

Organizers







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Day 3 Lecture 5

Parametric Speech Synthesis

Antonio Bonafonte







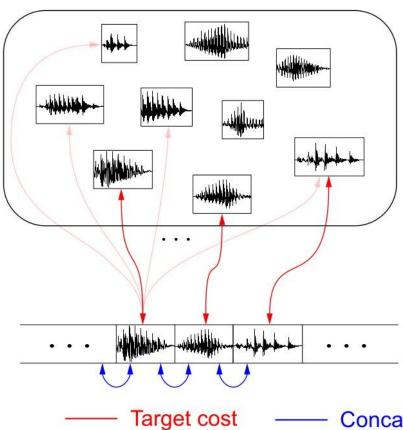


Main TTS Technologies

Concatenative speech synthesis + Unit Selection

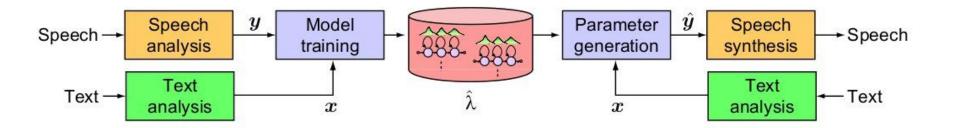
Concatenate *best* prerecorded speech *units* Speech data: 2-10 hours, professional speaker, carefully segmenten and annotated.

Concatenative



H. Zen - RTTHSS 2015 http://rtthss2015.talp.cat/ Concatenation cost

Statistical Speech Synthesis



Main TTS Technologies

Concatenative speech synthesis + Unit Selection Concatenate *best* pre-recorded speech *units*

Statistical Parametric Speech Synthesis
Represent speech waveform using parameters (eg 5ms)
Use statistic generative model
Reconstruct waveform from generated parameters

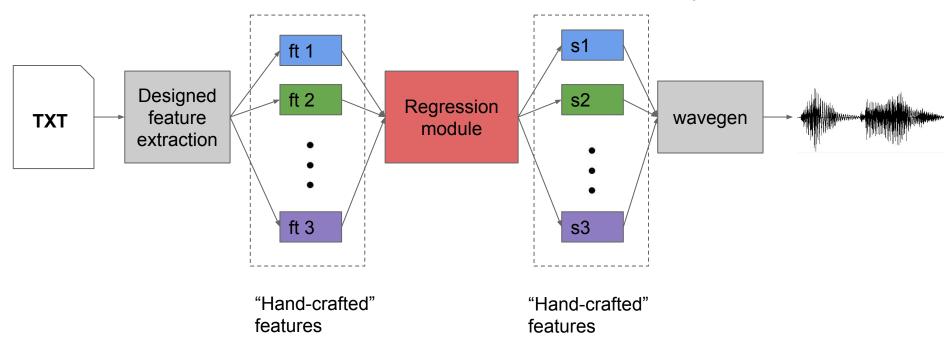
Hybrid Systems

Concatenative speech synthesis

Select best units attending a statistical parametric system

Deep architectures ... but not deep (yet)

Text to Speech: Textual features → Spectrum of speech (many coefficients)



Textual features (x)

From text to phoneme (pronunciation)

Disambiguation, pronuntiation (e.g.: Jan. 26)

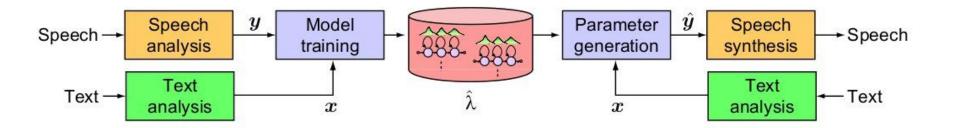
From phoneme to phoneme+ (with linguistic features)

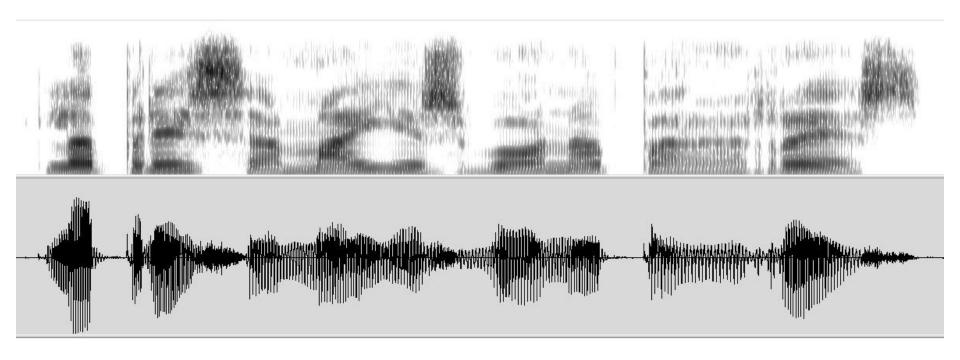
Textual features (x)

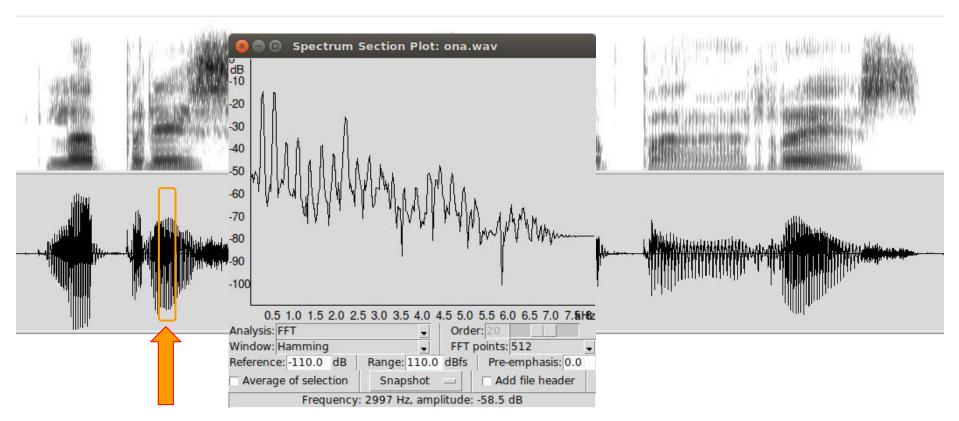
- {preceding, succeeding} two phonemes
- Position of current phoneme in current syllable
- # of phonemes at {preceding, current, succeeding} syllable
- {accent, stress} of {preceding, current, succeeding} syllable
- Position of current syllable in current word
- # of {preceding, succeeding} {stressed, accented} syllables in phrase
- # of syllables {from previous, to next} {stressed, accented} syllable
- Guess at part of speech of {preceding, current, succeeding} word
- # of syllables in {preceding, current, succeeding} word
- Position of current word in current phrase
- # of {preceding, succeeding} content words in current phrase
- # of words {from previous, to next} content word
- # of syllables in {preceding, current, succeeding} phrase

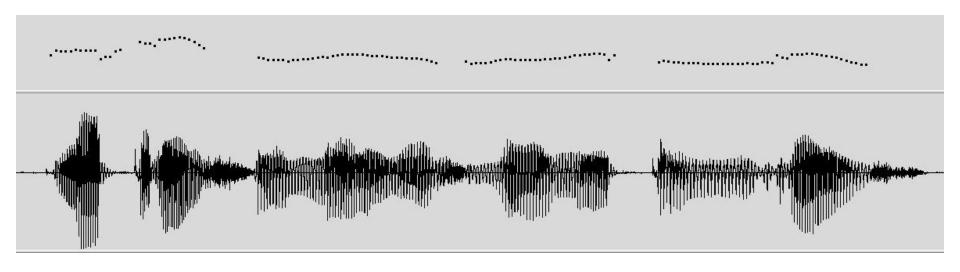
H. Zen - RTTHSS 2015 http://rtthss2015.talp.cat/

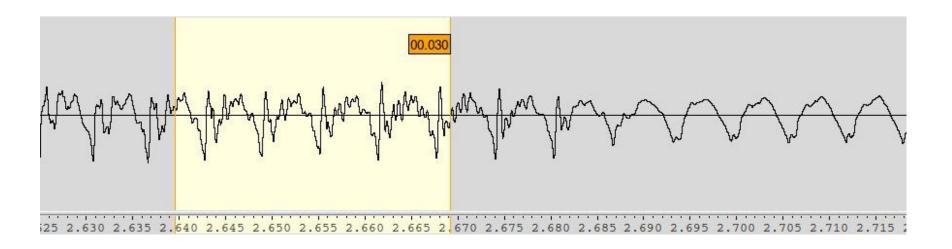
Statistical Speech Synthesis





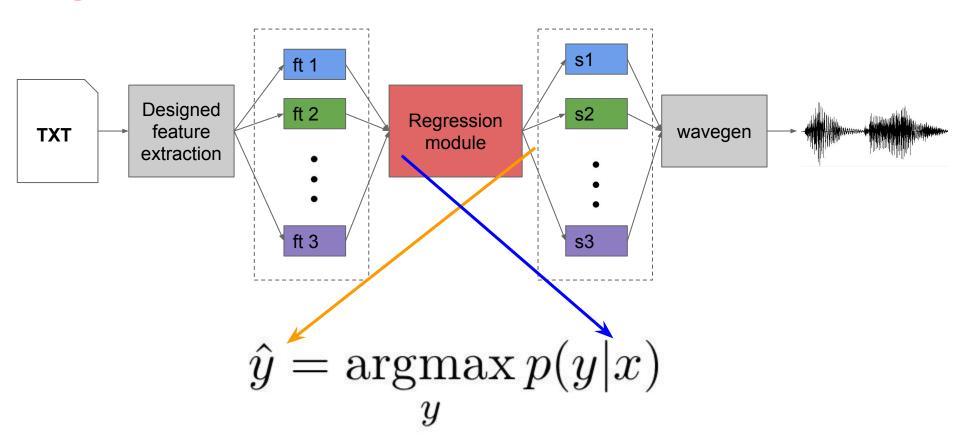




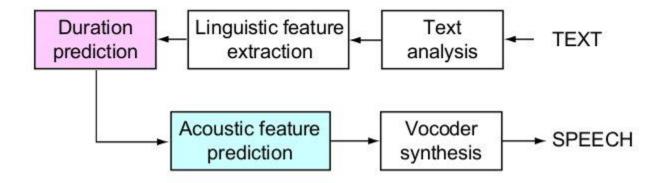


- Rate: ~ 5 ms. (200Hz)
- Spectral features (envelope)
- Excitation features (fundamental frequency, pitch)
- Representation that allows reconstruction: vocoders (Straight, Ahocoder, ...)

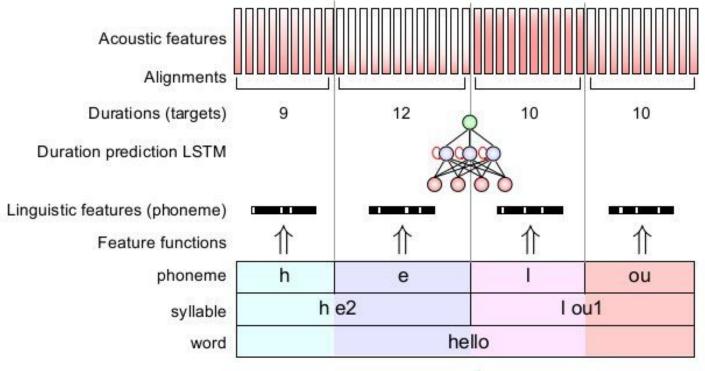
Regression



Phoneme rate vs. frame rate

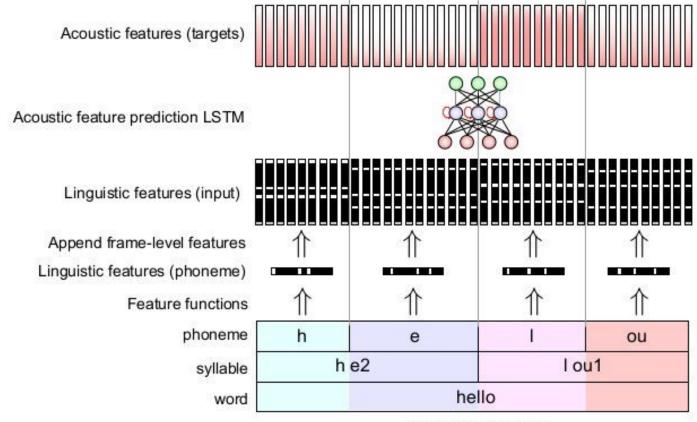


Duration Modeling



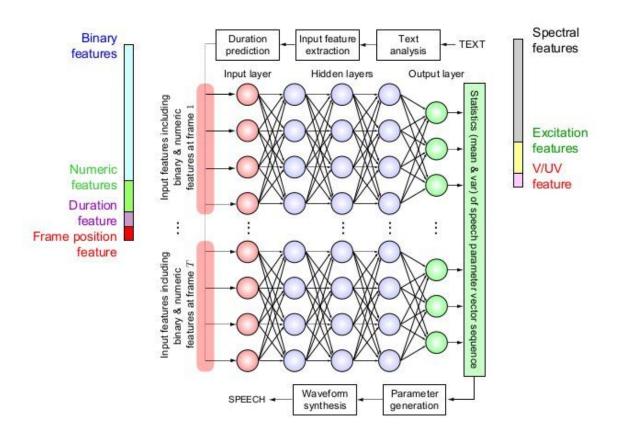
Linguistic Structure

Acoustic Modeling

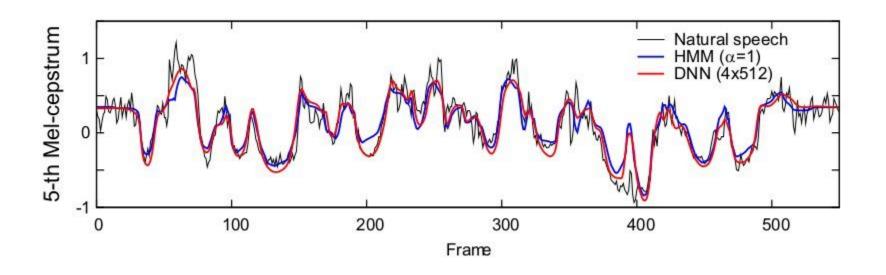


Linguistic Structure

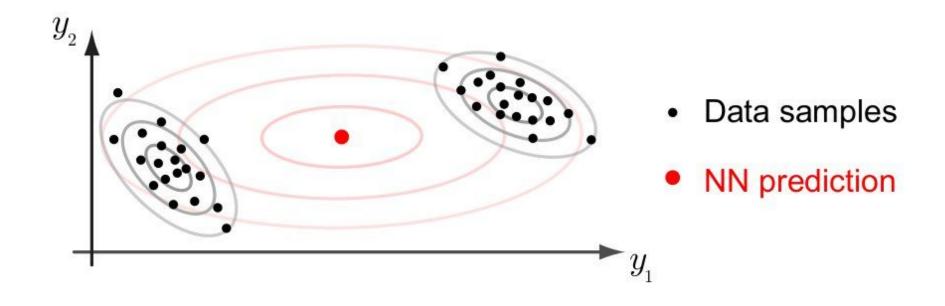
Acoustic Modeling: DNN



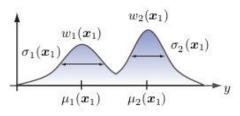
Acoustic Modeling: DNN

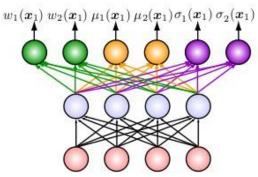


Regression using DNN (problem)



Mixture density network (MDN)





1-dim, 2-mix MDN

Inputs of activation function

$$z_j = \sum_{i=1}^4 h_i w_{ij}$$

○ : Weights → Softmax activation function

$$w_1(\mathbf{x}) = \frac{\exp(z_1)}{\sum_{m=1}^2 \exp(z_m)}$$
 $w_2(\mathbf{x}) = \frac{\exp(z_2)}{\sum_{m=1}^2 \exp(z_m)}$

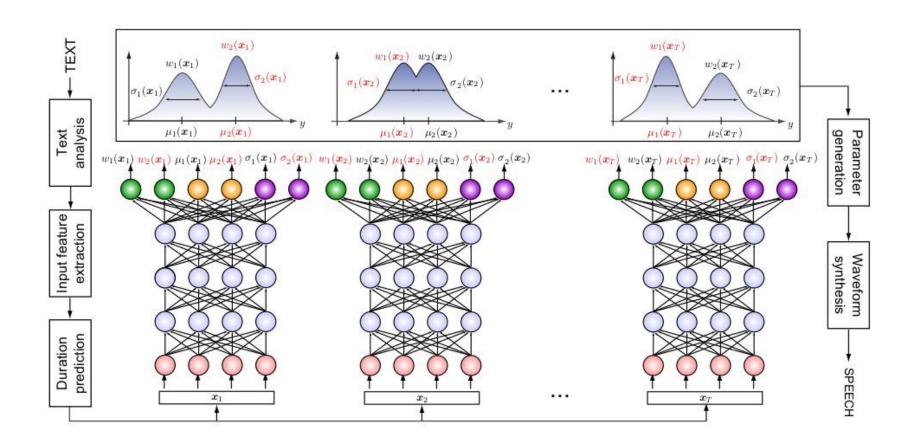
: Means → Linear activation function

$$\mu_1(\boldsymbol{x}) = z_3 \qquad \qquad \mu_1(\boldsymbol{x}) = z_4$$

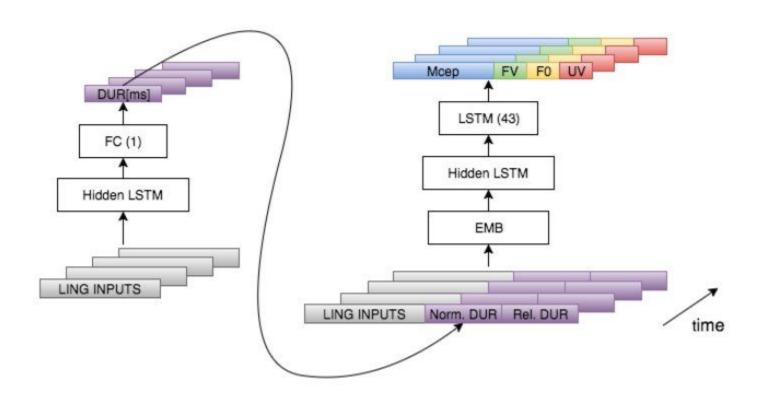
○ : Variances → Exponential activation function

$$\sigma_1(\boldsymbol{x}) = \exp(z_5)$$
 $\sigma_2(\boldsymbol{x}) = \exp(z_6)$

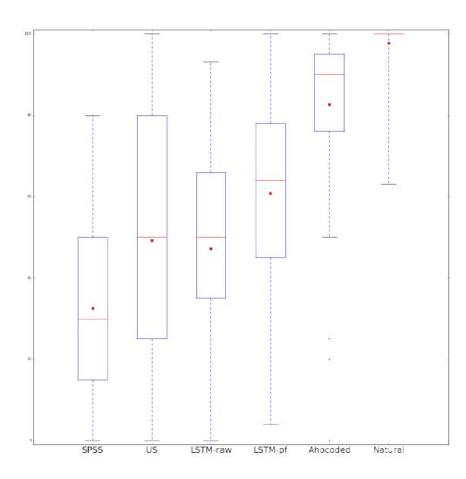
Mixture density network (MDN)



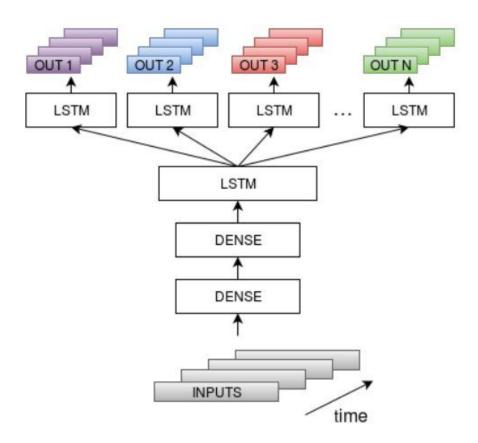
Recurrent Networks: LSTM



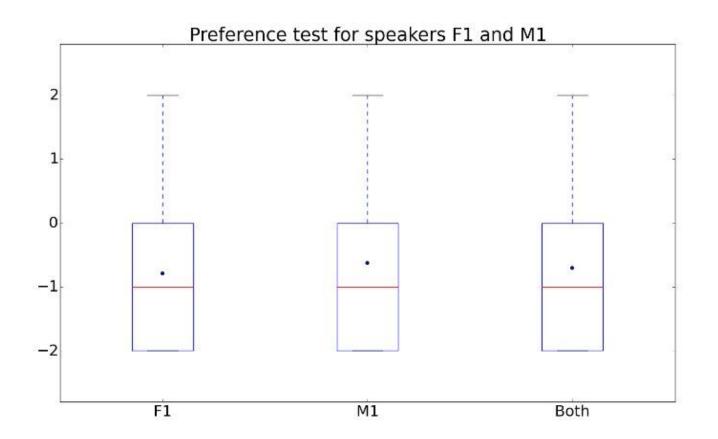
Recurrent Networks: LSTM



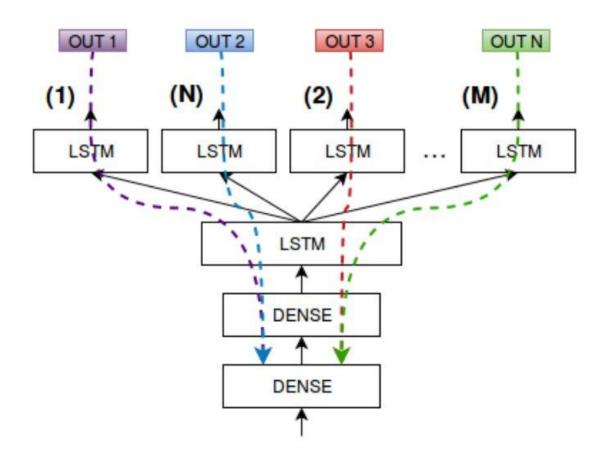
Multi-speaker



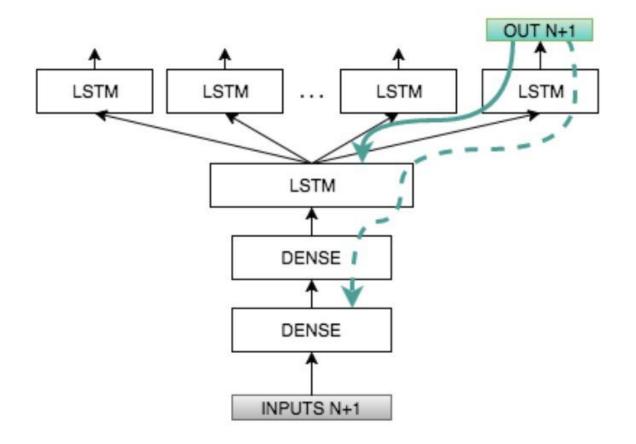
Multi-speaker



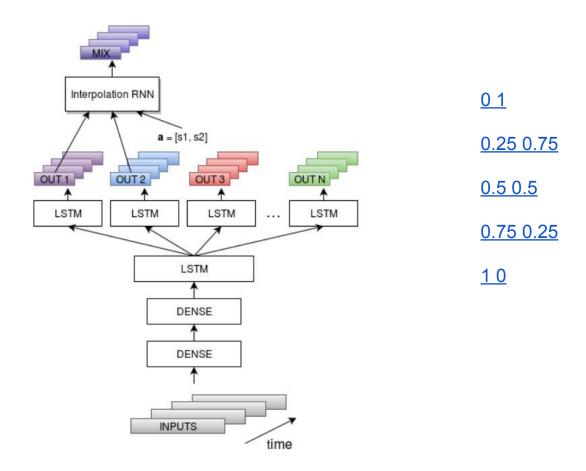
Multi-speaker



Adaptation to new speaker



Speaker interpolation



References

Statistical parametric speech synthesis: from HMM to LSTM-RNN. Heiga Zen, Google http://rtthss2015.talp.cat/

Deep learning applied to Speech Synthesis, Msc Thesis Santiago Pascual, UPC