Network Slice Optimization in 5G

Harshit Soni (202211027) Hridyansh Sharma (202211029)
Shreyas Makwana (202211046) Daksh Mehta (202211049)

Computer Science Department

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Outline

What is Network Slicing?

- Definition: Logical partitioning of 5G network to serve diverse services.
- Motivation: Ensure QoS, scalability, and efficient resource utilization.
- Use cases:
  - eMBB (Enhanced Mobile Broadband)
  - URLLC (Ultra-Reliable Low Latency Communications)
  - mMTC (Massive Machine Type Communications)

Importance of Optimization

- Challenges:
  - Dynamic traffic patterns
  - Heterogeneous service requirements
  - Resource allocation conflicts
- Goal: Maximize throughput, minimize latency, balance resource loads
- Approach: Machine learning-based predictive models

Methodology

Our approach consists of three key steps:

1. Create Synthetic Data
   - Generate network slice parameters
   - Simulate traffic patterns
2. Preprocess Data
   - Feature scaling and normalization
   - Prepare for CNN input
3. Define and Train CNN Model
   - Design neural network architecture
   - Train and evaluate performance

Synthetic Data Generation

- Network slice parameters:
  - Bandwidth requirement (Mbps)
  - Latency sensitivity (ms)
  - User density (users/km^2)
  - Mobility pattern
- Slice types:
  - eMBB: High bandwidth (100-1000 Mbps), moderate latency (30-100 ms)
  - URLLC: Moderate bandwidth (10-100 Mbps), ultra-low latency (1-10 ms)
  - mMTC: Low bandwidth (1-10 Mbps), relaxed latency (50-200 ms)
- Dataset size: 10,000 samples with balanced class distribution

CNN Model Architecture

- Input layer: Time series data (timesteps $\times$ features)
- Convolutional layers:
  - First layer: 32 filters, kernel size 3
  - Second layer: 64 filters, kernel size 3
  - Activation: ReLU
- Pooling layers: Max pooling with size 2
- Fully connected layers:
  - 128 neurons with ReLU activation
  - Dropout layer (50%) for regularization
- Output: 3 neurons with softmax activation (eMBB, URLLC, mMTC)

Model Training

- Model configuration:
  - Optimizer: Adam (adaptive learning rate)
  - Loss function: Categorical cross-entropy
  - Evaluation metric: Accuracy
- Training parameters:
  - Epochs: 50 (with early stopping)
  - Batch size: 32
  - Train/validation split: 80/20%
- Regularization techniques:
  - Dropout layers
  - Early stopping to prevent overfitting

Results and Analysis

- Performance metrics:
  - Training accuracy: 95.2%
  - Validation accuracy: 93.8%
  - Test accuracy: 94.1%
- Key findings:
  - Model successfully identifies appropriate slice types
  - High precision for all slice categories
  - Bandwidth is the most predictive feature
  - Quick convergence (23 epochs)
- Real-world implications: Enables automatic resource allocation and QoS optimization

Conclusion and Future Work

- Conclusion:
  - CNN approach achieves high accuracy for network slice classification
  - Framework enables automated slice optimization
  - Method works well on synthetic data
- Future work:
  - Apply to real network traffic datasets
  - Explore RNNs and Transformers for temporal patterns
  - Incorporate reinforcement learning for dynamic slice management
  - Develop edge-deployable lightweight models

References

M. Rost et al., "Network slicing to enable scalability and flexibility in 5G mobile networks," IEEE Communications Magazine, vol. 55, no. 5, pp. 72-79, 2017.

Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015.

3GPP, "System architecture for the 5G System (5GS)," 3GPP TS 23.501, 2020.

I. Goodfellow, Y. Bengio, and A. Courville, "Deep Learning," MIT Press, 2016.