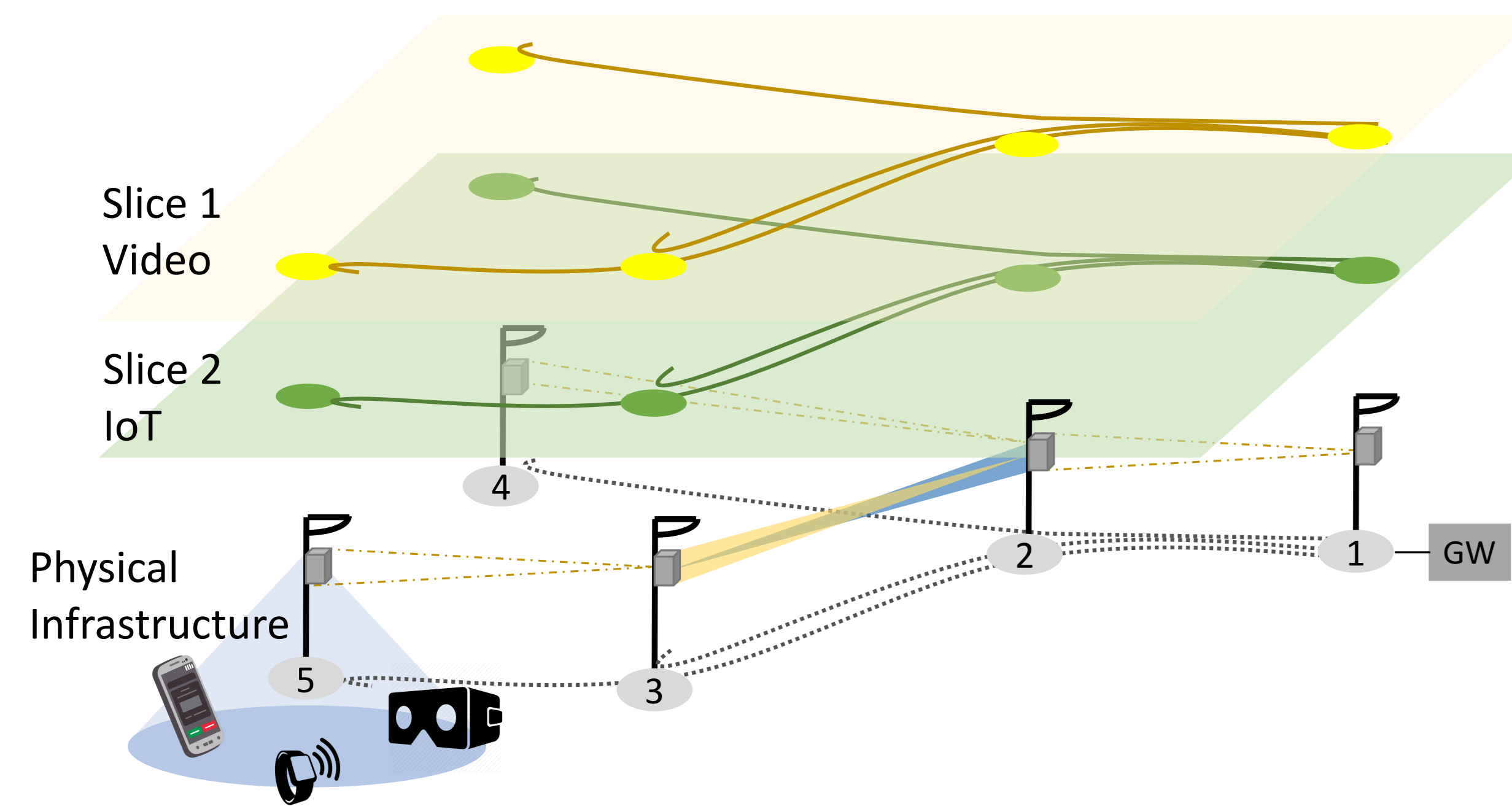


# A Deep Learning Approach to Maximising the Utility of 5G Backhaul Networks

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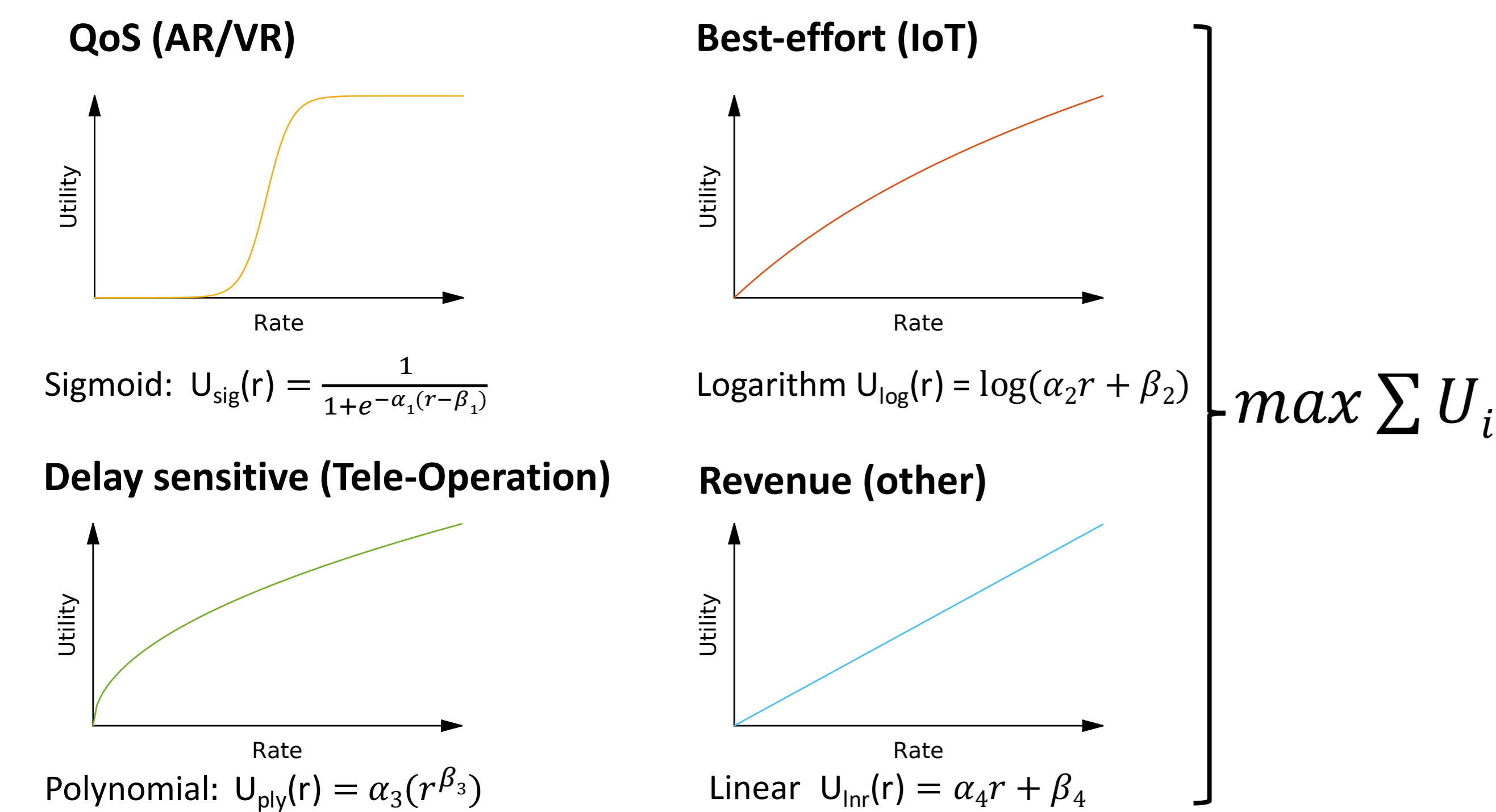
## 5G Networks

- Ramified use cases and distinct performance requirements
- Network virtualisation and densification
- Millimetre-wave (mm-wave) technologies
- ❖ Multi-Gbps link rates -> Tangible backhauling solution



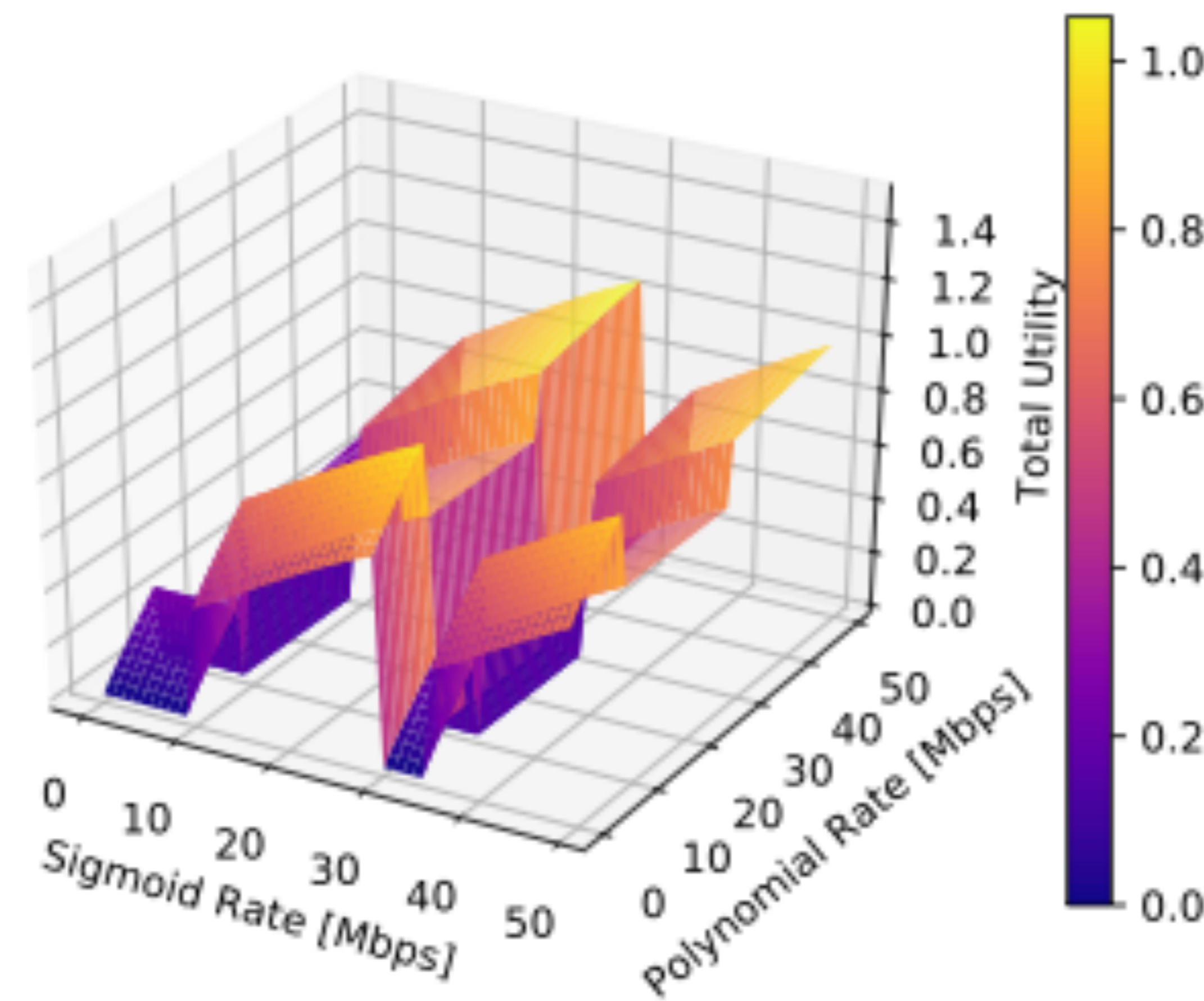
## Utility Framework

- Application scenarios -> utility functions
- Combing all known types of utility functions



## Finding the Optimal Rate Allocation

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

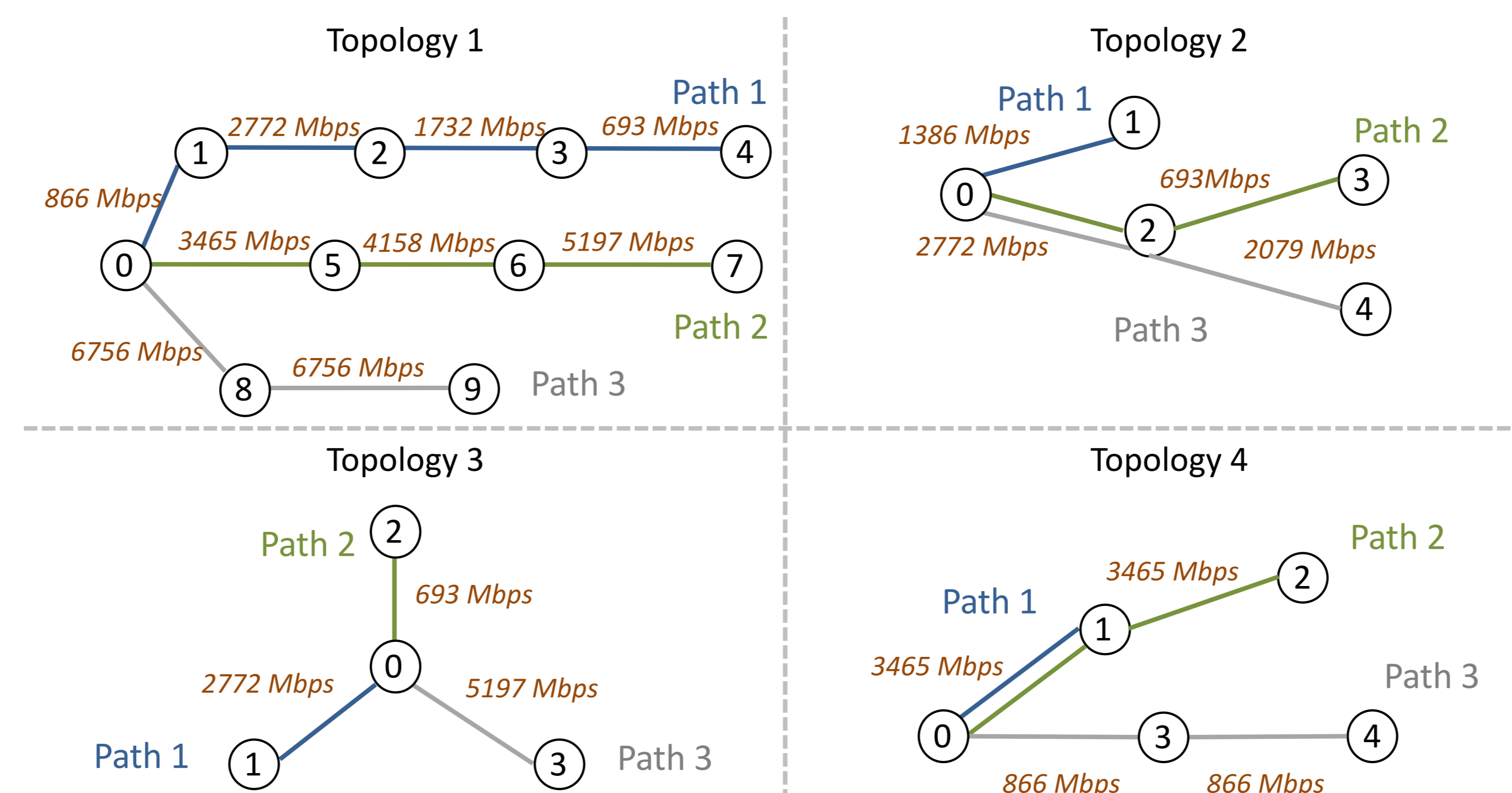


## The Deep Learning Approach

- Supervised learning with convolutional neural network (CNN)
  - ❖ 10 stacks of convolutional layers + batch normalisation + SeLU
  - ❖ Input: Flow demands ( $d_{i,j}$ ) and minimum service rates ( $\delta_{i,j}$ )
  - ❖ Output: Predicted flow rate ( $r_{i,j}$ )

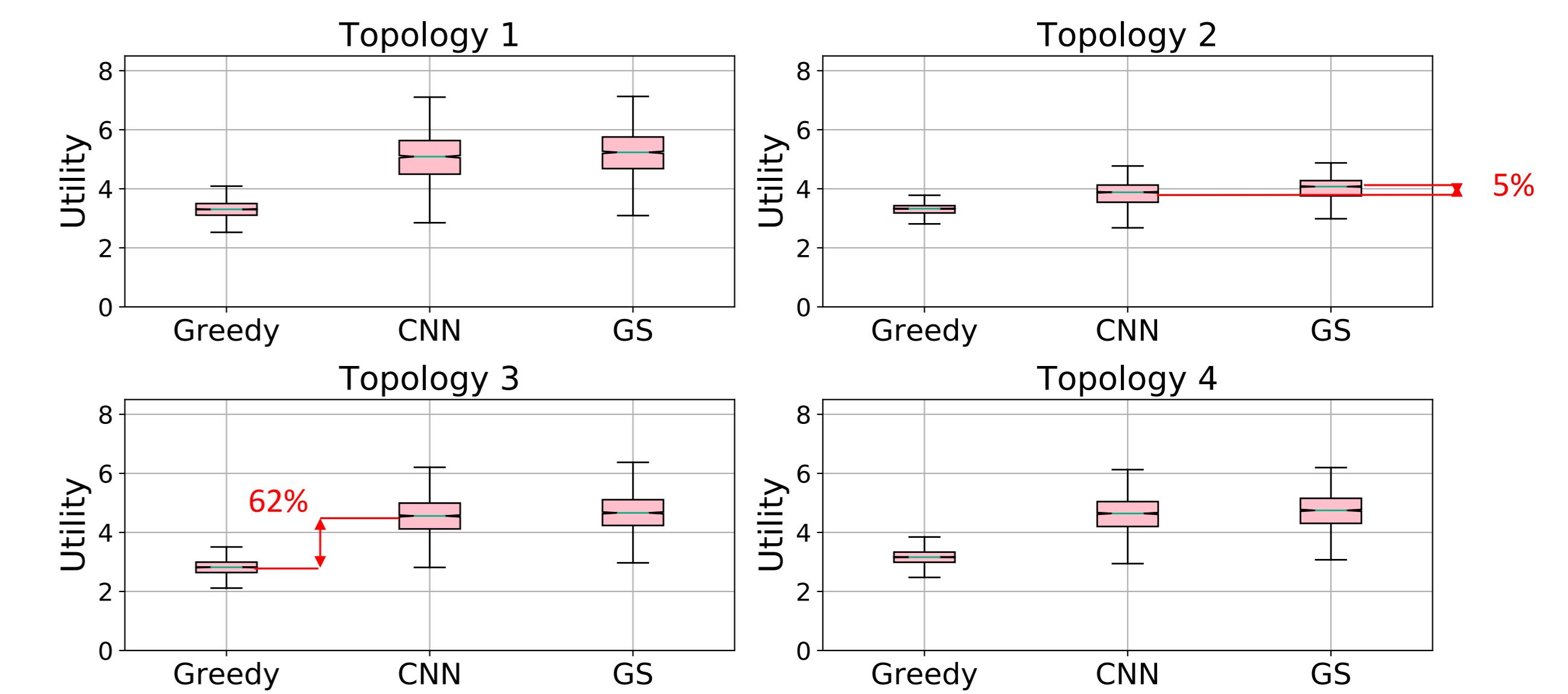
## Numerical Analysis

- 10,000 data points  $\{d_{i,j}, \delta_{i,j}, r_{i,j}\}$ 
  - ❖ Optimal solutions obtained from Global Search (GS)\*
  - ❖ Benchmark: Light-weight greedy solution



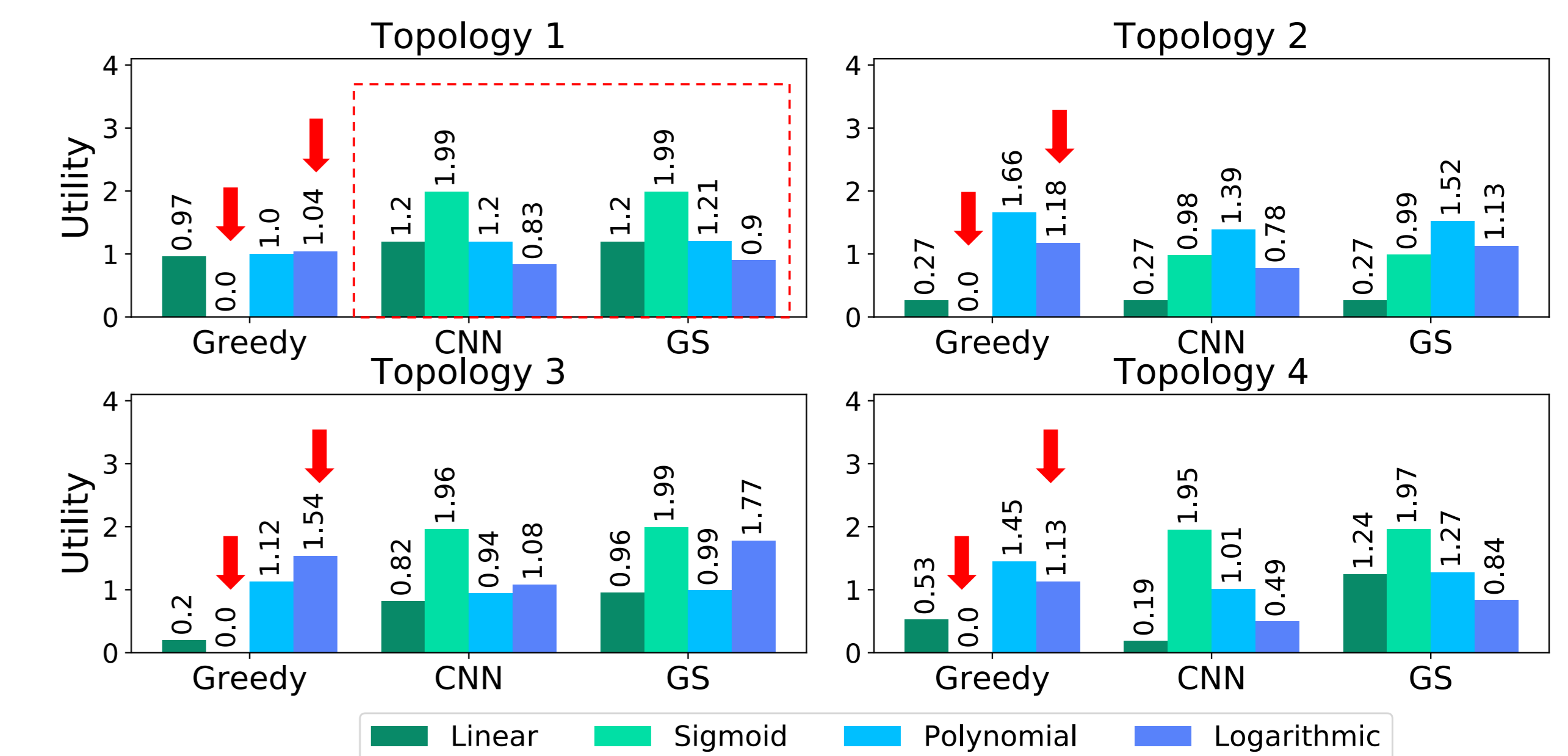
## Performance

- Total network utility distributions over 2k instances



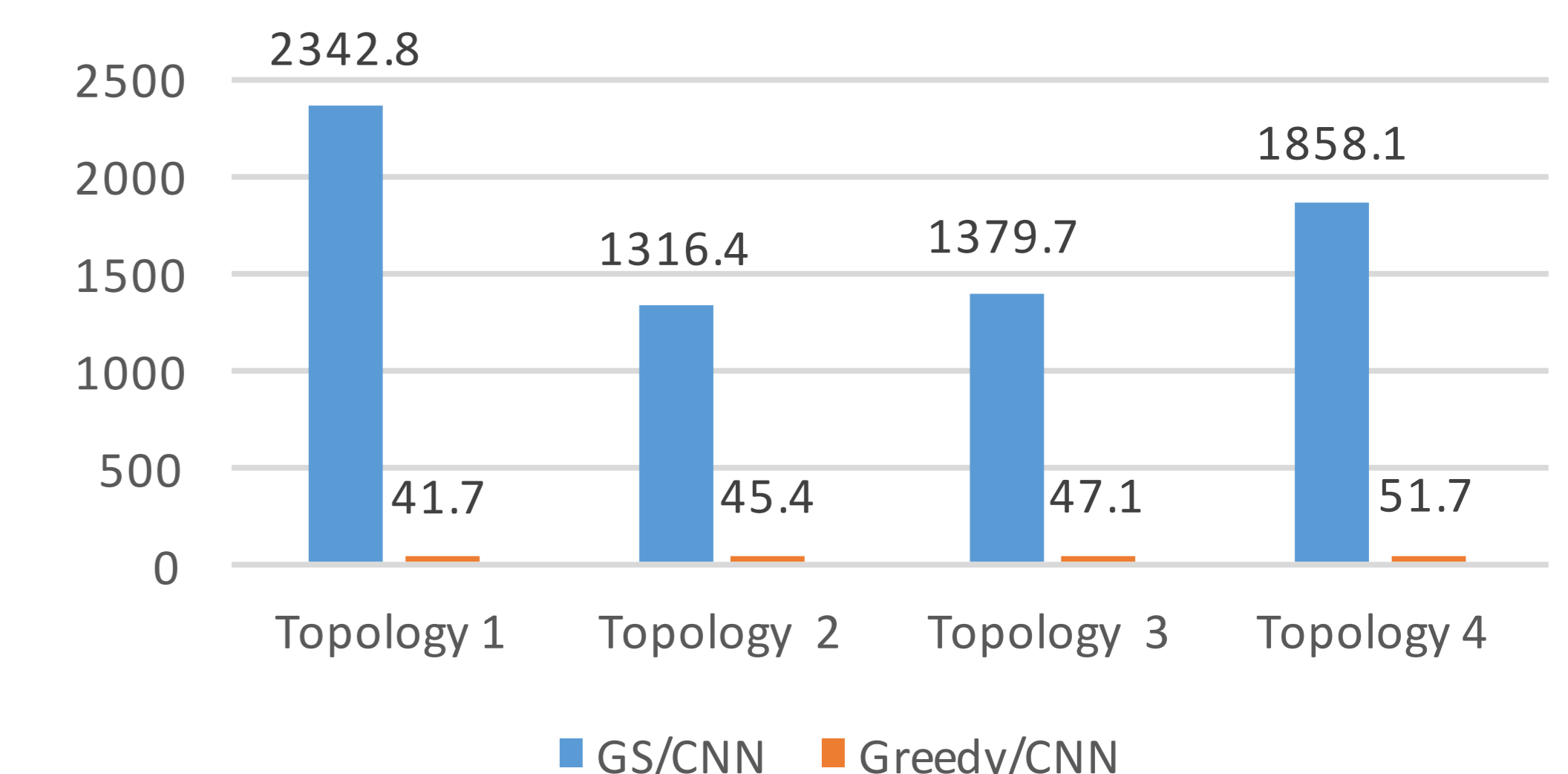
- ❖ CNN: close to optimal in terms of median, quartiles, etc.
- ❖ Achieves up to 62% total utility gain over greedy

- Per type utility allocation in a single instance



- ❖ CNN attains close to optimal allocations
- ❖ Greedy tends to starve Sigmoidal utilities

- Computation Time



- ❖ 2000x faster than GS
- ❖ 50x faster than Greedy