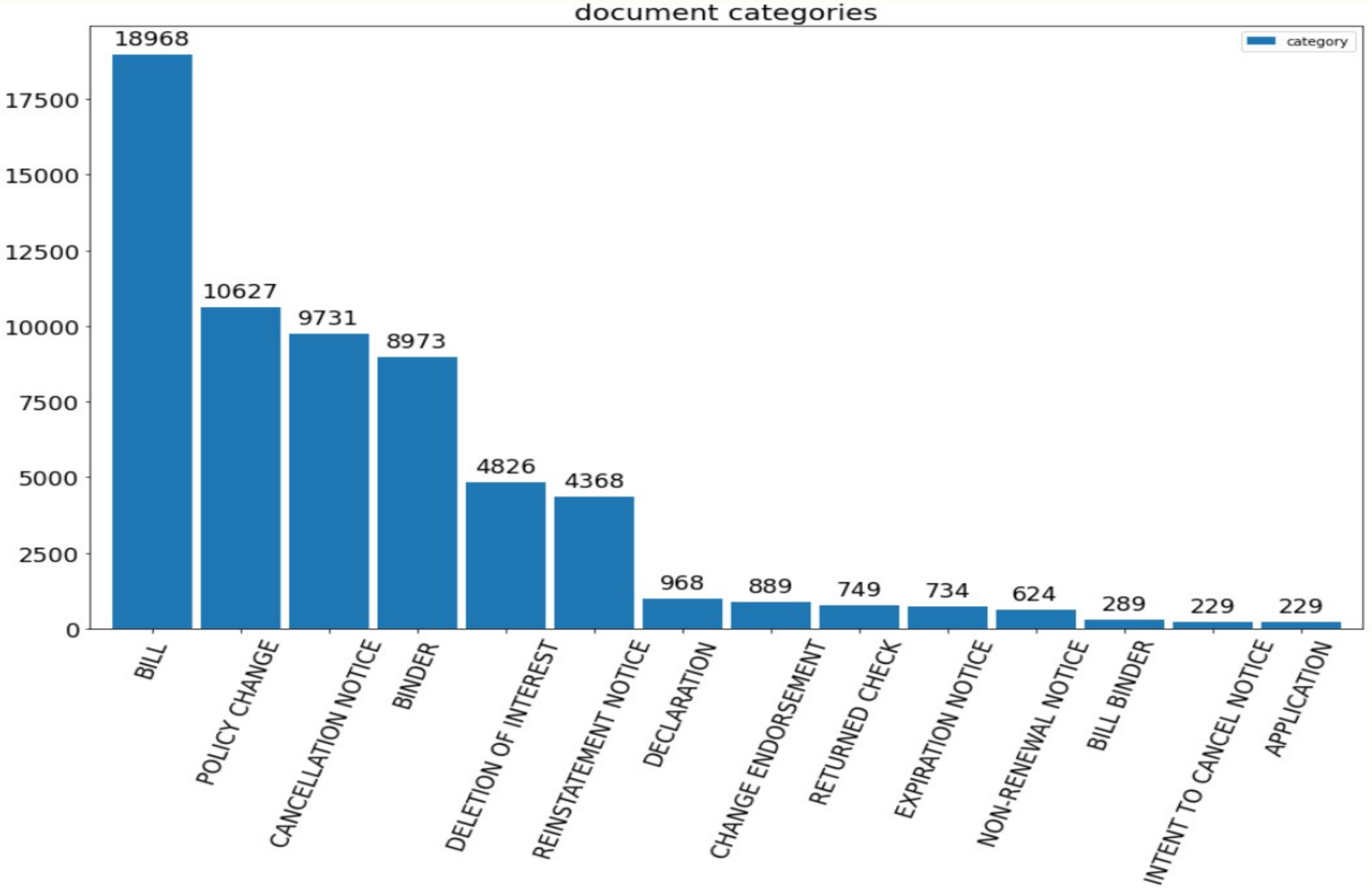
HeavyWater Machine Learning Problem

Solution by Mark Wilber

What we are dealing with

- 62 K documents, 14 categories



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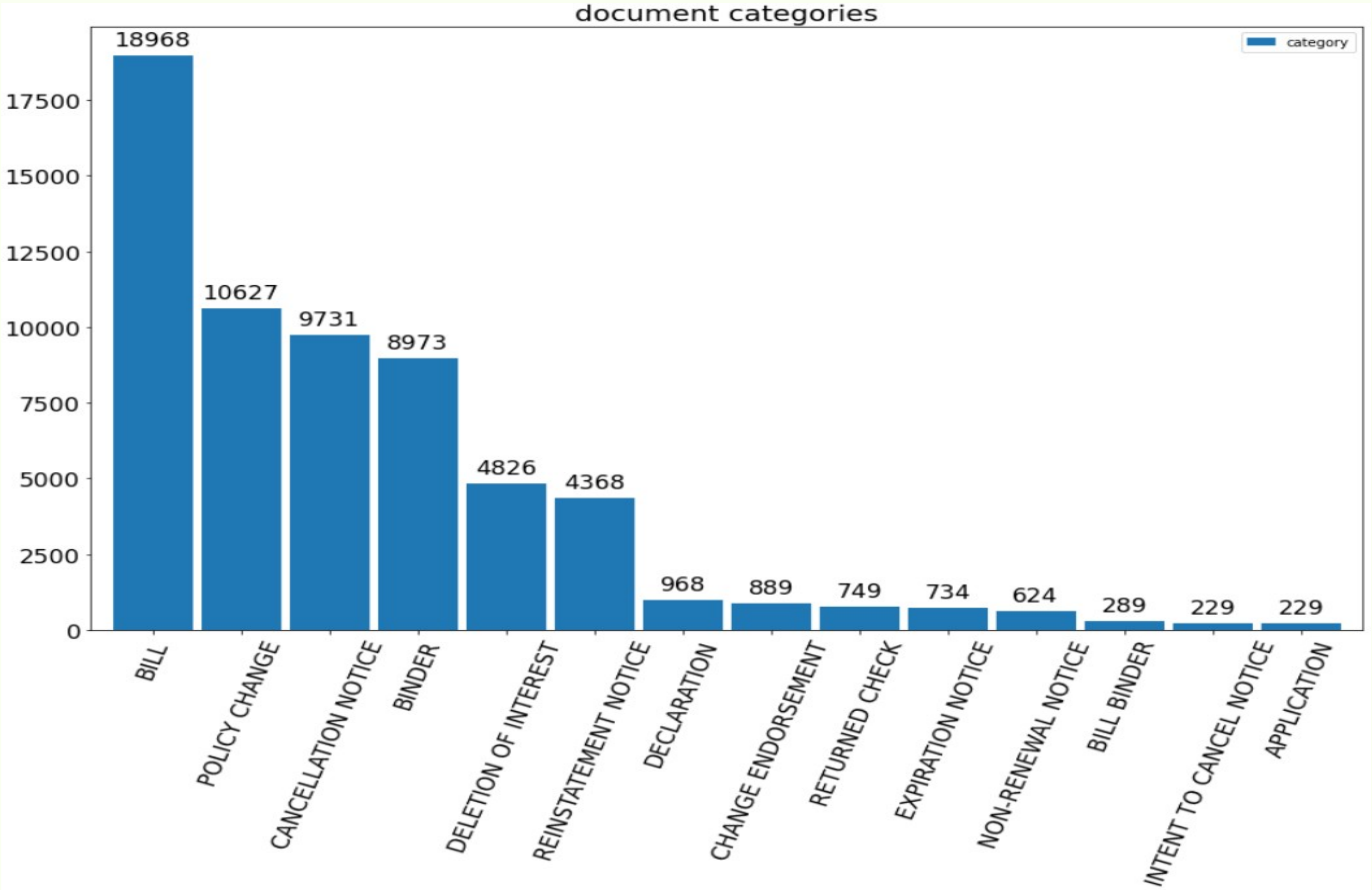
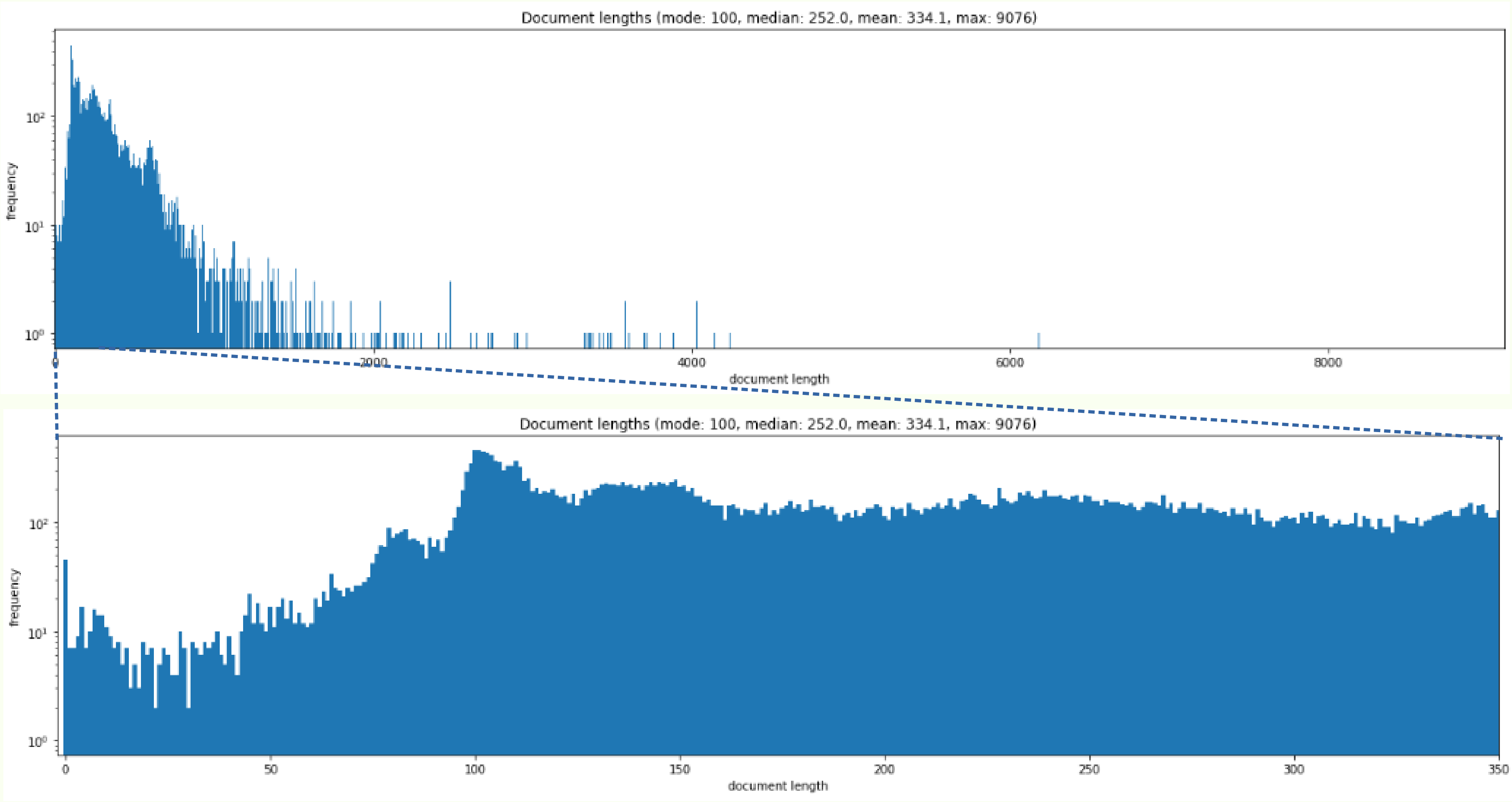
- 62 K documents, 14 categories
- unbalanced classes, spanning nearly 2 orders of magnitude



What we are dealing with

- document lengths spanning 0–9076 tokens (mode: 100, median: 252, mean: 334.1)



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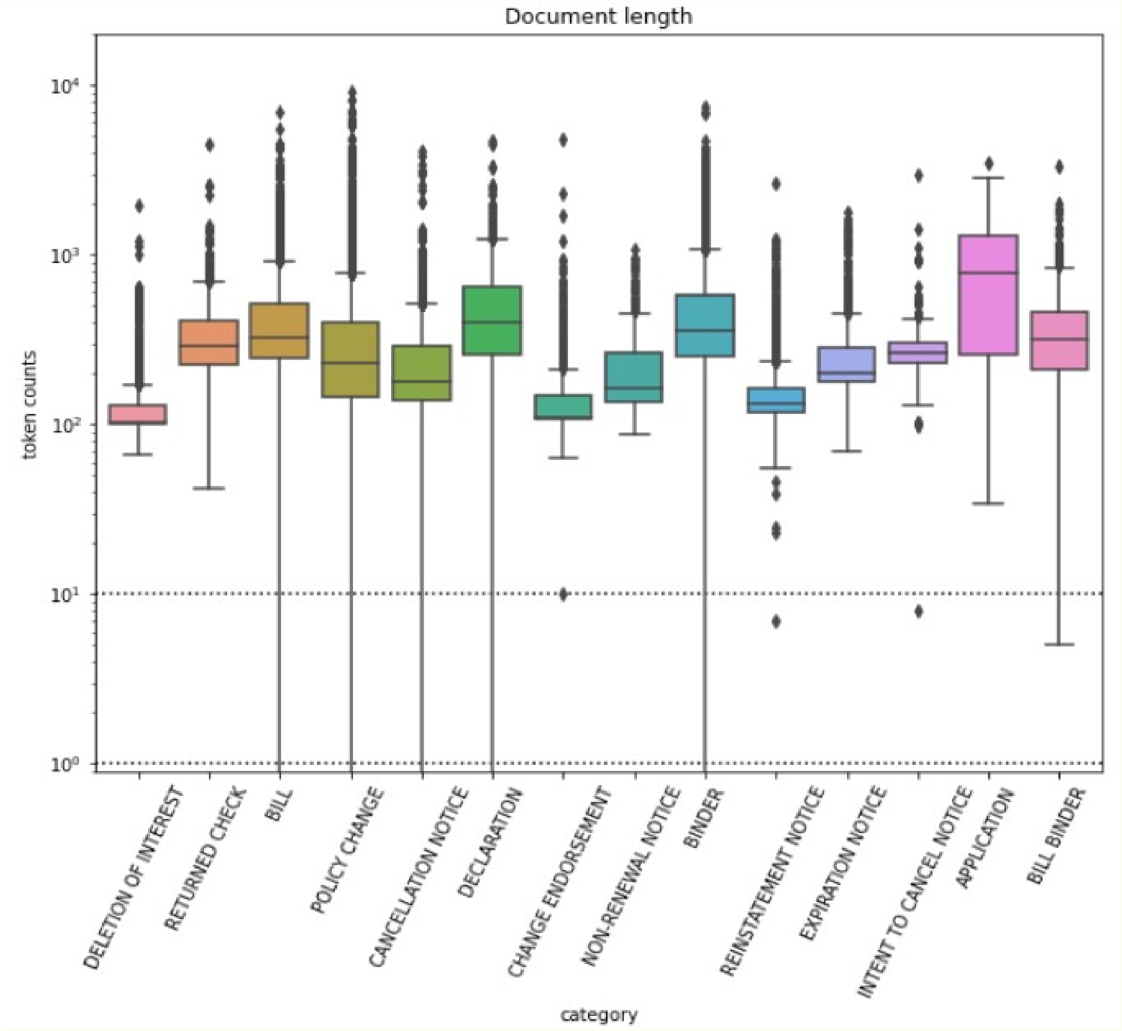
- document lengths vary widely by category, but few are shorter than 10 tokens



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⇨ *very* unlikely ∃ so much variation in the lexicon of mortgages and loans!

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- consider terms occurring with *lowest* frequencies

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⇨ *speculation:* rarely occurring terms are bogus, due to scan / OCR noise

⇨ smudges create nonsense terms

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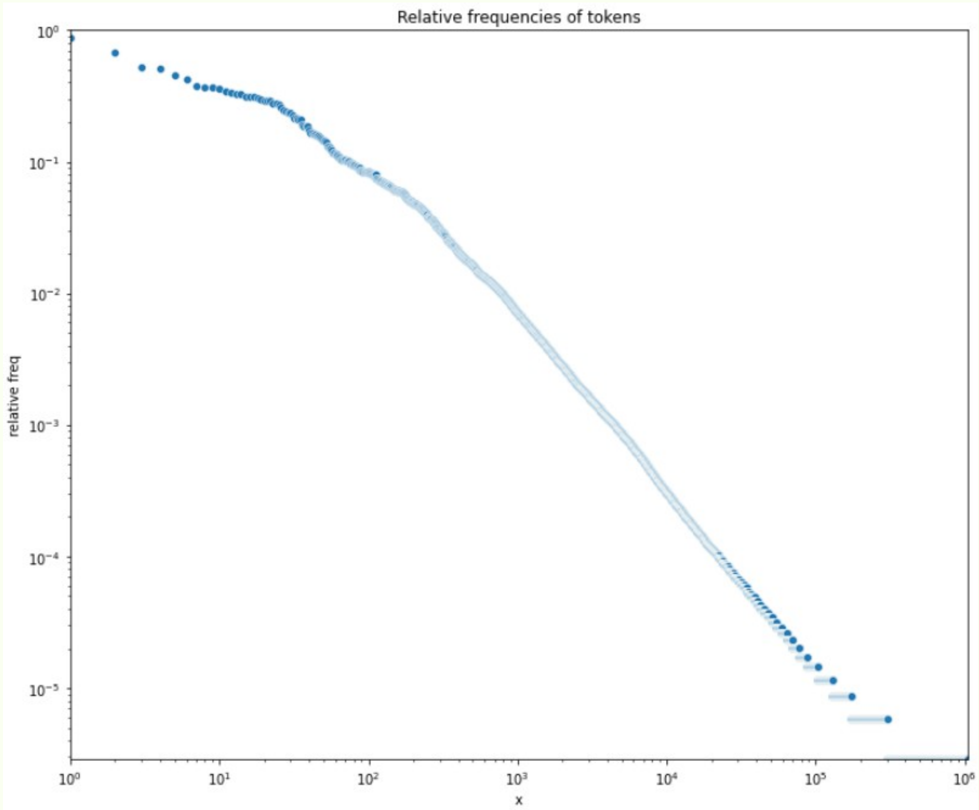
- Most frequent terms don't follow Zipf's relation



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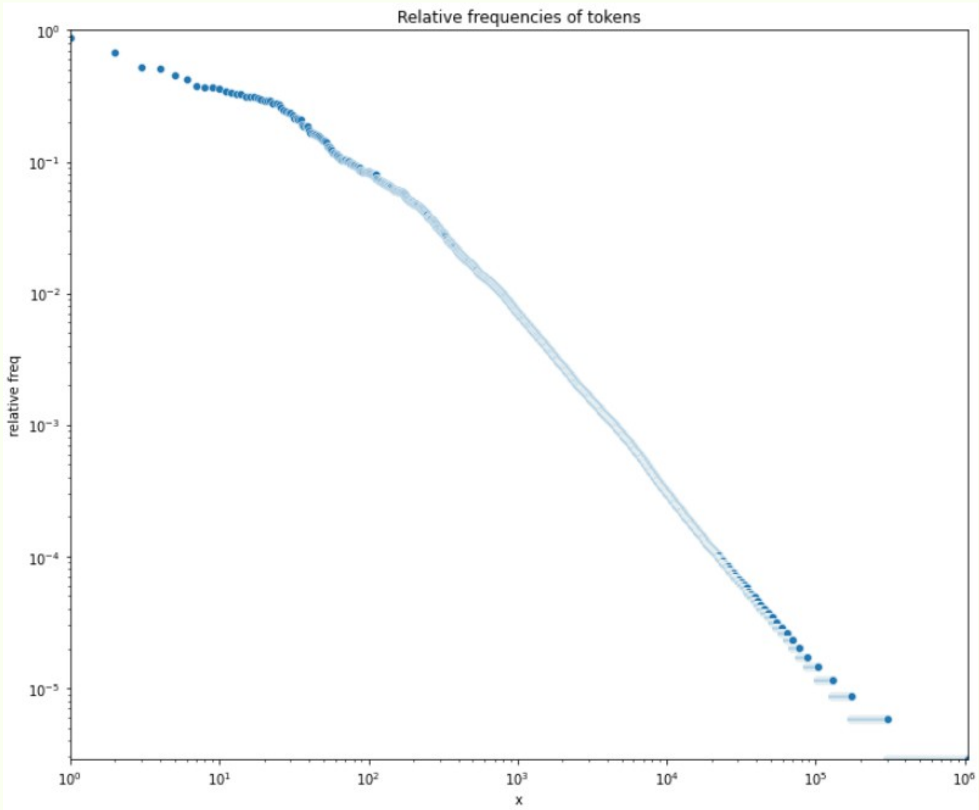

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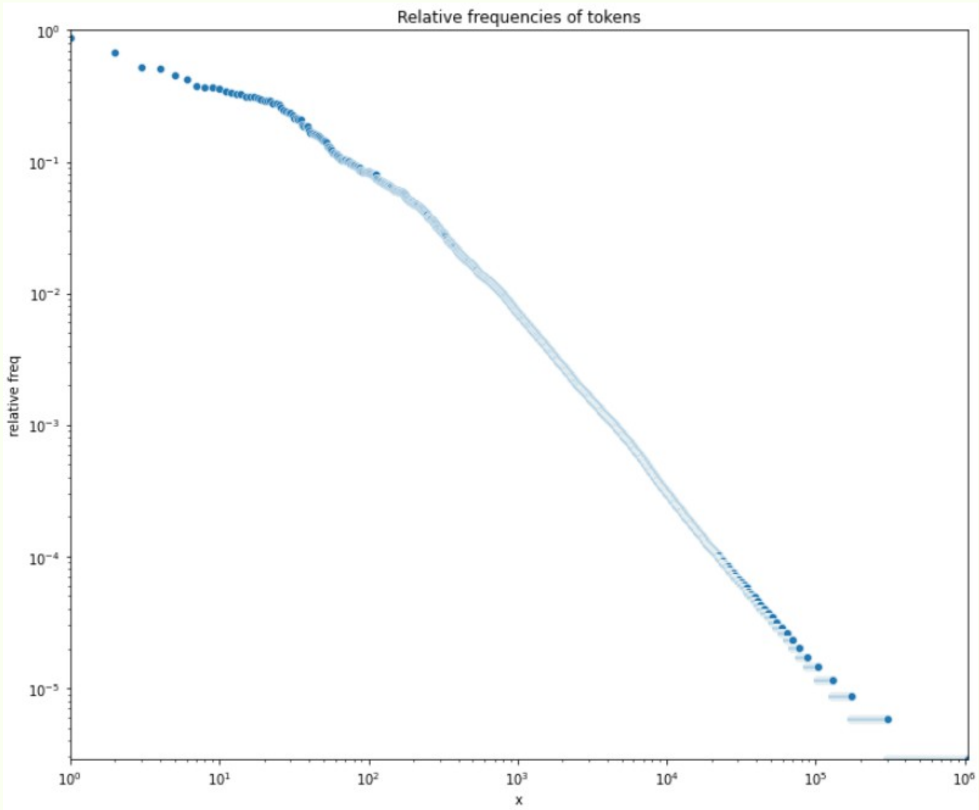

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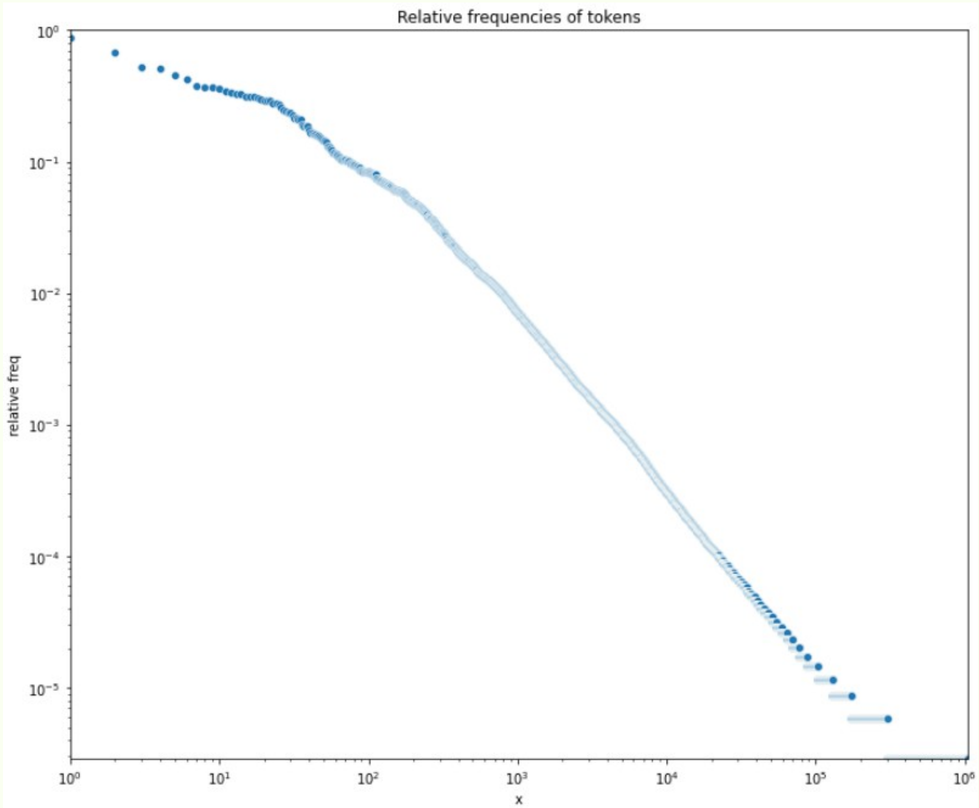

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⇨ *this corpus seems to be unusual ...*

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- given time and *justification*, could use statistical techniques, e.g.:

  Gerlach, M., Shi, H. & Amaral, L.A.N. A universal information theoretic approach to the identification of stopwords. Nat Mach Intell 1, 606–612 (2019). https://doi.org/10.1038/s42256-019-0112-6

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- after model selection, could train on full data set (but wouldn’t know how much better the results)

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tf-idf features

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- best with `alpha=0.0139 and norm=False` yielded substantial improvements

  ⇨ model *3 × larger*

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Model	Macro Averaged			Weighted Average			Model size (MB)
	precision	recall	f_1	precision	recall	f_1	
Naive Bayes default (baseline)	0.75	0.50	0.53	0.79	0.78	0.76	63
Naive Bayes best	0.80	0.58	0.62	0.81	0.81	0.80	272
Random Forest default	0.80	0.65	0.70	0.84	0.85	0.84	451
Random Forest best	0.80	0.75	0.77	0.87	0.87	0.87	273
Gradient Boosting default	0.81	0.64	0.69	0.81	0.81	0.80	1.2
XGBoost default	0.79	0.65	0.70	0.82	0.82	0.82	5.4
XGBoost best	0.82	0.73	0.76	0.87	0.87	0.87	21
Bidirectional LSTM	0.54	0.58	0.54	0.76	0.70	0.72	53
Bidirectional LSTM w/ `docLength`	0.50	0.61	0.52	0.78	0.69	0.73	202

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- Caution: errors in small classes $\mathcal{O}(10\%)$ ⇨ impact macro averages most

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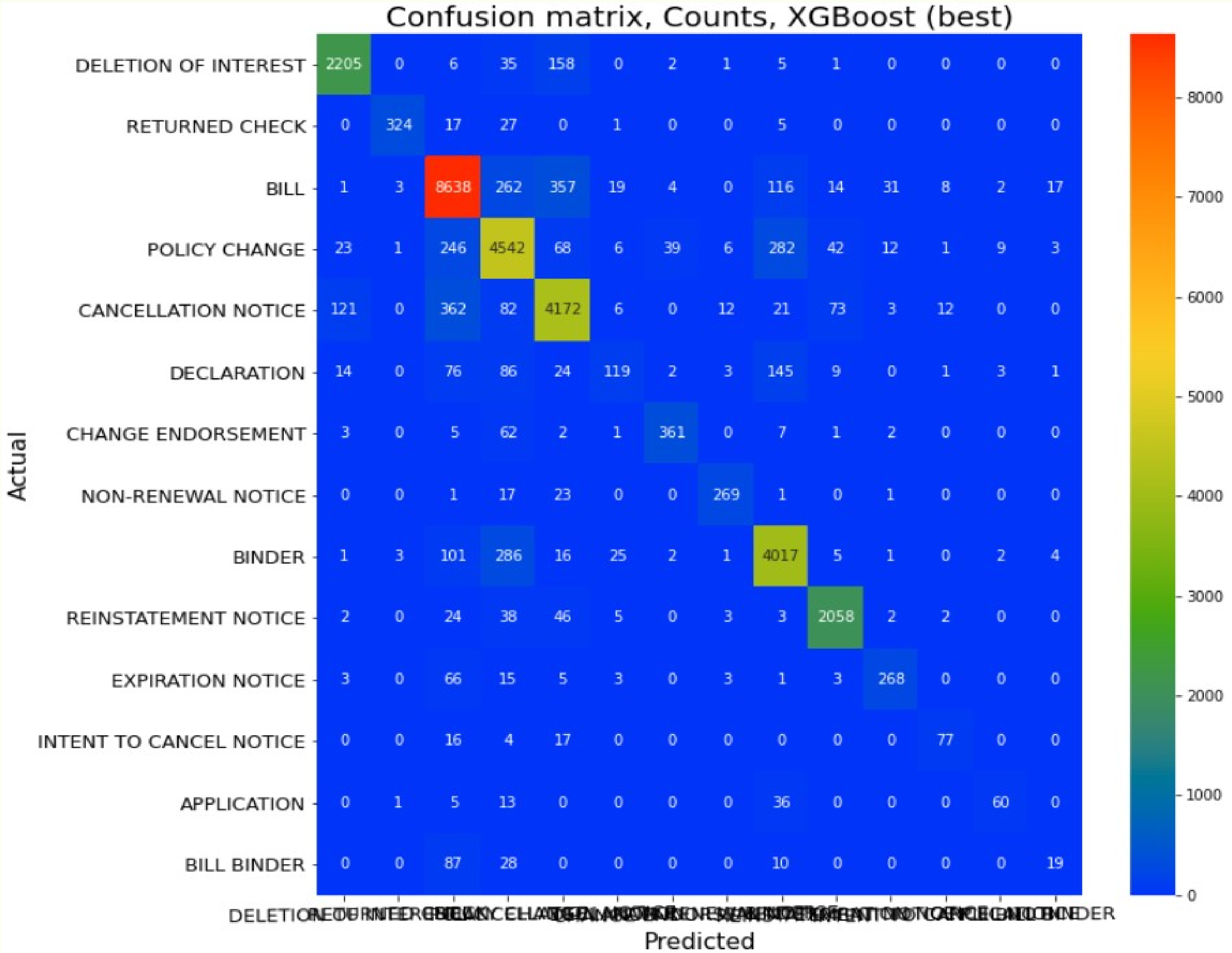

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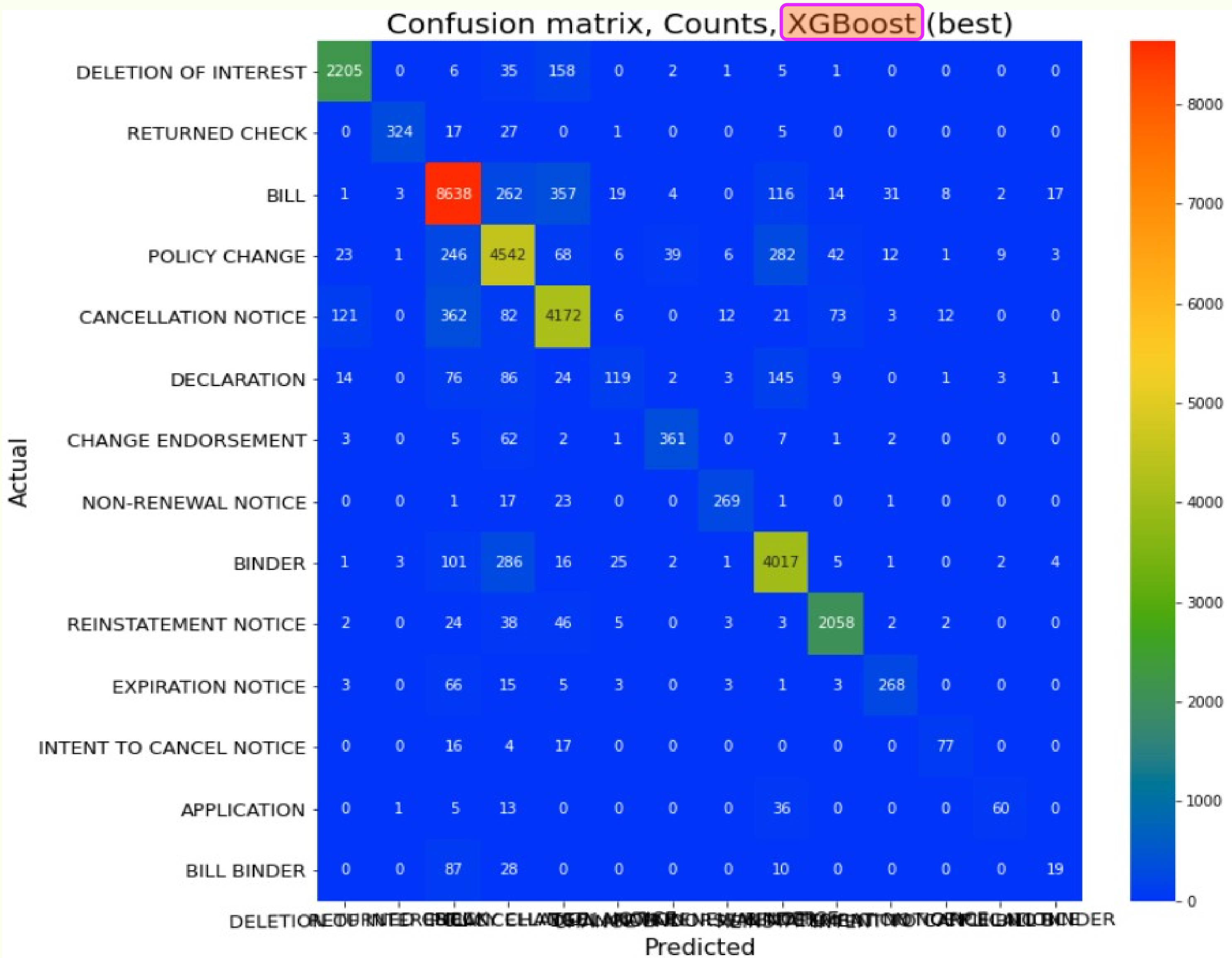

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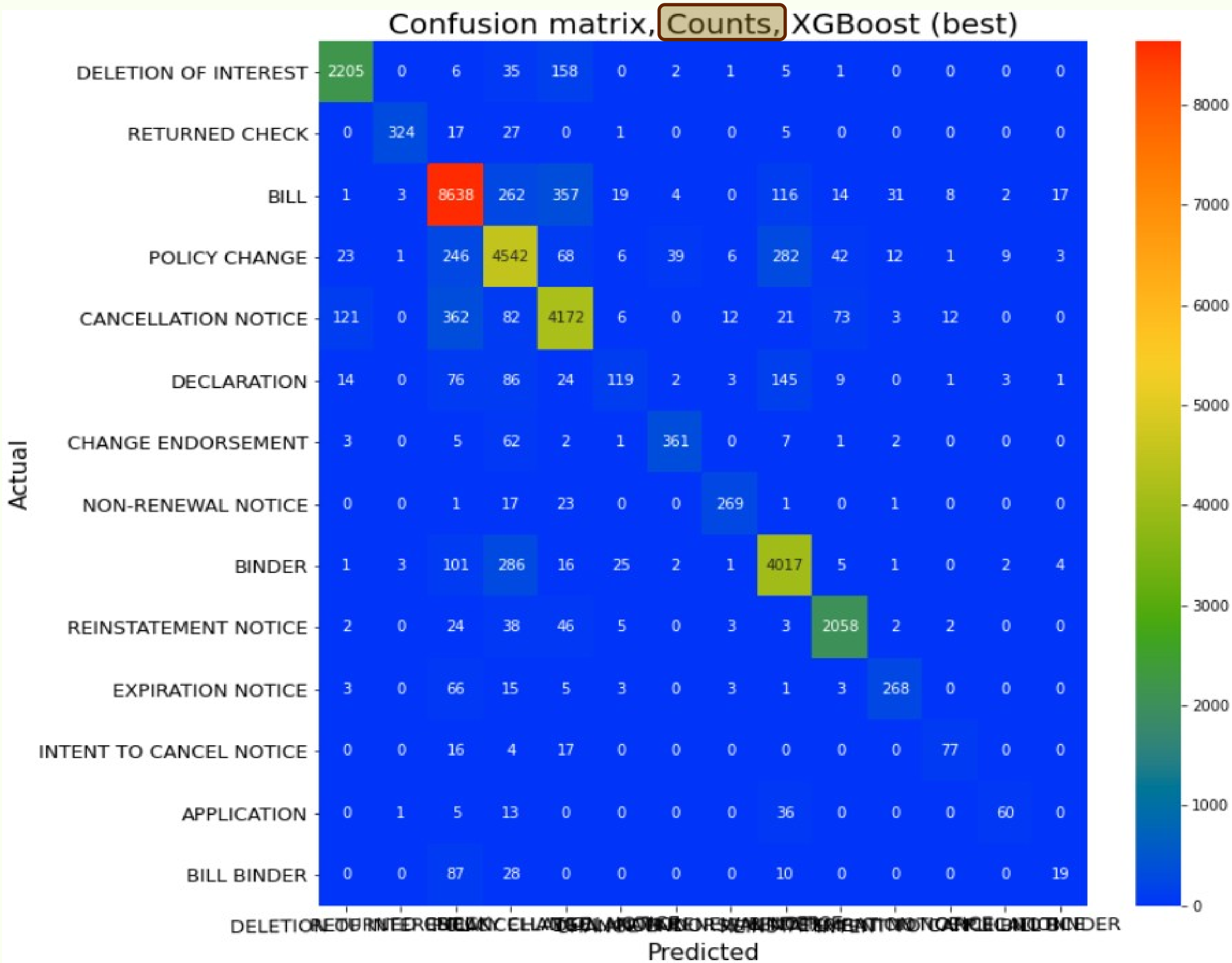

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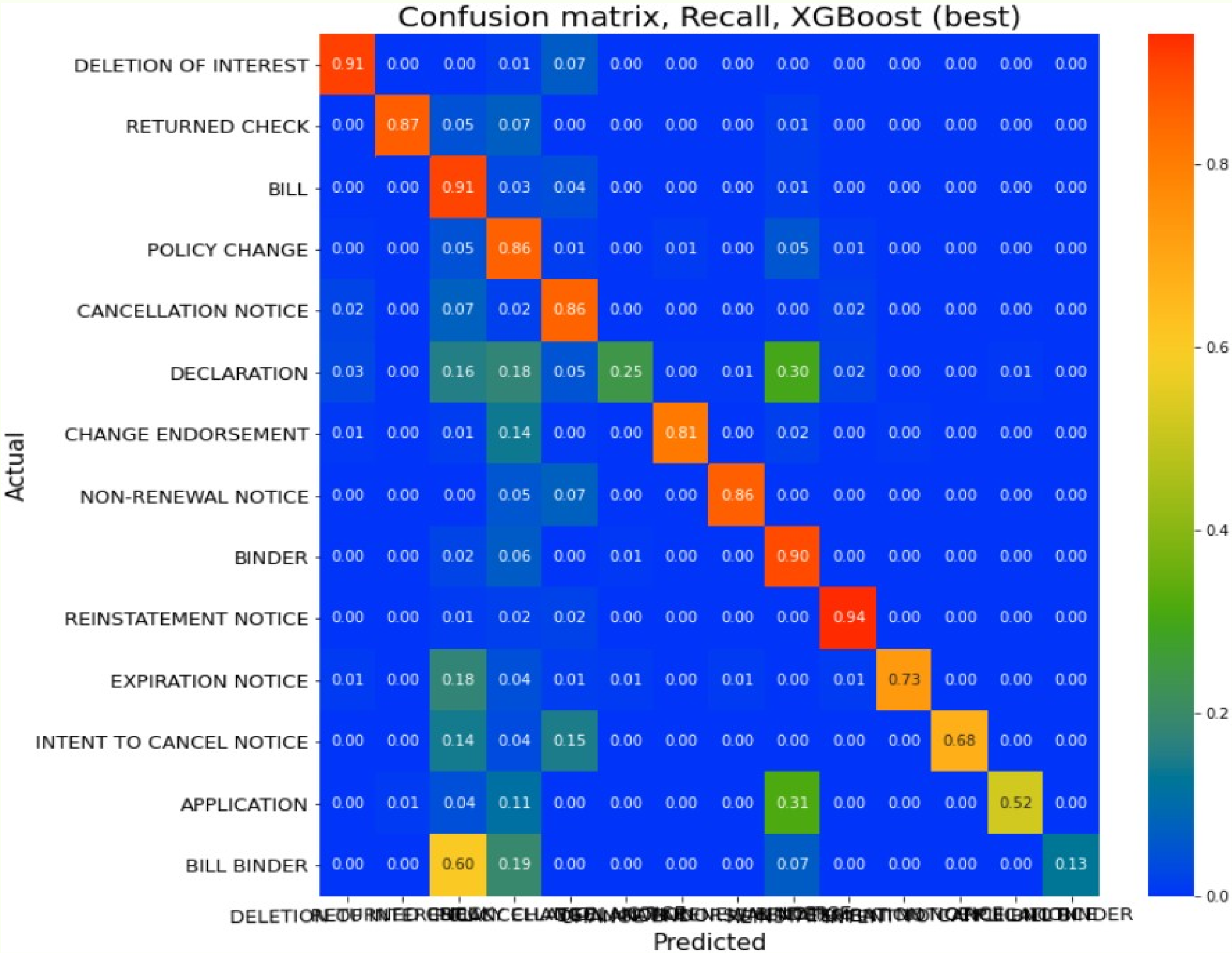

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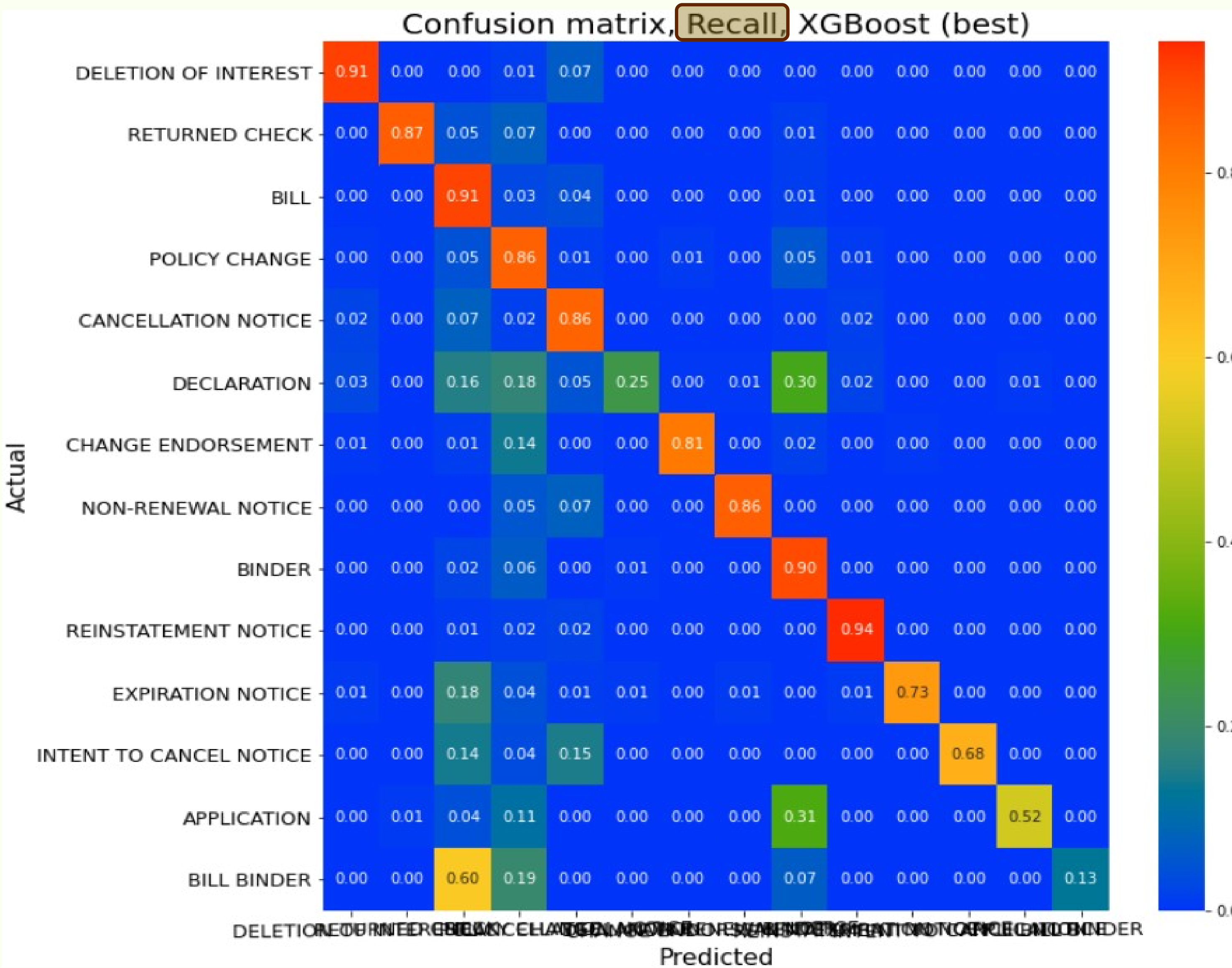

$$R = \frac{TP}{TP + FN}$$

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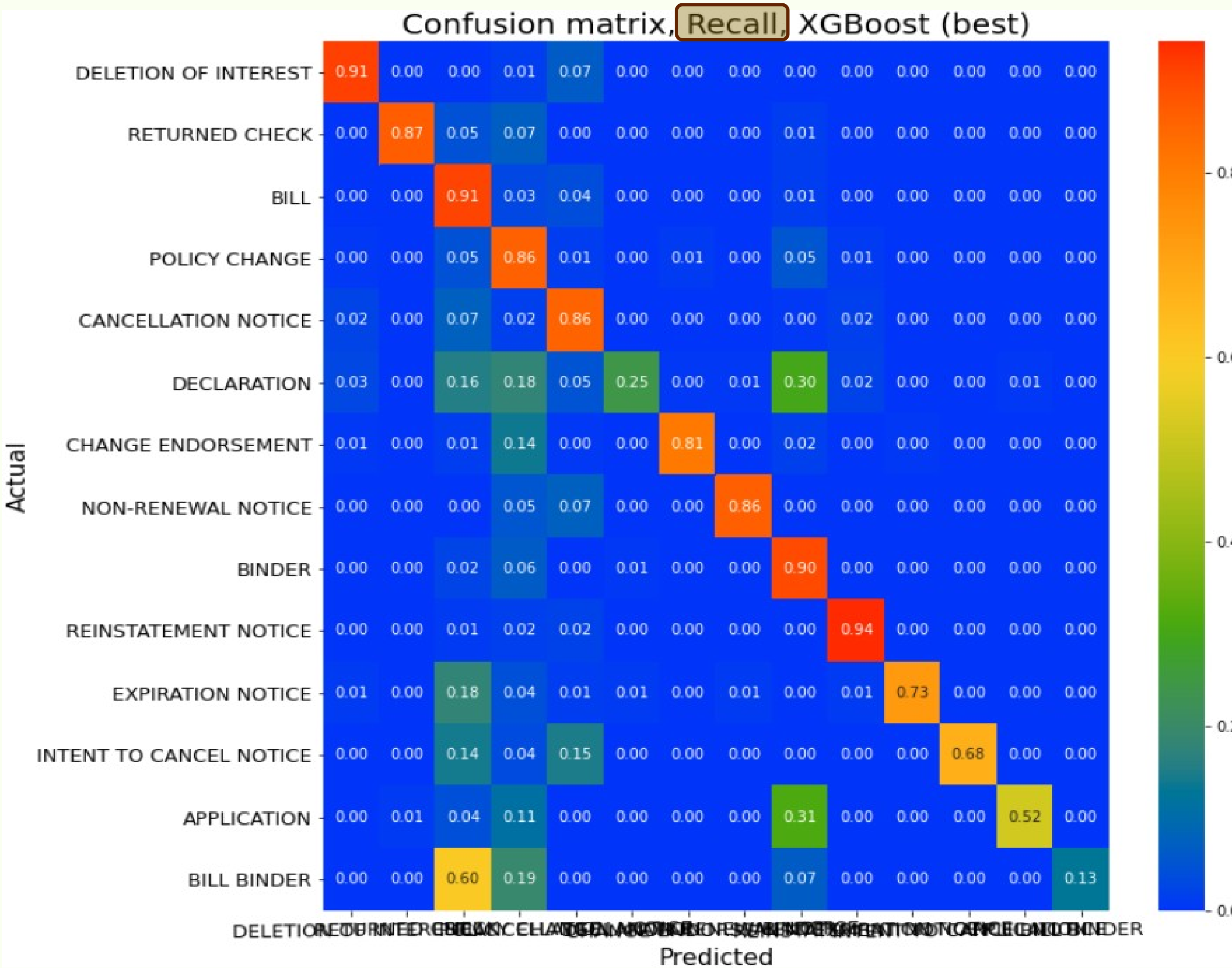

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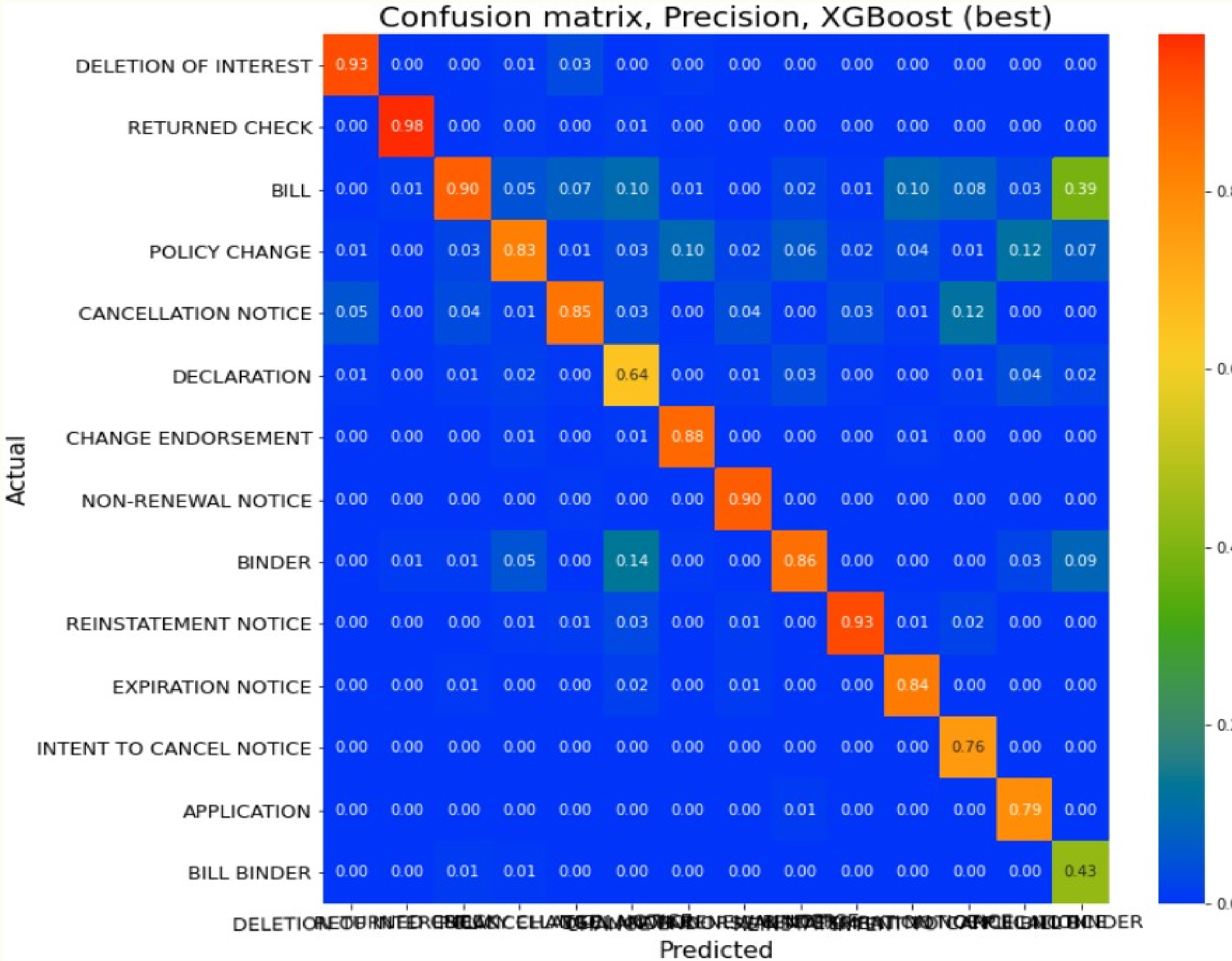

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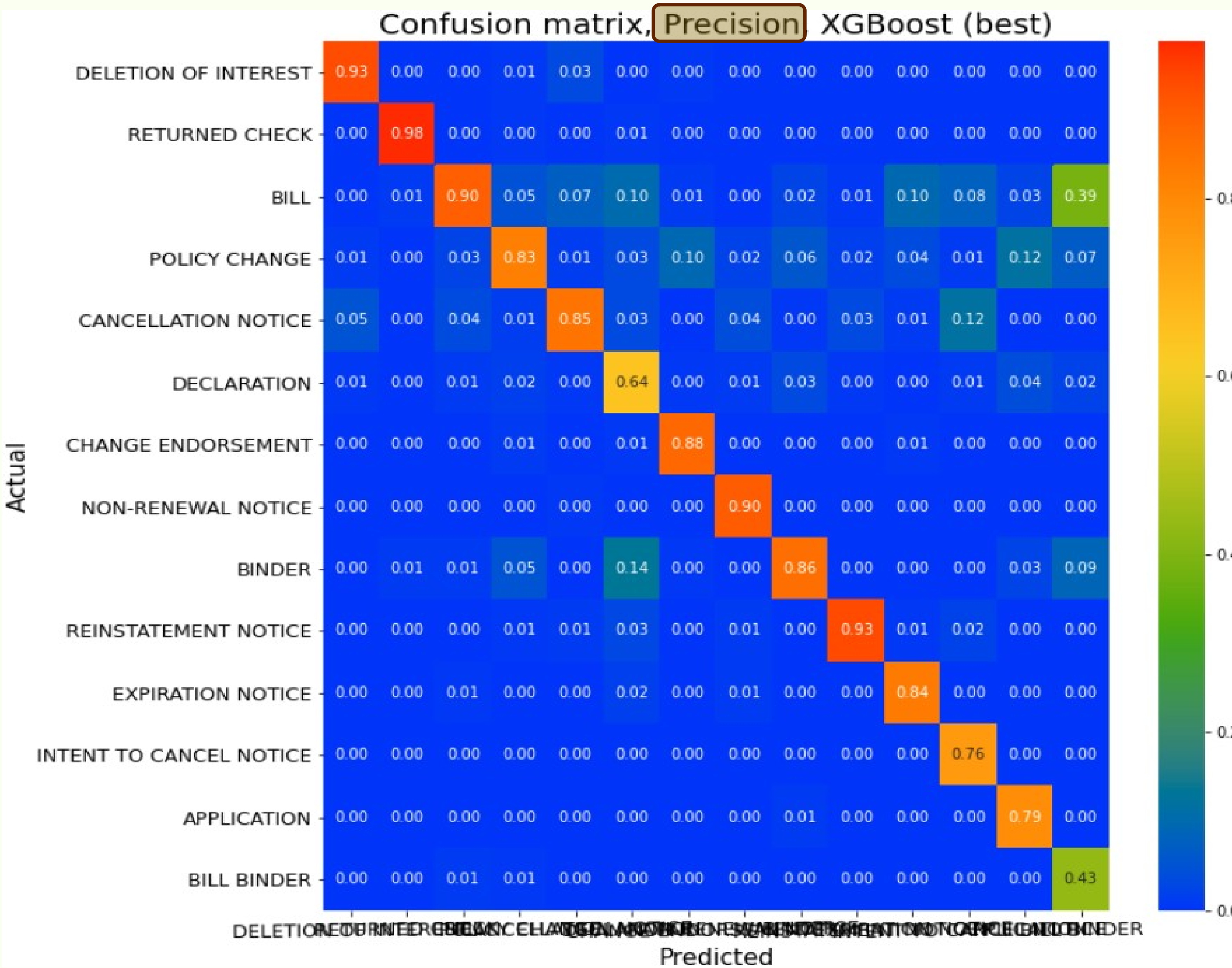

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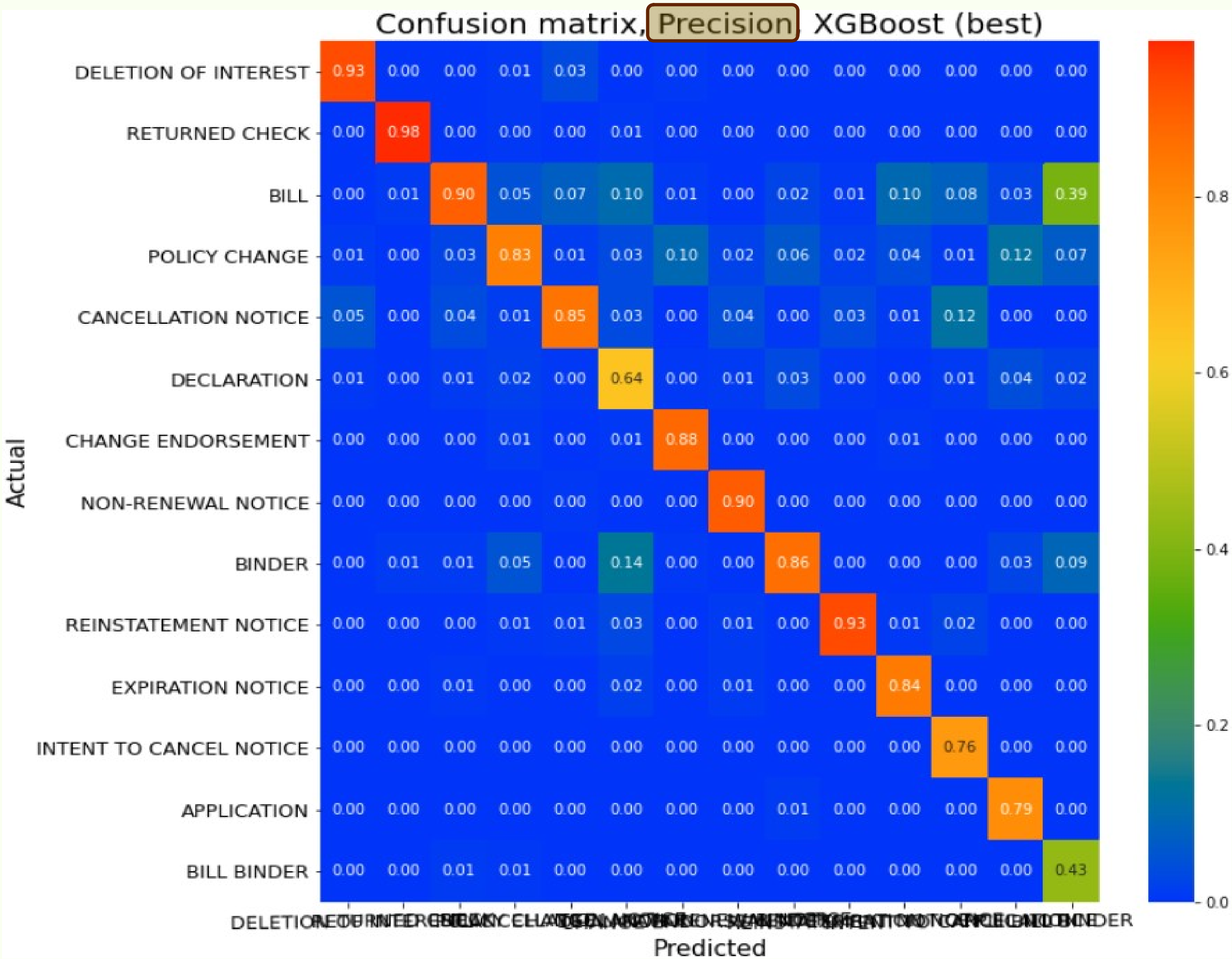

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Deployed Solution

General notes

- Find code in [github repo]

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- `Ubuntu:latest`, with minimal set of versioned python packages
- image size 912 MB

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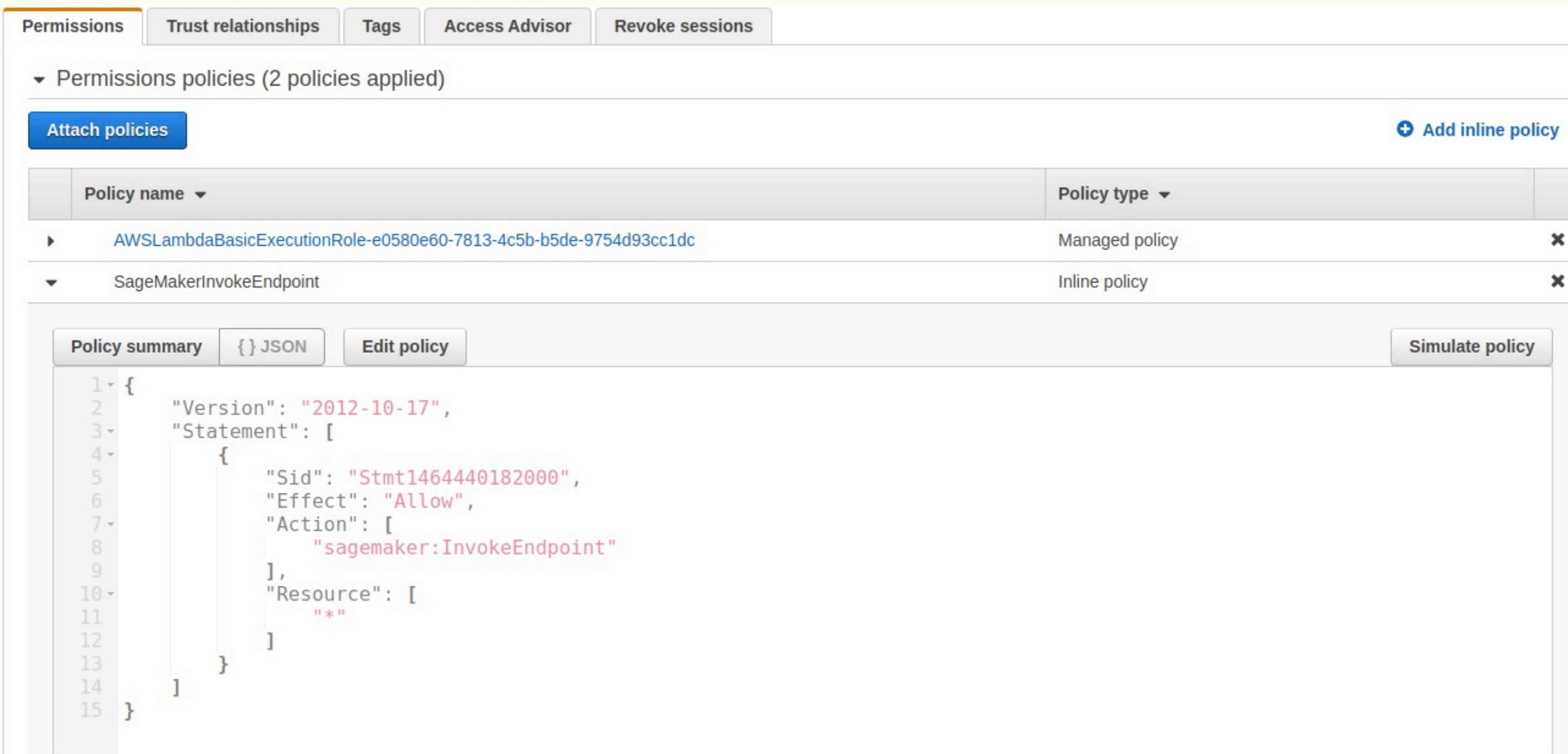
- endpoint success required extra permissions



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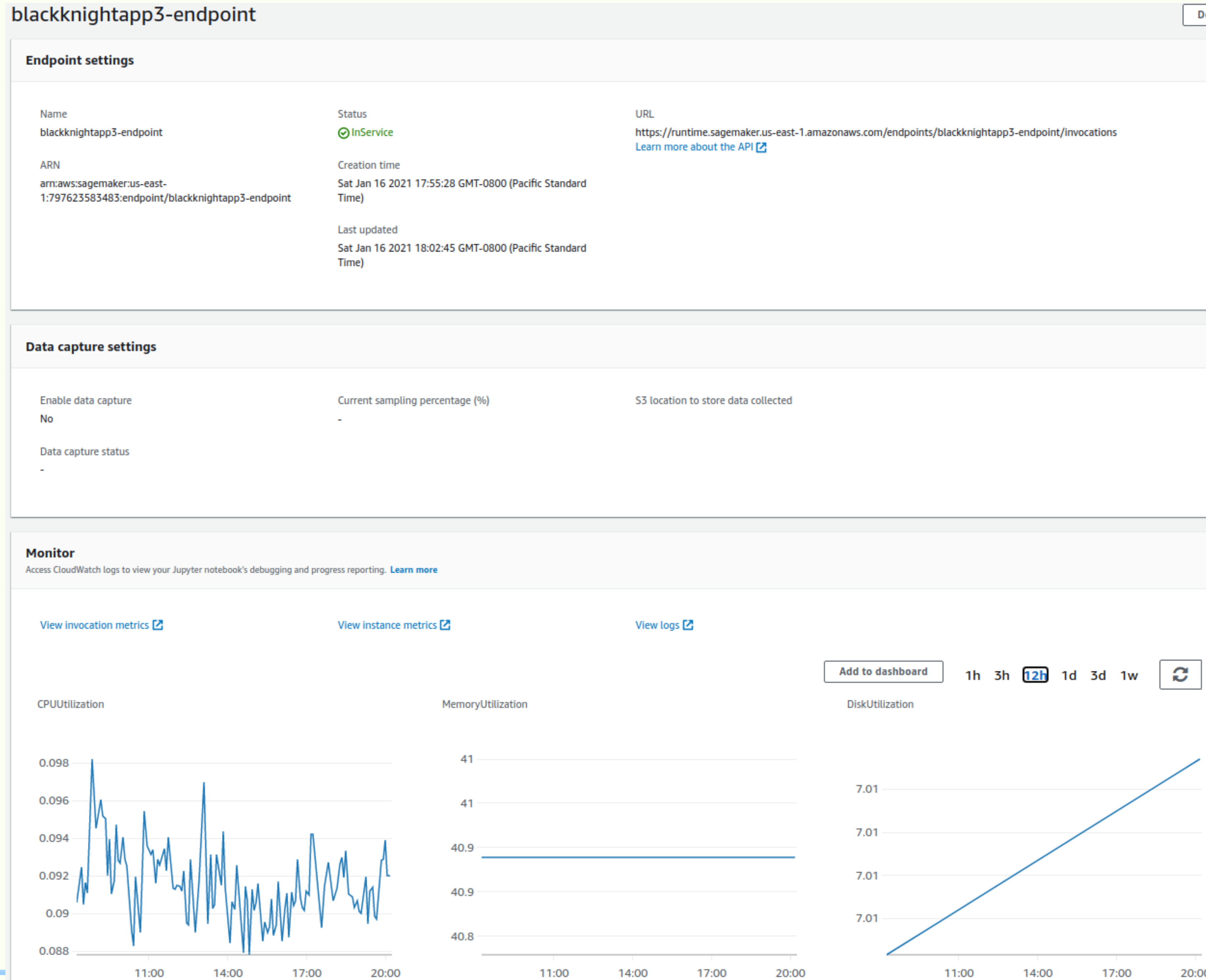

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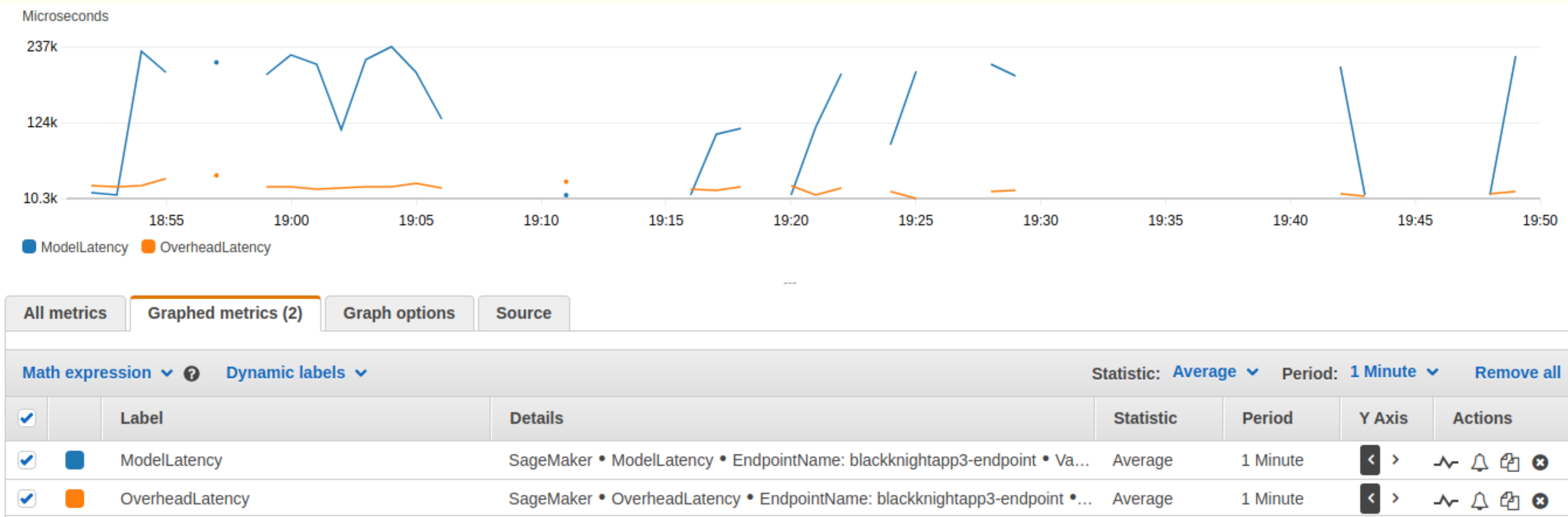
Latencies



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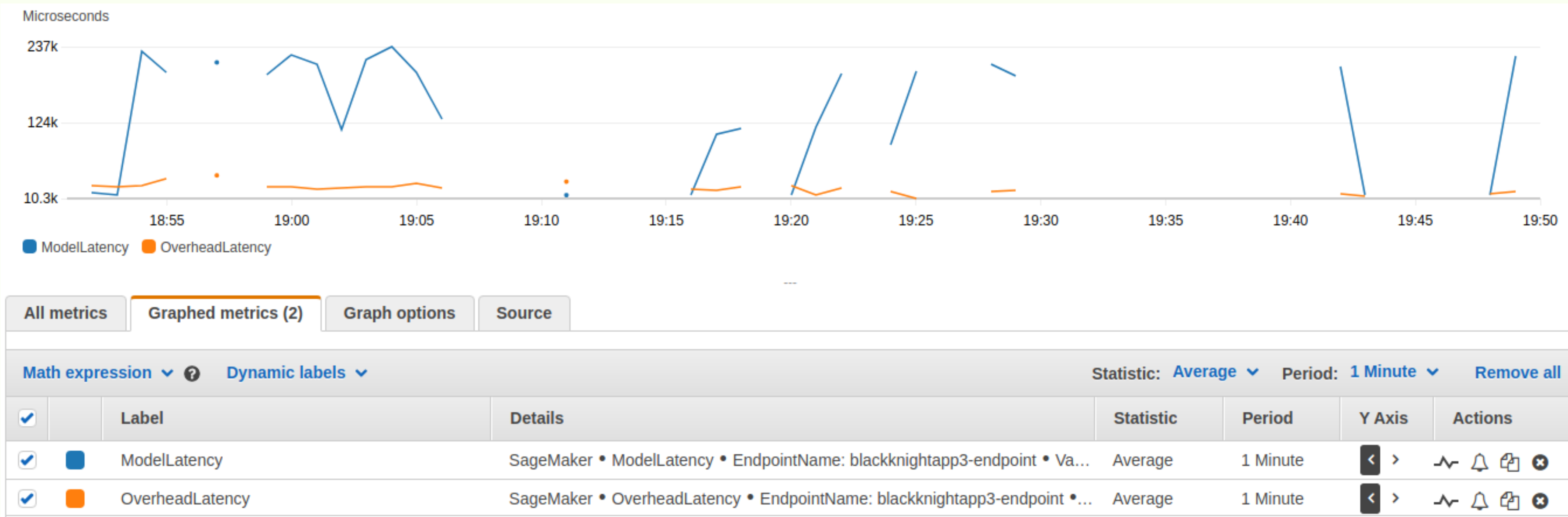

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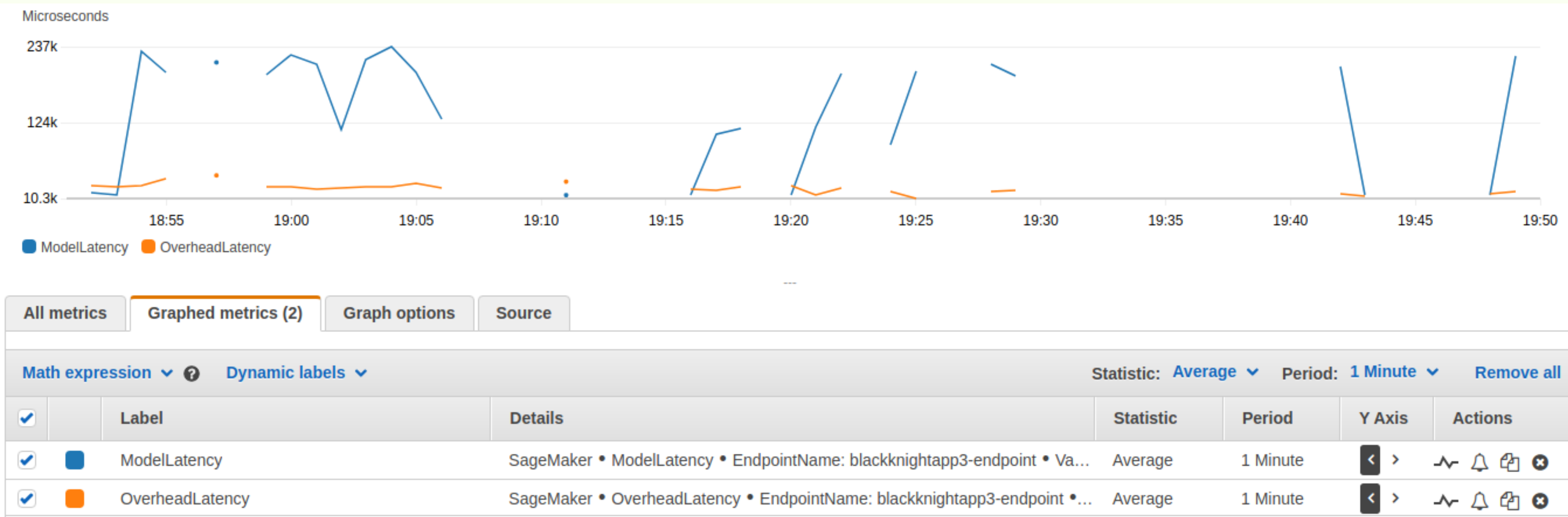

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- the Random Forest model has 250 estimators, with maximum depths of 250 – it's a little beast
- (the respective model sizes are 63 M and 273 M, and the shared TF-IDF vectorizer is 159 M)

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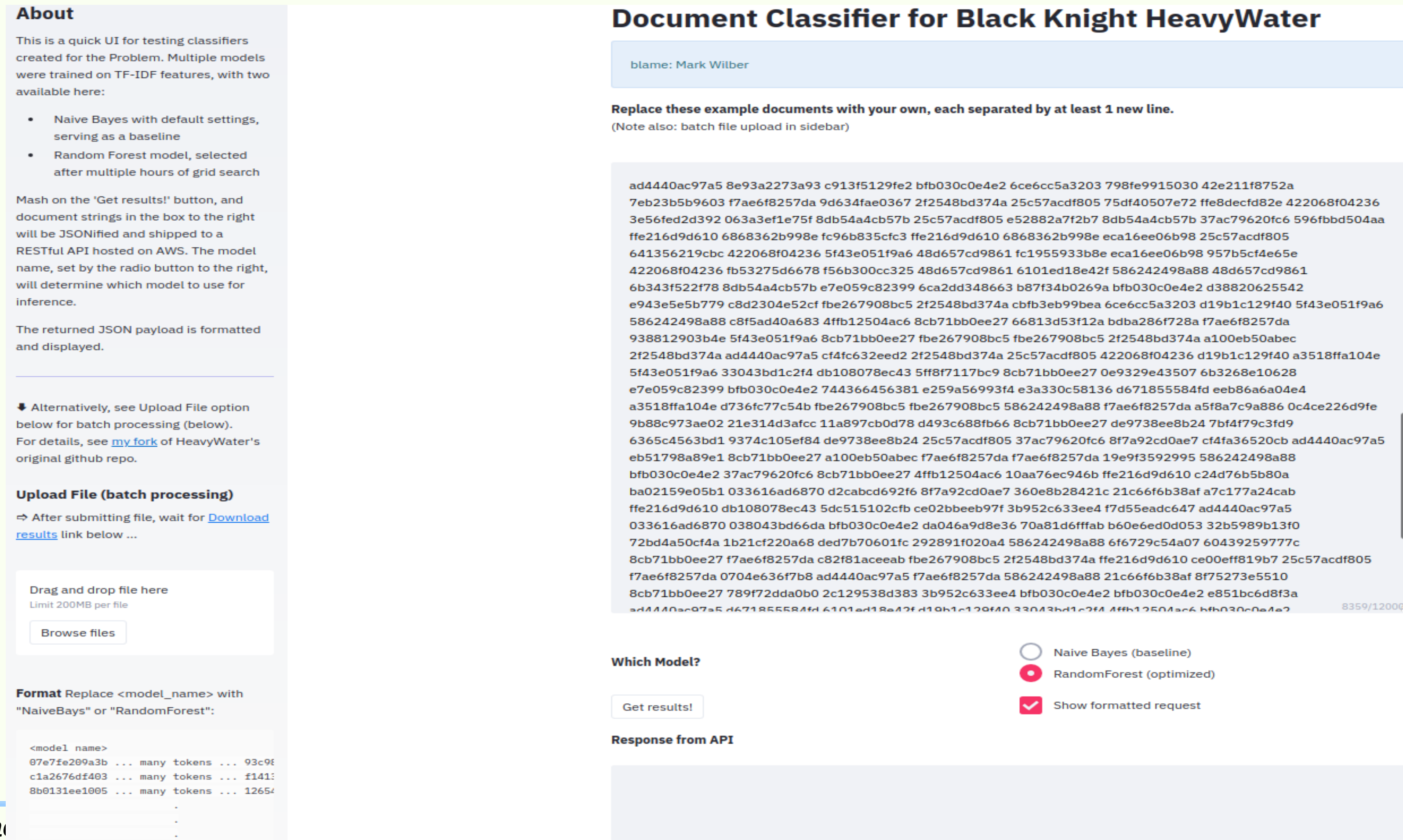

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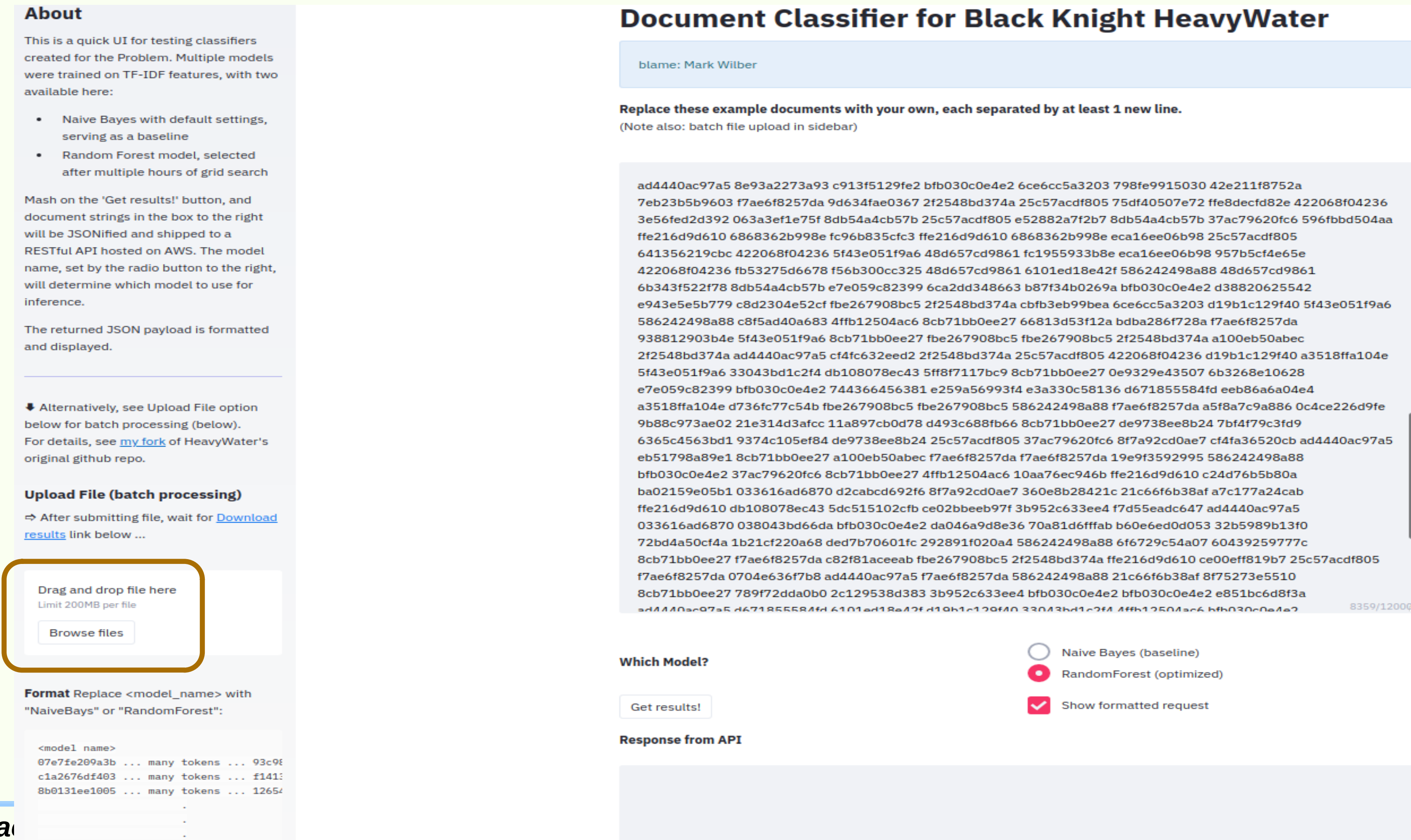

A 15-second demo

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    - sequence-based model (LSTM using sentence embeddings)

That’s all!