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\_i(x(i)) : i \in \mathcal{M}\_n\}, estimate the unknown signal strength \(\hat{s}\_i(x(j))\) at the same or different locations, \(x\_j\), under diverse and different network configuration domains, that is \(x\_j, j \in \mathcal{M}\_m\) with \(m \neq k\) and/or \(n \neq h\).
- \(K\) base stations and \(H\) number of tilt configurations
- \(s\_i(x)\) RSRP received at a geolocation in base station under configuration \(\mathcal{M}\_n\), set of locations where the measurements for base station \(K\) under configuration \(H\) were taken

Data Collection

- 3.5 - 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)

Machine Learning Solutions

- Location-aware Approach
  - Baseline
    \[ \hat{s}(x) = s(x), \quad x = \text{argmin}_{x \in \mathcal{M}} d(x, x). \] (1)
  - Adjusted Baseline:
    \[ \hat{s}(x) = s(x) + \Delta_{\theta}(x, x) + \Delta_{\beta}(x, x), \quad x = \text{argmin}_{x \in \mathcal{M}} d(x, x). \] (2)
    \[ \Delta_{\theta}(x, x) = \hat{\eta}(x) - \eta(x) \text{ and } \Delta_{\beta}(x, x) = \gamma(x) - \gamma(x). \] (3)
  - K-Nearest Neighbor with Inverse Distance Weighting
    \[ \hat{s}(x) = \sum_{i \in \mathcal{M}} w_i s(x_i), \quad w_i = \frac{d(x, x_i)}{\sum_{j \in \mathcal{M}} d(x, x_j)^{-1}}. \] (4)
- Geometric-aware Approach:
  - Multivariate Linear Regression
    \[ \hat{s}(x) = \Theta^T x, \quad x = \{1, \theta_1, \theta_2, \alpha, \beta\}^T \] (5)
  - Random Forest
  - XGBoost

Evaluation Metrics

- Performance Measures
  \[
  \text{MAE}(x, \hat{x}) = \frac{1}{n} \sum_{i=0}^{n} |x_i - \hat{x}_i| \]
  \[
  \text{MAPE} = \frac{100}{n} \sum_{i=0}^{n} \frac{|x_i - \hat{x}_i|}{x_i}.
  \]
- Domain Distance Measures
  \[
  D_{DD}(d) = \sum_{i=1}^{n} p^0(i) \log \frac{p^0(i)}{p^0(i)} + \sum_{i=1}^{n} p^1(i) \log \frac{p^1(i)}{p^0(i)}
  \]
  \[
  DD = D_{KL}(d) + D_{KL}(d) + D_{KL}(d).
  \]

Numeric Results

1. Tilt to Tilt Transfer Knowledge

2. PCI to PCI Knowledge Transfer

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