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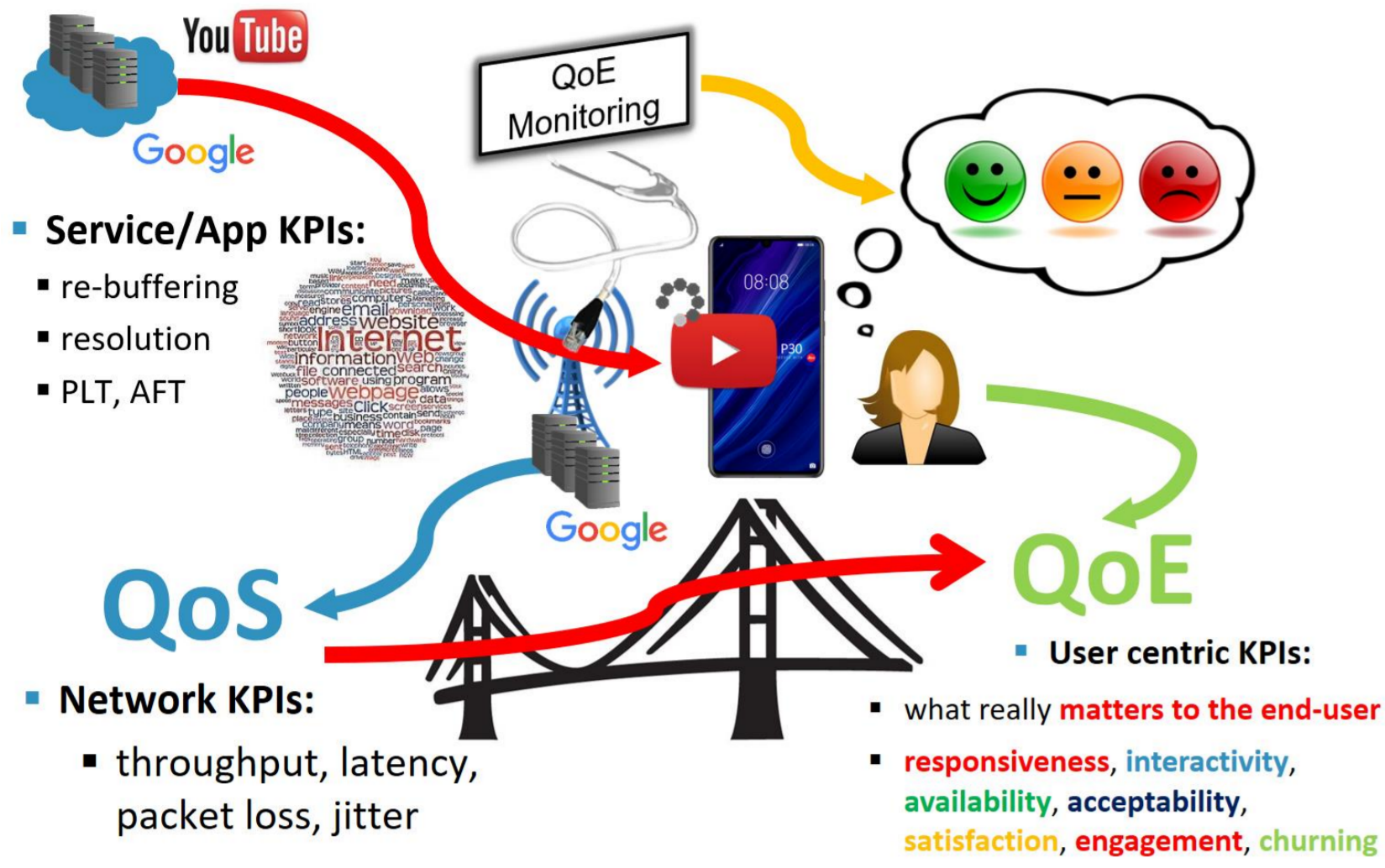
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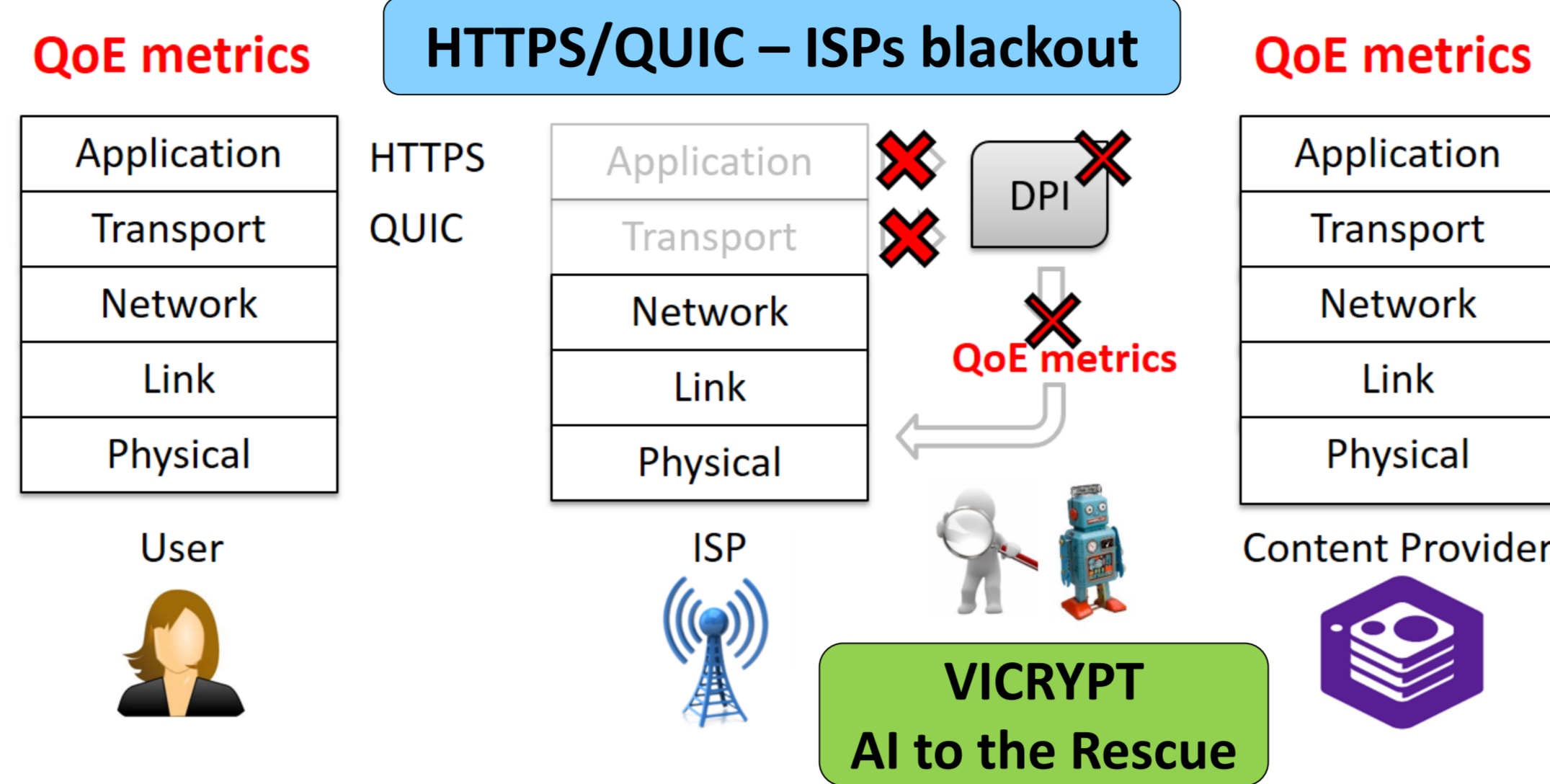
VICRYPT: Real-time, Fine-grained Prediction of Video Quality from Encrypted Streaming Traffic

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QoE-BASED NETMON (QoE-MON)



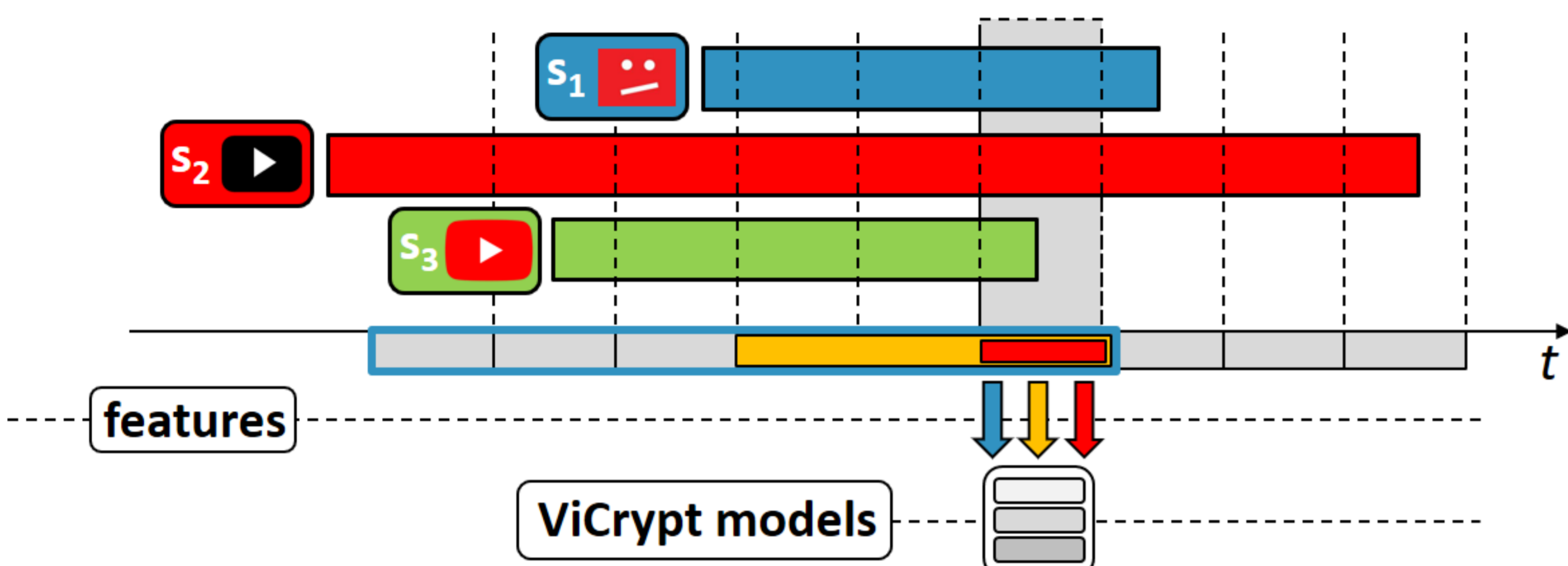
MOTIVATION & CHALLENGE



VICRYPT: ML-BASED QoE-MON

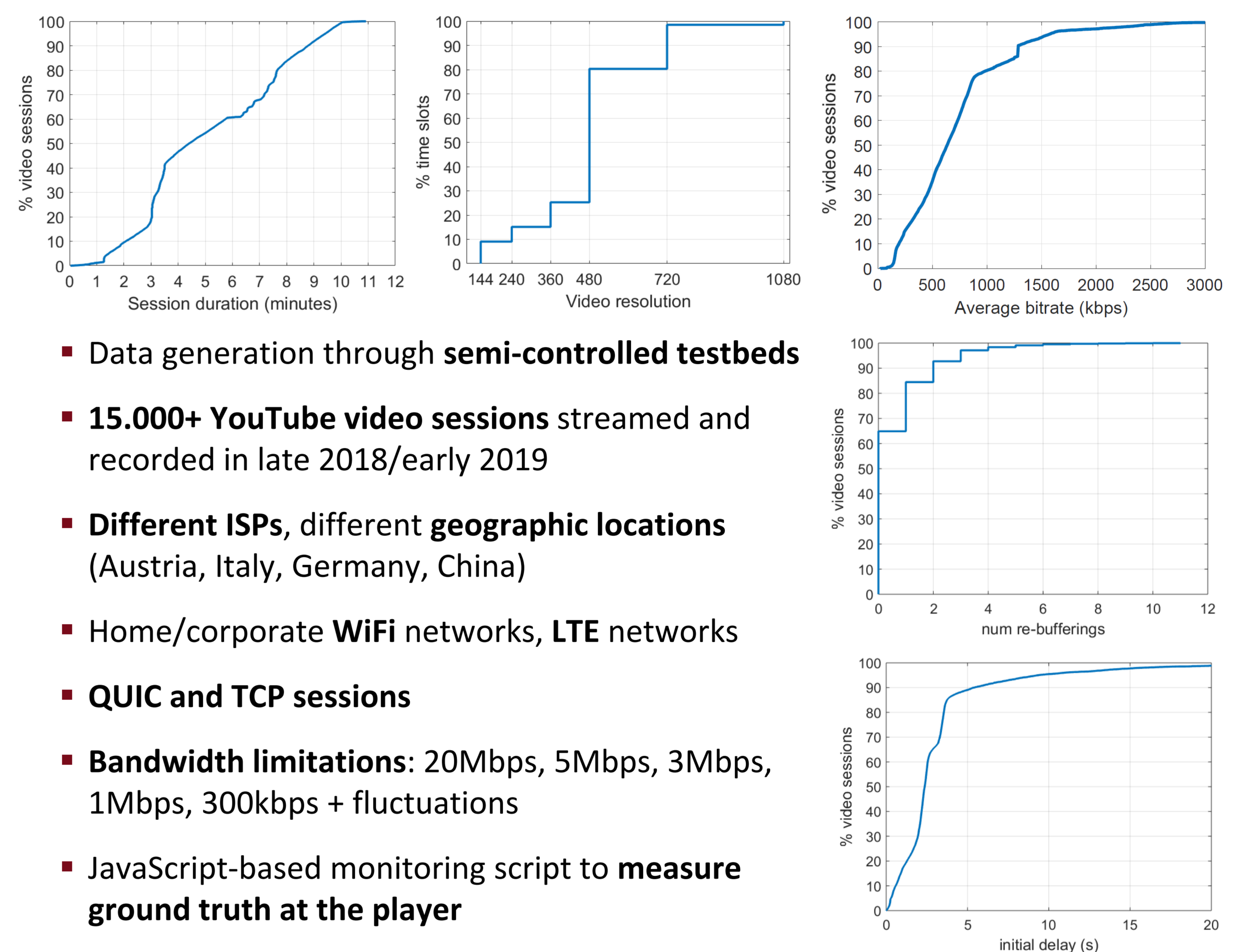
- Real-time (1-sec resolution) prediction of KQIs for video streaming
- Video chunk detection NOT NEEDED features are packet size/time based
- ML models for prediction of instant, per-sec:
 - re-buffering events
 - video resolution
 - video bitrate

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

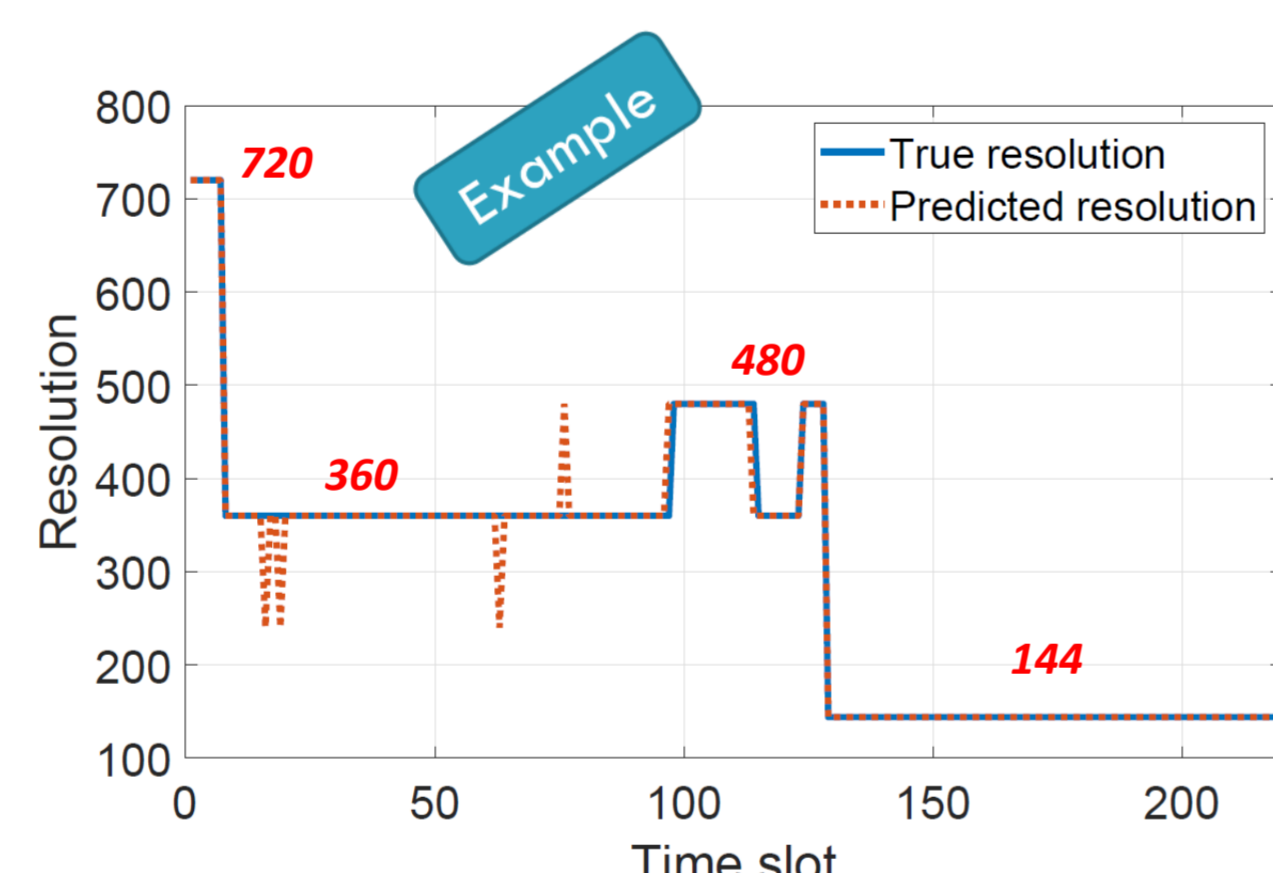


- Data generation through semi-controlled testbeds
- 15,000+ YouTube video sessions streamed and recorded in late 2018/early 2019
- Different ISPs, different geographic locations (Austria, Italy, Germany, China)
- Home/corporate WiFi networks, LTE networks
- QUIC and TCP sessions
- Bandwidth limitations: 20Mbps, 5Mbps, 3Mbps, 1Mbps, 300kbps + fluctuations
- JavaScript-based monitoring script to measure ground truth at the player

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

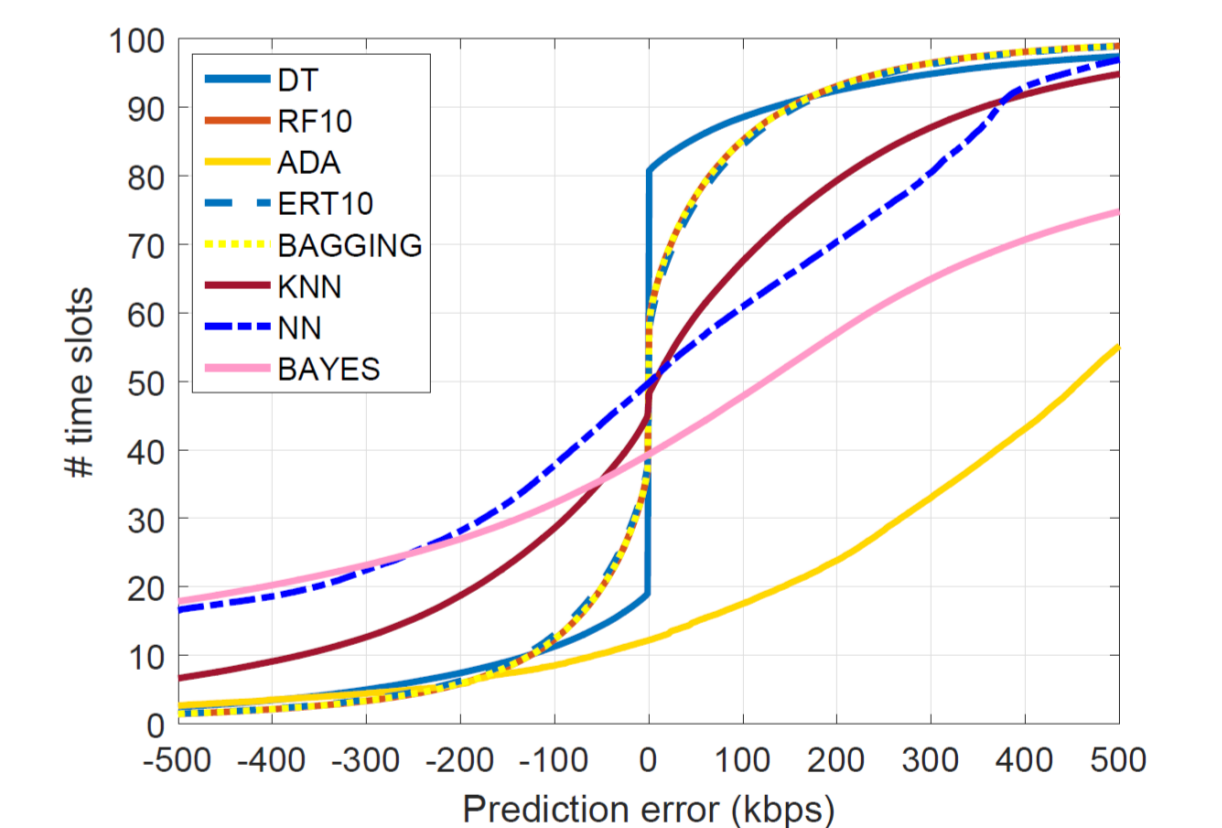


Video-resolution prediction.

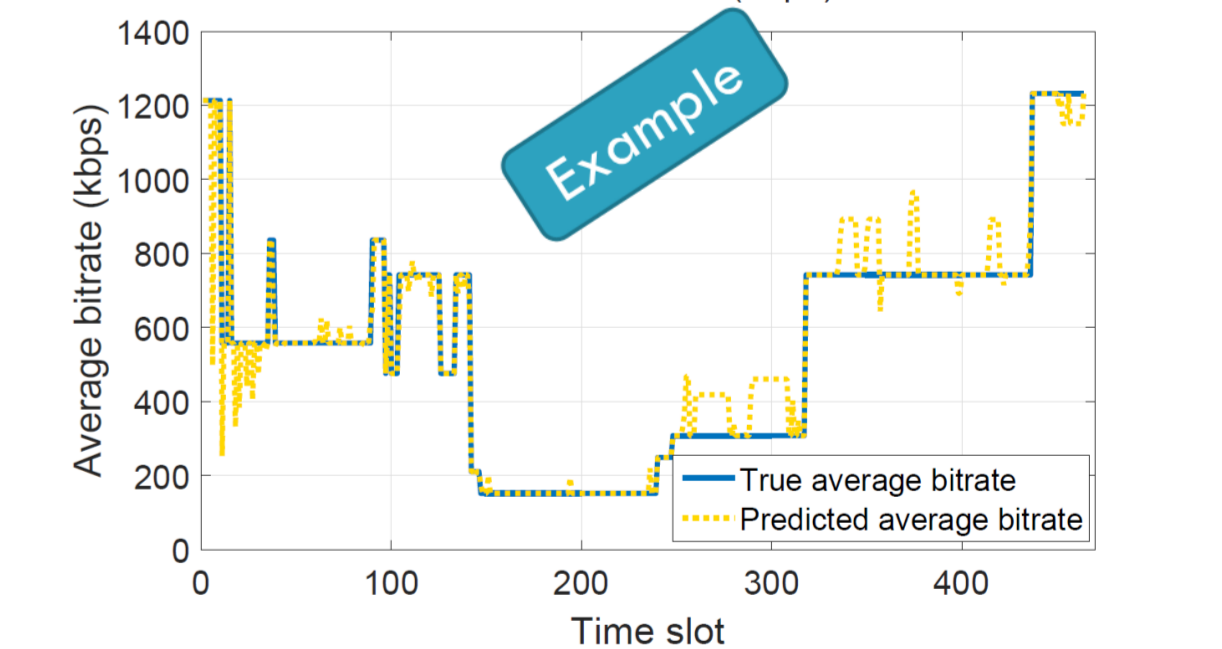
ONLINE PREDICTION OF VIDEO BITRATE

- 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 · 10 ²³	2 · 10 ²³	0.12



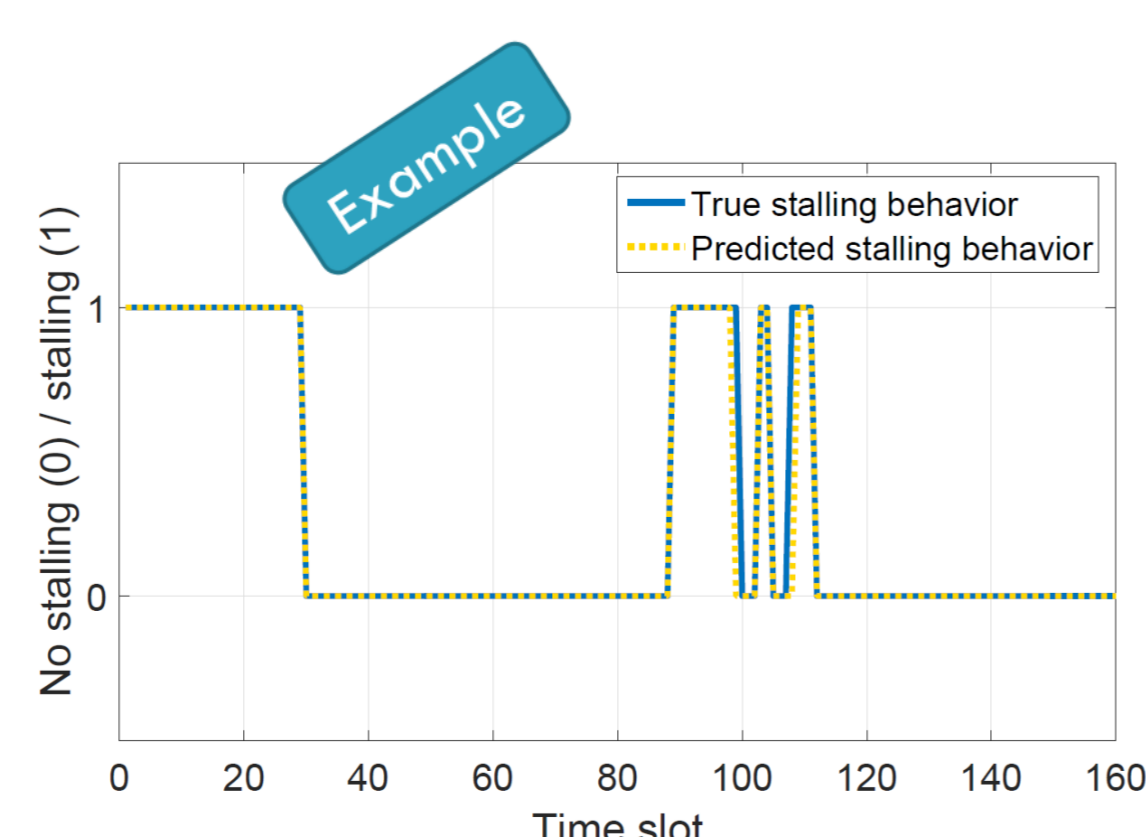
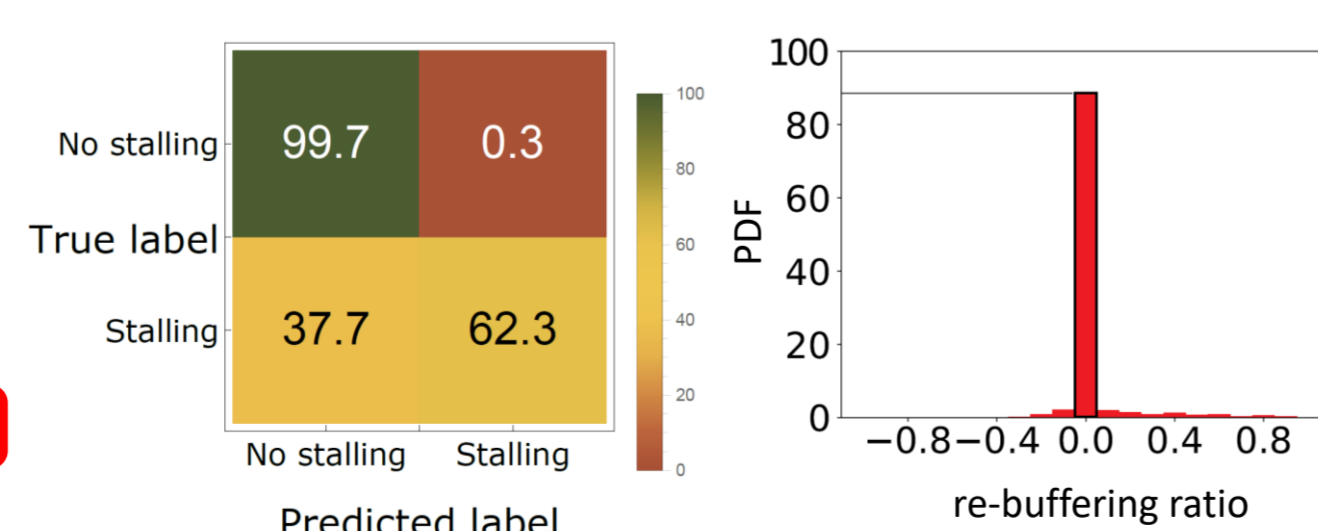
- ERT10 & BAGGING realize MAE below 100kbps, and RMSE below 190kbps (penalizes larger errors)
- 80% of the slots are estimated with errors below 100kbps
- Predictions are highly correlated with the target (PLCC = 0.93)



ONLINE PREDICTION OF STALLING

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

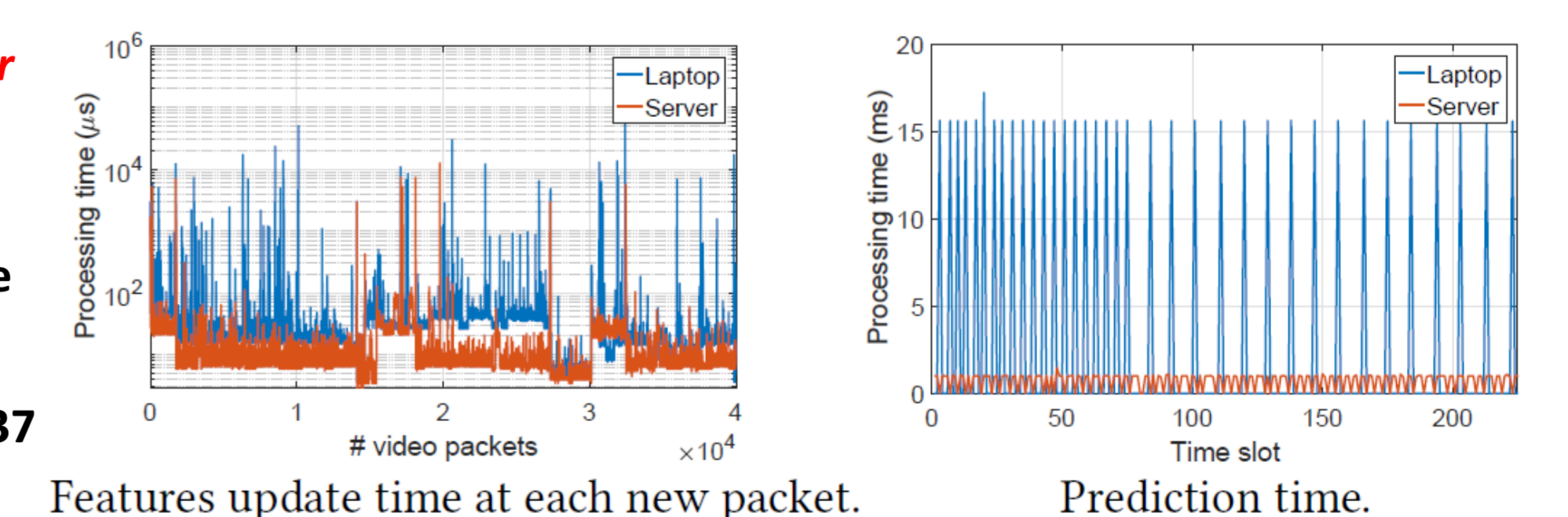
Model	Accuracy (%)	Recall (%)	Precision (%)	5-CV time (minutes)
DT	96	64	68	57
RF10	97	55	88	3
ADA	95	29	61	154
ERT10	97	54	88	1
BAGGING	97	65	87	63
BAYES	50	86	9	1
KNN	96	48	71	10
NN	94	0	0	600
SVM	84	62	21	36
ISO10	86	13	8	4
LOF	86	11	6	46



- 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 μs, prediction time below 1.4ms
- Laptop: avg. feature update takes 37 μs, 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