DISCRIMINATIVE SEGMENTAL CASCADES FOR FEATURE-RICH PHONE RECOGNITION

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ABSTRACT

Discriminative segmental models, such as segmental conditional random fields (SCRFs) and segmental structured support vector machines (SSVMs), have had success in speech recognition via both lattice rescoring and first-pass decoding. However, such models suffer from slow decoding, hampering the use of computationally expensive features, such as segment neural networks or other high-order features. A typical solution is to use approximate decoding, either by beam pruning in a single pass or by beam pruning to generate a lattice followed by a second pass. In this work, we study discriminative segmental models trained with a hinge loss (i.e., segmental structured SVMs). We show that beam search is not suitable for learning rescoring models in this approach, though it gives good approximate decoding performance when the model is already well-trained. Instead, we consider an approach inspired by structured prediction cascades, which use max-marginal pruning to generate lattices. We obtain a high-accuracy phonetic recognition system with several expensive feature types: a segment neural network, a second-order language model, and second-order phone boundary features.

***Index Terms*—** segmental conditional random field, structured prediction cascades, phone recognition, segment neural network, beam search

1. INTRODUCTION

Segmental models have been considered for speech recognition as an alternative to frame-based models such as hidden Markov models (HMMs), in order to address the shortcomings of the frame-level Markov assumption and introduce expressive segment-level features. Segmental models include **segmental conditional random fields** (SCRFs) [1], or semi-Markov conditional random fields [2]; **segmental structured support vector machines** (SSVMs) [3]; and generative segmental models [4, 5]. Previous work comparing segmental model training algorithms has shown some benefits of discriminative segmental models trained with hinge loss (SSVM-type learning) [6], and we consider this type of model here.

Discriminative segmental models have allowed the exploration of complex features, both at the word level [7] and at the phone level [8, 9, 6]. These powerful segmental features are a double-edged sword—on the one hand, the model becomes more expressive; on the other, it is computationally challenging to decode with and train such models. For this reason, SCRFs [10] and SSVMs [3] were initially applied to speech recognition in a multi-pass approach, where the segmental model considers only a subset of the hypothesis space contained in lattices generated by HMMs. Much effort has been devoted to removing the dependency on HMMs and instead developing **first-pass segmental models** [11, 9, 12]. However, working with the entire hypothesis space imposes an even larger burden on inference, especially when the features are computationally intensive or of high order.

If we wish to consider the entire search space in decoding, we can only afford features of low order or of specific types as in [9]. An alternative approach to the problem is to use approximate decoding. There are two widely used approximate decoding algorithms: beam search and multi-pass decoding. In the intuitive and popular beam search, the idea is to prune as we search along the graph representing the search space. It has been used for decoding in almost all HMM systems, and for generating lattices as well. Though popular, it offers no guarantees about its approximation. In the category of multi-pass decoding, lattice and n-best list rescoring [13] are commonly used alternatives.

We focus on a particular type of multi-pass approach based on structured prediction cascades [14], which we term **discriminative segmental cascades**. A cascade is a general approach for decoding and training complex structured models, using a multi-pass sequence of models with increasing order of features, while pruning the hypothesis space by a multiplicative factor to counteract the growth in feature computation. In this approach, the hypothesis space in each pass is pruned with **max-marginals**, which offers the guarantee that all paths with scores higher than the pruning threshold are kept.

Applying the discriminative segmental cascade approach to speaker-independent phonetic recognition on the TIMIT data set, we obtain a first-pass phone error rate of 21.4% with a unigram language model, and a two-stage cascade error rate of 19.9%, which includes a bigram language model, a segment neural network classifier, and second-order phone boundary features. This is to our knowledge the best result to date with a segmental model. In the following sections we define the discriminative segmental models we consider, describe how we represent a cascade of hypothesis spaces with a finite-state composition-like operation, present discriminative segmental cascades for decoding and training with max-marginal pruning, and discuss our experiments.

2. DISCRIMINATIVE SEGMENTAL MODELS

A **linear segmental model** for input space $\mathcal{X}$ and hypothesis space $\mathcal{Y}$ is defined formally as a pair $(\boldsymbol{\theta}, \boldsymbol{\phi})$, where $\boldsymbol{\theta} \in \mathbb{R}^d$ is the parameter vector and $\boldsymbol{\phi} : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}^d$ is the feature vector. For an input $x \in \mathcal{X}$, each hypothesis $y \in \mathcal{Y}$ is associated with a score $\boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y)$, and the goal of decoding is to find the hypothesis that maximizes the score,

$$\operatorname*{argmax}_{y \in \mathcal{Y}} \ \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y). \tag{1}$$

For speech recognition, we formally define the hypothesis space $\mathcal{Y}$ in terms of finite-state transducers (FST). Let Σ be the label set (e.g., the phone set in phone recognition), and $\overline{\Sigma} = \Sigma \cup \{\epsilon\}$, where ϵ is the empty label. Define a **decoding graph** as a standard FST $G = (V, E, I, F, w, i, o)$, where V is the set of vertices, $E \subseteq V \times V$ is the set of edges, $I \subseteq V$ is the set of initial vertices, $F \subseteq V$ is the set of final vertices, $w : E \to \mathbb{R}$ is a function that associates a weight to an edge, $i : E \to \overline{\Sigma}$ is a function that associates an input label to an edge, and $o : E \to \overline{\Sigma}$ is a function that associates an output label to an edge. In addition to the standard definition of FSTs, we equip G with a function $t : V \to \mathbb{R}$ that maps a vertex to a time stamp. For any edge $(u, v) \in E$, let $\text{tail}((u, v)) = u$, and $\text{head}((u, v)) = v$. For convenience, we will use subscripts to denote components of a particular FST, e.g., E_G is the edge set of G.

For an input utterance, let x be the sequence of acoustic feature vectors. We construct a decoding graph G from x, then define our hypothesis space $\mathcal{Y} \subseteq 2^E$ to be the subset of paths that start at an initial vertex in I and end at a final vertex in F. A path $y \in \mathcal{Y}$ of length m is a sequence of unique edges $\{e_1, \ldots, e_m\}$, satisfying $\text{head}(e_i) = \text{tail}(e_{i+1})$ for $i \in [m]$. Given a model $(\boldsymbol{\theta}, \boldsymbol{\phi})$, for each edge $e \in E$, the weight $w(e)$ is defined as $\boldsymbol{\theta}^\top \boldsymbol{\phi}(x, e)$. For convenience, for a path $y \in \mathcal{Y}$, we overload $\boldsymbol{\phi}$ and w and define $\boldsymbol{\phi}(x, y) = \sum_{e \in y} \boldsymbol{\phi}(x, e)$ and $w(y) = \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y) = \sum_{e \in y} w(e)$, where we treat a path y as a set of (unique) edges e.

If the decoding graph is the full hypothesis space with all possible segmentations and all possible labels, for example the graph on the left in Figure 1, then the model is a **first-pass segmental model**. Otherwise, it is a lattice rescoring model. By the above definitions, inference (decoding) in the model (1) can be solved with a standard shortest-path algorithm.

The model parameters $\boldsymbol{\theta}$ can be learned by minimizing the sum of loss functions on samples (x, y) in a training set. In general, the model can be trained with different losses. The model is an SCRF if we train it with log loss $-\log p(y|x)$ where $p(y|x) \propto \exp(\boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y))$. It is a segmental structured SVM if we use the structured hinge loss:

$$\ell_{\text{hinge}}(\boldsymbol{\theta}) = \max_{y' \in \mathcal{Y}} \left[\text{cost}(y, y') - \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y) + \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y') \right], \tag{2}$$

where $\text{cost} : \mathcal{Y} \times \mathcal{Y} \to [0, \infty)$ measures the badness of a hypothesis path y' compared with the ground truth y.

The loss can be optimized with first-order methods, such as stochastic gradient descent (SGD). The gradient (or subgradient, in this case) computation typically involves a forward-backward-like algorithm. For example, the subgradient of the hinge loss is

$$\nabla_{\boldsymbol{\theta}} \ell_{\text{hinge}}(\boldsymbol{\theta}) = -\boldsymbol{\phi}(x, y) + \boldsymbol{\phi}(x, \tilde{y}), \tag{3}$$

where computing the **cost augmented path**

$$\tilde{y} = \operatorname*{argmax}_{y' \in \mathcal{Y}} \ \text{cost}(y, y') + \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y'), \tag{4}$$

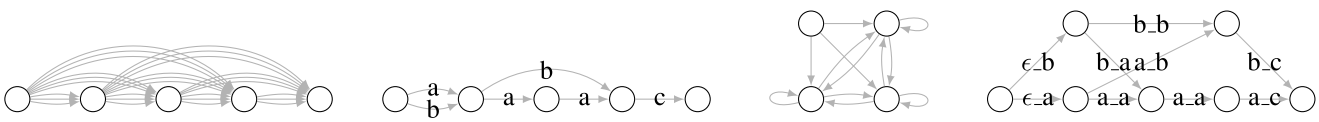
requires a forward pass over the graph. Compared to computing the gradient of other losses, which requires more forward passes and backward passes, hinge loss has computational advantages, and has been shown to perform well [6], so we will use hinge loss for the rest of the paper.

3. HIGH-ORDER FEATURES AND STRUCTURED COMPOSITION

The order of a feature is defined as the number of labels on which it depends. A feature is said to be a **first-order feature** if it depends on a single label, a **second-order feature** if it depends on a pair of labels, and so on. Features with no label dependency are called **zeroth-order features**.

High-order features in sequence prediction can be extended from low-order ones by increasing the number of labels considered. Formally for any label set Σ and any feature vector $\boldsymbol{\phi} \in \mathbb{R}^d$, the feature vector **lexicalized** with a label $s \in \Sigma$ is defined as $\boldsymbol{\phi} \otimes \mathbb{1}_s$, where $\mathbb{1}_s$ is a one-hot vector of length $|\Sigma|$ for the label s and $\otimes : \mathbb{R}^{m \times n} \times \mathbb{R}^{p \times q} \to \mathbb{R}^{mp \times nq}$ is the outer product. With a slight abuse of notation, we let $\boldsymbol{\phi} \otimes s = \boldsymbol{\phi} \otimes \mathbb{1}_s$. The resulting vector is of length $|\Sigma| d$. Similarly, we can lexicalize a feature vector with pairs of labels, $\boldsymbol{\phi} \otimes s_1 \otimes s_2 = \boldsymbol{\phi} \otimes \mathbb{1}_{s_1} \otimes \mathbb{1}_{s_2}$, giving a vector of length $|\Sigma|^2 d$.

For example, a common type of zeroth-order segmental feature is of the form $\psi(x, t_1, t_2)$ where x is the sequence of acoustic feature vectors, t_1 is the start time of the segment, and t_2 is the end time of the segment. To make it discriminative in a decoding graph H, we can compute the first-order feature $\boldsymbol{\phi}_H(x, e)$ for any edge e by first computing



H_1 H_2 L_2 $H_2 \circ_\sigma L_2$

Fig. 1. *From left to right*: An example of the full hypothesis space H_1 with four frames (five vertices) and three unique labels $\{$a, b, c$\}$ (three edges between every pair of vertices) with segment length up to three frames (actual labels omitted for clarity); H_2, a pruned H_1; a graph structure corresponding to a bigram language model L_2 over three labels; and H_2 σ-composed with L_2, where $s_1\_s_2$ denotes the bigram $s_1 s_2$.

$\psi(x, t(\text{tail}(e)), t(\text{head}(e)))$ and then lexicalizing it with the label $o_H(e)$.

To have a unified way of extending the order of features, we define the concept of FST **structured composition**, or **σ-composition** for short, as follows. For any two FSTs A and B, the **σ-composed** FST is defined as

$$G = A \circ_\sigma B \tag{5}$$

where

$$V_G = V_A \times V_B \tag{6}$$

$$E_G = \left\{ \langle e_1, e_2 \rangle \in E_A \times E_B : o_A(e_1) = i_B(e_2) \right\} \tag{7}$$

and

$$i_G(\langle e_1, e_2 \rangle) = i_A(e_1) \tag{8}$$

$$o_G(\langle e_1, e_2 \rangle) = o_B(e_2) \tag{9}$$

$$\text{tail}_G(\langle e_1, e_2 \rangle) = \langle \text{tail}_A(e_1), \text{tail}_B(e_2) \rangle \tag{10}$$

$$\text{head}_G(\langle e_1, e_2 \rangle) = \langle \text{head}_A(e_1), \text{head}_B(e_2) \rangle \tag{11}$$

where $\langle \cdot, \cdot \rangle$ denotes a tuple. Unlike in classical composition, we only constrain the structure of G and are free to define w_G differently. In particular, we let

$$w_G(\langle e_1, e_2 \rangle) = \boldsymbol{\theta}_G^\top \boldsymbol{\phi}_G(x, \langle e_1, e_2 \rangle), \tag{12}$$

and $\boldsymbol{\phi}_G$ is free to use $\boldsymbol{\phi}_A$ and $\boldsymbol{\phi}_B$ but is not constrained to do so. In other words, the weight function w_G can extract richer features than w_A and w_B.

With structured composition, we can easily convert low-order features to high-order ones. Continuing the above example, we can σ-compose the decoding graph H with a bigram language model (LM) L in its FST form [15] with a slight modification. We require the output labels of the LM FST to include the history labels alongside the current label. For example, the output labels of a bigram LM are of the form $s_1 s_2 \in \overline{\Sigma} \times \Sigma$, where s_1 is the history label (possibly ϵ) and s_2 is the current label. Let $G = H \circ_\sigma L$. We can define $t_G(\langle e_1, e_2 \rangle) = t_H(e_1)$. For an edge $e \in E_G$, we can compute first-order features $\varphi \otimes s_1$, and second-order features $\varphi \otimes s_1 \otimes s_2$ for $s_1 s_2 = o_G(e)$ and $s_1 \neq \epsilon$, where $\varphi = \psi(x, t_G(\text{tail}_G(e)), t_G(\text{head}_G(e)))$. If $s_1 = \epsilon$, everything falls back to the previous example. In general, by σ-composing with high-order n-gram LMs, we can compute high-order features by lexicalizing low-order ones.

4. DISCRIMINATIVE SEGMENTAL CASCADES

Our approach, which we term a discriminative segmental cascade (DSC), is an instance of multi-pass decoding, consisting of levels with increasing complexity of features and decreasing size of search space. We start with the full search space and a "simple" first-level discriminative segmental model using inexpensive features, and use the first-level model to prune the search space. We then apply a model using more expensive features, and optionally repeat the process for as many levels as desired. Rather than the typical beam pruning, we prune with **max-marginals** [16, 14], which have certain useful properties and turn out to be important for achieving good performance with our models. A max-marginal of an edge e in G is defined as

$$\gamma(e) = \max_{y \ni e} \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y). \tag{13}$$

In words, it is the highest score of a path that passes through the edge e. We prune the edge if its max-marginal is lower than a threshold, and keep it otherwise. In order to prune a multiplicative factor of edges at each level of the cascade, Weiss et al. [14] propose to use the threshold

$$\tau_\lambda = (1 - \lambda) \frac{1}{|E_G|} \sum_{e \in E_G} \gamma(e) + \lambda \max_{y \in \mathcal{Y}} \boldsymbol{\theta}^\top \boldsymbol{\phi}(x, y), \tag{14}$$

which interpolates between the mean of the max-marginals and the maximum. If λ is set to 1, we only keep the best path.

Lattice generation by max-marginal pruning guarantees that there is always at least one path left after pruning and that any y satisfying $w(y) > \tau_\lambda$ is kept, because for every $e \in y$, $\gamma(e) \geq w(y) > \tau_\lambda$. In particular, if the ground truth has a score higher than the threshold, it will still be in the search space for the next level of the cascade.

Computing max-marginals in a specific level of the cascade requires a forward pass and a backward pass through the graph. Pruning with max-marginals thus takes twice the time as searching for the best path alone.

Table 1. A summary of results in terms of phonetic error rate (%) on the TIMIT test set, for prior first-pass segmental models, a speaker-independent HMM-DNN system given by a standard Kaldi recipe [18], and our models.

	dev PER (%)	test PER (%)
HMM-DNN		21.4
first first-pass SCRF [8]		33.1
Boundary-factored SCRF [9]		26.5
Deep segmental NN [11]		21.87
our first-pass model (H_1)	22.15	21.73
DSC 2^{nd} level with bigram LM	19.80	
+ 2nd-order boundary features	19.22	
+ 1st-order segment NN	18.86	
+ 1st-order bi-phone NN bottleneck	18.77	19.93

Learning the cascade of models is also done level by level. We start with the entire hypothesis space H_1 limited only by a maximum segment length. A first set of computationally inexpensive features up to first order is used for learning. Let the first set of weights learned be $\boldsymbol{\theta}_1$. We can use $\boldsymbol{\theta}_1$ for first-pass decoding if it is good enough, or we can choose to generate the next level of the cascade and use more computationally expensive features, such as higher-order ones. Moving to the next level of the cascade, we compute max-marginals with $\boldsymbol{\theta}_1$ and prune H_1 with a threshold, resulting in a lattice H_2. If we wish increase the order of features, we σ-compose H_2 with a bigram LM L_2. A second set of features up to second order can then be used for learning. Suppose the second set of weights is $\boldsymbol{\theta}_2$. Again, we have the choice either to use $\boldsymbol{\theta}_2$ for decoding or to prune and repeat the process with more computationally expensive features.

5. EXPERIMENTS

We experiment with segmental models in the context of phonetic recognition on the TIMIT corpus [17]. We follow the standard TIMIT protocol for training and testing. We use 192 randomly selected utterances from the complete test set other than the core test set as our development set, and will refer to the core test set simply as the test set. The phone set is collapsed from 61 labels to 48 before training. In addition to the 48 phones, we also keep the glottal stop /q/, sentence start, and sentence end so that every frame in the training set has a label. A summary of prior first-pass decoding results with segmental models, along with our results and one from a standard speaker-independent HMM-DNN, is shown in Table 1.

5.1. First-pass segmental model

First we demonstrate the effectiveness of our first-pass decoder. The first-pass search graph, denoted H_1, contains all possible labels and all possible segmentations up to 30 frames per segment. Like some prior segmental phonetic recognition models [11, 9], many of the features in our first-pass decoder are based on averaging and sampling the outputs of a neural network phonetic frame classifier, specifically a convolutional neural network (CNN) [19], which we describe next.

5.1.1. CNN frame classifier

The input to the network is a window of 15 frames of log-mel filter outputs. The network has five convolutional layers, with 64–256 filters of size 5×5 for the input and 3×3 for others, each of which is followed by a rectified linear unit (ReLU) [20] activation, with max pooling layers after the first and the third ReLU layers. The output of the final ReLU layer is concatenated with a window of 15 frames of MFCCs centered on the current frame, and the resulting vector is passed through three fully connected ReLU layers with 4096 units each. The network is trained with SGD for 35 epochs with a batch size of 100 frames. Fully connected layers and the concatenation layer are trained with dropout at a 20% and 50% rate, respectively. This classifier was tuned on the development set and achieves a 22.1% frame error rate (after collapsing to 39 phone labels) on the test set. We will use $\text{CNN}(x, t)$ to denote the log of the final softmax layer, corresponding to the predicted log probabilities of the phones, given as input $[x_{t-7}; \dots; x_{t+7}]$.

5.1.2. First-order features

Below we list the features for each edge (u, v). We will use $L = t(v) - t(u)$ for short.

Average of CNN log probabilities The log of the CNN output layer is averaged over all frames in the segment:

$$\frac{1}{L}\sum_{i=0}^{L-1} \text{CNN}(x, t(u) + i) \tag{15}$$

Samples of CNN log probabilities The log of the CNN output layer is sampled from the middle frames of three equally split sub-segments, i.e.,

$$\text{CNN}\left(x, t(u) + \left\lfloor \frac{[k + (k+1)]L}{3 \cdot 2} \right\rfloor\right) \tag{16}$$

for $k = 0, 1, 2$.

Boundary features The log probabilities i frames before the left boundary $\text{CNN}(x, t(u) - i)$ and i frames after the right boundary $\text{CNN}(x, t(v) + i)$ are used as features. We use the concatenation of the boundary features for $i = 1, 2, 3$.

Length indicator $\mathbb{1}_{L=\ell}$ for $\ell = 0, 1, \dots, 30$.

Bias A constant 1.

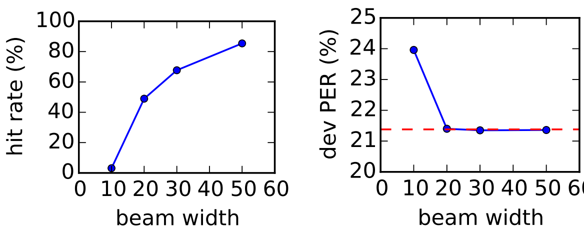


Fig. 2. Beam search on H_1 with different beam widths. *Left*: Hit rate on the development set. *Right*: PER on the development set. The dashed line is the PER of the exact search.

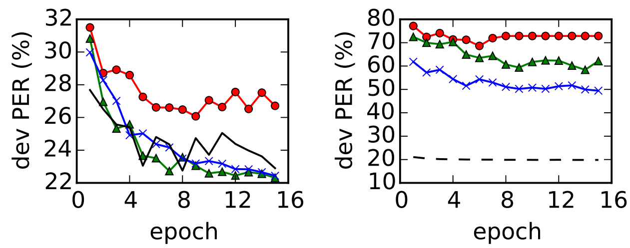


Fig. 3. Beam search for learning with different beam widths: beam=10 beam=20 beam=30 — exact. *Top*: Learning on H_1. *Bottom*: Learning on $H_1 \circ_\sigma L_2$. The dashed line is the learning curve of the second-level cascade $H_2 \circ_\sigma L_2$.

We lexicalize all of the above features to first order, and include a zeroth-order bias feature. We minimize hinge loss with the overlap cost function introduced in [6] with AdaGrad for up to 70 epochs with step sizes tuned in $\{0.01, 0.1, 1\}$. No explicit regularizer is used; instead we choose the step size and iteration that perform best on the development set (so-called early stopping). As shown in Table 1, our first-pass segmental model outperforms all previous segmental model TIMIT results of which we are aware.

5.2. Higher-order features and segmental cascades

We next explore multi-pass decoding with beam search and with discriminative segmental cascades. In the second pass we include features of order two and a bigram LM L_2. Backoff is approximated with ϵ transitions in the bigram LM. Let $G = H \circ_\sigma L_2$, where H can be H_1 or H_2, the pruned H_1. We consider the following additional features on edges $e \in E_G$.

Bigram LM score The bigram log probability $\log p_{\text{LM}}(s_2|s_1)$, where $s_1 s_2 = o_G(e)$ We do not lexicalize this feature because it is naturally second-order.

5.2.1. Beam search

Before experimenting with the second-order features, we compare beam search and exact search on the best model for H_1 to give a sense of the approximation quality of beam search. We measure the quality of approximation via the "hit rate", i.e., how often the exact best path is found. Results are shown in Figure 2. As expected, the hit rate decreases as the beam width decreases. However, the PER does not decrease significantly, which demonstrates that beam search is a good approximate decoding algorithm when the model is well-trained.

Judging from the decoding results, we use beam search with beam widths $\{10, 20, 30\}$ for learning. Since the runtime of beam search is controlled by the beam width when the decoding graph is large, we can search directly on $H_1 \circ_\sigma L_2$. The composition is done on the fly to avoid enumerating all edges in $H_1 \circ_\sigma L_2$. We compare learning on both H_1 and $H_1 \circ_\sigma L_2$. For H_1 we use the same features as the first-pass segmental model, while for $H_1 \circ_\sigma L_2$ we add the bigram LM score and second-order boundary features. For consistency, we use the same beam width for decoding. Hinge loss is minimized with AdaGrad with step sizes tuned in {0.01, 0.1, 1}. Results are shown in Figure 3 for the step size that achieves the lowest development set PER. When we train the segmental model on H_1 (top of Figure 3), learning with beam search is successful when the beam width is large enough, while for $H_1 \circ_\sigma L_2$ (bottom of Figure 3), learning completely fails.

5.2.2. Discriminative segmental cascades (DSC)

We next consider the proposed discriminative structured cascades (DSC) for utilizing the bigram LM and second-order features. We first prune H_1 with max-marginal pruning using our first-pass segmental model with weights $\boldsymbol{\theta}_1$, resulting in H_2, and σ-compose H_2 with L_2. Recall that the larger the pruning parameter λ, the sparser the lattice. We measure the density of the lattice by the number of edges in H_2 divided by the number of ground-truth (gold) edges. The quality of H_2's produced with different λ's is shown in Figure 4 (left). For the DSC second level, we define an additional feature:

Lattice score Instead of re-learning all of the weights for the features in the first-pass model, we combine them into an additional feature from the first level of the cascade $\boldsymbol{\theta}_1^\top \boldsymbol{\phi}_{H_1}(x, e_1)$, which is never lexicalized, where $e_1 \in H$ is such that $\langle e_1, e_2 \rangle \in E_G$.

To compare with beam search, we use the lattice score, the bigram LM score, second-order boundary features, first-order length indicators, and first-order bias as our features for the second level of the cascade. Hinge loss is minimized with AdaGrad for up to 20 epochs with step sizes optimized in $\{0.01, 0.1\}$. Again, no explicit regularizer is used except early stopping on the development set. Learning results on different lattices are shown in Figure 4 (right). We see that learning with the DSC is clearly better than with beam search.

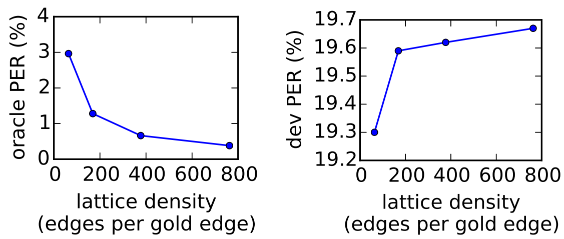


Fig. 4. Quality of H_2 for λ's in $\{0.8, 0.7, 0.6, 0.5\}$. *Left*: Oracle error rates for different lattice densities. *Right*: Corresponding second-pass development set PERs?

Table 2. TIMIT segment classification error rates (ER).

	test ER (%)
Gaussian mixture model (GMM) [23]	26.3
SVM [23]	22.4
Hierarchical GMM [22]	21.0
Discriminative hierarchical GMM [24]	16.8
SVM with deep scattering spectrum [25]	15.9
our CNN ensemble	15.0

5.2.3. Other expensive features

To add more context information, we use the same CNN architecture and training setup to learn a bi-phone frame classifier, but with an added 256-unit bottleneck linear layer before the softmax [21]. Each frame is labeled with its segment label and one additional label from a neighboring segment. If the current frame is in the first half of the segment, the additional label is the previous phone; if it is in the second half, then the additional label is the next phone. The learned bottleneck layer outputs are used to define features (although they do not correspond to log probabilities) with averaging and sampling as for the uni-phone case. We refer to the resulting features as **bi-phone NN bottleneck** features.

Finally, we also use the same type of CNN to train a *s*egment classifier. Here the features at the input layer are the log-mel filter outputs from a 15-frame window around the segment's central frame. The network architecture is the same as our frame classifier, but instead of concatenation with 15-frame MFCCs, we concatenate with a segmental feature vector consisting of the average MFCCs of three sub-segments in the ratio of 3-4-3, plus two four-frame averages at both boundaries and length indicators for length 0 to 20 (similar to the segmental feature vectors of [22, 23]). This CNN is trained on the ground-truth segments in the training set. Finally, we build an ensemble of such networks with different random seeds and a majority vote. This ensemble classifier has a 15.0% classification error on the test set, which is to our knowledge the best result to date on the task of TIMIT phone segment classification (see Table 2).

It is, however, still too time-consuming to compute the segment network outputs for every edge in the lattice. We instead compress the best-performing (single) CNN into a shallow network with one hidden layer of 512 ReLUs by training it to predict the log probability outputs of the deep network, as proposed by [26, 27]. We then use the log probability outputs of the shallow network and lexicalize them to first order. We refer to the result as **segment NN** features.

Results with these additional features are shown in Table 1. Adding the second-order features, bigram LM, and the above NN features gives a 1.8% absolute improvement over our best first-pass system, demonstrating the value of including such powerful but expensive features.

6. DISCUSSION

We have presented discriminative segmental cascades (DSC), an approach for training and decoding with segmental models that allows us to incorporate high-order and complex features in a coarse-to-fine approach, and have applied them to the task of phone recognition. The DSC approach uses max-marginal pruning, which outperforms beam search for learning the second-pass model. Starting from a first-pass large-margin model that outperforms previous segmental model results and is competitive with HMM-DNNs, the DSC second pass improves the phone error rate by another 1.8% absolute.

Further analysis may be needed to understand precisely why learning with beam search is not successful in the context of our models. One issue is that σ-composing H_1 and L_2 introduces many dead ends (paths that do not lead to final vertices) in the graph because we have to do the composition on the fly. Minimizing $H_1 \circ_\sigma L_2$ might help, but we would need to touch the edges of $H_1 \circ_\sigma L_2$ at least once, which is itself expensive. Second, even if we reach the final vertices, the cost-augmented path might still have a lower cost+score than the ground-truth path, which leads to no gradient update. This issue has been studied recently, and one possible solution is "premature updates" [28], but these are intended for the perceptron loss. Third, the edge weights in our models are not strictly negative. Beam search would tend to go depth-first when encountering edges with positive weights. On the other hand, if the edge weights are negative, beam search would tend to go breadth-first, which may explain why greedy search like beam search may cause problems for segmental models but works for HMMs.

Additional future work includes considering even more expressive features, higher-order features and additional cascade levels. There is also much room for exploration with segment neural network classifiers. One concern with our segment classifiers is that they are trained only with ground truth segments, so it is unclear how they behave when the input is an incorrect hypothesized segment. Alternatives include training on all hypothesized segments and allowing the network to learn to classify non-phones, similarly to the anti-phone and near-miss modeling of [5].

7. REFERENCES

[1] Geoffrey Zweig and Patrick Nguyen, "A segmental CRF approach to large vocabulary continuous speech recognition," in *IEEE Workshop on Automatic Speech Recognition & Understanding*, 2009, pp. 152–157.

[2] Sunita Sarawagi and William W Cohen, "Semi-Markov conditional random fields for information extraction," in *Advances in Neural Information Processing Systems*, 2004, pp. 1185–1192.

[3] Shi-Xiong Zhang and Mark Gales, "Structured SVMs for automatic speech recognition," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 21, no. 3, pp. 544–555, 2013.

[4] Mari Ostendorf, Vassilios V Digalakis, and Owen Kimball, "From HMM's to segment models: A unified view of stochastic modeling for speech recognition," *IEEE Transactions on Speech and Audio Processing*, vol. 4, no. 5, pp. 360–378, 1996.

[5] James Glass, "A probabilistic framework for segment-based speech recognition," *Computer Speech & Language*, vol. 17, no. 2, pp. 137–152, 2003.

[6] Hao Tang, Kevin Gimpel, and Karen Livescu, "A comparison of training approaches for discriminative segmental models," in *Proceedings of the Annual Conference of International Speech Communication Association*, 2014.

[7] Geoffrey Zweig, Patrick Nguyen, Dirk Van Compernolle, Kris Demuynck, Les Atlas, Pascal Clark, Greg Sell, Meihong Wang, Fei Sha, Hynek Hermansky, Damianos Karakos, Aren Jansen, Samuel Thomas, G.S.V.S. Sivaram, Samuel Bowman, and Justine Kao, "Speech recognition with segmental conditional random fields: A summary of the JHU CLSP 2010 summer workshop," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2011, pp. 5044–5047.

[8] Geoffrey Zweig, "Classification and recognition with direct segment models," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2012, pp. 4161–4164.

[9] Yanzhang He and Eric Fosler-Lussier, "Efficient segmental conditional random fields for phone recognition," in *Proceedings of the Annual Conference of the International Speech Communication Association*, 2012, pp. 1898–1901.

[10] Geoffrey Zweig and Patrick Nguyen, "SCARF: A segmental conditional random field toolkit for speech recognition," in *Proceedings of the Annual Conference of International Speech Communication Association*, 2010, pp. 2858–2861.

[11] Ossama Abdel-Hamid, Li Deng, Dong Yu, and Hui Jiang, "Deep segmental neural networks for speech recognition.," in *Proceedings of the Annual Conference of International Speech Communication Association*, 2013, pp. 1849–1853.

[12] Yanzhang He and Eric Fosler-Lussier, "Segmental conditional random fields with deep neural networks as acoustic models for first-pass word recognition," in *Proceedings of the Annual Conference of the International Speech Communication Association*, 2015.

[13] Mari Ostendorf, Ashvin Kannan, Steve Austin, Owen Kimball, Richard Schwartz, and Jan Rohlicek, "Integration of diverse recognition methodologies through reevaluation of n-best sentence hypotheses," in *Proceedings of the Workshop on Speech and Natural Language*, 1991, pp. 83–87.

[14] David Weiss, Benjamin Sapp, and Ben Taskar, "Structured prediction cascades," arXiv:1208.3279 [stat.ML], 2012.

[15] Cyril Allauzen, Mehryar Mohri, and Brian Roark, "Generalized algorithms for constructing statistical language models," in *Proceedings of the 41st Annual Meeting on Association for Computational Linguistics*, 2003, pp. 40–47.

[16] A. Sixtus and S. Ortmanns, "High quality word graphs using forward-backward pruning," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 1999, pp. 593–596.

[17] John S Garofolo, Lori F Lamel, William M Fisher, Jonathon G Fiscus, and David S Pallett, "Darpa timit acoustic-phonetic continous speech corpus cd-rom. nist speech disc 1-1.1," *NASA STI/Recon Technical Report N*, vol. 93, pp. 27403, 1993.

[18] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukáš Burget, Ondřej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlíček, Yanmin Qian, Petr Schwarz, et al., "The Kaldi speech recognition toolkit," 2011.

[19] Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv:1409.1556 [cs.CV], 2014.

[20] Matthew Zeiler, Marc'Aurelio Ranzato, Rajat Monga, Min Mao, Kun Yang, Quoc Le, Patrick Nguyen, Alan Senior, Vincent Vanhoucke, Jeffrey Dean, and Geoff Hinton, "On rectified linear units for speech processing," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2013, pp. 3517–3521.

[21] Tara Sainath, Brian Kingsbury, Vikas Sindhwani, Ebru Arisoy, and Bhuvana Ramabhadran, "Low-rank matrix factorization for deep neural network training with high-dimensional output targets," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2013, pp. 6655–6659.

[22] Andrew Halberstadt, *Heterogeneous Acoustic Measurements and Multiple Classifiers for Speech Recognition*, Ph.D. thesis, Massachusetts Institute of Technology, 1998.

[23] Philip Clarkson and Pedro Moreno, "On the use of support vector machines for phonetic classification," in *IEEE International Conference on Acoustics, Speech, and Signal Processing*, 1999, vol. 2, pp. 585–588.

[24] Hung-An Chang and James Glass, "Hierarchical large-margin Gaussian mixture models for phonetic classification," in *IEEE Workshop on Automatic Speech Recognition & Understanding*, 2007, pp. 272–277.

[25] Joakim Andén and Stéphane Mallat, "Deep scattering spectrum," *IEEE Transactions on Signal Processing*, vol. 62, no. 16, pp. 4114–4128, 2014.

[26] Jinyu Li, Rui Zhao, Jui-Ting Huang, and Yifan Gong, "Learning small-size DNN with output-distribution-based criteria," in *Proceedings of the Annual Conference of the International Speech Communication Association*, 2014.

[27] Jimmy Ba and Rich Caruana, "Do deep nets really need to be deep?," in *Advances in Neural Information Processing Systems*, 2014, pp. 2654–2662.

[28] Liang Huang, Suphan Fayong, and Yang Guo, "Structured perceptron with inexact search," in *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2012, pp. 142–151.