Scalable Edge Computing for Low Latency Data Dissemination in Topic-based Publish/Subscribe

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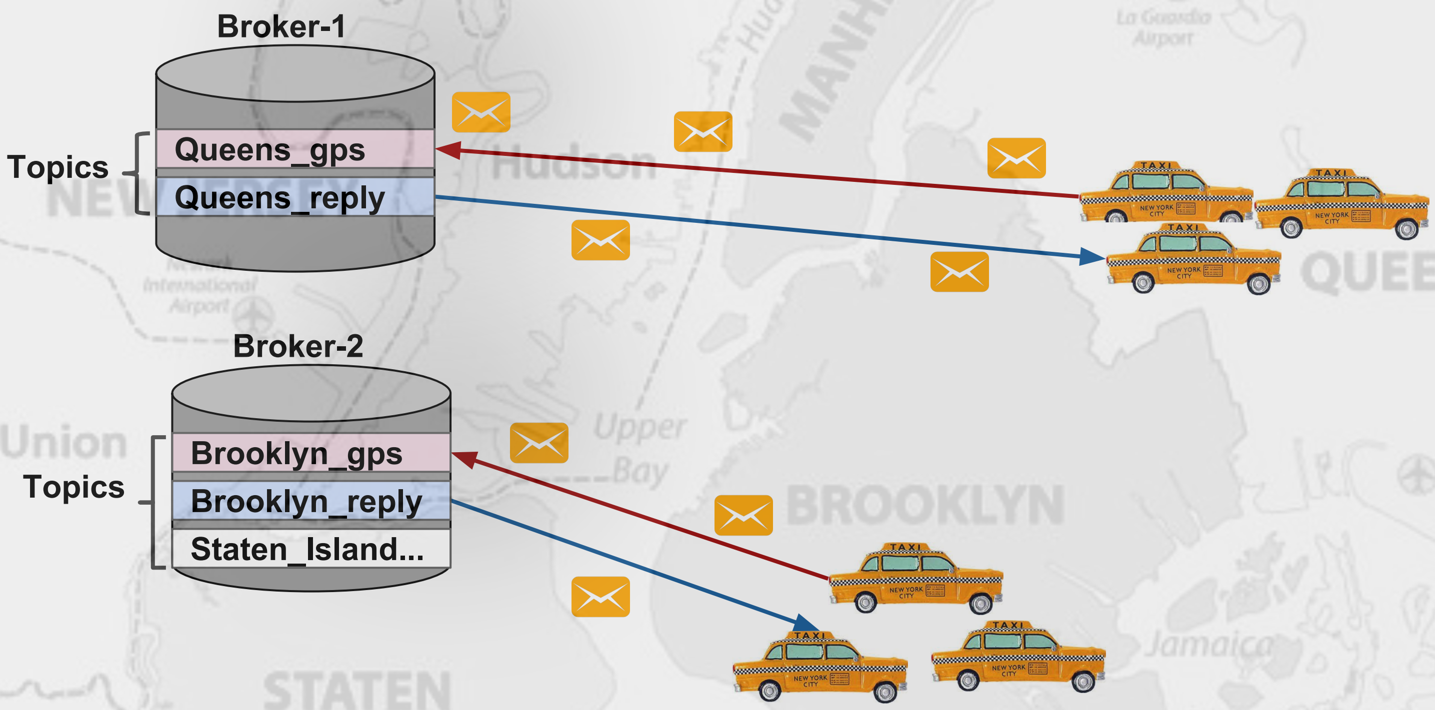
Latency Critical IoT Applications

- **Internet of Things (IoT):**
  - Interconnection via the Internet of computing devices embedded in everyday objects.
  - Smart City Applications
- **Real-time New York Taxi Service**
  - Location and time sensitive information
  - Sub-second delivery time requirement

Requirements

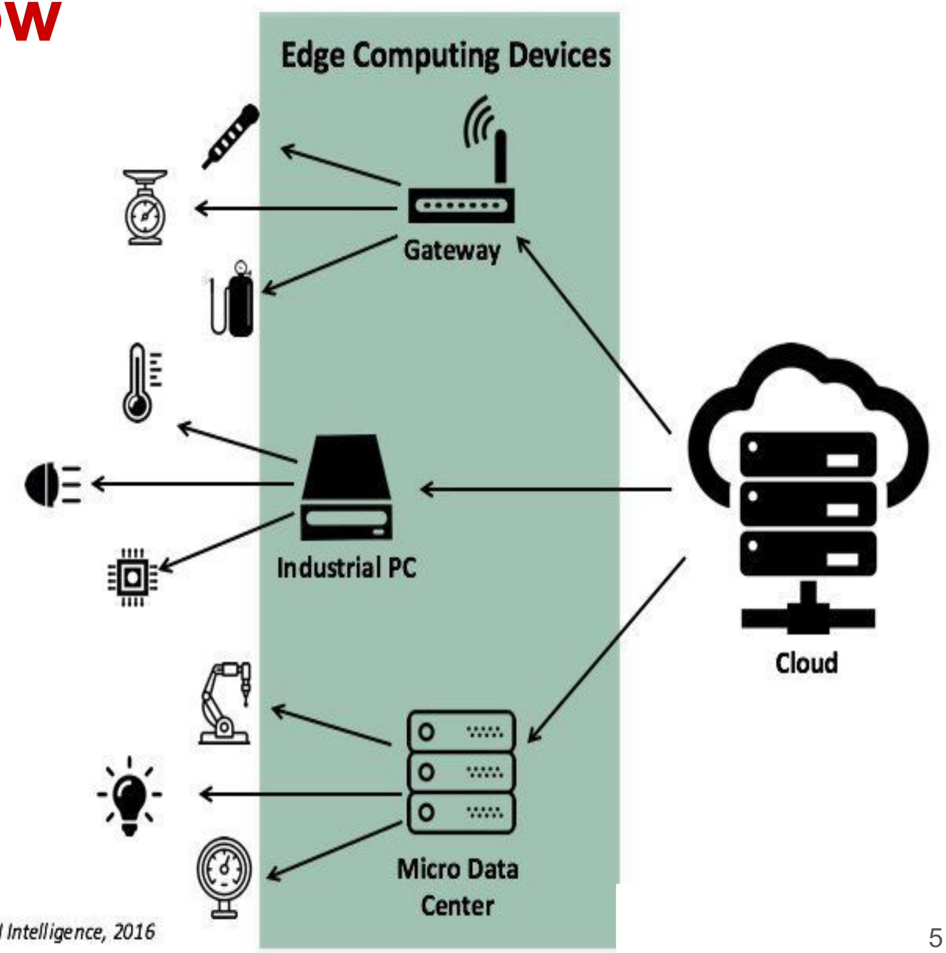
- Scalable Data Dissemination
- Low Latency Processing

Publish Subscribe for Scalable Data Dissemination



Edge Computing for Low Latency Processing

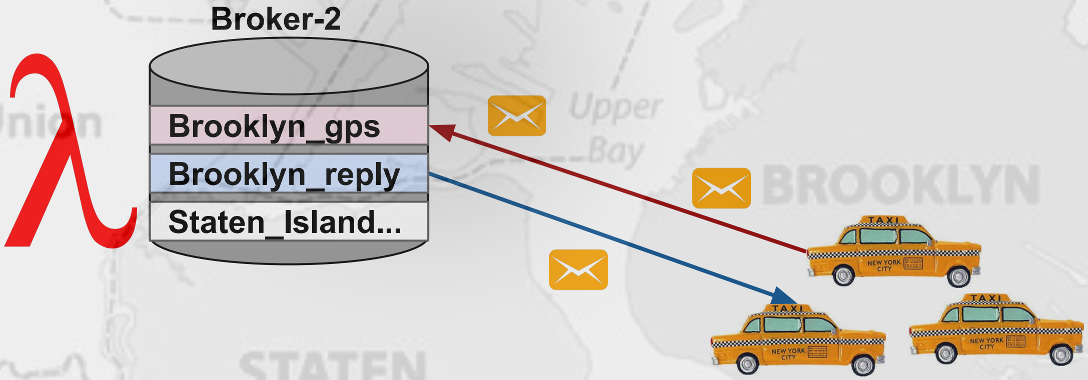
- Computation near the source of data on low-cost edge devices or micro data-centers.
  - Resource-Limited



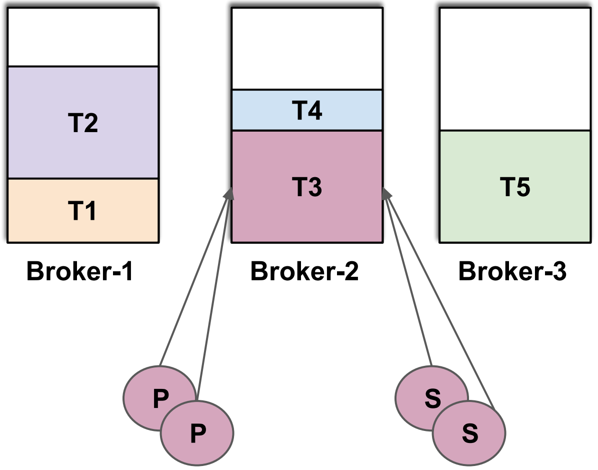
Source: BI Intelligence, 2016

Publish-Process-Subscribe:

Publish/Subscribe + Processing at the Edge



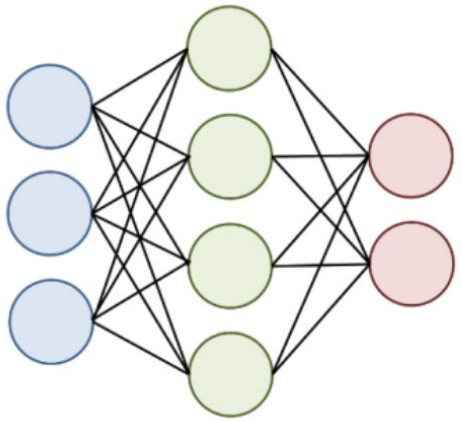
Latency Assurance in Existing Publish Subscribe Systems



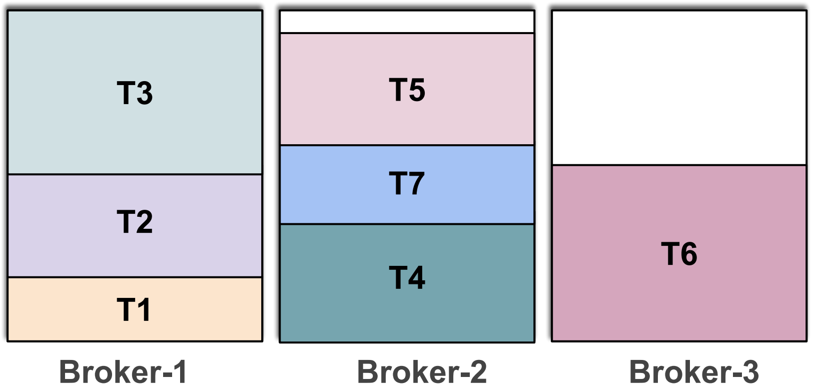
❖ Widely used, open-source systems don’t provide any latency assurance.

How can we provide latency QoS assurance for publish-process-subscribe systems?

Data Driven Approach towards Latency QoS Assurance



Learn a Latency Model for Broker Load



Latency Aware Topic placement

Laency QoS is specified as a topic’s 90th percentile latency

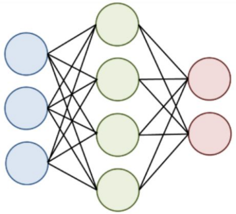
Contributions

❖ **Sensitivity Analysis**

To study the impact of pub/sub features on a topic's latency.

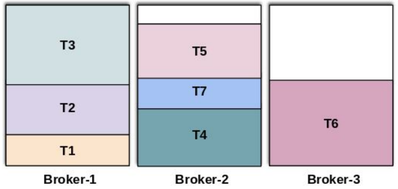
❖ ***k*-colocation Latency Model**

For predicting the latency of a topic co-located with *k* other topics.



❖ ***k*-colocation Topic Placement Problem**

Place upto *k* topics at a broker in a latency aware manner while also minimizing the number of brokers used.



***K* is the degree of co-location of topics at a broker**

Sensitivity Analysis of Pub/Sub Features

- ❖ Number of Subscribers
- ❖ Number of Publishers
- ❖ Publishing Rate
- ❖ Per-sample processing interval
- ❖ Impact of co-location/Background Load

To identify the dominant Pub/Sub features for the latency model

k-Colocation Latency Prediction Model

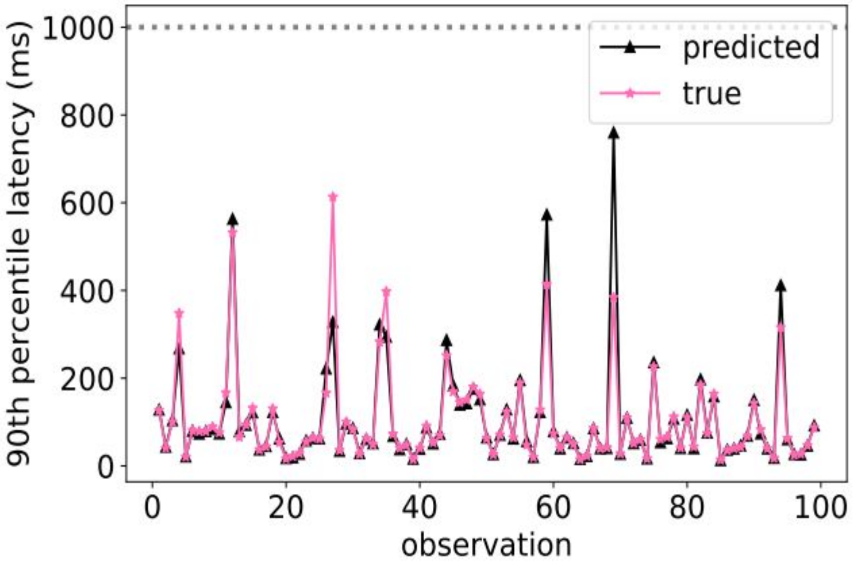
- **Selected Pub/Sub Features from Sensitivity Analysis:**
  - Publishing rate
  - Per-sample processing interval

- ***k*-colocation Latency Model input features:**
  - Features characterizing foreground topic
  - Features characterizing background load

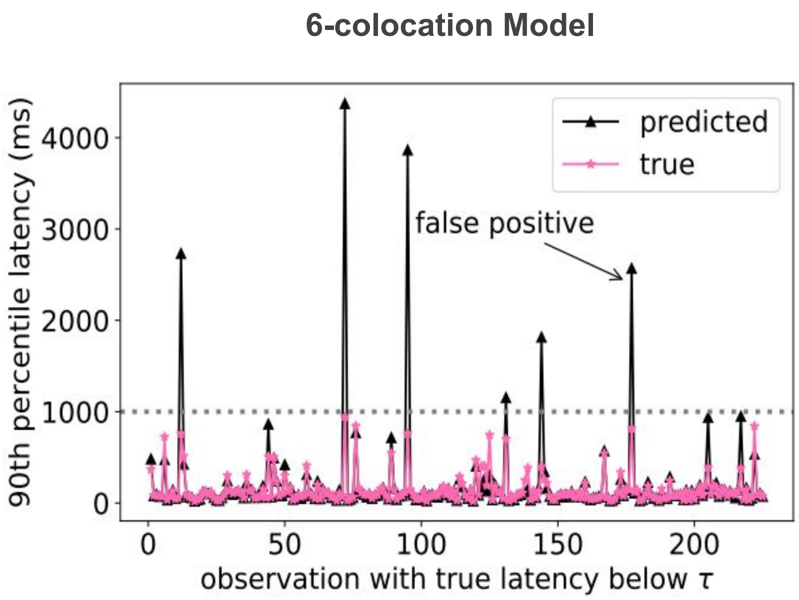
k-Colocation Latency Prediction Model

- For k>1, Neural Network Regression was used to capture the non-linear impact of background load on a topic's latency.
- For all k, the accuracy of the learned models was ~97%.

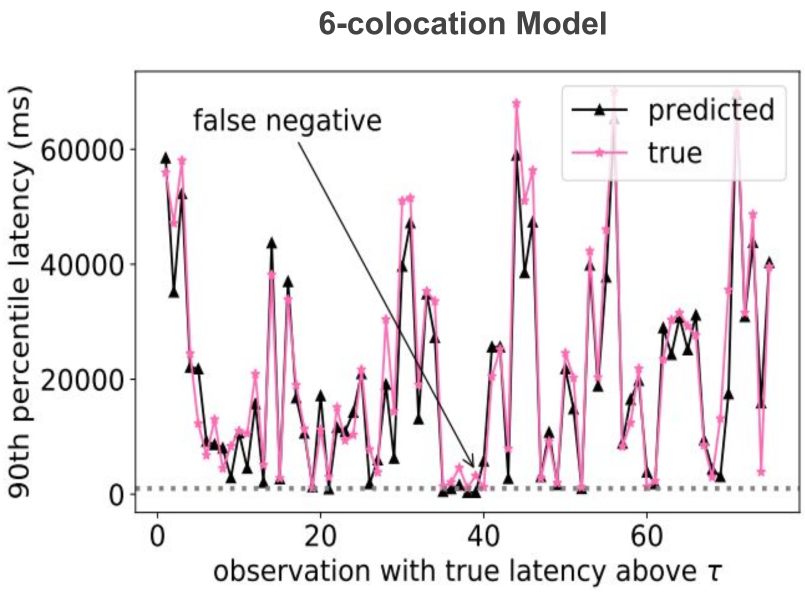
2-colocation Model



Prediction Model Inaccuracies



False Positives result in inefficient use of system resources.

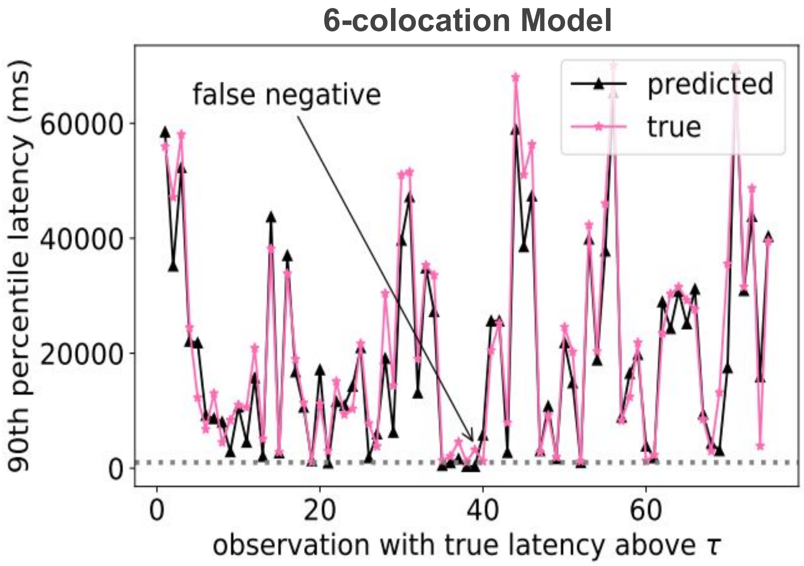


False Negatives result in QoS violations.

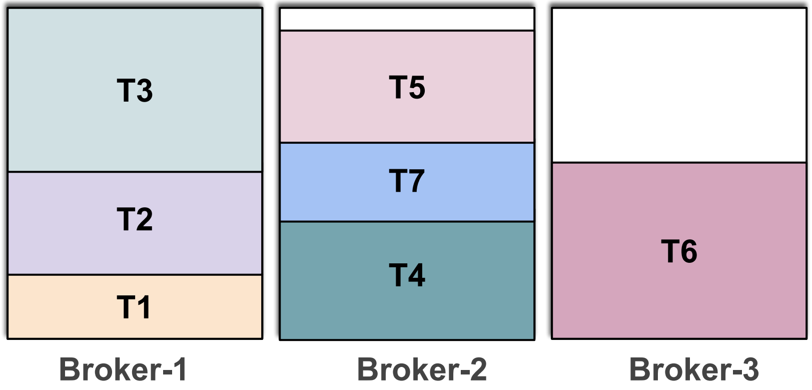
k-Colocation Model Limitations

❖ Inaccuracy in the latency model results in QoS violations

Our approach does not provide hard guarantees on QoS assurance.



k-Colocation Topic Placement Problem

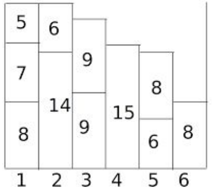


Given *k*, find a placement of topics on brokers such that latency QoS of all topics is satisfied while making minimal use of system resources.

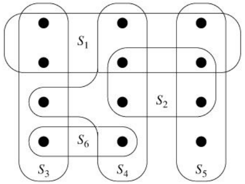
k-Colocation Topic Placement Heuristics

k-Colocation topic placement problem is NP-hard for k>=3

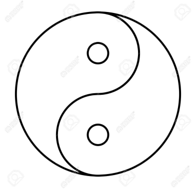
- **First-Fit Decreasing (FFD)**
  Inspired by bin packing



- **Largest Feasibility Set (LFS)**
  Inspired by set-cover

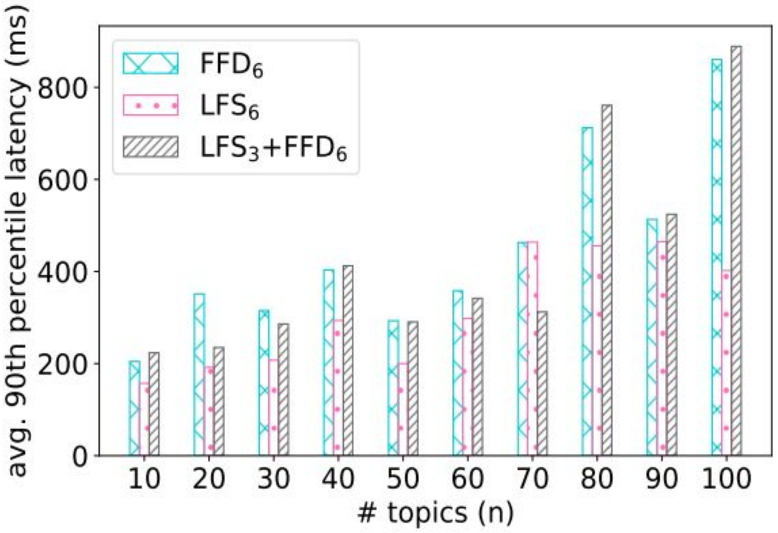


- **Hybrid (LFS+FFD)**
  Combination of LFS and FFD



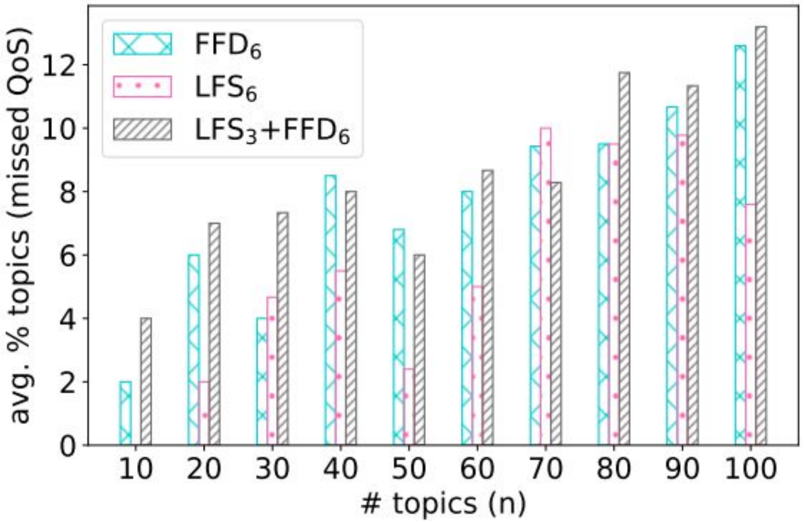
Comparison of Placement Heuristics

Average 90th Percentile Latency



LFS$_k$ yields a lower average 90th percentile latency for all values of *n.*

Percentage of topics with missed QoS



LFS$_k$ yields a lower percentage of topics with missed QoS in most cases

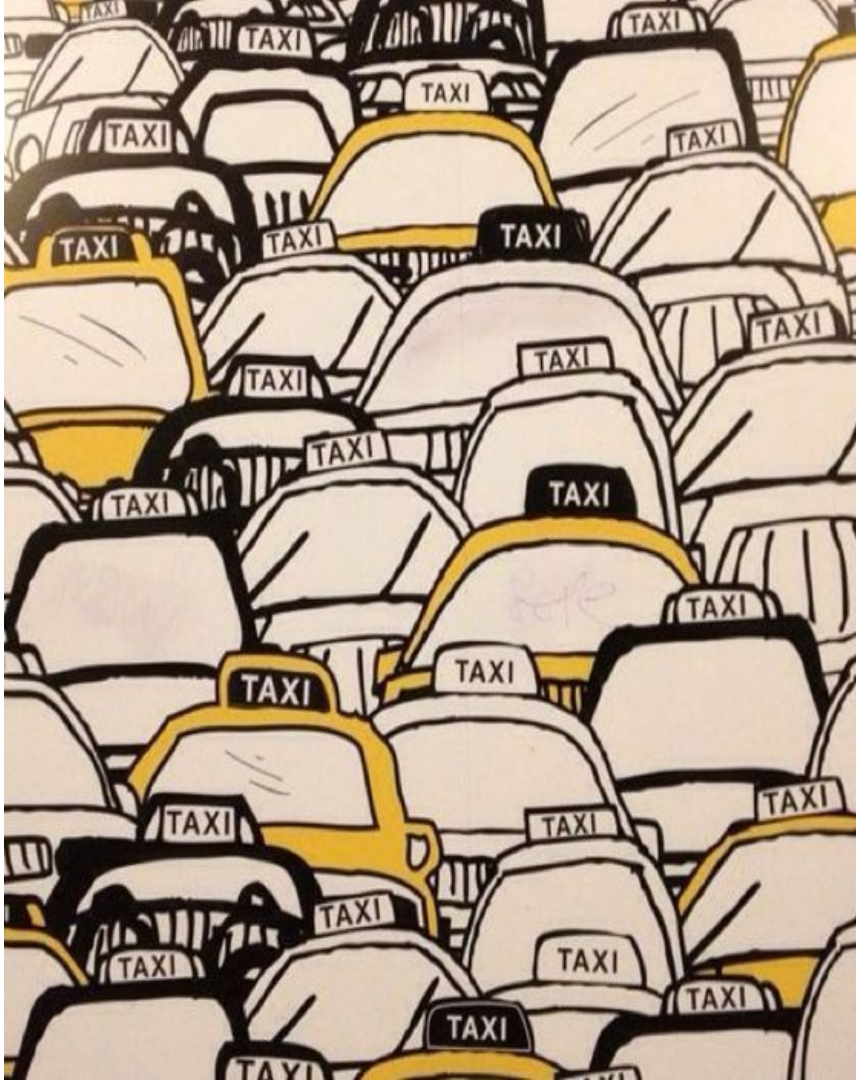
We are able to meet the QoS for at least 87% of topics in the system.

Lessons Learned

- Performance of *k*-Topic Co-location heuristics relies on the accuracy of the latency prediction model
  - Investigate more advanced machine learning algorithms

- Incorporate temporal dynamics and network link state

Thank you.

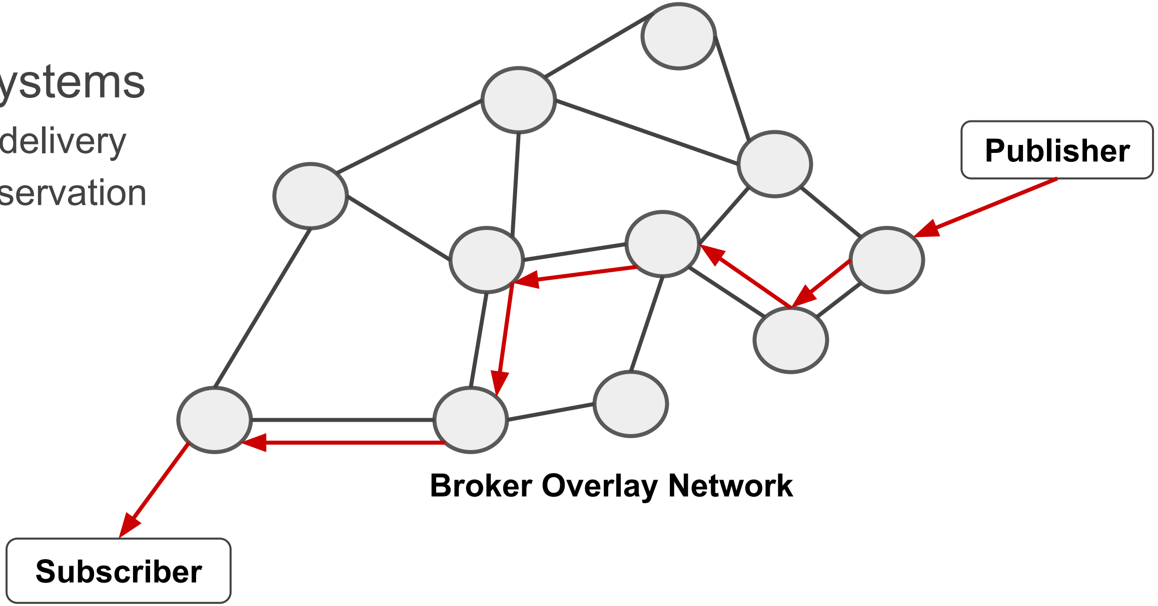


EXTRA SLIDES

Latency Assurance in Existing Publish Subscribe Systems

- ❖ Peer-to-Peer Pub/Sub Systems
  - ➢ Re-routing paths for data-delivery
  - ➢ Network level resource reservation

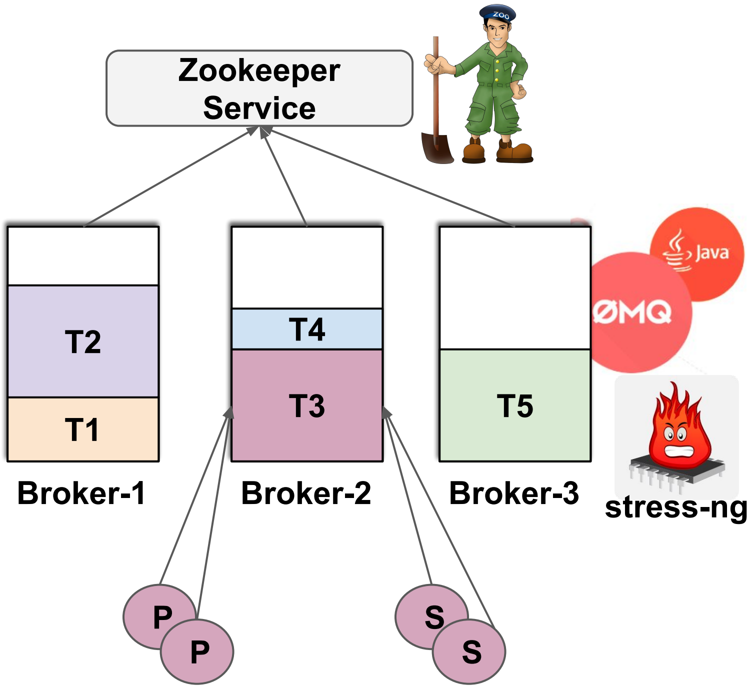
- ❖ Don't consider processing load at the broker



[1] Carvalho, Nuno, Filipe Araujo, and Luis Rodrigues. "Scalable QoS-based event routing in publish-subscribe systems."
[2] Yang, Hao, et al. "Message-oriented middleware with QoS awareness."
[3] Guo, Shuo, et al. "Delay-cognizant reliable delivery for publish/subscribe overlay networks."

System Description

- **System Architecture:**
  - ZMQ Java sockets library
  - Apache Zookeeper service for distributed coordination
  - Stress-ng for broker load emulation



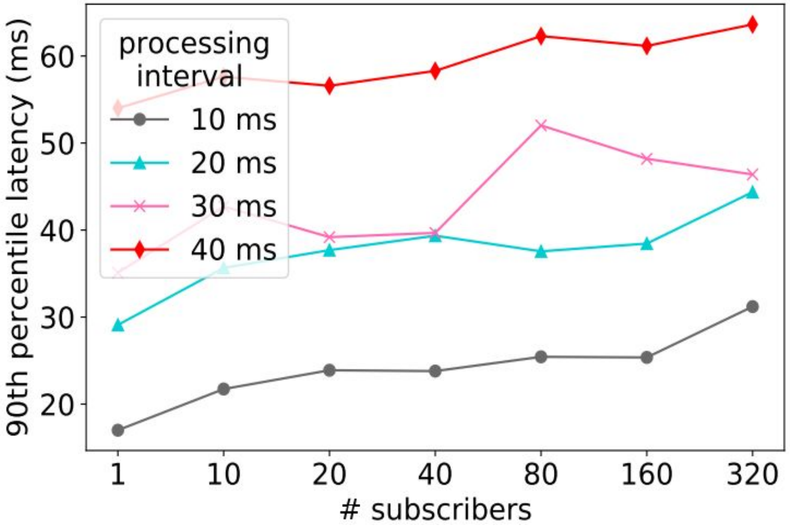
- **Dataset:**
  - New York TLC dataset on taxi pickups and drop-offs.
  - RIoTBench Stream processing benchmark on TLC dataset [1]: 10ms-40ms processing interval

NYC Taxi & Limousine Commission

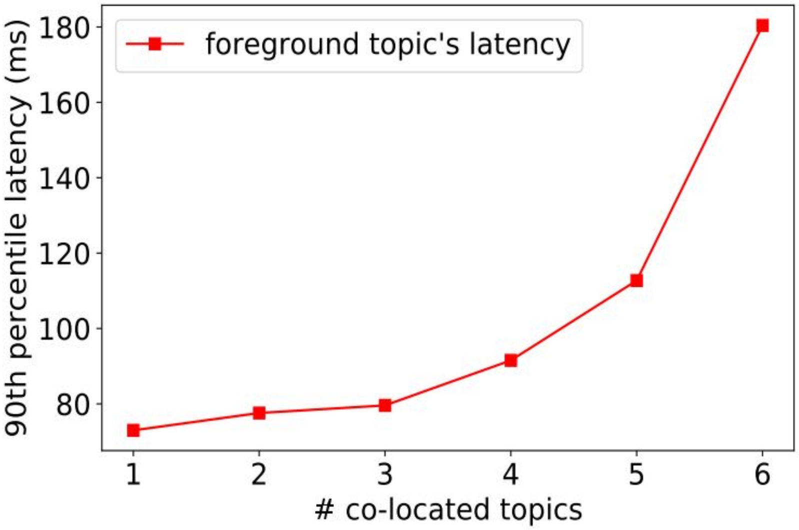
[1] Shukla Anshu, Shilpa Chaturvedi, and Yogesh Simmhan. "RIoTBench: An IoT benchmark for distributed stream processing systems."

Sensitivity Analysis- Subscription Size

Isolated Topic



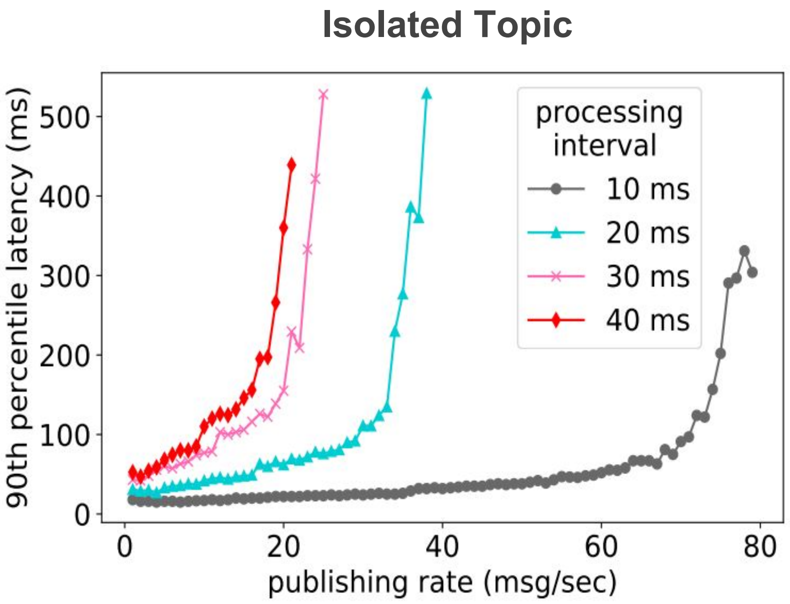
Co-located Topic

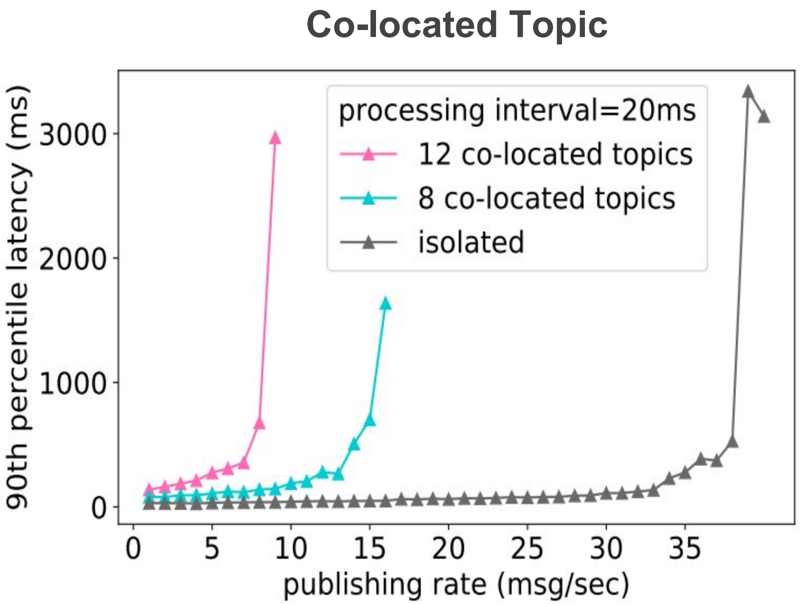


Latency is below sub-second deadline for upto 300 subscribers

Latency is below sub-second deadline even with broker CPU saturation

Sensitivity Analysis- Publishing Rate

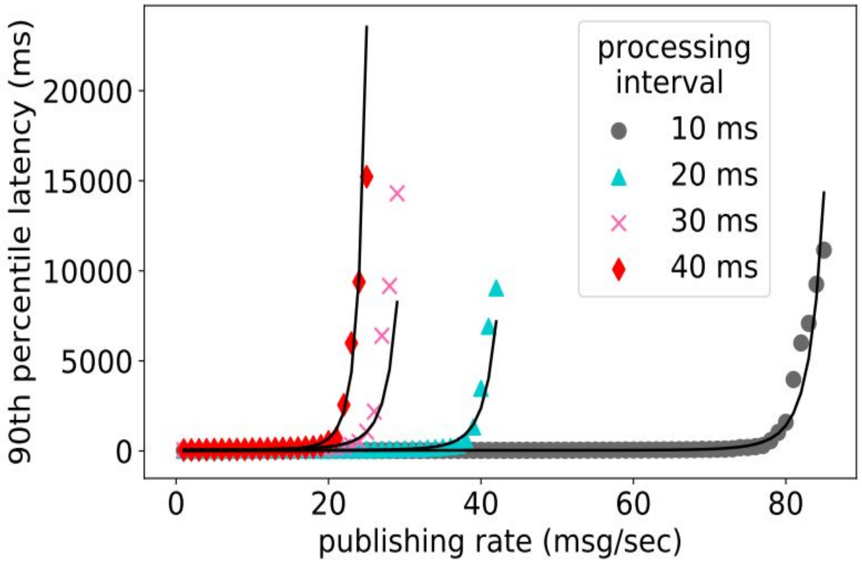




Latency increases linearly up to a threshold rate of publication, after which the increase is exponential.

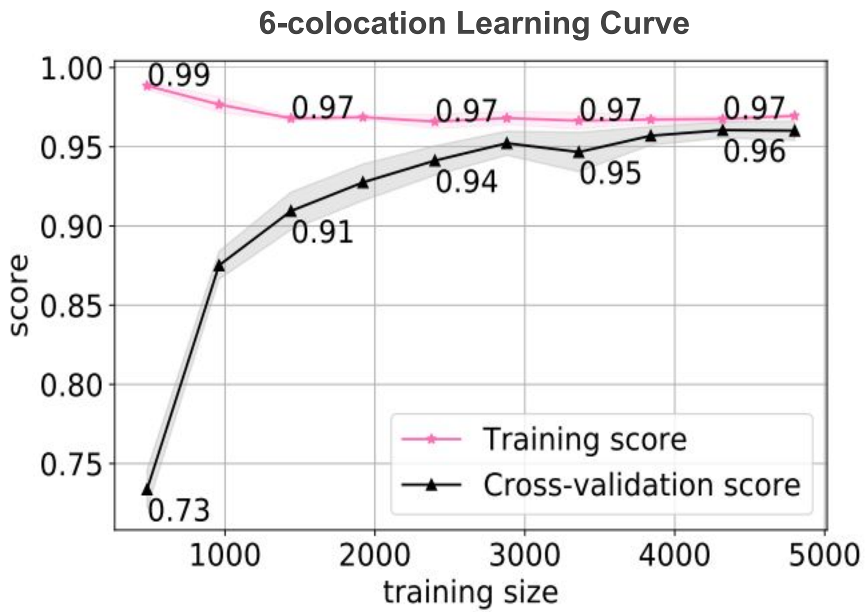
Threshold rate of publication decreases with increasing background load.

Isolated Topic Latency Prediction Model



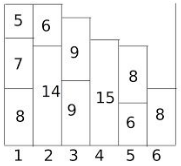
- 4 degree Polynomial Regression
- Training accuracy: 97.5%. Test Accuracy: 97%

k-Colocation Latency Prediction Model



Learned model does not suffer from over-fitting or under-fitting

First Fit Decreasing (FFD_k)



Algorithm 1: FirstFitDecreasing (FFD_k)

Input: Collection $T = \{t_1, t_2, \ldots, t_n\}$ of n topics, latency ℓ_i for each topic $t_i \in T$ when assigned to a broker in isolation, degree of co-location k, and feasibility function $\mathcal{F}$

Output: A partition of topics $\{T(b_1), T(b_2), \ldots, T(b_{|B|})\}$ for a set B of brokers with each broker $b_j \in B$ hosting a subset $T(b_j) \subseteq T$ of topics

begin
  Sort the topics in decreasing order of latency when assigned to a broker in isolation, i.e., $\ell_1 \geq \ell_2 \geq \cdots \geq \ell_n$;
  Initialize $|B| \leftarrow 0$;
  for *topic* t_i $(i = 1 \ldots n)$ **do**
    $mapped \leftarrow false$;
    for *broker* b_j $(j = 1 \ldots |B|)$ **do**
      if $|T(b_j)| = k$ **then**
        continue;
      end
      if $\mathcal{F}(T(b_j) \bigcup \{t_i\}) = 1$ **then**
        $T(b_j) \leftarrow T(b_j) \bigcup \{t_i\}$;
        $mapped \leftarrow true$;
        break;
      end
    end
    if $mapped = false$ **then**
      $|B| \leftarrow |B| + 1$;
      Start a new broker $b_{|B|}$ with $T(b_{|B|}) = \{t_i\}$;
    end
  end
end

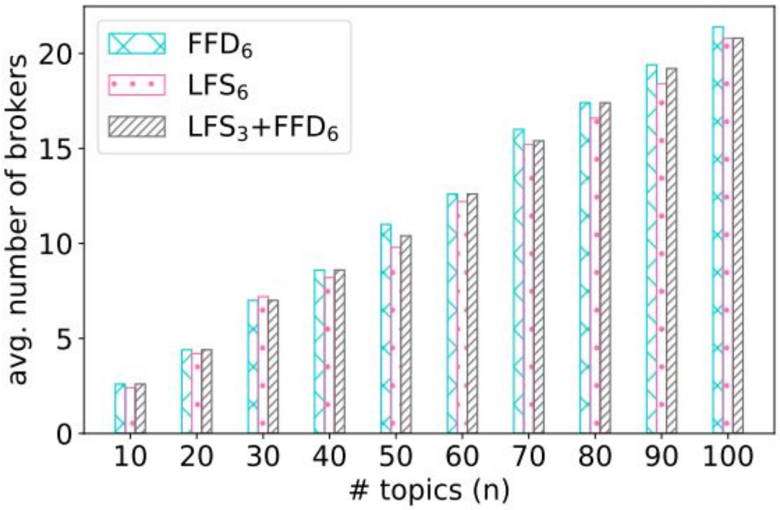
1. Sorts topics in decreasing order of latency when they are assigned to a broker in isolation.

2. Places the topic on the first broker that can feasibly host it along with already existing topics at the broker.

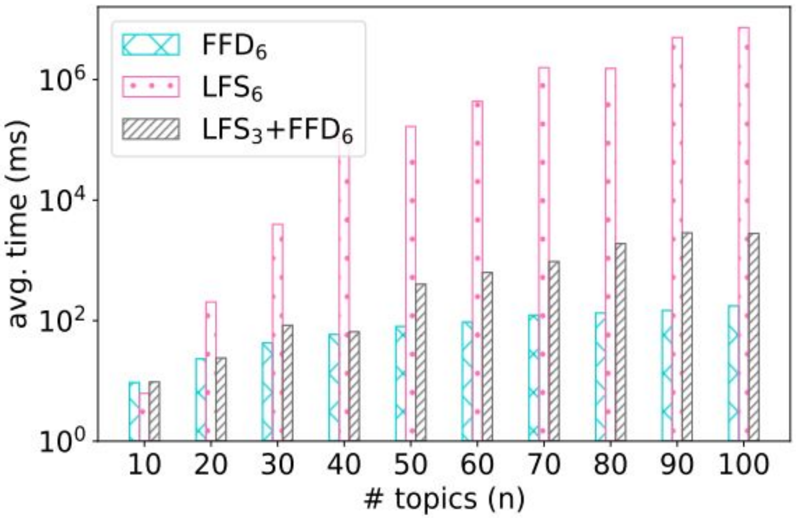
3. If no feasible broker is found, it starts a new broker/bin and assigns the topic to it.

Comparison of Placement Heuristics

Number of Brokers



Time for finding Placement



LFS_k is able to find a placement which uses less number of brokers than FFD_k and $LFS_{k'}$+FFD_k

LFS_k takes a much longer time to find the placement solution in comparison to FFD_k and $LFS_{k'}$+FFD_k