

# AI powered claims models

Using Large Language Models to predict  
injury compensation claim outcomes

## Data Science Masterclass

Presented by Michael McLean and Nikolay Nikolaev



# Important notice for all participants

This meeting is being conducted in accordance with Institute's Code of Conduct and attended by members in their professional capacity.

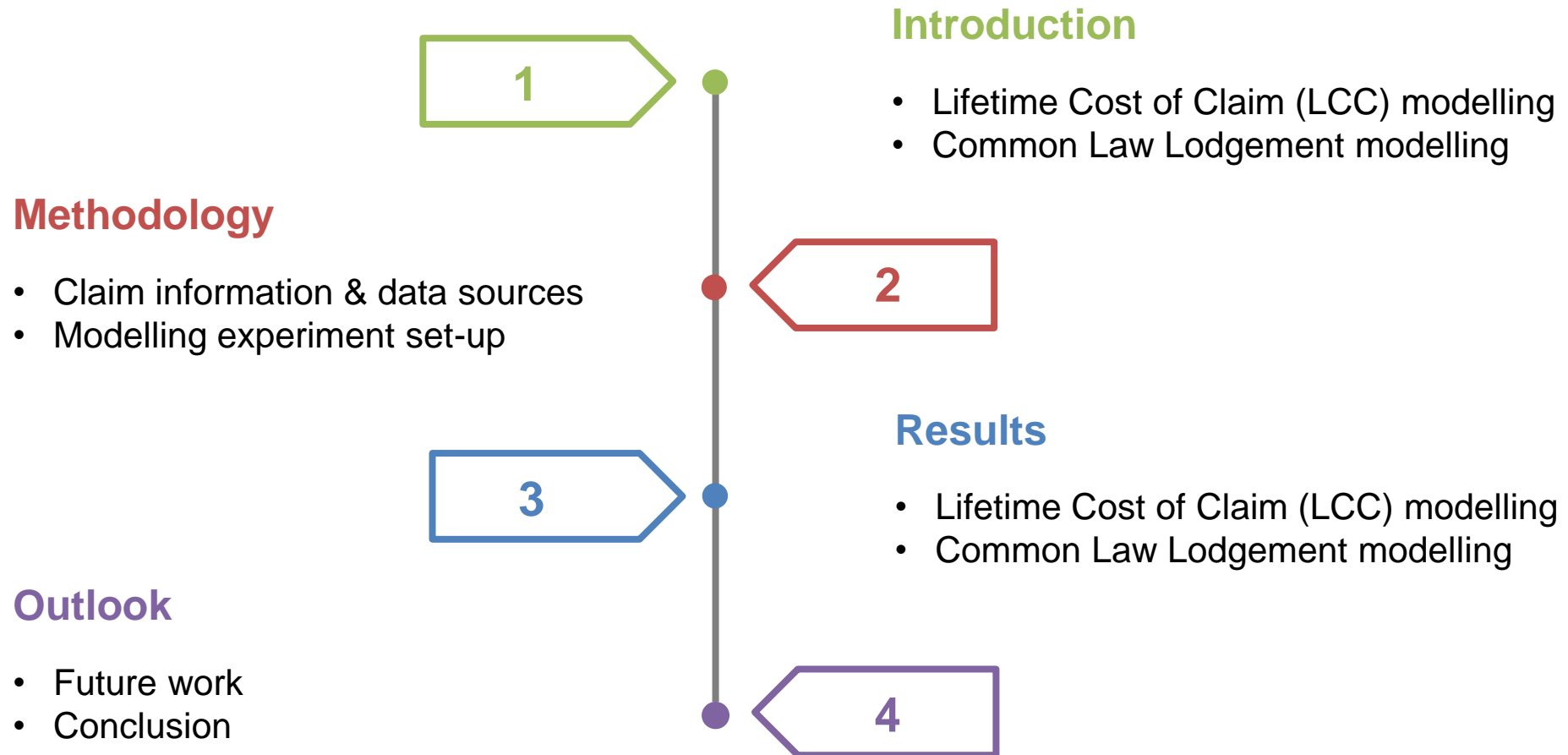
It is acknowledged that professional members in their employed capacity, may be active market participants in their respective industries who may compete with each other as defined by competition law.

Participants are, therefore, reminded that in accordance with their competition law compliance obligations they should not:

- discuss any matter that may be perceived as being cooperation by competitors in a market to influence that market;
- discuss any matters that could be regarded as fixing, maintaining or controlling prices, allocation of customers or territories, coordinating bids and/or restricting output or acquisitions in any circumstances;
- share commercially sensitive information relating to their employer; or
- share information for an anti-competitive purpose.



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# Introduction



## Lifetime Cost of Claim (LCC) model for accident compensation claims

- Case reserves
- Claim management
- Strategic intervention

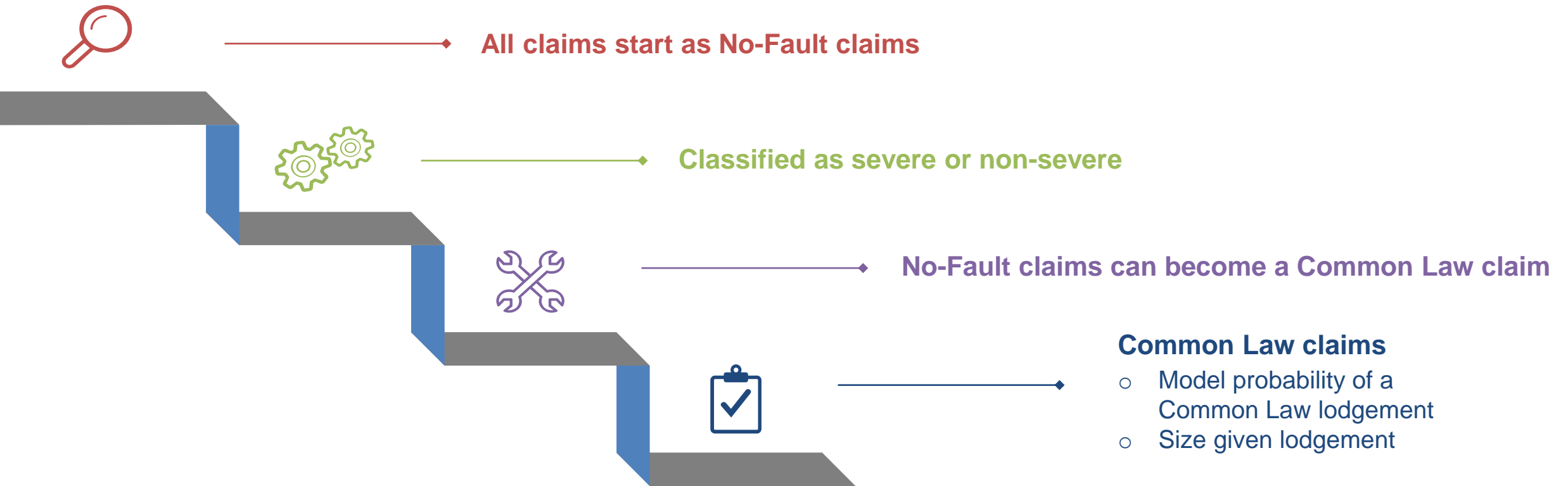


## Our research

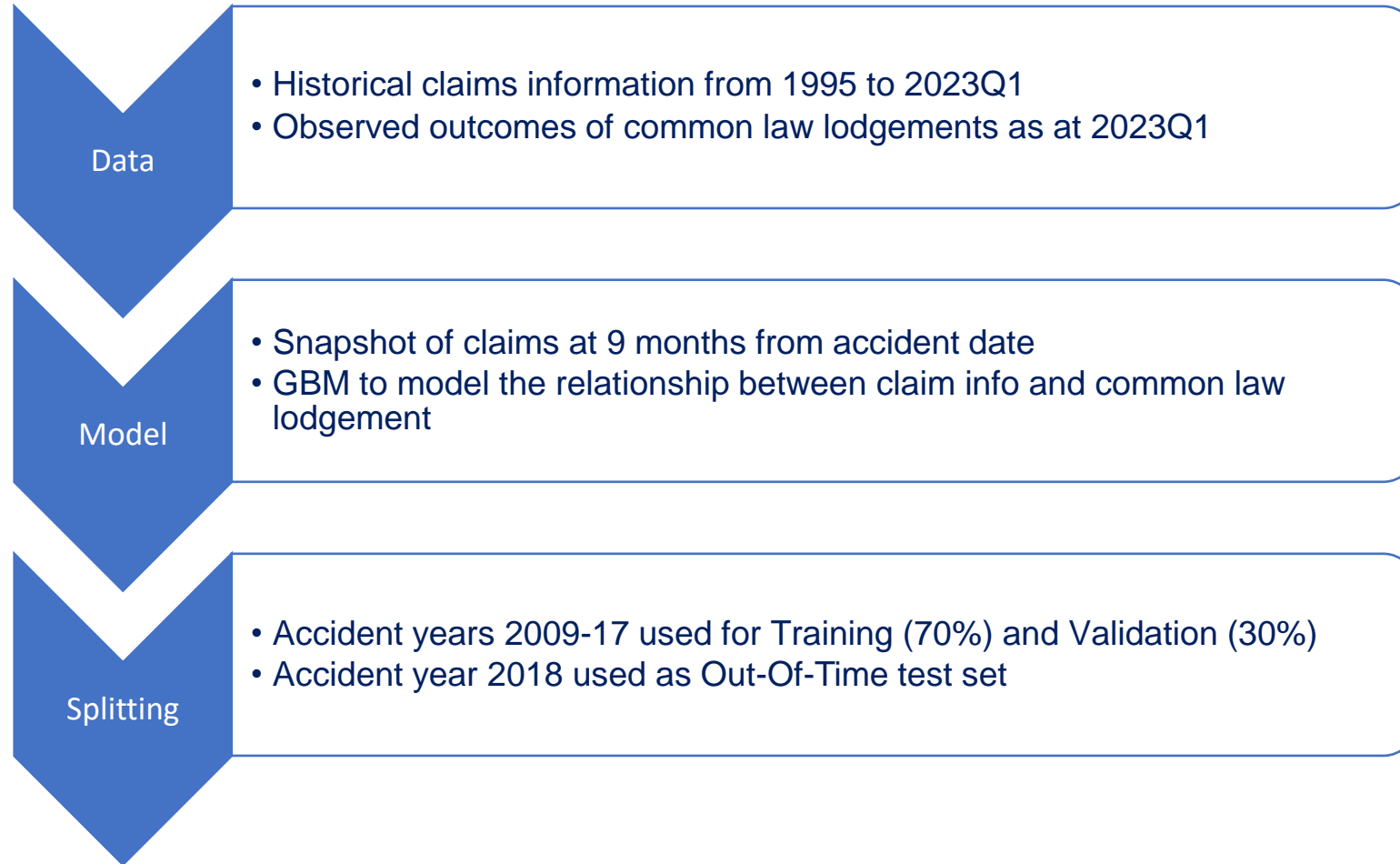
- Can unstructured text add value when modelling LCC?
- Test on one component of the LCC model we built for a large Scheme



# Lifetime Cost of Claim modelling



# Predicting the probability of CL lodgement



# Data



**Claims header file**  
All info relating to claimant,  
injury



**Payments**  
Transactions payment  
data



**Road safety data**  
Info on crash, vehicles,  
drivers involved, drugs,  
alcohol



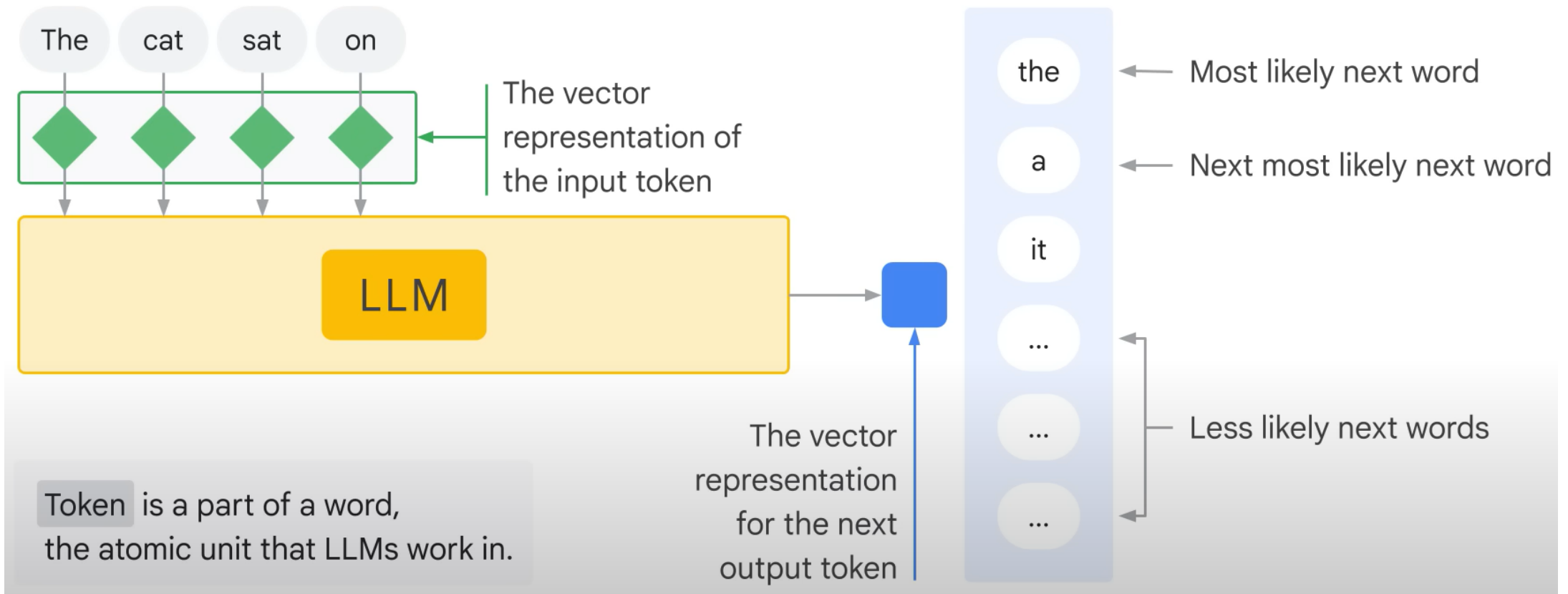
**Free form text data**  
Five distinct types (e.g.  
case notes, external  
documents, phone calls)



**Census data**  
SEIFA index,  
vehicle density,  
remoteness

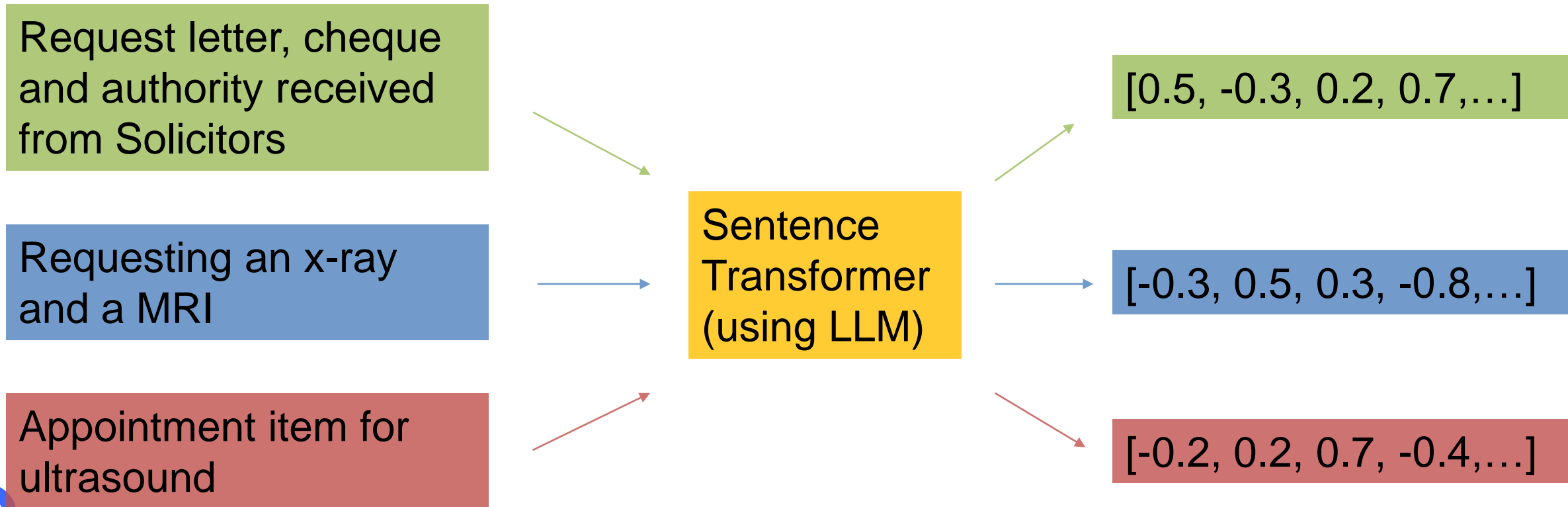


# Large Language Models

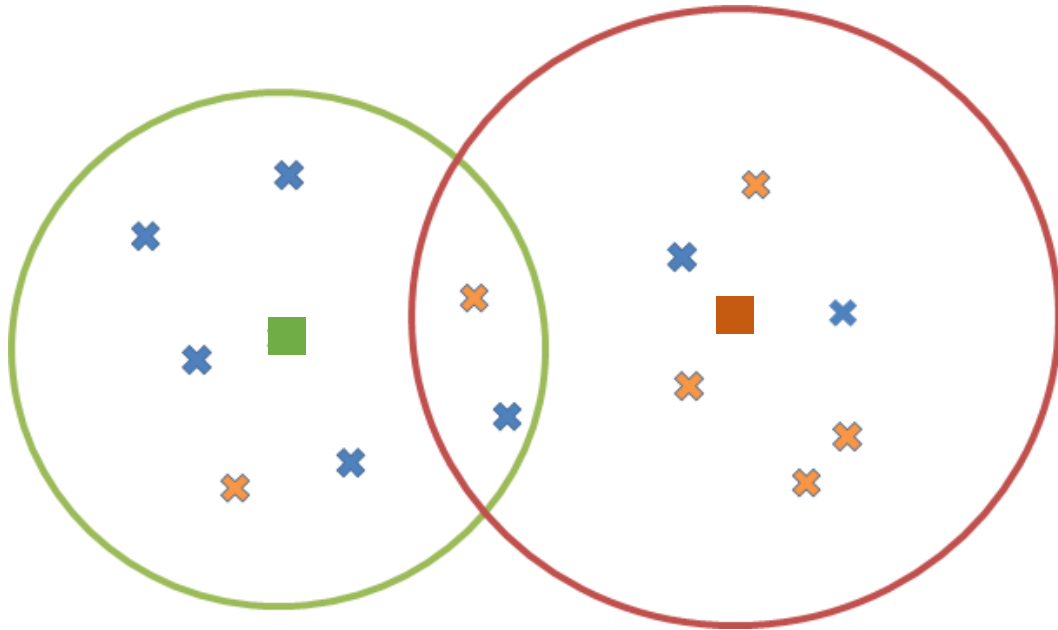




# Sentence embeddings



# Use LLM for finding similar claims

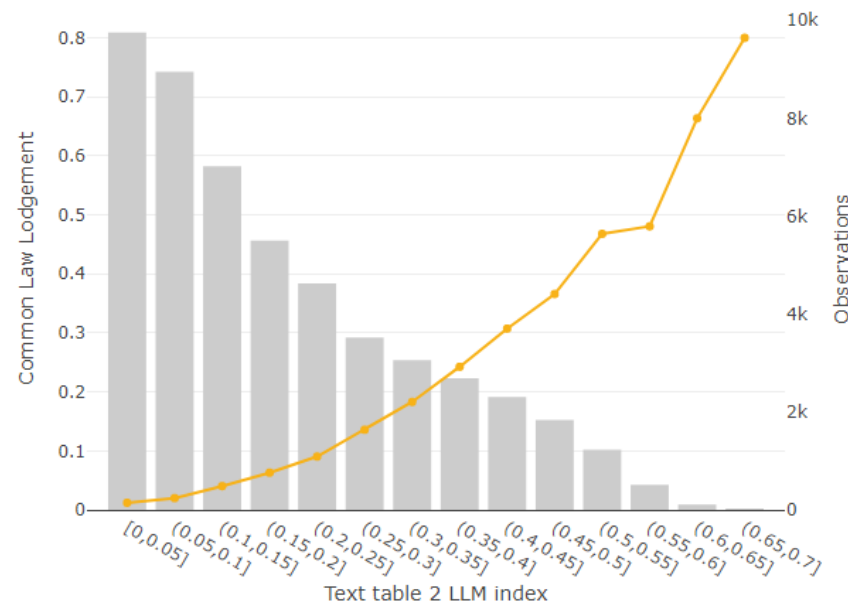
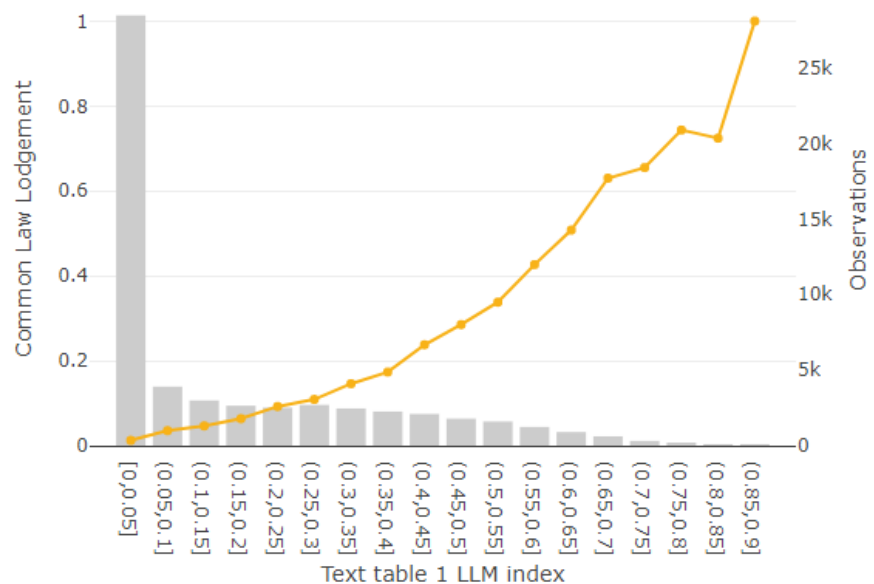


**Intuition:** Can historical claims with similar claim descriptions help predict the probability of a common law claim?

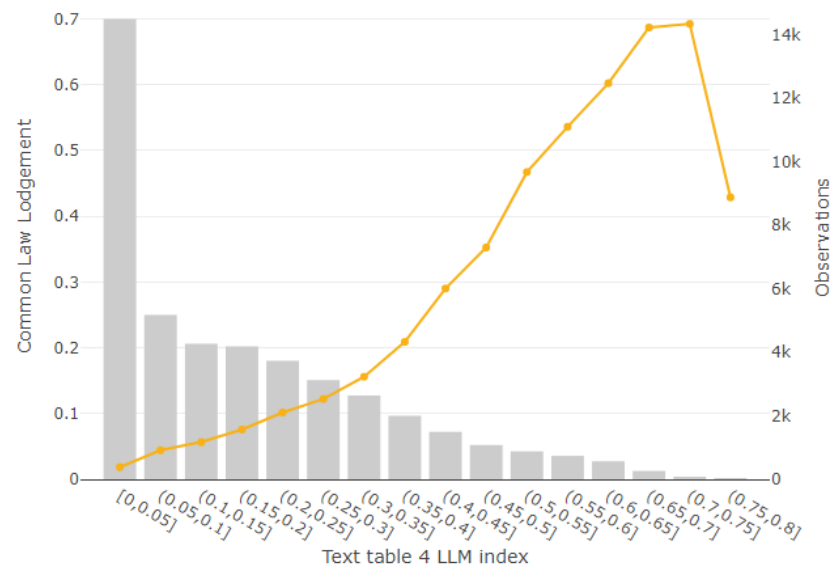
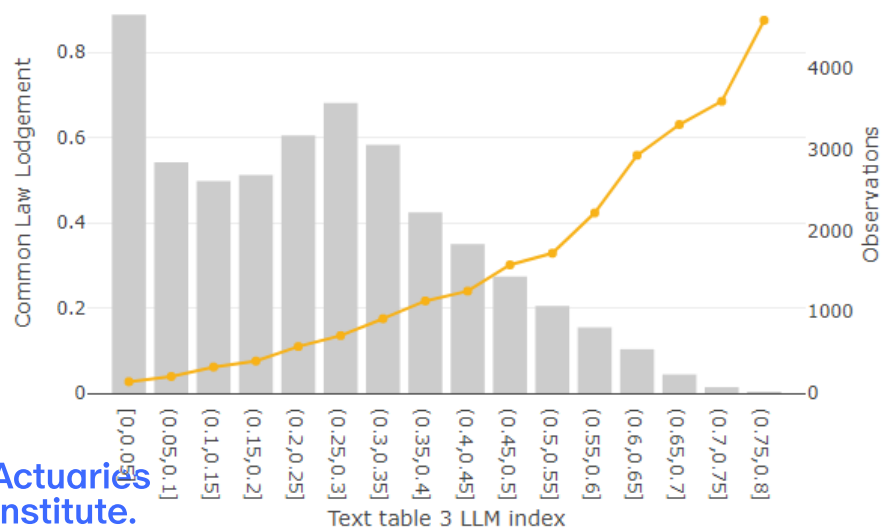


- Embed claim texts into numerical vectors that capture the meaning using open source LLMs (mpnet, gte)
- Average embeddings per claim and text type to represent claim as a whole
- For each claim
  - Find other claims that have similar text descriptions
  - Derive a score based on how many neighbours lodged a CL
- Use the derived score as a predictor in the modelling

# LLM based text score



Text-based neighbours strongly predict CL probability



# Experimental setup

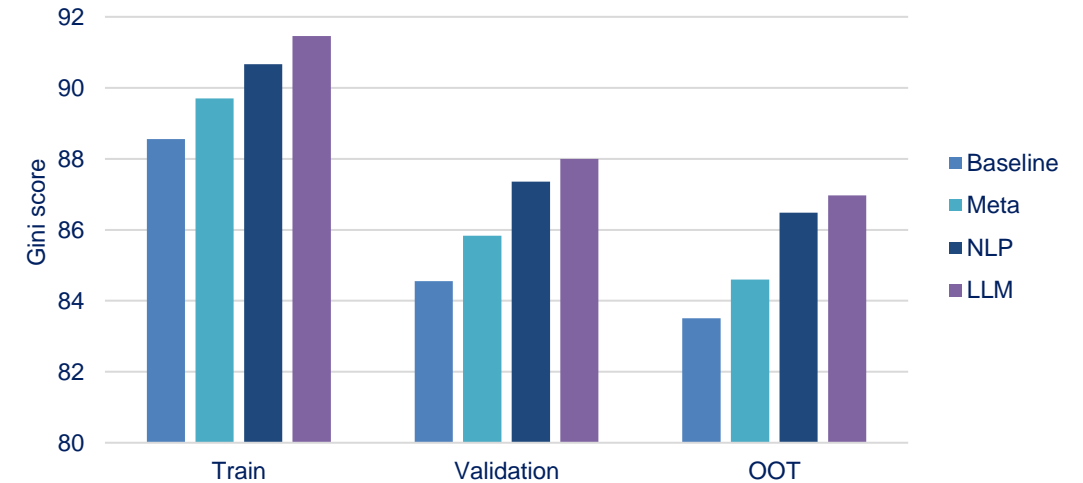
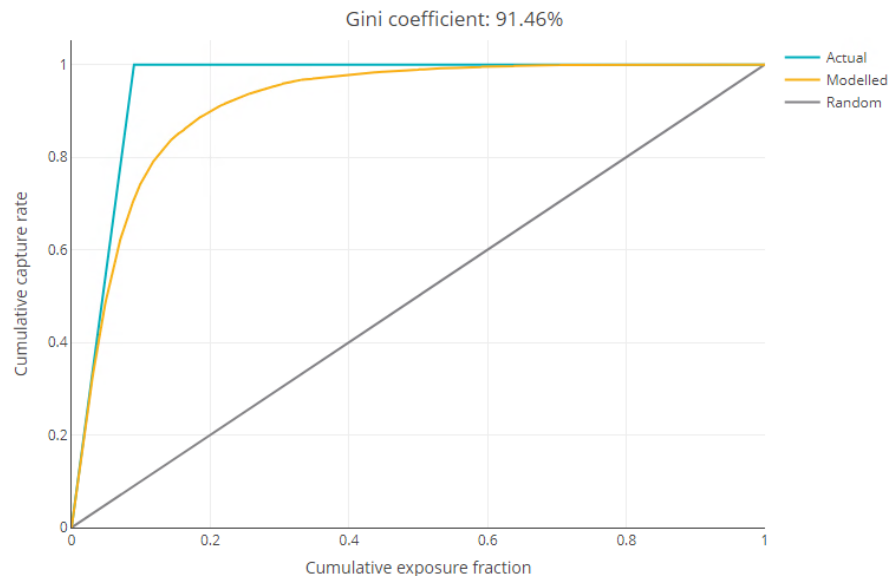
Models	Features			
	<i>Structured data</i>	<i>Text meta-data</i>	<i>NLP</i>	<i>Text data embeddings</i>
#1: Baseline				
#2: Meta				
#3: NLP				
#4: LLM				

**Evaluation:** Gini coefficient



# Results

- Model performance improves with each new set of features
- Results demonstrate the strong predictive power of claim text information
- Using LLM features results in the strongest model



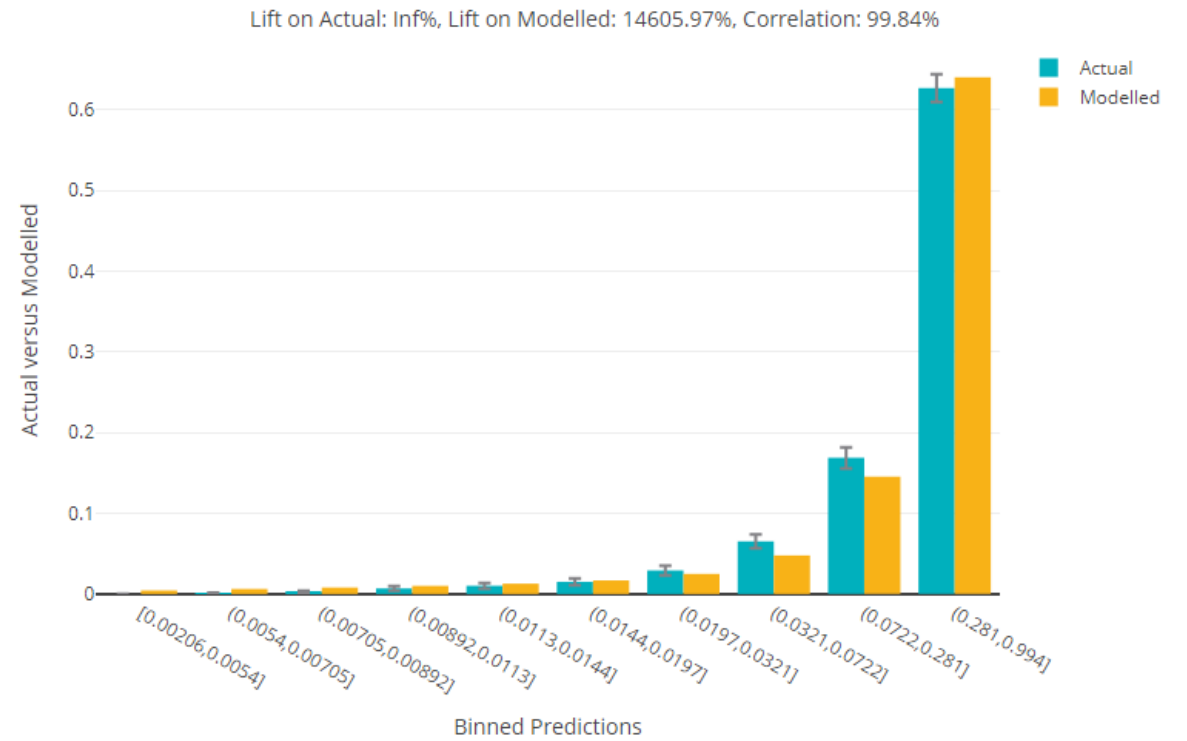
% Common Law Lodgements Identified					
Validation	% of claims	Baseline	Meta	NLP	LLM
	2%	20%	20%	20%	20%
	5%	42%	43%	45%	45%
	10%	64%	64%	68%	68%
	25%	87%	89%	89%	91%



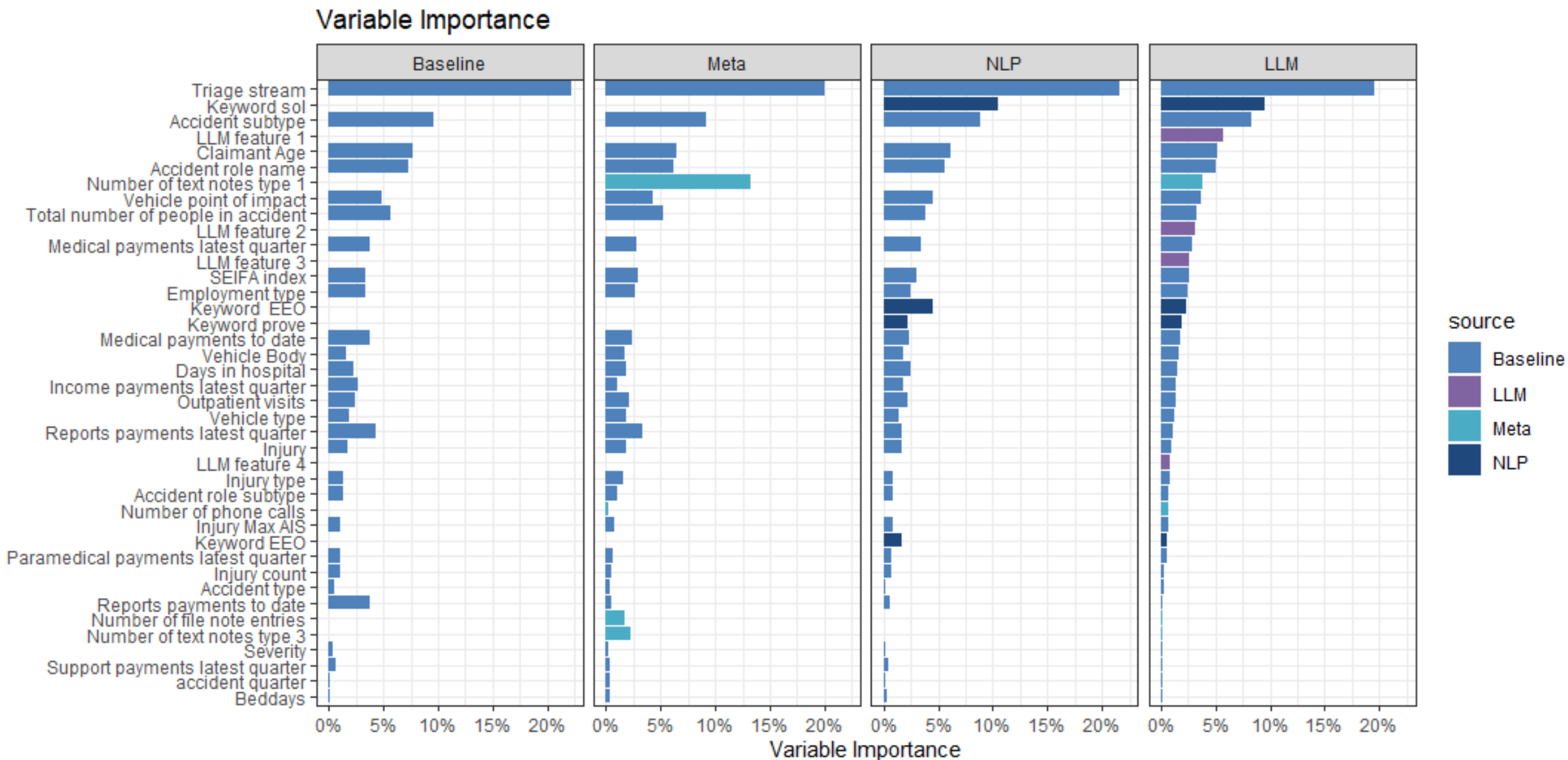
# Risk differentiation

- LLM based model achieves the best results and validates well on unseen data
- Well calibrated predictions for the probability of a claim to become a common law claim
- Strong risk differentiation achieving a high model lift

## Validation

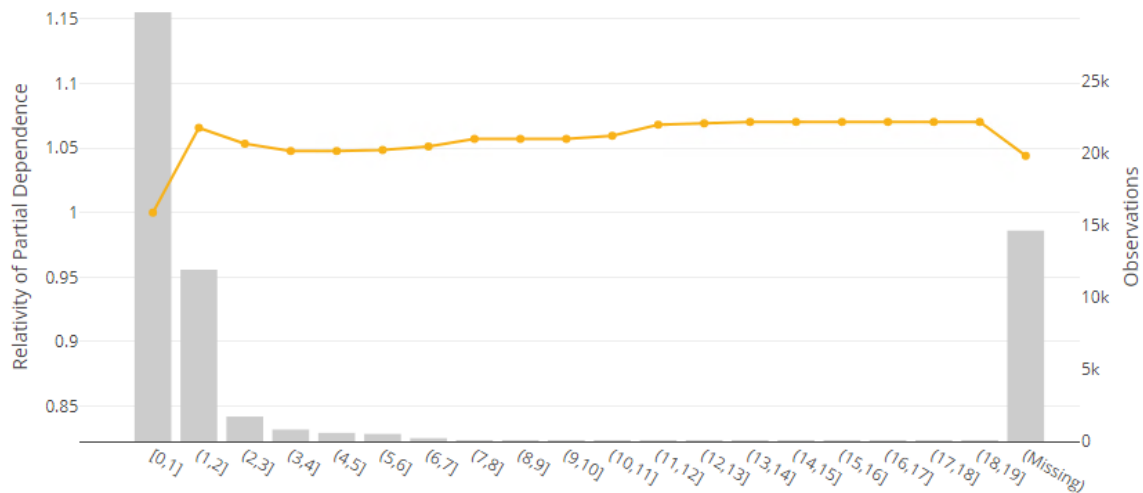


# Feature Importance

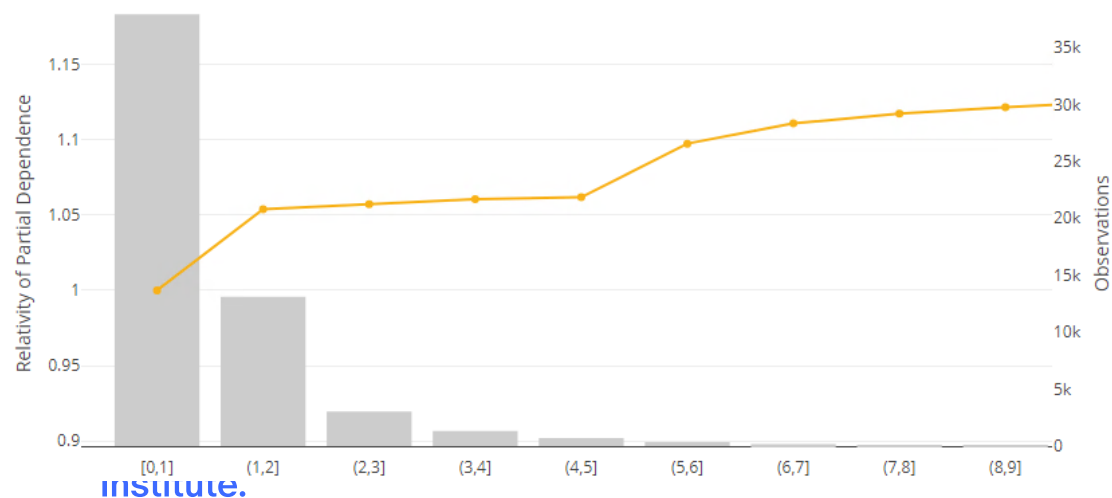


# Partial Dependence

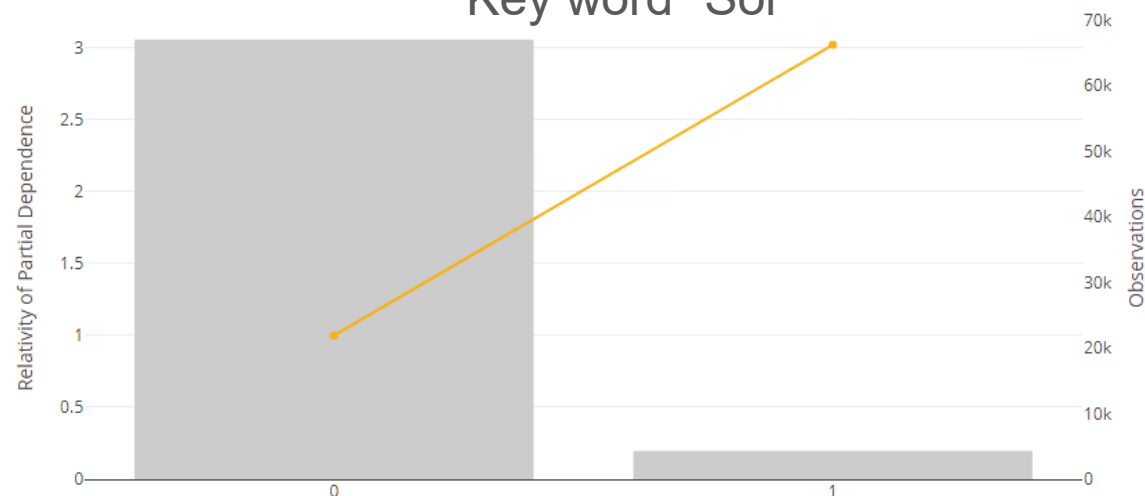
LLM Feature 1



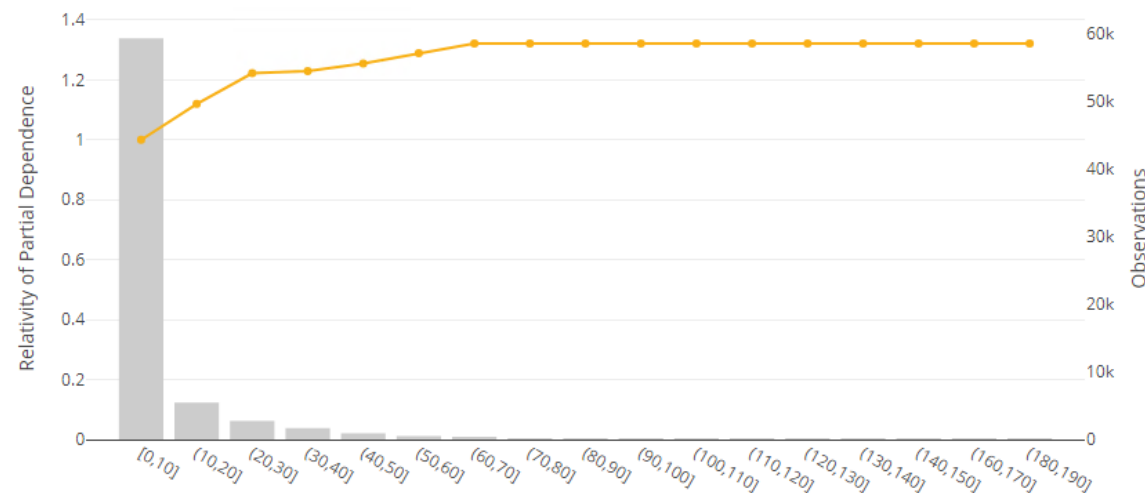
LLM Feature 2



Key word "Sol"

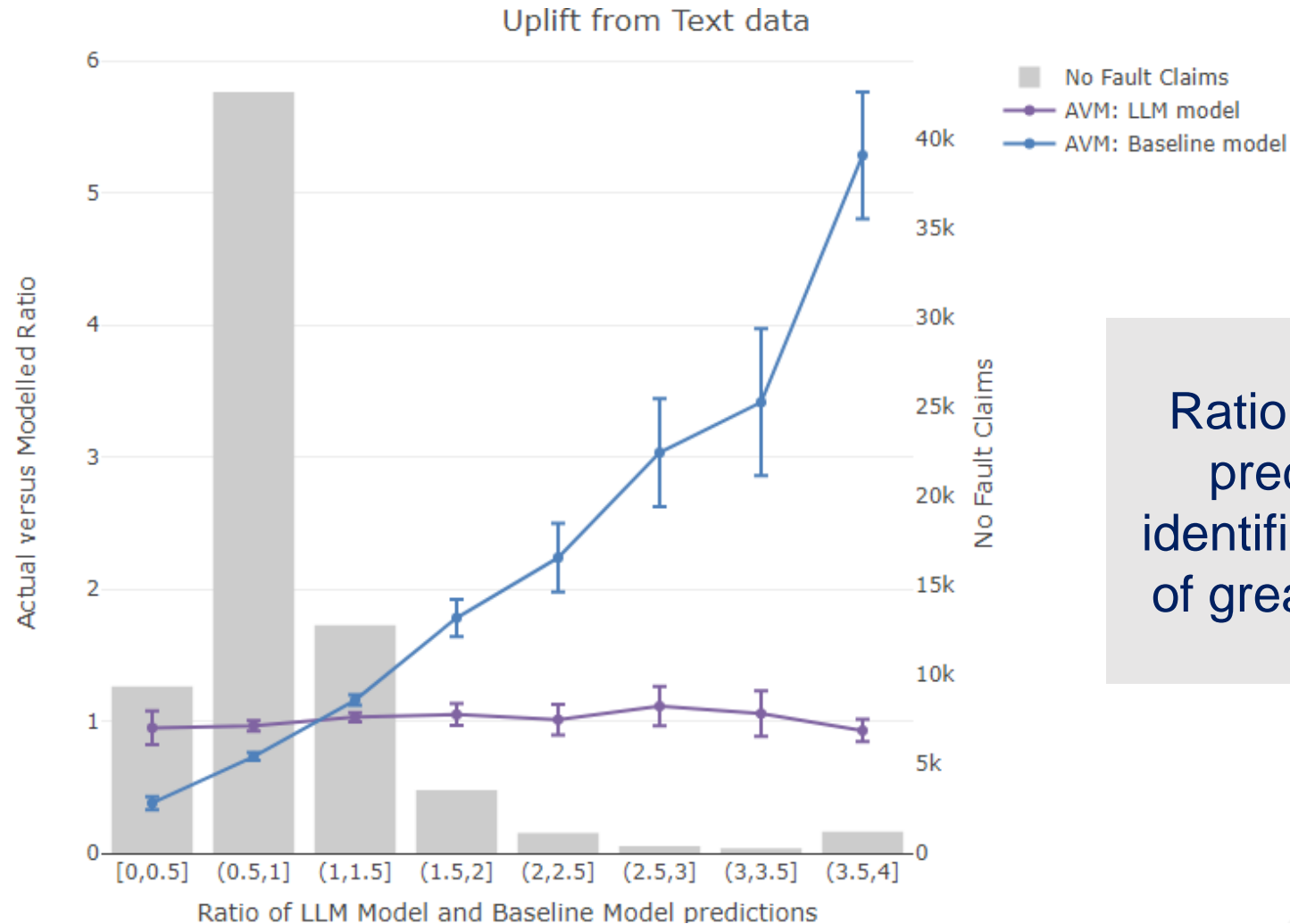


Count of external document notes





# Model Comparison



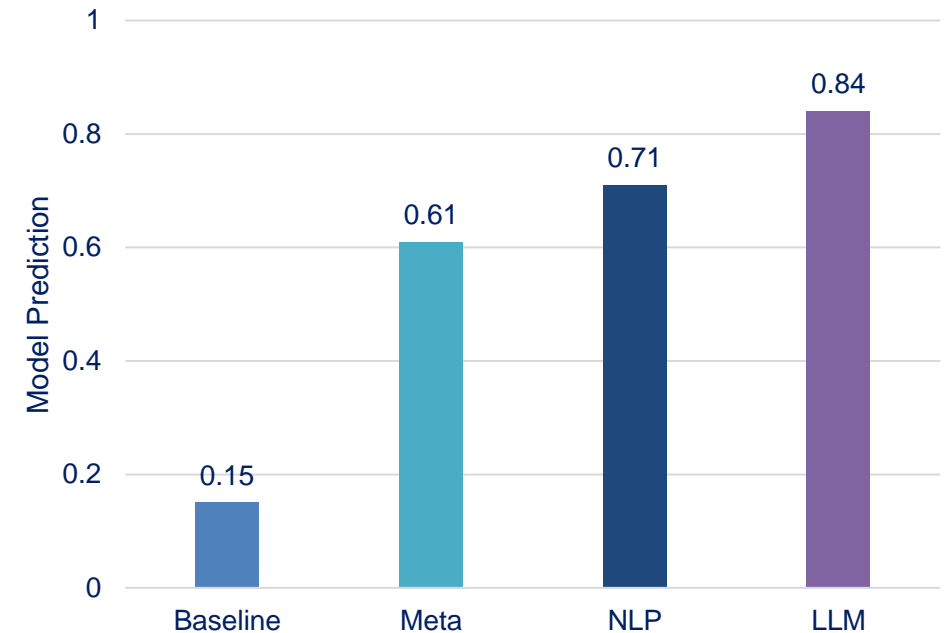
Ratio of model predictions identifies regions of greatest uplift



# Example – Claim 1

**Outcome:** Common Law Lodgement

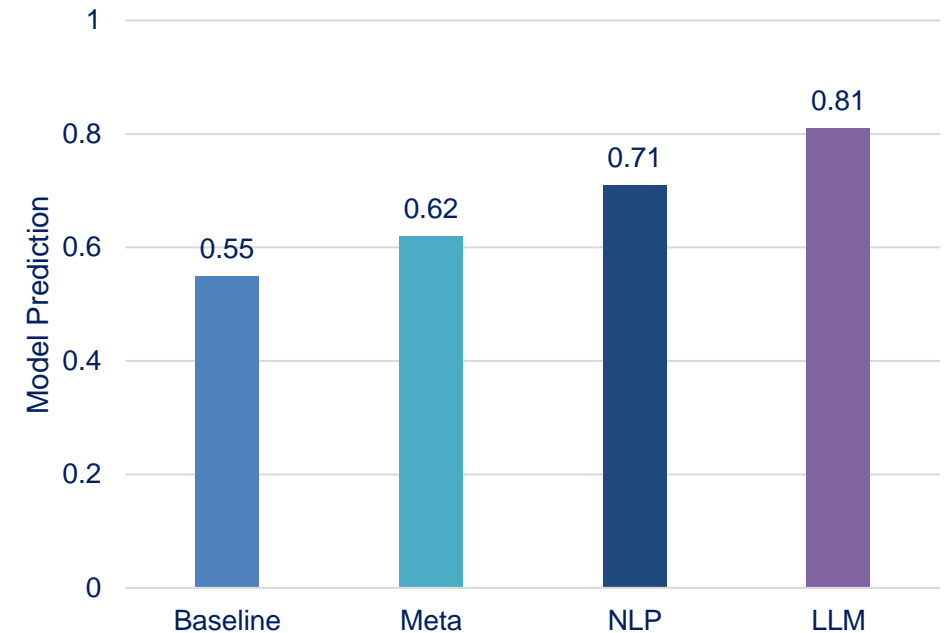
<b>Injury detail</b>	Fractures – Limb
<b>Role</b>	Passenger/Pillion
<b>Total sum to date</b>	\$24k
<b>Days in hospital</b>	9
<b>Age</b>	19
<b>Text records counts</b>	0-20
<b>LLM 10-NN scores</b>	0.7
<b>Common keywords</b>	TAXI, Support, Form, General, approval



# Example – Claim 2

**Outcome:** Common Law Lodgement

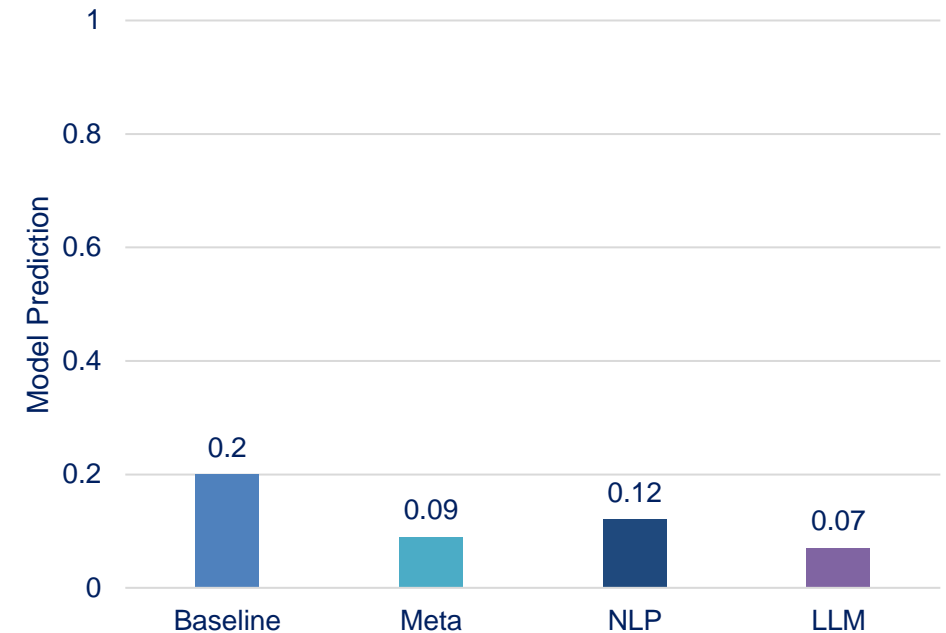
<b>Injury detail</b>	Brain Injury (Mild) / Head Injury (Ill defined)
<b>Role</b>	Bicyclist
<b>Total sum to date</b>	\$109k
<b>Days in hospital</b>	23
<b>Age</b>	49
<b>Text records counts</b>	70+
<b>LLM 10-NN scores</b>	0.9
<b>Common keywords</b>	Prove, Uploaded, Received, Correspondence, Benefits, Care, Dr, Report, LOE, Form, Rehabilitation, Support, Treating, Certificate, Services, RTW, letter, Practitioner, employer, Income



# Example – Claim 3

**Outcome:** No Common Law Lodgement

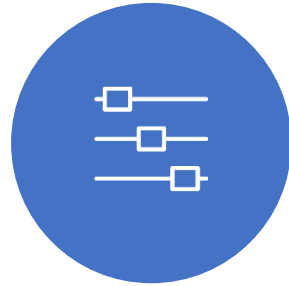
<b>Injury detail</b>	Fractures – Limb
<b>Role</b>	Bicyclist
<b>Total sum to date</b>	\$83k
<b>Days in hospital</b>	11
<b>Age</b>	51
<b>Text records counts</b>	0-7
<b>LLM 10-NN scores</b>	0.1
<b>NLP</b>	Prove
<b>Common keywords</b>	Police, Report, Incident, Confidential



# Future work



Utilize more unstructured text data – documents, e-forms, medical reports etc.



Fine-tuning the large language model or method of aggregation of the embeddings



Use commercial private versions of more powerful models (e.g. chat GPT) instead of the smaller open source LLMs



Apply to other components of lifetime cost of claims model (e.g. cost of No-Fault claims)



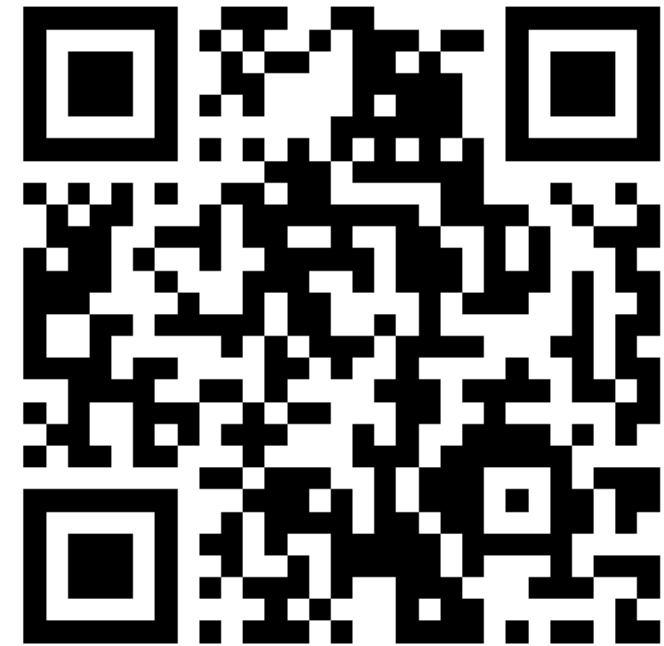
# Conclusions

- Unstructured text data significantly improves compensation claims predictive model performance
- Schemes, insurers and claims service providers have a valuable asset which can be utilized at scale with potential significant improvements in claim management and reserving
- Large Language Models are a powerful tool for extracting signal out of unstructured data
- LLM field is emerging and improving rapidly - expect better results in the future with advances in technology



# Q&A

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# Feedback

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