## A Machine Learning Based Approach to Mobile Network Analysis

Zengwen Yuan**1**, Yuanjie Li**1**, Chunyi Peng**2**, Songwu Lu**1**, Haotian Deng**2**, Zhaowei Tan**1**, Taqi Raza**<sup>1</sup>**

















Why machine learning for mobile network analysis







Why machine learning for mobile network analysis

Mobile network analysis: state-of-the-art and our approach







Why machine learning for mobile network analysis

Mobile network analysis: state-of-the-art and our approach

Case study: analyzing latency for mobile networks

- How mobile apps work over LTE
- How to breakdown app-perceived latency
- Challenges and ML scheme
- Primary results from crowdsourcing
- 
- 
- 







Why machine learning for mobile network analysis

Mobile network analysis: state-of-the-art and our approach

Case study: analyzing latency for mobile networks

- How mobile apps work over LTE
- How to breakdown app-perceived latency
- Challenges and ML scheme
- Primary results from crowdsourcing

**Conclusion** 

- 
- 
- 







# Ubiquitous cellular networks connect everyone,





## The race to 5G opens many new opportunities







### Yet, access to mobile network analytics is barred



Oh we cannot tell you unless you sign an NDA…



**Operators** 



### Yet, access to mobile network analytics is barred







### Plus, mobile networks are complex & distributed

More complex functions on both control and data planes

Operations are distributed across layers





- 
- 

### $\cdot$  UCLA  $\cdot$





Analytics for mobile networks is problem-specific, for example:





### Analytics for mobile networks is problem-specific, for example:

- Web browsers:
	- ✦ Why the time-to-first-byte (TTFB) is so long?
	- ✦ What's the major component of latency?









### Analytics for mobile networks is problem-specific, for example:

- Web browsers:
	- ✦ Why the time-to-first-byte (TTFB) is so long?
	- ✦ What's the major component of latency?
	- ✦ …

✦ …

- Instant message apps:
	- ✦ Does the recipient read my message?
	- Is my message delivered in time?











·· UCLA ··



Current 4G network analytics is primarily "infrastructure-based":





### Current 4G network analytics is primarily "infrastructure-based":







Current 4G network analytics is primarily "infrastructure-based":



**Cellular network (4G LTE)**







### Current 4G network analytics is primarily "infrastructure-based":





**Cellular network (4G LTE)**





Not Scalable

### Current 4G network analytics is primarily "infrastructure-based":

Not Scalable **Incomplete View** 





**Cellular network (4G LTE)**





### Current 4G network analytics is primarily "infrastructure-based":





**Cellular network (4G LTE)**



Not Scalable **Incomplete View** Providence Chapter Conservative Chapters and Chapters Chapters Chapters Chapters



### ML-based approach is a must-have feature for mobile network analytics











### Device-centric ML approach brings new hope

### ML-based approach is a must-have feature for mobile network analytics





Not Scalable **Incomplete View** Departments





### Device-centric ML approach brings new hope

### **Scalability**

### ML-based approach is a must-have feature for mobile network analytics



Mobile Apps Ba<sub>seba</sub>nda Mobile OS TCP/IP stack LTE int Application Stack User space

Not Scalable **Incomplete View** Departments





### ML-based approach is a must-have feature for mobile network analytics









### ML-based approach is a must-have feature for mobile network analytics









It is probably true that machine learning is a *must-have* approach, rather than a *nice-to-have* one, to our field for mobile network analysis

### Our proposal: two-level device-centric ML approach









- Via hardware-software coordination (e.g. MobileInsight [ACM MobiCom'16])
- Via higher-layer (application/transport/IP) and lower-layer (cellular-specific) integration
- Via ML-assisted data plane prediction from control plane protocol reconstruction

### Our proposal: two-level device-centric ML approach

### Local level: sensing mobile network data inside each smartphone









- Via hardware-software coordination (e.g. MobileInsight [ACM MobiCom'16])
- Via higher-layer (application/transport/IP) and lower-layer (cellular-specific) integration
- Via ML-assisted data plane prediction from control plane protocol reconstruction

### Global level:

- Crowdsourcing-based dataset
- Cloud-synthesized insights

### Our proposal: two-level device-centric ML approach

### Local level: sensing mobile network data inside each smartphone















### Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight









### Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight

![](_page_34_Picture_6.jpeg)

![](_page_34_Figure_4.jpeg)

![](_page_34_Picture_5.jpeg)

![](_page_34_Picture_7.jpeg)

### Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight

### Step 2: automated data preprocessing

• Data cleansing and integration of two sources

![](_page_35_Picture_8.jpeg)

![](_page_35_Picture_6.jpeg)

![](_page_35_Picture_7.jpeg)
## Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight

### Step 2: automated data preprocessing

• Data cleansing and integration of two sources



# Local analysis







## Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight

### Step 2: automated data preprocessing

- Control plane for protocol operations
- Data plane for performance



• Data cleansing and integration of two sources

### Step 3: local ML-based analysis

# Local analysis







## Step 1: open up the "black-box" operations

- At/above IP network data: TCPDUMP
- Below IP network data: MobileInsight

### Step 2: automated data preprocessing

- Control plane for protocol operations
- Data plane for performance

• Data cleansing and integration of two sources

### Step 3: local ML-based analysis

# Local analysis







# Global analysis

Enabled by cloud-based crowdsourcing (e.g. cniCloud [HotWireless'17])

Analytical Insights for:

- Geographical location
- Operators

• Phone models

- - -

• …







Case study: latency analysis in mobile networks



# Every millisecond of latency matters!

## Mobile network users want *fast* access

• 1 second latency in page response  $\rightarrow$  7% reduction in PageView [KissMetrics 2011]

Developers *lose revenue* due to long latency

- Every **100 ms** costs Amazon **1%** (**\$1.6 bn**) in sales
- An extra **400 ms** latency drops daily Google searches per user by **0.6%**

Latency does matter a lot!





## What happens under the hood?

How LTE impacts perceived latency on mobile web/IM app?





**Web server**







## What happens under the hood?







## What happens under the hood?







## What happens under the hood?

How LTE impacts perceived latency on mobile web/IM app?





**Web server**







## What happens under the hood?

How LTE impacts perceived latency on mobile web/IM app?





**Web server**







## What happens under the hood?









**Cellular network (4G LTE)**

## Background: how do mobile apps work over 4G LTE?

## What happens under the hood?









## What happens under the hood?







## What happens under the hood?





















·· UCLA ··







 $\sum_{i=1}^{n}$ 

·· UCLA ··







E

















**P2. Service request** 

·· UCLA ··




































































## Timing breakdown of control plane operations







## Timing breakdown of control plane operations







# Learning latency: latency data sensing



## Three-tiered timing data collection:

- App-specific semantic timing (e.g. Navigation Timing API, IM timing model)
- TCP/IP stack timing (from TCPDUMP)
- LTE stack timing (from MobileInsight)



·· UCLA ··

# Challenge: timestamp alignment



## How to align timestamps at these layers?

- Domain-specific event tracing and mapping
- Machine-learning assisted





·· UCLA ··



#### Run a small webpage (4 KB) in Chrome on Android

- User is static, under good 4G LTE signal (-95 dBm), T-Mobile
- 





Run a small webpage (4 KB) in Chrome on Android

• User is static, under good 4G LTE signal (-95 dBm), T-Mobile

Total Latency: 473 msec

• Clicking URL  $\rightarrow$  page loading complete, Steps (a)–(f)





Run a small webpage (4 KB) in Chrome on Android

• User is static, under good 4G LTE signal (-95 dBm), T-Mobile

#### Total Latency: 473 msec

• Clicking URL  $\rightarrow$  page loading complete, Steps (a)–(f)

Pinpointing the latency bottleneck

• How to breakdown?





·· UCLA ··



Major component from Navigation Timing API: DNS lookup, 250 ms out of 473 ms





Major component from Navigation Timing API: DNS lookup, 250 ms out of 473 ms

Is the DNS server slow to handle connection?





- Major component from Navigation Timing API: DNS lookup, 250 ms out of 473 ms
- Is the DNS server slow to handle connection?
- Further breakdown: *LTE service request* takes 172 ms before the DNS setup





- Major component from Navigation Timing API: DNS lookup, 250 ms out of 473 ms
	-
- Further breakdown: *LTE service request* takes 172 ms before the DNS setup



Is the DNS server slow to handle connection?

**Queueing Stalled** DNS Lookup Initial Connection Request Sent Waiting (TTFB) Content Download





## Data-plane latency breakdown: local analysis II



DNS-Wait Grant DNS (IPv6) DNS-Wait Grant DNS (IPv4) APP-OS overhead TCP SYN-Wait Grant TCP SYN-Send Data TCP ACK (local processing) HTTP GET (send request) HTTP GET-Wait Grant HTTP GET-req sent HTTP-server RTT+ DL latency LTE-to-TCP overhead HTTP page DL transmission HTTP DL retransmission 2.02 ms 11 ms 16 ms 17 ms 26 ms 12 ms

Further zoom in and breakdown the remaining LTE data access latency (291 ms):



**·· UCLA ··** 

# Latency mapping for failures: local analysis III

## Example: data plane suspension due to radio reconnection and head-of-line



blocking during handover



# Latency mapping for failures: local analysis III

## Example: data plane suspension due to radio reconnection and head-of-line



blocking during handover



**Blocking** Request Sent Waiting Grant Uplink Transmission Handover Disruption — No data Handover Disruption  $-$  Duplicate recv'd data Waiting (TTFB, due to parallel TCP connection) Content Download

5.05 ms 0.58 ms 4 ms 130 ms 263 ms 36 ms 275 ms 33.16 ms



# Machine learning scheme

We leverage domain-specific knowledge for ML-based predictions

Control plane: predict handover using a decision tree classifier

- Features from 3GPP standards
- Predicts handover 100ms before it occurs with >99% accuracy

Data plane: predict NACK/ACK hip at MAC layer



 $\cdot$  UCLA  $\cdot$ 









Four US carriers + Google Project Fi





## Four US carriers + Google Project Fi

23 phone models, 95,057 data sessions





- Four US carriers + Google Project Fi
- 23 phone models, 95,057 data sessions
- Overall latency: 77 2956 ms in 500K samples





- Four US carriers + Google Project Fi
- 23 phone models, 95,057 data sessions
- Overall latency: 77 2956 ms in 500K samples
	- Varies among different mobile carriers



Average Latency by LTE Data Access Setup (no mobility)





- Four US carriers + Google Project Fi
- 23 phone models, 95,057 data sessions
- Overall latency: 77 2956 ms in 500K samples
	- Varies among different mobile carriers
	- Insensitive to varying radio link quality





**·· UCLA ··** 

# LTE data access latency: how frequent?

#### *Frequent* data access setup operations

- every 10.8 sec (median); 17.3 sec (average)
- cause: inactivity timer (regulated by standards)



- every 58.8 sec (median); 133.6 sec (average)
- cause: frequently entering power-saving mode

### **Short-lived Radio connectivity lifetime**



# LTE data access latency: how frequent?

- every 58.8 sec (median); 133.6 sec (average)
- cause: frequently entering power-saving mode

### **Short-lived Radio connectivity lifetime**

#### *Frequent* data access setup operations

- every 10.8 sec (median); 17.3 sec (average)
- cause: inactivity timer (regulated by standards)



(a) CDF for consecutive request interval





# LTE data access latency: how frequent?

#### *Frequent* data access setup operations

- every 10.8 sec (median); 17.3 sec (average)
- cause: inactivity timer (regulated by standards)



(a) CDF for consecutive request interval



(b) Radio connectivity lifetime



- every 58.8 sec (median); 133.6 sec (average)
- cause: frequently entering power-saving mode

### **Short-lived Radio connectivity lifetime**





·· UCLA ··

# Findings Summary

## Tradio: *Radio connectivity setup*

- It contributes 67.5 −1665.0 ms of the overall LTE access latency.
- AT&T, Verizon, Sprint and Project-Fi, respectively.

• On average, it contributes 39.7%, 44.0%, 61.9%, 64.2% and 43.7% of total latency in T-Mobile,

• On average, it contributes 60.3%, 56.0%, 38.1%, 35.8% and 56.3% of total latency in T-Mobile,



#### Tctrl: *Connectivity state transfer*

- It contributes 28.75 ms to 2286.25ms of the overall LTE access latency.
- AT&T, Verizon, Sprint and Project-Fi, respectively.



# Impact on mobile Web app: Chrome

## Average page loading time for tested webpage: 411 ms

- LTE data access setup: 174 ms
- **42.3%** total latency perceived

### Similar results for Safari latency on iOS









# Impact on instant-messaging: WhatsApp

## Average time first data packet being ACKed: 341 ms

- LTE data access setup: 175 ms
- **51.4%** total latency perceived







# Discussion: reducing LTE latency

#### Data plane walk-arounds

• Mask the data setup latency by waking device in connected mode in advance

#### Control plane acceleration

• Speed up connectivity state transfer between the base station and the mobility controller (e.g. DPCM [ACM



- MobiCom'17])
- Handover prediction

#### Other issues

- Extending to other network metrics (e.g. loss, throughput, ...)
- Theoretical bounds
- **Privacy issues**



## Conclusion: ML-based analysis for next-gen mobile networks

- Mobile networks are successful and will continue to prosper (5G, self driving, …)
- Mobile network analysis: paradigm shift to **device-centric**, ML-based scheme



- Device-centric: unveil the tightly-guided operation issues over 4G/5G mobile networks
- Two-tiered approach: a more open solution approach for the research community









