



HAL
open science

ViCrypt: Real-time, Fine-grained Prediction of Video Quality from Encrypted Streaming Traffic

Sarah Wassermann, Michael Seufert, Pedro Casas, Li Gang, Kuang Li

► **To cite this version:**

Sarah Wassermann, Michael Seufert, Pedro Casas, Li Gang, Kuang Li. ViCrypt: Real-time, Fine-grained Prediction of Video Quality from Encrypted Streaming Traffic. ACM Internet Measurement Conference (IMC) 2019, Oct 2019, Amsterdam, Netherlands. hal-02375301

HAL Id: hal-02375301

<https://hal.science/hal-02375301>

Submitted on 21 Nov 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

VICRYPT: Real-time, Fine-grained Prediction of Video Quality from Encrypted Streaming Traffic

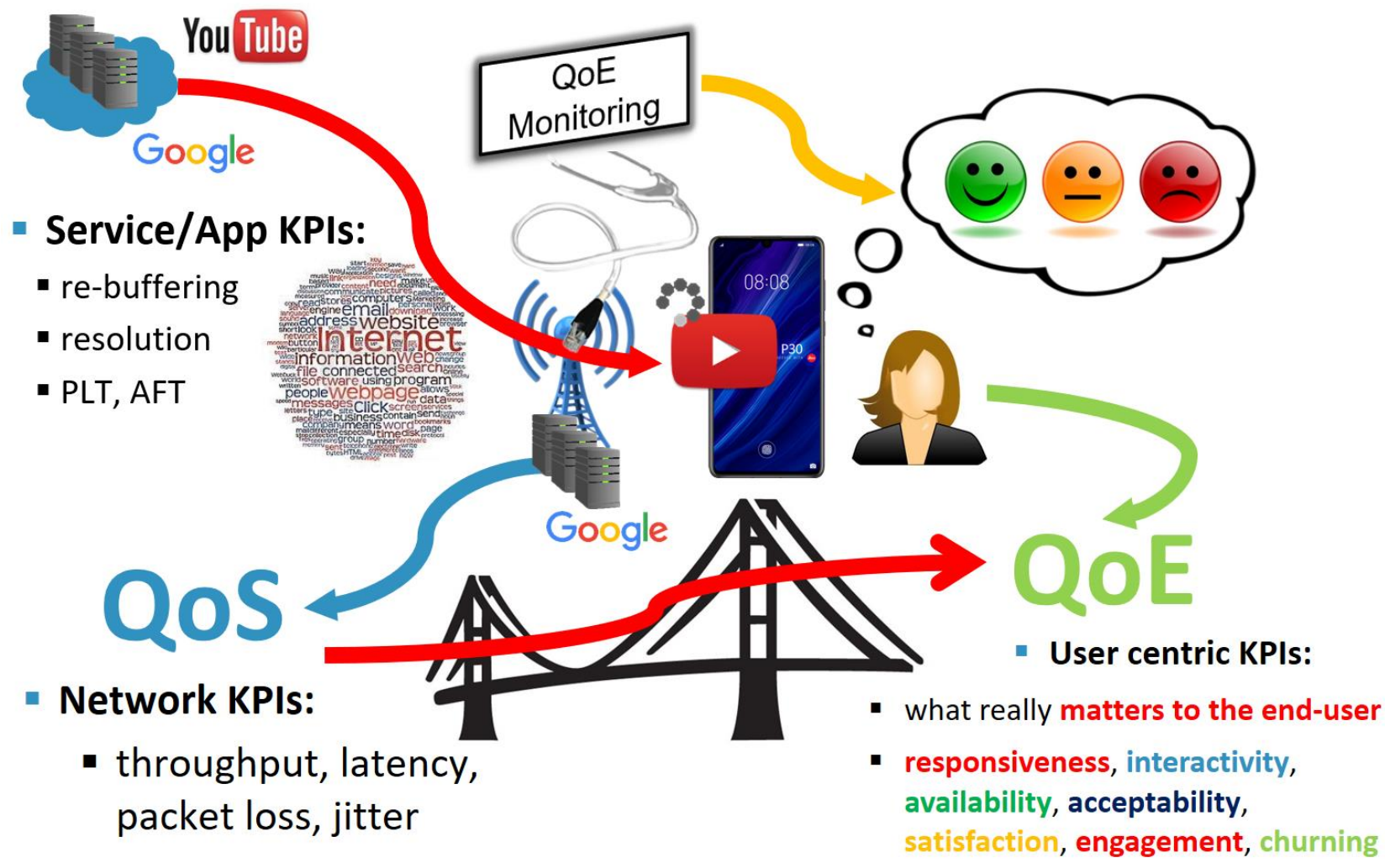
S. Wassermann (1), M. Seufert (2), P. Casas (1), L. Gang (3), K. Li (3)

(1) AIT Austrian Institute of Technology, Vienna, Austria

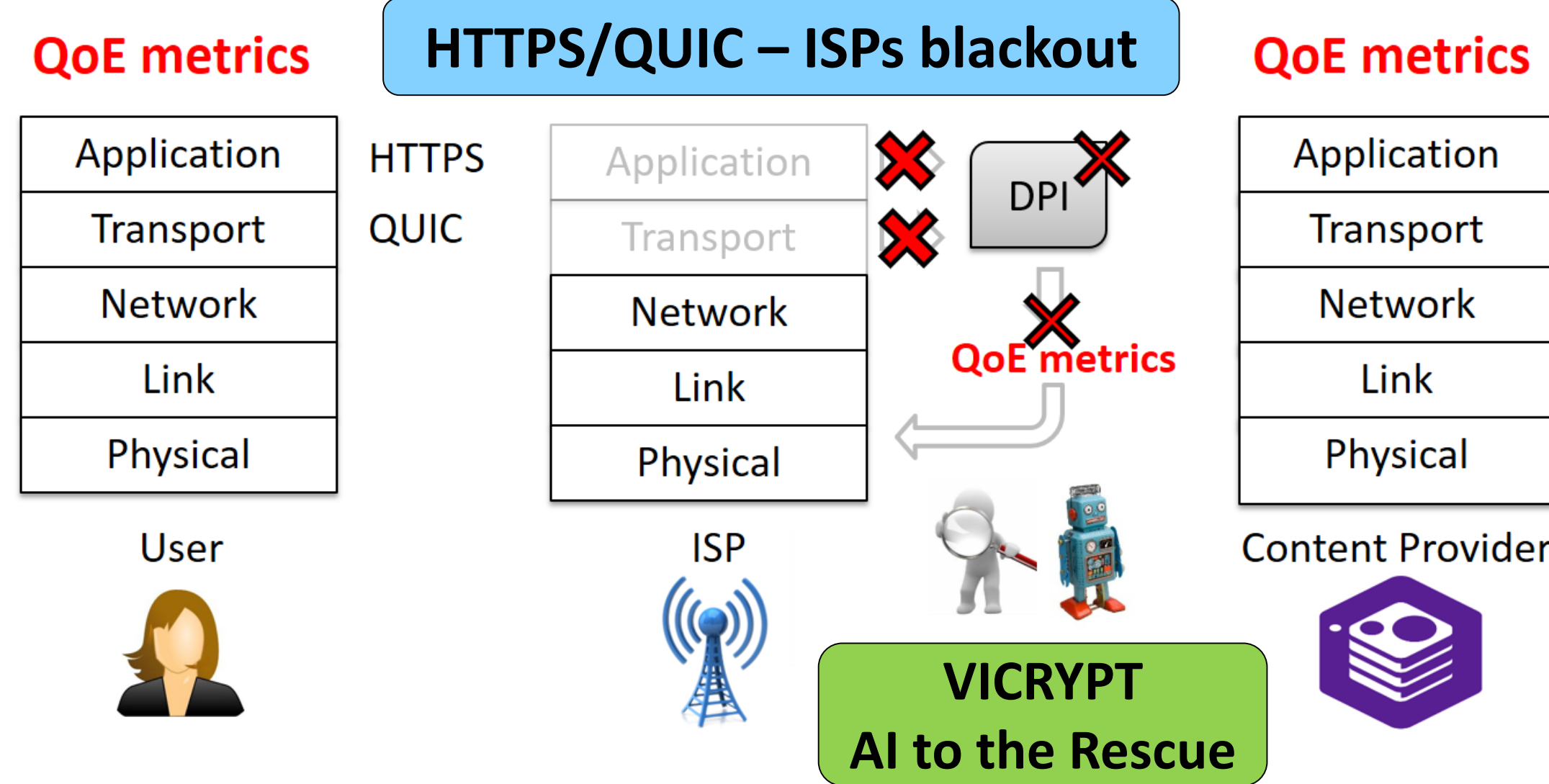
(2) University of Würzburg, Würzburg, Germany

(3) Huawei Technologies, Shenzhen, China

QoE-BASED NETMON (QoE-MON)



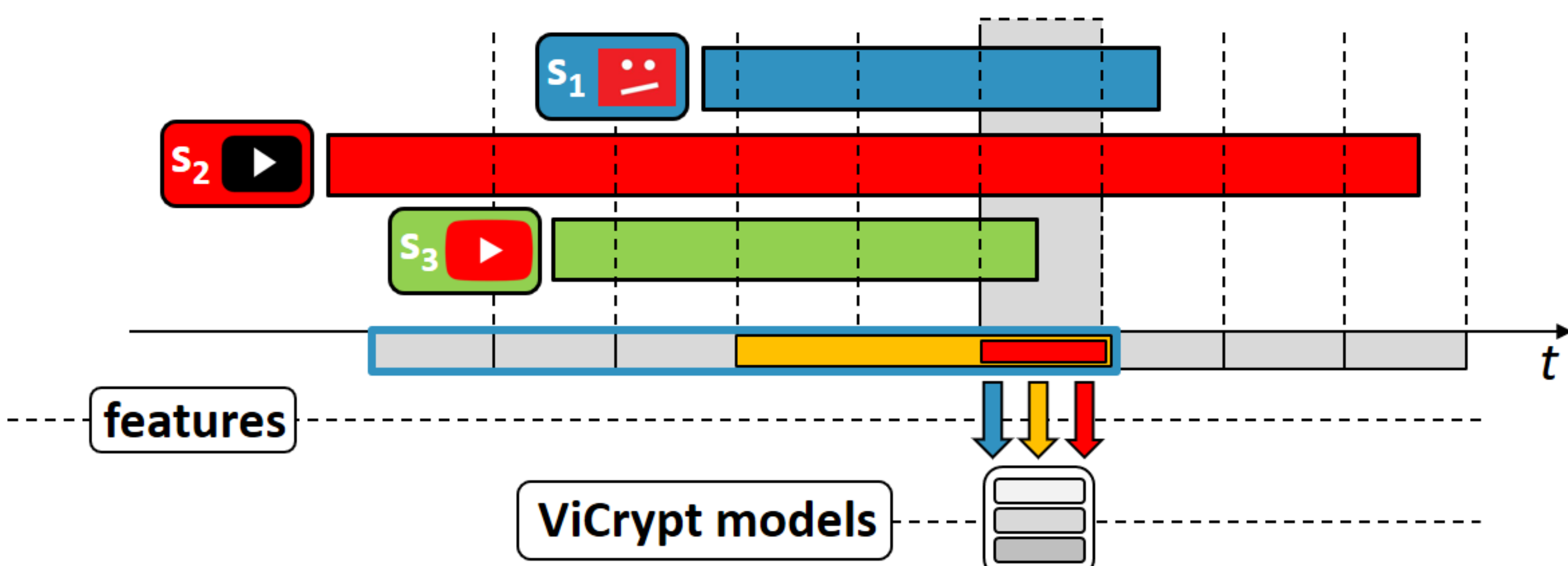
MOTIVATION & CHALLENGE



VICRYPT: ML-BASED QoE-MON

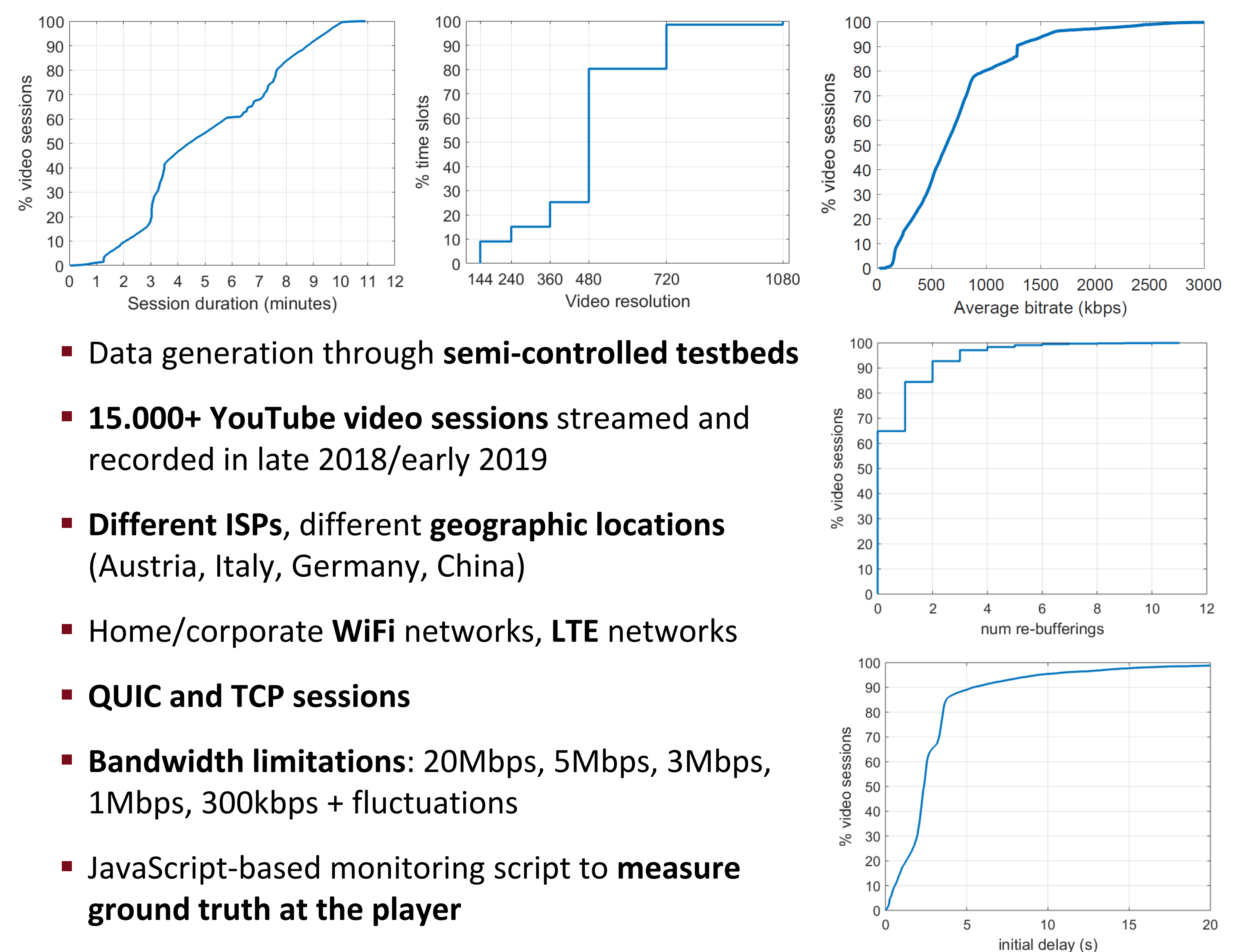
- Real-time (1-sec resolution) prediction of KQIs for video streaming
- Video chunk detection NOT NEEDED features are packet size/time based
- ML models for prediction of instant, per-sec:
 - re-buffering events
 - video resolution
 - video bitrate

STREAM-BASED PREDICTION OF VIDEO KQIs



- Video stream-based analysis, using multiple sliding windows, capturing different temporal phenomena (current time, short-term trend, session-aggregated)
- Analysis is done in real time: for every video session and for every new time slot of 1 second, we consider the following set of 207 features:
 - Features extracted from current time slot (C) – 69 features
 - Short-memory (trend) based features, extracted from last T (3) slots (CT) – 69 features
 - Cumulative based features, extracted from all past traffic for this video session (CS) – 69 features
- Feature computation is done continually, in constant-memory boundaries, using sketches

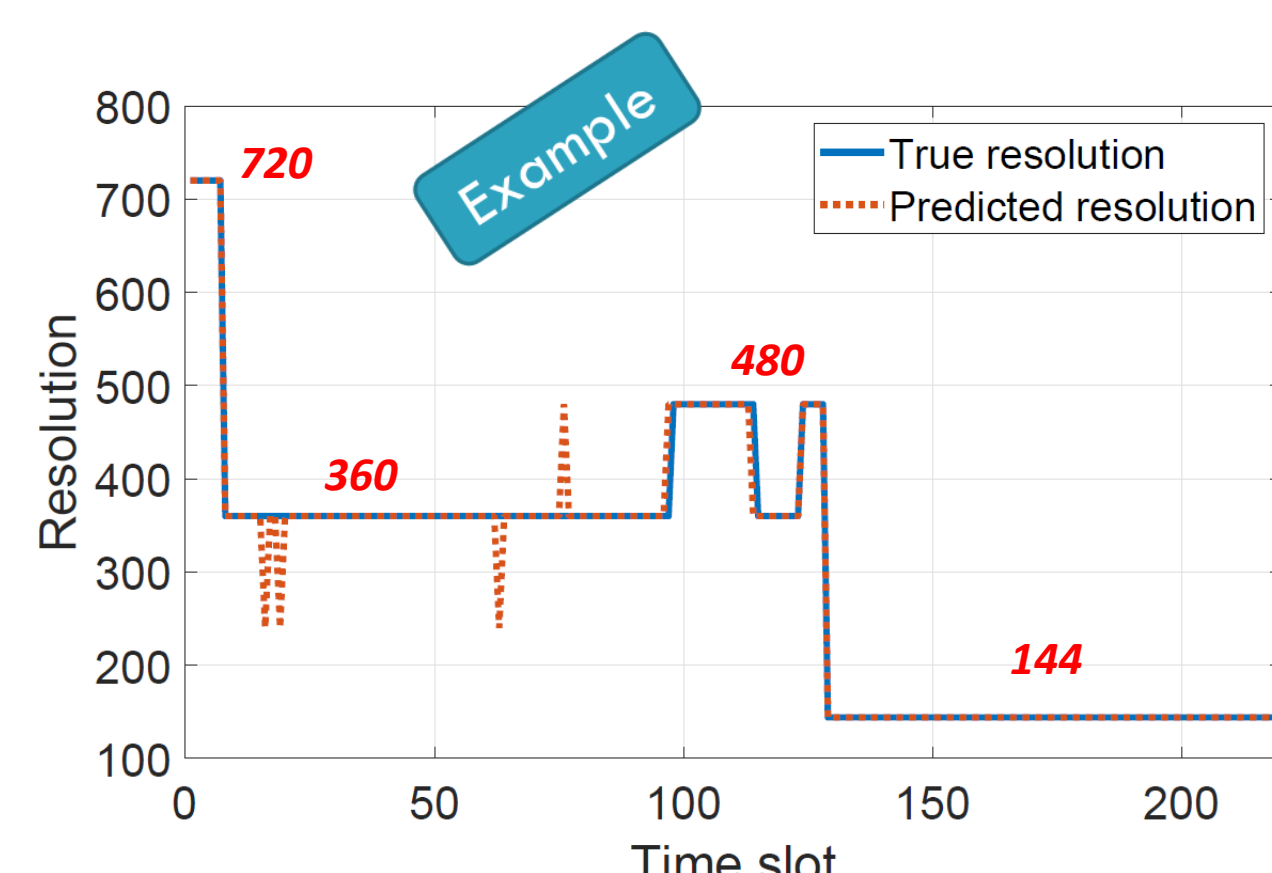
YouTube DATASET FOR TRAINING & VALIDATION



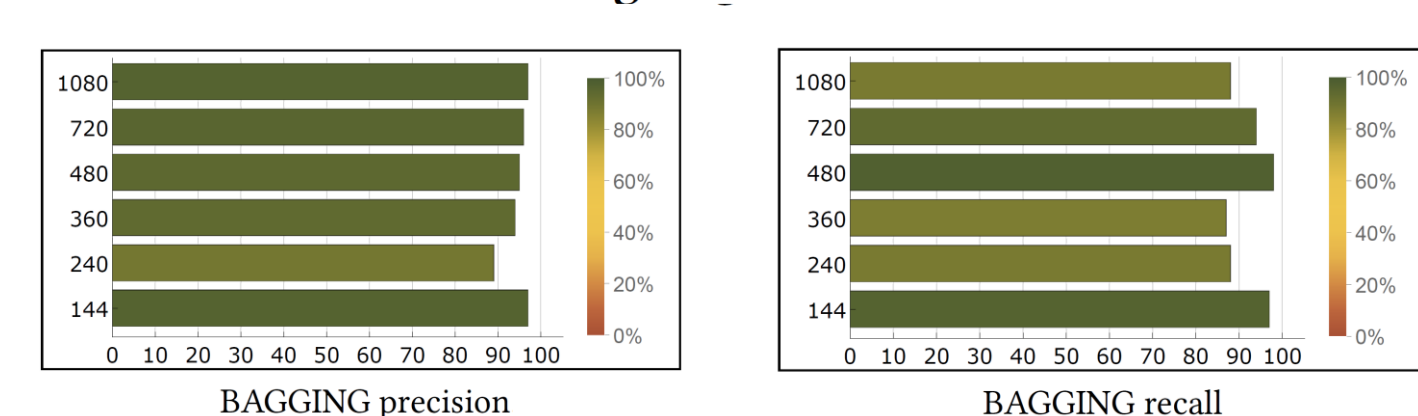
ONLINE PREDICTION OF VIDEO RESOLUTION

- Training multiple ML models over more than 4.6M individual, 1 sec. slots (5-fold cross validation) – here using all 207 inputs
- Classification task: per second video resolution, 6-classes: 144p, 240p, 360p, 480p, 720p, 1080p

Model	Training time (min)	Accuracy (%)
DT	43	92
RF10	2	92
ADA	125	68
ERT10	1	90
BAGGING	37	95
BAYES	1	42
KNN	9	73
NN	507	58
SVM	194	54



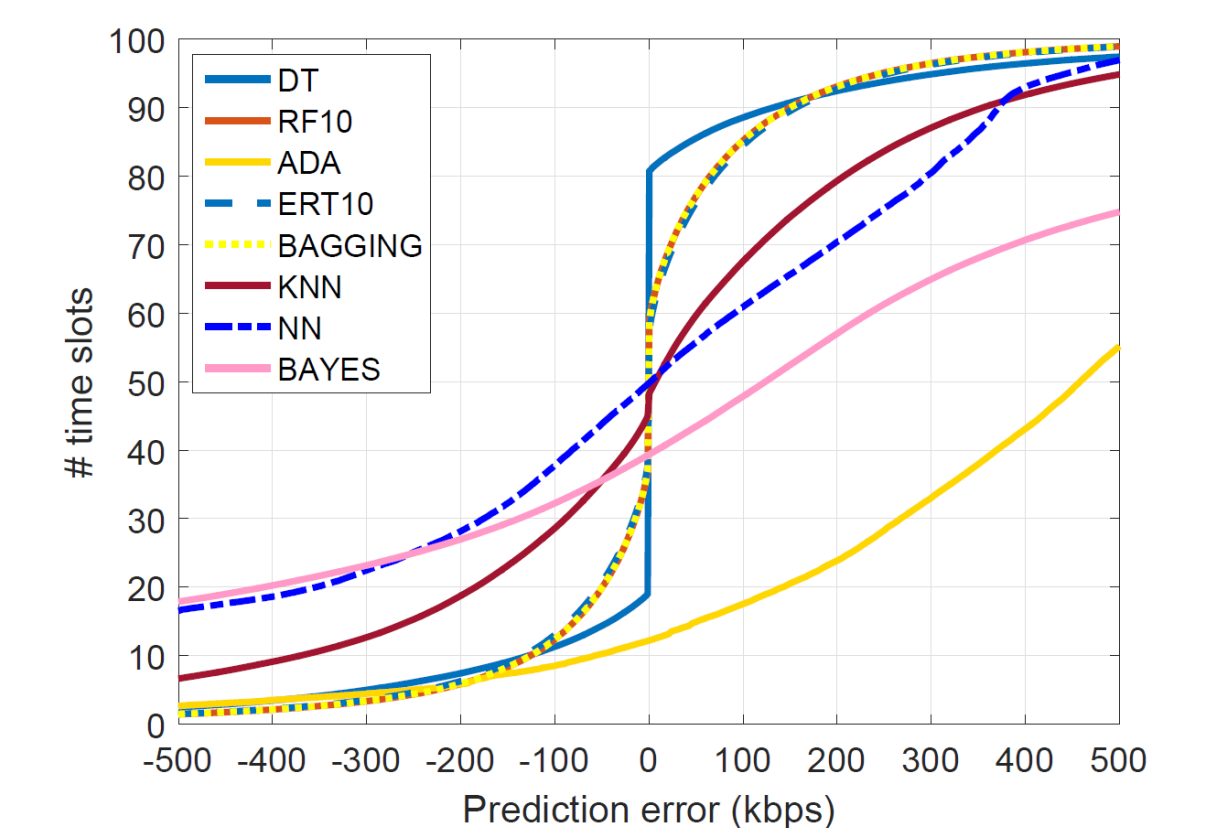
Video-resolution prediction.



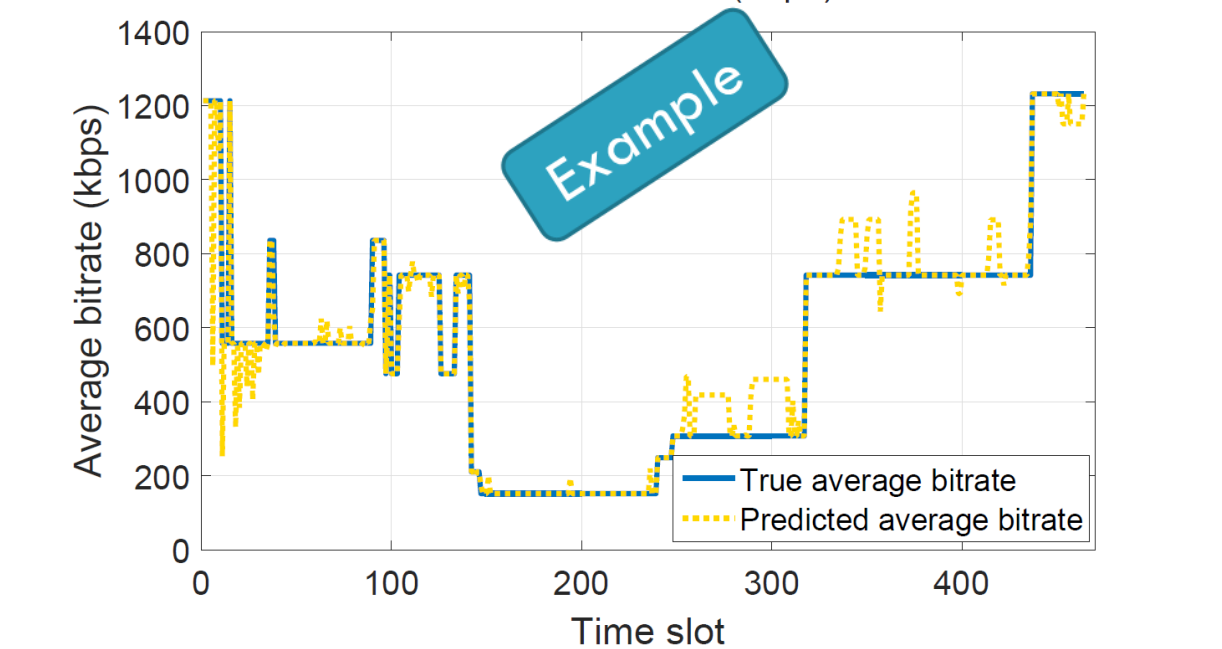
ONLINE PREDICTION OF VIDEO BITRATE

- Regression task: estimation of per second average video bitrate

Model	5-CV time (minutes)	MAE (kbps)	RMSE (kbps)	MRE (%)	PLCC
DT	31	94	246	18	0.88
RF10	36	89	179	18	0.93
ADA	126	492	573	130	0.59
ERT10	7	93	182	19	0.93
BAGGING	22	89	179	17	0.93
BAYES	3	2,540	6,530	545	-0.14
KNN	6	229	353	42	0.70
NN	305	333	489	70	0.20
SVM	143	10^{23}	$2 \cdot 10^{23}$	$2 \cdot 10^{23}$	0.12



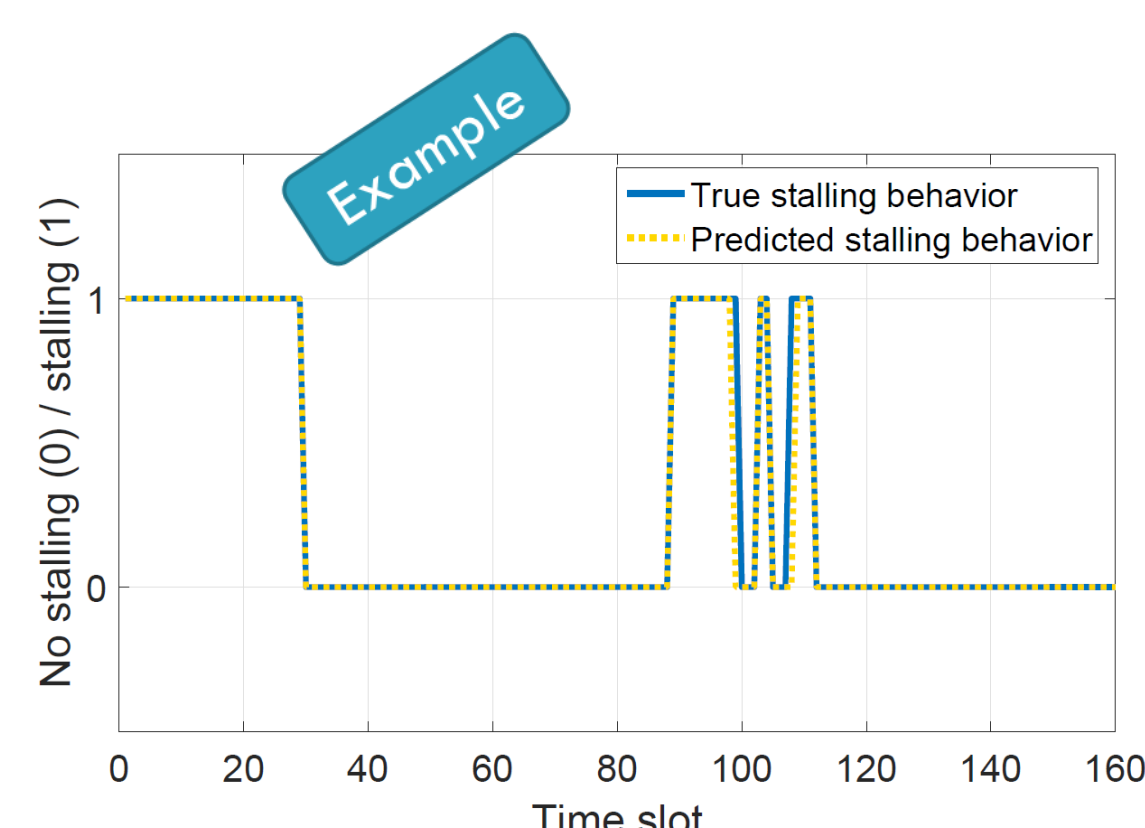
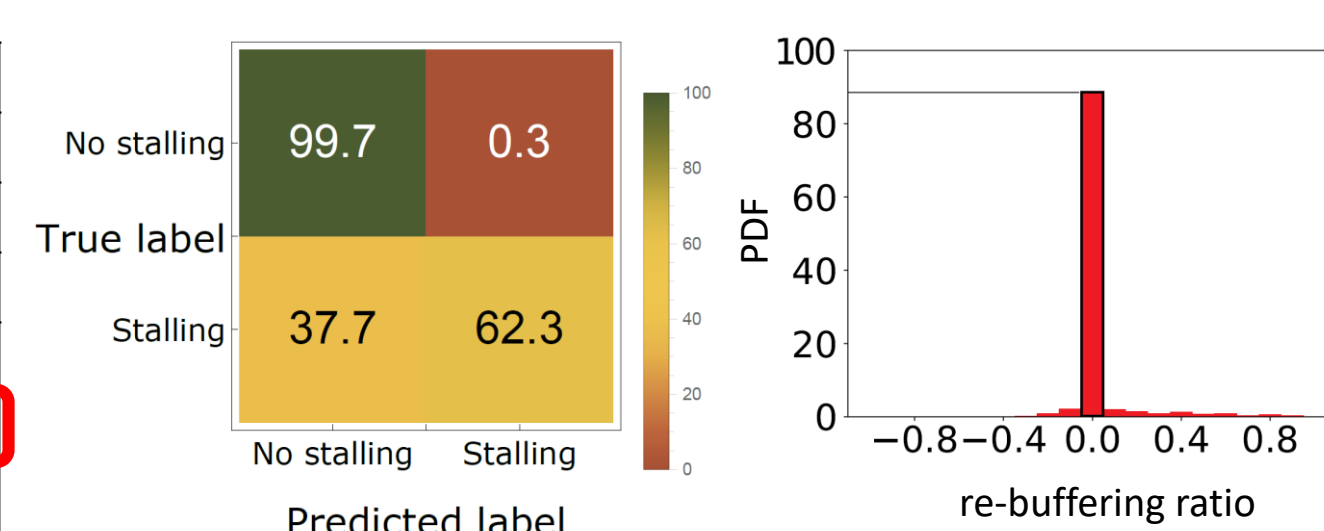
- ERT10 & BAGGING realize MAE below 100kbps, and RMSE below 190kbps (penalizes larger errors)
- 80% of the slots are estimated with errors below 100kbps
- Predictions are highly correlated with the target (PLCC = 0.93)



ONLINE PREDICTION OF STALLING

- Binary classification task: playback stalled/not-stalled at every new slot

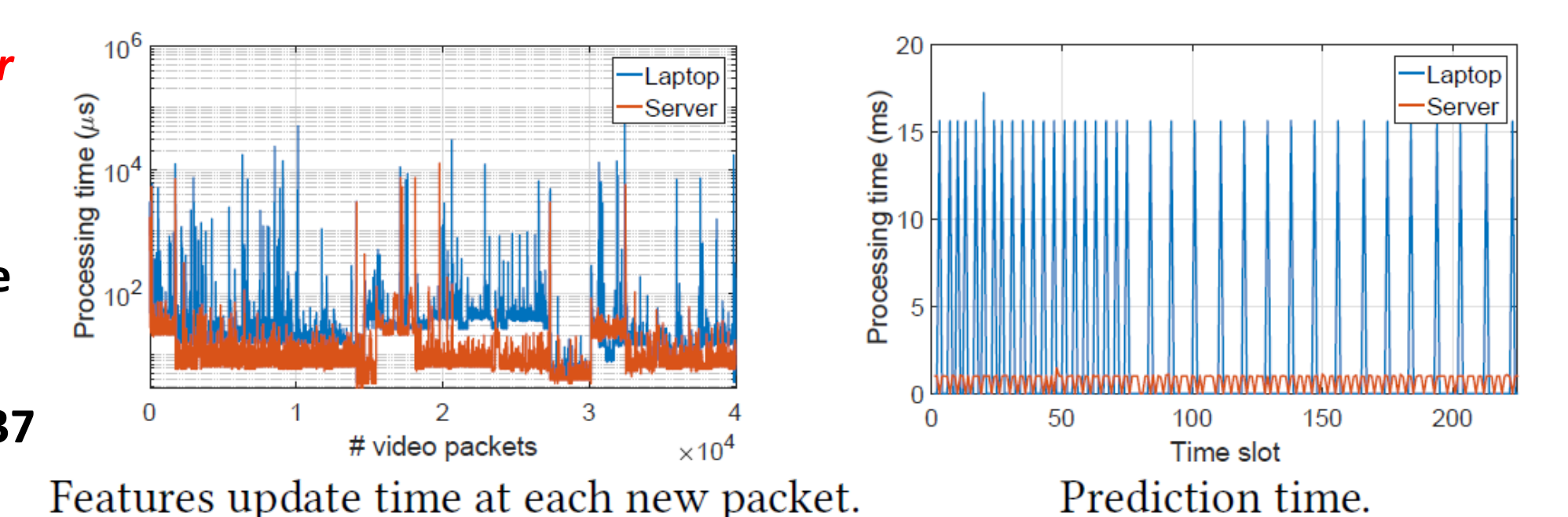
Model	Accuracy (%)	Recall (%)	Precision (%)	5-CV time (minutes)
DT	96	64	68	57
RF10	97	55	88	3
ADA	95	29	61	154
ERT10	97	54	88	1
BAGGING	97	65	87	63
BAYES	50	86	9	1
KNN	96	48	71	10
NN	94	0	0	600
SVM	84	62	21	36
ISO10	86	13	8	4
LOF	86	11	6	46



- per-slot re-buffering estimation errors are high, stalling slots under-estimated...
- ...but estimation of re-buffering ratio is perfect for almost 90% of the videos

COMPUTATIONAL TIME & IMPACT OF FEATURE SELECTION

- Evaluation of full feature set update time (done at every new incoming packet) and prediction time (done for every 1s slot), using an upper bound with all 207 features
- laptop (i5 CPU, 8GB RAM) vs. server (Xeon Silver, 48 cores, 128GB RAM)
- server: avg. duration of full feature set update is 13 μ s, prediction time below 1.4ms
- Laptop: avg. feature update takes 37 μ s, prediction time below 16ms



Features	Accuracy (%)	Features	MAE [kbps]	RMSE [kbps]	MRE [%]	PLCC	Features	Accuracy (%)	Recall (%)	Precision (%)
All	92	All	93	182	19	0.93	All	97	54	88
F_C	70	F_C	275	407	55	0.58	F_C	96	10	30
F_T	73	F_T	253	377	51	0.64	F_T	97	17	51
F_S	96	F_S	68	157	14	0.95	F_S	99	72	91
F_{DOWN}	90	F_{DOWN}	105	195	21	0.92	F_{DOWN}	98	41	87
F_{UP}	90	F_{UP}	106	198	21	0.92	F_{UP}	98	47	74
F_{TOP20}	95	F_{TOP20}	81	175	16	0.93	F_{TOP20}	97	56	86

- Automatic Feature Selection – CS features (F_S) alone provide the best results (69 features), improving overall performance. Top 20 features (F_{TOP20}) provide similar improvement with much less features