From Sound to Action: Deep Learning for Audio-Based Localization and Navigation in Robotics

Gaétan Lepage

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- *Reviewer:* Romain SERIZEL (Associate Professor, Université de Lorraine)
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- *President:* Didier SCHWAB (Professor, UGA)

Social Robotics

The ARI robot, PAL robotics

- Social robotics aims to build capable robotic agents.
- They must **collaborate with humans** (social acceptance, etc.)
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- **Human Robot Interactions** entail a wide range of challenges
- Key challenges:
  - **Perception:** Extract relevant information from *multi-modal data* captured by diverse sensors
  - **Action:** Learn relevant policies to achieve desirable behaviors (navigation, grasping, conversation, etc.)

Challenges of Auditory Perception in Robotics

- Humans mainly communicate through speech

TODO: Add image(s)

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- Robots must properly understand humans to have relevant interactions
- Sound can also be used to localize speakers

Learning Robot Behaviors

TODO: Add image(s)

- Robots need to react to their environment and take actions
- Several objectives and constraints can be described

Plan

1

Acoustic Robot Simulator

Simulate dynamic acoustic environments

2

(Active) Sound Source Localization

Accurately localize speaker(s) in a reverberant room

3

Deep RL for Sound-Based Navigation

Learn to navigate to hear humans better

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Motivation

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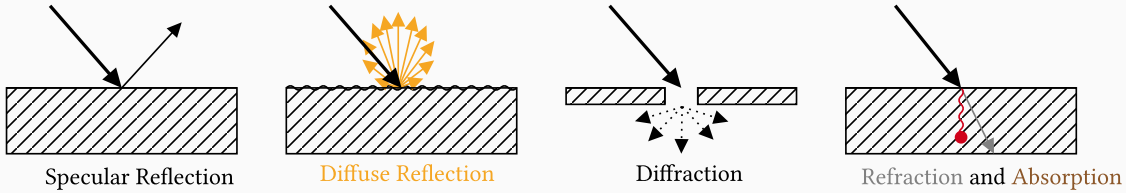

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- Modelling realistic acoustic environments
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- Provide high-level primitives for experimenting with robotic auditory perception

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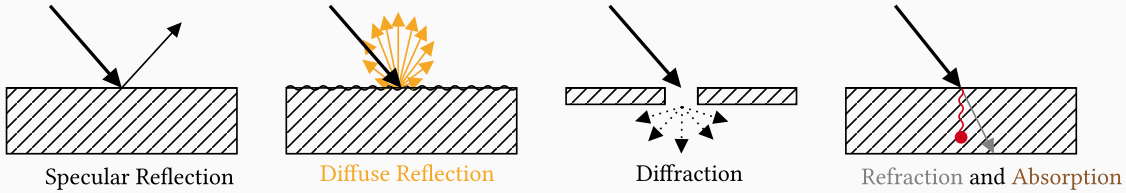

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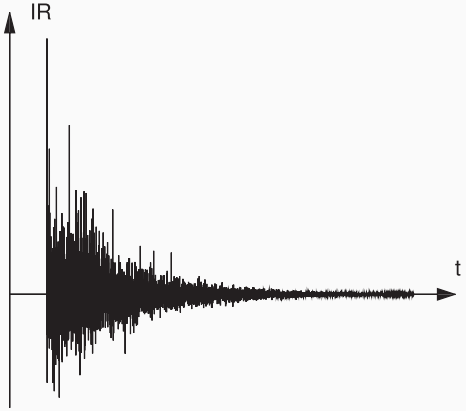
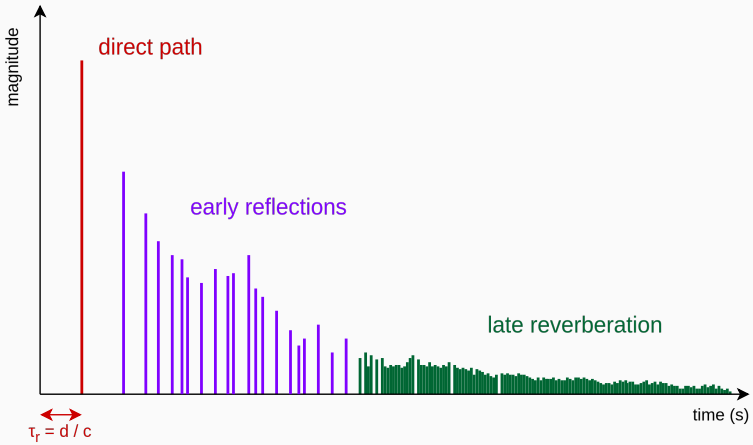
Motivations:

- Collecting significant amounts of data
- Lack of holistic approaches to interactive acoustic simulation

Room Impulse Response





Room Impulse Response:

- Characterizes the reverberation properties of the room
- Computed for each source-microphone pair
- T_{60} measures the reverberation level
- The resulting image/microphone signal is obtained by convolving each source signal with the corresponding RIR, and summing over the sources

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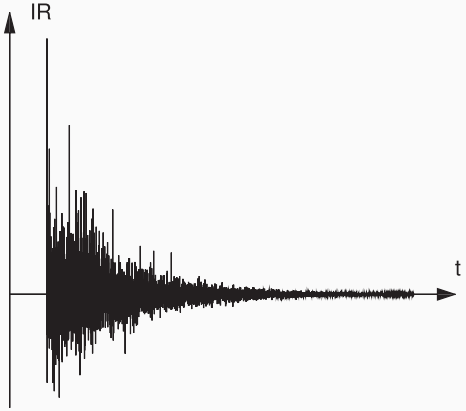

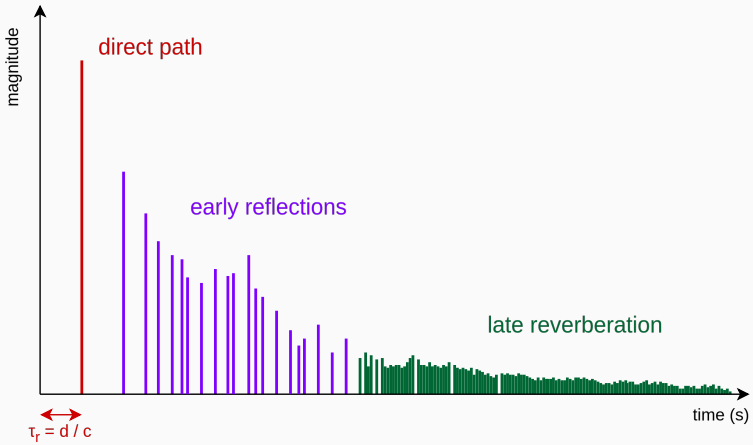

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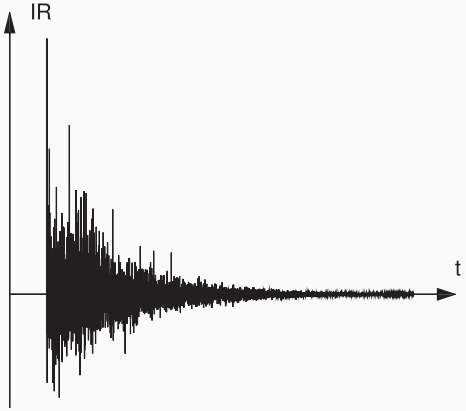

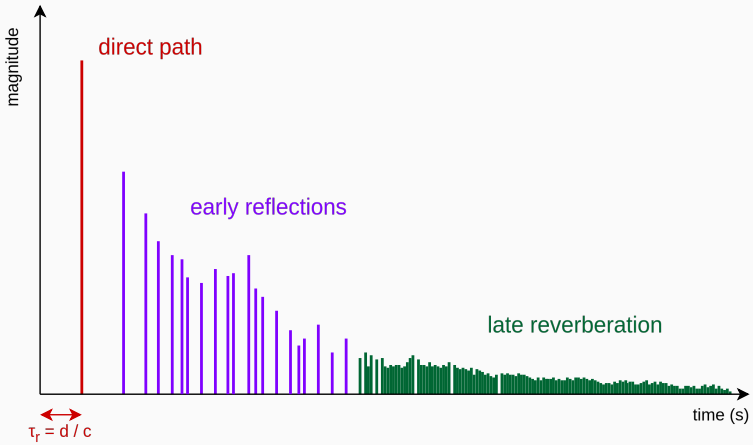

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Single source:

$$y[n] = (h * x)[n]$$

Multi source:

$$y[n] = \sum_{i=1}^{n_s} (h_i * x_i)[n]$$

Existing Simulation Methods

- Numerical simulation [1] [2]:

$$\nabla^2 \boldsymbol{p} = \frac{1}{c^2} \frac{\partial^2 \boldsymbol{p}}{\partial t^2} \quad \text{(Helmotz equation)}$$

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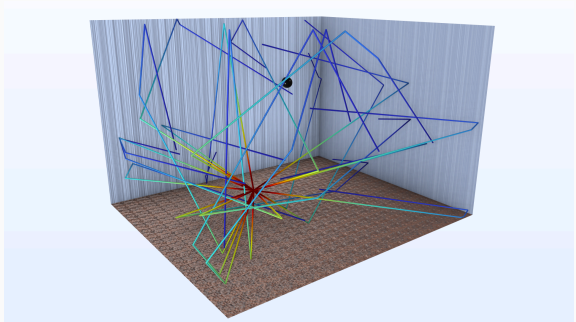
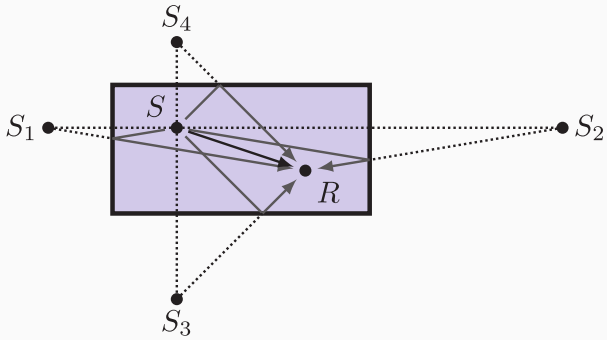
- Geometrical Acoustics
  - Ray-tracing [3],
  - Image Source Model [4]

-> Generate RIR from a 3D room specification





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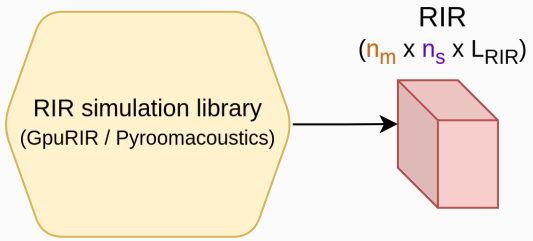

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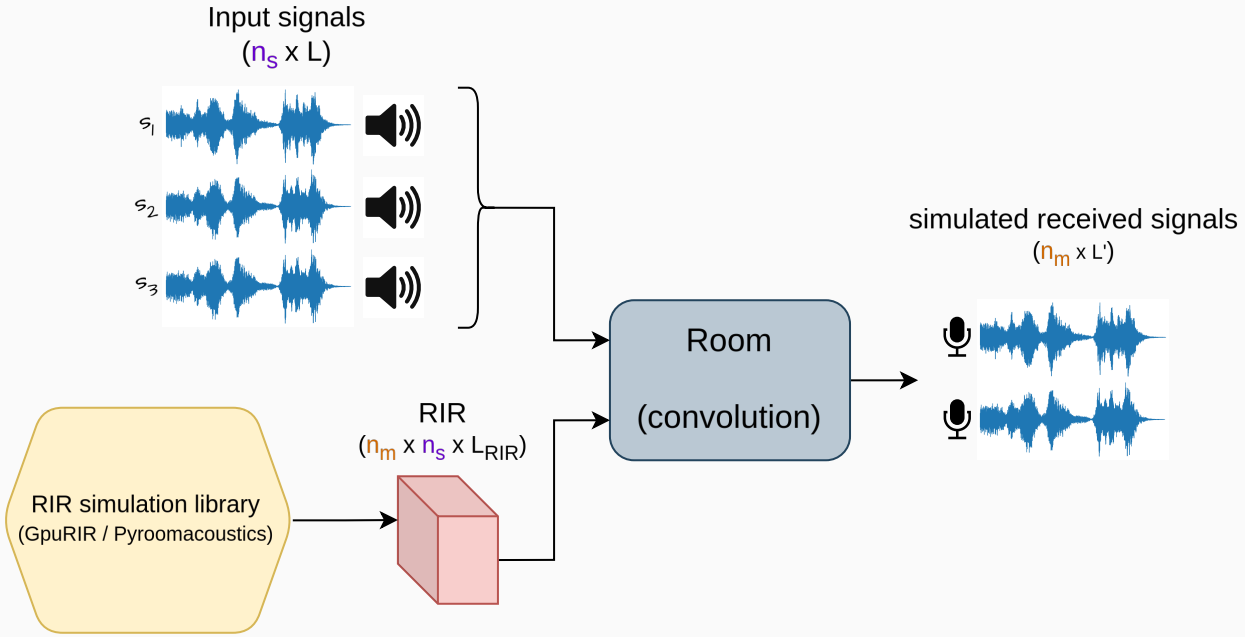

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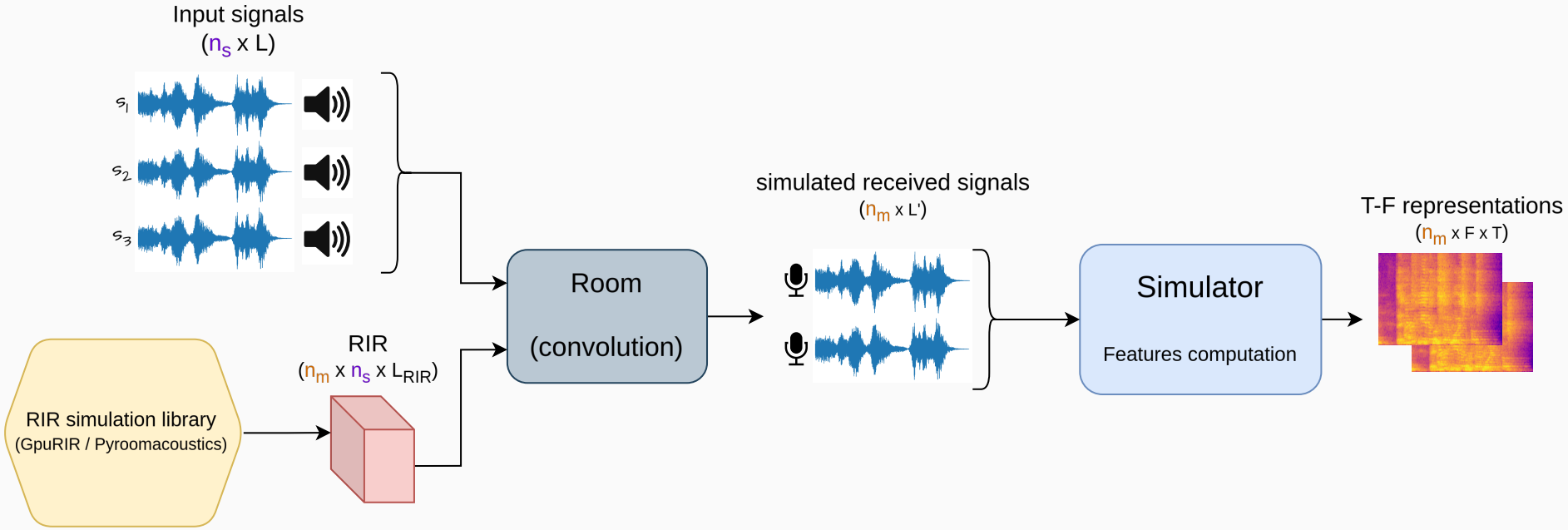

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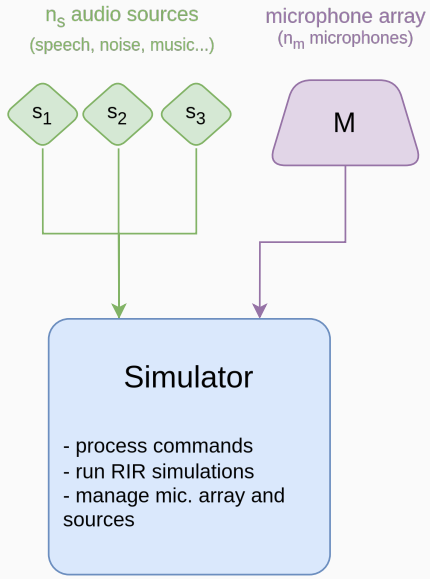

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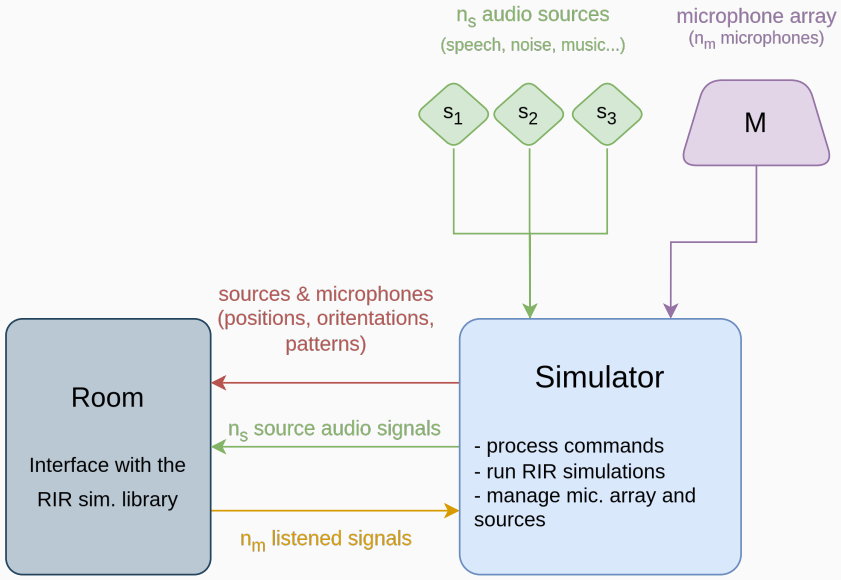

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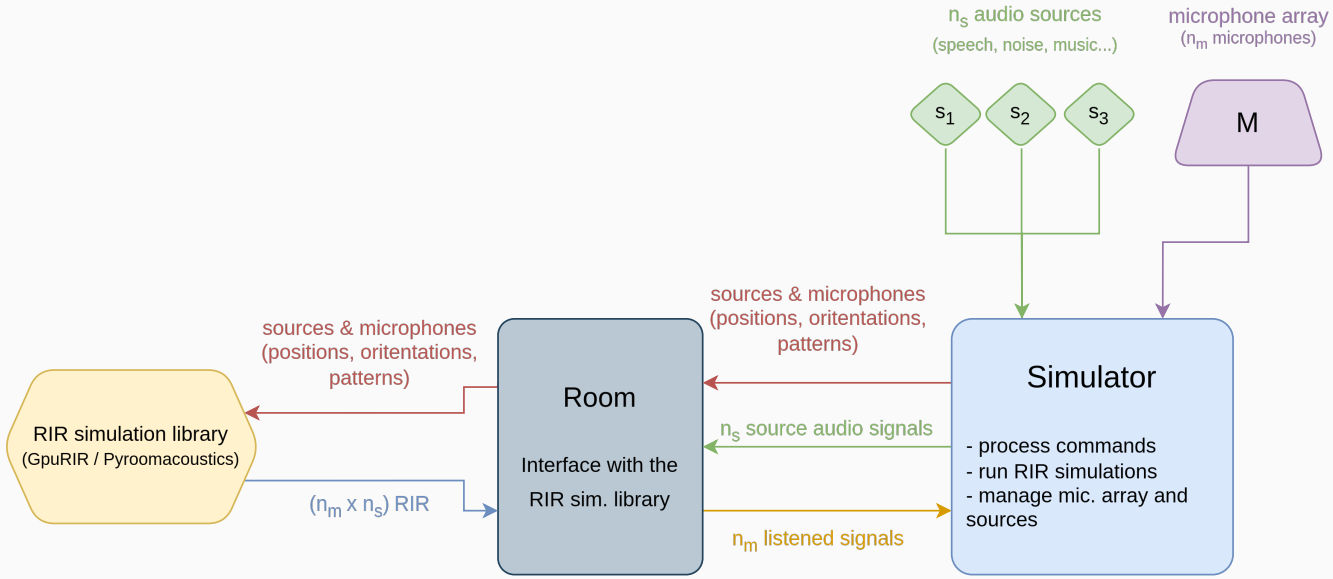

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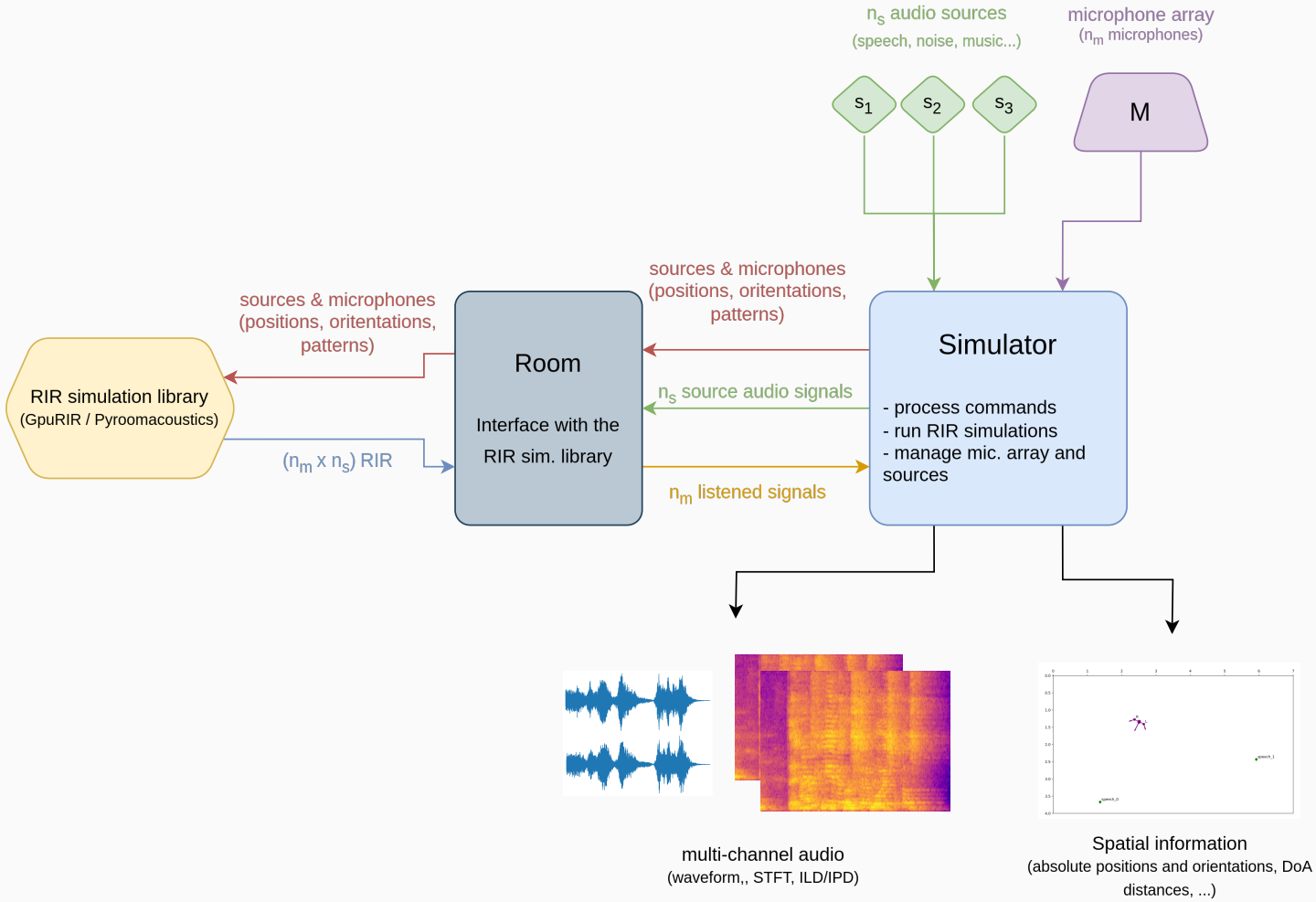

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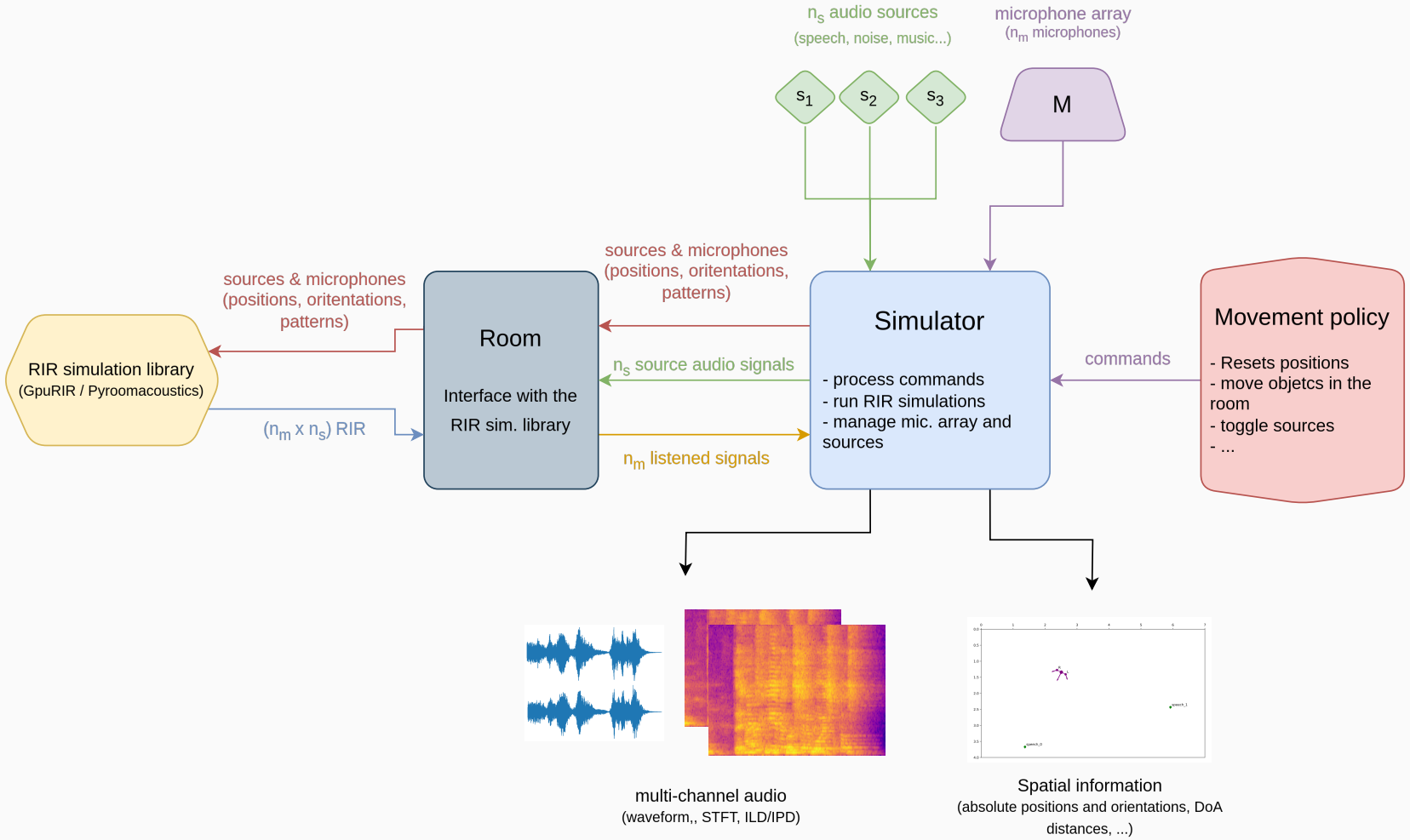

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# Compute the DoA with respect to the "speech_1" source
doa_source_1 = audio_simulator.get_doa("speech_1")
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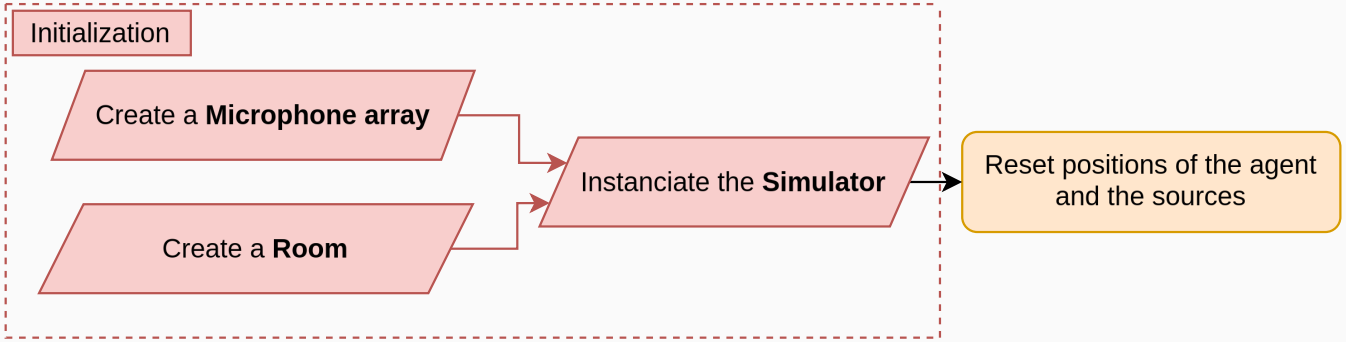
Modelling Active Scenarios



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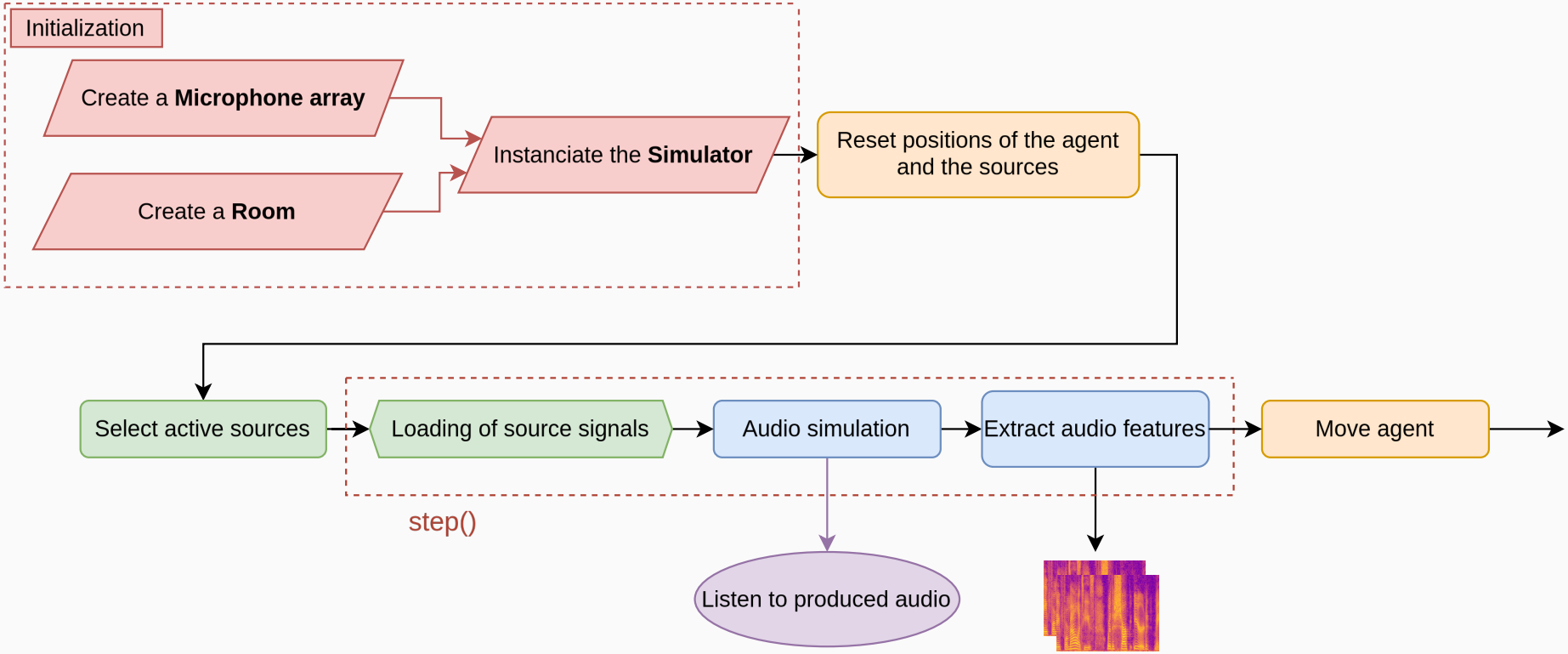

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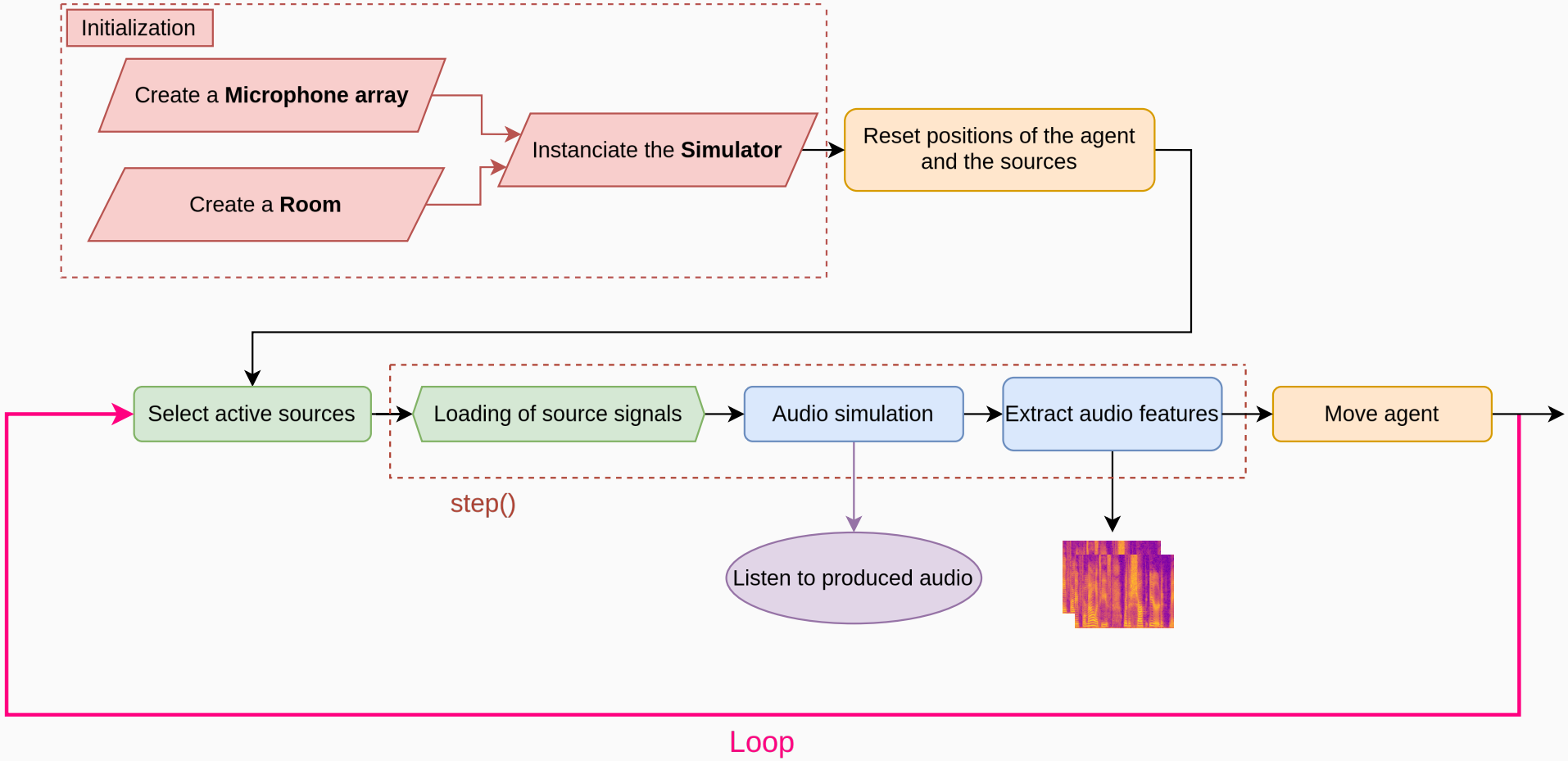

Summary

- Complete solution for modelling various acoustic robotics scenarios
- High-level, intuitive API to easily and quickly build on top of
- Extraction of various spectral representations of simulated signals
- Great flexibility allowing for various use-cases:
  - Dataset generation
  - Modelling interactive scenarios where both microphones and sources can move
  - Use as an environment to train Deep RL agents

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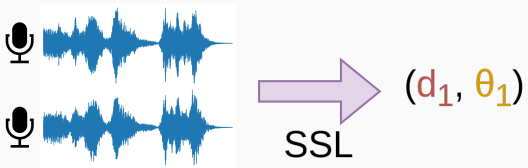
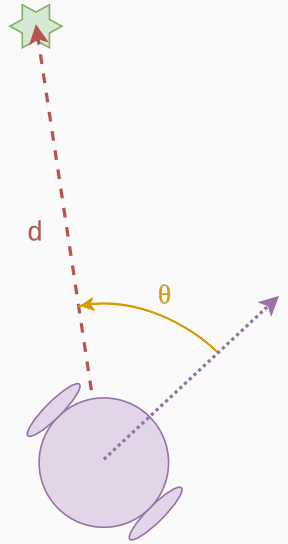
From Static to Active SSL

- SSL (Sound Source Localization): estimate the position of one or multiple sound sources
  - Multiple variations of the task
  - Dense scientific literature: from classical sound processing methods [1] [2] to deep learning techniques [3]
  - Often applied to robotics [4]





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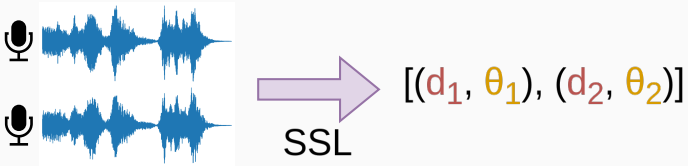

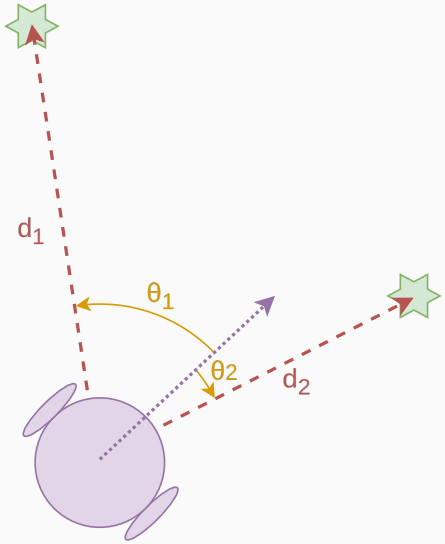

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- Real-world robotics scenarios are often dynamic
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Intuition:

- Aggregate instantaneous angular estimates over time
- Leverage the robot movement to refine the predictions of the sources' 2D position

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Literature:

- Several works in the Robotics literature[1][2][3]
- Lack of deep-learning-based methods
  Multiple works involving moving sources (e.g. LOCATA challenge[4]), but only few considering mobile microphones

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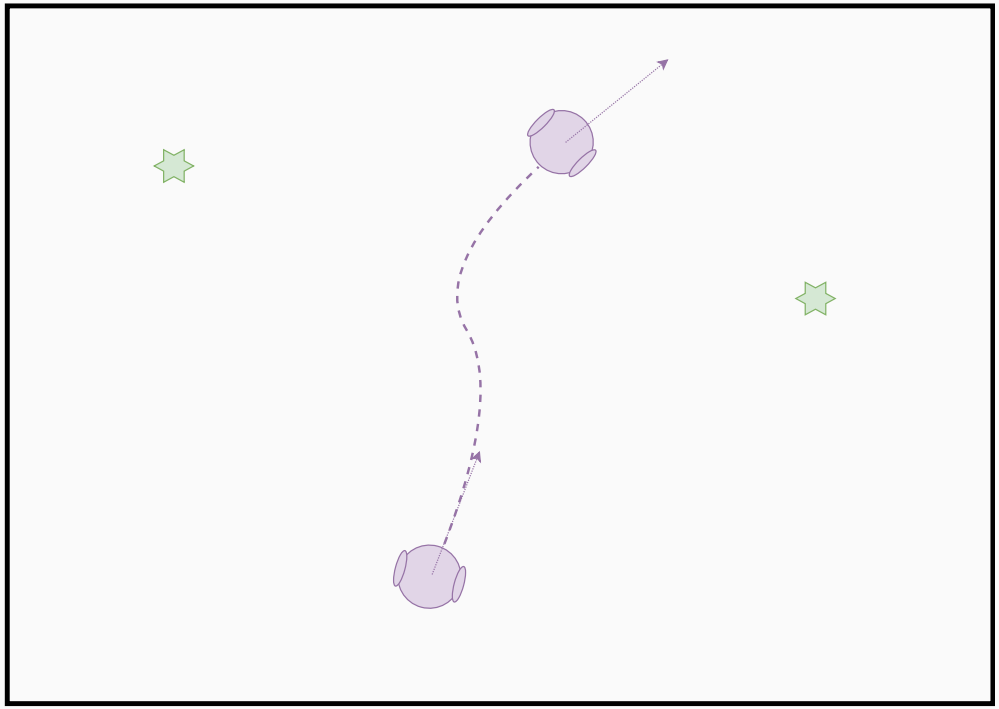
Approach

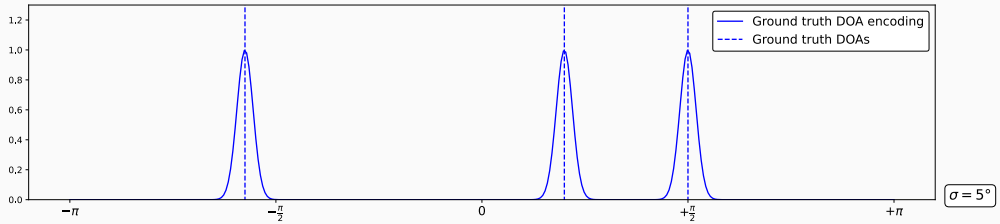
- Project static SSL DoA spectrum to egocentric maps
- Aggregate these maps into a single final heatmap



Static SSL Model (1/2): DoA Spectrum Regression

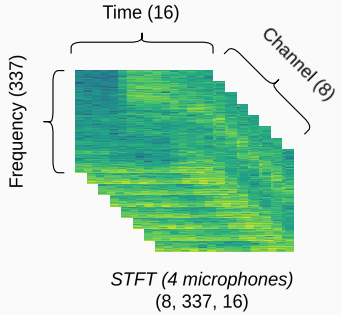
- Encode DoA as a continuous function over $[-\pi, \pi]$ [1]
- Discretized over 360 values
- Can represent an arbitrary number of sources
- Ground-truth DoA of each source is represented with a Gaussian window centered on it
- The SSL task becomes a DoA spectrum regression (with a DNN for e.g.):

$$\mathcal{L} = \|\hat{o} - o\|_2^2$$



[1] He et al., "Neural Network Adaptation and Data Augmentation for Multi-Speaker Direction-of-Arrival Estimation," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2021.

Static SSL Model (2/2): Network Architecture



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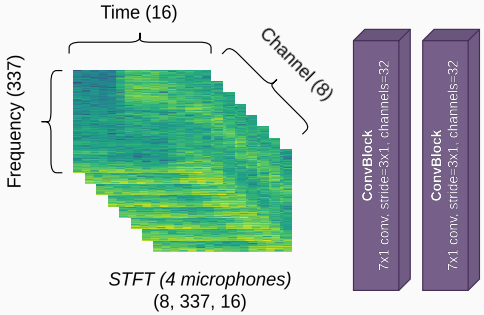

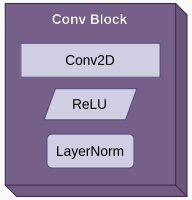

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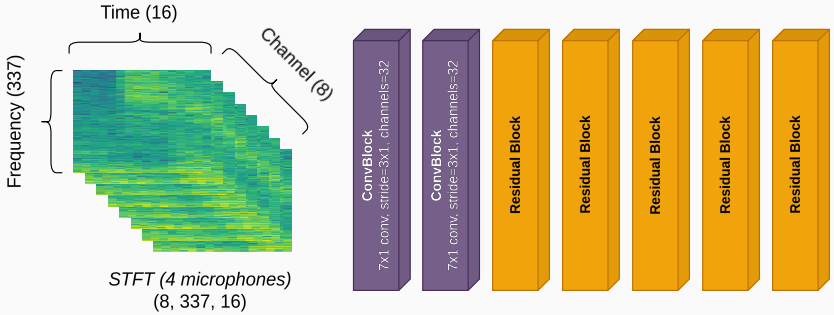

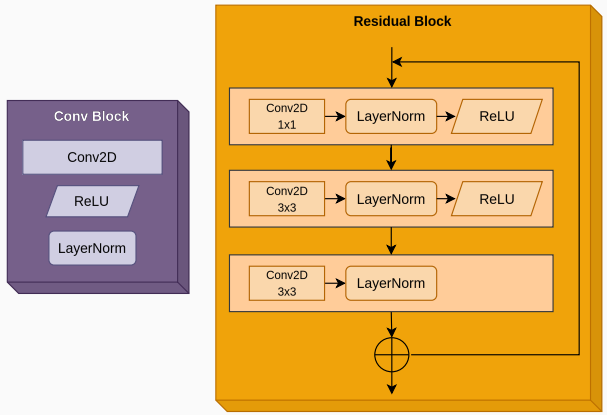

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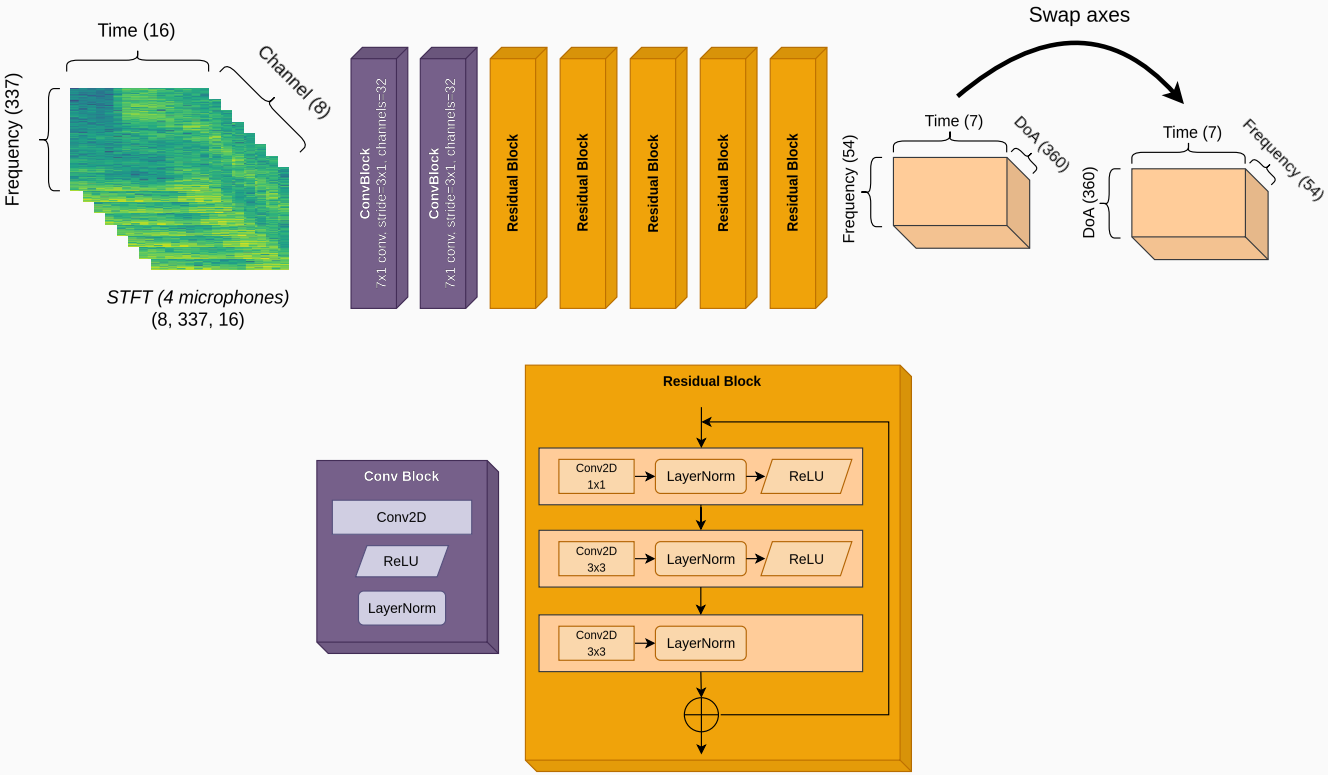

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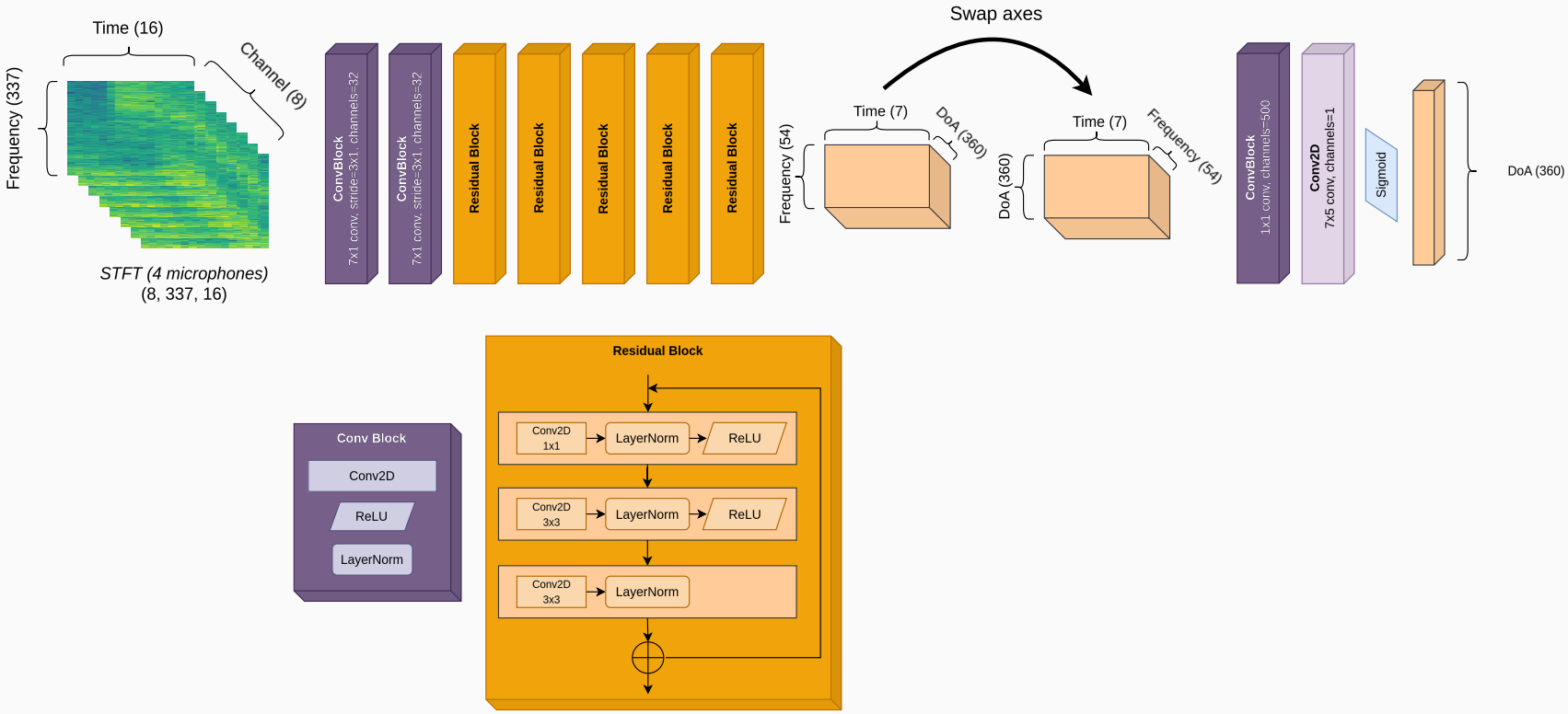
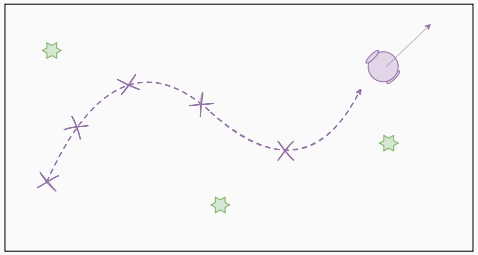


Active sound source localization pipeline



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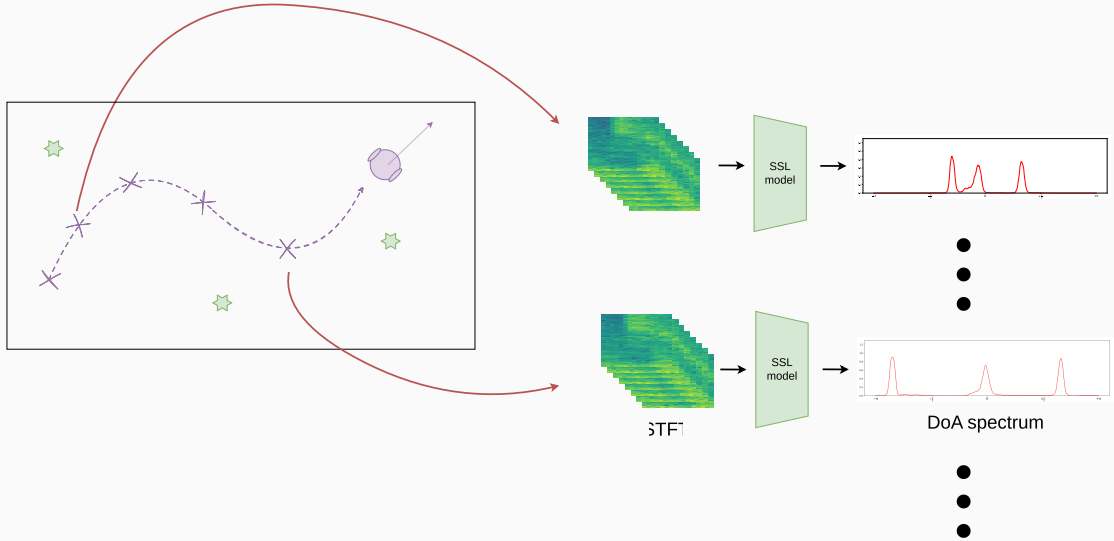

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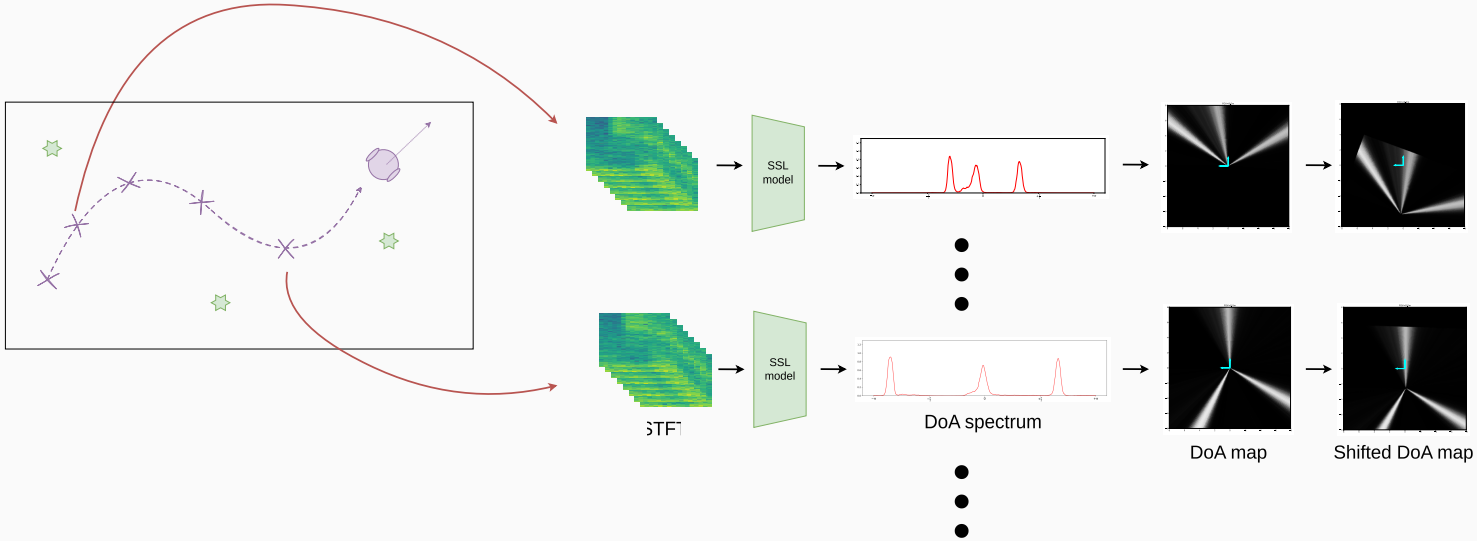

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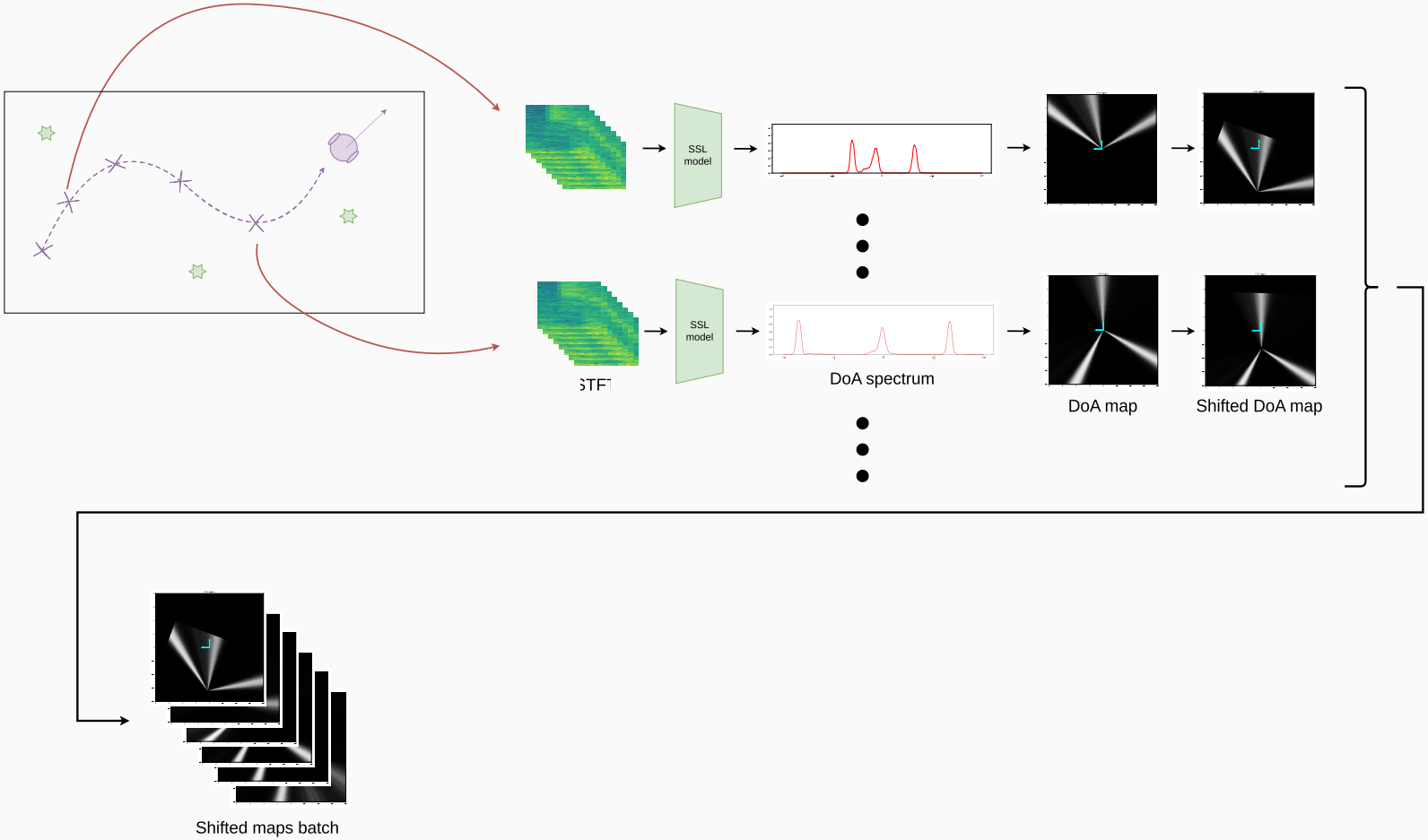

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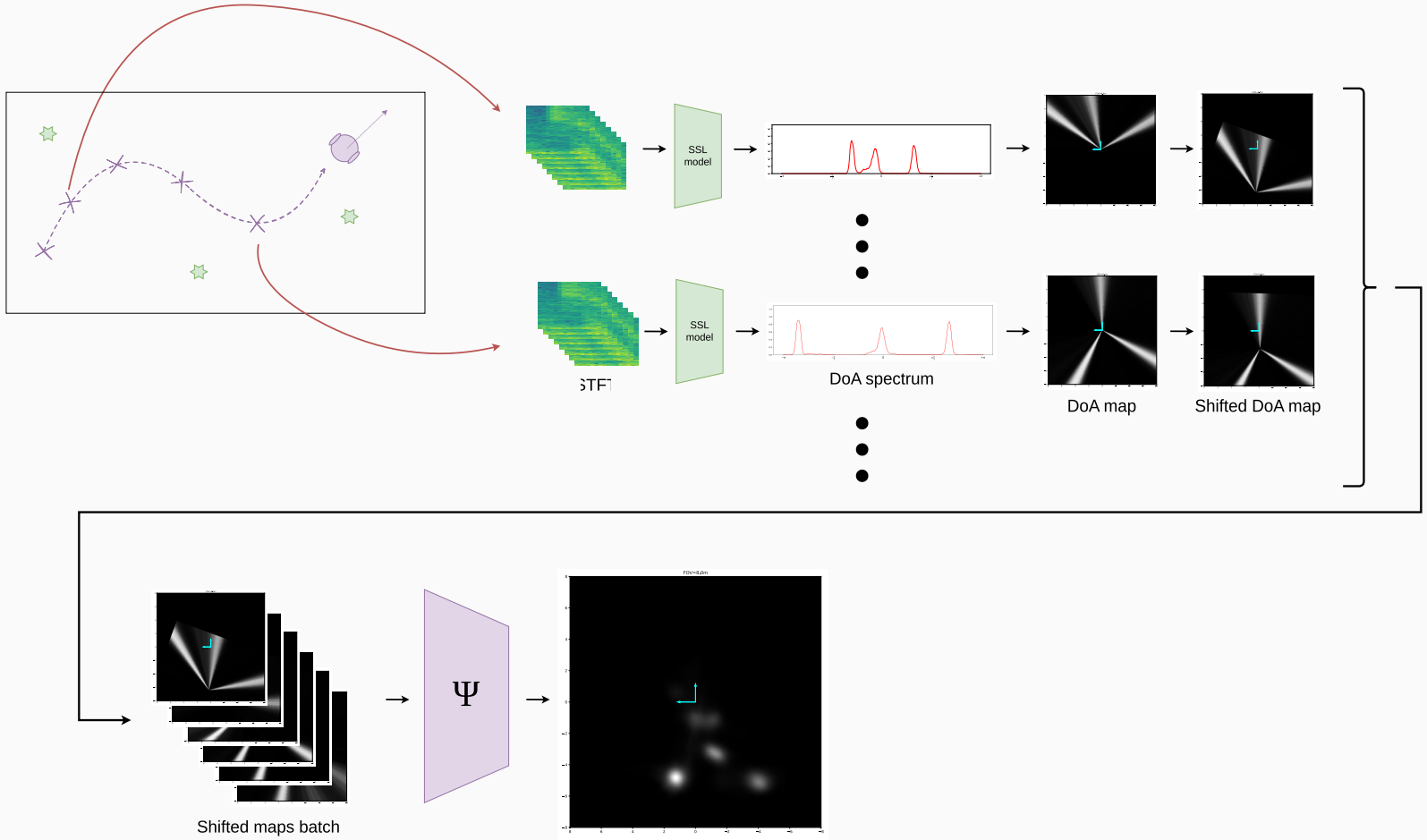

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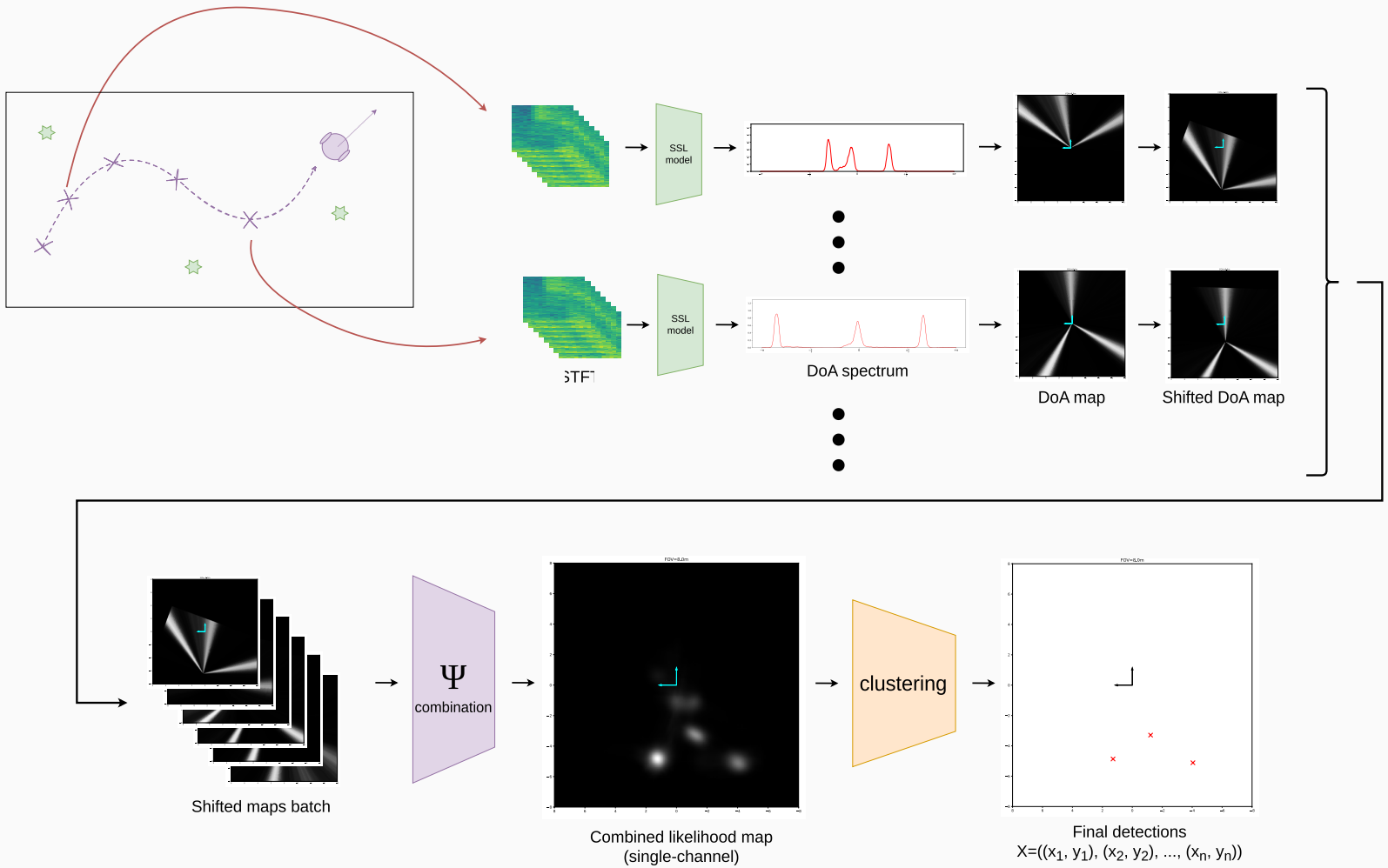

Aggregation strategy

→ **Aggregate shifted maps into a single heatmap**

Aggregation strategy

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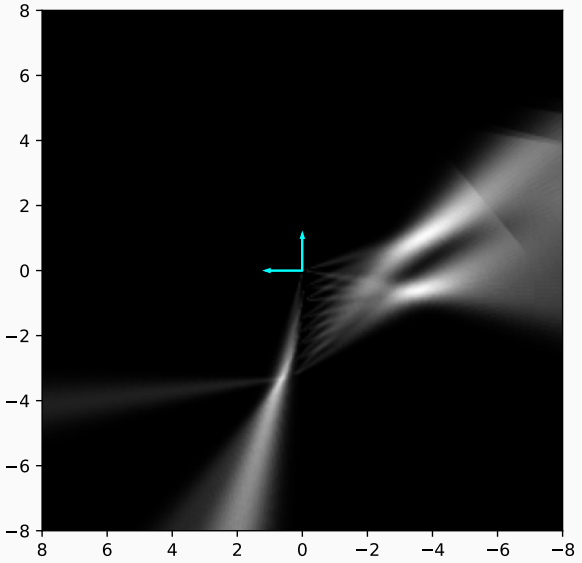
Two methods were explored:

- Averaging:

$$\widehat{M}_t = \frac{1}{H} \sum_{t'=0}^{H-1} M_{t-t'}$$



Averaging

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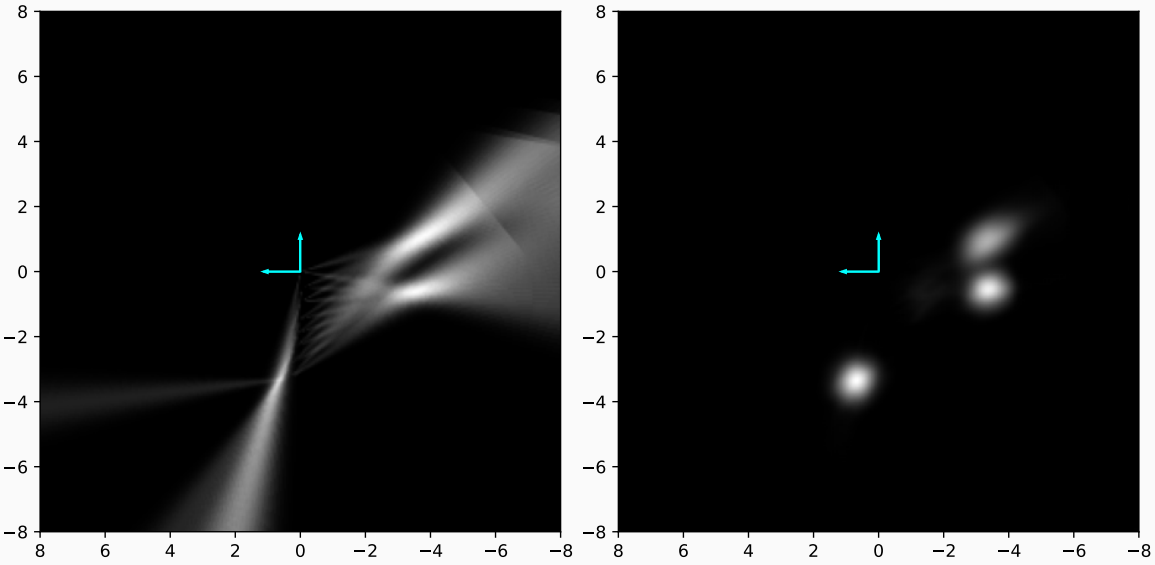
- U-Net [1]:

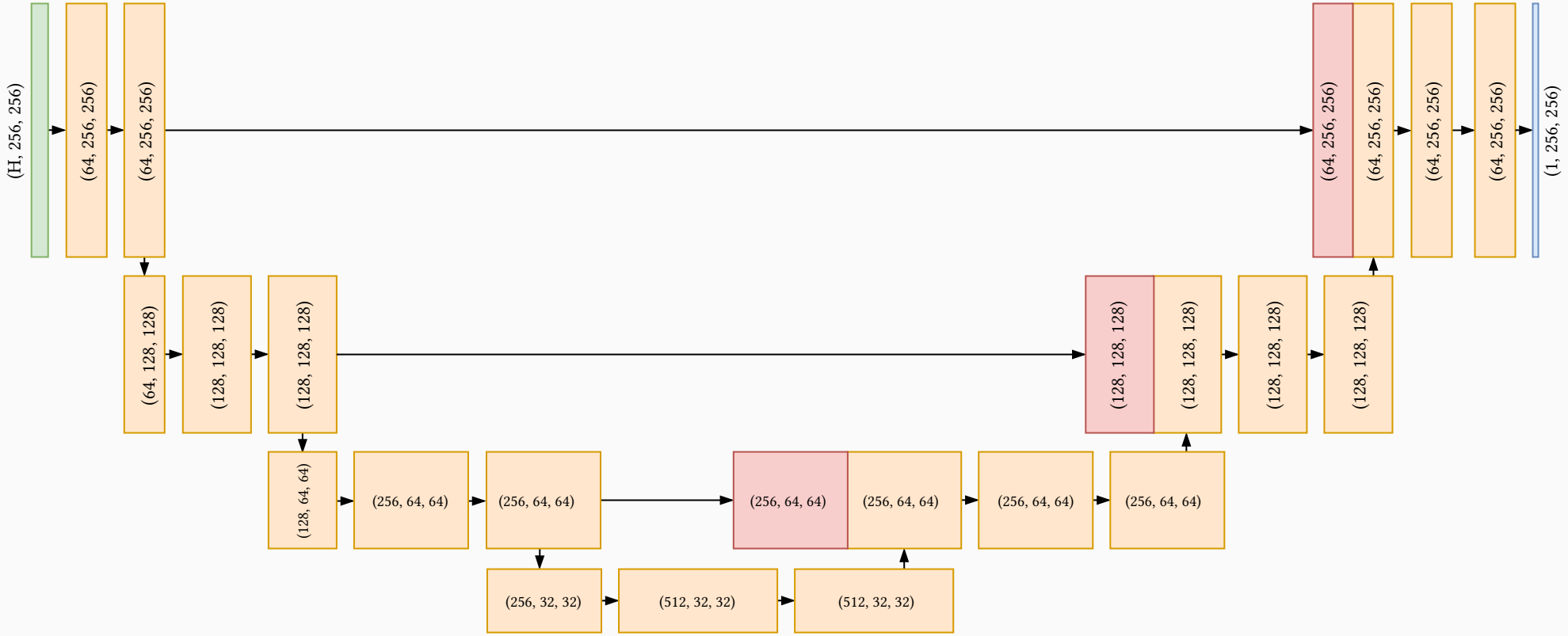
$$\widehat{M}_t = \Psi_{\text{DNN}}(M_{t-H+1}, \ldots, M_t)$$



Averaging DNN

[1] Ronneberger et al., "U-net: Convolutional networks for biomedical image segmentation," in *MICCAI*, 2015.

Neural network-based aggregation



→ **Extract discrete 2D position predictions from the heatmap**

1. Low values are filtered out from the egocentric heatmap (threshold τ)

[1] Schubert et al., "DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN," *ACM Trans. Database Syst.*

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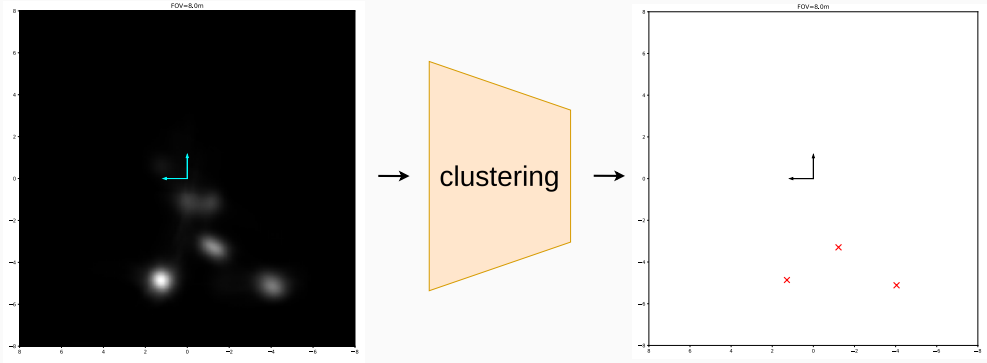
3. The position of the highest-value pixel of each cluster is used as the final detection

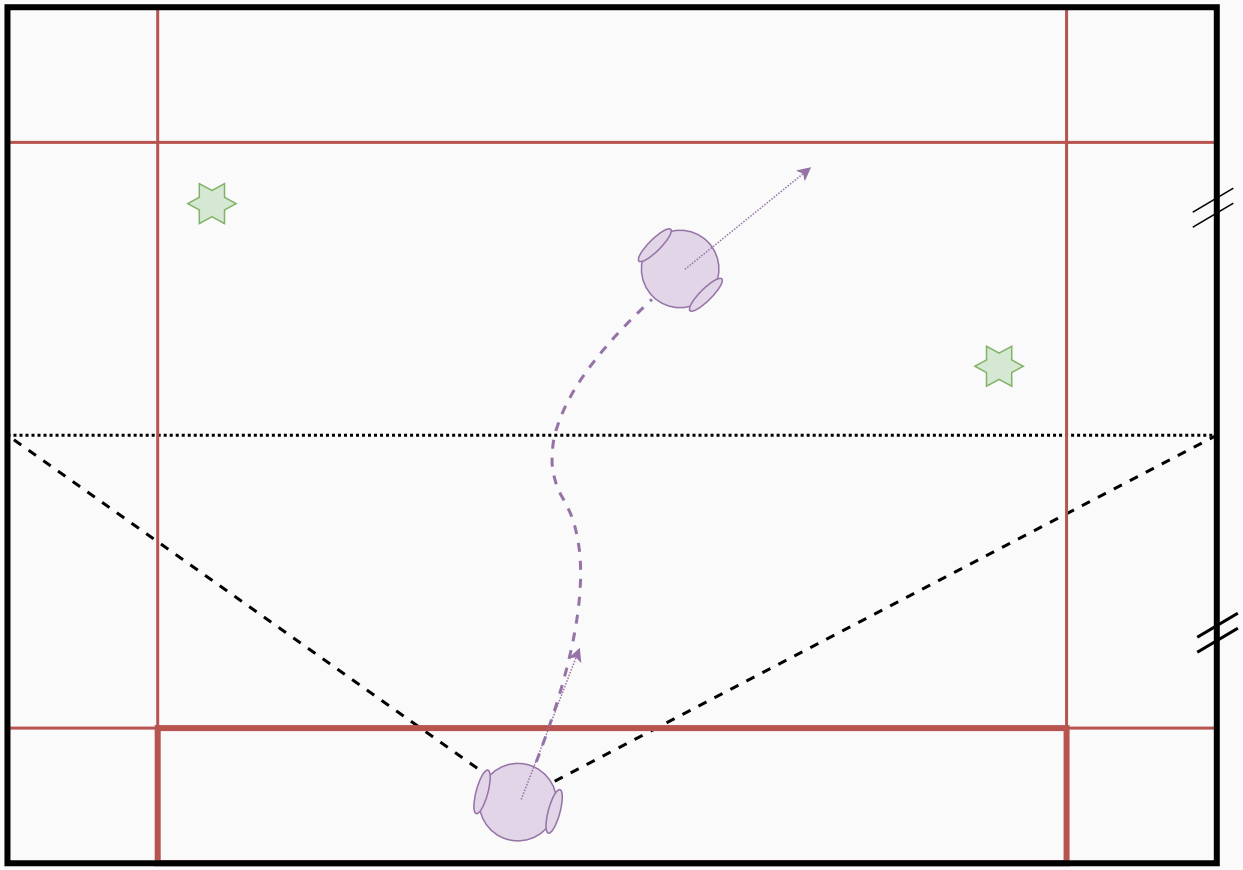


Combined likelihood map (single-channel)

Final detections
$X=((x_1, y_1), (x_2, y_2), ..., (x_n, y_n))$

[1] Schubert et al., "DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN," *ACM Trans. Database Syst.*

Experimental Setup



Starting zone

Other starting/turn-around zones

Speech sources

- Dataset collection:
  - The robot starts close to a wall
  - The orientation is drawn randomly at each step: $\theta_{t+1} \sim \mathcal{N}(\theta_t, \sigma_\theta^2)$
  - The agent moves forward in the new direction by 50cm
  -

Evaluation Metrics

We define a threshold δ for defining correct detections

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1. m counts the number of positive prediction-GT matches

$$m\left(\hat{X}_k^i, X_j^i\right) = \begin{cases} 1 & \text{if } \left\|\hat{X}_{i,k} - X_{i,k}\right\|_2 < \delta \\ & \quad \text{and } k = \underset{k' \in \{1,\ldots,\hat{z}_i\}}{\operatorname{argmin}} \left\|\hat{X}_{i,k'} - X_{i,k'}\right\|_2 \\ 0 & \text{otherwise,} \end{cases}$$

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$$\text{Precision} = \frac{\sum_i \sum_{j=1}^{z_i} \sum_{k=1}^{\hat{z}_i} m\left(\hat{X}_{i,k}, X_{i,k}\right)}{\sum_i \hat{z}_i},$$

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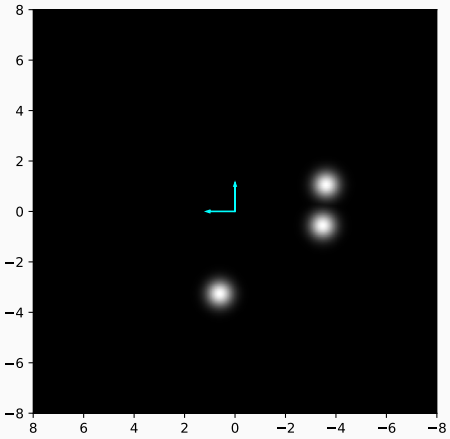
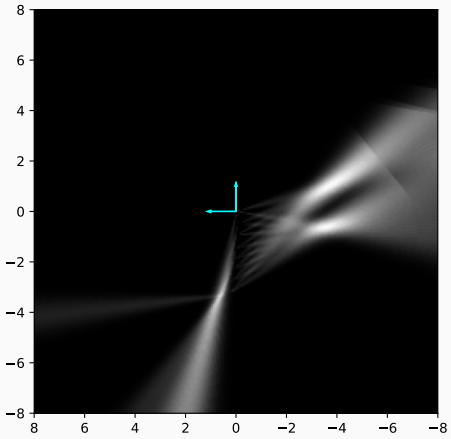
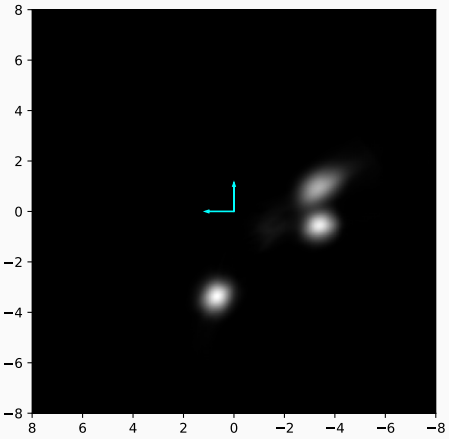
Comparison of Aggregation Methods



Ground truth

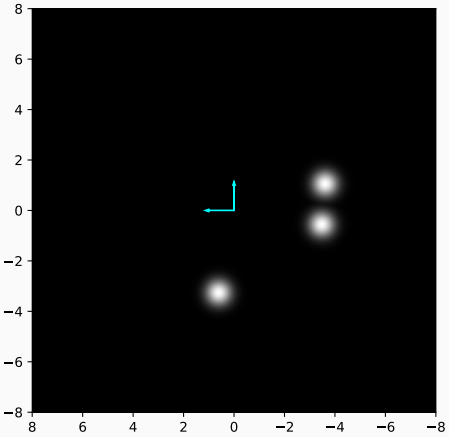


Average



DNN

Comparison of Aggregation Methods



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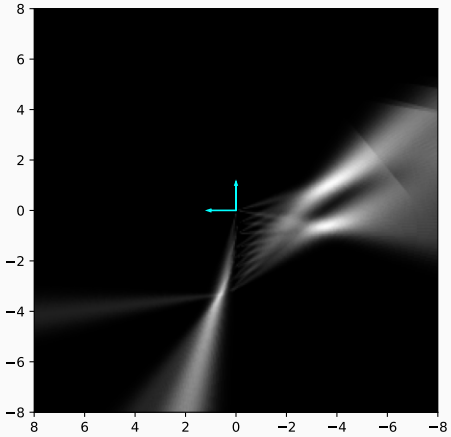

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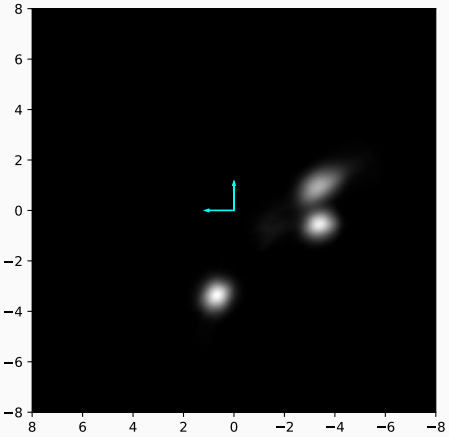

DNN

Aggregation method	Estimated DoA spectrum $\hat{o}_t$		Ground truth DoA spectrum o_t	
	Precision (%) ↑	Recall (%) ↑	Precision (%) ↑	Recall (%) ↑
Average	72.33	46.60	96.02	77.70
$\Psi_{\mathrm{DNN}(\theta)}$	**86.05**	**53.28**	**99.74**	**90.54**

Summary

- Complete pipeline for active multi-source localization
- Training of the static SSL model and the U-Net blender using synthetic datasets generated from our simulator
- Leveraging of a static SSL deep-learning model
- Aggregation of information accross time to build fine 2D position estimates
- Deep U-Net style architecture for combining heatmaps

Plan

1

Acoustic Robot Simulator

Simulate dynamic acoustic environments

2

(Active) Sound Source Localization

Accurately localize speaker(s) in a reverberant room

3

Deep RL for Sound-Based Navigation

Learn to navigate to hear humans better

Motivation & problem statement

Goal: Perceptually motivated navigation [1]

- Robots are expected to *understand* human speech
- *Automatic Speech Recognition (ASR)* is the first step of the speech understanding pipeline
- How can navigation help with improving the robot's ASR performance?

[1] Majumder et al., "Move2hear: Active audio-visual source separation," in *ICCV*, 2021.

Measuring ASR performance

The *Word Error Rate (WER)* measures the ASR performance.

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$$\text{WER} = \frac{s + d + i}{n}$$

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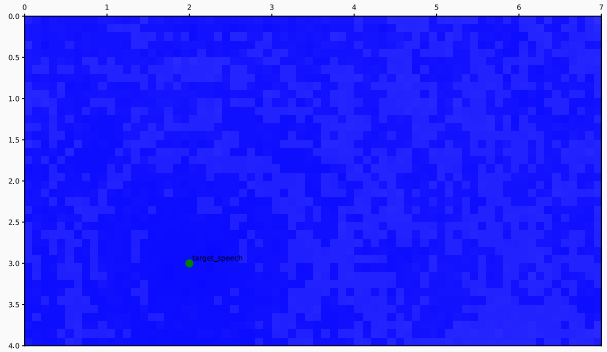
Example:

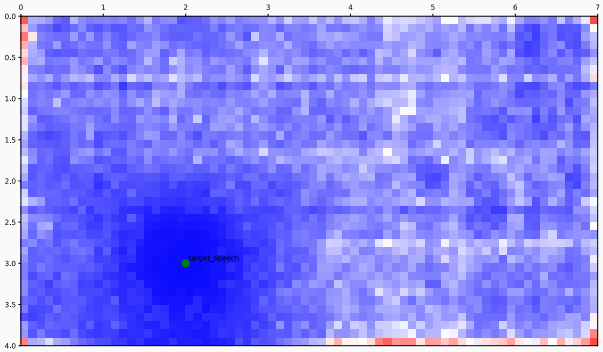
- Reference: *Obviously, he was __ able to catch the last bus on time today.*
- Prediction: *Obviously, he was not able to catch the past bus on time ____ .*

$\text{WER} = \frac{1+1+1}{12} = 0.25$

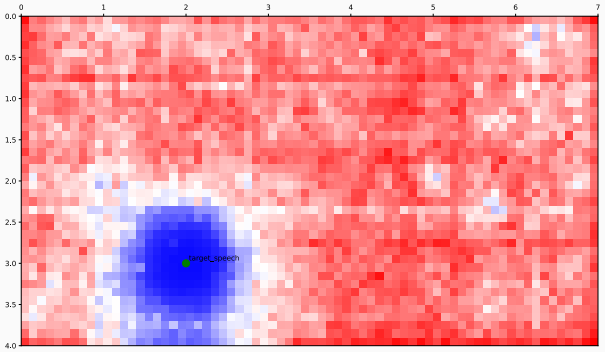
Reverberation impact on WER



(a) $T_{60} = 200\text{ms}$.



(b) $T_{60} = 500\text{ms}$.



(c) $T_{60} = 800\text{ms}$.

- WER increases as reverberation grows
- Robot positioning impacts ASR performance
- Correct positioning matters more as T_{60} increases

Problem statement

Idea: Frame the navigation problem as a sequential decision problem

- At each step, the robot records a short audio snippet;
- Based on this observation, it decides what its next move should be;
- The environment rewards the robot based on a WER estimate for its current position;

$\rightarrow$ Reinforcement learning is very well suited to this problem.

Reinforcement Learning

RL solves sequential decision problems, formalized as **Markov Decision Processes (MDPs)**.

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At each step:

- The agent senses the environment by observing the state $s_t \in \mathcal{S}$
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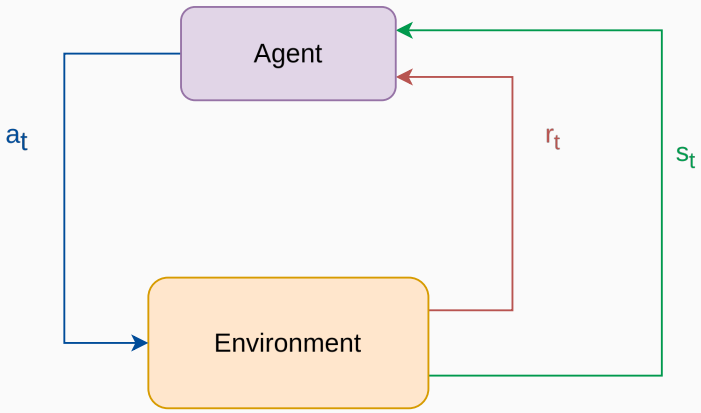

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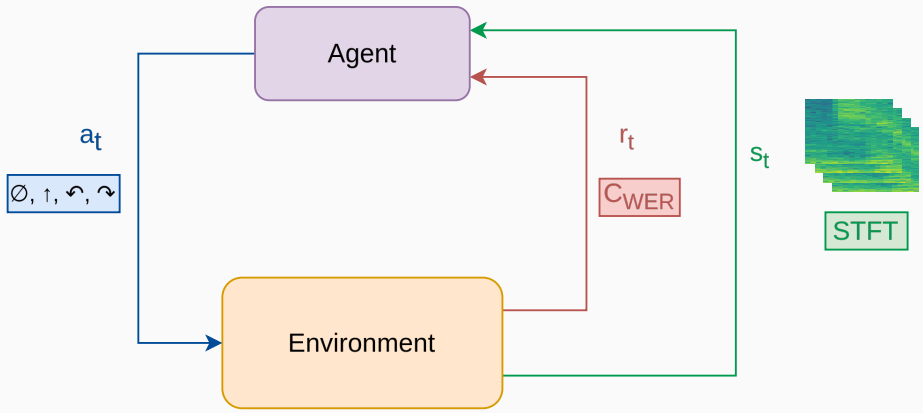


Our environment:

- the reward is a decreasing function of the WER:

$$r_t = \begin{cases} \mu_W & \text{if the agent tries to hit a wall} \\ \mu_C \exp(-\xi_C) - \mu_m \mathbb{1}(a_t = \text{`FORWARD`}) & \text{otherwise,} \end{cases}$$

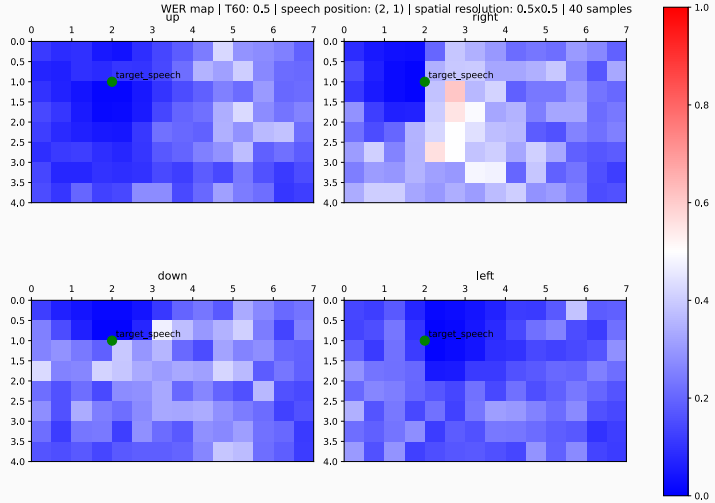
WER Cost Maps

- The cost of a state requires an estimate of the average WER for this position;
- The WER cost maps can be either **directional** or **omnidirectional**;

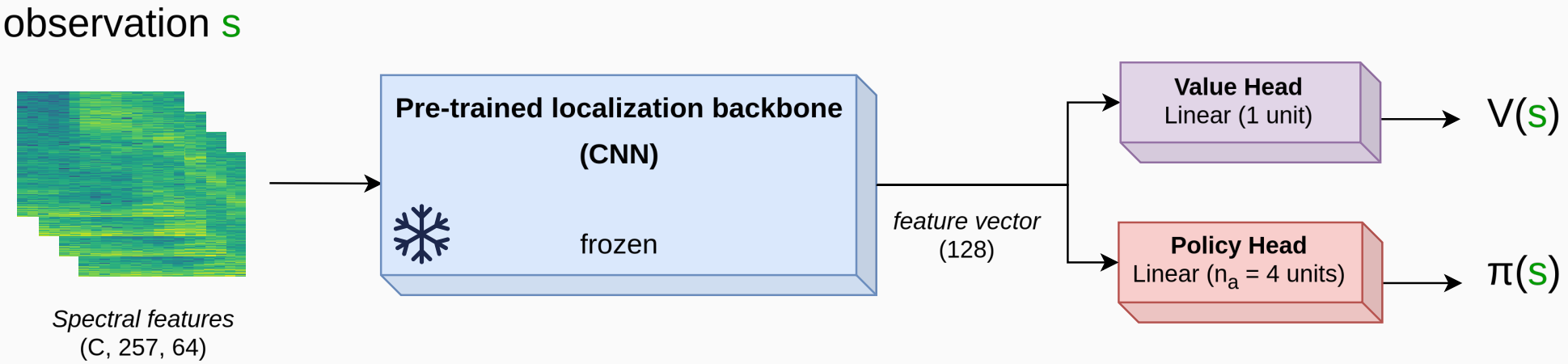
Problem: WER can't be computed at the environment run-time.

$\rightarrow$ Pre-compute statistical estimates of the theoretical WER cost of a state.

$$C_{\mathrm{WER}}(\boldsymbol{x}_a, \alpha_a) = \mathbb{E}_{(v,t)\in\mathcal{D}}\left[\frac{1}{100}\,\mathrm{WER}\left(\underbrace{\mathrm{ASR}_\psi\left[\mathrm{listened}(v, \boldsymbol{x}_a, \alpha_a, \boldsymbol{x}_s)\right]}_{\text{predicted transcript } \hat{t}}, t\right)\right]$$



Agent 1rchitecture

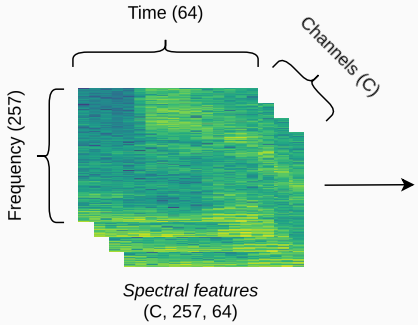


Two-stage training:

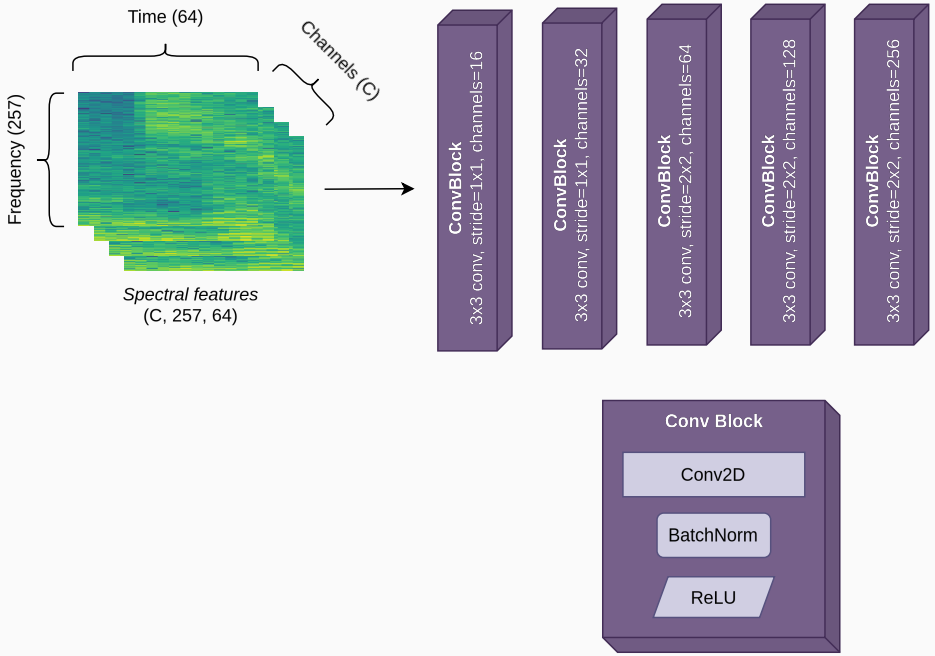
1. Train the backbone on a supervised single-source localization task
2. Train the value and policy heads with PPO [1]

[1] Schulman et al., "Proximal policy optimization algorithms," *arXiv preprint*, 2017.

SSL Backbone Architecture



SSL Backbone Architecture



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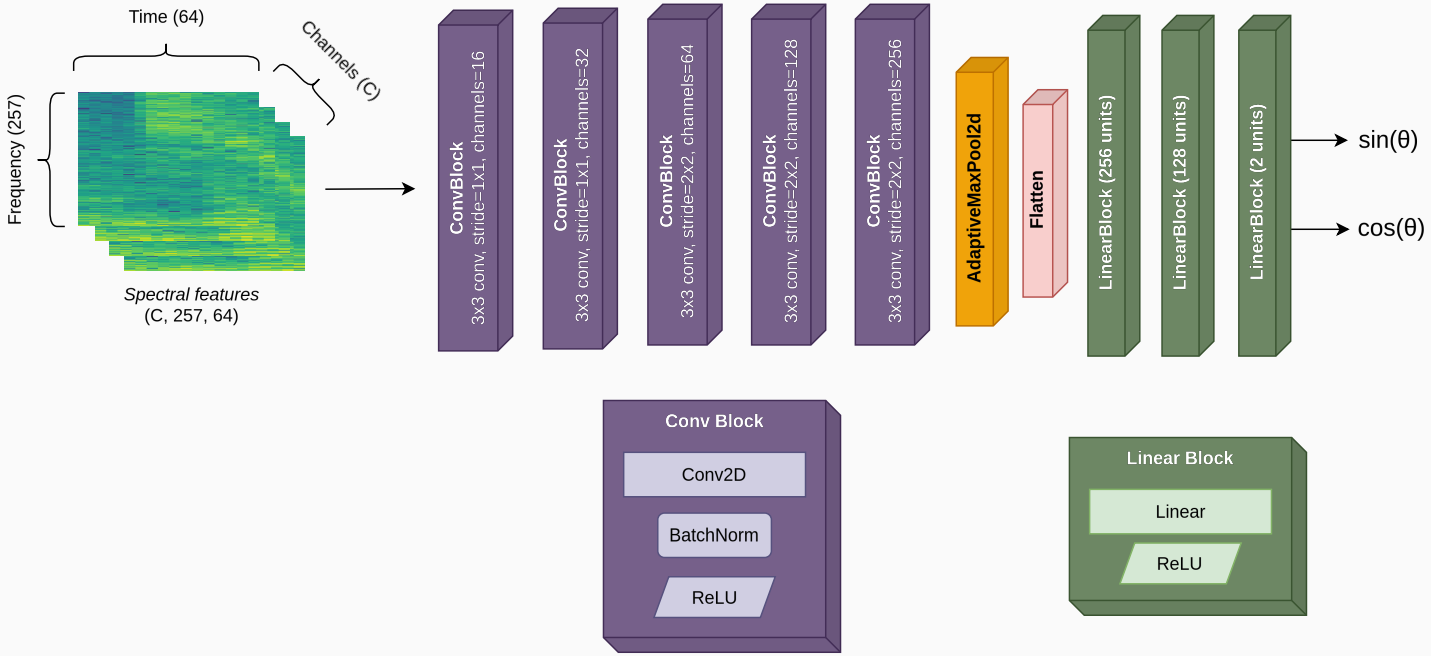

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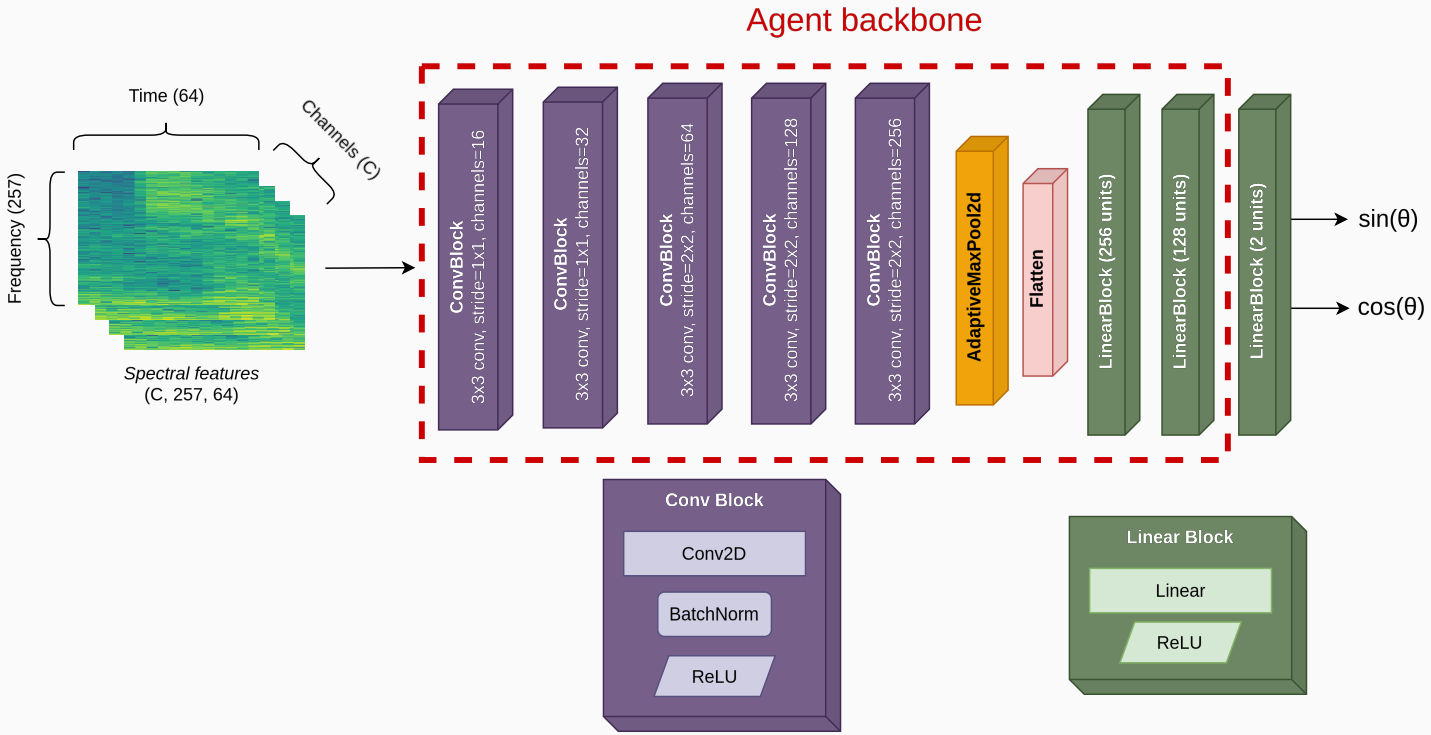

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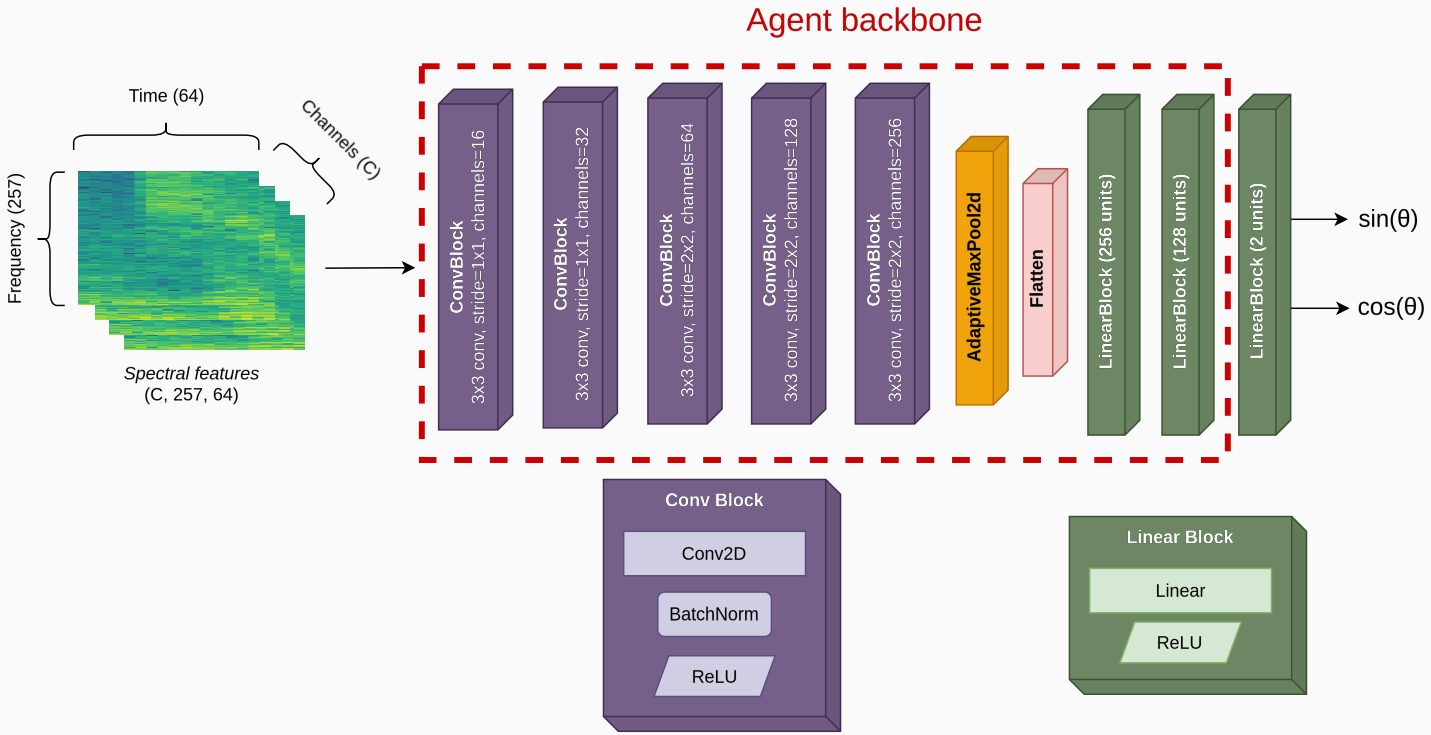
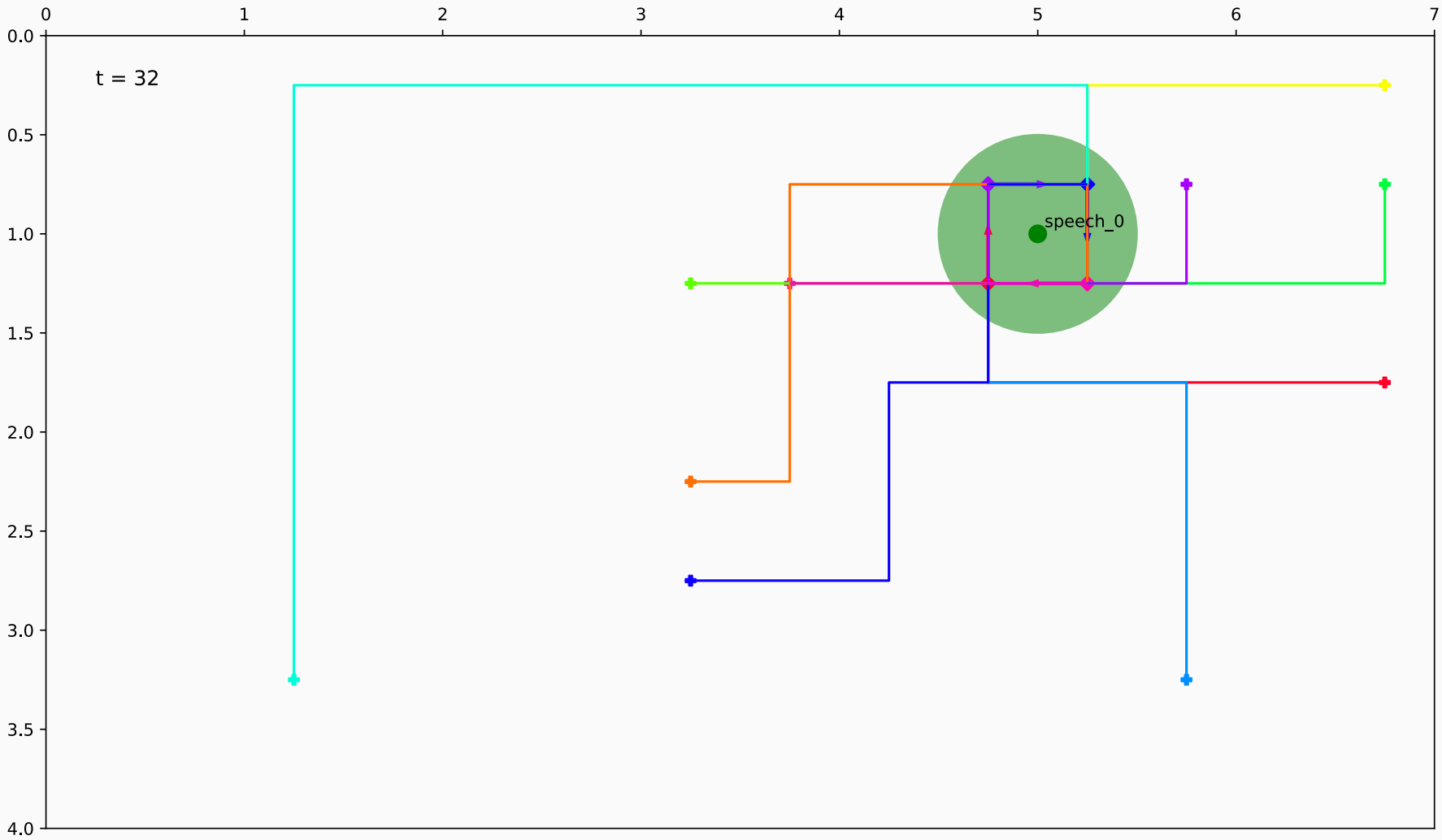


Training loss:

$$\mathcal{L}_{\mathrm{DoA}\left(\hat{\theta},\theta\right)} = 1 - \left(\sin(\theta)\sin\left(\hat{\theta}\right) + \cos(\theta)\cos\left(\hat{\theta}\right)\right)$$

Agent Trajectories



Metrics

Undiscounted cumulated reward:

$$\bar{R} = \frac{1}{n_{\text{ep}}} \sum_{i=1}^{n_{\text{ep}}} \sum_{t=1}^{T} r_{i,t}$$

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Results

Policy	Omnidirectional cost		Directional cost	
	$\bar{R} \uparrow$	$\hat{C}_F$ (%) $\downarrow$	$\bar{R} \uparrow$	$\hat{C}_F$ (%) $\downarrow$
π_{still}	1481	21.13	1512	21.37
π_{random}	−25	21.16	−22	22.2
$\pi_{\text{safe random}}$	1420	20.99	1408	22.38
π_{orient}	1495	20.87	1789	16.56
π_θ	**2432**	**4.18**	**2302**	**8.01**

Summary

- Definition of a novel **perceptually-motivated navigation task**
- Improving the **ASR performance** by position optimization
- Implementation of a complete Gym-compatible [1] environment from our simulator
- Training of a **Deep RL agent** that successfully solves the task

[1] Brockmana et al., "Openai gym," *arXiv preprint*, 2016.

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2. Extensive experimental studies of deep-learning-based methods solving two variations of the **static SSL** problem.
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4. Introduction of a perceptually-motivated robotic navigation task.
   Training and evaluation of Deep-RL agent solving this task.

Main Limitations

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  Targetting more challenging and realistic problem formulations would improve the overall relevance of the proposed methods.
- **Engineering and algorithmic challenges:**
  - The RL agent's training is expensive, and tedious. Numerous engineering considerations are required to ensure a successful policy learning.
  - Relying on pre-computed WER cost maps allows the RL environment to run at a high refresh rate, but doesn't easily scale to multiple moving sources.

Perspectives

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  - Combine auditory signals with visual cues to leverage social robots' sensors diversity.
- **Active perception beyond localization:**
  - Explore other navigation objectives: speaker-following, audio-based exploration, information-seeking policy, etc.
- **Model efficiency and generalization:**
  - Investigate RL agents' lack of generalization.
  - Solve more diverse and challenging MDPs (changing room geometries, moving sources, noisy conditions, etc.)

Thank you!