AI and Machine Learning for Localization:
An Overview and Future Perspectives

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Outline

- Why AI/ML for localization?
- Localization background
- AI/ML techniques for localization
- Use cases: indoor positioning with smartphone, autonomous robotics, deep learning in 5G localization
- Future perspectives: 6G localization

Background

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Why AI/ML for Localization?

- Radio-frequency propagation (non-line-of-sight, scattering, unknown properties)
- Dynamic and complex environments
- Large size of parameters
- Sensor fusion and data integration

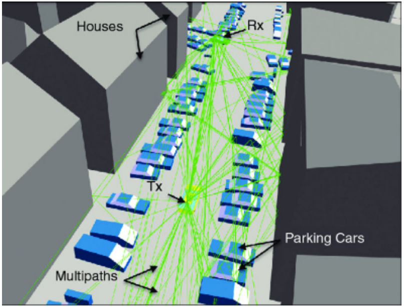
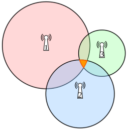
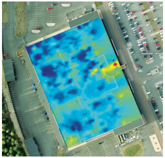
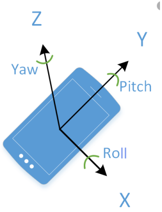


Image: M. Guillaud, "Dimensionality Reduction Techniques for Wireless Communication", CentraleSupelec, May 2020

Localization Background







- Position, heading, orientation, clock synchronization / bias (wireless systems)
- Trilateration/triangulation
  - Line-of-sight to multiple base stations
- GNSS / GPS
  - Line-of-sight (works in outdoors)
- Fingerprinting
  - Wireless RF signal, magnetic fields

Images: Wikipedia creative commons, IndoorAtlas Ltd.

Complex Localization Environments

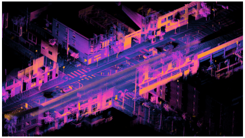
- Outdoor
  - Dense urban areas
  - High-accuracy applications (e.g., autonomous vehicles)
- Indoors
  - Large-scale buildings: malls, airports, etc.
  - Industrial environments

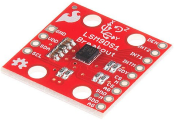
  

Images: Wikipedia creative commons

Sensors and Systems

- Wireless networks / RF signals
  - Cellular, WiFi, BLE, UWB, RFID
  - Multi-antenna systems (5G MIMO)
  - GPS
- Cameras, LiDAR, RADAR
- Smartphones, IoT devices, robotics
  - Inertia sensors (Accelelerometer, gyroscope, magnetometer), barometer, ambient light sensor, etc.





Images: Wikipedia creative commons

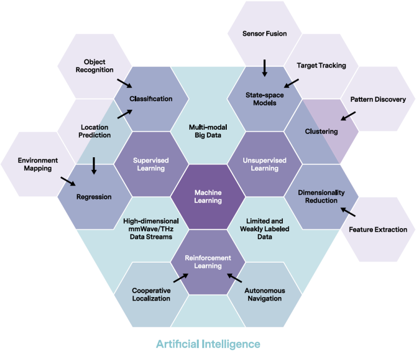
Traditional Localization Methods

- Distance and angle measurements with anchor points
  - Received signal strength indicators (RSSI)
  - Time of arrival (TOA), time difference of arrival (TDOA)
  - Angle of arrival (AOA), angle of departure (AOD)
- Trilateration and triangulation of multiple known reference points
  - Physical model of wireless signal propagation
  - Location estimation: least-squares, maximum likelihood, maximum a posterior
- Data-driven approaches are needed to overcome the limitations

Machine Learning for Localization

ML Concepts for Localization

- Supervised learning
  - Regression and classification
  - Direct prediction, parameter prediction, map interpolation
- Unsupervised learning
  - Clustering, pattern discovery
  - Dimensionality reduction
- Reinforcement learning
  - Cooperative localization, autonomous navigation
- Limited reference point data: semi-supervised and transfer learning, SLAM



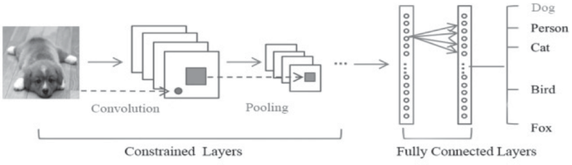
C. De Lima et al. (2020), "6G White paper on Localization Sensing". 6G Research Visions, No. 12

AI/ML Techniques

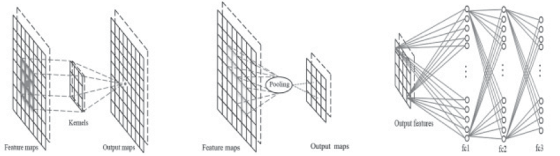
- Deep neural networks
  - Good feature extractors from structured data
  - Needs a lot of labeled examples to train (large n)
  - Blackbox modeling, no proper uncertainty quantification of predictions
- Gaussian processes
  - Handles prior knowledge and high-dimensional data (large p),
  - Challenges to scale on huge datasets (without approximation)
  - Uncertainty estimation
  - Can go deep too!
- Sequential Bayesian state-space models
  - Modeling of temporal and dynamic systems
  - Data fusion of heterogeneous sources

Convolutional Neural Networks

- Extracting high-level features from structured data (e.g, images, channel state information (CSI))
- Supervised learning between CSI and reference locations



(a) Convolutional Neural Network

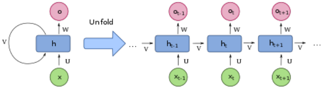


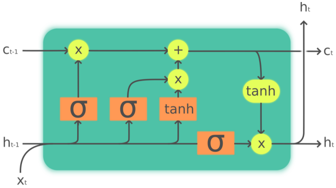
(b) Convolution Layer (c) Pooling Layer (d) Fully-connected Layer

Images: Gao, Jing and Li, Peng and Chen, Zhikui and Zhang, Jianing, "A Survey on Deep Learning for Multimodal Data Fusion", Neural Computation, Volume 32, Issue 5, 2020, pp. 829-864

Recurrent Neural Networks

- Modeling temporal and sequential data (e.g., localization sequences of moving targets)
  - Recurrent neural network (RNN)
  - Long short-term memory (LSTM)





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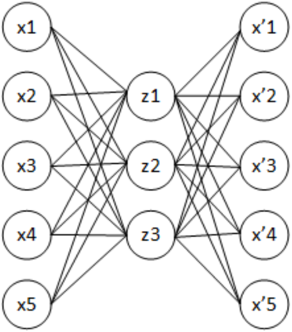
Autoencoders

- Unsupervised feature extractors
    - Nonlinear dimensionality reduction
        - Low-dimensional representation of input data
        - E.g., large-dimensional radio channel parameters
    - Compression
    - Anomaly detection
- Can be stacked to form deep models



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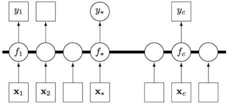
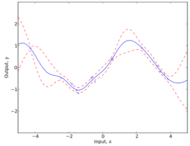
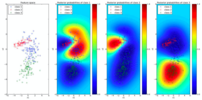
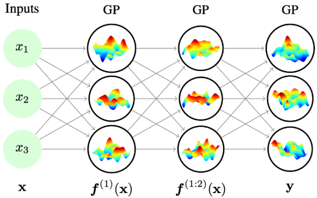
Gaussian Processes

- Probabilistic kernel method
  - Flexiple priors to learn from a small amount of data
  - Interpretable components
- Uncertainty quantification
  - Coherent way to process uncertainty
  - Calibrated confidence
  - Propagating uncertainty to high-level decision making





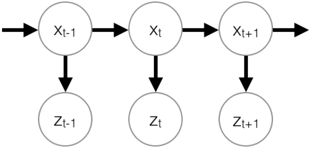


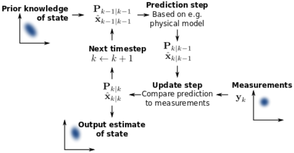


Images: Daniel Hernández-Lobato (deep GP), Rasmussen et al. (2006), "Gaussian Processes for Machine Learning", MITPress (graphical model), Jaakko Suutala (GPR and GPC fitting)

Bayesian State-space Models

- Dynamic graphical models
  - Recursive Bayesian estimation
  - Coherent way to combine motion and multi-source observations
- Kalman filters and smoothers
  - Linear-Gaussian systems
  - Non-linear approximation: EKF, UKF
- Particle filters and smoothers
  - Non-linear non-Gaussian systems
  - Sequential Monte Carlo sampling

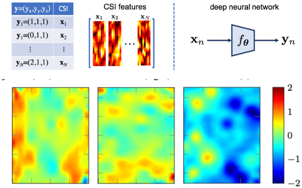


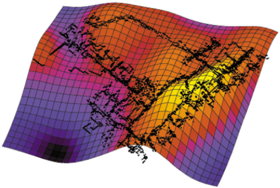


Images: Wikipedia creative commons

Supervised ML for Localization

- Direct location prediction
  - RSSI and CSI fingerprinting
  - Deep learning, Gaussian processes, ensemble learning etc.
- Hybrid methods for localization
  - Parameter prediction + traditional estimation (e.g., TOA)
  - Map interpolation and matching
  - ML-driven physics-based models of signal propagation and target motion
    - Physics-based priors and Bayesian inference (e.g., using GPs)
    - Bayesian filtering and smoothing for dynamics and sensor fusion





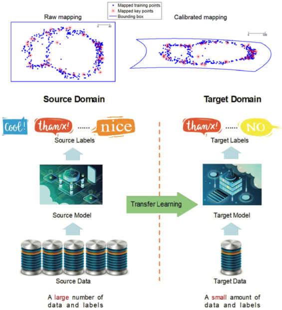
J. Vieira, E. Leitinger, M. Sarajlic, X. Li, and F. Tufvesson, "Deep convolutional neural networks for massive MIMO fingerprint-based positioning" IEEE PIMRC, Oct. 2017.

A. Solin et al., "Modeling and Interpolation of the Ambient Magnetic Field by Gaussian Processes", IEEE Transactions on Robotics, 34(4):1112–1127. 2018

Ferris et al, "Gaussian Processes for Signal Strength-Based Location Estimation", In Proc. of Robotics Science and Systems, 2006

Lack of Fingerprint Data

- Supervised fingerprint-based localization requires large amount of training data
  - Time-consuming to collect (offline process)
  - Difficult to tackle dynamic environments
- Semi-supervised learning
- Transfer learning
- Unsupervised learning
- Simultaneous localization and mapping (SLAM)
  - Graph SLAM, Bayesian filtering based techniques
- Combined modalities, hybrid systems

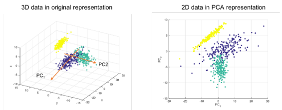


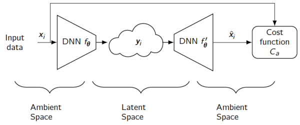
Pulkkinen et al., "Semi-supervised Learning for WLAN Positioning", ICANN, pp. 355-362, 2011

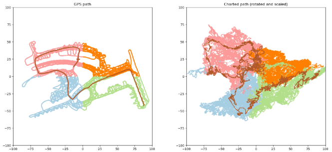
Li et al, "Machine-Learning-Based Positioning: A Survey and Future Directions", IEEE Network, 2019

Unsupervised ML for Localization

- Unsupervised learning
  - Extracting patterns/features from unlabeled data
  - Clustering
  - Dimensionality reduction
    - PCA, autoencoder neural networks, stochastic neighbor embedding methods etc.
- Channel charting
  - Pseudo-location information for network management, proximity detection





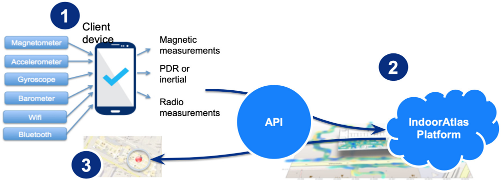


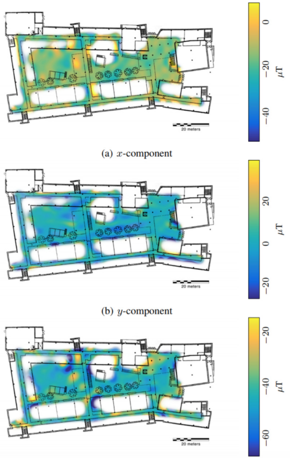
M. Guillaud, "Dimensionality Reduction Techniques for Wireless Communication", CentraleSupelec, May 2020

Use Cases

Indoor Positioning with Smartphone

- Geomagnetic mapping
- Wireless signals
- Probabilistic sensor fusion
  - Signal maps, human motion
- Efficient offline algorithm on mobile device
- APIs and platform for location service and data, AR applications





(a) x-component

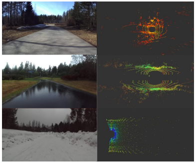
(b) y-component

(c) z-component

www.indooratlas.com, app.indooratlas.com

Localization in Autonomous Robotics

- Locating themselves and making decisions under uncertainty
- Machine learning and fusion are the keys
- High accurate outdoor localization
  - Maintenance and inspection work
  - Extended kalman filter fusion of IMU and radio positioning (GPS, 5G, UWB)
  - Other modalities recognition, e.g., RGB, thermal, and depth cameras
- Unknown (indoor) environments
  - Rescue tasks, harsh environments and conditions
  - SLAM (LiDAR), navigation and scene understanding



Images: Wikipedia creative commons, skyspecks.com, BISG Robotics Group

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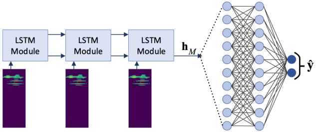
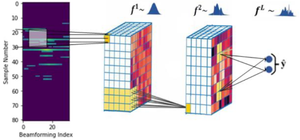
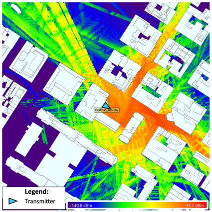
Deep Learning in mmWave 5G Localization

- Complex environments: indoors and urban outdoor canyons
- Supervised Learning
  - CSI fingerprinting
    - Predicting location directly from CSI
    - Power delay profile (PDP), angular delay profile (ADP)
  - Deep neural networks
    - Convolutional nets, LSTM
  - Deep Gaussian processes
    - Deep kernels, GP-LSTM







P. A. Patel, "Millimeter Wave Positioning with Deep Learning", Master Thesis, California State University, 2019.

J. Gante, G. Falcão and L. Sousa, "Deep Learning Architectures for Accurate Millimeter Wave Positioning in 5G", Neural Processing Letters, 2019

Future Perspectives: ML for 6G Localization and Sensing

6G Localization and Sensing

- 6G and beyond systems will even be more data-driven
  - Higher data rates, larger bandwidths, THz frequencies, mmWave and μmWave, massive antenna arrays, network densification
- ML as an enabler for combining communication, sensing, and localization from rich set of big data sources
  - Large-scale: large number of observations n and/or high-dimensionality p
  - Complex: noisy, non-linear, non-stationary, multimodal

C. De Lima et al. (2021), "Convergent Communication, Sensing and Localization in 6G Systems: An Overview of Technologies, Opportunities and Challenges", in IEEE Access.

6G Localization and Sensing (cont'd)

- Hybrid approaches: ML supporting traditional mathematical models and low-level signal processing algorithms
  - Optimizing a very large set of parameters
  - Producing low-dimensional representations of data
- Enabling high-level reasoning, adaptivity, predictivity, and proactivity

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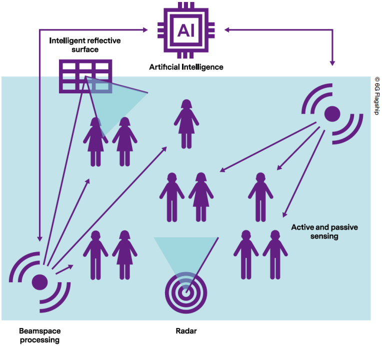
Opportunities and Applications

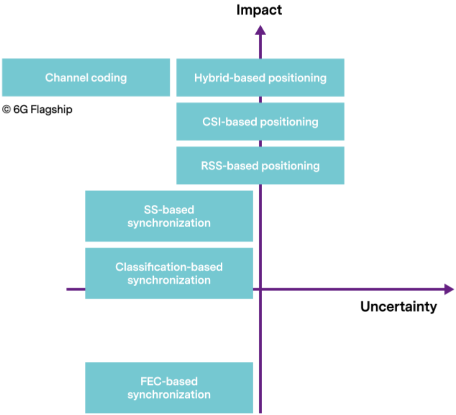
- AI/ML will be used to help integrating different 6G components and enabling novel services
- End-to-end learning and multisource data fusion
- Combined localization, sensing, and communication



C. De Lima et al. (2020), "6G White Paper on Localization Sensing". 6G Research Visions, No. 12

ML for 6G Localization

- ML-based localization/positioning will impact 6G physical layer modeling



S. Ali et al. (2020), "6G White Paper on Machine Learning in Wireless Communication Networks". 6G Research Visions, No. 7

ML for 6G Sensing

- Enchancing low-level sensing and imaging capabilities from noisy and weak non-linear signals
  - E.g, pre-processing of signals for 3D THz imaging
- Enabling high-level reasoning from the raw measurements
  - Novel classification and regression problems
    - E.g., active and passive sensing for detecting and recognizing objects
  - Combining signals from several sensing modalities optimally

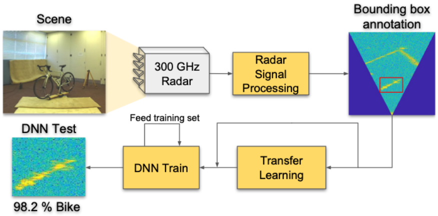
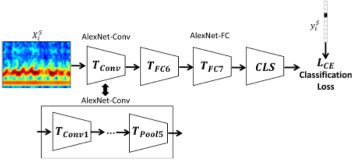
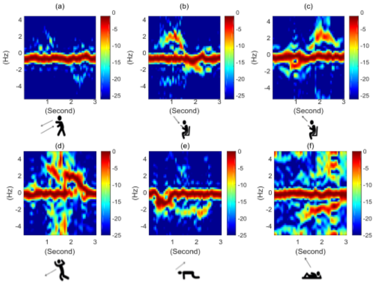


Image: Marcel Sheeny, Andrew Wallace, Sen Wang, "300 GHz Radar Object Recognition based on Deep Neural Networks and Transfer Learning, 2019, arXiv:1912.03157

ML for 6G Sensing (cont'd)

- Non-invasive recognition of human behaviour and context
  - Activities, gestures, biomedical conditions
- Remote sensing and parameter estimation
  - Environmental variables, materials, substances
- Feature extraction for localization
  - Supervised or unsupervised manner
  - As an intermediate step for more precise positioning





Images: Q. Chen, Y. Liu, B. Tan, K. Woodbridge and K. Chetty, "Respiration and Activity Detection Based on Passive Radio Sensing in Home Environments", in IEEE Access, vol. 8, pp. 12426-12437, 2020.

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Challenges and Open Problems

- Lack of labeled data
  - Semi-supervised learning, transfer learning, self-supervised learning
- Online learning and adaptation
  - Continual learning, reinforcement learning, sequential Bayesian modeling
- Interpretability of ML models
  - Uncertainty quantification, out-of-distributions modeling
- Distributed sensors and data
  - Distributed and federated learning, energy-efficient training of ML models
- Well-defined and large open datasets for development and validation

Thank You!

Data Analysis and Inference Group @ BISG:
`https://www.oulu.fi/bisg/data-ai`

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6G Flagship: `https://www.oulu.fi/6gflagship/`