Mixture-of-Experts (MoE) Architecture Analysis for Cybersecurity

Q Dataset Analysis: What Data Structures Do We Have?

☑ Expert 1: Tabular Expert - FULLY SUPPORTED

Current Implementation: ✓ FT-Transformer (already implemented and trained!)

Available Data:

- **CICIDS**: 72 numerical features (flow-level statistics)
- **UNSW**: 39 numerical + 3 categorical features

Features Include:

- Connection-level statistics (packets, bytes, duration)
- Protocol flags (SYN, ACK, FIN, etc.)
- Statistical aggregations (mean, std, min, max)
- Flow characteristics (rates, packet sizes, inter-arrival times)

Status: READY - FT-Transformer model already trained and achieving excellent results

⚠ Expert 2: Temporal Expert - PARTIALLY SUPPORTED

Goal: Capture temporal dependencies and attack patterns over time

Challenge: No explicit timestamps in current datasets!

What We Have (Flow-Level Temporal Features):

Both CICIDS and UNSW provide aggregated temporal statistics but NOT raw packet sequences:

CICIDS Temporal Features:

```
temporal_features = [
   "Flow IAT Mean",
                        # Mean inter-arrival time between packets
   "Flow IAT Std",
                        # Std dev of inter-arrival times
   "Flow IAT Max",
                        # Maximum inter-arrival time
   "Flow IAT Min",
                        # Minimum inter-arrival time
   "Fwd IAT Total/Mean/Std/Max/Min", # Forward direction timing
   "Bwd IAT Total/Mean/Std/Max/Min", # Backward direction timing
   "Active Mean/Std/Max/Min",
                               # Active time before idle
   "Idle Mean/Std/Max/Min",
                               # Idle time statistics
]
```

UNSW Temporal Features:

Workaround: Temporal Feature Expert (RECOMMENDED)

- Create a specialized MLP/Transformer that focuses on temporal statistics
- Input: IAT features, duration, jitter, timing-related columns
- Purpose: Learn temporal attack signatures (e.g., DDoS = low IAT variance, Port Scan = regular IAT patterns)
- This is NOT true time-series but captures temporal characteristics

X Expert 3: Graph Expert - NOT SUPPORTED

Goal: Capture communication topology (IP → IP, port relationships)

Challenge: NO IP ADDRESS DATA in datasets!

What's Missing: No Source IP, No Destination IP, No explicit port pairs

Workaround Option: Use UNSW's connection count features (ct_*) as pseudo-graph statistics

- ct_srv_src: Count of flows to same service from same source
- ct_dst_ltm: Count of flows to same dest in last time window
- NOT a true GNN, but captures graph-like relational properties

& Recommended MoE Architecture: **2-Expert System**

```
- Input: [Z_tab, Z_temporal]
  - Weights: softmax([w_tab, w_temporal])
  - Output: Z_final = w_tab * Z_tab + w_temporal * Z_temporal

↓
Classifier Head
  - Input: Z_final
  - Output: [Normal, Attack]
```

Why This Works:

- W Honest: Respects dataset limitations (no IPs, no packet sequences)
- **Novel**: Temporal expert learns timing-based attack signatures
- Practical: Both experts use available data effectively
- Academic: Demonstrates MoE concept without inventing fake data

Implementation Plan

Components to Build:

- 1. Temporal Expert (new)
- 2. Gating Network (new)
- 3. MoE Wrapper (new)
- 4. Feature Splitter in preprocessing (new)
- 5. **train_moe.py** (new unified training script)
- 6. **MLflow integration** for gating weights

Next Steps:

Would you like me to:

- 1. Implement 2-Expert MoE (Tabular + Temporal) RECOMMENDED
- 2. **Attempt 3-Expert MoE** (add Relational expert with ct_* features)
- 3. III Just analyze and document the architecture design

Ready to start coding when you give the go-ahead!