Machine learning approach for wireless communications

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outline

INTRO. TO MACHINE LEARNING

PROBLEMS FOR LEARNING-DRIVEN WIRELESS COMMUNICATIONS

SUMMARY
Intro. To Machine Learning

• ML: is “an algorithmic framework to identify computational models that describe empirical data and the phenomena underlying it”

• Today’s ML teaches the computer
  • Automatic detection of objects in an image (e.g., CAV)
  • Speech recognition (e.g., voice command Tech.)
  • Knowledge discovery in the medical science (e.g., medical diagnosis)
  • Predictive analytics (e.g., economic forecasting)
  • Etc.
Intro. To Machine Learning

- Emerging applications: ML (or DL) + Wcomm

- Traditional approaches based on theories and models
- To predict behaviors of, e.g., Machine Type Comm. in deployed environments
- ML approaches with the increasing complexity of Wireless Comm. Systems.

Machine Learning in Communications

Machine Learning (ML) has a long and extremely successful history. For example, the idea of using neural networks, as early as 1942 when a simple one-layer model was used to simulate the status of a single neuron. Since then, it has been successfully applied in many areas, including computer vision, robotics, and natural language processing. However, it was not until the introduction of deep learning models for feature representation in those areas, ML has proved to be a powerful tool as it demonstrates the power of these models from information theory to channel modelling. These traditional approaches are showing some limitations in the face of the increased complexity of communication networks. Therefore, research on ML applied to communications, is currently experiencing an incredible boom.

Best Readings focuses on ML in the physical and medium access control (MAC) layer of communications systems.
Wireless Roadmap

Hyper-digitalized society
Exploding data: Predictions beyond 2020

About an order of magnitude increase

Current focus

Source: Cisco
Impact of MTC

- Annual economic impact by IoT: 2.7~6.2 trillion USD by 2025
- Potential economic impact of sized IoT apps
Automatic process in Engineering problems in general, and Automatic (PHY+) resource allocation in Wireless Comm. in particular.
Machine Learning + Wireless Comm.

- Distinguishing problem between Cats and Dogs: a ML approach
  - Teaching a computer to distinguish between pictures with cats and those with dogs.
  - Pictures with cats: simply a category of data with label ‘cat’
  - Pictures with dogs: another category of data with label ‘dog’

- **Four basic steps** in most (if not all) ML approaches
  - Data collection
  - Feature design
  - Model training
  - Model validation
Data collection

- A device must be trained to
  - Recognize the difference between the two types of animals (or, wireless Tx modes)

• Learning from a batch of examples, => a **training** set of data

- A training set
  - Consisting of six images of cats and another six images of dogs
Data collection

• Intuitively,

The larger and more diverse experience

Training set of data

Better performance on a learning task
Feature design

• How to tell the difference between images/data
• What to use:
  • *Color, size, the shape of ears or nose, and/or some combination of these “features”*
  • Possible features in the WComm viewpoint: Channel state, SNRs, Error level, Activation patterns, considering N-dimensional space in general
  • (e.g., only 12 sub-channels at a 2-bit quantization -> over 16M patterns)

• To tell the difference,
  (i) Firstly need to pick out / design features from images (or data)
  (ii) Identify what it is that we are looking at

• Properly designed features
  • Essential to successfully train the computer to perform this task (or, ML tasks in general)
  • Can be provided or learn such features by itself (towards on-device intelligence)
Feature design

• Designing of quality features
  • not trivial
  • Greatly “application dependent”
  • (e.g., smart factory, smart cities, wearable healthcare)

• Extracting features from training images (or data)
  • Challenging with noisy images (or data), in practice
Model training

- The process of determining parameters (예, 기울기, 교차점)
  - By math. optimization tools

- Tuning such a set of parameters to a training set
  => called, "Training model"

- Mathematical func.
  - Used to define a cost (or loss) function
  - Compute the cost func. with each tuning trial (i.e., parameters)
Model validation

- Validation data set
Pipeline of classification problem

Training set

Validation set

최적 선형 직선 $w$ min. cost func
Application of ML algorithms

- Supervised learning (with labeled data)
  - Regression
  - KNN
  - Multi-class classification (MCC)
  - Etc.

- Unsupervised learning (with unlabeled data)
  - K-means clustering
  - General matrix factorization
  - Etc.
ML aided automatic data mapping

- Wireless app: wireless channels are **random** at every trials
  - Impossible to **label** such a set of random, wireless data

**Data collection**
- Data: Random, wireless channel coefficients in a multi-dimensional space
- Empirical or simulative data: A batch of such a multi-dim. Wireless channel coefficients.

**Feature design**
- Learn what feature(s) to use – error probability, tx mode with different parameters (e.g., power, data rate, activation pattern)

**Model training**
- **K-means clustering** algorithm => “unsupervised” multi-class classification problem

**Model validation**
- For validation dataset, compute the validation error based on the learned model
- Better learning model, more accurate prediction for the best mode to be used for transmission
- Larger dataset, more accurate prediction
- How to resolve **overfitting problems vs low complexity**
Main concept:

Unsupervised learning is adopted to automatically tune a multi-dimensional modulator (MDM) at the PHY layer:

- **Offline training** is to generate a training dataset and learn multiple clusters to represent behaviour of the MDM’s modes.
- **Real-time testing** is to predict the best Tx mode, which provides the max. data rate at acceptable reliability.

**Auto-MDM with Machine Learning**

- **No predefined** switching & adaptation protocols
- **A classification dataset**, after deployment & offline training!
- **Real-time prediction and adaptation** in MDM signal

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Multi-Dimensional Features

• Tx signal $\mathbf{x}$ over $N$ sub-carriers at every TTI
  $$\mathbf{x} = C_\theta \mathbf{s},$$
  depending on one of Tx modes
  $$C_\theta = [c_{i_1}, \ldots, c_{i_k}] \subseteq C = [c_1, \ldots, c_N] \quad \& \quad \mathbf{s} \in \mathbb{C}^{k \times 1}$$

• The training dataset, $\mathbf{z} = \{\mathbf{z}_1, \ldots, \mathbf{z}_Q\}$
  • $q$-th observation $\mathbf{z}_q$: (N+1) dimensional real-valued vector
  • First $N$ entries: energy levels of $N$ sub-carrier signals
  • $(N+1)$-th entry: index of Tx mode producing the best perf.
**Algorithm 1** $K$-means clustering algorithm

1. Select $K_c (\leq Q)$, and generate a set of input data $z_q, \forall q$.  
2. **procedure** CLUSTERING$(z, u, K_c)$  
3.   
   repeat  
4.     $i = i + 1$.  
5.     Form $K_c$ clusters by assigning all points $z_q, \forall q$ into the closest centroid.  
6.     Recompute the centroid of each cluster, $u_{(l)}, \forall l$.  
7.     until $\Sigma_i = \Sigma_{i-1}$  
   \hspace{1cm} $\triangleright$ We have the answer if the centroids don’t change  
8.     **return** $\Sigma_i$

\[ d_{e,l}^2 = \|u_{(l)} - z_q\|^2, \text{ for } l = 1, \cdots, K_c. \]
\[ (l) = \arg \min_l d_{e,l}^2 \]

\[ u_{(l)} = \frac{1}{n_{(l)}} \sum_{j=1}^{n_{(l)}} z_{j,(l)}, \]
\[ z_{j,(l)} \text{ is the } j\text{-th point within the cluster } (l) \]
ML aided automatic MDM

- **Potentials:** cost-effective, autonomous adaptation
  - Today's deep neural networks (DNNs) and their dataset are inaccessible to realistic mobile devices

An exemplary set for the Auto-MDM when \((N,k)=(2,1), \Mt=\{0,2,4\}\) and \(K_c=4\)

\[
\begin{align*}
\text{Energy of sub-carrier 1 (dB)} & \quad \text{Energy of sub-carrier 2 (dB)} \\
0 & \quad 0 \\
18 & \quad 20 \\
10 & \quad 14 \\
4 & \quad 12 \\
2 & \quad 10 \\
\end{align*}
\]

\[
\begin{align*}
\text{SNR (dB)} & \quad \text{Average Bit Error Probability} \\
0 & \quad 10^{-1} \\
5 & \quad 10^{-3} \\
10 & \quad 10^{-5} \\
15 & \quad 10^{-7} \\
20 & \quad 10^{-9} \\
25 & \quad 10^{-11} \\
\end{align*}
\]

- N=4, \(k=\{1,2\}\), \(K_c=100\), \(Q=500\)
Summary: Flood of new data

- Average monthly traffic per 5G user:
  - 11.7GB in 2019 to 84.4GB in 2028

- Next generation wireless network
  - Diverse innovation on everything from the digitalisation of everyday life objects to 'AI'
  - The flood of new data!
  - Artificial intelligence for each user and each application is quite challenging

But how?

“Autonomous” Mobile Networks

- **SP and AI algorithms**
  - Hyper-Autonomous Network with Blind Mapping
  - Self-Evolvable MTC: Federated Machine Learning
  - Security MTC with Randomized Mapping

Source: Intel
Thank you for your attention

Q/A ?

Open for Collaborations:
“Autonomous” mobile network

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References


