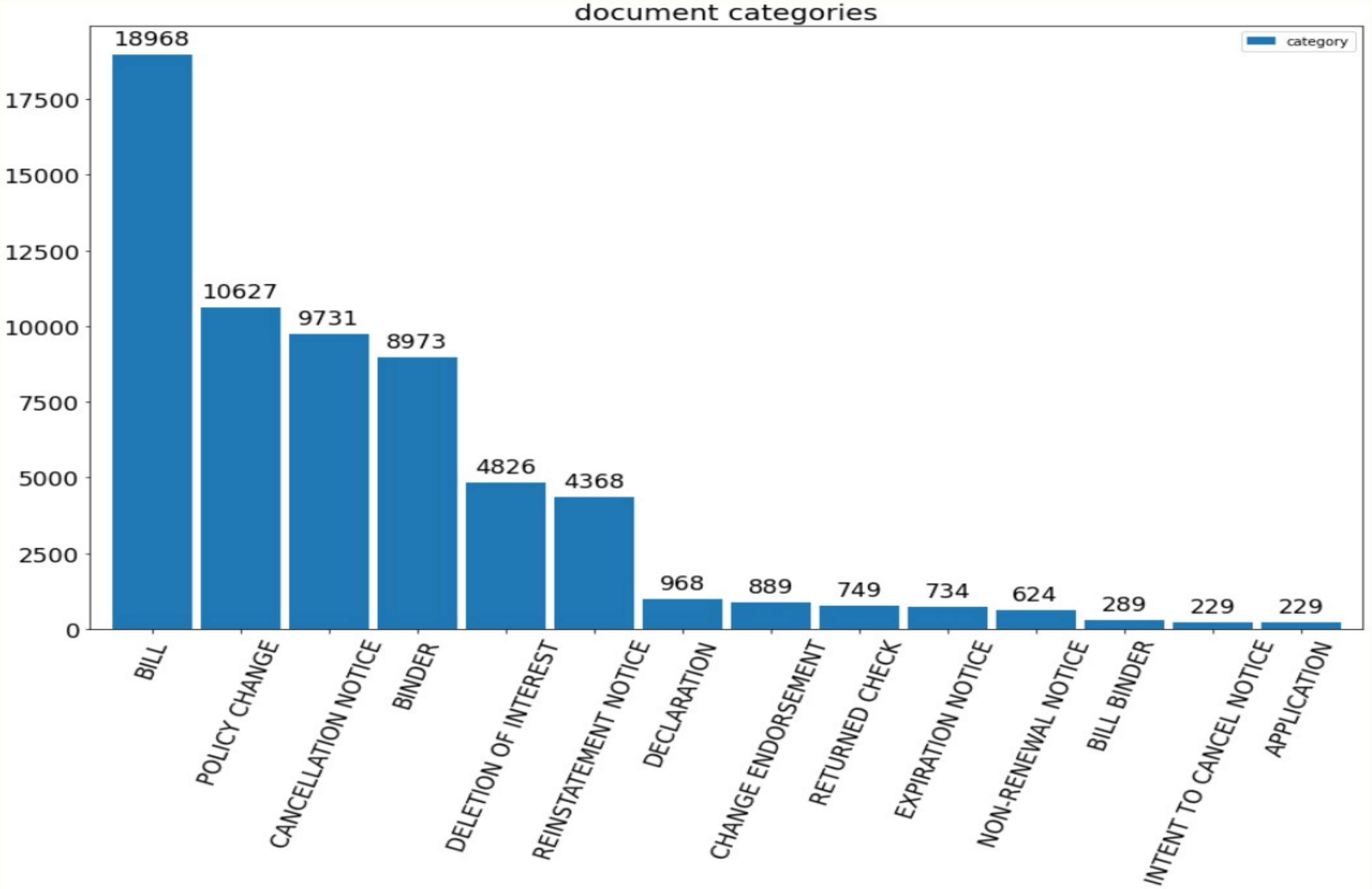
HeavyWater Machine Learning Problem

Solution by Mark Wilber

What we are dealing with

- 62 K documents, 14 categories



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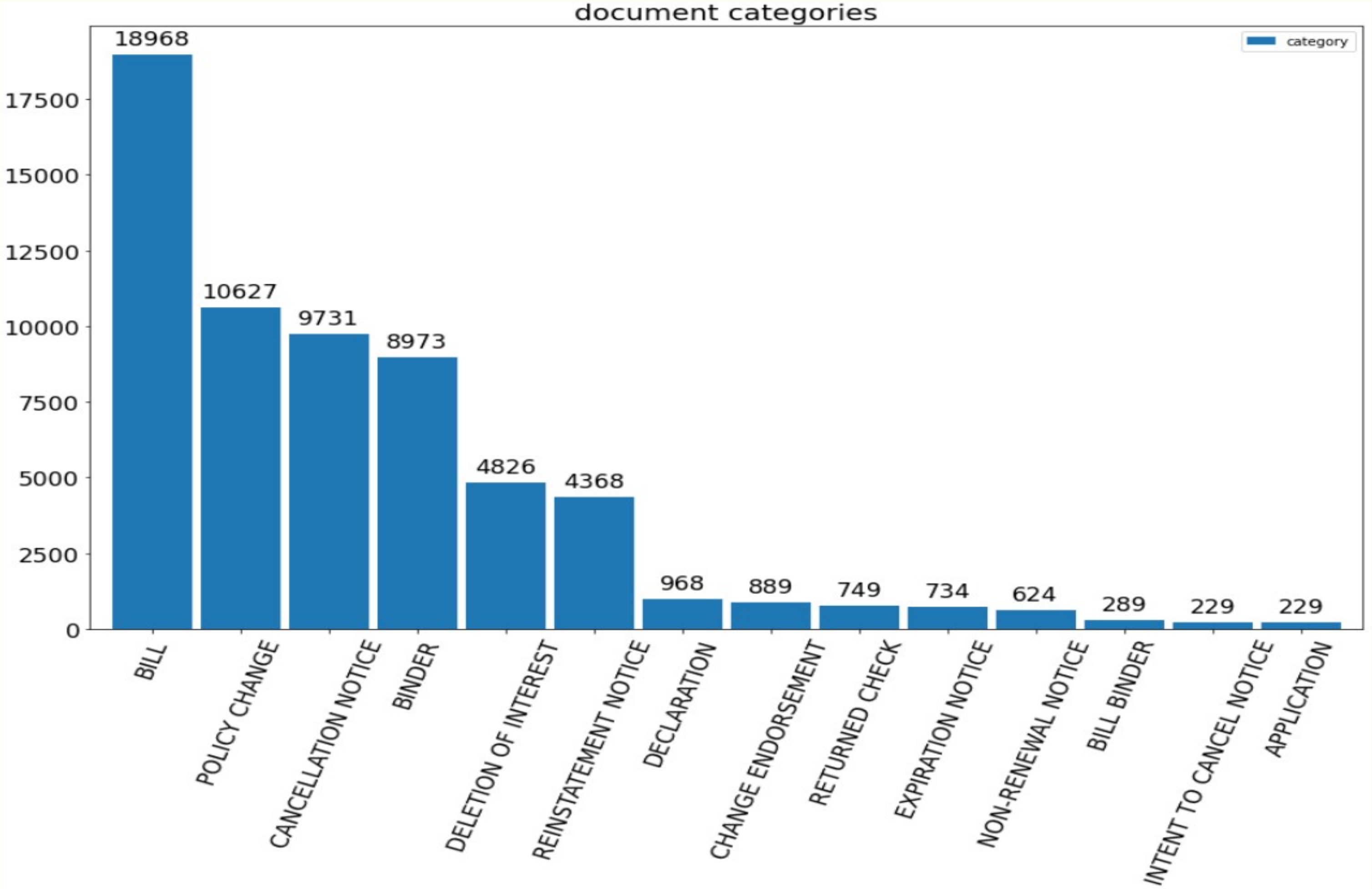
- 62 K documents, 14 categories
- unbalanced classes, spanning nearly 2 orders of magnitude



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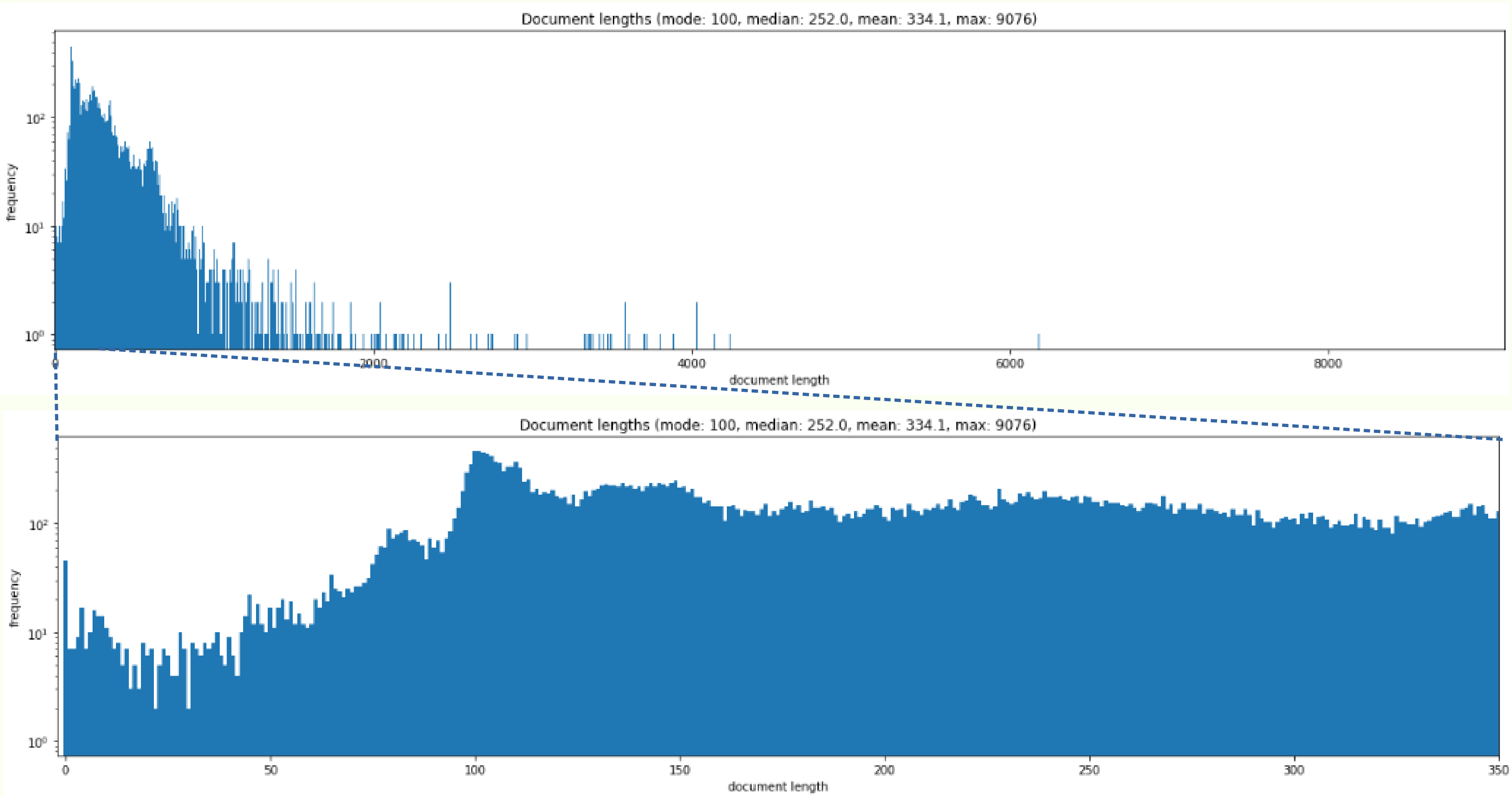
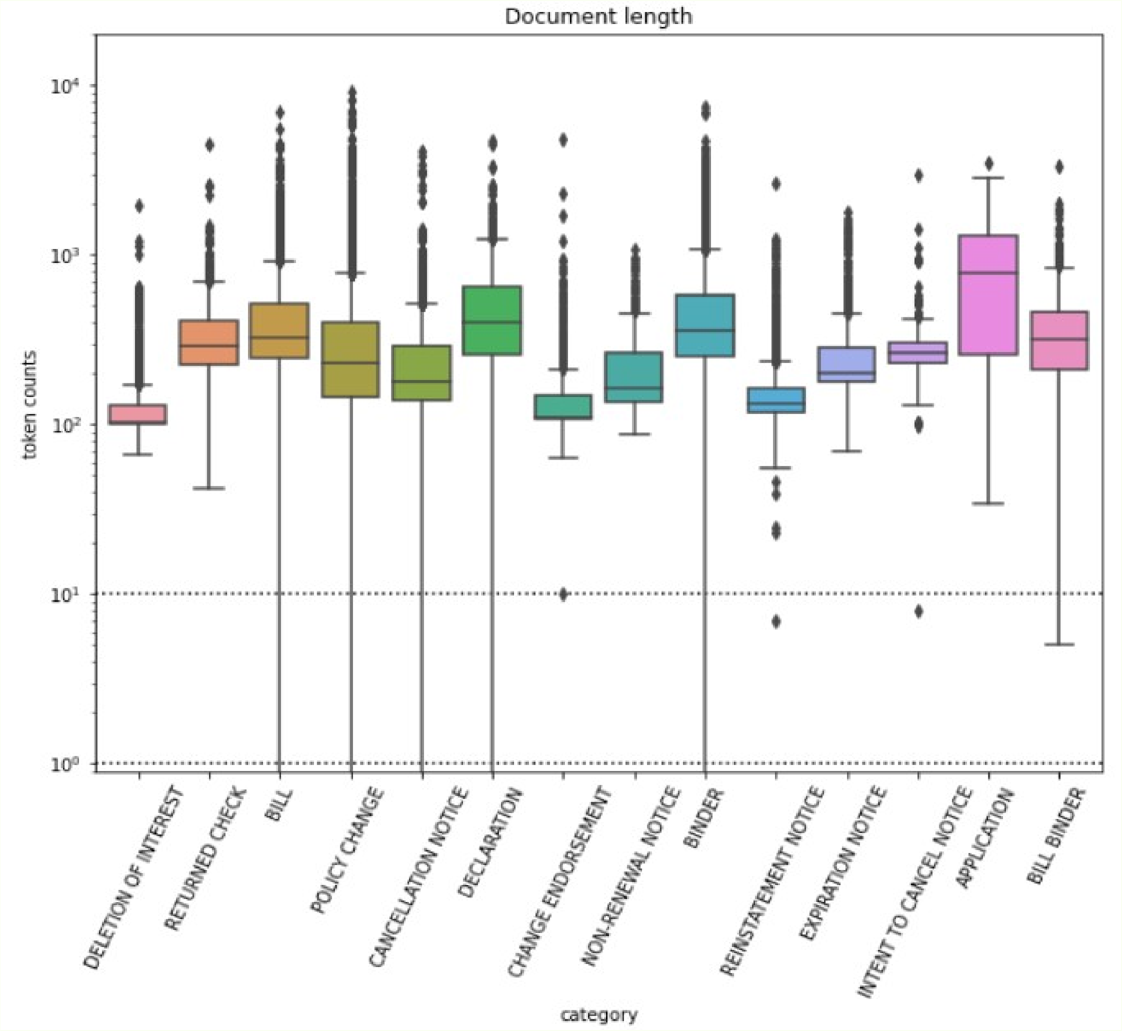
- document lengths spanning 0–9076 tokens (mode: 100, median: 252, mean: 334.1)



What we are dealing with

- 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!

What we are dealing with

- 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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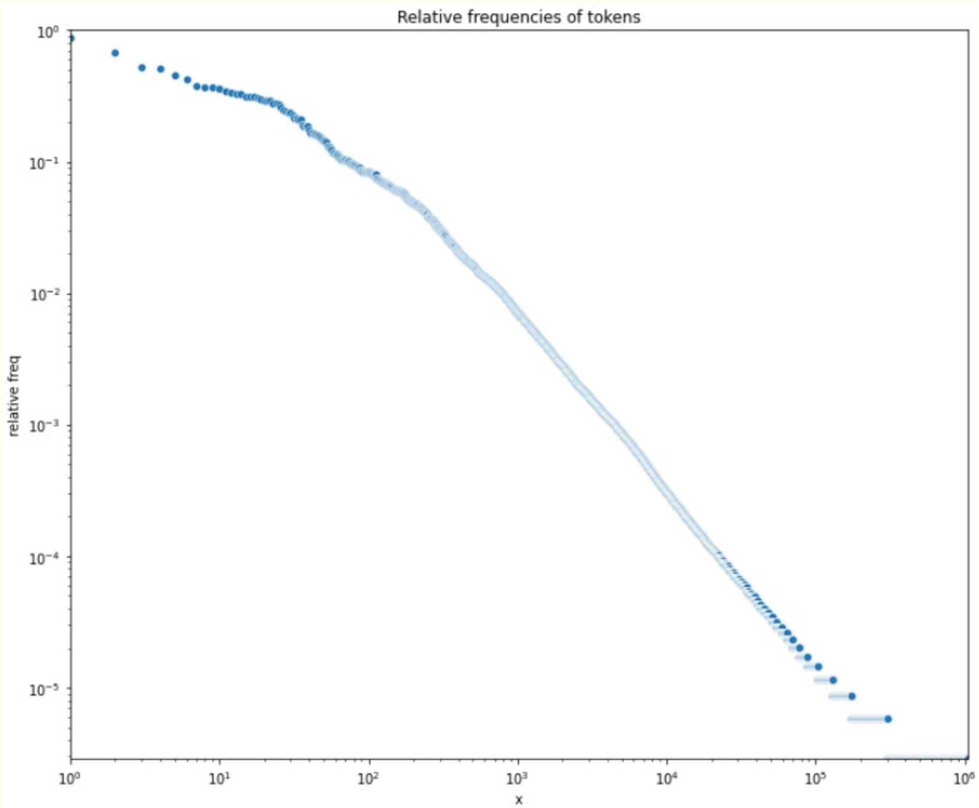

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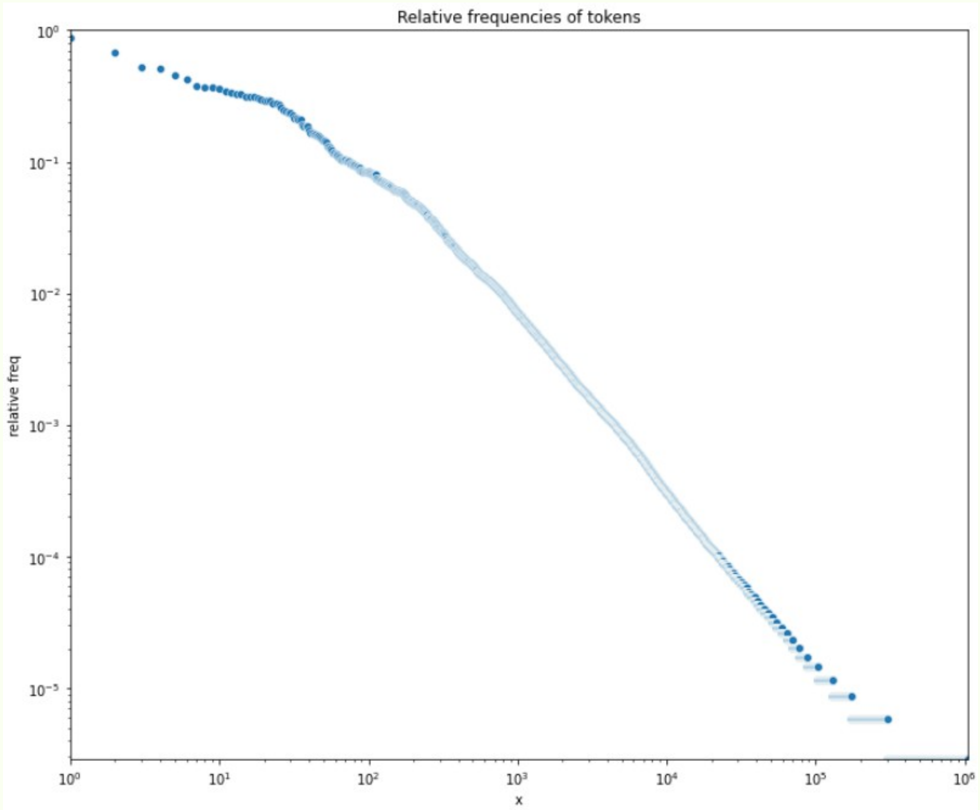

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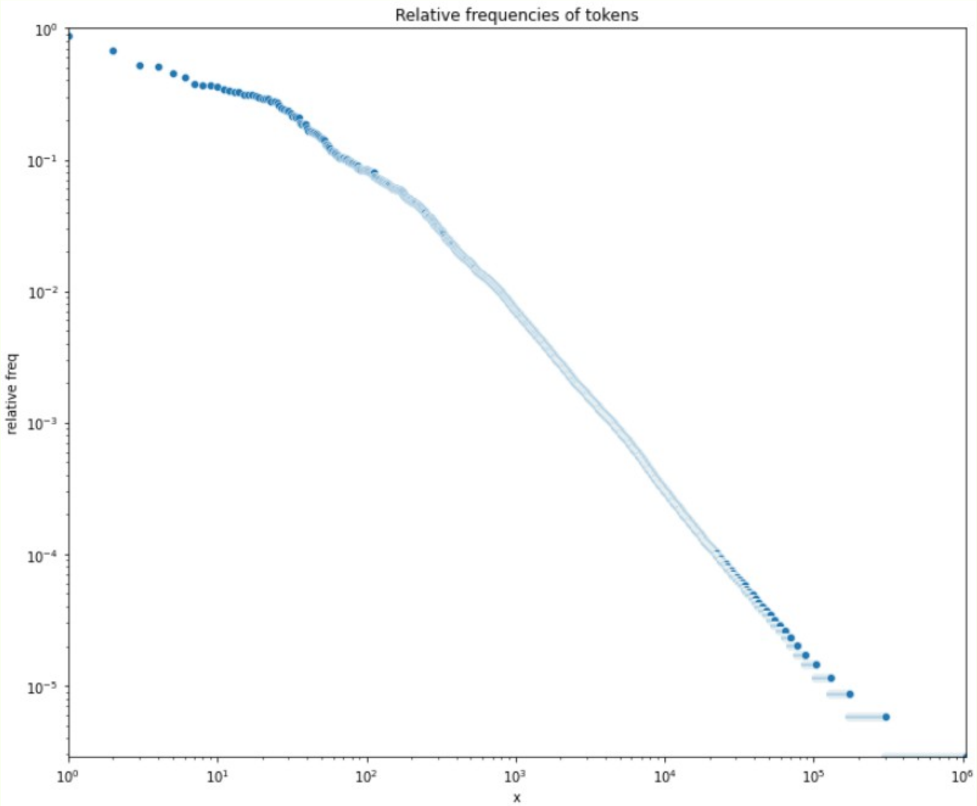

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⇨ *this corpus seems to be unusual ...*

Handling Data

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- test with `sklearn.feature_extraction.text.TfidfVectorizer` shows: `max_df=0.80` eliminates 9 tokens, but I can't guess what they are. *Probably* stop words ...
- 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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Complement Naive Bayes

- default settings for baseline
- followed by grid search
- best with `alpha=0.0139 and norm=False` yielded substantial improvements
  ⇨ model *3 × larger*

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- optimized model ⇨ best overall

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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
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Random Forest and XGBoost “identical” good results (may indicate limits of info in feature set)

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

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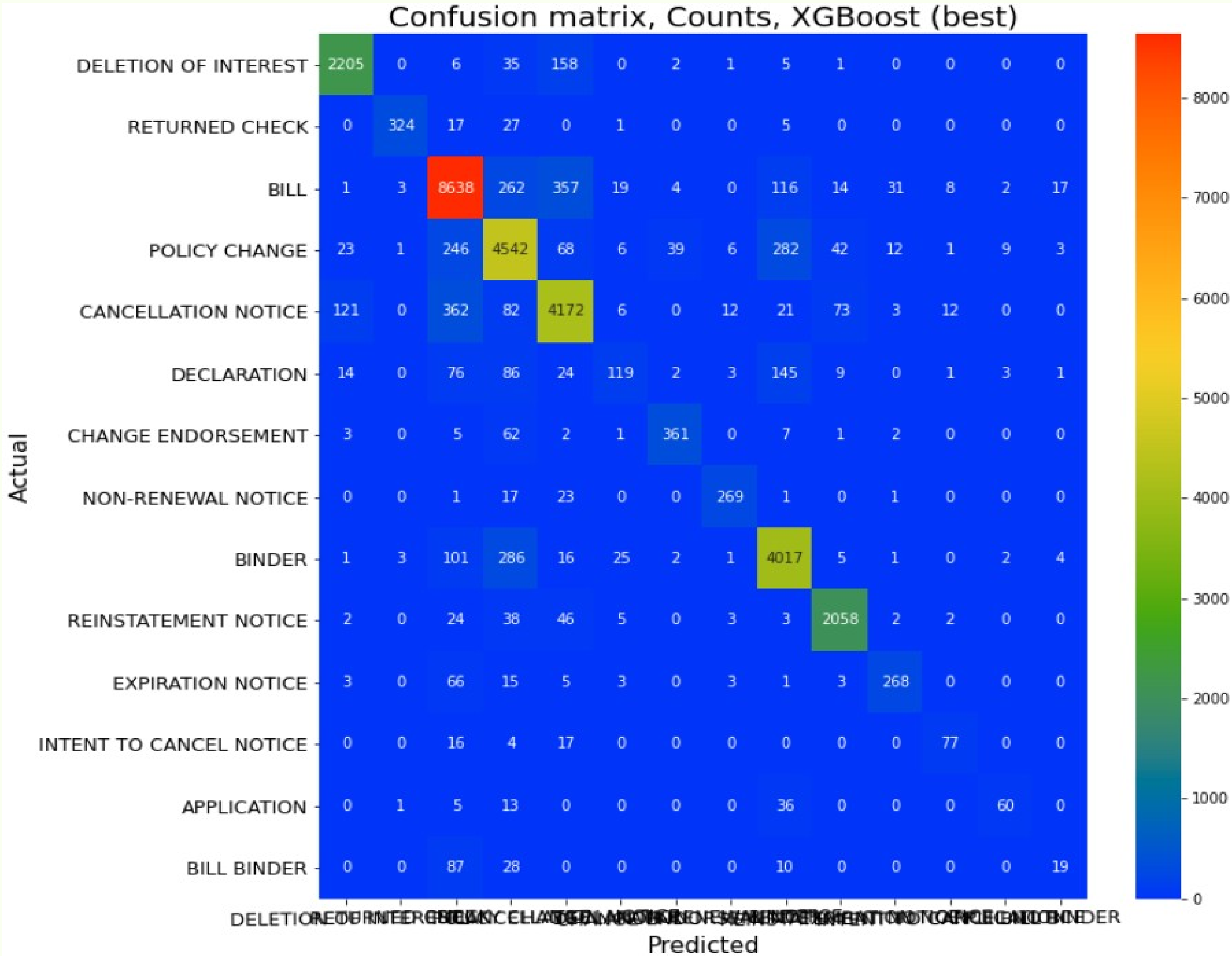

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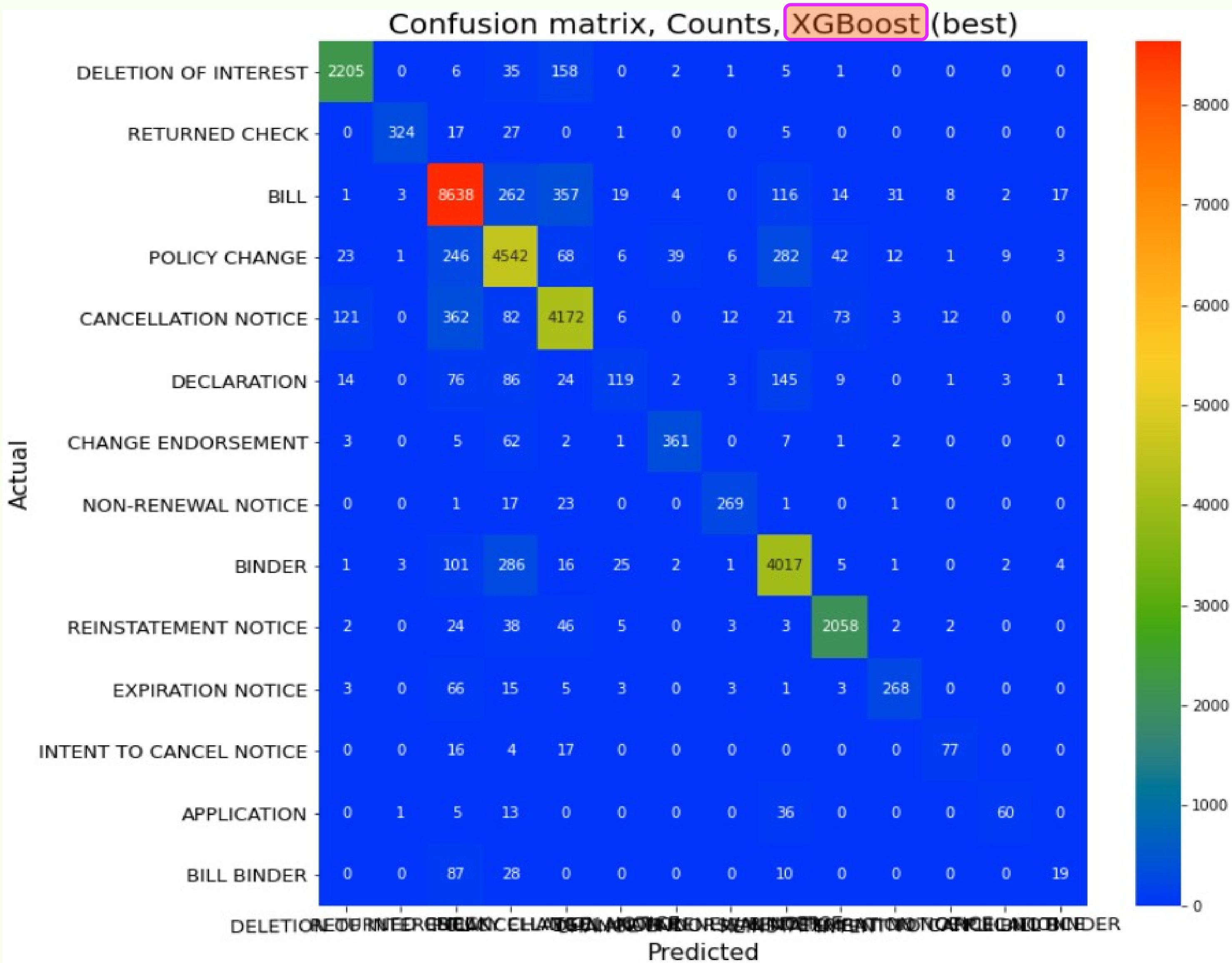

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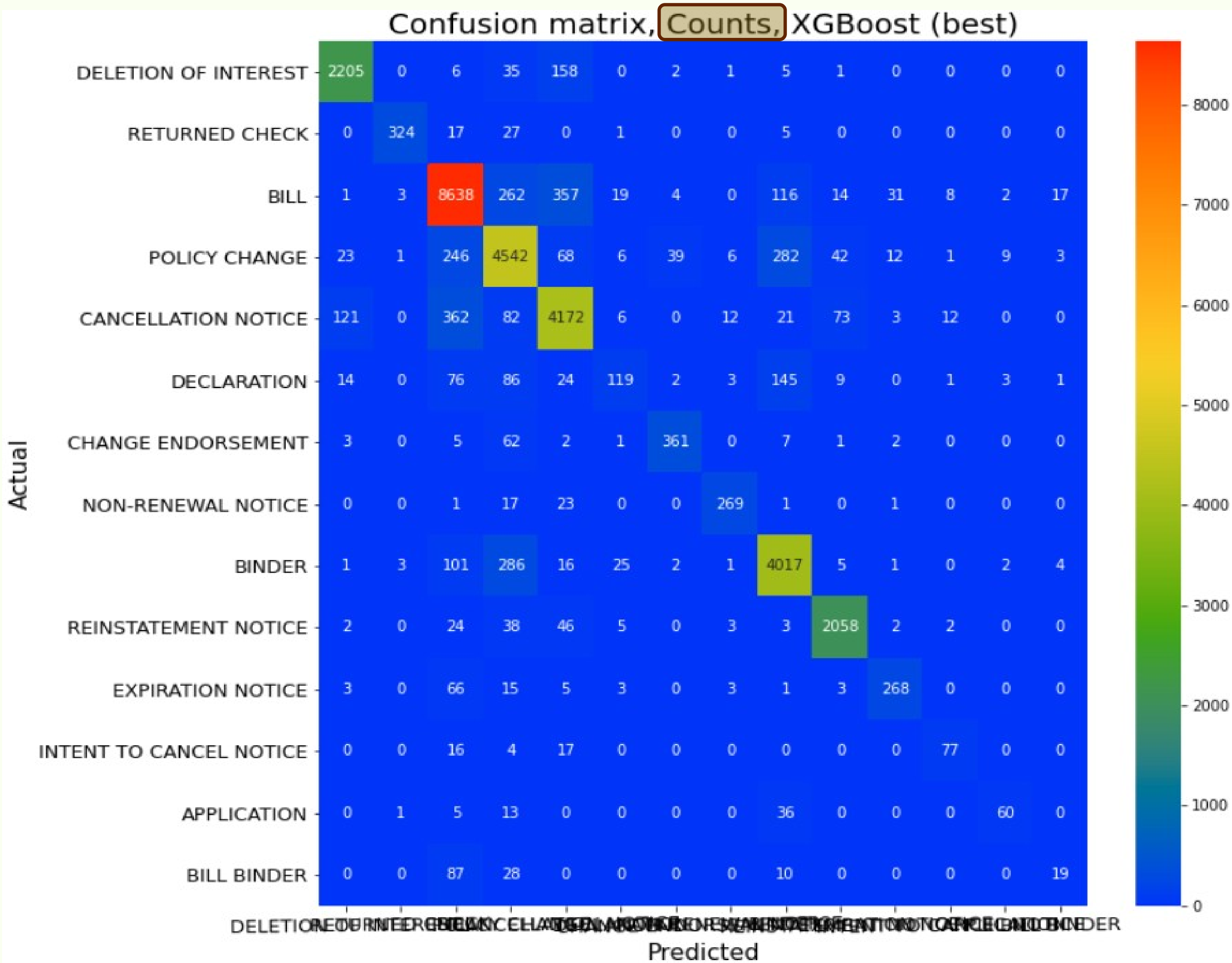

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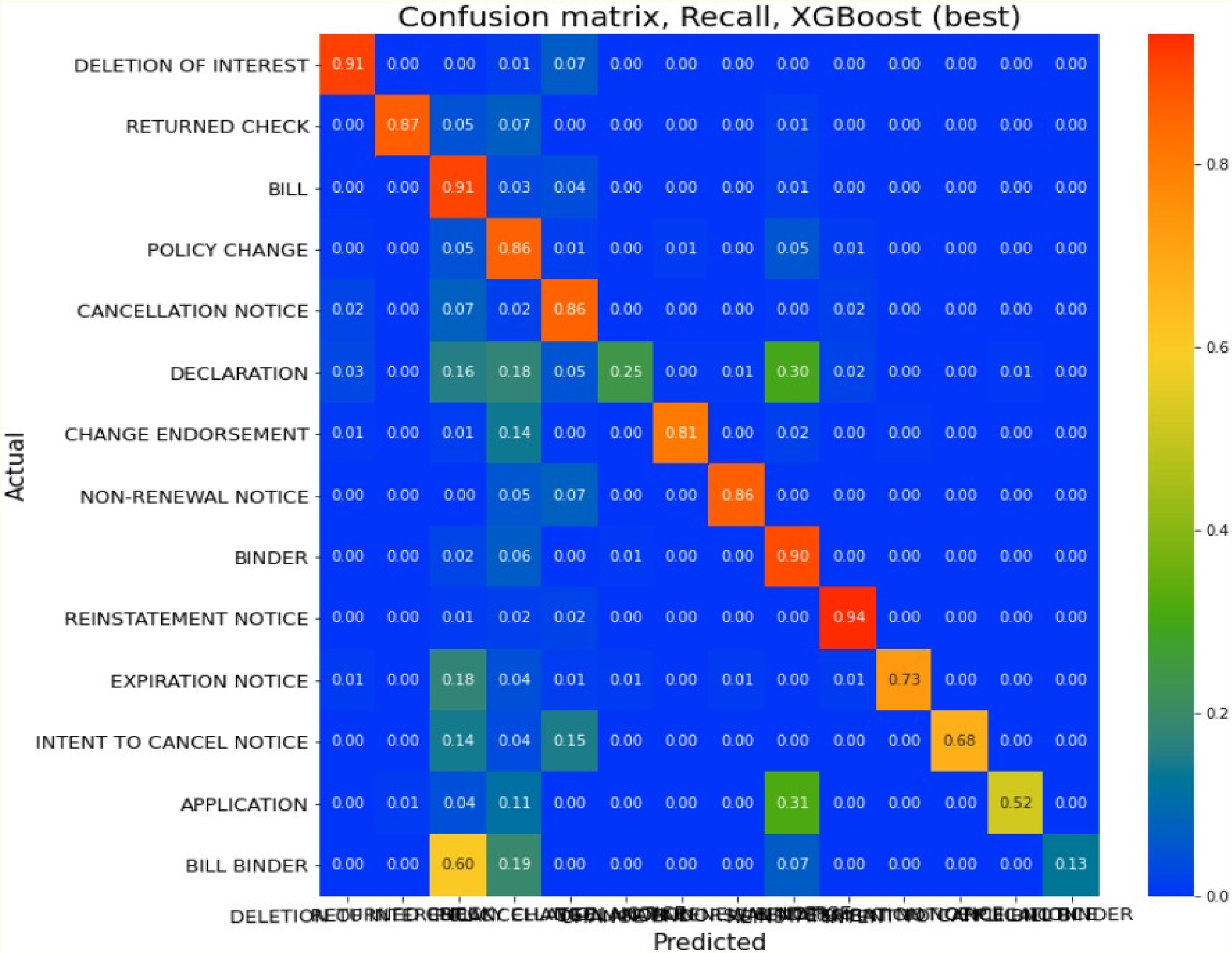

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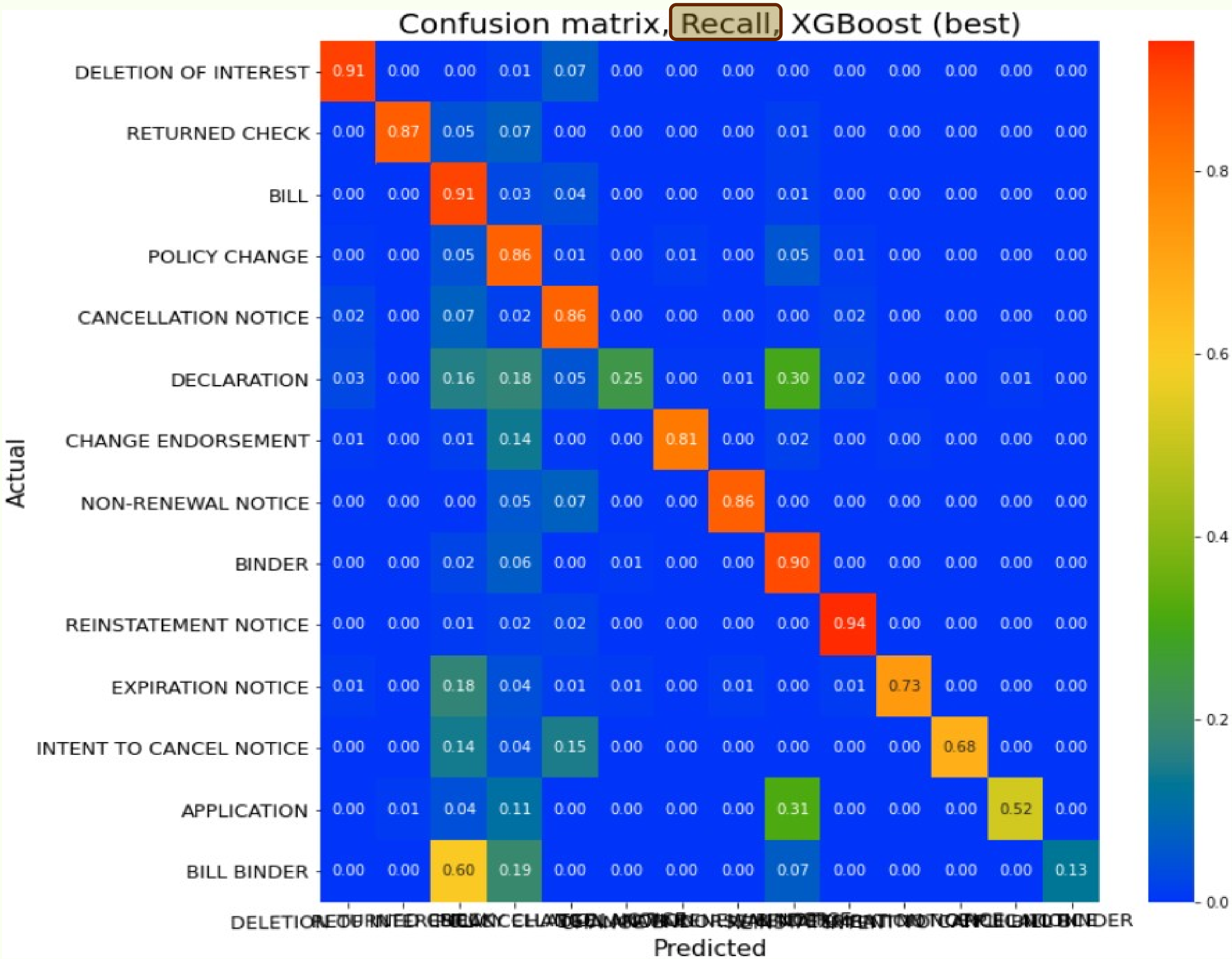

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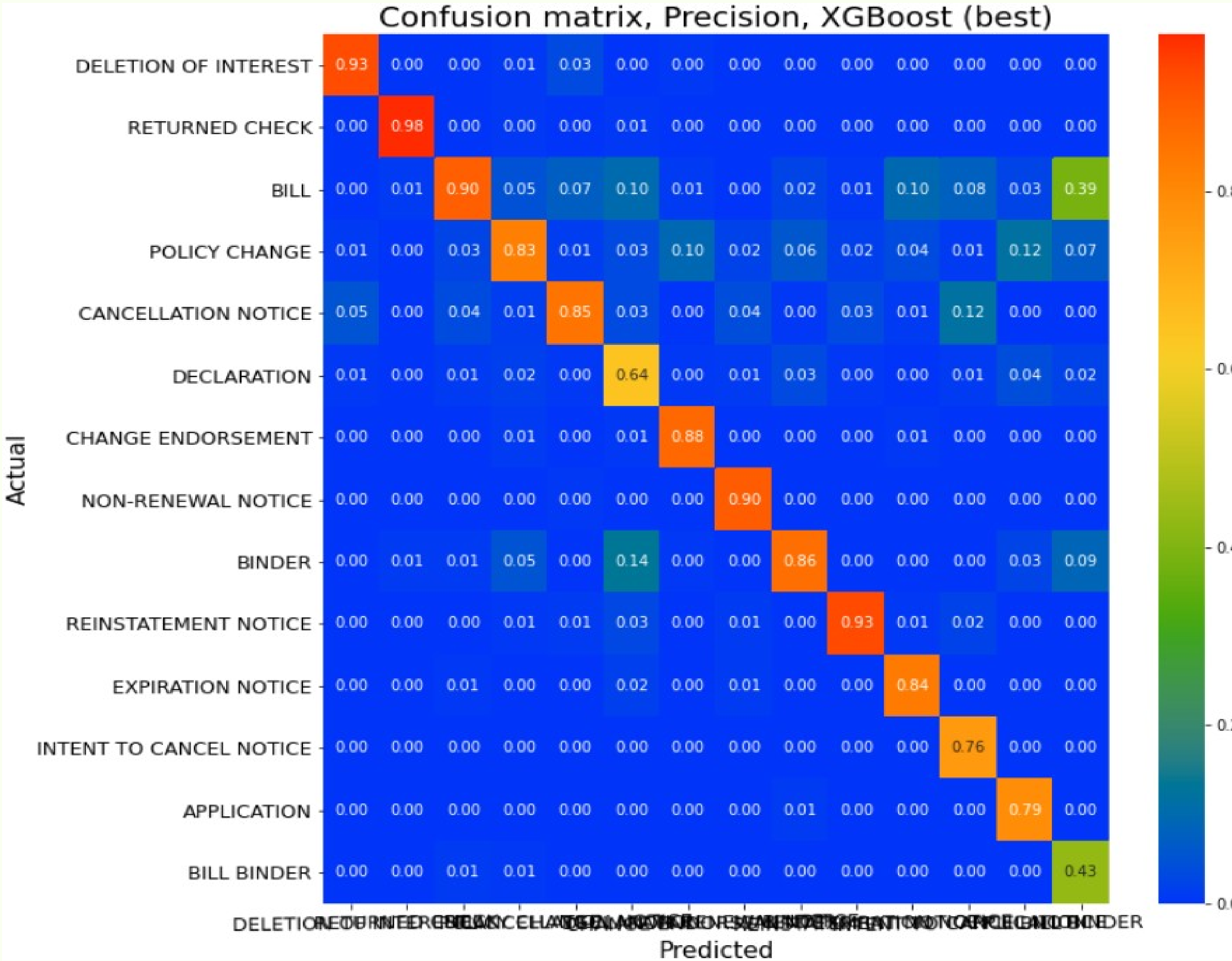

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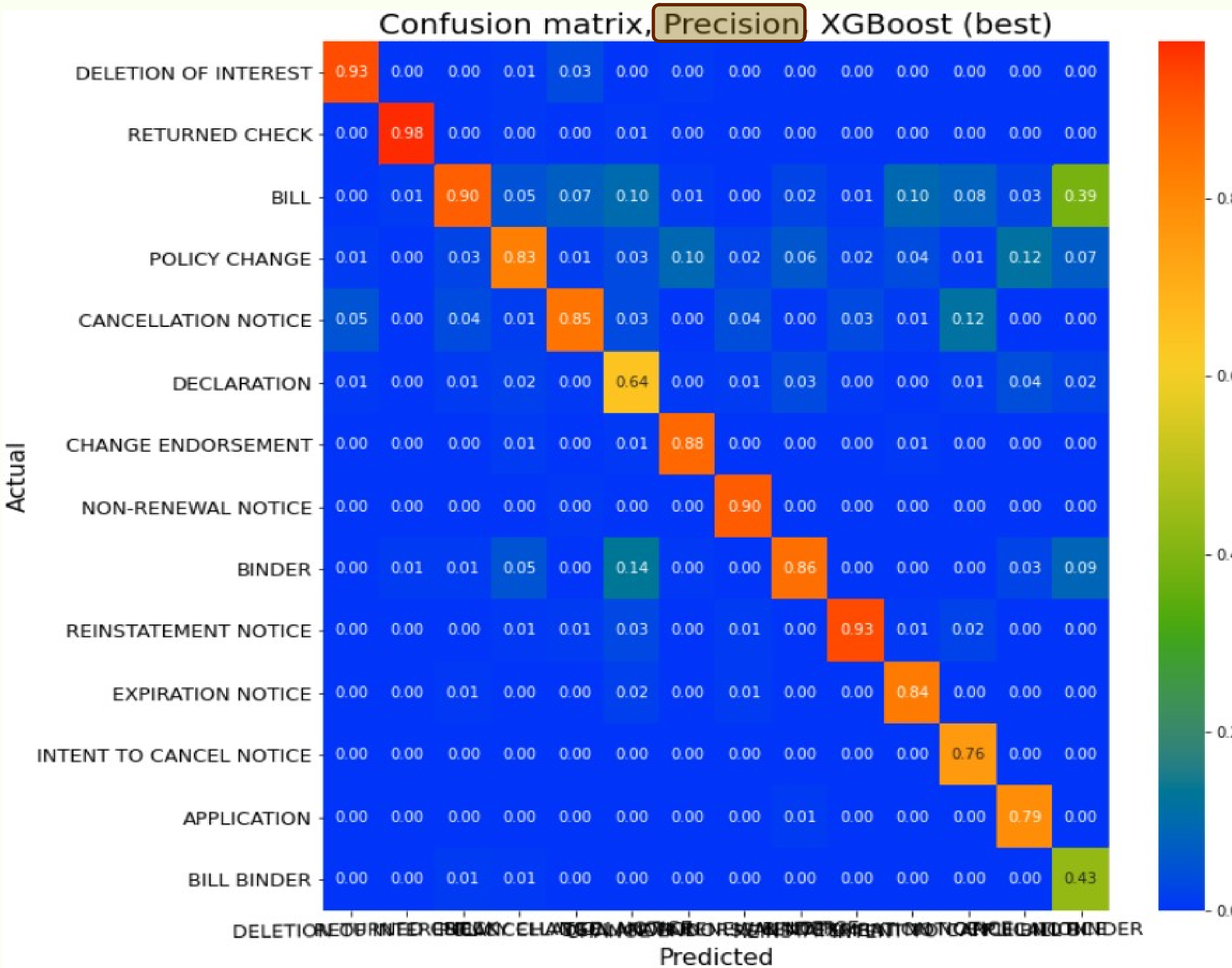

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Docker container

- `buildDockerImage.sh` for local testing

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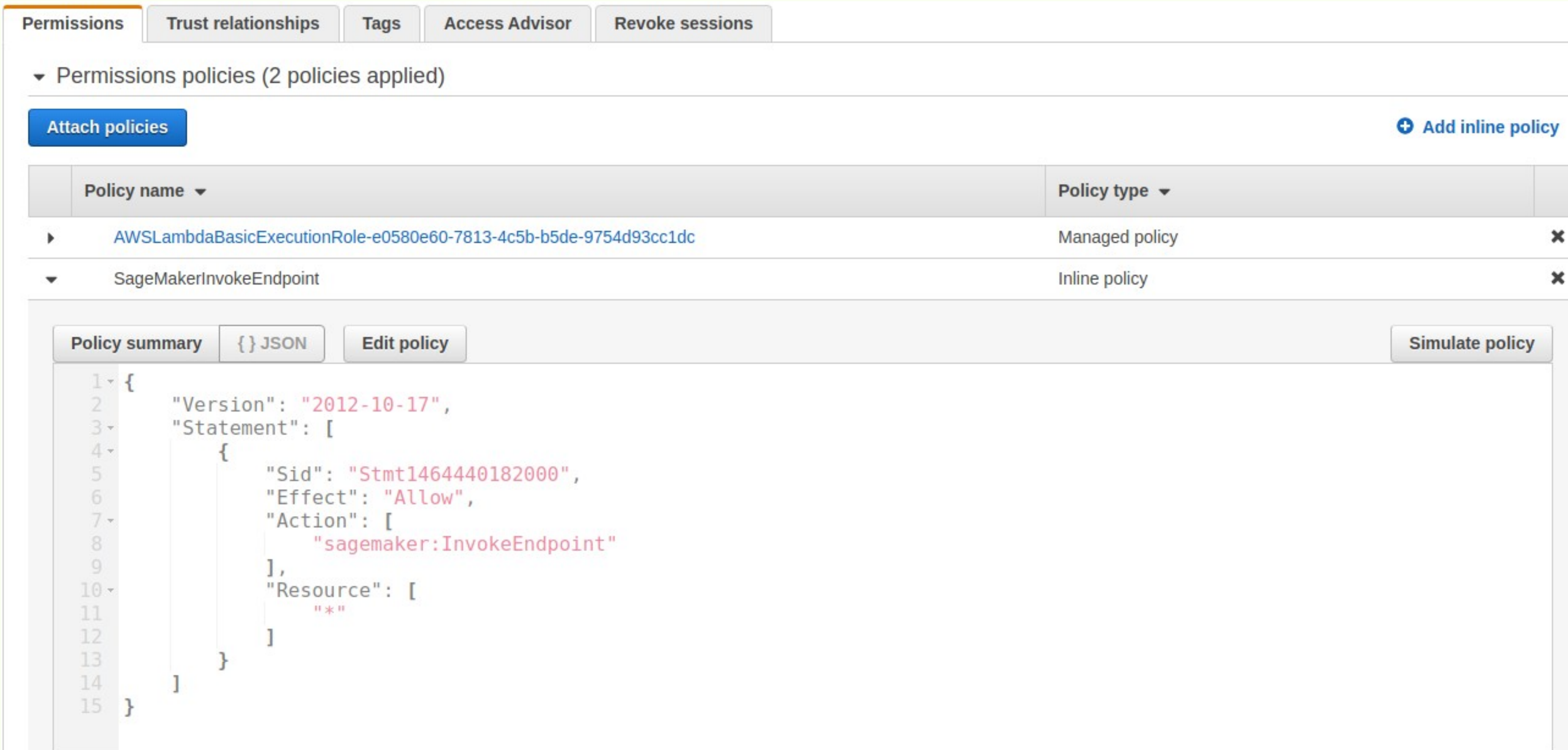

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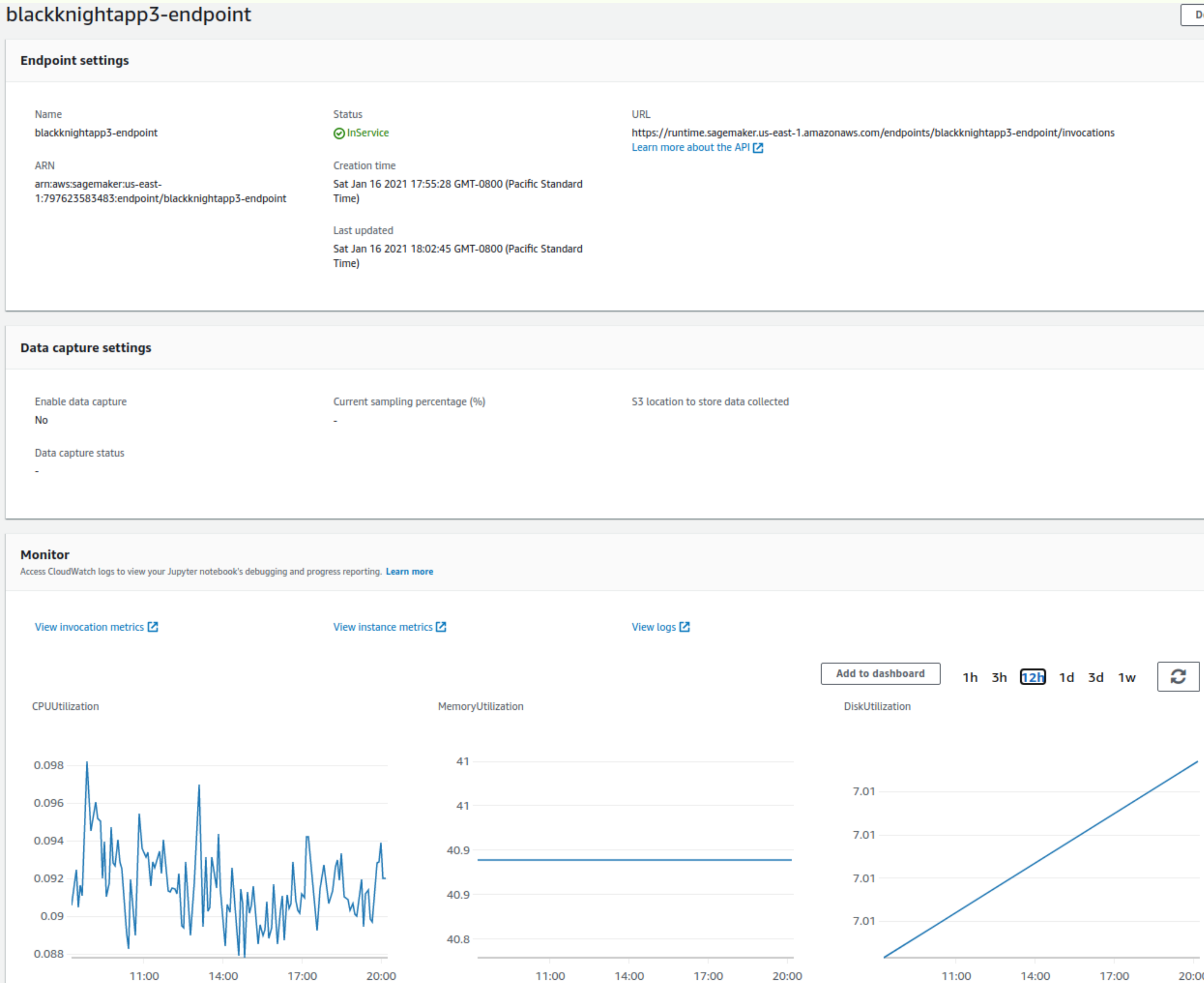

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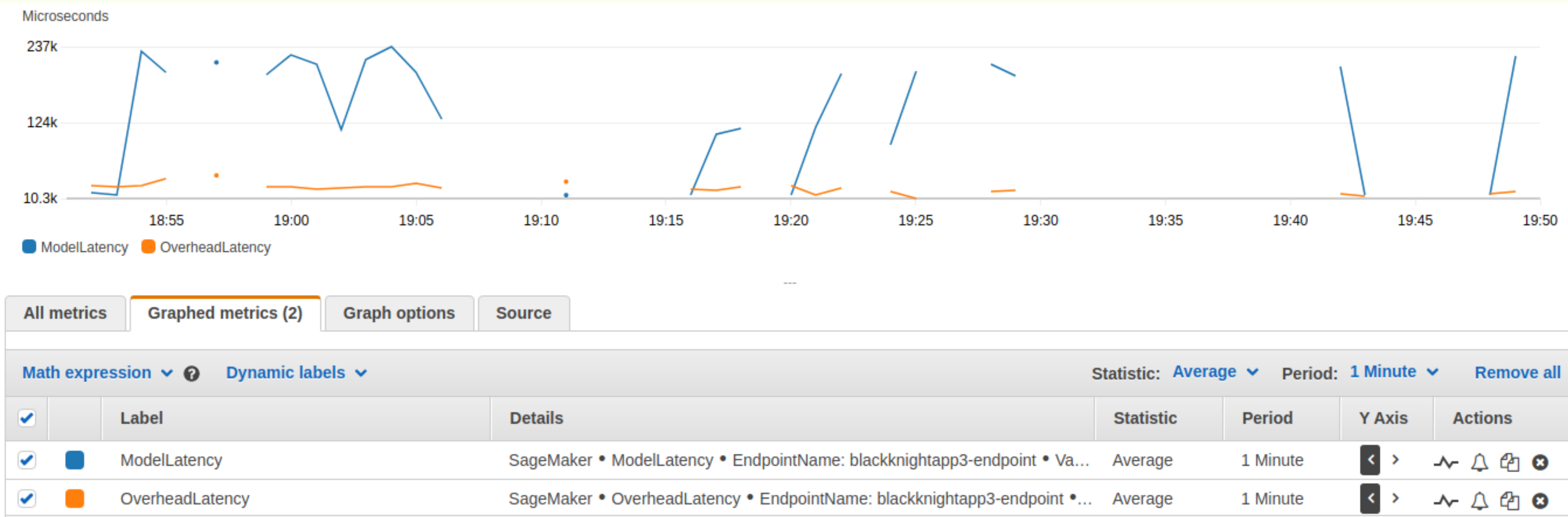
Latencies



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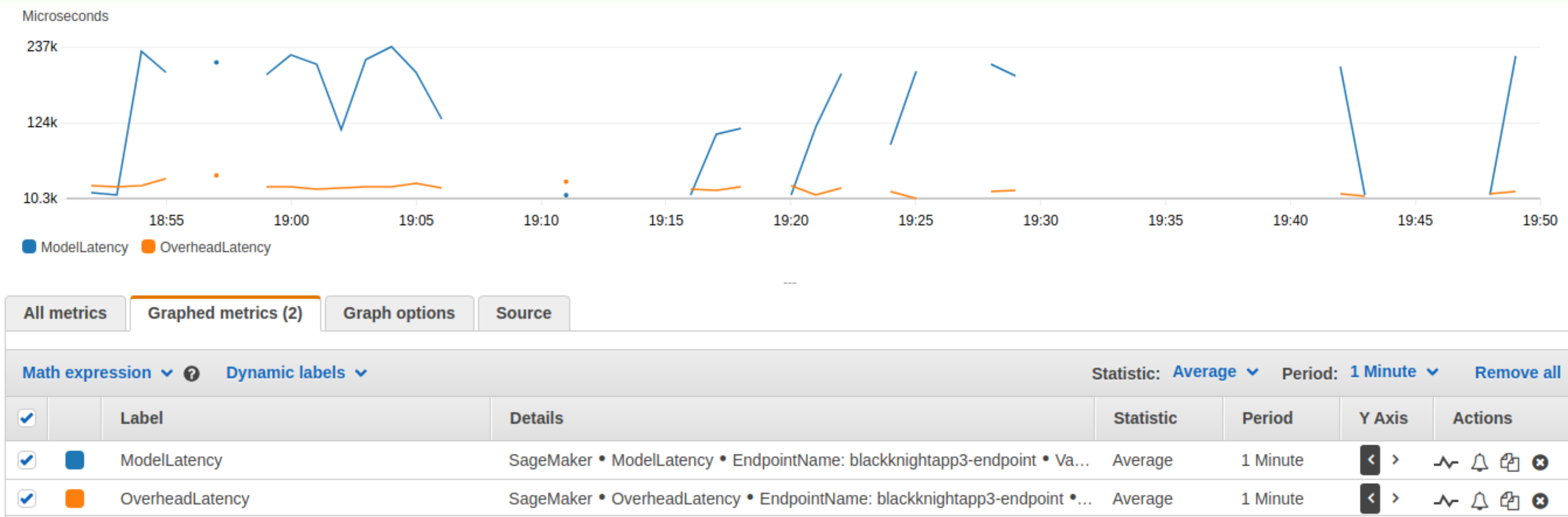

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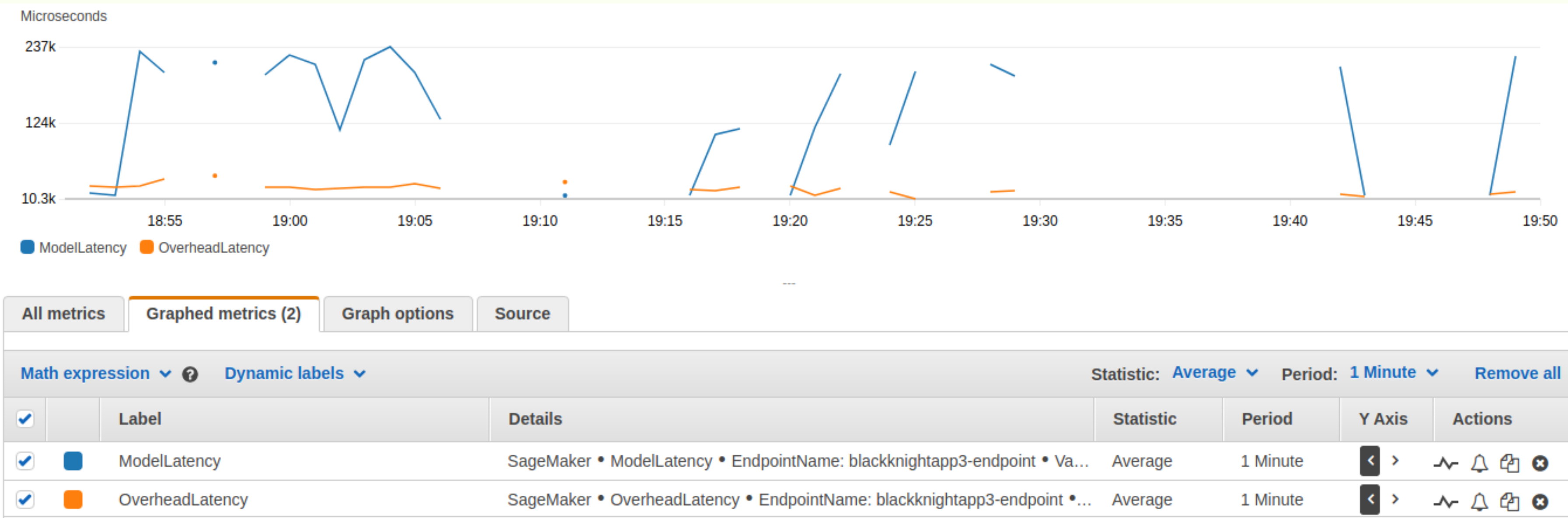

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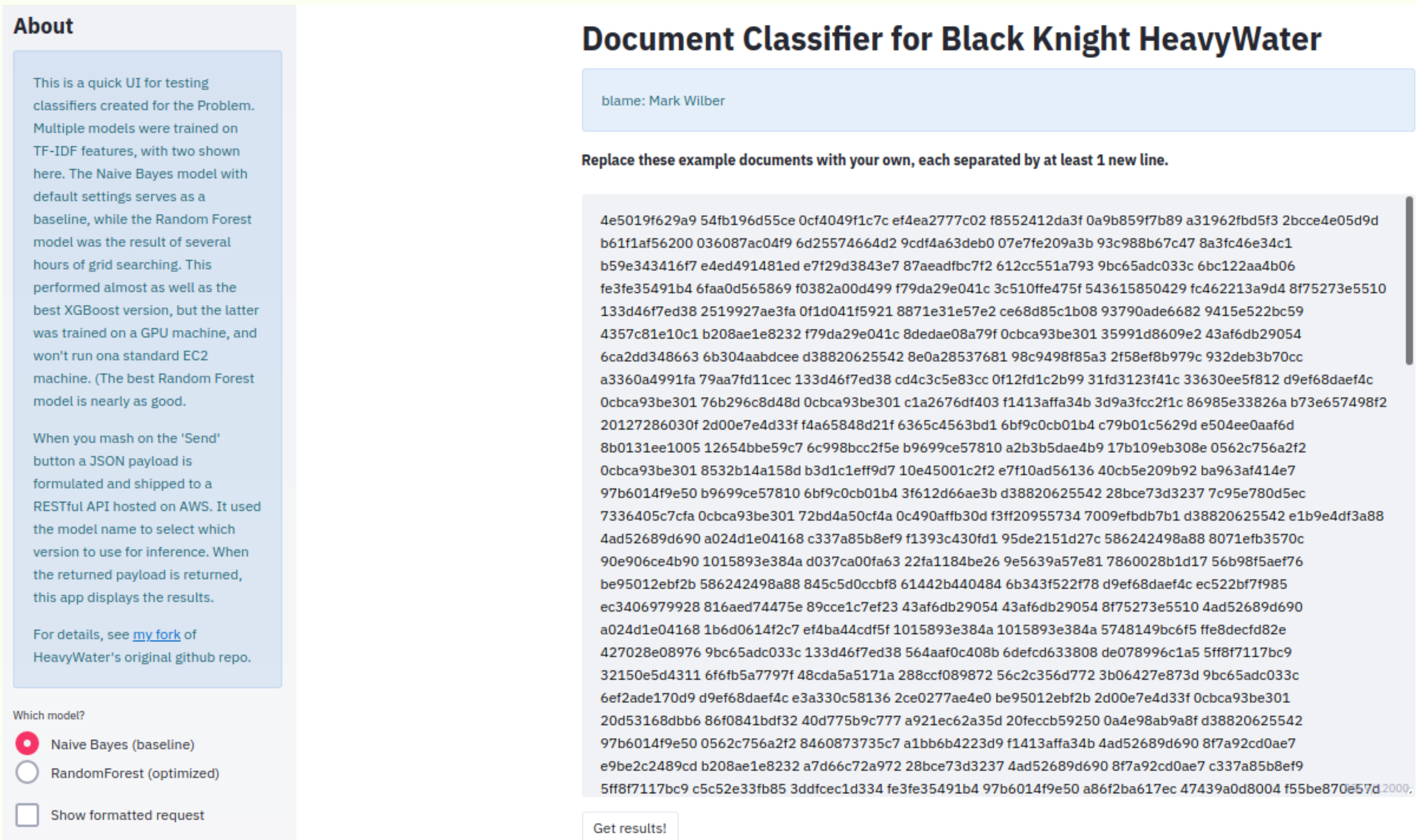

A 15-second demo

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    - sequence-based model (LSTM using sentence embeddings)

That’s all!