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Improving Web QoE Monitoring for Encrypted Network Traffic Through Time Series Modeling

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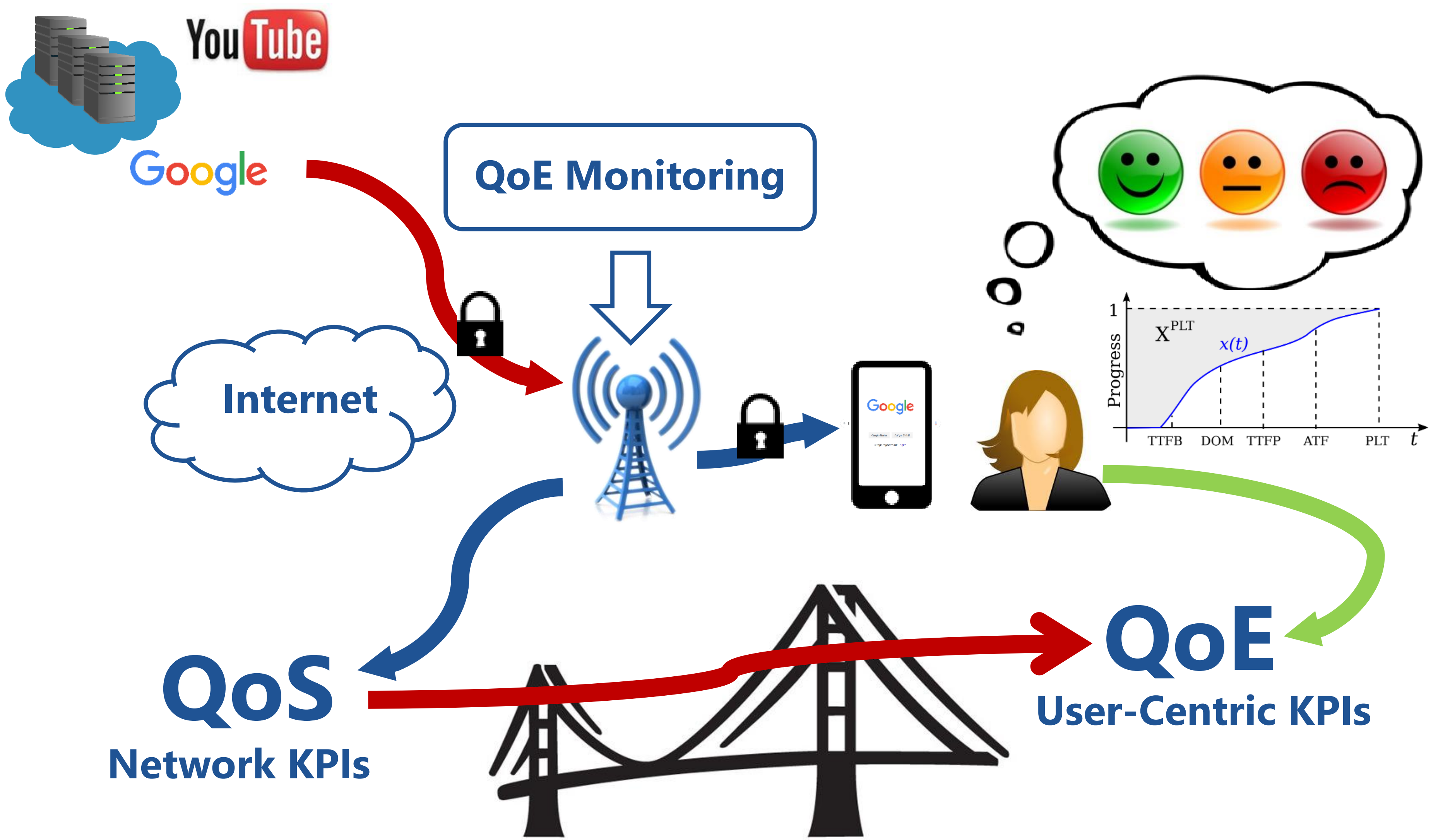
Motivation



YouTube
Google
QoE Monitoring
Internet
Google
1
Progress
X^PLT
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TTFB
DOM
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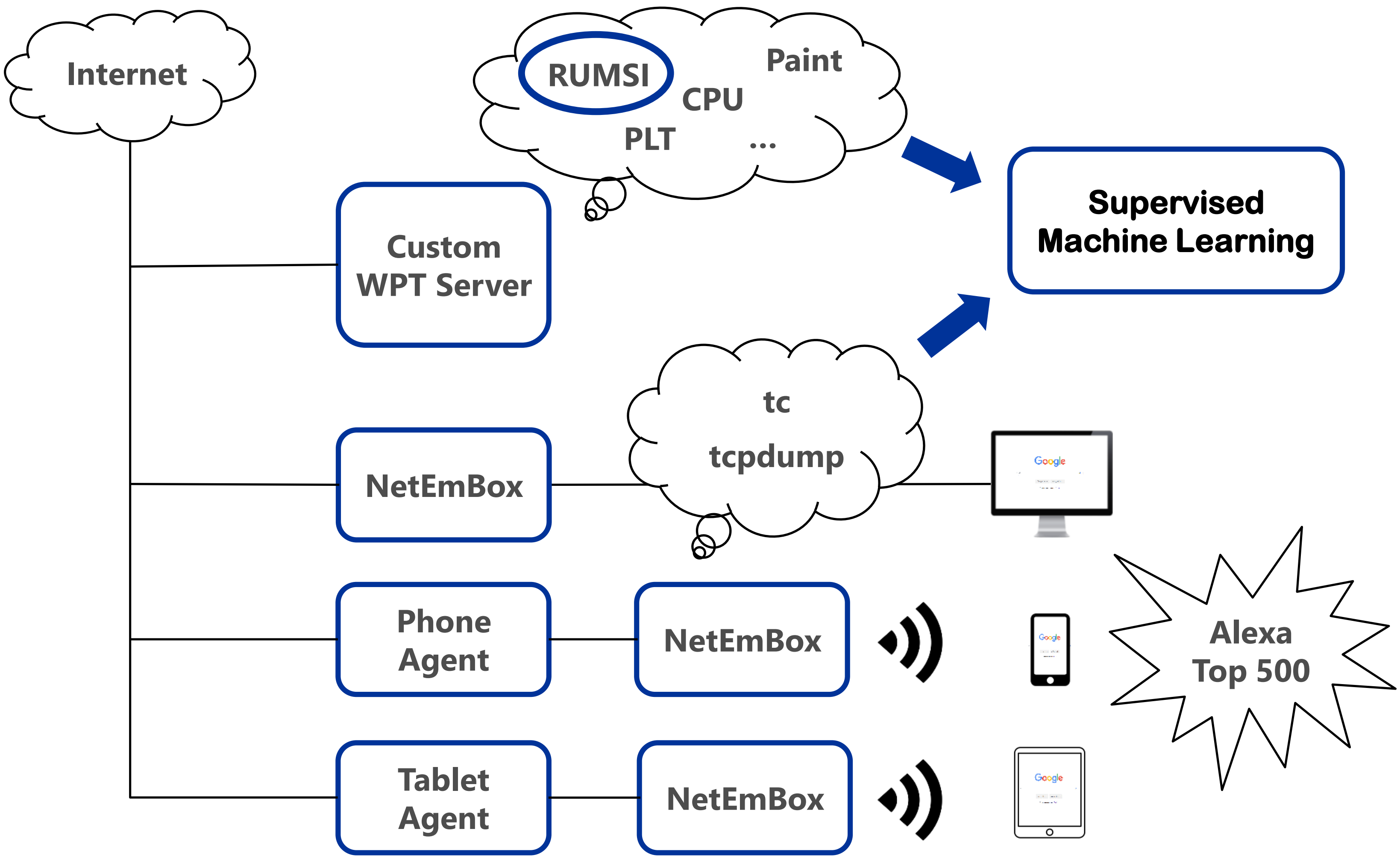
QoS
Network KPIs
QoE
User-Centric KPIs

Methodology



Considered Features for Machine Learning

- Real-time **temporal granularity**, e.g., **predictions in 100ms windows**

- Feature set includes
  - **Count-based** features, e.g., amount of transferred bytes
  - **Time-based** features, e.g., packet inter-arrival times
  - **Distribution-based** features
  - Features are computed for **total**, **downlink**, and **uplink** traffic each
  - Features are computed for **top three IP addresses** each
  - Features are computed for **varying subnets** of top three (24, 16, 8)

- **For every window** the following feature sets are computed
  - Features extracted from **current window (window features)**
  - Features extracted from **all previous windows (session features)**

  → **1979 features** in total

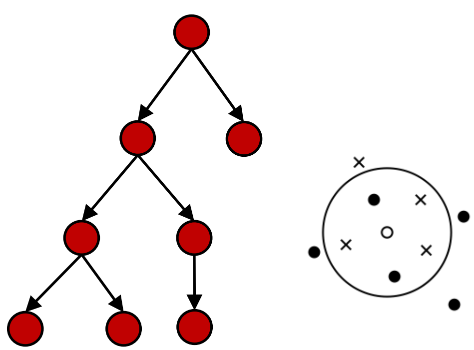
- Around **60000 web page loads** during November 2019
  (only a subset of all data)

Regression Models

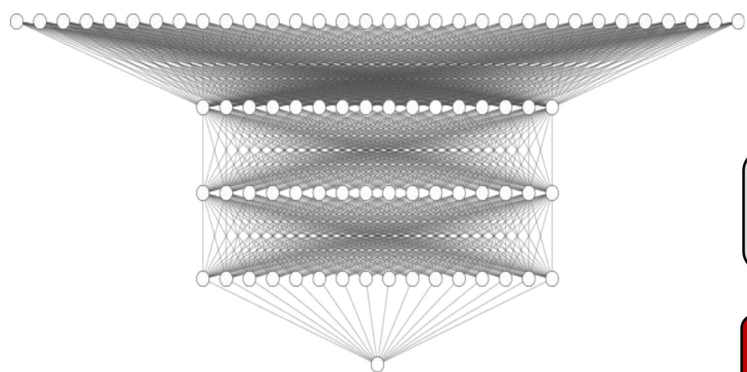
- Several regression models are tested
  - ML regression models with scikit-learn (CART, KNN, etc.)
  - Neural network regressor (DNN)
  - Recurrent neural network regressor (LSTM/GRU layers)

- Either session-based or time-series input features

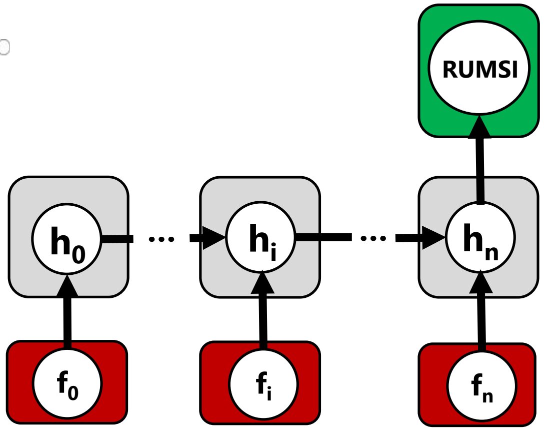
Scikit-Learn (CART, KNN)



DNN



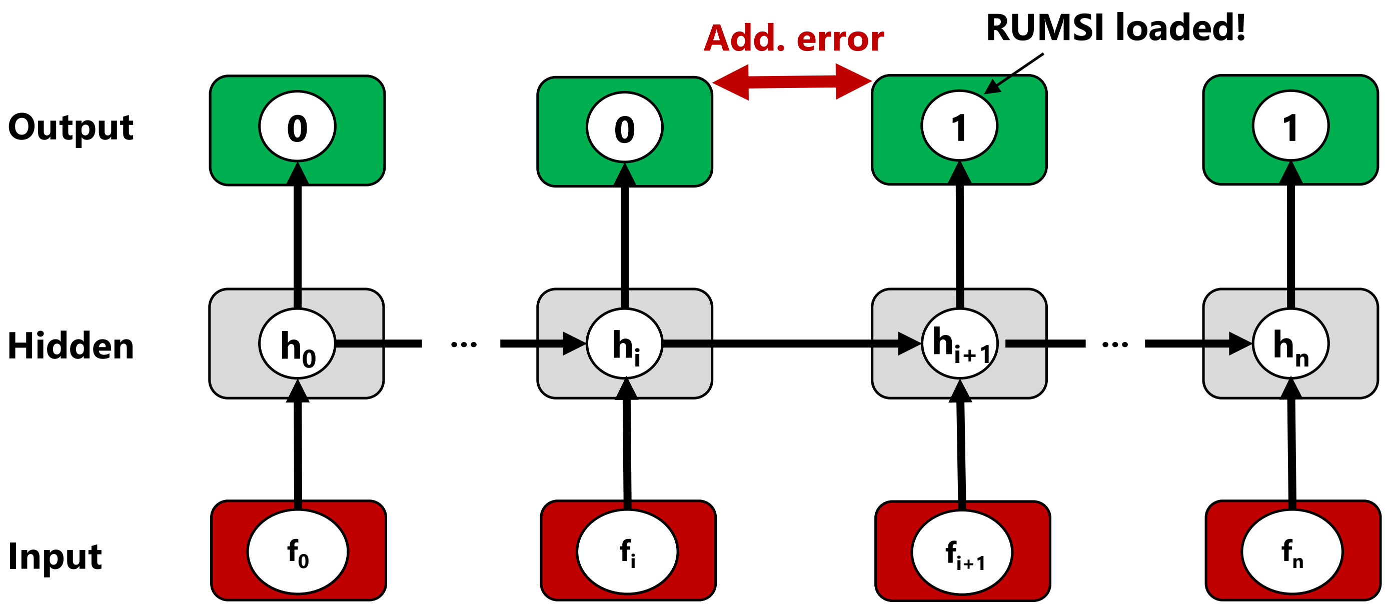
Recurrent Neural Network



Classification Models

- Estimate RUMSI with recurrent binary classification per window
  - Feed **window-based features** into recurrent neural network
  - Map RUMSI to **binary variable** and use as target for training
  - Predict binary RUMSI for 100ms windows **n times**

- **Aggregate binary window predictions** to approximate real RUMSI



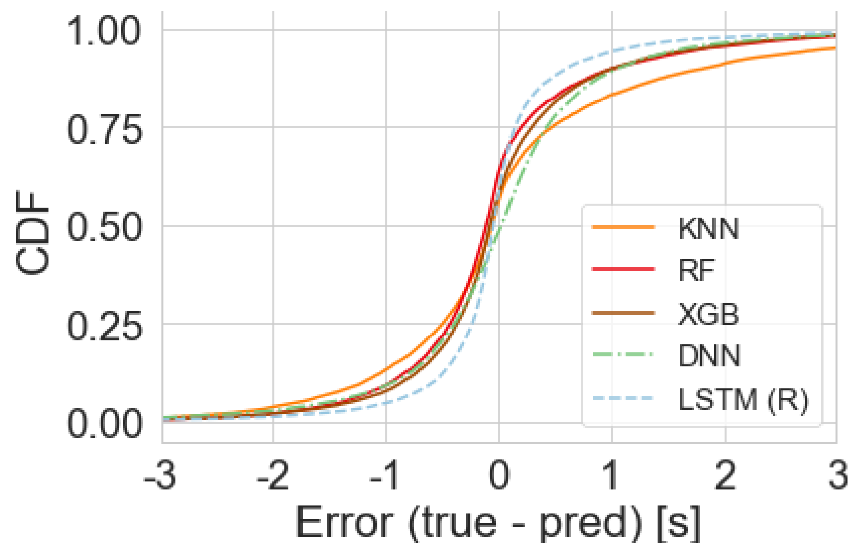
Evaluation of Regression Models

- Stratified website split for training, validation, and test data

- Ensemble methods perform much better than KNN and DNN

→ RF and XGB exhibit a median absolute error of 0.34 seconds

- LSTM outperforms all other models clearly

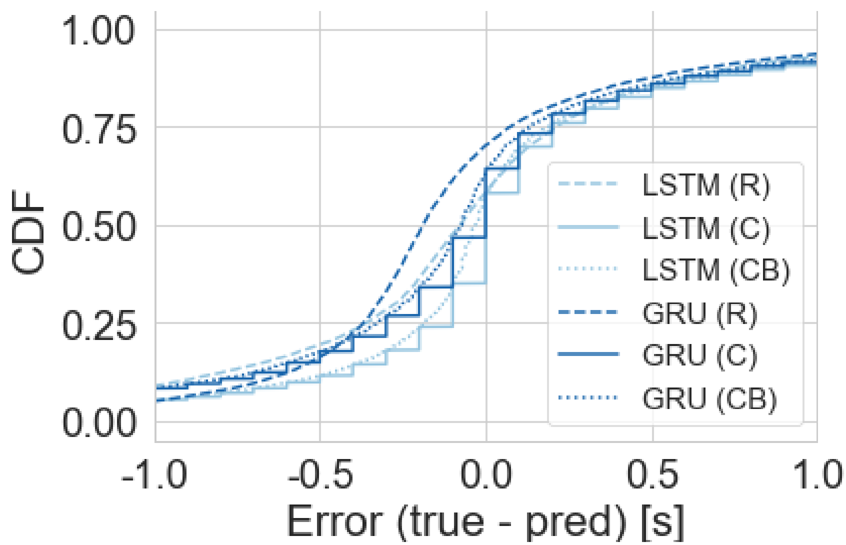


Evaluation of Recurrent Models

- Same evaluation with all recurrent models

- Binary classification (CB) outperforms the regression (R)
  - Additional error (CB-C) does not affect the performance much
  - LSTM layers work slightly better than GRU layers

- *Real-time* prediction is an additional benefit of this approach



Feature Importance Analysis

- Tested several feature subsets for recurrent models
  - A – All, S – Session, W – Window, T/TOP – Incl./Only Top 3
  - No large differences between subsets
  - Top three IP addresses sufficient for good results

	MSE [s]		MAE [s]		mAE [s]	
	GRU	LSTM	GRU	LSTM	GRU	LSTM
A	0.82	0.87	0.52	0.51	0.25	0.20
WT	1.03	0.93	0.58	0.53	0.27	0.24
ST	0.90	0.84	0.50	0.49	0.20	0.19
W	0.94	0.96	0.55	0.54	0.26	0.23
S	1.00	0.87	0.55	0.52	0.24	0.23
TOPW	1.01	0.87	0.61	0.51	0.32	0.22
TOPS	1.00	0.90	0.57	0.53	0.26	0.25

Summary and Outlook

- Testbed for Web QoE measurements on multiple devices

- **Accurate prediction of the RUMSI**
  - On session level with regression approaches
  - On window level with binary classification

- Future works
  - Evaluation on **more diverse data set**
  - Evaluation of multiple Web QoE metrics
  - Reduction of feature dimension
  - Usage of **more sophisticated models**
  - **Clustering of web page families** to enable more fine-grained models for different website families (news, messenger, etc.)

Thank you for your attention!

Questions?