

Modality-agnostic topology aware Localization

Farhad G. Zanjani, Ilia Karmanov, Hanno Ackerman, Daniel Dijkman, Simon Merlin,
Max Welling, Fatih Porikli

Qualcomm AI Research

Indoor Localization Problem

Camera-based system

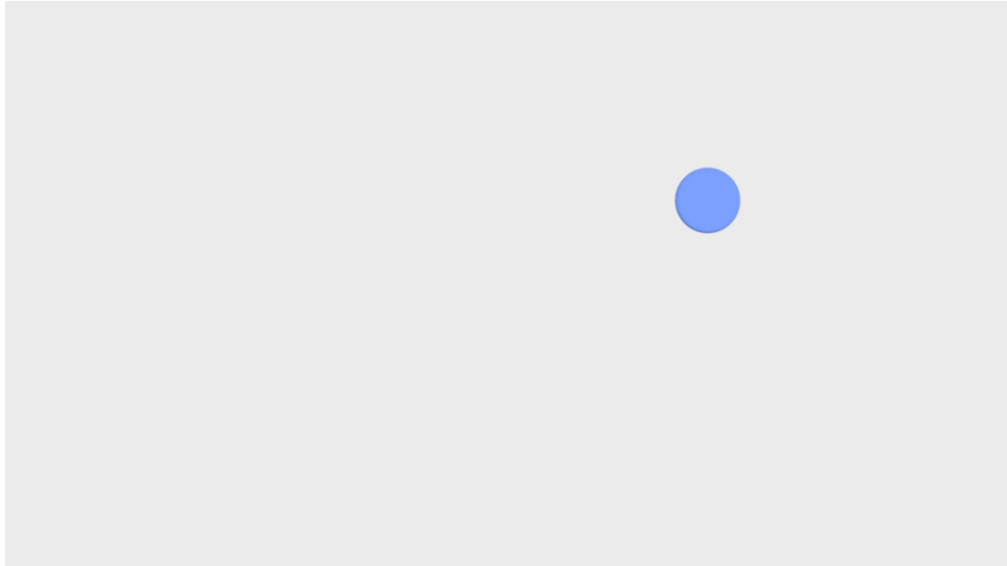


<http://svl.stanford.edu/igibson/>

Localizing a person on the 2D map of a building

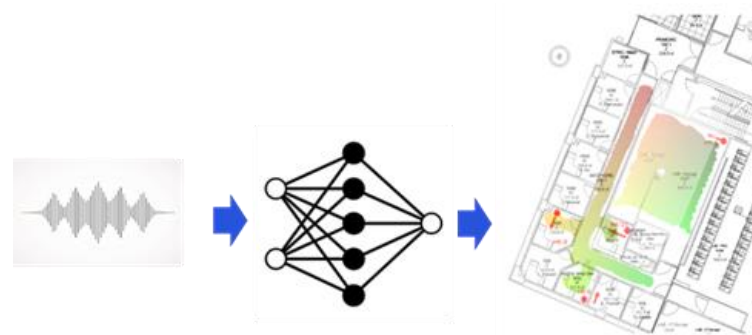
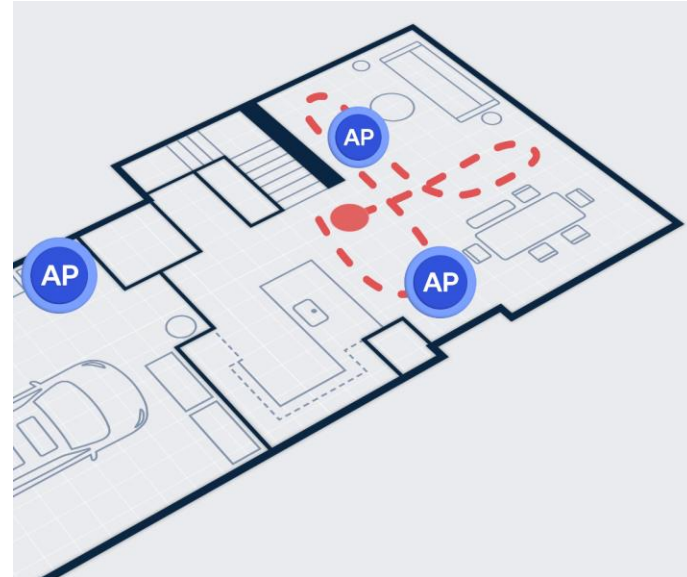


Indoor localization using RF signals (e.g. WiFi)



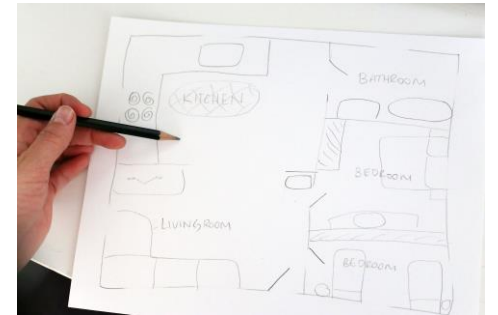
Play Video

WiFi sensing



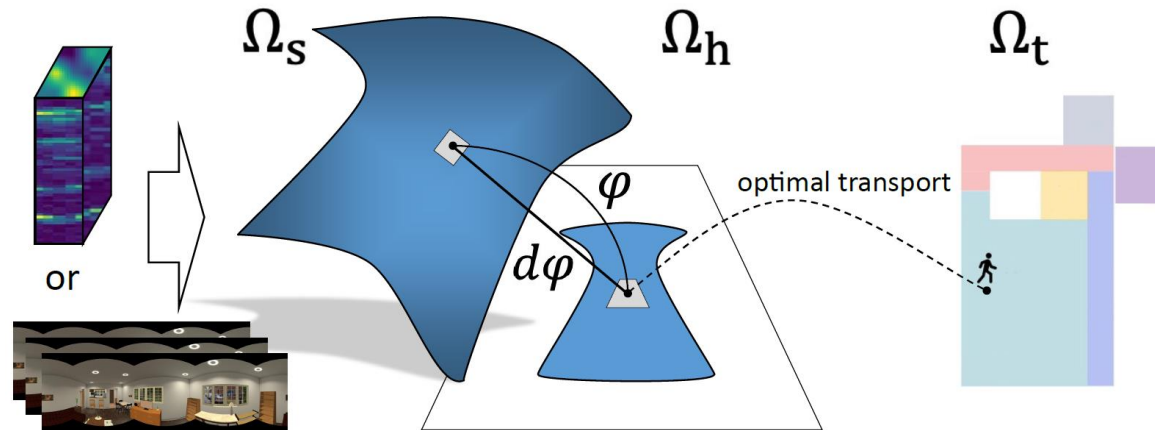
Assumptions

- Sequential data was recorded when the subject visited different locations in the environment
- The 2D/3D map of the environment is given
- The training set includes the (zone-) room-level labels



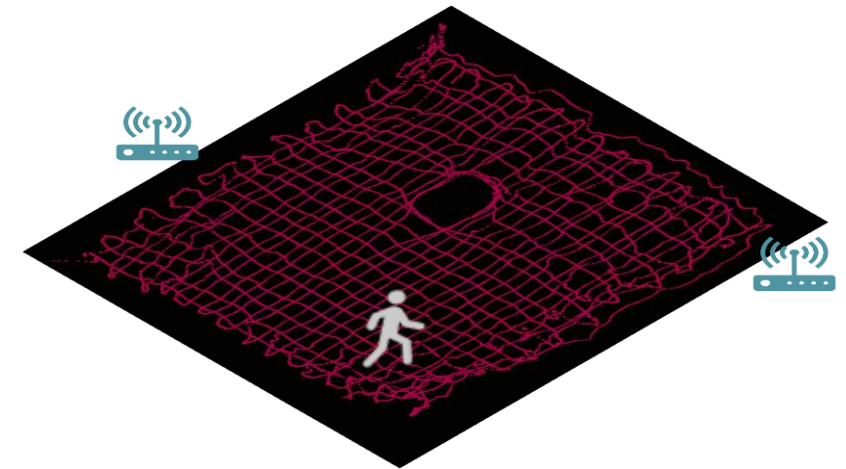
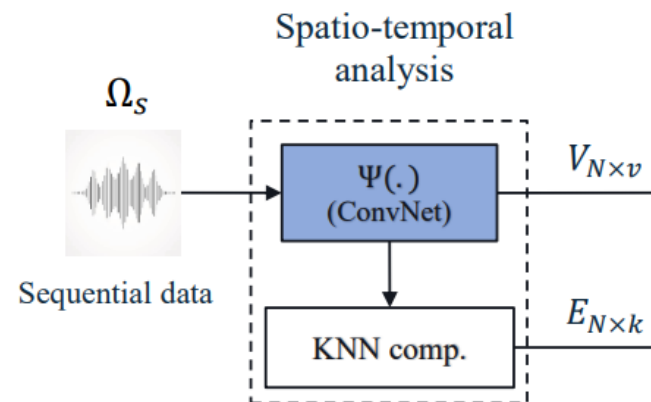
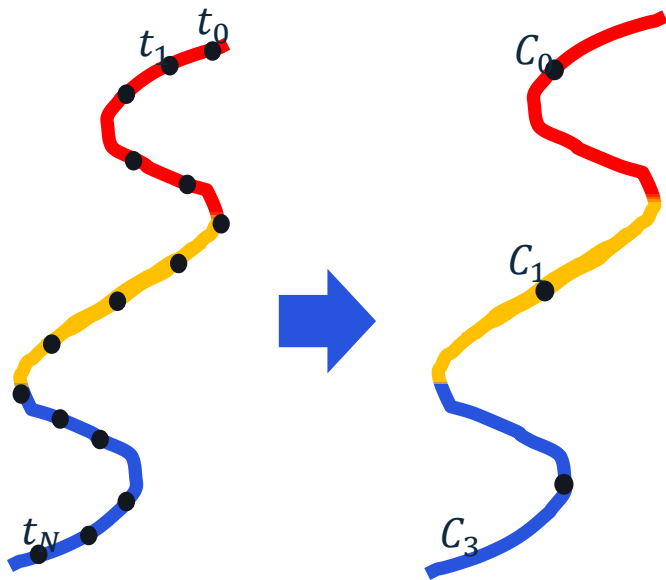
Overview of the proposed method

- Estimating the geodesic distances between samples on the data manifold in input space (Ω_s)
- Training a neural network (φ) to map the input samples into their 2D intrinsic space (Ω_h)
- Transporting the 2D representation into the floorplan (Ω_t)



Spatio-temporal analysis

- Estimating the geodesic distances by computing the shortest path on the KNN graph
- Detecting the KNN samples by minimizing the triplet margin loss



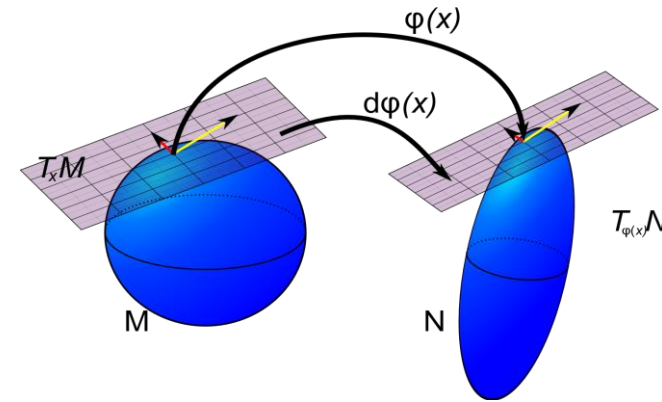
$$\mathcal{L}(x_i^a, x_i^p, x_i^n) = \max\left(0, d(h_i^a, h_i^p) - d(h_i^a, h_i^n) + \alpha\right) \quad \text{where } h_i = \Psi(x_i).$$

Isometric embedding

Estimating the pushforward around each vertex in the graph

$$\varphi: \mathbb{R}^m \rightarrow \mathbb{R}^n, \quad m > n$$

$$d\varphi: T_x M \rightarrow T_{\varphi(x)} N, \quad \mathcal{M}(y_i) = \left[\frac{d\varphi}{dx}(x_i) \frac{d\varphi}{dx}(x_i)^T \right]^\dagger$$

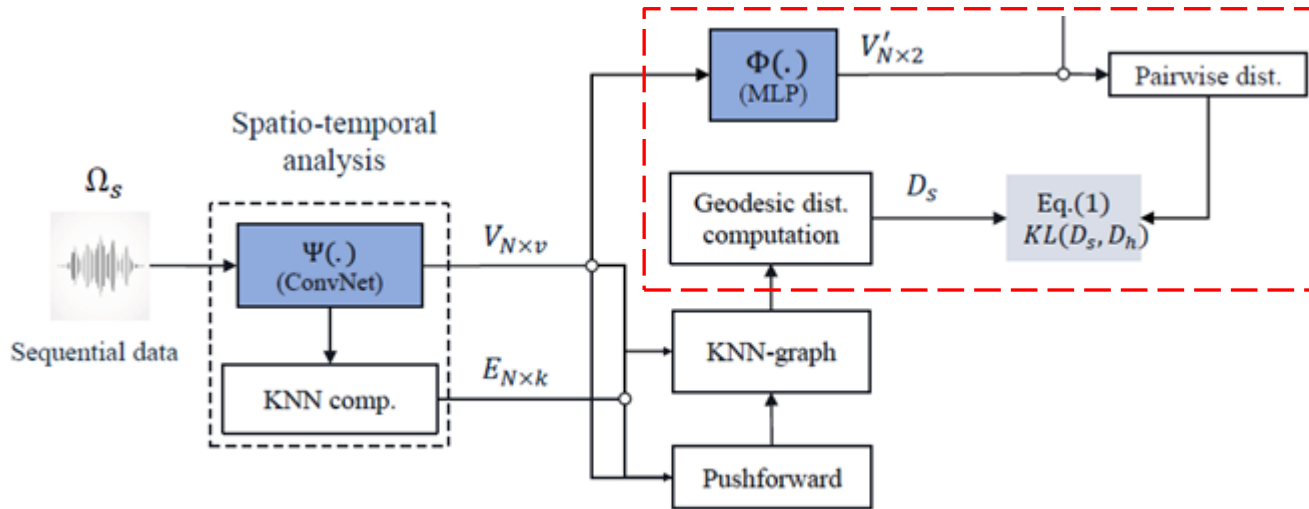


The pushforward at the location of each sample is proportional to the covariance matrix of a Gaussian distribution, centered at that sample [Dsilva et al. 2015]

$$\|\Phi(x_i) - \Phi(x_j)\|^2 \approx \frac{1}{2} [x_j - x_i]^\top \cdot [C^\dagger(x_i) + C^\dagger(x_j)] \cdot [x_j - x_i]$$

Learning the isometric embedding

- Training a neural network (Φ) to map the input samples into their 2D intrinsic space (Ω_h)

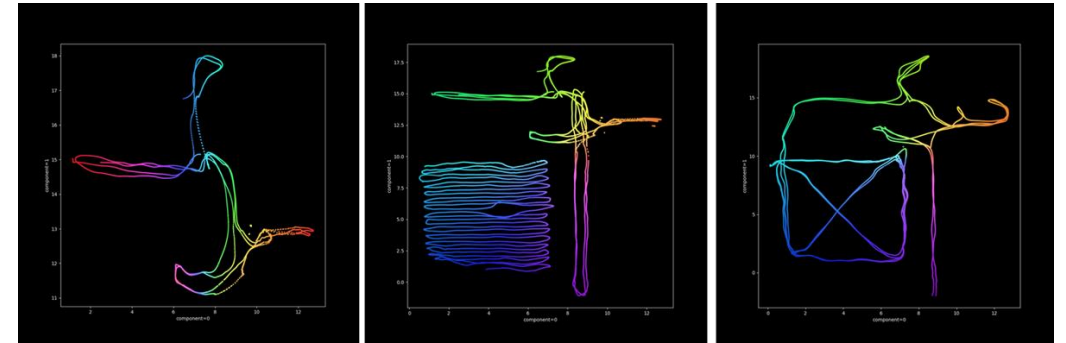


$$\min_{\Phi} D_{KL}(D_s || D_h), \quad \text{where } D_s, D_h \in \mathbb{R}^{N_s \times N_s}$$

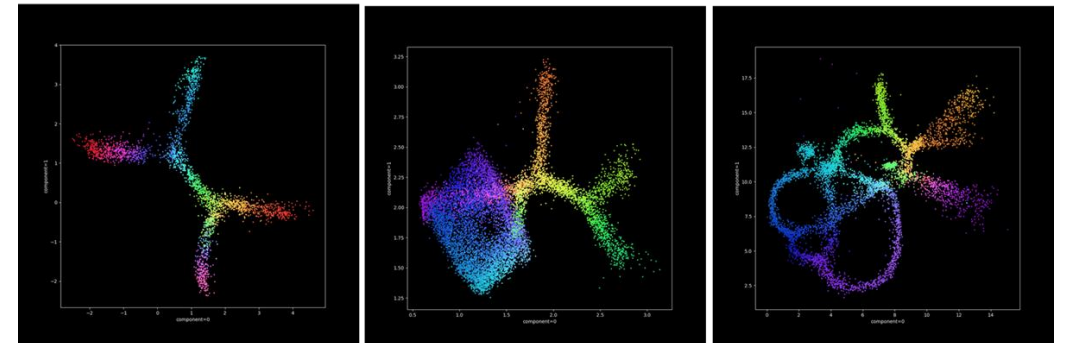
D_s : Geodesic distance matrix of samples in \mathbb{R}^M

D_h : Euclidean distance matrix of samples in \mathbb{R}^2

Ground truth

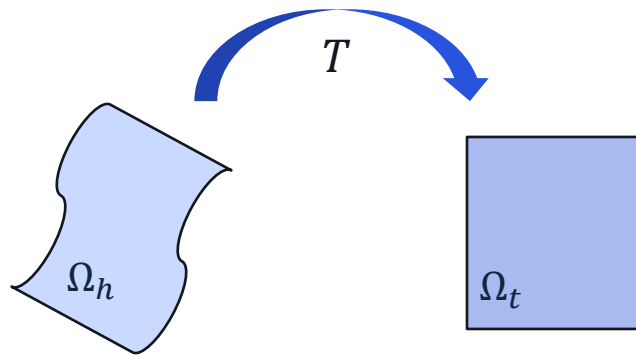


Intrinsic embedding



Discrete Optimal Transportation using Sinkhorn Distance

- Optimal transportation is used for solving the correspondence problem between the intrinsic space and the given topological map



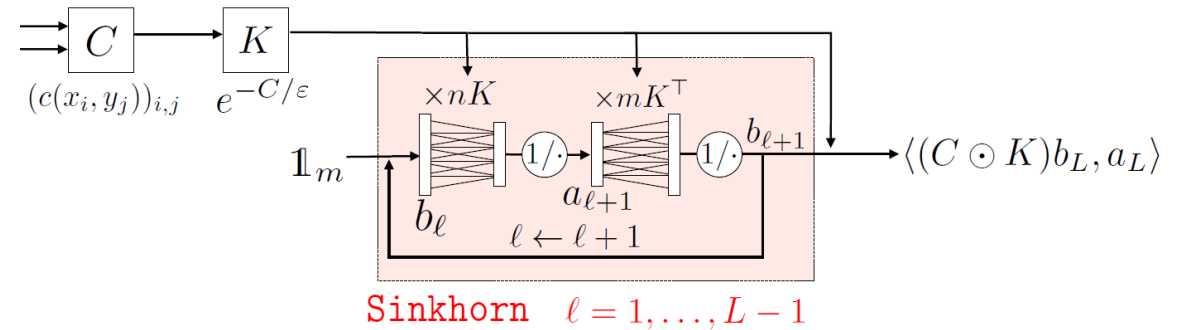
$$T(C, p, q) = \underset{T \in \gamma(p, q)}{\operatorname{argmin}} \langle T, C \rangle - \frac{1}{\lambda} H(T)$$

Fixed-point Sinkhorn iterations:

$$T(C, p, q) = \operatorname{diag}(a) K \operatorname{diag}(b)$$

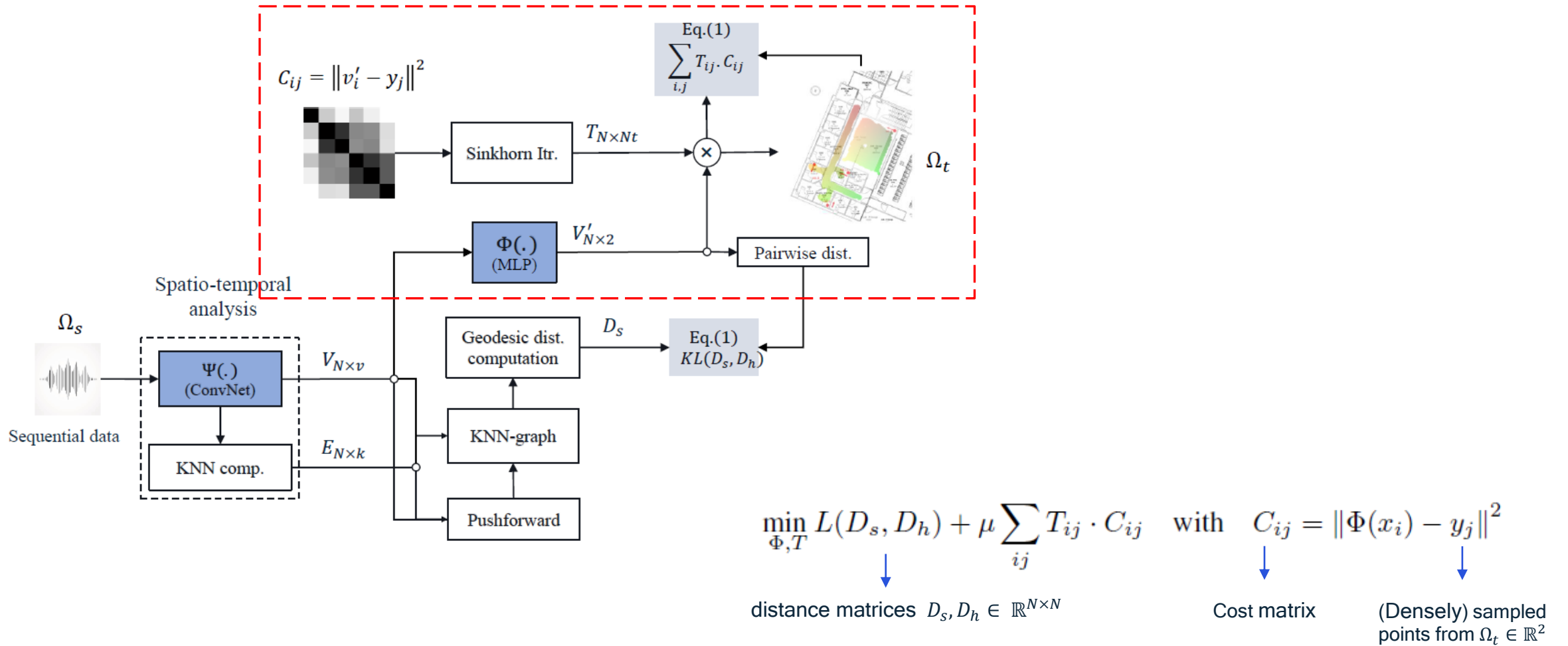
$$K = e^{-\lambda C} \in \mathbb{R}_+^{N_s \times N_t}$$

$$a \leftarrow \frac{p}{Kb} \quad \text{and} \quad b \leftarrow \frac{q}{K^\top a}$$



Sinkhorn divergence layer [Genevay et al., 2017]

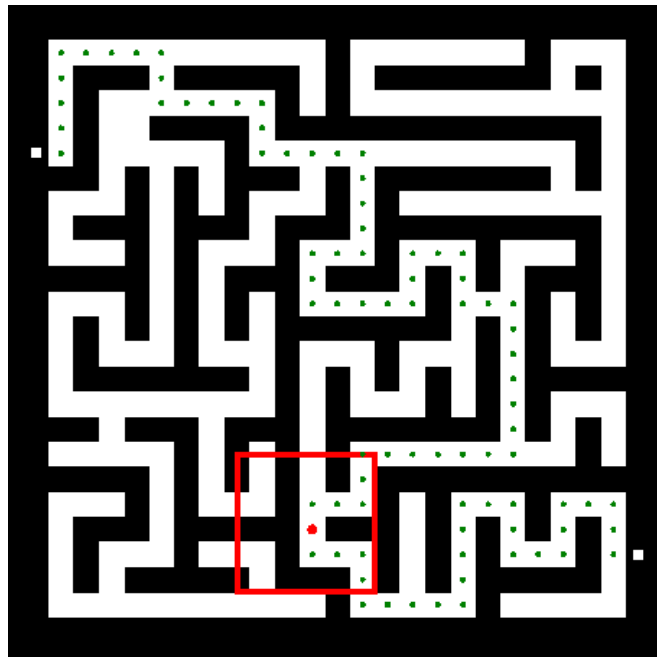
Jointly learning the embedding and transportation



Experiments

- Walking through a synthetic 2D Maze environment

Example of a trajectory

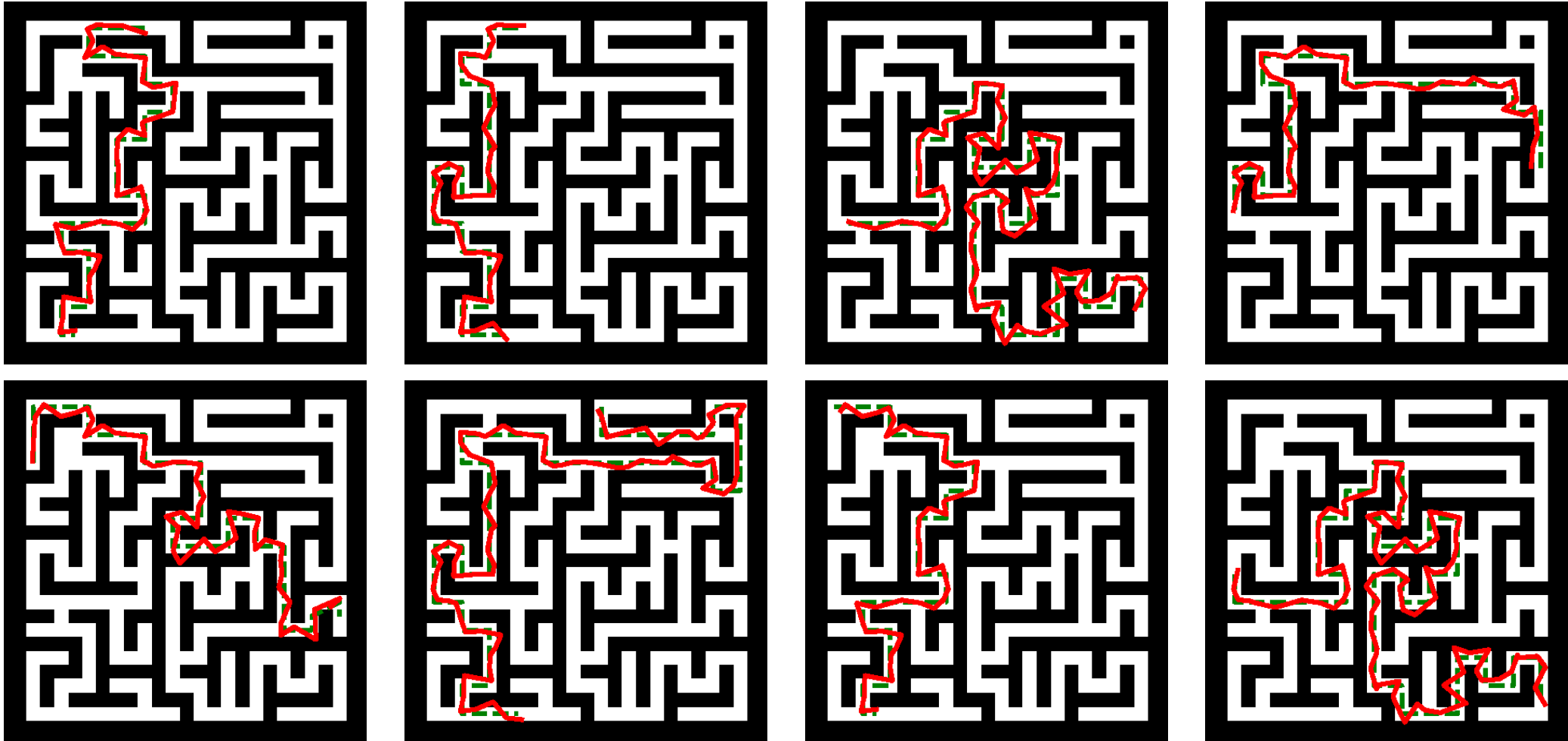


Sampled patches



Experiments

- Synthetic 2D Maze environment



Experiments

- Camera-based localization

iGibson 3D dataset



<http://svl.stanford.edu/igibson/>



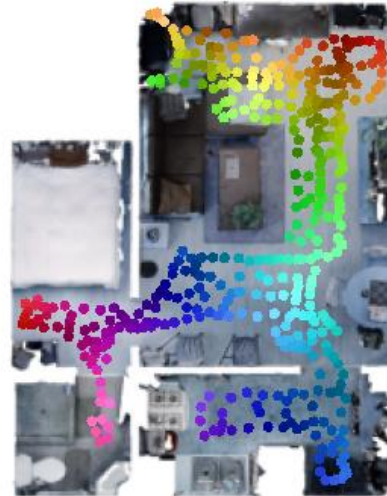
Experiments

- Camera-based localization

	Environments														
index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
ϵ	0.62	1.05	0.73	0.64	0.69	0.83	1.02	1.03	0.73	0.62	0.74	0.71	0.98	1.04	1.14



Embedding representation



Ground-truth positions



Test trajectory



prediction

Experiments

- Altering object appearance in the environment

Demo of iGibson dataset



<http://svl.stanford.edu/igibson/>

Mean and standard deviation of error

Rate	Perturbation rate					
	0%	10%	20%	30%	50%	70%
Mean of error	61.9	61.87 ± 0.09	62.2 ± 0.09	62.82 ± 0.17	63.77 ± 0.14	64.07 ± 0.26

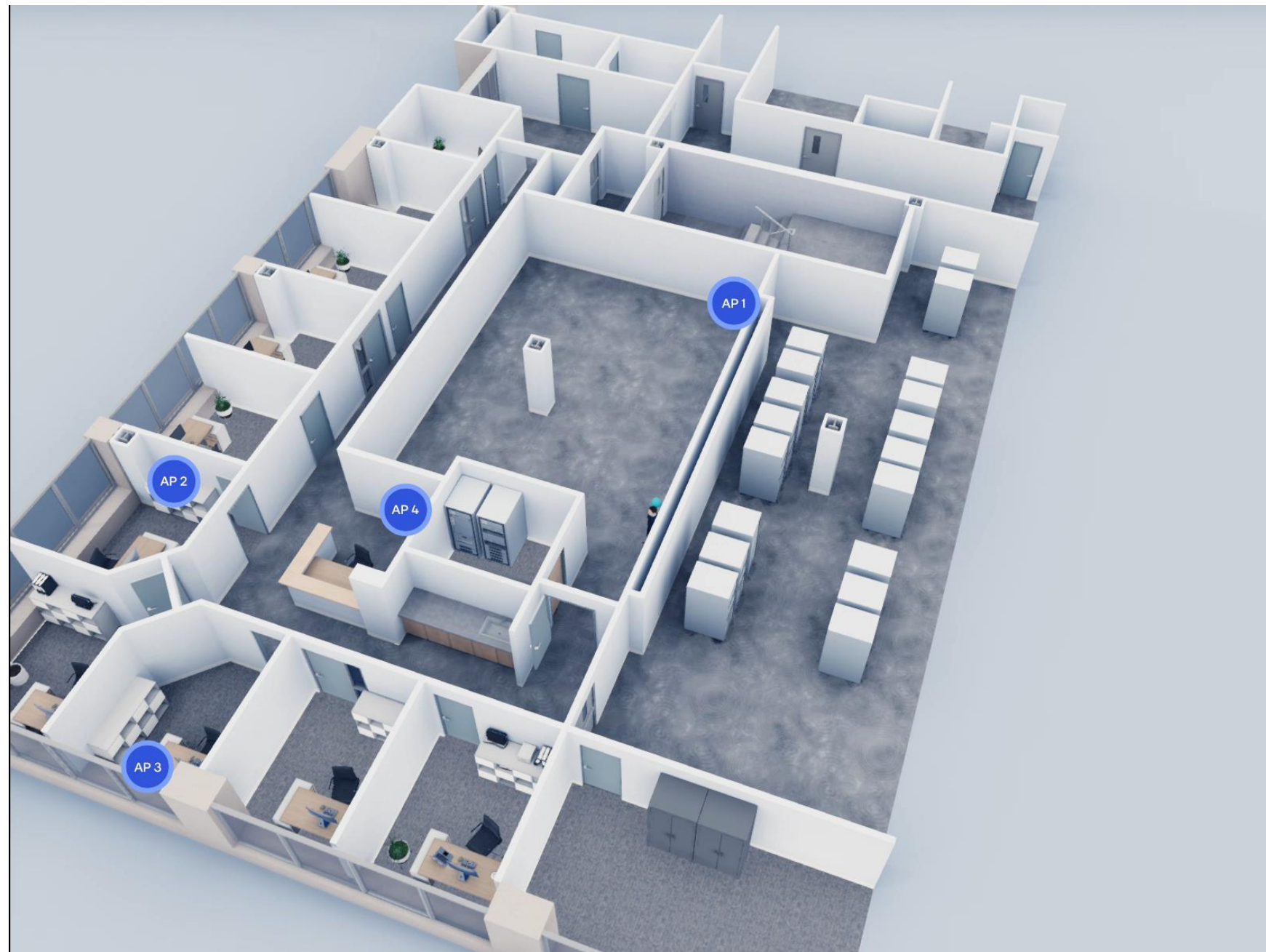
Training



Test

Experiments

- Localization in WiFi
- Commercial IEEE 802.11 access points (AP), 5GHz band
- Size of sensing environment 14×20 meters
- Mean error: 1.2 m







Summary

- We present a learning method for localization problem
- The proposed method is based on parametric manifold learning and optimal transportation
- Our method does not require the 2D coordinates of the moving target during training
- The proposed method does not make any assumption about the data modality in use and in that sense, it is modality agnostic and can be applied on a large family of sensory system.



Thank you

Follow us on:    

For more information, visit us at:

www.qualcomm.com & www.qualcomm.com/blog

All data and information contained in or disclosed by this document is confidential and proprietary information of Qualcomm Technologies, Inc. and/or its affiliated companies and all rights therein are expressly reserved. By accepting this material the recipient agrees that this material and the information contained therein will not be used, copied, reproduced in whole or in part, nor its contents revealed in any manner to others without the express written permission of Qualcomm Technologies, Inc. Nothing in these materials is an offer to sell any of the components or devices referenced herein.

©2018-2021 Qualcomm Technologies, Inc. and/or its affiliated companies. All Rights Reserved.

Qualcomm is a trademark of Qualcomm Incorporated, registered in the United States and other countries. Other products and brand names may be trademarks or registered trademarks of their respective owners.

References in this presentation to "Qualcomm" may mean Qualcomm Incorporated, Qualcomm Technologies, Inc., and/or other subsidiaries or business units within the Qualcomm corporate structure, as applicable. Qualcomm Incorporated includes our licensing business, QTL, and the vast majority of our patent portfolio. Qualcomm Technologies, Inc., a subsidiary of Qualcomm Incorporated, operates, along with its subsidiaries, substantially all of our engineering, research and development functions, and substantially all of our products and services businesses, including our QCT semiconductor business.