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Channel Estimation via Loss Field (CELF) for Shadowing Prediction

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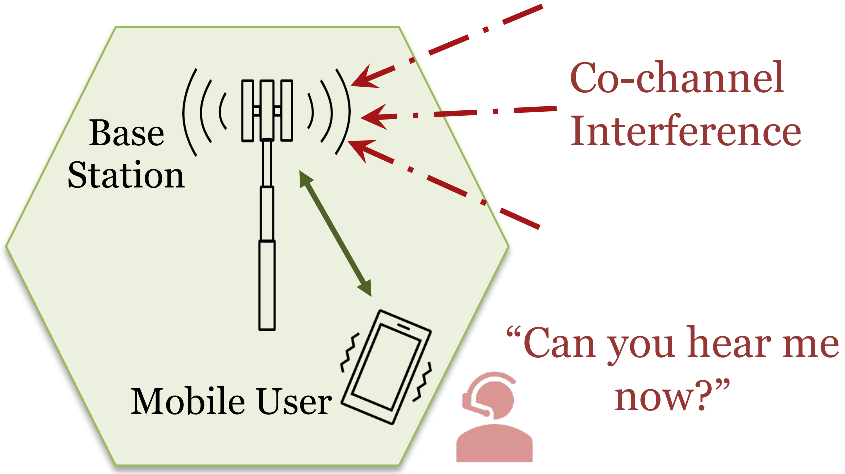
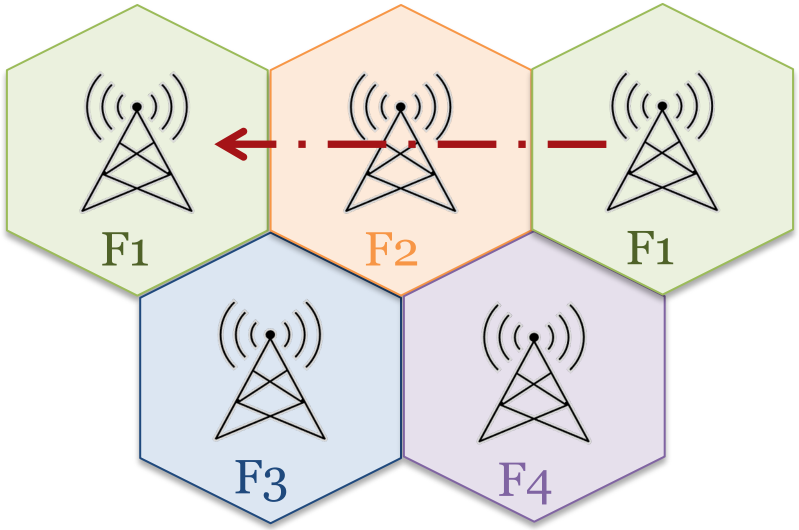
Motivation: Interference Prediction

Interference Prediction with Sharing



Communication degraded by co-channel interference



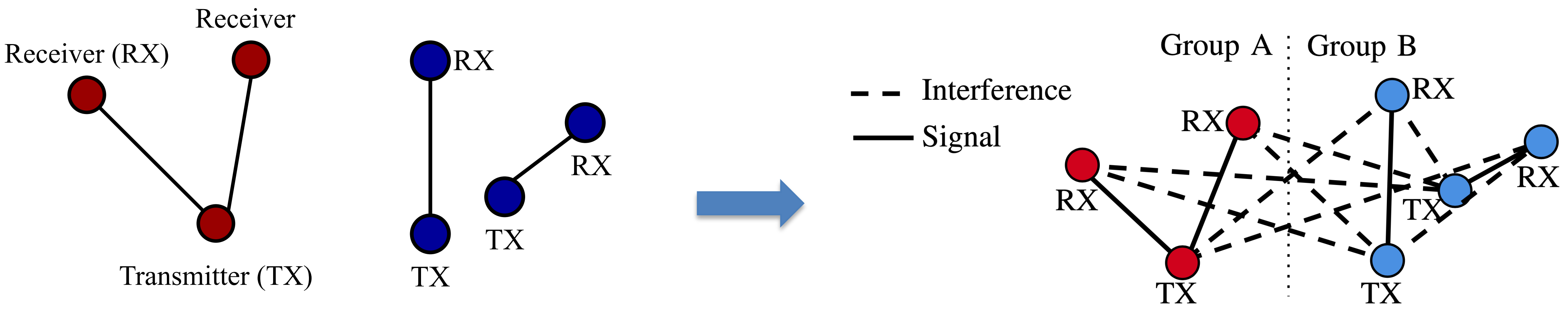
Fixed cellular pattern for frequency reuse

- Goal of interference prediction is to ensure that for all requested links:

  SINR, or Signal / (Interference + Noise) > Threshold

- Current cell deployment sharing solution:
  - Static and complex design for once
  - Issue: what if the design needs update every day?

Challenge: Dynamic Spectrum Access (DSA)



Ongoing communication

Requested co-channel communications

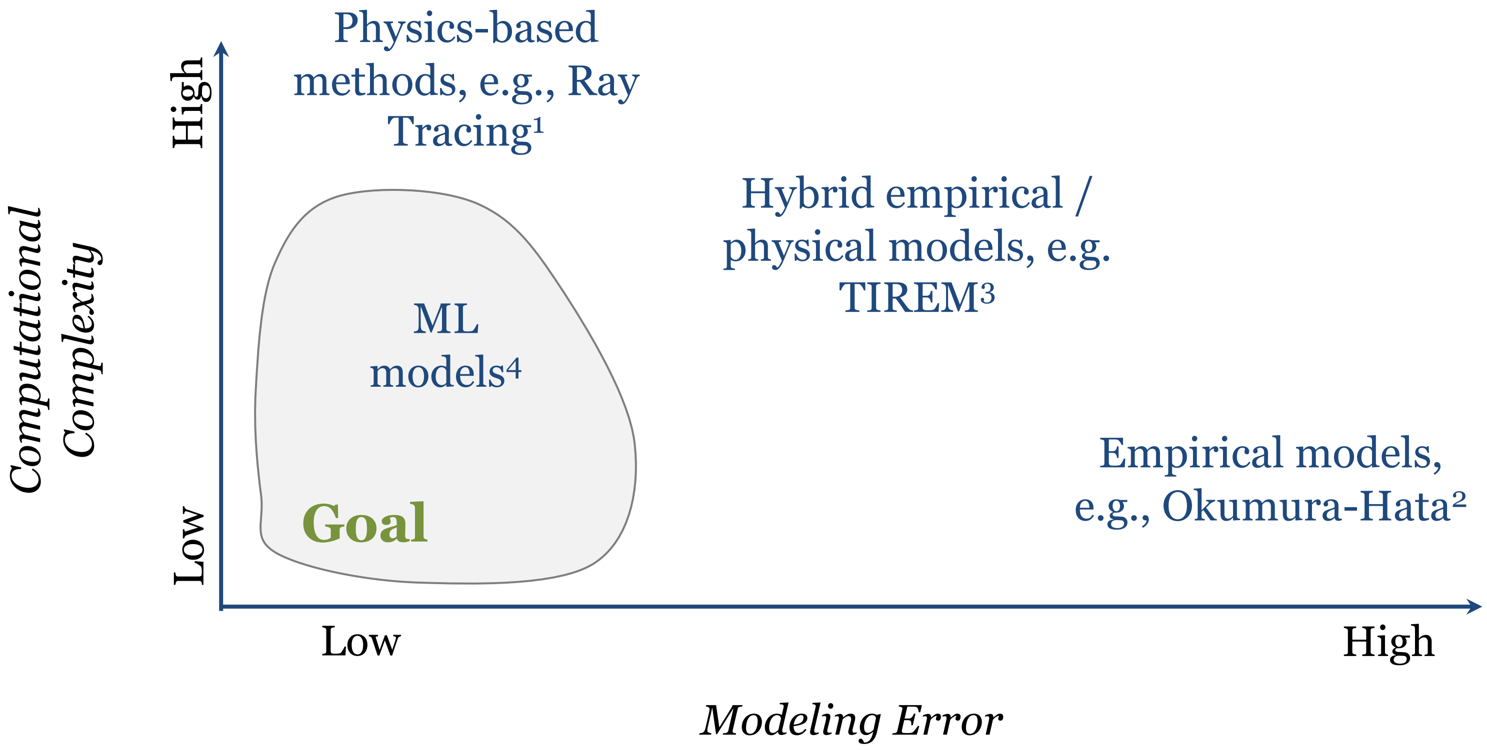
Interference prediction challenge in a DSA environment

Challenges of Dynamic Spectrum Access (DSA) in mobile networks:

- Multiple co-channel links and their interferences are temporally and geographically dynamic.
- The channel losses will change as users move and as environment changes.

Goal: Accurate, efficient, and continuous predictions of the changing channel losses.

Current Methods for Channel Estimation



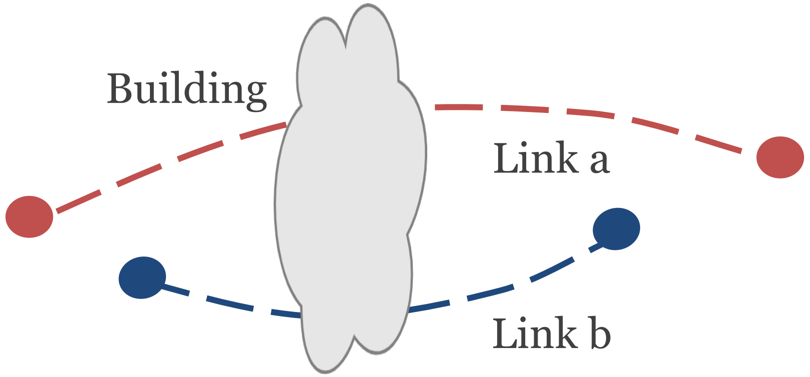
Goal: Low computational complexity and modeling error with physical explainability.

1. Z. Yun et al. "Ray tracing for radio propagation modeling: Principles and applications," IEEE access, vol. 3, pp. 1089–1100, 2015.
2. M. Hata. "Empirical formula for propagation loss in land mobile radio services," IEEE transactions on Vehicular Technology, vol. 29, no. 3, pp. 317–325, 1980.
3. D. Eppink et al. "TIREM/SEM handbook," Defense Technical Information Center, 1994.
4. Y. Zhang et al. "Path loss prediction based on machine learning: Principle, method, and data expansion," Applied Sciences, vol. 9, no. 9, p. 1908, 2019.

The Proposed CELF Model

The Proposed Model: Modeling Rationale

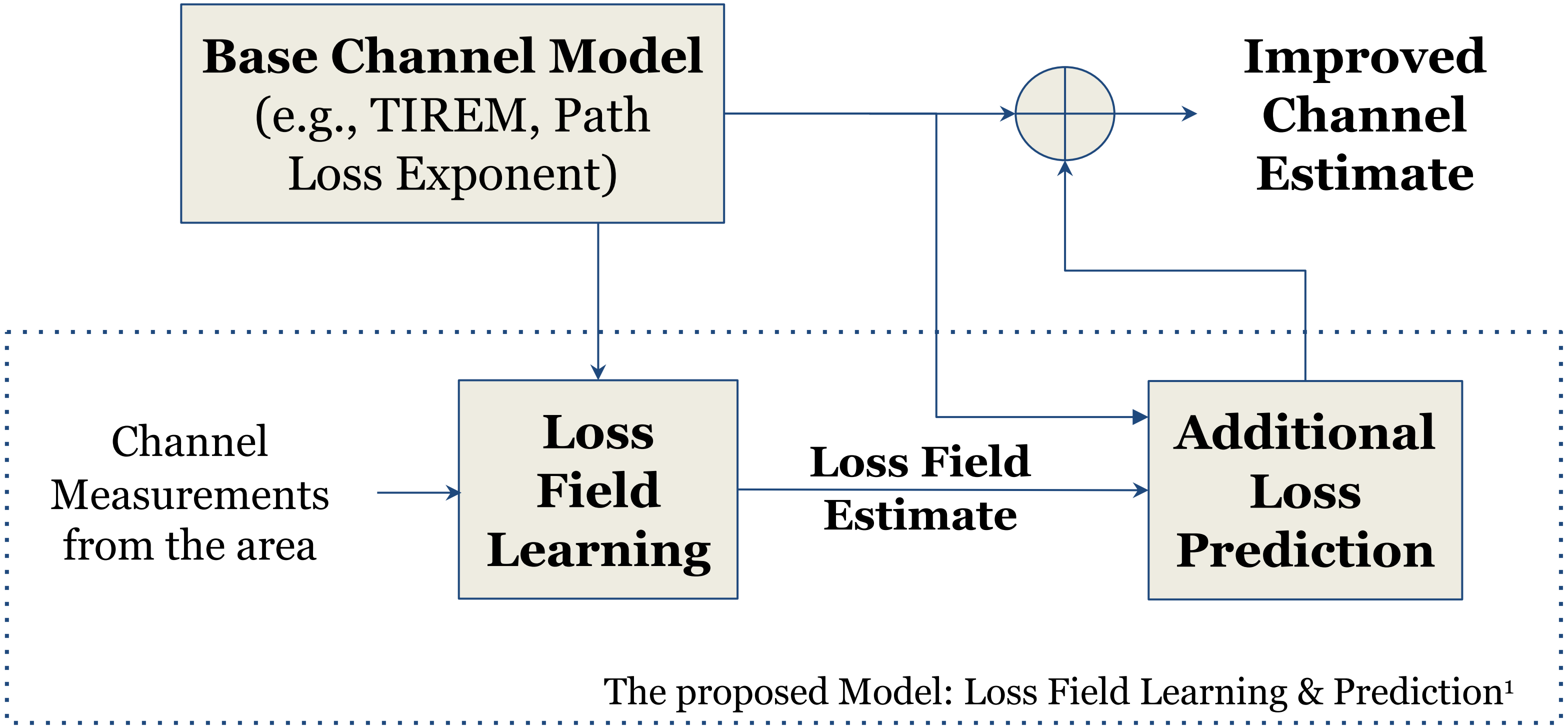
- Channel Estimation via Loss Field (CELF) uses any existing channel model as the *base model*.
- For most channel models, model errors are correlated across space because of the building and land use in the area[1].
  - CELF learns a spatially correlated *loss field* from measurements.
  - CELF predicts *additional channel loss* via the learned loss field.



Link a and Link b have correlated model error.

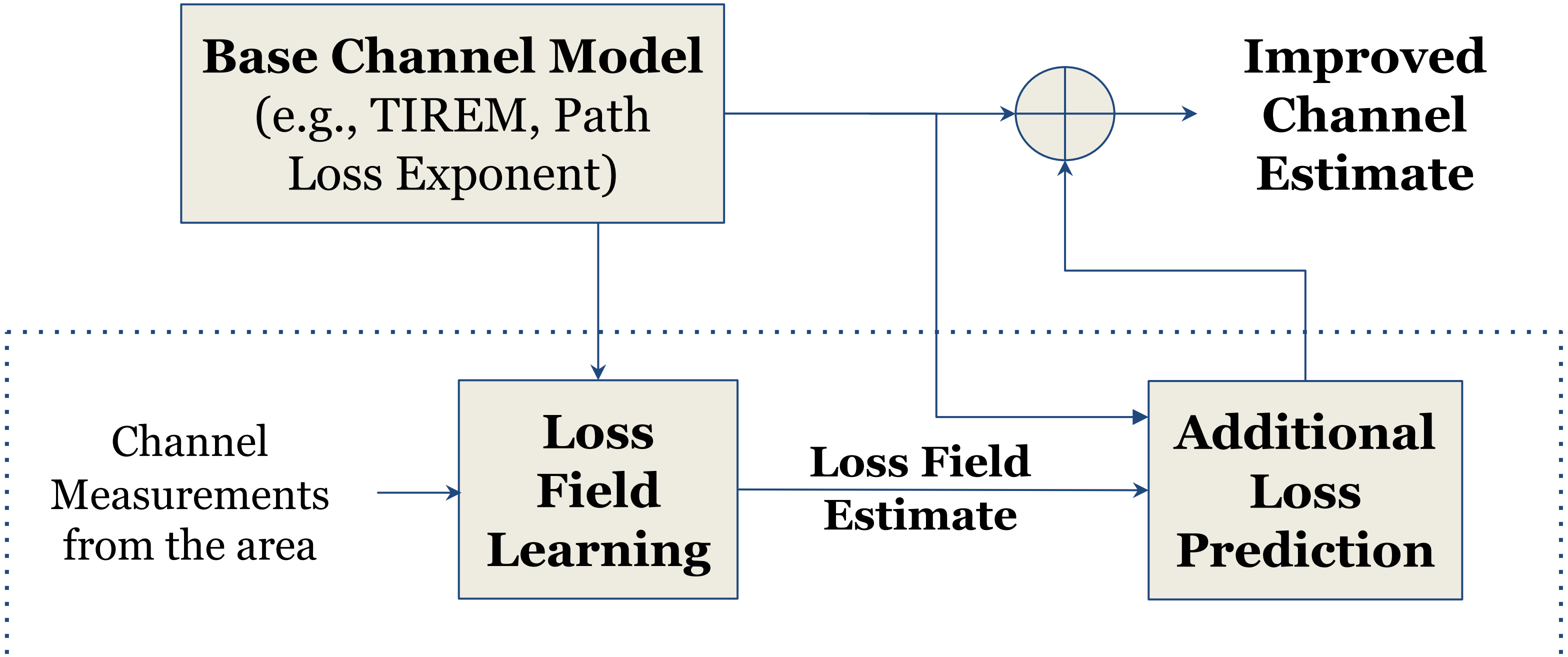
1. P. Agrawal and N. Patwari, "Correlated link shadow fading in multi-hop wireless networks," IEEE Transactions on Wireless Communications, vol. 8, no. 8, pp. 4024–4036, 2009.

The Proposed Model: Overview



1. N. Patwari, “Wireless Experimental Testbeds are an Exercise in Spectrum Sharing,” seminar talk, Nov 2023.

The Proposed Model: Overview



The proposed Model: Loss Field Learning & Prediction[1]

Advantages of the proposed model in comparison to current methods:

- No need of site-specific terrain or building information.
- The model is explainable via propagation physics.
- Low latency of model learning and high accuracy of channel prediction.

1. N. Patwari, "Wireless Experimental Testbeds are an Exercise in Spectrum Sharing," seminar talk, Nov 2023.

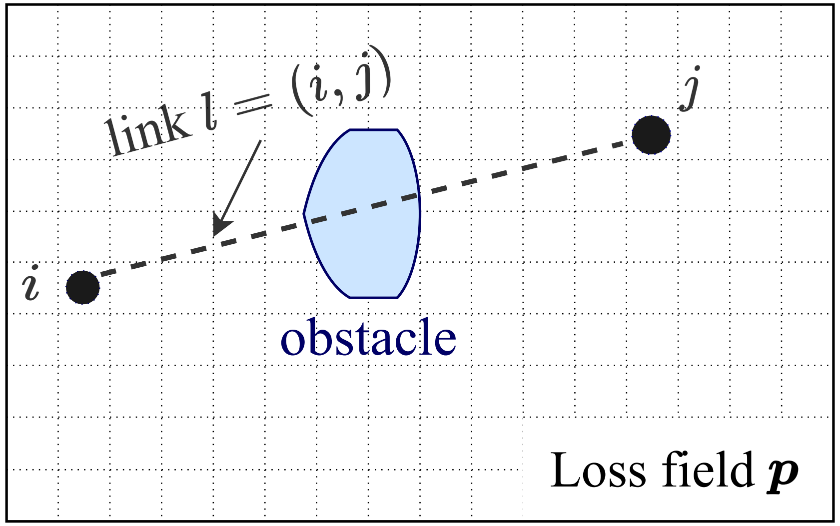
CELF: Spatial Loss Field Modeling

Network shadowing model

Channel Estimation via Loss Field (CELF) models the *additional loss* $\boldsymbol{z}$ as a spatial linear function of the *spatial loss field* $\boldsymbol{p} \in \mathcal{R}^{M\times 1}$:

$$\boldsymbol{z} = \boldsymbol{W}\boldsymbol{p} + \boldsymbol{n}$$

where $\boldsymbol{z} = [Z_1, Z_2, \dots, Z_L]^T \in \mathcal{R}^{L\times 1}$ is the additional loss vector, $\boldsymbol{W} \in \mathcal{R}^{L\times M}$ is the weight matrix, and $\boldsymbol{n} \in \mathcal{R}^{L\times 1}$ is measurement noise.



Explainable loss field

The loss field $\boldsymbol{p}$ accounts for the *shadowing effect* due to obstacles in the environment, e.g., buildings (for outdoor links) and furniture (for indoor links).

Two Priors for Loss Field Learning

Shadowing loss field $\boldsymbol{p}$ prior[1]

It characterizes the area of interest as an isotropic wide-sense stationary Gaussian random field with zero mean and the exponentially decaying covariance function:

$$C_{\boldsymbol{p}}(m,n) = Cov\{\boldsymbol{p}(m),\boldsymbol{p}(n)\} = \frac{\sigma^2}{\delta}\exp(-\frac{d_{m,n}}{\delta})$$

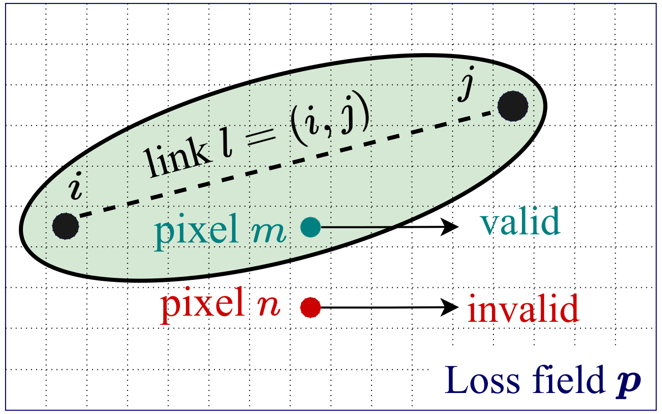
where $d_{m,n}$ is the Euclidean distance between pixel m and n, σ^2 is the shadowing loss variance, and δ is a space constant.

Weight matrix model[2]

A popular ellipse model constructs the weight to be:

$$w_{lm} = \frac{1}{\sqrt{d_l}}\begin{cases} 1, & \text{if valid} \\ 0, & \text{otherwise} \end{cases}$$

where d_l is the link distance and m is the considered pixel.



1. N. Patwari et al., "Effects of correlated shadowing: Connectivity, localization, and RF tomography," in IPSN. 2008.
2. J. Wilson et al., "Radio tomographic imaging with wireless networks," IEEE Transactions on Mobile Computing, vol. 9, no. 5, 2010.

Loss Field Learning and Shadowing Prediction

Bayesian linear regression

The Maximum a posterior (MAP) estimator of the loss field is:

$$\hat{\boldsymbol{p}} = \Pi \boldsymbol{z}$$

$$\Pi = \boldsymbol{C}_p \boldsymbol{W}^{\boldsymbol{T}} \left(\boldsymbol{W} \boldsymbol{C}_p \boldsymbol{W}^{\boldsymbol{T}} + \alpha \boldsymbol{I} \right)^{-1}$$

where $\alpha > 0$ is a regularizer.

Shadowing prediction

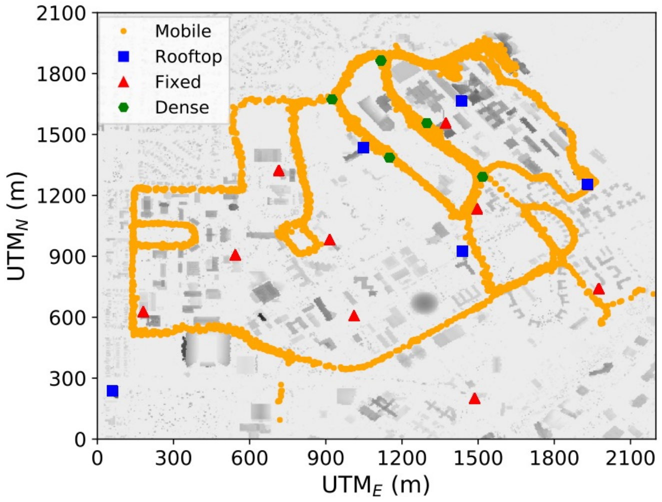
The shadowing loss on a new dataset T can be predicted via:

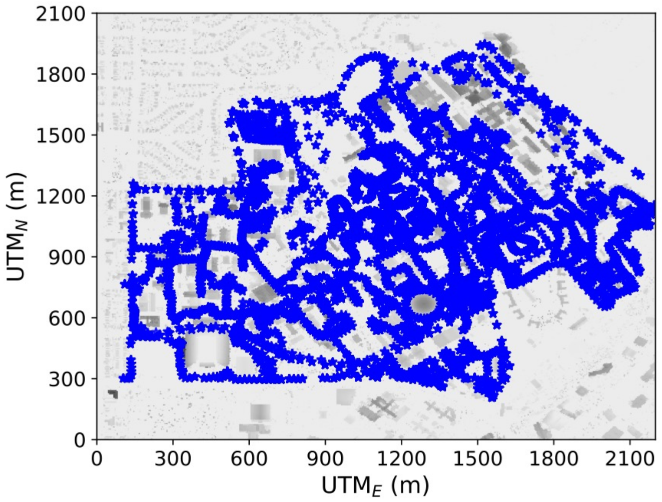
$$\hat{\boldsymbol{z}}_T = \boldsymbol{W}_T \ \hat{\boldsymbol{p}}$$

Experimental Results

Real-world Received Power Datasets

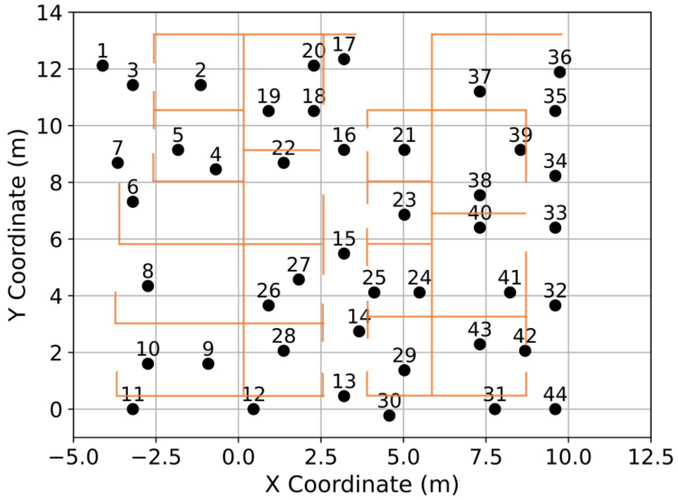
(a)
The outdoor transmitters' locations





(b)
The outdoor receivers' locations

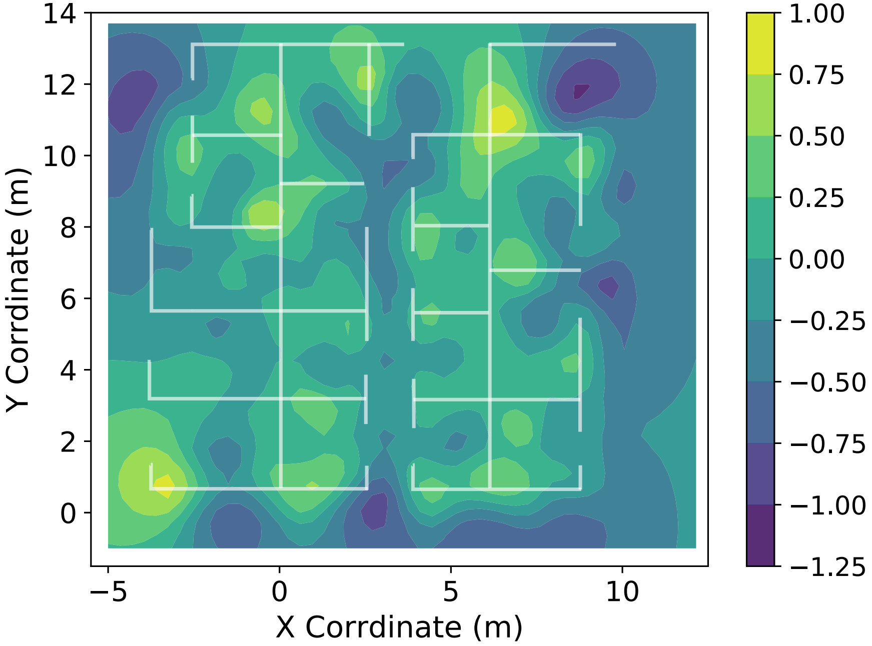
(c)
The 44 indoor locations



The datasets are collected in a 2200×2100 m² U of Utah campus area and a 17.5×15 m² indoor office with cubicles (--) respectively

Example Indoor Loss Field

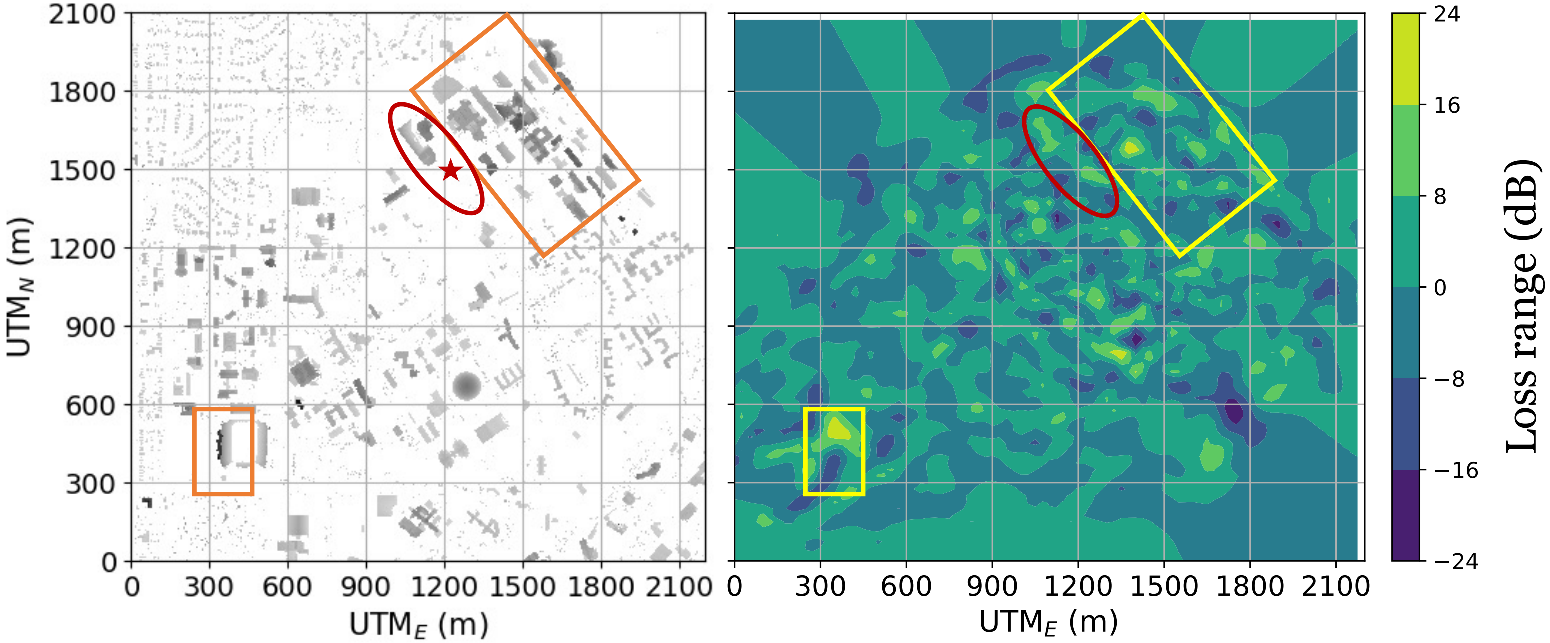
The layout from (-2, 12) to the bottom right

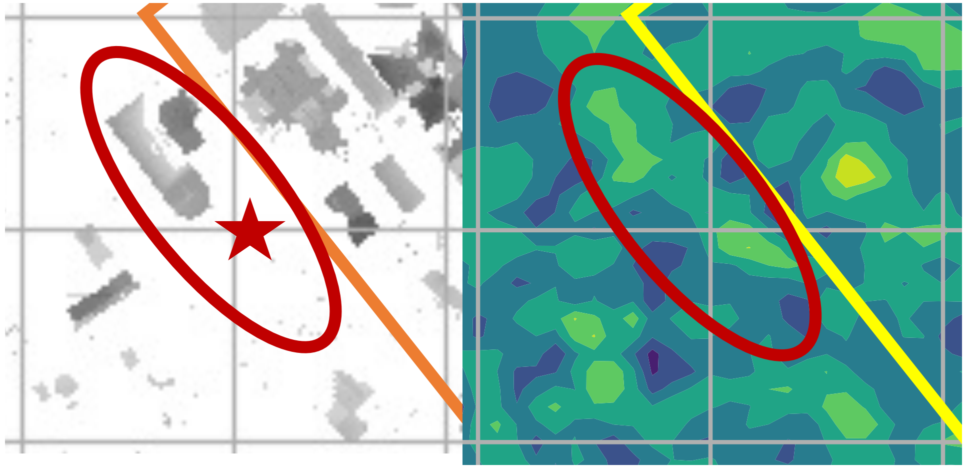


Example indoor loss field learned via CELF and the 17.5×15 m^2 office layout

- Total 1900 link measurements with 70% for training and 30% for testing.
- Higher loss can be seen near cubicle walls.
- Visualize the explainability of the loss field model.

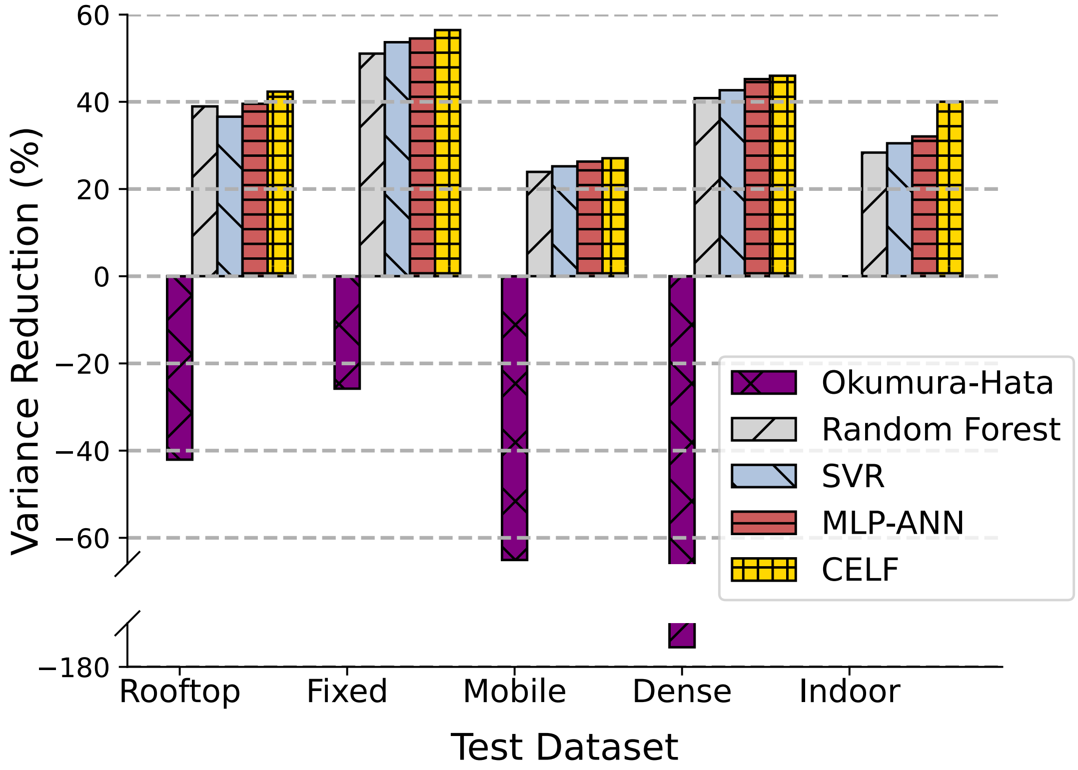
Example Outdoor Loss Field





Example outdoor loss field learned via CELF and the 2200×2100 m² campus building map as a reference.

Evaluation: Precision of CELF



Variance reductions on the test datasets via Okumura-Hata, three ML methods, and CELF.

Takeaway

CELF outperforms other methods across outdoor and indoor datasets in terms of precision improvement.

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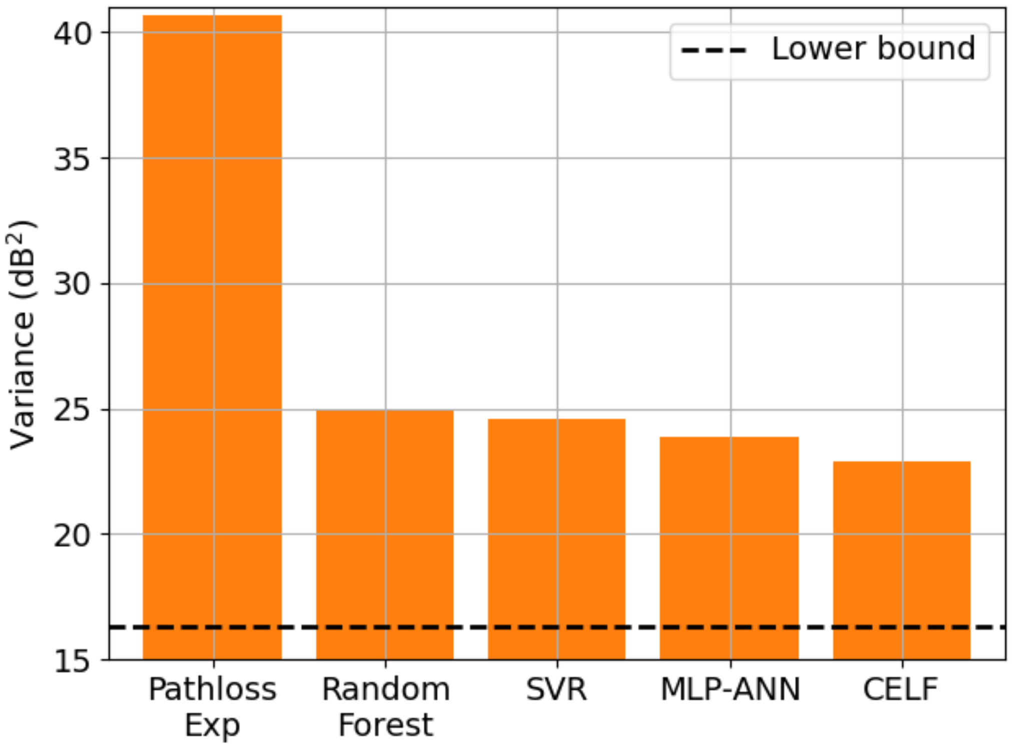

Variance of different methods by averaging the 5 datasets.

Takeaway

- CELF significantly improves the path loss exponent model (base model).
- CELF shows higher precision than ML methods.
- The lower variance bound (dashed line) is fading loss that we can't predict.

Evaluation: Efficiency of CELF

Running time comparison for loss field learning and shadowing prediction.

Receiver	Loss Field Learning Time (s)				Shadowing Prediction Time (s)				
	Random Forest	SVR	MLP-ANN	CELF	Okumura-Hata	Random Forest	SVR	MLP-ANN	CELF
Rooftop	1.210	7.411	26.753	8.215	0.001	0.018	0.726	0.011	0.402
Fixed	1.587	28.687	59.671	15.767	0.001	0.027	2.353	0.024	0.642
Mobile	1.605	4.247	13.552	4.837	0.001	0.014	0.311	0.004	0.243
Dense	0.700	7.105	25.524	6.036	0.001	0.014	0.755	0.005	0.357
DS-SS	0.131	0.041	2.402	0.133	–	0.007	0.006	0.002	0.005

For *fixed* dataset, we use 16,977 link measurements for training and test the learned loss field on 7,276 links

Main Takeaway:

- CELF is ~3 times faster than Multilayer Perceptron (MLP-ANN) for loss field learning.
- CELF is faster than Support Vector Regression (SVR) but slower than MLP-ANN for shadowing prediction due to the time-expensive weight matrix computation.
- CELF needs only <1 s for predicting shadowing loss of up to 7,276 links simultaneously.

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- Introduce the need for channel models with low computational complexity and high precision that adapt to DSA mobile networks.

- Proposes CELF, which learns an explainable loss field and uses it to predict shadowing loss on any new links in a deployment area.

- Evaluate CELF's precision and efficiency using indoor and outdoor real-world datasets.

- Comparison to ML and empirical methods validates CELF as a new and explainable learning model for precise and fast site-specific radio channel loss estimation.

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