AutoMOS: Learning a non-intrusive assessor of naturalness-of-speech

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Abstract

Developers of text-to-speech synthesizers (TTS) often make use of human raters to assess the quality of synthesized speech. We demonstrate that we can model human raters' mean opinion scores (MOS) of synthesized speech using a deep recurrent neural network whose inputs consist solely of a raw waveform. Our best models provide utterance-level estimates of MOS only moderately inferior to sampled human ratings, as shown by Pearson and Spearman correlations. When multiple utterances are scored and averaged, a scenario common in synthesizer quality assessment, AutoMOS achieves correlations approaching those of human raters. The AutoMOS model has a number of applications, such as the ability to explore the parameter space of a speech synthesizer without requiring a human-in-the-loop.

1 Introduction

To evaluate changes to text-to-speech (TTS) synthesizers, human raters are often employed to assess the synthesized speech. Multiple human ratings of an audio sample contribute to a *mean opinion score* (MOS). MOS has been crowdsourced with specific attention to rater quality by [12]. While crowdsourcing introduces a degree of parallelism to the rating process, it is still relatively costly and time-consuming to obtain MOS for TTS quality testing.

Numerous systems have been produced to algorithmically produce *objective* assessments of audio quality approximating the *subjective* human assessment, including some which assess speech quality. For example, MCD [8], PESQ [13] and POLQA [6] target this particular space. These are *intrusive* assessors in that they assume the presence of an undistorted reference signal to facilitate comparisons when deriving ratings, something that does not exist in the case of the synthesized speech of TTS. *Non-intrusive* assessments such as ANIQUE [7], LCQA [3] and P. 563 [9] have been proposed to evaluate speech quality where this reference signal is not available. Much research in quality assessment is targeted at telephony, with emphasis on detecting distortions and other artifacts introduced by lossy compression and transmission.

Throughout this work, a *synthesizer* constitutes a snapshot of the evolving implementation of a unit selection synthesis algorithm and a continually growing corpus of recorded audio, combined with a specific set of synthesis/cost parameters. When we partition or aggregate data by synthesizer, we take all utterances from a given synthesizer and allocate them *en masse* to a single training or evaluation fold, or to a single aggregate metric, e.g. *synthesizer-level mean MOS*.

In [10], the authors used human ratings to improve the correlation between MOS and unit selection TTS cost. Similarly, [1, 11] explore means of tuning cost functions to incorporate subjective preferences. Such works consider direct optimization of synthesizer MOS as a function of synthesizer parameters (e.g. cost function weights). In prior unpublished work we trained similar models and

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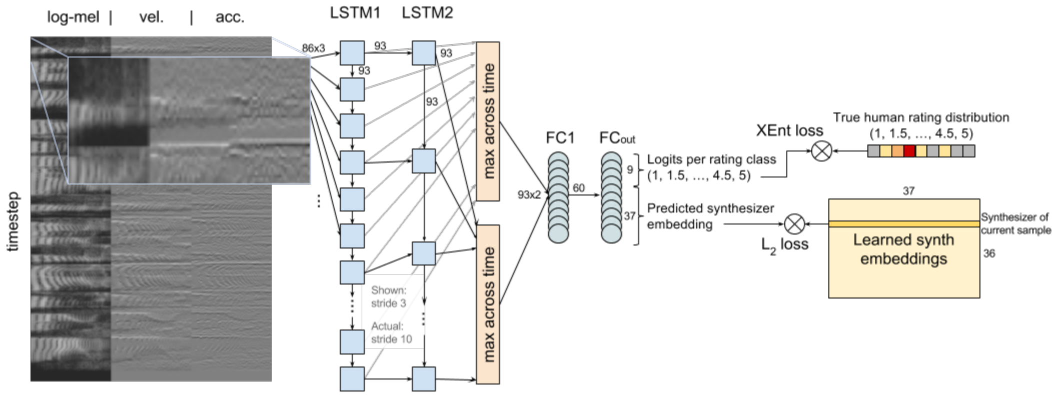


Figure 1: Diagram of the best performing AutoMOS network

found they could exceed 0.9 Spearman rank correlation between true and estimated synthesizer MOS. However, any modifications to parameter semantics or engine internals render this mapping invalid. It is desirable to learn a synthesizer assessment which operates independently of engine internals, directly assessing pools of TTS waveforms.

We demonstrate that deep recurrent networks can model *naturalness*-of-speech MOS ratings produced by human raters for TTS synthesizer evaluation, using only raw audio waveform as input. We explore a variety of deep recurrent architectures, to incorporate long-term time dependencies. Our tuned AutoMOS model achieves a Spearman rank correlation of 0.949, ranking 36 different synthesizers. (Sampling a single human rating for each utterance yields a Spearman correlation of 0.986.) When evaluating the calibration of AutoMOS on multiple utterances with similar predicted MOS, we find five-fold median correlations > 0.9 and MSE competitive with sampled human ratings, even when we quantize the predicted utterance MOS to the 0.5 increments of the human rater scale. Such results open the door for scalable, automated tuning and continuous quality monitoring of TTS engines.

2 Model & Results

Because audio data is of varying length for each example, either directly pooling across the time dimension or the use of recurrent neural networks (RNN) is suggested. To encode the intuition that valuable information exists at relatively large time-scales (consider phone or transition duration or inflection, which may vary according to context), we opt to explore a family of RNN models.

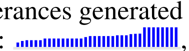
In particular, we test a family of models that layer one or more fully-connected layers atop the time-pooled outputs of a stack of recurrent Long Short-Term Memory [LSTM; 4] cells. The timeseries input to the LSTM is either a log-mel spectrogram or a time-pooled convolution as in [5], in each case over a 16kHz waveform. We consider the addition of single frame velocity and acceleration components to this timeseries. The final LSTM layer's outputs are max-pooled across time, and fed as inputs to the fully-connected hidden layers which compute final regression values. We explored a means of inducing learning across longer timeframes (a stacked LSTM where deeper layers use a stride of 2 or more timesteps over the outputs of of lower-level LSTM layers), but found performance comparable to that of a simpler stacked or single-layer LSTM. Max-pooling non-final LSTM layers' outputs and adding skip connections to the final hidden layers was not found to improve performance.

We explore multiple modes of predicting and training over input waveforms x: (1) predict sufficient statistics $\mu(x), \sigma(x)$ and train on log-likelihood of individual human ratings r_i under Gaussian $\log p(r_i|\mu(x), \sigma(x))$, (2) predict $MOS(x)$ and train on utterance-level L2 loss $(MOS(x) - MOS_{true})^2$, and (3) predict $logits(x)$ and train on cross-entropy between the true 9-category distribution of human ratings and $\mathrm{Cat}(logits(x))$ per-utterance. We train a separate set of outputs with a learned embedding of the ground-truth synthesizer, providing both regularization and gradients to the training process. Embeddings are initialized randomly; both the embedding and the prediction thereof receive a gradient (toward each other) in each training step. The best performing model is illustrated in Figure 1.

Table 1: Model Hyperparameters

Description	Range explored	Best Performer (Pearson r = 0.61)
Learning rate; decay / 1000 steps	0.0001 - 0.1; 0.9 - 1.0	0.057; 0.94
L1; L2 regularization	0.0 - 0.001	1.4e-5; 2.6e-5
Loss strategy	L2 | cross-entropy	cross-entropy
Synthesizer regression embedding dim	0 - 50	37
Timeseries type	log-mel | pooled conv1d	log-mel
Timeseries width (# mel bins, conv filters)	20 - 100	86
Timeseries 1-step derivatives	(none) | vel. | vel. + acc.	vel. + acc.
LSTM layer width; depth	20 - 100; 1 - 10	93; 2
LSTM timestep stride at non-0th layers	1 - 10	10
LSTM layers feeding hidden layer inputs	all | last	all
Post-LSTM hidden layer width; depth	20 - 200; 0 - 2	60; 1

All models were trained with Adagrad on batches of 20 examples asynchronously across 10 workers. We use five-fold cross-validation to evaluate the best found set of hyperparameters, with all utterances for any given synthesizer appearing exclusively in a single fold.

Data We use a corpus of TTS naturalness scores acquired over multiple years across multiple instances of quality testing for Google's TTS engines. All tests are iterations on a single English (US) voice used across multiple products. Raters scored each utterance given a 5-point Likert scale for naturalness, in half-point increments. We partition training data from holdout data such that all utterances for a given synthesizer are in the same partition. The data includes 168,086 ratings across 47,320 utterances generated by 36 synthesizers. The utterance quantity per synthesizer varies from 64 to 4800: , in log-scale.

Hyperparameter Tuning We used Google Cloud's HyperTune to explore a set of hyperparameters shown in Table 1. About 2 in 3 top-performing tuning runs used the cross-entropy categorical training mode. The top 10 configurations we found had eval-set Pearson correlations between utterance-level predicted and true MOS ranging from 0.56-0.61 after 20,000 training steps. When we constrained the search space to those models using convolution+pooling based timeseries (as opposed to log-mel), we found weaker best eval-set correlations around 0.48. This could indicate there is little value in the sample-level details when dealing in synthesized speech, or could signal insufficient training data. While [14] reported gammatone-like learned filter banks, their speaker-independent ASR covers a much wider range of voices, and we did not observe a similar set of emergent filters from random initialization. Initialization with gammatone filters yielded only nominal improvements in performance (r=0.51).

Relative to a simple L2 loss to the true MOS, we observed little benefit from training a Gaussian predictor against individual ratings. The estimated variance was typically higher than the true sample variance for a given utterance. Using a simpler L2 loss against the true MOS provided for faster training and convergence, allowing us to try a wider variety of structural changes. Treating predictions as categorical and using a cross-entropy loss slightly outperformed the L2 construction in the top tuning runs (0.61 categorical vs. 0.58 L2). The categorical form gives AutoMOS more weights and hence a greater capacity near the output layer.

Evaluation As simple baselines for comparison, we consider (1) a bias-only model which always predicts the mean of all observed utterances' MOS and (2) a small nonlinear model which takes only utterance length as input (two 10-unit hidden layers with rectified linear activation), with the intuition that a longer utterance includes more opportunities to make mistakes deemed unnatural. We draw one human rating for each utterance and show this comparison as a "Sample human rating" column.

If errors are unbiased, an increased sample size should reduce error. We sort utterances by predicted MOS and evaluate correlations between $\mathbb{E}_{group}(MOS_{predicted})$ and $\mathbb{E}_{group}(MOS_{true})$ (where $\mathbb{E}$ is the expected value operator) on groupings of 10 or more utterances with adjacent predicted MOS in a similar fashion to a calibration plot. We show such plots in Figure 2.

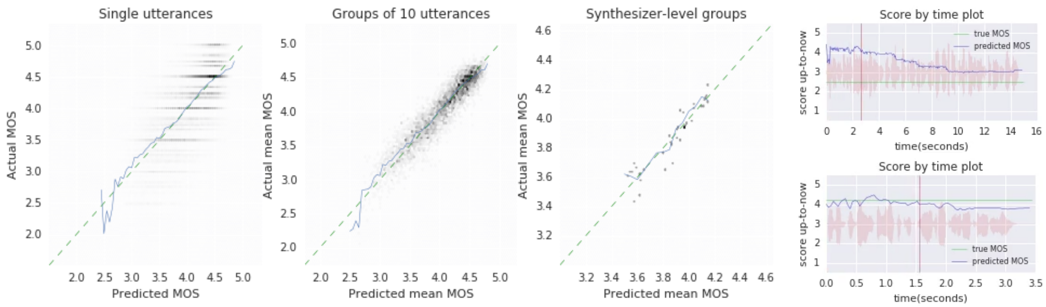


Figure 2: **Left:** Calibration plots (including all eval folds of AutoMOS): Green represents perfect calibration; blue plots $(\mathbb{E}_w(MOS_{predicted}), \mathbb{E}_w(MOS_{true}))$ within 0.05 windows w along the x-axis. **Right:** Samples from score-over-time animations. Visit `goo.gl/cnQbSn` to view.

Table 2: RMSE and correlation results (reflecting median fold, except as indicated)

	Baselines		AutoMOS		Ground-truth
Metric / Model	Bias-only	NNet(utt. length)	Raw	Quantized[a]	Sample human rating[a]
Utterance-level ($n_{fold} = 6000, 6424, 6624, 12348, 15924$)					
RMSE	0.618	0.553	0.462	0.483	0.512
Pearson r	–	0.454	0.668	0.638	0.764
Spearman r	–	0.399	0.667	0.636	0.757
10 utterance means ($n_{fold} = 600, 643, 663, 1235, 1593$)					
RMSE	0.203	0.213	0.172	0.171	0.358
Pearson r	–	0.812	0.930	0.933	0.962
Spearman r	–	0.657	0.925	0.925	0.956
Synthesizer-level means ($n = 36$; uses all folds)					
RMSE	0.252	0.132	0.073	0.075	0.034
Pearson r	–	0.795	0.938	0.935	0.987
Spearman r	–	0.679	0.949	0.947	0.986

[a]utterance scores from 1-5 in increments of 0.5

How well can we rank synthesizers relative to one another? To perform this evaluation, we use the above five-fold cross validation to predict a MOS for each utterance using the AutoMOS instance from which it was held-out. We then average at the synthesizer-level, giving us a total of 36 $\mathbb{E}_{synth}(MOS_{predicted}), \mathbb{E}_{synth}(MOS_{true})$ pairs upon which we evaluate. Results shown in Table 2.

3 Discussion

AutoMOS tends to avoid very-high or very-low predictions, likely reflecting the distribution of the training data. It also seems to learn patterns in the data around certain common "types" of utterances which usually achieve high ("OK, setting your alarm") or low MOS (reading dictionary definitions). It's possible that different distributions of texts per synthesizer could yield easily predictable differences in synthesizer-MOS. A future improvement would be predicting MOS for the raw text and evaluating the *advantage* of an utterance relative to this baseline. In [10], naturalness is predictable from unit selection costs; here, we want to remove the predictive baseline of the text.

We have begun tuning a TTS engine using AutoMOS. Subsequent human evaluations will provide concrete results on the model and evaluation criteria we've selected. Similarly, we will experiment with the system for continuous quality testing of a large-scale TTS deployment. It may be possible to leverage AutoMOS to do stratified sampling of utterances to send to human raters. This would allow raters to focus energy more evenly across the quality spectrum.

To probe what's been learned, we have explored artificial truncation, as in Figure 2 (right). Methods like layerwise relevance propagation [2] or activation difference propagation [15] have shown promise with image models, and could be interesting to apply to a unit selection cost function.

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