AI-driven Networks for Earth and Space

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Why is AI interesting for wireless networks?

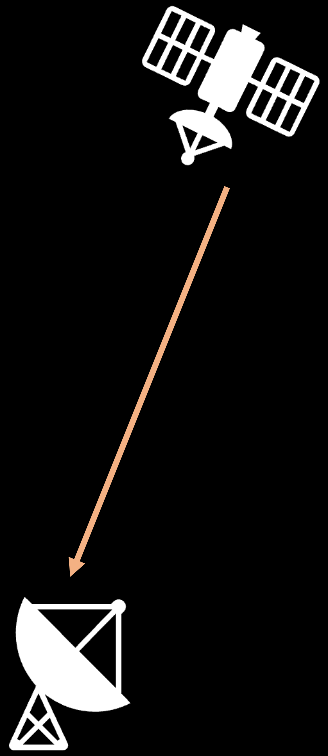
- New capabilities in networks → Much complexity
- Rich information embedded in traditional wireless signals
- Supervision is cheap, we already measure a lot!

Why is AI challenging for wireless networks?

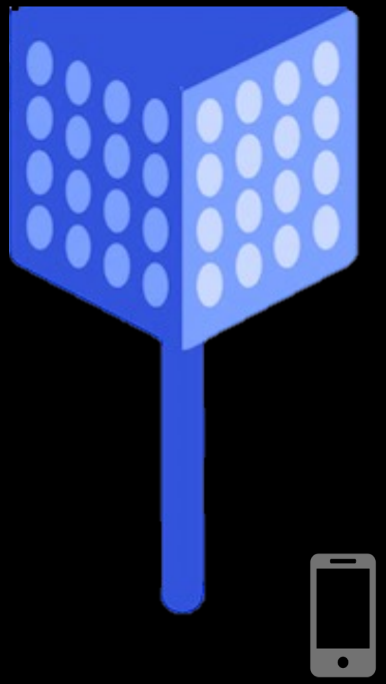
- Hardware induces randomness, e.g., clock offsets
- Structured and unstructured noise
- Complex–valued inputs

In this talk

Low-latency Satellite Networks

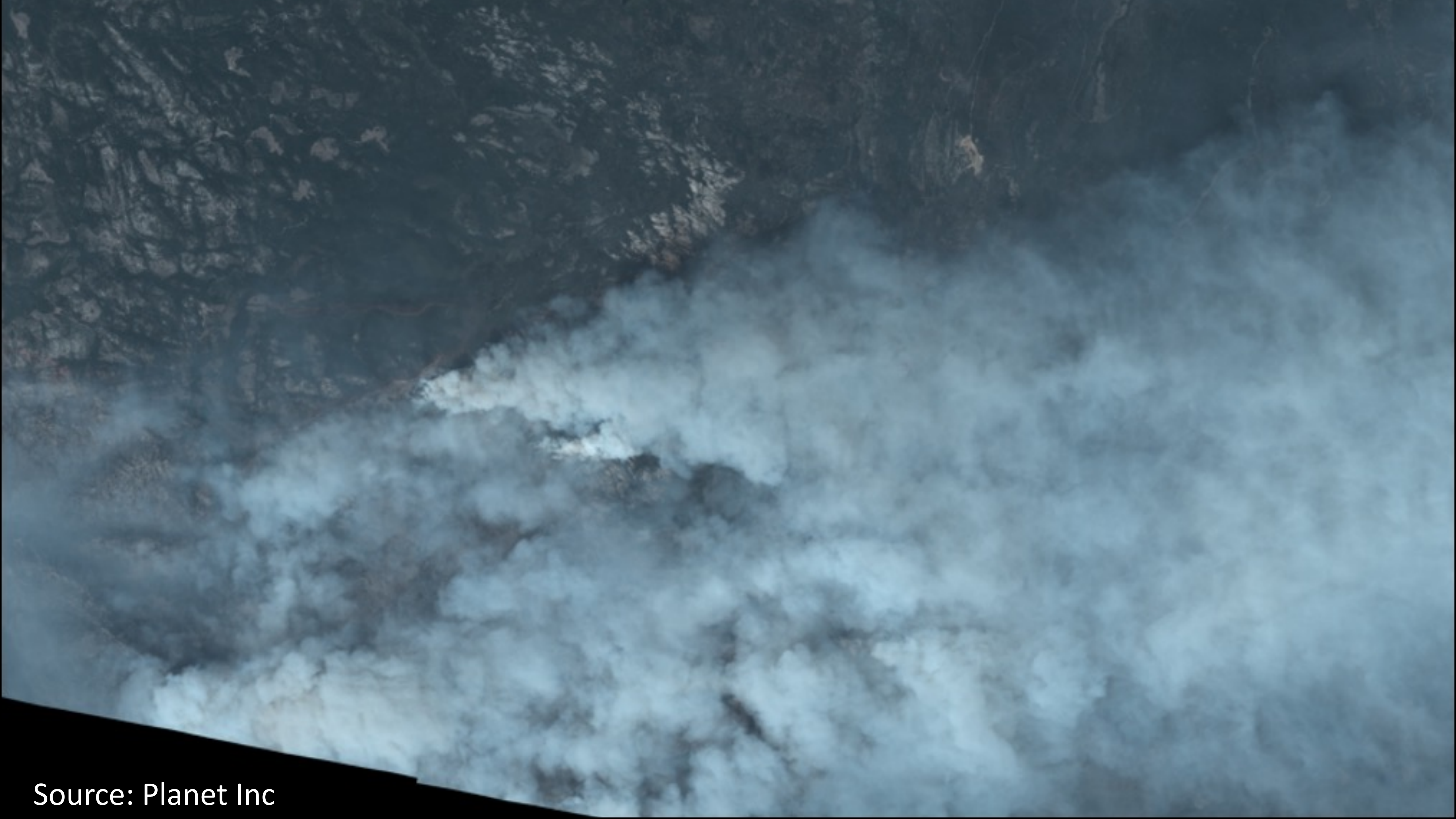


Zero-feedback Channel Estimation



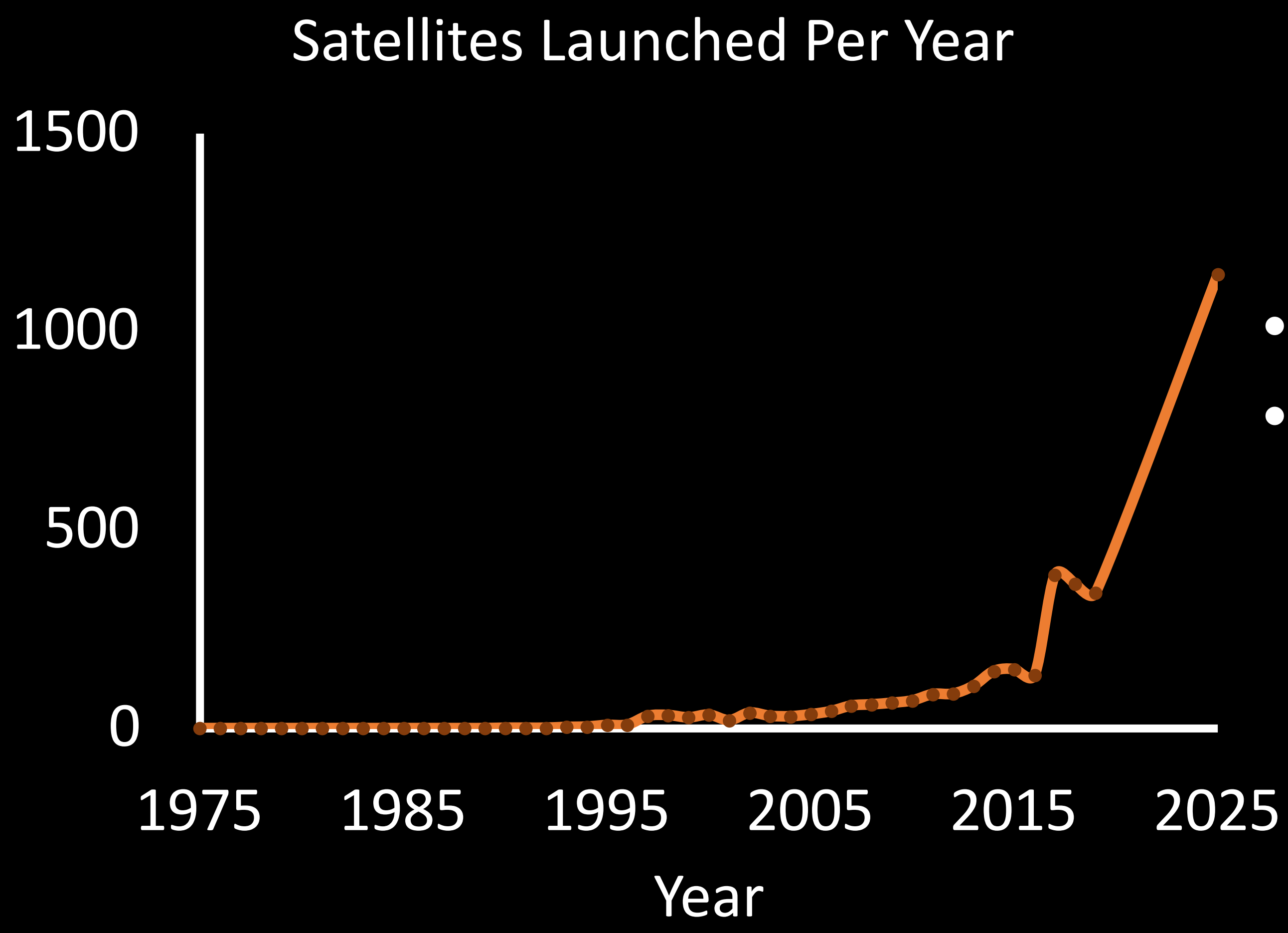
Privacy against RF-based Tracking

Source: Maxar/NYTimes

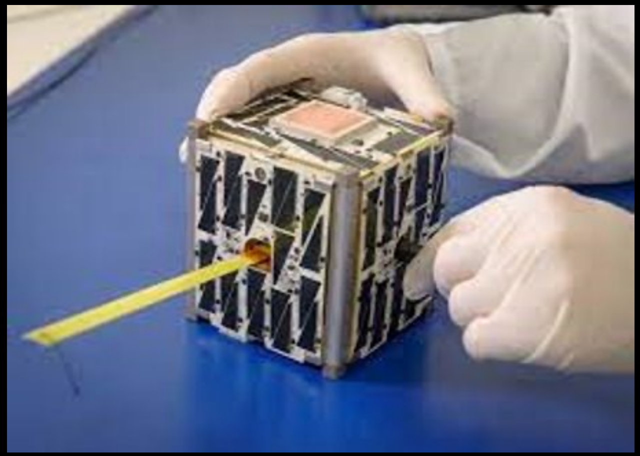


Source: Planet Inc


Source: Maxar



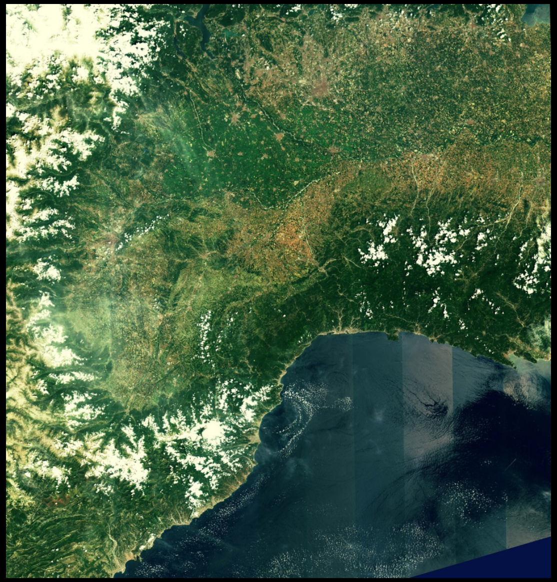
- Low-cost Cubesats
- Rideshare agreements for launch



Source: UCS Satellite Database

Communication

Earth Observation



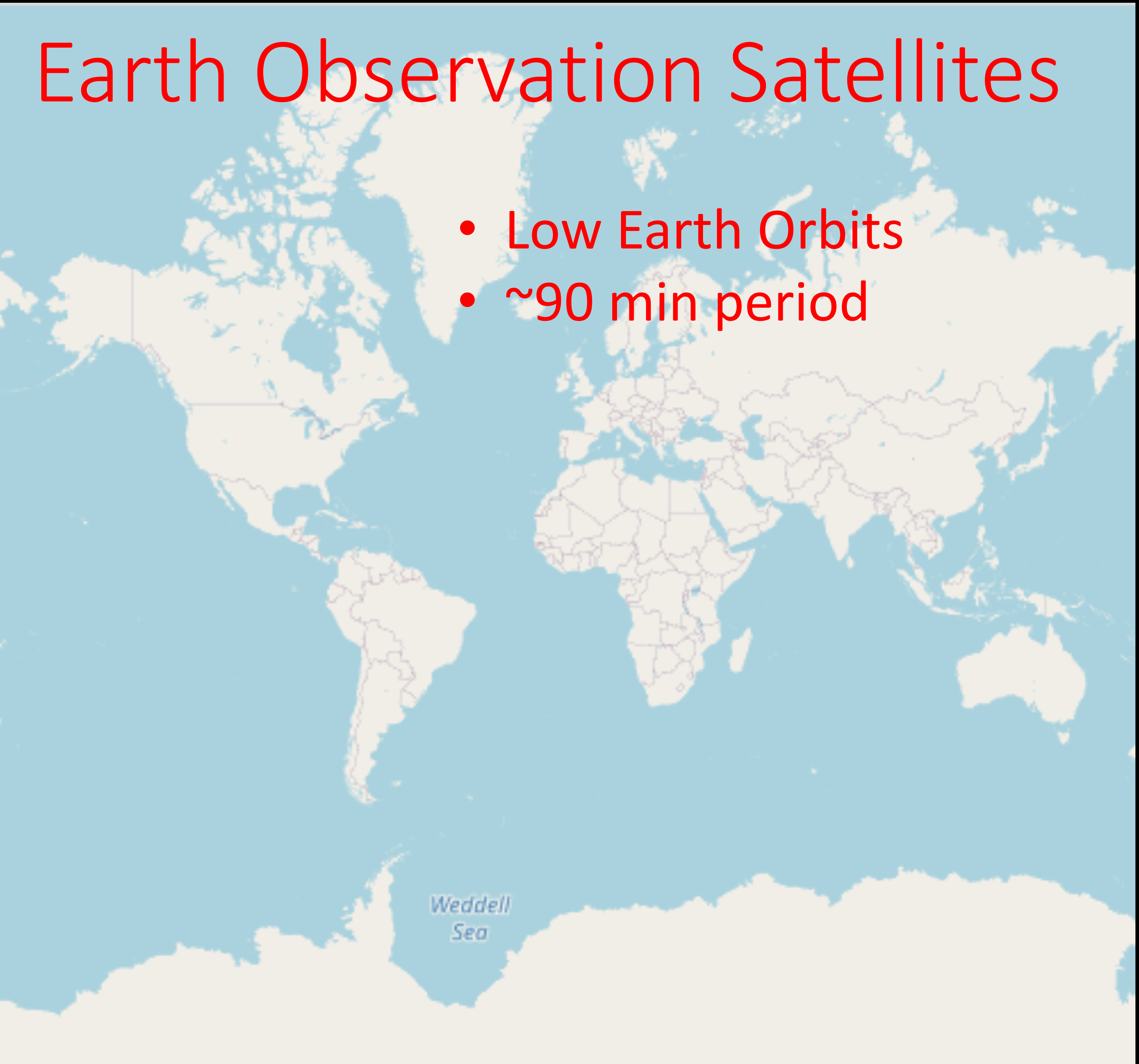
Global Internet Connectivity

Sensing from Space

Today, One-third of LEO satellites are Earth Observation

Earth Observation Satellites

- Low Earth Orbits
- ~90 min period



Earth Observation Satellites

Low orbits	Large constellation	Better Hardware
↓	↓	↓
High Resolution	Frequent revisits	Multi-spectral

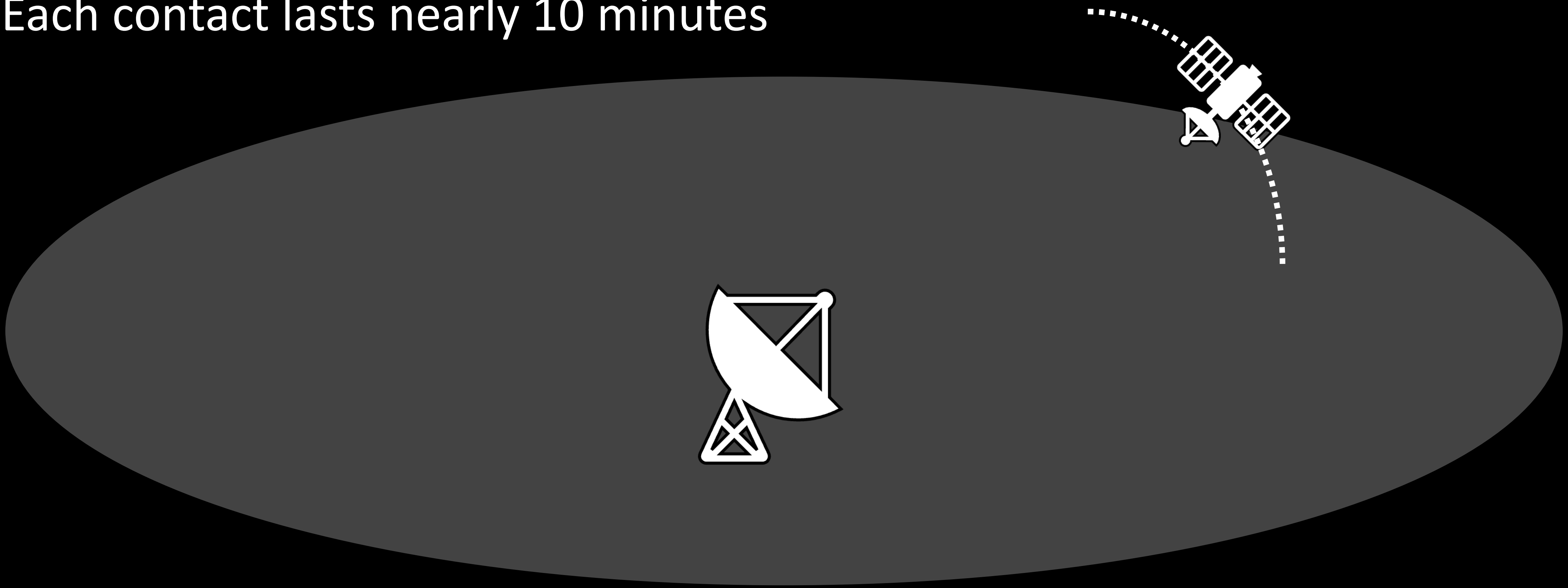
How long does an image take to download from satellite to consumer?

Hours to days!!

Goal: Reduce time-to-insight to few minutes

Challenge: Data Downlink

- Terabytes of data per day
- Each contact lasts nearly 10 minutes



Challenge: Data Downlink

- Collects Terabytes of data per day
- Only 10 minutes to download the data per contact

Need high-capacity downlink across 500 Km

Today: Large Complex Ground Stations

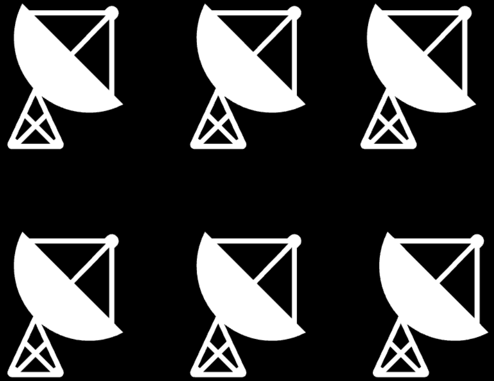
- Multi-million dollar investments
- 4 to 5 massive ground stations located close to the poles

Shortcomings

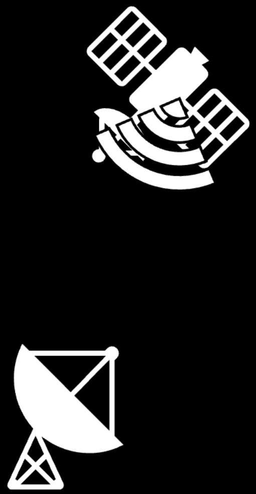
- Large latency (hours)
- Scaling is capital-intensive
- Failures (e.g. weather) are disruptive

Our Idea: Distributed Hybrid Ground Station

Low-Cost Ground Stations

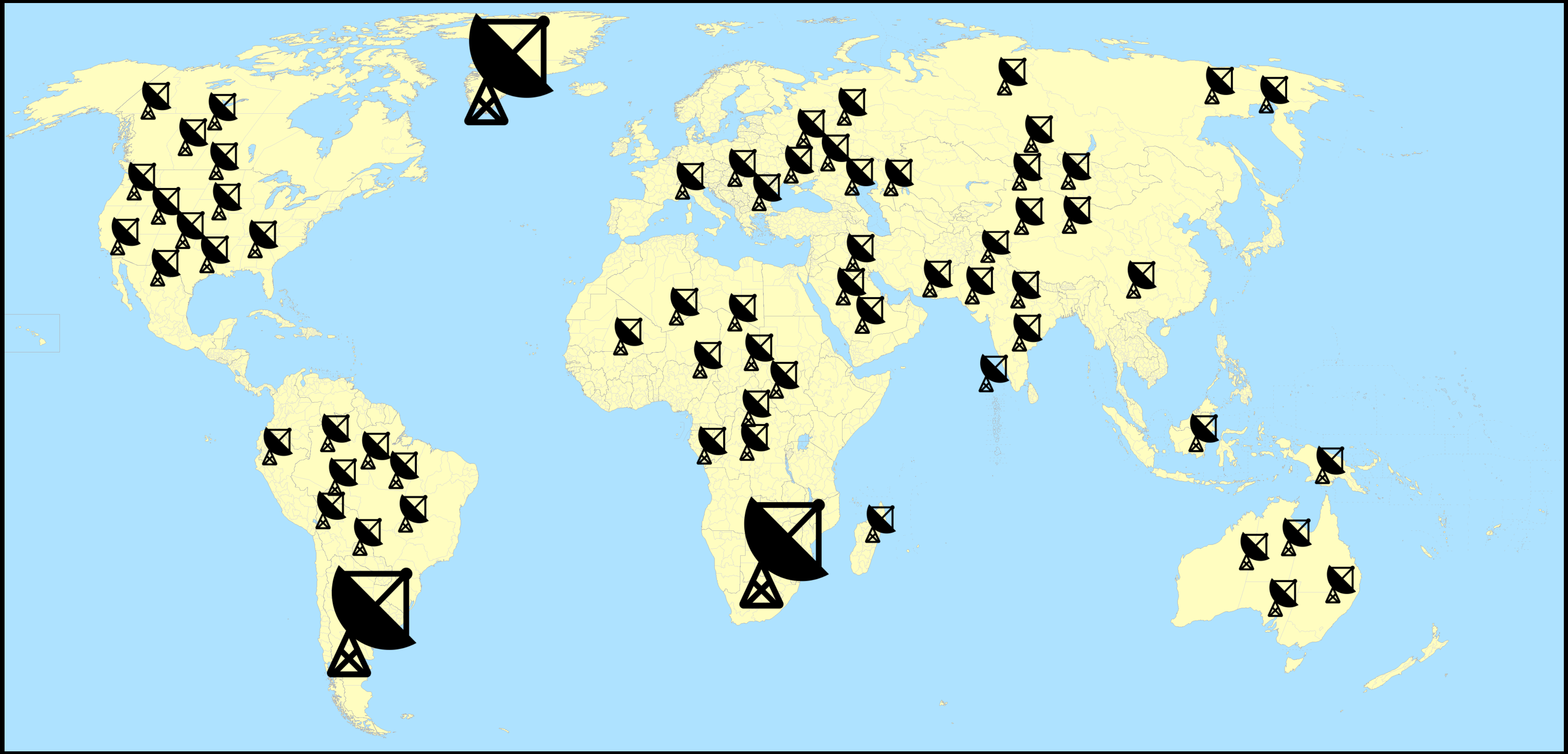


Distributed Geographically



Receive-only

Our Idea: Distributed Hybrid Ground Station



Distributed Hybrid Ground Station

- Fault-tolerant
- Low Latency
- Hybrid: not everyone needs to

05 Jun 2019 | 16:55 GMT

Is Amazon's Satellite Ground Station Service Ready for Primetime?

Amazon Web Services has promised immediate

Can a network of tiny ground stations outperform the capital-heavy huge ground stations?

Challenges

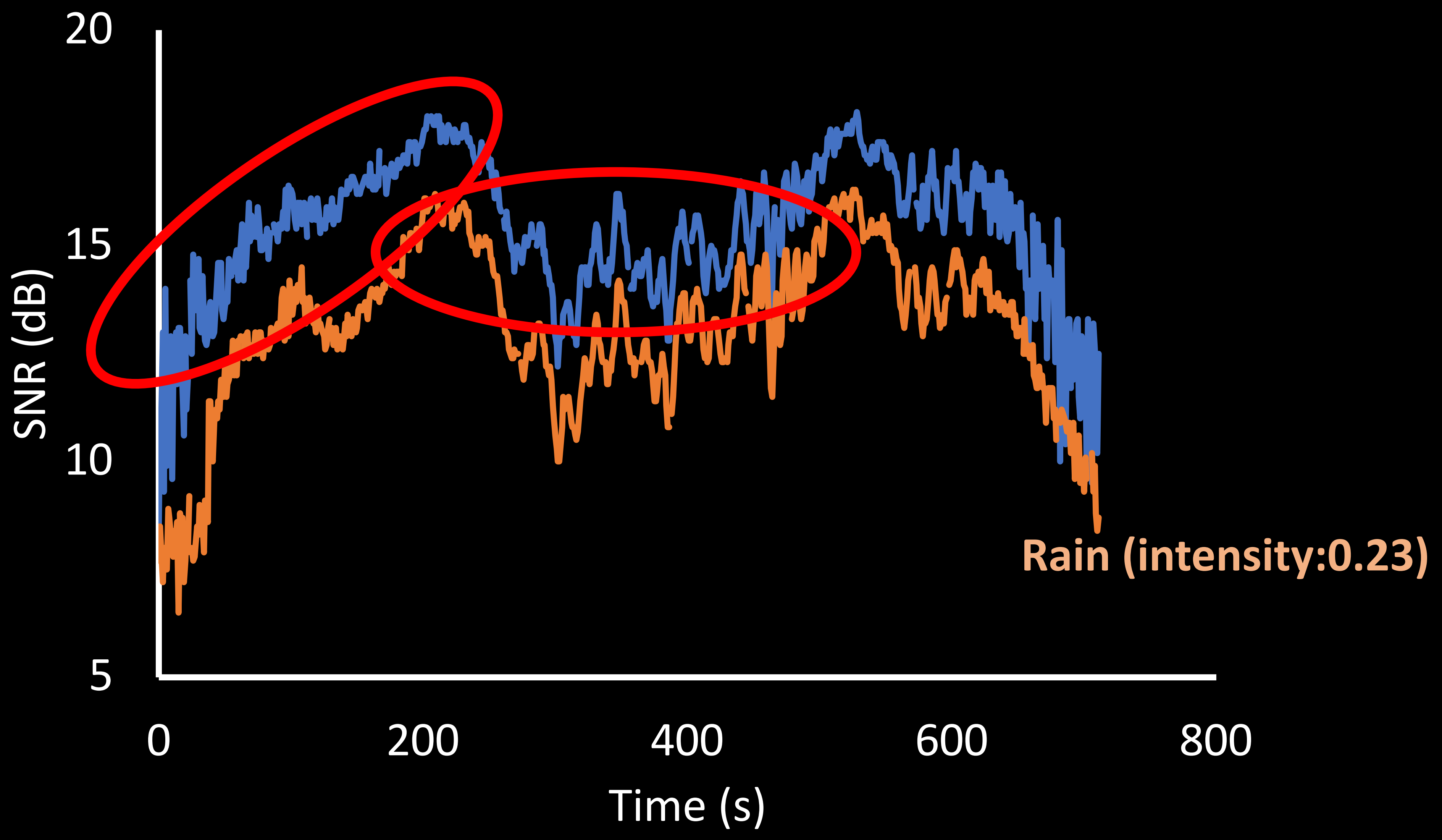
- Rate adaptation without feedback
- Scheduling satellite-ground station links
- Lack of acknowledgements

Challenge: Rate Adaptation

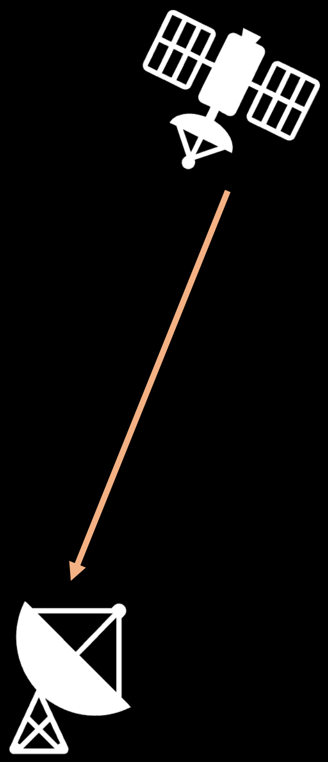
- Link quality varies by 10 to 20 dB
  - Depends on elevation
  - Weather (8-10 dB for X, Ku, Ka bands)
  - Equipment
- No feedback → No rate adaptation
  - Low rate → Wasted opportunity

Need rate adaptation without feedback

Link Quality: X-band



Solution: Link Quality Estimation

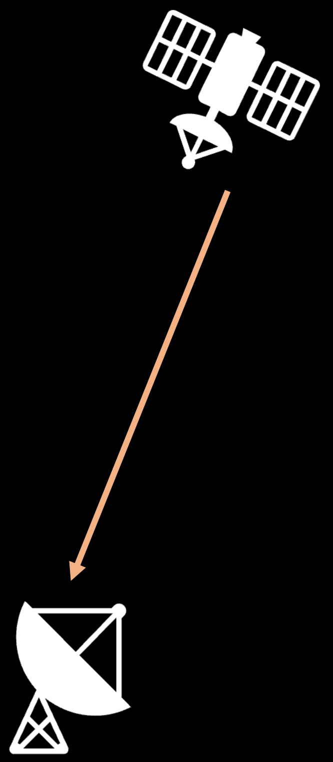


Propagation loss due to distance

Weather related loss

Device/location specific losses (multipath, etc.)

Intuition: Link Quality Estimation



Predict distance using orbit parameters

+

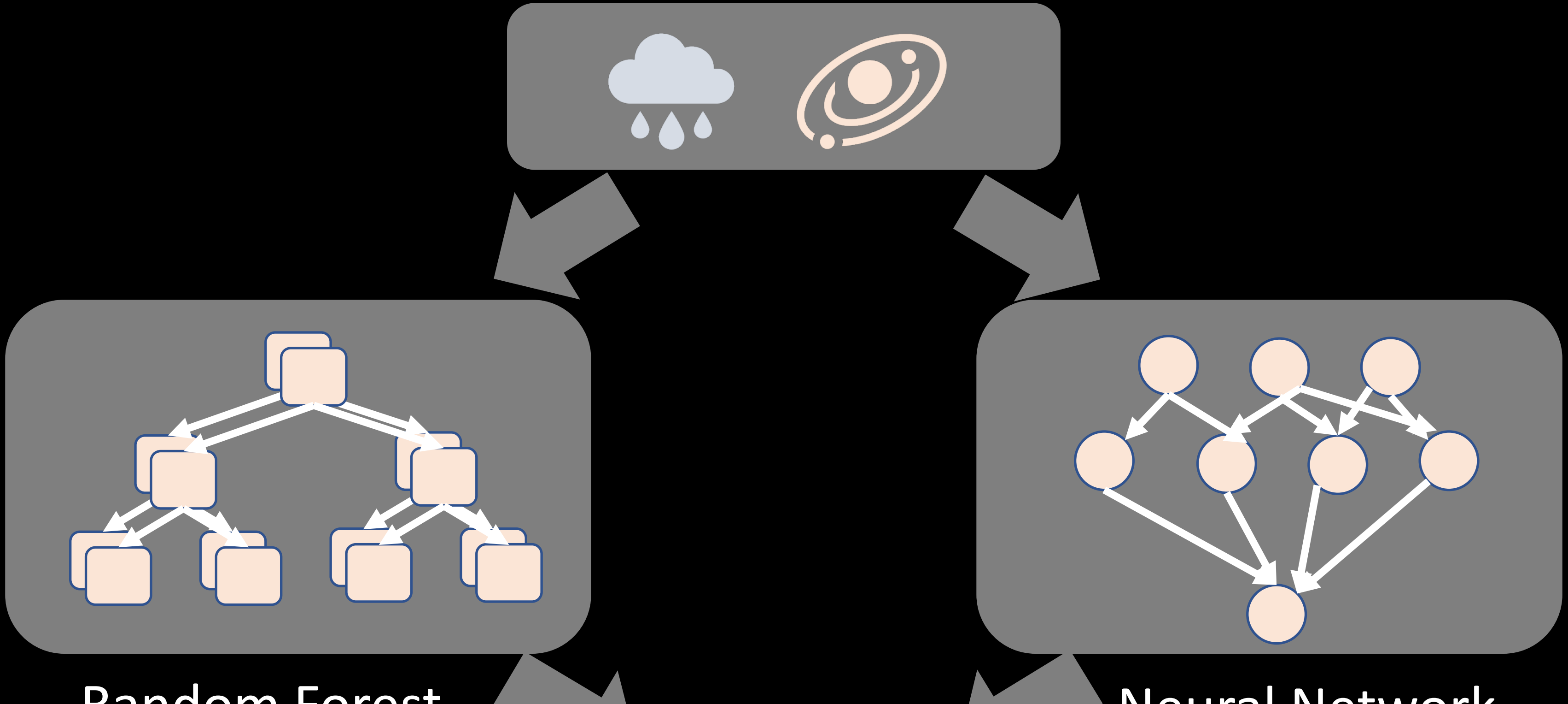
Use weather forecasts for weather loss

+

Train for multipath and hardware losses

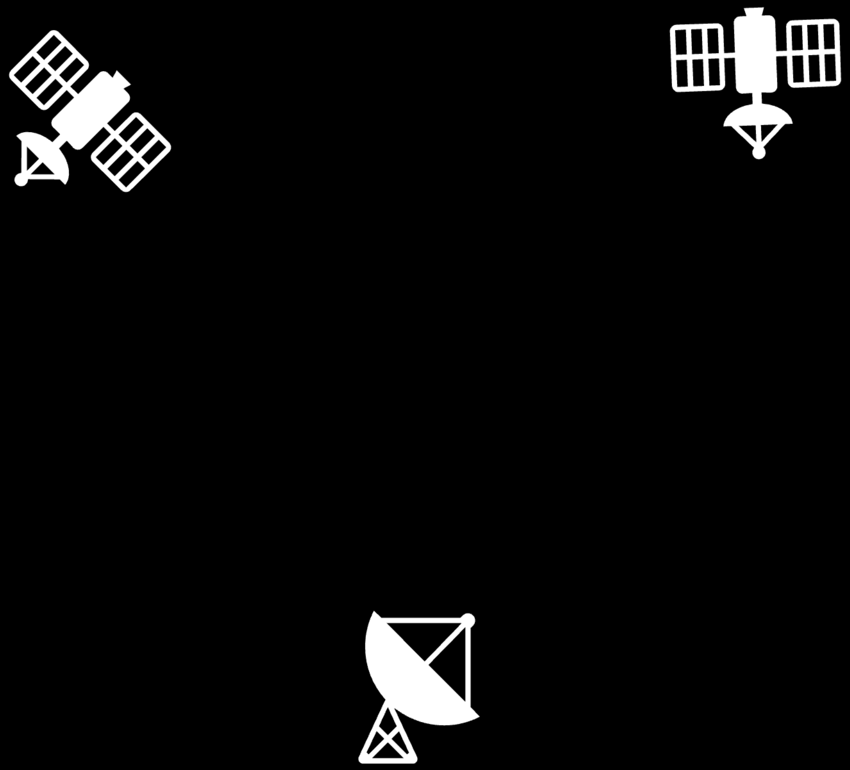
→ Datarate

ML Model to Predict Link Quality

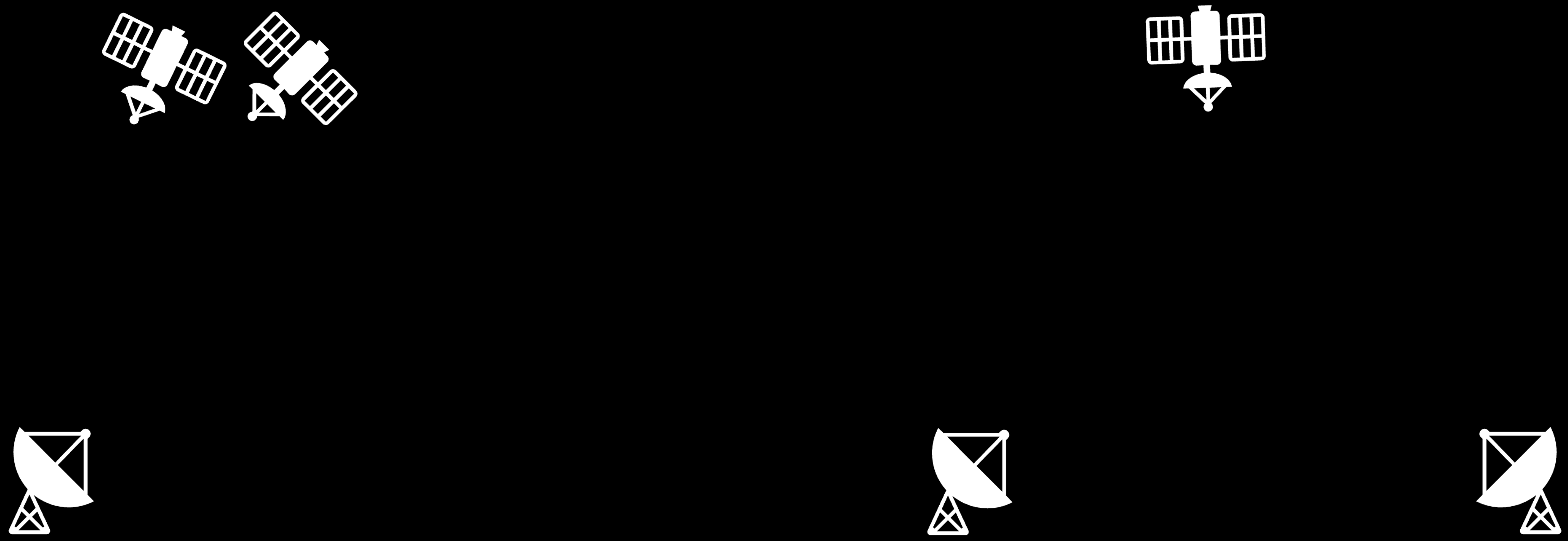


Our design leverages ML to predict ideal data rate

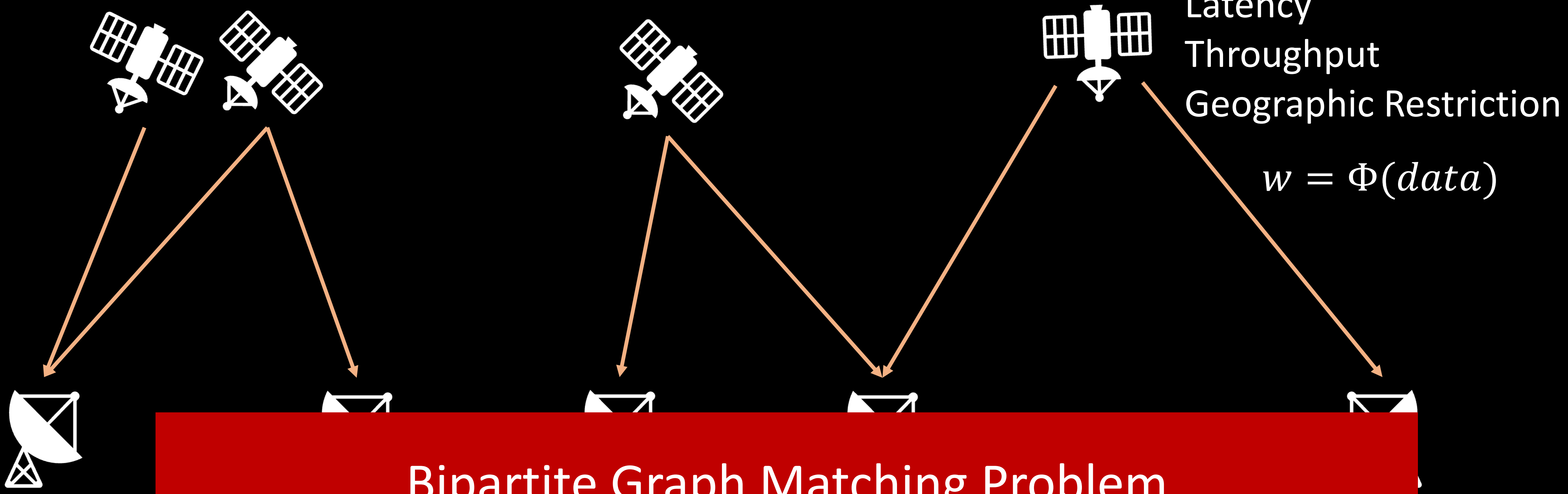
Challenge 2: Scheduling Satellite-GS Links



Challenge 2: Scheduling Satellite-GS Links

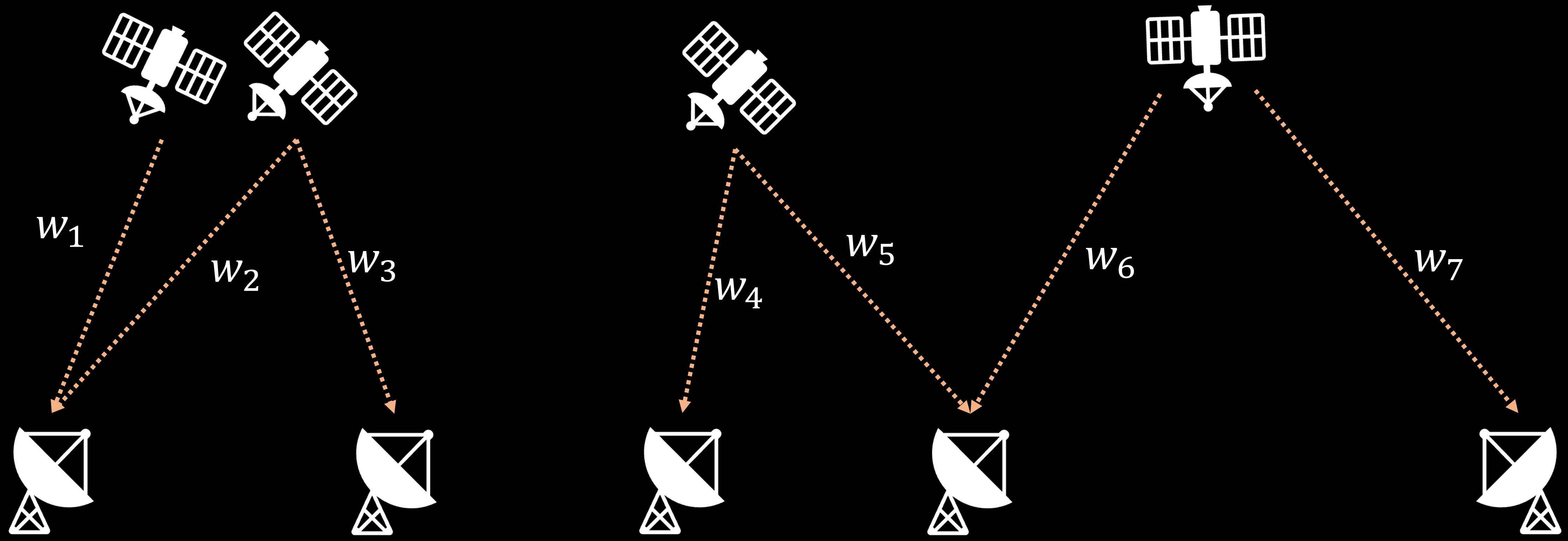


Challenge 2: Scheduling Satellite-GS Links

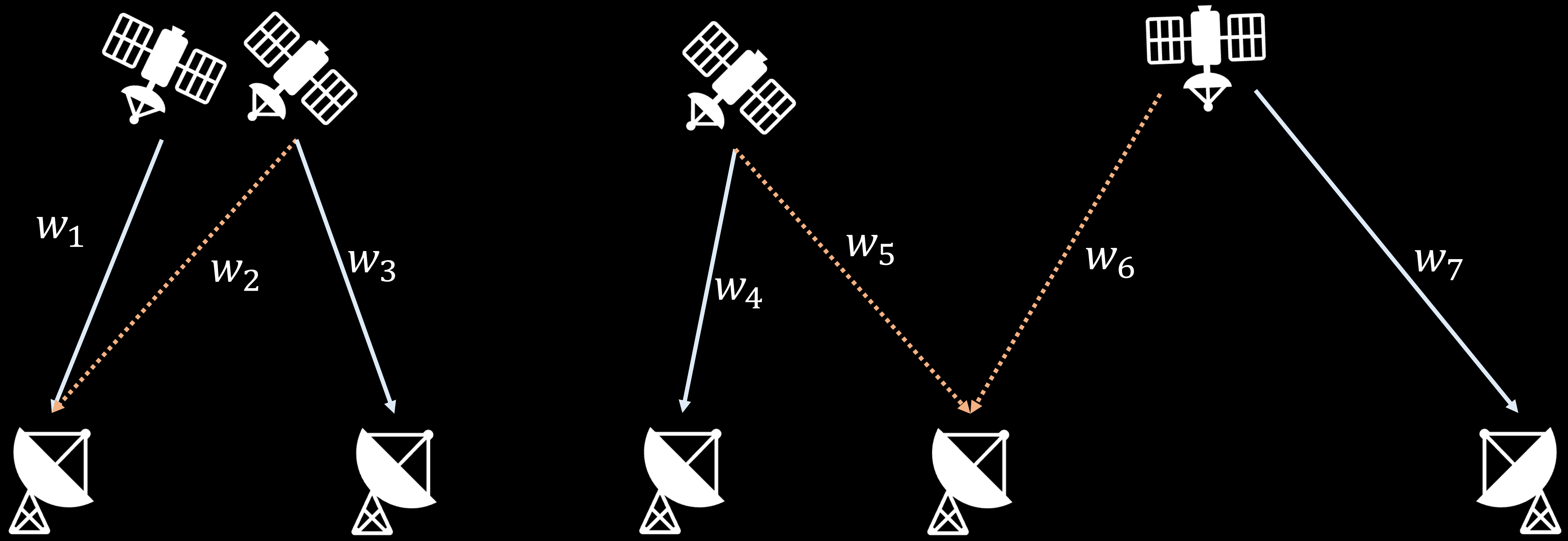


Bipartite Graph Matching Problem

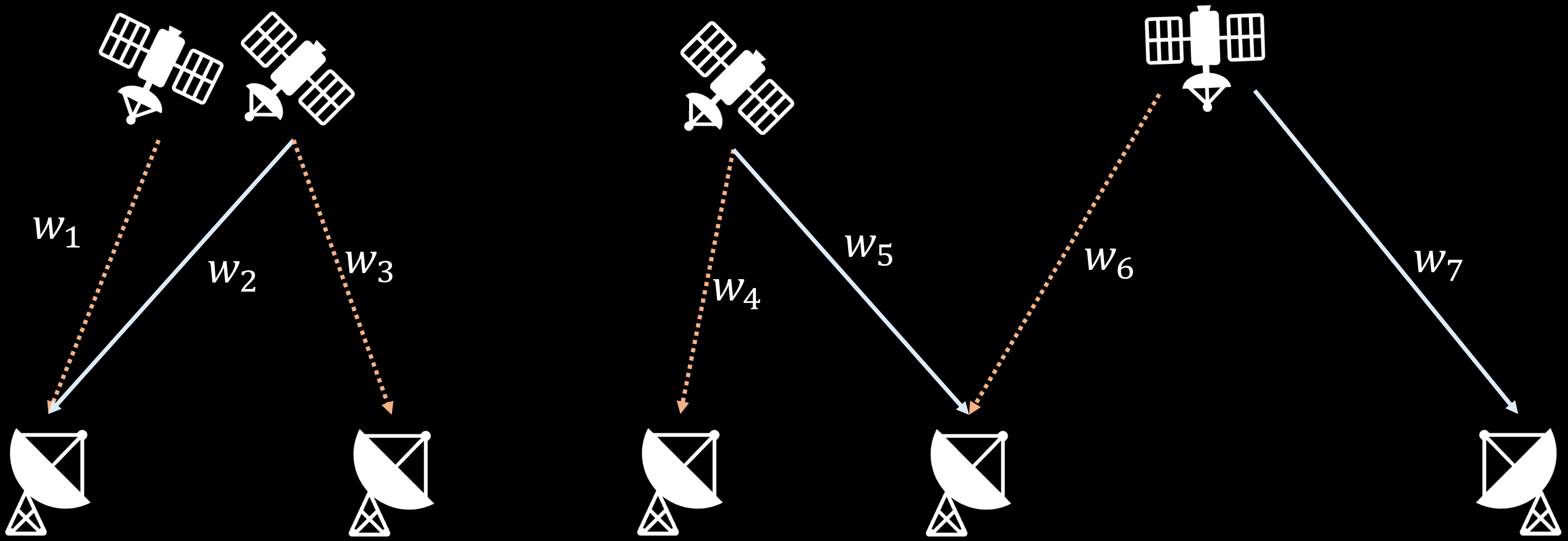
Scheduling Satellite-GS Links



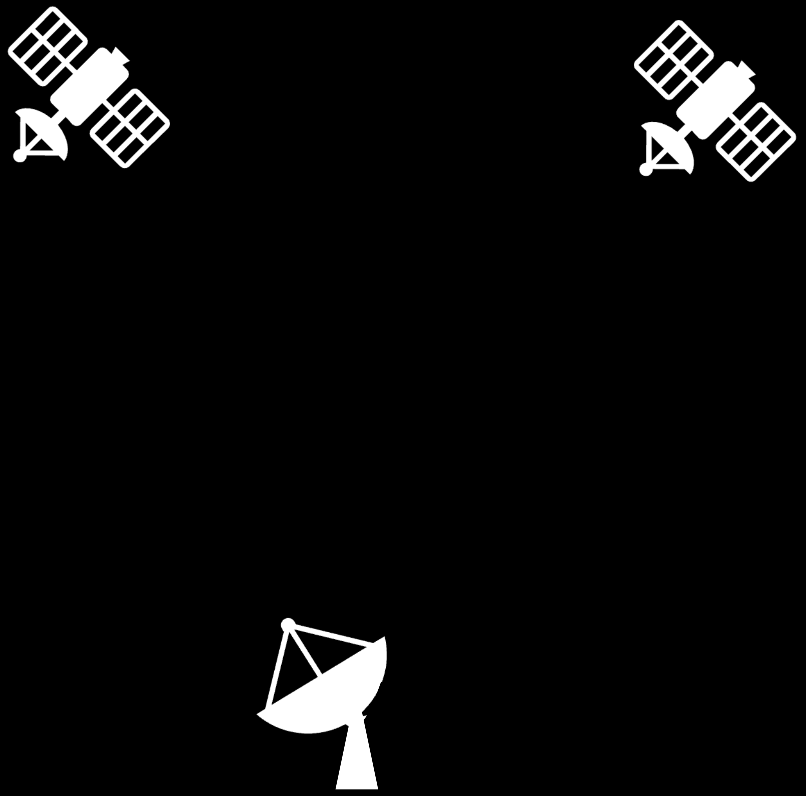
Scheduling Satellite-GS Links



Scheduling Satellite-GS Links



Scheduling Satellite-GS Links



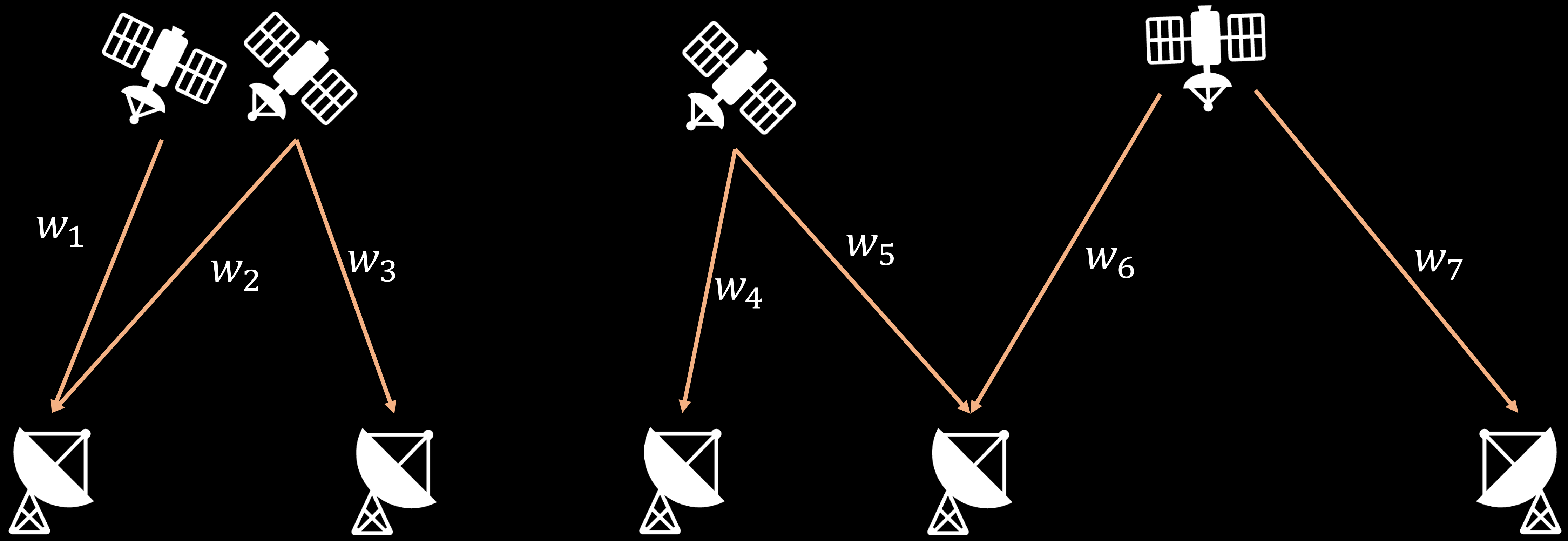
Switching links takes time

→ Matchings are not time-independent

→ Need to optimize links across time

NP Hard!

Solution: Greedy Algorithm with Sticky Links



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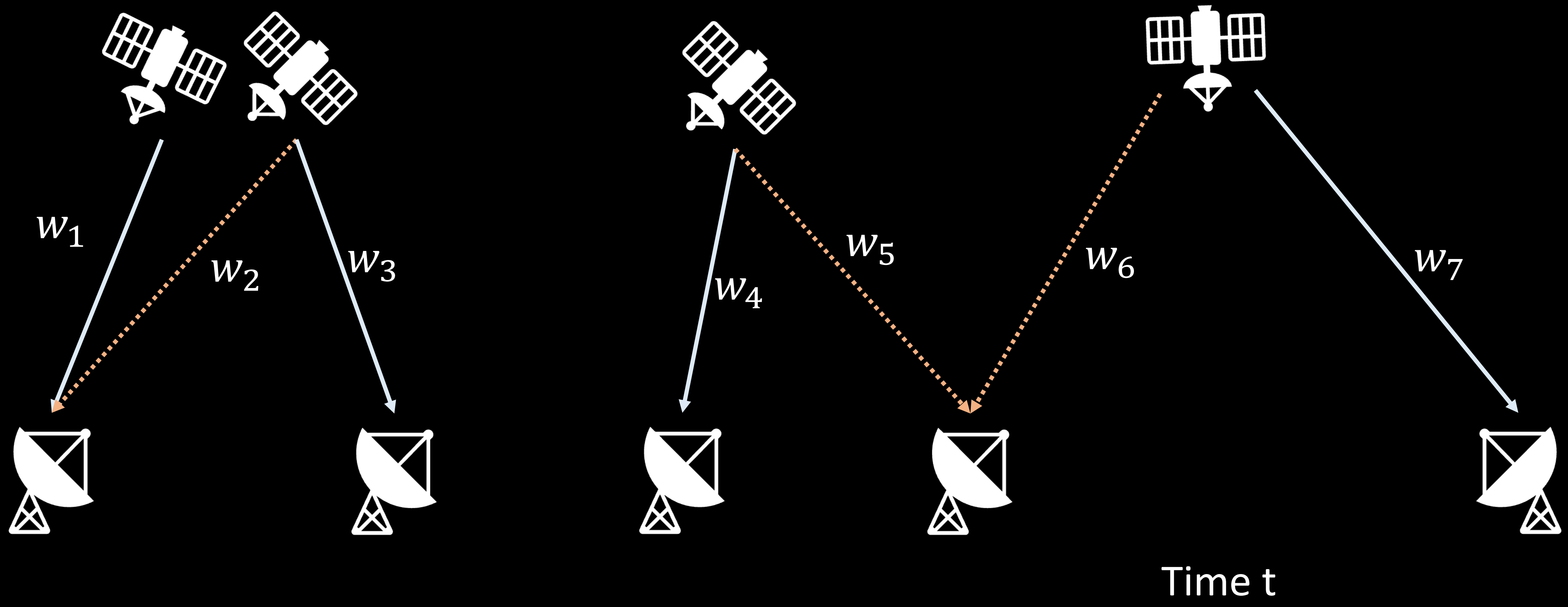

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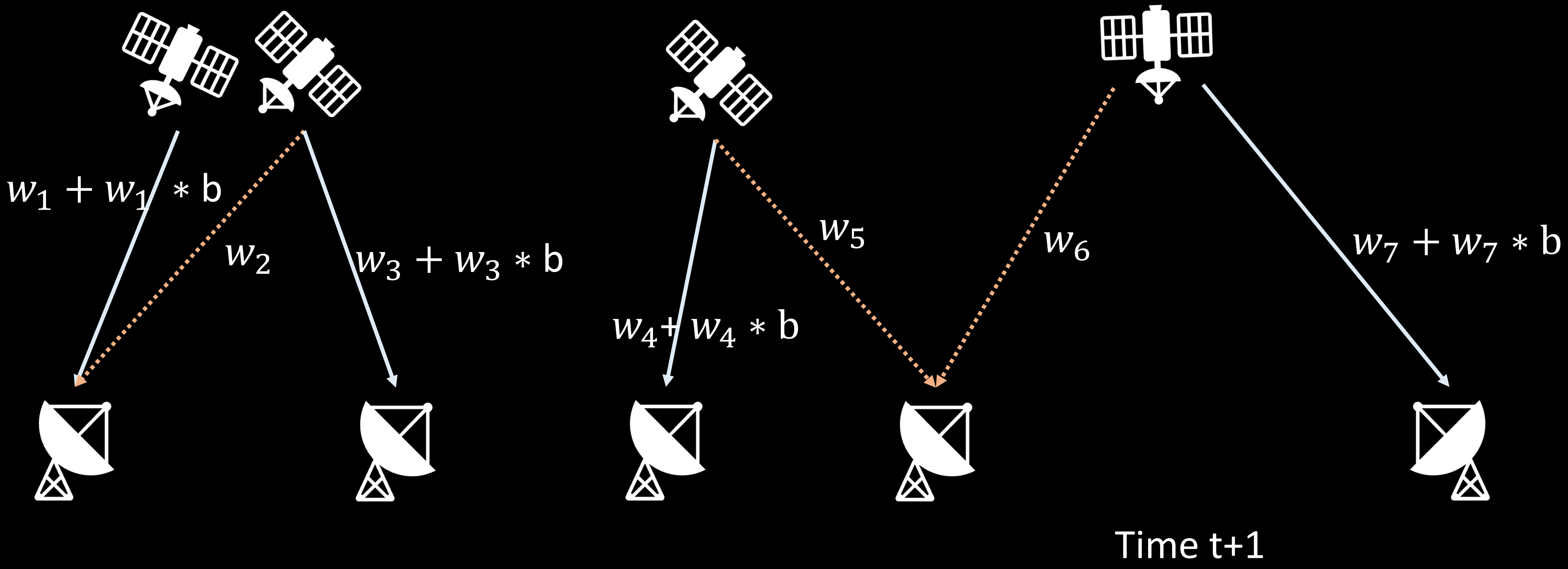
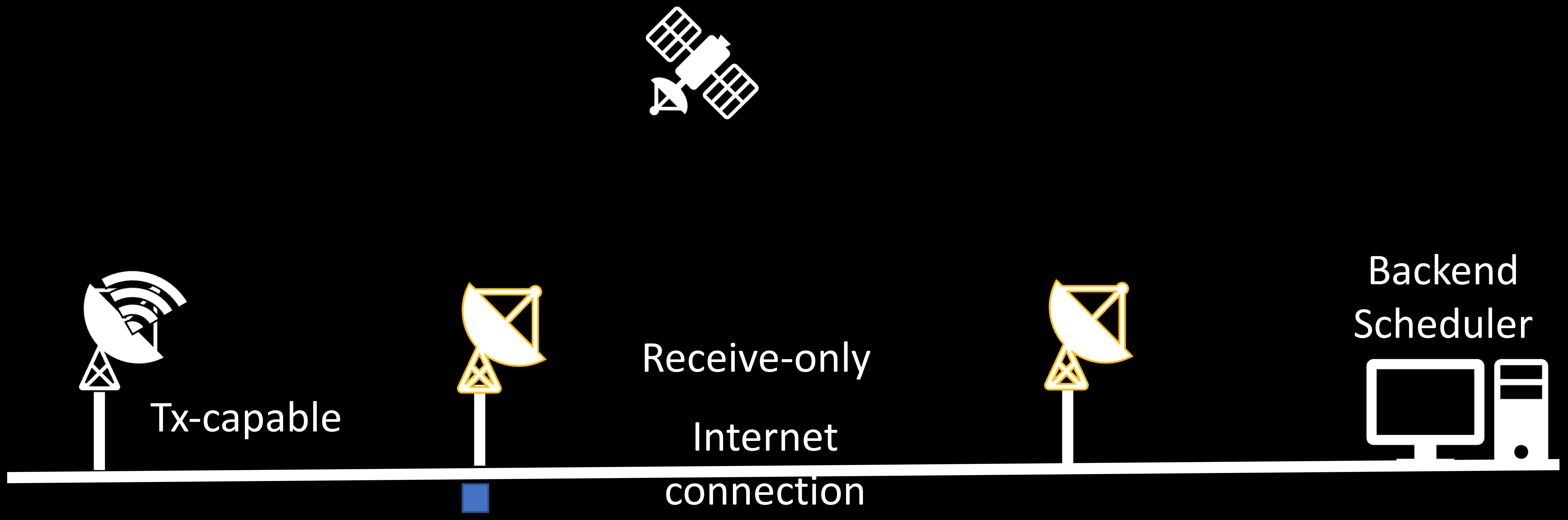


Solution: Greedy Algorithm with Sticky Link

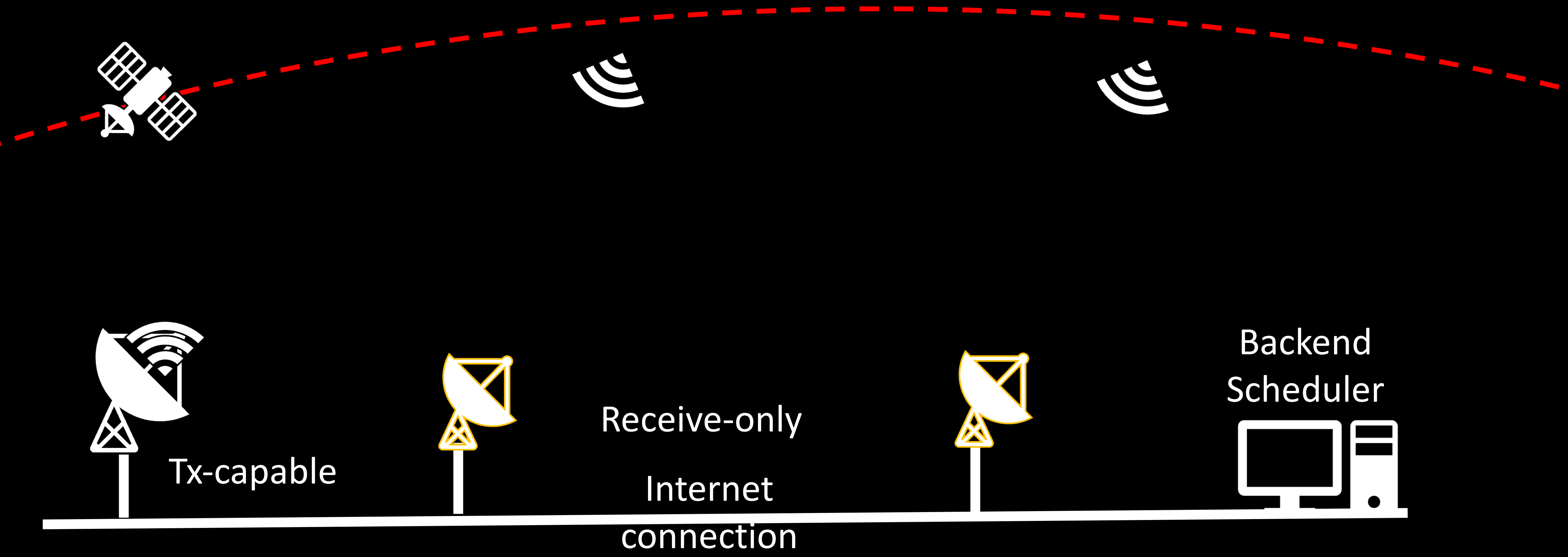
- Use Hungarian algorithm to find maximal matching
- Converges in O(K^3) where K=max(#satellite, #ground stations)
- Link estimation and schedule is computed and updated once a day

Challenge 3: No acks



Relay Acks Through Tx-Capable (With delay)

DGS: Distributed Ground Station



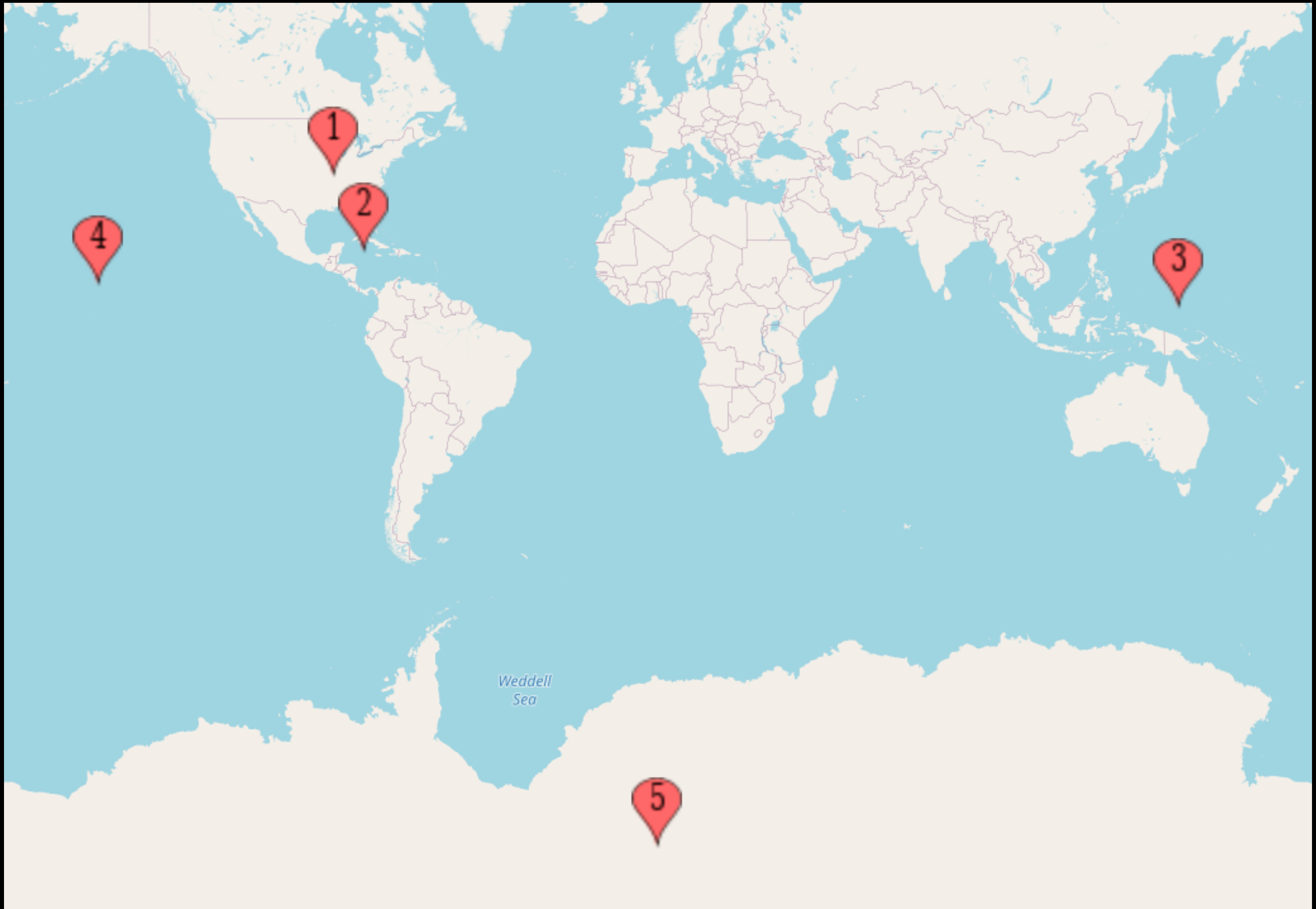
Experiments: Real-world Measurements

- 5 Ground Stations: Wisconsin, Florida, Guam, Hawaii, Antarctica

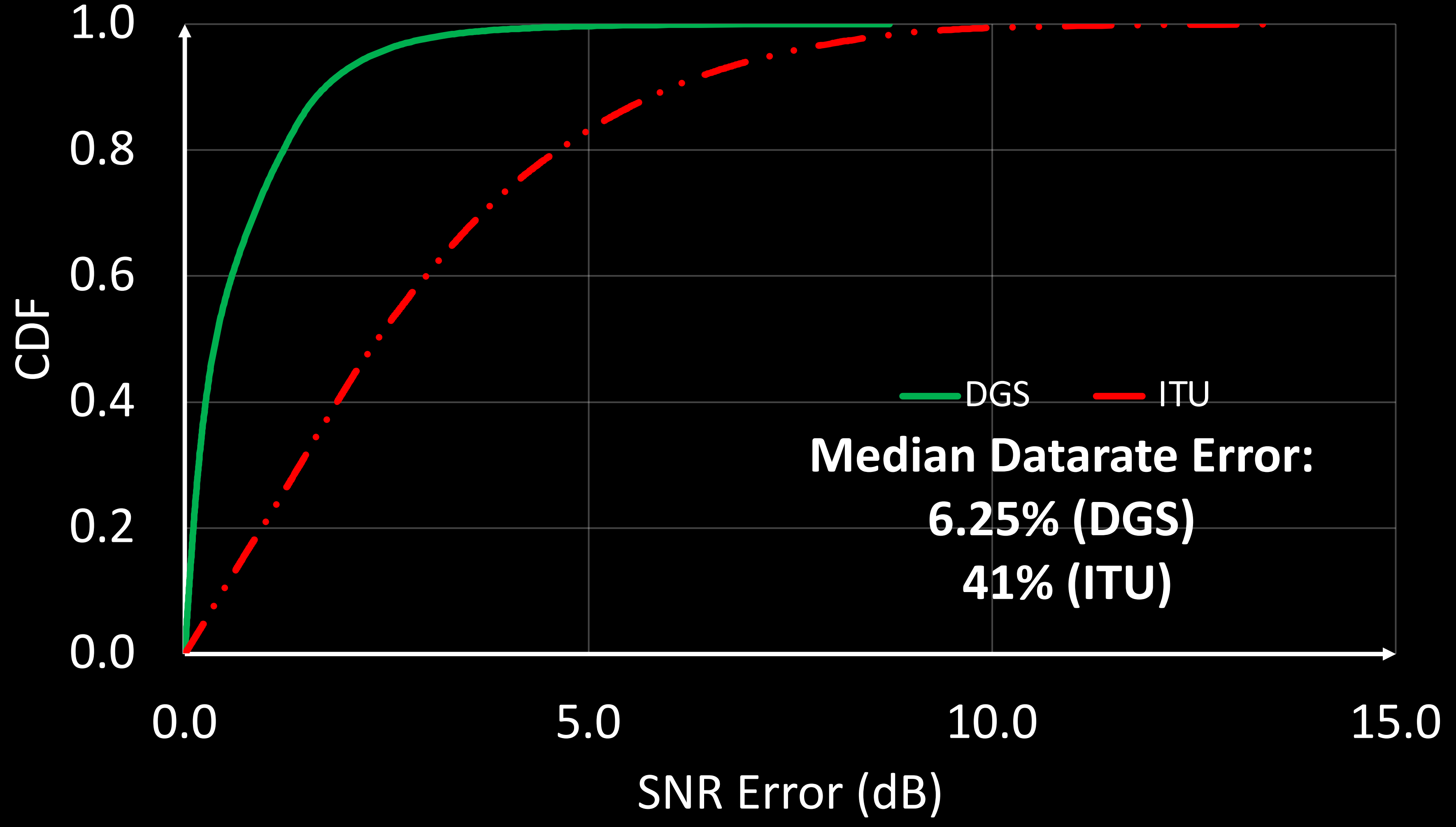
- 4 Satellites: JPSS, SNPP, Aqua, Terra
  - X-band Downlink: JPSS, SNPP, Aqua, Terra
  - Ka-band Downlink: JPSS

- Measurements across one month in 2020

Ground Station Locations



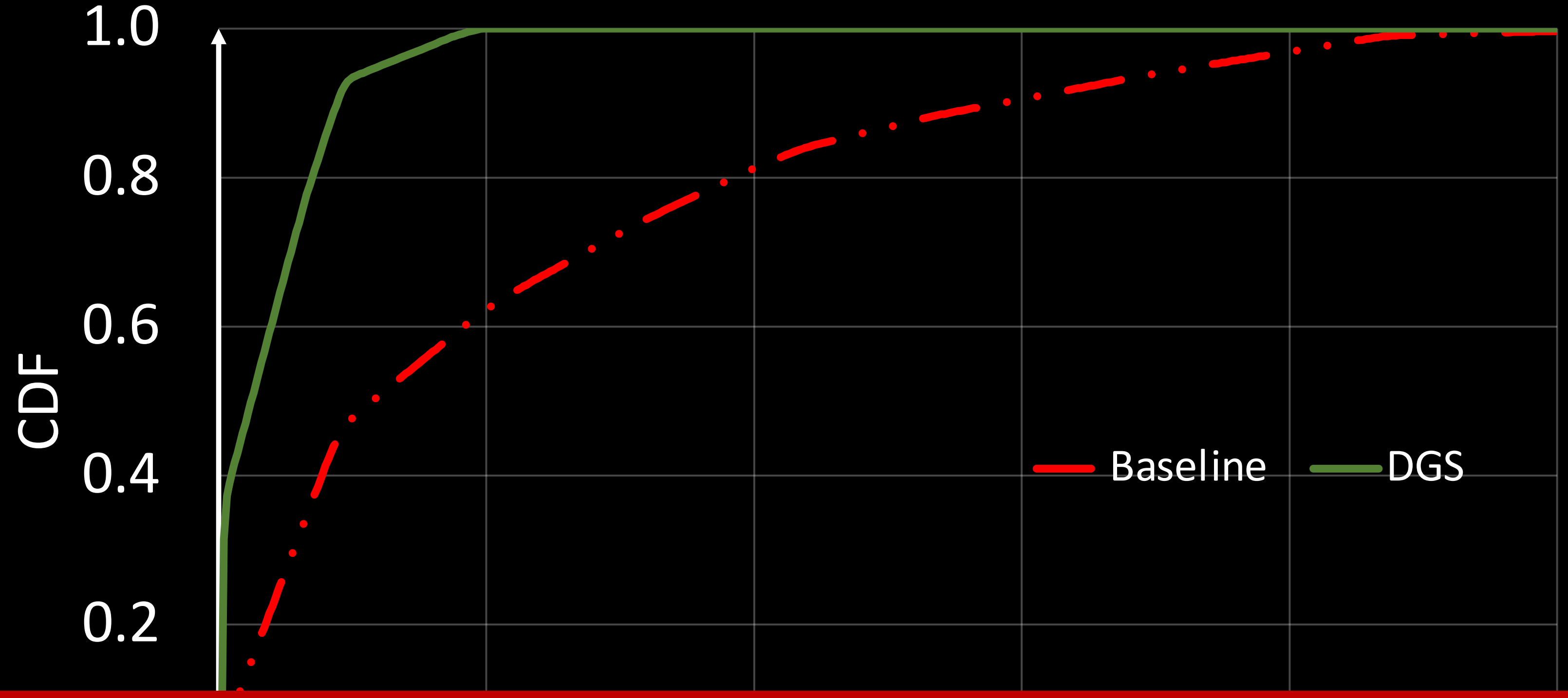
DGS → Accurate Link Prediction



Large Scale Emulation

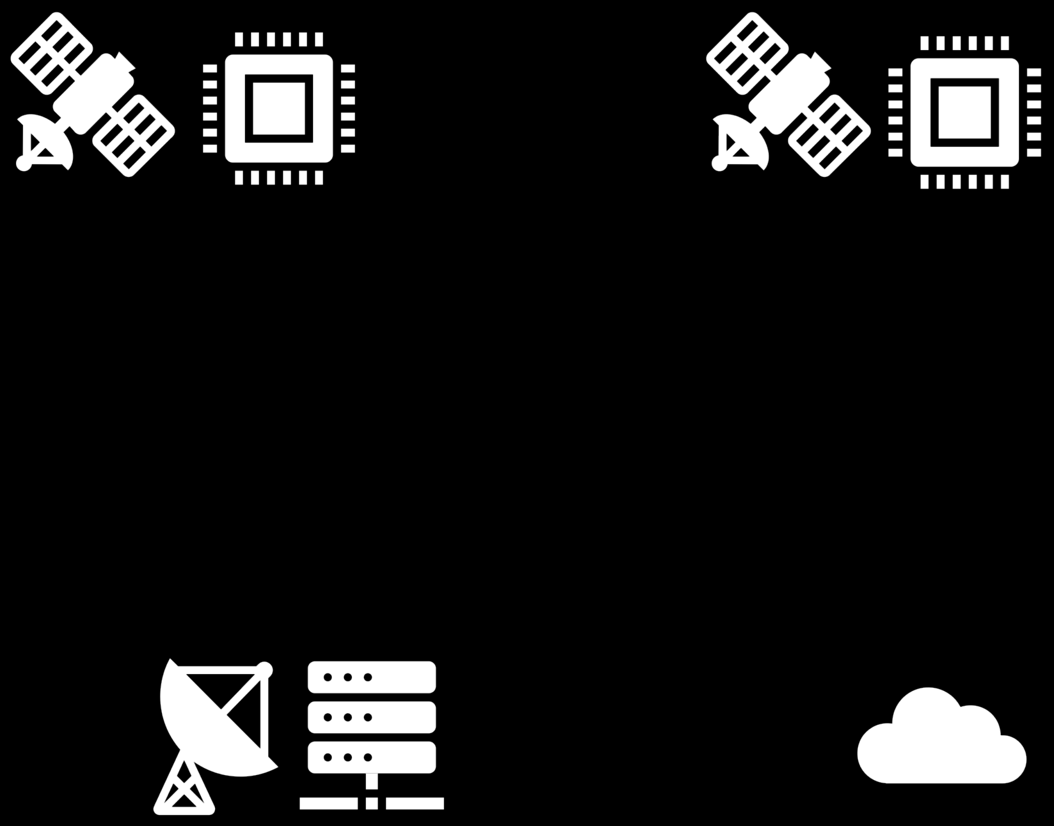
- SatNOGS: Open Source Ground Station Network
    - 259 satellites
    - 173 Ground Stations
- 100 GB data per day per satellite (26 TB total)
- Baseline: 5 Ground Stations
    - At least 10X higher median throughput

DGS → Lower Latency

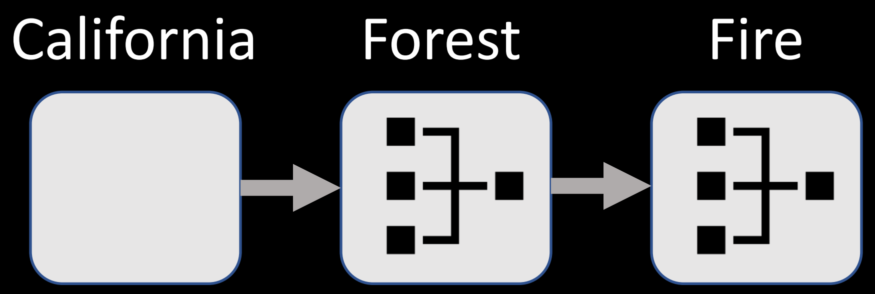


Distributed Ground Station reduces latency from hour to minutes

Ongoing Work: Edge Computing Pipeline

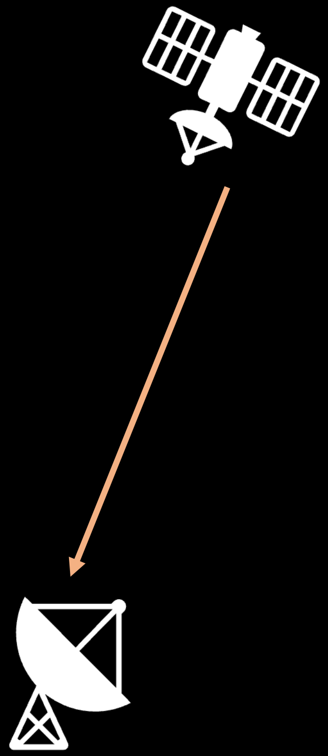


Goal: Find important data and send insights faster

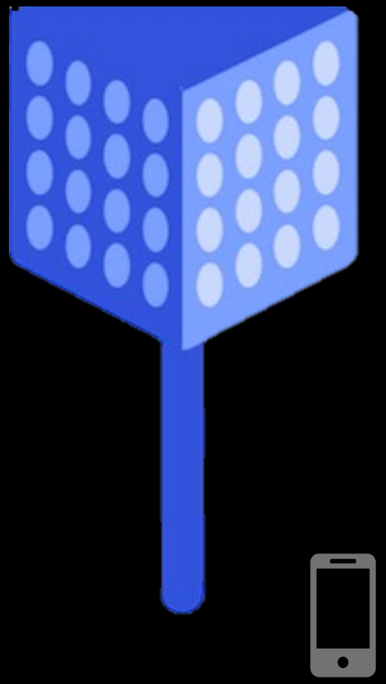


In this talk

Low-latency Satellite Networks

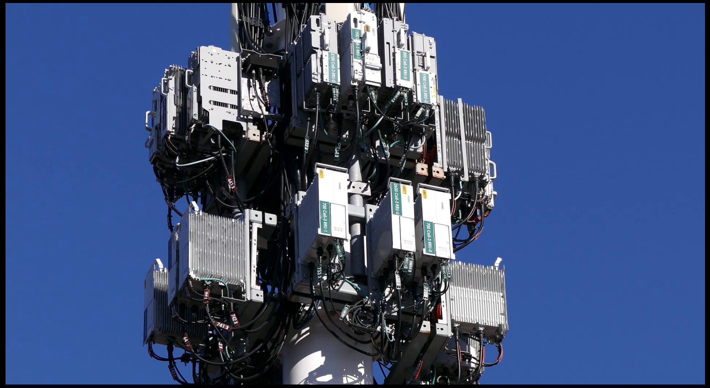


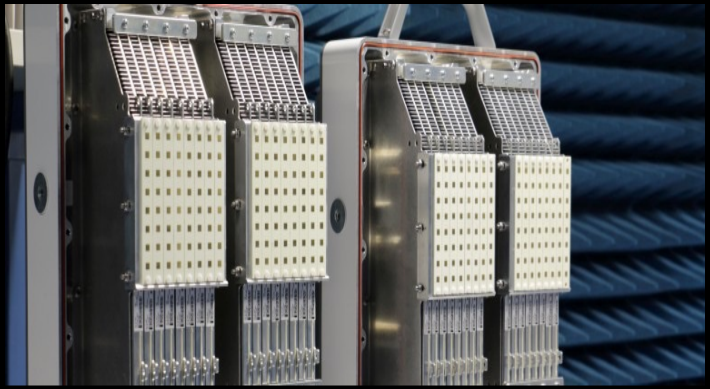
Zero-feedback Channel Estimation



Privacy against RF-based Tracking

Channel Feedback is An Important Problem for NextG Networks





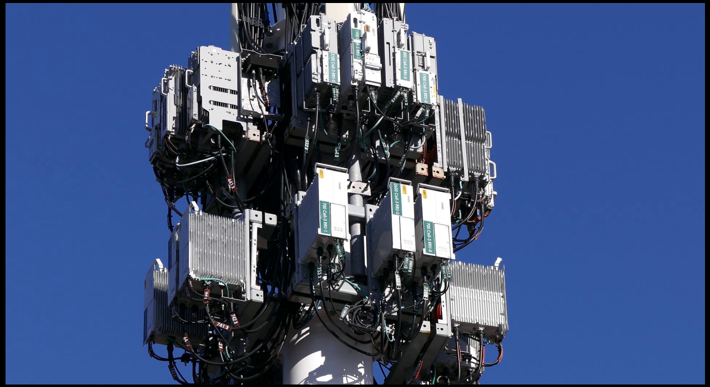
Cellular networks deploy many antennas at base station to increase throughput

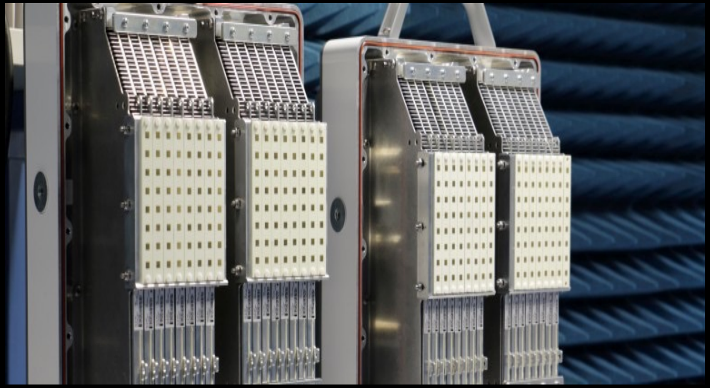
64 to 128 antennas deployed today!

Channel feedback overhead increases linearly with the number of antennas

Up to 50% overhead with just 64 antennas!

Channel Feedback is An Important Problem for NextG Networks





In academia: R2-F2 (SIGCOMM 2016), OptML (MobiCom 2019), FNN(2016), ICC 2019, IEEE Access 2019, ACSSC 2019, …

Industry

Our work: Zero channel feedback, maximal performance!

Our work: Zero Channel Feedback

- Problem: What is channel feedback?

- FIRE: End-to-end Machine Learning to remove channel feedback.

- Evaluation using public datasets and our hardware testbed

FIRE, MobiCom 2021, Zikun Liu, Chenren Xu, Gagandeep Singh, Deepak Vasisht

Our work: Zero Channel Feedback

- Problem: What is channel feedback?
- FIRE: End-to-end Machine Learning to remove channel feedback.
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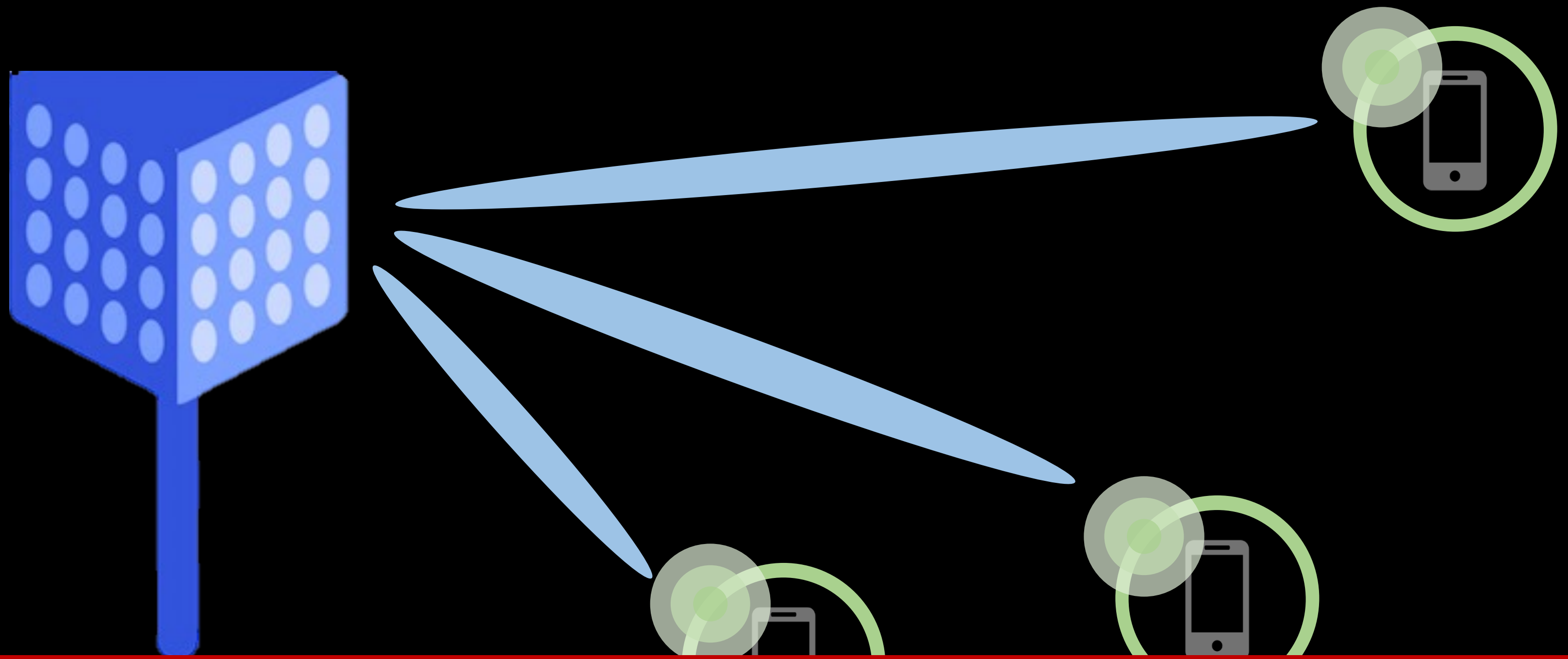
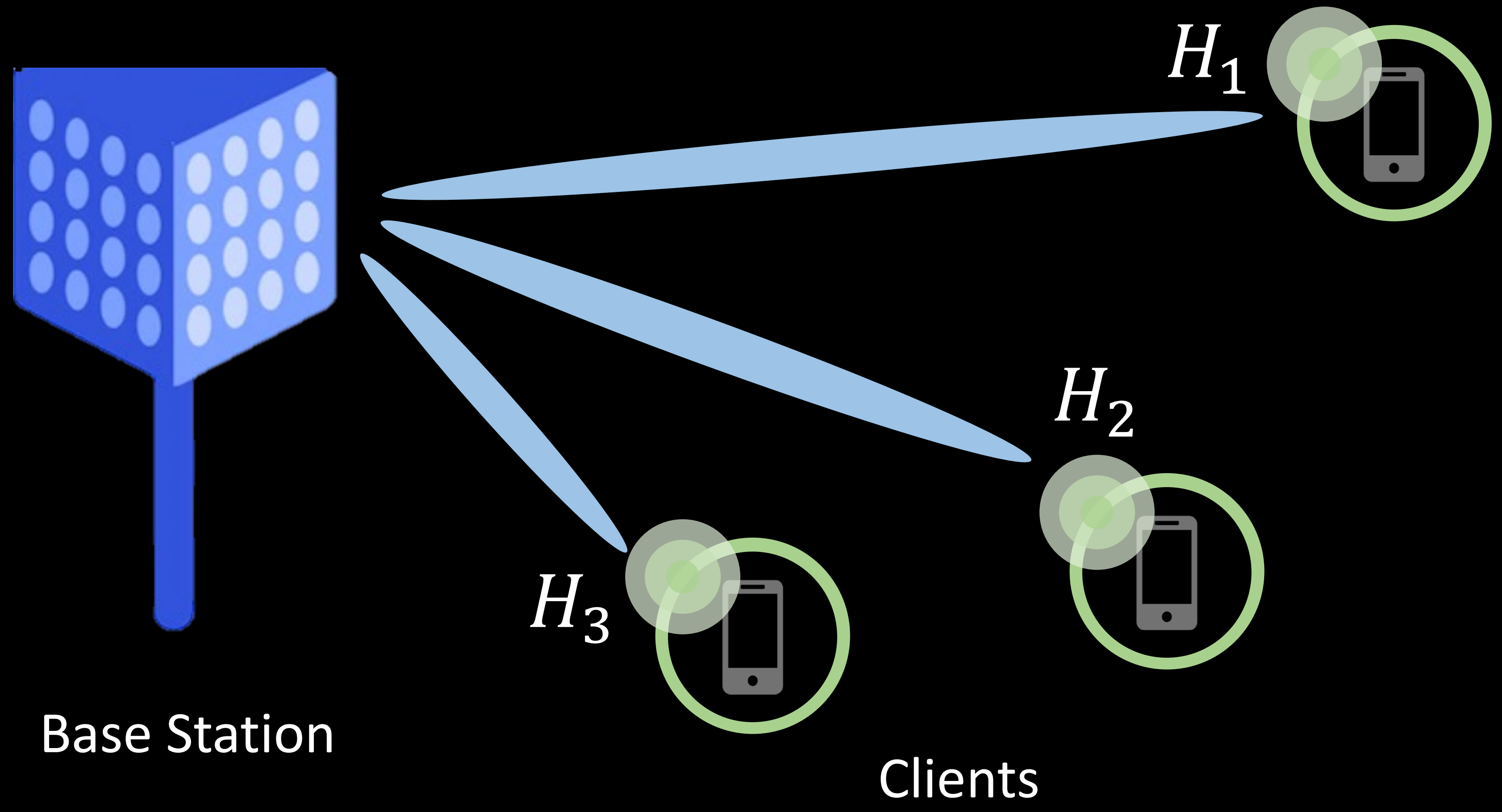
Multi-antenna base station can support multiple clients simultaneously



But needs to know the channel values to each client!

Base station needs to know the channel matrix to clients



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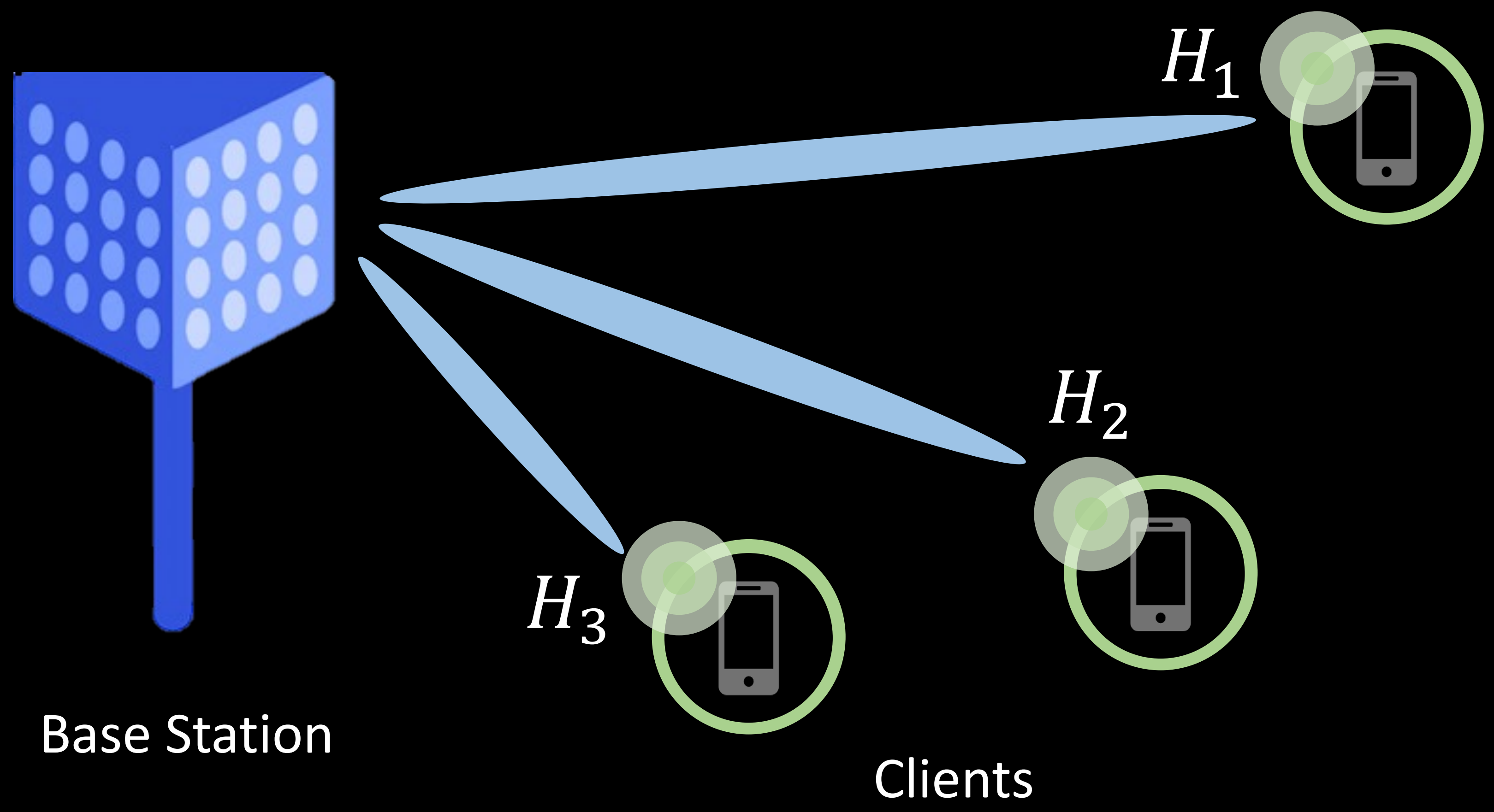
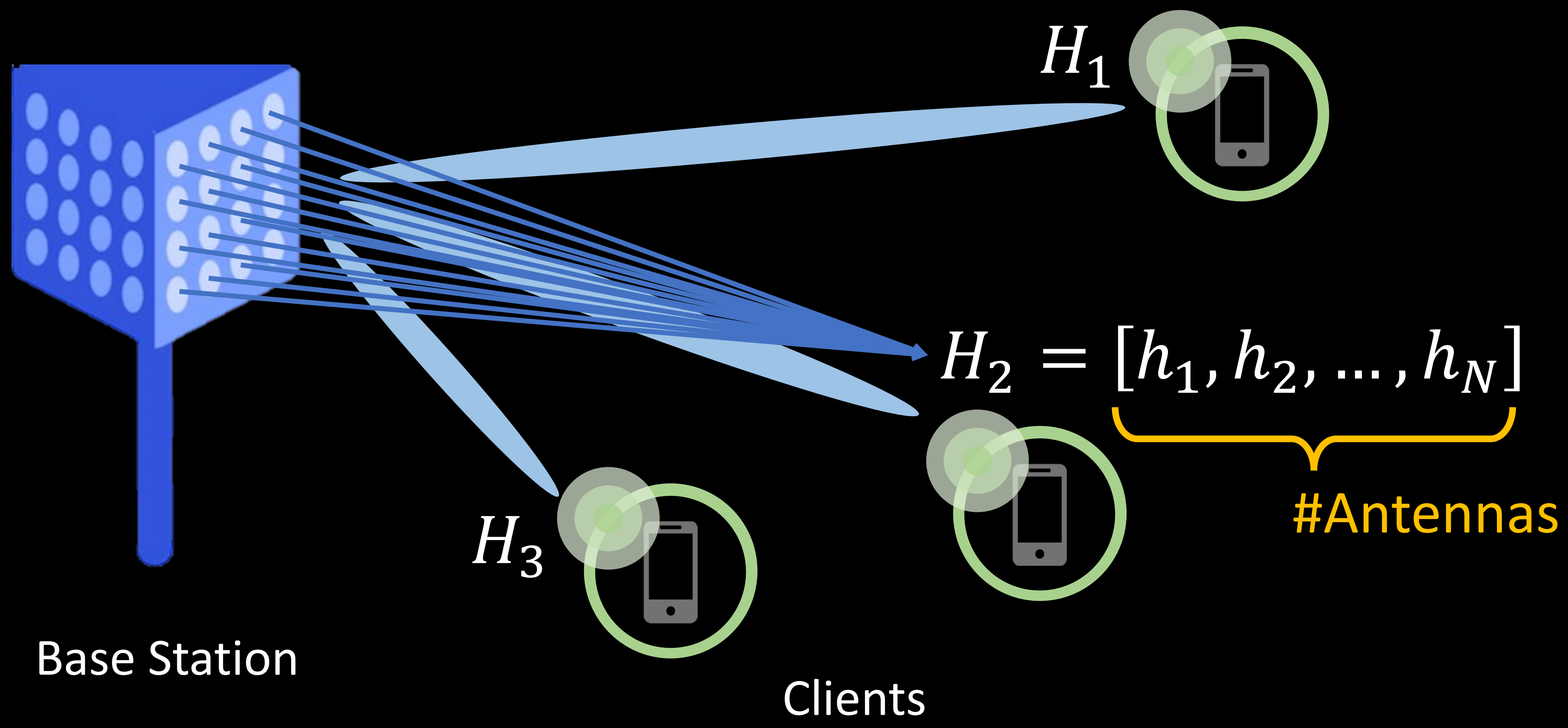
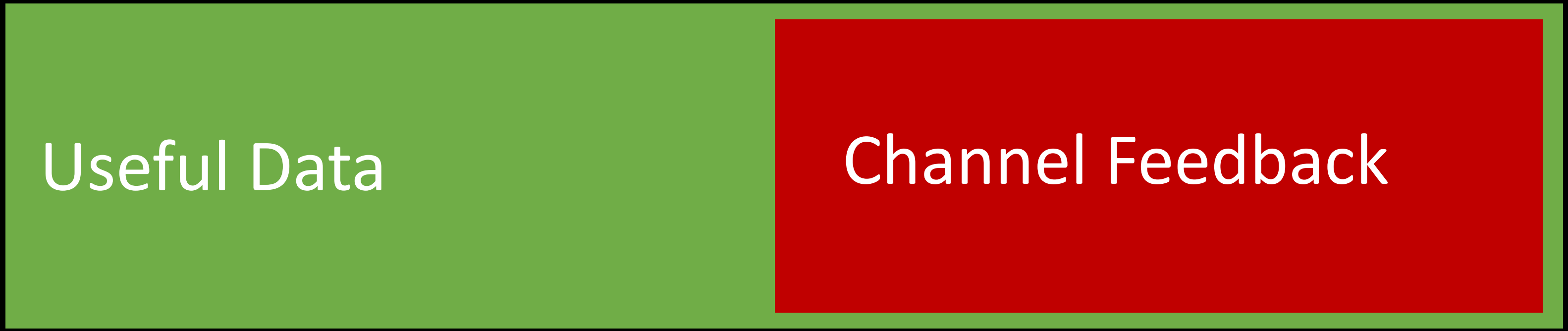


More Antennas → More Feedback Overhead



Channel Feedback Overhead is Huge

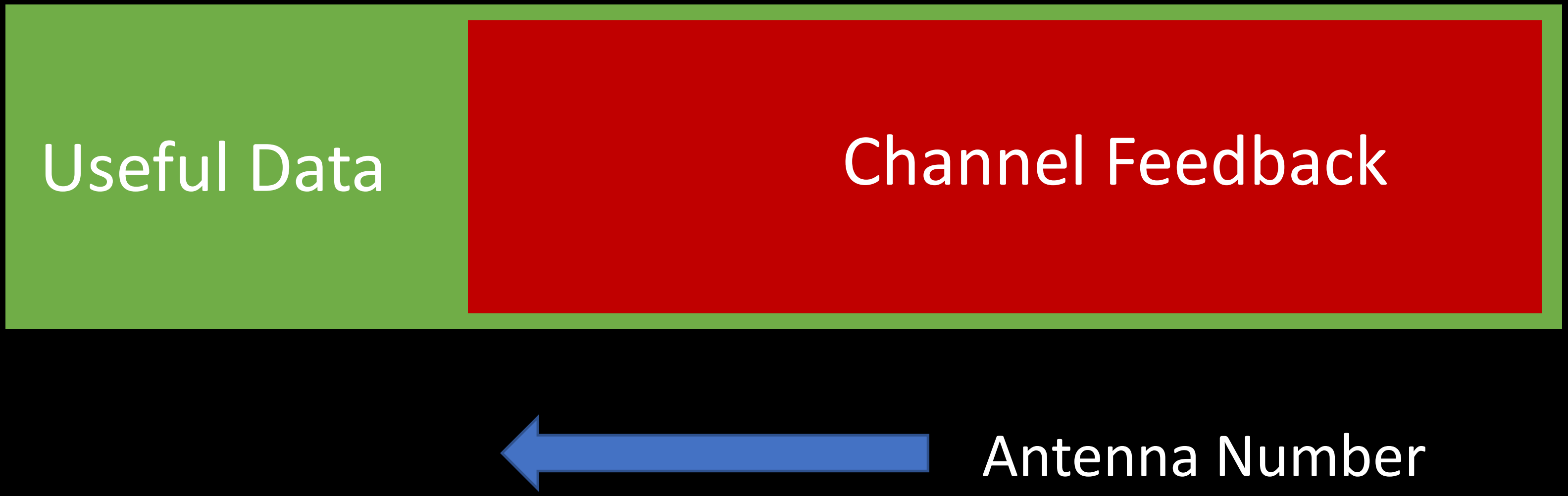
With a 64-antenna base station and 8 clients, explicit channel feedback can consume over half of the throughput



Channel Feedback Overhead is Huge

With a 64-antenna base station and 8 clients, explicit channel feedback can consume over half of the throughput

As number of antennas increases, the feedback increases



Our Work: Zero Channel Feedback

- Problem: What is channel feedback?
- FIRE: End-to-end Machine Learning to remove channel feedback.
- Evaluation using public datasets and our hardware testbed

FIRE: Zero Feedback Multi-Antenna Systems

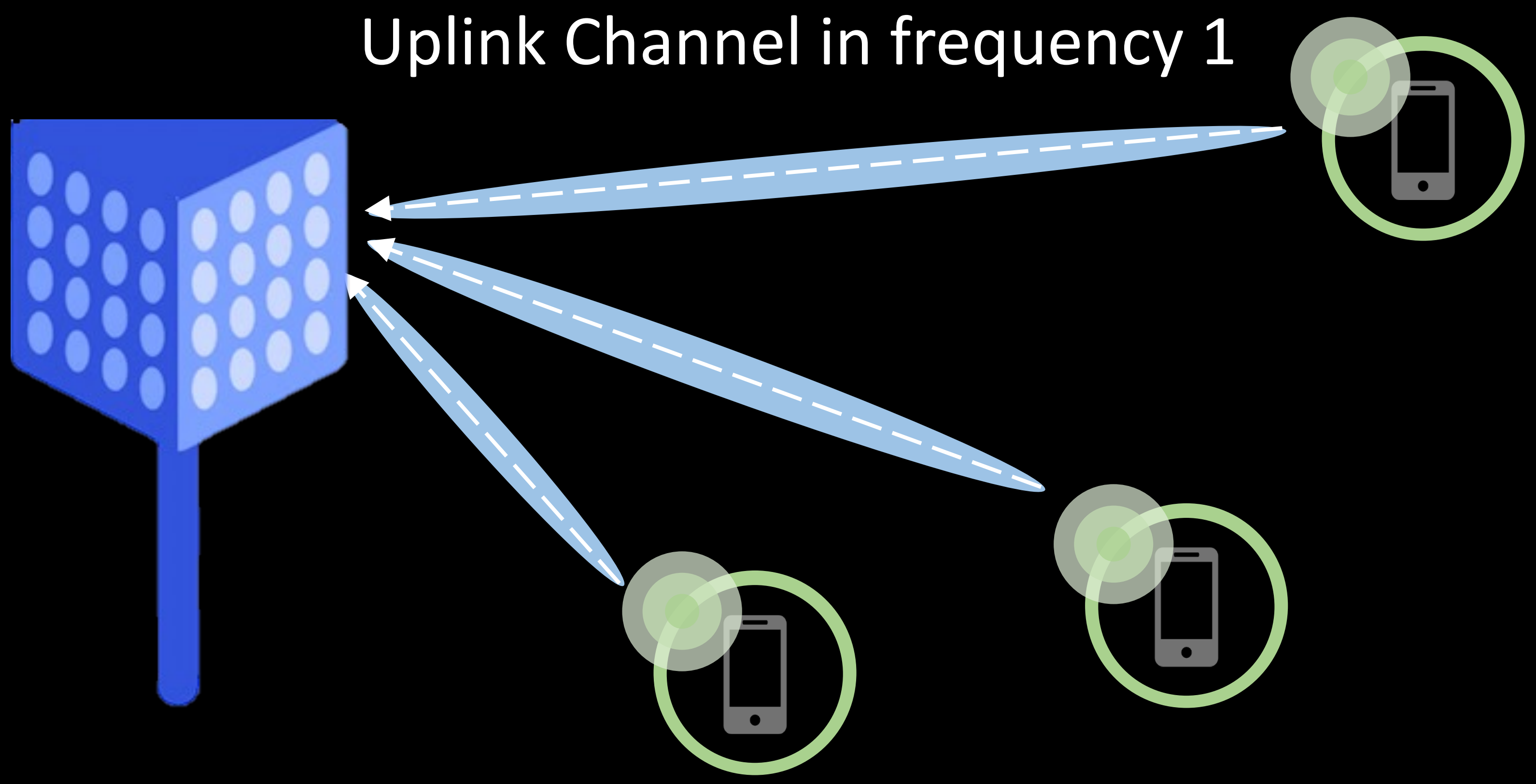
With a 64-antenna base station and 8 clients, explicit channel feedback can consume over half of the bandwidth*

As number of antennas increases, the feedback increases

Useful Data

Intuition Behind FIRE

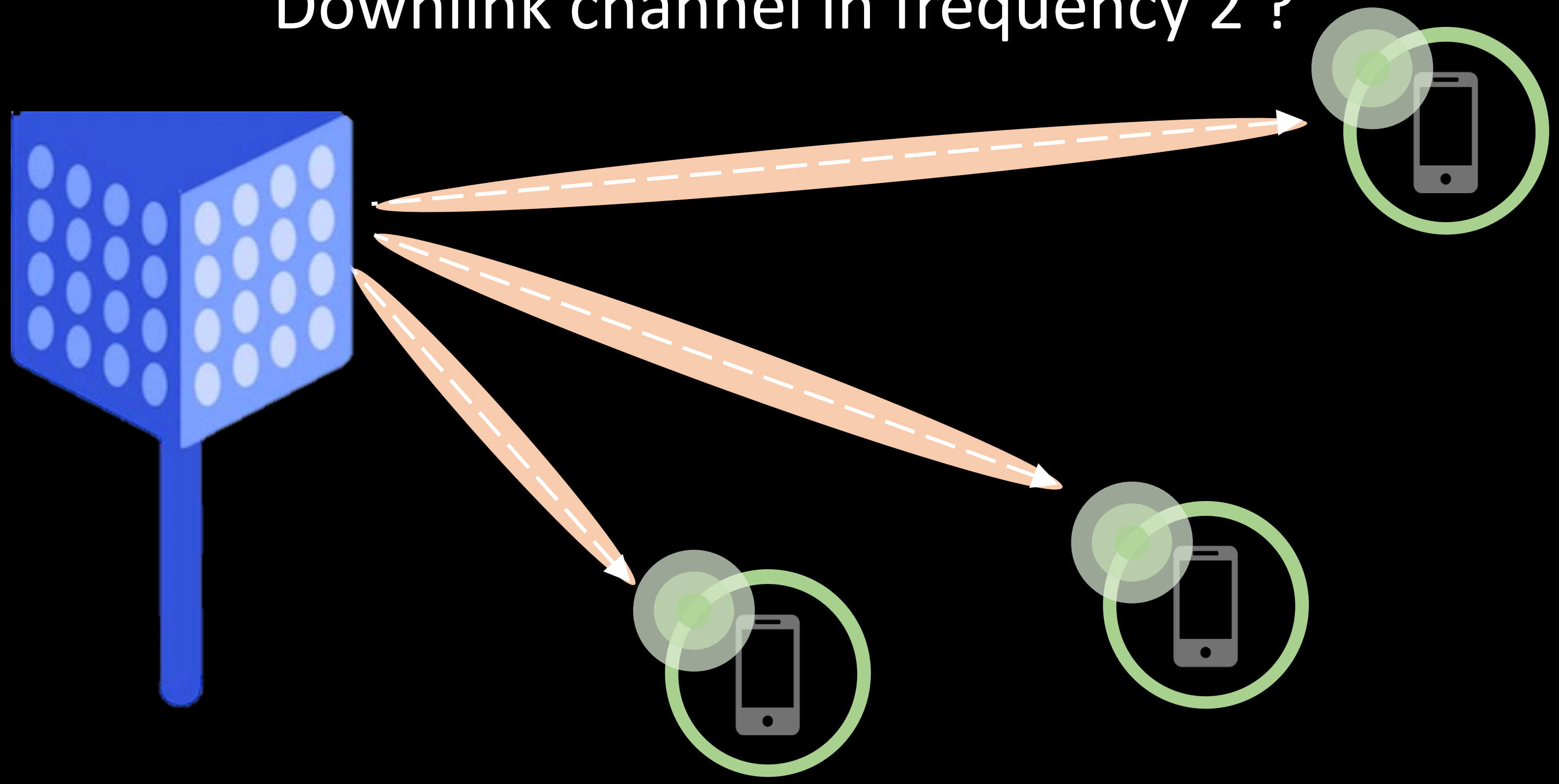
Base station knows the uplink channel, but needs downlink channel



Intuition Behind FIRE

Base station knows the uplink channel, but needs downlink channel

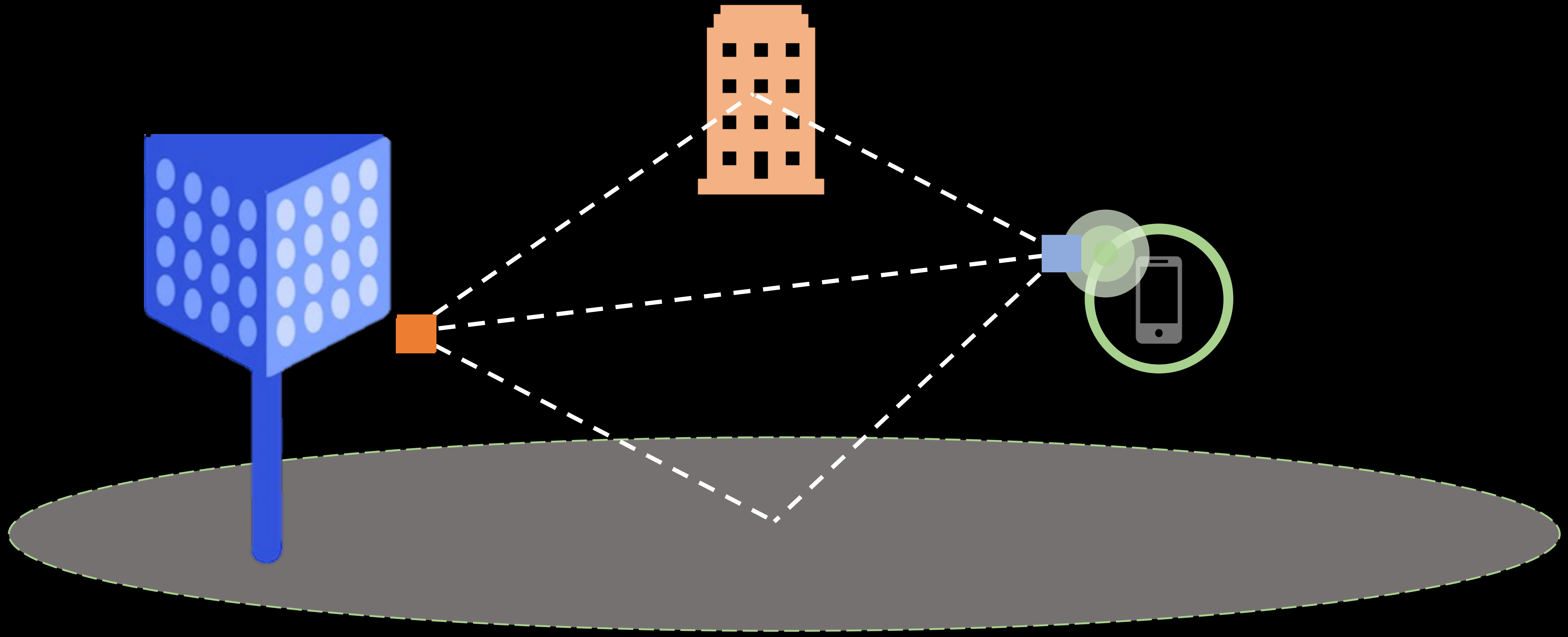
Downlink channel in frequency 2 ?



Intuition Behind FIRE

Uplink and downlink share the same physical path

[R2F2 in SIGCOMM 2016, OptML in Mobicom 2019]



Intuition Behind FIRE

Uplink and downlink share the same physical path

[R2F2 in SIGCOMM 2016, OptML in Mobicom 2019]

Distance and angle
of each path

Intuition Behind FIRE

Uplink and downlink share the same physical path

[R2F2 in SIGCOMM 2016, OptML in Mobicom 2019]

Uplink Channel ⇨ ***Path Parameters*** ⇨ ***Downlink Channel***

Distance and angle of each path

Needs to be very precise

Intuition Behind FIRE

Uplink and downlink share the same physical path

[R2F2 in SIGCOMM 2016, OptML in Mobicom 2019]

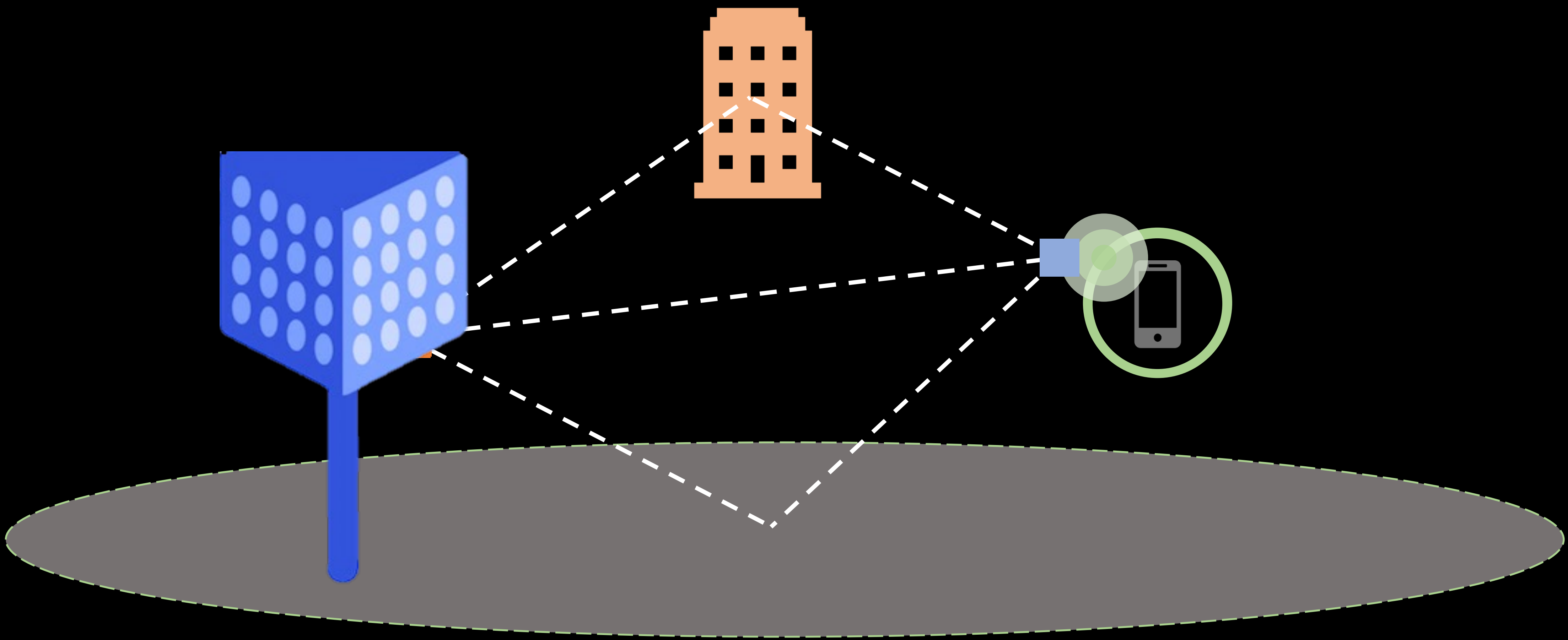
Uplink Channel → ***Path Parameters*** → ***Downlink Channel***

0.5 cm distance error reduces the SNR by 10 to 20dB

Fundamental limitation due to bandwidth!

Intuition Behind FIRE

Idea: Use ML to model the physical environment



Option 1: Use ML to infer Path Distance and Angle

Uplink Channel ⇨ ***Path Parameters***

Problem: No ground truth for paths

Option 2: Directly Predict Downlink Channels

Uplink Channel ⇨ ***Downlink Channel***

Problem: Does not accurately model the channel generation process

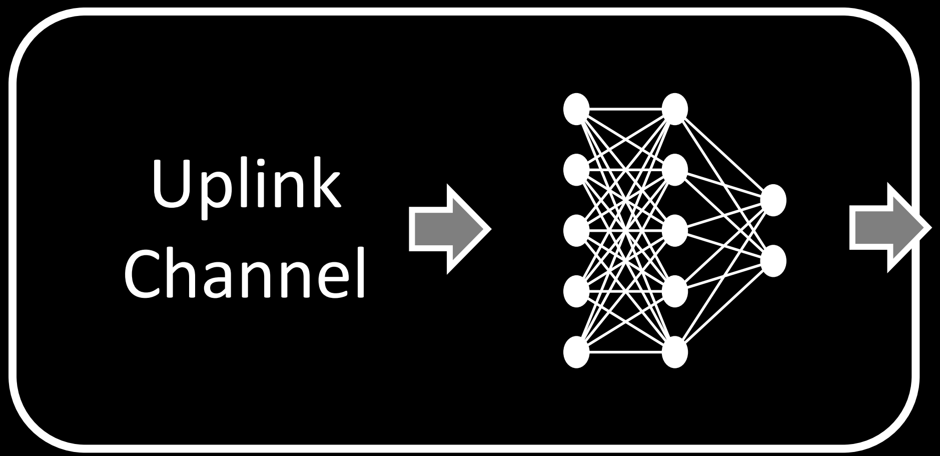
Our Idea: End-to-end Generative Model using VAE

Uplink Channel → ***Path Parameters*** → ***Downlink Channel***

Network Architecture

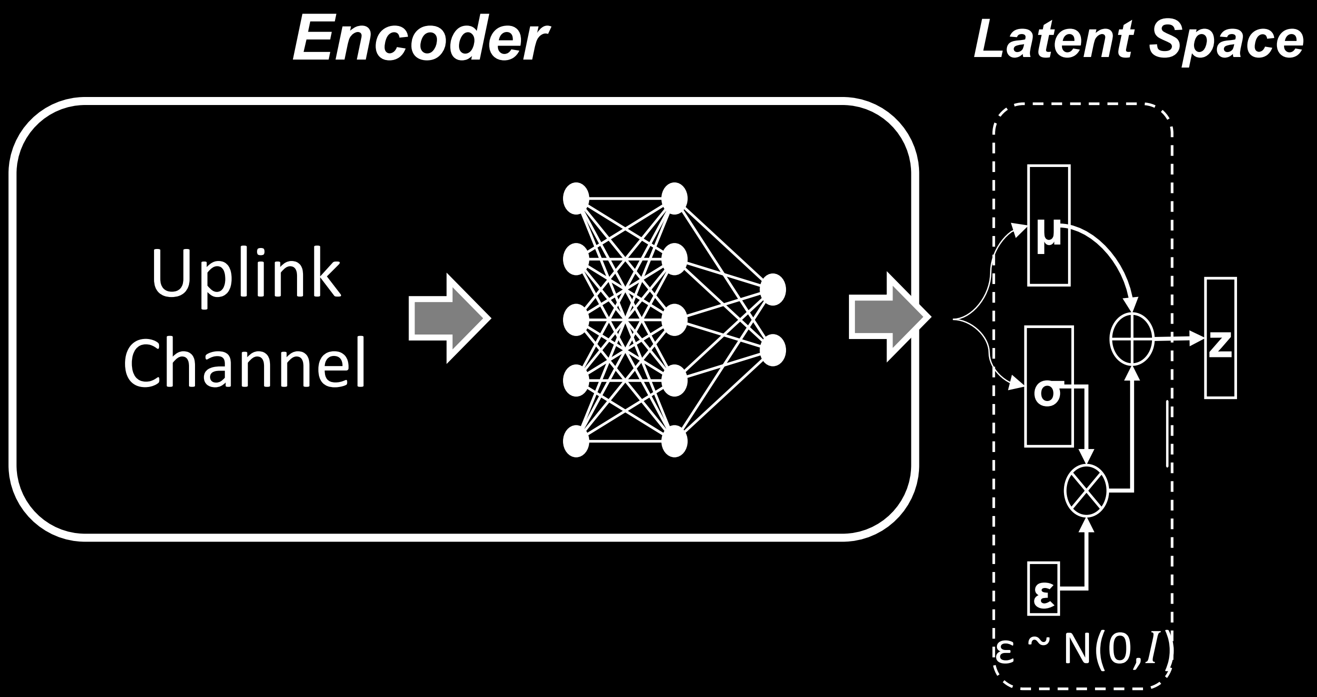
Uplink Channel → ***Path Parameters*** → ***Downlink Channel***

Encoder

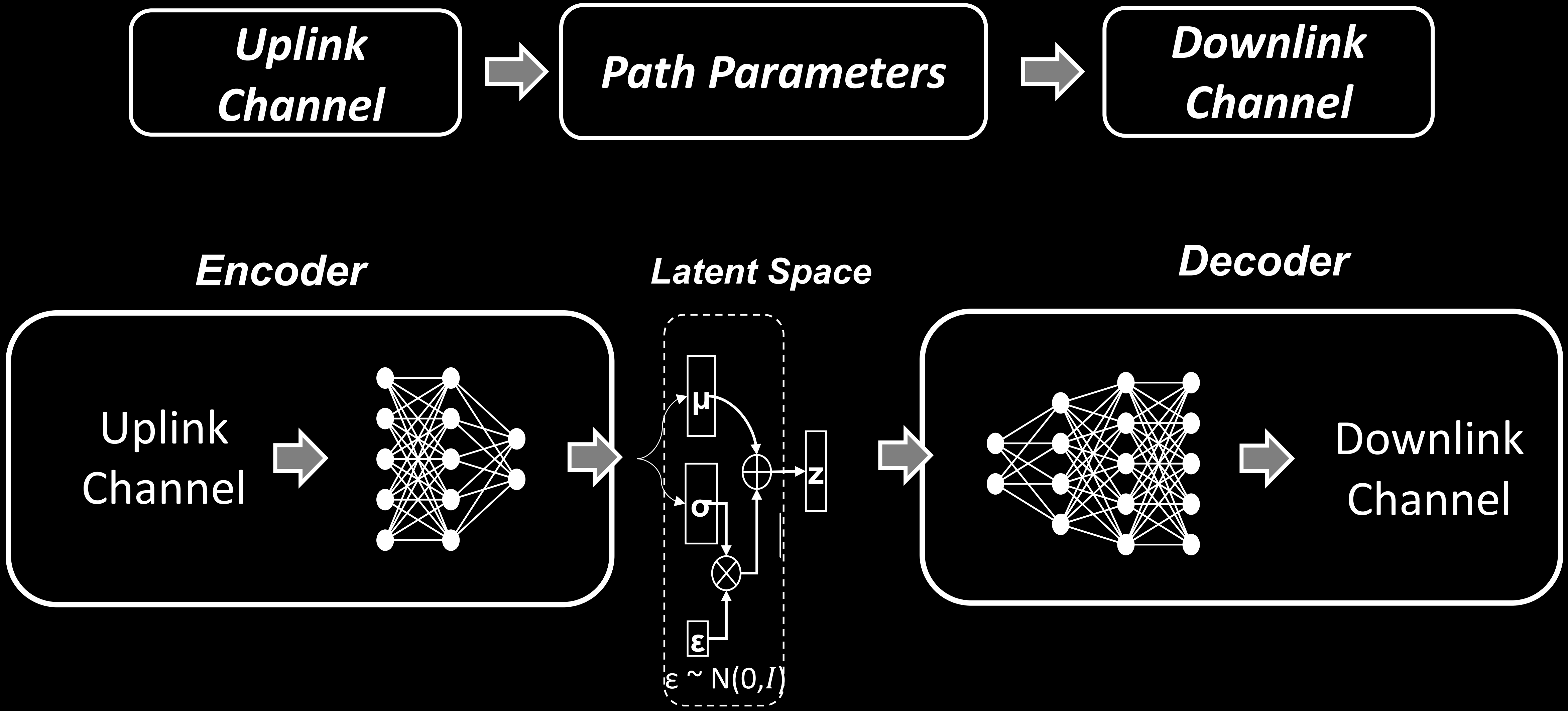


Network Architecture

Uplink Channel → ***Path Parameters*** → ***Downlink Channel***

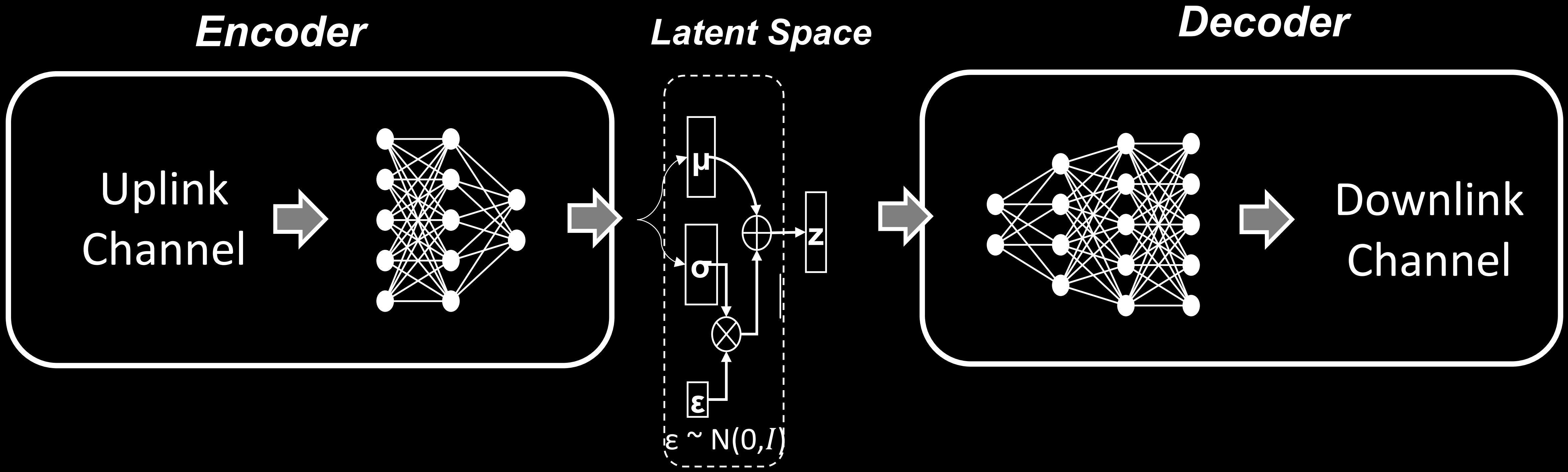


Network Architecture



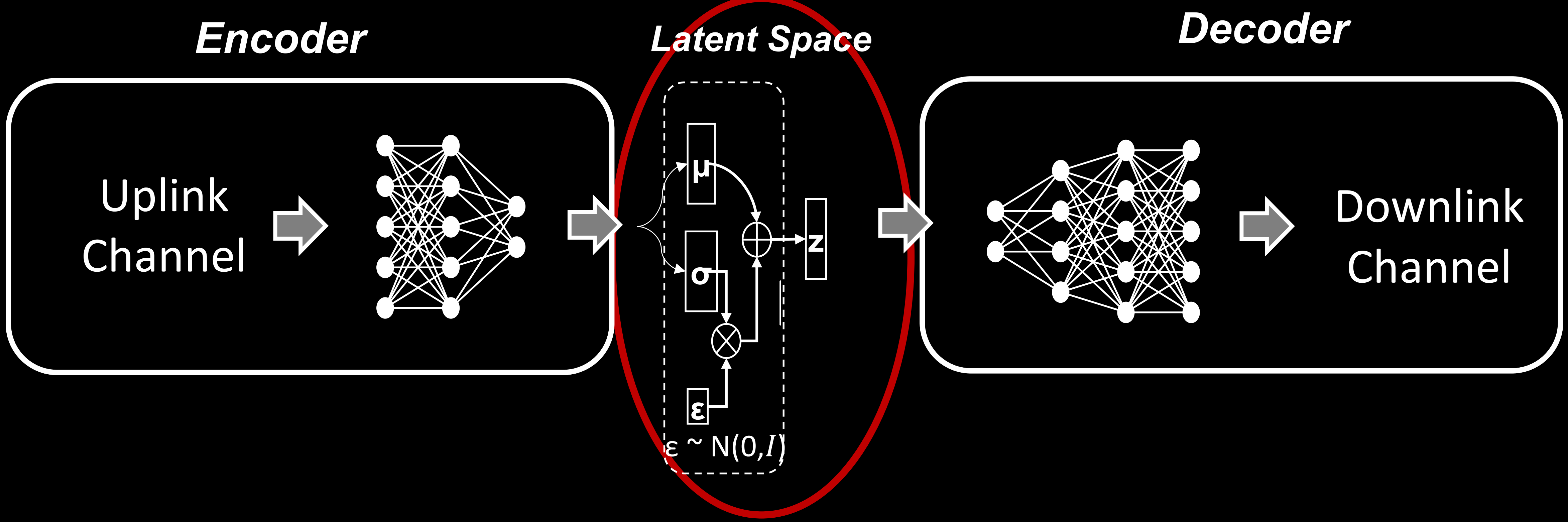
VAE Benefits

- VAEs can accurately model the generative process of creating channels

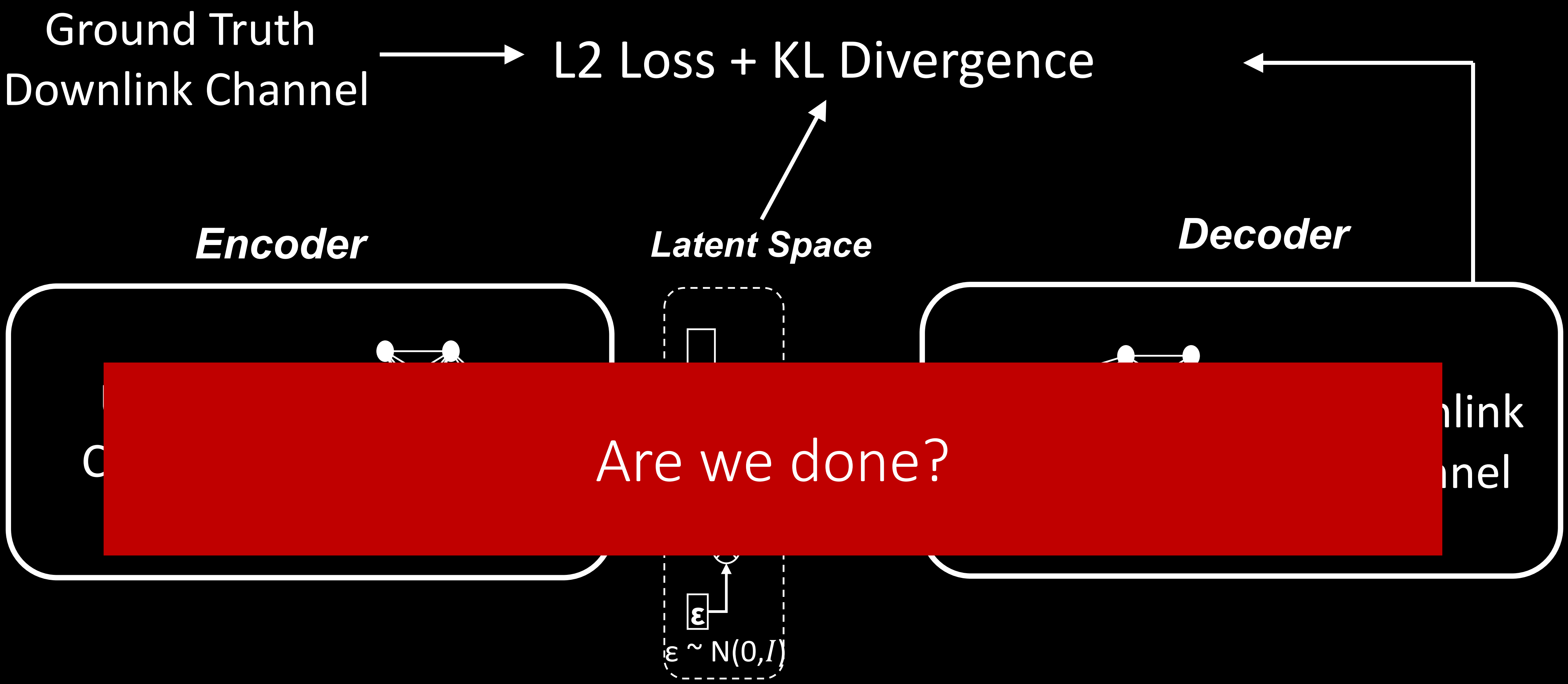


VAE Benefits

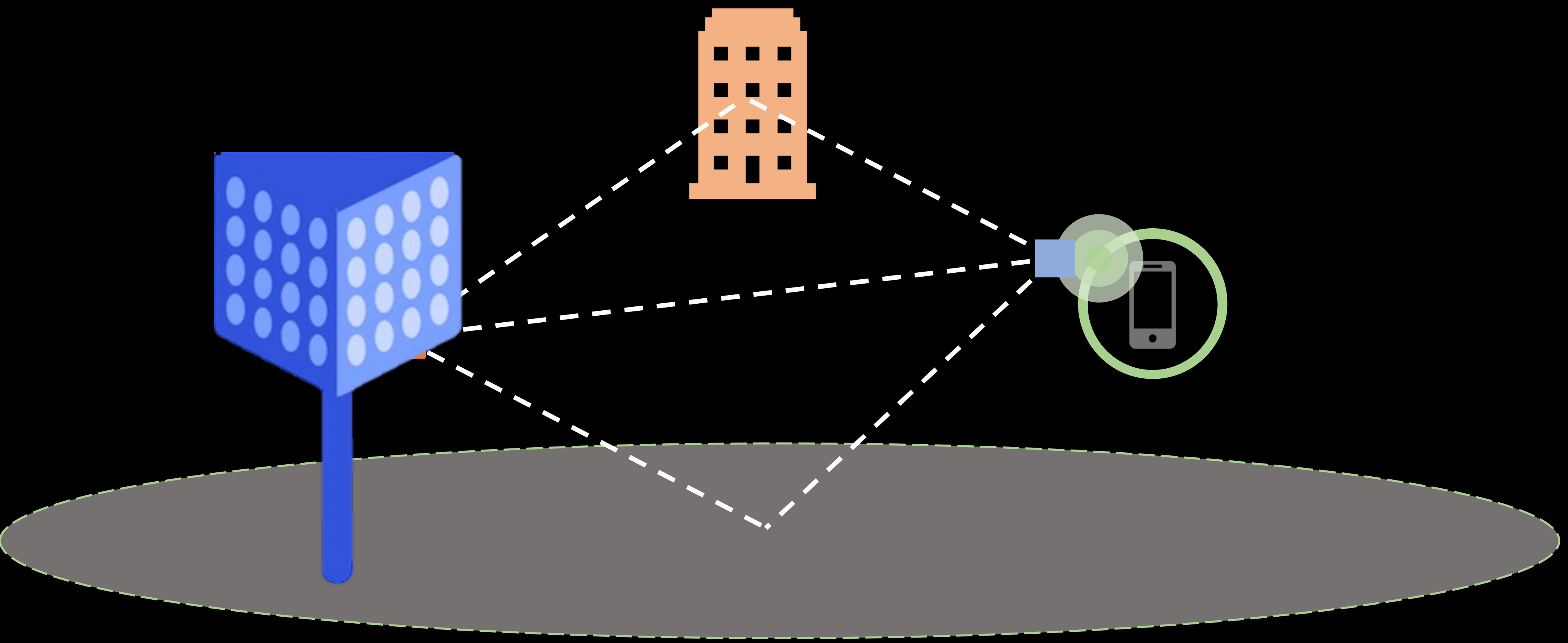
- VAEs can accurately model the generative process of creating channels
- The latent space is usually disentangled -> Interpretability



Network Architecture: Loss Function



Problem: Channel Changes, Even in Static Conditions



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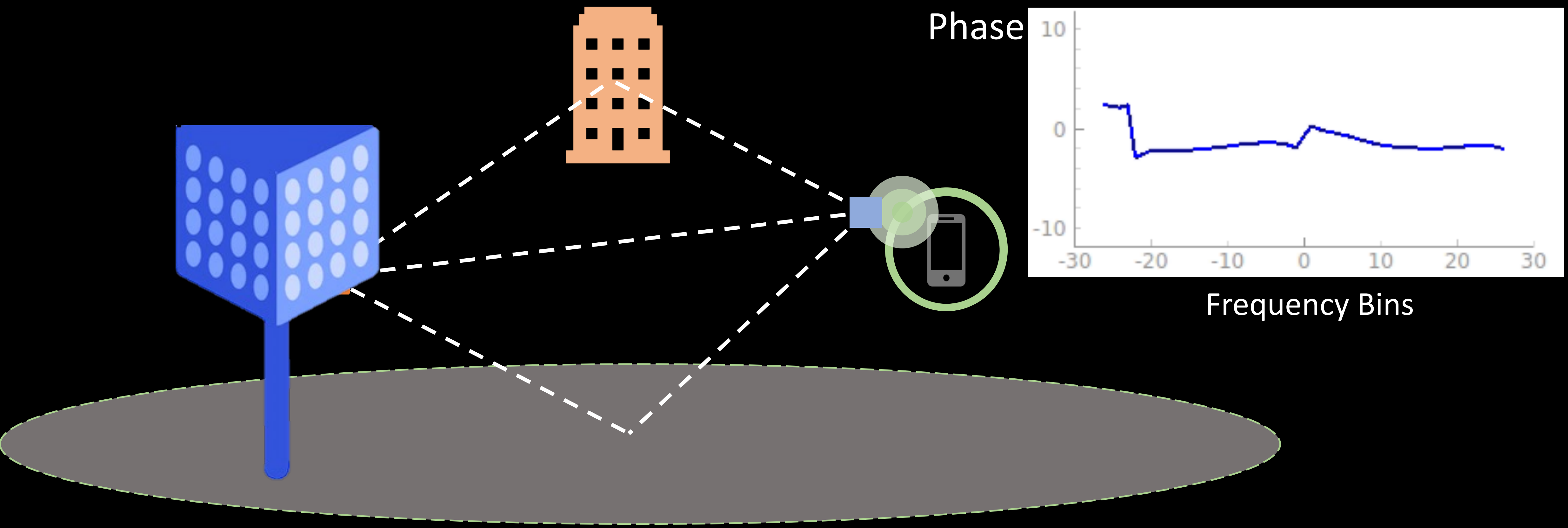
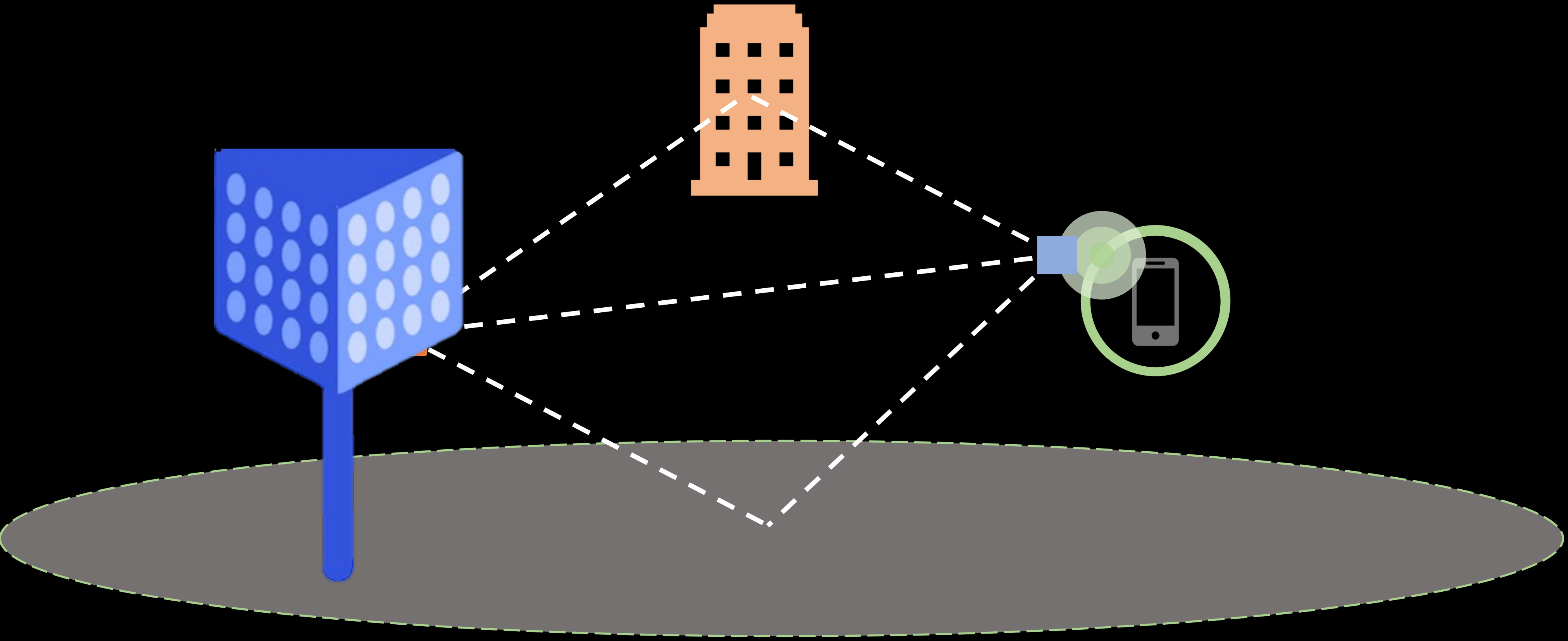


Problem: Channel Changes, Even in Static Conditions

Reason 1: Carrier Frequency Offsets (CFO)



Problem: Channel Changes, Even in Static Conditions

Reason 2: Packet detection delay

Δt

Problem: Impossible to remove these hardware offsets and variations

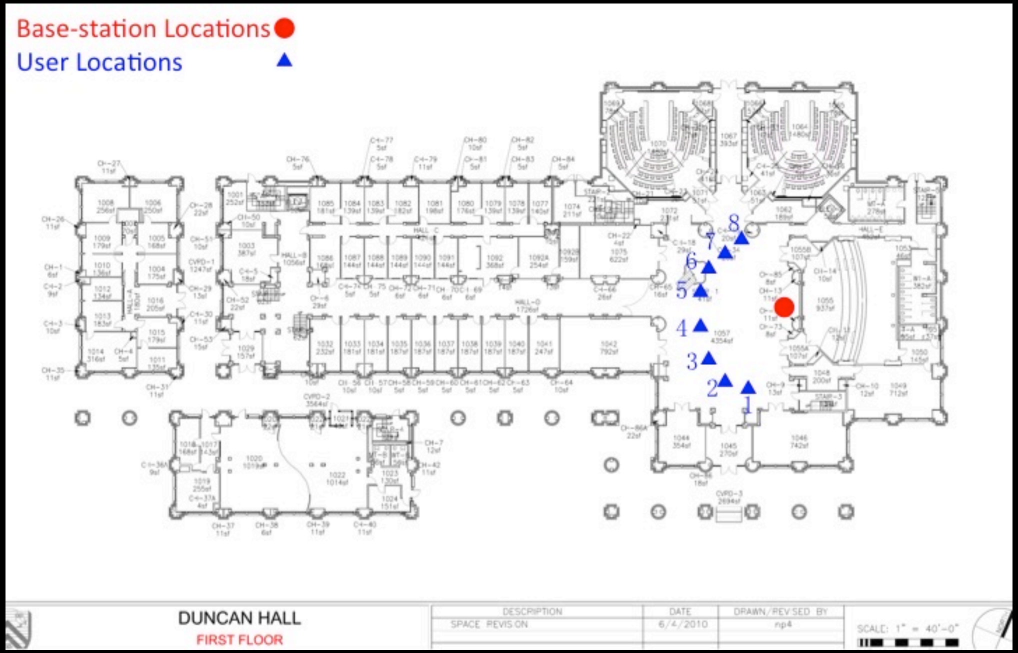
New normalization scheme ensures: One physical configuration -> One channel value

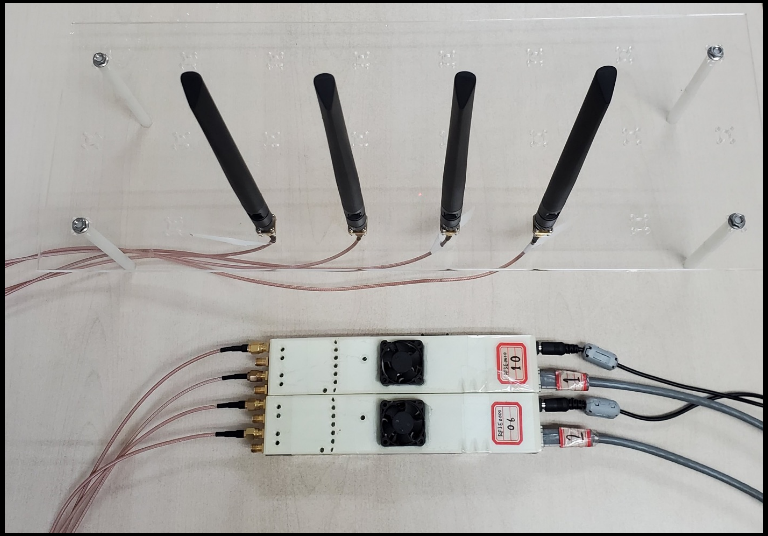
Our work: Zero Channel Feedback

- Problem: What is channel feedback?
- FIRE: End-to-end Machine Learning to remove channel feedback.
- Evaluation using public datasets and our hardware testbed

Evaluation

- Argos Dataset* with up to 64 antennas
- Custom hardware platform using Iris radios

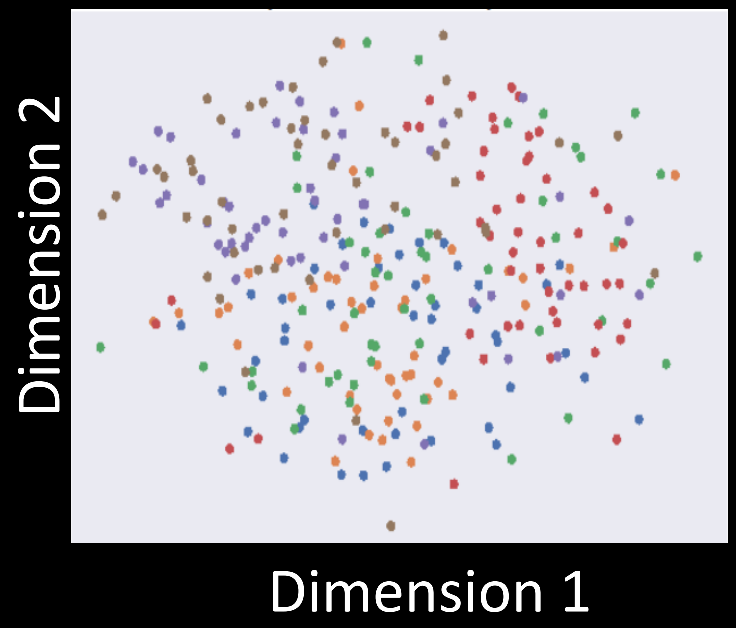




*https://renew.rice.edu/datasets.html

Do we encode physical information?

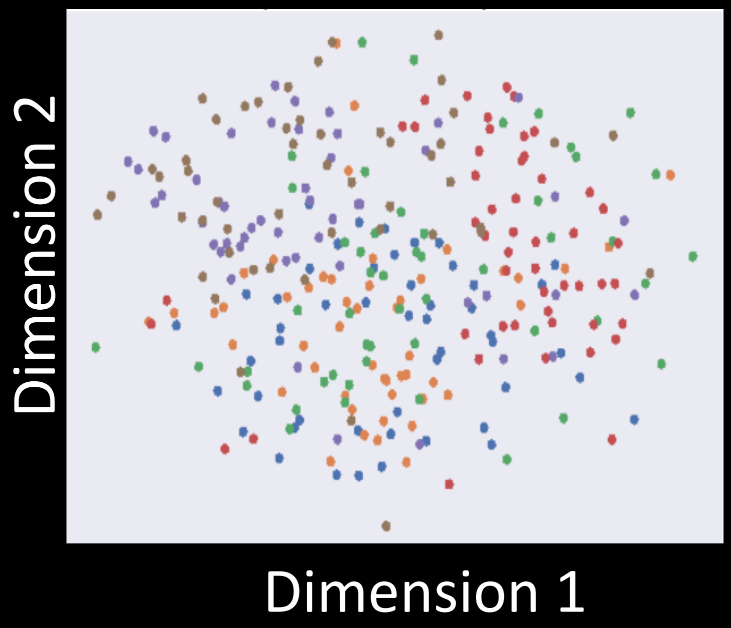
Reduce Channel Matrix Dimension to 2



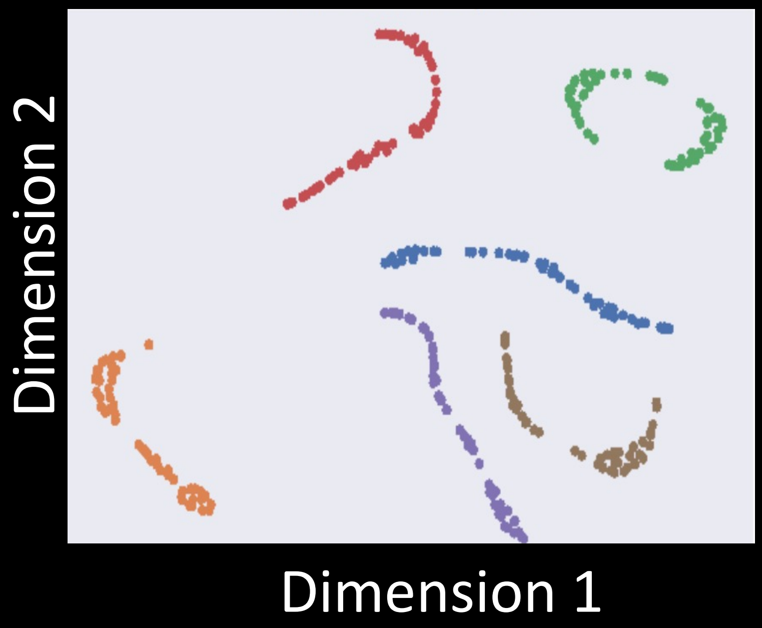
Uplink Channel Space

Do we encode physical information?

Reduce Channel Matrix Dimension to 2



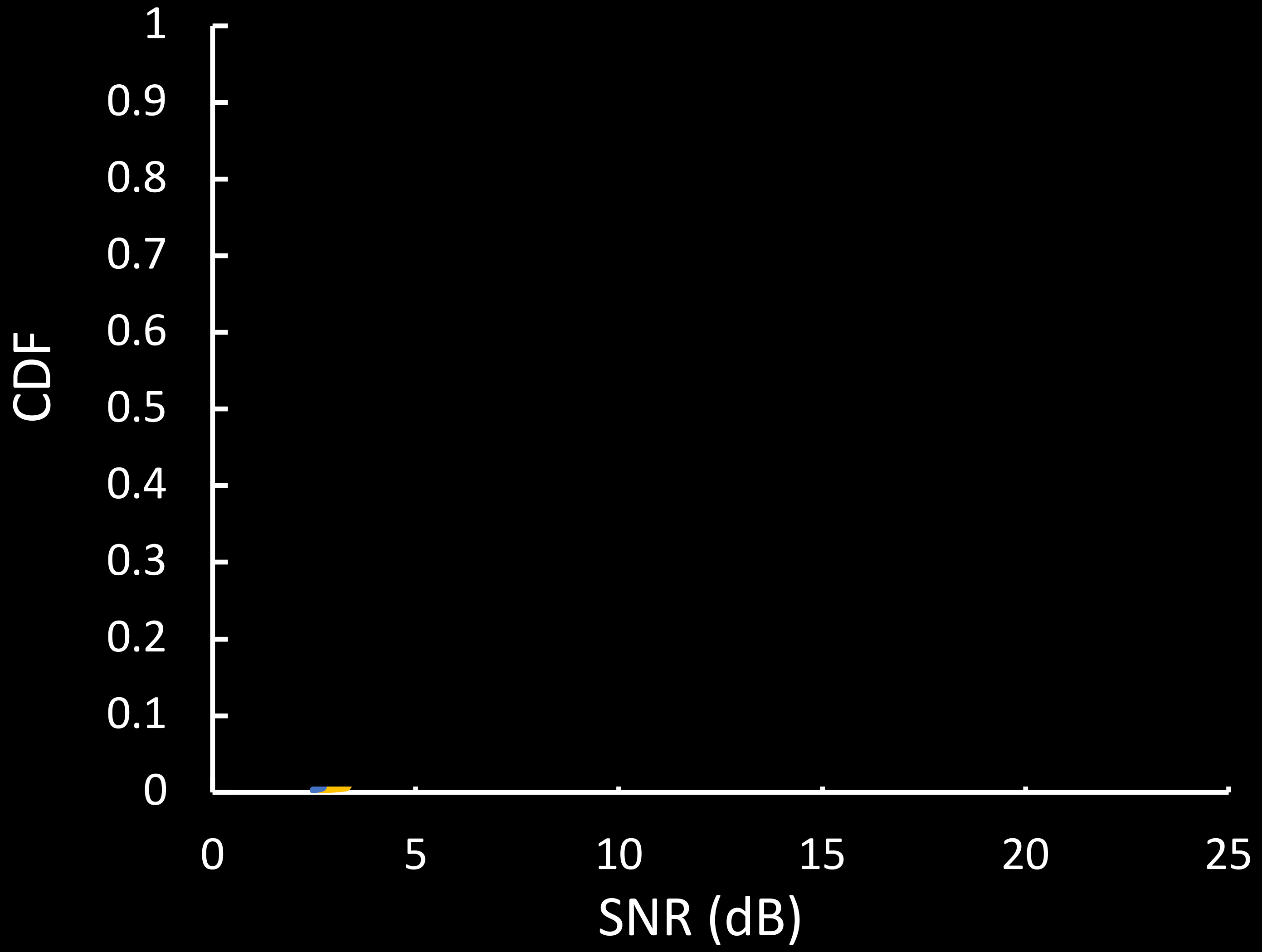
Uplink Channel Space



Latent Space

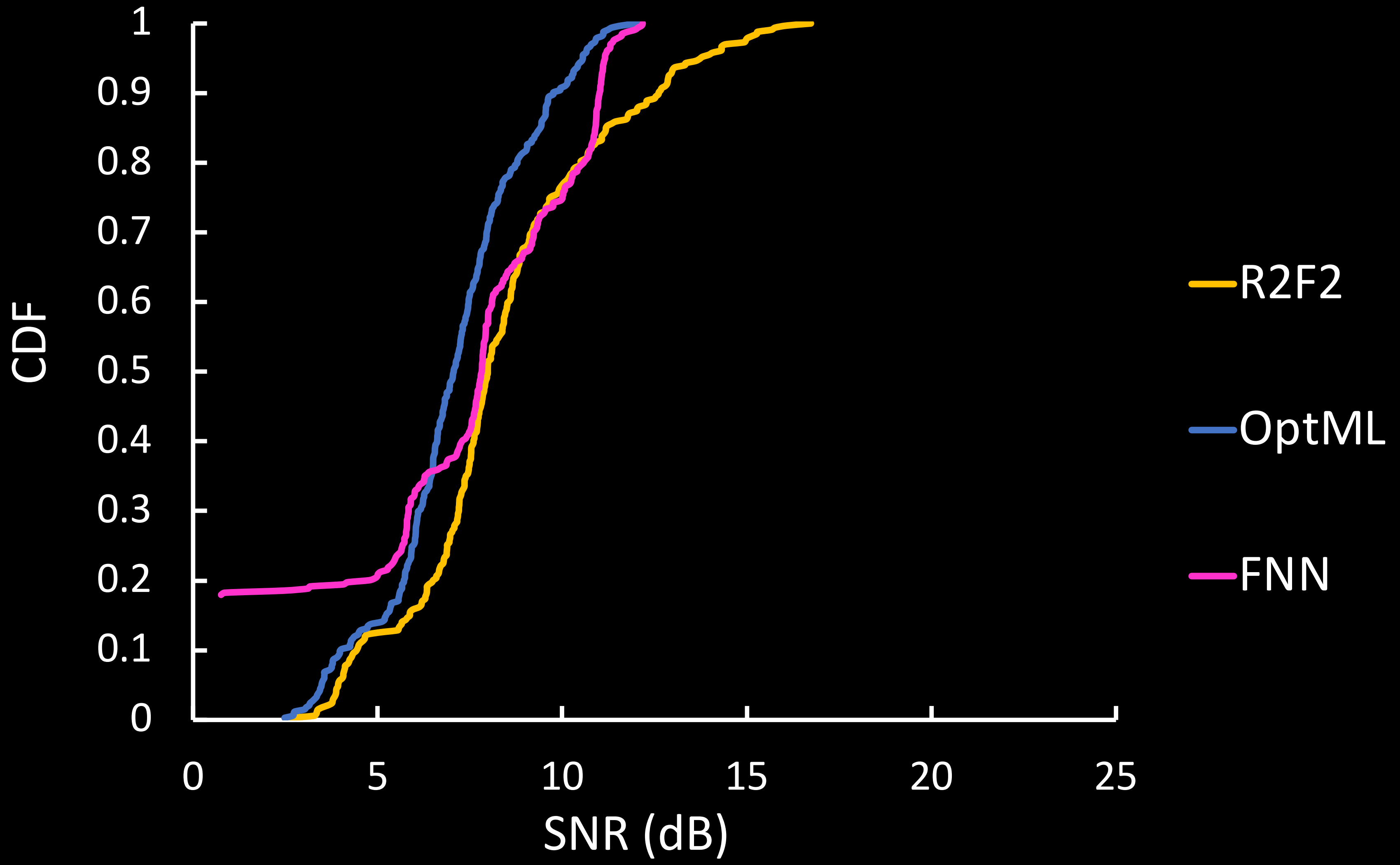
Channel Prediction Accuracy on Hardware Platform

SNR = log(‖H‖ /Prediction error)



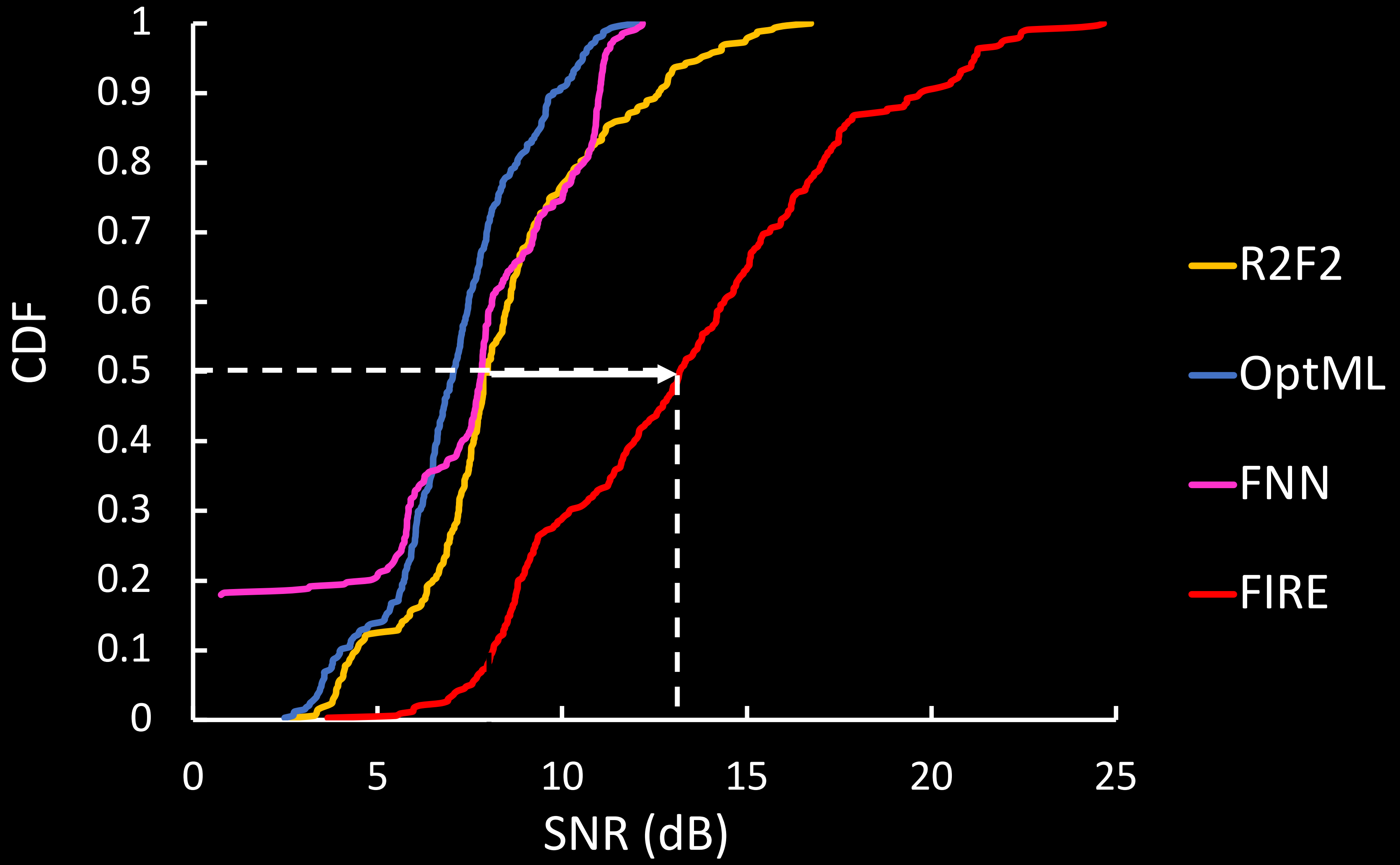
Channel Prediction Accuracy on Hardware Platform

SNR = $\log(\|H\| / \text{Prediction error})$



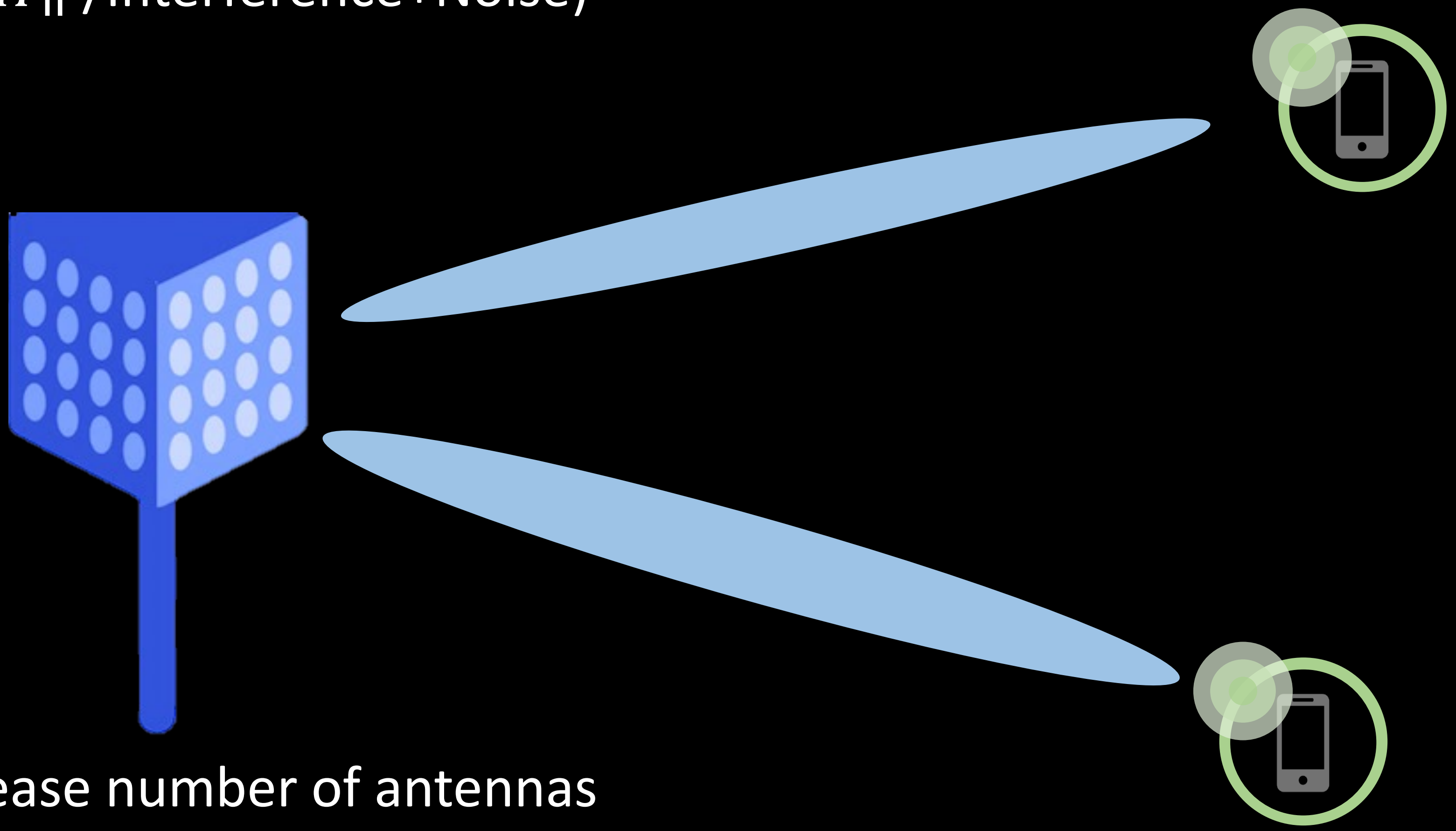
Channel Prediction Accuracy on Hardware Platform

SNR = log($\|H\|$ /Prediction error)



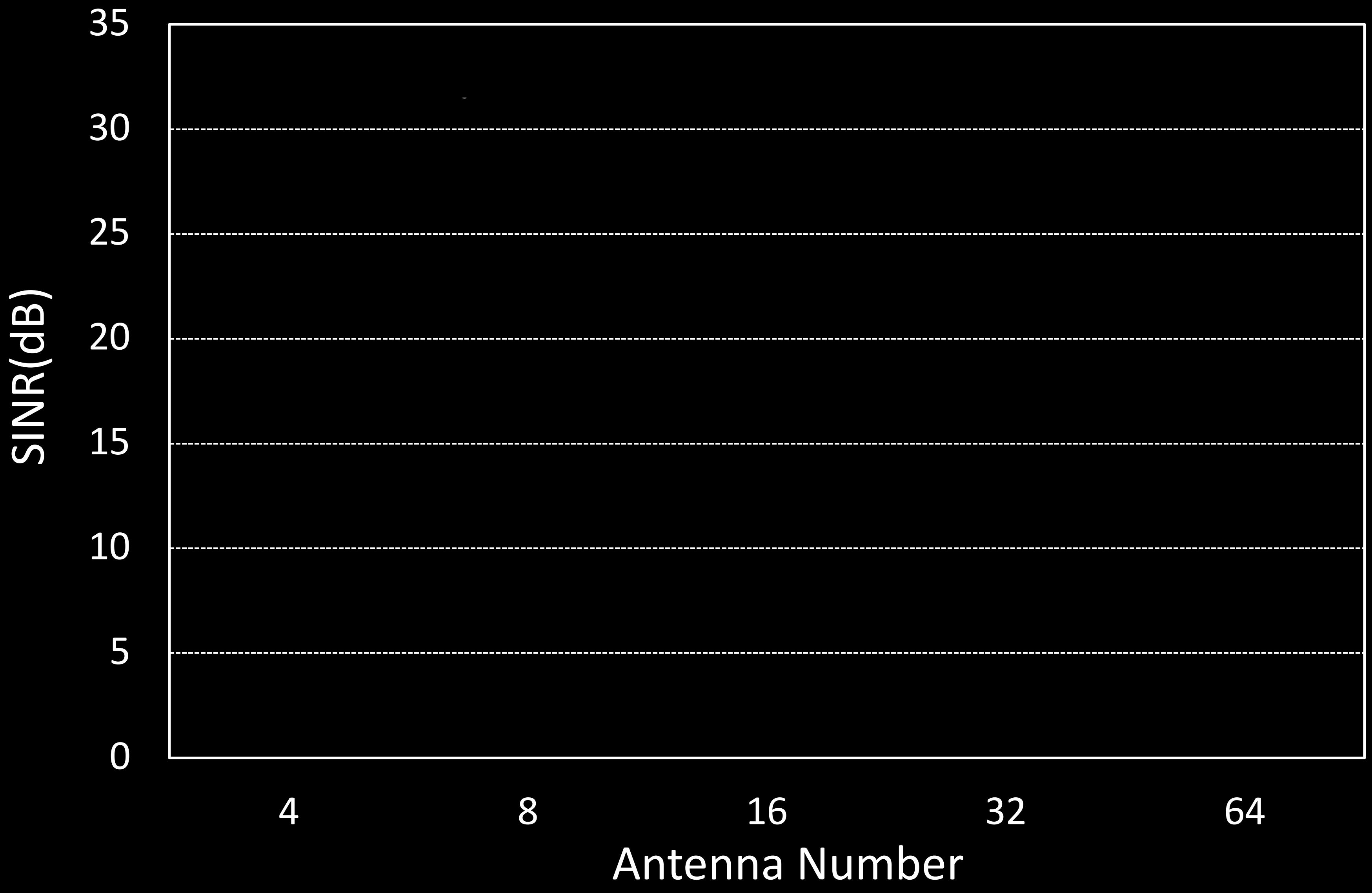
Massive MIMO Results on Argos

SINR = log($\|H\|$ /Interference+Noise)

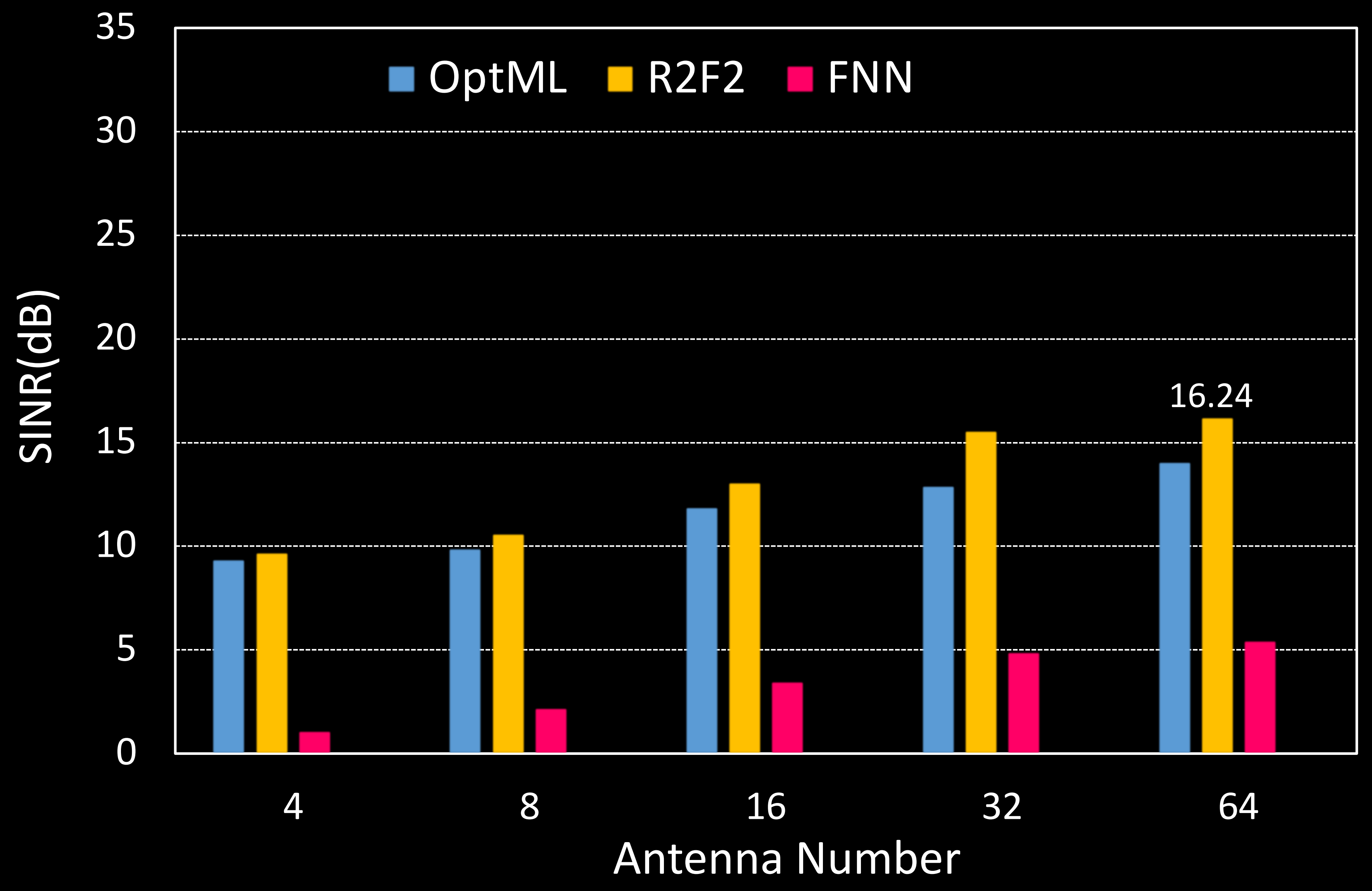


Increase number of antennas

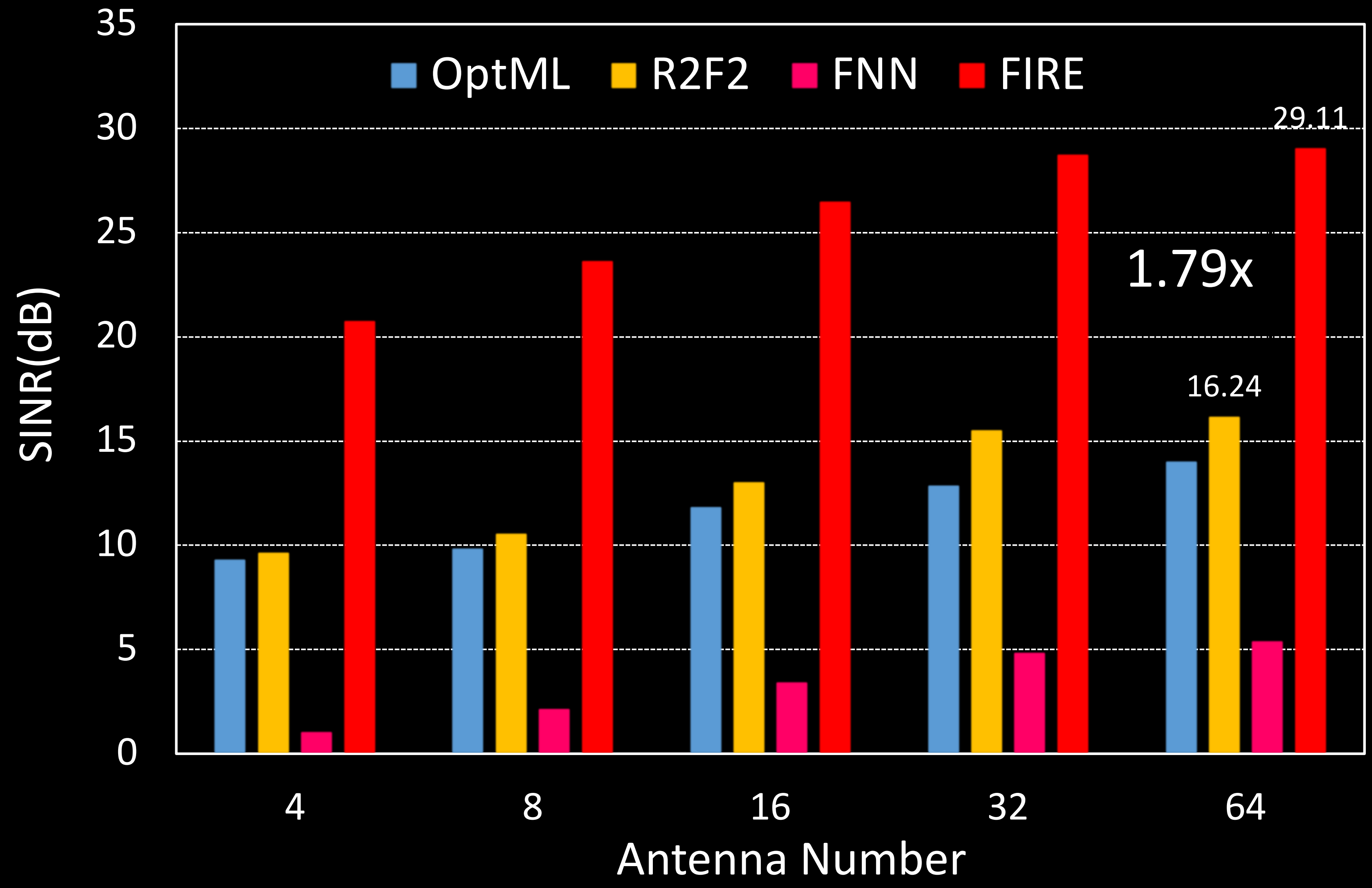
Massive MIMO Results on Argos



Massive MIMO Results on Argos



Massive MIMO Results on Argos



Related Works

- **Downlink Channel Prediction**: R2-F2 (SIGCOMM 2016), OptML (MobiCom 2019), FNN(2016), ICC 2019, IEEE Access 2019, ACSSC 2019, …