



Interactive control of Expressive Speech Synthesis

Olivier PERROTIN

30.11.2023

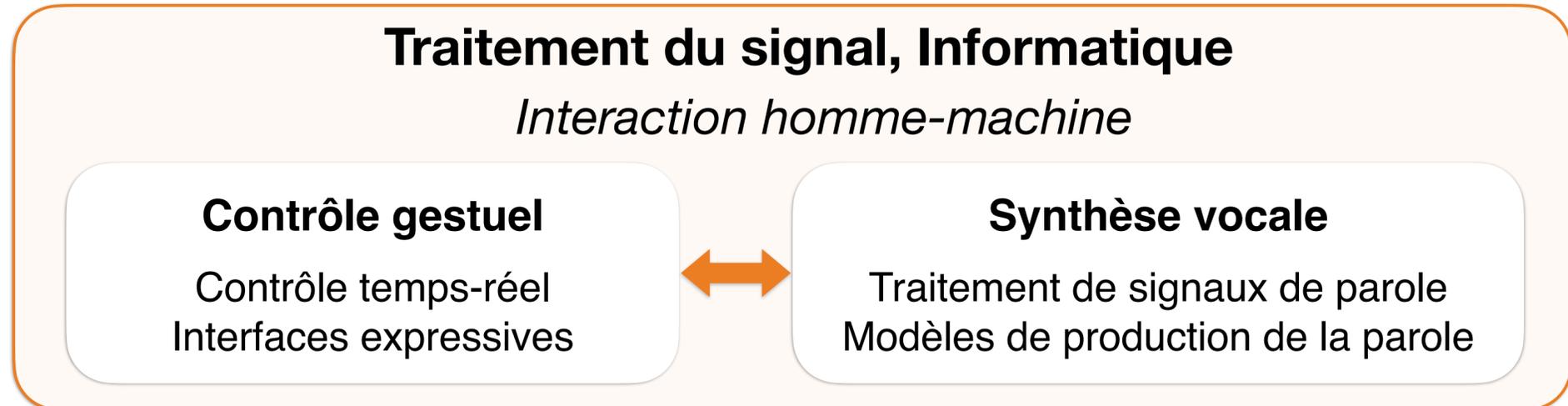
Rencontre des Jeunes Chercheurs en Parole 2023



Parcours

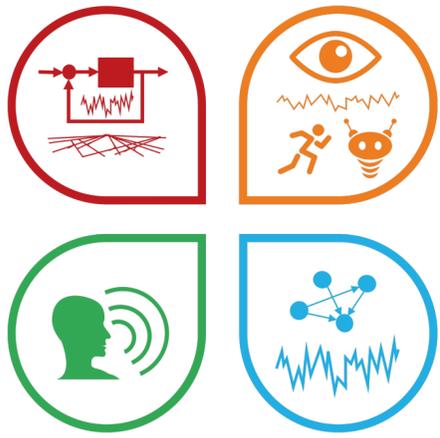
	Ecole d'ingénieur Grenoble INP - Phelma, <i>Spécialité traitement du signal (SICOM)</i>	TS	
2012	Thèse au LIMSI, Université Paris-Sud (dir. C. d'Alessandro) « <i>Singing with hands : chironomic interfaces for digital musical instruments</i> »	IHM	 
2015	Post-doctorat au LIMSI, CNRS « <i>Vocal effort control in Singing Synthesis</i> » - 16 months	TS	 
2017	Post-doctorat à University of Kent, School of Computing, Royaume-Uni « <i>Whisper-to-Speech conversion</i> » - 16 months	TS	
2018	Chargé de recherche CNRS, GIPSA-lab « <i>Interactive control of expressive speech synthesis</i> »	TS IHM	 

2023



Interactive control of expressive speech synthesis

- An overview of **speech synthesis**
- Analysis-synthesis of **expressive speech**
- **Interactive control** of synthesis



Generating voices

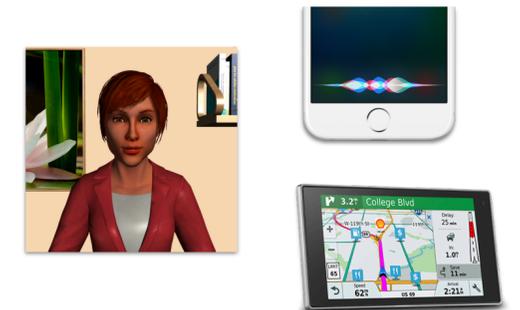
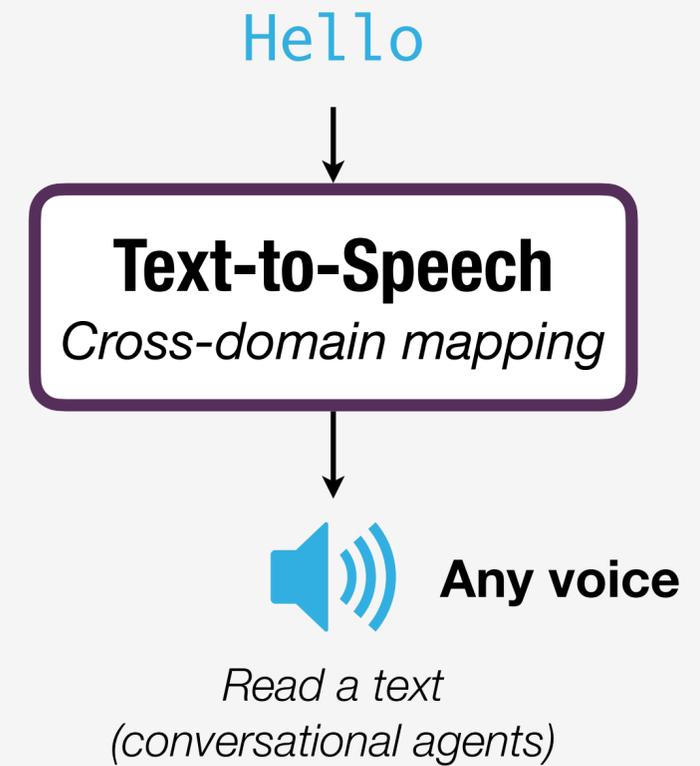
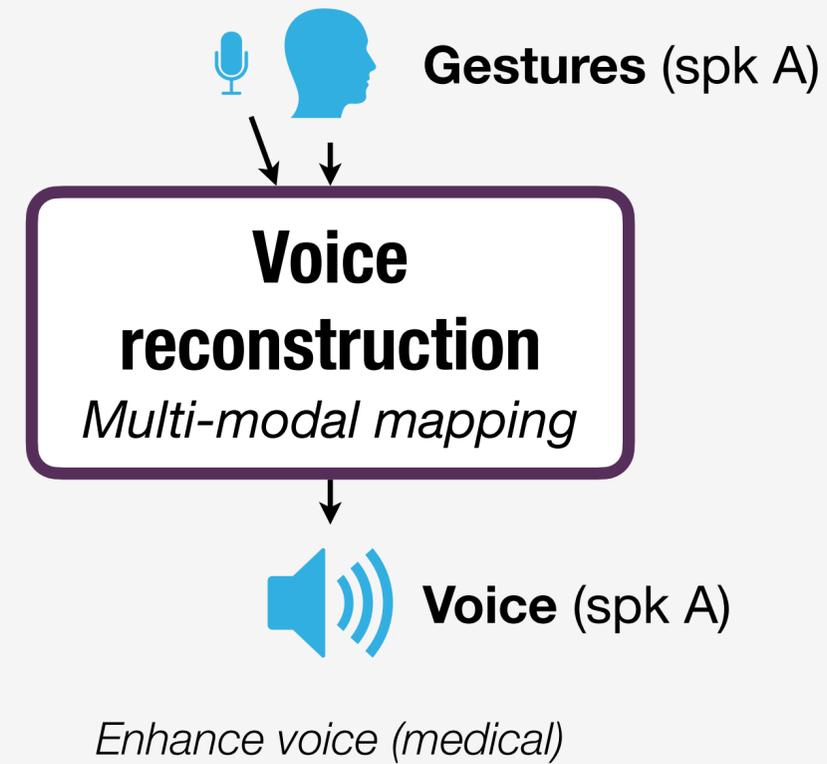
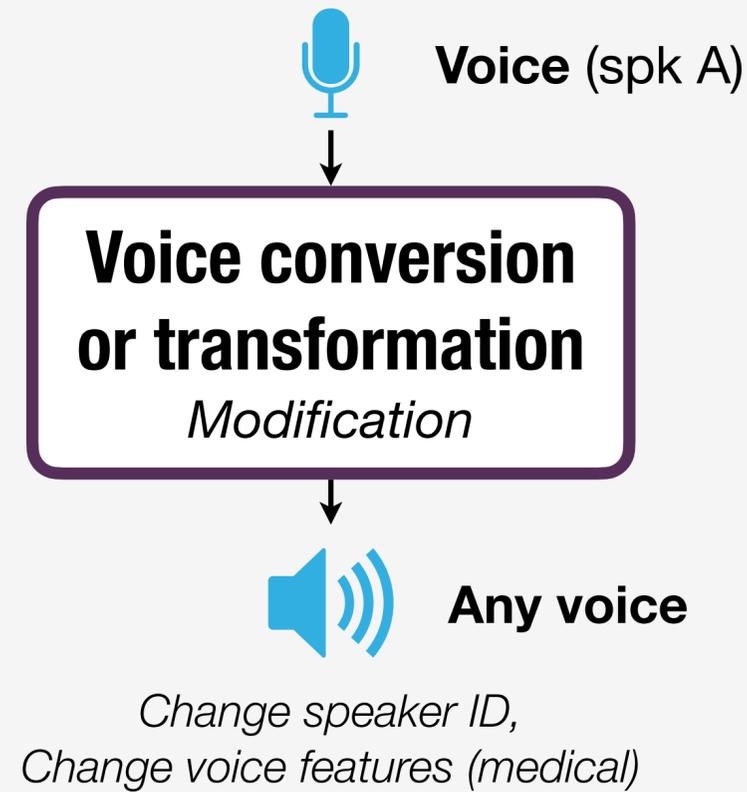
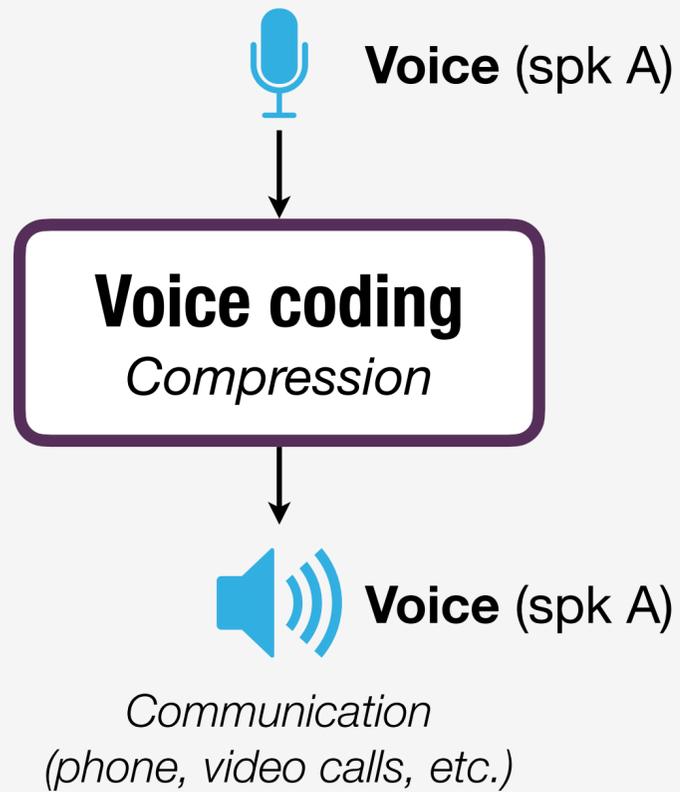


For whom?

To say what?

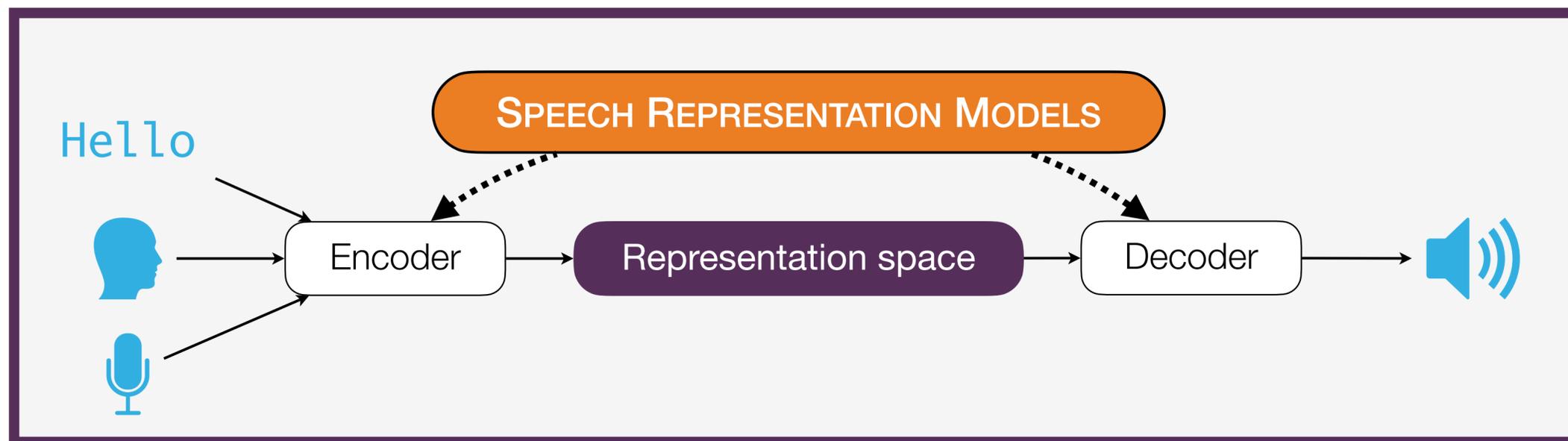
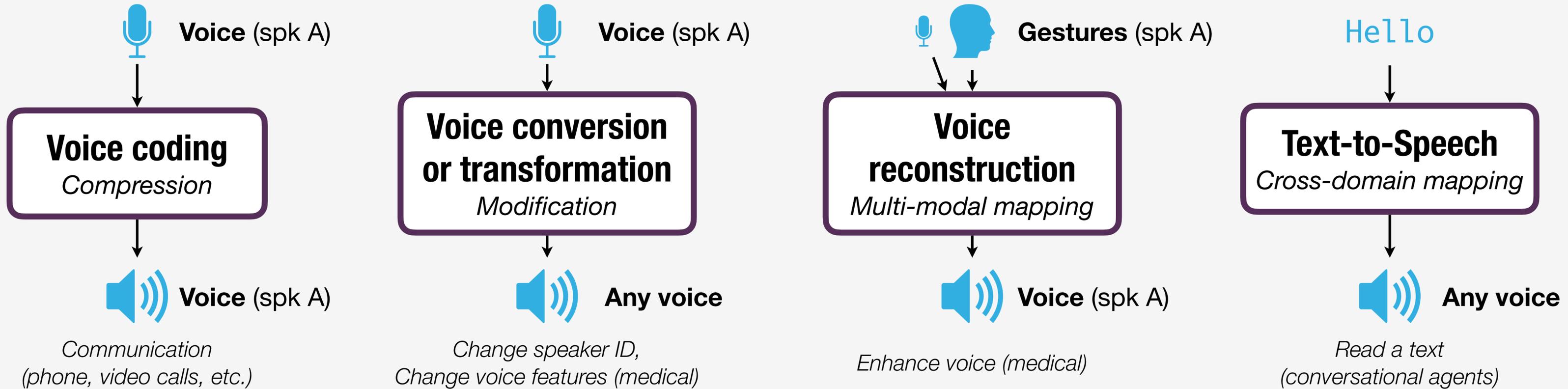
Voice generation

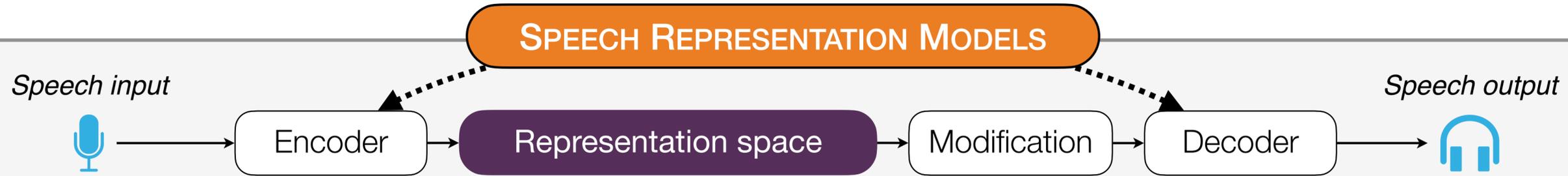
Applications



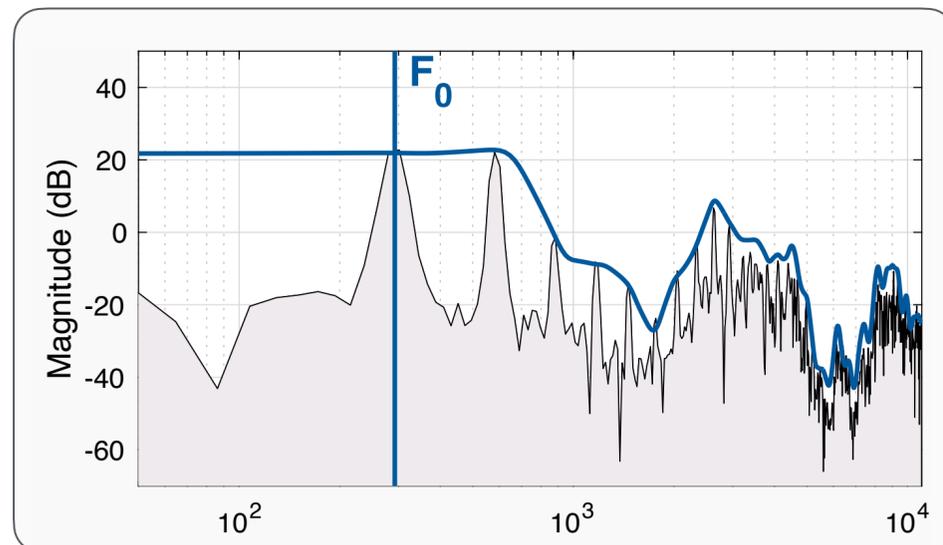
Voice generation

Applications



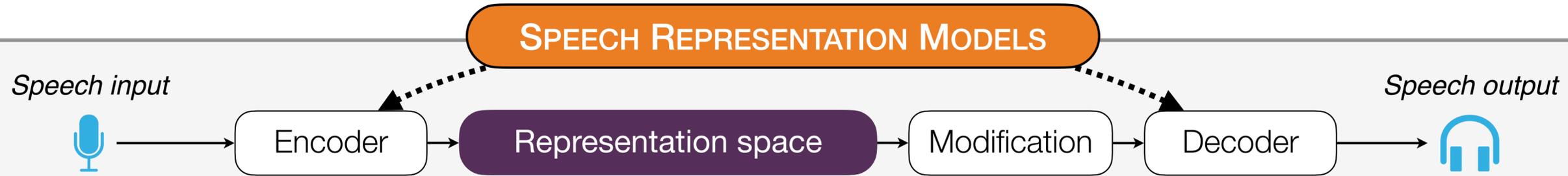


- Speech input and output → symmetric encoding/decoding process
- Two kinds of encoding
 - Signal-based (F0, spectral envelope, etc.)
 - Source-filter based (Vocal tract and glottal flow parameters)



(References are non-exhaustive)

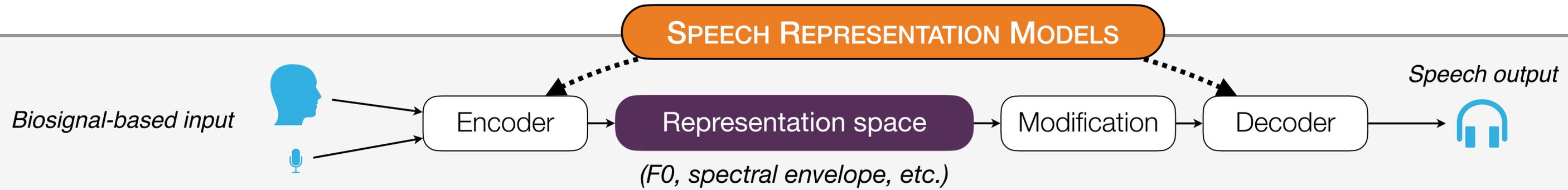
Compression	LPC Linear Predictive coding	<i>Makhoul J. (1975), Proc. of the IEEE, 63(4), pp. 561–580.</i>
	MLSA Mel log spectrum approximation	<i>Imai S. et al. (1983), Electronics and Communications in Japan, 66(2), pp. 10–18.</i>
	CELP Code-excited linear prediction	<i>Schroder M. et al. (1985), Proc. ICASSP, pp. 937–940.</i>
High-quality	HNM Harmonic plus Noise Model	<i>Stylianou Y. (1996),. PhD Thesis, Ecole Normale Supérieure des Télécommunications</i>
	STRAIGHT Speech Transformation and Representation using Adaptive Interpolation of weiGHTEd spectrum	<i>Kawahara H. et al. (1999),. Speech Communication, vol. 27, no. 3-4, pp. 187–207.</i>
	WORLD	<i>Morise M. et al. (2016),. IEICE Trans. on Information and Systems, pp. 1877–1884.</i>
Glottal model	IAIF Iterative Adaptive Inverse Filtering	<i>Alku P. (1992), Speech Comm., 11(2–3), pp. 109–118.</i>
	SVLN Separation of the Vocal tract with the Liljencrants–fant model plus Noise	<i>Degottex G. et al. (2013), Speech Comm., 55(2), pp. 278–294.</i>



- Speech input and output ➔ symmetric encoding/decoding process
- Two kinds of encoding
 - Signal-based (F0, spectral envelope, etc.)
 - Source-filter based (Vocal tract and glottal flow parameters)
- Reduced set of parameters ➔ **Voice coding**
- Modification of parameters
 - Change speaker ID ➔ **Voice conversion**
 - Change speaker voice ➔ **Voice transformation**

(References are non-exhaustive)

Coding	LPC Linear Predictive coding	Makhoul J. (1975), <i>Proc. of the IEEE</i> , 63(4), pp. 561–580.
	MLSA Mel log spectrum approximation	Imai S. et al. (1983), <i>Electronics and Communications in Japan</i> , 66(2), pp. 10–18.
	CELP Code-excited linear prediction	Schroder M. et al. (1985), <i>Proc. ICASSP</i> , pp. 937–940.
Conversion	Statistical GMM	Toda T. (2007), <i>Trans. IEEE TASLP</i> , 15(8), pp. 2222–2235.
	VC Challenge GMM / some DNN	Toda T. et al. (2016), <i>Proc. Interspeech</i> , pp. 1632–1636.
Transformation	SVLN	Degottex G. et al. (2013), <i>Speech Comm.</i> , 55(2), pp. 278–294.
	Whisper-to-Speech GMM- / Rule- based	Toda T. et al. (2012), <i>Trans. IEEE TASLP</i> , 20(9), pp. 2505–2517. Perrotin O. et al. (2020), <i>IEEE TASLP</i> , 28, pp. 889–900.



- Input specific encoding methods
 - Articulatory-to-acoustic mapping
 - Brain-to-acoustic mapping
 - Muscle activity-to-acoustic mapping
- ➔ Similar dynamics between input and output (causal effect)

Biosignal-based

Litt. review

Schultz T. et al. (2017),. IEEE TASLP, 25(12), pp. 2257–2271.

Vocal tract lab

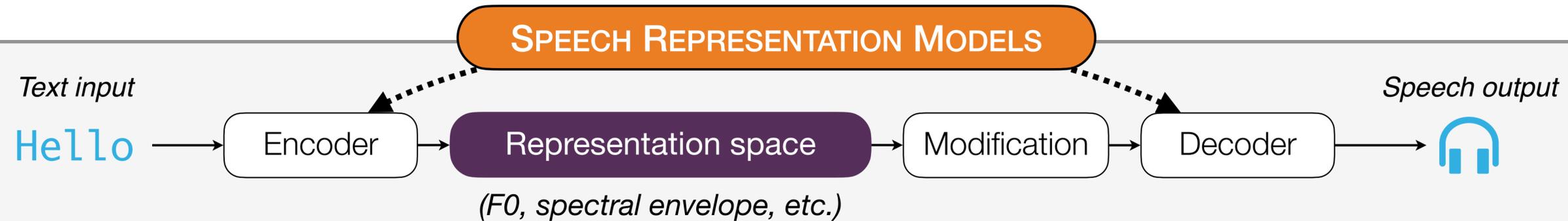
Articulatory synthesis

Birkholz P. (2013),. PLoS ONE, 8(4)

Silent Speech

HMM-based

Hueber T. et al. (2016),. Comp. Speech Lang., 36, pp. 274–293.



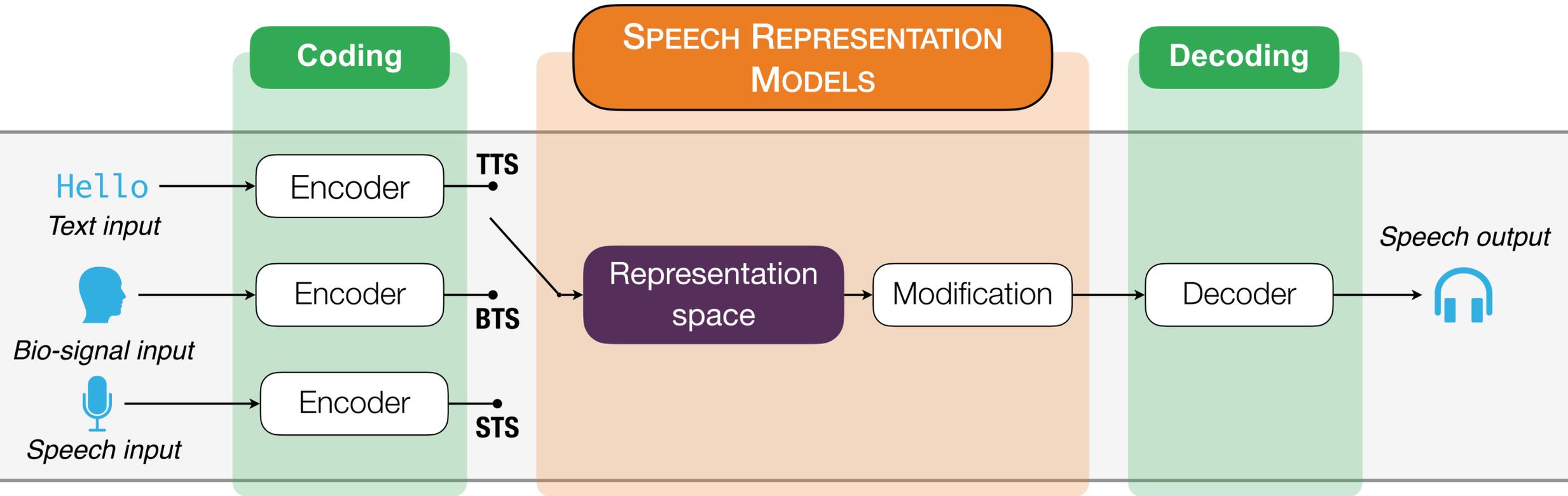
- Input specific encoding methods
 - Articulatory-to-acoustic mapping
 - Brain-to-acoustic mapping
 - Muscle activity-to-acoustic mapping

➔ Similar dynamics between input and output (causal effect)
- Natural language processing methods
 - Grapheme to phoneme conversion
 - Part of speech tagging
 - Etc.

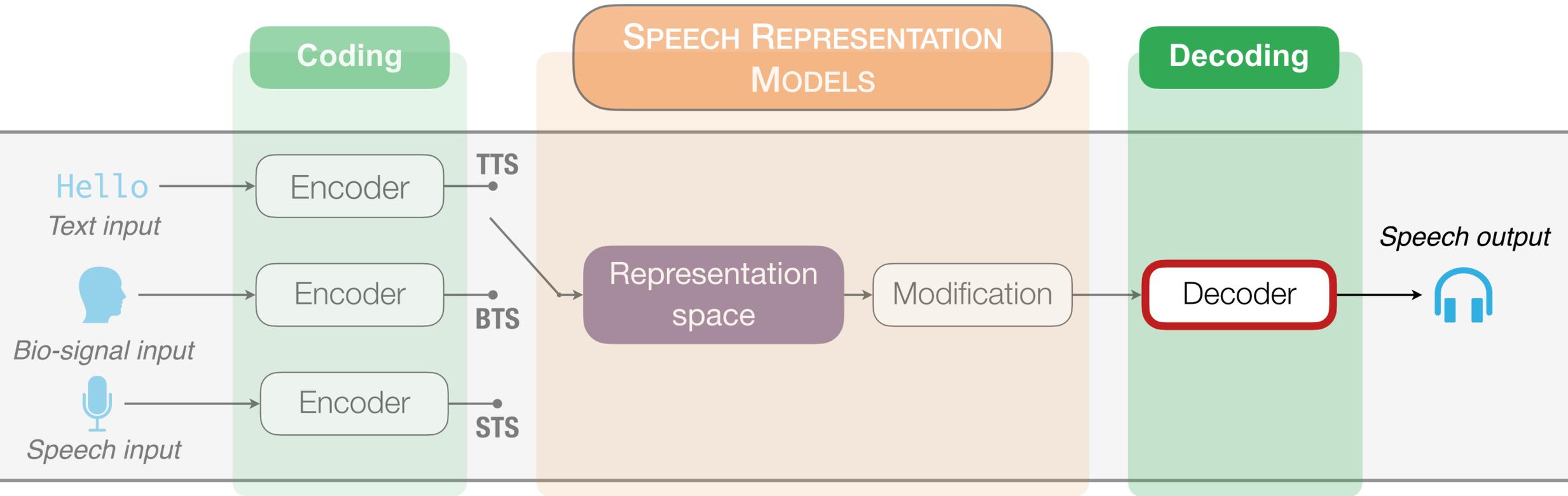
➔ Different dynamics between input and output (need to predict duration)

Biosignal-based Litt. review	<i>Schultz T. et al. (2017),. IEEE TASLP, 25(12), pp. 2257–2271.</i>
Vocal tract lab Articulatory synthesis	<i>Birkholz P. (2013),. PLoS ONE, 8(4)</i>
Silent Speech HMM-based	<i>Hueber T. et al. (2016),. Comp. Speech Lang., 36, pp. 274–293.</i>
Rule-based Formant synthesis	<i>Klatt D. et al. (1980),. J. Acoust. Soc. Am., 67(3), pp. 971–995.</i>
Concatenative Speech samples	<i>Hunt A. et al. (1996), Proc. ICASSP, pp. 373–376.</i>
Statistical Vocoder	<i>Tokuda K. et al. (2013),. Proc. of the IEEE, 101(5), pp. 1234–1252.</i>
Blizzard Challenge 2005 / 2013	<i>Black A. et al. (2005),. Proc. of Interspeech, pp. 77–80.</i> <i>King S. et al. (2013),. Evaluation of TTS systems.</i>

Voice generation



- All literature presented so far was < 2017
- Now everything is 'neural'
- How does this change the voice generation process?



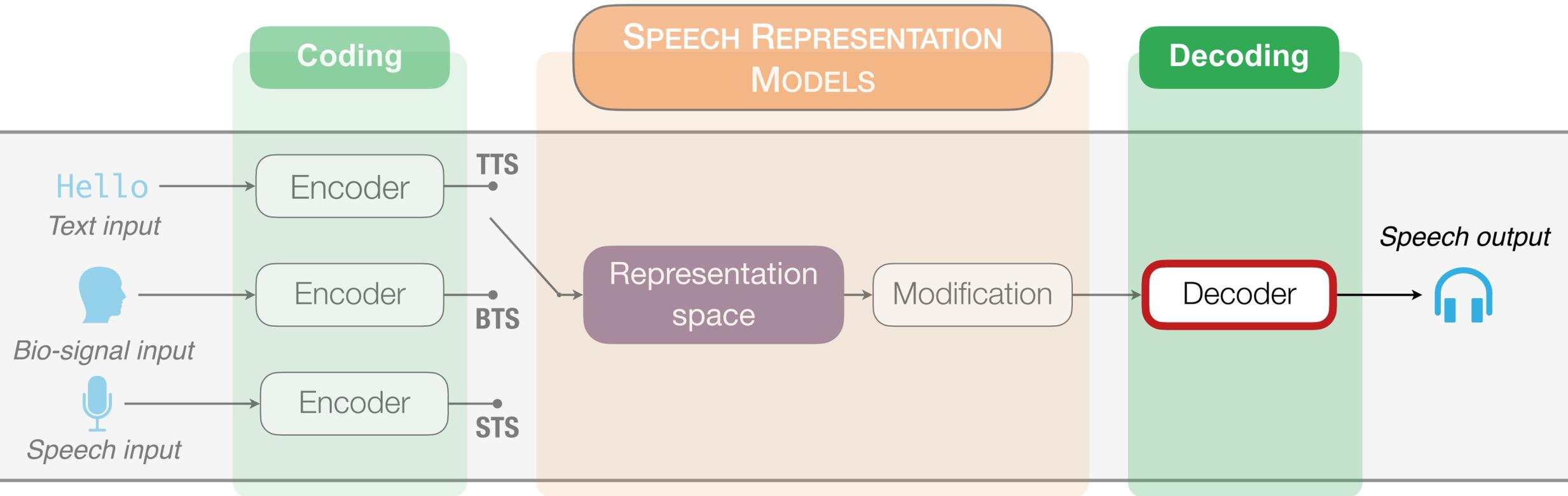
→ Neural decoders (wrongly called Neural Vocoders)

- From a speech representation to a waveform

(References are non-exhaustive)

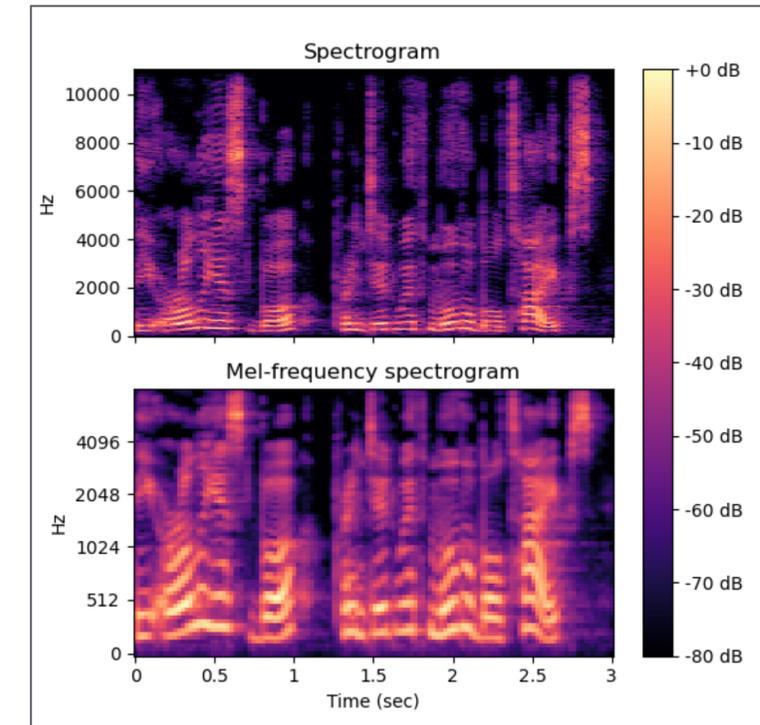
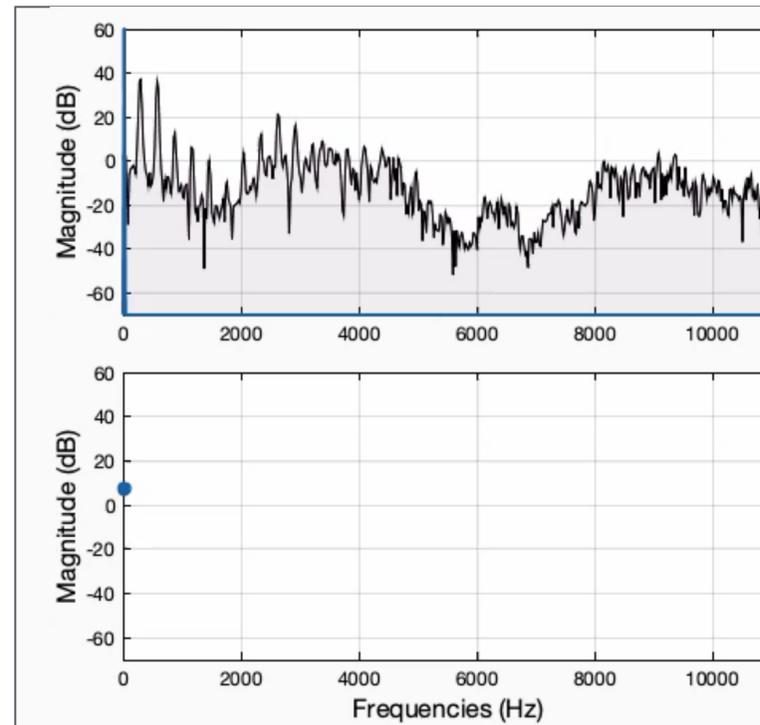
Text-to-Speech (TTS)	WaveNet	<i>van den Oord A. et al. (2016), arXiv, vol. abs/1609.03499</i>
Speech-to-Speech (STS) Conversion	Voice Conversion Challenge 2018 Neural generation	<i>Lorenzo-Trueba L. et al. (2018), Proc. Odyssey, pp. 195–202.</i>
Coding	Lyra Neural vocoder (WaveNet)	<i>Kleijn B. et al. (2018), Proc. ICASSP, pp. 676–680</i> <i>Kleijn B. et al. (2021), Proc. ICASSP, pp. 6478–6482</i>

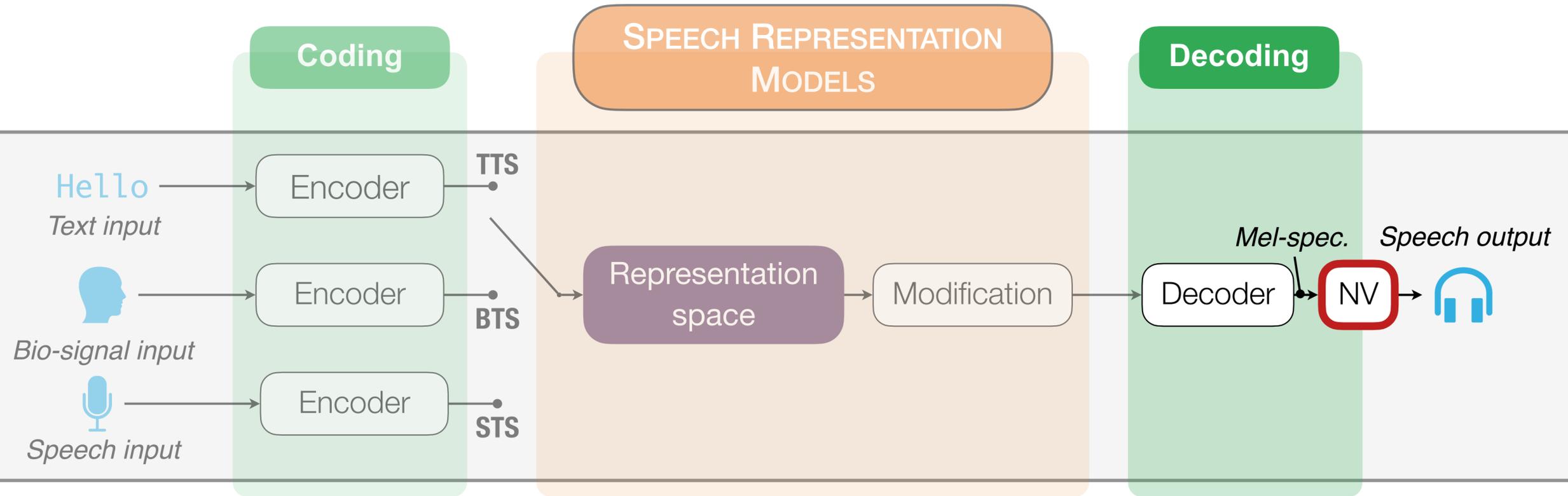




➔ Neural decoders (wrongly called Neural Vocoders)

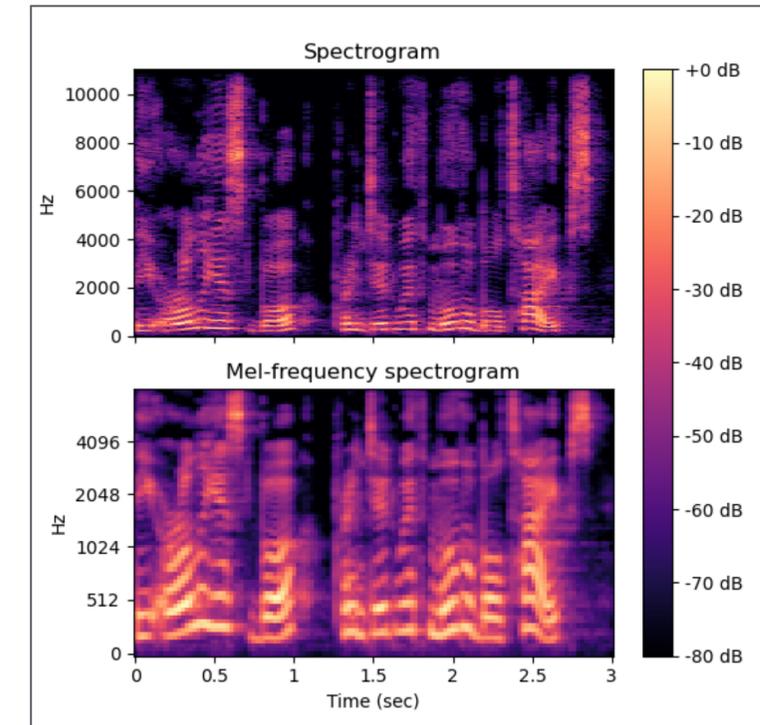
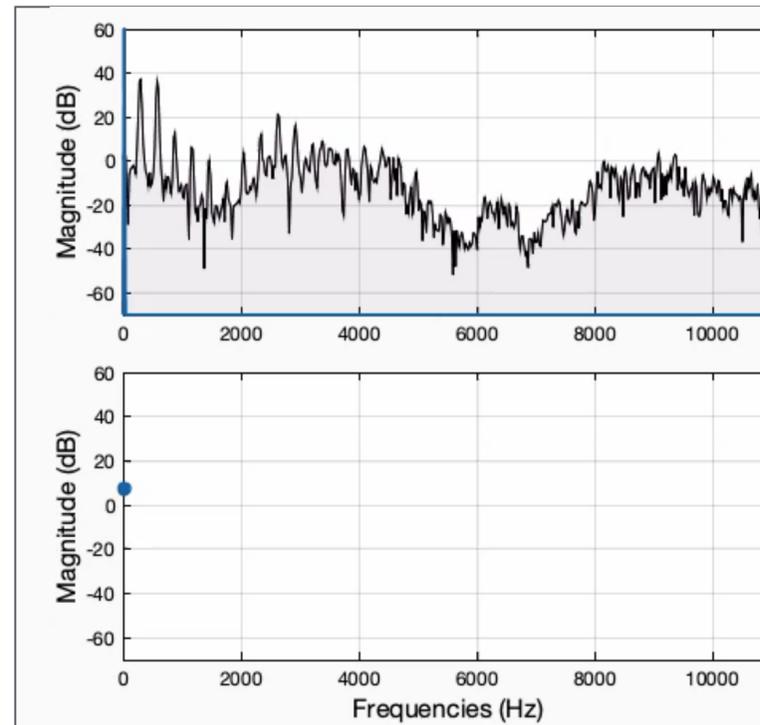
- From **mel-spectrogram** to waveform

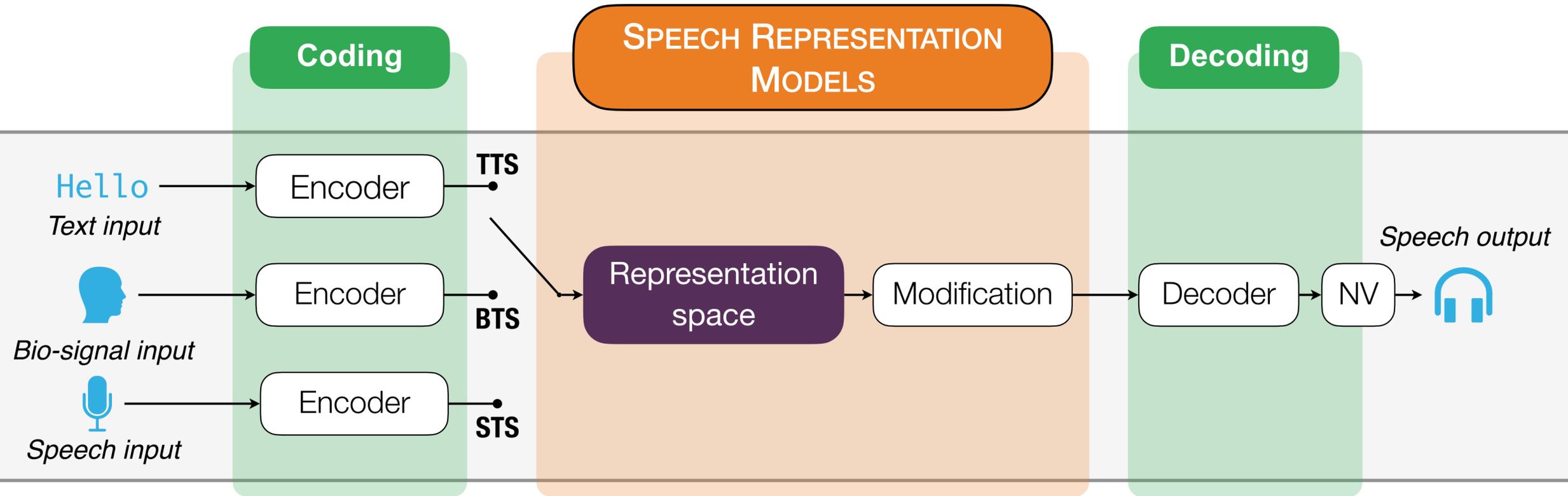




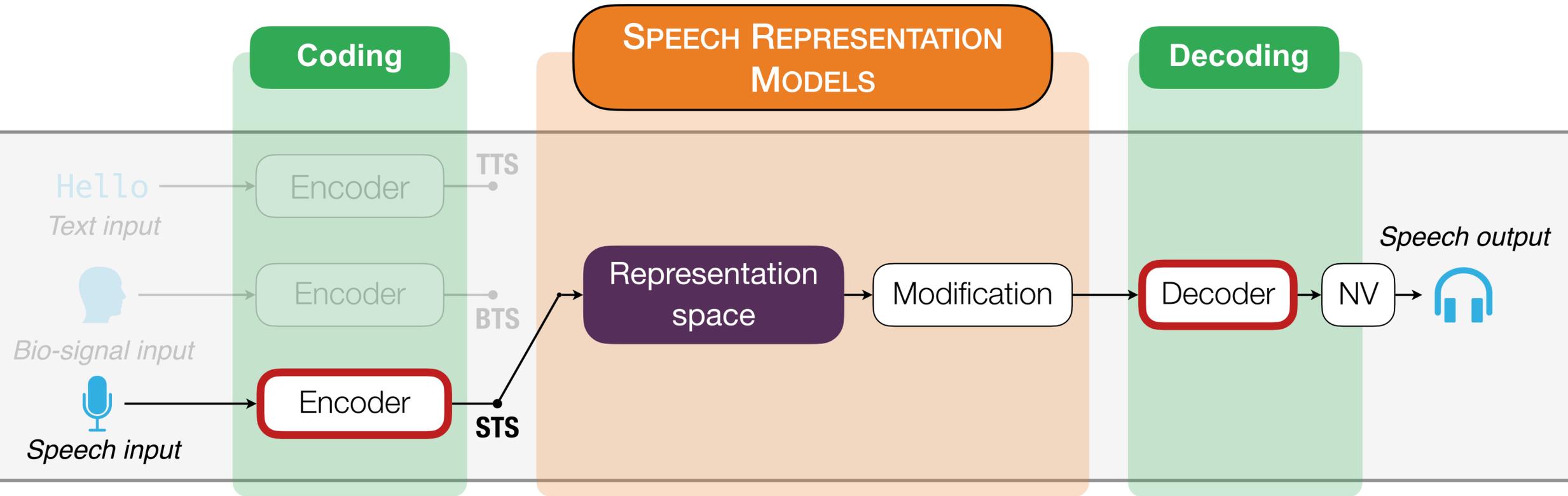
➔ Neural decoders (wrongly called Neural Vocoders)

- From **mel-spectrogram** to waveform





- Neural encoder-decoder
 - A neural network for the encoder and the decoder
 - Few constraints on the representation space, often considered as opaque



(References are non-exhaustive)

- Auto-encoders (unsupervised)
 - Low-dimensional representation space
 - Goal: Reconstruct input

Voice Conversion
From statistical to neural

Mohammadi S. H. et al. (2017), *Speech Comm.*, 88(C), pp. 65–82.

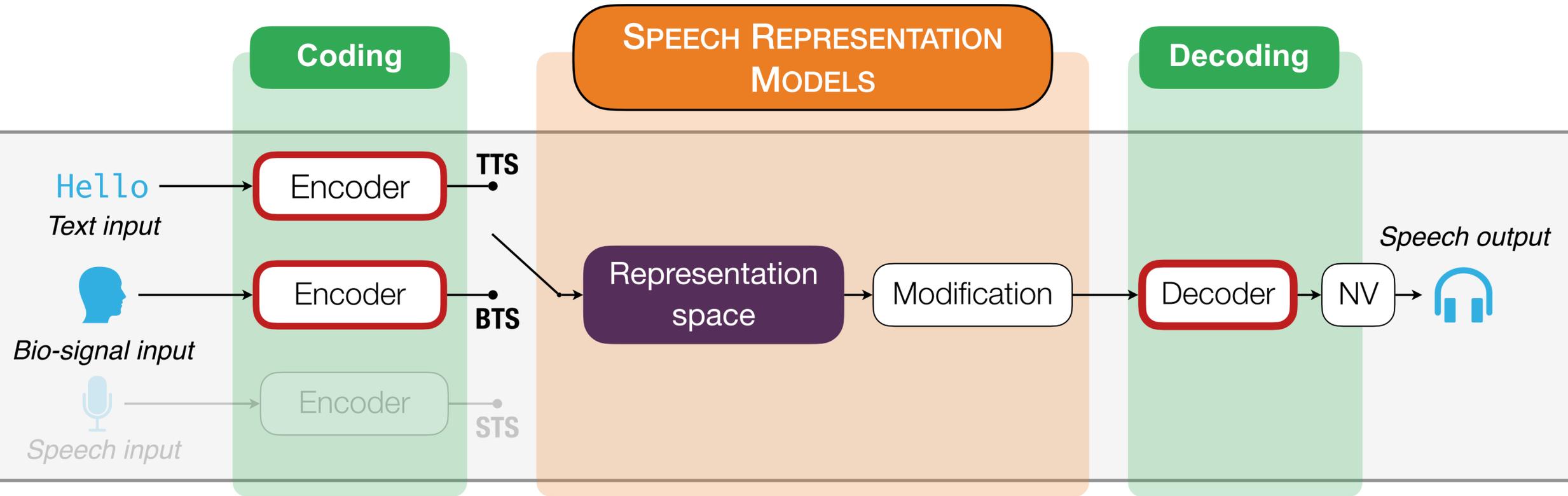
Sisman B. et al. (2021), *Trans. IEEE TASLP*, 29, pp. 132–157.

Hsu W.-N.. et al. (2019), *ICLR*.

Williams J. et al. (2021), *ISCA SSW*, pp. 124–129.

Sadock S. et al. (2023), *Speech Comm.*, 148, pp. 53–65.

Voice transformation
VAE / VQ-VAE



(References are non-exhaustive)

- Sequence-to-sequence (supervised)
 - Need for parallel data
 - Goal: predict audio from input

Autoregressive / Parallel

Tacotron / FastSpeech

Shen J. et al. (2018), *Proc. ICASSP*, pp. 4779–4783.

Ren Y. et al. (2021), *ICLR*.

Style modelling

GST / VAE

Wang Y. et al. (2018), *Proc. ICML*, 80, pp. 5180–5189.

Zhang Y.-J. et al. (2019), *Proc. ICASSP*, pp. 6945–6949

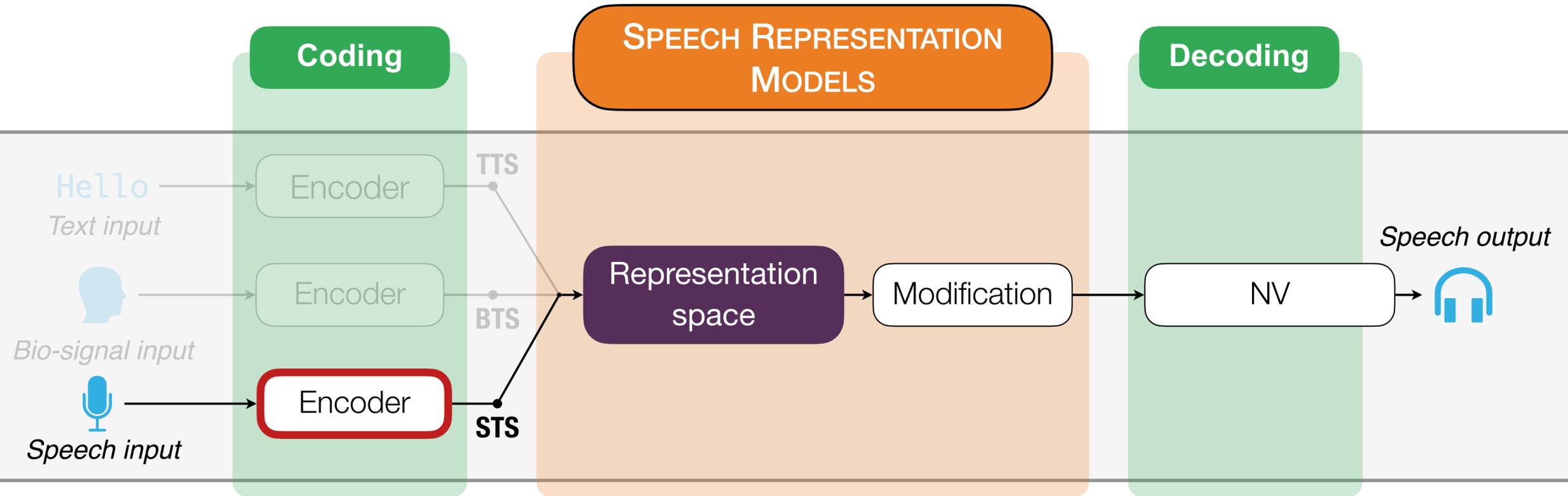
Blizzard Challenge 2023

Perrotin O. et al. (2023), *Proc. of Blizzard Challenge*, pp. 1–27.

Ultrasound-to-speech

Sequence-to-sequence

Zhang J.-X. et al. (2021), *AAAI Conf. on Artificial Intelligence*, 35(16), pp. 14402–14410.



- Self-supervised encoders

- Inspired from large language models (par ex. GPT)
- Learn audio representations (masking)
- Need for a separate decoder
- ➔ back to neural vocoders with any input

(References are non-exhaustive)

Audio SSL

CPC / wav2vec / HuBERT

van den Oord A. et al. (2018), arXiv, vol. abs/1807.03748.

Baevski A. et al. (2020), NeurIPS, 33, pp. 12449–12460.

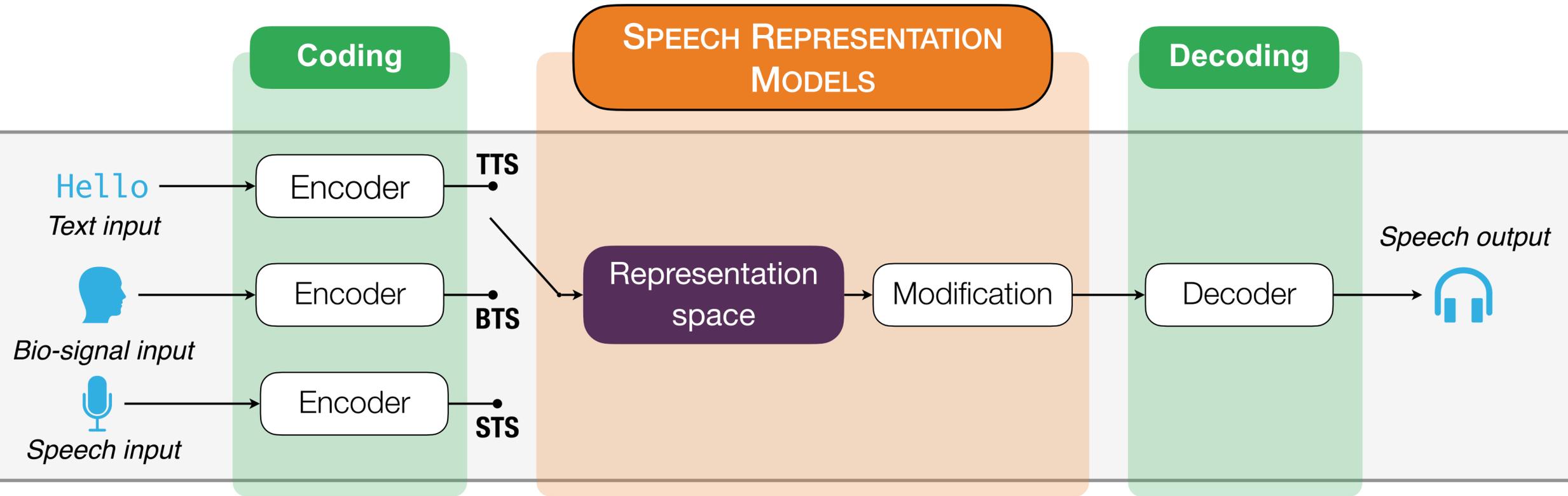
Hsu W.-H.. et al. (2021), IEEE TASP, 29, pp. 3451–3460.

GSLM

(HubERT encoder,
HiFiGAN decoder)

Lakhotia K. et al. (2021), Trans. Association for Comp. Linguistics, 9, pp. 1336–1354

Polyak A. et al. (2021), Proc. ICASSP, pp. 3615–3619



Signal-based

- Small model (10-100 parameters)
 - Explicit model (acoustically / signal / physiologically informed)
 - Generally fast to compute
- Limited modelling power
 - Light modelling of covariations
 - Not so high-quality synthesis

Neural-based

- Large model (M parameters)
 - Implicit model
 - Generally heavy to compute
- High modelling power
 - Modelling of covariations
 - High-quality synthesis

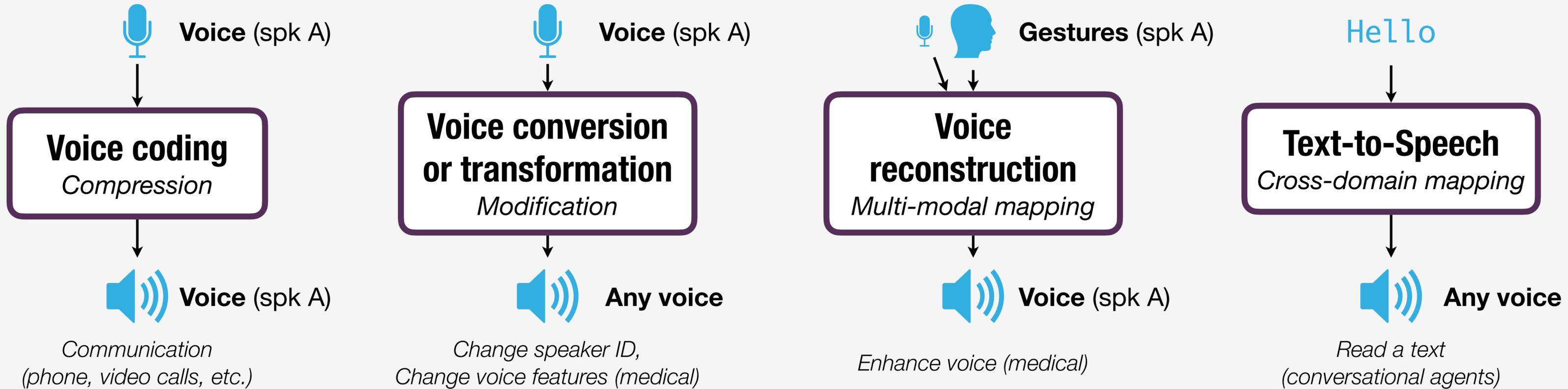
Do these voices sound ok?

- ➔ **Who** seems to speak? *Naturalness*
- ➔ **What** is being said? *Intelligibility*
- ➔ **How** is it said? *Expressivity*

Blizzard Challenge 2023 Perrotin O. et al. (2023),. Proc. of Blizzard Challenge, pp. 1–27.

Voice generation

Expressive speech synthesis



➔ Naturalness



On its way



➔ Intelligibility



On its way



➔ Expressivity

In the input

On its way

On its way

On its way

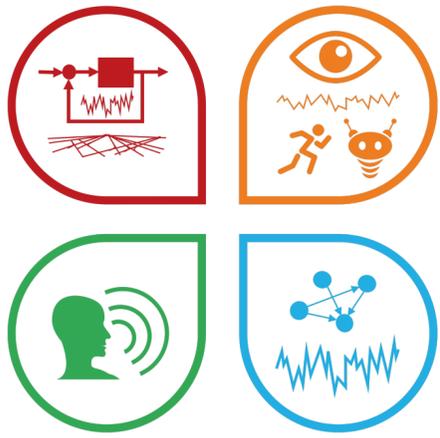
Interactive control of expressive speech synthesis

How to generate variations of expressivity within the representation space?

- **Axis 1: Analysis-synthesis of expressive speech**
 - Signal-based models : encoding / decoding and applications → **Voice reconstruction**
 - Neural-based models : study of representation spaces → **Voice transformation / Text-to-speech**

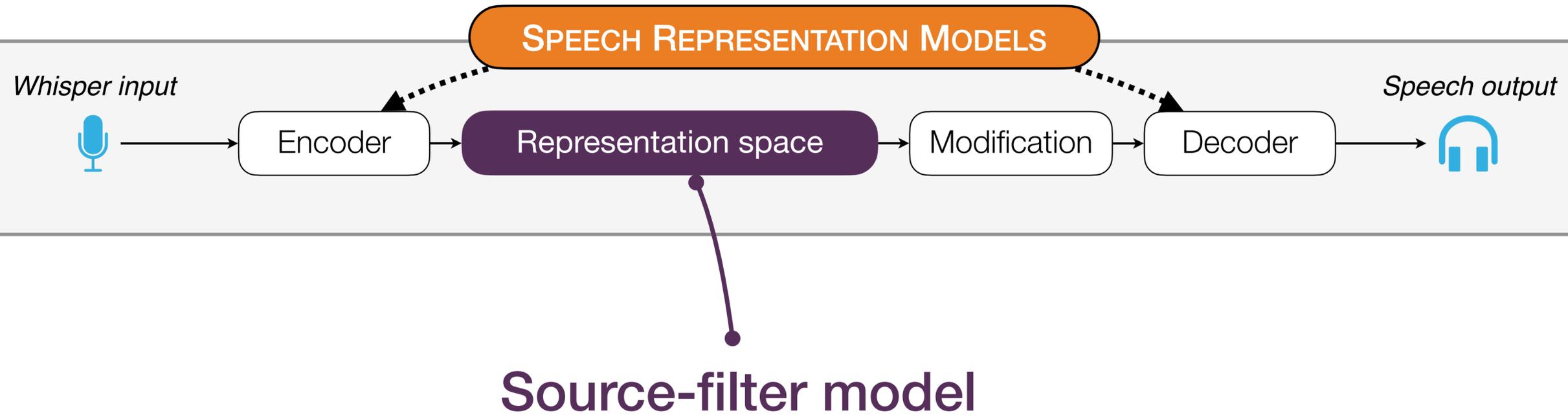
How to control the synthesiser to generate correct expressivity at the right time?

- **Axis 2: Interactive control of synthesis** → **Voice transformation**
 - Explicit control of F0 in singing
 - From implicit to explicit control of F0 in speaking
 - Towards a co-adaptation between human and machine learning of control mapping

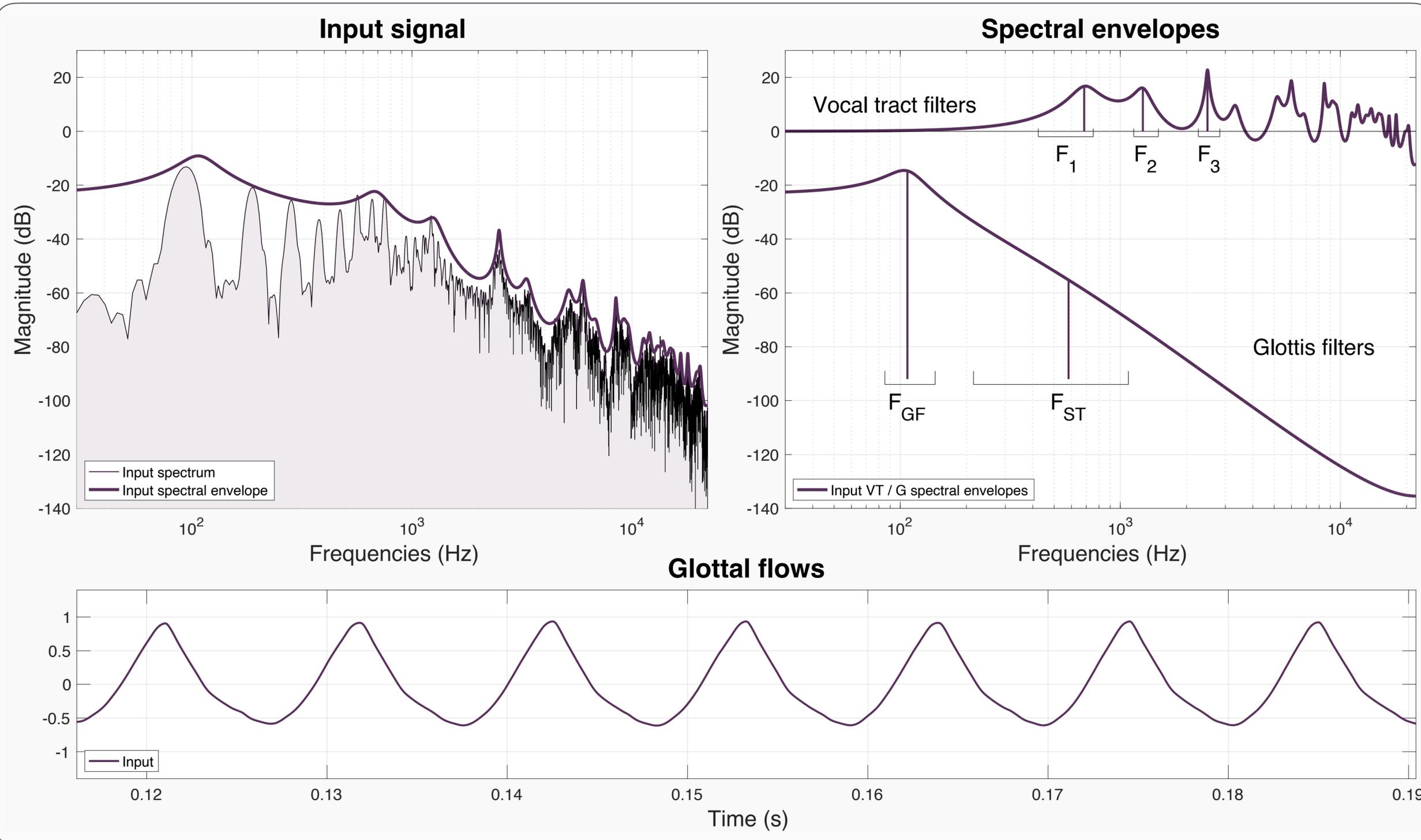


Analysis-synthesis of expressive speech

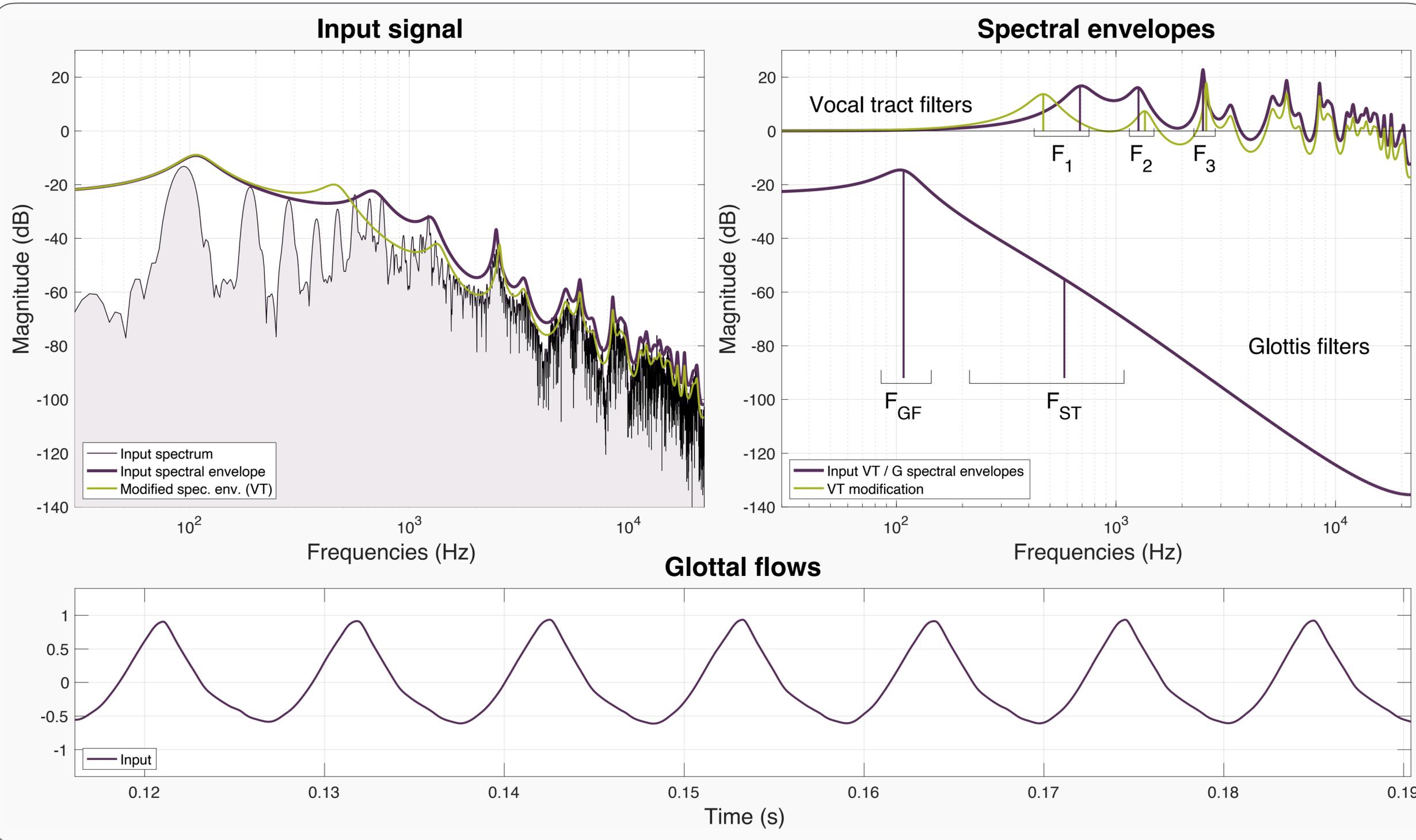
- Signal-based models : encoding / decoding and applications
- Neural-based models : study of representation spaces



Source-filter model



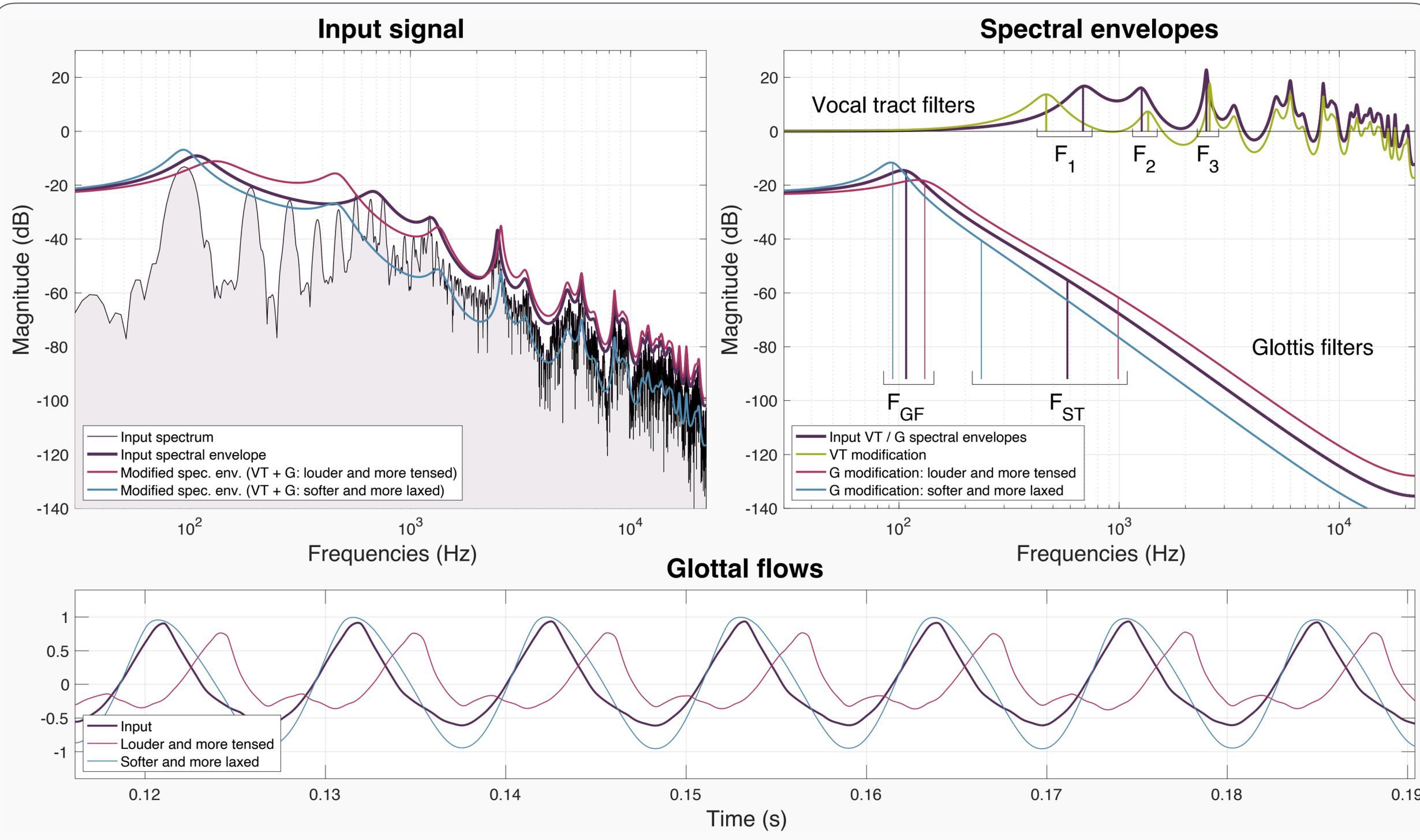
Perrotin, O. and McLoughlin, I. V. (2019), *Proc. Interspeech*, pp. 3685–3686



Acoustic correlates

Vocal Tract		
Jaw	Closing ↔ Opening	
F_1	Lower	Higher
Tongue	Backwards ↔ Forwards	
F_2	Lower	Higher
Lip	Rounding ↔ Stretching	
F_3	Lower	Higher

Perrotin, O. and McLoughlin, I. V. (2019), Proc. Interspeech, pp. 3685–3686



Acoustic correlates

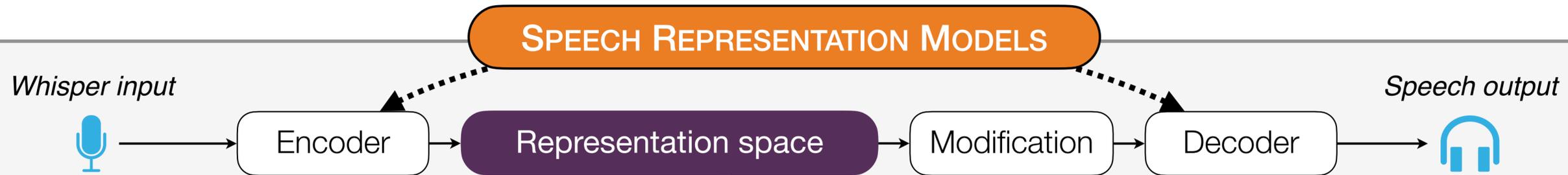
Vocal Tract

Jaw	Closing ↔ Opening
F₁	Lower ↔ Higher
Tongue	Backwards ↔ Forwards
F₂	Lower ↔ Higher
Lip	Rounding ↔ Stretching
F₃	Lower ↔ Higher

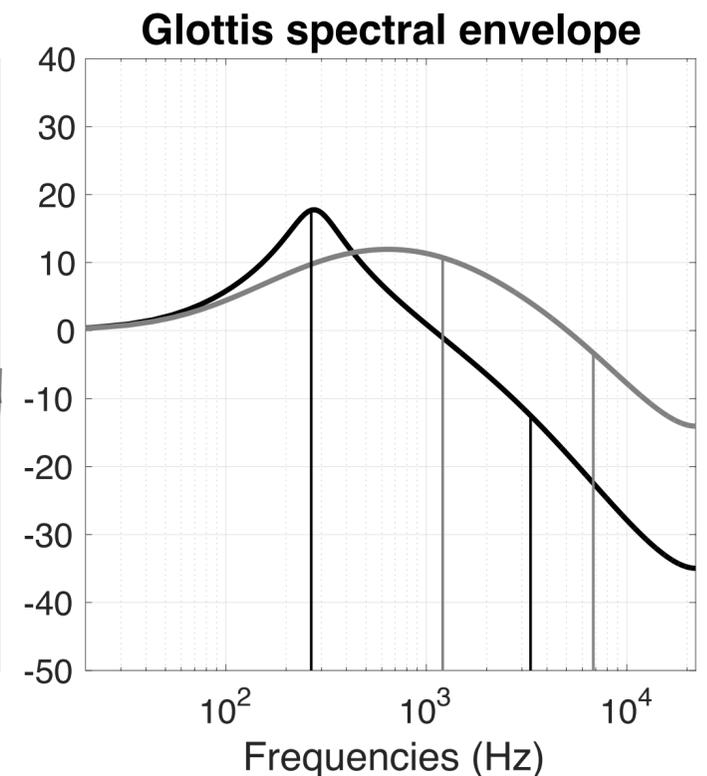
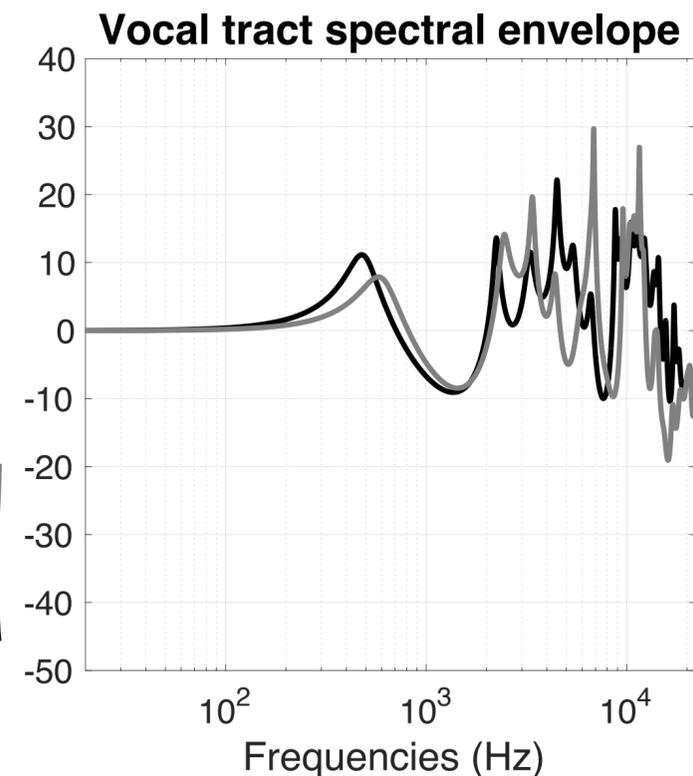
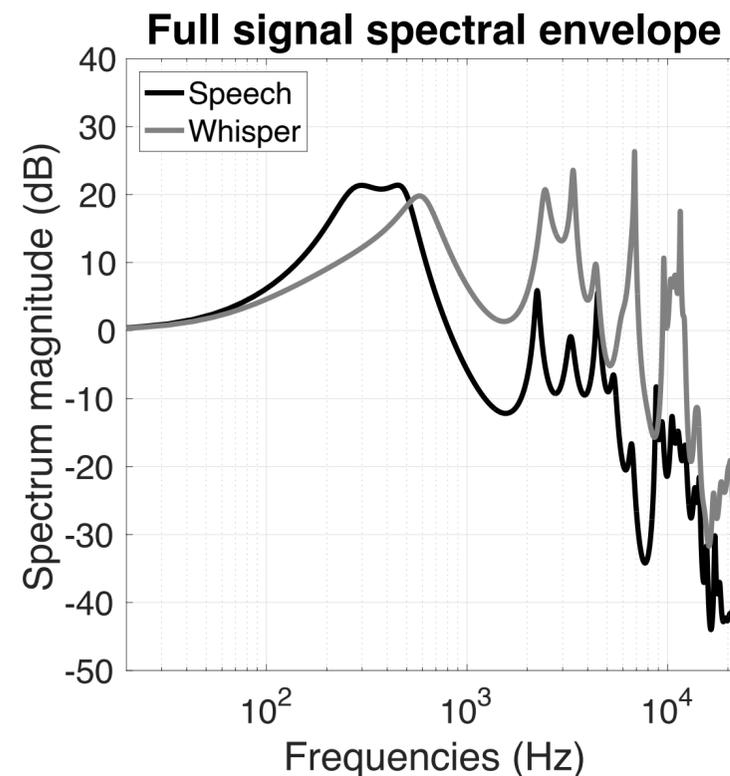
Glottis

Effort	Softer ↔ Louder
F_{GF}	Lower ↔ Higher
F_{ST}	Lower ↔ Higher
Tenseness	More lax ↔ More tensed
F_{GF}	Lower ↔ Higher
Q_{GF}	Narrower ↔ Wider

Perrotin, O. and McLoughlin, I. V. (2019), Proc. Interspeech, pp. 3685–3686



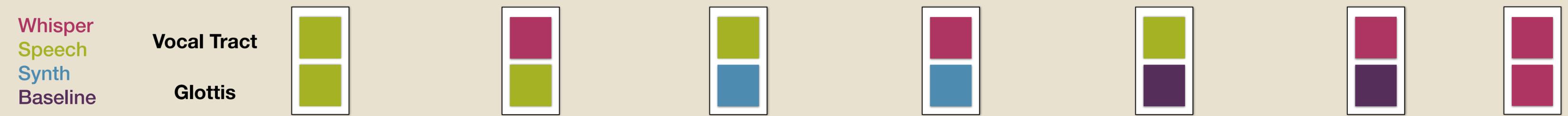
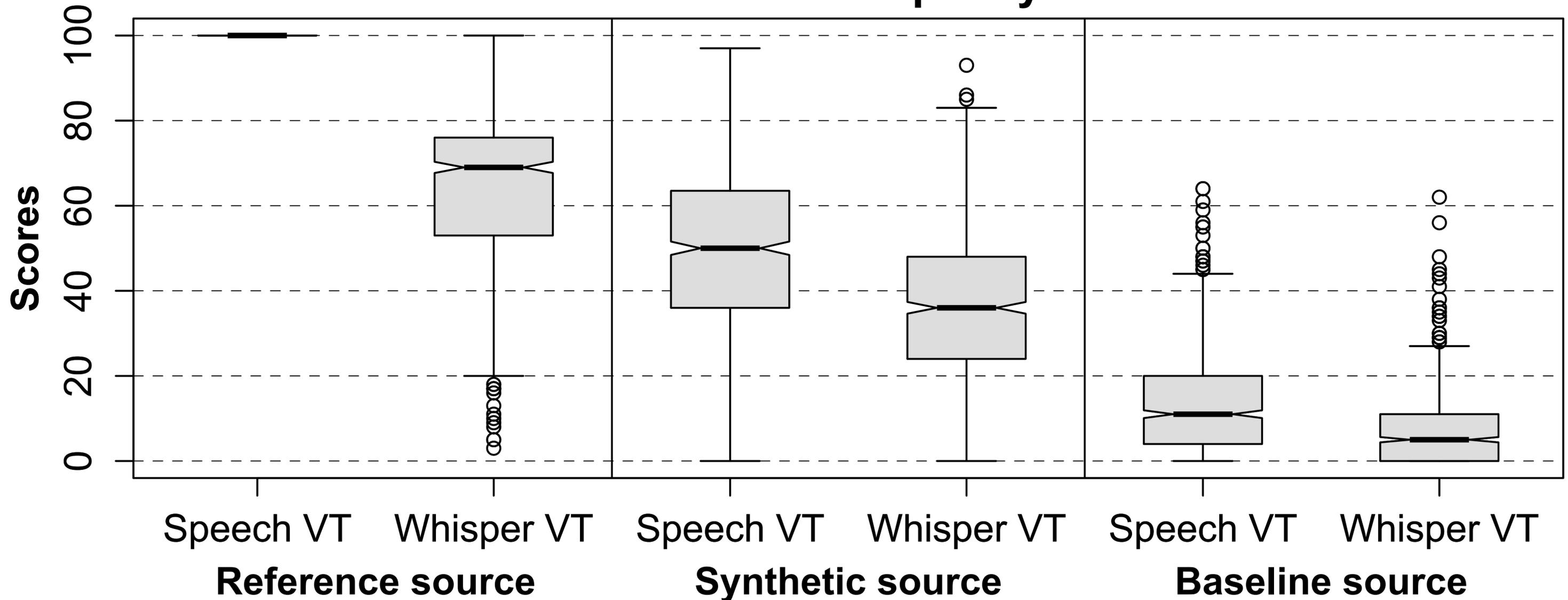
- Change noise to harmonic excitation (pulse train)
- Modify glottal parameters
- Leave vocal tract parameters (for now)



Extracted from vowel /i/ in 'is'

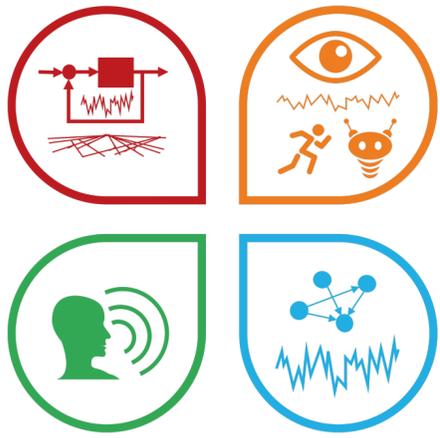
Perrotin, O. and McLoughlin, I. V. (2020), *IEEE TASLP*, 28, pp. 889–900

MUSHRA scores per system



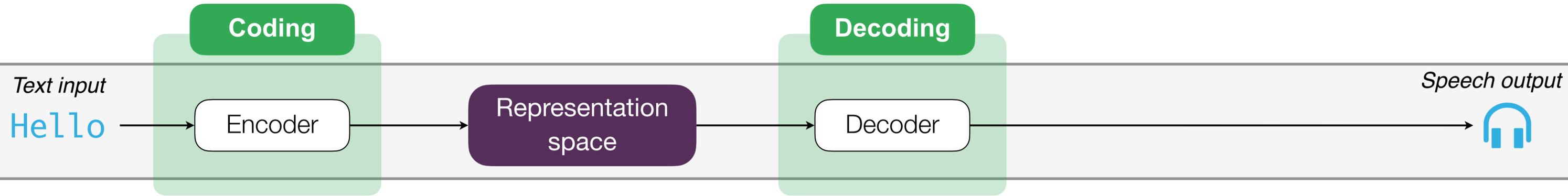
- **GFM-Voc: Analysis-Synthesis method**
 - Source-filter decomposition method based on a Glottal Flow Model
 - ➔ Allow to analyse / modify glottis and vocal tract parameters independently
- **Various applications since**
 - Real-time voice transformation
 - Vocalic formants and voice quality modification
 - Whisper to speech conversion **in real-time**
 - Voice analysis
 - Assessment of glottal dysfunction
- Small model (10-100 parameters)
 - Explicit model (acoustically / signal / physiologically informed)
 - Generally fast to compute
- Limited modelling power
 - Light modelling of covariations
 - Not so high-quality synthesis

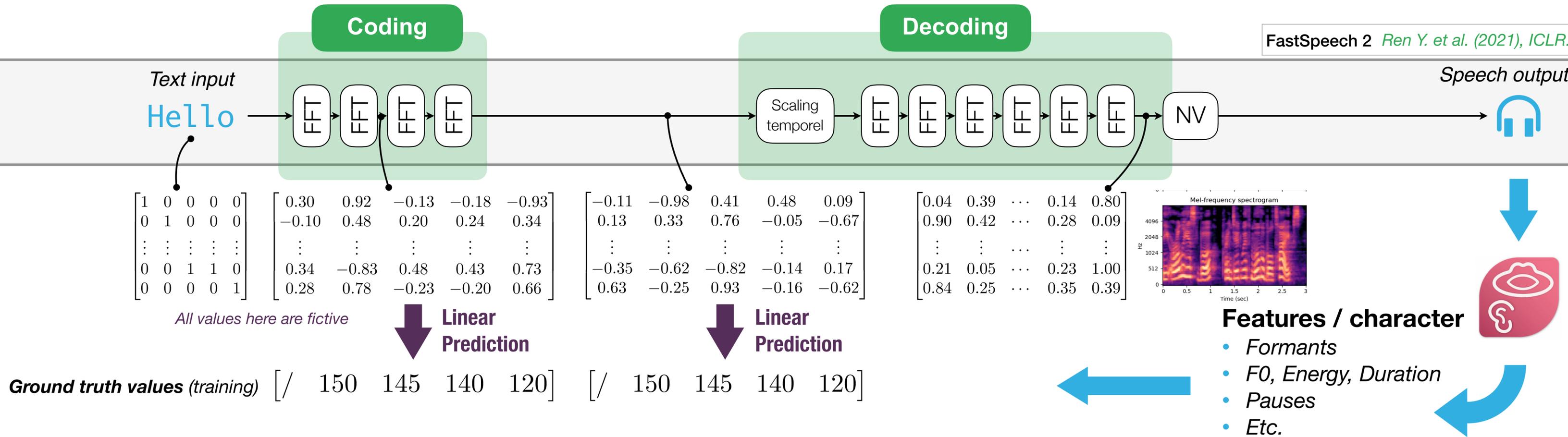




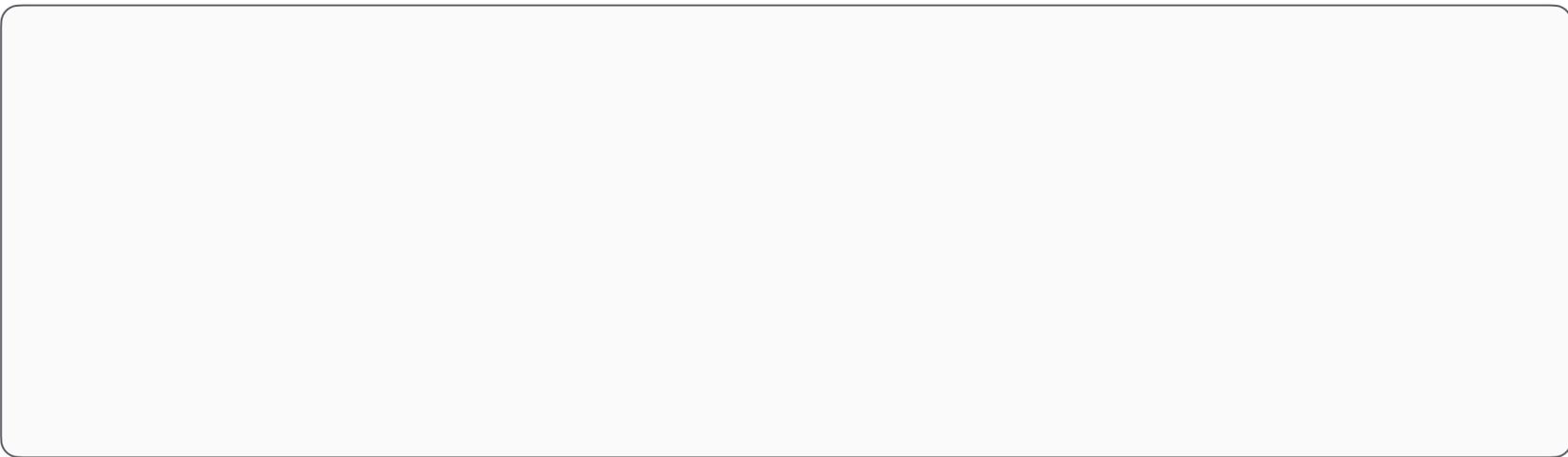
Analysis-synthesis of expressive speech

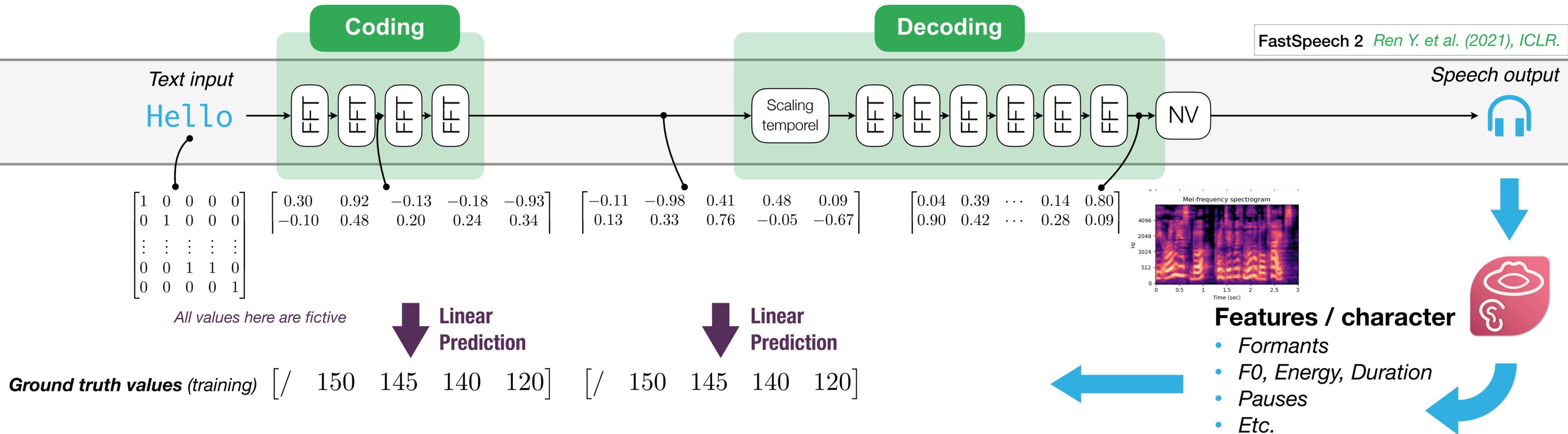
- Signal-based models : encoding / decoding and applications
- Neural-based models : study of representation spaces



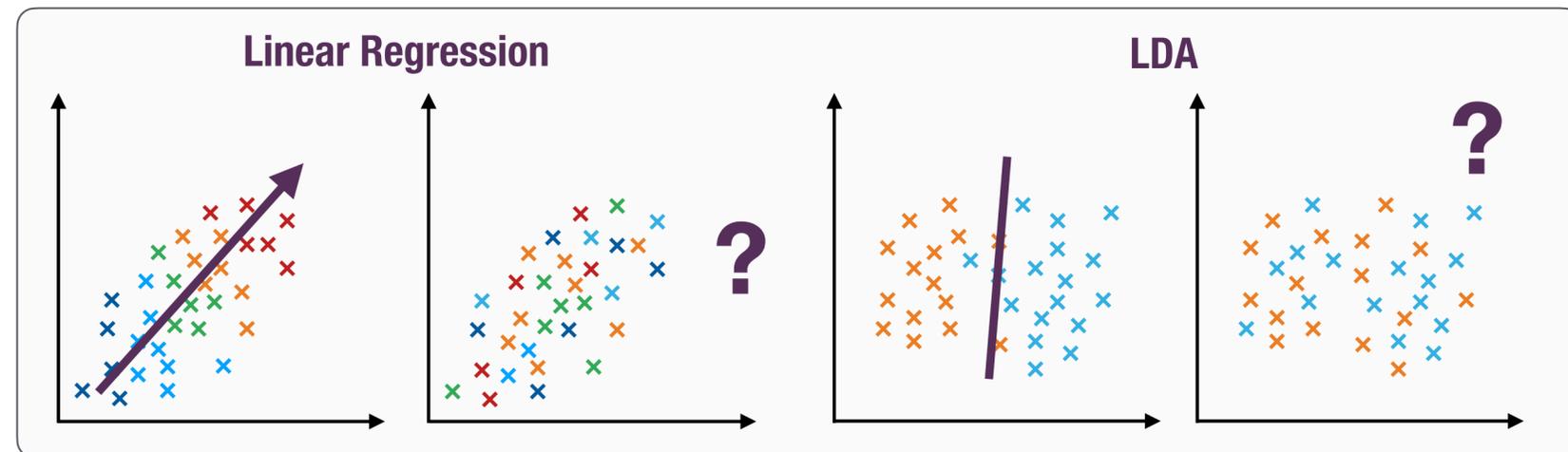


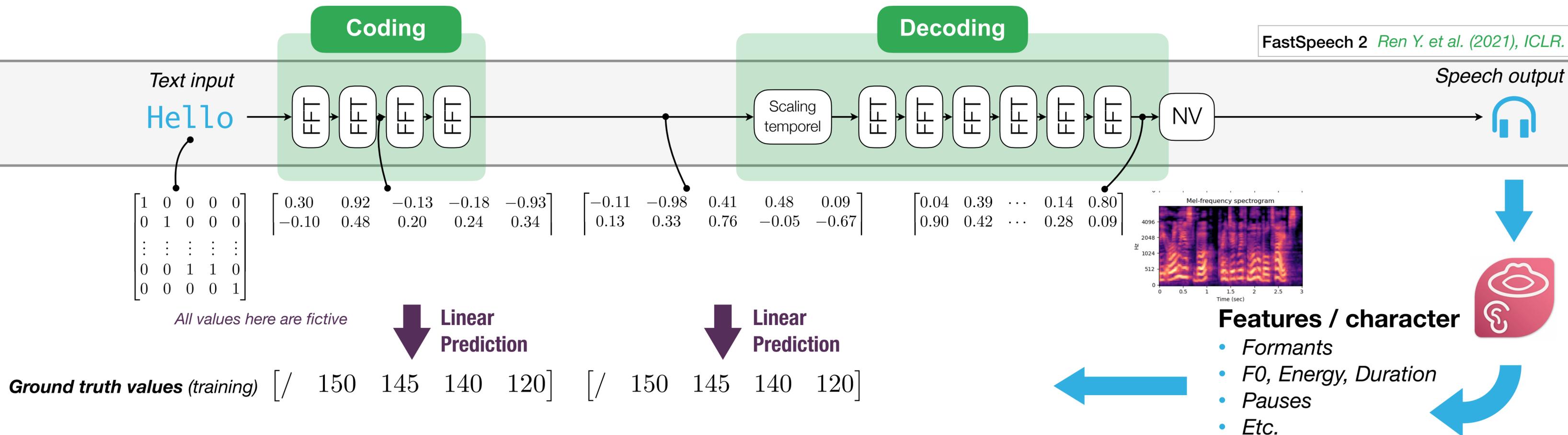
- Train the model on a dataset (33h French female speaker)
- Put ~2000 utterances in the model, save all layers, and acoustic analysis
- Learn a linear prediction of acoustic parameters at each layer
 - Linear regression for continuous parameters
 - Linear discriminant analysis (LDA) for discrete parameters



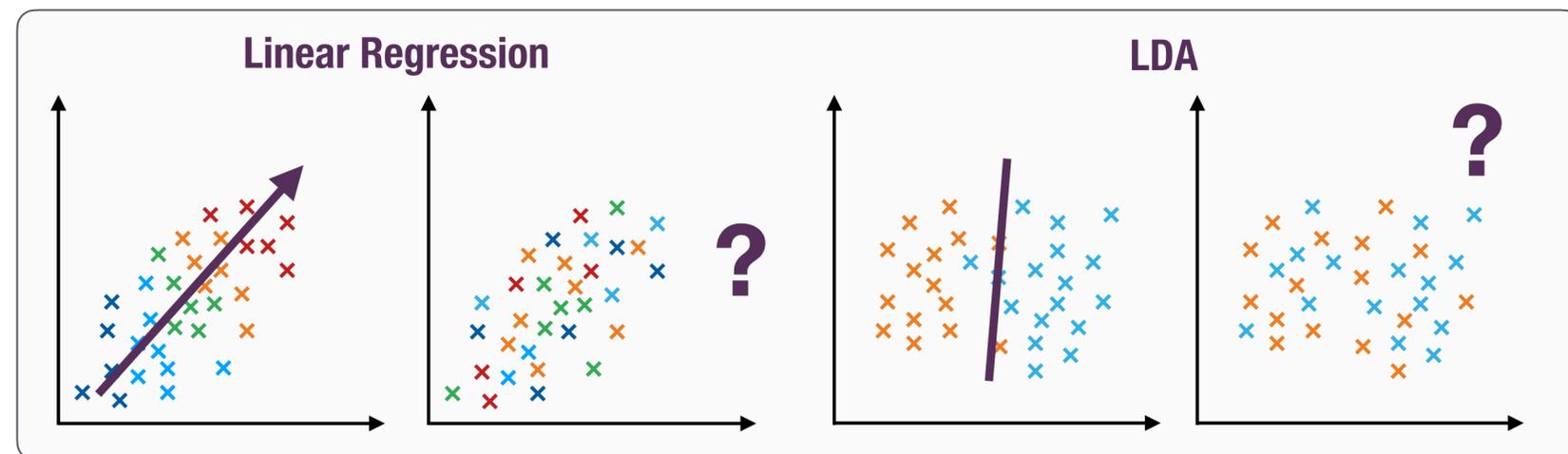


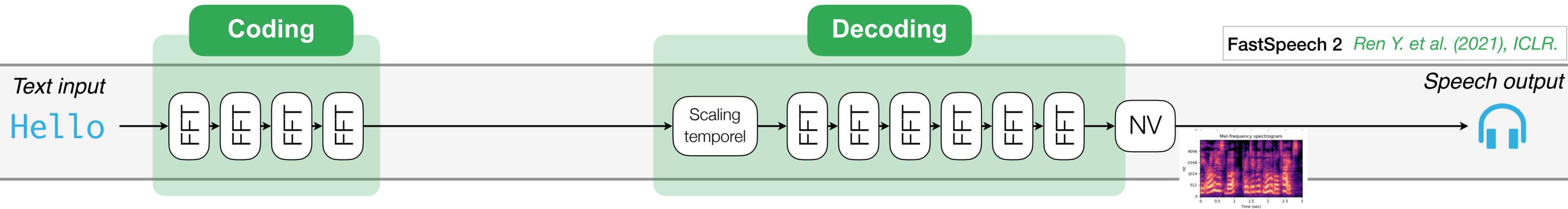
- Train the model on a dataset (33h French female speaker)
- Put ~2000 utterances in the model, save all layers, and acoustic analysis
- Learn a linear prediction of acoustic parameters at each layer
 - Linear regression for continuous parameters
 - Linear discriminant analysis (LDA) for discrete parameters



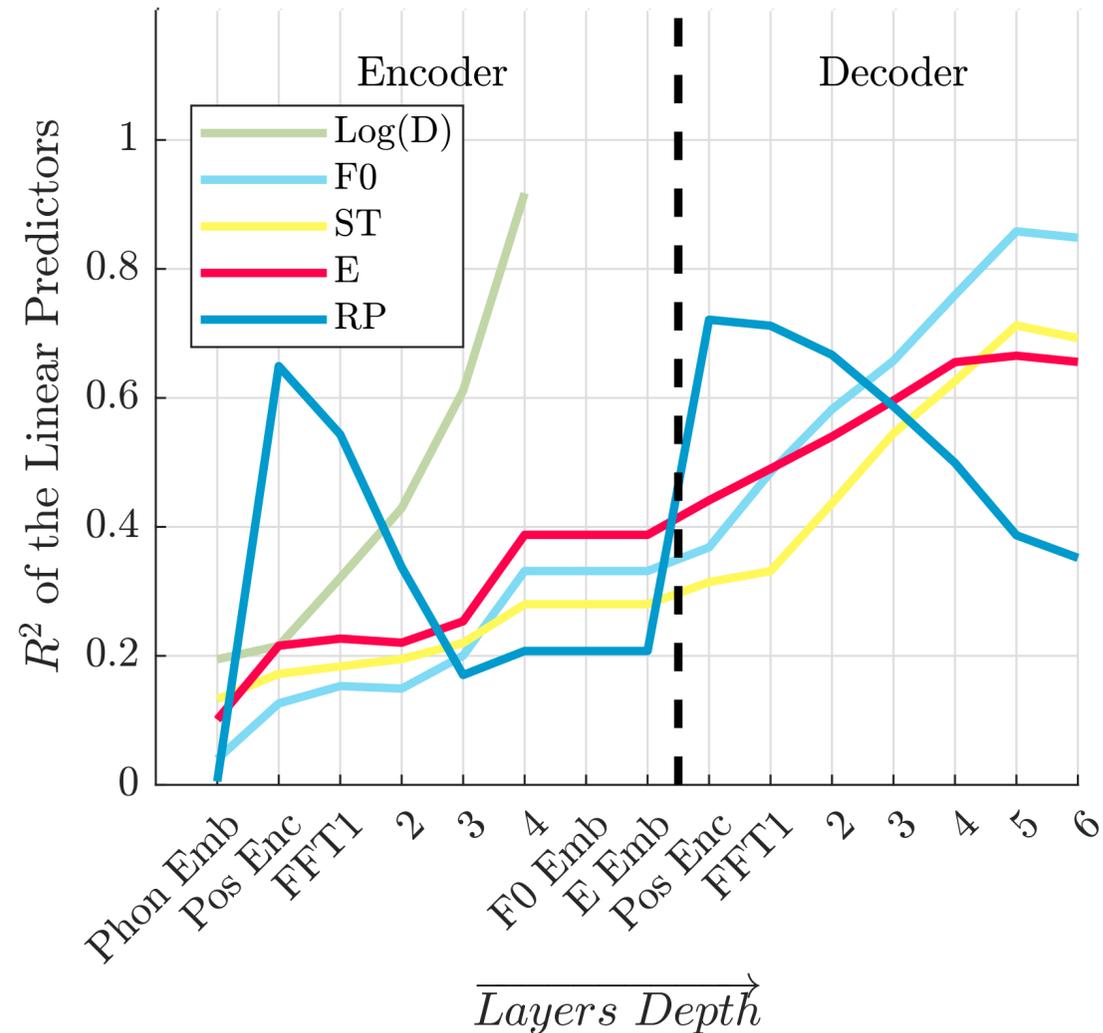


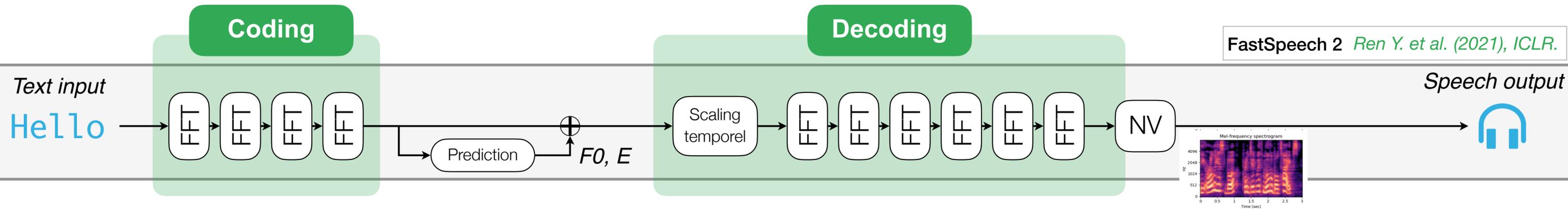
**Where in the model
are acoustic parameters linearly
encoded?**



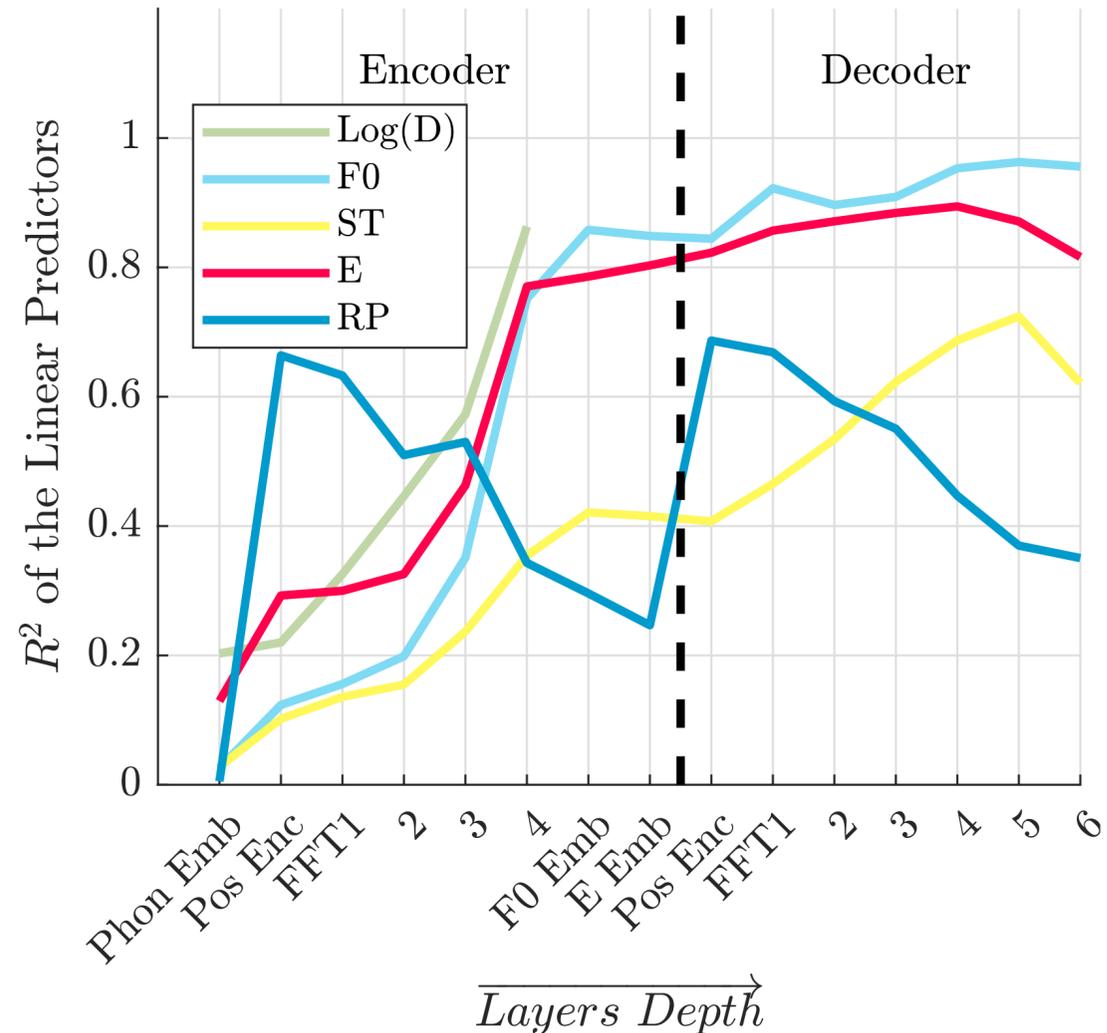


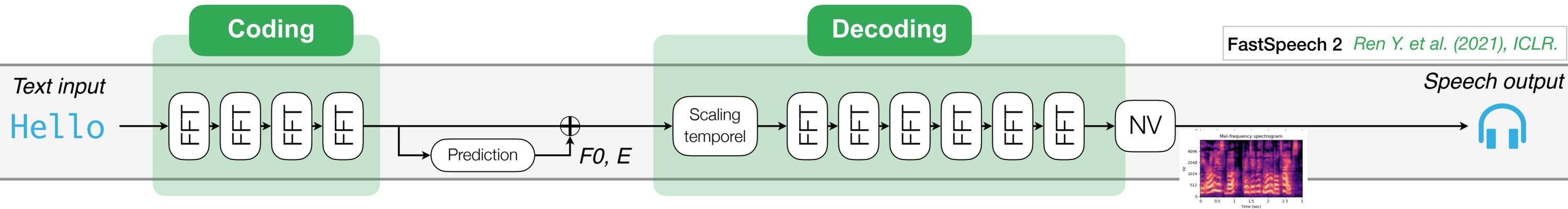
Supra-segmental parameters



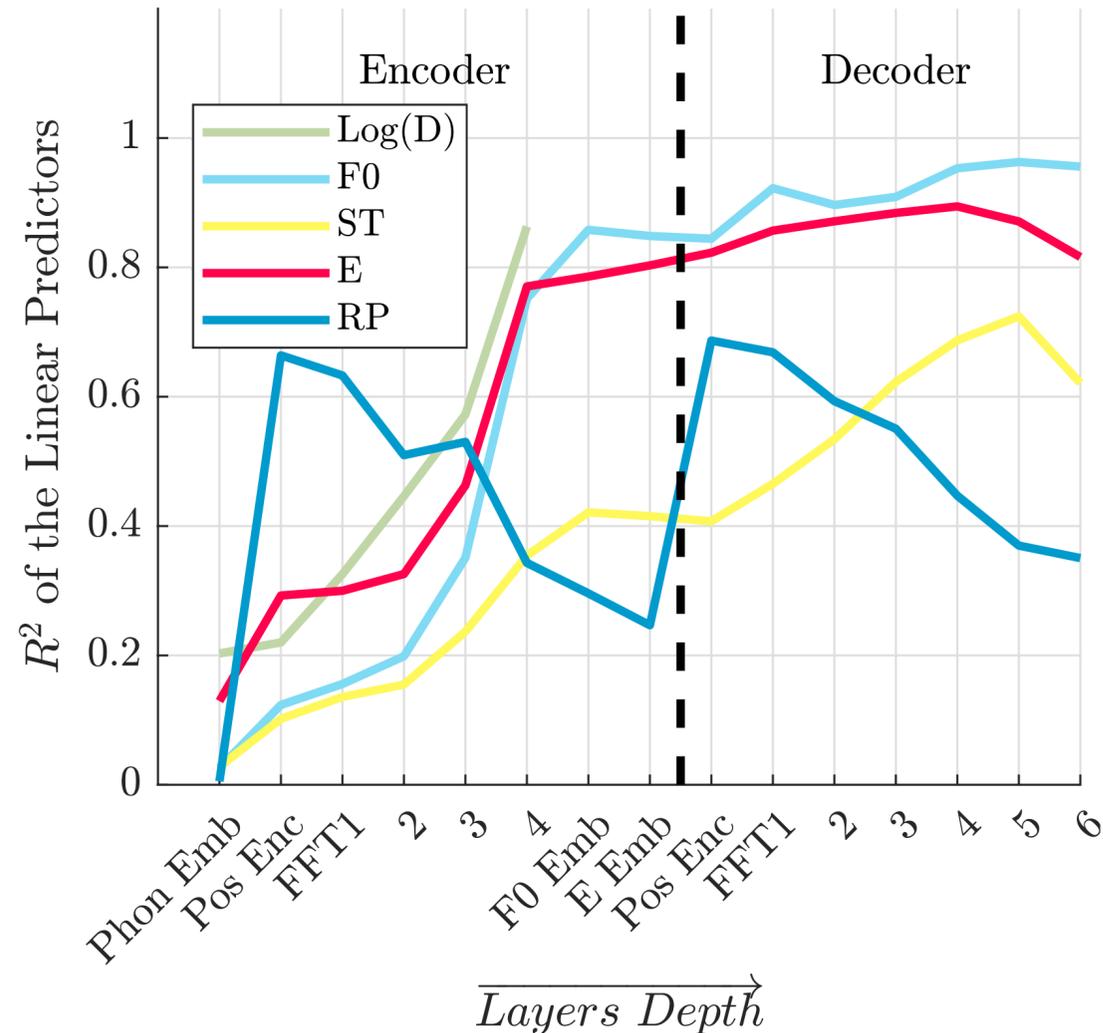


Supra-segmental parameters

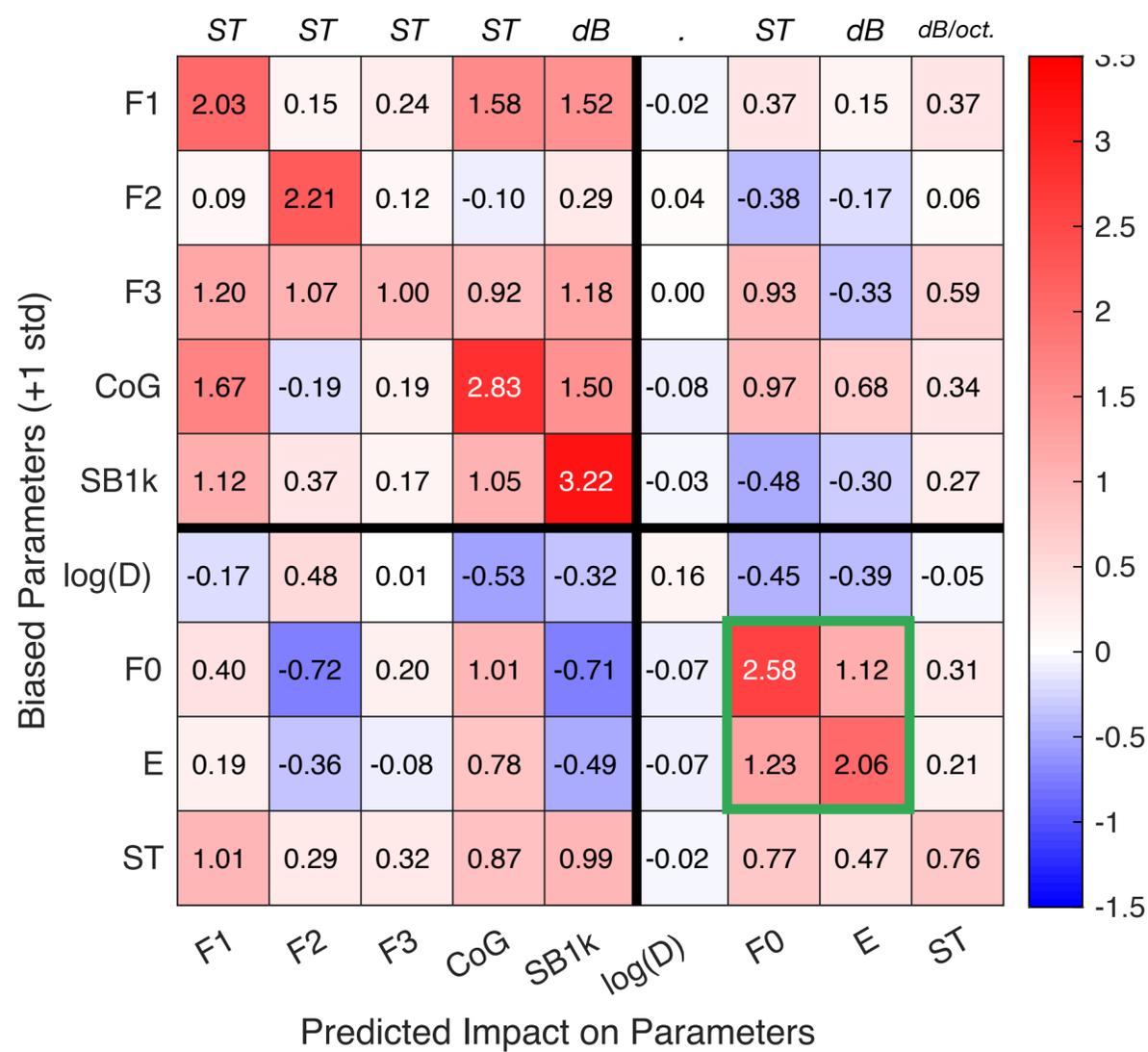
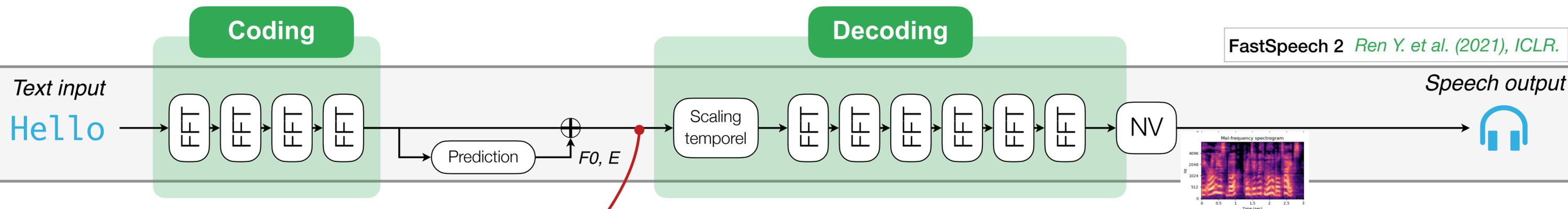




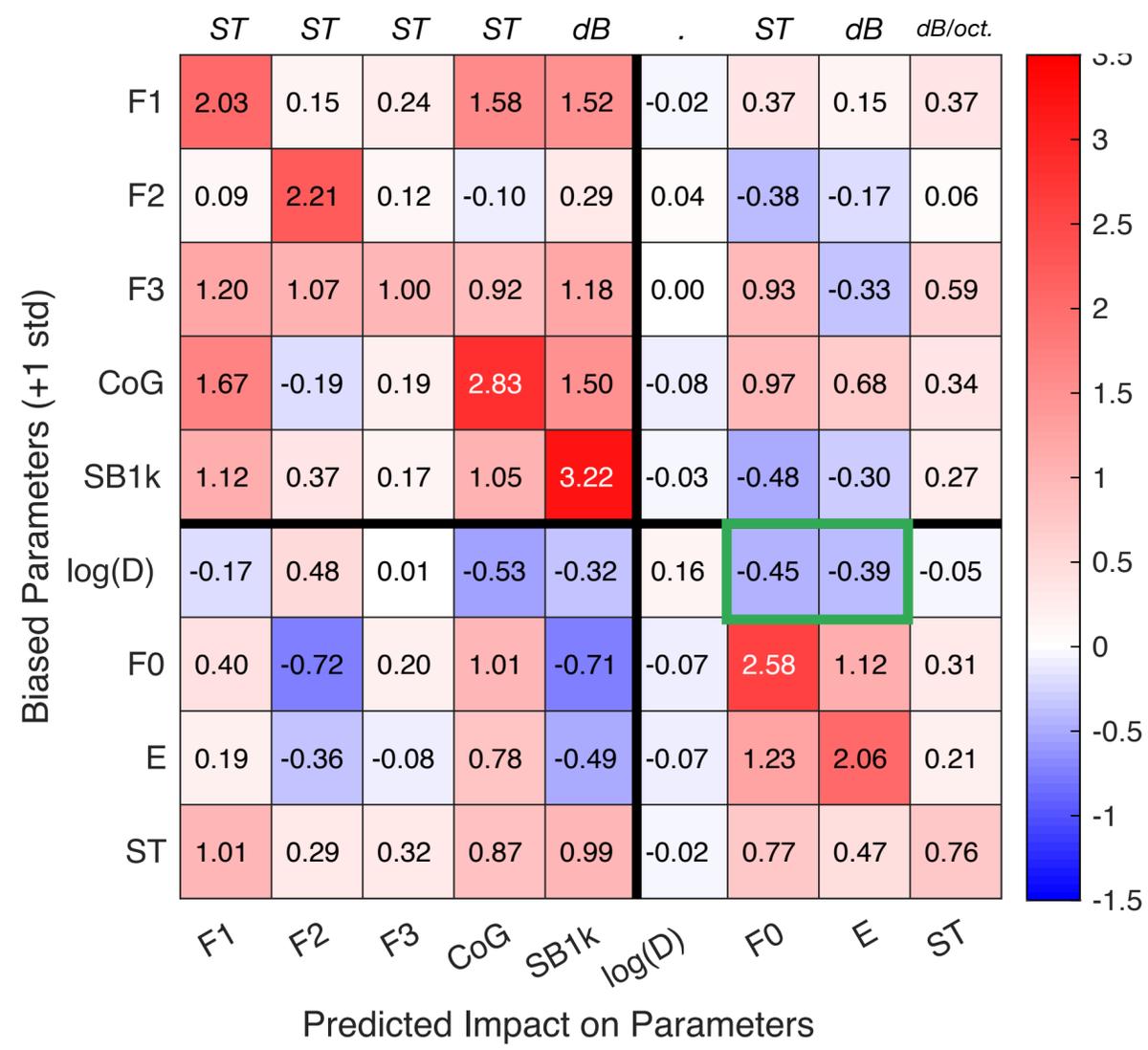
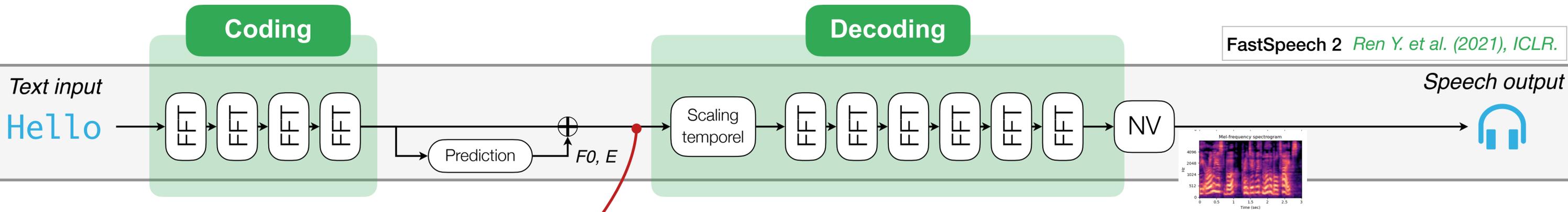
Supra-segmental parameters



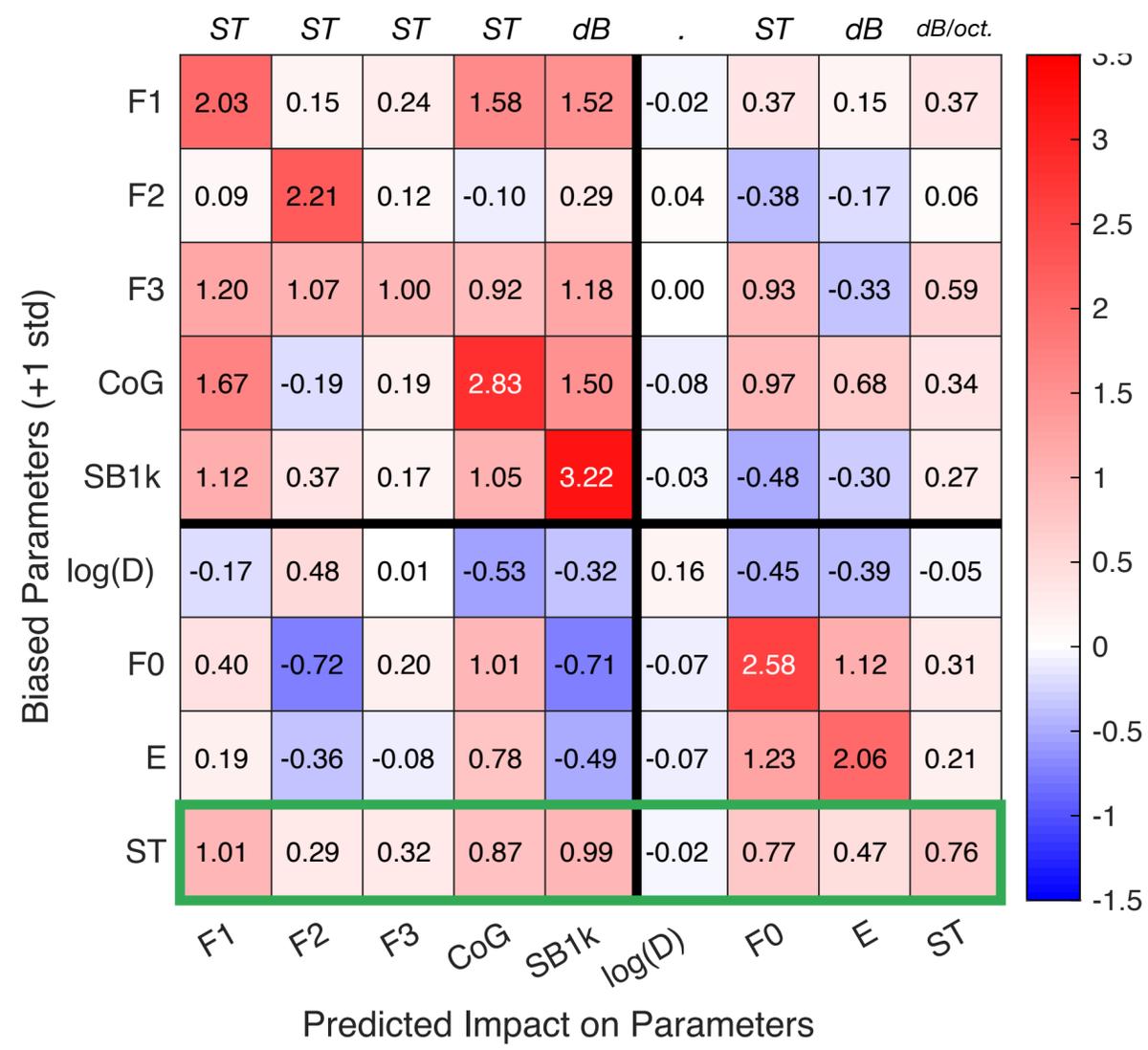
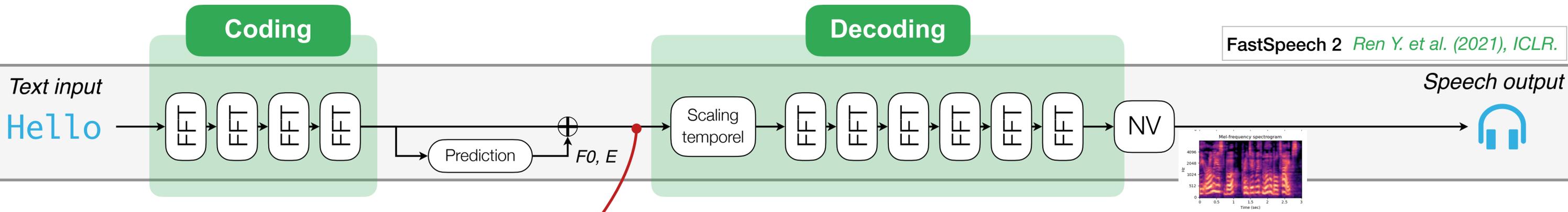
- Progressive linear coding of acoustic parameters
- Phonetic first, then prosodic
- Helped with forced predictions



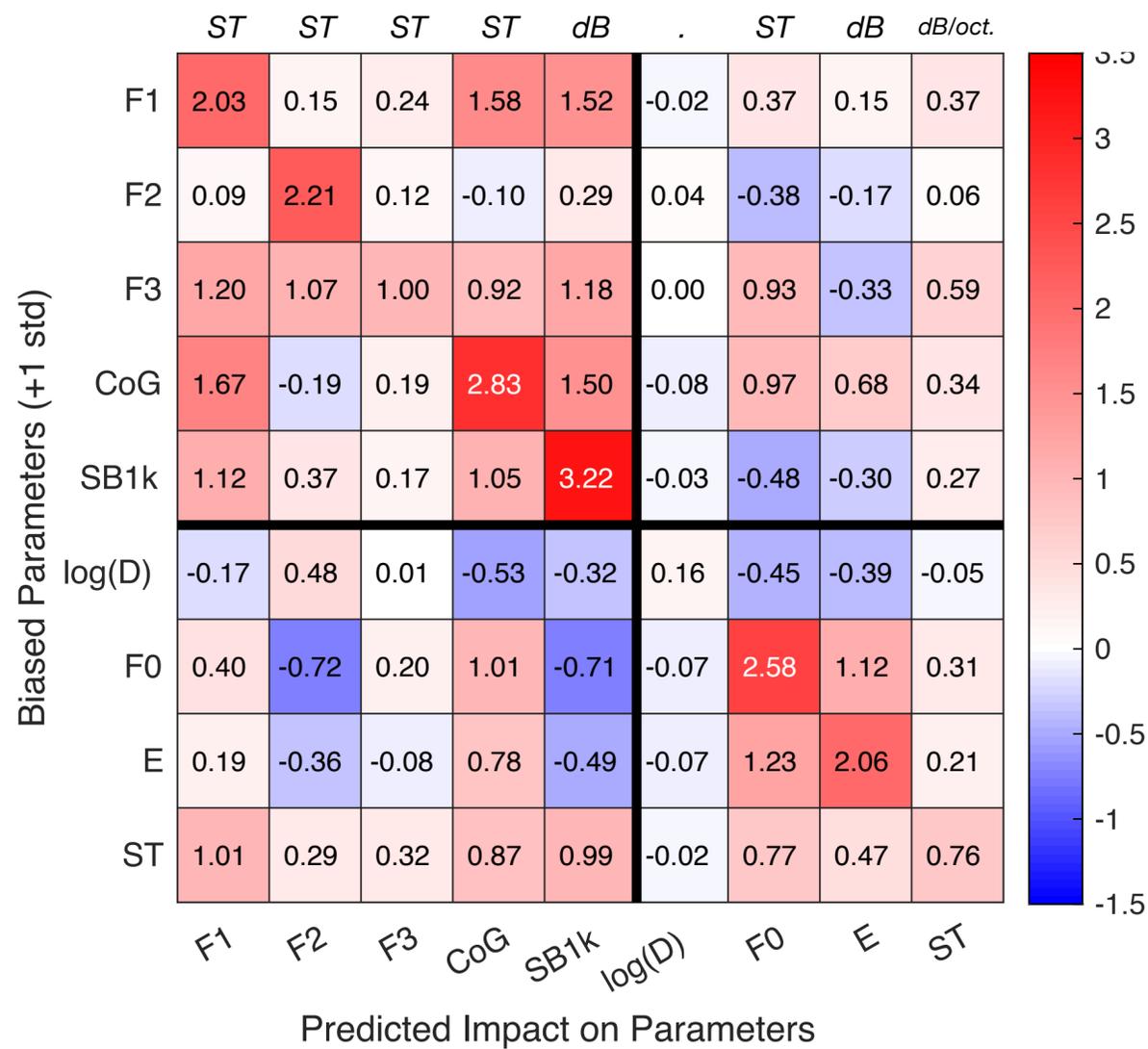
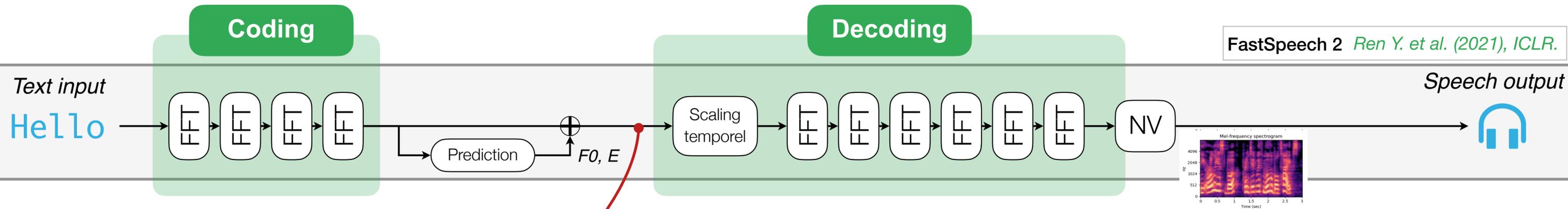
- Observation of covariations
- Consistent with literature
 - F0 and Energy



- Observation of covariations
- Consistent with literature
 - F0 and Energy
 - Duration, F0 and Energy



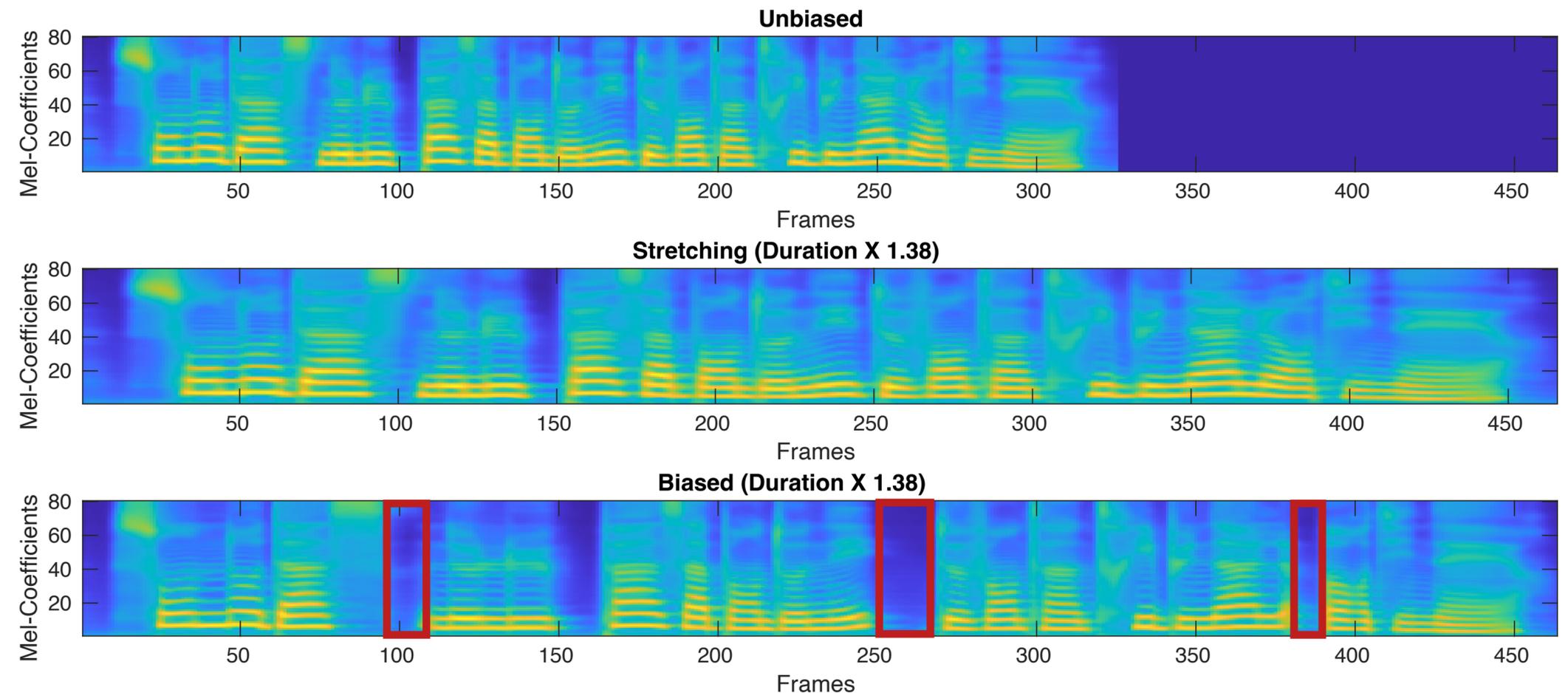
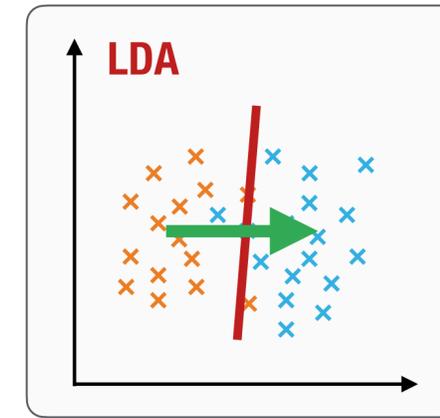
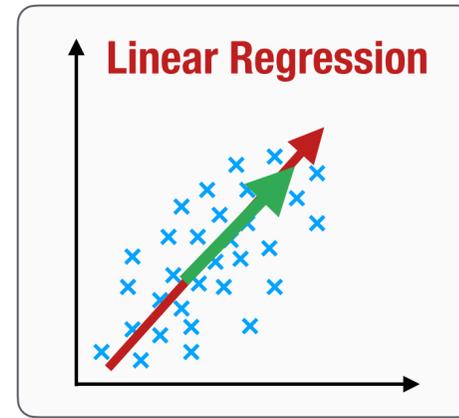
- Observation of covariations
- Consistent with literature
 - F0 and Energy
 - Duration, F0 and Energy
 - Vocal effort correlates (F0, Energy, F1, Spectral tilt)

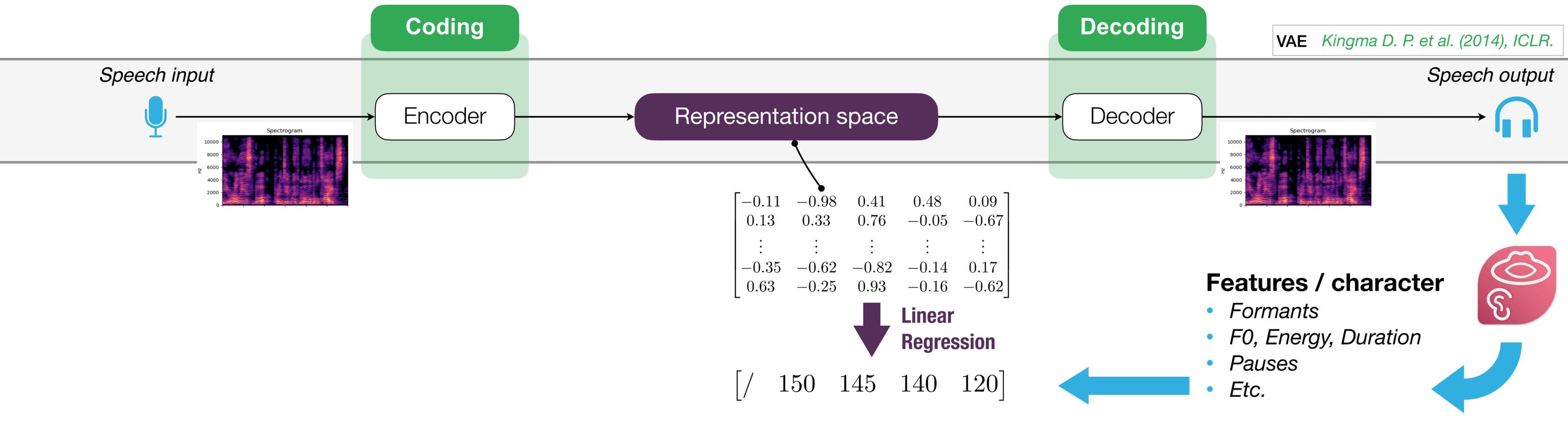


- Observation of covariations
 - Consistent with literature
 - F0 and Energy
 - Duration, F0 and Energy
 - Vocal effort correlates (F0, Energy, F1, Spectral tilt)
 - New ones to find?
- ➔ Powerful analysis tool learnt on massive data

Control of duration and pauses

- Control of duration in an utterance
 - Single modification for all phones
 - Different behaviour depending on segment
- ➔ Observe a saturation of elongation for final vowels and silences
- Control of percentage of pauses in an utterance
 - Data-grounded heuristic to link percentage of pause and duration
 - Position of pauses left to the model
- Evaluation of both
 - Significant preference (resp. worst score) when pauses are well (resp. wrongly) placed

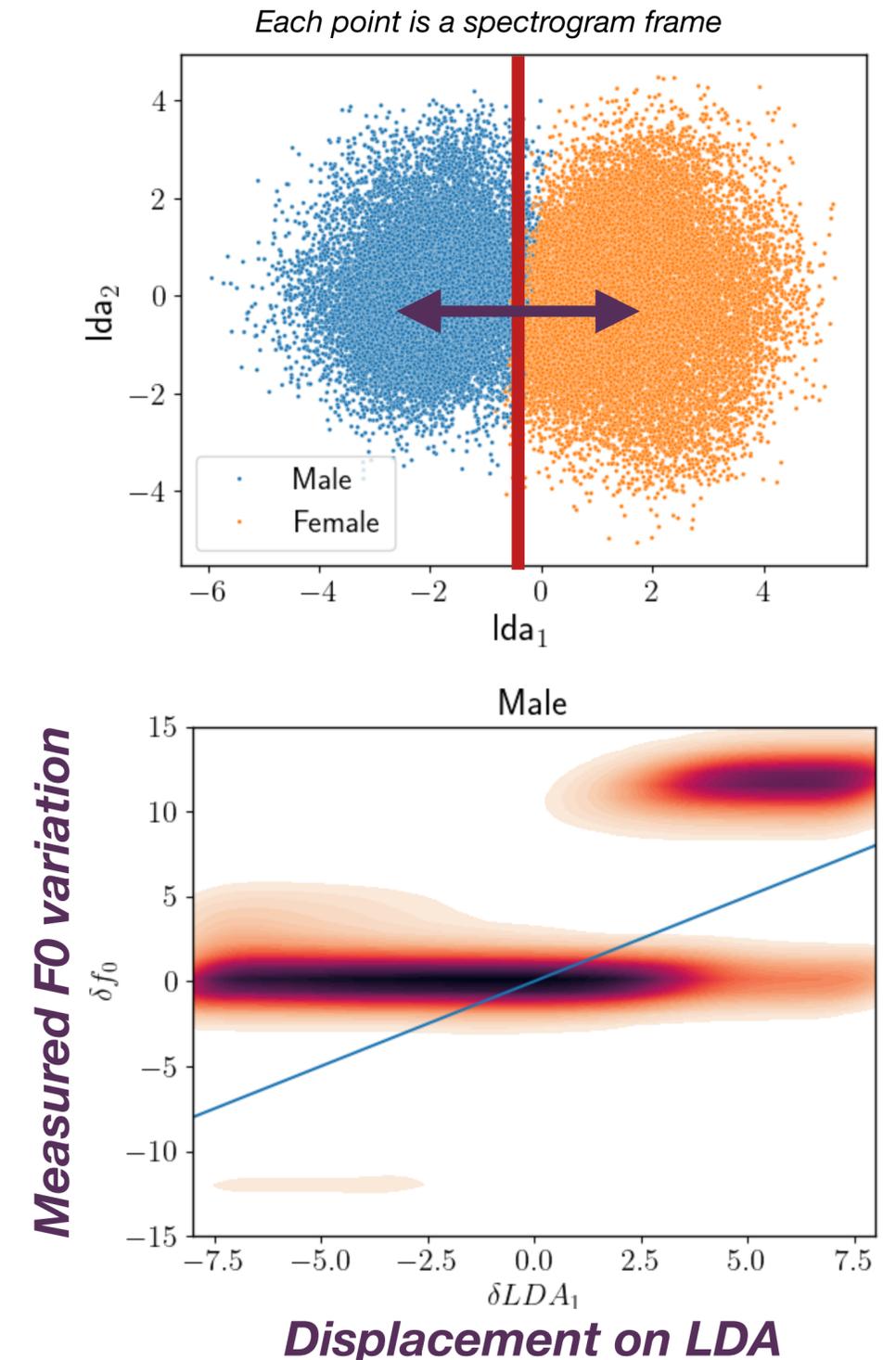




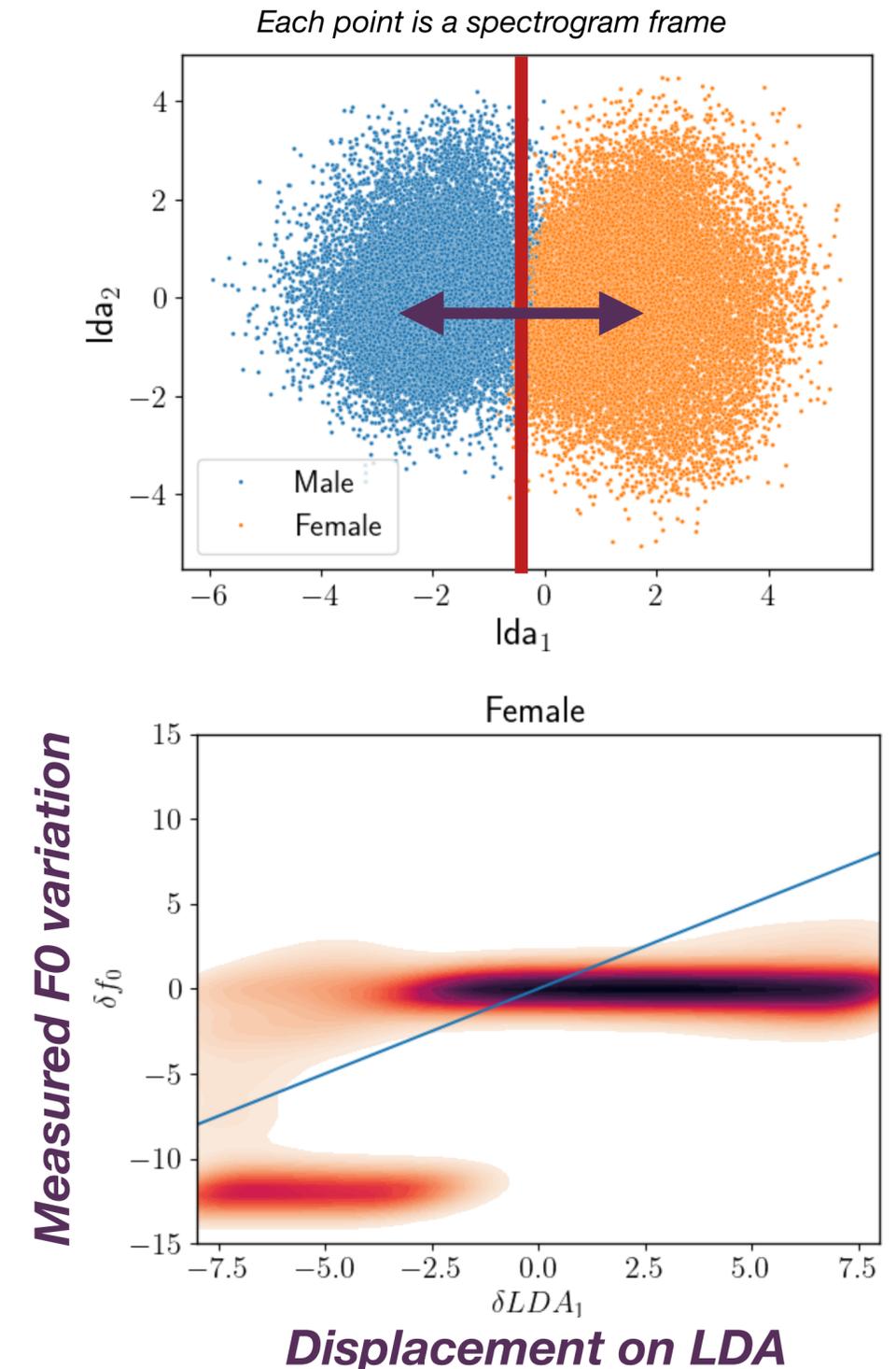
- **Multi-speaker** training (109 English Speakers M/F)
- Linear probing
 - Linear regression for continuous parameters: **consistent results with text-to-speech**
 - Linear discriminant analysis (LDA) for **speaker classes**

Jacquelin M., Garnier M., Girin L., Vincent R. Perrotin O., (2023), Proc. SSW, pp. 240–241

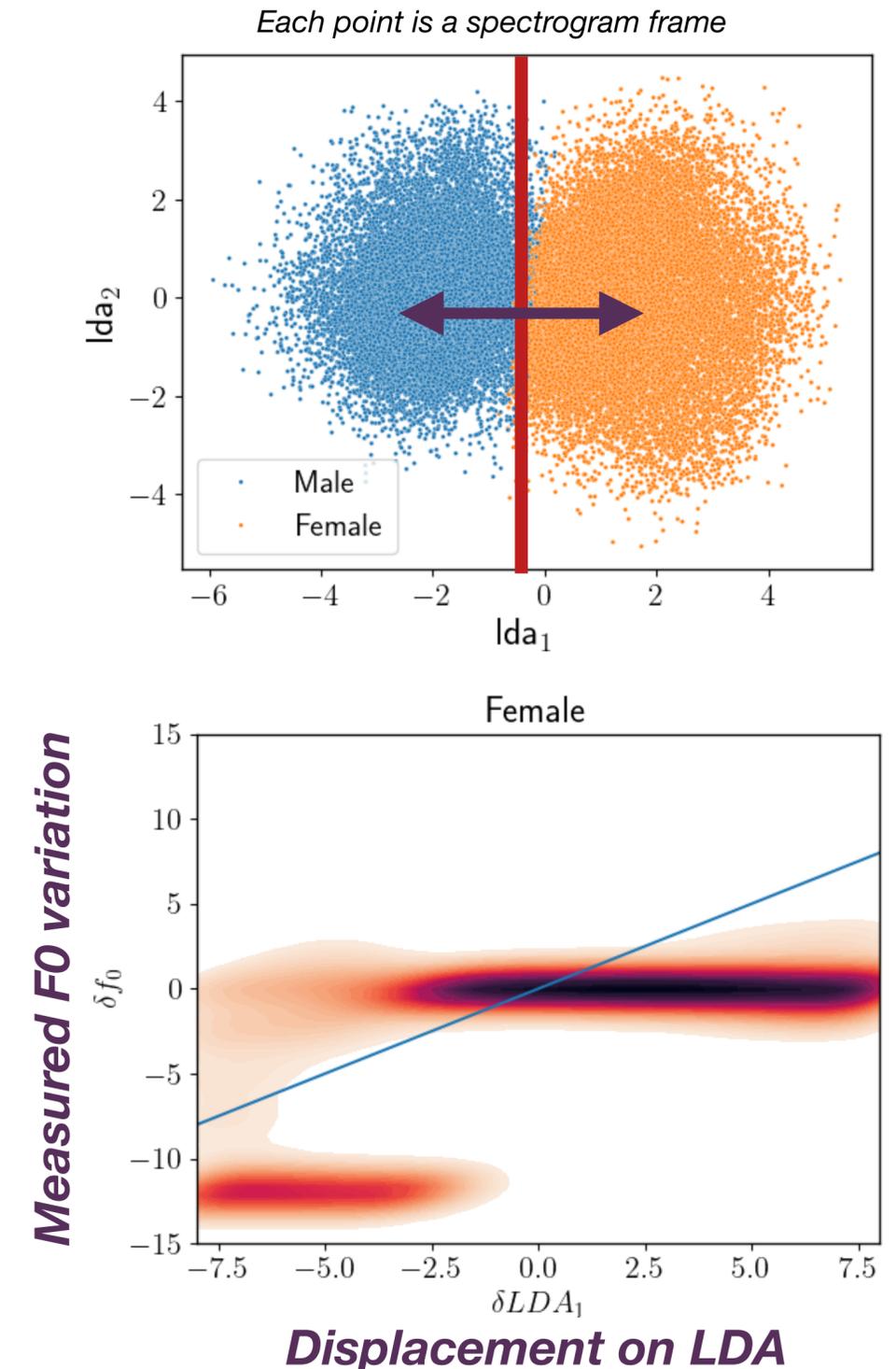
- First hyperplan of LDA discriminates gender
- Control across first LDA hyperplan
 - Discrete 1-octave jumps of F0



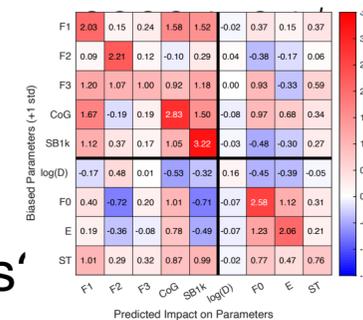
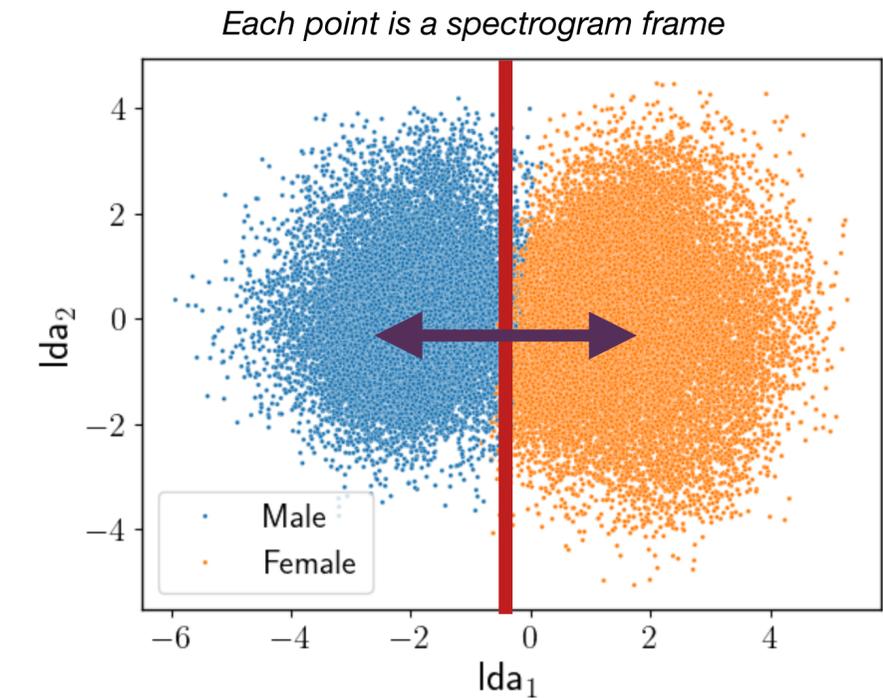
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- First hyperplan of LDA discriminates gender
- Control across first LDA hyperplan
 - Discrete 1-octave jumps of F0
- Dual coding behaviour of acoustic parameters
 - Continuous (via regressions)
Intra-class
 - Categorical (via LDA on speech production classes)
Inter-class



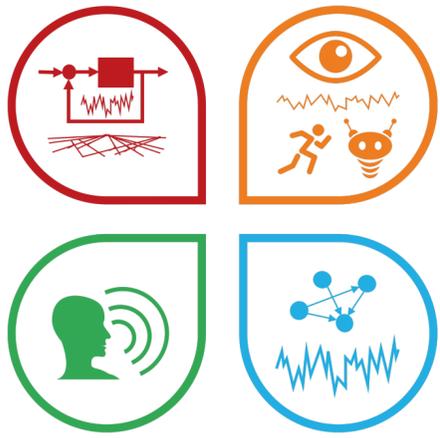
- First hyperplan of LDA discriminates gender
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- Dual coding behaviour of acoustic parameters
 - Continuous (via regressions)
Intra-class
 - Categorical (via LDA on speech production classes)
Inter-class
- Open the door to rich analysis of complex production modes in a single representation space
 - Future experiment on classes of vocal force
 - Can we expect categorical coding of covariations?
 - Can we expect speaker-dependant coding of covariations?
 - Can we control intra- and inter-class variations?



Linear probing and control in neural models

- Method
 - Linear probing: show the encoding of acoustic parameters at each layer
 - Causal control: non-linear control of both continuous and discrete acoustic parameters
- ➔ Powerful analysis tool learnt on massive data
- ➔ Works on different architectures (VAE, RNN, Transformers)

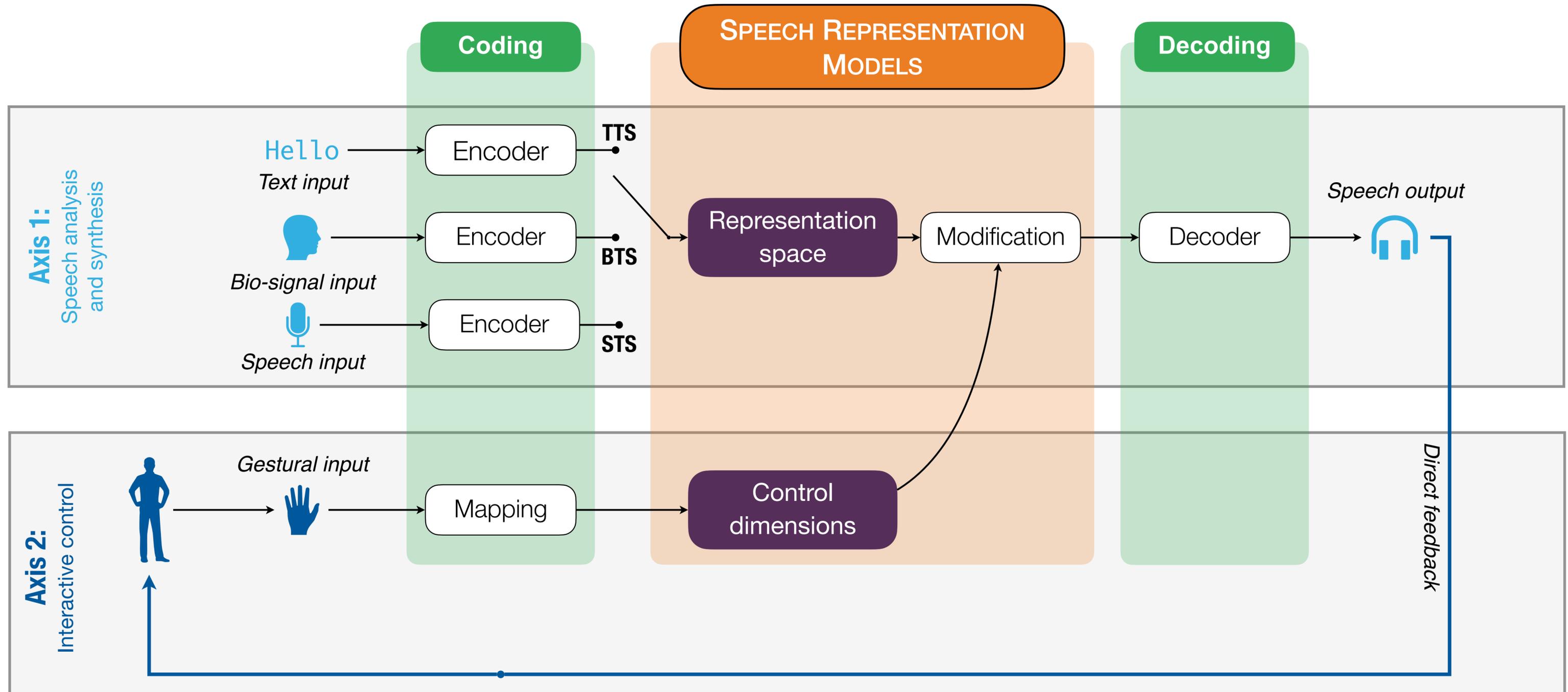
	Signal-based	Neural-based
• Generate high naturalness speech signals	Limited	✓
• Identify speech representation models which display interpretable and controllable expressive dimensions	Ceiling	Very promising
• Perform a robust modification of these parameters without degrading the signal quality	Within the limits of the model quality	Very promising
• Implement everything in real-time	✓	To come



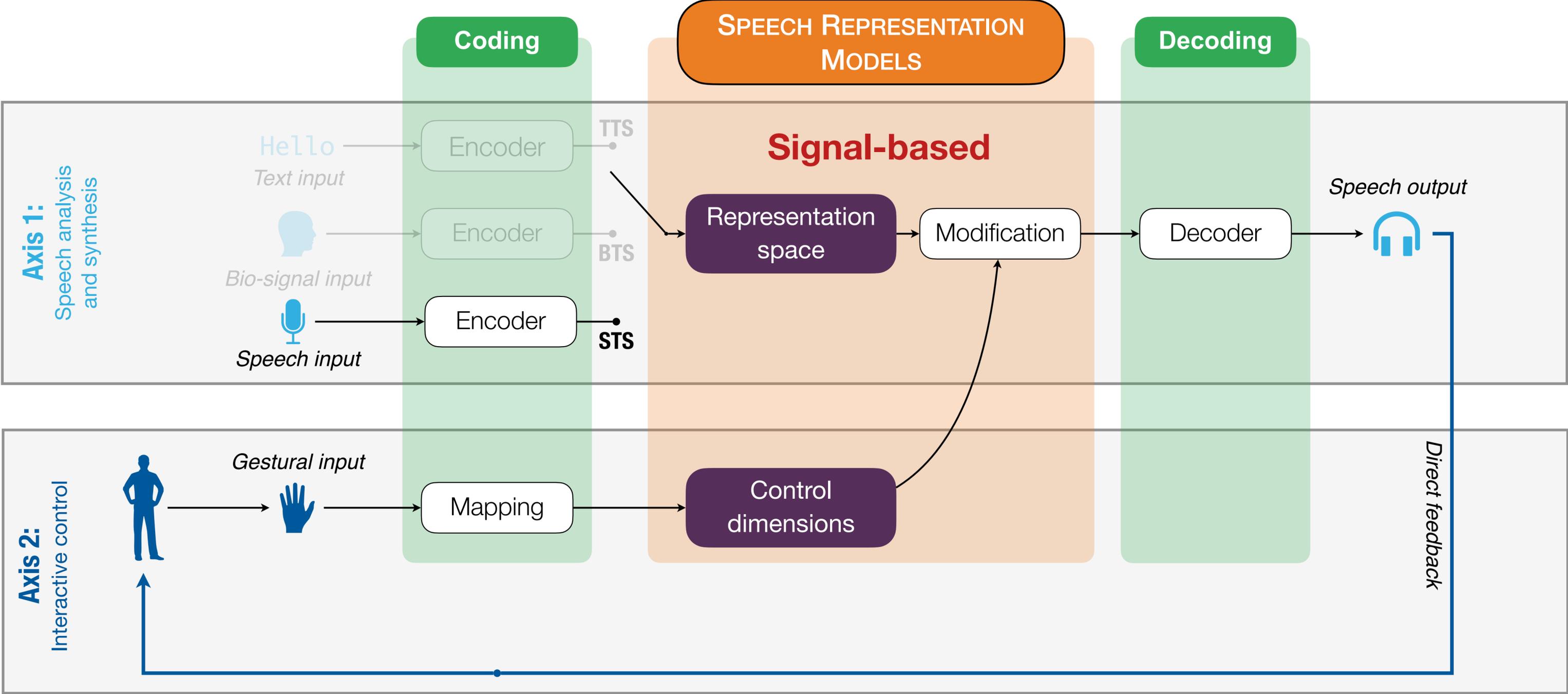
Interactive control of synthesis

- Explicit control of F0 in singing
- From implicit to explicit control of F0 in speaking
- Towards a co-adaptation between human and machine learning of control mapping

Interactive control of expressive speech synthesis



Interactive control of expressive speech synthesis



Litt. Review

d'Alessandro C. et al. (2022), JEP, pp. 625–636.

Speech Conductor

eNTERFACE - Belgique

Synthesis : formants / concatenative
Control : keyboard / data glove

*d'Alessandro C. et al. (2005),
eNTERFACE, pp. 52–61.*

Singing

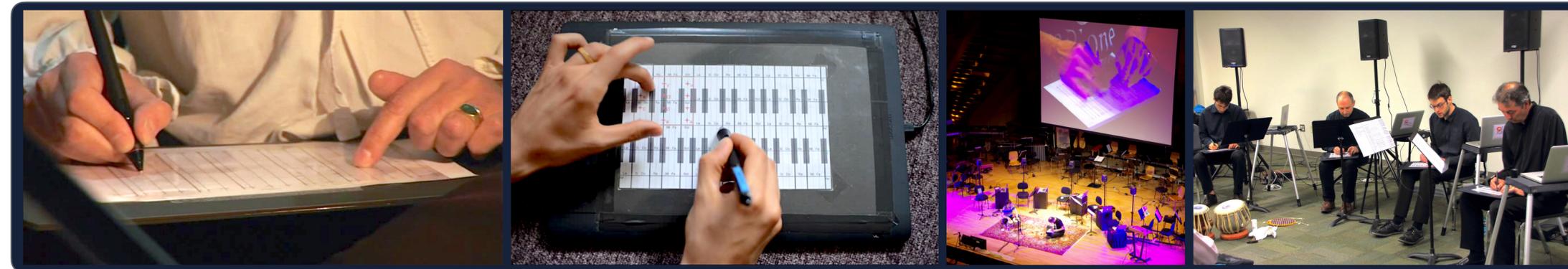
Cantor Digitalis

Le Beux / Feugère / Perrotin

Synthesis : formant

Control:

- Intonation: **graphic tablet**
- Vowels: **graphic tablet**



Feugère L., d'Alessandro C., Doval B., Perrotin O. (2017), JASM, 2017(2).

- **Evaluation of the interface for the control of intonation**
 - Evaluation of the precision allowed by the graphic tablet
 - Quantification of the influence of visual and auditive modalities on the control
 - Proposition of a series of gestures for expressive melodic control

*d'Alessandro C., Feugère L., Le Beux S., Perrotin O.,
Rilliard A. (2014), JASA, pp. 3601–3612.*

*Perrotin O., d'Alessandro C. (2016),
ACM Trans. Applied Perception, 14(2).*

Perrotin O. (2015), PhD Thesis.

➔ Singing intonation is **explicit**, speech intonation is **implicit**

Litt. Review

d'Alessandro C. et al. (2022), JEP, pp. 625–636.

Singing

Cantor Digitalis

Le Beux / Feugère / Perrotin

Synthesis : formant

Control:

- Intonation: **graphic tablet**
- Vowels: **graphic tablet**

Speech Conductor

eNTERFACE - Belgique

Synthesis : formants / concatenative

Control : keyboard / data glove

Speech

Voks (Calliphony/ Vokinesis)

Le Beux / Delalez / Locqueville / Xiao

Synthesis : transformation of playback

Control:

- Intonation: **graphic tablet / theremin**
- Biphasic rhythm: **foot pedal, hand button**

d'Alessandro C. et al. (2005), eNTERFACE, pp. 52–61.



Le Beux S. et al. (2007), ISCA SSW, pp. 345–350.

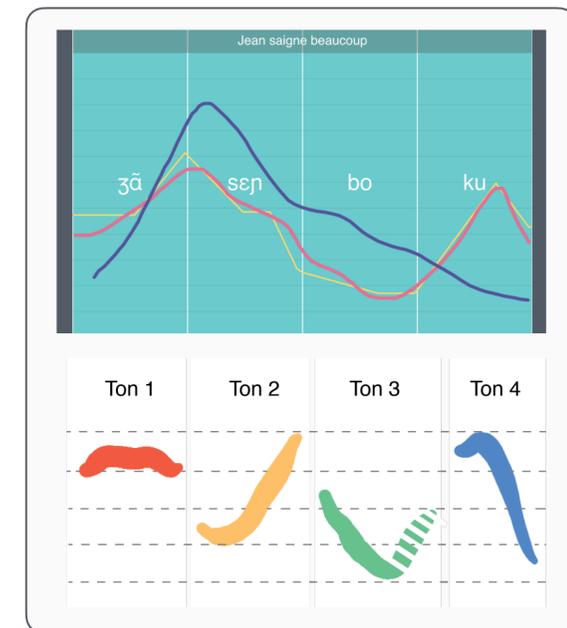
Delalez S. et al. (2017), Proc. NIME, pp. 198–203.

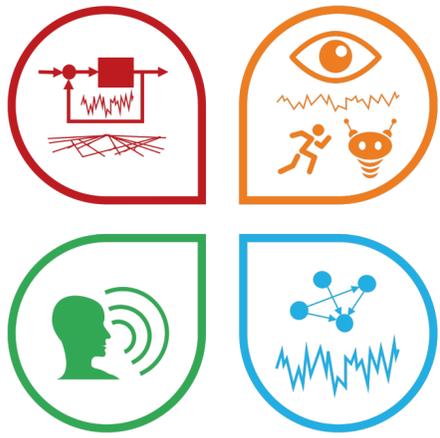
Delalez S. et al. (2017), Proc. Interspeech, pp. 864–868.

Locqueville G. et al. (2020), Speech Comm., 120, pp. 97–113.

- Control of pre-recorded sound samples (intonation, rhythm)
 - Very accurate in **imitation** paradigms *d'Alessandro C. et al. (2011), JASA, pp. 1594–1604.*
 - Use multi-modal reinforcement for learning intonation of foreign languages (English, French, Mandarin) *Xiao X. et al. (2021), Proc. Interspeech, pp. 516–520.*

- What about **production** tasks with a **simultaneous control of articulation**?

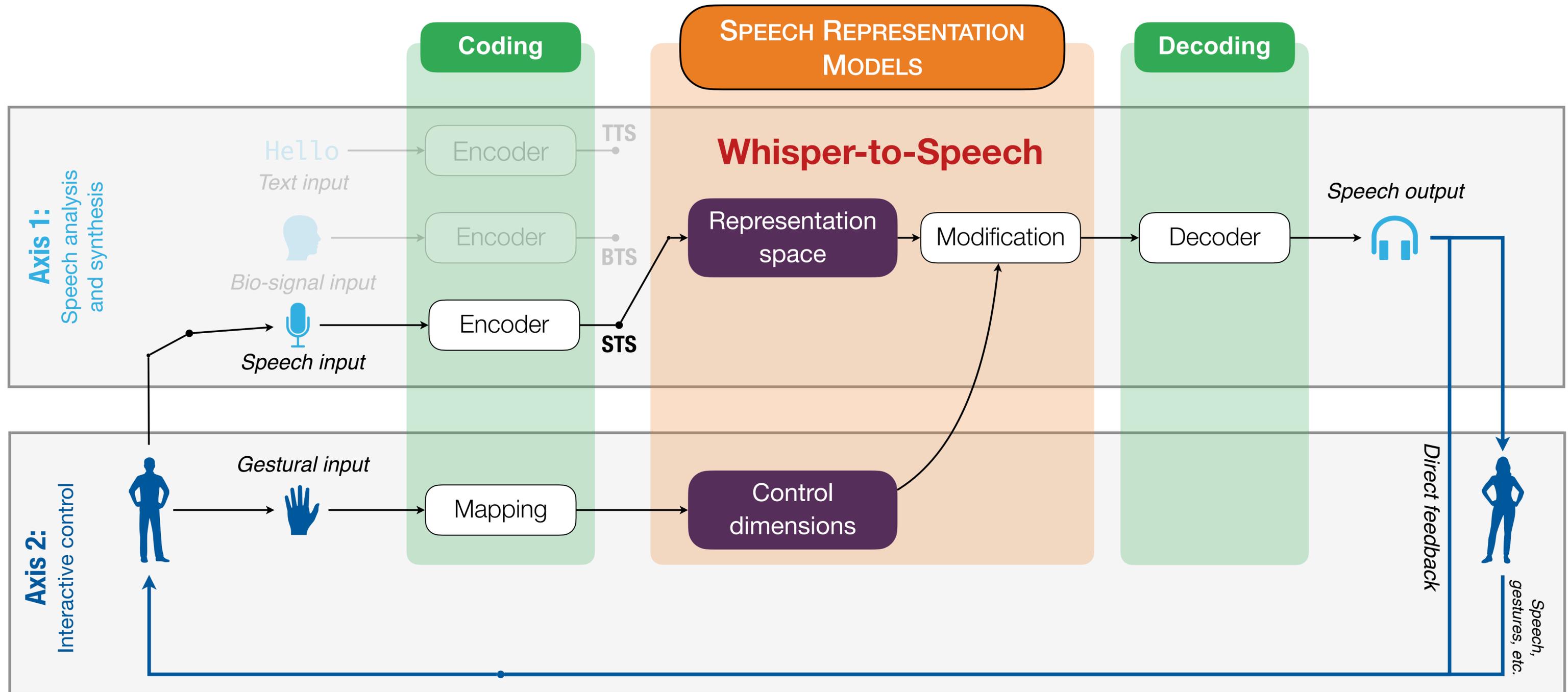




Interactive control of synthesis

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Interactive control of expressive speech synthesis



Implicit manual control of **contrastive focus** in a whisper-to-speech conversion set up

- Dual control
 - Natural control of articulation (whispering)
 - Manual control of intonation with either a wrist rotation (accelerometer) or a finger pressure
 - Reference : natural voice



- Elicitation of contrastive focus
 - Simulated dialogue
 - No explicit instructions on focus

Vous : - Lou du Mans a suivi le loup doux.
L'expérimentatrice : - Lou du Mans a suivi le chat doux ?
Vous : - Lou du Mans a suivi le loup doux.

Hypothesis

← No focus

← Focus

- Corpora
 - 6 sentences of 9 syllables
 - 3 constituents : subject (3 syll)-verbal (3 syll) –object (3 syll)
 - Target syllabe cible [lu]

S1 : **Lou** du Mans a suivi le loup doux
O2 : Lou du Mans a suivi le **loup** doux
S2 : Le **loup** doux a suivi le beau loup
O3 : Le loup doux a suivi le beau **loup**
S3 : Le beau **loup** a suivi Lou du Mans
O1 : Le beau loup a suivi **Lou** du Mans

- 16 participants

Interactive control of expressive speech synthesis Delphine Charauau Control of implicit F0

Duration

- Measure
 - Duration of each syllable [lu] relatively to the utterance
- Hypothesis
 - Only Post-cible is focused
 - Effect on all controls
- Observations
 - Post-cible longer than all other syllables
 - Valid for all controls

➔ Focus is produced with articulation

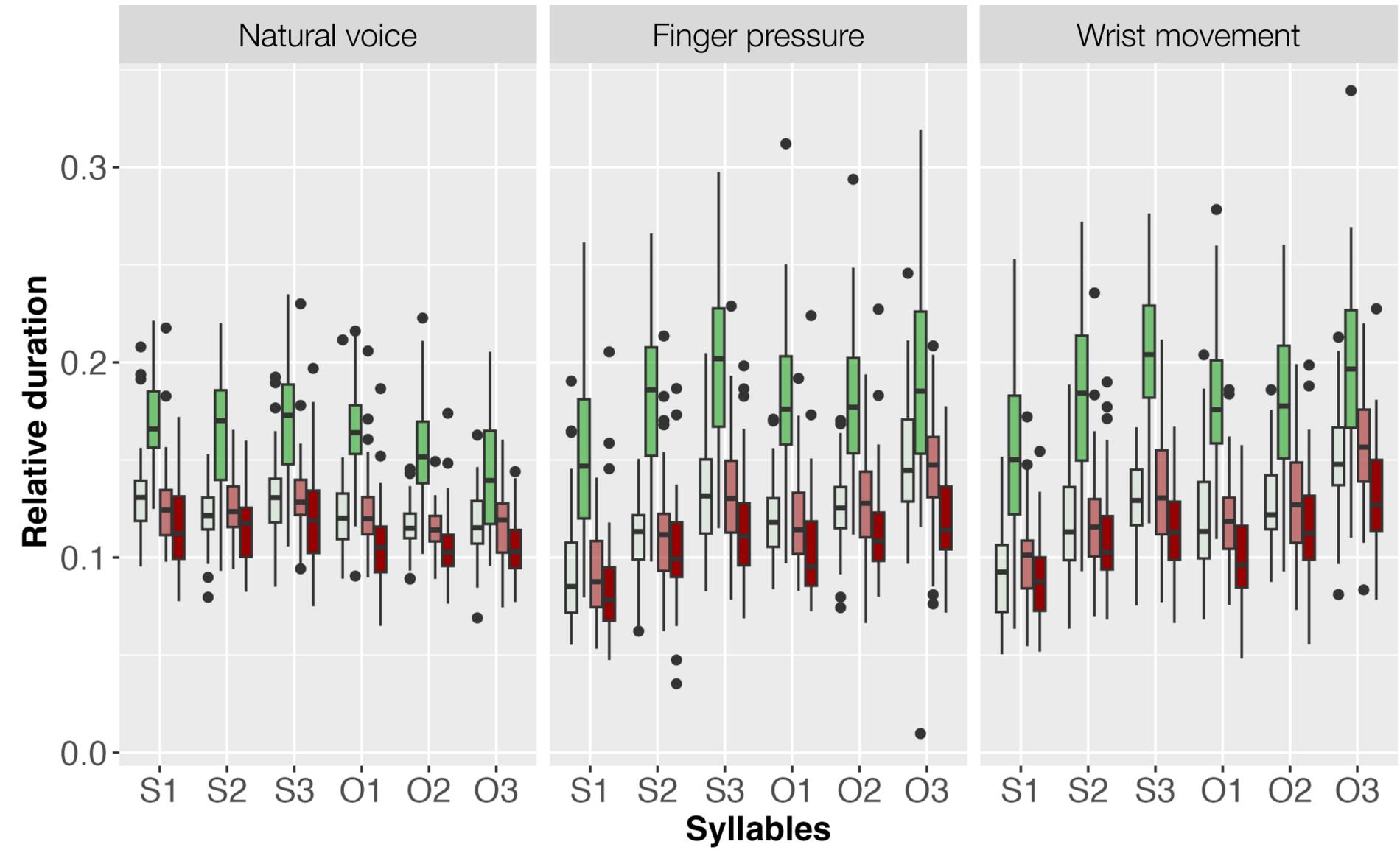
Vous : - Lou du Mans a suivi le loup doux.
Pre - non-cible Pre - cible

L'expérimentatrice : - Lou du Mans a suivi le chat doux ?

Vous : - Lou du Mans a suivi le loup doux.
Post - non-cible Post - cible

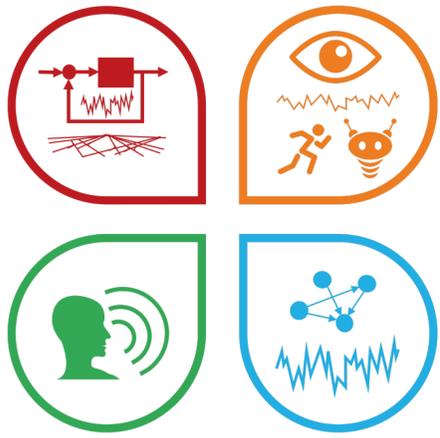
Condition

- Pre : Target
- Post : Target
- Pre : Non-Target
- Post : Non-Target



Conclusions

- Control of focus
 - Contrastive focus was elicited (no explicit instructions to realise a focus)
 - All but one participants produced a focus at the right place (syllable elongation, raise of F0)
- ➔ Successful explicitation of F0 contour by participants
 - Understood they had to produce some focus
 - Knew that a focus is done by a local raise of F0
 - Planned and produced the raise correctly (in terms of dynamics)
- ➔ Very encouraging for the explicit control of F0 paradigm
 - Participants have the potential to learn such a control
 - Learning curve quite long (many functions of F0 to learn)



Interactive control of synthesis

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Future work

Instead of having the human to fully learn the F0 control,
Can the system learn to predict F0?

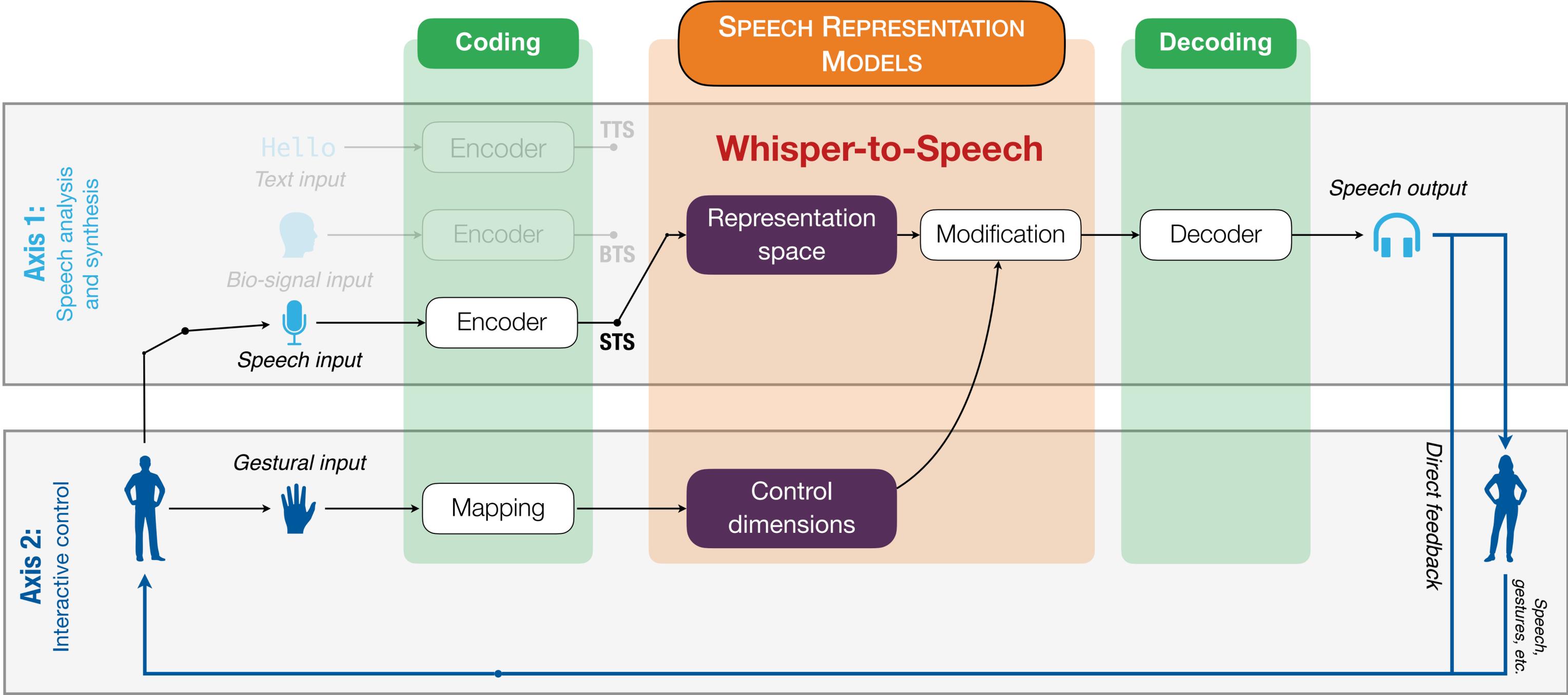


- Strong correlations between intonation and gestures

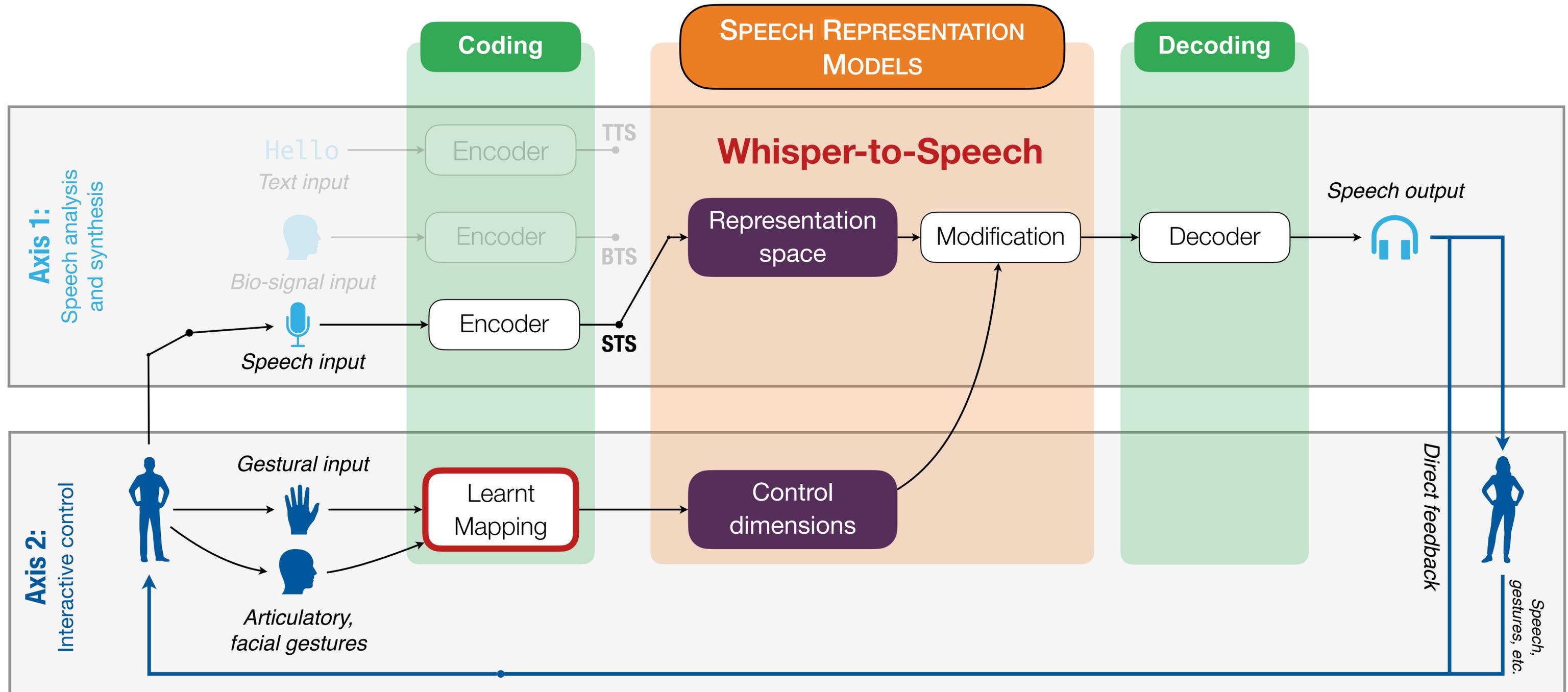
Fonction of prosody (not exhaustive)	Co-occurring speech gesture (not exhaustive)
Delimitative cues of prosodic phrasing (Fougeron & Keating, 1997)	Movements of: - the lips (Dohen et al., 2004), - the tongue (Krivokapić et al., 2017), - the eyebrows (Cave et al., 1996), - the head (Wagner et al., 2014), - the hands (Leonard & Cummins, 2011; Roustan & Dohen, 2010a, 2010b)
Focus (Jun & Fougeron, 2000)	
Social attitudes (Fónagy et al., 1983; Ward, 2019)	Intonation contour control (Evrard et al., 2015; Perrotin, 2015)
Emotions (Goudbeek & Scherer, 2010)	

➔ Can we use this correlations to automatically predict intonation patterns from those gestures?

Interactive control of expressive speech synthesis

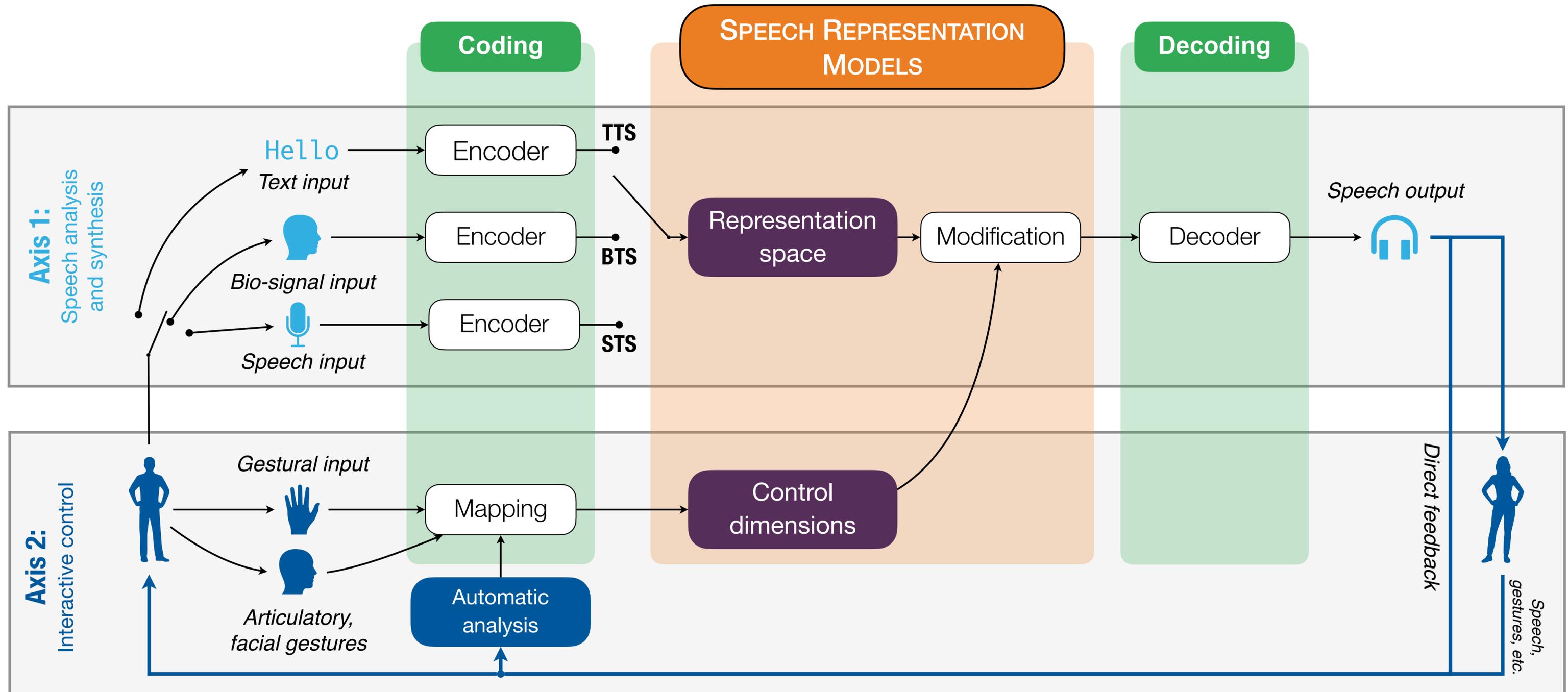


Interactive control of expressive speech synthesis



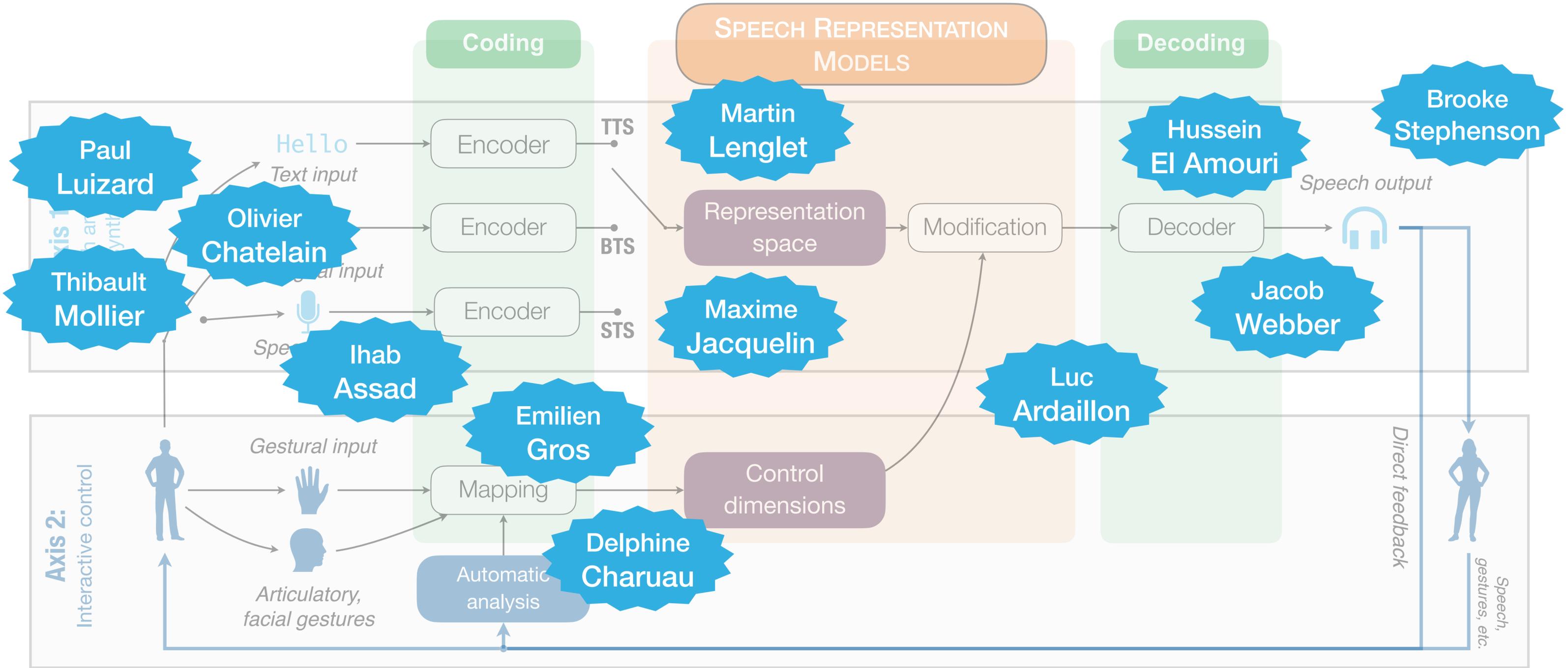
➔ Study the co-adaptation between human learning and machine learning in interaction

Interactive control of expressive speech synthesis



- **Axis 1: Analysis-synthesis of expressive speech**
 - Many applications (speech coding, voice transformation, text-to-speech)
 - Signal-based models: global understanding of acoustic variations linked to expressivity
 - Neural-based models: very powerful modelling tools that are often considered as opaque
- ➔ Using signal, acoustical, physiological knowledge to probe neural representation spaces open a highway to:
 - Complex and very fine-grained analysis of voice production on large datasets
 - High-quality synthesis in terms of expressivity rendering and control
- **Axis 2: Interactive control of synthesis**
 - Successful explicitation of F0 contour by participants in production tasks
 - Full intonation contour may have a long learning curve
- ➔ Exploitation of speaker and interlocutor data for a semi-automatic control of F0
 - Speech-to-speech: speech co-occurring gestures (co-adaptation between human and machine)
 - Text-to-speech: interlocutor behaviour

Merci !



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Thomas Hueber

Gérard Bailly

Et tous les autres