial speaker classifier on the content embeddings. The speaker classifier is trained to classify the speaker identity from a segment of content embedding means \( M_\ell = [\mu_\ell, \ldots, \mu_{\ell+l}] \), where \( l \) and \( r \) denote the left and right context of the classifier. The training objective is the cross entropy loss:

\[
L_{\text{clf}} = - \sum_{t=1}^{T} y_t \log(\hat{y}_t)
\]

with \( y \) denoting the one-hot encoded speaker identity and \( \hat{y}_t = f_{\text{clf}}(M_\ell) \) the classifiers prediction. By adding the negative cross entropy to the VAE objective:

\[
L_{\text{vae}} = L_{\text{rec}} + \beta L_{\text{kld}} - \lambda L_{\text{clf}}
\]

the content encoder is trained to not allow such classification which requires to drop information revealing the speaker identity. This ideally does not harm reconstruction as speaker information can be encoded in the speaker embedding.

The classifier has the same architecture as the encoder:

\[
f_{\text{clf}} = \text{Enc}(D_y, 1) \text{ with } D_y = \# \text{speakers}.
\]

5. Adversarial Contrastive Predictive Coding

The adversarial speaker classifier has some severe disadvantages. First, although it does not require text annotations it still requires speaker annotations. Second, it does not scale to large unbalanced databases with a huge number of speakers as the classification task itself becomes very uncertain such that no useful adversarial gradients can be obtained.

Therefore, in this work we propose adversarial CPC as an alternative which is fully unsupervised and independent of the (unobserved) number of speakers. Hence, this approach has the potential to be scaled to large unlabeled databases.

CPC [1] aims at extracting the mutual information from segments \( M_\ell \) and \( M_{\ell+n} \), which have a certain temporal distance of \( n \) steps. For this purpose the segments are encoded into the embeddings \( h_\ell = f_{\text{cpc}}(M_\ell) \) and \( h_{\ell+n} = f_{\text{cpc}}(M_{\ell+n}) \) such that \( h_\ell \) allows prediction of the future embedding \( h_{\ell+n} \):

\[
h_{\ell+n} = g_n(h_\ell)
\]

with \( g_n(\cdot) \) denoting the projection head that predicts \( n \) steps ahead. The CPC model is trained using a contrastive loss [1]:

\[
L_{\text{cpc}} = - \sum_{t=1}^{T} \log(\frac{\exp(h_t^T h_\ell)}{\sum_{h_i \in B_\ell} \exp(h_i^T h_\ell)})
\]

with \( B_\ell \) denoting the set of candidate embeddings \( \{h_i^{(b)} | 1 \leq b \leq B \} \) in the mini-batch of size \( B \). Note that Eq. (3) equals a cross entropy loss including a softmax, where the logits are given as the inner product of the predicted embedding \( h_\ell \) and the candidate embeddings \( h_i \in B_\ell \). Hence, for a given segment \( M_\ell \), the model is essentially being trained to be able to correctly classify the true future segment out of a couple of candidates. The number of steps \( n \) that the model predicts into the future controls the kind of mutual information that is encoded. If the segments are very close to each other the model probably learns to recognize content attributes, e.g., whether the segments are parts of the same acoustic unit. If the segments are further apart, however, the mutual information the model has to recognize are primarily the static properties such as speaker attributes.

For our purpose we therefore choose \( n=100 \) which corresponds to a segment distance of 1 s. To prevent the model from learning some kind of language model, the projection head \( g_n(\cdot) \) is chosen to be the identity: \( h_{\ell+n} = h_\ell \). Hence, the CPC encoder \( f_{\text{cpc}}(\cdot) \) is trained to extract similar embeddings for segments from the same utterance and orthogonal embeddings for segments from different utterances.

By adding the negative CPC loss to the VAE objective:

\[
L_{\text{vae}} = L_{\text{rec}} + \beta L_{\text{kld}} - \lambda L_{\text{cpc}}
\]

the content encoder is trained to remove mutual information between segments which are 1 s apart (or further) which prevents the content encoder from encoding speaker attributes and other static properties.

The CPC encoder has the same architecture as the VAE encoder: \( f_{\text{cpc}} = \text{Enc}(D_h, 1) \) with \( D_h = 256 \).

6. Experiments

Experiments are performed on the Librispeech corpus [26]. Here, the train-clean-100 subset is considered for training the VAE models. This set contains \( \approx 100 \) h of clean speech from 251 speakers. This subset is randomly split into 80 \% for training, 10 \% for validation and 10 \% for testing with each set containing utterances from all 251 speakers. This subset is termed clean-seen-speakers in the following.

For evaluation purposes a second dataset is composed of speakers, which have not been seen by the VAE models during training. This subset is therefore called clean-unseen-speakers here and consists of the utterances from 251 randomly sampled speakers from the train-clean-360 subset. This subset is again split into 80 \% and 10 \% for training and validation (of classifiers used for evaluation) and 10 \% for testing.

VAE models are trained on the training set for 10\(^5\) update steps using mini-batches of 48 segments with a segment length between 2 s and 3 s. When \( X_2 \neq X_1 \) during training, segments between 4 s and 6 s are split into two which ensures to have two segments from the same speaker without requiring supervision. Adam [27] is used for optimization with a learning rate of 5 \( \times 10^{-4} \) and gradient clipping is applied using thresholds of 10, 20 and 2 for encoder, decoder and adversarial networks, respectively. For all models content and speaker embedding sizes of \( D_y = 32 \) and \( D_h = 128 \) are used. After training, the checkpoint which achieves lowest reconstruction error on the validation portion is used to report results on the test portion.

Three different state-of-the-art disentanglement approaches are investigated and compared:

1) Information bottleneck [17]: By reducing the temporal resolution of the content embeddings, there is ideally just enough capacity to encode content information, while speaker information has to be encoded in the speaker embedding. Here a downsampling factor of \( S_{da}=32 \) is used. This is roughly the same bottleneck as suggested in [17]. We also tested wider and narrower bottlenecks by tuning \( S_{da} \) and \( D_a \) but found \( S_{da}=D_a=32 \) to have the best balance between disentanglement and reconstruction performance. The model is trained using the objective (1) without further regularizations.

2) Adversarial Speaker Classifier as described in Sec. 4. The model is trained using the training objective (2) with \( \lambda = 1 \), which was found to give a good balance between disentanglement and reconstruction performance.

3) Our proposed adversarial CPC as described in Sec. 5. The model is trained using the training objective (4) with \( \lambda = 2 \).

To obtain better adversarial gradients, the adversarial networks of the two latter approaches are updated three times exclusively before each joint update of all parameters.

Performance is measured in two ways. First, voice conversion performance is evaluated, which indirectly mea-
ensures the achieved disentanglement. For that purpose a speaker classifier $f_{spk}^{X_1}=\text{Enc}(251, 5, 1)$ and a phone classifier $f_{phon}^{X_1}=\text{Enc}(40, 5, 1)$, which make predictions at frame rate, are trained on clean log-mel-spectrograms of the training set. We report the recognition accuracies of the classifiers on converted test-spectrograms and compare them to the accuracies on clean test-spectrograms. Similar evaluations have been made in [28, 29]. The achieved source- (lower is better) and target-speaker (higher is better) accuracies measure the quality of the speaker exchange while the source-phone accuracy (higher is better) measures the reconstruction of the source content. Converted test-spectrograms are generated from the list of clean test-spectrograms by combining it with a randomly shuffled version of itself to obtain tuples ($X_1, X_2$) which are then forwarded through the VAE. Readers are encouraged to listen to the prepared voice conversion example.

Second, post-hoc [12, 16, 17] speaker and phone classifiers $f_{spk}^{X_2}=\text{Dec}(251, S_{bs}, S_{as})$ and $f_{phon}^{X_2}=\text{Dec}(40, S_{bs}, S_{as})$ are trained on the clean-seen-speakers subset to classifier speaker and phones from the content embeddings of a VAE model, which can be viewed as more direct measures of disentanglement performance than the ones above. Here the classifiers have a similar architecture as the decoder to map embeddings to predictions at frame rate for a fair comparison. The phone accuracy on the test-set that can be achieved (higher is better) indicates how much content information is encoded, while speaker accuracy (lower is better) measures the amount of encoded speaker information. Two setups for content embedding extraction are considered here. In the first setup, which is referred to as one-pass, the content embeddings are directly extracted from the clean input features. In the second setup, which is referred to as two-pass, we first convert the signals to a common speaker before re-extracting the content embeddings from the converted signals. As common speaker we choose that speaker embedding from the validation utterances which is closest to the mean of the validation speaker embeddings.

All classifiers are trained on the training portion of a subset for 10⁵ update steps using mini-batches of 64 segments with lengths between 1 s and 3 s. Adam is used for optimization with a learning rate of 5·10⁻⁴ and gradient clipping at a threshold of 20. The checkpoint which achieves highest accuracy on the validation portion is used to report results on the test portion.

For each of the investigated methods, experiments were made on whether to use $X_2=X_1$ or $X_2\neq X_1$ which cannot be presented in detail due to space constraints. When using an adversarial classifier with $X_2=X_1$ it was found that the model started to shift content information to the speaker embedding resulting in bad content reconstruction when performing voice conversion. When using an information bottleneck it was found that $X_2=X_1$ clearly outperformed $X_2\neq X_1$. Note that we also made experiments combining the information bottleneck with one-hot speaker representations as in [17], but found the suggested speaker encoder with $X_2=X_1$ to perform better.

Table 1 shows voice conversion performance for seen speakers as well as unseen speakers. “Clean” presents the accuracies achieved on the clean unconverted test-spectrograms. Note that all other models use instance normalization as explained in Sec. 3 and the column “Method” refers to an additional disentanglement approach. It can be seen that all methods are able to shift the speaker identity from the source speaker towards the target speaker while mostly preserving the content.

When not applying VTLP on the content encoder input, adversarial approaches only slightly outperform the information bottleneck on seen speakers. However, they benefit from VTLP a lot while it does not bring any gain to the information bottleneck. Thus, with VTLP the adversarial approaches outperform the bottleneck approach by >2% in target speaker accuracy and >4% in phone accuracy on seen speakers. Comparing the adversarial approaches to each other it can be seen that adversarial CPC reconstructs the content slightly better while the adversarial speaker classifier performs slightly better in exchanging the speaker traits. When considering unseen speakers it can be seen that all models have a performance deterioration in target-speaker accuracies while phone accuracies roughly stay the same. Especially models trained with $X_2\neq X_1$ have a large performance drop. Here, adversarial CPC with $X_2=X_1$ significantly outperforms the other approaches.

Table 2 presents post-hoc classification performance on the content embeddings using the clean-seen-speakers subset. It can be seen that if only instance normalization is performed only little speaker information is removed from the content embeddings for both one-pass and two-pass extraction. For the other methods speaker information is removed drastically especially with two-pass extraction. While the adversarial speaker classifier removes the most speaker information (which it was trained for) the adversarial CPC model retains the most content information with decently low speaker information.

### 7. Conclusions

The proposed adversarial CPC conducts disentanglement of speaker and content induced variations and allows zero shot many-to-many voice conversion. Unlike an adversarial classifier based approach its training is fully unsupervised and does not even require knowledge of speaker labels. Yet it achieves comparable, if not better disentanglement and voice conversion performance.

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