Maximising the Utility of Virtually Sliced Millimetre-Wave Backhauls

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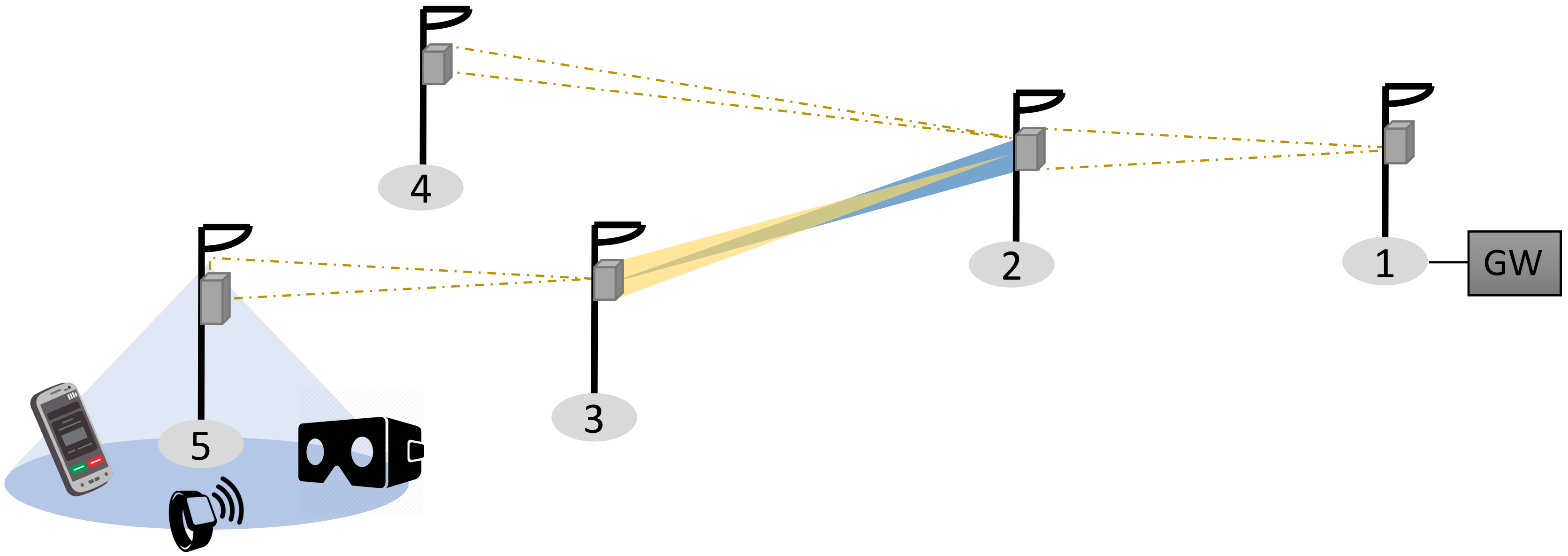
5G Networks

- Use cases with distinct performance requirements
  - Bandwidth: UHD video streaming and AR/VR
  - Delay: Autonomous vehicles and remote medical care

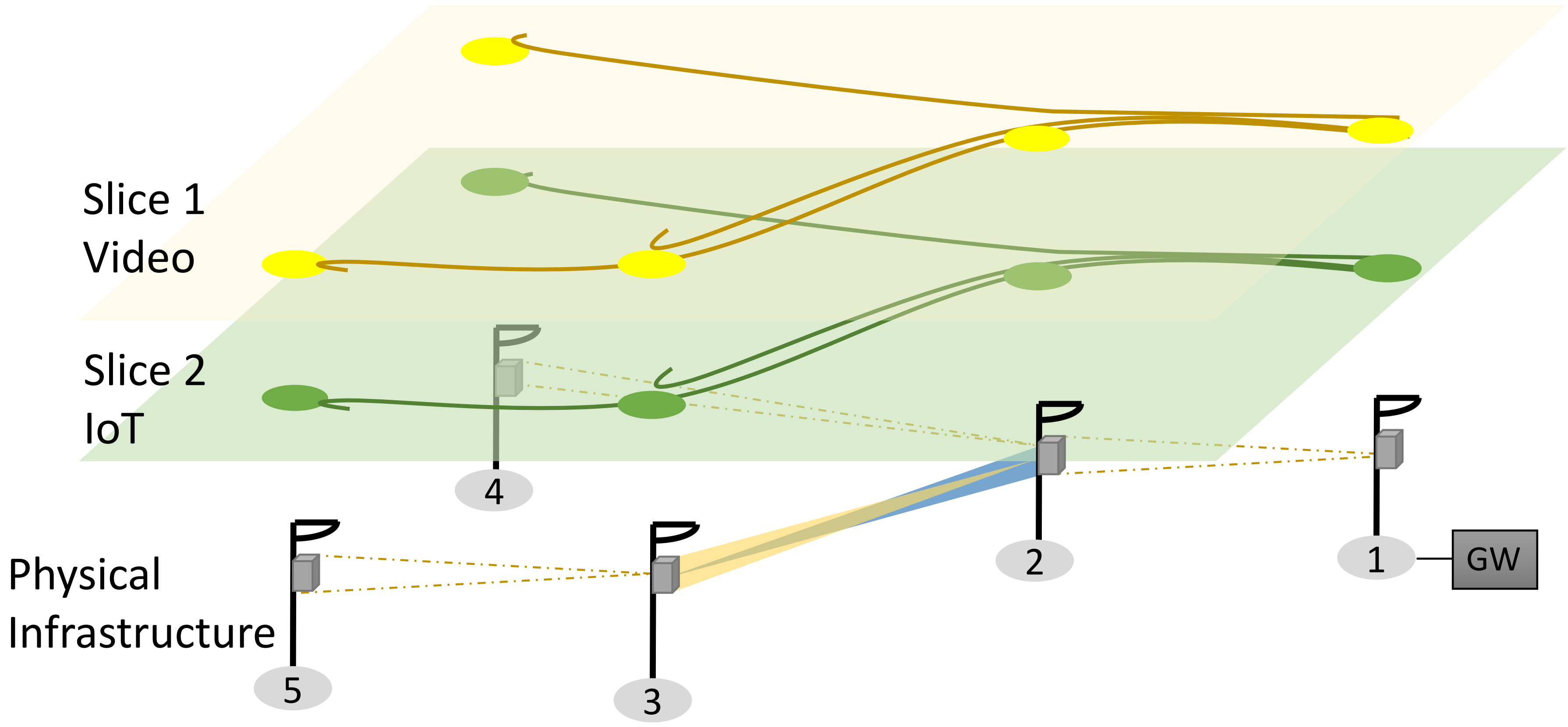
- Network slicing
  - Partition physical infrastructure into logically isolated networks

- Network densification
  - Millimetre-wave (mm-wave) enables multi-Gbps link rates
  - Tangible backhauling solution

Mm-Wave Small Cell Backhaul



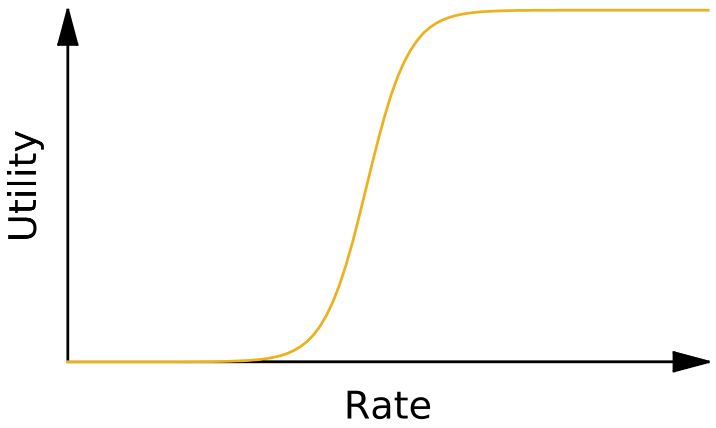
Virtually Sliced Mm-wave Backhaul Network



- Resource Allocation: Rate $r_{i,j}$ for flow $f_{i,j}$
- To meet the service requirements and to maximise resource utilitsation

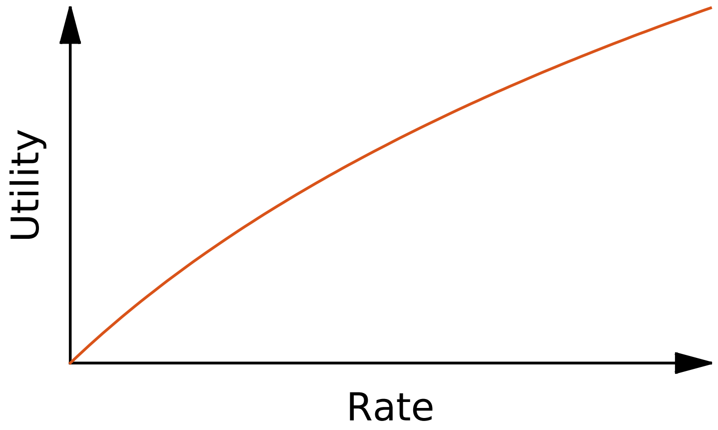
Utility Functions for Different Applications

QoS (AR/VR)



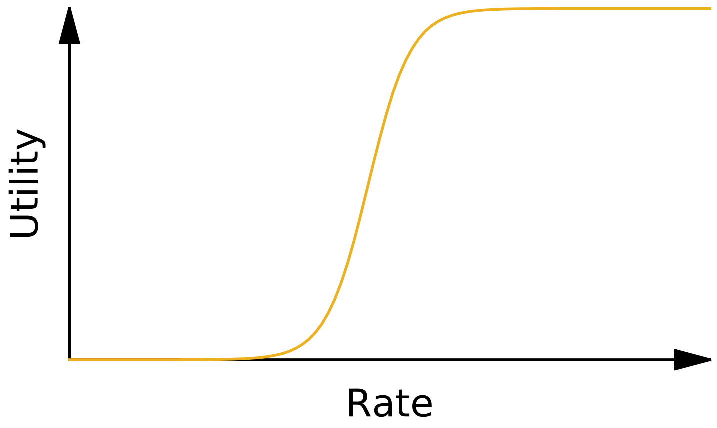
Sigmoid: $U_{sig}(r) = \frac{1}{1+e^{-\alpha_1(r-\beta_1)}}$

Best-effort (IoT)



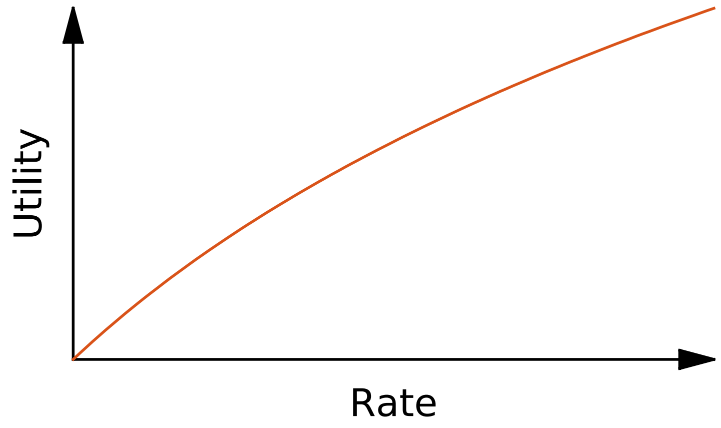
Logarithm $U_{log}(r) = \log(\alpha_2 r + \beta_2)$

QoS (AR/VR)



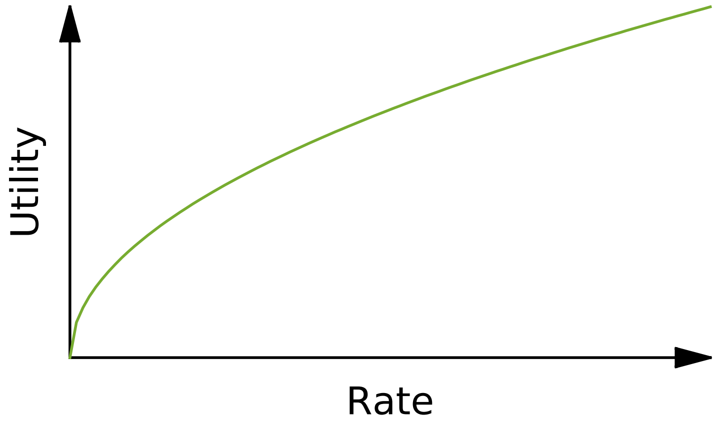
Sigmoid: $U_{sig}(r) = \frac{1}{1+e^{-\alpha_1(r-\beta_1)}}$

Best-effort (IoT)



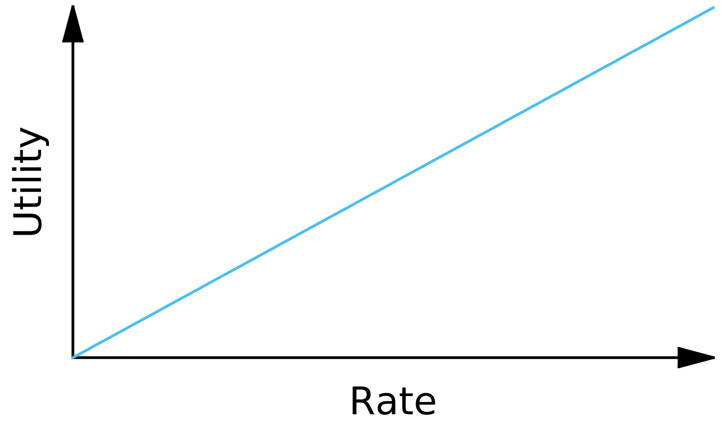
Logarithm $U_{log}(r) = \log(\alpha_2 r + \beta_2)$

Delay sensitive (Tele-Operation)



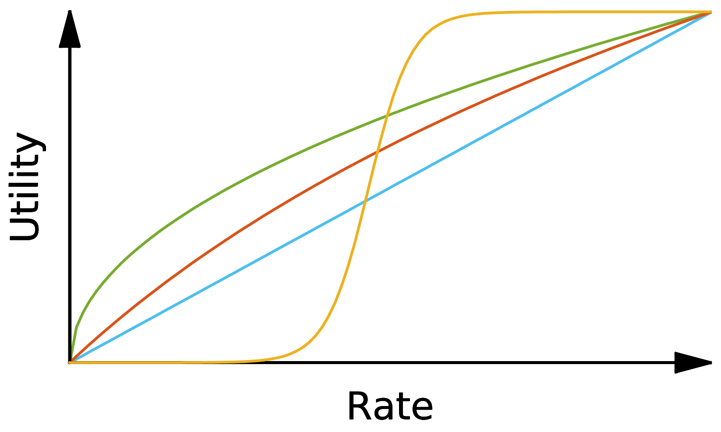
Polynomial: $U_{ply}(r) = \alpha_3(r^{\beta_3})$

Revenue (other)



Linear $U_{lnr}(r) = \alpha_4 r + \beta_4$

Utility Framework



Utility Framework

Sigmoidal: $U_{sig}(r) = \frac{1}{1+e^{-\alpha_1(r-\beta_1)}}$

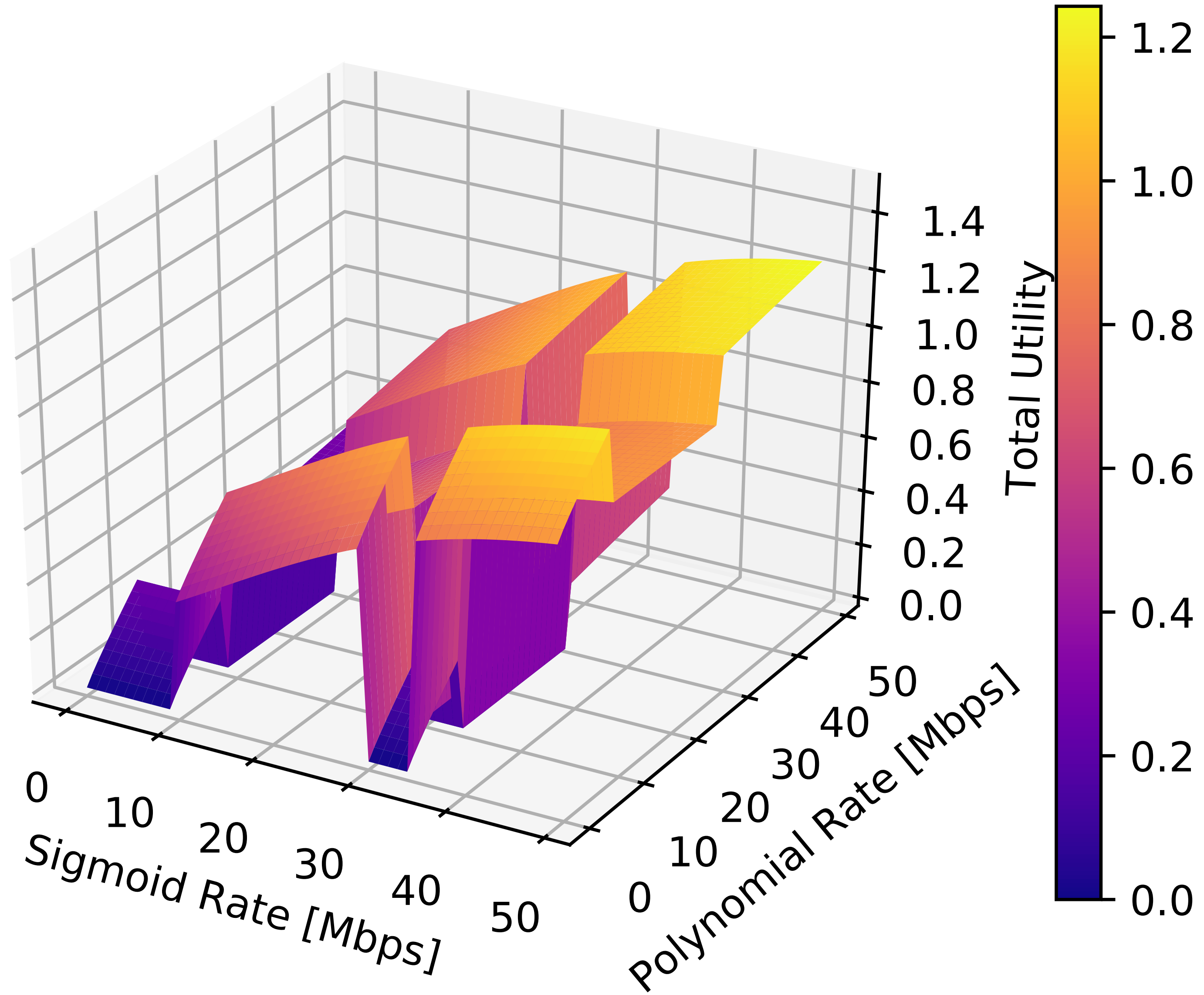
Polynomial: $U_{ply}(r) = \alpha_2(r^{\beta_2})$

Logarithmic: $U_{log}(r) = \log(\alpha_3 r + \beta_3)$

Linear: $U_{lnr}(r) = \alpha_4 r + \beta_4$

$$\left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \max \sum U_i(r_{i,j})$$

Combining these together *in a simple scenario…*

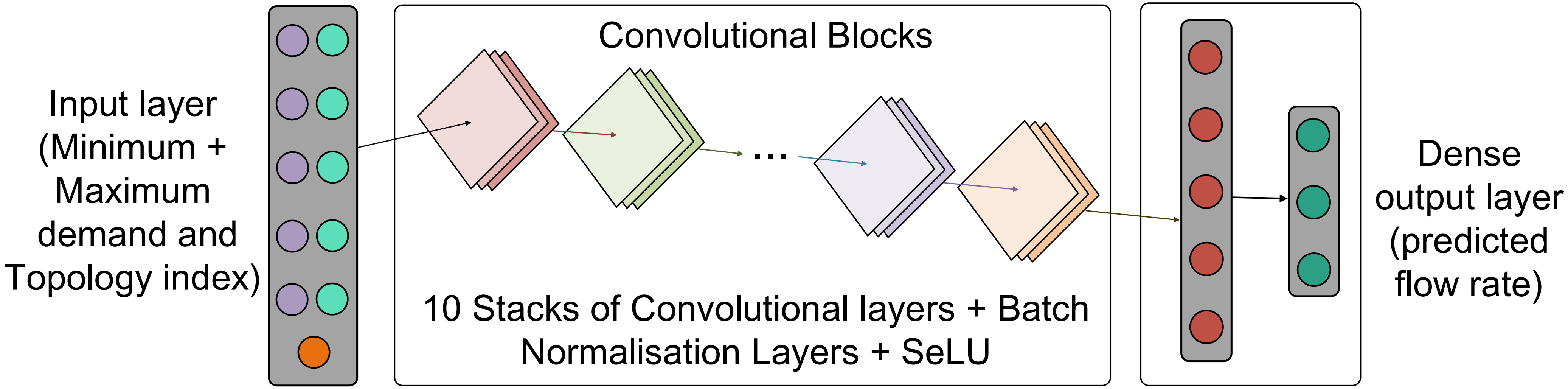


Utility Maximisation

- High-dimensional problem, highly non-convex
- Global search is time consuming
- Heuristic method can solve but sub-optimal

- Learn the correlation between flow demands and optimal allocations

Convolutional Neural Network (CNN) Solution



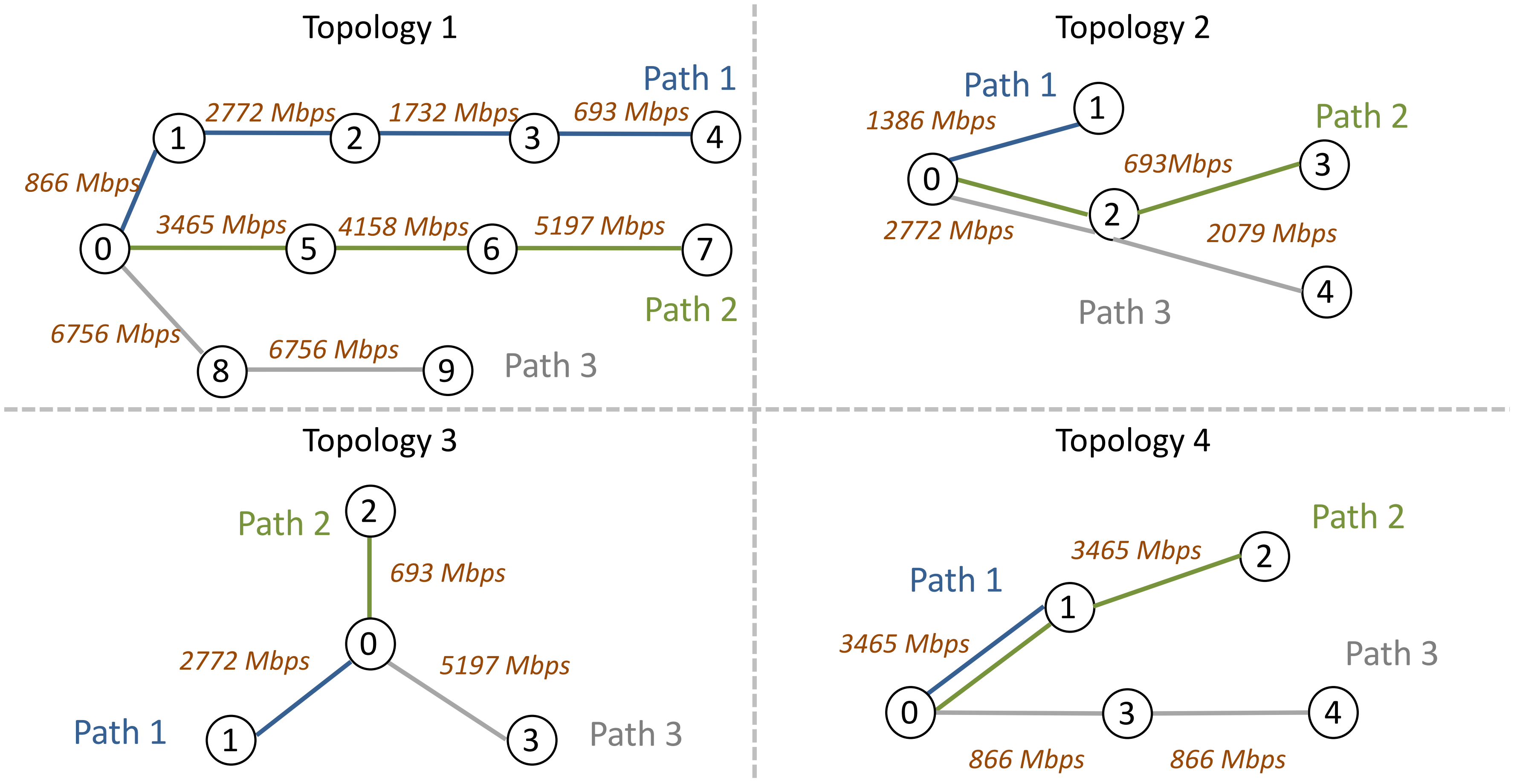
Numerical Evaluation - Methods

- 10,000 data points
  - Flow demands ($\mathrm{d}_{i,j}$) and minimum service rates ($\delta_{i,j}$)
  - Optimal solutions obtained from Global Search (GS) *
  - Training performed on GPU and inference on CPU

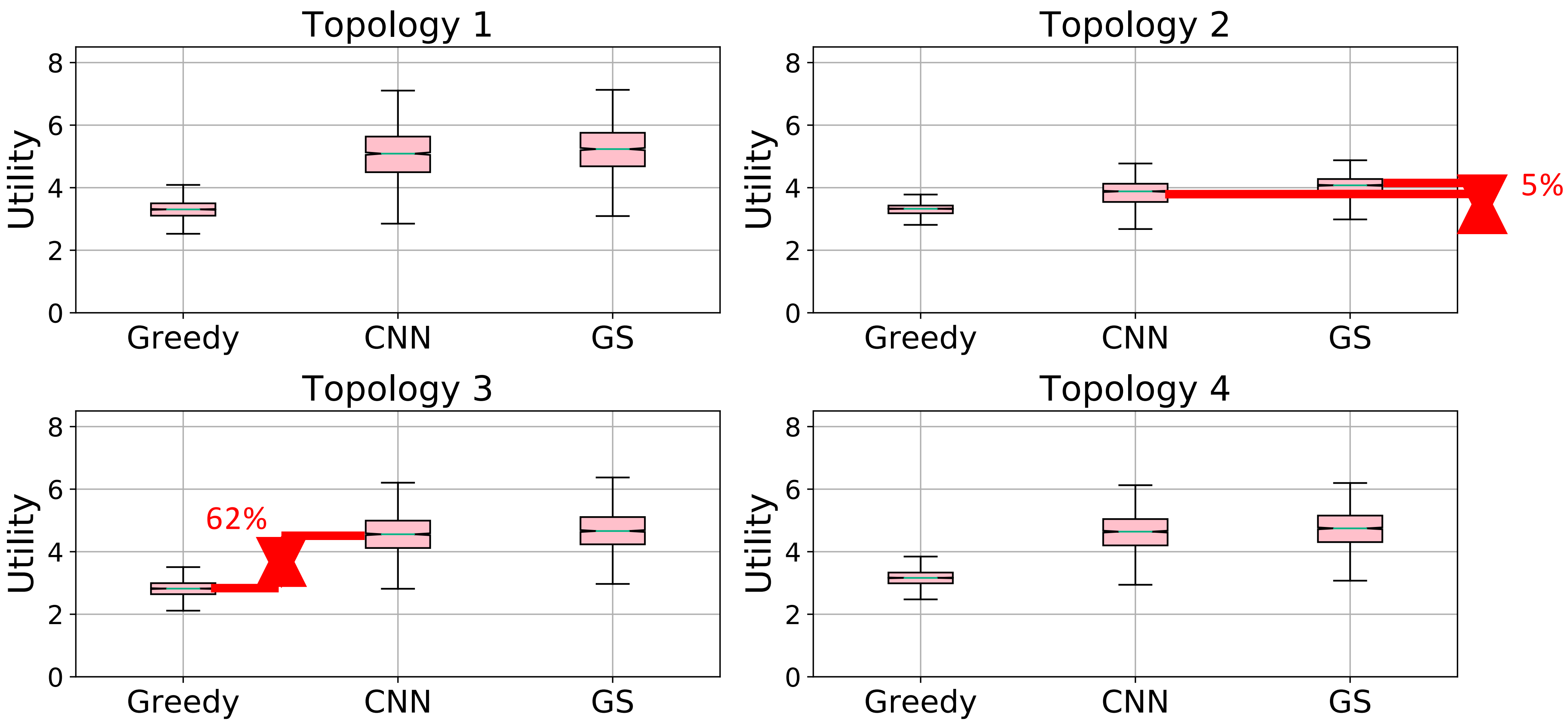
- Benchmark greedy solution
  - Supposed to work fast

* Optimality of GS is proven in Z. Ugray et al. Scatter search and local NLP solvers: *A multistart framework for global optimization*. Journal on Computing, 19(3), 2007.

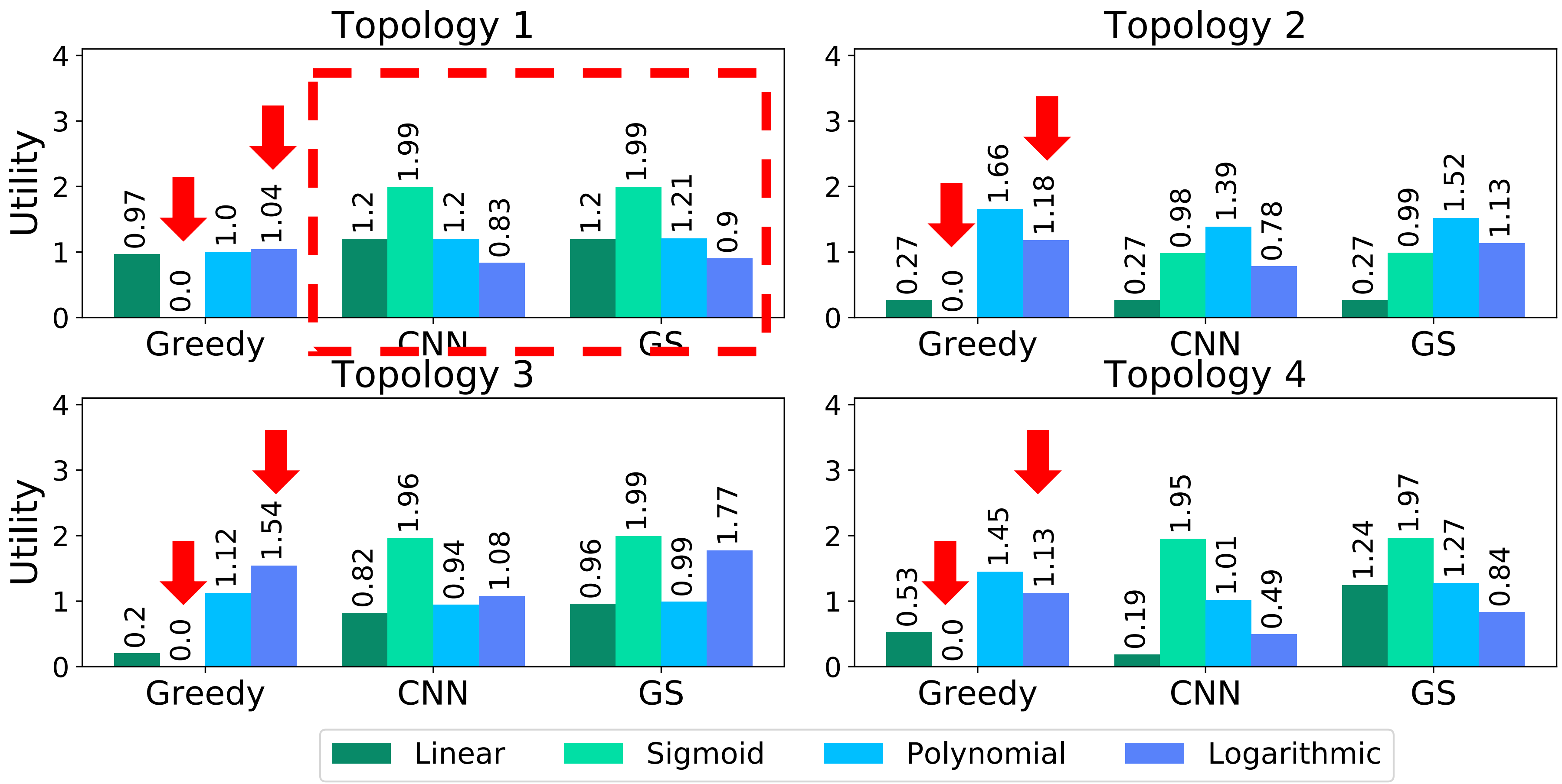
Numerical Evaluation - Topologies



Results: Total Utility Distribution



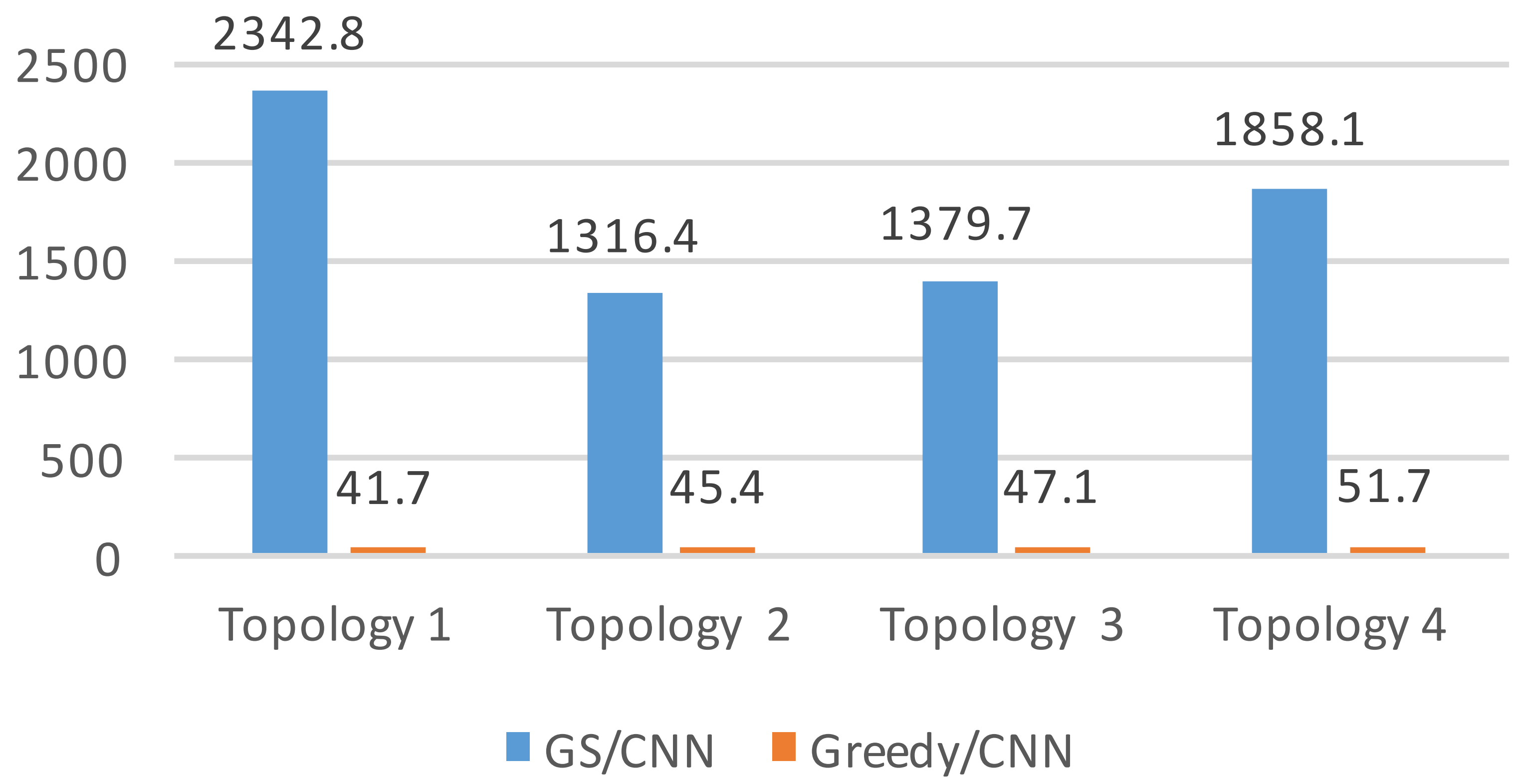
Results: Utility per Traffic Type



Computation Time

2000x faster than GS

50x faster than Greedy



CNN	0.0036s	0.0035s	0.0025s	0.0026s

Conclusions

- A general utility framework encompasses all known types of utility functions, and formulate an utility optimisation problem
- CNN achieves close-to-optimal solution, and makes rapid inference
- Suitable for 5G with real-time and dynamic requirements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তোমাকে ধন্যবাদ
감사합니다
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