QoE-aware Machine Learning:
An Optimization Approach

May 11, 2018

Eric Kaiyuan Chen

Two Problems Trying To Solve

- Why do we use machine learning instead of other methods?
- Optimization in terms of configurations

Background: Quality of Experience (QoE)

- Definition
  - customer-focused performance measurement of experience
  - impact of network behavior on end user
- Different from QoS: network characteristics/behavior measured by network provider

Background: Quality of Experience (QoE)

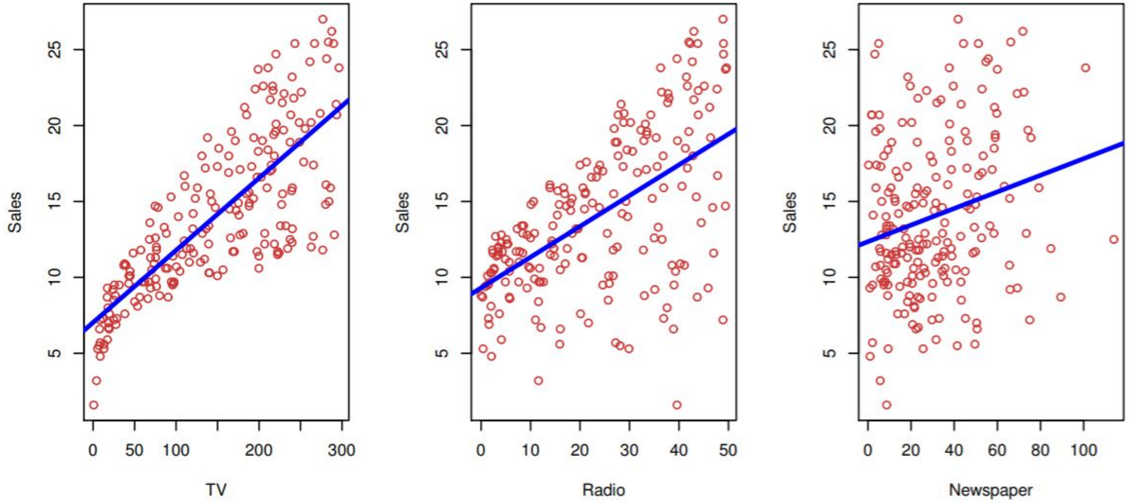
- Key considerations
  - Application specific
    - a 5% packet loss could be invisible if it affects background
    - a missed target due to a 100ms delay can affect game outcome
  - Measurement
    - Every paper has its own metric for QoE
    - Some papers use Mean Opinion Score(MOS): ITU-R has spec
    - Others use QoS-like metrics

Collecting QoE Information

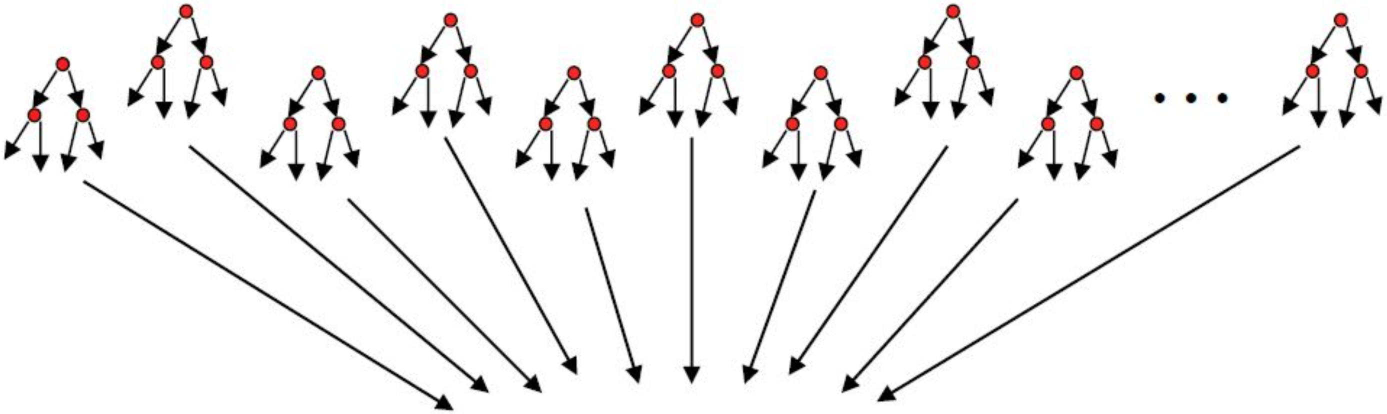
- Video
  - YouTube player reports to Google servers summary statistics at the end of each video playback.[1]
    - If the video successfully loaded
    - # of stalls and how long each one lasts
    - Rebuffering, wait component monitors[4]
  - Startup delay[2]
- Skype video conference
  - Peak signal-to-noise ratio(RSNR)[2]
  - rate, delay and jitter.[3]
- Web browsing
  - Facebook: upload post UI wait time
  - Pull-to-Update time
  - Webpage loading time

Background: Machine Learning.Regression

- Polynomial Regression



Background: Ensemble methods



Average prediction

(0.23 + 0.19 + 0.34 + 0.22 + 0.26 + … + 0.31) / # Trees = 0.24

Why is it good from a network perspective

Evaluating the network performance for a given configuration requires a dynamic system-level simulation, which requires high computational time

Index

- An important pipeline that summarizes all the papers I have seen
- Using regression and searching to detect underperforming sectors
- Configuration: A comparative approach for applying Genetic Algorithms

QoE-Aware Pipeline

Evaluation

Regression based

- configuration/kpi -> QoE
- Methods

Artificial Neural Network(ANN),
Bagged SVM,
Random Forest
LSTM/RNN

Optimization

Greedy Search based

- Searching for optimal parameter set
- Methods

Particle Swarm Optimization(PSO)
Genetic Algorithm(GA)
Reinforced Learning(RL)

The good, the bad, and the KPIs: how to combine performance metrics to better capture underperforming sectors in mobile networks

ICDE 17

Problem Setting

- Goal: bridging sector KPIs and per customer QoE for the whole network at scale
- Limitation: **rigid, static and empirical**
    - It is unknown whether current scoring function really reflects QoE
    - Lacks flexibility for user's need
        - Whether they need Voice more than LTE, weight should be different

Example of traditional KPI Thresholds

- Conventional Approach (where state of art is based on): Hotspot Score
  - Combines different KPI
  - The higher the score, the more problematic the sector is

$$s_b = S\left(\mathbf{k}_b, \mathbf{w}, \mathbf{t}\right) = \sum_{i=1}^{n} w_i \cdot H\left(k_{b,i} - t_i\right),$$

  - H is threshold that outputs 1 if > 0

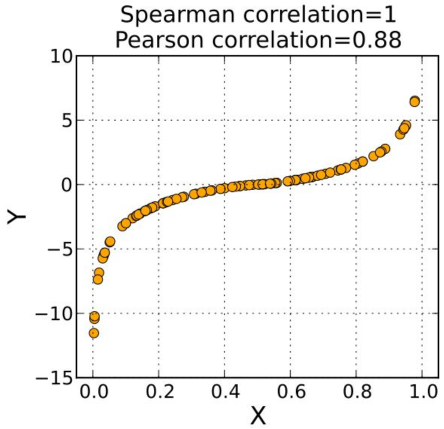
KPI	Thres.	Category
Failed RRC/RAB requests ratio	$> 5\%$	Signaling
Signaling failure	$> 1\%$	
Call setup failure rate	$> 2\%$	Voice
Call drop rate	$> 5\%$	
HSDPA/HSUPA session setup success %	$< 90\%$	Data
Average Users Queuing	> 2	
Time Slots Transmitting	$> 80\%$	
Noise Rise	$> 10db$	Radio

Metric for score function

Spearman Correlation of scoring function s and ground truth g

$$\rho(\mathbf{s}, \mathbf{g})$$

- Not differentiable but computationally cheap
- Solution
  - Use Machine Learning to establish relationship
    - Linear
    - Non-linear
  - Use Particle Swarm Optimization train the relationship



Approach	Configuration	Delay	Thput	Stalls
1 Baseline	All KPIs	0.15	-0.14	0.07
2 Baseline	Only data KPIs	0.19	-0.17	0.09
3 PSO on S	Only weights	0.29	-0.26	0.17
4 PSO on S	Only thresholds	0.30	-0.29	0.19
5 PSO on S	Weights and thresholds	0.41	-0.36	0.22
6 PSO on $\hat{S}$	weights	0.46	-0.42	0.23
7 Non-linear	Random forest regression	0.40	-0.32	0.23

Representation of Relationships of KPIs

- Linear Representation
  - Normalize all KPI
  - Use Linear Combination

$$\hat{S}_b(\mathbf{k}_b, \mathbf{w}) = \sum_{i=1}^{n} w_i \cdot k_{b,i}.$$

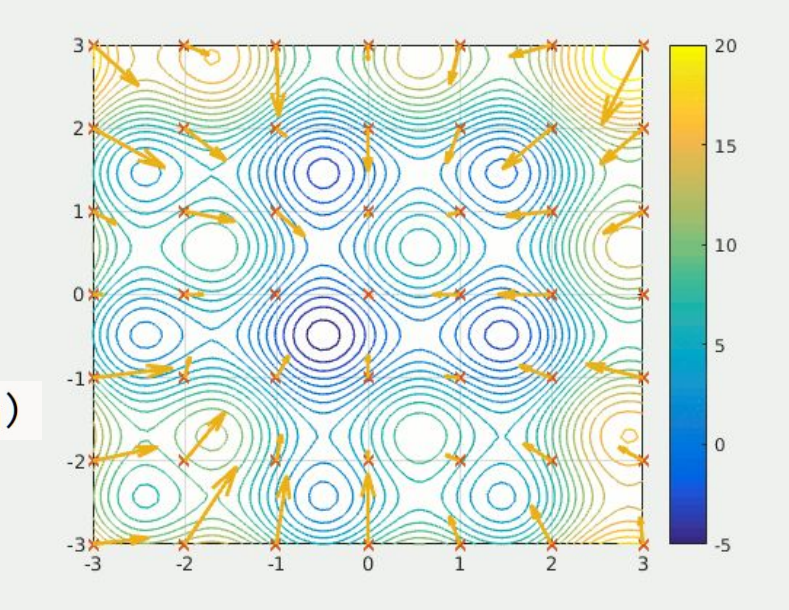
- Random Forest
  - Higher expressive power

Particle Swarm Optimization(PSO)

For each particle, it has two property: velocity and position

For each step, each particle update by finding the best known position among neighbors and adding a velocity to there iteratively.

$$\mathbf{v}_{i,d} \leftarrow \omega\, \mathbf{v}_{i,d} + \phi_p\, r_p\, (\mathbf{p}_{i,d} - \mathbf{x}_{i,d}) + \phi_g\, r_g\, (\mathbf{g}_d - \mathbf{x}_{i,d})$$



QoE-Aware Pipeline

Evaluation

Optimization

Regression based

- Sector kpi -> QoE

Random Forest

Greedy Search based

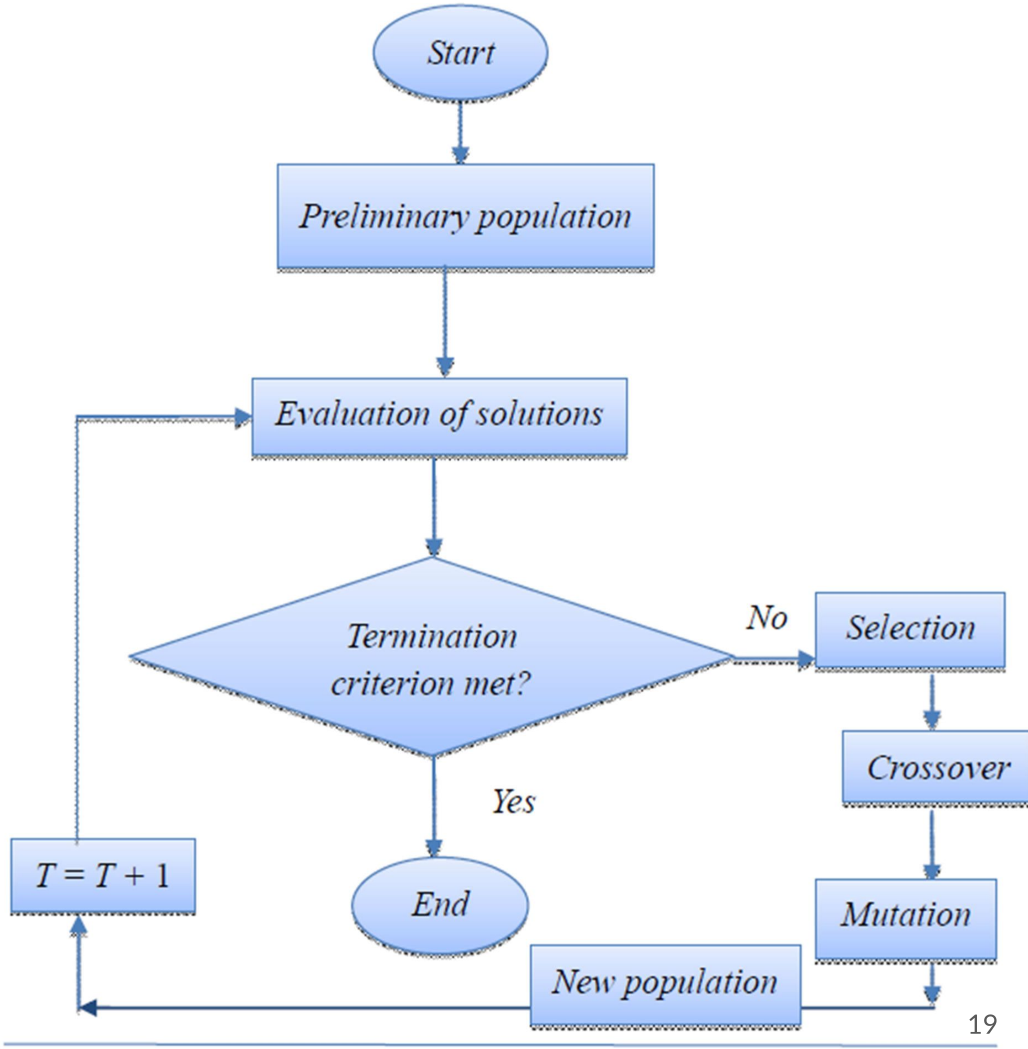
- Searching for optimal parameter set

Particle Swarm Optimization(PSO)

Comparing Two papers in Parallel: **One set of algorithms, two distinct contexts**

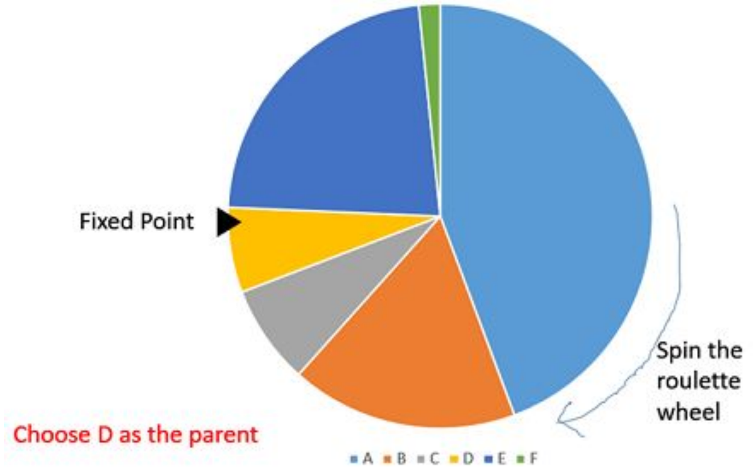
- QoE-aware Optimization of Video Stream Downlink Scheduling over LTE Networks using ANNs and Genetic Algorithm
  - Procedia Computer Science 16
- Conflict Resolution in Mobile Networks: A Self-Coordination Framework Based on Non-Dominated Solutions and Machine Learning for Data Analytics
  - May 2018 IEEE Computational intelligence magazine

Background: Genetic Algorithm



Genetic Algorithm

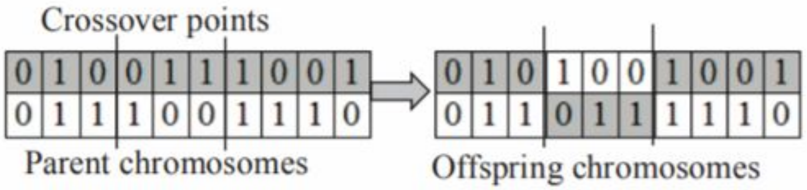
- Selection(roulette wheel selection)



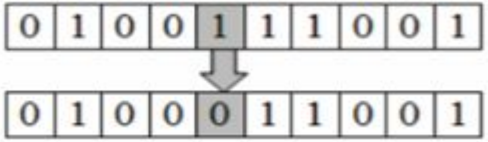
Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Genetic Algorithm

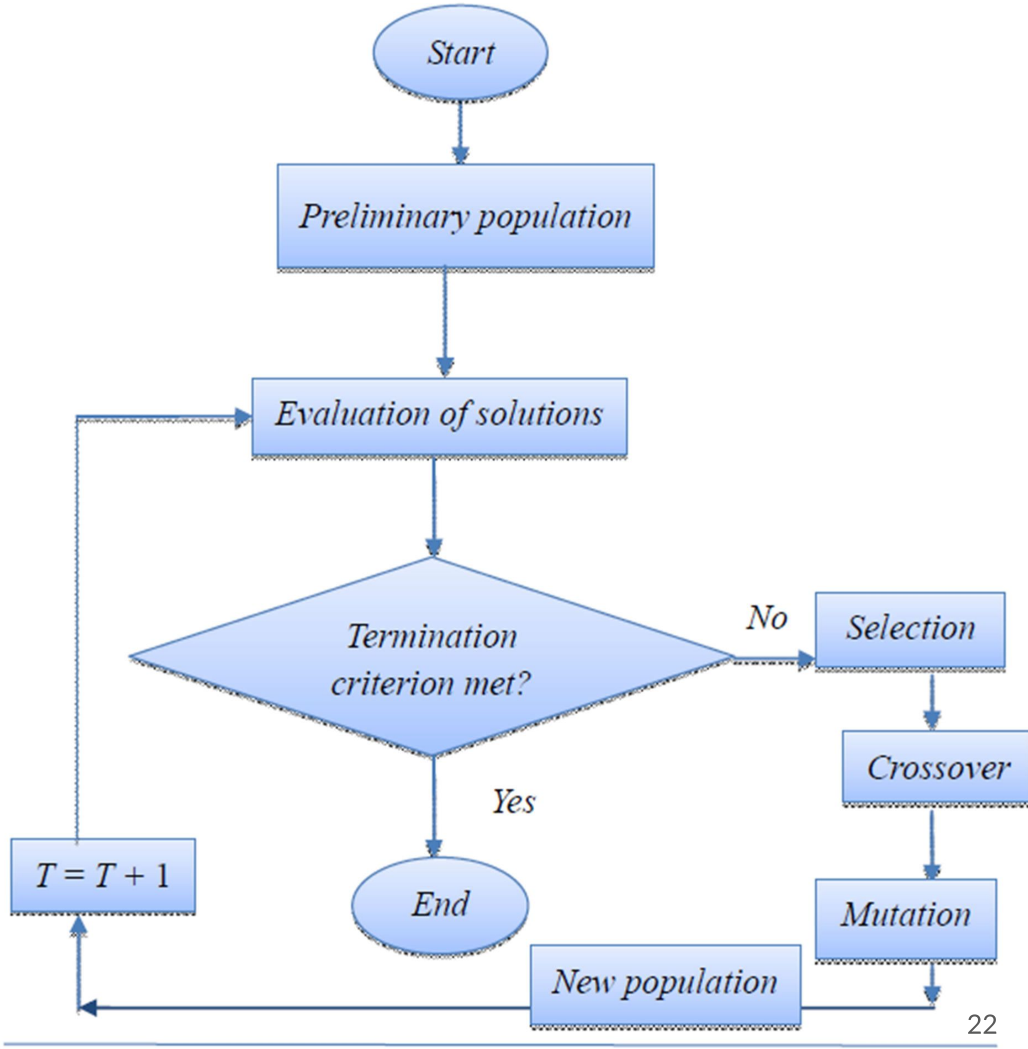
Crossover



Mutation

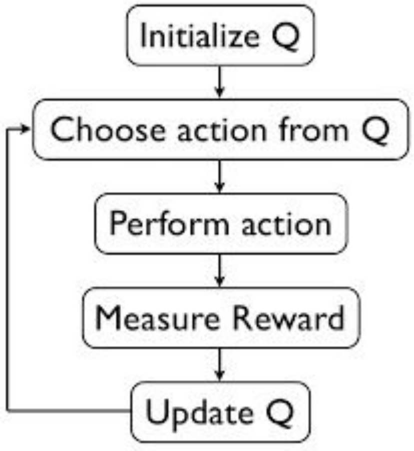


Background: Genetic Algorithm



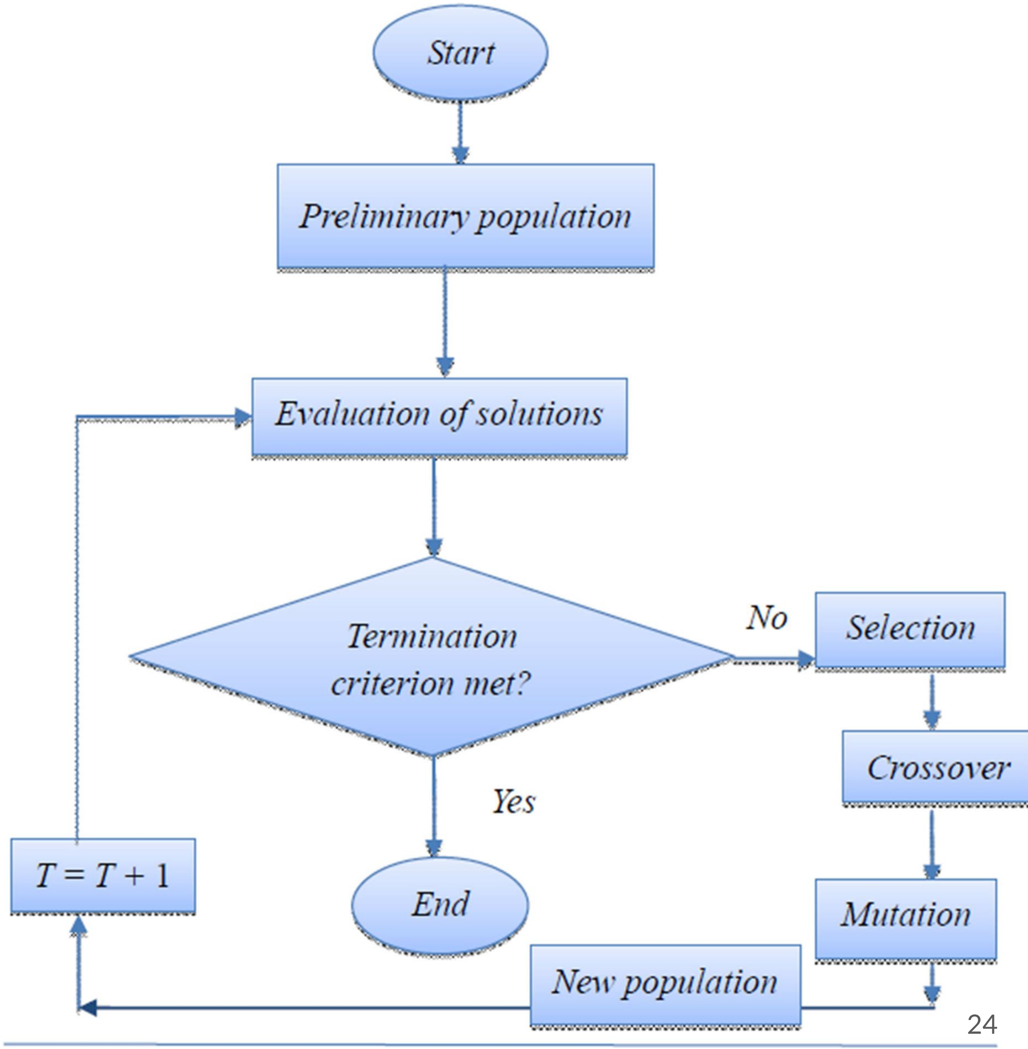
Advantages of Genetic Algorithm

- good for finding an approximate solution
- More scalable than Reinforcement Learning
    - Another class of algorithms that solve in term of reward/cost
    - Formulating solution by backtracking(e.g. DP)
    - RL requires a **huge state and action space**.
        - High variance on actions



Flowchart for Q-learn

In our case, QoE & Config!



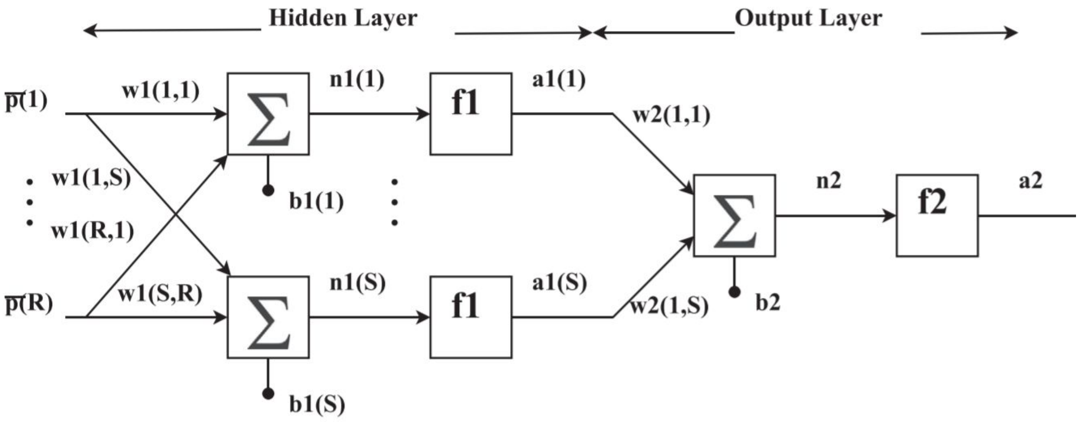
QoE-aware Optimization of **Video Stream Downlink Scheduling** over LTE Networks using ANNs and Genetic Algorithm

Procedia Computer Science 16

Context

- video content as one of the highest services enabled by LTE with the most revenue generating potential
- Using a scheduling scheme to obtain best QoE
  - By maximizing Mean Opinion Score(MOS)
  - The standard of their experiment is ITU-R, Subjective Video Quality Assessment Methods for Multimedia Applications,P.910

Artificial Neural Network(ANN)



$$\overline{p}(i) = (p(i) - p_{offset}(i)) \cdot p_{gain}(i) - 1;$$

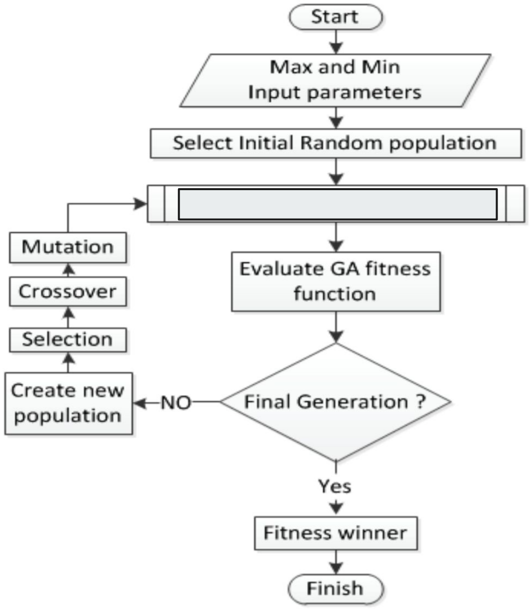
$$n1 = W1 \cdot \overline{p} + b1;$$

$$a1(i) = \frac{2}{1 + e^{-2 \cdot n1(i)}} - 1;$$

$$n2 = W2 \cdot a1 + b2;$$

$$\widehat{MOS}_{ANN} = a2 = \frac{n2 + 1}{n2_{gain}} + n2_{offset};$$

The rest directly follows GA...



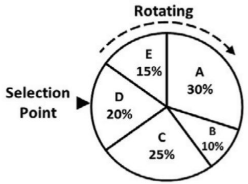


Fig. 2. Roulette wheel selection.

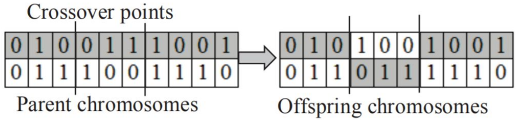


Fig. 3. Two-point crossover.

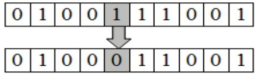


Fig. 4. Binary chromosomes mutation.

Conflict Resolution in Mobile Networks: A Self-Coordination Framework Based on Non-Dominated Solutions and Machine Learning for Data Analytics

May 2018 IEEE Computational intelligence magazine

Background: HO triggering procedure

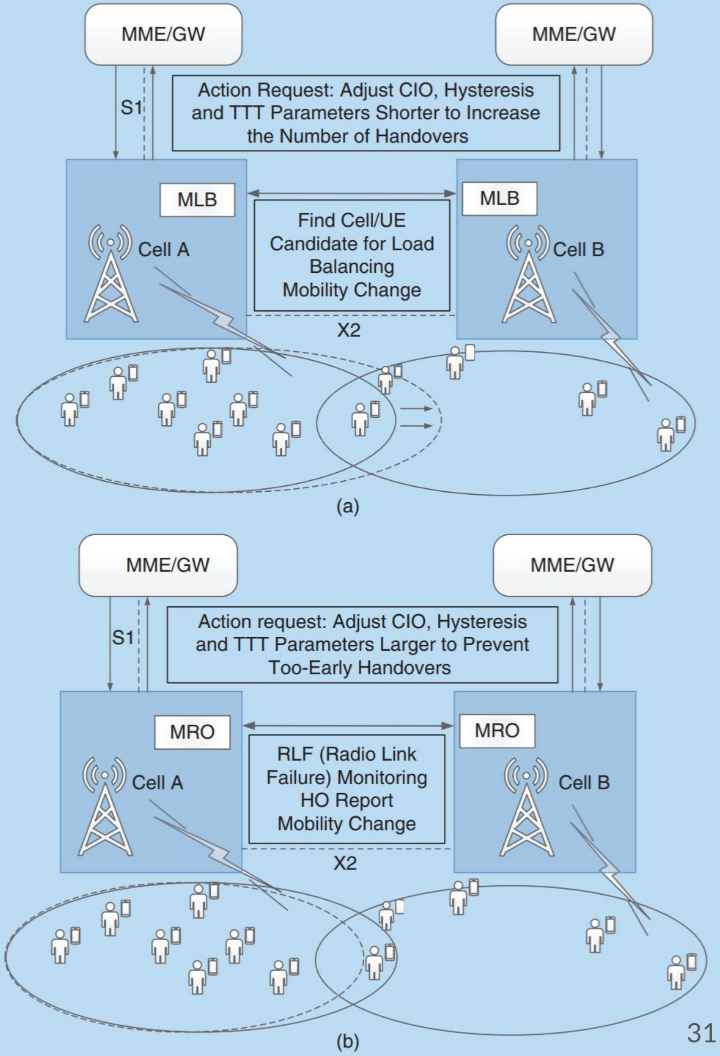
Handover triggers when

$$RSRP_{nc} > RSRP_{sc} + \text{offset} + \text{Hysteresis} - \text{CIO}$$

(offsets are added to prevent ping-pong effect)

Background: MLB and MRO

- Both of them aim at adjusting CIO, hysteresis
- mobility load balancing(MLB):
  - Transfer users to less loaded neighboring cells
  - Optimize QoS by evenly distributing
- mobility robustness optimization(MRO):
  - minimize radio link failure and unnecessary handover



Context: Handover Coordinations

- Self-organizing network(SON): self-configure, self-optimize and self-healing
- when two or more SON functions aim at adjusting the same output parameter with opposite values
  - mobility load balancing(MLB): transfer to less loaded neighboring cells
  - mobility robustness optimization(MRO): minimize radio link failure and unnecessary handover
- When multi-objectives are dealt, configurations may cancel each other
  - Making decision in real time
  - Need self-coordination

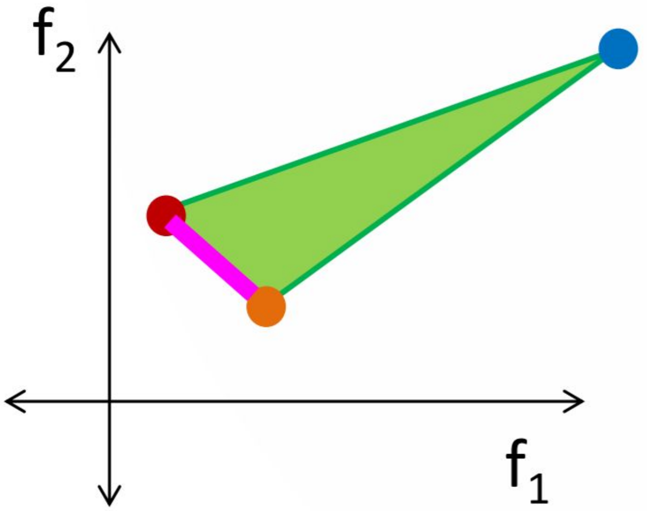
Multi-objective optimization

We feed in n SON configuration set functions, and we are trying to minimize **Pareto front**

$$\begin{bmatrix} \mathbf{s}_1 \\ \mathbf{s}_2 \\ \vdots \\ \mathbf{s}_n \end{bmatrix} \rightarrow \begin{bmatrix} \mathrm{SON}_1 \\ \mathrm{SON}_2 \\ \vdots \\ \mathrm{SON}_N \end{bmatrix} \rightarrow \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_K \end{bmatrix}$$

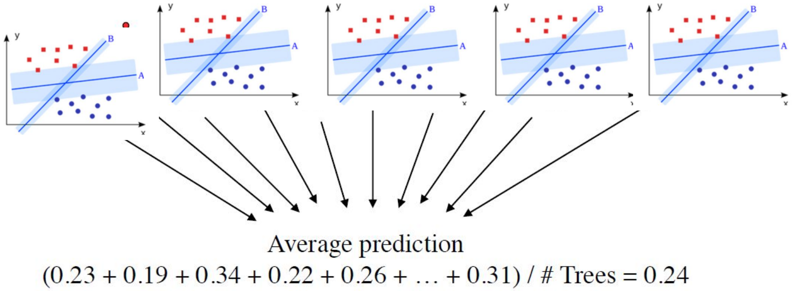
Then our objective is

$$\begin{array}{ll} \text{minimize} & (F_1(\mathbf{s}), F_2(\mathbf{s}), \ldots, F_K(\mathbf{s})) \\ \text{subject to} & \mathbf{s} \in \mathbf{S} \end{array}$$

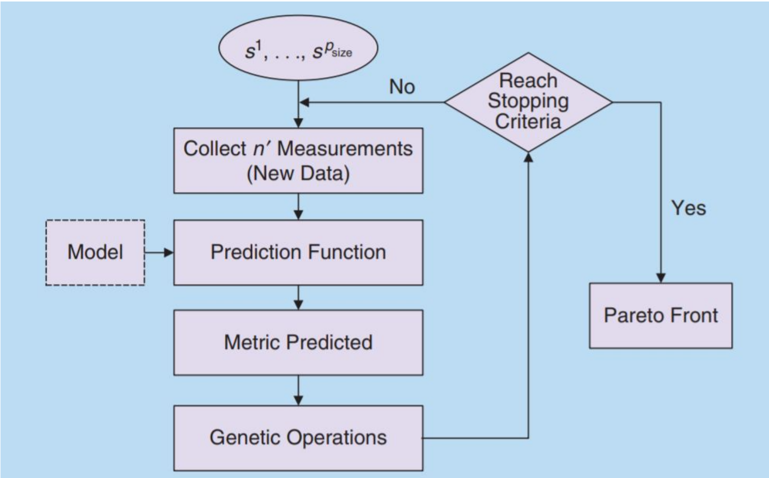


Solution:

- Regression: Bagged SVM



- Multi-objective optimization by genetic algorithm



Other papers also follow exactly the same pipeline

1. Cellular Network Traffic Scheduling with Deep Reinforcement Learning.
    a. AAAI 2018
2. Online Learning for Interference Coordination in Heterogeneous Networks
    a. ICC 2017
3. An Advanced SOM Algorithm Applied to Handover Management Within LTE
    a. IEEE Transaction on Vehicular Technology
4. A Cooperative Online Learning Scheme for Resource Allocation in 5G Systems
    a. ICC 2016
5. Traffic Prediction Based Power Saving in Cellular Networks: A Machine Learning Method
    a. SIGSPATIAL 2017

And So on...

7. APP-SON: Application characteristics-driven SON to optimize 4G/5G network performance and quality of experience
    a. IEEE BIG Data 2017
8. ExBox: Experience Management Middlebox for Wireless Networks.
    a. CoNEXT 2016
9. A joint multicast/D2D learning-based approach to LTE traffic offloading
    a. Computer Communications Dec 2015

…………………....

Why?

Evaluation

Optimization

Regression:
Fast,
Pre-trained: scalable
Online: adaptive,

Searching:
Non-differentiable, sometimes multi-objective
Only need to find a solution that is good enough

Potential

Evaluation

Optimization

Better regression scheme for QoE

Methods with faster convergence rate and less complexity

New Scenarios/contexts to be explored
“We have a hammer and we are looking for a nail”

Conclusion: Two Problems I have Solved

- Why do we use machine learning instead of other methods?
  - Dynamic and plug-and-play: Determining underperforming sectors by kpi
  - Versatile and agnostic: Comparison
- Optimization in terms of configurations

Machine Learning:
It generalizes.
It is flexible.
It is agnostic.

Questions?
Comments?

QoE-Aware Pipeline

Evaluation

Regression based

- configuration/kpi -> QoE
- Methods

Artificial Neural Network(ANN),
Bagged SVM,
Random Forest
LSTM/RNN

Optimization

Greedy Search based

- Searching for optimal parameter set
- Methods

Particle Swarm Optimization(PSO)
Genetic Algorithm(GA)
Reinforced Learning(RL)