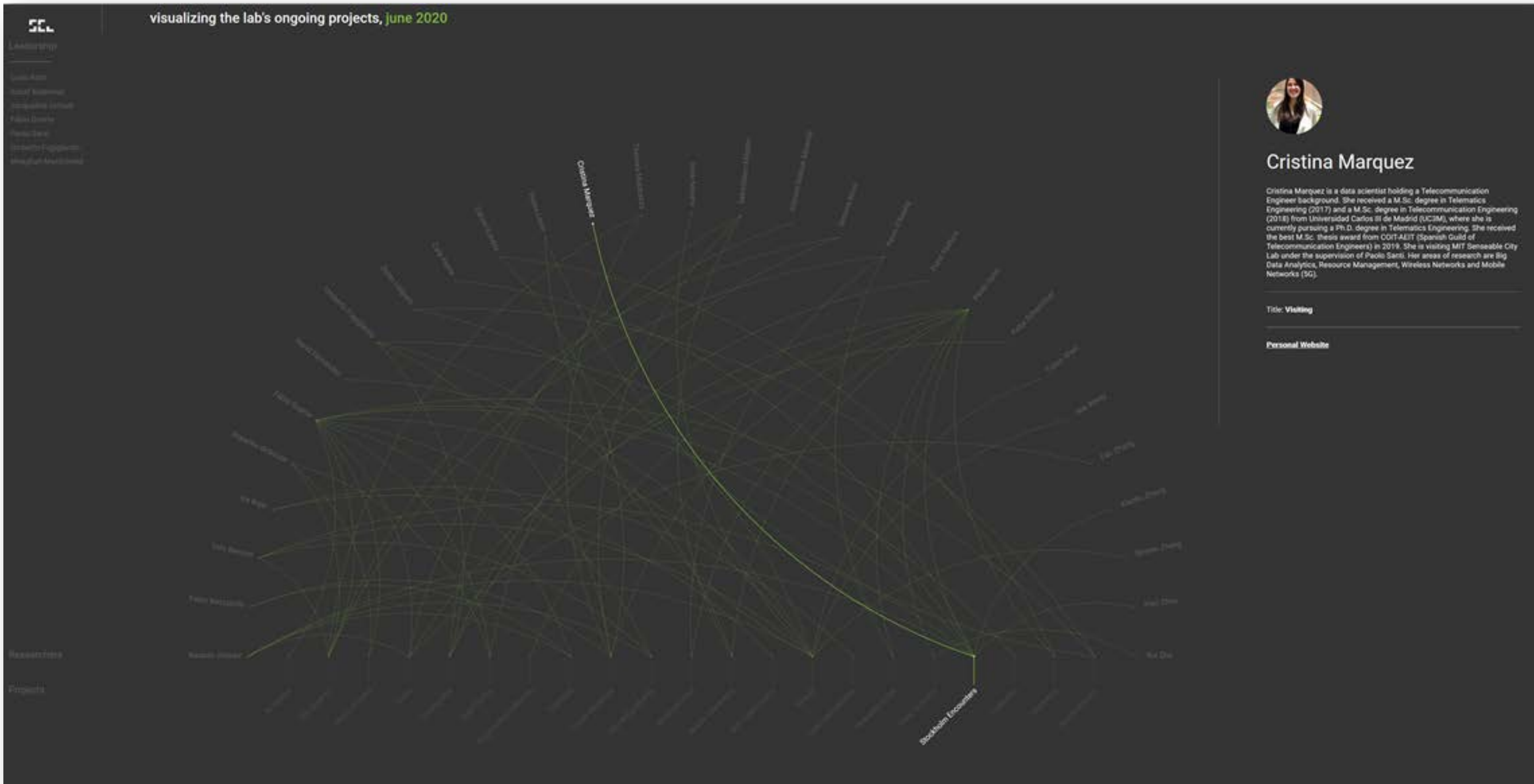
Cristina Marquez

Researcher | Data scientist

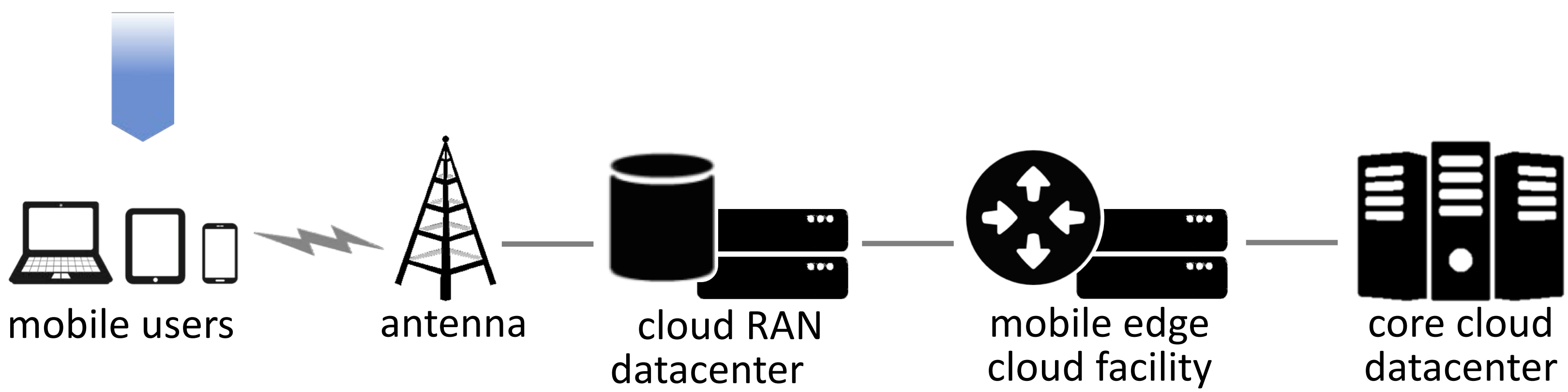
Signal Processing
&
FT Application



visualizing the lab's ongoing projects, june 2020
Cristina Marquez
Stockholm Encounters
Cristina Marquez
Cristina Marquez is a data scientist holding a Telecommunication Engineer background. She received a M.Sc. degree in Telematics Engineering (2017) and a M.Sc. degree in Telecommunication Engineering (2018) from Universidad Carlos III de Madrid (UC3M), where she is currently pursuing a Ph.D. degree in Telematics Engineering. She received the best M.Sc. thesis award from COIT-AEIT (Spanish Guild of Telecommunication Engineers) in 2019. She is visiting MIT Senseable City Lab under the supervision of Paolo Santi. Her areas of research are Big Data Analytics, Resource Management, Wireless Networks and Mobile Networks (5G).
Title: Visiting
Personal Website

How does the network work?

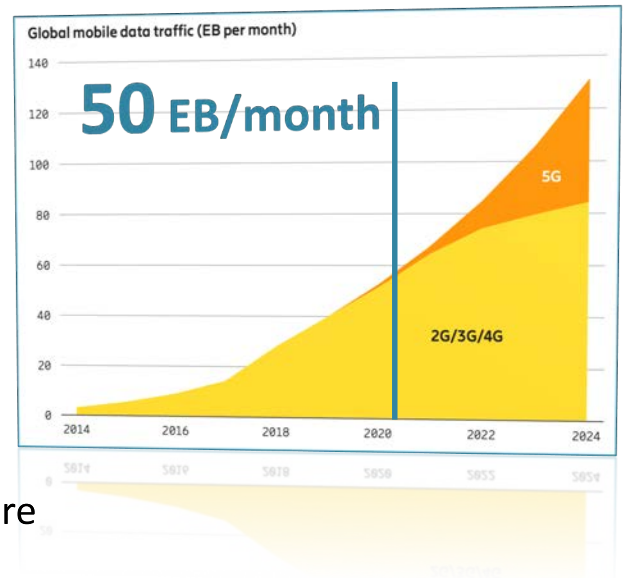
NETFLIX



Mobile services overview

Some are generating a substantial amount of data traffic, for example [1]

- Instagram
- YouTube
- Facebook
- Twitter
- Snapchat
- WhatsApp



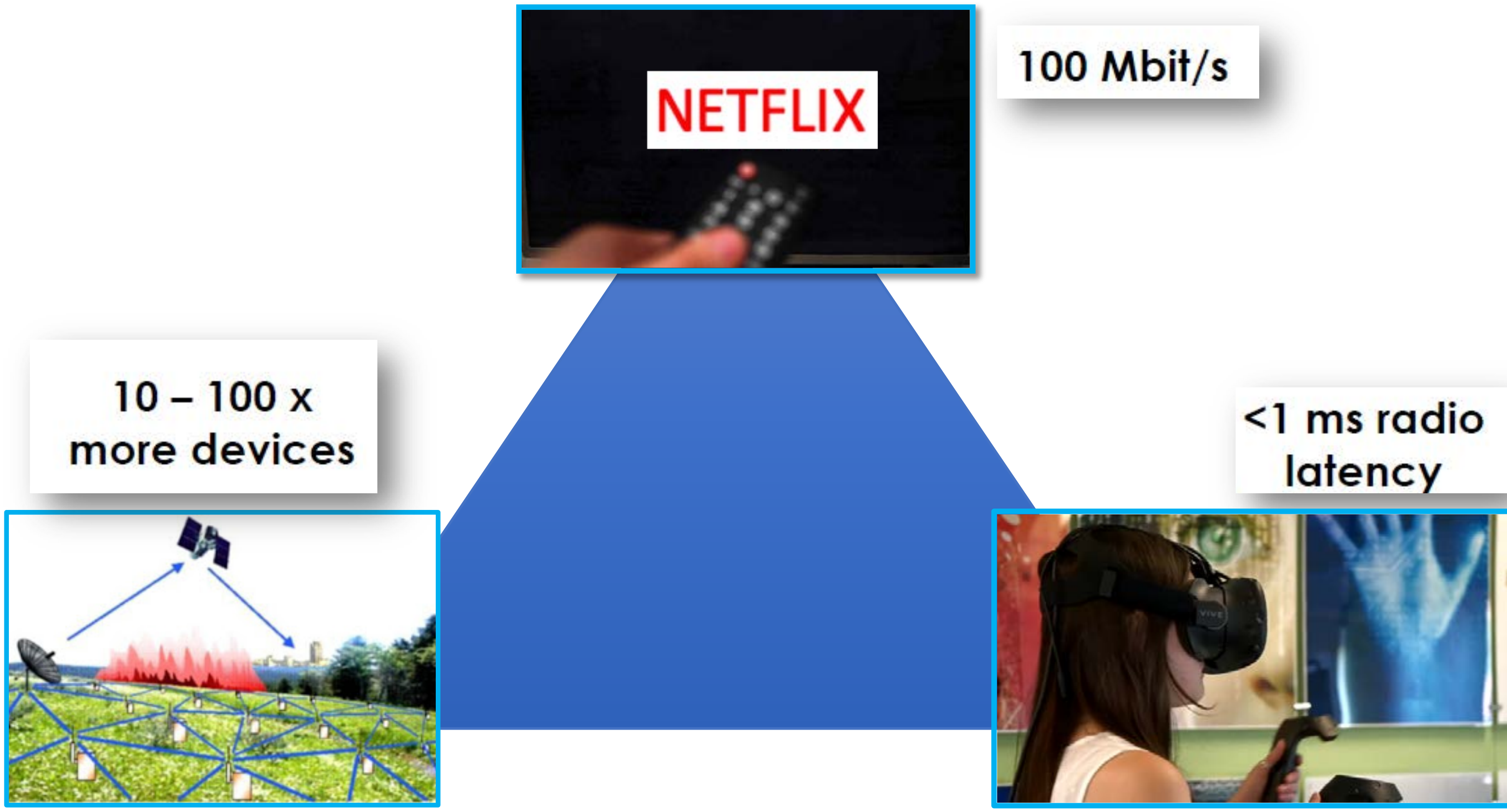
How do the dynamics of the demands for mobile services look like?

Answers have applications in technology and social sciences:

- Dimensioning and management of the communication infrastructure
- Data-driven planning of urban transport systems
- Understanding cultural factors in apps adoption
- Detecting psychiatric disorder states at scale

[1] Ericsson Mobility Report 2019

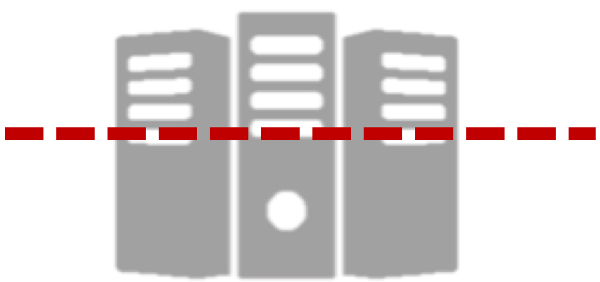
5G Service requirements: heterogeneity

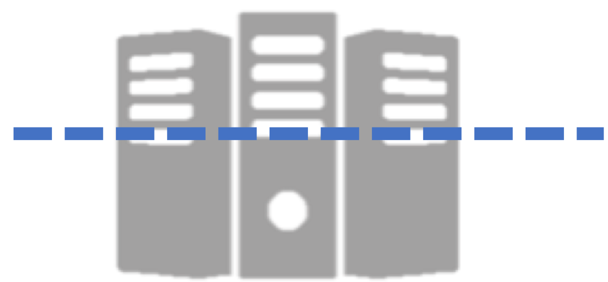


Network usage example

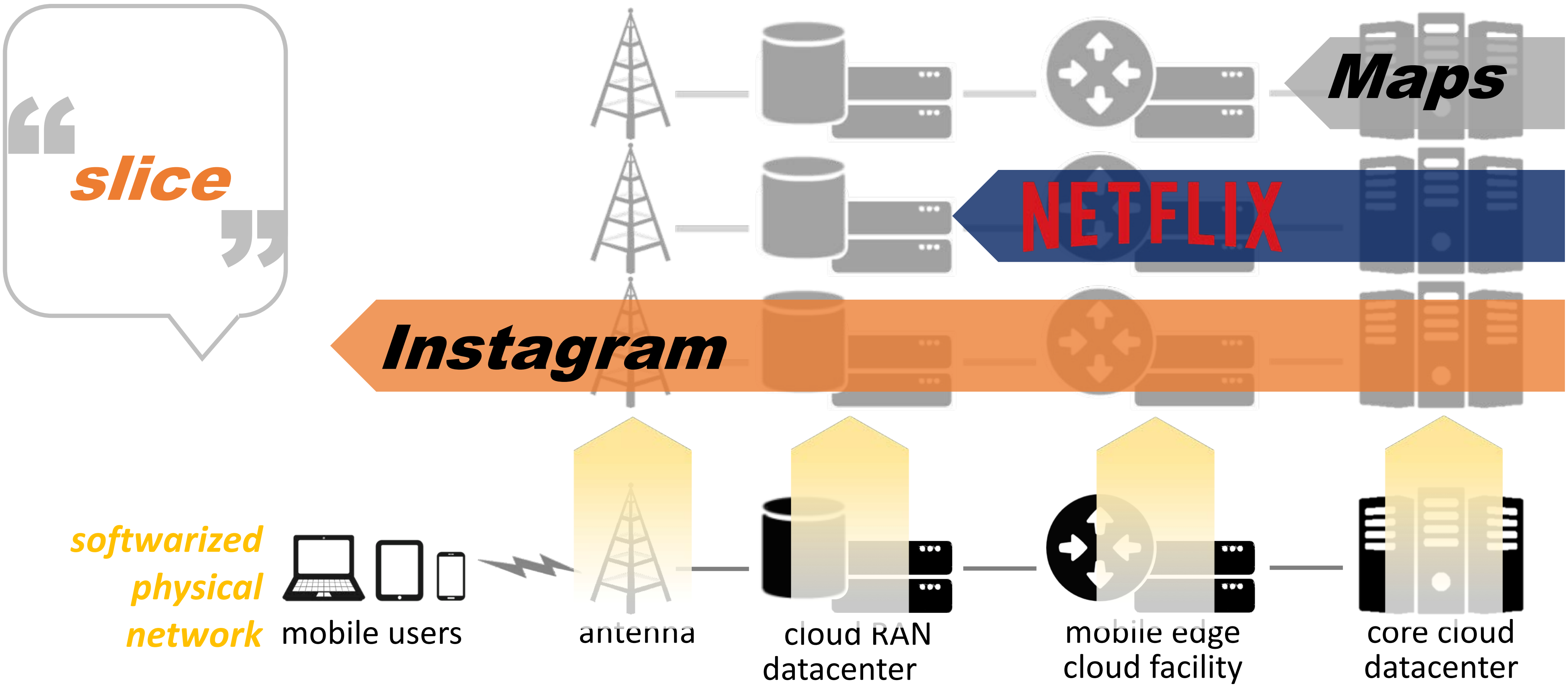
NETFLIX

Pokémon



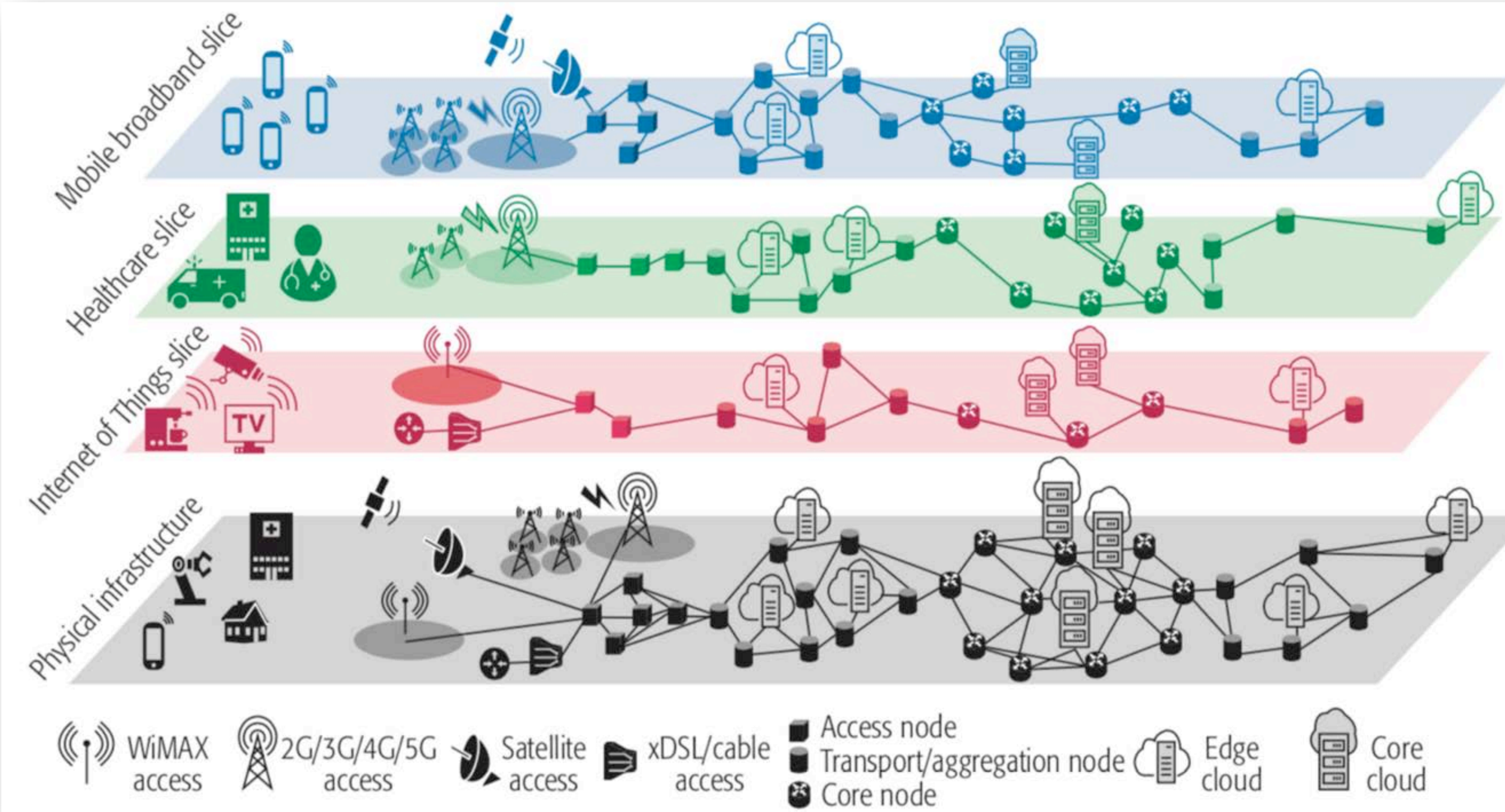


Network slicing

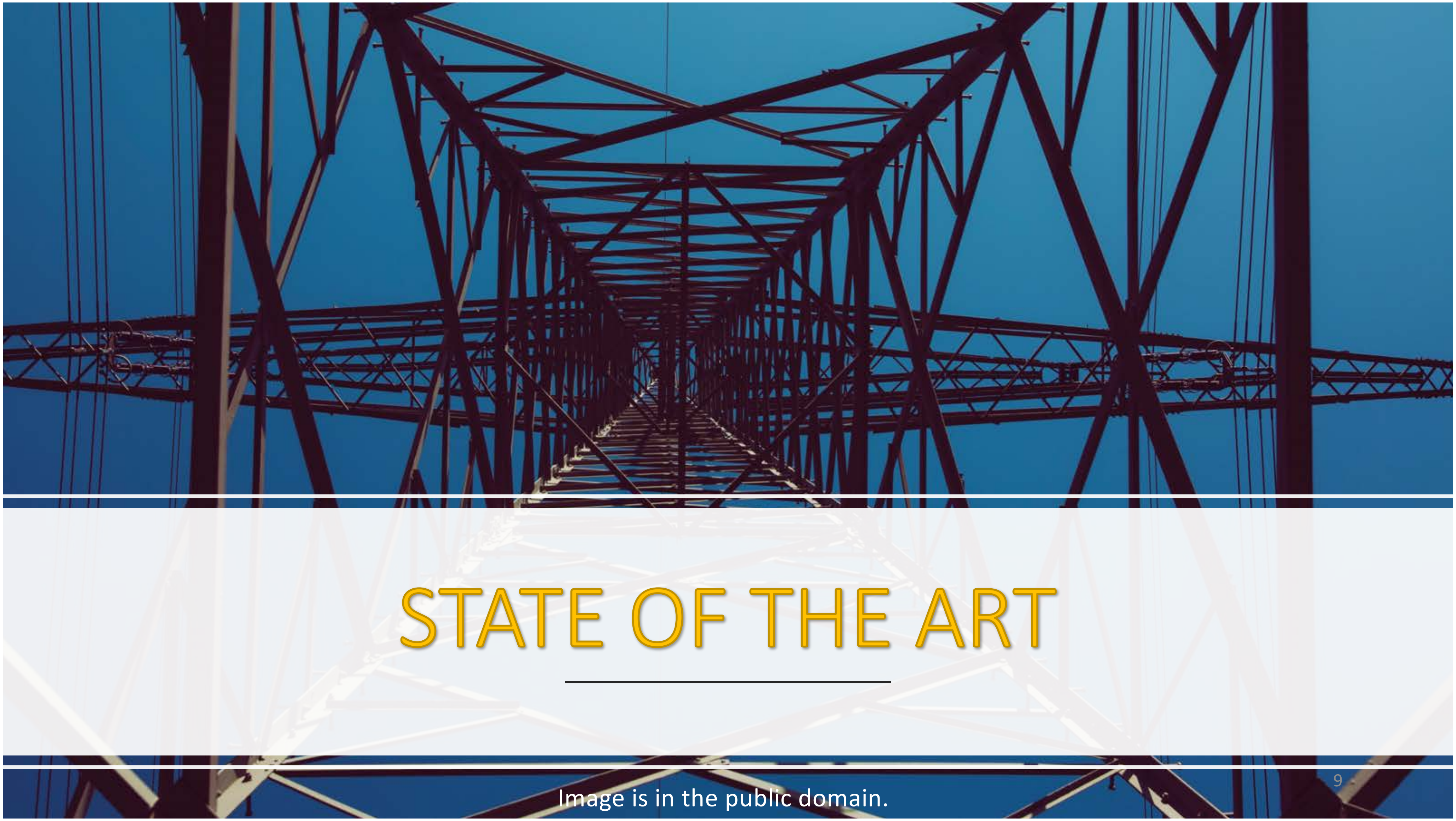


Why network slicing?

[2]

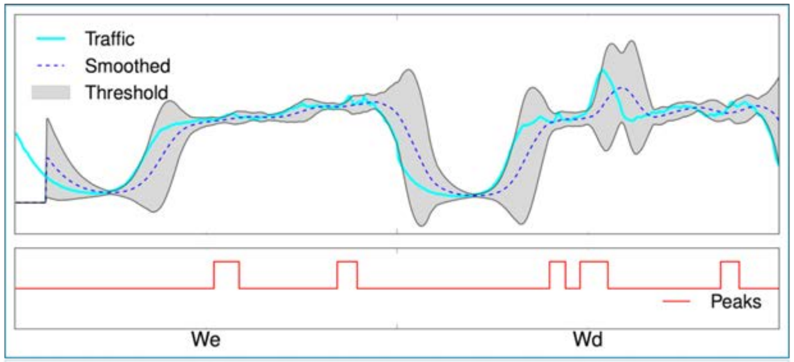


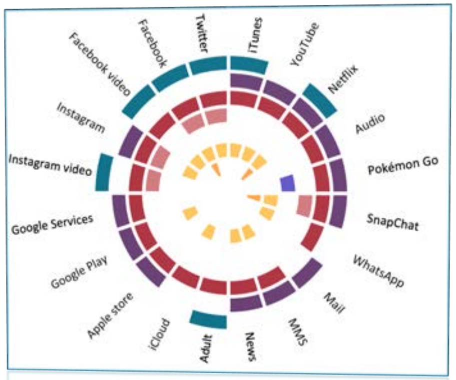
STATE OF THE ART



Main findings of studies comparing the demands of individual apps

- In ***time***, apps have very diverse time series with unique combinations of activity peaks [3]





- Attempts at grouping mobile services along the time dimension were vain to date

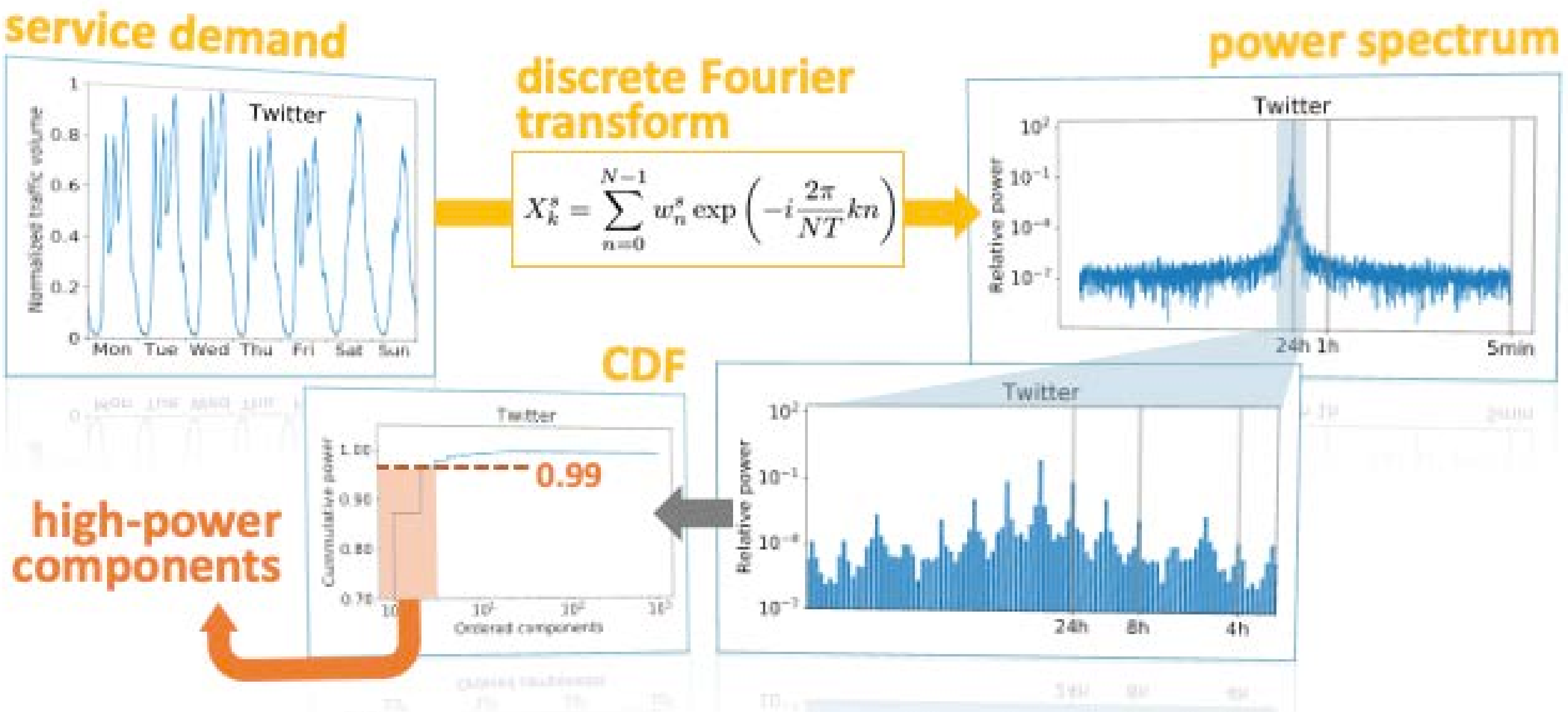

Image courtesy of NASA.

METHODOLOGY

Studying traffic demands in the frequency dimension

- Frequency components describe the periodicity of service consumption

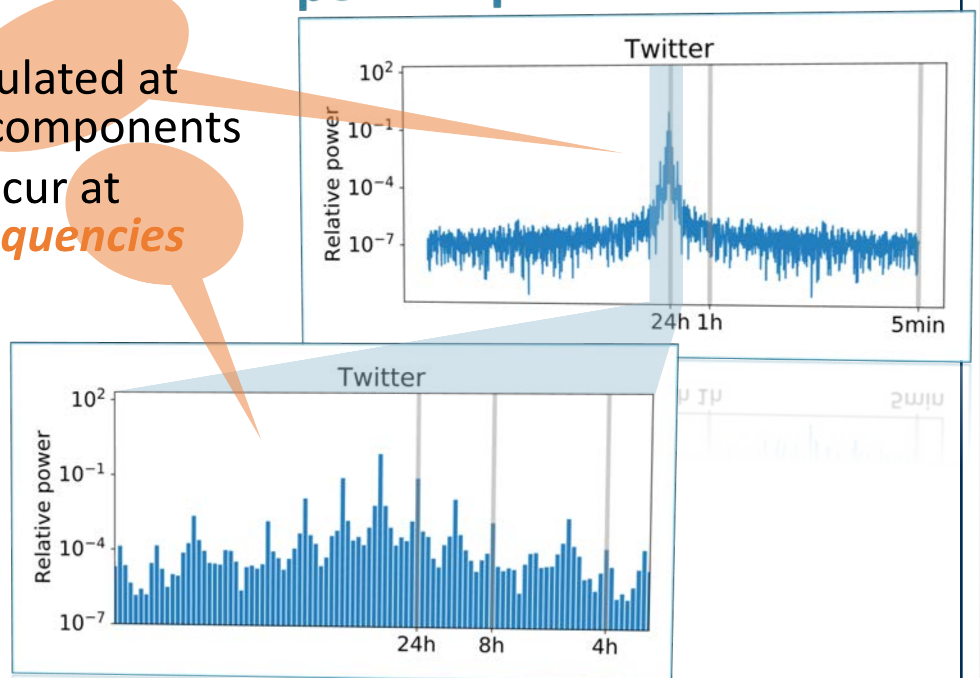
[4]



Frequency component analysis

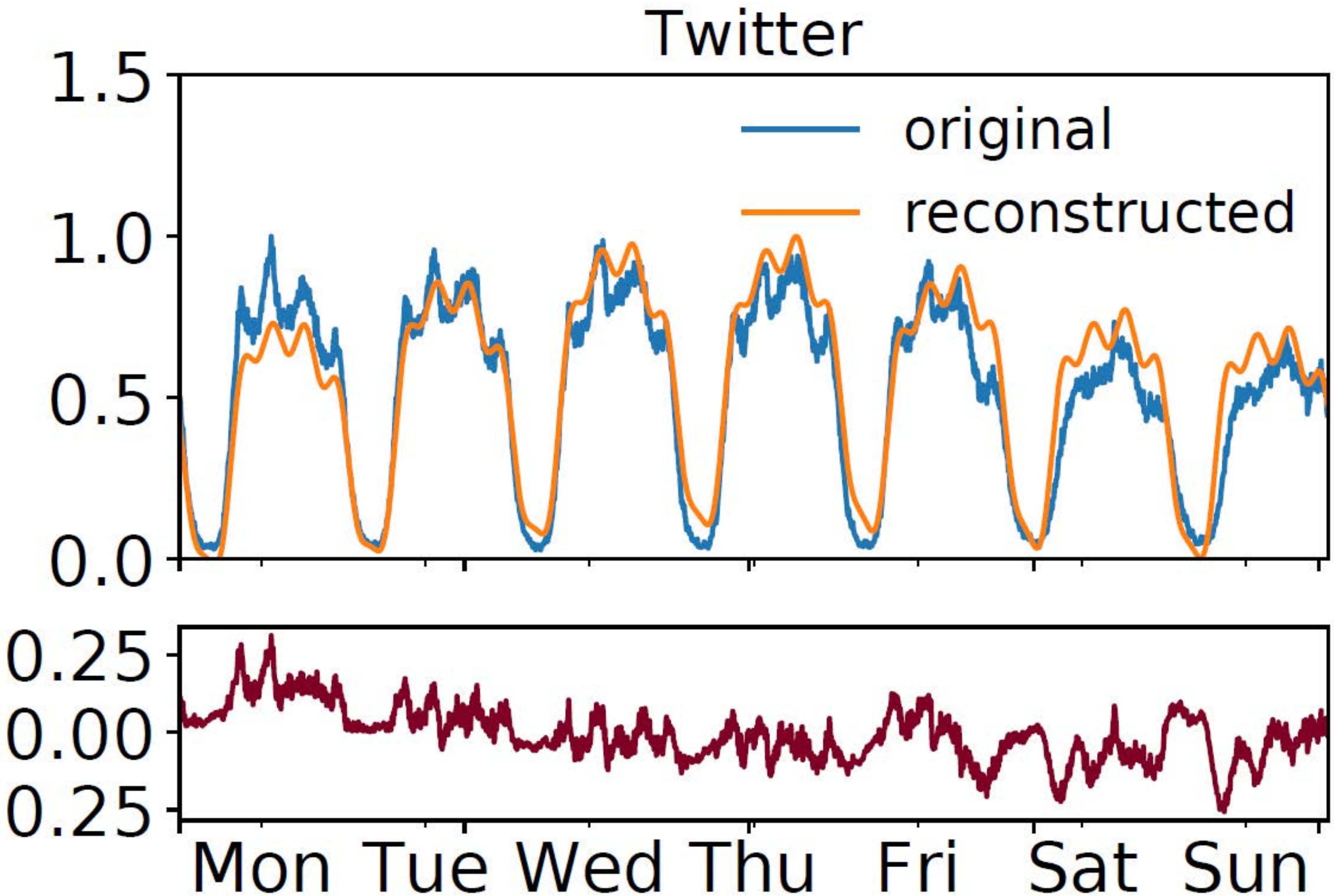
- ***The Twitter case***
  - Power is accumulated at *low frequency* components
  - Power spikes occur at very *specific frequencies*

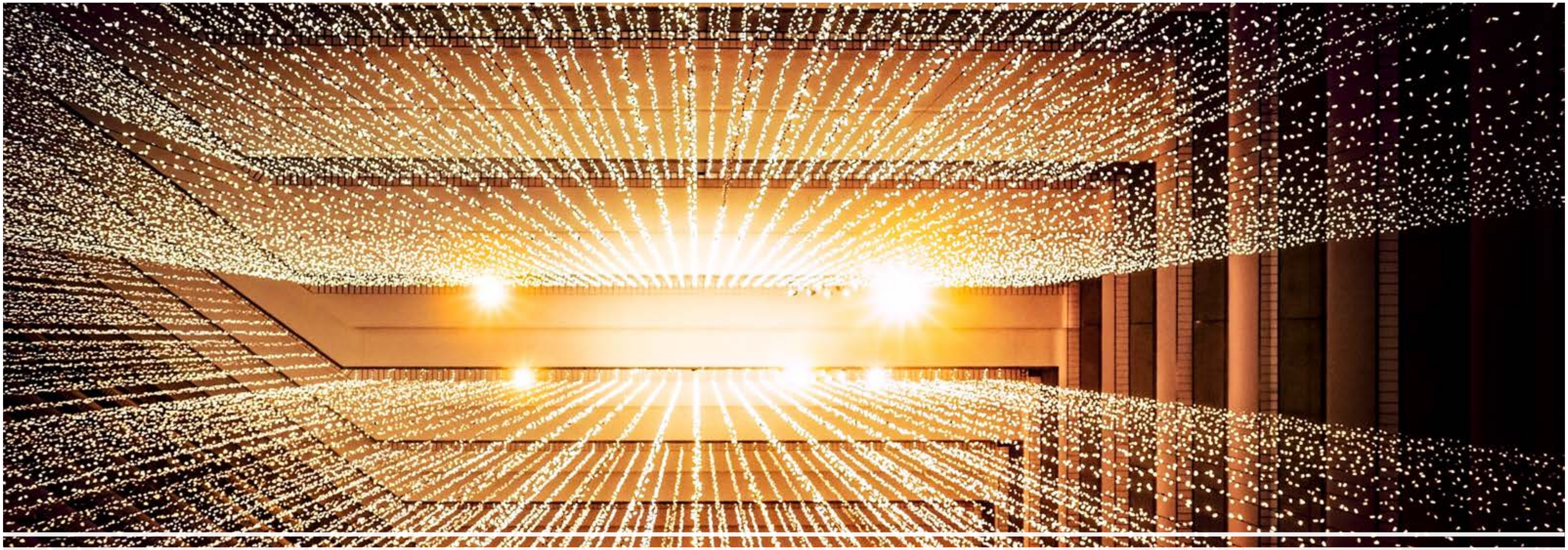
power spectrum



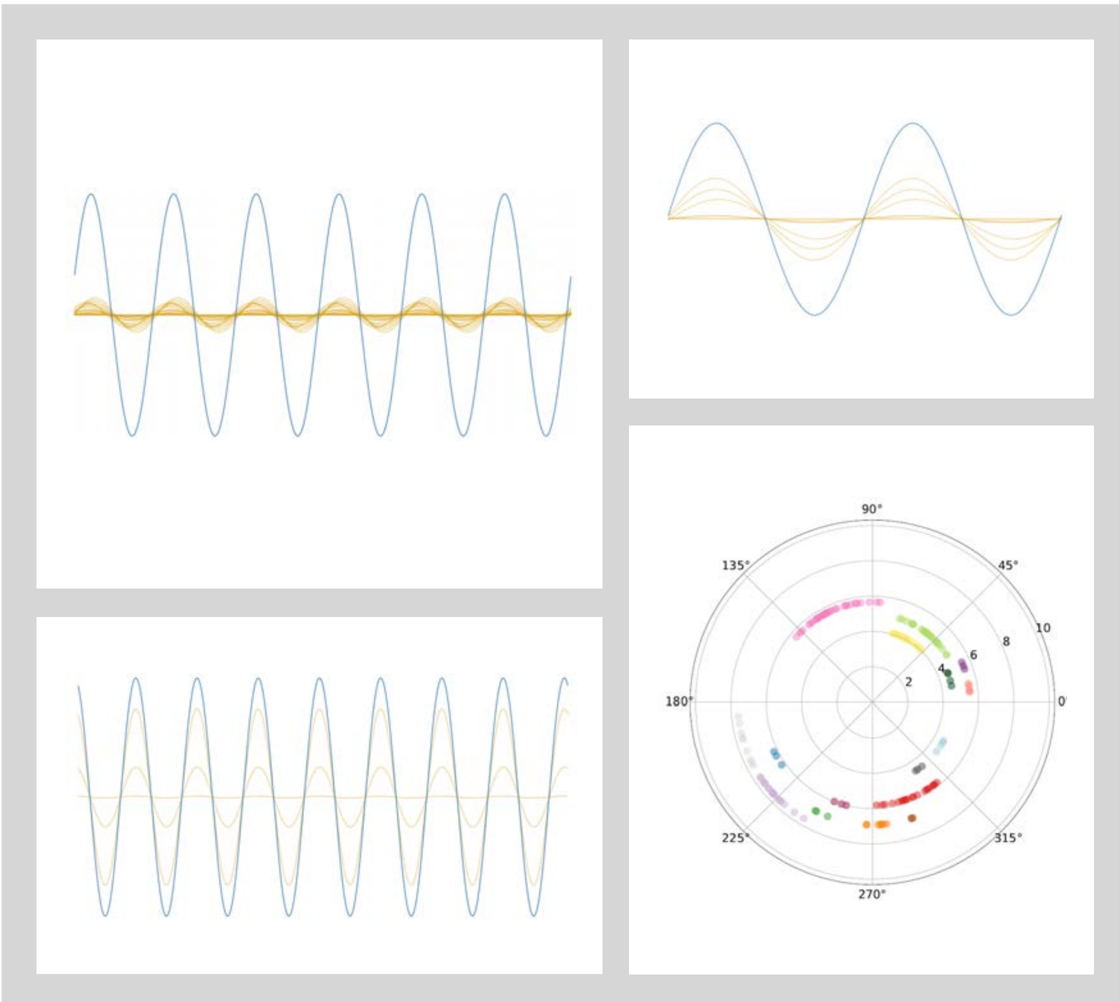
Services	# Components	Retained Power
WhatsApp	3	99.34 %
MMS	4	99.51 %
iCloud	5	98.87 %
Youtube	5	99.37 %
Generic messaging	5	99.42 %
Instagram	5	99.49 %
Instagram video	5	99.57 %
News	6	98.79 %
Generic video	6	99.32 %
Facebook	6	99.42 %
Google Services	6	99.42 %
Ads	6	99.43 %
DailyMotion video	7	98.50 %
E-commerce	7	98.74 %
iTunes	7	99.26 %
Facebook video	7	99.38 %
Generic web	7	99.51 %
NetFlix	8	98.97 %
Encrypted web	8	99.38 %
Twitter	8	99.40 %
Apple Store	8	99.43 %
VoIP	9	95.25 %
Google Drive	9	98.98 %
Generic cloud	9	99.29 %
Google Play	9	99.39 %
Snapchat	9	99.44 %
Supercell	9	99.47 %
Generic gaming	9	96.63 %
Gameloft	10	85.15%
Mail	10	99.37%
Adult	11	98.67%
P2P	15	96.31%
Gaming platforms	17	88.83 %
Audio streaming	17	98.72 %
King	17	98.85 %
Updates	18	96.72 %
Pokemon Go	19	99.09 %
Total number of components		326
Average retained power		98.24 %

- ***All services share similar characteristics***
  - *Less than 20 components* gather 99% of signal power


Twitter
original
reconstructed
1.5
1.0
0.5
0.0
0.25
0.00
0.25
Mon
Tue
Wed
Thu
Fri
Sat
Sun



RESULTS



The original 326 components result in 16 clusters

- Clusters include 3-35 components each (out of 37)
- 115 components are outliers, i.e., unique time dynamics

Selected insights

- Almost all services have a ***dominant component with 24-hour periodicity***, owing to human circadian rhythms
- Half have a ***weekly periodicity*** due to weekend activities
- 32 services also show an identical significant dynamic at a 12-hour periodicity, denoting ***activity peaks occurring twice a day***
- 22 services have a ***regularities at every 4.8 hours***

Conclusions and future directions

- ***Takeaway message***
  - Spectral methods allow identifying ***common periodic behaviors*** in demands generated by a large set of applications, which were not detected previously

- ***Further steps***
  - Explaining the ***root causes*** for these temporal similarities
  - Exploiting temporal similarity and complementarity for ***applications*** in network planning and resource management

References

[1] Ericsson Mobility Report 2019.

[2] J. Ordonez-Lucena, P. Ameigeiras, D. Lopez, J. J. Ramos-Munoz, J. Lorca and J. Folgueira, "Network Slicing for 5G with SDN/NFV: Concepts, Architectures, and Challenges," in *IEEE Communications Magazine*, vol. 55, no. 5, pp. 80-87, May 2017.

[3] C. Marquez, M. Gramaglia, M. Fiore, A. Banchs, C. Ziemlicki and Z. Smoreda, "Not All Apps Are Created Equal: Analysis of Spatiotemporal Heterogeneity in Nationwide Mobile Service Usage,“ ACM CoNEXT, Dec. 2017.

[4] C. Marquez, M. Gramaglia, M. Fiore, A. Banchs, and Z. Smoreda, "Identifying Common Periodicities in Mobile Service Demands with Spectral Analysis," in *IEEE Mediterranean Communication and Computer Networking Conference (MedComNet 2020)*, Jun. 2020.

Thank you very much for your attention!

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