

Speech Signal Processing Lab

- a short tour

<https://www.csd.uoc.gr/~sspl/index.html>

Yannis Stylianou,
Prof. of Speech Processing,
University of Crete

Speech Signal Processing Lab

- a short tour

<https://www.csd.uoc.gr/~sspl/index.html>

Topics:

1. General overview, about us
2. Introduction to Speech Technology
3. Text to Speech Synthesis

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BioSketch

[Yannis Stylianou](#) is Professor of Speech Processing at University of Crete, in Greece and Research Manager at Apple, Cambridge UK.

From 1996 until 2001 he was with AT&T Labs Research (Murray Hill and Florham Park, NJ, USA) and until 2002 he was with Bell-Labs Lucent Technologies, in Murray Hill, NJ, USA. He is with University of Crete since 2002.

From 2013 until 2018 (July) he was Group Leader of the Speech Technology Group at Toshiba Cambridge Research Lab in Cambridge UK. He joined Apple in Aug 2018. He holds MSc and PhD from ENST-Paris on Signal Processing and he has studied Electrical Engineering at NTUA Athens Greece (1991).

He is an IEEE Fellow and an ISCA Fellow.

Speech Processing Lab

- Key people



George Kafentzis
Signal Processing



Yannis Pantazis
Signal Processing



Vassilis Tsiaras
Machine Learning

Speech Signal Processing Lab

- Key people

Ph.Ds:

1. Yannis Agiomyrgiannakis, Google UK, Altered LTD London
2. Yannis Pantazis, FORTH
3. Andre Holzapfel, Assistant Professor KTH Sweden
4. Maria Koutsogiannaki, BCBL, Spain
5. Maria Markaki, FORTH
6. George Kafentzis, UoC/CSD
7. Muhammed Shifas PV (on going)
8. Dipjyoti Paul (on going)
9. Rafael Tsirbas (on going)
10. Irene Sissamaki (to start soon)

Speech Signal Processing Lab

- *Summary of topics*

- ✓ Speech Processing
- ✓ Audio Processing: Music, Marine mammals
- ✓ Biomedical Signal Processing:
 - ✓ Voice function assessment
 - ✓ Phonocardiography

Speech Signal Processing Lab

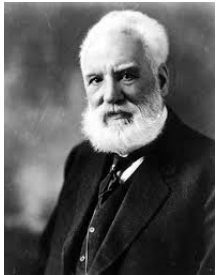
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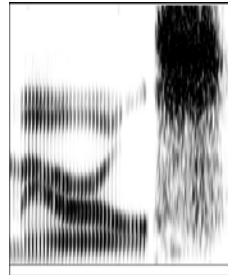
Speech has a central position in human communication



Bell (1876)
discovery of
telephone



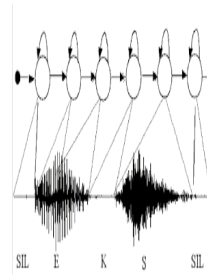
Rayleigh (1900)
theory of sound



Speech
spectrogram
(1946)



Shannon (1948)
speech & language
transmission



Markov chain
(Baum, 1960)



Békésy (1961)
frequency coding



Itakura (1970)
Autoregressive
modelling



Turing (1950)
thinking machine

Understanding speech production and acoustics led to ...

✓ Improved communication



✓ Enhanced hearing



✓ Advanced speech technologies



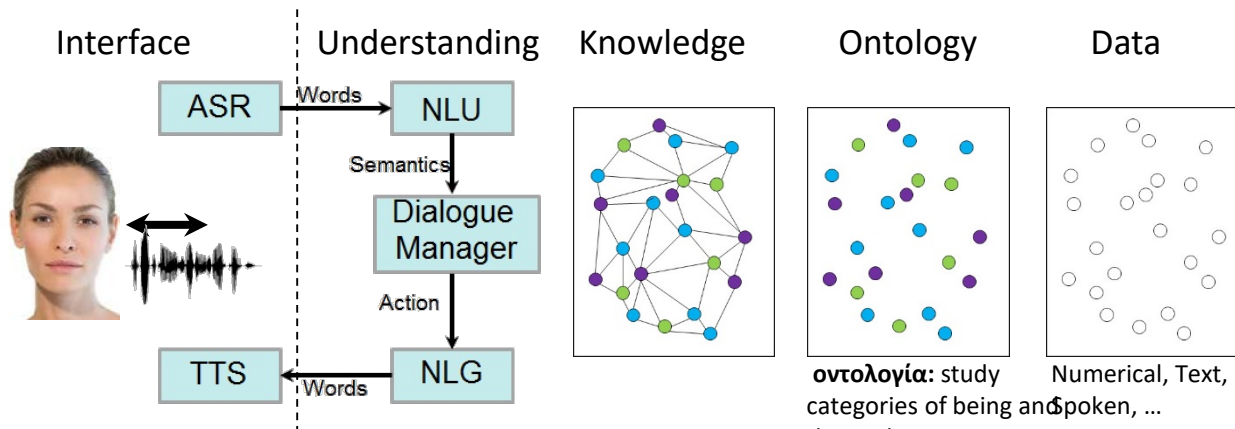
- Text-to-Speech Synthesis (TTS)
- Automatic Speech Recognition (ASR)

From information retrieval to thinking machines

Combining speech with machine learning will lead to effective human-machine communication

Learn from human:

Data driven approaches



1. natural, speech enabled, human-machine interface for information retrieval

2. learn human's procedures

- ❖ Design human centric information processing algorithms and services to create and access knowledge effectively, for improving productivity and quality of life

ASR: Automatic Speech Recognition; **NLU:** Natural Language Understanding;
NLG: Natural Language Generation; **TTS:** Text-to-speech

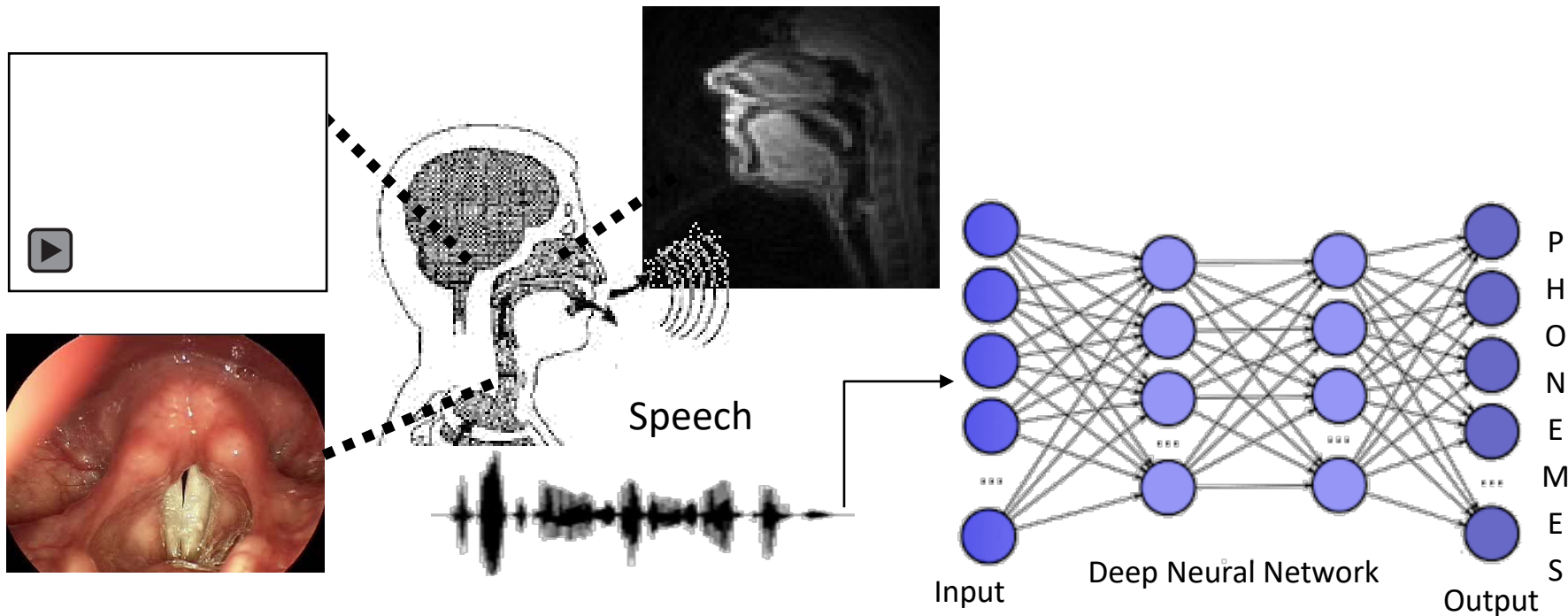
Human-like:




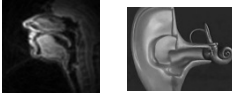
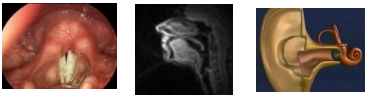
thinking machine



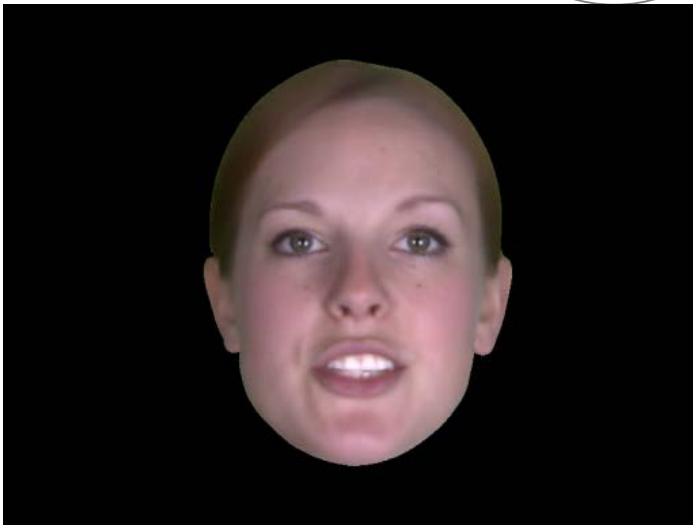
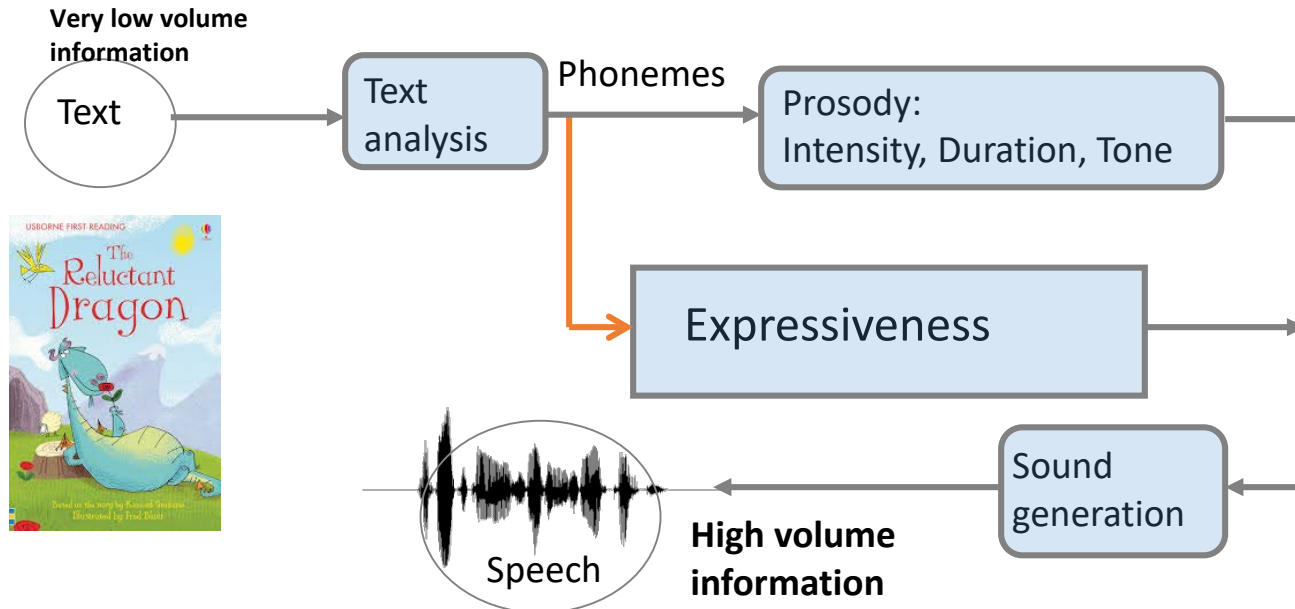
- make suggestions, compare, planning

Automatic speech recognition: speech to text

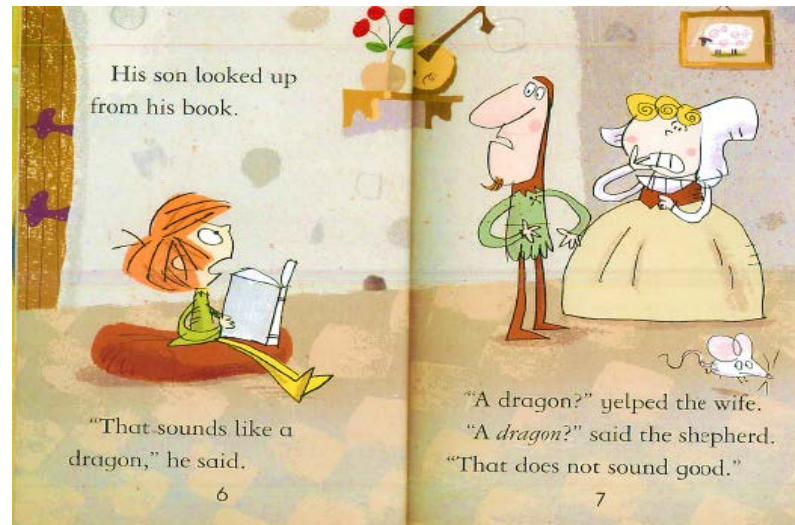


Approach	WER(%) 	WER(%) 
Waveform 	42	58
State of art 	14	34
CRL 	12	33

Flexible and high quality visual text-to-speech synthesis



Xpressive Talk™



BBC

NBC

sky
NEWS

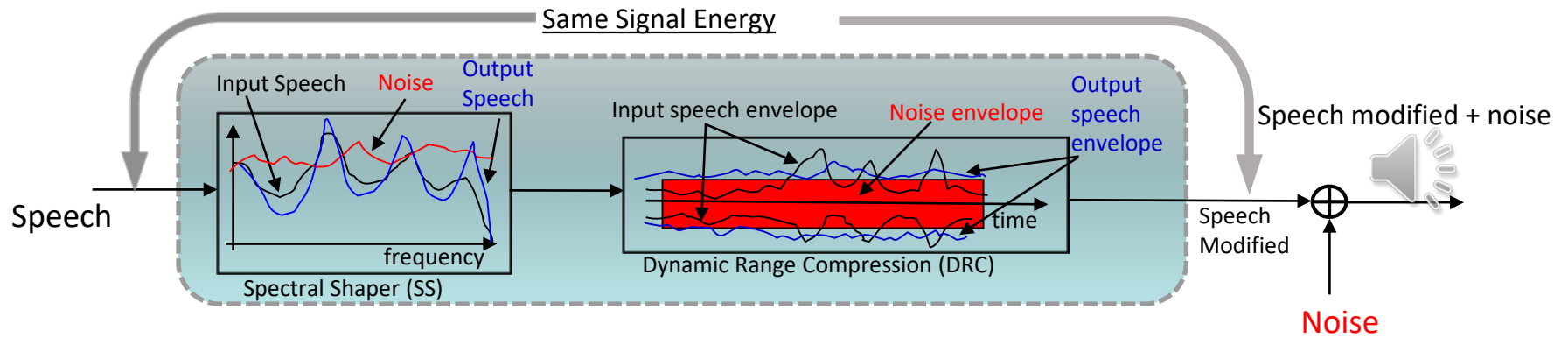
REUTERS

Intelligibility of speech in noise

➤ **Problem:** Speech Perception in Noise



➤ **Solution:** Spectral Shaping and Dynamic Range Compression (SSDRC)



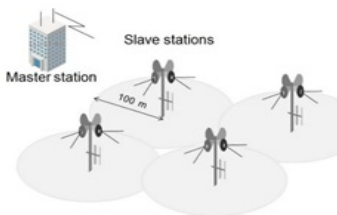
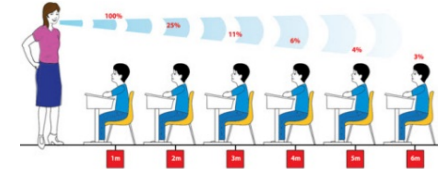
➤ **Applications:**



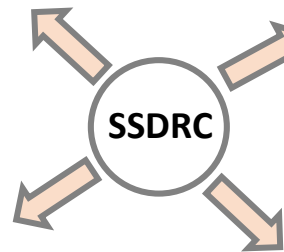
Transportation



Enhanced Hearing

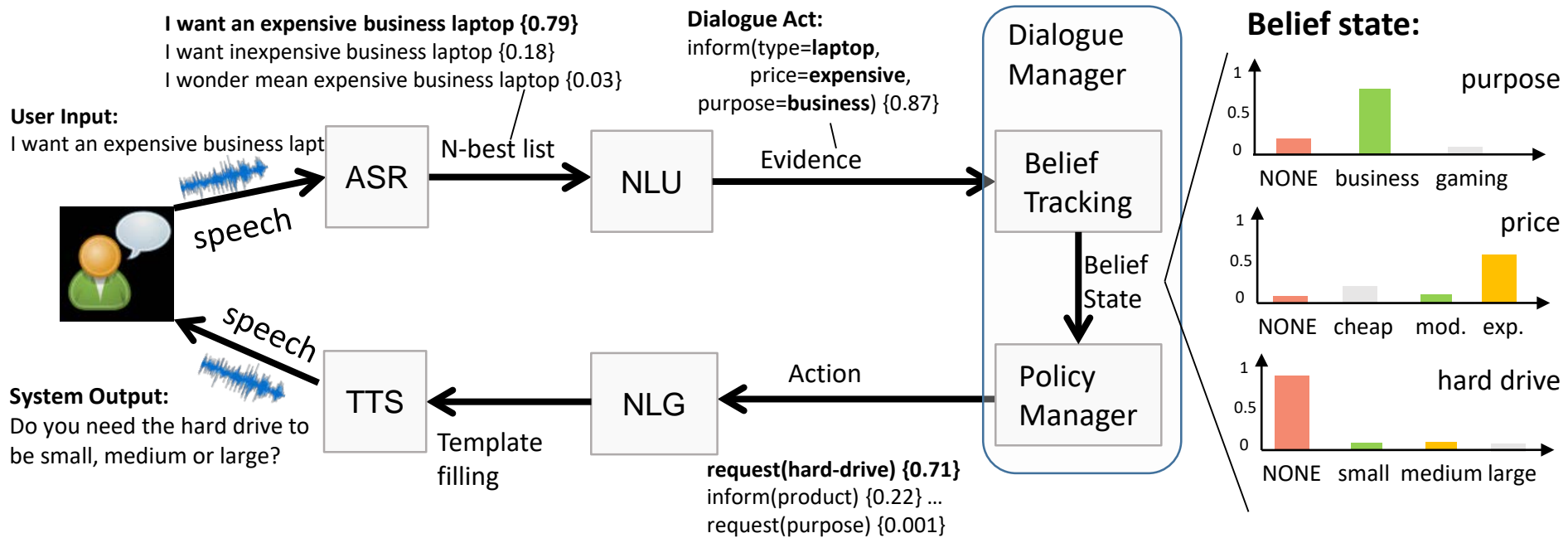


Public address systems

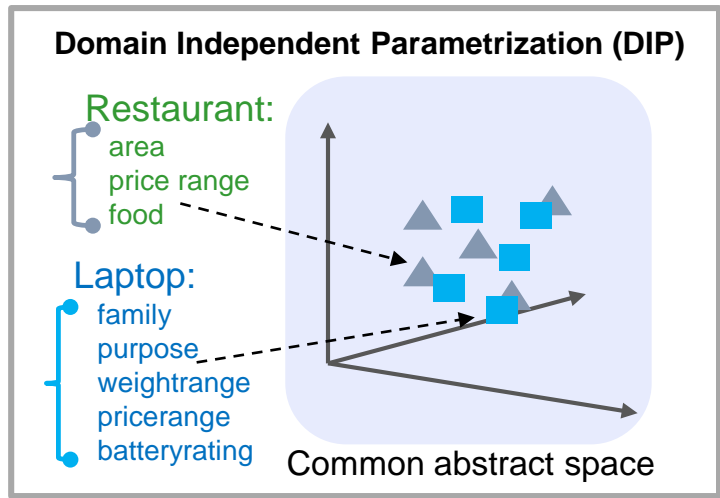


Telecommunications

Statistical Dialogue Manager



➤ Transfer learning



	In Domain	Transfer learning
Success rate	85%	82%

ASR: Automatic Speech Recognition; **NLU:** Natural Language Understanding; **NLG:** Natural Language Generation; **TTS:** Text-to-speech

Example of natural human-machine communication



... with the CRL statistical spoken dialogue manager

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- Statistical models – Regression
- Quick review of DNNs – a fast tour
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Definitions

- Speech synthesis is the artificial production of human speech
(Wikipedia)
- Text-to-Speech (TTS) refers to the conversion of text to intelligible, natural and expressive speech (it has a history of over 50 years)

Text-to-Speech









- Text-to-Speech (TTS) refers to the conversion of text to intelligible, natural and expressive speech
- An ill-posed problem:
 - **Text** - a narrow band information – **to Speech** - a wide band information
- A solution: record all the words and just play them back

read it!

I have read it!



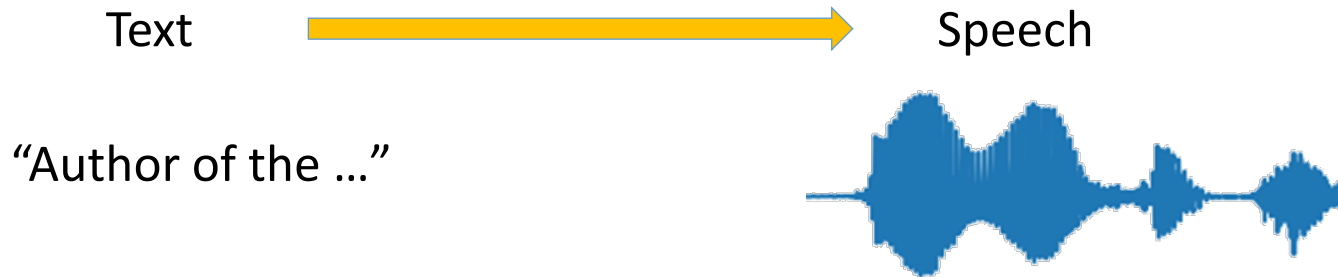
Text-to-Speech – the path so far

- Formant synthesizers 
- Diphones 
- Unit selection 
- Statistical Parametric    (Hybrid)
- Neural based  (wavenet vocoder)  (Tacotron)

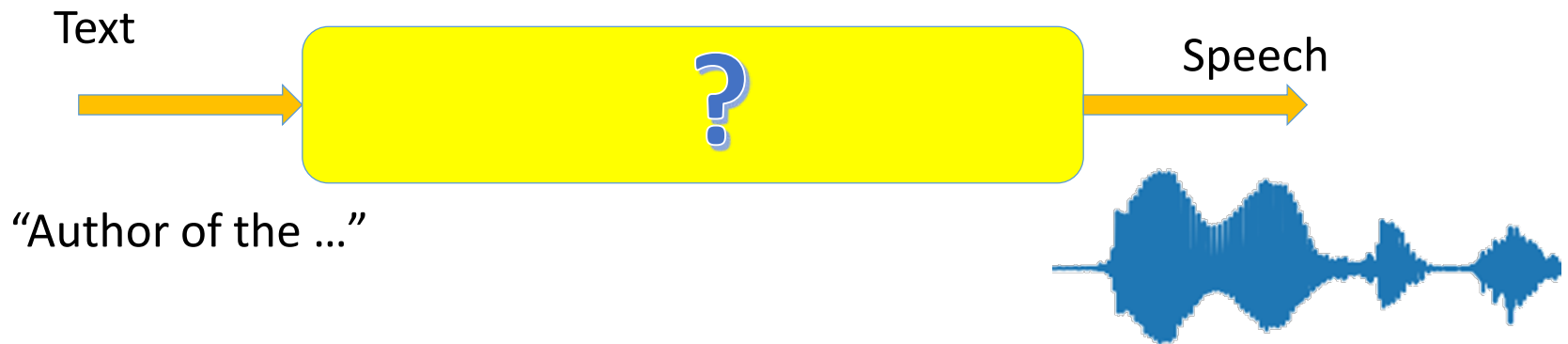
The first 3 audio files are from <https://www.ims.uni-stuttgart.de/institut/mitarbeiter/moehler/synthspeech/#english>

The last audio file (Tacotron) is from <https://google.github.io/tacotron/>

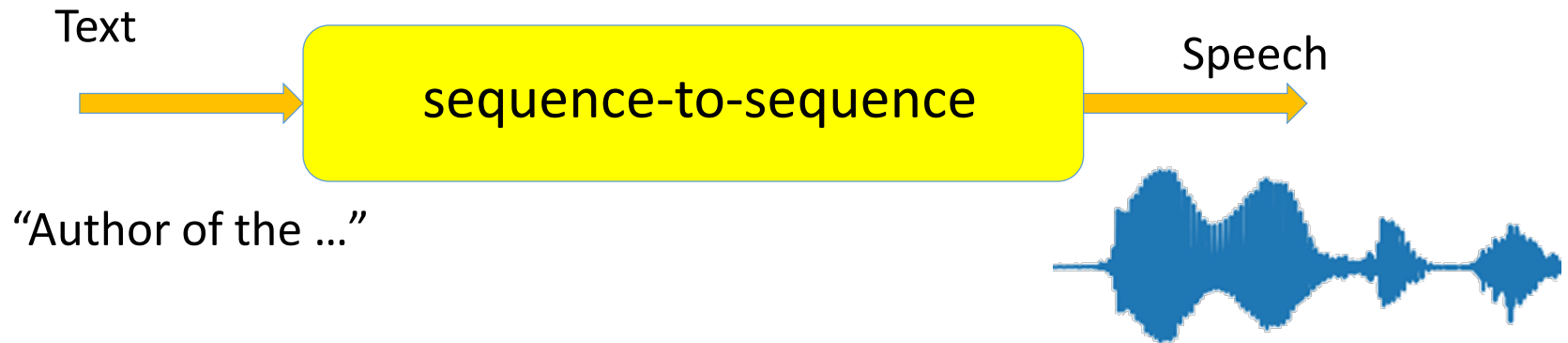
Text-to-Speech (as simple as that)



➤ End-to-end speech synthesis



Text-to-Speech ... a mapping problem

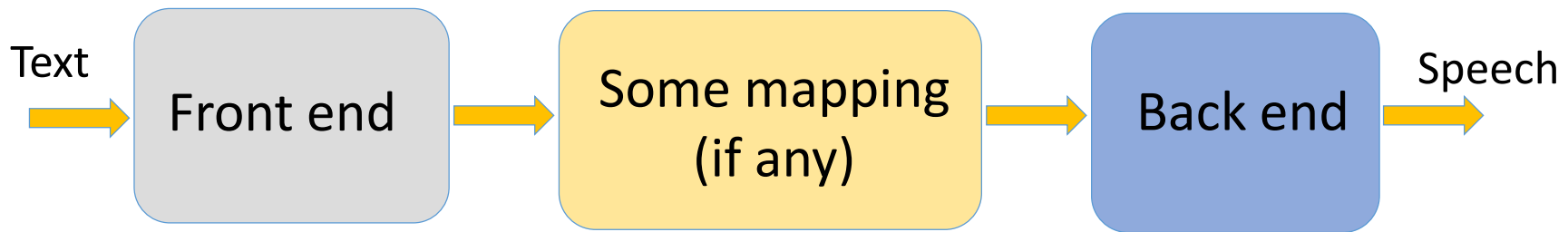
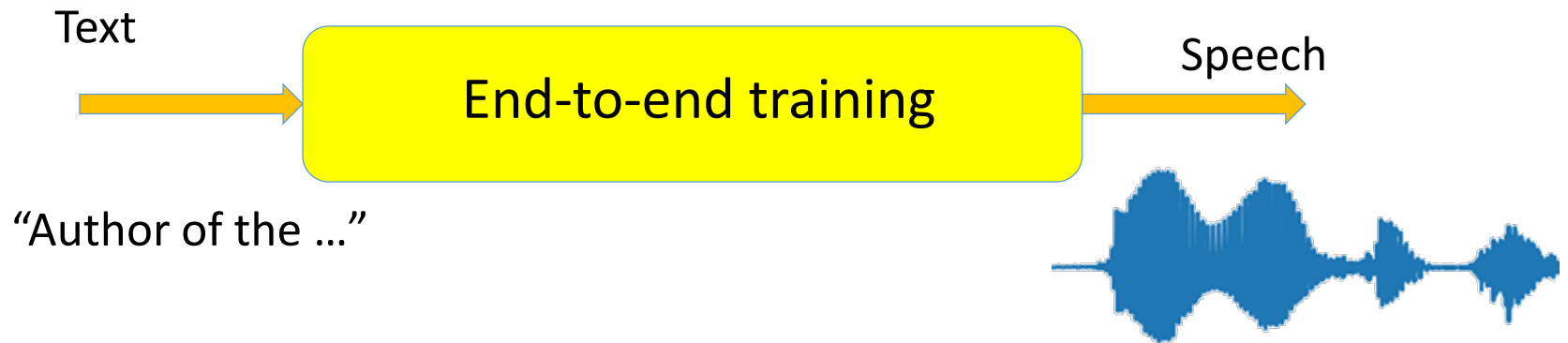


□ Options:

- Characters to samples
- Phonemes to speech features and then to samples
- Linguistic features to speech features and then to samples
- Linguistic features to samples

A sequence
to
sequence
problem

Text-to-Speech: the general framework



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Features from text - linguistics

“Author of the ...”

```
sil-sil-sil+ao=th@x_x/A:0_0_0/B:x-x-x@x-x&x-x#x-x$. . .
sil-sil-ao+th=er@1_2/A:0_0_0/B:1-1-2@1-2&1-7#1-4$. . .
sil-ao-th+er=ah@2_1/A:0_0_0/B:1-1-2@1-2&1-7#1-4$. . .
ao-th-er+ah=v@1_1/A:1_1_2/B:0-0-1@2-1&2-6#1-4$. . .
th-er-ah+v=dh@1_2/A:0_0_1/B:1-0-2@1-1&3-5#1-3$. . .
er-ah-v+dh=ax@2_1/A:0_0_1/B:1-0-2@1-1&3-5#1-3$. . .
ah-v-dh+ax=d@1_2/A:1_0_2/B:0-0-2@1-1&4-4#2-3$. . .
v-dh-ax+d=ey@2_1/A:1_0_2/B:0-0-2@1-1&4-4#2-3$. . .
```

Features from text - linguistics

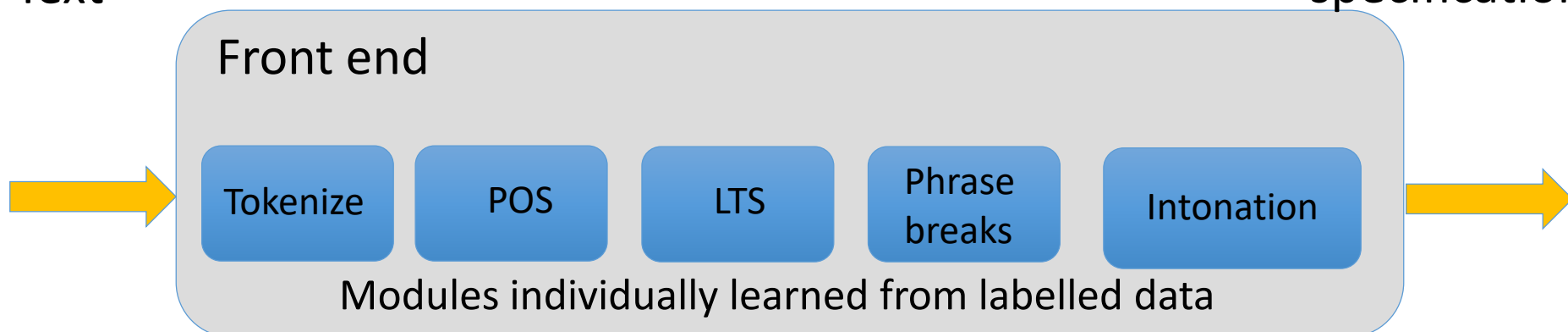
“Author of the ...”

```
sil-sil-sil+ao=thex_x/A:0_0_0/B:x-x-x@x-x&x-x#x-x$...  
sil-sil-ao+th=er@1_2/A:0_0_0/B:1-1-2@1-2&1-7#1-4$...  
sil-ao-th+er=ah@2_1/A:0_0_0/B:1-1-2@1-2&1-7#1-4$...  
ao-th-er+ah=v@1_1/A:1_1_2/B:0-0-1@2-1&2-6#1-4$...  
th-er-ah+v=dh@1_2/A:0_0_1/B:1-0-2@1-1&3-5#1-3$...  
er-ah-v+dh=ax@2_1/A:0_0_1/B:1-0-2@1-1&3-5#1-3$...  
ah-v-dh+ax=d@1_2/A:1_0_2/B:0-0-2@1-1&4-4#2-3$...  
v-dh-ax+d=ey@2_1/A:1_0_2/B:0-0-2@1-1&4-4#2-3$...
```



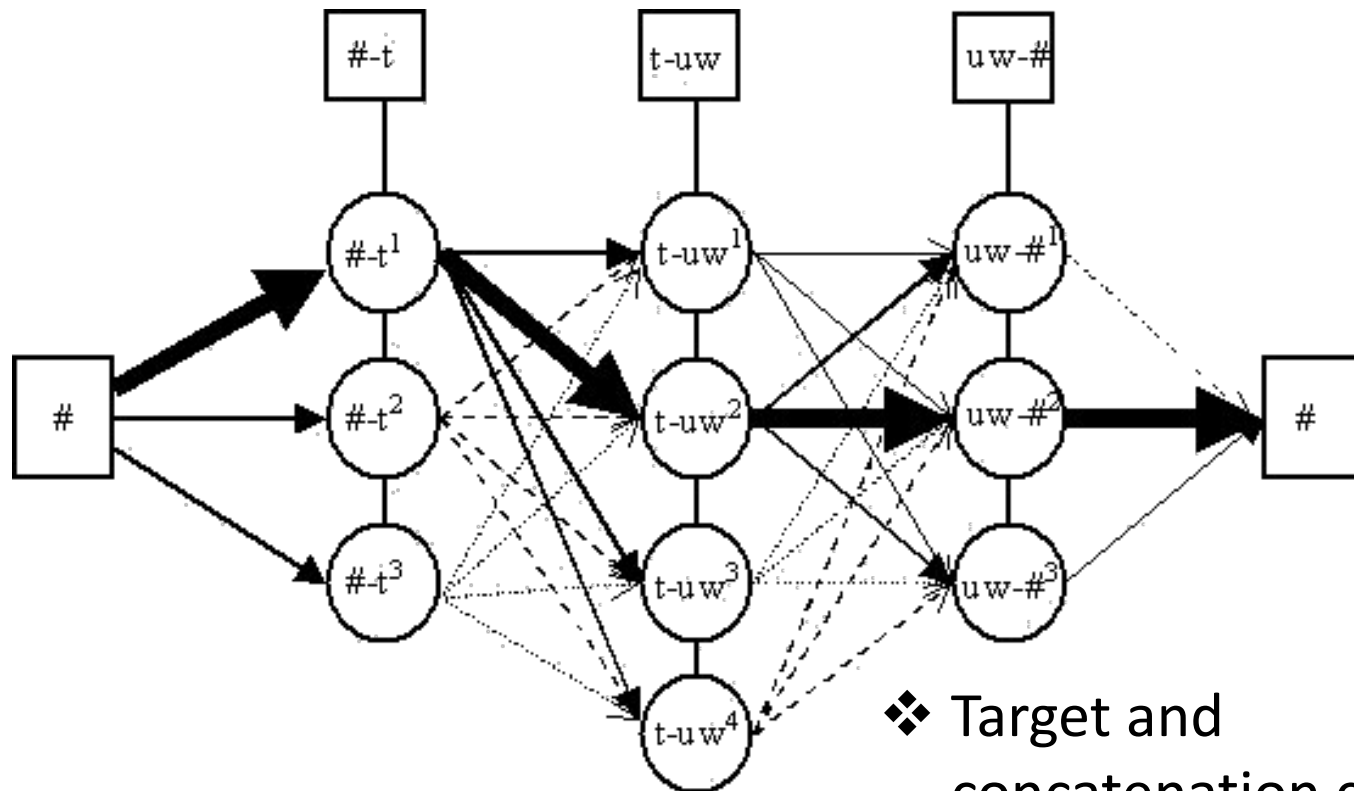
Text

Linguistic
specification



Concatenative systems (pure)

- From linguistic features to units (samples)

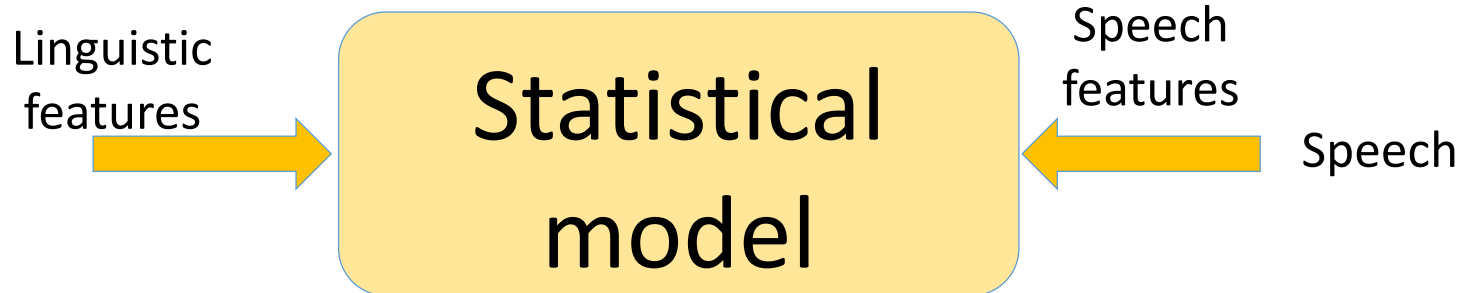
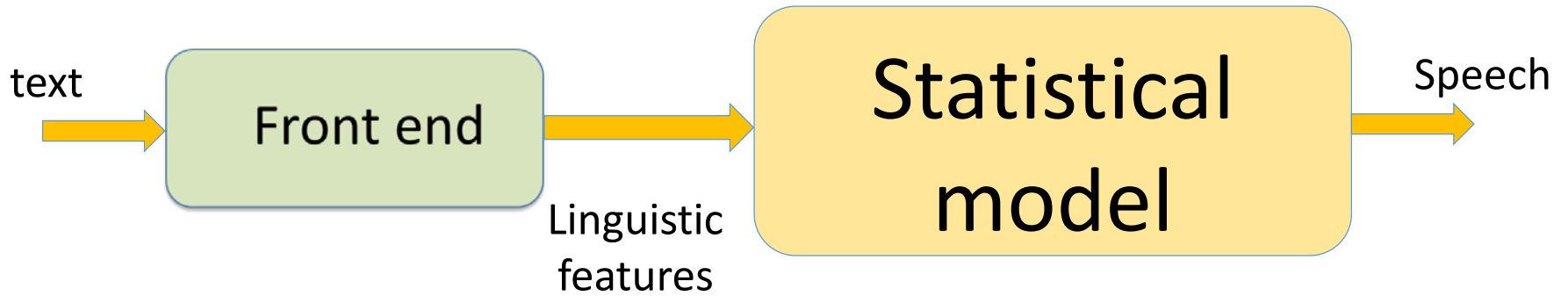


❖ Target and concatenation costs

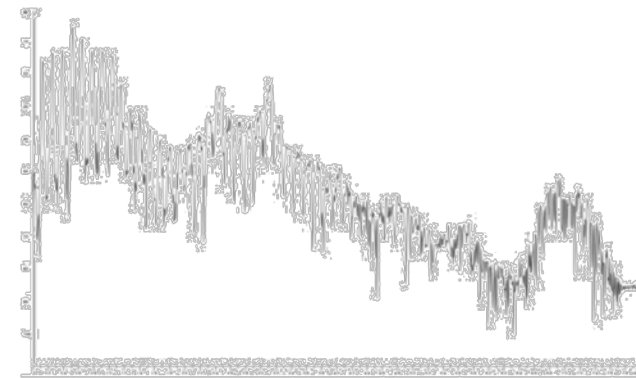
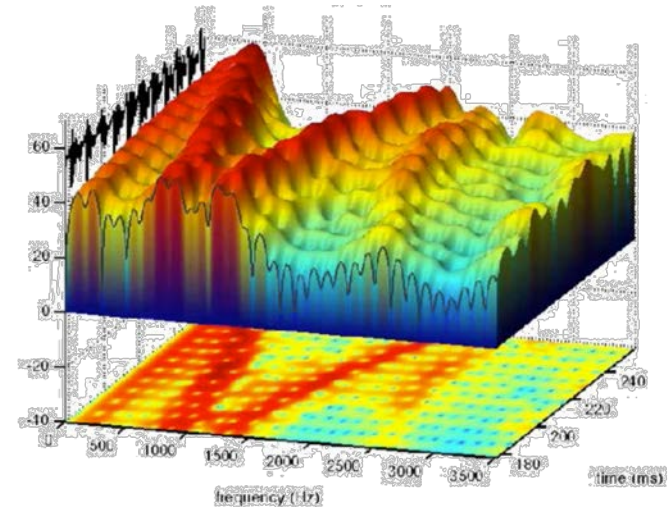
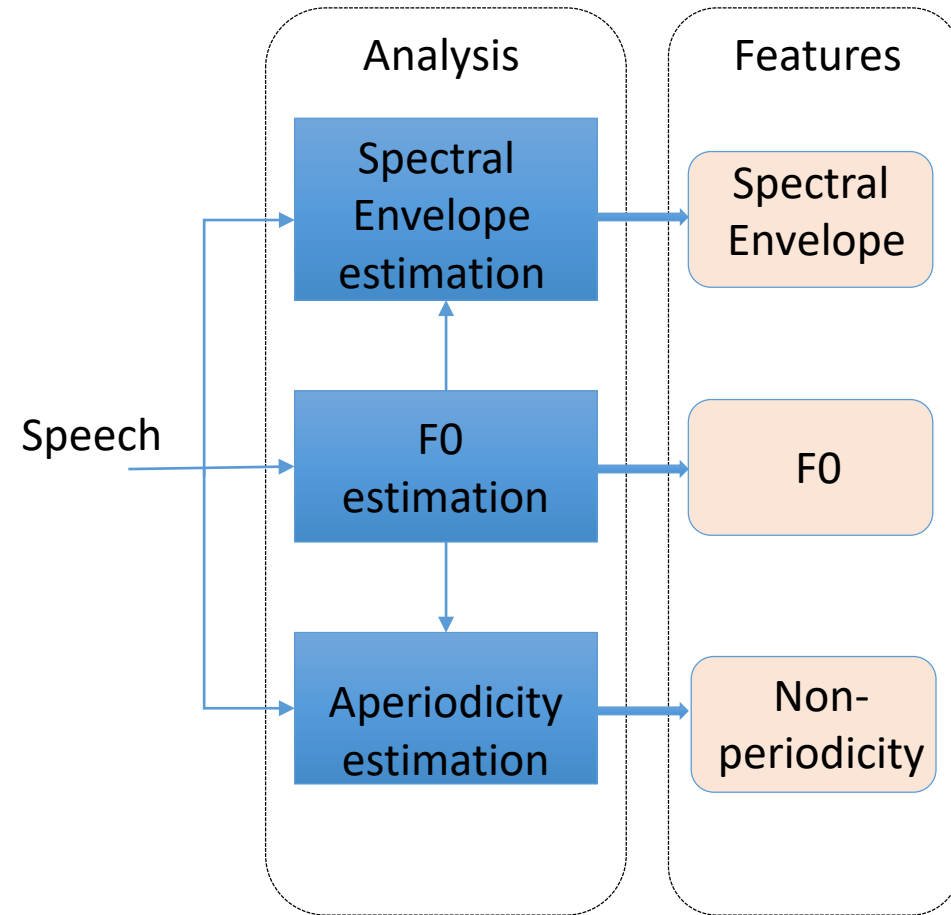
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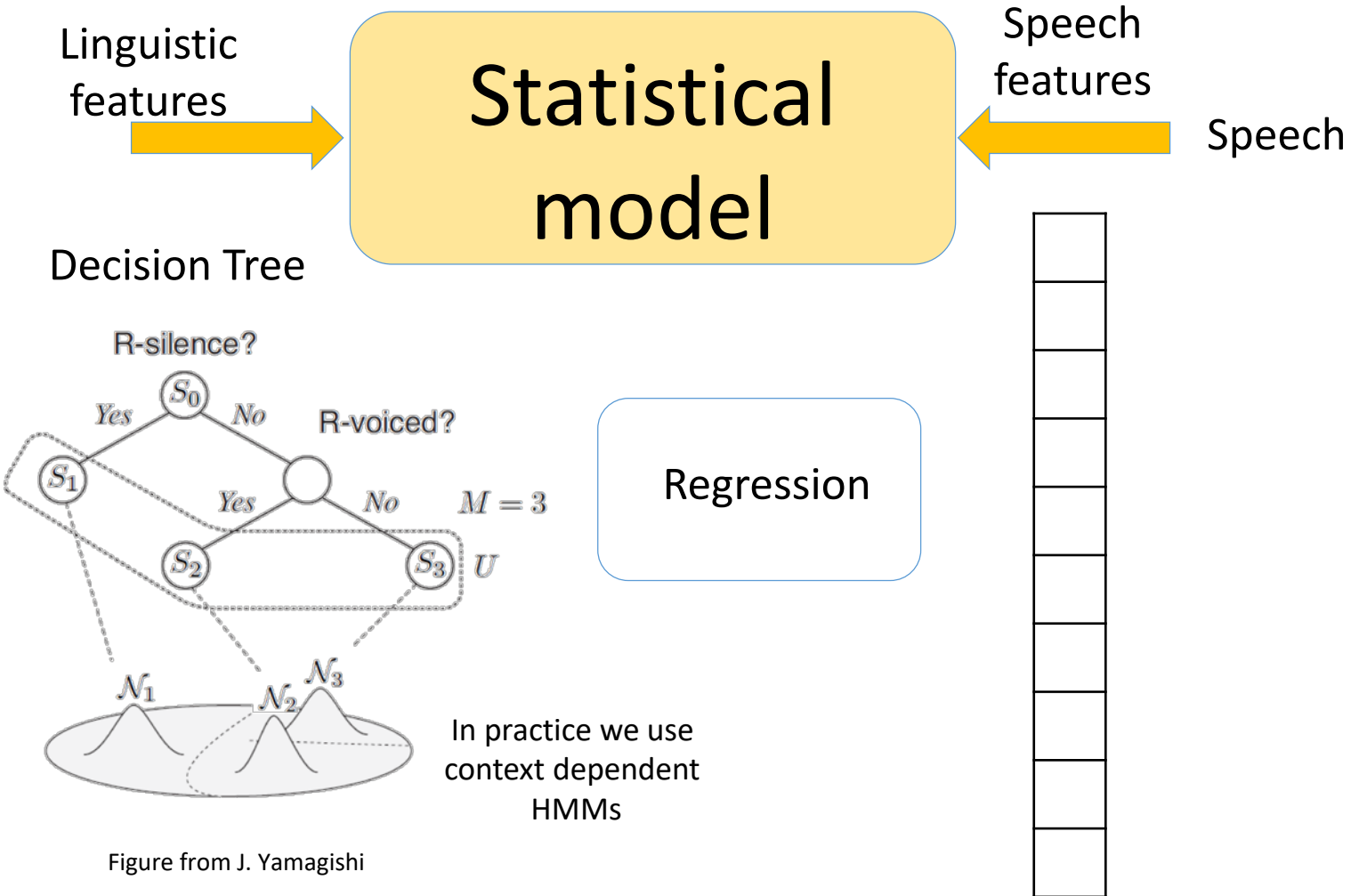
Start learning from data



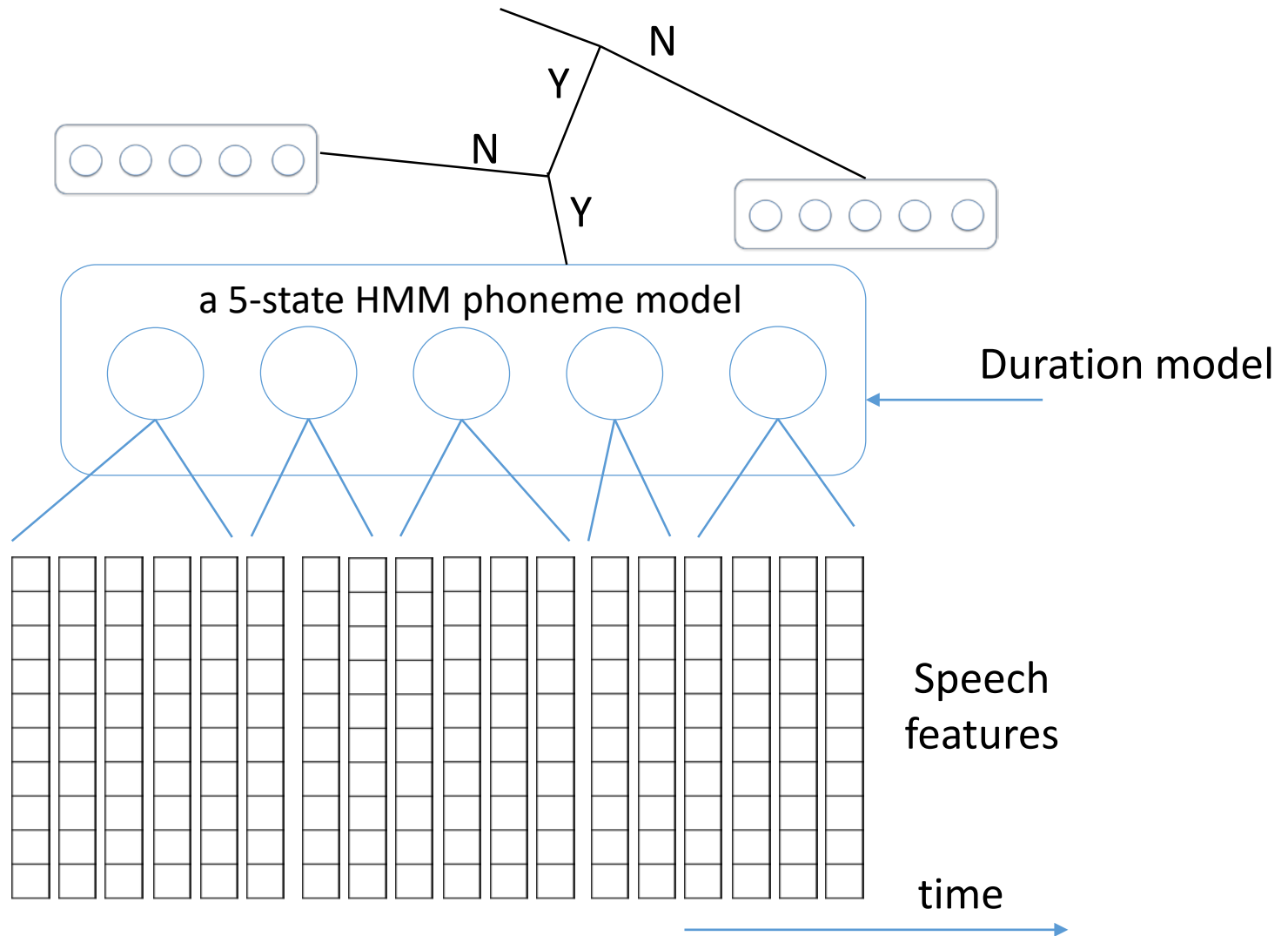
Speech features – STRAIGHT (H. Kawahara)



Start learning from data



Text-to-features using CART

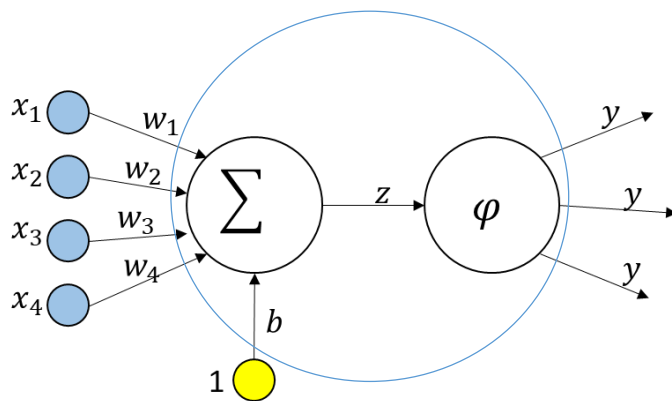
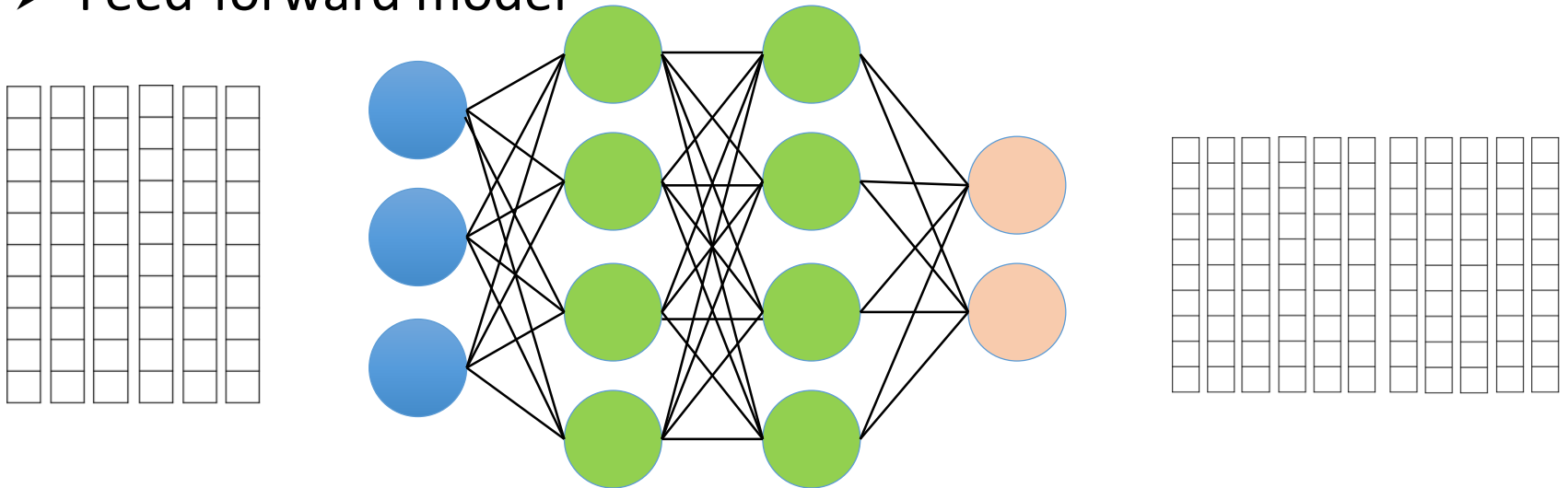


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Towards neural (based) TTS - DNN

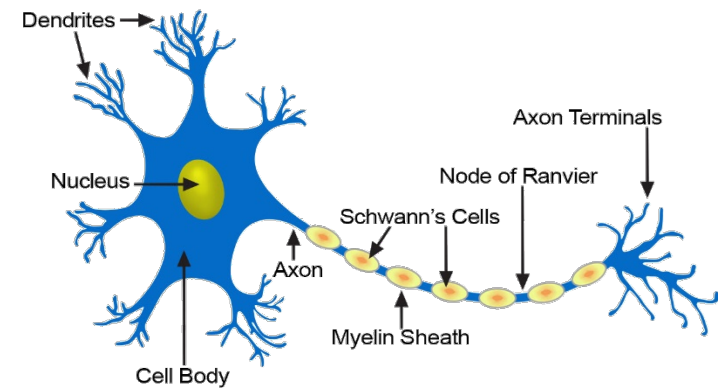
➤ Feed-forward model



$$z = \sum_i w_i x_i + b$$

$$y = \phi(z) = \begin{cases} 0, & z < 0 \\ 1, & z \geq 0 \end{cases}$$

Structure of a Typical Neuron



Going back to our problem: TTS (with DNNs)

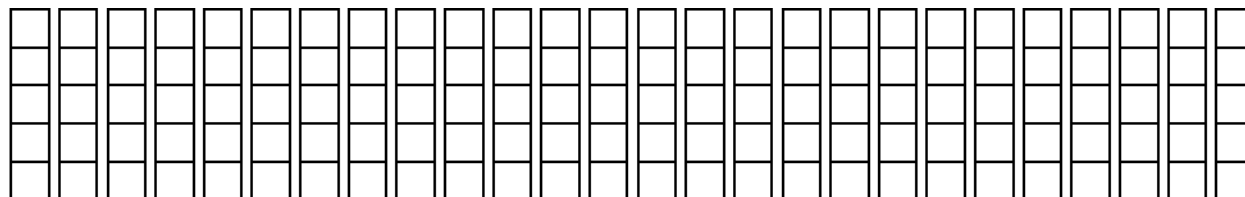
- Features encoded: context-dependent phone to a vector of binary features

```
sil-sil-sil+ao=th@x_x/A:0_0_0/B:x-x-x@x-x&x-x#x-x$...  
sil-sil-ao+th=er@1_2/A:0_0_0/B:1-1-2@1-2&1-7#1-4$...  
sil-ao-th+er=ah@2_1/A:0_0_0/B:1-1-2@1-2&1-7#1-4$...  
ao-th-er+ah=v@1_1/A:1_1_2/B:0-0-1@2-1&2-6#1-4$...  
th-er-ah+v=dh@1_2/A:0_0_1/B:1-0-2@1-1&3-5#1-3$...  
er-ah-v+dh=ax@2_1/A:0_0_1/B:1-0-2@1-1&3-5#1-3$...  
ah-v-dh+ax=d@1_2/A:1_0_2/B:0-0-2@1-1&4-4#2-3$...  
v-dh-ax+d=ey@2_1/A:1_0_2/B:0-0-2@1-1&4-4#2-3$...
```



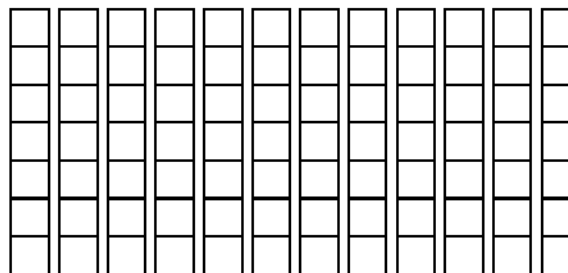
Neural TTS = a sequence-to-sequence regression

Output sequence:
speech features



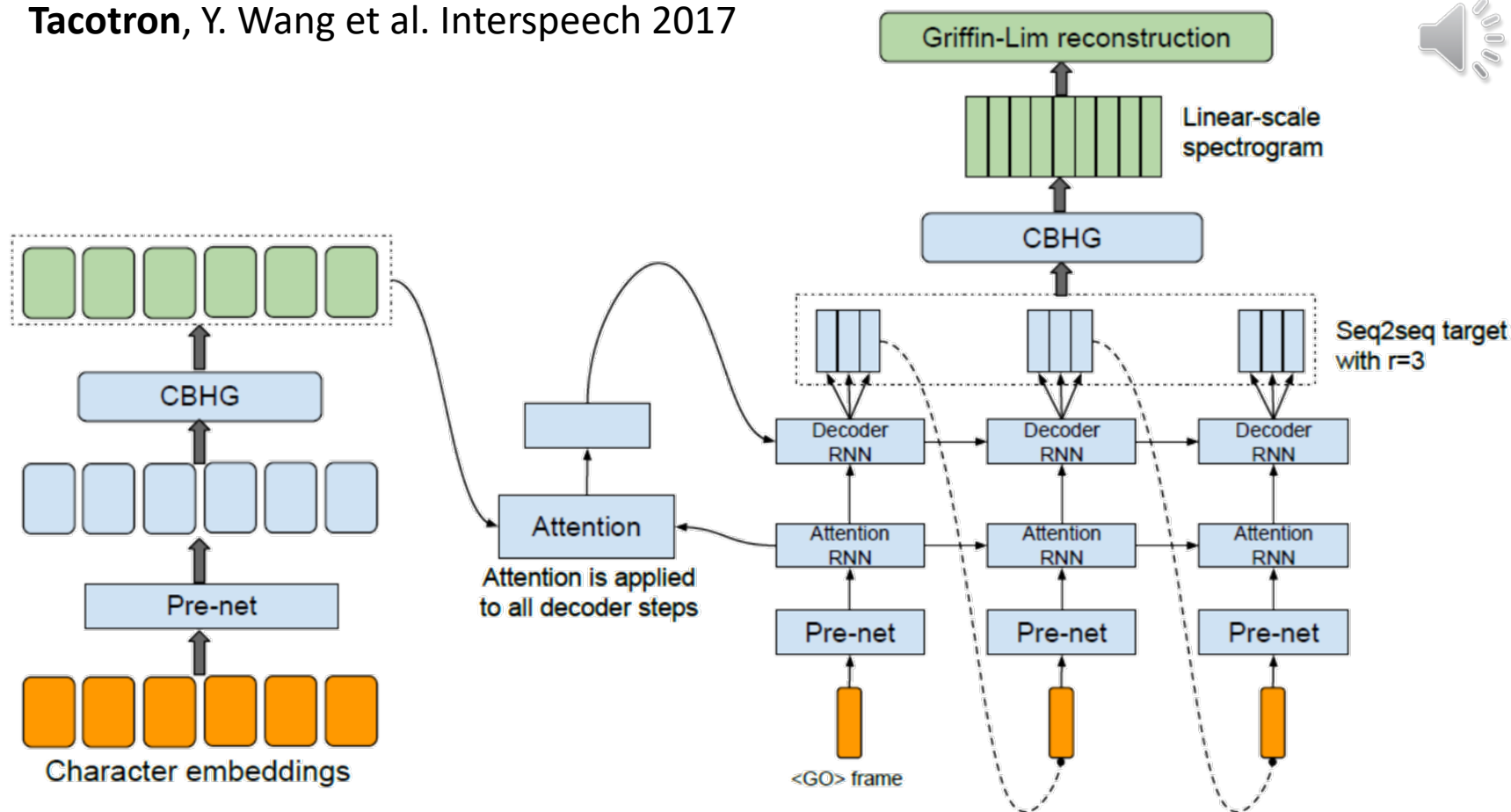
Different lengths, because of
different clock rates

Input sequence:
linguistic specification



Tacotron: a multiple sequence-to-sequence model

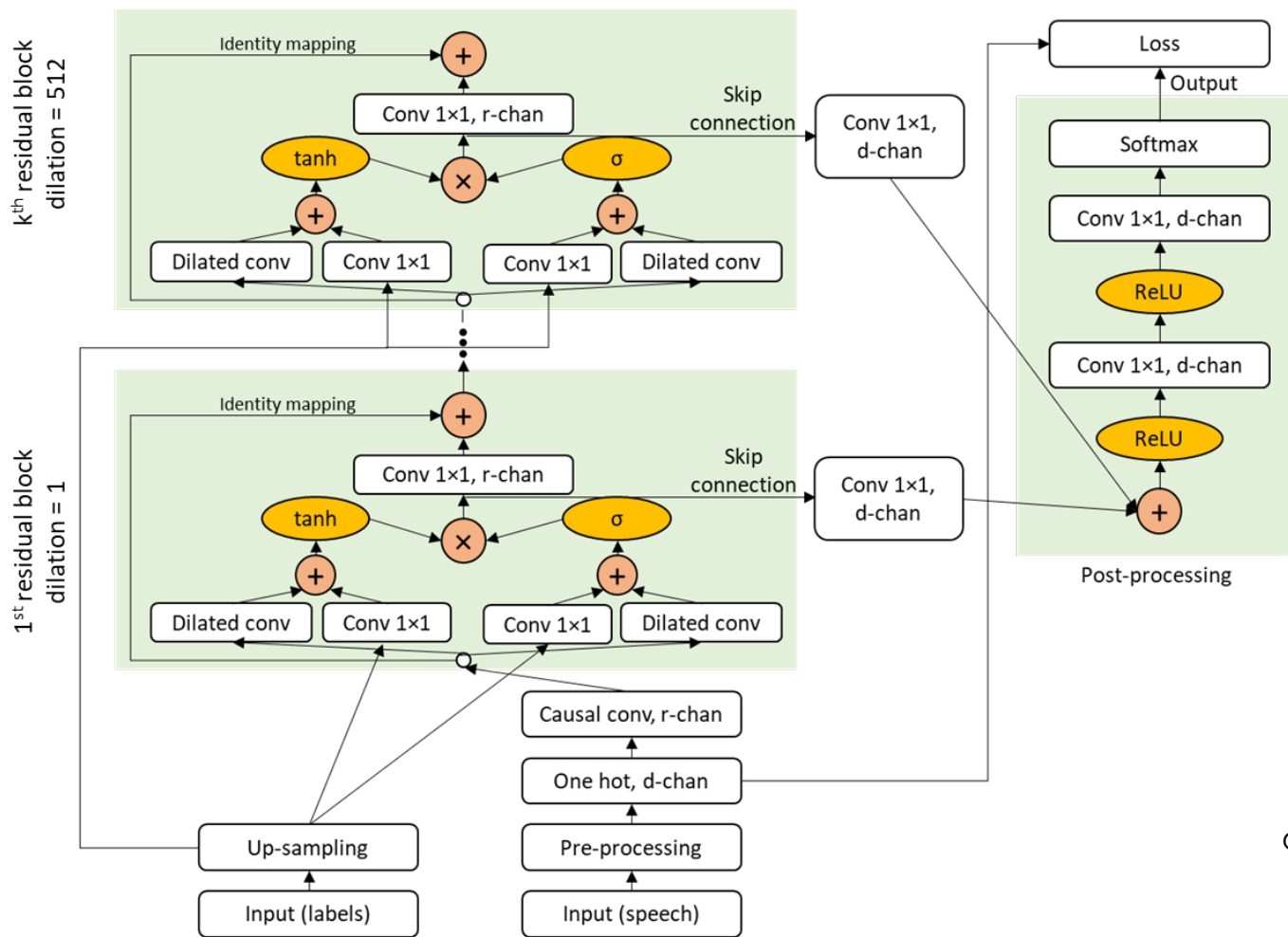
Tacotron, Y. Wang et al. Interspeech 2017



CHBG: Convolution bank – highway network – bidirectional Gated Recurrent Unit (GRU)

Wavenet

$$P(x_n | x_{n-1}, x_{n-2}, \dots, x_{n-r}, h_n)$$



Sound examples (16 kHz) [test data]:

- ❖ with natural prosody:
 - Google (40 hours)



- UoC (5 hours)



- ❖ with synthetic prosody (HMM):
 - UoC (5 hours)



Sound examples from Univ. of Crete trained on vocoded speech^{B9}

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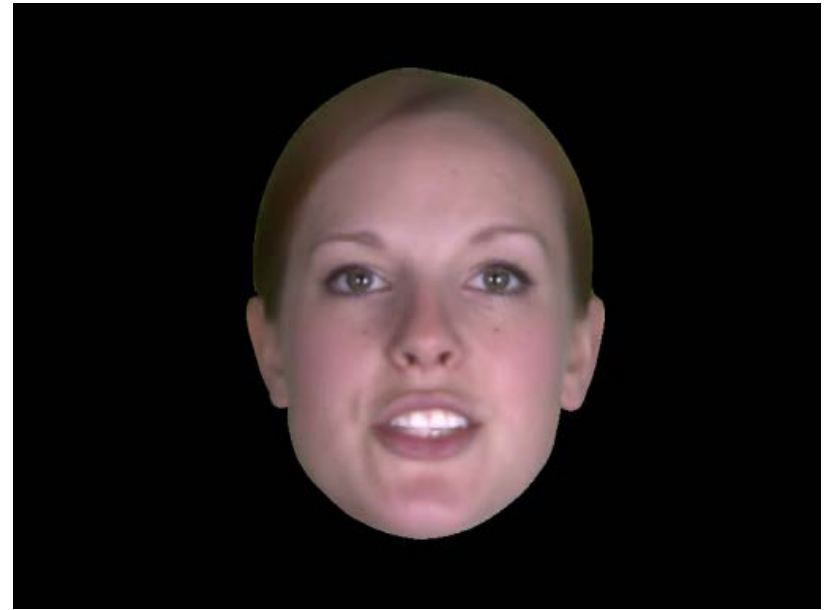
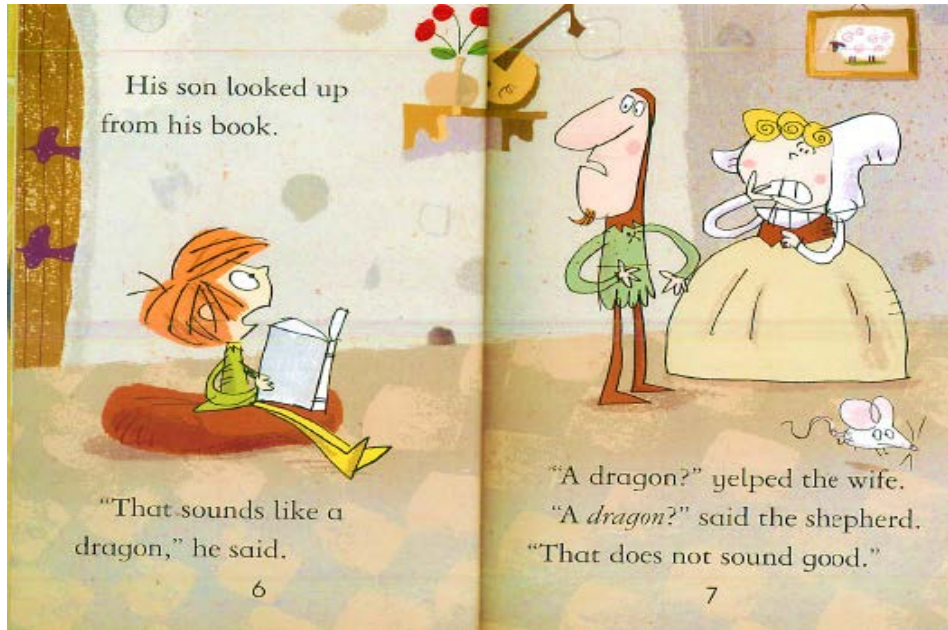
Speech Synthesis – current issues

- Robustness & running cost
 - Robust & fast front-end and back-end (Parallel Wavenet, WaveRNN, ...)
 - Robust to recordings quality and quantity
 - Robust training
- Context awareness
 - Adaptation to user acts in dialogue (conversational TTS, style token)
 - Adaptation to the listening conditions (intelligibility)

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The usual (suspect of) application



Xpressive Talk™ Toshiba Corp.

BBC



The real application: Conversational TTS



Toshiba: Statistical Dialogue System

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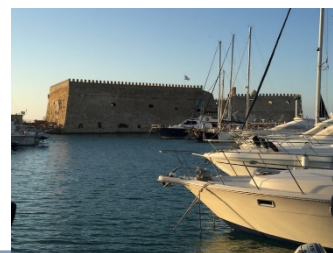
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Speech Processing Courses in Crete

SPCC

July 27-31, 2020

Crete, Greece



- Learn (with theory in the mornings and hands on in the afternoons) about:
 - ✓ Neural Source-Filter vocoders for synthesis (Junichi Yamagishi and Xin Wang, NII Japan)
 - ✓ Sample, autoregressive neural vocoders (Vassilis Tsiaras, UoC, Greece)
 - ✓ Neural Vocoders for coding (Jan Skoglund, Google, USA)
 - ✓ Neural based speech enhancement (Paris Smaragdis, Univ of Illinois, USA)