PsmBench: A Benchmark and Dataset for Evaluating LLMs Extraction of Protocol State Machines from RFC Specifications

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Abstract

Accurately extracting protocol-state machines (PSMs) from the long, densely written Request-for-Comments (RFC) standards that govern Internet-scale communication remains a bottleneck for automated security analysis and protocol testing. In this paper, we introduce Rfc2Psm , the first large-scale dataset that pairs 1,580 pages of cleaned RFC text with 108 manually validated states and 297 transitions covering 14 widely deployed protocols spanning the data-link, transport, session, and application layers. Built on this corpus, we propose PsmBench, a benchmark that (i) feeds chunked RFC to an LLM, (ii) prompts the model to emit a machine-readable PSM, and (iii) scores the output with structure-aware, semantic fuzzy-matching metrics that reward partially correct graphs.

A comprehensive baseline study of nine state-of-the-art open and commercial LLMs reveals a persistent state–transition gap: models identify many individual states (up to 0.82 F1) but struggle to assemble coherent transition graphs (≤ 0.38 F1), highlighting challenges in long-context reasoning, alias resolution, and action/event disambiguation. We release the dataset, evaluation code, and all model outputs as open-sourced[1], providing a fully reproducible starting point for future work on reasoning over technical prose and generating executable graph structures. Rfc2Psm and PsmBench aim to catalyze cross-disciplinary progress toward LLMs that can interpret and verify the protocols that keep the Internet safe.

1 Introduction

The current generation of large language models (LLMs) shows impressive ability to convert natural-language instructions into structured outputs, including tables, JSON records, and executable code. The conversion of technical specifications into *Protocol State Machines* (PSMs) remains an unsolved real-world challenge because PSMs serve as graph-structured abstractions for *security fuzzing* [Pham et al., 2020, De Ruiter and Poll, 2015], *formal verification* [Cremers et al., 2017, Beurdouche et al., 2017], and *implementation testing* of network protocols [Chen et al., 2023, Park et al., 2022, Pacheco

[1]Our dataset and benchmark are at RFC_PSM_Benchmark repository , promoting transparency and reproducibility in the community.

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et al., 2022a], such as TCP [Eddy, Wesley (Ed.), 2022] and FTP [Postel and Reynolds, 1985]. Creating PSMs from Request for Comments (RFC) documents through manual methods requires months of time and specialized domain knowledge, which blocks automated security analysis [Graham and Johnson, 2014].

Existing approaches, such as mGPTFuzz [Ma et al., 2024], are based on manually selecting a protocol standard's relevant sections to generate the corresponding state machine. In addition, they are often protocol-specific - e.g. mGPTFuzz is specific to the an Internet of Things protocol [Connectivity Standards Alliance, 2022]. Another approach - PROSPER [Sharma and Yegneswaran, 2023], shows that prompted GPT-3.5 helps to identify states and transitions in limited RFCs. However, there is a lack of a standardized benchmark for measuring extraction quality across diverse specifications, and a gap in the automated measurement of graph-level transition system accuracy at scale.

Consequently, there is an urgency for a *standardised, diverse* testbed to evaluate the ability of the state-of-the-art LLM models OpenAI [2023], DeepSeek-AI et al. [2025], DeepMind [2024] in reasoning over lengthy technical prose and generate executable graph structures [Pacheco et al., 2022a]. An open-sourced comprehensive benchmark and dataset with many protocols is also critical to evaluating the ability of LLMs to extract PSMs from a wide range of standard protocol documents.

To meet this need, we construct a comprehensive dataset, RFC2PSM , a curated corpus of 14 RFCs spanning application, session, transport, and link-layer protocols, paired with manually validated ground-truth PSMs. Building on this corpus, we also introduce PSMBENCH, the first benchmark that (i) feeds chunked RFC text to an LLM, (ii) asks the model to generate a machine-readable PSM, and (iii) scores the output with fuzzy structural and semantic metrics that reward partial but meaningful correctness. Figure 1 summarizes the pipeline.

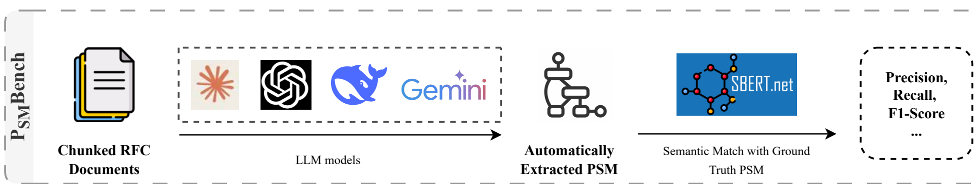


Figure 1: A workflow of PSMBENCH pipeline. The chunked RFC documents are input to LLM models to extract PSM automatically, and then the extracted PSM is compared with the ground truth PSM to evaluate completeness and correctness.

Our contributions are three-fold:

- **Comprehensive dataset.** RFC2PSM is the first open-sourced dataset providing 1580 pages of cleaned RFC text, 108 manually domain-experts verified states, and 297 transitions covering 14 widely deployed protocols. This provides a dataset for LLMs on understanding network protocol technical documents.
- **New evaluation framework.** PSMBENCH introduces semantic-based fuzzy graph-alignment metrics that capture both exact matches and near-misses in extracted PSMs. It provides a benchmark for evaluating the LLM's capabilities in extracting complicated graph-like structures from technical documents.
- **Empirical baselines.** We benchmark 9 state-of-the-art open-source and commercial LLMs, highlighting persistent challenges such as long-range dependency tracking and state aliasing.

With this work, we aim to accelerate research in LLM-guided protocol analysis, ultimately contributing to the development of automated protocol analysis tools in the network and security community.

1.1 Background and Terminologies

Network Protocols. Network protocols define rules and conventions for data exchange across networks. For example, the Transmission Control Protocol (TCP) [Eddy, Wesley (Ed.), 2022] facilitates reliable internet communication, while the File Transfer Protocol (FTP) [Eddy, Wesley (Ed.), 2022] standardizes file exchanges. Given their widespread use in critical applications, the security and reliability of these protocols are paramount.

Protocol Standards. Network protocols are designed as interacting transition systems called Protocol State Machines (PSMs) and are specified in the Request for Comments (RFCs). These RFCs are official standards published and maintained by the Internet Engineering Task Force (IETF). Typically written in detailed natural language, RFC documents specify the technical aspects of protocol operation, including message formats, state transitions, and expected behaviors. Due to their complexity and extensive length, which often spans hundreds of pages, extracting structured information from RFCs poses significant challenges.

Protocol State Machine (PSM) A Protocol State Machine (PSM) provides a structured, formal representation of the states and transitions that define a network protocol's behavior in the form of finite state machine.

Definition 1.1 (Protocol State Machine)**.** *Formally, it's defined as a tuple [Brand and Zafiropulo, 1983]:*

$$\mathcal{M} = (S, \Sigma, T, s_0, F)$$

where S is a finite set of states, representing all possible protocol states. $s_0 \in S$ is the initial state, where the protocol starts. $F \subseteq S$ is the set of final or terminal states, representing the valid end states of the protocol. Σ is a finite set of events (or inputs) that can trigger state transitions. $T \subseteq S \times \Sigma \times S \times A$ is the set of transitions.

Definition 1.2 (Transition)**.** *A transition in a PSM is defined as a directed edge between two states, representing a valid state change triggered by an event. Formally, a transition t is a 4-tuple: $t = (s_i, e, s_j, a)$, [Graham and Johnson, 2014] which can be represented as:*

$$s_i \xrightarrow{e/a} s_j$$

The transition indicates that the protocol can move from source state s_i to destination state s_j upon receiving the event e, with action a being executed.

2 Related Work

LLM-Based PSM Extraction. Recent work has demonstrated that LLMs can automate the PSM extraction process. For example, Sharma et al. introduced PROSPER [Sharma and Yegneswaran, 2023], which uses GPT-3.5 with carefully engineered prompts to identify states and transitions directly from RFC text. Ma et al. [Ma et al., 2024] further explored LLM-guided extraction by selecting relevant sections of the IoT protocol specification [Connectivity Standards Alliance, 2022] and prompting an LLM to generate the corresponding state machine. However, their extraction approach is protocol-specific and is evaluated on only a handful of examples. In summary, although LLM-based techniques can reduce manual effort in PSM extraction, a major research gap is that there is no general, open-source, diverse benchmark or dataset against which to evaluate their performance across multiple protocols. Our work fills these gaps by introducing a unified dataset and benchmark covering 14 distinct protocols.

Previously Proposed Benchmarks. PROSPER [Sharma and Yegneswaran, 2023] is an attempt that explored PSM extraction from RFC documents. However, it has several limitations. It focuses on fewer than 10 protocols and evaluates a single LLM (GPT-3.5). Thus, its evaluation is limited. In contrast, our work introduces a substantially larger, publicly available dataset covering 14 distinct protocols, providing a more comprehensive and unified benchmark. Additionally, we evaluate 9 state-of-the-art LLM models, enabling systematic comparison and testing across a diverse range of protocols and models.

3 RFC2PSM Dataset

We now introduce RFC2PSM , our comprehensive dataset designed to evaluate the ability of LLMs to extract complex protocol state machines (PSMs) from technical documents like RFCs. RFC2PSM covers 14 diverse protocols, each represented by a set of RFC document chunks as input source and manually annotated PSMs as the ground truth as shown in Figure 2. In this section, we detail the construction of RFC2PSM , including the protocol selection criteria, the RFC document preprocessing methods, and the structure of the ground truth PSMs.

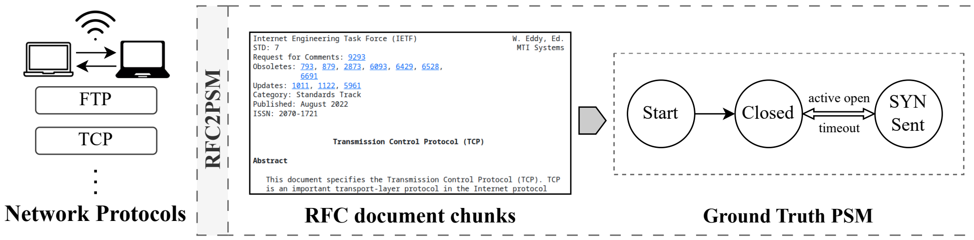


Figure 2: High-level overview of RFC2PSM , which includes 14 protocols, each protocol paired with RFC document chunks and ground truth PSM.

3.1 Protocol Selection and Dataset Statistics

We carefully select the protocols based on their widespread adoption and diverse coverage across different layers of the OSI (Open Systems Interconnection) model [iso, 1994], ensuring comprehensive representation across multiple communication contexts. RFC2PSM includes 14 protocols spanning the *Transport*, *Session*, *Application*, and *Data Link* layers, capturing a broad range of use cases. This diverse collection includes general-purpose network protocols (e.g., TCP, FTP), email protocols (e.g., SMTP, IMAP, POP3), real-time communication protocols (e.g., RTSP, SIP), routing protocols (e.g., BGP-4), and IoT-related protocols (e.g., MQTT). Collectively, the dataset encompasses **108** states, **297** transitions, and spans over **1580** pages of protocol specifications, reflecting the complexity and breadth of the selected standards. Detailed statistics, including protocol names, OSI layers, RFC standards, and other relevant information, are presented in Table 1 in the appendix.

3.2 RFC Document Collection and Preprocessing

For each protocol, we download the official RFC files, which serve as foundational references guiding real-world implementations. RFC documents are widely recognized within the security and network community as standards for protocol analysis tools, making them ideal sources for extracting ground truth PSMs in RFC2PSM .

Next, we outline the process of collecting and preprocessing these RFC documents:
① Each RFC document is first downloaded in plain text format from the official website of the Internet Engineering Task Force (IETF).
② The raw documents undergo a cleaning step to remove extra metadata, including page headers, footers, publication years, author information, and page numbers, ensuring that these elements do not introduce noise during LLM processing.
③ Given the token length limitations of LLMs, the cleaned RFCs are then segmented into structured, semantically coherent text chunks. This segmentation process first partitions the document at primary section boundaries (e.g., Sections 1, 2, 3). If a resulting chunk still exceeds the maximum token limit (e.g., 40,000 tokens), it is further divided at secondary-level subsections (e.g., Sections 1.1, 1.2).
④ During this segmentation, we retain section titles and numbers as explicit metadata, providing LLMs with crucial context for accurate PSM extraction.

As a result, each protocol's RFC is processed into a collection of structured chunks, where each chunk contains a *section identifier*, *section title*, and the corresponding *text content*, ensuring efficient and context-aware LLM processing.

3.3 Ground-Truth PSM

To evaluate the performance of PSM extraction, a well-defined ground-truth PSM is essential. In RFC2PSM , each network protocol is paired with a manually edited ground-truth PSM, capturing the valid protocol states and the events that trigger transitions between them.

To build reliable ground-truth PSMs, we first identify canonical state machines from existing trusted sources. Specifically, the PSM annotations for DCCP and TCP protocols are derived from prior work [Pacheco et al., 2022b] and have been manually validated for correctness. For the remaining protocols, we conduct a rigorous manual extraction process directly from the original RFC document. This manual step requires months of careful analysis and domain expertise to ensure the completeness and accuracy of the resulting state machines. To make this process reproducible, we followed a systematic annotation protocol rather than relying on ad hoc effort. The annotators first established a concise two-page guideline covering state naming, event terminology, and action description. One author, acting as the protocol specialist, independently extracted all states and transitions from each RFC. A second author then reviewed the extracted PSM and marked revision points. Any differences were resolved through discussion until consensus was reached. On a 10% stratified sample, independent pass-1/2 annotations achieved substantial agreement (κ=0.82 for states and κ=0.78 for transitions) on Landis and Koch's scale, with fewer than 6% of elements requiring discussion in step 3. The full process averages about three days per protocol. The annotation guideline, reconciliation logs, and raw diff data will be released in the supplementary materials.

Each manually annotated PSM in RFC2PSM adheres to the formal definition presented in Definition 1.1. To ensure flexibility and ease of integration with existing tools, we represent each PSM as a structured JSON object, which allows flexible conversion to other widely adopted representations. Each graph-like PSM is structured as a JSON object comprising the elements in Definition 1.1. This structured format also facilitates the automatic generation of visual state diagrams, enhancing usability. For example, the ground-truth PSM for the TCP protocol is shown in Figure 5 in the appendix, illustrating the full set of protocol states and the transitions between them. In this representation, each transition is defined by a concise label of the form "trigger_event / action," capturing both the triggering condition and the resulting action.

4 PSMBENCH Benchmark

To systematically evaluate the ability of LLMs to understand and extract structured information from complex technical documents, we introduce PSMBENCH. In this section, we present the overall task definition and workflow for PSMBENCH, describing how LLMs extract PSMs from RFC chunks. We then provide a detailed explanation of the evaluation metrics used to assess the fidelity of these extracted PSMs, focusing on their ability to accurately capture the semantic relationships within the protocol's *states* and *transitions*.

PSMBENCH Workflow. The core task in PSMBENCH is to extract structured (PSMs) from RFC documents, as illustrated in Figure 1. The inputs are the chunked protocol's RFC sections. The goal is for the LLM to produce a structured, graph-like PSM in JSON format, capturing both *states* and *transitions* that accurately reflect the protocol's intended behavior. The extracted PSM is then compared with the ground-truth PSMs in RFC2PSM using semantic matching techniques, evaluating the model's ability to perform structured information extraction.

Processing RFC Chunks with LLMs. To extract a complete PSM from RFC documents, the LLM processes the segmented chunks, each corresponding to a distinct section of the document. For each chunk, the LLM identifies and extracts a *partial PSM* if it contains relevant protocol behavior information. Formally, a partial PSM is defined as a tuple $(S_{\text{partial}}, T_{\text{partial}})$, where S_{partial} represents the set of protocol states mentioned in the section, and T_{partial} captures the corresponding transitions, consistent with the transition Definition 1.2. Once all sections of an RFC document are processed, the LLM is prompted to merge the extracted partial PSMs to form a complete, global PSM. To assess whether segmentation granularity affects extraction quality, we further conducted a *sliding-window ablation*. Each RFC was re-segmented with a 4k-token window and 0.5k overlap, and the same extraction pipeline (GPT-4o-mini, identical hyper-parameters) was rerun. As detailed in Table 2 in the appendix, seven protocols improved and seven degraded, yielding a macro-average F1 change of +0.05, well within run-to-run variance. Because overlapping windows increase input length by approximately 35%, we retain section-based segmentation as the default for its determinism and efficiency.

4.1 Evaluation Metrics

The automated evaluation of PSM extraction is challenging due to the variability in phrases of semantically equivalent states and transitions. This variability makes the syntactic comparison inaccurate. In this subsection, we outline our approach to address this challenge through a semantic similarity-based evaluation. We then introduce the specific metrics used to quantify the fidelity of extracted *states* and *transitions*, providing a comprehensive framework for evaluating the structural and semantic alignment of LLM-generated PSMs.

4.1.1 Challenge and Solution in PSM Matching

Challenge. Evaluating the fidelity of extracted PSMs is particularly challenging due to the variability in *state names*, *events*, and *actions*. Direct string matching is often inaccurate, as semantically equivalent labels can have different lexical forms (e.g., *"Established"* vs. *"Connected"*), while superficially similar terms can have entirely distinct meanings (e.g., *"ACK"* and *"NACK"* represent opposite concepts). This variability complicates automated comparison, as minor differences in phrasing can significantly impact matching accuracy. Previous approaches [Pacheco et al., 2022b, Ma et al., 2024, Sharma and Yegneswaran, 2023] have often relied on manual evaluation, where experts align extracted PSMs with ground-truth references through detailed inspection. However, this approach is time-consuming and difficult to scale, presenting a major bottleneck in large-scale PSM evaluation. To address these challenges, automated metrics that capture semantic equivalence are essential for effective benchmarking.

Solution. We compute semantic similarity with sentence encoders, using `all-MiniLM-L6-v2` by default, and verified robustness across `all-MPNet-base-v2` and `SimCSE-RoBERTa-unsup`; macro F1 changes by at most 0.06 with 11/14 protocols shifting by ≤ 0.15 F1 (Table 4 in the appendix). This model generates dense, context-aware embeddings for each phrase, capturing their semantic relationships beyond syntax text similarity. Formally, the semantic similarity between two phrases p_1 and p_2 is defined as the cosine similarity of their SentenceBERT embeddings:

$$\text{sim}(p_1, p_2) = \frac{\mathbf{e}_1 \cdot \mathbf{e}_2}{\|\mathbf{e}_1\|\|\mathbf{e}_2\|} \tag{1}$$

where $\mathbf{e}_1 := \text{SentenceBERT}(p_1)$, $\mathbf{e}_2 := \text{SentenceBERT}(p_2)$, $\mathbf{e}_1 \cdot \mathbf{e}_2$ denotes the dot product, and $\|\mathbf{e}\|$ represents the Euclidean norm of the embedding vector. Two phrases are considered semantically equivalent if: $\text{sim}(p_1, p_2) > \theta$, where θ is a predefined threshold, selected based on empirical analysis (e.g., $\theta = 0.5$ in our experiments, we set it via an ablation study A). This threshold ensures that the metric captures meaningful semantic matches while filtering out lexical similarities.

4.1.2 State-Level Matching

Formally, given a ground truth PSM and an extracted PSM:

$$\mathcal{M} = (S, \Sigma, T, s_0, F) \quad \text{and} \quad \mathcal{M}' = (S', \Sigma', T', s_0', F')$$

State Set Matching. We assess the overall accuracy of state extraction, as states are fundamental to modeling protocol behavior. we aim to identify the overlap between the state sets S and S' of ground truth PSM and LLM extracted PSM. The states' similarity is calculated by $\text{sim}(s_i, {s_j}')$. A state is considered matched if the highest similarity score exceeds a threshold θ (e.g., 0.5). This approach captures both exact matches and semantically equivalent state names.

4.1.3 Transition-Level Matching

To assess the transition-level match, we define two kinds of matching.

Exact Transition Match. A transition is considered an exact match if all its components, including the *from state*, *to state*, *trigger event*, and *action*, are semantically equivalent to the corresponding transition in the ground truth PSM. Formally, a transition t is considered a full match with transition t' if: $t = (s_i, e, s_j, a) \quad \text{and} \quad t' = (s_i', e', s_j', a')$ satisfy the following conditions:

$$\text{sim}(s_i, s_i') > \theta \wedge \text{sim}(s_j, s_j') > \theta \wedge \text{sim}(e \parallel a, e' \parallel a') > \theta$$

where s_i and s_i' are the source states, s_j and s_j' are the destination states, e and e' are the trigger events, and a and a' are the actions. The notation $e \parallel a$ represents the concatenation of the event and action, acting as a *transition label* in Definition 1.2.

Partial Transition Match. In cases where exact matching is too strict, we define a partial transition match based on semantic similarity, release the restriction of *event* or *action* descriptions. A partial match is considered valid if the semantic similarity of the source and destination states is above a predefined threshold, and at least one of the event or action components also satisfies the similarity requirement. Formally, a transition $t = (s_i, e, s_j, a)$ and $t' = (s_i', e', s_j', a')$ are considered a partial match if:

$$\text{sim}(s_i, s_i') > \theta \wedge \text{sim}(s_j, s_j') > \theta \wedge (\text{sim}(e, e') > \theta \vee \text{sim}(a, a') > \theta)$$

This approach reflects the practical observation that, while the fundamental state transitions remain consistent, the triggers and actions can be described with a wide range of context-dependent variations, making exact matching too restrictive.

4.1.4 Precision, Recall, and F1 Score for PSM Evaluation

To evaluate PSM extraction, we use precision, recall, and F1 score in a unified framework that can be applied to both *state*-level and *transition*-level matching. Let (Matched) be the set of elements that have been correctly identified by the extraction model; (Extracted) be the set of all elements produced by the LLM model; (Ground Truth) be the set of all reference elements from the ground-truth PSM. The evaluation metrics are then defined as:

$$\text{Precision} = \frac{|\text{Correct}|}{|\text{Extracted}|}, \quad \text{Recall} = \frac{|\text{Correct}|}{|\text{Ground Truth}|}, \quad \text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In this context, *Precision* quantifies the proportion of correctly identified *states* or *transitions* among all extracted elements. *Recall* measures the fraction of ground-truth *states* or *transitions* that are successfully extracted. The *F1 Score* provides a balanced assessment, integrating both precision and recall into a single metric, to evaluate overall model performance.

5 Experiments

We conducted extensive baseline experiments to benchmark 9 state-of-the-art LLMs on the RFC2PSM dataset with PSMBENCH benchmark. In this section, we describe the selection of both open and proprietary LLMs, detail the prompt design, and present parameter settings. Finally, we provide a quantitative analysis of the results, offering insights into the strengths and limitations of current LLMs in the context of PSM extraction.

5.1 Experiments Setting

Models. i) Proprietary LLMs: For proprietary models, we evaluate several state-of-the-art LLMs with extensive context capabilities, including *Gpt4o-Mini* (gpt-4o-mini) [OpenAI, 2023], *Claude3* (claude-3-7-sonnet-20250219) [Anthropic, 2024], and *Gemini2* (gemini-2.0-flash) [DeepMind, 2024]. ii) Open LLMs: We also include a diverse set of advanced open-source instruction-tuned LLMs, including *DS-R1* (deepseek-R1) [DeepSeek-AI et al., 2025], *DS-V3* (deepseek-V3-0324), *QWQ* (qwq:32b), *QWen3* (qwen3:32b), *Gemma3* (gemma3:27b), and *Mistral* (mistral-small3.1:24b).

Prompt Design. To effectively guide LLMs in extracting PSMs from RFC documents, we adopt a two-stage prompt design inspired by the Chain of Thought (CoT) framework [Zhang et al., 2024]. Given the complexity and length of RFCs, we first segment each document into manageable sections to avoid token limits and ensure coherent extraction. This processing enables the LLM to focus on extracting partial PSM components from each section before combining them into a complete state machine. First, we use a *Partial PSM Extraction Prompt* (Appendix B.1) to extract PSM components (states and transitions) from individual sections. This step isolates meaningful state machine elements without overwhelming the model with the entire document context. Next, we use a *PSM Combination Prompt* (Appendix B.2) to merge these partial PSMs into a unified global PSM, ensuring consistency and completeness across sections.

Parameter Settings. For our experiments, we set the model *temperature = 0.0*, as the task of PSM extraction relies exclusively on the provided context. This deterministic setting ensures that the extracted state machines are consistent across runs, reflecting the contents of the RFC documents. For the semantic similarity threshold used in state and transition matching, we chose a value of *0.5*. We determined this threshold to balance the need for flexibility in matching semantically similar phrases while maintaining alignment with human interpretation. For instance, $sim(\texttt{Error}, \texttt{Failure}) = 0.5194)$. From this example, we observe that a 0.5 threshold effectively captures meaningful semantic similarities without being overly strict.

5.2 Quantitative Results

In this subsection, we present the quantitative evaluation results for both *state*-level and *transition*-level matching, comparing LLM-extracted PSMs against their ground-truth counterparts. For each

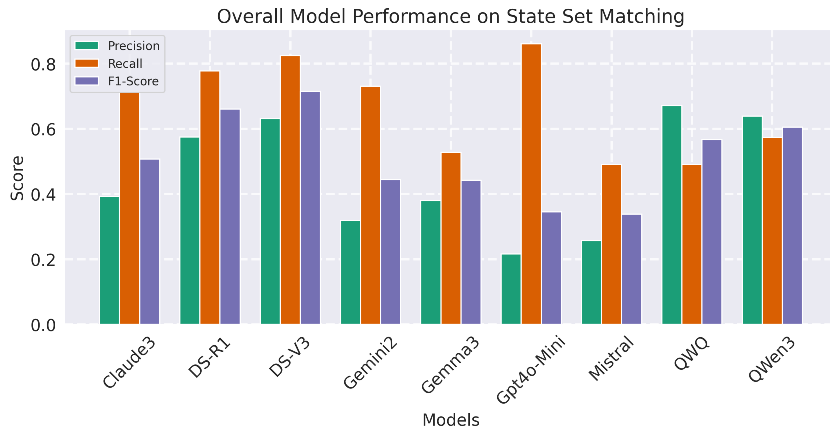


Figure 3: Model Performance on State Set Matching. Precision, recall, and F1-score for various models, highlighting differences in their ability to extract state sets accurately.

of the 14 protocols, we provide detailed performance tables covering *state set extraction*, *partial transition matching*, and *exact transition matching*. These tables are included in the Appendix for comprehensive reference, with an index to all detailed result tables provided in Table 5.

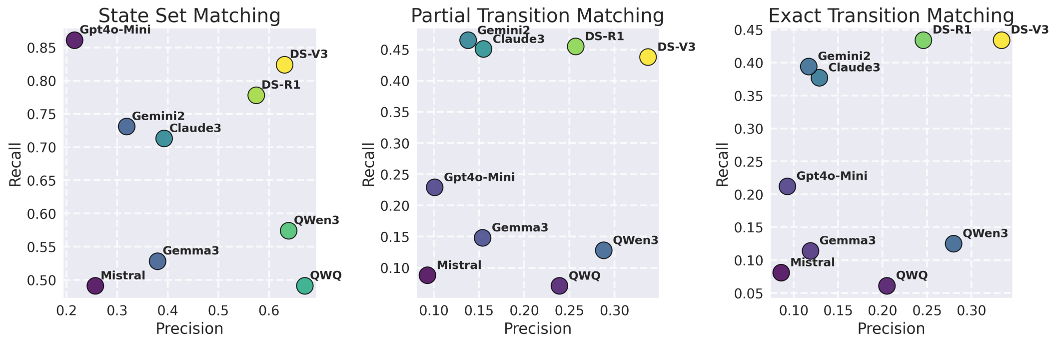
5.2.1 State-Level Matching Results

States Set Matching Results. Accurate state extraction is a critical component in reconstructing PSMs, as states define the fundamental stages of protocol behavior. In this evaluation, we measure the alignment between ground truth states (S) and extracted states (S') based on semantic similarity, as described in the metrics section. Figure 3 presents the performance of each model in terms of total extracted states, ground truth states, matched states, and the corresponding precision, recall, and F1-score. Overall, *DS-V3* demonstrates the strongest performance, achieving the highest F1-score of 0.715, reflecting a balanced ability to capture both precise and diverse state representations. In contrast, models like *Gpt4o-Mini* and *Gemini2*, while achieving high recall (0.861 and 0.731, respectively), suffer from lower precision (0.216 and 0.319), indicating a tendency to over-extract states, possibly due to more aggressive token matching or broader semantic interpretations. On the other hand, *QWQ* and *QWen3* achieved high precision (0.671 and 0.639), but with a noticeable drop in recall, suggesting a more conservative approach to state identification that may miss relevant but less directly phrased states, the tradeoff between precision and recall is shown in Figure 4a. The numeric details are shown in Table 6 in the appendix.

5.2.2 Transition Level Matching Results

Partial Transition Match Results. Partial transition matching provides a more flexible evaluation approach, allowing for minor variations in event and action descriptions while still requiring strong alignment of source and destination states. Figure 6 in the appendix presents the partial transition matching results for each model. Overall, *DS-V3* achieves the highest F1-score (0.381), indicating a strong balance between precision and recall despite the relaxed matching criteria. This suggests that DS-V3 effectively captures the essential transition structures while accommodating variations in trigger and action descriptions. In contrast, models like *Gemini2* and *Gpt4o-Mini* demonstrate high recall (0.465 and 0.229, respectively) but suffer from significantly lower precision (0.138 and 0.101), indicating a tendency to over-generate transitions, possibly capturing many loosely related state changes. On the other hand, *QWQ* and *QWen3*, while achieving higher precision (0.239 and 0.288), exhibit lower recall, suggesting a more conservative extraction strategy that may miss relevant but less directly phrased transitions. The tradeoffs between recall and precision are shown in Figure 4b. These results highlight the challenges of extracting structured PSMs, where the complicated relationships between states, triggers, and actions require both precise matching and flexible interpretation. The detailed numeric results are shown in Table 7 in the appendix.

Exact Transition Matching Results. Exact transition matching provides a stricter evaluation, requiring precise alignment of source state, destination state, trigger event, and action. As shown in



(a) (b) (c)

Figure 4: The figure presents the precision-recall distributions for (a) state set matching, (b) partial transition matching, and (c) exact transition matching, illustrating the varying performance of models across these metrics.

Figure 7 in the appendix, *DS-V3* achieved the highest F1-score (0.378), reflecting its ability to capture precise, context-aware transitions. In contrast, models like *Mistral* and *Gpt4o-Mini* struggled, with F1-scores of 0.083 and 0.130, respectively, indicating challenges in accurately aligning all transition components. These results underscore the difficulty of exact matching in PSM extraction, where even minor variations in state or event descriptions can significantly impact overall performance. The detailed numeric results are shown in Table 8 in the appendix.

5.3 Takeaways

The experimental results reveal several critical insights into the performance of state-of-the-art LLMs in extracting PSMs from RFC documents:

State-Level Advantage in Extraction. First, state-level extraction is generally more accurate than transition-level extraction across all models. This is evident from the higher F1-scores achieved in the *States Set Matching* task, where models like *DS-V3* (0.715) and *DS-R1* (0.661) significantly outperformed their transition-level counterparts, even under partially correct matching constraints. This suggests that capturing discrete, isolated states is a more straightforward task for LLMs than identifying the nuanced relationships represented by transitions, which involve multiple components.

Impact of Model Scale. Second, larger models with broader context capabilities, such as *DS-R1* and *DS-V3*, consistently outperformed smaller models like *QWQ* and *Mistral* across all metrics, including state and transition extraction matching. This highlights the advantage of large-scale models in handling the extensive, semantically complex inputs typical of RFC documents. However, these larger models also exhibited a tendency to over-extract, as reflected in their higher recall but lower precision, indicating potential challenges in accurately filtering relevant states and transitions.

Challenges in Exact Transition Matching. Third, the exact transition matching results underscore the difficulty of precise PSM extraction, where even the strongest models like *DS-V3* and *DS-R1* achieved only moderate F1-scores (0.378 and 0.314, respectively). This gap suggests that, despite their advanced reasoning capabilities, current LLMs struggle to consistently align all transition components accurately, reflecting the inherent complexity of protocol semantics.

6 Limitations and Future Work

While this work establishes a comprehensive benchmark PSMBENCH for PSM extraction from RFC documents, several limitations remain. First, our prompt design is straightforward, focusing on baseline evaluation without leveraging advanced strategies. This choice was made to provide a clear baseline, but it may limit the performance ceiling of some models. Second, while our dataset spans a diverse range of protocols, it primarily covers medium-sized, application-layer protocols. It excludes more complex, lower-layer protocols like Wi-Fi, whose specifications often exceed 1000 pages, posing significant challenges for current LLMs due to their extreme length and technical detail.

In future work, we plan to (i) extend RFC2PSM to ultra-long, lower-layer standards (e.g. Wi-Fi), (ii) explore adaptive chunk-merging and curriculum-style prompting to narrow the transition gap, and (iii) integrate richer graph-and-text co-evaluation metrics.

7 Conclusion

We present RFC2PSM , the first large-scale, manually validated corpus of 14 network-protocol specifications paired with ground-truth PSM, and PSMBENCH, a principled benchmark that evaluates LLM-driven PSM extraction through semantic, structure-aware metrics. Together they deliver a turn-key testbed for studying how current and future language models reason over long, technical documents and emit executable graph structures - an ability central to automated security analysis, software verification, and protocol testing.

Our extensive baseline study across 9 leading open-source and commercial LLMs reveals a clear state-transition gap: models achieve respectable recall on individual states yet struggle to assemble precise, end-to-end transition graphs. These findings pinpoint long-range dependency tracking, alias resolution, and fine-grained action/event disambiguation as open research challenges. By open-sourcing the dataset, evaluation code, and model outputs, we provide the community with a fully reproducible reference point and invite contributions ranging from prompt engineering and retrieval-augmented decoding to task-specific fine-tuning.

We hope this resource sparks broader collaboration across NLP, security, and networking, ultimately accelerating progress toward LLMs that can interpret and verify the protocols that run the Internet safely, accurately, and at scale.

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Table 1: Overview of the dataset RFC2PSM .

Protocol	Layer	RFC No.	# Pages	#Chunks	#States	#Transitions
RTSP	Application (L7)	RFC 7826	318	32	3	33
FTP	Application (L7)	RFC 959	69	11	10	24
SIP	Application (L7)	RFC 3261	269	31	5	20
SMTP	Application (L7)	RFC 5321	95	15	7	22
DCCP	Transport (L4)	RFC 4340	129	22	9	25
TCP	Transport (L4)	RFC 9293	98	10	11	20
DHCPv4	Application (L7)	RFC 2131	45	9	8	19
IMAP	Application (L7)	RFC 9051	163	11	5	11
POP3	Application (L7)	RFC 1939	23	17	3	18
NNTP	Application (L7)	RFC 3977	125	14	10	16
MQTT	Application (L7)	RFC 9431	33	11	12	17
PPTP	Session (L5)	RFC 2637	57	8	9	19
BGP-4	Application (L7)	RFC 4271	104	16	6	26
PPP	Data Link (L2)	RFC 1661	52	6	10	27

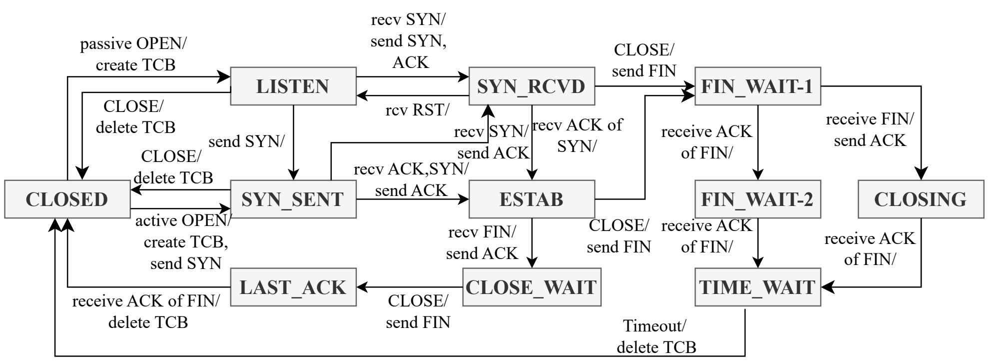

Figure 5: A manually extracted ground-truth PSM of TCP protocol in RFC2PSM .

A Threshold Ablation

When selecting the merge threshold, we systematically examined dozens of term pairs to balance false merges (distinct concepts collapsed) and false splits (identical concepts separated), and therefore set θ=0.50. To make this choice explicit, Table 3 reports per–protocol F1 on the full `deepseek-v3` run (14 protocols, 297 transitions) for $\theta \in 0.40, 0.45, 0.50, 0.55, 0.60$.

These results confirm the choice: varying θ within $[0.40, 0.55]$ leaves macro F1 at 0.692, and even θ=0.60 yields 0.664. At θ=0.50, pairs such as "*Established* $\approx$ *Connected*" (sim $= 0.77$) remain cleanly separated from "*ACK* vs. *NACK*" (sim < 0.2), so we use θ=0.50 as the default.

Table 2: Sliding-window ablation on state-matching F1. "Section" uses section-based chunks; "Overlap" uses a 4k window with 0.5k overlap.

Protocol	Section F1	Overlap F1	Δ F1
IMAP	0.307	0.277	-0.030
POP3	0.353	1.000	$+0.647$
MQTT	0.611	0.800	$+0.189$
PPP	0.689	0.869	$+0.180$
PPTP	0.414	0.485	$+0.071$
BGP	0.632	0.800	$+0.168$
SIP	0.064	0.070	$+0.006$
RTSP	0.120	0.079	-0.041
DCCP	0.361	0.361	$+0.000$
DHCP	0.842	0.800	-0.042
FTP	0.235	0.134	-0.101
NNTP	0.400	0.328	-0.072
SMTP	0.167	0.261	$+0.094$
TCP	0.909	0.526	-0.383
Macro Avg	**0.436**	**0.485**	**+0.049**

Table 3: Per–protocol F1 at different merge thresholds θ. Macro average is flat for $\theta \in [0.40, 0.55]$ and drops slightly at θ=0.60.

Protocol	F1@0.40	F1@0.45	F1@0.50	F1@0.55	F1@0.60
IMAP	0.889	0.889	0.889	0.889	0.889
POP3	0.750	0.750	0.750	0.750	0.750
MQTT	0.500	0.500	0.500	0.500	0.500
PPP	0.720	0.720	0.720	0.720	0.640
PPTP	0.477	0.477	0.477	0.477	0.477
BGP	1.000	1.000	1.000	1.000	1.000
SIP	0.589	0.589	0.589	0.589	0.589
RTSP	1.000	1.000	1.000	1.000	1.000
DCCP	0.857	0.857	0.857	0.857	0.857
DHCP	0.933	0.933	0.933	0.933	0.933
FTP	0.364	0.364	0.364	0.364	0.243
NNTP	0.444	0.444	0.444	0.444	0.370
SMTP	0.353	0.353	0.353	0.353	0.235
TCP	0.818	0.818	0.818	0.818	0.818
Macro avg.	**0.692**	**0.692**	**0.692**	**0.692**	**0.664**

Table 4: Per–protocol F1 with three sentence encoders (LLM, thresholds, and post–processing held fixed).

Protocol	MiniLM F1	MPNet F1	SimCSE F1
IMAP	0.889	0.889	0.889
POP3	0.750	0.750	0.750
MQTT	0.500	0.500	0.500
PPP	0.720	0.720	0.800
PPTP	0.477	0.477	0.667
BGP	1.000	1.000	1.000
SIP	0.589	0.589	0.589
RTSP	1.000	1.000	1.000
DCCP	0.857	0.857	0.857
DHCP	0.933	0.933	0.933
FTP	0.364	0.243	0.485
NNTP	0.444	0.444	0.519
SMTP	0.353	0.470	0.706
TCP	0.818	0.909	0.818
Macro Avg.	0.692	0.699	0.751

Table 5: References to Detailed Protocol Evaluation Tables

Metric	**BGP**	**FTP**	**IMAP**	**NNTP**	**POP3**	**SMTP**	**SIP**
States Extraction	Table 9	Table 12	Table 13	Table 15	Table 16	Table 21	Table 20
Partial Transition	Table 23	Table 26	Table 27	Table 29	Table 30	Table 35	Table 34
Exact Transition	Table 37	Table 40	Table 41	Table 43	Table 44	Table 49	Table 48
Metric	**TCP**	**DCCP**	**MQTT**	**PPTP**	**RTSP**	**DHCP**	**PPP**
States Extraction	Table 22	Table 10	Table 14	Table 18	Table 19	Table 11	Table 17
Partial Transition	Table 36	Table 24	Table 28	Table 32	Table 33	Table 25	Table 31
Exact Transition	Table 50	Table 38	Table 42	Table 46	Table 47	Table 39	Table 45

Table 6: Overall Model Performance on **State Set Matching** of Different Protocols

Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
Claude3	196	108	77	0.393	0.713	0.507
DS-R1	146	108	84	0.575	0.778	0.661
DS-V3	141	108	89	0.631	0.824	0.715
Gemini2	248	108	79	0.319	0.731	0.444
Gemma3	150	108	57	0.380	0.528	0.442
Gpt4o-Mini	431	108	93	0.216	0.861	0.345
Mistral	206	108	53	0.257	0.491	0.338
QWQ	79	108	53	0.671	0.491	0.567
QWen3	97	108	62	0.639	0.574	0.605

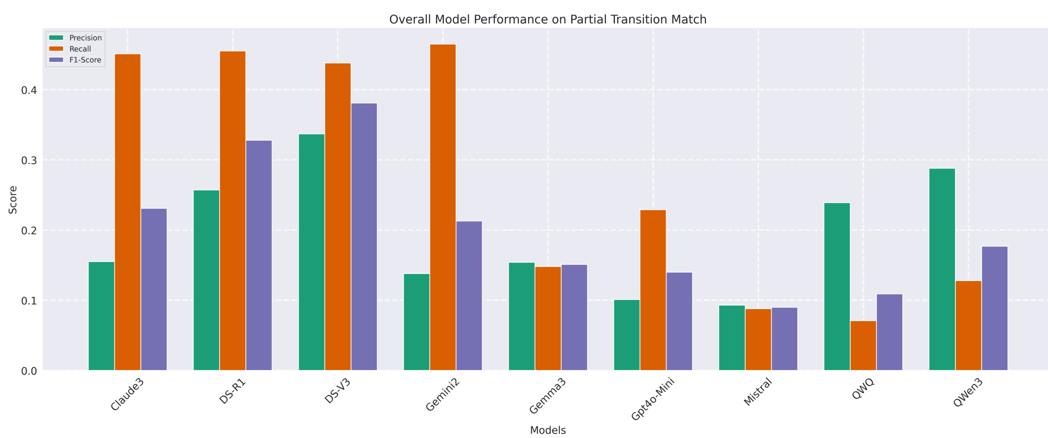

Figure 6: Model Performance on Partial Transition Matching. Precision, recall, and F1-score for various models, highlighting differences in their ability to extract transitions accurately.

Table 7: Overall Model Performance on **Partial Transition Match** of Different Protocols

Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
Claude3	865	297	134	0.155	0.451	0.231
DS-R1	525	297	135	0.257	0.455	0.328
DS-V3	386	297	130	0.337	0.438	0.381
Gemini2	1000	297	138	0.138	0.465	0.213
Gemma3	285	297	44	0.154	0.148	0.151
Gpt4o-Mini	674	297	68	0.101	0.229	0.140
Mistral	279	297	26	0.093	0.088	0.090
QWQ	88	297	21	0.239	0.071	0.109
QWen3	132	297	38	0.288	0.128	0.177

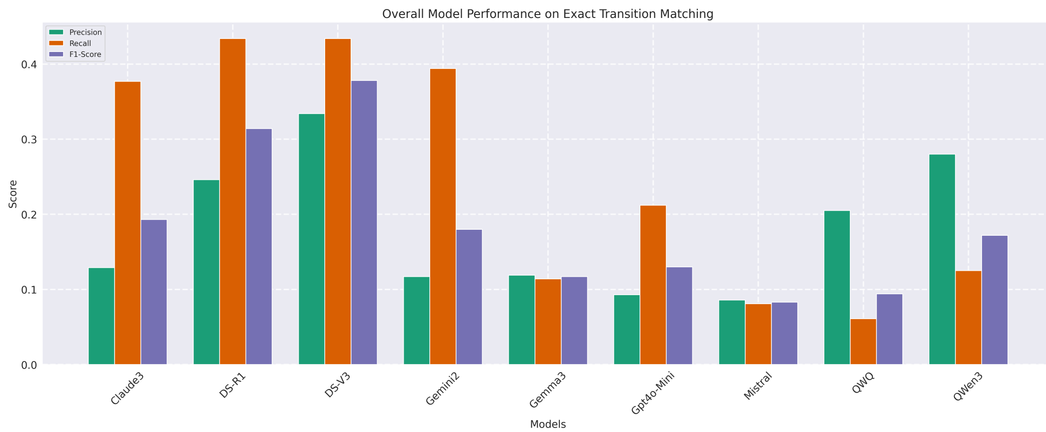

Figure 7: Model Performance on Exact Transition Matching. Precision, recall, and F1-score for various models, highlighting differences in their ability to extract transitions accurately.

Table 8: Overall Model Performance on Exact Transition Matching of Different Protocols

Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
Claude3	865	297	112	0.129	0.377	0.193
DS-R1	525	297	129	0.246	0.434	0.314
DS-V3	386	297	129	0.334	0.434	0.378
Gemini2	1000	297	117	0.117	0.394	0.180
Gemma3	285	297	34	0.119	0.114	0.117
Gpt4o-Mini	674	297	63	0.093	0.212	0.130
Mistral	279	297	24	0.086	0.081	0.083
QWQ	88	297	18	0.205	0.061	0.094
QWen3	132	297	37	0.280	0.125	0.172

B Prompts Design

B.1 Partial PSM Extraction Prompt

Partial PSM Extraction Prompt

You will be given the section "section_title" of an RFC document for protocol "protocol_name".

RESPONSE FORMAT (MANDATORY)
- Your reply must consist **exclusively** of the JSON object representing the state machine.
- That JSON must be wrapped in <json> and </json> tags.
- Do **not** include any extra text, explanation, code fences, or formatting.
<section> section_text </section>
Steps:
1. Determine if this section has any FSM-related information (states, transitions, diagrams, reply codes, sequences).
2. If **none**, reply exactly:
<json>None</json>
3. If there is FSM information, extract it and return a structured JSON in the following format (strictly):

```
{{
  "states": ["state1", "state2", "state3"],
  "transitions": [
    {{
      "from": "state1",
      "event": "recvCommand",
      "action": "replCcode",
      "to": "state2"
    }},
    ...
  ]
}}
```

FSM Field Constraints:
"states"‘:
List of all states appearing in ‘"from"‘ or ‘"to"‘ fields.
Each state must: Be 1 to 3 words (max 30 characters) Use ‘CamelCase‘ or ‘snake_case‘ Describe a protocol phase, status, or role (e.g., ‘Authenticated‘, ‘WaitingForReply‘) Contain no punctuation, spaces, or free-form descriptions
Good: ‘"AwaitingPassword"‘, ‘"transfer_in_progress"‘
Bad: ‘"State 1"‘, ‘"waiting for command"‘, ‘"cmd?"‘
"from" / "to":
- Same naming rules as above
"event":
- Describes the trigger that causes the transition
- Maybe begin with a fixed prefix:
- ‘"receive "‘ for received command - ‘"send "‘ for sent response - ‘"timeout "‘ for timing event - ‘"cond "‘ for internal condition - or other words
Examples: "receive USER", "send 230", "timeout 5s", "cond valid_credentials" ‘"action"‘:
- Describes what the system does in response
- It’s best start with an action verb from this fixed set or other verbs if needed: ‘reply‘, ‘send‘, ‘set‘, ‘log‘, ‘reset‘, ‘close‘, ’collect’, ‘open‘, ’record’, ’stop’
- Followed by one or two short arguments (max 4 words total) Examples: ‘"reply 230"‘, ‘"log failure"‘, ‘"set authenticated true"‘
Important:
- Do not generate free-text descriptions in any field.
- Each transition must contain **exactly**: ‘from‘, ‘event‘, ‘action‘, ‘to‘.
- Do not invent vague or inconsistent state or event names.
OUTPUT RULES:
- Wrap the JSON in **<json>...</json>** only.
- Do not include Markdown, explanations, comments, or extra text.
- If nothing is found, return exactly ‘<json>None</json>‘.

B.2 PSM Combination Prompt

Partial PSM Combination

You will be provided with multiple **partial protocol state machines** extracted from different sections of an RFC. Each partial state machine is a JSON object with the following fields:
- "states": list of state names
- "transitions": list of transition objects with these required fields:
- "from": source state name
- "event": trigger (e.g., received command, condition)
- "action": response or internal action
- "to": target state name

Each partial is wrapped in ‘<partial>...</partial>‘. Some may be ‘<json>None</json>‘ — ignore those.
— Your task is to **merge all valid partial FSMs into one global FSM** and return a single well-structured JSON object in the following format (wrapped in ‘<json>...</json>‘):
<json>

```
{{
  "states": ["state1", "state2", ...],
  "initial_state": "stateX",
  "final_states": ["stateY", ...],
  "transitions": [
    {{
      "from": "state1",
      "event": "recv COMMAND",
      "action": "reply CODE",
      "to": "state2"
    }}
  ]
}}
```

</json>
— FSM Construction Constraints **State Naming (‘states‘, ‘from‘, ‘to‘)**:
- Must be concise, meaningful, and consistent
- Format: 1 to 3 words, ‘CamelCase‘ or ‘snake_case‘, no spaces or punctuation
- Examples: ‘"Authenticated"‘, ‘"AwaitingPassword"‘, ‘"TransferReady"‘
Events (‘event‘):
- Format: 1 to 3 words
- Maybe begin with: ‘receive‘, ‘send‘, ‘timeout‘, or ‘cond‘
- Examples: ‘"receive USER"‘, ‘"timeout 10s"‘, ‘"cond valid_credentials"‘
Actions (‘action‘):
- Start with a verb from this list: ‘reply‘, ‘send‘, ‘set‘, ‘log‘, ‘reset‘, ‘close‘, ’collect’, ‘open‘, ’record’, ’stop’ or other verbs if needed
Followed by a short phrase (less than 4 words)
- Examples: ‘"reply 230"‘, ‘"set authenticated true"‘, ‘"log failure"‘

FSM Merging Rules
1. **Unify states**: Standardize naming (e.g., merge ‘"Init"‘ and ‘"Initialization"‘ into one state).
2. **Remove duplicates**: Transitions that differ only in phrasing should be merged.
3. **Preserve meaning**: If two similar states clearly serve different roles, retain both.
4. **Determine**:
- ‘"initial_state"‘: The state with **no incoming transitions**
- ‘"final_states"‘: All states with **no outgoing transitions**
Please return **only** the merged FSM in the required format, wrapped inside ‘<json>...</json>‘. Do **not** include explanations, commentary, or Markdown.

Here are the partial FSMs to merge:
partials_block

Table 9: BGP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
BGP	DS-R1	6	6	6	1.000	1.000	1.000
BGP	Gpt4o-Mini	13	6	6	0.462	1.000	0.632
BGP	Claude3	8	6	6	0.750	1.000	0.857
BGP	Gemini2	9	6	6	0.667	1.000	0.800
BGP	DS-V3	6	6	6	1.000	1.000	1.000
BGP	QWQ	6	6	6	1.000	1.000	1.000
BGP	QWen3	6	6	6	1.000	1.000	1.000
BGP	Gemma3	7	6	6	0.857	1.000	0.923
BGP	Mistral	10	6	3	0.300	0.500	0.375

Table 10: DCCP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
DCCP	DS-R1	12	9	9	0.750	1.000	0.857
DCCP	Gpt4o-Mini	41	9	9	0.220	1.000	0.361
DCCP	Claude3	12	9	9	0.750	1.000	0.857
DCCP	Gemini2	20	9	9	0.450	1.000	0.621
DCCP	DS-V3	12	9	9	0.750	1.000	0.857
DCCP	QWQ	4	9	6	1.500	0.667	0.923
DCCP	QWen3	11	9	8	0.727	0.889	0.800
DCCP	Gemma3	10	9	7	0.700	0.778	0.737
DCCP	Mistral	10	9	2	0.200	0.222	0.210

Table 11: DHCP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
DHCP	DS-R1	8	8	8	1.000	1.000	1.000
DHCP	Gpt4o-Mini	11	8	8	0.727	1.000	0.842
DHCP	Claude3	8	8	8	1.000	1.000	1.000
DHCP	Gemini2	6	8	4	0.667	0.500	0.572
DHCP	DS-V3	7	8	8	1.143	1.000	1.067
DHCP	QWQ	4	8	5	1.250	0.625	0.833
DHCP	QWen3	4	8	5	1.250	0.625	0.833
DHCP	Gemma3	4	8	5	1.250	0.625	0.833
DHCP	Mistral	3	8	4	1.333	0.500	0.727

Table 12: FTP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
FTP	DS-R1	14	10	5	0.357	0.500	0.417
FTP	Gpt4o-Mini	41	10	6	0.146	0.600	0.235
FTP	Claude3	14	10	2	0.143	0.200	0.167
FTP	Gemini2	15	10	6	0.400	0.600	0.480
FTP	DS-V3	23	10	8	0.348	0.800	0.485
FTP	QWQ	6	10	5	0.833	0.500	0.625
FTP	QWen3	11	10	2	0.182	0.200	0.191
FTP	Gemma3	15	10	5	0.333	0.500	0.400
FTP	Mistral	20	10	4	0.200	0.400	0.267

Table 13: IMAP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
IMAP	DS-R1	9	5	4	0.444	0.800	0.571
IMAP	Gpt4o-Mini	21	5	4	0.190	0.800	0.307
IMAP	Claude3	11	5	4	0.364	0.800	0.500
IMAP	Gemini2	12	5	4	0.333	0.800	0.470
IMAP	DS-V3	4	5	4	1.000	0.800	0.889
IMAP	QWQ	4	5	4	1.000	0.800	0.889
IMAP	QWen3	4	5	3	0.750	0.600	0.667
IMAP	Gemma3	10	5	4	0.400	0.800	0.533
IMAP	Mistral	10	5	4	0.400	0.800	0.533

Table 14: MQTT Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
MQTT	DS-R1	7	12	8	1.143	0.667	0.842
MQTT	Gpt4o-Mini	24	12	11	0.458	0.917	0.611
MQTT	Claude3	11	12	5	0.455	0.417	0.435
MQTT	Gemini2	26	12	10	0.385	0.833	0.527
MQTT	DS-V3	4	12	5	1.250	0.417	0.625
MQTT	QWQ	14	12	8	0.571	0.667	0.615
MQTT	QWen3	7	12	5	0.714	0.417	0.527
MQTT	Gemma3	11	12	5	0.455	0.417	0.435
MQTT	Mistral	20	12	11	0.550	0.917	0.688

Table 15: NNTP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
NNTP	DS-R1	12	10	3	0.250	0.300	0.273
NNTP	Gpt4o-Mini	40	10	10	0.250	1.000	0.400
NNTP	Claude3	13	10	6	0.462	0.600	0.522
NNTP	Gemini2	29	10	7	0.241	0.700	0.359
NNTP	DS-V3	17	10	7	0.412	0.700	0.519
NNTP	QWQ	3	10	0	0.000	0.000	0.000
NNTP	QWen3	4	10	0	0.000	0.000	0.000
NNTP	Gemma3	9	10	3	0.333	0.300	0.316
NNTP	Mistral	3	10	0	0.000	0.000	0.000

Table 16: POP3 Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
POP3	DS-R1	4	3	3	0.750	1.000	0.857
POP3	Gpt4o-Mini	14	3	3	0.214	1.000	0.353
POP3	Claude3	5	3	3	0.600	1.000	0.750
POP3	Gemini2	4	3	3	0.750	1.000	0.857
POP3	DS-V3	5	3	3	0.600	1.000	0.750
POP3	QWQ	4	3	1	0.250	0.333	0.286
POP3	QWen3	4	3	3	0.750	1.000	0.857
POP3	Gemma3	17	3	3	0.176	1.000	0.299
POP3	Mistral	12	3	3	0.250	1.000	0.400

Table 17: PPP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
PPP	DS-R1	15	10	10	0.667	1.000	0.800
PPP	Gpt4o-Mini	19	10	10	0.526	1.000	0.689
PPP	Claude3	15	10	10	0.667	1.000	0.800
PPP	Gemini2	13	10	10	0.769	1.000	0.869
PPP	DS-V3	15	10	10	0.667	1.000	0.800
PPP	QWQ	5	10	3	0.600	0.300	0.400
PPP	QWen3	11	10	6	0.545	0.600	0.571
PPP	Gemma3	6	10	2	0.333	0.200	0.250
PPP	Mistral	9	10	2	0.222	0.200	0.210

Table 18: PPTP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
PPTP	DS-R1	8	9	8	1.000	0.889	0.941
PPTP	Gpt4o-Mini	20	9	6	0.300	0.667	0.414
PPTP	Claude3	15	9	5	0.333	0.556	0.417
PPTP	Gemini2	11	9	0	0.000	0.000	0.000
PPTP	DS-V3	12	9	8	0.667	0.889	0.762
PPTP	QWQ	3	9	5	1.667	0.556	0.834
PPTP	QWen3	4	9	8	2.000	0.889	1.231
PPTP	Gemma3	4	9	6	1.500	0.667	0.923
PPTP	Mistral	6	9	6	1.000	0.667	0.800

Table 19: RTSP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
RTSP	DS-R1	5	3	3	0.600	1.000	0.750
RTSP	Gpt4o-Mini	47	3	3	0.064	1.000	0.120
RTSP	Claude3	20	3	2	0.100	0.667	0.174
RTSP	Gemini2	17	3	2	0.118	0.667	0.201
RTSP	DS-V3	3	3	3	1.000	1.000	1.000
RTSP	QWQ	3	3	0	0.000	0.000	0.000
RTSP	QWen3	3	3	3	1.000	1.000	1.000
RTSP	Gemma3	14	3	3	0.214	1.000	0.353
RTSP	Mistral	22	3	1	0.045	0.333	0.079

Table 20: SIP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
SIP	DS-R1	25	5	5	0.200	1.000	0.333
SIP	Gpt4o-Mini	88	5	3	0.034	0.600	0.064
SIP	Claude3	43	5	5	0.116	1.000	0.208
SIP	Gemini2	65	5	5	0.077	1.000	0.143
SIP	DS-V3	12	5	5	0.417	1.000	0.589
SIP	QWQ	7	5	0	0.000	0.000	0.000
SIP	QWen3	11	5	2	0.182	0.400	0.250
SIP	Gemma3	27	5	2	0.074	0.400	0.125
SIP	Mistral	32	5	1	0.031	0.200	0.054

Table 21: SMTP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
SMTP	DS-R1	10	7	2	0.200	0.286	0.235
SMTP	Gpt4o-Mini	41	7	4	0.098	0.571	0.167
SMTP	Claude3	10	7	2	0.200	0.286	0.235
SMTP	Gemini2	10	7	4	0.400	0.571	0.470
SMTP	DS-V3	10	7	3	0.300	0.429	0.353
SMTP	QWQ	7	7	1	0.143	0.143	0.143
SMTP	QWen3	8	7	2	0.250	0.286	0.267
SMTP	Gemma3	7	7	0	0.000	0.000	0.000
SMTP	Mistral	38	7	3	0.079	0.429	0.133

Table 22: TCP Protocol States Extraction Metrics

Protocol	Model	Total Extracted	Total GT	Matched	Precision	Recall	F1-Score
TCP	DS-R1	11	11	10	0.909	0.909	0.909
TCP	Gpt4o-Mini	11	11	10	0.909	0.909	0.909
TCP	Claude3	11	11	10	0.909	0.909	0.909
TCP	Gemini2	11	11	9	0.818	0.818	0.818
TCP	DS-V3	11	11	10	0.909	0.909	0.909
TCP	QWQ	9	11	9	1.000	0.818	0.900
TCP	QWen3	9	11	9	1.000	0.818	0.900
TCP	Gemma3	9	11	6	0.667	0.545	0.600
TCP	Mistral	11	11	9	0.818	0.818	0.818

Table 23: BGP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
BGP	DS-R1	20	26	14	0.700	0.538	0.609
BGP	Gpt4o-Mini	25	26	7	0.280	0.269	0.275
BGP	Claude3	60	26	23	0.383	0.885	0.535
BGP	Gemini2	101	26	26	0.257	1.000	0.409
BGP	DS-V3	32	26	15	0.469	0.577	0.517
BGP	QWQ	7	26	3	0.429	0.115	0.182
BGP	QWen3	11	26	4	0.364	0.154	0.216
BGP	Gemma3	21	26	3	0.143	0.115	0.128
BGP	Mistral	9	26	0	0.000	0.000	0.000

Table 24: DCCP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
DCCP	DS-R1	29	25	18	0.621	0.720	0.667
DCCP	Gpt4o-Mini	55	25	8	0.145	0.320	0.200
DCCP	Claude3	40	25	19	0.475	0.760	0.585
DCCP	Gemini2	44	25	16	0.364	0.640	0.464
DCCP	DS-V3	28	25	14	0.500	0.560	0.528
DCCP	QWQ	4	25	1	0.250	0.040	0.069
DCCP	QWen3	15	25	5	0.333	0.200	0.250
DCCP	Gemma3	18	25	6	0.333	0.240	0.279
DCCP	Mistral	9	25	0	0.000	0.000	0.000

Table 25: DHCP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
DHCP	DS-R1	20	19	12	0.600	0.632	0.615
DHCP	Gpt4o-Mini	26	19	9	0.346	0.474	0.400
DHCP	Claude3	18	19	14	0.778	0.737	0.757
DHCP	Gemini2	27	19	7	0.259	0.368	0.304
DHCP	DS-V3	15	19	10	0.667	0.526	0.588
DHCP	QWQ	6	19	4	0.667	0.211	0.320
DHCP	QWen3	4	19	2	0.500	0.105	0.174
DHCP	Gemma3	10	19	2	0.200	0.105	0.138
DHCP	Mistral	5	19	2	0.400	0.105	0.167

Table 26: FTP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
FTP	DS-R1	23	24	5	0.217	0.208	0.213
FTP	Gpt4o-Mini	53	24	4	0.075	0.167	0.104
FTP	Claude3	46	24	4	0.087	0.167	0.114
FTP	Gemini2	51	24	6	0.118	0.250	0.160
FTP	DS-V3	77	24	7	0.091	0.292	0.139
FTP	QWQ	7	24	3	0.429	0.125	0.194
FTP	QWen3	14	24	1	0.071	0.042	0.053
FTP	Gemma3	42	24	5	0.119	0.208	0.152
FTP	Mistral	33	24	3	0.091	0.125	0.105

Table 27: IMAP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
IMAP	DS-R1	35	11	6	0.171	0.545	0.261
IMAP	Gpt4o-Mini	56	11	5	0.089	0.455	0.149
IMAP	Claude3	48	11	7	0.146	0.636	0.237
IMAP	Gemini2	90	11	7	0.078	0.636	0.139
IMAP	DS-V3	16	11	6	0.375	0.545	0.444
IMAP	QWQ	4	11	3	0.750	0.273	0.400
IMAP	QWen3	4	11	2	0.500	0.182	0.267
IMAP	Gemma3	17	11	5	0.294	0.455	0.357
IMAP	Mistral	20	11	6	0.300	0.545	0.387

Table 28: MQTT Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
MQTT	DS-R1	16	17	2	0.125	0.118	0.121
MQTT	Gpt4o-Mini	37	17	3	0.081	0.176	0.111
MQTT	Claude3	45	17	2	0.044	0.118	0.065
MQTT	Gemini2	48	17	2	0.042	0.118	0.062
MQTT	DS-V3	6	17	0	0.000	0.000	0.000
MQTT	QWQ	18	17	1	0.056	0.059	0.057
MQTT	QWen3	6	17	1	0.167	0.059	0.087
MQTT	Gemma3	19	17	1	0.053	0.059	0.056
MQTT	Mistral	37	17	3	0.081	0.176	0.111

Table 29: NNTP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
NNTP	DS-R1	73	16	2	0.027	0.125	0.045
NNTP	Gpt4o-Mini	68	16	0	0.000	0.000	0.000
NNTP	Claude3	75	16	0	0.000	0.000	0.000
NNTP	Gemini2	116	16	2	0.017	0.125	0.030
NNTP	DS-V3	25	16	2	0.080	0.125	0.098
NNTP	QWQ	3	16	0	0.000	0.000	0.000
NNTP	QWen3	6	16	0	0.000	0.000	0.000
NNTP	Gemma3	14	16	0	0.000	0.000	0.000
NNTP	Mistral	4	16	0	0.000	0.000	0.000

Table 30: POP3 Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
POP3	DS-R1	21	18	12	0.571	0.667	0.615
POP3	Gpt4o-Mini	33	18	12	0.364	0.667	0.471
POP3	Claude3	26	18	9	0.346	0.500	0.409
POP3	Gemini2	39	18	13	0.333	0.722	0.456
POP3	DS-V3	20	18	10	0.500	0.556	0.526
POP3	QWQ	5	18	1	0.200	0.056	0.087
POP3	QWen3	8	18	4	0.500	0.222	0.308
POP3	Gemma3	38	18	10	0.263	0.556	0.357
POP3	Mistral	29	18	9	0.310	0.500	0.383

Table 31: PPP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
PPP	DS-R1	111	27	10	0.090	0.370	0.145
PPP	Gpt4o-Mini	33	27	5	0.152	0.185	0.167
PPP	Claude3	138	27	18	0.130	0.667	0.218
PPP	Gemini2	126	27	20	0.159	0.741	0.261
PPP	DS-V3	21	27	3	0.143	0.111	0.125
PPP	QWQ	5	27	0	0.000	0.000	0.000
PPP	QWen3	21	27	1	0.048	0.037	0.042
PPP	Gemma3	9	27	0	0.000	0.000	0.000
PPP	Mistral	12	27	0	0.000	0.000	0.000

Table 32: PPTP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
PPTP	DS-R1	18	19	12	0.667	0.632	0.649
PPTP	Gpt4o-Mini	29	19	1	0.034	0.053	0.042
PPTP	Claude3	56	19	4	0.071	0.211	0.107
PPTP	Gemini2	23	19	0	0.000	0.000	0.000
PPTP	DS-V3	34	19	11	0.324	0.579	0.415
PPTP	QWQ	2	19	0	0.000	0.000	0.000
PPTP	QWen3	6	19	4	0.667	0.211	0.320
PPTP	Gemma3	6	19	2	0.333	0.105	0.160
PPTP	Mistral	12	19	1	0.083	0.053	0.065

Table 33: RTSP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
RTSP	DS-R1	41	33	19	0.463	0.576	0.514
RTSP	Gpt4o-Mini	70	33	0	0.000	0.000	0.000
RTSP	Claude3	89	33	19	0.213	0.576	0.311
RTSP	Gemini2	78	33	12	0.154	0.364	0.216
RTSP	DS-V3	39	33	30	0.769	0.909	0.833
RTSP	QWQ	2	33	0	0.000	0.000	0.000
RTSP	QWen3	10	33	6	0.600	0.182	0.279
RTSP	Gemma3	24	33	4	0.167	0.121	0.140
RTSP	Mistral	33	33	0	0.000	0.000	0.000

Table 34: SIP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
SIP	DS-R1	58	20	12	0.207	0.600	0.308
SIP	Gpt4o-Mini	127	20	10	0.079	0.500	0.136
SIP	Claude3	164	20	2	0.012	0.100	0.022
SIP	Gemini2	180	20	20	0.111	1.000	0.200
SIP	DS-V3	43	20	14	0.326	0.700	0.444
SIP	QWQ	5	20	0	0.000	0.000	0.000
SIP	QWen3	11	20	3	0.273	0.150	0.194
SIP	Gemma3	47	20	2	0.043	0.100	0.060
SIP	Mistral	30	20	0	0.000	0.000	0.000

Table 35: SMTP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
SMTP	DS-R1	45	22	0	0.000	0.000	0.000
SMTP	Gpt4o-Mini	52	22	0	0.000	0.000	0.000
SMTP	Claude3	40	22	0	0.000	0.000	0.000
SMTP	Gemini2	32	22	2	0.062	0.091	0.074
SMTP	DS-V3	18	22	1	0.056	0.045	0.050
SMTP	QWQ	11	22	0	0.000	0.000	0.000
SMTP	QWen3	7	22	0	0.000	0.000	0.000
SMTP	Gemma3	6	22	0	0.000	0.000	0.000
SMTP	Mistral	35	22	0	0.000	0.000	0.000

Table 36: TCP Partially Correct Transition Extraction Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
TCP	DS-R1	15	20	11	0.733	0.550	0.629
TCP	Gpt4o-Mini	10	20	4	0.400	0.200	0.267
TCP	Claude3	20	20	13	0.650	0.650	0.650
TCP	Gemini2	45	20	5	0.111	0.250	0.154
TCP	DS-V3	12	20	7	0.583	0.350	0.438
TCP	QWQ	9	20	5	0.556	0.250	0.345
TCP	QWen3	9	20	5	0.556	0.250	0.345
TCP	Gemma3	14	20	4	0.286	0.200	0.235
TCP	Mistral	11	20	2	0.182	0.100	0.129

Table 37: BGP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
BGP	DS-R1	20	26	14	0.700	0.538	0.609
BGP	Gpt4o-Mini	25	26	8	0.320	0.308	0.314
BGP	Claude3	60	26	20	0.333	0.769	0.465
BGP	Gemini2	101	26	25	0.248	0.962	0.394
BGP	DS-V3	32	26	14	0.438	0.538	0.483
BGP	QWQ	7	26	2	0.286	0.077	0.121
BGP	QWen3	11	26	5	0.455	0.192	0.270
BGP	Gemma3	21	26	5	0.238	0.192	0.213
BGP	Mistral	9	26	0	0.000	0.000	0.000

Table 38: DCCP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
DCCP	DS-R1	29	25	11	0.379	0.440	0.407
DCCP	Gpt4o-Mini	55	25	4	0.073	0.160	0.100
DCCP	Claude3	40	25	14	0.350	0.560	0.431
DCCP	Gemini2	44	25	9	0.205	0.360	0.261
DCCP	DS-V3	28	25	12	0.429	0.480	0.453
DCCP	QWQ	4	25	1	0.250	0.040	0.069
DCCP	QWen3	15	25	5	0.333	0.200	0.250
DCCP	Gemma3	18	25	4	0.222	0.160	0.186
DCCP	Mistral	9	25	0	0.000	0.000	0.000

Table 39: DHCP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
DHCP	DS-R1	20	19	13	0.650	0.684	0.667
DHCP	Gpt4o-Mini	26	19	9	0.346	0.474	0.400
DHCP	Claude3	18	19	14	0.778	0.737	0.757
DHCP	Gemini2	27	19	6	0.222	0.316	0.261
DHCP	DS-V3	15	19	11	0.733	0.579	0.647
DHCP	QWQ	6	19	4	0.667	0.211	0.320
DHCP	QWen3	4	19	0	0.000	0.000	0.000
DHCP	Gemma3	10	19	0	0.000	0.000	0.000
DHCP	Mistral	5	19	2	0.400	0.105	0.167

Table 40: FTP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
FTP	DS-R1	23	24	5	0.217	0.208	0.213
FTP	Gpt4o-Mini	53	24	3	0.057	0.125	0.078
FTP	Claude3	46	24	4	0.087	0.167	0.114
FTP	Gemini2	51	24	6	0.118	0.250	0.160
FTP	DS-V3	77	24	7	0.091	0.292	0.139
FTP	QWQ	7	24	3	0.429	0.125	0.194
FTP	QWen3	14	24	1	0.071	0.042	0.053
FTP	Gemma3	42	24	5	0.119	0.208	0.152
FTP	Mistral	33	24	3	0.091	0.125	0.105

Table 41: IMAP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
IMAP	DS-R1	35	11	4	0.114	0.364	0.174
IMAP	Gpt4o-Mini	56	11	3	0.054	0.273	0.090
IMAP	Claude3	48	11	4	0.083	0.364	0.136
IMAP	Gemini2	90	11	6	0.067	0.545	0.119
IMAP	DS-V3	16	11	6	0.375	0.545	0.444
IMAP	QWQ	4	11	3	0.750	0.273	0.400
IMAP	QWen3	4	11	2	0.500	0.182	0.267
IMAP	Gemma3	17	11	3	0.176	0.273	0.214
IMAP	Mistral	20	11	5	0.250	0.455	0.323

Table 42: MQTT Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
MQTT	DS-R1	16	17	1	0.062	0.059	0.061
MQTT	Gpt4o-Mini	37	17	2	0.054	0.118	0.074
MQTT	Claude3	45	17	2	0.044	0.118	0.065
MQTT	Gemini2	48	17	2	0.042	0.118	0.062
MQTT	DS-V3	6	17	1	0.167	0.059	0.087
MQTT	QWQ	18	17	1	0.056	0.059	0.057
MQTT	QWen3	6	17	1	0.167	0.059	0.087
MQTT	Gemma3	19	17	1	0.053	0.059	0.056
MQTT	Mistral	37	17	2	0.054	0.118	0.074

Table 43: NNTP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
NNTP	DS-R1	73	16	1	0.014	0.062	0.022
NNTP	Gpt4o-Mini	68	16	3	0.044	0.188	0.071
NNTP	Claude3	75	16	2	0.027	0.125	0.044
NNTP	Gemini2	116	16	2	0.017	0.125	0.030
NNTP	DS-V3	25	16	1	0.040	0.062	0.049
NNTP	QWQ	3	16	0	0.000	0.000	0.000
NNTP	QWen3	6	16	0	0.000	0.000	0.000
NNTP	Gemma3	14	16	0	0.000	0.000	0.000
NNTP	Mistral	4	16	0	0.000	0.000	0.000

Table 44: POP3 Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
POP3	DS-R1	21	18	8	0.381	0.444	0.410
POP3	Gpt4o-Mini	33	18	10	0.303	0.556	0.392
POP3	Claude3	26	18	8	0.308	0.444	0.364
POP3	Gemini2	39	18	9	0.231	0.500	0.316
POP3	DS-V3	20	18	9	0.450	0.500	0.474
POP3	QWQ	5	18	1	0.200	0.056	0.087
POP3	QWen3	8	18	4	0.500	0.222	0.308
POP3	Gemma3	38	18	6	0.158	0.333	0.214
POP3	Mistral	29	18	9	0.310	0.500	0.383

Table 45: PPP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
PPP	DS-R1	111	27	10	0.090	0.370	0.145
PPP	Gpt4o-Mini	33	27	4	0.121	0.148	0.133
PPP	Claude3	138	27	9	0.065	0.333	0.109
PPP	Gemini2	126	27	19	0.151	0.704	0.248
PPP	DS-V3	21	27	3	0.143	0.111	0.125
PPP	QWQ	5	27	0	0.000	0.000	0.000
PPP	QWen3	21	27	1	0.048	0.037	0.042
PPP	Gemma3	9	27	0	0.000	0.000	0.000
PPP	Mistral	12	27	0	0.000	0.000	0.000

Table 46: PPTP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
PPTP	DS-R1	18	19	12	0.667	0.632	0.649
PPTP	Gpt4o-Mini	29	19	2	0.069	0.105	0.083
PPTP	Claude3	56	19	3	0.054	0.158	0.080
PPTP	Gemini2	23	19	0	0.000	0.000	0.000
PPTP	DS-V3	34	19	12	0.353	0.632	0.453
PPTP	QWQ	2	19	0	0.000	0.000	0.000
PPTP	QWen3	6	19	3	0.500	0.158	0.240
PPTP	Gemma3	6	19	0	0.000	0.000	0.000
PPTP	Mistral	12	19	1	0.083	0.053	0.065

Table 47: RTSP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
RTSP	DS-R1	41	33	29	0.707	0.879	0.784
RTSP	Gpt4o-Mini	70	33	2	0.029	0.061	0.039
RTSP	Claude3	89	33	20	0.225	0.606	0.328
RTSP	Gemini2	78	33	13	0.167	0.394	0.234
RTSP	DS-V3	39	33	32	0.821	0.970	0.889
RTSP	QWQ	2	33	0	0.000	0.000	0.000
RTSP	QWen3	10	33	8	0.800	0.242	0.372
RTSP	Gemma3	24	33	5	0.208	0.152	0.175
RTSP	Mistral	33	33	0	0.000	0.000	0.000

Table 48: SIP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
SIP	DS-R1	58	20	12	0.207	0.600	0.308
SIP	Gpt4o-Mini	127	20	9	0.071	0.450	0.122
SIP	Claude3	164	20	0	0.000	0.000	0.000
SIP	Gemini2	180	20	18	0.100	0.900	0.180
SIP	DS-V3	43	20	13	0.302	0.650	0.413
SIP	QWQ	5	20	0	0.000	0.000	0.000
SIP	QWen3	11	20	3	0.273	0.150	0.194
SIP	Gemma3	47	20	2	0.043	0.100	0.060
SIP	Mistral	30	20	0	0.000	0.000	0.000

Table 49: SMTP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
SMTP	DS-R1	45	22	0	0.000	0.000	0.000
SMTP	Gpt4o-Mini	52	22	0	0.000	0.000	0.000
SMTP	Claude3	40	22	0	0.000	0.000	0.000
SMTP	Gemini2	32	22	1	0.031	0.045	0.037
SMTP	DS-V3	18	22	1	0.056	0.045	0.050
SMTP	QWQ	11	22	0	0.000	0.000	0.000
SMTP	QWen3	7	22	0	0.000	0.000	0.000
SMTP	Gemma3	6	22	0	0.000	0.000	0.000
SMTP	Mistral	35	22	0	0.000	0.000	0.000

Table 50: TCP Exact Transition Match Metrics

Protocol	Model	TotalExtracted	TotalGT	Matched	Precision	Recall	F1-Score
TCP	DS-R1	15	20	9	0.600	0.450	0.514
TCP	Gpt4o-Mini	10	20	4	0.400	0.200	0.267
TCP	Claude3	20	20	12	0.600	0.600	0.600
TCP	Gemini2	45	20	1	0.022	0.050	0.031
TCP	DS-V3	12	20	7	0.583	0.350	0.438
TCP	QWQ	9	20	3	0.333	0.150	0.207
TCP	QWen3	9	20	4	0.444	0.200	0.276
TCP	Gemma3	14	20	3	0.214	0.150	0.176
TCP	Mistral	11	20	2	0.182	0.100	0.129