NMLRG #4 meeting in Berlin

"Mobile network state characterization and prediction"

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Outline

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- Mobile network state characterization & prediction
 - Motivation/Objectives
 - Considered approach using unsupervised & supervised ML techniques
 - Indicative Results
- Conclusions & Next steps

Service Classification in 5G Networks^{*} - Motivation & Objectives

- Motivation
 - Existence of diverse vertical/services with different requirements in terms of QoS & capacity:
 - Mobile Broadband (MBB)
 - Massive Machine Type Communications (MTC)
 - Mission Critical Communications (MCC)
 - Broadcast/Multicast Services (BMS)
 - Vehicular to X (V2X)
 - 5G system management → meet the requirements resulting from a large variety of services to be provided simultaneously optimizing the network in order to be resource and energy efficient
 - Prioritization of services and efficient allocation of resources → need for automated service classification schemes
- Our approach: use of supervised ML techniques (classification)
- **Goal**: Accurate identification of services to promote an efficient network tuning (optimal assignment of resources to satisfy the diverse QoS requirements)

*[Investigated under the framework of FANTASTIC-5G project, H2020 G.A.671660, http://fantastic5g.eu/]

- MBB \rightarrow diverse services (file downloading, streaming) usually larger packets
- MMC \rightarrow periodic communication (inter-arrival time), small packet size
- MCC → usually small packets (except P2P communications)
- BMS → larger packets, multicast/broadcast communication (not individual destination)
- V2X (V2V or V2I) \rightarrow high speed of nodes & combination with 4 others services

Service Parameter	MBB (Video streaming)	ммс	мсс	BMS	V2X
Packet length	Usually large	Small	Small	Medium	Depends on other characteristics
Statistics of Packet length (e.g. std)	Medium	Very small	Very small	Medium-Large	Depends on other characteristics
Packet inter- arrival time	Non periodic	Periodic	Non periodic (burst effect)	Non periodic	Usually non periodic
Statistics of Packet Inter-arrival time	Medium-Large	Very small	Large	Medium	Medium
Flow Direction	DL: large packets UL:small packets	UL	UL	DL	UL/DL
Flow length	Large	Small	Small	Medium	Small-Medium
Statistics of flow length (std)	Small-Medium	Small	Small	Medium	Medium
Mobility	Average	Low	Low	Low-Average	High

- We consider 3 types of services: MCC, MMC, MBB
- Generation of different types of MCC /MMC traffic following traffic models in 802.16p1
- Generation of MBB traffic following traffic models for video streaming (e.g. YouTube)²

Information of the collected traces:

- Simulation time
- Source

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- Destination
- Direction (Uplink/Downlink)
- Packet Size
- Device Name (e.g. Mobile128)
- Separation of traces in flows
 - Same source/destination
 - Interarrival time < threshold

Features generation for each flow:

- Interarrival time (Mean value/ Std)
- Packet Size (total/Mean/Std/Min/Max)
- Number of packets
- Source
- Destination
- Direction

- ¹IEEE 802.16p Machine to Machine (M2M) Evaluation Methodology Document (EMD)
- ² Ameigeiras, Pablo, et al. "Analysis and modelling of YouTube traffic." *Transactions on Emerging Telecommunications Technologies* 23.4 (2012): 360-377.



Classification

- •Use of predefined classes of training instances
- •3 phases: training, cross-validation, application of classifier
- •Goal: from the training dataset , find a function f(x) of the input features that best
- predicts the outcome of the output class y for any new unseen values of x

- Algorithms for investigation :
 - Support Vector Machine (SVM)
 - k-Nearest Neighbors
 - Logistic Regression
 - Adaboost
 - Gradient Boosting

Classification Mechanism	Accuracy
Support Vector Machine	0.887
K Nearest Neigbors	0.867
Logistic Regression	0.868
Adaboost Classifier	0.797
Gradient Boosting Classifier	0.591

Confusion Matrix- Evaluation Metrics for classification

Classification Service Result	ММС	Other services
ММС	ТР	FN
Other services	FP	TN

$$Precision = \frac{TP}{TP+FP} \qquad Recall = \frac{TP}{TP+FN}$$

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Class $0 \rightarrow MMC$, Class $1 \rightarrow MCC$, Class $2 \rightarrow MBB$

Support Vector Machines (SVM)

Class \ Metrics	Precision	Recall	F1-score
MMC	0.85	0.99	0.91
MCC	0.88	0.81	0.85
MBB	0.96	0.83	0.89
Avg/total	0.89	0.89	0.89

Logistic Regression

Class\ Metrics	Precision	Recall	F1-score
MMC	0.84	1.00	0.91
MCC	0.81	0.82	0.82
MBB	0.98	0.75	0.85
Avg/total	0.88	0.87	0.87

K Nearest Neighbor Classifier

Class \ Metrics	Precision	Recall	F1-score
MMC	0.85	0.98	0.91
MCC	0.84	0.79	0.81
MBB	0.93	0.80	0.86
Avg/total	0.87	0.87	0.86

Gradient Boosting Classifier

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Class \ Metrics	Precision	Recall	F1-score
MMC	0.98	0.57	0.72
MCC	0.41	1.00	0.58
MBB	1.00	0.27	0.42
Avg/total	0.83	0.59	0.58

- Analysis of the tradeoff between metrics (ROC curve)
- Optimization of metrics depending on the service (e.g. high values of Recall for MCC services)
- Definition of customized evaluation metric depending on the service

Mobile network state characterization & prediction – Motivation & Objectives

- Motivation
 - Diverse and complex actions (addition/removal of TRXs, transition from 2G→3G→4G features etc) take place in a real-world mobile network
 - Online optimization of network performance → automated analysis of each action's impact to the network KPIs (customized to the specific network characteristics)

• Our approach:

- Impact analysis of resource allocation actions using unsupervised ML techniques (clustering approach)
- Prediction of network traffic/quality metrics using supervised ML techniques

• Objectives:

- Identification of resource allocation actions that result in ameliorated/ deteriorated network performance
- Prediction of future network KPIs considering that a specific resource allocation action will take place

Mobile network state characterization & prediction – ML approach

- Impact Analysis of resource allocation actions using clustering mechanisms:
 - Input of ML mechanism: network traffic/quality data of cells that affected by these actions
 - ML mechanism: Clustering (k-Means)
 - Output of ML mechanism: groups of cells where the cells in the same group (called a cluster) are more similar to each other than to those in other groups



x-axis (silhouette coefficient values) : separation distance between the resulting clusters; how unsimilar each cell in one cluster is to cells in the neighboring clusters

Mobile network state characterization & prediction – ML approach

- Impact Analysis of resource allocation actions using clustering mechanisms:
 - Indicative clustering results (centroids representation) for traffic data of cells in a specific region
 - Input data: Voice traffic data during one month period
 - Ouput data: 4 clusters of cells (Low/Average/High/Very High Performance)



Mobile network state characterization & prediction – ML approach

- Prediction of network traffic/quality metrics using supervised ML techniques
- Input of ML mechanism: network traffic/quality data of cells that affected by these actions
- ML mechanism: Time series prediction mechanisms (SVM, Neural Networks etc)
- Output of ML mechanism: predicted future values of traffic/quality metrics for specific cells using past traffic/quality data
- Next steps:
- Use of accurate evaluation metrics for time series prediction
- Analysis of the tradeoff between metrics depending on the KPIs

Conclusion - Next steps

- Development of automation mechanisms based on machine learning for:
 - Service Classification in 5G networks
 - Mobile network state characterization
- Evaluation of service classification techniques for 5G networks
 - Definition/Selection of evaluation metrics
- Evaluation of predictive mechanisms for real-world mobile network scenario
 - Time series prediction using ML techniques
 - Selection of adequate evaluation metrics

Thank You!

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For details you can visit: http://tns.ds.unipi.gr http://incelligent.net http://wings-ict-solutions.eu