

3.7 From Legal Documents to Formalized Rules with Large Language Models

Stefan Griesche, Moritz Nekolla | Robert Bosch GmbH

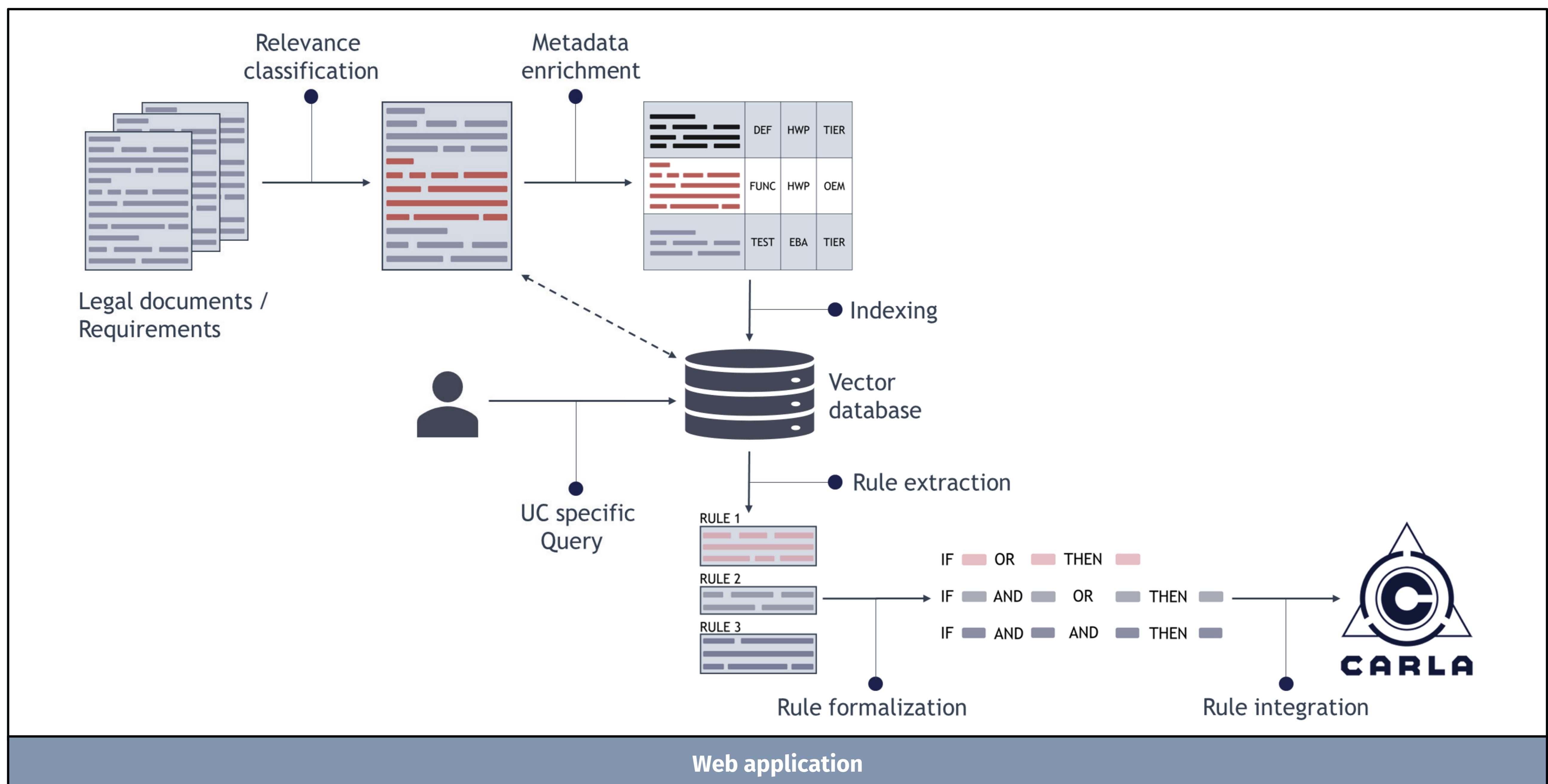


Figure 1: End-to-end approach for legal rule formalization with GenAI (© Robert Bosch GmbH)

Motivation

Bosch, as a Tier 1 supplier, develops products for assisted and automated driving functions globally. These products must be compliant to specific laws, standards, and regulations in each target market. Our approach utilizes AI to analyze, compare and check legal requirements of different markets more efficiently.

Relevance Classification

Two NLP pipelines (“TF-IDF + classifiers” and “embeddings + classifiers”) are implemented to classify documents and paragraphs on their relevance to certain product areas.

	Not relevant	Relevant	Weighted Acc.
Precision	0.99	0.68	0.97
Recall	0.98	0.84	
F1-Score	0.98	0.75	
Test split	94%	6%	

Table 1: Results for relevance classification on legal documents

Metadata Enrichment

The aim of the meta data enrichment (such as req., function type, similarity) is to optimize the retrieval in the following step.

Class (req. type)	No Req.	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5	Cat. 6	Cat. 7	Avg ACC
One-shot (GPT3.5)	0.00	0.14	0.08	0.10	0.95	0.27	0.39	0.30	0.23
One-shot (GPT4)	0.04	0.36	0.00	0.13	0.78	0.93	0.28	0.24	0.35
Few-shot (2 per class)	0.08	0.51	0.33	0.26	0.89	0.84	0.21	0.41	0.39
Finetuned	0.56	0.00	0.00	0.62	1.00	0.67	0.13	0.50	0.49
Embed.	0.54	0.86	0.60	0.58	0.92	0.62	0.62	0.38	0.63
TD-IDF	0.62	0.89	0.67	0.58	1.00	0.77	0.35	0.45	0.62
Test size	32	14	5	24	13	16	13	8	-

Table 2: Evaluation of different classification methods on an internal dataset with regard to requirement type

Pipelines from relevance classification are reused and extended by GPT, BILSTM and fine-tuned embeddings. Classification results highly depended on the input data and meta-data type. GPT methods showed no benefit.

Indexing

The relevant passages from legal documents are converted into vectors using an embedding model. These vectors, along with the metadata, are stored in a vector database.

Rule Extraction

A semantic search is performed on the vector database using use case specific queries (e.g., "what rules exist for lane changes?"). The search retrieves relevant entries (text sections). These entries are used to extract and formulate rules by a LLM (GPT4).

Rule Formalization

The formalization is done by a LLM (GPT4) with zero shot learning. Prompts are designed to map the rules to a set of nested if-else conditions. These conditions determine if a rule is applicable and satisfied in a given context. The context description is based on a fixed parameter set and their value ranges.

Rule Integration

The rule integration is application specific. The integration into CARLA is achieved by mapping the rules to CARLA variables in the previous step. Coupling the rules to vehicle and environment data from the CARLA simulation allows to check them in real time.

Partners



External partners



For more information contact:
stefan.griesche@de.bosch.com

KI Wissen is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.