

# Applied Data Science Semester Project 2025

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## Part A – Data Collection and Analysis

### 1. Approach Description

Initially, the Supreme Court website and the structure of its decisions were studied to determine the necessary specifications for the dataset.

- Developed a web crawler for data collection.
- Performed basic analysis and created visualizations for the results.
- Methodology based on course slides, with ChatGPT assisting in crawler implementation and regex creation.

### 2. Dataset Specifications

Based on the project requirements and the website structure, the following dataset specifications were defined.

Field	Type	Description
<b>decision_number</b>	String	Decision number
<b>year</b>	Int	Year of the decision (e.g., 2024)
<b>department_type</b>	String	Court department type
<b>department_number</b>	String	Department number
<b>judges</b>	List<String>	Judges involved in the decision
<b>introduction_text</b>	String	Introductory text of the decision
<b>main_text</b>	String	Main text of the decision
<b>conclusion_text</b>	String	Conclusion of the decision
<b>penal_code</b>	Set<String>	Articles of Penal Code (ΠΚ)
<b>code_of_criminal_procedure</b>	Set<String>	Articles of Code of Criminal Procedure (ΚΠΔ)
<b>civil_code</b>	Set<String>	Articles of Civil Code (ΑΚ)
<b>code_of_civil_procedure</b>	Set<String>	Articles of Code of Civil Procedure (Κπολδ)
<b>decision_link</b>	String	Link to the corresponding decision

### 3. Web Crawler

Python crawler developed (code in data\_science\_part1).

- Connected to the Supreme Court website using Selenium WebDriver.
- Discovered 2,475 article links and extracted information using BeautifulSoup and regex.

## 4. Results Analysis

- Successfully extracted decision number, year, department type, and department number.
- Text data and legal references were more challenging due to heterogeneous structures.
- Most articles follow a regex-detectable pattern; exceptions exist, causing some extraction errors.
- Legal references appear in multiple formats, complicating extraction using regular expressions.

Visualizations of the dataset are in data\_science\_part1.

Dataset link: decisions.csv

## Part B – Legal Document Analysis

### B1. Supervised Machine Learning for Document Classification

#### 1. Setup

- Installed necessary libraries for preprocessing and model building.
- Implemented functions to load datasets for each label (volume, chapter, subject) and each Hugging Face set (train, validation, test).
- Functions were created for model construction and training.
- Multiple hyperparameter tests conducted; final models selected based on performance and computational efficiency.

#### 2. Models and Hyperparameters

i) SVM

Label	Representation	C	Notes
<b>volume</b>	BoW	500	High performance
<b>volume</b>	TF-IDF	1000	High performance
<b>chapter</b>	BoW	1000	Slight decrease
<b>chapter</b>	TF-IDF	1000	Slight decrease
<b>subject</b>	BoW	1000	Lower performance due to few samples
<b>subject</b>	TF-IDF	1000	Lower performance due to few samples

ii) Logistic Regression

Label	C	Notes
<b>volume</b>	10	High performance
<b>chapter</b>	10	Performance decreases with more categories
<b>subject</b>	10	Performance lower due to few samples

### iii) Random Forest

Label	n_estimators	max_depth	Notes
<b>volume</b>	100	20	Good performance
<b>chapter</b>	200	20	Decreased performance
<b>subject</b>	200	20	Decreased performance

Note:  $n > 500$  caused MemoryError.

Observation: Many chapter and subject categories had very few samples, leading to zero precision, recall, and F1-score for these classes.

## B2. Topic Analysis of Supreme Court Decisions

### 1. Data Preparation

- Data split into train (60%), validation (10%), test (20%).
- Exploratory analysis showed 315 unique categories; most frequent: 'Adequacy of reasoning'.
- Distribution is imbalanced, which may affect algorithms like K-Means.

### 2. K-Means Clustering

- Preprocessed using TF-IDF + SVD (500 features).
- K-Means applied with  $K = 2-20$ ; evaluated using Macro/Micro Silhouette and NMI.

Text Type	Best K	Metric
<b>Full Text</b>	19	High NMI for case_category
<b>Summary</b>	20	Good NMI

Note: NMI preferred over Silhouette as it considers actual category labels.

### 3. LLM-based Title Extraction

- K-Means on summaries with  $K = 20$  clusters.
- Selected three decisions per cluster (centroid-near or random) to create prompts for LLM.
- LLM (model: llama-4-maverick:free via OpenRouter) generated titles describing main legal issues.

Findings:

- Centroid-near selections produced clearer and more accurate titles.
- Random selections were often more general or less relevant.
- Conclusion: Centroid-based selection is more reliable for representing cluster topics.