Transferring Knowledge for Tilt-Dependent Radio Map Prediction

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Motivation

- The next generation of mobile networks (5G) will support more users, higher data rates, reduced latency, improved energy efficiency, etc...
- In this complex scenario Machine Learning will play a major role for automatic network configuration
- Antenna deployment for all the possible tilt configurations is expensive in cost, time and performance even for operator and the final user

Problem Formulation

- How to predict the performance of a given network configuration by leveraging performance information of diverse network configurations analyzing:
  - a different tilt configuration of the same antenna
  - a different antenna with the same tilt configuration
- Given $\{s_{k,h}(\mathbf{x}_i) : i \in \mathcal{M}_k^h\}$, estimate the unknown signal strength $\hat{s}_{m,n}(\mathbf{x}_j)$ at the same or different locations, $\mathbf{x}_j$, under diverse and different network configuration domains, that is $\mathbf{x}_j$, $j \in \mathcal{M}_m^n$ with $m \neq k$ and/or $n \neq h$.
  - K base stations and H number of tilt configurations
  - $s_{k,h}(\mathbf{x}_i)$ RSRP received at a geolocation in base station under configuration
  - $\mathcal{M}_k^h$ set of locations where the measurements for base station K under configuration H were taken

Data Collection

- $3.5 \cdot 10^3$ Reference Signal Received Power (RSRP) outdoor measurements collected in Espoo, Finland, November 2016, using an Android device by walking an 8km path multiple times
- Two LTE commercial BSs with three different sectors (PCI)

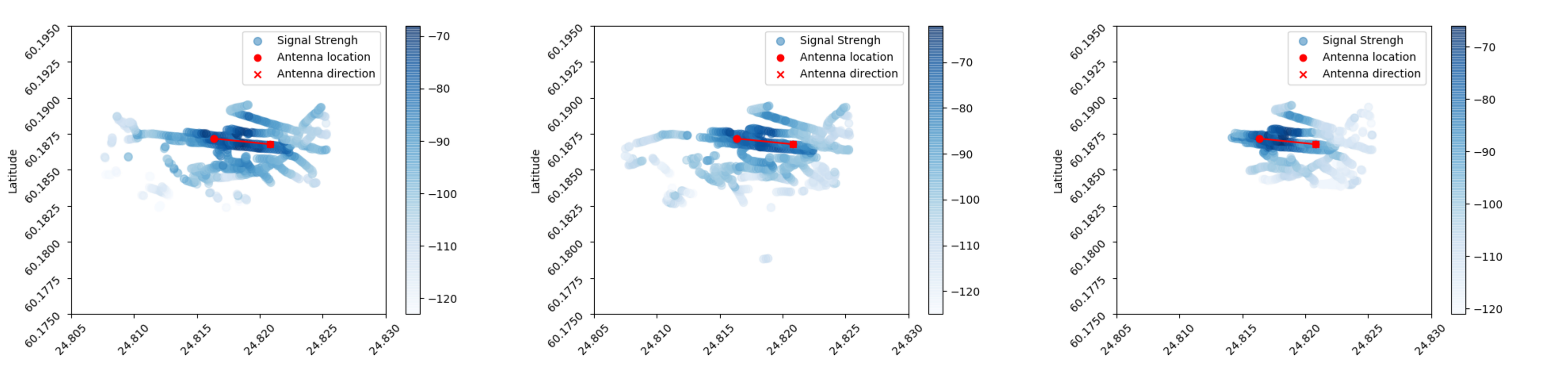


Figure: Relationship between Tilt Dependent Radio Maps for the different tilt configurations

Machine Learning Solutions

- Location-aware Approach
  - Baseline
$$\hat{s}(\mathbf{x}) = s(\mathbf{x}_i), \qquad \mathbf{x}_i = \operatorname*{argmin}_{\mathbf{x}_i, i \in \mathcal{M}} d(\mathbf{x}, \mathbf{x}_i). \tag{1}$$
  - Adjusted Baseline:
$$\hat{s}(\mathbf{x}) = s(\mathbf{x}_i) + \Delta_H(\mathbf{x}, \mathbf{x}_i) + \Delta_V(\mathbf{x}, \mathbf{x}_i),\ \mathbf{x}_i = \operatorname*{argmin}_{\mathbf{x}_i, i \in \mathcal{M}} d(\mathbf{x}, \mathbf{x}_i), \tag{2}$$
$$\Delta_H(\mathbf{x}, \mathbf{x}_i) = \eta(\mathbf{x}) - \eta(\mathbf{x}_i) \text{ and } \Delta_V(\mathbf{x}, \mathbf{x}_i) = \gamma(\mathbf{x}) - \gamma(\mathbf{x}_i), \tag{3}$$
  - K-Nearest Neighbor with Inverse Distance Weighting
$$\hat{s}(\mathbf{x}) = \sum_{i \in \mathcal{M}(\S)} w_i s(\mathbf{x}_i),\ w_i = \frac{d(\mathbf{x}_i, \mathbf{x})^{-1}}{\sum_{j \in \mathcal{M}(\mathbf{x})} d(\mathbf{x}_j, \mathbf{x})^{-1}}. \tag{4}$$
- Geometric-aware Approach:

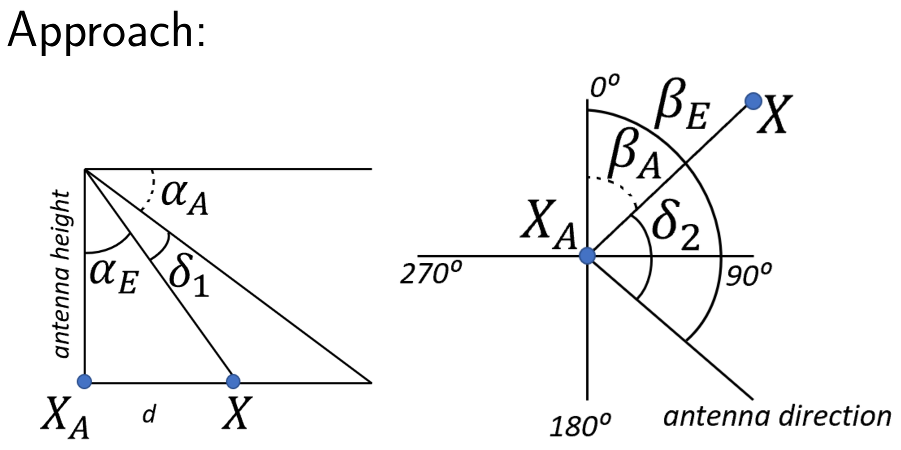


Figure: Relative angles in the vertical (left) and horizontal (right) planes between the antenna pointing direction and the direction towards the test position $\mathbf{x}$.

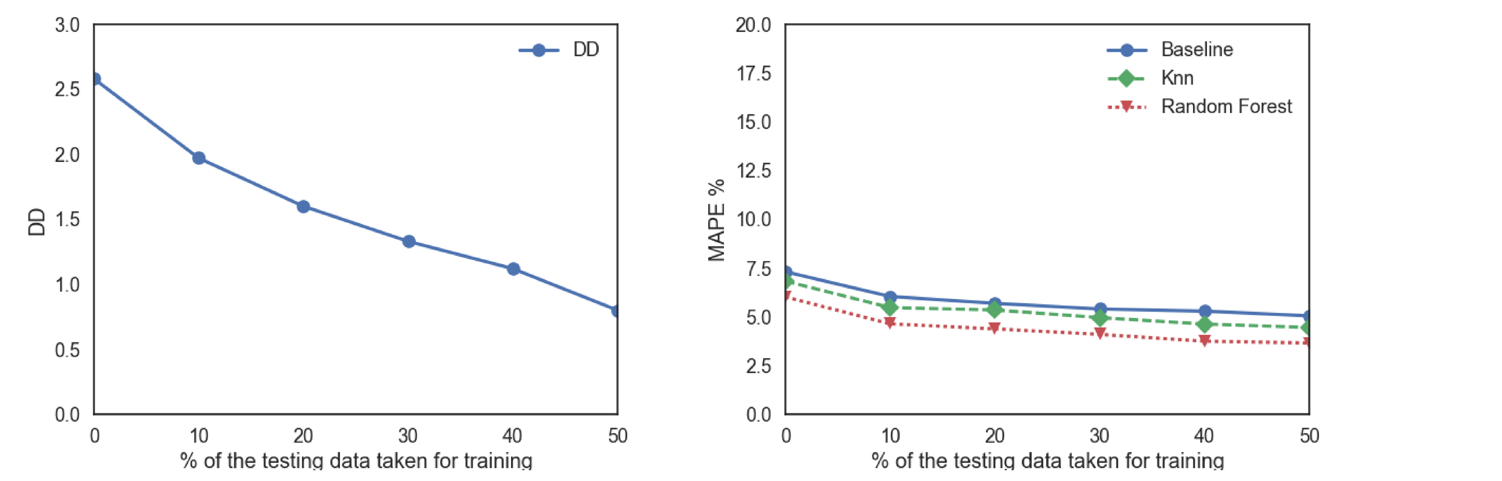
  - Multivariate Linear Regression
$$\hat{s}(\mathbf{x}) = \mathbf{\Theta}^T \mathcal{X}, \mathcal{X} = \{1, d, \delta_1, \delta_2, \alpha_A\}^T \tag{5}$$
  - Random Forest
  - XGBoost

Evaluation Metrics

- Performance Measures
$$\mathrm{MAE}(s, \hat{s}) = \frac{1}{n} \sum_{i=0}^{n-1} |s_i - \hat{s}_i| \tag{6}$$
$$\mathrm{MAPE} = \frac{100}{n} \sum_{i=0}^{n-1} \left| \frac{s_i - \hat{s}_i}{s_i} \right|. \tag{7}$$
- Domain Distance Measures
$$D_{KL}(d) = \sum_{i=1}^{k} P_d^{(\mathrm{tr})}(i) \log \frac{P_d^{(\mathrm{tr})}(i)}{P_d^{(\mathrm{te})}(i)} + \sum_{i=1}^{k} P_d^{(\mathrm{te})}(i) \log \frac{P_d^{(\mathrm{te})}(i)}{P_d^{(\mathrm{tr})}(i)}, \tag{8}$$
$$\mathrm{DD} = D_{KL}(d) + D_{KL}(\delta_1) + D_{KL}(\delta_2). \tag{9}$$

Numeric Results

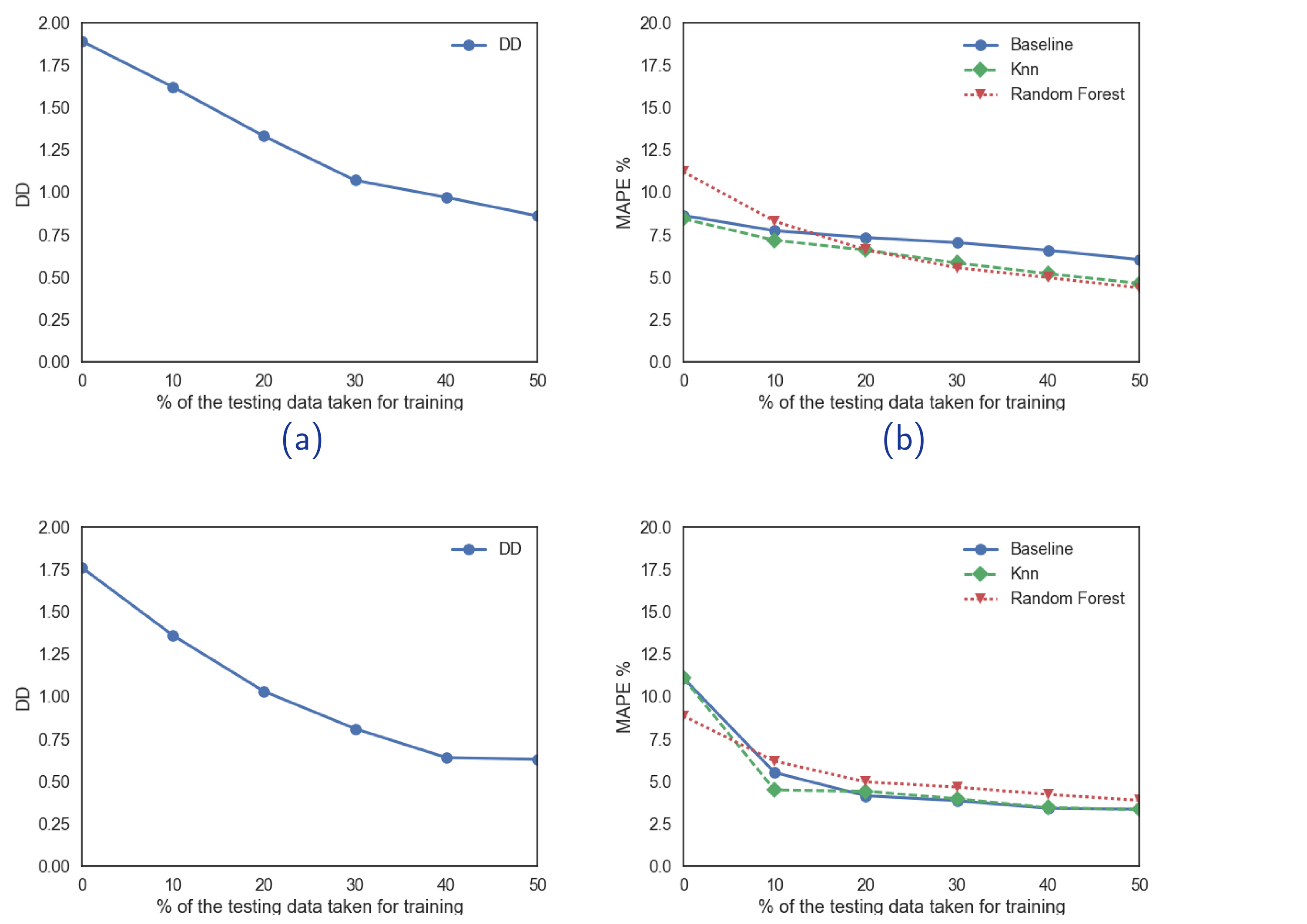
1. Tilt to Tilt Transfer Knowledge



(a) Domain Distance (DD) (b) MAPE

Figure: Relationship between Domain Distance and MAPE (a), (b): training on tilt 6, testing on tilt 3 for PCI 1.

2. PCI to PCI Knowledge Transfer



(a) (b) (c) (d)

Figure: DD vs MAPE. (a),(b): training on PCI 1, testing on PCI 2. (c),(d): training on PCI 3, testing on PCI 2 at tilt 2.

- 10-20 % of the testing data taken for training improves performance
- Prediction performance vs Domain Distance

Conclusions

- The prediction performance is highly dependent on the difference between data distributions of training and testing domains
- Different approaches applied to increase domain similarity:
  - Choosing the training set obtained from a tilt setting with higher similarity to the testing domain
  - Adding to the training set a limited number of samples from the testing domain

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