Challenges and opportunities in machine learning and data analytics for network monitoring and QoE assurance

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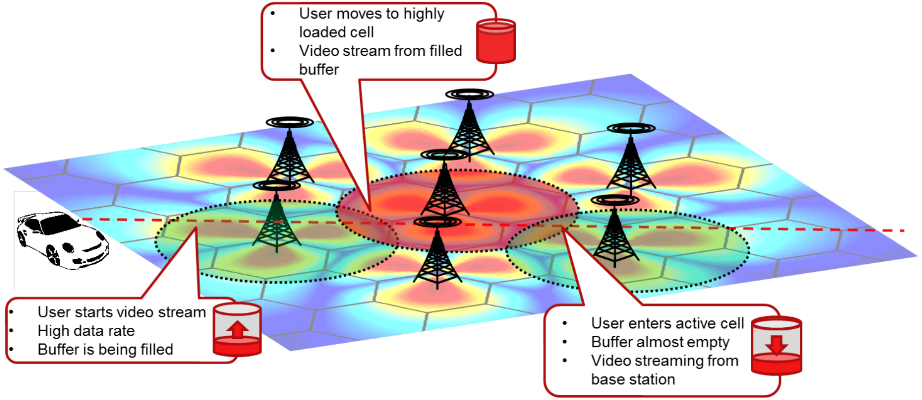
Outline

- Selected enablers for QoE assurance
  - → Traffic prediction
  - → Radio maps
  - → Interference management
  - → Localization

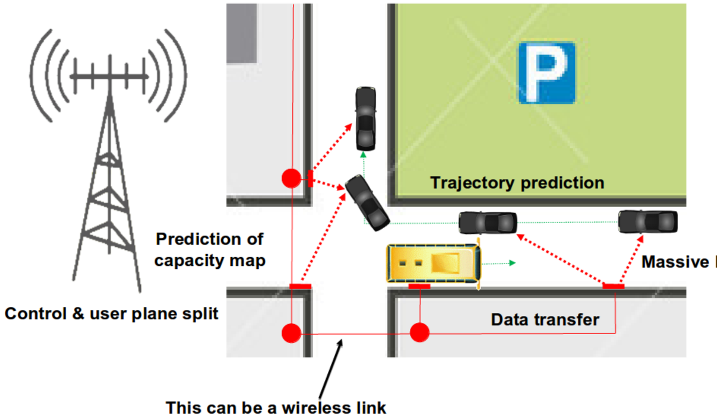
- Anomaly detection
  - → Human-in-the-loop

Examples

Video streaming



mmWave Networks



- Key ingredients:
  - Traffic prediction
  - Radio maps
  - Interference management / self-organizing networks
  - Localization

Use cases - Challenges

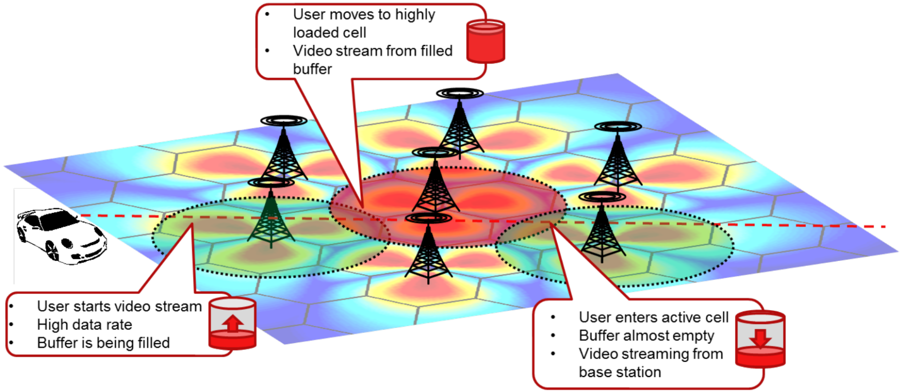
- Useful information is spread over a large area

  Questions:

  1) Size of the training sets

  2) Distributed, centralized, or hybrid approaches

  3) Standards for information exchange among network elements



- Networks are complex systems with highly coupled and dynamic interference patterns

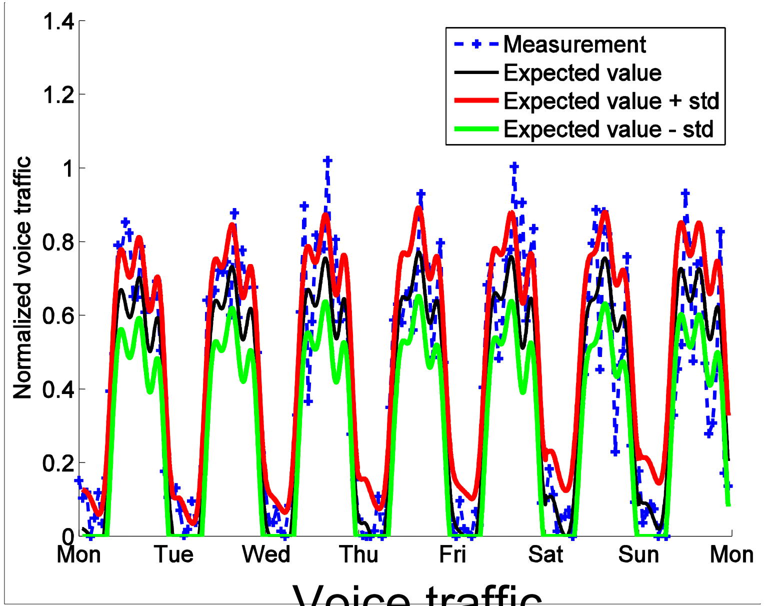
  1) Improving QoE/QoS in a given region may decrease the performance in every other region of the network

  2) Traditional models can be inaccurate – should we discard them?

Message 1: Do not try to learn too much

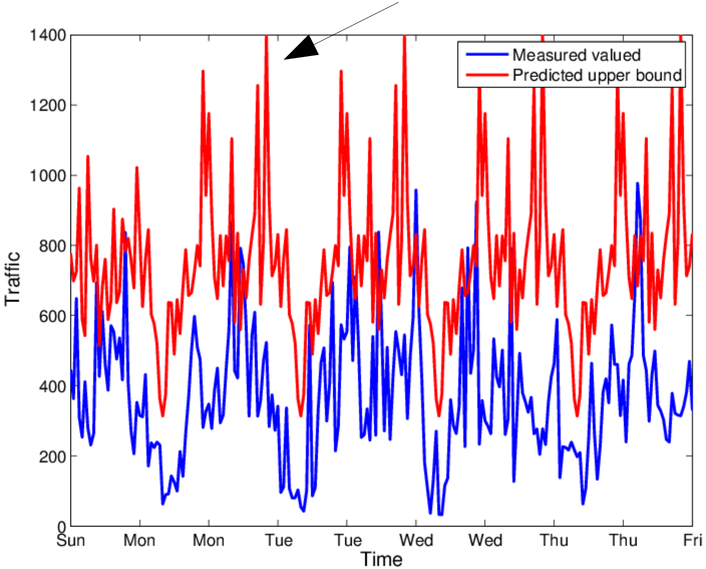
Forecasts

Short/medium term traffic forecasts



Voice traffic

Exact values are hard to predict, but upper bounds (with strong statistical guarantees) are easy



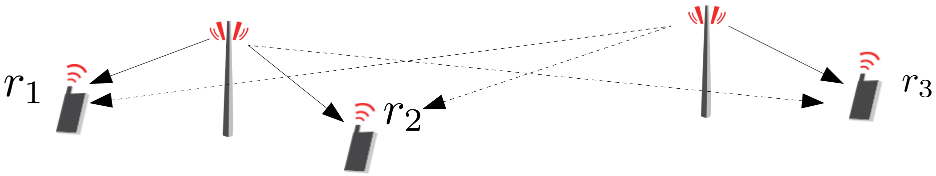
Data traffic

Source: R. L. G. Cavalcante, S. Stanczak, M. Schubert, A. Eisenblätter, and U. Türke, "Toward Energy-Efficient 5G Wireless Communication Technologies," IEEE Signal Processing Magazine, vol. 31, no. 6, pp. 24-34, Nov. 2014

Message 2: Use knowledge gained from models and any available side information

Load prediction

- **Objective:** Given a traffic demand, what is the load at each cell (fraction of used resources)?

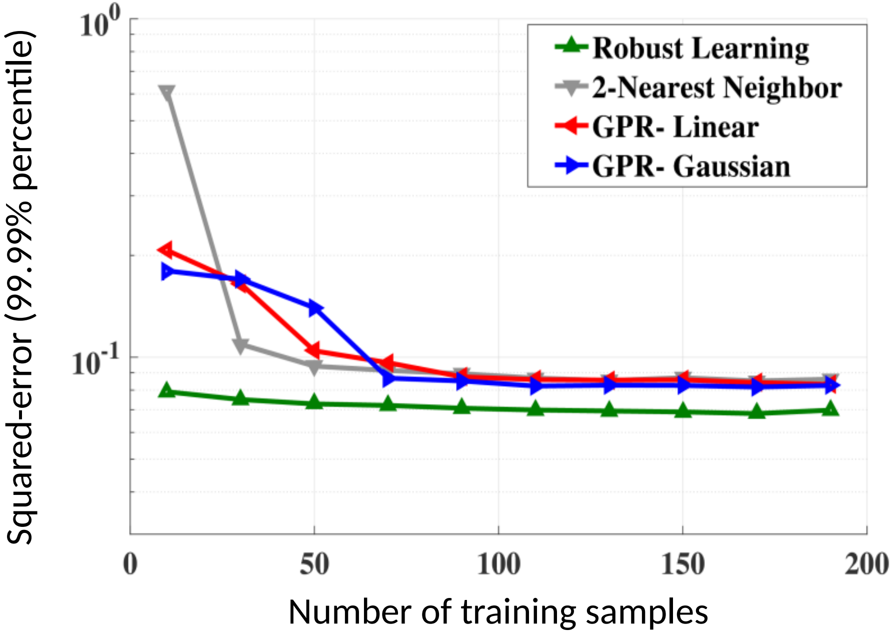


- **Challenge:** Highly dynamic wireless environment (propagation loss, interference patterns, etc.)
  → Not enough time to train traditional learning tools

- Models can be inaccurate, but they reveal important features of the function being learned:
  → Monotonicity (load increases with increasing rates)
  → Lipschitz continuity

- We should exploit these properties in machine learning tools:
  → Reduced training time and increased robustness

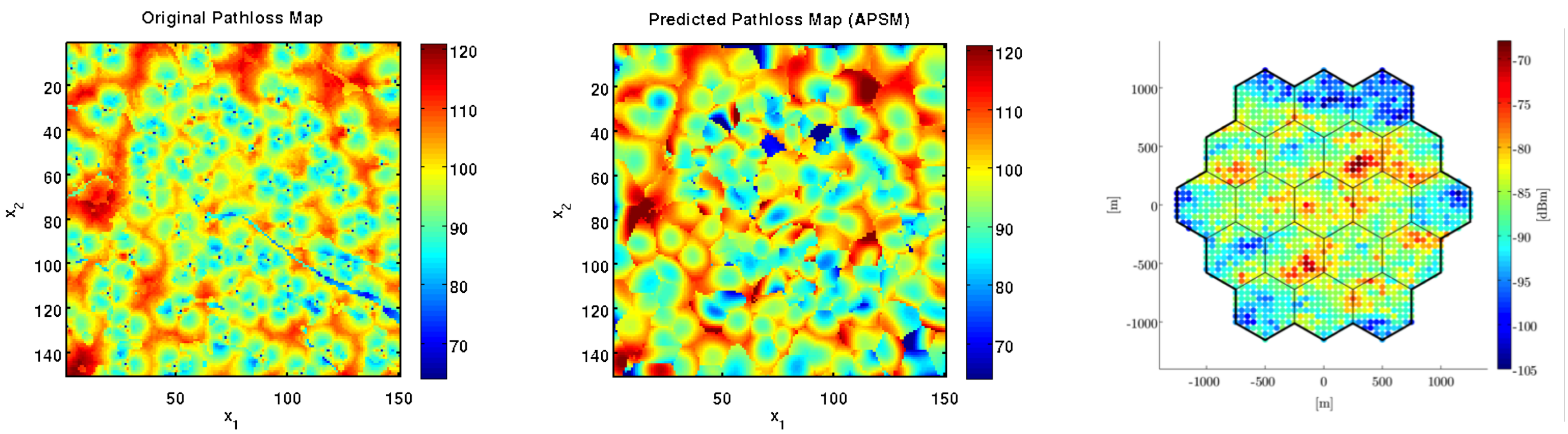
Load prediction



D. A. Awan, R. L. G. Cavalcante, and S. Stańczak, "A robust machine learning method for cell-load approximation in wireless networks," in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Apr. 2018

Reconstruction of Radio Maps

Pathloss reconstruction



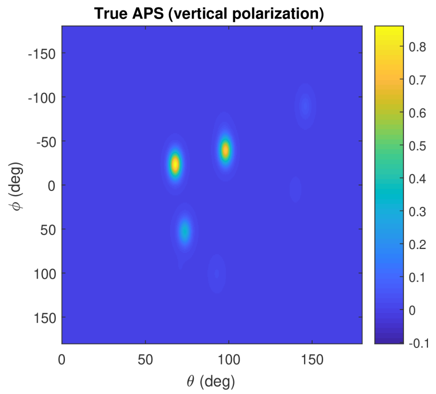
- Kasparick M., R. L. G. Cavalcante, S. Valentin, S. Stanczak, and M. Yukawa, "Kernel-Based Adaptive Online Reconstruction of Coverage Maps with Side Information," *IEEE Transactions on Vehicular Technology,* vol. 65, no. 7, pp. 5461-5473, July 2016
- K. Oltmann, R. L. G. Cavalcante, S. Stańczak, and M. Kasparick, "Interference Identification in Cellular Networks via Adaptive Projected Subgradient Methods," in Proc. IEEE Asilomar Conference on Signals, Systems, and Computers, Nov. 2013

Message 3: Do not ignore the lower layers of the communication stack

Localization

- Choices made on the physical layer impose fundamental performance limits on the network performance

  → Machine learning tools cannot compensate for bad network designs
- The physical layer has a lot of useful information (currently unavailable at the network layer)
  Example: Channel covariance matrices and the angular power spectrum for localization



- R. L. G. Cavalcante, L. Miretti, and S. Stańczak, "Error bounds for FDD massive MIMO channel covariance conversion with set-theoretic methods," in Proc. IEEE Global Telecommunications Conference (GLOBECOM), Dec. 2018
- L. Miretti, R. L. G. Cavalcante, and S. Stańczak, "Downlink channel spatial covariance estimation in realistic FDD massive MIMO systems," in Proc. IEEE Global Conference on Signal and Information Processing, Nov. 2018
- L. Miretti, R. L. G. Cavalcante, and S. Stańczak, "FDD massive MIMO channel spatial covariance conversion using projection methods," in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Apr. 2018
-Alexis Decurninge, Luis García Ordóñez, Paul Ferrand, He Gaoning, Li Bojie, Zhang Wei, Maxime Guillaud "CSI-based Outdoor Localization for Massive MIMO: Experiments with a Learning Approach," International Symposium on Wireless Communications System (ISWCS), 2018

Message 4: Experts can beat machine learning tools (depending on the application)

Anomally detection in networks

- Challenges
  → Huge number of KPIs (spurious correlations are likely to be observed)
  → Missing and unreliable data (software bugs, overflowing counters, etc.)

- Many state-of-the-art machine learning tools do not provide statistical guarantees

- Let machines explain humans why each action is appropriate

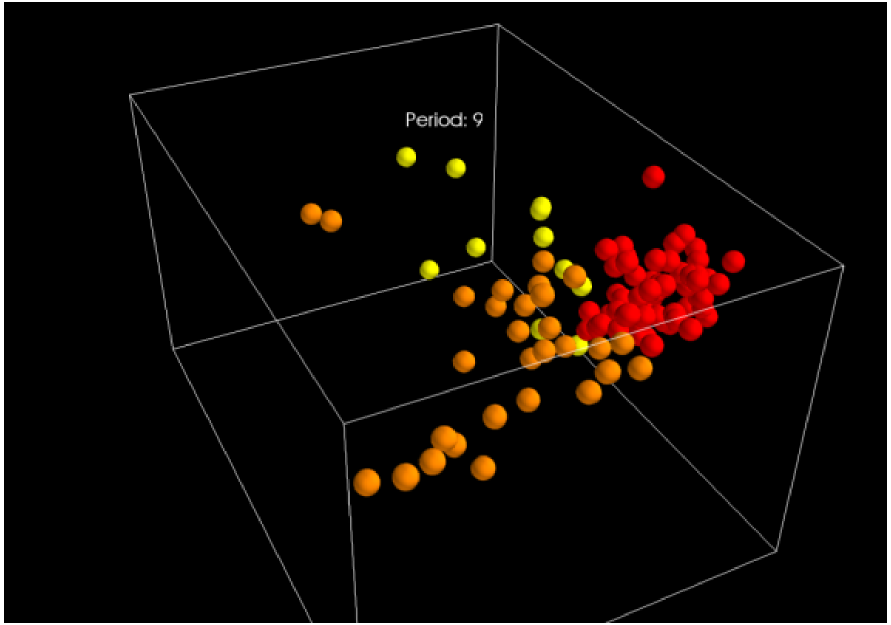
Visualization (1)

- Time-series analysis (cluster operators with similar performance)
- Evolution of the performance of

network elements over time.

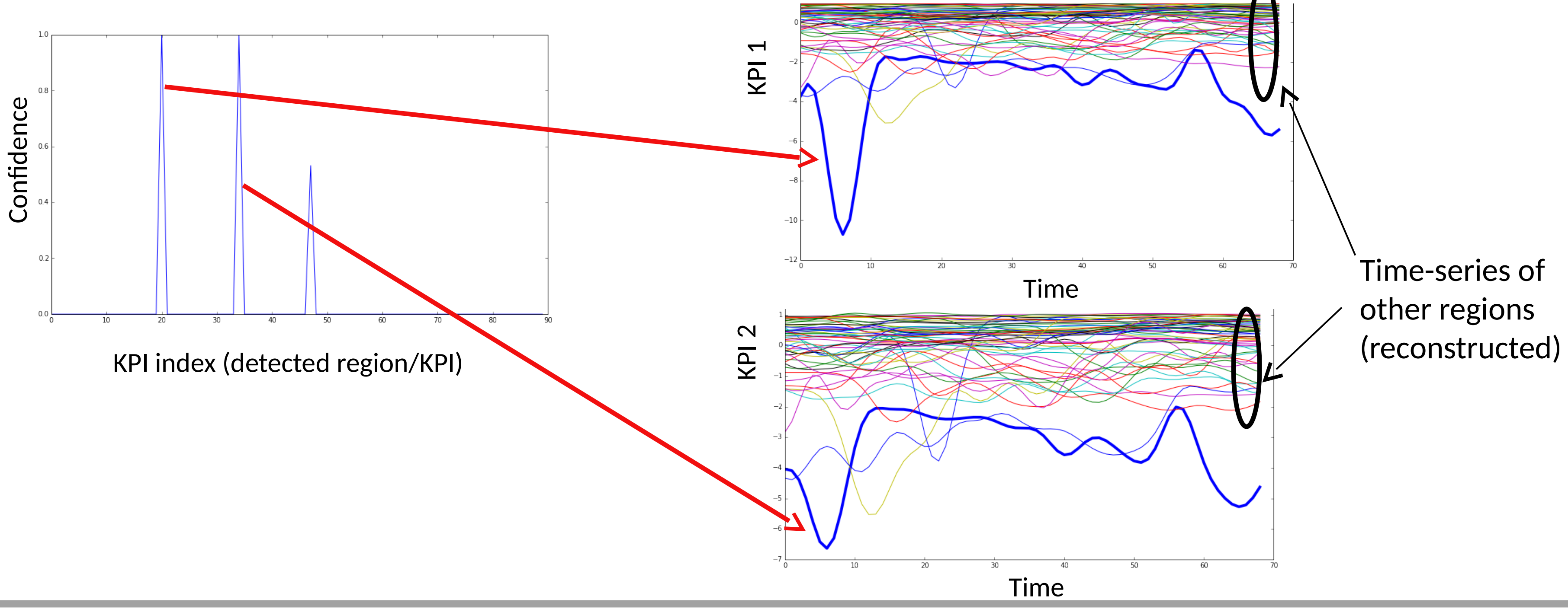
Objective: Detect network regions with performance issues

Challenges: Large number of (unreliable) time-series, misaligned data



Anomaly detection (1)

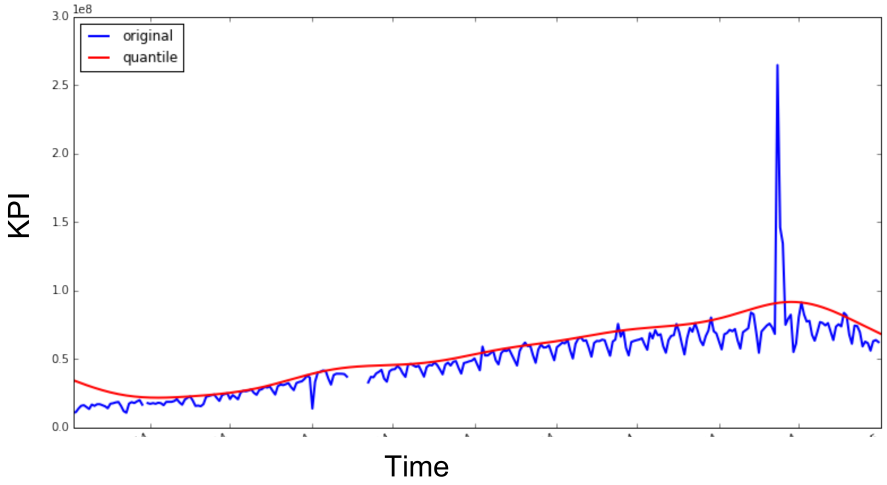
- Automatic extraction of atypical network regions and key performance indicators

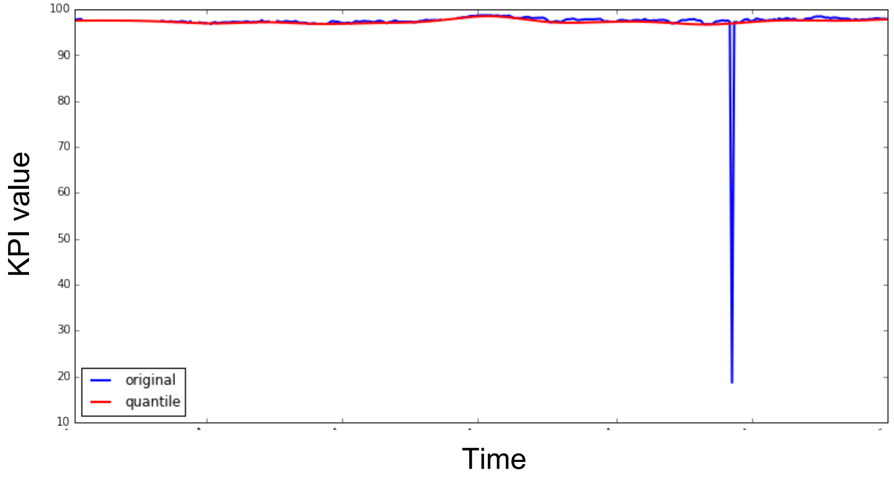


Anomaly detection (2)

Short/medium term forecasts

- Detect atypical days by also considering long term trends





Thank you for your attention!

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