Real-time Single-channel Speech Enhancement with Recurrent Neural Networks

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Recording has started.
Participation in the meeting indicates your consent to being included in the meeting recording.

Outline

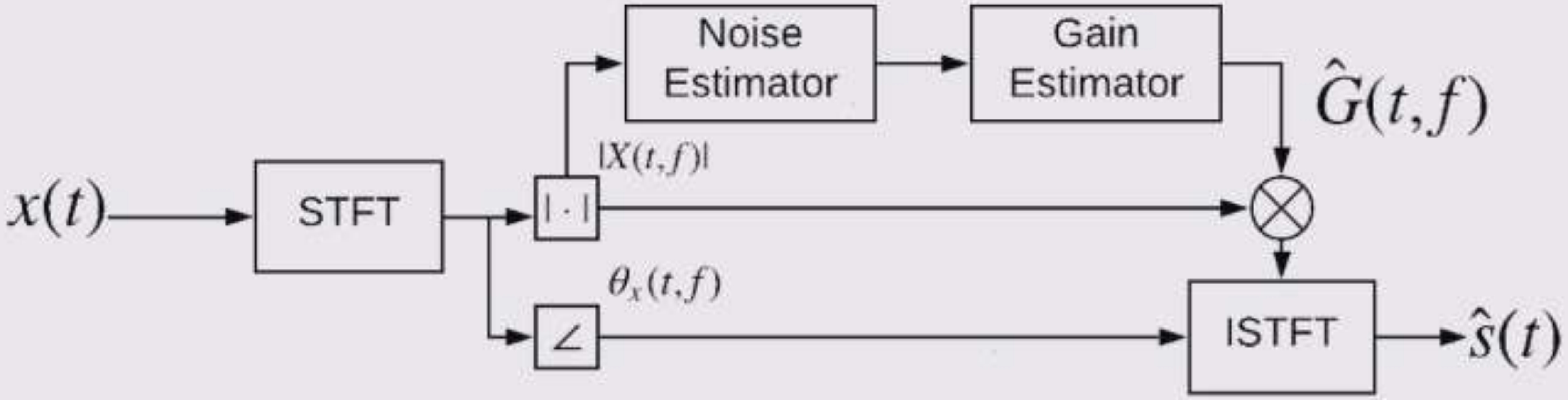
- Introduction to Single-channel Speech Enhancement
  - Classical signal processing vs. Deep learning
  - Considerations for online processing
- Our Method
  - Feature Representations
  - Learning Machines
  - Learning Objectives
  - Training Considerations
- Evaluation
  - Data
  - Metrics
  - Results
- Findings and Conclusions

Single-channel Speech Enhancement (SE)

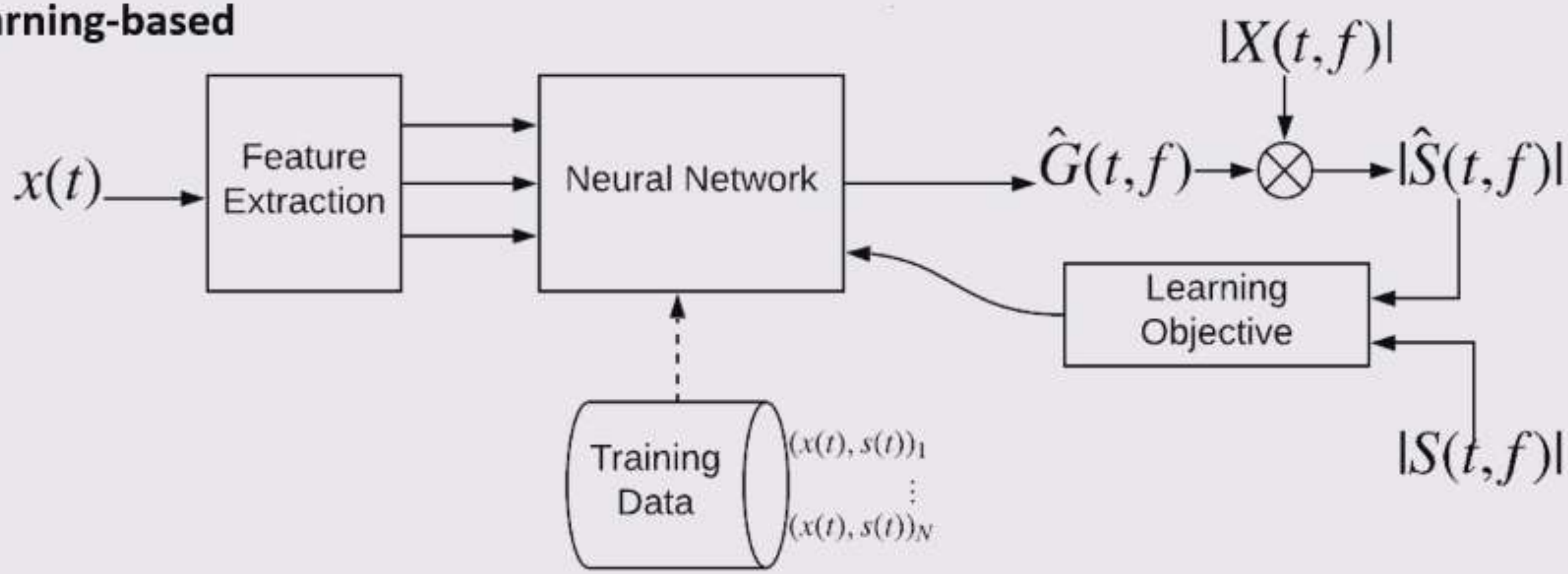
- Assumptions
  - Noisy speech = Speech + Noise
  - Noise attributes change slower than speech
- Goals
  - Suppress noise
  - Retain speech
  - Improve human or/and machine perception
- **Our goal: enhancing speech quality for human listeners**

Generic SE Pipelines

Classical



Deep-learning-based



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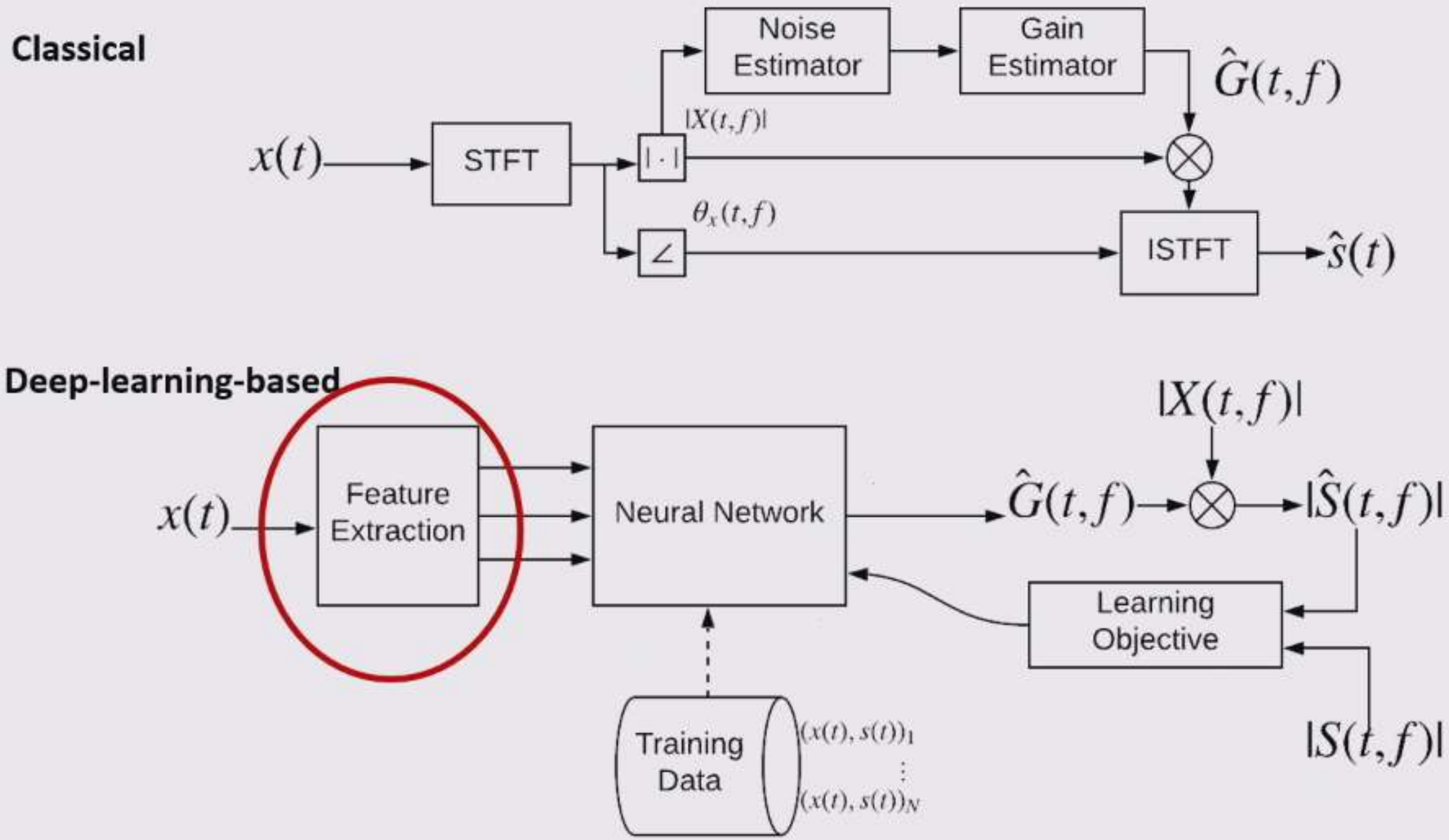

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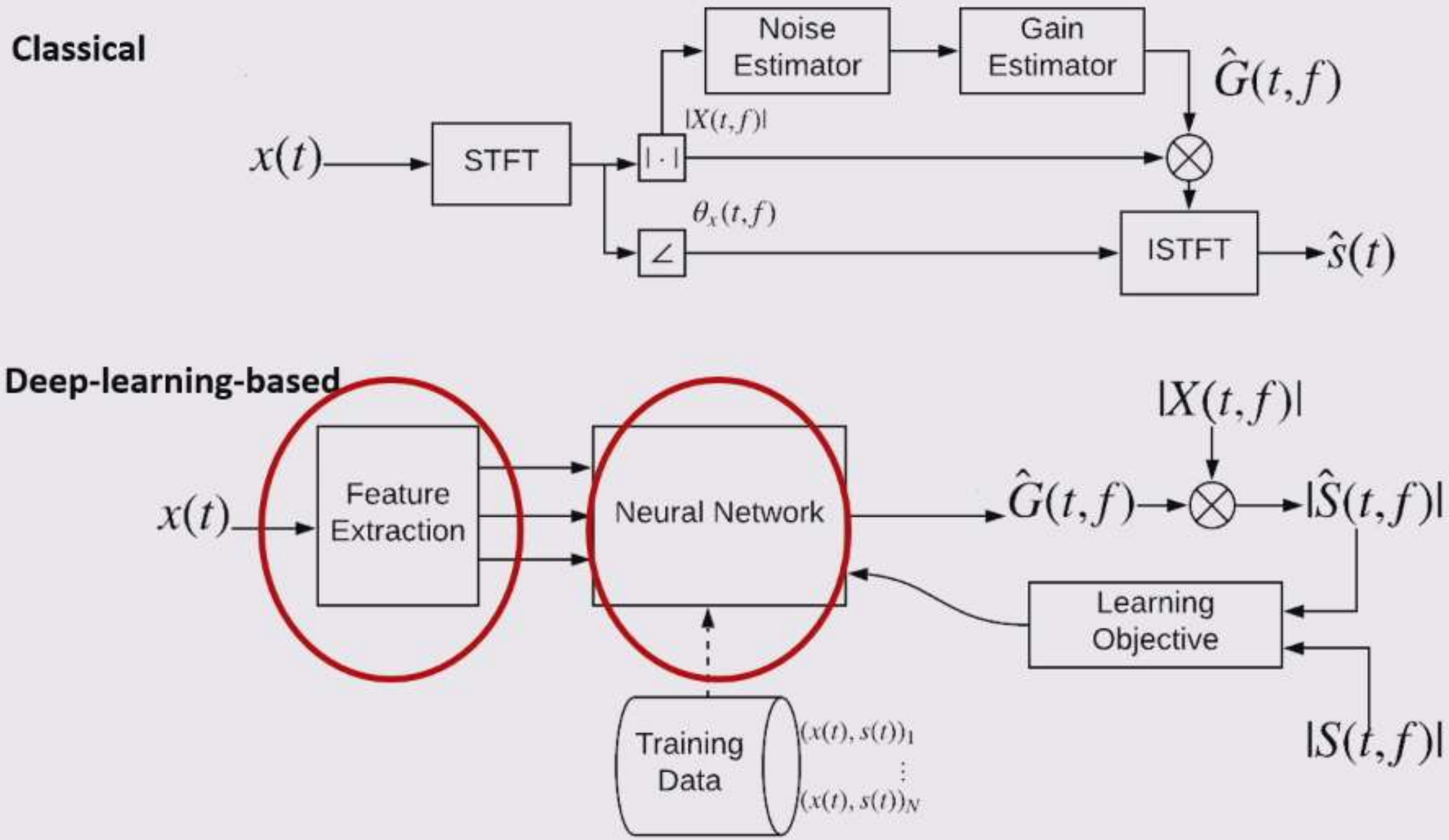

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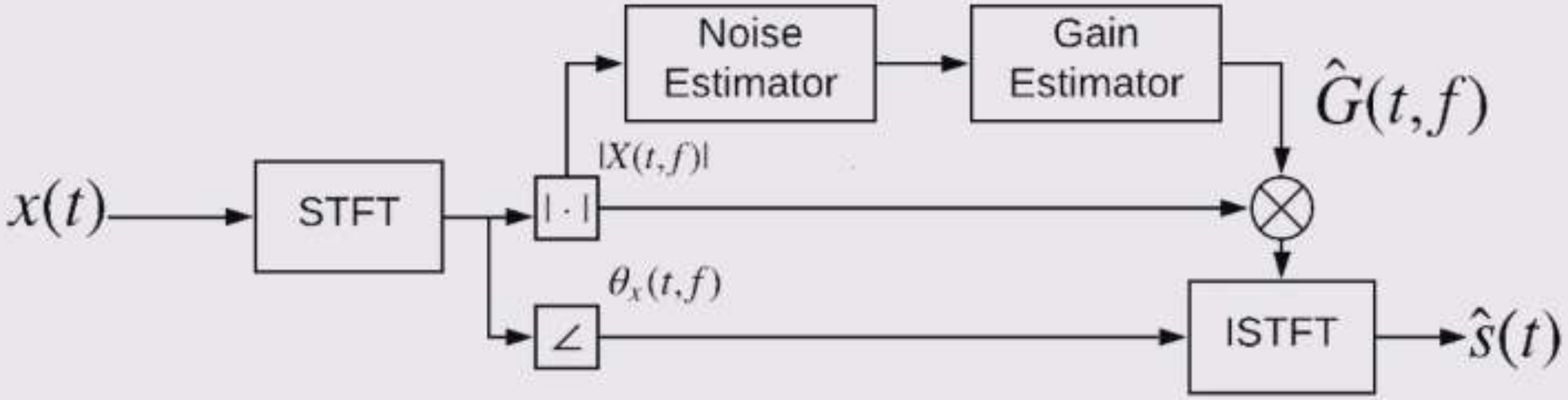

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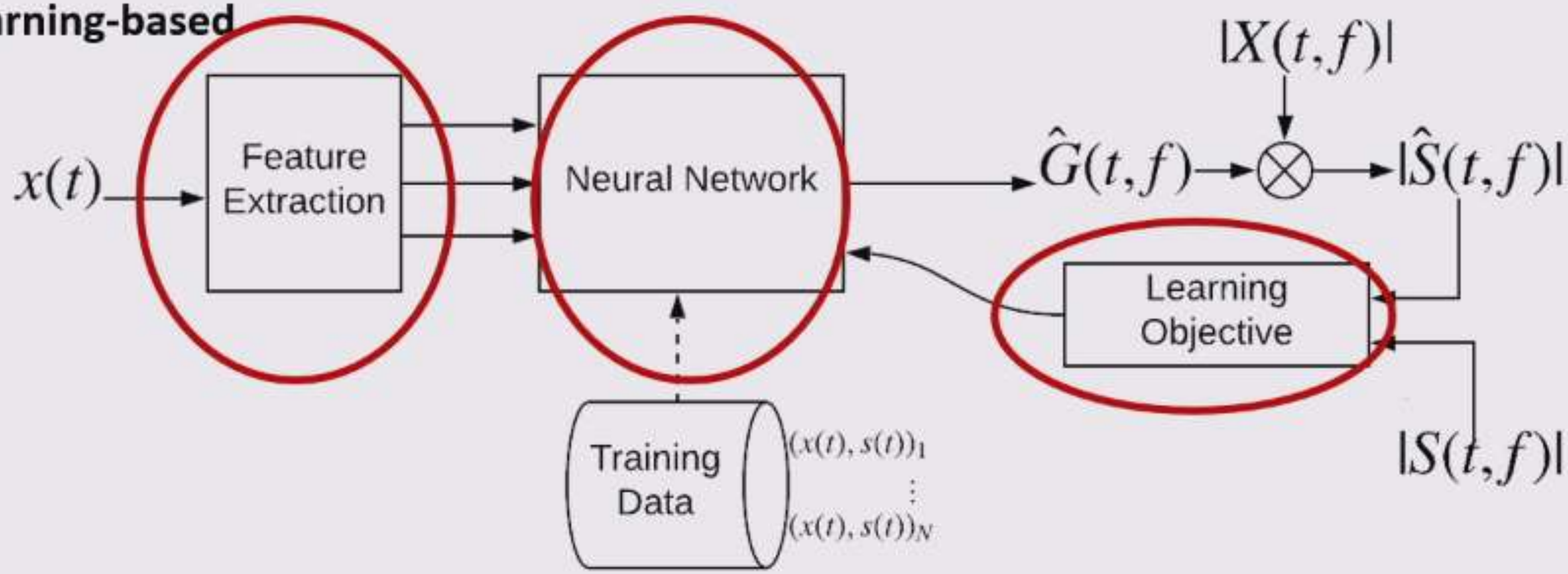

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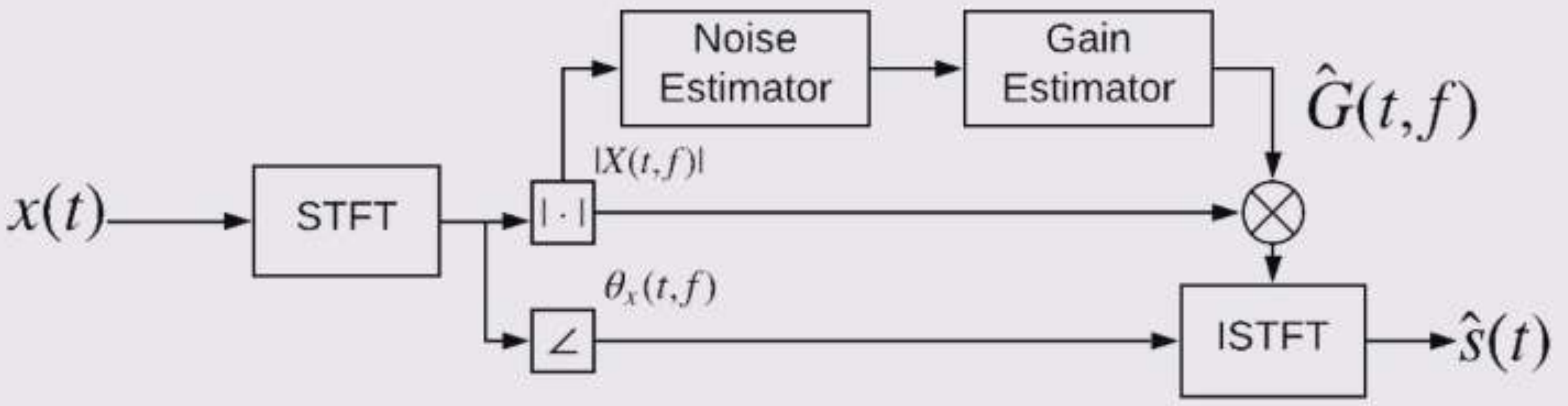

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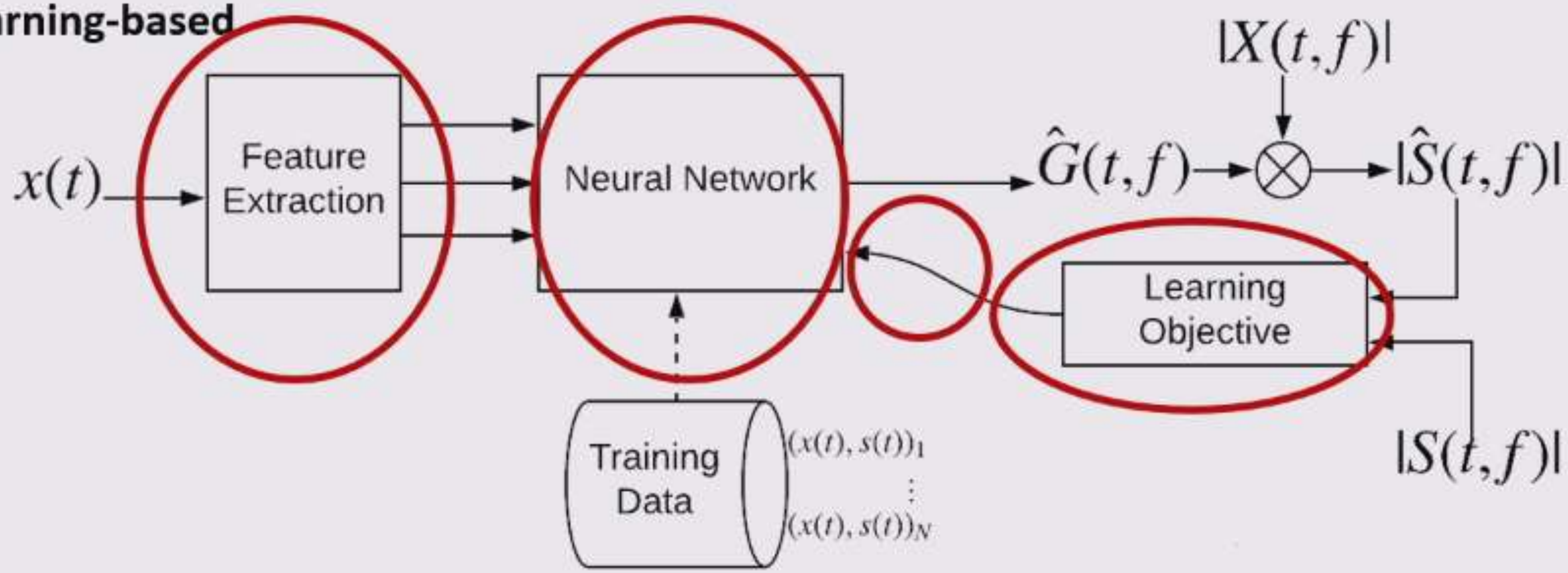

SP vs. DL for Online Enhancement

Name	Method related to Online Processing	Data-driven?	Online?
Spectral subtraction [Boll1979]	Estimate noise magnitude spectra by a **moving average** filter	No	Yes
Decision-directed [Ephraim1984]	Estimate SNRs by **smoothing instantaneous measurements** of SNRs	No	Yes
Deep clustering [Hershey2016]	Cluster each time-frequency bin based on feature embeddings generated from a **100-frame** spectrograms	Yes	No
Audio-visual speech separation [Ephrat2018]	**2-D convolution cross time and frequency** of a spectrogram	Yes	No
RNNoise [Valin2018]	Recurrent units **output one frame from one input frame**	Yes	Yes
SEGAN [Pascual2017]	Generate enhanced speech from a waveform segment	Yes	Maybe, if trained on a single frame.

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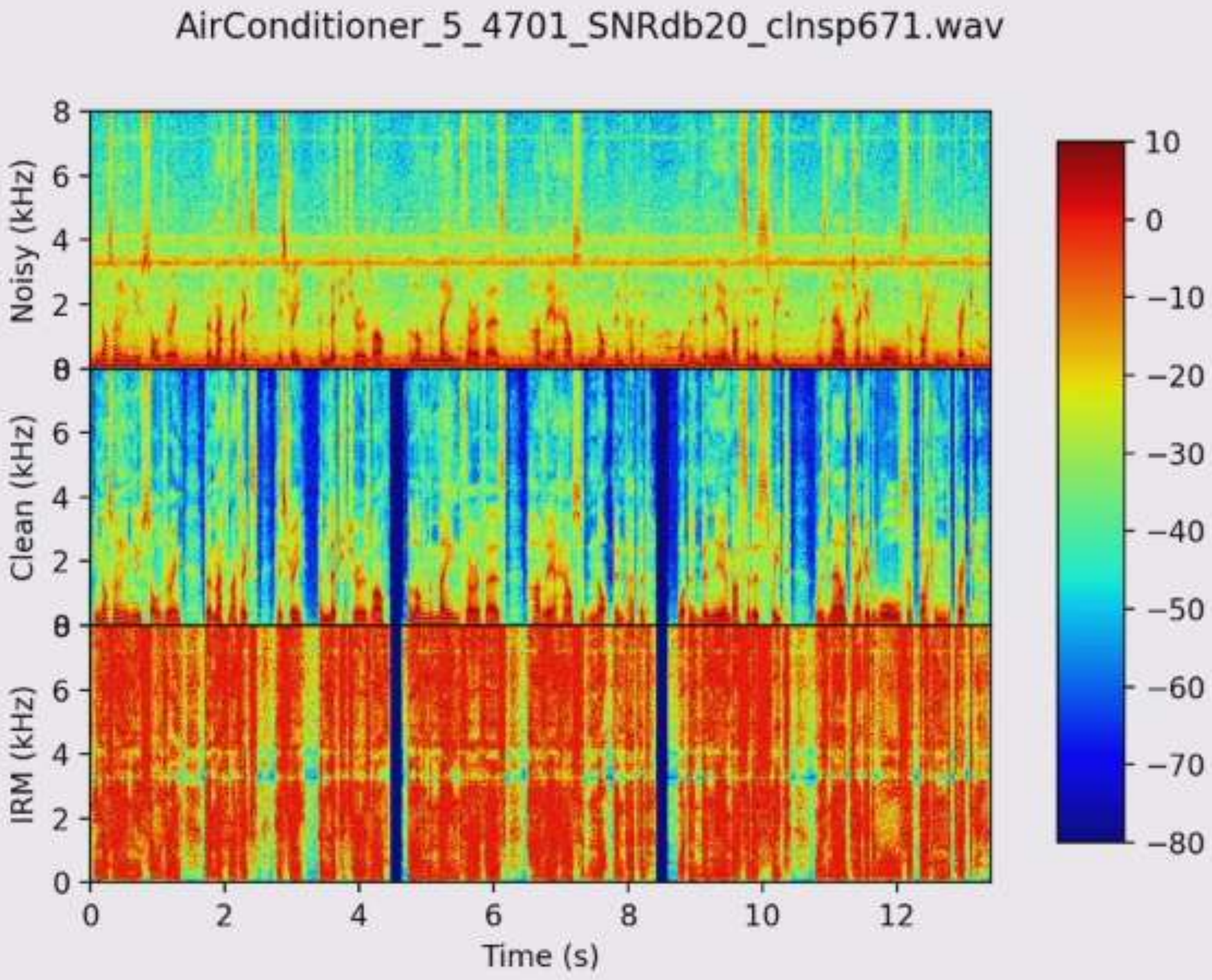
Input (Feature) & Output (Target)



- (In) Short-time Fourier transform magnitude (STFTM)
- (In) Short-time log power spectra (LPS) with -80 dB floor
- (Out) Real magnitude gain function in [0, 1]
- Technical details:
  - 16 KHz sampling rate
  - 32-ms analysis frame
  - Hamming window
  - 75% overlap between frames

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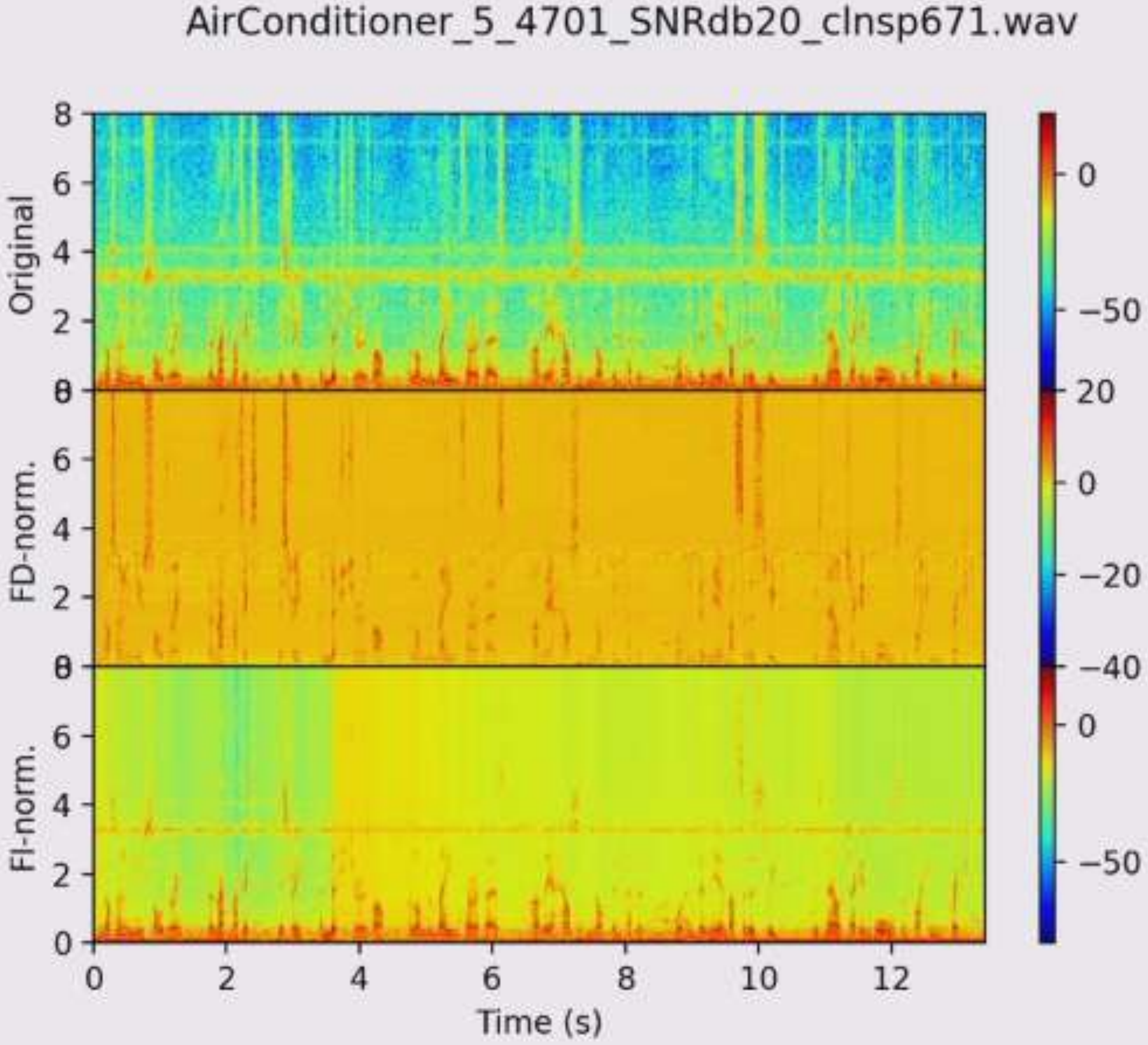

- Global mean and variance normalization
  - Statistics per frequency bin accumulated over 80 hours of randomly sampled speech from the training set
- Online mean and variance normalization
  - 3-second exponential smoothing
  - Frequency-dependent (FD) or frequency-independent (FI)

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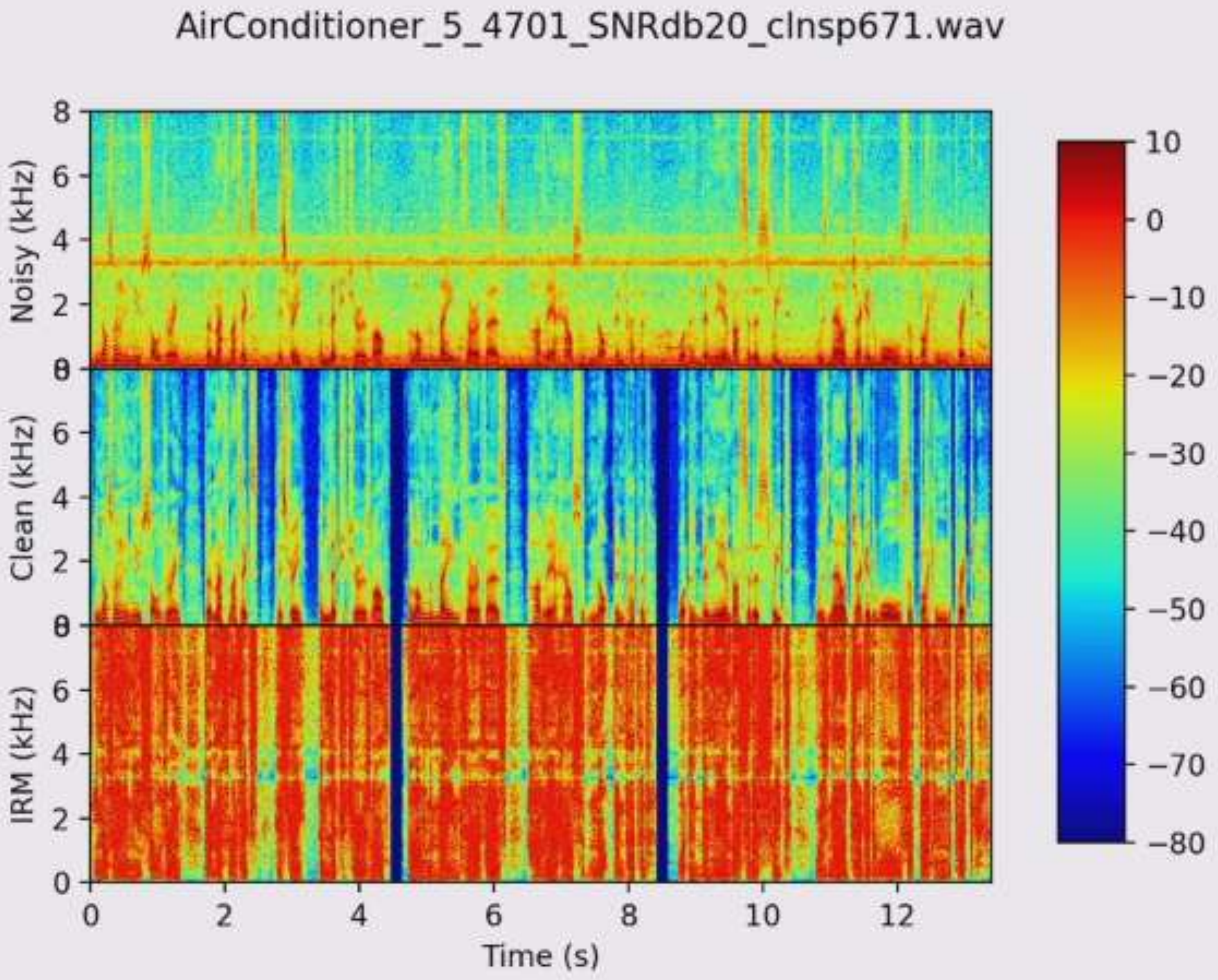

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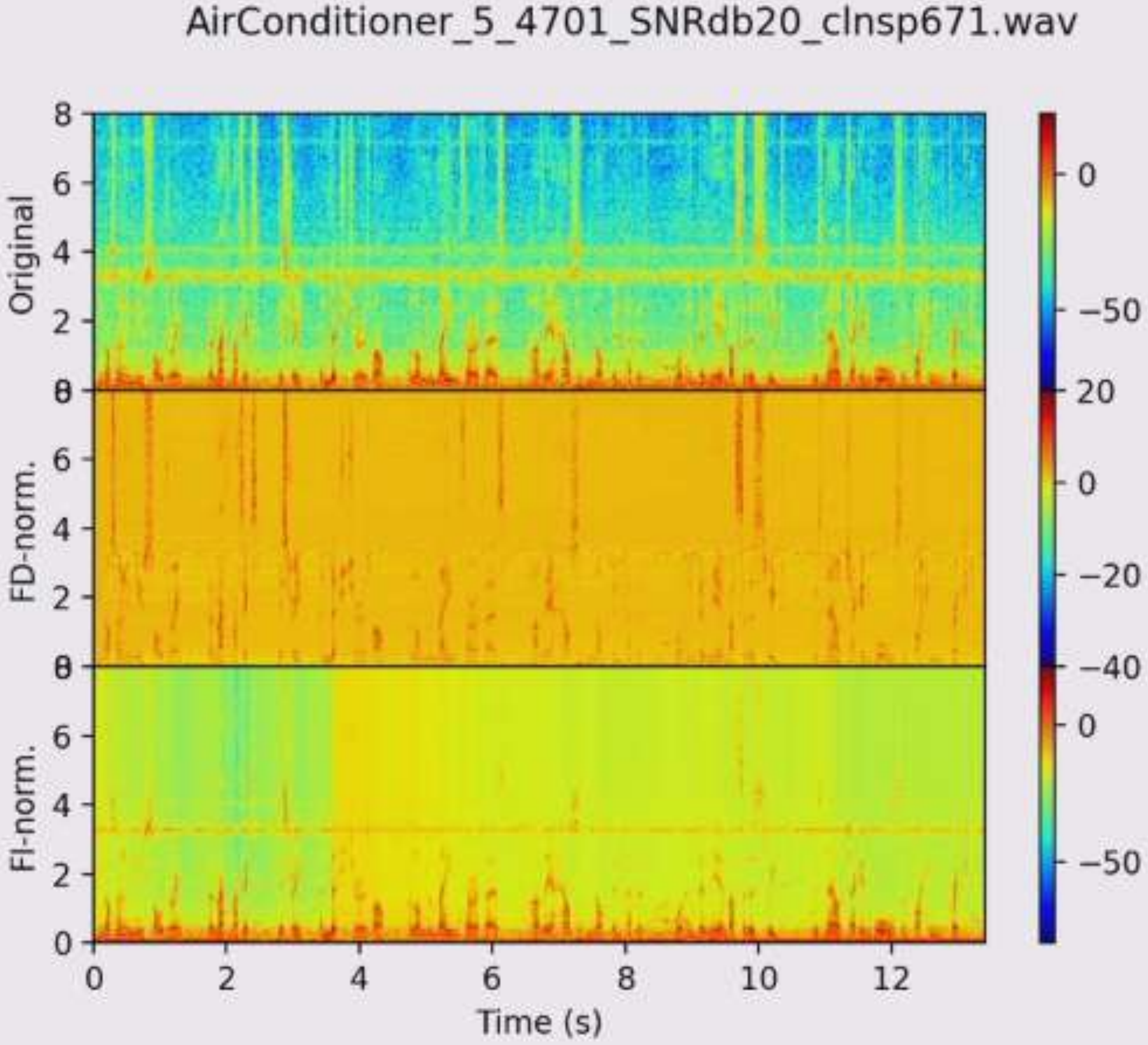

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Learning Machines

- Recurrent neural network (RNN) the most "natural" choice
  - Ability to encode long-term temporal patterns
  - Information exchange across frequencies
- Example: RNNoise [Valin2018]
  - GRUs [Bahdanau2014] encode temporal patterns
  - Full-connected (dense) layers transform composite features to a gain

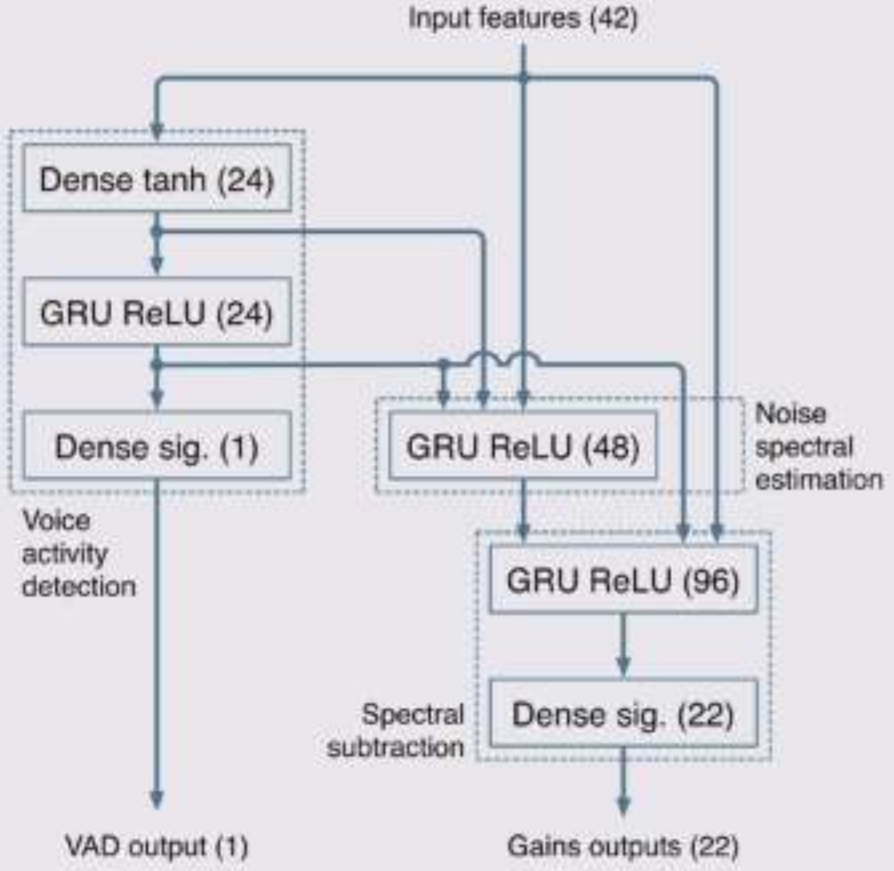
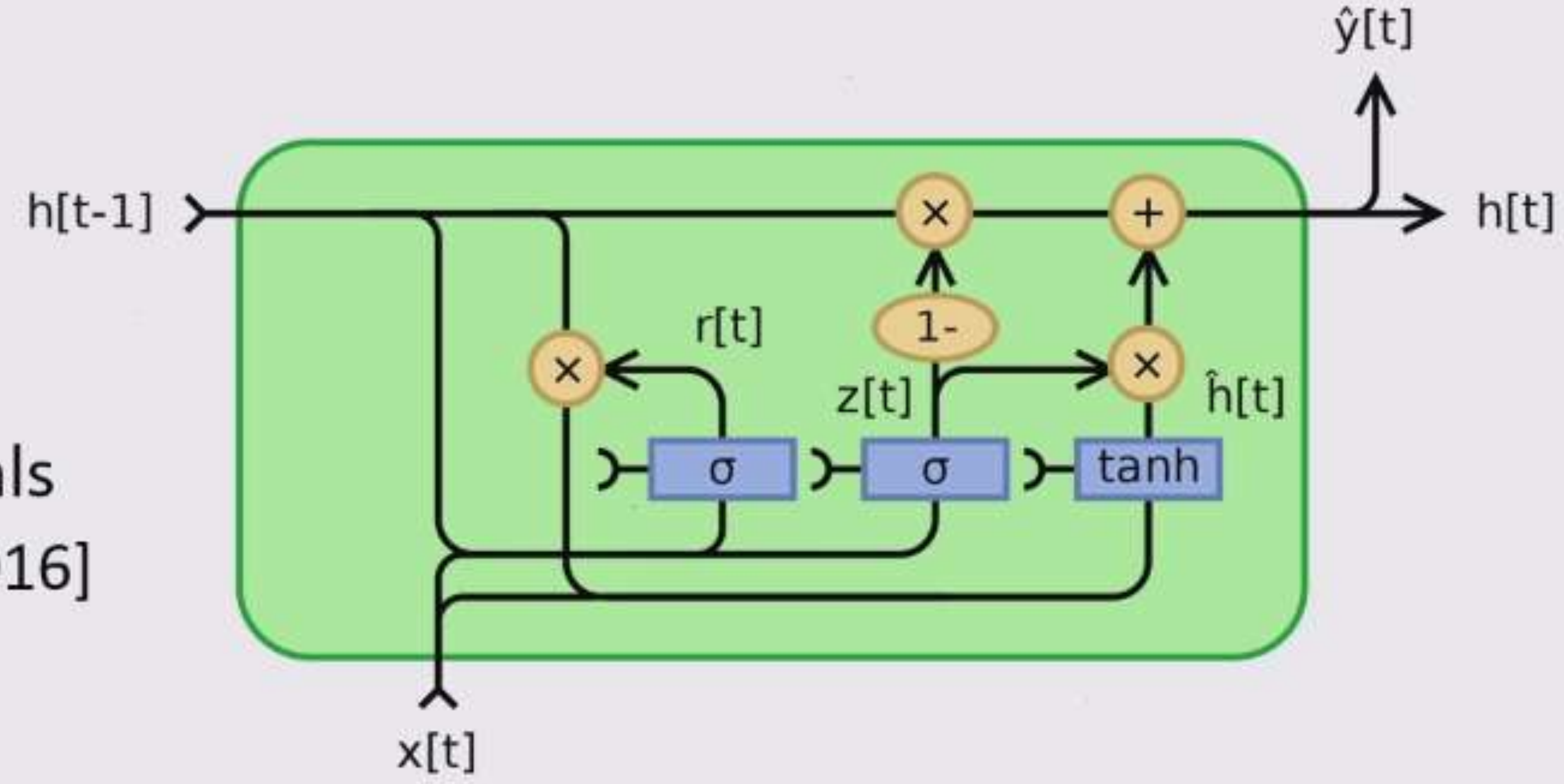


Image credit: [Valin2018]

Recurrent Units with Residual Connections

- Residual connections facilitate learning deep networks [He2016]
  - Depth = sequence length in our context
- Existing work using RNN + residuals
  - Sequence classification [Wang2016]
  - Automatic speech recognition [Kim2017]
  - Feature compensation for ASR [Chen2017]



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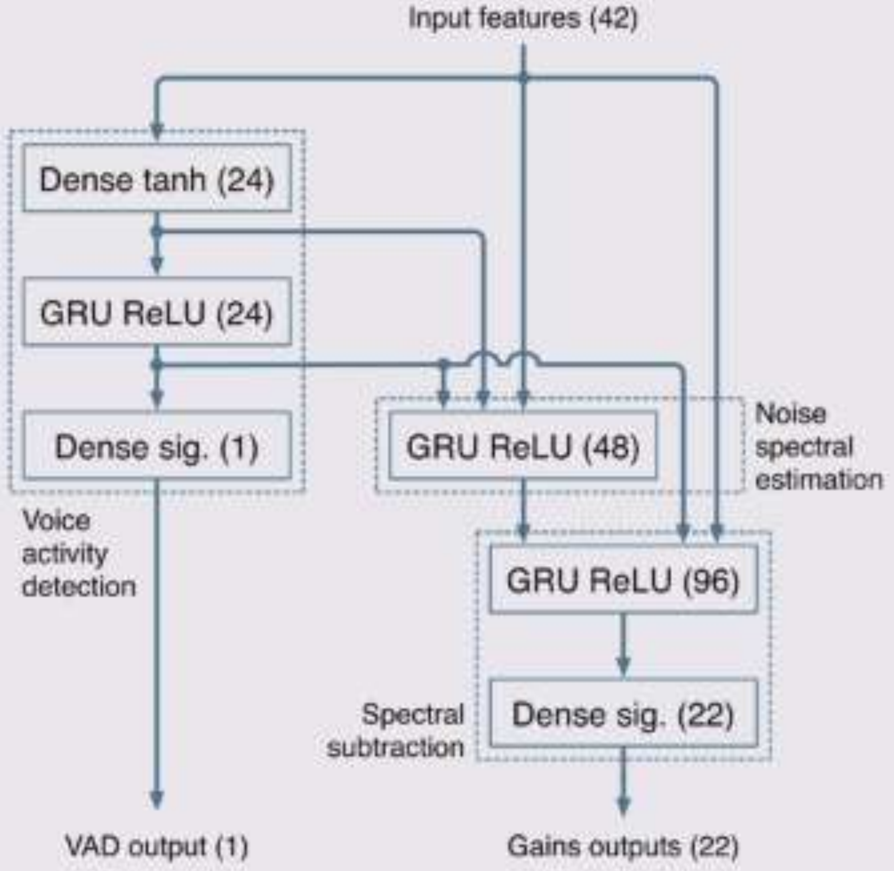

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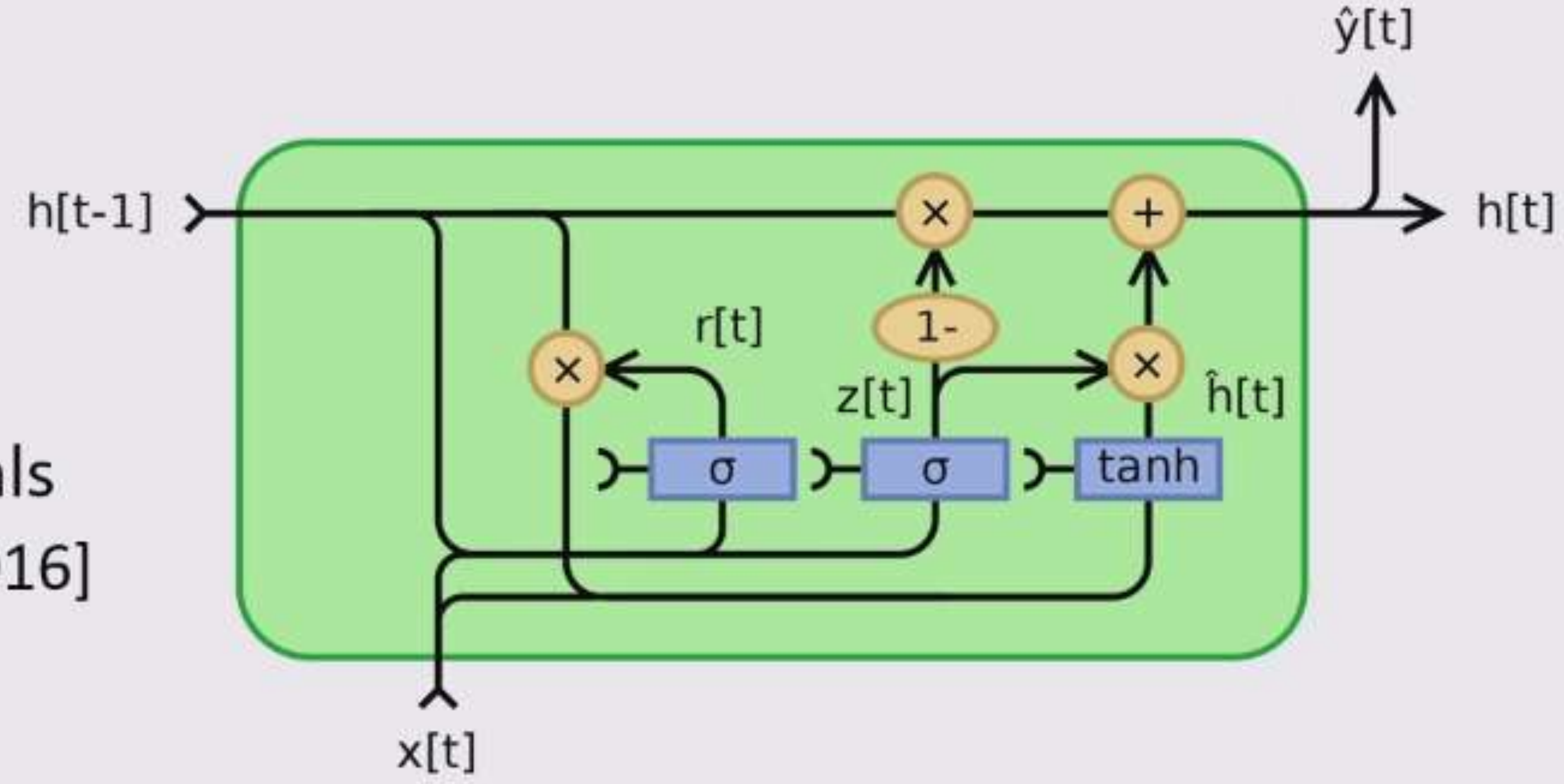

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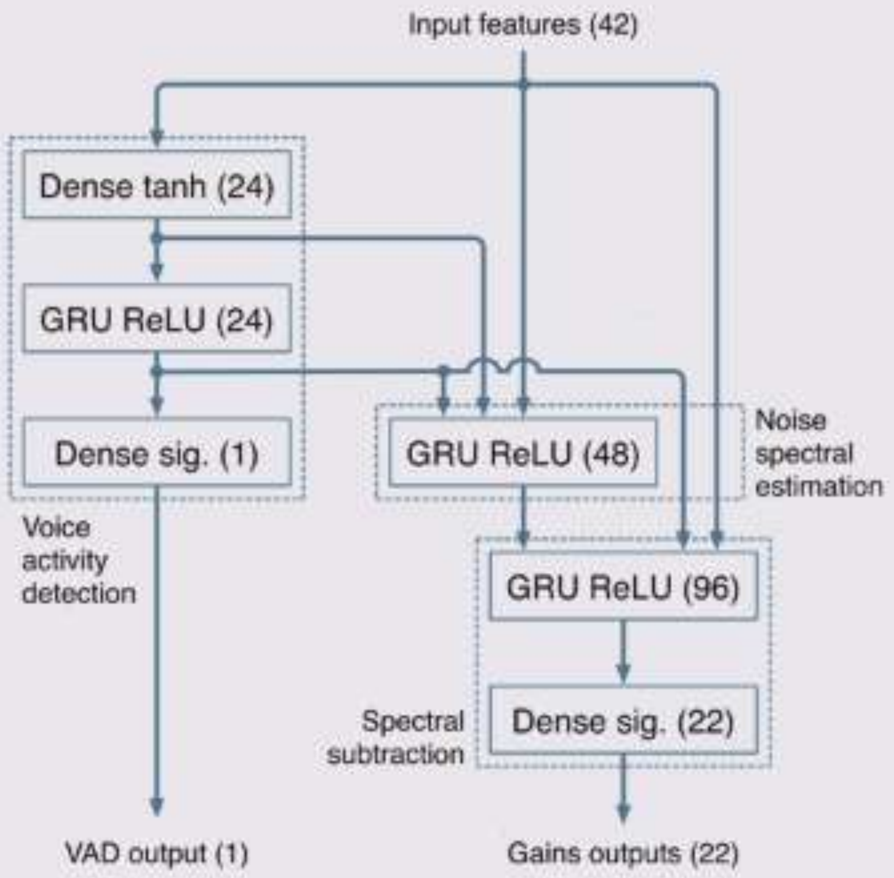

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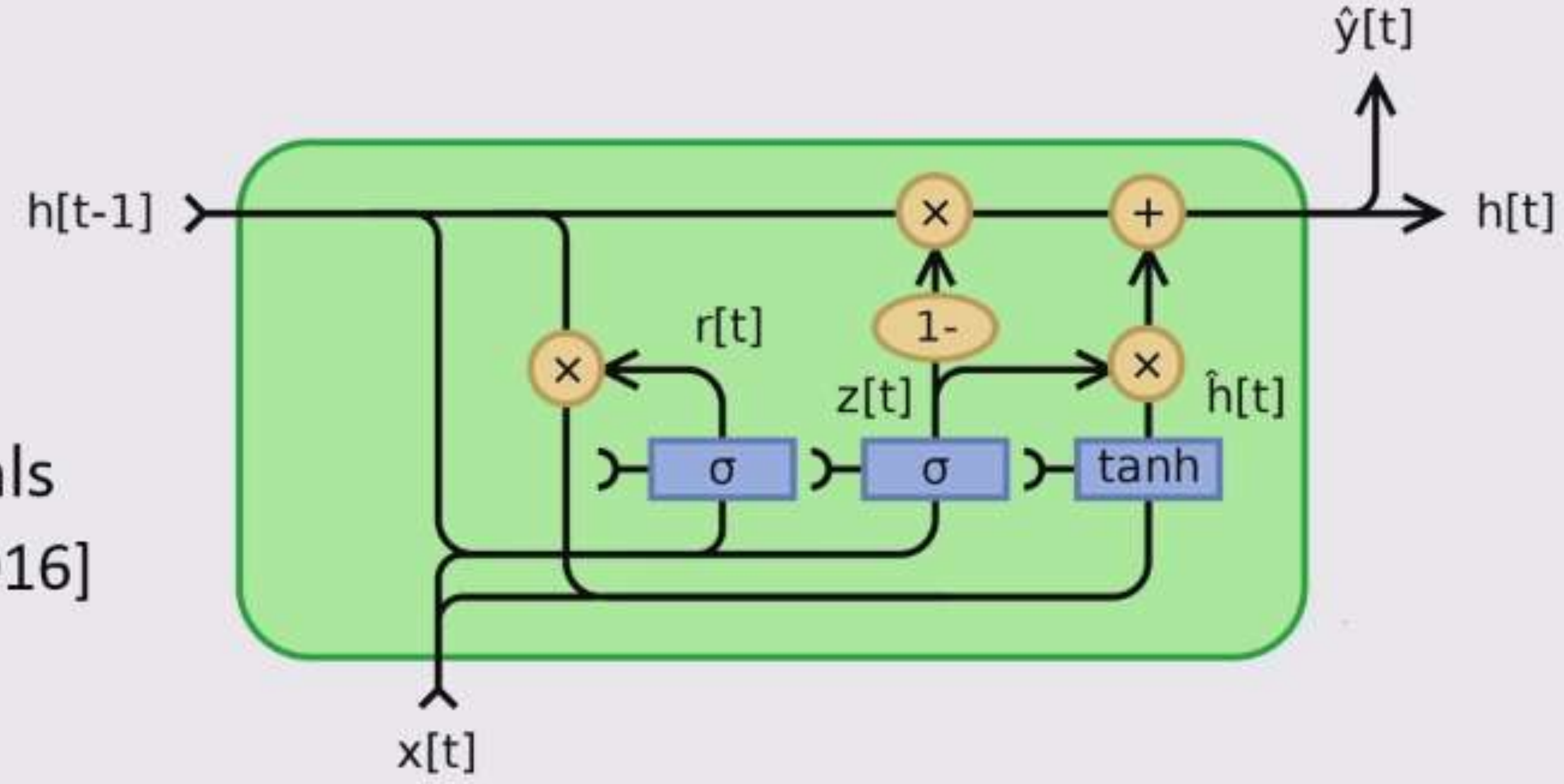

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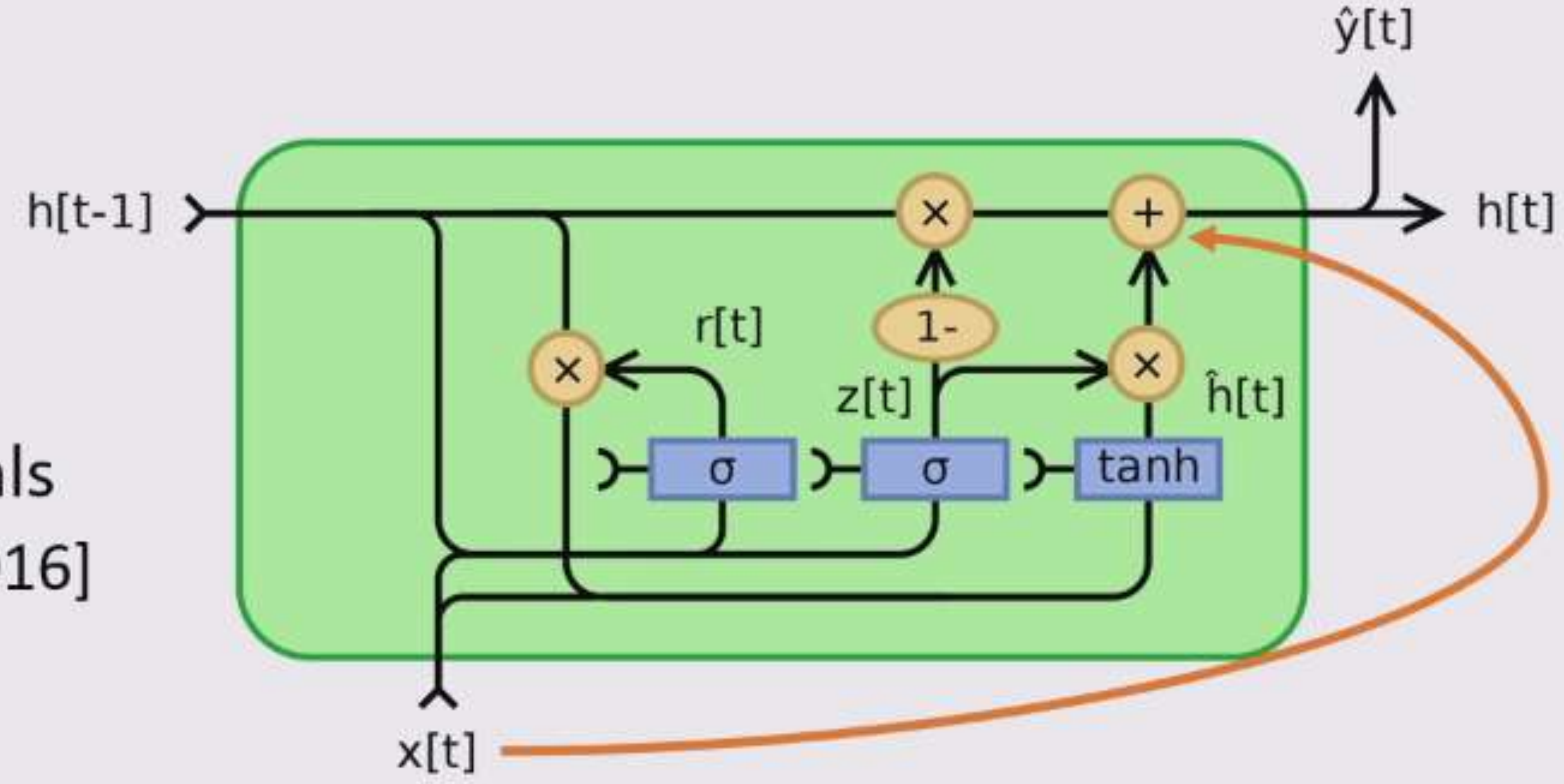

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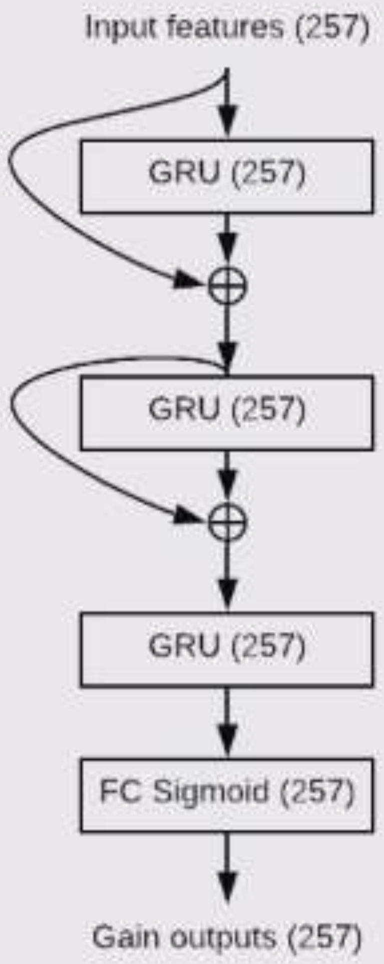
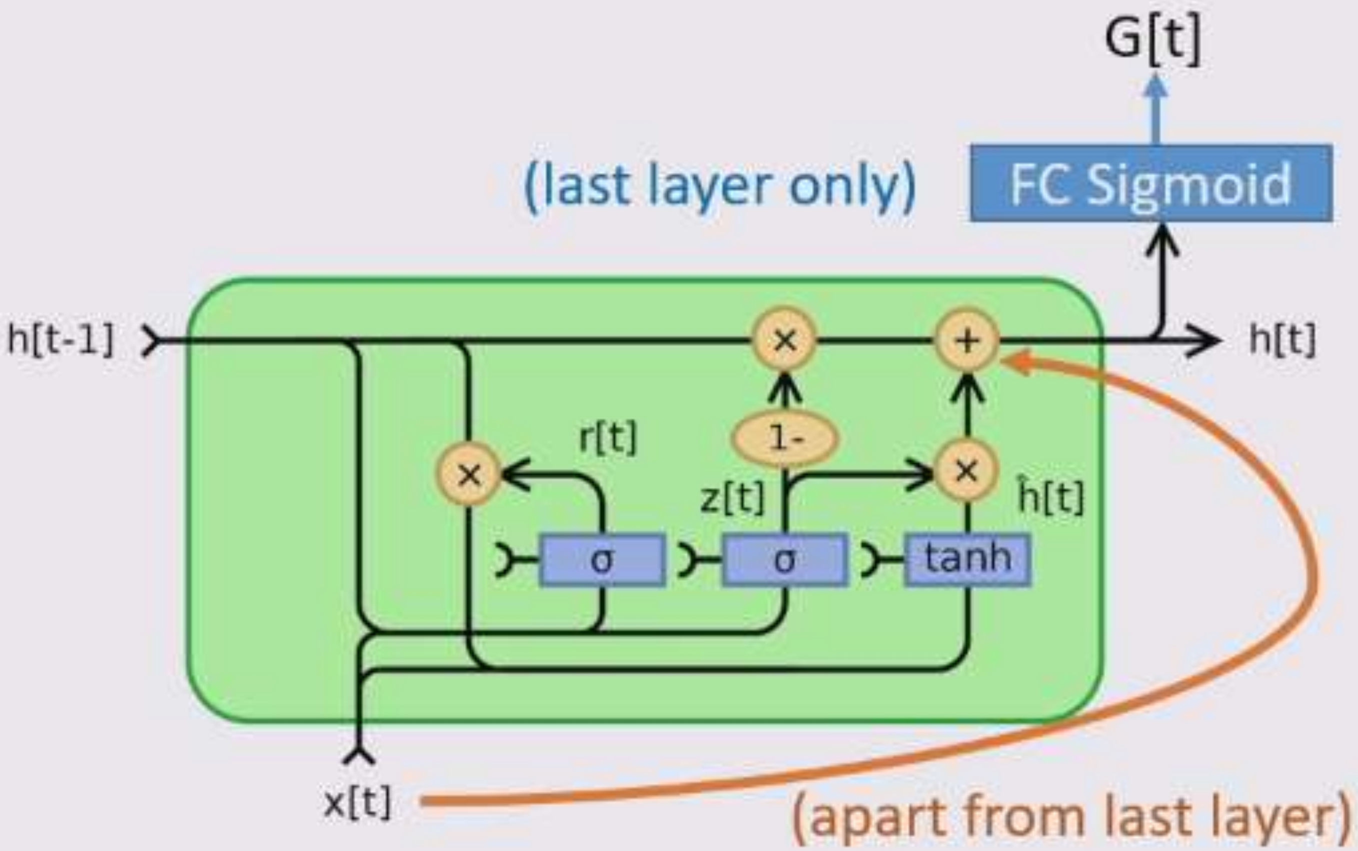
GRU + Residuals for Speech Enhancement

- Global view



- Zoomed-in view



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  - Solves for the optimal solution in MMSE sense
- Deep learning methods based on MSE
  - No assumptions about distributions
  - Solves for a “good” solution by stochastic gradient descent
    - Good = small MSE for both seen and unseen examples
  - Stable convergence (if able to learn at all)

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Cross terms ignored

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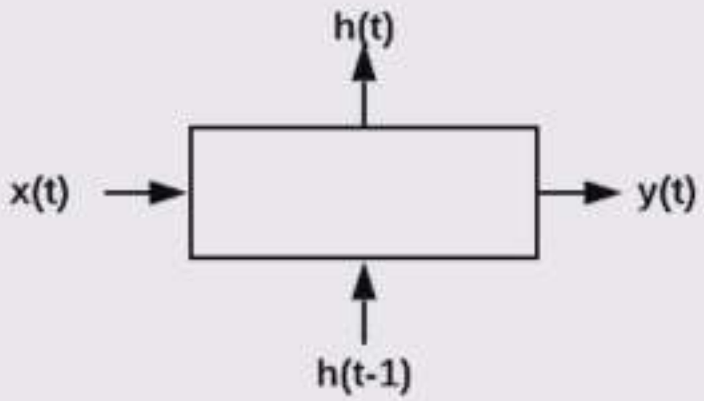
$$\boxed{L_{SNR}^{(i)}(\Theta; S^{(i)}, N^{(i)}) = \alpha \frac{\sigma^2_{S^{(i)}}}{\sigma^2_{N^{(i)}}} ||S_{SA}^{(i)} - GS_{SA}^{(i)}||^2 + (1-\alpha) \frac{\sigma^2_{S^{(i)}}}{\sigma_{N^{(i)}}} ||GN^{(i)}||^2}$$

Training Consideration

- Classical decision-directed approach [Ephraim1984]:
  - Transparent "hidden states" – *a priori* SNR, *a posteriori* SNR
  - Hidden states from the previous estimates affect the current by recursive smoothing
    - "Short-term memory that decays exponentially" in DL lingo
- RNN-based learning approach:
  - Black-box hidden states
  - LSTM/GRU are capable of learning long temporal patterns [Gers1999]
  - Patterns are learned through backpropagation through time [Werbos1990]

Training Consideration

- Backpropagation through time:



$$h(t) = y(t)$$

$$y(t) = f(x(t)+h(t-1))$$

$$\begin{aligned} y'(t) &= f'(x(t)+h(t-1))h'(t-1) \\ &= f'(x(t)+h(t-1))[f'(x(t-1)+h(t-2))h'(t-2)] \\ &= \dots \\ &= g(x(t), x(t-1), \dots, x(0)) \end{aligned}$$

- We want to compare a small batch of long sequences to a large batch of short sequences, given the same amount of information per batch.

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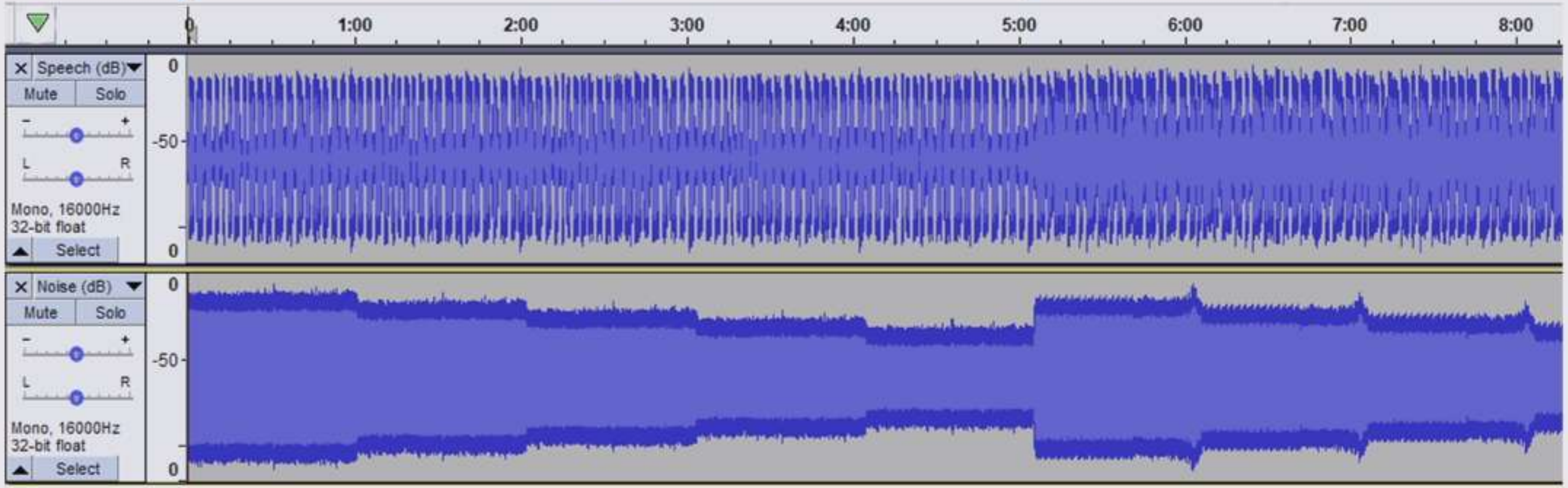
Evaluation: Data

- 84 hours of training data
  - Speech: Edinburgh 56 Speakers Corpus
  - Noise: 14 noise types from DEMAND Database and Freesound
    - Air Conditioner, airport announcements, appliances, car noise, copy machine, door shutting, eating, multi-talker babble, neighbor speaking, squeaky chair, traffic, road, typing, vacuum cleaner.
- 18 hours of test data in 5500 clips
  - Speech: Graz University 20 Speakers Corpus
  - Noise: 9 challenging classes from DEMAND and Freesound
    - Air conditioner, airport announcements, babble, copy machine, munching, neighbor, shutting door, typing, vacuum cleaner.
    - All clips are unseen in training
- SNR: {40, 30, 20, 10, 0} dB
- All clips sampled at 16 kHz

Evaluation: Data & Data Augmentation

Same utterance from the same speaker repeated 5 times



Same noise repeated 5 times with five discrete SNRs (assuming point-wise addition)

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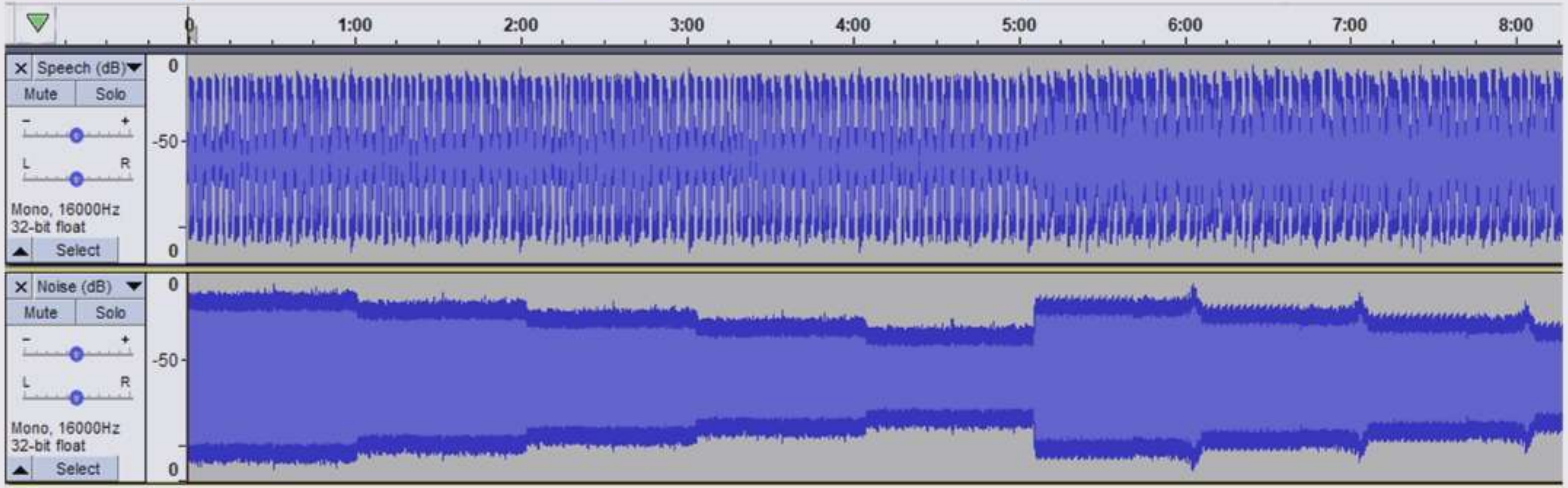

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Baseline Systems

- Noisy
- MSR's statistical-based
- Proposed
  - Log spectra with global and FD online normalization; Twelve 5-second segments/batch; various objectives
- RNN
  - Same as proposed, except no residual connections; MSE loss
- RNNoise [Valin2018]
  - Online enhancement of 22-dimensional energy envelope with 42-dimensional features
  - No augmented data
- Simplified RNNoise
  - Full-band (257) enhancement; same network architecture as RNNoise
  - No VAD during training
- Oracle information + Wiener filter rule

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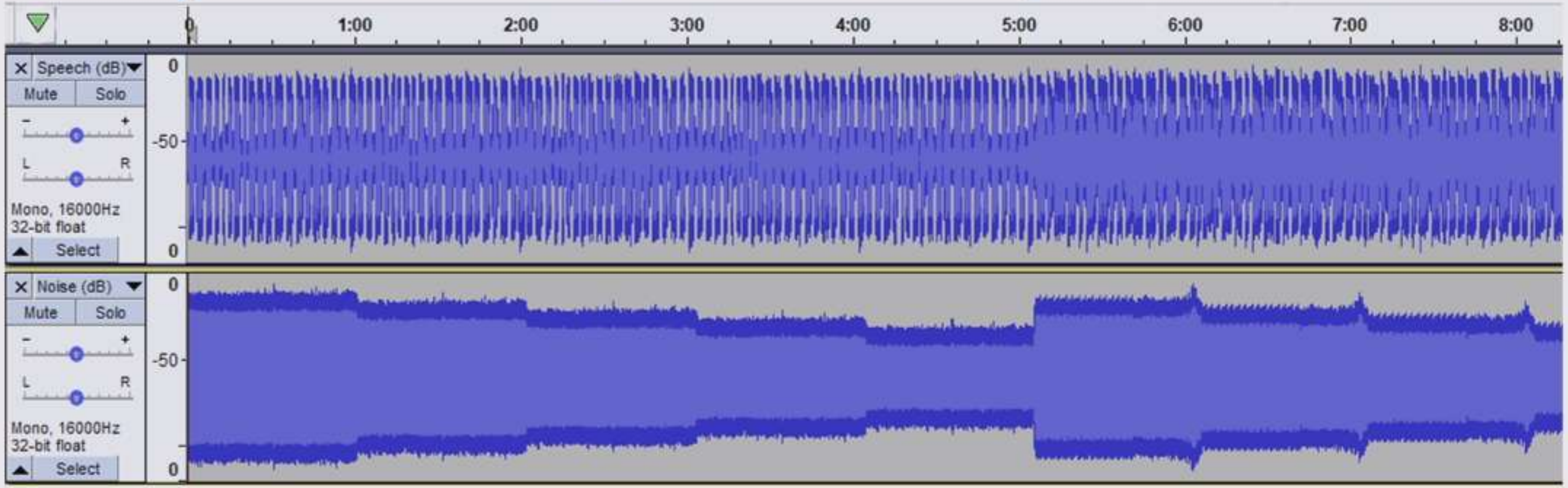

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Evaluation Metrics

- Classical speech quality/intelligibility measures
  - Scale-invariant signal-to-distortion ratio (SI-SDR) [LeRoux2019]
  - Cepstral distance (CD) [Hu2008]
  - Short-time objective intelligibility (STOI) [Taal2010]
  - Perceptual evaluation of speech quality (PESQ) [Rix2001]
- DNN-based mean opinion score (MOS) prediction
  - AudioMOS
    - Trained on MOS by real users
    - 0.89 Pearson correlation coefficient on test data

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Results: "Best" from each Category

Babble @ 20dB

Name	# Trainable Parameters	SI-SDR (dB)	CD	STOI (%)	PESQ (MOS)	AudioMOS (MOS)
Noisy	0	9.81	4.56	88.0	2.22	2.40
Statistical-based	0	6.10	4.64	84.7	2.33	2.61
RNNoise	61.2 K	10.4	4.24	84.3	2.33	2.73
RNN	1.26 M	10.4	4.48	88.6	2.39	3.15
Full-band RNNoise	2.64 M	13.0	3.88	89.3	2.56	2.95
Proposed (SNR wt.; a = 0.35)	1.26 M	**14.8**	**3.72**	**90.9**	**2.71**	**3.24**
Oracle Wiener	Oracle	20.5	2.13	98.1	3.82	3.75

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Enhanced 1 second audio in 39.6 milliseconds on a single CPU
Intel(R) Xeon(R) CPU E5-2690 v4 @ 2.60GHz, Python 3.6.8

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Enhanced 1 second audio in 39.6 milliseconds on a single CPU
Intel(R) Xeon(R) CPU E5-2690 v4 @ 2.60GHz, Python 3.6.8

Results: "Best" from each Category

Babble @ 20dB

Name	# Trainable Parameters	SI-SDR (dB)	CD	STOI (%)	PESQ (MOS)	AudioMOS (MOS)
Noisy	0	9.81	4.56	88.0	2.22	2.40
Statistical-based	0	6.10	4.64	84.7	2.33	2.61
RNNoise	61.2 K	10.4	4.24	84.3	2.33	2.73
RNN	1.26 M	10.4	4.48	88.6	2.39	3.15
Full-band RNNoise	2.64 M	13.0	3.88	89.3	2.56	2.95
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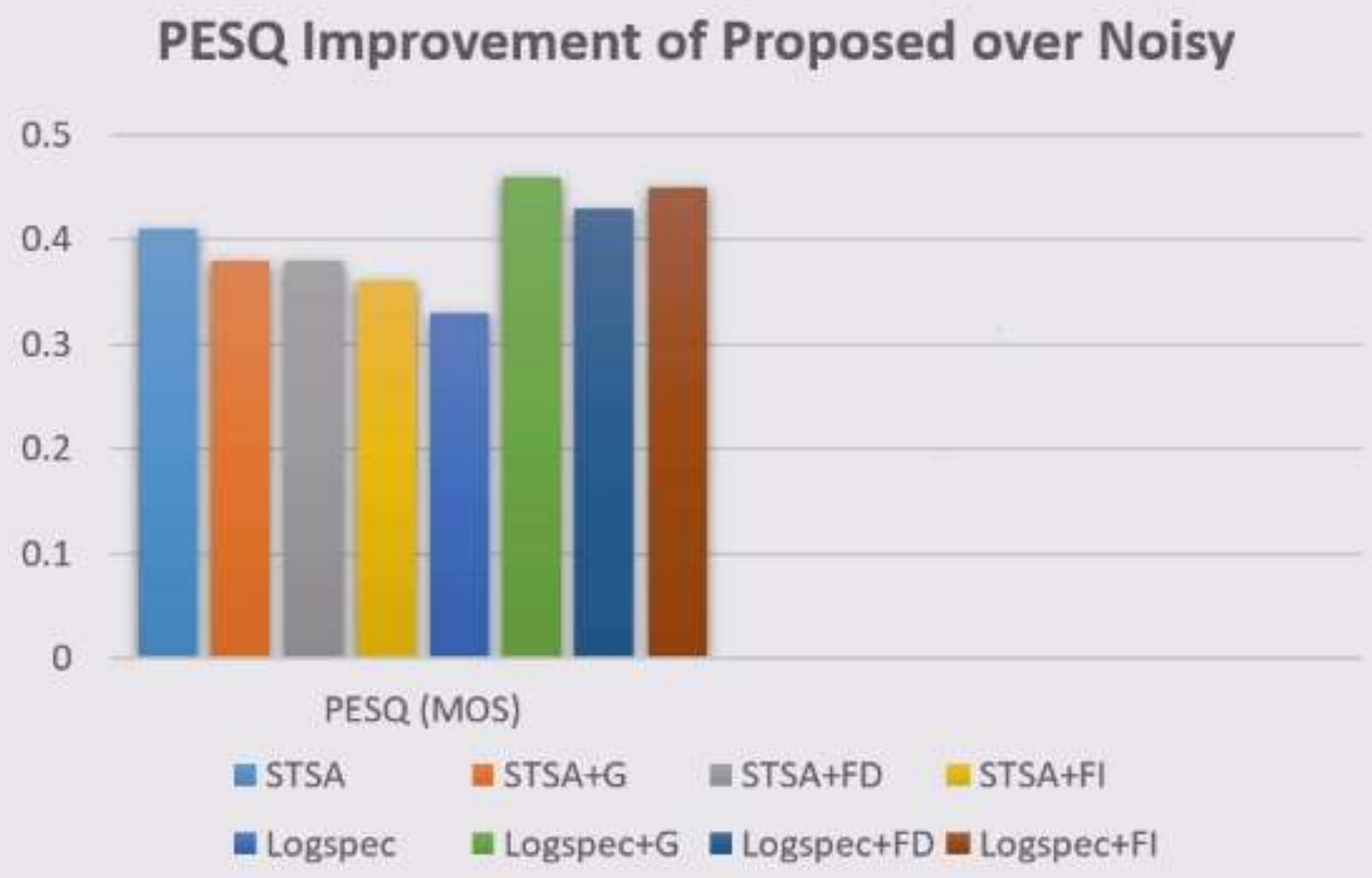
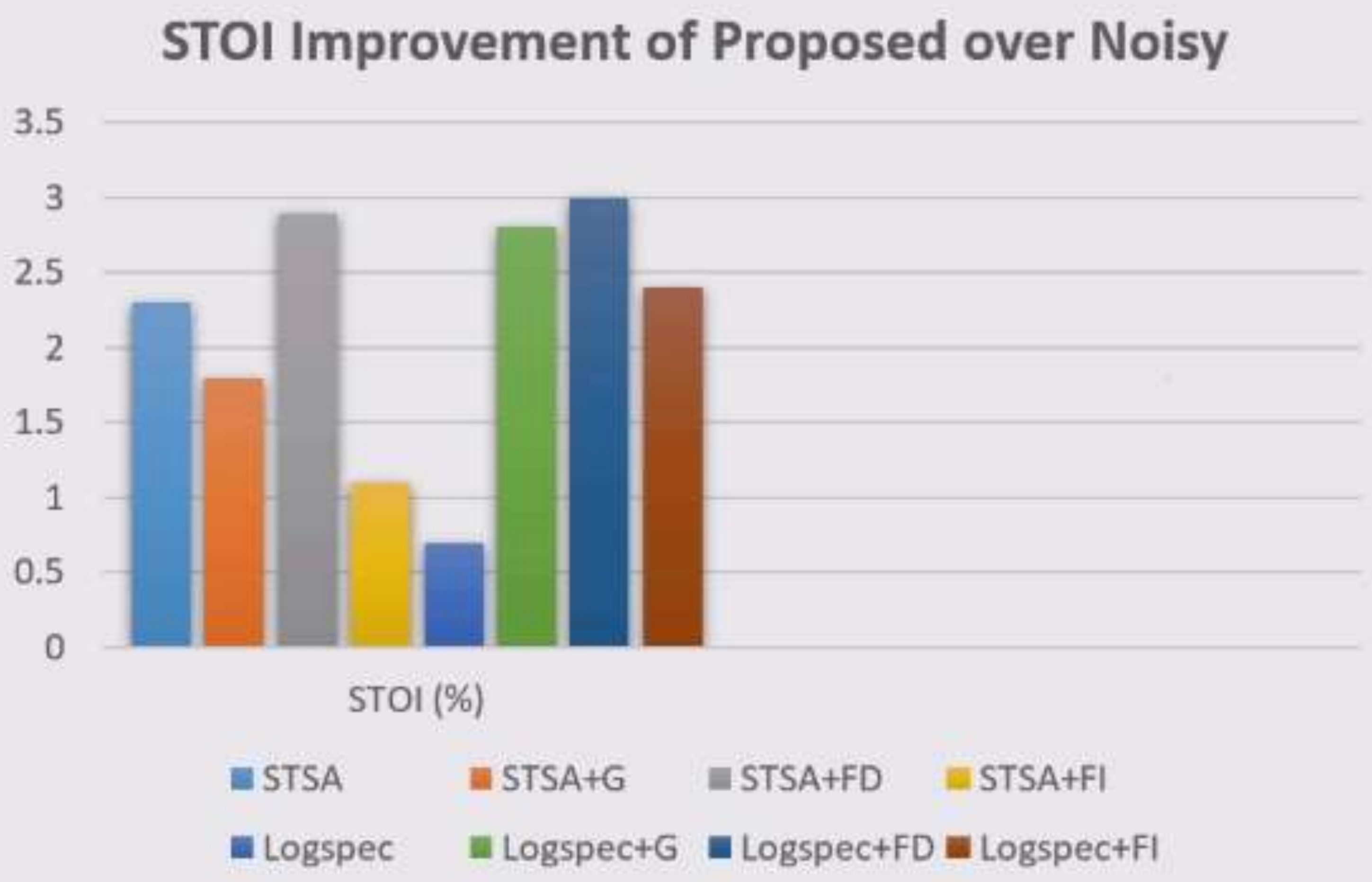
Results: Effect of Feature Normalization





STSA – short-time spectral amplitude
Logspec – short-time log power spectra
G – global normalization
FD – Frequency-dependent online norm.
FI – Frequency-independent online norm.

Results: Effect of Sequence Lengths

Duration (s/seg.)	# Seg. Per batch	SI-SDR (dB)	CD	STOI (%)	PESQ (MOS)	AudioMOS (MOS)
1	60	13.8	3.81	90.6	2.61	2.82
5	12	**14.1**	**3.67**	**91.0**	**2.64**	2.88
15	4	**14.1**	3.74	90.7	**2.64**	**2.96**
30	2	13.8	3.79	90.3	2.60	2.91

Stopped early at 53/100 epochs.

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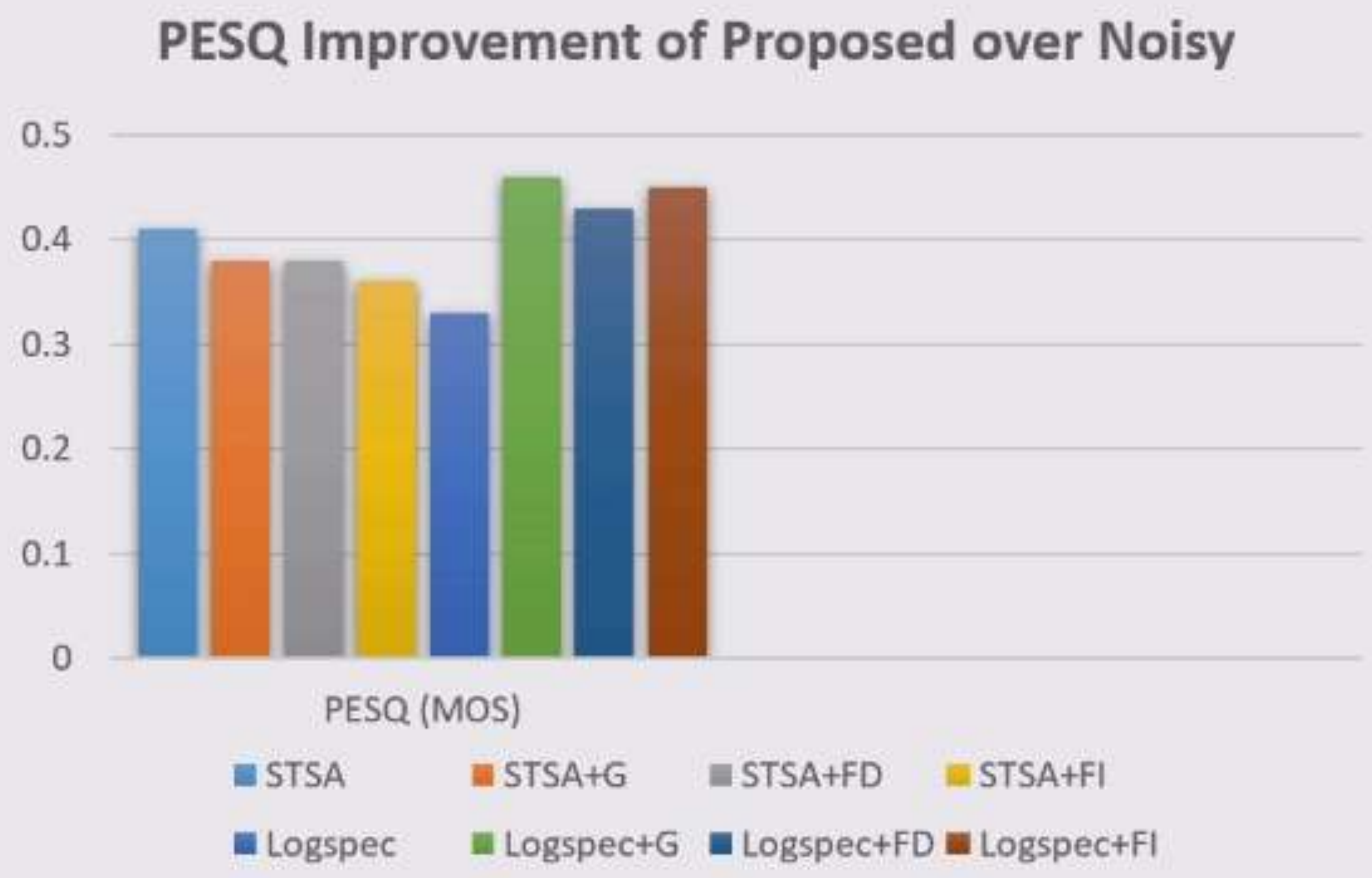

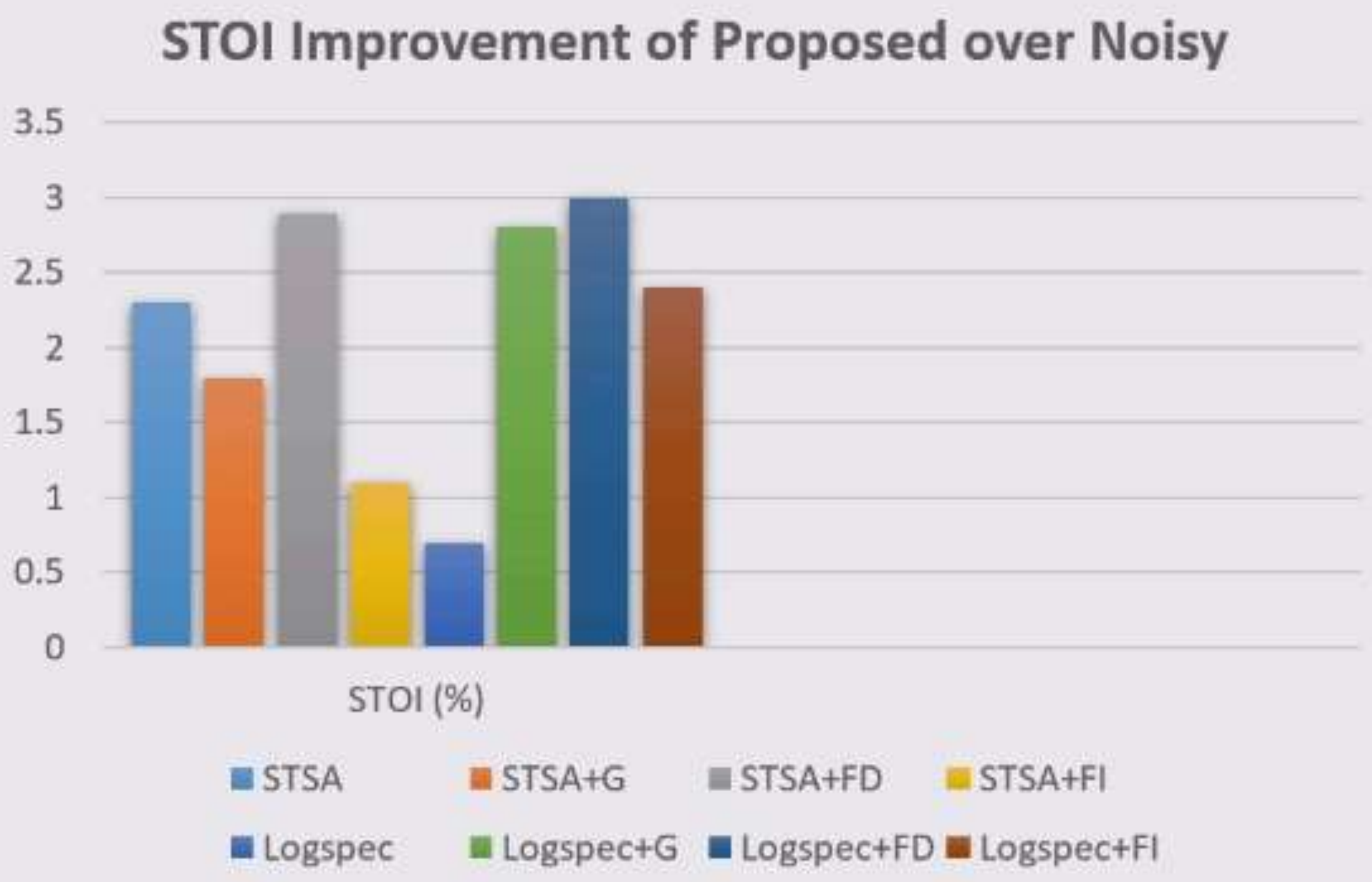

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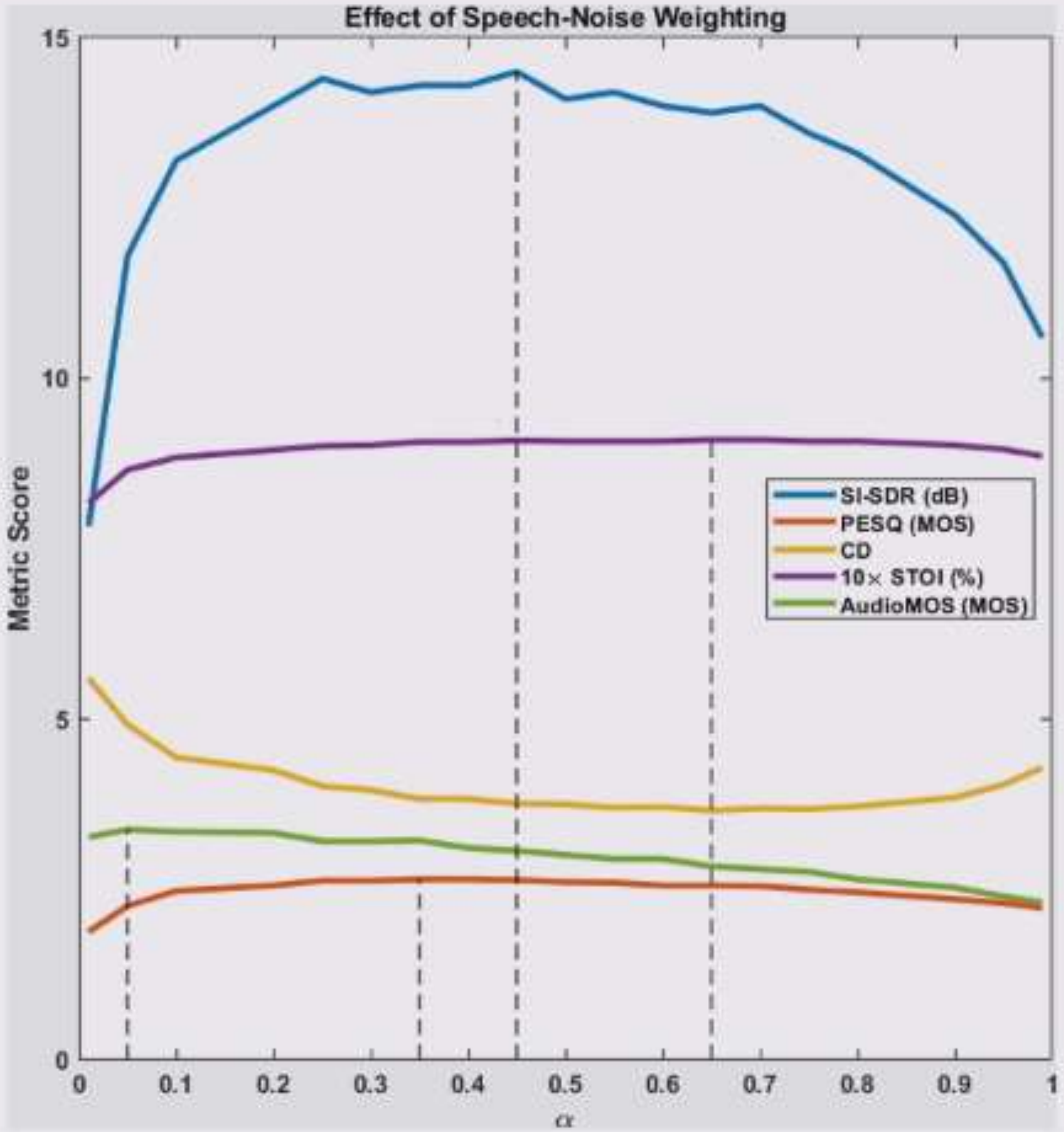
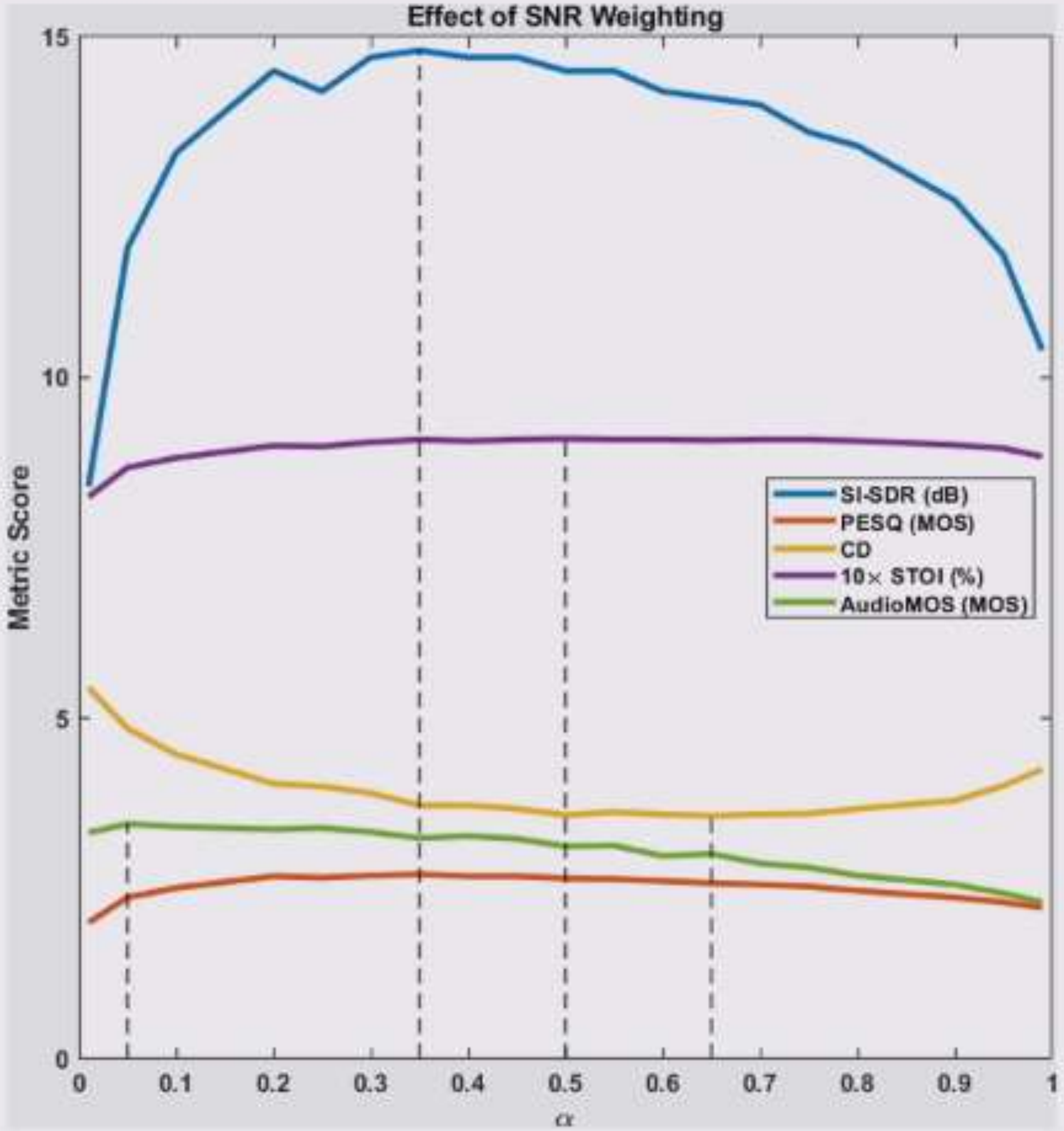
Results: Optimal Speech-Noise Weighting



- DEMO: Air Conditioner Noise

a \ SNR	20dB	10dB	0dB
0.05 (AudioMOS)			
0.35 (PESQ)			
0.45 (SI-SDR)			
0.65 (CD & STOI)			
Noisy			

Results: Optimal SNR-weighted SN Weighting



- DEMO: Airport Announcements

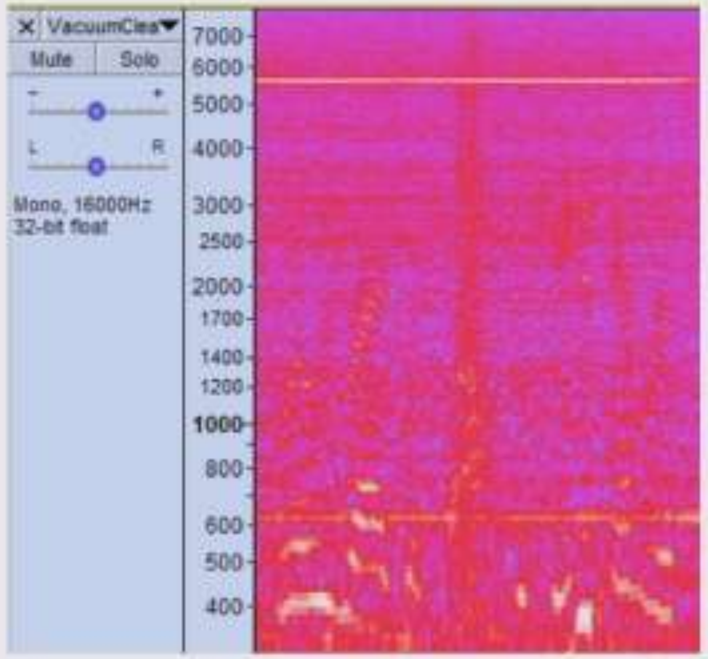
a \ SNR	20dB	10dB	0dB
0.05 (AudioMOS)			
0.35 (SI-SDR & PESQ)			
0.5 (STOI)			
0.65 (CD)			
Noisy			

Outline

- Introduction to Single-channel Speech Enhancement
    - Classical signal processing vs. Deep learning
    - Considerations for online processing
- Our Method
    - Feature Representations
    - Learning Machines
    - Learning Objectives
    - Training Considerations
- Evaluation
    - Data
    - Metrics
    - Results
- **Findings and Conclusions**

Major Findings

- Residual connections within recurrent cells really, really help
- GRUs are able to encode extremely long temporal patterns in high dimensional space (probably with the aid of residual connections)
  - 5-second waveform = 625 frames of 257-point spectra
- Trust the old faithful for stationary patterns?
  - The model learns to ALWAYS strongly suppress ~6 kHz



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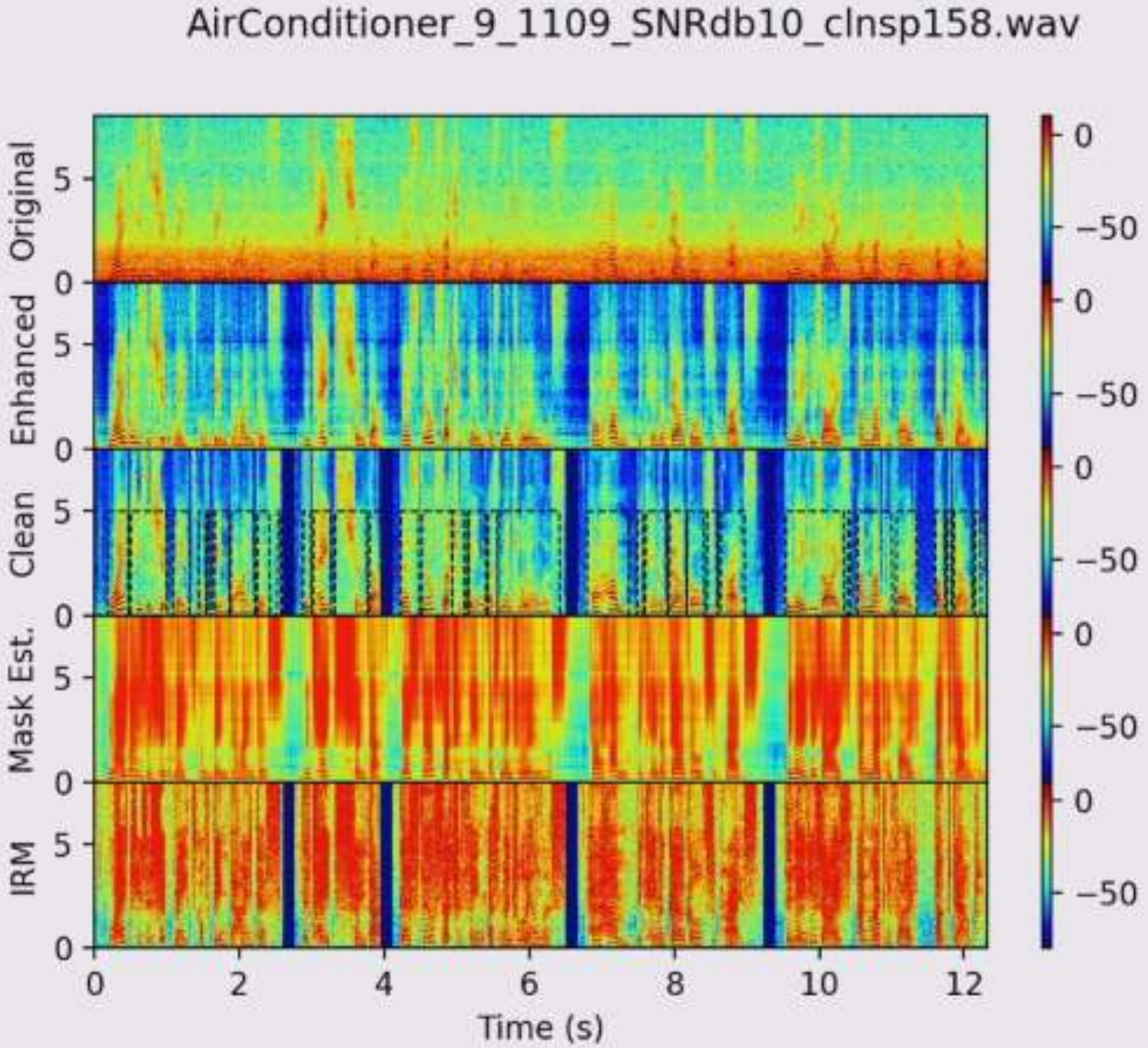
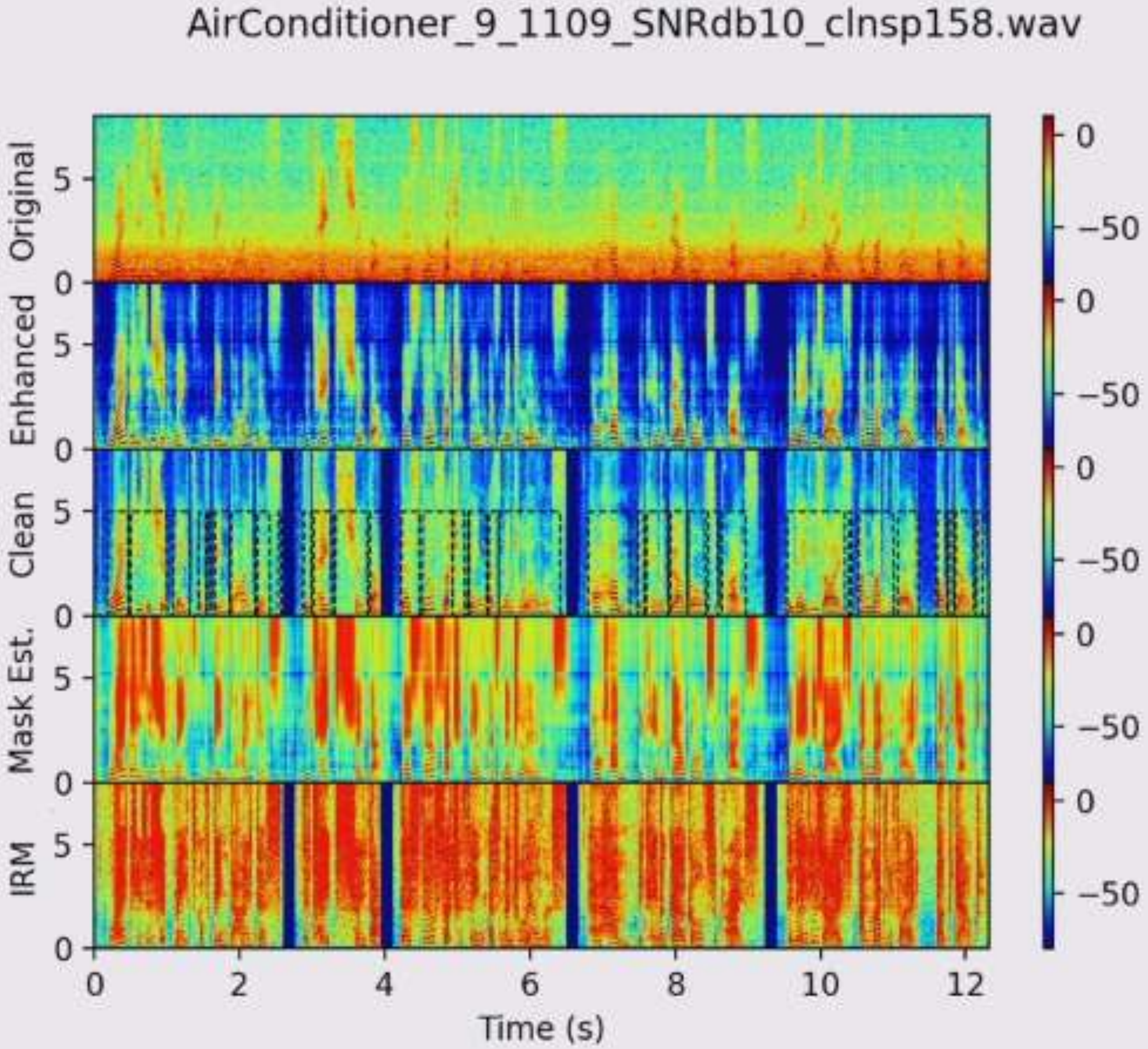


- SNR-weighted (a=0.2)



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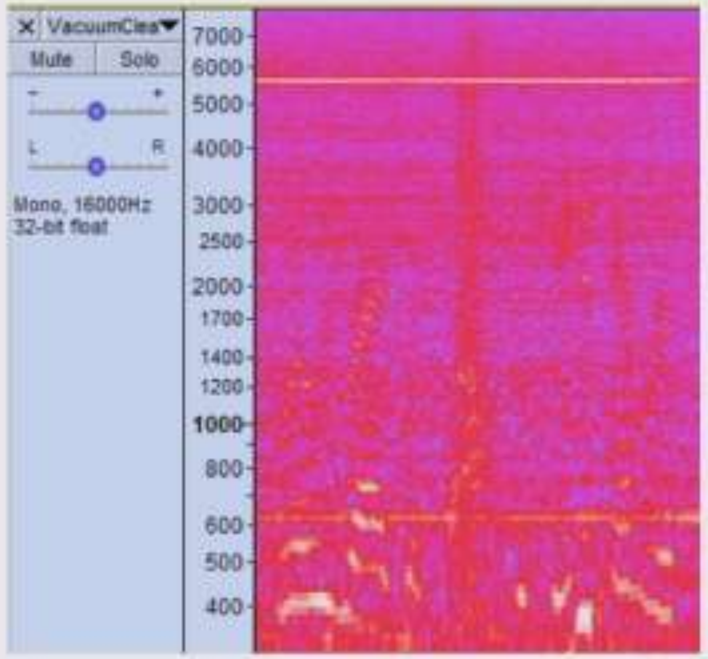

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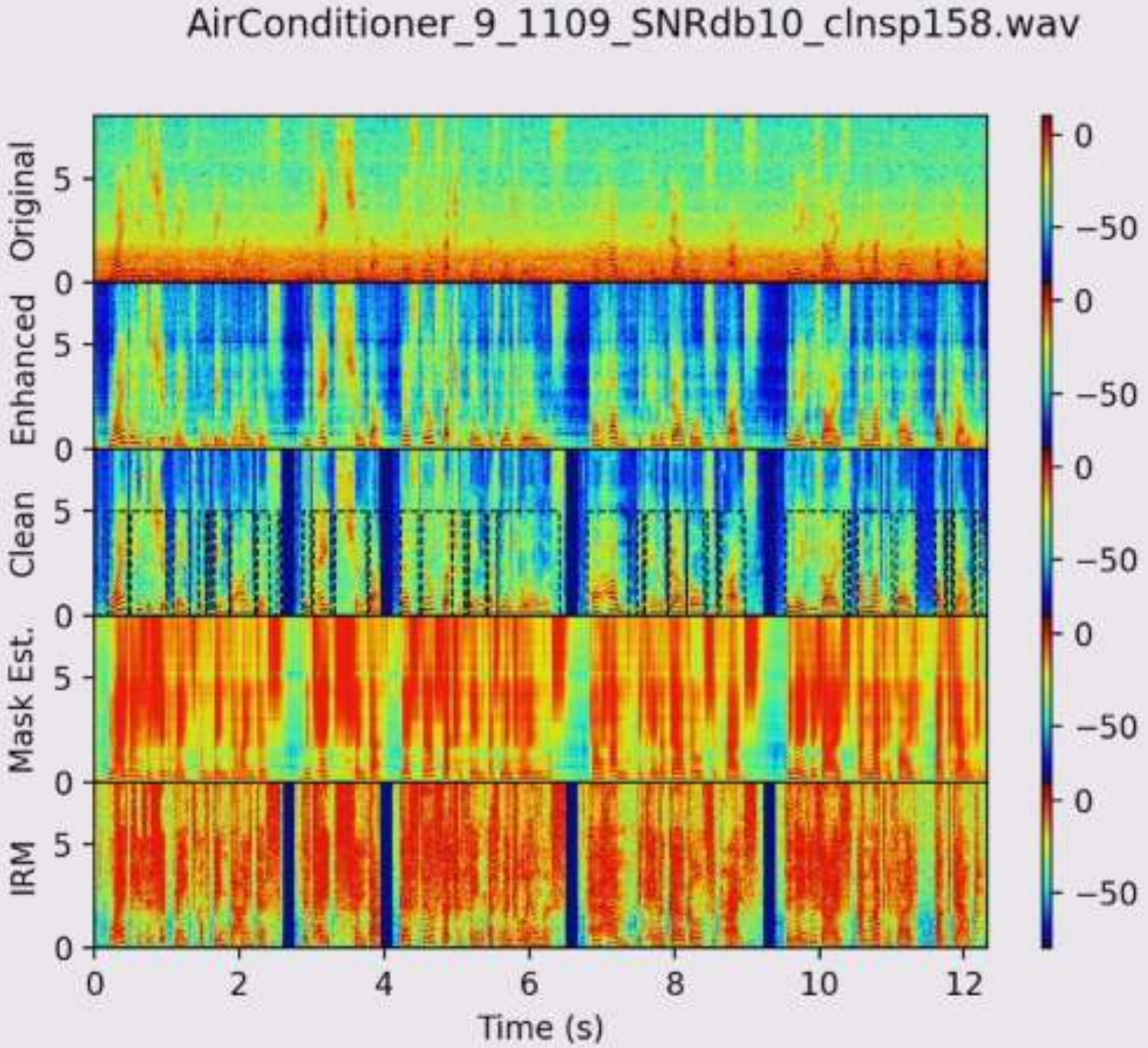

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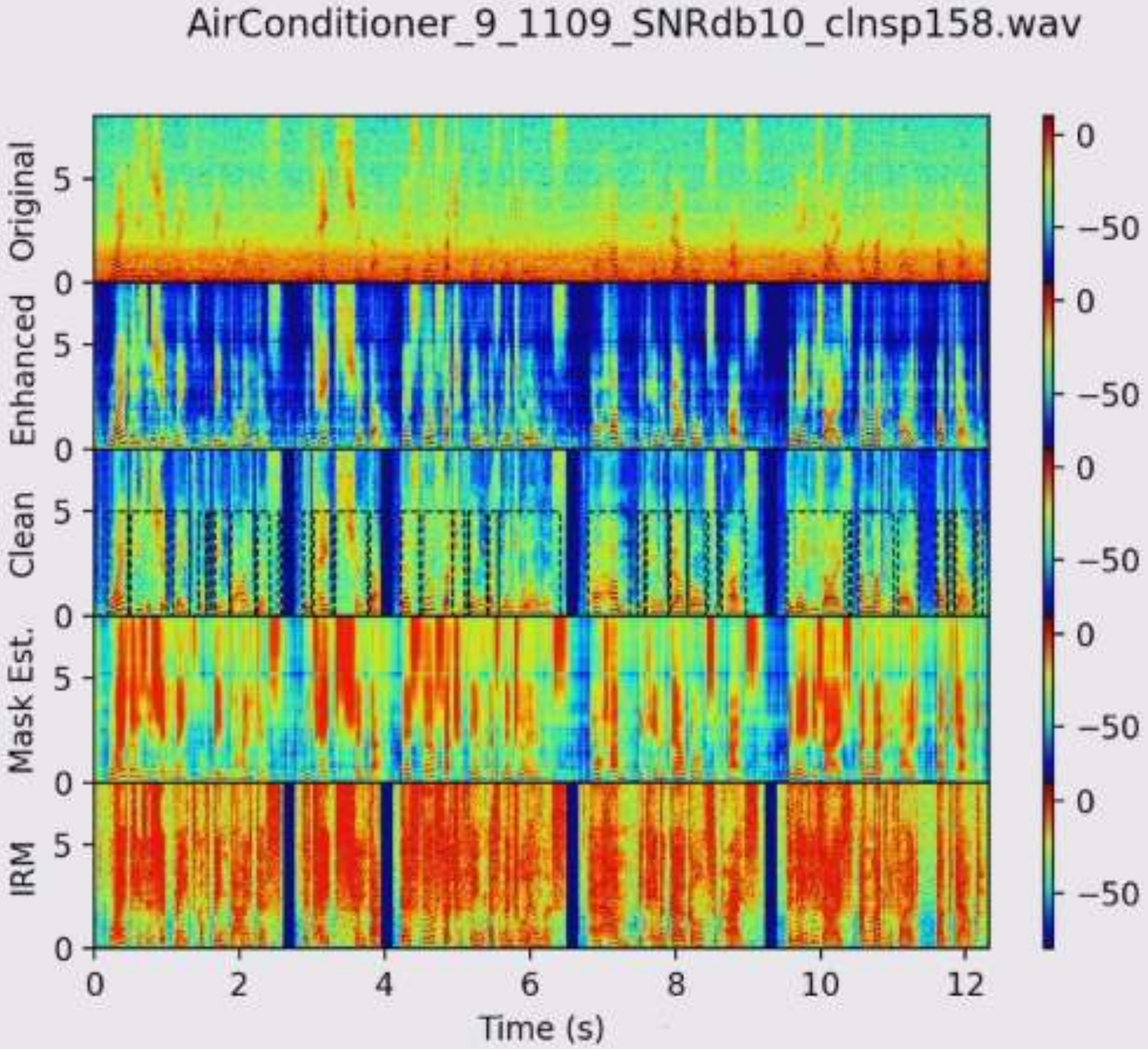

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- We studied the impact of multiple factors associated with training a RNN on speech quality
  - Feature normalization, sequence length, objective weightings
- We compared multiple competitive SP or DL-based online systems in terms of objective speech quality measures

Future Directions

- Study the speech quality improvement by SNR
- Investigate learning objectives to replace MSE
  - MAE, log-domain and cepstral-domain objectives
- Feature dimensionality reduction
  - Speech energy is sparse and noisy at very high frequencies

Thank you!

- Sebastian, Hannes, and all mentors from the Audio and Acoustics Group
- Ross, Chandan, and Hari from Skype
- All interns from the Audio and Acoustics Group

- Stay in touch!
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