STOI-Optimized Pruned Recurrent Deep Autoencoders for Low-Complexity Compression of the Stimulation Patterns of Cochlear Implants at Zero Delay

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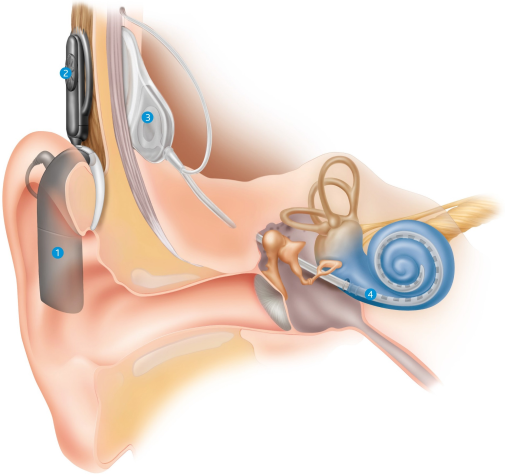
Cochlear Implant (CI)



Wireless Streaming for CIs

Background

Summary

- Cochlear Implants (CIs) can restore a sense of hearing
- Wireless audio streaming aims to improve speech understanding in background noise
- Coding of stimulation patterns of CI for low delay, low bitrate transmission[1][2]
- $\approx$ 4.67 kbit/s at zero delay and negligible objective speech intelligibility (VSTOI) degradation[3][4]

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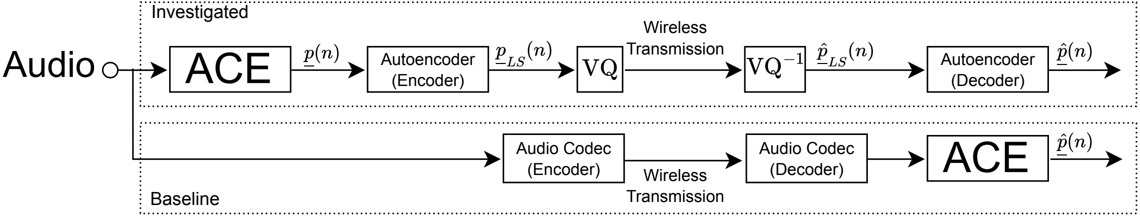
[1] Hinrichs, R., Gajecki, T., Ostermann, J., Nogueira, W. (2019). "Coding of Electrical Stimulation Patterns for Binaural Sound Coding Strategies for Cochlear Implants".

[2] Hinrichs, R., Gajecki, T., Ostermann, J., Nogueira, W. (2021). "A subjective and objective evaluation of a codec for the electrical stimulation patterns of cochlear implants".

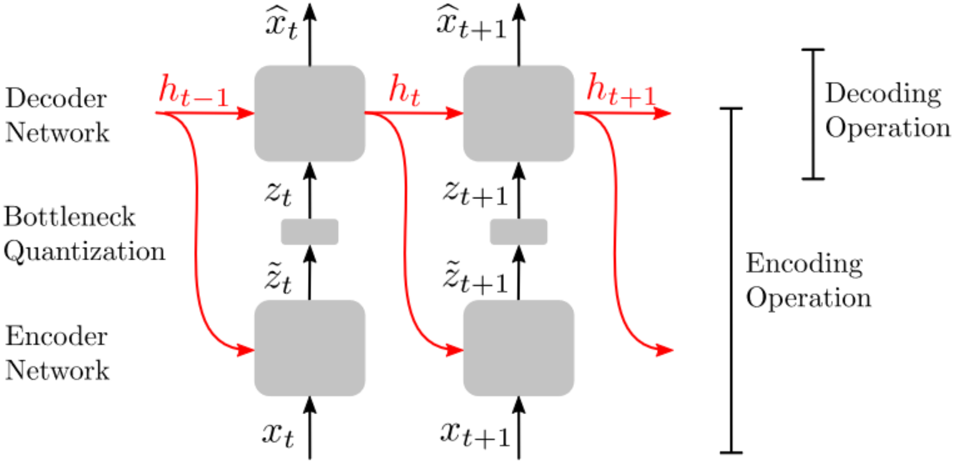
[3] R. Hinrichs, et al. (2022), "Vector-Quantized Zero-Delay Deep Autoencoders for the Compression of Electrical Stimulation Patterns of Cochlear Implants using STOI,"

[4] R. Hinrichs et al. (2023), "Vector-Quantized Feedback Recurrent Autoencoders for the Compression of the Stimulation Patterns of Cochlear Implants at Zero Delay,"

Background


Audio
Investigated
ACE
$\underline{p}(n)$
Autoencoder (Encoder)
$\underline{p}_{LS}(n)$
VQ
Wireless Transmission
VQ^{-1}
$\hat{\underline{p}}_{LS}(n)$
Autoencoder (Decoder)
$\hat{\underline{p}}(n)$
Audio Codec (Encoder)
Wireless Transmission
Audio Codec (Decoder)
ACE
$\hat{\underline{p}}(n)$
Baseline

Background/Feedback Recurrent Autoencoder (FRAE)



Background

Summary

- Cochlear Implants (CIs) can restore a sense of hearing
- Wireless audio streaming aims to improve speech understanding in background noise
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- $\approx$ 4.67 kbit/s at zero delay and negligible objective speech intelligibility (VSTOI) degredation[7][8]

Motivation

- Very limited computational resources on CI signal processors (e.g. 100-300 kB RAM)
- Model pruning for reduction of memory and cpu requirements

[5] Hinrichs, R., Gajecki, T., Ostermann, J., Nogueira, W. (2019). "Coding of Electrical Stimulation Patterns for Binaural Sound Coding Strategies for Cochlear Implants".
[6] Hinrichs, R., Gajecki, T., Ostermann, J., Nogueira, W. (2021). "A subjective and objective evaluation of a codec for the electrical stimulation patterns of cochlear implants".
[7] R. Hinrichs, et al. (2022), "Vector-Quantized Zero-Delay Deep Autoencoders for the Compression of Electrical Stimulation Patterns of Cochlear Implants using STOI,"
[8] R. Hinrichs et al. (2023), "Vector-Quantized Feedback Recurrent Autoencoders for the Compression of the Stimulation Patterns of Cochlear Implants at Zero Delay,"

Pruning

Pruning methods for neural networks usually consist of two-stages:

- The actual pruning
- Finetuning

Common pruning criteria:

- Magnitude-informed
- Loss-change:
  - Gradient-informed
  - Magnitude + Gradient-informed (Movement Pruning)
  - Hessian-informed

Core issue:

Optimal pruning "direction"

Novel Pruning Method

Pruning P of a neural network with weights ω:

$$P : \omega \to \hat{\omega}$$

with

$$\hat{\omega}_i \equiv P(\omega)_i = \begin{cases} 0 & i \in I_{pruned} \\ \omega_i & i \notin I_{pruned} \end{cases}$$

This is equivalent to

$$\hat{\omega} = \omega + \Delta\omega$$

with

$$\Delta\omega_i = \begin{cases} 0 & i \notin I_{pruned} \\ -\omega_i & i \in I_{pruned} \end{cases}$$

I call $\Delta\omega$ the pruning direction.

Novel Pruning Method

Issue of conventional pruning criteria:

- Pruning criteria based on loss changes attempt to find pruning direction based on derivatives of loss function
- But: Derivatives, evaluated at a single point, give local information only!
- In general, finite Taylor's expansion does not allow to globally assess loss changes
- If the network "knew", it was going to be pruned, weights more suitable for pruning could be found

Idea:

Choose a pruning direction and teach the network to be robust to it!

Pruning-aware Training

Given a loss $\mathcal{L}_\omega$, we can construct a pruning-aware (PA) loss according to

$$\mathcal{L}^{PA}_{\omega_n} = \mathcal{L}_{\omega_n} + \alpha|\mathcal{L}_{\omega_n} - \mathcal{L}_{\omega_n+\Delta\omega_n}|$$

with a given pruning direction $\Delta\omega_n$ (e.g. magnitude-informed) at iteration n and weighting factor $\alpha > 0$.

To allow the network to *gradually* reconfigure itself, $\Delta\omega_n$ is computed according to

$$\Delta\omega_n = g(\frac{n}{\#iterations})\tilde{\Delta\omega}_n$$

with perturbation-function $g : [0,1] \to [0,1]$. $\tilde{\Delta\omega}_n$ is the magnitude-informed pruning direction in iteration n.

Benefits of Pruning-aware Training

Gradually introducing the loss change due to pruning during training achieves two goals:

- The *global* loss change due to perturbating the weights is captured
- The network can reconfigure itself to be more robust towards pruning

In principle, this approach should allow to automatically yield networks optimally robust towards pruning – possibly independent of the network topology

Disadvantage: Slight to moderate increase in training complexity

Methods and Materials

Training and Evaluation

- Models: Pretrained FRAEs with 6 bit vector quantization ($\approx$ 4.67 kbit/s after entropy-coding)
- Optimizer: Stochastic Perturbation Simultenous Approximation (SPSA)
- Loss: Vocoder Short-Time Objective Intelligibility measure (VSTOI)
- Baseline: Magnitude-informed pruning + finetuning

Data[9]

- TIMIT + Noise (Head-related transfer functions)
- Noise: -5 dB, ..., 40 dB; restaurant, bus, office and CCITT-noise
- Acoustic scenarios: anechoic, cafeteria, office
- Sound Coding Strategy: Advanced Combinational Encoder (ACE)

[9] Hinrichs, R. et al. (2023), "Vector-Quantized Feedback Recurrent Autoencoders for the Compression of the Stimulation Patterns of Cochlear Implants at Zero Delay", DSP 2023

Pruning-aware Training

- 1000 iterations of training with pruning-aware loss
- $g(t) \in \{t, t^2, t^3\}$
- $\alpha \in \{0.5, 0.75, 1.0, 1.25, 1.5\}$
- Magnitude-informed pruning after training
- 7000 iterations of finetuning (8000 iterations for baseline)
- Pruning rate $pr \in \{0.05, 0.1, \dots, 0.95\}$
- Pruning-rates trained separately
- Whole model and decoder-only pruning

SPSA

Update equation:

$$\underline{\omega}_{k+1} = \underline{\omega}_k + a_k \frac{(y^+_{k+1} - y^-_{k+1})}{c_k} \Delta_k,$$

with $y^{\pm}_{k+1} = f(\underline{\omega}_k \pm c_k \Delta_k)$, $\Delta_k \in \{-1, 1\}^N$ iid noise, $a_k, c_k > 0$ with $a_k, c_k \to 0$. f is the objective function of interest - in our case VSTOI of coded stimulation patterns.
a_k and c_k are computed according to ($a = 1, \gamma = 0.602, \beta = 0.101$)

$$a_k = \frac{a}{(A + k + 1)^{\gamma}}$$

and

$$c_k = \frac{c}{(k + 1)^{\beta}}.$$

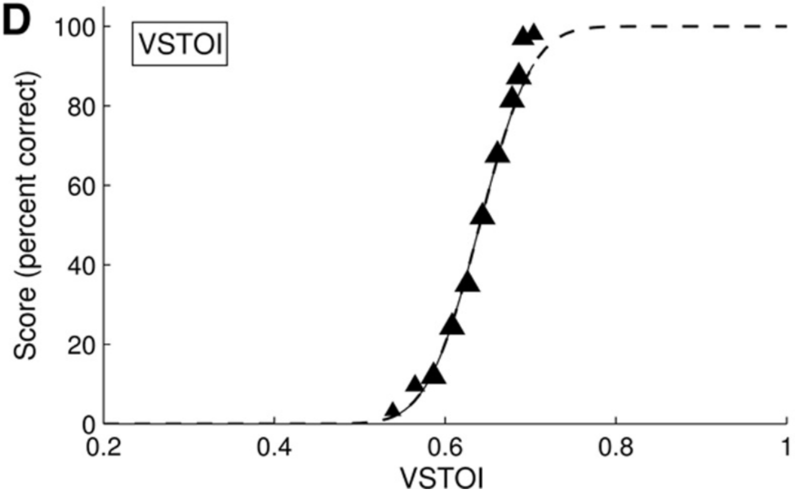
A and c are obtained through hyperparameter optimization[10].

[10] Hinrichs, R. et al. (2023), "Vector-Quantized Feedback Recurrent Autoencoders for the Compression of the Stimulation Patterns of Cochlear Implants at Zero Delay", DSP 2023

Preliminary Comments

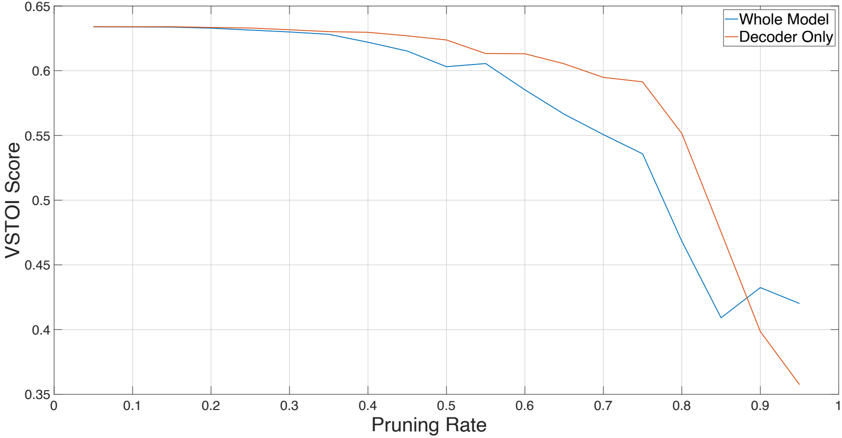
- Pruning of large neural networks (e.g. ResNets) sees little performance decay at very high pruning rates (e.g. 99 %)
- We cannot expect extreme overparametrization due to model sizes ($\approx$ 3,300–10,000 parameters)
- Therefore we cannot expect similar high pruning rates without considerable degredation
- Minor VSTOI Scores changes capture considerable changes in recognition scores

VSTOI to Word Recognition Score



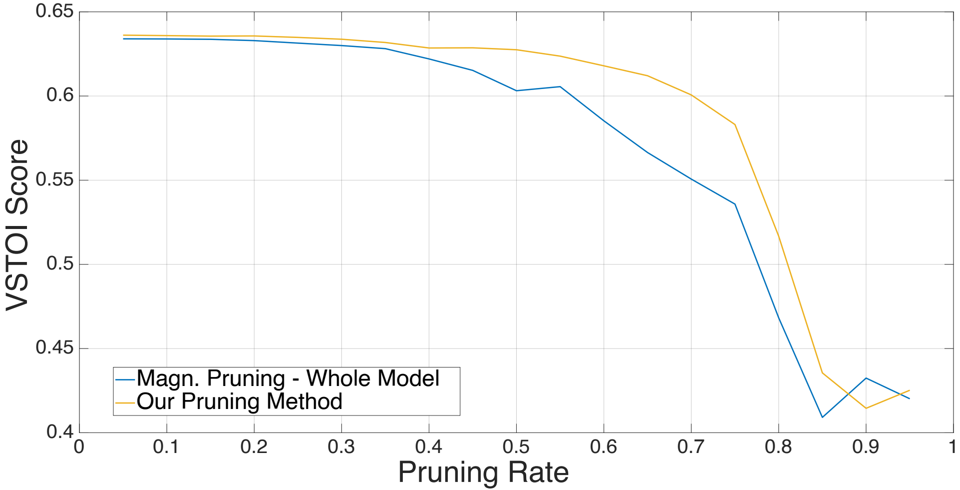
Watkins et al. (2018), "An Evaluation of Output Signal to Noise Ratio as a Predictor of Cochlear Implant Speech Intelligibility", Ear and Hearing

Results/Baseline

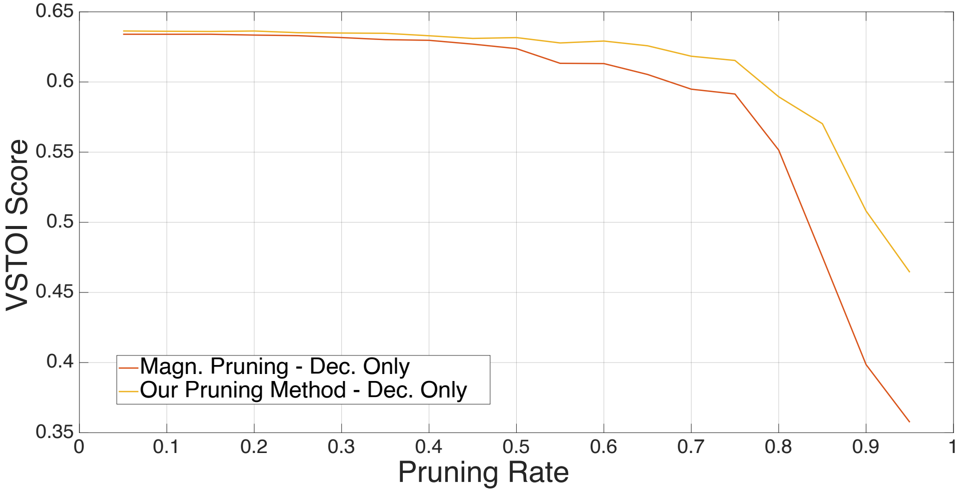


Baseline: Magnitude-Pruning (before finetuning)

Results/Whole Model Pruning



Results/Decoder Only Pruning



Results/Whole Model and Decoder Only Pruning

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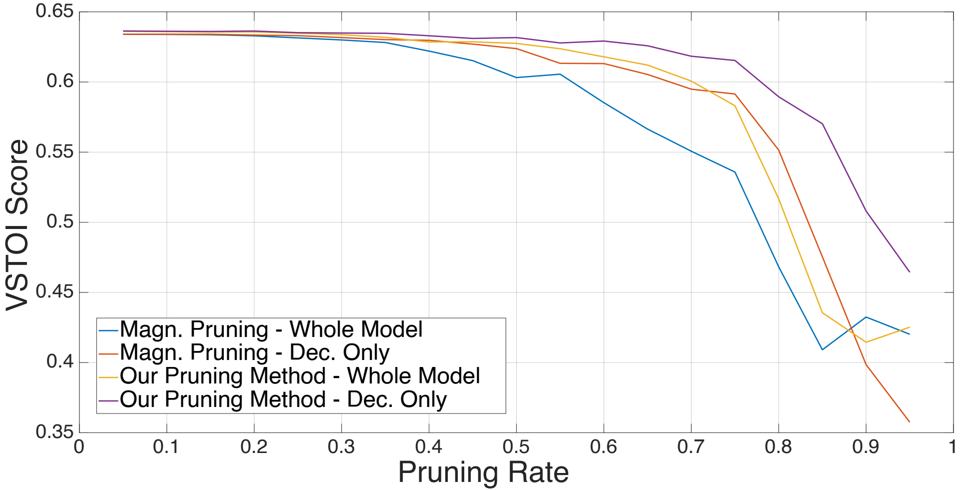
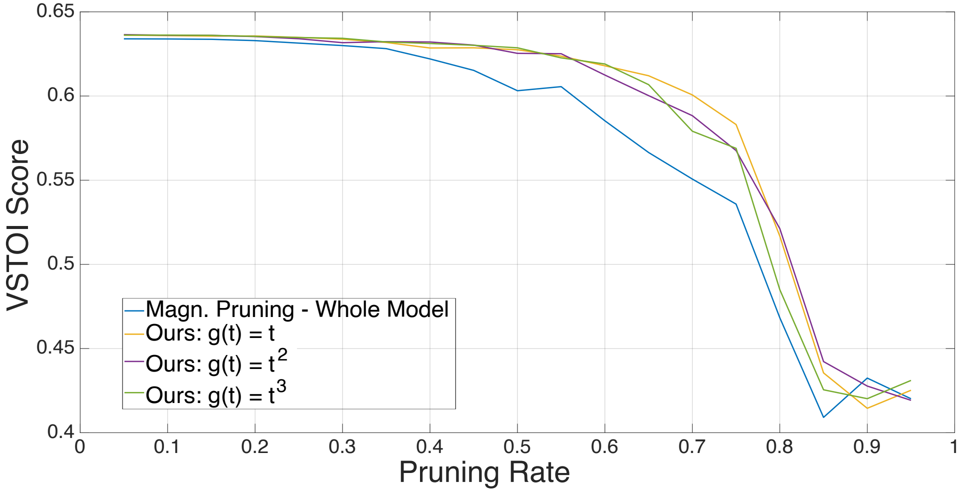


Results/Impact of Perturbation Function



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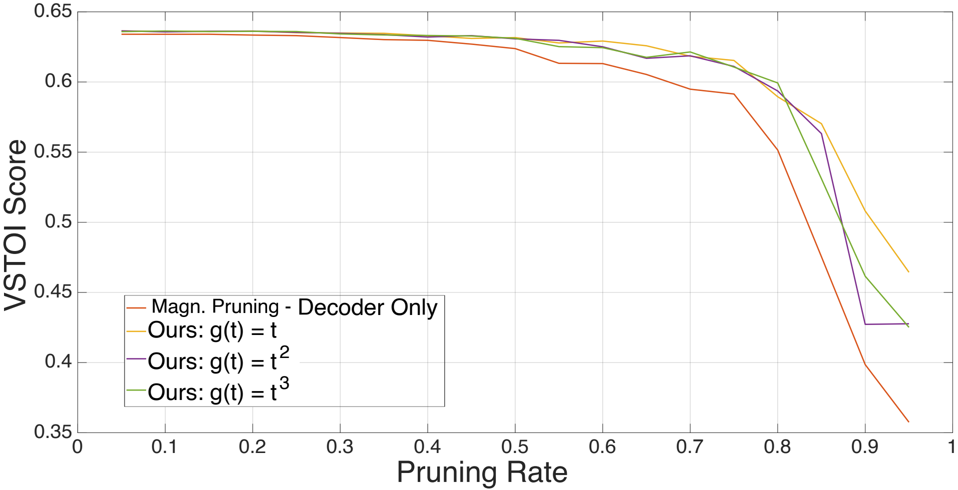
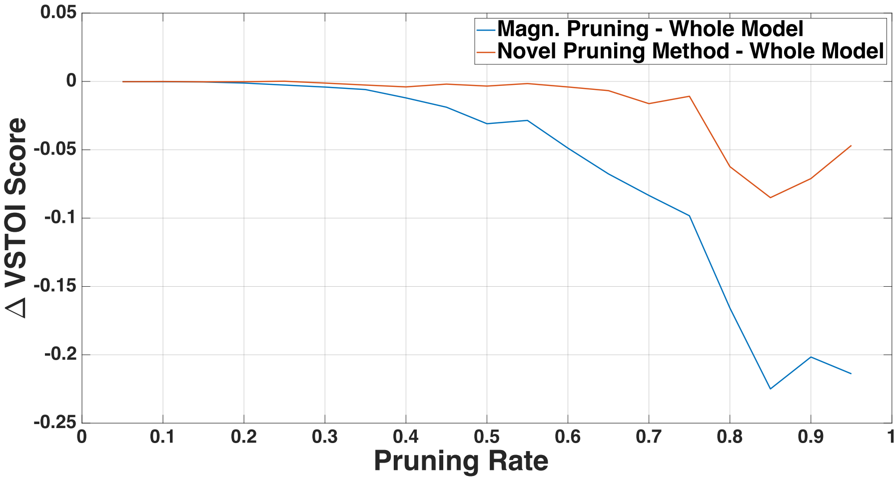
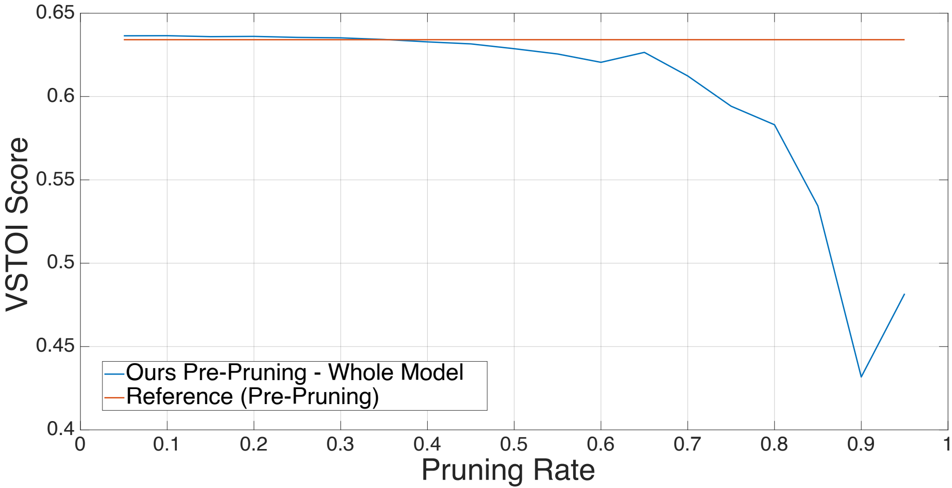


Results/Gained Robustness towards Pruning

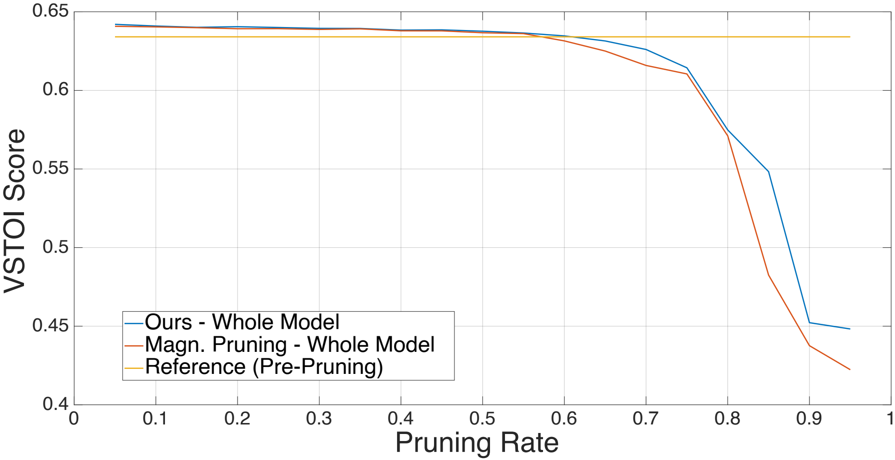


$\Delta VSTOI\ Score :=$ VSTOI Score after pruning – VSTOI Score before pruning

Results/Gained Robustness towards Pruning



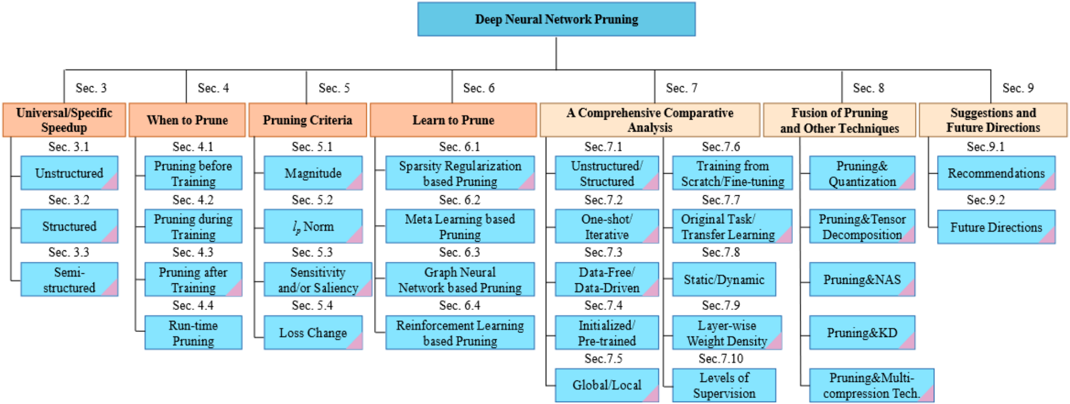
Results/Finetuning (Preliminary)



Discussion and Conclusion

- Pruning of deep recurrent autoencoders for low-complexity compression of the stimulation patterns of cochlear implants at zero latency
- Pruning-aware training achieved considerable improvements in post-pruning VSTOI scores
- Improvements for decoder-only and whole model pruning
- Requires additional forward/backward pass -> Minor to moderate increase in training complexity
- Post-finetuning difference to baseline smaller
- Little reduction of VSTOI scores post-finetuning up to a pruning rate of 65 %
- Greatest impact of training in last 100 iterations
- More aggressive weight perturbation may allow to reduce training time or to improve results

Backup



Cheng et al (2024), "A Survey on Deep Neural Network Pruning: Taxonomy, Comparison, Analysis, and Recommendations", arXiv:2308.06767