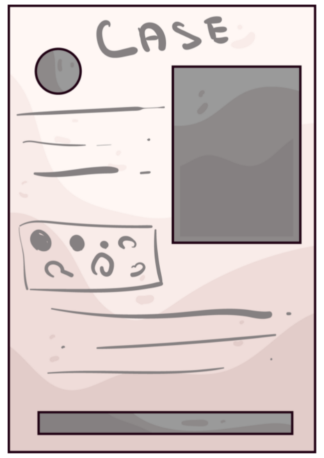


[40] ClearCase : Legal Text Classification with Explainable AI

CSCI 566 DEEP LEARNING AND ITS APPLICATIONS

Team 40

Meet Our Team

Workflow (Design) + Literature Review + References

INDIRA

MONA

BHAVYA

MOHAN

ARUN

ASHWIN

INDIRA, MONA:
EDA, Data Cleaning
&
Truncation + Chunking

BHAVYA (CARC), MOHAN (LOCAL):
Hyperparameter Tuning
&
Training (Fine-Tuning)

ARUN, ASHWIN:
Testing, Results
&
Explainability

Why is the problem interesting?

ClearCase aims to revolutionize legal document management by automating the classification of complex case texts leveraging advanced transformer models.

This project aims to support legal professionals in efficiently organizing case law while ensuring transparency and trust in AI-driven decisions.

01 Automating Legal Document Classification

02 Explainable AI for Transparent Decisions

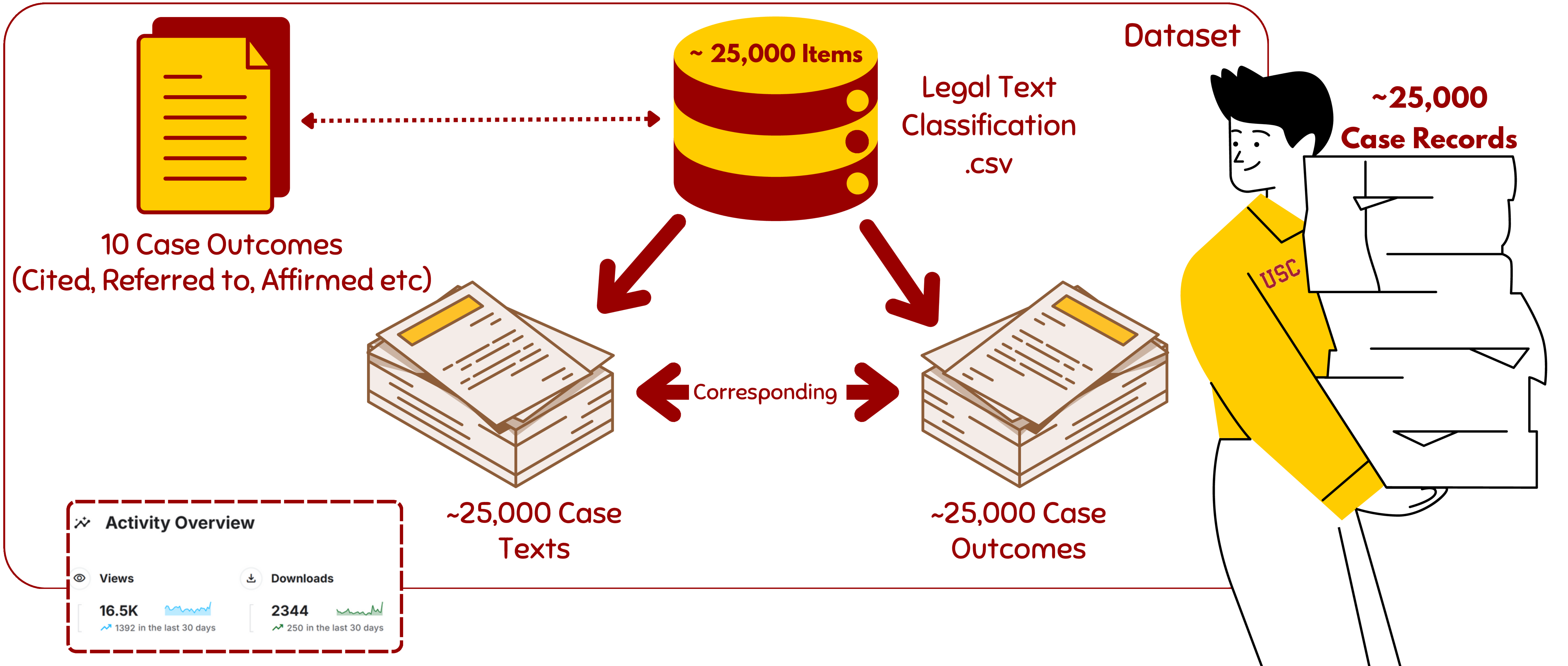
TRADITIONAL PROCESS

Manually analyzing case text and referenced precedents to estimate current case outcome.

PROPOSED PROCESS

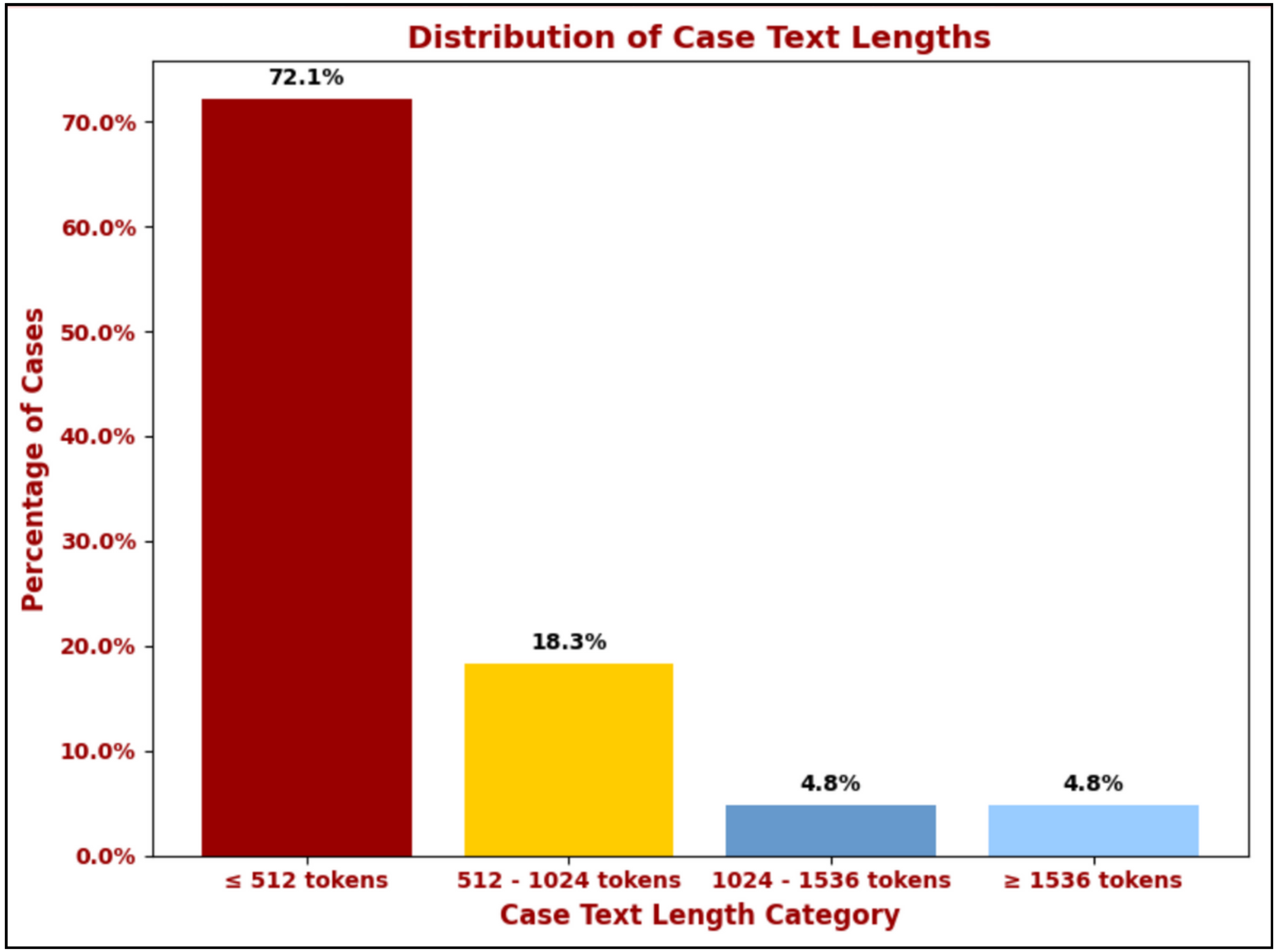
AI-driven classification of legal texts to predict outcomes with explainability.

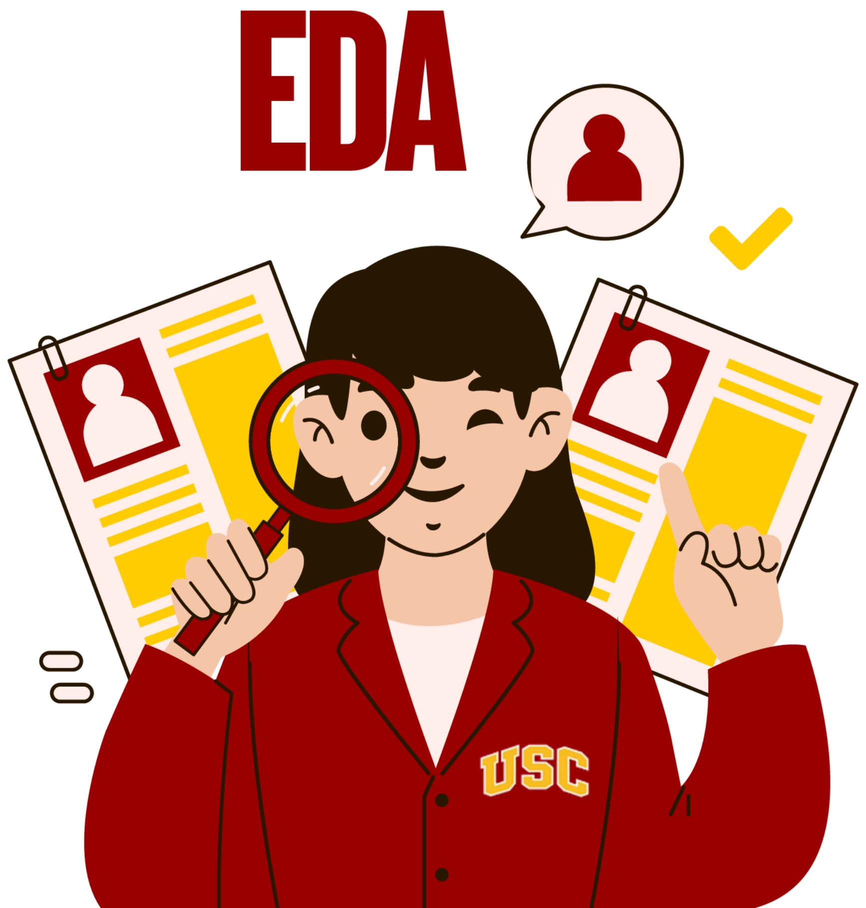
DATASET DESCRIPTION



EXPLORATORY DATA ANALYSIS

case_id	case_outcome	case_title	case_text
Case ID	Case Outcome	Case title	Case Text
24985 unique values	cited 49% referred to 18% Other (8382) 34%	18581 unique values	17921 unique values





Modeling Choices

01 roberta-large-mnli – 0 shot (Baseline)

02 roberta-large-mnli

03 legal-bert-base-uncased

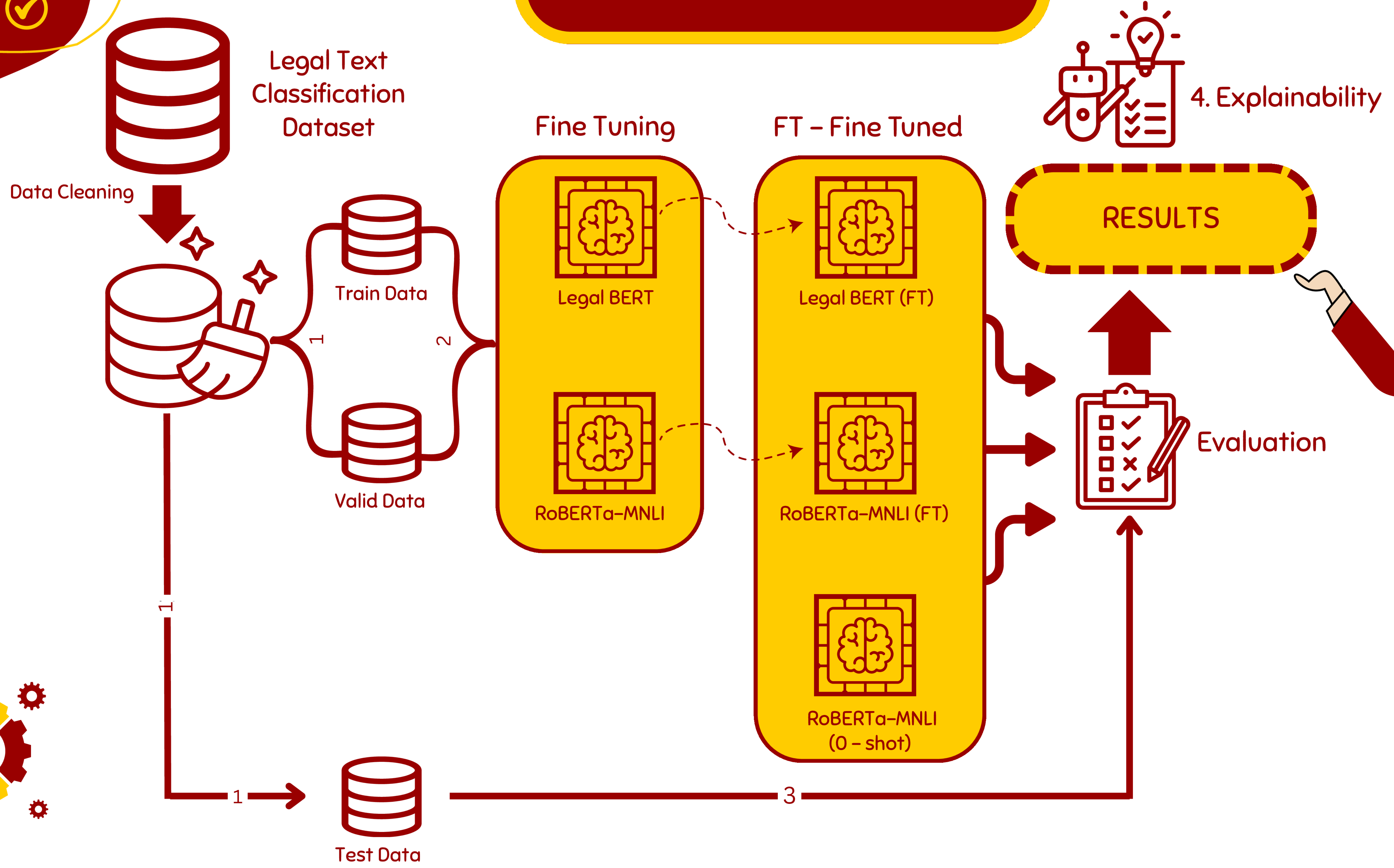
BERT Based Models

RoBERTa

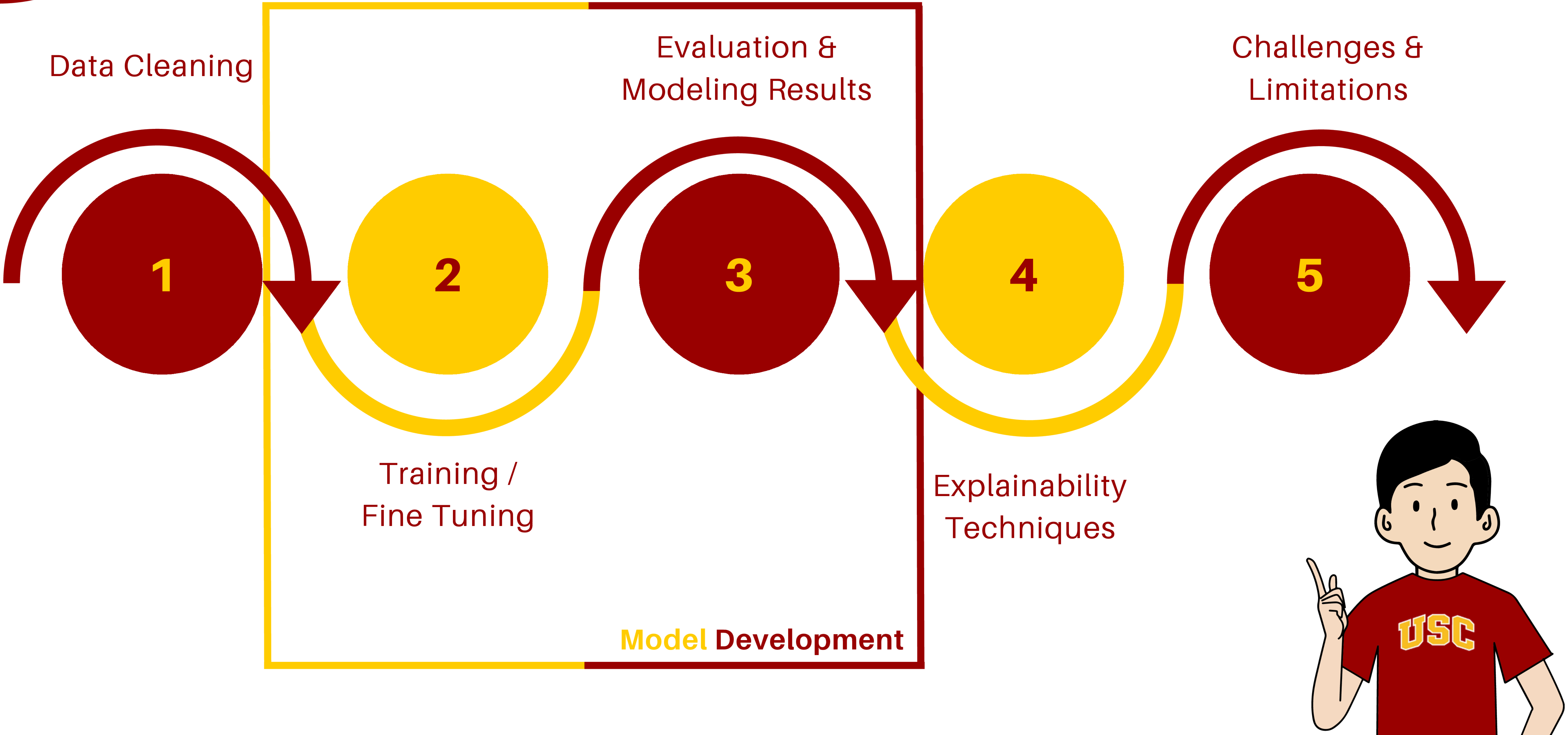
LegalBERT

Hugging Face

ClearCase Workflow



PROCESS OVERVIEW



DATA CLEANING

01 Filter out records with null values in key fields

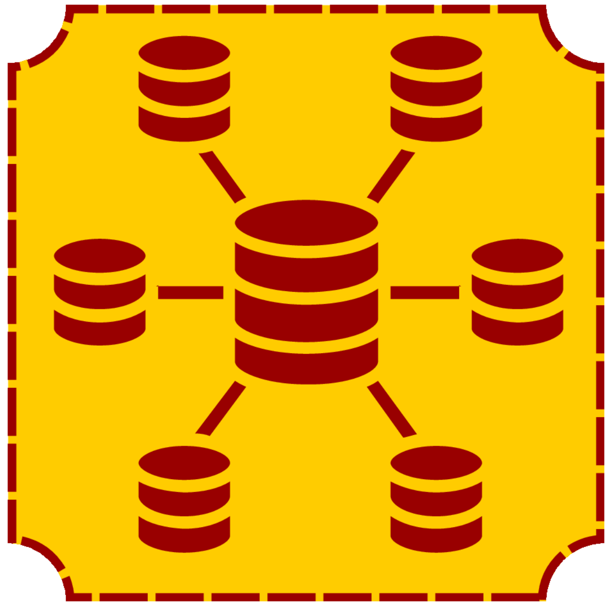
02 Drop duplicates where both case_text and case_outcome are identical

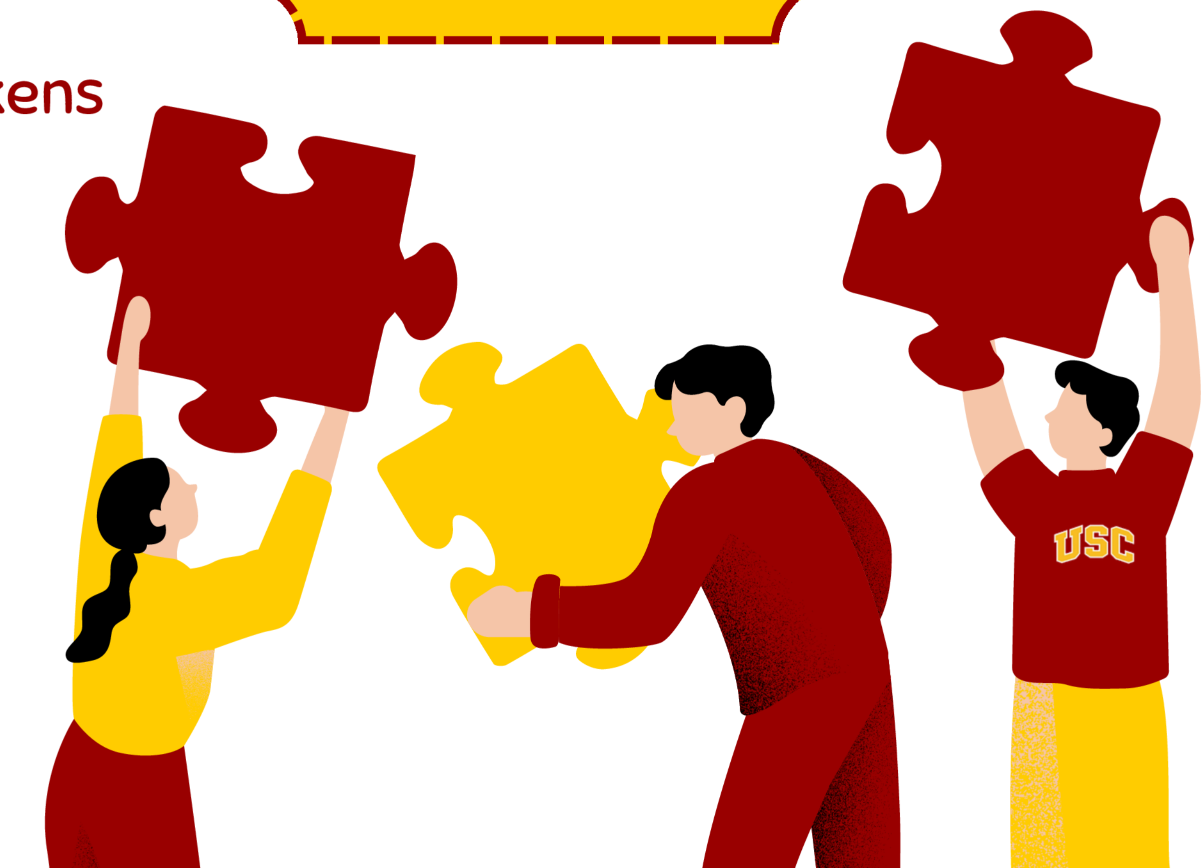
TRUNCATION

01 Head Method
(Consider First 512 Tokens)

02 Head –Tail Method
(Consider First 256 Tokens + Last 256 Tokens)

SOLUTION: CHUNKING





TRAINING / FINE-TUNING

01 BATCH SIZE : 8, 16, 32

02 EPOCHS: 4, 6

03 OPTIMIZER: ADAM

04 WEIGHT DECAY: 0.01

05 LEARNING RATE: 2e-5

Evaluation

Here are few evaluation metrics we computed to measure the model's performance

01 Accuracy

$$\text{Accuracy} = \left(\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}\right) \times 100$$

02 Precision

$$\text{Precision} = \left(\frac{\text{Number of True Positives}}{\text{Total Number of Positive Predictions}}\right) \times 100$$

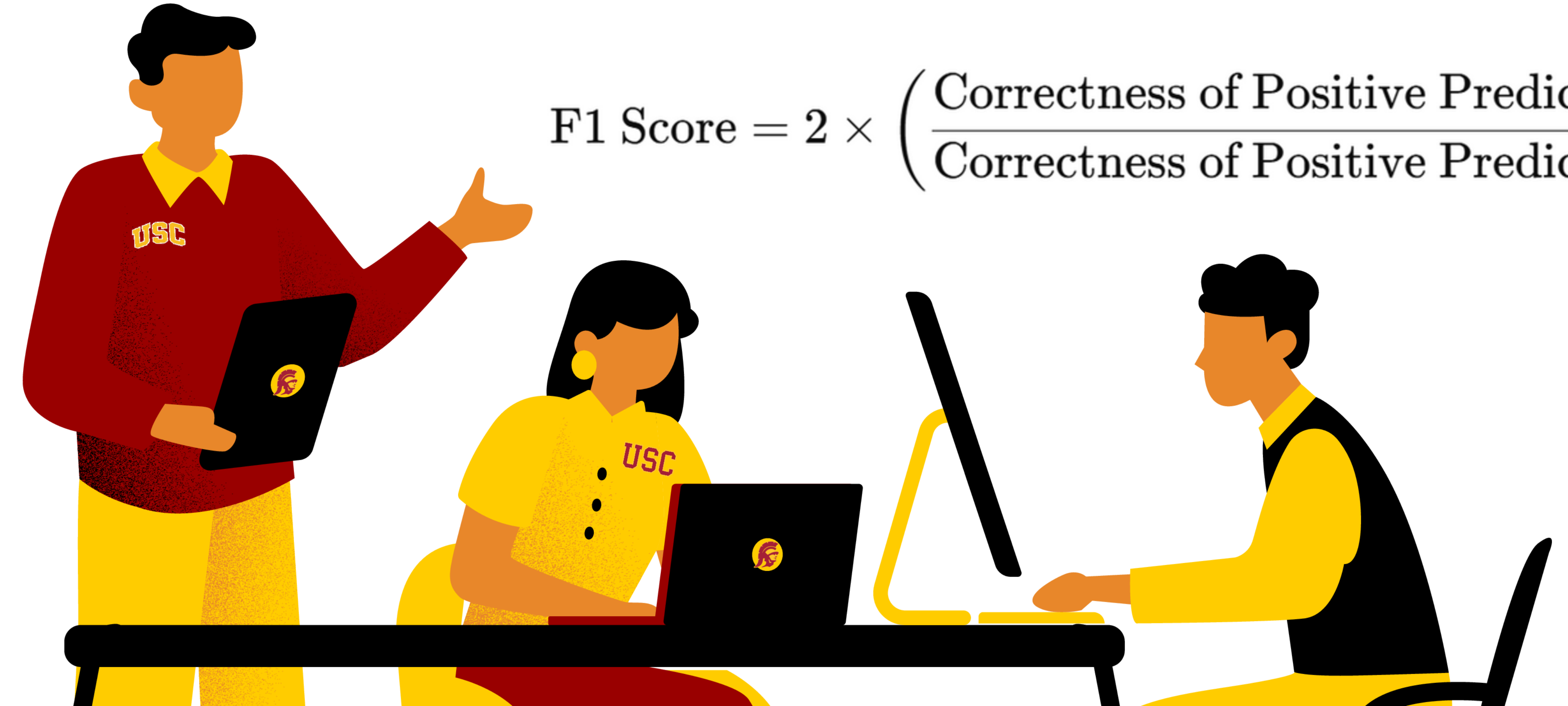
03 Recall

$$\text{Recall} = \left(\frac{\text{Number of True Positives}}{\text{Total Number of Actual Positives}}\right) \times 100$$

04 F1-Score

$$\text{F1 Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right)$$

$$\text{F1 Score} = 2 \times \left(\frac{\text{Correctness of Positive Predictions} \times \text{Coverage of Actual Positives}}{\text{Correctness of Positive Predictions} + \text{Coverage of Actual Positives}}\right)$$



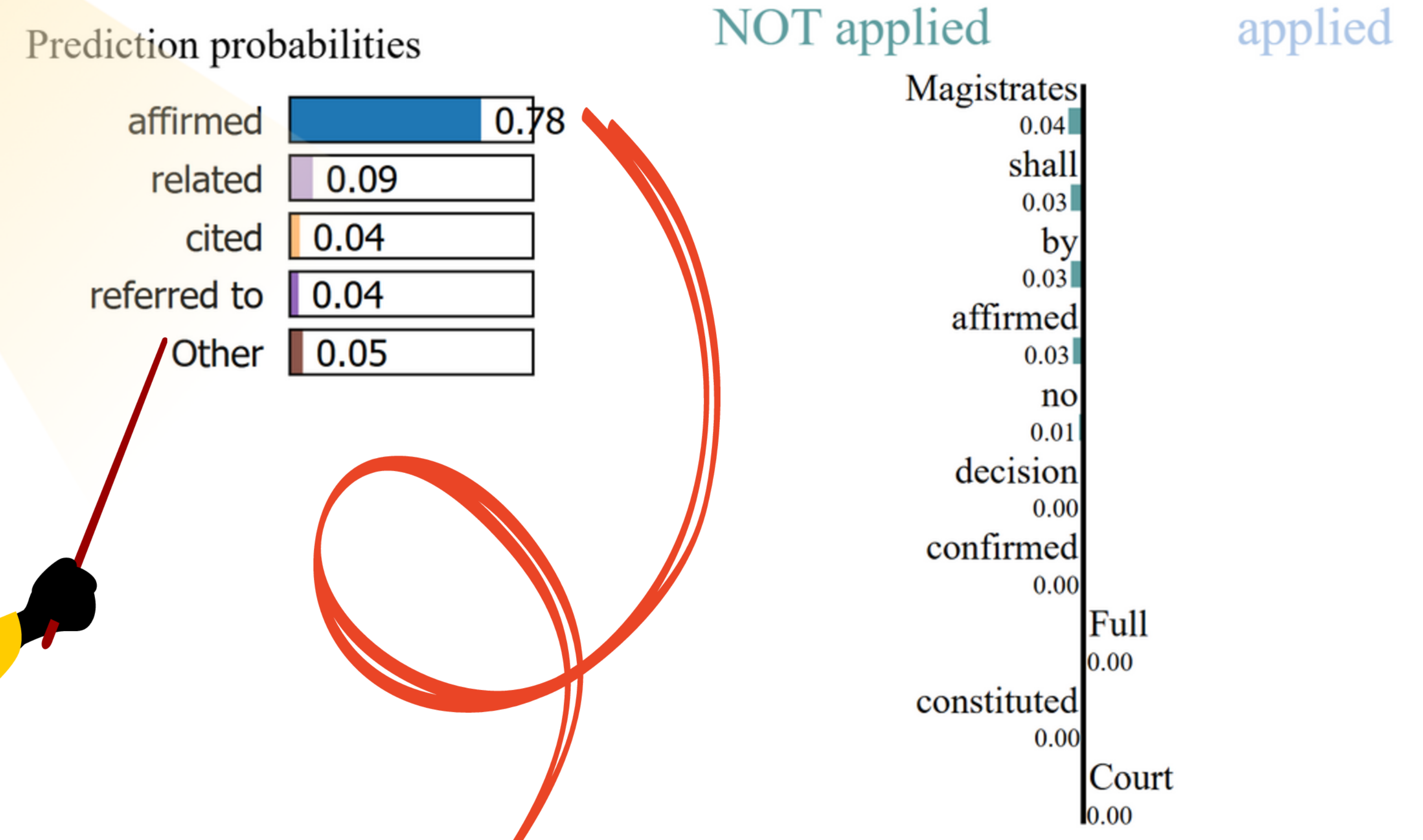
Modeling Results

We fine-tuned with different parameters for these models and followed different chunking strategies. Only the best results for each model (checkpoint) is shown in the below table

FT – Finetuned
H – Head Method
HT – Head Tail Method
C – Chunking

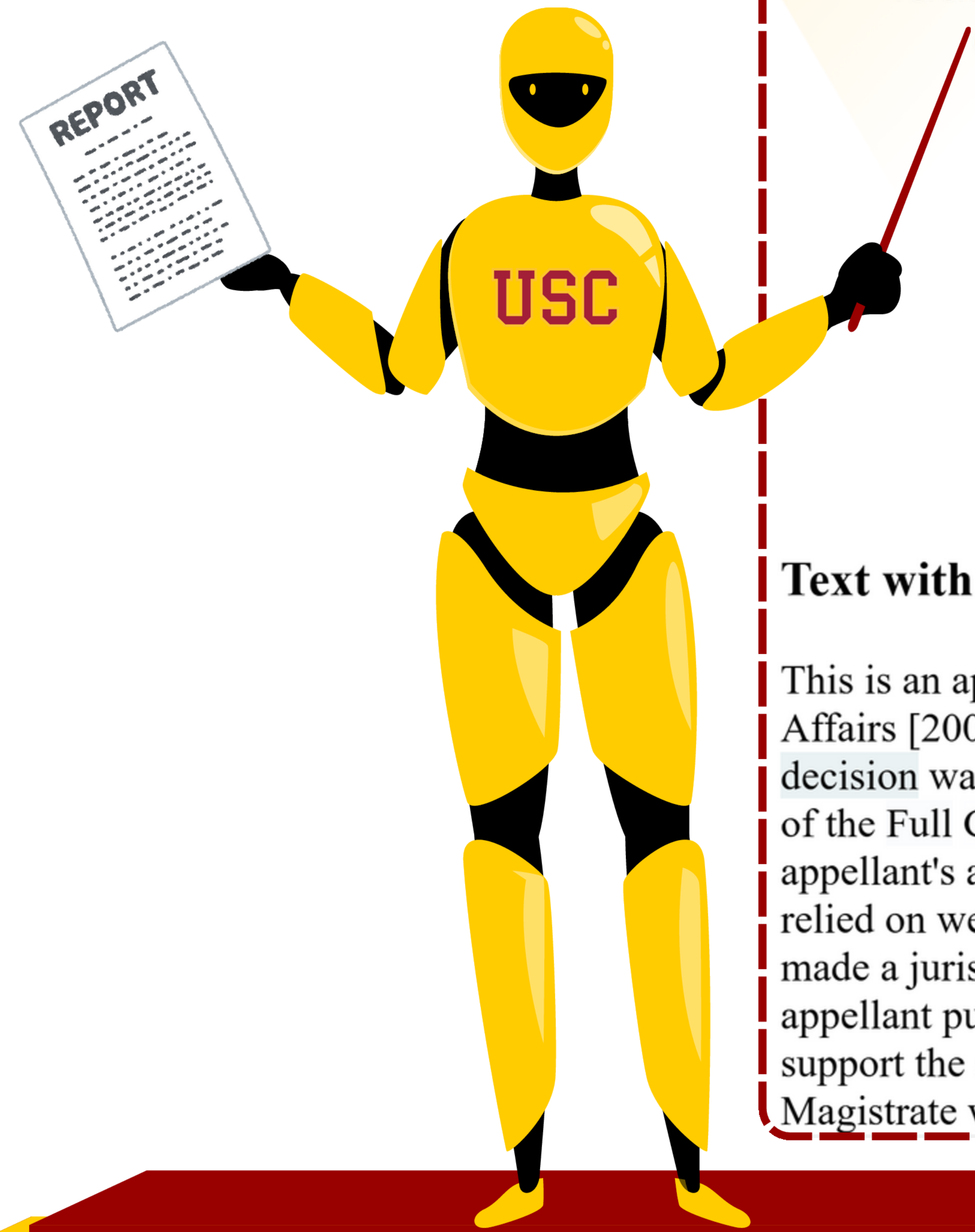
MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
robeta-large-mnli – 0 shot (Baseline)	29.15%	16.84%	14.60%	11.95%
legal-bert-base-uncased (FT) – H	53.32%	49.79%	52.25%	50.02%
roberta-large-mnli (FT) – H	53.68%	51.35%	52.12%	51.74%
legal-bert-base-uncased (FT) – HT	54.79%	52.94%	54.74%	52.97%
roberta-large-mnli (FT) – HT	54.83%	50.44%	54.78%	51.67%
legal-bert-base-uncased (FT) – C	62.27%	64.26%	62.19%	62.57%

Explainability (LIME)



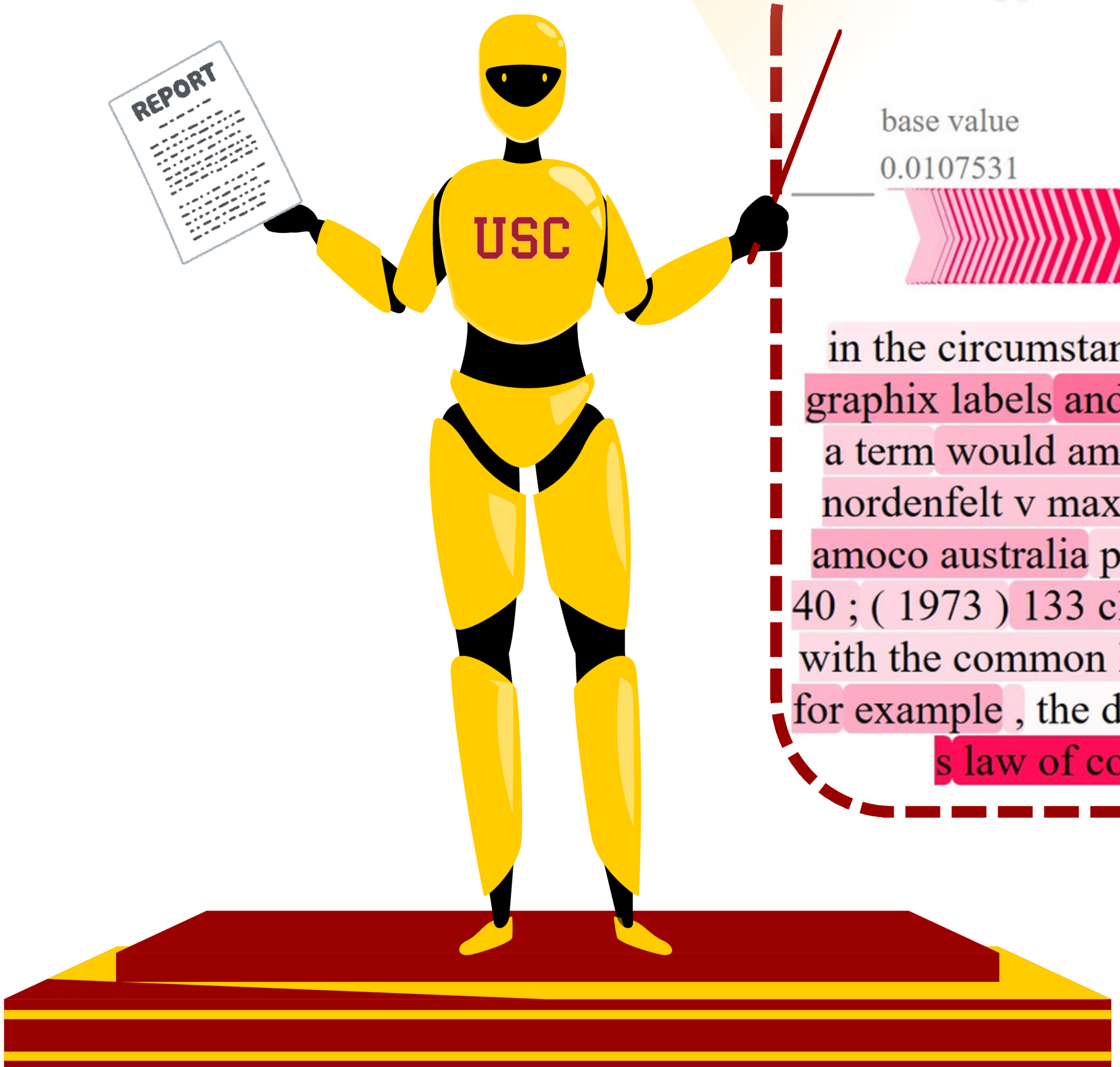
Text with highlighted words

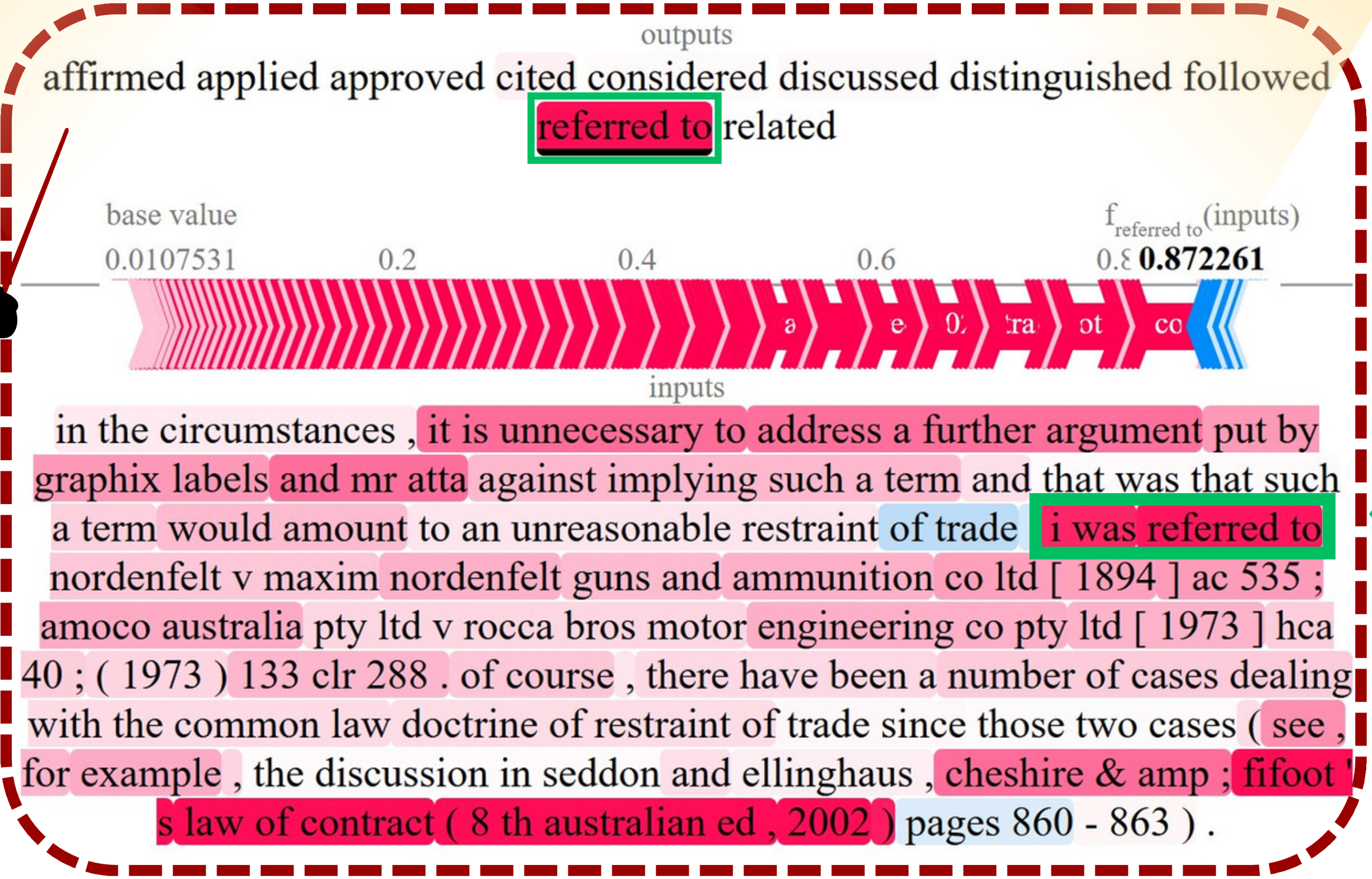
This is an appeal from the Federal Magistrates Court: SZDDZ v Minister for Immigration |amp; Multicultural Affairs [2006] FMCA 1174. The appellant, a citizen of India, applied for a protection visa which was refused. That decision was affirmed by the Refugee Review Tribunal but the Tribunal's decision was set aside by a consent order of the Full Court. On the second hearing of the review by a Tribunal differently constituted the refusal of the appellant's application was again confirmed. 2 On the appeal to the Federal Magistrate, it appears that the grounds relied on were, first, the appellant did not have a fair hearing before the Tribunal and, secondly, that the Tribunal made a jurisdictional error when it "took advantage of the situation created by the interpreter" which led to the appellant putting himself in a "scary situation". In essence, the Magistrate found that there was no evidence to support the allegations of the appellant. I shall not repeat the full discussion of the appellant's claims by the Magistrate which are set out in his decision which is obtainable on the Internet.



SCAN ME

Explainability (SHAP)





SCAN ME

REFERENCES

Ilias Chalkidis, Manos Fergadiotis, Prodromos Malakasiotis, Ion Androutsopoulos, and Nikolaos Aletras. 2020. LEGAL-BERT: The muppets straight out of law school. *arXiv preprint arXiv:2010.02559*.

Sarthak Jain and Byron C. Wallace. 2019. Attention is not explanation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*.

Nut Limsopatham. 2021. Effectively leveraging BERT for legal document classification. In *Proceedings of the Natural Legal Language Processing Workshop (NLLP)*.

Scott M. Lundberg and Su-In Lee. 2017. A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems (NeurIPS)*.

Dimitris Mamakas, Ilias Chalkidis, Ion Androutsopoulos, and Nikolaos Aletras. 2022. Processing long legal documents with pre-trained transformers: Modding legalbert and longformer. In *Proceedings of the Natural Legal Language Processing Workshop (NLLP)*.

CARC USAGE

01 A100

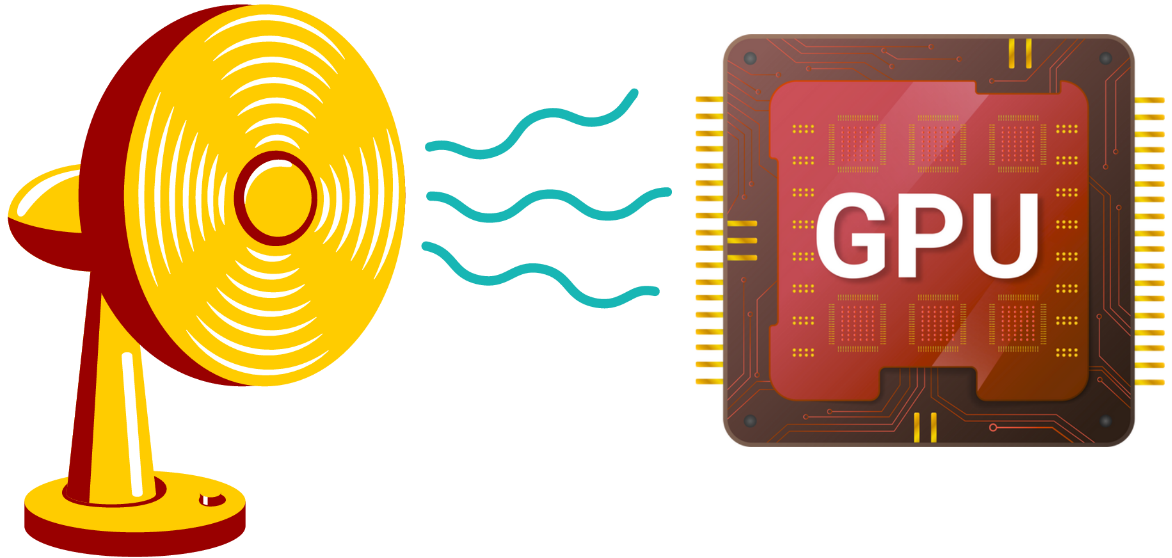
02 (All Sessions Included) Number of Hours: 52

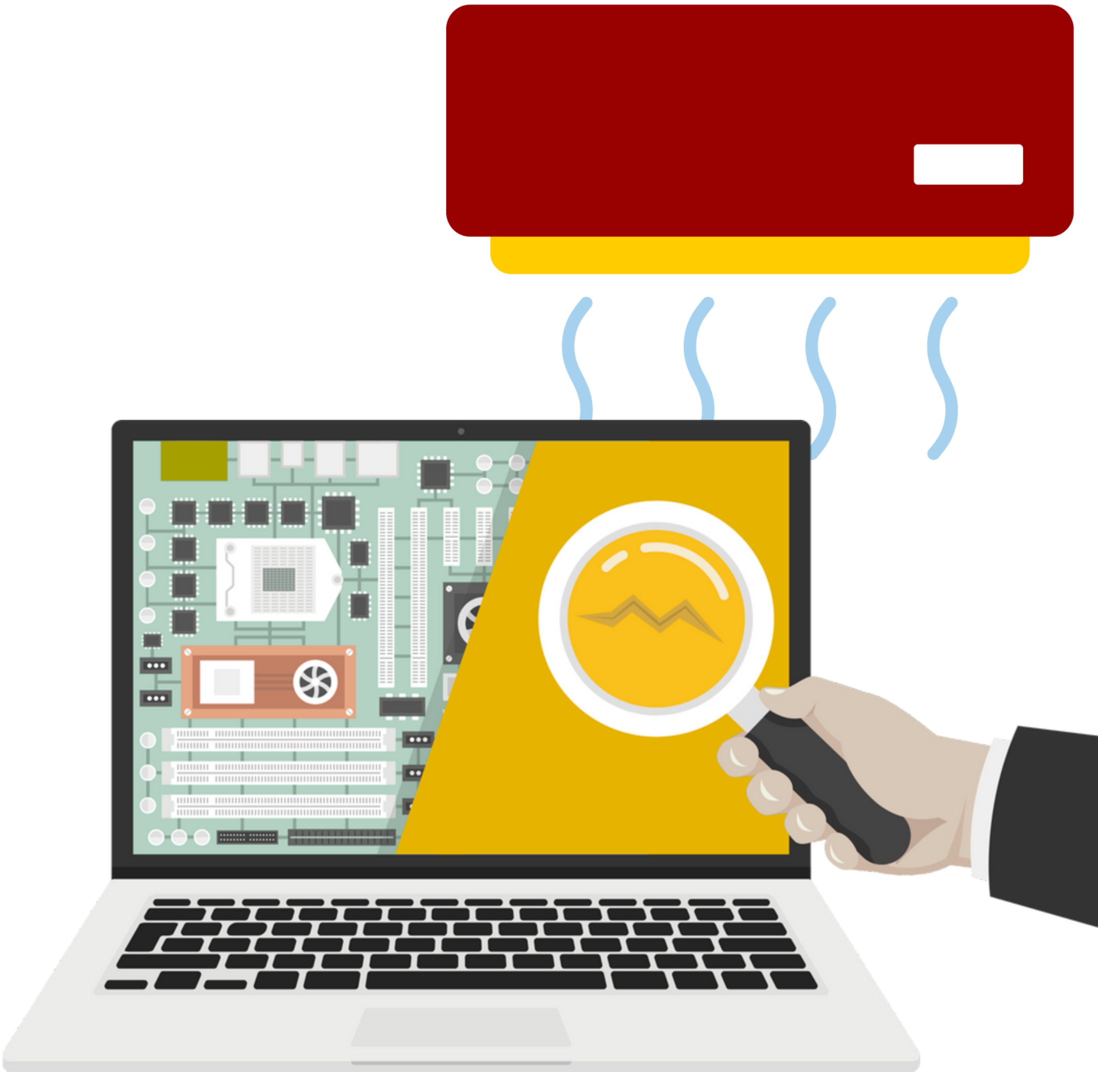
03 Number of GPUs: 2

LOCAL SPEC

01 NVIDIA GeForce RTX 4060

02 (All Sessions Included) Number of Hours: 64

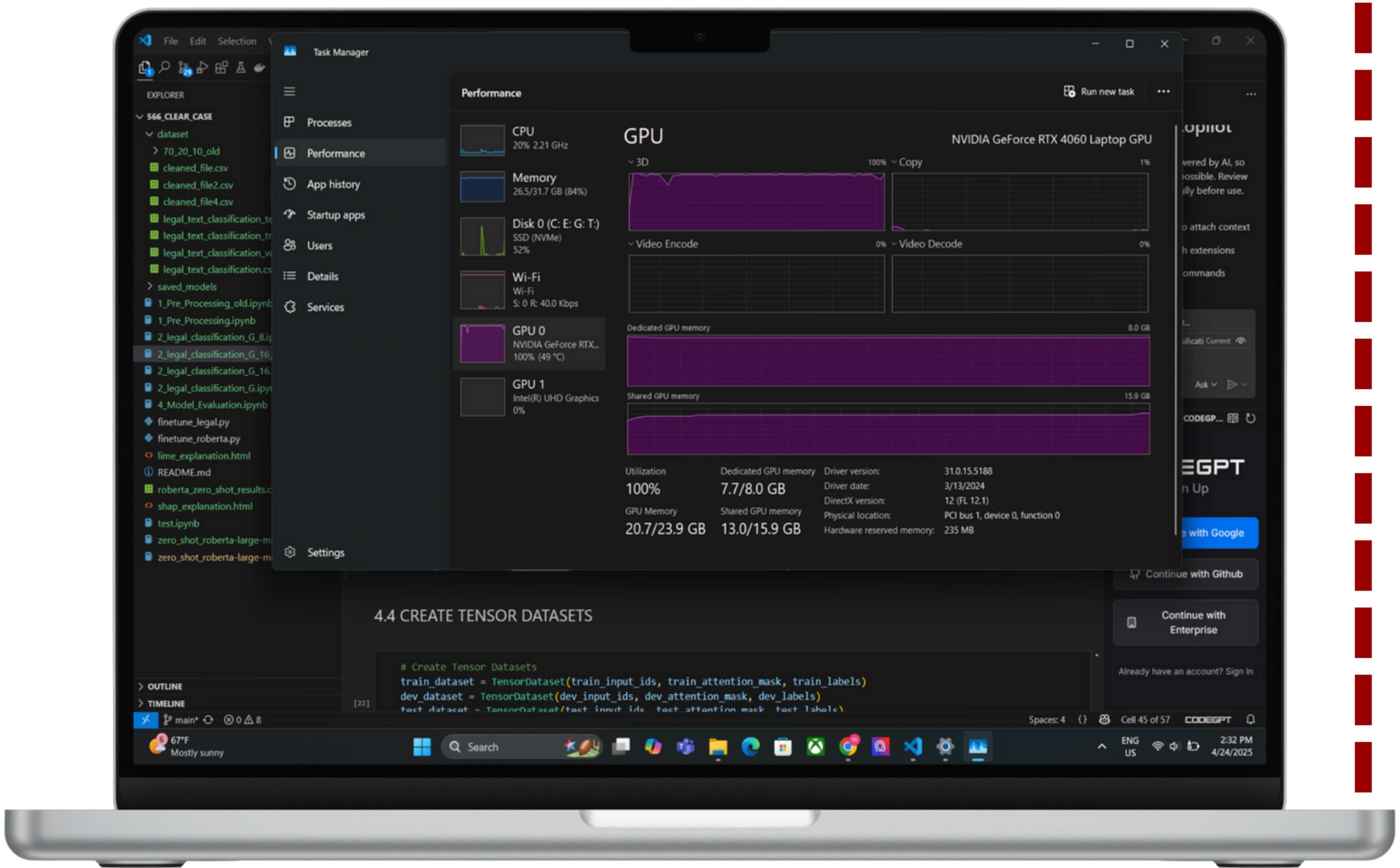




Limitations

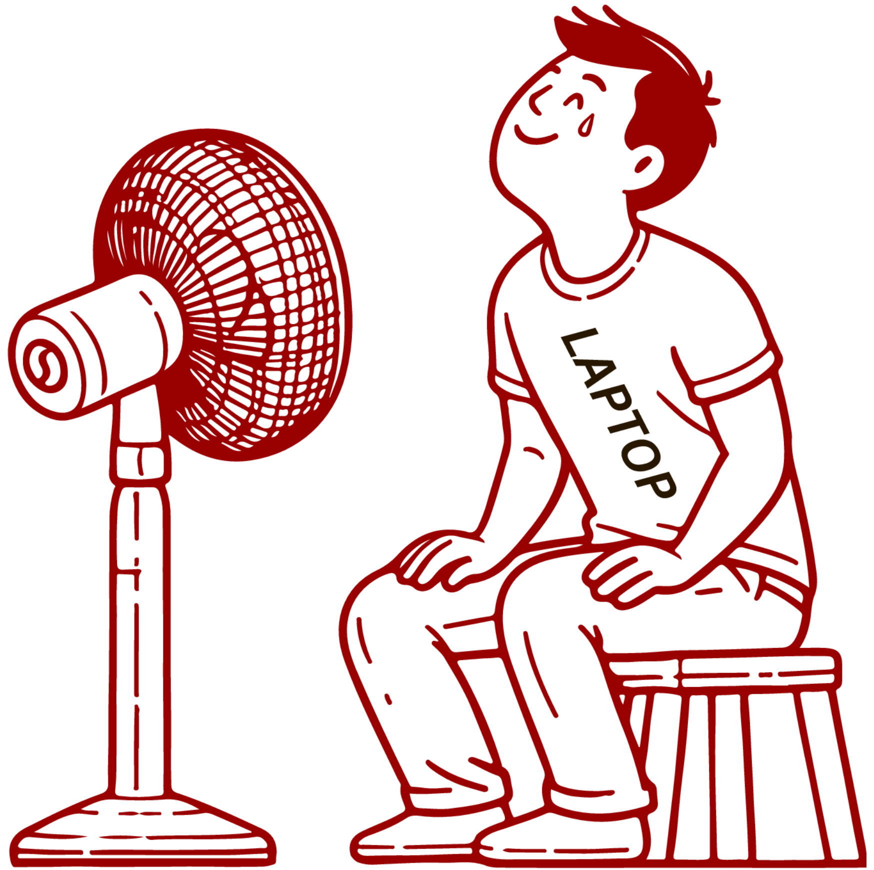
We are currently facing limitations with the Processing and Computational constraints. Details are as follows :

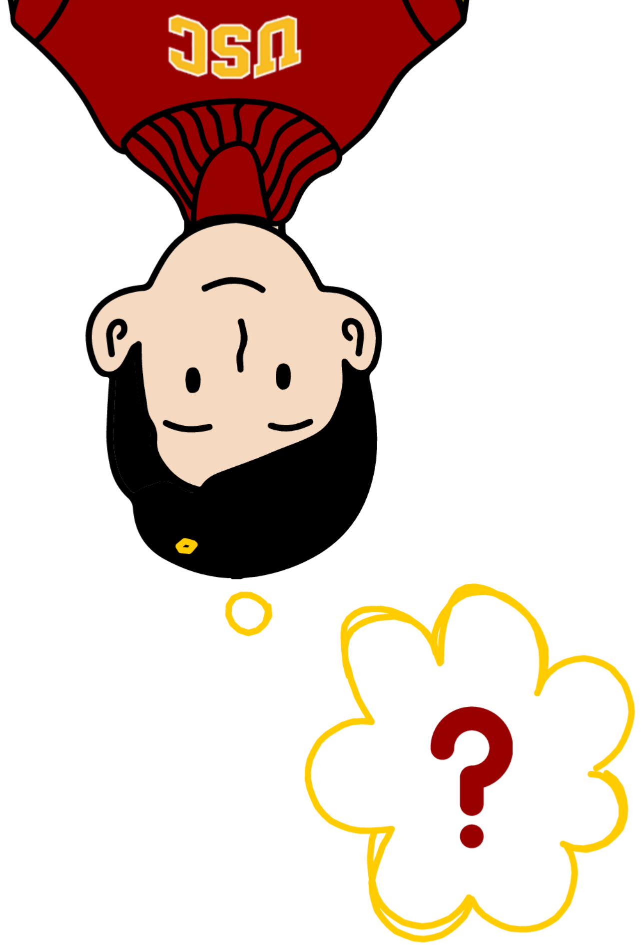
01 Computation



02 Context Window Size

Model	Window
roberta-large-mnli	512 Tokens
legal-bert-base-uncased	512 Tokens





Future Scope

Try to leverage Class-Weighted Loss Functions and Data Augmentation

Explore the possibility to increase the context window using models like Longformer.

Try more Explainability Methods & Evaluation Metrics

Longformer

Thank You!

Special Thanks to...

Haoyan Xu