TOWARDS USING CONTEXT-DEPENDENT SYMBOLS IN CTC WITHOUT STATE TYING DECISION TREES

Jan Chorowski, Adrian Lancucki, Bartosz Kostka, Michal Zapotoczny
University of Wroclaw, Poland

ABSTRACT

Deep neural acoustic models benefit from context dependent modeling of output symbols. However, their usage requires state-tying decision trees that are typically transferred from classical GMM-HMM systems. In this work we consider direct training of CTC networks with context dependent outputs. A state-tying decision tree is replaced with a neural network that predicts the weights of the final SoftMax classifier in a context-dependent way. This network is trained together with the rest of the acoustic model and lifts one of the last cases in which neural systems have to be bootstrapped from GMM-HMM ones. We describe changes to the CTC cost function that are needed to accommodate context-dependent symbols and validate this idea on bigram context dependent system built for character-based WSJ.

Index Terms— LSTM, CTC, context dependent phones, state tying, decision trees

1. INTRODUCTION

Acoustic models built using end-to-end trained deep neural networks are general enough to read raw waveforms [1] and output characters [2], bypassing steps of feature extraction and building of pronunciation lexicons. However, even with abundant training data the performance of end-to-end networks can be improved by introducing elements from classical GMM-HMM models, most notably the concept of context-dependent (CD) output symbols that are clustered using state-tying decision trees [3,4].

In this work we consider Connectionist Temporal Classification (CTC) [5] networks with context dependency: for each frame of acoustic features, the network produces a probability distribution over CD targets (phonemes or characters). However, we do not simply introduce one output class per CD symbol with no sharing of representation across contexts. Instead, the representations of output symbols used by the final SoftMax layer are computed using an auxiliary network that is a neural analogue to the classical state-tying decision tree. This way, CD output symbols are not independent from each other, the network can exploit similarities between contexts, and it can generalize to previously unseen contexts. Moreover, the training procedure does not require building an auxiliary GMM-HMM system.

2. BACKGROUND

2.1. GMM-HMMs with Decision Trees

The classical GMM-HMM acoustic model assumes that each speech segment (typically a 25ms long acoustic frame) is emitted from a single Gaussian mixture specified by the hidden state of the HMM [6, 7]. This simple emission model requires that frames emitted from a state are similar to each other and dissimilar to frames emitted from other states. This is achieved by careful modeling of acoustic phenomena. Each phoneme is partitioned into three sub-phonemic states. Furthermore, context dependent changes in pronunciation (e.g., voicing) are handled by differentiating between the emissions of the same phoneme from different contexts. Particularly popular are triphones, i.e., phonemes considered in their left and right contexts, but larger ones like quinphones are possible. To cope with the large amount of possible CD symbols the emission GMMs are shared between contexts, with the mapping performed by state-tying decision trees [8]. Typically, such trees map each CD symbol to one of a few thousand GMMs (also called tied states).

In a hybrid DNN-HMM model the Gaussian mixture representation of speech frames is replaced with a deep neural network that is tasked with predicting the HMM state aligned with each frame. In principle, the network can become invariant to many acoustic phenomena and it is no longer necessary to model them explicitly. Indeed, little to no gains are reported for dividing phonemes into subphonemic states [3]. However, explicit modeling of the context still improves recognition accuracy [3,4]. For this reason, a typical DNN-HMM system employs neural networks that predict the tied states of a previously trained GMM-HMM model. Consequently, the application of neural networks still depends on decision trees that map CD symbols to individual network outputs.
2.2. Connectionist Temporal Classification

Connectionist Temporal Classification (CTC) \[^5\] is a loss function designed for sequence labelling with neural networks. It assumes that the length of the input sequence (the number of possibly time-decimated acoustic frames) for which the network is making predictions is longer than the desired labeling. CTC then introduces two important concepts:

1. Let \( Y \) be a desired output sequence of symbols over an alphabet \( \mathcal{L} \). An extended output \( \hat{Y} \) of symbols from the alphabet \( \hat{\mathcal{L}} = \mathcal{L} \cup \{\emptyset\} \) is a longer sequence formed by repeating elements of \( Y \) and padding them with a special blank (\( \emptyset \)) token. Consecutive elements in \( \hat{Y} \) correspond to input frames. Furthermore, \( Y \) can be uniquely recovered from \( \hat{Y} \) by removing repetitions and removing blanks, using a function \( B^{-1}(\hat{Y}) = Y \).[1]

2. The conditional probability of sequence \( Y \) given acoustic frames \( X \) is equal to

\[
p(Y|X) = \sum_{\hat{Y} : B^{-1}(\hat{Y}) = Y} p(\hat{Y}|X) = \sum_{\hat{Y} : B^{-1}(\hat{Y}) = Y} \prod_t p(\hat{Y}_t|X),
\]

where \( p(\hat{Y}_t|X) \) are computed for each frame of the input \( X \) by a deep neural network. The CTC loss and its derivative can be efficiently computed using a forward-backward algorithm.

2.3. Final SoftMax Layer

A neural network produces a probability distribution over classes with the help of the SoftMax layer \[^9\]. An \( N \)-class SoftMax operates by maintaining a set of \( N \) prototypes, one for each possible output class. SoftMax input is matched (in the dot-product sense) to all prototypes, and the match scores are normalized to be non-negative and sum to one.

An \( N \)-class SoftMax has \( O(N) \) parameters. Because CD targets are essentially strings of \( D \) symbols from alphabet \( \hat{\mathcal{L}} \), producing a distribution over CD targets naively requires \( O(|\hat{\mathcal{L}}|^D) \) parameters. This combinatorial explosion with \( D \) can be alleviated by fixing the number of tied states, and mapping each of \( |\hat{\mathcal{L}}| \) strings to a tied state in the SoftMax output with a decision tree. The next section proposes an alternative, fully neural approach replacing the state-tying decision tree.

3. DESCRIPTION OF THE PROPOSED SYSTEM

3.1. CD SoftMax with Tied Parameters

We propose another way to reduce the number of parameters of the final context dependent SoftMax: keep the full set of output symbols (which grows exponentially with the size of the context), but make the prototypes co-dependent by generating them with an auxiliary neural network, analogous to a state-tying decision tree. In this way, the SoftMax can have fewer parameters than outputs, learn similarities between contexts, and generalize to previously unseen ones.

In the case of a naive CD output SoftMax layer, exponentially many outputs are treated as mutually exclusive. First, this scales poorly computational-wise. Second, it means that even if an output symbol is context independent, the network is forced to distinguish between its uses in different contexts. A state-tying decision tree would map all occurrences of such symbol in all contexts to the same GMM. We resolve both problems by conditioning output probability distribution of output symbols on the context. This way, two occurrences of the same symbol in different contexts are not normalized together, saving computations by computing the probabilities only for contexts that appear in the corpus.

3.2. CTC over Conditional Probabilities of CD Symbols

CTC assumes that the probabilities assigned to all valid extended sequences \( \hat{Y} \) sum to one. This is trivially the case for context independent models – every string over the alphabet \( \hat{\mathcal{L}} \) is a valid extended sequence and network’s predictions are normalized for each frame. Context dependent symbols violate this implicit normalization. Let CD symbols be bicharacters. The contexts should overlap with previous symbols, e.g., \( [\emptyset a, ab, bc] \) is a valid labeling, whereas \( [\emptyset a, ab, dc] \) is not. By default, CTC loss would assign non-zero probability to invalid, non-overlapping labelings, making the sum of probabilities of all valid labelings smaller than one. We resolve this issue by adapting CTC to context-conditional output distributions as described next.

We enforce the overlap during training and decoding by fixing the context at every time step. After emitting a bicharacter, e.g., ‘an’, the probability distribution of emitting the next symbol is \( p(c'|n') \) normalized over \( \{n\emptyset, na, \ldots, nz\} \), rather than \( p(c) \) normalized over all possible bicharacters. Consider a bicharacter model in which the probability of each character is conditioned on its left context. The probability of an output sequence \( Y \) is

\[
p(Y|X) = \sum_{\hat{Y} : B^{-1}(\hat{Y}) = Y} \prod_t p(\hat{Y}_t|X, last(\hat{Y}_{t-1})),
\]

where \( last(\hat{Y}_{t-1}) \) denotes the last previously emitted non-blank symbol. Let the target sequence be \( anna \). The sequence of CD tokens, i.e., bicharacters is \( \{\emptyset a, a\emptyset, an, na, n\emptyset, mn, nn, n\emptyset, na, a\emptyset\} \). The probability of emitting a symbol \( c_n \) is conditioned on the preceding character \( p(c_n|c_{n-1}) \).

Repetition of symbols in CTC with conditional emission probabilities complicates normalization. For instance, after first emission of the ‘an’ bicharacter, CTC would allow emitting any token from the set \( \{an, n\emptyset, na, nb, \ldots, nz\} \). However, this means that the probability of all outgoing arcs is greater than one: we can either emit a symbol in the context of ‘n’ (which sums to one) or repeat ‘an’ in the old context ‘a’. To alleviate the problem we disallow regular repetition
where \( s \) text and of the contextualized blank, as described above: the new interpretation of emitting a symbol from its own con-

In CTC, the forward variable is a probability \( \alpha_t \) of a correct extended labelling \( \mathbf{l}' \) of the first \( s \) labels at time \( t \), calculated as follows [5]:

\[
\alpha_t = \begin{cases} 
    p_t(\mathbf{l}'_s) (\alpha_{t-1}^s + \alpha_{t-1}^{s-1}) & \text{if } \mathbf{l}'_s = \emptyset \text{ or } \mathbf{l}'_s = \mathbf{l}'_{s-2} \\
    p_t(\mathbf{l}'_s) (\alpha_{t-1}^s + \alpha_{t-1}^{s-1} + \alpha_{t-1}^{s-2}) & \text{otherwise},
\end{cases}
\]

where \( p_t(\mathbf{l}'_s) \) denotes probability assigned by the model to symbol \( \mathbf{l}'_s \) for frame \( t \).

We modify these equations in order to keep normalization and overlapping of neighboring \( n \)-grams, so that the sum of probabilities of every valid labeling is equal to one. We use the new interpretation of emitting a symbol from its own context and of the contextualized blank, as described above:

\[
\bar{\alpha}_t = \begin{cases} 
    \alpha_{t-2}^s + \alpha_{t-1}^s + \alpha_{t-1}^{s-1} & \text{if } \mathbf{l}'_s \text{ in state 1} \\
    \alpha_{t-2}^s + \alpha_{t-1}^s + \alpha_{t-1}^{s-1} & \text{if } \mathbf{l}'_s \text{ in state 2 and } \mathbf{l}'_s \neq \mathbf{l}'_{s-3} \\
    \alpha_{t-1}^s & \text{if } \mathbf{l}'_s \text{ in state 2 and } \mathbf{l}'_s = \mathbf{l}'_{s-3} \\
    \alpha_{t-1}^s + \alpha_{t-1}^{s-1} & \text{if } \mathbf{l}'_s \text{ in state 3}
\end{cases}
\]

\[
\alpha_t = p_t(\mathbf{l}'_{s-1} | \mathbf{l}'_{s-1}) \bar{\alpha}_t^s,
\]

We use the Wall Street Journal dataset of press news, composed of over 80 hours of transcribed utterances, in the typical split into si284, dev93, and eval92 as train, dev and test sets, respectively. We calculate 80 filterbank features along with the energy in each frame, as well as temporal \( \Delta \) and \( \Delta \Delta \) features, and apply a global cepstral mean and variance normalization (CMVN). Our model has two convolutional layers, followed by four BiLSTM layers with 320 cells each. SoftMax prototype vectors have 320 dimensions. The alphabet has \(|\mathcal{L}| = 49\) symbols, which account for 2401 bicharacters.

The model is trained with batches of 16 utterances using Adam optimizer [10] and learning rate 0.001, which is halved every 5 epochs starting from the 32\textsuperscript{nd} epoch. We combat overfitting with a significant amount of Gaussian weight noise with \( \sigma = 0.115 \) [11], which increases linearly during initial 20\( k \) steps (about 8.5 epochs).

Hyperparameters have been adjusted on the baseline model with vanilla CTC loss. We denote models with context-dependent SoftMax as CDSM. Those models, which have
CD symbols in neural ASR systems improve performance of CTC \cite{3} and 1-state “chain” HMM models \cite{4}. However, best results use decision trees that map contexts to network targets. In \cite{3} this tree is built from activations of the neural network, while \cite{4} used a full bigram output which was slightly inferior to a decision tree obtained using a HMM model. We aim to recover the benefits of context-dependent outputs, but in a fully neural model that is trainable from scratch.

Several authors have proposed to use multicharacter, or multiphonne output tokens to reduce the number of emissions. The DeepSpeech 2 model used non-overlapping character bigrams \cite{2}, while \cite{13} and \cite{14} dynamically chose a decomposition of the output sequence. This idea was also explored in \cite{15} in the context of sequence-to-sequence models. We do not aim to reduce the length of target sequences, but to enable expressing of dependency of symbol emissions on their context.

Perhaps most similar to our work is \cite{16} in which a neural network is trained to replace a state-tying decision tree. However, this implies a multistage training procedure in which both classical GMM-HMM and neural systems are built. In contrast, we strive to keep a simple, one stage training procedure that can be started from scratch.

Finally, Hypernetworks \cite{17} expand on the idea of generating weights of neural network using an auxiliary module. We employ this idea to generate the final SoftMax weights for context dependent symbols.

6. CONCLUSIONS

In this paper, we propose a way of training CTC models with CD targets and decision trees replaced with neural networks. Embeddings of individual symbols from CD targets are combined with a small neural network, in order to provide prototypes for the SoftMax classifier. To properly normalize probabilities of CD symbols, we introduce context-conditional normalization of emission probabilities in the CTC loss function. The generalization ability of neural models makes inputs with similar characteristics, under-represented or unseen, have similar outputs. We leverage this property to perform implicit state-tying, and train the model end-to-end.

The scope for future work includes better LM integration, larger contexts end experiments with LF MMI chain models. We would also like to test the method on larger datasets.
7. REFERENCES

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