TECHNISCHE UNIVERSITÄT CHEMNITZ

Machine Learning based KPI Monitoring of Video Streaming Traffic for QoE Estimation

Özge Celenk, Thomas Bauschert, Marcus Eckert
Presenter: Özge Celenk
WAIN Workshop 2020

Technische Universität Chemnitz
Chair of Communication Networks
Chemnitz, Germany
06.11.2020

Outline:

- Introduction
  - Motivation
- Methodology
  - Workflow
  - Data Collection & Test Setup
  - Network Scenarios
  - Preprocessing
  - Statistical features
  - Handling the Imbalanced Dataset
- Results
  - Offline Results
  - Online Results
- Conclusion & Future Work

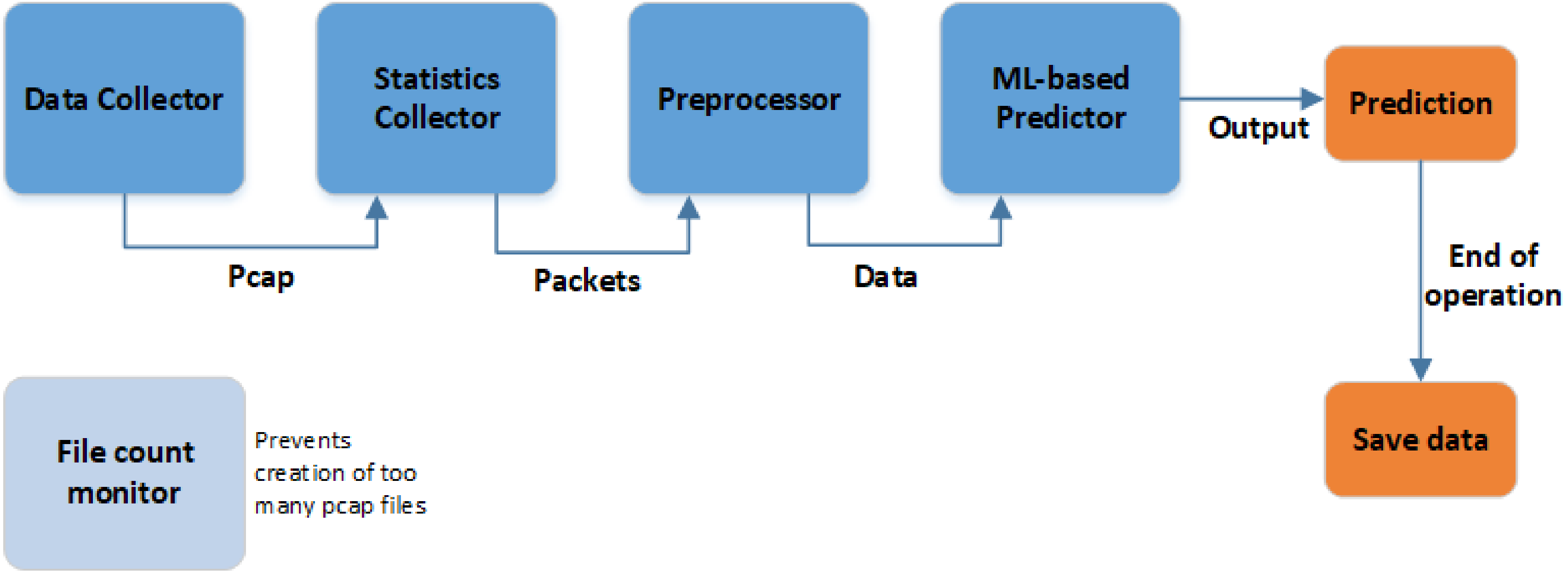
Introduction

Motivation:

- Assessing the video streaming QoE is challenging due to encryption.
- Alternative solution: Machine Learning (ML) approach
- Aim: Detecting key video events (Playing, Buffering, Quality Changes)

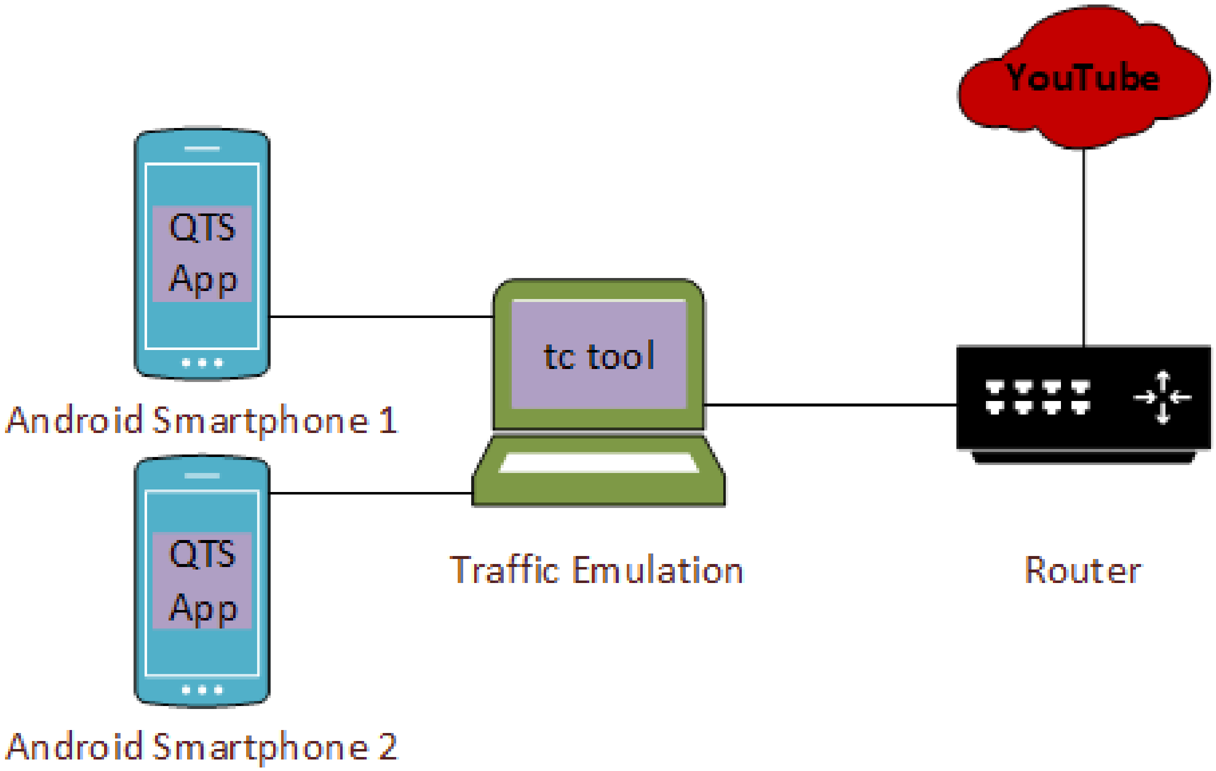
Methodology

Workflow:



Methodology

Data Collection & Test Setup:



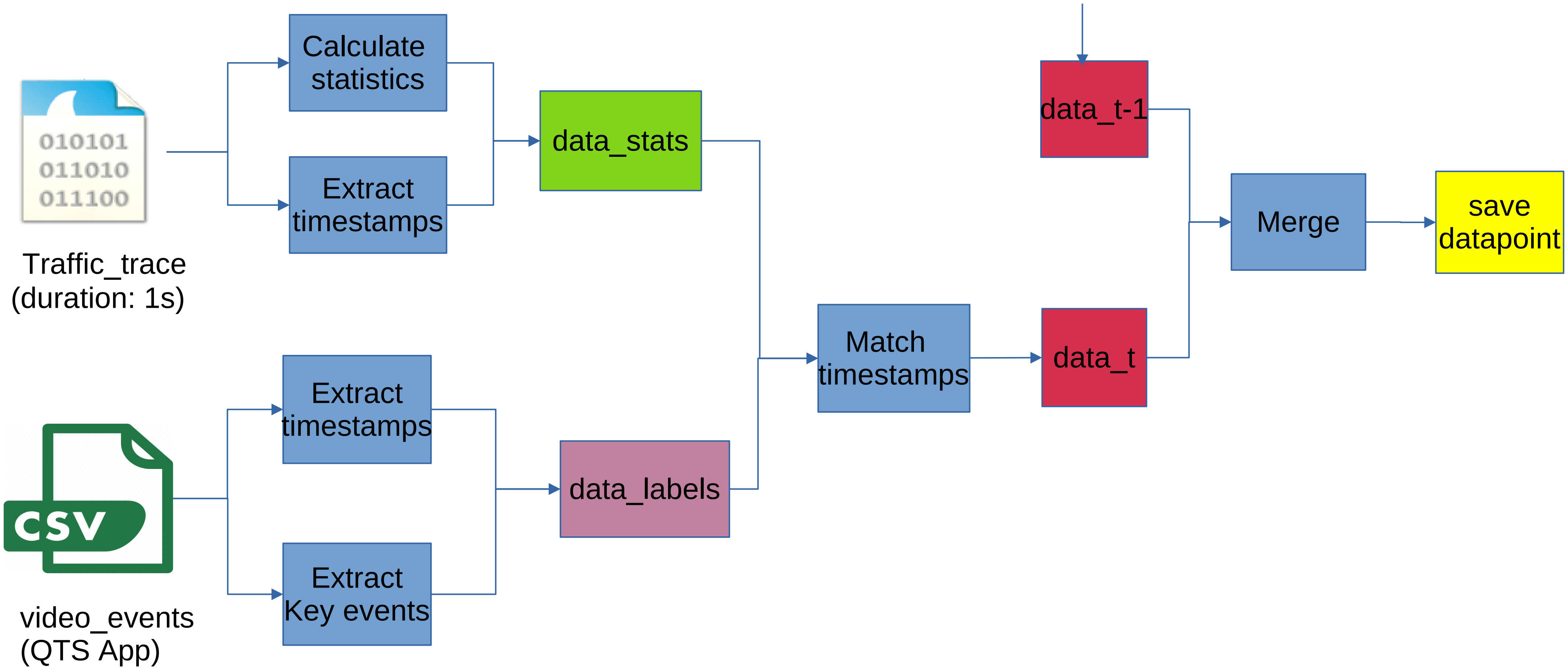
Methodology

Traffic Scenarios:

Scenario	Conditions
Reference	No manipulation
Bandwidth Limit	Limit downlink bandwidth between 500kbit/s and 3Mbit/s
Packet Delay	Add 50 ms (average) delay in downlink
Packet Loss	Create 5% packet loss in downlink
Packet Corruption	Corrupt 5% of downlink packets
Packet Loss II	Create between 25% and 50% packet loss in downlink

Methodology

Preprocessing:



Methodology

Statistical Features:

- Packet-based statistical features are computed from raw traffic data (bidirectional):
  - Total & average number of packets
  - Total, average, max & min packet sizes
  - Total, average, max & minimum inter-arrival times

Methodology

Handling the Imbalanced Dataset:

- Application of SMOTE (Synthetic Minority Oversampling Technique)

Class	Before SMOTE	After SMOTE
Playing	9214	9214
Buffering	1983	9214
Quality Downgrade	455	9214
Quality Upgrade	364	9214

Methodology

ML Model Training (Offline)

- Algorithm: Random Forest
- Training dataset size: 36856 examples
- Test dataset size: 3004 examples
- Validation: 10-fold cross-validation

Methodology

ML Model Training (Offline)

- Algorithm: Random Forest
- Training dataset size: 36856 examples
- Test dataset size: 3004 examples
- Validation: 10-fold cross-validation

Results

ML Model Testing (Offline)

Class	Precision	Recall	F1-Score
Buffering	0.80	0.78	0.79
Playing	0.95	0.94	0.94
Quality Down	0.36	0.38	0.38
Quality Up	0.86	0.88	0.88

- Testing Accuracy= 88.91 %

Results

Online Testing (Preliminary Results)

	Real Events			Predicted Events		
	Playing Duration (s)	Buffering Duration (s)	Buffering (%)	Playing Duration (s)	Buffering Duration (s)	Buffering (%)
1	20	33	62	32	21	39
2	69	14	16	75	8	9
3	88	7	7.3	90	5	5.2
4	69	25	26.5	72	22	23.4
5	90	2	2.1	87	5	5.4

Conclusion

Conclusion:

- Predicting the key video events on-the-fly with ML is possible
- Dependency between the network conditions and online performance
- More data is needed to improve the online accuracy

Future Work:

- Training and testing with more data and other streaming services
- Improve the feature engineering
- Adaptation of a continual learning strategy