

# |REGULATION

## PROJECT:

Regulatory texts are lengthy, highly technical, and require **strict factual accuracy**. General-purpose LLMs often **hallucinate** and fail to capture legal nuance, making them unreliable for regulatory reasoning.

**Goal:** accurate, grounded Q&A over banking regulations.

**Solution:** Domain-aware RAG + FT models.

## The Data:

- Official Bank of Israel banking & financial regulations.
- Synthetic Q&A generation to ensure coverage and consistency.
- Questions designed to test precision, grounding, and edge cases.



# MODELS & METRICS



## Models Evaluated:

- **Llama + MiniLM** – strong general baseline.
- **Llama + LegalBERT** – domain-aware embeddings.
- **SaulLM + MiniLM** – legal LLM with generic retrieval.
- **SaulLM + LegalBERT** – full legal-domain stack.



## Metrics Used:

- **Verdict Accuracy** – correct regulatory conclusion.
- **Hit@K** – relevant source retrieved in top-K.
- **Citation Accuracy** - verifies that the model's answer is correctly supported by the cited regulatory source.
- **Hallucination Rate** – unsupported or fabricated claims.

# | NOVELTY & ACHIEVEMENTS

## Project Novelty:

- Systematic comparison of legal vs general model stacks in a regulatory RAG setting.
- Introduced citation-level evaluation for regulatory correctness.
- Combined synthetic legal Q&A generation with real regulatory texts.
- Focused on trustworthiness, not just language fluency.

## Project Achievements:

- Built a full end-to-end RAG system for regulatory question answering.
- Benchmarked general vs legal LLMs and embeddings under identical conditions.
- Designed a quantitative evaluation framework beyond generic accuracy.
- Improved answer grounding and source alignment in regulatory Q&A.

# METHODOLOGY

## Part 1

### Fine Tuning:

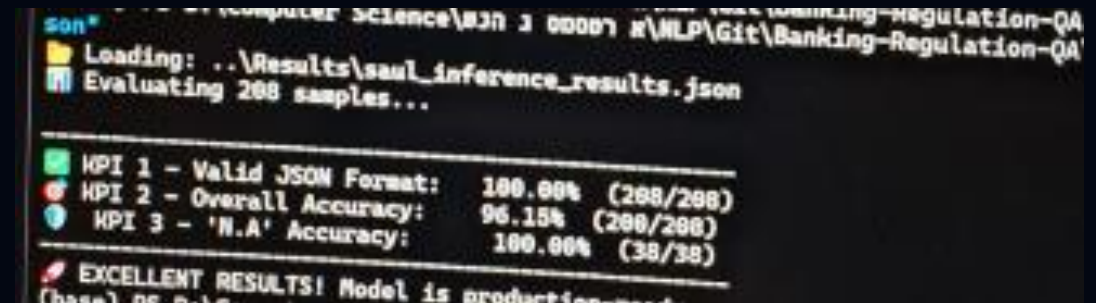
Updating the model itself to optimize it for the task.

- **Domain Specialization:-** Enhanced the model's regulatory expertise
- **Robustness to Negatives** - Trained the model on hard and soft negative samples to improve its ability to identify irrelevant information and avoid false positives.
- **Structured Output Optimization:** Fine-tuned the model to ensure consistent and valid JSON formatting

- **Model Selection:** Evaluated and compared **Llama 3.1** and **Saul-7B** (pre-trained on the legal domain).

- **Dataset Construction:** Compiled a dataset of **2,000+ examples**, including **15-20% negative samples** to enhance robustness and prevent hallucinations.

- **FT KPI'S:**



```
son* ... Computer Science\m3n 3 00007 n\MLP\Git\Banking-Regulation-QA
Loading: ..\Results\saul_inference_results.json
Evaluating 208 samples...

KPI 1 - Valid JSON Format: 100.00% (208/208)
KPI 2 - Overall Accuracy: 96.15% (200/208)
KPI 3 - 'N.A' Accuracy: 100.00% (38/38)

EXCELLENT RESULTS! Model is production-ready.
```

# METHODOLOGY

## Part 2

### RAG:

Providing the model with external data to ensure factual accuracy.

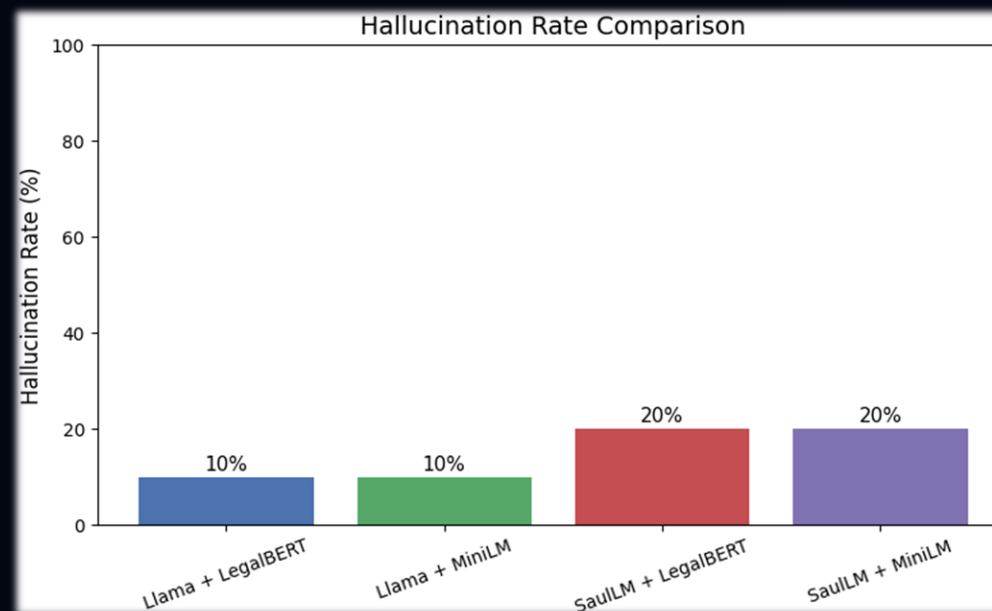
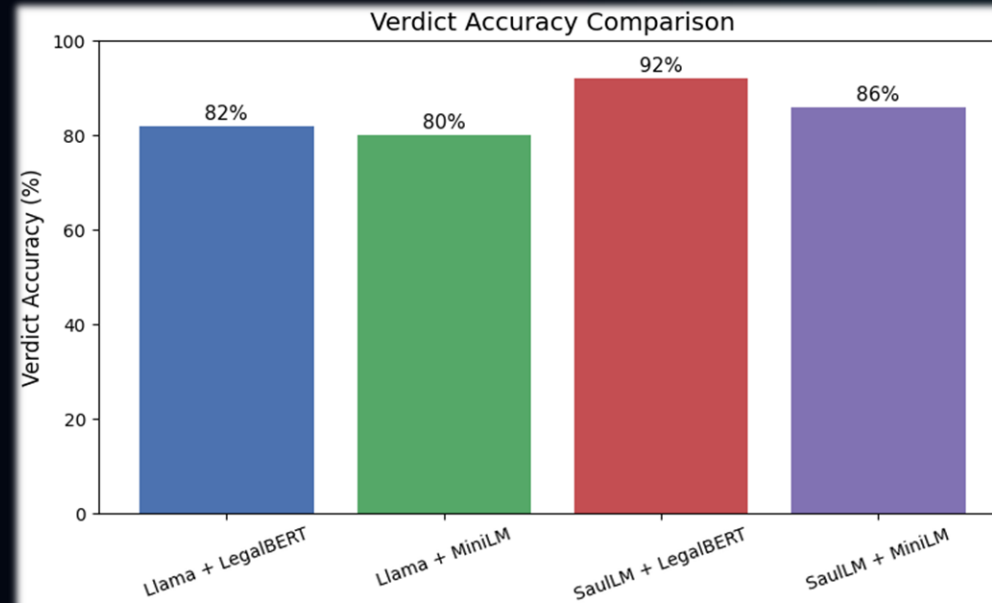
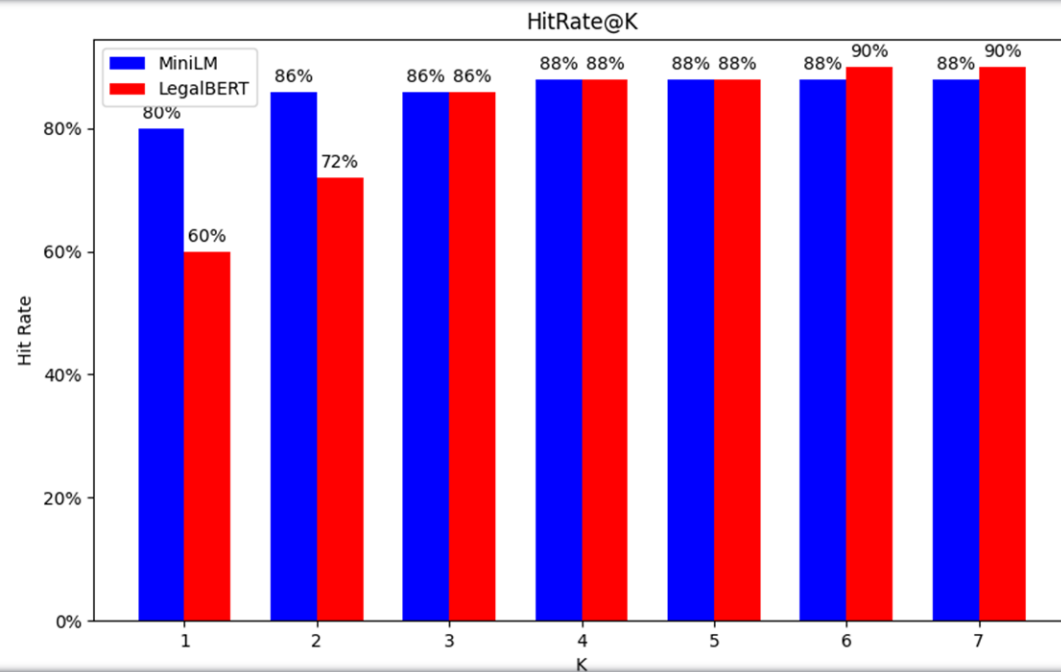
- **Context Injection:** Supplies relevant regulatory text for every query.
- **Evidence-Based:** Grounds all answers in **official sources** (B.O.I) to eliminate hallucinations.
- **Dynamic Knowledge:** Accesses the latest documents without the need for retraining.

- **Vector Database:** Engineered a vector database using **ChromaDB**, consisting of **518 text chunks** extracted from official regulations.
- **Dual-Encoder Strategy:** Compared **all-MiniLM** and **LegalBERT** to determine the most effective embedding model for banking and legal terminology.
- **Retrieval Evaluation:** Measured **Hit@K (HitRate)**

```
Starting Retrieval Benchmark for: [MINILM]
Connecting to DB at: /content/drive/MyDrive/Regulation/Data/RAG_db_all
Checking 50 questions...
100% 50/50 [00:18<00:00, 2.71it/s]

=====
HIT RATE RESULT: MINILM
=====
Valid Questions:      50
Successful Hits:      43
Hit Rate @3:          86.00%
=====
Full report saved to: /content/drive/MyDrive/Regulation/Results/retrieva
```

# RESULTS



# |CONCLUSION

## Looks Good... But Can Be Better:

- Minor hallucinations are still present.
- The model identifies the correct chunk in most cases, but consistency is not guaranteed.
- In a high-stakes domain like this, even small errors are unacceptable.

## Things We (Painfully) Learned:

- Each model comes with its own pros and cons.
- Hallucination handling needs to be significantly stricter.
- A diverse set of KPIs is needed to properly evaluate model quality.

## Where Do We Go From Here?

- Experiment with additional models and architectures.
  - Introduce more rigorous validation and consistency checks in the RAG pipeline.
  - Add a faithfulness metric using an LLM judge to verify citation-explanation alignment.
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