Mean Absorption Estimation from Room Responses Using Virtually-Supervised Learning

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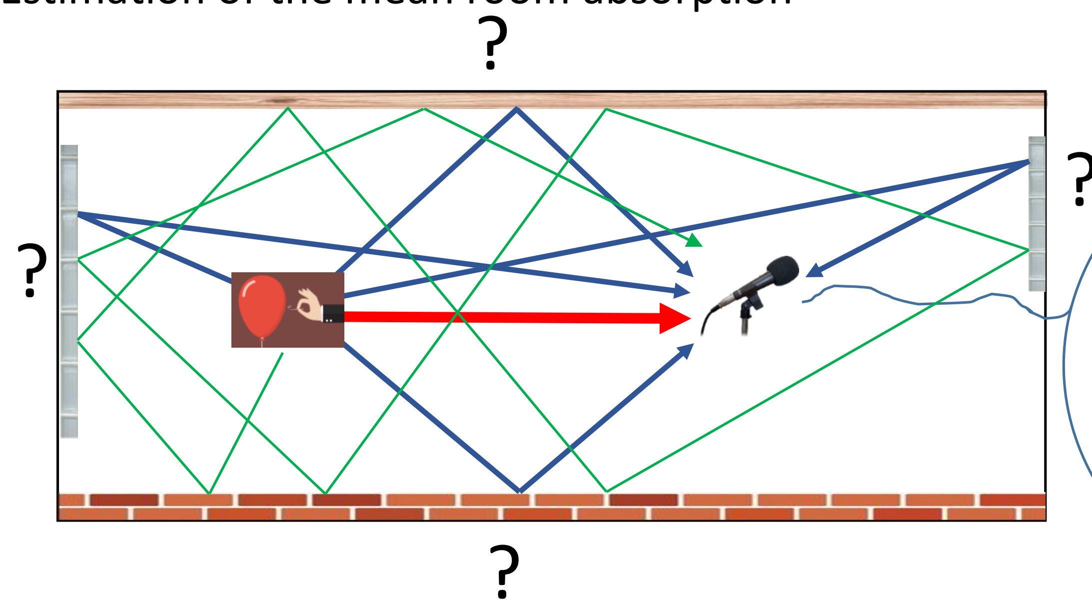
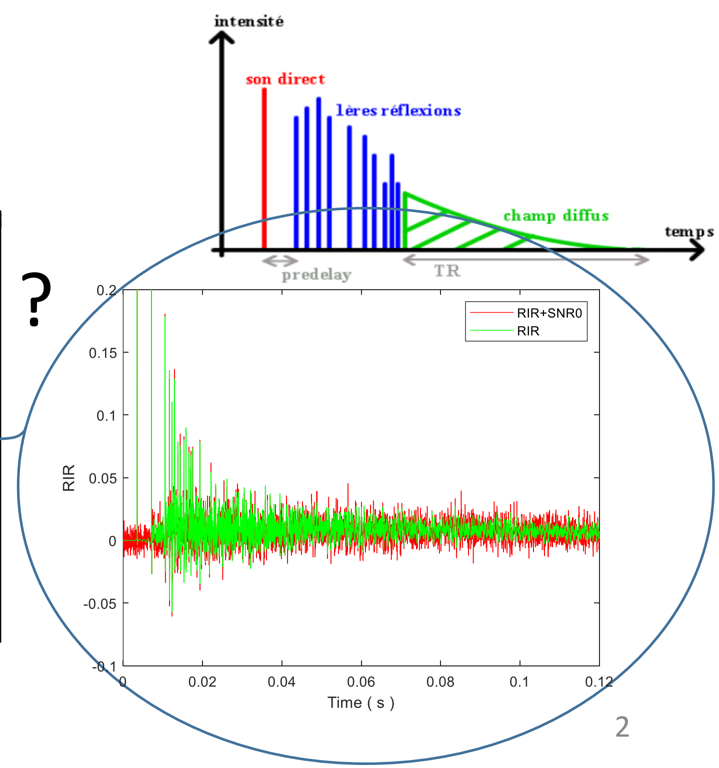
- Acoustic rehabilitation

- Need to quantify the existing absorption in order to be able to propose an optimal acoustic solution (in terms of acoustic comfort, cost, etc.).

- Difficulty to determine the sound absorption α_i of each material i present in the room

- Estimation of the mean room absorption





Reverberation Theory and Mean Absorption

- Mean absorption of the room (“*th*” : theoretical)

$$\overline{\alpha}_{th}(b) = \sum_i \alpha_i(b)\, S_i \qquad \left(b \in \{125, 250, 500, 1000, 2000, 4000\}\ \mathrm{Hz}\right)$$

α_i : **material absorption coefficient** i **(ISO354 : 2003)**

- Usual approach: inversion of the Sabine’s and Eyring’s models (diffuse field hypothesis)

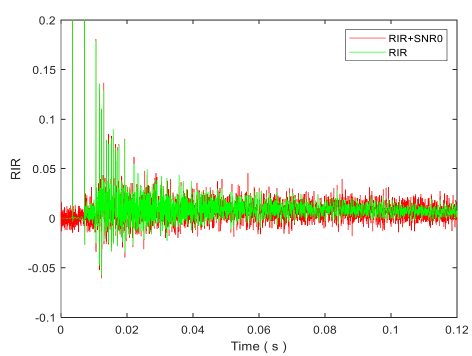
$$\overline{\alpha}_{\mathbf{Sa}}(b) = 0.163 \frac{V}{RT(b) \times S}$$

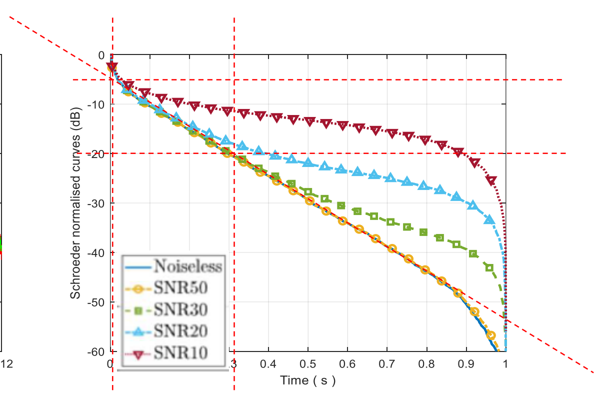
$$\overline{\alpha}_{\mathbf{Ey}}(b) = -\ln\left(1 - \overline{\alpha}_{\mathbf{Sa}}(b)\right)$$

Limitations and estimations steps:

- Diffuse field: cubic rooms, low and uniform absorption
- Knowledge of volume V and surface area S
- Difficulty in estimating $RT(b)$
  - Choice of the method to estimate the RIR (alarm gun, balloon, MLS, Sweep…)
  - Frequency filtering on RIR : RIR(b)
  - Integration of Schroeder on filtered RIR(b) : S(b)
  - Linear regression not always obvious or possible on Schroeder curves S(b)
  - Spatial averaging over several RIRs to assimilate the sound field to a diffuse field
  - Imprecise estimate of $RT(b)$

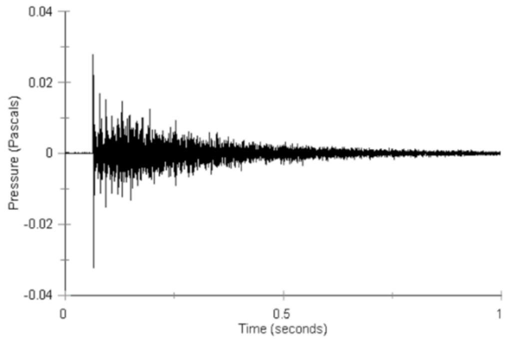
- Reverberation time RT estimation by Schroeder integration

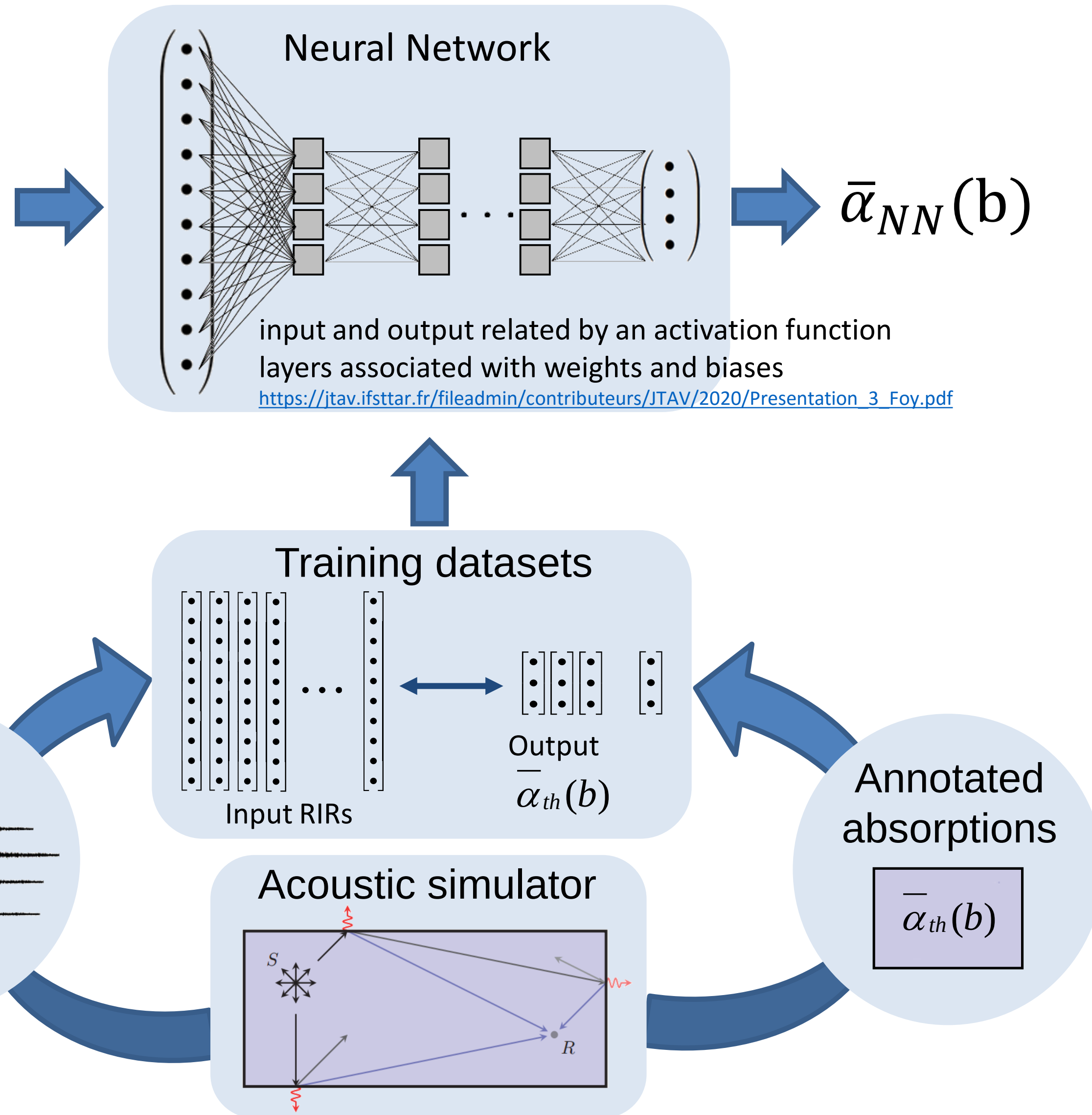




TR

Proposed Approach: Neural Networks





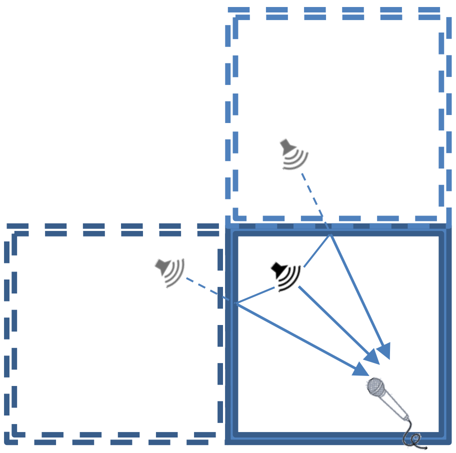
Principle of a neural network approach

- Choosing a neural network shape, dimensioning it (Perceptron, CNN....)
- Training the neural network (training and development sets)
- Testing the neural network (test set)

Training Databases - Numerical Approach

Bases resulting from a numerical approach

Roomsim *[Schimmel et al. 2007]* (shoebox)



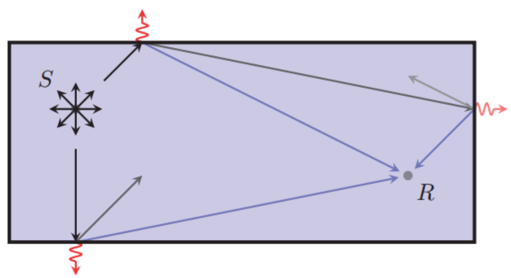
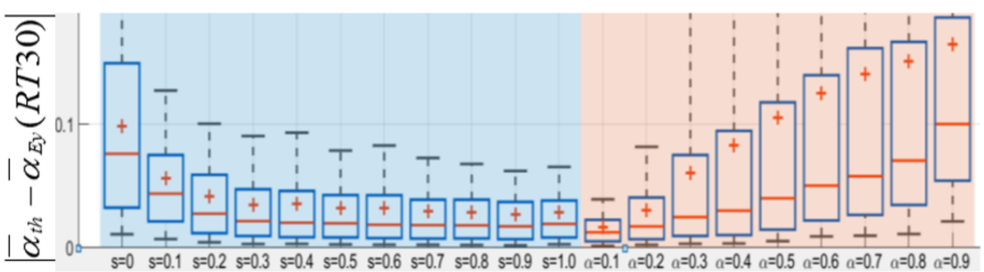
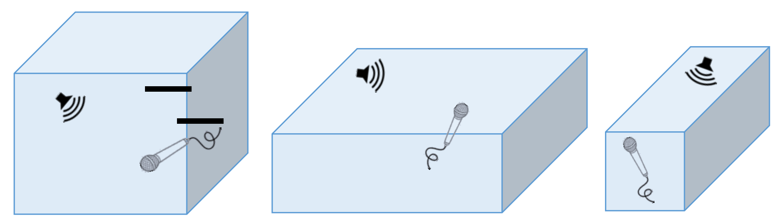


Image source method + Diffuse rain algorithm



Size versus computing time

- Focus on housing or office-type buildings:
  - Heights in [2.5, 4] meters
  - Length/Width in [1.5, 10] meters



- Omnidirectional source and receiver placed uniformly at random in the room

  D_au_paroi > 0,5m and D_sce_recp > 1m

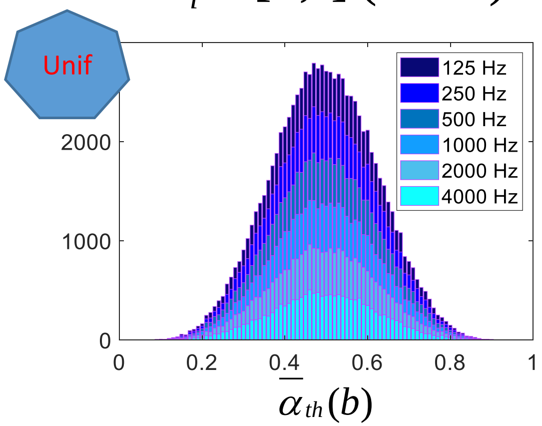
- Training set: 15,000 RIRs

Training Databases - Pre-treatment

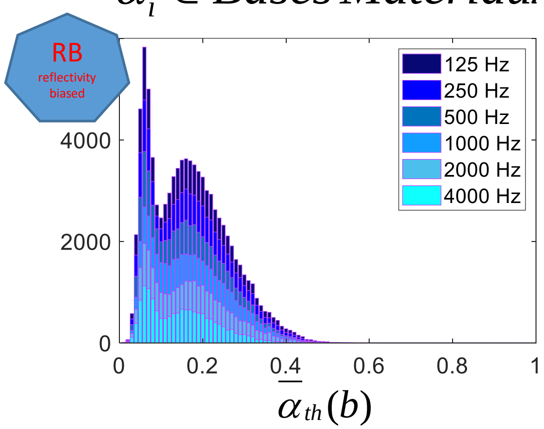
- Two Mean Absorption Distribution "Unif" & "RB"

$$\overline{\alpha}_{th}(b) = \sum_i \alpha_i(b)\, S_i$$

$\alpha_i \in [0,1]\,(rand)$

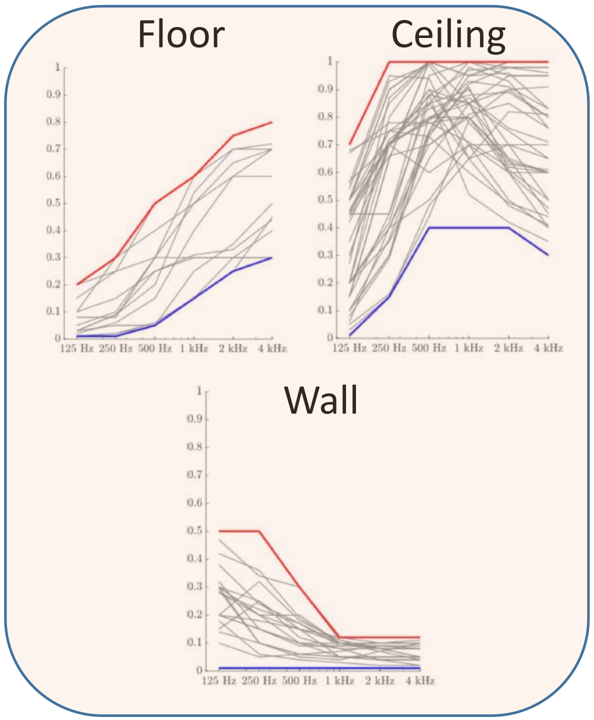


$\alpha_i \in Bases\ Matériaux$

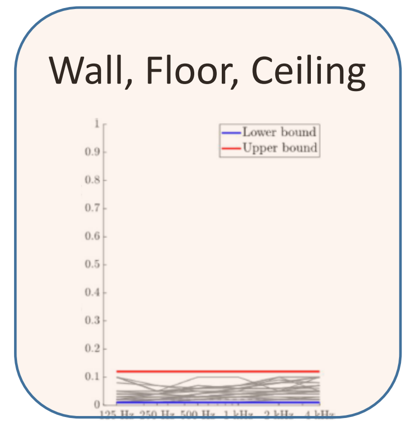


toss a coin !

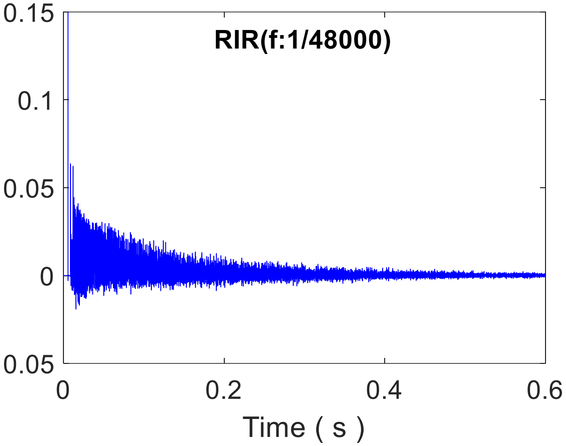
On heads : predefined ranges frequency-dependant

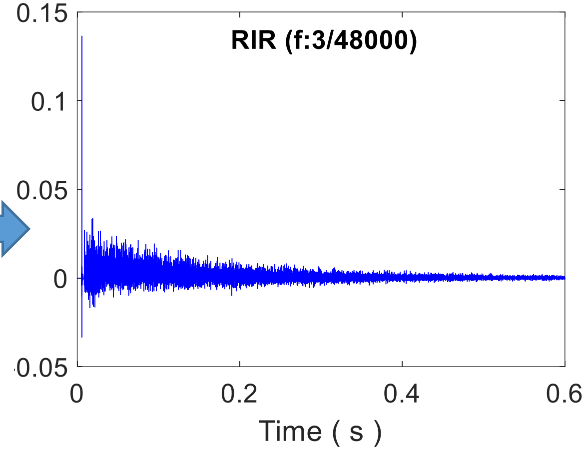


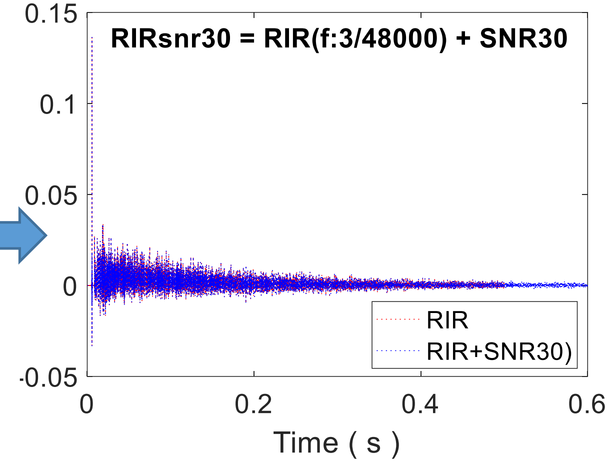
On tails : reflective frequency-independant absorption



- Resampling from 48 kHz to 16 kHz + Additional noise (SNR30)
- The first 500 ms of RIRs preserved







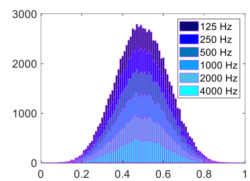
- Two training databases

« Unif » (uniform)

15000 RIRsnr30

Lx,Ly=[1,5:10]

Lz=[2,5:4]



$s_i(125,250,500) \in [0:0.3]\,;\, s_i(1000,2000,4000) \in [0.2:1.0]$

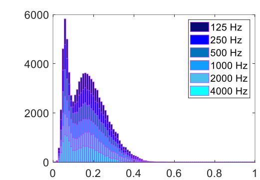
$\alpha_i \in [0,1]\,(rand)$

« RB » (reflectivity biased)

15000 RIRsnr30

Lx,Ly=[1,5:10]

Lz=[2,5:4]



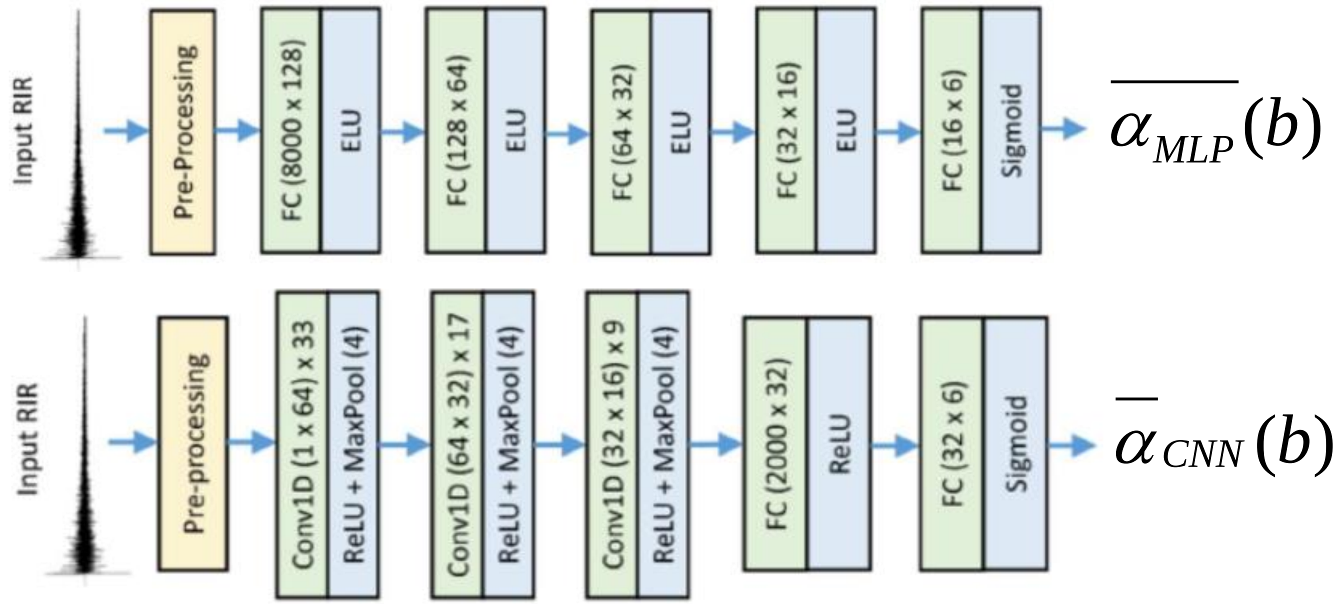
$s_i(125,250,500) \in [0:0.3]\,;\, s_i(1000,2000,4000) \in [0.2:1.0]$

$\alpha_i \in Bases\ Matériaux$

- Choice of two known neural networks, used in other fields of application

Multilayer Perceptron « MLP »

Convolutional Neural Network « CNN »



In summary

Neural Network « MLP » + Training Database « Unif » → MLP - Unif

Neural Network « MLP » + Training Database « RB » → MLP - RB

Neural Network « CNN » + Training Database « Unif » → CNN-Unif

Neural Network « CNN » + Training Database « RB » → CNN-RB

Comparative study on simulated test sets: Influence of the geometry

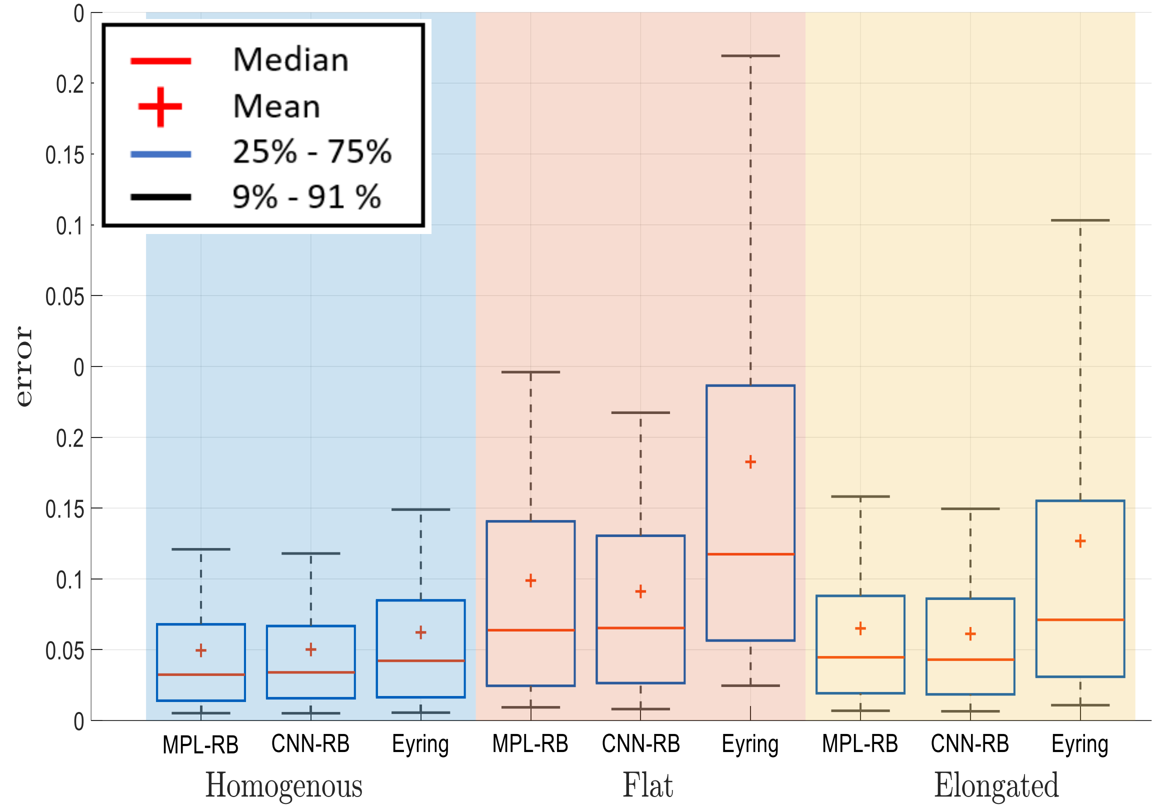
Test set 2 (cubic rooms)
- Identical to Test 0
- except: $w, l \in [2:4]$

Test set 3 (flat rooms)
- Identical to Test 0
- except: $w, l \in [8:10]$

Test set 4 (elongated rooms)
- Identical to Test 0
- except: $w \in [2:4]$

  $l \in [8:10]$

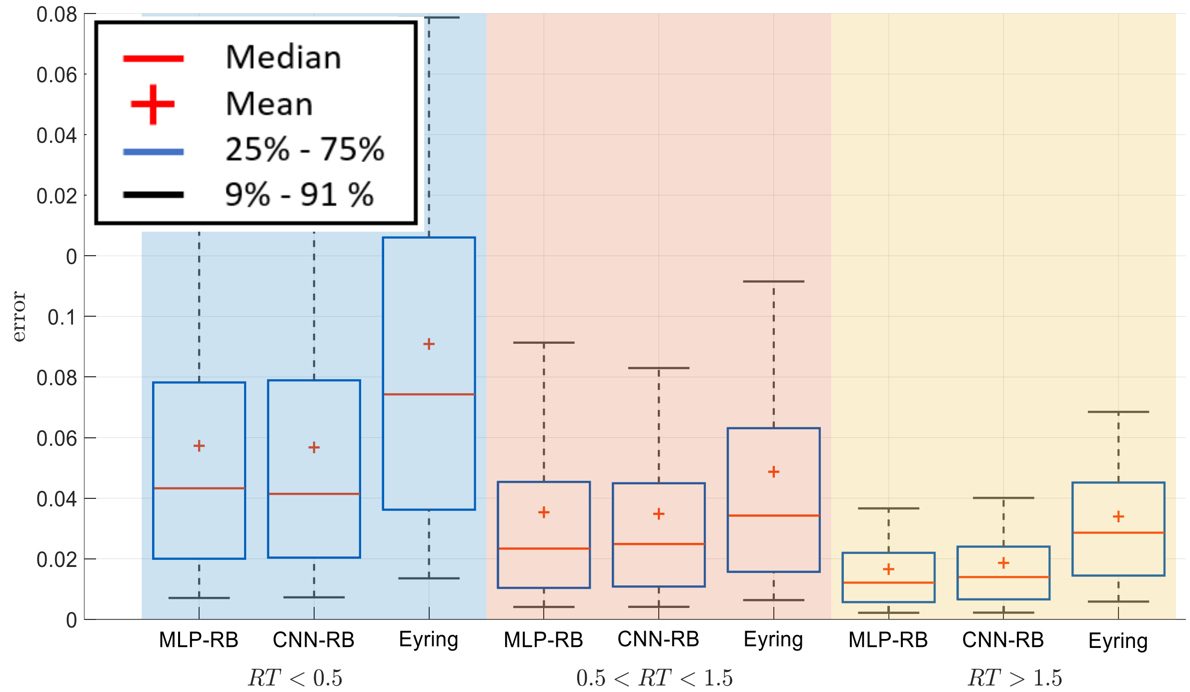
In all cases h=2,5m



- Cubic rooms :
  - Unsurprisingly, Sabine's and Eyring's models more reliable for cubic rooms
  - Similar results from neural networks

- Other geometries : Neural networks "better" than Sabine's and Eyring's models

Comparative study on simulated test sets: Influence of the reverberation



Test set 5
- Identical to Test 0
- except: $RT < 0{,}5s$

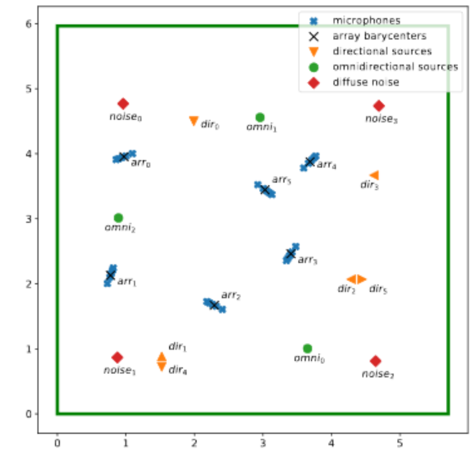
Test set 6
- Identical to Test 0
- except: $0{,}5s < RT < 1{,}5s$

Test set 7
- Identical to Test 0
- except: $RT > 1{,}5s$

- Reverberants rooms :
  - Unsurprisingly, Sabine's and Eyring's models more reliable for cubic rooms
  - Similar results from neural networks

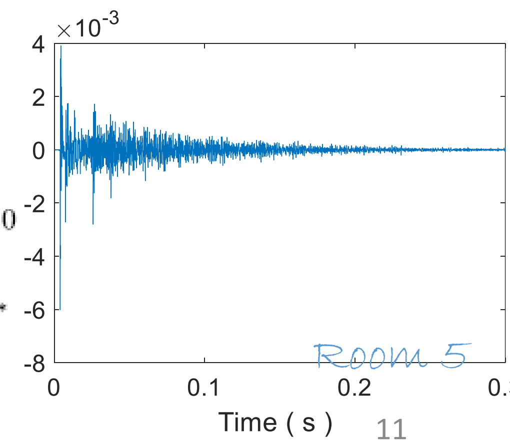
- Semi-reverberant or absorbent rooms: Neural networks "better" than Sabine's and Eyring's models

A fully calibrated multichannel RIR database with accurate annotation of the geometry and echo timings in different configurations of a cuboid room with varying wall acoustic profiles. The database currently features 1800 annotated RIRs obtained from 6 arrays of 5 microphones each, 6 sound sources and 10 different acoustic conditions. All the measurements were performed in the acoustic lab at Bar-Ilan university (Tel-Aviv).



- Double-sided panels with one reflective face (formica laminate sheets) and one absorbing face (perforated panels filled with rock wool)
- XXXXXX= floor Ceiling West South East North
- X= 1 non absorbant, X= 0 absorbant

	Room 1	Room 2	Room 3	Room 4	Room 5	Room 6	Room 7	Room 8	Room 9	Room 10
Config.	000000	011000	011100	011110	011111	001000	000100	000010	000001	010001*



Comparative study on real test sets: methodology

Two constraints

- A large number of Schroeder curves are non-linear or of weak sound dynamic range
- Test sets separated into two groups

A: possible estimate of RT10 → $\bar{\alpha}_{Sabine}$ $\bar{\alpha}_{Eyring}$ estimable

B: impossible estimate of RT10 → Unusable Eyring's and Sabine 's models!

- Unknown material absorption coefficients $\alpha_i(b)$
- Impossibility to estimate the theoretical mean absorption

$$\overline{\alpha}_{th}(b) = \sum_i \alpha_i(b) S_i$$

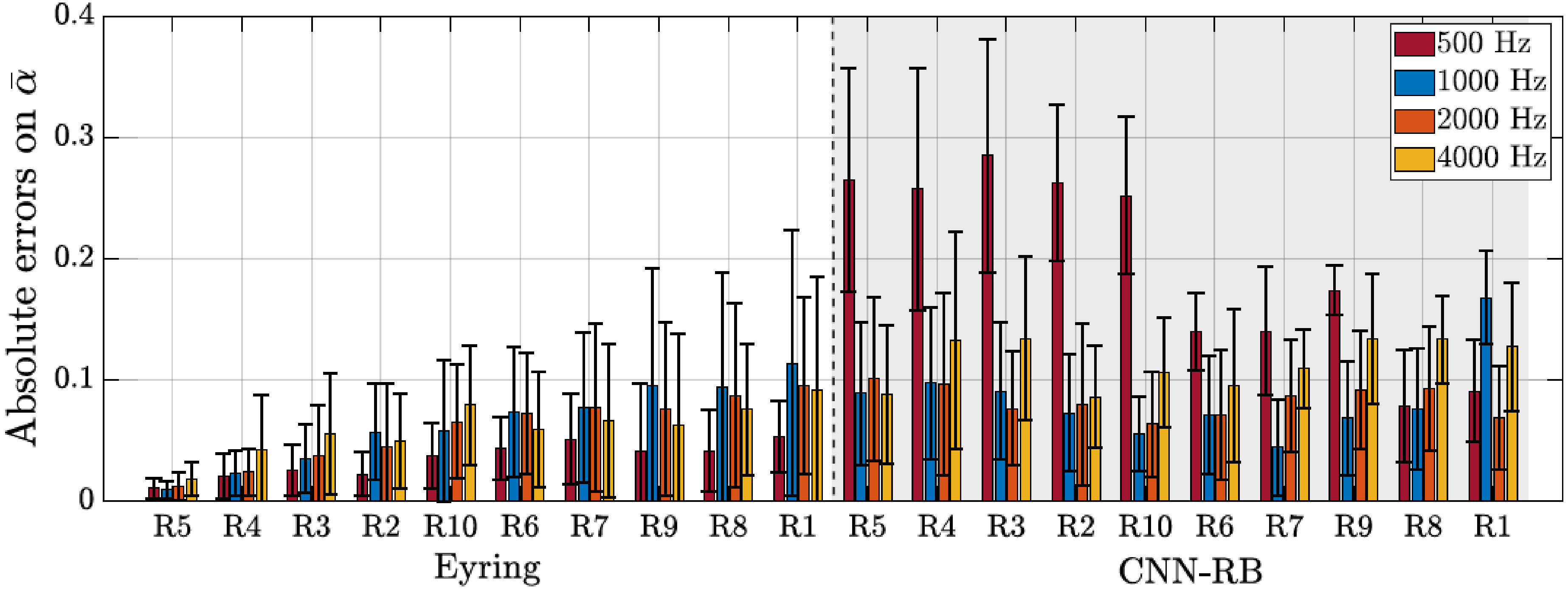
unknown!

$$\overline{\alpha}_{th}(b) \approx \left(\overline{\alpha}_{Ey}\right)_A$$

	Room 1	Room 2	Room 3	Room 4	Room 5	Room 6	Room 7	Room 8	Room 9	Room 10
Config.	000000	011000	011100	011110	011111	001000	000100	000010	000001	010001*
500 Hz	0.42 (11)	0.23 (7)	0.20 (20)	0.17 (51)	0.13 (48)	0.39 (8)	0.38 (5)	0.40 (8)	0.35 (7)	0.23 (12)
1000 Hz	0.52 (62)	0.28 (83)	0.25 (86)	0.17 (89)	0.13 (90)	0.44 (79)	0.41 (74)	0.44 (69)	0.43 (70)	0.33 (72)
2000 Hz	0.50 (65)	0.34 (81)	0.30 (86)	0.19 (82)	0.14 (88)	0.44 (74)	0.42 (64)	0.44 (66)	0.44 (67)	0.37 (69)
4000 Hz	0.37 (15)	0.35 (17)	0.29 (22)	0.16 (16)	0.12 (29)	0.38 (17)	0.33 (12)	0.32 (14)	0.34 (18)	0.32 (14)

Comparative study on real test sets: Results

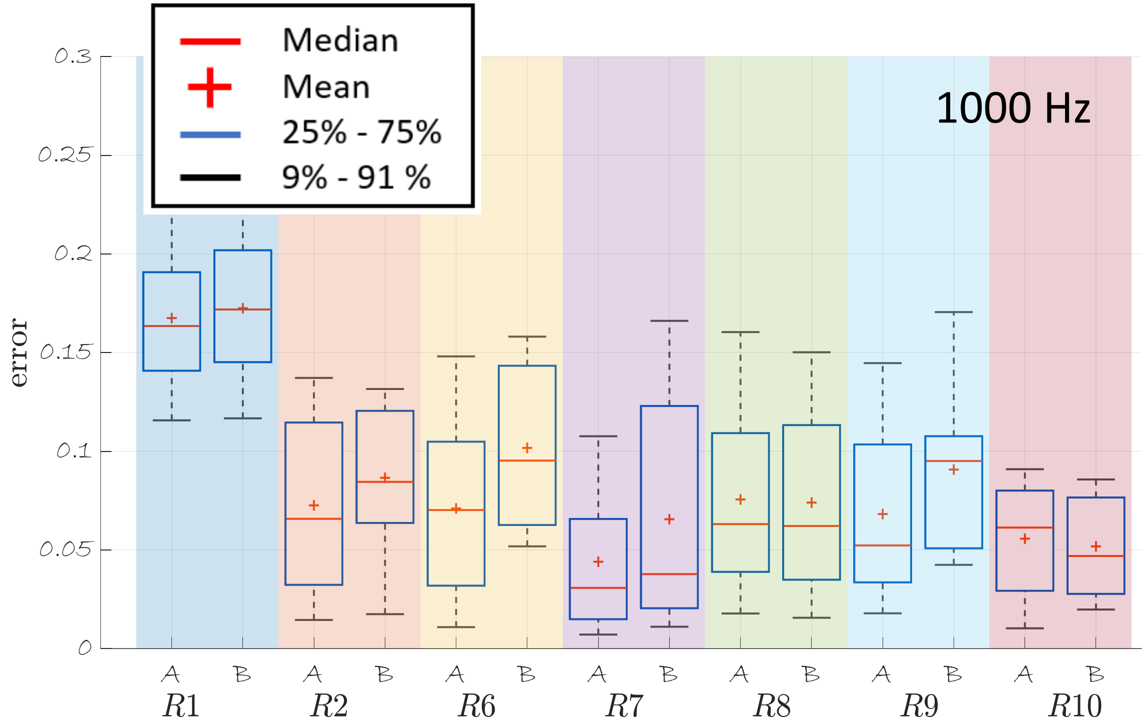
Group A - CNN



- Encouragingly, for the 1 kHz, 2 kHz and 4 kHz octave bands, the learning-based method yields errors below or around 0.1 for all rooms, which is a reasonable uncertainty in the context of acoustic diagnosis.
- At 4 kz, the CNN-RB errors increase slightly (directivity of the source ?)
- At 500 Hz, the CNN-RB errors are much larger in all rooms except R1 and R8 (existence a wave phenomenon ?).

Comparative study on real test sets: Results

Group B - CNN



- R3, R4, R5 omitted (not enough curves in group B)
- Similar neural network results for groups A and B
- CNN is largely unaffected by the non-linear or insufficient log-energy decays of Schroeder curves in B.
- The neural network is probably not very sensitive to the general shape of RIRs, and more sensitive to events (peak arrival time, relative energy of peaks....)

Conclusion

- Comparison of trained models versus Eyring's and Sabine's models
- Similar or better results for trained models
- **1 input parameter** for trained models (RIR) versus 3 input parameters for reverb approach (V, S, RT)
- More noise-tolerant trained models

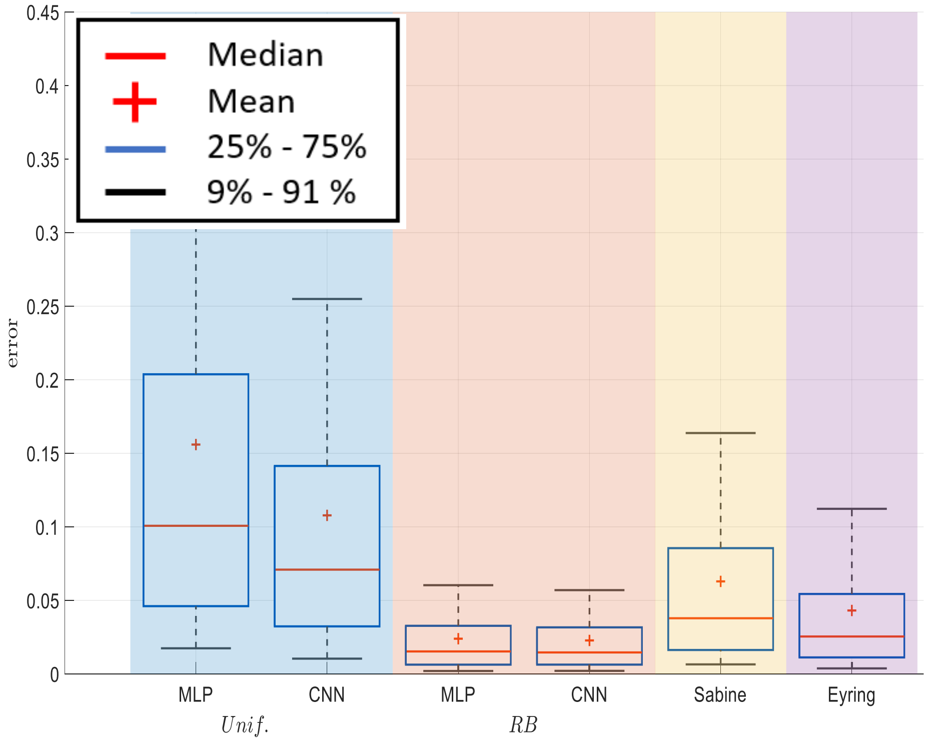
Perspectives

- Need to have a database of measured data specific to building acoustics
  RIR measurements (MLS, Sweep…), Measuring material absorption *in situ*….
- *Estimation of material absorption profiles rather than the mean absorption*

Test set 0

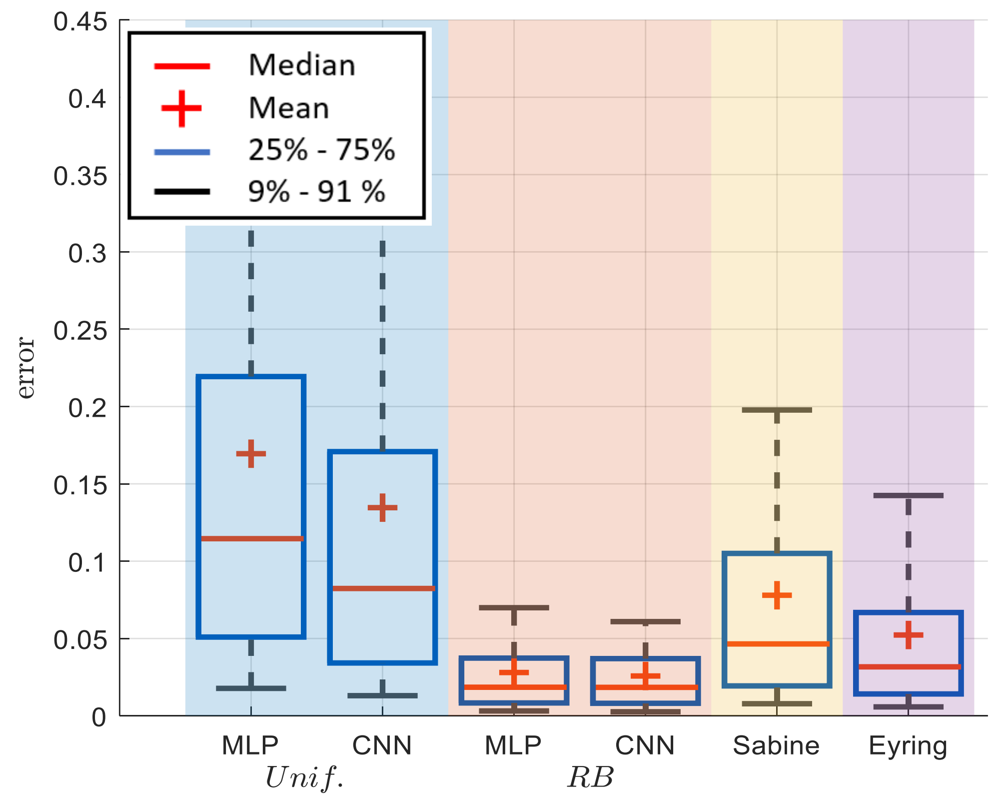
- Identical to the “RB” Training Base
- 500 simulations

- MLP-Unif CNN-Unif MLP-RB CNN-RB
- Significance of the choice of the training base if it is small (15000)
- CNN seems slightly better than MLP
- RB : Median value 0,02
- Neural networks “better” than reverberation theory



Test set 1

- Identical to Test 0
- except : only 5 rooms $[w:l:h]=[4:5:3],[2:10:3],[5:10:3],[5:8:2.5],[10:10:5]$

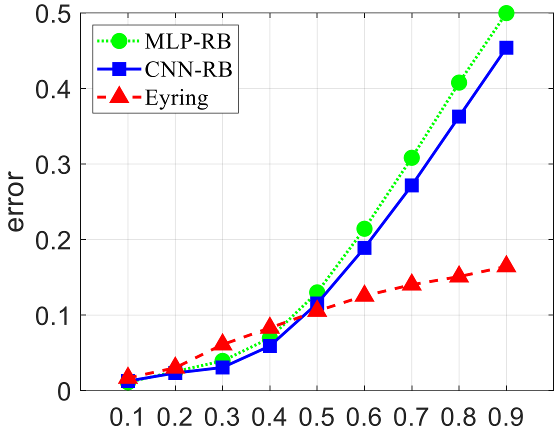


- MLP-RB CNN-RB
- Robustness with regard to the source and receiver positions
- Neural networks “better” than Sabine’s and Eyring’s models
- without knowledge of the volume V or the surface S of the room.

Influence of other parameters

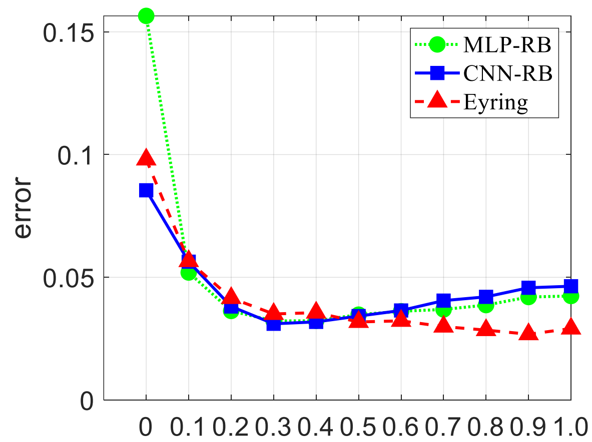
wall absorption

Test set 8
- Identical to Test 0
- except: α_i *fixed*



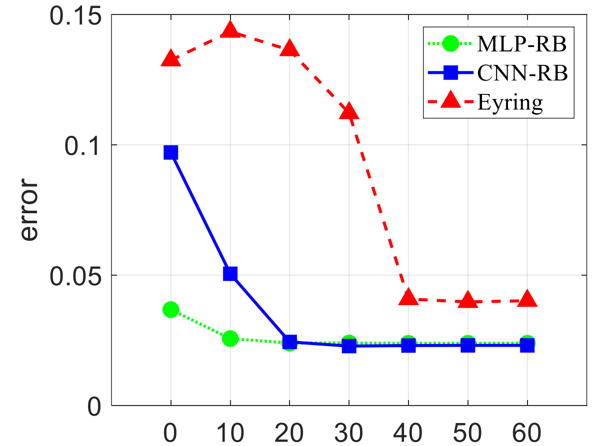
wall diffusivity

Test set 9
- Identical to Test 0
- except: s_i *fixed*



noise

Test set 10
- Identical to Test 0
- except: SNR



- for α_i < 0,5 and s_i < 0,5
- Learned models perform similarly or better than Eyring'model

- Learning-based methods much more robust to noise